DIET Architecture for Users' Comments in Myanmar Language

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***Abstract*— Since the emergence of AI applications, several related research and development projects have been carried out in every industry. AI-based applications in customer services such as chatbots, personalization and recommendation help business to understand their users and clients better; and these applications make customer experience better. The task of intent classification is important task under Natural Language Understanding (NLU) task and the result of the intent classifier acts as the final interpretation of the user query in such AI applications. The problem of intent classification is addressed using various techniques. In this paper, the experiment of intent classification and entity recognition have been conducted simultaneously by adapting the Dual Intent and Entity Transformer (DIET) on inhouse data of users' comments in Myanmar Language. The accuracy and F1-score for intent classification are 95.2% and 96.1%. For entity recognition, the accuracy is 94.2% and F1-score is 93.4% respectively.**

Keywords—intent classification, entity recognition, DIET, Rasa, Myanmar

I. Introduction

Usually, the majority of the social media users post comments when they want to express their opinion, give feedbacks about the services or products; and even when they want to inquiry about particular information. Analysis of the social media content such as comments on posts (especially about the products or services) has turned into an important task to aware the intentions of users behind those comments that can be too beneficial for decision making and also for the business. Intent classification is very useful to gain valuable insights into the intentions behind customer queries. Moreover, given a query, it is needed to identify the entities in message and then extract the most important information about those entities.

Recently, Rasa [1], an open-source machine learning framework, provides a convenient architecture to identify the user queries (intent classification) and extract structured data from unstructured data that can be useful to understand the user queries (entity recognition). A customizable infrastructure is provided in Rasa NLU pipeline for intent classification and entity recognition. Recently, in Rasa NLU, the Dual Intent and Entity Transformer (DIET) architecture [2] has been introduced to effectively and simultaneously deal with intent classification and entity recognition at the end of the pipeline. In this paper, the experiment result on using DIET architecture for intent classification and entity recognition modeling for users' comments data in Myanmar language will be described.

II. Experiment

In this section, the training process of dual intent classification and entity recognition model on Myanmar social media comments by applying DIET architecture will be described.

A. Data

Users' comments from official social media Facebook pages of shopping malls and commercial vendors that are written in Myanmar language are collected and prepared the training data and test data. There are over 10K sentences that are collected and prepared as data corpus. Detail data preparation can be checked in [4]. The collected data are manually labeled and annotated with the predefined seven different intent categories and thirteen different types of entity.

Ther are seven different intent categories are predefined and used to classify users' comments. To label the comments that are written when the users want to buy goods or something from the vendors, the intent "*purchase*" is applied. The intent "*payment*" is used for comments when the users ask about the process or action of paying for the purchase. The intent label "*delivery*" is for labeling the comments associated with the delivery services. When the comments appear with the intention of applying for a job or inquiring for a job position, the intent label "*job*" is used. When the comments seem to give feedbacks or express the opinion about the products or services, the label "*opinion*" is applied for these comments. When the users want to know something about the services provided or about the goods, the comments appear as questions and these questions are labelled with the intent "*general_info*". The last intent "*contact_info*" is utilized to label the comments that are posted when inquiring about the contact information of the vendors or services, and at where the products can be purchased.

For this dual intent classification and entity recognition, thirteen different types of entity are predefined by examining the nature of data context (social media comments) to annotate the entities in text. The names of the shop or shopping malls in the comments are annotated as "*shop*". The "*product*" is used to annotate the specific name of the products. For all the general product items, the entity tag, "*item*" is used. For the name of the food, the entity tag, "*food*" is applied; and for the color of the product item, the "*color*" is used to annotate. The entity words described the types of the items are annotated with the entity tag "*type*". The "*currency*" tag is for the entity words that are related to the system of money. The entity "*card*" is used to denote the different types of cards in the comments. The entity words describe the time are annotated with "*time*". Different types of services are annotated with "*service*" tag. When the words are related to job descriptions, the entity tag "*job_position*" is applied. All the location and address entities are annotated with the "*location*". Another entity tag "*number*" is for all the number format in the text. Table I shows the data statistic of manually labeled data and also the distribution of each intent category in the data.

As for the entity data distribution, the entity "*item*" is the most appeared in the data; about 45% of all entities whereas the entity "*currency*" is the least appeared which is only 0.4% of all entities. The "*location*" is the second most found entity which is about 25% followed by nearly 9% of the "*product*" entity. The "*number*" is found about nearly 6% and all other entities are less than 5%. By seeing these data statistics, it is obvious that this manually labeled and annotated data is unbalanced. Data is partitioned into 80% for training and 20% for testing.

TABLE I. DATA STATISTIC AND INTENT DISTRIBUTION

Data	**Size**	**Data distribution**
Total Data	10335	
purchase	2165	20.94%
contact_info	1196	11.57%
payment	586	5.67%
opinion	1535	14.852%
general_info	2858	27.65%
delivery	1837	17.77%
job	158	1.52%

B. *Intent Classification using Convolutional Neural Network (CNN)*

The intent classification on this user's comment data is previously modeled by applying CNN neural training. For this work, firstly, manually labelled data were segmented by using UCSY-NLP word segmentor [7] into words as preprocessing. In data, many name words are being found as well. It is needed to extract the name entities (NE) in text correctly seeing that it might also affect the intent classification accuracy. Accordingly, to locate name words and recognize names in comments precisely, named normalization process was carried out as a preprocessing task by applying NE recognizer for Myanmar language from UCSY-NLP research lab [5]. Subsequently, named entities were normalized with respective name words as another preprocessing step. During intent classifier modeling with CNN, two types of experiments were carried out. One experiment is that the training data are only word segmented data and another experiment is carried out with both word segmented and name normalized data.

C. *Dual Intent Classification and Entity Recognition with DIET Architecture and RASA toolkit*

To discover the performance of the DIET architecture on this in- house unbalanced data, firstly all the data are formatted as NLU training data format. A lookup is used to represent the "location" entity. DIET architecture can be completely parameterized from the Rasa toolkit. To perform the model training, a typical sequential process, (tokenization, featurization, intent classification, and entity extraction are included), are applied sequentially by specifying a pipeline configuration file on the samples included in the labeled and annotated data input. Before anything else is to tokenize the utterance, by breaking the sequence of textural data into tokens such as characters, syllables or words. Secondly, each token is turned into features. Features may be sparse or dense. In this modeling, only sparse features are used.

To calculate the entity loss, tokens features are extracted and are then fed into the transformer layer through feed-forward layers. The output sequence from the transformer layer, turns as the entity labels sequence of input token sequence; and then, it becomes as an input sequence for Conditional Random Fields (CRFs). The entity loss is computed using the negative log-likelihood of CRFs. For intent classification, features for the entire sentence or utterance are also generated which are calculated as the sum of the sparse features of each token and represented as CLS token. Once the original utterance has been transformed into features, the CLS token and intent labels, which refer to the sentence encoding of an input sentence sequence, are fed into the corresponding embedding layers. Tokens including mask tokens, and values that are output from the transformer layer following feed-forward layers, are then input into the embedding layers (embedding layers for mask tokens and unmasked tokens). Then, the model is trained to minimize the total loss which is the sum of intent loss, entity loss and mask loss. (See in Fig. 1). To test the performance of DIET on Myanmar language, the model is trained with the standard configuration setting.

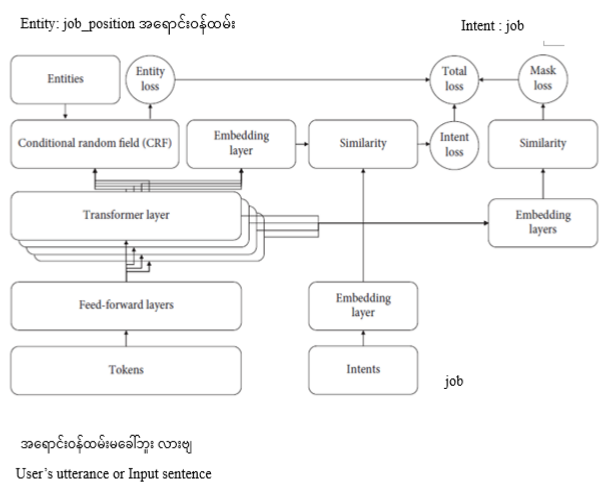

Fig. 1. DIET architecture on Users' comments

III. EXPERIMENTAL RESULT

In this paper, three different experiments (two are intent classification only and another is dual intent classification and entity recognition) conducted on users' comments in Myanmar language. From the experiments, apparently CNN is still working properly while modeling on a low amount of data which is well preprocessed and prepared. Moreover, for dual intent classification and entity recognition modeling, with standard configurations and sparse features only, Rasa DIET provides the leading performance.

TABLE II. F1-SCORE OF EACH MODEL

Model	F1-score
Intent classification model (with only word segmentation)	0.704
Intent classification model (with both word segmentation and name normalization)	0.863
DIET architecture model (for intent classification)	0.961
DIET architecture model (for entity recognition)	0.934

IV. CONCLUSION

Intent classification and entity recognition tasks are important under NLU. DIET architecture provides the improvement upon the current state of the art. In this paper, the performance of the DIET architecture is tested on our manually prepared in house unbalanced data by using the Rasa toolkit. Although the data is a low resource, unbalanced, and it is trained with only sparse features, it performed very well. The result shows that even with the simple configurations of the NLU pipeline leads to better accuracy. In the future, we will explore the performance by configuring different parameters of the NLU pipeline. Moreover, to get the best result, with more data, the model will be trained with pre-trained word embeddings and dense featurization. With more experiments, better results and more new findings will be reported in the future.

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