Implementing Artificial Neural Network to Identify Influencers for Crowdfunding Campaigns on Twitter

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***Abstract*—This study proposes an Artificial Neural Network (ANN) model for ranking potential influencers for crowdfunding campaigns on Twitter. Because influencers have a strong connection with their followers and are considered trustworthy key opinion leaders, identifying them provides opportunities for start-up companies to reach highly relevant audiences and promote their campaigns. In this study, the social authority value, a mechanism developed by Followerwonk, was employed to examine the influence strength of a Twitter user. Followerwonk is one of the most popular Twitter marketing platforms in the United States. A total of 20 influence factors of 1969 Twitter users were collected to train the ANN model. The results revealed that 13 of the 20 influence factors were significant for measuring influence strength, which improved the time efficiency of the process of evaluating potential influencers. This model can be effectively and cost- efficiently applied to support start-up companies, thus increasing the success rate of campaigns by utilizing influencer marketing.**

Keywords- social media analysis; influencer marketing; artificial neural network; sentiment analysis.

I. INTRODUCTION

Crowdfunding has flourished in the Internet age as a revolutionary means of raising capital and gaining publicity [1][2]. To increase the success rate of fundraising, determining strategies for attracting more people to contribute to fundraising campaigns is crucial for fundraisers [3]; therefore, influencer marketing on social media plays the role of "force multiplier" for crowdfunding.

Influencer marketing is a trending marketing strategy that entails companies partnering with influential individuals to relay brand messages to the individuals' audiences [4]. In the age of social media, everyone can be an influencer [5]. An influencer can be a popular fashion photographer on Instagram, a well-known product reviewer who uses Twitter, or a respected marketing executive who frequently shares ideas on LinkedIn. Through recurrent communication, an influencer can influence a prospective consumer by providing campaign information and advice for funding decisions, thereby affecting their beliefs, motivations, attitudes, and opinions [6][7]. However, because of the high intricacy of social media characteristics and the haphazard action of influencers, identifying influencers in a limited time is difficult [8].

Different approaches have been developed for identifying influencers; however, none of such approaches have focused on crowdfunding. Therefore, the objective of this study was to identify suitable influencers who can promote crowdfunding campaigns on Twitter. This study selected Twitter, a representative microblog, because it is a suitable platform for comprehending people's behaviors in the physical world [9]. To achieve the study objective, an Artificial Neural Network (ANN) model was used to rank the influence strength of Twitter users, and the social authority value on Followerwonk [10] was employed in the training process. A total of 20 influence factors of 1969 Twitter users were collected to train the ANN model. Furthermore, the Marketing Influential Value (MIV) model [11] was applied to classify the 20 influence factors into three primary categories.

The remainder of this paper is organized as follows: Section II reviews related work on surveying influencer identification and measurement. Definitions of 20 key influence factors for measuring the influence strength of a Twitter user are provided in Section III. Section IV details the executed experiment, and Section V presents the results. Finally, conclusions are drawn in Section VI.

II. RELATED WORK

Over the past decade, an increasing number of studies on influencer identification has been a trending research topic. Studies have extensively applied three approaches for identifying influencers: centrality measures [12] applied with graph theory for examining the influence of a given node in a graph; prestige ranking [13] adapted for ranking influencers and inspired by the PageRank algorithm [14], which is the underlying algorithm for the Google search engine; and information diffusion [15] applied to identify the optimal path for spreading information.

A. Measurement of Influence on Blogosphere

Several studies have focused on different social media platforms, such as Facebook [16][17], Twitter [18][19], and other renowned platforms [20]. Moreover, the blogosphere is a widely used target for identifying influencers. Li et al. [11] proposed the MIV model to calculate the strength of influence and identify influential bloggers in the blogosphere. They divided the marketing influence value into three primary categories: network-based factors, referring to the explicit relationship between links or visits

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and social interaction (e.g., number of comments and citations); content-based factors, including the subjective degree, length, and lifetime a certain blog; and activeness-based factors, including the number of posts and replies. Under the consideration of time-stamped observations of posts and the assumption that transmission was governed by an independent cascade model, Gruhl et al. [21] attempted to construct a transmission network between bloggers. Adar and Adamic [22] used a similar approach to reconstruct diffusion trees among bloggers. Other similar approaches can be found in the next section regarding influencer identification on Twitter.

B. *Measurement of Influence on Twitter*

In earlier studies measuring influence on Twitter, the challenge was to define influence and determine the key factors of influential Twitter users. Anger and Kittl [23] compared three different measures of influence: indegree, representing the popularity of a specific user; retweets, representing the content value of a user's tweets; and mentions, representing the name value of a user. They concluded that indegree is not always related to the ability to engage an audience. This finding suggests that indegree alone reveals little information on user influence.

Kwak et al. [24] compared three different measures of influence: number of followers, page rank, and number of retweets. They observed that the rankings of most influential users differed depending on the applied measure. Similarly, Cha et al. [25] compared the number of followers, number of retweets, and number of mentions. They found that the most followed users did not score the highest on the other measures. Finally, Weng et al. [26] compared the number of followers and page rank with a modified page rank measure that accounted for topics; they also revealed that ranking depended on the influence measure. These studies have provided the foundation for future researchers; nevertheless, their results cannot be easily applied by marketing experts because of the lack of a mechanism to identify influential Twitter users. Moreover, the studies have considered a limited number of factors, which may engender a significant bias in the definition of Twitter user influence.

C. *Machine Learning for Influencer Identification*

Researchers at the Thomas J. Watson Research Center of IBM developed a supervised rank aggregation model for predicting influencers on Twitter; the model combines different influence measures to produce a composite ranking mechanism that is most effective for a desired task [27]. They compared 13 different ranking measures for identifying influencers and concluded that previous retweets were the most effective measure with the highest accuracy. Some studies have focused on analyzing factors that are crucial for increasing the influence of a Twitter user. Such studies have extracted factors from several Twitter marketing platforms: one of them is Twinfluence, which includes the velocity metric that determines the average number of first- and second-order followers [28]; TwitterGrader, which measures the number of followers and friends [28]; and Klout, which provides an influence ranking value [18]. Several regression models have been trained based on different services for evaluating factors that are crucial for increasing the influence of a Twitter user. Bakshy et al. [5] investigated the attributes and relative influence of 1.6 million Twitter users by tracking 74 million diffusion events occurring on Twitter follower graphs. They found that the largest cascades tend to be generated by users with many followers. Moreover, they observed that the most influential users are also the most cost effective, therefore, to achieve cost-effective marketing strategies, managers can increase the degree of influence of ordinary influencers, that is individuals exerting average or below average influence.

In summary, influencer identification has been prominently discussed in academia. On the basis of related work, this study can be addressed by using machine learning and deep learning techniques. These techniques can facilitate the consideration of a relatively high number of measures, which may provide new insights into marketing

III. KEY INFLUENCE FACTORS

Although studies have generally defined influencers as individuals who can have a disproportionate effect on the spread of information, this definition is ambiguous without general measurable standards. A feasible solution to the problem of defining influencers is to apply the ranking mechanism of current influencer marketing services. IZEA [29] has a quality score that ranks potential influencers on different levels from 1 to 5; however, this ranking service cannot be accessed without subscription. Followerwonk is a leading online application that provides several Twitter marketing features, one of which is the "Search Bios" tool. This tool enables users to obtain a list of Twitter users who are relevant to a search keyword. Furthermore, users can search specific Twitter profiles and obtain a summary of its influence. Followerwonk also provides the social authority value, a ranking mechanism that ranks the influence strength of a Twitter user from 0 to 100. A higher social authority value indicates a stronger influence. The score is based on three components:

- The retweet rate of a few hundred of a measured user's last non-@mention tweets [10].
- A time decay to favor recent activity versus ancient history [10].
- Other data for each that are optimized via a regression model trained to retweet rate.

Because retweets constitute a common measure of the effectiveness of a marketing campaign on Twitter, the social authority value is a reasonable reference of the ground truth data for ranking influence.

The Twitter ecosystem is suitable for studying the effect of influencers. This is because interactions between users can be observed using structured data among their tweets and profiles. To examine the degree of influence of Twitter users, this study collected 20 influence factors from profiles of Twitter users and tweets from their user timelines. These factors might exert significant or nonsignificant effects on the social authority value of users. The factors were evaluated using a Backpropagation Neural Network (BPNN). Before their evaluation, the 20 factors were classified into three categories by adjusting the present MIV model [11]: network-based, activeness-based, and content-based factors. These categories are described in the following sections.

A. Network-Based Factors

People tend to follow someone with a fine reputation, which represents their popularity and trustworthiness within a social network. Network-based factors represent the popularity and trustworthiness of a user. In a Twitter network, which comprises a user's followers and followings, tweeting is analogous to spreading seeds on a field. The more influential a user is, the higher is the likelihood that the user's seeds will sprout.

1) Popularity: To follow conversations of other communities and users, Twitter users must subscribe to such communities and users; the tweets of such communities and users would then appear on the users' own newsfeeds. Different from other social media platforms, Twitter users do not require consent to follow other users' activities. Two basic indicators represent the popularity of Twitter users: number of followers, which indicates their reputation but is not necessarily related to their influence; and number of followings (users one follows), which can indirectly increase the visibility of accounts. When users follow other users, they have a relatively high opportunity for interacting with the followed users. The higher the popularity of a Twitter user is, the higher the number of people who can access the user's tweets within a certain period. Therefore, the two aforementioned indicators must be considered:

- Number of followers: The number of followers of a Twitter user.
- Number of followings (users one follows): The number of users followed by the Twitter user.

2) Trustworthiness: Trustworthy Twitter users are responsible when sharing information on Twitter. They are reliable and honest with respect to delivering consistent values and behaviors and understand the importance of nourishing their relationship with subscribers [30]. To evaluate the trustworthiness of a Twitter user, the following factors are usually examined:

- Account age: This refers to the duration for which the account has existed. The credibility of an account can be evaluated using the account age.
- Number of statues: This refers to the number of tweets posted in the lifetime of the account. The number of statues indicates the effort of the Twitter user in managing the account. Twitter users with a high number of statues may be more trustworthy than others.
- Listed number: This refers to the number of times the Twitter account has been added to other users' favorite list in its lifetime. Twitter users can add accounts into their favorite lists. The higher the number of times the account has been listed, the higher the trustworthiness of the account is.

B. Activeness-Based Factor

Twitter is different from other social media platforms or microblogging service providers in that it can highlight some social interactions. First, most interactions occur on tweets. Second, Twitter users can repost other users' tweets to their followers, an action that is popularly known as retweeting. Finally, users can respond to other users' tweets. Users can respond to tweets on Twitter through two approaches: replying and mentioning. Replies can be indicated by tweets starting with @username, excluding retweets. A tweet that starts with @username is not broadcast to all followers but to only the corresponding user. Mentions can be indicated by tweets containing @username in the middle of its text. Such tweets are broadcast to all followers. Twitter users can "like" other users' tweets by clicking or tapping on the "favorite" button. All these interactions can be adequately tracked through the application programming interface (API) of Twitter. These interactions can be further categorized as passive and active.

1) Passive Interactions: When Twitter users tweet, they passively receive likes, retweets, and replies. Influential Twitter users can induce others to interact with them by initiating discussions and creating trending topics. The measurement of passive interactions indicates the ability of Twitter users to induce interactions.

- Most favorited: This represents the number of favorites observed on the most favorited tweet in a Twitter user's account lifetime.
- Average favorites per tweet: This represents the average number of favorites of each tweet in a Twitter user's account lifetime.
- Average favorites per user: This represents the average number of contributed favorites of each follower of a Twitter user in the user's account lifetime.
- Most retweeted: This represents the number of retweets observed on the most retweeted post in a Twitter user's account lifetime.
- Average retweets per tweet: This represents the average number of retweets of each tweet in a Twitter user's account lifetime.
- Average retweets per user: This represents the average number of contributed retweets of each follower of a Twitter user in the user's account lifetime.

An analysis that considers reply measures is comprehensive; nevertheless, an enterprise-level application of Twitter's official API is to acquire relevant objects on Twitter. Because retweeting is considered to be

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similar to replying, employing retweet measures is sufficient.

2) Active Interaction: In addition to passively receiving favorites, retweets, and replies from others, Twitter users can actively interact with other users to strengthen their influence by favoriting, retweeting, and replying to other users' tweets. Active interactions increase a user's probability of acquiring more followers. The higher the number of active interactions contributed by a user is, the more active the user becomes. Some of the existing active interaction measures can be outlined as follows:

- Average tweets per day: This represents the average number of tweets a Twitter user posts per day.
- Average favorites per day: This represents the average number of favorites a Twitter user contributes per day.
- Average retweets per day: This refers to the average number of retweets a Twitter user contributes per day.

These interactions describe the methods through which users use Twitter. This study was conducted to evaluate the mechanisms through which these interactions affect user influence. Notably, all factors were averaged to moderate the effects induced by the lifetime of an account and the number of followers.

C. Content-Based Factors

The role of content cannot be excluded from this study. Some content types may exhibit a stronger tendency to spread than others. Although Twitter restricts the length of tweets to less than 140 characters, it permits users to include videos, pictures, URLs, and other media on their tweets. Moreover, tweets with emotionally stimulating contents show different tendencies to spread than others [31]. Therefore, VADER [32], an open-source sentiment analysis tool, was applied to provide an averaged sentiment score for each Twitter user; this score indicates the degree to which each user's tweets are positive or negative.

1) Content Analysis: VADER is an open-source Python library for performing sentiment analysis. In VADER, sentiment classification is executed using the lexicon and rule-based sentiment analysis library; the tool performs adequately on text originating from microblogs [32]. This tool was utilized to calculate each Twitter user's average sentiment score, which was measured on a scale ranging from -4 to $+4$, with the midpoint 0 representing a neutral sentiment. This study considered the following content factors:

- Sentiment score: This represents the average sentiment score of each tweet on a Twitter user's timeline.
- Average length of tweets: This represents the average length of a tweet on a Twitter user's timeline.
- Average number of hashtags per tweet: This represents the average number of hashtags used in each tweet on Twitter user's timeline.

The length of a tweet and number of hashtags used in the tweet may affect the level of influence of the tweeted content. Hashtags are used to express a tweet's similarity with certain clusters of contents and can increase the exposure of the tweet to other users.

2) Types of Media: Twitter allows users to tweet with several types of media. Videos, pictures, and URLs are the most common options. Different levels of difficulty may be experienced in spreading various types of information on social media. To spread information, selecting an appropriate type of media is crucial for a Twitter user. For example, This study considered the following factors to reveal the usage habits of Twitter users and determine the effectiveness of such factors for influence measurement:

- Tweets with hashtags: This represents the number of tweets with hashtags on a Twitter user's timeline, and the corresponding ratio ranges from 0 to 1.
- Tweets with media: This represents the number of tweets containing media (videos or pictures) on a Twitter user's timeline, and the corresponding ratio ranges from 0 to 1.
- Tweets with URLs: This represents the number of tweets containing URLs on a Twitter user's timeline, and the corresponding ratio ranges from 0 to 1. Tweets with media and URLs are separated into two factors, as videos and pictures bring stronger interaction than URLs.

To identify influencers on Twitter, this study collected and processed the 20 aforementioned factors, divided into three categories, from the profiles of Twitter users; the processing results served as inputs for training the neural network model. As mentioned, the effectiveness of some of these factors in revealing the features of influencers may be significant or nonsignificant, and this is discussed in the following sections.

IV. Experiments

Numerous new projects are being implemented on Kickstarter daily, and most of them are in the top five campaign categories: games, technology, design, publishing, and arts. Entrepreneurs must identify different types of influencers during the marketing process. For example, a fundraiser who owns a campaign selling a new smartwatch product might prefer a tech influencer rather than an art influencer. Existing influencer marketing platforms usually rank Twitter users by their general influence rankings, which cannot measure their influence among different categories of campaigns.

To observe the difference between categorical influencers and general influencers, the first step is to train a neural network model, which fits the existing influencer ranking mechanism. Accordingly, this study collected the 20 aforementioned influence factors from the profiles of Twitter users who had recently tweeted about crowdfunding campaigns. These Twitter users were ranked according to the corresponding social authority value derived on Followerwonk. After the datasets were prepared, they were fed into the BPNN. Finally, the predicted social authority value and the actual value on Followerwonk were compared.

This study was considered the expandability of the model for its practicality. The ANN model was applied in this study for the following reasons: First, the proposed marketing research framework could handle more than 20 analyzed factors. Second, accessibility was considered, thus rendering the ANN model the first choice for addressing the proposed research problem for numerous existing free open-source libraries. Finally, the model can help to capture the complex nonlinear relation between this study's input factors and output results.

A. *Data Collection*

With the basic usage limitation of Twitter's API, this study collected only tweets posted within a 7-day period. To obtain a sufficient number of Twitter users, the data collection period was from May 8, 2018, to July 3, 2018, a total of 8 weeks. First, all data of live crowdfunding campaigns were crawled on Kickstarter from the top five categories [33]. These campaigns were filtered using pledged percentages. Campaigns with a pledged percentage of more than 50% were selected to moderate the effect of campaign quality (Table I). A statistical report [34] supported that 95.6% of unsuccessful campaigns did not have a pledged percentage of more than 50%; this thus indicates that unsuccessful campaigns were excluded from the analysis in the present study.

TABLE I. NUMBER OF CAMPAIGNS ABOVE 50% PLEDGED CRAWLED ON KICKSTARTER

Category	***Art***	***Design***	***Technology***	***Game***	***Publishing***
Campaigns	360	754	236	646	302

TABLE II. STATISTICS OF THE TWITTER USER DATASET

Statistics from Our Examined Blogger Set	
Number of total Twitter users	1969
Average account live time	2048.789/per user
Average number of statuses per user	21378.363/per user
Average number of followers per user	39391.371/per user
Average number of friends (followings) per user	3282.032/per user
Average listed number per user	323.231/per user
Average number of favorites per tweet	6.741/per tweet
Average number of retweets per tweet	926.577/per tweet
Average social authority value of all users	43
First quartile of social authority value of all users	32
Third quartile of social authority value of all users	56

Second, using the list of campaigns as search keywords, this study collected all tweets containing search keywords by using Twitter's API Tweepy. Tweepy is a free Python library that allows users to access Twitter and obtain the required data. From the collected tweets, this study acquired the usernames and their profile information for further evaluation. Finally, on the basis of each Twitter username, each Twitter user was ranked in terms of the social authority value on Followerwonk. The initial dataset was prepared by combining the collected data (Table II).

B. *Experimental Design*

The initial dataset was divided into a training set and testing set at a ratio of 8:2. The complete process for training the prediction model involved influence factor calculation, model training, and performance evaluation (Figure 1).

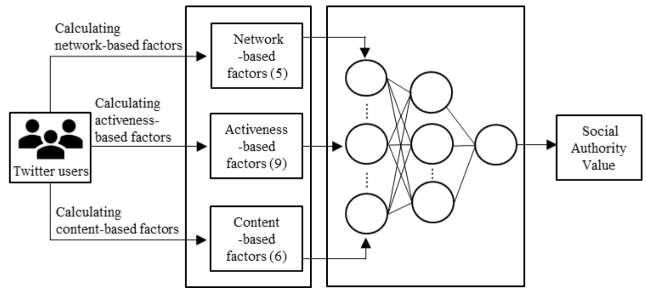

Figure 1. Model training process.

1) Influence Factor Calculation: The entire data of Twitter users collected in this study must be evaluated to derive the influence factors. A total of 20 influence factors, comprising the network-based factors, activeness-based factors, and content-based factors, were derived.

2) Model Training: In this study, an ANN with a two-hidden layer BPNN was used to address the problem of uncertainty in the weighting process. The 20 influence factors were used for social authority value prediction. The BPNN is the most widely applied ANN model because of its strength [34] of managing complex nonlinear relationships between input data and output results. The original sigmoid function is [0,1], and this study performs rescaling to get the results in the range [0, 100] to fit in the bracket of social authority value.

3) Performance Evaluation: To evaluate the performance of the BPNN model, the predicted social authority value and the actual value on Followerwonk were compared, and efficiency of the model was examined. A different combination of parameters of the network structure was tested to fine tune the model. The grid search algorithm was applied for finalizing the parameter settings (Table III).

TABLE III. PARAMETER SETTINGS FOR THE BPNN MODEL

Parameters	**Value**	**Parameters**	**Value**
Number of hidden layers	2	***Loss function***	MSE
Kernel initializer	Normal	***Batch size***	32
Activation function (hidden layer)	Rectifier	***Epochs***	256
Activation function (output layer)	Sigmoid	***Optimizer***	Rmsprop

C. *Structure of BPNN*

Keras on Tensorflow [35], an open-source ANN library written in Python, was applied to construct the three-layer BPNN for training and testing the proposed prediction model. The constructed three-layer BPNN was composed of an input layer, a hidden layer, and an output layer. The input layer had 20 neurons to adopt the 20 influence factors, comprising the network-based factors, content-based factors, and activeness-based factors. In the hidden layer, 10 neurons were used for adaptive weight adjustment. Only one neuron was included in the output layer for the output data, which was the predicted social authority value. Table III details the parameter settings for the BPNN model.

V. RESULTS AND DISCUSSION

After the model training process, the model performance was evaluated to optimize the training process. The grid search algorithm was applied to determine the optimal set of parameters to train the BPNN model. A feature selection technique was then applied to determine the factors with relatively high effects and eliminate irrelevant factors. Thus, the resulting factors can help brands to identify influencers by using the minimum required amount of data, thereby improving time efficiency. Finally, the data of categorical influencers were selected. Their Twitter influence was ranked based on the social authority value predicted by the model. The difference between general influencers and categorical influencers was observed with reference to the origin of the social authority value.

A. *Results*

Several parameter sets were tested to optimize the performance of the BPNN model by using the grid search algorithm. Grid search is an approach of parameter tuning that methodically develops and evaluates a model for each combination of algorithm parameters specified in a grid. Because the output value of the BPNN model is a continuous value between 0 and 100, this research problem is naturally defined as a multiple linear regression problem. Therefore, selecting a mean squared error to score each parameter set is the most appropriate approach. The calculated mean squared error value was averaged after the application of 10-fold validation (Table IV).

TABLE IV. RESULTS OF EACH TESTING PARAMETER SET

Parameters Set	Batch Size	Epochs	Optimizer	MSE
Set #1	32	256	Adam	0.0118
Set #2	32	256	Rmsprop	0.0116
Set #3	50	512	Adam	0.0128
Set #4	50	512	Rmsprop	0.0125
Set #5	64	1024	Adam	0.0126
Set #6	64	1024	Rmsprop	0.0133

The variance of all the results was under 0.01, signifying that the model performance was acceptable without overfitting. Moreover, when identifying the influencers on Twitter, a brand is concerned with the accuracy of the model in detecting high-influence Twitter users. Therefore, the best 25 influencers were extracted from the dataset as highly influential users with a social authority value of higher than 82. The performance of the prediction model in identifying these 25 users was examined. A confusion matrix was used for accuracy evaluation, and Table V shows the results.

This study also examined different numbers of layers of the ANN model and determined that the three-layer model exhibited a relatively high performance level (Table VI). The main explanation for the derived results is that the number of highly influential users selected for evaluating the model corresponded to the extreme values of the dataset. The model was trained to fit most of the observed data, but not the extremely large data. Furthermore, a deeper network is required for training a large amount of data, particularly for unstructured data. Accordingly, the three-layer ANN model was deemed suitable for this study's analysis.

TABLE V. ACCURACY OF MODEL WITH HIGH-INFLUENCE USERS

Parameters Set	Accuracy	True Positive Rate	False Positive Rate
Set #1	94.67%	52.63%	0.53%
Set #2	94.92%	57.89%	0.27%
Set #3	95.18%	42.10%	0.00%
Set #4	95.18%	36.84%	0.00%
Set #5	94.67%	57.89%	0.53%
Set #6	95.18%	42.10%	0.00%

TABLE VI. EXAMINING DIFFERENT NUMBER OF LAYERS OF THE ANN MODEL

Layers	MSE	Variance	Accuracy	True Positive Rate	False Positive Rate
3	0.0116	0.0029	94.92%	57.89%	0.27%
4	0.0119	0.0025	91.17%	28.07%	5.63%
5	0.0116	0.0025	97.21%	10.52%	2.4%

On the basis of the model evaluation process and the aforementioned results, set#2 was selected as the optimal parameter set for constructing the BPNN model. However, performance could still be improved for highly influential users. The model was still determined to be effective for conducting further analysis.

B. *Feature Selection*

Although the model was appropriately trained and exhibited adequate performance, data collection was the most time-consuming part of this process. The collection of 20 influence factors for the targeted Twitter users required considerable time. To improve time efficiency and avoid the problem of dimensionality, feature selection techniques must be used. This study thus applied the backward elimination process to select the features that were most relevant for measuring the social authority value of Twitter users.

1) Backward Elimination: Backward elimination is a widely used feature selection technique for multiple linear regression problems. Before the initiation of the selection process, the significance level (0.05) required for features to remain in the model must be determined first. The model was fitted with all possible features, and features with the highest p value were considered. If the p value was higher than the significance level, the feature was removed from the model. After the completion of the iterations, 13 features were selected from the 20 influence factors. As shown in Table VII, all network-based factors were selected, and the content-based factors were considered relevant. By contrast, most activeness-based factors were eliminated based on the selected significance level.

TABLE VII. SUMMARY OF FEATURE SELECTION

Features	Category	P-value
Account age	Network-based factors	0.000
Number of statues		0.000
Number of followers		0.000
Number of followings (friends)		0.000
Listed number		0.003
Average favorites per day	Activeness-based factors	0.000
Average favorites per tweet		0.000
Average favorites per user		0.000
Average length of tweets	Content-based factors	0.000
Sentiment score		0.049
Tweets with hashtags		0.007
Tweets with URLs		0.000
Tweets with media		0.047

2) Eliminate Activeness-based Factors: The preceding result shows that activeness-based factors were less relevant features for measuring the social authority value. The model was retrained to improve its performance in identifying the top 25 influencers. First, the activeness-based factors were eliminated from the features, and the true-positive rate was then improved to 63.19%, without increasing the variance (Model #1). Subsequently, according to the feature selection result, the features that were not eliminated were considered. The true-positive rate was then highly improved to 89.47% (Model #2) (Table VIII).

TABLE VIII. RETRAINED MODEL PERFORMANCE

Model	MSE	Variance	Accuracy	True Positive Rate	False Positive Rate
#1	0.017	0.010	96.19%	63.16%	2.13%
#2	0.010	0.003	97.46%	89.47%	2.13%

C. Observing Effect of Categories

As mentioned, existing influencer marketing applications, such as Followerwonk, can rank Twitter users based on the general influence. Understating whether a Twitter user is more influential on some topics than others is difficult. To observe the effect of categories, data obtained from 40 Twitter users were selected from the dataset. These users were highlighted for focusing on a certain category of campaigns. Their data were modified and fed into the fine- tuned ANN model to compare the social authority value predicted by our model and the original value on Followerwonk.

Eliminate Tweets without URLs: To examine the impact of categories, tweets without URLs were excluded from the analysis. These tweets were crawled from the timelines of the 40 categorical users. Table IX presents tweets with URLs containing information that users intended to share. These tweets are shown to contain a “call to action.” The objective of a piece of content was to induce followers to perform a specific act. Such tweets are more important for ranking the influence of Twitter users compared with other tweets.

TABLE IX. PREDICTED VALUE OF CATEGORICAL USERS (PARTIAL)

User	Category	Social Authority	Predicted Value
18dMedia	Design	25	64.32
5toclose		33	57.93
bikeradar		66	69.96
designtaxi		76	84.48
gadgetfeedco		39	57.37
werdcom		31	51.24
Ellerium_Games	Games	26	33.33
ETBoard_Games		55	61.09
ssoebmizan		38	47.65
tgn_news		47	57.40
NewsWatchTV	Technology	51	57.14

After predicting the modified data of the 40 categorical users, this study observed that the predicted social authority value of some categorical users was increased (Figure 2).

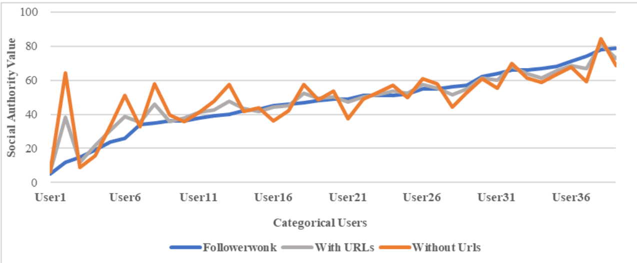

Figure 2. The predicted value of categorical users.

Although the study cannot attribute the differences to the effect of categories, the predicted social authority value of some users increased under the condition where tweets without URLs were excluded.

VI. CONCLUSION

This study proposes a research framework, involving data collection, influence factor calculation, and ANN model training, for identifying potential influencers for crowdfunding on Twitter. The processes involved in the framework can be easily applied through open-source libraries without incurring any costs. The MIV model and feature selection technique were applied in this study to identify the optimal measures of the influence strength of a Twitter user. Thirteen factors were selected from a total of 20 influence factors. Activeness-based factors were determined to be the least relevant features for measuring influence. These results may be explained by the fact that the quality of tweets by influencers could be inversely proportional to the number of tweets posted. These findings can improve time efficiency for companies in the execution of marketing research. After observing the effects of different categories, this study determined that the social authority value of some of the categorical users increased after the exclusion of tweets without URLs from the analysis.

Future research directions include the development of a fair ranking mechanism because predicted values are limited by the original social authority value, which may be inaccurate in case of promotional activities. Furthermore, this study suggests that future studies monitor changes in crowdfunding campaigns to determine and measure the actual effects of potential influencers. Finally, it would be difficult to conclude that the observed differences between the predicted value and original social authority value were the result of categorical effects. Therefore, this study highly recommends the implementation of a posterior examination framework in future research.

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