# A Study on Thai Word Segmentation and an Analysis of Brand Crisis as Its Application

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# *Abstract*

Chapter 1 introduces a Thai word segmentation problem and its role in an analysis of a brand crisis. Word boundary ambiguity has been a challenge in Thai language processing. Incorrect word segmentation may result in misleading interpretations. Chapter 2 explains Thai language fundamentals that are related to word segmentation. The chapter describes word formation, which is a sequential combination of words that form a new word. The roots of a compound word may have different meanings or can be interpreted differently from the word. Because of this difference, word segmentation may not produce a meaning that is similar to the meaning of the whole word, making the outcome ambiguous.

Chapter 3 proposes word segmentation rule and two post-processing algorithms to the existing machine-learning model, a Conditional Random Fields (CRF). The two proposed algorithms are word-merging and word-splitting algorithms. CRF is one of the most accurate word segmentation models among Thai word segmentation methods. The existing CRF-based word segmentation model was trained on Benchmark for Enhancing the Standard of Thai Language Processing (BEST2009) corpus developed by National Electronics and Computer Technology Center. The first problem is that the corpus does not address the compound word issue. In solving this problem, this study proposes changes to the original BEST2009 rule to prevent compound words with semantically relevant roots from being segmented and their meanings being altered. The rule of BEST2009 corpus stated that compound words with semantically relevant components should be segmented, but compound words with irrelevant components should not be segmented. The proposed rule stated that compound words, regardless of their relations to their components, should not be segmented. Based on this changed rule, this study proposed a dictionary-based algorithm that merges compound words after the CRF-based word segmentation. The algorithm merges any sequential combination of segmented words if the combined words are in a dictionary.

In the evaluation of the word-merging algorithm, one native Thai speaker relabeled part of BEST2009 for testing. The relabeling was done according to the

proposed rule. The algorithm looks up its candidate words in three dictionaries – Wiktionary, LibThai, and LEXiTRON – and three named-entity dictionaries – BEST2009, LibThai, and GeoNames. The experiment consists of two conditions: condition (1) segments words using the CRF model alone, which is the method used in the previous study. The CRF model was trained using BEST2009 corpus, which was created based on the original BEST2009 rule. Condition (2) performs the word-merging algorithm after the CRF model segmented the words. The CRF model in condition (2) was also trained on the same BEST2009 corpus as in condition (1). However, the segmented words were later merged by the word-merging algorithm, which followed the proposed rule. Finally, the result of each condition was compared to the relabeled corpus to measure the accuracy. The evaluation result indicates that applying the algorithm to condition (2) improves the accuracy by 12.14 percent on the test using the relabeled corpus. The evaluation of all combinations of the six dictionaries indicates a moderately positive correlation between the number of dictionaries and accuracy.

The second problem this study address is a sentence boundary ambiguity. A CRF model is among the most accurate sentence segmentation methods. The CRF model uses part-of-speech (POS) tags to increase its accuracy of sentence segmentation. The limitation is that POS-tagging algorithms cannot recognize some of the words due to limited training corpus. As a result, these words do not have POS tags, thus decreasing the accuracy of the CRF model. The proposed POS-based word-splitting algorithm in this study addresses this problem by splitting words that do not have POS tags if all of the segmented words can be tagged.

Since BEST2009 does not include POS tags, the word-splitting algorithm was instead tested against ORCHID corpus. ORCHID contains the POS tags, as well as word boundary and sentence boundary annotations necessary for the evaluation. Before the experiment, a benchmark had been established by training the CRF-based sentence segmentation model using ORCHID corpus with word and sentence annotations and POS tags. The CRF model was then tested using ORCHID corpus with only word annotations and POS tags. The experiment consists of two conditions: condition (1) segments words with the CRF model alone, which is the existing method, while condition (2) performs the proposed word-splitting algorithm after the CRF-based word segmentation. The result shows that the word-splitting algorithm in condition (2) tagged 1.39 percent more POS and was able to recover the average F1-score of sentence segmentation by 3.58 percent in relation to the loss margin. The recovery percentage was computed from the improvement of the F1-score from condition (1) to condition (2) divided by the loss of F1-score from the benchmark to condition (1).

The applications of the proposed algorithms were evaluated in three language processing tasks: Thai-to-English translation, summarization, and topic extraction. For the Thai-to-English translation, the proposed method looks for words that are not in dictionaries. These unrecognizable words are split if any parts of them can be found in the dictionaries. Finally, the method applies the word-merging algorithm to the text. This study hypothesized that the proposed method would repair incorrectly segmented words. The test corpus includes 50 Thai and English abstracts from journal articles. In condition (1) of the experiment, the words in the Thai abstracts were segmented by the CRF model. In condition (2), the segmented texts were split and merged. All Thai abstracts were fed into a machine translation model created in this study and Google Translate. The English translations were compared to their human-translated references using Recall-Oriented Understudy for Gisting Evaluation (ROUGE) metrics. The test using Google Translate indicates an improvement in condition (2) over condition (1): ROUGE-1 = 1.12 percent, ROUGE-2 = 1.34 percent, and ROUGE-L = 1.24 percent.

For summarization, a TextRank summarization algorithm decides which sentences are the most important and should be in a summary. With inaccurate sentence segmentation, parts of important sentences may be omitted, while a segment of their less-important neighbors may be included. This study hypothesized that utilizing the word-splitting algorithm would improve sentence segmentation, which would eventually improve summarization. In the summarization experiment, the test corpus was 50 online articles across different topics, summarized by one native Thai speaker. In condition (1), the articles were segmented using the CRF model before being summarized. In condition (2), the segmented words were split before the summarization. The result indicates improvement in in condition (2) over condition (1): ROUGE-1 = 2.41 percent, ROUGE-2 = 2.08 percent, and ROUGE-L = 1.70 percent.

The problem with a topic extraction in Thai is that the segmented topic keywords with altered meaning can mislead human interpretation. This study hypothesized that by merging compound words, preserving their original meaning, would make the interpretation more accurate. The topic extraction model was evaluated using 2,000 tweets, half of which were related to flooding and the rest were related to traffic. Both corpora were fed into the Latent Dirichlet Allocation (LDA) and Hierarchical Dirichlet Process (HDP) topic extraction models. The words in the corpora were segmented by the CRF model, then merged. In the case of LDA, the result shows that 7.60 percent of topic keywords of the flood corpus and 10.00 percent of the keywords of the traffic corpus were merged. For HDP, the percentages were 23.60 and 16.00, respectively. The results show that the proposed methods can be used effectively in analyzing data obtained from social media. Hence, the following chapter explores the possibility of enhancing the proposed algorithms to be applied for social media analysis.

The results of the topic extraction showed that the proposed methods could be applied to social media analysis. Hence, Chapter 4 utilizes the proposed word-merging algorithm and the summarization method in order to examine whether this study can enhance analysis of a brand crisis in Thai social media. The analysis investigates the entertainment aspect of the crisis. The chapter proposes a conceptual framework that underlines a psychological process of the entertainment experience. The process begins with social media users, who are the audience, making a moral judgment of the brand and other involved parties based on five moral foundations. The foundations include care/harm, fairness/unfairness, loyalty/disloyalty, authority/subversion, and sanctity/degradation. This judgment then triggers their hedonic and non-hedonic entertainment experience. For the hedonic dimension, the audience develops an affective disposition, leading to anticipation and enjoyment, while the non-hedonic dimension involves reflective thoughts, reinforcement of moral self and appreciation.

The framework was validated using content analyses in three studies. The first study used an English moral foundations dictionary created by Graham, Haidt, and Nosek

(2009) to quantify moral foundations in Facebook comments related to brand crises. The study found evidence of moral judgment in all five moral domains. The second study extended the moral dictionary and found more topics of discussion related to the moral foundations. The third study summarized comments from Thai social media, then extracted moral words and validated their consistency with the English moral dictionaries. The study found that the public's moral judgment can be classified into five moral foundations. However, some of the dictionary's compound keywords were not found in the data which compound words were segmented. To solve this problem, the analysis was conducted in two conditions: condition (1) uses only the CRF model for word segmentation, and condition (2) merges compound words after the CRF-based word segmentation. The result shows that in condition (2), 12.47 percent more moral words were found in the data.

The chapter also demonstrates the possible application of the proposed word segmentation methods in analyzing the hedonic dimension. Its fourth study analyzed the dimension from the English Facebook comments. The study found three types of enjoyment in the comments: humor, satisfaction, and schadenfreude. This analysis can be conducted in Thai once a corpus is available to train a Thai sentiment analysis model, and the proposed word segmentation methods can be used for preparing data for the analysis in the future.

Lastly, Chapter 5 discusses the results of the word segmentation study, as well as the brand crisis study, including limitations of both studies. The chapter concludes that the proposed algorithms improve Thai language processing and facilitate human interpretation in the study of a brand crisis in social media.

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# Chapter 1

# Introduction

## 1.1 Thai Word Segmentation

Processing languages without word boundary delimiters, such as Thai, require word tokenization. Failing to chunk precisely may result in misleading interpretations. The ambiguity of a compound word, also called a compositional word, contributes to the problem. In word formation, a sequential combination of words forms a new word with a different meaning, grammatical property or communication role; the reverse process, word segmentation, may or may not produce a meaning that is similar to the meaning of the initially whole word, making the outcome ambiguous. For example, 'นักร้อง' |nag rong| (singer), when chunked, becomes 'นัก' |nag| (much) and 'ร้อง' |rong| (cry).

Early word chunking methods evolved around the use of dictionary. Longest matching (Poowarawan, 1986), a simple greedy algorithm, finds and separates, from the beginning of a sentence, the longest recognizable word, then moves to the next one. The more sophisticated Maximum matching (Rarunrom, 1991) chooses, from possible segmentation choices, one that contains the fewest words. Later, with help of grammatical information, statistics came into play (A. Kawtrakul, Kumtanode, Jamjanya, & Jewriyavech, 1995; Pornprasertkul, 1994) Years of development seemed productive for dictionary-based methods, but there are limits to how far they can accomplish: the evolving language, particularly that no dictionary can always capture every word.

To progress beyond this limitation, a machine must learn. Machine-learning-based approaches began to involve the context in which words appear (Meknavin, Charoenpornsawat, & Kijsirikul, 1997). Decision tree and character clustering methods outperformed the dictionary-based (T. Theeramunkong, Sornlertlamvanich, Tanhermhong, & Chinnan, 2000; Thanaruk Theeramunkong & Usanavasin, 2001); and, above all, we have witnessed an outstanding performance of a CRF model (Haruechaiyasak & Kongyoung, 2009) across diverse contents. That said, as accurate as it gets, the compound word issue still exists and building another training corpus to tackle this problem would be economically inefficient.

We built on top of CRF-based word segmentation two post-processing methods. The former, designed to enhance semantic interpretation, merges segmented compound words in a text chunked by the machine-learning approach, restoring the words' original meaning and context. The latter splits words to boost POS tagging, resulting in better CRF-based sentence segmentation. We evaluated the applications of the proposed algorithms in three language processing tasks, including Thai-to-English translation, text summarization, and topic extraction.

The evaluation results show that the proposed methods can be used effectively in analyzing data obtained from social media. Hence, we explored the possibility of enhancing the proposed algorithms to be applied for social media analysis. We utilized the proposed word-merging algorithm and the summarization method in order to examine whether this study can enhance analysis of a brand crisis in Thai social media.

## 1.2 Brand Crisis, Social Media, and Entertainment

The rare and unpredictable nature of a brand crisis makes it of low immediate interest and not compelling for a company to invest in preparation and prevention. A misfortune is as old as humankind, and so we have and continue to witness crisis after crisis sink brand after brand in the harsh sea amid the storm of public indignation (Greyser, 2009). The calamity is not unfamiliar to the academic community. Researches have shown that such crisis can be a company's high-stakes Gordian knot full of the unexpected (Barton, 2001; Coombs, 2007). It may vitiate brand image, tamper with business performance and distance customers, to name but a few risks (Basuroy, Chatterjee, & Ravid, 2003; Ho-Dac, Carson, & Moore, 2013; Kim, Su Jung; Wang, Rebecca Jen-Hui; Malthouse, 2015; Yannopoulou, Koronis, & Elliott, 2011). General advice and guidance have long been available to practitioners, while crisis communication strategies continue to evolve as scholars delve into the complexity of ever-changing public reactions (Greyser, 2009; McQuail, 2003; Veil, Buehner, & Palenchar, 2011). Many have dedicated to unraveling people's thinking process and reactions, especially to the company's conducts, e.g., apology, during the crisis (He, 2016; S. Kim, Marina Choi, & Atkinson, 2017; Shi, Wang, & Liu, 2018; Yuan, Cui, & Lai, 2016). From these empirical evidences, we have learned how the crisis affects brand attitude, trust, loyalty, perceived efficacy and much more. However, our understanding of the subject in the densely connected word of the internet remains deficient.

Traditional mass media was once at the center stage, then came the age of social media, where studies encourage companies to utilize the medium to both observe and respond to the public (Coombs, 2007; Seeger, 2006; Wright & Hinson, 2009). While fundamental theories such as Situational Crisis Communication Theory (SCCT) provide stable foundation for contemporary researches to build upon, social media appears to be transforming the landscape (Coombs & Holladay, 2002; Roshan, Warren, & Carr, 2016). Not only that the medium enables direct, two-way communication and fuels message propagation at a frightening speed, it profoundly influences perceived reputation, secondary crisis communication, and public reactions (Schultz, Utz, & Göritz, 2011). Respond strategies by means of social media can mitigate the unsettling situation or it may pose an even greater complication inexplicable to those merely familiar with conventional practices (K. Kim, Kim, & Reid, 2017; Roshan et al., 2016; Xia, 2013). That said, much can be learned from the medium itself. Both quantitative and qualitative methods, as well as clustering and classification, have been proven to be effective in systematic observation and interpretation of brand's communication strategies and consumer response (Byrd, 2012; Wang, 2016; Wenjun & Erna, 2018). Regarding consumer response, brand crises drew as much, or even more, attention in social media than they sparked off condemnation in the medium. Since we have learned that social media use is an entertaining experience, perhaps, in retrospect, the crises have not been all about an acrimonious atmosphere (Reinecke, Vorderer, & Knop, 2014). Rather, they seemed to resemble an amphitheater in the modern world, where the crowd find their pleasure in observing a corrupt brand flounder.

The aforementioned thought, the seemingly cruel pleasure, approximates a sense of schadenfreude. Despite moral ambivalence of the term, the joy derived from the misfortunes of others is a moral emotion, one that media entertainment can elicit (Jonathan Haidt, 2003; Portmann, 2014; Raney, 2011). If such joy exists in the event of brand crisis, then it should not be preposterous to propose that the crisis, the misfortune of the brand, can be entertaining; ergo, we intended to study the entertainment aspect in two dimensions: *enjoyment* and *appreciation* (Vorderer, 2011). Theories and empirical researches on *enjoyment* evolved around the hedonistic values of pleasure, amusement and diversion (Oliver & Raney, 2014; Waterman, 1993). *Appreciation*, on the other hand, is a moving and though-provoking effect of meaningful entertainment (Oliver & Bartsch, 2010; Oliver & Raney, 2011). We expected to see both dimensions through content analysis; but before examining the manifestation of the experience, we first needed to find out what in the crisis constitutes the experience. In dramas, the thought that protagonists deserve glory and villains must be condemned to ruin is the indication of the audience making moral judgment and forming affective dispositions (Eden & Tamborini, 2017; Zillmann & Cantor, 1972). Likewise, public condemnation of the brand in crisis indicates that people judge, and their dispositions are the key to being entertained (Zillmann & Bryant, 1994). Hence, our primary objective is to be able to explain, in the context of brand crisis, whether and how do people make moral judgement.

Moral judgment is an evaluation of good and bad with regard to a set of virtues held by a culture or subculture (Jonathan Haidt, 2001). Once thought to be sole deliberate moral reasoning, it became a dual-process when social intuitionists brought to light the notion that there appears to be an element of intuition as well (Shweder & Haidt, 1993). Moral intuitions include moral emotions and occur first as a fast-cognitive process, before longer reasoning process begins. The notion has been thoroughly explained in relatively-recent, well-established moral foundations theory (MFT); (Jonathan Haidt & Graham, 2007; Jonathan Haidt & Joseph, 2004). The theory connects anthropological and evolutionary accounts of morality in terms of moral intuitions. Exploring cultural institutions and practices, Haidt and his collaborators instituted five moral foundations that are culturally universal and applicable across various research domains, including entertainment (Tamborini, 2011, 2012). Finding out how moral judgments vary across the political spectrum, (Graham, Haidt, & Nosek, 2009) created moral foundations dictionary (MFD). The dictionary has since been used to observe moral thoughts in different forms of text data, including data gathered from social media (Garten, Boghrati, Hoover, Johnson, & Dehghani, 2016; Leidner & Castano, 2012). The success implementations of MFD gave us confidence to employ it at the core of our analysis.

The content analysis comprises four studies. The first two studies concern moral-judgment aspect of the entertainment experience. Based on MFD, in the first study, we quantified and interpreted moral judgment in brand crisis incidents among social media audience. The second study extends MFD to widen the comprehension of moral judgment. The third study applies the proposed word segmentation methods to analyze moral judgment in brand crises in Thai social media. The forth study investigates the *enjoyment* dimension of the experience, as well as discussing the *appreciation* dimension. The study demonstrates the possible application of the proposed word segmentation methods in analyzing the hedonic dimension in Thai in the future.

## 1.3 **Objectives**

The first objective of this dissertation is to improve Thai word segmentation by solving the problem of compound-word boundary ambiguity. Although researchers have been solving the issue of ambiguity in word segmentation for many years, there is still no perfect solution to the problem. Word segmentation is a basic operation that enables the use of English language processing methods in the Thai language. This reason has become the second objective, which is to evaluate how much the proposed methods can improve other language processing tasks. The evaluation is specific to Thai-to-English translation, summarization, and topic extraction. The result of the evaluation using social media data gave us the idea that the proposed methods may have a broader contribution than language processing tasks. Thus, the third objective is to examine how the proposed methods can improve an analysis of social media data. The examination is specific to the topic of entertainment in brand crisis in social media.

For the analysis, the question is whether a brand crisis can be entertaining, and if it does, what is the psychological process behind the audience's entertainment experience. In order to answer the question, we have looked into the studies of entertainment in general, and morality in particular. We established a theoretical framework, and the first objective of the analysis is to find out whether and how the audience make moral judgment. Specifically, we attempt to translate moral domains as defined in MFT into the context of brand crisis through the analysis of social media data. Once we have learned the relationship between the moral domains and the audience's moral judgment, our second objective of the analysis is to examine further the two dimensions of the entertainment experience – in particular, how the moral judgment constitutes the experience. The third objective of the analysis is to apply the proposed word segmentation methods to analyze part the entertainment experience in brand crisis, particularly the moral judgment. A successful application of the proposed word segmentation methods would produce an evidence that the proposed methods can improve an analysis of social media data.

## 1.4 **Contribution**

This dissertation involves three major fields of study, i.e., Thai natural language processing, marketing, media psychology. First, we have improved the accuracy of Thai word and sentence segmentation. Since the segmentation is a basic operation required before performing other language processing tasks, improving it benefits other tasks as well. We proved the benefits by evaluating the improvements of Thai-to-English translation, summarization, and topic extraction. The contribution of the proposed methods extends to the analysis of brand crisis in social media. Applying the methods helped us to analyze brand crises in Thai social media. The analysis results became the second contribution, particularly to the field of marketing.

The contribution to the field of marketing is our newly established understanding of brand crisis from the entertainment perspective. The knowledge gained from this study would help researchers and organizations understand better why and how a brand crisis escalates so rapidly in social media, as well as how the audience perceive and react to the incident in terms of their entertainment experience. Organizations can also learn how people make moral judgment and how the judgment affect their reactions during the crisis. This knowledge would help the crisis response teams to determine appropriate strategies that avoid moral violations.

Lastly, the contribution to the field of media psychology is our demonstration of the well-established theories in social media context. Entertainment has been extensively studied in various subjects – e.g., television dramas, politics, interactive games, public health (Bartsch & Schneider, 2014; Igartua, 2010) – but researches of the topic in social media and marking is still limited, especially ones that employ content analysis method. This dissertation not only offers an insight into the entertainment experience but also tools for future studies involving text analysis.

## 1.5 **Dissertation Outline**

This dissertation is structured as follows: Chapter 2 will explain Thai language fundamentals related to word segmentation. Chapter 3 will describe the proposed word-segmentation rules and algorithms, followed by our experiments on word and sentence segmentation in the Thai language. The chapter also includes evaluations of the three applications of the proposed methods, which are Thai-to-English translation, summarization, and topic extraction. In Chapter 4, we will first review previous literatures on brand crisis and entertainment, with elaboration on both dimensions of the entertainment experience, as well as the dual-process models. Next, the chapter will explicate our conceptual framework and its fundamentals, which are MFT (in relation to brand crisis), *enjoyment* (with particular focus on affective disposition), and *appreciation*. The theoretical framework consists of two part, i.e., moral judgment and entertainment experience. The chapter will then describe three of our studies with regard to moral judgment, one on MFD, another on expanding it, and the last one on translating MFT into Thai. Next, the chapter will move on from morality to the two dimensions of the entertainment experience. We will explain our experiment on *enjoyment* and will expound on *appreciation* based on our observation of prior experiments. Chapter 5 will present general discussion, limitations, and future research direction, then finally conclude this dissertation.

# Chapter 2

# Thai Linguistic Fundamentals

This chapter explains common linguistic fundamentals relevant to Thai word segmentation. The rules are based on the BEST2009 word segmentation corpus developed by Thailand's National National Electronics and Computer Technology Center, with several amendments for the purpose of this study, which will be described in detail in the next chapter. The content is divided into six main sections according to word segmentation methods: word components, grammar, communication roles, word origins, and language classes. These specifications are essential to corpus construction and the proposed word segmentation algorithm, and therefore, are introduced before we continue to the segmentation method. Throughout this chapter, ∅ represents words or syllables with no meaning, → describes how the whole word on the left side can be segmented into component words on the right side.

BEST2009 stated that words in the corpus will always be chunked if the outcome (segmented words) can still somewhat maintain the meaning of the original word. For example, these words can be segmented:

| | | | | | |
|---|---|---|---|---|---|
| เงินเดือน | → | เงิน + เดือน | Salary | → | Money + month |
| การเดิน | → | การ + เดิน | Walking | → | Task + walk |
| น้ำอัดลม | → | น้ำ + อัด + ลม | Soda | → | Water + compress + air |
| จดทะเบียน | → | จด + ทะเบียน | Register | → | Write + register |
| หลอดลม | → | หลอด + ลม | Windpipe | → | Pipe + wind |
| ลงทุน | → | ลง + ทุน | Fund | → | Down + fund |

These cannot be segmented:

| | | | | | |
|---|---|---|---|---|---|
| ดินฟ้าอากาศ | = | Weather | ดีใจ | = | Delighted |
| ท้องตลาด | = | Market | ใจเสีย | = | Worry |
| แม่บ้าน | = | Housemaid | สะบักสะบอม | = | Battered |

Deciding whether to chunk these words depends on the context:

ว่าความ

In case it is a sequence of words, it needs to be segmented:

ว่าความ → ว่า + ความ

Example of ว่าความ in a sentence:

เขาคิดว่าความสะอาดเป็นเรื่องสำคัญ → เขา + คิด + ว่า + ความ + สะอาด + เป็น + เรื่อง + สำคัญ

He thinks that cleanliness is an important matter → He + think + that + case + clean + is + matter + important

In case it is a compound word, ว่าความ means "try" (present and argue for a position in court) and needs not to be segmented. For example:

ทนายว่าความคดีทำร้ายร่างกาย → ทนาย + ว่าความ + คดี + ทำร้าย + ร่างกาย

A layer tries a case of physical assault →
Lawyer + try + case + assault + body

มีอายุ

In case it is a sequence of words, it needs to be segmented:

มีอายุ → มี + อายุ

Example of มีอายุ in a sentence:

โดยปกติจะผสมพันธุ์หมูสาวเมื่อมีอายุได้ราว ๗ - ๙ เดือน →

โดย + ปกติ + จะ + ผสมพันธุ์ + หมู + สาว + เมื่อ + มี + อายุ + ได้ + ราว + ๗ + - + ๙ + เดือน

Normally a young female pig is bred when it becomes 7 – 9 months old → By + normal + will + breed + pig + young female + when + have + age + can + 7 + - + 9 + month

In case it is a compound word, มีอายุ means old and needs not to be segmented. For example:

ผู้หญิงคนนี้ดูมีอายุ → ผู้หญิง + คน + นี้ + ดู + มีอายุ

This lady looks old → Lady + person + this + look + old

With the complication of word segmentation explained, a comprehensive set of rules has to be established. The following are BEST2009's rules, which we will explain our proposed changes later in the next chapter.

## 2.1 Segmentation by Word Components

### 2.1.1 Words

A word refers to a single distinct meaningful element of speech or writing that cannot be separated into a combination of other elements, for example, พ่อ (father), แม่ (mother), ช้าง (elephant), นก (bird), น้ำ (water). A word may contain multiple syllables which may or may not have meaning and may not be relevant to the word. For example, กระถาง means a pot for planting. When segmented into syllables, กระ means a certain type of turtle and ถาง means to use a sharp tool to cut plants so that they form a flat top surface.

In this case, all syllables are not semantically relevant to the word. Another example is นาฬิกา, which means watch. นา means a rice field, ฬิ does not have meaning, and กา means a crow. Again, the word and syllables are not relevant. Therefore, a word consisting of multiple syllables should not be chunked.

### 2.1.2 Compound Words

Compound words are made of at least two words. These words can be nouns, verbs, quantity words, ordinal numbers, or preposition. Most of compound words are nouns or verbs. There are two types of compound words: ones that their component words are not semantically relevant and ones that are relevant. Most of words in the former type has a comparative meaning; some are used as names of animals and plants. The following are examples of general compound words with semantically irrelevant components:

| | | | | | |
|---|---|---|---|---|---|
| กินใจ | → | กิน + ใจ | Appreciative | → | Eat + heart |
| ใจหาย | → | ใจ + หาย | Frighten | → | Heart + lose |
| มือถือ | → | มือ + ถือ | Mobile phone | → | Hand + hold |
| ลูกน้ำ | → | ลูก + น้ำ | Mosquito larva | → | Offspring + water |
| ว่าความ | → | ว่า + ความ | Try (a case in court) | → | That + case |
| หางเสือ | → | หาง + เสือ | Helm | → | Tail + tiger |

Some are animal names:

| | | | | | |
|---|---|---|---|---|---|
| ปลาดุก | → | ปลา + ดุก | Catfish | → | Fish + ∅ |
| ปลากระดี่ | → | ปลา + กระ + ดี่ | Gouramis | → | Fish + sea turtle + ∅ |
| ปลากัด | → | ปลา + กัด | Fighting fish | → | Fish + bite |

| | | | | |
|---|---|---|---|---|
| ปลาหมึก | → | ปลา + หมึก | Squid → | Fish + ink |
| แมงมุม | → | แมง + มุม | Spider → | Insect + corner |

Some are plant names:

ทุเรียนหมอนทอง → ทุเรียน + หมอน + ทอง

Certain type of durian (Durio zibethinus Murr) → Durian + pillow + gold

ผักกระเฉด → ผัก + กระ + เฉด

Water mimosa → Vegetable + sea turtle + shade

ผักกูด → ผัก + กูด

Paco fern (Diplazium esculentum) → Vegetable + ∅

มะม่วงน้ำดอกไม้ → มะม่วง + น้ำ + ดอก + ไม้

Mango (Mangifera indica L. c.v.) → Mango + water + flower + wood

However, words which means part of a plant – for example, leaf, branch – are not part of compound words:

| | | | | |
|---|---|---|---|---|
| ดอกกุหลาบ | → | ดอก + กุหลาบ | Rose → | Flower + rose |
| ดอกแค | → | ดอก + แค | Sesban → | Flower + ∅ |
| ใบกระเพรา | → | ใบ + กระเพรา | Basil leaf → | Leaf + basil |
| ใบมะม่วง | → | ใบ + มะม่วง | Mango leaf → | Leaf + mango |

ต้นพญาไร้ใบ → ต้น + พญา + ไร้ + ใบ

Euphorbia tirucalli → Tree + ∅ + without + leaf

Many of the compound words with semantically relevant components begin with ก้าน (branch), ข้อ (item), เครื่อง (tool), ช่าง (technician), ชาว (citizen), นัก (much), ผ้า (cloth), ล้อ (wheel), and so on:

| | | | | | |
|---|---|---|---|---|---|
| ก้านบีบเลี้ยว | → | ก้าน + บีบ + เลี้ยว | Strut | → | Branch + squeeze + turn |
| ข้อกฎหมาย | → | ข้อ + กฎหมาย | Legal provision | → | Item + law |
| เครื่องครัว | → | เครื่อง + ครัว | Kitchenware | → | Tool + kitchen |
| ช่างเชื่อม | → | ช่าง + เชื่อม | Welder | → | Technician + weld |
| ชาวไทย | → | ชาว + ไทย | Thais | → | Citizen + Thai |
| นักเรียน | → | นัก + เรียน | Student | → | Much + study |
| ผ้าคลุมไหล่ | → | ผ้า + คลุม + ไหล่ | Shawl | → | Cloth + cover + shoulder |

ล้อเครื่องเป่าลม → ล้อ + เครื่อง + เป่า + ลม

Blower wheel → Wheel + tool + blow + air

Some are geometric units:

| | | | | | |
|---|---|---|---|---|---|
| ตารางนิ้ว | → | ตาราง + นิ้ว | Square inch | → | Table + inch |
| ลูกบาศก์เมตร | → | ลูกบาศก์ + เมตร | Cubic meter | → | Cubic + meter |

Some are geometric shapes:

| | | | | | |
|---|---|---|---|---|---|
| สามเหลี่ยม | → | สาม + เหลี่ยม | Triangle | → | Three + angle |
| วงกลม | → | วง + กลม | Circle | → | Loop + round |

Lastly, there are also compound words of this type that begin with การ, ความ, and อย่าง:

| | | | | | |
|---|---|---|---|---|---|
| การเดิน | → | การ + เดิน | Walking | → | ∅ + walk |
| ความประสงค์ | → | ความ + ประสงค์ | Desire | → | ∅ + desire |
| อย่างเร็ว | → | อย่าง + เร็ว | Quickly | → | ∅ + quick |

### 2.1.3 Complex Words

Multiple words with relevant meaning form a complex word. These component words may have the exact same, similar, or opposite meanings. A complex word is used for clarifying the meaning of the word. There are two types of complex words: meaningfully-related complex words and phonetically-related complex words. Words in the former type consist of multiple words with similar or opposite meaning:

| | | | | | |
|---|---|---|---|---|---|
| คอยท่า | → | คอย + ท่า | Wait | → | Wait + wait |
| จิตใจ | → | จิต + ใจ | Mind | → | Mind + heart |
| เจ็บป่วย | → | เจ็บ + ป่วย | Sick | → | Hurt + sick |
| ตัดสิน | → | ตัด + สิน | Decide | → | Cut + cut |
| ทรัพย์สิน | → | ทรัพย์ + สิน | Asset | → | Asset + asset |
| ป่วยไข้ | → | ป่วย + ไข้ | Sick | → | Sick + sick |

Phonetically-related complex words consist of multiple single-or-multiple-syllable words which have phonetically-identical first characters, phonetically-similar-or-different last characters, and phonetically-different vowels. At least one of the words' syllables contains the meaning of the word; all syllables altogether may form the meaning of the word. The following examples are phonetically-related complex words, their phonetic annotation (italicized), and their meanings:

เกะกะ → เกะ + กะ Disorder → ∅ + estimate

is pronounced: *Keaka*

ขมุกขมัว → ขมุก + ขมัว Dim → Dim + ∅

is pronounced: *K̄hmukk̄hmạw*

จัดจ้าน → จัด + จ้าน Bold → Extreme + extreme

is pronounced: *Cạdĉān*

ทาบทาม → ทาบ + ทาม Approach → Brace + ∅

is pronounced: *Thābthām*

เหินห่าง → เหิน + ห่าง Distance → Fly + far

is pronounced: *H̄einh̄̀āng*

### 2.1.4 Repetitive Words

Repetitive words consist of two identical component words. The second word is not explicitly written; instead, it is replaced with ๆ symbol. In other word, the symbol indicates the repetition of the first word. For example, เด็ก (children) is pronounced dek and เด็กๆ is pronounced dek-dek, ดำ (black) is pronounced dum and ดำๆ is pronounced dum-dum, ดี (good) is pronounced dee and ดีๆ is pronounce dee-dee. Repetitive words maintain the same meaning as their component words. Some are fully repetitive:

คนแก่ๆ → คน + แก่ + ๆ Elders → Person + old + ∅

ชิ้นเล็กๆ → ชิ้น + เล็ก + ๆ Small pieces → Piece + small + ∅

| | | | | | |
|---|---|---|---|---|---|
| พวกเด็กๆ | → | พวก + เด็ก + ๆ | Children | → | Gang + child + ∅ |
| สีดำๆ | → | สี + ดำ + ๆ | Black | → | Color + black + ∅ |

Some are partially repetitive:

| | | | | | |
|---|---|---|---|---|---|
| ต่างๆ นานา | → | ต่าง + ๆ + นานา | Various | → | Different + ∅ + many |
| ต่อๆ ไป | → | ต่อ + ๆ + ไป | Afterward | → | Next + ∅ + go |
| ทั้งๆ ที่ | → | ทั้ง + ๆ + ที่ | Although | → | All + ∅ + at |
| ทั่วๆ ไป | → | ทั่ว + ๆ + ไป | Generally | → | Over + ∅ + go |

Some words are not repetitive words but contain ๆ to indicate the repetition of their last syllable:

ครั้งก่อนๆ → ครั้ง + ก่อน + ๆ

Previous times → Time + before + ∅

เถียงฉอดๆ → เถียง + ฉอด + ๆ

Argue relentlessly → Argue + ∅ + ∅

ของต่างๆ → ของ + ต่าง + ๆ

Miscellany → Thing + different + ∅

ดูเผินๆ → ดู + เผิน + ๆ

Look superficially → Look + ∅ + ∅

พูดปาวๆ → พูด + ปาว + ๆ

Talk relentlessly → Talk + ∅ + ∅

Excessive words are also not repetitive words. The excessive part (underlined) usually does not have any meaning but added for fluency:

กระปิ๋งกระเป๋า → กระปิ๋ง + กระเป๋า Bag → ∅ + bag

is pronounced: *Krap̌ngkrapěā*

จงจาน → จง + จาน Dish → ∅ + dish

is pronounced: *Cngcān*

ตู้เต้อ → ตู้ + เต้อ Closet → Closet + ∅

is pronounced: *Tū̂têx*

หอมเหิม → หอม + เหิม Fragrant → Fragrant + bold

is pronounced: *H̄xmh̄eim*

ซั้งซื้อ → ซั้ง + ซื้อ Buy → ∅ + buy

is pronounced: *Ŝngsụ̄̂x*

## 2.2 **Word Segmentation by Grammar**

### 2.2.1 Conjunctions

Similar to English, conjunctions in Thai are used to connect words, clauses, or sentences. There are two types of conjunctions as classified by word formation: single conjunctions – such as กระนั้น (however), ทว่า (however), แต่ (but), จึง (thus), บน (on), ใน (in), นอก (outside), หน้า (front), กับ (with), และ (and), or (หรือ), ฉะนั้น (therefore), เพราะ (because), แม้ (although), หาก (if), ถ้า (if) – and compound conjunctions such as:

| | | | | | |
|---|---|---|---|---|---|
| เพราะฉะนั้น | → | เพราะ + ฉะนั้น | Therefore | → | Because + therefore |
| อย่างไรก็ตาม | → | อย่างไร + ก็ตาม | However | → | How + whatever |
| ถ้าเผื่อ | → | ถ้า + เผื่อ | In case | → | If + if |
| ด้วยเหตุนี้ | → | ด้วย + เหตุ + นี้ | Because | → | By + cause + this |
| ตราบเท่าที่ | → | ตราบ + เท่า + ที่ | As long as | → | As long as + equal + at |
| แม้แต่ | → | แม้ + แต่ | Even | → | Even + but |

โดยทั่วไปแล้ว → โดย + ทั่วไป + แล้ว

In general → By + general + already

BEST2009 suggested that conjunctions consisting of semantically irrelevant or complex component words should not be chunked:

| | | | | | |
|---|---|---|---|---|---|
| ก็ดี | → | ก็ + ดี | As well | → | Subsequent + good |
| ก็ตาม | → | ก็ + ตาม | No matter | → | Subsequent + follow |
| ก่อนหน้า | → | ก่อน + หน้า | Previously | → | Previous + front |
| ครั้นเมื่อ | → | ครั้น + เมื่อ | When | → | When + when |

Some conjunctions are made of multiple conjunctions:

Conjunction indicating contradictory + conjunction indicating condition

| | | | | | |
|---|---|---|---|---|---|
| แต่ถ้า | → | แต่ + ถ้า | But if | → | But + if |

Conjunction indicating contradictory + conjunction indicating cause

| | | | | | |
|---|---|---|---|---|---|
| แต่เนื่องจาก | → | แต่ + เนื่อง + จาก | But because | → | But + relevant + from |

Conjunction indicating cause + conjunction indicating condition

| | | | | | |
|---|---|---|---|---|---|
| เพราะถ้า | → | เพราะ + ถ้า | Because if | → | Because + if |

Conjunction indicating cause + conjunction indicating exception

เพราะนอกจาก → เพราะ + นอก + จาก

Because besides → Because + outside + from

Some have semantically relevant component words:

| | | | | | |
|---|---|---|---|---|---|
| ก่อนที่ | → | ก่อน + ที่ | Before | → | Before + at |
| ขณะเดียวกัน | → | ขณะ + เดียว + กัน | Meanwhile | → | While + one + together |
| ข้างนอก | → | ข้าง + นอก | Outside | → | Side + out |
| ดังนั้น | → | ดัง + นั้น | Thus | → | As + that |
| โดยที่ | → | โดย + ที่ | By | → | By + at |
| นอกจากนี้ | → | นอก + จาก + นี้ | In addition | → | Outside + from + this |

**2.2.2 Determiners**

There are two types of determiners: falling-tone determiners – e.g., นี่ (Nı̀; this), นั่น (Nạn; that), โน่น (Nòn; over there), นู่น (Nùn; over there) – and high-tone determiners, e.g., นี้ (Nî; this), นั้น (Nận; that), โน้น (Nôn; over there), นู้น (Nûn; over there) (Lancker & Fromkin, 1973). Some determiners are part of a conjunction, for example:

| | | | | | |
|---|---|---|---|---|---|
| ดังนี้ | → | ดัง + นี้ | As follows | → | As + this |
| ดังนั้น | → | ดัง + นั้น | Hence | → | As + that |

| | | | | | |
|---|---|---|---|---|---|
| นอกจากนี้ | → | นอก + จาก + นี้ | In addition | → | Outside + from + this |
| นอกจากนั้น | → | นอก + จาก + นั้น | Moreover | → | Outside + from + that |
| ทั้งนี้ | → | ทั้ง + นี้ | As mentioned | → | Altogether + this |
| ทั้งนั้น | → | ทั้ง + นั้น | All | → | Altogether + that |

### 2.2.3 Interjections

Interjections are words representing vocal expression of emotions, feelings, or any other purposes. Component words of interjections are usually irrelevant, for example:

| | | | | | |
|---|---|---|---|---|---|
| ตายจริง! | → | ตาย + จริง | Good gracious! | → | Die + real |
| อุ๊ยตาย! | → | อุ๊ย + ตาย | Ouch! | → | Oops! + die |
| คุณพระช่วย! | → | คุณ + พระ + ช่วย | God help me! | → | You + monk + help |

## 2.3 Word Segmentation by Word Positions

Ending words are word at the end or in the ending part of a sentence. There are two types of ending words: single and compound:

ยังไม่กลับหรอก → ยัง + ไม่ + กลับ + หรอก

Not going back yet → Yet + no + back + ∅

พร้อมแล้วครับผม → พร้อม + แล้ว + ครับ + ผม

Ready sir → Ready + already + sir + me

อยู่นี่ขอรับกระผม → อยู่ + นี่ + ขอ + รับ + กระ + ผม

Here sir → Be + this + ask + receive + sea turtle + me

นั่นน่ะซิ → นั่น + น่ะ + ซิ

Agreed → That + ∅ + ∅

ดีทีเดียวแหละ → ดี + ที + เดียว + แหละ

Quite good → Good + time + unique + ∅

## 2.4 **Word Segmentation by Communication Roles**

### 2.4.3 Question Words

Question words are, for example, ไหม (∅), มั้ย (∅), ใด (which), ไหน (which), อะไร (what), ทำไม (why):

คุณชอบดอกไม้มั้ย → คุณ + ชอบ+ ดอก + ไม้ + มั้ย

Do you like flowers? → You + like + flower + wood + ∅

เขาจะทำอะไร → เขา + จะ + ทำ + อะไร

What will he do? → He + will + do + what

ทำไมคุณไม่มา → ทำไม + คุณ + ไม่ + มา

Why don’t you come? → Why + you + no + come

Some question words are compound words consisting of semantically relevant component words:

| | | | | | | |
|---|---|---|---|---|---|---|
| ที่ใด | → | ที่ + ใด | Where | → | At + which |
| ที่ไหน | → | ที่ + ไหน | Where | → | At + where |
| เท่าใด | → | เท่า + ใด | How much | → | Equal + which |
| เท่าไหน | → | เท่า + ไหน | How much | → | Equal + which |
| เมื่อไหร่ | → | เมื่อ + ไหร่ | When | → | When + ∅ |
| หรือเปล่า | → | หรือ + เปล่า | Or not | → | Or + not |
| หรือไม่ | → | หรือ + ไม่ | Or not | → | Or + not |

Some question words contain classifiers:

ร่มของเธอคือคันไหน → ร่ม + ของ + เธอ + คือ + คัน + ไหน

Which one is your umbrella? → Umbrella + belong to + you + is + ∅ + which

ลูกหมาตัวใดวิ่งเร็วที่สุด → ลูก + หมา + ตัว + ใด + วิ่ง + เร็ว + ที่ + สุด

Which puppy runs fastest? → Baby + dog + ∅ + which + run + fast + at + most

มันอยู่ข้างไหน → มัน + อยู่ + ข้าง + ไหน

Which side is it? → It + is + side + which

**2.4.4 Idioms**

Idioms are a sequence of words used for specific purpose and in specific context. Their component words are normally semantically irrelevant and may or may not rhyme; however, all together form a meaning, usually for comparison or teaching, for example:

กำแพงมีหู ประตูมีช่อง → กำแพง + มี + หู + ประตู + มี + ช่อง

Walls have ears, doors have niches → Wall + have + ear + door + have + niche

เกลือเป็นหนอน → เกลือ + เป็น + หนอน

Salt becomes worm → Salt + become + worm

ขี่ช้างจับตั๊กแตน → ขี่ + ช้าง + จับ + ตั๊กแตน

Riding an elephant to catch grasshoppers →
Ride + elephant + catch + grasshopper

## 2.5 **Word Segmentation by Word Origin**

### 2.5.3 Bali Sanskrit

*2.5.3.1 True nominal compounds*

Sanskrit-based nominal compounds (samāsa) are words consisting of multiple component words according to the rules of Sanskrit. The component words are Sanskrit and are interpreted backward. There may or may not be a connecting sound between syllables. Nominal compounds of this type are called "true nominal compounds," for example:

จิตรกรรม (painting)

| | | |
|---|---|---|
| is pronounced | จิต – ตฺระ – กรรม | *Citrkrrm* |
| and consists of | จิตร + กรรม | Portraying + action |

ชีววิทยา (biology)

| | | |
|---|---|---|
| is pronounced | ชี – วะ – วิด – ทะ – ยา | Chīwwithyā |
| and consists of | ชีว + วิทยา | Bio + science |

อัคคีภัย (conflagration)

| | | |
|---|---|---|
| is pronounced | อัก – คี – ไพ | Xạkhkhīp̣hạy |
| and consists of | อัคคี + ภัย | Fire + danger |

*2.5.3.2 Artificial nominal compounds*

Some words are similar to true nominal compounds, but their compound words are not Sanskrit, i.e., their component words may be a combination of Sanskrit and Thai (or other languages). These words are called "artificial nominal compounds," for example:

คริสตกาล (before Christ)

| | | |
|---|---|---|
| is pronounced | คริด – ตะ – กาล | Khrīstkāl |
| and consists of | คริสต์ + กาล | Christ + time |
| which are | English and Sanskrit | |

ทุนทรัพย์ (capital)

| | | |
|---|---|---|
| is pronounced | ทุน – นะ – ซับ | Thunthrạphy̒ |
| and consists of | ทุน + ทรัพย์ | Fund + asset |
| which are | Thai and Sanskrit | |

สรรพสินค้า (merchandise)

| | | |
|---|---|---|
| is pronounced | สับ – พะ – สิน – ค้า | S̄rrphs̄inkĥā |
| and consists of | สรรพ + สินค้า | All + product |
| which are | Sanskrit and Thai | |

When the sounds of two component words blend together, as a result, changing one or both sounds, or combining into a single sound, or having additional sound, the combined word is called portmanteau. When the component words are Sanskrit, it becomes Sanskrit-based portmanteau and is interpreted backward, for example:

ราชูประโภค (royal articles of use)

| | | |
|---|---|---|
| is pronounced | รา – ชู – ปะ – โพก | Rāchūpp̣hokh |
| and consists of | ราช + อุปโภค | Royal + consume |

วิทยาลัย (college)

| | | |
|---|---|---|
| is pronounced | วิด – ทะ – ยา – ไล | Withyālạy |
| and consists of | วิทยา + อาลัย | Knowledge + mourn |

มหาวิทยาลัย (university)

| | | |
|---|---|---|
| is pronounced | มะ – หา – วิด – ทะ – ยา – ไล | Mh̄āwithyālạy |
| and consists of | มหา + วิทยา + อาลัย | Great + knowledge + mourn |

### 2.5.4 English and Other Languages

According to BEST2009, all words with English or other languages origins should be segmented based on the segmentation in the original language, for example:

| | | | |
|---|---|---|---|
| คอมพิวเตอร์ + โน้ตบุค | Notebook computer | → | Computer + notebook |
| แคลเซียม + ฟอสเฟต | Calcium Phosphate | → | Calcium + Phosphate |
| ทีม + ฟุตบอล | Football team | → | Team + football |
| บางกอก + ดอลล์ | Bangkok Doll | → | Bangkok + Doll |

However, if the English or other languages origins words are plant or animal or plant/animal family names, they should not be chunked, for example:

| | |
|---|---|
| กูดข้อต่อภูหลวง | Arthromeris phuluangensis |
| ปรงทอง | Acrostichum aureum |
| ไก่ฟ้าพญาลอ | Lophura diardi |
| ปูเจ้าฟ้า | Phricotelphusa sirindhorn |
| พันธุ์ + อเมริกันเซตเดิล | American Saddle Horse |
| พันธุ์ + คลีฟแลนด์ เบย์ | Cleveland Bay |
| พันธุ์ + เฟิร์สท์ไพรซ์ | First Prize |
| พันธุ์ + ซีโฟม | Sea Foam |

## 2.6 **Word Segmentation by Language Classes**

Thai language has multiple classes, each associated with certain societal class: king, royal family, monks, and ordinary individuals. Most royal words have Bali, Sanskrit or Khmer origin. BEST2009 defines segmentation rules for royal words as followed:

### 2.6.3 Inseparable Royal Words

Royal words that should not be segmented includes ones that are royal words by themselves, i.e., do not need to be combined with other words to become a royal word, for example, กันแสง (cry), เจ้าจอม (minor wife of the king), เจ้าจอมมารดา (royal mother), ชายา (princess), ตำหนัก (palace), ทรงเครื่อง (haircut), ธิดา (daughter), ประชวร (sick), พระทัย (heart), รับสั่ง (say), สุบิน (dream), อุระ (chest), โอรส (son).

Some words when combined with certain prefixes can become royal words:

พระบรมอรรคราชบรรพบุรุษ → พระบรมอรรคราช + บรรพบุรุษ

Royal ancestor → Royal + ancestor

พระบรมหาราชวัง → พระบรมหาราช + วัง

Royal palace → Royal + palace

พระบรมราโชวาท → พระบรมราช + โอวาท

Royal discourse → Royal + discourse

A prefix พระ (monk) constitutes royal nouns and is semantically irrelevant, for example:

ฉลอง<u>พระ</u>เนตร → ฉลอง + พระ + เนตร

Glasses → Celebrate + monk + eye

ทองพระกร → ทอง + พระ + กร

Bracelet → Gold + monk + hand

ธารพระกร → ธาร + พระ + กร

Staff → Bear + monk + hand

The prefix also constitutes royal verbs with "normal verb + royal noun" or "royal noun + normal verb" structure, for example:

| | | | | | |
|---|---|---|---|---|---|
| ตกพระทัย | → | ตก + พระทัย | Shocked | → | Fall + heart |
| พระทัยหาย | → | พระทัย + หาย | Frightened | → | Hear + lose |
| สระพระเจ้า | → | สระ + พระเจ้า | Wash hair | → | Wash + God |

### 2.6.4 Separable Royal Words

Royal words when combining with normal word usually become royal nouns and are semantically relevant, for example (royal words are underlined):

| | | | | | | |
|---|---|---|---|---|---|---|
| ของเสวย | → | ของ + เสวย | Food | → | Thing + eat |
| ที่บรรทม | → | ที่ + บรรทม | Bed | → | Place + sleep |
| ข้อพระบาท | → | ข้อ + พระบาท | Ankle | → | Segment + foot |
| น้ำสรง | → | น้ำ + สรง | Shower water | → | Water + shower |

Prefixes ต้น and หลวง (both mean “belong to the king”) transform normal words into royal words, for example:

| | | | | | |
|---|---|---|---|---|---|
| ลูกหลวง | → | ลูก + หลวง | Son of a king | → | Offspring + king’s |
| รถหลวง | → | รถ + หลวง | King’s car | → | Car + king’s |
| เครื่องต้น | → | เครื่อง + ต้น | King’s utensils | → | Tool + king’s |
| ช้างต้น | → | ช้าง + ต้น | King’s elephant | → | Elephant + king’s |

Some royal verbs have a prefix ทรง (∅) added to normal verbs, for example:

| | | | | | |
|---|---|---|---|---|---|
| ทรงเรียน | → | ทรง + เรียน | Learn | → | ∅ + study |
| ทรงสอน | → | ทรง + สอน | Teach | → | ∅ + teach |
| ทรงระลึกถึง | → | ทรง + ระลึก + ถึง | Remind | → | ∅ + remind + to |

Some royal verbs have a prefix ทรง (∅) added to royal nouns or verbs, for example:

ทรงพระราชสมภพ → ทรง + พระราชสมภพ

Born (refer to a king only) → ∅ + born

ทรงพระบรรทม → ทรง + พระบรรทม

Sleep (refer to a king only) → ∅ + sleep

Lastly, some royal verbs are a combination of verbs. These component verbs may all be royal verbs, or some may have the "ทรง + royal verb" structure, for example:

เสด็จพระราชดำเนินทอดพระเนตร → เสด็จพระราชดำเนิน + ทอดพระเนตร

Go to see → Go + see

เสด็จประพาสต้น → เสด็จ + ประพาสต้น

Take a vacation → Go + take a vacation

ทรงพระกรุณาโปรดเกล้าฯ พระราชทาน → ทรง + พระกรุณา + โปรดเกล้า + ฯ[1] + พระราชทาน

Kindly give → ∅ + kind + kind + ∅ + give

ทรงมีพระราชปฏิสันถารกับผู้ถวายการต้อนรับ → ทรง + มี + พระราชปฏิสันถาร + กับ + ผู้ + ถวาย + การ + ต้อนรับ

Greet people who welcome → ∅ + have + greet + with + person + offer + task + welcome

[1] ฯ shortened the word โปรดเกล้า from โปรดเกล้าโปรดกระหม่อม, which has the same meaning

# Chapter 3

# Thai Word Segmentation

In this chapter, we will explain our methods to better word and sentence segmentation in the Thai language. Next, we will demonstrate how our methods can help improve topic extraction, Thai-English translation, and summarization, which will be useful in conducting the content analysis in the future. The word-merging algorithm and summarization has played a major role in our analyses in the following chapter. A more effective word-merging algorithm and summarization method would help make our interpretation more accurate.

## 3.1 **Improving Thai Word and Sentence Segmentation Using Linguistic Knowledge**

Word boundary ambiguity in word segmentation has long been a fundamental challenge within Thai language processing. The Conditional Random Fields (CRF) model is among the best-known methods to have achieved remarkably accurate segmentation. Nevertheless, current advancements appear to have left the problem of compound words unaccounted for. Compound words lose their meaning or context once segmented. Hence, we introduce a dictionary-based word-merging algorithm, which merges all kinds of compound words. Our evaluation shows that the algorithm can accomplish a high-accuracy of word segmentation, with compound words being preserved. Moreover, it can also restore some incorrectly segmented words. Another problem involving a different word-chunking approach is sentence boundary ambiguity. In tackling the problem, utilizing the part of speech (POS) of a segmented word has been found previously to help boost the accuracy of CRF-based sentence segmentation. However, not all segmented words can be tagged. Thus, we propose a POS-based word-splitting algorithm, which splits words in order to increase POS tags. We found that with more identifiable POS tags, the CRF model performs better in segmenting sentences. To demonstrate the contributions of both methods, we experimented with three of their applications. With the word merging algorithm, we found that intact compound words in the product of topic extraction can help to preserve their intended meanings, offering more precise information for human interpretation. The algorithm, together with the POS-based word-splitting algorithm, can also be used to amend word-level Thai-English translations. In addition, the word-splitting algorithm improves sentence segmentation, thus enhancing text summarization.

In the next section, we begin with relevant Thai linguistic fundamentals. From there, we explore the evolution of word segmentation before bringing forward our new methods. We then explain the evaluation settings and experiment results, followed by the demonstration of our methods in improving three different text processing tasks, and the conclusion.

### 3.1.1 Linguistic Fundamentals

Perhaps the word 'ตากลม' best represents the problematic word boundary ambiguity. One may choose to visualize a perfect round eye – 'ตา' |ta| for *an eye* and 'กลม' |klom| attributing *round shape* to the noun – or a restful vacation basking ('ตาก' |tak|) in *the wind* ('ลม' |lom|). 'ตากลม' alone can never tell us which message it is meant to convey in the absence of context. We adapted segmentation rules from Benchmark for Enhancing the Standard of Thai Language Processing (BEST2009) [2] with a different approach to preserve compound words, that is, word-merging conditions, highlighted as follows:

[2] Developed by Human Language Technology Laboratory, National Electronics and Computer Technology Center, Thailand

*3.1.1.1 Word Segmentation Based on Word Formation*

Thai linguists have categorized compound words according to two types: ones with entirely unrelated roots, and ones with roots that are semantically comparable. Once merged, they become a new word, usually a noun or a verb. Dividing the former type would leave us with entirely irrelevant roots. For example, segmenting 'แมวมอง' |maew mong| (*scout*) would create 'แมว' |maew| (*cat*) and 'มอง' |mong| (*look*). Chunking the latter type may as well lead to ambiguity. Chunking 'นักร้อง' |nag rong| (*singer*), 'นัก' |nag| may either mean *much* or be used as a modifier; 'ร้อง' |rong| means *to utter* or *to cry*.

*3.1.1.2 Word Segmentation Based on Grammatical Rules*

Compound conjunctions have multiple roots. We support our proposition that, even though their roots may resemble their meaning somewhat, they should also not be chunked – for example, 'ดังนั้น' |dung nan| means *therefore*; 'ดัง' |dung| means *similar*, and 'นั้น' |nan| refers to a noun or a sentence that has already been said – the same applies to those with non-comparable roots and those containing a determiner. Nonetheless, chunking becomes a sensible approach for compound conjunctions cosisting of multiple conjunctions of different types – for example, 'แต่' |tae| means *but*; 'ถ้า' |ta| means *if*, and 'แต่ถ้า' |tae ta| means *but if*.

*3.1.1.3 Word Segmentation Based on Communication Roles*

As with compound conjunctions, interrogative words are not all indivisible; again, chunking them would merely complicate the overall interpretation of a sentence (for example, 'เท่าใด' |tao dai| as an interrogative word means *how much*, 'เท่า' |tao| means *equal*, and 'ใด' |dai| means *which*). However, a conjunction sometimes appears next to a classifier ('คน' |kon| is a unit classifier for a human; 'ไหน' |nai| means *which*); as they are treated as different words, they should be chunked.

### 3.1.2 Literature Review

Relying solely on a dictionary, longest matching and maximum matching struggle with dictionary size and unknown words. Attempts were made to push beyond the limits, to cope with the unknown, e.g., the unknown word collecting framework by Haruechaiyasak and his colleagues (Haruechaiyasak, Sangkeettrakarn, Palingoon, Kongyoung, & Damrongrat, 2006). Theirs is an integrative framework that extracts from the Web unrecognizable words, which are then reviewed and corrected by human before adding to a dictionary. Another long-term project, LEXiTRON (Trakultaweekoon, Chai, & Supnithi, 2009), was launched in 1995 and has since hosted an online dictionary with an expertise-based vocabulary suggestion system. The community-driven dictionary currently holds over a hundred thousand words; of which over twenty thousand were added by its members[3]. Alternative to the expanding dictionaries is a statistical approach. Collected from a hand-tagged corpus, Asanee and Chalathip's work (Asanee Kawtrakul & Thumkanon, 1997) proved that a statistical data information can be of a great help to diminish not only the problem of word boundary ambiguity but POS tagging ambiguity and implicit spelling errors as well.

Ever since the arrival of machine learning, the eclipse of dictionary-dominant age cannot be overstated. Learning from Thai character clusters (TCCs), a decision tree C4.5 model (T. Theeramunkong et al., 2000; Thanaruk Theeramunkong & Usanavasin, 2001), which is a non-dictionary word segmentation approach, could outperform the traditional dictionary-based techniques. Each of TCCs contains contiguous characters, ones that

[3] Available at http://lexitron.nectec.or.th

normally inseparable. The clusters are as well a vital part of Limcharoen et al.'s work (Limcharoen, Nattee, & Theeramunkong, 2009), which applies Generalized Left-to-Right (GLR) parsing and a statistical language model to word segmentation, and Kruengkrai et al.'s word and character-cluster hybrid model (Kruengkrai & Uchimoto, 2009), which is effective in handling unknown words. Another approach, a statistical machine translation (Bangcharoensap, Porkaew, & Supnithi, 2009), also has its place in word boundary identification. It selects from segmented sentences one that maximizes the probabilities of translation model and language model of a given unsegmented sentence.

CRF is behind the success of highly accurate word segmentation methods across multiple languages (Peng, Feng, & McCallum, 2004). Designed to learn and predict sequential data, CRF is without doubt a preferable choice for various text processing tasks such as POS tagging, named-entity recognition, and sentence segmentation (McCallum & Li, 2003; Zhou, AiTi, Lertcheva, & Xuangcong, 2016). As for Thai word segmentation, (Suesatpanit, Punyabukkana, & Suchato, 2009), as well as (Haruechaiyasak & Kongyoung, 2009), demonstrated their effective implementations of CRF. With several adjustments, they could leverage the characteristics of the language, achieving even greater accuracy. Despite all those triumphs, however, the problem of compound word ambiguity and the lack of POS tags in CRF-based sentence segmentation are yet to be conquered. These are where our algorithms contribute.

### 3.1.3 Methodology

The entire process comprises two steps. First, we refine the CRF model for word segmentation, then perform the post-processing. The word merging algorithm is the post-processing method aimed at tackling the compound word issue, while the word splitting algorithm targets the sentence segmentation problem.

*3.1.3.1 CRF-based Word Segmentation*

CRF offers flexibility in customizing feature set and template. Here, we apply a feature set introduced and tested by (Haruechaiyasak & Kongyoung, 2009); (Table 3.1). They found that character and character-type feature sets together yield more accurate result (F-score of 0.94 against 0.92 for character-only and 0.63 for character-type-only).

*Table 3.1* Character-type feature set (Haruechaiyasak & Kongyoung, 2009)

| Tag | Type of Characters | Items |
|---|---|---|
| c | Consonant which can be a word ending character | ก ข ฃ ค ฆ ง จ ช ซ ญ ฎ ฏ ฐ ฑ ฒ ณ ด ต ถ ท ธ น บ ป พ ฟ ภ ม ย ร ล ว ศ ษ ส ฬ อ |
| n | Consonant which cannot be a word ending character | ฅ ฉ ผ ฝ ฌ ห ฮ |
| w | Vowel that can be at the beginning of a word | เ แ โ ใ ไ |
| v | Vowel that cannot be at the beginning of a word | ะ ◌ิ ◌ี ◌ึ ◌ื ◌ุ ◌ู ◌ั า ◌ำ ๅ |
| t | Tonal | ◌่ ◌้ ◌๊ ◌๋ |
| s | Symbol | ◌์ ๆ ฯ . |
| d | Digit | 0 – 9 |
| q | Quote | ‘_‘ “_“ |
| p | Space within a word | _ |
| o | Other | a-z A-Z |

Haruechaiyasak and Kongyoung’s settings regard each character and its character type individually. We consider up to two characters (including their types) before and after the character of interest. Suppose $C_t$ is the character of interest and $T_t$ is its character-type: $C_{t-1}$ and $T_{t-1}$ would be the previous ones, and $C_{t+1}$ and $T_{t+1}$ would be the ones that follow. We introduce three feature-set templates: *Single*, which comprises only the character of interest and its character-type, *Combine-1*, which adds combinations of up to one character before and after, and *Combine-2*, which adds up to two characters. Looking further than two adjacent characters causes an inordinate leap in demand for computational resources; thus, is not cost-effective. Table 3.2 describes our feature-set templates.

*Table 3.2* Feature set templates

| | Type | Feature |
|---|---|---|
| Character | *Single* | $C_t$ |
| | *Combine-1* | $C_{t-1}, C_t, C_{t+1}, C_{t-1}C_t, C_tC_{t+1}, C_{t-1}C_tC_{t+1}$ |
| | *Combine-2* | $C_{t-1}, C_t, C_{t+1}, C_{t-1}C_t, C_tC_{t+1}, C_{t-1}C_tC_{t+1},$ $C_{t-2}C_{t-1}C_t, C_tC_{t+1}C_{t+2}, C_{t-2}C_{t-1}C_tC_{t+1}C_{t+2}$ |
| Category | *Single* | $T_t$ |
| | *Combine-1* | $T_{t-1}, T_t, T_{t+1}, T_{t-1}T_t, T_tT_{t+1}, T_{t-1}T_tT_{t+1}$ |
| | *Combine-2* | $T_{t-1}, T_t, T_{t+1}, T_{t-1}T_t, T_tT_{t+1}, T_{t-1}T_tT_{t+1},$ $T_{t-2}T_{t-1}T_t, T_tT_{t+1}T_{t+2}, T_{t-2}T_{t-1}T_tT_{t+1}T_{t+2}$ |

For example, the word 'เรือใบ' has six characters: เ, ร, ื, อ, ใ, บ. Suppose the forth character is the character of interest, the set of characters should be: $C_{t-2}$ = ร, $C_{t-1}$ = ื, $C_t$ = อ, $C_{t+1}$ = ใ, $C_{t+2}$ = บ. In the combined sequence, we would have, for example, $C_{t-2}C_{t-1}C_t$ = รือ. The characters' category should be: $T_{t-2}$ = c, $T_{t-1}$ = v, $T_t$ = c, $T_{t+1}$ = w, $T_{t+2}$ = c and $T_{t-2}T_{t-1}T_t$ = cvc.

With introduced feature set templates, we expected to boost the accuracy of the CRF model. In fact, similar idea was mentioned by (Suesatpanit et al., 2009). (Zhao, Huang, & Li, 2006) also defined feature set template partly from unigram and bigram of the characters and observed improvement in their Chinese word segmentation model.

*3.1.3.2 Study 4: Dictionary-based Word Merging*

Together with released BEST2009 corpus, Human Language Technology Laboratory at National Electronics and Computer Technology Center in Thailand published detailed instruction of how they constructed it. The document explained relevant linguistic definitions and segmentation rules, laying the foundation upon which we built our study. As explained in the *linguistic fundamentals* section, we hypothesized that compound words, conjunctions, and interrogative words with semantically comparable roots should not be chunked; otherwise, we would risk altering their message or context. The rules are different in the BEST2009 corpus; in which these words are all chunked. That being said, we are not repudiating the original labeling. Instead, we prefer the idea that different chunking methods serve different purposes. In an attempt to reverse the chunking, we could relabel the corpus and preserve the compound words, but that would not be cost effective. Instead, since compound words are considered to be a single word in terms of their dictionary definition, they ought to be defined in a dictionary. Therefore, if any sequential combination of multiple segmented words appeared in a dictionary, we merged it.

For a set of all vocabularies $V$ in a dictionary, suppose a sentence $S$ contains the words $w_1 \ldots w_n$. For each $w_j$ where $1 \leq j \leq n(S)$, the merging algorithm first attempts to find the longest recognizable sequential combinations $w_j \ldots w_{j+l-1}$, then the shorter ones until $w_j w_{j+1}$. The longest sequence possible is the length of the longest word ($l$) in the dictionary. This is the case wheen the longest word appears in the sentence and its characters are all separated, which is highly unlikely. If a combination of $m = w_j \ldots w_{j+k}$ where $1 \leq k \leq l - 1$ is a word, $w_j$ would be replaced by $m$ and $w_{j+1}, \ldots, w_{j+k}$ would be removed from the sentence. Figure 3.1 shows our word merging algorithm.

Our aim is for the algorithm to be able to preserve compound words efficiently without compromising on the accuracy achieved by the CRF model. The algorithm will also offer the simplicity of not having to change the design of the CRF model to perform the task.

```
Definition:
S = w_1 … w_n is a sentence
n(S) returns number of words in S
---
Input: Document D, Dictionary V
N ← Ø // output document
l ← length of the longest word in V
for each S in D:
    O ← Empty string // output string
    for i from l – 1 to 1:
        for j from 1 to n(S):
            if i + j ≤ n(S):
                m ← w_i … w_j
                if m is in V:
                    w_j ← m
                    for k from 1 to i:
                        w_{j+k} ← empty
    for j from 1 to n(S):
        if w_j is not empty:
            O ← O w_j
    N ← N + O
Output: Document N
```

*Figure 3.1* Dictionary-based word merging algorithm

#### *3.1.3.3 Study 5: POS-based Word Splitting*

Nothing marks the end of a sentence in Thai. A space may be the most consistent as a sentence delimiter, but it is used for other purposes as well, such as separating numbers from characters. Moreover, (Zhou et al., 2016) found no spaces at the end of about 23% of the sentences in TaLAPi's news corpus (5,489 articles; over three million words); (Aw, Aljunied, Lertcheva, & Kalunsima, 2014). For developing a reliable sentence segmentation method, Zhou et al. turned to CRF. The task is to determine whether a word, with a space included, is the last in a sentence. Since this is a word-level operation, they have the advantage of utilizing POS as a feature set. However, following their method, we noted words lacking a POS tag. The dearth of POS tags could be the result of inaccurate word segmentation, or the inability of the POS tagger to cope with obscure words. If vocabulary size is the problem, then compound words may be the cause. First, as they are highly diverse, one corpus, even a large one, may omit a considerable number of them. Second, if compound words with roots resembling their meaning were chunked and their roots were assigned a POS tag in a corpus, it may be better to divide them whenever possible to increase POS tags.

We defined our POS-based word-splitting algorithm (Figure 3.2) as follows: If a word does not have a POS tag but all its roots can be tagged, split it. For a word $w$ consisting of characters $c_1 \ldots c_n$, where $n$ is the length of the word, we split the characters into $p$ sequential groups, where $2 \leq p \leq n$-1. Each group, $g$, becomes a candidate root. At every iteration, we generate all possible splitting outcomes; for example, at $p = 2$, $w = c_1c_2c_3c_4$, we would have $g_{2,1} = c_1, c_2c_3c_4$; $g_{2,2} = c_1c_2, c_3c_4$; $g_{2,3} = c_1c_2c_3, c_4$. For every splitting outcome, if all the roots can be tagged, the outcome would be considered a candidate. From the pool of candidates, we then choose the one with the most roots to be the outcome; that is, the split words.

More POS tags mean more information is available for the sentence segmentation model to make predictions; ergo, more accurate chunking. We hypothesized that an increased number of POS tags would make sentence segmentation more accurate.

```
Definition:
S = w1 … wn is a sentence
n(S) returns number of words in S
n(w) returns number of characters in S
Split(w, p) is a function that splits w into p groups and returns,
        if exists, the outcome with most tagged roots,
        otherwise, returns empty.
---
Input: Document D, Dictionary V with POS tags
N ← Ø // output document
for each S in D:
    O ← Empty string // output string
    for i from 1 to n(S):
        if wi is not in V:
            for p from 2 to n(wi):
                m ← Split(wi, p)
                if m is not empty:
                    O ← O m
                else:
                    O ← O wi
        else:
            O ← O wi
    N ← N + O
Output: Document N
```

*Figure 3.2* POS-based word-splitting algorithm

### 3.1.4 Experiments and Results

*3.1.4.1 CRF-based Word Segmentation*

Our methods modify the result of the CRF model. Thus, it was imperative that we first found the CRF model's setting that yielded the highest accuracy. While we did not alter Haruechaiyasak and Kongyoung's character-type feature set, we needed to choose from our three feature templates, *Single*, *Combine-1*, and *Combine-2*. We expected *Combine-2* to outperform the other two, since this template takes the greatest length of the neighbors into consideration.

We trained and tested the CRF model using BEST2009. The corpus contains over five million words (over 21 million characters) across eight genres. Eighty percent of the corpus are for training; the rest are for testing. We incorporated Python package sklearn-crfsuite[4], a wrapper of python-crfsuite[5], which implements Lafferty et al.'s work (Lafferty, McCallum, & Pereira, 2001). The training implemented L-BFGS algorithm for gradient descent, with the coefficients of both L1 and L2 regularizations set to 0.1. The optimization algorithm was iterated at the maximum of 100 iterations. We configured the CRFSuite to generate state features that associated all of the possible combinations between attributes and labels, enabling the CRF model to learn the condition in which an item was not predicted by its reference label[6].

The model was trained on Amazon EC2 r3.4xlarge instance (16 vCPU on Intel Xeon E5-2670 v2 2.5 GHz, 122 GiB memory, and 320 GB SSD storage)[7]. The testing does not require a substantial amount of memory; thus, a computer with 1.7 GHz Intel Core i7 processor, 8 GB 1600 MHz DDR3 memory, and 256 GB SSD storage suffices; the same goes for every experiment hereafter.

---

[4] Available at https://pypi.python.org/pypi/sklearn-crfsuite

[5] Available at http://www.chokkan.org/software/crfsuite

[6] More information at https://sklearn-crfsuite.readthedocs.io

[7] Available at https://aws.amazon.com/ec2

*Table 3.3* CRF-based word segmentation on BEST2009 corpus

| Feature Template | Precision | Recall | F1 |
|---|---|---|---|
| *Single* | .93 | .93 | .93 |
| *Combine-1* | .96 | .96 | .96 |
| *Combine-2* | .99 | .99 | .99 |

In

Table 3.3, with the Combine-2 feature template, we were able to increase the accuracy up by six percent. This increase corroborates (Zhao et al., 2006) finding that incorporating neighboring characters augments the accuracy of the CRF model. Once we had ascertained the preeminent feature template, if we were to have retained the original BEST2009 corpus' rules without change, we would already have had a highly reliable CRF-based word segmentation model at hand; however, as we aimed to leave all the compound words intact, we continued.

*3.1.4.2 Dictionary-based Word Merging*

When building a test corpus, we assigned one native Thai speaker to relabeled 509 paragraphs that were chosen randomly chosen from all the document categories in BEST2009, yielding a total of 25,603 words. Following the rules in the *linguistic fundamentals* section, compound words, conjunctions, and interrogative words with semantically comparable roots were all preserved; we changed nothing else.

The word merging algorithm looks up its candidate words in three dictionaries – Wiktionary [8], LibThai [9], and LEXiTRON [10]. In their work, Haruechaiyasak and Kongyoung proposed named-entity (NE) merging as a post-CRF process that helps

[8] Available at https://www.wiktionary.org

[9] More information at https://linux.thai.net/projects/libthai

[10] More information at https://www.nectec.or.th

enhance word segmentation. They extracted NEs from BEST2009 corpus, and so did we. In addition, we merged with our NE list names from LibThai and GeoNames[11].

Table 3.4 shows the evaluation results. We tested all the combinations of the six corpora and found a moderately positive correlation between the number of corpora and the accuracy ($r$ = .48, $n$ = 64, $p$ < 0.01). The best combination for our test data was the one that incorporated all the corpora except GeoNames ($F1$ = .9835). The F1-score decreased slightly when all corpora were included ($F1$ = .9834). Therefore, it is best to include more corpora to increase the accuracy.

In the results, we found compound words that retained their meaning after the merging; for example, 'ผล' (result), 'ประกอบ' (assemble), 'การ' (task) become 'ผลประกอบการ' (turnover). However, the algorithm sometimes mistakenly combined correctly chunked words. For example, 'เป็นหนึ่ง' (be number one) should not be chunked unless it is a part of 'เป็นหนึ่งใน.' In this case, the correct segmentation would be 'เป็น' (is), 'หนึ่ง' (one), 'ใน' (of). Such a case is not common, but doubtless contributed to the inaccuracy observed. Another unexpected case was word correction, as in the case of 'เ' and 'หตุ,' which were segmented incorrectly; neither has a meaning individually, but become 'เหตุ' (cause) together.

*Table 3.4* Evaluation of word merging algorithm on relabeled corpus

| Template | Merging Rule | Precision | Recall | F1 |
|---|---|---|---|---|
| *Single* | - | .88 | .85 | .86 |
| | All NE | .88 | .82 | .83 |
| *Combine-2* | - | .95 | .94 | .95 |
| | NE: BEST2009 | .92 | .86 | .88 |
| | NE: LibThai | .94 | .91 | .92 |
| | NE: GeoNames | .95 | .94 | .94 |
| | All NE | .92 | .86 | .87 |
| | Dict.: LEXiTRON | .98 | .98 | .98 |
| | Dict.: Wiktionary | .95 | .94 | .94 |
| | Dict.: LibThai | .95 | .94 | .94 |

[11] More information at http://www.geonames.org

| | | | |
|---|---|---|---|
| All Dict. | .98 | .98 | .98 |
| **All NE & Dict.** | **.98** | **.98** | **.98** |

All NE combines NEs from BEST2009, Libthai and GeoNames.
All Dict. combines vocabularies from LEXiTRON, Wiktionary, and LibThai.

*3.1.4.3 POS-based Word Splitting*

Having anticipated that our word splitting algorithm should help improve sentence segmentation, we tested it on ORCHID corpus (Sornlertlamvanich, Takahashi, & Isahara, 1999). ORCHID is equipped with POS tags and sentence-level boundary annotations, which we need for the evaluation. In training the CRF-based sentence segmentation model, we employed sklearn-crfsuite with identical configuration as in the word segmentation experiment. (Zhou et al., 2016) original CRF feature template includes up to one neighboring word, word-type (English word, Thai word, punctuation, digits and spaces), and POS. Our extended template covers two adjacent words. We used eighty percent of the corpus for training and the rest for testing.

*Table 3.5* Accuracy measurement on original ORCHID corpus

| Template | Measure | Precision | Recall | F1 | #POS Tagged |
|---|---|---|---|---|---|
| Original | *E* | .81 | .56 | .66 | |
| | *I* | .97 | .99 | .98 | |
| | **Avg.** | **.96** | **.96** | **.96** | **100%** |
| Extended | *E* | .86 | .77 | .81 | |
| | *I* | .98 | .99 | .99 | |
| | **Avg.** | **.97** | **.98** | **.97** | **100%** |

In Table 3.5, E represents words at the end of a sentence; *I* represents the rest, including spaces between words. Extending the feature set template gave us a boost in F1-score by .15; therefore, it was our pick in the subsequent evaluation of the word splitting algorithm. This time, we trained the sentence segmentation model with the entire corpus. Preparing the test corpus, we removed from ORCHID corpus word-level annotations and POS tags, then chunked all sentences and labeled every word as *E* or *I*, depending on their position in the sentence, and removed sentence-level annotations.

*Table 3.6* Accuracy measurement on processed ORCHID corpus

| Template | Measure | Precision | Recall | F1 | #POS Tagged |
|---|---|---|---|---|---|
| WS + CRF using ET | *E* | .80 | .73 | .76 | |
| | *I* | .98 | .99 | .99 | |
| | **Avg.** | **.97** | **.97** | **.97** | **93.71%** |
| WS + CRF & Split using ET | *E* | .79 | .74 | .77 | |
| | *I* | .99 | .99 | .99 | |
| | **Avg.** | **.97** | **.98** | **.97** | **95.10%** |

WS stands for word segmentation

As expected, not all the segmented words could be tagged via POS; hence, the sentence-segmentation model decreased in accuracy. The splitting algorithm was able to recover the average F1-score by 3.58 percent in relation to the loss margin[12], with 1.39 percent more POS being tagged. Overall, the word splitting algorithm improved CRF-based sentence segmentation.

### 3.1.5 Applications of Proposed Algorithms

*3.1.5.1 Topic Extraction*

The Latent Dirichlet Allocation (LDA) (Blei et al., 2003) and Hierarchical Dirichlet Process (HDP); (Teh & Jordan, 2010; Teh, Jordan, Beal, & Blei, 2005) models are capable of discovering underlying topic structures in discrete data. Both generate small sets of words, each associated with a latent topic. From these words, humans interpret the topics, making it vital that the words' meanings and contexts are easily

[12] $(F1_{WS + CRF \& Split} - F1_{WS + CRF}) / (F1_{CRF} - F1_{WS + CRF}) \times 100$

comprehensible. Therefore, we hypothesized that by merging compound words, preserving their original meaning, would make the interpretation more accurate.

To investigate this, we collected 2,000 tweets, half of which were flood-related and the rest pertained to traffic. All the tweets in the flood corpus contained a hashtag #thaiflood. The traffic tweets were from two prominent Twitter accounts, @js100radio and @fm91trafficpro, both dedicated to providing traffic information. Each tweet had all the URLs, usernames, and hashtags removed before the words were chunked and merged. We then fed both corpora separately into LDA and HDP models of Python package *genism*[13], creating a total of four tests.

*Table 3.7* Word merging in topic extraction results

| Corpus | Model | Selected Most Relevant Words | Percentage of Merged Words in Relation to Selected Most Relevant Words |
|---|---|---|---|
| Flood | LDA | 250 | 7.6% |
| | HDP | 250 | 23.6% |
| Traffic | LDA | 250 | 10% |
| | HDP | 250 | 16% |

As shown in Table 3.7, in each of the four tests, we selected the 50 most relevant words from five topics, yielding 250 words in total. We found merged words, meaning that the algorithm affected topic extraction. The examples in Table 3.8 further explain the results.

*Table 3.8* Examples of merged words in topic extraction

| Corpus | Chunked Compound Words | Merged Words |
|---|---|---|
| Flood | ระดับ (*level*), น้ำ (*water*) | ระดับน้ำ (*water level*) |
| | ผู้ (*person*), ประสบภัย (*face disaster*) | ผู้ประสบภัย (*victim*) |
| | ต้อง (*must*), การ (*task*) | ต้องการ (*need*) |
| Traffic | ขา (*leg*), เข้า (*in*) | ขาเข้า (*inbound*) |

[13] Available at https://pypi.python.org/pypi/gensim

| | |
|---|---|
| แ (*no meaning*), ยก (*lift*) | แยก (*intersection*) |
| รถ (*car*), ติด (*stuck*) | รถติด (*traffic jam*) |

If a topic extraction model regards the chunked words separately, it will omit the relation the words once had, potentially leading to poor interpretation. For example, 'น้ำ' (*water*) as in 'ระดับน้ำ' (*water level*) may also be a part of 'น้ำดื่ม' (*drinking water*) in some other sentences. While 'water level' conjures a sense of a situation report, 'drinking water' may be in sanitation guidelines, which is a different topic. Isolating the words 'water,' 'level' and 'drink' does not convey meaning to interpret. Thus, by applying our word-segmentation algorithm, compound words remained intact and their meaning was preserved, enhancing the interpretation of topic extraction.

*3.1.5.2 Study 6: Thai-English Translation*

We investigated whether splitting and merging words improved translation. Using the fact that the word-merging algorithm could merge incorrectly segmented words, we searched for words that were not found in any dictionary, attempted to split them to remove incomprehensible characters, and then merged them. For example, 'ในน ามีข้ าว' are three wrongly separated tokens with no meaning. Splitting the sentence produces 'ใน น า มี ข้ าว', which consists of six tokens, two of which are meaningful ('ใน' means *in* and 'มี' means have). After merging, the sentence becomes 'ใน นา มี ข้าว', which is sequentially translated as *in* (ใน), *field* (นา), *has* (มี) and *rice* (ข้าว).

We collected 50 abstracts from the Journal of King Mongkut's University of Technology North Bangkok[14]. All the abstracts had an English translation, which we used as a test data. We created two experimental conditions. In the first condition, we

[14] Available at http://ojs.kmutnb.ac.th/index.php/kjournal/

segmented words in the Thai abstracts. The chunked texts were then split and merged in the second condition.

We fed the processed Thai abstracts in both conditions into our pre-trained machine translation model and into Google Translate[15], creating four conditions in total. We trained the Thai-English Transformer model [28] using tensor2tensor[16] and 75,535 parallel sentences obtained from TED Talks[17]. The English translations were then compared to their human-translated references using three of ROUGE metrics (Lin, 2004).

*Table 3.9* Paired samples test of F1-scores between the two conditions (Transformer)

| | WS | | WS + Split & Merge | | | | Sig. |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | t | df | (2-tailed) |
| ROUGE-1 | .23 | .04 | .22 | .04 | 1.31 | 49 | .194 |
| ROUGE-2 | .05 | .03 | .04 | .02 | 1.16 | 49 | .247 |
| ROUGE-L | .18 | .04 | .18 | .03 | .59 | 49 | .554 |

ROUGE-N compares an overlap of N-grams;

ROUGE-L compares Longest Common Subsequence (LCS).

*Table 3.10* Paired samples test of F1-scores between the two conditions (Google Translate)

| | WS | | WS + Split & Merge | | | | Sig. |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | t | df | (2-tailed) |
| ROUGE-1 | .42 | .01 | .43 | .01 | 2.13 | 49 | .038* |
| ROUGE-2 | .16 | .01 | .18 | .01 | 3.37 | 49 | .001** |
| ROUGE-L | .32 | .01 | .34 | .01 | 2.52 | 49 | .015 |

* $p \leq 0.05$, ** $p \leq 0.01$; WS stands for word segmentation;

[15] Available at https://translate.google.com

[16] Available at https://github.com/tensorflow/tensor2tensor

[17] Available at https://www.ted.com

As shown in Table 3.9 and Table 3.10, Google Translate outperformed our pre-trained model by a wide margin. We speculate that this may have been the result of the small amount of training data. There was no significant difference regarding the accuracy between the two conditions when translated using the Transformer model. For Google Translate, on the other hand, a paired-samples t-test of the 50 abstracts' ROUGE evaluations, as shown in Table 10, indicated a significant improvement in translation. However, this improvement may be limited by factors beyond our control due to Google Translate's ability to repair incorrectly separated words and merge compound words. That being said, the improvement observed tells us that our method can help to make word-level Thai-English translation more accurate. Note that character-level translation is beyond the scope of this study, since our focus is on word segmentation.

#### *3.1.5.3 Study 7: Summarization*

A graph-based algorithm, TextRank (Mihalcea & Tarau, 2004), has long been well known in text summarization. The relationship between nodes determines a connection between two sentences in terms of similarity measured as a function of their content overlap. The overlap can be as simple as the number of common lexical tokens in the two sentences, which was the setting for our implementation, or it may involve more sophisticated syntactic features such as POS. The algorithm, operating at both the word level and sentence level, ranks important sentences based on the graph.

In Thai, the word-level operation is not a serious problem since, although not perfect, the CRF-based word chunking is reasonably reliable. Sentences, on the other hand, are a different conundrum to solve. If, for example, the important sentence is mistakenly segmented, parts of it may be omitted, while a segment of its less-important neighbors may be included. In either case, the error undermines what should have been, as decided by TextRank, the best summary of the document.

Our summarization experiment tested whether the improved sentence segmentation could enhance text summarization. We used the TextRank-based summarization function of *gensim* with a default summarization ratio (0.2). The test corpus, summarized manually by one Thai native speaker, contained 50 on-line articles from various publishers and across different topics. The first experimental condition involved word chunking; of an average of 1163.3 words per article, 85.31 percent could be tagged. In the second condition, we performed the POS-based word splitting on the segmented text from the first condition, thus increasing the POS tags by 1.19 percent.

*Table 3.11* Paired samples test of F1-scores between the two conditions

| | WS | | WS + POS Split | | | | Sig. |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | t | df | (2-tailed) |
| ROUGE-1 | .61 | .06 | .63 | .05 | 5.46 | 49 | < .001* |
| ROUGE-2 | .36 | .07 | .38 | .06 | 4.73 | 49 | < .001* |
| ROUGE-L | .38 | .07 | .39 | .07 | 3.66 | 49 | < .001* |

* $p \leq 0.001$; WS stands for word segmentation;

As evidenced in the test results shown in Table 3.11, our POS-based word-splitting algorithm improved the summarization significantly. In conclusion, the splitting method increased the POS tags, leading to more accurate sentence segmentation and better summarization.

### 3.1.6 Discussion

We introduced two post-processing methods for CRF-based word segmentation. The first method, a dictionary-based word-merging algorithm, addresses the compound-word ambiguity issue by implementing the notion that all kinds of compound words should stay intact to maintain their precise meaning and context. Our experiment has demonstrated that the algorithm can preserve the compound words, meaning that the entire corpus does not have to be recreated by the researchers for the task.

The second method, a POS-based word-splitting algorithm, targets the sentence-boundary ambiguity. The algorithm increases POS tags with segmented words, giving the

CRF-based sentence-chunking model more information for the prediction of sentence boundaries. Our experiment verified that the method improves results.

The word-merging method benefits topic extraction by making human interpretation more comprehensive. In combination with dictionary-based word splitting, the algorithm enhances word-level Thai-English translations. Lastly, the POS-based word-splitting method improves both sentence segmentation and text summarization.

The results show that the proposed methods can be used effectively in analyzing data obtained from social media. Hence, the following chapter explores the possibility of enhancing the proposed algorithms to be applied for social media analysis.

# Chapter 4

# Brand Crisis in Social Media

The first section of this chapter will present related studies on brand crisis and social media. The section will explain the definition and types of brand crisis, as well as consequences to a brand. We will review crisis communication strategies, current understanding of consumer behavior during the crisis, and practices to recover brand reputation. Next, we will focus on word-of-mouth (WOM) – which is the important part of crisis communication, especially electronic word-of-mouth (eWOM) since this dissertation is about social media. The section will describe how WOM is conveyed and perceived. It will also present a relationship between WOM and revenue – to emphasize the severity of consequences of negative WOM to a brand. Later in the section, we will explain in detail the effects of WOM on brand perception and emotions involved in WOM. The second section will introduce theories in the psychology of entertainment, both on *enjoyment* and *appreciation* dimensions, as well as the dual-process models. The topic will then move on to entertainment experience in social media, with the last section dedicated to the *appreciation* dimension of the experience. The third section will describe three studies which analyze MFT's moral foundations in the context of brand crises, both in English and in Thai. The forth section will describe an analysis of the hedonic dimension of the entertainment experience in brand crisis, followed by a discussion of the non-hedonic dimension.

## 4.1 **Brand Crisis and Entertainment**

### 4.1.1 Brand Crisis

*4.1.1.1 Overview*

A crisis is an unpredictable event that can negatively impact stakeholder expectancies and organization's performance (Coombs, 2007). The probability of such event is low and mostly unexpected, but the damage can be acute (Barton, 2001). A damaged brand image could generate serious consequences for brand equity and trust in the brand (Dawar & Pillutla, 2000). Sellnow and Seeger suggested that multiple methods are necessary for building a complete understanding of complex crisis events. It is also essential for crisis managers to adapt their interpretive frameworks during crises in order to ascertain the unique nature of each crisis, regardless of their previous experiences with similar crises (Sellnow & Seeger, 2001). Consumers' perception plays an important role when we consider a crisis in the extent of a brand crisis. (Greyser, 2009) classified reputational threads to a brand into the nine categories of (i) product failure, (ii) social responsibility gap, (iii) corporate misbehavior, (iv) executive misbehavior, (v) poor business results, (vi) spokesperson misbehavior and controversy, (vii) death of the company symbol, (viii) loss of public support and (ix) controversial ownership. For the thread to be a crisis, the following four elements should present: '(i) severe consequence(s), (ii) threats to the fundamental value of an organization, (iii) limitations in response time and (iv) unexpectedness of the event' (Xu & Li, 2013).

Product harm crisis is a good example to understand consumers' brand perception in the crisis. Several studies have successfully shaded the light in this area of research. Yannopoulou et al. found that consumers' perceived risk depends on social influence and perceived reliability of the content. The outcomes of perceived risk are also important as it affects brand trust and attitude towards the organization, and generate negative emotions (Yannopoulou et al., 2011). Also, they concluded that consumers who are familiar with the brand are affected by a relevant crisis but not by an irrelevant crisis when they evaluate the brand. On the other hand, consumers who are unfamiliar with the brand are affected regardless of crisis relevance.

Greyser also suggests four key areas that organizations should examine to prevent reputational threats in the time of crisis (Greyser, 2009). The first area concerns brand elements, which exists prior to the crisis, including brands' marketplace situation, brand strengths/weaknesses, and an essence of brand's meaning. The second area is the seriousness of the crisis and its threat to brand's position/meaning. The model in this study explains and measures this area, and also provides strategies for organizations to initiate their communication to stakeholders, which is the third area. The last area is the results of the effectiveness of initiatives in terms of recovery and favorability or market share. This explanation is consistent with Coombs' suggestion that organization responds are extremely important to its reputation (Coombs & Holladay, 2002). In fact, traditional literatures view crisis as events and accidents (Fink, 1986), while a notion of communication-based phenomena was later added and linked to negative images in public perception (Coombs, 1999; Yannopoulou et al., 2011).

The scope to which the brand is referenced should be restricted to that of a company, i.e., a commercial business. However, the restriction does not entail a line of business, scale of the crisis, time of occurrence or demographics of the audience. The audience are the users of social media, which include, but are not limited to, social networking sites (SNS) and content community (Kaplan & Haenlein, 2010). Contents and reactions, including negative word-of-mouth, that do not threaten brand essence, such as a negative review of a product, are not part of the crisis.

#### *4.1.1.2 Crisis Communication*

The influence of mass media in a brand crisis had been studied in early studies. The knowledge of these studies is important to the understanding of crisis communication in the online world, especially in social media. Mass media tend to reinforce risks and fear as an effort to gain attention from the audience (McQuail, 2003). Interestingly, bad news seems to be more attractive for mass media when compared to good news (Dennis & Merrill, 1996) and that can be problematic as the mass media are more credible source of information than marketer-driven communication (Bond & Kirshenbaum, 1998).

Moreover, negative information could change consumers' knowledge of a brand, as well as their trust and favorability (Dawar & Pillutla, 2000; Keller, 1993). However, some negative effects of the crisis can be mitigated by the report of company's action in a socially responsible way. Jolly and Mowen investigated factors that may affect consumer perceptions of companies making product recalls. They found that when information indicating that the company acted in a socially responsible manner was present, consumers held more favorable feelings toward the company (Jolly & Mowen, 1985). Siomkos proposed a new measure of organizational success in dealing with product-harm caused crises and presented suggestions regarding a troubled organization's appropriate response to the crisis (G. Siomkos, 1989). He and Kurzbard later published another study focusing on product replacement. They proposed a model that is provided to assist managers in making product replacement decisions on the basis of empirical standards. Also, they suggested a monitoring mechanism to assess the efficacy of company responses after they have been undertaken (G. J. Siomkos & Kurzbard, 1992). In fact, when compared to social media, some publics think that traditional media is more reliable (H. Seo, Kim, & Yang, 2009). Traditional media seems to be indispensable if an organization aims to reach as largest audience as possible (Veil et al., 2011).

The emergence of social media allows the expression of idea/opinion and facilitates the dissemination of information. Indubitably, it is an exceptionally effective environment for the diffusion of brand crisis as well as a compelling opportunity to be used for crisis communication (Colley & Collier, 2009). Word-of-mouth news is perceived as more trustworthy than mainstream media on some occasion (Bryant, 2004). In fact, according to Veil et al., best communication channels for public offline, online, or in the community should be incorporated in crisis communication. They also concluded best practices that are also applicable to brand crisis in their literature review regarding social media in risk and crisis communication (Veil et al., 2011). The model in this study aims to help practitioners understand distinctive characteristics of public and community in social media and improve their communication when following these practices.

This study proposes the model based on social media users' behavior as social media now becomes more crucial in determining the outcome of the crisis. According to Marken, people in general trust social media and use it to search for information (Marken, 2007). It is, therefore, an opportunity for organizations to monitor what users are exchanging and search for warning signs. Social media sites like Facebook are suitable for organizations to monitor people's discussions and look for any issue that they might be involved (Wright & Hinson, 2009), while Twitter particularly useful for observing public perceptions (Goolsby, 2009). A conversation regarding organizations can take place without organizations' acknowledgment and even participation (Veil et al., 2011). Thus, organizations are suggested to develop a plan to assess the efficacy of using social media in crisis communications. As for this study, learning characteristics of social media users is vital to understand their perception changes when they receive negative information about brands.

#### *4.1.1.3 Word-of-Mouth*

*Definition*

Traditional (offline) WOM has been studied for a long time in the marketing field. It contributes significantly on customers' buying decisions (Richins & Root-Shaffer, 1988). Online WOM has extended the opportunity for customers to gain unbiased product information from other customers, as well as to share their information and opinions. The term eWOM is defined for online WOM as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). While Hennig-Thurau et al. emphasized the definition of eWOM on current customers, Stauss illustrated eWOM consider a wider target: "Any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions" (Stauss, 2000). According to Yap et al., social media users are motivated to engage in eWOM because of their intention to avail social benefits, seek for advices and help the organizations, as well as concern for other consumers, inclination for positive self-enhancement, and deliberation for venting negative feeling (Yap, Soetarto, & Sweeney, 2013).

*Characteristic of WOM*

To learn how eWOM is conveyed, it is important to understand consumer complaint. In consumer complaining behavior (CCB) studies, negative feelings or emotions from perceived dissatisfaction are found to trigger complaints. The dissatisfied consumer could react differently from doing nothing to engaging in complaining. Regarding CCB, Day presented a conceptualization emphasizing the nature of dissatisfaction in terms of emotions and how situational and personal factors are important in the post-dissatisfaction decision-making process (Day, 1984). Nyer and Gopinath conducted another interesting study regarding consumer's WOM behavior. They reviewed the motivation for voice behavior by dissatisfied consumers and demonstrated that facilitating complaining behavior helps reduce negative WOM activity. The reason is that dissatisfied consumers who complain to the marketer will experience a venting-induced reduction in dissatisfaction, and as a result, they tend to engage in reduced levels of negative WOM. However, dissatisfied consumers who engage in negative WOM publicly become committed to their level of dissatisfaction and are less likely to express any venting-induced reduction in dissatisfaction (Nyer & Gopinath, 2005). Note that individual can detect a majority opinion and is likely to avoid expressing their opinion if it contradicts the majority thoughts (Noelle - Neumann, 1974).

On the receiver side of WOM, Park and Lee examined how eWOM information direction (positive and negative) and a website's reputation (established and unestablished) contribute to the eWOM effect (C. Park & Lee, 2009). They focused on the moderating role of two product types: search and experience. Information about search goods can be acquired prior to purchase while experience goods consist of attributes that customers can perceive only when purchased and after use product (Klein, 1998; Nelson, 1974). Park and Lee found that eWOM effect is greater for negative eWOM than for positive eWOM, greater for established websites than for unestablished websites, and greater for experience goods than for search goods. Also, the impact of a negative eWOM effect is greater for experience goods than for search goods and the impact of website reputation on the eWOM effect is greater for experience goods than for search goods. Related to CCB, Chan and Cui studied the effects of negative word of mouth from worse-off or similar others in the post-consumption stage. Interestingly, they found that Attribute-based negative WOM has a negative (aggravating) effect on dissatisfied consumers, whereas experience-based negative WOM has a positive (i.e., alleviating) effect (Chan & Cui, 2011). Note that attribute-based WOM highlights the product, which is what it is and how it performs, whereas experience-based WOM highlights the consumer. Laczniak et al. used attribution theory to explain consumers' responses to negative word-of-mouth communication (WOMC); (Laczniak, DeCarlo, & Ramaswami, 2001). They proposed that causal attributions mediate the negative WOMC brand evaluation relation. Receivers' attributions depend on the way the negative WOMC is conveyed. One of their conclusions is that brand name affects attributions. According to Hoch and Deighton, a more favorable brand name is expected to reduce the effect of negative WOMC (Hoch & Deighton, 1989). Laczniak also concluded the categories of causal attributions that people generate in response to information, which include stimulus (i.e., brand), person (i.e., communicator), circumstance, or a combination of these three. These attributions were adopted from attribution theory and are thought to have an effect on brand evaluations in the negative WOMC context (H.H. Kelley, 1967; Harold H Kelley, 1973).

Type of product also contributes to how WOM receivers perceive the message. Sen and Lerman conducted an interesting study regarding this topic. They investigated a negative effect in e-WOM consumer reviews for utilitarian versus hedonic products, and the influence of the reader's attributions regarding the reviewer's motivations. They found that the reader's attributions about the motivations of the reviewer affect their attitude about the review. Readers of negative hedonic product reviews tend to attribute negative opinions to the reviewer's internal reasons instead of product-related reasons and are less likely to find the negative reviews useful. In the case of utilitarian product, readers are more likely to attribute the reviewer's negative opinions to external motivations, specifically product-related reasons, and therefore find negative reviews more useful than positive reviews (Sen & Lerman, 2007).

In term of revenue, negative WOM activities decrease purchase intentions and sales. Chevalier and Mayzlin examined the effect of consumer reviews on relative sales of books in some online websites. They found that when a book's reviews improved, it leads to an increase in relative sales at that site. For most samples in their study, the impact of positive reviews is smaller than the impact of negative reviews. Interestingly, previous evidence suggests that customers read review text rather than relying only on summary statistics (Chevalier & Mayzlin, 2006). Ho-Dac et al. investigated a relationship between online customer reviews (OCRs) and sales in both the emerging Blu-ray and mature DVD player categories. They found that Positive OCRs increase the sales of weak brands, which do not possess significant positive brand equity. Negative OCRs in weak brand results in an opposite direction. However, OCRs was found to have no significant impact on the sales of strong brands, although these selling models receive a significant sales boost from their greater brand equity (Ho-Dac et al., 2013). Basuroy et al. studied WOM from box office revenue. They found that both positive and negative reviews were correlated with weekly box office revenue. The results suggested that critics could influence and predict box office revenue. However, positive reviews have a smaller impact than negative reviews on product sales (Basuroy et al., 2003).

*WOM and Brand*

WOM is proved to have effects on brand perception. This finding is important because negative perception could damage a brand in long term and results in a huge loss of revenue. Liu interested in the effect of WOM on brand attitude, specifically, the effect of WOM valence (whether WOM is positive, negative, or neutral). Valence suggests the cognitive consequence of consumers' attitudes toward a brand. His results show that positive WOM increases expected product quality and brand attitude, whereas negative WOM diminishes them. Positive WOM leads to a recommendation for product purchase, and negative WOM leads to criticizing, rumor, and private complaining. In his research context, he uses actual WOM information to examine the dynamic patterns of WOM and how it helps explain box office revenue. He emphasized that WOM information offers significant explanatory power for both aggregates and weekly box office revenue, especially in the early weeks after a movie opens (Liu, 2006).

*Word-of-mouth and Emotion*

Emotion plays an important role in word-of-mouth activities. Consumption emotion involves many kinds of emotion: Hostile, aggressive, outraged, surprised, calm, distressed, tolerant, irritable, anxious, relaxed (Bitner, 1990; Schmitt, Dube, & Leclerc, 1992). Maute and Dubés proposed four patterns of emotional response to dissatisfaction, which were positioned in a tridimensional space defined by acceptance/calmness, anger/surprise, and anxiety dimensions. They investigated the patterns of emotional responses to a dissatisfactory consumption experience and the relationship between these patterns and consumer post-purchase responses. The result show that the angry/hostile group of participants was more likely to engage in negative word-of-mouth and less likely to remain loyal, compared to the surprised/worried group (Maute & Dubé, 1999). Westbrook examined consumer affective responses to product/consumption experiences and their relationship to selected aspects of post-purchase processes. His analysis confirms hypotheses about the existence of independent dimensions of positive and negative affect. Both dimensions of affective response are found directly related to the favorability of consumer satisfaction judgments, the extent of seller-directed complaint behavior, and the extent of word-of-mouth transmission (Westbrook, 1987).

Stephens and Gwinner reported the development of a theoretical model of consumer complaint behavior based on cognitive appraisal theory. They showed how different appraisal dimensions are associated with ten different consumption emotions and suggested how each emotion, based on its appraisal dimensions, will affect consumers' judgment and behavior. Their model presents cognitive appraisal as the key element to evaluate consumer threat and harm, which may result in psychological stress. They suggested that using stressful appraisal outcomes to elicit emotive reactions, together with cognitive appraisal, can influence the type of coping strategy (problem focused, emotion focused, and avoidance were discussed) used by the consumer (Stephens & Gwinner, 1998). Bonifield and Cole predicted that two negatively valence emotions (anger and regret) emphasize or mediate the effects of consumers' appraisals about service failure on post-purchase behaviors. Anger is important when explaining retaliatory behaviors, and both anger and regret affect conciliatory behaviors. They also found in their laboratory and web-based study that recovery efforts that reduce anger decrease retaliatory behaviors (Bonifield & Cole, 2007).

Many of WOM studies employ sentiment analysis. Berger et al. applied sentiment analysis to understand how positive, neutral, or negative emotions expressed in online WOM affect a consumer's product evaluation (Berger, Sorensen, & Rasmussen, 2010). Pullman et al. stated that the best way to gain a full understanding of a customer's feelings about a brand (in their study, a hotel) is to analyze the context of the customer's comments. They did content analysis and linguistic analysis, which examines the semantics, syntax, and context of customers' verbal communications. They emphasized that linguistic analysis applications help the analyst identify the key ideas in a text, indicate how important each idea is, and help develop a prediction of a customer's behavior (Pullman, McGuire, & Cleveland, 2005). Kim et al. also applied sentiment analysis techniques as a part of their study. They found that viewing NWOM has a negative effect on future purchases. Redemption behavior moderates the positive effect of posting (whether a customer is engaged with the brand or not). Also, expressing emotions, especially more intense emotions such as anger tends to discourage purchase behaviors. When customers have a chance to vent their negative feelings and be reminded of a brand's benefit, it produces a synergy effect (Kim, Su Jung; Wang, Rebecca Jen-Hui; Malthouse, 2015). (Schweidel & Moe, 2014) conducted another interesting study that employed sentiment analysis. They modeled data collected from different social media venues (blogs, Facebook, Twitter, etc.), to determine if consumer brand sentiment varies by venue type. This study reveals the risks of using social media metrics only for particular venues. They found that consumers often join online communities that the members share their interests and opinions. Moreover, a limited number of characters in a post have an impact on how an opinion is expressed. On microblogs like Twitter where a text is limited, consumers tend to post more extreme opinions so that they can convey their perspective clearly.

#### *4.1.1.4 Brand Crisis in Social Media*

Social media has been considered as a part of a brand crisis as it facilitates negative eWOM, as well as a positive one. Thus, it should be closely monitored (Goolsby, 2009; Wright & Hinson, 2009). The combination of brand crisis and social media dimensions is important to marketers whether or not they want to incorporate social media into their marketing strategies or more specifically, crisis communication practices. The reason is that consumers have become a source of brand stories weaken the role of marketers as an author of brand stories (Hennig-Thurau, Hofacker, & Bloching, 2013). These consumer-generated stories in social media are more impactful than marketer-generated stories in traditional channels because they utilize existing social networks and are available in real-time (Hennig-Thurau et al., 2010). With user-generated stories, brands are now expanding their role from building their reputation on consumers' networks to spread viral message and introduce new products to engaging with consumers at a personal level as another individual in the consumers' social networks (Gensler, Völckner, Liu-Thompkins, & Wiertz, 2013). This change brings together and integrates consumers' social networks and brand-centric networks. As a result, activities between a brand and consumers in social media (e.g. people following or liking the brand) complicates brand identity management as target consumers take characteristic of consumers involving in such activities into their brand evaluations and purchase intentions (Naylor, Lamberton, & West, 2012). Another aspect of the changing environment is that brands have become humanized through the interaction with consumers in social networks. Humanizing of brands leads to more favorable consumer attitudes and enhances brand performance in consumer's perception. However, it can also negatively affect consumers' brand evaluations when the brand faces negative publicity, or in a brand crisis (Puzakova, Kwak, & Rocereto, 2013). The topic of humanizing of brands is very much similar to the way people consume various kinds of entertainment products (e.g. movies). The studies in issues related to entertainment product consuming were reviewed in the previous section. However, the integration of entertainment and brand crisis dimension deserves attentions as it helps explain the role of entertainment in the crisis.

People are connected to brands in a profound way and these connections have evolved since social media. Puzakova and her colleagues explained the humanizing of a brand. However, the followed question is how connections are formed between consumers and the brand, which is perceived as if it is a person. Escalas has a good explanation on this question in her literature back in 2004 (Edson Escalas, 2004). Her explanation, which emphasizes the combination of entertainment and brand crisis dimension, is that consumers create (or enhance) their self-brand connections through a narrative processing. People, in general, interpret the meaning of their experiences by creating a story based on the experiences. Consumers map an ad that tells a story, which is considered as an incoming narrative information, onto existing stories in their memory (Shanke & Abelson, 1995). This process creates a relationship between the brands and consumers themselves (Edson Escalas, 2004). The stories of a brand in consumers' mind involve associations with self and psychological/symbolic benefits, which are related to the value of the brand (Aaker, 1991; Keller, 1993). In a brand crisis, this study proposes that negative and positive WOM are a story about a brand. This concept fits Escalas's explanation, and we should, therefore, expect a self-brand connection when consumers receive WOM. It is this part that the disposition-based theory and studies regarding justice in entertainment fulfill the combination between entertainment and brand crisis dimensions. When the brand is humanized and the self-brand connect is created, this explains the beginning point of moral judgment process and subsequent emotions, all of which lead to the foundation of proposed model.

### 4.1.2 Entertainment

*4.1.2.1 Overview*

Down through history, from ancient civilizations to our time, humankind has never lacked entertainment. Although it has never left us, not every scholar has thought it is essential (Vorderer & Reinecke, 2015). The turning point was when Zillmann and his collaborators conceptualized entertainment, giving it much more meaning than merely a waste of time. Since then, extensive resources have been spent on exploring gratifications (Oliver & Bartsch, 2010). Theories and empirical researches evolved around the hedonistic values of pleasure, amusement and diversion — all of which are associated with literal meaning of *entertain* (Oliver & Raney, 2014). Enjoyment was the center of attention (Vorderer, Klimmt, & Ritterfeld, 2004) and theories on hedonistic motivations dominated the landscape of entertainment study. Enjoyment over negative emotions (e.g. sadness, melancholy and anxious) is attributed to *meta-emotion* (Mayer & Gaschke, 1988), whereby unpleasant emotions are on an object level, upon which an experience of appreciation, pride or enjoyment on a meta-emotional level reflects.

Later, scholars began to realize that another emotion also involves appreciation, a moving and though-provoking effect of meaningful entertainment (Oliver & Bartsch, 2010; Oliver & Raney, 2011). A meaningful entertainment experience is intrinsically rewarding in the sense that it satisfies three fundamental intrinsic motivations (*autonomy*, *competence* and *relatedness*), as described in self-determination theory (SDT); (Ryan & Deci, 2000; Vorderer & Ritterfeld, 2009). The notion was extended to *hedonic happiness*, or pleasure, and *eudaimonic happiness*, which conceptualizes personal expressiveness, self-realization and personal development (Waterman, 1993). Waterman's work later inspired (Oliver & Raney, 2011) to introduce the *meaningfulness-seeking* dimension (eudaimonic) to the existing *pleasure-seeking* (hedonic) dimension of entertainment motivations. *Truth-seeking* or *meaningfulness-seeking*, they argued, may portray a distinct need in addition to those in the SDT.

Entertainment offers meaning and gratification, although not always at once. We would be blind to one side of the fact should we abandon either of the dimensions. That is why we need dual-process models, and it is the same reason that they are laying a foundation for contemporary entertainment research. Among these, Vorderer's two-level model has had a profound influence (Vorderer, 2011). The model depicts users' motivation in the two dimensions of *enjoyment* and *appreciation*. (Bartsch & Beth Oliver, 2011) model is also a two-level model, where emotional meaning is the base and more elaborate forms of sociomoral reasoning are built on top. They proposed that affective factors can trigger a cognitive elaboration process in a thought-provoking entertainment experience. (Bartsch & Schneider, 2014) subsequently conducted an empirical study of a similar process in a political setting. In the context of brand crisis, we observed expressions of serious thoughts and truth-seeking. The truth-seeking may not always be valid but is likely to be corrected in a subsequent discussion.

#### *4.1.2.2 Entertainment in Social Media*

Hedonic (arousal and affect) and non-hedonic (competence and autonomy) need satisfaction are complementary, although distinctive (Tamborini, 2011); and it is likewise the harmonic effect of intrinsic and extrinsic need satisfaction on enjoyment in Facebook use (Reinecke et al., 2014). This gives us one clear conclusion: entertainment is a contributing factor for social media use (Quan-Haase & Young, 2010), and that in terms of intrinsic need satisfaction, relatedness is the most salient factor (Smock, Ellison, Lampe, & Wohn, 2011). This is somewhat intuitive since humans are a social animal, but people also seek autonomy, which is associated with a freedom of self-presentation (Krämer & Haferkamp, 2011), resulting in a positive feeling (Reinecke & Trepte, 2014) that fosters self-esteem (Gonzales & Hancock, 2011) and may eventually satisfy their need for competence.

Social media users have their own inner motivation, but they are also socially pressured (Reinecke et al., 2014). Social pressure is a strong extrinsic motivation that threatens intrinsic motivation and need satisfaction, but at the same time fulfils social expectation, which satisfies the intrinsic needs for relatedness and competence. Simply put, it is a paradox; and to emphasize it even more, (Deci, Ryan, & Koestner, 1999) concluded that social approval, being an external reward, can significantly undermine the satisfaction of the need for autonomy. Altogether, the influence of social pressure on the intrinsic need satisfaction is rather heterogeneous.

*4.1.2.3 Social Media and Well-being*

The relationship between social media use and well-being, as part of the non-hedonic dimension of the entertainment experience (Hofmann, Wisneski, Brandt, & Skitka, 2014; Oliver, Hartmann, & Woolley, 2012; Ryan & Deci, 2001), is a complex one. In their review, (Verduyn, Ybarra, Résibois, Jonides, & Kross, 2017) reported that passively using SNS provokes social comparisons and envy (negative well-being) but the active use creates social capital and connectedness (positive well-being). In contrast, (Utz & Breuer, 2017) found no effect of SNS use on either stress or life satisfaction. It appeared to us that, unlike general explanations from diverse contents shared and perceived among different social media users, our context of brand crisis is finite and so lessens the complexity. While we do not expect social comparison or envy to play a major role here, connectedness to those who have similar thoughts cannot be underestimated. Moreover, if the entertainment experience is to be described by the satisfaction of human's three fundamental needs (SDT), we might already have the advantage of simplicity: the audience read or engage in the crisis story voluntarily, satisfying the need of autonomy; the story is intelligible and the audience should find themselves capable of apprehending shared moral values, that is being competent; and the shared moral values or congruent opinions, especially against the despicable brand, create the feeling of relatedness.

## 4.2 **Entertainment in Brand Crisis**

We proposed a framework as a basis not only for this dissertation but for future study on the subject as well. The framework consists of two parts. The first part concerns moral judgment, the element essential to the entertainment experience of the audience in a brand crisis incident. In the first section, we will explain the five moral domains of Moral Foundations Theory, and the aspects that relate them to a brand crisis. Understanding the associations would shed light on how the audience make moral judgment in this specific context of the crisis. For the second part, based on our explanation earlier in the first chapter about the role of moral judgment in entertainment experience, the second and third sections will expound theoretical connections between moral judgment and the *enjoyment* and *appreciation* dimensions of the entertainment experience in the context of brand crisis in social media. All theoretical bases will culminate in the conceptual framework described in the last section.

### 4.2.1 Moral Foundations Theory

Moral judgment was once thought to be merely a deliberate process of moral reasoning (Kohlberg, 1981). Social intuitionists later brought to light the notion that there appears to be an element of intuition as well. Moral intuitions are "gut feelings": an instant response, involving affective valances of good vs. bad and like vs. dislike without any conscious awareness of seeking, weighing and inferring evidence (Jonathan Haidt, 2001). Not to be misunderstood here, however, the viewpoints of moral intuitions and moral reasoning are neither right nor wrong, but instead the two comprise a dual-process, starting with the former and sometimes extending to the latter. The process was proposed in Haidt's moral foundations theory (MFT). Moral intuitions are a "domain-specific bit of mental structure" connecting our perception of a pattern of a virtue and a vice in the social world with our evaluation and, in many cases, a specific moral emotion (Haidt & Joseph, 2004, 2007).

(Jonathan Haidt & Joseph, 2007) proposed five domains of intuitive ethics that are valid across all cultures, although the extent to which each becomes salient can vary. A brand crisis, on the other hand, is context-specific, which, by demarcating the context, may diminish the variance contributing to the saliency. Take for example the *harm/care* domain, its foundation is built from the principles of evolutionary biology concerning parental care and compassion (Royle, Smiseth, & Kölliker, 2012). People feel approval towards those who prevent or relieve harm (Jonathan Haidt & Graham, 2007), and so it should not be a surprise to see public disapproval or even aggression when a product or service causes harm, especially if all that people perceive is the company's lack of or inadequate intention to mitigate the harm.

The *fairness/reciprocity* domain is perhaps as equally pertinent. The foundation is rooted in Trivers's model of reciprocally altruistic behavior in natural selection (Trivers, 1971). A business works in a reciprocal way: a company offers products or services at a price the customers are willing to pay. It is an agreement built on a pillar of trust (Chaudhuri & Holbrook, 2001). Product defect or dissatisfying service devalues the offer; failing to bring back customer satisfaction is to dishonor what was agreed upon. Providing less and receiving more is cheating. A chain of occurrences then follows, which approximates what an altruist's protective mechanism would trigger: the affected customers suspend or withdraw themselves from the business; they become aggressive while seeking justice (Yannopoulou et al., 2011); other concerned customers discontinue purchasing products or using services (Kim, Su Jung; Wang, Rebecca Jen-Hui; Malthouse, 2015); the company apologizes and gets a chance to gain back its customer trust (Pace, Corciolani, & Gistri, 2017). Although we would not expect a peaceful ending for every incident, all that could happen underlines the saliency of the domain.

The *intergroup/loyalty* domain explains a brand community. *Loyalty*, as described by (Jonathan Haidt & Joseph, 2004), is human's tendency to aggregate into groups that compete with other groups. A virtual non-geographically bound community of brand admirers can be profound on both individual and collective levels (Muniz & O'Guinn, 2001). There are elements of shared consciousness of kind and moral responsibility or obligation to the society. These are what makes brand community a community, and not merely a gathering of people with some mutual interests (Laroche, Habibi, Richard, & Sankaranarayanan, 2012)(. Aligning oneself to a community is one way a person fulfills psychological and social needs to express self-identity (Elliott & Wattanasuwan, 1998). Brand community is no different from the perspective of social identity, social comparison, self-categorization and brand culture theories (Ewing, Wagstaff, & Powell, 2013). In a time of crisis, finding oneself on the defensive side of the furor is not entertaining. Those on the other side, however, are against the corrupt brand and *that*, as we delineated earlier, can be entertaining.

The fourth domain, *Authority/Respect*, apparently is not entirely relevant since business-to-customer relationships are not hierarchically-structured in-groups and most commercial businesses are not authorities. Still, people feel respect, awe and admiration towards good leadership and the opposite towards bad leaders who are despotic, exploitative or inept (Jonathan Haidt & Graham, 2007). Brand admirers align themselves to a brand community in part to express their identity. This implies a leadership role the brand may be taking, not by exercising 'authority', 'power' or 'dominance' but rather by 'prestige' (Henrich & Gil-White, 2001). A company's or employee's misbehavior can turn that respect into a critical opprobrium. And as a leader, any exploitative act can cause a company reputational damages in the eyes of its customers and among the strong base of its admirers.

The *Purity/Sanctity* domain is developed from the evolution of human's diet, particularly the emotion of disgust. Disgust itself conveys much broader meanings, ranging from a protective mechanism against disease transmission to social emotion attributed to appearance or occupation. In the commercial world, food contamination holds a strong connection to disgust and, by extension, this moral foundation. Such incidents have attracted a great deal of public attention and could become a crisis, not only to a brand but an entire industry (Custance, Walley, & Jiang, 2012).

So far, we have discussed the characteristic of each moral foundation and how it may influence the judgment in the mind of the audience in the context of brand crisis. Moral judgement may as well be described by the model of intuitive morality and exemplars (MIME); (Tamborini, 2011, 2012). Developed from the social intuitionist perspective of MFT, MIME presents a notion of reciprocal influence between entertainment media and moral intuition. Tamborini described intuitive and rational moral judgment systems as short- and long-term appraisal processes, which, he concluded, differentiate enjoyment and appreciation.

### 4.2.2 Enjoyment and Affective Disposition

Enjoyment is a function of a viewers' affective disposition and the outcomes associated with the characters (Zillmann & Cantor, 1972). The affective disposition theory states that the audiences make a moral judgement about the characters and they expect positive outcomes for the morally good, and the opposite for the villains. In drama, affective disposition leads to suspense, which is, as put by (Wulff, 1996), a calculation, expectation and evaluation of a coming event. Wulff called it anticipation. Drama viewers are willing to experience unpleasant feelings in witnessing a sympathetic protagonist suffer through distressing situations when, in the end, they would be relieved as the dilemma resolved (Zillmann, Hay, & Bryant, 1975). This explanation brings us back to the reflection on moral judgment in online controversy and wide-spread criticism, with one problem: a lack of, or an ambiguous, presence of a good or bad guy therein.

Media viewer's dispositional categorization is not limited to a character individually but to a group as well (Zillmann, Taylor, & Lewis, 1998). We may streamline our problem by letting the brand take the villain's place. The question then turns upon how well the implication comprehends the crises. To give an example, product failure is not always a result of intentional substandard manufacturing but rather an unpredicted malfunction. Even so, subsequent miscommunication may derail the attempt to contain and mitigate public outburst. Different types of crises require different strategies and practices (Dutta & Pullig, 2011). Failing to react properly may result in an unwanted catastrophe. Putting morality into perspective, the corporate's inability to protect its customers from product harm (e.g. by issuing product replacement) after incidents may be interpreted as an ignorance of consumer safety, a denial of responsibility that many deem to be morally intolerable and often will spark vehement public debates and condemnations.

Assuming an unfavorable role for the brand leaves us another loose end to tie up: who is the good guy? A literal interpretation of good guy should refer to one that possesses or displays moral virtue (McKean, 2005). Following the incidents, victims are often inevitable. Unlike dramas, however, these victims are not a protagonist or a hero, i.e., no evidence observable by the audience indicates an excellent moral character or disposition, even if, in fact, there may be. Yet, should they be considered the good guy? A proper clarification may best be drawn from Aristotle's statement:

> That moral virtue is a mean, then, and in what sense it is so, and that it is a mean between two vices, the one involving excess, the other deficiency, and that it is such because its character is to aim at what is intermediate in passions and in actions, has been sufficiently stated (Aristotle, 1999).

The audiences generally hold limited knowledge of the victims' actions, and even less of their behavior. Still, so long as the realm of the two vices are untouched, there is no reason the observers should believe that the victims fail to live up to moral expectations; hence, they ought to be the good guy. Be that as it may, being good does not necessarily mean being liked, at least not without perceivable attitude or interpersonal similarity (Byrne, 1961), or justifiable moral manifestations (Raney, 2011). Lacking potent favorability, the affective disposition theory would forecast a weak sympathetic emotional reaction from the audience, which should bring about a relatively small contribution to their suspense. All in all, the liking of the victims should not be as powerful as the disliking of the brand.

Then, there are people commenting. For a drive to evaluate his/her opinion, intrinsically and with the absence of objective physical bases, one's subjective judgment of his/her opinion depends upon his/her comparison to those of others (Festinger, 1954). So, the opinions may be challenged; but can or does the person expressing the opinion get to be judged too? After all, evaluating beyond merely the opinions seems to require inordinate cognitive resources; and only from somewhat scarce clues where a partial aspect of the commenter is inferred. That said, we observed in the online comments some moral contretemps that extended the judgment to a personal degree. However, to say that this is generally true, and in what circumstances it might arise, would require further structured analysis of the comments. In the end, if the judgment occurs as such, then so should the affective disposition in the mind of the audience; and we may come to realize that this all is, in fact, a bit of entertainment experience embodied within the larger one.

### 4.2.3 Moral Self and Appreciation

It is somewhat ironic that witnessing unfortunate incidents can be enjoyable; but is it, in any aspect, meaningful to the audience themselves? Appreciation seems to have no place in the crisis. However, the audience makes a moral judgment, and while they enjoy the misfortune of the despicable brand, they may as well appreciate their judgment and self as morally good. This section explains the process from moral judgement to appreciation in the entertainment experience.

People read comments to get a sense of others' opinions, but do not let us forget that the passive audience also forms their own opinion when they make a moral judgment. A lot of the audience come across the crisis story while it is still ongoing, meaning that the objective conclusion is not yet present. Without the objective conclusion, the audience is inclined to compare their position with others to evaluate the validity of their opinion (Festinger, 1954; Harold H. Kelley, 1952). Opinion comparison is typically biased under the influence of similarity between a person comparing his/her opinion and those with whom their opinion is being compared (Gerard & Orive, 1987; Orive, 1988). Social media itself allows people to observe their similarity with others, but being a member of a brand community (to be similar to other members) is another complexity added to the comparison process. It seems more likely, however, that the audience would compare their opinion with people they do not know, and so the effect of similarity should not make a great contribution. Nevertheless, the bias still exists because people generally seek hypothesis-consistent information, that is a positive test strategy (Klayman & Ha, 1987; Kunda, 1990). Although people may hold different moral beliefs and express discordant opinions, there are still common social standards. Social-cognitive domain theory posits that people learn these standards as they develop social knowledge, including morality (Judith G. Smetana, 2006). Since moral violation is a prominent ingredient of brand crisis — as much as it is for social knowledge — there is a good chance that the audience would find opinions of others consistent with their own, and so reinforce their opinion.

It is once the opinion is strengthened that the reflection of moral self may be appreciated. In other words, having a moral opinion that is compatible with most comments should reinforce one's moral self, for a person acquires a sense of morality in part from social interactions. Social-cognitive domain theory proposed that reciprocal individual-environment interactions (simply termed as social interactions) contribute to a person's understanding of morality (Judith G. Smetana, 2006; Turiel, 1983). The social intuitionist model also suggested a similar idea that social interactions lead to most moral change (J. Haidt, 2007). This does not necessarily mean that most opinions would be morally right by social standards, nor do they represent any moral value of the society. We know for certain, however, that the social environment has an influence on an individual's moral thoughts. The process may as well have an indirect effect on the individual's perception of moral self.

Thinking is passive. The passive audience does not engage in any moral act or express any thought that they may have. Those who comment to blame the brand express their thought to defend social values and expectations (Durkheim, 1984) but the rest only read and judge passively. Even so, in general we all resent a wrongdoer, such as a criminal, because we value ourselves (Murphy & Jean Hampton, 1988), and it is even morally right to hate (Stephen, 1883). The same psychological process of interpersonal moral evaluation applies to ethical issues in business (Forsyth, 1992). Thus, there is a reason to believe that the passive audience may resent the deplorable brand and they should be morally right to have negative moral emotions. That said, there are individual differences when it comes to moral belief and reactions to immoral acts. People understand, to various extents, the objective importance of morality, and for many, moral concerns become the sense of self that they feel responsible to protect (Blasi, 1993). Thus, the reaction to the crisis story and the brand is likely to vary according to individual differences and so does the appreciation of moral self.

Extending the above statement, can being morally good lead to the appreciation of self? In terms of entertainment experience, the non-hedonic dimension is closely linked to the eudaimonic well-being, which emphasizes self-determined behavior and psychological growth (Ryan & Deci, 2001). (Oliver et al., 2012) offered empirical evidence that meaningful entertainment stimuli can elicit feelings of moral virtue and elevation, as well as activating central values and feelings of purpose in life. Well-being refers to 'optimal psychological functioning and experience', or living a good life (Ryan & Deci, 2001). From a hedonic viewpoint, it is happiness that is a more positive affect and a greater life satisfaction. The eudaimonic viewpoint adds meaningfulness to the former. The well-lived life, as (King & Napa, 1998) described, includes the importance of happiness and a sense of purpose. Devoting one's life to a meaningful purpose, one that benefits others, is morally good and happiness is a by-product of being a 'good person'. (Hofmann et al., 2014) also found that moral acts are associated with higher levels of momentary happiness and contribute the most purpose to people's lives.

So, we may expect the passive audience who believe (by comparing opinions) that their judgment is morally appropriate to then see themselves as moral and so to be satisfied as, for a moment, they have fulfilled their purpose of being good. As (Oliver & Bartsch, 2011) stated, entertainment can be meaningful when it portrays human moral virtues, in the sense that it 'inspires insight into such virtues, or it causes the viewer to contemplate such virtues and what it means to live a "just" or "true" life.' Downward comparison is also within the bounds of possibility: upholding moral belief in harmony with the majority of comments as opposed to those voicing contradictory and most likely controversial opinions can be satisfying not only because one's thought is right (by opinion comparison), but also it demonstrates moral superiority over the 'wrong ones.' Hence, although the crisis story itself may not be very inspiring, when the moral aspect of the conversations instigates the reflection of moral self, it fulfills all the appreciation of the entertainment experience.

### 4.2.4 Appreciation and Reflective Thoughts

*Appreciation* entails the motivation to elaborate on thoughts and feelings inspired by the entertainment experience (Oliver & Bartsch, 2010). The elaboration is associated with eudaimonic needs for insight, meaning, and self-development (Oliver & Bartsch, 2011; Oliver et al., 2012). *Truth-seeking*, as part of eudaimonic motivation (Oliver & Raney, 2011) and in contrast to *pleasure-seeking* (Bartsch & Hartmann, 2017), reflects not only a need to understand the self but a more general realization of human condition as well. The urge to do so results in a preference for realistic and personally relevant media content. The fact that brand crisis is real has already fulfilled the former. The latter, however, still needs further investigation, especially in relation to the concept of identification (Igartua, 2010). The question would be whether and how the audience may identify themselves with anyone in the incident. In terms of experience, eudaimonic entertainment is associated with a need for meaning-making triggered by negative experience, e.g., justice violation (Anderson, Kay, & Fitzimons, 2013). In the absence of just or happy endings, such as some of our cases, the audience would engage in meaning-making process to resolve cognitive conflict and restore their belief in a just world (C. L. Park, 2010).

In relation to *truth-seeking* motivation, (Bartsch & Schneider, 2014) found that eudemonic forms of emotional involvement, which characterized by negative valence – such as sadness (Wirth, Hofer, & Schramm, 2012), moderate arousal, and feeling moved, stimulate reflective thoughts, which then lead to issue interest and information seeking. They posited that individuals who seek meaning and insight should be motivated to focus on moving, thought-provoking, and personal relevant media experience.

### 4.2.5 Conceptual Framework

A brand crisis in social media can be entertaining. This, of course, does not mean that it is always entertaining nor that it would be entertaining to everyone. The crisis will often originate from immoral conduct or a lack of an appropriate response. Either way, it is perceived by the audience as contradictory to moral values, for it violates moral domains. Moral judgment then triggers chains of psychological processes on hedonic and non-hedonic dimensions. For the hedonic dimension, the audience develops an affective disposition and anticipation. While the situation remains unresolved, this suspense continues to hold until a satisfying outcome creates a feeling of relief that fulfills the enjoyment, or the absence thereof ends the period of attention.

The non-hedonic dimension is closely tied to eudaimonic well-being. Being morally good serves as a meaningful purpose of life. Living a 'just' life constitutes happiness, which is fundamental to well-being. People develop a sense of morality, in part, from social interactions and social media provides just the right environment. Moral judgment is an opinion, one that is likely to be compared to those of others. Depending on how much the person values or merges into the moral domains that involve self, having congruent opinions with the majority should reinforce the perception of moral self or being a 'good person.' It is at this point that the audience could appreciate all that they have read or thoughts that they expressed about the crisis.

We summarized the entire process for both dimensions as a conceptual model in Figure 4.1 and the interaction between the audience and social media in Figure 4.2. In line with MIME, we suggest that responses to entertainment experience on both dimensions constitute patterns of audience's selective exposure, which, in turn, shape the future content production by prominent users (who act as media outlets), leading to more content that underlines the ongoing crisis or future incidents with similar pattern of moral domain saliencies.

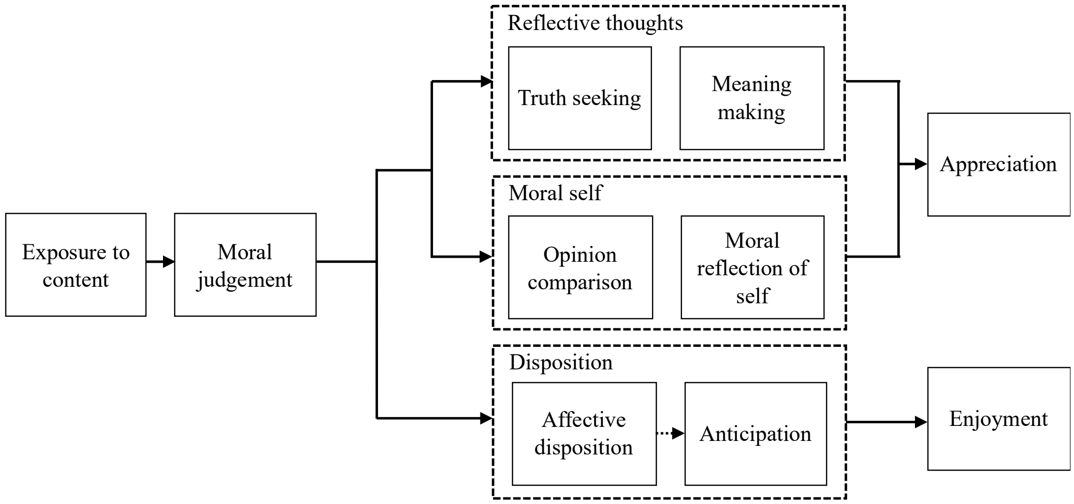


*Figure 4.1* Conceptual framework of the social media audience's entertainment experience in brand crisis. Depending on the situation when the audience learn of the crisis, anticipation may not always be part of the thought process

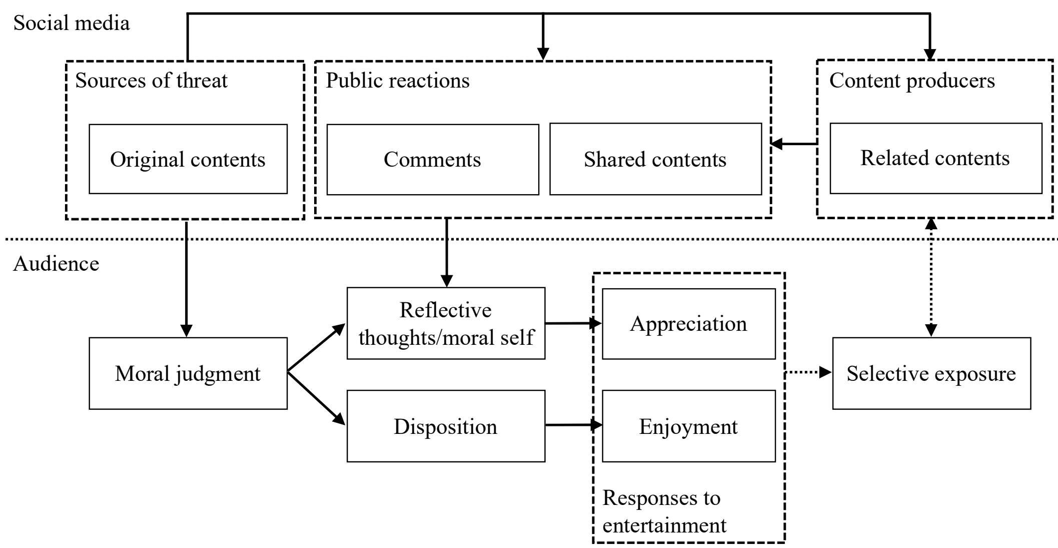


*Figure 4.2* Interaction between entertainment experience and social media. Original contents, such as a post or a blog, are a direct threat to brand reputation. Related contents contain a direct or indirect reference to the original contents. Shared contents (as part of public reactions) are related content social media users share with their contacts or followers. Content producers act as a media outlet by creating and distributing related contents to the public audience. Dotted arrows present Tamborini's concept of reciprocal influence between entertainment media and moral intuition, which can evolve long after the crisis conclude.

## 4.3 **Content Analyses of Moral Judgment in Brand Crisis**

MFT defines its moral foundations to be context-independent. While it is convenient to have such flexible definitions on hand, without proper domain-specific translation, our interpretation would be clouded by ambiguity. This section, consisting of three studies, will translate and interpret MFT to the context of brand crisis. We will investigate moral judgment based on MFT, which is the first part of our theoretical framework. Our first study seeks to establish a good understanding of moral judgment in brand crisis through the analysis of MFT on the data that we collected from Facebook. The second study explores moral judgment beyond MFD by creating additional dictionary from semantic representations of MFD words. In both studies, we will discuss how the audience make moral judgment in accord with MFT based on our interpretation of the results. The third study translate MFT into Thai. The study involves a content analysis of public reaction to five brand crises in Thai social media.

### 4.3.1 Data Collection

We gathered brand crisis scandals from three online articles published by Fortune (Shen, 2017), Forbes (Torossian, 2017) and Meltwater (Le, 2017). Learning from the articles, we created a set of terms to search for public posts on Facebook. After trying different combinations of the terms, we discarded the scandals that we could not obtain sufficient related public posts, leaving ten scandals for the analysis.

*Table 4.1* Data collection of the ten incidents from Facebook

| Incident | Category | Source | Search Terms | Posts | Comments |
|---|---|---|---|---|---|
| Apple intentionally slowed down iPhones | Corporate misbehavior | Shen, 2017 | Apple slow down iPhone | 143 | 52,671 |
| Bill O'Reilly fired amid sexual harassment claims | Employee misbehavior | Shen, 2017 | Bill O'Reilly firing | 274 | 61,854 |
| Equifax's customer data breach | Poor business conduct | Shen, 2017 | Equifax leak breach | 197 | 9,421 |
| Fyre Festival postponed amid chaos | Poor business conduct | Le, 2017 | Fyre festival Bahamas | 73 | 3,679 |

| | | | | | |
|---|---|---|---|---|---|
| Pepsi's controversial advertisement | Loss of public support | Torossian, 2017 | Pepsi ad | 150 | 16,738 |
| Samsung Galaxy Note 7 exploded | Product failure | Shen, 2017 | Samsung explode | 194 | 36,816 |
| Samsung's washing machine exploded | Product failure | Shen, 2017 | Samsung explode | 44 | 5,293 |
| Uber CEO heated argument with a driver | Executive misbehavior | Shen, 2017 | Uber CEO driver | 40 | 2,854 |
| United Airlines staffs forcefully removed a passenger | Corporate misbehavior | Torossian, 2017 | United Airlines passenger | 133 | 97,340 |
| Wells Fargo employees opened fake accounts | Corporate misbehavior | Shen, 2017 | Wells Fargo fake account | 154 | 23,142 |

We retrieved public posts and comments from Facebook Graph API[18] and used a Python package NLTK[19] for text preprocessing, which includes username (tag) and URL removal, stemming, and lemmatization. Table 4.1 summarizes the collected data, including crisis categorization adapted from (Greyser, 2009). Attempting to make the categorization more comprehensive and accurate, we added *employee misbehavior* and *poor business conduct* to the original categories. We collected – after removing unrelated posts – a total of 1,402 posts and 309,808 comments.

The Samsung device explosion incidents were mentioned in a section of the company's related incident reported in the Fortune's article. We separated posts containing 'wash' from the search result of 'Samsung explode'. Dates are in Greenwich Mean Time.

[18] Available at https://developers.facebook.com

[19] Available at http://www.nltk.org

### 4.3.2 Study 1: Moral Foundations Dictionary

#### *4.3.2.1 Introduction*

By interpreting the comments, we sought to determine whether the incident triggered any response within the five moral domains among the audience, particularly the commenters. The activation of moral intuitions would be the indication of moral judgment. We have learned that certain words reflect moral thoughts, as demonstrated by (Graham et al., 2009) when his team developed MFD. The dictionary has been used in text analysis across a broad array of behavioral researches (Fulgoni, Carpenter, Ungar, & Preot, 2016; Sagi & Dehghani, 2014). Originally, it was created for text analysis software Linguistic Inquiry and Word Count (LIWC)[20], which basically counts words in psychologically meaningful categories. The software was built on solid researches in the fields of social, clinical, health, and cognitive psychology and has been systematically validated (Tausczik & Pennebaker, 2010). Since LIWC, recent progress on MFD-based moral domain classifier has been promising, with new approaches harnessing the potential of a semantic representation (Garten et al., 2018, 2016). Nonetheless, it seems that we are not yet at the point where we can reasonably be confident to rely on a classifier alone, especially when we are to apply it on domain-specific data such as ours. So, while the advancement continues, we decided to employ an alternative method that can as well answer the question we were asking. Our focus is still on MFD words, except that the context in which they appear is what matters most.

#### *4.3.2.2 Methodology*

LIWC shows us text surrounding MFD words, but the amount of comments is simply inordinate to be comprehended by human. We tried to extract latent topics, but the keywords produced by Latent Dirichlet Allocation (Blei, Ng, & Jordan, 2003) as implemented for topic extraction by Python package Gensim are too ambiguous to interpret – they do not have intelligible connections within the same topic nor do they

[20] Available at https://liwc.wpengine.com

exhibit distinguishable qualities when compared to other topics. We instead decided to create summaries representing groups of similar comments, then study the context from them. We automated the summarization task with help of TextRank (Mihalcea & Tarau, 2004) on Amazon EC2 r4 2xlarge-type (8 vCPU, 27 ECU, 61 GiB of memory). The algorithm, adapted from the powerful PageRank (Brin & Page, 1998), operates on a graph, which nodes represent sentences and edges determine relationships between two sentences in terms of similarity measured as a function of their content overlap. The overlap function that we employed takes a number of common lexical tokens between the two sentences as an input. Once created the graph, the algorithm ranks and extracts important sentences, which then become the summary.

For each incident, we created eleven sets of MFD words representing vice and virtue of the five moral domains, plus general moral words defined in MFD. We filtered out words that appear less than ten times, leaving a total of 830 words which appear 75,106 times in all incidents combined. We grouped words by their lemma, then gathered, within the same incident, the comments where each lemma appears, then summarized with adjusted summarization ratio that yield between ten to twenty summaries per word. Python package Gensim that we used produced 17,248 summaries, which were still excessive for human interpretation; hence, we employed reducing strategy. Some of the lemmas appear more often, some appear less; those that appear less were eliminated. The remaining lemmas constitute at least half of the number of occurrences every lemma in the same moral domain combined (virtue and vice are considered separately). We ended up having 4,236 summaries after the removal. One of the researchers in our team read the summaries and manually produced 1,388 shortened sentences, each categorized in terms of moral-domain-relevant, incident-relevant, supporting or opposing the brand, and whether there are any indications of expectation. He discarded some summaries if they were found to be similar to any of the existing shortened sentences which share the same lemma. From over a thousand sentences, he selected at most three sentences per lemma and at most six MFD lemmas per moral domain for validation, amounting to a total of 168 words and 498 sentences to be coded by two coders.

The task is to code whether there exists a mention in the sentences that is relevant to any of the moral domains. Prior to the coding process, the researcher read all of the sentences, then established a coding guideline. When the process began, the coders spent up to two hours studying basic information about this research, each of the ten incidents, the definition of each moral foundation – including taxonomy and example adapted from (Graham et al., 2011, 2013; Jonathan Haidt & Joseph, 2004; Hofmann et al., 2014), general and domain-specific coding guidelines, and coding instruction, followed by a discussion with the researcher. There are 34 items to code for each incident, 29 of which measure moral relevance and the rest simply ask whether there were any mentions of the five moral domains in the sentences. We adapted the moral relevance measuring items from (Graham et al., 2009), with a few adjustments. First, we adjusted the measuring items, asking the coders to only find evidences in the sentences to support their decision, for example, "whether or not there is any mention that someone was, should or could be prevented from harm?" They were also reminded verbally and in writing not to let their thoughts on the scandals interfere with their decision. Second, we rephrased the items so that they are more specific, narrowing down the coders' possible interpretations. For example, the *should* and *could* are explicitly stated in the above question because whether or not the harm was actually prevented is irrelevant, only the commenters' opinions matter. Third, after studying the summaries prior to the coding, we decided to add a few more questions as included in Table 4.2. The coders spent three hours over one to two days to complete the task. Once the coding had completed, we concluded the existence of each moral domain in each incident and created a heatmap showing the frequency of MFD words as they appear in the comments.

*Table 4.2* Moral relevance items

| Dimension | Item | Graham et al.'s original items* (2009) | Items in this study** |
|---|---|---|---|
| Care/ | C1 | Someone was, should or could be prevented from harm | |
| | C2 | Someone cared or should care for someone weak or vulnerable | Someone cared for someone weak or vulnerable |
| Harm | C3 | Someone does not care to prevent someone weak or vulnerable from harm | |
| | C4 | Someone was or could be harmed | Someone was harmed |
| | C5 | Someone suffered or could suffer | Someone suffered emotionally |
| | C6 | | Someone used violence |

| | | | |
|---|---|---|---|
| | | emotionally<br>Someone used violence | |
| Fairness/ | F1 | Everyone was or should be treated equally | |
| | F2 | Someone acted or should act fairly | |
| Unfairness | F3 | Some people were treated differently than others | Some people were treated differently than others |
| | F4 | Someone was denied his/her rights | Someone was denied his/her rights |
| | F5 | Someone acted unfairly | Someone acted unfairly |
| | F6 | Someone ended up profiting more than others | Someone ended up profiting more than others |
| Loyalty/ | L1 | Someone put or should put the interests of the group above his/her own | Someone put the interests of the group above his/her own |
| | L2 | An action done or expected to be done by a friend or relative of the commenter | The action was done by a friend or relative of yours |
| | L3 | An action that affected or could affect someone's group | The action affected your group |
| Disloyalty | L4 | Someone did something to betray his/her group | Someone did something to betray his or her group |
| | L5 | Someone showed a lack of loyalty | Someone showed a lack of loyalty |
| Authority/ | A1 | Someone respected or should respect the traditions of society | Someone respected the traditions of society |
| | A2 | Someone's act was or should be within the confines of the law | |
| | A3 | An authority protected or should protect his/her subordinates | |
| | | | The people involved were of the same rank or status |
| Subversion | A4 | Someone failed to fulfill the duties of his or her role | Someone failed to fulfill the duties of his or her role |
| | A5 | Someone showed a lack of respect for legitimate authority | Someone showed a lack of respect for legitimate authority |
| | A6 | Someone's act is against the law | |
| | A7 | An authority failed to protect his/her subordinates | An authority failed to protect his/her subordinates |
| Sanctity/ | S1 | Someone acted or should act in a virtuous or uplifting way | Someone acted in a virtuous or uplifting way |
| | S2 | Someone was or should be able to control his or her desires | Someone was able to control his or her desires |
| Degradation | S3 | Someone did something disgusting | Someone did something disgusting |
| | S4 | Someone violated standards of purity and decency | Someone violated standards of purity and decency |
| | S5 | Someone did something unnatural or degrading | Someone did something unnatural or degrading |

* All items begin with "whether or not…"
** All items begin with "whether or not there is any mention that …"

### *4.3.2.3 Results*

This section explains the results generated from MFD according to the moral foundations. We relied on our two measurements in explicating the audience's moral judgement. One is the moral domain existence indications, the other is the adjusted Graham et al.'s moral relevance items (Graham et al., 2009). The coders were asked to include references should they find any of the shortened sentences to be relevant to a moral domain or a moral relevance measuring item. We interpreted the results based on the compiled collections of the references and included the number of comments ($n_{lemma}^{incident}$) in which the lemma of particular set of words appears. These numbers roughly indicate the magnitude of the topic being discussed.

The commenters had their belief, their version of truth, and their knowledge of what is relevant to the incidents. Whether their argument was sound, or did they have a valid evidence to support their claim, is irrelevant. We did not seek to verify any version of the truth, nor did we intend to lean towards any side of the arguments. Neutrality is of utmost importance, and therefore, we withheld our thoughts regarding the incidents and all involved parties. However, some of our discussion points may comprise our interpretation of the comments, with reference to the involved parties. In such case, we will point out the part that is our opinion.

#### *Moral Domain Existence*

The reactions to eight out of ten scandals appeared to have the element of moral judgment, i.e., we found them to be relevant to at least one of the five moral domains. It was particularly intriguing for us to see so much diversity in the moral thoughts; some scandals even evoked debates in all moral domains. As shown in Table 4.3 and Table 4.4, Apple, Wells Fargo, and United Airlines scandals involved every aspect of the five moral foundations, although more foundations do not indicate severer moral violation, nor that the offenders' actions were worse than those in other scandals.

*Table 4.3* Moral domain existence in the comments

| Incident | Care/Harm | Fairness/ Unfairness | Loyalty/ Disloyalty | Authority/ Subversion | Sanctity/ Degradation | # 'yes' answers |
|---|---|---|---|---|---|---|
| Apple | Yes | Yes | Yes | Yes | Yes | 5 |
| Bill | Yes | Yes | No | Yes | Yes | 4 |
| Equifax | Yes | Yes/No | No | Yes/No | Yes | 3 |
| Fyre | No | No | No | No | No | 0 |
| Pepsi | Yes | Yes | No | Yes | Yes | 4 |
| Note | Yes | No | No | No | No | 1 |
| Wash | No | No | No | No | No | 0 |
| Uber | Yes | Yes | No | Yes | No/Yes | 3.5 |
| UA | Yes | Yes | No/Yes | Yes | Yes | 4.5 |
| WF | Yes | Yes | Yes | Yes | Yes | 5 |
| # 'yes' answers | 8 | 6.5 | 2.5 | 6.5 | 6.5 | |

Each 'yes' answer carries .5 scores

*Table 4.4* Reactions relevant to moral domains as pointed out by the coders

| Incident | Care/Harm | Fairness/ Unfairness | Loyalty/ Disloyalty | Authority/ Subversion | Sanctity/ Degradation |
|---|---|---|---|---|---|
| Apple | Lack of caring for customers | Slowing down iPhones is not fair | Taking advantage of loyal customers | Slowing down iPhones was/should be illegal | Deliberate lie, shady practices |
| Bill | Sexual harassment; reputation damage from accusation | Victims do not get fair legal; Fox News should be fair and balance | - | Using superior position to intimidate women | Misogyny; disgusting personality |
| Equifax | People's lives were ruined because their money was stolen | Different US justice systems for the rich and ordinary people | - | Credit agencies allowed customers' data to be illegally used | People's lives were ruined |
| Fyre | - | - | - | - | - |
| Pepsi | The commercial hurts protesters | The commercial promotes equality | - | People should respect law enforcement officers | Disgusting marketing and advertisers |
| Note | The phones caused injuries | - | - | - | - |
| Wash | - | - | - | - | - |
| Uber | The company did not care who they hurt | The company needs to offer fair wages and benefits | - | Illegal cab company; filming the CEO may be illegal | The CEO should learn to be a decent human being |

| | | | | | |
|---|---|---|---|---|---|
| UA | The passenger got hurt physically and emotionally | Discrimination act against Asian | People need to stand together against UA | The passenger did not respect the authorities | Pure greed/evil; disgusting way to do business |
| WF | Lack of caring for employees | Rich corporation gets special justice system | Betrayal to all US citizens | The employees' actions were illegal | Banks should act with integrity; disgusting fraud |

A lack of care, as in the *harm/care* foundation, is the one element of moral violation shared among the three scandals. Apple cared less about its customers than its investors, as one commenter said ($n_{respect}^{Apple} = 214$); others condemned, the CEO of United Airlines did not care about the passenger ($n_{care}^{UA} = 888$), and Wells Fargo did not care about its employees ($n_{care}^{WF} = 260$). The harm can also be interpreted as the disruption to someone's well-being, feelings and reputation. Sexual harassment, as in the case of Bill O'Reilly, is by its definition both physical and emotional harm ($n_{harass}^{Bill} = 1549$); (Fitzgerald, Drasgow, Hulin, Gelfand, & Magley, 1997). Nonetheless, Bill's supporters had quite a different view, seeing that Bill unfairly suffered reputational damage from the accusations that lack actual evidence; some believed that it was a political hit job. Critics said Wells Fargo hurt many hard-working Americans ($n_{hurt}^{WF} = 68$). Equifax, on the contrary, did not harm its customer, but the data breach put people at risk of their money being stolen, which in turn could ruin their life ($n_{ruin}^{Equifax} = 33$). Pepsi's commercial was criticized for hurting the feelings of Black Lives Matter protesters, although some disagreed with the criticism ($n_{hurt}^{Pepsi} = 155$). Samsung phones' explosions evoked the least reactions, which mostly are some concerns that the accident could cause injuries ($n_{injur}^{Note} = 14$).

Moving to the *fairness/unfairness* foundation, social inequality many times occupied the minds of those who deplore the unfairness of the scandal. While some said that the passenger who was dragged out of the United plane was randomly picked, some disagreed, arguing that it was an act of discrimination against Asian ($n_{discrimin}^{UA} = 98$; $n_{racist}^{UA} = 253$). Wealthy establishments such as Equifax and Wells Fargo were accused of taking advantage of special justice system for the rich, while ordinary people would never have access to such privilege. The issue of seemingly broken justice system also appeared in Bill O'Reilly scandal when some asserted that victims of sexual harassment are not getting fair legal support. In addition to inequality in general, the commenters attributed unfairness to the companies as well. Apple and Uber's alleged unfair business practices are good examples – slowing down iPhone was unfair to customers, and Uber needs to offer fair wages and benefits to its driver ($n_{fair}^{Apple} = 87$; $n_{fair}^{Uber} = 25$).

For the *loyalty/disloyalty* foundation, the result was somewhat scarce. MFD-based analysis found only three scandals that stimulated pertinent discussions. Even so, all three evince different points of view. Apple taking advantage of its loyal customers, as some argued, is the matter between the company and its customers ($n_{loyal}^{Apple} = 72$). The concept of loyalty here seems to be reciprocal in that while the customers are loyal to the brand, the company too should be loyal to its paying customers. Wells Fargo was put in an even more embarrassing position – the betrayer of all US citizens. The commenters used terms like public trust, taxpayers, American people, emphasizing the scale of the scandal ($n_{betray}^{WF} = 33$). United Airlines, on the contrary, was not accused of betraying anyone, but some commenters urged people to stand together against, or to boycott, the company ($n_{boycott}^{UA} = 2770$).

Seven scandals involved several aspects of the *authority/subversion* foundation. The audience interpreted the law in their own way or had their speculation that some acts might be against the law. In the Apple case, some commenters were confident that slowing down iPhones was illegal, some conjectured that it *might* be illegal, and some did not think Apple broke any law but would want to see relevant legislation being promulgated ($n_{illeg}^{Apple} = 69$). Similar pattern of thoughts appeared in two other scandals: Equifax allowed customers' data to be illegally used and Uber is an illegal cab company ($n_{illeg}^{Equifax} = 40$; $n_{illeg}^{Uber} = 13$). Critics of Bill O'Reilly and United Airlines scandals raised the questions of an abuse of power and violation of ethics, in addition to legitimacy ($n_{abus}^{UA} = 443$). Many called Bill an abuser for using his superior position to intimidate women ($n_{abus}^{Bill} = 283$), some believed his actions were illegal ($n_{illeg}^{Bill} = 85$). In their counter-argument, Bill's supporters questioned the lack of evidence to support the allegations. United Airlines opposers questioned the legitimacy of removing the passenger; commenters on the other side of the argument defended that the airline has absolute authority on the plane, citing security reasons, and that the passenger is obliged to follow the authorities' order ($n_{illeg}^{UA} = 220$). While many despised United for being disrespectful to other human beings, some disapproved of the passenger's disrespect for the authorities ($n_{respect}^{UA} = 635$). Lastly, Wells Fargo scandal evoked both discussions of misconduct and authority. Its employees were at the center of the disagreement where they were accused of illegal conduct, while also being vindicated as some believed they were under the pressure from their superiors and had done it only to keep their job ($n_{illeg}^{WF} = 163$).

The *sanctity/degradation* foundation centers around disgust, and it is likewise the reactions as germane to the moral domain. The commenters expressed their feeling of disgust – many were enraged – once they learned about what had happened on the United plane ($n_{disgust}^{UA} = 2307$). The repugnance was so much that some even called United Airlines an evil. Bill O'Reilly's behavior disgusted the audience too, but in the sense that he was a sexual pervert and a misogynist ($n_{perv}^{Bill} = 406$; $n_{disgust}^{Bill} = 394$). Wells Fargo's fraud disgusted less of the audience ($n_{disgust}^{WF} = 117$). Still, some comments seemed to be as much furious. The blame on Pepsi commercial was attributed to disgusting marketing and advertising ($n_{disgust}^{Pepsi} = 69$), and Apple scandal was seen as deliberate lies and disgusting business practices ($n_{disgust}^{Apple} = 43$).

### *Moral Relevance*

Figure 4.3 illustrates the coders' decision on each of the measuring items. Throughout this section, we included the average score of the items relevant to our explanation. The detail of each item is provided in Table 4.2. We omitted some explanations related to the measuring items if the details have already been clarified in the previous section.

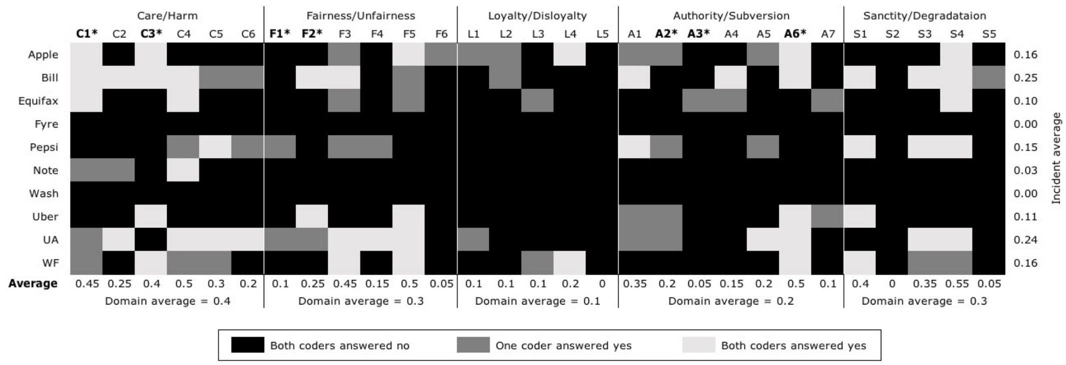


*Figure 4.3* Coding result of moral relevance items. Items with asterisk are the extension to Graham et al.'s (2009). Each 'yes' carries .5 scores.

For the *care/harm* foundation, the most prevalent mentions in all incidents were harm inflicted on, or potentially inflict on, someone (C4 = .5), as well as preventing someone from harm (C1 = .5) or lack of the intention to do so (C3 = .4). Emotional suffering was less common (C5 = .3), and so were the mentions of care (C2 = .25). Criticizing United Airlines, some comments said the passenger was hurt not only physically but emotionally as well ($n_{hurt}^{UA} = 358$). The use of violence was the least among the items (C6 = .2), with sexual harassment in Bill O'Reilly scandal, police-protesters violence in Pepsi scandal, and the violent removal of the passenger constituted the coders' decisions.

Someone acting unfairly (F5 = .5) and, as a result, some people being treated unfairly (F3 = .5), were the major concerns with regard to the *fairness/unfairness* foundation. Gender and race discrimination, two-standards justice system, and unfair business practices were the issues being discussed. Nonetheless, Bill O'Reilly supporters believed, despite the accusation of gender discrimination, that Bill and Fox News are "fair and balance," as in the media's motto (F2 = .3; $n_{fair}^{Bill} = 354$). Another subject within the foundation is rights. In the argument regarding the Pepsi commercial, some commenters brought up the issue of unequal rights, saying that people protest to voice their concerns over the rights of minority groups ($n_{righ}^{Pepsi} = 54$). Critics of United Airlines incident said that the passenger forcefully removed was denied his rights (F4 = .2; $n_{right}^{UA} = 532$).

There was no clear indication of a discussion regarding undeserved profit. The closest case was that Apple unfairly profited from manipulating its customers into buying a new phone (F6 = .5).

The *loyalty/disloyalty* foundation has the least score of just .11. Betrayal is in the lead as far as the scores are concerned. It appeared in Apple and Well Fargo scandals, which we have already discussed (L4 = .2). One of the coders pointed out a sentence saying, "we need to stand together against United Airlines." In the context, *we* could mean everyone but the airline. Although the sentence does not refer to any particular group, it gives the sense of *us* against *them*, and the collective interest is to stand together (L1 = .1). In another part of the foundation, there were mentions of some commenters' family members (L2 = .1), e.g., their family switched from iPhones to Android phones ($n_{famili}^{Apple} = 45$), and never again will anyone in their family watch Fox News ($n_{famili}^{Bill} = 331$). For the mentions of family members in general (L3 = .1), a comment warned that Equifax data leak could affect anyone's family livelihoods ( $n_{famili}^{Equifax} = 25$ ), and some commenters sympathized with Wells Fargo employees for having to do wrong in order to provide for family ($n_{famili}^{WF} = 95$). There is no indication of someone showing a lack of loyalty (L5 = 0).

Five scandals involved certain activities some audience considered illegal. Determining whether someone's act is against the law was the point most commonly discussed in the *authority/subversion* domain (A6 = .5). Respecting the traditions of society was the second (A1 = 3.5), where critics condemned Bill O'Reilly for having no respect for women and lacking self-restraint ($n_{respect}^{Bill} = 252$). Some commenters to United Airlines incident said that they would leave respectfully if asked; a comment to the Pepsi commercial said respect should be shown by both law enforcement officers and civilians ($n_{respect}^{Pepsi} = 110$); lastly, a few commenters said Uber's business is unethical, notwithstanding its legitimacy ( $n_{ethi}^{Uber} = 6$ ). Approving an act as being within the confines of the law is another topic being discussed (A2 = .2), e.g., the passenger who was removed had boarded the United plane legally and he has the rights to stay. The counter-argument was that the passenger showed no respect to the authorities (A5 = .2).

Disrespect to the authorities was also attributed to the protesters in the case of Pepsi, and the company pulling its commercial was seen as an upsetting capitulation to the protesters. The next topic of discussion is the failure of authorities to protect their subordinates, such as the data breach in Equifax scandal (A7 = .1). Equifax attempted to protect its customers by advising them to enroll in its identity theft protection program (A3 = .5).

The audience regarded six scandals as violating standards of decency (S4 = .55). Apple's lie and greed ($n_{lie}^{Apple} = 124; n_{greed}^{Apple} = 94$), Bill O'Reilly's sexually harassing behavior, Equifax as a criminal organization ($n_{crimin}^{Equifax} = 81$), Wells Fargo ruining people's credit ($n_{ruin}^{WF} = 58$), Pepsi pulling its commercial, and United Airlines' pure greed ($n_{greed}^{UA} = 191$) are all a violation of decency. Nevertheless, some acts were regarded as virtuous or uplifting (S1 = .4): Fox News' decision to fire Bill O'Reilly, Pepsi's commercial promoting peace and unity, and Uber CEO's attempt to have a decent conversation with the driver. On a more specific topic, Bill's behavior was considered not only indecent but degrading (S5 = .05); some comments called him a sexual pervert.

The average scores of the moral relevance items somewhat resemble those of the moral domain existence, as shown in Figure 4.4. The coding instruction stated that the decision to code each moral domain existence item should be based on the coding guideline, regardless of how they coded the moral relevance items. In terms of intercoder reliability, the moral domain existence appears to be more reliable than the other: Cohen's kappa of .83 as compared to .60; PABAK of .84 and .70; 92% and 85% coder agreement (see Table 4.5 for more detail) (Byrt, Bishop, & Carlin, 1993; Cohen, 1960). Some of our added items contribute quite strongly to the disagreement between the coders – C1 and A2 in particular (four and three disagreements out of ten incidents respectively). Two adjusted items, F3 and A1, contribute almost as much disagreement (each has three disagreements).

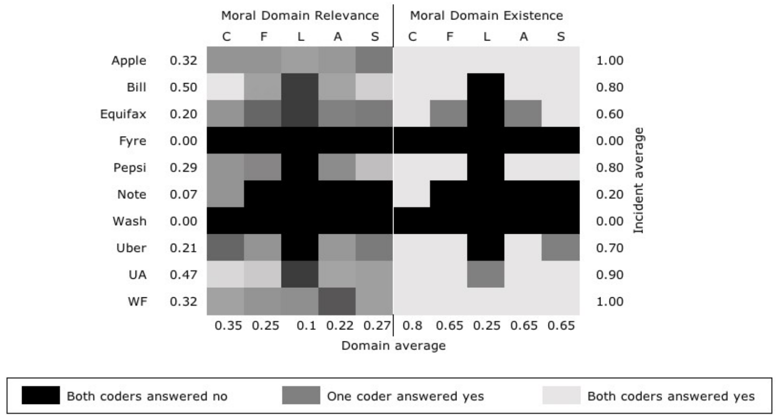


*Figure 4.4* Average scores of adjusted Graham et al.'s items (2009) as compared to moral domain existence

*Table 4.5* Intercoder reliability based on original MFD

| Measurement | # Data points | Cohen's kappa | PABAK | Krippendorff's α | Agreement |
|---|---|---|---|---|---|
| Adjusted moral relevance | 290 | .62 | .71 | .62 | 85% |
| Adjusted moral relevance with additional items | 290 | .60 | .70 | .60 | 85% |
| Moral domain relevance | 50 | .83 | .84 | .84 | 92% |

*4.3.2.4 Discussion*

The *care/harm* foundation concerns physical, emotional, or reputational harm that affects customers, company's staff, or other involved party, such as Samsung Galaxy Note 7 explosion, threats to Bill O'Reilly's career as a television host at Fox News, and the impact of Pepsi commercial on Black Live Matter movement. The audience expect the company – and sometimes other parties as well, e.g., law enforcement offers – to protect the vulnerable from harm, as in the case of Equifax, where the company is expected to ensure maximum security of its customers' data against digital threats. Failing to protect the vulnerable – or being perceived as not having enough intention to do so, or simply lacking compassion – may result in enraged reactions. Our interpretation excludes any mention of an attempt of any party to protect its own ideologies, properties, or financial interests.

The *fairness/unfairness* foundation places emphasis on consumer trust, which is a pillar of business (Chaudhuri & Holbrook, 2001). A business works in a reciprocal way, i.e., a company offers products or services at a price the customers are willing to pay. Failing to deliver or maintain services as promised is to dishonor what was agreed upon, as in the case of Apple. Providing less and receiving more is cheating, and cheating can lead to public backlash. Another fundamental concern is equal service to all customers and fair treatment to the company's staff. Any form of discrimination – e.g., racism and sexism – and violation of rights is intolerable. Interestingly, among the reactions to Bill O'Reilly's scandal, racism and sexism were often mentioned together, which seems to highlight their long history of association in politics, perceptions of women and minorities, and prejudicial beliefs (Swim, Aikin, Hall, & Hunter, 1995).

Between a brand and its customer, loyalty is not a one-way street. When the brand wrongs its customers, they can feel betrayed; they can choose to leave because their loyalty is not a commitment. That, in fact, is what Apple customers had been saying since they learned about the slowdown. Upon a closer look at the scandal, particularly the Apple fans, we have come to realize that the *loyalty/disloyalty* foundation can be far more complicated than what we have learned from the analysis. Brand-customer relationship can range from no commitment at all to shared identity, which is the case of Apple fans (Elliott & Wattanasuwan, 1998; Ewing et al., 2013; Heskett, Jones, Loveman, Sasser, & Schlesinger, 2008; Muniz & O'Guinn, 2001). The strong attachment shapes their behavior as a consumer, leading to positive and negative behaviors such as trash-talking, schadenfreude, and anti-brand actions (Japutra, Ekinci, & Simkin, 2018). Brand fans navigate across social media, attack rival brands' fans, and defend incoming attacks to their beloved brand (Ilhan, Kübler, & Pauwels, 2018). In our case, Apple fans were the target of trash-talks, e.g., "This is for blind Apple fan."

The reactions in terms of the *authority/subversion* foundation involve legal interpretation, condemnation of legal violation, and opinions on current legislation, as well as issues related to authority. The audience's support or urge for legal action against the company, e.g., the involvement of airport security officers in United Airlines incident, is also part of the foundation. We have noticed that legal action seems to be the most preferable choice of punishment. News of legal action brought against the company, even without court decisions, can elicit satisfaction, as in Fyre Festival scandal.

At heart of the *sanctity/degradation* foundation, our moral existence analysis shows how the feeling of disgust is associated with various types of wrongdoings; EMFD offers an addition set of words comparable to the term. Even so, most of our cases only portray disgust as an indignant response to an unfair business practice. The original sense of the term as related to the development of foundation – the evolution of human's diet – is still missing. A scandal involving food contamination may further the understanding in this regard.

### 4.3.3 Study 2: Expanding Moral Foundations Dictionary

#### *4.3.3.1 Introduction*

MFD has its limitation when it comes to the complexity of the language. Explaining how people choose certain words to communicate is a delicate subject and MFD is simply not equipped with the capability to understand the language beyond its finite vocabulary (Fulgoni et al., 2016). However, we have seen a significant progress since the adaptation of a semantic representation. (Sagi & Dehghani, 2014) applied Latent Semantic Analysis (LSA); (Landauer & Dumais, 1997) to measure moral loading of their concept of interest within a collection of documents. LSA creates vector representations of words from their co-occurrence patterns. The authors calculated semantic similarity between the terms associated with a moral dimension and the terms associated with a concept of interest. Their approach demonstrated a shift in the topic of discussion as influenced by moral rhetoric. (Garten et al., 2018, 2016) also leveraged the potential of semantic representation not only to measure moral rhetoric changes in political landscape but to unravel moral implication in online discussion as well. Their method, Distributed Dictionary Representation (DDR), creates distributed concept representations of MFD words and of words in a document, then compute a distributional similarity of MFD to the document. Essentially, theirs is a classifier, which performs well on a short document such as microblog.

### *4.3.3.2 Methodology*

Similar to those who had done before, we relied on a semantic representation. Our objective is to expand MFD, and in doing so, learn further how MFT can be translated in the context of brand crisis. We used 300-dimensional vector representations pre-trained on part of Google News dataset (about 100 billion words)[21]. (Garten et al., 2018, 2016) demonstrated the superior accuracy of this set of vectors in their classifiers. We assigned the vector representations to 110 sets of MFD words, each associated with one of the eleven moral domains in one of the ten incidents. The process took less than an hour on Amazon EC2 r4 large-type (2 vCPU, 7 ECU, and 15.25 GiB of memory)[22] running Amazon Linux, with comments stored in MongoDB[23]. Once finished, we calculated distributed representation of the moral domains.

For a dictionary D, a set of m moral words $W_{i,j}^{D} = \{w_1, \dots, w_m\}$ is created from $D_j \cap V_i$, where vocabulary Vi is built from all comments in the $i^{th}$ incident and $j \in$ {C+, C-, F+, F-, L+, L-, A+, A-, S+, S-, M} is a moral domain associated with the incident (C = care/harm, F = fairness/unfairness, L = loyalty/betrayal, A = authority/subversion, S = sanctity/degradation, M = morality general). A pre-trained n dimensional distributed representation R maps w to is vector representation: $R(w) = [r_1, \dots, r_n], v \in \mathbb{R}$. A vector representation of a moral domain $R(W_{i,j}^{D})$ is a simple mean of the projection weight vectors of words in the moral domain $W_{i,j}^{D}$ and m randomly selected words in other moral domains $W_{i,j}^{D}{}'$:

$$R\left(W_{i,j}^{D}\right) = \frac{\sum_{\forall w \in W_{i,j}^{D}} R(w) - \sum_{\forall w\prime \in W_{i,j}^{D}{}'} R(w\prime)}{\left|W_{i,j}^{D} \cup W_{i,j}^{D}{}'\right|}, \left|W_{i,j}\right| = \left|W_{i,j}'\right| \qquad (1)$$

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[21] Available at https://code.google.com/archive/p/word2vec/

[22] More information at https://aws.amazon.com/ec2/

[23] More information at https://www.mongodb.com

The expanded dictionary (EMFD) includes 110 sets of moral words $W_{i,j}^{EMFD} \in V_i$. Each set contains $q$ words $W_{i,j}^{EMFD} = \{w_1, \dots, w_q\}$ that have highest cosine similarity with $R(W_{i,j}^{MFD})$:

$$\cos\left(R(v), R\left(W_{i,j}^{MFD}\right)\right) = \frac{R(v) \cdot R\left(W_{i,j}^{MFD}\right)}{\|R(v)\|\left\|R\left(W_{i,j}^{MFD}\right)\right\|}, v \in V_i - W_{i,j}^{MFD} \qquad (2)$$

We measure how close each set of moral words is to other sets by:

$$sim\left(W_{i,j}^{D}\right) = \frac{\sum_{k \in J-\{j\}} \cos\left(R\left(W_{i,j}^{D}\right), R\left(W_{i,k}^{D}\right)\right)}{|J|-1}, j \in J \qquad (3)$$

After removing words with a frequency of less than 10, EMFD comprises 1,750 words, which appear 98,911 times in total and have 32,126 associated summaries. We eliminated the entire set of extended words if the original set contains no word with a frequency of at least 10, also cut down all remaining sets by at most half of their words' frequencies combined. The researcher then manually shortened the summaries and categorized the shortened sentences in terms of moral-domain-relevant, incident-relevant, supporting or opposing the brand, and whether there are any indications of expectation. We measured the consistency between MFD and EMFD by counting the comments comprising MFD words and EMFD words. Each post has 10 data points, divided into two identical sets. Each of the 5 data points in each set is the number of comments comprising words in a moral domain (virtue and vice combined). We calculated the correlation between each pair of the data points and used it as the indication of the consistency.

From the first study, the coders validated the existence of each moral domain based on MFD. We hypothesized that if we remove the non-existent moral domains before the expanding process, we should be able to yield better domain vector representations, thus achieve better consistency. To evaluate, we repeated the entire expanding process again, this time with non-existent moral domains removed, then compare the consistency tests.

#### 4.3.3.3 Results

In six out of eight incidents, removing the non-existent moral domains prior to the expanding process significantly distances the domain vector representations further away from each other, as shown in Table 4.6 and Table 4.7. The distances become even greater when we removed the morality general domain. The t-SNE visualization in Figure 4.5 shows better divided sets of MFD words in Equifax incident after domain removal. t-SNE is a widely used technique to visualize high-dimensional data by mapping the data points to two or three-dimensional map (Maaten & Hinton, 2008). In the figure, the green and red dots represent the care/harm foundation, while the blue and purple dots represent the fairness/unfairness foundation. The change in the Equifax case is the clearest among all incidents in terms of mean difference of the distances, and visualization. Changes in other incidents may be less noticeable but still significant. Note that in Table 4.6 and Table 4.7, we omitted the result of Samsung Galaxy Note 7 incident after removing the morality general domain because there is only one domain left.

*Table 4.6* Distance between domains after domain removal

| Incident | Removed Moral Domain and Their Opposite Polarity (RM) | Averages of Distances between Moral Domains (n = 1,000) | | | | | |
|---|---|---|---|---|---|---|---|
| | | All domain | | RM Removed | | | |
| | | Mean | SD | Mean | SD | t | Sig. |
| Apple | None | -.073 | .005 | -.073 | .005 | .70 | .481 |
| Bill | Loyalty | -.080 | .003 | **-.101** | .004 | -126.67 | <.001 |
| Equifax | Fairness, Loyalty, Authority | -.069 | .006 | **-.193** | .011 | -319.63 | <.001 |
| Fyre | All domains | -.065 | .007 | | | | |
| Pepsi | Loyalty | -.076 | .004 | **-.095** | .005 | -93.17 | <.001 |
| Note | Fairness, Loyalty, Authority, Sanctity | -.066 | .007 | **-.457** | .008 | -1191.32 | <.001 |
| Wash | All domains | -.067 | .007 | | | | |
| Uber | Loyalty, Sanctity | -.070 | .005 | **-.125** | .008 | -185.90 | <.001 |
| UA | Loyalty | -.079 | .003 | **-.101** | .004 | -139.04 | <.001 |
| WF | None | -.077 | .004 | -.077 | .004 | -.54 | .592 |

Two-sided t-test of the averages of distances between all moral domains and the other two conditions with some domains removed (df = 999)

*Table 4.7* Distance between domains after domain removal (Morality General domain removed)

| Incident | Removed Moral Domain and Their Opposite Polarity (RM) | Averages of Distances between Moral Domains (n = 1,000) | | | | | |
|---|---|---|---|---|---|---|---|
| | | All domain | | RM and Morality General Removed | | | |
| | | Mean | SD | Mean | SD | t | Sig. |
| Apple | None | -.073 | .005 | **-.081** | .006 | -31.04 | <.001 |
| Bill | Loyalty | -.080 | .003 | **-.118** | .004 | -231.34 | <.001 |
| Equifax | Fairness, Loyalty, Authority | -.069 | .006 | **-.260** | .015 | -382.72 | <.001 |
| Fyre | All domains | -.065 | .007 | | | | |
| Pepsi | Loyalty | -.076 | .004 | **-.110** | .006 | -150.07 | <.001 |
| Note | Fairness, Loyalty, Authority, Sanctity | -.066 | .007 | | | | |
| Wash | All domains | -.067 | .007 | | | | |
| Uber | Loyalty, Sanctity | -.070 | .005 | **-.150** | .010 | -215.29 | <.001 |
| UA | Loyalty | -.079 | .003 | **-.116** | .004 | -216.71 | <.001 |
| WF | None | -.077 | .004 | **-.085** | .005 | -40.91 | <.001 |

Two-sided t-test of the averages of distances between all moral domains and the other two conditions with some domains removed (df = 999)

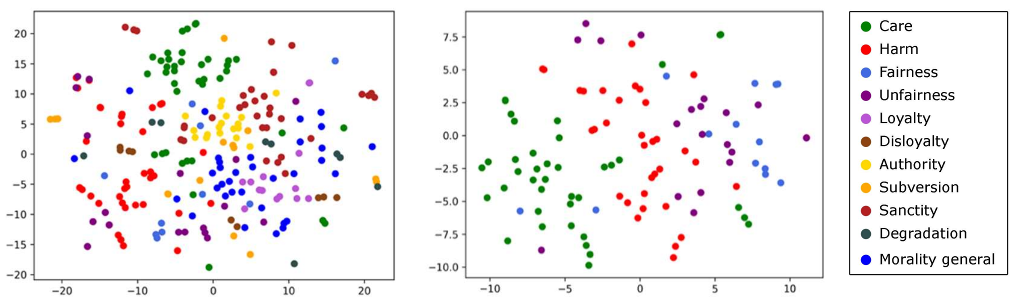


*Figure 4.5* t-SNE visualization of MFD word vectors before and after domain removal. The vectors in this figure were calculated from the comments related to Equifax incident.

Table 4.8 and Table 4.9 shows Pearson correlation coefficients between MFD and EMFD, before and after domain removal. Each $k^{th}$ post belongs to the $i^{th}$ incident and comprises of comments $P_{i,k} = \{C_1, \dots, C_p\}$, where a comment C is a set of words. A set of moral words $M_{i,j'}^D$ is a combination of opposite polarities (virtue and vice), $M_{i,j'}^D = W_{i,j}^D \cup W_{i,-j}^D$ , $|j'| = 5$. We measured a number of comments containing moral words per post for each moral domain in each incident as follows:

$$x^{D}_{i,j',k} = \sum_{l=1}^{p} f^{D}(C_l, i, j')\,; f^{D}(C, i, j') = \begin{cases} 1 & C \cap M^{D}_{i,j'} \neq \emptyset \\ 0 & C \cap M^{D}_{i,j'} = \emptyset \end{cases} \quad (5)$$

and calculated the correlation between each pair of moral domains by:

$$dcorr(i, j') = corr\left(X^{MFD}_{i,j'}, X^{EMFD}_{i,j'}\right);\ x \in X \quad (6)$$

Without domain removal, 93% of the correlation coefficients are highly positive, r > .70, p < .001, n = 43 (Hinkle et al., 2003). The *authority/subversion* foundation has the strongest correlation (M = .88, SD = .13), while the *sanctity/degradation* foundation has the weakest one (M = .76, SD = .18). Our speculation was that the weak correlations may be due to insufficient MFD words to compute reliable representation of the moral domains, and so we reviewed the numbers of MFD words as shown in Table 4.10. There is a low positive correlation between the coefficients and the numbers of words, $r(41) = .43, p = .001$. However, when looked specifically into the extremely small sets of words, we found that of eight moral domains with the coefficient lower than .7, seven have vector representation calculated from a set of less than four words; in total, there are eleven sets of less than four words. If human resource is unavailable for validation, a close look at these set of words may be an alternative approach for domain removal.

With domain removal, 92 percent of the correlation coefficients are highly positive, r > .70, p < .001, n = 26. The percentage is down by .2 percent, which is negligible. The averages of the coefficients, on the other hand, are up by 1.83 to 8.33 percent in all domains. The care/harm foundation has the strongest correlation (M = .94, SD = .07), while the sanctity/degradation foundation has the weakest one (M = .81, SD = .05). Only two coefficients are below .7 but still indicate a moderately positive correlation.

*Table 4.8* Pearson correlation coefficients between MFD and EMFD without domain removal

| Incident | df | Care/Harm | Fairness/ Unfairness | Loyalty/ Disloyalty | Authority/ Subversion | Sanctity/ Degradation |
|---|---|---|---|---|---|---|
| Apple | 141 | **.90** | **.86** | **.84** | **.92** | .76 |
| Bill | 272 | **.93** | **.81** | **.94** | .60 | .74 |
| Equifax | 195 | **.95** | .69 | .78 | **.87** | .51 |
| Fyre | 71 | .37* | - | .33* | - | - |
| Pepsi | 148 | **.99** | **.91** | **.96** | **.97** | **.98** |
| Note | 192 | **.95** | .35 | **.86** | **.82** | .50 |
| Wash | 42 | .77 | - | .27** | - | - |
| Uber | 38 | **.95** | **.86** | - | **.95** | .79 |
| UA | 131 | **.97** | **.96** | **.97** | **.97** | **.88** |
| WF | 152 | **.98** | **.93** | **.95** | **.98** | **.94** |
| Average | | **.88** | **.80** | .77 | **.89** | .76 |

* $p < .01$; ** $p < .1$; other correlations have $p < .001$
Coefficients having a value of at least .70 are highlighted in bold.
Coefficients could not be computed if $W_{i,j}^{D} = \emptyset$.

*Table 4.9* Pearson correlation coefficients between MFD and EMFD with domain removal

| Incident | df | Care/Harm | Fairness/ Unfairness | Loyalty/ Disloyalty | Authority/ Subversion | Sanctity/ Degradation |
|---|---|---|---|---|---|---|
| Apple | 141 | **.90** | **.87** | **.85** | **.92** | **.85** |
| Bill | 272 | **.93** | **.88** | - | .63 | **.80** |
| Equifax | 195 | **.92** | - | - | - | .54 |
| Fyre | 71 | - | - | - | - | - |
| Pepsi | 148 | **.98** | **.90** | - | **.98** | **.96** |
| Note | 192 | **.94** | - | - | - | - |
| Wash | 42 | - | - | - | - | - |
| Uber | 38 | **.96** | **.86** | - | **.96** | - |
| UA | 131 | **.95** | **.88** | - | **.97** | **.91** |
| WF | 152 | **.96** | **.86** | - | **.96** | - |
| Average | | **.94** | **.88** | **.85** | **.90** | **.81** |

All correlation has $p < .001$
Coefficients having a value of at least .70 are highlighted in bold.
Coefficients could not be computed if $W_{i,j}^{D} = \emptyset$.

*Table 4.10* Numbers of MFD words and related comments

| | Care/Harm | | Fairness/ Unfairness | | Loyalty/ Disloyalty | | Authority/ Subversion | | Sanctity/ Degradation | |
|---|---|---|---|---|---|---|---|---|---|---|
| Incident | #W | #C | #W | #C | #W | #C | #W | #C | #W | #C |
| Apple | 19 | 501 | 9 | 209 | 4 | 143 | 13 | 974 | 10 | 218 |
| Bill | 57 | 3222 | 27 | 1594 | 28 | 1401 | 36 | 1836 | 30 | 2460 |
| Equifax | 16 | 1037 | 3 | 97 | 8 | 203 | 11 | 528 | 3 | 67 |
| Fyre | 2 | 26 | 0 | - | 1 | 12 | 0 | - | 0 | - |
| Pepsi | 32 | 1565 | 8 | 254 | 15 | 953 | 17 | 871 | 8 | 250 |
| Note | 14 | 367 | 1 | 12 | 5 | 95 | 5 | 83 | 2 | 30 |
| Wash | 3 | 34 | 0 | - | 1 | 16 | 0 | - | 0 | - |
| Uber | 3 | 65 | 1 | 10 | 0 | - | 5 | 85 | 1 | 10 |
| UA | 66 | 5781 | 21 | 1412 | 25 | 1547 | 44 | 5030 | 25 | 3161 |
| WF | 26 | 798 | 11 | 444 | 15 | 444 | 26 | 1161 | 15 | 436 |
| **Average** | 11.9 | 669.8 | 4.05 | 202 | 5.1 | 241 | 7.85 | 519.4 | 4.65 | 331 |

#W = Number of words, #C = Number of comments in which the words appear

We listed top five words of each EMFD moral domain, sorted by the number of comments in which they appear, in Table 4.10. Additional words in EMFD describes the moral domains even more specifically than what has already been explained by MFD. Nevertheless, human interpretation is still required since some of the word sets seem to be irrelevant to their moral domain. Throughout our explanation in this section, we italicized words that are included in Table 4.11.

*Table 4.11* Top five words of each EMFD moral domain, sorted by the number of comments in which they appear

| Incident | Care/Harm | Fairness/ Unfairness | Loyalty/ Disloyalty | Authority/ Subversion | Sanctity/ Degradation |
|---|---|---|---|---|---|
| Apple | Side, prevent, storage, edge, removable | All, plus, sense, absolute, perfectly | Customer, join, consumer, recently, fan | Next, plan, contract, join, install | Good, well, simple, nice, perfectly |
| | Lose, crash, affect, lost, die | Wrong, hate, ridiculous, unethical, mislead | - | Deliberately, unethical, boycott, sabotage, cheat | Crap, stupid, fuck, ridiculous, horrible |
| Bill | Support, help, thank, handle, response | Good, great, real, sense, trumps | - | Member, join, elect, appoint, privilege | Good, faith, loofah, wash, beauty |

| | | | | | |
|---|---|---|---|---|---|
| | Lost, hit, assault, destroy, dead | Racist, racism, sexist, ignorance, hate | - | Racist, leftist, corrupt, angry, boycott | Scumbag, horrible, misogynist, perv, vile |
| Equifax | Monitor, service, provide, access, privacy | - | - | - | Every, date, set, entire, nice |
| | Affect, sue, impact, cause, victim | - | - | - | Crap, ridiculous, stupid, ugh, shame |
| Pepsi | Unity, family, support, officers, help | All, we, good, great, real | - | Support, continue, able, approve, offer | Cool, perfect, simple, beautiful, complete |
| | Lost, die, hit, cause, missing | Hate, racist, minority, blacks, oppression | - | Protest, racist, boycott, cowards, angry | Crap, pathetic, horrible, bitch, awful |
| Note | Best, sure, technology, smart, removable | - | - | - | - |
| | Bad, cause, blow, suck, explode | - | - | - | - |
| Uber | Need, service, response, help, support | All, good, much, reliable, always | - | Model, top, independent, place, president | - |
| | - | - | - | Wrong, boycott, complain, stupid, arrogant | - |
| UA | Help, personnel, support, trust, handle | Sense, fact, manner, justify, absolute | - | Rule, select, follow, license, request | Nice, perfect, good, modern, water |
| | Assault, lost, victim, hit, cause | Disgrace, racist, uncalled, unprofessional, irrelevant | - | Outrage, disgrace, racist, thug, refuse | Pathetic, shitty, ugh, scumbag, shameless |
| WF | Need, help, thank, support, insure | Accountability, amount, full, plus, current | Thank, country, president, local, organization | Place, requirement, post, receive, request | Ethical, bless, filled, standards, water |
| | Lost, pummel, hit, cause, affect | Ridiculous, stupid, unethical, outrageous, shameful | Criminals, crook, evil, democrat, fool | Corrupt, criminals, stupid, gutless, scum | Bad, greedy, horrible, terrible, awful |

Fyre Festival and Samsung washing machine incidents are not included in this table

With regard to the *care/harm* foundation, not only that Apple has slowed down iPhone to prevent an abrupt shutdown, some defended that the company did so to prevent battery explosion, which is hazardous ($n_{prevent}^{Apple} = 51$). In addition to sexual harassment in the Bill O'Reilly case, the commenters also mentioned sexual assault ($n_{assault}^{Bill} = 199$), along with losing job, political hit job, and destroying career. Credit monitoring service is the prevention measure Equifax has provided for its customers ($n_{monit}^{Equifax} = 319$), although many were against the free service, warning that those affected would lose the ability to sue the company if they decided to enroll ($n_{sue}^{Equifax} = 184$). Privacy advocates argued for Equifax to strengthen data protection, some insisted on pursuing the privacy act class action against the company ($n_{privaci}^{Equifax} = 27$). In terms of reputational damage, Pepsi has lost many of its customers because of the commercial itself and the company's decision to pull the commercial ($n_{lost}^{Pepsi} = 88$). The Samsung Galaxy Note 7 case involves the terms blow and explode, which straightforwardly describe the incident ($n_{blow}^{Note} = 88; n_{explode}^{Note} = 65$). Interestingly, the devices, not human, caused harm in this incident. Nonetheless, Samsung as the manufacturer was held responsible for the harm. United Airlines scandal involves harm that caused by human, and so it is not surprising to see the terms assault, victim, and hit among the top five words ($n_{assault}^{UA} = 742$; $n_{victim}^{UA} = 295$; $n_{hit}^{UA} = 279$). United also took a hit from drastic revenue loss, some commenters said ($n_{lost}^{UA} = 490$).

*Racism* and *sexism*, the fundamental violations of the *fairness/unfairness* foundation, are the key topics in Bill O'Reilly scandal ($n_{racist}^{Bill} = 968$; $n_{sexist}^{Bill} = 140$). The commenters attributed racism and sexism to not only Bill but other persons, groups, or organizations as well – e.g., the Republicans, and Fox News – depending on their argument. Hateful rhetoric was also a major subject, both in the scandal – either referring to Bill or other parties – and among the comments ($n_{hate}^{Bill} = 60$); many were irritated by the quarrel. Hate exists in Pepsi incident as well ($n_{hate}^{Pepsi} = 312$). The argument was that whoever opposes the commercial is a hateful person, and so are Black Lives Matter (BLM) movement and the liberals. *Oppression* of the African-American community, police brutality and systemic racism in particular, provoked the BLM movement

($n_{oppress}^{Pepsi} = 25$; Carney, 2016). The issue became part of the dispute, with emphasis on the violence between the African-American community and the law enforcement officers ($n_{blacks}^{Pepsi} = 41$).

Of our particular interest to the *loyalty/disloyalty* foundation is the topic of Apple fan ($n_{fan}^{Apple} = 60$). Many said that they are a fan of Apple but because of the scandal, they are considering switching to another brand. There were also some trash-talk from non-Apple-fan commenters, which we will discuss more in the discussion section. Wells Fargo does not seem to have any fan, and so the topic was, once again, the betrayal of "the citizens of this country". Interestingly, however, the use of the terms "this country" or "our country" underlines the feeling of the commenters that they are part of their country ($n_{countri}^{WF} = 206$).

The *authority/subversion* foundation has quite a few patterns that we have noticed. "The corporate is corrupt" ($n_{corrupt}^{Apple} = 14; n_{corrupt}^{Bill} = 81; n_{corrupt}^{WF} = 153$) and "we should all boycott" are the most common – boycott Apple for cheating its customers ($n_{boycott}^{Apple} = 38$), Fox News for firing Bill O'Reilly ($n_{boyco}^{Bill} \quad = 62$), Pepsi for caving in to BLM ($n_{boycott}^{Pepsi} = 118$), and Uber for its greed ($n_{boycott}^{Uber} = 43$). United Airlines was not accused of being corrupt but was instead denounced as a company who hires thugs to drag the passenger out of the plane ($n_{thug}^{UA} = 173$).

The *sanctity/degradation* foundation involves intense feelings and profanities. We found words that approximate the feeling of disgust, i.e., crap, awful, shitty, puke, and ugh. At least one of these words appear each of the eight scandals in the foundation. Bill O'Reilly was called a misogynistic scumbag ($n_{misogynistic}^{Bill} = 58; n_{scumbag}^{Bill} = 130$) and a perv ($n_{perv}^{Bill} = 53$); United Airlines was a pathetic ($n_{pathet}^{UA} = 174$), shameless ($n_{shameless}^{UA} = 22$), racist scumbag ($n_{scumbag}^{UA} = 23$); Wells Fargo was greedy ($n_{greedi}^{WF} = 135$); and, "shame on Equifax", said some commenters ($n_{shame}^{Equifax} = 20$).

MFD and EMFD words are distributed in almost all posts, meaning that moral judgment is not limited to a small group of discussions; rather, our findings suggest that it is prevalent. Figure 4.6 shows our supporting evidence for United Airlines scandal, visualized as a heatmap.

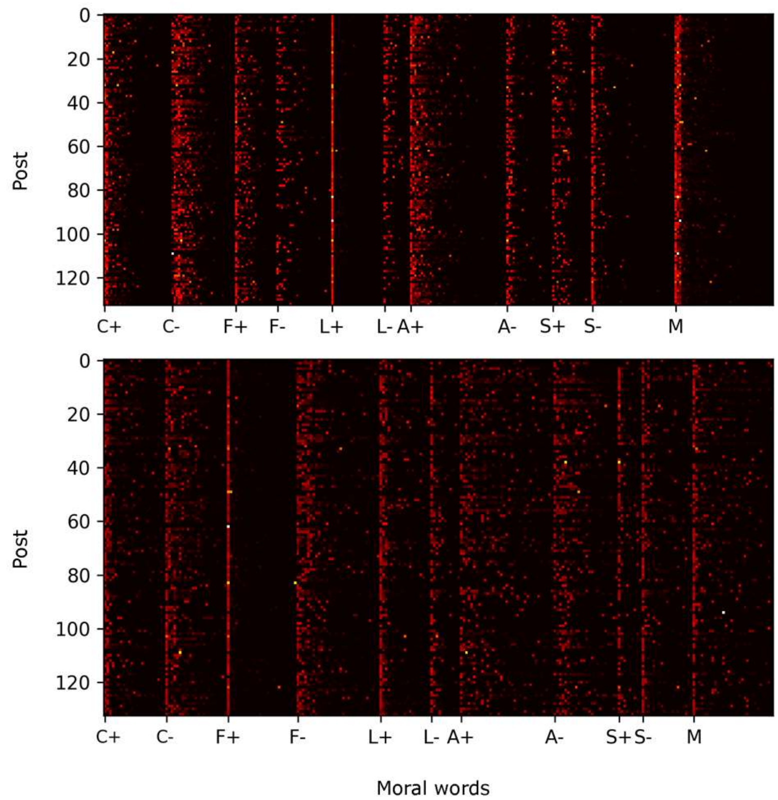


*Figure 4.6* Frequency of MFD words and EMFD words (top and bottom, respectively) as they appear in the posts related to United Airlines incident. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains. The moral domains are abbreviated as follows:
C = care/harm, F = fairness/unfairness, L = loyalty/betrayal,
A = authority/subversion, S = sanctity/degradation, M = morality general.

#### *4.3.3.4 Discussion*

A simple word-counting method in the first study was quite effective in helping us interpret the comments, in addition to its primary purpose, which is to determine the frequency of words in MFD. However, we have clearly seen that words in the dictionary alone cannot capture every aspect of a moral domain, which is why expanding the dictionary is crucial to our understanding of how people make moral judgment and how do they express their thought.

We have tried different ways to optimize the numerical properties of the expanded dictionary, especially to minimize the outcome of sim function (Equation 3) for all of the incidents. We hypothesized that as we push the domain vectors further away from each other, we would attain the sets of words that are more coherent. One simple way to effectively separate the domain vectors is to computationally remove an entire moral domain, starting from the one that the removal would reduce the result of sim function most, then ones that do less. The algorithm suggested us which domain to get rid of, but it did not understand beyond the mathematical point of view, nor did we. In other words, while we were successful in boosting the numbers, we fell flat to comprehend the results. Another way to achieve better numerical properties is to omit words in the expanded dictionary. We tried to do so by minimizing the variance, i.e., removing words that contribute most to the variance of their moral domain. We were able to reduce the variance, but then again, we could not fathom semantic properties of the words. The same problem occurred when we applied a supervised classifier Support Vector Machine in the word-removing process (Cortes & Vapnik, 1995). Thus, perhaps our best course of action is to still involve human in the process, which is what we did, until such time as the calculation could yield sufficiently intelligible result.

### 4.3.4 Study 3: Moral Judgment in Thai

We applied the proposed word segmentation algorithm to observe and interpret MFT in Thai social media users' reactions to five brand crisis scandals. We collected 4,669 comments in total from five brand-crisis-related posts in a website Pantip.com, which hosts public forums of various interests. The information of collected data is shown in Table 4.12.

Each post is associated with each incident. We summarized the comments of each post using the summarization algorithm we mentioned earlier. From 4,669 comments in total, the summarization algorithm produced 698 summaries at summarization rate of 0.05. One coder then read the summaries and categorized into the five moral foundations. He extracted keywords related to the moral domains from the summaries, then verify whether the keywords are in the English version of MFD and EMFD. Twenty-two keywords are in at least one of the dictionaries and, therefore, constitute the Thai version of MFD. Note that this Thai MFD was built based on the data that we had collected only. Further content analysis of other data should expand the dictionary. With the Thai MFD being built, we selected only the comments that contain MFD words. The result in terms of percentage of comments containing Thai MFD words in relation to all comments is shown in Figure 4.7.

*Table 4.12* Data collection of the five incidents from Pantip.com

| Incident | Category | Comments | Summaries |
|---|---|---|---|
| AIS (mobile phone operator) data leakage | Employee misbehavior | 1,266 | 203 |
| Pruksa Real Estate built unsafe house | Poor business conduct | 1,006 | 165 |
| Pruksa Real Estate built unsafe house | Employee misbehavior | 950 | 163 |
| Worms found in food at Shabushi restaurant | Food contamination | 806 | 89 |
| Major Cineplex's employee had an altercation with a customer over failing AC | Employee misbehavior | 641 | 98 |

We found that MFT is quantifiable in our Thai corpus. Regarding the care/harm foundation, AIS scandal involves data leakage, which the commenters thought could be a threat to those affected; many agreed that the house built by Pruksa Real Estate was unsafe to live; and, Dapper employee assaulting and intimidating the customer was considered a harm. There were a few mentions concerning the fairness/unfairness foundation, including unfair business practice in the case of AIS and Pruksa, and mistreatment of the customer in Dapper scandal. Most of the mentions related to the authority/subversion foundation are about filing lawsuit against the companies or to get the authorities involved. With regard to the sanctity/degradation foundation, the case of food contamination at one of Shabushi restaurants stimulated a discussion of the company's unclean restaurant and a feeling of disgust. Lastly, although the loyalty/disloyalty foundation does not exist in the data, certain incidents beyond the scope of this study may involve the moral foundation. We speculate that such incidents should involve a brand with admirers or community, such as the case of Apple mentioned earlier.

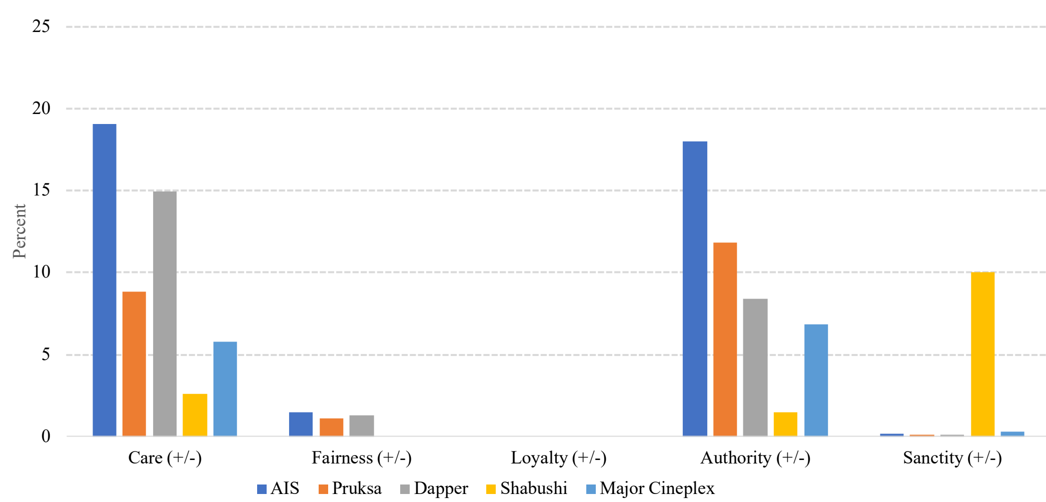


*Figure 4.7* Percentage of comments containing Thai MFD words

Another problem that we encountered is that some of the dictionary's compound keywords were not found in the data which compound words were segmented. To solve this problem, the analysis was conducted in two conditions: condition (1) uses only the CRF model for word segmentation, and condition (2) merges compound words after the

CRF-based word segmentation. The result shows that in condition (2), 12.47 percent more moral words were found in the data.

## 4.4 **Content Analyses of Entertainment Experience in Brand Crisis**

This section shifts the focus from morality to the entertainment experience, which is the second part of our theoretical framework. The section consists of two parts. The first part will explain our forth study, which we measured and interpreted the *enjoyment* dimension of the entertainment experience in forms of emotions and sentiments. The second part will move on to the *appreciation* dimension. We have decided that a quantitative analysis on this dimension presents too much complication and uncertainty to be reasonably reliable; thus, in the scope of this dissertation, we will instead discuss our interpretation based on observation from the three studies.

### 4.4.1 Study 4: Enjoyment in Brand Crisis

#### *4.4.1.1 Introduction*

Before we get into the design of the study, it is best to first establish a clear understanding about who may be involved, how should we refer to them, and what should we measure. First, there is a brand, and sometimes a victim. We regard the post creators as the media who report, disseminate information, produce original content, and quite often, shape the discussion. The audience may react, in such case we are interested in their comments, or they may simply read and keep their opinions to themselves. From our data alone, we cannot produce a reliable approach to unravel the thoughts of those who did not react. Likewise, we cannot infer emotions beyond what were made explicit. This means we cannot measure meta-emotions, and so, trying to explain the negative emotions would not serve our purpose. Hence, we narrowed our focus down to the positive emotions.

*4.4.1.2 Methodology*

We employed two different approaches. First, LIWC has a dictionary of aggregated positive and negative emotions, also added in the 2015 version was emotional tone (Cohn, 2004). Emotional tone or emotional-positivity index is a score of range 0 to 1 (negative to positive) calculated from the different between the LIWC scores of positive emotion words and negative emotion words. Second, we performed sentiment classification on all comments. (Socher, Perelygin, & Wu, 2013) introduced Recursive Neural Tensor Network (RNTN), a recursive deep model of neural nets in a tree structure. Its structure was designed specially to process natural language, with 85.4% accuracy on positive/negative sentiment classification task (Stanford Sentiment Treebank corpus[24]). RNTN also demonstrates its impressive performance on short informal texts such as tweets and SMS (Kiritchenko, Zhu, & Mohammad, 2014) as well as other types of informal texts (Cambria, Poria, Hazarika, & Kwok, 2018; Hussain & Cambria, 2018). Socher et al.'s classifier is part of Stanford CoreNLP toolkit (Manning et al., 2014), available as a Java package.

For each incident, we created two ranks of the posts, one sorted in descending by their emotional tones, and another by their sentiment scores. LIWC calculates emotional tone of a post from a single document containing all of its comments merged. Socher et al.'s classifier calculates five sentiment scores per comment – each between 0 and 1 – from very negative to very positive (--, -, 0, +, ++). A sentiment score of a post is the average of sentiment scores of its comments. We aggregated the scores $s = \{s^{--}, s^{-}, s^{0}, s^{+}, s^{++}\}$ by:

$$arg(s) = \frac{(2s^{++} + s^{+} - s^{-} - 2s^{--})(1 - s^{0}) + 3}{6} \in [0,1] \qquad (4)$$

We performed sentiment analysis on Amazon EC2 t2 medium-type (2 vCPU, variable ECU, 4 GiB of memory). For each rank, one of the researchers in our team reviewed the posts – including their top-ten comments sorted by the sentiment scores – starting from the one with the highest score. He identified the sentiment polarity of the

[24] Available at https://nlp.stanford.edu/sentiment/

top-ten comments regardless of their sentiment scores. The process continued until he could not detect positive sentiment in five consecutive posts, then stopped. After comments below the top-ten had been removed, his review of the LIWC rank yielded 125 posts and 1,250 comments; the sentiment rank yielded 183 posts and 1,830 comments. Of all the posts in both ranks combined, 230 are unique, adding up to 2,300 comments. The researcher studied the result and found three incidents in particular that have relatively significant amount of posts with positive sentiment (other incidents have at most two of such posts). Upon examining the comments, he defined three aspects of interest, which became the coding categories (type of reactions). Estimated from the sentiment scores (Figure 4.8, Figure 4.9, and Figure 4.10), he selected 45 top positive posts (25 from United Airlines incident, 10 from Bill O'Reilly, and 10 from Fyre Festival; 450 comments) to be coded by two coders. The coding task requires the coders to read the posts, watch attached video should any post have, and read the top ten comments sorted by the sentiment scores. The researcher asked the coders to categorize each post by content type (text, image, or video) and reaction sentiment (humorous, satisfaction, or schadenfreude). After validating the intercoder reliability, the researcher determined the reaction sentiment of the posts which conflicting decisions between the coders had been made, then concluded the content and reactions of the posts identified as having positive-sentiment reactions.

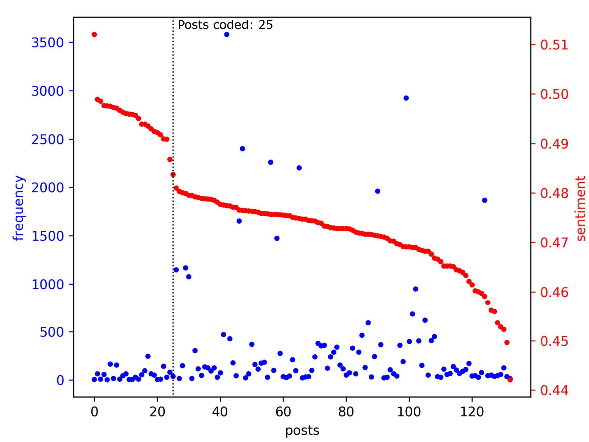


*Figure 4.8* Frequency of MFD words in the comments to United Airlines incident. The posts are sorted by their sentiment score. The reactions to the 25 posts were coded into three categories, i.e., humorous, satisfaction, and schadenfreude.

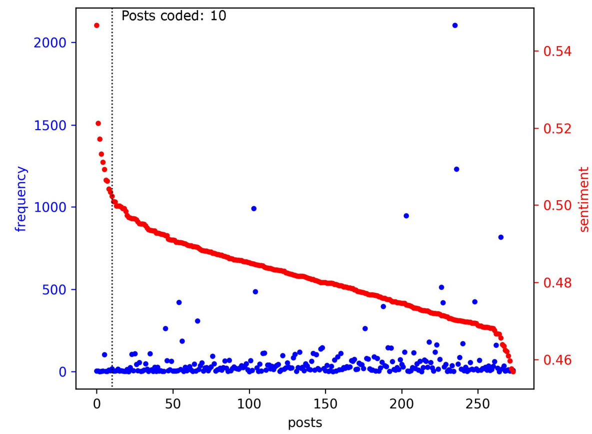


*Figure 4.9* Frequency of MFD words in the comments to Bill O'Reilly incident. The posts are sorted by their sentiment score. The reactions to the 10 posts were coded into three categories.

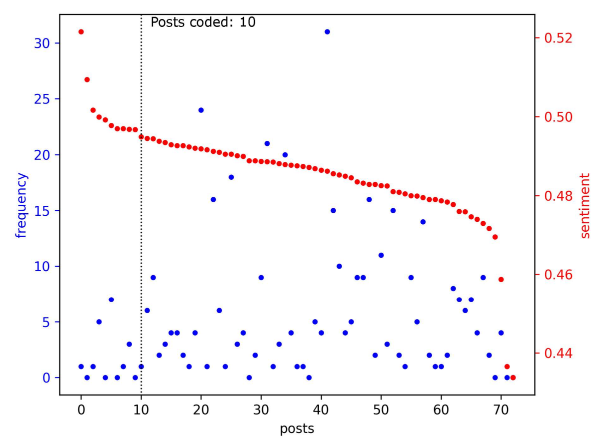


*Figure 4.10* Frequency of MFD words in the comments to Fyre Festival incident. The posts are sorted by their sentiment score. The reactions to the 10 posts were coded into three categories.

*4.4.1.3 Results*

We compiled two lists of posts, one sorted by LIWC emotional tone, another by sentiment scores calculated using Socher et al.'s model (Socher et al., 2013). One researcher in our team reviewed 230 unique posts in total, 125 of which are in the LIWC list and 183 are in the sentiment list. In terms of overlapping between the lists, 75 posts in the LIWC list are also in the sentiment list and 73 posts in the opposite comparison. The researcher identified 57 posts in the LIWC list as having comments with positive sentiment reactions (PSR), of which 49 posts are also in the sentiment list; 91 PSR posts were identified in the sentiment list, the overlap with the LIWC list is just about half (48 posts). Only three scandals have more than five PSR posts.

Thirty-eight unique PSR posts (of the LIWC and sentiment lists combined) are associated with Bill O'Reilly scandal, with aggregated sentiment scores ranged between 0.4872 and 0.5111 (M = .4950, SD = .0053) and emotional tones between .01 and .9774 (M = .2324, SD = .2256). Thirty posts are news and reports about Bill's firing; two more are about firing of another reporter and public figure, with a mention of or a connection to Bill's firing. While some audience were outraged by the firing, some expressed great gratification, which include the satisfaction of vengeance ($n_{karma}^{Bill} = 257$), approval of the riddance ($n_{good\ rid}^{Bill} = 378$), delight ($n_{awesom}^{Bill} = 74; n_{wonderful}^{Bill} = 45; n_{happ}^{Bill} = 258$), and enthusiasm ($n_{great\ news}^{Bill} = 44; n_{best\ news}^{Bill} = 62$), as well as emotional expressions such as bwhaha, yaaaa, yay, lol, and lmao. Three posts contain videos of Bill-related part of American late-night talk shows, e.g., "The Late Show with Stephen Colbert." The late-night shows are famous for their humorous qualities, and so the comments are related to the humor ($n_{funny}^{Bill} = 298$). The other three posts are about the ongoing situation before the firing, i.e., Bill facing accusation of misconduct, companies pulling commercial from Bill's show "The O'Reilly Factor," and dispute between Bill and U.S. Representative Maxine Waters. The commenters expressed their satisfaction to the commercial pulling and the accusation; some showed their support to the Representative.

Thirty-six unique PSR posts are about Fyre Festival scandal. The aggregated sentiment scores are between .4729 and .5094 (M = .4888, SD = .0073) and the emotional tones between .1388 and .99 (M = .6158, SD = .2458). Twenty-five posts are news and articles about the chaos at Fyre Festival. The audience experienced satisfaction in the form of schadenfreude, i.e., they enjoyed seeing "rich kids" or "rich people", which refer to the festival goers, got caught up in the "disaster" ( $n_{rich}^{Fyre} = 176; n_{rich\ kid}^{Fyre} = 62; n_{schadenfreud}^{Fyre} = 7$). They – the commenters – found the incident to be hilarious ($n_{hilar}^{Fyre} = 21; n_{funni}^{Fyre} = 33$), with emotional expressions, e.g., bwhaha, haha, lol. Four posts are news about the festival organizers being arrested and a class action lawsuit against the organizers; the audience were satisfied with the justice. Three other posts are news about the organizers' responses after the festival was cancelled, which include an apology, a promised refund, and a blame on a storm for the failure of the event. The comments with positive sentiment are similar to those of the posts mentioned earlier; some commenters said they found the whole scandal hilarious. Lastly, two posts are an article about a collection of "funny" tweets; one post is an article about "the man behind Fyre" and another post is the news reporting policy change in Bahamas, where the festival was held. Again, no noticeable difference regarding the PSR.

United Airlines scandal has the least related unique PSR posts. The aggregated sentiment scores among the 21 posts are between .4909 and .5120 (M = .4962, SD = .0045) and the emotional tone between .028 and .9127 (M = .2822, SD = .2514). Fourteen posts are satirical videos and image, all from violent scenes in various movies and self-defense classes. Five of the posts said, sarcastically, that they are a "video footage" of United Airlines' training for its staff; eight mocked the violent incident; one said the self-defense class video is "just in case you get dragged from United plane." The reactions were that the videos are funny, great, and amazing ($n_{funni}^{UA} = 329; n_{amaz}^{UA} = 93$), with emotional expressions similar to the other two incidents. Two other posts are a parody commercial from a late-night talk show "Jimmy Kimmel Live!"; two are self-created mocking videos; one is a video of entertainment news produced by Mashable; another one is an article collecting "hilarious new slogans" for United Airlines from the internet. The reactions with positive sentiment are similar to the others within the scandal.

Figure 4.8, Figure 4.9, and Figure 4.10 show the frequency of MFD words and the sentiment scores of the three scandals. We have noticed that posts with relatively high sentiment scores tend to have less MFD words in their comments. Two coders categorized the PSR of the 45 posts into humorous, satisfaction, and schadenfreude (or none). The intercoder reliability test resulted in Cohen's kappa of .70 with 90% agreement rate (more detail in Table 4.13). The coders agreed that the reactions to six out of ten posts in Bill O'Reilly scandal indicate the audience's satisfaction; one post is humorous. Five out of ten posts in Fyre Festival scandal are categorized as humorous; three other posts indicate the feeling of schadenfreude. Lastly, 18 out of 25 posts in United Airlines are humorous. A brief summary of the categorized posts is in Table 4.14.

*Table 4.13* Intercoder reliability of 45 positive posts

| Measurement | # Data points | Cohen's kappa | PABAK | Krippendorff's α | Agreement |
|---|---|---|---|---|---|
| Reactions | 270 | .70 | .86 | .70 | 90% |

*Table 4.14* Summary of the posts and reactions agreed by all coders as belonging to at least one of the three categories of positive sentiment defined by the researcher

| Incident | Humor | Satisfaction | Schadenfreude |
|---|---|---|---|
| Bill | *1 post:*<br>- Mocking video<br><br>*Reactions:*<br>- Find the video funny<br>- Like the video | *6 posts:*<br>- News on Bill firing<br>- News on Bill returning<br>- Other news<br>*Reactions:*<br>- Express happiness<br>- Like the news<br>- Laugh satisfactorily<br>- Satisfy the firing<br>- Support Bill | *0 post* |
| Fyre | *5 posts:*<br>- News/update<br>*Reactions:*<br>- Find the content funny<br>- Mock the festival goers | *0 post* | *3 posts:*<br>- News/update<br>*Reactions:*<br>- Find the news hilarious<br>- Enjoy rich kids' misfortunes<br>- Enjoy rich people's problem |

| | | | |
|---|---|---|---|
| UA | *18 posts:*<br>- Mocking video/image<br>- Entertainment news<br>*Reactions:*<br>- Find the video/image funny<br>- Find the content informative<br>- Like the video/image<br>- Want to share the video | *0 post* | *0 post* |

*4.4.1.4 Discussion*

As the analysis suggested, the audience enjoyed satirical videos, images, and posts related to United Airlines scandal. The feeling of enjoyment reflected on the comments is straightforward, indicating the light, superficial, and pleasurable experience. The other two incidents elicited pleasure as well, but in quite a different way. Pleasure in the case of Bill O'Reilly stems from satisfaction by mean of affective disposition. As mentioned earlier, the affective disposition theory states that the audiences make a moral judgement about the characters and they expect positive outcomes for those they like – whom they judged as morally good – and the opposite for the ones they dislike (Zillmann & Cantor, 1972). Media viewer's dispositional categorization is not limited to a character individually but also to a group – a company in our case (Zillmann et al., 1998). Enjoyment is a function of a viewers' affective disposition and the outcomes associated with the characters. The audience's advocacy for legal, financial, and career punishment – e.g. lawsuit, boycotting, and firing – not just in Bill's case but most of the scandals implies their judgment of right and wrong, and their affective disposition. Bill was the disliked character who had done wrong and had been eluding punishment for some time until public outcry led to his doom. Thus, when his opposers learned of the firing, they expressed their ultimate satisfaction with joy – to them it seems justice prevailed after all. In a similar process, excitation transfer theory explains that drama viewers are willing to experience unpleasant feelings in witnessing a sympathetic protagonist suffer through distressing situations when, in the end, they would be relieved as the dilemma resolved (Wulff, 1996; Zillmann, 1996). The residual of the desire to see Bill being brought to justice combined with the satisfaction upon hearing the news of the firing eventually elicited the sense of enjoyment.

Interestingly, enjoyment in the instance of Fyre Festival scandal is fundamentally different. There were no mentions of any wrongdoing done by the festival goers. The pleasure seemed to be a product of schadenfreude in relation to envy, specifically social injustice. Envy is a negative emotion that entails the feelings of inferiority, hostility, injustice, and discontent arisen from social comparison where a person desires another's superior quality, achievement, or possession or wish that the other did not have it (Parrott, 1991; Parrott & Smith, 1993; Smith, 1991). The terms "rich kids" and "rich people," and the context in which they were used suggest that the commenters envy those whose wealth transcends theirs. Thus, when they learned of the misfortune of the rich, whom they resent, they experienced joy (Feather & Sherman, 2002; Hareli & Weiner, 2002; Van Dijk, Ouwerkerk, Goslinga, Nieweg, & Gallucci, 2006).

### 4.4.2 Appreciation: Reflective Thoughts

We found that some comments imply the process of easing psychological discomfort by reappraising the victims' trouble as self-caused. For instance, Apple slowing down iPhone was seen by many as unjust to its customers, whereas some said, in what would rather be considered as a trash-talk, that it was Apple fans' fault that they blindly loyal to the brand; reacting to Fyre Festival scandal, some expressed no sympathy for "rich idiots" who paid several thousand dollars; and, the cause of sexual harassment in Bill O'Reilly scandal was attributed to inappropriate dress in workplace. Such comments imply the process of easing psychological discomfort by reappraising the victims' trouble as self-caused.

While none of our brand crisis incidents seem to be moving, the abundant evidences of negative emotions indicate the existence of negative valence. The scandals can be thought-provoking with regard to social reality for certain audience (Bartsch, 2012), for example, some of the commenters raised the issue of racial discrimination in the dispute over the Pepsi commercial, United Airlines incident, and Bill O'Reilly scandal. Lastly, with their interest in the issue, the audience's attempt to seek the truth reflected on the truth, or what is believed to be the truth, they provided, e.g., information regarding relevant regulation.

# Chapter 5

# Discussion and Conclusion

## 5.1 General Discussion

This dissertation revealed the entertainment aspect of brand crisis, particularly in relation to moral judgment. We aim to establish a direction for research on this subject, as well as providing tools for further content analysis. Our theoretical framework simplifies the audience's mind into two aspects, i.e., moral judgment and the two dimensions of the entertainment experience, so that we could examine the psychological process without getting into too much complexity. We are certain, however, that much more has yet to be explored, experimented, and explained.

The fact that the audience interpreted the scandals in so many different ways – even cover all five moral domains – is intriguing, although some interpretations may not be directly related to the incidents. The company in crisis needs to monitor closely how and in what aspect people make moral judgment because while its response may address problems in certain moral domains, it may violate others. For example, the decision of Fox News to settle with Bill O'Reilly's accusers might be judged as appropriate by Bill's supporters, his opposers thought it is wrong to protect the man who used his position to sexually harassed colleagues. It may be impractical in some circumstances to respond in the way that satisfies all moral domains. That said, understanding how the audience judge can help the company develop response strategies that effectively mitigate public outcry.

To understand the audience's reaction better, we expanded MFD. There have been attempts to expand the dictionary and those studies successfully gained more insight of MFT in their context. We believe that there is still so much room for improvement, and as the field of natural language processing progresses, we expect to see more accurate dictionaries in the future, whether in a form of sets of words as we have now or a machine learning model. With the advancement in machine translation models, we may be able to connect the MFD model with the translation model in the near future, thus, avoiding the complexity of trying to translate MFD into other languages. We will discuss more about this complication in the next section.

With regard to the entertainment experience, content analysis can only show us a narrow perspective of the experience. Bill O'Reilly, United Airlines, and Fyre Festival are special in the sense that we could observe the indications that the audience enjoyed the content they read or watch in social media. This does not imply, however, that the audience did not enjoy other scandals. We believe that there should be the element of entertainment experience in those incidents. However, in order to measure this latent psychological process, we need to examine more than texts from social media. There is also much more to learn about other contributing factors to the moral judgement and the entertainment experience, for example, personality, mood, and culture.

Specifically, we expect to observe, in the context of brand crisis, people in different cultures make moral judgment and be entertained in different ways. We know for a fact that the sense of entertainment varies across different cultures (Trepte, 2008), and so does morality (Graham et al., 2011). It is, therefore, important that we tackle the challenges of translating MFT into different languages. All in all, every factor that contribute to the differences in morality and entertainment can also affect the entertainment experience in brand crisis.

We have also noticed that the topics of discussion, sentiments, and opinions are shaped by the content of the posts. We rarely saw positive-sentiment comments outside certain posts that have such comments. However, posts with positive-sentiment comments usually have negative-sentiment comments as well. How much the topic of the posts influences the reactions still needs further investigation. Also, temporal changes of sentiments and opinions have yet to be studied, especially with the effect of situational changes in the crisis, as well as the interference of other relevant events, e.g., the firing of other celebrities not long after Bill's firing.

## 5.2 Limitations

### 5.2.1 Word and Sentence Segmentation

The validation of the segmentation algorithm is limited by the testing data. Even so, we believe that the amount of the testing data that we created is sufficient to demonstrate the accuracy of the algorithm without us having to relabel the entire corpus for testing. In which case, we could rather train the CRF model with the relabeled corpus without having to develop the merging and splitting algorithm. However, doing so would be costly in terms of time and financial resource.

Another limitation is in the translation experiment. We used a commercial product Google Translate for the translation task. The disadvantage is that we do not understand the process behind the translation, and therefore, cannot explain any error caused by the translation tool.

### 5.2.2 Moral Judgment

Our translation of the moral foundations into the context of brand crisis, as well as the interpretation of the entertainment experience, are essentially based on the audience' reactions to the scandals. These reactions are the residual of thought the audience left in the public space. To acquire an insight into the audience's mind would require further controlled experiment with human subjects. Our coding guidelines, interpretations, and measuring items can be useful in this regard.

MFD was built in English and some of its vocabulary are only part of a word. This allows LIWC to count a single word in many forms, for example, *empath** tells the software to count every word that begins with *empath*, e.g., *empathy*, *empathize*. Translating the dictionary to another language would require a systematic analysis of the words and their forms. Moreover, a word in English can be translated to multiple words in another language. These translated words can be a synonym with slightly different meaning or feeling as perceived by the native speakers. Thus, the translation method needs to be carefully designed and validated not to alter the meaning of words and moral domains.

#### 5.2.3 Enjoyment

While the sentiment analysis model that we used has been shown to be impressively accurate, it still contributes to the error unexplained by our validation procedure, i.e., some false-negative predictions might be left unchecked, which means that there may be other posts with positive-sentiment reactions that we did not consider because their sentiment score is low. To eliminate this problem entirely, we would need to manually validate every post. Alternatively, we could randomly select certain amount of posts to validate. However, since we have very limited number of posts with positive-sentiment reactions and our purpose within the scope of this dissertation is to interpret such posts, we chose to validate as many of them as possible while try not to overwhelm the coders with too much data, which could lead to tiredness and drop of coding accuracy. Therefore, we sorted the sentiment scores first and chose to validate the posts and comments with top sentiment scores.

## 5.3 Conclusion

In this dissertation, we introduced a word segmentation rule and proposed two post-processing methods for CRF-based word segmentation. The first method, a dictionary-based word-merging algorithm improves the accuracy of word segmentation according to the proposed rule, which aims to preserve compound words. The second method, a POS-based word-splitting algorithm, improves the accuracy of sentence segmentation. Proving the contributions of both methods, we experimented on three of their applications and found that: First, with the word merging algorithm, intact compound words in the product of topic extraction can preserve their intended meaning, offering more precise information for human interpretation; second, the algorithm can also be a part to amend Thai-English translation; lastly, the POS-based word splitting algorithm, by improving sentence chunking, betters text summarization. The proposed methods and text summarization also enable us to conduct the content analysis of brand crisis in Thai social media.

For the analysis of brand crisis in social media, we aimed to explore the audience's minds in the new era of impactful phenomena that are critical to a brand entity. The framework offers a novel perspective to brand crisis study in marketing research, as well as a theoretical ground for empirical studies on this subject. In the moral judgment part of the framework, we explained the connections between moral domains of MFT and a brand crisis. These connections were then quantified and interpreted from the evidence we gathered from social media. MFD, in combination with text summarization, assisted us in interpreting the online reactions and creating context-specific definitions of MFT in the context of brand crisis. We also found EMFD to be consistent with MFD in the sense that the frequencies of words in both dictionaries, as they appear in the comments, are significantly correlated. Moreover, since not all moral domains have to be present in one crisis incident, removing certain moral domains as suggested by the coders in the first study helps improve vector representations of the domains. All in all, both MFD and EMFD helped us better our understanding of MFT in the brand crisis context.

In the entertainment part of the framework, our study demonstrated the manifestations of enjoyment in the entertainment experience. Interestingly, enjoyment can be associated with different types of reactions, including satisfaction, humor, and schadenfreude. We believe that there may also be other types of emotions and feelings that can be associated with enjoyment in the context of brand crisis. Applying our method to analyze other incidents may help discover more. The appreciation dimension of the entertainment experience, on the other hand, presents a tremendous challenge in content analysis, especially quantification. The alternative strategy would be to conduct a controlled experiment involving human subjects.

## 5.4 **Future Research**

MFD and EMFD enable us to quantify the moral domains and observe how the audience made moral judgement. However, we have yet to explain in a quantitative setting the audience's affective disposition. Such task would require a language processing technique that takes context and entities -- e.g., persons, companies -- into consideration. Machine comprehension seems to be a promising direction. The technique involves creating and training a model that comprehends texts then answer questions (M. Seo, Kembhavi, Farhadi, & Hajishirzi, 2016). Applying to our context, we asked, for example, "who should be sued?" Using Seo et al.'s Bidirectional Attention Flow network, we found that some answers are highly relevant, e.g., "United Airlines". Note that we only performed the operation on the comments containing "sue" and pre-selected by the summarization algorithm. The problem is even though comments are short and simple -- which should be easy to comprehend, they are commonly written informally and with ignorance to grammar. We would need a training corpus that entails such form of the language, or a machine translation model that translates comment-style English into proper English (Hieber et al., 2017)[25], to solve the problem. Unfortunately, current advancement of machine comprehension and translation has not yet reached the point where we can confidently rely on. There may be some time before the machine could comprehend the audience's affective disposition, but we are optimistic that it would not be long until we are able to develop such capability.

Translating MFD directly into Thai would allow us to replicate the studies involving both MFD and EMFD in the language. However, there are several challenges in translating the dictionary, i.e., word form and structure, and synonym. Thus, the translation method needs to be carefully designed and tested. For the experiment involving sentiment and emotion, unfortunately, there has been a very limited advancement on sentiment analysis in the Thai language, largely due to a lack of large

[25] NUS Social Media Text Normalization and Translation Corpus is available at: http://www.comp.nus.edu.sg/~nlp/corpora.html

corpus for training a machine learning model. For now, we may have to rely entirely on human to conduct the study.

# Appendix A

# Brand Crisis Scandals in the Studies

## A.1 Apple intentionally slowed down iPhones

The crisis came after reports of Apple purposely slowing down older iPhones to prevent the devices from shutting down because of decaying batteries. There had been speculations long before the crisis, but eventually when Apple admitting publicly, lawsuits and public outrage followed. Apple later apologized and offer battery replacements for a lower price.

## A.2 Bill O'Reilly fired amid sexual harassment claims

The crisis arose from sexual harassment allegations against television host Bill O'Reilly of entertainment company Fox. O'Reilly reportedly paid millions of dollars to five accusers to prevent them from going public and Fox had knowledge of the payment. In an attempt to mitigate the scandal, Fox paid millions of dollars to settle the claims and created a council to ensure proper workplace environment. Neither O'Reilly nor Fox admitted any wrongdoing.

## A.3 Equifax's customer data breach

Credit rating firm Equifax admitted that the information of some 145 million people was breached. The revelations that Equifax had been aware of the data breach two months before it made public announcement forced CEO Richard Smith, chief information officer, and chief security officer to step down. The Justice Department reportedly investigated top Equifax executives for committing insider trading as they sold some $1.8 million in shares just before the company's public announcement.

### A.4 Wells Fargo employees opened fake accounts

Wells Fargo & Co. employees created some 1.5 million unauthorized deposit and credit-card accounts. The bank was fined $185 million while still struggling to move past a scandal that led to congressional investigations. Later, an outside review found additional unauthorized accounts, placing the number of fraudulent accounts at about 3.5 million. The bank replaced its leaders, clawed back executives' pay and overhauled its retail division.

### A.5 Fyre Festival postponed amid chaos

Billy McFarland and musician Ja Rule announced the launch of a luxury festival on a private island in the Bahamas. Tickets ran from several thousand dollars to $250,000 for the deluxe packages, promising luxury amenities. Instead, people who arrived on the island found a "disaster tent city" with no villas, no bands, and no models. Fyre announced that the festival is "postponed" and all attendees will have to go home. The organizers issued an apology, while several lawsuits followed the chaos.

### A.6 Samsung Galaxy Note 7 exploded

After dozens of reports of Galaxy Note 7 smartphone overheating and exploding, Samsung recalled 2.5 million phones. According to the company's report, two separate battery malfunctions caused some phones to overheat and even catch fire. The company recalled the first batch and manufactured the second batch with a battery from a different supplier. The overheat problem persisted and Samsung ended up recalling all Note 7 phones and cancelling the production. Samsung said it has developed a new battery check to prevent future incident.

## A.7 Pepsi's controversial advertisement

Pepsi defended its advertisement featuring Kendall Jenner as a model who leaves a photo shoot and joins a protest, saying that it meant to portray "global message of unity, peace and understanding." The company's reaction came after widespread criticism that the ad trivialized recent protests and the Black Lives Matter (BLM) movement. Later, Pepsi decided to pull the ad and apologized. However, the viewers interpreted the apology as directing towards Jenner rather than the protesters, BLM, and those who were offended, provoking further backlash.

## A.8 United Airlines staffs forcefully removed a passenger

Some videos of a passenger being violently dragged of an overbooked United Airlines' plane went viral on the internet. United initially stood by its staffs and the securities who removed the passenger but later issued a "cold apology", saying "This is an upsetting event to all of us here at United. I apologize for having to re-accommodate these customers." After widespread backlash, United took full responsibility and made another apology: "We have committed to our customers and our employees that we are going to fix what's broken so this never happens again." Even after the company apologized, its consumer perception dropped to a 10-year low.

## A.9 Uber CEO heated argument with a driver

Bloomberg News published a video of CEO Travis Kalanick arguing with his own Uber driver over the company's treatment of drivers. The video shows Kalanick riding in the back seat. At the end of the ride, driver Fawzi Kamel complained: "You're raising the standards, and you’re dropping the prices. He said, “People are not trusting you anymore … I lost $97,000 because of you. I’m bankrupt because of you ... You keep changing every day.” Kalanick denied that the prices have fallen that much, saying, “Bullshit.” Then he got personal with Kamel: “Some people don’t like to take responsibility for their own shit,” he said. “They blame everything in their life on somebody else. Good luck!” Then he slammed the door. Later, Kalanick apologized, saying, “This is the first time I’ve been willing to admit that I need leadership help and I intend to get it.”

## A.10 Samsung’s washing machine exploded

Samsung, at the time still reeling from its fire-prone Galaxy Note 7 smartphone, recalled almost 3 million washing machines in fear of explosion. The recall was issued after reports that the lids of the machines can pop off violently while the laundry is spinning, posing an injury risk. A customer in Texas filed a class action over the machine, saying that her washer “exploded with such ferocity that it penetrated the interior wall of her garage.”

Appendix B

# Moral Foundations Definitions for Coders

## B.1 The Care/harm foundation

The original triggers of the Care/harm foundation are visual and auditory signs of suffering, distress, or neediness expressed by one's own child. There are now many ways to trigger feelings of compassion for victims, an experience that is often mixed with anger toward those who cause harm. These moral emotions are not just private experiences; typically includes moral evaluations of those parties' actions. And as long as people engage in moral discourse, they develop virtue terms such as "kind" and "cruel" to describe people who care for or harm vulnerable others.

## B.2 The Fairness/cheating foundation

The original triggers of the Fairness/cheating foundation involved acts of cheating or cooperation by one's own direct interaction partners, but the current triggers of the foundation can include interactions with inanimate objects (e.g., you put in a dollar, and the machine fails to deliver a soda), or interactions among third parties that one learns about through gossip. People who come to be known as good partners for exchange relationships are praised with virtue words such as fair, just, and trustworthy.

## B.3 The Loyalty/betrayal foundation

Recognizing, trusting, and cooperating with members of one's co-residing ingroup while being wary and distrustful of members of other groups. Because people value their ingroups, they also value those who sacrifice for the ingroup, and they despise those who betray or fail to come to the aid of the ingroup, particularly in times of conflict. Most cultures therefore have constructed virtues such as loyalty, patriotism, and heroism. Sports fandom and brand loyalty are examples of how easily modern consumer culture has built upon the foundation and created a broad set of current triggers.

## B.4 The Authority/subversion foundation

People often feel respect, awe, and admiration toward legitimate authorities, and many cultures have constructed virtues related to good leadership, which is often thought to involve magnanimity, fatherliness, and wisdom. Bad leaders are despotic, exploitative, or inept. Conversely, many societies value virtues related to subordination: respect, duty, and obedience.

## B.5 The Sanctity/degradation foundation

Disgust responds to elicitors that are biologically or culturally linked to disease transmission (feces, vomit, rotting corpses). In many cultures, disgust supports a set of virtues and vices linked to bodily activities, and religious activities. Those who seem ruled by carnal passions (lust, gluttony, greed, and anger) are seen as debased, impure, and less than human, while those who live so that the soul is in charge of the body (chaste, spiritually minded, pious) are seen as elevated and sanctified. Disgust and the behavioral immune system have come to undergird a variety of moral reactions, e.g., to immigrants and sexual deviants.

# Appendix C

# Coding Taxonomy

*Table C.1* General coding taxonomy and moral emotions based on the five domains

| Dimension | Key Elements | Relevant Virtues and Vices | Characteristic emotions |
|---|---|---|---|
| Care/ | Kindness, gentleness, nurturance, generosity, help with regard to other living beings or environment | Caring, kindness | Compassion |
| Harm | (Threat of) physical or emotional harm to living beings, environmental harm, lack of care | Cruelty | |
| Fairness/ | Concern for justice, equality/equity, and reciprocity | Fairness, justice, honesty | Anger, gratitude, guilt |
| Cheating | Injustice, stealing, inequality/ inequity, non-reciprocity | Dishonesty | |
| Loyalty/ | Patriotism, self-sacrifice for the ingroup (e.g., family, friends, nation) | Loyalty, patriotism, self-sacrifice | Group pride, belongingness; rage at traitors |
| Betrayal | Lack of loyalty towards ingroup, betrayal of ingroup | Treason, cowardice | |
| Authority/ | Leadership, deference to legitimate authority, respect for traditions, obedience to laws and regulations | Obedience, deference | Respect, fear |
| Subversion | Disregard of legitimate authority, disrespect for traditions, disobedience of laws and regulations | Disobedience, uppitiness | |
| Sanctity/ | Concern for elevation (including religious activities) and standards of purity and sanctity | Temperance, chastity, piety, cleanliness | Disgust |
| Degradation | Violation of purity, decency, and religious standards | Lust, intemperance | |

*Table C.2* General examples of the five moral domains

| Dimension | Example Responses |
|---|---|
| Care/ | - Assisted a tourist with directions because he looked lost.<br>- I gave a homeless man an extra sandwich that I had. |
| Harm | - A woman was driving and smoking a cigarette with small children in the car.<br>- Hired someone to kill a muskrat that's ultimately not causing any harm. |
| Fairness/ | - Talked to someone about treating others equally.<br>- Reminded waitress I did not pay for my bill when she thought I did. |
| Cheating | - Congress making cuts across the board and not solving debt problems for the country.<br>- At work someone stole my partner's nice balsamic vinegar while he was off shift and most likely took it home with them. |
| Loyalty/ | - Since this is Memorial Day, I've read a number of posts paying tribute to our veterans' family, friends, nation). and families that have lost a loved one.<br>- I am putting my family before my own fun (chance to get drunk). |
| Betrayal | - Gave up on my team.<br>- Arranging adulterous encounter. |
| Authority/ | - Enforced a rule.<br>- Appropriately disciplined a youth not my own. |
| Subversion | - Disrespecting my mother.<br>- Had drinks with a colleague during work hours without the boss knowing. |
| Sanctity/ | - Talked about God with a family member.<br>- Yoga Nidra meditation class. |
| Degradation | - Caught my teenage son looking at hard core porn.<br>- Woman made 3-year-old eat her feces for having an accident. |

Appendix D

# Coding Guidelines

## D.1 General guidelines

a. The sole objective is to determine whether the commenters made moral judgment; in other words, whether the comments can be associated with any of the moral foundations. As a coder, your judgment on any part of the incident should not interfere with how you code. For example, in your opinion the company may have done enough to show their compassion for those who were harmed, but there is no mention in any comment whatsoever that can be related to the care/harm foundation. In such case your conclusion should be that the care/harm foundation is irrelevant in the minds of the commenters; thus, there is no moral judgment regarding the care/harm foundation.
b. Any mention of unrelated parties with no connection to the incident should be deemed irrelevant, notwithstanding the evidence of a moral foundation being discussed. For example, a mention of particular political party as a traitor to their country without any logical connection to the incident should be ignored.
c. For a moral foundation to be considered relevant, there must be at least one comment that demonstrate the connection. The same condition applies to the "whether or not there is any mention of" questions.
d. Comments have already been assigned to their moral foundation but can be considered in relation to other foundations as well. For example, you may find a comment assigned to the authority/subversion foundation saying that the authorities should protect their citizens. While you may have decided that

the comment mentions the authority/subversion foundation, protecting citizens also falls within the definition of care/harm foundation; ergo, both foundations should be considered relevant.

## D.2 Moral Existence

For a moral foundation to be considered relevant, at least one comment must:

### D.2.1 The *care/harm* foundation

a. Includes any mention of a company's action, or an expectation that a company should take action, to prevent harm to its customers, staffs or stakeholders
b. Includes any mention of a third-party's action to prevent harm or defend the company, its customers, or other third-parties if such action is in any way related to the incident
c. Includes any mention of protection services a company offers, or should offer, as an obligation or a commitment to ensure the safety of its customers
d. Includes any mention of harm or potential harm caused by product, service, staffs, or any third-party
e. Includes any mention of physical, emotional, or reputational harm that could affect personal well-being of other party
f. <u>Excludes</u> any mention of an attempt of any party to protect its own ideologies, properties, or financial interests

### D.2.2 The fairness/cheating foundation

a. Includes any mention of ensuring equal service to all customers
b. Includes any mention of unbiased justice and balanced treatment to all parties
c. Includes any mention of company's honesty in conducting its business

d. Includes any mention of ensuring no violation of any rights to which each party is entitled
e. Includes any mention of ensuring proper compensation, in case a company is obliged to recompense those affected by the incident
f. Includes any mention of the opposite of item a-e: unequal service, biased justice, unbalanced treatment, dishonesty, violation of rights, and unfair compensation

### D.2.3 The *loyalty/betrayal* foundation

a. Includes any mention of loyalty to the company in crisis or other rival companies
b. Includes any mention of a person's group, family or affiliation
c. Includes any mention of a member of a group, family or affiliation
d. Includes any mention of shifting or diminishing of loyalty
e. Includes any mention of betrayal, including but not limited to a company's betrayal to its loyal customers or to the country

### D.2.4 The *authority/subversion* foundation

a. Includes any mention of legal obligation of any involved party, or an expectation that the obligation should be fulfilled
b. Includes any mention of compliance or respect to authorities, including a company should it be designated by the law or a contract agreed upon by customers
c. Includes any mention of leadership in either government or private organization, including the company in crisis

d. Includes any mention of any violation of the law, or a failure of any party to fulfill his/her legal obligation[26]
e. Includes any mention of a lack of respect for legitimate authority, either done by a company or any other party
f. Includes any mention of resistance or criticism to authority or leadership
g. Excludes any mention of an expectation of a new law being introduced to prevent similar incidents in the future
h. Excludes the commenter's suspicious of any activity as being illegal, or an expectation that such activity should be illegal

### D.2.5 The *sanctity/degradation* foundation

a. Includes any mention of integrity or decency of a company, including its employees and/or leadership
b. Includes any mention of innocence of any party
c. Includes any mention of a lack of integrity or decency, as opposite to item a
d. Includes the commenter's feeling of, or similar to, disgust, in his/her reaction to perceived wrongdoing

[26] Facts do not matter in this regard. Whether or not the commenter was able to provide supporting evidence is irrelevant as long as he/she believes that an action or inaction is illegal.

# Appendix E

# Frequency of MFD and EMFD words

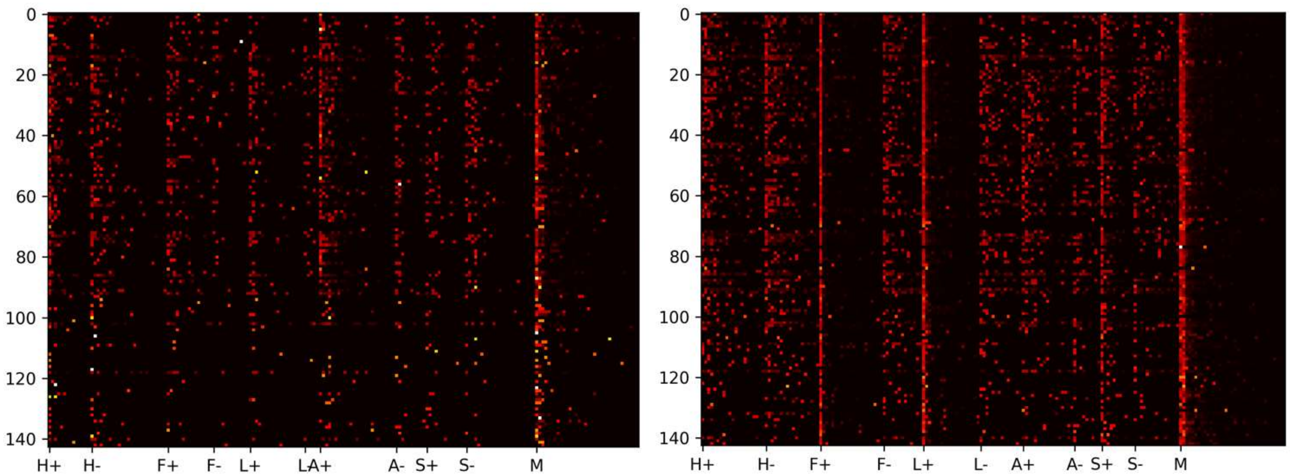


*Figure E.1* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Apple scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

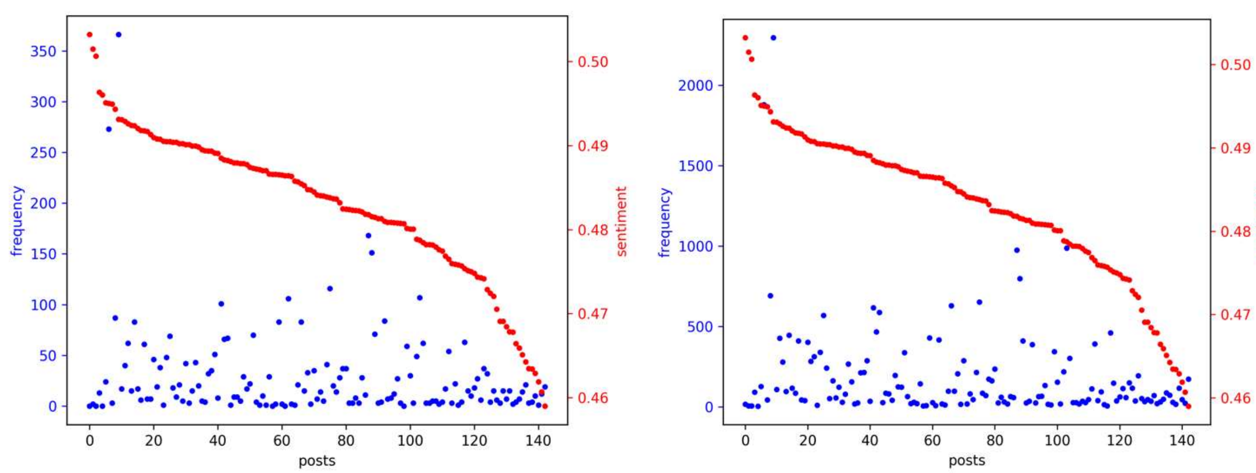


*Figure E.2* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Apple scandal. The posts are sorted by their sentiment score.

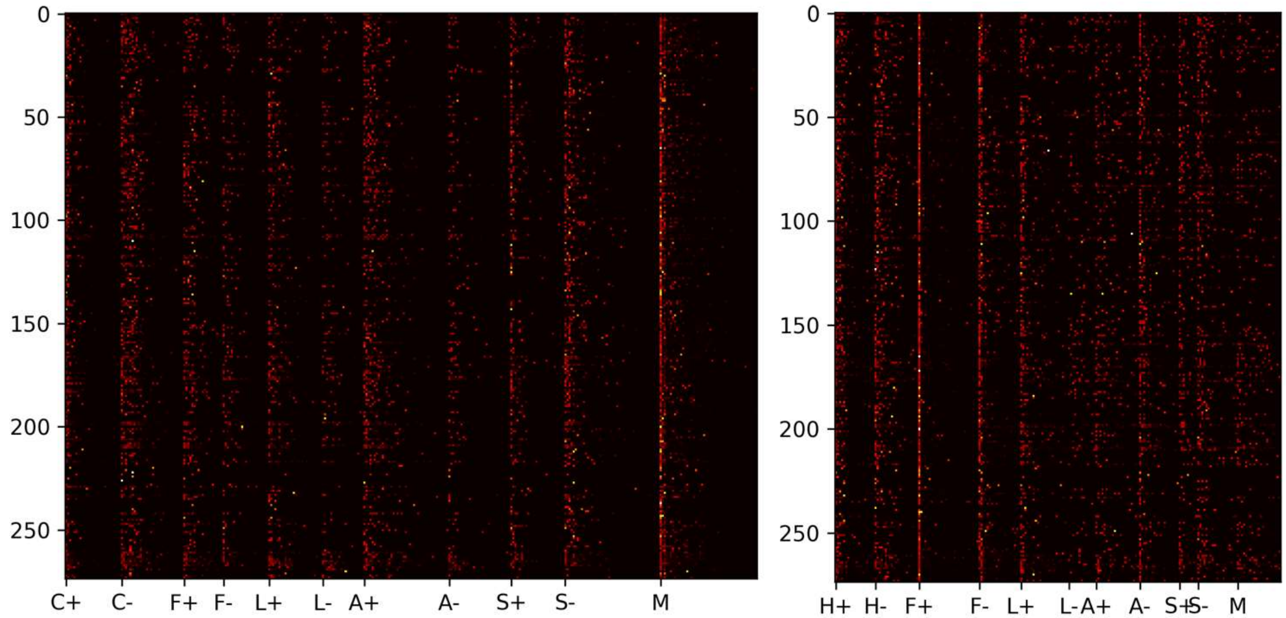


*Figure E.3* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Bill O'Reilly scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

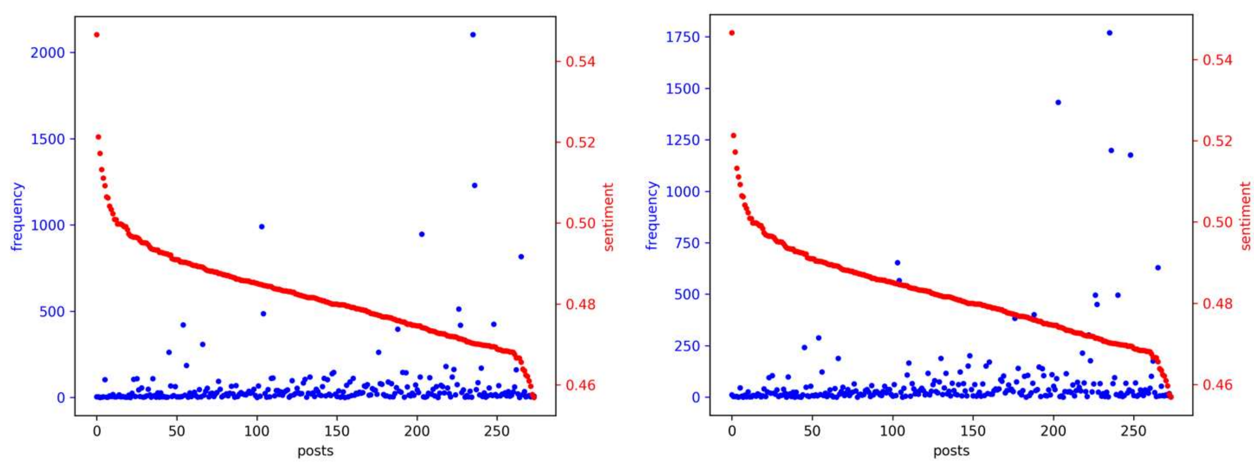


*Figure E.4* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Bill O'Reilly scandal. The posts are sorted by their sentiment score.

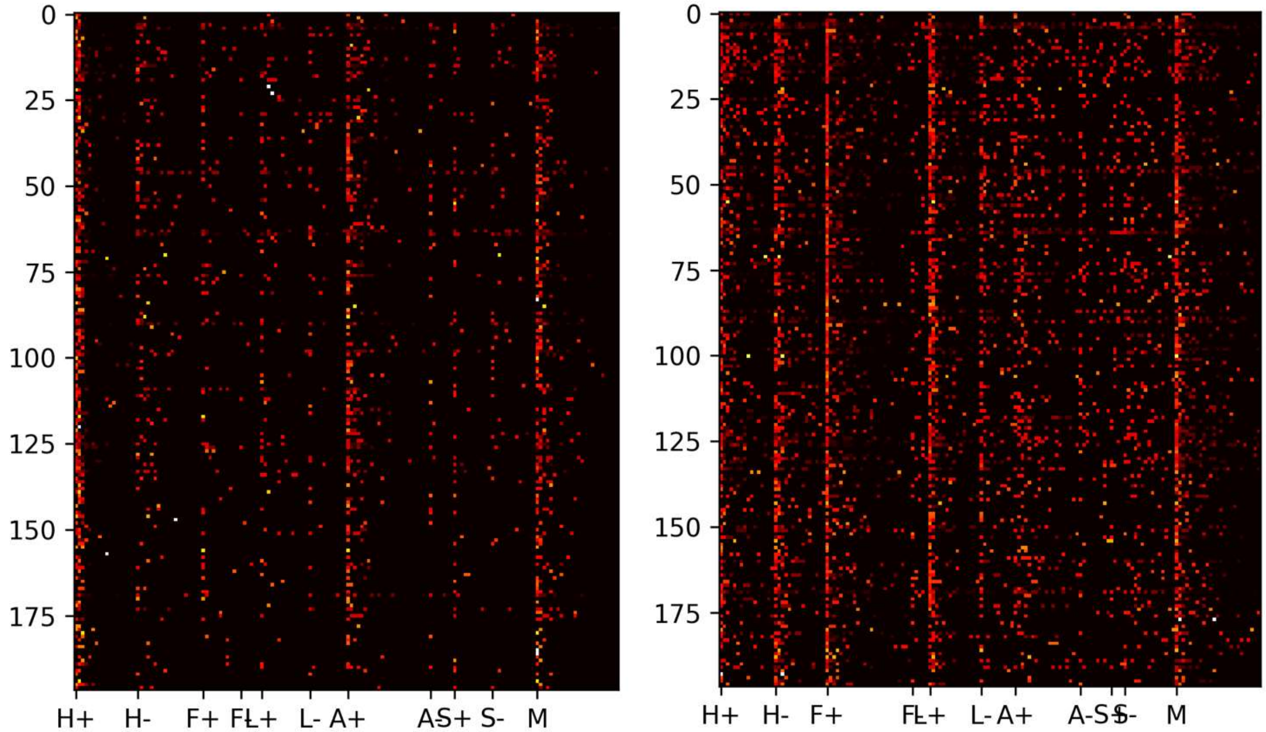


*Figure E.5* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Equifax scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

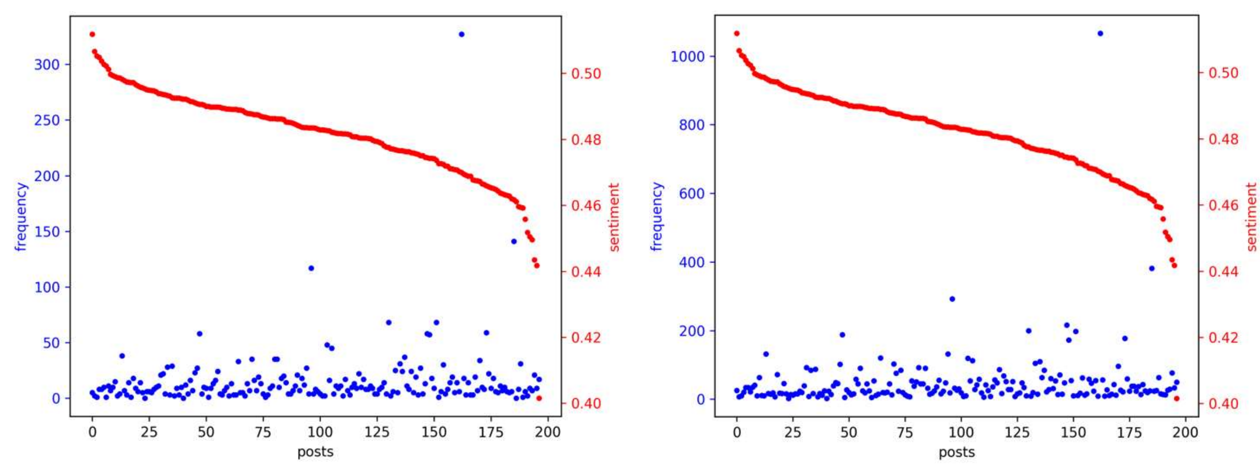


*Figure E.6* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Equifax scandal. The posts are sorted by their sentiment score.

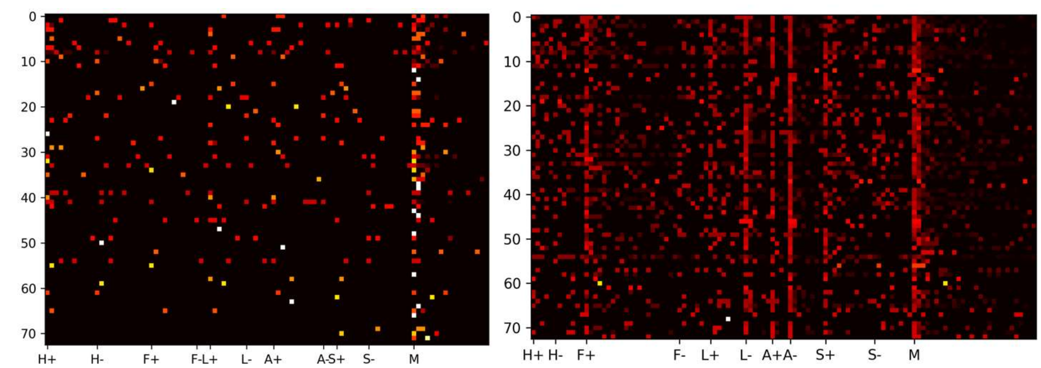


*Figure E.7* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Fyre Festival scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

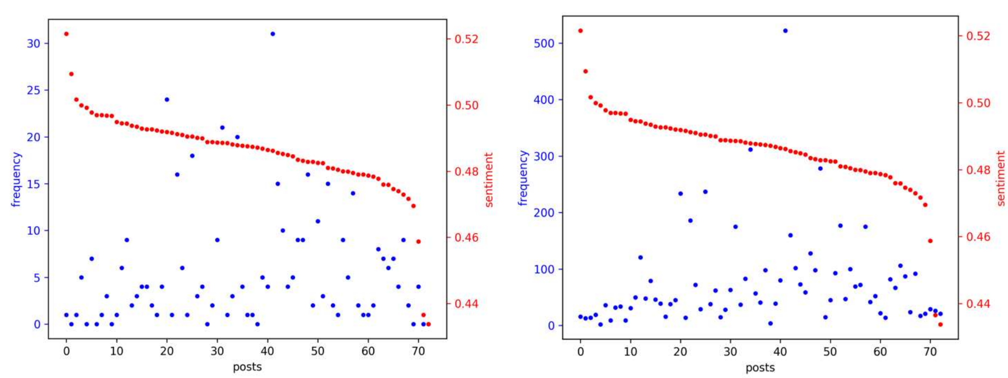


*Figure E.8* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Fyre Festival scandal. The posts are sorted by their sentiment score.

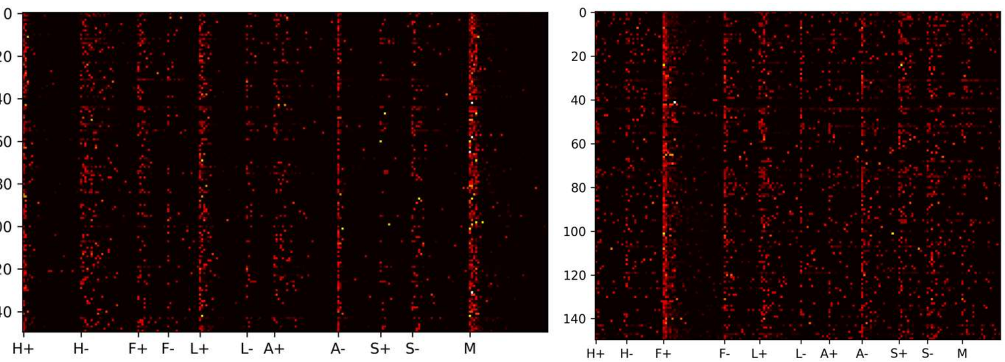


*Figure E.9* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Pepsi scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

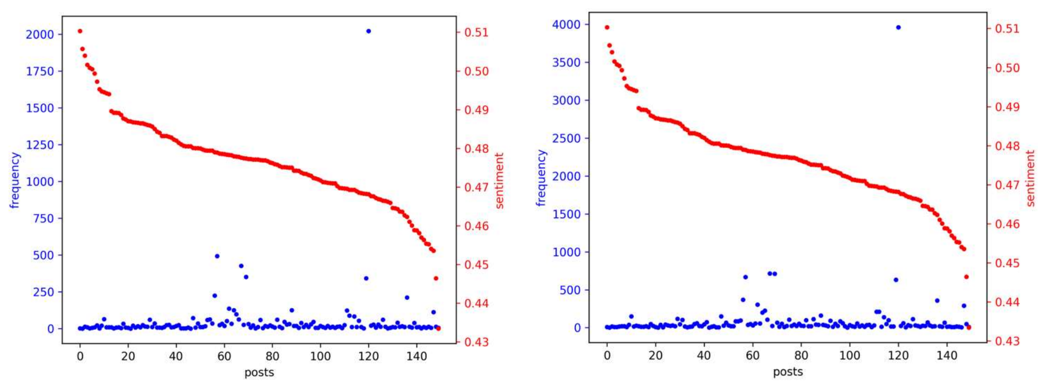


*Figure E.10* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Pepsi scandal. The posts are sorted by their sentiment score.

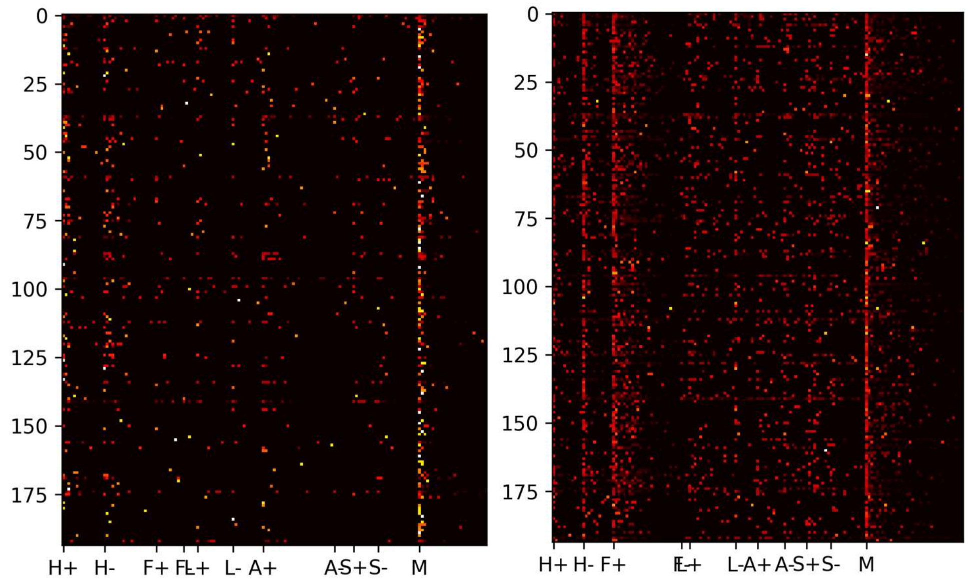

*Figure E.11* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Samsung Galaxy Note 7 scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

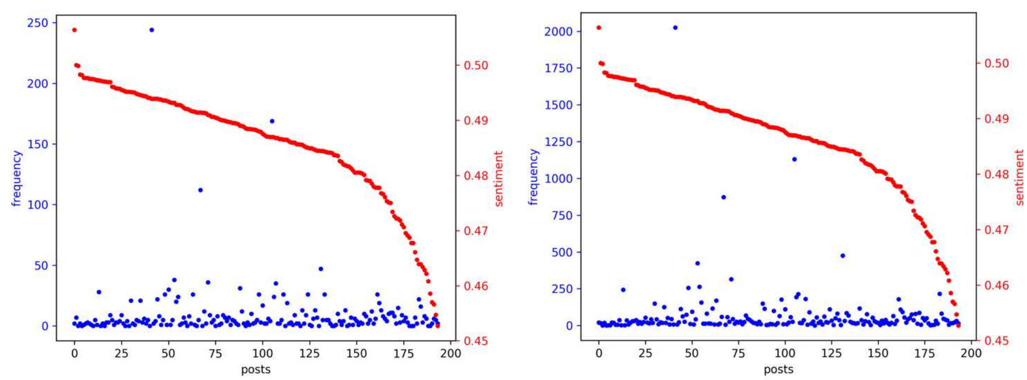


*Figure E.12* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Samsung Galaxy Note 7 scandal. The posts are sorted by their sentiment score.

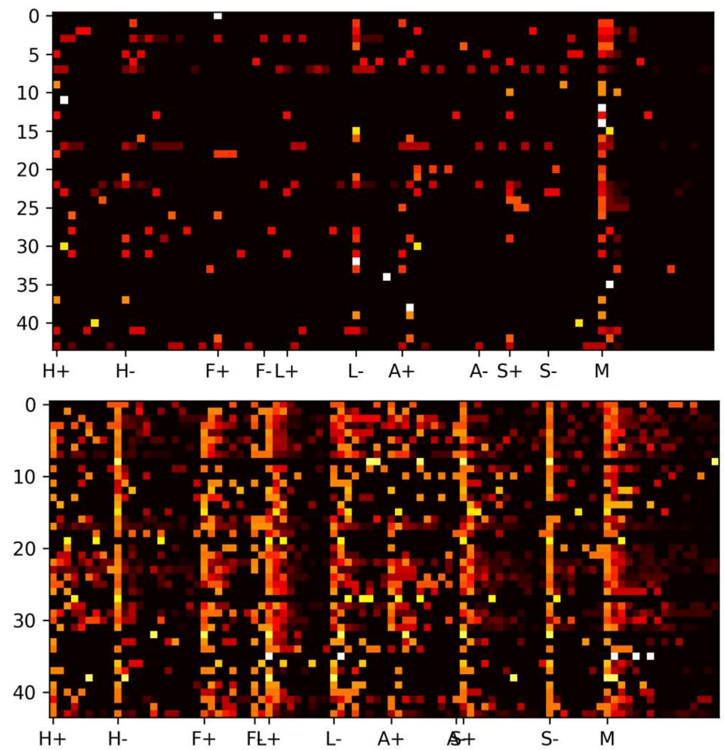


*Figure E.13* Frequencies of MFD words (top) and EMFD words (bottom) as they appear in the posts related to Samsung washing machine scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

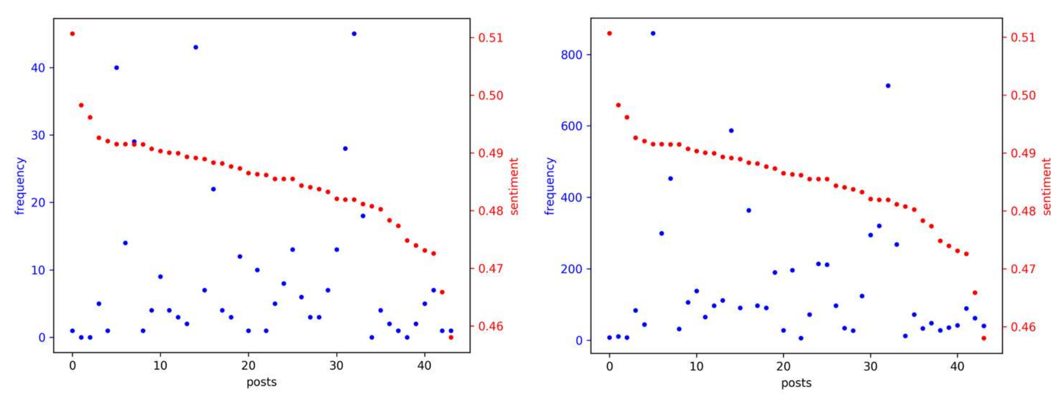


*Figure E.14* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Samsung washing machine scandal. The posts are sorted by their sentiment score.

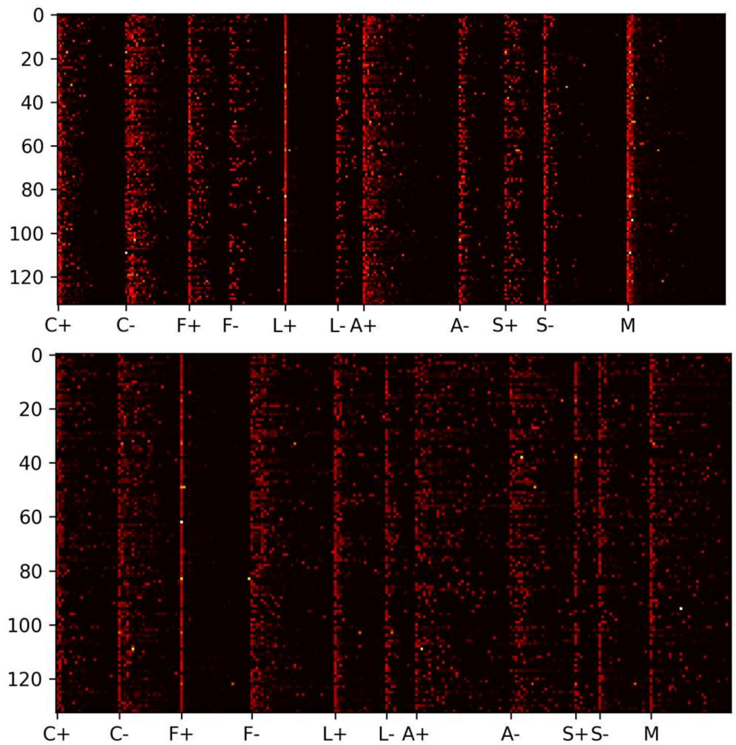


*Figure E.15* Frequencies of MFD words (top) and EMFD words (bottom) as they appear in the posts related to United Airlines scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

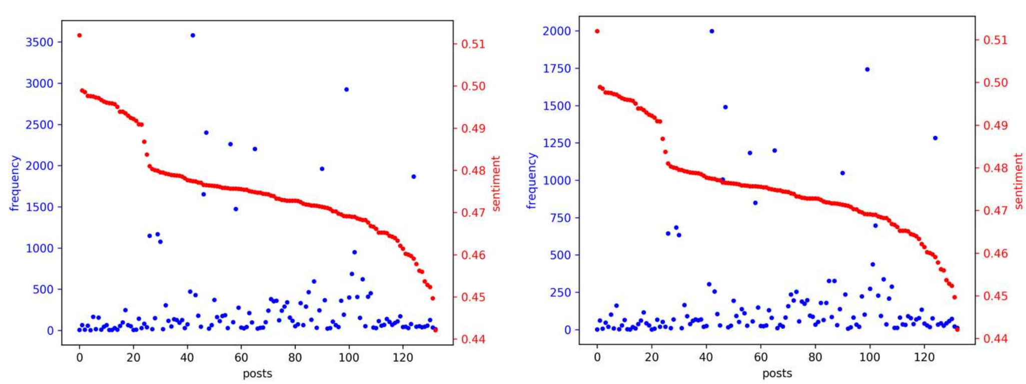


*Figure E.16* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to United Airlines scandal. The posts are sorted by their sentiment score.

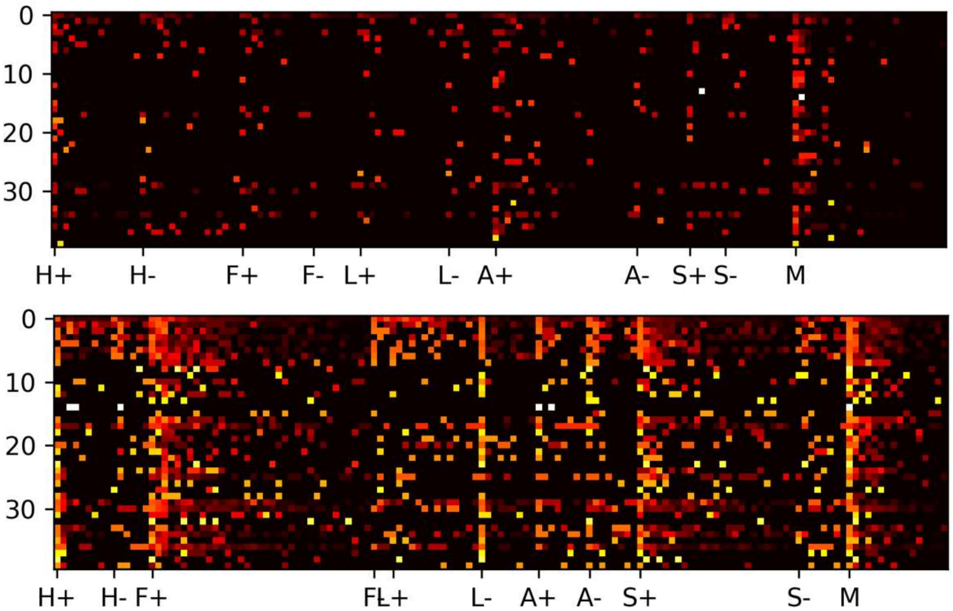


*Figure E.17* Frequencies of MFD words (top) and EMFD words (bottom) as they appear in the posts related to Uber scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

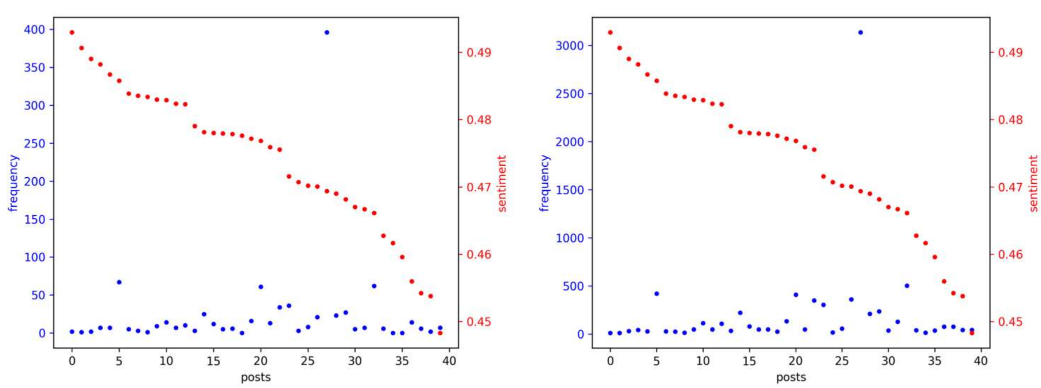


*Figure E.18* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Uber scandal. The posts are sorted by their sentiment score.

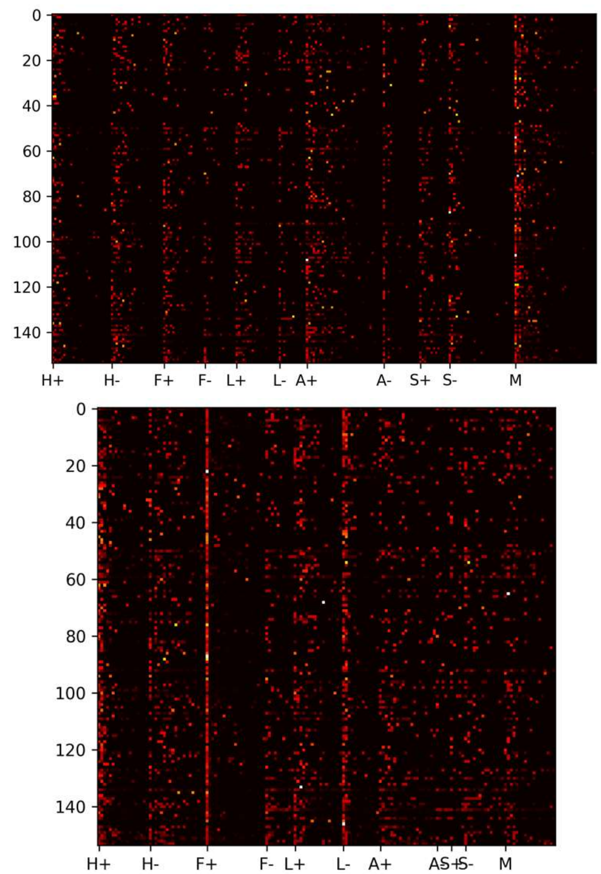


*Figure E.19* Frequencies of MFD words (top) and EMFD words (bottom) as they appear in the posts related to Wells Fargo scandal. Each point represents the frequency of each moral word. From top to bottom are the posts sorted by created time. The words are grouped by moral domains and sorted from left to right by their frequency within the domains.

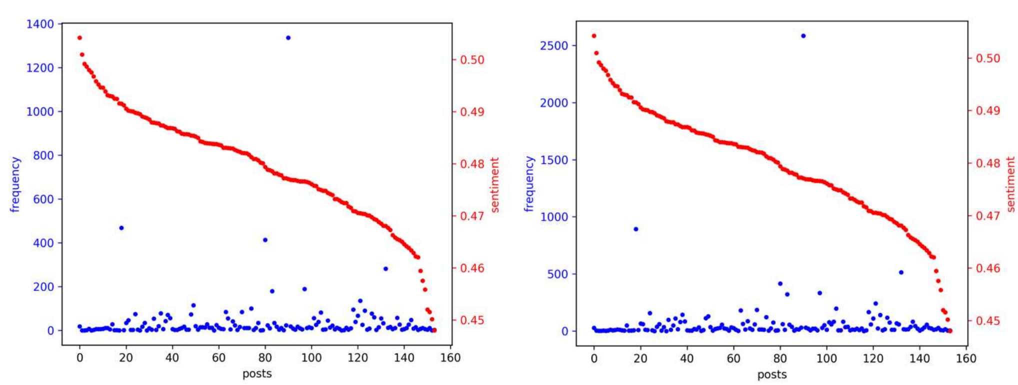


*Figure E.20* Frequencies of MFD words (left) and EMFD words (right) as they appear in the posts related to Wells Fargo scandal. The posts are sorted by their sentiment score.

Appendix F

# Visualization of Vector Representations

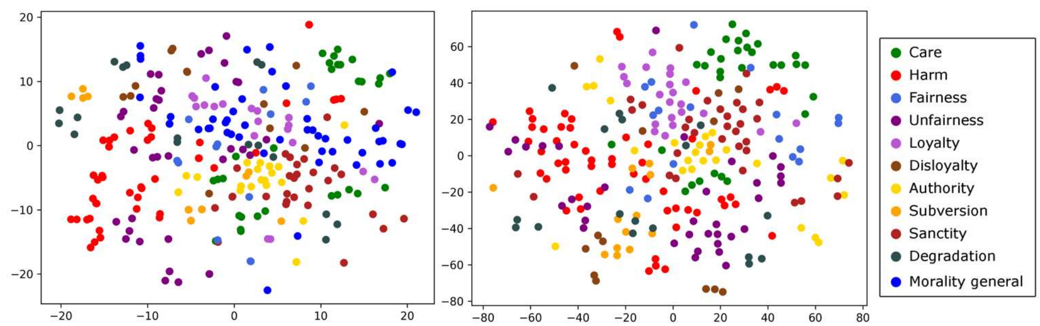


*Figure F.1* t-SNE visualization of MFD word vectors before and after domain removal. The vectors were built from the comments related to Apple scandal.

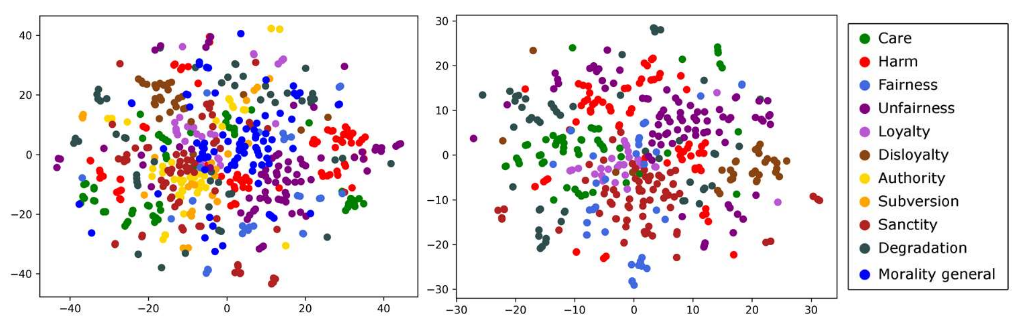


*Figure F.2* t-SNE visualization of MFD word vectors before and after domain removal. The vectors were built from the comments related to Bill O'Reilly scandal.

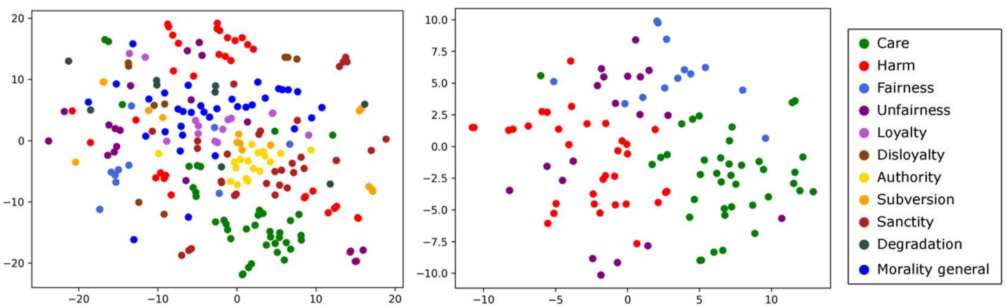


*Figure F.3* t-SNE visualization of MFD word vectors before and after domain removal. The vectors were built from the comments related to Equifax scandal.

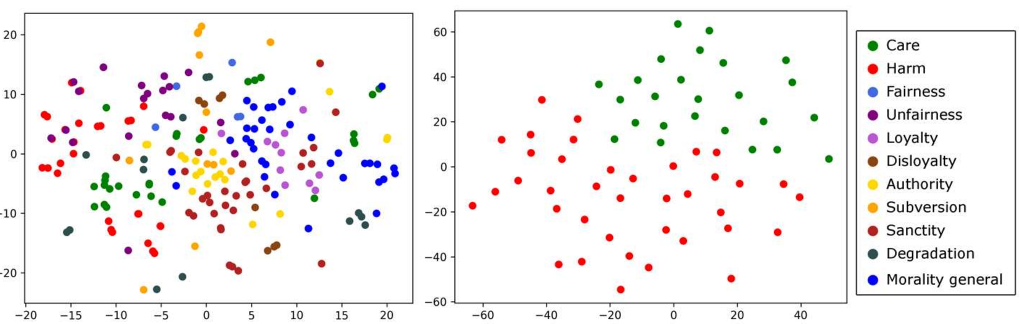


*Figure F.4* t-SNE visualization of MFD word vectors before and after domain removal. The vectors were built from the comments related to Samsung Galaxy Note 7 scandal.

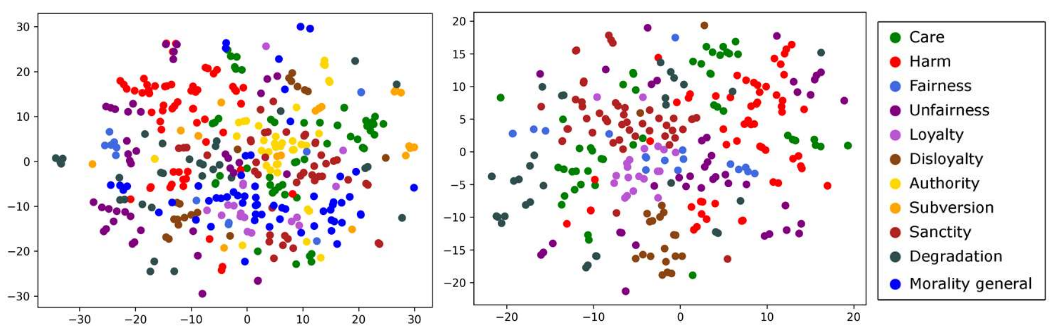


*Figure F.5* t-SNE visualization of MFD word vectors before and after domain removal. The vectors were built from the comments related to Pepsi scandal.

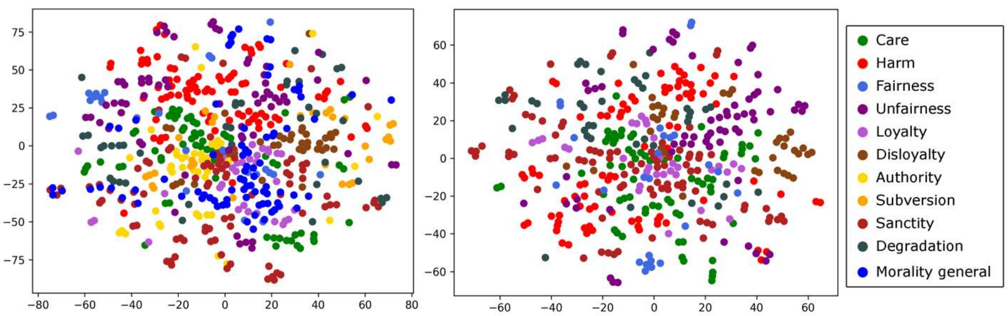


*Figure F.6* t-SNE visualization of MFD word vectors before and after domain removal. The vectors were built from the comments related to United Airlines scandal.

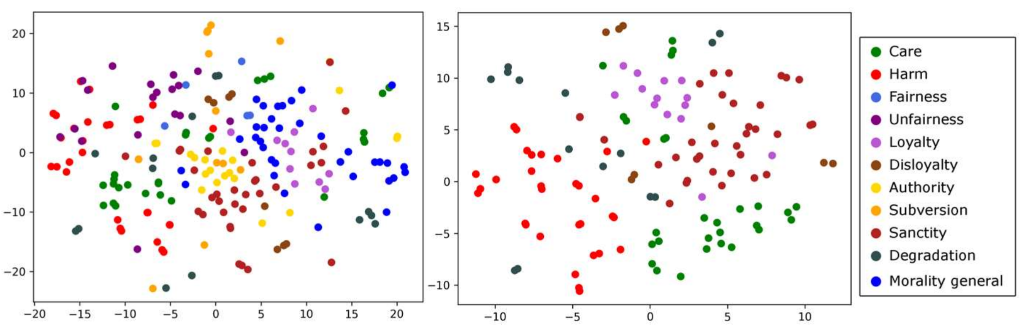


*Figure F.7* t-SNE visualization of MFD word vectors before and after domain removal. The vectors were built from the comments related to Uber scandal.

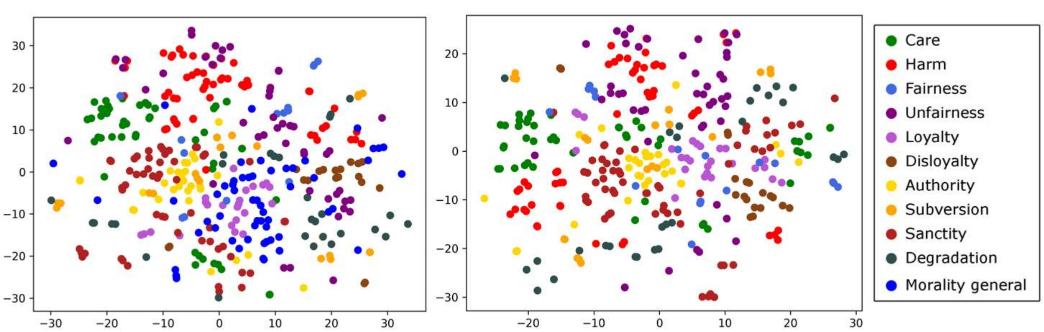


*Figure F.8* t-SNE visualization of MFD word vectors before and after domain removal. The vectors were built from the comments related to Wells Fargo scandal.

# Bibliography

Aaker, D. A. (1991). *Managing brand equity: Capitalizing on the value of a brand name*. New York: Free Press.

Anderson, J. E., Kay, A. C., & Fitzimons, G. M. (2013). Finding silver linings: Meaning making as a compensatory response to negative experiences. In K. D. Markman (Ed.), *The psychology of meaning* (pp. 279–295). Washington, DC: American Psychological Association. http://doi.org/10.1037/14040-014

Aristotle. (1999). *Nicomachean Ethics (W. D. Ross trans.)*. Kitchener, Ontario: Batoche Books.

Aw, A., Aljunied, S. M., Lertcheva, N., & Kalunsima, S. (2014). TaLAPi – A Thai Linguistically Annotated Corpus for Language Processing The Structural-Grammatical Approach for Thai Word Segmentation. In *the Ninth International Conference on Language Resources and Evaluation (LREC 2014)* (pp. 125–132). Retrieved from http://www.lrec-conf.org/proceedings/lrec2014/pdf/59%7B_%7DPaper.pdf

Bangcharoensap, P., Porkaew, P., & Supnithi, T. (2009). *A Statistical- Machine-Translation Approach to Word Boundary Identification: A Projective Analogy of Bilingual Translation*. Thailand.

Barton, L. (2001). *Crisis in organizations : managing and communicating in the heat of chaos*. Cincinnati: Southwestern Publishing Company.

Bartsch, A. (2012). Emotional Gratification in Entertainment Experience. Why Viewers of Movies and Television Series Find it Rewarding to Experience Emotions. *Media Psychology*, *15*(3), 267–302. http://doi.org/10.1080/15213269.2012.693811

Bartsch, A., & Beth Oliver, M. (2011). Making sense of entertainment. *Journal of Media Psychology*, *23*(1), 12–17. http://doi.org/10.1027/1864-1105/a000026

Bartsch, A., & Hartmann, T. (2017). The Role of Cognitive and Affective Challenge in

Entertainment Experience. *Communication Research*, *44*(1), 29–53. http://doi.org/10.1177/0093650214565921

Bartsch, A., & Schneider, F. M. (2014). Entertainment and Politics Revisited: How Non-Escapist Forms of Entertainment Can Stimulate Political Interest and Information Seeking. *Journal of Communication*, *64*(3), 369–396. http://doi.org/10.1111/jcom.12095

Basuroy, S., Chatterjee, S., & Ravid, S. A. (2003). How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets. *Journal of Marketing*, *67*(4), 103–117. http://doi.org/10.1509/jmkg.67.4.103.18692

Berger, J., Sorensen, A. T., & Rasmussen, S. J. (2010). Positive Effects of Negative Publicity: When Negative Reviews Increase Sales. *Marketing Science*, *29*(5), 815–827. http://doi.org/10.1287/mksc.1090.0557

Bitner, M. J. (1990). Evaluating service encounters: The effects of physical surrounding and employee responses. *Journal of Marketing*, *54*(2), 69–82. http://doi.org/10.2307/1251871

Blasi, A. (1993). The development of identity: Some implications for moral functioning. In G. G. Noam & T. E. Wren (Eds.), *The moral self* (pp. 99–122). Cambridge, MA: MIT Press.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, *3*(Jan), 993–1022.

Bond, J., & Kirshenbaum, R. (1998). *Under the radar: talking to today's cynical consumer*. New York: John Wiley.

Bonifield, C., & Cole, C. (2007). Affective responses to service failure: Anger, regret, and retaliatory versus conciliatory responses. *Marketing Letters*, *18*(1–2), 85–99. http://doi.org/10.1007/s11002-006-9006-6

Brin, S., & Page, L. (1998). The anatomy of a large-scale hypertextual Web search engine. *Computer Networks and ISDN Systems*, *30*(1–7), 107–117. http://doi.org/10.1016/S0169-7552(98)00110-X

Bryant, J. (2004). Presidential address: Critical communication challenges for the international era. *Journal of Communication*, *54*, 389–401.

Byrd, S. (2012). Hi fans! Tell us your story!Incorporating a stewardship-based social media strategy to maintain brand reputation during a crisis. *Corporate Communications: An International Journal*, *17*(3), 241–254. http://doi.org/10.1108/13563281211253502

Byrne, D. (1961). Interpersonal attraction and attitude similarity. *The Journal of Abnormal and Social Psychology*, *62*(3), 713–715. http://doi.org/10.1037/h0044721

Byrt, T., Bishop, J., & Carlin, J. B. (1993). Bias, prevalence and kappa. *Journal of Clinical Epidemiology*, *46*(5), 423–429. http://doi.org/10.1016/0895-4356(93)90018-V

Cambria, E., Poria, S., Hazarika, D., & Kwok, K. (2018). SenticNet 5: Discovering Conceptual Primitives for Sentiment Analysis by Means of Context Embeddings. In *AAAI Conference on Artificial Intelligence*. Retrieved from http://sentic.net/senticnet-5.pdf

Chan, H., & Cui, S. (2011). The contrasting effects of negative word of mouth in the post-consumption stage. *Journal of Consumer Psychology*, *21*(3), 324–337. http://doi.org/10.1016/j.jcps.2010.11.005

Chaudhuri, A., & Holbrook, M. B. (2001). The Chain of Effects from Brand Trust and Brand Affect to Brand Performance: The Role of Brand Loyalty. *Journal of Marketing*, *65*(2), 81–93. http://doi.org/10.1509/jmkg.65.2.81.18255

Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, *43*(3), 345–354. http://doi.org/10.1509/jmkr.43.3.345

Cohen, J. (1960). A Coefficient of Agreement for Nominal Scales. *Educational and Psychological Measurement*, *20*(1), 37–46. http://doi.org/10.1177/001316446002000104

Colley, K. L., & Collier, A. (2009). An Overlooked Social Media Tool? Making a Case for Wikis. *Public Relations Strategist*, 34–35.

Coombs, W. T. (1999). *Ongoing crisis communication: Planning, managing, and responding*. Thousand Oaks, CA: Sage.

Coombs, W. T. (2007). *Ongoing Crisis Communication: Planning, Managing, and Responding (2nd ed.)*. Thousand Oaks, CA: Sage.

Coombs, W. T., & Holladay, S. J. (2002). Helping crisis managers protect reputational assets: Initial Tests of the Situational Crisis Communication Theory. *Management Communication Quarterly*, *16*(2), 165–186. http://doi.org/10.1177/089331802237233

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20*(3), 273–297.

Custance, P., Walley, K., & Jiang, D. (2012). Crisis brand management in emerging markets. *Marketing Intelligence & Planning*, *30*(1), 18–32. http://doi.org/10.1108/02634501211193895

Dawar, N., & Pillutla, M. M. (2000). Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations. *Journal of Marketing Research*, *37*(2), 215–226. http://doi.org/10.1509/jmkr.37.2.215.18729

Day, R. L. (1984). Modeling Choices Among Alternative Responses to Dissatisfaction. *Advances in Consumer Research*, *11*, 469–499. http://doi.org/papers://7BD1C3A1-7031-4D4B-BF1F-51DB426534AC/Paper/p10052

Deci, E. L., Ryan, R. M., & Koestner, R. (1999). A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychological Bulletin*, *125*(6), 627–668. http://doi.org/10.1037/0033-2909.125.6.627

Dennis, E. E., & Merrill, J. C. (1996). *Media debates: issues in mass communication*. White Plains, NY: Longman.

Durkheim, E. (1984). *The Division of Labor in Society (W. D. Halls, trans.)*. The Free Press.

Dutta, S., & Pullig, C. (2011). Effectiveness of corporate responses to brand crises: The role of crisis type and response strategies. *Journal of Business Research*, *64*(12), 1281–1287. http://doi.org/10.1016/j.jbusres.2011.01.013

Eden, A., & Tamborini, R. (2017). Moral intuitions: Morality subcultures in disposition formation. *Journal of Media Psychology*, *29*(4), 198–207. http://doi.org/10.1027/1864-1105/a000173

Edson Escalas, J. (2004). Narrative Processing: Building Consumer Connections to Brands. *Journal of Consumer Psychology*, *14*(1–2), 168–180. http://doi.org/10.1207/s15327663jcp1401&2_19

Elliott, R., & Wattanasuwan, K. (1998). Brands as symbolic resources for the construction of identity. *International Journal of Advertising*, *17*(2), 131–144. http://doi.org/10.1080/02650487.1998.11104712

Ewing, M. T., Wagstaff, P. E., & Powell, I. H. (2013). Brand rivalry and community conflict. *Journal of Business Research*, *66*(1), 4–12. http://doi.org/10.1016/j.jbusres.2011.07.017

Feather, N. T., & Sherman, R. (2002). Envy, resentment, schadenfreude, and sympathy: Reactions to deserved and undeserved achievement and subsequent failure. *Personality and Social Psychology Bulletin*, *28*(7), 953–961. http://doi.org/10.1177/01467202028007008

Festinger, L. (1954). A Theory of Social Comparison Processes. *Human Relations*, *7*(2), 117–140. http://doi.org/10.1177/001872675400700202

Fink, S. (1986). *Crisis Management: Planning for the Inevitable*. *American Management Association* (Authors Gu). Lincoln, NE.

Fitzgerald, L., Drasgow, F., Hulin, C., Gelfand, M., & Magley, V. (1997). Antecedents and Consequences of Sexual Harassment in Organizations: A Test of an Integrated Model. *Journal of Applied Psychology*, *82*(4), 578–589. http://doi.org/10.1037/0021-9010.82.4.578

Forsyth, D. R. (1992). Judging the morality of business practices: The influence of personal moral philosophies. *Journal of Business Ethics*, *11*(5–6), 461–470. http://doi.org/10.1007/BF00870557

Fulgoni, D., Carpenter, J., Ungar, L. H., & Preot, D. (2016). An empirical exploration of moral foundations theory in partisan news sources. In *Proceedings of the 10th* *edition of the Language Resources and Evaluation Conference* (pp. 3730–3736).

Garten, J., Boghrati, R., Hoover, J., Johnson, K. M., & Dehghani, M. (2016). Morality Between the Lines: Detecting Moral Sentiment In Text. In *proceedings of IJCAI 2016 workshop on Computational Modeling of Attitudes*. New York, NY. Retrieved from http://staff.vbi.vt.edu/swarup/wcma2016/morality-lines-detecting.pdf

Garten, J., Hoover, J., Johnson, K. M., Boghrati, R., Iskiwitch, C., & Dehghani, M. (2018). Dictionaries and distributions: Combining expert knowledge and large scale textual data content analysis: Distributed dictionary representation. *Behavior Research Methods*, *50*(1), 344–361. http://doi.org/10.3758/s13428-017-0875-9

Gensler, S., Völckner, F., Liu-Thompkins, Y., & Wiertz, C. (2013). Managing brands in the social media environment. *Journal of Interactive Marketing*, *27*(4), 242–256. http://doi.org/10.1016/j.intmar.2013.09.004

Gerard, H. B., & Orive, R. (1987). The dynamics of opinion formation. *Advances in Experimental Social Psychology*, *20*(C), 171–202. http://doi.org/10.1016/S0065-2601(08)60414-1

Gonzales, A. L., & Hancock, J. T. (2011). Mirror, Mirror on my Facebook Wall: Effects of Exposure to Facebook on Self-Esteem. *Cyberpsychology, Behavior, and Social Networking*, *14*(1–2), 79–83. http://doi.org/10.1089/cyber.2009.0411

Goolsby, R. (2009). Lifting Elephants: Twitter and Blogging in Global Perspective. In H. Liu, J. Salerno, & M. J. Young (Eds.), *Social Computing and Behavioral Modeling* (pp. 1–6). New York: Springer. http://doi.org/10.1007/978-1-4419-0056-2

Graham, J., Haidt, J., Koleva, S., Motyl, M., Iyer, R., Wojcik, S. P., & Ditto, P. H. (2013). Moral Foundations Theory: The Pragmatic Validity of Moral Pluralism. *Advances in Experimental Social Psychology*, *47*, 55–130. http://doi.org/10.1016/B978-0-12-407236-7.00002-4

Graham, J., Haidt, J., & Nosek, B. A. (2009). Liberals and Conservatives Rely on Different Sets of Moral Foundations. *Journal of Personality and Social Psychology*, *96*(5), 1029–1046. http://doi.org/10.1037/a0015141

Graham, J., Nosek, B. A., Haidt, J., Iyer, R., Koleva, S., & Ditto, P. H. (2011). Mapping the moral domain. *Journal of Personality and Social Psychology*, *101*(2), 366–385. http://doi.org/10.1037/a0021847

Greyser, S. A. (2009). Corporate brand reputation and brand crisis management. *Management Decision*, *47*(4), 590–602. http://doi.org/10.1108/00251740910959431

Haidt, J. (2001). The emotional dog and its rational tail: A social intuitionist approach to moral judgment. *Psychological Review*, *108*(4), 814–834. http://doi.org/10.1037//0033-295X.108.4.814

Haidt, J. (2003). The Moral Emotions. In R. J. Davidson, K. R. Sherer, & H. H. Goldsmith (Eds.), *Handbook of affective sciences* (pp. 852–870). Oxford: Oxford University Press. http://doi.org/10.1037/a0022408

Haidt, J. (2007). The New Synthesis in Moral Psychology. *Science*, *316*(5827), 998–1002. http://doi.org/10.1126/science.1137651

Haidt, J., & Graham, J. (2007). When morality opposes justice: Conservatives have moral intuitions that liberals may not recognize. *Social Justice Research*, *20*(1), 98–116. http://doi.org/10.1007/s11211-007-0034-z

Haidt, J., & Joseph, C. (2004). Intuitive ethics: how innately prepared intuitions generate culturally variable virtues. *Daedalus*, *133*(4), 55–66. http://doi.org/10.1162/0011526042365555

Haidt, J., & Joseph, C. (2007). The moral mind: How 5 sets of innate moral intuitions guide the development of many culture-specific virtues, and perhaps even modules. In P. Carruthers, S. Laurence, & S. Stich (Eds.), *The innate mind (Vol. 3)* (pp. 367–391). New York: Oxford University Press.

Hareli, S., & Weiner, B. (2002). Dislike and envy as antecedents of pleasure at another's misfortune. *Motivation and Emotion*, *26*(4), 257–277. http://doi.org/10.1023/A:1022818803399

Haruechaiyasak, C., & Kongyoung, S. (2009). TLex: Thai Lexeme Analyser Based on the Conditional Random Fields. In *Proceedings of SNLP'09* (pp. 1–5). Retrieved from http://thailang.nectec.or.th/interbest/downloads/InterBEST_3.pdf

Haruechaiyasak, C., Sangkeettrakarn, C., Palingoon, P., Kongyoung, S., & Damrongrat, C. (2006). A Collaborative Framework for Collecting Thai Unknown Words from the Web. In *Proceedings of the COLING/ACL 2006 Main Conference Poster Sessions* (pp. 345–352). http://doi.org/10.3115/1273073.1273118

He, J. (2016). Research on the Influence of Conflicting Brand Crisis Information on Consumers ' Brand Attitude. *American Journal of Industrial and Business Management*, *6*(May), 600–607.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, *18*(1), 38–52. http://doi.org/10.1002/dir.10073

Hennig-Thurau, T., Hofacker, C. F., & Bloching, B. (2013). Marketing the pinball way: Understanding how social media change the generation of value for consumers and companies. *Journal of Interactive Marketing*, *27*(4), 237–241. http://doi.org/10.1016/j.intmar.2013.09.005

Hennig-Thurau, T., Malthouse, E. C., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A., & Skiera, B. (2010). The Impact of New Media on Customer Relationships. *Journal of Service Research*, *13*(2009), 311–330. http://doi.org/10.1177/1094670510375460

Henrich, J., & Gil-White, F. J. (2001). The evolution of prestige: freely conferred deference as a mechanism for enhancing the benefits of cultural transmission. *Evolution and Human Behavior*, *22*(3), 165–196. http://doi.org/10.1016/S1090-5138(00)00071-4

Heskett, J. L., Jones, T. O., Loveman, G. W., Sasser, W. E., & Schlesinger, L. A. (2008). Putting the service-profit chain to work. *Harvard Business Review*, *86*(7–8). http://doi.org/10.1037/e459772008-014

Hieber, F., Domhan, T., Denkowski, M., Vilar, D., Sokolov, A., Clifton, A., & Post, M. (2017). *Sockeye: A Toolkit for Neural Machine Translation*. Retrieved from http://arxiv.org/abs/1712.05690

Ho-Dac, N. N., Carson, S. J., & Moore, W. L. (2013). The Effects of Positive and Negative Online Customer Reviews: Do Brand Strength and Category Maturity Matter? *Journal of Marketing*, *77*(6), 37–53. http://doi.org/10.1509/jm.11.0011

Hoch, S. J., & Deighton, J. (1989). Managing What Consumers Learn from Experience. *Journal of Marketing*, *53*(2), 1. http://doi.org/10.2307/1251410

Hofmann, W., Wisneski, D. C., Brandt, M. J., & Skitka, L. J. (2014). Morality in everyday life. *Science*, *345*(6202), 1340–1343. http://doi.org/10.1126/science.1251560

Hussain, A., & Cambria, E. (2018). Semi-supervised learning for big social data analysis. *Neurocomputing*, *275*, 1662–1673. http://doi.org/10.1016/j.neucom.2017.10.010

Igartua, J. J. (2010). Identification with characters and narrative persuasion through fictional feature films. *Communications*, *35*(4), 347–373. http://doi.org/10.1515/COMM.2010.019

Ilhan, B. E., Kübler, R. V, & Pauwels, K. H. (2018). ScienceDirect Battle of the Brand Fans : Impact of Brand Attack and Defense on Social Media ☆. *Journal of Interactive Marketing*, *43*, 33–51. http://doi.org/10.1016/j.intmar.2018.01.003

Japutra, A., Ekinci, Y., & Simkin, L. (2018). Positive and negative behaviours resulting from brand attachment. *European Journal of Marketing*, EJM-10-2016-0566. http://doi.org/10.1108/EJM-10-2016-0566

Jolly, D. W., & Mowen, J. C. (1985). Product Recall Communications: The Effects of Source, Media, and Social Responsibility Information. *Advances in Consumer Research*, *12*(1), 471–475. http://doi.org/Article

Judith G. Smetana. (2006). Social-cognitive domain theory: Consistencies and variations in children's moral and social judgments. In M. Killen & J. G. Smetana (Eds.), *Handbook of moral development* (pp. 119–154). Mahwah, NJ: Erlbaum.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53*(1), 59–68. http://doi.org/10.1016/j.bushor.2009.09.003

Kawtrakul, A., Kumtanode, S., Jamjanya, T., & Jewriyavech, C. (1995). A Lexibase Model for Writing Production Assistant System. In *Proceedings of Symposium on National Language Processing in Thailand*.

Kawtrakul, A., & Thumkanon, C. (1997). A statistical approach to thai morphological analyzer. In *Proceedings of of the 5th Workshop on Very Large Corpora*.

Keller, K. L. (1993). Conceptualizing, measuring, and managing consumer-based brand equity. *Journal of Marketing*, *57*, 1–22.

Kelley, H. H. (1952). Two functions of reference groups. In T. M. Newcomb & E. L. Hartley (Eds.), *Readings in social psychology* (pp. 210–214). New York: Holt, Rinehart, and Winston.

Kelley, H. H. (1967). Attribution theory in social psychology. In D. Levine (Ed.), *Nebraska symposium of motivation* (pp. 192–238). Lincoln: University of Nebraska Press.

Kelley, H. H. (1973). The process of causal attribution. *American Psychologist*, *28*(2), 107–128. http://doi.org/10.1037/h0034225

Kim, Su Jung; Wang, Rebecca Jen-Hui; Malthouse, E. C. (2015). The good and the bad of negative word of mouth: empirical investigation into the effect of online messages. *Advances in Advertising Research*, *4*, 73–85. http://doi.org/10.1007/978-3-658-02365-2

Kim, K., Kim, J., & Reid, L. N. (2017). Experiencing motivational conflict on social media in a crisis situation: The case of the Chick-fil-A same-sex marriage controversy. *Computers in Human Behavior*, *71*, 32–41. http://doi.org/10.1016/j.chb.2017.01.035

Kim, S., Marina Choi, S., & Atkinson, L. (2017). Congruence Effects of Corporate Associations and Crisis Issue on Crisis Communication Strategies. *Social Behavior and Personality: An International Journal*, *45*(7), 1085–1098. http://doi.org/10.2224/sbp.6090

King, L. A., & Napa, C. K. (1998). What makes a life good? *Journal of Personality and Social Psychology*, *75*(1), 156–165. http://doi.org/10.1037/0022-3514.75.1.156

Kiritchenko, S., Zhu, X., & Mohammad, S. M. (2014). Sentiment analysis of short informal texts. *Journal of Artificial Intelligence Research*, *50*, 723–762. http://doi.org/10.1613/jair.4272

Klayman, J., & Ha, Y. (1987). Confirmation, disconfirmation, and information in hypothesis testing. *Psychological Review*, *94*(2), 211–228. http://doi.org/10.1037/0033-295X.94.2.211

Klein, L. R. (1998). Evaluating the Potential of Interactive Media through a New Lens: Search versus Experience Goods. *Journal of Business Research*, *41*(3), 195–203. http://doi.org/10.1016/S0148-2963(97)00062-3

Kohlberg, L. C. N.-J. or A. B. G. or A. S. R. R. B. M. K. (1981). *Essays on moral development*. San Francisco: CA: Harper & Row.

Krämer, N. C., & Haferkamp, N. (2011). Online Self-Presentation: Balancing Privacy Concerns and Impression Construction on Social Networking Sites. In S. Trepte & L. Reinecke (Eds.), *Privacy online: Perspectives on privacy and self-disclosure in the Social Web* (pp. 127–141). Heidelberg, Berlin: Springer. http://doi.org/10.1007/978-3-642-21521-6_10

Kruengkrai, C., & Uchimoto, K. (2009). A Word and Character-Cluster Hybrid Model for Thai Word Segmentation. In *Proceedings of 8th International Symposium on Natural Language Processing*. Retrieved from http://canasai.tcllab.org/pubs/interbest09-thaiwordseg.pdf

Kunda, Z. (1990). The case for motivated reasoning. *Psychological Bulletin*, *108*(3), 480–498. http://doi.org/10.1037/0033-2909.108.3.480

Laczniak, R. N., DeCarlo, T. E., & Ramaswami, S. N. (2001). Consumers' Responses to Negative Word-of-Mouth Communication: An Attribution Theory Perspective. *Journal of Consumer Psychology*, *11*(1), 57–73. http://doi.org/10.1207/15327660152054049

Lafferty, J., McCallum, A., & Pereira, F. C. N. (2001). Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In *ICML '01 Proceedings of the Eighteenth International Conference on Machine Learning* (Vol. 8, pp. 282–289). http://doi.org/10.1038/nprot.2006.61

Lancker, D. Van, & Fromkin, V. a. (1973). Hemispheric specialization for pitch and "tone": Evidence from Thai. *Journal of Phonetics*, (October), 101–109. http://doi.org/10.2500/aap.2013.34.3671

Landauer, T. K., & Dumais, S. T. (1997). A Solution to Plato's Problem: The Latent Semantic Analysis Theory of Acquisition, Induction, and Representation of Knowledge. *Psychological Review*, *104*(2), 211–240. http://doi.org/10.1037/0033-295X.104.2.211

Laroche, M., Habibi, M. R., Richard, M.-O., & Sankaranarayanan, R. (2012). The effects of social media based brand communities on brand community markers, value creation practices, brand trust and brand loyalty. *Computers in Human Behavior*, *28*(5), 1755–1767. http://doi.org/10.1016/j.chb.2012.04.016

Le, M. (2017). PR Crisis Comms in Action: Top 7 Social Media Fires of 2017 (So Far). Retrieved May 14, 2018, from https://www.meltwater.com/blog/pr-crisis-comms-in-action-top-7-social-media-fires-of-2017-so-far/

Leidner, B., & Castano, E. (2012). Morality shifting in the context of intergroup violence. *European Journal of Social Psychology*, *42*(1), 82–91. http://doi.org/10.1002/ejsp.846

Limcharoen, P., Nattee, C., & Theeramunkong, T. (2009). Thai Word Segmentation based-on GLR Parsing Technique and Word N-gram Model. In *Thailangnectecorth*. Retrieved from http://thailang.nectec.or.th/interbest/downloads/InterBEST_1.pdf

Lin, C. Y. (2004). Rouge: A package for automatic evaluation of summaries. In *Proceedings of the workshop on text summarization branches out (WAS 2004)* (pp. 25–26).

Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing*, *70*(3), 74–89. http://doi.org/10.1509/jmkg.70.3.74

Maaten, L. der, & Hinton, G. (2008). Visualizing data using t-SNE. *Journal of Machine Learning Research*, *9*(Nov), 2579–2605.

Manning, C., Surdeanu, M., Bauer, J., Finkel, J., Bethard, S., & McClosky, D. (2014).

The Stanford CoreNLP Natural Language Processing Toolkit. In *Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations* (pp. 55–60). http://doi.org/10.3115/v1/P14-5010

Marken, G. a. “Andy.” (2007). Social Media... The Hunted Can Become the Hunter. *Public Relations Quarterly*, *52*(4), 9–12.

Maute, M. F., & Dubé, L. (1999). Patterns of emotional responses and behavioural consequences of dissatisfaction. *Applied Psychology*, *48*(3), 349–366. http://doi.org/10.1080/026999499377529

Mayer, J. D., & Gaschke, Y. N. (1988). The experience and meta-experience of mood. *Journal of Personality and Social Psychology*, *55*(1), 102–111. http://doi.org/10.1037/0022-3514.55.1.102

McCallum, A., & Li, W. (2003). Early results for named entity recognition with conditional random fields, feature induction and web-enhanced lexicons. In *Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003* - (Vol. 4, pp. 188–191). http://doi.org/10.3115/1119176.1119206

McKean, E. (2005). *The New Oxford American Dictionary*. Oxford University Press.

McQuail, D. (2003). *McQuail’s mass communication theory (4th ed.)*. London: Sage.

Meknavin, S., Charoenpornsawat, P., & Kijsirikul, B. (1997). Feature-based Thai Word Segmentation. In *Proceedings of the Natural Language Processing Pacific Rim Symposium 1997 (NLPRS’97)* (Vol. 2). http://doi.org/10.1017/CBO9781107415324.004

Mihalcea, R., & Tarau, P. (2004). TextRank: Bringing order into texts. In *Proceedings of EMNLP* (Vol. 85, pp. 404–411). http://doi.org/10.3115/1219044.1219064

Muniz, A. M., & O’Guinn, T. C. (2001). Brand Community. *Journal of Consumer Research*, *27*(4), 412–432. http://doi.org/10.1086/319618

Murphy, J. G., & Jean Hampton. (1988). *Forgiveness and mercy*. New York: Cambridge University Press.

Naylor, R. W., Lamberton, C. P., & West, P. M. (2012). Beyond the “Like” Button: The Impact of Mere Virtual Presence on Brand Evaluations and Purchase Intentions in

Social Media Settings. *Journal of Marketing*, *76*(6), 105–120. http://doi.org/10.1509/jm.11.0105

Nelson, P. (1974). Advertising as Information. *Journal of Political Economy*, *82*(4), 729–754. http://doi.org/10.1086/260231

Noelle-Neumann, E. (1974). The spiral of silence a theory of public opinion. *Journal of Communication*, (24), 43–51. http://doi.org/10.4135/9781412959384.n360

Nyer, P. U., & Gopinath, M. (2005). Effects of complaining versus negative word of mouth on subsequent changes in satisfaction: The role of public commitment. *Psychology and Marketing*, *22*(12), 937–953. http://doi.org/10.1002/mar.20092

Oliver, M. B., & Bartsch, A. (2010). Appreciation as audience response: Exploring entertainment gratifications beyond hedonism. *Human Communication Research*, *36*(1), 53–81. http://doi.org/10.1111/j.1468-2958.2009.01368.x

Oliver, M. B., & Bartsch, A. (2011). Appreciation of Entertainment: The Importance of Meaningfulness via Virtue and Wisdom. *Journal of Media Psychology*, *23*(1), 29–33. http://doi.org/10.1027/1864-1105/a000029

Oliver, M. B., Hartmann, T., & Woolley, J. K. (2012). Elevation in Response to Entertainment Portrayals of Moral Virtue. *Human Communication Research*, *38*(3), 360–378. http://doi.org/10.1111/j.1468-2958.2012.01427.x

Oliver, M. B., & Raney, A. A. (2011). Entertainment as Pleasurable and Meaningful: Identifying Hedonic and Eudaimonic Motivations for Entertainment Consumption. *Journal of Communication*, *61*(5), 984–1004. http://doi.org/10.1111/j.1460-2466.2011.01585.x

Oliver, M. B., & Raney, A. A. (2014). An introduction to the special issue: Expanding the boundaries of entertainment research. *Journal of Communication*, *64*(3), 361–368. http://doi.org/10.1111/jcom.12092

Orive, R. (1988). Social projection and social comparison of opinions. *Journal of Personality and Social Psychology*, *54*(6), 953–964. http://doi.org/10.1037//0022-3514.54.6.953

Pace, S., Corciolani, M., & Gistri, G. (2017). Consumers’ responses to ethical brand crises on social media platforms. *Mercati & Competitività*, (1), 141–157. http://doi.org/10.3280/MC2017-001008

Park, C. L. (2010). Making sense of the meaning literature: An integrative review of meaning making and its effects on adjustment to stressful life events. *Psychological Bulletin*, *136*(2), 257–301. http://doi.org/10.1037/a0018301

Park, C., & Lee, T. M. (2009). Information direction, website reputation and eWOM effect: A moderating role of product type. *Journal of Business Research*, *62*(1), 61–67. http://doi.org/10.1016/j.jbusres.2007.11.017

Parrott, W. G. (1991). The emotional experience of envy and jealousy. In P. Salovey (Ed.), *The psychology of jealousy and envy* (pp. 3–30). New York: Guilford Press.

Parrott, W. G., & Smith, R. H. (1993). Distinguishing the experiences of envy and jealousy. *Journal of Personality and Social Psychology*, *64*(6), 906–920. http://doi.org/10.1037/0022-3514.64.6.906

Peng, F., Feng, F., & McCallum, A. (2004). Chinese segmentation and new word detection using conditional random fields. In *Proceedings of the 20th international conference on Computational Linguistics - COLING '04* (p. 562–es). http://doi.org/10.3115/1220355.1220436

Poowarawan, Y. (1986). Dictionary-based thai syllable separation. In *Proceedings of the Ninth Electronics Engineering Conference* (pp. 409–418).

Pornprasertkul, A. (1994). *Thai Syntactic Analysis*.

Portmann, J. (2014). Morality and schadenfreude. In W. W. van Dijk & J. W. Ouwerkerk (Eds.), *Schadenfreude: Understanding Pleasure at the Misfortune of Others* (pp. 17–28). Cambridge University Press. http://doi.org/10.1007/9781139084246.003

Pullman, M., McGuire, K., & Cleveland, C. (2005). Let me count the words: Quantifying open-ended interactions with guests. *Cornell Hotel and Restaurant Administration Quarterly*, *46*(3), 323–343. http://doi.org/10.1177/0010880405276309

Puzakova, M., Kwak, H., & Rocereto, J. F. (2013). When Humanizing Brands Goes

Wrong: The Detrimental Effect of Brand Anthropomorphization Amid Product Wrongdoings. *Journal of Marketing*, *77*(3), 81–100. http://doi.org/10.1509/jm.11.0510

Quan-Haase, A., & Young, A. L. (2010). Uses and Gratifications of Social Media: A Comparison of Facebook and Instant Messaging. *Bulletin of Science, Technology & Society*, *30*(5), 350–361. http://doi.org/10.1177/0270467610380009

Raney, A. A. (2011). The role of morality in emotional reactions to and enjoyment of media entertainment. *Journal of Media Psychology*, *23*(1), 18–23. http://doi.org/10.1027/1864-1105/a000027

Rarunrom, S. (1991). *Dictionary-based Thai Word Separation*.

Reinecke, L., & Trepte, S. (2014). Authenticity and well-being on social network sites: A two-wave longitudinal study on the effects of online authenticity and the positivity bias in SNS communication. *Computers in Human Behavior*, *30*, 95–102. http://doi.org/10.1016/j.chb.2013.07.030

Reinecke, L., Vorderer, P., & Knop, K. (2014). Entertainment 2.0? The Role of Intrinsic and Extrinsic Need Satisfaction for the Enjoyment of Facebook Use. *Journal of Communication*, *64*, 417–438. http://doi.org/10.1111/jcom.12099

Roshan, M., Warren, M., & Carr, R. (2016). Understanding the use of social media by organisations for crisis communication. *Computers in Human Behaviour*, *63*(2016), 350–361. Retrieved from https://ac.els-cdn.com/S0747563216303405/1-s2.0-S0747563216303405-main.pdf?_tid=a1b3faeb-eff8-40ce-8ab0-76d2dedd003c&acdnat=1522662159_a509cc2b1c89c391ed0484dd6b7cf30f

Royle, N. J., Smiseth, P. T., & Kölliker, M. (2012). *The Evolution of Parental Care*. Oxford, UK: Oxford University Press.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. http://doi.org/10.1037/0003-066X.55.1.68

Ryan, R. M., & Deci, E. L. (2001). On Happiness and Human Potentials: A Review of Research on Hedonic and Eudaimonic Well-Being. *Annual Review of Psychology*, *52*(1), 141–166. http://doi.org/10.1146/annurev.psych.52.1.141

Sagi, E., & Dehghani, M. (2014). Measuring Moral Rhetoric in Text. *Social Science Computer Review*, *32*(2), 132–144. http://doi.org/10.1177/0894439313506837

Schmitt, B. H., Dube, L., & Leclerc, F. (1992). Intrusions into waiting lines: Does the queue constitute a social system? *Journal of Personality and Social Psychology*, *63*(5), 806–815. http://doi.org/10.1037/0022-3514.63.5.806

Schultz, F., Utz, S., & Göritz, A. (2011). Is the medium the message? Perceptions of and reactions to crisis communication via twitter, blogs and traditional media. *Public Relations Review*, *37*(1), 20–27. http://doi.org/10.1016/j.pubrev.2010.12.001

Schweidel, D. A., & Moe, W. W. (2014). Listening In on Social Media: A Joint Model of Sentiment and Venue Format Choice. *Journal of Marketing Research*, *51*(4), 387–402. http://doi.org/10.1509/jmr.12.0424

Seeger, M. W. (2006). Best practices in crisis communication: An expert panel process. *Journal of Applied Communication Research*, *34*(3), 232–244. http://doi.org/10.1080/00909880600769944

Sellnow, T. L., & Seeger, M. (2001). Exploring the boundaries of crisis communication: The case of the 1997 red river valley flood. *Communication Studies*, *52*(2), 153–167. http://doi.org/10.1080/10510970109388549

Sen, S., & Lerman, D. (2007). Why are you telling me this? An examination into negative consumer reviews on the web. *Journal of Interactive Marketing*, *21*(4), 76–94. http://doi.org/10.1002/dir.20090

Seo, H., Kim, J. Y., & Yang, S. U. (2009). Global activism and new media: A study of transnational NGOs' online public relations. *Public Relations Review*, *35*(2), 123–126. http://doi.org/10.1016/j.pubrev.2009.02.002

Seo, M., Kembhavi, A., Farhadi, A., & Hajishirzi, H. (2016). *Bidirectional Attention Flow for Machine Comprehension*. Retrieved from http://arxiv.org/abs/1611.01603

Shanke, R., & Abelson, R. (1995). Knowledge and memory: The real story. In R. S. Wyer Jr (Ed.), *Knowledge and memory: The real story* (pp. 1–85). Hillsdale, NJ:

Lawrence Erlbaum Associates, Inc.

Shen, L. (2017). The 10 Biggest Business Scandals of 2017. Retrieved May 14, 2018, from http://fortune.com/2017/12/31/biggest-corporate-scandals-misconduct-2017-pr/

Shi, B., Wang, H., & Liu, W. (2018). Dialectical mind can be sweet toward crisis-associated products/brands. *Psychology and Marketing*, *35*(1), 20–35. http://doi.org/10.1002/mar.21068

Shweder, R. A., & Haidt, J. (1993). The Future of Moral Psychology: Truth, Intuition, and the Pluralist Way. *Psychological Science*, *4*(6), 360–365. http://doi.org/10.1111/j.1467-9280.1993.tb00582.x

Siomkos, G. (1989). Managing product-harm crises. *Organization & Environment*, *3*(1), 41–60. http://doi.org/10.1177/108602668900300103

Siomkos, G. J., & Kurzbard, G. (1992). Product harm crisis at the crossroads: monitoring recovery of replacement products. *Industrial Crisis Quarterly*, *6*(4), 279–294. http://doi.org/10.1177/108602669200600402

Smith, R. H. (1991). Envy and the sense of injustice. In P. Salovey (Ed.), *The psychology of jealousy and envy* (pp. 79–99). New York: Guilford Press.

Smock, A. D., Ellison, N. B., Lampe, C., & Wohn, D. Y. (2011). Facebook as a toolkit: A uses and gratification approach to unbundling feature use. *Computers in Human Behavior*, *27*(6), 2322–2329. http://doi.org/10.1016/j.chb.2011.07.011

Socher, R., Perelygin, A., & Wu, J. (2013). Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on empirical methods in natural language processing* (pp. 1631–1642). http://doi.org/10.1371/journal.pone.0073791

Sornlertlamvanich, V., Takahashi, N., & Isahara, H. (1999). Building a Thai part-of-speech tagged corpus (ORCHID). *Journal of the Acoustical Society of Japan (E)*, *20*(3), 189–198. http://doi.org/10.1250/ast.20.189

Stauss, B. (2000). Using New Media for Customer Interaction: A Challenge for Relationship Marketing. In T. Hennig-Thurau & U. Hansen (Eds.), *Relationship*

*Marketing* (pp. 233–253). Berlin: Springer. http://doi.org/10.1017/CBO9781107415324.004

Stephen, J. F. (1883). *A history of the criminal law of England*. London: Macmillan.

Stephens, N., & Gwinner, K. P. (1998). Why Don't Some People Complain? A Cognitive-Emotive Process Model of Consumer Complaint Behavior. *Journal of the Academy of Marketing Science*, *26*(3), 172–189. http://doi.org/10.1177/0092070398263001

Suesatpanit, K., Punyabukkana, P., & Suchato, A. (2009). *Thai Word Segmentation using Character-level Information*. Thailand.

Swim, J. K., Aikin, K. J., Hall, W. S., & Hunter, B. A. (1995). Sexism and racism: Old-fashioned and modern prejudices. *Journal of Personality and Social Psychology*, *68*(2), 199–214. http://doi.org/10.1037/0022-3514.68.2.199

Tamborini, R. (2011). Moral intuition and media entertainment. *Journal of Media Psychology*, *23*(1), 39–45. http://doi.org/10.1027/1864-1105/a000031

Tamborini, R. (2012). Model of intuitive morality and exemplars. In R. Tamborini (Ed.), *Media and the moral mind* (pp. 43–74). London, England: Routledge.

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, *29*(1), 24–54. http://doi.org/10.1177/0261927X09351676

Teh, Y. W., & Jordan, M. I. (2010). Hierarchical Bayesian nonparametric models with applications. *Bayesian Nonparametrics*, 1–48. http://doi.org/10.1017/CBO9780511802478

Teh, Y. W., Jordan, M. I., Beal, M., & Blei, D. (2005). Hierarchical Dirichlet processes. *Journal of the American Statistical Association*, 1–41.

Theeramunkong, T., Sornlertlamvanich, V., Tanhermhong, T., & Chinnan, W. (2000). Character-Cluster Based Thai Information Retrieval. In *Proceedings of the 5th international Workshop on Information Retrieval with Asian Languages* (pp. 75–80).

Theeramunkong, T., & Usanavasin, S. (2001). Non-dictionary-based Thai word segmentation using decision trees. In *Proceedings of the first international conference on Human language technology research* (pp. 1–5). Retrieved from http://portal.acm.org/citation.cfm?id=1072133.1072209

Torossian, R. (2017). The Biggest PR Crises Of 2017. Retrieved May 14, 2018, from https://www.forbes.com/sites/forbesagencycouncil/2017/05/23/the-biggest-pr-crises-of-2017/

Trakultaweekoon, K., Chai, W. N., & Supnithi, T. (2009). *An Expertise- based Vocabulary Suggestion System: A Case Study of LEXiTRON*. Thailand.

Trepte, S. (2008). Cultural proximity in TV entertainment: An eight-country study on the relationship of nationality and the evaluation of U.S. prime-time fiction. *Communications*, *33*(1), 1–25. http://doi.org/10.1515/COMMUN.2008.001

Trivers, R. L. (1971). The Evolution of Reciprocal Altruism. *The Quarterly Review of Biology*, *46*(1), 35–57.

Turiel, E. (1983). *The development of social knowledge: Morality and convention*. Cambridge, UK: Cambridge University Press.

Utz, S., & Breuer, J. (2017). The Relationship Between Use of Social Network Sites, Online Social Support, and Well-Being. *Journal of Media Psychology*, *29*(3), 115–125. http://doi.org/10.1027/1864-1105/a000222

Van Dijk, W. W., Ouwerkerk, J. W., Goslinga, S., Nieweg, M., & Gallucci, M. (2006). When people fall from grace: Reconsidering the role of envy in Schadenfreude. *Emotion*, *6*(1), 156–160. http://doi.org/10.1037/1528-3542.6.1.156

Veil, S. R., Buehner, T., & Palenchar, M. J. (2011). A Work-In-Process Literature Review: Incorporating Social Media in Risk and Crisis Communication. *Journal of Contingencies and Crisis Management*, *19*(2), 110–122. http://doi.org/10.1111/j.1468-5973.2011.00639.x

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do Social Network Sites Enhance or Undermine Subjective Well-Being? A Critical Review. *Social Issues and Policy Review*, *11*(1), 274–302. http://doi.org/10.1111/sipr.12033

Vorderer, P. (2011). What’s next? *Journal of Media Psychology*, *23*(1), 60–63.

http://doi.org/10.1027/1864-1105/a000034

Vorderer, P., Klimmt, C., & Ritterfeld, U. (2004). Enjoyment: At the heart of media entertainment. *Communication Theory*, *14*(4), 388–408. http://doi.org/10.1111/j.1468-2885.2004.tb00321.x

Vorderer, P., & Reinecke, L. (2015). From Mood to Meaning: The Changing Model of the User in Entertainment Research. *Communication Theory*, *25*(4), 447–453. http://doi.org/10.1111/comt.12082

Vorderer, P., & Ritterfeld, U. (2009). Digital games. In R. Nabi & M. B. Oliver (Eds.), *Handbook of media effects* (pp. 455–467). London: Sage.

Wang, Y. (2016). Brand crisis communication through social media: A dialogue between brand competitors on Sina Weibo. *Corporate Communications: An International Journal*, *21*(1), 56–72. http://doi.org/10.1108/CCIJ-10-2014-0065

Waterman, A. S. (1993). Two Conceptions of Happiness: Contrasts of Personal Expressiveness (Eudaimonia) and Hedonic Enjoyment. *Journal of Personality and Social Psychology*, *64*(4), 678–691. http://doi.org/10.1037/0022-3514.64.4.678

Wenjun, X., & Erna, Q. (2018). Research on brand crisis identify index model based on cluster analysis. *Cluster Computing*, 1–10.

Westbrook, R. A. (1987). Product/Consumption-Based Affective Responses and Postpurchase Processes. *Journal of Marketing Research*, *24*(3), 258. http://doi.org/10.2307/3151636

Wirth, W., Hofer, M., & Schramm, H. (2012). Beyond Pleasure: Exploring the Eudaimonic Entertainment Experience. *Human Communication Research*, *38*(4), 406–428. http://doi.org/10.1111/j.1468-2958.2012.01434.x

Wright, D. K., & Hinson, M. D. (2009). Examining How Public Relations Practitioners Actually Are Using Social Media. *Public Relations Journal*, *3*, 1–33. http://doi.org/10.1109/34.56205

Wulff, H. J. (1996). Suspense and the Influence of Cataphora on Viewers' Expectation. In P. Vorderer & H. J. Wulff (Eds.), *Suspense: Conceptualizations, theoretical analyses, and empirical explorations* (pp. 1–18). Mahwah, NJ: Lawrence Erlbaum

Associates.

Xia, L. (2013). Effects of Companies' Responses to Consumer Criticism in Social Media. *International Journal of Electronic Commerce*, *17*(4), 73–100. http://doi.org/10.2753/JEC1086-4415170403

Xu, K., & Li, W. (2013). An Ethical Stakeholder Approach to Crisis Communication: A Case Study of Foxconn's 2010 Employee Suicide Crisis. *Journal of Business Ethics*, *117*(2), 371–386. http://doi.org/10.1007/s10551-012-1522-0

Yannopoulou, N., Koronis, E., & Elliott, R. (2011). Media amplification of a brand crisis and its affect on brand trust. *Journal of Marketing Management*, *27*(5–6), 530–546. http://doi.org/10.1080/0267257X.2010.498141

Yap, K. B., Soetarto, B., & Sweeney, J. C. (2013). The relationship between electronic word-of-mouth motivations and message characteristics: The sender's perspective. *Australasian Marketing Journal*, *21*(1), 66–74. http://doi.org/10.1016/j.ausmj.2012.09.001

Yuan, D., Cui, G., & Lai, L. (2016). Sorry seems to be the hardest word: consumer reactions to self-attributions by firms apologizing for a brand crisis. *Journal of Consumer Marketing*, *33*(4), 281–291. http://doi.org/10.1108/JCM-02-2015-1306

Zhao, H., Huang, C.-N., & Li, M. (2006). An Improved Chinese Word Segmentation System with Conditional Random Field. In *Proceedings of the Fifth SIGHAN Workshop on Chinese Language Processing* (pp. 162–165). Retrieved from http://www.aclweb.org/anthology/W/W06/W06-0127

Zhou, N., AiTi, A., Lertcheva, N., & Xuangcong, W. (2016). A Word Labelling Approach to Thai Sentence Boundary Detection and POS Tagging. In *Proceedings of the 26th International Conference on Computational Linguistics (COLING-16)* (pp. 319–327).

Zillmann, D. (1996). The psychology of suspense in dramatic exposition. In P. Vorderer, H. J. Wulff, & M. Friedrichsen (Eds.), *Suspense: Conceptualizations, theoretical analyses, and empirical explorations* (pp. 199–231). Mahwah, NJ: Lawrence Erlbaum Associates.

Zillmann, D., & Bryant, J. (1994). Entertainment as Media Effect. In J. Bryant & D. Zillmann (Eds.), *Media effects: Advances in theory and research* (pp. 437–461). Hillsdale, NJ: Erlbaum.

Zillmann, D., & Cantor, J. R. (1972). Directionality of transitory dominance as a communication variable affecting humor appreciation. *Journal of Personality and Social Psychology*, *24*(2), 191–198. http://doi.org/10.1037/h0033384

Zillmann, D., Hay, T. A., & Bryant, J. (1975). The effect of suspense and its resolution on the appreciation of dramatic presentations. *Journal of Research in Personality*, *9*(4), 307–323. http://doi.org/10.1016/0092-6566(75)90005-7

Zillmann, D., Taylor, K., & Lewis, K. (1998). News as nonfiction theater: How dispositions toward the public cast of characters affect reactions. *Journal of Broadcasting & Electronic Media*, *42*(2), 153–169. http://doi.org/10.1080/08838159809364441