CEPOC: The Cambridge Exams Publishing Open Cloze dataset

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Abstract

Open cloze tests are a standard type of exercise where examinees must complete a text by filling in the gaps without any given options to choose from. This paper presents the Cambridge Exams Publishing Open Cloze (CEPOC) dataset, a collection of open cloze tests from world-renowned English language proficiency examinations. The tests in CEPOC have been expertly designed and validated using standard principles in language research and assessment. They are prepared for language learners at different proficiency levels and hence classified into different CEFR levels (A2, B1, B2, C1, C2). This resource can be a valuable testbed for various NLP tasks. We perform a complete set of experiments on three tasks: gap filling, gap prediction, and CEFR text classification. We implement transformer-based systems based on pre-trained language models to model each task and use our dataset as a test set, providing promising benchmark results.

Keywords: open cloze, blank-filling, language learning, second language testing, Cambridge examinations

1. Introduction

The cloze test (Taylor, 1953) is a standard testing procedure where certain words are replaced with gaps in a piece of text, which must then be filled by the student. There are different variations of the original cloze test:

- **Open cloze** No options are given to fill in the blank. Students must produce the answer with no help.
- **Multiple choice** An answer must be chosen from a set of given options containing the key (i.e. correct answer) and distractors.
- **C-test** A modified version of the open cloze test where the first few letters of the answer are kept in the gap as a hint (Raatz and Klein-Braley, 1981).

An example of each cloze type is given in Figure 1. Cloze tests are widely used for testing language proficiency due to their simplicity and efficiency (Fotos, 1991; Jonz, 1991; Tremblay, 2011; Trace, 2020). However, they must be carefully designed in order to provide accurate measures of ability, often requiring calibration using methods such as those from Item Response Theory (IRT) (Lord, 1980).

Although there is vast research into modelling multiple-choice cloze tests (mainly in the field of reading comprehension, e.g. Xie et al. (2018) or Kurdi et al. (2020), to the best of our knowledge, public datasets of calibrated cloze tests are non-existent, hindering research into automated testing. In this paper, we attempt to address this problem by making the following contributions: 1) we release the first dataset of expertly designed and calibrated open cloze tests at different proficiency levels in English, 2) we provide benchmark results for three tasks: gap generation, gap filling and full-text proficiency level prediction, and 3) we offer insights into how our dataset can help further research into language learning and assessment.

The rest of this paper is organised as follows; Section 2 briefly discusses related work on the available cloze datasets. In Section 3 we detail the composition of our CEPOC dataset, its source, statistics and some lexical analysis. Section 4 elaborates on our experiments on three interesting applications of the dataset. We describe how we model the tasks and report the results of state-of-the-art transformer-based models that can be used as promising benchmarks for the three tasks. Section 5 describes other possible applications of CEPOC and Section 6 concludes with a summary of our work.

2. Related Work

Most work on cloze tests is aimed at reading comprehension or question answering, with less emphasis on second language learning. The Microsoft Research Sentence Completion Challenge, for example, consists of 1,040 multiple choice sentences from Sherlock Holmes stories where a content word is blanked and four alternatives are given (Zweig and Burges, 2012). The CNN/Daily Mail Reading Comprehension Task (Hermann et al., 2015), on the other hand, presents short newspaper passages with a summary that must be filled with an entity from the text. The task served as inspiration for other similar datasets such as the “Who-did-What” dataset (Onishi et al., 2016), the Children’s Book Test (Hill et al., 2016) for the comprehension of children’s stories, the People Daily and Children’s Fairy Tale dataset (Cui et al., 2016) for Chinese, and BioRead (Pappas et al., 2018) and BIOMRC (Pappas et al., 2020) for the biomedical domain.
Table 1: Dataset composition. The average number of tokens and Type-Token Ratio (TTR) are per task.

| Exam          | CEFR level | # tests | VOCAB. size | Avg. # tokens | Avg. TTR |
|---------------|------------|---------|-------------|---------------|----------|
| Key (KET)     | A2         | 6       | 290         | 128           | 65.21%   |
| Preliminary (PET) | B1        | 21      | 854         | 163           | 61.91%   |
| First (FCE)  | B2         | 36      | 1,759       | 176           | 61.84%   |
| Advanced (CAE)| C1         | 30      | 1,562       | 191           | 62.23%   |
| Proficiency (CPE) | C2       | 21      | 1,270       | 192           | 63.56%   |

Table 2: Distribution of tasks by number of gaps.

| # gaps | KET | PET | FCE | CAE | CPE |
|--------|-----|-----|-----|-----|-----|
| 6      | -   | 9   | -   | -   | -   |
| 8      | -   | -   | 12  | -   | -   |
| 9      | -   | -   | 9   | 8   | 15  |
| 10     | -   | -   | -   | 18  | 7   |
| 11     | 4   | -   | 9   | 8   | 5   |
| 12     | 2   | -   | -   | 6   | -   |
| 13     | -   | -   | -   | 1   | -   |
| Total tasks | 6 | 21 | 36 | 30 | 21 |

Table 3: Distribution of gaps per exam with a specific number of valid answers.

| # answers | KET | PET | FCE | CAE | CPE |
|-----------|-----|-----|-----|-----|-----|
| 1         | 54  | 126 | 296 | 241 | 159 |
| 2         | 12  | 18  | 45  | 37  | 31  |
| 3         | 2   | 5   | 16  | 6   | 4   |
| 4         | -   | 1   | 2   | 3   | 5   |
| 5         | -   | -   | 1   | 1   | 1   |
| Total gaps | 68 | 130 | 360 | 288 | 200 |

Cloze question datasets for language learners are less common. The Chengyu Cloze Test (Jiang et al., 2018) and ChID (Zheng et al., 2019) datasets contain short passages and sentences where a Chinese idiom has been removed and has to be chosen from a list. For English, the CLOTH dataset (Xie et al., 2018) is probably the closest to our proposal, since each exercise contains a full-text passage with multiple gaps. However, gaps in CLOTH are multiple choice questions that test a range of abilities such as reasoning, grammar and paraphrasing. The HyTeC-cloze system (Kleijn et al., 2019) also creates multiple gaps for full-text passages but, unlike CLOTH, they are open cloze items and only available for Dutch.

Unlike previous work, the CEPOC dataset we present in this paper comprises full-passage open cloze tests containing multiple gaps each. These gaps are specifically aimed at testing English grammar and vocabulary, have been calibrated using IRT and are graded by proficiency level.

3. CEPOC Dataset Composition

3.1. The Open Cloze Test

Whereas existing datasets focus on multiple choice tests, the Cambridge Exams Publishing Open Cloze (CEPOC) dataset is novel in providing open cloze tests and across a range of proficiency levels. CEPOC thus constitutes a more challenging dataset since answers are not given in advance as a list of candidate options and must be produced from scratch. This not only enables the testing of productive skills in students (Pino et al., 2008) but also serves as a more realistic benchmark for testing language model prediction capabilities (Donahue et al., 2020; Gonçalo Oliveira, 2021).

CEPOC contains a collection of open cloze tasks that have been previously published as practice material by Cambridge Exams Publishing, a division of Cambridge University Press & Assessment (CUP&A)[]. CUP&A’s English examinations span five different proficiency levels of the Common European Framework of Reference (CEFR) for languages (Council of Europe, 2001), ranging from A2 (elementary) to C2 (proficient). Each examination tests four basic skills (reading, writing, listening and speaking) using a variety of tasks (word completion, direct questions, multiple matching, multiple choice, open cloze tests, etc.). These tasks are created by expert ‘item writers’ following strict design principles (ALTE, 2005; ALTE, 2011) and are further validated and calibrated using standard IRT procedures (Corrigan and Crump, 2015). CEPOC only focuses on open cloze tasks from the ‘Reading’ and ‘Use of English’ sections of the exams.

3.2. Dataset Statistics

Each open cloze task in CEPOC consists of a short written passage that is adapted to the CEFR level of the corresponding examination. Details of CEPOC’s composition are reported in Table 1. Each test contains a variable number of blanks or ‘gaps’ depending on the level, as shown in Table 2. Each of these gaps must be filled by a single word and may allow more than one possible answer, with a maximum of 5. The distribution of possible answers per gap is shown in Table 3. The first gap in each test is an example which is included for illustrative purposes only and should not be used for testing since it has not been calibrated. Figure 2 shows a shortened sample test.

3.3. Gap analysis

CEPOC comprises tests for a range of CEFR proficiency levels, enabling cross-level comparisons. Firstly, we report gap distribution statistics in Table 4. The distance between gaps is fairly homogeneous at around 20 tokens, except for KET where it is roughly

Figure 2: Shortened sample from CEPOC (FCE level).
Table 4: Gap distribution and location in the sentences.

|             | KET | PET | FCE | CAE | CPE |
|-------------|-----|-----|-----|-----|-----|
| Avg. gap distance | 10.81 | 19.36 | 17.74 | 19.23 | 19.49 |
| Avg. gaps/sentence | 0.97 | 0.69 | 1.15 | 1.07 | 1.14 |
| Gaps at the beginning | 27 | 57 | 116 | 111 | 66 |
| Gaps in the middle | 26 | 48 | 119 | 85 | 68 |
| Gaps at the end | 15 | 45 | 125 | 92 | 66 |

Table 5: PoS distribution of the gaps in CEPOC.

| Gap PoS | KET | PET | FCE | CAE | CPE |
|---------|-----|-----|-----|-----|-----|
| ADJ     | 2   | 4   | 16  | 6   | 17  |
| ADP     | 13  | 33  | 74  | 86  | 42  |
| ADV     | 6   | 13  | 51  | 41  | 38  |
| AUX     | 8   | 14  | 39  | 23  | 4   |
| CCONJ   | 2   | 2   | 9   | 11  | 6   |
| DET     | 10  | 23  | 50  | 34  | 22  |
| INTJ    | 0   | 0   | 1   | 1   | 0   |
| NOUN    | 0   | 6   | 12  | 5   | 16  |
| NUM     | 0   | 3   | 10  | 4   | 2   |
| PART    | 5   | 10  | 6   | 8   | 2   |
| PRON    | 10  | 18  | 34  | 19  | 8   |
| SCONJ   | 8   | 21  | 50  | 34  | 18  |
| VERB    | 4   | 3   | 8   | 16  | 25  |
| Function words | 88% | 85% | 78% | 82% | 64% |
| Content words | 12% | 15% | 22% | 18% | 36% |

Table 6: Accuracy of different masked language models on the “gap-filling” task.

| Model                | KET | PET | FCE | CAE | CPE |
|----------------------|-----|-----|-----|-----|-----|
| bert-base-uncased    | 95.45 | 97.99 | 95.51 | 89.58 | 85.20 |
| bert-large-uncased   | 94.03 | 98.00 | 97.77 | 92.01 | 90.36 |
| roberta-base         | 98.53 | 99.33 | 96.38 | 94.79 | 93.50 |
| roberta-large        | 100.00 | 99.33 | 98.33 | 97.92 | 96.50 |

Figure 3: Frequency of words in the English language (x axis, decreasing) vs. their frequency as gaps in the different exams represented in CEPOC (y axis).

10, likely due to the smaller size of the passages. The average number of gaps per sentence is roughly 1 in all cases however. When splitting each sentence into three equal-sized parts, we observe that gaps are fairly equally distributed between the beginning, middle and end of the sentence. However, over 60% of gaps tend to occur from the middle onwards, suggesting that they require more context. By design, no gaps are created for the first token in the passage.

Secondly, we carry out an analysis of the gapped words and their frequency by level. Figure 3 shows that gaps in examinations at the lower CEFR levels tend to be very high frequency words in the English language (e.g., a, to, the, if), while gaps at higher levels feature less frequent vocabulary (whose, regardless, extent). This is in line with the expectations that students with higher proficiency should be able to use a wider vocabulary.

Lastly, we look into the parts of speech (PoS) of the words that are gapped at each CEFR level. The distribution of PoS tags is shown in Table 5. In general, the majority of gaps correspond to function words (prepositions, determiners, conjunctions, etc.) although this proportion tends to decrease moderately at higher CEFR levels in favour of content words (adverbs, adjectives and nouns). This behaviour is by design: while elementary students are expected to demonstrate a good use of grammar, more advanced students are expected to know a wider range of lexico-grammatical items, such as idioms and collocations.

4. Experiments

We show three possible applications of our corpus by using it as a benchmark dataset for three tasks: 1) gap filling, 2) gap prediction and 3) text-level CEFR level estimation. Each task is modelled using fine-tuned transformer-based systems and evaluated on CEPOC, as described in the following sections. While we encourage the use of CEPOC as a benchmark, it also lends itself to other uses such as fine-tuning or corpus analysis.

4.1. Gap Filling

We use two state-of-the-art (SOTA) pre-trained language models, BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), for the task of solving our open cloze tests automatically. These masked language models are naturally well-suited to the “gap-filling” task, so we apply them to our dataset in order to provide a benchmark. We use the top prediction from each model as the predicted answer.

Results in Table 6 show that both BERT and RoBERTa can solve our open cloze tasks with exceptional accuracy, reaching over 90% in the majority of cases. As expected, performance decreases at the higher levels, confirming that test difficulty increases as we go up the CEFR scale. We also observe that larger models are able to answer more gaps thanks to their bigger vocabulary size, with RoBERTa consistently outperforming BERT, especially at the higher levels.

Prediction errors can occur for gaps with modal verbs (the lighting {must/should} can X), multiple answers (With/In/After X During X) the aerobic exer-

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2Estimated using the wordfreq Python library: [https://github.com/rspeer/wordfreq](https://github.com/rspeer/wordfreq)

3PoS tagging was done using spaCy v2 [https://spacy.io](https://spacy.io), which uses the Universal Dependencies tagset: [https://universaldependencies.org/u/pos/](https://universaldependencies.org/u/pos/)

4From Hugging Face: [https://huggingface.co/](https://huggingface.co/).
Table 7: Accuracy of gap prediction systems on the different sections of the CEPOC dataset.

| Exams | KET | PET | FCE | CAE | CPE |
|-------|-----|-----|-----|-----|-----|
| # gaps | 68  | 150 | 360 | 288 | 200 |
| Random baseline | 23.28 | 12.58 | 14.95 | 14.79 | 11.00 |
| Exercise Maker | 23.17 | 15.28 | 10.50 |   |   |
| ELECTRA model | 60.29 | 40.67 | 53.89 | 47.22 | 50.00 |

4.2. Gap Prediction

We also built a system that attempts to automatically create open cloze tests from a text passage by predicting which words would make good potential gaps. The task is modelled as a supervised sequence tagging problem where each token is classified as being a good potential gap or not. We employ ELECTRA’s discriminator (Clark et al., 2020), a SOTA pre-trained language model. ELECTRA’s objective for pre-training is to detect the tokens that are randomly replaced by a generator, rather than generating words for masked tokens (as in BERT). We use ELECTRA’s discriminator by adding a linear layer on top for token classification. A model is built for each exam in CEPOC and trained on a larger private collection of open cloze tests. This training data contains 267 tasks for KET, 180 for PET, 356 for FCE, 281 for CAE and 146 for CPE. Our model is compared to two other systems: a) a random baseline, that randomly predicts gaps based on PoS gap frequency for each exam, and b) Exercise Maker (Malafeev, 2014), a rule-based system based on the most frequently gapped words in CUP&A’s exams. All systems are set to predict the same number of gaps per task as they have in the gold standard. We evaluate our prediction results based on a strict matching between the gaps predicted by our models and those in the gold standard. Table 7 reports accuracy for all our systems, fine-tuned separately for each exam. Results for the random baseline and Exercise Maker correspond to the average of 5 runs. Exercise Maker’s generation mode was set to the appropriate exam in each case but was not available for KET nor PET. As expected, results show that the random baseline has very low performance and is only slightly outperformed by Exercise Maker on FCE and CAE. Performance of both systems, however, decreases as the CEFR level goes up, suggesting that gaps are less predictable at higher proficiency levels. Our ELECTRA model outperforms the other systems by a large margin and, while results are less homogeneous, they also exhibit decreasing accuracy. Further experiments involving human evaluation show that many gaps predicted by our model are also equally useful, despite not being matched by the gold standard (Felice et al., 2022).

4.3. CEFR Classification

For this experiment, we built a classification model to classify text passages into different CEFR proficiency levels (A2, B1, B2, C1 and C2). We employ the SOTA pre-trained transformer-based sequence classification model RoBERTa and fine-tune it for a few epochs using the same training data as in Section 4.2. We feed the text passages of our open cloze tests, where gaps are filled with their first acceptable answer, as input to the classifier and label the texts with the CEFR level of the exam they were extracted from. The accuracy of automatically assigning all 114 tasks in CEPOC to their CEFR level (as described in Table 1) is 94.55% for our model vs. 20% for random and 32% for the majority class. This shows that tests at each level are clearly distinguishable from the rest, confirming that they have been carefully tailored to the needs of students at each level.

5. Research Directions

CEPOC fills a gap in the realm of automated second language learning, where public datasets of calibrated proficiency-graded open cloze tests are non-existent. As mentioned in Section 4, we encourage the use of CEPOC as a benchmark dataset but believe it can be exploited in other ways too. Some potential applications we envisage include:

- using the tests in CEPOC with cohorts of students to collect gap difficulty statistics, which could be used to perform gap difficulty prediction;
- characterising students’ expected proficiency at each CEFR level by analysing the grammatical structures, lexical complexity and other linguistic indicators in the tests;
- investigating the factors that determine the effectiveness of gaps, such as context, distance to other gaps, entropy (Felice and Buttery, 2019), etc.

CEPOC is free to use for research purposes and is available at [https://github.com/CambridgeALTA/ce poc](https://github.com/CambridgeALTA/ce poc).

6. Conclusion

This paper presented CEPOC, the first dataset of open cloze tests for learners of English at different CEFR levels. The tests in CEPOC have been designed and calibrated following strict procedures and are part of preparation materials for well-known English proficiency examinations. We described how CEPOC could serve as an ideal dataset for a number of applications and provided encouraging benchmark results for three tasks: gap filling, gap prediction, and CEFR text classification. CEPOC is free to use for research purposes.
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