

Sentiment Analysis of Twitter Posts About the 2017 Academy Awards

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Abstract. *This paper aims to perform the sentiment analysis of Twitter posts related to the movies nominated for Best Picture of the 2017 Oscars in order to find out if there is a correlation between the posts and the Oscar winners. A tweets database was built, pre-processed, and later evaluated by three distinct approaches: Naive Bayes, Distant Supervision Learning, and Polarity Function. It was possible to predict which movie would be considered the winner and which would be among the less prestigious ones. It was noted that Twitter users prefer to post positive comments about movies rather than saying bad things about the ones they did not like. Furthermore, it was verified that award shows such as the Oscars cause a growth in the number of posts on Twitter.*

1. Introduction

Social networks are online platforms where different entities – such as users, groups or organizations – can create and share different kinds of content and also access publications of the other entities on the network [Teixeira and Azevedo 2011]. Some of these platforms gather millions, or even billions of users, representing more than two-thirds of the global online population [Benevenuto et al. 2011].

The social network Twitter was launched in 2006¹ proposing that each of the posts (tweets) published by its users must not exceed 140 characters.² Since then, its popularity has been growing, and its main goal has been the exchange of ideas and information among its more than 313 million monthly active users¹.

The film industry benefits from social networks to promote movies and keep track of their clients' profiles and opinions about its movies. Besides the immense visibility provided by the social networks, they also provide access to a wide range of opinions [Bothos et al. 2010] that may influence future movie releases and how promotion is done.

Social networks and entertainment are usually strongly attached. Therefore several users use their accounts to express their opinion, enthusiasm or disappointment on a movie, its cast, and production – especially the movies that are nominated for the Oscars, the most famous and respected award show in the film industry [Wong 2013].

Despite the numerous tweets and notable excitement about the theme, there are only a few studies that try to find correlations between the opinion of the Twitter audience

¹Available on: <https://about.twitter.com/company> (Accessed on 19 Apr. 2017)

²On November 2017, the limit was expanded to 280 characters (Available on <http://bit.ly/TwLim>), but the data collection was conducted before this date. Thus, the original limit will be considered in this paper.

and the votes of the Academy [Bothos et al. 2010]. Twitter is one of the social networks that is most used in Sentiment Analysis papers because it is an abundant source of personal opinions that come from the whole world [Pak and Paroubek 2010].

About 350,000 tweets are published per minute³ by users from multiple social groups with different interests [Pak and Paroubek 2010]. Therefore, it is relevant to find out if there is a correlation between the opinion of Twitter users and the Oscars result.

The aim of this paper is to evaluate the potential of text mining and sentiment analysis on social networks by verifying if there is a correlation between the winners of the 2017 Oscars and the sentiment expressed by people through Twitter. To achieve this goal, a tweets database was created, and preprocessing techniques were applied to adjust the dataset. Subsequently, the tweets were automatically classified as positive, negative, or neutral. Finally, the sentiment of the tweets was compared to the Oscars results by different similarity measures.

Once the results were available, it was possible to explore the connections between the opinion of the Twitter audience and the winners chosen by the Academy. The goal was to find out if it was possible to predict which movies would be winners or losers of the ceremony by only using the tweets related to the theme.

The contributions of this paper can be summarized as follows:

- Creation of a tweets database related to movies nominated for Best Picture of the 2017 Oscars containing 889,840 preprocessed tweets written in English and a labeled database containing 3,235 tweets manually labeled.⁴
- Formulation of a measure to build an Oscars ranking based on the number of nominations and wins earned by each of the analyzed movies.
- Development of a public Java tool able to perform several preprocessing steps in a database, which can be used in different contexts. This tool also includes dictionaries for translation of emoticons, slangs, and abbreviations⁴.
- Comparison of several text classifiers to perform Twitter sentiment analysis, suggesting the Naive Bayes classifier as promising to perform classification tasks.
- Analysis of the correlation between the sentiment expressed on Twitter and the movies nominated to the Best Picture category of the 2017 Academy Awards.

2. Related Work

Several researchers have been exploring different methods and techniques that can be applied to data from social networks that are related to distinct themes [Bothos et al. 2010].

The work of [Almeida 2012] exposed the massive occurrence of cyberbullying targeting teachers on Twitter. In one week, the author collected tweets referencing teachers, and after applying a Bayesian classification filter on the tweets database, he discovered that virtual violence against teachers is a recurrent problem that happens on a daily basis.

[Teixeira and Azevedo 2011] found meaningful connections between the sentiment of social media users and the financial performance of movies. They extracted

³Available on: <http://www.internetlivestats.com/twitter-statistics/> (Accessed on 20 Apr. 2017)

⁴The original and preprocessed databases, as well as the labeled database and the pre-processing algorithm used in this paper, are available on <http://bit.ly/TCCIgor>.

data from Facebook and Twitter related to movies that were not yet released, treating and classifying the data, and using Spearman's correlation to determine if there was a relation between the posts and the financial performance of the movies.

In [Krauss et al. 2008], the authors were able to predict Oscar nominees according to user opinions published on IMDb. After collecting the data, the authors created a customized dictionary to measure the levels of positivity on a text, thus proving that it is possible to predict Oscar nominees based on movie reviews in online forums like IMDb.

[Cetinsoy 2017] aimed to predict the winners of the 2017 Oscars by using the machine learning platform BigML. A very rich dataset was built by gathering information of previous Oscar editions, and other movie awards. The models developed by the author correctly predicted winners of five out of eight categories analyzed.

As previously noted, there are not many papers that aim to analyze the correlation between the public opinion about movies and the Oscars result. This paper explores if the sentiment expressed by Twitter users is sufficient to predict Oscar winners.

3. Methodology

To achieve the goal proposed by this study, a set of steps was executed to analyze the sentiment of the tweets.

3.1. Data Collection

The collection of data was made considering the period between the day when nominees were announced (January 24th, 2017) and the day before the ceremony was presented (February 25th, 2017). The tool *GetOldTweets*⁵ was chosen to perform this step, and nine queries were executed to search for tweets written in English.

The keywords used as parameters were the original titles of the nine analyzed movies. The data is summarized in Table 1.

3.2. Labeled Database

In order to obtain a training set to build a supervised classification model and validate the best classifier, a labeled tweet database was created. A random sample of tweets was selected from the original database, and each tweet was manually labeled as "positive", "negative", or "neutral". Considerable amounts of tweets representing each of the three sentiments were included, even though this kind of sorting is one of the greatest challenges while building a labeled database.

The labeled database contains 3,235 tweets which represent 0.36% of the preprocessed database. It contains 1,444 tweets labeled as "positive", 1,362 labeled as "negative", and 429 labeled as "neutral".

3.3. Preprocessing of Tweets

Once the tweets collection was done, the data needed to be preprocessed in order to discard what is irrelevant to the classification step [Felix 2016]. A Java tool capable of performing several preprocessing steps was developed especially for this study.

⁵Available on: <https://bit.ly/2pm3LII> (Accessed on: 02 Apr. 2017)

The preprocessing steps conducted in this study, using the tool referred above, are listed below. The algorithm was executed individually for each movie.

- Conversion of upper case letters to lower case, in order to standardize the text.
- Removal of links, non-alphabetic characters, punctuation, and user mentions (preceded by “@” on Twitter) because they have no semantic value.
- Replacement of emoticons with matching words, with the intention of improving the classification model. In order to do this, a dictionary of emoticons and their respective translation was built based on a list of frequently used emoticons⁶.
- Removal of the movie titles, since the presence of some terms could mislead the results generated by the classifiers. For instance, the word “hell” (in the movie title “Hell or High Water”) usually expresses a negative feeling, which could corrupt a positive tweet’s classification.
- Removal of repeated letters. Twitter users often repeat word letters to intensify a feeling, but those words with repeated letters are not recognized by classifiers – for this reason, the repeated letters have been removed. For example, “i looooved la la land” turns into “i loved la la land”.
- Replacement of slangs and abbreviations with complete words or expressions. Twitter users generally write slangs and abbreviations considering that there is a character limit for each tweet. A dictionary containing 367 slangs and abbreviations was built to incorporate new terms to the tweets and ensure that the semantics of each tweet was preserved.
- Removal of stop words. These are words that are very common in a language and do not have relevant semantic value, like “a”, “the”, and “what”. Therefore, they were removed from the tweets – for instance, “this movie is awesome” turns into “movie awesome”. A list of stop words, part of the Onix Text Retrieval Toolkit⁷ was used in this step.
- Removal of non-related tweets. The titles of the movies “Arrival”, “Fences”, “La La Land”, “Lion”, and “Moonlight” refer to other words and expressions spoken in the English language. Besides, some movie titles can also refer to other movies, songs, etc. To minimize the effects of this challenge and ensure that the tweets being analyzed indeed refer to these movies, for each of them a list of unrelated terms was created. For example, the list of terms unrelated to “Fences” contains terms like “picket”, “neighbor”, “garden”, “wall”, “refugee”, “trump”, “border”, and “government”. Tweets containing at least one of the terms in the list of its respective movie were removed from the movie database.

The number of tweets originally collected (before preprocessing) and the number of tweets contained in the resulting database (after preprocessing) is detailed in Table 1.

3.4. Tweets Classification

In this paper, three different text classification approaches were considered: supervised learning, distant supervision learning, and polarity function.

The labeled database was used to validate the algorithms. Each of these learning methods is briefly explained below.

⁶Available on: <http://bit.ly/wikiEmot> (Accessed on 21 Apr. 2017)

⁷Available on: <http://www.lextek.com/manuals/onix/index.html> (Accessed on 28 Aug. 2017)

Table 1. Number of Tweets in the Database Before and After Preprocessing

Movie	Before preprocessing	After preprocessing
<i>Arrival</i>	138,825	135,214
<i>Fences</i>	53,211	41,682
<i>Hacksaw Ridge</i>	54,689	48,740
<i>Hell or High Water</i>	14,919	13,320
<i>Hidden Figures</i>	145,868	137,151
<i>La La Land</i>	250,942	244,213
<i>Lion</i>	186,295	150,641
<i>Manchester by the Sea</i>	31,768	28,601
<i>Moonlight</i>	108,121	90,278
Total	1,035,739	889,840

3.4.1. Supervised Learning

The Naive Bayes is one of the most widely used supervised learning methods in the scope of Sentiment Analysis, because of its remarkable performance in text classification [Ribeiro 2015]. For that reason, it was the supervised learning algorithm chosen to be tested in this paper. It is a probabilistic algorithm that is based on prior knowledge of the problem and training examples to determine the probability of a document belonging to a certain class [Baeza-Yates and Ribeiro-Neto 2013] [Schmitt 2013].

3.4.2. Distant Supervision Learning

Distant supervision learning uses an alternative way to generate training data. In this strategy, an existing database is used to collect instances related to the relation to be analyzed. Then, these instances are used to automatically generate training sets [DeepDive 2017].

Sentiment140 is a specific tool for Twitter Sentiment Analysis. It uses distant supervising learning and a Maximum Entropy classifier [Go et al. 2017] to calculate the polarity of a sentence based on a database labeled according to the emoticons found on the tweets that are in it [Go et al. 2009].

According to [Go et al. 2009], the method used by Sentiment140 – using tweets that contain emoticons as a training set – has proven itself as a good technique to classify tweets, since classification algorithms like Naive Bayes, Maximum Entropy, and Support Vector Machines achieved excellent accuracy indices when tested.

3.4.3. Unsupervised Learning

TextBlob is a Python library for word processing that provides solutions to different tasks related to natural language processing [Loria et al. 2017]. This tool integrates with the NLTK (Natural Language Toolkit)⁸ platform and with the web mining module Pattern⁹.

One of the text classification methods available on TextBlob is the polarity function, which returns the polarity of a sentence given as input. This function uses an unsupervised learning algorithm to classify the sentences based on a lexicon built by a spe-

⁸Available on: <http://www.nltk.org/> (Accessed on 10 Apr. 2017)

⁹Available on: <http://www.clips.uantwerpen.be/pattern> (Accessed on 14 Jun. 2017)

cialist and manually labeled according to its polarity strength, subjectivity, and intensity of each word. The built lexicon is a dictionary including frequent adjectives present in online product reviews [De Smedt and Daelemans 2012].

3.5. Assessment of the Classifiers

Each of the classifiers was tested using the labeled dataset, and the model validation technique applied was the 10-fold cross-validation. After the classifiers were tested, confusion matrices were built derived from the real sentiment stated for each tweet on the labeled base and the classification result. Thus, the quality measures accuracy, precision, and recall were calculated – allowing us to evaluate the classifiers.

Once the assessment of the classifiers was done, the best one according to the measures calculated was chosen to classify the complete preprocessed tweets database.

3.6. The 2017 Academy Awards Ranking

In order to facilitate the comparison between the result of the 2017 Oscars and the one obtained with the classification, a measure was created especially for this paper.

It can be noted on the official Oscars website¹⁰ that the visual representation of the winners is presented in three different sizes. The most relevant categories are more prominent on the web page. Therefore it was decided that they would have a higher weight. Taking this into account, weights were assigned to each category based on how relevant they are according to the way they appear on the Oscars website.

Consequently, the Table 2 was built. It shows all of the categories considered and the respective weight (w) that each one sums up on the score of the movies.

Table 2. The Weights of the Categories

i	Categories	w
1	Picture	3
2-6	Directing, Actor, Actress, Supporting Actor, Supporting Actress	2
7-16	Original Screenplay, Adapted Screenplay, Original Score, Original Song, Sound Editing, Sound Mixing, Production Design, Cinematography, Costume Design, Film Editing	1

The categories were included only if at least one of the Best Picture nominees was competing in it. According to the Oscars website, the Best Directing category would have weight 1, but for this paper, it was decided that it would have weight 2, because it is also a very relevant category as it is considered one of the “Big Five” Oscar awards¹¹.

The number of nominations and wins that each movie got was obtained from the official Oscars website. Then, the score of each movie was calculated according to Equation 1, where i indicates the index of each of the 16 categories (described in Table 2). Besides, the weight to be multiplied by the number of nominations received by each movie is reduced by half, since the wins are more important.

$$score_{movie} = \sum_{i=1}^{16} (win_i \times w_i) + (nom_i \times \frac{w_i}{2}) \quad (1)$$

¹⁰ Available on <http://oscar.go.com/winners>

¹¹ Available on: <http://www.imdb.com/list/ls075321784/> (Accessed on 17 Nov. 2017)

The terms of Equation 1 are explained below.

- win_i represents the number of wins that the *movie* has received on the category i .
- nom_i represents the number of nominations that the *movie* has received on the category i .
- w_i represents the weight of the category i .

4. Experiments

The objective of this section is to analyze the complete preprocessed database and its relation to the 2017 Oscars result.

4.1. Building the 2017 Oscars Ranking

For this paper, only the nine movies nominated for the Best Picture category were considered. Table 3 indicates the number of nominations and wins that each of these movies got on the 2017 Oscars.

Table 3. Nominations and Wins Received by the Movies

Movie	<i>Arrival</i>	<i>Fences</i>	<i>Hacksaw Ridge</i>	<i>Hell or High Water</i>	<i>Hidden Figures</i>	<i>La La Land</i>	<i>Lion</i>	<i>Manchester by the Sea</i>	<i>Moonlight</i>	Total
Nominations	8	4	6	4	3	14	6	6	8	59
Wins	1	1	2	0	0	6	0	2	3	15

Once having the information contained in Table 2 and Table 3, and knowing which categories each movie has won or has been nominated (available on the Oscars website), it was possible to build the ranking of the 2017 Academy Awards by using Equation (1). The ranking is exposed on column “Ind. 4” of Table 6.

4.2. Number of Tweets Collected for Each Movie

This first experiment aimed to analyze the number of tweets collected for each movie throughout the weeks and draw conclusions about the data.

The graph in Figure 1 shows the number of tweets in the complete preprocessed database according to the movie and the week the tweets were posted. It can be noted that the biggest frequency of tweets happened in the first week of analysis, i.e., the week when the 2017 Academy Awards nominees were announced.

It is possible to perceive that there is a relation between the movement on the social network and the 2017 Oscars, once the number of tweets posted about the movies in the week when the nominees were announced was bigger than the other weeks. Besides, during the fifth week of analysis – closer to the date of the ceremony – the number of tweets posted about most of the movies have gradually increased comparing to the third and fourth weeks.

Also, based on Figure 1 it is possible to discover that the most commented movies were “Arrival”, “Hidden Figures”, “La La Land”, and “Moonlight” – it is interesting to observe that “Arrival”, “La La Land”, and “Moonlight” are among the top 5 positions of the proposed 2017 Oscars ranking (Table 6, Ind. 4).

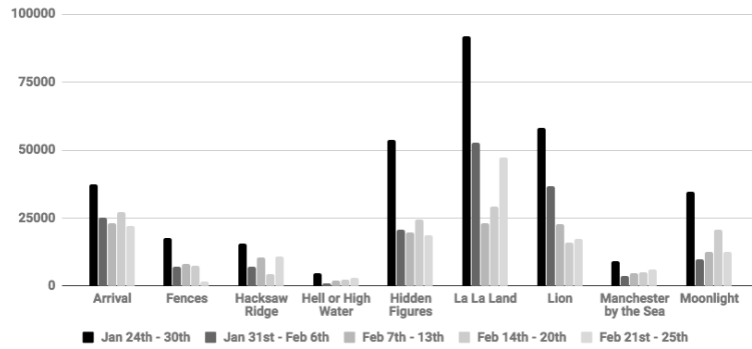


Figure 1. Number of tweets posted about each movie throughout the weeks.

4.3. Tweets Classification

The goal of this experiment was to compare the performance of the three classifiers being analyzed and choose the best one of them to classify the complete database.

After the classifiers were tested and their respective quality measures were calculated, Table 4 was built. It is possible to see that the Naive Bayes classifier got the best results according to all of the three measures calculated, therefore it was decided that this algorithm was the best one to be applied over the complete preprocessed database.

This result was expected since the Naive Bayes is the only supervised learning classifier being tested. Therefore it was expected that its performance was better than the others. The polarity function from the TextBlob library considers the terms of a sentence individually, so it was not able to classify each tweet as a whole. Finally, the Sentiment140 classifier, which uses distant supervising learning and has a training set based on emoticons, might not have been able to represent the database of this paper accordingly.

Table 4. Assessment of the Classifiers

Classifier	Accuracy	Precision	Recall
<i>Naive Bayes</i>	74.1%	69.8%	68.8%
<i>TextBlob</i>	63.9%	62.7%	64.2%
<i>Sentiment140</i>	26.2%	60.6%	42.3%

After the generation of the classification model based on the Naive Bayes algorithm, the test sets – that is, the individual files containing the tweets posted about each movie – were loaded into the classifier. This process was performed individually for each of the nine movies being analyzed.

Later, a summary of the tweets classified by the multinomial Naive Bayes classification was built, and it is shown in Table 5. Each line of the table shows one of the nine movies being analyzed, followed by the number of tweets classified as “positive” by the classifier and the percentage of these tweets in relation to the movie’s tweets. The next columns show the same for the “negative” and “neutral” tweets.

4.4. Twitter and Oscar Indicators

Several indicators can be obtained from all the data and information that was gathered, as it can be seen in Figure 2. These indicators can help comparing the sentiment of the tweets

Table 5. Sentiment of Tweets According to Naive Bayes Classifier

Movie	Positive		Negative		Neutral	
	Count	Percentage	Count	Percentage	Count	Percentage
<i>Arrival</i>	68,485	51%	27,002	20%	39,727	29%
<i>Fences</i>	20,199	48%	8,687	21%	12,796	31%
<i>Hacksaw Ridge</i>	31,998	66%	6,380	13%	10,362	21%
<i>Hell or High Water</i>	7,077	53%	2,064	15%	4,179	31%
<i>Hidden Figures</i>	77,314	56%	16,212	12%	43,625	32%
<i>La La Land</i>	104,507	43%	57,237	23%	82,469	34%
<i>Lion</i>	75,906	50%	36,978	25%	37,757	25%
<i>Manchester by the Sea</i>	14,879	52%	5,410	19%	8,312	29%
<i>Moonlight</i>	49,668	55%	17,130	19%	23,480	26%
Total	450,033	50.6%	177,100	19.9%	262,707	29.5%

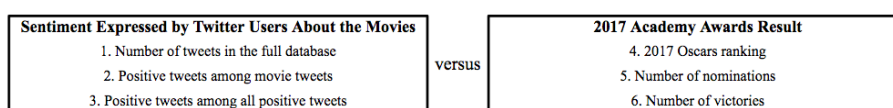


Figure 2. Indicators obtained from the data and information gathered.

and the 2017 Oscars result, making it possible to know if the Twitter users sentiment could predict the Oscar winners.

Within the scope of the sentiment expressed by Twitter users, there are three indicators that were obtained: the number of tweets in the database for each movie (Ind. 1), the number of positive tweets among all of the instances classified as “positive” for each movie (Ind. 2), and the number of positive tweets among all of the instances classified as “positive” in the complete database (Ind. 3).

From the 2017 Academy Awards result, there were also three indicators obtained: the 2017 Oscars ranking created for this paper (Ind. 4), the number of nominations received by each movie (Ind. 5), and the number of wins gotten by each movie (Ind. 6).

Table 6 shows rankings based on the six indicators and they help provide a more detailed analysis of the correlation between the two data scopes.

Table 6. Rankings Based on the Indicators

Movie	Rankings Based on Twitter Indicators			Rankings Based on Oscars Indicators		
	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6
<i>Arrival</i>	4th (15.2%)	6th (51%)	4th (15.2%)	5th	2nd (14%)	5th (7%)
<i>Fences</i>	7th (4.7%)	8th (48%)	7th (4.5%)	6th	7th (7%)	5th (7%)
<i>Hacksaw Ridge</i>	6th (5.5%)	1st (66%)	6th (7.1%)	4th	4th (10%)	3rd (13%)
<i>Hell or High Water</i>	9th (1.5%)	4th (53%)	9th (1.6%)	8th	7th (7%)	7th (0%)
<i>Hidden Figures</i>	3rd (15.4%)	2nd (56%)	2nd (17.2%)	9th	9th (5%)	7th (0%)
<i>La La Land</i>	1st (27.4%)	9th (43%)	1st (23.2%)	1st	1st (24%)	1st (40%)
<i>Lion</i>	2nd (16.9%)	7th (50%)	3rd (16.9%)	7th	4th (10%)	7th (0%)
<i>Manchester by the Sea</i>	8th (3.2%)	5th (52%)	8th (3.3%)	3rd	4th (10%)	3rd (13%)
<i>Moonlight</i>	5th (10.1%)	3rd (55%)	5th (11.0%)	2nd	2nd (14%)	2nd (20%)

4.4.1. Comparing the Sentiment of the Tweets with the the 2017 Oscars Result

By analyzing Table 6, it can be noted that “La La Land” has the biggest amount of tweets in the complete database, although it also has the smallest percentage of tweets classified as “positive” among its tweets. However, “La La Land” obtained the biggest amount of tweets classified as “positive” (Table 5). This Twitter analysis corresponds to the fact that

it is the movie that received most nominations and wins, and it has gotten the first place on the proposed Oscars ranking, which makes “La La Land” the winner of the ceremony.

On the other hand, Tables 5 and 6 also show that “Hell or High Water” can be considered one of the least prestigious among the movies being analyzed. The amount of tweets about this movie represents only 1.5% of the complete database and it is the movie with the smallest amount of positive tweets among all of the tweets classified as “positive” on the full base, implying that the Twitter audience showed little interest in this movie during the period when the data was collected. This reflects on the fact that “Hell or High Water” also did not get any win on the 2017 Academy Awards.

Thereby, it can be noted by comparing the two groups of indicators that there are some cases in which there is a conformity between the Oscars results and the sentiment expressed on the tweets.

However, although “Hidden Figures” is the third movie with the biggest amount of tweets in the complete database, having more than half of these tweets classified as “positive”, the movie got the smallest number of nominations among the movies analyzed and did not win any category, thus getting the last place on the proposed 2017 Oscars ranking. This is one of the unconformities that can be found by analyzing these tables.

A controversy also happens regarding the movie “Manchester by the Sea” which has gotten the third place on the proposed Oscars ranking, but it is the second movie with the smallest amount of tweets in the complete database. It also fills the eighth place in the ranking based on the Indicator 3.

In order to conduct a mathematical analysis of the correlation between the sentiment of the tweets and the Oscars result, Spearman’s ranking correlation coefficient was calculated between the two groups of indicators. The results are displayed in Table 7.

Table 7. Spearman’s Ranking Correlation Coefficient between the indicators

Indicators	Ind. 4	Ind. 5	Ind. 6
Ind. 1	0.15	0.43	0.12
Ind. 2	-0.23	-0.35	-0.12
Ind. 3	0.11	0.36	0.12

According to Table 7, statistically there is no strong evidence of an association between the rankings. The most significant coefficients were found between the ranking of nominations (Ind. 5) and the rankings of the number of tweets in the complete database (Ind. 1) and the positive tweets among all positive (Ind. 3). The latter has gotten a 0.43 coefficient, which indicates a moderate correlation between the rankings [Guilford 1957]. Consequently, it is possible to infer that the 2017 Oscars nominations affect the Twitter discussion, causing a significant amount of tweets to be published about the theme.

Therefore, it is possible to notice that although none of the obtained coefficients exhibit a high correlation between the rankings, predicting which movie will be the winner of the ceremony and which ones will be among the losers by using Twitter data is very likely to be correct. That is, this methodology allows the prediction of the extremities of the proposed Oscars ranking, even though the correlation between the rankings is low.

There are pieces of evidence that the opinions expressed on Twitter correlate with the opinion of the Academy, especially regarding the movies that stand out positively

since there is a significant amount of tweets about them and most of them express a positive sentiment. Even though it was not possible to establish a general correlation between the Oscars result and the tweets, the experiments show that this is a promising work that can be studied more deeply.

5. Conclusion

This paper aimed to discover if there is a correlation between the sentiment of Twitter users about the 2017 Oscars nominees and the result of the ceremony by performing the sentiment analysis of tweets related to the movies nominated for Best Picture. Steps of a Sentiment Analysis task focused on Twitter were executed: tweets collection, construction of a labeled database, tweets preprocessing, tweets classification, and validation.

After testing the classifiers with the labeled database and evaluating the results by using different quality measures, the multinomial Naive Bayes algorithm was chosen to classify the complete database. It was possible to recognize that this classifier is a great choice for similar tasks, once it has obtained high accuracy, precision, and recall levels.

From the results, it can be concluded that this methodology is useful to conduct observations about the Oscar-nominated movies. However, only moderate mathematical associations were found between the proposed 2017 Oscars ranking and the other rankings based on the classifier results. This means that the collected data must be more deeply interpreted instead of using only mathematical interpretations. Another explanation would be that the movies that please the Twitter audience not always will be chosen as the best ones by the Academy.

It is important to highlight that the methodology used in this paper can also be applied to future award shows or other situations in which it is desired to obtain an overview of social network users opinions regarding specific topics.

As future work, a more precise prediction might be performed by using an additional database with critics and movie reviews, such as the IMDb. Besides, in this paper, the title of each movie nominated for Best Picture of the 2017 Oscars was used as a keyword when collecting the tweets. A more profound analysis might be made considering the other categories of the award show, making it possible to predict the sentiment of Twitter users regarding the best actors, actresses, directors, songs, etc.

A different approach could be conducted by considering only the “hashtags” present on each tweet and verifying if they contain a sentiment that reflects on the respective tweet. Additionally, performing this study using a database composed of tweets posted after the Oscars would be an interesting way of observing the sentiment of Twitter users regarding the winners of the ceremony.

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