What Propels Celebrity Follower Counts? Language Use or Social Connectivity

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Abstract

Follower count is a factor that quantifies the popularity of celebrities. It is a reflection of their power, prestige and overall social reach. In this paper we investigate whether the social connectivity or the language choice is more correlated to the future follower count of a celebrity. We collect data about tweets, retweets and mentions of 471 Indian celebrities with verified Twitter accounts. We build two novel networks to approximate social connectivity of the celebrities. We study various structural properties of these two networks and observe their correlations with future follower counts. In parallel, we analyze the linguistic structure of the tweets (LIWC features, syntax and sentiment features and style and readability features) and observe the correlations of each of these with the future follower count of a celebrity. As a final step we use these features to classify a celebrity in a specific bucket of future follower count (HIGH, MID or LOW). We observe that the network features alone achieve an accuracy of 0.52 while the linguistic features alone achieve an accuracy of 0.69 grossly outperforming the network features. We also discuss some final insights that we obtain from further data analysis – celebrities with larger follower counts post tweets that have (i) more words from ‘friend’ and ‘family’ LIWC categories, (ii) more positive sentiment laden words, (iii) have better language constructs and are (iv) more readable.

Introduction

The number of followers (aka follower count) that an individual has on a social media platform (e.g., Twitter) has become a symbol of ‘popularity’, ‘prestige’, ‘power’ and is an indicator of the overall social reach of the individual. While some debate, that this is only a ‘game’, there is a growing consensus that this is a determinant of social status and can also have monetary implications. In fact, various political, business and competition campaigns are reported to buy followers to propagate and make such campaigns successful.

Celebrities are no exceptions in this race of acquiring follower counts. In fact, they are, in most cases at the forefront of the race. There are certain celebrities who are known to have millions of followers and follower losses due to Twitter’s policy change or otherwise makes a big news these days.

A pertinent question that arises is what strategies do celebrities employ early on to enhance their follower counts? Do they invest more on enriching their social connectivity or is the type/linguistic structure of their tweets that plays the key role in this enterprise. In the current paper we put forward for the first time this question and investigate in detail the correlations between social connectivity, language use and the follower count of 471 Indian celebrities with verified Twitter accounts.

Some of the key contributions of this work are

Contributions:

- We prepare a list of 471 Indian celebrities with verified Twitter accounts. We collect all their tweets, their retweet and mention history as well as their follower counts.
- We define novel types of retweet and mention networks and investigate the centrality properties of the nodes in these networks.
- We perform an extensive linguistic analysis of the tweet text for each individual celebrity. In particular, we extract LIWC features, syntactic features, sentiment features, style features as well as readability features.
- Finally, we build a classifier to predict the range of future follower count of a celebrity using the network and the language features that we extract.

Key results and observations:

Some of the important results and observations are as follows,

- We observe that network features such as betweenness, degree and PageRank centrality are positively correlated to the future follower count. In contrast, clustering coefficient is negatively correlated to the future follower count.
- We observe that certain LIWC features such as ‘positive emotion’, ‘affection’, ‘cognitive mechanics’ and ‘social’ show high correlation with the future follower count; in contrast, features like ‘sad’, ‘anger’, ‘anxiety’, ‘death’ and ‘swear words’ show low correlation with the future

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1https://techcrunch.com/2009/04/16/should-twitter-remove-its-followers-count/?guccounter=1
2https://moz.com/blog/guide-to-buying-legit-twitter-followers, http://twitterboost.co/why-politicians-buy-twitter-followers-and-retweets/
3https://www.teenvogue.com/story/celebs-lose-millions-of-twitter-followers-following-new-account-policy
Some of the interesting observations are – (i) LIWC categories like ‘anger’ and ‘negate’ are in larger proportions for celebrities who are less popular (i.e., lower follower counts). On the other hand, highly popular celebrities (i.e., higher follower counts) have larger proportions of words from the LIWC categories like ‘family’ and ‘friend’ in their tweets, (ii) tweets of celebrities with higher follower counts are laden with positive sentiments and (iii) celebrities with larger follower counts post tweets that seem to have better language construct and are more readable.

Related works

Celebrities in news: Castillo et al. (Castillo et al. 2013) analyzed linguistic style of people when they post news related to the celebrities. Sweetser et al. (Sweetser and Kaid 2008) studied the effects of personalized and ‘stealth’ political discourse on the weblogs (or blogs), and repercussions on the levels of political trust, information efficacy and political uses/gratifications. Ogan et al. (Ogan and Cagiltay 2006) in their study found that diversion drives most reading on the site, but social interaction provides the largest gratification to those who participate through writing confessions, commenting on others confessions and meeting people offline. Moynihan et al. (Moynihan 2004) studied effect of celebrity marketing in pharmaceutical domain. Sheridan et al. (Sheridan et al. 2007) studied the concept of celebrity worship and its relation to criminality and addiction. Cheng et al. (Cheng et al. 2007) studied the influence of media reporting of the celebrity suicides on the suicide rates. Hayward et al. (Hayward et al. 2004) studied the causes and consequences of a CEO Celebrity. Maltby et al. (Maltby et al. 2004) studied the relation between celebrity worship and mental health. Elberse et al. (Elberse and Verleun 2011) studied economic value of celebrity endorsements.

Celebrities on social media: There have been a number of studies investigating the social behavior of celebrities. Kumar et al. (Kumar et al. 2015) proposed a topic model analysis of social media content, following celebrity suicides which revealed the presence of derogatory tone in the content. Romero et al. (Romero et al. 2011) proposed an algorithm to measure the influence and passivity of users, based on information forwarding activity. Cha et al. (Cha et al. 2010) did a comparative study of user influence across topics with three influence measures: in-degree, retweets and mentions. Sakaki et al. (Sakaki and Matsuo 2010) identified various parameters related to social networks that are found to be a factor for celebrity popularity. Marwick in his study (Marwick 2011) described various celebrity practices including language of acknowledging fans and cultural references to create fan affiliation. Hoffman et al. (Hoffman and Tan 2015) described biological, psychological and social processes that explain celebrities’ influence on patients’ health-related behaviors. Zhao et al. (Zhao et al. 2014) proposed a computational approach to measure the correlation between expertise and social media influence, for celebrities on microblogs. Kim et al. (Kim, Beznosov, and Yoneki 2014) concluded that, in social networks, information can be efficiently propagated using neighbors having high potential of propagation rather than having high number of neighbors. Brzozowski et al. (Brzozowski and Romero 2011) in their study compared a variety of features for recommending users, and presented design implications for social networking services. Bakshy et al. (Bakshy et al. 2011) proposed several measures to quantify influence in the social networks like Twitter. Sharma et al. (Sharma, Suman, and Shannigrahi 2014) proposed methods to infer social ties from common activities in Twitter. Abbasi et al. (Abbasi et al. 2014) analyzed homophily effect in the directed social networks. Taxidou et al. (Taxidou et al. 2015) modeled information diffusion in the social media. Zhou et al. (Zhou, Wang, and Chen 2016) analyzed the deleted tweets to understand and identify regrettable ones. Taxidou et al. (Taxidou and Fischer 2014) studied effect of different influence models on the cascades.

Present work: Our work is different from the ones reviewed above. We study the celebrity profiles, their social connectivity and tweeting behavior and observe correlations of these variables with the future follower count. We show for the first time that the language use is way more important than social connectivity in acquiring follower counts.

Dataset description

Data collection process

In this study, we consider a list of 471 Indian celebrities from five different areas – Movie, Music, News, Tech and Sports. We start with certain verified celebrity accounts and then use Twitter’s recommendations in the “You may also like” section (Figure 1) to get more celebrities. In most cases, these recommendations correspond to colleagues of the initial set of celebrities in the same category. Table 1 shows the distribution of the number of celebrities across the different categories.

Table 1: Distribution of celebrities across the five categories.

| Category | Celebrities |
|----------|-------------|
| Movies   | 92          |
| Music    | 95          |
| News     | 92          |
| Tech     | 95          |
| Sports   | 97          |
| Total    | 471         |

We gathered tweets generated by these handles using the

Celebrity list: https://github.com/zorroblue/language-matters/tree/master/data
Twitter streaming API\(^5\) for the duration of June and July 2017. We collected the tweets of two different categories – (i) tweets posted by the celebrities themselves in this period, and (ii) tweets posted by other users who either mention or retweet one or more of these celebrities. We removed all the invalid and duplicate tweets. We also collect the future follower count of each celebrity\(^6\) for the month of October 2017.

### Basic statistics of the data collected

The data collection and filtering process resulted in 23,57,070 tweets, out of which 15269 are tweets from the celebrities. We calculate average retweet density (ARD) for each category of celebrities by taking the ratio of the cumulative count of the number of retweets obtained by the celebrities’ tweets to the total number of tweets done by the celebrities in that category. Figure 2 shows the ARD across the five categories. Interestingly, the movie and the news categories have the highest ARD, the former possibly due to the huge fan following of movie stars and the latter due to the sharing of the latest and ‘hot’ news.

### Social connectivity

In this section we construct two different networks that approximate the social connectivity of the celebrities. One of these is based on retweets and the other on mentions. We finally extract various features from these networks and observe how they correlate with the celebrity follower buckets.

#### Retweet network

We consider each celebrity as a node in this network. There is an edge between two nodes if at least five common users\(^7\) have retweeted both of their tweets (may be different tweets) in our dataset. The edge weight is the normalized number of common retweeters, given by

\[
weight_{rt}(A, B) = \frac{\text{common\_retweeters}(A, B)}{\sum_{(i,j)} \text{common\_retweeters}(i, j)}
\]

Using this criteria, we get a network of 324 nodes and 20502 edges.

#### Mention network

Similar to the retweet network, here we consider celebrities as nodes. However, here an edge between two nodes form if at least five common users\(^8\) have mentioned both celebrities independently in their tweets in our data set. The edge weight is the normalized number of common mentioners, given by

\[
weight_{men}(A, B) = \frac{\text{common\_mentioners}(A, B)}{\sum_{(i,j)} \text{common\_mentioners}(i, j)}
\]

Using this criteria we obtain 368 nodes and 44072 edges.

### Network features

We extract the following network properties from the retweet as well as the mention network.

#### Network centrality measures

We compute traditional network centrality measures such as betweenness centrality (\(C_{bet}\)) (Freeman 1977), closeness centrality (\(C_{clo}\)) (Sabidussi 1966), clustering coefficient (\(Clust_{coff}\)) (Holland and Leinhardt 1971), degree centrality (\(C_{deg}\)) (Mej 2010) and PageRank centrality (\(C_{pr}\)) (Sullivan 2007) for our analysis. We obtain the Spearman’s rank correlation between the follower count and these network measures for all the celebrities. In the Table 2 we report these correlations. We observe that in both the networks, betweenness, degree and PageRank centralities are strongly positively correlated to the future follower count.

\(^5\)Twitter streaming API: https://developer.twitter.com/en/docs/tutorials/consuming-streaming-data.html\n
\(^6\)Follower count list: https://github.com/zorroblue/language-matters/tree/master/data\n
\(^7\)The number five has been set empirically.

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Table 2: Spearman’s rank correlation between network features and the follower counts.

| Feature   | $\rho_{rt}$ | $\rho_{men}$ |
|-----------|-------------|--------------|
| $C_{clo}$ | 0.14        | -0.13        |
| $C_{bet}$ | 0.55        | 0.57         |
| $C_{deg}$ | 0.63        | 0.59         |
| $Clust_{cof}$ | -0.43   | -0.57        |
| $C_{pr}$  | 0.57        | 0.58         |

count. On the other hand, cluster coefficient is negatively correlated to the future follower count in both the networks.

**Linguistic structure of the tweets**

In this section we analyze the linguistic structure of the tweets posted by the celebrities. Prior to the analysis, we preprocess all tweets by removing non-ASCII characters, urls, ellipses, special characters like #, @, {, } and stop words, followed by word stemming using the Porter stemmer.9

**LIWC analysis**

As a first step, we compute the fraction of different LIWC10 categories in the celebrity tweets. For every individual celebrity, we compute the fraction of words per tweet in each LIWC category. We term this fraction as the category density. Based on this factor we prepare a rank list of celebrities for each category. We then compute the Spearman’s rank correlation between these rank lists and the follower count based rank. Tables 3 and 4 show the top and the bottom ten LIWC categories that have the largest and the smallest correlations. We observe that the categories like ‘positive emotion’, ‘affect’, ‘cognitive mechanism’ and ‘social’ are highly correlated to future follower count. Categories like ‘assent’, ‘death’ and ‘swear words’ are least correlated to future follower count.

Table 3: Top ten LIWC categories showing higher Spearman’s correlation with follower count based ranking.

| LIWC category | $\rho$ |
|---------------|-------|
| Posemo        | 0.71  |
| Affect        | 0.70  |
| Funct         | 0.68  |
| CogMech       | 0.67  |
| Social        | 0.66  |
| Relativ       | 0.66  |
| Article       | 0.66  |
| Prep          | 0.65  |
| Pronoun       | 0.65  |
| Incl          | 0.64  |

Table 4: Bottom ten LIWC categories showing lower Spearman’s correlation with follower count based ranking.

| LIWC category | $\rho$ |
|---------------|-------|
| SheHe         | 0.31  |
| Sad           | 0.28  |
| Anger         | 0.27  |
| Filler        | 0.27  |
| Nonflu        | 0.24  |
| Ingest        | 0.24  |
| Anx           | 0.23  |
| Assent        | 0.23  |
| Death         | 0.19  |
| Swear         | 0.11  |

**Use of in-vocabulary words**

In this section we analyze the propensity of the use of in-vocabulary words by the different celebrities. For this purpose, we compute the ratio of the total number of in-vocabulary to the out-of-vocabulary words from all the tweets posted by each celebrity. We use the GNU Aspell dictionary11 to find the number of in-vocabulary words. We then rank the celebrities based on this ratio and report Spearman’s rank correlation with the follower counts. We observe very low negative rank correlation with the value -0.057.

**Tweet sentiment analysis**

In this section we analyze the overall sentiment in the tweets posted by each celebrity. We use the NLTK’s VADER sentiment extraction tool12 for our analysis. The analyzer returns four different scores – positive (pos), negative (neg), neutral (neu) and compound (comp). The last score is calculated by applying a normalized function over the first three scores. We rank the celebrities using the above scores and compute the Spearman’s rank correlation with the follower counts. The results are reported in Table 5. While positive sentiment is correlated with future follower count the negative sentiment is anti-correlated. Highly followed celebrities therefore seem to have more positive sentiment in their tweets.

Table 5: Spearman’s rank correlation between sentiment based rank lists and follower count based rank list.

| Sentiment | $\rho$ |
|-----------|-------|
| pos       | 0.17  |
| neg       | -0.12 |
| neu       | -0.05 |
| comp      | 0.21  |

**POS tag entropy analysis**

For the sentences to be well formed, intuitively the probability distribution of POS tags in the sentences has to follow a

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9https://tartarus.org/martin/PorterStemmer/index.html
10LIWC Companion :http://www.liwc.net/comparison.php
11http://aspell.net/
12http://www.nltk.org/_modules/nltk/sentiment/vader.html
uniform distribution (Márquez, Padro, and Rodriguez 2000). This means that the following expression for entropy over the POS tag probability distribution has to be maximum for the most well formed sentences.

$$\text{Entropy}_{\text{pos}} = - \sum_{X \in \text{postags}} p(X) \log p(X) \quad (3)$$

We rank the celebrities using this entropy value and compute the correlation between this rank list and the follower count based rank list. We obtain a low Spearman’s rank correlation value of -0.04.

**Style feature analysis**

Style is one of the key factors in any linguistic analysis. (Karlsgren and Straszheim 1997) reported various measures of styles in running text (see Table 6). We compute these measures from the collection of tweets of each individual celebrity. In Table 7 we report Spearman’s rank correlation between the style feature based rank list and the follower count based rank list of the celebrities. None of the style features seem to be strongly correlated to the future follower count.

**Readability analysis**

Readability is a way to quantify the reading convenience of a running text. Usually estimations are done by counting the number of syllables, words and sentences. While there are quite a few quantitative variants, the automatic readability number of syllables, words and sentences. While there are a running text. Usually estimations are done by counting the

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**Readability analysis**

Readability is a way to quantify the reading convenience of a running text. Usually estimations are done by counting the number of syllables, words and sentences. While there are quite a few quantitative variants, the automatic readability index (ARI) is the most popular one. The ARI is defined as,

$$\text{ARI} = 4.17 \left( \frac{\text{characters}}{\text{words}} \right) + 0.15 \left( \frac{\text{words}}{\text{sentences}} \right) - 21.53 \quad (4)$$

As per the above definition, the lower the value of ARI the better. We rank the celebrities again by ARI scores and compute the Spearman’s rank correlations with the follower counts. Once again we obtain a low Spearman’s rank correlation of -0.01.

**Popularity prediction**

In this section we predict the popularity, i.e., the follower count bucket for a celebrity, using network and linguistic features in turn. We present separate results of predictions using only network features as well as only linguistic features. We also study the effect of using different categories of linguistic features on the prediction results. As a final step, we combine the most relevant network and linguistic features for the purpose of prediction. We use supervised classification methods with ten fold cross-validation for the popularity prediction.

**Dataset for classification**

We place the celebrities into one of the three buckets – **HIGH**, **MID** or **LOW**. We consider only those celebrities who are present in both the retweet and the mention network. In effect, therefore we have 324 celebrities for classification. There are 108 celebrities in the **HIGH** and the **MID** bucket each in order of the number of their follower counts. The rest are placed in the **LOW** bucket.

**Network features**

**All network features** Here, we consider all the network features extracted from the retweet and the mention network for the classification. The accuracy obtained for various classifiers are shown in Table 8.

**Few highly correlating network features** Here we experiment with various highly correlating network features to predict the class. We observe that the following features – betweenness, degree and PageRank centralities, and the clustering coefficient of both the retweet and the mention network work as the best combination of features.

The accuracy of the different classifiers for these set of features are noted in Table 9.

**Linguistic features**

**All linguistic features** Here we consider all the linguistic features as described in the previous section for the classification. The accuracy obtained from the different classifiers are noted in Table 10. We observe that the linguistic features by far outperforms the network features in classification. This indicates that the choice of language plays a very crucial role in framing the future popularity of a celebrity. In fact, this choice is much more important than building social connections.

**Only LIWC features** Here we consider all the LIWC features for the classification. The results are shown in Table 11. The results show that among the linguistic features, the LIWC features themselves are one of the strongest discriminators.

**Linguistic features other than LIWC** The classification results for different classifiers considering all linguistic features except the LIWC categories are shown in Table 12. In isolation, these features do not seem to perform well.

**Few handpicked linguistic features** Here we consider only those linguistic features that show high Spearman’s rank correlation with follower count. These features include positive emotion (‘posemo’), affection words (‘af-fect’), function words (‘funct’), cognitive words (‘cog-mech’) and social words (‘social’) from LIWC. The accuracy of classifiers using these features are shown in Table 13. It turns out that using all linguistic features marginally improves the accuracy over using these set of handpicked features.

**Network + linguistic features:**

Here we consider a subset of linguistic and network features showing high Spearman’s rank correlation with follower count to predict the popularity of celebrities. The linguistic features in this subset include ‘affect’ words, function words (‘funct’), cognitive words (‘cogmech’) and ‘social’ words from LIWC and compound sentiment from the tweet sentiment analysis. Similarly, the network features in this subset include betweenness, degree and PageRank
Table 6: Different style metrics discussed in (Karlgren and Straszheim 1997)

| Variable name | Statistic                      | Typical Range  |
|---------------|-------------------------------|----------------|
| *TTR*         | Type token ratio              | 0.13-0.89      |
| *CPW*         | Average word length in characters | 4.59-9.95   |
| *WPS*         | Average sentence length in words | 2.45-63.1    |
| *P1*          | Proportion first person pronouns of words | 0-105       |
| *P2*          | Proportion second person pronouns of words | 0-20        |
| *P3*          | Proportion third person pronouns of words | 0-60        |
| *IT*          | Proportion ‘it’ of words      | 0-44          |

Table 7: Spearman’s correlation between style based features’ rank lists and follower count based rank list.

| Style feature | ρ    |
|---------------|------|
| *TTR*         | 0.03 |
| *CPW*         | -0.05|
| *WPS*         | 0.01 |
| *P1*          | -0.08|
| *P2*          | 0.04 |
| *P3*          | -0.10|
| *IT*          | -0.07|

Table 8: Accuracy of classifiers considering all the network features.

| Classifier      | Accuracy |
|-----------------|----------|
| Random forest   | 0.51     |
| XGBoost         | 0.51     |
| SGD Classifier  | 0.49     |
| Gaussian Naive Bayes | **0.52** |

Discussion

In this section we report some of the interesting insights that we find from the further analysis of the data.

Network centrality measures: We compute and report the average centrality values for both the retweet and the mention network in Table 15. The betweenness and the degree centralities in the retweet and the mention networks for the *HIGH* bucket are drastically larger (3 to 4 times) than the other two buckets.

LIWC: Some of the interesting insights that we obtain from the LIWC analysis is illustrated in Figure 3. We note that while celebrities in the *HIGH* bucket mostly tweet about

Table 9: Accuracy of classifiers considering few highly correlating network features.

| Classifier      | Accuracy |
|-----------------|----------|
| Random forest   | 0.50     |
| XGBoost         | **0.54** |
| SGD Classifier  | 0.40     |
| Gaussian Naive Bayes | 0.50     |

Table 10: Classification accuracy using all the linguistic features.

| Classifier      | Accuracy |
|-----------------|----------|
| Random forest   | **0.69** |
| XGBoost         | 0.67     |
| SGD Classifier  | 0.34     |
| Gaussian Naive Bayes | 0.63     |

Table 11: Classification accuracy using all the LIWC features.

| Classifier      | Accuracy |
|-----------------|----------|
| Random forest   | **0.66** |
| XGBoost         | 0.65     |
| SGD Classifier  | 0.61     |
| Gaussian Naive Bayes | 0.63     |

Table 12: Classification accuracy for all the linguistic features excluding LIWC.

| Classifier      | Accuracy |
|-----------------|----------|
| Random forest   | 0.34     |
| XGBoost         | **0.38** |
| SGD Classifier  | 0.30     |
| Gaussian Naive Bayes | 0.35     |

Table 13: Classification accuracy using highly correlating linguistic features.

| Classifier      | Accuracy |
|-----------------|----------|
| Random forest   | **0.66** |
| XGBoost         | 0.65     |
| SGD Classifier  | 0.6      |
| Gaussian Naive Bayes | 0.656    |

Table 14: Classification accuracy for a mix of linguistic and network features.

| Classifier      | Accuracy |
|-----------------|----------|
| Random forest   | 0.73     |
| XGBoost         | 0.71     |
| SGD Classifier  | 0.46     |
| Gaussian Naive Bayes | **0.76** |
Table 15: Bucket wise average network centrality measures.

| Feature  | HIGH | MID | LOW |
|----------|------|-----|-----|
| $RT - C_{clo}$ | 0.086 | 0.085 | 0.082 |
| $MEN - C_{clo}$ | 0.078 | 0.08 | 0.08 |
| $RT - C_{bet}$ | 221.57 | 52.05 | 36.09 |
| $MEN - C_{bet}$ | 140.35 | 50.55 | 28.76 |
| $RT - C_{deg}$ | 186.81 | 120.43 | 72.42 |
| $MEN - C_{deg}$ | 312.12 | 263.71 | 214.94 |
| $RT - C_{pr}$ | 0.005 | 0.002 | 0.001 |
| $MEN - C_{pr}$ | 0.005 | 0.002 | 0.001 |

‘friend’ and ‘family’, those in the LOW bucket tend to tweet about matters related to ‘anger’ and ‘negation’. This further shows that how language choice could be a very crucial factor in framing the overall ‘social’ reputation of a celebrity.

Figure 3: Selected LIWC categories.

Table 16: Bucket wise proportion of in-vocabulary words.

|  | HIGH | MID | LOW |
|---|------|-----|-----|
|  | 0.89 | 0.86 | 0.89 |

bucket have slightly high negative sentiment in their tweets.

Table 17: Bucket wise average score of tweet sentiments.

| Category | HIGH | MID | LOW |
|----------|------|-----|-----|
| pos      | 0.26 | 0.19 | 0.18 |
| neg      | 0.04 | 0.05 | 0.06 |
| neu      | 0.61 | 0.65 | 0.68 |
| comp     | 0.25 | 0.17 | 0.14 |

Table 18: Bucket wise value of average POS tag entropy.

|  | HIGH | MID | LOW |
|---|------|-----|-----|
|  | 3.23 | 3.21 | 3.17 |

POS tag entropy: The average entropy values in each of the buckets are shown in Table 18. The HIGH bucket shows a slightly larger entropy (i.e., better language construct) compared to the other two buckets.

Table 19: Bucket wise average value of various style features.

| Style feature | HIGH | MID | LOW |
|---------------|------|-----|-----|
| friends       |      |     |     |
| Negate        |      |     |     |

Style features: We report the average values of various style features for each of the follower count buckets in Table 19. There is no significant difference observable among the three categories.

Readability: We calculate the average ARI value of the celebrities in the HIGH, the MID and the LOW buckets (see Table 20). We clearly observe that the celebrities in the HIGH bucket post the most readable tweets.

Conclusion

In this paper we have presented a variety of linguistic features over celebrities’ tweets and network features over retweet and mention network to do an extensive analysis of the features correlating with popularity of celebrities. We have seen that a compact set of LIWC features including positive emotion, affection, function, cognitive and social words outperform highly correlating network features in predicting the popularity. Thus from this work we can conclude that language bears an important role in propelling popularity/follower count of celebrities. This indeed a strong message to aspiring candidates for celebrities to carefully choose their language over social media so that they can get more popularity. Finally, we have seen that best accuracy(0.76) is achieved for a combination of linguistic and network features. In future we would like to expand span of linguistic and network features to make an even more in-depth study of relation of these features with the popularity of celebrities.

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Table 19: Bucket wise average score of style features.

| Category | HIGH | MID | LOW |
|----------|------|-----|-----|
| TTR      | 0.21 | 0.23| 0.2 |
| CPW      | 4.29 | 4.39| 4.39|
| WPS      | 11   | 10  | 11  |
| P1       | 0.01 | 0.01| 0.02|
| P2       | 0.02 | 0.02| 0.01|
| P3       | 0.01 | 0.01| 0.01|
| IT       | 0.01 | 0.01| 0.01|

Table 20: Bucket wise value of average ARI.

|     | HIGH | MID | LOW |
|-----|------|-----|-----|
|     | 4.23 | 4.25| 4.76|

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