Shallow Semantics for Coreference Resolution

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Noun Phrase Coreference

Identify all noun phrases (NPs) that refer to the same entity

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Standard Machine Learning Approach

Step 1: Classification

- given a description of two noun phrases, $NP_i$ and $NP_j$, classifies the pair as coreferent or not coreferent.
Standard Machine Learning Approach

Step 2: Clustering

- coordinates pairwise classification decisions

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

not coref

[Queen Elizabeth], coref

Clustering

Algorithm

Queen Elizabeth

her

King George VI

husband

King George VI

the King

his

Logue

Logue

a renowned speech therapist

not coref
Machine Learning Issues

§ Training instance creation
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  ‣ Pair each NP with each of its preceding NPs
  ‣ Label an instance as positive iff the two NPs are coreferent
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Development of linguistic features for coreference resolution
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  - Resolvers operate by relying on morpho-syntactic cues
    - String matching, gender/number agreement, binding constraints
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  ▸ However, there are coreference relations that cannot be identified by using string-matching facilities and syntactic cues
    ▷ Coreference relations between two lexically dissimilar common nouns (e.g., talks and negotiations)
    ▷ Coreference relations between a proper NP and a common NP (e.g., George W. Bush and the president)
Goal

Investigate features that encode semantic and other non-morpho-syntactic knowledge for improving the performance of a learning-based coreference system
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- Investigate features that encode semantic and other non-morpho-syntactic knowledge for improving the performance of a learning-based coreference system.

- Focus on *inducing* linguistic features:
  - one feature exploits the fact that we are doing ACE coreference.
Plan for the Talk

§ Six linguistic features for coreference resolution

§ The baseline feature set

§ Evaluation
Plan for the Talk

§ Six linguistic features for coreference resolution

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§ Evaluation
1. The Semantic Class Agreement Feature

Determines whether the semantic classes of two NPs agree
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- Goal: improve computation of the semantic class of an NP
The Semantic Class Induction Algorithm

Given a large, unannotated corpus

- Extract appositive relations
  - <Eastern Airlines, carrier>, <George Bush, president>, ...

- Use a named entity (NE) recognizer to find the semantic classes of the proper names

- Infer the semantic class of a common nouns from the associated proper name
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$\text{Given a large, unannotated corpus}$ \quad \Rightarrow \quad \text{BLLIP+Reuters}

- Extract appositive relations \quad \Rightarrow \quad \text{MINIPAR}
  - $<\text{Eastern Airlines, carrier}>, <\text{George Bush, president}>, \ldots$

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Given a large, unannotated corpus

- Extract appositive relations
  - <Eastern Airlines, carrier>, <George Bush, president>, ...

- Use a named entity (NE) recognizer to find the semantic classes of the proper names
  - Identifinder (MUC-style NER)

- Infer the semantic class of a common nouns from the associated proper name
Potential Problem

- Identifinder is not perfect
  - Mislables proper names

- MINIPAR is not perfect
  - Extracts NP pairs that are not in apposition

A common noun could be labeled with more than one semantic class.
## Potential Problem

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### Potential Problem

- **Identifinder is not perfect**
  - Mislables proper names

- **MINIPAR is not perfect**
  - Extracts NP pairs that are not in apposition

- **Need a more robust method of inferring the semantic class of a common noun**
  1. Compute the probability that the common noun co-occurs with each of the named entity types
  2. If the most likely NE type has a probability above 0.7, label the common noun with the most likely NE type

A common noun could be labeled with more than one semantic class.
Other Problems

Common nouns that do not belong to one of the seven MUC NE types will remain unlabeled
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- Common nouns that do not co-occur with any NE type with a probability above 0.7 will remain unlabeled
Other Problems

$\$ Common nouns that do not belong to one of the seven MUC NE types will remain unlabeled

$\$ Common nouns that do not co-occur with any NE type with a probability above 0.7 will remain unlabeled

$\$ Solution: fall back on the first-sense heuristic
2. The ACE-Specific Semantic Agreement Feature

**Motivation**

- The **SEM_CLASS** feature was developed for use in a general-purpose coreference system.
- We may be able to improve performance on the ACE data if we develop an ACE-specific semantic agreement feature.
2. The ACE-Specific Semantic Agreement Feature

§ Motivation
  ▶ The SEM_CLASS feature was developed for use in a general-purpose coreference system
  ▶ We may be able to improve performance on the ACE data if we develop an ACE-specific semantic agreement feature

§ ACE coreference
  ▶ Resolve references to NPs that belong to one of the five ACE semantic classes (ASCs)
      PERSON, ORGANIZATION, FACILITY, GSP, LOCATION
Definition of ACE Semantic Classes

§ PERSON (human)
  ▸ Mahatma Ghandi, the postman, ...


Definition of ACE Semantic Classes

§ PERSON (human)
   ‣ Mahatma Ghandi, the postman, …

§ ORGANIZATION (corporation, agency, government)
   ‣ Indian Institute of Technology, the company, …
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   ‣ Hyderabad International Convention Center, the building, …
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§ GSP (geo-political region)
  ▸ India, Hyderabad, the city, the province, …
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§ GSP (geo-political region)
   ▸ India, Hyderabad, the city, the province, …

§ LOCATION (geographical area, landmass, body of water)
   ▸ The Bay of Bengal, the Himalayas, the mountain, …
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§ Goal: develop a feature that considers two NPs compatible if and only if the two NPs have a common ASC
Determining the ASC of an NP

Based in part on the semantic class of the NP as computed by the SEM_CLASS feature
Determining the ASC of an NP

Based in part on the semantic class of the NP as computed by the **SEM_CLASS** feature

Rough correspondence between SEM_CLASS and ASC

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§ If its SEM_CLASS is not PERSON, ORGANIZATION, or LOCATION, its ASC will be OTHERS

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§ If its SEM_CLASS is LOCATION, need to determine whether its ASC is GSP or LOCATION

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The ASC Determination Algorithm (Cont’)

If its SEM_CLASS is LOCATION, need to determine whether its ASC is GSP or LOCATION

- Check whether its head noun is a hypernym of a GSP-related word or a LOCATION-related word in WordNet
The ASC Determination Algorithm (Cont’)

§ If its SEM_CLASS is LOCATION, need to determine whether its ASC is GSP or LOCATION

- Check whether its head noun is a hypernym of a GSP-related word or a LOCATION-related word in WordNet
  - GSP-related words: country, province, government, town, city, administration, society, island
  - LOCATION-related words: dry land, region, landmass, body of water, geographical area, geological formation
The ASC Determination Algorithm (Cont’)

$\$ If its SEM_CLASS is **LOCATION**, need to determine whether its ASC is **GSP** or **LOCATION**

- Check whether its head noun is a **hypernym** of a **GSP-related word** or a **LOCATION-related word** in WordNet
  - **GSP-related words**: country, province, government, town, city, administration, society, island
  - **LOCATION-related words**: dry land, region, landmass, body of water, geographical area, geological formation

- If head noun is a **LOCATION** word, its ASC is **LOCATION**
- Else if head noun is a **GSP** word, its ASC is **GSP**
- Otherwise, its ASC is both **GSP** and **LOCATION**
The ASC Determination Algorithm (Cont’)

$\$ If its SEM_CLASS is LOCATION, need to determine whether its ASC is GSP or LOCATION

- Check whether its head noun is a hypernym of a GSP-related word or a LOCATION-related word in WordNet
  - GSP-related words: country, province, government, town, city, administration, society, island
  - LOCATION-related words: dry land, region, landmass, body of water, geographical area, geological formation

Bay of Bengal

- If head noun is a LOCATION word, its ASC is LOCATION
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- Else if head noun is a GSP word, its ASC is GSP
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The ASC Determination Algorithm (Cont’)

§ If its SEM_CLASS is ORGANIZATION, need to determine whether its ASC is FACILITY or ORGANIZATION

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The ASC Determination Algorithm (Cont’)

§ If its SEM_CLASS is ORGANIZATION, need to determine whether its ASC is FACILITY or ORGANIZATION

- Check whether its head noun is a hypernym of an ORGANIZATION-related word or a FACILITY-related word
  - ORGANIZATION-related words: social group
  - FACILITY-related words: establishment, construction, building, facility, workplace

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- Knowledge of anaphoricity could improve system precision.
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§ Anaphoricity determination is the problem of determining whether an NP has an antecedent or not
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§ Previous approaches
  ‣ Unsupervised: Bean and Riloff (1999)
  ‣ Supervised: Evans (2001), Ng and Cardie (2002)
3. The Anaphoricity Feature

- **Anaphoricity determination** is the problem of determining whether an NP has an antecedent or not
  - Knowledge of anaphoricity could improve system precision

- **Previous approaches**
  - **Unsupervised**: Bean and Riloff (1999)
  - **Supervised**: Evans (2001), Ng and Cardie (2002)

- **Goal**: examine whether shallow anaphoricity information could benefit a learning-based coreference resolution
Computing the Anaphoricity Feature

Given a corpus labeled with coreference information

- Compute the anaphoricity of an NP as the probability that it has an antecedent in the corpus
  - If the NP never appears in the corpus, set its anaphoricity value to -1
Computing the Anaphoricity Feature

Given a corpus labeled with coreference information

- Compute the anaphoricity of an NP as the probability that it has an antecedent in the corpus
  - If the NP never appears in the corpus, set its anaphoricity value to -1

Data sparseness is a problem, but the feature still captures some useful information

- *it* is only moderately anaphoric
- *the contrary* (from *on the contrary*) is never anaphoric
4. The Coreferentiality Feature

- Adapt the method for generating the anaphoricity feature to create a coreferentiality feature.

- Feature encodes the probability that two NPs are coreferent.
  - Estimate the probabilities from a coreference corpus.
    - If one or both of the given NPs do not appear in the corpus, set the coreferentiality value to -1.
The Remaining Features

5. The Semantic Similarity Feature
   - Determines the semantic similarity of two common NPs
The Remaining Features

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  - Two semantically similar NPs are more likely to be coreferent than two semantically dissimilar NPs
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   - Computed using information provided by an algorithm that learns patterns for extracting coreferent NP pairs
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   - Computed using information provided by an algorithm that learns patterns for extracting coreferent NP pairs

Employing this pattern-based feature does not yield significant improvement in coreference performance
Plan for the Talk

§ Six linguistic features for coreference resolution

§ The baseline feature set

§ Evaluation
The Baseline Feature Set (34 Features)

- **String-matching features**
  - Exact string match, substring match, head noun match

- **Grammatical features**
  - Agreement w.r.t. gender, number, animacy, grammatical role

- **Positional feature**
  - Distance between the two NPs in sentences

- **Semantic features**
  - Alias, semantic class agreement
The Baseline Feature Set (34 Features)

- **String-matching features**
  - Exact string match, substring match, head noun match

- **Grammatical features**
  - Agreement w.r.t. gender, number, animacy, grammatical role

- **Positional feature**
  - Distance between the two NPs in sentences

- **Semantic features**
  - Alias, semantic class agreement

For a proper name, use a named entity finder
For a common noun, use WordNet + the first-sense heuristic
Plan for the Talk

- Six linguistic features for coreference resolution
- The baseline feature set
- Evaluation
  - How effective are the proposed features in improving the baseline coreference system?
Experimental Setup

$\text{The 2003 ACE coreference corpus}$
  $\rightarrow$ comprises a training set and a test set

$\text{Two coreference scoring programs}$
  $\rightarrow$ MUC scoring program (Vilain et al., 1995)
  $\rightarrow$ CEAF scoring program (Luo, 2005)
  $\rightarrow$ recall, precision, F-measure

$\text{NPs extracted automatically}$
The Baseline Coreference System

- **Feature set**: the baseline feature set (34 features)
- **Learning algorithm**: C4.5
- **Clustering**: single-link clustering
## Results (Baseline System)

<table>
<thead>
<tr>
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How Strong are the Baseline Results?

Replace the 34 baseline features with the 12 features employed by Soon et al.’s (2001) system

- The first learning-based resolver that achieves performance comparable to the best MUC coreference systems
### Results (Duplicated Soon et al. System)

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Augment the baseline feature set with our six linguistic features

- SEM_CLASS
- ACE_SEMCLASS
- SEM_SIM
- PATTERN_BASED
- ANAPHORICITY
- COREFERENTIALITY
Using the Expanded Feature Set

- Augment the baseline feature set with our six linguistic features
  - SEM_CLASS
  - ACE_SEMCLASS
  - SEM_SIM
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  - ANAPHORICITY
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- Remove the heuristic-based semantic class agreement feature from the feature set
Using the Expanded Feature Set

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- Remove the heuristic-based semantic class agreement feature from the feature set

Requires an annotated corpus
Where does this annotated corpus come from?

Partition the available training texts into two sets of roughly the same size: training subset and development subset.
Where does this annotated corpus come from?

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Training coreference classifier.
Where does this annotated corpus come from?

Partition the available training texts into two sets of roughly the same size: training subset and development subset.

Training coreference classifier

Computing ANAPHORICITY and COREFERENTIALITY
## Results (Expanded Feature Set)

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Performance difference is statistically significant compared to baseline: $p=0.004$ (MUC) and $p=0.0016$ (CEAF)
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Summary

- Investigated the utility of six semantic and non-morpho-syntactic features for coreference resolution
- Showed improved performance on the ACE corpus
- Performance gains are limited in part by the difficulty in accurately computing these features