Knowledge-Driven Distractor Generation for Cloze-style Multiple Choice Questions

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Abstract

In this paper, we propose a novel configurable framework to automatically generate distractive choices for open-domain cloze-style multiple choice questions, which incorporates a general-purpose knowledge base to effectively create a small distractor candidate set, and a feature-rich learning-to-rank model to select distractors that are both plausible and reliable. Experimental results on datasets across four domains show that our framework yields distractors that are more plausible and reliable than previous methods. This dataset can also be used as a standard benchmark for distractor generation in future.

1 Introduction

Cloze-style multiple choice question (MCQ) is a common form of exercise used to evaluate the proficiency of language learners, frequently showing up in homework, exams and official tests. Figure 1 shows a cloze-style MCQ, which typically consists of: a question stem with a blank to be filled in, the correct answer and multiple wrong answers used to distract testees. Despite the high demand, manual crafting of such MCQs is very time-consuming for educators, which calls for the automatic generation of practice material for students from readily available plain texts.

Figure 1: A Cloze-style MCQ

In our wildflower population, the pool of _____ remains constant from one generation to the next
(a) genes
(b) DNA
(c) factors
(d) generic code

Distractor generation (DG), which aims to generate distractive alternatives (i.e., distractors) of the correct answer given the question stem, is a critical part of cloze-style MCQ construction. However, it is not only time-consuming but also non-trivial to come up with appropriate distractors without rich experience in language education. Literature in language pedagogy [Haladyna et al., 2002; Pho et al., 2014] generally recommends two criteria for designing distractors: plausibility and reliability. By plausibility, it means distractors should be semantically related to the key and grammatically consistent with the context given by stem to adequately discriminate learners’ proficiency. By reliability, it means the distractor, when filled into the blank of the stem, results in a logically incorrect or inconsistent statement.

Automatically generating distractors has been previously explored as part of cloze-style MCQ construction in a few studies. However, those methods generally assume advance knowledge of a specific domain (e.g., science) of the given question and then use corresponding domain-specific vocabulary as candidate distractor set to rank based on using various unsupervised similarity heuristics (Sumita et al., 2005; Kumar et al., 2013; Jiang and Lee, 2017; Ha and Yaneva, 2018) or supervised machine learning model (Sakaguchi et al., 2013; Welbl et al., 2017; Liang et al., 2018). Since identifying the concrete domain of each question and preparing large-scale domain-specific vocabulary require substantial human labor, such corpus-based methods cannot be easily applied in real-world scenarios.
Another issue is that previous approaches mainly focus on selecting plausible distractors while rarely adopt reliability checks to ensure that the generated distractors are logically incorrect. Despite some attempts in early approaches (Sumita et al., 2005; Jiang and Lee, 2017), they both used it in the post-processing step to filter out candidate distractors rejected by diverse predefined filters, which is sometimes too strict as it may exclude useful distractors like DNA in Figure 1.

In this paper, we propose a configurable distractor generation framework for English cloze-style MCQ in open domain, whose design is motivated by the shortcomings identified above. It mainly consists of two components: (1) a context-dependent candidate set generator, which constructs a small set of candidate distractors from a general-purpose knowledge base, based on contextual information formed by the stem and the key; (2) a learning-to-rank model which takes both reliability checking and plausibility measures into consideration. By incorporating structured, human-curated general-purpose knowledge base and conducting context-dependent conceptualization on the answer, we are able to effectively extract semantically-related candidate distractors without the need of domain-specific vocabulary. These candidate distractors are further re-ordered by a ranking model, trained with elaborately designed features to automatically control the trade-off between plausibility and reliability.

Previous DG methods (Kumar et al., 2015; Liang et al., 2017; Liang et al., 2018) are evaluated either with sole human annotation or on ad hoc datasets that are often narrow in domain. To the best of our knowledge, there is no open-source benchmark dataset for DG that is diverse enough to comprehensively evaluate the model performance. We construct a cross-domain cloze-style MCQ dataset covering science, trivia, vocabulary and common sense, which can be used as a benchmark for future research in DG. We further investigated various instantiations of proposed framework.

The contributions of this paper are three-folds:

- we compile and open-source a diverse and comprehensive benchmark dataset for training and evaluating distractor generation model (Section 3.1).
- we propose a novel configurable distractor generation framework for open-domain cloze-style MCQ, which requires no domain-specific vocabulary and jointly evaluates the plausibility and reliability of distractors (Section 2).
- we conduct comprehensive experiments to evaluate and analyze various instantiations of our framework and show that it consistently outperforms previous methods in both automatic ranking measures (about 2% F1 score) and human evaluation (Section 3.5).

2 The Framework

As illustrated in Figure 2, our framework includes two components: Candidate Set Generator (CSG) and Distractor Selector (DS). The first component CSG is an efficient and effective technique to extract candidate distractors semantically similar to the key from a general-purpose knowledge base (KB). The second component DS, a generic feature-rich ranking model, then re-ranks those candidates according to more fine-grained assessment of grammatical consistency and reliability.

2.1 Task Formulation

Formally, given the stem $q$ and key $a$, the task of distractor generation is to generate $n$ most appropriate distractors $D = \{(d_1, s_1), (d_2, s_2), \cdots, (d_n, s_n)\}$ with predicted ranking scores $s_i$ in descending order.
2.2 Candidate Set Generator (CSG)

The proposed CSG explicitly leverages the observation that distractors to an open-domain cloze-style MCQ are often words or short phrases living in a knowledge base (e.g., Probase (Wu et al., 2012), WordNet (Leacock and Chodorow, 1998)) and stored as nodes in a way that they are connected with the key through a common parent node (which we refer to as concept later). Instead of enumerating all words in a huge domain-specific vocabulary in early approaches, such hierarchical structure in knowledge base allows us to extract candidate distractors by only considering a reasonably small number of concepts that are semantically related to the key, which can be efficiently identified using KB-specific interface.

Nevertheless, the specific meaning of the key varies given different stems. For example, given sentence: “These survivors managed to swim to the bank,” where bank is the key, we would like to generate candidates like shore rather than the more commonly used financial-related terms.

Inspired by the idea of context-dependent conceptualization (Kim et al., 2013), we utilize a probabilistic topic model, LDA (Blei et al., 2003), to discover the latent topic distribution of the context as well as the topic distribution of all concepts in the concept set C. The posterior probability \( p(c|a, q) \) of key \( a \) belonging to concept \( c \) conditioned on the stem \( q \), is given by:

\[
p(c|a, q) \propto p(c|a) \sum_{k=1}^{K} \pi_{a,q}^{(k)} \gamma_c^{(k)}
\]

where \( c \) is the concept, \( \pi_{a,q} \) is the topic distribution of complete sentence formed by the stem and key, \( \gamma_c \) denotes the topic distribution of concept \( c \), \( p(c|a) \) is the prior probability of \( a \) belonging to \( c \) corresponding to the specific choice of knowledge base, and \( K \) is total number of topics. Intuitively, concepts whose topic distribution resembles that of the complete sentence will be weighted higher than others.

After obtaining the conditional probability \( p(c|a, q) \) of all concepts in \( C \), by following the descending chain of is-A relation and collecting hyponyms of these concepts, we get a probability distribution over all entities subsumed by the concepts in \( C \):

\[
p_i = p(d_i|a, q) \propto \sum_{c \in C} p(d_i|c)p(c|a, q)
\]

where the probability \( p(d_i|c) \) is also known as typicality (Wu et al., 2012). The prior probability \( p(c|a) \) and typicality \( p(d_i|c) \) can be used off-the-shelf in some KBs (e.g., Probase) while for some other KBs (e.g., WordNet) it is not the case, which endows our framework with the flexibility to be combined with a broad class of KBs and to be customized with different ways of calculating these two probabilities.

Then we remove candidates that occur in the stem and finally the top \( m \) candidates with largest probabilities form a candidate distractor set \( D_0 = \{(d_1, p_1), (d_2, p_2), \cdots , (d_m, p_m)\} \).

2.3 Distractor Selector (DS)

Given the previously constructed candidate distractor set \( D_0 \), the final \( n \)-best distractors are generated in the following steps.

2.3.1 Feature Extractor

Given a triplet \((q; a; d)\) where \( q \) is the stem, \( a \) is the key and \( d \) is a candidate distractor, our DS first transforms it into a feature vector \( f(q, a, d) \in \mathbb{R}^l \), in which the features are defined below:

- **Embedding Similarity** Embedding similarity between \( q \) and \( d \) and the similarity between \( a \) and \( d \) calculated using Word2Vec (Mikolov et al., 2013), which is effective for finding semantically similar distractors (Guo et al., 2016). We use the average word embedding as the sentence embedding.

- **Contextual Embedding Similarity** Cosine similarity between the ELMo (Peters et al., 2018) embedding of \( a \) and \( d \). This feature is complementary to Emb Similarity since Word2Vec only capture static blended semantic of words, of which the significance is verified in Section 3.5.
- **Morphological Similarity** Edit distance, token/character length difference, singular/plural consistency, absolute and relative length of a and d’s longest common prefix/suffix/subsequence. These features measure the morphological similarity and are useful for cases such as abbreviation (e.g., DNA and RNA).

- **POS Similarity** Jaccard similarity between the POS tags of a and that of d. The intuition is that good distractor should share similar linguistic property as the answer.

- **Frequency** Average unigram frequency of a and d. Frequency has been previously utilized as a proxy for word’s difficulty level (Coniam, 1997). This feature aids model to select distractors with similar difficulty as a.

- **Compositional Similarity** Jaccard similarity between token-level unigram set and bigram set of a and d. This feature is motivated by the observation that distractors might share tokens with answer.

- **Web-search Score** Detail of this feature is described later in this section.

Features except Web-search Score are integrated to mainly evaluate the plausibility of d in various aspects and granularities. Web-search Score is specifically introduced to assess the validity of the sentence restored by each candidate in order to further strengthen reliability. First, search results are retrieved from the web by passing the full sentence concatenated from q and d to the Bing search engine automatically. Then, we use ReVerb (Fader et al., 2011) to extract (argument1, relation phrase, argument2) triplets involving d from the sentence formed by q and d, \{t_{11}, t_{12}, \ldots, t_{1n}\}, as well as triplets in the titles and snippets returned by the search engine, \{t_{21}, t_{22}, \ldots, t_{2m}\}. After that, we calculate embedding similarities between triplets and keep the maximal score, \(T(q, d)\), that represents the correctness of triplet extracted from a sentence:

\[
T(q, d) = \max_{i \in \{1, 2, \ldots, n\}} \max_{j \in \{1, 2, \ldots, m\}} \text{EmbSim}(t_{1i}, t_{2j})
\]

where \(\text{EmbSim}(t_{1i}, t_{2j})\) represents the word2vec embedding similarity between \(t_{1i}\) and \(t_{2j}\). If \(T(q, d)\) is small, then the sentence restored with the distractor d is unlikely, thus d should be a reliable distracter.

### 2.3.2 Ranker

Given the feature vector \(f(q, a, d) \in \mathbb{R}^l\) where q and a are the stem and key of triplet \((q; a; D_g)\) in the dataset, we propose to utilize a feature-based learning-to-rank model, which is trained in a supervised manner and learns to assign higher score to those d within the ground-truth distractor set \(D_g\) than those in \(D_0 - D_g\). Reasonable distractors outside of \(D_g\) are likely to be close to ground-truth distractors in the feature space \(\mathbb{R}^l\), which can implicitly guide the ranker to learn relative ranking of negative examples during training.

Note that we do not restrict the ranker to be any specific model. One can choose to implement it using any state-of-the-art point-wise, pair-wise or list-wise learning-to-rank models. Theoretically, training a learning-to-rank model requires a relevance score associated with each distractor, which is not available in existing cloze-style MCQ dataset. We remedy this by setting the relevance score for \(d \in D_g\) as 1 and \(d \in \{D_0 - D_g\}\) as 0. For point-wise ranker, it reduces into a binary-classifier (Liang et al., 2018). The major difference between point-wise ranking model and pair/list-wise ranking model is that the latter may learn latent pattern in the features for discriminating better and worse distractors through supervised training signal.

At test time, the ranking score \(s_i\) for each candidate distractor \(d_i\) predicted by the ranker is then used to sort the candidates in \(D_0\) extracted by CSG and output the final n-best ranked list \(D = \{(d_1, s_1), (d_2, s_2), \ldots, (d_n, s_n)\}\).

### 3 Experiments

In this section, we first present dataset and evaluation metrics used in our experiments. Then we investigate several design choices of our framework and compare their effectiveness against previous methods.
3.1 Dataset

Our MCQ dataset covers multiple domains including science, vocabulary, common sense and trivia. It is compiled from a wide variety of open source MCQ dataset including SciQ (Welbl et al., 2017), MCQL (Liang et al., 2018), AI2 Science Questions as well as trivia, and vocabulary MCQs crawled from websites. We filter out MCQs whose keys are not short phrases since this paper only focuses on extractive cloze-style DG, resulting in 2,880 items in total among which 1176 are from SciQ, 300 are from MCQL, 275 are from AI2 and the rest from website resources. Statistics of the dataset are summarized in Table 4 and Figure 3.

We convert questions to cloze form by constructing Penn Treebank style trees using Stanford Parser (Klein and Manning, 2003), and adjusting node order according to the identified question type. For the following experiments, the dataset is randomly devided into train/valid/test with an approximate ratio of 8:1:1. We use the tokenizer and POS tagger from NLTK (Loper and Bird, 2002) to preprocess the stems and keys when constructing features.

3.2 Evaluation Metrics

Human Evaluation. Following (Jiang and Lee, 2017), we ask three proficient English speakers to evaluate distractors’ reliability and plausibility by showing them the key. We evenly sample 50 items (same for all annotators) in all domains from test set, each item contains multiple distractors including 3 generated by each method and all ground truth distractors designed by human experts. For each distractor, the judges decided whether it is correct or incorrect given the context. For a distractor deemed to be incorrect, the reliability score is 1 and the judges further assess its plausibility on a 3-point scale: “Obviously Wrong” (0 point), “Somewhat Plausible” (1 point), or “Plausible” (2 points). We then conduct preliminary application-centric evaluation using another 50 samples without keys from test set by extending original sample with additionally generated distractors and asking testees to answer the quiz.

Automatic Evaluation. Following (Liang et al., 2018), we report top F1 score(F1@3), precision(P@1, P@3) and recall (R@3) to show how well the generated distractors match the ground truth distractors, as well as the mean reciprocal rank (MRR) and normalized discounted cumulative gain (NDCG@10) to show the positions of ground truth distractors in the output ranked list. Sometimes the generated distractors do not exactly match the ground truth, but are semantically very close. Word2vec model trained on Wikipedia dump is utilized to measure the averaged cosine similarity (Semantic Similarity@3) between top three generated distractors and ground truth distractors.

3.3 Design Choices of CSG and DS

We investigate Probase and WordNet as the knowledge base in CSG and additionally extract all words and phrases from WordNet as a baseline of CSG in following experiments. For Probase, both $p(c|a)$ and $p(d|c)$ are natively supported and can be obtained using official APIs. Size of concept set $C$ is set to be 20. For nouns and verbs in WordNet, we treat the set of unique hypernyms (as well as their siblings) of all synsets for $a$ as concept set $C$ and compute $p(c|a)$ using the Laplace-smoothed Bayes rule on the lemma frequency provided in WordNet (count on sense tagged text). We choose all synsets and their
Table 1: Comparison of combinations of different choices of CSG and DS. - means no ranking.

| Instantiation | CSG | DS | F1@3 | P@1 | P@3 | R@3 | MRR | NDCG@10 | Semantic Similarity@3 |
|---------------|-----|----|------|-----|-----|-----|-----|---------|----------------------|
| WordNet       | -   | -  | 3.14 | 3.49| 2.33| 5.43| 7.19| 8.66    | 0.27                 |
|               | point-wise ranker | 7.26 | 9.30 | 5.55| 11.95| 14.30| 14.63| 0.36 |
|               | pair-wise ranker  | 7.11 | 10.07| 5.30| 12.14| **14.40**| 14.84| 0.35 |
|               | list-wise ranker  | **7.71** | 9.31 | **5.81** | **12.98** | 14.34 | **14.94** | **0.36** |
| Probase       | -   | -  | 5.88 | 6.98| 4.39| 9.95| 12.07| 13.40    | 0.35                 |
|               | point-wise ranker | 7.91 | 8.14 | 5.94| 12.98| 15.09| 17.69| 0.41 |
|               | pair-wise ranker  | **9.42** | 10.08| **7.00** | 15.88 | 17.33 | **19.70** | **0.40** |
|               | list-wise ranker  | 9.19 | 10.85| 6.72| **15.88** | **17.51** | **19.31** | **0.41** |
| w/o CSG       | -   | -  | 5.59 | 4.63| 3.98| 10.29| 8.67| 11.02    | 0.36                 |
|               | point-wise ranker | 5.62 | 5.01 | 3.98| 10.10| **9.28**| 11.60| **0.36** |
|               | pair-wise ranker  | **5.94** | 4.24 | **4.24** | **10.81** | 8.81| 11.46| 0.35 |

similar/antonymic sets as concept set $C$ for adjectives and adverbs in WordNet. Topic distributions $\pi_{a,q}$ and $\gamma_c$ are obtained using LDA pre-trained on Wikipedia dump and $K$ is set to 100.

For DS, we experiment with point-wise, pair-wise and list-wise ranking models to find the best practice. Specifically, we employ AdaBoost (Freund and Schapire, 1997) as point-wise ranker and LambdaMART (Burges, 2010) as both pair-wise and list-wise ranker. The dimensionality of feature vector $l$ is 33. Unigram frequency is calculated on Wikipedia dump. For the training of DS, negative examples are sampled using top 100 candidates extracted by CSG excluding those that are within ground truths. At test time, DS takes as input top 30 candidates extracted by CSG and 30 candidates sampled from WordNet’s own vocabulary having the same POS tag. All hyperparameters are tuned on dev set.

3.4 Baselines

We name our framework CSG+DS and compare it against the following baselines:

- **Thesaurus-based Method (TM)** (Sumita et al., 2005) ranks candidate distractors from synonyms of the key in WordNet based on path similarity and applies post-filtering via IR.

- **RevUP** (Kumar et al., 2015) ranks candidate distractors based on weighted average of word2vec similarity, dice coefficient and language model probability.

- **EmbSim+CF** (Jiang and Lee, 2017) combines word2vec similarity and tri-gram/dependency in ranking and filtering respectively.

- **ED** calculate the edit distance to measure the spelling similarity between distractors and key.

- **BERT** (Devlin et al., 2018) ranks candidates based on cosine similarity of their BERT embeddings with that of the key.

- **LR+RF** (Liang et al., 2018) combines logistic regression and random forest as a two-stage cascaded ranker with features measuring the plausibility of distractors.

- **LR+LM** (Liang et al., 2018) replaces random forest in LR+RF with LambdaMART.

Trigram and 5-gram Kneser Ney language model are built upon the original corpus of our dataset. Word2Vec (CBOW) is pre-trained on Wikipedia dump and fine-tuned on our corpus. Dependency parsing tree is obtained using Spacy toolkit (Honnibal and Montani, 2017). We fetch the uncased base version of BERT (Wolf et al., 2019) and fine-tune it on our corpus.
3.5 Results & Analysis

**Combinations of CSG and DS.** Table 1 shows the automatic evaluation results for different combinations of CSG and DS. Without CSG, distractor selector trained with trivial negative examples is forced to select distractors from a rather large and noisy candidate set therefore the performance is clearly worse. We also find that combining CSG with DS yields consistent improvement by all metrics and the improvement is more significant for WordNet CSG, which is mainly because \( p(c|a) \) and \( p(d|c) \) in WordNet are partly biased due to the limited scale of corpus they are estimated on, hence the supervised training will lead to more performance gain. Pair/list-wise ranker achieve comparable performance mainly due to the binarized relevance score. Since named entities and common nouns mainly underpin Probase, DS with Probase CSG naturally get higher ranking scores on our dataset than its counterpart with WordNet CSG.

**Domain Effect & Feature Importance.** Figure 5 shows the F1@3 of CSG+DS in different domains. The performance drops most drastically when applied in vocabulary domain because adjectives and adverbs in Probase and WordNet are either rare or not hierarchically organized. Another possible explanation is that the ground truth distractors in vocabulary domain are less semantically-related to the key, which makes learning process of the ranker oscillatory. Our framework is especially better at generating distractors in science and commonsense domain, in which the keys and distractors are mostly subject-specific (e.g. physics) terminologies, real-world entities and other common nouns. Trivia domain has similar characteristic but the keys are often rarer, therefore Probase suffers less due to its larger scope. To have more insights on the proposed features, we also conduct feature importance analysis of DS based on mean reduced impurity. It is defined as the total decrease in node impurity, weighted by the probability of reaching that node, averaged over all base classifier. Figure 6 reveals that semantic relation between \( a \) and \( d \) and web search score play more important role than features of other aspects.

**End-to-End Comparison.** Table 2 shows the end-to-end results. Despite the significantly reduced number of candidates, ranking methods with our candidate set generator can achieve much higher performance than with unstructured vocabulary in much shorter runtime. TM performs badly due to its naive path similarity ranking criterion. The results of ED are worst among all unsupervised methods while embedding based methods can even achieve comparable performance against LR+LM/RF when provided with a high-quality candidate set. BERT ranks distractors using contextualized representation thus leading to lowest reliability according to human evaluation. LR+RF/LM achieves similar ranking performance yet obtain poorer reliability than CSG+DS since they only focus on the plausibility of selected distractors. CSG+DS, despite its relative simplicity, obtain consistent improvements over LR+RF/LM without two-stage cascaded training. We observe certain inconsistency between plausibility and automatic metrics of baselines, part of the reason may be that methods such as LR+RF/LM focus much on shallow feature patterns of ground-truth distractors and fail to unearth potential acceptable distractors. However, distractors generated by CSG+DS yield highest ranking measures while rated as most plausible by human annotators. Unsupervised methods work solely relying on the semantic similarity hence their reliabilities are generally lower than supervised ones, among which our DS turns out to be the most reliable. Exceptionally, EmbSim+CF gets higher reliability with WordNet, whose unreliable candidates get more chance to be eliminated by post-filtering than those in Probase.

| Probase CSG                                                                 | WordNet CSG                                                                 |
|----------------------------------------------------------------------------|----------------------------------------------------------------------------|
| contextual embed sim(a,d)                                                | contextual embed sim(a,d)                                                   |
| word2vec embed sim(a,d)                                                  | word2vec embed sim(a,d)                                                    |
| word2vec embed sim(q,d)                                                  | word2vec embed sim(q,d)                                                    |
| web search score                                                         | web search score                                                            |
| relative LCS len(d)                                                      | relative LCS len(d)                                                         |
| relative LCS len(a)                                                      | relative LCS len(a)                                                         |
| character len(d)                                                         | character len(d)                                                            |
| character len difference(a,d)                                             | character len difference(a,d)                                               |
| edit distance(a,d)                                                       | edit distance(a,d)                                                          |
| POS similarity(a,d)                                                      | relative common suffix len(a)                                               |
### Table 2: End-to-end comparison on test set. - means no ranking algorithm to evaluate and “ground truth” denotes the score of ground-truth distractors associated with each item.

| Method               | Human Evaluation | Automatic Evaluation |
|----------------------|------------------|-----------------------|
|                      | Reliability      | Plausibility         | F1@3 | P@1 | P@3 | R@3 | MRR  | NDCG@10 | Semantic Similarity@3 |
| TM                   | 95.57%           | 1.25±0.41            | 1.74  | 0.40 | 1.16 | 3.48 | 2.69  | 4.79     | 0.21                  |
| WordNet CSG          | 98.66%           | 1.25±0.34            | 3.14  | 3.49 | 2.33 | 5.43 | 7.19  | 8.66     | 0.26                  |
| + ED                 | 90.66%           | 1.26±0.41            | 0.41  | 0.12 | 0.26 | 0.58 | 2.10  | 1.93     | 0.20                  |
| + RevUP              | 93.65%           | 1.22±0.34            | 4.07  | 5.79 | 3.21 | 6.43 | 9.31  | 9.60     | 0.32                  |
| + EmbSim+CF          | 99.12%           | 1.21±0.49            | 4.62  | 6.17 | 3.60 | 7.40 | 10.32 | 10.94    | 0.36                  |
| + BERT               | 89.94%           | 1.23±0.58            | 5.68  | 6.93 | 4.23 | 9.57 | 11.10 | 11.66    | 0.30                  |
| + LR+LM              | 96.66%           | 1.25±0.35            | 6.48  | 9.25 | 4.89 | 10.81| 13.42 | 13.66    | 0.29                  |
| + LR+RF              | 95.56%           | 1.25±0.38            | 6.67  | 8.10 | 5.14 | 10.81| 13.18 | 13.73    | 0.30                  |
| + DS(list-wise)      | 98.66%           | 1.35±0.40            | 7.71  | 9.31 | 5.81 | 12.98| 14.34 | 14.94    | 0.36                  |
| Probase CSG          | 99.23%           | 1.26±0.35            | 5.88  | 6.98 | 4.39 | 9.95 | 12.07 | 13.40    | 0.34                  |
| + ED                 | 94.33%           | 1.23±0.38            | 0.82  | 1.16 | 0.65 | 1.30 | 5.02  | 4.92     | 0.28                  |
| + RevUP              | 94.87%           | 1.26±0.36            | 6.27  | 5.40 | 4.63 | 10.68| 11.74 | 14.23    | 0.37                  |
| + EmbSim+CF          | 96.98%           | 1.19±0.47            | 7.01  | 8.10 | 5.14 | 12.34| 13.86 | 16.33    | 0.41                  |
| + BERT               | 95.00%           | 1.27±0.58            | 7.05  | 7.72 | 5.14 | 12.23| 13.60 | 16.21    | 0.36                  |
| + LR+LM              | 98.98%           | 1.25±0.30            | 7.62  | 8.53 | 5.81 | 12.27| 15.56 | 16.83    | 0.40                  |
| + LR+RF              | 99.13%           | 1.24±0.31            | 7.48  | 8.52 | 5.42 | 13.17| 15.87 | 19.03    | 0.40                  |
| + DS(list-wise)      | 99.33%           | 1.30±0.34            | 9.19  | 10.85| 6.72 | 15.88| 17.51 | 19.31    | 0.41                  |

| w/o CSG              |                  |                      |      |     |     |     |      |         |                      |
| + ED                 | 93.98%           | 1.00±0.12            | 0.19  | 0.38 | 0.12 | 0.38 | 0.54  | 0.53     | 0.11                  |
| + RevUP              | 92.88%           | 1.02±0.14            | 2.01  | 2.35 | 1.35 | 4.21 | 3.95  | 5.12     | 0.38                  |
| + EmbSim+CF          | 94.77%           | 0.93±0.52            | 2.12  | 2.70 | 1.41 | 4.24 | 4.19  | 5.24     | 0.42                  |
| + BERT               | 93.87%           | 1.02±0.24            | 3.03  | 2.88 | 2.15 | 5.14 | 5.29  | 6.78     | 0.39                  |
| + LR+LM              | 96.77%           | 1.05±0.28            | 4.22  | 4.34 | 2.79 | 8.69 | 7.02  | 10.16    | 0.41                  |
| + LR+RF              | 97.78%           | 1.02±0.20            | 4.05  | 4.21 | 2.66 | 8.55 | 6.91  | 10.08    | 0.40                  |
| + DS(pair-wise)      | 98.43%           | 1.06±0.14            | 5.59  | 5.01 | 3.98 | 10.10| 9.28  | 11.60    | 0.36                  |

| ground truth         | 100%             | 1.41±0.35            | -     | -    | -    | -    | -     | -        |                      |

Table 3: Comparison on the frequency of being chosen as answer for each model paired with Probase CSG. DS denotes our list-wise distractor selector.

### Application-Centric Evaluation.

The frequency of generated distractors being chosen as answer for each tested model is shown in Table 3. Our DS obtains the highest distracting rate compared to all baselines. The pearson correlation coefficient between frequency and F1@3 is 0.46, implying certain positive correlation between automatic metrics and actual distracting capacity.

### 3.6 Case Study

| #   | key      | RevUP  | ED     | EmbSim+CF | BERT   | LR+RF | LR+LM | DS |
|-----|----------|--------|--------|-----------|--------|-------|-------|----|
| 1   | protein  | protein| aldehydes | starch    | glycosaminoglycans | hydrocarbon | methane | fat |
| 2   | alcohol  | alcohol| carboxylic acid | glycerol | glycerol | methane | protein | protein |
| 3   | benzene  | amino acid | alcohol | glucose | aldehydes | hormone | hormone | peptide |

Table 4: Top 3 distractors from different ranker running with Probase CSG(- denotes sole Probase CSG) given the stem “The main source of energy for your body is ___” and the key “carbohydrate”. Red colored distractors are the ground truth, bold distractors are unreliable distractors.

Table 5 compares predictions made by all baselines and DS (list-wise) running with Probase CSG. We
can see that Probase CSG alone and RevUP are both able to generate distractors belonging to the same concept level as the key and accurately match one ground truth. However, running Probase CSG with ED yields distractors that are more semantically distant from the key. Despite the use of candidate filtering, EmbSim+CF still produces candidates like “glucose”, which is an eligible answer to the stem. BERT instead generate compound names that are too technical and belong to lower concept level than ground truth. Among all the supervised rankers, DS hits another ground-truth distractor “fat” while LM+RF/LM predict some obviously wrong distractors such as “methane” due to its coarse-grained features.

4 Related Work

Extractive distractor generation typically involves two steps: candidate set generation and distractor selection. In the common scenarios, only the key and the stem is known beforehand and the set of candidates needs to be automatically generated. A solution used in previous work is to construct distractor candidate sets from domain-specific vocabulary, thesauri (Sumita et al., 2005; Smith et al., 2010) or taxonomies (Mitkov et al., 2009; Ding and Gu, 2010). These domain-specific candidate source are still not large or general enough, however, to support open-domain distractor generation.

Previous approaches usually select distractors according to different metrics based on the key, including embedding-based similarities (Guo et al., 2016), difficulty level (Hoshino and Nakagawa, 2007; Brown et al., 2005; Coniam, 2013; Shei, 2001), WordNet-based metrics (Mitkov and others, 2003) and syntactic features (Agarwal and Mannem, 2011). Some approaches also consider the semantic relatedness of distractors with the whole stem (Pino et al., 2008; Mostow and Jang, 2012) with domain restriction. Other researchers (Liang et al., 2018; Sakaguchi et al., 2013; Liang et al., 2017) investigate how to apply learning-based ranking models to select distractors that resemble those in actual exam MCQs, and quantitatively evaluate the top generated distractors.

To generate reliable distractors, a supervised classifier (Lee and Seneff, 2007) is trained to do this job where they have a limited list of potential target words and distractors. Another way to perform reliability checking is by considering collocations involving the target word (Smith et al., 2010; Jiang and Lee, 2017). This approach is effective, but requires strong collocations statistics to discriminate between valid and invalid distractors and may not be applied to the sentence in Figure 1 which contains rare word combinations. A web search approach is applied by Sumita et al. (2005) to discard words that can be found on the web search results of the stem with blank filled by the distractor.

5 Conclusion

In this paper we presented a novel distractor generation framework for cloze-style open-domain MCQs. We experimentally observe substantial speed and performance gain when using the proposed framework other than corpus-based approach. Depending on the characteristics (e.g. capacity, POS distribution) of different general-purpose knowledge bases, the generated distractors may vary. Importantly, as knowledge bases with larger coverage and more advanced ranker inevitably emerge, they can be expediently incorporated into our framework for further performance gain.

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