Gracie: And then Mr. and Mrs. Jones were having matrimonial trouble, and my brother was hired to watch Mrs. Jones.
George: Well, I am imagine she was a very attractive woman.
Gracie: She was, and my brother watched her day and night for six month.
George: Well, what happened?
Gracie: She finally got a divorce.
George: Mrs. Jones?
Gracie: No, my brother’s wife.
**Motivation**

- Information extraction
- Question-Answering
- Machine-Translation
  
  Pronoun in the Malay language is translated by its antecedent (Mitkov, 1999)
- Summarization

**When something goes wrong**

Why would the media use this specific word, so often with relation to Muslims?

Before the term fundamentalist was branded for Muslims, it was, and still is, being used by certain Christian denominations. Most of them are radical Baptist, Lutheran and Presbyterian groups.

**Today’s Topics**

- Motivation
- Types of referential expressions
- Syntactic and semantic constraints on coreference
- Preferences in coreference interpretation
- Algorithm’s for coreference resolution

**When something goes wrong**

In the past decade almost all Islamic revivalist movements have been labeled fundamentalists, whether they be of extremist or moderate origin. The widespread impact of the term is obvious from the following quotation from one of the most influential Encyclopedias under the title ‘Fundamentalist’: “The term fundamentalist has... been used to describe members of militant Islamic groups.” Why would the media use this specific word, so often with relation to Muslims? Most of them are radical Baptist, Lutheran and Presbyterian groups.
**Pronouns**

Stronger constraints on using pronouns than on noun phrase references.

- Require a high degree of activation from a referent
- Have short activation span

| a. John went to Bob’s party, and parked next to a Acura Integra. |
| b. He went inside and talked to Bob for more than an hour. |
| a. Bob told him that he recently got engaged. |
| b. ??He also said that he bought *it* yesterday. |

---

**Types of referential expressions: Nouns**

- Indefinite Noun Phrases:
  - I saw an Acura Integra today.
  - Some Acura Integras were being unloaded.
  - I saw this awesome Acura Integra today.

- Definite Noun Phrases
  - I saw an Acura Integra today. The Integra was white and needed to be washed.
  - The fastest car in the Indianapolis 500 was an Integra.

---

**Demonstratives and One Anaphora**

- Demonstratives (this, that) capture spatial proximity
  - I like this one, better than that

- One Anaphora evokes a new entity into the discourse whose description is dependent of this new entity
  - I saw no less that 6 Acuras today. Now I was one.

---

**Troublemakers**

- Inferrables: inferential relation to an evoked entity
  - I almost bought an Acura today, but a door had a dent and the engine seemed noisy.

- Discontinuous Sets: refer to entities that do not form a set in a text
  - John has an Acura, and Mary has a Mazda. They drive them all the time.

- Generics: refer to general set of entities (in contrast to a specific set mentioned in text)
  - I saw no less than six Acuras today. They are the coolest cars.
Syntactic Constraints

- Gender Agreement
  John has an Acura. It is attractive.

- Syntactic Agreement
  John bought himself a new Acura.
  John bought him a new Acura.

Semantic Constraints

- Selectional restrictions of the verb on its arguments
  1. John parked his Acura in the garage. He had driven it around for hours.
  2. John parked his Acura in the garage. It is incredibly messy, with old bike and car parts lying around everywhere.
  3. John parked his Acura in downtown Beverly Hills. It is incredibly messy, with old bike and car parts lying around everywhere.
Preferences in Pronoun Interpretation
Verb Semantics: emphasis on one of verb’s arguments
- “implicit causality” of a verb causes change in salience of verb arguments
  John telephoned Bill. He lost the pamphlet on Acuras.
  John criticized Bill. He lost the pamphlet on Acuras.
- thematic roles (Goal, Source) cause change in salience of verb arguments
  John seized the Acura pamphlet from Bill. He loves reading about cars.
  John passed the Acura pamphlet to Bill. He loves reading about cars.

Reference Resolution 16/??

Generic Algorithm (cont.)
- Filtering
  Remove all the members of $C_j$ that violate reference constraints
- Scoring/Ranking
  Order the candidates based on preferences and soft constraints
- Searching/Clustering
  Clustering of instances with the same antecedent

Reference Resolution 19/??

Preferences in Pronoun Interpretation
- Grammatical Role: Hierarchy of candidate entities based on their grammatical role
  John went to the Acura dealership with Bill. He bought an Integra.
  Bill went to the Acura dealership with John. He bought an Integra.
- Parallelism:
  Mary went with Sue to the Acura dealership. Sally went with her to the Mazda dealership.

Reference Resolution 17/??

Generic Algorithm
- Identification of Discourse Entities
  Identify nouns and pronouns in text
- Characterization of Discourse Entities
  Compute for each discourse entity $NP_i$ a set of values from $\{K_{i1}, \ldots, k_{im}\}$ from $m$ knowledge sources
- Anaphoricity Determination
  Eliminate non-anaphoric expressions to cut search space
- Generation of Candidate Antecedents
  Compute for each anaphoric $NP_j$ a list of candidate antecedents $C_j$
Knowledge-Lean Multi-strategy Approach

(Lappin&Leass, 1994)
- Integrates the effects of the recency and syntactically-based preferences
- Doesn’t rely on semantic or pragmatic knowledge
- Follows greedy strategy
- Two stages: discourse model update and pronoun resolution

Salience Factors

<table>
<thead>
<tr>
<th>Factor</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentence Recency</td>
<td>100</td>
</tr>
<tr>
<td>Subject Emphasis</td>
<td>80</td>
</tr>
<tr>
<td>Existential Emphasis</td>
<td>70</td>
</tr>
<tr>
<td>Accusative</td>
<td>50</td>
</tr>
<tr>
<td>Indirect Object</td>
<td>40</td>
</tr>
<tr>
<td>Non-adverbial Emphasis</td>
<td>50</td>
</tr>
<tr>
<td>Head-noun Emphasis</td>
<td>80</td>
</tr>
</tbody>
</table>

Reference Resolution: Trends

- Knowledge-Rich Approaches vs Knowledge-Lean Approaches
- Semi-automatic Fully-Automatic Preprocessing
- Small-scale vs Large-Scale Evaluation

Discourse Model Update

(Lappin&Leass, 1994)
- Add every new discourse entity to discourse model
- Update its value based on salience factors
- Cut in half recency values when process new entity (recency enforcement)
**Algorithm**

1. Remove potential referents that do not agree in number or gender with the pronoun
2. Remove potential referents that do not pass intrasentential syntactic coreference constraints
3. Update the total salience value of the referent
4. Select the referent with the highest value

Accuracy on unseen data: 86%

---

**Clustering for Coreference**

(Cardie&Wagstaff:1999)

- Each group of coreferent noun phrases defines an equivalence class
- Distance measure incorporates “linguistic intuition” about similarity of noun phrases
- Hard constraints enforce clustering construction

---

**Instance Representation**

Based noun phrases (automatically computed) are represented with 11 features:

- Individual Words
- Head Word
- Position
- Pronoun type (nominative, accusative)
- Semantic Class: Time, City, Animal, Human, Object (WordNet)
- Gender (WordNet, specified list)
- Animacy (based on WordNet)

---

**Syntactic Factors**

subject > existential predicate nominal > object > indirect object > demarcated adverbial PP

1. An Acura Integra is parked on the lot. (subject)
2. There is an Acura Integra parked in the lot.
3. ...
4. Inside his Acura Integra, John kissed Mary. (demarcated adverbial PP)

Penalty for non-head occurrences
Score for equivalence classes
**Distance Metric**

\[ \text{dist}(NP_i, NP_j) = \sum_f w_f \times \text{incomp}_f(NP_i, NP_j) \]

**Clustering Algorithm**

- Initialization: every noun is a singleton
- From right to left, compare each noun to all proceeding clusters
- Combine “close enough” clusters unless there exist any incompatible NP

Example: The chairman spoke with Ms. White. He ...

**Supervised Learning**

(Soon et al., 2001)

- Decision Tree Induction
- Shallow feature representation (12 features):
  - “corrective” clustering
  - Significant performance gain over rule-based algorithms

**Results**

MUC-6 (30 documents): Recall 48.8\*, Precision 57.4\%, F-measure 52.8\%
Baseline: 34.6\%, 69.3\%, 46.1\%
Types of Mistakes:
  - Parsing mistakes
  - Coarse entity representation and mistakes in feature computation
  - Greedy nature of the algorithm
Adding Linguistic Knowledge

Rich Linguistic representation for learning (Ng & Cardie 2002)

- 53 features
- manual feature selection
- significant gain in performance over (Soon et al., 2001)