Feature-augmented Machine Reading Comprehension with Auxiliary Tasks

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Abstract

While most successful approaches for machine reading comprehension rely on single training objective, it is assumed that the encoder layer can learn great representation through the loss function we define in the predict layer, which is cross entropy in most of time, in the case that we first use neural networks to encode the question and paragraph, then directly fuse the encoding result of them. However, due to the distantly loss back-propagating in reading comprehension, the encoder layer cannot learn effectively and be directly supervised. Thus, the encoder layer cannot learn the representation well at any time. Base on this, we propose to inject multi granularity information to the encoding layer. Experiments demonstrate the effect of adding multi granularity information to the encoding layer can boost the performance of machine reading comprehension system. Finally, empirical study shows that our approach can be applied to many existing MRC models.

1 Introduction

Machine Reading Comprehension (MRC) is a field having gained tremendous popularity among researchers in the last few years. In this field, a MRC model is designed to process and understand the context and the question in order to provide a reasonable answer. Recently, Rajpurkar et al. (2018) released the SQuAD 2.0 dataset, which, compared to SQuAD 1.1 (Rajpurkar et al., 2016), incorporates unanswerable questions to make it more difficult to answer the questions accurately. Figure 1 gives an example of the MRC task, whose inputs are passage and question, and predict the answer as output to the question. A large number of models have been explored for this question answering task, including RNN-based models, CNN-based models, transformer-based models, and pre-trained language models, and have been shown to be useful on SQuAD 2.0.

Conventional MRC framework can be seen in 2, where passage and question are encoded seperately and then passed to a match layer for choosing the best answer candidate. However, due to the distantly loss back-propagating in MRC, the encoder layer need to experience a long distant parameter update and could not be learnt effectively without directly supervised, which may lead to the bad representation ability of encoder layer. As we all know, encode the text sequence with better representation plays a vital role in various NLP task. What's more, this becomes more obvious when encountering the MRC task, because of the complex and multi encoding layer most MRC system used (Seo et al., 2017; Wang and Jiang, 2017; Wang et al., 2017; Xiong et al., 2017; Chen et al., 2021).

Ideally, the encoding layer should be able to learn multi-granular text information. Inspired by the great performance of jointly training in Spoken Language Understanding (SLU) (Qin et al., 2019; Chen et al., 2022c; Xu et al., 2021; Zhou et al., 2022a; Zhu et al., 2022; Zhou et al., 2020; Huang et al., 2020, 2022, 2021d; Chen et al., 2022a,b), of which Intent classification (IC) and slot filling (SF) are two main tasks, we know that fine-grained and coarse-grained tasks can effectively complement and boost each other. Based on this, we propose to use directly loss back propagation to strengthen the encoding with both coarse-grained and fine-grained information.

This work describes a stack learning framework for Machine Reading Comprehension, which aims to strengthen the encoder layer by introducing multi-granularity text task. Specifically, we use IC task and SF task to extract the multi-granularity information of question and passage, then inject them to the encoder layer of MRC system. Intent classification module can encode the sentences with coarse-granularity language embedding, which can better learn the representations at sentence level. Slot filling module can encode the sentences with
The Normans (Norman: Nourmands; French: Normands; Latin: Normanni) were the people who in the 10th and 11th centuries gave their name to Normandy, a region in France. They were descended from Norse ("Norman" comes from "Norseman") raiders and pirates from Denmark, Iceland and Norway who, under their leader Rollo, agreed to swear fealty to King Charles III of West Francia. Through generations of assimilation and mixing with the native Frankish and Roman-Gaulish populations, their descendants would gradually merge with the Carolingian-based cultures of West Francia. The distinct cultural and ethnic identity of the Normans emerged initially in the first half of the 10th century, and it continued to evolve over the succeeding centuries.

Input Question (Answerable): In what country is Normandy located?
Output Answer: France

Input Question (Not Answerable): Who gave their name to Normandy in the 1000’s and 1100’s?
Output Answer: None

Figure 1: An example of SQuAD2.0.

fine-granularity language representation, to better capture the respective representations at token level. Then, the encoding layer of SLU is used to fully fuse information from both sentence level and token level representations in the MRC module. In this paper, we adopt a classical Bi-DAF model for both single passage and multi passage machine reading comprehension as a baseline. Jointly train the paragraph selection and paragraph span extraction model for reduce the distantly loss back-propagating problem, in order to further boost the performance of Machine Reading Comprehension.

Overall, this paper proposes to extract multi-granularity representations as the external input features for the basic MRC model. The contributions of our paper are as follows:

- We propose to jointly learn coarse and fine text information to strengthen the encoder for Machine Reading Comprehension.
- Experiment on three model shows that our propose framework have obvious improved, while use strong language model, i.e. BERT, as the baseline, our model get remarkable results in SQuAD2.0.

2 Related Work

2.1 Machine Reading Comprehension

Reading comprehension, which aims to answer questions about a document, has become a major focus of NLP research. Many algorithm has been proposed to solved this problem. A model must be able to process and understand a context and question in order to provide a reasonable answer.

A large amount of model has been explored to this question answering task, including RNN-based model, transformer-based model, Pre-trained Contextual Embeddings model, Pre-trained Language Module, and have been proved to be effective on this dataset (Seo et al., 2017; Wang and Jiang, 2017; Xiong et al., 2017; Kadlec et al., 2016; Sordoni et al., 2016; Devlin et al., 2019; Yang et al., 2019; Hou et al., 2020).

2.2 Spoken Language Understanding

Many models have been proposed to solve the intent classification and slot filling problems, and they are the two main tasks of SLU (Chen et al., 2022a,b,c; Huang et al., 2021d, 2020; Zhu et al., 2022; Zhou et al., 2020). Depending on whether intent classification and slot filling are modeled separately or jointly, past models have been classified into independent modeling approaches (Zhou et al., 2022a; Xu et al., 2021) and joint modeling approaches (Chen et al., 2019).

2.3 Feature Integration

Inspired by the successful usage of Stack-Propagation Framework in Spoken Language Understanding (Qin et al., 2019) and successful usage of implicit representation integration in Semantic Role Labeling (Xia et al., 2019), as well as feature fusion and enhancement methods across different modalities and tasks (Chong et al., 2022; Zeng et al., 2022; Zhou et al., 2022c; Huang et al., 2021c,b), we design a jointly learning framework to train MRC and SLU tasks interactively, so as to reduce the distantly loss backward problem.
3 Conventional Text Feature Representation in MRC

3.1 Input Representation

Following (Xia et al., 2019), we utilize CNNs to encode characters for each word $\vec{E}_i$ into its character representation, denoted as $\vec{E}_{i \text{char}}$. Then, we employ word embedding Glove to represent the word-level features, denoted as $\vec{E}_{i \text{word}}$. Besides, we employ BERT feature representations (Devlin et al., 2019) to bring more representation message in our model, which we denote as $\vec{E}_{i \text{BERT}}$. Formally, the input representation of $\vec{E}_i$ is:

$$\vec{E}_i = \vec{E}_{i \text{char}} \oplus \vec{E}_{i \text{word}} \oplus \vec{E}_{i \text{BERT}} \tag{1}$$

3.2 Encoder Layer

We use Bi-LSTM to encode our contexts and queries. For the contexts, first Bi-LSTM is modeling to capture the forward message of contexts, then set the final hidden state as $\vec{H}_L$, while do the same operation backward, then set the first hidden state as $\vec{H}_1$, finally we concatenate these two state as $\vec{H}_1 \oplus \vec{H}_L$. And queries likewise.

$$\vec{E}_{\text{Context}} = \vec{H}_1 \oplus \vec{H}_L$$
$$\vec{E}_{\text{Query}} = \vec{H}_1 \oplus \vec{H}_L \tag{2}$$

4 Approach

From Figure 3, we can see that the proposed framework includes two modules, a basic Machine Reading Comprehension module and a jointly training of intent classification and slot filling module. In this section, we will illustrate the integration of the jointly training module to the MRC module.

4.1 Encoder layer

For the Strengthen-Encoder, intent detection task and slot filling task share the same encoder. Following (Qin et al., 2019), BiLSTM and self-attention are used for both advantages of temporal features and contextual information.

Given input sentence $\vec{X} = (\vec{y}_1, \vec{x}_2, \ldots, \vec{x}_T) \in \mathbb{R}^{d \times T}$, BiLSTM (Hochreiter and Schmidhuber, 1997) encodes it forwardly and backwardly to produce context-aware hidden state $\vec{H} = (\vec{h}_1, \vec{h}_2, \ldots, \vec{h}_T) \in \mathbb{R}^{d \times T}$.

For self-attention mechanism (Vaswani et al., 2017), we first map the input sequence $\vec{X} \in \mathbb{R}^{d \times T}$ to queries (Q), keys (K), values (V) vectors by using different linear projections, and the output $\vec{C} \in \mathbb{R}^{d \times T}$ is a weighted sum of V, the process is as follow:

$$\vec{C} = \text{softmax} \left( \frac{\vec{Q} \vec{K}^T}{\sqrt{d_k}} \right) \vec{V} \tag{3}$$

After obtaining the output of self-attention and
BiLSTM. We concatenate these two representations as the final encoding representation.

4.2 Feature Integration Module

We employ the model proposed by Qin et al. (2019). As can be seen in Figure 3. Specifically, Eqn 1 is used to embed the sentences, then we encode the sentences by self-attention layer and Bi-LSTM layer. After concatenation of encoder, they are transferred to different LSTM decoder, which represent different downstream tasks. When we train the MRC module, we inject the hidden state of SLU encoder to the MRC encoder, and the parameters of decoder layer in SLU module will not be updated.

4.3 Training Objective

After we inject the hidden state of encoder layer of SLU task to the embedding layer of MRC task, the loss function of our framework consists of three parts. The total loss function is the sum of the negative log-likelihood loss of the three tasks:

\[
- \sum_{(Y^i_M, X_M) \in M} \log P(Y^i_M|X_M) + \alpha \sum_{(Y^*_d, X_d) \in D} \log P(Y^*_d|X_d)
\]  

(4)

where \(M\) is the set of MRC data and \(D\) is the set of SLU data, which includes intent classification data \(I\) and slot filling data \(S\).

5 Experiment

This section describes the experimental approach. We explored the effectiveness of our encoder-strengthen framework on three machine reading comprehension models. The EM and F1 scores for these models are shown in Table 1.

5.1 Datasets

As a widely used MRC benchmark dataset, SQuAD 2.0 (Rajpurkar et al., 2018) combines the 100k questions from SQuAD 1.1 (Rajpurkar et al., 2016) with over 50k new. Compared to SQuAD 1.1, SQuAD 2.0 requires models not only answer questions when possible, but also discards answers in passages that are not supported by answers. We chose two metrics to evaluate the performance of the model: Exact Match (EM) and a F1 score. An example of SQuAD2.0 is shown in Figure 1.

We use SNIPS dataset (Coucke et al., 2018) as the SLU dataset. We follow the same format and partition as (Goo et al., 2018). The dimension of the word embedding is 512 for SNIPS dataset. The self-attentive encoder hidden units are set as 256.

5.2 Experimental Details

We train our Machine Reading Comprehension task together with Intent Classification task and Slot filling task. Specifically, we train MRC task in SQuAD 2.0 for one iteration, and both IC task and SF task for another. While training one certain task, the parameters of other tasks are fixed. Batch size
Table 1: Performance of our method and other models on dev set of SQuAD2.0

| Method                      | EM   | F1   |
|-----------------------------|------|------|
| BiDAF (Seo et al., 2017)    | 57.60| 61.10|
| w/ SLU                      | 59.80(+2.2) | 62.80(+1.7) |
| QA-Net (Yu et al., 2018)    | 63.38| 67.16|
| w/ SLU                      | 65.52(+2.14) | 68.49(+1.33) |
| SAN (Liu et al., 2017)      | 69.52| 72.73|
| w/ SLU                      | 72.76(+3.24) | 74.84(+2.11) |
| BERT (Devlin et al., 2019)  | 80.01| 83.06|
| w/ SLU                      | 81.90(+1.89) | 84.68(+1.62) |

is set to different according to different baseline systems. Training is terminated after 11 epoch.

5.3 Results

Experiment results are shown in Table 1. For the non pre-trained model, our framework has obvious improvement, especially, there are 3.24% and 2.11% absolute growth on EM and F1 for SAN model. Besides, in order to prove the effectiveness of our framework, we also perform equivalent experiments on a strong pre-trained language model, i.e. BERT, which achieved great results in Machine Reading Comprehension and other tremendous NLP tasks. From the result, we can see that though BERT has considerable results, its improvements are smaller compared to the other methods, in the assumption that BERT itself is one of an excellent sentence encoding model.

6 Conclusion

Due to the distantly loss back-propagating in reading comprehension, the encoder layer cannot learn effectively and directly supervised. Thus, the encoder layer can not learn the representation well at any time. In this paper, We propose a framework that can inject multi granularity message information to the encoding layer. Empirical results show that our method can be effectively applied to existing MRC models.

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