

Deep Learning for Automated Sentiment Analysis of Social Media

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ABSTRACT

The spread of information on Facebook and Twitter is much more efficient than on traditional social media platforms. For word-of-mouth (WOM) marketing, social media have become a rich information source for companies or scholars to design models to examine this repository and mine useful insights for marketing strategies. However, social media language is relatively short and contains special words and symbols. Most natural language processing (NLP) methods focus on processing formal sentences and are not well-suited to such short messages. In this study we propose a novel sentiment analysis framework based on deep learning models to extract sentiment from social media. We collect data from which we compile a dataset. After processing these special terms, we seek to establish a semantic dataset for further research. The extracted information will be useful for many future applications. The experimental data have been obtained by crawling several social media platforms.

.KEYWORDS: Sentiment analysis, deep learning; social media

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1 Introduction

Social media platforms such as Facebook and YouTube collect massive amounts of user reviews, forming a rich source of information for companies to understand their customers. Word-of-mouth (WOM) marketing activities also positively influence customer purchase decisions. Messages posted on social media have a great impact on and provide guidance for individuals, organizations, and social communities in the decision-making process [1].

These reviews and messages can be used to analyze opinions towards different brands, companies, products, and even individuals. Sentiment analysis is the process of determining whether a given text or speech is positive, negative, or neutral. Many text mining algorithms are based on NLP techniques such as part-of-speech tagging (POG), syntactic parsing, and other types of linguistic analysis [2].

Sentiment analysis has gained popularity with the rise of Web 2.0. However, natural language processing tools are not always useful in the social media domain [3]. Unlike product reviews and lengthy comments, microblogs (e.g., tweets) and messages posted on fan pages are short and informal text. Social media language is relatively short and contains special words including emoticons, emphasis, and social media slang. In emoticons, specific characters are used to express emotions. Slang words include lol and omg. These words are usually important for sentiment analysis, but are not always included in sentiment lexicons [4]. Traditional NLP cannot be used to process such text. We extend our previous approach [5] in which we apply opinion mining techniques to analyze movie reviews obtained from IMDb fan pages. In this study we propose a deep-learning based framework to handle slang and special social language. Taking into account such special terms, we mine crowd intelligence by processing customer reviews from different types of social media. We will publish our own semantic database for further research

. 2 Related work

Esuli and Sebastiani [6] develop the SentiWordNet lexicon which contains the opinion strength for each term. SentiWordNet has been used to classify reviews [7] and to identify aspects of a review [8]. Allahyari, Pouriyeh, Assefi, Safaei, Trippe, Gutierrez and Kochut [2] suggest preprocessing text using tokenization, filtering,

lemmatization, and stemming. Rout, Choo, Dash, Bakshi, Jena and Williams [9] apply both unsupervised and supervised approaches for sentiment identification of tweets. Their experiment illustrates a supervised approach in which the combination of unigram, bigram, and part-of-speech features is proved efficient in finding the emotion and sentiment of unstructured data. Deep neural networks (DNNs) can be described as a set of neuron layers, each layer outputting a modified version of its input to the next layer. DNN is a kind of supervised machine learning and has achieved success in various tasks [10]. Convolutional neural networks (CNNs) are a widely used type of DNN consisting of convolutional layers and pooling layers. Recurrent neural networks (RNNs) are effective approaches for sequential data modeling, maintaining hidden states for long-term history. Long short-term memory

(LSTM) based networks are composed of an input layer, one or more hidden layers, and an output layer. LSTM networks have been shown successful for many NLP tasks [11].

Bidirectional long short-term memory (BiLSTM) networks utilize NLP tools and employ a bidirectional RNN to learn patterns of relations from raw text data [12]. Gated recurrent units (GRUs) have shown success in several applications involving sequential or temporal data [13]. In this study we apply LSTM, BiLSTM, and GRUs.

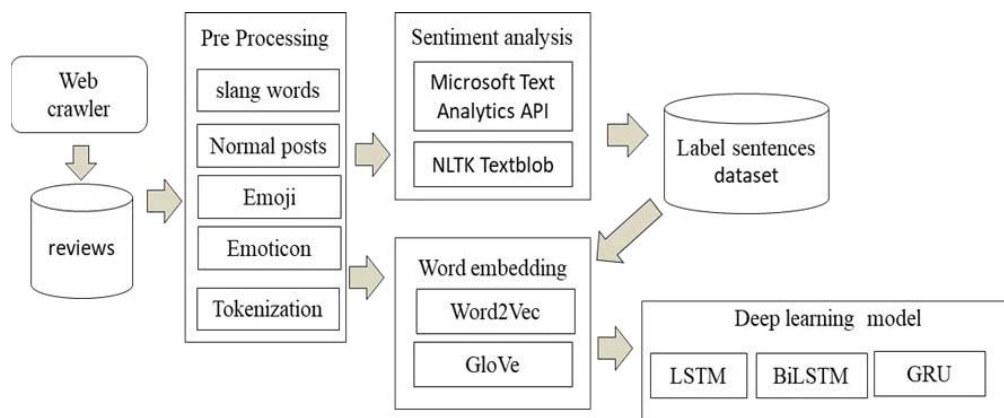


Figure 1. Proposed framework

3 PROPOSED FRAMEWORK

Social media is an effective platform for movie WOM marketing. This study proposes a framework based on deep learning models to process movie reviews. The proposed framework contains several modules and is illustrated in Figure. 1. Below we describe these modules in detail.

- **Web crawler:** In the first module we use a Python crawler to collect review data from sources such as YouTube and Facebook. We will follow our previous design [5] to collect data for experiments.
- **Preprocessing:** The short messages are informal and contain special words and symbols, including emoticons and slang. As such we cannot use standard natural language processing (NLP) tools to preprocess these reviews. Figure. 2 is a typical example of a short message. It is an informal post containing special expressions such as LOOOL, abbreviations, emoji (“😊”), and emoticons (“:))”).

“LOOOL. The movie is gr8😊:))):)”

Figure 2. Review extracted from fan page

- Laughing can be represented as hahah, lol, rofl, and lmao. Authors use words such as OMGGGGG with repeated letters to emphasize their feelings [14]. In our algorithm we define rules to eliminate these extra letters. In the example above, we separate the parts illustrated in Figure. 3. The first part is LOOOL, which can be converted to token lol.

“LOOOL. The movie is gr8😊:))):)”

- Different parts of a review
- Chat messages make rich use of slang. Thus it is important to detect, translate, and identify the polarity of slang for determining the sentence’s semantic orientation. We convert these slang words into their standard forms using the Internet slang word dictionary illustrated in Table 1, and then add them to the post [3].

Table 1 Slang dictionary

Slang term	Meaning
AFAIK	As far as I know
LOL	laugh out loud

GR8	great
...	...

The second part is gr8, which in the slang dictionary maps to great. Common acronyms such as omg are expanded into their known full forms (oh my god) [15].

Additionally, posts include emoticons such as :) , :D, of :(, and ;). Emoticons are widely used in social media channels; 20% of all posts contain emoticons. Wikipedia contains a complete emoticon table, including :-), (^ ^), (> <), and so on.

- **Labeled normal posts:** Sentiment analysis can be used to extract and analyze the thoughts and feelings of comments written about a specific target movie. In this study, we apply three tools to analyze the sentiment of user posts: NLTK Textblob, and the Google Cloud Natural Language API. NLTK, the Natural Language Toolkit, is a Python package that assists programmers in solving natural language processing problems [16]. We evaluate each sentence using these three tools to produce a sentiment score. According to the voting results, each sentence is labeled either positive or negative. Examples are given in Table 2.

Table 2 Example sentences

ID	Comment	NLTK	Google	Our Label
1	That movie it's amazing	1	1	1
2	I do not likethe actors play	0	0	0
3	Hardy it's thebest one ever ;)	1	1	1

As shown in Figure. 3, each sentence is analyzed using several steps including shrinking, slang mapping, sentence labeling, and tokenization.

Comment 1 = "LOOOL. The movie is gr8☺:)):):")

Shrink	"lol. the movie is gr8☺:)):):")
Slang mapping	"laugh out loud. the movie is great☺:)):):")
Sentence labeling	"laugh out loud. the movie is great☺:)):):") Label = 1 (Positive)
Tokenization	['lol', 'the', 'movie', 'is', 'gr8', '☺', ':)', ':)', ':)'] Label = 1 (Positive)

Figure 3: Example of sentiment analysis results

- **Word embedding:** There are two common ways to represent a document as a vector: bag of words (BOW) and term frequency inverse document frequency (TF-IDF). However,

the average social media text is only 28 characters long, which makes these two methods unsuitable [17], as such a data matrix is very sparse. In word2vec, a novel word-embedding procedure, the model learns a vector representation for each word using a neural network language model [18]. Global vectors for word representation (GloVe) is a specific weighted least-squares model that maps words onto a meaningful space where the distance between words is related to semantic similarity [19]. We use word2vec [20] and GloVe for word representations of input words [21].

To evaluate the effectiveness of semantic embedding for emotion detection, we train our three deep learning models using each of these embeddings. As shown in Figure. 4, we conduct experiments on LSTM, BiLSTM, and GRU models.

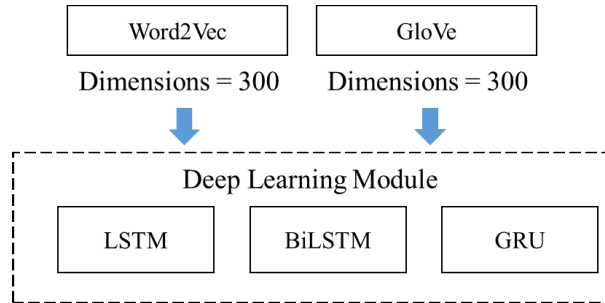


Figure 4. Proposed sentiment analysis models

We label each sentence with a sentiment to compile a training dataset containing an equal number of positive and negative sentences. After preprocessing the training dataset with word embeddings, we build the three deep-learning based sentiment classification models.

To evaluate the performance of the proposed model, we crawled trailer comments at YouTube to obtain experimental data. A snapshot of the crawled data is shown in Figure.5.

From this data we selected 3000 positive sentences and 3000 negative sentences. The proposed sentiment analysis models were used to build a classifier trained on the labeled dataset to predict sentiment. We compared the three proposed sentiment analysis models by evaluating their classification performance in terms of precision, recall, F-measure, and accuracy. The results are summarized in Table 3

movieName	releaseYear	releaseMonth	MIDiaIMDb	channelName	videoTitle	videoid_resp	commentId	authorDisplayName	textDisplay	likeCount	publishedAt	updatedAt
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	Ug9Gme-c477fYOpUR4AaABAg	slav slalovich	Nice propaganda for brainless sheep	0	2018-01-17T11:25:09.000Z	2018-01-17T11:25:09.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	Ugw0mzZ_YAImTilpM4AaABAg	RIPkripper	Tom Petty cover? too soon. TOO SOON!	6	2017-10-20T13:39:27.000Z	2017-10-20T13:39:27.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	UgymfZKoiNda474bCR14AaABAg	BOI 19	<a href="https://www.youtube.com/watch?v=Dencii...	0	2018-01-17T10:55:01.000Z	2018-01-17T10:55:01.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	UgwTbCFBFOmVS-Z4AaABAg	piere rockpiere	This movie deserves an Oscar like if agree	0	2018-01-17T10:07:53.000Z	2018-01-17T10:08:05.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	Ug996gpkly1Y6VUq94AaABAg	*BlEj *	This looks like in the COD black ops 2	0	2018-01-17T09:57:06.000Z	2018-01-17T09:57:06.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	Ugw9jhaUaUqfo008-v4AaABAg	A-Team Online Marketing	You all know that this was an inside job and America...	0	2018-01-17T08:02:01.000Z	2018-01-17T08:02:01.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	Ugdcf14Mqyrb6R9j61F4AaABAg	pwnedafel	I like how actors are sent war until they are shown a c...	0	2018-01-17T06:45:07.000Z	2018-01-17T06:45:07.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	UgCRthhFZAJa8354AaABAg	Alpha Omega	America is Evil country. Controlled by Elite jew	0	2017-10-20T13:27:37.000Z	2017-10-20T13:27:37.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	Ugw0YDVZF1oRb9p3kV4AaABAg	Alpha Omega	What special force	0	2017-10-20T13:26:34.000Z	2017-10-20T13:26:34.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	Ug2Nm55mam3YD22D4AaABAg	Spidey_unbosers	Looks better than the crap Charlie sheen is in	0	2017-10-20T13:24:15.000Z	2017-10-20T13:24:15.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	Ugw0U4x0Hm9ZGHjM4AaABAg	Antonio Kuro	Some of this was filmed on an Indian reservation wh...	0	2018-01-17T06:03:51.000Z	2018-01-17T06:03:51.000Z
12 Strong	2018	1	tt413492	Warner Bros. Pictures	12 STRONG - Official Trailer	-Dencie5oA	Uv9B4ZiOvnh1Vd0uoM4AaABAg	davidnash2003	truroazende	0	2018-01-17T05:23:34.000Z	2018-01-17T05:23:34.000Z

Figure 5 Snapshot of collected dataset

t

Table 3 Experimental results

	Accuracy	Precision	Recall	Specificity	F1 score
LSTM	80.83%	81.03%	80.32%	74.47%	80.54%
BiLSTM	87.17%	85.80%	88.89%	82.88%	87.29%
GRU	64.92%	64.33%	65.71%	63.61%	64.96%

4 Conclusion and future work

Sentiment analysis is a useful tool to analyze user-generated content on social media sites. However, the complexity and dynamic nature of social media data makes it difficult to accurately identify sentiment. We collect reviews from social media platforms to build a dataset for future research. To analyze comments extracted from social media platforms, we propose three deep learning based models to classify review sentiment. In the future, we will build a framework based on the proposed sentiment models to analyze the crawled intelligence from our review dataset.

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