Filtering-based Automatic Cloze Test Generation

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Abstract

We propose a method to generate high-quality cloze test questions using a computational approach. Previous methods for automatic cloze test generation have contained some problems; specifically, there can be multiple correct answers. We found that approximately 50% of the generated answers have such errors with previous methods, which requires human post-editing was necessary in previous research. We propose an N-gram filtering method that can detect the answer to a given question. We compare the errors of the generated questions before and after applying the filtering methods. We found that our filtering method can select quality distractors by reducing errors in the generated questions. Moreover, when we generate cloze tests using semantic similarity, non-native speakers are very hard to answer the questions.

Index Terms: Cloze Test Generation, Sentence Completion Task, Vocabulary Question Generation

1. Introduction

A cloze test is an activity in which students must fill in the blanks in a text with appropriate words. Although this type of test has been widely used in language learning to assess learner’s proficiency in the target language, it requires significant labor to create because writing test questions by hand is a laborious task even for experienced teachers. To lessen the burden of test development, automatic question generation techniques have been sought. The goal of these techniques is to provide questions with constant quality and appropriate difficulty that, lead to an objective assessment. Mitkov and Ha [6] proposed an NLP-based methodology for the construction of test items from instructive texts such as textbook chapters and encyclopedia entries [5]. The system for generation of multiple-choice test described in Mitkov and Ha [6] and in [7] was evaluated in a practical environment in which the user was offered the option to post-edit and in general to accept, or reject the test items generated by the system. The formal evaluation demonstrated that a significant fraction of the generated test items needed to be discarded. The primary motivation of our work is that a considerable number of generated questions are not sufficiently good or practical use in language learning. Human post-editing processing is still needed in automatic cloze test generation. Our purpose in this paper is to reduce the cost of the human post-editing step by filtering improper distractors.

In section 2, previous works are introduced. In section 3, we will introduce methods. And then, the experiment result is explained in section 4. Finally, we give a conclusion in section 5.

2. Previous Work

So far, very little work has been devoted to filtering distractors. Several studies suggested implementing naïve filtering steps using a web-based approach [8], [1]. In this approach, distractors are eliminated when sentences receive a non-zero number of hits in a web search because distractors must be incorrect. However, this approach has many problems. First, hits may come from non-native speakers’ websites and contain invalid language usage. Second, even if sentence fragments cannot be located on the web, it does not necessarily imply that they are incorrect. Additionally, the number of web searches performed using Google and Bing each month is limited. Grammaticality and collocation to select distractors are used and semantically similar words are removed to avoid multiple answers [4]. However, semantic similarity is also a useful feature for generating cloze items and a mixed strategy demonstrates the best performance as described in [5]. To overcome these limitations, we suggest including a sophisticated filtering strategy in automatic question generation techniques to improve the acceptance rates of generated test items. If a distractor candidate is considered a possible answer to the question, it is eliminated from the candidate list. The filtering method is independent of candidate distractors selection. Thus, we can deploy more varied features and can apply a mixed strategy to generate cloze items using our filtering method. In this paper, we generated the distractors using semantic similarity for test data sets.

3. Method

3.1. Overview

We propose performing automatic cloze test generation using the following steps (Figure 1). 1) Input the sentence with a blank position 2) We select the distractor candidates using a target based on previous research such as semantic and phonetic similarity [5], synonym or related word using thesaurus extraction [9], WordNet [10], collocation and grammaticality [4] methods, or mixed strategy etc. 3) To make all distractors have the same Part-of-
speech (POS) form, we save the part-of-speech of the target word (answer word); then, we change all words to the same form as the answer word using the English Synthesizer\(^1\). 4) N-grams can be used to remove potential multiple answers

3.2. Filtering Distractor

N-gram scores are used for filtering the words among distractor candidates. We build a probabilistic language model using the Google Web1T N-gram Count corpus\(^2\), which is built by a huge amount of data. One of baselines is established with Laplace smoothing the N-gram model\(^{[11]}\) which avoids zero probability in equation (1).

\[
\hat{P}_\text{Laplace}(w_i|w_{i-1}w_{i-2}w_{i-3}) = \frac{C(w_{i-3}w_{i-2}w_{i-1}w_i) + 1}{C(w_{i-3}w_{i-2}w_{i-1}) + |V|} \quad (1)
\]

Zero probability problems are not evitable when considering 5-gram probability. Backoff N-gram models were introduced by Katz (1987). If the N-gram that we need has zero counts, we approximate it by backing off to the (N-1)-gram, as shown in equation (2).

\[
P_{\text{katz}}(w_i|w_{i-1}w_{i-2}w_{i-3}) = \begin{cases} 1 & \text{if } C(w_{i-1}w_{i-2}w_{i-3}) > 0 \\ \alpha(w_{i-1}w_{i-2}w_{i-3})P_{\text{katz}}(w_i|w_{i-2}w_{i-3}) & \text{otherwise} \end{cases} \quad (2)
\]

However, we recognize that the Google N-gram corpus cannot be used to build previous smoothing methods because of the frequency cut-offs, which implies that only N-grams appearing more than 40 times were kept and appear in the N-gram tables. Some methods need low-order word counts. However, all N-grams with counts lower than 40 were discarded, we cannot use most of previous smoothing methods Calculating normalized frequency \(\alpha\) in the Katz backoff is also difficult. Our purpose to use N-gram is to find the most proper word among distractor candidates in the question sentence as equation (3).

\[
E = \arg \max_{x \in \{C_0, C_1, ..., C_n\}} P(x|\text{Stem}) \quad (3)
\]

\(C\) denotes that distractor candidates (e.g., \(C = \{\text{addressing, coming, recognizing, greeting, saluting, presenting, receiving, contenting, bidding, accosting}\}\)). Stem denotes the words in the question sentence (e.g., Stem = “The manager suggested [ ______ ] the resort guests with a culture themed show after they had finished settling into their private rooms.”) (Figure 1). \(E\) denotes the potential answers from N-gram filtering model.

Previous N-gram model has low performance (the accuracy is 52\%) for the sentence completion task (see the results in Table 4). Only half of questions in the close test could be correctly answered by the N-gram approach which implies that it is a challenging task. However, to filter the potential answer words in the distractor candidates, the accuracy of finding the correct answer by N-gram must be much higher than current state-of-art performance. Thus, we improved the performance of N-gram model on sentence completion task by considering more effective features when calculating the N-gram probability. The preceding words and following words are already given in a question sentence, so we can consider the both directions and various ranges. Our proposed for using N-gram model can consider both forward and backward N-gram probability and has much less data sparseness problem for the filtering model. From 5-gram to 2-gram count information are used to develop the proposed N-gram model.

A backoff proposed N-gram model is used for the N-gram filtering model as in equation (4). If the N-gram probabilities we need have all zero counts for every \(C\), we approximate them by backing off to the (N-1)-grams.

\[
E = \arg \max_{x \in \{C_0, C_1, ..., C_n\}} P_\text{N}(x|\text{Stem}) \quad (4)
\]

where

\[
P_\text{N}(x|\text{Stem}) = \begin{cases} P_\text{N}(x|\text{Stem}) & \text{if not } \sum_{i=0}^{n} P_\text{N}(C_i|\text{Stem}) = 0 \\ P_{N-1}(x|\text{Stem}) & \text{otherwise} \end{cases}
\]

The model uses a variety of contexts and different sizes and positions to replace the distractor candidates’ words in C, where \(C = \{\text{addressing, coming, recognizing, greeting, saluting, presenting, receiving, contenting, bidding, accosting}\}\) in Figure 1. We can retrieve a count for each context pattern of length-N with a filler word replacing \(c_i\), which constitutes a single N-gram. We then retrieve a count using the Google 5-gram for sequences

\(^1\) http://www.languagetool.org

\(^2\) Available from the LDC as LDC2006T13.

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**Figure 1.** Overall Process of Generating Cloze test
including N-grams of length 2 to 5. For each target word $c_i$, five separate 5-gram context patterns that span its range are found. We describe the notation of $P_N$ in more detail in Table 1).

### 4. Experiment and Result

#### 4.1. Data

For our proposed filtering strategies, we used Google N-gram corpus which contain 1 trillion words of running text and the counts for all 1 billion five-word sequences that appear at least 40 times. There are 13 million unique words after words that appear less than 200 times are discarded. We used WordNet-based semantic similarity to generate candidate distractors in this paper. For computing the WordNet-based semantic similarity, we employed a popular word similarity measure using the Python NLTK package [12]: Jiang and Conrath’s (JCN) measure [13] to generate the distractor candidates. A total 100 questions are generated using WordNet-based semantic similarity. Each question has 10 distractor candidates. Four experts in English Education annotated every generated distractors in the JCN question has 10 distractor candidates. Four experts in English Education annotated every generated distractors in the JCN measure regarding whether distractors could be potential answers. Two annotators’ native language is English, the others are non-native speakers. Kappa value between two native was 0.7. However, the agreement between non-native speakers and native speakers was 0.409, 0.401, 0.45, and 0.455. Between two non-native speakers, Kappa value is 0.764. Even though they are all experts in English Education, it is a challenging tasks for non-native speakers; the kappa value is about 0.4 (Table 2, Table3). It indicates that questions by semantic similarity could be good test items for identifying native speakers. Moreover, it would be good test items for non-native speakers to teach the real usage of words among the similar meanings. To investigate the performance of the filtering method that uses N-gram model, we use 500 semantic
We only explore content words (verbs and nouns) in this paper. To evaluate our filtering method, we must select the N-best candidate distractors. For the experiment, we selected the N-best semantically similar words to the target vocabulary scheduled by JCN WordNet based semantic similarity measure in Figure 1, such as addressing, coming, recognizing, greeting, saluting, presenting, receiving, contenting, bidding, and accosting. The goal of the filtering method is to remove Greeting, presenting, receiving, and contenting which labeled as multiple answers using N-gram model. Among the 100 test items, each item has 10 distractor candidates, which yields a total 1000 distractors candidates labeled as multiple answers or proper distractors. If a distractor could be an answer in the given text, we count the question as an instance of “multiple answers”. The performances are quantified using precision, recall, and F-score. To explore the filtering performance for multiple answers, we deploy the proposed N-gram. Because the number of web searches performed using Google and Bing in a month is limited, it is improper to use these corpora as the baseline system. Thus, the baseline is randomly selected from distractor candidate. We consider two perspectives of the results: one is the proper distractors perspective and the other is filtering perspective.

**Proper distractor perspective:**

Precision = \(\frac{\text{# of proper distractor in final}}{\text{# of distractors in final}}\)

Recall = \(\frac{\text{# of proper distractors in final}}{\text{# of proper distractors in candidates}}\)

**Filtering perspective:**

Precision = \(\frac{\text{# of filtered improper distractors in final}}{\text{# of total filtered distractors}}\)

Recall = \(\frac{\text{# of filtered improper distractors in final}}{\text{# of total improper distractors in candidates}}\)

From the proper distractor perspective, eliminating the proper distractors is not a critical problem when final distractors are all proper distractors which indicate precision is important from this perspective. The reason of the low recall rate is that many proper distractors are also removed until the final number of distractors K is remains (K=the number of Distractors). Therefore, low recall is not a critical problem. However, from the filtering perspective, recall is much more important than precision. If recall is 100%, the filtering method can eliminate every improper distractor. We found that the recall rate is much higher than the baseline which implies that our method filters improper distractors properly (Table 3). We compared the performance after applying filtering model in as shown (Table 4). The 46.8% of generated questions have distractors that are improper for practical use without human editing. After applying our proposed filtering strategies, significant parts of questions are removed the improper distractors.

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of “proposed N-gram” in Table 6 are only our experimental result, others results such as (1), (2), and the combination (1)+(2) are from the [15] paper. The accuracy of our proposed method is 87.4%, which is significantly improved. The annotated distractors and experimental results are made available to the public.

5. Conclusions

We found that machine generated test items have many errors, such as multiple answers. To solve these problems, we proposed filtering method to remove improper words from candidate distractors. We found that proposed methods significantly reduce the generated test item error rate. Moreover, our method also performs well on sentence completion challenge. We also found that the annotation agreement between native speakers are much higher than between native speaker and non-native speakers. It indicates that questions made by semantic similarity are challenging test items for non-native speakers. We have plan to explore a real student test for evaluations on generated cloze test set.

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7. References


1 https://sites.google.com/site/dataforslate/