Reference Resolution

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February 18, 2004

Reference Resolution: Example

The Salesgirl (Burns and Allen)

Gracie: And then Mr. and Mrs. Jones were having matrimonal 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.

Reference Resolution

- Task: determine which noun phrases refer to each real-world entity mentioned in a document
- Goal: partition noun phrases in a text into coreference equivalence classes, with one cluster for each set of coreferent NPs
- Difference between anaphora and coreference

In the previous example: {Mrs. J2ones, she, she, Mrs. Jones}, {my brother, my brother}, {my brother's wife}

Today's Topics

- Motivation
- Types of referential expressions
- Syntactic and semantic constraints on coreference
- Preferences in coreference interpretation2
- Algorithm's for coreference resolution

Motivation

- Information extraction
- Question-Answering
- Machine-Translation

  pronoun in the Malay language is translated by its antecedent (Mitkov, 1999)
- Summarization

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.

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.

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.

Pronouns

Stronger constrains 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.

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 on Coreference

- Number Agreement

  * John has a new Acura. They are red.

  John has three New Acuras. It is red.

- Person and Case Agreement

  * John and Mary have Acuras. We love them.

  You and I have Acuras. We love them.

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

- Recency: Entities introduced in recent utterances are more salient than those introduced further back

  John has an Integra. Bill has a Legend. Mary likes to drive it.

- Repeated mention: Entities that have been focus on in the prior discourse are more likely to continue to be focused on in subsequent discourse

  John needed a car to get his new job. He decided that he wanted something sporty. Bill went to the Acura dealership with him. He bought an Integra.

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.

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.

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

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: Trends

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

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

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)

Salience Factors

Sentence Recency	100
Subject Emphasis	80
Existential Emphasis	70
Accusative	50
Indirect Object	40
Non-adverbial Emphasis	50
Head-noun Emphasis	80

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

Algorithm

1. Remove potential referents that do not agree in number or gender with the pronoun
2. Remove potential referents that do not pass intrasentetial 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)

Distance Metric

$$dist(NP_i, NP_j) = \sum_f w_f * incomp_f(NP_i, NP_j)$$

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 ...

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

Supervised Learning

(Soon et al.,2001)

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

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)