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Although existing machine reading comprehension models are making rapid progress on many datasets, they are far from robust. In this paper, we propose an understanding-oriented machine reading comprehension model to address three kinds of robustness issues, which are over sensitivity, over stability and generalization. Specifically, we first use a natural language inference module to help the model understand the accurate semantic meanings of input questions so as to address the issues of over sensitivity and over stability. Then in the machine reading comprehension module, we propose a memory-guided multi-head attention method that can further well understand the semantic meanings of input questions and passages. Third, we propose a multi-language learning mechanism to address the issue of generalization. Finally, these modules are integrated with a multi-task learning based method. We evaluate our model on three benchmark datasets that are designed to measure models' robustness, including DuReader (robust) and two SQuAD-related datasets. Extensive experiments show that our model can well address the mentioned three kinds of robustness issues. And it achieves much better results than the compared state-of-the-art models on all these datasets under different evaluation metrics, even under some extreme and unfair evaluations. The source code of our work is available at: https://github.com/neukg/RobustMRC.

CCS Concepts: • Information systems \rightarrow Question answering.

Additional Key Words and Phrases: question & answering, robust machine reading comprehension, over sensitivity, over stability, generalization, memory-guided multi-head attention, multi-task and multi-language learning, DuReader (robust), SQuAD

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1 INTRODUCTION

Machine reading comprehension (MRC) aims to answer questions by reading given passages (or documents). It is considered one of the core abilities of artificial intelligence (AI) and the foundation of many AI-related applications like next-generation search engines and conversational agents.

At present, MRC is achieving more and more research attention and lots of novel models have been proposed. On some benchmark datasets like SQuAD [Rajpurkar et al. 2018] and MS MARCO [Nguyen et al. 2016], some models like BERT [Devlin et al. 2018] have achieved higher performance than human. However, recent work [Gan and Ng 2019; Jia and Liang 2017; Liu et al. 2020; Si et al. 2020; Tang et al. 2021; Wu and Xu 2020; Zhou et al. 2020] shows that current MRC test sets tend to overestimate an MRC model's true ability to unseen data due to the following reason: the test set on which an MRC model evaluated is typically randomly selected from the whole set of data collected and thus follows the same distributions as the training and development sets, while in real world, it is impossible to ask the unseen data follow such known distributions. Thus it is very necessary to evaluate MRC models on some unseen test data to reveal their robustness.

In this study, we focus on following three kinds of robustness issues that are defined by [Tang et al. 2021]. (i) Over sensitivity issue which refers to semantically invariant text perturbations cause a models' prediction to change when it should not; (ii) Over stability issue which refers to input text is meaningfully changed but the model's prediction does not, even though it should; (iii) Generalization issue which refers to models usually perform well on in-domain test sets yet perform poorly on out-of-domain test sets. All these issues are widely existed in real world, and they will lead to a significant decrease in performance for most of existing state-of-the-art MRC models [Gan and Ng 2019; Jia and Liang 2017; Liu et al. 2020; Tang et al. 2021; Welbl et al. 2020]. Fig. 1 shows two examples about the issues of over sensitivity and over stability respectively, both of which are extracted from the DuReader (robust) dataset [Tang et al. 2021] and all the questions in them are really asked by users in the *Baidu* search engine.

Existing methods address above issues mainly with a kind of data augmentation based methods or a kind of adversarial training based methods. For example, Gan and Ng[2019] use a neural paraphrasing model to generate multiple paraphrased questions for a given source question that is paired with a set of paraphrase suggestions. Then an MRC model is retrained on the training set where the paraphrased samples are integrated. However, neither of these two kinds of methods can truly solve the mentioned issues. Essentially, they still focus on the effort of making a model "see" as many samples as possible so that the model can make decisions based on the "saw" knowledge. But both the paraphrased and adversarial questions are "generated", so it is very possible that they may not be present in real world. Besides, many real questions could not be fully "generated". Taking the questions in Fig. 1 as examples, for the first one, there are many different ways to express "how old" or "die" in Chinese. For the second one, there is only ONE different Chinese CHARACTER in the two questions, but they have completely different semantic meanings. Both examples are difficult to be addressed by existing data augmentation or adversarial training based methods because of the following reasons. For the over sensitivity example, there are too many diverse and flexible expression manners for a same meaning question to be enumerated or paraphrased. As for the over stability example, it is impossible to paraphrase it because the aim of data augmentation methods is to generate some paraphrased questions that have the same semantic meaning with the source question. And it is also impossible to handle this over stability example by the adversarial training based methods because these methods usually use some context words near a wrong answer candidate to generate some adversarial examples based on which the models are trained [Gan and Ng 2019]. Thus these methods do not have capabilities to distinguish the slight perturbations between two questions that have a significant high string match similarity.

		史蒂夫.乔布斯,1955年2月24日生于美国加利福尼亚洲旧金山, 美国发明家,企业家,美国莱果公司联合创办人,2011年10月5								
		日,因 <u>胰腺癌病逝,享年 59 岁</u>								
	Document	(Steve Jobs, born in San Francisco, California on February 24, 1955, is								
0		an American inventor, entrepreneur and co-founder of apple. In October								
Over		5, 2011, he died at the age of 59 because of pancreatic cancer)								
Sensitivity	0	乔布斯 <mark>多少岁去世</mark> ?	Answer: 50 出							
	(How old	乔布斯 <mark>多大年纪去世的</mark> ?	(59 years old)	Т						
	did Steven Jobs die?)	乔布斯 <mark>死于多少岁</mark> ?	(5) years old.)							
		乔布斯 多大死的 ?	Answer: 胰腺癌	F						
	,		(pancreatic cancer)							
	Document	水槽的合理 宽度 是在 430 到 480mm,水槽的深度大于 180mm 比较								
		合适,这样可以防止水花飞溅,水槽的厚度要适中,以0.8~1.0mm								
		为宜,过薄影响水槽的强度,过厚会影响洗涤效果								
		(The reasonable width of the sink is 430 to 480mm, and the depth of the								
	Document	sink is more than 180mm, which can prevent water splashing. The								
Over		thickness of the sink should be moderate, 0.8 ~ 1.0mm is appropriate.								
Stability		Too thin will affect the strength of the sink, and too thick will affect the								
		washing effect)								
	Q1	水槽一般 多宽 比较合理?	100 :	т						
		(How wide is the sink generally reasonable?)	Answer: 430 to	1						
	Q2	水槽一般 <mark>多厚</mark> 比较合理?	480mm	Б						
		(How thick is the sink generally reasonable?)	(430 to 480mm)	г						
1										

Fig. 1. Examples of over sensitivity and over stability (extracted from DuReader (robust)). The words with the same color have the same meaning. All the answers are generated by BERT (large).

In contrast, human can handle all above three kinds of robustness issues effectively, the main reason of which is that human can understand the semantic meanings of the given text precisely. In fact, the *understanding* capability is also the key of solving these diverse kinds of robustness issues [Jia and Liang 2017]. Inspired by this, we propose an understanding-oriented MRC model that can address the mentioned three kinds of robustness issues well. First, we view both the issues of over sensitivity and over stability as a semantic meaning understanding problem, which requires the MRC model have the ability of distinguishing the semantic meanings of a question and its paraphrased expressions that may have similar or dissimilar semantic meanings with the source question. To this end, we introduce a nature language inference (NLI) [Ido Dagan 2006] module to judge whether two input sentences have the same semantic meaning. Second, in the MRC module, we propose a memory-guided multi-head attention method that can better understand the interactions between questions and passages. Third, we propose a multi-language learning mechanism to prevent the model from over-fitting in-domain data and enhance the generalization ability of the model. We introduce several language-specific MRC datasets to train the model together, which makes the distributions of training set and test set be completely different. During training, each dataset can be viewed as an adversarial dataset of others. Accordingly, none of a dataset can dominant the training process and the model will be pushed to learn more generalized knowledge for predictions. And these modules are jointly trained with a multi-task learning manner. We evaluate the proposed method on three benchmark MRC datasets, including DuReader (robust) [Tang et al. 2021] and two SQuAD-related datasets [Gan and Ng 2019]. All of these datasets are designed to measure the capabilities of an MRC model for addressing the issues of over sensitivity, over stability and generalization. Extensive experiments show that our model achieves very competitive results on all of these datasets. On DuReader (robust), it outperforms the compared strong baselines by a large margin and ranks No.3 on the final test set leader-board. On the other two SQuAD-related datasets, it achieves much competitive results even under two kinds of extreme and unfair evaluations.

2 RELATED WORK

Common MRC Research In the early study of MRC, researchers pay much attention to design diverse attention methods to mine the interactions between questions and passages. These interactions have been proven to be much helpful for improving the performance of an MRC model. BiDAF [Seo et al. 2016] is one of the most representative work, where the authors design a Context-to-query and Query-to-context bi-directional attention method. [Yu et al. 2018] and [Clark and Gardner 2018] also use a BiDAF-style attention method. Besides, researchers also propose many other kinds of attention methods. For example, [Cui et al. 2017] designs an attention-over-attention model that uses a 2-dimension similarity matrix between the question and the context words to compute the weighted query-to-context attention. [Wang et al. 2018c] propose a multi-granularity hierarchical attention method. [Hu et al. 2019a] use the self-attention based method.

Recently, there are two kinds of research lines that are dominant in the MRC task, both of which achieve competitive results on many benchmark MRC datasets.

The first one is to imitate some reading patterns used by human when designing an MRC model. For example, [Sun et al. 2019b] explicitly use three human's reading strategies in their MRC model, including: (1) back and forth reading, (2) highlighting, and (3) self-assessment. [Wang et al. 2018a] imitate human's following reading pattern: first scans through the whole passage; then with the question in mind, detects a rough answer span; finally, come back to the question and select the best answer. [Liu et al. 2018b] design their MRC model by simulating human's multi-step reasoning pattern: human often re-read and re-digest given passages many times before a final answer is found. [Wang et al. 2018b] use an extract-then-select reading strategy. They further regard the candidate extraction as a latent variable and train the two-stage process jointly with reinforcement learning. [Peng et al. 2020] design their MRC model by simulating two ways of human thinking when answering questions, including reverse thinking and inertial thinking. [Zhang et al. 2021] imitate human's "read + verify" reading pattern: first to read through the full passage along with the question and grasp the general idea, then re-read the full text and verify the answer. Some other researchers [Clark and Gardner 2018; Hu et al. 2019b; Wang et al. 2018c; Yan et al. 2019] also imitate human's this "read + verify" reading pattern. There are other kinds of human reading patterns imitated. For example, [Tian et al. 2020] imitate the pattern of restoring a scene according to the text, [Malmaud et al. 2020] imitate the pattern of human gaze during reading comprehension, and [Chen et al. 2020] imitate the pattern of tactical comparing and reasoning over candidates while choosing the best answer, etc.

The second one is to use diverse large-scale pretrained language models like BERT [Devlin et al. 2018] and lots of its variants including XLNet [Yang et al. 2019], RoBERTa [Liu et al. 2019], and ALBERT [Lan et al. 2020], etc. These language models have a strong capacity for capturing the contextualized sentence-level language representations [Zhang et al. 2021]. With these language models, researchers can design an MRC model very easily because the language models can be used either as MRC models themselves, or as the encoder part of an MRC model and researchers only need to focus on designing the decoder part. For example, lots of recent MRC models [Banerjee

et al. 2021; Chen and Wu 2020; Gong et al. 2020; Guo et al. 2020a,b; Huang et al. 2020; Li et al. 2020b,a; Long et al. 2020; Luo et al. 2020; Zhang et al. 2020; Zheng et al. 2020] only consist of a language model based encoder module and a careful designed decoder module.

Robust MRC Research [Jia and Liang 2017] explore the over sensitivity and over stability issues by testing whether an MRC model can answer paraphrased questions that contain adversarial sentences. Recently, [Náplava et al. 2021] extensively evaluated several state-of-the-art AI-related downstream systems including some MRC models with their robustness to input noise. Their experiments show that there is no published open-source models which are robust to the addition of adversarial sentences. Thus, the robustness issues in MRC are attracting more and more research attentions, and lots of novel methods have been proposed. Generally, these existing methods can be classified into following two kinds.

The first kind is the data augmentation based methods that address the robustness issues by training a model with additional careful generated training data. For example, [Wang and Bansal 2018] augment the training datasets by incorporating some adversarial examples, and then the MRC model is trained on the augmented dataset. [Welbl et al. 2020] investigate data augmentation and adversarial training as defenses. [Liu et al. 2020] propose a model-driven approach to generate adversarial examples that can attack given MRC models. Then they retrain and strengthen the MRC model by using the generated adversarial examples. [Li et al. 2021] introduce a new knowledge distillation method by taking advantage of data augmentation and progressive training on a wide range of AI-related applications including the MRC task. [Shinoda et al. 2021] focus on questionanswer pair generation to mitigate the robustness issue. But different from most existing methods that aim to improve the quality of synthetic examples, they try to generate multiple diverse questionanswer pairs to mitigate the sparsity of training sets so as to improve the robustness of a model. Usually, this kind of methods are simple and effective. However, [Liu et al. 2020] point out that the augmented datasets are often capable of simulating the known types of adversarial examples, while ignoring other unobserved types. [Gan and Ng 2019] further point out that the main deficiency in the data augmentation based methods is that the adversarial examples created are unnatural and not expected to be present in real world. [Rosenberg et al. 2021] draw similar conclusion that data augmentation based methods cannot address the robustness issues effectively.

The second kind is the adversarial training based methods that explore to design better MRC models to improve models' robustness. For example, [Liu et al. 2018b] average multi-predictions to improve the model's robustness. [Min et al. 2018] notice that most questions can be answered by using only a few sentences and without the consideration of context over entire passage, then they design a sentence selector to select the minimal set of sentences to the MRC model to answer a question. Their method reduces the risk of adversarial attacks by reducing passage length, which is proven to be robust to adversarial inputs. [Baradaran and Amirkhani 2021] investigate the effect of ensemble learning approach to improve the generalization of MRC models. After separately training several base models with different structures on different datasets, these base models are ensembled by using weighting and stacking approaches in probabilistic and non-probabilistic settings. Conversely, [Hu et al. 2018] train a robust single model based on ensemble ones through distillation training approach. They first apply the standard knowledge distillation to mimick output distributions of answer boundaries from an ensemble model, then propose two distillation approaches to further transfer knowledge between the teacher model and the student model. [Bartolo et al. 2021] use synthetic adversarial data generation to make MRC models more robust.

Besides, some researchers also explore the methods of introducing extra knowledge to address the robustness issues. For example, [Wang and Jiang 2019] address the robustness issues by proposing a data enrichment method that uses WordNet to extract inter-word semantic connections as general knowledge from each given passage-question pair, then they uses the extracted knowledge to

assist the attention mechanism in their MRC model. [Zhou et al. 2020] address the over confidence issue and the over sensitivity issue simultaneously with the help of external linguistic knowledge. Specifically, they first incorporate external knowledge to impose different linguistic constraints (entity constraint, lexical constraint, and predicate constraint), and then regularize MRC models through posterior regularization. Linguistic constraints induce more reasonable predictions for both semantic different and semantic equivalent adversarial examples, and posterior regularization provides an effective mechanism to incorporate these constraints. [Wu and Xu 2020] address the robust issues from two aspects. First, they enhance the representation of the model by leveraging hierarchical knowledge from external knowledge bases. Second, they introduce an auxiliary unanswerability prediction module and perform multi-task learning with a span prediction task. Some researchers explore to use auxiliary tasks to address the robustness issues. For example, [Chen and Durrett 2021] propose a MRC model that through sub-part alignment, their basic idea is that if every aspect of the question is well supported by the answer context, then the answer produced should be trustable; if not, they suspect that the model is making an incorrect prediction. And the sub-parts used are predicates and arguments from the results of a *Semantic Role Labeling* task.

Natural Language Inference Given two sentences, often called as a premise and a hypothesis respectively, Natural Language Inference (NLI), also known as *Recognizing Textual Entailment* [Ido Dagan 2006], is usually defined as the task of determining whether the premise has a relation of *entailment*, *neutral*, or *contradiction* with the hypothesis [Ido Dagan 2006; Zhou and Bansal 2020; Zylberajch et al. 2021]. According to [Ido Dagan 2006], a premise entails a hypothesis if a human reading the premise would infer that the hypothesis is most likely true. For example, given a premise "*iPhone13 has seen strong sales in China*." and a hypothesis "*Strong sales for iPhone13 in China*.", their relation should be *entailment*. That is, the given premise entails the hypothesis. In contrast, the relation would be *contradiction* if the hypothesis is "*iPhone13 is not popular in China*", and the relation would be *neutral* if the hypothesis is "*Strong sales for iPhone13 in Japanese*.".

Recently, there are many large-scale standard datasets released, like SciTail [Khot Tushar 2018], SNLI [Bowman et al. 2015], Multi-NLI [Williams et al. 2018], etc. These datasets facilitate the study of NLI greatly, and some state-of-the-art neural models have achieved very competitive performance on these datasets [Belinkov et al. 2019; Chen et al. 2021b; Jiang et al. 2021; Meissner et al. 2021; Zhou and Bansal 2020]. From the definition of NLI we can see that it is based on (and assumes) common human understanding of language as well as common background knowledge, thus it has been considered by many as an important evaluation measure for language understanding [Bowman et al. 2015; Ido Dagan 2006; Williams et al. 2018; Zylberajch et al. 2021]. Accordingly, more and more researchers use the NLI task into diverse downstream applications with the expectation that NLI would be useful for these downstream applications. For example, [Welleck et al. 2019] use the NLI models to improve the consistency of a dialogue model where utterances are re-ranked using a NLI model. [Falke et al. 2019] use the entailment predictions of NLI models to re-rank the generated summaries of some state-of-the-art models. [Huang et al. 2021] use the NLI models to improve unsupervised commonsense reasoning. [Koreeda and Manning 2021] use the NLI models to assist contract review.

Like our method, [Chen et al. 2021a] also use an NLI model in their MRC model. But they aim to train NLI models to evaluate the predicted answers by an MRC model. Specifically, they leverage large pretrained models and recent prior datasets to construct powerful question conversion and decontextualization modules, which can reformulate question-answer instances as premise-hypothesis pairs with very high reliability. Then, they combine standard NLI datasets with the NLI examples automatically derived from MRC training data to train the NLI model.

Essentially, our model makes full use of the advantages in diverse existing research lines, but pays more attention to precisely *understanding* the semantic meanings of questions and passages.



Fig. 2. The Architecture of Our Model.

3 METHODOLOGY

In this study, both the issues of over-sensitivity and over-stability are viewed as a *semantic meaning understanding* problem. On the other hand, according to the task definition of NLI we can draw the conclusion that if two sentences have the same semantic meaning, they would always be assigned an *entailment* relation. Inspired by this, we convert the traditional NLI task into the task of judging whether two questions have the same semantic meaning. Concretely, we roughly regard the *entailment* relation between two sentences as an equivalent alternative for the relation of *having the same semantic meaning*. That is, we think two sentences would have an *entailment* relation if they have the same semantic meaning, and they would have a *contradiction* relation if they do not have the same semantic meaning. Furthermore, to make our MRC model be sensitive to subtle semantic changes, the converted NLI task is combined with the MRC task with a *multi-task learning* framework. Finally, the architecture of our model is shown in Fig. 2. It has three main modules: (i) a encoder module (Fig. 2(b)); (ii) an MRC module (Fig. 2(c)); (iii) an NLI module (Fig. 2(a)).

For description convenience, here we first give some basic notations about the MRC module. Given a passage with *n* tokens (denoted as $p = \{p_i\}_{i=1}^n$) and a question with *m* tokens (denoted as $q = \{q_j\}_{j=1}^m$), an MRC model is to predict an answer *a* that is constrained as a contiguous span in *p*, i.e., $a = \{p_i\}_s^e$, where *s* and *e* indicate the beginning and ending positions of the answer. The training set of an MRC task can be denoted as $\mathcal{D}^M = \{(p^i, q^i, a^i)\}_{i=1}^M$ where *M* is the number of samples. In this set, each sample consists of a passage *p*, a question *q* and an answer *a*.

3.1 Shared Encoder Module

In our model, we use RoBERTa [Liu et al. 2019] as the shared encoder module to generate representations for the inputs of both MRC and NLI. This encoder module will output a context-aware representation for each token of the input text. Both NLI and MRC take text pairs as input (NLI takes question pairs as inputs and MRC takes *passage-question* pairs as inputs), so for simplicity, here we use S_l and S_r to denote the two text parts of an input text pair and denote the output of this encoder module as **H** which is computed by Equation 1.

$$\mathbf{H} = \operatorname{RB}([\langle CLS \rangle \oplus S_l \oplus \langle Sp \rangle \oplus S_r \oplus \langle Sp \rangle]) \tag{1}$$

where RB denotes the RoBERTa model, *<CLS>* is a padding token, *<Sp>* is a separator token defined to separate the token sequences of S_I and S_r , and \oplus denotes the concatenation operation.

The padded question representation sequence $\mathbf{H}_Q = \{\boldsymbol{h}_1^q, ..., \boldsymbol{h}_m^q, \boldsymbol{h}_{<Sp>}, \boldsymbol{0}_1, ... \boldsymbol{0}_{n+1}\}$ and the padded passage representation sequence $\mathbf{H}_P = \{\boldsymbol{0}_1, ... \boldsymbol{0}_{m+1}, \boldsymbol{h}_1^p, ..., \boldsymbol{h}_n^p, \boldsymbol{h}_{<Sp>}\}$ are used for the subsequent operations in the MRC module. Here $\boldsymbol{0}_i$ is a padded zero vector whose items are all zeros. Obviously, after the padding operations, \mathbf{H}_P and \mathbf{H}_Q have the same vector dimension.

Note the notations in Fig. 2(b) (like *segment encoding, positional encoding*, etc) have completely the same meanings as those defined in the original paper of BERT [Devlin et al. 2018] or RoBERTa [Liu et al. 2019], so one can read these original papers for detailed information.

3.2 MRC Module

The structure of our MRC module is shown in Fig. 2(c). It consists of N identical computation blocks followed by a multi layer perception (MLP) based output layer. Each computation block has three components: (i) a multi-head self-attention component that is used to compute a kind of self-aware representations for the input question and passage, with which the model could "see" the entire context information; (ii) a "memory-guided interaction mining" component that can mine richful interactions between question and passage; and (iii) a softmax based output component.

Our MRC module is based on the decoder component in RoBERTa, thus as shown in Fig. 2(c), it has a similar structure as that in *Transformer*'s decoder [Vaswani et al. 2017]. The main difference between our model and the original decoder in *Transformer* lies in the second component.

Multi-head Self-Attention Component. Here we denote the outputs of this component at the *l*-th computation block as \mathbf{R}_Q^l and \mathbf{R}_P^l , which are the generated vector representations of the input question and passage respectively. And they are computed by the following Equation 2.

$$\mathbf{R}_{O}^{l} = MultiHeadSelfAttention(\mathbf{H}_{Q}); \qquad \mathbf{R}_{P}^{l} = MultiHeadSelfAttention(\mathbf{H}_{P})$$
(2)

In above equation, the computation method for the *multi-head self-attention* operation is the same as the one in *Transformer*'s decoder [Vaswani et al. 2017], thus readers can read the original paper of *Transformer* for more detailed information if necessary.

Memory-Guided Interaction Mining Component. Here we design a *memory-guided multi-head* attention method to mine the interactions between the input question and passage. Its structure is shown in the right part of Fig. 3 where "*query*" and "*key*" denote the representations of question and passage respectively. During the interaction mining process, both "*query*" and "*key*" are dynamically updated guided by "*value*". "*value*" stores some "*memory*" information about the input question and passage, and would keep unchanged during the interaction mining process.

The basic component in this proposed interaction mining method is a "*memory-guided attention unit*" whose structure is shown in the left part of Fig. 3. We can see that this component first computes two kinds of attentions: one is a *key-to-query* attention (denoted as *k2qAtt* in Fig. 3), and the other is a *query-to-key* attention (denoted as *q2kAtt* in Fig. 3). Then these two kinds of attentions are integrated with the "*value*" part.

Formally, we use use Q, K, and V to denote the vector representations of "query", "key", and "value" respectively. Then the "memory-guided attention unit" computes the attention with Equation



Fig. 3. Illustration of the Memory-Guided Multi-Head Attention method.

3, where *d* is the scaling factor as the one defined in *Transformer*.

MemAtt (Q, K, V) =
$$[softmax\left(\frac{QK^{\top}}{\sqrt{d}}\right) + softmax\left(\frac{KQ^{\top}}{\sqrt{d}}\right)]V$$
 (3)

We denote $\mathbf{H} = \mathbf{H}_{\mathbf{P}} + \mathbf{H}_{\mathbf{Q}}$ (here "+" is an element-wise add operation, note as described in the section 3.1, $\mathbf{H}_{\mathbf{P}}$ and $\mathbf{H}_{\mathbf{Q}}$ have been padded into the same dimension). Based on \mathbf{H} , we define "value" as $\mathbf{HW}^{\mathbf{V}}$. Accordingly, the "memory-guided multi-head attention" at the *l*-th computation block can be written with following Equation 4 and 5, where *h* is the number of the heads (we set *h* to 8 in experiments), \mathbf{W}_{i}^{Q} , \mathbf{W}_{i}^{K} , \mathbf{W}_{i}^{V} , \mathbf{W}^{O} are trainable parameter matrices for the *i*-th head, and *ReLU* is the activation function that is widely used in diverse neural models.

$$\mathbf{O}_{\mathbf{mrc}}^{\mathbf{l}} = ReLU(Concat(\text{head}_{1}^{\mathbf{l}}, ..., \text{head}_{\mathbf{h}}^{\mathbf{l}})\mathbf{W}^{O})$$
(4)

$$head_{i}^{l} = MemAtt\left(\mathbf{R}_{Q}^{l}\mathbf{W}_{i}^{Q}, \mathbf{R}_{P}^{l}\mathbf{W}_{i}^{K}, \mathbf{H}\mathbf{W}^{V}\right)$$
(5)

From above process we can see that during training, as the computation blocks iterated, both **Q** and **K** are repeatedly updated, while **V** keeps unchanged and will be reloaded at each iteration.

Compared with the multi-head attention method used in *Transformer* [Vaswani et al. 2017], there are two important improvements in our method. First, it computes a kind of cross attentions that mine interactions from both the directions of "*query to key*" and "*key to query*", which can mine more richful and comprehensive interactions between questions and passages. This process is somewhat like a human's reading pattern that understand the semantic meanings of questions by taking passages as context, and vice versa. So it would be much helpful for *understanding* the semantic meanings of questions and passages. Second, its whole process is guided by a memory cell H where the original information of the question and passage is stored. This is very necessary for an MRC task: without H, the mined interactions would "*forget*" more and more original input information as the computation blocks iterated. However, the original information is the foundation of interactions, so "*forget*" them will increase the risk that the mined interactions are actually irrelevant to what are needed. In fact, setting a memory cell to store original input information is in line with a human's reading pattern that keeping the input text in mind when finding the answer. So our interaction mining method is superior to existing methods like BiDAF [Seo et al. 2016] or the original decoder in *Transformer* [Vaswani et al. 2017] by nature since lots of existing researches

have proven that imitating human's reading patterns in an MRC model always brings performance gains (see previous *Related Work* section for details).

Output Component. As shown in Fig. 2 (c), the output of the last computation block in the *memory guided interactions mining* component will be fed into a feed forward network in each computation block. We denote this output as O_{mrc}^{N} . Then we perform two *softmax* based operations to predict the probabilities of each token in the passage being the start and end positions of an answer with following Equation 6, where W_s , W_e , b_s , and b_e are learnable parameters.

$$P_{s} = softmax(\mathbf{W}_{s}\mathbf{O}_{mrc}^{N} + b_{s});$$

$$P_{e} = softmax(\mathbf{W}_{e}\mathbf{O}_{mrc}^{N} + b_{e})$$
(6)

Finally, following loss function is defined to train the MRC module, where a_i^s and a_i^e denote the start and end positions for the answer of the *i*-th sample.

$$\mathcal{L}_{MRC} = -\frac{1}{2M} \sum_{i}^{M} \left[log(P_s^{a_i^s}) + log(P_e^{a_i^e}) \right]$$
(7)

3.3 NLI Module

As analyzed above, we convert the traditional NLI task into the task of judge whether two question have the same semantic meaning. Accordingly, it is a natural way to design a classification based NLI module here. Specifically, the training set for the converted NLI task can be denoted as $\mathcal{D}^N = \{(s_1^i, s_2^i, s^i)\}_{i=1}^N$ where N is the number of samples. In this set, each sample consists of following three items: the first sentence s_1 , the second sentence s_2 , and the answer s ($s \in \{0, 1\}$) whose value indicates whether these two sentences have the same semantics meaning or not.

In BERT (or other pre-trained language models like RoBERTa) based models, the embedding representation of the padding token *CLS* is believed to contain the global information of the whole input text. Thus, here $h_{<CLS>}$ (the context-aware vector representation of <CLS>, see the descriptions in the 3.1 section) is used as a contextualized sentence-level representations of the input two questions. Taking $h_{<CLS>}$ as input, the NLI module uses following affine function to score the probability of the two input sentences having the same semantic meaning.

$$\hat{y} = softmax \left(\mathbf{w}\boldsymbol{h}_{\langle CLS \rangle} + b\right) \tag{8}$$

where \mathbf{w} and b are learnable parameter.

Finally, following loss function is defined to train the NLI module, where $y_i \in \{0, 1\}$ denotes the true label for the *i*-th sample.

$$\mathcal{L}_{NLI} = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)]$$
(9)

3.4 Multi-Task and Multi-Language Learning

We use a multi-task learning framework to train the modules of MRC and NLI simultaneously. The whole loss function is defined with Equation 10.

$$\mathcal{L} = \alpha \mathcal{L}_{NLI}(\theta_N, \theta_S) + \beta \mathcal{L}_{MRC}(\theta_M, \theta_S)$$
(10)

where α and β are two hyperparameters which are set to 0.5 and 1 respectively in our experiments, θ_S represents the task-independent parameter set shared by the modules of MRC and NLI, θ_M and θ_N are the task-dependent parameter sets for the MRC module and the NLI module respectively.

Besides, as analyzed above that an MRC model tends to perform well on in-domain test sets but perform poorly on out-of-domain test sets, which is mainly caused by the similar distributions

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Algorithm 1 Algorithm of the Multi-Task and Multi-Language Learning.

Require: the NLI dataset \mathcal{D}^N and the mixed MRC dataset $\mathcal{D}^M = \{\mathcal{D}_{lg_1}^M, \mathcal{D}_{lg_2}^M, ..., \mathcal{D}_{lg_k}^M\}$ where each sub-dataset corresponds to an MRC dataset of a specific language.

Ensure:

- 1: Preprocessing: compute a Bernoulli distribution based sampling probability for each sub-dataset in the mixed MRC dataset according to the ratio of the number of samples in this sub-dataset to the total number of samples in the mixed MRC dataset.
- Sampling: randomly select which task to be trained. If NLI is selected, randomly select a sample from D^N. Else, select a sample from an MRC sub-dataset according to its sampling probability.
- 3: Generate a batch: repeat above sampling step until selecting a predefined number of samples to build up a batch *B*.
- 4: Training: joint train the MRC and NLI modules on *B* with the multi-task learning based method.
- 5: Iteration: repeat above steps of 2-4 until reaching the predefined training epoch.

between training sets and test sets. To overcome this issue, we generate a mixed MRC training set which consists of several MRC training sets of different languages. Then the MRC module is trained based on the samples in this mixed training set. For example, one can form a mixed training set by combining an English MRC training set with a Chinese MRC training set, but still testing the MRC model on an English test set (or a Chinese test set). By this way, the distributions of the training set and the test set will be completely different, which will push the MRC model learn more generalized knowledge during training because none of a specific language's training set could dominant the process of model training. Accordingly, the generalization issue will be alleviated greatly. We call this new training method as *multi-language learning*, it is then combined with the multi-task learning method to form a new *multi-task and multi-language learning* mechanism.

Specifically, the detailed process of this new learning mechanism is shown in Algorithm 1. The input of this algorithm includes an NLI dataset and a mixed MRC dataset. In the *multi-task learning* mechanism, the samples of different tasks are randomly selected. However, for the mixed MRC dataset, if its sub-datasets of different languages have the same probability of being used as a data source to select training samples, the samples in the smaller sub-datasets would be over-trained while the samples in the larger sub-datasets would be under-trained. To overcome this problem, we assign different selected probabilities for the sub-datasets of different languages. Our basic idea is that the larger the number of a sub-dataset, the more possible its samples should be selected. In our algorithm, we design a Bernoulli distribution based method to compute a *sampling probability* for each sub-dataset in the mixed MRC dataset, as shown in the *Preprocessing* step in our algorithm. Based on these probabilities, the samples in different sub-datasets in the mixed MRC dataset are selected and batched with the samples in the NLI dataset, then the batched samples are jointly trained with the *multi-task learning* mechanism. To more clearly demonstrate our Algorithm 1, we further use Fig. 4 to illustrate its whole learning process with some concrete samples.

It should be noted that our *multi-language learning* does not focus on the effort of making a model "*see*" some samples that are expected to be present during testing. Thus it is much different from existing data augmentation based methods. Beside, our *multi-language learning* is also much different from some existing models like the one that uses *multi-lingual pre-trained language models* [Hsu et al. 2019] or the one that uses *cross-lingual pre-trained language models* [Nuo Chen 2022]. Although all of these existing models are trained on datasets of a source language but tested on datasets of a target language, all of them heavily depend on the pre-trained *multi-lingual*



Fig. 4. Illustration of the multi-task and multi-language learning.

or *cross-lingual* language models. In contrast, our method does not use any of these kinds of language models. During training, the tokens of different languages learn their own embedding representations, while the model parameters are shared among samples of different languages. If a token could not be found in the vocabulary of a pre-trained language model, it would be regarded as an out-of-vocabulary token and its embedding would be randomly initialized and updated during model training. As the study of [Hsu et al. 2019] shows that tokens from different languages might be embedded into the same space with close spatial distribution. Their study further shows that even though during the fine-tuning only data of a specific language is used, the embedding of tokens in another language changed accordingly. These results show that the *multi-language learning* does have the capability of pushing the model learn more generalized knowledge during training, which is much helpful for alleviating the mentioned *generalization* issue.

4 **EXPERIMENTS**

4.1 Experimental Settings

MRC Datasets In this study, we evaluate the performance of our model on the following benchmark MRC datasets, all of which are designed to measure the robustness of an MRC model, including the abilities of addressing the issues of over sensitivity, over stability and generalization.

(i) **DuReader (robust).** DuReader (robust) [Tang et al. 2021] is a large benchmark Chinese MRC dataset released in the MRC Competition of "2020 Language and Intelligence Challenge¹" (LIC-2020). It is a variant of DuReader [He et al. 2018] and is designed to measure an MRC model's ability for addressing the issues of over sensitivity, over stability and generalization. Its training and development sets consist of 15K and 1.4k samples respectively. In these two sets, the questions are all real questions issued by users in *Baidu* search engine. The passages are extracted from the search results of *Baidu* search engine and *Baidu Zhidao* (a question answering community).

The test set of DuReader (robust) includes four subsets. (i) *In-domain subset*: the construction method and source of this subset is the same as the training set and the development set. (ii) *Over*

¹https://aistudio.baidu.com/aistudio/competition/detail/28

sensitivity subset: the samples in this subset are randomly sampled from the *in-domain* subset. The new samples are constructed by paraphrasing the questions. But the questions generated here are all real questions asked by users in *Baidu* search engine. (iii) *Over stability subset*: the samples in this subset are sampled from the *in-domain* subset by rules, but annotated by human experts. The passages in this subset are all real passages. (vi) *Generalization subset*: the samples in this subset have a different distribution from that of the training set. The samples include real questions and passages extracted from *educational* and *financial* passages. There are 1.3K, 1.3K, 0.8K, and 1.6K samples in these four subsets respectively.

DuReader (robust) divides its test set into two versions. The first one consists of most of samples in the in-domain subset and a small portion of samples in the other three robustness subsets. And the second one consists of all the four subsets. For convenience, we denote these two versions' test sets as Test1 and Test2 respectively. It should be noted that DuReader (robust) DOES NOT release its answer labeled test set to avoid models achieve overestimated performance by a test set guided training. Instead, researchers have to submit their results to the competition organizers so that the performance of their models can be evaluated.

(ii) SQuAD-related Datasets. To explore the robustness of MRC models, [Gan and Ng 2019] create two TEST sets consisting of paraphrased questions that are generated by taking some questions in the development set of SQuAD 1.0 [Rajpurkar et al. 2018] as source questions. The first test set is a non-adversarial paraphrased set that is generated with a neural paraphrasing model trained on a dataset where each sample has a tuple form of (*source question, multiple paraphrase suggestions*). The paraphrased results in this test set are subsequently verified by human annotators. The second one is an adversarial paraphrased test set that is generated manually by going through question and context pairs from the SQuAD development set and re-writing the question using context words near a confusing answer candidate if such a candidate exists and there are suitable nearby context words for use in paraphrasing. We denote these two test sets as SQuAD (Non-Adv-Paraphrased) and SQuAD (Adv-Paraphrased) respectively. The first test set consists of 1,062 questions and the second test set consists of 56 questions.

NLI Dataset Here LCQMC² [Liu et al. 2018a] is used as the training set for the NLI module. LCQMC is a dataset that focuses on the intent matching of two sentences. Thus it is suitable to be used to train our NLI module. Totally, this dataset contains 260,068 question pairs with manual annotations. And it is divided into three parts: a training set that contains 238,766 question pairs, a development set that contains 8,802 question pairs, and a test set that contains 12,500 question pairs.

Multi-language Learning Setting In the multi-language learning, we use SQuAD 1.0 as an auxiliary MRC dataset. SQuAD 1.0 is a widely used large scale English MRC benchmark dataset. Here we select it mainly due to the following two reasons. First, both SQuAD 1.0 and DuReader (robust) belong to the single-passage MRC dataset³. Second, the average lengths of passages in both datasets are close. These two characteristic of SQuAD 1.0 allow us to concentrate on the robustness issues other than some data preprocessing work. Besides, there are more than 100,000 questions in SQuAD 1.0, which will make the distributions of the training set and the test set different greatly. Thus it helps to provide an ideal platform to evaluate the generalization of an MRC model.

Other Settings A Chinese RoBERTa [Cui et al. 2019] is used as the required *shared encoder module*. In subsequent sections, for all the mentioned language models, we use their large versions. The ensemble model is obtained by averaging 4 single models' prediction probabilities. Extract match (EM) and F1 are used as evaluation metrics. During training, AdamW [Kingma and Ba 2015] is used

²http://icrc.hitsz.edu.cn/info/1037/1146.htm

³There is a kind of multi-passage (also called multi-document) MRC datasets that provides multiple passages (or documents) for each question, like DuReader, MS MARCO, TriviaQA (web) [Joshi et al. 2017], etc.

Test1						
Model	F1	EM				
BERT (zh) [Devlin et al. 2018]	70.74	54.45				
XLNet (zh) [Yang et al. 2019]	68.79	53.70				
RoBERTa (zh) [Cui et al. 2019]	73.76	56.75				
Our Model (Single)	80.39	66.55				
Our Model (Ensemble)	82.70	68.50				
Test2						
Our Model (Ensemble)	79.45	64.76				

Table 1. Main Results on DuReader (robust).

Table 2. Ablation Experiments on Test1 of DuReader (robust). "- *Memory-Guided Multi-head Attention*" means replacing it with a common multi-head attention method as used in *Transformer's* decoder. "*zh*" denotes the corresponding model is a Chinese version.

Model	F1	EM
Our Model (Single)	80.39	66.55
- NLI module	76.26	60.6
- Multi-language learning	77.47	62.8
- Memory-Guided Multi-head Attention	78.65	64.5

to train our model and word embeddings are not updated. Based on the results on development sets, the learning rate, batch size, and training epoch are set to 0.001, 16, and 3 respectively.

4.2 Experiments on DuReader (robust)

Main Results The main results on DuReader (robust) are shown in Table 1. On Test1, we can see that our model achieves much better results than all the compared strong baselines. Especially, our model achieves much better results than RoBERTa which has achieved much better results than many existing Chinese pre-trained models (like BERT and ERNIE [Sun et al. 2019a]) on various natural language processing tasks including several Chinese MRC tasks [Cui et al. 2019]. These results show that our model is very effective and it can better address the robustness issues.

In fact, we participated in the MRC Competition of LIC-2020. Finally, our model ranked **NO.2** on the test set leader board of Test1. On Test2, our model achieved very competitive results again: it ranked **No.3** on this full DuReader (robust) test set leader board⁴.

Note that there are no detailed comparison results on Test2. This is because the final competition results of LIC-2020 were decided by the results on Test2. And LIC-2020 took a closed way to evaluate an MRC model's performance: researchers must submit their results within a specified deadline, and there was a submission limit per system per day. Thus, researchers usually tried to find the best model based on the results on Test1, and then tried to obtain the best results on Test2 by tuning the selected model. In other words, there was almost no chance for researchers to compare the performance of different models on Test2.

Now, the competition of LIC-2020 was closed, thus we could not make more detailed comparisons with the latest state-of-the-art MRC models. And we leave such comparisons in subsequent sections.

⁴Here we could not compare our model with the top 2 models, because we could not find any papers about their model details either in conferences, journals, or on arXiv.



Fig. 5. A Case Study (The words with the same color have the same meaning.).

Ablation Results To demonstrate the contributions of different modules in our model, we conduct ablation experiments on Test1 and the results are shown in Table 2.

From these results we can draw following conclusions. First, each component of our model is helpful for improving the performance. Second, NLI plays more roles than the other two modules, which indicates that the key of developing a robust MRC model is to precisely *understand* the semantic meanings of input questions. Third, introducing a completely different language's MRC training set is helpful for improving the robustness of an MRC model. Fourth, the proposed *memory-guided multi-head attention* is effective for addressing the robustness issues and it performs better than the traditional *multi-head attention* method.

Case Study Fig. 5 illustrates a case study of our model. In this example, the semantic meanings of two questions (Q1 is the source question and Q2 is the paraphrased question) are the same. We can see that if we do not use the NLI module, the model (*"Single Task Model"* in Fig. 5) outputs a wrong answer for the paraphrased question (Q2). In contrast, the full model precisely distinguishes the semantic meanings of these two questions and outputs correct answers for both of them. These results further confirm the effectiveness of the proposed model for addressing the robustness issues.

4.3 Experiments on SQuAD-related Datasets

On SQuAD (Non-Adv-Paraphrased) and SQuAD (Adv-Paraphrased), we evaluate the robustness of our model based on following two kinds of extreme evaluations: (i) testing our model that is designed for DuReader (robust) on these two English test sets directly; and (ii) comparing an English version of our model with the models that are retrained by a data augmentation based method.

Obviously, both kinds of evaluations are significant unfair to our model. For the first kind of evaluation, although there is a multi-language learning mechanism, most of the modules in our model, including the shared encoder module and the NLI module, are trained on Chinese datasets. For the second kind of evaluation, our model would not use any additional training data while some compared baselines would be retrained by the data augmentation based method. However, we think both kinds of evaluations are very meaningful: the first kind of evaluation provides an ideal scenario to evaluate the generality ability of an MRC model because the distributions of training sets and test sets are completely different; and the second kind of evaluation provides an ideal scenario to evaluate the true potentiality of an MRC model for addressing the robustness issues because the data augmentation based methods are not always available, especially in some cases where constructing the augmented data is time-consuming and high-cost.

In subsequent experiments, we use the single version of our model for evaluations, and all the models marked by \dagger denote their corresponding results are directly copied from [Gan and Ng 2019].

Table 3. Extreme Evaluations 1 (a): on SQuAD (Non-Adv-Paraphrased). S-Questions and P-Questions refer to the source questions from SQuAD's development set and their corresponding paraphrased questions respectively.

	E	М	F1		
Model	S-Questions P-Questions		S-Questions	P-Questions	
BiDAF [†] [Seo et al. 2016]	67.8	63.84	76.85	73.51	
DrQA [†] [Chen et al. 2017]	67.33	65.25	76.25	74.25	
BERT [†] [Devlin et al. 2018]	83.62	79.85	90.78	87.63	
Our Model	77.91	76.90	87.38	85.87	

Table 4. Extreme Evaluations 1 (b): on SQuAD (Adv-Paraphrased). S-Questions and A-Questions refer to the source questions from SQuAD's development set and their corresponding adversarial paraphrased questions respectively.

	E	М	F1		
Model	S-Questions A-Questions		S-Questions	A-Questions	
BiDAF [†] [Seo et al. 2016]	75	30.36	81.55	38.3	
DrQA [†] [Chen et al. 2017]	71.43	39.29	81.02	48.94	
BERT [†] [Devlin et al. 2018]	82.14	57.14	89.31	63.18	
Our Model	77.36	56.79	85.74	62.22	

Extreme Evaluation 1. The results of the first kind of extreme evaluation are shown in Table 3 and 4. We can see that on both test sets, our model achieves very competitive results. First, when compared with the models that are fully trained under the common settings, our model achieves significant better results than DrQA and BiDAF. Our model also achieves close results to the well trained BERT on the robust parts (denoted as *P-Questions* and *A-Questions* in Table 3 and 4) of the two datasets. Second, the source questions (denoted as S-Questions in Table 3 and 4) in SQuAD (Non-Adv-Paraphrased) and SQuAD (Adv-Paraphrased) form two common MRC datasets, and our model performs much well on them. These results indicate that our model is effective on both the robustness datasets and the common datasets even under an extreme and unfair evaluation.

It should be noted that [Hsu et al. 2019] leverage the pre-trained multilingual BERT (multi-BERT) in cross-lingual zero-shot reading comprehension. That is, multi-BERT is fine-tuned on data of a language, but is tested on data of another language. Obviously, this zero-shot setting is similar to the setting of our first kind of extreme evaluation. But here we do not take multi-BERT as a baseline. This is mainly because we could not provide a fair platform for comparisons: if we fine-tune multi-BERT on DuReader (robust) but test it on the mentioned SQuAD-related datasets, it would be unfair for multi-BERT because our model uses the training set of SQuAD in the multi-language learning while multi-BERT not. This is also the reason why we do not compare our model with other state-of-the-art MRC models under this kind of extreme evaluation.

Extreme Evaluation 2. Based on the evaluation results on SQuAD (Non-Adv-Paraphrased) and SQuAD (Adv-Paraphrased), [Gan and Ng 2019] argue that the original training dataset does not contain sufficiently diverse phrased questions, which leads to the models not learning to respond correctly to various ways of asking the same question. They further argue that the capabilities of models for addressing the robustness issues can be improved by a *data augmentation* based method. So they use the similar methods as used when creating the mentioned two test sets to generate two additional training sets: the first one contains 25,000 non-adversarial paraphrased

1:16

	EM		F1		EM		F1	
Model	Before	After	Before	After	Before	After	Before	After
BERT [†] [Devlin et al. 2018]	79.85	80.89	87.63	88.62	57.14	69.64	63.18	73.85
DrQA [†] [Chen et al. 2017]	65.25	67.33	74.25	75	39.29	41.07	48.94	49.86
BiDAF [†] [Seo et al. 2016]	63.84	66.2	73.51	75.94	30.36	39.24	38.3	47.49
ALBERT-large [Lan et al. 2020]	-	83.24	-	89.85	-	69.64	-	74.68
Retro-Reader [Zhang et al. 2021]	-	82.20	-	89.40	-	69.64	-	75.04
Our Model	76.90	82.96	85.87	89.78	56.79	76.79	62.22	80.92

Table 5. Extreme Evaluation 2 (a): performance of different models before and after re-training on SQuAD (Non-Adv-Paraphrased) (the left part) and on SQuAD (Adv-Paraphrased) (the right part).

Table 6. Extreme Evaluation 2 (b): performance of different models on SQuAD (dev) before and after retraining. For the baselines marked by [†], After₁ and After₂ denote the results re-trained with additional *Non-Adv-Additional Data* and *Adv-Additional Data* respectively. For other baselines and our model, we use After₁ to denote their English versions.

		EM			F1	
Model	Before	$After_1$	$After_2$	Before	$After_1$	After ₂
BERT [†] [Devlin et al. 2018]	84.02	83.76	83.33	91	90.88	90.49
DrQA [†] [Chen et al. 2017]	69.04	68.74	67.93	78.38	77.86	77.45
$BiDAF^{\dagger}$ [Seo et al. 2016]	67.67	67.49	66.23	77.46	77.1	76.19
ALBERT-large [Lan et al. 2020]	-	84.56	-	-	91.63	-
Retro-Reader [Zhang et al. 2021]	-	84.09	-	-	91.09	-
Our Model	78.42	85.50	-	87.35	92.46	-

questions, and the second one contains 25,000 adversarial paraphrased questions. For simplicity, we denote these two additional training sets as *Non-Adv-Additional Data* and *Adv-Additional Data*, and denote the original training set and development set of SQuAD as SQuAD (training) and SQuAD (dev). With these additional data, [Gan and Ng 2019] report following four kinds of comparison results to demonstrate the effectiveness of the data augmentation method. (i) On SQuAD (Non-Adv-Paraphrased), the results of models between trained with SQuAD (training) and "SQuAD (training) + *Non-Adv-Additional Data*"; (ii) On SQuAD (Adv-Paraphrased), the results of models between trained with SQuAD (training) and "SQuAD (training) + *Non-Adv-Additional Data*"; (iii) On SQuAD (training) + *Adv-Additional Data*"; (iii) On SQuAD (training) and "SQuAD (training) an

Instead, we make another kind of extreme evaluation by comparing the English version of our model with the models retrained by using the mentioned two additional training sets. To this end, we make two modifications on our model. First, we use the Quora Question-pair dataset⁵ as the training set for the NLI module. Second, we change RoBERTa to its English version. Besides, we also take several state-of-the-art models as baselines. In experiments, to make a fair comparison,

⁵https://www.kaggle.com/c/quora-question-pairs/data?select=train.csv.zip

	P-Questions		A-Que	estions	SQuAD (dev)	
Model	EM	F1	EM	F1	EM	F1
multi-BERT	76.65	83.94	58.93	66.26	81.39	88.57
Our Model	82.96	89.78	76.79	80.92	85.50	92.46

Table 7. Results of multi-BERT. P-Questions and A-Questions refer to the paraphrased questions in SQuAD (Non-Adv-Paraphrased) and adversarial questions in SQuAD (Adv-Paraphrased) respectively.

we replace the version of AlBERT used in Retro-Reader [Zhang et al. 2021] from *xxlarge* to *large* since as mentioned previously that for all the language models, we use their large versions.

Finally, the comparison results are shown in Table 5 and 6. We can see that the English version of our model achieves very competitive results again on all these three test sets. First, when compared with the models that are retrained by the *data augmentation* based method, we can see that on both SQuAD (Non-Adv-Paraphrased) and SQuAD (Adv-Paraphrased), the performance of our model is far better than the models like DrQA or BiDAF. And the results of our model are also better than the data augmentation retrained BERT. Second, when compared with the models that could not use the additional training data either, we can see that on both SQuAD (Non-Adv-Paraphrased) and SQuAD (Adv-Paraphrased), our model achieves much competitive results: its results are the best or very close to the best. Third, [Gan and Ng 2019] have pointed out that although the data augmentation based method is usually helpful for models achieve better results on the paraphrased test sets, it always causes a negligible drop to the performance of models on the original development set. However, from the results in Table 6 we can see that on SQuAD (dev), a common MRC dataset, our model achieves better results than all the compared baselines. These results demonstrate an important merit of our model that although it is designed for addressing the robustness issues, there is almost no any negative affects to the performance when it is used to handle common MRC datasets. In a word, our model is a very strong and is competent for diverse application scenarios.

Furthermore, as mentioned above that [Hsu et al. 2019] leverage the pre-trained multi-BERT in cross-lingual zero-shot reading comprehension, which has a similar scenario settings to the robustness issues here because both of them aim to evaluate the performance of models when the distributions of training sets and testing sets are different. Thus there would be a concern that whether multi-BERT would also perform well on addressing the robustness issues in MRC. To answer this concern, we further conduct experiments to demonstrate the performance of multi-BERT⁶ on these SQuAD-related datasets. Specifically, we fine-tune multi-BERT on SQuAD (training), and test it on the mentioned test sets. Here we think it is fair to compare multi-BERT with our model because both models use SQuAD (training) and some multi-lingual resources. Finally, the results are shown in Table 7. We can see that our model achieves far better results than multi-BERT on all datasets. These results indicate that a straightforward multilingual language model based method could not address the robustness issues in MRC well.

5 CONCLUSIONS

In this study, we propose an *understanding-oriented* MRC model that can well address the issues of over sensitivity, over stability, and generalization. We conduct extensive experiments to evaluate it on three benchmark MRC robustness datasets. Experimental results show that it achieves consistent better results not only on all of these robustness MRC datasets, but also on some common MRC datasets. Even on some extreme and unfair evaluations, it still achieves much better results.

⁶https://github.com/google-research/bert

The main novelties of our model is summarized as follows. First, to the best of our knowledge, this is the first work that systematically addresses all three kinds of robustness issues simultaneously from the model level. Second, we propose a *memory-guided multi-head attention* method that can mine better interactions between questions and passages. Third, we propose a multi-task and multi-language learning based method to integrate the NLI task and the multi-language MRC task together, which is proven to be much effective for addressing the robustness issues in MRC.

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