Multi-span Style Extraction for Generative Reading Comprehension

Junjie Yang1,3,4, Zhuosheng Zhang2,3,4, Hai Zhao2,3,4*,
1SJTU-ParisTech Elite Institute of Technology, Shanghai Jiao Tong University, Shanghai, China
2Department of Computer Science and Engineering, Shanghai Jiao Tong University
3Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, Shanghai Jiao Tong University, Shanghai, China
4MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University, Shanghai, China
jj-yang@sjtu.edu.cn, zhangzs@sjtu.edu.cn, zhaohai@cs.sjtu.edu.cn

Abstract
Generative machine reading comprehension (MRC) requires a model to generate well-formed answers. For this type of MRC, answer generation method is crucial to the model performance. However, generative models, which are supposed to be the right model for the task, in generally perform poorly. At the same time, single-span extraction models have been proven effective for extractive MRC, where the answer is constrained to a single span in the passage. Nevertheless, they generally suffer from generating incomplete answers or introducing redundant words when applied to the generative MRC. Thus, we extend the single-span extraction method to multi-span, proposing a new framework which enables generative MRC to be smoothly solved as multi-span extraction. Thorough experiments demonstrate that this novel approach can alleviate the dilemma between generative models and single-span models and produce answers with better-formed syntax and semantics. We will open-source our code for the research community.

1 Introduction
Machine Reading Comprehension (MRC) is considered as a nontrivial challenge in natural language understanding. Recently, we have seen continuous success in this area, partially benefiting from the release of massive and well-annotated datasets from both academic (Rajpurkar et al., 2018; Reddy et al., 2019) and industry (Bajaj et al., 2018; He et al., 2018) communities.

The widely used span-extraction models (Seo et al., 2017; Ohsugi et al., 2019; Lan et al., 2020), formulate the MRC task as a process of predicting the start and end position of the span inside the given passage. They have been proven effective on the tasks which constrain the answer to be an exact span in the passage (Rajpurkar et al., 2018). However, for generative MRC tasks whose answers are highly abstractive, the single-span extraction based methods can easily suffer from incomplete answers or redundant words problem. Thus, there still exists a large gap between the performance of single-span extraction baselines and human performance.

In the meantime, we have observed that utilizing multiple spans appearing in the question and passage to compose the well-formed answer could be a promising method to alleviate these drawbacks. Figure 1 shows how the mechanism of multi-span style extraction works for an example from the MS MARCO task (Bajaj et al., 2018), where the well-formed answer cannot simply be extracted as a single span from the input text.

Therefore, in this work, we propose a novel answer generation approach that takes advantage of the effectiveness of span extraction and the concise spirit of multi-span style to synthesize the free-formed answer, together with a framework as a whole for the multi-passage generative MRC. We call our framework MUSST for MUlti-Span STyle...
Our framework MUSST is also empowered by well pre-trained language model as encoder component of our model. It provides deep understanding of both the input passage and question, and models the information interaction between them. We conduct a series of experiments and the corresponding ablations on the MS MARCO v2.1 dataset.

Our main contributions in this paper can be summarized as follows:

- We propose a novel multi-span answer annotator to transform the initial well-formed answer into a series of spans that distribute in the question and passage.
- We generalize the single-span extraction based method to the multi-span style by introducing a lightweight but powerful answer generator, which supports the extraction of various number answer spans during prediction.
- To make better usage of the large dataset for the passage ranking task, we propose dynamic sampling during the training of the ranker that selects the passage most likely to entail the answer.

2 MUSST

In this section, we present our proposed framework, MUSST, for multi-passage generative MRC task. Figure 2 depicts the general architecture of our framework, which consists of a passage ranker, a multi-span answer annotator, and a question-answering module.

2.1 Passage ranker

2.1.1 Problem formulation

Given a question $Q$ and a set of $k$ candidate passages $P = \{P_1, P_2, ..., P_k\}$, the passage ranker is responsible for ranking the passages based on their relevance to the question. In other words, the model is requested to output conditional probability distribution $P(y|Q, P; \theta)$, where $\theta$ is the model parameters and $P(y = i|Q, P; \theta)$ denotes the probability that passage $P_i$ can be used to answer question $Q$.

2.1.2 Encoder

For each input question and passage pair $(Q, P_i)$, we represent it as a single packed sequence of length $n$ of the form “[CLS]$Q$[SEP]$P_i$[SEP]”. We pass the whole sequence into a contextualized encoder, thereby to produce its contextualized representation $E \in \mathbb{R}^{n \times h}$ where $h$ denotes the hidden size of the Transformer blocks. Following the fine-tuning strategy of Devlin et al. (2019) for the classification task, we consider the final hidden vector $c \in \mathbb{R}^h$ corresponding to the first input token ([CLS]) as the input’s aggregate representation. Our encoder also models the interaction between the question and the passage.

2.1.3 Ranker

The ranker is responsible for ranking the passages based on its relevance to the question. Given the output of the encoding layer $c$, we pass it through a fully connected multi-layer perceptron which consists of two linear transformations with a Tanh activation in between:

$$s = \text{softmax}(W_2 \text{tanh}(W_1 c + b_1) + b_2) \in \mathbb{R}^2$$

$$u_i = s_0 \text{ and } r_i = s_1$$

where $W_1 \in \mathbb{R}^{h \times h}$, $W_2 \in \mathbb{R}^{2 \times h}$, $b_1 \in \mathbb{R}^h$ and $b_2 \in \mathbb{R}^2$ are trainable parameters. Here, $r_i$ and $u_i$ are respectively the relevance and unrelevance
score for the pair \((Q, P_i)\). The relevance scores are consequently normalized across all the candidates passages of the same question:

\[
\hat{r_i} = \frac{\exp (r_i)}{\sum_{j=0}^{k} \exp (r_j)}
\]

Here, \(\hat{r_i}\) indicates the probability that passage \(P_i\) entails the answer \(Q\).

### 2.1.4 Training

We define the question-passage pair where the passage entails the question as a positive training sample. The positive passage is noted as \(P^+\). During the training phase, we adopt a negative sampling with one negative sample. Specifically, for each positive instance \((Q, P^+)\), we randomly sample a negative passage \(P^-\) from the unselected passages of the same question. The model is trained by minimizing the following cost function:

\[
J(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \log(r(Q_t, P^+_t)) + \log(u(Q_t, P^-_t))
\]

where \(T\) is the number of questions in the training set, \(r(Q_t, P^+_t)\) denotes the relevance score of \((Q_t, P^+_t)\) and \(u(Q_t, P^-_t)\) denotes the unrelevance score of \((Q_t, P^-_t)\).

Moreover, motivated by Liu et al. (2019), we resample the negative training instances at the beginning of each training epoch, to avoid using the same training pattern for the question during each training epoch. We name it **dynamic sampling**.

### 2.2 Syntactic multi-span answer annotator

In this section, we introduce our syntactic multi-span annotator. Before the training of our question-answering module, we need to extract non-overlapped spans from the question and passage based on the original answer from the training dataset. Our annotator is responsible for transforming the original answer phrase into multiple spans that distribute in the question and passage with subject to syntactic constraints. The attempt to extract the answer spans syntactically is motivated by our first intuition that the human editors compose the original answer in an analogous way.

As shown in the middle of Figure 2, we transform the answer phrase into a parsing tree and traverse the parsing tree in a DFS (Depth-first search) way. At each visit of the subtree, we check if the span represented by the subtree appears in the question or passage text. We obtain a span list after traversing the whole parsing tree. However, in some cases, the original answer still cannot be perfectly composed by the words from the input text even in a multi-span style. We get rid of these bad samples by comparing their edit distances with a threshold value which is set by the model beforehand.

### Algorithm 1 Syntactic Multi-span Answer Annotation

**Input:** Question \(Q = \{q_1, q_2, \ldots, q_m\}\), passage \(P = \{p_1, p_2, \ldots, p_n\}\) and gold answer \(A = \{a_1, a_2, \ldots, a_k\}\)

**Parameter:** Edit distance threshold \(d_{\text{max}}\)

**Output:** A list of start and end position of answer spans in the question and passage

1: Let \(M\) be an empty list
2: Pack question \(Q\) and passage \(P\) into a single sequence \(C\) in a certain way.
3: Get the syntactic parsing tree \(T\) of gold answer \(A\) by a constituency parser.
4: Let \(S\) be the stack of subtrees to be traversed.
5: Initialize \(S\) with the root \(R\) of the tree \(T\).
6: while \(S\) is not empty do
   7:      \(V = \text{Pop}(S)\)
   8:      Get a list of all the leaves of subtree \(V: L = \{l_1, l_2, \ldots, l_n\}\)
   9:      if \(L\) is a sublist of \(C\) then
      10:         Get the start index \(s\) and end index \(e\) of \(L\) in \(C\) by Knuth-Morris-Pratt pattern searching algorithm
      11:         Add \((s, e)\) into the span position list \(M\)
      12:      else
      13:         for childtree \(U\) in \(V\) (From right to left) do
      14:            \(\text{Push}(S, U)\)
      15:         end for
      16:      end if
   17:   end while
18: Reconstruct answer \(A'\) from span position list \(M\)
19: Let \(d = \text{EDITDISTANCE}(A, A')\)
20: if \(d > d_{\text{max}}\) then
21:    Empty the list \(M\)
22: end if
23: \(M^* = \text{PRUNING}(M)\)
24: return \(M^*\)

An important final step is to prune the answer span list. The **pruning** procedure sticks to the following principle: if two spans adjoin in the list are contiguous in the original text, we joint
them together. Pruning reduces heavily the number of spans needed to recover to the original answer phrase. The more comprehensive detail of our annotator is described in Algorithm 1.

2.3 Question-answering module

2.3.1 Problem formulation

Given a question \( Q \) and a passage \( P \), the question-answering module is requested to answer the question based on the information provided by the passage. In other words, the model outputs the conditional probability distribution \( P(y|Q, P) \), where \( P(y = A|Q, P) \) denotes the probability that \( A \) is the answer.

2.3.2 Question-passage reader

The architecture of the reader is analogous to the encoder module of the ranker in section 2.1.2, where we take a pre-trained language model as encoder. But instead of getting only the aggregate representation, we pass the whole output of the last layer to predict the answer spans as the follows:

\[
M = \text{Encoder}(Q, P) \in \mathbb{R}^{h \times n}
\]

where \( n \) is the length of the input token sequence, and \( h \) is the hidden size of the encoder.

2.3.3 Multi-span style answer generator

Our answer generator is responsible for composing the answer in a multi-span style extraction. Let \( n \) be the number of span to be extracted.

For each single span prediction, we treat it as the single span extraction MRC task. Following Lan et al. (2020), we adopt a linear layer to predict start and end positions of the span in the input sequence. It is worth noticing that our model is also enabled to predict the answer span from the question. The probability distribution of \( i \)-th span’s start position over the input tokens is obtained by:

\[
\hat{p}^{j,\text{start}} = \text{softmax}(W^{j} \cdot M + b^{j})
\]

where \( W^{j} \in \mathbb{R}^{1 \times h} \) and \( b^{j} \in \mathbb{R} \) are trainable parameters and \( \hat{p}^{j,\text{start}} \) denote the probability of token \( k \) being the start of the answer span \( j \). The end position distribution of the answer span \( j \) is obtained by using the analogous formula:

\[
\hat{p}^{j,\text{end}} = \text{softmax}(W^{j} \cdot M + b^{j})
\]

2.3.4 Training and inference

During training, we add a special virtual span, with start and end position values equaling the length of the input sequence, at the end of the annotated answer span list. This approach enables our model to generate a various number of answer spans during prediction with the virtual span serving as a stop symbol. The cost function is defined as follows:

\[
J(\theta) = \frac{1}{T} \sum_{t=1}^{T} \sum_{j=1}^{m_t} \log(\hat{p}^{j,\text{start}}_{y^{j,\text{start}}_t}) + \log(\hat{p}^{j,\text{end}}_{y^{j,\text{end}}_t})
\]

where \( T \) is the number of training samples, \( m_t \) is the number of answer span for sample \( t \), \( y^{j,\text{start}}_t \) and \( y^{j,\text{end}}_t \) are the true start and end position of the \( t \)-th sample’s \( j \)-th span.

During inference, at each time step \( j \), we choose the answer span \( (k, l) \) where \( k < l \) with the maximum value of \( \hat{p}^{j,\text{start}}_{y^{j,\text{start}}_t} \). The decoding procedure terminates when the stop span is predicted. Sometimes, the model tends to generate repeatedly the same spans. In order to alleviate the repeating problem, at each prediction time step \( j \), we mask out the predicted span positions of previous time steps \( (j < j) \) during the calculation of probability distribution of new start and end positions. Since the masking depends on the previously predicted spans, we name it as **conditional masking**. The extracted spans are later joined together to form a final answer phrase.

3.1 Dataset

We evaluate our framework on the MS MARCO v2.1\(^1\) (Bajaj et al., 2018), which is a large scale open-domain generative task. MS MARCO v2.1 provides two MRC tasks: Question Answering (QA) and Natural Language Generation (NLG). The statistics of the corresponding datasets’ size are presented in Table 1. Both datasets consist of sampled questions from Bing’s search logs, and each question is accompanied by an average of ten passages that may contain the answers. \( Q.A \) and \( N.LG \) are subsets of \( A.LL \), which also contains the unanswerable questions.

\(^1\)The datasets can be obtained from the official site (https://microsoft.github.io/msmarco/)
Table 1: Statistics of MS MARCO v2.1 dataset. The numbers in parenthesis indicate the percentage of examples whose answer is single span in gold passage.

Table 2: Performance comparison with our baselines on the QA and NLG development set. Here, we use the same single ranker for MUSST and the baselines.

Table 3 compares our model performance with the competing models on the leaderboard. Although our model utilizes only a standalone classifier for

maximum edit distance between the answer reconstructed from the annotated spans, and the original answer is 32 and 8 respectively for the NLG and QA training sets.

The ranker and question-answering module of MUSST are implemented with PyTorch (Paszke et al., 2019) and Transformers package (Wolf et al., 2020). We adopt ALBERT (Lan et al., 2020) as the encoder in our models and initialize it with the pre-trained weights before the fine-tuning. We choose ALBERT-base as the encoder of passage ranker and ALBERT-xlarge instead for question answering module.

Following Lan et al. (2020), we use SentencePiece (Kudo and Richardson, 2018) to tokenize our inputs with a vocabulary size of 30,000. We adopt Adam optimizer (Kingma and Ba, 2015) to minimize the cost function. Two types of regularization methods during training: dropout and L2 weight decay. Hyperparameter details for the training of the different models of our framework are presented in Appendices. MUSST-NLG and MUSST-QA are trained respectively on the NLG and QA subsets. The maximum number of spans for them is set to 9 and 5, respectively.

The single-span baseline is implemented with the same packages as MUSST while the seq2seq baseline is implemented with Fairseq (Ott et al., 2019).

3.4 Results

Table 2 shows the results of our single model and the baseline models on the QA and NLG development datasets. MUSST outperforms significantly the baselines including the generative seq2seq model over the NLG set in terms of both ROUGE-L and BLEU-1. Even on the QA set, our model yields better results regarding ROUGE-L.

3.2 Baseline models

We compare our MUSST with the following baseline models: single-span extraction and seq2seq. For the single-span extraction baseline, we employ the model for the SQuAD dataset from ALBERT (Lan et al., 2020). The model is trained only with samples where the answer is a single span in the passage. In the meantime, We adopt the Transformer model from Vaswani et al. (2017) as our seq2seq baseline. For a fair comparison, the baseline models share the same passage ranker as the one in MUSST.

3.3 Implementation details

For the multi-span answer annotation, we use constituency parser from Standford CoreNLP (Manning et al., 2014). NLTK (Bird et al., 2009) package is also used to implement our annotator. The official evaluation scripts can be found in https://github.com/microsoft/MSMARCO-Question-Answering/tree/master/Evaluation
Table 3: The performance of our framework and competing models on the MS MARCO v2.1 test set. All the results presented here reflect the MS MARCO leaderboard (microsoft.github.io/msmarco/) as of 28 May 2020. † refers to the model whose results are not reported in the original published paper. BiDAF for MARCO is implemented by the official MS MARCO Team. ‡ refers to the ensemble submission. Whether the other competing models are ensemble or not is unclear. \(^{a}\) Seo et al. (2017); \(^{b}\) Indurthi et al. (2018); \(^{c}\) Wang et al. (2018b); \(^{d}\) Yan et al. (2019); \(^{e}\) Nishida et al. (2019).

| Model                        | ROUGE-L | BLEU-1 |
|------------------------------|---------|--------|
| MUSST w gold passage        | 75.39   | 74.41  |
| w/o pruning                 | 66.24   | 64.23  |
| w/o conditional masking     | 65.50   | 64.31  |

Table 4: Ablation study on the \(NLG\) development set.

passage ranking, multi-span style extraction still helps us rival with state-of-the-art approaches.

4 Analysis and discussions

4.1 Ablation study on model design choice

We perform ablation experiments that quantify the individual contribution of the design choices of MUSST. Table 4 shows the results on the \(NLG\) development set. Both pruning and conditional masking contribute the model performance, which indicates that pruning can help the model to converge more easily by reducing the number of spans, while conditional masking can better generate answers without suffering from the repeating problem. We also observe using the gold passage can significantly improve question-answering. It shows there still exists a great improvement space for the passage ranker.

4.2 Quality of multi-span answer annotator

On the \(NLG\) development set, we evaluate the answers generated by our syntactic multi-span annotator. The results shows our annotated answers can obtain 89.35 in BLEU-1 and 90.19 in ROUGE-L with the gold passages, which demonstrates the effectiveness of our annotator. For MUSST, the results are 74.41 and 75.39 respectively (in Table 4). So there is still much room for improvement with respect to the question-answering module.

4.3 Effect of maximum number of spans

Figure 3 presents the distribution of span numbers with edit distance less than 4 over the QA and \(NLG\) training sets after the annotation procedure. It is seen that most QA-style answers are only one span, while the NLG-style answers distribute more uniformly in the range of \([1, 9]\).

To better understand the effect of the maximum
number of spans to be generated in the answer generator, we let it vary in the range of [2, 12] and conduct experiments on the \( \mathcal{NLG} \) set with our best single passage ranker. The edit distance threshold is set to be 8. The results are presented in Figure 4. Generally, increasing the number of the span will augment the token coverage rate, thus yielding better results. But the gain becomes less significant when the maximum number of span is already large enough. From Figure 4, we can see that the results vary imperceptibly when the maximum number of spans reaches 5. However, since each span only introduces 4k parameters, which is negligible before the encoder (60M), we still choose the maximum number to be 9, which corresponds to the best performance on the development set.

![Figure 4: Effect of maximum number of spans.](image)

4.4 Effect of edit distance threshold

Figure 5 shows the results of MUSST on \( \mathcal{NLG} \) development set for various edit distance threshold. Interestingly, it indicates that BLEU-1 is impacted more heavily by the variation of edit distance than ROUGE-L. And setting the edit distance threshold too large may damage the model performance by introducing too many incomplete samples.

![Figure 5: Effect of edit distance threshold.](image)

4.5 Effect of encoder size

Table 5 presents experimental results on ALBERT encoder with various model sizes. Unsurprisingly, the model yields stronger results as the encoder gets larger.

| Encoder    | Parameters | ROUGE-L | BLEU-1 |
|------------|------------|---------|---------|
| ALBERT-base| 12M        | 62.03   | 60.48   |
| ALBERT-large| 18M    | 64.93   | 61.67   |
| ALBERT-xlarge| 60M    | **66.24** | **64.23** |

Table 5: Effect of ALBERT encoder size.

4.6 Performance of the ranker

Table 6 presents our ranker performance in terms of MAP and MRR. The results show that dynamic sampling leads to slightly better results.

| Model                | Training set | MAP   | MRR   |
|----------------------|--------------|-------|-------|
| Bing (initial ranking) | -            | 34.62 | 35.00 |
| MUSST (single)        | QA           | **71.10** | **71.56** |
| w/o dynamic sampling  | QA           | 70.82 | 71.26 |

Table 6: The performance of ranker with various configurations on the QA development set.

4.7 Case study

**Question:** how long should a central air conditioner last

**Selected Passage:** 10 to 20 years - sometimes longer. You should have a service tech come out once a year for a tune up. You wouldn’t run your car without regular maintenance and tune ups and you shouldn’t run your a/c that way either - if you want it to last as long as possible. Source(s): 20 years working for a major manufacturer of central heating and air conditioning.

**Reference Answer:** A Central air conditioner lasts for in between 10 and 20 years./ A central air conditioner should last for 10 to 20 years.

**Prediction (Baseline):** 10 to 20 years.

**Prediction (MUSST):** a central air conditioner should last for 10 to 20 years.

Table 7: A prediction example from the baseline and MUSST. The highlighted texts are the spans predicted by our model to compose the final answer phrase.

To have an intuitive observation of the prediction ability of MUSST, we show a prediction example on MS MARCO v2.1 from the baseline and
5 Related work

5.1 Generative MRC

Generative MRC is considered as a more challenging task where answers are free-form human-generated text. More recently, we have seen an emerging wave of generative MRC tasks. MS MARCO (Bajaj et al., 2018) is a large scale real-world reading comprehension dataset where the questions are the anonymized search queries issued through Bing or Cortana. NarrativeQA (Koisk et al., 2018) is the first large-scale question-answering dataset on full-length books and movie scripts, requiring understanding the underlying narrative rather than relying on shallow pattern matching or salience. DuReader (He et al., 2018) is the Chinese counterpart of MARCO but with longer documents and answers. CoQA (Reddy et al., 2019) is a conversational MRC dataset which contains free-form answers.

The most earlier approaches tried to generate the answer in a single-span extractive way (Tay et al., 2018b,a; Wang et al., 2018b; Yan et al., 2019; Ohsugi et al., 2019). The models using a single-span extractive method show effectiveness for the dataset where abstractive behavior of answers includes mostly small modifications to spans in the context (Ohsugi et al., 2019; Yatskar, 2019). Whereas, for the datasets with answers of deep abstraction, this method fails to yield promising results.

The first attempt to generate the answer in a generative way is to apply an RNN-based seq2seq attentional model to synthesize the answer, such as S-NET (Tan et al., 2018), where seq2seq learning was first introduced by Sutskever et al. (2014) for the machine translation.

The most recent models adopt a hybrid neural network Pointer-Generator (See et al., 2017) to generate answer, such as ConZNet (Indurthi et al., 2018), MHPGM (Bauer et al., 2018) and Masque (Nishida et al., 2019). Pointer-Generator was firstly proposed for the abstractive text summarization, which can copy words from the source via the pointer network while retaining the ability to produce novel words through the generator. Different from ConZNet and MHPGM, Masque adopt a Transformer-based (Vaswani et al., 2017) Pointer-Generator, while the previous ones utilizing GRU (Cho et al., 2014) or LSTM (Hochreiter and Schmidhuber, 1997).

5.2 Multi-passage MRC

For each question-answer pair, the Multi-passage MRC dataset contains more than one passage as the reading context, such as SearchQA (Dunn et al., 2017), TriviaQA (Joshi et al., 2017), MS MARCO, and DuReader.

Existing approaches designed specifically for Multi-passage MRC can be classified into two categories: pipeline and end-to-end. Pipeline-based models (Chen et al., 2017; Wang et al., 2018a; Clark and Gardner, 2018) adopt a ranker to first rank all the passages based on its relevance to the question and then utilize a question-answering module to read the selected passages. The ranker can be based on traditional information retrieval methods (BM25 or TF-IDF) or employ a neural re-ranking model. End-to-end models (Wang et al., 2018b; Tan et al., 2018; Nishida et al., 2019) read all the provided passages at the same time, and produce for each passage a candidate answer assigned with a score which is consequently compared among passages to find the final answer. Passage ranking and answer prediction are usually jointly done as multi-task learning. More recently, Yan et al. (2019) proposed a cascade learning model to balance the effectiveness and efficiency of the two approaches mentioned above.

5.3 Pre-trained model in MRC

Employing the pre-trained language models has been a common practice for tackling MRC. The appearances of more elaborated architectures, larger corpora, and more well-designed pre-training objectives speed up the achievement of new state-of-the-art in MRC (Devlin et al., 2019; Liu et al., 2019; Lan et al., 2020). Moreover, Glass et al. (2019) adopts span selection, a MRC task, as an auxiliary pre-training task. Another mainstream line of research attempts to drive the improvements during the fine-tuning, which includes integrating better verification strategies for unanswerable question (Zhang et al., 2020), leveraging external knowledge for commonsense reasoning (Yang et al., 2019; Lin et al., 2019) or cooperating with a graph network for multi-hop reading comprehension (Qiu et al., 2019; Ding et al., 2019).
6 Conclusion
In this work, we present a novel solution to generative MRC, multi-span style extraction framework (MUSST), and show it is capable of alleviating the incompleteness and abundant problems when generating an answer. We apply our model to a challenging abstractive MRC dataset MS MARCO v2.1 and significantly outperform the single-span extraction baseline. This work indicates a new research line for generative MRC in addition to the existing two methods, one-span extraction and sequence generation. With the support of only a standalone ranking classifier, our proposed method still gives an overall performance approaching state-of-the-art, showing great potential.

References
Payal Bajaj, Daniel Campos, Nick Craswell, Li Deng, Jianfeng Gao, Xiaodong Liu, Rangan Majumder, Andrew McNamara, Bhaskar Mitra, Tri Nguyen, Mir Rosenberg, Xia Song, Alina Stoica, Saurabh Tiwary, and Tong Wang. 2018. MS MARCO: A Human Generated MAchine Reading COmprehension Dataset. arXiv preprint arXiv:1611.09268.

Lisa Bauer, Yicheng Wang, and Mohit Bansal. 2018. Commonsense for Generative Multi-Hop Question Answering Tasks. In Empirical Methods in Natural Language Processing (EMNLP), pages 4220–4230.

Steven Bird, Ewan Klein, and Edward Loper. 2009. Natural language processing with Python: analyzing text with the natural language toolkit. O'Reilly Media, Inc.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to Answer Open-Domain Questions. In Association for Computational Linguistics (ACL), pages 1870–1879.

Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fedor Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. In Empirical Methods in Natural Language Processing (EMNLP), pages 1724–1734.

Christopher Clark and Matt Gardner. 2018. Simple and Effective Multi-Paragraph Reading Comprehension. In Association for Computational Linguistics (ACL), pages 845–855.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NACCL-HLT), pages 4171–4186.

Ming Ding, Chang Zhou, Qibin Chen, Hongxia Yang, and Jie Tang. 2019. Cognitive Graph for Multi-Hop Reading Comprehension at Scale. In Association for Computational Linguistics (ACL), pages 2694–2703.

Matthew Dunn, Levent Sagun, Mike Higgins, V. Ugur Guney, Volkam Cirik, and Kyunghyun Cho. 2017. SearchQA: A New Q&A Dataset Augmented with Context from a Search Engine. arXiv preprint arXiv:1704.05179.

Michael Glass, Alfonso Girollo, Rishav Chakravarti, Anthony Ferritto, Lin Pan, G. P. Shirivatsa Bhargav, Dinesh Garg, and Avirup Sil. 2019. Span Selection Pre-training for Question Answering. arXiv preprint arXiv:1909.04120.

Wei He, Kai Liu, Jing Liu, Yajuan Lyu, Shiqi Zhao, Xinyan Xiao, Yuan Liu, Yizhong Wang, Hua Wu, Qiaoqiao She, Xuan Liu, Tian Wu, and Haifeng Wang. 2018. DuReader: a Chinese Machine Reading Comprehension Dataset from Real-world Applications. In Proceedings of the Workshop on Machine Reading for Question Answering, pages 37–46.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long Short-Term Memory. Neural Comput., 9(8):1735–1780. Place: Cambridge, MA, USA Publisher: MIT Press.

Sathish Reddy Indurthi, Seunghak Yu, Seohyun Back, and Heriberto Cuayhuitl. 2018. Cut to the Chase: A Context Zoom-in Network for Reading Comprehension. In Empirical Methods in Natural Language Processing (EMNLP), pages 570–575.

Mandar Joshi, Eunsol Choi, Daniel Weld, and Luke Zettlemoyer. 2017. TriviaQA: A Large Scale Distantly Supervised Challenge Dataset for Reading Comprehension. In Association for Computational Linguistics (ACL), pages 1601–1611.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. In International Conference on Learning Representations (ICLR).

Tom Koisk, Jonathan Schwarz, Phil Blunsom, Chris Dyer, Karl Moritz Hermann, Gbor Melis, and Edward Grefenstette. 2018. The NarrativeQA Reading Comprehension Challenge. Transactions of the Association for Computational Linguistics (TACL), 6:317–328.

Taku Kudo and John Richardson. 2018. SentencePiece: A simple and language independent subword tokenizer and detokenizer for Neural Text Processing. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 66–71.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2020. ALBERT: A Lite BERT for Self-supervised Learning. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 66–71.
Learning of Language Representations. In International Conference on Learning Representations (ICLRL).

Bill Yuchen Lin, Xinyue Chen, Jamin Chen, and Xiang Ren. 2019. KagNet: Knowledge-Aware Graph Networks for Commonsense Reasoning. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 2829–2839.

Chin-Yew Lin. 2004. ROUGE: A Package for Automatic Evaluation of Summaries. In Text Summarization Branches Out, pages 74–81.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A Robustly Optimized BERT Pretraining Approach. arXiv preprint arXiv:1907.11692.

Christopher D. Manning, Mihai Surdeanu, John Bauer, Jenny Finkel, Steven J. Bethard, and David McClosky. 2014. The Stanford CoreNLP Natural Language Processing Toolkit. In Association for Computational Linguistics (ACL) System Demonstrations, pages 55–60.

Kyosuke Nishida, Itsuhiro Saito, Kosuke Nishida, Kazutoshi Shinoda, Atsushi Otsuka, Hisako Asano, and Junji Tomita. 2019. Multi-style Generative Reading Comprehension. In Association for Computational Linguistics (ACL), pages 2273–2284.

Yasuhiito Ohsugi, Itsuhiro Saito, Kyosuke Nishida, Hisako Asano, and Junji Tomita. 2019. A Simple but Effective Method to Incorporate Multi-turn Context with BERT for Conversational Machine Comprehension. In Proceedings of the First Workshop on NLP for Conversational AI, pages 11–17.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A Fast, Extensible Toolkit for Sequence Modeling. In Proceedings of NAACL-HLT 2019: Demonstrations.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a Method for Automatic Evaluation of Machine Translation. In Association for Computational Linguistics (ACL), pages 311–318.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In Advances in Neural Information Processing Systems (NIPS), pages 8024–8035.

Lin Qiu, Yunxuan Xiao, Yanru Qu, Hao Zhou, Lei Li, Weinan Zhang, and Yong Yu. 2019. Dymmetrically Fused Graph Network for Multi-hop Reasoning. In Association for Computational Linguistics (ACL), pages 6140–6150.

Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. Know What You Don’t Know: Unanswerable Questions for SQuAD. In Association for Computational Linguistics (ACL), pages 784–789.

Siva Reddy, Danqi Chen, and Christopher D. Manning. 2019. CoQA: A Conversational Question Answering Challenge. Transactions of the Association for Computational Linguistics (TACL), 7:249–266.

Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. Get To The Point: Summarization with Pointer-Generator Networks. In Association for Computational Linguistics (ACL), pages 1073–1083.

Minjoon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. 2017. Bidirectional Attention Flow for Machine Comprehension. In International Conference on Learning Representations (ICLR).

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to Sequence Learning with Neural Networks. In Advances in Neural Information Processing Systems (NIPS), pages 3104–3112.

Chuanqi Tan, Furu Wei, Nan Yang, Bowen Du, Weifeng Lv, and Ming Zhou. 2018. S-Net: From Answer Extraction to Answer Synthesis for Machine Reading Comprehension. In Association for the Advancement of Artificial Intelligence (AAAI).

Yi Tay, Anh Tuan Luu, and Siu Cheung Hui. 2018a. Multi-Granular Sequence Encoding via Dilated Compositional Units for Reading Comprehension. In Empirical Methods in Natural Language Processing (EMNLP), pages 2141–2151.

Yi Tay, Anh Tuan Luu, Siu Cheung Hui, and Jian Su. 2018b. Densely Connected Attention Propagation for Reading Comprehension. In Advances in Neural Information Processing Systems (NIPS), pages 4906–4917.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, ukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. In Advances in Neural Information Processing Systems (NIPS), pages 5998–6008.

Shuohang Wang, Mo Yu, Xiaoxiao Guo, Zhiguo Wang, Tim Klinger, Wei Zhang, Shiyu Chang, Gerry Tesauro, Bowen Zhou, and Jing Jiang. 2018a. R3: Reinforced Ranker-Reader for Open-Domain Question Answering. In Association for the Advancement of Artificial Intelligence (AAAI).

Yizhong Wang, Kai Liu, Jing Liu, Wei He, Yuanlu Lyu, Hua Wu, Sujian Li, and Haifeng Wang.
A Appendices

A.1 Training details

We trained the passage ranker and the question-answering module of MUSST-NLG on a machine with four Tesla P40 GPUs. The question-answering module of MUSST-QA is trained with eight GeForce GTX 1080 Ti GPUs. It takes roughly 9 hours to train the passage ranker. For the question-answering module in MUSST-NLG and MUSST-QA, the training time is about 10 hours and 17 hours respectively. The full set of hyperparameters is listed in Table 8.
| Hyperparameter          | Ranker | MUSST-QA | MUSST-NLG |
|-------------------------|--------|----------|-----------|
| Learning rate           | 1e-5   | 3e-5     | 3e-5      |
| Learning rate decay     | Linear | Linear   | Linear    |
| Training epoch          | 3      | 3        | 5         |
| Warmup rate             | 0.1    | 0.1      | 0.1       |
| Adam $\epsilon$         | $10^{-6}$ | $10^{-6}$ | $10^{-6}$ |
| Adam $\beta_1$          | 0.9    | 0.9      | 0.9       |
| Adam $\beta_2$          | 0.999  | 0.999    | 0.999     |
| MSN                     | 256    | 256      | 256       |
| Batch size              | 128    | 32       | 32        |
| Encoder dropout rate    | 0      | 0        | 0         |
| Classifier dropout rate | 0.1    | 0.1      | 0.1       |
| Weight decay            | 0.01   | 0.01     | 0.01      |

Table 8: Training hyperparameters of different modules of MUSST on MS MARCO v2.1 dataset. Here, MUSST-QA and MUSST-NLG refer to its question-answering module. MSN means maximum sequence length.