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, \textit{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, \textit{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).

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: \textit{English} and \textit{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

\(^1\)https://github.com/shabnam-b/ELQA
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 pre-processing 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 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-

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\(^2\)https://english.stackexchange.com/
\(^3\)https://ell.stackexchange.com/
\(^4\)https://archive.org/details/stackexchange
\(^5\)http://creativecommons.org/licenses/by-sa/3.0/
| Question Type          | Title                                                                 | Body                                                                                                                                              |
|-----------------------|----------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|
| Fluency               | "On my own way vs. "in my own way"?                                  | Which one is correct <strong>in</strong> or <strong>on</strong> own way? <blockquote> I usually help my closest friends on/in my own way. </blockquote> |
| Form to Meaning       | Wondering what "get by" means in this context                        | He tries to <strong>get</strong> by <strong>work</strong> possible <strong>work</strong>. <blockquote> Could you tell me what this sentence means? </blockquote> |
| Meaning to Form       | Word for a passed down language?                                     | When a language is only taught from the adults that speak it. I know there’s a word for it, but I can’t for the life of me remember what it is! |
| Grammatical Analysis  | Should I modify a gerund using an adjective or an adverb?            | I know that a gerund is a <strong>noun</strong>, so it should be modified by an <em>adjective</em>. However, it is also a <strong>verb form</strong>. Can I modify it by using an <em>adverb</em>? |
| Other                 | School and school of fish                                            | Why is a group of fish called "school"? And is it anyhow etymologically connected 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)

- **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):** Questions where the user gives some explanation/definition and asks for the term or expression. (≈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:

- 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 (electra-base-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.

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6 Post URL and Author profile URL of all examples in the paper are available in the Appendix.
Table 3: Binary classification results (Accuracy and Macro-F1) on Q&A pairs

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

|                | Neg-F1 | Pos-F1 | Accuracy |
|----------------|--------|--------|----------|
| DeBERTa        |        |        |          |
| 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     |

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 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 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 responsive to the question.

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...
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 types 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)

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 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,
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 (≈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 high-score 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

| Question | Human Answers | Model Generated |
|----------|---------------|-----------------|
| Title: How to refer to particular years in a specific century in one expression? | 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 > They have a collection of paintings painted in the 70s, in the twentieth century. > or > They have a collection of paintings painted in the 70s, in the twentieth century. > or > or > or or > |
| Title: What is an appropriate word for a “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. > or > a continuing process of development or improvement, especially one that is > temporary or intermittent. > or > ([Dictionary.com](https://www.dictionary.com)([SOME LINK])) |

1 Evaluators 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 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 "semiprod-
uct"?”, 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 model-generated answers (especially from T5-11B) are usually very relevant to the question, and in most cases are easy to read. Moreover, the models seem 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 WordPress (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 it-

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8 We 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.

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

self, 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...
We presented ELQA, a novel dataset containing Q&As about the English language. We provided an 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/185516/did-vs-have-done (Q by learner)
• https://english.stackexchange.com/questions/28889/using-generify-to-mean-to-make-generic (Q by citizen, A by Grant Thomas)
• https://english.stackexchange.com/questions/238824/is-there-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[323.6785] (Q by Abhishek Ranjan)
• https://ell.stackexchange.com/questions/62645/i-have-to-go-to-school-i-have-to-go-to-the-school (Q by i-dont-know-who-i-am)
• https://ell.stackexchange.com/questions/16792/late-for-school-or-late-for-the-school (Q by dexterox)
• https://ell.stackexchange.com/questions/71779/singular-vs-plural-in-different-type-types-of-question-questions (Q by kakkadi-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-distinguish-between-use-of-types-of-approach-or-types-of-approaches (Q by tomaza274)
• 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-x (Q by rafat)
• https://english.stackexchange.com/questions/18511/a-word-or-phrase-to-describe-someone-who-is-obessed-with-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-one-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-rise (Q by kdaker, first A by chaos, second A by kris)
• https://english.stackexchange.com/questions/11010/is-the-kinds-of-problems-are-ones-to-be-construction (Q by axarydax)

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