

Event Coreference Resolution: A Survey of Two Decades of Research

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Event Coreference Resolution

Determine event mentions that refer to the same real-world event

Nelson Mandela has died at age 95.

The world has lost a great man, former Prime Minister Julia Gillard said.



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Nelson Mandela has **died**(ev1) at age 95.

The world has **lost**(ev2) a great man, former Prime Minister Julia Gillard **said**(ev3).

a word or phrase that triggers an event mention

| | Trigger Word | Event Type | Arguments | Entity Coreference |
|-----|--------------|------------|-----------|--------------------|
| ev1 | died | | | |
| ev2 | lost | | | |
| ev3 | said | | | |



Event Coreference Resolution

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Coreferent event mentions have the same event type

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| ev1 | died | Life.Die | | |
| ev2 | lost | Life.Die | | |
| ev3 | said | Contact. Broadcast | | |



Event Coreference Resolution

Determine event mentions that refer to the same real-world event

Nelson Mandela has **died**(ev1) at age 95.

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Coreferent event mentions have compatible arguments

| | Trigger Word | Event Type | Arguments | Entity Coreference |
|-----|--------------|-----------------------|---------------------------------------|--------------------|
| ev1 | died | Life.Die | Nelson Mandela (Victim) | |
| ev2 | lost | Life.Die | a great man (Victim) | |
| ev3 | said | Contact. Broadcast | Prime Minister Julia Gillard (Person) | |

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To determine the compatibility of event arguments

| | Trigger Word | Event Type | Arguments | Entity Coreference |
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| ev1 | died | Life.Die | Nelson Mandela (Victim) | (Nelson Mandela, a great man) |
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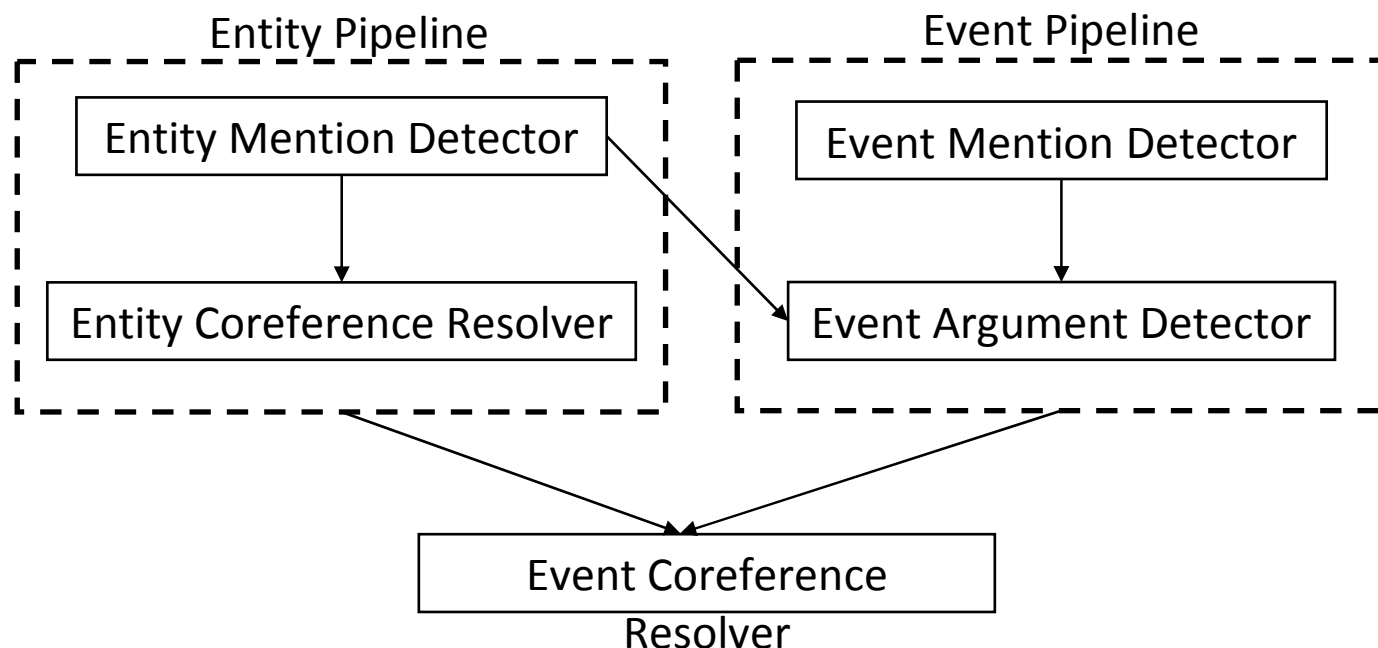
Event Coreference Resolution

More challenging than entity coreference resolution

Event Coreference Resolution

More challenging than entity coreference resolution

- Using the noisy outputs of a larger set of upstream components

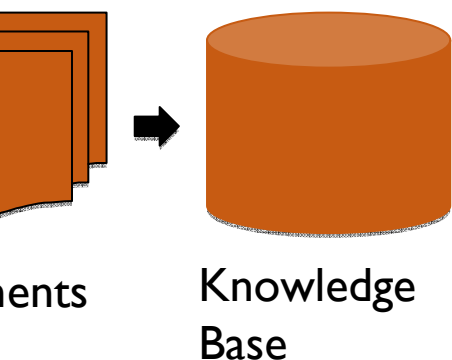


Event Coreference Resolution

Core task in information extraction from text

- Consolidate the textual information about an event
- Crucial for high-level NLP applications

- E.g., template filling, automated population of knowledge bases, topic detection and tracking, question answering, summarization, contradiction detection



A **separatist group** claimed responsibility for an **explosion (ev1)** late on **Monday** which wounded **six people** in an **Istanbul supermarket**. Istanbul governor told news agency the **explosion (ev2)** in the **Bahcelievler district** injured **six people**.

Bombing Template

Perpetrator: **A separatist group**

Target: **six people**

Time: **Monday**

Location: **an Istanbul supermarket, Bahcelievler district**



Plan for the talk

Corpora

Models

Features

Evaluations and State-of-the-Art

Challenges



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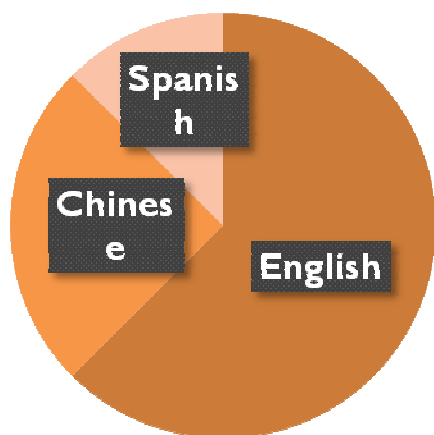
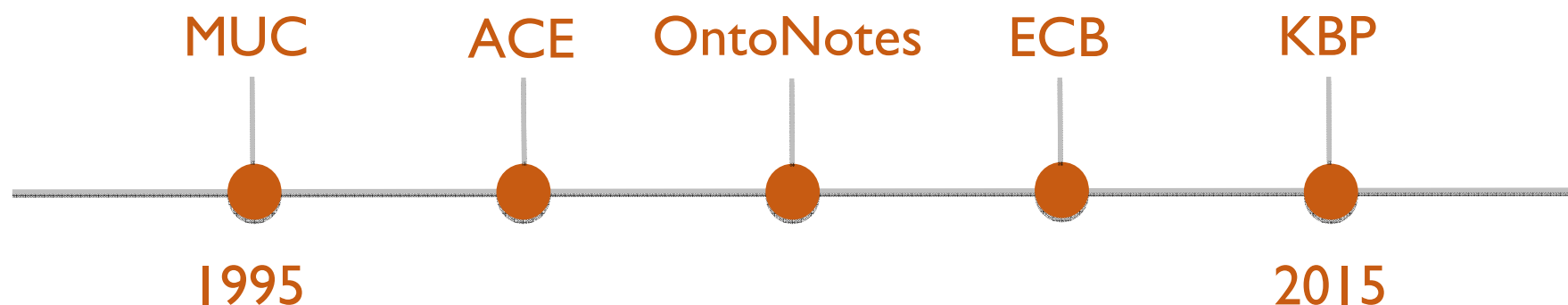
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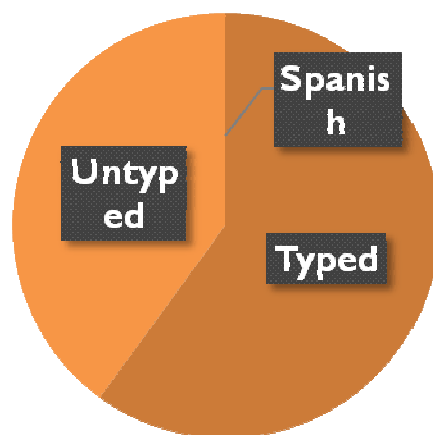
Challenges

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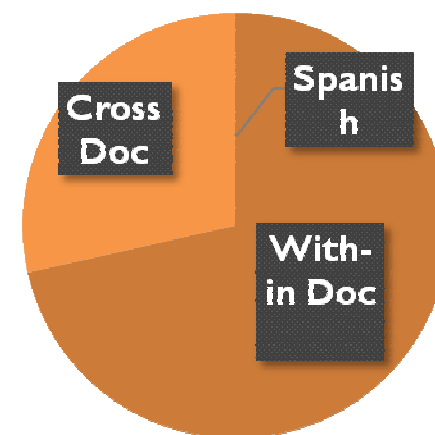
5 publicly available corpora



Language



Event Annotation



Coreference Chain Type



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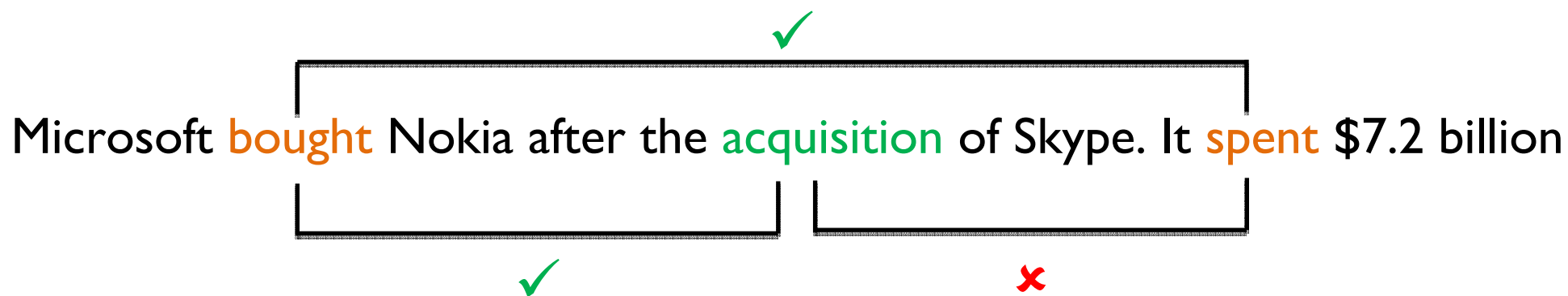
Challenges



Mention-Pair Models

A two-step resolution framework

- Step I: use a binary classifier to determine whether two event mentions are coreferent.
 - Pairwise classification decisions could violate transitivity

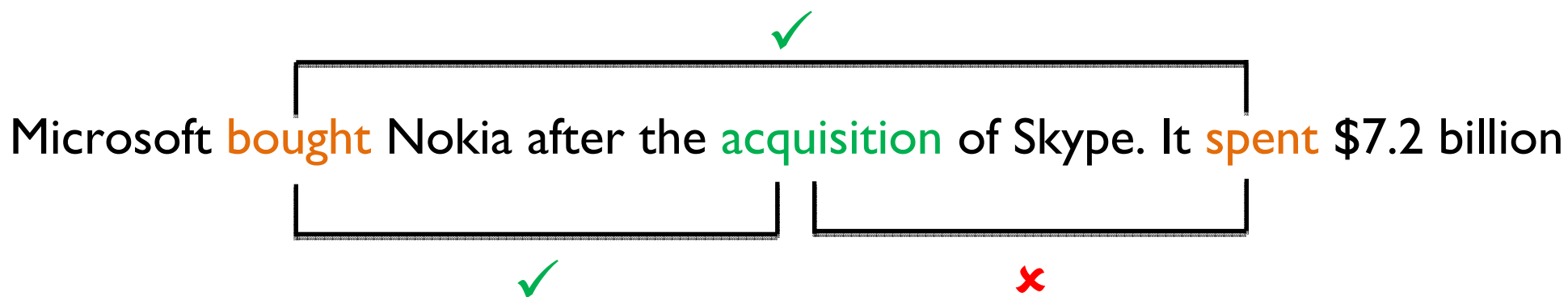




Mention-Pair Models

A two-step resolution framework

- Step 1: use a binary classifier to determine whether two event mentions are coreferent.
 - Pairwise classification decisions could violate transitivity



- Step 2: use clustering to coordinate the pairwise decisions and construct a partition.
 - Agglomerative clustering, graph partitioning



Weaknesses of the Mention-Pair Models

Two-step approach suffers from error propagation

- Errors made by a mention-pair model can propagate to the clustering step

Improvement: Generative Model

- Yang et al. (2015)

- Idea: combine distance-based and distribution-based methods to perform guided

Bayesian clustering

- A clustering model
- A Bayesian model: encode the knowledge provided by a mention-pair model as prior
- Employ rich features in the modeling process



Weaknesses of the Mention-Pair Models

Can't determine which candidate antecedent is the best

- only determine how good a candidate antecedent is relative to the event mention, but not how good it is relative to other candidate antecedents



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Solution: Mention-Ranking Models

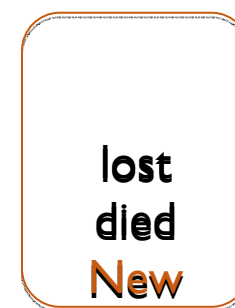
- allowing candidate antecedents of a mention to be ranked simultaneously so that its correct antecedent has the **highest** rank.



Mandela has died...



The world has lost...



His wife passed away...



Easy-First Models

The aforementioned models resolve mentions from left to right

Easy-first models operate in an iterative fashion

- make easy linking decisions first
- subsequently exploit these easy decisions (as additional knowledge) to make hard linking decisions.



Easy-First Models

Nelson Mandela has **died** at age 95 at his Houghton residence.

The world has **lost** a great man.

Later President Jacob Zuma confirmed Mandela, one of the greatest man in South Africa, **passed away** at his home.

| | |
|-------------|--|
| died | Nelson Mandela(victim), his Houghton residence (location) |
| lost | a great man (victim) |
| passed away | Mandela, one of the greatest man in South Africa (victim), his home (location) |

lost

died

passed away



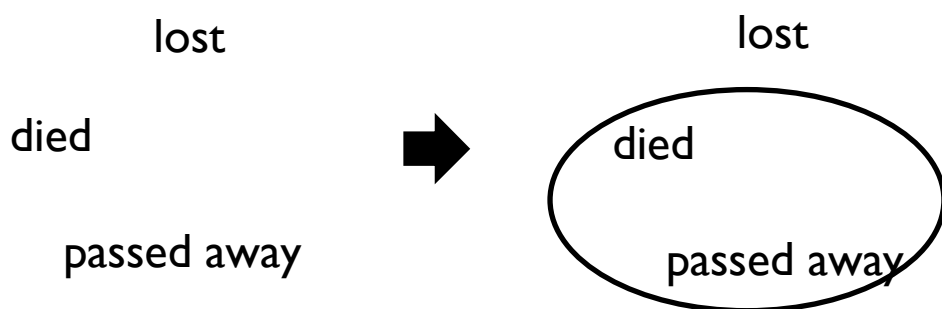
Easy-First Models

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Later President Jacob Zuma confirmed Mandela, one of the greatest man in South Africa, **passed away** at his home.

| | |
|---------------------|--|
| died passed away | Nelson Mandela/Mandela, one of the greatest man in South Africa (victim), his Houghton residence / his home (location) |
| lost | a great man (victim) |



Argument propagation
in each iteration



Easy-First Models

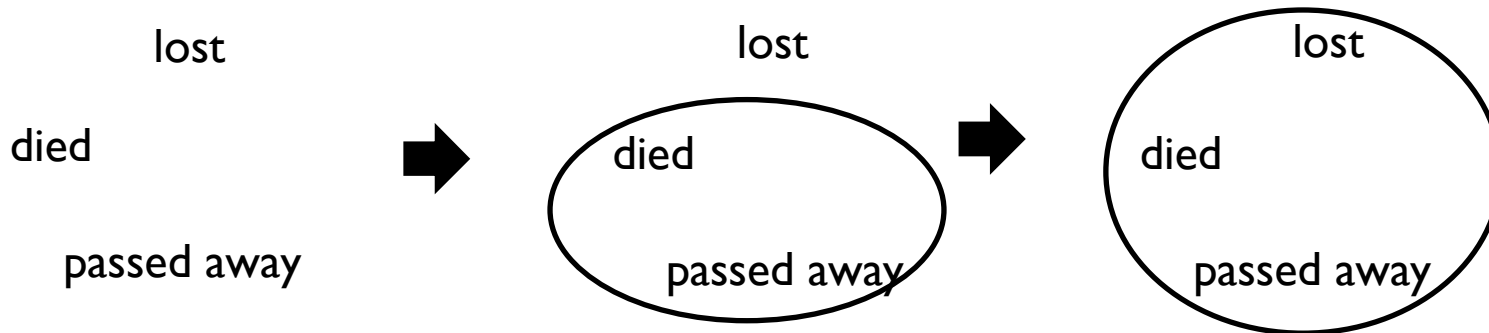
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| | |
|-----------------------------|---|
| died passed away lost | Nelson Mandela/Mandela, one of the greatest man in South Africa/a great man (victim) his Houghton residence / his home (location) |
|-----------------------------|---|

Could bootstrap entity coreference output (Lee et. al 2012)



Joint Models

The aforementioned models all adopt a pipeline architecture

– Error propagation

Event pipeline

Entity pipeline



Event
Coreference

Joint Models

The aforementioned models all adopt a pipeline architecture

- Error propagation

Event pipeline

Entity pipeline

Event
Coreference

- Not able to employ the interdependence between event detection and event coreference resolution

Life.Die

Nelson Mandela has **died** at age 95



The world has **lost** a great man...

Life.Die

~~Personnel.End-Position~~

~~Life.Injury~~

~~NULL~~



Joint Models

Joint inference over the outputs of different tasks in the IE pipeline

- Integer Linear Programming (ILP)
 - encode hard constraints, e.g. two triggers that do not have the same event subtype cannot coreferent.
- Markov Logic Networks (MLNs)
 - encode both soft and hard formulas

Joint learning over different tasks

- E.g., jointly learn event extraction and coreference
- Recast as a structured prediction problem
 - Use the structured perceptron training algorithm (Araki and Mitamura, 2015)
 - Use a structured conditional random field model (Lu and Ng, 2017)



Semi-Supervised Models

Data acquisition bottleneck

- manually annotating data for all the components in the IE pipeline is expensive

Solution

- Use active learning to select informative instances (Chen and Ng, 2016)
- Utilize large amounts of out of domain text data (Peng et. al, 2016)
 - represent event structures by five event semantic components
 - Convert each event component to its corresponding vector representation

$$\begin{array}{c} [\dots] \\ \text{event} \end{array} = \begin{array}{c} [[\dots] [\dots] [\dots] [\dots] [\dots] [\dots]] \\ \text{action} \quad \text{agent}_{\text{sub}} \quad \text{agent}_{\text{obj}} \quad \text{location} \quad \text{time} \quad \text{sentence} \\ \text{or} \\ \text{clause} \end{array}$$



Unsupervised Models

Eliminate a model's reliance on annotated data.

Probabilistic generative models

- Use a set of Dirichlet Processes (DPs), in which each DP is associated with each document, and each mixture component is an event coreference cluster shared across documents (Bejan and Harabagiu, 2014)
- Use a latent variable to represent coreference decisions (Chen and Ng, 2015)



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Models

Features

Evaluations and State-of-the-Art

Challenges



Features

Lexical features

- Explicitly or implicitly compare the event triggers of a pair of event mentions
- Commonly used features:
 - Pair features: Trigger pairs. POS pairs of triggers
 - String-matching features
 - Trigger similarity features
- **String-matching features** have been shown to contribute significantly



Features

Argument features

- Event mentions having incompatible arguments are unlikely to be coreferent
- Commonly used features:
 - Number of overlapping and unique arguments
 - Argument similarity: whether entities are coreferent, similarity metrics
- An event argument extractor and an entity coreference resolver are typically needed
- Improving existing argument extractors and entity coreference resolvers can further improve event coreference resolver



Features

Semantic features

- Compute the similarity between two event mentions from lexical semantic resources (e.g., WordNet), Brown clusters, and the word embeddings
- Experiments show that **the embedding-based similarity feature** has the highest weight among all features, hence suggesting its usefulness
- **Event (sub)type match** has also been shown to be a strong indicator
 - died (Life.die) vs. lost (Personnel.End-Position)



Features

Discourse features

- Encode the token, event and sentence distance between two event mentions
- Experiment shows discourse features do not contribute to event coreference performance as much as other types of features



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Evaluation

End-to-end event coreference resolver

- event coreference performance is significantly affected by event mention (i.e., trigger) detection performance

Evaluation Metrics

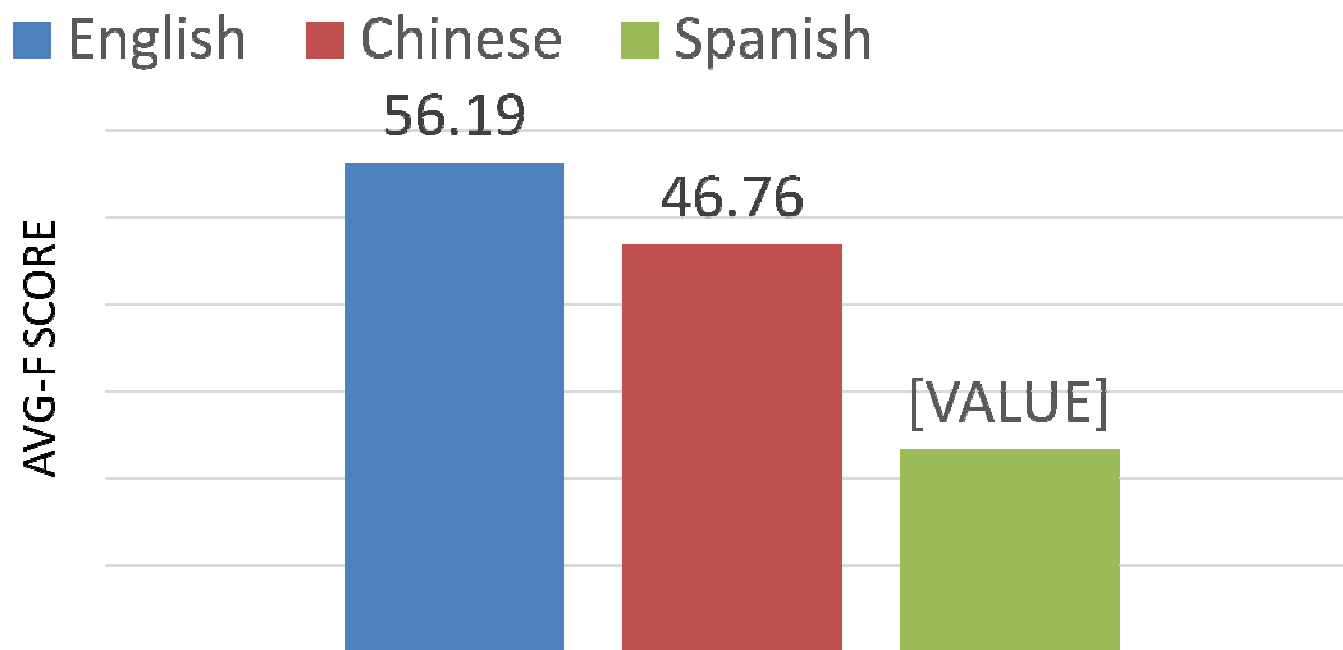
- Since researchers cannot agree on which evaluation metric is the best to use, multiple metrics are typically used
 - Link-based MUC metric (Vilain et al., 1995)
 - Mention based B^3 metric (Bagga and Baldwin, 1998)
 - Entity based $CEAF_e$ metric (Luo, 2005)
 - Rand index-based BLANC metric (Recasens and Hovy, 2011)
 - CoNLL score and AVG score



Results

The best results to date on multi-lingual KBP 2017 dataset

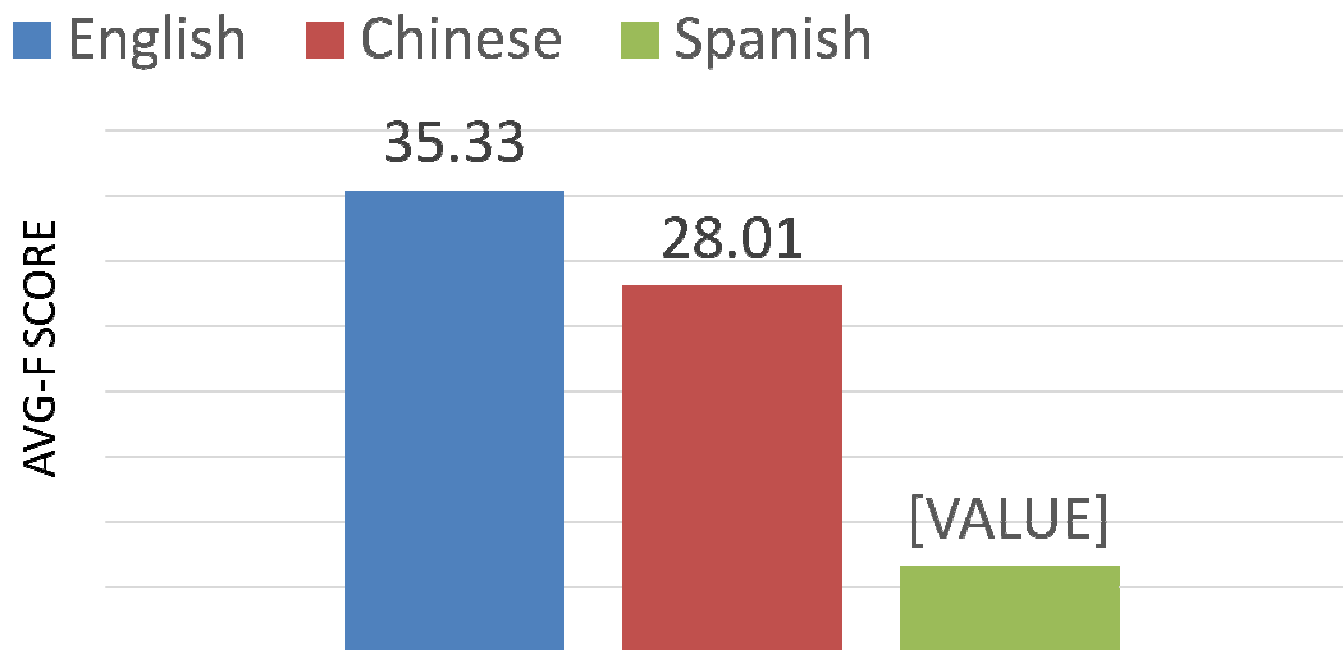
Event Trigger Detection result





Results

The best results to date on multi-lingual KBP 2017 dataset
Event Coreference result





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Challenges

It may be worthwhile to investigate joint models further.

- Previous work has applied joint **inference** to the four key tasks in IE
- Can we jointly **learn** these four tasks?



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Challenges

We may need to employ sophisticated features

- Given recent successes on employing word vectors for event coreference resolution, can we learn representations from complex features?
 - features that are derived from computed arguments and entity coreference chains.



Challenges

Low-resource languages

- How can we learn models if coreference-annotated corpora may not be available?
- How can we obtain semantic knowledge if large lexical knowledge bases do not exist?