Abstract

Co-reference of Events and of Entities are commonly formulated as binary classification problems, given a pair of events or entities as input. Earlier work addressed the main challenge in these problems — the representation of each element in the input pair by: (i) modeling the representation of one element (event or entity) without considering the other element in the pair; (ii) encoding all attributes of one element (e.g., arguments of an event) into a single non-interpretable vector, thus losing the ability to compare cross-element attributes.

In this work we propose paired representation learning (PAIRED RL) for coreference resolution. Given a pair of elements (Events or Entities) our model treats the pair’s sentences as a single sequence so that each element in the pair learns its representation by encoding its own context as well the other element’s context. In addition, when representing events, PAIRED RL is structured in that it represents the event’s arguments to facilitate their individual contribution to the final prediction. As we show, in both (within-document & cross-document) event and entity coreference benchmarks, our unified approach, PAIRED RL, outperforms prior state of the art systems with a large margin.

1 Introduction

In this work, we study the coreference resolution problem for both events and entities. Coreference resolution is commonly modeled as a binary classification problem (Lee et al., 2012; Barhom et al., 2019; Lee et al., 2017): first learn features for each (event or entity) mention, then classify two given mentions (a clustering might be employed afterwards as a postprocessing step) 1. The essential step in this framework lies in the representation learning of each mention. However, prior work often failed to learn representations with powerful expressivity due to the following two reasons:

Point-wise representation learning. Most work tries to learn mention representations by extracting features merely from that particular sentence including the mention. We argue that this routine of representation learning in coreference does not match the end task we are coping with: relation recognition of mention pairs. The predicted relation is for the input mention pair rather than individual mentions. By different context, two mentions can be referring to each other or not. To fit the different scenarios, a mention should learn its representation by considering what its counterpart is.

Unstructured representation learning. An event mention consists of multiple arguments to describe the event: what, who, when, where, etc. Most prior work tried to encode all those elements into a single distributed representation vector and then compare the vectors of two mentions. This is less optimal since humans can recognize subjects, objects etc. and often compare event arguments of the same type (e.g., subject vs. subject, location vs. location, etc.). If, for instance, the event locations are different, people can make a judgement quickly even without comparing other mention arguments. Denoting a mention with a single distributed vector lets machines lose the opportunity to conduct fine-grained reasoning as humans do and uneasy to explain the model’s prediction.

To promote the expressivity of representations, this work proposes paired representation learning (PAIRED RL). PAIRED RL alleviates the aforementioned two limitations with two designs:

Pairwise representation learning. In this work, we treat each mention pair rather than a single mention as the object for the representation learning.
Specifically, we will concatenate the two sentences (with a mention in each) as a whole sequence and forward it into a ROBERTa (Liu et al., 2019) system. RoBERTa takes the “whole sequence” as an input so that each token, including the mention spans, in the two sentences are able to compare with other tokens from the very beginning. This is better than comparing the two mentions after learning a representation for each of them separately. We apply this pairwise representation learning to both event and entity coreference tasks. The binary classifier or an mention matching function in the end will take a pair of contextualized mention representations for reasoning.

Structured representation learning. Looking at the following two sentence \( s_1 \) and \( s_2 \) (event trigger is underlined; argument #0 is in blue, location is in purple)

\[
\begin{align*}
\text{s}_1: & \quad \text{“Over 69,000 people lost their lives in the quake, including 68,636 in Sichuan province.”} \\
\text{s}_2: & \quad \text{“Up to 6,434 people lost their lives in Kobe earthquake and about 4,600 of them were from Kobe.”} 
\end{align*}
\]

First, humans often determine the relationship between the two event mentions in \( s_1 \) and \( s_2 \) by comparing their triggers and arguments separately (then maybe compose their results as a whole decision) as follows:

- “69,000 people” vs. “6,434 people”
- “lost” vs. “lost”
- “Sichuan province” vs “Kobe”

Second, the mismatch of some components may be decisive or more decisive than that of others. For example, when people find the location “Sichuan province” does not match with “Kobe”, they can directly claim the two events are not coreference even without looking at the whole sentence. This human behavior indicates that we should make full of the structure in an event, and an overall representation encompassing all event elements is less informative to perform fine-grained cross-mention comparison which can actually improve the interpretability of the model predictions.

Overall, our PAIREdRL enables two mentions to learn from the context of each other, and improves the model’s explainability by performing fine-grained reasoning. We report PAIREdRL on both event coreference (within-document & cross-document) and entity coreference benchmarks. Despite its simple architecture, PAIREdRL surpasses the prior SOTA system by big margins.

2 Related Work

In this section, we discuss prior representation learning approaches for event coreference and entity coreference, respectively.

2.1 Event Coreference

Earlier work uses hand-engineered event attribute features to represent events (Chen et al., 2009; Bejan and Harabagiu, 2010).

Most of recent neural models use contextual embedding and character-based embedding of event trigger with some additional pairwise features to represent events (Huang et al., 2019; Cattan et al., 2020; Kenyon-Dean et al., 2018). These work did not use argument information, and expected that the contextual embedding included all the necessary information.

Both (Lee et al., 2012) and (Barhom et al., 2019) jointly train Entity Coreference model and Event Coreference model based on the intuition that if two mention triggers are referring to the same event, their arguments very likely refer to the same, and vice versa. They do argument clustering and use the cluster features to represent an event.

Peng et al. (2016) propose a representation of events that not only uses representation of each argument, but also combines event trigger with each single argument as a new text fragment to generate features to enhance the interactions between the trigger and each argument.

Choubey and Huang (2017) generate arguments score for each overlapping argument. However, their representation for both event trigger and arguments is point-wise, and they only generate argument representation for exactly overlapping arguments.

2.2 Entity Coreference

The representation of entities is not as complicated as the representation of events, because entities do not have arguments. Earlier works use hand-engineered features as the representation of entities (Peng et al., 2015; Wiseman et al., 2015; Clark and Manning, 2016).

Lee et al. (2017) propose an end-to-end neural model that uses LSTM to encode the entity span. Recent end-to-end models use pre-trained contextual embeddings as the representation of the
The whole trigger-based event pair \((i, j)\) refers to the event/entity mentions (for simplicity, we assume one mention exists in one sentence) denotes by \(v_t(i, j)\) which is the concatenation: \([v^t_1, v^t_2, v^t_i \circ v^t_j]\).

To the best of our knowledge, we are the first to (i) study pairwise representation by letting two event/entity mentions learn from each other’s context from the beginning; and (ii) build structured representation between events by fine-grained argument reasoning, without any hand-engineered features.

### 3 PAIREDRL for Coreference

In this work, we will study event coreference (within-document and cross-document) and entity coreference. All of tasks share the same representation learning approach PAIREDRL.

#### 3.1 PAIREDRL

PAIREDRL takes two sentences as the input, outputting a score indicating how likely the two event/entity mentions (for simplicity, we assume one mention exists in one sentence) refers to the same event/entity.

Since both event triggers and entity mentions are consecutive spans, and events often have arguments other than triggers. Technically, entity coreference can be treated as a simplified case of event coreference. Therefore, we directly introduce our system PAIREDRL for event coreference, then briefly introduce how to apply PAIREDRL to entity coreference.

As a preprocessing, we first use SRL model to predict arguments \([\text{arg0}; \text{arg1}; \text{loc}; \text{time}]\) for each event mention \(e_i\). Given the mention pair \(e_i\) and \(e_j\) with their arguments, as shown in Fig 1, we concatenate the sentences of \(e_i\) and \(e_j\), and encode the concatenated sentence using RoBERTa (Liu et al., 2019). RoBERTa will learn a representation vector for each token of the input sequence. We then sum up element-wisely the token-level representations as the representations for event trigger and event arguments respectively: \(v_t\) for event trigger, \(v_{\text{arg0}}/v_{\text{arg1}}\) for argument #0 or #1, \(v_{\text{loc}}\) for location and \(v_{\text{time}}\) for time.

Next, we conduct fine-grained coreference reasoning, as Figure 2 shows. The goal is to let each role of event arguments learn its decisiveness to the final task. For each role, where role \(\in\{t, \text{arg0}, \text{arg1}, \text{loc}, \text{time}\}\), we first build the following role-wise representation:

\[
v_{\text{role}}(i,j) = [v^t_i \circ v^j_i, v^t_i \circ v^j_t] \tag{1}\]

where \(\circ\) is element-wise multiplication.

We keep the \(v_t\) as the main representation in PAIREDRL, and let each of the remaining four arguments contributes a feature value indicating their own decisiveness. The feature value is learnt with a MLP as follows:

\[
a_{\text{role}}(i,j) = \text{MLP}_1(v_{\text{role}}(i,j)) \tag{2}\]

where “role” refers to other mention arguments other than the trigger.

As a result, the final pair representation PAIREDRL for event coreference is:

\[
v(i,j) = [v_t(i,j), a_{\text{arg0}}, a_{\text{arg1}}, a_{\text{loc}}, a_{\text{time}}] \tag{3}\]

Since entity does not have arguments, the final pair representation PAIREDRL for entity coreference is:

\[
v(i,j) = v_t(i,j) \tag{4}\]

Once obtaining the pairwise representation \(v(i,j)\), another MLP, as shown in Figure 2, will act as a binary classifier (i.e., is coreference or not)

\[
p(i,j) = \text{MLP}_2(v(i,j)) \tag{5}\]

where \(p(i,j) \in \mathbb{R}^2\) and \(p(i,j)[0]\) is the probability that the two mentions \(i\) and \(j\) are coreference.

**Explainability of PAIREDRL for event coreference.** In Equation 3, the features of a pair of event mentions consist of the trigger-specific representation \(v_t(i,j)\) and four matching scores \((a_{\text{arg0}}, a_{\text{arg1}}, a_{\text{loc}}, a_{\text{time}})\).
Figure 2: The full reasoning process in PAIREDRL. The final PAIREDRL representation is the concatenation of the trigger’s representation and four feature values, each coming from a mention argument.

Table 1: ECB+ statistics. We follow the data split by Cybulska and Vossen (2015): Train: 1, 3, 4, 6-11, 13-17, 19-20, 22, 24-33; Validation: 2, 5, 12, 18, 21, 23, 34, 35; Test: 36-45. Event Clusters includes singletons.

|         | Train | Dev  | Test |
|---------|-------|------|------|
| Topics  | 25    | 8    | 10   |
| Documents | 574   | 196  | 206  |
| Sentences | 1,037 | 346  | 457  |
| Event mentions | 3,808 | 1,245 | 1,780 |
| Event Singletons | 1,116 | 280  | 623  |
| Event Clusters | 1,527 | 409  | 805  |

Table 2: KBP statistics. We use KBP2015 for training, KBP 2016 for validation and KBP 2017 for testing. Event Clusters includes singletons.

|         | Train | Dev  | Test |
|---------|-------|------|------|
| Documents | 360   | 169  | 167  |
| Event mentions | 12,976 | 4,155 | 4,375 |
| Event Singletons | 5,256 | 2,709 | 2,358 |
| Event Clusters | 7,460 | 3,191 | 2,963 |

Table 3: ACE statistics. We use the preprocessed data split by Lin et al. (2020). Event Clusters includes singletons.

|         | Train | Dev  | Test |
|---------|-------|------|------|
| Documents | 2,802 | 343  | 348  |
| Entity mentions | 155,560 | 19,156 | 19,764 |
| Entity Singletons | 0    | 0    | 0    |
| Entity Clusters | 35,143 | 4,546 | 4,532 |

Table 4: OntoNotes 5.0 statistics.

|             | Train | Dev  | Test |
|-------------|-------|------|------|
| Documents   | 3,806 | 343  | 348  |
| Entity mentions | 155,560 | 19,156 | 19,764 |
| Entity Singletons | 0    | 0    | 0    |
| Entity Clusters | 35,143 | 4,546 | 4,532 |

4 Experiments

4.1 Cross-document Event Coreference

Dataset We use the ECB+ corpus to train and test our model (Cybulska and Vossen, 2014). ECB+ is the largest and most popular dataset for cross-document Event Coreference, which is extended from ECB (Bejan and Harabagiu, 2010). For each topic in ECB, Cybulska and Vossen (2014) added a subtopic that talks about a different event belongs to a same topic. We follow the same setup that previous work did (Cybulska and Vossen, 2015; Kenyon-Dean et al., 2018; Barhom et al., 2019), and the detailed statistics is shown in Table 1. For both training and evaluation, we use gold event mentions. ECB+ annotates arguments of each event in the same sentence, but does not annotate the role of the arguments, and also does not annotate which event the arguments belong to.

Preprocessing:

Argument generation We use AI2 SRL system, which is a reimplementation of Shi and Lin (2019), to predict arguments for each event mention, and map to the annotation of gold arguments.

Topic Clustering Barhom et al. (2019) implemented a very strong topic clustering model that uses the K-Means algorithm on the documents represented by TF-IDF scores of unigrams, bi-grams, and trigrams. They chose K based the Silhou-

[^3]: https://demo.allennlp.org/semantic-role-labeling
| Model                        | MUC R | MUC P | MUC F1 | B3 R | B3 P | B3 F1 | CEAFɛ R | CEAFɛ P | CEAFɛ F1 | CoNLL F1 |
|-----------------------------|-------|-------|--------|------|------|-------|--------|--------|--------|---------|
| same head lemma            | 76.5  | 79.9  | 78.1   | 71.7 | 85   | 77.8  | 75.5   | 71.7   | 73.6   | 76.5    |
| Barhom et al. (2019)        | 77.6  | 84.5  | 80.9   | 76.1 | 85.1 | 80.3  | 81     | 73.8   | 77.3   | 79.5    |
| Cattan et al. (2020)        | 85.1  | 81.9  | 83.5   | 82.1 | 82.7 | 82.4  | 75.2   | 78.9   | 77.0   | 81.0    |

**PAIREDRL**

- trigger only: 91.6 | 83.1 | 87.2 | 89.4 | 81.1 | 85.1 | 75.0 | 85.5 | 79.9 | 84.0
- trigger & arg: 88.1 | 85.1 | 86.6 | 86.1 | 84.7 | 85.4 | 79.6 | 83.1 | 81.3 | 84.4

Table 5: Cross-document event coreference performance on ECB+. Using gold mentions and predicted topics. Details in Sec 4.1

ette Coefficient method (Rousseeuw, 1987), and perfectly got the number of gold topics. Though there still exists wrong documents in each topic cluster, their nearly perfect clustering allows very simple baseline models to achieve very good results (Barhom et al., 2019). Since we focus on the improvement that the pairwise representation can bring, we use exactly the same topic clustering model they implemented. We use gold topics for training, and predicted topics for inference.

**Postprocessing: Mention Clustering.** After training the pairwise coreference scorer, same as previous work, we apply agglomerative clustering to the event pairs by the score we get from the trained scorer (Choubey and Huang, 2017; Kenyon-Dean et al., 2018; Barhom et al., 2019; Cattan et al., 2020). Agglomerative clustering merges event clusters until no cluster pairs have a similarity score higher than a threshold. We define the cluster pair similarity score as the average score of all the event pairs across two clusters. Threshold is tuned on development data.

**Results:** We compare with two state-of-the-art cross-document Event Coreference models using different methods: Barhom et al. (2019), which jointly trained Entity Coreference and Event Coreference, and Cattan et al. (2020), which jointly learned mention detection and coreference. We also compare with the same head lemma baseline implemented by Barhom et al. (2019), which simply clusters events with same head lemma.

In Table 5, we report our system PAIREDRL by considering trigger only or both the trigger and mention arguments. By “trigger only”, our system uses the Equation 4 to denote the representation of a pair of mention; by “trigger & argument”, the structured representation depicted in Equation 3 is used. Table 5 shows that PAIREDRL, even considering trigger only, outperforms the state-of-the-art model on all of the evaluation metrics with big margins, particularly 84.0 vs. 81.0 by CoNLL F1 score. Please note that all the baselines have relatively complex systems to learn event features as well as entity features. Our system only models the trigger representations give the context of two involved mentions. No information of the arguments are explicitly encoded. It clearly demonstrates the superiority of our model in learning the even-pair representation. When incorporating arguments, the system obtains further improvement (from 84.0 to 84.4 by CoNLL F1).

### 4.2 Within-document Event Coreference

Within-document event coreference regard each document as a single topic, and focuses on event pairs in the same document. Therefore, topic clustering is not needed. We use the same pairwise scorer and mention clustering algorithm described in Section 4.1.

We first evaluate on the most widely used KBP benchmark. Similar to (Huang et al., 2019) and (Lu et al., 2020), we use KBP 2015 dataset (Ellis et al., 2015) as training data, KBP 2016 dataset (Ellis et al., 2016) as dev data, and KBP 2017 (Getman et al.) as test data. The detailed statistics is shown in Table 2.

We compare with two state-of-the-art systems on KBP benchmark: Huang et al. (2019), which exploits unlabeled data to learn argument compatibility in order to improve coreference performance, and Lu et al. (2020), which jointly learns event detection and event coreference. Lu et al. (2020) claims the state of the art performance when predicting event coreference given predicted events, and they also reported numbers using gold event
Table 6: Within-document event coreference performance on KBP17. Please note that the KBP15 corpus (training data) only provides trigger annotation.

| Model | MUC    | B³     | CEAF_e | BLANC | AVG-F  |
|-------|--------|--------|--------|-------|--------|
| (Huang et al., 2019) Predicted Mentions | 35.66  | 43.20  | 40.02  | 32.43  | 36.75  |
| (Lu et al., 2020) Predicted Mentions | 39.06  | 47.77  | 45.97  | 30.60  | 40.85  |
| Gold Mentions | -      | -      | -      | -      | 53.72  |
| PAIREDRL Gold Mentions | 63.31  | 57.77  | 54.40  | 49.89  | 56.34  |

Table 7: Within-document event coreference performance on ACE05. Note that our numbers are not directly comparable with the baselines due to different data splits. Peng et al. (2016) used more training data, by virtue of doing 10-fold cross validation. In addition, our system used only triggers while Peng et al. (2016) and Chen et al. (2009) combined triggers, arguments and other available gold information.

| Model | MUC    | B³     | CEAF_e | CoNLL |
|-------|--------|--------|--------|-------|
| Chen et al. (2009) triggers only | 38.6   | 86.8   | -      | -     |
| + arguments | 53.0   | 87.9   | -      | -     |
| + attributes | 72.3   | 91.9   | -      | -     |
| Peng et al. (2016) | 74.9   | 92.8   | 87.1   | 84.93 |
| PAIREDRL triggers only | 76.1   | 90.7   | 87.2   | 84.65 |

ments. Our model does not conduct mention detection, so we report our performance on gold mentions only (this is still fair since the prior SOTA system (Lu et al., 2020) reported on gold mentions too) and leave our numbers on predicted mentions as future work. As shown in Table 6, our model PAIREDRL outperforms the prior state-of-the-art model with a big margin as well: 56.34 vs. 53.72 (by “AVG-F”). This further verifies the effectiveness of our system in modeling event coreference regardless, whether it is within-document or cross-document.

In addition, we also report on the benchmark ACE2005\(^4\) which has been rarely studied for event coreference recently. We use the data split preprocessed by Lin et al. (2020), and the detailed statistics is shown in Table 3. The prior state-of-the-art system on ACE2005 dataset is by Peng et al. (2016); they used gold event mentions, and event arguments information with the help of external knowledge bases, like Wikipedia to train the model. A even earlier work by Chen et al. (2009) showed that adding arguments and event attributes improves the performance.

Table 7 shows that, by only using gold triggers, we can achieve a very close number to Peng et al. (2016). It is worth mentioning that our numbers and that by Peng et al. (2016) are not directly comparable because of two reasons: (i) Peng et al. (2016) used 10-fold cross validation, which is different with the data split we used; (ii) Peng et al. (2016) used gold triggers, event arguments and external Wikipedia to train the model while we only used triggers. Chen et al. (2009) shows good number on B³ when adding gold information of event attributes, which include polarity, modality, genericity and tense. These gold information is usually inaccessible for downstream tasks, and also hard to predict in real application. Our numbers are pretty close to theirs by B³ and beat theirs by a big margin by the MUC metric even though our system uses triggers only. This experiment also confirm the powerfulness of our representation learning and indicates that our system might get further boost if integrating more information. We leave it as future work.

### 4.3 Within-document Entity Coreference

Unlike events, entities do not have arguments. For entities, we just use PAIREDRL to learn the pairwise representation as Equation 4. The pairwise scorer and mention clustering method is same as described in Section 4.1.

**Dataset** We use the OntoNotes 5.0 corpus (Weischedel et al., 2013). This is the largest dataset for document-level Entity Coreference, and has been widely used (Lee et al., 2017; Joshi et al., 2020; Wu et al., 2020). The detailed statistics is

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\(^4\)https://www.ldc.upenn.edu/collaborations/past-projects/ace
shown in Table 4. We compare with two baselines that stand as the state-of-the-art:

• (Wu et al., 2020): formulating the task as query-based span prediction in question answering;

• (Joshi et al., 2020): using a new pre-training representation SpanBERT as the embedding of the end-to-end coreference model by Lee et al. (2017).

Both baselines are end-to-end systems for exhaustive entity span generation and entity coreference resolution; they didn’t report performance on gold mentions. We temporarily report performance on gold mentions only in Table 8, and leave the joint detection of entity spans and entity coreference as future work.

5 Discussion

It is worth mentioning that our model PAIREDRL has a pretty simple architecture: RoBERTa concatenates two sentences as input, providing as output contextualized mention representations which are further composed to a pairwise representation. Our approach does not rely on any algorithms for argument mining, argument linking and etc. We basically treat the event/entity coreference problem as mention-pair classification problem conditioned on the context. This way, our approach unifies the treatment of event and entity coreference.

Moreover, the strong performance of our system in both event and entity coreference motivates rethinking the contribution of arguments and other attributes to the problem of coreference, and the best approach to integrate them. Some earlier approaches detected event arguments or developed joint learning algorithms to facilitate interaction between coreference and mention detection; our system, instead, learns the mention representation merely based on the sentence encoding. It strongly suggests that using RoBERTa to encode the sentence pair may already implicitly encodes the argument information into the mention representation. That means that the learnt representation for the event’s trigger already encodes the argument features to some extent. Finally, we note that despite the relatively simple approach, our structured representations enables us to analyze which arguments are important and what their contribution is. This could lead to better interpretation of the model outcome.

6 Conclusion

In this work, we presented a simple and unified representation learning framework, PAIREDRL, for event and entity coreference. PAIREDRL learns a mention-pair representation by forwarding concatenated sentences into RoBERTa, where sentences provide the context of mentions. This algorithm is applied to both event and entity coreference benchmarks and obtains state of the art performance. In addition, we augmented this pairwise representation with structured argument features to further improve its performance in event coreference.

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