Reference Resolution

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Outline

• What is Reference Resolution?
• Linguistic Analysis of Coreference
• Coreference Algorithms: Proper Nouns, Pronouns, Common Nouns
• Evaluation Issues
• Summary
Reference Resolution

• Reference Resolution:
  – Which words/phrases refer to some other word/phrase?
  – How are they related?

• Anaphora vs. Cataphora
  – Anaphora: an *anaphor* is a word/phrase that refers back to another phrase: the *antecedent* of the anaphor
    • *Mary thought that she lost her keys.*

  – Cataphora (less common): a *cataphor* is a word/phrase that refers forward to another phrase: its *precedent*.
    • *She was at NYU, when Mary realized that she lost her keys.*

  – *Anaphora* is often used as a synonym for *Reference Resolution* and the term *antecedent* is often used instead of *precedent.*
Types of Anaphora I

• Coreference: Antecedent = Anaphor
  – Though **Big Blue** won the contract, this official is suspicious of **IBM**.
  – **Mary** could not believe what **she** heard.

• Similar to Coreference
  – Type Coreference (vs. Token)
    • AKA, identify of sense (vs. identify of reference)
    • John ate **a sandwich** and Mary ate **one** also.
  – Bound variable
    • Every **lioness** guards **its** cubs
    • \((\forall \text{lioness } L)(L \text{ guards } L's \text{ cubs})\)

• Predication and Apposition: some (not all) specs label as coreference
  – **Mary** is **a basketball player**
  – **Mary, a basketball player from NYU**
Types of Anaphora II

• **Bridging Anaphora:** links between “related” objects
  
  – *The amusement park* is very dangerous. *The gate* has sharp edges. *The rides* have not been inspected for years.

• Some IE relation instances can be viewed as bridging
  
  – *When the baby* cried, *the parents* rushed into the room.
  – ACE Relation: Per-Social.family(*the baby*, *the parents*)

• **“Other” Anaphora:** words including *other* and *another* invoke an “other instance of type” relation
  
  – *This book* is valuable, but *the other book* is not.

• **Non-NP Anaphora,** e.g., events/propositions
  
  – *Mary left the room.* *This* upset her parents.
  – *John read the dictionary.* Then *Mary did it* too.
2 Models of NP Coreference

- **Chains of Coreference**: Which words/phrases co-refer with which other words/phrases, possibly forming a chain of the form:
  - $N_{nP_n} \leftarrow N_{nP_{n-1}} \leftarrow \ldots \leftarrow N_{P_2} \leftarrow N_{P_1}$
  - IBM $\leftarrow$ Big Blue $\leftarrow$... $\leftarrow$ The company $\leftarrow$ they

- **Mentions and Entities (ACE)**: Which phrases refer to the same object in the real world?

  - **Entity**: International Business Machines
  - NP
  - IBM  Big Blue  …  The company  they
Chain vs. Entity Model

• Entity model
  – Especially suited for fully spelled out names
  – Instances where coreference is based entirely by the discourse context and not limited by proximity
    • Instances that are many lines apart
    • Cross-document coreference

• Chain Model
  – Especially suited to pronouns and definite common nouns that refer back to antecedent NPs
  – Instances in which the anaphor abbreviates, or provides is a less specific descriptor than the antecedent
  – Instances of coreference where proximity of anaphor and antecedent is a factor
Coreference with different types of Nouns

• Coreference between Proper Nouns (NEs), including abbreviations, nicknames and substrings
  – Focus of most NLP systems: high precision/recall, links most informative NPs, ...

• Coreference between common noun phrases (CNPs) and preceding NPs (NEs and CNPs)
  – Worst system performance, least studied

• Coreference between pronouns and other NPs
  – Focus of largest body of theoretical work
  – Moderate system performance
Coreference between Proper Nouns (NEs)

- Instances of the same name string in a document usually refers to the same entity
  - *IBM, IBM, IBM, IBM, … → Entity.ibm*
  - *George Bush, George Bush, … → Entity.gb*

- Abbreviations and Nicknames match full name (full name is often first)
  - Abbreviations: mostly rule based (acronyms, subsequences, etc), Nicknames need a lexicon
  - Examples:
    - *International Business Machines, IBM, Big Blue… → Entity.ibm*
    - *St. Petersburg → Saint Petersburg*
    - *George Bush, George Bush, W, … → Entity.gb*
    - *New York Yankees ←New York, New York Times ←New York* (place names only match some orgs)

- Simple rules work, links most informative NPs, results in high 90s, very little literature
  - Important component of IE systems

- One interesting problem: Name disambiguation
  - Distinguishing multiple individuals with the same name
  - Usually, a problem across documents
    - Exception: *George Bush and his son George W were there.*
  - Abbreviation rules may allow two possible antecedents (*and then George said*)
  - Standardized abbreviations may not be unique,
    - *AMEX → American Express or American Stock Exchange*
Pronouns in English

- **Definite Pronouns**: typically refer to specific NPs
  - 3rd person personal pronouns
    - *he, him, his, she, her, hers, it, its, they, them, their, theirs*
  - 3rd person Reflexive pronouns
    - *herself, herself, itself, themselves*
  - *each other* – reciprocal pronoun, similar to reflexives
  - 1st and 2nd person pronouns
    - *I, me, my, myself, mine, our, ours, ourselves, you, your, yours, yourself*
    - Dialogues between 2 people; or writer/speaker and audience

- **Indefinite Pronouns**:
  - *one* – can be used for type coreference
  - Other indefinites – no antecedents in text
    - *something, someone, everything, everyone, ...*
3rd Def Prons: NonSyntactic Constraints/Preferences

• Usually have an antecedent

• Gender/number/person agreement (language specific)
  – *Robert* ← *he*, *Robert* ← *she*, *Robert* ← *it*, *Robert* ← *they*
  – *IBM* ← *he*, *IBM* ← *she*, *IBM* ← *it*, *IBM* ← *they*
  – *I* ← *she*, *me* ← *her*, *you* ← *they*

• Selection Restrictions
  – *Children* have many toys. *They* love to play.
  – *Children* have many toys. *They* are always breaking.

• Pragmatics
  – *Mary* yelled at *Alice*. *She* interrupted the phone call.
  – *Mary* yelled at *Alice*. *She* can be so mean sometimes.

• Others: closer antecedents preferred, repeated NPs are more likely to be antecedents, etc. (J&M have several more examples)
Binding Theory Constraints

• An Antecedent of personal pronouns cannot be “too close” to the pronoun.
• An Antecedent of a reflexive/reciprocal pronoun cannot be “too far” from the pronoun.
• Definitions of “too close” and “too far”
  – Vary from language to language
  – Vary among different classes of pronouns/reflexives
  – Are defined using different primitive concepts within different linguistic theories
• Binding Theory Constraints are usually defined in terms of syntactic configurations
Binding Theory for English 3rd Pers Prons

- Case 1: If the pronoun \( p \) is inside an NP premodified by a possessive, the antecedent needs to be outside of this NP
  - *John* likes *Mary's drawing of him*
  - *John* likes *his drawing of Mary*

- Case 2: Otherwise, the antecedent must be outside the immediate tensed clause containing the personal pronoun.
  - *John* said that *he* liked pizza.
  - *John* wanted for *him* to like pizza.
  - *John* liked *him*.

- Theories of binding vary about how these (and similar) constraints are encoded, but the differences in the final result (quality of system output) is minimal. While the above 2 rules cover most cases, there are also some exceptions:
  - *John* always carries a slice of pizza with *him*. 
Binding Theory for English Reflexives/Reciprocals

• The antecedent of a reflexive/reciprocal must be the closest subject or possessive such that:
  – The antecedent precedes and “commands” the pronoun
    • A commands B if A is the sibling of a phrase that dominates B.
  – There is no possessive or subject for phrases in the path in the phrase structure tree between antecedent and pronoun

• Examples:
  – *Mary saw herself vs. Mary saw herself
  – *Mary said that John would meet herself soon vs. Mary's picture of herself
  – *Mary saw John's picture of herself

• These rules covers most cases.
  – Exception: Pictures of themselves made the actors nervous.
Reflexive Pronoun Constraint

These phrases cannot have possessives or subjects

Antecedent

Reflexive Pronoun
Binding Theory Details Described Above are English Specific

• \textit{zìjǐ} – Chinese reflexive pronoun (example)
  – Ambiguous Example from Choi 1997
    • \textit{Zhangsan renwei Lisi zhidao Wangwu xihuan zìjǐ}
      • \textit{Zhangsan thinks Lisi knows that Wangwu likes self}
    • \textit{Zìjǐ} can be coreferential with \textit{Zhangsan, Lisi} or \textit{Wangwu}
      – In quasi-translated English, Wangwu would be the antecedent
        • \textit{Zhangsan thinks Lisi knows that Wangwu likes himself}

• Reflexive/Nonreflexive distinction holds across languages, but constraints on how close/far differ across languages: Icelandic, Chinese, etc.
Pronoun Resolution Methodology

• Hobbs search:
  – a simple system that provides a high baseline
  – Lappin and Leas (1994) report 82% F-score for Hobbs Search
• Sets a High Baseline for Pronoun Coreference
• Higher Scoring Systems Tend to be Much More Complex
Hobbs Search Algorithm to Find Antecedent of Anaphors

1. Go to NP immediately dominating pronoun
2. Go up to 1st dominating NP or S node. This node = X
   path to X = p.
3. Traverse branches below X to the left of p, left-to-right and and breadth first. Propose each NP n as an antecedent if there is an NP or S between n and X.
4a. Is X the highest S in the sentence? (Recursive)
   No
   Antecedent Found?
   Yes
   No
   4b. Search previous sentences in order from right to left. Search each tree from left to right, breadth 1st, proposing each NP as antecedent
5. From Node X, go up to the 1st NP or S. Call this node X and the path to X p.
6. If X = NP and there is no N’ in p, propose X as antecedent
7. Search for antecedent in branches below X, left-to-right, breadth first. Propose each NP.
8. If X is an S node, traverse all branches of X preceding p, left-to-right, breadth first, but not going below any S or NP node found. Propose each NP.
9. Antecedent Found?
   Yes
   End
   No
   No
   End
Hobbs Search Example

1. Mary saw the chicken.

2. Jim said that she laughed.

Diagram:

- S
  - NP
    - Mary
  - VP
    - saw
    - NP
      - the
      - chicken

- S
  - NP
    - Jim
  - VP
    - said
    - S-bar
      - that
      - NP
        - she
      - VP
        - laughed
Testing the Hobbs Algorithm

• Try Hobbs on instances of PRP in wsj_0003 from WSJ Penn Treebank
• How many cases does the Hobbs algorithm get correct?
• How many incorrect?
• Are there some tweaks that would give better results?
• Or would these tweaks hurt other cases?
No-Parse Hobbs-like Search

• Only Consider Nouns/NGs satisfying constraints
• Continue searching until antecedent or loop exits

1. Initialize sentence_counter to 0 and search current sentence from left to right, ending before pronoun.
2. Repeat the following step until an antecedent is found or sentence_counter reaches the maximum (e.g., 3)
   i. Search previous sentence from left to right
   ii. Increment sentence_counter by 1
More Pronoun Coreference Systems

- Lappin and Leass (1994): Hobbs-Search-like procedure, Morphological filter, Binding Theory, Pleonastic Pronoun Handler, preferences based on grammatical role hierarchy (subject > object > ind-object), preference for same grammatical role, frequency of noun, recency, decision procedure for finding pronoun coreference
  - 4% over Hobbs Search

- Other Systems Using Statistical Weights or Machine Learning Score a Little Bit Better, e.g., Dagan et. al. (1995) score another 3% better (89% vs. 82%).
Common Noun Coreference

• Definite Common Nouns
  – Poessio and Veira (2000) baseline:
    • A common noun phrase $NP_1$ with determiner “the” can be coreferential with a preceding $NP_2$ if:
      – $NP_1$ and $NP_2$ have the same head
      – And (ignoring determiners) $NP_1$ has a subset of the modifiers of $NP_2$
  
• There has been very little improvement on this baseline and very few systems that correctly identify the other cases with any large degree of accuracy

• Other factors:
  – Distance between $NP_1$ and $NP_2$
  – Other determiners, modifiers, possessives, etc.
Why is Common Noun Coreference Difficult?

- Only some common noun phrases are anaphoric
  - Definite vs. Generic
    - *The officers* vs. *officers* vs. *an officer*
  - Limit to *the* phrases is a conservative decision
    - *this, that, those*, possessives, ... improves recall, lowers precision

- When can a common noun corefer to another noun?
  - Limit to identical nouns is a conservative decision
  - Other choices improve recall, lower precision
    - My experience: a hand-crafted list of matches to NE classes
      - Ex: PERSON matches: man, human, person, individual, woman, ..., officer, attorney, ...
      - Hurts approximately as much as it helps (paper wasn't accepted to conference)
Scoring Coreference 1

- Basics: $\text{Precision} = \frac{\text{Correct}}{\text{System Output}}$, $\text{Recall} = \frac{\text{Correct}}{\text{Answer Key}}$, $\text{F-Score} = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}}$

- Problem: How do you measure number of correct?

- MUC-6:
  - Coreference Chains = Partitions of NPs
  - Recall and Precision are based on mismatches (edit distance) between partitions: numbers of links added and/or subtracted to change incorrect partitions to correct ones
  - Given 7 NPs in a system output chain: $A_1, A_2, A_3, A_4, A_5, B_1, B_2$ such that:
    - The sets \{A_1, A_2, A_3, A_4, A_5\} and \{B_1, B_2\} belong to separate chains in the Answer Key
    - The system output contains: 5 correct links and 1 incorrect link
      » Precision = 5/6 = 83%
    - The system has found all 5 correct links
      » Recall = 5/5 = 100%
    - F-Score = 91%
Scoring Coreference 2

• B-Cubed (Bagga and Baldwin 1998)
  – Precision calculated for each system chain (and averaged)
    • Given 7 NPs in a system output chain: $A_1, A_2, A_3, A_4, A_5, B_1, B_2$ such that:
      – The sets $\{A_1, A_2, A_3, A_4, A_5\}$ and $\{B_1, B_2\}$ belong to separate chains in the Answer Key
      – The precision calculated for each item in chain and averaged:
      – $(5 \times \frac{5}{7} + 2 \times \frac{2}{7}) \times \frac{1}{7} \approx .59$
  – Recall calculated for each answer key chain (and averaged)
    • $(5 \times \frac{5}{5} + 2 \times \frac{2}{2}) \times \frac{1}{7} = 1$
  – F-score = $.74$
    \[
    \frac{2}{(\frac{1}{.59} + 1)} = .74
    \]
  – Difference with MUC Score: penalizes incorrect links among more NPs for precision; credit for NPs that are not coreferential with other NPs

• ACE: complex weighted average designed to count names more than other types of NPs and Person names most of all.
Cross Document Coreference

- So far: coreference with a single discourse
  - within a single document
  - Names usually are unambiguous
  - Disambiguation strategies for Exceptions, e.g., most recent instance
    - George Bush Sr. vs George W. Bush
      - Bush, George Bush, Mr. Bush, President Bush
    - New York City, New York State
      - New York

- Reference Independent of Individual Documents
  - Same person name, abbreviation, organization name
  - How do we know when they have different referents?
Baseline Strategy For CrossDoc

- Do single document coreference in each document
- Entity = set of “mentions” that are coreferential
- Select only those Entities which include Name mentions
- Choose longest name string as representative label
  - (don't use abbreviations as label)
- Compare representative labels across documents
  - Merge if labels match exactly
  - Merge if labels match modulo minor modifications
    - Delete middle initial or match middle names
    - Possibly delete titles
  - Similar to name coreference, but more conservative
Hard Cases: Ambiguity and Aliases

- Same name, different middle initial, e.g., *George Bush*
- Ambiguous abbreviations
  - *AMEX*: American Stock Exchange or American Express
- People famous in specific domains
  - *Michael Jackson*: Musician, basketball player, football player, executive, …
- Places
  - *New York* (City vs State)
  - *Paris* in (France, Texas, Ontario, Denmark)
- Metonymy
  - *New York*: Rangers, Mets, Yankees, Giants, Jets, …
- Spelling Variation Across Documents (typos, transliteration, etc.)
  - *Osama bin Ladin, Usama ibn Ladin*
  - *(Moammar|Muammar) (Gaddafi|Gaddafì|Gathafì|Kadafì|Kaddafì|Khadafy|Qadhafì|Qathafì)*
- Name Changes over time
  - *Beijing, Beiping*
  - *Leningrad, Saint Petersburg*
Entity Linking Tasks

- TAC KBP2014 and 2015 Entity Linking Tasks
  - http://nlp.cs.rpi.edu/kbp/2014/
  - Do within document coreference
  - For each people, organization, GPE entity E, either
    - Link E to an entry in the existing wikipedia-based database OR
    - Link E with a cross-document cluster of entities that your system created
    - Or create a new cross-document entity

- Database created semi-automatically from Wikipedia
  - Database entries correspond to Wikipedia pages
    - Ex: there are several Paris pages, one for each “sense” of Paris
Strategies Researchers Use

- Machine Learning with lots of features
- Baseline strategies as described
- Contextual features: similar contexts/diff docs
  - Ngrams, relations, vocabulary distribution of whole document
- Extract from Wikipedia Info Boxes
- Other features of documents
  - News articles from the same date and similar location
  - Genre or topic of article
Summary

• Reference Resolution Covers a Wide Area
  – Most Studied Area is Coreference
    • Proper Noun Coreference
      – Easiest to find correct answer
      – Most important for many applications
    • Pronoun Coreference
      – Most thoroughly studied in linguistics
  – Opportunities for research:
    • common noun coreference, other types of reference resolution, connection with relation extraction

• Simple hard-to-beat baselines:
  – Hobbs
  – Poessio and Veira

• Evaluation is Non-Trivial
Readings

• J&M: Chapter 21:3-8, 21:9
• Lappin and Leas (1994)
• I also can make available a coref corpus, the one used for MUC-6