A Survey of Interaction Modeling and Prediction on Social Media

Zeng Xingshan*

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. But 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 Online social media become more and more important in people's daily life, research about social media analysis has been carried out in a large amount. And the topics are diverse, from modeling user's behaviors to predicting central issues. Since the topic of this survey is mainly about prediction tasks and interactions modeling, in this section I focus on the prediction tasks in post level, including predicting user's preferences through different posts (formulated as a recommendation task), and predicting responses a certain post may get.

2.1 Post Recommendation

The function of most Online social media is to express and share. But as the platforms like Twitter and Sino Weibo become more and more popular, users may face Online information overload problem. Such problem influences user experience, since most of posts are irrelevant to users' interests and it is hard for users to find the posts of topics they like. Therefore, how to filter the irrelevant posts and predict the ones a user likes becomes a very popular research topic in past several years. This can be viewed as a recommendation task on Online social media.

Post recommendation on Online social media is very different from traditional recommender systems. First, *user preferences* are generally indicated by implicit feedbacks. For example, researches about tweet recommendation in Twitter [8] [25] take the retweeting actions as a symbol of being interested. Second, the *target items* in post recommendation, posts, are mainly constructed by texts of limited words, which means that techniques for text analysis can be exploited. Finally, there are many other information like social relations on Online social media, which may play a big role in recommendation task.

*The survey is done by June, 2018.

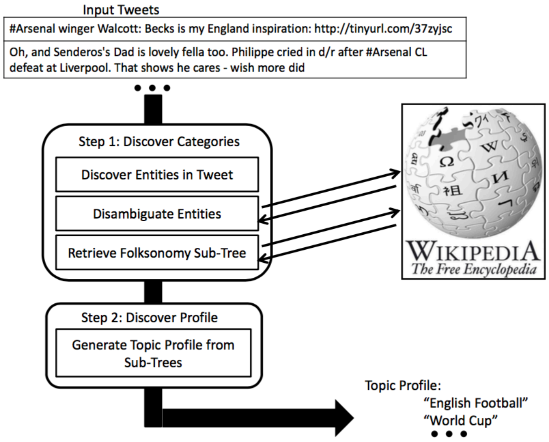


Figure 1: Use two steps to discover user's interests

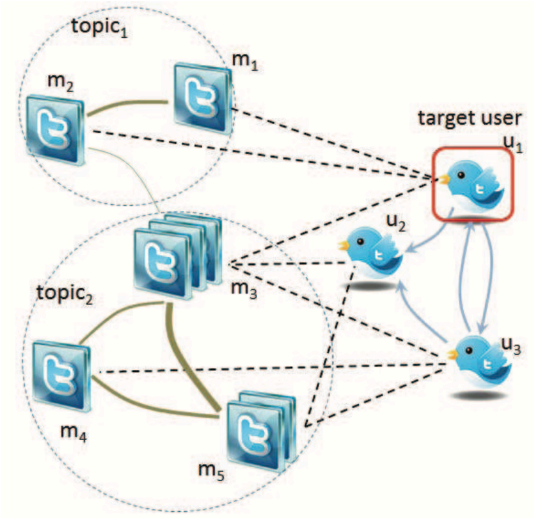


Figure 2: Three graphs for co-ranking

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

2.1.1 Traditional Method

In traditional recommender systems, the most common methods are content-based filtering and collaborative filtering. Most methods can be categorized into these two kinds 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 method is a method that mainly takes advantage of the contents of user profiles and items, finding similarity between them and then doing recommendation.

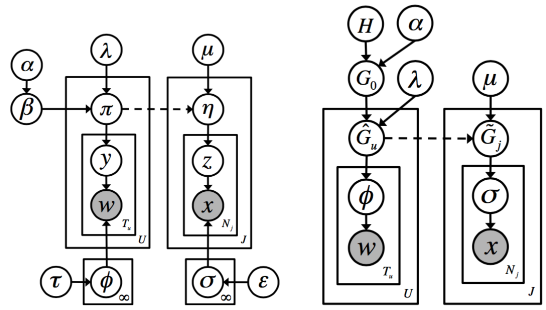
In post recommendation, items are the posts presented by the users, user profiles may include the user's brief introduction, gender, location, post and repost history, etc. So in content-based method, the most important thing is to analyze the content of posts. [11] proposes a ranking method which uses not only the content relevance of a tweet, but also the account authority and post-specific features such as whether a URL link is included in the post. And [15] uses two steps to find the user's interests of topics and doing recommendation based on them (Figure 1).

Collaborative 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, by analyzing the rating matrix (user-item), the latent features of users and items can be found(Generally use a vector to represent). And then predicted ratings can be constructed.

In post recommendation, since we lack of rating information, some researchers choose to use collaborative ranking methods [8] [22], under the assumption that users prefer posts they have reposted/replied rather than those they didn't. Another try is to use other models like topic model to model users' preferences [24].

2.1.2 Graph-Based Method

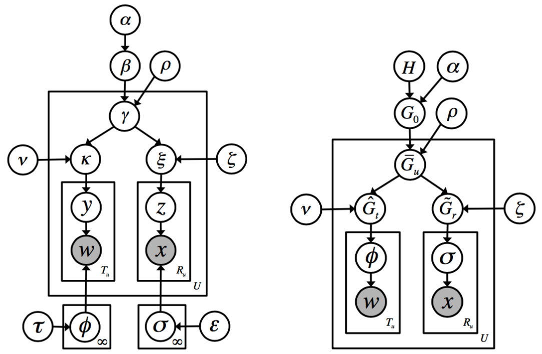
Graph-based method is not a traditional method for recommendation. It is proposed specifically for those can be constructed graphs based on existing information. On Online social media, graphs can be constructed using different kinds of sources, e.g., the following behaviors or reposting behaviors in microblog services.



(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

[17] uses diffusion 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). The graph constructed by follower-followee relationship is the most used graph for recommendation, since the following behaviors can indicate user's preferences. For example, [1] creates a graph called user's ego-network, which is constructed by taking target user as center and including all two-step neighbors of the target user, to recommend novel tweets. [18] uses followee network to model user's interests for list recommendation. While in [25], 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 authorship (Figure 2).

2.1.3 Neural Network Method

As the techniques of deep learning become more and more popular, researchers are trying to exploit neural network methods in the field of recommendation. However, there is still few work using such methods in post recommendation on Online social media. A representative work is done by [26]. 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

The task of post recommendation is user-based, which means it is to predict from user's perspective. Sometimes, we need perspective of a certain post. For example, after you have written a post, you want to know whether this post will receive responses (replying or reposting). Many researchers have worked on such a task, which can be called response prediction task.

2.2.1 Traditional Classification Method

An intuitive method for response prediction is to treat it as a classification task. Given a post, design a model to classify it into to two categories, 1 (will get responses) or 0 (won't get responses). A first try is to use a linear classifier – [23] fit a general linear model to do the experiment and hope to find out which features impact the retweet in Twitter network. And in [28], the authors use logistic regression to classify, while experiments in [2] show that performance of MART model is better than logistic regression. The difference is that what features they choose to use. Finding the most influential features is also an important target of these works. According to ablation study, not surprisingly, results all show that history features and social network features impact most in performance.

2.2.2 Probabilistic Graphical Method

Another method is to use a probabilistic model to model the user's behaviors on Online social media, and then predict whether a user will reply/repost a post based on the model. For example,

[29] extend a model called Hierarchical Dirichlet Process to model the author, structure, and content information in a social network, and the probability of retweeting can be calculated with the sampling results. Similarly, in [4], the authors also 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.

In [28], the authors propose using 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 social media 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 he can express his own opinions about the tweet to the author and others. With such reply behaviors, conversations are formed on social media.

Recent years, more and more researchers focus on conversations on social media. They find ways to model the conversations and investigate the interactions through the conversations. In this survey, we mainly care about two kinds of work related to conversations: conversation modeling, and predictions and detections with conversations.

3.1 Conversation Modeling

Many works about conversation focus on analyzing internal structure of conversations and finding ways to model conversations. I call this kind of work is about *Conversation Modeling*. The reasons behind *Conversation Modeling* is to find out what and how the conversations are formed [6][12], and to model the internal attributes of conversations, like topic segments [14], dialog acts [19].

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][12]. For example, in [12], the authors use content analysis, interaction analysis, and Dynamic Topic Analysis method to analyze a large collection of tweets sample and find out the functions of "@" symbol, and coherence of Twitter conversations.

Probabilistic Model Method. This kind of method aims to design a probabilistic model to learn and provide insight into the shape of communication in a conversation. In [14], the authors use a probabilistic grammar model to characterize the content of a forum thread as a conversation tree of topics; while in [19], the authors use an unsupervised conversation model to model dialogue acts in an open domain. Let's take the model in [19] for explicit explanation.

Figure 5 is the base model the authors use. And 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 sources π_k. Multinomial θ_k represents topics, ψ_E represents general English, and Dirichlet priors are placed over all multinomials. Finally, they use Gibbs sampling to inference, following LDA convention.

3.2 Predictions and Detections

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

An intuitive thought of such task is to predict whether a user will engage in a conversation. Considering characteristic of conversations, such task can be divided into two sorts: 1) Given a

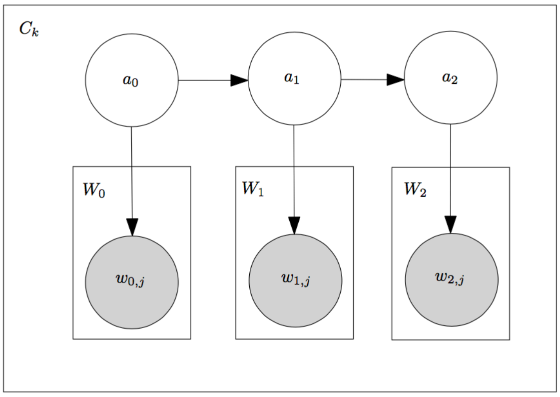


Figure 5: Conversation Model

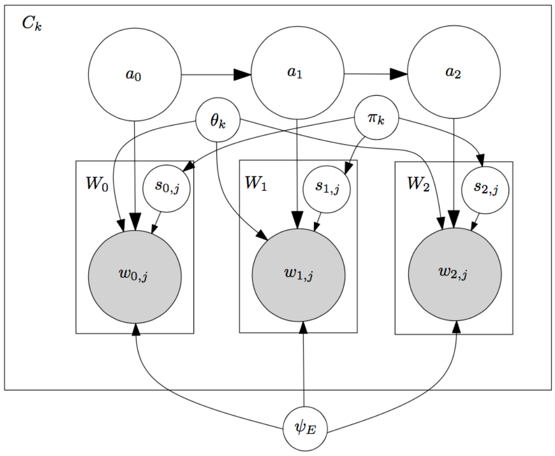


Figure 6: Conversation + Topic Model

portion thread of a conversation, predicting whether a specific user will be likely to participate in; 2) Given a portion thread of a conversation, predicting whether a user that has been involved will return. The first kind, which can be called *The First Time Reply Prediction*, is very similar to the recommendation task stated in Section 2.1. The main difference is that what we concern this time is conversations rather than single posts, which means we can make use of conversation-specific features to give an more appropriate result. I call the second kind of task *Re-entry Prediction*. Several works have explored such a task [3][7][21], I will introduce them in detailed in the following subsection.

In addition to engagement prediction, researchers also find many other conversation-specific tasks and explore ways to tackle them [13][20][10][16]. These will be introduced in the next of following subsection.

3.2.1 Engagement Prediction

The First Time Reply Prediction. To the best of our knowledge, there are still no works that focus on the first time reply prediction, i.e., formulate it as a recommendation task. This is mainly because that first time reply prediction is kind of a difficult task. Generally, most conversations on online social media can be categorized into two kinds: focused and expansionary [3]. The focused conversations means that they are formed by only a small group of people keep engaging. While the expansionary conversations are those formed by many people's one-time comments. For example, the congrats received in a marriage announcement post form a expansionary conversations. Either of these two kinds of conversations needs different aspects of features and so 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 seem more interested in the task of *Re-entry Prediction* [3][7][21]. However, so far, these works mainly concern about what features influence whether a user will keep engaging 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* gives the best performance among these five factors, while *Geographic Proximity* only mildly influence performance. For [21], the authors mainly want to find how different kinds of features would affect the engagement dynamics in different Online social media platforms. The authors do the experiments 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 to do the experiments and find that different platforms achieve better performance with different features, but all perform best with both social and content features.

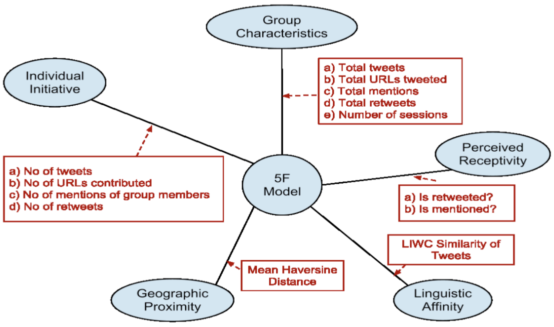


Figure 7: 5F Model

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]

[3] is the first one to propose the task of *Re-entry Prediction*. The main purpose of this paper is to characterizing the conversations. So the authors first analyze the conversations on Online social media, and find that they all can be categorized into two kinds: focused and expansionary. Then they try the prediction tasks (including predicting thread length and re-entry) with features in Figure 8, using bagged decision 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 Tasks

The tasks of predictions and detections in conversational level are not only about engagement. As more and more researchers put their eyes on conversations in Online platforms, many interesting researches have been carried out.

[16] 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 [10], authors analyze large-scale of data and try to find out the causes of trolling behavior in Online discussions. The results show that negative moods and negative contexts both play a big role in making users tend to troll in discussions. To find out the role of conversational structure in detecting agreement and disagreement in Online discussion, the authors in [20] set up experiments using different features. As a result, conversation structure and accommodation information can significantly improve performance compared to using lexical features alone.

In addition to these very interesting topics, there is a kind of predicting task related to engagement predictions, which is called *cascade growth prediction*[9]. This kind of task focuses on the future growth of a certain conversation, i.e., predicting whether a certain conversation will reach a given length 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 [9] set the threshold to be double size of original treads. Both works use linear models with content and structure features (mainly) to do the classification. In [13], the authors set their target as finding *conversation killers*, which means the thread-ending posts. I think it is very similar to *cascade growth prediction*, as we can set the threshold to be 0. The paper designs a neural network call ConverNet for the prediction task. Figure 9 describes the details of the designed framework. In general, the authors use BiLSTM as a basic model, incorporating side information like reply structure and adding an attention layer to take full usage of the information.

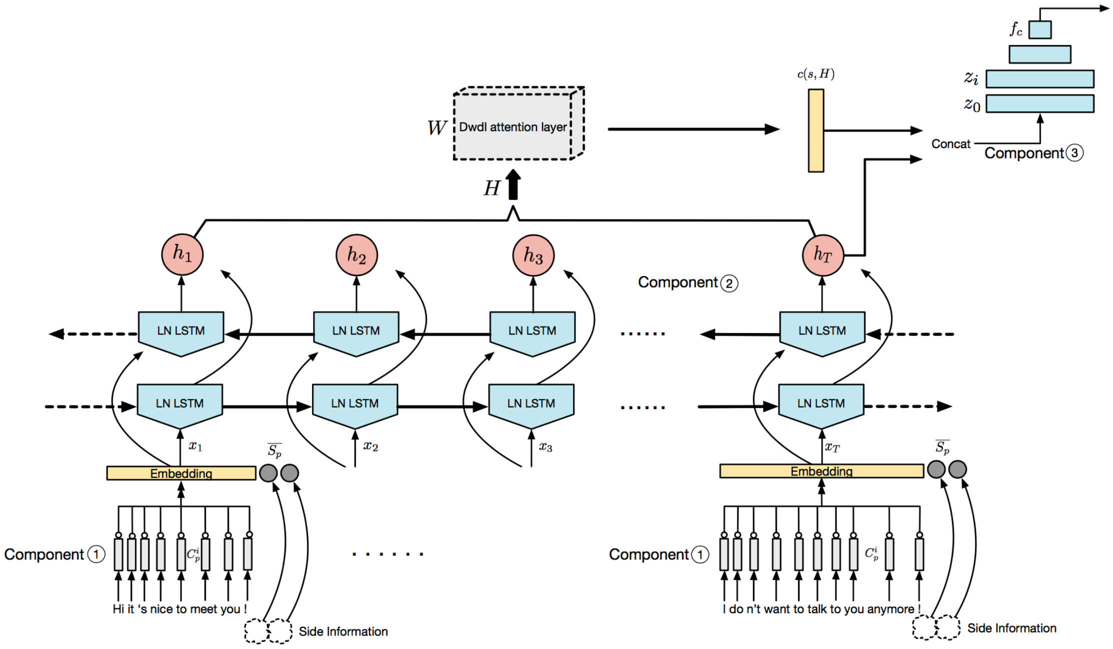


Figure 9: ConverNet for predicting conversation killers

4 Consideration and Future Work

Above I introduce diverse kinds of tasks related to predictions and interactions modeling on Online social media, and the methods used for these tasks. In general, most methods for these tasks have taken full use of side information that depends on different platforms. This can effectively improve the performance, but at the same time, is adverse to universality, which means that 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 of such function, then the methods cannot be used in this platform.

Therefore, I think a potential direction for future work lays on designing a model that can be used in different platforms. This means that we should use those platform-specific features as few as possible. Under such consideration, I think the tasks in conversational level may be more suitable. Since the conversation structure itself can provide sufficient information about the conversation.

A first try has been done in recommendation task in conversational level [27]. I have stated in Subsection 3.2.1 that few works have put their eyes on the task of *The First Time Reply Prediction*. The work in [27] has tried such task and found that it is indeed a difficult task if we only use the features of conversation structure and history.

As for the methods, I think neural network methods deserve a try since it has been proven that it is powerful in many NLP task while still not many works have tried in tasks about Online social media.

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