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TwitCID: A Collection of Data Sets for Studies on Information Diffusion on Social Networks

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Abstract. Online social networks play a crucial role in spreading information at a very large scale. Modeling information propagation on social networks has been attracting a lot of attention from researchers. However, none of the data sets used in past works are made available to the research community, while they would be very useful for comparative studies. In this paper, we detail a collection of tweets composed of five data sets for a total of 18 million tweets that we release, and which is designed to evaluate methods on modeling the information spread, in the case of general information and brands marketing information. In addition to tweet IDs and a script to retrieve the whole tweet in JSON from the Twitter API, we release the values of the 29 extracted features for these data sets. These features consist of user based, content based and temporal based features. Finally, we provide the results of information diffusion prediction models (80% accuracy) which could serve as strong baselines for this research topic.

Keywords: Information diffusion · Evaluation collection · Tweet collection · Retweets · Social networks

1 Introduction

Predicting information diffusion is an important challenge for many tasks from marketing [6] to information check-worthiness [11]. It has attracted a lot of attention in social networks research community [1, 5, 12, 18] and which is not yet solved. However, in past studies, the data sets used in the evaluation part of the studies are not made available while it is well acknowledged that benchmark collections are very useful for comparative studies.

In this paper, we introduce the TwitCID collection which consist of a set of five data sets of tweets. In total, there are more than 18 million of tweets in about

“general” information (two data sets) and “brand marketing” information (three data sets), of which million tweets are forwarded hundreds to dozen thousand times. In addition, we include the description of features we extracted from these tweets and release their values for the five data sets. These features cover 29 characteristics related to the users who created the tweets, the content of the tweets and the time the tweets were created. Finally, we provide effectiveness results of two information diffusion prediction models defined respectively by Suh et al. [19] and Hoang et al. [7]. These models reach up to 80% accuracy and could serve as a strong baselines although there is still room for improving these results.

Other researchers can use our released material (data sets, extracted features, results of strong predictive models) to evaluate their method of predicting information diffusion. The TwitCID collection and the extracted feature values are provided at <http://doi.org/10.5281/zenodo.3246705>.

The rest of the paper is organized as follows: Sect. 2 presents the related work. Section 3 describes the TwitCID collection, the extracted features along with the descriptive analysis of the most peculiar features. In Sect. 4, we report the results of information diffusion prediction models on our collection which could serve as strong baseline for future studies. We conclude the paper in Sect. 5.

2 Related Work

While Twitter-based data sets are available for information extraction [2, 14], name entity recognition evaluation [15, 17], for sentiment analysis evaluation [13, 16, 20] and information cascade modeling [3, 22], there is no reference data sets to evaluate predicting information diffusion despite the growing interest in this domain [4, 5, 7, 9, 19, 21].

In the area of predicting the information diffusion on social networks, various studies have been carried on and widely referenced. Guille *et al.* [5] developed a model to predict the temporal dynamics of information spreading on social networks based on machine learning algorithms and the inference of time dependent diffusion probabilities from a multidimensional individual behaviors analysis. They evaluated their method on a large data set which includes 467 million Twitter posts. Also using machine learning approach evaluated on a tweet data set, Varshney *et al.* [21] proposed a model to predict the information diffusion probabilities on social networks. They used a Bayesian network considering user interests and content similarity models. Dong *et al.* [4] used two data sets of around one million of tweets posted by Sina-Weibo to evaluate their approach on predicting the propagation of natural disaster information while Kafeza *et al.* [9] used 13,000 tweets related to the Malaysia airline flight 370 disappearance (#MH370) to evaluate their model on predicting the information spread patterns. However, none of these data sets have been made available to the research community.

Suh *et al.* [19] introduced several features that may affect the diffusion of a given message on social networks. Analysing a large scale data set of 74 million tweets, they showed that the number of followers and followees, the age

of the user account and the number of favourites strongly correlate with the retweetability. Conversely, the total of the user’s past tweets and the presence of hashtag/URL do not highly impact on the number of retweets. Hoang *et al.* proposed a model to predict whether a tweet is going to be diffused and the level of diffusion using machine learning algorithms. Their model is based on various features including Suh’s that were shown effective for diffusion prediction evaluation. For this reason, we extract the features proposed in Suh and Hoang studies and release them to the community.

Two twitter-based data sets have been made available on information cascade. Domenico *et al.* [3] distributed a data set that includes about 450 thousand nodes and 15 million edges representing the spreading processes on Twitter, the relationships between friends and followers, between who retweets/replies/mentions from whom. Xie *et al.* [22] distributed a data set of 6 million URLs and 540 thousand hashtags extracted from a data flow of 32 millions tweets that they consider as identities of cascades. Each row in the released data set includes one URL/hashtag along with list of anonymized user-timestamp pairs. These two released data sets show which users interact with which users [3], or which users mentioned the same URLs/hashtags in their messages [22] but neither the tweet ID nor related information regarding the users’ profile, the message contents or the time tweets were created which are main objects in a Tweet JSON and which are very crucial in predicting the diffusion of a message on social networks [9, 10]. That make these data sets of limited use for information diffusion prediction evaluation.

In this paper we describe the TwitCID collection consisting of 5 Twitter data sets (around 18M tweets) that we make available for research purposes. It is designed to evaluate studies on predicting information diffusion on social networks. In addition, we provide a set of extracted features corresponding to data sets, along with results of predictive models of 80% accuracy which can be used as a baseline for other works in this area.

3 The TwitCID Collection

3.1 Data Sets on General and Brand Marketing Information

The TwitCID collection consists of five Twitter data sets which were extracted from the 1% of the tweets that Twitter agrees to be collected. The Firstweek and Secondweek data set were collected during the first week and second week of January 2017 while the Iphone, Gucci and Galaxy data sets were collected from 21 September 2015 to 31 May 2017 using the keywords “iphone”, “gucci” and “galaxys” respectively. We designed the TwitCID collection so that it contains “general” information (Firstweek and Secondweek data sets) and more “marketing”-oriented information (the three other data sets). In that way, information diffusion can be studied in different scenario using the TwitCID collection.

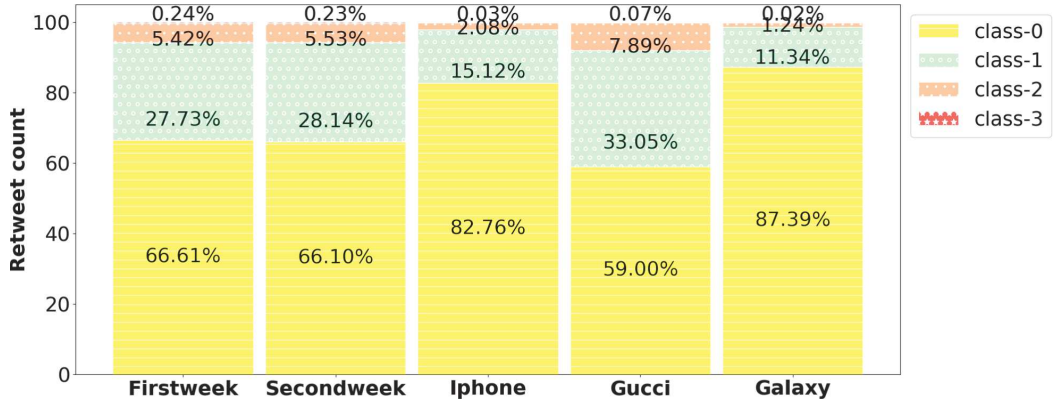
Table 1 reports the number of tweets, the number of non-retweeted and the number of unique retweeted tweets for the five data sets. We can see that the

Table 1. The number of tweets and their distribution for our TwitCID collection.

	Firstweek	Secondweek	Iphone	Gucci	Galaxy
# of tweets	8,009,112	8,171,080	2,188,923	242,956	174,909
# of non-retweeted tweets	4,025,157	4,058,066	1,483,705	74,543	134,443
# of (unique) retweeted tweets	2,017,979	2,080,962	312,003	51,805	19,391

Table 2. The number of tweets and their distribution according to the level of retweets on the TwitCID collection. Class-0 corresponds to the tweets that are not retweeted, class-1 are retweeted less than 100 times, class-2 from 100 times to 10,000 times, and class-3 more than 10,000 times.

	Firstweek	Secondweek	Iphone	Gucci	Galaxy
Class-0	4,025,157	4,058,066	1,483,705	74,543	134,443
Class-1	1,675,859	1,727,666	271,147	41,752	17,446
Class-2	327,381	339,328	37,355	9,968	1,915
Class-3	14,739	13,905	501	85	30

**Fig. 1.** Distributions of tweets in classes over our five data sets. Class-0 corresponds to the tweets that are not retweeted, class-1 are retweeted less than 100 times, class-2 from 100 times to 10,000 times, and class-3 more than 10,000 times.

proportion of tweets in each of these classes is about the same for the first and second week data sets, while they differ in the three other data sets.

Table 2 presents the distribution of tweets when we consider the level of retweets on the five data sets. In the Table 2, class-0 corresponds to the tweets that are not retweeted at all, class-1 are tweets that are retweeted less than 100 times, class-2 from 100 times to 10,000 times, and class-3 are tweets retweeted more than 10,000 times. To make the distribution more visual, we plot it in the Fig. 1. FirstWeek and SecondWeek data sets are very similar in terms of class distribution. Moreover, in general, the tweets that are not retweeted are the majority (from 59% to 87% depending on the data sets). The second most populated class is class-1, whatever the data set is and corresponds to from 11% to 33%. Class-2 is from 1% to 8%. Unsurprisingly, there are very few tweets in

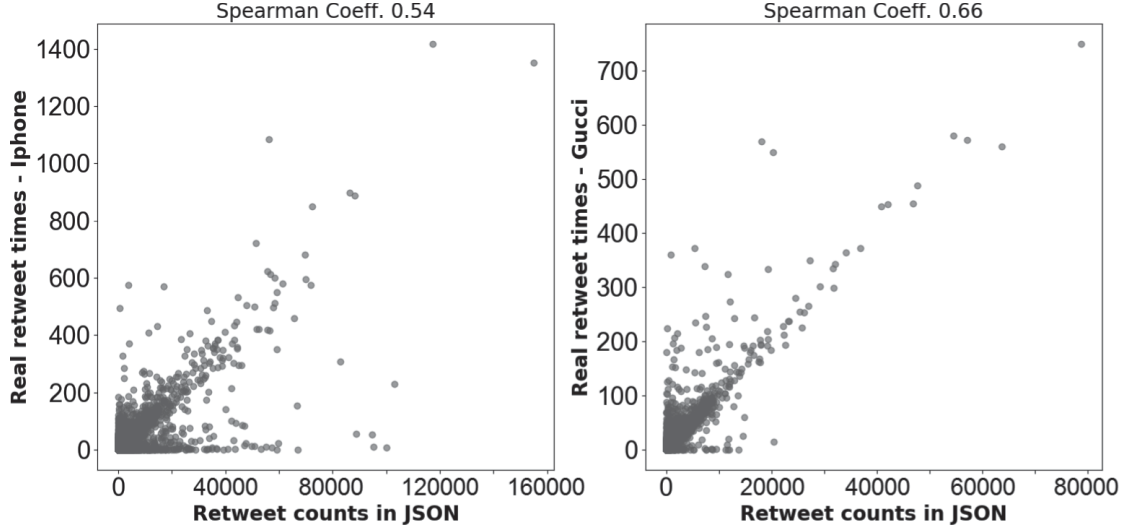


Fig. 2. Spear correlations between the number of times a tweet is retweeted in the data sets and retweet counts in the tweet objects.

class-3, less than 1% for all the data sets. Having data sets with different distributions is of interest to be able to evaluate the information diffusion prediction in different contexts.

Since we are using the 1% of tweets from Twitter, it is important to check whether our data sets keeps the original distribution of re-tweets. In Fig. 2, we consider the Spearman correlation between the number of times each tweet is retweeted in our data sets and the number of times this tweet is retweeted on Twitter (stored in `retweet_count` field of the tweet object). Spearman coefficient is from 0.5 to 0.7 for our data sets which indicate a good correlation (plots in Fig. 2 confirm a strong correlation). This result makes our data sets appropriate to evaluate information diffusion prediction for real world applications.

3.2 Tweet Features

In this section, we shortly describe the features representing a tweet that are released at the same time as the collection and that could be of use for research in the domain of microblog information diffusion. We also briefly present a descriptive analysis of the released data sets focusing on features that have been shown to be the most important to predict retweetability [7, 19].

There are three categories of features: related to the tweets' authors (features F1 to F9), the tweet content (feature F14 to F29) and to the time when the tweet was created (features F10 to F13). Seven features come from [19] (features with a^+) and 24 features from [6, 7]. Table 3 presents a short description of all the features.

Followers and Followees. In Twitter, followers are people who follow a user and followees are people whom a user follows. These two features have been shown to be important to predict retweetability: the higher the number of followers and followees, the higher the retweetability [19].

Table 3. The released features which are also used in the baselines for information diffusion prediction. Features with a⁺ are from Suh *et al.* [19] while the others are from Hoang *et al.* [7]

Features	Features	Data Type
F1.Total.tweets ⁺	Total of the user’s past tweets	#Numeric
F2.Followers ⁺	# of users who follow the author	#Numeric
F3.Followees ⁺	# of users that the author is following	#Numeric
F4.Age.account ⁺	# days since the account has been created	#Numeric
F5.Favourite ⁺	# tweets that the author has liked	#Numeric
F6.Groups	# groups that the author is joining	#Numeric
F7.Aver_favourite	Average of tweets the author likes per day	#Numeric
F8.Aver_tweets	Average of tweets the author write per day	#Numeric
F9.Name_length	The length of the author’s name	#Numeric
F10.Posted.holiday	The tweet is posted on a public holiday	Boolean
F11.Posted.noon	The tweet is posted at noon or not	Boolean
F12.Posted.eve	The tweet is posted in the evening or not	Boolean
F13.Posted.weeke	The tweet is posted at the weekend or not	Boolean
F14.Has_location	The tweet contains a location name or not	Boolean
F15.Has_org	The tweet contains an organization name	Boolean
F16.Has_tvshow	The tweet contains a TV show name or not	Boolean
F17.Sent_level	The tweet is positive, negative or neutral	P, N, Neu
F18.Has_video	The tweet contains a video or not	Boolean
F19.Has_Image	The tweet contains a picture not	Boolean
F20.Has_Uword	The tweet contains an upper word or not	Boolean
F21.Has_number	The tweet contains a number or not	Boolean
F22.Has_excl	The tweet contains an exclamation mark	Boolean
F23.Has_rt	The tweet contains the “RT” term or not	Boolean
F24.Has_username	The tweet mentions a user name or not	Boolean
F25.Has_suggest	The tweet contains a retweet suggestion	Boolean
F26.Has_URL ⁺	The tweet contains an URL or not	Boolean
F27.Num_hashtag ⁺	The number of hashtags contained in the tweet	#Numeric
F28.Opt.len	The tweet length is from 70 to 100 characters	Boolean
F29.Length_tweet	The length of the tweet content	#Numeric

In the rest of this section, we briefly present a descriptive analysis of our five data sets considering the most important features to predict retweetability according to [7, 19]. Although other features could be developed by researchers in the future, this analysis provides some cues on the features that are related the most to retweetability.

In Fig. 3, we present the rate of tweets of which the authors have 1,000 followers or more (called F1000) for TwitCID. The diamond elements present the rate of F1000 tweets from class-0 and the circles present this rate from the



Fig. 3. Rate of tweets from authors who have 1,000 followers or more. CI-0 represents for tweets that are not retweeted while CI-RT represents tweets that are retweeted.

class-RT (the union of class-1, class-2 and class-3). As can be seen in this figure, a very large percentage of retweeted-tweets in these data sets are written by authors who have from 1,000 followers. This is shown by the fact that the rate of F1000 tweets from class-RT is very high in all data sets, from 73% to 79%. In addition, there is a low proportion of these F1000 tweets that are not retweeted. The rate of F1000 tweets from class-0 is 19% for the Galaxy data set and 22% for the Iphone data set.

Similarly, for the Followees feature, the rate of tweets created by authors who have 1,000 followees or more (called Fe1000) in class-RT is pretty high, about 34% to 38% depending on the data sets while this rate from class-0 is very low, around 18%. This means tweets created by users who are followed by many other users have a high possibility to be retweeted and low possibility to be non-retweeted.

Groups. Groups denote the number of lists or groups that a Twitter user is a member of. In our five data sets, the number of groups strongly correlate with retweet. We studied the rate of tweets created by authors who are members of at least 50 groups (called Gr50) in each class. This rate is low for class-0 but very high for other classes for all data sets, especially for class-3. For the Galaxy data set, there 34% Gr50 tweets from class-0 but 76% Gr50 tweets from class-2 and 93% from class-3 respectively. For other data sets, the percentage of Gr50 from class-0 is around 20% while this rate is from 39% to 83% for other classes. This result shows that the tweets of authors who join in at least 50 groups have high possibility to be retweeted and there is a high percentage of tweets that are retweeted more than 100 times belong to these users.

Image and Video. The image (resp. video) feature specifies whether a tweet contains an image (resp. video) or not. Figure 4 depicts the rate of tweets that contain either an image or a video (called ImVi). Each group of bars corresponds to a data set. Within a data set, each bar corresponds to a class of retweet level. From this figure, we can see that the trend is similar across the data sets. The

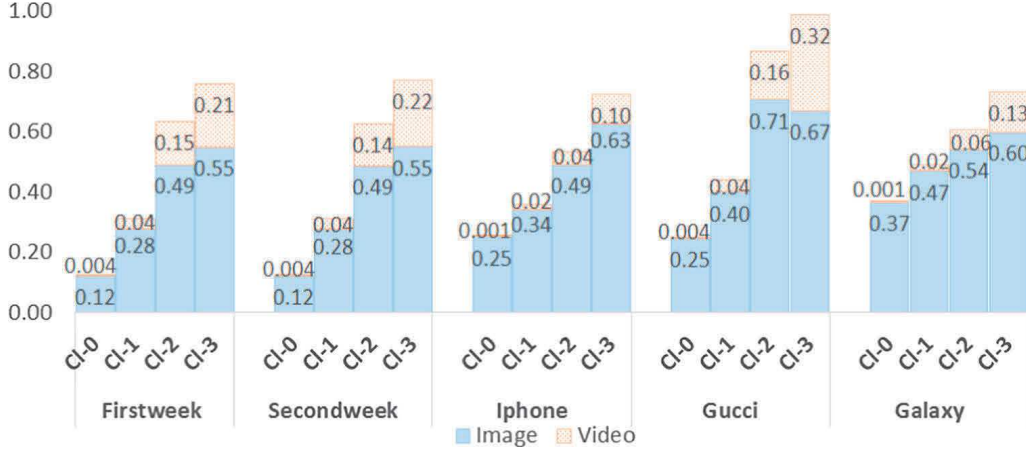


Fig. 4. Rate of tweets which contain either an image or a video (a very few contain both) for each data set and each retweet class.

rate of ImVi tweets increases with the class of retweet level; this holds even more for videos than for images. For example, the Firstweek, 12% tweets from class-0 contain a pictures while this percentage is much higher for class-1, class-2 and class-3: 28%, 49% and 55% respectively. The rate of tweets containing a video from class-0 is 0.4%, while this rate for class-1 is ten times more: 4%. This rate for class-2 and class-3 are significantly higher: 15% and 21%.

In Fig. 4, we can also observe that the rate of tweets containing an image or a video is generally higher in the “marketing” data sets (Iphone, Gucci and Galaxy) than in the “general” data sets (Firstweek and Secondweek).

Favourite. Favourite is the number of tweets that a user has liked in his timeline. In our collection, the rate of tweets of which the authors have at least 1,000 favourites (called Fav1000) is pretty high: around 50% for the Firstweek, Secondweek and Gucci data sets, and around 30% for the Iphone data set. For the Galaxy data set, although there is only 15% Fav1000 tweets in the whole data set, this rate on class-3 is 77%. The other data sets also have high rate of Fav1000 tweets in class-3: 77% for the Gucci data set and around 60% for the Iphone, Firstweek and Secondweek data sets. This result shows that tweets of authors who have likes at least 1,000 posts on their timeline are highly likely to be retweeted several times.

Age of Account. The Age of an account presents the number of days a user account is registered from.

We analyzed the relationship between the age of the author account and the retweet rate for the data sets of the TwitCID. We found that whatever the data set is, the age of account and retweet rate is linearly strongly correlated (see plot in Fig. 5).

Figure 5 presents the normalized retweet rate of different types of users. The junior users: who have registered their account less than 1,000 days, the intermediate users: from 1,000 days to 3,000 days and the senior users: greater than 3,000 days. In this figure, the retweet rate represents a normalized ratio of the

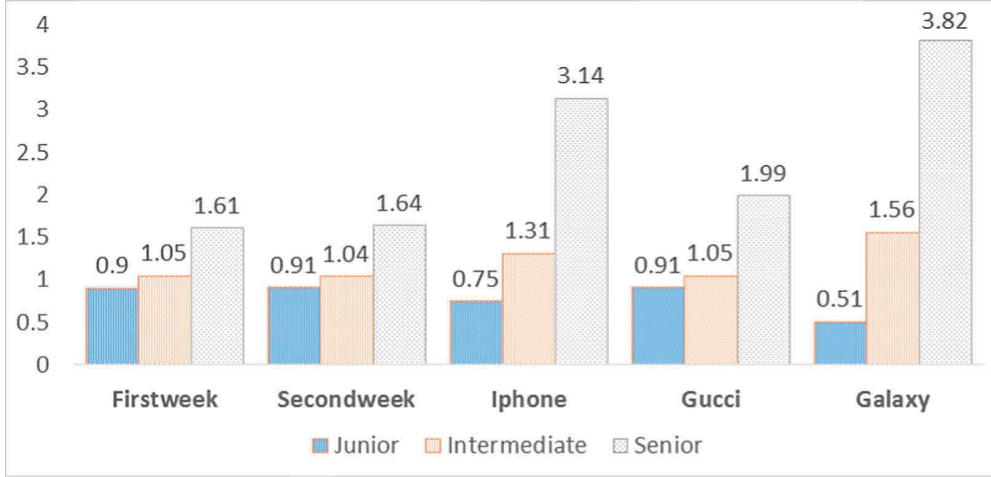


Fig. 5. Retweet rate vs Age of account on the five data sets. Junior are users who have created their account less than 1,000 days; Intermediate: from 1,000 days to 3,000 days; Senior: greater than 3,000 days.

number of retweeted tweets to the number of tweets. For example, the first bar in Fig. 5 presents the retweet rate of junior users’ tweets for the Firstweek data set. We first divided the total of retweeted tweets of juniors (765,125 tweets) by the total of tweets of juniors (2,534,102 tweets). We then normalized this rate by a factor so that a value of 1.0 represents the average retweet rate. This normalization factor is calculated by the total of tweets (6,043,136) over the total of retweeted tweets in the whole data set (2,017,979).

Figure 5 shows a very strong relationship between the age of the account and the retweet rate for all data sets. Interestingly, the retweet rate of tweets from senior users for the “marketing” data sets is much higher than the one for the “general” data sets. For the Galaxy data set for example, the retweet rate for senior users is 3.82, for intermediate users it is 1.56 and for junior users it is 0.51 while this rate for senior, intermediate and junior for the Firstweek is 1.61, 1.05 and 0.9 respectively.

Our collection includes a large number of tweets in which million tweets are retweeted hundreds to dozen thousand times. In addition, this collection covers several important features regarding user profile, the content and the time the tweet is posted. Thus it is appropriate for studies on predicting information diffusion on social networks.

3.3 Released Data

Being compliant with Twitter developer agreement and policy¹, we publish our TwitCID collection on behalf of our academic institution IRIT² for the sole purpose of non commercial research, under the licence CC BY-NC-SA (Attribution -

¹ <https://developer.twitter.com/en/developer-terms/agreement-and-policyid34>.

² Institut de Recherche en Informatique de Toulouse, UMR5505 CNRS, France.

NonCommercial - ShareAlike). For each data set, we release all tweet IDs accompanied by a script so that researchers can retrieve the tweets in JSON from the Twitter API. We also provide extracted features described in the Table 3 corresponding to each data set in arff form. All these materials are available at <http://doi.org/10.5281/zenodo.3246705>

4 Baseline for Information Diffusion Prediction

In this section, we briefly describe a model for predicting information diffusion on social networks proposed in [7] evaluated on the TwitCID collection considering two sets of features as defined in [19] and [7]. Given a tweet, the model predicts whether this tweet is going to be diffused or not and the level of diffusion.

In [7], the authors considered the prediction of retweetability either as a binary classification problem or as a multi-class classification one like Hong *et al.* did [8]. For a binary problem, tweets are classified into two classes: class-0 and class-RT. For multi-class problem, tweets are categorized into the four classes as we presented before (class-0 for non retweeted, class-1 to -3 depending on the level of retweet).

The predictive model proposed by Hoang *et al.* [7] uses Random Forest (RF) implemented on Java Weka library³. The authors showed that RF consistently outperforms the other machine learning methods on this task; we thus report the results obtained by this model. The results of this model considering the features presented in the Table 3 We also report the result Hoang *et al.*'s model on Suh *et al.*'s features (features with a⁺ in the Table 3).

Table 4. Averaged -measure over the sub-sets for each data set - Binary prediction on retweet on the TwitCID collections; * indicates statistically significant differences by Student's t-test with p-value < 0.05 between Suh and full feature set.

		Firstweek	Secondweek	Iphone	Gucci	Galaxy
Cl-0	Suh's	0.79	0.79	0.82	0.79	0.86
	Full set	0.83*	0.82*	0.85*	0.82*	0.88*
Cl-RT	Suh's	0.77	0.77	0.82	0.78	0.86
	Full set	0.81*	0.81*	0.85*	0.82*	0.87*
Aver.	Suh's	0.78	0.78	0.82	0.78	0.86
	Full set	0.82*	0.82*	0.85	0.82*	0.88*

Since the number of tweets in classes are highly different, the data was balanced during the classification process by: (a) each data set was divided into several subsets where the tweets from minor classes (class-1 to 3) are kept the same for all subsets and the tweets from major class (class-0) are divided into

³ <http://weka.sourceforge.net>.

subsets so that the number of tweets from major class are approximated to the number of tweet from minor class. (b) SMOTE⁴ technique is used to synthetic minority over sampling.

From the Table 4, we can see that using the full set of features remarkably increases the F-measure on each class and on average compared to when using the reduced feature set for all the data sets both for binary classification.

On average, the complete model improves the F-measure by 4% (from 0.78 to 0.82) for the Firstweek, Secondweek and the Gucci data sets; by 3% (from 0.82 to 0.85) for the Iphone and by 2% (from 0.86 to 0.88) for the Galaxy data set compared to the reduced model. All these improvement are statistically significant. One interesting point is that the improvement on class-RT is equal or higher than on class-0 although the number of tweets in class-RT is smaller than the number of tweets in class-0. For the Gucci data set, F-measure is increased by 3% on class-0 while this increase is by 4% on class-RT. The complete model also achieved higher improvement on class-RT than on class-0 for the Galaxy data set that the reduced one (Table 4).

Table 5. F-measure of the model when predicting the level of retweet on the TwitCID collection. * indicates statistically significant differences when using Student’s t-test with p-value < 0.05 when comparing the full set of features and the Suh’s subset.

		Firstweek	Secondweek	Iphone	Gucci	Galaxy
Cl-0	Suh’s	0.79	0.79	0.82	0.79	0.86
	Full set	0.82*	0.82*	0.85*	0.82*	0.88*
Cl-1	Suh’s	0.64	0.65	0.72	0.65	0.77
	Full set	0.70*	0.74*	0.76*	0.68*	0.80
Cl-2	Suh’s	0.73	0.73	0.59	0.62	0.58
	Full set	0.74*	0.74*	0.64*	0.62	0.61
Cl-3	Suh’s	0.58	0.57	0.13	0.02	0.12
	Full set	0.57	0.57	0.10	0.05	0.12
Aver.	Suh’s	0.72	0.72	0.75	0.71	0.80
	Full set	0.76*	0.76*	0.79*	0.74*	0.82*

Similarly to the case of binary classification, the complete model increases the F-measure on average and on every class compared to the reduced model for all the data sets for multi-class classification. On average, F-measure is increased by 4% for the Firstweek, Secondweek and Iphone data sets, by 3% for the Gucci data set and by 2% for the Galaxy data set compared to the reduced model. All these improvements are significantly different.

When considering each class, the complete model obtains higher F-measure on class-0, class-1 and class-2 but lower F-measure on class-3 compared to the

⁴ This algorithm creates synthetic observations based upon the existing minority observations.

reduced model. The reason may be the number of tweets from class-3 which is extremely small compared to those from the other classes (see Table 2). For the Gucci data set, the complete model achieves 0.79, 0.65 and 0.62 (F-measure) on class-1, class-2 and class-3 respectively but only 0.02 on class-3. The highest F-measure is obtained on class-0 and class-1 for the Iphone data set which are 0.85 and 0.76 respectively.

5 Conclusions

In this paper, we introduced the TwitCID collection of 18 million tweets that is designed to evaluate studies on predicting information diffusion on social networks, both for 'general' information and 'marketing' information. We also provide extracted features corresponding to each data set regarding the user profile, tweet content and temporal information. In addition, we report results of information diffusion prediction models evaluated on our collection (around 80% accuracy) which could be strong baselines for comparative studies.

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