ABSTRACT
We study the problem of event extraction from text data, which requires both detecting target event types and their arguments. Typically, both the event detection and argument detection subtasks are formulated as supervised sequence labeling problems. We argue that the event extraction models so trained are inherently label-hungry, and can generalize poorly across domains and text genres. We propose a reading comprehension framework for event extraction. Specifically, we formulate event detection as a textual entailment prediction problem, and argument detection as a question answering problem. By constructing proper query templates, our approach can effectively distill rich knowledge about tasks and label semantics from pretrained reading comprehension models. Moreover, our model can be fine-tuned with a small amount of data to boost its performance. Our experiment results show that our method performs strongly for zero-shot and few-shot event extraction, and it achieves state-of-the-art performance on the ACE 2005 benchmark when trained with full supervision.

ACM Reference Format:
Rui Feng, Jie Yuan, and Chao Zhang. 2020. Probing and Fine-tuning Reading Comprehension Models for Few-shot Event Extraction. In Proceedings of ACM Conference (Conference’17). ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION
Event extraction is one of the most important and challenging tasks in information extraction. Event extraction consists of two subtasks: 1) The first task, event detection, is to detect if natural language text describes the occurrence of certain events. 2) The second task, argument detection, aims to find the attributes and participants, such as “when”, “where”, and “who”, to the events. Typically, both tasks are formulated as supervised sequence labeling problems: event detection is usually formulated as detecting the trigger words or phrases that best “indicate” an event; and argument detection is formulated as identifying entities that serve as arguments, such as “who”, “when”, and “where” for that event type. Various sequence labeling models [3, 4, 10, 14, 21, 25, 28–31, 33, 39, 40, 46, 47] have been proposed, which can be trained on an annotated corpus and then used for recognizing event triggers and arguments at test time.

For example, the following sentence is extracted from ACE05 event extraction benchmark [9]:

“Orders went out today to deploy 17,000 US soldiers in the Persian Gulf region.”

In the above example, an event “Transport” happened, deploy is annotated as its trigger word, and Persian Gulf region is the Destination argument to the event, and 17,000 US soldiers would be the Artifact (interpreted as passengers).

However, formulating event extraction as supervised sequence labeling tasks have several drawbacks. For event detection, the annotation of event trigger words is of high variance. As the definition of “trigger words” is the word that most “clearly” expresses the occurrence of the event [5, 22], it is inherently noisy and time-consuming to label, especially in complex documents [22]. This requires developing a specific set of rules governing ambiguity during annotation. Even so, the model is not necessarily able to recognize, or benefited from, such knowledge. The annotation of arguments suffers from the same problem, as the span can be arbitrary (is it “U.S. soldiers” or “17,000 U.S. soldiers”, or just simply “soldiers”? All of them are valid answers.) Some existing approaches [11, 21, 24, 39, 44] attempt to resolve these issues by introducing more complex structural features (such as dependency parses and document-level information) or use more complex neural sequential models. But as a result, learning such complex models becomes highly label hungry, even when powerful pretrained language models are used [10, 40, 46]. Furthermore, the learned model can easily overfit and be vulnerable to domain shift. As reported in [33], when rigorously tested with multiple random initializations, many works suffer from a severe performance drop compared with the best performance reported in their papers.

We propose to formulate event extraction as a machine reading comprehension task. The general format of machine reading comprehension is that given a query and a context sentence, the algorithm finds the answer to the query conditioned on the context sentence. Specifically, we formulate event detection as a textual entailment prediction task. The underlying intuition is that, suppose a sentence describes an event, then a statement that this event has happened then used for recognizing event triggers and arguments at test time.

We formulate argument extraction as a question answering problem. Finding an argument to an event can be naturally posed as
Where is the destination of the transport? In principle, argument when the model is fed a small amount of labeled data. In fully-
we construct natural language questions about the argument
discarding trigger words for event detection.

found that trigger words do not improve performance for either
supervised settings, it achieve state-of-the-art performance. (3) We
achieve strong performance for zero-shot event detection without
training data. (2) The performance of our model increases largely
in zero-shot, few-shot, and fully-supervised settings in Section 4.

Our major findings from the experiments are: (1) We propose a reading comprehension framework for event
detection and argument detection. Comparing with existing works, our
framework is more capable in exploiting pre-trained reading
comprehension models on tasks and event semantics.

(2) We are the first to propose a reading comprehension frame-
work of event detection and argument detection without trigger
words.

(3) By probing and fine-tuning pretrained reading comprehen-
sion models, our approach achieves much stronger perform-
ance for low-shot event extraction compared with the base-
lines; and it achieves state-of-the-art performance for fully-
supervised event detection on the ACE 2005 benchmark.

2 PRELIMINARY

2.1 Tasks Definition

Event extraction. The event extraction task consists of two sub-
tasks: event detection and argument detection. We describe these
tasks as follows.

• Event Detection. Following [22], we formulate event
detection as a multi-class sentence classification problem. Each
input sentence \( X = [x_1, \ldots, x_n] \) is associated with a binary
label vector \( y \in \mathbb{R}^m \) where \( m \) is the number of event types.
Each component corresponds to an event type and is 1 if and
only if the input sentence describes that event. Our goal is
to predict for each event whether it is described in the given
sentence.

• Argument detection. Following most related works, e.g. [4],
each sentence is annotated entities as candidate arguments.
Argument detection aims to determine, given the sentence,
a described event and an entity, whether the entity serves as
one of the predefined argument roles to that event.

Machine Reading Comprehension. We here give a working def-
nition of machine reading comprehension (MRC) tasks. Given a
context sentence \( X \), we feed the machine (model) a query \( Q \) in form
of natural language sentences. The model is expected to return the
answer to \( Q \) conditioned on the context \( X \).

Specifically, we consider two MRC tasks: 1) textual entailment
prediction and 2) question answering.

(1) Textual Entailment Prediction (TE). Textual entailment pre-
diction, as the name suggests, aims at classifying if a sentence
is the entailment of another. Specifically, given sentence \( X \)
and \( Q \), we query the model if \( Q \) is contradictory to, entailed
by, or neutral to \( X \). Recognizing textual entailment can be
formulated as a three-way classification task over sentence
pair \((X, Q)\).

(2) Question Answering (QA). We consider span-selection based
question answering. In other words, we assume that the an-
swer to the question can be found as a span of words in a
given piece of text. Specifically, given sentence \( X \) and ques-
tion \( Q \), the model finds a span in \( X \) by predicting the starting
and ending token of the span and returns it as the answer.

3 OUR APPROACH

In this section, we introduce our framework to solve event extraction
tasks by formulating them into reading comprehension problems.
We cast event detection as a textual entailment prediction problem
based on the intuition that a sentence should entail an event if the
latter is described in that sentence. We cast argument detection as a
question answering problem since questions can be naturally asked
about the specific arguments of an event. In the following, we first
provide high-level descriptions of such a framework in Section 3.1
and Section 3.2. We describe how we generate queries for these two
subtasks in Section 3.3, and finally detail our model along with its
probing and training procedures in Section 3.4.

3.1 Event Detection as Textual Entailment

To pose event detection as textual entailment prediction, given sen-
tence \( X \) and an event type, we first construct a statement \( Q \) that
claims the event type has happened. The task of determining whether an event has happened in $X$ is then translated to judging if $Q$ is a natural entailment to $X$. For example:

\[
(X) \text{ David is leaving to become chairman of London School of Economics. (Q) Hence, an event about Start of Position occurred.}
\]

In the above, the first sentence is the original input sentence to event detection, and the second italic sentence is a statement constructed for the queried event type, Start-Position. If the statement is entailed by the first sentence, we predict that the event has happened. We will describe in detail how to construct such $Q$ statements in Section 3.3.

3.2 Argument Detection as Question Answering

To convert argument detection to question answering, we construct a “Wh”-question $Q$ (a question that starts with an interrogative word, such as “What”, “Who”, and ‘Where’, etc.) about the concerned event and argument type, like the following:

\[
(Q) \text{ Where did the Meeting take place? (X)}
\]

But the Saint Petersburg summit ended without any formal declaration on Iraq.

Where the first italic sentence is a question about event Meet and the queried argument type is “Place”. We construct questions from fixed templates as well as manually written question forms for each possible combination of events and argument types. See Section 3.3 for details.

3.3 Query Generation

We introduced event extraction and machine reading comprehension tasks in Section 2.1, and how can the former be transformed as the latter in Section 3.1, 3.2. In this section, we describe how to generate queries for the two event extraction tasks, and how are combined with input sentences. After this, all preparations would be made for the model computation flow.

It is of crucial importance to generate high quality queries, i.e. statements about events for entailment-prediction-based event detection, and questions about events and argument types for question-answering-based argument detection, because the quality of queries determines 1) how the model distills information about tasks and labels from pretrained weights, and 2) how the model connect the semantics of events, arguments, and the sentence context.

**Statements for events.** We assume that each event type has a label name. To construct a statement about an event, we simply fill in the label name in the following template:

\[
\text{Hence, an event about [EVENT] happened.}
\]

where [EVENT] is the placeholder for event names.

This statement is supposed to serve as a guide to distill knowledge from the language model about both the task and the label. For the task, i.e. event detection, an ideal model should be informed that it is supposed to recognize “what has happened”. For the label, the model should recognize clues on the semantics of the event by its label name. In addition to label name, we expect that an natural language description of the event would further help us distill knowledge from the model. So, we append an optional piece of description on the event, acquired from the data’s annotation guide [5], to the above statement. Some examples of event descriptions are given in Table 1.

| Event   | Description                                                                 |
|---------|-----------------------------------------------------------------------------|
| Be-Born | A Be-Born Event occurs whenever a PERSON Entity is given birth to. Please note that we do not include the birth of other things or ideas. |
| Marry   | Marry events are official Events, where two people are married under the legal definition. |
| Divorce | A Divorce event occurs whenever two people are officially divorced under the legal definition of divorce. We do not include separations or church annulments. |
| Transfer-Money | Transfer-Money events refer to the giving, receiving, borrowing, or lending money when it is not in the context of purchasing something. The canonical examples are: (1) people giving money to organizations (and getting nothing tangible in return); and (2) organizations lending money to people or other orgs. |

**Table 1: Example event descriptions.**

**Questions for events and argument types.** Similar to events, each argument type has a label name as well. We have two options to construct a question for a pair of event and argument. First and most straightforwardly, we could use a fixed template similar to event statement:

\[
\text{Who or what participated as role [ARGUMENT] in the event [EVENT] ?}
\]

where argument names and event names are filled in respective slots.

This rather inflexible approach does not provide much information on the relation between events and arguments, since we assume the same query structure between all event-argument pairs. It is more natural to ask questions differently, specific to the concerned event and argument. For example, “What is the Person in event Start-Position?” is a lot less natural than “Who started a new position?”.

So, we manually composed a question for every pair of events and arguments based on descriptions in the annotation guide [5]. We do so by converting the description text to a question with minimal edit while ensuring that the concerned argument type appears in the question. For example, from “The people who are married.” we construct “Who are the married person?” “People” are changed to “Person” to match the concerned argument type name. Examples are given in Table 2.

| Event   | Arg. Type | Question                                      |
|---------|-----------|-----------------------------------------------|
| Marry   | Person    | Who are the married person?                   |
|         | Where     | Where does the marriage take place?           |
| Attack  | Attacker  | Who is the attacker?                          |
|         | Target    | Who is attacked?                              |

**Table 2: Example questions for event-argument pairs.**
3.4 Model Details

In the previous section we described how to transform event extraction tasks to reading comprehension tasks. In this section, we detail our model for solving these tasks, as well as how the model works in zero-shot and supervised settings.

BERT masked language model. First, we give an introduction to the backbone BERT model that outputs hidden representations for tokens and sentences as the backbone for textual entailment prediction and question answering.

BERT [8] model is a masked language model that consists of deep multihead attention layers. Given a pair of input sentences \( X(1), X(2), \) BERT first runs WordPiece [38] tokenizer to tokenize the both sentences into a sequence of token ids: \( \{x_1^{(1)}, \ldots, x_n^{(1)}\}, i = 1, 2 \). Then, two sentences are concatenated into one sequence:

\[
S = [(CLS), x_1^{(1)}, \ldots, x_n^{(1)}, [SEP], x_1^{(2)}, \ldots, x_n^{(2)}, [SEP]]
\]

(1)

where [CLS] is a special token at the beginning that is supposed to aggregate information in the two sentences, [SEP] is another special token used to inform separation between sentences. This combined sequence of tokens is the input to BERT model.

Textual entailment for event detection. To perform textual entailment prediction, we attach a linear classifier on top of the sentence embedding function:

\[
\ell = \text{softmax}(l_0 + l_1, l_1)
\]

(4)

The final loss function is the cross entropy function:

\[
\ell = \text{cross_entropy}(p_0, p_1; y) = -((1 - y) \log p_0 + y \log p_1)
\]

(5)

where \( y \) is a binary label that indicates whether the described event happens.

Question answering for argument detection. Given a question about an event and argument type, we need to predict the probability for each token as the starting or ending of the answer span. First, we collect the output embeddings from BERT for each token in the original sentence \( X \):

\[
[S_1, \ldots, S_n] = \text{BERT}(S)
\]

(6)

To obtain possible spans, we use two linear classifiers on token embeddings:

\[
[s^l_i, s^r_i] = \text{softmax}([S_1, \ldots, S_n] \ell W_l)
\]

\[
[s^l_i, s^r_i] = \text{softmax}([S_1, \ldots, S_n] \ell W_r)
\]

(7)

4 EXPERIMENTS

We report in this section the experiemnt results on event detection. In Section 4.1 we briefly introduce the dataset, ACE 2005, that we experiment on. For both of the two tasks, first, we probe the pretrained language model’s ability to infer events without specific training in Section 4.2.1, 4.3.1. Then, in Section 4.2.2,4.3.2, we report results when the model is finetuned on event detection and argument detection. Ablation studies were reported separately in Section 4.2.4, 4.3.4.

4.1 Data

We use ACE05 Multilingual Training Corpus [9] for event detection and argument detection. It contains 33 event types, 28 argument types, and sentences that come with various documents.

ACE2005 is observed to have domain shifts between its official training, development, and test set split: the training and dev. set contain informal documents such as web logs, while the test set is a collection of newswire articles [9, 33].

We follow the data split used by [4]. Table 3 gives data statistics.

| Data split | # sentences | # events | # arguments |
|------------|-------------|----------|-------------|
| Train      | 14626       | 4309     | 7702        |
| Dev        | 870         | 492      | 923         |
| Test       | 708         | 422      | 887         |

Table 3: Data statistics for training, development, and test set. We list here number of sentences, events, and arguments.

where \( W_l, W_r \in \mathbb{R}^{d \times 1} \), \( \text{softmax} \) normalizes logits across tokens, and \( s_i^l, s_i^r \) are scores of the ith token being the start or end of the answer span. Given ground-truth labels of span starts \( y_i^l \) and ends \( y_i^r \), the model optimizes the cross entropy loss:

\[
\ell = \ell^l + \ell^r
\]

\[
\ell^l = -\sum_{i=1}^n y_i \log s_i^l
\]

\[
\ell^r = -\sum_{i=1}^n y_i \log s_i^r
\]

(8)
to make a prediction, we follow [8] and predicts the span as \( i, j \) with the highest \( s_i^l + s_j^r \) satisfying \( i < j \). Additionally, unlike in the QA setting in SQuAD [36] and adopted by BERT [8], not every queried event and argument type pair has an answer. Hence, we only predict the answer when both \( s_i^l \) and \( s_j^r \) are greater than a certain threshold, typically 0.5.
Table 4: Zero-shot learning for event detection. Precision, Recall, F1-scores are evaluated on test set, with Threshold chosen to maximize F1-score on the development set. Any instance with predicted probability greater than the Threshold is classified to maximize F1-score on the development set. In addition, for each of the methods, we performed a statistical test on whether the distribution of scores on the ground-truth events is significantly different from the distribution of scores on false events. We use the standard Kolgomorov-Smirnov 2-sample test [13, 26] and report the $p$-value, the lower the better.

Table 4 shows the results for zero-shot event detection. We show the following metrics: Precision, Recall, F1, the optimal threshold on the development set. In addition, for each of the methods, we performed a statistical test on whether the distribution of scores on the ground-truth events is significantly different from the distribution of scores on false events. We use the standard Kolgomorov-Smirnov 2-sample test [13, 26] and report the $p$-value, the lower the better.

From the results, we clearly see that entailment is a more natural formulation for BERT model as it contains more prior knowledge than question answering framework. If we use a question answering model to predict trigger span, the best performance is obtained when $p_0 = 0.0$, effectively providing no useful information at all. We believe that it is because trigger words are not natural “answers” to questions, events are, but event names are not necessarily present in the text where events occur. Textual entailment does not rely on question answering formulation, where we attach a question like “Did any event about [MASK] happen?” before the input sentence.

In common binary classification settings, one predicts positive when the predicted probability is greater than 0.5. However, when the model is not trained the concerned data, although the model may contain certain bias towards the task, it is not necessarily calibrated - i.e. it might predict favorably towards the right answer, but not necessarily to the extent that the predicted probability is always larger than 0.5. Hence, we manually choose a threshold $p_0$ from 0 to 1 with step 0.01 that maximizes F1-score on the development set, and we use this threshold to separate predicted negative and positive class and report the performance on test set using this threshold.

Concretely, we mostly experiment with BERT and the smaller DistilBERT models pretrained on textual entailment prediction dataset, MNLI [41].

We report performance on these following methods:

- Random. This method simply generates random scores from uniform distribution on [0, 1] as predictive probability as a reference.
- Textual entailment (TE). This is the our approach introduced in Section 3.1 with BERT.
- Question answering (QA). We ask models question like “What is the trigger for [EVENT]?” and let the model do span detection of the trigger word, following the same method as in 3.2. We convert the prediction to sentence-level detection by predicin an event if any span with scores greater than threshold is predicted for that event. For this particularly model, we use BERT pretrained on SQuAD [36].
- Masked token prediction (MTP). Instead of filling in event labels in query templates, we fill in [MASK] special token as a placeholder and let BERT model predict what this token might be. Events are classified based on the event label name’s average score predicted by BERT to replace [MASK]. For this model, the original pretrained BERT is used [8]. The scores here are obtained by sigmoid function on individual logits, instead of softmax across entire vocabulary, to avoid arithmetic underflow. Specifically,
  - MTP+TE predicts the [MASK] token based on textual entailment formulation.
  - MTP+QA predicts the [MASK] token based on a question answering formulation, where we attach a question like “Did any event about [MASK] happen?” before the input sentence.

In common binary classification settings, one predicts positive when the predicted probability is greater than 0.5. However, when the model is not trained the concerned data, although the model may contain certain bias towards the task, it is not necessarily calibrated - i.e. it might predict favorably towards the right answer, but not necessarily to the extent that the predicted probability is always larger than 0.5. Hence, we manually choose a threshold $p_0$ from 0 to 1 with step 0.01 that maximizes F1-score on the development set, and we use this threshold to separate predicted negative and positive class and report the performance on test set using this threshold.

Table 4 shows the results for zero-shot event detection. We show the following metrics: Precision, Recall, F1, the optimal threshold on the development set. In addition, for each of the methods, we performed a statistical test on whether the distribution of scores on the ground-truth events is significantly different from the distribution of scores on false events. We use the standard Kolgomorov-Smirnov 2-sample test [13, 26] and report the $p$-value, the lower the better.

From the results, we clearly see that entailment is a more natural formulation for BERT model as it contains more prior knowledge than question answering framework. If we use a question answering model to predict trigger span, the best performance is obtained when $p_0 = 0.0$, effectively providing no useful information at all. We believe that it is because trigger words are not natural “answers” to questions, events are, but event names are not necessarily present in the text where events occur. Textual entailment does not rely on this, hence it is more able than question answering to solve event detection.

In Table 5 we showcase some examples of wrong predictions made by masked token prediction based on textual entailment. We see that when BERT doesn’t predict the correct event as the one with
4.2.2 Few-shot Learning. Following zero-shot learning, we naturally want to test the model’s ability to transfer knowledge to event detection given a few examples for each event type. We naturally want to test the model’s ability to transfer to event detection task with a few learning examples and if the model can build upon a few samples the link between model’s semantic knowledge and the reasoning of events.

Table 5: Examples of masked token predictions. We show the original sentence, ground-truth labels, top candidate for the [MASK] placeholder from both the entire vocabulary and only from the set of event names. For each top candidate event name, we also show their predicted probabilities.

| Sentence                                                                 | Ground-truth          | Top candidates from vocab | Top candidates from event names |
|--------------------------------------------------------------------------|-----------------------|---------------------------|--------------------------------|
| Jay Garner the retired general will go into Iraq soon with his troops soon. | Movement: Transport   | just time to never what war has this today now | Attack (0.98) Injure (0.96) Transport (0.92) |
| It would not have been necessary to fire those 17 people right away.     | Personnel: End-Position | never just to time had christmas not certainly have now | Die (0.97) Injure (0.92) Trial-Hearing (0.91) |
| Why wouldn’t he file a lawsuit on the basis of the USCF’s violation of its own bylaws, which unquestionably ARE applicable to the USCF? | Justice: Sue           | just never to has what not have already having had | Trial-Hearing (0.98) Sue (0.98) |

Table 6: Results on few-shot event detection. We show mean scores and standard variances on micro F1-scores. We tried both DistilBERT and BERT as the backbone model. “TED” means pretrained DistilBERT on textual entailment, and “TE” means pretrained BERT on the same task. “+D” means trained with event description, and the number in the following parenthesis means the max number of used sentences in the description.

| Method                        | Precision | Recall | F1    |
|-------------------------------|-----------|--------|-------|
| DMCNN [4]                     | 75.6      | 63.6   | 69.1  |
| Delta [25]                    | 67.30     | 69.62  | 68.44 |
| VERB-OA [10]                  | 71.12     | 73.70  | 72.39 |
| BERT [8]                      | 71.52 (±0.19) | 70.48 (±1.65) | 70.99 (±0.82) |
| Delta [25]                    | 70.97     | 70.78  | 70.88 |
| DS-DMCNN [22]                 | 75.7      | 66.00  | 70.5  |
| TE                            | 73.28 (±2.13) | 76.29 (±1.30) | 75.43 (±1.48) |
| TE-D (1)                      | 73.04 (±3.21) | 75.82 (±1.41) | 74.39 (±2.29) |
| TE-D (5)                      | 72.95 (±3.03) | 78.20 (±3.89) | 75.38 (±0.53) |

Table 7: Supervised results. The first group of methods are based on trigger detection, while the second group predicts events without triggers.

Table 6 shows experiemnt results on few-shot learning. We would like to highlight the following observations:

(1) BERT and DistilBERT on their own is not capable of few-shot learning for our tasks, resulting in converging to trivial solutions.
(2) BERT model does significantly outperform DistilBERT. When $K = 1$, DistilBERT works even better in textual entailment without description.
(3) BERT’s becomes advantageous when the number of training data increases.
(4) Both BERT and DistilBERT cannot efficiently utilize description information when $K$ is small, resulting in a lower F1-score. When $K$ increases, the performance gradually increases and matches the model without description.

Generally, in few-shot settings, using DistilBERT could be a better choice, balancing performance and efficiency. As a comparison, [34] achieved 67.6. They profiled possible argument slots for candidate events using semantic role labeling tools, effectively summarizing event structures, and this piece of information is not readily available to BERT model. In the future, it would be an interesting direction to investigate if it is possible to use BERT model to more effectively extract event structures.

4.2.3 Fully Supervised.
**Baselines.** Because the commonly used data for event detection, ACE05, is not freely available, there are only so few works that are open source whose code are complete and immediately runnable given data. This creates a problem for us to evaluate traditional methods in terms of sentence-level event detection performance. Hence, for many of them, we could only report the results from the original paper.

During our attempts to reproduce the experiments, event with official code, we still struggle to produce results consist with what was reported in papers. The same phenomenon was observed by [33] where metrics can drop from 5 to 10 points in rigorously designed testing compared with reported results. Based on observations, we suspect such inconsistencies could be a result from lack of adherence to standard practices in terms of evaluation schemes, data processing, split of training/dev/test sets, and model selection, which all could influence the variance of validity of reported performance.

Based on these reasons, we could only vouch for the validity of performances methods reported with standard variances, and the same observations and conclusion extends to argument detection as well. The following baselines are used as comparable sentence-level event detection methods without triggers:

- BERT [8]. This based on the original pretrained BERT model, where event classification is done by learning a linear classifier on top of the pooled sentence embeddings.
- Delta 2 [25]. This method is based on an adversarial framework where the model learns both discriminative and generalizable information. Although it is originally a trigger-based event detection method, we evaluate it here in terms of sentence-level scores.
- DS-DMCNN [22]. This method performs event detection without trigger based on [4].

The following baselines are trigger-based event detection methods, which we report here as a reference:

- DMCNN [4]. This method proposed a dynamic pooling layer for CNN for event detection.
- Delta2 [25]. This is the same method as mentioned above.
- VERB-QA [10]. This is a QA based event detection framework where “verb” is used as a query to hint the model for trigger word detection and classification.

Our methods include TE, TE-D (1) and TE-D (5), which are the same as in the few-shot learning setting with BERT model. We observed significant performance drop with DistilBERT, with only 70.04 average F1 score. Therefore, we focus on performances on BERT model only, which can apparently utilize more data more effectively. From Table 7, our model achieves the best performance among baselines.

**4.2.4 Discussions.**

**Effect of query structure.** In query templates we infused two kinds of knowledge: 1) information about the event detection task by providing a statement sentence, and 2) information about labels (event types) by filling in the statement event names. A natural question one would ask is if the statement structure is actually helpful or is it just the event names are enough.

**Do event descriptions help?** Based on experiments on few-shot (Table 6) and fully supervised (Table 7) settings, we see that event descriptions can be a burden to model learning when the number of data is extremely small. While with increased data size and in the fully supervised setting, model with descriptions could have comparable performance with the model without descriptions, it does not outperform the latter.

However, event descriptions do provide valuable information on what are events and is sufficient on its own for a human annotator. This could suggest that BERT model cannot learn from descriptions more than it can learn from the data. This suggests that more work should be done on improving language models in understanding how to “read” a “description” or “manual”.

**BERT vs DistilBERT.** In Figure 2 we compare the performance of BERT and DistilBERT. It is clear from the figures that in few-shot settings, there is no statistically significant difference in performance, except for 1-shot learning, where DistilBERT is better without description and BERT, however, is better with descriptions. In fully supervised learning, the difference is significant where DistilBERT achieves only 70 F1-score in average and BERT achieves 75. Therefore, when training labels are extremely scarce, it is sufficient to use DistilBERT to effectively learn from these samples with less memory consumption and computational burden. In fully supervised learning, however, BERT’s ability to utilize massive data is significantly better than DistilBERT.

**4.3 Argument Detection Experiments**

**4.3.1 Probing without Supervision.** Like in event detection experiments, we first probe pretrained BERT for QA tasks on SQuAD [36] and see if they can predict arguments without training 7. We experiment on the following query types:

1. QA-Template. This constructs questions from templates in Section 3.2
2. QA-Guide. This constructs questions from descriptions in the annotation guide [5].
3. QA-Triger. This constructs questions from a template similar to the one in Section 3.2, but the question is asked about the trigger, like: “What is the [ARGUMENT] in [TRIGGER]?”.
4. QA-Triger-Plus. This is based on a similar template which includes both trigger word and event name. For example: “What is the [ARGUMENT] in event [EVENT] triggered by [TRIGGER]?”. 3 and 4 is the method used by [10]. Since we are doing event detection without triggers, it is necessary to include 3 as well to demonstrate the effect of removing trigger words on argument detection.

Table 8 shows results of models without training. Unlike in event detection, no threshold probability was manually chosen. We see that all four query templates perform similarly, and are all much better than random baseline. Also, we observe that questions with trigger words perform slightly better than those without. However, this is based on ground-truth annotation trigger words.

---

7This method was originally proposed to detect and classify triggers. We report the performance of their method on both trigger-based event detection and sentence-level event detection, while the former is computed by ignoring if the span matches. The performance on this method is reported based on reproduction of their method of the authors’ published code. The paper reported about 74.7 F1-score on trigger detection and classification.

8We used deepset/bert-large-uncased-whole-word-masking-squad2.
Table 8: Zero-shot learning for argument detection. We report Precision, Recall, F1, and p-values. The arguments are predicted based on ground-truth event labels and trigger word annotations.

| Method       | Precision ↑ | Recall ↑ | F1 ↑ | p-value ↓ |
|--------------|-------------|----------|------|----------|
| Random       | 10.64       | 15.53    | 12.63| 0.56     |
| QA-Temp      | 31.83       | 22.96    | 26.67| 0.00     |
| QA-Guide     | 31.89       | 23.08    | 26.78| 0.00     |
| QA-Trig      | 28.03       | 26.26    | 27.12| 0.00     |
| QA-Trig-Plus | 30.05       | 24.80    | 27.17| 0.00     |

In Table 9, we show some examples of zero-shot predictions by generated queries. Additionally, we manually wrote customized queries for each sentence based on the principle that the query should specify as much information as possible about the event, including other relevant arguments, like “London’s financial world”, and “by the end of the year”, that are present in the input sentence.

From Table 9, we can observe that the custom query is much more semantically and contextually related to the input sentence. Compared with template-based queries which might ask “Who started a new position”, or “What is the artifact in Transfer-Ownership”, the written query is much more context specific. It provides stronger guidance for BERT model to extract the actual answer. Unfortunately, such queries are specific to sentence contexts and requires human writing, and it is hard to scale-up to the entire dataset at this time.

4.3.2 Few-shot learning. To the best of our knowledge, we are the first to do few-shot argument detection without using external semantic role labeling tools. We show our results in Table 10.

In Table 10, we report argument prediction scores based on both event predictions using TE model from Section 4.2.2 and on ground-truth event labels. Errors in event predictions would propagate in the first scenario. We see that the hand-written query based on guides perform a lot better, especially when \( K \) is low, than template-based queries.

4.3.3 Fully Supervised. For fully supervised argument detection, we compare our approach to DMCNN [4] and VERB-QA [10] described in Section 4.2.2.

VERB-QA [10] curates the argument with a trigger-word based QA framework. Specifically, their template is: “[Wh-word] is the Argument in Trigger?”, where “Wh-word” means interrogative words such as “What”, “Who” and “When”, and “Trigger” is the detected trigger word. This is essentially equivalent to our QA-Trig. In 11 we report the experiment results. Our method with

4.3.4 Discussions.

Does trigger word help? The potential drawback of event detection without triggers is that it might lose the trigger information that could be important for subsequent argument detection tasks. In Section 4.3.1, we see that questions with trigger words perform slightly better than questions with only event and argument names. Since trigger words contain the only clue in the query about the context of the sentence, it is indeed reasonable that questions with triggers should perform better.

However, this is based on golden trigger words. In real application, predicting trigger words tend to propagate more errors than predicting sentence-level event labels. Hence, in supervised setting, we see that methods based on sentence-level event predictions (QA-Temp, QA-Guide) perform slightly better than VERB-QA, which predicts arguments based on predicted trigger words and questions constructed with them. We may conclude that trigger words are non-essential to both event detection and argument detection.

5 RELATED WORK

In this section, we review related works from closely relevant fields. First, we review the most relevant reading comprehension framework and applications to NLP tasks (Section 5.1). Second, we review relevant papers from event extraction, in both standard supervised setting (Section 5.2) and few-shot learning setting (Section 5.3). At last, since our method implicitly treat BERT as a knowledge base, we review relevant papers in Section 5.4.

5.1 Reading Comprehension Frameworks

We first review methods that reframe various NLP tasks as machine reading comprehension. Most trending natural language processing tasks can be formulated as reading comprehension tasks. [18] used pre-BERT model for question answering for zero-shot relation extraction. Later on, more works formulated tasks reading comprehension, such as [17] for sentence classification, [20] for NER, [32] for relation extraction with entailment prediction, [43] for coreference resolution, and [42] for slot filling. [27] unified 10 tasks into one question answering based multi-task learning framework. [6] used reading comprehension as a tool to build knowledge graphs. [12] proved whether or when the format of question answering is useful. [2] designed a pipeline to do zero-shot event detection by reading information from the annotation guide.

Formulating tasks as machine reading comprehension has one key advantage, that it is able to better utilize knowledge in modern language models, such as BERT [8], ideally improving label efficiency. For example, among above mentioned works, [2, 18, 32, 42] all employed reading comprehension as a tool for zero- or few-shot learning.

[10] is closely related to our work in that they also developed a reading comprehension framework for event detection. The key difference is that, they used a QA framework for event trigger detection and classification. As shown in Section 4.2, this isn’t necessarily the most natural way to utilize BERT. Indeed, [10] found that the most effective question form is a single word “verb”, essentially not a question and only hinting the model that verbs are more possible trigger words, which is not the ideal kind of knowledge one expects to extract from BERT.

5.2 Event Detection

The early attempts to solve event detection rely on hand-crafted features [19] and probabilistic rules [23]. More recent works utilize neural networks for learning salient representations for event detection, such as CNN [4, 31, 31], RNN [11, 15, 30, 39], and GNN [24, 29, 44].

Unlike other sequence tagging problems, such as NER, event extraction relies more heavily on the structural information in the
Table 9: Zero-shot learning for question answering examples. The bold first sentence is the “Custom” query that human manually wrote given the context. We list predictions by three generated queries and the custom query. Some non-essential parts are removed from sentences due to space limitations.

| Sentence                                                                 | Event, Argument, & Answer            | Query Type          | Prediction | Result     |
|-------------------------------------------------------------------------|--------------------------------------|---------------------|------------|------------|
| What is the organization he said that is going to start?                | QA-Temp Organization, Organization, "a monster" | “a monster”         | Correct    |
| “Prostitution is completely discriminated in Sydney and we are going to build a monster,” he said. | QA-Guide                                    | None                | Wrong      |
| Who started a new job in London’s financial world? Former senior banker Callum McCarthy begins what is one of the most important jobs in London’s financial world in September, when incumbent Howard Davies steps down. | QA-Temp Start-Position, Person, “Former … McCarthy” | “Former … McCarthy” | Correct    |
|                                                                         | QA-Guide                                    | None                | Wrong      |
| What are the entertainment assets Vivendi tries to sell by the end of the year? Vivendi confirmed that it planned to shed its entertainment assets by the end of the year, including its famed Universal movie studio and television assets. | QA-Temp Transfer-Ownership, Artifact, “its famed. . . studio” | None                | Wrong      |
|                                                                         | QA-Guide                                    | None                | Wrong      |
| When did the meeting that Jean-Rene Fourtou participated in take place? Chief executive Jean - Rene Fourtou told shareholders at the group’s annual general meeting Tuesday that negotiations were already under way. | QA-Temp Meet, Time-Within, “Tuesday”       | None                | Wrong      |
|                                                                         | QA-Guide                                    | None                | Wrong      |

Table 10: Results on few-shot argument detection. The first part predicts and compute metrics based on predicted events with the best text entailment model trained in Section 3.1. The second part is based on ground-truth event labels.

| Events       | K-shot   | K = 1     | K = 3     | K = 5     | K = 7     | K = 9     |
|--------------|----------|-----------|-----------|-----------|-----------|-----------|
| K-shot       | QA-Temp  | 1.35 (±2.34) | 37.27 (±2.28) | 44.08 (±1.74) | 44.74 (±2.87) | 46.59 (±0.94) |
|              | QA-Guide | 19.58 (±2.45) | 41.38 (±1.61) | 45.41 (±1.48) | 44.92 (±1.12) | 46.86 (±0.74) |
| Ground Truth | QA-Temp  | 1.62 (±2.81) | 45.49 (±2.46) | 52.49 (±1.32) | 54.44 (±3.19) | 56.15 (±1.13) |
|              | QA-Guide | 22.67 (±3.03) | 50.97 (±2.42) | 55.48 (±1.68) | 54.39 (±0.85) | 57.66 (±1.23) |

Table 11: Fully supervised learning for argument detection. Similar to in few-shot setting, we report our scores on both ground-truth and predicted event labels.

| Events | Method | Precision | Recall | F1     |
|--------|--------|-----------|--------|--------|
| Pred.  | DMCNN  | 62.2      | 46.9   | 53.5   |
|        | VERB-QA | 56.77     | 50.24  | 53.31  |
|        | QA-Temp | 56.24 (±1.21) | 52.14 (±3.52) | 54.01 (±2.13) |
|        | QA-Guide | 57.69 (±0.45) | 51.90 (±3.39) | 54.61 (±1.67) |
| G. Truth | QA-Temp | 71.06 (±1.58) | 65.84 (±2.14) | 68.25 (±0.98) |
|        | QA-Guide | 72.20 (±2.45) | 65.79 (±3.09) | 68.79 (±0.57) |

5.3 Few-shot Learning

There exists two approaches to few-shot event detection. The first is based on defining prototype vectors for events [16, 34]. They both extract a graphical structure for each candidate trigger words with external resources, including semantic role labeling [34] and abstract meaning representation [16]. SRL and AMR themselves are tantamount to argument detection already, so their works can be viewed as event detection based on given arguments. Since we focus on doing both event detection and argument detection from scratch, their methods aren’t directly comparable to ours. It would be a promising direction to incorporate their structural knowledge into our framework.

The second approach that has been applied to few-shot event detection is meta-learning in [7]. They have built their own data based on ACE05 [9]. Since we do not have access to their customized data or their implementation, we could not compare our method with theirs.

5.4 BERT as a Knowledge Base

There have been works that investigate whether BERT is a knowledge base itself. The hypothesis is that BERT, while learning from massive corpora, could memorize factual and commonsense knowledge about the world. [35, 37]. [35] BERT might have inferred right relations, without having the right understanding, but instead based on “learned associations of objects with subjects from co-occurrence patterns”. Still, the work of [1] shows that fine-tuned Bert model can consistently outperform simple word-vector-based models in inferring relations. [37] extends to use Bert to answer more complex natural language queries, instead of traditional triplet queries, and sentence. Hence, one way to predict events and arguments jointly is by utilizing dependency parse [24, 29, 39, 44]. Many researchers exploit the hierarchical information as well [11, 21, 28, 45, 47].

Similarly to our setting, [22] considers event detection a sentence classification task, citing that the subjectivity in tagging event triggers can harm model performance and the knowledge of triggers is “non-essential to the task” [22]. However, they did not further extend the framework to include argument detection. To the best of our knowledge, we are the first to implement argument detection without relying on trigger information.
shows that Bert outperforms open-domain retrieval baselines by a large margin.

6 CONCLUSION

We propose a reading comprehension framework for event extraction tasks. We design a textual entailment based method for event detection and question answering for argument detection. Experiment findings suggest our framework can effectively distill knowledge from BERT as well as guide the model with semantic information, achieving state-of-the-art results on few-shot and supervised settings.

Our experiments also suggest several promising research directions. We summarize them here. It is clear that while the current framework with mostly template-based queries can achieve superior performance already, the queries are not ideal since they do not relate to actual sentence context and the casual relation between distinctive events and arguments. One promising direction is generating queries that are (1) more flexible and authentic, (2) relevant to input sentence’s context, and (3) reveals causal relations between events and arguments. We believe this would enable a more label efficient and robust zero-shot and few-shot learning framework.

In our current framework and, indeed, all existing reading comprehension frameworks to our best knowledge, one must construct multiple queries for one input instance for complete classification results. This could be burdensome when there’s a large number of queries to be constructed, usually a result of large number of label types. One problem is how to do so efficiently by enabling information sharing between different queries.

Experiments show that the current BERT model cannot learn efficiently from long event descriptions. A significant advancement in language modeling would be enabling it for zero- or few-shot learning with only a few descriptions and annotation guides.

We manually select reading comprehension tasks for two event extraction tasks. A key ingredient to a more general reading comprehension solution to NLP tasks is a principle to measure the transferability between tasks.

REFERENCES

[1] Bouraoui, Z., Camacho-Collados, J., and Schokkaert, S. Inducing relational knowledge from bert. arXiv preprint arXiv:1911.12753 (2019).

[2] Chen, Y., Chen, T., Ehrn, S., and Van Durme, B. Reading the manual: Event extraction as definition comprehension. arXiv preprint arXiv:1912.01586 (2019).

[3] Chen, Y., Liu, S., Zhang, X., Liu, K., and Zhao, J. Automatically labeled data generation for large scale event extraction. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (2017), pp. 409–419.

[4] Chen, Y., Xu, L., Liu, K., Zeng, D., and Zhao, J. Event extraction via dynamic multi-pooling convolutional neural networks. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers) (Beijing, China, July 2015), Association for Computational Linguistics, pp. 167–176.

[5] Consortium, L. D. Ace (automatic content extraction) english annotation guidelines for events. https://www.ldc.upenn.edu/sites/www. ldc.upenn.edu/files/english-events-guidelines-v5.4.3.pdf.

[6] Das, R., Munkhdalai, T., Yuan, X., Trischler, A., and McCallum, A. Building dynamic knowledge graphs from text using machine reading comprehension. arXiv preprint arXiv:1810.05682 (2018).

[7] Deng, S., Zhang, N., Kang, J., Zhang, Y., Zhang, W., and Chen, H. Meta-learning with dynamic-memory-based prototypical network for few-shot event detection. In Proceedings of the 33rd International Conference on Web Search and Data Mining (2020), pp. 151–159.

[8] Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018).

[9] Doddington, G. R., Mitchell, A., Przybocki, M. A., Ramshaw, L. A., Strassel, S. M., and Weischedel, R. M. The automatic content extraction (ace) program-tasks, data, and evaluation. In Lrec (2004), vol. 2, Lisbon, pp. 837–840.

[10] Du, X., and Cardie, C. Event extraction by answering (almost) natural questions. arXiv preprint arXiv:2004.13625 (2020).

[11] Duann, S., He, R., and Zhao, W. Exploiting document level information to improve event detection via recurrent neural networks. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers) (Taipei, Taiwan, Nov. 2017), Asian Federation of Natural Language Processing, pp. 352–361.

[12] Gardner, M., Berant, J., Haishirzhi, H., Talmon, A., and Min, S. Question answering is a format: when is it useful? arXiv preprint arXiv:1909.11291 (2019).

[13] Hodges, J. L. The significance probability of the smirnov two-sample test. Arkiv for Matematik 3, 5 (1958), 469–486.

[14] Hong, Y., Zhang, J., Ma, B., Yao, J., Zhou, G., and Zhu, Q. Using cross-entity inference to improve event extraction. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1 (2011), Association for Computational Linguistics, pp. 1127–1136.

[15] Hong, Y., Zhou, W., Zhang, J., Zhou, G., and Zhu, Q. Self-regulation: Employing a generative adversarial network to improve event detection. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (Melbourne, Australia, July 2018), Association for Computational Linguistics, pp. 515–526.

[16] Huang, L., Ji, H., Cho, K., and Voss, C. R. Zero-shot transfer learning for event extraction. arXiv preprint arXiv:1707.01666 (2017).

[17] Keskar, N. S., McCann, B., Xiong, C., and Socher, R. Unifying question answering, text classification, and regression via span extraction. arXiv preprint arXiv:1904.09260 (2019).

[18] Levy, O., SEO, M., Choi, E., and Zeltzlemeyer, L. Zero-shot relation extraction via reading comprehension. arXiv preprint arXiv:1706.04115 (2017).

[19] Li, Q., Ji, H., and Huang, L. Joint event extraction via structured prediction with global features. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (2013), pp. 73–82.

[20] Li, X., Feng, J., Meng, Y., Han, Q., Wu, F., and Li, J. A unified nrc framework for named entity recognition. arXiv preprint arXiv:1910.14176 (2019).

[21] Liao, S., and Grishman, R. Using document level cross-event inference to improve event extraction. In Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics (2010), Association for Computational Linguistics, pp. 789–797.

[22] Liu, S., Li, Y., Zhang, F., Yang, T., and Zhou, X. Event detection without triggers. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers) (2019), pp. 735–744.

[23] Liu, S., Liu, K., He, S., and Zhao, J. A probabilistic soft logic based approach to exploiting latent and global information in event classification. In Thirteenth AAAI Conference on Artificial Intelligence (2016).

[24] Liu, X., Luo, Z., and Huang, H. Jointly multiple events extraction via attention-based graph information aggregation. arXiv preprint arXiv:1809.09078 (2018).

[25] Lu, Y., Lin, H., Han, X., and Sun, L. Distilling discrimination and generalization knowledge for event detection via delta-representation learning. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (2019), pp. 4366–4376.

[26] Massey Jr, F. J. The kolmogorov-smirnov test for goodness of fit. Journal of the American statistical Association 46, 233 (1951), 68–78.

[27] McCann, B., Keskar, N. S., Xiong, C., and Socher, R. The natural language decathlon: Multitask learning as question answering. arXiv preprint arXiv:1806.08730 (2018).

[28] Mehta, S., Islam, M. R., Rangwala, H., and Ramakrishnan, N. Event detection using hierarchical multi-aspect attention. In The World Wide Web Conference (New York, NY, USA, 2019), WWW ’19, ACM, pp. 3079–3085.

[29] Nguyen, T., and Grishman, R. Graph convolutional networks with argument-aware pooling for event detection. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers) (2019), pp. 735–744.

[30] Nguyen, T. H., Cho, K., and Grishman, R. Joint event extraction via recurrent neural networks. In HLT-NAACL (2016), pp. 300–309.

[31] Nguyen, T. H., and Grishman, R. Event detection and domain adaptation with convolutional neural networks. In Proceedings of the 33rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers) (2015), pp. 365–371.

[32] Obamuyide, A., and Vlachos, A. Zero-shot relation classification as textual entailment. In Proceedings of the First Workshop on Fact Extraction and
VERification (FEVER) (2018), pp. 72–78.

[33] ORR, J. W., TADEPALLI, P., AND FERN, X. Event detection with neural networks: A rigorous empirical evaluation. arXiv preprint arXiv:1808.08504 (2018).

[34] PENG, H., SONG, Y., AND ROTH, D. Event detection and co-reference with minimal supervision. In Proceedings of the 2016 conference on empirical methods in natural language processing (2016), pp. 392–402.

[35] PETRONI, F., ROCKTÄSCHEL, T., LEWIS, P., BAKHTIN, A., WU, Y., MILLER, A. H., AND RIEDEL, S. Language models as knowledge bases? arXiv preprint arXiv:1909.01066 (2019).

[36] RAJPURKAR, P., HAN, J., LOPYREV, K., AND LIANG, P. Squad: 100,000+ questions for machine comprehension of text. arXiv preprint arXiv:1606.05250 (2016).

[37] ROBERTS, A., RAFFEL, C., AND SHAZEER, N. How much knowledge can you pack into the parameters of a language model? arXiv preprint arXiv:2002.08910 (2020).

[38] SCHUSTER, M., AND NAKAJIMA, K. Japanese and korean voice search. In 2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (2012), IEEE, pp. 5149–5152.

[39] SHI, L., QIAN, F., CHANG, B., AND SUI, Z. Jointly extracting event triggers and arguments by dependency-bridge rnn and tensor-based argument interaction. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers) (2019), pp. 998–1008.

[41] WILLIAMS, A., NANGIA, N., AND BOWMAN, S. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers) (2018), Association for Computational Linguistics, pp. 1112–1122.

[42] WU, T., WANG, M., GAO, H., QI, G., AND LI, W. Zero-shot slot filling via latent question representation and reading comprehension. In Pacific Rim International Conference on Artificial Intelligence (2019), Springer, pp. 123–136.

[43] WU, W., WANG, F., YUAN, A., WU, F., AND LI, J. Corefqa: Coreference resolution as query-based span prediction. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (2020), pp. 6953–6963.

[44] WU, W., WANG, F., YUAN, A., WU, F., AND LI, J. Corefqa: Coreference resolution as query-based span prediction. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (2020), pp. 6953–6963.

[45] WANG, X., HAN, X., LIU, Z., SUN, M., AND LI, P. Adversarial training for weakly supervised event detection. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP) (2019), pp. 5770–5774.

[46] WANG, H., CHEN, Y., LIU, K., XIAO, Y., AND ZHAO, J. Dcfee: A document-level chinese financial event extraction system based on automatically labeled training data. ACL 2018 (2018), 30.

[47] WANG, S., FENG, D., QIAO, L., KAN, Z., AND LI, D. Exploring pre-trained language models for event extraction and generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (2019), pp. 5284–5294.

[48] WANG, Z., YANG, D., DVER, C., HE, X., SMOLA, A. J., AND HOVY, E. H. Hierarchical attention networks for document classification. In HLT-NAACL (2016).