ELQA: A Corpus of Questions and Answers about the English Language

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Abstract

We introduce a community-sourced dataset for English Language Question Answering (ELQA), which consists of more than 180k questions and answers on numerous topics about English language such as grammar, meaning, fluency, and etymology. The ELQA corpus will enable new NLP applications for language learners. We introduce three tasks based on the ELQA corpus: 1) answer quality classification, 2) semantic search for finding similar questions, and 3) answer generation. We present baselines for each task along with analysis, showing the strengths and weaknesses of current transformer-based models. The ELQA corpus and scripts are publicly available for future studies.¹

1 Introduction

The use of natural language processing (NLP) technology has become an important part of the language learning process. In fact, NLP for educational purposes has been applied for several different tasks and applications such as automated grammatical error correction (Dale et al., 2012; Ng et al., 2014; Bryant et al., 2019; Wang et al., 2021, *inter alia*), question and quiz generation for language learning (Sakaguchi et al., 2013; Chinkina and Meurers, 2017; Marrese-Taylor et al., 2018; Vachev et al., 2021), and automated essay scoring (Burstein, 2003; Farag et al., 2018, *inter alia*).

Nevertheless, an application that has not been taken up by the educational NLP community is free-form question answering about language—encompassing questions and answers on topics of grammar, meaning, fluency, pronunciation, and etymology. Community Question Answering (CQA) websites such as Stack Exchange have sites for language learners' questions and answers (Figure 1).

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These sites require considerable effort by volunteers, and learners may have to wait for an answer—if an answer is provided at all.

Is it possible to build NLP models that can directly answer language learners' questions? How well does the current state-of-the art NLP technology deal with question answering in English language domain? To investigate these questions, we first introduce English Language Question Answering (ELQA) corpus, which is collected from two sites on Stack Exchange: *English* and *English Language Learners*. ELQA contains more than 180k questions with at least one reference answer (over 200k questions in total; §2). These questions are asked by English language learners and native speakers, all about the English language. The covered topics include grammar, fluency, pronunciation, etymology, etc.

With the ELQA corpus, we propose three different tasks: 1) answer quality classification, 2) semantic search for finding similar questions, and 3) answer generation. In the answer quality classification task, a question and an answer are given and the task is to decide whether the answer is acceptable or not. The semantic search task is to find similar or duplicate questions to a given question. The answer generation task is to generate an appropriate answer for a given English language-related question. These tasks are unique in that they require not only general text understanding but also *linguistic knowledge and reasoning*.

We run baselines using state-of-the-art transformer-based models for all these tasks. For the answer quality classification task (§3), we find that the accuracy (65%) is better than chance-level but also find that the models often rely on spurious lexical cues. For the retrieval task (§4), our experiments show that 85% of the retrieved results are of acceptable quality, although there is still room for improvement. For the answer generation task (§5), our results show that the best

¹https://github.com/shabnam-b/ELQA

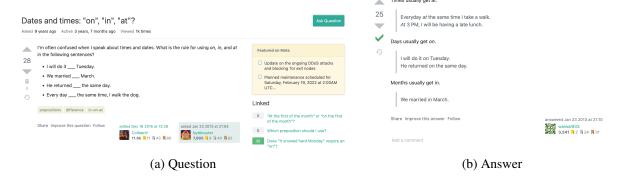


Figure 1: Page screenshots from ELL Stack Exchange.

model generates answers fairly well in fluency and structure but there is much room to improve in the validity toward human written answers. §6 discusses related work.

2 Constructing the Dataset

We collect our data from two sites on Stack Exchange: *English* (ENG)² and *English Language Learners* (ELL).³ Sample screenshots of the site are shown in Figure 1. Every few months, a data dump from Stack Exchange is released publicly, containing metadata and XML files.⁴ This data is under CC-BY-SA 3.0 license,⁵ which can be shared and remixed but requires attribution.

Though we are the first to focus on QA tasks in the English language discussion setting, other researchers have worked with Stack Exchange data across many domains (§6). We followed Gustavo Penha and Hauff (2019) for the initial preprocessing steps but applied them to different parts of the original data dump (the parts relevant to our tasks). In our data collection, each entry (question) has various unique features including title, body, user bio (if available), score (which is calculated based on up-votes and down-votes by other users), tags (user-assigned, related to the area/topic of the question), favorite count and a list of answers. We create ELQA in three formats: HTML, HTML converted to Markdown, and lastly, plain text in which all HTML tags were removed.

We used the data dump published on 2021-12-06. After some initial cleanup (e.g., removing posts marked as "spam" or "offensive") we ended up

| | ELL | ENG |
|---------------------------|---------|---------|
| Total # of Qs | 89,084 | 119,924 |
| Total # of As | 132,705 | 258,173 |
| Max. # of As for one Q | 18 | 109 |
| Avg. # of As (non-0) | 1.61 | 2.38 |
| Total # of Qs with no A | 6,911 | 11,253 |
| Avg. Q length | 92.24 | 101.40 |
| Avg. A length | 145.92 | 136.05 |
| Max. A score | 392 | 827 |
| Min. A score | -13 | -28 |
| Avg. A score | 2.48 | 3.45 |
| Total # of available tags | 547 | 978 |

Table 1: ELQA statistics on Qs (questions) and As (answers). To calculate avg. length, sequences were tokenized using SpaCy (https://spacy.io/).

with 89,084 questions from ELL and 119,924 questions from ENG. Table 1 contains statistics on the collection. Figure 2 shows the distribution of the 10 most common tags in each of the sites. Since users assign these tags to their questions (0 to multiple), similar or near-duplicate tags are common within the collection. Some form more general and more fine-grained variants, e.g. 'phrases' and 'phrase-requests'.

We also did a manual inspection of a large subset of the data to identify salient types of questions. These are defined below and illustrated in Table 2. We then labeled 100 random questions to get a rough estimate of their frequencies.

• Fluency: Usually asking about a particular sentence, comparison of multiple sentences, and/or probing how an expression should be used in general. The user wants to know if X is correct, or between multiple choices, which one is correct. "Correct" could mean grammatical, most natural/idiomatic, stylistically appropriate, con-

²https://english.stackexchange.com/

³https://ell.stackexchange.com/

⁴https://archive.org/details/stackexchange

⁵http://creativecommons.org/licenses/by-sa/3.0/

| Question Type | Title | Body |
|----------------------|---------------------------|---|
| Fluency | "On my own way vs. "in | Which one is correct in or on own way? <blockquote> </blockquote> |
| | my own way"? | <pre>I usually help my closest friends on/in my own way.</pre> |
| | | quote> |
| Form to Meaning | Wondering what "get by" | <blockquote> He tries to get by with the least amount of</blockquote> |
| | means in this context | <pre>work possible. Could you tell me what this</pre> |
| | | sentence means? |
| Meaning to Form | Word for a passed down | When a language is only taught from the adults that speak it. I know there's a |
| | language? | word for it, but I can't for the life of me remember what it is! |
| Grammatical An- | Should I modify a gerund | I know that a gerund is a noun , so it should be modified by |
| alysis | using an adjective or an | an adjective . However, it is also a verb form . |
| | adverb? | Can I modify it by using an adverb ? |
| Other | School and school of fish | Why is a group of fish called "school"? And is it anyhow etymologically con- |
| | | nected with the word "school" denoting an educational establishment? |

Table 2: Example posts from ELL and ENG sites for different question types. (Original post URLs and author profile URLs are all available in Appendix)

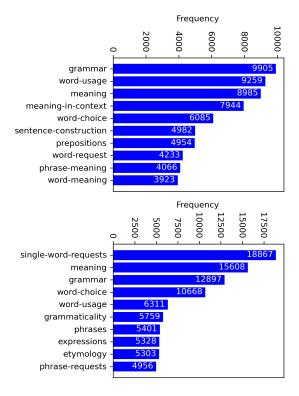


Figure 2: Top 10 user-assigned tag frequencies in ELL (top) and ENG (bottom)

veying the intended meaning, etc. In Qs where options are provided by the user, there are cases in which 1) none of the choices are correct, 2) multiple choices are correct, and 3) only one is correct. ($\approx 38\%$ of questions)

- Form to Meaning (Interpretation): Questions such as "What does X mean?" (of an expression in general, or an encountered passage) or "What's the difference in meaning between X and Y?". (≈19% of questions)
- Meaning to Form (Encoding): In these ques-

tions, the user gives some explanation/definition and asks for the term or expression. ($\approx 20\%$ of questions)

- **Grammatical Analysis:** Questions about parts of speech and other aspects of syntactic analysis. (e.g. "Is this a verb or an adjective?"; "Can an article ever go after the noun it modifies?"). Note that Fluency questions may mention grammatical terminology, but the grammatical categories are not the focus. (≈13% of questions)
- Other: Any other type of question not listed above. This includes question about pronunciation, etymology, etc. (≈8% of questions)

As can be seen from the illustrative examples in Table 2, it is common for questions and answers to contain example usages, often visually distinguished with Markdown formatting (such as blockquotes, bullets, and italics). Examples can be incorporated into a post in a variety of ways—e.g., asking for an interpretation of one usage, as in the Form to Meaning example in Table 2, or contrasting multiple usages such as in the following question:

Did VS Have done

What is difference between the following statements: Did you tell your parents yet? Have you told your parents yet? Haven't you told your parents yet? Are these questions correct? why do we use one over another in some cases? What is the difference in meaning?

Usage examples provided in a question may be instances that the author encountered "in the wild" (such as in a novel or film), or in a grammar book or dictionary, or they may have been constructed

by the user. Answers sometimes include examples found through a corpus search.

3 Answer Quality Classification Task

In this task, we would like to evaluate whether the answer to a question is correct or incorrect/low-quality. If solved, this task could be very useful for instant evaluation of answers posted on online Q&A communities and prioritization for moderation (§6). For this task, we pair together the question body and the answer, and define the task as a binary sequence classification task.

Due to the complexity of the questions and the background knowledge needed to answer them correctly, the task is very challenging. We show that current LMs, despite gaining respectable scores on the task, are still not very reliable. Not surprisingly, careful evaluation reveals that off-the-shelf models are not evaluating the correctness of the answers, but are relying on other aspects (length, style, lexical items, etc.) to make predictions.

3.1 Data

To have a balanced dataset of negative and positive classes, this dataset is a subset of ELQA. We place answers having a score less than −1 in the negative class, and answers having a score greater than 1 or that were "accepted" in the positive class. In the positive class, for each question, we picked the answer with the highest score. However, the number of negative samples in the collection is much lower than the number of positive samples. Hence, we use all the negative samples available in ELQA, but randomly downsampled the positive class in order to have a more balanced dataset. Given the wide diversity of criteria that could be used for stratification (length, vocabulary size, complexity) and the large size of the sub-sample, we decided to use random sampling rather than risk biasing the positive class data. This results in 13,672 text sequence pairs: 7,000 positive (out of 138,583) and 6,672 negative. We created train/dev/test (80%/10%/10%) splits from this data for the experiments. Below, an example of each class is provided:⁶

• *Positive:* **Q:** Can one use the term generify to mean 'to make generic'? E.g. a software programmer being told: 'generify this segment of code'. If not, what may be a single word replacement of this phrase? **A:** Genericise / genericize

- is the version I most frequently hear. Out of interest, I ran an ngram test, with generify not getting a single hit. Genericize, however, has risen in usage from the '80s.
- Negative: Q: Is there a word that means cheating and legitimate at the same time? For example: I play a quiz game and set the number of questions to one. So, I get 100% of my answers correct. That's cheating, but it's legit. So how do I describe what I did in one word? A: Perhaps "Gaining an edge" or "Gaining an advantage".

The negative example shows the challenging nature of this task. The answer is not completely incorrect, but it has a low score since "cheating" is not implied in the provided expressions, and also the user asked for "one word" and the suggested answer has three words.

3.2 Experiments and Analysis

As described before, the aim of this task is to classify whether an answer is correct or incorrect based on the questions. We used ELECTRA (electrabase-discriminator, Clark et al., 2020) and DeBERTa (deberta-base, He et al., 2021) in our experiments for this task. The best epoch was tuned on the dev set (3rd epoch for ELECTRA and 14th for DeBERTa) and final results are shown in Table 3. Both models perform almost the same (but ELECTRA converged in earlier epochs).

The scores appear reasonably high. However, top-line scores could reflect learning of simple biases/heuristics. To address this possibility, we conducted adversarial stress tests (Naik et al., 2018), meant to trick models if they primarily rely on lexical cues such as scholarly vocabulary items (indicating high quality answers) or spelling mistakes (suggesting lower quality).

First, we created a test set with *Length Manipulation*. Looking at the training set, mean answer length of *positive* samples is 178.34, but this quantity is 110.89 for *negative* samples (this pattern persists in the dev and test splits). We believe the model might rely on the differences in sequence lengths to classify. We test this hypothesis as follows: We added tokens to all negative samples in the test set, taking care to select very general sentences that would not affect the correctness of the answer, for example: "I have the following answer for you:" at the beginning of the answer and, "I think this should answer your question. Let me know in the comments." at the end of the answer.

⁶Post URL and Author profile URL of all examples in the paper are available in the Appendix.

| | ELECTRA | DeBERTa |
|-------------|---------|---------|
| Acc on dev | 0.64 | 0.66 |
| Acc on test | 0.63 | 0.65 |
| F1 on dev | 0.64 | 0.65 |
| F1 on test | 0.63 | 0.64 |

Table 3: Binary classification results (Accuracy and Macro-F1) on Q&A pairs

| DeBERTa | Neg-F1 | Pos-F1 | Accuracy |
|---------------------|--------|--------|----------|
| Baseline | 0.60 | 0.68 | 0.65 |
| Length Manipulation | 0.49 | 0.64 | 0.58 |
| ELECTRA | | | |
| Baseline | 0.62 | 0.64 | 0.63 |
| Length Manipulation | 0.59 | 0.63 | 0.61 |

Table 4: Classification task – adversarial stress test evaluation results on *Negative* and *Positive* classes

Results of the this experiment are shown in Table 4. As observed from these tables, ELECTRA seems to be less sensitive to Length Manipulation than DeBERTa. However, we still see a 2% drop on Accuracy when we add tokens to negative samples. This change results in 7% drop in Accuracy for the DeBERTa model which suggests that the model is indeed sensitive to the length. Even though shorter answers may mean less explanations for the learner, they do not imply the answer is incorrect. Answer length can also vary based on the question that is being asked, suggesting that the model should not be too sensitive to answer length if it is meant to tackle the actual underlying task.

Additionally, we wanted to see whether the model would correctly reject possibly well-formed but *irrelevant* answers at test time, or whether it was checking that the answer was responsive to the question. To test this, we shuffled the answers in the test set so they would be mismatched to questions. Despite the mismatch, DeBERTa predicted the answer was a good answer to the question 58% of the time and ELECTRA 51%—an indication that the models are not properly factoring the question into its classification of the answer.

Lastly, we ran another experiment, training new models classifying only answers (questions were not included in the input sequence). This resulted in an F1 score of 0.65 and 0.68 for ELECTRA and DeBERTa respectively. These scores are higher than when questions were included, showing that the baseline models are not actually classifying the Q&A as a pair, but mostly relying on the cues from the answer.

4 Semantic Search and Clustering Task

For this task, we would like to find questions that are similar to each other. Providing the learner with posts similar to their question can help them find their answer more quickly, and also expose them to more examples and various explanations.

4.1 Data

To find similar posts, we collected "duplicate" questions from Stack Exchange. Because moderators can mark questions as duplicates, information on duplicate questions (as pairs) is available in the Stack Exchange data dump itself. We therefore clustered any pairs that had a question in common. This resulted in 1,429 clusters in ELL and 4,199 clusters in ENG, with at least 2 samples in each cluster. The largest clusters in ELL and ENG have 55 samples and 1,908 samples respectively. An example of a cluster with 3 members is provided below:

- "I didn't go to the office yesterday. I didn't go to work yesterday. Why is the article 'the' omitted in the second sentence."
- "I have to go to school. I have to go to the school. Which is correct sentence? Can we use article before the word "School"?"
- "Why is this sentence wrong about the article usage? Don't be late for the school. I was told that the correct sentence is Don't be late for School." We also created a "query set" from all these clusters for ELL and ENG which have 1,459 and 4,692 data entries respectively. These queries were selected randomly. For these queries, "title" and "body" are concatenated with a "[SEP]" token.

4.2 Experiments and Analysis

To evaluate clusters, we first looked at a low-dimension visualization of the questions using UMAP (McInnes et al., 2018) and Sentence Transformers (Reimers and Gurevych, 2019). To be able to better visualize, we selected a subset of the data. From clusters that had at least 15 members, we randomly select 10. This resulted in 249 samples in ELL and 467 samples in ENG. We then used two pre-trained models from Sentence Transformers, MPNet and RoBERTa (all-mpnet-base-v2 and all-roberta-large-v1), to embed the body of the posts.

Clusters are labeled and visualized in Figure 3. The plots were produced with the UMAP algorithm to reduce to 2 dimensions. The clusters appear more distinct when RoBERTa was used and show

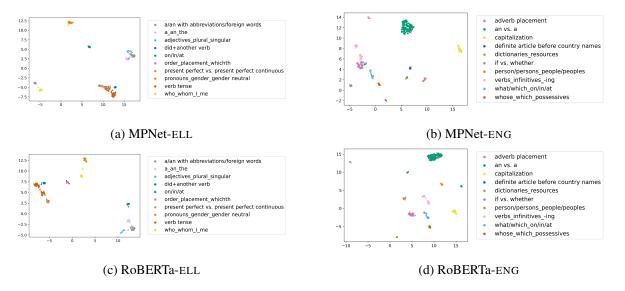


Figure 3: 2D visualisation of a random subset of clusters using UMAP and Sentence Transformers. Each color indicates a gold cluster from the dataset. Labels are a rough (manual) description of the topic of the questions within their clusters.

promising results on this subset. In Figure 3c we can see that clusters related to "verbs" in general are closer to each other and far from others. The same pattern is found for clusters related to "articles". In Figure 3d, the cluster which contains questions about the usage of "if" vs. "whether" is far from all other clusters. Even though the questions usually contain different examples and use cases of a general phenomenon, they are still close to each other semantically in the plots, suggesting that sentence transformers perform well in capturing the metalinguistic topics.

Next, we looked into the Semantic Search task, which is our end goal for this subset. When doing semantic search, we seek to enhance search accuracy by looking into semantics and not just lexical information. This is usually done by embedding the entries in the collection and the search query and finding the entries from the collection which are closer to the search query. We use the query set (explained in the previous subsection) for evaluation and try to find the top 3 related posts from the rest of the collection. Here we use RoBERTa again as a baseline to embed the posts, along with cosine similarity to find nearest neighbors. We realized that we could not use measures such as Mean Average Precision at K (MAP@K) for evaluation since the dataset does not necessarily contain all duplicates, meaning the MAP@K for a query could be very low, even though the predicted results are similar. We therefore selected 50 random queries

from both ELL and ENG, and manually checked the top 3 predicted outputs. With this experiment, we still cannot tell if the model is predicting the best possible similar posts in terms of recall. However, we can tell whether the posts are *related* and thus likely helpful to the user.

Even with such a simple method for semantic search, looking at the outputs for both ENG and ELL, out of 100 queries, only 15 sets of outputs did not have a good quality (in the top 3 results, unrelated posts were ranked higher than the ones available in the original cluster). In many cases, even though the posts were not marked as "duplicate", they were still related. For example, for the following question: "Singular vs. plural in "Different type / types of question / questions" [SEP] Different types of questions or Different type of questions or Different type of question or Different type of question. Can anybody tell me, which one is the correct usage?", the titles of the retrieved outputs were as follows:

- 1) How to distinguish between use of "types of approach" or "types of approaches"?
- 2) Types of books or Types of book?
- 3) kind of X / kinds of X / kinds of Xs

Only item #2 was in the same cluster as the query in the original data.

Interestingly, when questions are relatively specific (usually in a cluster with only 2 members in the original data), the model is reliably able to rank the related post at the top of the predictions. For ex-

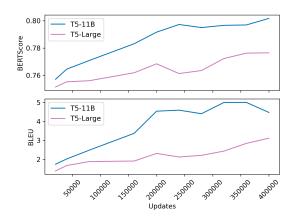


Figure 4: BERTScore (top) and BLEU score (bottom) for update points on the dev set (T5-Large and T5-11B)

ample, for the following question title: "A word or phrase to describe someone who is obsessed with words?", the model retrieves: "Is there a word for being addicted to words?".

5 Generation Task

The goal of this task is to generate answers to English questions. If solved, this could be very useful since learners can get instant responses to their questions. There is no available external context/reference at test time for this task, so this would constitute a closed-book question answering task. Roberts et al. (2020) shows that large pre-trained language models without any access to external knowledge can attain competitive results on open-domain question answering benchmarks. As a baseline, we follow similar approaches in our experiments; however, we believe the questions in ELQA are more challenging since they require different types of knowledge/understanding to be able to generate answers. Additionally, these questions contain a lot of noise (grammatical errors) and cases of textual metalanguage which is likely harder to comprehend for a model.

5.1 Data

To create data for this task, we filtered questions and answers having a score higher than 1 or labeled as "accepted". We divided the data into train/test/dev splits. In the train set, a question may appear multiple times with different answers. In the dev and test sets, each question appears only once, but in some cases, we can have multiple reference answers for an entry at evaluation time. This resulted in 174,893 Q&A pairs in the train split and 14,369 and 14,370 Q&A pairs in dev and test splits

| Source | C1 | Var. | C2 | Var. |
|------------------|------|-------|------|-------|
| High-score human | 4.88 | 0.037 | 4.47 | 0.374 |
| Low-score human | 4.73 | 0.106 | 3.80 | 0.994 |
| T5-11B | 4.60 | 0.344 | 3.75 | 1.046 |
| T5-Large | 3.38 | 1.969 | 2.50 | 1.467 |

Table 5: Human evaluation scores (out of 5): mean and variance on 2 criteria, C1 (well-formedness) and C2 (correctness/completeness), as described in the text.

respectively. For this task, we include the "title" of the question in the sequence pair and used the Markdown version of ELQA since in our evaluation and analysis, we realized the plain text format is sometimes more challenging to comprehend (even for humans) for these types of questions (which have many cases of metalanguage).

5.2 Experiments and Analysis

Here, we use T5 (Raffel et al., 2020) as our model. T5 is an encoder-decoder (i.e., sequence-to-sequence) model built on top of the transformer architecture (Vaswani et al., 2017) which is pre-trained using a combination of masked language modeling and multitask training such as summarization, machine translation, and sentiment classification.

In the experiment, we encode the question sentences and fine-tune the model to decode the answer sentences. We fine-tune T5-Large (770M parameters) and T5-11B (11B parameters) with the following hyper-parameters: batch size = 8, learning rate = 0.001, maximum gradient updates = 400k, and maximum input and output lengths = 512. We saved multiple checkpoints during fine-tuning and evaluated them with the interpolation of BLEU (Papineni et al., 2002) and BERTScore (Zhang et al., 2020) on the dev set to choose the best-performing one (checkpoint at 400k updates). These scores are shown in Figure 4. From the plots we can observe the improvement across different checkpoints and that not surprisingly, T5-11B outperforms T5-Large in both BLEU and BERTScore.

We also conducted a small-scale human evaluation for deeper analysis given the well-known limitations of automatic metrics for evaluating generation tasks (Kasai et al., 2021). Human evaluators were presented with the question title and body, and then asked to rate 4 answers: a high-score human-provided answer, a low-score human-provided answer, an answer generated by T5-11B,

| Question | Human Answers | Model Generated |
|---|---|--|
| Title: How to refer to particular years in a specific century in one expression? Body: If I need to mention the year and the century how do I say that in one sentence? 1. They moved abroad in the 70s in the twentieth century. 2. They have a collection of paintings painted in the 70s in the twentieth century. | High-score human: The clearest and most concise way would be "in the 1970s" (pronounced "nineteen seventies"). Low-score human: When discussing centuries, as in Norwegians came to the New World in the eleventh century, you may have to resort to some old fashioned sounding sentences. I would say Hrvald the Norwegian sailed the ocean in the ninety second year of the eleventh century (1092), or if you want to get really uncommon, sailed the ocean in the ninety second year of the second millennium. | T5-11B: You can say "the seventies" and "the twentieth century" in the same sentence. >> They moved abroad in the seventies of the twentieth century. >> They have a collection of paintings painted in the seventies of the twentieth century. >>> I'm not sure if it's grammatically correct to say "in the 70s in the twentieth century" but people do that. On the other hand, you can say "they moved abroad in the 1970s of the twentieth century" because "the 70s" is a noun that refers to a period of time, not a specific year. T5-Large: It's not a matter of century, but of century. The "70s" refers to the decade of the 20th century. The "20th century" refers to the 20th century. So, you could say: >> They moved abroad in the 70s, in the twentieth century. >> or >> They moved abroad in the 1970s, in the twentieth century. >> or >> They have a collection of paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. >> or paintings painted in the 70s, in the twentieth century. |
| Title: What is an appropriate word for a "rerise"? Body: I'm wondering if there is a more appropriate term in English that describes a rise of something (like a nation) that has already achieved that status before, like a second rise or rerise. | High-score human: We've been known to get some mileage out of the term renaissance. ("Re-nascence", or rebirth.) In contexts less fraught with pomp and circumstance we would probably speak of a comeback. Low-score human: Rerise is not a regular or commonly used word. Rise serves both purposes most of the time. The sun sets, and rises the next morning. You rise from sleep. The Phoenix rises from the ashes. Similarly, dynasties that fell have risen after decades. Rise can thus be used, with 'again' if needed. | T5-11B: "Sustained upsurge" or "continuous upsurge" are not bad single-word options. If you're looking for a noun, something like "resurgency" might work, but it's still a bit clumsy. T5-Large: I think "regression" is the word you are looking for. >> a continuing process of development or improvement, especially one that is > temporary or intermittent. >>> ([Dictionary.com]([SOME LINK]) |

Table 6: Example posts with human and model-generated answers. Here we omit links and Markdown formatting. Some model-generated answers contain spurious characters due to invalid Markdown.

and an answer generated by T5-Large. For each answer, continuous ratings were requested for the criteria:

- 1. Does the answer look grammatically/structurally like a good answer (ignoring whether it answers the question)?
- 2. Is the information in this answer a valid response to the question (ignoring formatting/stylistic issues)?

The first criterion aims to get a score for *fluency* and coherency and the second one for correctness and completeness. Ratings were input via a slider widget on a scale from 0 to 5 (the higher, the better).

We collected ratings for a set of 40 questions (160 different answers). Each question with its set of answers was evaluated by at least 3 people, and then the average score was calculated based on their responses.⁷

The results of this study are shown in Table 5. Not surprisingly, T5-11B and T5-Large do not perform very well. Of the two, T5-11B's answers are superior to T5-large's answers on both criteria. Yet

even the better model's answers are not correct or complete in many cases, resulting in an average C2 score of 3.75. Evaluators reported redundant repetitions in some T5-large responses (\approx 65% of a small random subset). Out of 40 questions, in only 27% of cases, the average fluency and coherency score for T5-large was equal or better than T5-11B, and in only 10% of cases, the average correctness and completeness score was equal or better than T5-11B.

Comparing T5-11B and high-score human answers for correctness and completeness, 32% of T5-11B answers got an equal or better score than highscore human answers. The type of questions for these cases were mostly Form to Meaning, Meaning to Form and Fluency. Lastly, we realized in some cases (23%) low-score human answers got equal or better average scores for correctness and completeness compared to high-score human answers. This shows that even though in most cases the website scores seem reliable, they are not completely in agreement with our raters' judgments. There could be several reasons: for example, an older answer might have a higher score, only because it has been available for a longer period of time; or regular users of the site could have based

⁷Evaluators consisted of 12 senior NLP researchers or graduate students (native speakers or fluent L2 speakers familiar with linguistics). Evaluators did not know the source of the answers, and the order of the 4 answers was randomized for each question to avoid bias.

their votes on different criteria than our evaluators.⁸

Finally, Table 6 shows 2 examples with their 4 answers similar to what we used for human evaluations. Clearly, the answers are not always correct and complete. One issue with model-generated answers is that sometimes they include invalid Markdown formatting which displays as superfluous characters (e.g., extra ">" characters). We also realized that in some cases the model contradicts itself (e.g. Q title: "Is there such a word as "semiproduct"?", T5-11B: "Semi-product would be a correctly formed word. Semi-product is not a word. As a native speaker, I would not know what you meant by semi-product."). However, The modelgenerated answers (especially from T5-11B) are usually very relevant to the question, and in most cases are easy to read. Moreover, the models seems to perform better for shorter questions and questions of the Form to Meaning and Meaning to Form varieties.

6 Related Work

Data Community Question Answering websites exist for numerous topics, and researchers have created various data collections and defined different tasks using them in the past few years (Patra, 2017; Rogers et al., 2021). The most common CQA platforms used are WikiAnswers (Abujabal et al., 2019), Reddit (Fan et al., 2019), Yahoo! Answers (Hashemi et al., 2020), Quora⁹ and Stack Exchange (Yao et al., 2013; Hoogeveen et al., 2015; Ahmad et al., 2018; Gustavo Penha and Hauff, 2019; Campos et al., 2020; Kumar and Black, 2020). Stack Exchange is a network of numerous CQA sites (originally and most famously, Stack Overflow) built on a common platform. Previous research datasets based on Stack Exchange have included the English site (our ENG) along with others such as Ask Ubuntu, Android, Gaming and Word-Press (dos Santos et al., 2015; Nakov et al., 2017). Our focus, of course, is not on general QA, but rather on questions about the English language itself, for which we have compiled a dataset based on the ENG and ELL sites.

Tasks Each post in CQA websites, including Stack Exchange, contains several useful pieces of information (tags, scores, linked posts, etc.) and several different components (question, answers, comments, user profiles, etc.) which has led to the introduction of multiple new and interesting research directions and tasks (Nakov et al., 2015, 2016, 2017; Mihaylova et al., 2019).

The first task we looked into in this paper was answer quality classification (a version of answer selection task). Similar tasks have been proposed on other CQA datasets in the past couple of years. Statistical models (Qu and Liu, 2011), models with heavy feature engineering (Tran et al., 2015) and deep learning models (Tay et al., 2018; Wu et al., 2018; Deng et al., 2020) have all been proposed to solve this task in other domains.

Next, we looked into *semantic similarity and duplicate question detection* tasks. This task has attracted a lot of attention in recent years. Bogdanova et al. (2015) compares the performance of classic standard machine learning methods with convolutional neural networks on this task. Haponchyk et al. (2018) leverages supervised clustering methods for this task. Kunneman et al. (2019) compare and combine a few of the top-performing models along with analyzing the impact of preprocessing steps. More recently, transformers have become a very popular and dominant approach for this task (Poerner and Schütze, 2019; Ha et al., 2021).

Lastly, we defined the answer generation task on ELQA. So far, most QA tasks are set up to have a question and a reference document, where finding the answer based on the document is the objective (Fan et al., 2019). More recently, Rozen et al. (2021) leveraged answers available for similar questions, to answer new yes/no questions. In this paper, we explored a type of "closed-book" question answering task, which means that the model has to only rely on the information learned during training to generate the answers (Roberts et al., 2020). To the best of our knowledge, this task has not been explored to date within the English language questions scope and this is the first work exploring this task and proposing a standard processed dataset.

We believe that the questions in ELQA offer new challenges for all of the task types above, for the following reasons: 1) They contain substantial amounts of noise, since many posts include

⁸We also realized that in a few cases (2 in 40 random samples) the questions require too much effort/time that even humans might not respond to them completely (e.g., a question about how to parse 5 challenging sentences). What sometimes happens in these cases is that people complete each other's answers as they come across the question. This usually happens over a long period of time and still, in the end, the complete answer might not be available for the learner. Having a model generating the complete answer right away could be extremely helpful for such scenarios.

⁹https://www.kaggle.com/c/quora-question-pairs

examples that are grammatically incorrect and, 2) the questions and answers contain different cases of textual metalanguage (mentioning, rather than using words and phrases) which may degrade the performance of SOTA models not used to this type of text.

7 Conclusion

We presented ELQA, a novel dataset containing Q&As about the English language. We provided analysis and a taxonomy of the data, along with experiments on three tasks: answer quality classification, semantic search and free-form answer generation. Even though some of our baselines showed promising results, we believe there is still a lot of room for improvement on all of these tasks. We also strongly suspect that current language models overly rely on style and task-irrelevant information for decisions that in principle require logical inferences and world knowledge, as suggested by our stress tests for answer quality classification. In free-form answer generation, we observe that larger models generated superior answers than smaller models, and in some cases produced good answers—-but there is still a large gap between human performance and these baselines.

ELQA contains a variety of useful information that can be used for different Applied Linguistics and NLP studies. With three formats of ELQA publicly available, new tasks can easily be defined using the data. Finally, since many of the questions in ELQA are asked by language learners, it forms a potentially useful and so far untapped resource for educational NLP purposes.

A Appendix

The Stack Exchange license requires that any Internet use of the content should include a hyperlink directly to the original question and the profile of the authors. Below are URLs for all the examples used in this paper. The post URL incorporates the post title.

- https://ell.stackexchange.com/questions/12/dates-and-times-on-in-at (Q by bytebuster, A by waiwai933)
- https://ell.stackexchange.com/questions/146633/on-my-o wn-way-vs-in-my-own-way (Q by bavyan-yaldo)
- https://ell.stackexchange.com/questions/19684/wonderin g-what-get-by-means-in-this-context (Q by nima)
- https://english.stackexchange.com/questions/289565/wor d-for-a-passed-down-language (Q by clip)
- https://english.stackexchange.com/questions/134352/sho uld-i-modify-a-gerund-using-an-adjective-or-an-adverb (Q by worawit-tepsan)
- https://ell.stackexchange.com/questions/230595/schooland-school-of-fish (Q by marie-mit)

- https://ell.stackexchange.com/questions/185516/did-vshave-done (Q by learner)
- https://english.stackexchange.com/questions/28889/us ing-generify-to-mean-to-make-generic (Q by citizen, A by Grant Thomas)
- https://english.stackexchange.com/questions/238824/isthere-a-word-that-means-cheating-but-legitimate (Q by saka, A by user1359)
- https://ell.stackexchange.com/questions/284951/i-didnt-go-to-the-office-yesterday-i-didnt-go-to-work-yesterday?r=SearchResults&s=1|232.6785 (Q by Abhishek Ranjan)
- https://ell.stackexchange.com/questions/62645/i-ha ve-to-go-to-school-i-have-to-go-to-the-school (Q by i-dont-know-who-i-am)
- https://ell.stackexchange.com/questions/16702/late-for-school-or-late-for-the-school (Q by dexterous)
- https://ell.stackexchange.com/questions/71779/singular -vs-plural-in-different-type-types-of-question-quest ions (Q by kaikadi-bella)
- https://ell.stackexchange.com/questions/1269/analysing -the-kinds-of-problems-are-ones-to-be-construction (Q by user114 (link not available))
- https://ell.stackexchange.com/questions/1377/how-to-di stinguish-between-use-of-types-of-approach-or-typesof-approaches? (O by tomasz74)
- https://ell.stackexchange.com/questions/44976/types-of-books-or-types-of-book? (Q by francisco)
- https://ell.stackexchange.com/questions/26470/kind-of-x-kinds-of-x-kinds-of-xs? (Q by rafat)
- https://english.stackexchange.com/questions/185111/a-w ord-or-phrase-to-describe-someone-who-is-obsessed-wi th-words (Q by vickyace)
- https://english.stackexchange.com/questions/351842 /is-there-a-word-for-being-addicted-to-words? (Q by mikey-c)
- https://ell.stackexchange.com/questions/295767/how-to-refer-to-particular-years-in-a-specific-century-in-o ne-expression (Q by antonia-a, first A by andy-bonner, second A by elliek)
- https://english.stackexchange.com/questions/68073/what
 -is-an-appropriate-word-for-a-rerise (Q by kdaker, first A
 by chaos, second A by kris)
- https://english.stackexchange.com/questions/11010/is-t here-such-a-word-as-semiproduct (Q by axarydax)

References

Abdalghani Abujabal, Rishiraj Saha Roy, Mohamed Yahya, and Gerhard Weikum. 2019. ComQA: A community-sourced dataset for complex factoid question answering with paraphrase clusters. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 307–317, Minneapolis, Minnesota. Association for Computational Linguistics.

Arshad Ahmad, Chong Feng, Shi Ge, and Abdallah Yousif. 2018. A survey on mining stack overflow: question and answering (q&a) community. *Data Technol. Appl.*, 52:190–247.

Dasha Bogdanova, Cícero dos Santos, Luciano

- Barbosa, and Bianca Zadrozny. 2015. Detecting semantically equivalent questions in online user forums. In *Proceedings of the Nineteenth Conference on Computational Natural Language Learning*, pages 123–131, Beijing, China. Association for Computational Linguistics.
- Christopher Bryant, Mariano Felice, Øistein E. Andersen, and Ted Briscoe. 2019. The BEA-2019 shared task on grammatical error correction. In *Proceedings of the Fourteenth Workshop on Innovative Use of NLP for Building Educational Applications*, pages 52–75, Florence, Italy. Association for Computational Linguistics.
- Jill Burstein. 2003. The e-rater® scoring engine: Automated essay scoring with natural language processing. In *Automated essay scoring: A cross-disciplinary perspective*, pages 113–121. Lawrence Erlbaum Associates Publishers.
- Jon Ander Campos, Arantxa Otegi, Aitor Soroa, Jan Deriu, Mark Cieliebak, and Eneko Agirre. 2020. DoQA accessing domain-specific FAQs via conversational QA. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7302–7314, Online. Association for Computational Linguistics.
- Maria Chinkina and Detmar Meurers. 2017. Question generation for language learning: From ensuring texts are read to supporting learning. In *Proceedings of the 12th Workshop on Innovative Use of NLP for Building Educational Applications*, pages 334–344, Copenhagen, Denmark. Association for Computational Linguistics.
- Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. 2020. ELECTRA: Pretraining text encoders as discriminators rather than generators. In *International Conference on Learning Representations*.
- Robert Dale, Ilya Anisimoff, and George Narroway. 2012. HOO 2012: A report on the preposition and determiner error correction shared task. In *Proceedings of the Seventh Workshop on Building Educational Applications Using NLP*, pages 54–62, Montréal, Canada. Association for Computational Linguistics.
- Yang Deng, Wai Lam, Yuexiang Xie, Daoyuan Chen, Yaliang Li, Min Yang, and Ying Shen. 2020. Joint learning of answer selection and

- answer summary generation in community question answering. In *Association for the Advancement of Artificial Intelligence*.
- Angela Fan, Yacine Jernite, Ethan Perez, David Grangier, Jason Weston, and Michael Auli. 2019. ELI5: Long form question answering. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3558–3567, Florence, Italy. Association for Computational Linguistics.
- Youmna Farag, Helen Yannakoudakis, and Ted Briscoe. 2018. Neural automated essay scoring and coherence modeling for adversarially crafted input. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 263–271, New Orleans, Louisiana. Association for Computational Linguistics.
- Alexandru Balan Gustavo Penha and Claudia Hauff. 2019. Introducing mantis: a novel multi-domain information seeking dialogues dataset.
- Thi-Thanh Ha, Van-Nha Nguyen, Kiem-Hieu Nguyen, Kim-Anh Nguyen, and Quang-Khoat Than. 2021. Utilizing sbert for finding similar questions in community question answering. In 2021 13th International Conference on Knowledge and Systems Engineering (KSE). IEEE.
- Iryna Haponchyk, Antonio Uva, Seunghak Yu, Olga Uryupina, and Alessandro Moschitti. 2018. Supervised clustering of questions into intents for dialog system applications. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2310–2321, Brussels, Belgium. Association for Computational Linguistics.
- Helia Hashemi, Mohammad Aliannejadi, Hamed Zamani, and William Bruce Croft. 2020. Antique: A non-factoid question answering benchmark. *Advances in Information Retrieval*, 12036:166 173.
- Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. 2021. Deberta: Decodingenhanced bert with disentangled attention. In *International Conference on Learning Representations*.

- Doris Hoogeveen, Karin M. Verspoor, and Timothy Baldwin. 2015. Cqadupstack: A benchmark data set for community question-answering research. In *Proceedings of the 20th Australasian Document Computing Symposium (ADCS)*, ADCS '15, pages 3:1–3:8, New York, NY, USA. ACM.
- Jungo Kasai, Keisuke Sakaguchi, Ronan Le Bras, Lavinia Dunagan, Jacob Morrison, Alexander R Fabbri, Yejin Choi, and Noah A Smith. 2021. Bidimensional leaderboards: Generate and evaluate language hand in hand. *arXiv preprint arXiv:2112.04139*.
- Vaibhav Kumar and Alan W Black. 2020. ClarQ: A large-scale and diverse dataset for clarification question generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7296–7301, Online. Association for Computational Linguistics.
- Florian Kunneman, Thiago Castro Ferreira, Emiel Krahmer, and Antal van den Bosch. 2019. Question similarity in community question answering: A systematic exploration of preprocessing methods and models. In *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2019)*, pages 593–601, Varna, Bulgaria. INCOMA Ltd.
- Edison Marrese-Taylor, Ai Nakajima, Yutaka Matsuo, and Ono Yuichi. 2018. Learning to automatically generate fill-in-the-blank quizzes. *arXiv* preprint arXiv:1806.04524.
- L. McInnes, J. Healy, and J. Melville. 2018. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction. *arXiv* preprint arXiv:1802.03426.
- Tsvetomila Mihaylova, Georgi Karadzhov, Pepa Atanasova, Ramy Baly, Mitra Mohtarami, and Preslav Nakov. 2019. SemEval-2019 task 8: Fact checking in community question answering forums. In *Proceedings of the 13th International Workshop on Semantic Evaluation*, pages 860–869, Minneapolis, Minnesota, USA. Association for Computational Linguistics.
- Aakanksha Naik, Abhilasha Ravichander, Norman Sadeh, Carolyn Rose, and Graham Neubig. 2018. Stress test evaluation for natural language inference. In *Proceedings of the 27th International*

- Conference on Computational Linguistics, pages 2340–2353, Santa Fe, New Mexico, USA. Association for Computational Linguistics.
- Preslav Nakov, Doris Hoogeveen, Lluís Màrquez, Alessandro Moschitti, Hamdy Mubarak, Timothy Baldwin, and Karin Verspoor. 2017. SemEval-2017 task 3: Community question answering. In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, pages 27–48, Vancouver, Canada. Association for Computational Linguistics.
- Preslav Nakov, Lluís Màrquez, Walid Magdy, Alessandro Moschitti, Jim Glass, and Bilal Randeree. 2015. SemEval-2015 task 3: Answer selection in community question answering. In *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, pages 269–281, Denver, Colorado. Association for Computational Linguistics.
- Preslav Nakov, Lluís Màrquez, Alessandro Moschitti, Walid Magdy, Hamdy Mubarak, Abed Alhakim Freihat, Jim Glass, and Bilal Randeree. 2016. SemEval-2016 task 3: Community question answering. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pages 525–545, San Diego, California. Association for Computational Linguistics.
- Hwee Tou Ng, Siew Mei Wu, Ted Briscoe, Christian Hadiwinoto, Raymond Hendy Susanto, and Christopher Bryant. 2014. The CoNLL-2014 shared task on grammatical error correction. In *Proceedings of the Eighteenth Conference on Computational Natural Language Learning: Shared Task*, pages 1–14, Baltimore, Maryland. Association for Computational Linguistics.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.
- Barun Patra. 2017. A survey of community question answering. arXiv preprint arXiv:1705.04009.

- Nina Poerner and Hinrich Schütze. 2019. Multiview domain adapted sentence embeddings for low-resource unsupervised duplicate question detection. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1630–1641, Hong Kong, China. Association for Computational Linguistics.
- Zhonghua Qu and Yang Liu. 2011. Finding problem solving threads in online forum. In *Proceedings of 5th International Joint Conference on Natural Language Processing*, pages 1413–1417, Chiang Mai, Thailand. Asian Federation of Natural Language Processing.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.
- Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.
- Adam Roberts, Colin Raffel, and Noam Shazeer. 2020. How much knowledge can you pack into the parameters of a language model? In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5418–5426, Online. Association for Computational Linguistics.
- Anna Rogers, Matt Gardner, and Isabelle Augenstein. 2021. Qa dataset explosion: A taxonomy of nlp resources for question answering and reading comprehension. *arXiv preprint arXiv:2107.12708*.
- Ohad Rozen, David Carmel, Avihai Mejer, Vitaly Mirkis, and Yftah Ziser. 2021. Answering product-questions by utilizing questions from other contextually similar products. In *Proceedings of the 2021 Conference of the North Amer-*

- ican Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 242–253, Online. Association for Computational Linguistics.
- Keisuke Sakaguchi, Yuki Arase, and Mamoru Komachi. 2013. Discriminative approach to fill-in-the-blank quiz generation for language learners. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 238–242, Sofia, Bulgaria. Association for Computational Linguistics.
- Cícero dos Santos, Luciano Barbosa, Dasha Bogdanova, and Bianca Zadrozny. 2015. Learning hybrid representations to retrieve semantically equivalent questions. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 694–699, Beijing, China. Association for Computational Linguistics.
- Yi Tay, Anh Tuan Luu, and Siu Cheung Hui. 2018. Cross temporal recurrent networks for ranking question answer pairs. In *Association for the Advancement of Artificial Intelligence*.
- Quan Hung Tran, Vu Duc Tran, Tu Thanh Vu, Minh Le Nguyen, and Son Bao Pham. 2015. JAIST: Combining multiple features for answer selection in community question answering. In *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, pages 215–219, Denver, Colorado. Association for Computational Linguistics.
- Kristiyan Vachev, Momchil Hardalov, Georgi Karadzhov, Georgi Georgiev, Ivan Koychev, and Preslav Nakov. 2021. Generating answer candidates for quizzes and answer-aware question generators. In *Proceedings of the Student Research Workshop Associated with RANLP 2021*, pages 203–209, Online. INCOMA Ltd.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Neural Information Processing Systems (NIPS)*.
- Yu Wang, Yuelin Wang, Kai Dang, Jie Liu, and Zhuo Liu. 2021. A comprehensive survey of

- grammatical error correction. *ACM Trans. Intell. Syst. Technol.*, 12(5).
- Wei Wu, Xu Sun, and Houfeng Wang. 2018. Question condensing networks for answer selection in community question answering. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1746–1755, Melbourne, Australia. Association for Computational Linguistics.
- Yuan Yao, Hanghang Tong, Tao Xie, Leman Akoglu, Feng Xu, and Jian Lu. 2013. Want a good answer? ask a good question first! *arXiv* preprint arXiv:1311.6876.
- Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with bert. In *International Conference on Learning Representations*.