JOINT TRAINING OF CLASSIFICATION MODEL AND SIMILARITY MODEL FOR LOW-RESOURCE TEXT CLASSIFICATION IN CHATBOT

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ABSTRACT

Building conversational chatbot system has become a popular solution to customer services under various business scenarios. A conversational chatbot needs to detect user's intent given a few words, which essentially equals to short-text classification problem in the field of Natural Language Processing. Moreover, each time for a new service, the task-specific chatbot system often needs to perform well in few-shot setups due to lack of domain-specific data, which is quite a challenge for single-model system such as text classification model system or sentence-pair semantic similarity model system under such a low-resource condition. Therefore, in this paper, we propose SFC, a 2-stage joint system with multi-task training technique for both text classification task and sentence-pair semantic similarity task to overcome this challenge. Furthermore, we additionally propose an improved version of SFC to allow text classification model and sentence-pair model be combined into a joint model organized in hierarchical structure. We also conduct extensive experiments on 4 public and 1 private datasets in few-shot setup (i.e., with only 5 to 20 training data per class). The experimental results show that our system can steadily outperform several competitive single-model baselines by 2 percent in average accuracy.

1. INTRODUCTION

Task-specific conversational chatbot[1] are designed to share the working pressure of human customer service agents who are responsible for solving customers' questions or queries about certain products or services. Regardless of whether the conversation is single-turn or multi-turn, the essential technical solution behind the chatbot is intent classification model which can identify the correct intent behind user's input text and find the corresponding answer.

Although task-specific conversational chatbot already has a wide application in various business and industries, it's still a quite challenging task due to its natural properties of low-resource. First, customers' utterance within a conversation is usually quite short and completed in a few words. Short text[2] are generally more ambiguous in comparison with long texts such as paragraphs or documents since they don't contain enough contextual information, which poses a great challenge[3] for classification task[4, 5, 6]. Second,

at the initial stage of building a chatbot for specific task or service, it's often extremely hard to collect sufficient data samples for each class. The reason is that it's usually too expensive and time consuming to extract different ways of natural language expression for each intent class from history conversation log or even manually compose the corpus from nothing. Therefore, the key to building a task-specific chatbot with high performance becomes solving the challenge of short-text classification[7] problem under few-shot setting[8].
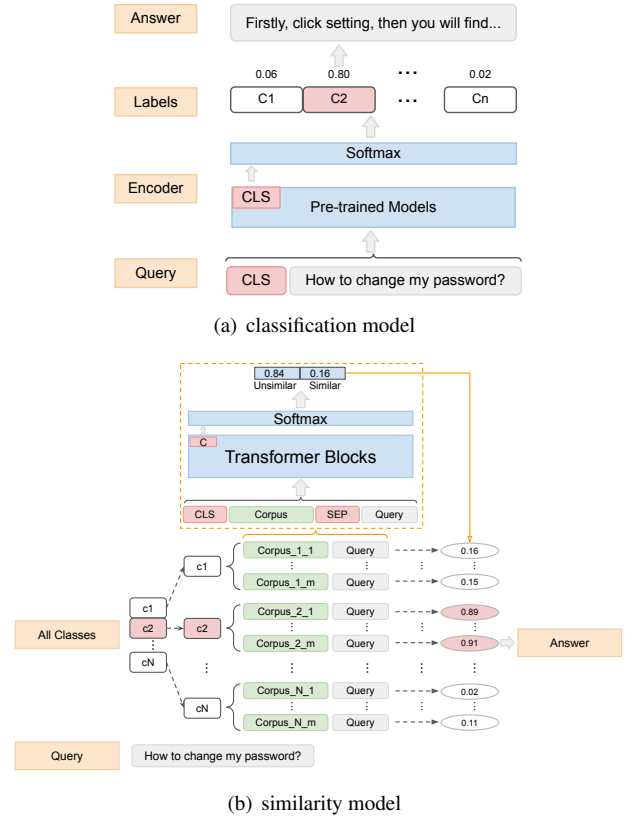

(a) classification model

(b) similarity model

Fig. 1. Two popular structures of building task-specific conversational chatbot

One of the most popular approach among existing work was text classification model based on neural network. Since the length of the text is quite short, many previous work[1] choose neural network such as convolutional neural networks

(CNNs)[9, 10, 11] or long short term memory networks (LSTMs)[12, 13] to accomplish the task of extracting semantic feature from limited amount of words. A common model structure is adding a softmax classifier to the top of the neural network. Afterwards, pre-trained language models on large corpus like BERT[14] and RoBERTa[15] has been proven more powerful in solving many NLP tasks including short-text classification[16]. Especially for few-shot scenarios[8], pre-trained model based on transformers[17], shown in Fig. 1(a), tends to do more help to reducing the negative effects brought by scarcity of training data.

Another popular approach among previous work was based on sentence-pair model. The motivation of this approach was started from the idea of Information Retrieval (IR) based chatbot[18, 19]. Having a Q-A (Question-Answer) pairs dataset and user query Q, the IR based conversational system will look up in the Q-A dataset for the pair (Q', A') that best matches query Q through semantic analysis and returns A' as the answer to Q[20]. In this way, sentence-pair model pre-trained on large corpus of semantic similarity identification task can be applied for being used as a tool to identify the class with highest semantic similarity to customer's query. A common model structure of pre-trained[14] sentence-pair model is based on multiple cross-attention mechanism[21], shown in Fig. 1(b). Due to the fact that many experiment results have shown that RoBERTa[15] is an improved version of BERT, and has achieved amazing results on both text classification and sentence-pairs semantic similarity tasks, we choose RoBERTa as an important baseline approach in this paper.

Despite the success of these 2 approaches, they still have some limitations in task-specific chatbot scenario. As for the text classification model approach, it's quite hard to use data augmentation method to solve the data insufficiency challenge since the it's usually unfeasible to get large amount of domain-specific data when facing a new task. With respect to the sentence-pair model approach, though we can obtain large amount of data in semantically duplicate sentence pair identification domain for transfer learning[22], it's still quite hard to perform well on task-specific dataset because the training objective of sentence-pair model is semantic similarity, which is slightly different from the target of classification task. That is to say, there always exists some intent classes which cannot be distinguished by each other merely depending on semantic similarity. For example, we have 2 user query saying, A: What should I do if I want to change my password? B: What is the modification rule if I want to change my password? In this case, sentence A is semantically similar to B, since they both express the desire for changing password. However, it's still reasonable to classify them into 2 intent classes, since A is asking for the method for changing password, while B is asking for the rule to follow when creating a new password.

The above limitation motivates us to propose a joint system of both text classification task and sentence-pair seman-
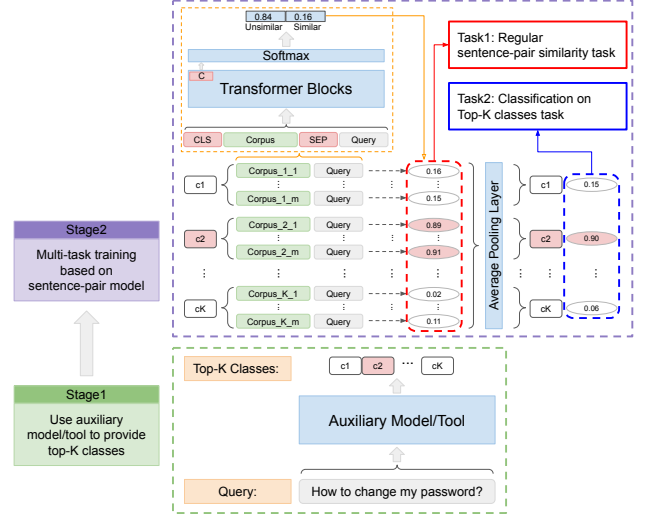

Fig. 2. **Network Structure of 2-stage SFC:** a joint system of multi-task for both text classification task and sentence-pair semantic similarity task.

tic similarity task, named SFC here, shown in Fig. 2. Our goal is to utilize the advantage of the feasibility of transfer learning based on semantic similarity, while in the mean time, add the classification task's target into the training process of sentence-pair model for multi-task learning[23, 24]. To obtain such a joint system, we first start with preparation work, which is pre-training a sentence-pair model on external corpus for sentence pair duplication identification, and then find an auxiliary model or tool which can help us sample out top-K most related intent classes. This auxiliary model or tool can either be searching engine such as elasticsearch[25] or a text classification model trained on task-specific chatbot data. Afterwards, we further fine-tune the sentence-pair model with 2 training tasks: 1) the regular sentence pair similarity tasks. Here we use the text classification model as an auxiliary model in this paper to sample sentence pairs for training based on negative sampling strategy[26]. The reason is that a task-specific chatbot often has hundreds of intent classes, which forms too many sentence pairs for training since any two sentences from two different classes can form a sentence-pair of negative sample. Besides, according to Bamler[26], training on negative samples from most confusing wrong label can help model converge faster and obtain better performance. 2) the classification task on top-K (here K is a hyperparameter) candidate classes provided by our auxiliary model or tool. Here we use the average pooling of the representation given by sentence-pair model for sentence pairs formed by the user input query and the corpus sentences in each class as the feature. We stack the task-specific layers on the top of the shared-parameter sentence-pair model structure, which is a classic parameter sharing mechanism[24, 27, 28] for multi-task[22]. In this way, spe-

cific knowledge contained in these 2 tasks can be fully explored and deeply interact with each other to obtain better overall performance.

However, since the auxiliary tool in joint system mentioned above works in a separate stage from sentence-pair model, we find the the quality of sampled candidate classes might limit the overall performance of SFC, since the candidate classes for each user query is always fixed during the multi-task training process. This observation motivates us to further improve SFC into a joint model of sentence-pair model and text classification model in a hierarchical architecture by putting different tasks at different network layers[29, 30] and then training them together, shown in Fig 3. Here, the text classification model involved in joint training process replace the role of auxiliary tools. In this way, the sentence pairs selected from top-K classes becomes dynamic, which means the text classification model will also be further optimized to provide better top-K classes pooling result.

We summarize our contributions as follow:

1) We propose a novel joint system named SFC with multi-task training technique designed for task-specific conversational chatbot with low-resource, in which we make full utilization of the advantages brought by both the text classification task and sentence-pair semantic similarity task.

2) To further improve the system performance of SFC, we also propose an innovative joint model structure, in which the text classification model and sentence-pair model are fused into one single model for joint training.

3) Experiment results on 4 public and 1 private short-text classification datasets with respect to intent recognition tasks under conversational chatbot scenario all demonstrated that our proposed SFC joint system with multi-task, as well as the improved version of SFC, can both achieve remarkable improvement comparing to some powerful single-task and single-model baselines, especially under few-shot settings.

2. METHODOLOGY

In this section, we will describe a system of similarity model fused with classification model, named as SFC, in detail. We come up with 2 different approaches for implementation of SFC system, in which hierarchical SFC is a further improvement of 2-stage SFC for better performance.

2.1. 2-stage SFC with multi-task learning

The detailed network structure of 2-stage SFC is shown in Fig. 2. It is composed with 2 separate stages in charge of different jobs. In stage 1, we can use any auxiliary model or tool to provide top-K most related classes for sampling sentence pairs of both positive samples and negative samples for stage 2. Suppose we have a training data set $\mathcal{D} = \{x_i, y_i\}_{i=1}^{N}$ of N data points, in which x_i is the user input query and y_i is a single class label from a class label set of C classes in

total. If we want to generate sentence pair data set $\mathcal{D}' = \{[(x, x')_j, l_j]\}_{j=1}^{M}$, where $(x, x')_j$ is sentence pair grouped by 2 user input queries and $l_j \in \{0, 1\}$ is similarity class label, see Equ. 1,

$$l_j = \begin{cases} 0 & y_{s_1} \neq y_{s_2} \\ 1 & y_{s_1} = y_{s_2} \end{cases} \tag{1}$$

directly from original data set $\mathcal{D}$ without any sampling strategy, then $\mathcal{D}'$ will have $M = N^2$ data points of sentence pairs, which might be too time-consuming for the training process of stage 2 since we often have hundreds of class labels under task-specific chatbot scenario. Although we may only have a few data points for a single class label, N is still quite a big number.

Therefore, we adopt the idea of adversarial negative sampling strategy raised by [26]. The key idea of this sampling strategy is to train with negative samples that are hard to distinguish from positive samples. Now suppose we have a user input query x_i as s_1 and top-K most related class labels set $\mathcal{C}' = \{c_1', \ldots, c_K'\}$ found by auxiliary model or tool in stage 1, where K is a hyperparameter set by us that controls candidate class number, we apply the adversarial negative sampling strategy into our sentence pair sampling process by the following 2 steps:

1. positive sentence pair sampling: During the training process, we have to first make sure that the ground truth class label y_i for x_i is within the candidate class label set $\mathcal{C}'$. If $y_i \notin \mathcal{C}'$, we will manually add y_i into $\mathcal{C}'$ by replacing c_K' with y_i. Afterwards, we will randomly sample P sentences $\{x_0', x_1', \ldots, x_P'\}$ with the same class label as y_i from data set $\mathcal{D}$ to form the set of sentence pairs with positive label $\mathcal{P}'_i = \{[(x_i, x_0'), 1], [(x_i, x_1'), 1], \ldots, [(x_i, x_P'), 1]\}$, where P is also a hyperparameter set by us that controls the number of sentences we should sample from each class.

2. negative sentence pair sampling: As for negative sentence pairs, we will also randomly sample P sentences for each class in the negative candidate class label set $\mathcal{C}' \backslash \{y_i\}$. The class labels in $\mathcal{C}' \backslash \{y_i\}$ are the set of most confusing classes comparing to the ground truth y_i, so we assume that the sentence pairs with negative label grouped by user input query x_i and sentences with class labels in $\mathcal{C}' \backslash \{y_i\}$ are also strong adversarial negative samples that can help enhance the training speed and performance. According to the same method as positive sentence pair sampling, we can obtain the set of sentence pairs with negative label as $\mathcal{N}'_i = \{[(x_i, x_0'), 0], [(x_i, x_1'), 0], \ldots, [(x_i, x_{P \cdot (K-1)}'), 0]\}$

In this way, we can generate the sentence pair data set $\mathcal{D}'$ for stage 2 based on the top-K class label set $\mathcal{C}'$ provided by stage 1 as $\mathcal{D}' = \{\mathcal{P}'_i \cup \mathcal{N}'_i\}_{i=1}^{N}$, in which we will have $M = N \cdot K \cdot P$ data points of sentence pairs in total.

After explaining the data sampling principle for sentence pairs and how the 2 stages in SFC system connect with each other, let's go deeper into model structure within these 2 stages respectively to see how it works.
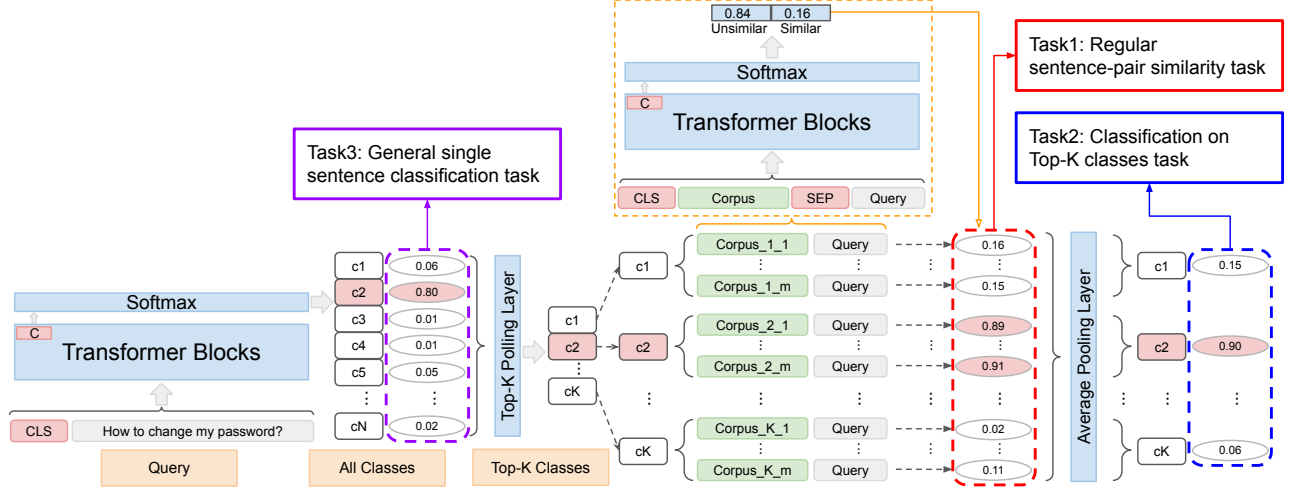
Fig. 3. **Network Structure of hierarchical SFC:** a joint model of sentence-pair model and text classification model organized in hierarchical structure by completing different tasks at different network layers.

2.1.1. stage 1: classification model for providing top-K classes

As for stage 1, our SFC system can adapt to any auxiliary model or even searching tool based on Term Frequency-Inverse Document Frequency (TF-IDF) retrieval. In this paper, however, we choose to fine-tune RoBERTa on our task-specific data set $\mathcal{D}$ by adding a softmax classifier on top of it, the same as the structure shown in Fig. 1(a), for better overall performance. According to our experimental result, RoBERTa can guarantee that approximately 95% ground truth label be included in top-5 candidate classes with highest probability after being fine-tuned on task-specific data set with top-1 weighted F score at around 0.75. So we use RoBERTa as encoder of classification model in our setting at stage 1 to ensure low limitation for the performance of stage 2.

For single-sentence text classification tasks, given a data point x_i with class label y_i from data set $\mathcal{D}$, RoBERTa takes the final hidden state h_i of the first token [CLS] as the representation for the whole sequence of x_i. Let's suppose we have a linear layer as $\Phi_i^C = W^C h_i + b^C$, where W^C and b^C are trainable parameters, the probability score for x_i can be calculated as $p_i^C = softmax(W^C h_i + b^C) = softmax(\Phi_i^C)$. Then, the loss for stage 1 classification model is shown in Equ. 2, in which the first term Φ_{i,y_i}^C encourages high probability for prediction of the correct label y_i.

$$
\begin{aligned}
\mathcal{L}^C &= \frac{1}{N} \sum_{i=1}^{N} -log(\frac{exp(\Phi_{i,y_i}^C)}{\sum_{j=1}^{C} exp(\Phi_{i,j}^C)}) \\
&= \frac{1}{N} \sum_{i=1}^{N} -\Phi_{i,y_i}^C + log(\sum_{j=1}^{C} exp(\Phi_{i,j}^C))
\end{aligned}
\tag{2}
$$

2.1.2. stage 2: sentence-pair model for multi-task learning

As for stage 2, we also choose RoBERTa as the encoder for sentence pairs, as shown in Fig. 2. Before sending sentence pairs to Roberta, we pack sentence pairs into a single sequence and separate them with a special token [SEP]. Roberta will also use a learned embedding to every token indicating whether it belongs to the first sentence or the second one. Then, we utilize the cross-attention mechanism inside RoBERTa, and then extract semantic relationship between 2 sentences from the output softmax layer, which is placed on top of the last hidden representation of the [CLS] token.

Before we start to fine-tune our sentence-pair model on task-specific dataset, we first fine-tune RoBERTa on Quora dataset[31], which contains 404,290 potential duplicate question pairs, for transfer learning. Then we continue to do multi-task training on sentence-pair dataset $\mathcal{D}'$ sampled from the top-K candidate classes provided by stage 1.

The 2 tasks for stage 2 training process are listed below.

• **Task 1: Regular sentence-pair similarity task**

For sentence pair semantic similarity task, given a data point $(x, x')_i$ with similarity label l_i from data set $\mathcal{D}' = \{[(x, x')_i, l_i]\}_{i=1}^{M}$, Roberta takes the final hidden state h_i of the first token [CLS] as the representation for the sequence of packed sentence pair $(x, x')_i$. Let's suppose we have a linear layer as $\Phi_i^S = W^S h_i + b^S$, where W^S and b^S are trainable parameters, and the probability score for $(x, x')_i$ can be calculated as $p_i^S = softmax(\Phi_i^S)$.

Due to the fact that sentence pairs within the same class is much less than sentence pairs from different classes, the data set $\mathcal{D}'$ is imbalanced. Therefore, we will accommodate a weight variable $w^S = [K - 1, 1]$ to the loss to eliminate the bias brought by imbalanced data, shown in Equ. 3.

$$\mathcal{L}^S = \frac{1}{M} \sum_{i=1}^{M} -w_{l_i}^S \cdot log(\frac{exp(\Phi_{i,l_i}^S)}{\sum_{j=0}^{1} exp(\Phi_{i,j}^S)})$$

$$= \frac{1}{M} \sum_{i=1}^{M} -w_{l_i}^S \cdot \Phi_{i,l_i}^S + w_{l_i}^S \cdot log(\sum_{j=0}^{1} exp(\Phi_{i,j}^S)) \qquad (3)$$

• Task 2: Classification task on top-K classes based on sentence-pair model

As for top-K classification task, we share the same sentence-pair similarity model structure with task 1. The only difference is that we add a task-specific average pooling layer, shown in Fig. 2 to implement the classification task based on sentence-pair model.

We already know that the size of Φ^S in task 1 is $M \times 2 = (N \cdot K \cdot P) \times 2$, where N is the total number of data points in original training data $\mathcal{D}$, K is a hyperparameter that controls the number of candidate classes provided by stage 1, and P is also a hyperparameter that controls the number of sentences we should randomly sample from each candidate class. Now, for the average pooling layer, we first reshape Φ^S into the size of $N \times K \times P \times 2$, and then split it into $\Phi^{K,pos}$ and $\Phi^{K,neg}$, and both of them will have the size of $N \times K \times P$. In this way, $\Phi^{K,pos}$ can represent the level of similarity for each sentence pair, and in the mean time, $\Phi^{K,neg}$ can represent the level of dissimilarity for each sentence pair. Then, we can do average pooling for each candidate class among the top-K classes as shown in Equ. 4 and Equ. 5.

$$\xi_{i,j}^{K,pos} = \sum_{p=1}^{P} \Phi_{i,j,p}^{K,pos} \qquad (4)$$

$$\xi_{i,j}^{K,neg} = \sum_{p=1}^{P} \Phi_{i,j,p}^{K,neg} \qquad (5)$$

With the average pooling result $\xi^{K,pos}$ and $\xi^{K,neg}$, we also generate a top-K class label $l_i^K \in [1, \ldots, K]$ for each $\xi_i^{K,pos}$ and $\xi_i^{K,neg}$. The loss for top-K classification task is shown in Equ. 6. In Equ. 7 and Equ. 8, the first term $\xi_{i,l_i^K}^{K,pos}$ and $\xi_{i,l_i^K}^{K,neg}$ encourage high level of similarity and low level of dissimilarity for prediction of the correct label l_i^K within the top-K candidate classes.

$$\mathcal{L}^K = \frac{1}{N} \sum_{i=1}^{N} (\mathcal{L}_i^{K,pos} - \mathcal{L}_i^{K,neg}) \qquad (6)$$

where,

$$\mathcal{L}_i^{K,pos} = -log(\frac{exp(\xi_{i,l_i^K}^{K,pos})}{\sum_{j=1}^{K} exp(\xi_{i,j}^{K,pos})})$$

$$= -\xi_{i,l_i^K}^{K,pos} + log(\sum_{j=1}^{K} exp(\xi_{i,j}^{K,pos})) \qquad (7)$$

$$\mathcal{L}_i^{K,neg} = -log(\frac{exp(\xi_{i,l_i^K}^{K,neg})}{\sum_{j=1}^{K} exp(\xi_{i,j}^{K,neg})})$$

$$= -\xi_{i,l_i^K}^{K,neg} + log(\sum_{j=1}^{K} exp(\xi_{i,j}^{K,neg})) \qquad (8)$$

Therefore, the overall loss function for multi-task learning in stage 2 is shown in Equ. 9. The training objective of stage 2 is to minimize the weighted sum of task-specific losses. Here α_S and α_K are weights of task 1 and task 2 respectively, which are $\alpha_S = 0.125$ and $\alpha_K = 0.875$ in our setting.

$$\mathcal{L} = \alpha_S \mathcal{L}^S + \alpha_K \mathcal{L}^K \qquad (9)$$

2.2. hierarchical SFC with joint model structure

Despite the outstanding experimental result of 2-stage SFC on various tasks, we still find a limitation brought by the 2-stage system structure. In 2-stage SFC, Stage 1 and stage 2 are separate, so they do not interact with each other during training. In this case, the performance of stage 1 can limit the potential of stage 2, meanwhile, stage 2 also cannot give training feedback back to stage 1 for fine-tuning.

Therefore, to further improve the overall performance of SFC, we proposed a hierarchical SFC joint model structure, shown in Fig. 3. In hierarchical SFC, classification model is being placed in lower level to dynamically provide top-K candidate classes for the sentence-pair similarity model placed in higher level through a top-K pooling layer. In this way, classification model and similarity model can be merged into one single joint-model for multi-task training, thus avoiding the limitation brought by 2 separate stage structure.

There are 3 tasks in total during the training process of hierarchical SFC, shown in Fig. 3, and the overall loss is also the weighted sum of all the task-specific losses, shown in Equ. 10. Here, α_S, α_K and α_C are the weights for task 1: sentence-pair similarity, task 2: top-K classification and task 3: general single sentence classification respectively, which are $\alpha_S = 0.25$, $\alpha_K = 0.25$ and $\alpha_C = 0.5$ in our setting.

$$\mathcal{L} = \alpha_S \mathcal{L}^S + \alpha_K \mathcal{L}^K + \alpha_C \mathcal{L}^C \qquad (10)$$

Finally, when doing inference, for each user input query x, we will choose the class label that contains the sentence

x' with highest similarity score Φ, after being packed into a sentence pair (x, x') with query x, as our final result for prediction.

3. EXPERIMENTS

In this section, we conduct extensive experiments over 5 task-specific dataset to evaluate the performance of our proposed SFC system and the effectiveness of the methodology of multi-task learning and hierachical joint-model structure under low-data settings.

3.1. Datasets

The dataset used in our experiments aims to help us study low-resource text classification problem under task-specific conversational chatbot scenario. Therefore, we keep all the dataset under low-resource chatbot corpus setting, which is a large number of class labels (50-250) with a few examples(5-20) in short text for each class, by sampling smaller subsets from the full scale when the raw datasets are oversized, see Table 1.

According to the task and domain, we categorize our experimental datasets into the following 3 categories:

• **full-scale real-world task-specific faq chatbot dataset**
ITG is a real-world FAQ chatbot dataset composed of question and answer pairs about online English teaching. It contains 3,938 sample questions for 228 class labels, where each class label corresponds to an unique answer for a bunch of similar sample questions.

We divide the whole dataset into 3 folds randomly with approximately the same amount of data within each fold, and then choose 2 folds as the training set, the remaing 1 fold as the test set for our experiments. We can obtain 3 different combinations among the 3 folds, and we will use the average experimental results of these 3 combinations as the final evaluation result for this dataset.

• **subset of customer review dataset for extreme classification**

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Dataset	Domain	#Class	#Samples	#Samples/Class	Experimental Settings
ITG	FAQ chatbot	228	3938	17	3-fold
Amazon-670k	Product review	250	1942	8	class sampling
HWU64	Intent detection	64	[320, 640, 960, 1280]	[5, 10, 15, 20]	data sampling
CLINC150	Intent detection	150	[750, 1500, 2250]	[5, 10, 15]	data sampling
BANKING77	Intent detection	77	[385, 770, 1155, 1540]	[5, 10, 15, 20]	data sampling

Table 1. Key statistics for experimental datasets and few shot settings

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