

Learning to Filter User Explicit Intents in Online Vietnamese Social Media Texts

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Abstract. Today, Internet users are much more willing to express themselves on online social media channels. They commonly share their daily activities, their thoughts or feelings, and even their intention (e.g., *buy a camera, rent an apartment, borrow a loan*, etc.) about what they plan to do on blogs, forums, and especially online social networks. Understanding intents of online users, therefore, has become a crucial need for many enterprises operating in different business areas like production, banking, retail, e-commerce, and online advertising. In this paper, we will present a machine learning approach to analyze users' posts and comments on online social media to filter posts or comments containing user plans or intents. Fully understanding user intent in social media texts is a complicated process including three major stages: *user intent filtering*, *intent domain identification*, and *intent parsing and extraction*. In the scope of this study, we will propose a solution to the first one, that is, building a binary classification model to determine whether a post or comment carries an intent or not. We carefully conducted an empirical evaluation for our model on a medium-sized collection of posts in Vietnamese and achieved promising results with an average accuracy of more than 90 %.

Keywords: Intention mining · User intent identification · Social media text understanding · Content filtering · Text classification

1 Introduction

The past decade has seen an explosive growth of online social media services. In this highly interactive ecosystem, users become the key players¹ who incessantly contribute and enrich the social media channels via their online activities and behaviors. In this cyberspace, people tend to express themselves and are willing to share their daily activities, their thoughts and feelings, and even their intents about anything they would do. As a result, user posts and comments on online

¹ *Time Person of the Year* (2006): You (i.e., the Internet users).

forums and social networks can actually reflect a lot about the public opinion and people’s intention. Analyzing those posts and comments, therefore, becomes an effective approach for enterprises and businesses to understand what their potential customers really care and want, helping them to have a better online marketing plan and finally penetrate the market faster and more efficiently.

Being aware of this important trend, many previous researches focused on the understanding of user intents behind their online activities like web search [1, 8, 10, 12, 13, 18] or computer/mobile interactions [5, 6]. Most of these studies attempted to guess or determine the user *implicit* intents behind their search queries and browsing behaviors. Understanding search intent helps improving the quality of web search significantly. *Explicit* intent, on the other hand, is a directly or explicitly written statement by a user about what he or she plans to do. According to Bratman (1987), intent or intention is a mental state that represents a commitment to carrying out an action or actions in the future [3]. As more and more users are willing to share their intents explicitly on the web, we have an opportunity to access to an invaluable source of knowledge about a huge number of online users or probably potential customers. However, there have been few previous studies really focusing on analyzing and identifying user *explicit* intents from their posts or comments on forums or social networks. This is explainable. In spite of its huge potential for application, the identification of user explicit intents is actually a natural language understanding problem which is inherently a hard research direction in natural language processing.

It, however, does not mean that this problem is unsolvable. In this paper, we will present a definition of user explicit intents in the form of a quintuple (5-tuple) and propose a three-stage process for understanding or identifying them from user posts or comments on online forums or social networks. This process consists of three major stages: (1) the filtering phase that will determine which posts/comments hold an explicit intent; (2) the domain identification phase that helps to recognize what an intent is about (e.g., *finance*, *real estate*, *tourism*, *automobile*, etc.); and (3) the intent parsing and extraction that helps to acquire all intent’s information. In this process, the first and the second phases can be seen as classification problems. The last one is actually an information extraction task that extracts the intent’s properties or constraints. As a user intent can be about anything in any domain, it is hard to pre-define a fixed set of domains and a fixed set of intent properties. As a result, understanding user explicit intent in open domain is extremely challenging. We, therefore, cannot solve the whole problem at once. The process should be broken down into sub-problems with feasible solutions. In this work, we will propose a machine learning approach to the first phase, that is, building a classifier to filter user posts or comments from social media to determine which ones actually carry a user explicit intent. All in all, our work has the following contributions:

- We propose a definition of user explicit intent (I_u^e) that consists of five elements. The detailed explanation is given in Sect. 3.1.
- We also propose a three-stage process or roadmap for full understanding of user explicit intents. The description and explanation are in Sect. 3.2.

- We attempted to solve the first problem, intent filtering for user text posts or comments, with maximum entropy classification. We also built a medium-sized data set of text posts in Vietnamese collected from online forums and social networks for evaluation and achieved promising results.

The remainder of the paper is organized as follows. Section 2 reviews related work. Section 3 describes the process of user intent identification from online social media texts. Section 4 presents our main study: building a classifier to filter text posts or comments carrying a user intent. Experimental results and analysis are reported in Sect. 5. Finally, conclusions are given in Sect. 6.

2 Related Work

User intent understanding can be defined in different ways for different application domains. In this section, we will review several studies on understanding user goals or intents that are more or less related to our work.

A major number of previous studies working on the problem of identifying user goals or intents behind their web search activities. Lee et al. (2005) proposed the use of features like user-click behavior and anchor-link distribution to identify user goals in web search. They classified user goals into two classes: navigational and informational [12]. Ashkan et al. (2009) proposed a method for understanding user intents underlying their search queries [1]. Their method used ad click-through logs and query specific information to determine whether a query carries a commercial intent. Hu et al. (2009) proposed the use of Wikipedia concepts for identifying intent behind user’s queries [8]. Li (2010) proposed a machine learning approach for understanding user query intent by recognizing intent heads and intent modifiers using Markov and semi-Markov conditional random fields (CRFs) [13]. Jethava et al. (2011) used tree structure distribution to determine different dimensions or facets or user intents behind their search queries [10]. Shen et al. (2011) proposed sparse hidden dynamic conditional random fields to model user intents from their search sessions. This method can model the dynamics between intent labels and user behavior variables [18]. The user intents behind their search queries can also be classified into *commercial* and *non-commercial*. Hu et al. (2009) proposed the use of skip-chain CRFs to determine a query is commercial or not [9]. Dai et al. (2006) also proposed the use of machine learning to identify online commercial intention [7].

Some other researches model the intent behind user actions on their computers or mobile devices. Chen et al. (2002) used Naive Bayes classifier to model user’s action intention on a computer. This simply recognize five types of action: browse, click, query, save, and close [5]. Church and Smyth (2009) focused on studying the information need of mobile users. They studied what mobile users need when the context changes like at home, at work, or on-the-go [6].

Among the previous studies, the following are more relevant to our work. Chen (2014) [4] attempted to understand the user intent behind their questions posted on community question answering sites. They classified the

question intent into five categories: subjectivity, locality, navigationality, procedurality, and causality. This helps users understand others' questions better and give more relevant answers. Kroll and Strohmaier (2009) [11] determined the user intents/goals in text documents. They constructed and enriched a taxonomy of human intentions and a knowledge base with 135 action categories. To parse intents in a document, they took each sentence as a query to the knowledge base. The intent assignment was performed based on the full-text index search (using Lucene). These studies limit the intents in a small number of categories. The latter also used search-based method to query intent from a knowledge base rather than an accurate intent identification.

3 User Intent Identification from Social Media Texts

3.1 User Explicit Intents

In a broad sense, intent or intention refers to an agent's specific purpose in performing an action or a series of actions. According to Bratman (1987) [3], intent or intention is a mental state that represents a commitment to carrying out an action or actions in the future. Intention involves mental activities such as planning and forethought. Intent can be stated explicitly or implicitly, directly or indirectly. In scope of our work, we will only focus on user *explicit* intents. Figure 1 shows several text posts by users on online forums and social networks. Some of which contain explicit intents and some do not.

In order to model and analyze user intents on online social media, we formally define a user explicit intent as a quintuple (5-tuple) as follows:

$$\mathbf{I}_u^e = \langle u, \mathbf{c}, d, w, \mathbf{p} \rangle \quad (1)$$

in which:

- u is the user identifier, e.g., user nickname or id on social media services.
- \mathbf{c} is the current context or condition around this intent. For example, a user may currently be pregnant, sick, or having baby. Context \mathbf{c} also includes the time at which the intent was expressed or posted on online.
- d is the domain of the intent. For example, the three sample intents shown in Fig. 1 belong to *housing*, *finance-banking*, and *education*, respectively.
- w is a key word or phrase representing the intent. It may be the name of a thing or an action of interest. The w values of the three intents listed in Fig. 1 can be *rent-house*, *borrow-loan*, and *study-english*, respectively.
- \mathbf{p} is a list of properties or constraints associated with an intent. It consists of a list of property-value pairs related to the intent. For example, for the first intent in Fig. 1, \mathbf{p} can be $\{\text{location}=\text{"Phuong Mai, Bach Khoa or Ton That Tung"}, \text{number-people}=\text{"4"}, \text{price}=\text{"3 million VND"}\}$.

Online Vietnamese social media texts	Intent?
Tình hình là mình đang cần thuê nhà quanh khu vực Phương Mai, Bách Khoa hoặc Tôn Thất Tùng cho ba người lớn và một cháu nhỏ. Tầm tiền khoảng 3 triệu. Bạn nào có thông tin gì xin liên hệ với mình theo số 0905231880. Cảm ơn nhiều. (I am looking for a house to rent near Phuong Mai, Bach Khoa or Ton That Tung street for three adults and one child. The price is about 3 million vnd. Please contact me at 0905231880 if you have any information. Thank you a lot.)	Explicit intent
Thực tế thì bây giờ nếu bạn vay tiền ở bất kỳ ngân hàng nào bạn cũng phải chịu lãi suất cao. (Actually, if you borrow money from any banks at this time, you have to pay high loan interest rate)	Non-intent
Mình đang định vay ngân hàng một khoản bằng bảng lương của mình. Không biết có mẹ nào ở đây có kinh nghiệm về việc này có thể tư vấn cho mình được không ạ. Mặc dù mình biết không thể vay được nhiều tiền theo cách này nhưng mình thấy nó đơn giản và hơn nữa cơ quan mình lại trả lương qua tài khoản ATM. (I intend to borrow an amount of money from any bank using my payroll. If any mom here has experience about this, please give me a tip ...)	Explicit intent
Với số tiền bạn có thì khó có thể mua được một căn hộ tại ở khu vực Cầu Giấy hoặc Thanh Xuân. (It is impossible to buy an apartment in Cau Giay or Thanh Xuan areas with your amount of money.)	Non-intent
Mình đang tìm một lớp luyện IELTS 6.5, học 2 ngày một tuần (trong đó một ngày là thứ 7 hoặc chủ nhật), từ 16h30 đến 18h30. Nhà mình ở Long Biên, mình đi làm ở Lò Đúc. Mẹ nào biết lớp học nào gần khu vực này thì cho mình xin thông tin với nhé. Mình cảm ơn nhiều. (I am looking for an IELTS 6.5 class, studying 2 days a week (one is Saturday or Sunday), from 16:30 to 18:30. I live in Long Bien and work at Lo Duc. If any mom knows any class in these areas, please let me know. Thanks a lot.)	Explicit intent

Fig. 1. Examples of texts with non-intent and explicit intents

3.2 Process of Analyzing and Understanding User Intents

The process of analyzing and understanding user intents includes three major stages as shown in Fig. 2, that are:

1. **User Intent Filtering:** This phase helps to filter text posts on online social media channels to determine which posts contain user intents and which do not. Posts carrying user intents will be forwarded to the next stage below.
2. **Intent Domain Identification:** Given a text paragraph or a text post containing a user intent, this phase will analyze and identify the domain of the intent. As explained in the previous subsection, the domain of an intent can be about *education*, *real-estate*, *finance-banking*, *tourism-vacation*, *automobile* or any other area that the intent is related to.
3. **Intent Parsing and Extraction:** Given a text post containing an intent and its domain, this stage will parse, analyze, and extract all the information about the intent. In other words, this step will extract important information from the text to fill the key word/phrase w and the list of properties/constraints \mathbf{p} of the intent as defined in Formula 1 above.

Figure 3 shows a specific example of the user intent understanding process. The input is a text post on social media talking about the plan of a couple to find and book a honeymoon trip after getting married. User Intent Filtering module

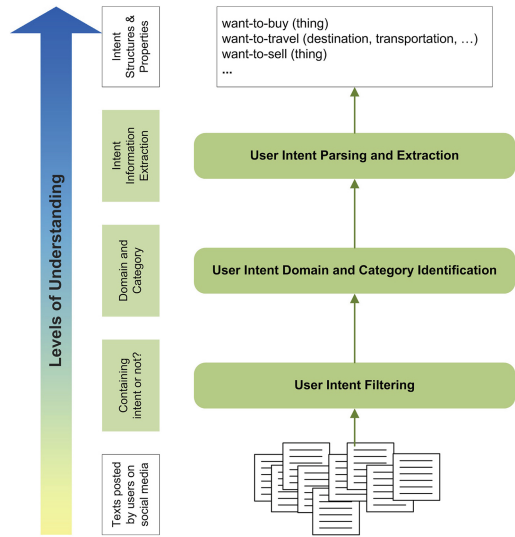


Fig. 2. Process of mining/identifying user intent from (online social media) texts

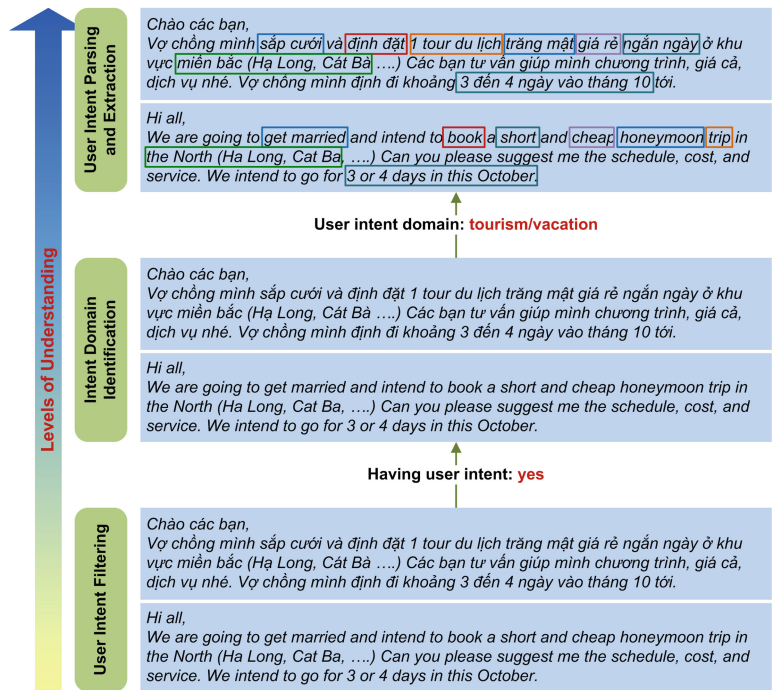


Fig. 3. Example of the user intent mining process

determined that this post holds an intent. In the next step, Intent Domain Identification module determined its domain (*tourism/vacation*). The post and its domain were then forwarded to the final phase, User Intent Parsing and Extraction. At this step, the properties/constraints of the intent were parsed and extracted: $\mathbf{P} = \{\text{price}=\text{"giá rẻ (cheap)"}, \text{duration}=\text{"3 đến 4 ngày (3 or 4 days)"}, \text{time}=\text{"tháng 10 (October)"}, \text{destination}=\text{"Hà Long, Cát Bà"}\}$.

The process of full understanding of user intents is complex and needs a combination of different methods. The first phase, User Intent Filtering, is probably the simplest among the three phases. This is a binary classification problem. The second stage is more challenging because the number of domains is probably large. It is harder to solve this problem because we need to handle a large output space. The third stage is the most difficult. We need to parse and extract all relevant information in the texts. This is extremely hard because the list of properties or constraints \mathbf{p} of an intent can vary a lot depending on its domain.

4 Filtering User Intents in Online Social Media Texts

As stated earlier, the whole process of understanding user intents in online social media texts is complicated and challenging. It needs a holistic solution combining different methods. In this section, we only focus on solving User Intent Filtering.

4.1 User Intent Filtering as a Binary Classification Problem

As described above, user intent filtering takes text posts/comments as inputs and determine which ones carry user intents. This can be seen as a binary classification problem. User intents can be diverse, they can be implicit or indirect. However, in this study, we only consider explicit intents. All text posts/comments with implicit intents will be classified into the class *no-intent*. Thus, we have two classes: *EI* (explicit intent) and *NI* (non-intent).

Basically, we can use any classification method for building a classifier. However, we decided to use maximum entropy (MaxEnt) for several reasons. First, MaxEnt is suitable for sparse data like natural language [2, 16]. Second, MaxEnt can encode a variety of rich and overlapping features at different levels of granularity for better classification. Also, MaxEnt is very fast in training/inference.

4.2 Building Filtering Model with Maximum Entropy Classification

The MaxEnt principle is to build a classification model based on what have been known from data and assume nothing else about what are not known. This means MaxEnt model is the model having the highest entropy while satisfying constraints observed from empirical data. Berger et al. (1996) [2] showed that MaxEnt model has the following mathematical form:

$$p_{\theta}(y|x) = \frac{1}{Z_{\theta}(x)} \exp \sum_{i=1}^n \lambda_i f_i(x, y) \quad (2)$$

where x is the data object that needs to be classified, y is the output class label. $\theta = (\lambda_1, \lambda_2, \dots, \lambda_n)$ is the vector of weights associated with the feature vector $F = (f_1, f_2, \dots, f_n)$, and $Z_\theta(x) = \sum_{y \in \mathcal{L}} \exp \sum_i \lambda_i f_i(x, y)$ is the normalizing factor to ensure that $p_\theta(y|x)$ is a probabilistic distribution. Feature in MaxEnt is defined as a two-argument function: $f_{\langle cp, l \rangle}(x, y) \equiv [cp(x)][y = l]$, where $[e]$ returns 1 if the logical expression e is *true* and returns 0 otherwise. Intuitively feature $f_{\langle cp, l \rangle}(x, y)$ indicates correlation between a useful property, called *context predicate* (cp), of the data object x and an output class label $l \in \mathcal{L}$.

Training or estimating parameters for MaxEnt model is to search the optimal weight vector $\theta^* = (\lambda_1^*, \lambda_2^*, \dots, \lambda_n^*)$ that maximizes the conditional entropy $H(p_\theta)$ or maximizes the log-likelihood function $L(p_\theta, \mathcal{D})$ with respect to a training data set \mathcal{D} . Because the log-likelihood function is convex, the search for the global optimum is guaranteed. Recent studies [15] have shown that quasi-Newton methods like L-BFGS [14] are more efficient than the others. Once trained, the MaxEnt model will be used to predict class labels for new data. Given a new object x , the predicted label is $y^* = \operatorname{argmax}_{y \in \mathcal{L}} p_{\theta^*}(y|x)$.

4.3 Feature Templates for Building the Filtering Model

For building the classification model with MaxEnt, we need to define our feature templates. Table 1 shows two types of features in our model. The first is n-gram. We used 1-grams (word tokens themselves), 2-grams (two consecutive word tokens), and 3-grams (three consecutive word tokens). When combining consecutive word tokens to form 2-grams and 3-grams, we did not join two consecutive word tokens if there is a punctuation mark between them.

We also used a dictionary for look-up features. Two consecutive word tokens were joined and looked up in the dictionary. This dictionary contains key phrases indicating there is an intent or not. Here are some examples: *muốn mua* (*want-buy*), *cần tìm* (*looking-for*), *đang cần* (*currently-need*), *định vay* (*intend-borrow*), *cần bán* (*need-sell*), *muốn thuê* (*want-rent*), and many more.

Table 1. Feature templates to train the MaxEnt model for user intent filtering

N-grams	Context predicate templates
1-grams	$[w_{-2}], [w_{-1}], [w_0], [w_1], [w_2]$
2-grams	$[w_{-2}w_{-1}], [w_{-1}w_0], [w_0w_1], [w_1w_2]$
3-grams	$[w_{-2}w_{-1}w_0], [w_{-1}w_0w_1], [w_0w_1w_2]$
Dictionaries	Text templates for matching dictionaries
2-words	$[w_{-2}w_{-1}], [w_{-1}w_0], [w_0w_1], [w_1w_2]$ in dictionary

5 Evaluation

5.1 Experimental Data

In order to evaluate the classification model, we collected a medium-sized collection of Vietnamese text posts and comments on online social media channels like Facebook and Webtretho (one of the most active forums in Vietnam). The collection consists of 1315 text posts/comments. A group of students were asked to label the data. They read the texts and assigned labels (either *EI* or *NI*) to the texts based on the agreement among them. The resulting collection contains 588 explicit-intent posts and 727 non-intent posts. The collection were then divided randomly into four parts. We in turn took three parts for training and the one left for test to perform 4-fold cross-validation tests. The experimental results will be reported in the next subsection.

5.2 Experimental Results and Analysis

Table 2 shows the experimental results of the 4th fold. *Human* is the number of manually annotated intents in the corresponding test set. *Model* is the number of explicit-intent posts/comments classified by the model. *Match* is the number of correctly classified posts/comments by the model, that is, the true positive. The last three columns are precision, recall, and F_1 -score calculated based on *Human*, *Model*, and *Match* values. We achieved the macro-averaged F_1 -measure of 91.98 and the micro-averaged F_1 -measure of 92.07. This is a significantly high result because we only have n-gram and one dictionary look-up features.

Figure 4 shows the accuracy (i.e., micro-averaged F_1 -score) of the four folds and the average value over the four folds. For each fold, we report to results, the first is the test result using n-gram features only while the second used both n-gram and dictionary look-up features. As we can see, classification using dictionary look-up features can give a better performance. Dictionary look-up features can improve the accuracy for more than 1.5% on average. With the results of 4-fold cross-validation tests, we can see that the results are quite stable over the four folds. This shows that the classification model can work well on this data set.

We also calculated the average precision, recall, and F_1 -measure of the two classes: non-intent and explicit-intent over the four folds. The results are shown

Table 2. Feature templates to train the MaxEnt model for user intent filtering

Class	Human	Model	Match	Precision	Recall	F_1 -score
Non-intent	181	185	170	91.89	93.92	92.90
Explicit intent	147	143	132	92.31	89.80	91.03
Average _{macro}				92.10	91.86	91.98
Average _{micro}	328	328	302	92.07	92.07	92.07

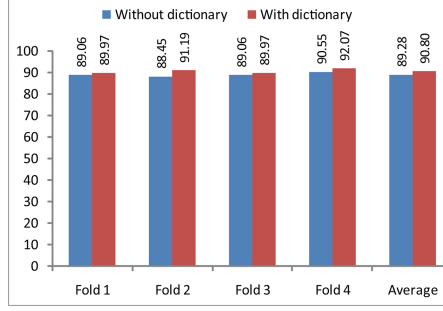


Fig. 4. The accuracy of the 4-fold cross-validation tests

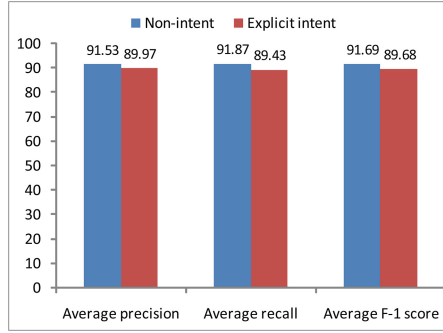


Fig. 5. The average precision, recall, and F_1 -score of non-intent and explicit-intent over the 4 folds (with dictionary)

in Fig. 5. As we can see, the performance of explicit-intent class is a bit lower than that of non-intent. This is in part because the number of posts/comments carrying explicit intents is smaller (588 versus 727).

There are several hard posts/comments for classification. Some non-intent posts/comments have all keywords or phrases that commonly appear in explicit-intent texts. This is highly ambiguous and needs more sophisticated and high-level features to distinguish. For example, a post like “*cách đây vài năm mình định mua Camry nhưng sau đó ...*” (*I intended to buy a Camry couple of years ago but after that ...*) will be ambiguous. This contains an intent in the past and cannot be classified into explicit-intent. However, many of its keywords and phrases (in Vietnamese) indicate that it is an intent. Another example is that “*chị em nào muốn mua loại sữa này cho em bé thì suy nghĩ kỹ nhé*” (*think thoroughly if you want to buy this milk product*). This post/comment is actually a piece of advice or a warning message, not an explicit intent. However, it is classified into explicit-intent class. To deal with these difficult cases, we need to integrate more high-level features to capture past tense, sentence type, etc.

6 Conclusions

In this work, we have built a classification model based on the maximum entropy method to classify text posts/comments on online social media to determine which ones carry user explicit intents. This is the first stage (user intent filtering) of a complex process that aims at fully understanding user intents. We have achieved an average F_1 -score of 90.80, a promising result for further work on this problem. We also realized that we need to add better and higher level features to the model in order to effectively discriminate highly ambiguous text posts/comments. This will be our focus in the future work.

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