On the Identification of Suggestion Intents from Vietnamese Conversational Texts

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ABSTRACT

Fully understanding suggestion intents in conversational texts is a complicated process that includes three major stages: user suggestion intents filtering, suggestion domain identification, and arguments extraction of suggestion intents. In the scope of this paper, we study the first phase, that is, building a binary classification model to determine whether a text unit carries suggestion intents or not. We come up with a new text unit to analysis suggestion based on functional segment in the ISO 24617-2 standard. We investigate two approaches to filter functional segments containing suggestion intents: machine learning using maximum entropy model and deep learning using convolutional neural networks model. The results of these experiments on Vietnamese online media texts are very promising. To the best of our knowledge, this is the first study to analyze suggestion at functional segment level.

CCS CONCEPTS

• **Artificial Intelligence** → Social Media; • **Computing methodologies** → Information extraction; • **Computing methodologies** → Natural language processing;

KEYWORDS

Intention identification; suggestion intents; Vietnamese conversational text understanding; Vietnamese suggestion mining.

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1 INTRODUCTION

Today, people who have similar interests can easily share their ideas, attitudes, and opinions in online communities such as forums, groups in the social network. Moreover, most people usually join small communities to help each other in searching information, advertising, and decision-making. Therefore, there is a lot of useful information on online communities in specific domains such as food, travel, health, games, movies, products, services, and so on. Community members can share experiences from their practice on a certain topic. In addition, other members can review and comment on the posted experiences. They will post recommendations and feedbacks after they read those experiences. It is valuable information to suggest solutions to other users' problem. It is also useful information to suggest to producers to improve their products quality or services quality. Although these advice, hints, and experiences are shared on the internet but information is not often. Users can not easily search for suggestions related to their problems. They must spend a lot of time to wander around different forums and read entire posts or reviews, which may include lengthy descriptions and historical facts. Therefore, automatically identifying suggestion intent from the user writing in online communities is beneficial for recommendation systems and community-based question answering. Recently, researchers' attention is being hooked in the detection of suggestions in texts which is referred as suggestion mining that can be a potential new research [3, 6, 15, 16, 18, 19]. However, it has not been completely defined yet [14]. In this paper, we give a user suggestion intent definition in general from conversational texts (reviews, posts, comments, messages and spoken texts). Then, we present a roadmap for fully understanding suggestion intents in conversational texts, that is a complicated process including three major stages: (1) user suggestion intents filtering, (2) suggestion domain identification, and (3) arguments extraction of suggestion intents.

Fully understanding user suggestion is a complex process and needs to combine different methods. For that reason, in the scope of our work, we solve the first phase, i.e., determine whether a text unit carries suggestion intent or not. The text unit in suggestion mining is mostly sentence [18]. However, it was observed that in some very long sentences only one or few segments/clauses express suggestion intent while other clauses describe the context of suggestion. For example, *"The hotel should count the parking price in the total room price it will be more convenient for customers than current parking paying for every time I go out which is very troublesome."* The suggestion part is from the first segment *"The hotel should count parking price in the total room price"*. The remainder of the sentence provides the context of the suggestion intent.

In this study, we focus on suggestion mining at a novel text unit, functional segment, to filter the smallest meaningful parts of sentence/utterance that carry suggestion intent. Functional segment (FS), according to ISO 24617-2 standard [4], is *"minimal stretch of communicative behavior that has one or more communicative functions"*. We investigate two approaches to filter functional segment containing suggestion intents: (1) machine learning approach with maximum entropy (Maxent) model and (2) deep learning with convolutional neural networks model (CNN). The experiments were conducted with Vietnamese posts on forums.

Our work has the following main contributions:

- We propose the definition of user suggestion intent that consists of five elements. We also propose the three–stage processor roadmap for fully understanding of user suggestion intent. The detailed description and explanation are given in Section 3.
- We also propose a novel unit of suggestion mining which is *functional segment*, i.e., the smallest semantic unit of communicative behavior in discourse [4]. The suggestion mining at functional segment level has two advances: (1) improvement of the understanding in the sense of complex utterances, (2) significant separation of the suggestion part, which has meaningful communicative behavior, from the context part in an utterance.
- We attempted to solve the first problem, suggestion filtering for user text posts or comments, reviews. We present an extensive evaluation of machine learning approach and deep learning approach.
- We also built a dataset from posts and reviews in Vietnamese for evaluation. The empirical results show that automatic extraction of suggestion intent from conversational texts is feasible.

The paper is structured as follows: the next section is a brief summary of the related studies. Then, we give the suggestion intent definition in online social media texts and spoken texts in Section 3. In the Section 3, a detailed explanation about the characteristics of suggestion intents and the suggestion mining process is also presented. Section 4 describes our methods to filter FS which express suggestion intents, including building data, experiment, and result evaluation. Finally, Section 5 concludes the paper and provides outlining direction in the future.

2 RELATED WORK

In the past, only a limited number of studies have been performed about suggestion identification. In the field of understanding spoken text, a suggestion is a dialog act and suggestion identification is considered dialog act classification. However, there are no studies on suggestion intent in this regard. In suggestion detection problem from texts, Goldberg et al.[9] first introduced that a wish is a suggestion to improve the product/service in the context of opinion mining. Wish detection problem for improvements was emphasized by Ramanand et al. [19]. Later, Brun et al.[3] identify suggestions for product improvement using manually crafted linguistic rules. Dong et al.[6] performed classification of given tweets, i.e., whether it is a suggestion or not. Wicaksono et al. [21] detected advice-revealing sentences from related discussion threads in travel domain. Ynzhong Liu et al.[13] studies suggestion for patients and perform context-aware experience extraction with experiences from online health forums. Weber et al [20] and Ido Guy et al. [10] refer to a tip as "a concise piece of practical non-obvious self-contained advice, which may often lead to an action". All of those studies just refer one of suggestion kind. Until the Sapna Negi's works [15, 18], suggestion mining is fully defined includes advice, counsel, hint, tip... A comprehensive research on users' suggestion intent was done by Sapna Negi. Nevertheless, her work just focuses on the context of opinionated texts.

Our work has several following different points from previous studies:

- We extend this definition to conversational texts (posts, comments, reviews, messages chat and spoken texts) in the context of communication.
- The above studies consider the sentence as a unit of suggestion. We use functional segment as a unit of suggestion. This is useful for user's utterance understanding in the systems using a conversational interface such as chat-bot, virtual personal assistant, and conversational search.

3 SUGGESTION INTENT DEFINITION

3.1 Suggestion Intent

In this section, we will present a complete definition of the components of the suggestion intents in the context of dialogue. A dialogue, according to ISO 24617-2 standard, is *"exchange of utterances between two or more person or artificial conversational systems"* and an utterance may be *"anything said, written, keyed, gesticulated or otherwise expressed"*[4]. In our work, a dialogue may be a thread about a certain topic on online forums. In which, a post is a turn in dialogue; a status and comments of that status on social media network; a dialog in text chat or voice chat. To consider suggestion intents in the context of dialogue, we consider suggestion intents expressed in conversational texts (posts, comments, reviews, messages and spoken texts).

An intention or intent, according to Bratman, 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"* [2]. According to the Oxford English Dictionary, a suggestion is *"an idea or plan given for consideration"* [1]. Its synonyms are proposal, proposition, recommendation, advice, counsel, hint, tip, clue etc. We show examples about suggestion intention in Table 1 and generalize the components and attributes of suggestion intents in Figure 1.

In order to model and analyze user suggestion intents on conversational texts, we formally define suggestion intention (SI) as a quintuple (5–tuple) as follows:

$$Suggestion = \langle u, t, c, d, args \rangle \tag{1}$$

[1]https://en.oxforddictionaries.com/definition/suggestion

Table 1: Examples of suggestion intents

Suggestion	Target	Type	Explain
They will try and make your stay memorable. Excellent service and good food	fellow customer	implicit	positive review to suggest for fellow customer
The hotel should require paying for room including the parking it will more convenient for customers than current parking paying for every time go out is very troubles	brand owner	explicit	advice and suggestions for Hotel owner improve server quality
If you want to know more about Vietnamese cuisine this is the place to go	fellow customer	explicit	advice
So much effort and hard works have gone into the garden, where he hosts the class. It's beautiful. I wish it has more guide-board for guest	brand owner	implicit	suggestion to improvements
I have sunburn when traveling here	fellow customer	implicit	experiment of a customer to suggest fellow customers bring a sunscreen
you don't forget to bring sunscreen fellow customer	fellow customer	explicit	advice to suggest to bring a sunscreen
you can buy fake when you buy souvenirs on the sidewalk	fellow customer	implicit	tip
- I am going to do my homework - It is the best for you when you start from exercise 2 instead of exercise 1 because it is easier than other	addressee (listener)	explicit	advice

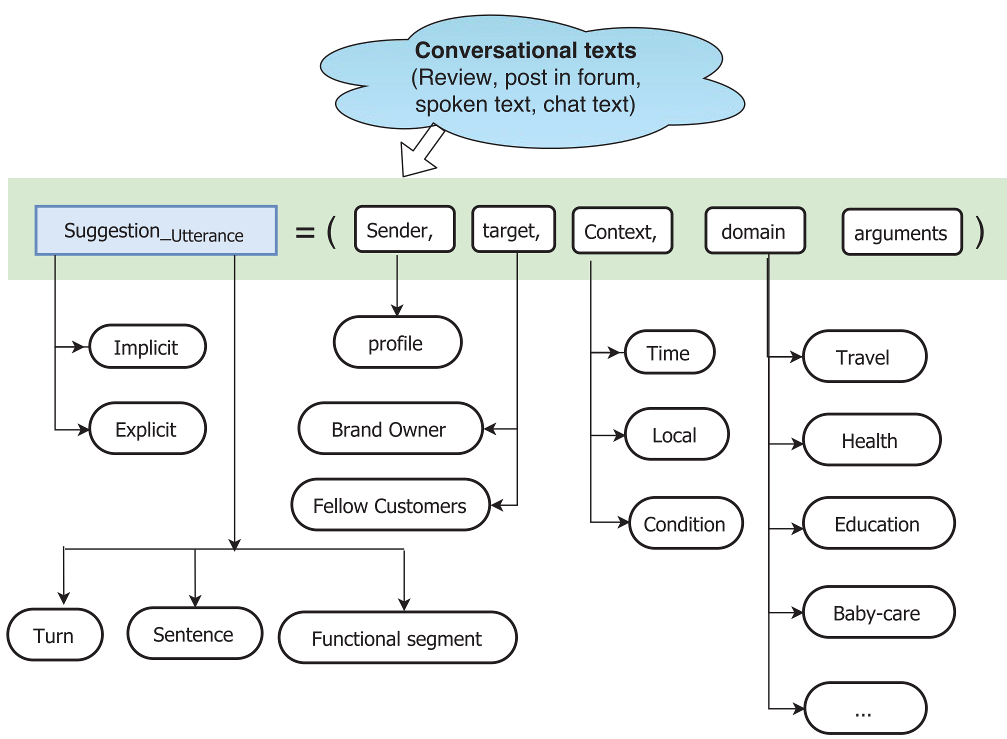

Figure 1: Suggestion Intents definition.

in which:

- *u* is who speaks or writes this utterance, it is called *sender* in ISO 24617-2 standard. *u* is also a user of systems, e.g., user nickname or id on a system or social media network.
- *t* is an addressee; i.e., "dialogue participant-oriented to by speaker in a manner to suggest that his utterances are particularly intended for this participant and that some response is therefore anticipated from this participant, more so than from the other participants"[8]. In detail, in dialog systems, an addressee is a listener; in online forums or social media network, an addressee is a reader and is divided into 2 subjects of suggestion intention: fellow customer and brand owner.
- *c* is the current context or condition around this intent. For example, local and time of interaction between user and dialog system; status of users such as currently pregnant, sick; assumed, condition or reason of suggestion...
- *d* is the domain or topic of the intention. For example, education, travel, booking and so on. A domain can contain sub-domains such as weather, book room, calling, ...
- *args* 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, an intent in Figure 2, *Arguments* can be{plan="*go to Sapa, reason: the fare of train ticket to Sapa is very expensive at the weekend*"}.

3.2 Types of Suggestion Intents

SI can be divided into two types: explicit and implicit. On this issue, we agree with [18]. An explicit SI is as the text which directly proposes recommends, or advise an action or an entity. An implicit SI provides the information from which the action suggests or entity can be inferred. Herein, examples of explicit SI and implicit SI are shown in Table 1 and Figure 2. For an example,

Ex(1) "Hi the fare train ticket to Sapa is very expensive at the weekend if you intend to go Sapa, you should book tickets early the fare of 4 room soft wooden normal ticket of Green Train and King express is the 540k in a day of week more expensive at the weekend".

The user intention is a suggestion to fellow customers to *book tickets early*. "the fare train ticket to Sapa is very expensive at the weekend" is implicit SI. "if you intend to go Sapa, you should book tickets early" is explicit SI.

3.3 Unit of Suggestion Intent

As observed in the example Ex(1), although the full sentence provides context, the suggestion is identifiable at two clauses: "the fare train ticket to Sapa is very expensive at the weekend" and "if you intend to go Sapa, you should book tickets early". Other parts of this post are the context part that clarifies or explains an SI in more detail with contextual information. It usually describes when, where, or in what situation people would find the SI potentially helpful. Determining exactly which part of an utterance is SI, which part is giving the context of SI, will improve significantly effective of suggestion mining. We intend to build classification models which can identify the exact clauses/phrases containing SI.

Nevertheless, SI segment/phrase identification from conversational text has many challenges. Writings in online social media network usually are very noisy due to spelling mistakes, acronym, omitting syntactical components in the sentence, and arbitrary punctuation by users. On the other hand, spoken text is not only short and missing syntax components but also has no punctuation and contains some errors from the returned result of automatic speech recognition. So in both online text and spoken text, identifying sentence boundaries is very difficult. Therefore, suggestion mining at sentence level is not as practical as we might think.

To tackle the challenges as mentioned early, we propose a novel unit of suggestion mining called **Functional segment** (FS). FS, as defined in the ISO 24617-2 standard, which is annotation standard for the dialog act annotation of plentiful texts (written, spoken, and multimodal dialogue), "FS is minimal stretch of communicative behaviour that has one or more communicative functions". For example (Figure 2), "Hi the fare train ticket to Sapa is very expensive at the weekend if you intend to go Sapa, you should book tickets early the fare of 4 room soft wooden normal ticket of Green Train and King express is the 540k in a day of week more expensive at the weekend" is segmented into four FSs.

3.4 Process of Analyzing and Understanding Suggestion Intent

Automatic SI detection is considered a problem, that is identifying the full components of above SI definition. It can be broken down into steps as described in Figure 2. A specific example of the user SI understanding process is shown in Figure 2. The input is texts of a turn in dialogue (a turn speech, a post, a comment, a review). These conversational texts are pre-processed and segment into FS unit. Then FSs will be forwarded to the process of analyzing and understanding user SI includes three following major stages:

1. **User SI Filtering**: This phase helps to determine which FSs contain user SI and which FSs provide the context information of SI.
2. **SI Domain Identification**: after identifying suggestion FS in the first step, we identify which domain/topic that the text belongs to. Given a **turn** containing suggestion FS, this step will analyze and identify the domain/topic of the SI. A **turn** is defined in the ISO 24617-2 as "the stretch of communicative activity produced by one participant who occupies the speaker role bounded by periods where another participant occupies the speaker role". We can understand that a turn is a talking section in spoken dialog systems, a post/comment in forums, a twice/status in social media networks.
3. **SI Parsing and Extraction**: Given a turn containing an SI and its domain, this step will analyze, and extract all the information about SI such as where, when, reason, contents of SI. This step will extract important information from the text reveal to SI as in Formula 1 above.

The process of full understanding of SI is complex and need to combine different methods. Consequently, in the scope of this

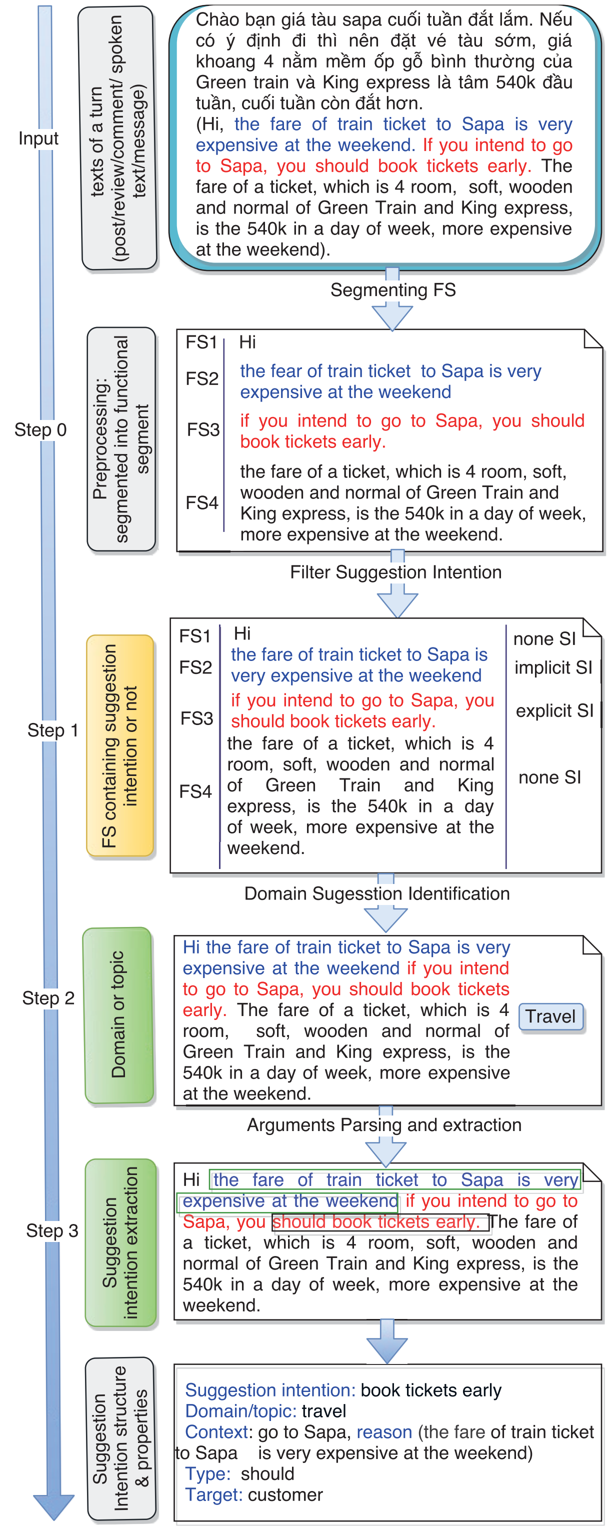

Figure 2: Example of the user suggestion intents mining process.

Table 2: Feature template to train the MaxEnt model for SI classification

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	$[w_{-2}w_{-1}w_0]$, $[w_{-1}w_0w_1]$, $[w_0w_1w_2]$

paper, we will present the first phase, i.e., SI Filtering. This is a binary classification problem.

4 SUGGESTION INTENTS FILTER

As described above, Suggestion Intents Filter includes two sub-steps: segmenting turns into FS unit and classifing FSs into two classes {Suggestion, None suggestion}. All FS with implicit SI or explicit SI will be classified into the class *Suggestion*. The sub-step, FS segmentation, was presented in our previous study[17]. In this section, we explore two approaches to build a classification model.

4.1 Building Filtering Model with Maximum Entropy Classification

We choose Maximum entropy (MaxEnt) model to investigate the effect of machine learning on SI classification. Because MaxEnt is suitable for sparse data like natural language can use a virtually unrestricted and rich feature set in the framework of a probability model. It is a flexible technique widely used for a variety of text classification task. A Maxent model can be shown to have the following form [1]:

$$p^*(y|x) = \frac{1}{Z(x)} exp\left(\sum_i \lambda_i f_i(x, y)\right) \quad (2)$$

In which:

- x is input object
- y is the classified label
- f_i is a feature. Features of our MaxEnt model for SI classification are the n-grams (uni-gram, bi-gram, and tri-gram).
- λ_i is a weight (large value implies informative feature)
- $Z(x) = \sum_y exp(\sum_i \lambda_i f_i(x, y))$ is a normalisation constant ensuring a proper probability distribution.

Model estimation involves setting the weight values. We use quasi-Newton methods like L–BFGS [12] since recent studies have shown it is fast and efficient. We used a window of size 5 sliding along a FS. The context predicate templates for generating n-gram is given in Table 2.

4.2 Building Filtering Model with Convolutional Neural Networks

Convolutional neural networks (CNNs) requires parsers to get the semantic structures of the text. It deals well with learning timeâĂŞsequential features and has good performances in text classification [5, 11]. Thus, in the deep learning approach, we build a CNN model to filter SI functional segments. The model architecture, shown in Figure 3, is a model used for SI classification in this work. During training, the model assumes that these features are not restricted by their absolute positions. Neurons in CNN are locally connected with neurons in the previous layer. Weights of the same filter are shared across the same layer.

We implement the method of Kim et al. [11] [2] for SI classification. In the first layer, words are embedded into low-dimensional vectors by mapping vocabulary word indices using a lookup table that learns from data during training. The next layer performs convolutions over the embedded word vectors using multiple filter sizes. Then, in the softmax layer, the result of the convolutional layer is max-pool into a long feature vector. The model uses dropout method to regularize convolutional neural networks. It "disables" a fraction of its neurons to prevent neurons from co-adapting and forces them to learn individually useful features. The result classification is done in the softmax layer.

4.3 Building data

Basically, our suggestion intent definition can apply in spoken conversation or written conversation (post in forums, reviews in websites, comment in social media network) and open domains in different languages. Nevertheless, in the scope of this study, we choose posts on travel domain in the Vietnamese language for experiments. We crawled posts on forum https://www.webtretho.com/, which is one of the most active forums in Vietnam. Then we filter the posts by topic and segment posts into FS by manual. We build a guideline for SI annotation and label post manually. Our data has 4318 FSs. It includes 2670 FSs which express SI, 1648 FSs do not. The agreement score of our corpus is 0.62 Fleiss' Kappa measure [7]. It is little low because of ambiguity between implicit SI and none suggestion.

4.4 Results

In order to evaluate the classification model, we divide the corpus into five parts, in which four parts for training and the one left for testing to perform 5–fold cross–validation tests on both of models. Table 3 and Table 4 show the experimental results of the best fold using the Maxent method and the CNN method. The number of manually annotated intents in the corresponding FS set is reported in the *Human* column. *Model* is the number of FSs classified by the model. *Match* is the number of correctly classified FSs by the model. Precision, recall, and F_1–score are expressed in the next columns, pre., rec. and F_1. The experimental results of 5 folds is shown in Figure 4 (using Maxent model) and Figure 5 (using CNN model). They express the accuracy (i.e., *precision*, *recall* and F_1 base on macro–averaged) of the five folds and the average value over the five folds. We can see that the results are quite stable over the five folds. Using the Maxent model, we achieved the macro–averaged F_1–measure of 77.68 and the micro–averaged F_1–measure of 79.35. Using the CNN model, we achieved the macro–averaged F_1–measure of 78.45 and the micro–averaged F_1–measure of 80.19.

Table 5 shows the comparison of the accuracy of two models. The CNN model obtains slightly higher results than the Maxent model. This is a promising result because we only use basic features, i.e, n–gram. Our initial experiments reveal that there is a need for new methods or variations in the existing standard algorithms in tasks like sentence classification for addressing the specific challenges in SI classification.

[2] https://github.com/yoonkim/CNN_sentence

Table 3: The precision, recall, and F_1–score of SI classification of the best fold using Maxent

Label	Manual	model	match	prec.	rec.	F1
SI	528	567	463	81.66	87.69	84.57
None SI	335	296	231	78.04	68.96	73.22
Average (*macro*)				79.85	78.32	**78.89**
Average (*micro*)	863	863	694	80.42	80.42	**80.42**

Table 4: The precision, recall, and F_1–score of SI classification of the best fold using CNN

Label	Manual	model	match	prec.	rec.	F1
SI	530	535	450	84.11	84.91	84.51
None SI	329	324	244	75.31	74.16	74.73
Average (*macro*)				79.71	79.53	**79.62**
Average (*micro*)	859	859	694	80.79	80.79	**80.79**

Table 5: Macro, micro average f_1 score of SI classification using ME model and CNN model

Model	Maxent			CNN		
Label	prec.	rec.	F1	prec.	rec.	F1
SI	78.98	78.59	78.57	81.69	87.66	84.53
None SI	78.37	75.65	76.78	77.56	68.08	72.38
Average (macro)	78.67	77.12	77.68	79.63	77.87	78.45
Average (micro)	79.35	79.35	79.35	80.19	80.19	80.19

There are several hurdles for classification. FSs are mostly short text, even, there are many short FS which is only one or two words (6,3% in our corpus). On the other hands, human suggestion intent has so many ways to express suggestion intent in the natural language such as advice, tips, hint, wishes, experiments. So SI classification has high ambiguity. In particular, many implicit SI can be easily confused with none SI. It needs other contextual information of the whole conversation as the previous utterances, conversation topic, and needs more sophisticated and high–level features to distinguish.

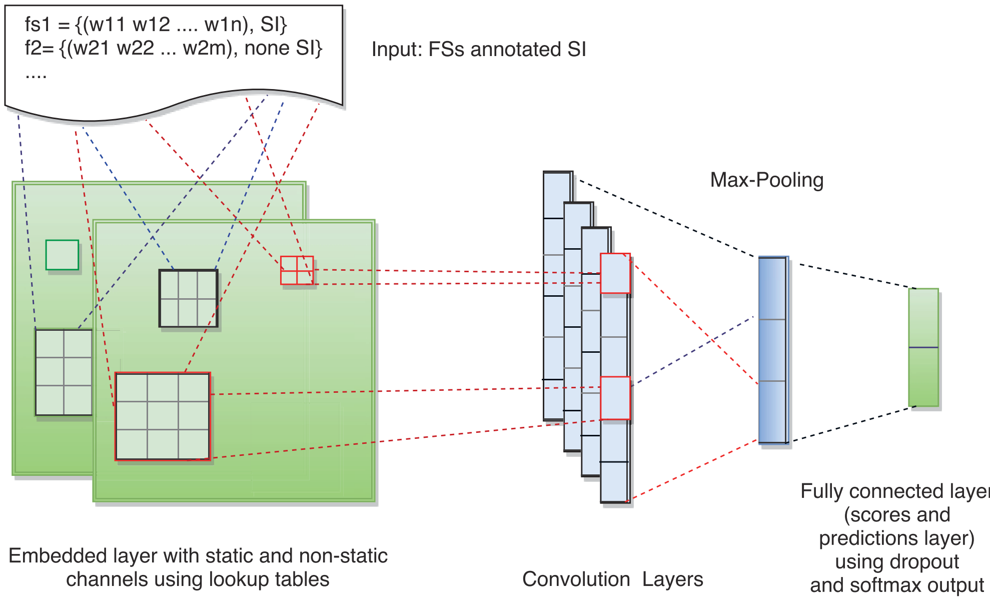

Figure 3: An example CNN model architecture with two channels for SI classification of FSs.

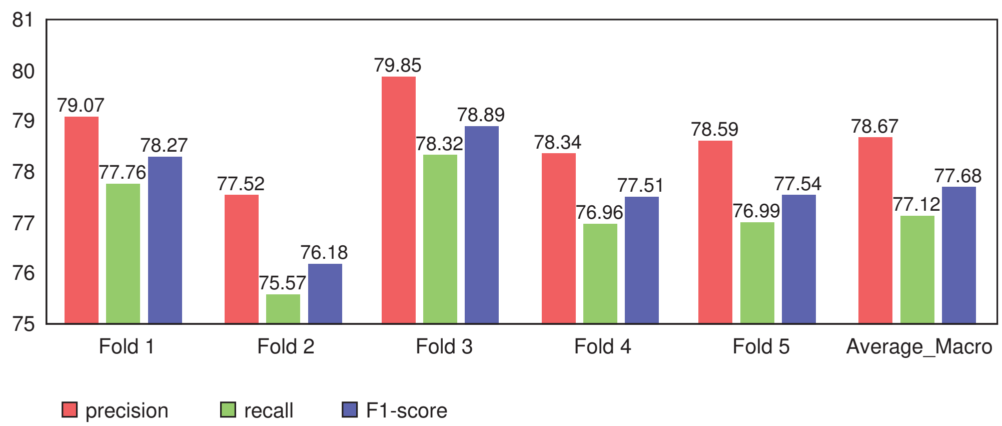

Figure 4: The accuracy of the 5–fold cross–validation tests of the Maxent model.

5 CONCLUSIONS

In this paper, we propose a user suggestion intent definition in general from conversational texts along with steps to fully understand suggestion intent. We address a novel task, that is, suggestion intent identification at functional segment unit. An utterance can contain different suggestions. Therefore trying to study suggestion mining at the smallest meaningful unit, the functional segment unit, can help us to understand the best suggestion intents of texts. For solving this task, we try two models: Maximum entropy and Convolutional neural networks. These two models show very promising results. In the future, we intend to increase, diversify our data and continue to study about domain identification of suggestion and suggestion extraction.

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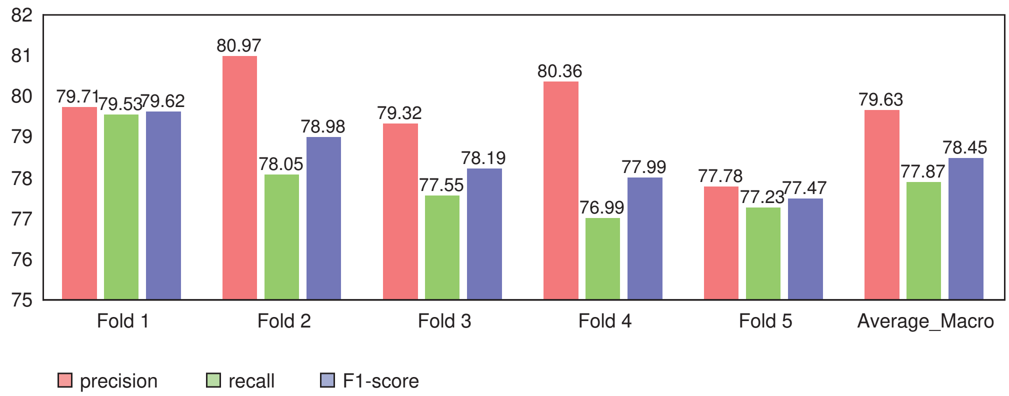

Figure 5: The accuracy of the 5–fold cross–validation tests of the CNN Model.

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