Analyzing information sharing strategies of users in online social networks

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Abstract—**User information sharing is an important behavior in online social networks. Understanding such behavior could help in various applications such as user modeling, information cascade analysis, viral marketing, etc. In this paper, we aim to understand the strategies users employ to make retweet decision. We are interested in investigating whether these strategies in online social network contain significant information about users and can be used to further characterize users. We propose a flexible model that captures a number of behavior signals affecting user's retweet decision. Our empirical results show that the inferred strategies can help increase the performance of retweet prediction.**

I. INTRODUCTION

In recent years, millions of people have used online social networks to express opinions, ideas, perspectives through connecting and communicating with each others. In some social networks such as Facebook or Twitter, a central behavior that empowers such process of information propagation is the information sharing, or retweeting behavior. It is a function that allows a user to share a valuable message with all of his neighbors.

In this work, we focus on analyzing the information sharing behavior of users in online social networks. In particular, we investigate the strategies users employ, that is, the factors that affect users' decision of retweeting a piece of information. Some examples of these factors include the interest of users in the information, the trustability of the information itself or of the information source, and the freshness of the information. Understanding the underlying factors not only brings deeper insight into interpreting user information sharing behavior, but also offers other important benefits: 1) Predicting information cascades on the macro level and individual information sharing behavior in the micro level; and 2) Studying the patterns of sharing behavior, which can be considered as the characters or habits of users in information sharing and are useful to identify users that can be easily influenced by rumors or advertisements.

The problem of investigating user retweet behavior has been studied extensively in previous work [1] [2] [3] [4] [5] [6]. These studies mainly focus on investigating the degree to which the features or learned latent factors are beneficial towards predicting users' retweet decision. Here, we are more interested in understanding users' retweet strategies and to what degree such strategies can be used to characterize users. Our hypothesis is that since the strategies are summarization of users' retweet behavior, they must contain some additional information about users. The process of learning these strategies is similar to that of learning users' representations such that the representations contain significant information about the users for supervised and unsupervised learning tasks. In this work, we mainly focus on user retweet behavior in Twitter social network as a running example and try to see how informative such strategies could be.

Our main contributions in this work consist of the followings.

1) We focus on studying user retweet strategies and propose to use the learned strategies to characterize users.
2) We introduce a model that considers a number of major factors affecting user retweet behavior, such as interest matching, trustability, freshness and linguistic patterns.
3) We apply the learned user strategies to perform retweet prediction in a real Twitter dataset and demonstrate that the learned strategies actually contain significant information about users and can help improve the performance of the prediction task.

The rest of the paper is organized as follows. In Section II, we first review several families of works that are related to our research. Then we describe our method to derive user retweet strategies in Section III. Dataset for the experiments is described in Section IV. In Section V, we conduct detailed analysis and experiments to show the learned user strategies and their effectiveness to represent users.

II. RELATED WORK

There are three main lines of work that are related to our research.

User retweet behavior factors: A number of studies have been proposed to understand the factors affecting user retweet behavior. [1] identifies features to perform retweet prediction and measures the importance of each feature. [2] analyzes the underlying reasons why people retweet. It examines the similarity of user-tweet, the similarity of user-user profile, etc. Experiments were conducted to see which model best explains the majority of user retweet behavior. [3] examines a number of features and investigates their effects on the retweetability of the message using correlation analysis. [4] builds a probabilistic model to measure the contribution of major aspects impacting user behaviors such as social correlation, user, item and sparsity. The authors show that the predictive model using all these factors results in the highest performance. [5] models the posting behavior of users on social media. The authors hypothesize that user behavior is mainly influenced by three factors, namely breaking news, posts from social friends and user's intrinsic interest. They then propose a mixture latent topic model combining all these factors. [6] studies the interplay between the role of user in social network and its effects on the macro-level of user retweet behavior, that is, the information diffusion process. These studies differ from our work in that they mainly aim at analyzing the importance of the factors that best explain user retweet behavior. We want to see if such learned factors can be used to further characterize the users.

Representation learning for user retweet modeling: Some proposed works also aim at learning user representation. [7] attributes user's retweet actions to three orthogonal factors, namely topic virality, topic-specific user virality and susceptibility. The authors then model retweet action as tensor and develop a tensor factorization method to simultaneously learn these behavior factors, which could be used to predict future retweet actions. [8] learns an interpretable user representation for retweet prediction by using Factorization machine to jointly model user decision and interest. The authors further improve such latent representation by incorporating features to account for multiple aspects of user behavior. [9] converts the problem of retweet prediction into the framework of matrix completion. The authors incorporate message similarity derived from a clustering process and feed into factorization so that the factorization process can better learn user's latent representation. A similar line of work that applies user representation to investigate the effect of individual behavior at macro level is also conducted. [10] studies the problem of temporal diffusion of information. They embed nodes participating in the cascades into a continuous latent space such that the information diffusion process can be modeled efficiently by the heat diffusion process. [11] aims at mining and forecasting complex temporal interactions between users and URLs. The authors model such interactions as tensor and derive a probabilistic graphical model to learn latent representations for objects such as users, URLs and time. These latent representations are then used to perform prediction of future interactions. Even though these studies learn a representation that captures multiple aspects of user behaviors and show its effectiveness in retweet or interaction prediction, they do not further investigate whether such representation contains significant information for other tasks.

Complex user behavior modeling: There have been a number of studies related to representation learning that can capture complex behaviors of users in social networks. In [12], the main task is to predict the preference of a user for a specific topical item. Instead of analyzing the item preference from a single behavior, the authors separate it into multiple preferences along different behaviors so that the learned representation in each behavior becomes much cleaner. These representations are then used to make final item preference prediction. In [13], the authors analyze various combinations of basic user behaviors and predict future behavior states. The studies mentioned above tend to focus more on multiple behaviors, and learn user behavior model from these behavioral signals. Our work is orthogonal to this line of work. We want to understand whether strategies learned from retweet logs can further be used to characterize users.

III. METHODOLOGY

In this section, we first explain some definitions and define our research problem. Then we introduce the intuitions behind our approach, and describe our model.

A. Preliminaries

In this work, a social network is represented as a directed graph $G = (V, E)$, where V is a set of users, $E \subseteq V \times V$ is a set of links between users, $e_{u,v} \in E$ denotes a directed (follow) link from user u to user v ($u, v \in V$). u is called *follower* of v, and v is called *followee* of u. Being a follower means that he can receive all the tweets from the users he follows. We consider a small example to illustrate our problem setting. Let A, B, C, D be the users in the social network, where B follows A; C, D follow B. Once user A tweets a message on the network, user B can automatically receive this message. User B may further retweet this content to all of his followers. Once he does so, the message again can be seen by all of B's followers, which in this case are C and D. In this paper, there are two key questions that we want to address: 1) What are the strategies underlying a user's retweet action, that is, the main factors influencing the retweet decision of a user? 2) Once we infer a user strategy, can we use it to better understand the user?

Given that a user receives a message from one of his followees, his decision whether to further forward the message to all of his followers depends on a number of factors. Each factor will account for the probability the retweet decision is influenced by a strategy. Our formal definition of user retweet strategies is described as below.

Definition 1. ***User Retweet Strategies:*** *The retweet strategies of user $u \in V$ is denoted as θ_u, which is a K-dimensional vector satisfying $\sum_{i=1}^{K} \theta_{u,i} = 1; \theta_{u,i} \geq 0$. $\theta_{u,i}$ is the* *probability that user u is influenced by the i^{th} strategy when performing retweeting decision.*

Here are some observations that affect our choice of determining the main strategies of user's retweet decision.

- **Interests Matching.** User's retweet decision is because of the similarity between user's interest and topics of message content. This can be observed in a number of scenarios. For example, machine learning researchers are interested in content about machine learning. Technology enthusiasts are interested in news about new technical products, etc.
- **Linguistics.** Retweet decision can be attributed to the proper language used in tweet content. Such linguistic features can signify the degree of informativeness of the message. For example, longer messages may contain richer information compared with shorter ones; messages that contain links or hashtags may provide additional information compared with those that do not, and thus might be more likely retweeted.
- **Information Trustability.** User may retweet because he trusts the information. This can be measured by the trust in the author of the message. For example, if a user often reposts messages from the same author, his trust towards the author increases. The users with high trustability tend to be verified users, official organizations, or public figures, etc. who are followed by a large number of users.
- **Information Freshness.** The retweet decision can be attributed to the novelty of the message content across all the messages posted by the followees of the user.

In this work, we attribute a user's retweeting decision mainly to these four strategies, i.e. $K = 4$. Additional strategies will be further investigate. In order to infer the strategies from users' retweeting logs, we choose to extract behavioral signals, i.e. features, from retweet observations. These features contain information from the user who performs retweet, tweet's author, and the tweet itself. They represent different aspects of the retweet behavior, and can be grouped into more common categories, which we termed as "behavior groups".

Definition 2. ***Behavior Group:*** *Let $u \in V$ be the user in consideration, F be the set of behavioral signals (features), and $F_u := \{f_{u,j} \mid j = \{1, .., |F|\}; \forall j, f_{u,j} \in R\}$ be all features of a sharing case of user u. The i^{th} behavior group $B_{u,i} \subset F_u$ of user u is defined as $B_{u,i} := \{f^i_{u,j} \mid f^i_{u,j} \in F_u; \forall i \neq j : B_{u,i} \cap B_{u,j} = \emptyset; B_{u,1} \cup ... \cup B_{u,|B_u|} = F_u\}$.*

Each behavior group is chosen to correspond to each strategy we defined above, i.e. "Interest Matching", "Linguistics", "Trustability", and "Freshness". We adopted the features from previous works [1][3][14] for each behavior group. Details of these features and the corresponding behavior groups are described in Table I.

Behavior Group	Feature details
Interest Matching	TF-IDF: user's tweeted content vs. target tweet
	TF-IDF: user's retweeted content vs. target tweet
	Hashtag similarity
Linguistics	Length, number of words
	Number of URLs
	Number of Hashtags
	Number of Mentions
Trustability	Whether the user is the followee of this author
	Number of retweets from this author
	Number of followers of this author
	Number of followees of this author
	Whether the author is verified
	Total number of tweets
	Account age, measured as the total number of days
	Number of retweets/day the user has made with the author
Freshness	Novelty of message among all tweets from user's followees (local). Measured as sum of TF-IDF of terms in the target message against local tweets. (Equation 5 in [14])
	Novelty of message among tweets chosen randomly from global network (global). Measured as sum of TF-IDF of terms in the target message against global tweets. (Equation 5 in [14])

TABLE I
DETAILS OF FEATURES USED IN MODEL

Based on the above definition, we introduce our problem of modeling retweet strategies of users in online social network as follows.

Problem 1. ***User Retweet Strategy Model:*** *Given online social network $G = (V, E)$ and all retweet observations of users set V, the goal is to output for each user $u \in V$ the strategies vector θ_u that best summarizes u's retweet observations.*

B. User Retweet Strategy Model

We rely on the following observations to derive our user retweet strategies vector.

Observation 1: Each behavioral signal (feature) has specific strength to characterize user retweet behavior. For example, one user might retweet because he is mainly interested in the content of the tweet. Thus, the strength of interest feature of this user needs to be higher than the strength of other features. The other user might retweet because of the high authority of the author, resulting in higher strength of authority feature compared to others. Therefore, in order to characterize user retweet behavior, we need to capture the strength of the features towards user retweet decision.

Observation 2: Once the strength of the feature is known, we also want to capture the relationship of such feature towards user decision. One example is user A and B both rely on authority to make retweet decision. However, user A normally retweets from high authority people, whereas user B usually retweets from common users. Thus, using feature strength alone cannot distinguish among these users. Therefore, even though user behavior is highly complex and non-linear, equipping the strategies with such relationship could help further characterize users and provide additional explanation towards user behavior.

Feature strength in *Observation 1* can be captured using Gini importance coefficient or Permutation accuracy importance [15]. Gini importance is based on the principle of impurity reduction before and after using the feature to split the data, and is used in most traditional classification tree algorithms. However, it has been shown to be biased when the predictor variables vary in their number of categories or scale of measurement [16]. Therefore, in this work, we adopt the latter approach, i.e. Permutation accuracy importance, to measure the strength of feature. We implement this method under the framework of Random Forest classifier. The idea of this approach is to estimate the increase in out-of-bag error across all decision trees of a random forest when randomly permuting the feature values. By doing this, the original association between predictor feature with the response variable is broken, which is equivalent to elimination of the feature. The amount of increase in error before and after permutation signifies the strength of such feature in the prediction task.

Definition 3. ***Feature Strength:*** *Let $t : R^{|F|} \mapsto \{0, 1\}$ be a decision tree built for user $u \in V$ with specific bootstrap samples, and the remaining out-of-bag samples of size M, $OB_u := \{(x_{u,k}, y_{u,k})\}_{k=\{1,...,M\}}$, are used to estimate the performance of t. Let $x_u = \{x_{u,1}, ..., x_{u,M}\}$ be the observations for user u, $y_u = \{y_{u,1}, ..., y_{u,M}\}$ be the corresponding labels, and $P_d(\cdot) : R^d \mapsto R^d$ be a function performing random permutation of a vector of dimension d. The strength of feature $f_j \in F$ w.r.t the decision tree t is defined as:*

$$s_t(f_j) = \frac{\sum_{i \in OB_u} I(y_{u,i} = t(x_{u,i}))}{|OB_u|} - \frac{\sum_{i \in OB_u} I(y_{u,i} = t(x_{u,i}^{f_j}))}{|OB_u|}$$

where $I(\cdot)$ is the indicator function equaling 1 if the relational expression in the bracket is true and 0 otherwise; $x_u^{f_j} := P_M(f_j(x_u))$ denotes the observations of user u after randomly permuting the values of feature f_j across all OB_u samples, and $x_{u,i}^{f_j}$ is the i^{th} observation.

The raw feature strength of feature f_j across all decision trees of random forest T is defined as:

$$s(f_j) = \frac{1}{|T|} \sum_{t \in T} s_t(f_j)$$

The strategy of user u with respect to behavior group $B_{u,i}$ is calculated as:

$$\theta_{u,i} = \frac{\max_{f_{u,j}^i \in B_{u,i}} \{s(f_{u,j}^i)\}}{\sum_{k=1}^{4} \max_{f_{u,j}^k \in B_{u,k}} \{s(f_{u,j}^k)\}}$$

The intuition is that we can drop the other features and keep the most significant one in each behavior group. This resembles feature selection where we eliminate some features to reduce the dimensionality of the input feature space, while retaining most of the informative features.

Observation 2 is an augmentation to the strategies derived above. To capture the relationship between feature f_j and the output label y_u in *Observation 2*, we simply use Pearson correlation coefficients. Let $r(f_j)$ be such relationship, $r(f_j) = sgn(Pearson(f_j(x_u), y_u))$, where $f_j(x_u)$ represents values of f_j in the observations of user u, and y_u represents the corresponding labels; $sgn(\alpha) : [-1, 1] \mapsto \{-1, 1\}$ is the indicator function equaling 1 if $\alpha \geq 0$, and -1 if $\alpha < 0$. The augmented strategy of user u with respect to behavior group $B_{u,i}$ is defined as:

$$\gamma_{u,i} = \frac{r(f_{u,j}^i) s(f_{u,j}^i) \mid_{j=\mathrm{argmax}_j \{s(f_{u,j}^i)\}}}{\sum_{k=1}^{4} \max_{f_{u,j}^k \in B_{u,k}} \{s(f_{u,j}^k)\}}$$

Here, $\theta_{u,i} = |\gamma_{u,i}|$. We will investigate the effectiveness of strategies and augmented strategies in the evaluation section.

IV. DATASET

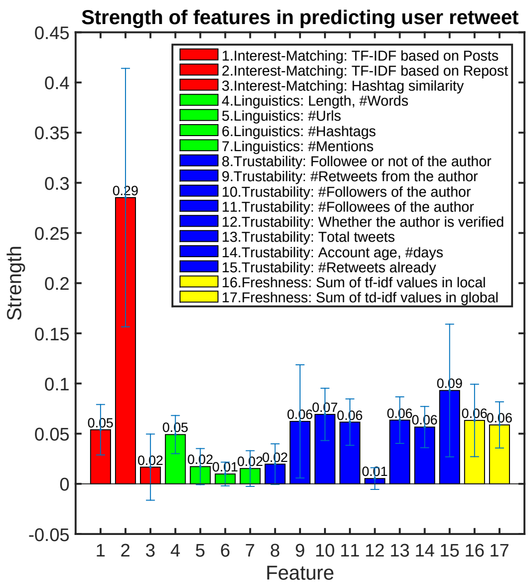
We crawled data from Twitter using Twitter API in 64 days, from June 19, 2014 to August 21, 2014. We randomly choose 12,550 users as experimental users and crawled their tweets during the 64 days period. To guarantee the quality of learning, we only keep users, who have at least 20 retweet observations (positive samples). These are the observed retweet actions the user made with the tweets of his followees during 64 days. This results in a dataset with 10,803 users. Since the number of negative samples, that is, the tweets the user might see from his followees but end up not being retweeted, can be much larger than the number of positive samples, we randomly select the number of negative samples twice as large as the number of positive samples, similar to [1]. Finally, this dataset contains 10,803 users, with a total of 4,752,501 retweets observations, containing 33% positive samples, and 67% negative samples.

V. EVALUATION

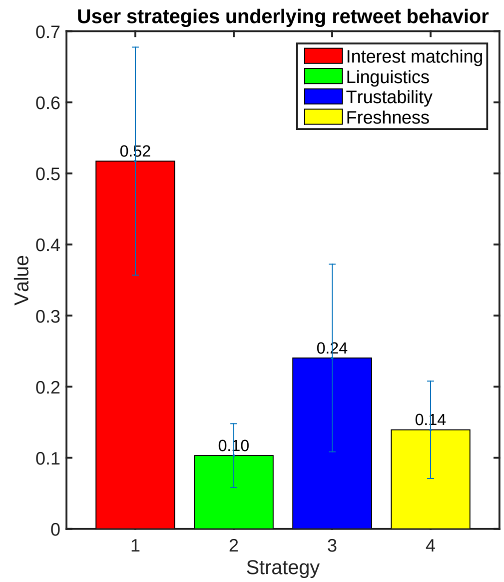
In the subsequent subsections, we perform the following experiments: 1) We conduct a detailed analysis on the characterization capability of the learned user strategies and what insights these strategies offer. 2) We perform user retweet prediction experiment using user strategies to understand whether these strategies contain any significant information about the users. All the following experiments were conducted on a server with 4 Xeon E7-8837 2.67GHz CPUs (32 cores) and 1TB of memory.

A. User Strategies Analysis

In this section, we show our results about user strategies. Specifically, how strategies can help better understand the user's retweet decision.



(a) Feature strength.



(b) User strategies.

Fig. 1. Feature strength and User strategies across all users. Error-bar represents standard deviation

1) Evaluation settings: From the dataset achieved in section IV, we use stratified sampling to partition the data into two disjoint subsets: 80% data for training and 20% data for testing. This guarantees the training and testing data will have the same ratio of positive and negative samples. For each user, we train the retweet model to learn user strategies using Random Forest classifier. To avoid the overfitting effect, we use 5-folds cross validation on the training data to select the optimal hyper parameters of Random Forest model such as the number of decision trees, depth and number of attributes used in each tree. Since the data is imbalance, we rebalance the class for Random Forest model during the training process by upsampling the minor class.

2) Analyze user strategies: First, we investigate what the strength of each feature and the derived user strategies are. For each user, once the strength of each feature is learned, we normalize and average the absolute magnitude of features strength across all users, and plot in Figure 1a. It shows that the similarity between reposted content with the target tweet, and the number of retweets per day between user and author contain strongest signals for prediction. User strategies plotted in Figure 1b show that Interest matching strategy significantly characterizes user retweet behavior. This agrees with one of the findings in [7] that interest similarity gives a strong retweet prediction performance. Users also rely on Trustability of tweet's author to make retweet decision, even though it's not as significant as Interest similarity. In contrast, Linguistics and Freshness strategies don't have such high characterization capability. We further group users based on their main strategy. Statistics of such groups are shown in Table III. It shows that majority of users retweet based on Interest similarity between his content profile and the topics of the tweet. A much smaller portion of users rely on the Trustability of tweet's author to determine retweet decision. Users rarely rely on Linguistics or Freshness of content to perform retweet.

3) Content adoption among users: To further understand and validate user retweet strategies, we investigate the hashtags adopted by these users. The idea is to see how distinct or similar the hashtags adopted by different types of users are. To this end, first, we group users based on the main strategy they use to perform retweet, that is, the strategy with highest value among the four strategies. We then extract the hashtags adopted by users in each group. Results of top-30 hashtags in each group are shown in Table II. Since the Linguistics group contains a significantly small number of users, it can be considered as noise and we omit the analysis for this group.

In the group of users mainly influenced by Trustability, the propagated hashtags seem focused and are mainly about Entertainment. In particular, users in this group tend to discuss about music (e.g. *mtvhottest* - trending videos in a popular music channel), events of celebrities (e.g. *vote5sos* - campaign to vote for a music band namely 5SoS), or other entertaining news (e.g. *teenchoiceaward* - a music award voted by teens, *alsicebucketchallenge* - an event to raise awareness of a disease), etc. This effect can be explained by the fact that users in this group are influenced by the trustability of authors, that is, users with high credibility. Majority of highly trustable authors in this group from our data fall into the categories of singer, entertainer, music band, or public figure, who are influential and followed by a large number of users. Examples of top-5 most frequently retweeted authors include *BieberAnnual* (fan of a singer), *5SoS* (music band), *CameronDallas* (entertainer), *Ashton5SoS* (singer), and *JaconWhiteSides* (entertainer). They

TABLE II
TOP-30 HASHTAGS PROPAGATED IN USERS WITH THE SAME MAIN STRATEGY. NUMBER IN THE BRACKET REPRESENTS THE NUMBER OF USERS (OF THE SAME GROUP) ADOPTED THE HASHTAG.

Top-30 hashtags propagated in users with the same main strategy			
Interest. $\|users\| = 8930$	**Linguistics.** $\|users\| = 28$	**Trustability.** $\|users\| = 1644$	**Freshness.** $\|users\| = 201$
#ferguson (1733)	#ferguson (6)	#mtvhottest (734)	#ferguson (44)
#oomf (1182)	#oomf (6)	#vote5sos (423)	#oomf (43)
#worldcup (872)	#wcw (5)	#rt (248)	#rt (40)
#mtvhottest (852)	#gaza (4)	#callmecam (243)	#mtvhottest (37)
#rt (798)	#gazaunderattack (4)	#nashsnewvideo (211)	#worldcup (32)
#mikebrown (693)	#respect (4)	#bestfandom2014 (204)	#gaza (29)
#gaza (677)	#mtvhottest (3)	#selfie (199)	#mh17 (26)
#retweet (677)	#retweet (3)	#alsicebucketchallenge (186)	#retweet (25)
#ger (626)	#worldcup (3)	#worldcup (166)	#gazaunderattack (25)
#betawards (619)	#ger (3)	#amnesiamusicvideo (162)	#ger (24)
#tbt (596)	#mh17 (3)	#imagine (160)	#lhhatl (24)
#twitterpurge (592)	#betawards (3)	#lifeoftheparty (160)	#twitterpurge (24)
#ifwedate (543)	#freepalestine (3)	#mtvclash (150)	#usa (23)
#bra (532)	#tbt (3)	#nashsnewvid (150)	#riprobinwilliams (23)
#lhhatl (526)	#twitterpurge (3)	#4yearsofonedirection (143)	#arg (22)
#gazaunderattack (515)	#worldcup2014 (3)	#teenchoiceawards (141)	#tbt (22)
#mh17 (485)	#makeuptransformation (3)	#vma (140)	#alsicebucketchallenge (20)
#usa (475)	#soundcloud (3)	#followmecam (132)	#respect (20)
#wcw (459)	#good (3)	#retweet (129)	#breaking (19)
#arg (454)	#vote5sos (2)	#5sosupindisstream (126)	#wcw (19)
#prayforgaza (444)	#lhhatl (2)	#riprobinwilliams (124)	#makeuptransformation (19)
#tweetlikejadensmith (404)	#libra (2)	#mattto2mill (124)	#betawards (18)
#iftheygunnedmedown (403)	#prayforgaza (2)	#bestmassageever (119)	#prayforgaza (18)
#freepalestine (401)	#tweetlikejadensmith (2)	#5sosrockoutwithyoursocksouttour (118)	#freepalestine (18)
#riprobinwilliams (393)	#col (2)	#jackandjackcoldhearted (117)	#ifwedate (18)
#breaking (376)	#betawards2014 (2)	#beafanday (117)	#israel (17)
#respect (363)	#louisvillepurge (2)	#camsupdatevideo (115)	#bra (17)
#israel (358)	#honestyhour (2)	#ger (109)	#iftheygunnedmedown (17)
#alsicebucketchallenge (341)	#tweetsomethingyougetalot (2)	#teenchoice (109)	#worldcup2014 (16)
#worldcup2014 (339)	#relationshipgoals (2)	#5sosthealbum (109)	#tweetlikejadensmith (15)

	Interest	Linguistics	Trustability	Freshness
Ratio of users	82.66%	0.25%	15.22%	1.86%

TABLE III
PERCENTAGE OF USERS CATEGORIZED BY THE MAIN STRATEGY

frequently discuss about popular topics such as those discovered above. Due to the social correlation theories of homophily and influence [17], users in this group follow social correlation effect and tend to discuss similar topics. Therefore, even though there are a number of other significant events happened during the period of the data, from June 19, 2014 to August 21, 2014, such as the crash of MH17 airplane, the conflict between Israel and Gaza, or the retirement of Ferguson - a well-known coach of Manchester United soccer team, these events are less likely to be prevalent in this group of users.

In the group of users mainly influenced by Interest, the propagated hashtags tend to belong to a broad range of topics, including Sport (e.g. *ferguson*, *worldcup*, *ger* - Germany soccer team, *bra* - Brazil soccer team), Music (e.g. *mtvhottest*, *betawards*), Politics (e.g. *mikebrown* - the shooting of Michael Brown; *gazaunderattack*, *gaza* - conflict between Israel and Gaza), etc. This is understandable, since even though this group consists of users retweeting mainly based on interest matching, users' interests tend to vary across users. Top-5 most retweeted users follow the same trend and include *MySportsLegion* (sport news), *Facts* (channel about facts), *Ashton5SoS* (singer), *SportsCenter* (sport news), and *5SoS* (music band). This is different from the group of users mainly influenced by Trustability, where the hashtags tend to focus on Entertaining. Jaccard similarity (measured as $JS(U,V) = |U \cap V|/|U \cup V|$) between these two groups of hashtags is 0.13, which indicates dissimilar content and shows that the strategies can be used to distinguish between two groups of users.

In the group of users mainly influenced by Freshness, the propagated hashtags seem to follow similar trend as that of the propagated hashtags in users influenced by Interest. Jaccard similarity between the two sets of hashtags in Freshness and Interest groups is measured to be 0.63, which indicates significant similarity. A possible explanation for this is that since Freshness measures the novelty of the target message against all messages from the followees of a user (by using TF-IDF), if the new contents from his followees resonate with his retweeted contents, the measure of Freshness will be similar to that of Interest. Under this scenario, Freshness strategy could be merged into Interest strategy, which finally results in the two main strategies affecting user retweet decision, i.e. Interest and Trustability.

Thus, over the four strategies, it seems that Interest and Trustability strategies play major role in accounting for user retweet behavior. The results observed in these two groups agree with the social correlation theories of homophily and influence [17], that is, user's behavior/preference should be similar to and influenced by the behaviors/preferences of his neighbors. We want to note that in Trustability group, since the high trustability users are in Entertainment domain, users in this group follow social correlation effect and tend to be interested in entertaining news. It suggests that incorporating finer-grained topics and trustability along these topics would further characterize the users.

B. Predicting User Retweets

In this section, we investigate if the inferred strategies contain any significant information about the users. For this, we rely on the task of predicting retweeting event of users. Specifically, given a tweet posted by a user, we want to predict which followers of the user will retweet that content. We cast this task as a classification problem, where we try to classify the followers of the author into either positive (retweet) or negative (non-retweet) class. Our hypothesis is if the strategies contain information about the user, adding these strategies as additional features on top of an available user representation could improve the prediction performance. Here, we choose topic model [18] as the baseline representation for user.

1) Evaluation settings: For this task, since we have already used the dataset mentioned in IV to train user retweet model, using the same dataset for a similar task would pose a risk of introducing information from training data to testing data. Therefore, to be fair, we get new retweet data in the next 17 days, from August 22, 2014 to September 8, 2014. We extract all the tweets that are retweeted during this period by 10,803 users. This results in a total of 858,848 retweet observations. We keep tweets that have been retweeted at least 20 times to properly learn the predictive model. This results in a set of 299 tweets. The negative samples are chosen randomly among followers of the author who did not retweet the tweet. We keep the number of negative samples ten times as large as the positive samples, since in practice the number of retweeters is much less than the number of non-retweeters. We use Random Forest classifier to train user retweet model. Other settings are derived in the same manner as in Section V-A1.

2) Comparative methods: We consider the following models in our experiment. Note that these models are all trained using Random Forest classifier, however, they differ in the features vector representing the retweet action.

STRAT-RAND: Features in this model are user's strategies with random values. Strategies components are chosen randomly in range [0,1]. Then we normalize these values across strategies so that the sum of them equals one.
STRAT-NPR: Features in this model are user's strategies inferred from our method, without considering the sign of Pearson correlation coefficient.
STRAT: Features in this model are user's augmented strategies inferred from our method, which consider the sign of Pearson correlation coefficients.
LDA: Features in this model are user's latent topics vector learned from his/her bag-of-words using topic modeling [18].

Model	AUC-ROC	F1
STRAT-RAND	0.5017±0.0051	0.0057±0.0029
STRAT-NPR	0.7916±0.0026	0.2577±0.0069
STRAT	0.8115±0.0024	0.3093±0.0078
LDA	0.8809±0.0025	0.3580±0.0089
STRAT-NPR-LDA	0.8912±0.0027	0.3513±0.0083
STRAT-LDA	0.8952±0.0027	0.3736±0.0069

TABLE IV
RESULTS FOR RETWEET PREDICTION

Here, for a fair comparison, we choose the number of latent topics the same as the number of strategies a user has, which is 4. We use lda[1] package to learn the latent topic model.
STRAT-NPR-LDA: Features in this model are a concatenation of both user latent topics and user strategies (the sign of Pearson correlation coefficients is not used in this case).
STRAT-LDA: Features in this model are a concatenation of both user latent topics and user's augmented strategies.

3) Evaluation metrics: We borrow metrics from Information Retrieval domain to measure the performance of the models with respect to retweet prediction. Specifically, we use area under the ROC curve (AUC-ROC) to measure model's recall capability; and F1 - the harmonic mean between precision and recall. The higher the values of these metrics, the better the model.

4) Performance comparison: We perform prediction and calculate the AUC-ROC, F1 metrics for various models above. Results are shown in Table IV. From this, we can see that the inferred strategies in STRAT-NPR model from our method improve the predictive performance significantly compared with random strategies in STRAT-RAND. This suggests that the inferred strategies contain significant information about the users. The model with the sign of Pearson correlation significantly improves the performance compared with model without the sign of Pearson correlation coefficient. When comparing the models using strategies alone, e.g. STRAT-NPR and STRAT, with the model using latent topics alone, i.e. LDA, it can be seen that the performance of LDA outperforms the performance of models using only strategies as features. It is reasonable since in previous section, our empirical result also shows that majority of users rely on interest matching to perform retweet. Breaking down a major interest into smaller interest topic components would capture finer-grained topical retweet behavior. The decrease in F1 value of STRAT-NPR-LDA compared with LDA can be attributed to the inability of the model to differentiate between users having high values in some strategies but in fact these strategies are inversely proportional. Thus, it is necessary to capture these relationships, whose effect shows clearly in the result of the last model. It can also be inferred from the last three models that the learned strategies is complementary to the latent topics, since they capture other dimensions such as trustability, linguistics and freshness information, which are not already captured in topic model. This further suggests that the strategies can be inferred more properly if the interest matching feature is decomposed

[1]https://pypi.python.org/pypi/lda

into multiple topics, and strategies are then inferred across these topics.

VI. Conclusion

In this paper, we study the problem of analyzing the strategies underlying user retweet behavior, with an emphasis on investigating to what degree the strategies can be used to represent user. We proposed a method to infer such strategies, which could be fully extensible to different types of user behaviors in online social networks. Our experiments on Twitter dataset show that the inferred strategies contain significant information about the users and can be used to improve the performance of prediction task.

In the future, we would like to develop a more unified framework to infer users' strategies that simultaneously learns latent topics and strategies over these topics to capture finer-grained topical user retweet behavior. Such information will provide additional interpretation and can help understand more about user behavior. Moreover, since retweet is one of many dimensions of user behaviors in online social network, strategies across multiple behaviors are also necessary to be investigated. This would bring additional insights into user behavior modeling.

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