# Effective Subword Segmentation for Text Comprehension

Zhuosheng Zhang, Hai Zhao, Kangwei Ling, Jiangtong Li, Zuchao Li, Shexia He, Guohong Fu

Abstract—Representation learning is the foundation of machine reading comprehension and inference. In state-of-theart models, character-level representations have been broadly adopted to alleviate the problem of effectively representing rare or complex words. However, character itself is not a natural minimal linguistic unit for representation or word embedding composing due to ignoring the linguistic coherence of consecutive characters inside word. This paper presents a general subword-augmented embedding framework for learning and composing computationally-derived subword-level representations. We survey a series of unsupervised segmentation methods for subword acquisition and different subword-augmented strategies for text understanding, showing that subword-augmented embedding significantly improves our baselines in various types of text understanding tasks on both English and Chinese benchmarks.

Index Terms—Subword Embedding, Machine Reading Comprehension, Textual Entailment, Word Segmentation

#### I. INTRODUCTION

The fundamental part of deep learning methods applied to natural language processing (NLP), distributed word representation, namely, *word embedding*, provides a basic solution to text representation for NLP tasks and has proven useful in various applications, including textual entailment [49, 56] and machine reading comprehension (MRC) [10, 42, 52, 53]. However, deep learning based NLP models usually suffer from rare and out-of-vocabulary (OOV) word representation [31, 41], especially for low-resource languages. Besides, most word embedding approaches treat word forms as atomic units, which is spoiled by many words that actually have a complex internal structure. Especially, rare words like morphologically

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Part of this study has been published as Subword-augmented Embedding for Cloze Reading Comprehension [54] in COLING-2018. This paper extends the previous byte pair encoding (BPE) subword method to introduce a unified segmentation framework, and conducts comprehensive experiments on both reading comprehension and textual entailment tasks, considering multilingual effectiveness, generalization ability on different benchmarks and thorough case studies. The codes have been released at https://github.com/cooelf/subword\_seg.

complex words and named entities, are often expressed poorly due to data sparsity. Actually, plenty of words share some conjunct written units, such as morphemes, stems and affixes. The models would benefit a lot from distilling these salient units automatically.

Character-level embedding has been broadly used to refine the word representation [25, 27, 31, 51], showing beneficially complementary to word representations. Concretely, each word is split into a sequence of characters. Character representations are obtained by applying neural networks on the character sequence of the word, and their hidden states form the representation.

However, character is not the natural minimum linguistic unit, which makes it quite valuable to explore the potential unit (subword) between character and word to model subword morphologies or lexical semantics. For English, there are only 26 letters. Using such a small character vocabulary to form the word representations could be too insufficient and coarse. Even for a language like Chinese with a large set of characters (typically, thousands of), lots of which are semantically ambiguous, using character embedding below the word-level to build the word representations would not be accurate enough, either. For example, for an internet neologism 老司机 (experienced driver), the characters <老(experienced, old), 司(manage), 机(machine)> would be somewhat from the meaning of the word while the subwords <老(experienced, old), 司机(driver)> with proper syntactic and semantic decomposition give exactly the minimal meaningful units below the word-level which surely improve the later word representation. Thus, in either type of languages, effective representation cannot be done accurately only via the character based process.

In fact, morphological compounding (e.g. sunshine or play-ground) is one of the most common and productive methods of word formation across human languages, and most of rare or OOV words can be segmented into meaningful fine-grained subword units for accurate learning and representation, which inspires us to represent word by meaningful subword units. Recently, researchers have started to work on morphologically informed word representations [2, 4, 7, 18], aiming at better capturing syntactic, lexical and morphological information. With flexible subwords from either source, we do not necessarily need to work with characters, and segmentation could be stopped at the subword-level. With related characters grouping into subword, we hopefully reach a meaningful minimal representation unit.

Splitting a word into sub-word level subwords and using these subwords to augment the word representation may recover the lost syntactic or semantic information that is

TABLE I: A machine reading comprehension example.

Passage	Robotics is an interdisciplinary branch of engineering and science that includes mechanical engineering, electrical engineering, computer science, and others. Robotics deals with the design, construction, operation, and use of robots, as well as computer systems for their control, sensory feedback, and information processing. These technologies are used to develop machines that can substitute for humans. Robots can be used in any situation and for any purpose, but today many are used in dangerous environments (including bomb detection and deactivation), manufacturing processes, or where humans cannot survive. Robots can take on any form but some are made to resemble humans in appearance. This is said to help in the acceptance of a robot in certain replicative behaviors usually performed by people. Such robots attempt to replicate walking, lifting, speech, cognition, and begically anything a human can do
	and basically anything a human can do.
Question	What do robots that resemble humans attempt to do?
Answer	replicate walking, lifting, speech, cognition

supposed to be delivered by subwords. For example, *understanding* could be split into the following subwords: <under, stand, ing>. Previous work usually considered prior linguistic knowledge based methods to tokenize each word into subwords (namely, *morphological based subword*). However, such treatment may encounter two main inconveniences. First, the linguistic knowledge resulting subwords, typically, morphological suffix, prefix or stem, may not be suitable for the targeted NLP tasks. Second, linguistic knowledge or related annotated lexicons or corpora even may not be available for a specific language or task. Thus in this work we consider computationally motivated subword tokenization approaches instead.

We present a unified representation learning framework to sub-word level information enhanced text understanding and survey various computationally motivated segmentation methods. Specifically, we consider the subword as the basic unit in our models and manipulate the neural architecture accordingly. The proposed method takes variable-length subwords segmented by unsupervised segmentation measures, without relying on any predefined linguistic resource. First, a goodness score is computed for each n-gram using the selected goodness measure to form a dictionary. Then segmentation or decoding method is applied to tokenize words into subwords based on the dictionary. The proposed subword-augmented embedding will be evaluated on text understanding tasks, including textual entailment and machine reading comprehension, both of which are quite challenging due to the need of accurate lexical-level representation. Furthermore, we empirically survey various subword segmentation methods from a computational perspective and investigate the better way to enhance the tasks with thoughtful analysis and case studies.

The rest of this paper is organized as follows. The next section reviews the related work. Section 3 will demonstrate our subword augmented learning framework and implementation. Task details and experimental results are reported in Section 4, followed by case studies and analysis in Section 5 and conclusion in Section 6.

TABLE II: A textual entailment example.

Premise	Man grilling fish on barbecue   Label	
Hypothesis	The man is cooking fish. The man is sailing a boat. The man likes to eat fish.	Entailment Contradiction Neutral

#### II. RELATED WORK

# A. Augmented Embedding

To model texts into vector space, the input tokens are represented as embeddings in deep learning models [28, 29, 30, 45, 46, 55, 57]. Previous work has shown that word representations in NLP tasks can benefit from character-level models, which aim at learning language representations directly from characters. Character-level features have been widely used in language modeling [34, 38], machine translation [31, 41] and reading comprehension [42, 51]. Seo et al. [42] concatenated the character and word embedding to feed a two-layer Highway Network. Cai et al. [6] presented a greedy neural word segmenter to balance word and character embeddings. High-frequency word embeddings are attached to character embedding via average pooling while low-frequency words are represented as character embedding. Miyamoto and Cho [34] introduced a recurrent neural network language model with LSTM units and a word-character gate to adaptively find the optimal mixture of the character-level and wordlevel inputs. Yang et al. [51] explored a fine-grained gating mechanism to dynamically combine word-level and characterlevel representations based on properties of the words (e.g. named entity and part-of-speech tags).

However, character embeddings only show marginal improvement due to a lack of internal semantics. Recently, many techniques were proposed to enrich word representations with sub-word information. Bojanowski et al. [3] proposed to learn representations for character n-gram vectors and represent words as the sum of the n-gram vectors. Avraham and Goldberg [1] built a model inspired by Joulin et al. [22], who used morphological tags instead of n-grams. They jointly trained their morphological and semantic embeddings, implicitly assuming that morphological and semantic information should live in the same space. Our work departs from previous ones on morphologically-driven embeddings by focusing on embedding data-driven subwords. To handle rare words, Sennrich et al. [41] introduced the byte pair encoding (BPE) compression algorithm for open-vocabulary neural machine translation by encoding rare and unknown words as subword units. Zhang et al. [54] applied BPE for cloze-style reading comprehension to handle OOV issues. Different from the motivation of subword segmentation for rare words modeling, our proposed unified subword-augmented embedding framework serves for a general purpose without relying on any predefined linguistic resources with thorough analysis, which can be adopted to the enhance the representation for each word by adaptively altering the segmentation granularity in multiple NLP tasks.

# B. Text Comprehension

As a challenging task in NLP, text comprehension aims to read and comprehend a given text, and then answer questions

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or make inference based on it. These tasks require a comprehensive understanding of natural languages and the ability to do further inference and reasoning. In this paper, we focus on two types of text comprehension, document-based question-answering (Table I) and textual entailment (Table II), which share the similar genre of machine reading comprehension, though the task formations are slightly different.

In the last decade, the MRC tasks have evolved from the early cloze-style test [19, 20, 54] to span-based answer extraction from passage [36, 39, 40]. The former has restrictions that each answer should be a single word in the document and the original sentence without the answer part is taken as the query. For the span-based one, the query is formed as questions in natural language whose answers are spans of texts. Notably, Chen et al. [8] conducted an in-depth and thoughtful examination on the comprehension task based on an attentive neural network and an entity-centric classifier with a careful analysis based on handful features. Then, various attentive models have been employed for text representation and relation discovery, including Attention Sum Reader [23], Gated attention Reader [15], Self-matching Network [47] and Attended over Attention Reader [12].

With the release of the large-scale span-based datasets [21, 35, 39, 40, 48], which constrain answers to all possible text spans within the reference document, researchers are investigating the models with more logical reasoning and content understanding [47, 48].

For the other type of text comprehension, natural language inference (NLI) is proposed to serve as a benchmark for natural language understanding and inference, which is also known as recognizing textual entailment (RTE). In this task, a model is presented with a pair of sentences and asked to judge the relationship between their meanings, including entailment, neutral and contradiction. Bowman et al. [5] released Stanford Natural language Inference (SNLI) dataset, which is a high-quality and large-scale benchmark, thus inspiring various significant work.

Most of existing NLI models apply attention mechanism to jointly interpret and align the premise and hypothesis, while transfer learning from external knowledge is popular recently. Notably, Chen et al. [9] proposed an enhanced sequential inference model (ESIM), which employed recursive architectures in both local inference modeling and inference composition, as well as syntactic parsing information, for a sequential inference model. ESIM is simple with satisfactory performance, and is thus widely chosen as the baseline model. Mccann et al. [32] proposed to transfer the LSTM encoder from the neural machine translation (NMT) to the NLI task to contextualize word vectors. Pan et al. [37] transfered the knowledge learned from the discourse marker prediction task to the NLI task to augment the semantic representation.

# III. OUR UNIFIED REPRESENTATION LEARNING FRAMEWORK

For generality, we consider an end-to-end model for either of text comprehension tasks. Fig. 1 overviews the unified representation learning framework. The input tokens are segmented into subword units to further obtain the subword

embeddings, which are then fed to downstream models along with word embedding. For textual entailment, the two input sequences are premise and hypothesis and the output is the label. For reading comprehension, the two input sequences are document and question and the output is the answer.

We apply unsupervised subword segmentation to produce the subwords for each token in the input sequence. Our subwords are formed as character n-gram and do not cross word boundaries. After splitting each word k into a subword sequence, an augmented embedding (AE) is formed to straightforwardly integrate word embedding WE(k) and subword embedding SE(k) for a given word k.

$$AE(k) = WE(k) \diamond SE(k)$$
 (1)

where  $\diamond$  denotes the integration strategy. In this work, we investigate concatenation (*concat*), element-wise summation (*sum*) and element-wise multiplication (*mul*).

Suppose that word k is formed with a sequence of subwords  $[s_1, \ldots, s_l]$  where l is the number of subwords for word k. Then the subword-level representation of k is given by the matrix  $C^k \in \mathbb{R}^{d \times l}$  where d denotes the subword dimension.

We employ a narrow convolution between  $C^k$  and a filter  $H \in \mathbb{R}^{d \times w}$  of width w to obtain a feature map  $f^k \in \mathbb{R}^{l-w+1}$ . We take one filter operation for example, the i-th element of  $f^k$  is given by

$$f^{k}[i] = \tanh(\langle C^{k}[*, i: i+w-1], H \rangle + b)$$
 (2)

where  $C^k[*,i:i+w-1]$  denotes the *i*-th to (i+w-1)-th column of  $C^k$  and  $\langle A,B\rangle=\mathrm{Tr}(AB^T)$  represents the Frobenius inner product. Then, a max pooling operation is adopted after the convolution and we fetch the feature representation corresponding to the filter H.

$$y^k = \max_{i} f^k[i] \tag{3}$$

Here we have described the process by which one feature is obtained from one filter matrix. For a total of h filters,  $[H_1,\ldots,H_h]$ , then  $y^k=[y_1^k,\ldots,y_h^k]$  is the distilled subword-level representation of word k. We then fed  $y^k$  to a highway network [44] to select features individually for each subword-derived word representation, and the final subword embedding (SE) is obtained by

$$SE(k) = t \odot q(W_H y^k + b_H) + (1 - t) \odot y^k$$
 (4)

where g is a nonlinear function and  $t = \sigma(W_T y^k + b_T)$  represents the transform gate.  $W_H$ ,  $W_T$ ,  $b_H$  and  $b_T$  are parameters.

The downstream model is task-specific. In this work, we focus on the textual entailment and machine reading comprehension, which will be discussed latter.

## A. Unsupervised Subword Segmentation

To segment subwords from word that is regarded as character sequence, we adopt and extend the generalized unsupervised segmentation framework proposed by Zhao and Kit [58], which was originally designed only for Chinese word segmentation.

Fig. 1: Architecture of the proposed Subword-augmented Embedding framework.

Word token | little white rabbit

The generalized framework can be divided into two collocative parts, goodness measurement which evaluates how likely a subword is to be a 'proper' one, and a segmentation or decoding algorithm. The framework generally works in two steps. First, a goodness score  $g(w_i)$  is computed for each n-gram  $w_i$  (in this paper gram always refers to character) using the selected goodness measure to form a dictionary  $W = \left\{ \{w_i, g(w_i)\}_{i=1,\dots,n} \right\}$ . Then segmentation or decoding method is applied to tokenize words into subwords based on the dictionary.

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Zhao and Kit [58] originally considered two decoding algorithms.

- a) Viterbi: This style of segmentation is to search for a segmentation with the largest goodness score sum for an input unsegmented sequence T (to be either words or Chinese sentence).
- b) Maximal-Matching (MM): This is a greedy algorithm with respect to a goodness score. It works on T to output the best current subword  $w^*$  repeatedly with  $T=t^*$  for the next round as follows,

$$\{w^*, t^*\} = \underset{wt=T}{\arg\max} g(w)$$
 (5)

with each  $\{w, g(w)\} \in W$ .

10%

 $\overline{UNK}$ 

In this work, we additionally introduce the second segmentation algorithm.

c) Byte Pair Encoding (BPE): Byte Pair Encoding (BPE) [17] is a simple data compression technique that iteratively replaces the most frequent pair of bytes in a sequence by a single, unused byte. Different from the previous two algorithms

that segment the input sequence into pieces in a top-down way, BPE segmentation actually merges a full single-character segmentation to a reasonable segmentation in a bottom-up way. We formulize the generalized BPE style segmentation in the following.

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At the very beginning, all the input sequences are tokenized into a sequence of single-character subwords, then we repeat,

- 1) Calculate the goodness scores of all bigrams under the current segmentation status of all sequences.
- Find the bigram with the highest goodness score and merge them in all the sequences. Note the segmentation status has been updated at this time.
- 3) If the merging times does not reach the specified number, go back to 1, otherwise the algorithm ends.

In our work, we investigate three types of goodness measures to evaluate subword likelihood, namely *Frequency*, *Accessor Variety* and *Description Length Gain* <sup>1</sup>.

Frequency (FRQ): FRQ is simply defined as the counting in the entire corpus for each n-gram being subword candidate. We take a logarithmic form as the goodness score,

$$g_{ESR}(w) = \log(\hat{p}(w)) \tag{6}$$

where  $\hat{p}(w)$  is w's frequency in the corpus.

Accessor Variety (AV): AV is proposed by Feng et al. [16] to measure how likely a subword is a true word. The AV

<sup>1</sup>Zhao and Kit [58] considered four types of goodness measures but *Branch Entropy* is excluded here due to its similar performance as *Accessor Variety* according to their results

of a subword  $x_i x_{i+1} \dots x_j$  (also denoted as  $x_{i...j}$ ) is defined as

$$AV(x_{i..j}) = \min\{L_{av}(x_{i..j}), R_{av}(x_{i..j})\}$$
 (7)

where the left and right accessor variety  $L_{av}(x_{i..j})$  and  $R_{av}(x_{i..j})$  are the number of distinct predecessor and successor characters, respectively. The same as FRQ, the goodness score is taken in logarithmic form,  $g_{AV}(w) = \log AV(w)$ .

Description Length Gain (DLG): Wilks [50] proposed this goodness measure for compression-based segmentation. The DLG replaces all occurrences of  $x_{i..j}$  from a corpus  $X = x_1x_2...x_n$  as a subword and is computed by

$$DLG(x_{i..j}) = L(X) - L(X[r \to x_{i..j}] \oplus x_{i..j})$$
 (8)

where  $X[r \to x_{i..j}]$  represents the resultant corpus by replacing all items of  $x_{i..j}$  with a new symbol r throughout X and  $\oplus$  denotes the concatenation.  $L(\cdot)$  is the empirical description length of a corpus in bits that can be estimated by the Shannon-Fano code or Huffman code, following classic information theory [43].

$$L(X) \doteq -|X| \sum_{x \in V} \hat{p}(x) \log_2 \hat{p}(x) \tag{9}$$

where  $|\cdot|$  denotes the string length, V is the vocabulary of X and  $\hat{p}(x)$  is x's frequency in X. The goodness score is given by  $g_{DLG}(w) = DLG(w)$ .

It is easy to find that BPE style segmentation with FRQ goodness measures (denoted as BPE-FRQ) could be identical to the BPE subword encoding in [41] in neural machine translation which is originally motivated for word representation for infrequent (rare or OOV) word representation in neural machine translation. Instead, we aim to refine the word representations by using subwords, for both frequent and infrequent words, which is more generally motivated. To this end, we adaptively tokenize words in multi-granularity.

#### IV. EXPERIMENTS

In this section, we evaluate the performance of subwordaugmented embedding on two kinds of challenging text understanding tasks, *textual entailment* and *reading comprehension*. Both of the concerned tasks are quite challenging, let alone the latest performance improvement has been already very marginal. However, we present a new solution in a new direction instead of heuristically stacking attention mechanisms. Namely, we show that subword embedding could be potential to give further advances due to its meaningful linguistic augments, which has not been studied yet for the concerned tasks. Our evaluation aims to answer the following empirical questions:

- 1) Can subword-augmented embedding enhance the concerned tasks?
- 2) Can using subword-augmented embedding be generally helpful for different languages?
- 3) Can subword embedding help effectively model OOV or rare words?
- 4) Which is the best unsupervised subword segmentation method for text understanding?

TABLE III: Accuracy on SNLI dataset. SOTA is short for state-of-the-art.

Model	Dev	Test
Baseline (Word + Char)	88.39	87.61
Word + Viterbi-AV	88.35	87.70
Word + Viterbi-FRQ	88.15	87.46
Word + Viterbi-DLG	88.31	87.53
Word + MM-AV	88.58	88.16
Word + MM-FRQ	88.45	88.05
Word + MM-DLG	88.61	88.28
Word + BPE-AV	88.42	88.11
Word + BPE-FRQ	88.56	88.36
Word + BPE-DLG	88.68	88.56
SOTA [24]	/	88.9

5) Which is the best strategy to integrate word and subword embedding?

The default subword vocabulary size is set 10k for textual entailment task and 1k for the two reading comprehension tasks. The default integration strategy is *concatenation* for the following experiments. The above choices are based on the model performance on the development set and the detailed analysis will be given in Section 6. Word embeddings are 200d and pre-trained by word2vec [33] toolkit on *Wikipedia* corpus<sup>2</sup>. Both character and subword embeddings are also 200d and randomly initialized with the uniform distribution in the interval [-0:05; 0:05]. Note that character could be regarded as the minimal case of subwords so we separately depict them in our experiments for better comparison and convenient demonstration.

In our preliminary experiments, we thoroughly explore all nine subword segmentation methods by considering there are three segmentation algorithms and three goodness measures. We find that all Viterbi based segmentation fails to show satisfactory performance, and we only report three best performing segmentation-goodness collocations for each task. Our baseline models are selected due to their simplicity and state-of-the-art performance in each task. We are interested in a subword-based framework that performs robustly across a diverse set of tasks. To this end, we follow the same hyperparameters or each baseline model as the original settings from their corresponding literatures [9, 15, 42] except those specified (e.g. subword dimension, integration strategy). Since ensemble systems and pre-training enhanced methods are commonly integrated with multiple heterogeneous models and resources and thus not completely comparable, we only focus on the evaluations on single models.

#### A. Textual Entailment

Textual entailment is the task of determining whether a *hypothesis* is *entailment, contradiction* and *neutral*, given a *premise*. The Stanford Natural Language Inference (SNLI) corpus [5] provides approximately 570k hypothesis/premise pairs.

Our baseline model is Enhanced Sequential Inference Model (ESIM) [9] which employs a biLSTM to encode the premise

<sup>&</sup>lt;sup>2</sup>https://dumps.wikimedia.org/

CMRC-2017 PD CFT Train Valid Test Train Valid Test human 354,295 # Query 2,000 3,000 870,710 3,000 3,000 1,953 Max # words in docs 486 481 484 618 536 634 414 Max # words in query 184 72 106 502 153 265 92 321 307 379 425 410 153 Avg # words in docs 324 Avg # words in query 27 19 23 38 38 41 20 94,352 # Vocabulary 21,821 38,704 248,160

TABLE IV: Data statistics of CMRC-2017, PD and CFT.

and hypothesis, followed by an attention layer, a local inference layer, an inference composition layer. To keep the model simplicity and concentrate on the performance of subword units, we do not integrate extra syntactic parsing features or increase the dimension of word embeddings. However, with the subword augmentation, our simple sequential encoding model yields substantial gains and achieves competitive performance with more complex state-of-the-art models<sup>3</sup>.

The dimensions for all the LSTM and fully connection layers were 300. We set the dropout rate to 0.5 for each LSTM layer and the fully connected layers. All feed forward layers used ReLU activations. Parameters were optimized using Adam [26] with gradient norms clipped at 5.0. The initial learning rate was 0.001, which was halved every epoch after the second epoch. The batch size was 32.

Results in Table III show that, subword-augmented embedding can boost our baseline (Word + Char) by +0.95% on the test set. Among the subword algorithms, BPE-DLG performs the best whose key difference with other approaches is that BPE-DLG gives finer-grained bi-grams like {*ri, ch, ne, ss*} which could be potentially important for short text modeling with small word vocabulary like textual entailment task.

# B. Reading Comprehension

To investigate the effectiveness of the subword-augmented embedding in conjunction with more complex models, we conduct experiments on machine reading comprehension tasks. The reading comprehension task can be described as a triple < D, Q, A >, where D is a document (context), Q is a query over the contents of D, in which a word or span is the right answer A. This task can be divided into cloze-style and query-style. The former has restrictions that each answer should be a single word and should appear in the document and the original sentence removing the answer part is taken as the query. For the query-style, the query is formed as questions in natural language whose answer is a span of texts. To test the subword-augmented embedding in multi-lingual case, we select three Chinese datasets, Chinese Machine Reading Comprehension (CMRC-2017) [14], People's Daily (PD) [11], Children Fairy Tales (CFT) [11] and two English ones, Children's Book Test (CBT) [20], the Stanford Question Answering Dataset (SQuAD) [39] in which the first four sets are cloze-style and the last one is query-style.

1) Cloze-style: To verify the effectiveness of our proposed model for Chinese, we conduct multiple experiments on three

TABLE V: Accuracy on CMRC-2017 dataset.

Model	Dev	Test
Baseline (Word + Char)	76.15	77.73
Word + MM-AV	77.80	77.80
Word + MM-DLG	77.30	77.17
Word + BPE-FRQ	78.95	78.80
SOTA [13]	77.20	78.63

Chinese Machine Reading Comprehension datasets, namely CMRC-2017, PD and CFT <sup>4</sup>. Table IV gives data statistics. Different from the current cloze-style datasets for English reading comprehension, such as CBT, Daily Mail and CNN [19], the three Chinese datasets do not provide candidate answers. Thus, the model has to find the correct answer from the entire document.

Our baseline model is the Gated-Attention (GA) Reader [15] which integrates a multi-hop architecture with a gated attention mechanism between the intermediate states of document and query. We used stochastic gradient descent with ADAM updates for optimization. The batch size was 32 and the initial learning rate was 0.001 which was halved every epoch after the second epoch. We also used gradient clipping with a threshold of 10 to stabilize GRU training (Pascanu *et al.*, 2013). We used three attention layers. The GRU hidden units for both the word and subword representation were 128. We applied dropout between layers with a dropout rate of 0.5.

a) CMRC-2017: Table V gives our results on CMRC-2017 dataset <sup>5</sup>, which shows that our Word + BPE-FRQ model outperforms all other models on the test set, even the state-of-the-art AoA Reader [13]. With the help of the proposed method, the GA Reader could yield a new state-of-the-art performance over the dataset. Different from the above textual entailment task, the best subword segmentation tends to be BPE-FRQ instead of BPE-DLG. The divergence indicates that for a task like reading comprehension involving long paragraphs with a huge vocabulary <sup>6</sup>, high frequency words weigh more. In fact, as DLG measures word through more type statistics than the direct frequency weighting, it can be seriously biased by a lot of noise in the vocabulary. Using frequency instead of DLG can let the segmentation resist the noise by keeping concerns over those high frequency (also

<sup>&</sup>lt;sup>3</sup>We only compare with currently published work from SNLI Leaderboard: https://nlp.stanford.edu/projects/snli/

<sup>&</sup>lt;sup>4</sup>Note that the test set of CMRC-2017 and human evaluation test set (Testhuman) of CFT are harder for the machine to answer because the questions are further processed manually and may not be accordance with the pattern of automatic questions.

<sup>&</sup>lt;sup>5</sup>CMRC-2017 Leaderboard: http://www.hfl-tek.com/cmrc2017/leaderboard/.

<sup>&</sup>lt;sup>6</sup>The word vocabulary sizes of SNLI and CMRC-2017 are 30k and 90k respectively.

TABLE VI: Accuracy on PD and CFT datasets. Results of AS Reader and CAS Reader are from [11]. The result for GA Reader is based on our implementation. Previous state-of-theart model is marked by †.

Model	PD		CFT
Model	Valid	Test	Test-human
AS Reader	64.1	67.2	33.1
CAS Reader†	65.2	68.1	35.0
GA Reader	67.2	69.0	36.9
Word + BPE-FRQ	72.8	75.1	43.8

TABLE VII: Accuracy on CBT dataset. Results except ours are from previously published works [11, 15, 51]. Previous state-of-the-art model is marked by †.

Model	CBT-NE		CBT-CN	
Wodel	Valid	Test	Valid	Test
Human	-	81.6	-	81.6
LSTMs	51.2	41.8	62.6	56.0
MemNets	70.4	66.6	64.2	63.0
AS Reader	73.8	68.6	68.8	63.4
Iterative Attentive Reader	75.2	68.2	72.1	69.2
EpiReader	75.3	69.7	71.5	67.4
AoA Reader	77.8	72.0	72.2	69.4
NSE	78.2	73.2	74.3	71.9
FG Reader†	79.1	75.0	75.3	72.0
GA Reader	76.8	72.5	73.1	69.6
Word + BPE-FRQ	78.5	74.9	75.0	71.6

usually regular) words. Since we found the stable performance gain in all our preliminary experiments, we focus on BPE-FRQ in later similar cloze-style evaluation and comparison.

b) PD & CFT: Since there is no training set for CFT dataset, our model is instead trained on PD training set. Note that CFT test set is processed by human evaluation, and may not be accordance with the pattern of PD training dataset. The results on PD and CFT datasets are listed in Table VI, which shows our Word + BPE-FRQ significantly outperforms the CAS Reader in all types of testing, with improvements of 7.0% on PD and 8.8% on CFT test sets, respectively. Considering that the domain and topic of PD and CFT datasets are quite different, the results indicate the effectiveness of our model for out-of-domain learning.

c) CBT: To verify if our method can work for more than Chinese, we also evaluate the proposed method on English benchmark, CBT, whose documents consist of 20 contiguous sentences from the body of a popular children's book, and queries are formed by deleting a token from the 21st sentence. We only focus on its subsets where the answer is either a common noun (CN) or NE, so that our task here is more challenging as the answer is likely to be rare words. For a fair comparison, we simply set the same parameters as before. We evaluate all the models in terms of accuracy, which is the standard evaluation metric for this task.

Table VII shows the results for CBT. We observe that our model outperforms most of the previously published works, with 2.4 % gains on the CBT-NE test set compared with GA Reader which adopts word and character embedding concatenation. Our Word + BPE-FRQ also achieves comparable performance with FG Reader who adopts neural gates to combine word-level and character-level representations with

TABLE VIII: Exact Match (EM) and F1 scores on SQuAD dev set. BiDAF $_{\alpha}$  denotes BiDAF + Self-Attention and BiDAF $_{\beta}$  denotes BiDAF + Self-Attention + ELMO.

	Model	EM	F1
	Word + Char	71.22	80.42
$BiDAF_{\alpha}$	Word $+$ MM-AV	72.46	81.28
ыраг $_{\alpha}$	Word + MM-DLG	72.21	81.03
	Word + BPE-FRQ	72.79	81.78
	Word + Char	77.43	85.03
D:DAE.	Word $+$ MM-AV	77.49	85.23
$BiDAF_{\beta}$	Word + MM-DLG	77.46	85.22
	Word + BPE-FRQ	77.84	85.48
	Word + Char	68.23	77.95
BiDAF	Word $+$ MM-AV	68.86	78.44
	Word + MM-DLG	68.82	78.40
	Word + BPE-FRQ	69.35	<b>78.97</b>

TABLE IX: Embedding combinations on CMRC-2017.

Model	Dev	Test
Word Only	74.90	75.80
Char Only	71.25	72.53
BPE-FRQ Only	74.75	75.77
Word + Char	76.15	77.73
Word + BPE-FRQ	78.95	78.80
Word + Char + BPE-FRQ	79.05	78.83

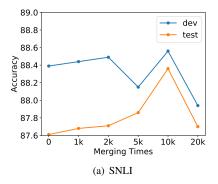
assistance of extra features including NE, POS and word frequency while our model is much simpler and faster. This comparison shows that our Word + BPE-FRQ is not restricted to Chinese reading comprehension, but also effective for other languages.

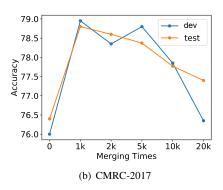
2) Query-style: The Stanford Question Answering Dataset (SQuAD) [39] contains 100k+ crowd sourced question-answer pairs where the answer is a span in a given Wikipedia paragraph. Our basic model is Bidirectional Attention Flow [42] and we improve it by adding a self-attention layer [47] and ELMO [38], similar to [10], to see whether subword could still improve more complex models. The augmented embeddings of document and query are passed through a bi-directional GRU which share parameters, and then fed to the BiDAF model. Then, we obtain the context vectors and pass them through a linear layer with ReLU activations, followed by a self-attention layer against the context itself. Finally, the results are fed through linear layers to predict the start and end token of the answer. For the hyper-parameters, the dropout rates for the GRUs and linear layers are 0.2. The dimensions for GRU and linear layers are 90 and 180, respectively. We optimize the model using ADAM. The batch size is 32. Table VIII shows the results on the dev set 7. We can see that for all the models, subword embeddings boost the performance significantly. Even for BiDAF $_{\alpha}$  and BiDAF $_{\beta}$ , BPE-FRQ could also yield substantial performance gains (+1.57%EM, 1.36%F1 and +0.41%EM, 0.45%F1 respectively).

#### V. ANALYSIS

The experimental results have shown that the subwordaugmented embedding can essentially improve baselines, from

 $<sup>^{7}</sup>$ Since the test set is not released, we train our models on training set and evaluate them on dev set.





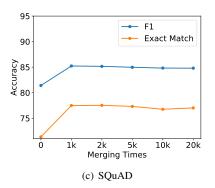


Fig. 2: Case study of the subword vocabulary size of BPE-FRQ.

the simple to the complicated, among multiple tasks with different languages. Though the performance of BPE-FRQ tends to be the most stable overall, the best practice for subword embedding might be task-specific. This also discloses that there exists potential for a more effective goodness measure or segmentation algorithm to polish up the subword representations.

#### A. Using Diverse Embedding Together

To see if we can receive further performance improvement when using different embedding together, we compare the following embeddings: Word Only, Char Only, BPE-FRQ only and Word + Char, Word + BPE-FRQ and Word + Char + BPE-FRQ. Table IX shows the result. For each type of embedding alone, word embedding and BPE-FRO subword embedding turn out to be comparable. BPE-FRQ performs much better than char embedding, which again confirms that subwords are more representative as minimal natural linguistic units than single characters. Any embedding combination could improve the performance as the distributed representations can be beneficial from different perspectives through diverse granularity. However, using all the three types of embeddings only shows marginal improvement. This might indicate that increasing embedding features or dimension might not bring much gains and seeking natural and meaningful linguistic units for representation is rather significant.

#### B. Subword Vocabulary Size

The segmentation granularity is highly related to the subword vocabulary size. For BPE style segmentation, the resulting subword vocabulary size is equal to the merging times plus the number of single-character types. To have an insight of the influence, we adopt merge times of BPE-FRQ from 0 to 20k, and conduct quantitative study on SNLI, CMRC-2017 and SQuAD for BPE-FRQ segmentation. Fig. 2 shows the results. We observe that with 1k merge times, the models could obtain the best performance on CMRC-2017 and SQuAD though these two tasks are of different languages while 10k shows to be more suitable for SNLI. The results also indicate that for a task like reading comprehension the subwords, being a highly flexible grained representation between character and word, tends to be more like characters instead of words. However,

TABLE X: Different merging functions with word embeddings on SNLI and CMRC-2017.

Model	Strategy	Dev	Test
	concat	88.68	88.56
SNLI	sum	88.30	87.14
	mul	88.47	87.77
	concat	77.45	77.47
CMRC	sum	75.95	76.43
	mul	78.95	<b>78.80</b>

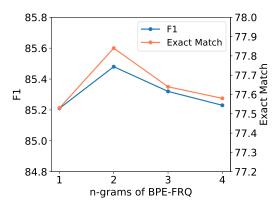


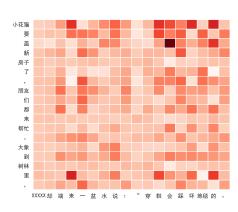
Fig. 3: Results of n-gram of BPE-FRQ on SQuAD dataset.

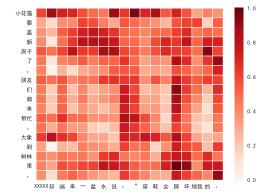
when the subwords completely fall into characters, the model performs the worst. This indicates that the balance between word and character is quite critical and an appropriate grain of character-word segmentation could essentially improve the word representation.

# C. Subword and Word Embedding Integration Strategies

We investigate the combination of subword-augmented embedding with word embedding. Table X shows the comparisons based on our best models of SNLI and CMRC-2017, BPE-DLG and BPE-FRQ, respectively. The models with *concat* and *mul* significantly outperform the model with *sum*. This reveals that *concat* and *mul* operations might be more informative than *sum* and the best practice for the choice would be task-specific. Though *concat* operation may result in high dimensions, it could keep more information for downstream models to select from. The superiority of *mul* might be

Fig. 4: Pair-wise attention visualization.





(a) Embedding of document and query

(b) Final document and query representation

Doc (extract): The cat was going to build a new house. His friends came to help. The elephant went into the woods for logs. The goat and dog cut the logs into planks. Soon afterwards the bear constructs a beautiful house. The cat said happily, "After decorating my house, I'll invite everybody to have a party in it." A few days later, friends came to the party happily. Upon entering the door, the cat fetched a small basin of water and said, "Your shoes will trample the carpet. Please take off your shoes and wash your feet, or leave." The elephant and bear looked at their own feet and the small basin, felt upset, saying, "Forget it, we'll never go in." Since then, no animal played with him any more. The house was his last friend.

Query: \_\_\_\_\_\_fetched a small basin of water and said, "Your shoes will trample the carpet.Please take off your shoes and wash your feet, or leave."

due to element-wise product being capable of modeling the interactions and eliminating distribution differences between word and subword embedding which is intuitively similar to endowing subword-aware *attention* over the word embedding. In contrast, *sum* is too simple to prevent from detailed information loss.

# D. Effect of the n-grams

The goodness measures commonly build the subword vocabulary based on neighbored character relationship inside words. This is reasonable for Chinese where words are commonly formed by two characters which is also the original motivation for Chinese word segmentation. However, we wonder whether it would be better to use longer n-gram connections. We expand the n-grams of BPE-FRQ from 1 to 4. Fig. 3 shows the quantitative study results. We observe the n-grams of BPE-FRQ segmentation might slightly influence the result where 2 or 3 tends to be better choice.

#### E. Visualization

To analyze the learning process of our models, we draw the attention distributions at intermediate layers based on an example from CMRC-2017 dataset. Fig. 4 shows the result of model with BPE-FRQ. We observe that the right answer (*The cat*) could obtain a high weight after the pair-wise matching of document and query. After attention learning, the key evidence of the answer would be collected and irrelevant parts would be ignored. This shows that our subword-augmented embedding is effective at selecting the vital points at the fundamental embedding layer, guiding the attention layers to collect more relevant pieces.

#### F. Subword Observation

In text understanding tasks, if the ground-truth answer is OOV word or contains OOV word(s), the performance of deep

neural networks would severely drop due to the incomplete representation, especially for a task like cloze-style reading comprehension where the answer is only one word or phrase. To get an intuitive observation for the task, we collect all the 118 questions whose answers are OOV words (with their corresponding documents, denoted as OOV questions) from CMRC-2017 test set, and use our model to answer these questions. We observe only 2.54% could be correctly answered by the best Word + Char embedding based model. With BPE-FRQ subword embedding, 12.71% of these OOV questions could be correctly solved. This shows that the subword representations could be essentially useful for modeling rare and unseen words. In fact, the meaning of complex words like indispensability could be accurately refined by segmented subwords as shown in Table XI. This also shows subwords could help the models to use morphological clues to form robust word representations which is especially potential to obtain fine-grained representation for low-resource languages.

TABLE XI: Examples of BPE-FRQ subwords.

Word	Subword
indispensability	in disp ens ability
intercontinentalexchange	inter contin ent al ex change
playgrounds	play ground s
大花猫	大 花猫
一步一个脚印	一步 一个 脚印

## VI. CONCLUSION

Embedding is the fundamental part of deep neural networks, which could also be the bottleneck of the model strength. Building a more fine-grained representation at the very beginning could potentially guide the following networks, especially attention component to collect more important pieces. This paper presents a general yet effective architecture, subwordaugmented embedding to enhance the word representation

and effectively handle rare or unseen words. Experiments on five datasets from textual entailment and reading comprehension tasks demonstrate significant performance gains over the baselines. Unlike most existing works, which introduce either complex attentive architectures, handcrafted features or extra knowledge resources, our model is much more simple yet effective. The proposed method takes variable-length subwords segmented by unsupervised segmentation measures, without relying on any predefined linguistic resource. Thus the proposed method is also suitable for various open vocabulary NLP tasks. Our work discloses that the deep internals of sub-word level embeddings are crucial, helping downstream models to absorb different signals.

#### REFERENCES

- [1] Oded Avraham and Yoav Goldberg. The interplay of semantics and morphology in word embeddings. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics* (EACL), pages 422–426, 2017.
- [2] Toms Bergmanis and Sharon Goldwater. From segmentation to analyses: a probabilistic model for unsupervised morphology induction. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, pages 337–346, 2017
- [3] Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics (TACL)*, 5:135–146, 2017.
- [4] Jan A. Botha and Phil Blunsom. Compositional morphology for word representations and language modelling. *Proceedings of the 31st International Conference on Machine Learning (ICML)*, 32:1899–1907, 2014.
- [5] Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. A large annotated corpus for learning natural language inference. In *Proceedings* of the 20th conference on Empirical Methods in Natural Language Processing (EMNLP), pages 632–642, 2015.
- [6] Deng Cai, Hai Zhao, Zhisong Zhang, Yuan Xin, Yongjian Wu, and Feiyue Huang. Fast and accurate neural word segmentation for Chinese. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 608–615, 2017.
- [7] Kris Cao and Marek Rei. A joint model for word embedding and word morphology. In *The Workshop on Representation Learning for NLP*, pages 18–26, 2016.
- [8] Danqi Chen, Jason Bolton, and Christopher D Manning. A thorough examination of the CNN/Daily Mail reading comprehension task. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics* (ACL), pages 2358–2367, 2016.
- [9] Qian Chen, Xiaodan Zhu, Zhenhua Ling, Si Wei, Hui Jiang, and Diana Inkpen. Enhanced lstm for natural language inference. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics* (ACL), pages 1657–1668, 2017.

- [10] Christopher Clark and Matt Gardner. Simple and effective multi-paragraph reading comprehension. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 845–855, 2018.
- [11] Yiming Cui, Ting Liu, Zhipeng Chen, Shijin Wang, and Guoping Hu. Consensus attention-based neural networks for Chinese reading comprehension. In *Proceedings of COLING 2016*, the 26th International Conference on Computational Linguistics: Technical Papers (COLING), pages 1777–1786, 2016.
- [12] Yiming Cui, Zhipeng Chen, Si Wei, Shijin Wang, Ting Liu, and Guoping Hu. Attention-over-attention neural networks for reading comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 1832–1846, 2017.
- [13] Yiming Cui, Zhipeng Chen, Si Wei, Shijin Wang, Ting Liu, and Guoping Hu. Attention-over-attention neural networks for reading comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 593–602, 2017.
- [14] Yiming Cui, Ting Liu, Zhipeng Chen, Wentao Ma, Shijin Wang, and Guoping Hu. Dataset for the first evaluation on Chinese machine reading comprehension. *arXiv* preprint arXiv:1511.02301, 2017.
- [15] Bhuwan Dhingra, Hanxiao Liu, Zhilin Yang, William W. Cohen, and Ruslan Salakhutdinov. Gated-attention readers for text comprehension. In *Proceedings of the 55th annual meeting of the Association for Computational Linguistics (ACL)*, pages 1832–1846, 2017.
- [16] Haodi Feng, Kang Chen, Xiaotie Deng, and Weimin Zheng. Accessor variety criteria for chinese word extraction. *Computational Linguistics*, 30(1):75–93, 2004.
- [17] Gage and Philip. A new algorithm for data compression. *C Users Journal*, 12(2):23–38, 1994.
- [18] Harald Hammarstrom and Lars Borin. Unsupervised learning of morphology. *Computational Linguistics*, 37 (2):309–350, 2011.
- [19] Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. Teaching machines to read and comprehend. In *Advances in Neural Information Processing Systems* 28 (NIPS), pages 1693–1701, 2015.
- [20] Felix Hill, Antoine Bordes, Sumit Chopra, and Jason Weston. The goldilocks principle: Reading children's books with explicit memory representations. arXiv preprint arXiv:1511.02301, 2015.
- [21] Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL), pages 1601–1611, 2017.
- [22] Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. Bag of tricks for efficient text classification. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, pages 427–431, 2017.
- [23] Rudolf Kadlec, Martin Schmid, Ondrej Bajgar, and Jan

- Kleindienst. Text understanding with the attention sum reader network. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 908–918, 2016.
- [24] Seonhoon Kim, Jin Hyuk Hong, Inho Kang, and Nojun Kwak. Semantic sentence matching with denselyconnected recurrent and co-attentive information. *arXiv* preprint arXiv:1805.11360, 2018.
- [25] Yoon Kim, Yacine Jernite, David Sontag, and Alexander M Rush. Character-aware neural language models. In *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (AAAI)*, pages 2741–2749, 2016.
- [26] Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.
- [27] Haonan Li, Zhisong Zhang, Yuqi Ju, and Hai Zhao. Neural character-level dependency parsing for Chinese. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence (AAAI)*, pages 5205–5212, 2018.
- [28] Zuchao Li, Jiaxun Cai, Shexia He, and Hai Zhao. Seq2seq dependency parsing. In *Proceedings of the 27th International Conference on Computational Linguistics* (COLING), pages 3203–3214, 2018.
- [29] Zuchao Li, Shexia He, Jiaxun Cai, Zhuosheng Zhang, Hai Zhao, Gongshen Liu, Linlin Li, and Luo Si. A unified syntax-aware framework for semantic role labeling. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2401–2411, 2018.
- [30] Zuchao Li, Shexia He, Hai Zhao, Yiqing Zhang, Zhuosheng Zhang, Xi Zhou, and Xiang Zhou. Dependency or span, end-to-end uniform semantic role labeling. *arXiv* preprint arXiv:1901.05280, 2019.
- [31] Minh-Thang Luong and Christopher D Manning. Achieving open vocabulary neural machine translation with hybrid word-character models. *arXiv preprint arXiv:1604.00788*, 2016.
- [32] Bryan Mccann, James Bradbury, Caiming Xiong, and Richard Socher. Learned in translation: Contextualized word vectors. Advances in Neural Information Processing Systems 30 (NIPS), 2017.
- [33] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv* preprint arXiv:1301.3781, 2013.
- [34] Yasumasa Miyamoto and Kyunghyun Cho. Gated wordcharacter recurrent language model. In *Proceedings of* the 2016 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1992–1997, 2016.
- [35] Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. Ms marco: A human generated machine reading comprehension dataset. *ArXiv:1611.09268v2*, 2016.
- [36] Kyosuke Nishida, Itsumi Saito, Atsushi Otsuka, Hisako Asano, and Junji Tomita. Retrieve-and-read: Multi-task learning of information retrieval and reading comprehension. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, pages 647–656, 2018.

- [37] Boyuan Pan, Yazheng Yang, Zhou Zhao, Yueting Zhuang, Deng Cai, and Xiaofei He. Discourse marker augmented network with reinforcement learning for natural language inference. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics* (ACL), pages 989–999, 2018.
- [38] M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer. Deep contextualized word representations. *arXiv preprint arXiv:1802.05365*, 2018.
- [39] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2383–2392, 2016.
- [40] Pranav Rajpurkar, Robin Jia, and Percy Liang. Know what you don't know: Unanswerable questions for SQuAD. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 784–789, 2018.
- [41] Rico Sennrich, Barry Haddow, and Alexandra Birch. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the* Association for Computational Linguistics (ACL), pages 1715–1725, 2016.
- [42] Minjoon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. Bidirectional attention flow for machine comprehension. In *ICLR 2017 : 5th International Conference on Learning Representations*, 2017.
- [43] C. E. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27(3):379–423, 1948.
- [44] Rupesh Kumar Srivastava, Klaus Greff, and Jürgen Schmidhuber. Training very deep networks. *arXiv* preprint arXiv:1507.06228, 2015.
- [45] Rui Wang, Andrew Finch, Masao Utiyama, and Eiichiro Sumita. Sentence embedding for neural machine translation domain adaptation. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 560–566, 2017.
- [46] Rui Wang, Masao Utiyama, Andrew Finch, Lemao Liu, Kehai Chen, and Eiichiro Sumita. Sentence selection and weighting for neural machine translation domain adaptation. *IEEE/ACM Transactions on Audio, Speech,* and Language Processing, 26(10):1727–1741, 2018.
- [47] Wenhui Wang, Nan Yang, Furu Wei, Baobao Chang, and Ming Zhou. Gated self-matching networks for reading comprehension and question answering. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 189–198, 2017.
- [48] Yizhong Wang, Kai Liu, Jing Liu, Wei He, Yajuan Lyu, Hua Wu, Sujian Li, and Haifeng Wang. Multipassage machine reading comprehension with crosspassage answer verification. *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 1918–1927, 2018.
- [49] Zhiguo Wang, Wael Hamza, and Radu Florian. Bilateral multi-perspective matching for natural language sen-

- tences. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence (IJCAI)*, pages 4144–4150. 2017.
- [50] Yorick Wilks. Unsupervised learning of word boundary with description length gain. CoNLL-99: The SIGNLL Conference on Computational Natural Language Learning, pages 1–6, 1999.
- [51] Zhilin Yang, Bhuwan Dhingra, Ye Yuan, Junjie Hu, William W. Cohen, and Ruslan Salakhutdinov. Words or characters? fine-grained gating for reading comprehension. In *ICLR 2017 : 5th International Conference* on Learning Representations, 2017.
- [52] Shuailiang Zhang, Hai Zhao, Yuwei Wu, Zhuosheng Zhang, Xi Zhou, and Xiang Zhou. Dual co-matching network for multi-choice reading comprehension. *arXiv* preprint arXiv:1901.09381, 2019.
- [53] Zhuosheng Zhang and Hai Zhao. One-shot learning for question-answering in gaokao history challenge. In *Proceedings of the 27th International Conference on Computational Linguistics (COLING)*, pages 449–461, 2018.
- [54] Zhuosheng Zhang, Yafang Huang, and Hai Zhao. Subword-augmented embedding for cloze reading comprehension. In *Proceedings of the 27th International Conference on Computational Linguistics (COLING)*, pages 1802–1814, 2018.
- [55] Zhuosheng Zhang, Jiangtong Li, Pengfei Zhu, and Hai Zhao. Modeling multi-turn conversation with deep utterance aggregation. In *Proceedings of the 27th International Conference on Computational Linguistics (COLING)*, pages 3740–3752, 2018.
- [56] Zhuosheng Zhang, Yuwei Wu, Zuchao Li, Shexia He, Hai Zhao, Xi Zhou, and Xiang Zhou. I know what you want: Semantic learning for text comprehension. *arXiv* preprint arXiv:1809.02794, 2018.
- [57] Zhuosheng Zhang, Yafang Huang, and Hai Zhao. Open Vocabulary Learning for Neural Chinese Pinyin IME. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL)*, 2019.
- [58] Hai Zhao and Chunyu Kit. An empirical comparison of goodness measures for unsupervised Chinese word segmentation with a unified framework. In *Proceedings* of the Third International Joint Conference on Natural Language Processing (IJCNLP), pages 9–16, 2008.



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