Abstract

We show that the task of question answering (QA) can significantly benefit from the transfer learning of models trained on a different large, fine-grained QA dataset. We achieve the state of the art in two well-studied QA datasets, WikiQA and SemEval-2016 (Task 3A), through a basic transfer learning technique from SQuAD. For WikiQA, our model outperforms the previous best model by more than 8%. We demonstrate that finer supervision provides better guidance for learning lexical and syntactic information than coarser supervision, through quantitative results and visual analysis. We also show that a similar transfer learning procedure achieves the state of the art on an entailment task.

1 Introduction

Question answering (QA) is a long-standing challenge in NLP, and the community has introduced several paradigms and datasets for the task over the past few years. These paradigms differ from each other in the type of questions and answers and the size of the training data, from a few hundreds to millions of examples.

We are particularly interested in the context-aware QA paradigm, where the answer to each question can be obtained by referring to its accompanying context (paragraph or a list of sentences). Under this setting, the two most notable types of supervisions are coarse sentence-level and fine-grained span-level. In sentence-level QA, the task is to pick sentences that are most relevant to the question among a list of candidates (Yang et al., 2015). In span-level QA, the task is to locate the smallest span in the given paragraph that answers the question (Rajpurkar et al., 2016).

In this paper, we address coarser, sentence-level QA through a standard transfer learning technique of a model trained on a large, span-supervised QA dataset. We demonstrate that the target task not only benefits from the scale of the source dataset but also the capability of the fine-grained span supervision to better learn syntactic and lexical information.

For the source dataset, we pretrain on SQuAD (Rajpurkar et al., 2016), a recently-released, span-supervised QA dataset. For the source and target models, we adopt BiDAF (Seo et al., 2016), one of the top-performing models in the dataset’s leaderboard. For the target datasets, we evaluate on two recent QA datasets, WikiQA (Yang et al., 2015) and SemEval 2016 (Task 3A) (Nakov et al., 2016), which possess sufficiently different characteristics from that of SQuAD. Our results show 8% improvement in WikiQA and 1% improvement in SemEval. In addition, we report state-of-the-art results on recognizing textual entailment (RTE) in SICK (Marelli et al., 2014) with a similar transfer learning procedure.

2 Background and Data

Modern machine learning models, especially deep neural networks, often significantly benefit from transfer learning. In computer vision, deep convolutional neural networks trained on a large image classification dataset such as ImageNet (Deng et al., 2009) have proved to be useful for initializing models on other vision tasks, such as object detection (Zeiler and Fergus, 2014). In natural language processing, domain adaptation has traditionally been an important topic for syntactic...
There have been several QA paradigms in NLP, which can be categorized by the context and supervision used to answer questions. This context can range from structured and confined knowledge bases (Berant et al., 2013) to unstructured and unbounded natural language form (e.g., documents on the web (Voorhees and Tice, 2000)) and unstructured, but restricted in size (e.g., a paragraph or multiple sentences (Hermann et al., 2015)). The recent advances in neural question answering lead to numerous datasets and successful models in these paradigms (Rajpurkar et al., 2016; Yang et al., 2015; Nguyen et al., 2016; Trischler et al., 2016). The answer types in these datasets are largely divided into three categories: sentence-level, in-context span, and generation. In this paper, we specifically focus on the former two and show that span-supervised models can better learn syntactic and lexical features. Among these datasets, we briefly describe three QA datasets to be used for the experiments in this paper. We also give the description of an RTE dataset for an example of a non-QA task. Refer to Table 1 to see the examples of the datasets.

**Span-level QA** (Rajpurkar et al., 2016) is a recent span-based QA dataset, containing 100k/10k train/dev examples. Each example is a pair of context paragraph from Wikipedia and a question created by a human, and the answer is a span in the context.

**SQuAD-T** is our modification of SQuAD dataset to allow for sentence selection QA. (‘T’ for senTence). We split the context paragraph into sentences and formulate the task as classifying whether each sentence contains the answer. This enables us to make a fair comparison between pretraining with span-supervised and sentence-supervised QA datasets.

**WikiQA** (Yang et al., 2015) is a sentence-level QA dataset, containing 1.9k/0.3k train/dev answerable examples. Each example consists of a real user’s Bing query and a snippet of a Wikipedia article retrieved by Bing, containing 18.6 sentences on average. The task is to classify whether each sentence provides the answer to the query.

**SemEval 2016 (Task 3A)** (Nakov et al., 2016) is a sentence-level QA dataset, containing 1.8k/0.2k/0.3k train/dev/test examples. Each example consists of a community question by a user and 10 comments. The task is to classify whether each comment is relevant to the question.

**SICK** (Marelli et al., 2014) is a dataset for recognizing textual entailment (RTE), containing 4.5K/0.5K/5.0K train/dev/test examples. Each example consists of a hypothesis and a premise, and the goal is to determine if the premise is entailed by, contradicts, or is neutral to the hypothesis (hence classification problem). We also report results on SICK to show that span-supervised QA dataset can be also useful for non-QA datasets.

### 3 Model

Among numerous models proposed for span-level QA tasks (Xiong et al., 2016; Wang and Jiang, 2016b), we adopt an open-sourced model, BiDAF\(^2\) (Seo et al., 2016).

**BiDAF.** The inputs to the model are a question \( q \) and a context paragraph \( \pi \). BiDAF uses recurrent neural networks to model sequential dependencies within each question and context paragraph and use attention mechanism to...
model the interaction between them. The last layer of BiDAF is the answer module, which produces the pseudo-probability distributions of the start and the end positions of the answer span, $y^{\text{start}}, y^{\text{end}} \in [0, 1]^N$, where $N$ is the length of the context words. Then the best answer span is $\text{arg max}_{(i,j)} y^{\text{start}}_i y^{\text{end}}_j$, where $i <= j$.

Here, we briefly describe the answer module which is important for transfer learning to sentence-level QA. The input to the answer module is a sequence of vectors $\{h_i\}$ each of which encodes enough information about the $i$-th context word and its relationship with its surrounding words and the question words. Then the role of the answer module is to map each vector $h_i$ to its start and end position probabilities, $y^{\text{start}}_i$ and $y^{\text{end}}_i$.

**BiDAF-T** refers to the modified version of BiDAF to make it compatible with sentence-level QA. In this task, the inputs are a question $q$ and a list of sentences, $x_1, \ldots, x_T$, where $T$ is the number of the sentences. Note that, unlike BiDAF, which outputs single answer per example, here we need to output a $C$-way classification for each $k$-th sentence.

Since BiDAF is a span-selection model, it cannot be directly used for sentence-level classification. Hence we replace the original answer module of BiDAF with a different answer module, and keep the other modules identical to those of BiDAF. Given the input to the new answer module, $\{h^k_1, \ldots, h^k_N\}$, where the superscript is the sentence index ($1 \leq k \leq T$), we obtain the $C$-way classification scores for the $k$-th sentence, $\tilde{y}^k \in [0, 1]^C$ via max-pooling method:

$$\tilde{y}^k = \text{softmax}(W \max(h^k_1, \ldots, h^k_N) + b) \quad (1)$$

where $W \in \mathbb{R}^{C \times d}$, $b \in \mathbb{R}^C$ are trainable weight matrix and bias, respectively, and max() function is applied elementwise.

For WikiQA and SemEval-2016, the number of classes ($C$) is 2, i.e. each sentence (or comment) is either relevant or not relevant. Since some of the metrics used for these datasets require full ranking, we use the predicted probability for “relevant” label to rank the sentences.

Note that BiDAF-T can be also used for the RTE dataset, where we can consider the hypothesis as a question and the premise as a context sentence ($T = 1$), and classify each example into ‘entailment’, ‘neutral’, or ‘contradiction’ ($C = 3$).

### Transfer Learning.

Transfer learning between the same model architectures\(^3\) is straightforward; we first initialize the weights of the target model with the weights of the source model pretrained on the source dataset, and then we further train (fine-tune) on the target model with the target dataset. To transfer from BiDAF (on SQuAD) to BiDAF-T, we transfer all the weights of the identical modules, and initialize the new answer module in BiDAF-T with random values. For more training details, refer to Appendix ??.

### 4 Experiments

| Pretrained dataset | Fine-tuned | WikiQA | SemEval-2016 |
|--------------------|-----------|--------|--------------|
|                    |           | MAP    | MRR | P@1 | MAP    | MRR | AvgR |
| SQuAD-T            | No        | 74.33  | 75.45 | 78.37 | 74.17  | 75.88 | 64.61 |
| SQuAD              | No        | 75.19  | 76.31 | 62.55 | 75.19  | 76.27 | 63.57 |
| SQuAD-T            | Yes       | 76.44  | 77.65 | 64.61 | 76.30  | 82.51 | 86.64 |
| SQuAD              | Yes       | 79.90  | 80.01 | 70.37 | 78.37  | 85.58 | 87.68 |
| SQuAD*             | Yes       | 83.20  | 84.58 | 75.31 | 80.20  | 86.44 | 89.14 |

#### Table 2: Results on WikiQA and SemEval-2016 (Task 3A).

The first row is a result from non-pretrained model, and * indicates ensemble method. Metrics used are Mean Average Precision (MAP), Mean Reciprocal Rank (MRR), Precision at rank 1 ($P@1$), and Average Recall (AvgR). Rank 1,2,3 indicate the results by previous works, ordered by MAP. For WikiQA, they are from Wang and Jiang (2016a) \& Tymoshenko et al. (2016); Miller et al. (2016), respectively. For SemEval-2016, they are from Filice et al. (2016); Joty et al. (2016); Mihaylov and Nakov (2016).

#### Question Answering Results.

Table 2 reports the state-of-the-art results of our transfer learning on WikiQA and SemEval-2016 and the performance of previous models as well as several ablations that use no pretraining or no finetuning.

There are multiple interesting observations from Table 2. First, if we only train the BiDAF-T model on the target datasets (first row of Table 2), the results are poor. This shows the effect of both pretraining and finetuning. Second, pretraining on SQuAD and SQuAD-T with no finetuning (second and third row) achieves results close to the state-of-the-art in the WikiQA dataset, but not in SemEval-2016. Interestingly, our result on SemEval-2016 is not better than only training without transfer learning. We conjecture that this is due to the significant difference between the domain of SemEval-2016 and that of SQuAD. Third, pretraining on SQuAD and SQuAD-T with finetuning (fourth and fifth row) significantly outper-

\(^3\)Strictly speaking, this is a domain adaptation scenario.
forms (by more than 5%) the highest-ranking systems on WikiQA. It also outperforms the second ranking system in SemEval-2016 and is only 1% behind the first ranking system. Fourth, transfer learning models achieve better results with pretraining on span-supervision (SQuAD) than coarser sentence supervision (SQuAD-T).

Finally, we also use the ensemble of 12 different training runs on the same BiDAF architecture, which obtains the state of the art in both datasets. This system outperforms the highest-ranking system in WikiQA by more than 8% and the best system in SemEval-2016 by 1% in every metric. It is important to note that, while we definitely benefit from the scale of SQuAD for transfer learning to smaller WikiQA, given the gap between SQuAD-T and SQuAD (> 3%), we see a clear sign that span-supervision plays a significant role well.

**Analysis.** Figure 1 shows the latently-learned attention maps between the question and one of the context sentences from a WikiQA example in Table 1. The top map is pretrained on SQuAD-T (corresponding to SQuAD-T&Y in Table 2) and the bottom map is pretrained on SQuAD (SQuAD&Y). The more red the color, the higher the relevance between the words. There are two interesting observations here. First, in SQuAD-pretrained model (bottom), we see a high correspondence between question’s `airbus` and context’s `aircraft` and `aerospace`, but the SQuAD-T-pretrained model fails to learn such correspondence. Second, we see that the attention map of the SQuAD-pretrained model is more sparse, indicating that it is able to more precisely localize correspondence between question and context words. In fact, the average sparsity of all WikiQA test examples in SQuAD&Y is 0.84 while that in SQuAD-T&Y is 0.56. For more analyses and details, refer to Appendix ??.

| Pretrained dataset / Previous work | Accuracy |
|-----------------------------------|----------|
| SQuAD-T                           | 81.49    |
| SQuAD                             | 82.86    |
| SQuAD*                            | 84.38    |
| SNLI                              | 83.20    |
| SQuAD-T + SNLI                    | 85.00    |
| SQuAD + SNLI*                     | 86.63    |
| SQuAD + SNLI*                     | 88.22    |
| Yin et al. (2016)                 | 86.2     |
| Lai and Hockenmaier (2014)        | 84.57    |
| Zhao et al. (2014)                | 83.64    |
| Jimenez et al. (2014)             | 83.05    |
| Mou et al. (2016)                 | 70.9     |
| Mou et al. (2016) (pretrained on SNLI) | 77.6 |

Table 3: Results on SICK after finetuning. The first row is only trained on SICK. * indicates ensemble method.

**Entailment Result.** In addition to QA experiments, we also show that the models trained on span-supervised QA can be useful for textual entailment task (RTE). Table 3 shows the transfer learning results of BiDAF-T on SICK dataset (Marelli et al., 2014), with various pretraining routines. Note that SNLI (Bowman et al., 2015) is a similar task to SICK and is significantly larger (150K/10K/10K train/dev/test examples). Here we highlight three observations. First, BiDAF-T pretrained on SQuAD outperforms that without any pretraining by 6% and that pretrained on SQuAD-T by 2%, which demonstrates that the transfer learning from large span-based QA gives a clear improvement. Second, pretraining on SQuAD+SNLI outperforms pretraining on SNLI only. Given that SNLI is larger than SQuAD, the difference in their performance is a strong indicator that we are benefiting from not only the scale of SQuAD, but also the fine-grained supervision that it provides. Lastly, we outperform the previous state of the art by 2% with the ensemble of SQuAD+SNLI pretraining routine. It is worth noting that Mou et al. (2016) also shows improvement on SICK by pretraining on SNLI.

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