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Microblog Sentiment Analysis for Celebrity Endorsed Products

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Abstract: Celebrity endorsed products such as NBA basketball star player endorsed shoes are typical examples of star marketing. For the purpose of star marketing, companies need to monitor customer's emotion and sentiment to celebrities through social media such as Twitter, Instagram and Facebook. One step forward, in this study, we aim to predict sales of celebrity endorsed products using sentiment analysis on social media data on celebrities. Major fan group of celebrities are usually young generation and they use social media popularly and frequently to share their emotion on celebrities. To apply sentiment analysis on the context we propose a sentiment lexicon modification method based on supervised learning approach. Based on manually evaluated social media contents on celebrities we identify domain-specific terms and their polarities which can contribute to improve sentiment analysis performance. Using tweets on 10 NBA basketball star players and their endorsed shoes sales data we perform experiments to show the usefulness of the proposed approach.

Key words: Start marketing, celebrity endorsed products, sentiment analysis, sentiment lexicon, NBA basketball

INTRODUCTION

In the modern world, celebrities appear in every aspect of a person's daily life whether it be through online or offline marketing. Companies have taken note of this growing celebrity influence and have found a way to market stars as a bridge between the consumer and brand. Primarily towards young adults who follow current stars and events more attentively, celebrities have become one of the pillars of marketing these days. This influence has been significant today, an example of such being star NBA basketball players who endorse shoes with their own names. These players do not simply advertise the shoes they define the shoes and become part of an identity that directly connects with the consumers.

Star marketing goes beyond simply commercial models or product promotion; it presents important social, economic and cultural implications based on how it is used and perceived. Thus, star marketing has a strong enough influence to affect brand recognition, commercial effects and even buying behavior. It therefore, safe to assume that star marketing will expand itself even more within markets such as the sports, fashion and food industries. A central part of star marketing, celebrity endorsements are the contractual agreements of well known people such as athletes and movie stars, to use and endorse specific products (Erdogan, 1999). The influence of celebrities is significant in advertising, brand recognition and recall and purchase intention and behavior.

The cultural impact of celebrities in star marketing makes it highly correlated to social media use amongst customers. Especially for young adults, social media has become the platform by which networking is done and the preferred platform to receive and send information. To use star marketing effectively, companies need to understand consumer's sentiments or emotions to celebrities on social media in order to select proper celebrities who will contribute to their product sales and brand image. As a part of text mining, sentiment analysis techniques can be applied to analyze consumer's emotion to celebrities using social media data.

There are different sentiment analysis approaches including "bag-of-words" approach, statistic approach and hybrid approach (Cambria, 2016). Even though "bag-of-words" approach has clear limitations by ignoring linguistic rules and only considering terms in documents, it is popularly used due to its simplicity and cost efficiency. In the "bag-of-words" approach, sentiment dictionaries or lexicons have central roles to classify

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documents. Lexicons include terms and their polarities. There are several available sentiment lexicons such as VADER (Valence Aware Dictionary for Entiment Reasoning), SentiWordNet, SenticNet and MPQA (Esuli and Sebastiani 2006; Wiebe *et al*., 2005). These sentiment lexicons provide rich sets of sentiment terms and work for the foundation of sentiment analysis. However, these dictionaries can fail to provide appropriate performance when the application domain includes many domain specific terms and domain specific polarities.

Texts on celebrities in social media are short and casual and reflect young adult's terms and slangs. So to apply sentiment analysis on such contents, it is necessary to update sentiment lexicons to improve the performance of sentiment analysis. In this study, we propose a sentiment lexicon update method based on supervised learning approach. Also, an experiment has been performed to show the usefulness of the proposed approach using real tweets of NBA basketball star players.

Literatur review: Recently, the term "celeb-economy" has appeared as value of celebrities continue to increase, testament to the power celebrities hold. With brands competing against each other to differentiate themselves, various types of advertisement and marketing strategies have been developed and utilized. However, delivering a clear and effective message that persuades the consumer is not an easy task and celebrity endorsements have shown to be a bright spot in this regard. Specifically, celebrities are able to clearly and persuasively deliver brand messages and content which explains this recent growth trend.

A product can be divided into two types, a utilitarian product and a hedonic product. A sentiment analysis approach is more appropriated for a hedonic product, since purchase action of this type of product is especially associated with pleasure, fun or self-expression (Kim and Lee, 2013). In this respect, the sentiment analysis of social media is especially important for the marketing of celebrity endorsed products.

Sentiment analysis refers to techniques to identify and extract subjective information in source materials using natural language process, text analysis and computational linguistics (Cambria, 2016). Sentiment analysis can be used for various purposes. One typical example is for understanding consumer's attitude or emotion to products, brands and companies using social media data (He *et al*., 2013; Mostafa, 2013). Also, it can be used to sensing public opinions of social issues and political issues (Kim and Kim, 2014; Tumasjan *et al*., 2010). It can be used to predict stock prices, movie sales and product sales (Jeong *et al*., 2015; Lee *et al*., 2016).

There are several issues to apply sentiment analysis on micro-blog data such as tweets in Twitter (Barbosa and Feng, 2010; Camara *et al*., 2014). One problem is that a text in micro-blog is limited in length. Due to the space limitation, users use abbreviations and slang.

There are different approaches to integrate domain-specific semantics in sentiment analysis. A common approach is updating or modifying lexicons to reflect domain-specific semantics in terms and their polarities. Machine learning approaches can be applied to update lexicons (Lee *et al*., 2016). Collective intelligence approach also tries to use the power of crowd (An and Kim 2015; Spry *et al*., 2011).

In this study we use VADER as a base sentiment analysis tool. VADER is a sentiment analysis tool which reflects characteristics of texts on social media. Its lexicon is developed considering linguistic rules of online texts and emoticons. A previous research shows relatively high performance on Twitter data, movie review data and product review data than other lexicons.

MATERIALS AND METHODS

Sentiment analysis for sale prefiction of athlete endorsed shoes: In this study, we aim to predict sales of athlete endorsed shoes using sentiment analysis. Specifically, we try to use tweets on Twitter about star players as the main input in predicting sales volumes of athlete endorsed shoes.

We collect sales data and tweets on 10 famous NBA players during 2010-2011 and 2014-2015 seasons. Sales data is gathered by web sites such as Matt Powell and Forbes or by requesting via e-mail to sports data professionals. The tweets which mention the players are collected using a web crawling program and the detail numbers of tweets per player and season are shown in Table 1. The total number of records (per player and season) is 39.

The basic approach in predicting sales volumes using sentiment analysis is following. First we apply sentiment analysis algorithm VADER (Valence Aware Dictionary Entiment Reasoning) to calculate sentiment polarities of tweets (He *et al*., 2013). Based on calculated sentiment polarities which are close to 1 if it is positive or close to-1 if it is negative, sentiment polarity of a player per season is calculated as the average of sentiment polarities of tweets of the player per season. Using two input variables, volume of tweets and sentiment polarity of tweets, we generate a linear regression model to predict sales volumes (Table 2).

Table 1: Sales and the number of tweets per player

Players	Season	Sales (M.USD)	No. of tweets
Lebron James	10-11	80	313
Lebron James	11-12	50	6547
Lebron James	12-13	300	16982
Lebron James	13-14	300	12412
Lebron James	14-15	340	8796
Kevin Duran	10-11	7	948
Kevin Duran	11-12	7	3760
Kevin Duran	12-13	7	3850
Kevin Duran	13-14	7	12339
Kevin Duran	14-15	7	10401
Kyrie Irving	14-15	7	10791
Kyrie Irving	15-16	51	12400

Table 2: Initial regression model to predict sales

Variables	B	SE	Sig.
Constant	14.474	34.643	0.679
Volume of tweets	0.002	0.000	0.000***
Polarity of tweets	-236.694	282.505	0.408

$R^2 = 0.832$; N = 39; *, **, ***p<0.1<0.05<0.01

In Table 2, R^2 is 0.832 which implies the social media data is valuable to predict sales of athlete endorsed shoes. However, it is necessary to notice the coefficient of 'Polarity of Tweets' is negative and insignificant. That is opposite to our expectation; the polarity of tweets is positively correlated with sales. We reviewed the sentiment analysis results and found that the quality of sentiment analysis was poor due to disregarding domain specific semantics of terms of younger adults.

Integration of domain-specific semantics for sentiment analsysis: To improve the performance of sentiment analysis on celebrity-related mentions in social media we update the original lexicon using supervised learning approach. To perform supervised learning we prepare two data sets: training data set and test data set. Records of two data sets are randomly selected from tweets of 10 players during five seasons from 2010-2011 to 2014-2015. Two data sets are disjoint and each data set consists of 1,000 records. The polarities of tweets are evaluated by two basketball fans. To enhance reliability of judgements, two person's evaluations are compared and final decisions are made based on discussion of two persons when initial judgements on a tweet are split. The polarity of a tweet is classified into three categories: positive, neural and negative. The distributions of two data sets are shown in Table 3.

To improve the performance of sentiment analysis we perform two operations to the lexicon: polarity updates on existing terms and additional term addition. The detail procedure to update the original lexicon is shown in Fig. 1.

Table 3: Polarity distribution of two data sets

Data set	Positive	Neutral	Negative	Total
Train set	279	597	124	1,000
Test set	264	611	125	1,000
Total	543	1,208	249	2,000

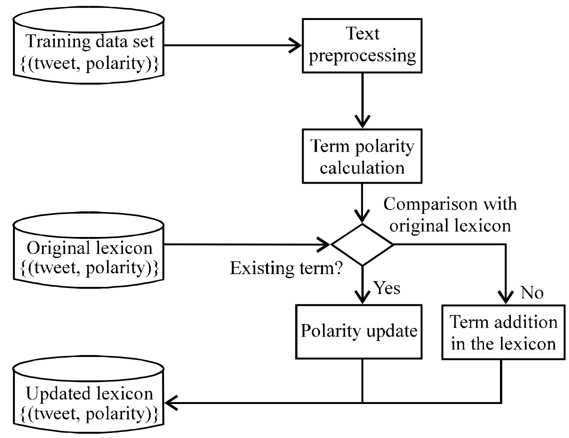

Fig. 1: Lexicon update procedure

Training data set includes pairs of a tweet and its polarity (N = 1.000). First, text preprocessing is performed before the following steps. The text preprocessing includes two tasks: removing stop words, URLs and punctuations and stemming of terms in tweets in training data set.

The next step is the calculation of term polarities and frequencies. Term polarity is calculated as the average polarity of tweets which includes the specific terms like the following in Eq. 1:

$$\text{Polarity}(t) = \frac{\sum_{i=1}^{N_t} \text{Polarity}(\text{tweet}_i)}{N_t} \quad (1)$$

In the equation above, t is a term and N_t is the number of tweets which include term t. Term frequencies are also calculated for use in the 'Term Addition in the Lexicon' step. Term polarity calculation results are sorted based on term frequencies in descendent order.

After calculating term's polarities, each term is checked whether it exists in the original lexicon or not. If the term already exists in the lexicon, the polarity score of the term is updated by the calculated polarity. Some terms change their polarities dramatically. For example, 'hate' and 'fuck' were negative terms in the original lexicon. They have however, a positive meaning in the updated lexicon because they are found more frequently in positive tweets than negative tweets in training data set. Also, 'joke' was positive term in the original lexicon. However, it turns to a negative term in the updated lexicon.

Table 4: Term addition strategies

Strategyes	Description
A(0,0)	No term is added
A(1,50)	Top 50 terms are added
A(1,100)	Top 100 terms are added
A(1,150)	Top 150 terms are added
A(1,200)	Top 200 terms are added
A(1,250)	Top 250 terms are added
A(1,300)	Top 300 terms are added
A(51,80)	Top-50 terms are excluded and next 30 terms are added (Top 51~80)
A(51,110)	Top-50 terms are excluded and next 60 terms are added (Top 51~110)
A(51,140)	Top-50 terms are excluded and next 90 terms are added (Top 51~140)
A(51,170)	Top-50 terms are excluded and next 120 terms are added (Top 51~170)
A(51,200)	Top-50 terms are excluded and next 120 terms are added (Top 51~200)

Table 5: Examples of top-50 terms

Terms	Player names	Team name	Common term
	Kyrie (cp3) stephcurry (kobe) howard (derrickrose)	Rockets, thunder, wizards, lakers, warriors,	Up, shoes, player, season, nbaplayoff
N. of terms	30	11	9

If the term does not exist in the lexicon, the term will be a candidate to include in the lexicon. We found that the performance of sentiment analysis is poor when we include new terms as a whole. Based on term frequency we test 12 different term addition strategies like (Table 4).

The last 5 strategies in Table 4 remove Top-50 frequent terms because the Top-50 frequent terms are player names, player nicknames, team names and common terms. So, last 5 strategies are established based on the assumption that top frequent term addition does not improve the performance of sentiment analysis. Table 5 shows example terms in Top-50 frequent terms.

After updating the lexicon, the performances of different updated lexicons are compared using test data set. The test data set includes tweets with ternary classification (positive, neutral and negative). The accuracy rate is used as a performance measure. The use of Eq. 2 to calculate classification accuracy is as:

$$\text{Accuracy}(1) = \frac{\text{No. of correctly classified using 1}}{\text{Total number of tweets}} \quad (2)$$

Equation 1 and 2 is an updated lexicon which are generated using one of strategies in Table 4.

RESULTS AND DISCUSSION

The experiment results are shown in Table 6. In the table, the 'base' column is about the performance of the original lexicon. The best performing lexicon is generated by strategy A(51,110) in Table 4. The lexicon provides

Table 6: Classification accuracies of two lexicons

Strategy	Positive (%)	Neutral (%)	Negative (%)	Total
Base	40.9	57.8	40.8	51.2
A(0,0)	43.6	55.2	40.8	50.3
A(1,50)	83.7	4.7	48.8	31.1
A(1,100)	86.7	4.9	48.8	32.0
A(1,150)	83.0	5.7	46.4	31.2
A(1,200)	89.8	6.1	42.4	32.7
A(1,250)	83.3	7.9	48.0	32.8
A(1,300)	82.6	9.5	47.2	33.5
A(51,80)	42.0	57.0	40.8	51.0
A(51,110)	40.9	68.1	34.4	56.7*
A(51,140)	45.5	61.7	37.6	54.4
A(51,170)	45.8	61.4	42.4	54.9
A(51,200)	45.1	61.4	42.4	54.7

*Best performance

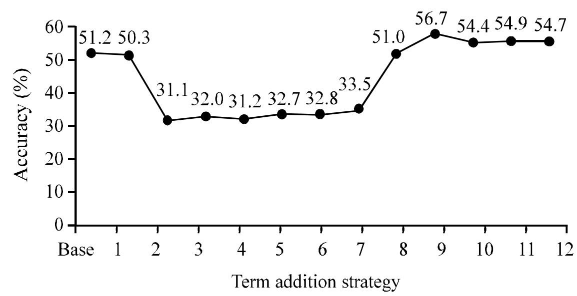

Fig. 2: Classification accuracies of thirteen lexicons

5.5% accuracy improvement compared to that of the original lexicon. Figure 2 shows the visual comparison of the performances of thirteen lexicons. We can find that A(51,*) strategies (strategies excluding Top-50 terms) provide better performance than the original lexicon (8~12 in Fig. 2). Also, A(1,*) strategies (strategies including Top-* terms) provide low performance than the original lexicon (2~7 in Fig. 2).

The findings of the experiments are as follows. First, polarity update using the proposed supervised learning approach provides performance improvement of sentiment analysis. Second, domain-specific term addition using the proposed approach also improve the performance. Finally, removing most frequent terms in the addition term list can contribute to improving the performance.

CONCLUSION

In this study, we propose a lexicon update method to improve microblog sentiment analysis. Based on supervised learning approach, we calculate domain specific polarities of terms and update polarities of existing terms in the lexicon. Also, frequent terms which do not exist in the lexicon are added with calculated polarities based on the training data set. An experiment has been performed using tweets of NBA basketball celebrities. The experimental results show that the proposed approach provides a performance improvement of sentiment analysis. We test twelve different term addition strategies in the experiment. From the comparison of experimental results we find that removing the top frequent terms provides, better performance than including terms from top frequent terms.

The research shows that general-purpose lexicon cannot work well in sentiment analysis on microblog contents which are mainly contributed by the young generation. This research also has several limitations and further research issues. To apply the proposed supervised learning approach, it requires manual polarity evaluation phase. It is necessary to improve reliability of manual evaluation and needs to find an automatic way to replacing manual human evaluation. Also, it is necessary to perform experiments with different data sets to generalize the results of this study.

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