Coreference

CS 690N, Spring 2017

Advanced Natural Language Processing http://people.cs.umass.edu/~brenocon/anlp2017/

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[Including slides from Luke Vilnis and Chris Manning]

Noun phrase reference





Barack Obama nominated Hillary Rodham Clinton as his secretary of state. He chose her because she had foreign affairs experience.

Referring expressions reference discourse entities e.g. real-world entities

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http://harrypotter.wikia.com/wiki/Harry_Potter

Harry James Potter (b. 31 July, 1980) was a half-blood wizard, the only child and son of James and Lily Potter (née Evans), and one of the most famous wizards of modern times ... Lord Voldemort attempted to murder him when he was a year and three months old ...

Referring expressions reference discourse entities e.g. real-world entities (... or non-real-world)

Terminology

http://harrypotter.wikia.com/wiki/Harry_Potter

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an **Entity** or **Referent** is a ~real-world object (discourse entity) ("HARRY_POTTER_CONCEPT")

Referring expressions a.k.a. Mentions

14 NPs are underlined above (are they all referential?)

Coreference: when referring mentions have the same referent.

Coreference resolution: find which mentions refer to the same entity.

l.e. cluster the mentions into entity clusters.

Applications: text inference, search, etc.

- Who tried to kill Harry Potter?

Exercise

Do within-document coreference in the following document by assigning the mentions entity numbers:

```
[The\ government]_{---}\ said\ [today]_{---}\ [it]_{---}\ 's\ going\ to\ cut\ back\ on\ [[[the\ enormous\ number]_{---}]
of [people]___]__ who descended on [Yemen]___ to investigate [[the attack]___ on [the "USS
Cole]___]___. " [[[So many people]___ from [several agencies]___]___ wanting to par-
ticipate that [the Yemenis]___ are feeling somewhat overwhelmed in [[their]___ own country]___.
[Investigators]___ have come up with [[another theory]___ on how [the terrorists]___ operated]___.
[[ABC 's]_{--}] John Miller]___ on [[the house]_{--}] with [a view]_{--}]_{--}. High on [[a hillside]_{--}], in
[[a run - down section]_{---} of [Aden]_{---}]_{---}, [[the house]_{---} with [the blue door]_{---}]_{---} has
[[a perfect view]___ of [the harbor]___]__. [American and Yemeni investigators]___ believe [that
view]___ is what convinced [[a man]___ who used [[the name]___ [Abdullah]___]___ to rent
[the house]___ [several weeks]___ before [[the bombing]___ of [the "USS Cole]___]__. " Early
on [investigators]___ theorized [it]___ was [an inside job]___ and [[much]___ of [the focus]___]___
was on [[employees]___ of [[the Mansoon shipping company]___, which was under [[contract]___ by
[the Navy]___ to refuel [U.S. warships]___]__ and would have had [[advance information]___ about
[[the "Cole's"]___ arrival]___]___. Now [the FBI]___ believes [[all]___ [the terrorists]___
needed to do]___ was look out [the window]___, to go through [precisely the same drill]___, well before
[the "Cole"]___ [arrived]___. [[The man]___ in [this house]___]__ would have had [[plenty]___ of
[[time]_{--}] to signal [[two bombers]_{--}] waiting with [the boat]_{--} across [the bay]_{--}]_{--}]_{--}.
[Investigators]___ say [[clues]___ collected over [the last few days]___]__ have already pointed
[them]_{--} to [[locations]_{--} both near and far outside [[the port city]_{--} of [Aden]_{--}]_{--},
but [they]___ wo n't say [there]___ 's [any indication that [[the plot]___ here]___ goes beyond
[[Yemen 's]___ boarders]___]__. Learning [[the true identities]___ of [[those]___ involved in [the
bombing]___]___ would help answer [that question]___, but [the two suicide bombers]___ died in
[the attack]___, and after [the explosion]___, [[the man]___ who lived behind [the blue door]___]___
simply vanished. [John Miller]___, [ABC News]___, [Aden]___.
```

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```

Kinds of Reference

- Referring expressions
 - John Smith
 - President Smith
 - the president
 - the company's new executive

More common in newswire, generally harder in practice

- Free variables
 - Smith saw his pay increase
- Bound variables
 - The dancer hurt *herself*.

More interesting grammatical constraints, more linguistic theory, easier in practice

"anaphora resolution"

- Lexical cues
 - I saw a house. The house was red.
 - I saw a house. The other house was red.

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 - John saw Mary. She was eating salad.
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- Deeper semantics (world knowledge)
 - The city council denied the demonstrators a permit because they feared violence.
 - The city council denied the demonstrators a permit because they advocated violence.
 - State-of-the-art coref uses with the first three

Coreference approaches

- Architectures
 - Mention-Mention linking
 - Entity-Mention linking
- Models
 - Rule-based approaches (e.g. sieves)
 - Supervised ML
 - (Unsupervised)
- Datasets: Ontonotes, CoNLL shared tasks (newspapers)
- Available systems
 - CoreNLP (rule-based)
 - BookNLP (supervised, works on book-length texts)
 - Berkeley Coref ... etc. etc.

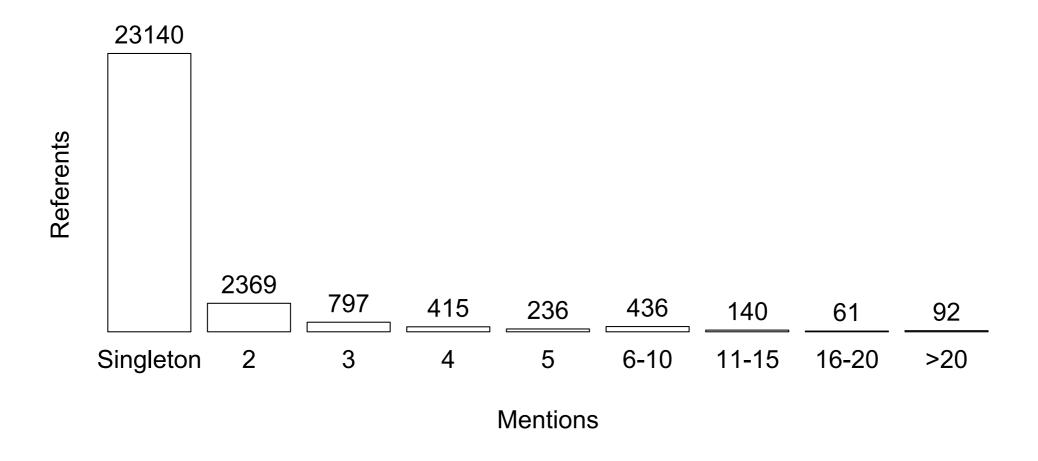
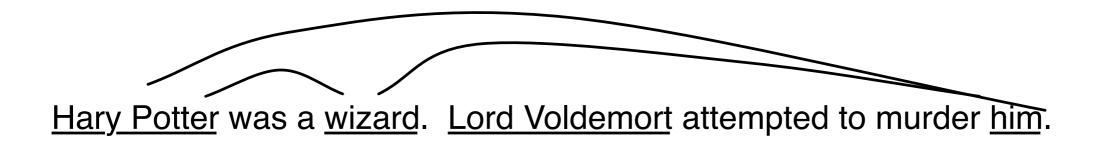


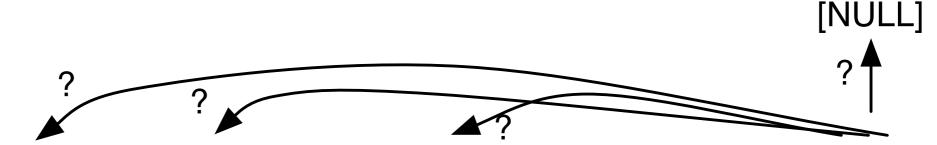
Figure 1: Distribution of referent lifespans in the 2012 OntoNotes development set.

Supervised ML: Mention pair model



- View gold standard as defining links between mention pairs
- Think of as binary classification problem: take random pairs as negative examples
- Issues: many mention pairs. Also: have to resolve local decisions into entities

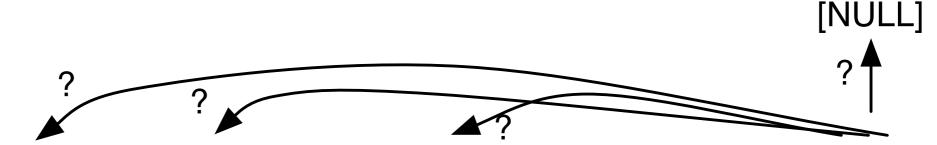
Antecedent selection model



Hary Potter was a wizard. Lord Voldemort attempted to murder him.

- View as antecedent selection problem: which previous mention do I corefer with?
 - Makes most sense for pronouns, though can use model for all expressions
- Process mentions left to right. For the n'th mention, it's a n-way multi-class classification problem: antecedent is one of the n-l mentions to the left, or NULL.
 - Features are asymmetric!
 - Use a limited window for antecedent candidates, e.g. last 5 sentences (for news...)
- Score each candidate by a linear function of features.
 Predict antecedent to be the highest-ranking candidate.

Antecedent selection model



Hary Potter was a wizard. Lord Voldemort attempted to murder him.

- Training: simple way is to process the gold standard coref chains (entity clusters) into positive and negative links. Train binary classifier.
- Prediction: select the highest-scoring candidate as the antecedent. (Though multiple may be ok.)
- Using for applications: take these links and form entity clusters from connected components [whiteboard]

Features for pronoun resolution

- English pronouns have some grammatical markings that restrict the semantic categories they can match. Use as features against antecedent candidate properties.
 - Number agreement
 - he/she/it vs. they/them
 - Animacy/human-ness? agreement
 - it vs. he/she/him/her/his
 - Gender agreement
 - he/him/his vs. she/her vs. it
- Grammatical person interacts with dialogue/ discourse structure
 - I/me vs you/y'all vs he/she/it/they

Other syntactic constraints

- High-precision patterns
 - Predicate-Nominatives: "X was a Y ..."
 - Appositives: "X, a Y, ..."
 - Role Appositives: "president Lincoln"

Features for Pronominal Anaphora Resolution

- Preferences:
 - Recency: More recently mentioned entities are more likely to be referred to
 - John went to a movie. Jack went as well. He was not busy.
 - Grammatical Role: Entities in the subject position is more likely to be referred to than entities in the object position
 - John went to a movie with Jack. He was not busy.
 - Parallelism:
 - John went with Jack to a movie. Joe went with him to a bar.

Recency

- Not too recent, but can override
 - (I) John likes him
 - (2) John likes his mother
 - (3) John likes himself
 - (4) John likes that jerk
- Typical relative distances [via Brian Dillon]
 - reflexive > possessive > pronoun > anaphoric NP
- Salience: Subject of previous sentence is typical antecedent for a pronoun
 - Hobbs distance on constituent trees

Features for Pronominal Anaphora Resolution

- Preferences:
 - Verb Semantics: Certain verbs seem to bias whether the subsequent pronouns should be referring to their subjects or objects
 - John telephoned Bill. He lost the laptop.
 - John criticized Bill. He lost the laptop.
 - Selectional Restrictions: Restrictions because of semantics
 - John parked his car in the garage after driving it around for hours.
- Encode all these and maybe more as features

Features for non-pronoun resolution

- Generally harder!
 - String match
 - Head string match
 - I saw a green house. The house was old.
 - Substrings, edit distance
 - For names: Jaro-Winkler edit distance...
- Cross-document coreference and entity linking
 - Name matching: string comparisons
 - Contextual information

Recent coref results

System	MUC			B^3			$CEAF_e$			
	P	R	F_1	P	R	F_1	P	R	F_1	CoNLL
B&K (2014)	74.3	67.46	70.72	62.71	54.96	58.58	59.4	52.27	55.61	61.63
M&S (2015)	76.72	68.13	72.17	66.12	54.22	59.58	59.47	52.33	55.67	62.47
C&M (2015)	76.12	69.38	72.59	65.64	56.01	60.44	59.44	52.98	56.02	63.02
Peng et al. (2015)	-	-	72.22	-	-	60.50	-	-	56.37	63.03
Wiseman et al. (2015)	76.23	69.31	72.60	66.07	55.83	60.52	59.41	54.88	57.05	63.39
This work	77.49	69.75	73.42	66.83	56.95	61.50	62.14	53.85	57.70	64.21

Table 1: Results on CoNLL 2012 English test set. We compare against recent state of the art systems, including (in order) Bjorkelund and Kuhn (2014), Martschat and Strube (2015), Clark and Manning (2015), Peng et al. (2015), and Wiseman et al. (2015). F_1 gains are significant (p < 0.05 under the bootstrap resample test (Koehn, 2004)) compared with Wiseman et al. (2015) for all metrics.