Abstract
This paper presents a new dataset to benchmark selection-based question answering. Our dataset contains contexts drawn from the ten most prevalent topics in the English Wikipedia. For the generation of a large, diverse, and challenging dataset, a new annotation scheme is proposed. Our annotation scheme involves a series of crowdsourcing tasks that can be easily followed by any researcher. Several systems are compared on the tasks of answer sentence selection and answer triggering, providing strong baseline results for future work to improve upon. We hope that providing a large corpus will enable researchers to work towards more effective open-domain question answering.

1 Introduction
Selection-based question answering is a question answering task that finds a context containing an answer to an open-domain question, where the context comprises of one or more sentences. Let us define a context as being a document section, multi-sentence selection, or sentence. In answer sentence selection, the answer context is guaranteed to exist within the provided contexts. The task is defined as answering triggering when there is no such guarantee. Several corpora have been created for these tasks \cite{Wang et al., 2007, Yang et al., 2015, Feng et al., 2015}, allowing researchers to build effective question answering systems \cite{Yu et al., 2014, Wang and Nyberg, 2015, Severyn and Moschitti, 2015}. However, most of these datasets contain a limited number of questions and answers. Moreover, the questions in these datasets are restricted in their scope of topics. We attempt to mitigate these limitations, allowing for a more thorough evaluation of open domain question answering systems.

This paper presents a new corpus of annotated question answer pairs drawn from contexts of various topics. An effective annotation scheme is proposed to create a large corpus that is both challenging and realistic. Questions are additionally annotated with its topic, type, and paraphrase that enable to make comprehensive analyses of the answer sentence selection and answering triggering tasks. Two recent state-of-the-art systems based on convolutional and recurrent neural networks are implemented to analyze this corpus and to provide strong baseline measures for future work. In addition, our systems are evaluated on another dataset, WikiQA \cite{Yang et al., 2015}, for a fair comparison to previous work. Our analysis suggests extensive ways of evaluating selection-based question answering, providing meaningful benchmarks to question answering systems. The contributions of this work include:

- Creating a new corpus for answer sentence selection and answer triggering (Section 3).
- Developing QA systems using the latest advances in neural networks (Section 4).
- Analyzing various aspects of selection-based question answering (Section 5).

2 Related Work
The TREC QA datasets have been a popular choice for evaluating answer sentence selection.\footnote{All our work is publicly available at: \url{anonymous_url}} Wang et al. (2007) combined the TREC-[8-12] datasets for training and divided the TREC-13 dataset for development and evaluation. This dataset, known as QASent, has been used as the standard benchmark for answer sentence selection although it is rather small (277 questions with manually picked answer contexts). Yang et al. (2015) introduced a larger
dataset, WikiQA, consisting of questions collected from the user logs of the Bing search engine. Our corpus is similar to WikiQA but has more diverse question topics, a larger number of questions (about 6 times larger for answer sentence selection and 2.5 times larger for answer triggering), and makes use of more contexts by using the entire article instead of only the abstract. Feng et al. (2015) distributed another dataset, InsuranceQA, including questions in the insurance domain. WikiQA introduced the task of answer triggering and was the only answer triggering dataset. Our corpus provides a new automatically generated answer triggering dataset.

Our convolutional neural network model is inspired by the previous work utilizing the tree-edit distance and the tree kernel (Heilman and Smith, 2010; Wang and Manning, 2010; Severyn and Moschitti, 2013), although we introduce a different way of performing subtree matching facilitating word embeddings. Our recurrent neural network model with attention mechanisms is based on established state-of-the-art systems for answer sentence selection (Tan et al., 2015; Santos et al., 2016).

3 Corpus

Our annotation scheme provides a framework for any researcher to create a large, diverse, pragmatic, and challenging dataset for answer sentence selection and answer triggering, while maintaining a low cost using crowd sourcing.

3.1 Data Collection

A total of 486 articles are uniformly sampled across the following 10 topics from the English Wikipedia, dumped on August, 2014:

Arts, Country, Food, Historical Events, Movies, Music, Science, Sports, Travel, TV.

These are the most prevalent topics categorized by DBPedia. The original data is preprocessed into smaller chunks. First, each article is divided into sections using the section boundaries provided in the original dump. Each section is then segmented into sentences by the open-source toolkit, NLP4J.

In our corpus, documents refer to individual sections in the Wikipedia articles.

| Type                     | Count      |
|--------------------------|------------|
| Total # of articles      | 486        |
| Total # of sections      | 8,481      |
| Total # of sentences     | 113,709    |
| Total # of tokens        | 2,810,228  |

Table 1: Lexical statistics of our corpus.

3.2 Annotation Scheme

Four annotation tasks are conducted in sequence on Amazon Mechanical Turk for answer sentence selection (Tasks 1-4), and a single task is conducted for answer triggering using Elasticsearch (Task 5; see Figure 1 for the overview).

Task 1

Approximately two thousand sections are randomly selected from the 486 articles in Section 3.1. All the selected sections consist of 3 to 25 sentences; we found that annotators experienced difficulties accurately and timely annotating longer sections. For each section, the annotator is instructed to generate a question and select one or more sentences containing the answer from the provided section. The annotator is provided with the instruction, the topic, the article title, the section title, and the list of numbered sentences in the section (Table 2).

http://dbpedia.org
https://dumps.wikimedia.org/enwiki
https://github.com/emorynlp/nlp4j
1. The premiere episode was met with mixed reviews, receiving a score of 42 out of 100 on Metacritic, indicating "mixed or average" reviews.
2. Dorothy Rabinowitz said, in her review for the Wall Street Journal, that "From the evidence of the first few episodes, Criminal Minds may be a hit, and deservedly"...
3. The New York Times was less than positive, saying "The problem with Criminal Minds is its many confusing maladies, applied to too many characters" and felt that "as a result, the cast seems like a spilled trunk of broken toys, with which the audience - and perhaps the creators - may quickly become bored."
4. The Chicago Tribune reviewer, Sid Smith, felt that the show "May well be worth a look" though he too criticized "the confusing plots and characters".

Table 2: Given a section, Task 1 asks to generate a question regarding to the section. Task 2 crosses out the sentence(s) related to the first question (line 1), and asks to generate another question. Task 3 asks to paraphrase the first two questions. Finally, Task 4 asks to rephrase ambiguous questions.

**Task 2**
Annotators are asked to create another set of ≈2K questions from the same selected sections, but this time, sentences regarding to the questions in Task 1 are discarded. The goal of Task 2 is to generate questions from contexts different from those used in the Task 1. The annotators are provided with the same information, except that the sentences used as the answer contexts in Task 1 are crossed out (line 1 in Table 2). Annotators are instructed not to use these sentences to generate new questions.

**Task 3**
Although our instruction encourages the annotators to create questions in their own words, annotators will still often use vocabulary similar to the target context to create the question. The intention of this task is to mitigate the bias of using similar vocabulary for the question and answer contexts because the goal of this corpus is to evaluate a model’s ability to understand the question and answer contexts, not word co-occurrences. Annotators are asked to generate another set of questions by paraphrasing the questions from the previous tasks. The annotators are provided with the same information as the first two tasks and the previously generated questions and answer contexts; they are instructed to paraphrase these questions using different terms.

**Task 4**
Most questions generated by Tasks 1-3 are of high quality; however, few of them are ambiguous and difficult for even humans to answer correctly. These ambiguous questions often assume that the contexts are provided with the questions. For instance, it is impossible to answer the question from Task 3.1 in Table 2 unless the related section is provided with the question. These ambiguous questions are sent back to the annotators for revision.

For finding ambiguous questions, Elasticsearch is used, a Lucene-based open-source search engine. First, an inverted index of 8,481 sections is built, where each section is considered a document. Each question is queried to this search engine. If the answer context is not included within the top 5 sections in the search result, the question is considered ‘suspicious’ although it may not be ambiguous. Among 7,904 questions generated by Tasks 1-3, 1,338 of them are found to be suspicious. These questions are sent to the annotators, and rephrased by the annotators if deemed necessary.

**Task 5**
By using the previously generated answer sentence selection data, the answer triggering corpus can be automatically generated again using Elasticsearch. To generate answer contexts for answer triggering, all 14M sections from the entire English Wikipedia are indexed, and each question from Tasks 1-4 is queried. Every sentence in the top 5 highest scoring sections from Elasticsearch are collected as candidates, which may or may not include the answer context that resolves the question.

### 3.3 Corpus Analysis
The entire annotation took about 130 hours, costing $770 in total; each mturk job took on average approximately 1 minute and costed about $0.10. A total of 8,481 sections were annotated, and 7,904 questions were generated by Tasks 1-3. Among them, 1,338 questions were considered suspicious and sent back to the annotators for revision.

www.elastic.co/products/elasticsearch
| Task   | Qs  | Qm  | Qs+m | Ωq  | Ωa  | Ωf  | Time | Credit |
|--------|-----|-----|------|------|------|------|------|--------|
| Task 1 | 1.824 | 154 | 1.978 | 44.99 | 23.65 | 28.88 | 71 sec. | $0.10  |
| Task 2 | 1.828 | 148 | 1.976 | 44.64 | 23.20 | 28.62 | 64 sec. | $0.10  |
| Task 3 | 3.637 | 313 | 3.950 | 38.03 | 19.99 | 24.41 | 41 sec. | $0.08  |
| Task 4 | 682  | 55  | 737  | 31.09 | 19.41 | 21.88 | 54 sec. | $0.08  |
| Our corpus | 7,289 | 615 | 7,904 | 40.54 | 21.51 | 26.18 | - | - |
| WikiQA | 1,068 | 174 | 1,242 | 39.31 | 9.82  | 15.03 | - | - |

Table 3: Q\textsubscript{m}: number of questions whose answer contexts consist of single/multiple sentences, Ω\textsubscript{q|a}: macro avg. of overlapping words between q and a, normalized by the length of q|a, Ω\textsubscript{f} = (2Ω\textsubscript{q}Ω\textsubscript{a})/(Ω\textsubscript{q}+Ω\textsubscript{a}), Time/Credit: avg. time/credit per mturk job. WikiQA statistics here discard questions w/o answer contexts.

of 7,904 questions were generated from Tasks 1-4, where 92.2% of them found their answers in single sentences. It is clear that Task 3 was effective in reducing the percentage of overlapping words between question and answer pairs (about 4%; Ω\textsubscript{f} in Table 3). The questions from Task 3 can be used to develop paraphrasing models as well. Multiple pilot studies on different tasks were conducted to analyze quality and cost; Tasks 1-4 were proved to be the most effective in the pilot studies. Following Ho et al. (2015), we paid incentives to those who submitted outstanding work, which improved the overall quality of our annotation.

Our corpus could be compared to WikiQA that was created with the intent of providing a challenging dataset for selection-based question answering (Yang et al., 2015). Questions in this dataset were collected from the user logs of the Bing search engine, and associated with the specific sections in Wikipedia, namely the first sections known as the abstracts. We aim to provide a similar yet more exhaustive dataset by broadening the scope to all sections. A notable difference was found between these two corpora for overlapping words (about 11% difference), which was expected due to the artificial question generation in our scheme. Although questions taken from the search queries are more natural, real search queries are inaccessible to most researchers. The new annotation scheme proposed here can prove useful for researchers needing to create a corpus for selection-based QA.

Our answer triggering dataset has 5 times more answer candidates per question than WikiQA because WikiQA includes only sections clicked on by users. Manual selection is eliminated from our framework, making our corpus more practical since finding the relevant section no longer rely on the user clicks. In WikiQA, 40.76% of the questions have corresponding answer contexts for answer triggering, as compared to 39.25% in our corpus.

### 4 Systems

Two models using convolutional neural networks are developed, one is our replication of the best model in Yang et al. (2015), and the other is an improved model using subtree matching (Section 4.1). Two more models using recurrent neural networks are developed, one is our replication of the attentive pooling model in Santos et al. (2016), and the other is a simpler model using one-way attention (Section 4.2). These are inspired by the latest state-of-the-art approaches, providing sensible evaluations.

#### 4.1 Convolutional Neural Networks

Our CNN model is motivated by Yang et al. (2015). First, a convolutional layer is applied on the image of text using the hyperbolic tangent activation function. The image consists of rows standing for consecutive words in two sentences, the question (q) and the answer candidate (a), where the words are represented by their embeddings (Mikolov et al., 2013). Next, the max pooling is applied

\[
\text{max pooling} = \frac{\sum_{i}^{n} \text{max}(q_i, a_i)}{n}
\]

and the sentence vectors for q and a are generated. Unlike Yang et al. (2015) who performed the dot product between these two vectors, we added another hidden layer to learn their weights. Finally, the sigmoid activation function is applied and the entire network is trained using the binary cross-entropy.

The CNN score from the output layer is used as one of the features for logistic regression, in addition to the number of overlapping words between q and a, say Ω, Ω normalized by the IDF, and the question length. A threshold is applied on each logistic regression prediction; the candidate with the highest score is considered the answer context if it is above the threshold found during development; otherwise, the model assumes no existence of the answer context in this document for that question.

\[\text{Avg. time/credit per mturk job. WikiQA statistics here discard questions w/o answer contexts.}\]
Subtree Matching

We propose a subtree matching mechanism for measuring the contextual similarity between two sentences. All sentences are automatically parsed by the NLP4J dependency parser (Choi and McCallum, 2013). First, a set of co-occurring words between $q$ and $a$, say $T$, is created. For each $w_i \in T$, $w_i$’s parents ($p^q_i$, $p^a_i$), siblings ($S^q_i$, $S^a_i$), and children ($C^q_i$, $C^a_i$) are extracted from $q$ and $a$. Then, three matching scores are measured as follows:

$$\mu_p = \sum_{w_i \in T} f_c(p^q_i, p^a_i)$$

$$\mu_s = \sum_{w_i \in T} f_m(\{f_c(x, y) : (x, y) \in S^q_i \times S^a_i\})$$

$$\mu_c = \sum_{w_i \in T} f_m(\{f_c(x, y) : (x, y) \in C^q_i \times C^a_i\})$$

When the word-forms are used as the comparator, $f_c(x, y)$ returns 1 if $x$ and $y$ have the same form; otherwise, 0. When the word embeddings are used as the comparator, $f_c(x, y)$ returns the cosine similarity between $x$ and $y$. The function $f_m$ takes a list of scores and returns either the $\sum$, $\text{avg}$, or $\max$ of the scores. Finally, $\mu_p$, $\mu_s$, and $\mu_c$ are used as the additional features to the logistic regression model. Although it adds only 3 more features, our experiments show significant performance gains for both answer sentence selection and answer triggering.

4.2 Recurrent Neural Network

Our RNN model is based on the bidirectional Long Short-Term Memory (LSTM) using attentive pooling introduced by Santos et al. (2016), except that our network uses a gated recurrent unit (GRU; Cho et al. (2014)) instead of LSTM. From our preliminary experiments, we found that GRU converged faster than LSTM while achieving similar performance for these tasks. Let $w^q_j \in q$, $w^a_j \in a$, where $q$ is the question and $a$ is the answer candidate, and $e(w)$ returns the embedding of a word $w$. Embeddings are encoded by a single bidirectional GRU $g$ that consists of the forward ($\vec{g}$) and the backward ($\bar{g}$) GRUs, each with $h$ hidden units. Given $w$, $g$ outputs the vector concatenation of the hidden states of $\vec{g}$ and $\bar{g}$:

$$g(e(w)) = \vec{g}(e(w)) || \bar{g}(e(w))$$

Let $c = 2 \cdot h$ represent the dimensionality of the output of $g$. Then, sentence embedding matrices $Q \in \mathbb{R}^{\left|q\right| \times c}$ and $A \in \mathbb{R}^{\left|a\right| \times c}$ are generated by $g$ as $Q_i = g(e(w^q_i))$ and $A_j = g(e(w^a_j))$.

Both the attentive pooling and one-way attention models below are trained by minimizing the pairwise hinge ranking loss. In addition, RMSProp is used for the optimization and the $\ell_2$ weight penalty is applied on all parameters except for embeddings. All network parameters except the embeddings are initialized using orthogonal initialization.

Attentive Pooling

Attentive Pooling (AP) is a framework-independent two-way attention mechanism that jointly learns a similarity measure between $q$ and $a$. AP learns the similarity measure over the hidden states of $q$ and $a$. The AP matrix $H \in \mathbb{R}^{\left|q\right| \times \left|a\right|}$ has a bilinear form and is followed by a hyperbolic tangent non-linearity, where $U \in \mathbb{R}^{c \times c}$:

$$H = \tanh(Q^TUA)$$

The importance vectors $h^q \in \mathbb{R}^{\left|q\right|}$ and $h^a \in \mathbb{R}^{\left|a\right|}$ are generated from the column-wise and row-wise max pooling over $H$, respectively:

$$[h^q]_j = \max_{i \in [1, |q|]} [H_{j,i}]$$

The normalized attention vectors $\sigma^q$ and $\sigma^a$ are created by applying the softmax activation function on $h^q$ and $h^a$:

$$\sigma^q = \frac{\exp([h^q]_j)}{\sum_{i \in [1, |q|]} \exp([h^q]_i)}$$

The final representations $r^q = Q\sigma^q$ and $r^a = A\sigma^a$ for $q$ and $a$ are created using the dot products of the sentence representations and their corresponding attention vectors. The score is computed for each pair using cosine similarity:

$$s(q, a) = \frac{r^q^T r^a}{||r^q|| ||r^a||}$$

One-Way Attention

Our one-way attention model is a simplified version of the attentive pooling model above, which is most similar to the global attention model introduced by Luong et al. (2015). We did not use the one-way attention from Tan et al. (2015) to avoid deviating the attention mechanism significantly. Replacing $Q$ with $Q_{\lfloor q \rfloor}$, the last hidden state of $g$, $H$ becomes the importance vector $h$. Again, we create the normalized attention vector $\sigma^a$ by applying the softmax activation function. The final representations are $r^q = Q^a_{\lfloor q \rfloor}$ and $r^a = A\sigma^a$. 
5 Experiments

Our systems are evaluated for the answer sentence selection (Section 5.2) and answer triggering (Section 5.3) tasks on both WikiQA and our corpus.

5.1 SelQA: Selection-based QA Corpus

Table 4 shows the distributions of our corpus, called SelQA. Our corpus is split into training (70%), development (10%), and evaluation (20%) sets. The answer triggering data (AT) is significantly larger than the answer sentence selection data (ASS), due to the extra sections added by Task 5 (Section 5.2).

Table 4: Distributions of our corpus. Q/Sec/Sen: number of questions/sections/sentences.

| Set  | Q   | ASS | AT  |
|------|-----|-----|-----|
| TRN  | 5529| 5529| 66.438 | 27.645 | 205.075 |
| DEV  | 785 | 785 | 9.377  | 3.925  | 28.798  |
| TST  | 1.590| 1.590| 19.435 | 7.950  | 59.845  |

Table 5: Answer sentence selection results on SelQA. Two metrics are used, mean average precision (MAP) and mean reciprocal rank (MRR), for the evaluation of this task.

| Model                  | Development | Evaluation |
|------------------------|-------------|------------|
|                       | MAP  | MRR  | MAP  | MRR  |
| CNN0: baseline         | 69.93 | 70.66 | 65.62 | 66.46 |
| CNN1: avg + word       | 70.75 | 71.46 | 67.40 | 69.30 |
| CNN2: avg + emb        | 69.22 | 70.18 | 68.78 | 70.82 |
| RNN0: one-way          | 71.19 | 71.80 | 66.64 | 68.70 |
| RNN1: attn-pool        | 67.56 | 68.31 | 67.47 | 68.92 |

Table 5: Answer sentence selection results on the development and evaluation sets of WikiQA.

CNN0 is our replication of the best model in Yang et al. (2015). CNN1 and CNN2 are the CNN models using the subtree matching in Section 4.1, where the comparator of \( f_c \) is either the word form or the word embedding respectively, and \( f_m = \text{avg} \). The subtree matching models consistently outperform the baseline model. Note that among the three metrics of \( f_m, \text{avg}, \text{sum}, \) and \( \text{max}, \text{avg} \) outperformed the others in our experiments for the answer sentence selection task although no significant difference was found.

RNN0 and RNN1 are the RNN models using the one-way attention and the attentive pooling in Section 4.2. Note that RNN1 converged much faster than RNN0 at the same learning rate and fixed number of parameters in our experiments, implying that two-way attention helps with optimization. It is interesting to see how CNN1 and RNN0 outperform CNN2 and RNN1 respectively on the development set, but not on the evaluation set. This result may be explained by the larger percentage of overlapping words in the development set, enabling the simpler models perform more effectively.

Table 6: Answer sentence selection results on SelQA.

| Model                  | Development | Evaluation |
|------------------------|-------------|------------|
|                       | MAP  | MRR  | MAP  | MRR  |
| CNN0: baseline         | 84.62 | 85.65 | 83.20 | 84.20 |
| CNN1: avg + word       | 85.04 | 86.17 | 84.00 | 84.94 |
| CNN2: avg + emb        | 85.70 | 86.67 | 84.66 | 85.68 |
| RNN0: one-way          | 82.26 | 83.68 | 82.06 | 83.18 |
| RNN1: attn-pool        | 87.06 | 88.25 | 86.43 | 87.59 |

Table 6: Answer sentence selection results on SelQA.

Table 7: MRR scores on the SelQA evaluation set for answer sentence selection with respect to topics.

Table 7: MRR scores on the SelQA evaluation set for answer sentence selection with respect to topics. All models show strength on topics such as ‘Country’ and ‘Historical Events’, which is comprehensible since questions in these topics tend to be deterministic. On the other hand, most models show weakness on topics such as ‘TV’, ‘Arts’, or ‘Music’. This may be due to the fact that not many overlapping words
are found between question and answer pairs in these documents, which also consist of many segments caused by bullet points.

| Type | CNN0 | CNN2 | RNN0 | RNN1 | Q |
|------|------|------|------|------|---|
| What | 84.54 | 85.36 | 83.50 | 87.66 | 678 |
| How  | 81.92 | 84.01 | 82.04 | 87.32 | 233 |
| Who  | 85.46 | 88.17 | 80.36 | 85.99 | 195 |
| When | 84.21 | 85.56 | 86.16 | 90.35 | 180 |
| Where| 83.78 | 87.44 | 84.59 | 82.54 | 85  |
| Why  | 78.55 | 82.64 | 80.61 | 84.07 | 41  |
| Misc | 84.17 | 84.80 | 85.20 | 89.66 | 215 |

Table 8: MRR scores on the SelQA evaluation set for answer sentence selection w.r.t. question types.

Table 9 shows the MRR scores with respect to question types. The CNN models show strength on the ‘who’ type, whereas the RNN models show strength on the ‘when’ type. Each model varies on showing their weakness, which we will explore in the future.

| Type  | CNN0 | CNN2 | RNN0 | RNN1 | Q |
|-------|------|------|------|------|---|
| Original | 86.70 | 88.31 | 85.57 | 89.90 | 810 |
| Paraphrase | 81.67 | 83.00 | 81.12 | 85.24 | 789 |

Table 9: MRR scores on the SelQA evaluation set for answer sentence selection w.r.t. paraphrasing.

Table 9 shows comparisons between questions from Tasks 1 and 2 (original) and Task 3 (paraphrase) in Section 3.2. As expected, noticeable performance drop is found for the paraphrased questions, which have much fewer overlapping words to the answer contexts than the original questions.

Table 10 shows the answer triggering results on WikiQA. Note that RNN0 using one-way attention was dropped for these experiments because it did not show comparable performance against the others for this task. Interestingly, the CNN model with $f_m = \text{max}$ outperformed the other metrics for answer triggering, although avg was found to be the most effective for answer sentence selection. The CNN subtree matching models consistently gave over 2% improvements to the baseline model.

5.3 Answer Triggering

Due to the characteristic of answer triggering, metrics used for evaluating answer sentence selection are not used here, because those metrics assume that models are always provided with contexts including the answers. Broadly speaking, the answer sentence selection task is a raking problem, while answer triggering is a binary classification task with additional constraints. Thus, the F1-score on the question level was proposed by Yang et al. (2015) as the evaluation for this task, which we follow.

Table 10: Answer triggering results on WikiQA.
Table 11 shows the answer triggering results on SelQA. Unlike the results on WikiQA (Table 10), CNN₂ outperforms CNN₃ on our corpus. On the other hand, RNN₁ shows a similar score to Yang et al. (2015) as it does on WikiQA. CNN₂ using subtree matching gives over a 5% improvement to the baseline model, which is significant.

Table 11: Answer triggering results on SelQA.

Table 12 shows the accuracies on SelQA with respect to different topics. The accuracy is measured on the subset of questions that contain at least one answer among candidates; the top ranked sentence is taken and checked for the correct answer. Similar to answer sentence selection, CNN₂ stills shows strength on topics such as ‘Country’ and ‘Historical Events’, but the trend is not as clear for the other models. Interestingly, the standard deviation is much smaller for RNN₁ (3.9%) compared to the CNN models (10-12%) although RNN₁’s overall performance is lower.

Table 12: Accuracies on the SelQA evaluation set for answer triggering with respect to topics.

Table 13 shows the accuracies on SelQA with respect to paraphrasing, which is similar to the trend found in Table 9 for answer sentence selection.

Table 13: Accuracies on the SelQA evaluation set for answer triggering w.r.t. question types.

6 Conclusion

In this paper we present a new benchmark for two major question answering tasks: answer sentence selection and answer triggering. Several systems using neural networks are developed for the analysis of our corpus. Our analysis shows different aspects about the current QA approaches, beneficial for further enhancement.

Researchers devoted to relatively small datasets reveal useful characteristics of the question answering tasks. Techniques that result in improvements on smaller datasets are often significantly diminished with larger datasets. Current hardware trends and the availability of larger datasets make large scale question answering more accessible. We plan to continue our work on providing large scale corpora for open-domain question answering. We also intend to work towards providing context-aware frameworks for question answering.
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