Coreference Resolution

Slides are modified from Prof. Claire Cardie’s
Plan for the Talk

Linguistic background for coreference resolution
- supervised machine learning approach
- weakly supervised approaches
Reference resolution

- **Reference**: the process by which speakers use expressions like “John Simon” and “his” to denote a real-world entity
  - **Referring expressions**: NL expression used to perform reference
  - **Referent**: the entity that is referred to
  - **Shorthand form**: *his* refers to John Simon

John Simon, Chief Financial Officer of Prime Corp. since 1986, saw *his* pay jump 20%, to $1.3 million, as the 37-year-old also became the financial-services company’s president...
Coreference

- **Coreference:** two referring expressions that are used to refer to the same entity are said to corefer
- *John Simon* is the **antecedent** of *his*.
- Reference to an entity that has been previously introduced into the discourse is called **anaphora**; and the referring expression used is said to be **anaphoric**.

John Simon, Chief Financial Officer of Prime Corp. since 1986, saw his pay jump 20%, to $1.3 million, as the 37-year-old also became the financial-services company’s president...
Types of referring expressions

- **Definite Noun Phrases**
- **Indefinite Noun Phrases**
- **Pronouns**
- **Demonstrative pronouns**
- **One-Anaphora**
**Indefinite** noun phrases
- Introduce entities that are new to the hearer into the discourse context
  - I saw *a Subaru WRX* today.
  - I saw *this awesome Subaru WRX* today.

**Definite** noun phrases
- Refer to an entity that is identifiable to the hearer
- It has already been mentioned in the discourse
- It is contained in the hearer’s set of beliefs about the world
- The uniqueness of the object is implied by the description itself
  - I saw a Subaru WRX today. *The WRX* was blue and needed a wash.
  - *The Indy 500* is the most popular car race in the US.
  - *The fastest car in the Indy 500* was a Subaru WRX.
Pronouns

- Another form of *definite* reference
- Also known as *Anaphora*
- Referent must have a high degree of activation or *saliency* in the discourse model
  - John went to Bob’s party, and parked next to a beautiful Subaru WRX. He went inside and talked to Bob for more than an hour. Bob told him that he recently got engaged.
    - (a)?? He also said that he bought *it* yesterday.
    - (a’) He also said that he bought *the WRX* yesterday.

- *Cataphora*: referring expression is mentioned before its referent
  - Before *he* bought *it*, John checked over the WRX carefully.
Types of referring expressions

- **Definite Noun Phrases**
- **Indefinite Noun Phrases**
- **Pronouns**
- **Demonstrative pronouns**
- **One-Anaphora**
Demonstrative pronouns

- Behave somewhat differently than simple definite pronouns
- Can appear alone or as determiners
- Choice of *this* or *that* depends on some notion of spatial or temporal proximity
  - I bought a WRX yesterday. It’s similar to the one I bought a year ago. *That one* was really nice, but I like *this one* even better.

One-anaphora

- Blends properties of definite and indefinite reference
  - I saw no fewer than 6 Subaru WRX’s today. Now I want *one*.
- May introduce a new entity into the discourse, but it is dependent on an existing referent for the description of this new entity.
Noun Phrase Coreference Resolution

- Identify all phrases that refer to each real-world entity mentioned in the text

John Simon, Chief Financial Officer of Prime Corp. since 1986, saw his pay jump 20%, to $1.3 million, as the 37-year-old also became the financial-services company’s president...
Why It’s Hard

Many sources of information play a role

- head noun matches
  - IBM *executives* = the *executives*
  - Microsoft *executives*

- syntactic constraints
  - John helped himself to...
    -
  - John helped him to...
    -

- discourse focus, recency, syntactic parallelism, semantic class, agreement, world knowledge, ...
Why It’s Hard

No single source is a completely reliable indicator

• semantic preferences
  • Mr. Callahan = president =? the carrier

• number and gender
  • assassination (of Jesuit priests) = these murders
  • the woman = she = Mary =? the chairman
Coreference strategies differ depending on the type of referring NP

- definiteness of NPs
  - ... Then Mark saw the man walking down the street.
  - ... Then Mark saw a man walking down the street.

- pronoun resolution alone is notoriously difficult
  - resolution strategies differ for each type of pronoun
  - some pronouns refer to nothing in the text

I went outside and it was snowing.
Types of referents: complications

- Inferable
  - A referring expression does not refer to an entity in the text, but to one that is inferentially related to it.
    - I almost bought a WRX today, but a door had a dent and the engine seemed noisy.
  - Mix the flour, butter, and water. Stir the batter until all lumps are gone.

- Discontinuous sets
  - Referents may have been evoked in discontinuous phrases
    - John has a Volvo, and Mary has a Mazda. They drive them all the time.

- Generics – refer to a class of entities
  - I saw no fewer than 6 WRX’s today. They are the coolest cars.
Traditional Knowledge-Based Approaches

Lappin and Leass [1994]

- hand-crafted heuristics and filters
  - syntactic filters [Lappin and McCord 1990a]
  - morphological filter
  - pleonastic pronoun filter (“It was raining.”)
  - procedure for identifying possible antecedents [Lappin and McCord 1990b]
  - salience assignment w.r.t. grammatical role, proximity, parallelism, etc.

- decision procedure
Problems with hand-written rules

- Portability
- Robustness
- Few large-scale evaluations
- Evaluations make a number of simplifying assumptions
  - perfect parse
  - omit many difficult cases, e.g. pleonastic pronouns
- **Impose coreference resolution strategies rather than learn them empirically**
Plan for the Talk

- Linguistic background for coreference resolution
- Supervised machine learning approach
- Weakly supervised approaches
Noun Phrase Coreference

Identify all noun phrases that refer to the same entity

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, a renowned speech therapist, was summoned to help the King overcome his speech impediment...
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A Machine Learning Approach

Typical Steps:

- Step1: Noun Phrase Identification
- Step2: *Pairwise* Classification
- Step3: Clustering (Why?)
A Machine Learning Approach

- Step 1: Find all noun phrases
  - Using “partial parsers” or “chunkers”

[Queen Elizabeth] set about transforming [her] [husband], ...
A Machine Learning Approach

• Step 2: Pair-wise Classification (using machine learning)

• given a description of two noun phrases, $NP_i$ and $NP_j$, classify the pair as \textit{coreferent} or \textit{not coreferent}

\[ \text{coref} ? \quad \text{coref} ? \]

[Queen Elizabeth] set about transforming [her] [husband], ...

\[ \text{coref} ? \]

Aone & Bennett [1995]; Connolly et al. [1994]; McCarthy & Lehnert [1995];
Soon et al. [2001]; Ng & Cardie [2002]; ...
A Machine Learning Approach

- Step3: Clustering
  - coordinates pairwise coreference decisions

[Queen Elizabeth], set about transforming [her] [husband] ...
Machine Learning Issues

- Training data creation
- Instance representation
- Learning algorithm for pair-wise decisions
- Clustering algorithm (to combine pair-wise decisions)
Supervised Inductive Learning

Examples of NP pairs (features + class)

ML Algorithm

(novel) pair of NPs (features)

Concept description

(program)

→ class
Training Data Creation

- Creating training instances
  - texts annotated with coreference information

- one instance $\text{inst}(\text{NP}_i, \text{NP}_j)$ for each ordered pair of NPs
  - $\text{NP}_i$ precedes $\text{NP}_j$
  - feature vector: describes the two NPs and context
  - class value:
    - $\text{coref}$ pairs on the same coreference chain
    - $\text{not coref}$ otherwise
Instance Representation

- **lexical**
  - string matching for pronouns, proper names, common nouns

- **grammatical**
  - pronoun_1, pronoun_2, demonstrative_2, indefinite_2, ...
  - number, gender, animacy
  - appositive, predicate nominative
  - binding constraints, simple contra-indexing constraints, ...
  - span, maximalnp, ...

- **semantic**
  - same WordNet class
  - alias

- **positional**
  - distance between the NPs in terms of # of sentences

- **knowledge-based**
  - naïve pronoun resolution algorithm
Why It’s Hard

Many sources of information play a role

- string matching, syntactic constraints, semantic class,
- number agreement, gender agreement,
- discourse focus, recency,
- world knowledge...

- No single source is a completely reliable indicator

- Identifying each of these features automatically, accurately, and in context, is hard
Clustering Algorithm

- Best-first single-link clustering
  - Mark each $NP_j$ as belonging to its own class: $NP_j \in c_j$
  - Proceed through the NPs in left-to-right order.
    - For each NP, $NP_j$, create test instances, $inst(NP_i, NP_j)$, for all of its preceding NPs, $NP_i$.
    - Select as the antecedent for $NP_j$ the highest-confidence coreferent NP, $NP_i$, according to the coreference classifier (or none if all have below .5 confidence);
    - Merge $c_j$ and $c_j$.

➔ Pros?
➔ Cons?
Clustering Algorithm

- Best-first single-link clustering
  - Pros: Simple but works surprisingly well!
  - Cons: Can’t go back and revise previous decisions

- Clustering algorithms that make collective decisions:
  - Corelational Clustering
  - Multi-cut
  - NP-hard, often hard to beat single-link clustering
Evaluation

- MUC-6 and MUC-7 coreference data sets
- Documents annotated w.r.t. coreference
- 30 + 30 training texts (dry run)
- 30 + 20 test texts (formal evaluation)
- Scoring program
  - Recall
  - Precision
  - F-measure: $2PR/(P+R)$
### Baseline Results

<table>
<thead>
<tr>
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<th>R</th>
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<tr>
<td><strong>Baseline</strong></td>
<td>40.7</td>
<td>73.5</td>
<td><strong>52.4</strong></td>
<td>27.2</td>
<td>86.3</td>
<td><strong>41.3</strong></td>
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<tr>
<td><strong>Worst MUC System</strong></td>
<td>36</td>
<td>44</td>
<td>40</td>
<td>52.5</td>
<td>21.4</td>
<td>30.4</td>
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<td><strong>Best MUC System</strong></td>
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<td>61.8</td>
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Problem 1

- Coreference is a rare relation
  - skewed class distributions (2% positive instances)
  - remove some negative instances

farthest antecedent
Problem 2

- Which pair do you think is harder for computers to learn/predict?

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, the renowned speech therapist, was summoned to help the King overcome his speech impediment...
Problem 2

- Order the following in the order of difficulties:
  (assuming best-first single-link clustering)
  - Pronouns
  - Proper Nouns
  - Common nouns

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, the renowned speech therapist, was summoned to help the King overcome his speech impediment...
Problem 2

• Order the following in the order of difficulties
  < common nouns < pronouns < proper nouns
  (hardest) (easiest)

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, the renowned speech therapist, was summoned to help the King overcome his speech impediment...
Problem 2

- Coreference is a discourse-level problem with different solutions for different types of NPs
- positive example selection: selects easy positive training instances (cf. Harabagiu et al. (2001))

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, the renowned speech therapist, was summoned to help the King overcome his speech impediment...
Problem 3

- Coreference is an *equivalence relation*
  - loss of transitivity during pair-wise classification
  - need to tighten the connection between classification and clustering

[Queen Elizabeth] set about transforming [her] [husband], ...

*coref?*  
*coref?*  
*not coref?*
## Results

<table>
<thead>
<tr>
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<td>POS-SELECT</td>
<td>53.1</td>
<td>80.8</td>
<td>64.1</td>
<td>41.1</td>
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<tr>
<td>NEG-SELECT + POS-SELECT</td>
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<td>76.3</td>
<td>69.3</td>
<td>59.5</td>
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<tr>
<td>NEG-SELECT + POS-SELECT + RULE-SELECT</td>
<td>63.3</td>
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- Ultimately: large increase in F-measure, due to gains in recall
Comparison with Best MUC Systems

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Plan for the Talk

• noun phrase coreference resolution
• a (supervised) machine learning approach
• weakly supervised approaches
  • background
  • two techniques
  • evaluation
Weakly Supervised Approaches

• Idea:
  bootstrap (NP coreference) classifiers using a *small amount of labeled data* (expensive) and a *large amount of unlabeled data* (cheap)

• Methods
  • Co-training
  • Self-training
Co-Training [Blum and Mitchell, 1998]

Labeled data (L)

Unlabeled data (U)
Co-Training [Blum and Mitchell, 1998]

- Labeled data (L)
- Unlabeled data (U)
- Classifier $h_1$
- Classifier $h_2$
- Views $V_1$ and $V_2$
Co-Training [Blum and Mitchell, 1998]

Labeled data (L)

Classifier $h_1$

view $V_1$

Classifier $h_2$

view $V_2$

Unlabeled data (U)
Co-Training [Blum and Mitchell, 1998]

Labeled data (L)

Unlabeled data (U)

Classifier $h_1$

Classifier $h_2$

Data pool (D)

view $V_1$

view $V_2$
Co-Training [Blum and Mitchell, 1998]

Labeled data (L)

view $V_1$

Classifier $h_1$

Unlabeled data (U)

view $V_2$

Classifier $h_2$

Data pool (D)
Potential Problems with Co-Training

- Strong assumptions on the “views” (Blum and Mitchell, 1998)
  - each view must be sufficient for learning the target concept
  - the views must be conditionally independent given the class
  - empirically shown to be sensitive to these assumptions (Muslea et al., 2002)

- A number of parameters need to be tuned
  - views, data pool size, growth size, number of iterations, initial size of labeled data
  - algorithm is sensitive to its input parameters (Nigam and Ghani, 2000; Pierce and Cardie, 2001; Pierce 2003)
Potential Problems with Co-Training

- Multi-view algorithm
  - Is there any natural feature split for NP coreference?
    - view factorization is a non-trivial problem for coreference
      - Mueller et al.’s (2002) greedy method
Self-Training with Bagging [Banko and Brill, 2001]

Labeled data (L)

Unlabeled data (U)
Self-Training with Bagging [Banko and Brill, 2001]

Labeled data (L)

Bagged Classifier $h_1$

Bagged Classifier $h_2$

\[ \ldots \]

Bagged Classifier $h_n$

Unlabeled data (U)
Self-Training with Bagging [Banko and Brill, 2001]

Unlabeled data (U) → Bagged Classifier $h_1$ → Labeled data (L) → Bagged Classifier $h_2$ → … → Bagged Classifier $h_n$ → Unlabeled data (U)
Self-Training with Bagging [Banko and Brill, 2001]

consistently labeled

Labeled data (L)

Bagged Classifier $h_1$

Bagged Classifier $h_2$

Bagged Classifier $h_n$

Unlabeled data (U)
Evaluation

• MUC-6 and MUC-7 coreference data sets
• labeled data (L): one dryrun text
  • 3500-3700 instances
• unlabeled data (U): remaining 29 dryrun texts
• vs. fully supervised ML
  • ~500,000 instances (30 dryrun texts)
Learning Curve for Co-Training (MUC-6)

pool size: 5000; growth size: 50; views: feature type
Learning Curve for Co-Training (MUC-6)

pool size: 5000; growth size: 50; views: feature type; $|L| = 1000$
Learning Curve for Co-Training (MUC-6)

pool size: 5000; growth size: 50; **views: Mueller’s**
Self-Training Parameters

- Number of bags
  - tested all odd number of bags between 1 and 25

- 25 bags are sufficient for most learning tasks (Breiman, 1996)
Results (Self-Training with Bagging)

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- Self-training performs better than co-training
Self-Training: Effect of the Number of Bags (MUC-6)
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Summary

- Supervised ML approach to NP coreference resolution
  - Good performance relative to other approaches
  - Still lots of room for improvement

- Weakly supervised approaches are promising
  - Not as good performance as fully supervised, but use much less manually annotated training data

- For problems where no natural view factorization exists...
  - Single-view weakly supervised algorithms
    - Self-training with bagging