Do We Know What We Don’t Know?  
Studying Unanswerable Questions beyond SQuAD 2.0  
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Unanswerable Questions in Extractive QA

- **Extractive QA**: A system must extract a correct answer to a question from a context paragraph or document.

  Context: John was born in New York.  
  Question: Who was born in New York?  
  Answer: John

- **Unanswerable Questions (IDK)**: Cases where the answer is not in the sentence.

  Context: John was born in New York.  
  Question: Who was born in France?  
  Answer: IDK

- **Existing Dataset**: SQuAD 2.0 (Rajpurkar et al., 2018)
  - Includes unanswerable questions
  - Contexts are multi-sentence paragraphs

<table>
<thead>
<tr>
<th>Split</th>
<th>#Examples</th>
<th>IDK Proportion (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train</td>
<td>130,319</td>
<td>33</td>
</tr>
<tr>
<td>Dev</td>
<td>11,873</td>
<td>50</td>
</tr>
</tbody>
</table>

Statistics for the SQuAD 2.0 dataset

ACE-whQA

We compile a test corpus for wh-questions - ACE-whQA, derived from ACE 2005 (Walker et al., 2006), focusing on time and location event arguments. The contexts are single sentences. It is composed of three portions:

1. **Has Answer**: The sentences include the answer to the time or location-related question.

   Context: She lost her seat in the 1997 election.  
   Question: When was the loss?  
   Answer: 1997

2. **Compet. IDK**: The sentences include an entity of the same type as the expected answer.

   Context: She travelled to Mexico after she lost her seat in the 1997 election.  
   Question: Where was the loss?  
   Answer: IDK

3. **Non-Compet. IDK**: The sentences have no entity of the same type as the expected answer.

   Context: He was arrested for his crimes.  
   Question: When was the arrest?  
   Answer: IDK

<table>
<thead>
<tr>
<th>Portions</th>
<th>#Examples</th>
<th>IDK Proportion (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Has-answer</td>
<td>238</td>
<td>0</td>
</tr>
<tr>
<td>Compet. IDK</td>
<td>250</td>
<td>100</td>
</tr>
<tr>
<td>Non-Compet. IDK</td>
<td>246</td>
<td>100</td>
</tr>
</tbody>
</table>

Statistics for the ACE-whQA test dataset

Evaluating on Out-of-domain Datasets

- Current systems trained on SQuAD 2.0 achieve good in-domain performance. A system based on BERT-LARGE (Devlin et al., 2019) achieves **80.96 F1** (Has answer: 83.53 F1; No-answer: 78.40 F1) on the SQuAD 2.0 dev set.

- Informative evaluation requires out-of-domain test sets
  - Testing on datasets different from the ones they have been trained and finetuned
  - Ask very simple questions whose answer is obvious to humans. (Dunietz et al. 2020)
  - QA applications involve out-of-domain test sets
  - Zero-shot event extraction (Lyu et al., 2021)
  - Evaluation of summarization (Deutsch et al. 2021)

Training Methods

- **BERT-based method** for training on SQuAD 2.0 (Devlin et al., 2019):
  - IDK questions are treated as questions having an answer that is a span with start and end at the [CLS] token.
  - The “no-answer” is predicted if the best non-null span is bigger than the probability of the no-answer span by a threshold θ that is selected on the dev set to maximize the F1 score.

- **Leveraging the Recognizing Textual Entailment task** (RTE; Dagan et al., 2013):
  - Finetuning BERT-LARGE on MNLI (Williams et al., 2018), removing the classification layer and then further finetuning on SQuAD 2.0.

Evaluating on ACE-whQA

<table>
<thead>
<tr>
<th>test</th>
<th>SQuAD 2.0</th>
<th>MNLI + SQuAD 2.0</th>
<th>c(MNLI) + SQuAD 2.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Has Answer</td>
<td>68.75</td>
<td>71.68</td>
<td><strong>78.13</strong></td>
</tr>
<tr>
<td>Compet. IDK</td>
<td>20.80</td>
<td><strong>46.40</strong></td>
<td>26.00</td>
</tr>
<tr>
<td>Non-Compet. IDK</td>
<td>28.46</td>
<td>75.61*</td>
<td>47.15</td>
</tr>
</tbody>
</table>

F1 scores of the BERT-LARGE system evaluated on ACE-whQA.  
* Significantly higher than the baseline (p<0.05)

- Low performance of a top system trained on SQuAD 2.0
- First training on MNLI that includes an IDK option (“neutral”) improves the performance, in particular for non-competitive IDK questions.
- This improvement is not replicated in the case of Binary TE (c(MNLI); contradiction/non-contradiction).
  - Control for the size of the data
  - Control for the format similarity between TE and the test set

Conclusion

- We provide a new test set to evaluate the ability of Extractive QA systems to identify unanswerable questions, beyond the SQuAD 2.0 domain.
- We find that SQuAD 2.0 alone is not sufficient to address IDK in these cases, even in the non-competitive ones.
- RTE can be useful, particularly for non-competitive IDK questions.