A Survey of Interaction Modeling and Prediction on Social Media

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Abstract

This survey focuses on interaction modeling and prediction tasks on social media. These tasks can be divided into two categories, i.e. post level and conversational level, based on the target items. We probe into the details of previous methods in these tasks, and then point out a potential direction for future work.

1 Introduction

Online world has revolutionized our daily life since people now tend to use online platforms to discuss and interact with others. Meanwhile, the vast bulk of online content is irrelevant or unpalatable to any individuals. Online world becomes a place full of treasure but hard to be investigated. Therefore, recent researchers make many efforts to investigate methods modeling the huge online world, with the goal of extracting important information, analyzing or predicting user behaviors. so that online users can involve in the platforms more conveniently.

To model interactions and behaviors on social media, and then complete some interesting tasks like predicting specific events, is a popular direction. This survey focuses on such an interesting topic. And the following will introduce several previous work on different levels, i.e., post level and conversational level. Tasks in post level mean the core issues concerned are single posts; while tasks in conversational level concern the whole conversation structure.

2 Tasks in Post Level

As social media becomes more and more important in people's daily life, research about social media analysis has been carried out in diverse forms, from modeling user's behaviors to predicting central issues. In this section we focus on the prediction tasks in post level, including user's preference prediction(formulated as a recommendation task, i.e. post recommendation) and response prediction. Below we describe them in turn.

2.1 Post Recommendation

The functions of most online platforms are to express and share. But as the platforms like Twitter and Sino Weibo become increasingly popular, online users might face information overload problem. Such a problem harms user experience, since most of posts are irrelevant to users' interests and it is hard for users to find the posts with the topics they like. Therefore, how to filter the irrelevant posts and predict the ones a user likes serve as a popular research direction in past several years. Most of works formulate such a task as recommendation, i.e. *post recommendation* for online users.

Post recommendation on social media is very different from traditional recommendation. First, user preferences are usually indicated by implicit feedbacks. For example, researches about tweet recommendation in Twitter [9, 27] take the retweeting actions as symbols of interests. Such implicit feedbacks might not be as reliable as explicit feedbacks, since they can not be exactly viewed as user interests. Second, the target items in post recommendation, posts, are mainly constructed by combination of limited words, which means that techniques for text analysis can be exploited. Finally, there are many other information like social relations on social media, which may be important in recommendation.

The methods for post recommendation can be categorized into three kinds: traditional method, graph-based method, and neural network method. We introduce them respectively.

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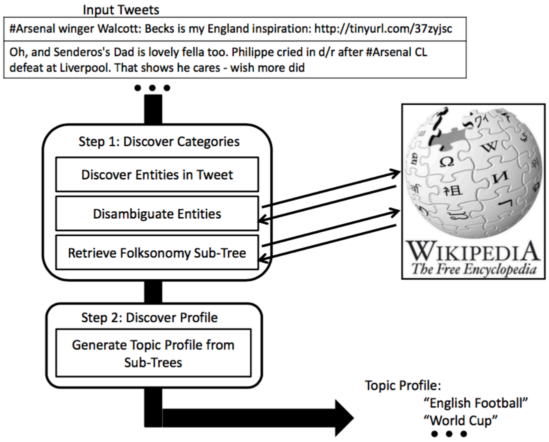


Figure 1: Two steps to discover user's interests

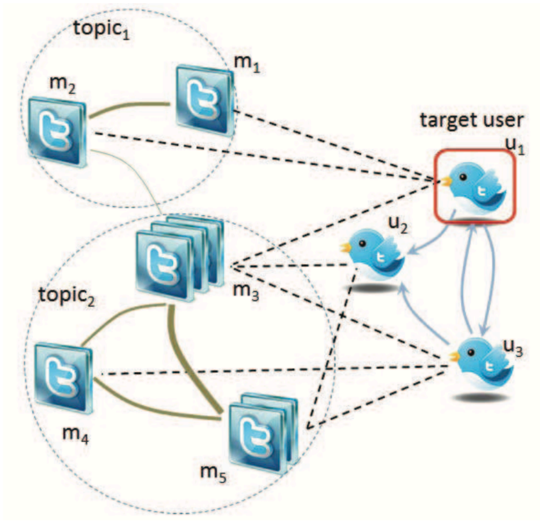


Figure 2: Co-ranking graphs

2.1.1 Traditional Method

In traditional recommender systems, the most common methods are content-based methods, collaborative filtering methods, or the hybrid of them. As a subfield of recommender systems, post recommendation can also be implemented by these kinds of methods.

Content-based Method. Content-based methods are a kind of methods that mainly take advantage of the content of user profiles and items. They find the similarity between users and items, and then recommend based on them.

In post recommendation, items are the posts presented by the users. User profiles may include the user's brief introduction, gender, location, post and repost history, etc. So in content-based methods, how to analyze the content of posts is critical. [12] proposes to rank tweets (posts in Twitter) based on not only the content relevance of tweets, but also the account authority and post-specific features such as whether a URL link is included in the tweet. And [17] uses two steps to find the user's interests of topics and recommend based on them (Figure 1).

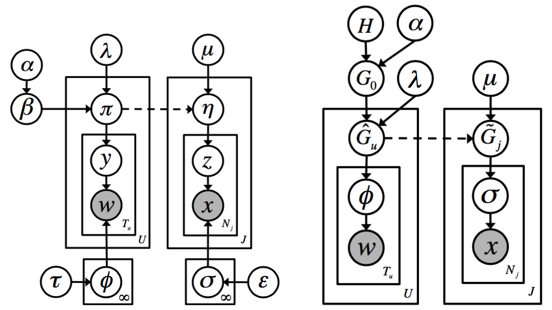
Collaborative Filtering Method. Collaborative filtering is a very popular method in traditional recommendation. The motivation for collaborative filtering comes from the idea that people often get the best recommendations from someone with tastes similar to themselves. In traditional recommendation, the latent features of users and items can be learned by analyzing the user-item rating matrix (Matrix Factorization). And then the preferences of users over items can be predicted based on them.

In post recommendation, since the lack of rating information, some researchers choose to use collaborative ranking methods [9, 24], under the assumption that users prefer posts they have reposted/replied rather than those they didn't. Other attempts use different models like topic model to help model user's preferences [26].

2.1.2 Graph-Based Method

Graph-based method is not a traditional method for recommendation. It is proposed specifically for those who can construct graph structures based on existing information. On social media, graphs can be constructed with different kinds of sources, e.g., the following behaviors or reposting behaviors in Twitter-like services.

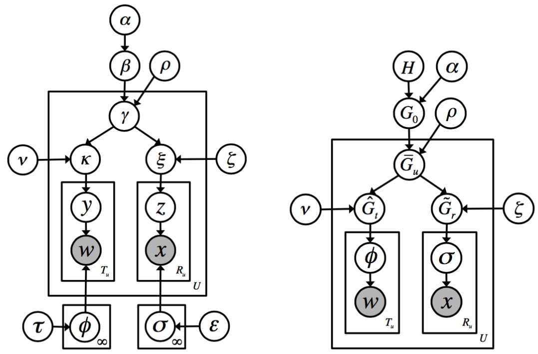
[19] uses specific features in diffusion process to construct a diffusion-aware model. The diffusion graph is formed based on the information diffusion paths (by reposting in microblog, for example). Another kind of graph, which can be constructed with follower-followee relationship, is the most frequently used graph for recommendation. This is because the following behaviors can indicate user's preferences. For example, [1] creates a graph called user's ego-network, which is constructed



(a) Stick-breaking representation of URM

(b) URM as a DP hierarchy

Figure 3: Graphical model for URM



(a) Stick-breaking representation of UCM

(b) UCM as a DP hierarchy

Figure 4: Graphical model for UCM

based on the target user (as center node) and includes all two-step neighbors, to recommend novel tweets. [20] uses followee network to model user's interests for list recommendation. While in [27], the authors build a multiple network for a PageRanking algorithm with three graphs: tweet graph based on content similarity, author graph based on following behaviors, and co-ranking graph based on tweets' authorship (Figure 2).

2.1.3 Neural Network Method

As the deep learning techniques advance, researchers also work on exploiting neural network methods in the field of recommendation. There is a few attempts in post recommendation on social media. A representative work is done by [28]. In this work, the authors propose a framework based on word embeddings and Paragraph Vector model to learn user's vectors and then recommend posts determined by cosine similarity between user's vectors and text vectors.

2.2 Response Prediction

Post recommendation is user-based, which means that the prediction is from user's perspective. Sometimes, we need to predict from the view of posts. For example, you might want to know whether your posts will receive responses (replying or reposting). Such tasks can be referred to as *response prediction*. We summarize the methods for response prediction into two categories: traditional classification methods and probabilistic graphical methods.

2.2.1 Traditional Classification Method

An intuitive method for response prediction is to classify as a binary problem based on some extracted features. This means that given a post, we classify it into to two categories, 1 (would get responses) or 0 (would not get responses). Linear classifiers deserve first try — [25] fits a general linear model to do the prediction and hope to find out which features impact the retweet behaviors in Twitter network. And in [30], the authors use logistic regression to classify; while experiments in [2] show that performance of MART model is better than logistic regression. However, such classifiers depend a lot on the features they employ. Exploring the most influential features is also very important for these works. According to some ablation study, not surprisingly, history features and social network features impact most in performance.

2.2.2 Probabilistic Graphical Method

Another kind of methods is to use a probabilistic model to model the user's behaviors on social media, and then predict whether a user will reply/repost a post based on the model. For example, [31] extend a model called Hierarchical Dirichlet Process to model the authors, structures, and content information in a social network, and the probability of retweeting can be calculated with the sampling results. Similarly, in [4], the authors propose two models to model a retweet network based on Dirichlet Process (Figure 3 and Figure 4). The difference is that, URM characterizes each user and each retweet as a unique mixture model, while in UCM, tweet and retweet interests are separated. The authors in [30] propose to use a factor graphic model to model the correlation between instances of retweeting behaviors, under the observation that the behaviors of one user may be influenced by the action statuses of the neighbors.

3 Tasks in Conversational Level

Most of online platforms allow users to reply or give comments to the original posts. For example, in Twitter, a user can reply or retweet a tweet so that they can express their own opinions about the tweet to the original author and their followers. With such reply behaviors, conversations are formed on social media.

In recent years, more and more researchers focus on conversations on social media. They find algorithms to model the conversations and investigate the interactions through the conversations. In this survey, we mainly care about two kinds of works related to conversations: conversation modeling, and prediction based on conversation.

3.1 Conversation Modeling

Many works about conversation focus on analyzing internal structure of conversations and finding algorithms to model conversations. They can be referred to as *conversation modeling*. The reasons behind conversation modeling are to find out what and how the conversations are formed [6, 14], and to model the internal attributes of conversations, like topic segments [16], dialog acts [21], etc. The methods for conversation modeling explored here are: statistical analytical methods and probabilistic model methods.

Statistical Analytical Method. This kind of method mainly analyzes the content and symbols in large-scale data, to find out what the authors care about [6, 14]. For example, in [14], the authors use content analysis, interaction analysis, and Dynamic Topic Analysis method to analyze a large collection of tweet samples and find out the functions of "@" symbol, as well as the coherence of Twitter conversations. Such methods depend on big data analysis, but are not for specific conversations.

Probabilistic Model Method. This kind of method aims to design a probabilistic model, which can learn and provide insights into the patterns of communication in a conversation. In [16], the authors use a probabilistic grammar model to characterize the content in a forum thread, which is viewed as a conversation tree of topics. In [21], the authors use an unsupervised conversation model to model dialogue acts in an open domain. We take the model in [21] for further explanation.

The authors focus on the sequential dialogue structure of conversation, with a goal to model dialog acts in an unsupervised manner. Figure 5 is the base model, where they assume each turn in a conversation is generated by a single act. They adopt a Latent Dirichlet Allocation (LDA) [5] framework to extend the model and separate content words from dialogue indicators (Figure 6). The authors assume that each word is generated from three kinds of sources: the current post's dialogue act, the conversation's topic, and general English. The variable s determines the source and is drawn from a conversation-specific distribution over π_k. Multinomial θ_k represents topics and ψ_E represents general English. Dirichlet priors are placed over all multinomials. Finally, they use Gibbs sampling to inference, following LDA convention.

3.2 Prediction Based on Conversation

As we mention in Section 1, one of the purposes of research on social media is to help users manage so much online information and use these online platforms more conveniently. Therefore, a very popular and essential research domain is about prediction. Predicting whether a user will be interested in a post, predicting whether a post will be popular, or predicting whether a post will get response, etc. On conversational level, since what we concern becomes the conversations, prediction task is also a little different from post-level prediction.

An intuitive thought of such a task is to predict whether a user will engage in a conversation. Concerning the engaging types of conversations, such a task can be divided into two sorts: 1) Given a conversation, predicting whether a user will be likely to participate in; 2) Given a conversation, predicting whether a user that has been involved will return. The first kind, which can be referred

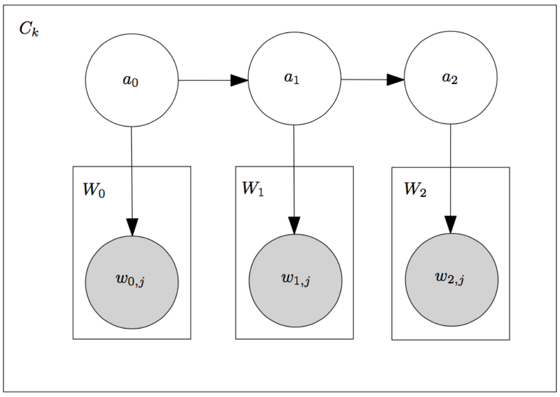


Figure 5: Conversation Model

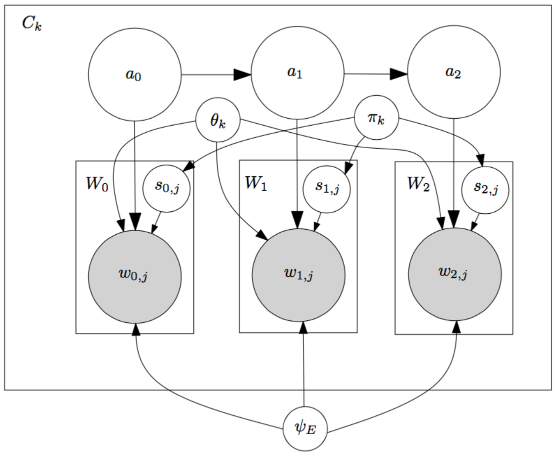


Figure 6: Conversation + Topic Model

to as *the first time reply prediction*, is very similar to the recommendation task stated in Section 2.1. The main difference is that we concern about conversations now, which means we can make use of conversation-specific features to give an more appropriate result. The second kind is called *re-entry prediction*. Several works have explored such a task [3, 7, 23]. I will introduce them in detailed in the following subsection. In addition to engagement prediction, researchers also deal with many other conversation-specific predictions and explore ways to tackle them [15, 22, 11, 18].

3.2.1 Engagement Prediction

The First Time Reply Prediction. To the best of our knowledge, there are still few works that focus on the first time reply prediction, i.e., formulate it as a recommendation task. The authors in [8] first introduce conversation-level recommendation. However, they haven't defined the formal settings of such recommendation, and only describe some simple ranking strategies.

The first time reply prediction is a difficult task. Generally, most online conversations can be categorized into two kinds: focused and expansionary [3]. The focused conversations means that they are formed by only a small group of users. While the expansionary conversations are those formed by many users' one-time comments, e.g., the congrats received under a marriage announcement post. These two kinds of conversations need different aspects of features to model. It is difficult for us to predict the first time replies given only a small set of conversation history.

Re-entry Prediction. On the other hand, researchers are more interested in the task of re-entry prediction [3, 7, 23]. However, so far, these works mainly concern about what features influence a user's continuous engagement in a conversation.

In [7], the authors propose a 5F Model to study whether an individual will continue to participate in a Twitter chat group (Figure 7). "5F" means five different aspects of factors that probably determine an individual's continued participation, including *Individual Initiative*, *Group Characteristics*, *Perceived Receptivity*, *Linguistic Affinity*, and *Geographic Proximity*. The authors use logistic regression for statistic analysis and find that *Linguistic Affinity* holds the best performance among these five factors, while *Geographic Proximity* only mildly influence performance.

For [23], the authors mainly want to find how different kinds of features would affect the engagement dynamics in different online platforms. The authors experiment on different platforms, including Twitter, Facebook, SAP Community Network, etc. And the features include social features (*In-degree, Out-degree, Post Count*, etc.) and content features (*Complexity, Readability, Informativeness*, etc.). The authors also use logistic regression model for classification and find that different platforms achieve better performance with different features, but all perform best with both social and content features.

[3] is the first work proposing the task of re-entry prediction, with the main purpose of to characterize the online conversations. The authors first analyze the conversations on social media, and find that they all can be categorized into two kinds: focused and expansionary (described in Section 3.2.1). Then they exploit re-entry prediction with features in Figure 8, using bagged deci-

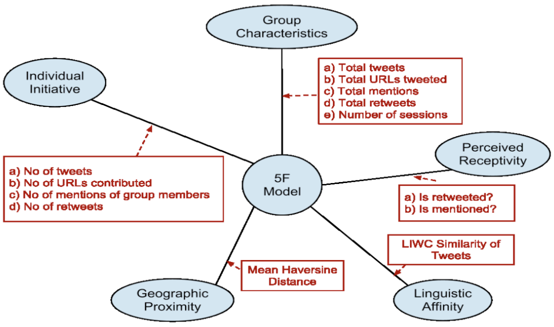


Figure 7: 5F Model in [7]

LINKS	
$edges\_prev[i]^*$	Number of links from commenter to previous commenters
$mutual\_poster[i]^*$	Number of links from commenter to users linked to the original poster
ARRIVAL PATTERNS	
$id\_code[i]$	commenter ID code as described in §4.2
$uniq\_comm[i]$	Unique commenters through comment i
TIME	
$time[i]$	Time taken for the first i comments to arrive
TEXT REGRESSION FEATURES	
$Orig\_post\_terms$	"comment", "agree", etc.: see §5.1
MISC	
$num\_words[i]$	Number of words in comment i
$num\_chars[i]$	Number of characters in comment i
$question[i]^*$	Comment i has a '?'
$exclaim[i]^*$	Comment i has a '!'
$likes[i]^*$	Num likes on original post before comment i is made
$comment\_likes[i]^*$	Num likes on comments before comment i

Figure 8: Features Used in [3]

sion trees. The results show that the most important features are the identities of the individuals posting the comments and the time between the two most recent comments. To further investigate the patterns of re-entry, the authors also formulate a set of probabilistic generative models considering two kinds of arrival patterns (focus and expansion) and find it is quite challenging to be analyzed.

3.2.2 Other Prediction Tasks

The prediction tasks in conversational level are not only about engagement. As more researchers put their eyes on online conversations, many interesting works have been carried out.

[18] defines a kind of conversations called *good conversations*, which consist of an *Engaging*, *Respectful*, and/or *Informative* Conversation. The authors try methods like CRF, logistic regression and CNN with different features to identify such conversations. In [11], authors analyze large-scale data and try to find out the causes of trolling behavior in Online discussions. The results show that negative moods and negative contexts both have an impact in making users troll in discussions. To find out the roles of conversational structure in detecting agreement and disagreement in online discussion, the authors in [22] set up experiments with different features. As a result, conversation structure and accommodation information can significantly improve performance compared to using lexical features alone.

There is also a kind of prediction task related to engagement prediction, which is called *cascade growth prediction*[10]. This kind of task focuses on the future growth of a certain conversation, i.e., predicting whether a certain conversation will reach a length threshold in the future. In [3], the authors set two thresholds, length 5 and 8, based on different situations in different platforms; while the authors in [10] set the threshold to be double size of original treads. Both works use linear models with content and structure features to do the classification. In [15], the authors aim to find the *conversation killers*, i.e. the thread-ending posts. It can be viewed as a special case in cascade growth prediction, since we can set the threshold to be 0. The authors design a neural network call ConverNet for the prediction task. Figure 9 describes the details of the designed framework. Specifically, the authors use a two-layer BiLSTM as basic framework, incorporating side information like reply structure to enhance the learned representations. They also add an attention layer to take full usage of the conversation representations.

4 Conclusion and Future Work

This survey introduces diverse kinds of tasks related to interaction modeling and prediction on social media, as well as the methods used for these tasks. In general, most methods for these tasks

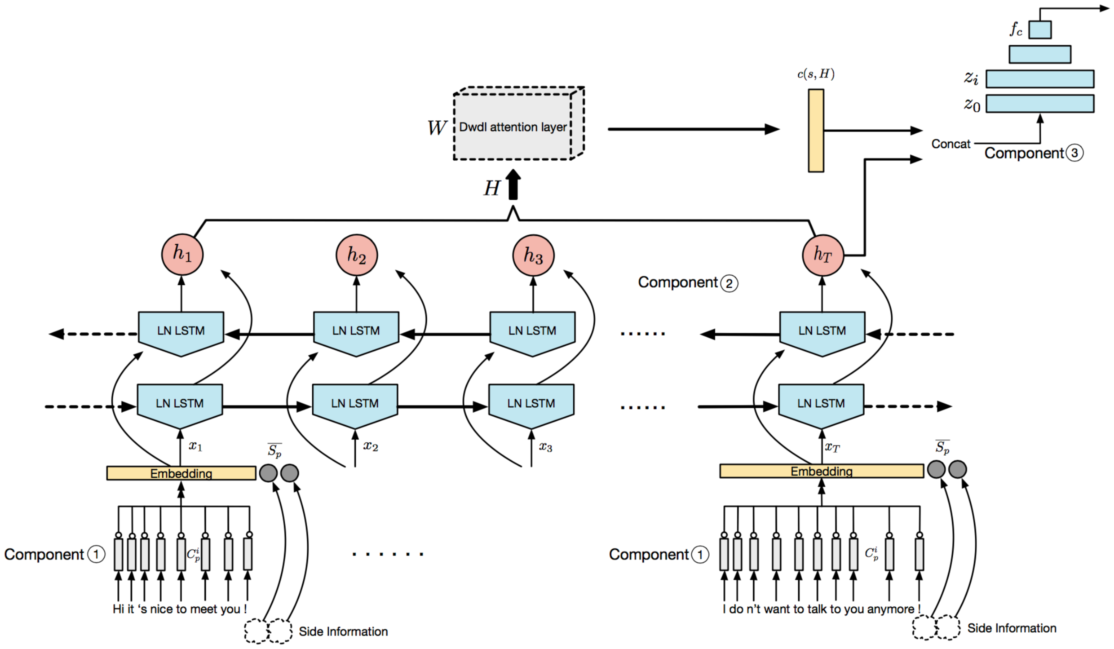


Figure 9: ConverNet for predicting conversation killers

have taken full use of side information that available on different platforms. This can effectively improve the performance, but at the same time, is adverse to universality. This means that the same methods may be not suitable or perform worse in a different situation. For example, many methods for post recommendation in Twitter use the following behaviors to indicate the user's preferences. If an online platform lacks such function, then the methods cannot be applied to this platform. Therefore, a potential direction for future work lays on designing a generally applicable model that can be utilized in different platforms. This means that we should not use those platform-specific features. Under such consideration, the tasks in conversational level might be more suitable, as the content within one conversation can provide sufficient information about the conversation.

A first attempt has been done in conversation recommendation [29]. The work in [29] has tried the first time reply prediction task (stated in Section 3.2.1) and found that it is indeed a difficult task if we only leverage on the conversation content and interaction history. In next step, we will try to employ neural-based methods, as neural-version CF methods (NCF) have been proposed and proved effective in many recommendation tasks [13]. With NCF model, we can easily incorporate neural models like CNN or RNN to model online conversations and recommend based on them.

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