Mining User Intents in Online Interactions: Applying to Discussions About Medical Event on SinaWeibo Platform

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Abstract. Mining user intents in online interactive behavior from social media data can effectively identify users' motives behind communication and provide valuable information to aid medical decision-making and improve services. However, it is a challenging task due to the ambiguous semantic, irregular expressions and obscure intention classification categories. In this paper, we first define user intent categories based on speech act theory. On the basis of this, we develop a novel method to further classify users' utterances according to their pragmatic functions. First, we design topic independent features by regularizing the utterance and categorizing the textual features. Then, we build a hierarchical model based on Hidden Markov Model (HMM) [1] to mine user intents in context sequence at both sentence and microblog level. Finally, we construct a dataset of microblogs about hot topics related to the medical event by a semi-automatic method. Experimental study shows the effectiveness of our method.

Keywords: User intention recognition · Speech act theory · Online communication · Markov multinomial model · Medical event

1 Introduction

Social media provides the major platform for people to discuss various issues through online interactions. Topics about medical events, and especially medical disputes, often provoke hot discussions. Mining communicative purposes from online discussions of medical events can help effectively identify users' motives and intents providing valuable information to improve services, ease doctor-patient relationship, and facilitate medical decision-making according to public demands.

Different from topic detection concerned with affairs and sentiment analysis concerned with polarities, mining user intents in online interactions pays more attention to current actions and future results. For example, in a microblog "Black-hearted hospital should publish video evidence!" topic detection concerns the subject "video evidence"; sentiment analysis concerns the negative feeling expressed with "black-hearted". Differently, intention mining focuses on the action "should publish". By mining directive

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intent from the microblog, the hospital can quickly notice this public demand and adjust strategy to fulfill it.

Although recently, recognizing user intents in online interactions has been studied, it is usually confined to the particular application domain and corpus. Existing research on mining user intents in online communication has focused on two specific domains, search query [2, 3] and commercial purchase [4, 5]. Recent work [6, 7] applies user intention recognition from social media data, using domain-dependent intent classification scheme. Different from the previous research, our work aims to recognize users' communicative intents in online interactions by proposing a computational method and apply it to the medical related domain which has abundant online data resources.

However, recognizing user intents from online communication in social media platform is challenging due to the ambiguous semantic, irregular expressions and obscure categories. To deal with the challenges, in this paper, we identify user intent categories in online interactions based on speech act theory and propose a method to mine user intents. Firstly, we design features and employ a filtering process to characterize topic independent features. Then, we build a hierarchical model based on HMM that captures user intent types at both sentence level and microblog level. We apply this model to a microblog dataset about a medical event in China. The training data is generated by a semi-automatic label method and experimental study shows the effectiveness of our proposed method.

2 Related Works

2.1 Speech Acts and Chinese Sentence Patterns

Speech act theory is a subfield of pragmatics concerned with the ways in which words can be used not only to present information but also to carry out actions [8]. Founded by Austin [8] and further developed by Searle [9], speech acts are traditionally classified into five broad categories [9]: directive, commissive, expressive, representative, and declarative.

The speech act coding schemes can help identifying the speaker's intent in an utterance. According to Wu [10], the function of sentences is the intention of speech act. He reasons out 8 functional categories of Chinese sentences, including declarative, statement, directive, interrogative, expressive, provocative, commissive, and cooperative. Inspired by this, in our work, we define user intents based on this classification scheme and classify users' utterances according to their pragmatic functions.

2.2 Intention Recognition

Intention recognition is an essential component of text mining applications. It has been widely studied in AI field to detect agent's behavior in relatively close-systems, typically with predefined plan libraries. With the rapid development of social media platforms and online communication, recognizing user intents in online interactions has become an important research issue in text mining research and applications.

Current work on user intention mining in online communication and social media analytics is carried out in limited domains. Query intention mining focuses on expanding query characteristics and recovering semantics because data in search engine log usually lacks complete utterance. External knowledge is taken into consideration, such as Q&A websites [2] and users' feedback [3]. Purchase intention mining focuses on recognizing product entity [4] and judging users' consumption intents by means of natural language processing (NLP) methods [5].

Recent work applies user intention recognition to more general social media domain, but the definition of the intent classification scheme is still dependent on the specific domain. Wang et al. [6] propose a method to recognize six daily life intents from intent twitter, like "I want/plan to". Another work on Twitter identifies two specific intents "seeking" and "offering" help for crisis rescue application [7]. Different from aforementioned research, our work aims to recognize users' communicative intents in online interactions according to the pragmatic functions, which are more general.

3 User Intent Categories in Online Interactions

According to the speech act theory [8], speech is a kind of action with certain intent. On this view, we associate users' communicative intents with speech acts and define the categories of user intents exhibited in online texts. We examine the taxonomy of speech acts manifested in online texts by reviewing a large number of microblogs and divide user intents into nine broad categories. Besides, we also identify subcategories within each broad one. The categories are described as following (Table 1):

Table 1. Description of user intent categories in online interactions.

Intent categories	Description
Directive (D_1)	Want the others (not) to do something, including subcategories: general directive and moral directive. The moral directive force others to act through moral power
Question (Q)	Ask for information, including subcategories: yes-or-no question, alternative question, and specific questions
Statement (S)	Narrate events, describes something or explains relations, including subcategories: narration, description, and explanation
Comment (C_1)	Evaluate the possibility or necessity of something by subjective judgment, including subcategories: assertion, speculation, and prediction
Desire (D_2)	Describe one's desire/wish or plan of doing something
Commissive (C_2)	Promise (not) to do something in the future
Expressive (E_1)	Express his/her feelings or attitudes with polarity about something, including subcategories: sentiment and evaluation
Provocative (P)	Inspire certain emotions in others, including subcategories: blame and manners
Declarative (D_3)	Announce objective information

4 Features Representation

We use a filtering process to remove redundancy and characterize topic independent features. Inspired by the previous filtering work [11], we first regularize the utterance into grammatical skeletons as subject, object, predicate, attributive and tone.

Considering semantics, grammar and pragmatics, we then represent terms/phrases features in each skeletons with different attributes using external knowledge sources, including LIWC (Linguistic Inquiry and Word Count) dictionary [13] and HowNet [14]. We design feature classes according to the following attributes: personal pronoun (first/second/third), tense (past/present/future), modality (dynamic/deontic/epistemic), sentimental polarity (evaluation/emotion/positive/negative), objective degree and other special attributes like interrogative, temporal, positional, etc.

In terms of the corpus statistical property, we find the objective class contains more entity nouns (such as dates, organizations, and places) but fewer sentiment adjectives. So, we calculate the objective degree as (1) and characterize it as an objective person if the score is above a certain threshold.

$$S_{\mathrm{obj}} = \left(C_e - C_s\right) / \left(C_w\right) \tag{1}$$

Where S_{obj} denotes the score of objective degree, C_e, C_s and C_w denote the count of entity nouns, sentiment adjectives and words, respectively.

We also distinguish performative verbs [12], modal particles, punctuations, manner words and dirty words since non-illocutionary meanings, intonations and idioms are important in intention recognition. Finally, we represent each feature with a three-tuple (feature class, grammatical class, position in syntax tree).

5 Hierarchical Model for User Intention Mining

HMM is a statistical model which describes the system using a Markov process with hidden states [1]. Since intents are not observable but can be inferred from linguistic characters, HMM is very suitable to describe our problem. In detail, we describe interactive intents implied in each sentence from a document as hidden states and the utterances represented with features as observable states. Moreover, as a sequence learning model, HMM can represent both the sentences of context in a single microblog and the microblogs in a whole dialog with a sequence of states.

On the basis of this, we build a Hierarchical Model based on HMM. The model consists of two layers (see Fig. 1). The upper layer HMM aims to recognize user intent categories in each microblog. Each hidden state in upper layer represents an intent category in one microblog, which we called intent. The lower layer HMM aims to recognize user intent categories in each sentence. Each hidden state in lower layer represents an intent category in one sentence, which we called sub-intent. Since one microblog consists of several sentences, each hidden state in upper layer is naturally coupled with one Markov process of hidden states in lower layer. Each observable state is a sentence utterance represented with features we design.

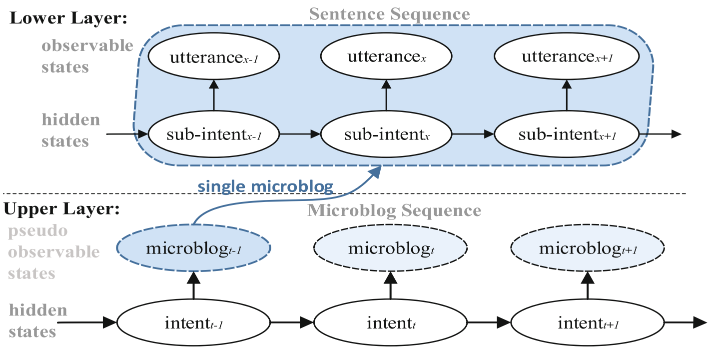

Fig. 1. Hierarchical model for user intention mining.

In general, the model describes a physical process of intention comprehension and expression: When user expresses an intent with a microblog in dialog, the audience first observes utterances composed of words. Then, audience captures a sequence of sub-intents by reading the microblog sentence by sentence. Finally, the audience understands the main intent in the whole microblog by summarizing the sub-intents. To continue the dialog, the audience can express another intent and start a new round. The task of intention mining corresponds to the decoding process [1] of hidden intent states according to observable utterance states. We can train model with the Baum-Welch algorithm and recognize user intents using decoding process with Viterbi algorithm [1].

6 Experiment

6.1 Datasets and Labeling Strategy

We crawl microblogs about a hot medical topic during 2016 from SinaWeibo, the most popular microblog platform in China. They cover a variety of discussions on medical events about "Maternal death in Peking University Third Hospital". After spam filtering and preprocessing, we get totally 35,128 microblogs for our analysis.

By reviewed a large number of microblogs and studied taxonomy, we annotate the microblogs with a semi-automatic method based on the intent classification scheme. Given a seed set of the intent markers in each category according to [10], for example, "you should", "I wonder", "In my opinion", we classify sentences into different intent categories. Then, we extract frequently co-occur phrases using sentence sets within each category. We examine the extracted phrases and regarded them as new intent markers for classifying. For instance, we extract phrase "by the report" using intent maker "Xinhua News reported" as they always appear together. This new phrase is kept as an intent marker of "declarative" by manual examination.

Through this iterative process, we extract many intent markers. Finally, we get a labeled corpus consisting of 81,097 sentences within 25,374 microblogs. Further, we use some simple priority rules to label intent categories for microblogs according to intent categories in sentences of microblog. The distribution of microblogs for each intent category D_1, Q, S, C_1, D_2, C_2, E_1, P and D_3 is 22.3%, 13.2%, 22.7%, 34.8%, 1.4%, 6.6%, 10.6%, 6.4% and 10.5%, respectively. And the distribution of sentences for each intent category is 12.5%, 8.4%, 39.2%, 22.0%, 0.4%, 2.1%, 9.8%, 2.1% and 3.5%.

To verify the validity of the labeled corpus, we manually labeled 2,000 random sampled microblogs. We test our labeling method on these microblogs and the average accuracy is pretty high as shown in Table 2. We use this manually labeled corpus for testing and the rest corpus for training.

Table 2. The evaluation result of labeling strategy.

Level	Sentence level	Microblog level
Average accuracy	0.819	0.750

6.2 Evaluation

With F1 value as performance metric, we compare our method with other classifiers (Logistic Regression, Decision Tree, and SVM) on both sentence and microblog level (Table 3).

Table 3. Performance Comparison with Other Methods (in terms of F1 value).

Intent categories	Sentence level				Microblog level			
	LR	DT	SVM	Our method	LR	DT	SVM	Our method
Directive (D_1)	0.685	0.692	0.734	**0.742**	0.673	0.670	**0.674**	0.654
Question (Q)	0.663	0.733	0.773	**0.790**	0.622	0.602	0.655	**0.731**
Statement (S)	0.614	0.583	0.595	**0.691**	0.604	0.561	0.590	**0.651**
Comment (C_1)	0.561	0.595	0.581	**0.683**	0.545	0.582	0.552	**0.673**
Desire (D_2)	0.613	0.640	0.591	**0.641**	0.613	**0.640**	0.593	0.530
Commissive (C_2)	0.665	**0.705**	0.635	0.667	0.665	**0.706**	0.635	0.679
Expressive (E_1)	0.667	0.614	**0.701**	0.690	0.666	0.621	**0.695**	0.661
Provocative (P)	0.734	0.740	**0.800**	0.784	0.678	0.720	0.642	**0.794**
Declarative (D_3)	0.832	0.832	0.832	**0.835**	0.832	0.831	0.832	**0.838**
Macro-average	0.670	0.682	0.694	**0.725**	0.655	0.659	0.652	**0.690**

We note that the performance on sentence level is better than microblog level since the features in one sentence are more concise and the training dataset on sentence level is more precise. We also find "desire", "commissive" and "expressive" categories don't achieve better results. It is worth noting that "directive" performs better at sentence level but weaker at microblog level. But "provocative" is the opposite.

The results provide several insights of user intention mining in medical events. First, users express self-related intents (desire/commissive/expressive) through clear expressions without being affected by context. Second, "directive" intent is implied in rich context but independent of dialogue sequence. Third, "provocative" intent has a strong correlation with dialogue sequence. And from the intent category distribution, we note that users express "statement" and "comment" intents to share their knowledge, experiences and opinions in most of the time. Moreover, "directive" and "question" takes a large proportion which need someone to solve and answer. So, we can infer that medical organizations can avoid negative attitudes of users by guiding the conversation online, such as providing the solution, answering the question and responding with politeness.

7 Conclusions and Future Work

In this paper, we explore user intents in online interactions based on speech act theory and propose a method to mine user intent categories. We first use a filtering process to represent features according to grammatical and semantic factors. Then, we propose a hierarchical model to mine user intents at sentence and microblog levels. Finally, we apply the model to a microblog dataset about an influential medical event on SinaWeibo platform. The experimental study demonstrates the effectiveness of our method. One limitation of our method we have presented is that the labeling method still requires a lot of manual examination of key terms. Going forward, we hope to address the limitation to automatically generate key terms suitable for different domains.

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