Event Coreference Resolution using Convolutional Neural Networks

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Outline

Introduction

Task Definition What is an Event?

Learning to Identify Events

Identifying an Event Event Extraction Related Work

Coreference Resolution

Recent Work Our CNN Architecture Conclusion

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<u>Parag</u> broke his arm when <u>he</u> fell down the stairs. It was Nirbhay who pushed <u>him</u>.

Two or more expressions in a text are coreferent if they refer to the same entity.

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 The task of identifying coreferent expressions is called Entity Coreference Resolution

What is an Event?

An event is any occurrence or happening, typically associated with a trigger word or phrase called an event trigger.

In Baghdad, a cameraman <u>died</u> when an American tank <u>fired</u> on the Palestine Hotel.

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In Baghdad, a cameraman <u>died</u> when an American tank <u>fired</u> on the Palestine Hotel.

- What does the event Die consist of?
 - Trigger Word(s) "died"
 - Victim "cameraman"
 - Instrument "American Tank"
 - Place "Baghdad"

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Identifying an Event



- Upper side: Event mentions Die and Attack
- Lower size: A subset of dependency parse tags

Source: Chen et. al. in "Event Extraction via Dynamic Multi-Pooling Convolutional Neural Networks"

Inherent Ambiguity in Events

Multiple events in a sentences, overlap in arguments

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Multiple events in a sentences, overlap in arguments

- Same trigger words, different event types
 - E1: Donald Trump beats Clinton.
 - E2: Muhammad Ali beats his opponent.

Inherent Ambiguity in Events

Multiple events in a sentences, overlap in arguments

- Same trigger words, different event types
 - E1: Donald Trump beats Clinton.
 - E2: Muhammad Ali beats his opponent.
- Trigger words are not discriminatory enough!

A Machine Learning Approach

- The aim is learn how to differentiate between true and false event triggers.
- What discriminatory information can be used to automatically identify true event triggers?

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Syntactic features such as POS, dependency tags.

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- The aim is learn how to differentiate between true and false event triggers.
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- Syntactic features such as POS, dependency tags.
- Semantic information, estimated using word vectors.

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- The aim is learn how to differentiate between true and false event triggers.
- What discriminatory information can be used to automatically identify true event triggers?

- Syntactic features such as POS, dependency tags.
- Semantic information, estimated using word vectors.
- Learning features automatically using deep learning.

Related Work

Event Extraction using CNNs

 Recently Chen et. al. proposed a convolutional neural network approach for event extraction.

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 Incorporated multiple event sentences by using a dynamic multi-pooling framework.

Chen's CNN Architecture



Figure 2: The architecture for the stage of argument classification in the event extraction. It illustrates the processing of one instance with the predict trigger *fired* and the candidate argument *cameraman*.

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Source: Chen et. al. in "Event Extraction via Dynamic Multi-Pooling Convolutional Neural Networks"

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Coreference Resolution

Classifying event pairs as coreferent or not - simple binary classification?

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Coreference Resolution

- Classifying event pairs as coreferent or not simple binary classification?
- Best performance (a coreference metric related to F-score) until 2015 was around 60 for the ACE 2005 dataset.

Coreference Resolution

- Classifying event pairs as coreferent or not simple binary classification?
- Best performance (a coreference metric related to F-score) until 2015 was around 60 for the ACE 2005 dataset.
- We aim to empirically analyse the performance of a CNN approach for feature extraction.

Our CNN Architecture

Features of the two events taken by the CNN are:

- Word vectors of event trigger context window
- Position feature embeddings of event triggers
- A single convolutional layer with multiple convolution filter sizes, followed by a dynamic max-pooling layer
- Three FC (fully connected) layers followed by softmax over the three predicted classes:

- ▶ 1 First event is true or false
- 2 Second event is true or false
- 3 The two events are coreferent or not

Conclusion

- Our joint CNN architecture is the first such approach for Coreference Resolution and Event Extraction
- We hope to test whether sequence learning methods (RNNs) can provide better features for coreference resolution.

Thank You

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