Making Social Media Advertisements Viral in WWW

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Abstract. Social media marketing is a form of Internet marketing that utilizes social networking websites as a marketing tool. Marketers post advertisements on social networking websites to promote their products and services. Most often, advertisements on social media are paid advertisements. However, not all advertisements reach the target audience. The gain obtained through advertisements is far less than the expenditure. This study proposes a model to increase the popularity of advertisements posted on social media. The cosmetics industry was taken as the case study and advertisements posted by cosmetics companies on Twitter were studied. This study identifies the most prominent features that impact Twitter advertisements to go viral. In order to reach a larger number of viewers, improvements to these features are suggested.

Keywords: Popularity, Emotions, Sentiment, Text Mining

1 Introduction

Social media marketing is the use of social media platforms and websites to promote a product or a service. Companies market their products on social media by posting advertisements. Social media advertising helps businesses find new potential clients by using the information shared by users, to identify the interests of the user. Likewise, most social media platforms consist of built-in data analytics tools. This enables companies to track the engagement and progress of advertising campaigns. However, the number of viewers the advertisement reaches is determined by the amount paid by the advertiser to the social media platform. Usually, these companies post these advertisements without considering the user's interest. Even though the advertisements reach many viewers, it does not ensure that the users will click and open the advertisement, visit the company's website and purchase the product. The users will scroll down without even reading the advertisements, and the money invested in these advertisements will be worthless.

There are posts on social media where the content and structure of the advertisement are enough to attract the attention of the viewers. People engage with these posts and share these posts among their followers. As a result, these posts reach a considerable audience.

The ultimate aim of this study is to develop a system that will enhance the popularity of social media advertisements by providing suggestions to make improvements amid the creation of advertisements. This will make social media advertising more efficient.

The rest of the paper is organized as follows. Next section reviews the related work. Section III contains a detailed explanation of the proposed model. Feature selection and implementation of the model are explained under section IV. Data selection and experiments are explained under section V. Section VI evaluates the results of the experiments and evaluates the performances of our approach.

2 Related work

Social media advertisements consist of several features that determine how popular they are. The initial step in this research was to identify these features.

Heimbach et al. (2015) [1] studied how content characteristics impact the sharing likelihood of news articles on Social Media. It is found that time period in the day, day in the week, the field which the news talks about, emotions, sentiments, and the number of pictures and videos impacts the popularity of news articles on Social Media Summary.

Multi-dimensional feature space derived from properties of an article is constructed in Bandari et al. (2012) [2] and evaluates the efficacy of these features to serve as predictors of online popularity. They consider four different characteristics for a given article: the news source, the category of the news, the subjectivity of the language in the article (phrases that communicate personal opinions) and named entities mentioned in the article.

Emotions and sentiments in the advertisements can contribute a lot to the success or failure of the advertisement. Miller et al. (2017) [3] talks about improving the email marketing strategy by analyzing the psychological effects induced in the email recipient. They identify that the subject line of an email and the email address of the sender are the two major factors which make a receiver to open an email or leave it. Further, they find that email subjects with some parser alignments have received more reader attention than others.

While, Koto et al. (2015) [4] study the tendencies of sentence pattern which distinguish between positive, negative, subjective and objective Tweets. Their approach also shows that Part of Speech (POS) sequence can improve Sentiment Analysis accuracy. Libert et al. (2018) [5] discusses how to attract new customers using online marketing. They also identify that emotional activation is the key to viral success.

It is the algorithm of social media platforms that determine where the advertisements are displayed and how long they stay in the user timelines. Keneshloo et al. (2016) [6] integrate a range of popularity measurements across the Washington Post (WP) news channel and identify which measurements affect the popularity. They recognize that the log-transformed number of views in the first hour decides the overall views.

The study by Guerini et al. (2009) [7] is about how the content itself affects the virality. The work considers appreciation (number of likes), spreading (shares), simple buzz, white buzz (positive comments), black buzz (negative comments), raising discussion (the ability to induce discussion among users), and controversiality (the ability to split the audience into different parties) as the factors affecting virality.

The above researches support to identify the attributes that impact the popularity of online content. Yet, there are attributes not covered in the literature. The online content we considered are the Tweets by cosmetics companies. The features were extracted from the Tweets as well as discussed the external factors such as a number of followers, the time the Tweet was posted, etc.

In Rodriguez et al. (2017) [8] the issue of developing one such strategy for spreading the news on Twitter is discussed. The study showed that the effective dissemination of a Tweet depends not only on its content but also on the user who posts it. Further, this study shows that using mentions, hashtags, URLs and media content leads to more Retweets.

Tsagkias et al. (2009) [9] studies the comment volume of news articles before publication. This study analyses the online news articles and their comments. Then tries to predict the comment volume of news articles that are yet to be published.

Most of the above papers dealt with identifying the features impacting the popularity of online content and predicting popularities.

Dilip et al. (2018) [10] discusses how to analyze a piece of text and gives suggestions on how to make that text to go viral on the web. They rely on the generation of rules, giving suggestions as to how to improve the post to make it viral and intention mining. They suggested how the possibility of content becoming popular can be increased by replacing keywords, improving sentiment and intention mining using a rule-based approach.

This study shows how the features that impact the popularity of Twitter advertisements can be adjusted and how the popularity of these Tweets can be enhanced. During the literature review, the identified features were the presence of images/videos, emojis, and hashtags in the Tweets, the time the Tweet was posted, keywords, sentiment, emotions and the number of followers of the user. The number of retweets and number of favorites of Tweets is taken to measure the popularity of the Tweets. The system will suggest improvements to be made in the Tweet based on what it learned from the past data in order to increase the popularity.

3. Proposed Solution

3.1 Data selection

A large dataset of social media advertisements was required to study how Twitter advertisements can be made popular. Cosmetics industry was selected as the domain for study and Twitter advertisements related to cosmetics products were collected. Advertisements posted by popular cosmetics companies on their Twitter user timeline were downloaded to a CSV file using Tweepy API [11]. The Tweets along with Tweet id, posted date and time, information about whether the Tweet has hashtags or mentions, emojis, followers count, retweet count, and favorites count are stored.

Several preprocessing was done in order to clean the data and extract additional features. Then the Tweets were tokenized, and words were tagged with part of speech tags. The features in the data were plotted against Popularity to analyze the dependence of Popularity on each feature.

It was found that Tweets posted in specific hours are more popular (Fig 1).

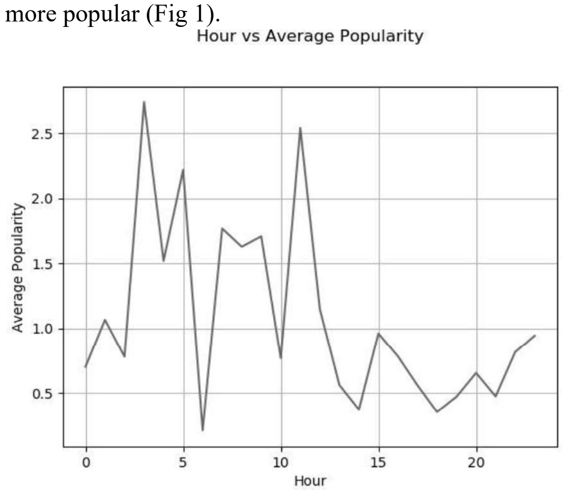

Fig 1 - Average Popularity against Hour

When the polarity of sentiment increases, the Average Popularity increases (Figure 2). Therefore, positive Tweets are popular than negative Tweets.

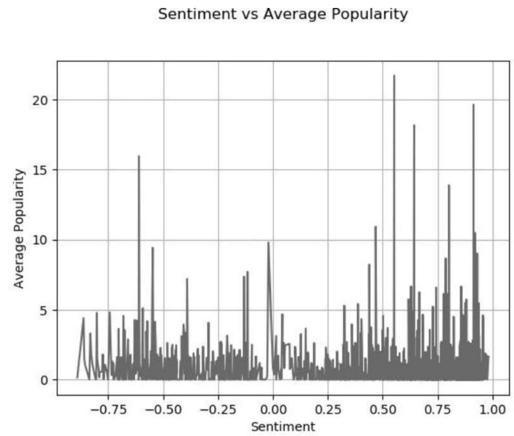

Fig 2 - Average Popularity against Sentiment

Also, it was found that including images, videos and hashtags in the Tweets increases the Popularity (Fig 3). Some of the most prominent hashtags that give high Popularity are given below.

#NakedHeat	#UrbanDecay	#wetnwildbeauty
#NakedCherry	#Makeup	#Beauty
#crueltyfree	#tartetalk	#ABHxNorvina
#LipstickisMyVice	#AnastasiaBeverlyHills	

As it can be seen including the brand names or the product names as the hashtags brings more popularity.

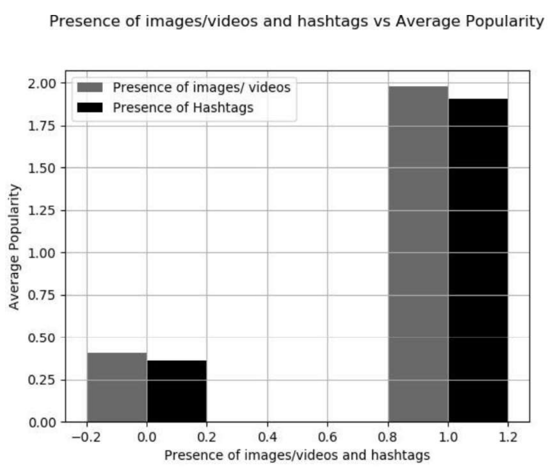

Fig 3 - Average Popularity against the Presence of images, videos, and hashtags

3.2 Feature Selection

The features considered when predicting popularity are,

- Presence of images/videos
- Presence of hashtags
- Presence of emojis,
- Keywords
- POS tag sequence
- Sentiment value of the Tweet
- Emotions in the Tweet
- The hour the Tweet was posted
- The number of followers of the Twitter account

The number of retweets and favorites are taken as the target features and these are used to measure the popularity of the Tweets.

VADER [12] sentiment analysis library was used to determine the sentiment of the Tweet. Tweets generally contain abbreviations, irregular words, emojis and icons which can harm the accuracy of sentiment analysis. VADER is a tool that is specifically attuned to determine the sentiment of social media posts. Therefore, instead of developing a model for sentiment analysis, Vader Sentiment Analysis has been used which can identify the sentiments of Tweets more accurately. This assigns a polarity value for the Tweet ranging from -1 to 1.

In order to analyze the emotions in the Tweet, we adopted a lexicon based approach which is somewhat similar to the methodology proposed by Miller et al. (2016) [3]. The lexicon-based approach is more accurate and robust than the traditional bag-of-words approach and also we believe it to be a better way to analyze emotions because the emotions cannot be expressed other than using words. The NRC Emotions Lexicon (a list of English words and their associations with eight basic emotions) has been used for the creation of these dictionaries. The word level lexicon contains a large list of words and for each word, each of the eight emotions is assigned to either 1 or 0 (1 if the word belongs to that emotion, otherwise 0). The number of words belonging to each emotion in each Tweet is counted. A sample result for a given Tweet would be:

anger 0, anticipation 0, disgust 0, fear 0, joy 2, sadness 0, surprise 2, trust 1

Term frequency and inverse document frequency (TF-IDF) scores method have been used to extract keywords. The TF-IDF score is used to evaluate the importance of words to a document in a collection of documents. TF-IDF score is composed of two terms. Term Frequency (TF) is the ratio between the count of a word in a document compared to the total number of words in the document. Inverse Document Frequency (IDF) is the score of each word across all documents in the corpus. Combining these two we come up with the TF-IDF score for a word in a document in the corpus. It is the product of TF and IDF.

The hour the Tweet posted was extracted from the timestamp of the Tweet and is included as one of the features (hour). The presence of images, videos (hasMedia), the presence of hashtags (hasHashtag) and the presence of emojis (emoji) are defined as binary features. If these elements exist, the feature value is 1 and 0 otherwise.

The number of followers the advertiser has (followers count) was downloaded along with the Tweets using the Tweepy API. Finally, the number of retweets (retweet count) and the number of favorites (favorite count) are included as the target features in the research that need to be predicted and enhanced. [13]

3.3 Model

The design of the solution comprises of two major components. The first is to predict the popularity of Twitter advertisements. Here, machine learning models are trained to predict the number of retweets and the number of favorites of the Tweets. The latter component tries to make improvements in the Tweet in order to increase popularity. Finally, enhanced popularity is predicted.

Features are extracted from the dataset and are transformed into numerical features. The number of retweets and the number of favorites were identified as the target features that needed to be predicted. Separate machine learning models were trained to predict the number of retweets and the number of favorites for each Tweet.

When creating a new Twitter advertisement, first the text is preprocessed and features in the text are extracted. The initial count of the number of retweets and the number of favorites is predicted. Then the model tries to increase the probable number of retweets and number of favorites by improving the text. As part of the improvements first, the keywords in the text are replaced with synonyms that would enhance the popularity of the Tweet. Then the words that have negative polarity are replaced with synonyms that have positive polarity. POS tag sequences that make the text negative are removed. Hashtags and emojis are included and images/ videos are attached with the Tweet. A time to post the advertisement on Twitter is suggested. After all the adjustments are made, the enhanced counts of retweets and favorites are predicted.

3 Implementation

4.1 Predicting Popularity

In order to measure the popularity of Twitter advertisements, separate models were trained to predict retweet count and favorite count. Since the target features are continuous variables, regression algorithms were used to predict the target variables. The trained models are stored as .pkl files. The input Tweet is also preprocessed, and features are extracted from the input. Then using the trained models, the retweet count and favorite count are predicted. [14]

For some Tweets, the retweet counts were higher, and the favorite counts were lower, whereas for some Tweets it was the opposite. Determining the popularity using both retweet count and favorite count at once was confusing. Therefore, it was necessary to derive a single metric to represent the popularity of the Tweet. The weighted average of retweet count and the favorite count was calculated and was defined as the Popularity. Weights for retweet count and favorite count were identified from Octoboard [15] which is a data visualization dashboard that shows business and social media metrics for companies, marketing agencies and individuals. They assign 1 for favorites and 20 for retweets.

$$Popularity = \frac{((FVC \times 1) + (RTC \times 20))}{NT} \quad [15]$$

Equation 1 - Equation for calculating popularity

FVC – Favorite count
RTC – Retweet count
NT – Number of Tweets

The Average Popularity of the Tweets in the dataset is considered as the threshold for Popularity and Tweets that get Popularity values greater than this threshold are considered as Popular and Tweets that get Popularity values less than this threshold are considered unpopular.

4.2 Reforming Tweets to Enhance Popularity

After the Popularity was predicted, the Tweets had to be improved in order to enhance the Popularity in social media. The user is suggested to make changes to several features in order to improve the advertisement and enhance Popularity.

Improving the sentiment

Improving the sentiment polarity is one of the possible ways to enhance the Popularity. If words in the Tweets have negative polarity, synonyms of these words that have positive polarity are suggested. To identify synonyms, we use the WordNet thesauri [16]. WordNet has synonyms and antonyms for most of the English words and phrases. The Popularity is predicted for each possible word combinations and the positive words that give the highest Popularity are suggested.

Suggesting keywords

Suggesting relevant keywords is another way to improve the advertisement. Once the keywords are extracted from the Tweet, the synonyms for these keywords are identified using WordNet. Then using different combinations of these synonyms, different type of text is generated. The Popularity is predicted for each of this text. The text with the highest Popularity is selected as the best set of synonyms. The system suggests which keyword to be replaced with which synonym.

Eliminating pos-tag sequences that diminish the Popularity

As mentioned before, Koto et al. (2015) [4] finds that the POS tag sequence for a text determines whether it creates a positive sentiment or a negative sentiment [17]. The results from Koto et al reveal that negative Tweets tend to have POS sequence of PRPRB (personal pronoun-adverb), PRP-VBD (personal pronoun-verb, past tense), RB-VB (adverb-verb, base form), PRP-VBP-RB (personal pronoun- verb, non-3rd person singular present- adverb), and MD-RB-VB (modal-adverb-verb, base form). Eliminating these tag sequences from the Tweets can improve the positivity and improve Popularity. Therefore, if these POS tag sequences are found in the Tweets, the system suggests removing these words.

Adjusting numerical features

The time when the Tweet was posted is found to have an impact on the Popularity.

From Fig 0.1 it can be seen that the Average Popularity is high for Tweets posted around 3 am and 11 am. The system suggests the possible hours to post the Tweet. If the Tweet has no hashtags, image or video, the user is suggested to include these elements in order to improve the Popularity. After the changes are made, the enhanced Popularity is calculated.

5 Experiments and evaluations

5.1 Experiments

The Popularities that were predicted by the trained model had to be evaluated in a realworld scenario. Sample Tweets were processed using the program, and the content of each Tweet was improved in order to reach a larger audience. The predicted Popularities for each of these Tweets were recorded.

In order to evaluate the results, an experiment was conducted among 100 participants. A survey consisting of 10 Original Twitter Advertisements in the cosmetics industry, and the modified versions of the advertisements were distributed to the participants. For the purpose of the study, only the following three tweets were considered.

1. Original Advertisement (OA)
2. Modified Advertisement with Highest Predicted Popularity (HPP)
3. Modified Advertisement with Lowest Predicted Popularity (LPP)

The Tweets were given in random order and the participants were asked if they would retweet and/or give a favorite for each of the Tweet. Thus, the popularity of the Original Twitter advertisements and the modified advertisements were measured, using a realworld experiment.

5.2 Evaluation of Experiments

Using the retweet counts and favorite counts gathered from the experiment, the popularities, for each version of every Tweet, were calculated. The average popularity for the OAs, HPPs and LPPs were calculated. HPPs produced the highest average popularity in the experiment and LPPs produced the lowest.

Table 1 - Average Popularities of original and modified versions of Tweets

	OA	HPP	LPP
Average Popularity	3.43	6.57	2.50

In addition to the above results, it was also found that in all 10 sample Tweets, Popularities for HPP were the greatest. In 8 out of 10 Tweets, Popularities for OAs were more significant than the Popularities for LPPs.

5.3 Performance Evaluation

Since the target features are continuous, Regression algorithms were used to predict the target features. Each of these models was evaluated for their performance and accuracy.

With the use of metrics in Sci-kit learn [18], Mean Absolute Error and Root Mean Squared Error was calculated. The hyperparameters of the regressors were tuned in order to minimize the error values. The estimators performed best with the hyperparameter values given in Table 2.

Table 2 - Performance evaluation of Regression Algorithms

ML Algorithm	Predicting RTC		Predicting FVC	
	MAE	RMSE	MAE	RMSE
Linear Regressor	20.90	49.01	96.10	185.87
Random Forest Regressor Maximum depth = 4 Number of trees = 100	16.74	48.55	63.52	164.10
Multi-layer Perceptron Regressor Hidden layers = 10 Learning rate = 0.001	24.87	73.87	141.98	235.78
Epsilon-Support Vector Regression. C = 1.0, Epsilon = 0.5	21.5	73.8	111.25	256.6
Bayesian Ridge Regressor Number of iterations =300	22.16	68.72	95.79	183.14

RTC – Retweet Count FVC – Favorite Count

MAE - Mean Absolute Error
RMSE - Root Mean Squared Error

In predicting both retweets and favorites, Random Forest Regressor performed better than all the other Regressors. Therefore, Random Forest Regression is used to predict the Popularity of the input Tweets.

6. Conclusions and further works

Studies revealed that several features in Twitter advertisements have a larger impact on their popularity. Adjusting these features can result in the advertisement reaching a broader audience.

In this research, a machine learning model was trained to predict the retweet count and favorite count of Twitter advertisements. Then the system tried to enhance the popularity by making modifications to the features. Finally, the potential number of retweets and favorites were predicted, and the improved Popularity was calculated.

Several regression algorithms were tried in predicting retweets and favorites. Out of those Random Forest Regressor performed the best.

When suggesting keywords in order to increase the popularity, the best set of synonyms are suggested. However, this can change the actual meaning of the Tweet. This problem has not been considered in this research. The POS sequences that diminish the popularity are identified and eliminated. However, possible replacements for the words that produce these POS sequences are not suggested.

We look forward to solving the above drawbacks in the future.

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