Incidental Supervision from Question-Answering Signals

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Abstract

Human annotations are costly for many natural language processing (NLP) tasks, especially for those requiring NLP expertise. One promising solution is to use natural language to annotate natural language. However, it remains an open problem how to get supervision signals or learn representations from natural language annotations. This paper studies the case where the annotations are in the format of question-answering (QA) and proposes an effective way to learn useful representations for other tasks. We also find that the representation retrieved from question-answer meaning representation (QAMR) data can almost universally improve on a wide range of tasks, suggesting that such kind of natural language annotations indeed provide unique information on top of modern language models.\textsuperscript{1}

1 Introduction

It is often labor-intensive to have humans directly annotate data for NLP tasks which require research expertise and/or have lengthy guidelines. For instance, one needs to understand thousands of semantic frames in order to provide semantic role labelings (SRL) (Palmer et al., 2010). A promising approach to address this issue is to use natural language (NL) to annotate NL. Throughout this paper, we refer to this kind of annotations as NL annotations.

Existing works along this line include natural logic for textual entailment (TE) (MacCartney and Manning, 2007), QA-SRL (He et al., 2015), QAMR (Michael et al., 2017), and zero-shot relation extraction (RE) via reading comprehension (Levy et al., 2017). When annotators are not required to understand those convoluted concepts defined by experts, they can focus more on the actual meaning of text and even laymen can provide indirect annotations using NL.

Despite the lower cost of NL annotations, it raises an issue of how to use them effectively. For example, even if we know a task needs predicate-argument information, it remains unclear how to improve the task given QA-SRL, although we believe QA-SRL can provide useful information. This is in general a critical issue when using NL annotations.

The key to many NLP tasks is to learn representations from data, either as explicit discrete symbols or as latent continuous vectors. Based on NL annotations, we often cannot reliably get symbolic representations due to the ambiguity and variability nature of NL. For example, QA-SRL data are, in their surface form, very different from SRL. As we show later in Section 5.1, it is challenging to learn a good SRL parser purely based on QA-SRL. Furthermore, NL can flexibly express things that are not covered by pre-defined formalism, so converting NL annotations to a fixed inventory of symbols will actually lose information.

Therefore, we propose to learn latent continuous representations from NL annotations. Note that many existing works have studied how to learn latent continuous representations for language from massive text data instead of NL annotations, mainly from the perspective of language modeling (LM) (Pennington et al., 2014; Peters et al., 2018; Devlin et al., 2019; Yang et al., 2019; Liu et al., 2019). However, Tenney et al. (2019b) show that as compared to non-contextual LMs, those contextual LMs (e.g., ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019)) could only offer marginal improvements on semantic tasks, suggesting that contextualization alone is not the solution to semantic representations. We hence believe that representations learned purely from unlabeled text will not be enough for all types

\textsuperscript{1}Our code and online demo are publicly available at https://github.com/HornHehhf/ISfromQA.
Table 1: Some examples of question-answer pairs in QA-SRL and QAMR datasets. The first two examples are from QA-SRL dataset and predicates are bolded. The last two examples are from QAMR dataset. We show two phenomena that are not modeled by traditional representations of predicate-argument structure, inferred relations (INF) and implicit arguments (IMP).

| Sentence | Ann. | Question | Answers |
|----------|------|----------|---------|
| (1) Mr. Agnew was vice president of the U.S. from 1969 until he resigned in 1973. | INF | What did someone resign from? | vice president of the U.S. |
| (2) This year, Mr. Wathen says the firm will be able to service debt and still turn a modest profit. | INF | When will something be serviced? | this year |
| (3) Mahlunga has said he did nothing wrong and Judge Horn said he “failed to express genuine remorse”. | INF | Who doubted his remorse was genuine? | Judge Horn |
| (4) Volunteers are presently renovating the former post office in the town of Edwards, Mississippi, United States for the doctor to have an office. | IMP | What country are the volunteers renovating in? | United States |

of tasks. This is consistent with one underlying philosophy of BERT: while an LM like BERT can handle syntactic variations very well, it still needs fine-tuning on some annotations to acquire the “definition” of the target task.

Specifically, we study how to learn latent representations from NL annotations in the format of QA, which can be viewed as retrieving incidental supervision signals from QA data. Our first contribution is that we propose a practical method to do it. We fine-tune BERT with these QA signals and obtain representations carrying the necessary information to answer these questions. We term this procedure as QA-driven language modeling (QALM). Experiments show that improvements can be achieved by adding the resulting representations from QALM as a feature vector to existing neural architectures. Specifically, QALM has outperformed BERT on seven tasks by an average of 1.2 F1 score in the small data setting, and 0.2 F1 score in the full data setting.

We work on two types of NLP tasks: tasks with a single-input sequence, e.g., SRL and named entity recognition (NER); and tasks with a pair of inputs, e.g., TE and machine reading comprehension (MRC). We argue that if a task is single-input, then QALM should focus more on the input itself, which we call standard QALM; if a task is paired-input, then QALM should also consider the interaction between the two inputs, which we call conditional QALM. Since QA is itself a paired-input task (i.e., a sentence and a question), if we want to do standard QALM, then we should restrict the interaction between the sentence and question, as shown in Fig. 1(a). Results show that this distinction is important for QALM to perform effectively for single-input tasks. In summary, our second contribution is that we are the first to distinguish between these two types of semantic representations, and we also propose separate models for each of them.

Our third contribution is the discovery that QALM based on QAMR data can almost universally improve on a wide range of tasks, especially when direct training data are limited. This suggests that, while AMR (Banarescu et al., 2013) is a useful symbolic representation for semantics, we can also take advantage of AMR by learning from much cheaper QA pairs dedicated to it. The appealing idea is that if we guide human annotators to propose and solve questions related to a certain semantic phenomenon, then we may obtain latent representations dedicated for that phenomenon, and then, improve on relevant tasks.

The rest of this paper is organized as follows. Section 2 describes our QALM framework in detail, including the distinction between standard QALM and conditional QALM, and Section 3 shows our experiments using QALM. Section 4 focuses on analyzing the usage and extension of our framework, and Section 5 discusses the difficulties of alternative methods. Section 6 concludes our work and points out future directions.

2 QA-driven Language Modeling

The recent decade has seen significant progress in NLP due to the success of machine learning, but most methods heavily rely on costly annotations. The importance of being able to use cheap signals
has attracted researchers’ attention. For instance, Roth (2017) proposes the concept of getting supervision signals that occur incidentally. The incidental signals can be noisy, partial, or only correlated with the target task. Dehghani et al. (2018) and Ning et al. (2019) are two recent examples among the large number of works along this line. Here our goal is to learn latent semantic representations from QA pairs,\(^2\) which is also an example of incidental supervision (Roth, 2017). Since we extensively use BERT to help us handle the syntactic and lexical variations in QA, we also call it QA-driven language modeling (QALM). However, the specific choice of LM is orthogonal to our proposal and the same idea still applies for other LMs (e.g., RoBERTa (Liu et al., 2019)).

\(^2\) We consider the same format of questions and answers as those in (Michael et al., 2017) except that the answer must be a continuous span in a sentence.

2.1 Two Semantic Representations

Previous semantic representations try to encode as many meaning ingredients as possible for a sentence. However, these semantic representations might not be a good choice for paired-input tasks, such as MRC and TE. MRC aims to predict the start and end positions of the answer given a paragraph and a question, and TE determines whether a hypothesis can be entailed by a premise. In these two tasks, not all the semantic information about the paragraph or hypothesis is needed. Instead, we only care about the information that is related to the question or premise. Therefore, we propose to distinguish these two types of semantic representations as standard semantic representation and conditional semantic representation.

Standard semantic representation encodes all semantic information \( h(S) \) for a sentence \( S \), while conditional semantic information encodes the information based on the attention \( h(S|A) \) for the sentence \( S \) given some attention \( A \). In a perfect world, standard semantic representation also includes conditional semantic representation. However, we believe that there is a trade-off between the quality and the quantity of semantic information that a model can encode in practice. As shown later in Fig. 2, the quality of our standard QALM that tries to encode as much semantic information as possible, is significantly worse than that of conditional QALM, which only cares about the semantic information based on some attention. For example, in sentence (4) of Table 1, when asked “What country is the former post office in?”, our conditional QALM answers correctly: “United States,” while standard QALM gives the wrong prediction: “Mississippi.”

To retrieve semantic information from simple question-answer pairs for downstream tasks, we propose two different models, standard QALM and conditional QALM for two different types of semantics. Both models try to encode semantic information into the latent distributional represen-
Table 2: The results of standard QALM on SRL, SDP, NER, RE and Coref. Baselines(BERT) denotes baseline models using BERT embeddings. We also show the improvement of standard QALM by training on a small set of the dataset. For NER, SRL, SDP, we use the development set as a small training set. For SDP and RE, we use 10% of the training examples as a small set, because there are no development sets in related datasets.

Table 3: The results of conditional QALM on NER, sentiment, TE and MRC. To show the benefit of conditional QALM on a small number of examples, we also train our models on 10% of training set. For simplicity, we use the uncased NER for BERT fine-tuning, because our conditional QALM is uncased.

For standard semantic representation, our goal is to encode as many meaning ingredients as possible into our latent distributional representation. We use standard QALM as shown in Fig. 1(a) for single-input tasks. In order to force the sentence component to encode more semantic information, the interaction layer of the architecture should be as simple as possible.

For conditional semantic representation, we directly use BERT as our model to pre-train on simple question-answer pairs, because the bidirectional transformer is a good architecture to learn how to attend. We use components in the black box in Figure 1(b) to provide semantic information for paired-input tasks.

### 2.2 Standard QALM

#### 2.2.1 Learning

Our models consist of three basic components: a semantic sentence encoder for the sentence component, a question encoder for the question component, an interaction layer between the sentence component and the question component. We experiment on five variants of our basic model as follows: (I) Basic model: a fixed BERT and one-layer bidirectional transformer for semantic sentence encoder, a fixed BERT and one-layer bidirectional transformer for question encoder, and a two-layer multi-layer perceptron (MLP) for the interaction layer; (II) a fine-tuned BERT; (III) the same as model II, with a bi-directional attention flow added to the question component; (IV) the same as model III, with the interaction layer changed from a two-layer MLP to a bidirectional transformer; (V) the same as model IV, with the interaction layer changed from a one-layer bi-directional transformer to a two-layer one, and beam search is used in the inference stage.

We call the best model (i.e., model V) “standard QALM” and its architecture is shown in Figure 1(a). Tenney et al. (2019a) conclude that lower layers of BERT encode more local syntax, while higher layers capture more complex semantics. This finding is consistent with the intuition of standard QALM, because we add a sentence modeling layer on top of above BERT to capture semantic information.

#### 2.2.2 Application: Single-Input Tasks

Given a sentence \([w_1, w_2, \ldots, w_n]\), our standard QALM can provide a sequence of hidden vectors as \([h_1, h_2, \ldots, h_n]\).\(^3\) In single-input tasks, we use standard QALM to extract extra semantic features, and concatenate it to word embeddings of the original model at the input layer. Standard QALM

\(^3\)The hidden vector can be the last layer or the weighted sum of all layers as discussed in Section 4.3
can be fine-tuned when trained on specific tasks. Therefore, it can be directly applied to different tasks based on word embeddings.

2.3 Conditional QALM

2.3.1 Learning

We use BERT to pre-train on QAMR and get conditional QALM as shown in Figure 1(b) for paired-input tasks. Why do we choose to pre-train our models on QAMR rather than other MRC datasets? Because QAMR has a simpler concept class and is more general than MRC. Therefore, the training of QAMR requires less examples and the model pre-trained on QAMR can help more tasks.

2.3.2 Application: Paired-Input Tasks

Given a sentence \( S = [w_1, w_2, \ldots, w_n] \) based on an attention \( A = [q_1, q_2, \ldots, q_m] \), our conditional QALM can provide a latent distributional representation \( h(S|A) = [h_1, h_2, \ldots, h_n] \). We add conditional QALM to the layer before the classification layer, and fine-tune it on downstream tasks.

Machine Reading Comprehension. In this task, our conditional QALM will provide a conditional semantic representation for paragraph \( P \) with the attention of question \( Q \) as \( h(P|Q) = [h_1, h_2, \ldots, h_n] \). For each token in the paragraph, the hidden vector \( h_t \) will be concatenated to the original token embeddings before the classification layer. It is a general method for token classification tasks.

Textual Entailment. Similarly, in this task, our conditional QALM will provide a conditional semantic representation for hypothesis \( H \) with the attention of premise \( P \) as \( h(H|P) = [h_1, h_2, \ldots, h_n] \). We first use the max pool and average pool to get related hidden vectors \( h_{\text{max}} \) and \( h_{\text{avg}} \), and then we concatenate these two vectors to the original BERT embeddings before the classification layer. It is a general method for sentence classification tasks.

3 Experiments

3.1 Standard QALM Experiments

To evaluate the efficiency of standard QALM, we first investigate whether it can provide extra information to BERT for strong baselines, and whether it can be used to improve current state-of-the-art (SoTA) models for single input tasks. In order to demonstrate that standard QALM embeddings contain semantic information, we evaluate our models on two different types of formal semantic schemes: SRL and semantic dependency parsing (SDP), and three tasks with different levels that require semantic information: NER, RE, and co-reference resolution (Coref). We use the re-implementation of AllenNLP for SRL, NER and Coref, and we implement SDP and RE ourselves.

Semantic Role Labeling. We use the CoNLL-2012 2012 English subset of OntoNotes 5.0 (Pradhan et al., 2013). There are about 278K training examples, 38.4K development examples, and 29.7K test examples in this dataset. We use the deep neural model in (He et al., 2017), and replace GloVe embeddings with BERT embeddings as a strong baseline. The state-of-the-art model is the same SRL model with ELMo embeddings.

Semantic Dependency Parsing. We use the dataset from SemEval 2015 shared task (Oepen et al., 2015) with DELPH-IN MRS-Derived Se-

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Table 4: The effect of adding existing resources, Large QA-SRL and QA-RE, on pre-training RL and RE. BERT denotes baseline models using BERT embeddings. QALM denotes baseline models using standard QALM embeddings. QALM(+) for SRL means the standard QALM is pre-trained on QAMR and Large QA-SRL, and QALM(+) for RE means the standard QALM is pre-trained on QAMR and QA-RE.

| Tasks            | SRL  |
|------------------|------|
| Split            | 10%  |
| BERT             | 34.16|
| QALM             | 100% |
| QALM(+QA-RE)     | 45.15|
| QALM(+LargeQA-SRL) | 53.37|

Table 5: The effect of adding different existing resources, Large QA-SRL and QA-RE, on pre-training RL and RE. BERT denotes baseline models using BERT embeddings. QALM denotes baseline models using standard QALM embeddings. QALM(+) for SRL means the standard QALM is pre-trained on QAMR and Large QA-SRL, and QALM(+) for RE means the standard QALM is pre-trained on QAMR and QA-RE.

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Although LISA (Strubell et al., 2018) has performed slightly better on SRL, they didn’t report the results on CoNLL-2012 with gold predicates.
Figure 2: Error analysis for standard QALM on the sentence length. We compare the performance of standard QALM and conditional QALM on examples with different sentence lengths in the test set.

Semantic Dependencies (DM) target representation. There are 35,656 training examples and 1,410 test examples in the dataset. We use the same biaffine network as that in Dozat and Manning (2018) without part-of-speech (PoS) tags and replace GloVe with BERT embeddings. This re-implementation also serves as the state-of-the-art model without PoS tags, character embeddings and lemmas.

Named Entity Recognition. We use CoNLL 2003 dataset (Tjong Kim Sang and De Meulder, 2003). There are 14,987 examples in the training set, 3,466 examples in the development set, and 3,684 examples in the test set. We use the same baseline of NER in (Peters et al., 2018) and replace GloVe with BERT embeddings as a strong baseline. The state-of-the-art model (Flair) uses contextual string embeddings and a BiLSTM-CRF sequence tagger (Akbik et al., 2018).

Relation Extraction. We use Semeval 2010 Task 8 (Hendrickx et al., 2009) as our data. The dataset contains 8,000 sentences for training, and 2,717 for testing. We use a attention-based BiLSTM (Zhou et al., 2016) as a strong baseline, and use BERT embeddings as word embeddings. This model also serves as our current state-of-the-art model.

Co-reference Resolution. We use CoNLL 2012 shared task (Pradhan et al., 2012). This dataset contains 2,802 training documents, 343 development documents, and 348 test documents. The average number of words per document is 454, and the longest document has 4,009 words. We use the model of (Lee et al., 2017) and replace GloVe with BERT embeddings as a strong baseline. The baseline uses independent LSTMs for every sentence, since cross-sentence context is not helpful in experiments. The same model with ELMo embeddings is considered as the state-of-the-art model.

Result. Experimental results are shown in Table 2. The performance of baseline models has improved on all five tasks with small training data, when standard QALM embeddings are concatenated to BERT embeddings. If the number of training data increases, baseline models with standard QALM embeddings still perform as well as those without standard QALM embeddings. It indicates that our standard QALM can provide extra information to BERT, and can be used to improve BERT embeddings by simple concatenation. Similarly, if standard QALM embeddings are concatenated to embeddings in state-of-the-art models, even though embeddings used in original SOTA models are various (ELMo, Flair etc.), the performance has nevertheless improved on all five tasks with small training data. Empirical results reveal that our standard QALM can help outperform current state-of-the-art models by simple concatenation.

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6In practice, we do not have gold PoS tags as input for SDP, so we think that this is a more realistic and simpler setting for our experiments.

7The state-of-the-art model (Wang et al., 2016) didn’t release their code. Several re-implementations, including ours, don’t achieve comparable results.

8Although Lee et al. (2018) achieves better performance, they only adapted a higher-order inference for co-reference without changing the model itself.
| Models | Model I | Model II | Model III | Model IV | Model V |
|--------|---------|----------|-----------|----------|---------|
| Average EM | 34.97   | 41.64   | 55.68     | 64.18    | 66.77   |
| Average F1  | 40.05  | 45.49   | 62.98     | 72.96    | 76.20   |

Table 6: The results of five variants of standard QALM on the development set of QAMR. We use the average exact match (EM) and average F1 as our evaluation metrics.

| Train | 0-10 | 10-20 | 20-30 | 30-40 | 40-50 | >=50 |
|-------|------|-------|-------|-------|-------|------|
| Average QA Pairs | 3 | 8 | 13 | 18 | 24 | 33 |

| Test | 0-10 | 10-20 | 20-30 | 30-40 | 40-50 | >=50 |
|------|------|-------|-------|-------|-------|------|
| Average QA Pairs | 8 | 23 | 38 | 56 | 77 | 92 |

Table 7: The average number of QA pairs with different sentence lengths in QAMR.

3.2 Conditional QALM Experiments

We compare the results of BERT and BERT concatenated with conditional QALM embeddings on two core tasks, MRC and TE. Because conditional QALM is based on attention, which is universal in NLP tasks, we further apply it to two single-input tasks, NER and sentiment analysis.

3.2.1 Paired-Input Tasks

Machine Reading Comprehension. We use SQuAD 1.0 (Rajpurkar et al., 2016) as our dataset, and BERT as a strong baseline. The model is tested on the development set and the dataset consists of 87599 training examples and 10570 development examples.

Textual Entailment. We use MNLI (Williams et al., 2018) as our dataset. BERT is used again as a strong baseline. The model is tested on the development set for matched examples. There are 392702 training examples, 9815 development examples and 9796 test examples in the dataset.

3.2.2 Single-Input Tasks

Named Entity Recognition. We use CoNLL 2003 dataset. There are 14987 examples in the training set and 3466 examples in the development set. Our model is trained on the train set and evaluated on the development set.

Sentiment Analysis. We use Stanford Sentiment Treebank (Socher et al., 2013), which is also SST-2 in GLUE (Wang et al., 2018). There are 67349 training examples and 872 examples in the development set for binary sentiment classification. We use BERT as a strong baseline. The model is trained on the training set and evaluated on the development set.

Result. Experimental results are shown in Table 3. Conditional QALM can improve BERT on both paired-input and single-input tasks with small training data. If the number of training data increases, BERT with conditional QALM still performs as well as BERT. In addition to BERT, conditional QALM can capture extra information and can be used to improve BERT by concatenating two representations before the classification layer and fine-tuning them together. The efficiency of conditional QALM on single-input tasks also verifies the adaptability of our proposals.

3.3 Comparison with Formal Semantic Representations

Comparison with SRL. He et al. (2015) show that question-answer pairs in QA-SRL often contain inferred relations, especially for why, when and where questions. These inferred relations are typically correct, but outside the scope of PropBank annotations (Kingsbury and Palmer, 2002). This indicates that QA-SRL contains some extra information about predicates. Some examples are shown in Table 1. We further verify that conditional QALM can correctly answer questions in the examples, which means that our model can encode some extra information that SRL cannot.

Comparison with AMR. Michael et al. (2017) show that QAMR can capture a variety of phenomena that are not modeled in traditional representations of predicate-argument structure, including instances of co-reference, implicit and inferred arguments, and implicit relations (for example, between nouns and their modifiers). Some examples of QAMR are shown in Table 1. Similar to SRL, we find that conditional QALM precedes traditional representations, such as AMR, by correctly answering questions in the examples and hence encoding extra information.

Discussion. These simple examples show that our
Table 8: Different combinations of BERT and QALM on NER. f-BERT denotes a fine-tuned BERT, f-QALM denotes a fine-tuned QALM, and f-QALM(modeling) is a QALM with a fine-tuned modeling component and a fixed BERT component. All models are trained on the development set and tested on the test set.

| Tasks               | NER  |
|---------------------|------|
| BERT                | 88.89|
| f-BERT              | 72.00|
| BERT+QALM           | 89.79|
| BERT+f-QALM         | 88.38|
| f-BERT+f-QALM       | 71.13|
| BERT+f-QALM(modeling)| **89.89** |

conditional QALM can encode extra information which previous formal semantic representations don’t include, because of the flexibility of natural format of question-answer pairs.

4 Analysis

4.1 Improving QALM with Existing Resource

We investigate whether adding Large QA-SRL dataset (FitzGerald et al., 2018) and QA-RE\(^9\) dataset (Levy et al., 2017) in the pre-training stage can help SRL and RE. For simplicity, we use a simple BiLSTM baseline with the input of BERT embeddings and binary features of predicates for SRL and a simple CNN baseline with the input of BERT embeddings and position features for RE. We use QALM embeddings to replace\(^10\) BERT embeddings rather than concatenate the two embeddings.

Improving SRL with Large QA-SRL dataset.

We add Large QA-SRL dataset to QAMR for pre-training to see whether more question-answer pairs related to SRL can get a better sentence representation for SRL\(^11\).

Improving SRL with QA-RE dataset. We add QA-RE dataset to QAMR for pre-training and test the model on SRL to see whether more question-answer pairs related to the semantics of the sentence can get a better sentence representation in general.

Improving Relation Classification with QA-RE dataset. We add QA-RE dataset to QAMR for pre-training to see whether more question-answer pairs related to RE can get a better sentence representation for RE.

Discussions. The effect of adding existing resources, Large QA-SRL and QA-RE, on pre-training SRL and RE are shown in Table 4 and Table 5. We find that adding related question-answer pairs in the pre-training stage can help improve specific tasks. Noteworthy is the fact that QA-RE can also help SRL, the improvement is minor compared to Large QA-SRL though. This indicates that adding more question-answer pairs related to the semantics of the sentence can get a better semantic representation in general.

4.2 Error Analysis

The results of our models on the development set of QAMR\(^{12}\) dataset are shown in Table 6. The F1 scores of standard QALM and conditional QALM on the test set are 66.78 and 84.11. In general, the results of our standard QALM are similar to BiDAF (Seo et al., 2017) but are significantly worse than the conditional QALM on QAMR. We conduct thorough error analysis including: sentence length, answer length, question length, question words and the PoS tag of the answer. We find that standard QALM is not good at dealing with long sentences compared to conditional QALM. The analysis of sentence length is shown in Figure 2. We also find that the average number of question-answer pairs is much larger when the sentence is longer as shown in Table 7. The distribution of training set and dev/test set is quite different, which makes the situation more complicated. We further compare standard QALM and conditional QALM on Large QA-SRL whose distribution of train, dev and test are same. The result still shows that standard QALM is not as good as conditional QALM.

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\(^9\)Because the training set of QA-RE is too large, we randomly choose 100,000 training examples.

\(^{10}\)In general, replacing is similar to concatenation, but it has more impact on the performance of models. Therefore, replacing can either better improve, or worsen the performance.

\(^{11}\)We use propbank for experiments, because ontonotes dataset is too large and training it is time-consuming.

\(^{12}\)We only consider question-answer pairs whose answer is a continuous span in the sentence.
| Tasks                  | NER     |
|------------------------|---------|
|                         | 10%     | 100%  |
| Standard QALM(SQuAD)   | 89.78   | 91.77 |
| Standard QALM          | 89.79   | 92.14 |

Table 10: To show the importance of QAMR, we compare our standard QALM with a standard QALM pre-trained on SQuAD (denoted as QALM(SQuAD)) for NER. We simply concatenate the standard QALM features with BERT embeddings at the input layer without fine-tuning any components.

| Tasks                  | NER     |
|------------------------|---------|
|                         | 10%     | 100%  |
| Conditional QALM(SQuAD)| 86.57   | 93.89 |
| Conditional QALM       | 86.89   | 94.10 |

Table 11: To show the importance of QAMR, we compare our conditional QALM with a conditional QALM pre-trained on SQuAD (denoted as Conditional QALM(SQuAD)) for uncased NER.

as conditional QALM at long sentences. We conclude that the failure of standard QALM in long sentences is mainly because there are more relations to encode, while conditional QALM only needs to encode information based on specific questions.

4.3 Using Standard QALM

Different Layers of Standard QALM. We mainly consider two types of features extracted from QALM, the last hidden layer and the weighted sum of all layers like ELMo. We compare these two types of features in NER. The F1 score of NER baseline with the last hidden layer and weighted sum of all layers in QALM is 91.58 and 92.14 respectively. The results are consistent with those of (Devlin et al., 2019). We find that the weighted sum of all layers is a better choice in general, but the last hidden layer is also a good substitute.

Fine-tuning Standard QALM. We compare different combinations of BERT and QALM on NER as shown in Table 8. We find that fine-tuning all models does not yield good results as one may expect, while fine-tuning the modeling component is the best choice in some situations. Although fine-tuning the modeling component can be worse than the one without – for example, fine-tuning the modeling component of NER in the full data setting achieves an F1 score of 91.68, while it achieves 92.14 without fine-tuning – they are at least close in general.

4.4 Why Standard QALM on Feature Based Single-Input Tasks?

Since conditional QALM can also capture semantic information, a natural question arises: Why don’t we use conditional QALM instead of standard QALM for feature-based single-input tasks? The intuitive answer is that, we need to encode as much information as possible into a sentence embedding for single-input tasks, while conditional QALM can only encode the information related to the attention. We further compare standard QALM with conditional QALM on two feature based single-input tasks, SRL and SDP. The results are shown in Table 9. Rather than concatenate two embeddings, we replace BERT embeddings with QALM embeddings. For simplicity, we use a simple BiLSTM model for SRL\(^\text{13}\) and a simple Biaffine model based on BiLSTM for SDP. The results indicate that QALM has a great advantage in feature based single-input tasks.

4.5 The Choice of Pre-training Data

Our standard QALM vs standard QALM pre-trained on SQuAD. We compare our standard QALM with standard QALM pre-trained on SQuAD for the task of NER. The results are shown in Table 10, and ours outperforms in both settings.

Our conditional QALM vs conditional QALM pre-trained on SQuAD. We compare our conditional QALM with conditional QALM pre-trained on SQuAD for the task of uncased NER. The results are shown in Table 11. Again, the original conditional QALM yields better results.

Discussions. The results are consistent with our analysis in Section 2.3.1. Because the concept class of QAMR is simpler than SQuAD, we can achieve better results using standard and conditional QALM with less training examples (51K in QAMR and 88K in SQuAD). This is of low annotation cost, because SQuAD is based on paragraphs (117 words on average), while QAMR is based on sentences (24 words on average). We are aware that QAMR is not a perfect dataset because of its limited number of examples. It is not surprising that other datasets can outperform it in some tasks. However, QAMR is a good dataset.

\(^{13}\)We use Propbank here because of the large size of ontonotes.
for our model to be pre-trained on and it can help many tasks in general. As shown in Section 4.1, we also find that if the question-answer pairs are more related to a task, for example, Large QA-SRL is more related to SRL than QA-RE, then these QA pairs can better improve the task.

5 Difficulties of Alternative Methods

We propose to retrieve latent distributional representations from question-answer pairs based on the sentence meaning and apply them to downstream tasks. Can we use other semantic representations? In this section, we discuss the difficulties of two other possible methods and conclude that neither of them is as tractable as ours.

5.1 Formal Semantic Schemes

5.1.1 Learning Formal Semantic Schemes from Question-Answer Pairs

We consider learning a SRL parser from QA-SRL. It reduces the problem of learning formal semantic schemes from QA pairs to a simplified case.

Challenges. There are four main challenges to learn a SRL parser from Large QA-SRL.

• Partial issues. We get partial supervision: Only 78% of the arguments have overlapped with answers; 47% of the arguments are exact match; 65% of the arguments have Intersection/Union $\geq 0.5$.

• Irrelevant question-answer pairs. Supporting statistics: 89% of the answers are “covered” by SRL arguments; 54% of the answers are exact match with arguments; 73% of the answers have Intersection/Union $\geq 0.5$. These statistics show that we also get some irrelevant signals: some of the answers are not really arguments (for the corresponding predicate).

• Different guidelines. Even if the arguments and the answer overlap, the overlap is only partial.

• Cross domain issues. We need to evaluate the trained SRL model on Propbank, but corresponding QA pairs are not annotated in Propbank dataset. For example, Large QA-SRL annotates sentences in three domains: Wikipedia, Wikinews and Science.

A reasonable upperbound. We treat the answers that have overlapped with some arguments as our predicted arguments. If two predicted arguments intersect each other, we will use the union of them as new predicted arguments. The results are shown in Table 12. We know from the table that this mapping algorithm achieves a span F1 of 56.61, which is a reasonable upper bound of our SRL system.

Baselines. We consider three strong baselines to learn a SRL parser from Large QA-SRL dataset.

• Rules + EM. We first use rules to change question-answer pairs to labels of SRL. We keep the labels with high precision and then use an EM algorithm to do bootstrapping. A simple BiLSTM is used as our model for SRL. The results are shown in Table 12. We think that low token F1 is due to the low partial rate of tokens ($37.97\%$) after the initialization.

• PerArgument + CoDL + Multitask. We consider a simpler setting here. A small number of gold SRL annotations are provided as seeds. To alleviate the negative impact of low partial rate, we propose to train different BiLSTM models for different arguments (PerArgument) and do global inference to get structured predictions. We first use seeds to train the PerArgument model and then use CoDL (Chang et al., 2007) to introduce constraints,

### Table 12: Results of learning a SRL parser from question-answer pairs.

| Models                                    | Span          |                |            | Token         |                  |                  |                  |                  |
|-------------------------------------------|---------------|----------------|------------|---------------|------------------|------------------|------------------|------------------|
|                                           | Precision     | Recall         | F1         | Precision     | Recall           | F1               | Precision     | Recall           | F1               |
| Rules + EM                                | 24.31         | 22.78          | 23.52      | 34.34         | 32.27            | 33.27            | 50.46         | 28.19            | 36.17            |
| PerArgument + CoDL + Multitask            | 32.02         | 12.30          | 17.77      | 46.99         | 18.06            | 26.09            | 70.76         | 17.80            | 25.45            |
| Argument Classifier + Argument Classifer  | 49.19         | 43.09          | 45.94      | 57.84         | 50.82            | 54.10            | 69.37         | 47.60            | 56.45            |
| Mapping: upper-bound                      | 67.82         | 48.58          | 56.61      | 89.09         | 65.82            | 75.70            | 91.57         | 70.25            | 79.50            |

14These statistics of partial issues and irrelevant question-answer pairs are based on the PTB set of QA-SRL.

15Given a predicate in the sentence with three arguments and one of them is annotated, the sentence is partial for a traditional SRL model but not partial for a PerArgument model.
such as SRL constraints, into bootstrapping. At the same time, we train a model to predict the argument type from question-answer pairs. These two tasks (argument type prediction and SRL) are learned together through soft parameter sharing. In this way, we make use of the information from question-answer pairs for SRL. We use 500 seeds to bootstrap. The span F1 of our method is 17.77 and the span F1 with only seeds is 13.65. More details are in Table 12. The performance of baseline model has only improved several percents compared to the model trained only on seeds.

- **Argument Detector + Argument Classifier.**
  Given a small number of gold SRL annotations and a large number of question-answer pairs, there are two methods to learn an end-to-end SRL system. One is to assign argument types to answers in the context of corresponding questions using rules, and learn an end-to-end SRL model based on the predicted SRL data. This is exactly our first baseline, Rules + EM. However, the poor precision of argument classification leads to unsatisfactory results. Another method is to learn from small seeds and bootstrap from large number of QA pairs. This is our second baseline model, PerArgument + CoDL + Multitask. However, bootstrapping can not improve argument detection much, leading to mediocre results. We also notice that argument detection is hard with a small number of annotated data, but argument classification is easy with little high-quality annotated data. Fortunately, most answers in Large QA-SRL overlap with arguments. Furthermore, the mapping results of argument detection is about 56.61, good enough compared to two baselines. We propose to learn two components for SRL, one is for argument detection and the other is for argument classifier. We use the span-based model in (FitzGerald et al., 2018) for argument detection. The argument classifier is trained on predicates in the PTB set of QA-SRL. The results are shown in Table 12.

5.1.2 Using Formal Semantic Schemes in Downstream Tasks

There have already been some attempts to use formal semantic schemes in downstream tasks. We discuss three types of application here. Traditionally, semantic parsers can be used to extract semantic abstractions, and can be applied to question answering (Khashabi et al., 2018). Second, dependency graphs, such as SDP, can be incorporated into neural networks. For example, (Marcheggiani and Titov, 2017) encodes semantic information in Graph Convolution Networks (GCN). In order to use constituent based formal semantic representations, one can encode related semantic information by multi-task learning (MTL). (Strubell et al., 2018) mentioned such an example of application. **Discussions.** The main difficulty of retrieving formal semantic representations for downstream tasks is to learn a good parser for formal semantic schemes from question-answer pairs.

5.2 QAMR as a symbolic representation

**Learning a QAMR parser.** In Large QA-SRL, the exact match for question generation is only 47.2, although the span detector achieves an exact match of 82.2. As for QAMR, Michael et al. (2017) show that question generation can only achieves a precision of 28%, and a recall of 24%, even with fuzzy matching (multi-BLEU > 0.8). From these results, we know that it is question generation that mainly hinders learning a QAMR parser. **Using QAMR in Downstream Tasks.** Stanovsky et al. (2018) show that a QAMR can be converted to a list of OpenIE extractions by using a syntactic dependency parser, and augmenting their training data with conversion of the QAMR dataset yields state-of-the-art performance on several OpenIE benchmarks. However, similar to SRL, OpenIE is more of a formal semantic representation than a downstream task. Is it still unclear how to use QAMR on downstream tasks, such as general QA and textual entailment. Another direction is to use the QAMR graph as shown in (Michael et al., 2017) for downstream tasks. However, the labels of graph edges are questions, making the graph difficult to put into use directly. Alternatively, We can simply utilize the relations without labels, but it will definitely lose some important information. **Discussions.** In a word, learning a QAMR parser

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16 Note that an end-to-end SRL system is with gold predicates. This is different from an end-to-end SRL task in previous publications.

17 An average of BLEU1–BLEU4 scores.
for downstream tasks is mainly hindered by question generation, and how to use the full information of QAMR for downstream tasks is still unclear.

6 Conclusion and Future Work

In this paper, we investigate an important problem in NLP: Can we make use of low-cost signals, such as QA signals, to help related tasks? We retrieve signals from sentence-level QA pairs to help NLP tasks via two types of semantics. For tasks with a single-input sequence, such as SRL and coreference, we propose standard QALM that provides latent sentence-level representations. For tasks with a paired-input sequence, such as TE and MRC, we propose conditional QALM that provides latent sentence-level representations related to some attentions (e.g., questions for paragraphs in MRC and premises for hypotheses in TE). Experiments on five single-input tasks and two paired-input tasks show our standard QALM and conditional QALM are indeed effective, especially in the low-resource setting.

This paper can be viewed from three perspectives. First, we propose a new practical framework for incidental supervision. We successfully retrieve incidental supervision signals by pre-training standard QALM and conditional QALM on question-answering data. This pre-training method distinguishes itself from previous incidental supervision methods, such as response-driven learning (Clarke et al., 2010), in that it can use general signals for many tasks rather than task-specific signals.

Second, QALM is a new and applicable semantic representation. Previous formal semantic representations, such as SRL and AMR, not only suffer from costly annotations, but is also not flexible because of the pre-defined formalism. Moreover, it still remains unclear how other tasks can take advantage of QA pairs in QA-SRL and QAMR. In order to benefit from cheap annotation labor and flexibility, we still use the format of question-answer pairs to collect data as in QA-SRL/QAMR. However, instead of using question-answer pairs as the final semantic representation, our standard and conditional QALM retrieve a latent distributional representation of the signals carried by these question-answer pairs.

Third, QALM is a new language model for contextualized word representations. Previous unsupervised LMs (ULMs), such as Elmo and BERT, do not perform well in semantic tasks (Tenney et al., 2019b). Although CoVe (McCann et al., 2017) is trained on translation signals, it is significantly worse than Elmo and BERT in helping NLP tasks (Peters et al., 2018) and probing analysis(Tenney et al., 2019b). Our standard and conditional QALMs are able to provide extra information that BERT doesn’t include especially on semantic tasks. Our QALMs precede these ULMs by making use of low-cost signals, and it is orthogonal to other ULMs (e.g., we can have a similar QALMs for XLNet (Yang et al., 2019)).

Future work involves various directions. We list a few here. First, probing the contextualized word embeddings of our QALMs and understanding their sentence representations are worth exploring. Second, it is interesting to see how existing resources can be mostly utilized by QALMs. An example is to design some heuristic rules to generate simple question-answer pairs from coreference dataset. Additionally, our QALMs can be improved with the help of stronger language models, such as XLNet or RoBERTa (Liu et al., 2019). The problem of QALM performing poorly in long sentences also needs to be addressed.

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