Topics for Today

- Pragmatics of discourse context
  - reference resolution
  - noun phrase coreference resolution
  - machine learning approach to NP coreference resolution

The problem of reference resolution

Gracie: Oh yeah…and then Mr. And Mrs. Jones were having matrimonial trouble, and my brother was hired to watch Mrs. Jones.

George: Well, I imagine she was a very attractive woman.

Gracie: She was, and my brother watched her day and night for six months.

George: Well, what happened?

Gracie: She finally got a divorce.

George: Mrs. Jones?

Gracie: No, my brother's wife.

George Burns and Gracie Allen in *The Salesgirl*

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

- 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.

Types of referring expressions

- Pronouns
  - Another form of definite reference
  - Referent must have a high degree of activation or **salience** 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

- 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

Why It's Hard

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

- Inferrables
  - 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.
- Discontinous sets
  - Referents may have been evoked in discontinous 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.

Topics for today

- Pragmatics of discourse
  - reference resolution
  - noun phrase coreference resolution
  - machine learning approach to NP coreference resolution
    - just the basics

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

- 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**

A Machine Learning Approach

- Classification
  - given a description of two noun phrases, NP_i and NP_j, classify the pair as *coreferent* or *not coreferent*

? ?

[John Simon], [Chief Financial Officer] of [Prime Corp.]

?

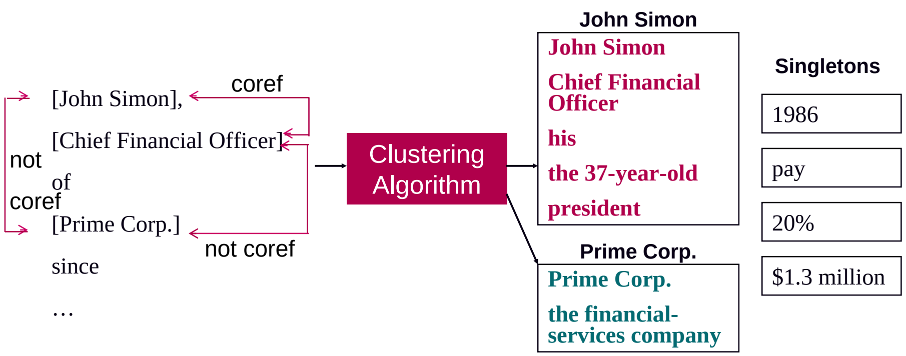
since 1986, saw his pay jump 20%, to $1.3 million,

as the 37-year-old also became the ….

Aone & Bennett [1995]; Connolly et al. [1995]; McCarthy & Lehnert [1995]; Soon, Ng & Lim [2001]; Ng & Cardie [2002]

A Machine Learning Approach

- Clustering
  - coordinates pairwise coreference decisions

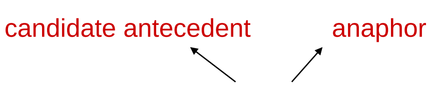


Issues

- Training data
- Instance representation
- Learning algorithm
- Clustering approach

Training Data Creation

- Creating training instances
  - texts annotated with coreference information



  - one instance $inst(NP_i, NP_j)$ for each *ordered* pair of NPs
    - » NP_i precedes NP_j
    - » feature vector: describes the two NPs and context
    - » class value:

      coref pairs on the same coreference chain
      not coref otherwise

Instance Representation

- 25 features per instance
  - lexical (3)
    - » string matching for pronouns, proper names, common nouns
  - grammatical (18)
    - » pronoun_1, pronoun_2, demonstrative_2, indefinite_2, …
    - » number, gender, animacy
    - » appositive, predicate nominative
    - » binding constraints, simple contra-indexing constraints, …
    - » span, maximalnp, …
  - semantic (2)
    - » same WordNet class
    - » alias
  - positional (1)
    - » distance between the NPs in terms of # of sentences
  - knowledge-based (1)
    - » naïve pronoun resolution algorithm

Learning Algorithm

- RIPPER (Cohen, 1995)
  C4.5 (Quinlan, 1994)
  - rule learners
    - » input: set of training instances
    - » output: coreference classifier

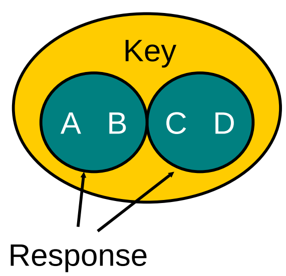
- Learned classifier
    - » input: test instance (represents pair of NPs)
    - » output: classification
      confidence of classification

Clustering Algorithm

- Start with each NP in its own partition
- For each NP in the document
  - Consider each NP to its left
  - If ML algorithm says “coreferent”, merge the partitions for the two NPs.

Evaluation

- MUC-6 and MUC-7 coreference data set
- 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)



Baselines…

	MUC-6		
	R	P	F
Match Any Word			41.3
Match Head Word			45.7
Single Cluster	93.8	33.4	49.2
Top System	59	72	64.9

Results

	MUC-6			MUC-7		
	R	P	F	R	P	F
Ng & Cardie	63.3	76.9	69.5	54.2	76.3	63.4
Best MUC System	59	72	65	56.1	68.8	61.8

Classifier for MUC-6 Data Set

```
ALIAS = C: +
ALIAS = I:
| SOON_STR_NONPRO = C:
| | ANIMACY = NA: -
| | ANIMACY = I: -
| | ANIMACY = C: +
| SOON_STR_NONPRO = I:
| | PRO_STR = C: +
| | PRO_STR = I:
| | | PRO_RESOLVE = C:
| | | | EMBEDDED_1 = Y: -
| | | | EMBEDDED_1 = N:
| | | | | PRONOUN_1 = Y:
| | | | | | ANIMACY = NA: -
| | | | | | ANIMACY = I: -
| | | | | | ANIMACY = C: +
| | | | | PRONOUN_1 = N:
| | | | | | MAXIMALNP = C: +
| | | | | | MAXIMALNP = I:
| | | | | | | WNCLASS = NA: -
| | | | | | | WNCLASS = I: +
| | | | | | | WNCLASS = C: +
| | | PRO_RESOLVE = I:
| | | | APPOSITIVE = I: -
| | | | APPOSITIVE = C:
| | | | | GENDER = NA: +
| | | | | GENDER = I: +
| | | | | GENDER = C: -
```

Summary

- Perform better than the best non-learning approaches on two standard data sets
- Still lots of room for improvement
  - common noun resolution remains a major limiting factor