

Know What You Don't Know: Unanswerable Questions for SQuAD

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Abstract

Extractive reading comprehension systems can often locate the correct answer to a question in a context document, but they also tend to make unreliable guesses on questions for which the correct answer is not stated in the context. Existing datasets either focus exclusively on answerable questions, or use automatically generated unanswerable questions that are easy to identify. To address these weaknesses, we present SQuAD 2.0, the latest version of the Stanford Question Answering Dataset (SQuAD). SQuAD 2.0 combines existing SQuAD data with over 50,000 unanswerable questions written adversarially by crowdworkers to look similar to answerable ones. To do well on SQuAD 2.0, systems must not only answer questions when possible, but also determine when no answer is supported by the paragraph and abstain from answering. SQuAD 2.0 is a challenging natural language understanding task for existing models: a strong neural system that gets 86% F1 on SQuAD 1.1 achieves only 66% F1 on SQuAD 2.0.

1 Introduction

Machine reading comprehension has become a central task in natural language understanding, fueled by the creation of many large-scale datasets (Hermann et al., 2015; Hewlett et al., 2016; Rajpurkar et al., 2016; Nguyen et al., 2016; Trischler et al., 2017; Joshi et al., 2017). In turn, these datasets have spurred a diverse array of model architecture improvements (Seo et al., 2016; Hu et al., 2017; Wang et al., 2017; Clark and Gardner, 2017; Huang et al., 2018). Recent work has

Article: Endangered Species Act

Paragraph: "... Other legislation followed, including the Migratory Bird Conservation Act of 1929, a 1937 treaty prohibiting the hunting of right and gray whales, and the Bald Eagle Protection Act of 1940. These later laws had a low cost to society—the species were relatively rare—and little opposition was raised."

Question 1: "Which laws faced significant opposition?"

Plausible Answer: later laws

Question 2: "What was the name of the 1937 treaty?"

Plausible Answer: Bald Eagle Protection Act

Figure 1: Two unanswerable questions written by crowdworkers, along with plausible (but incorrect) answers. Relevant keywords are shown in blue.

even produced systems that surpass human-level exact match accuracy on the Stanford Question Answering Dataset (SQuAD), one of the most widely-used reading comprehension benchmarks (Rajpurkar et al., 2016).

Nonetheless, these systems are still far from true language understanding. Recent analysis shows that models can do well at SQuAD by learning context and type-matching heuristics (Weissenborn et al., 2017), and that success on SQuAD does not ensure robustness to distracting sentences (Jia and Liang, 2017). One root cause of these problems is SQuAD's focus on questions for which a correct answer is guaranteed to exist in the context document. Therefore, models only need to select the span that seems most related to the question, instead of checking that the answer is actually entailed by the text.

In this work, we construct SQuAD 2.0,¹ a new dataset that combines answerable questions from the previous version of SQuAD (SQuAD 1.1)

¹ In the ACL version of this paper, we called our new dataset SQuADRUN; here we use the name SQuAD 2.0, to emphasize that it is in fact the new version of SQuAD.

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with 53,775 new, unanswerable questions about the same paragraphs. Crowdworkers crafted these questions so that (1) they are *relevant* to the paragraph, and (2) the paragraph contains a *plausible answer*—something of the same type as what the question asks for. Two such examples are shown in Figure 1.

We confirm that SQuAD 2.0 is both challenging and high-quality. A state-of-the-art model achieves only 66.3% F1 score when trained and tested on SQuAD 2.0, whereas human accuracy is 89.5% F1, a full 23.2 points higher. The same model architecture trained on SQuAD 1.1 gets 85.8% F1, only 5.4 points worse than humans. We also show that our unanswerable questions are more challenging than ones created automatically, either via distant supervision (Clark and Gardner, 2017) or a rule-based method (Jia and Liang, 2017). We release SQuAD 2.0 to the public as new version of SQuAD, and make it the primary benchmark on the official SQuAD leaderboard.² We are optimistic that this new dataset will encourage the development of reading comprehension systems that know what they don’t know.

2 Desiderata

We first outline our goals for SQuAD 2.0. Besides the generic goals of large size, diversity, and low noise, we posit two desiderata specific to unanswerable questions:

Relevance. The unanswerable questions should appear relevant to the topic of the context paragraph. Otherwise, simple heuristics (e.g., based on word overlap) could distinguish answerable and unanswerable questions (Yih et al., 2013).

Existence of plausible answers. There should be some span in the context whose type matches the type of answer the question asks for. For example, if the question asks, “*What company was founded in 1992?*”, then some company should appear in the context. Otherwise, type-matching heuristics could distinguish answerable and unanswerable questions (Weissenborn et al., 2017).

3 Existing datasets

Next, we survey existing reading comprehension datasets with these criteria in mind. We use the

² As with previous versions of SQuAD, we release SQuAD 2.0 under the CC BY-SA 4.0 license.

term “negative example” to refer to a context passage paired with an unanswerable question.

3.1 Extractive datasets

In extractive reading comprehension datasets, a system must extract the correct answer to a question from a context document or paragraph. The Zero-shot Relation Extraction dataset (Levy et al., 2017) contains negative examples generated with distant supervision. Levy et al. (2017) found that 65% of these negative examples do not have a plausible answer, making them easy to identify.

Other distant supervision strategies can also create negative examples. TriviaQA (Joshi et al., 2017) retrieves context documents from the web or Wikipedia for each question. Some documents do not contain the correct answer, yielding negative examples; however, these are excluded from the final dataset. Clark and Gardner (2017) generate negative examples for SQuAD by pairing existing questions with other paragraphs from the same article based on TF-IDF overlap; we refer to these as TFIDF examples. In general, distant supervision does not ensure the existence of a plausible answer in the retrieved context, and might also add noise, as the context might contain a paraphrase of the correct answer. Moreover, when retrieving from a small set of possible contexts, as in Clark and Gardner (2017), we find that the retrieved paragraphs are often not very relevant to the question, making these negative examples easy to identify.

The NewsQA data collection process also yields unanswerable questions, because crowdworkers write questions given only a summary of an article, not the full text (Trischler et al., 2017). Only 9.5% of their questions are unanswerable, making this strategy hard to scale. Of this fraction, we found that some are misannotated as unanswerable, and others are out-of-scope (e.g., summarization questions). Trischler et al. (2017) also exclude negative examples from their final dataset.

Jia and Liang (2017) propose a rule-based procedure for editing SQuAD questions to make them unanswerable. Their questions are not very diverse: they only replace entities and numbers with similar words, and replace nouns and adjectives with WordNet antonyms. We refer to these unanswerable questions as RULEBASED questions.

3.2 Answer sentence selection datasets

Sentence selection datasets test whether a system can rank sentences that answer a question higher

Reasoning	Description	Example	Percentage
Negation	Negation word inserted or removed.	Sentence: “Several hospital pharmacies have decided to outsource high risk preparations . . .” Question: “What types of pharmacy functions have never been outsourced?”	9%
Antonym	Antonym used.	S: “the extinction of the dinosaurs. . . allowed the tropical rainforest to spread out across the continent.” Q: “The extinction of what led to the decline of rainforests?”	20%
Entity Swap	Entity, number, or date replaced with other entity, number, or date.	S: “These values are much greater than the 9–88 cm as projected . . . in its Third Assessment Report.” Q: “What was the projection of sea level increases in the fourth assessment report ?”	21%
Mutual Exclusion	Word or phrase is mutually exclusive with something for which an answer is present.	S: “BSkyB. . . waiv[ed] the charge for subscribers whose package included two or more premium channels.” Q: “What service did BSKyB give away for free unconditionally ?”	15%
Impossible Condition	Asks for condition that is not satisfied by anything in the paragraph.	S: “Union forces left Jacksonville and confronted a Confederate Army at the Battle of Olustee. . . Union forces then retreated to Jacksonville and held the city for the remainder of the war.” Q: “After what battle did Union forces leave Jacksonville for good ?”	4%
Other Neutral	Other cases where the paragraph does not imply any answer.	S: “Schuenemann et al. concluded in 2011 that the Black Death. . . was caused by a variant of <i>Y. pestis</i> . . .” Q: “Who discovered <i>Y. pestis</i> ?”	24%
Answerable	Question is answerable (i.e. dataset noise).		7%

Table 1: Types of negative examples in SQuAD 2.0 exhibiting a wide range of phenomena.

than sentences that do not. Wang et al. (2007) constructed the QASent dataset from questions in the TREC 8-13 QA tracks. Yih et al. (2013) showed that lexical baselines are highly competitive on this dataset. WikiQA (Yang et al., 2015) pairs questions from Bing query logs with sentences from Wikipedia. Like TFIDF examples, these sentences are not guaranteed to have plausible answers or high relevance to the question. The dataset is also limited in scale (3,047 questions, 1,473 answers).

3.3 Multiple choice datasets

Finally, some datasets, like MCTest (Richardson et al., 2013) and RACE (Lai et al., 2017), pose multiple choice questions, which can have a “none of the above” option. In practice, multiple choice options are often unavailable, making these datasets less suited for training user-facing systems. Multiple choice questions also tend to be quite different from extractive ones, with more emphasis on fill-in-the-blank, interpretation, and summarization (Lai et al., 2017).

4 SQuAD 2.0

We now describe our new dataset, which we constructed to satisfy both the relevance and plausible answer desiderata from Section 2.

4.1 Dataset creation

We employed crowdworkers on the Daemo crowdsourcing platform (Gaikwad et al., 2015) to write unanswerable questions. Each task consisted of an entire article from SQuAD 1.1. For each paragraph in the article, workers were asked to pose up to five questions that were impossible to answer based on the paragraph alone, while referencing entities in the paragraph and ensuring that a plausible answer is present. As inspiration, we also showed questions from SQuAD 1.1 for each paragraph; this further encouraged unanswerable questions to look similar to answerable ones. Workers were asked to spend 7 minutes per paragraph, and were paid \$10.50 per hour. Screenshots of our interface are shown in Appendix A.1.

We removed questions from workers who wrote 25 or fewer questions on that article; this filter helped remove noise from workers who had trouble understanding the task, and therefore quit before completing the whole article. We applied this filter to both our new data and the existing answerable questions from SQuAD 1.1. To generate train, development, and test splits, we used the same partition of articles as SQuAD 1.1, and combined the existing data with our new data for each split. For the SQuAD 2.0 development and test sets, we removed articles for which we did not

	SQuAD 1.1	SQuAD 2.0
Train		
Total examples	87,599	130,319
Negative examples	0	43,498
Total articles	442	442
Articles with negatives	0	285
Development		
Total examples	10,570	11,873
Negative examples	0	5,945
Total articles	48	35
Articles with negatives	0	35
Test		
Total examples	9,533	8,862
Negative examples	0	4,332
Total articles	46	28
Articles with negatives	0	28

Table 2: Dataset statistics of SQuAD 2.0, compared to the previous SQuAD 1.1.

collect unanswerable questions. This resulted in a roughly one-to-one ratio of answerable to unanswerable questions in these splits, whereas the train data has roughly twice as many answerable questions as unanswerable ones. Table 2 summarizes overall statistics of SQuAD 2.0.

4.2 Human accuracy

To confirm that our dataset is clean, we hired additional crowdworkers to answer all questions in the SQuAD 2.0 development and test sets. In each task, we showed workers an entire article from the dataset. For each paragraph, we showed all associated questions; unanswerable and answerable questions were shuffled together. For each question, workers were told to either highlight the answer in the paragraph, or mark it as unanswerable. Workers were told to expect every paragraph to have some answerable and some unanswerable questions. They were asked to spend one minute per question, and were paid \$10.50 per hour.

To reduce crowdworker noise, we collected multiple human answers for each question and selected the final answer by majority vote, breaking ties in favor of answering questions and preferring shorter answers to longer ones. On average, we collected 4.8 answers per question. We note that for SQuAD 1.1, Rajpurkar et al. (2016) evaluated a single human’s performance; therefore, they likely underestimate human accuracy.

4.3 Analysis

We manually inspected 100 randomly chosen negative examples from our development set to understand the challenges these examples present. In Table 1, we define different categories of negative

examples, and give examples and their frequency in SQuAD 2.0. We observe a wide range of phenomena, extending beyond expected phenomena like negation, antonymy, and entity changes. In particular, SQuAD 2.0 is much more diverse than RULEBASED, which creates unanswerable questions by applying entity, number, and antonym swaps to existing SQuAD 1.1 questions. We also found that 93% of the sampled negative examples are indeed unanswerable.

5 Experiments

5.1 Models

We evaluated three existing model architectures: the BiDAF-No-Answer (BNA) model proposed by Levy et al. (2017), and two versions of the DocumentQA No-Answer (DocQA) model from Clark and Gardner (2017), namely versions with and without ELMo (Peters et al., 2018). These models all learn to predict the probability that a question is unanswerable, in addition to a distribution over answer choices. At test time, models abstain whenever their predicted probability that a question is unanswerable exceeds some threshold. We tune this threshold separately for each model on the development set. When evaluating on the test set, we use the threshold that maximizes F1 score on the development set. We find this strategy does slightly better than simply taking the argmax prediction, possibly due to the different proportions of negative examples at training and test time.

5.2 Main results

First, we trained and tested all three models on SQuAD 2.0, as shown in Table 3. Following Rajpurkar et al. (2016), we report average exact match and F1 scores.³ The best model, DocQA + ELMo, achieves only 66.3 F1 on the test set, 23.2 points lower than the human accuracy of 89.5 F1. Note that a baseline that always abstains gets 48.9 test F1; existing models are closer to this baseline than they are to human performance. Therefore, we see significant room for model improvement on this task. We also compare with reported test numbers for analogous model architectures on SQuAD 1.1. There is a much larger gap between humans and machines on SQuAD 2.0 compared to SQuAD 1.1, which confirms that SQuAD 2.0 is a much harder dataset for existing models.

³ For negative examples, abstaining receives a score of 1, and any other response gets 0, for both exact match and F1.

System	SQuAD 1.1 test		SQuAD 2.0 dev		SQuAD 2.0 test	
	EM	F1	EM	F1	EM	F1
BNA	68.0	77.3	59.8	62.6	59.2	62.1
DocQA	72.1	81.0	61.9	64.8	59.3	62.3
DocQA + ELMo	78.6	85.8	65.1	67.6	63.4	66.3
Human	82.3	91.2	86.3	89.0	86.9	89.5
Human–Machine Gap	3.7	5.4	21.2	21.4	23.5	23.2

Table 3: Exact Match (EM) and F1 scores on SQuAD 1.1 and 2.0. The gap between humans and the best tested model is much larger on SQuAD 2.0, suggesting there is a great deal of room for model improvement.

System	SQuAD 1.1 + TfIDF		SQuAD 1.1 + RULEBASED		SQuAD 2.0 dev	
	EM	F1	EM	F1	EM	F1
BNA	72.7	76.6	80.1	84.8	59.8	62.6
DocQA	75.6	79.2	80.8	84.8	61.9	64.8
DocQA + ELMo	79.4	83.0	85.7	89.6	65.1	67.6

Table 4: Exact Match (EM) and F1 scores on the SQuAD 2.0 development set, compared with SQuAD 1.1 with two types of automatically generated negative examples. SQuAD 2.0 is more challenging for current models.

5.3 Automatically generated negatives

Next, we investigated whether automatic ways of generating negative examples can also yield a challenging dataset. We trained and tested all three model architectures on SQuAD 1.1 augmented with either TfIDF or RULEBASED examples. To ensure a fair comparison with SQuAD 2.0, we generated training data by applying TfIDF or RULEBASED only to the 285 articles for which SQuAD 2.0 has unanswerable questions. We tested on the articles and answerable questions in the SQuAD 2.0 development set, adding unanswerable questions in a roughly one-to-one ratio with answerable ones. These results are shown in Table 4. The highest score on SQuAD 2.0 is 15.4 F1 points lower than the highest score on either of the other two datasets, suggesting that automatically generated negative examples are much easier for existing models to detect.

5.4 Plausible answers as distractors

Finally, we measured how often systems were fooled into answering the plausible but incorrect answers provided by crowdworkers for our unanswerable questions. For both computer systems and humans, roughly half of all wrong answers on unanswerable questions exactly matched the plausible answers. This suggests that the plausible answers do indeed serve as effective distractors. Full results are shown in Appendix A.2.

6 Discussion

SQuAD 2.0 forces models to understand whether a paragraph entails that a certain span is the answer to a question. Similarly, recognizing tex-

tual entailment (RTE) requires systems to decide whether a hypothesis is entailed by, contradicted by, or neutral with respect to a premise (Marelli et al., 2014; Bowman et al., 2015). Relation extraction systems must understand when a possible relationship between two entities is not entailed by the text (Zhang et al., 2017).

Jia and Liang (2017) created adversarial test examples that fool models trained on SQuAD 1.1. However, models that are trained on similar examples are not easily fooled by their method. In contrast, the adversarial examples in SQuAD 2.0 are difficult even for models trained on examples from the same distribution.

In conclusion, we have presented SQuAD 2.0, a challenging, diverse, and large-scale dataset that forces models to understand when a question cannot be answered given the context. We are optimistic that SQuAD 2.0 will encourage the development of new reading comprehension models that know what they don’t know, and therefore understand language at a deeper level.

Reproducibility. All code, data, experiments are available on the CodaLab platform at <https://bit.ly/2rDHBgY>.

Acknowledgments. We would like to thank the anonymous reviewers, Arun Chaganty, Peng Qi, and Sharon Zhou for their constructive feedback. We are grateful to Durim Morina and Michael Bernstein for their help with the Daemon platform. This work was supported by funding from Facebook. R.J. is supported by an NSF Graduate Research Fellowship under Grant No. DGE-114747.

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A Supplementary material

A.1 Crowdsourcing details

Figure 2 shows the instructions that crowdworkers were given at the beginning of each question writing task. Figure 3 shows the interface they used to write unanswerable questions for each paragraph. In the interface, workers first write an unanswerable question, then highlight a plausible answer in the paragraph.

A.2 Plausible answers as distractors

As mentioned in Section 5.4, we measured how often systems were fooled into answering the plausible answers provided by crowdworkers for our unanswerable questions. For each system, we first isolated their false positive errors—cases where they predicted an answer to an unanswerable question—on the development set. Within this set of examples, we measured exact match and F1 scores between the system predictions and plausible answers. These numbers are shown in Table 5. Plausible answers account for roughly half of the false positive errors made by each of the computer systems, as well as by human answerers. We conclude that the plausible answers in our dataset do indeed serve their purpose of being distracting spans that could be mistaken for the correct answer.

	EM	F1
BNA	48.6	63.0
DocQA	55.0	69.9
DocQA +ELMo	54.9	69.2
Human	46.4	60.6

Table 5: Exact match (EM) and F1 scores between system predictions and plausible answers, in cases where the system made a false positive error.

Ask Impossible Reading Comprehension Questions

Instructions

In this article about Geology, you will be asked to pose and answer reading comprehension questions based on the paragraph. There is a twist! The question you pose must be impossible to answer based on the paragraph alone, but should be about the same topic and same people/places/things! Additionally, the paragraph must contain a phrase/word that seems like a plausible answer to the question. Read each paragraph, pose an impossible question, and then highlight a phrase from the paragraph that looks like a plausible (but of course, incorrect) answer. We'll clarify the task with the help of an example below.

Estimated Time For Task Completion - 3.2 hours

This article consists of 25 paragraphs. We recommend a time of 7 minutes per paragraph. Submit each paragraph after you are done to save partial progress. Feel free to take breaks -- if you come back to the task, you do not need to resubmit paragraphs already submitted in an earlier session. After completing all paragraphs, click the submit task button at the end of the page.

The processes of decentralization redefines structures, procedures and practices of governance to be closer to the citizenry and to make them more aware of the costs and benefits; it is not merely a movement of power from the central to the local government. According to the United Nations Development Programme it is "more than a process, it is a way of life and a state of mind." The report provides a chart-formatted framework for defining the application of the concept 'decentralization' describing and elaborating on the "who, what, when, where, why and how" factors in any process of decentralization.

Prompt Questions

What is decentralization according to the United Nations Development Programme?

it is "more than a process, it is a way of life and a state of mind."

What is a way of life and state of mind, more than a process?

The processes of decentralization

What does the report from the United Nations Development Programme show?
a chart-formatted framework for defining the application of the concept 'decentralization'

What does the report from the United Nations Development Programme go into

Task Tutorial

1. On the left, you'll see a reading passage and 'prompt questions' underneath it. First read the passage, and skim over the questions.
2. Now, based on what you've read in the passage, your task is to come up with questions that don't have a correct answer in the passage, but have feasible answers.
3. Start by picking a question from the prompt questions. For the purposes of this example, let's pick **What is decentralization according to the United Nations Development Programme?**
4. Note that this question does have an answer in the passage. We're going to modify it so that it doesn't have an answer. For instance, we can modify the question to **What is decentralization according to the local government?** Note that this question doesn't have an answer in the passage, but still contains entities present in the passage such as **local government**.
5. You will also be asked to pick a *plausible* answer for our question. This is an answer that looks possibly correct if someone hadn't read the passage. You select the plausible answer by highlighting a segment of the passage. For our example question, we would highlight **it is "more than a process, it is a way of life and a state of mind."**
6. Let's come up with another example. This time, we will use the inspiration question **What is a way of life and state of mind, more than a**

Figure 2: The instructions shown to crowdworkers at the beginning of each question writing task.

Paragraph 2 of 25

Spend around 7 minutes on the following paragraph to ask 5 **impossible** questions! If you can't ask 5 questions, ask 4, but do your best to ask 5. Select a plausible answer from the paragraph by clicking on 'Select Plausible Answer', and then highlight the smallest segment of the paragraph that is a plausible answer to the question.

In the 1960s, a series of discoveries, the most important of which was seafloor spreading, showed that the Earth's lithosphere, which includes the crust and rigid uppermost portion of the upper mantle, is separated into a number of tectonic plates that move across the plastically deforming, solid, upper mantle, which is called the asthenosphere. There is an intimate coupling between the movement of the plates on the surface and the convection of the mantle: oceanic plate motions and mantle convection currents always move in the same direction, because the oceanic lithosphere is the rigid upper thermal boundary layer of the convecting mantle. This coupling between rigid plates moving on the surface of the Earth and the convecting mantle is called plate tectonics.

Questions for inspiration

What was the most important discovery that led to the understanding that Earth's lithosphere is separated into tectonic plates?
seafloor spreading

Which parts of the Earth are included in the lithosphere?
the crust and rigid uppermost portion of the upper mantle

What is another word for the Earth's upper mantle?
asthenosphere

Plate tectonics can be seen as the intimate coupling between rigid plates on the surface of the Earth and what?
the convecting mantle

In what decade was seafloor spreading discovered?
the 1960s

Scroll down the questions to hit 'Submit Paragraph' once you're done with the paragraph.

Ask a question here. Use your own words, instead of copying from paragraph

Select Plausible Answer

Ask a question here. Use your own words, instead of copying from paragraph

Select Plausible Answer

Ask a question here. Use your own words, instead of copying from paragraph

Select Plausible Answer

Ask a question here. Use your own words, instead of copying from paragraph

Select Plausible Answer

Ask a question here. Use your own words, instead of copying from paragraph

Select Plausible Answer

Figure 3: The interface crowdworkers used to write unanswerable questions and annotate plausible answers.