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Discovering underlying sensations of human emotions based on social media

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Abstract

Analyzing social media has become a common way for capturing and understanding people's opinions, sentiments, interests, and reactions to ongoing events. Social media has thus become a rich and real-time source for various kinds of public opinion and sentiment studies. According to psychology and neuroscience, human emotions are known to be strongly dependent on sensory perceptions. Although sensation is the most fundamental antecedent of human emotions, prior works have not looked into their relation to emotions based on social media texts. In this paper, we report the results of our study on sensation effects that underlie human emotions as revealed in social media. We focus on the key five types of sensations: sight, hearing, touch, smell, and taste. We first establish a correlation between emotion and sensation in terms of linguistic expressions. Then, in the second part of the paper, we define novel features useful for extracting sensation information from social media. Finally, we design a method to classify texts into ones associated with different types of sensations. The sensation dataset resulting from this research is opened to the public to foster further studies.

1 | INTRODUCTION

Emotions as a conscious mental reaction (such as joy or anger) are strongly involved in many aspects of everyday life (James, 1884). Human behavior, from decision-making to social activity, tends to a large degree, be derived from emotions triggered by specific events or situations (Dolan, 2002). Accordingly, there is a growing recognition that emotion analysis can help understand the cause of human behavior. With the significant growth of both emotion-rich textual contents (such as microblog posts and forum discussions) and the development of their analysis techniques (such as sentiment analysis and opinion mining), there is an opportunity to utilize emotions verbalized in the text; for example, for marketing and promotion, trend prediction, and recommendation (Bagozzi, Gopinath, & Nyer, 1999; Deng, Wang, Li, & Xu, 2015).

Identifying the complex nature of emotion creation has been the focus of neuroscience and other related fields. For several decades, it has been known that both cognitive and non-cognitive processes intervene in the emotion activation (Izard, 1993; Tomkins, 1962). However, the recent studies provide clues that three major factors create emotions: *current emotion status*, *homeostatic drives/motivational experiences*, and *sensory affects* (Tyng, Amin, Saad, & Malik, 2017), as indicated in Figure 1. The sensory affect, in particular, is a highly engaging property as the emotions depend on the perception of human sensory organs. In other words, what humans feel can be heavily influenced by what their senses are exposed to. Therefore, the senses, which are the representation of sensing the environment through sensory organs, such as eyes, nose, mouth, skin, and ears, can be considered as important information (*called*

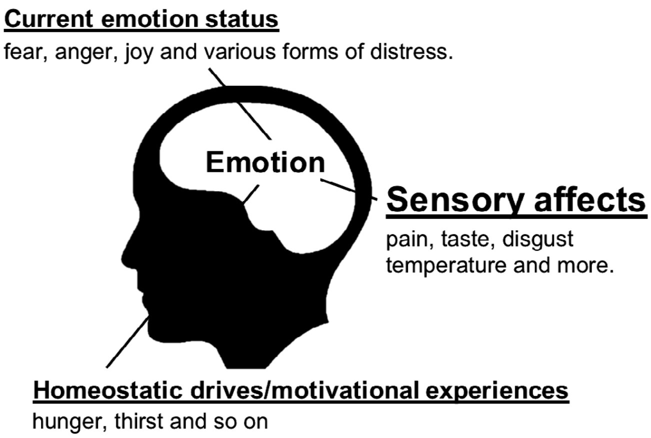

FIGURE 1 Primary factors affecting emotion activation

sensation information; Lee, Kim, Kwon, & Ogawa, 2017) to analyze better how emotions are affected and formed.

The sensation information has already been used for an effective marketing strategy, called sensory marketing, aiming to stimulate the senses of customers for positively affecting their behavior, judgment, or feelings (Hultén, 2011). Companies benefit from the effectiveness of the sensation information by harnessing the theory of embodied cognition, which substantiates that human decision-making behavior is not only based on rational thinking but largely depends on the emotions. For example, pairing sounds with food and drink has been scientifically proven to enhance the human experience of flavor. The study of (Spence & Shankar, 2010) found that high-frequency sounds help to stimulate the sweet taste sensation, while low tones bring out bitterness. According to Knoferle, Spangenberg, Herrmann, and Landwehr (2012), the tempo of songs in a store can affect the customer's purchase behavior. Furthermore, human-computer interaction (HCI) research studies begin to consider the sensory experience as a medium connecting multi-modal systems in state-of-the-art devices (Cibrian, Peña, Ortega, & Tentori, 2017; Obrist, Tuch, & Hornbaek, 2014).

It is then necessary to consider the sensory experience as a primary element determining human emotions and behaviors. One investigation angle is in terms of textual characteristics and features suggestive of the sensations embedded in social media utterances. Social media is nowadays a popular medium for representing daily life experiences. It contains rich descriptions of what users sensed (saw, heard, touched, smelled, and tasted). If we can extract sensation information from these rich textual data and find the relationship between sensation and emotions, we could better understand how emotions are generated from external sensory stimuli. While the sentimental analysis in the text has been investigated as one of major tasks of text mining, the sensation information was a focus of only a few studies (Monteiro, Costa, Loureiro, & Rodrigues, 2018; Zeile, Resch, Exner, & Sagl, 2015). This might be somewhat surprising given that practical methods for sensation recognition in text can have immediate application for supporting estimating of the credibility of reviews, storytelling, HCI as well as for enhancing and improving information retrieval techniques.

In this paper, we focus on the sensation analysis aiming at (a) discovering correlations between emotions and the sensation experience and (b) categorizing sensations embedded in texts. For these purposes, we firstly prepare a dataset with an elaborated annotation process and then compute correlations between emotions and sensations. Next, we propose effective features to pick up the sensation information in social media textual data. In particular, we classify the sensation expression into five types of senses (i.e., sight, hearing, touch, smell, and taste) using regression methods as well as up-to-date machine learning approaches. The contributions of this paper are summarized follows:

- Discovering sensation and emotion correlation: To shed light on the possible causal link between sensory experience and emotions, we determine the strength of the relationship between emotion and sensation by statistical approaches, that is, correlation methods in terms of linearity, monotonicity, and connectivity. Although such correlation has been studied in the psychology field, to the best of our knowledge, this is the first attempt for investigating how strongly the sensation intensity influences the emotion intensity in terms of computational linguistics driven analysis on large textual corpora.
- Feature selection for sensation classification: We propose distinguishing features to classify sensation information from social media texts. The features are extracted and selected based on diverse characteristics of sensations mentioned in the textual data, including co-occurrences, topics, intensities, and the aforementioned established correlations.
- Comprehensive experimental evaluation: The experiments are performed with the proposed features through two steps: at first, we extract the sensation information from social textual data; after that, we classify the data into five-sense types. The performance of the classification is evaluated in terms of accuracy and compared to traditional approaches, such as Multinomial Naive Bayes (NB), Support Vector Machine (SVM) and bi-LSTM.

To sum up, our work contributes to the study of emotion formation and addresses which sensation types are closely related to which emotions. In addition, we provide practical techniques for detecting sensory traces in tweets. We also open our dataset annotated with sensation types to the public, in order to foster the related research (https://bit.ly/32ovMi1). We believe that the reported findings could be useful not only for research but also for marketers to craft their marketing campaigns better.

The remainder of this paper is organized as follows. Section 2 surveys the related work. We present our approaches for estimating correlations between sensations and emotions in Section 3. Section 4 describes our methods for selecting effective features for the sensation classification. The experimental results for the binary- and multi-class sensation classification are reported in Section 5. Finally, Section 6 concludes the paper and outlines our future work.

2 | RELATED WORK

2.1 | Multidisciplinary studies of emotion

From Aristotle's "Rhetoric" to Darwin (Darwin & Prodger, 1998) and up to the present day, understanding emotions has been central to the continuous attempt to understanding human nature. Emotion, although there is no scientific consensus in the literature on its definition, is defined as a mental state associated with a particular physiological pattern such as anger, disgust, fear, joy, sadness, and surprise (Ekman, 1992). Since emotion is deeply involved in human behavior and social interactions in social situations (i.e., interpersonal interactions) as well as in decision-making, it draws attention from fields of science outside of psychology, including neuroscience, biology, computer science, and behavioral economics; to the point that the field is now often called emotion science or affective science (Niedenthal & Ric, 2017). Recent technological developments, such as Positron Emission Tomographic or Functional Magnetic Resonance Imaging scans, contribute to the understanding of the functioning and role of the nervous system in the brain (Vuilleumier, Armony, Driver, & Dolan, 2001).

The brain science and neuroscience studies have discovered how the brain forms emotion. Three main factors: sensory affects, current emotion status, and homeostatic drives and motivational experiences, are involved in the formation of emotions (McCauley & Franklin, 1998; Tyng et al., 2017). Even though emotions are scientifically determined to be accompanied by complex physiological and biological changes, they naturally have some rational, understandable aspects. For example, assume that someone has been fasting to lose weight all day. In this situation, she may feel hungry (i.e., homeostatic drives) and recall memories (i.e., motivational experiences) of eating delicious food. Eventually, when the person puts food in mouth (i.e., sensory affects), undoubtedly a pleasure or happiness (i.e., emotion) will be felt. Recent theories of embodied cognition hold that an embodiment perspective applies particularly well to thinking about emotion with unconscious body interactions and representations (Effron, Niedenthal, Gil, & Droit-Volet, 2006; Winkielman, Niedenthal, Wielgosz, Eelen, & Kavanagh, 2015). HCI research studies, especially ones working on human-robot interaction (HRI), have been influenced by the embodied cognition studies that provide them solid theoretical background (Brave & Nass, 2007).

Although physical actions such as facial reaction, gesture, or posture are unquestionably trustworthy evidence of emotion expressions, textual contents are also a valuable resource for detecting various types of emotions in terms of both the quantity and quality. In computer science, affective computing has come up with designing and implementing systems and devices that can recognize, interpret, and process human emotions. In particular, emotional expressions (e.g., speech and text) could be recognized as affective dimensions, which are modeled by the hourglass of emotions (Cambria, Livingstone, & Hussain, 2012). In addition novel techniques, involved fuzzy linguistic modeling, aspect-based extraction, flow of emotions modeling and others, have proposed to identify an affective state (i.e., emotions) based on the rich text of social media (Brenga, Celotto, Loia, & Senatore, 2015a; Maharjan, Kar, Montes, González, & Solorio, 2018; Weichselbraun, Gindl, Fischer, Vakulenko, & Scharl, 2017). In this regard, social media data have boosted the utilization of emotional texts to understand human behaviors, observations, opinions, and so on. This issue will be dealt with in more detail in Section 2.3.

2.2 | Human sensory experience and its effectiveness

Humans have five fundamental senses: sight (ophthalmoception), hearing (audioception), touch (tactioception), smell (olfacception), and taste (gustaoception). These senses are in charge of perceiving external stimuli that influence a physical condition, underlying mood, emotional state, and behavior. Although the five senses are known as the only sensory receptors, the senses are actually felt in our body as a human sensory experience (i.e., sensation information) after perceiving five senses from external sensory organs (exteroceptive senses) or internal organs (interoceptive senses) (Craig, 2003). This information is composed of our brains, and then it significantly influences physical condition, reaction, and also emotion as discussed in Section 2.1. Specifically, the sensation information is involved in many aspects of human behavior driven in part by conscious and unconscious mind. Among a variety of individual and social behaviors, a decision making is worthy of discussion to understand how deeply the sensation information is intertwined with human behaviors; for example, in marketing and business areas, some companies strive to improve revenues and brand values based on it.

In recent, the concept of embodied cognition as a medium between IoT (Internet of Things) devices and human perception has received much recognition. Various state-of-the-art HCI devices have been developed in a wide range of areas in combination with IoT sensors, which are basically relying on the sensory experiences of human, such as Oculus Rift, HaptX Gloves, Amazon Alexa, and so on. Accordingly, for HRI research studies, along with development of sensors, the sensation information is an essential, connective element between a human and robot. For example, in Kowadlo and Andrew Russell (2004), the authors tried to enable a robot to locate the source of an odor in a cluttered indoor environment. Furthermore, haptic devices have greatly contributed to an endoscopic surgery to help the operating surgeon with tactile feedback (Bethea et al., 2004).

However, even though many IoT applications combined with sensory experience (e.g., smart assistant speakers) have being realized based on human natural language, there are still some significant challenges in connecting the devices and language in terms of representing sensation information. For instance, if a user asks "today's weather," then the device only provides the numeric temperature, such as 16°C; however, based only on the numeric value, that is, 16°C it is rather difficult to estimate how a human body feels. If, instead, the device could give an information such as "you will feel a little cold," it would be really easier for many users to understand the weather situation. Hence, understanding of sensation information can be considered useful to connect human and devices seamlessly in terms of services related to our daily life. Accordingly, we firstly focus on the understanding sensation information in natural language in this work, and then we quantify the intensity of sensation information.

2.3 | Social media text mining

As introduced in the previous sections, many studies have been done for human sensory experience and sensation information in different areas, such as psychology, marketing, or robotics. However, to the best of our knowledge, this is the first attempt for understanding the sensation information in terms of natural language. Therefore, to begin with, we first survey social media text mining techniques, especially ones for sentiment analysis and emotion classification.

Text mining is essential analytics for natural language texts realized through the process of structuralization (i.e., cleansing, tokenizing, and Part-of-Speech [POS] tagging), transformation (i.e., attribute generation), feature selection (i.e., attribute extraction), and evaluation and interpretation of the output. It has become a trendy field being incorporated in various research areas such as computational linguistics, information retrieval, and data mining. In the recent decade, social networks have played significant role of information channels allowing for disseminating information on our everyday lives. Dialogues expressed in form of short messages in online social networks constitute then an endless stream of human observations, emotions, sentiments, and opinions. The vast amounts of textual data offer great opportunities to solve difficult questions about humans and their behaviors.

The sentiment analysis is an active study in social media mining to classify the polarity of text, such as into positive, negative, or neutral classes. Early work in the sentiment analysis of Turney (Turney, 2002) and Pang et al. (Pang, Lee, & Vaithyanathan, 2002) detected the polarity of product and movie reviews using machine learning techniques. Later, the research spectrum has been spreading out toward understanding emotion (happy, sad, etc.), mood (cheerful, depressed, etc.), interpersonal stances (friendly, distant, etc.), attitudes (like, love, etc.), and personality traits (nervous, anxious, etc.) along with the advancement of machine learning techniques. Finding and monitoring sentiments or opinions have been widely applied in the real-life applications, such as personal recommendation (Sun, Wang, Cheng, & Fu, 2015), stock prediction (Bai, 2011), and supporting political campaigns (Watts, George, Kumar, & Arora, 2016).

SemEval-2007 initiated a task of "affective text" for annotating short headline texts with predefined lists of emotions and polarity orientations (positive and negative) (Strapparava & Mihalcea, 2007). Six types of emotions (i.e., anger, disgust, fear, happiness, sadness, and surprise) were automatically identified by knowledge- and corpus- based methods from (Strapparava & Mihalcea, 2008). In particular, (Loia & Senatore, 2014) defined six levels of activation, called "sentic" levels, to represent an emotional state of mind ranked by its intense level. Moreover, the shared task on emotion intensity (Mohammad & Bravo-Marquez, 2017b), as a part of WASSA-2017 workshop at EMNLP-2017, was carried out detecting the intensity of emotions felt by the speaker of a tweet using a technique called best-worst scaling.

With the widespread interest of research community in emotional texts, several noteworthy studies focused on how the emotions aroused by the text can affect the human behaviors. Filipczuk, Pesce, and Senatore (2016) tried to predict altruistic behaviors from readers of social web pages (Reddit.com), by extracting dominant emotions expressed in the satisfied requests (i.e., getting a free pizza) using Kaggle dataset. Furthermore, the study using Twitter posts by (De Choudhury, Monroy-Hernandez, & Mark, 2014) identified a desensitization behavior to protracted violence as country-level homicides from Mexican Drug War over a 2-year period. In terms of a collective behavior, some research studies revealed that positive emotions tend to be more interesting (Stieglitz & Dang-Xuan, 2013) and provoke higher levels of arousal (Berger, 2011), which can influence social sharing behaviors (Berger & Milkman, 2012).

Following the success of the previous works on emotion analysis over textual contents, some research studies expanded the analysis scope by migrating from text to video/image data for the general objective of fostering multimodal emotion recognition. Development of AI techniques especially makes it possible to detect important features determining emotions from facial expressions, gestures, and from speech (e.g., tone) (Fan, X., Li, & Liu, 2016; Glowinski, Camurri, Volpe, Dael, & Scherer, 2008). As social media also reflects our personal perceptual experience based on the five sensation features, it is naturally a good data for studying sensation-related aspects. This means that textual contents reflecting perceptual experience of multiple users can be also harnessed for analyzing emotions in terms of sensory-based human experiences using natural language processing techniques.

3 | CORRELATION BETWEEN SENSATION AND EMOTION

As mentioned before, human senses are preceding stimuli that take part in formulation of emotions according to psychology and medical sciences. In this paper, we investigate whether it is feasible to estimate the correlation between sensation and emotion in terms of their textual representation. Above all, in this section, we introduce our dataset involved in the overall task of this work. We next try to identify (a) whether the correlation exists based on analysis of social media texts, (b) which emotions are connected to which sensations, and (c) how strong is the correlation.

3.1 | Dataset preparation

We utilize the Tweet Emotion Intensity Dataset (EmoInt) Mohammad and Bravo-Marquez (2017a) that contains about seven thousands of social media texts (i.e., tweets) categorized by four types of emotions: joy, sadness, fear, and anger. Each tweet has an intensity value that is real-valued score between 0 (weak) and 1 (strong) indicating the degree of emotions felt by the authors of tweets. The annotations of emotion intensities were determined manually through best-worst scaling by crowdsourcing Mohammad and Bravo-Marquez (2017b); for example, a tweet, "*Who the hell is drilling outside my house?! Literally got to sleep at half four after a busy shift and these twats have woken me up*" is classified to *anger* emotion with the intensity value of 0.976 as shown in Table 1.

In order to extract human sensory experience as well as discover an evidence of sensation effects on emotions, the dataset has been annotated again in terms of sensation types using the crowdsourcing platform (i.e., Amazon Mechanical Turk (MTurk)) (https://www.mturk.com/). Note that, to the best of our knowledge, until now no dataset for sensation analysis has been proposed, and this is the first type of such dataset. The tweets in EmoInt were then shown to 5 annotators who rated them in terms of five kinds of sensations using the 4-point Likert scale "0 (definitely not)", "1 (perhaps not)", "2 (perhaps yes)", and "3 (definitely yes)."

TABLE 1 Examples of emoInt dataset

Tweet	Emotion	Intensity
I've seen the elder watching me during my community hours and i honestly do not have an idea about what my assignment will be. #apprehensive	Fear	0.625
It's so gloomy outside. I wish it was as cold as it looked	Sadness	0.667
Happy birthday sweety .. Sweet 21 Hun hope u have a wonderful day and a wonderful joyful year better than the last one, luv U #love	Joy	0.833
Who the hell is drilling outside my house?! Literally got to sleep at half four after a busy shift and these twats have woken me up #angry #mad	Anger	0.976

TABLE 2 Examples of sensation tweets

Tweet	Sensation	Scale
So if whichever butt wipe pulled the fire alarm in Davis because I was sound asleep	Hearing	3
It's so gloomy outside. I wish it was as cold as it looked	Sight	3
*Someone let snakes in my house, I bet it @Yt** I kill that bugger when I get my hand on him #rage*	Sight&touch	3 and 2
*@li** I had a nice Italian ice-cream whilst resting my tired paws. Honey flavored, naturally!*	Taste	3
Sometimes the worst place you can be is in your own head.	None	0

Table 2 shows few examples. For instance, the above-mentioned tweet can be evaluated into (*hearing, 3*) and (*touch, 2*) because its author definitely heard a loud noise from the drilling, and also he/she would likely feel a slight vibration stimulated by the touch sense. As this example shows, annotators can choose indication of implicit or explicit activation of one or multiple human senses based on a tweet content (including its main text, hashtag, and emoji).

To improve the evaluation quality following our objective, the annotators needed to (a) pass a qualification test with 70% accuracy, (b) reside in an English-speaking country, and (c) had high credibility from the previous tasks they contributed to. We have decided to directly accept a result if it was annotated with the same decision by three out of five individuals. If there was no agreement from at least three annotators, then we used the majority value out of the five values. As a result of the annotation, the proportion of tweets annotated with a score higher than 1 (i.e., ones that can be considered as sensation texts) are 78.03, 28.17, 11.59, 1.04, and 1.42% for sight, hearing, touch, smell, and taste emotions, respectively, as shown in Figure 2:

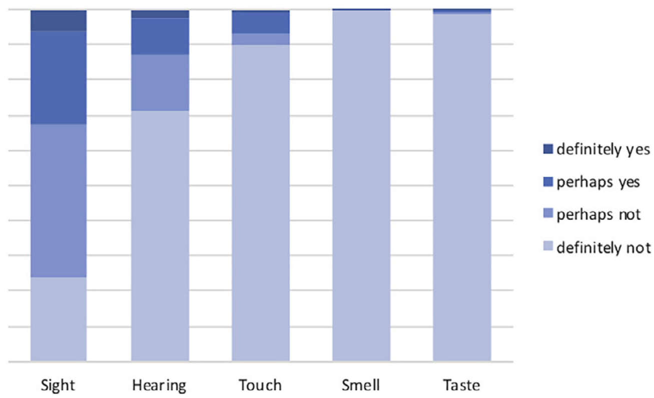

FIGURE 2 Sensation scale distribution [Color figure can be viewed at wileyonlinelibrary.com]

3.2 | Estimation of correlation

To discover how the human sensation could influence emotions based on textual expressions, we firstly validate the dependency between emotion and sensation using *Chi-square statistical test*. Next, we analyze the strength of relationships between emotions and sensations by employing correlation methods in terms of linearity, monotonicity, and connectivity.

3.2.1 | Dependency validation

The Chi-square (χ^2) statistical test has been generally accepted as a statistical hypothesis test to evaluate the dependency between two categorical variables (Cochran, 1952) as in Equation (1):

$$\tilde{\chi}^2 = \sum_{j=1}^{n}\sum_{k=1}^{n}\frac{\left(O_{j,k}-E_{j,k}\right)^2}{E_{j,k}} \quad (1)$$

where j, k are for emotional and sensation terms, respectively, $O_{j,k}$ is the number of observations of type j, k, and $E_{j,k}$ is the expected count of type j, k, asserted by the null hypothesis that the fraction of type i in the population is p_i.

First of all, we validate the dependency between emotion and sensation using the crowdsourcing dataset from Section 3.1. The *emotion intensity* value is converted to a categorical variable, such as strong emotion (≥0.5), normal emotion (<0.5), and no-emotion (=0). Moreover, we mark a tweet as a sensation, in the case when "*perhaps yes (2)*" and "*definitely yes*" are the majority selection for at least one sensation type among the five sensation types. Finally, the test is performed with the following 2×3 table:

From the distribution, we can deduce the existence of positive correlation between emotion and sensation as shown in Figure 3.

Here, the emotional null hypothesis is that the sensation does not affect the formulation of emotion feelings. The result shows chi-square = 241.04, 2d.f., and $p < 2.2\text{e-}16$. This indicates that we can reject the null hypothesis by p value; thus, the emotional feelings have a significantly strong relationship with sensation perception. With this evidence, we next show what types of senses have an effect on the formation of each emotion and get

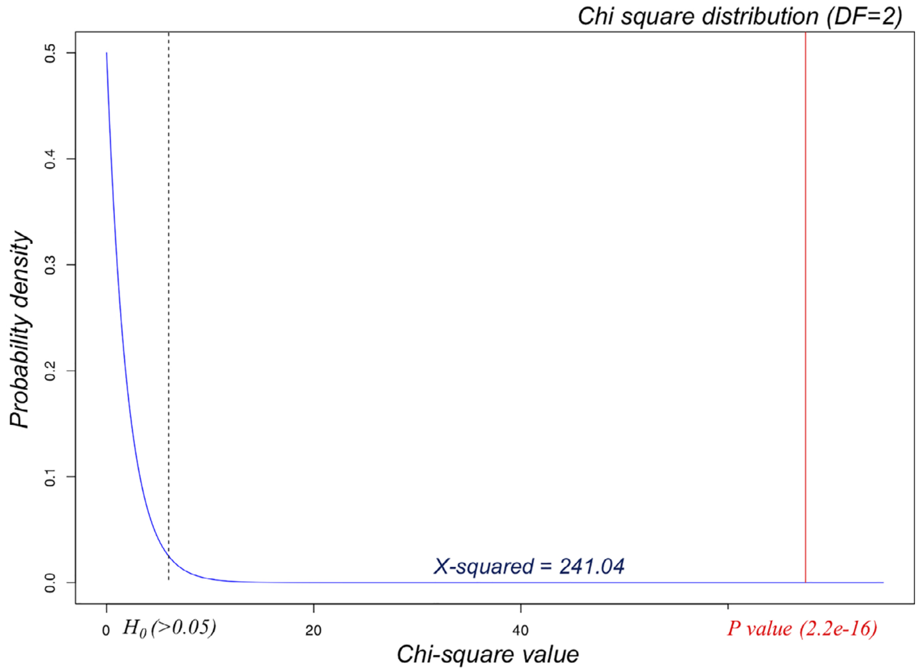

FIGURE 3 Result of chi-square statistical test for the emotion and sensation variables [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 *p* Values from chi-square test between all emotions and sensation types

	Sight	Hearing	Touch	Smell	Taste
Anger	2.14e-09	2.2e-16	.00044	.1825	.0580
Fear	2.2e-16	9.72e-13	1.65e-1	.8213	.0199
Joy	2.2e-16	2.2e-16	1.52e-10	.0481	.6735
Sadness	.08866	.04374	.00357	.5306	.7630

the following *p* values from each test as indicated in Table 3.

The result from Table 3 shows that for almost all pairs of emotions and sensations (i.e., gray colored) the null hypothesis (H_0) can be rejected, except for few pairs (e.g., smell and taste). In other words, we can accept that there are some meaningful relationships, as at least one sensation is definitely involved in formation of emotions. On the basis of the test findings, we will next measure the intensity of the relationships.

3.2.2 | Correlation metrics

Following the results described in the previous section, we verify the correlation intensities of each sensation and each emotion. Particularly, we wish to understand which sensations have strong possible influence on which emotions and how strong are these relations. For this, we first assign sensation values to each tweet based on 4-point Likert scale annotations from crowdsourcing. The correlation between a single emotion and sensation is then estimated on the basis of correlation metrics. We employ correlation coefficients of *Pearson*, *Kendall*, and *Point-biserial* in terms of three aspects: linearity, monotonicity, and connectivity, respectively.

First, *Pearson's coefficient (γ)* is used to identify a linear correlation as follows:

$$r_{x^s,y^e} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2(y_i-\bar{y})^2}} \quad (2)$$

where x is a sensation score of each tweet distinguished by the sensation types (s), and y is a emotion intensity value obtained from the emotion type (e); thus, we measure relationship strengths between a given type of sensation and a type of emotion (e.g., between heard and fear, sight and anger, and so on). After that, we choose the largest one as the resulting coefficient (γ) value, representing a relationship between the sensation and emotions. Second, we employ *Kendall's tau (τ)* to measure the degree of a monotone relationship between sensations and emotions. It calculates the dependence between ranked variables, which is appropriate for non-normal distributed data as follows:

$$\tau = \frac{c-d}{c+d} = \frac{S}{\binom{n}{2}} = \frac{2S}{n(n-1)} \tag{3}$$

where c is the number of concordant pairs between each sensation and emotion, and the number of discordant pairs is notated as d. Third, *Point-biserial coefficient* (ρ), as given in Equation (4), calculates the strength and direction of the association that exists between one continuous variable and one dichotomous variable. For this,

$$\rho = \frac{(Y_h - Y_l) \times \sqrt{pq}}{\sigma_Y} \tag{4}$$

where h and l are the groups of tweets categorized by the emotion intensity (refer to the result of Figure 5), specifically, the group h includes tweets which have the mean value of emotion intensities (over 4 emotion types) larger than 0.3. Otherwise tweets are classified to the group l. Y_h is an average value of sensation scores of tweets in the group h and Y_l is opposite (i.e., the mean of sensation scores from the group l). p is the proportion of tweets belonging to the group h, and $q = 1 - p$ indicates the rest (l). σ_Y is the population SD of sensation scores over all the tweets.

3.2.3 | Data statistics and measurement result

We first look into a statistical characteristics of the dataset before we start the correlation estimation. This is because the data distribution could provide an evidence for the analysis of a correlation between features in the dataset. Figure 4 shows three bar graphs including distributions of the number of emotion tweets by sensation class (1), the sum of sensation scores by emotion types (2), and the relation of sensation scores and emotion intensities (3).

From Figure 4(1) we can observe more detailed information based on Table 4 such that the stronger the tweets imply emotional feelings, the more they seem to contain sensation expressions. Hence, it is suggestive that there should be a strong correlation between the two factors in

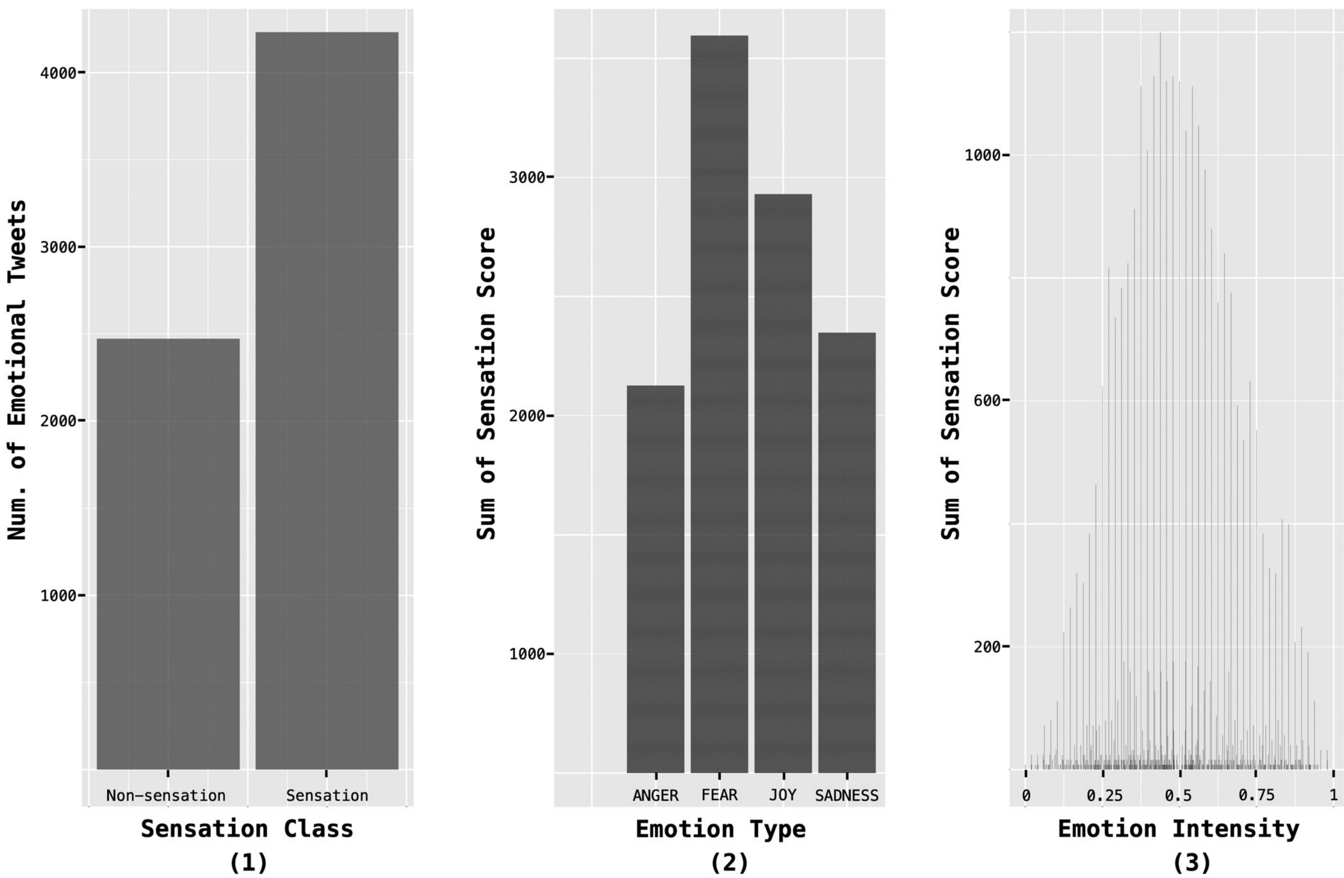

FIGURE 4 Data distribution of emotion, sensation and emotion intensity

terms of the intensity of their co-occurrences. Figure 4 (2) shows the distribution tendency of sensation expressions for each emotion. The sensation expressions appear to be rather common across emotions, but we can see that *fear* emotion contains relatively higher sensation expressions than anger. From this, we can assume that an emotion may be related to a specific sensation type. We will investigate this assumption later in the paper. For correlation tests, we usually assume that two variables are sampled from a normal distribution; fortunately, the distribution of relationships between emotion intensity and sensation scores in Figure 4(3) follows a normal distribution. Accordingly, it can serve as an evidence for the statistical assumption for correlation tests. Moreover, we take a closer look at an emotion intensity distribution with regards to tendency of co-occurrence between sensation and emotion. In other words, we want to identify the frequency of cases of emotion intensities when a tweet contains both sensation and emotion related content. Accordingly, we divided tweets into two groups: *true* (sensation and emotion) and *false* (non-sensation and non-emotion) based on 0.5 threshold in terms of the confidence of containing sensation and emotion, respectively. As shown in Figure 5, almost all tweets including emotion intensity less than 0.2 are definitely involved in the false group. On the other hand, the true group contains all tweets with higher than 0.3 intensity. From the distribution, we can assume that the level of emotion intensity is clearly related to the sensation expression.

Based on the statistical evidences derived from the distributions, we estimate correlations between emotion and sensation and, then in more detail, ones between each sensation type and emotion intensity. For this, we categorize tweets to emotion and non-emotion groups based on 0.3 threshold of the emotion intensity following the distribution of Figure 5. The experiment was performed using the correlation metrics that we discussed in the previous section (Section 3.2.2).

Table 5 shows the results of correlation estimations. The estimated coefficients with the * mark are deemed statistically significant with *p*-values smaller than .01. It is clear that they are subject to correlations in terms of both linearity (Equation (2)) and monotonicity (Equation (3)). The *All* index of Table 5 indicates the results of correlation tests between the sum of sensation score over 5 types of sensations and the total of intensity value from 4 types of emotion. Since both correlation coefficients are estimated as greater than 0.3 considering emotion and all the sensation types, we believe that there is a direct correlation between emotions and sensations. Furthermore, a correlation estimation between the emotion intensity and sensation following Equation (4) indicates correlations larger than 0.4; that is to say, the emotion intensity is clearly influenced by sensation score (or vice versa). Specifically, *sight* sense is the most influencing factor for emotions with correlation values larger than 0.2. In addition, *hearing* and *touch* senses also can be considered as having meaningful relationships with emotions. In some cases such as *smell* and *taste*, however, the results are statistically rejected or have low correlations (less than 0.1). This might be due to the lack of sufficient amounts of tweets annotated with smell and taste sensations (only 0.37 and 1.51% tweets are tagged as associated with smell and taste, respectively).

* $p < .001$

With these substantial evidences of relationship between emotion and sensation, we will classify, in the following section, emotional texts based on the types of sensations they represent. Furthermore, the correlation coefficients that we compute will be used as features for improving the classification performance.

TABLE 4 2X3 Distribution table of emotion and sensation variables

Emotion intensity	Sensation	None sensation
Strong intensity ($E_{int} \geq 0.5$)	756	453
Normal intensity ($E_{int} < 0.5$)	2,270	1,230
None ($E_{int} = 0$)	1,594	1796

4 | MEASUREMENT OF SENSATION CLASSIFICATION

In this section, we propose features used to extract the sensation information from tweets based on sensation characteristics, relationships between topic and sensational expressions, co-occurrence words with sensation representations, and the sensation-emotion correlations that were identified in Section 3.

4.1 | Sensation intensity feature

Sensation intensity is a measurement of how strong a natural language (e.g., social media text) expresses human sensations. It can be considered as a crucial feature to discriminate a text in terms of human sensation. In the recent work (Lee, Ogawa, Kwon, & Kim, 2018), a dedicated measure was proposed for estimating the sensation intensity. In particular, the authors identified meaningful regional differences of sensation intensity

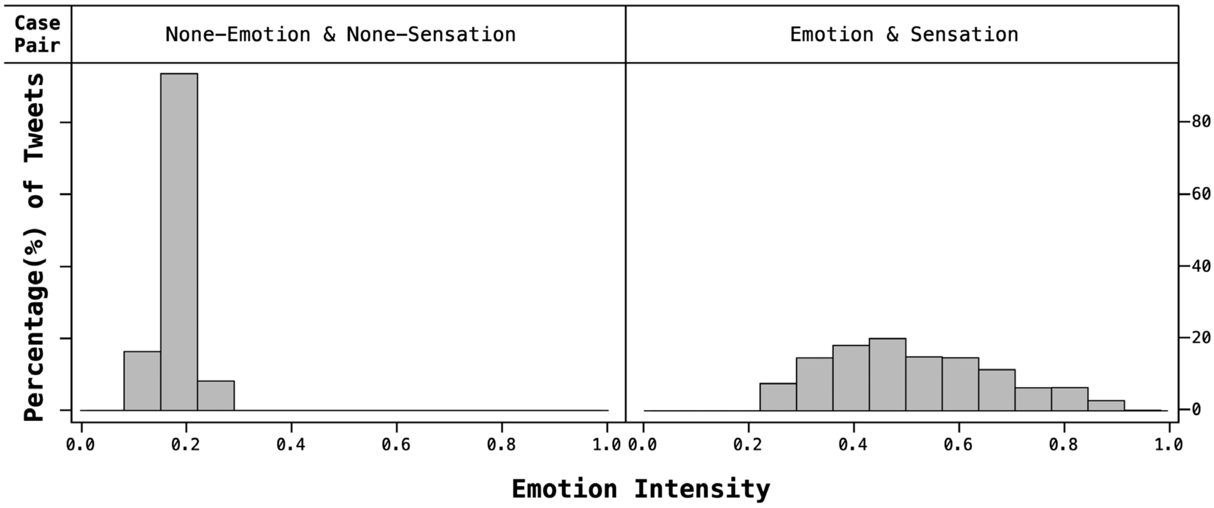

FIGURE 5 Emotion intensity differences of emotion-sensation case pairs

TABLE 5 Correlations between emotion and sensation types by correlation metrics

		Sensation					
		All	**Sight**	**Hearing**	**Touch**	**Smell**	**Taste**
Emotion	Equation (3)	**0.384***	0.212*	0.133*	0.104*	0.023	0.033
	Equation (4)	**0.336***	**0.231***	0.142*	0.112*	0.022	0.038*
	Equation (5)	**0.427***	**0.250***	0.183*	0.147*	**0.221***	0.018

Note: Bold values indicate a statistically significant correlation with a p-value less than 0.001.
$^*p < .001$.

depending on a native language and temperature. (Lee, Thabsuwan, Pongpaichet, & Kim, 2018) improved that method taking into account a lexical semantic relation of words based on Wordnet (Miller, 1995) graph structure. Accordingly, we adopt those measures of sensation intensity as a feature for the sensation classification:

- *Sensation Intensity* (Lee, Ogawa, et al., 2018)

$$I^c(T) = \sum\nolimits_{t \in T} S_t^c, \tag{5}$$

where c represents a sensation type among five sensations, thus $c = (sight, hearing, touch, smell, taste)$. T is a social media text containing words t, which can only be nouns, verbs, adverbs, or adjectives based on their part-of-speech tags. The sensation intensity $I^c(T)$ is computed by summing sensation weights of words t in T (i.e., S_t^c) as follows (Lee, Thabsuwan, et al., 2018):

$$S_t^c = \sum_{j=1}^{k} \sum_{i=1}^{n} \alpha Sim\left(t_i, w_j^c\right) \tag{6}$$

where α is the pre-calculated personalized pagerank (PPR) value between t_i and w_j^c over the Wordnet-induced graph, w_j^c is word of one class from W_{sw}—a word set consisting of manually collected fundamental sensation words, and Sim is a similarity measure used to estimate how strongly the words are related (Jiang & Conrath, 1997). As a result, we can obtain a sensation intensity feature value for a social media text as a five-dimensional vector, that is, $\{sight, hearing, touch, smell, taste\}$ where each component represents the corresponding value of sensation intensity as computed by Equation (5).

4.2 | Sensation topic model feature

There are a variety of studies to infer a specific topic from a natural language, especially from social media texts, for understanding and analyzing public trends, sentiments, interests, and so on (Huang, Peng, Li, & Lee, 2013; Xu, Qi, Huang, Wu, & Fu, 2018). For example, the recent research (Guntuku, Buffone, Jaidka, Eichstaedt, & Ungar, 2019) tried to measure not only sentiments (positive and negative aspects) but also psychological impacts by extracting related topics using social media.

Particularly, an interesting result was revealed that human sensations can be biased in terms of a topic (Lee et al., 2017). For instance, a social media text about fashion was found to be mainly involved with sight and touch sensation, while a music topic tends to include hearing and taste sensation expressions due to a nature of sensory perception and expression.

According to the intuitive relationship between topics and sensations, we use derived topics from tweets as a classification feature. For this, we employ *Latent Dirichlet Allocation* (LDA)-based state-of-the-art technique, namely *Empath* (Fast, Chen, & Bernstein, 2016), which can generate categories (i.e., topic words) from a small set of seed terms. As tweets have a short size of less than 140 characters (usually smaller), this method is appropriate to catch major topics inside tweets. In this study, we exploited *social media* category in the Empath, involved 200 topical words. For The topic feature TP_f is defined containing the Top-N topics as in Equation (7):

$$Topic\,feature\left(\overleftarrow{TP}_{f_N}\right)=\left\{tp_{f_1},tp_{f_2},\cdots,tp_{f_N}\right\} \tag{7}$$

where TP is a social media text (i.e., a tweet) and N is the dimension number of extracted topics which are decided empirically, such as 10 or 50. For example, we can get the top 10 topic words of a tweet "*I hate my lawn mower. If it had a soul, I'd condemn it to the fiery pits of Hell.*" from Empath library as follows (ordered by the relevance of the tweet): *{envy, rage, fire, negative emotion, plant, crime, lust, religion, hate, warmth}*.

4.3 | Co-occurrence sense word feature

Language (i.e., linguistic expressions) is a fundamental link between an individual awareness of sensation (i.e., individual expressions) and the sensory events in surrounding environment, such as smells, tastes, colors, shapes, spaces, and sounds that we perceive (Majid & Levinson, 2011). Particularly, sensation (i.e., sensory) words are manifested as key descriptive words which describe how human being perceives surroundings through sensory organs. They appear quite frequently in tweets in our dataset which are annotated as sensation tweets compared with non-sensation ones. For instance, "*see*" and "*laugh*" as a verb are used 182 and 43 times in sensation texts, respectively, compared to being used only 27 and 13 times in non-sensation texts.

For the designation of basic sensation words, we firstly collected fundamental words from Wordnet synsets; here, synsets are chosen by the name of sensation type (i.e., sight, hearing, touch, smell, and taste) and then fundamental words are considered from *sibling terms* being verbs or adjectives. Next, we ordered all words by frequency of their use in the social media corpus to distinguish words, which tend to be commonly used in social media posts, and then we finally selected five words by the order of their frequency of use as shown in Table 6.

Based on the co-occurrence pattern between sensation words and sensation sentences, we define a co-occurrence word feature calculated by *Pointwise Mutual Information* (PMI) (Church & Hanks, 1990) between basic sensation words and their co-occurring words in the same tweets by using as the following Equation (8):

$$\overleftarrow{CO}_t^b=\frac{\sum_{w\in t}PMI(b,w)}{n} \tag{8}$$

where t is a tweet text and w is a term which has a part-of-speech tag being noun, verb, adverb, or adjective. n denotes the number of terms in the text, b is the basic word of each sense type following Table 6, and $PMI(b, w)$ represents a pointwise mutual information value between each basic sense word and co-occurrence term as in Equation (9):

$$PMI(x,y)=\frac{\log(x,y)}{\log(x)\log(y)} \tag{9}$$

Each term has assigned five PMI values (for 5 sensation types). $CO^b(t)$ represents a summarized five-dimensional PMI which is normalized by the number of words in the sentence. For calculation, we construct a matrix of PMI values computed by considering co-occurrence terms from all the sensation sentences. For instance, a tweet labeled with the sight and touch sensations, with a content as follows "*i had an hour of football practice under the boiling sun and now i have 2hr volleyball practice under the BOILING SUN AGAIN*" has the computed co-occurrence feature values of {0.03337776, 0, 0.13094247, 0, 0} which

TABLE 6 Basic sensation word list

Sense types	Basic words
Sight	*{see, seem, look, watch, find}*
Hearing	*{hear, listen, tell, say, laugh}*
Touch	*{touch, feel, hurt, put, shake}*
Smell	*{smell, scent, stink, bitter[a], sweet[a]}*
Taste	*{taste, eat, sweet[a], bitter[a], sparkling[a]}*

[a]Adjective word.

correspond to sight, hearing, touch smell and taste, respectively.

4.4 | Sense-emotion correlation feature

Based on the correlation results as identified in Section 3, we can accept the prior assumption that emotions are closely related to human sensations in terms of statistical significance. The correlations as measured with respect to linearity, monotonicity, and connectivity suggest that, to some degree, it should be possible to recognize a sensation text based on its emotional characteristics including the emotion type and intensity; in other words, we tried to gauge the possibility of estimating sensations from the correlations. Accordingly, Equation (10) is defined as the sense-emotion correlation feature by distributing the sensation intensity value to sensation types based on their correlation strength:

$$\overleftarrow{CR}_t = \overleftarrow{t^e_{bias}} + \left\{ t^e_{int} \bullet \left(\frac{\overleftarrow{avg(\gamma,\tau,\rho)}}{\sum avg(\gamma,\tau,\rho)} \right) \right\} \tag{10}$$

where t^e_{int} is the emotion intensity value of tweet t, *avg* (γ, τ, ρ) is a five dimension vector being the average of correlation measurement values (Equations (2), (3) and (4) in Table 5, respectively) to consider the three aspects of the correlations, and operator • calculates a scalar multiplication between t^e_{int} (scalar) and the normalized five dimension correlation values (vector). Thus, we try to distribute the emotion intensity value according to a relative correlation strength with the sensation types. Moreover, this feature exploits an inherent relationship between a specific emotion and sensation, as a reliability weigh t^e_{bias} represented a five dimensions vector as follows:

$$\overleftarrow{t^e_{bias}} = \left| \frac{\log_{10} \overleftarrow{R_n}}{\sum \log_{10} R_n} \right| \tag{11}$$

where e is an emotion type of tweet, R_n is the measure of sensation reliability for each emotion type (Table 3) and n is the number of sensation types (i.e., $n = 5$). In other words, t^e_{bias} serves for adjusting the relation strength between an emotion and a sensation, since a specific emotion has varying influence on certain sensations as revealed in Section 3. For instance, we can assume implicit relations between an emotion and a sensation type with a small p-value (i.e., strong evidence) from chi-square test, such as anger with sight, joy with sight and hearing, and sadness with hearing and touch according to the results in Table 3.

5 | EXPERIMENTS

In order to quantify the effectiveness of the proposed features constructed based on sensation and emotion characteristics, we first carry out the classification task to determine whether a text is related to the sensation information or not. Furthermore, we next classify tweets to six classes including the five types of sensations (i.e., sight, hearing, touch, smell, and taste) as well as a non-sensation class, as a multi-class classification task. The result of the classification will be evaluated in terms of accuracy comparing with several baselines, such as NB, SVM, and Bi-LSTM classifiers. After classification, we will investigate the importance of each feature.

5.1 | Sensation classification

5.1.1 | Binary classification

First, we focus on the binary classification to recognize sensation information in social media. As decided in Section 3, sensation category of test data is classified by the average of the Likert scale value from the inter-annotator agreement. Since the experiment is conducted for binary classification, we assigned a tweet in our dataset to the sensation class, if it has any of values greater than 1 among all sensation types (hence, all values equal to 1 or less than 1 indicate non-sensation).

For the task, we consider four types of features proposed in Section 4 including tweet text and emotion types. The tweet text and features were converted to numerical values; that is, tweets were processed as word vectors using TF/IDF with bigram approaches (as having the best performance among unigrams, bigrams, and trigrams), emotion types were assigned as categorical values (i.e., emotion and non-emotion), and topics were converted to numbers by alphabetical order. The result of each classifier was evaluated by 10-fold cross validation in terms of accuracy, due to the lack of large datasets. The classification experiment was performed under the *python* environment using *tensorflow*, *scikit*, *nltk*, and *libsvm* (Chang & Lin, 2011) libraries.

Table 7 summarizes the results of binary classification on the overall task in terms of accuracy. The baseline methods are in the upper part, and the lower part illustrates our approaches using all the proposed features (Equations (5), (7), (8) and (10)). The results of the Neural network classifications (bi-LSTM) are better than the ones of the conventional classifiers (i.e., NB and SVM) when we only consider the tweet text for the classification. However, although Bi-LSTM showed the best performance among baselines, it is still not able to classify

TABLE 7 Experiment result of binary sensation classification

Classifiers	Accuracy (%)
Baseline methods (based on TF/IDF with bigram)	
Multinomial Naive Bayes	49.86
Support vector machine	51.76
Bi-LSTM	56.67
By all proposed features	
Multinomial Naive Bayes	63.82
Support vector machine	**70.13**

Note: Values in bold denote the best performance.

TABLE 8 Experiment result of multi sensation classification

Classifiers	Accuracy (%)
Baseline methods (based on TF/IDF with bigram)	
Naive bayes	42.21
Support vector machine	48.16
Bi-LSTM	50.33
With all proposed features	
Multinomial Naive Bayes	56.75
Support vector machine	**72.02**

TABLE 9 Feature effectiveness

Features	Accuracy (%)
Single feature	
Sensation intensity (I_T^c)	**66.12**
Sensation topic model (TP_{fN})	56.62
Co-occurrence sense word (CO_t^b)	57.75
Sensation-emotion correlation (CR_t)	56.48

the sensation information well (unlike, typically in the case of sentiment analysis studies). On the other hand, the lower part of the table shows remarkable results including the best result of 70.13% accuracy using SVM classifier. Even in the case of NB, the accuracy of 63.82% is the highest accuracy when compared with the results of baselines.

5.1.2 | Multi-sensory classification

We next investigate the multi-sensation classification according to each sensation type. All the same features are considered as in the case of the binary classification (i.e., the proposed features, emotion types, and tweet text). We trained baselines on six classes, including the classes representing the sensation types and the non-sensation class. As many tweets can be assigned to two or more classes due to multi-sensation expressions as identified in Section 3, several classes could be assigned to a tweet (i.e., multiple labels) at the same time, resulting thus in multi-sensory classification.

Table 8 describes the results of the multi-class classification using the same baselines and evaluation measurement as in the case of the binary classification. Since multi-class classification is generally more difficult than the binary classification, the results of the former are lower (almost 6% on average). Still however, our approaches demonstrate the best accuracy in comparison with the baselines. In particular, SVM equipped with our features shows remarkably better performance in comparison with the result of the binary classification. Although there are still many problems left, above all the lack of large sensation datasets, the results show that sensation classification can be effectively achieved even with a small amount of training data.

5.2 | Feature effectiveness

The proposed features derived from the emotion and sensation characteristics result in a better performance not only for the binary but also for the multi-sensation classification. In this section, we identify which features are actually important for the sensation classification. For this, we evaluated the accuracy of the classification using each individual feature only and then the combination of the features under the multi-sensation classification scenario.

Table 9 lists the results of classification based on each feature. In the experiment, we used the selected feature with text and emotion type only with the SVM classifier. As a result, the sensation intensity feature (5) is the most important feature (66.12% accuracy), while others ((7), (8), and (10)) result in the mid-50% level of the accuracy. Even though the sensation intensity feature shows the highest performance, other features used alone allow for better results than the ones of the baselines (see Section 5.1.1). From this result, we conclude that the proposed features can be applied to classify the sensation information from the emotion text.

In addition, we try to combine features based on the most important feature. In other words, we want to find which feature is well-suited to be used with the sensation intensity feature. Features are then combined with the sensation intensity feature (5) to verify the combination

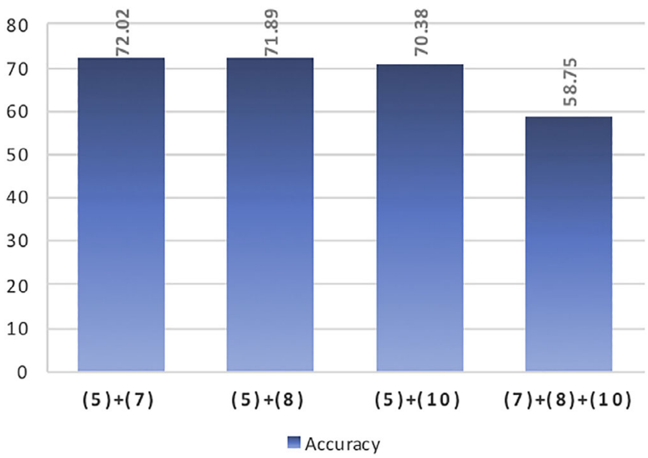

FIGURE 6 Combinations of features [Color figure can be viewed at wileyonlinelibrary.com]

performance. Moreover, the features (except feature (5)) are combined together, too.

As we can see in Figure 6, the first pair consisting of the sensation intensity and topic features shows the best performance of 72.02% accuracy. However, other pairs also give a good result with accuracy over 70%. Since, the *SD* over the three results was only 0.744, so there were not big differences when the features were combined with the sensation intensity feature. In the case of the combination of (7), (8), and (10), the result is 58.75% accuracy. This is still better than the baselines' result, however, lower than when considering sensation intensity feature. From this result, we observe that the best performance can be achieved when all the features are used for classification. Moreover, the *sensation intensity* feature is the most influential one in the sensation classification, as it turned out from the feature effectiveness analysis.

6 | CONCLUSIONS

The sensation information can be considered as an important factor for determining human emotions as well as behaviors, and has many applications as mentioned in the Introduction section. In this paper, we have focused on the emotion and sensation as reflected in social media data (tweets) to first reveal their correlation. In particular, we identified the correlation between emotion and sensation by using statistical approaches. In addition, the correlation values were later used as a feature to extract sensation information from tweet texts.

The used features reflected well the characteristics of emotions and sensations, including the relationships between topic and sensational expressions, co-occurrence words with sensation representations, and sensation-emotion correlations. Binary classification showed that our features achieved the best accuracy of 70.13% using SVM classifier. In the case of multi-sensation classification, the effectiveness of the proposed features was also proven achieving the outstanding result of 72.02%, about 20% greater than the one by the bi-LSTM classifier.

For the future work, we will design more elaborate features to boost the performance of sensation classification. In particular, we will construct the sensation knowledge database (e.g., ontology) to extract sensation concepts, in a similar way to SentiWordNet (Baccianella, Esuli, & Sebastiani, 2010), SentiWordSKOS (Brenga, Celotto, Loia, & Senatore, 2015b), WordNet-Affect (Strapparava & Valitutti, 2004) or SentiStrength (Thelwall, Buckley, Paltoglou, Cai, & Kappas, 2010) that are applied for sentimental analysis, and eventually we plan to open the database to the public for supporting further sensation-related studies.

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