Self-Teaching Machines to Read and Comprehend with Large-Scale Multi-Subject Question Answering Data

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Abstract

In spite of much recent research in the area, it is still unclear whether subject-area question-answering data is useful for machine reading comprehension (MRC) tasks. In this paper, we investigate this question. We collect a large-scale multi-subject multiple-choice question-answering dataset, ExamQA, and use incomplete and noisy snippets returned by a web search engine as the relevant context for each question-answering instance to convert it into a weakly-labeled MRC instance. We then propose a self-teaching paradigm to better use the generated weakly-labeled MRC instances to improve a target MRC task. Experimental results show that we can obtain an improvement of 5.1% in accuracy on a multiple-choice MRC dataset, C³, demonstrating the effectiveness of our framework and the usefulness of large-scale subject-area question-answering data for machine reading comprehension.

1 Introduction

At some level, machine reading comprehension (MRC) and question answering (QA) seem to be quite related tasks: machine reading comprehension aims to answer questions derived from a given document (Richardson et al., 2013; Hermann et al., 2015; Rodrigo et al., 2015), while the standard question answering formulation (Voorhees and Tice, 2000; Burger et al., 2001; Fukumoto and Kato, 2001) requires retrieval of snippets of text from a large corpus that answer a given question.

And it has been demonstrated that medium-scale MRC datasets can be employed to improve performance on small-scale question-answering systems. Sun et al. (2019b) and Pan et al. (2019), for example, obtain performance gains on subject-area question-answering datasets about science such as ARC (Clark et al., 2016, 2018) and OpenBookQA (Mihaylov et al., 2018) by pre-training the QA models on MRC data collected from language exams (e.g., RACE (Lai et al., 2017)). The general approach has been to retrieve for each QA instance complete documents or sentences from a relevant in-domain corpus or Wikipedia article, and then use a machine reading comprehension pipeline on the (context, question) pair to answer questions. See Figure 1 for an overview. Conversely, there actually exists large-scale real-world question-answering data created by subject-matter experts, but rarely is it studied to improve machine reading comprehension.

This paper aims to study whether the massive amount of multi-subject QA data can improve machine reading comprehension. For many years it has been demonstrated that human readers’ reading comprehension performance is affected by their prior knowledge about the topic of the given text (Johnston, 1984; Laufer and Sim, 1985; Hirsch, 2003). Instead of retrieving and imparting topic-specific subject knowledge for a given text to a machine reader in an on-demand manner, we hypothesize that incorporating rich knowledge from

Figure 1: A typical framework for using medium-scale MRC data to improve small-scale QA.
all — or as many as possible — subjects into a machine reader may improve its ability to comprehend text on different topics. As most of the existing multi-subject area question-answering datasets are relatively small-scale, we first collect a large-scale Question Answering dataset from Exams covering a wide range of subjects (e.g., sociology, education, and psychology), which contains 638k multiple-choice instances, called ExamQA.

We then present a new method to convert QA instances in ExamQA into training instances for a target MRC task, which may benefit from knowledge transfer (Ruder et al., 2019). In contrast to previous studies that augment each QA instance with relevant sentences/documents retrieved from offline corpora, we are interested in another practical reading process to add context to QA instances: human readers type their questions on a web search engine and only read through the snippets returned by the search engine to seek potential answers. Imitating this process, we use relevant snippets retrieved by a web search engine as the context of each question-answering instance. We regard such an MRC instance as weakly-labeled as the context is a form of distant supervision: while it might contain the answer to the question as required for MRC, it is equally likely to be noisy, irrelevant, incomplete, and/or too informal to constitute a proper answer (Section 2).

To better leverage the large-scale weakly labeled MRC data, we propose a self-teaching paradigm that iteratively uses a student model that outperforms its teacher model as the new teacher to generate soft labels for data. First, we train a multi-skilled teacher model using both the weakly labeled data and the data of a target MRC task. We then train a multi-skilled student model using the same data while replacing the hard labels of answer options with the soft labels predicted by the multi-skilled teacher. Finally, we initialize an expert student model with the resulting multi-skilled student model and fine-tune it on the target MRC data, whose labels are set based on the soft labels generated by the multi-skilled student (Section 3).

We study the effect of the generated QA-based weakly labeled MRC data under the self-teaching paradigm on a multiple-choice MRC dataset, C3 (Sun et al., 2020b), in which most questions cannot be solved solely by matching or paraphrasing. Experimental results show that we can obtain an improvement of 5.1% in accuracy over a state-of-the-art baseline (Xu et al., 2020; Cui et al., 2020), demonstrating the effectiveness of our framework. Furthermore, we present an easy way to adapt this paradigm to additionally leverage multiple types of weakly labeled MRC data wherein noise is introduced by different factors (e.g., context retrieval, machine translation, and knowledge construction), again by using soft labels predicted by teacher models. Augmenting the MRC training data in this way leads to further improvements (up to +2.5% in accuracy on C3).

The contributions of this paper are as follows:

- We offer the largest multi-subject QA dataset to date, ExamQA.
- Our study examines whether large-scale subject-area QA data can be useful for improving machine reading comprehension. We introduce a new approach that adds noisy and incomplete contexts retrieved by a web search engine to each QA instance to convert them into weakly-labeled MRC data.
- We propose a simple yet effective self-teaching paradigm to better leverage large-scale weakly-labeled data of different types (i.e., in which the source of noise varies). Experimental results show that we can achieve up to +7.6% in accuracy on a challenging multiple-choice MRC dataset.

2 Weakly-Labeled Data Generation

2.1 Question-Answering Data Collection

We collect large-scale question-answering instances from freely accessible exams (including mock exams) designed for a variety of subjects such as sociology, journalism, and ecology. We only keep multiple-choice single-answer instances written in Chinese. After deduplication, we obtain 638,436 question-answering instances.

To assess the subject coverage of ExamQA, we obtain a list of subjects from China national standard (GB/T 13745-2009) (Standardization Administration of China, 2009) and check for each subject in the list if the name of the subject appears in the title of any exam to estimate the lower bound of subject coverage. The estimation indicates that ExamQA covers at least 48 out of 62 first-level subjects and 187 out of 676 second-level subjects. Note that the actual subject coverage of ExamQA may be greatly underestimated, as only 24.2% of titles contain a subject name.
We do not annotate a small subset of questions for human performance, as most of the subject-area questions are from higher education exams that require advanced domain knowledge.

2.2 Comparisons with Existing Subject-Area QA Datasets
Subject-area question answering is an increasingly popular direction in question answering, focusing on closing the performance gap between humans and machines in answering questions collected from real-world exams that are carefully designed by subject-matter experts. These tasks are mostly in multiple-choice forms. In Table 1, we list several representative subject-area multiple-choice question-answering datasets: NTCIR-11 QA-Lab (Shibuki et al., 2014), QS (Cheng et al., 2016), MCQA (Guo et al., 2017), ARC (Clark et al., 2018), GeoSQA (Huang et al., 2019), HEAD-QA (Vilares and Gómez-Rodríguez, 2019), EXAMS (Hardalov et al., 2020), JEC-QA (Zhong et al., 2020), and MEDQA (Jin et al., 2020).

| dataset       | # of subjects | size  |
|---------------|---------------|-------|
| QS            | 1/history     | 0.6K  |
| GeoSQA        | 1/geography   | 4.1K  |
| JEC-QA        | 1/legal       | 26.4K |
| ARC           | 1/science     | 7.8K  |
| QA-Lab        | 1/history     | 0.3K  |
| HEAD-QA       | 1/healthcare  | 6.8K  |
| MEDQA         | 1/medical     | 61.1K |
| MCQA          | 6/multi-subject | 14.4K |
| EXAMS         | 24/multi-subject | 24.1K |
| ExamQA        | 48/multi-subject | 638.4K |

Table 1: Representative subject-area question-answering datasets collected from exams (◦: we simply report the number of subjects claimed by previous studies and the number of first-level subjects in ExamQA).

2.3 Bringing Contexts to Question Answering
In this section, we present a method to convert question-answering instances into MRC instances to make the resulting data and target MRC task in a similar format, which may benefit from knowledge transfer (Ruder et al., 2019).

Previous studies attempt to convert a multiple-choice subject-area QA task to a multiple-choice MRC task by retrieving relevant sentences for each question from a clean corpus to form a document. Instead of relying on a relatively clean resource, we retrieve the top ranked snippets using a publicly available search engine. Specifically, we send each question to the search engine as the query and collect snippets from the first result page. Typically, we can collect ten snippets for each question-answering instance. Since all instances are freely accessible online, it is likely that a retrieved snippet simply contains the original question-answering instance rather than suitable contexts relevant for answering the question. Therefore, we discard a snippet if more than one answer option appears as a substring in the snippet. We concatenate the remaining snippets into a document as the context of each question-answering instance. We show data statistics of ExamQA and retrieved contexts in Table 2. Due to this construction method, it is very likely that a document is noisy, incomplete, informal, or irrelevant. We provide sample instances in Table 3.

| metric                     | value  |
|----------------------------|--------|
| average # of answer options| 4.0    |
| average question length (in characters) | 39.5 |
| average option length (in characters)   | 6.7    |
| average context length (in tokens)      | 907.6  |
| character vocabulary size             | 13,258 |
| non-extractive correct option (%)      | 68.4   |

Table 2: Data statistics of ExamQA with contexts.

3 Self-Teaching Paradigm
In this section, we introduce a self-teaching paradigm to leverage large-scale QA-based weakly-labeled data to improve the performance of existing supervised methods on an MRC task of interest, which is relatively small-scale.

3.1 Training a Multi-Skilled Teacher
In previous teacher-student frameworks (You et al., 2019; Wang et al., 2020b; Sun et al., 2020a), multiple teacher models are trained using different data. However, it is difficult to divide the weakly-labeled data based on existing QA instances into sub-datasets by subjects or fine-grained types of knowledge required for answering questions. Instead, we train a multi-skilled teacher model using both the weakly-labeled data and the data of a target MRC, which requires a diverse skill set and knowledge from multiple domains.

Let $V$ denote a set of labeled instances and $W$ denote a set of weakly-labeled instances. For each
C1: 1. $a + b / b$ is equivalent to $(\text{int} \ a) + (b / b)$, which can be obtained according to the priority of the processor. (Int) This is a forced type conversion. After the forced conversion $(\text{int} \ a)$ is generally the double conversion to the int type, most platforms round to zero... $2 / b$, both sides of the division sign are doubletype. The result is also doubleType. That is $1.000000$; integer. The first 5 is the int type, int... 3 : a = 5.5; b = 2.5; c = $(\text{int}) \ a + \ b / \ b$; printf(c). Best answer: $(\text{int}) \ a + \ b / \ b = 6$, should be $(\text{int}) \ a$ a means round a, and round a is 5 (rounding cannot be used here, rounding is discarded, then $b / b$ is 2.5 / 2.5, etc... 2019 July 25th, 2016: Analysis: The type of the value of the mixed expression is determined by the type with the highest precision in the expression, so it can be seen that option B can be excluded. Note that the result of $b / b$ should be 1.00000, and $(\text{int}) \ a$ is 5, and the result of the addition is still doubl...

Q1: Suppose a and b are double constants, and a=5.5, b=2.5, the value of the expression $(\text{int})a+b/b$ is ()
A. 5.500000
B. 6.000000
C. 6.500000
D. 6

C2: July 21, 2014: Friedman believes that the transmission variable of monetary policy should be (). Please help to give the correct answer and analysis, thank you! Reward: 0 answer bean Questioner: 00***42 Release time: 2014-07-21 View...

Q2: Friedman believes that the transmission variable of monetary policy should be ()
A. excess reserve
B. interest rate
C. currency supply
D. base currency

Table 3: English translation of sample instances in ExamQA with retrieved contexts (*: the correct answer option).

3.2 Training a Multi-Skilled Student
We then train a multi-skilled student model $S$ using the same data as the multi-skilled teacher model $T$ while replacing the hard labels of answer options with the soft labels predicted by $T$. We define soft-label vector $s^{(t)}_k$ for $t \in V \cup W$ such that

$$ s^{(t)}_k = \lambda h^{(t)}_k + (1 - \lambda)p_{\theta}(k \mid t), $$

where $\lambda \in [0, 1]$ is a weight parameter, and $k = 1, \ldots, m_t$.

We optimize multi-skilled student $S$ by minimizing $\sum_{t \in V \cup W} L_2(t, \theta_S)$, where $L_2$ is defined as

$$ L_2(t, \theta) = -\sum_{1 \leq k \leq m_t} s^{(t)}_k \log p_{\theta}(k \mid t). $$

3.3 Training an Expert Student
Finally, we initialize an expert student $E$ with the resulting multi-skilled student model $S$, and we fine-tune $E$ on the target data $V$ to help it achieve expertise in the task of interest, following most of the recent MRC methods (Radford et al., 2018; Devlin et al., 2019). Our method differs from previous work in that we use the soft labels generated by the multi-skilled student model (Section 3.2) based on our assumption that a student model tends to learn better from a stronger teacher model. We will discuss more details in the experiment section and show that a student model tends to outperform its teacher model that provides soft labels to make itself a stronger teacher (Section 4).

We define new soft-label vector $\tilde{s}^{(t)}_k$ for $t \in V$ such that

$$ \tilde{s}^{(t)}_k = \lambda h^{(t)}_k + (1 - \lambda)p_{\theta_S}(k \mid t), $$

where $\lambda \in [0, 1]$ is a weight parameter, and $k = 1, \ldots, m_t$.

In this stage, we optimize $E$ by minimizing $\sum_{t \in V} L_3(t, \theta_E)$, where $L_3$ is defined as

$$ L_3(t, \theta) = -\sum_{1 \leq k \leq m_t} \tilde{s}^{(t)}_k \log p_{\theta}(k \mid t). $$

Figure 2 shows an overview of the proposed self-teaching paradigm.

3.4 Integrating Different Types of Weakly-Labeled Data
We study the integration of multiple types of weakly-labeled data during weakly-supervised
training with soft labels to save time and effort in retraining models on \( W \) with hard labels.

Take another weakly-labeled multiple-choice MRC data extracted automatically from television show and film scripts (Sun et al., 2020a) as an example, denoted as \( W_s \), besides the weakly-labeled data \( W \) we construct based on existing question-answering instances. Following the above three-step procedure, we first train a multi-skilled teacher \( T_s \) using \( W_s \) to generate soft labels of \( W_s \) and \( V \). We then train a multi-skilled student \( S \) upon the combination of soft-labeled \( W_s \), \( W \) (Section 3.2), and \( V \). Note that we simply use two versions of soft-labeled \( V \) generated by \( T \) and \( T_s \), respectively. The resulting student \( S \) is used to generate the final soft labels of \( V \) for training an expert student. We will discuss and compare with other variants of integrating the two types of weakly-labeled data (e.g., training a multi-skilled teacher using two types of large-scale weakly-labeled data) in Section 4.3.

4 Experiments

4.1 Implementation Details

In our experiments, we follow recent state-of-the-art machine reading comprehension methods for the model architecture that consists of a pre-trained language model and a classification layer. We use the same architecture for all teacher and student models. We use RoBERTa-wwm-ext-large (Cui et al., 2020) as the pre-trained language model, which achieves state-of-the-art performance on the \( C^3 \) dataset and other tasks such as natural language inference and coreference resolution in Chinese (Xu et al., 2020). We train a model for one epoch when we train multi-skilled teacher/student models on large-scale weakly-labeled data and eight epochs when we train an expert student model on the \( C^3 \) dataset. We set \( \lambda \) (defined in Section 3.1-3.3) to 0.5 in all experiments following Sun et al. (2020a) to allow easy comparisons. We are aware of the emerging powerful pre-trained language models for Chinese, and we leave the exploration of these models on ExamQA for future studies.

4.2 Data Statistics

We show statistics of the MRC task of interest \( C^3 \) (Sun et al., 2020b) and two kinds of weakly-labeled MRC data in Table 4.

| data source | # of instances |
|-------------|----------------|
| human-annotated: \( C^3 \) | language exams 19,577 |
| weakly-labeled: SCRIPT | TV/movie scripts 700,816 |
| ExamQA | multi-subject exams 638,436 |

Table 4: Human-annotated and weakly-labeled machine reading comprehension data statistics.

4.3 Main Results and Observations

As shown in Table 5, our self-teaching paradigm (5) improves the state-of-the-art baseline (1) based on the same model architecture by up to 5.1% in average accuracy. We also compare it, its variant (4), and the intermediate teacher models (2 and 3) and have the following observations.

Student models tend to outperform their corresponding teacher models in self-teaching. Under the self-teaching paradigm, we observe that student models always achieve higher accuracy on the MRC task of interest and demonstrate smaller standard deviations than their teacher models that generate soft labels. For example, the multi-skilled student (3) has a 1.5% higher average accuracy than the multi-skilled teacher (2) that achieves 75.6%.
Using a strong multi-skilled model to provide soft labels helps across settings. We consider a teacher model to be strong if it achieves good performance on the task of interest. We already demonstrate that training a student model with soft labels generated by a multi-skilled teacher model instead of hard labels yields positive improvements (3 vs. 2). In addition, using the multi-skilled student (3), which is stronger than the multi-skilled teacher (2), to provide soft labels of C³ to train an expert student provides a boost of +0.5 average accuracy (5 vs. 4).

To explore whether it also applies to a strong expert model, we experiment with a variant of the expert student (5): still starting from the same multi-skilled student (3), we now put back the expert student (5) as the teacher model to generate soft labels of C³ to train an expert student variant. However, this variant does not yield further gains (78.2 (0.4)) on the development set. Seeing more data than the expert student may make the more “knowledgable” multi-skilled student a better teacher to provide soft labels of the downstream task. While it is possible to use the multi-skilled student itself to obtain a stronger multi-skilled student, it is much less efficient to retrain a model upon the large-scale weakly-labeled data than the above variant. We leave the exploration of iterative self-teaching over weakly-labeled data to future work.

Large-scale weakly-labeled data based on multi-subject QA instances can be helpful for machine reading comprehension. As shown by 2 in Table 5, we do not lead to noticeable gains by merely combining large-scale weakly-labeled data and small-scale data and training a model over the resulting data for one epoch. Nevertheless, helping train multi-skilled models, especially the multi-skilled student that is further used as a good starting point of the expert student, reflect the usefulness of the large-scale weakly-labeled data. Though starting from the multi-skilled teacher slightly boosts (0.3% in accuracy) a multi-skilled student’s performance, using the resulting multi-skilled student to initialize and teach the expert student actually hurts performance by −0.7% in average accuracy on the development set, perhaps due to the overuse of the same weakly-labeled data (both soft and hard labels) upon a model or the convergence between the multi-skilled teacher and multi-skilled student. Therefore, we do not use the multi-skilled teacher to initialize the multi-skilled student in our main experiment (3 in Table 5).

| id | model | init. | teacher | training data name | label | dev | test |
|----|-------|-------|---------|---------------------|-------|-----|------|
| 0  | RoBERTa-wwm-ext-large (Xu et al., 2020) | – | – | ◊ | hard | – | 73.8 |
| 1  | baseline (our implementation of 0) | – | – | ◊ | hard | 73.9 (0.5) | 73.4 (0.5) |
| 2  | multi-skilled teacher | – | – | ◊ + ExamQA | hard | 74.0 (0.8) | 75.6 (0.5) |
| 3  | multi-skilled student | – | 2 | ◊ + ExamQA | soft | 75.7 (0.5) | 77.1 (0.4) |
| 4  | expert student (variant) | 3 | 2 | ◊ | soft | 77.8 (0.4) | 78.0 (0.3) |
| 5  | expert student | 3 | 3 | ◊ | soft | 78.2 (0.3) | 78.5 (0.2) |

Table 5: Average accuracy and standard deviation (%) (five runs based on different random seeds) on the development and test sets of the C³ dataset. ◊ is the training set of C³ for all experiments; init. means the starting point, and – in this column means using the pre-trained language model for initialization.

Introducing more weakly-labeled data can lead to further gains. Using the method mentioned in Section 3.4, introducing additional weakly-labeled MRC instances that are generated based on contextualized verbal-nonverbal knowledge from scripts, we observe a 1.3% improvement in average accuracy over the best-performing expert student in Table 5, which also outperforms the expert student obtained when we only use one third
of weakly-labeled data constructed based on ExamQA by 0.4% on the development set of C3 (Table 7). These results suggest the flexibility and scalability of self-teaching, and it is likely that further increasing the amount of weakly-labeled data of different types, may also yield positive improvements.

Furthermore, we also show it is possible to use the same procedure to adapt self-teaching to incorporate extra noisy human-labeled multiple-choice MRC instances as there is a growing trend in constructing MRC benchmarks. As far as we know, C3 is the only multiple-choice free-form MRC dataset for Chinese. Therefore, we automatically translate instances from its English counterparts RACE (Lai et al., 2017) and DREAM (Sun et al., 2019a) that are also collected from language exams into Chinese (referred to as MRCMT in Table 7). However, We do not study how to further improve machine reading comprehension by just using extra clean human-labeled MRC data, which is not our main focus.

### Table 7: Accuracy comparison of expert students, which are obtained when different size of weakly-labeled MRC data is used during self-teaching, on the development and test sets of the C3 dataset.

| weakly-labeled data          | size | dev  | test  |
|------------------------------|------|------|-------|
| subset of ExamQA             | 0.2M | 77.8 | (0.2) |
| ExamQA                      | 0.6M | 78.2 | (0.3) |
| ExamQA + SCRIPT             | 1.3M | 79.5 | (0.2) |

| mixed-labeled data           |      |      |       |
|------------------------------|------|------|-------|
| ExamQA + MRCMT              | 0.7M | 80.4 | (0.1) |

| weakly-labeled data          | size | dev  | test  |
|------------------------------|------|------|-------|
| subset of ExamQA             | 0.2M | 77.8 | (0.2) |
| ExamQA                      | 0.6M | 78.2 | (0.3) |
| ExamQA + SCRIPT             | 1.3M | 79.5 | (0.2) |

4.4 Comparing Self-Teaching and Multi-Teacher Paradigms

Previous work shows that it is better to train multiple teacher models upon different types of weakly-labeled data with hard labels and then use these teachers to generate soft labels for both the weakly-labeled data and the small-scale MRC data for further training the multi-skilled student model and the expert student, compared against training one model over the entire weakly-labeled data with hard labels and then fine-tuning it on the small-scale MRC task (Sun et al., 2020a). However, herein lies an unanswered question: whether teacher models’ data diversity or number matters to the expert student’s performance.

As it is difficult to divide ExamQA into subsets by subjects, which can result in hundreds of teachers, we shuffle ExamQA and divide it into two subsets of similar size and follow the multi-teacher paradigm mentioned above. We compare it with the self-teaching paradigm and find that self-teaching provides larger accuracy gains compared against multi-teacher when knowledge-based data segmentation is tricky (Table 8).

We also consider the case when it is easy to split data into subsets by the type of knowledge: we compare self-teaching with multi-teacher given the weakly-labeled data based on four types of verbal-nonverbal knowledge extracted from scripts. Results reveal that the two paradigms have similar performance, indicating that the impact of the number of teacher models may be limited. To study the impact of data diversity of teachers, we shuffle SCRIPT and divide it into four subsets of similar size to train four teacher models. Using the same multi-teacher paradigm, we experimentally demonstrate that there is a weak correlation between the data diversity of teachers and the final performance of the expert student.

4.5 The Impact of Context

As mentioned previously, contexts returned by a web search engine tend to be noisy. For example, given a question as the search query, the question and all its answer options are included in contexts. We conduct a preliminary experiment to evaluate the impact of context cleanliness by removing wrong answer options from the context of each weakly-labeled MRC instance. However, context cleaning hurts accuracy by 1.2% on the development set of C3. It is possible that noisy contexts help improve the generalization ability of both teacher and student models, similar to the role of noise (e.g., dropout and data augmentation) that is intentionally injected to the student models during self-training in previous studies (He et al., 2020; Xie et al., 2020b).

5 Related Work

5.1 From Question Answering to Machine Reading Comprehension

Here we do not compare with transfer learning or domain adaption in machine reading comprehension when the source and target tasks are all MRC tasks (Chung et al., 2018; Wang et al., 2018; Shakeri et al., 2020; Nishida et al., 2020), as it is expensive and time-consuming to construct high-
| paradigm       | weakly-labeled data | segmentation criteria | # of multi-skilled teachers | dev   | test  |
|---------------|---------------------|-----------------------|----------------------------|-------|-------|
| self-teaching | ExamQA              | –                     | 1                          | 78.2 (0.3) | 78.5 (0.2) |
| multi-teacher | ExamQA              | random                | 2                          | 77.3 (0.5) | 78.1 (0.2) |
| multi-teacher | ExamQA              | random                | 4                          | 77.5 (0.5) | 77.9 (0.2) |
| self-teaching | SCRIPT              | –                     | 1                          | 77.9 (0.4) | 77.9 (0.4) |
| multi-teacher | SCRIPT              | random                | 4                          | 77.7 (0.2) | 77.5 (0.3) |
| multi-teacher | SCRIPT              | knowledge type        | 4                          | 77.7 (0.4) | 77.9 (0.3) |

Table 8: Comparison of self-teaching and multi-teacher framework using different types of weakly-labeled data in average accuracy (%) on the development and test sets of the C3 dataset.

quality large-scale machine reading comprehension datasets considering factors such as ensuring the high relevance between questions and contexts and the degree of difficulty of questions.

This work is related to data augmentation in semi-supervised MRC studies, which partially or fully rely on the document-question-answer triples (Yang et al., 2017; Yuan et al., 2017; Yu et al., 2018; Zhang and Bansal, 2019; Zhu et al., 2019; Dong et al., 2019; Sun et al., 2019b; Alberti et al., 2019; Asai and Hajishirzi, 2020; Renjie et al., 2020) of target MRC task or at least similar domain corpora (Dhingra et al., 2018). We mainly focus on studying leveraging multi-domain question-answering pairs to improve MRC tasks in which most answers cannot be answered by matching and paraphrasing and, at first glance, subject-area knowledge is seldom required.

To the best of our knowledge, ExamQA is the largest multi-subject QA datasets collected from exams to date. We offer ExamQA mainly for the purpose of using large-scale multi-subject QA pairs to improve other natural language understanding tasks such as machine reading comprehension, rather than focusing on improving single-subject or multi-subject question answering.

5.2 Teacher-Student Paradigms

Teacher-student paradigms are widely used for knowledge distillation (Ba and Caruana, 2014; Li et al., 2014; Hinton et al., 2015). We aim to let the student model outperform its teacher model to improve existing competitive supervised methods and simply use the same architecture for all teacher and student models.

Our work is related to self-training (Yarowsky, 1995; Riloff, 1996), as we also leverage unstructured texts for data generation. The main difference is that we generate weakly-labeled data based on existing large-scale QA pairs covering a wide range of domains, instead of the same domain (He et al., 2020; Xie et al., 2020a; Zhao et al., 2020; Chen et al., 2020) or at least approximately in-domain (Du et al., 2020) as the target task. Different from previous studies that iteratively use new teacher models to generate new pseudo data from unlabeled data (e.g., (Wang et al., 2020a)), we use the new teacher model to generate new soft labels for fixed weakly-labeled and target data. Furthermore, we use a search engine to retrieve noisy and incomplete snippets instead of full sentences or even documents, which are seldom used as contexts for structured knowledge via distant supervision for downstream natural language processing tasks (Ye et al., 2019).

Compared with previous multi-teacher student paradigms (You et al., 2019; Wang et al., 2020b; Yang et al., 2020), we conduct iterative training and leverage large-scale weakly-labeled data to train models to be teachers, instead of using human-labeled clean data of similar/relevant tasks.

6 Conclusions

It is still understudied how to improve machine reading comprehension using large-scale subject-area question-answering data. In this paper, we collect a large-scale multiple-choice question-answering dataset ExamQA covering a wide range of subjects. We use incomplete and noisy snippets returned by a web search engine as the relevant context of each question-answering instance to convert it into a weakly-labeled MRC instance. Furthermore, we propose a self-teaching paradigm to use these weakly-labeled MRC instances to improve an MRC task of interest. Experimental results show that we can obtain an improvement of 5.1% in average accuracy on a multiple-choice MRC dataset C3, demonstrating the effectiveness of our framework and the usefulness of large-scale question-answering data for MRC.
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