A Pilot Study on Multiple Choice Machine Reading Comprehension for Vietnamese Texts

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Abstract

Machine Reading Comprehension (MRC) is the task of natural language processing which studies the ability to read and understand unstructured texts and then find the correct answers for questions. Until now, we have not yet had any MRC dataset for such a low-resource language as Vietnamese. In this paper, we introduce ViMMRC, a challenging machine comprehension corpus with multiple-choice questions, intended for research on the machine comprehension of Vietnamese text. This corpus includes 2,783 multiple-choice questions and answers based on a set of 417 Vietnamese texts used for teaching reading comprehension for 1\textsuperscript{st} to 5\textsuperscript{th} graders. Answers may be extracted from the contents of single or multiple sentences in the corresponding reading text. A thorough analysis of the corpus and experimental results in this paper illustrate that our corpus ViMMRC demands reasoning abilities beyond simple word matching. We proposed the method of Boosted Sliding Window (BSW) that improves 5.51\% in accuracy over the best baseline method. We also measured human performance on the corpus and compared it to our MRC models. The performance gap between humans and our best experimental model indicates that significant progress can be made on Vietnamese machine reading comprehension in further research. The corpus is

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freely available at our website[1] for research purposes.

*Keywords:* Machine reading comprehension, multiple choice, Vietnamese, Boosted Sliding Window

1. Introduction

A primary goal of computational linguistics or natural language processing is to make computers able to understand natural language texts as well as human beings do. One of the common tests of natural language understanding ability requires computers to read documents and answer any questions related to their contents, resulting in different research problem settings of machine reading comprehension [1] [2] [3] [4]. MRC can also be the extended task of question answering (QA). There are many studies on QA [5] [6] [7] [8] [9], which are also the foundation for development of MRC. Findings of this research field are implemented into various artificial intelligence applications such as next-generation search engines, intelligent agents (Alexa, Google Assistant, Siri, Cortana, etc), chatbots and robots.

Recently, multiple-choice reading comprehension tests have been widely used for MRC tasks for many languages such as English, Japanese. This type of test can measure abilities such as causal or counterfactual reasoning, inference among relations, or basic understanding of the world in a set of reading texts. However, for the Vietnamese language, there is no related research works. Therefore, we propose a multiple-choice reading comprehension task as a way to evaluate progress on Vietnamese machine reading comprehension. We have built a Vietnamese reading comprehension corpus called ViMMRC which contains 417 reading texts and at least 5 multiple-choice questions per reading text. In this study, we focus on reading texts suitable for 1st to 5th grade students. The corpus is open-domain, yet restricted to concepts and words that 6 to 11-year-old children are expected to understand.

Our problem is stated as follows.

**Input:** Given a Vietnamese reading text $T$ and a question $Q$ with a list of four answer options $O_i$ ($1 \leq i \leq 4$).

**Output:** The best answer choice to the question.

To illustrate, Table 1 shows several examples taken from the ViMMRC corpus.

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[1] https://sites.google.com/uit.edu.vn/uit-nlp/
### Table 1: Examples of Multiple-choice Reading Comprehension of Vietnamese Texts.

| Reading Text | Vietnamese: Ngay giữa sân trường, sừng súng một cây bàng. Mùa đông, cây vuông dại những cánh kháng khiu, truí lá. Xuân sang, cành trên cành dưới chỉ chít những lộc non mơn mò. Hè về, những tán lá xanh um che mát một khoảng sân trường. Thu đến, từng chòm quả chín vàng trong kẽ lá.  

**(English translation): In the middle of the school yard stood a towering tropical almond tree. In winter, the tree stretches out its slender, leafless branches. As spring arrives, its branches on the branches below are spangled with young buds. Summer approaches and its green foliage shades the yard. Autumn comes, revealing bunches of gold ripen fruits dangling in its leaves.)** |
|---|
| Question | Cây bàng được trồng ở đâu? (Where is the tropical almond tree planted?)  
A. Ngay giữa sân trường. **(In the middle of the school yard.)**  
B. Trồng ở ngoài đường. **(In the street.)**  
C. Gần sông. **(Near the river.)**  
D. Dưới mái hiên trường. **(Under the porch.)** |
| Answer | A |
| Question | Những bộ phận nào của cây được nhắc đến trong bài đọc? (What parts of the tree are mentioned?)  
A. Cành và lá. **(Branches and leaves.)**  
B. Lá và quả. **(Leaves and fruit.)**  
C. Cành, lá, lộc, tán lá và quả. **(Branches, leaves, buds, foliage and fruit.)**  
D. Lộc, quả và tán cây. **(Buds, fruit and foliage.)** |
| Answer | C |

In this paper, we have three main contributions as follows:  
- First and foremost, we have constructed the first corpus for Vietnamese
multiple-choice reading comprehension task. The corpus is available freely for the research community and is expected to contribute to the research development of in machine reading comprehension for the Vietnamese language.

- Secondly, we proposed the method called Boosted Sliding Window for Vietnamese multiple choice reading comprehension, achieving the best performance of 61.81% in accuracy. In addition, we have compared this model with different baseline models including the state-of-the-art neural-based models on other languages.

- Lastly, we analyzed the experimental results on different aspects such as question length, grade level, word embedding and training data size. These analyses give insights into Vietnamese multiple choice machine reading comprehension in different ways.

The rest of this paper is structured as follows. Section 2 reviews related corpora and methods. Section 3 introduces the creation process and analysis of the ViMMRC corpus. Section 4 presents our proposed method and other approaches for Vietnamese multiple-choice machine reading comprehension. Section 5 shows experiments and results on the corpus. Section 6 describes error analysis for these experimental results. Finally, section 7 concludes the paper and discusses future work.

2. Related Work

In this section, we aim to review recent corpora and techniques in machine reading comprehension. In particular, the typical MRC corpora and methodologies are described as follows.

2.1. Related Corpora

In the last decade, we have witnessed a fast growth of research interest in machine reading comprehension (MRC) and an explosion of corpora for MRC studies for popular languages like English and Chinese.

In terms of types of answers, MRC corpora are divided into three categories including extractive, abstractive and multiple-choice. Extractive MRC requires computers to locate the correct segment in a provided reading text that answers a specific question related to that text. Recently, there have been a dramatic increase in the construction of extractive MRC corpora with
formal written texts such as SQuAD [2], CNN/Daily Mail [1], CBT [10], NewsQA [11], TriviaQA [12], and WIKIHOP [13]. There are also corpora of which reading texts are spoken language, such as ODSQA [14] and Spoken SQuAD [15] and conversation-based corpora such as [16] and [17].

In contrast to extractive MRC, abstractive MRC requires computers to generate answers or synthetic summaries because answers to such questions in abstractive MRC are usually not spans in the reading text. Corpora for abstractive MRC include [18], SearchQA [19], and NarrativeQA [20].

Multile-choice MRC includes both extractive and abstractive MRCs; however, the correct answer options are primarily abstractive. Most of the multiple-choice MRC corpora are created using crowdsourcing methods in major steps of corpus construction including generating questions, correct answer options and distractors. MCTest [21], ROCStories [22], MultiRC [23] and MCScript [24] are typical corpora of this type. The crowd workers also assign to each question the reasoning mechanism that is needed to figure out the answer. Apart from the basic reasoning mechanism - the matching type, a dramatic number of questions require complex reasoning mechanisms which are based on multiple sentences and require external knowledge. Other corpora are collected from examinations designed by educational experts QALD [25], NTCIR-11 QA-Lab [26], corpus from TOEFL exams [27], corpus from NY Regents 4th Grade Science exams [28], and RACE [29], which aim to evaluate learners.

2.2. Related Methods

2.2.1. Machine Reading Comprehension Models

**Sliding Window.** We reimplemented the Sliding Window algorithm, a lexical-based approach developed by Richardson et al. [21], as our first baseline model. This method was also used as a baseline in other studies [2, 24, 29]. Sliding Window finds an answer based on simple lexical information. Motivated by TF-IDF, this algorithm uses inverse word count as a weight of each lexical unit, and maximizes the bag-of-word similarity between the answer option and lexical units in the given reading text in a window size.

**Neural-based Approach.** With the popularity of neural network approach, end-to-end models such as Stanford AR [30], GA Reader [31], HAF [32] and Co-Match [33] have produced promising results on multiple-choice MRC. Recently, pre-trained language models have also been added [34, 35, 36, 37]. These models do not rely on complex manually-devised features as in traditional machine learning approaches, but are able to outperform them.
In this paper, we employ an end-to-end model called Co-match \cite{33} with different pre-trained word embeddings as another baseline model.

Regarding to the Vietnamese language processing, there are quite a number of research works on other tasks such as parsing \cite{38, 39, 40}, part-of-speech \cite{41, 42}, named entity recognition \cite{43, 44, 45}, sentiment analysis \cite{46, 47, 48}, question answering \cite{49, 50, 51}. However, to the extent of our knowledge, there are no research publications on machine reading comprehension. Therefore, we decided to build a new corpus of Vietnamese multiple-choice reading comprehension for the research community and evaluated MRC state-of-the-art models on our corpus. We also proposed an improvement to the Sliding Window algorithm for Vietnamese multiple choice machine reading comprehension.

2.2.2. Word Embeddings

A fundamental task in natural language processing is how to represent words to enable computing machines to understand their meanings. Word representation also plays a significant role in machine reading comprehension. In 1986, Rumelhart et al. \cite{52} proposed word embedding, a technique that maps each word to a vector space and can accurately capture a large proportion of syntactic and semantic relationships in text. Using pre-trained word embedding \cite{53, 54, 55, 56, 57}, there are two most common methods to represent words in machine reading comprehension models: word-level embedding and character-level embedding. However, these methods seem to be insufficient because it simply concatenates word-level and character-level embeddings; generated vectors stay the same in different contexts. To tackle these problems, Peters et al. \cite{58} proposed deep contextualized word representations called ELMo which is pre-trained by language model first and fine-tuned according to the learning task. Devlin et al. \cite{35} introduced BERT, which utilizes bidirectional transformer to encode both left and right contexts to the representations. Until now, BERT remains the best word representation method for the MRC task in English.

It is interesting to evaluate the above successful word embedding techniques in both lexical-based models and deep neural network models on the Vietnamese MRC corpus. This is also the aim of our work.
3. Vietnamese Multiple Choice Reading Comprehension Corpus

3.1. Corpus Creation

The process of constructing the ViMMRC corpus includes three different phases: reading-text collection, multiple-choice question creation, and corpus validation. These phases are described in detail as follows.

Reading-text collection: We decided to focus on the reading comprehension levels at primary schools because they only require general knowledge, not too specific knowledge. We collected the Vietnamese reading texts suitable for the 1st to 5th graders from the subject named Vietnamese. In addition, we collected reading comprehension tests from two reliable websites where all reading comprehension tests from 1st to 5th grades are made public for free of charge. As a result, 417 reading texts were gathered.

Multiple-choice question collection: Questions, answer options and correct answers are created by primary-school teachers. These questions are intended to test the reading comprehension ability of elementary learners. The teachers are asked to create at least five questions per text. Each question is accompanied by four answer options, of which only one is correct. For those texts with fewer numbers of questions or answer options, it is necessary to create more to meet the above conditions. Spelling errors were corrected. At the end of this phase, we achieved the ViMMRC corpus.

Validation: During this phase, primary-school teachers reviewed the multiple-choice questions, their answer options and their correct options again to ensure there is no mistakes. Finally, we obtained a highly-qualified corpus for research purpose for the computer multiple choice reading comprehension mechanism. In the following section, we analyze the characteristics of the corpus.

3.2. Corpus Analysis

Table 2: Statistics of the ViMMRC corpus

| Grade | 1   | 2   | 3   | 4   | 5   | All  |
|-------|-----|-----|-----|-----|-----|------|
| Number of texts | 10  | 70  | 188 | 99  | 120 | 417  |
| Vocabulary size (words) | 595 | 3,325 | 4,666 | 5,006 | 5,702 | 10,099 |
| Number of questions    | 60  | 514 | 759 | 709 | 741 | 2,783 |
We randomly divided our corpus into train, development, and test sets of 292 (70%), 42 (10%), and 83 (20%) texts, respectively. The statistics of the training, development and test sets are summarized in Table 3. In the table, the number of questions, the average words of texts, questions, answer options, correct answers, and vocabulary sizes are also listed.

In this section, we present analysis of our corpus from different aspects. Table 2 shows statistics of our corpus with different grades. Vocabulary size, text length, question length, answer option length, and correct answer length are calculated in words. We used the word segmentation pyvi. We found that the number of reading texts for the 1st grade is small, which is obvious because the 1st grade focuses on developing basic language skills rather than reading comprehension skill. We can observe that the vocabulary size increases as the grade increases. It can be inferred that the vocabulary sizes are correlated with the difficulty level of reading comprehension task.

The types of reasoning required to solve the multiple choice machine reading comprehension (MMRC) task directly influence the performance of MMRC models. In this paper, we classified the questions in our corpus following the same reasoning types as used in the analysis of the well-known corpus RACE [29]. These types are shown as follows, in ascending order of difficulty:

- **Word Matching (WM)**: Important tokens in the question exactly match tokens in the reading text. Thus, it is easy to use a keyword search algorithm for finding the correct answer of this question based

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Table 3: Statistics about the training, development and test sets according to different aspects

| Corpus                        | Train | Dev | Test | All  |
|-------------------------------|-------|-----|------|------|
| Number of texts               | 292   | 42  | 83   | 417  |
| Number of questions           | 1,975 | 294 | 514  | 2,783|
| Average text length (words)   | 223.7 | 230.1| 247.3| 229.0|
| Average question length (words)| 12.3  | 13.3| 13.0 | 12.5 |
| Average answer option length (words) | 7.5  | 7.4 | 7.6  | 7.5  |
| Average correct answer length (words) | 8.7  | 8.4 | 8.9  | 8.7  |
| Vocabulary size (words)       | 8,422 | 2,878| 4,502| 10,099|

[2]https://pypi.org/project/pyvi/
on the reading text.

- **Paraphrasing (PP):** The question is paraphrased from a single sentence in the reading text. In particular, we may use synonymy and world knowledge to create the question.

- **Single-sentence Reasoning (SSR):** The answer is inferred from a single sentence in the reading text. Such answers can be created by extracting incomplete information or conceptual overlap.

- **Multi-sentence Reasoning (MSR):** The answer is inferred from multiple sentences in the reading text by information synthesis techniques.

- **Ambiguous/Insufficient (AoI):** The question has many answers or answers are not found in the reading text.

We manually annotated all questions in our corpus according to these types. Examples and percentages of these type are listed in Table A.11. It can be seen from the table that single-sentence reasoning and ambiguous-or-insufficient make up the lowest proportions in our corpus (7.35% for single-sentence reasoning and 6.12% for ambiguous-or-insufficient). Meanwhile, word matching and multiple-sentence reasoning types account for the largest percentage, at 25.85% and 36.73% respectively. This demonstrates that ViMMRC is a challenging corpus for evaluating reading comprehension models for the Vietnamese language.

### 3.3. Comparison with the MCTest corpus

In this section, we compare our corpus with the MCTest corpus. The size of the MCTest corpus is approximately the same as our corpus. Table 4 shows differences between our corpus and the MCTest corpus. As can be seen from the table, although the number of reading texts in our corpus is less than that of the MCTest corpus, the number of questions of our corpus is greater. Besides, the average numbers of words per reading text, per question and per answer in our corpus are also higher than those of the MCTest corpus.
Table 4: Comparison between our corpus and the MCTest corpus

| Corpus       | #Text | #Question | Average words per: |
|--------------|-------|----------|-------------------|
|              |       |          | Text  | Question | Answer |
| MCTest (160) | 160   | 640      | 204   | 8.0      | 3.4    |
| MCTest (500) | 500   | 2,000    | 212   | 7.7      | 3.4    |
| MCTest (560) | 660   | 2,640    | 210   | 7.8      | 3.4    |
| Our corpus   | 417   | 2,783    | 229   | 12.5     | 7.5    |

4. Methodology

4.1. Pre-processing techniques

We want to get rid of meaningless and confusing words, so we cleaned this data by following the steps shown in Algorithm 1 and Algorithm 2. There are many techniques in natural language processing are applied in the pre-processing phase. In particular, Algorithm 1 pre-processes for a sentence, applied to sentence processing in the reading text, questions and answer options.

Algorithm 1: Pre-processing a raw Vietnamese sentence $S$

Input: A raw Vietnamese sentence $S$.
Output: A list of Vietnamese words after pre-processing $L$.

procedure PREPROCESSING A VIETNAMESE SENTENCE
\[ X = \text{tokenizing } S \text{ into a list of tokens.} \]
Removing punctuations in $X$.
Removing Vietnamese stop words in $X$.
$S' = \text{converting } X \text{ into a lower-case sentence.}$
$L = \text{segmenting } S' \text{ into a list of Vietnamese words by Vietnamese word segmentation.}$
return $L$.
end procedure

In Algorithm 1, firstly we use the tokenizer to break a sentence into a list of Vietnamese tokens $X$. In our work, this step performed in three steps, removing punctuation marks, stop words and noise words (short vowels) in...
the list $X$. After that, we convert the list $X$ into a lower-case sentence $S'$. Lastly, we use the Vietnamese word segmentation tool to parse the sentence $S'$ into a list of Vietnamese words $L$ which is the output of this algorithm. We also apply Algorithm 1 to both questions and answer options. We used the tool pyvi\(^3\) for word segmentation in this algorithm.

**Algorithm 2 : Pre-processing a Vietnamese reading text $T$**

**Input:** A Vietnamese reading text $T$.
**Output:** A pre-processed reading text $T'$.

```
procedure Pre-processing a Vietnamese reading text
  \( L = \text{splitting } T \text{ into a list of single sentences.} \)
  \( i = 1 \text{ to } \text{len}(L) \) do
    \( L_i = \text{Pre-processing for a raw Vietnamese sentence}(L_i). \)
    \( T' = \text{a pre-processed reading text converted from the list } L. \)
  end for
  return $T'$.
end procedure
```

In Algorithm 2, first of all, we split an input reading text into a list of sentences $L$. Then, we run the Pre-processing function (Algorithm 1) for each sentence on all items of the list $L$. The output of this algorithm is a pre-processed reading text $T'$ converted from the list $L$. Algorithm 1 and Algorithm 2 are implemented in reading texts and multiple-choice questions on MMRC models.

### 4.2. Machine Reading Comprehension Models

To quantify the difficulty level of our corpus for current methods, we carried out experiments on several MMRC models, both lexical-based and neural network-based. In particular, we used a random baseline, sliding window algorithm \[^{21}\] and a neural network-based model inspired from previous work \[^{33}\]. We proposed an improvement to the sliding window algorithm which we call Boosted Sliding Window. The neural network model is one of the best performing models for the multiple-choice machine reading comprehension task for the English language. In addition, we investigated how

[^3]: https://pypi.org/project/pyvi/
different kinds of general world knowledge affect different MMRC models. We describe these models in details as follows.

**Algorithm 3 : Sliding Window [21]**

**Input:** Reading text $T$, set of words in question $Q$, set of words in answer options $O_{1..4}$.

**Output:** Returning the score of the best answer option.

```
procedure Sliding Window
    $C(w) = Count(w, T)$
    for $i = 1$ to len($O$) do
        $S = O_i \cup Q$
        if $T_j+l \in S$ then
            $sw_i = \max_{j=1}^{T} \sum_{l=1}^{S} \log(1 + \frac{1}{C(T_j+l)})$
        else
            $sw_i = 0$
        end if
    end for
    return $\arg \max_{i=1}^{O} sw_i$
end procedure
```

4.3. Original Sliding Window

We present our attempt to adapt Vietnamese textual structures into the original sliding window algorithm (SW), a lexical-based approach developed by Richardson et al. (2013) [21]. This approach matches a bag of words, constructed from a question $Q$ and an answer option $O_i$, with a given reading text, and calculates a TF-IDF style matching score for each answer option.

To study the effects of different types of world knowledge to lexical-based approaches, we incorporated word embedding into the Sliding Window algorithm. We start with formal definitions of Vietnamese multiple choice reading comprehension task. Let $T$ denote the reading text, $Q$ denote the question text, $O_{1..4}$ denote the texts of four answer options. The aim of the task is to predict the correct one among four answer options $O_{1..4}$ with regard to the question $Q$ and the given reading text $T$. In particular, Algorithms [3] and Algorithm [4] were proposed by Richardson et al. (2013) [21] to solve English multiple-choice reading comprehension on the corpus MCTest.
Algorithm 4: Distance-based Sliding Window [21]

**Input:** Reading text $T$, set of reading-text words $TW$, set of words in question $Q$, set of words in answer options $O_{1,4}$.

**Output:** Returning the score of the best answer option.

```plaintext
procedure DISTANCE-BASED SLIDING WINDOW
    $C(w) = \text{Count}(w, T)$
    for $i = 1$ to $\text{len}(O)$ do
        $SQ = Q \cap TW$
        $SO_i = O_i \cap TW$
        if $|SQ| = 0$ or $|SO_i| = 0$ then
            $d_i = 1$
        else
            $d_i = \frac{1}{|T|-1} \max_{q \in SQ, a \in SO_i} d_T(q, a)$
        end if
        where $d(T, q, a)$ is the minimum number of words an occurrence of $q$ and an occurrence of $a$ in $T$, increase 1
    end for
    return $\arg \max_{i=1}^{\text{len}(O)} (sw_i - d_i)$
end procedure
```

4.4. Boosted Sliding Window

We proposed the method **Boosted Sliding Window** for the ViMMRC task (Algorithm 5). In addition to the original Sliding Window, we added one more element to incorporate the world knowledge. To understand this algorithm, we introduce two notations $V^T$ and $V^{O_i}$ to denote the ordered sets of words in the reading text $T$ and in the answer option $O_i$, respectively. We calculate $\text{web}[i]$, the maximum cosine similarity between $V^{O_i}$ and consecutive words of the same length in $V^T$. $\bar{v}$ is the average of the word embeddings of the lexical units in $v$.

To explore the effectiveness of word embeddings, we evaluated the performance of our proposed model on with several pre-trained word embeddings including W2V (Word2vec) [59], W2V-C2V (Word2vec and Character2vec) [60], fastText [61], ELMo [58], BERT [35] and MULTI [62]. In particular, we use pre-trained embeddings on Vietnamese Wikipedia proposed by Vu et al. [62] for all experiments of our proposed method.
Algorithm 5: Boosted Sliding Window

Input: Reading text $T$, set of reading-text words $TW$, set of words in question $Q$, set of words in answer options $O_{1..4}$. Note that $T$, $Q$, and $O_{1..4}$ are pre-processed by Algorithms 1 and Algorithm 2.

Output: Returning the score of the best answer option.

procedure Boosted Sliding Window

$C(w) = \text{Count}(w, T)$

for $i = 1$ to $\text{len}(O)$ do

$S = O_i \cup Q$

if $T_{j+l} \in S$ then

$sw_i = \max_{j} |T| \sum_{l=1}^{\text{|S|}} \log(1 + \frac{1}{C(T_{j+l})})$

else

$sw_i = 0$

end if

end for

for $i = 1$ to $\text{len}(O)$ do

$SQ = Q \cap TW$

$SO_i = O_i \cap TW$

if $|SQ| = 0$ or $|SO_i| = 0$ then

$d_i = 1$

else

$d_i = \frac{1}{|T|-1} \max_{q \in SQ, a \in SO_i} d_T(q, a)$

where $d(T, q, a)$ is the minimum number of words an occurrence of $q$ and an occurrence of $a$ in $T$, increase 1

end if

end for

for $i = 1$ to $\text{len}(O)$ do

$web_i = \max_{j} |T| \cos \left( \overline{V_{O_i}} \cdot \overline{V_{j..j+\text{|O_{i}|}-1}^T} \right)$

end for

return $\arg\max_{i=1}^{\text{|O|}} (sw_i - d_i + web_i)$

end procedure

4.5. Other Neural Network-based Approaches

We would also like to compare our proposed model (Boosted Sliding Window) with other neural network-based methods. In this section, we briefly
introduce the neural network-based models employed.

Co-match [33] is a state-of-the-art MMRC model. Figure 1 shows an overview of the Co-match architecture that builds a matching representation for a triplet \( \{Q, T_i, O\} \), where \( Q, T_i, O \) is the question, the \( i^{th} \) sentence in the reading text \( T \) and the option answer \( O \), respectively. For every word in sentence \( T_i \), we match it with the attention-weighted vectors computed based on the question and the answer option, respectively. A hierarchical LSTM aggregates the Co-matching representations of the triplets \( \{\text{question } Q, \text{ sentence in the reading text } T_i, \text{ answer option } O\} \) and computes the final scoring.

![Figure 1: An Overview of the Co-match method with a matching representation for a triplet \( \{Q, T_i, O\} \)](image)

For the word embedding layer, we conducted experiments with various Vietnamese pre-trained word embeddings provided by Vu et al. [62] as we did for Boosted Sliding Window. We would like to evaluate their effectiveness of the word embeddings when combined with this neural-based method.

5. Empirical Evaluation

In this section, we compare the performance of our proposed model with baseline models, neural-based models and human performance on our
dataset. We used accuracy as the main evaluation metric which is computed as follows:

\[
\text{Accuracy} = \frac{\text{Number of questions correctly answered}}{\text{Total number of questions}}
\]

5.1. Experimental Settings

In all experiments, we used the word segmentation pyvi\(^4\) and six different pre-trained word embeddings proposed by Vu et al. \(62\). For the model Co-match, we use a mini-batch size of 32, and the hidden memory size of 10. The number of epochs is set to 30. Adamax optimizer is used for optimization with a starting learning rate of 0.002. The training, development and test sets are divided as shown in Table 3. Besides, we implement three methods such as Random, Sliding Window and Distance-based Sliding Window as baseline models on our corpus.

5.2. Human Performance

We randomly took 100 questions from the test set and 100 questions from the development set. We conducted the tests on 10 students. As a result, human performance reached 91.20\% in accuracy on the development set and 91.10\% on the test set. These results are much higher than our best model.

\(^4\)https://pypi.org/project/pyvi/
5.3. Model Performance

Table 5: Experimental results of different models with various pre-trained word embeddings on our corpus ViMMRC

| Model Group        | Method          | Dev (%) | Test (%) |
|--------------------|-----------------|---------|----------|
| Baselines          | Random          | 24.49   | 24.80    |
|                    | Sliding Window (SW) | 58.50   | 56.30    |
|                    | SW + Distance (DSW) | 60.55   | 56.30    |
| Boosted Sliding Window | DSW + W2V    | 61.91   | 60.04    |
|                    | DSW + W2V-C2V  | 61.91   | 60.04    |
|                    | DSW + fastText | 63.27   | 60.04    |
|                    | DSW + Bert-base| 63.27   | 61.24    |
|                    | DSW + Elmo     | **65.99** | **61.81** |
|                    | DSW + Multi    | 63.61   | 60.24    |
| Other Neural-based Approach | Co-match + W2V | 43.97   | 41.49    |
|                    | Co-match + W2V-C2V | 43.77   | 43.87    |
|                    | Co-match + fastText | 43.39   | 41.84    |
|                    | Co-match + Bert-base | 42.61   | 43.88    |
|                    | Co-match + Elmo | **45.58** | **44.94** |
|                    | Co-match + Multi | 43.00   | 43.23    |
| Human Performance  |                 | 91.20   | 91.10    |

We report the performances of the baseline models, our proposed model and other neural network-based models in Table 5. Sliding Window and Distance-based Sliding Window achieve different performances, 58.50% and 60.55%, on the development set but they have the same accuracy of 56.30% on the test set. Our proposed method achieves the accuracies over 60% on the test set and over 61% on the development set. Specifically, this method with the ELMO word embedding achieves the highest results on both of the test and development sets, 65.99% and 61.81%, respectively. This proves that our proposed method is more effective than the other methods for the Vietnamese MMRC task at present.

Comparing the experimental results of the Co-match model with different word embeddings, we can see that ELMO only achieves the best accuracy of 45.58% and 44.94% on development and test sets. However, ELMO is still the best word embedding on both lexical-based and neural-based approaches. In addition, the best performance of the Co-match model on the
test set is 11.36% lower than that of the Distance-based Sliding Window model. It is also much lower than the human performance of 46.16%. This is a great challenge in study of Vietnamese multiple-choice machine reading comprehension.

6. Experimental Result Analysis

To gain insights into the best model Boosted Sliding Window (DSW + ELMO), we analyzed the experimental results in terms of different aspects such as question length, reading-text level, reasoning type and word embedding. Besides, we want to evaluate how the size of our training set has an impact on the neural-based method.

Impact of question length: To verify whether the length of question was a reason for the poor performance of our best model, we measured the performances of the best model according to the question length. In particular, we divided the development set into 5 groups corresponding to the following question lengths: ≤ 10, 10 – 15, 16 – 20, 21 – 25 and ≥ 26 words. The accuracies are presented in Table 6 and visualized in Figure 2. As can be seen from the table, questions of the 16 – 20 words length resulted in better performance than questions of other lengths. For short questions, our method predicts less effective. This may be because short questions contain less information beneficial to searching for the correct answer. In particular, the performances on shorter questions (64.15% for the ≤ 10-word questions and 65.18% for 10 – 15 word questions) are lower than the performances on longer questions which are over 66% in accuracy.

| Question Length | #Correct | #Total | Acc.(%) |
|-----------------|----------|--------|---------|
| ≤ 10            | 68       | 106    | 64.15   |
| 11 – 15         | 73       | 112    | 65.18   |
| 16 – 20         | 35       | 49     | 71.43   |
| 21 – 25         | 12       | 18     | 66.67   |
| ≥ 26            | 6        | 9      | 66.67   |

Table 6: Analysis of the best model with different groups of the question length

Figure 2: Visualization of the analysis of the best model with different groups of the question length
Impact of reading text level: Table 7 and Figure 3 show the accuracies of the best model according to different levels of reading text - the first to fifth grades. We can observe that the difficulty of reading comprehension task increases together with the level of reading text. The system could answer questions of the 2nd grade well, over 78% in accuracy. It was more difficult to predict correct answers for questions of the 3rd to 5th grades (less than 68%). The performance on 1st grade questions is not as high as that on the 2nd grade questions because the amount of questions of the 1st grade is much fewer than those of other grades.

| Grade | Correct | Total | Acc. (%) |
|-------|---------|-------|----------|
| 1     | 5       | 7     | 71.43    |
| 2     | 41      | 52    | 78.85    |
| 3     | 57      | 84    | 67.86    |
| 4     | 47      | 78    | 60.26    |
| 5     | 44      | 73    | 60.27    |

Table 7: Analysis of the best model with different reading-text levels

Impact of reasoning type: We also performed analysis to see how the reasoning types influence the best MMRC model. Figure 4 shows the analysis results. We found that the system determines answers more easily for the word matching and the paraphrasing reasoning types (WM and PP), 92.11% and 82.93% in accuracy, respectively. In contrast, complex forms of reasoning resulted in lower performances. They include single-sentence reasoning, multi-sentence reasoning and ambiguous-or-insufficient.
**Impact of word embeddings:** Table 5 shows the experimental results with various pre-trained word embeddings. It can be seen that the results are influenced by the methods when combined with these word embeddings. In particular, both of the lexical-based method and the neural network based method have better results when using word embeddings, nearly 5% higher. The experimental results showed that ELMo is the best among the other word embeddings.

In addition, we conducted the analysis of the effect of word embeddings on the best baseline model (DSW) and our proposed model (BSW) according to different aspects such as the question length and reasoning type. In particular, Table 9 shows statistics of the performance and improvement of our proposed model according to different types of reasoning. Our model improves the results of short questions ($\leq 10$) with an increasing accuracy of 7.55% and average-length questions with an improvement of 5.36% for 11–15 questions and the one of 6.12% for 16–20 questions. For longer questions, this model does not improve its performance, increasing the incorrect prediction by 5.55%. However, this number is not significant because the number of long questions accounts for low percentage. Table 10 shows statistics of the performance and improvement of our proposed model according to different types of reasoning. We found that our proposed model is a good solution for three types of reasoning, word matching, paraphrasing and ambiguous or insufficient, increasing 7.90%, 12.20% and 11.11% of the total number of solved questions, respectively. However, the number of questions of word matching and paraphrasing improved significantly because they account for a high proportion in the corpus.
Table 9: Statistics of the performance and improvement of our proposed model according to different lengths of question

| Question Length (words) | Ratio (%) | Accuracy (%) | Improvement (%) |
|------------------------|-----------|--------------|-----------------|
|                        |           | Best Baseline | Our Proposed Method (Best Model) |               |
| ≤ 10                   | 36.05     | 56.60        | 64.15           | +7.55          |
| 11 – 15                | 38.10     | 59.82        | 65.18           | +5.36          |
| 16 – 20                | 16.67     | 65.31        | 71.43           | +6.12          |
| 21 – 25                | 6.12      | 72.22        | 66.67           | -5.55          |
| ≥ 26                   | 3.06      | 66.67        | 66.67           | 0              |

Table 10: Statistics of the performance and improvement of our proposed model according to different types of reasoning

| Reasoning Type | Ratio (%) | Accuracy (%) | Improvement (%) |
|----------------|-----------|--------------|-----------------|
|               |           | Best Baseline | Our Proposed Method (Best Model) |               |
| WM            | 25.85     | 84.21        | 92.11           | +7.90          |
| PP            | 13.95     | 70.73        | 82.93           | +12.20         |
| SSR           | 17.35     | 50.98        | 52.94           | +1.96          |
| MSR           | 36.73     | 48.15        | 50.00           | +1.85          |
| AoI           | 6.12      | 38.89        | 50.00           | +11.11         |

Impact of training data size: To verify whether the size of training data was a reason for the poor accuracy of the model, we evaluated the neural network-based model on different sizes of training data including 508, 1010 and 1975 human-created questions. These results (in accuracy) on the test set are presented in Figure 5. The figure shows that the model performance was improved when we increased the training data. These observations suggest that increasing training data size would improve the accuracy. This is also a future direction for addressing this problem.
7. Conclusion and Future Work

In this paper, we have introduced a new corpus for studies of multiple-choice machine reading comprehension task for the Vietnamese language. This corpus includes 2,783 multiple-choice questions and answers based on a set of 417 Vietnamese reading texts. In addition, we proposed the Boosted Sliding Window method and performed experiments to compare the performance of this method and other methods. The experimental result shows that our proposed method is effective on the ViMMRC corpus. The best performance reached 61.81% in accuracy. However, there is still a large gap between the human performance and the best model (a significant difference of 29.29%). We also analyzed the best models in different aspects to
gain insights into the corpus. The analysis results show that ViMMRC is a challenging task and need further studies.

In future, we plan to increase the size of the corpus in terms of the number of reading texts. The analysis results also suggest that we should focus on methods to improve the performance on long questions and difficult reasoning types. Besides, when corpus is large enough, we will further research on state-of-the-art methodologies such as deep neural networks and transfer learning to explore suitable models for Vietnamese multiple-choice reading comprehension.

Acknowledgements

We would like to thank the editors and anonymous reviewers for their helpful feedback. This research is funded by University of Information Technology - Vietnam National University HoChiMinh City under grant number D1-2019-08.

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Appendix A. Statistics of different reasoning types

Table A.11 illustrates the ratio of each reasoning type in the development set. Those types of reasoning have been described in Section 3. Besides, we have an example for each reasoning type.

Table A.11: Statistics of different reasoning types in the development set

| Reasoning Type | Example                                                                 | Ratio (%) |
|----------------|------------------------------------------------------------------------|-----------|
| **Word Matching** | **Reading text:** Vừa sắp sách vở ra bàn, Tưíng bông nghe có tiếng chuông điện thoại. (Just putting the books on the table, Tuong suddenly heard a phone ring.) **Question:** Việc gì đã xảy ra khi Tưíng vừa sắp sách vở ra bàn? (What happened when Tuong just put his books on the table?)
A. Mẹ nhí Tưíng đi chợ. (Mom asked Tuong to go to the market.)
B. Có tiếng chuông điện thoại. (There is a phone ringing.)
C. Bạn rủ Tưíng đi chìi. (Tuong’s friends invite him to go out.)
D. Nghe tiếng ai dó bên ngoài. (Hearing someone’s voice outside.) | 25.85     |
| Paraphrasing | **Reading text**: Tôi đang nắn nét viết từng chữ thì Cô-rét-ti chạm khuỷu tay vào tôi, làm cho cây bút nguệch ra một đường rất xấu.  
(When I was sharpening the letters word for word, Co-ret-ti touched my elbows, making the pen scribble very badly.)  
**Question**: Khi nhân vật tôi đang nắn nét viết bài, chuyện gì đã xảy ra?  
(When the character “I” was writing the lesson, what happened?)  
A. Nhân vật tôi làm nguệch chữ của Cô-rét-ti. (The character “I” made Co-ret-ti’s written characters really ugly.)  
B. Cô-rét-ti cãi cọ nhau vì một chữ viết nguệch. (Co-ret-ti quarreled over a scribble.)  
C. Cô-rét-ti chẳng khuỷu tay làm tôi bị nguệch chữ. (Co-ret-ti Co-ret-ti touched the elbows, making me scribble.)  
D. Nhân vật tôi và Cô-rét-ti làm tranh nhau do dủng. (The character “I” and Co-ret-ti competed together for getting something.) | 13.95 |
Reading text: Khi tiếng đàn, tiếng hát của A-ri-on vang lên, một đàn cá heo đã bơi đến vây quanh tàu, say sưa thưởng thức tiếng hát của nghệ sĩ tài ba.

(As the sound of A-ri-on’s musical playing and singing started, a group of dolphins swam around the ship, passionately enjoying the singing of the talented artist.)

Question: Điều kì lạ gì đã xảy ra khi nghệ sĩ A-ri-on cất tiếng hát giã biệt cuộc đời? (What strange thing happened when the artist A-ri-on sang goodbye to life?)

A. Đàn cá heo đã ăn thịt ông. (The dolphins swallowed him.)
B. Đàn cá heo đã bỏ chạy đi mất. (The dolphins ran away.)
C. Đàn cá heo đã nhận chim ông xuống biển. (The dolphins drop him to the sea.)
D. Đàn cá heo đã bơi đến vây quanh tàu. (The dolphins swam around the boat.)
| Multiple-sentence Reasoning | **Reading text**: Chim đừng hât núa, bà em ốm rồi, lắng cho bà ngủ. Bàn tay bé nhỏ, vẫy quạt thật đều. Ngấn nắng thiu thiu, đậu trên tưíng trắng. Căn nhà đã vắng. cèc chén nằm im. Đôi mắt lim dim, ngủ ngon bà nhé.  
(Bird! Please don’t sing, my grandma is sick, keep silent for her to sleep. Tiny hands are waving fans evenly. Sunlight stale parked on the white wall. The house is empty. The cup lies still. Eyes dim sleep. Sleep well, my grandma.)  
**Question**: Bạn nhỏ đang làm gì?  
(What was the young boy doing?)  
A. Ngắm cây cối trong vườn. (Viewing the trees in the garden.)  
B. Nói chuyện với chim chích chèo. (Talking with the warbler.)  
C. Dọn dẹp nhà cửa. (Cleaning his house.)  
D. Quạt cho bà ngủ. (Waving fans for his grandma’s sleep.) | 36.73 |
Reading text: Cậu bé nhìn bà, suy nghĩ một chút rồi thì thầm: những nếp nhăn, bà ạ! (The boy looked at his grandma, thought for a while and whispered: "The wrinkle, grandma!")

Question: Câu trả lời cuối cùng của cậu bé muốn nói lên điều gì? (What is the meaning of the boy’s last answer?)

A. Cậu rất thích những người có nếp nhăn. (The boy likes people with wrinkles very much.)

B. Cậu thấy những nếp nhăn rất đẹp. (The boy thinks that wrinkles are very beautiful.)

C. Trong đôi mắt cậu, những nếp nhăn của bà rất đẹp và cậu rất yêu những nếp nhăn ấy. (In the boy’s eyes, wrinkles are very beautiful and he loves these wrinkles.)

D. Trong đôi mắt cậu, hiện ra những vết nhăn của cô gái. (In the boy’s eyes, there are the girl’s wrinkle.)