18th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing

Extracting Gamers' Opinions from Reviews

Dorinela Sirbu, Ana Secui, Mihai Dascalu
Computer Science Department
University Politehnica of Bucharest
Bucharest, Romania
{maria.sirbu, ana.secui}@cti.pub.ro, mihai.dascalu@cs.pub.ro

Scott Andrew Crossley
Applied Linguistics & ESL
Georgia State University
Atlanta, USA
scrossley@gsu.edu

Stefan Ruseti, Stefan Trausan-Matu
Computer Science Department
University Politehnica of Bucharest
Bucharest, Romania
stefan.ruseti@cs.pub.ro, stefan.trausan@cs.pub.ro

***Abstract*—Opinion mining and sentiment analysis are a trending research domain in Natural Language Processing focused on automatically extracting subjective information, feelings, opinions, ideas or emotions from texts. Our study is centered on identifying sentiments and opinions, as well as other latent linguistic dimensions expressed in on-line game reviews. Over 9500 entertainment game reviews from Amazon were examined using a Principal Component Analysis applied to word-count indices derived from linguistic resources. Eight affective components were identified as being the most representative semantic and sentiment-oriented dimensions for our dataset. These components explained 51.2% of the variance of all reviews. A Multivariate Analysis of Variance showed that five of the eight components demonstrated significant differences between positive, negative and neutral game reviews. These five components used as predictors in a Discriminant Function Analysis, were able to classify game reviews into positive, negative and neutral ratings with a 55% accuracy.**

Keywords—Natural Language Processing; sentiment analysis; opinion mining; game reviews; lexical analysis

I. Introduction

The World Wide Web, which emphasizes social dimensions and online interaction, affords people the opportunity to share their opinions, thoughts and feelings digitally. For the most part, this data is freely available and can be used to examine discourse patterns. Much of this data is found on popular web sites such as Facebook, Twitter, Tumbler, YouTube or Amazon. From a practical perspective, online comments provided by people can play a major role in popularizing a movie, TV show, invention, or any number of media products. The attractiveness and popularity of a product can increase and decrease depending on the opinions, feelings and thoughts expressed by the people familiar with it.

Sentiment analysis tools usually focus on the identification of the overall affective feature of a text using Natural Language Processing techniques [1]. The text is analyzed in order to identify words or text segments that express sentiments, have subjective information and that can be used to categorize the text (usually into positive, neutral or negative classifications). Recently, opinion mining and sentiment analysis have become increasingly common and exploited because of the large amount of data found on the web [1]. Sentiment analysis has a broad applicability as it has been shown to be effective at determining the preferences of online users, the favorite candidate for an election, or readers' opinions towards specific news. Sentiment analysis has useful applications in industry because it allows businesses to see potential positive and/or negative reactions to a product they sell. In addition, sentiment analysis can provide insights through the analysis of online opinions in a manner that can sometimes be more useful than polls or written feedback because the comments cover a greater number and diversity of individuals. The comments can come from different genders, different social groups, celebrities, or politicians, thus providing a better overview of the overall sentiment towards the target entity.

The purpose of this study is to examine the potential usage of sentiment analysis to classify gaming texts into positive, neutral and negative opinions. Thus, the starting point of this study is to examine the natural language used to describe games in on-line reviews. In doing so, we introduce a sentiment analysis model for game reviews written in English. We plan to later extend this model to other languages, including French, Romanian and Dutch. In addition to classifying texts into positive, neutral and negative opinions, of particular interest are the emerging dimensions that characterize a successful game, including relations and communication, motivation, activities, and roles.

Overall, this study presents new methods and features to better understand user experiences in games from a linguistic point of view. The next section focuses on key approaches in opinion mining and sentiment analysis. The third section introduces our integrated method and the corpora used (which consists of 9,750 game reviews). The fourth section presents our results, which is followed by our conclusions and future work.

II. State of the Art

Sentiment analysis (or opinion mining) refers to the automatic extraction of semantic subjective information related to human feelings and opinions from natural language texts [1, 2]. Sentiments are therefore associated with opinions, feelings or emotions expressed by users, in our case, in written form. Sentiment analysis is widely adopted in different disciplines such as sociology, education, psychology, business, political science, and economics [2], as well as research fields such as

DOI 10.1109/SYNASC.2016.38

Natural Language Processing (NLP), data mining, and information retrieval [3].

There are two major NLP-based approaches for extracting sentiments, for which representative models are presented in the following paragraphs: one based on lexicons and the other employing machine learning techniques. However, we must highlight even from the beginning the limitations of the two major directions. While lexicon-based approaches usually fail to identify context-sensitive semantics due to isolated word occurrences, machine learning approaches require a large number of human labeled training examples [4]. In addition, context is very important for word meaning as some words indicate a positive sentiment in a context and induce a negative sentiment in another, an extremely delicate aspect when relying on bag-of-words approaches that disregard word order.

First, sentiment lexicon methods use sets of dictionaries in which bag-of-word vectors, reflecting the polarity of each concept (word or phrase) on certain dimensions, are used to classify texts into positive and negative valences. These vectors can contain information about semantic valences (e.g., negation or intensification) [5] and parts of speech [6], and can be split into two categories: domain dependent vectors (e.g. games review, movies review) and domain independent vectors (a general list of words). Domain dependent classifiers built on these vectors are pretty accurate in the domain they were trained in, but their main problem is underperformance if being used in other domains. Here is where domain independent vectors intervene and there are many dictionaries or tools, described in detail in the following section: The General Inquirer (GI), SenticNet, Affective Norms for English Words (ANEW), Geneva Affect Label Coder (GALC), Linguistic Inquiry and Word Count (LIWC) or EmoLex.

Second, machine learning approaches use supervised learning algorithms and different techniques are applied for classifying positive and negative opinions, such as: Naïve Bayes, Maximum Entropy and Support Vector Machines. Pak and Paroubek [7] analyze Twitter messages using Naïve Bayes and two classifiers were trained: one using n-grams presence and the other based on part-of-speech (POS) tags allocation. Their method was tested on 300,000 twitter posts while considering the emoticons used in the texts, as well. The results indicated that bigrams offer the best performance and increasing datasets lead to more precise data classification.

Pang and Lee provide an overview of the current techniques used in sentiment analysis [8] and discovered that machine learning methods applied on movie reviews provide better results than the simple counting ones [9]. One of the encountered difficulties consisted of comments with more negative words than positive ones, that actually reflect a positive review, or the other way around. In their paper, an example of a review of a movie with Spice Girls is presented in detail. The author starts by saying how he hates the group of girls and how he shouldn't have liked the movie, but in the end he concludes that the movie was amazing. For a human it is easy to observe that this comment is positive, but for a machine it's significantly more difficult due to the high contrast between the words. Similar situations are also encountered in game reviews, where users tend to emphasize the drawbacks of a game, whereas the final rating is subjective to a comparative view to other similar games. In a follow-up of their movie review analysis, Pang and Lee [8] discovered that results are significantly more accurate only by using subjective texts obtained after removing the sentences that are neutral. Their method of extracting only the subjective sections of a text is derived from the minimum-cut formulation.

In conclusion, there are multiple approaches that compete in the development of sentiment analysis models. The aim of this study is to introduce an extensible model, applicable for multiple languages, that is specifically tailored for game reviews. We select game reviews because they do not represent the primary focus of previous analyses.

III. METHOD

A. Selected Corpora

Our dataset consisted of 9750 game reviews from Amazon.com that were ranked on a 5 values Likert scale: rate 1 - "I hate it" (2108), rate 2 - "I don't like it" (1384), rate 3 - "It's ok" (1856), rate4 - "I like it" (2387) and rate 5 - "I love it" (2015). Crawler4j was used for extracting all relevant reviews with more than 50 content words from 44 games. A content word is a dictionary concept, not considered a stop-word (i.e., frequent word with no contextual information – "a", "at", "the"), and that has as corresponding POS tag a noun, verb, adjective or adverb.

B. Integrated Approach

We take as our foundation the approach used by Crossley, et al. [10] in their development of the sentiment analysis tool SEANCE (Sentiment Analysis and Social Cognition Engine). Like Crossley et al., we opted to integrate multiple linguistic resources consisting of various word lists or vectors used in general text classification, as well as words with particular semantic valence in accordance to predefined taxonomies. Even from the beginning we must highlight the main differentiator of this approach which is designed to provide multi-lingual sentiment analyses integrated in the *ReaderBench* framework (http://readerbench.com/, [11-13]). As stated in the introduction, this paper presents a pilot study for extracting gamers' opinions expressed in English language that will be later on extended using the *ReaderBench* framework which already supports multiple languages including English, French and Romanian, as well as partial support for Spanish, Dutch, Italian and Latin. This work considers the following linguistic resources and models for English language.

The *General Inquirer* (GI, http://www.wjh.harvard.edu/~inquirer/homecat.htm) [14] consists of 4 dictionaries: the Harvard IV-4 dictionary, the Lasswell dictionary, marker categories and another category based on social cognition. For our analysis, we selected from the Harvard IV-4 dictionary the following word categories:

1. Words expressing arousal (excitation, aside from pleasures or pains, but including arousal of affiliation and hostility), pleasure (enjoyment, confidence, interest and commitment),

vice (moral disapproval or misfortune) and virtue (moral approval or good fortune);

2. Words indicating overstatement (emphasis on speed, frequency, causality, quantity, accuracy, validity, scope, size, etc.) or understatement (de-emphasis and caution);
3. Words reflecting a sociological perspective, business (commercial, economic, industrial, or business orientation, including roles, collectivities, acts, abstract ideas), as well as expressivity (arts, sports, and self-expression);
4. Words referring to role (individual human behavior patterns), work (socially defined ways for doing work), interpersonal relations (including processes);
5. General references to humans (including roles), objects or communication (form, format or media corresponding to the communication transaction).

The *Lasswell* [15] dictionary refers to power, respect, rectitude, affiliation, skill, losses, gains, wealth, as well as: formats (including standards, tools and conventions of communication), additional skills (other skills than aesthetic, trades and professions), negative affect (negative feelings and emotional rejection), and positive affect (positive feelings, acceptance, appreciation and emotional support). *Marker categories* contain position adjective, degree adverbs, dimensionality adjective, evaluative adjective, frequency, emotions, color, social places, distance. The *categories based on social cognition* introduce adjectives referring to relations between people, verbs reflecting emotional states.

SenticNet [16] was extended from WordNet, contains about 13,000 words and provides a set of semantics, sentics and word polarities. Sentics refers to emotions evaluated by four affective dimensions: pleasantness, attention, sensitivity and aptitude. The polarity is a number between -1 and +1, where -1 means extreme negativity and +1 means extreme positivity.

Affective Norms for English Words (ANEW) [17] includes the associated scores for each word on three dimensions using a ten values Likert scales: affective (Happy/ Unhappy), arousal (Calm/ Excited) and dominance (Controlled/ In-Control). The first two dimensions are considered to form the core emotional state, while the third dimension (dominance) is less strongly related [18]. If the score is greater than 5 then the sentiment is positive, else it's considered negative.

The *Geneva Affect Label Coder* (GALC) [19] contains several word list referring to emotions (e.g., envy, joy, guilt) that are divided into multiple categories, such as: admiration, amusement, anger, boredom, desperation, disappointment, happiness, interest, pleasure, sadness, positive, negative, etc. The major problem with GALC is its low linguistic coverage as some lists contain only few concepts and are not representative for the whole corpora in terms of usage.

Linguistic Inquiry and Word Count (LIWC) [20] contains words that refer to psychological phenomena and personal concerns. LIWC is based on simple frequent words and does not consider parts of speech or negation rules. These words are divided in several categories out of which, for our study, we decided to rely on: affective processes (positive and negative emotions, anger, anxiety and sadness), perceptual processes (see, hear, feel), cognitive processes (causation, inhibition), personal concerns (assent, leisure, death), as well as relativity (time and space).

*EmoLex (*also known as the *NRC* Word-Emotion Association Lexicon [21]) vectors were obtained through a crowdsourcing experiment and consists of 10 lists of words and bigrams that express particular emotions (anger, anticipation, disgust, fear, joy, sadness, surprise and trust), besides general negative and positive emotions. In addition, two general opinion lexicons [22] with about 2,000 positive concepts and 4,500 negative concepts were also considered in our analysis.

In addition to these domain independent word vectors, we also decided to integrate the Stanford Core NLP sentiment analysis model [23] based on recursive deep models. Their Recursive Neural Tensor Network was trained on fine grained sentiment labels for 215,154 phrases from the parse trees of 11,855 sentences. In addition, their model is also capable of capturing the effects and scope of negation at various tree levels for both positive and negative phrases [23]. Although trained on movie reviews, there is a high similarity in language between film and game reviews, making appropriate the usage of their model within our integrated approach.

C. Principal Component Analysis

Starting from the individual word lists and resources mentioned beforehand, we conducted a Principle Component Analysis (PCA) in order to reduce the number of indices to a smaller set of components, representative for gaming. The PCA clustered the indices into groups that co-occurred frequently, enabling a macro-feature approach in which more than 200 word lists were reduced into a smaller set of derived variables (i.e., the components). A cutoff value of .4 for eigenvalues frequently used for PCA analyses was used to establish the inclusion of each index into a component, therefore ensuring that only strongly related indices are included in the analysis. All variables were first checked for linguistic coverage and for normal distribution. Afterwards, variables were checked for multicollinearity (defined as $r > .90$) so that the selected variables were not measuring the same construct. For the included component scores, we used the eigenvalues for each included index to create weighted component scores.

In total, 8 components were identified as being the most representative semantic and sentiment-oriented dimensions for our dataset, and explained 51.22 % of the variance in the game reviews (see Table I for loadings):

1. *Negative Emotions* was the strongest component and was derived from 7 lists that contain words with negative loadings expressing, for example, user frustration or functionalities that are not working well enough;
2. *Relations and Power* contains words about interpersonal relationships, as well as descriptions and quality of actions, and describes reviews talking about gameplay and action, available achievements, the relationships between game characters or with the other gamers in multiplayer sessions;

TABLE I. WORD LISTS INCLUDED IN EACH PCA COMPONENT.

Index	1	2	3	4	5	6	7	8
NRC Emotion Lexicon Negative	.86							
NRC Emotion Lexicon Anger	.79							
NRC Emotion Lexicon Fear	.77							
General Negative Opinion Lexicon	.76							
GI Negative (words of negative outlook)	.71							
GI Vice (moral disapproval / misfortune)	.62							
LIWC Negative Emotions (anxiety or fear, anger, sadness or depression)	.60							
GI Interpersonal Social Relations		.77						
GI Active orientation		.74						
GI Interpretive verbs		.70						
GI Strong (words implying strength)		.62						
GI Affiliation or supportiveness		.61						
GI Complete/goals were achieved		.59						
GI Power, control or authority		.54						
General Positive Opinion Lexicon			.79					
Stanford Sentiment Analysis Model			.63					
GI Virtue (moral approval or fortune)			.60					
GI Positive (words of positive outlook)			.59					
LIWC Affective/Emotional Processes			.52					
Lasswell Other Skills (e.g., aesthetic, trades and professions)				.84				
GI Expressivity (e.g., arts, sports, and self-expression)				.82				
LIWC Leisure activity (home, sports, television and movies, music)				.70				
ANEW Affective Norms for valence, pleasure, arousal, and dominance				.47				
NRC Emotion Lexicon Trust					.81			
NRC Emotion Lexicon Positive					.71			
NRC Emotion Lexicon Surprise					.66			
SenticNet Attention Dimension					.42			
GI Human (general references to humans, including roles)						.94		
GI Role (identifiable individual human behavior patterns)						.94		
GI Communication (form, format or media of communication transaction)							.91	
Lasswell Formats (format, standards, tools and conventions of communication)							.90	
GI Emotion								.77
GI Passive orientation								.67

3. *Positive Emotions* contained word lists that have positive loadings and emotions, including: General Positive Words, GI Positive or GI Virtue;
4. *Activities and Skills* contained different actions in the game, activities and their characteristics reflected by lists like: GI Expressivity and LIWC Leisure activity;
5. *Motivation* comprised the overall impression induced by the game as it incorporates words showing a general positive emotion (e.g., trust, surprise, attention);
6. *Human and Roles* described human functions like leader or authority, expressed in reviews that contain characters that are for example commanders or that talk about multiplayer modes for games (e.g., “Call of Duty”);
7. *Communication* contains words that talk about ways and types of communication derived from two word lists: GI Human and GI Role;
8. *Ambiguous and Passive Language* comprises words that do not have an active meaning, including concepts like “admire”, “admiration”, “passive”, or “fell”.

IV. RESULTS

A Multivariate Analysis of Variance (MANOVA) [24] was conducted using the eight PCA components as the dependent variables and three categories of game reviews (*positive* – ratings of 4, 5; *neutral* – ratings of 3; and *negative* – ratings of 1 and 2) as independent variables. MANOVA is a method commonly used to compare multivariate sample means, thus highlighting relationships between dependent and independent variables. All components (input variables) were normally distributed and no multicollinearity ($r < .899$) was reported between any variables. The MANOVA indicated that six of our previously identified components, representative of game reviews, demonstrated significant differences between the three categories of game reviews (in descending order of effect size, see Table II): Positive Emotions, Negative Emotions, Relations and Power, Activities and Skills, Humans and Roles, Ambiguous and Passive Language.

The six significant variables from the MANOVA analysis were used as predictor variables in a Discriminant Function Analysis [25] classification. The significance level for a variable to be entered or removed from the model was set at $p \leq .05$.

TABLE II. DESCRIPTIVE AND MANOVA STATISTICS FOR GAME REVIEWS.

PCA Component	Negative reviews M (SD)	Neutral reviews M (SD)	Positive reviews M (SD)	*F*	*p*	η^2 partial
1. Negative Emotions	0.25 (1.04)	0.12 (0.94)	-0.25 (0.93)	272.10	<.01	.053
2. Relations and Power	0.12 (1.03)	-0.02 (0.98)	-0.08 (0.97)	39.22	<.01	.008
3. Positive Emotions	-0.50 (0.83)	-0.06 (0.85)	0.42 (0.99)	1004.72	<.01	.171
4. Activities and Skills	0.10 (1.00)	-0.11 (0.91)	-0.04 (1.03)	32.13	<.01	.007
5. Motivation	0.02 (1.05)	0.03 (0.95)	-0.03 (0.98)	2.66	.07	.001
6. Humans and Roles	-0.06 (1.04)	0.03 (0.98)	0.03 (0.98)	9.01	<.01	.002
7. Communication	0.00 (1.06)	0.04 (0.96)	-0.01 (0.97)	1.82	.163	.000
8. Ambiguous and Passive Language	0.03 (1.06)	0.01 (0.95)	-0.03 (0.98)	3.67	.025	.001

The stepwise DFA retained the first 5 variables and the results demonstrate that the DFA using these 5 component scores correctly allocated 5,371 of the 9,750 game reviews in the total set, $\chi 2$ ($df = 4$, $n = 9{,}750$) = 51.750, $p < .001$, for an accuracy of 55.1% (the chance level for this analysis is 33.3%). For the leave-one out cross-validation (LOOCV), the discriminant analysis allocated 5,364 of the 9,750 game reviews for an accuracy of 55.0% (see the confusion matrix in Table III for detailed results). The measure of agreement between the actual game rating and that assigned by our model produced a weighted Cohen's Kappa of .309 demonstrating fair agreement.

TABLE III. CONFUSION MATRIX FOR DFA CLASSIFYING GAME REVIEWS

	Valence	Predicted Group Membership		
		Negative	Neutral	Positive
Original	Negative	2122	820	550
	Neutral	631	648	577
	Positive	736	1065	2601
Cross-validated	Negative	2120	821	551
	Neutral	632	646	578
	Positive	736	1068	2598

V. CONCLUSIONS AND FUTURE WORK

This research, which aims to provide a better understanding of gamers' opinions, is important because it provides information about the language used by gamers when expressing opinions about game quality. To date, only a few papers focusing on gaming topics exist, although it is a very popular activity among people of all ages. Starting from a corpus of 9,750 game reviews collected from Amazon, we were able to perform a PCA that yielded eight components that explained more than 50% of the variance in language across all game reviews. The performed DFA classification highlighted promising insights into the language used by gamers to classify game quality. As expected, neutral reviews were the hardest to predict because they actually represent a mixture of positive and negative opinions.

Our model opens new educational perspectives in terms of evaluating gamers' opinions and engagement in serious games. The extensibility of our approach, corroborated with a shift towards learning, can be used to better understand learner's opinions and to facilitate an in-depth assessment of their text productions. The emergent dimensions identified within the conducted PCA analysis provide the mechanisms to automatically evaluate learners' interests and opinions based on their reviews and feedback in serious games.

In terms of future directions, our next steps will consider the integration of valence shifting as reported in Crossley et al. [10] and focusing only on positive and negative reviews (and disregarding neutral statements). Our approach should be extendible allowing multi-lingual models based on specific language resources to be trained to accommodate the evaluation of game reviews written in French, Dutch and Romanian languages.

ACKNOWLEDGMENT

The work presented in this paper was partially funded by the EC H2020 project RAGE (Realising and Applied Gaming Eco-System) http://www.rageproject.eu/ Grant agreement No 644187, as well as by the FP7 208-212578 LTfLL project. This paper represents a detailed view of the experiments performed by the authors which were first introduced in [26].

REFERENCES

[1] B. Liu, *Sentiment Analysis and Opinion Mining*. San Rafael, CA: Morgan & Claypool Publishers, 2012.

[2] C. J. Hutto and E. Gilbert, "Vader: A parsimonious rule-based model for sentiment analysis of social media text," in *8th Int. AAAI Conf. on Weblogs and Social Media*, Ann Arbor, MI, 2014, pp. 216–225.

[3] H. Zhang, W. Gan, and B. Jiang, "Machine Learning and Lexicon Based Methods for Sentiment Classification: A Survey," in *11th Web Information System and Application Conference (WISA 2014)*, Tianjin, China, 2014, pp. 262–265.

[4] O. K. M. Cheng and R. Y. K. Lau, "Probabilistic Language Modelling for Context-Sensitive Opinion Mining," *Scientific Journal of Information Engineering,* vol. 5, pp. 150–154, 2015.

[5] L. Polanyi and A. Zaenen, "Contextual Valence Shifters," in *Computing Attitude and Affect in Text: Theory and Applications*, J. G. Shanahan, Y. Qu, and J. Wiebe, Eds., ed Dordrecht: Springer Netherlands, 2006, pp. 1-10.

[6] A. Hogenboom, F. Boon, and F. Frasincar, "A Statistical Approach to Star Rating Classification of Sentiment," in *1st Int. Symposium on Management Intelligent Systems*, Berlin, Heidelberg, 2012, pp. 251-260.

[7] A. Pak and P. Paroubek, "Twitter as a Corpus for Sentiment Analysis and Opinion Mining," in *LREC 2010*, Valletta, Malta, 2010.

[8] B. Pang and L. Lee, "Opinion mining and sentiment analysis," *Foundations and Trends in Information Retrieval,* vol. 2, pp. 1–135, 2008.

[9] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs Up? Sentiment Classification Using Machine Learning Techniques," in *Conf. on Empirical Methods in Natural Language Processing (EMNLP 2002)*, Philadelphia, PA, 2002.

[10] S. Crossley, K. Kyle, and D. S. McNamara, "Sentiment Analysis and Social Cognition Engine (SEANCE): An Automatic Tool for Sentiment, Social Cognition, and Social Order Analysis," *Behavior Research Methods,* in press.

[11] M. Dascalu, *Analyzing discourse and text complexity for learning and collaborating, Studies in Computational Intelligence* vol. 534. Cham, Switzerland: Springer, 2014.

[12] M. Dascalu, L. L. Stavarache, P. Dessus, S. Trausan-Matu, D. S. McNamara, and M. Bianco, "ReaderBench: An Integrated Cohesion-Centered Framework," in *10th European Conf. on Technology Enhanced Learning*, Toledo, Spain, 2015, pp. 505–508.

[13] M. Dascalu, L. L. Stavarache, S. Trausan-Matu, P. Dessus, M. Bianco, and D. S. McNamara, "ReaderBench: An Integrated Tool Supporting both Individual and Collaborative Learning," in *5th Int. Learning Analytics & Knowledge Conf. (LAK'15)*, Poughkeepsie, NY, 2015, pp. 436-437.

[14] P. Stone, D. C. Dunphy, M. S. Smith, D. M. Ogilvie, and associates, *The General Inquirer: A Computer Approach to Content Analysis*. Cambridge, MA: The MIT Press, 1966.

[15] H. D. Lasswell and J. Z. Namenwirth, *The Lasswell Value Dictionary*. New Haven: Yale University Press, 1969.

[16] E. Cambria, M. Grassi, S. Poria, and A. Hussain, "Sentic computing for social media analysis, representation, and retrieval," in *Social Media Retrieval*, N. Ramzan, R. Zwol, J. S. Lee, K. Clüver, and X. S. Hua, Eds., ed New York, NY: Springer, 2013, pp. 191–215.

[17] M. M. Bradley and P. J. Lang, "Affective norms for English words (ANEW): Stimuli, instruction manual and affective ratings," The Center for Research in Psychophysiology, University of Florida, Gainesville, FL1999.

[18] A. Mehrabian and J. A. Russell, *An approach to environmental psychology*. Cambridge, US: MIT Press, 1974.

[19] K. R. Scherer, "What are emotions? And how can they be measured?," *Social science information,* vol. 44, pp. 695–729, 2005.

[20] J. W. Pennebaker, R. J. Booth, and M. E. Francis, "Linguistic inquiry and word count: LIWC [Computer software]," in *Austin, TX: liwc. net*, ed. Austin, TX: University of Texas, 2007.

[21] S. M. Mohammad and P. D. Turney, "Crowdsourcing a word–emotion association lexicon," *Computational Intelligence,* vol. 29, pp. 436–465, 2013.

[22] M. Hu and B. Liu, "Mining and Summarizing Customer Reviews," in *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD-2004)*, Seattle, WA, 2004.

[23] R. Socher, A. Perelygin, J. Y. Wu, J. Chuang, C. D. Manning, A. Y. Ng, *et al.*, "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank," in *Conf. on Empirical Methods in Natural Language Processing (EMNLP 2013)*, Seattle, WA, 2013.

[24] G. D. Garson, *Multivariate GLM, MANOVA, and MANCOVA*. Asheboro, NC: Statistical Associates Publishing, 2015.

[25] W. R. Klecka, "Discriminant analysis," Sage Publications, Thousand Oaks, CA1980.

[26] A. Secui, M. D. Sirbu, M. Dascalu, S. A. Crossley, S. Ruseti, and S. Trausan-Matu, "Expressing Sentiments in Game Reviews," in *17th Int. Conf. on Artificial Intelligence: Methodology, Systems, and Applications (AIMSA 2016)*, Varna, Bulgaria, 2016.