DUMA: Reading Comprehension with Transposition Thinking

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Abstract

Multi-choice Machine Reading Comprehension (MRC) requires model to decide the correct answer from a set of answer options when given a passage and a question. Thus in addition to a powerful Pre-trained Language Model (PrLM) as encoder, multi-choice MRC especially relies on a matching network design which is supposed to effectively capture the relationships among the triplet of passage, question and answers. While the newer and more powerful PrLMs have shown their mightiness even without the support from a matching network, we propose a new DUal Multi-head Co-Attention (DUMA) model, which is inspired by human's transposition thinking process solving the multi-choice MRC problem: respectively considering each other's focus from the standpoint of passage and question. The proposed DUMA has been shown effective and is capable of generally promoting PrLMs. Our proposed method is evaluated on two benchmark multi-choice MRC tasks, DREAM and RACE, showing that in terms of powerful PrLMs, DUMA can still boost the model to reach new state-of-the-art performance.

Introduction

Machine Reading Comprehension has been a heated topic and challenging problem, and various datasets and models have been proposed in recent years (Trischler et al. 2017; Zhang et al. 2018a; Nguyen et al. 2016; Rajpurkar et al. 2016; Hermann et al. 2015; Sun et al. 2019a; Lai et al. 2017; Zhang et al. 2018b; Zhu et al. 2018b; Zhang et al. 2020b; Bhargav et al. 2020; Hu et al. 2019). For the tasks of MRC, given passage and question, the task can be categorized as *generative* and *selective* according to its answer style (Baradaran, Ghiasi, and Amirkhani 2020). *Generative* tasks require the model to generate answers according to the passage and question, not limited to spans of the passage, while *selective* tasks give model several candidate answers

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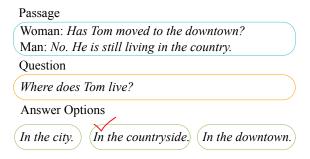


Figure 1: An example of DREAM dataset.

to select the best one. Multi-choice MRC is a typical task in *selective* type, xwhich is the focus of this paper. Figure 1 shows one example of DREAM dataset (Sun et al. 2019a), whose task is to select the best answer among three candidates given particular passage and question.

The kernel method for a model to solve MRC problem is a two-level hierarchical process, 1) representation encoding which is done by an encoder such as PrLM; and 2) capturing the relationship among the triplet of passage, question and answer which has to be carefully handled by various matching networks such as OCN (Ran et al. 2019) and DCMN (Zhang et al. 2020a). With the development of PrLMs, matching network design tends to become more complicated for more effective improvements.

Table 1 shows that as the newer variant of the PrLM such as ALBERT (Lan et al. 2020) has shown its powerfulness even without the support from a proper matching network, in the meantime, the previous models¹ (Ran et al. 2019; Kim and Fung 2020; Zhang et al. 2020a) either brings very limited improvements or even cause drop on the PrLM's (Devlin et al. 2018; Yang et al. 2019; Lan et al. 2020; Clark et al. 2020) performance, which motivates us to develop an more effective mechanism to support the powerful enough PrLMs. Instead of designing more complicated matching

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¹We re-implement OCN and WAE, and obtain codes of DCMN through personal communication with its authors. Besides, results denoted with * are from original papers.

		+OCN	+WAE	+DCMN
$\overline{\mathrm{BERT}_{\mathrm{large}}}$		71.7(+0.7)*	73.1(+2.1)	75.8(+4.8)*
	71.0			
$XLNet_{\mathrm{large}}$		80.9(+0.8)	81.8(+1.7)	82.8(+2.7)*
	80.1			
$ALBERT_{\mathrm{xxlarge}}$		87.2(+0.6)	87.3(+0.7)	85.7(-0.9)
	86.6			
$ELECTRA_{\mathrm{large}}$		86.3(+0.2)	86.9(+0.8)	84.9(-1.2)
	86.1			

Table 1: Improvements of several prior models for representative PrLMs (sorted by releasing time) on RACE dataset.

network patterns, we choose a going-back-to-the-basic way to have obtained inspiration from human experience on solving MRC problems, which intuitively is to first 1) quickly read through the overall content of passage, question and answer options to build up a global impression, followed by a transposition thinking process: 2) based on dedicated information from question and answer options, re-considerate details of the passage and collect supporting evidences for question and answer options, 3) based on dedicated information from passage, re-considerate the question and answer options to decide the correct option and exclude wrong options. When humans are re-reading the passage, they tend to extract key information according to their impression of question and answer options, and it is the same when rereading question and answer options. It can be regarded as a bi-directional process in terms of transposition thinking pattern, and we adopt an attention inside network design to simulate this procedure, whose details are shown in the following Section Model.

Since attention mechanism was proposed (Bahdanau, Cho, and Bengio 2015) originally for Neural Machine Translation, it has been widely used in MRC tasks to model the relationships between passage and question, and effectively enhances nearly all kinds of tasks (Seo et al. 2017; Zhang et al. 2018b, 2020a). Attention mechanism computes relationships of each word representation in one sequence to a target word representation in another sequence and aggregates them to form a final representation, which is commonly named as passage-to-question attention or question-to-passage attention.

Transformer (Vaswani et al. 2017) uses self-attention mechanism to represent dependencies and relationships of different positions in one single sequence, which is an effective method to obtain representations of sentences for global encoding. Since (Radford et al. 2018; Devlin et al. 2018) use it to improve the structure of PrLMs (Peters et al. 2018), many kinds of PrLMs has been proposed to constantly refresh records of all kinds of tasks (Liu et al. 2019; Lan et al. 2020). For PrLMs, the more layer and bigger hidden size they use, the better performance they achieve. Benefited from large-scale unlabeled training data and multiple stacked layers, PrLMs are able to encode sentences into very deep and precise representations. Moreover, (Lan et al. 2020) reveals the importance of generalization for models,

that is parameter sharing among layers can efficiently improve the performance. However, training a LM has been a time and labor consuming work, which usually needs amounts of engineering works to explore parameter settings. The bigger the model is, the more resource it consumes and the harder it can be implemented. Moreover, despite the great success they achieve in different tasks, we find that for MRC tasks, using self-attention of the Transformer to model sequences is far from enough. No matter how deep the structure is, it suffers from the nature of self-attention, which is only drawing a global relationship, while for MRC tasks the passage and the question are remarkable different in contents and literal structures and the relationship between them necessarily needs to be carefully considered. However, previous models (Bahdanau, Cho, and Bengio 2015; Seo et al. 2017; Zhang et al. 2020a) only obtain limited improvement when applied on the top of PrLMs even though they use very complicated structure.

Rather than seeking a complicated matching network pattern, we are inspired by the human thinking experience solving MRC problems and put forward a new network design named as **DU**al **M**ulti-head Co-**A**ttention (DUMA) to sufficiently capture relationships among passage, question and answer options for multi-choice MRC, as a result it may effectively improve the performance when cooperating with newer and more powerful PrLMs. Our model is based on the Multi-head Attention module, which is the kernel module of Transformer. Similar to BiDAF (Seo et al. 2017) and DCMN (Zhang et al. 2020a), we use the bi-directional way to obtain sufficient modeling of relationships. The contributions can be summarized as:

- 1) For multi-choice MRC tasks, we investigate effects of previous models over Pre-trained Language Models.
- 2) We propose a new **DU**al **M**ulti-head Co-**A**ttention (DUMA) model which well simulates the procedure human solving MRC tasks, and show its effectiveness and superiority to previous models through extensive experiments.
- 3) We have reached new state-of-the-art on two benchmark multi-choice MRC tasks, DREAM and RACE.

Related Works

(Bahdanau, Cho, and Bengio 2015) first propose attention mechanism for Neural Machine Translation. The jointly learning of alignment and translation effectively improves the performance. Since then, attention model has been introduced to all kinds of Natural Language Processing tasks and various of architectures has been proposed (Tu et al. 2020; Chen et al. 2019; Gao et al. 2019; Yan et al. 2019). (Seo et al. 2017) uses a multi-stage architecture to hierarchically model representation of the passage, and uses a bi-directional attention flow. These works are before PrLMs was proposed, and are able to model the representations well on the top of traditional encoder such as Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber 1997). In fact, the experimental results show that they can still improve the representations of PrLMs, but the improvements are suboptimal.

Based on PrLMs, (Ran et al. 2019) propose a method to model relationship and interaction among answer options to the benefit of distinguishing them. (Kim and Fung

2020) ensemble a model which learns to select the wrong answer. (Zhang et al. 2020a) propose a sentence selection method to select more important sentences from passage to improve the matching representations, and considers interactions among answers for multi-choice MRC tasks. Even though the matching network design becomes more complicated, it cannot fully exploit powerful PrLMs and even cause drop on performance when applied on newer PrLMs².

In a word, when applied on the top of PrLMs, previous models are not effective enough to improve the performance by a large margin. Thus inspired by the experience human solving MRC problems we design a new model which can effectively utilize well-modeled representations of PrLMs for even better performance.

Task Definition

Multi-choice MRC tasks have to handle a triplet of passage P, question Q and answer A. When given the passage and question, the model is required to make a correct answer. The passage consists of multiple sentences, and its content can be dialogue, story, news and so on, depending on the domain of the dataset. The questions and corresponding answers are single sentences, which are usually much shorter than the passage. The target of multi-choice MRC is to select the correct answer from the candidate answer set $A = \{A_1, ..., A_t\}$ for a given passage and question pair < P, Q >, where t is the number of candidate answers. Formally, the model needs to learn a probability distribution function $F(A_1, A_2, ..., A_t | P, Q)$.

Model

Figure 2 illustrates the overall architecture of our model. An encoder takes text input to form a global sequence representation, which is similar to human reading through the whole content for the first time to obtain an overall impression, and a decoder is to perform the answer prediction which is similar to human aggregating all the information to select the correct answer option. Our proposed Dual Multi-head Co-Attention (DUMA) layer is between the encoder and the decoder, which simulates human transposition thinking process to capture relationships of key information from passage, question and answer options.

Encoder

To encode input tokens into representations, we take PrLMs as the encoder. To get global contextualized representation, for each different candidate answer, we concatenate it with its corresponding passage and question to form one sequence and then feed it into the encoder. Let $P = [p_1, p_2, ..., p_m]$, $Q = [q_1, q_2, ..., q_n]$, $A = [a_1, a_2, ..., a_k]$ respectively denote the sequences of passage, question and a candidate answer, where p_i , q_i , a_i are tokens. The adopted encoder with encoding function $Enc(\cdot)$ takes the concatenation of P, Q and A as input, namely $E = Enc(P \oplus Q \oplus A)$. The encoding output E has a form $[e_1, e_2, ..., e_{m+n+k}]$, where e_i is a vector of fixed dimension d_{model} that represents the respective token.

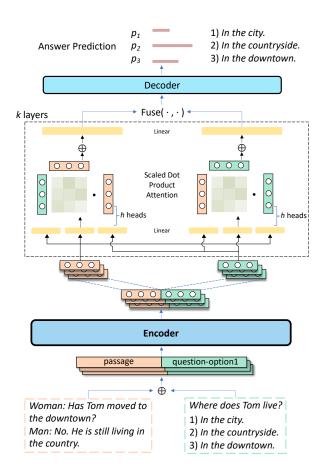


Figure 2: The overall architecture. Our proposed DUMA is between the Encoder and Decoder.

Dual Multi-head Co-Attention

We use our proposed Dual Multi-head Co-Attention module to calculate attention representations of passage and question-answer. Figure 2 shows the details of our proposed DUMA, which may be stacked as k layers. The following formula takes k = 1 for simplicity. Our model is based on the Multi-head Attention module (Vaswani et al. 2017). The proposed DUMA reuses the architecture of Multi-head Attention, while for the inputs, K and V are the same but Q is another sequence representation (Note this Q here denotes Query from the original paper, different from previous Q in this paper. And K, V are Key, Value respectively). We first separate the output representation from Encoder to obtain $E^P = [e_1^p, e_2^p, ..., e_{l_p}^p]$ and $E^{QA} = [e_1^{qa}, e_2^{qa}, ..., e_{l_{qa}}^{qa}]$, where e_i^p , e_i^{qa} denote the *i*-th and *j*-th token representation of passage and question-answer respectively and l_p , l_{qa} are the length. Then we calculate the attention representations in a bi-directional way, that is, take 1) E^P as Query, E^{QA} as Key and Value, and 2) E^{QA} as Query, E^P as Key and Value.

²As shown in Table 1.

$$\begin{aligned} & \operatorname{Attention}(E^P, E^{QA}, E^{QA}) = \operatorname{softmax}(\frac{E^P(E^{QA})^T}{\sqrt{d_k}}) E^{QA} \\ & \operatorname{head_i} = \operatorname{Attention}(E^P W_i^Q, E^{QA} W_i^K, E^{QA} W_i^V) \\ & \operatorname{MHA}(E^P, E^{QA}, E^{QA}) = & \operatorname{Concat}(\operatorname{head_1}, \dots, \operatorname{head_h}) W^O \\ & \operatorname{MHA_1} = \operatorname{MHA}(E^P, E^{QA}, E^{QA}) \\ & \operatorname{MHA_2} = \operatorname{MHA}(E^{QA}, E^P, E^P) \end{aligned}$$

$$DUMA(E^{P}, E^{QA}) = Fuse(MHA_1, MHA_2)$$
 (1)

where $W_i^Q \in \mathbb{R}^{d_{model} \times d_q}$, $W_i^K \in \mathbb{R}^{d_{model} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{model} \times d_v}$, $W_i^O \in \mathbb{R}^{hd_v \times d_{model}}$ are parameter matrices, d_q, d_k, d_v denote the dimension of Query vectors, Key vectors and Value vectors, h denotes the number of heads, $MHA(\cdot)$ denotes Multi-head Attention and $DUMA(\cdot)$ denotes our Dual Multi-head Co-Attention. The $Fuse(\cdot, \cdot)$ function first uses mean pooling to pool the sequence outputs of $MHA(\cdot)$, and then aggregates the two pooled outputs through a fusing method. In Subsection Investigation of $Fusing\ Method$, we investigate three fusing methods, namely element-wise multiplication, element-wise summation and concatenation.

As shown in the Figure 2, the left part of DUMA calculates question-answer-aware passage representation, which simulates human re-reading details in the passage with impression of question and answer, and the right part calculates passage-aware question-answer representation, which simulates re-considering the question-answer with deeper understanding of the passage. The $Fuse(\cdot,\cdot)$ function means fusing all the key information before deciding which is the best answer option.

Decoder

Our model decoder takes the outputs of DUMA and computes the probability distribution over answer options. Let A_i denote the i-th answer option, $O_i \in \mathbb{R}^l$ denote the output of i-th $< P, Q, A_i >$ triplet, and A_r denote the correct answer option, the loss function is computed as:

$$O_i = \text{DUMA}(E^P, E^{QA_i})$$

$$L(A_r|P, Q) = -\log \frac{\exp(W^T O_r)}{\sum_{i=1}^s \exp(W^T O_i)}$$

where $W \in \mathbb{R}^l$ is a learnable parameter and s denotes the number of candidate answer options.

Experiments

Our proposed method is evaluated on two benchmark multichoice MRC tasks, DREAM and RACE. Table 2 shows their data statistics, which indicates RACE is a large-scale dataset covering a broad range of domains, and DREAM is a small dataset presenting passage in a form of dialogue.

DREAM DREAM (Sun et al. 2019a) is a dialogue-based dataset for multiple-choice reading comprehension, which is collected from English exams. Each dialogue as the given

	DREAM	RACE
# of source documents	6,444	27,933
# of total questions	10,197	97,687
Train/Dev/Test split	3:1:1	18:1:1
Extractive (%)	16.3	13.0
Abstractive (%)	83.7	87.0
Average answer length	5.3	5.3
# of answers per question	3	4
Avg./Max. # of turns per dialogue	4.7 / 48	-
Avg. passage length	85.9	321.9
Vocabulary size	13,037	136,629

Table 2: Statistical data of DREAM and RACE dataset. # denotes the number. "Extractive" means the answers are spans of the passage, and "Abstractive" means the answers are not spans.

model			
	dev	test	source
BERT _{large} (Devlin et al. 2018)			
	66.0	66.8	
$BERT_{large}$ +WAE		69.0	
(Kim and Fung 2020)	-	09.0	leaderboard
XLNet _{large} (Yang et al. 2019)			
	-	72.0	
$RoBERTa_{large}$ + MMM	88.0	88.9	
(Jin et al. 2020)	00.0	00.9	
ALBERT _{xxlarge} (Lan et al. 2020)			
	89.2	88.5	
ALBERT _{xxlarge} +DUMA	89.9	90.5	aum madal
		91.8	our model
+multi-task learning(Wan 2020)	-		

Table 3: Results on DREAM dataset. Results with multitask learning are reported by (Wan 2020).

passage has multiple corresponding questions and each question has three candidate answers. The most important feature of the dataset is that most of the questions are non-extractive and need reasoning from more than one sentence, so the dataset is small but still challenging.

RACE RACE (Lai et al. 2017) is a large dataset collected from middle and high school English exams. Most of the questions also need reasoning, and domains of passages are diversified, ranging from news, story to ads.

Evaluation

For multi-choice MRC tasks, the evaluation criteria is accuracy, $acc=N^+/N$, where N^+ denotes the number of examples the model selects the correct answer, and N denotes the number of the whole evaluation examples.

model	test (M/H)	
	, ,	source
HAF (Zhu et al. 2018a)	46.0(45.0/46.4)	
MRU (Tay, Tuan, and Hui	50.4(57.7/47.4)	
2018)		
HCM (Wang et al. 2018)	50.4(55.8/48.2)	
MMN (Tang, Cai, and	54.7(61.1/52.2)	publication
Zhuo 2019)		publication
GPT (Radford et al. 2018)	59.0(62.9/57.4)	
RSM (Sun et al. 2019b)	63.8(69.2/61.5)	
OCN (Ran et al. 2019)	71.7(76.7/69.6)	
XLNet (Yang et al. 2019)	81.8(85.5/80.2)	
$XLNet_{xxlarge} + DCMN+$	82.8(86.5/81.3)	
(Zhang et al. 2020a)	62.6(60.3/61.3)	
RoBERTa + MMM	85.0(89.1/83.3)	
(Jin et al. 2020)	03.0(09.1/03.3)	
ALBERT (single)	86.5(89.0/85.5)	
(Lan et al. 2020)	00.3(09.0/03.3)	
T5*(Raffel et al. 2019)	87.1(-/-)	
UnifiedQA	89.4(-/-)	
(Khashabi et al. 2020)	09.4(-/-)	leaderboard
ALBERT(ensemble)	89.4(91.2/88.6)	
(Lan et al. 2020)	07.4(71.2/00.0)	
Megatron-BERT (single)	89.5(91.8/88.6)	
(Shoeybi et al. 2019)	02.5(21.0/00.0)	
Megatron-BERT (ensem-	90.9(93.1/90.0)	
ble)(Shoeybi et al. 2019)	70.7(73.1170.0)	
$ALBERT_{xxlarge}$	86.6(89.0/85.5)	
(Lan et al. 2020)	00.0(07.0/03.3)	
ALBERT _{xxlarge} +DUMA	88.0(90.9/86.7)	
$ALBERT_{xxlarge} + DUMA$	89.8(92.6/88.7)	our model
(ensemble)	02.0(22.0/00.7)	

Table 4: Results on RACE dataset.

model	dev	test (M/H)
$ALBERT_{xxlarge}$	87.4	86.6(89.0/85.5)
$ALBERT_{\rm xxlarge}$	88.1 (+0.7)	88.0(90.9/86.7) (+1.4)
+DUMA	00.1(10.7)	00.0(50.5700.7)(11.1)

Table 5: Comparison with ALBERT baseline on RACE dataset.

Experimental Settings

Our model takes $ALBERT_{xxlarge}$ as encoder, and use k=2 layers of DUMA. We make the left and right part of DUMA and all the layers share parameters. Using the PrLM, our model training is done through a fine-tuning way for both tasks.

Our codes are written based on Transformers³, and results of ALBERT (Lan et al. 2020), ELECTRA (Clark et al. 2020) and BERT (Devlin et al. 2018) models as baselines are our re-running unless otherwise specified.

For DREAM dataset, the learning rate is 1e-5, batch size is 8 and the warmup steps are 100. We train the model for 2 epochs in 4 hours. For RACE dataset, the learning rate is 1e-5, the batch size is 8 and the warmup steps are 1000. We train the model for 3 epochs in 2 days. For each dataset, we

model	dev	test	
ALBERT _{base}	64.51	64.43	
+Vanilla SA	66.27	66.34	
+DUMA	67.06	67.56	
+TB-DUMA	67.79	67.17	

Table 6: Comparison among vanilla Multi-head Selfattention, DUMA and TB-DUMA on DREAM dataset.

use FP16 training from Apex⁴ for accelerating the training process. We train the models on eight nVidia P40 GPUs. In the following Section *Analysis Studies*, for other re-running or re-implementation including PrLM baselines and PrLM plus other models for comparison, we use the same learning rate, warmup steps and batch size as mentioned above.

We choose the result on dev set that has stopped increasing for three checkpoints (382 steps for DREAM and 3000 steps for RACE). To obtain stable results, we run experiments 5 times with different random seeds and select the median as the ultimate performance.

Results

Tables 3, 4 and 5 show the experimental results. Megatron-BERT (Shoeybi et al. 2019) is a variant of BERT (Devlin et al. 2018) which has 8.3 billion parameters and is nearly 40 times bigger than the largest size of ALBERT, so usually it is very hard applied in practice with present common computation power and its results are not strictly comparable to our ALBERT+DUMA. Except for this, our model both achieves state-of-the-art performance on RACE leader-board⁵ and DREAM leaderboard⁶, and it can be further improved with multi-task learning method MMM (Wan 2020; Jin et al. 2020).

Analysis Studies

We perform ablation experiments on the DREAM dataset to investigate key features of our proposed DUMA, such as attention modeling ability, structural simplicity, bi-directional setting and low coupling.

Comparison with Vanilla Self-attention and Transformer Block

We investigate whether the improvements are simply caused by the increase of parameters. Thus we conduct the experiments of ALBERT plus vanilla Multi-head Self-attention (Vaswani et al. 2017), whose inputs $Q,\,K,\,V$ are all concatenation of passage, question and answer. Results shown in Table 6 indicate the effectiveness of our bi-directional coattention model design.

Moreover, we observe that the original Transformer Block (TB) (Vaswani et al. 2017) consists not only *Multi-head Attention* module but also *Layer Normalization (LN)* and *Feed-Forward Network (FFN)*. In consideration of the extensive

³https://github.com/huggingface/transformers

⁴https://github.com/NVIDIA/apex

⁵http://www.qizhexie.com/data/RACE_leaderboard

⁶https://dataset.org/dream/

model	$ALBERT_{\rm base/xxlarge}$	$ELECTRA_{\mathrm{large}}$
baseline	64.4/88.5	88.2
+Soft Attention(2015)	65.4(+1.0)/88.9(+0.4)	88.8(+0.6)
+BiDAF(2017)	65.6(+1.2)/89.3(+0.8)	89.1(+0.9)
+OCN(2019)	65.8(+1.4)/89.2(+0.7)	89.0(+0.8)
+WAE(2020)	66.5(+2.1)/89.9(+1.4)	89.5(+1.3)
+DCMN ⁷ (2020a)	63.3(-1.1)/87.8(-0.7)	87.7(-0.5)
+DUMA	67.6(+3.2)/90.5(+2.0)	89.8(+1.6)

Table 7: Comparison among different models on DREAM dataset.

application and great success of TB for global encoding (Devlin et al. 2018; Liu et al. 2019; Lan et al. 2020), we investigate whether the Transformer Block better model the coattention relationships than Multi-head Attention using TB-based DUMA (TB-DUMA). Experimental results shown in Table 6 indicate TB-DUMA has no obvious difference with our DUMA in modeling relationships. However, our proposed DUMA holds more brief structure and equally effective performance.

Comparison with Related Models

We compare our attention model with several representative works, which have been discussed in Section *Related Works*. Soft Attention (Bahdanau, Cho, and Bengio 2015) and BiDAF (Seo et al. 2017) are originally based on traditional encoder such as LSTM (Hochreiter and Schmidhuber 1997), and DCMN (Zhang et al. 2020a), OCN (Ran et al. 2019), WAE(Kim and Fung 2020) are based on BERT (Devlin et al. 2018). For fair comparison with Soft Attention, we simply use it to replace the attention score computing in our model.

Table 7 compares the effectiveness of various model designs, and our proposed DUMA outperforms all other models. The performance of Soft Attention is much lower than our DUMA, which indicates the DUMA's similarity in structure with ALBERT (both use Multi-head Attention) makes it better to utilize information from encoded representation. Even though BiDAF has been a successful attention model since a long time ago, it is suboptimal for PrLMs. WAE uses an ensemble model design with nearly twice sized parameters as our model. DCMN adopts a much more complicated model structure design for better matching, but the result with ALBERT and ELECTRA is not satisfactory, which indicates it may be specially optimized for specific PrLM, while our DUMA achieves the absolutely highest accuracy with a intuitive structure design. In fact, our DUMA has nice generalization ability because it also works well with many kinds of PrLMs.

model	dev	test
$ALBERT_{base}$	64.51	64.43
element-wise multiplication	65.29	64.58
element-wise summation	66.32	65.51
concatenation	67.06	67.56

Table 8: Comparison among different implementation of the fusing method on DREAM dataset. The last three rows are our DUMA applying three kinds of implementations.

model	para. num.
ALBERT _{base}	11.7M
+Soft Attention(2015)	13.5M (+1.8M) (+15.4%)
,	12.0M (+0.3M) (+2.6%)
+BiDAF(2017)	14.8M (+3.1M) (+26.5%)
+OCN(2019)	22 414 11 714 (1009)
+WAE(2020)	23.4M (+11.7M) (+100%)
D G1 D1/2020 \	19.4M (+7.7M) (+65.8%)
+DCMN(2020a)	
	13.5M (+1.8M) (+15.4%)
+DUMA	

Table 9: Comparison of number of parameters among different models. The models are same as listed in Table 7.

Investigation of Fusing Method

We investigate different implementations of fusing function from equation (1), namely element-wise multiplication, element-wise summation and concatenation. The results are shown in Table 8. We see that concatenation is optimal because it retains the matching information and lets network learn to fuse them dynamically.

Number of Parameters

We compare number of parameters among different models in Table 9. BiDAF requires the least model enlargement, however it is far less effective than our model. Besides, our model enlargement is far less than DCMN. In a word, our DUMA can obtain the best performance while requiring a little model enlargement.

Number of DUMA Layers

We stack 2 layers of our DUMA, that is to make passage and question-answer interact more than once to obtain deeper representations. Besides, we make different layers share parameters, which is the same as ALBERT.

Figure 3(a) shows the results. We can see that as the number of layers increases the performance fluctuates, and too

⁷The results of ALBERT+DCMN are our re-running of the official codes which we obtained through personal communication with its authors.

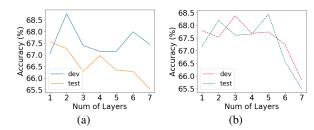


Figure 3: (a) Different numbers of DUMA layers on DREAM dataset. (b) Different numbers of TB-DUMA layers on DREAM dataset.

	dev	test	avg
model			
	64.51	64.43	64.47
$ALBERT_{\rm base}$			
	64.61 (+0.10)	64.72 (+0.29)	64.67 (+0.20)
P-to-Q			
	66.76 (+2.25)	66.29 (+1.86)	66.53 (+2.06)
Q-to-P			
	67.06 (+2.55)	67.56 (+3.13)	67.31 (+2.84)
Both(DUMA)			

Table 10: Bi-directional vs. uni-directional attentions on DREAM dataset.

many layers even lead to slight drop. It is much like when human solving MRC tasks, excessive thinking and hesitation may make them misunderstand the meaning of some information. For the network with current number of parameters, it shows that interacting twice is enough to capture the key information, and stacking too many layers may disorder the well-modeled representations and make the model harder trained.

Note that PrLMs (Devlin et al. 2018; Liu et al. 2019; Lan et al. 2020) stacks Transformer Blocks (described in Subsection Comparison with Vanilla Self-attention and Transformer Block) instead of Multi-head Attention modules, which raises a doubt that it is the lack of LN and FFN that makes the DUMA improper for stacking deeper network. Thus we further conduct an experiment with TB-DUMA (the same as described in Subsection Comparison with Vanilla Self-attention and Transformer Block). Experimental results in Table 3(b) show the same performance trend as the original DUMA, which again verifies the effectiveness of our DUMA design.

Effect of Bi-direction

As figured out by (Zhang et al. 2020a), bi-directional matching is a very important feature for sufficiently modeling the relationship between passage and question. To investigate the effect, we perform experiments on two settings, namely P-to-Q only and Q-to-P only. In other words, we respectively remove the right part and left part of our DUMA. Table 10 shows the results. We see that for bi-directional model, the overall improvement is 2.84%, while for uni-directional

model	dev	test	avg
$\overline{\text{ALBERT}_{\text{base}}}$	64.51	64.43	64.47
	67.06 (+2.55)	67.56 (+3.13)	67.31 (+2.84)
+DUMA			
$BERT_{base}$	61.18	61.54	61.36
	64.82 (+3.64)	64.03 (+2.49)	64.43 (+3.07)
+DUMA			

Table 11: Results using BERT as encoder on DREAM dataset. Results of BERT $_{\rm base}$ are our re-running.

model	dev	test
ALBERT _{base} (SA)	64.51	64.43
$ALBERT_{base}$ (SA) + DUMA (CA)	67.06	67.56
ALBERT _{base} (SA+CA)	41.18	40.08

Table 12: Results with and without self-attention on DREAM dataset. "SA" means self-attention and "CA" means co-attention. "SA+CA" means straightforwardly using CA to replace SA in ALBERT.

model the improvement is only 2.06% at most. The setting of bi-direction effectively improves the performance, which reveals its efficiency for modeling the relationship and agrees to the conclusion of (Zhang et al. 2020a). Also it is the same as our intuitive understanding that all the passage, question and answer options should be deliberated.

Cooperation with PrLMs

Though the proposed DUMA is supposed to enhance state-of-the-art PrLM like ALBERT and ELECTRA, we claim that it is generally effective for less advanced models. Thus we simply replace the adopted ALBERT by its early variant BERT to examine the effectiveness of DUMA. Table 11 shows the results. We see that our model can be easily transferred to other PrLMs, thus it can be seemed as an effective module for modeling relationships among passage, question and answer for Multi-choice MRC.

Effect of Self-attention

Our overall architecture can be split into two steps from the view of attention, of which the first is self-attention (AL-BERT) and the second is co-attention (DUMA). To examine whether the structure can be further simplified, that is only using co-attention, we straightforwardly change all of the Multi-head Self-attention of ALBERT model to our Dual Multi-head Co-attention, while still using its pre-trained parameters. The results are shown in Table 12, showing that putting co-attention directly into ALBERT model may lead to much poorer performance compared to the original AL-BERT and our ALBERT+DUMA integration way. To conclude, a better way for modeling is our PrLM plus DUMA model, which is to firstly build a global relationship using self-attention of the well trained encoder and then further enhance the relationship between passage and question-answer and distill more matching information using co-attention.

Comparison of Predictions

Table 13 shows a hard example which needs to capture important relationships and matching information. Benefited from well-modeled relationship representations, DUMA can better distill important matching information between passage and question-answer.

Passage	Woman: So, you have three days off, what are you going to do? Man: Well, I probably will rent some movies with my friend bob.			
Question	What will the man probably do?			
Answer	 Ask for a three-day leave. Go out with his friend. Watch films at home. √ 			
ALBERT	+BiDAF	+Sf Att	+DCMN	+DUMA
Prediction	1)	1)	2)	3) √

Table 13: Predictions of different models which are same as in Table 7. "Sf Att" means Soft Attention.

Conclusion

In this paper, we simulates human transposition thinking experience when solving MRC problems and propose a novel **DUal Multi-head Co-Attention** (DUMA) to model the relationships among passage, question and answer for multi-choice MRC tasks, which is able to cooperate with popular large-scale Pre-trained Language Models and brings effective performance improvements. Besides, we investigate previous attention mechanisms or matching networks applied on the top of PrLMs, and our model is shown as optimal through extensive experiments, which achieves the best performance with an intuitive motivated structure design. Our proposed DUMA enhancement has been verified effective on two benchmark multi-choice MRC tasks, DREAM and RACE, which achieves new state-of-the-art over strong PrLM baselines.

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