Discourse: Coreference

Deep Processing Techniques for NLP
Ling 571
March 4, 2015

Roadmap

- Coreference
  - Referring expressions

  - Syntactic & semantic constraints
  - Syntactic & semantic preferences

  - Reference resolution:
    - Hobbs Algorithm: Baseline
    - Machine learning approaches
    - Sieve models

  - Challenges

Entity-based Coherence

- *John went to his favorite music store to buy a piano.*
- *He had frequented the store for many years.*
- *He was excited that he could finally buy a piano.*

- VS
  - *John went to his favorite music store to buy a piano.*
  - *It was a store John had frequented for many years.*
  - *He was excited that he could finally buy a piano.*
  - *It was closing just as John arrived.*
- Which is better? Why?

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- Which is better? Why?
  - 'about' one entity vs two, focuses on it for coherence

Reference Resolution

- Match referring expressions to referents
- Syntactic & semantic constraints
- Syntactic & semantic preferences

- Reference resolution algorithms

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- Linguistic form that picks out entity in some model
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  - When introduces entity, "evokes" it
  - Set up later reference, "antecedent"
- 2 refexps with same referent "co-refer"

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  - Refers to previously introduced item ("accesses")
    - Referring expression is then anaphoric

Referring Expressions

- Many alternatives:
  - Queen Elizabeth, she, her, the Queen, etc
  - Possible correct forms depend on discourse context
    - E.g. she, her presume prior mention, or presence in world

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  - Possible correct forms depend on discourse context
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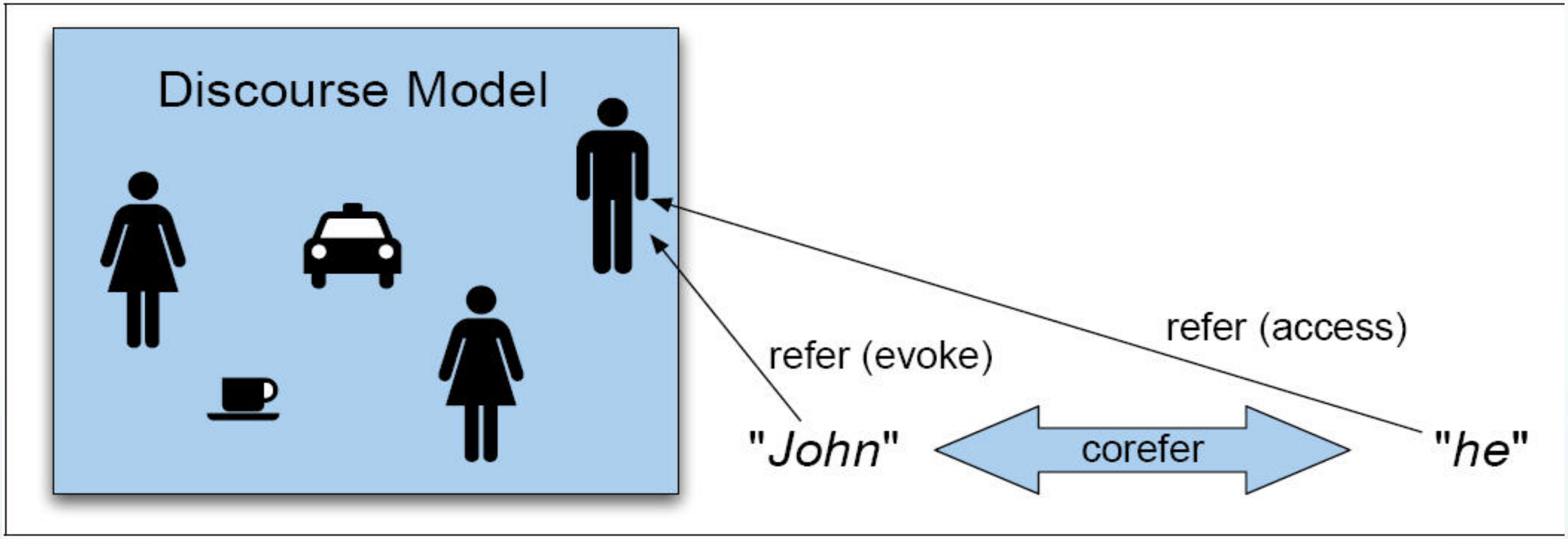
- Interpretation (and generation) requires:
  - Discourse Model with representations of:
    - Entities referred to in the discourse
    - Relationships of these entities
  - Need way to construct, update model
  - Need way to map refexp to hearer's beliefs

Reference and Model



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Coreference resolution:

Find all expressions referring to same entity, ‘corefer’

Colors indicate coreferent sets

Pronominal anaphora resolution:

Find antecedent for given pronoun

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- Names: e.g. “Miss Woodhouse”,”IBM”
  - New or old entities

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The givenness hierarchy:

in focus >	activated >	familiar >	uniquely identifiable >	referential >	type identifiable
{it}	{*that*, *this*, *this* N}	{that N}	{the N}	{indef. *this* N}	{*a* N}

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- Accessibility:
  - More salient elements easier to call up, can be shorter
    Correlates with length: more accessible, shorter refexp

Complicating Factors

- Inferrables:
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- Non-referential cases:
  - *It's raining.*

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  - Gender: he vs she vs it

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- Binding constraints:
  - Reflexive (x-self): corefers with subject of clause
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- "Selectional restrictions":
  - "animate": The cows eat grass.
  - "human": The author wrote the book.
  - More general: drive: John drives a car….

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Reference Resolution Approaches

- Common features
  - “Discourse Model”
    - Referents evoked in discourse, available for reference
    - Structure indicating relative salience
  - Syntactic & Semantic Constraints
  - Syntactic & Semantic Preferences
- Differences:
  - Which constraints/preferences? How combine? Rank?

Hobbs' Resolution Algorithm

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  - Constraints: binding theory, gender, person, number

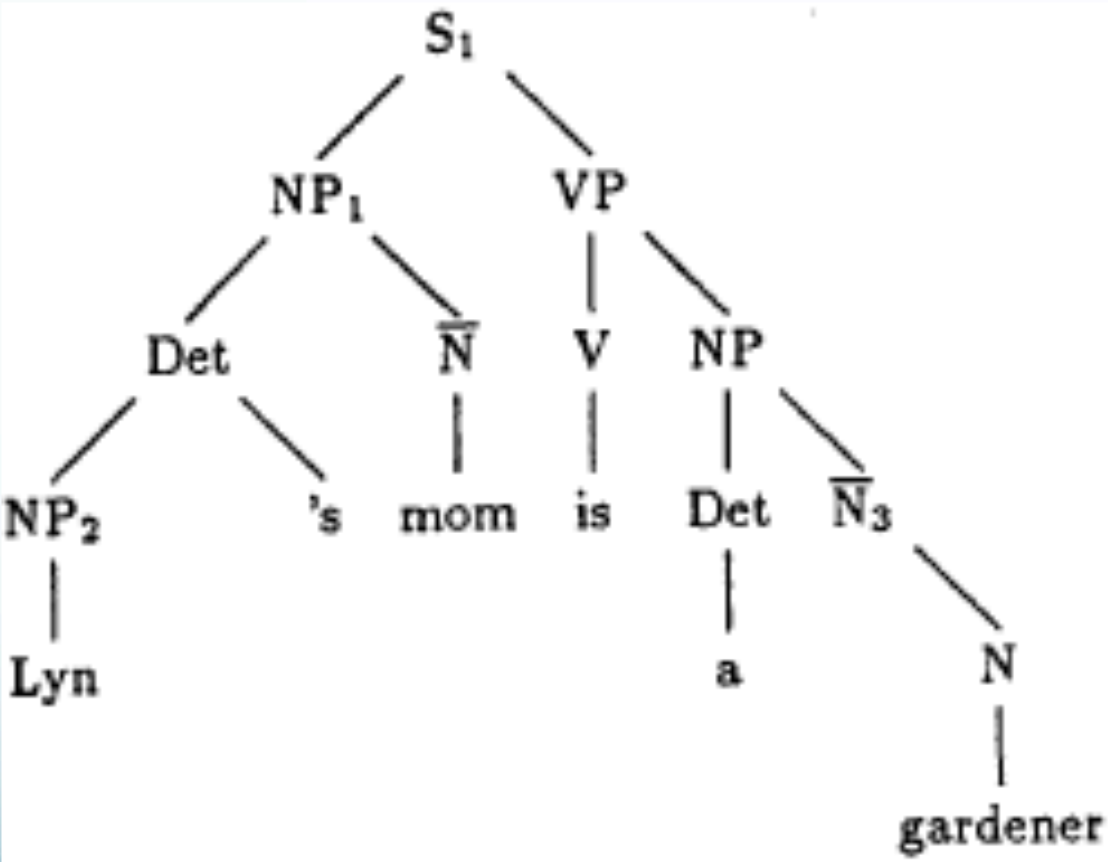
Hobbs Algorithm

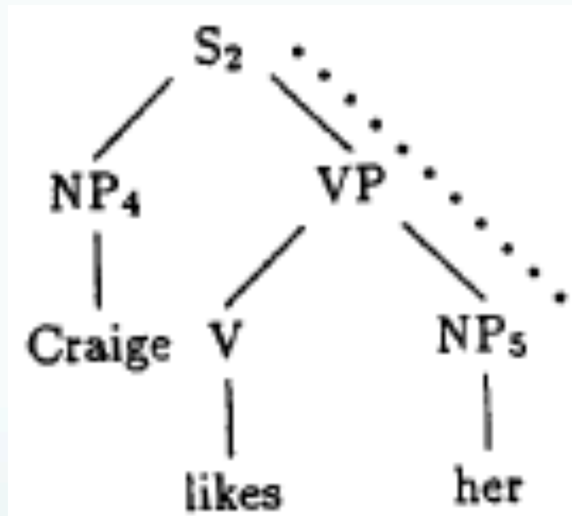
- Intuition:
  - Start with target pronoun
  - Climb parse tree to S root
  - For each NP or S
    - Do breadth-first, left-to-right search of children
      - Restricted to left of target
    - For each NP, check agreement with target
  - Repeat on earlier sentences until matching NP found

Hobbs Algorithm Detail

- Begin at NP immediately dominating pronoun
- Climb tree to NP or S: X=node, p = path
- Traverse branches below X, and left of p: BF, LR
  - If find NP, propose as antecedent
    - If separated from X by NP or S
- Loop: If X highest S in sentence, try previous sentences.
- If X not highest S, climb to next NP or S: X = node
- If X is NP, and p not through X's nominal, propose X
- Traverse branches below X, left of p: BF,LR
  - Propose any NP
- If X is S, traverse branches of X, right of p: BF, LR
    - Do not traverse NP or S; Propose any NP
  - Go to Loop

Hobbs Example





Lyn's mom is a gardener. Craige likes her.

Another Hobbs Example

- The castle in Camelot remained the residence of the King until 536 when he moved it to London.

- What is **it**?

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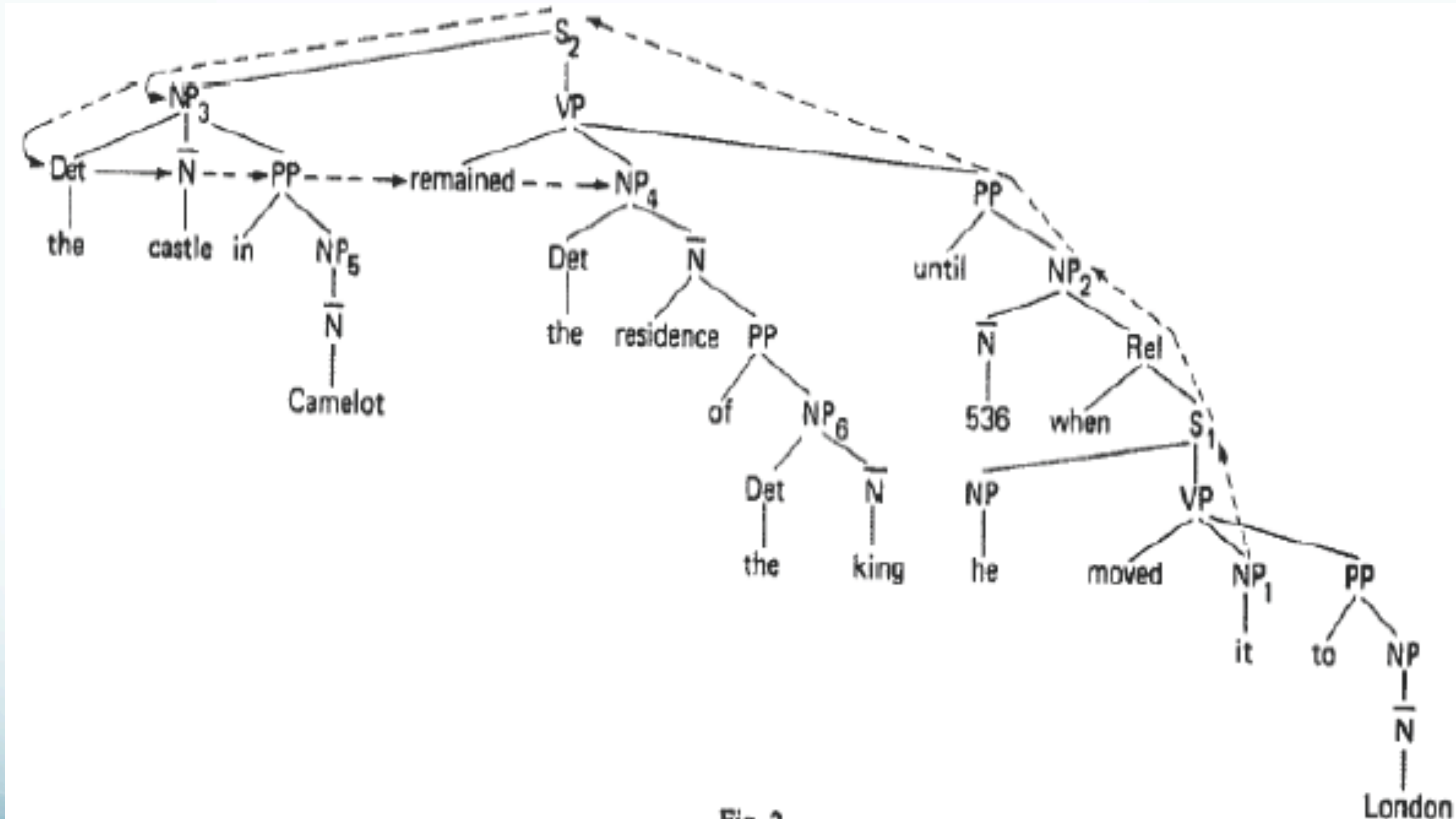

Hobbs, 1978

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    - Captures: Binding theory, grammatical role, recency
    - But not: parallelism, repetition, verb semantics, selection

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      - For each pair NP_k and cluster $C_{j,,}$ should the NP be in the cluster?
    - Ranking models
      - For each NP_k, and all candidate antecedents, which highest?

NP Coreference Examples

- Link all NPs refer to same entity

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King George VI, into a viable monarch. Logue,
a renowned speech therapist, was summoned to help
the King overcome his speech impediment...

Example from Cardie&Ng 2004

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  - German, Czech, Japanese, Spanish, Catalan, Medline

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    - WordNet similarity
    - Wikipedia: broader coverage
  - Lexico-syntactic patterns:
    - E.g. X is a Y

Typical Feature Set

- 25 features per instance: 2NPs, features, class
  - 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

Coreference Evaluation

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  - Which NPs are evaluated?
    - Gold standard tagged or
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  - How good is the partition?
    - Any cluster-based evaluation could be used (e.g. Kappa)
    - MUC scorer:
      - Link-based: ignores singletons; penalizes large clusters
      - Other measures compensate

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  - F-measure: MUC-6: 62-66%; MUC-7: 60-61%
    - Soon et. al, Cardie and Ng (2002)

Multi-pass Sieve Approach

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      - Not really transitive
      - Can't exploit global constraints
      - Low precision features may overwhelm less frequent, high precision ones

Multi-pass Sieve Strategy

- Basic approach:
  - Apply tiers of deterministic coreference modules
    - Ordered highest to lowest precision
  - Aggregate information across mentions in cluster
    - Share attributes based on prior tiers
  - Simple, extensible architecture
    - Outperforms many other (un-)supervised approaches

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    - Same sentence: by Hobbs algorithm
    - Prev. sentence:
      - For Nominal: by right-to-left, breadth first: proximity/ recency
      - For Pronoun: left-to-right: salience hierarchy

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    - W/in cluster: aggregate attributes, order mentions
    - Prune indefinite mentions: can't have antecedents

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- Pass 2: Precise constructs
  - Predicate nominative, (role) appositive, re;. pronoun, acronym, demonym
- Pass 3: Strict head matching
  - Matches cluster head noun AND all non-stop cluster wds AND modifiers AND non i-within-I (embedded NP)

Multi-pass Sieve Modules

- Pass 1: Exact match (N): P: 96%
- Pass 2: Precise constructs
  - Predicate nominative, (role) appositive, re;. pronoun, acronym, demonym
- Pass 3: Strict head matching
  - Matches cluster head noun AND all non-stop cluster wds AND modifiers AND non i-within-I (embedded NP)
- Pass 4 & 5: Variants of 3: drop one of above

Multi-pass Sieve Modules

- Pass 6: Relaxed head match
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Multi-pass Sieve Modules

- Pass 6: Relaxed head match
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- Pass 7: Pronouns
  - Enforce constraints on gender, number, person, animacy, and NER labels

Multi-pass Effectiveness

Passes	MUC P	MUC R	MUC F1
{1}	95.9	31.8	47.8
{1,2}	95.4	43.7	59.9
{1,2,3}	92.1	51.3	65.9
{1,2,3,4}	91.7	51.9	66.3
{1,2,3,4,5}	91.1	52.6	66.7
{1,2,3,4,5,6}	89.5	53.6	67.1
{1,2,3,4,5,6,7}	83.7	74.1	78.6

Sieve Effectiveness

- ACE Newswire

This work (sieve)	**83.8**	73.2	**78.1**
This work (single pass)	82.2	71.5	76.5
Haghighi and Klein (2009) +S	77.0	**75.9**	76.5
Poon and Domingos (2008)	71.3	70.5	70.9
Finkel and Manning (2008) +G	78.7	58.5	67.1

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  - Dialogue?
    - Multiple speakers introduce referents
  - Multimodal communication?
    - How else can entities be evoked?
    - Are all equally salient?

More Questions

- Good accuracies on (clean) (English) text: What about..
  - Other languages?

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    - Zero anaphora?
      - How do you resolve a pronoun if you can't find it?

Reference Resolution Algorithms

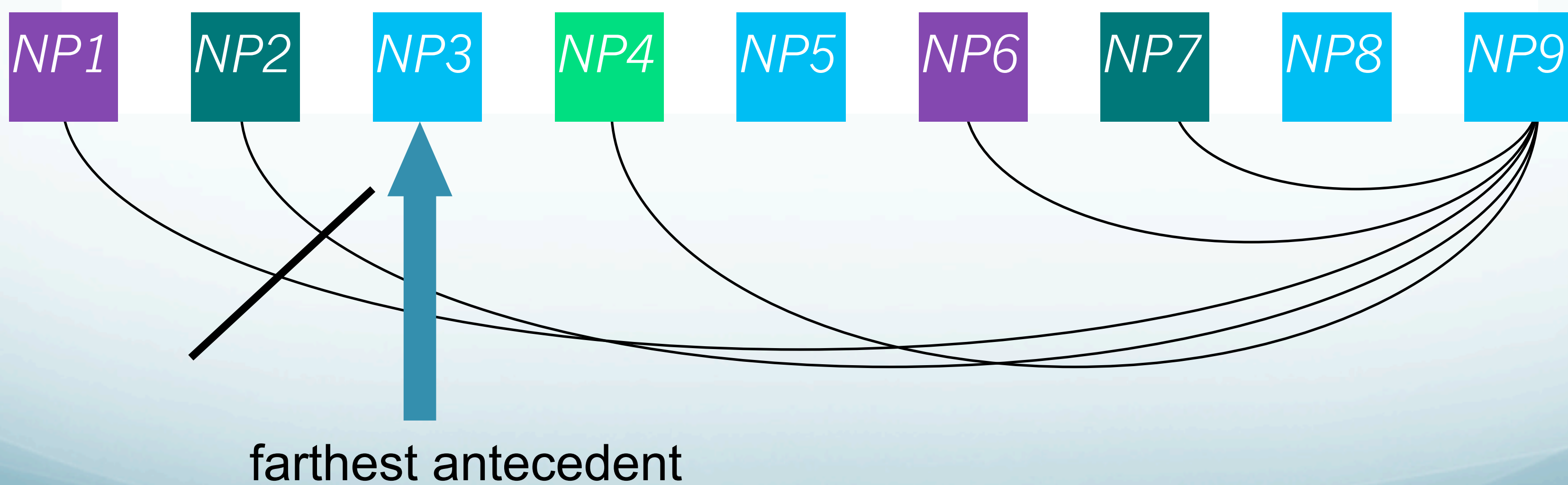
- Many other alternative strategies:
  - Linguistically informed, saliency hierarchy
    - Centering Theory
  - Machine learning approaches:
    - Supervised: Maxent
    - Unsupervised: Clustering
  - Heuristic, high precision:
    - Cogniac

Conclusions

- Co-reference establishes coherence
- Reference resolution depends on coherence
- Variety of approaches:
  - Syntactic constraints, Recency, Frequency,Role
- Similar effectiveness - different requirements
- Co-reference can enable summarization within and across documents (and languages!)

Problem 1

- Coreference is a rare relation
  - skewed class distributions (2% positive instances)
  - *remove some negative instances*



Problem 2

- Coreference is a discourse-level problem
  - different solutions for different types of NPs
    - proper names: string matching and aliasing
  - inclusion of "hard" positive training instances
  - *positive example selection*: selects easy positive training instances (cf. Harabagiu *et al.* (2001))
    - Select most confident antecedent as positive instance

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, the renowned speech therapist, was summoned to help the King overcome his speech impediment...

Problem 3

- Coreference is an equivalence relation
  - loss of transitivity
  - need to tighten the connection between classification and clustering
  - *prune learned rules w.r.t. the clustering-level coreference scoring function*

coref ? *coref ?*

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

not coref ?

Results Snapshot

System Variation	MUC-6 R	MUC-6 P	MUC-6 F	MUC-7 R	MUC-7 P	MUC-7 F
Original Soon et al.	58.6	67.3	62.6	56.1	65.5	60.4
Duplicated Soon Baseline	62.4	70.7	66.3	55.2	68.5	61.2
Learning Framework	62.4	73.5	67.5	56.3	71.5	63.0
String Match	60.4	74.4	66.7	54.3	72.1	62.0
Training Instance Selection	61.9	70.3	65.8	55.2	68.3	61.1
Clustering	62.4	70.8	66.3	56.5	69.6	62.3
All Features	70.3	58.3	63.8	65.5	58.2	61.6
Pronouns only	–	66.3	–	–	62.1	–
Proper Nouns only	–	84.2	–	–	77.7	–
Common Nouns only	–	40.1	–	–	45.2	–
Hand-selected Features	64.1	74.9	69.1	57.4	70.8	63.4
Pronouns only	–	67.4	–	–	54.4	–
Proper Nouns only	–	93.3	–	–	86.6	–
Common Nouns only	–	63.0	–	–	64.8	–

Classification & Clustering

- Classifiers:
  - C4.5 (Decision Trees)
  - RIPPER – automatic rule learner

Classification & Clustering

- Classifiers:
  - C4.5 (Decision Trees), RIPPER
- Cluster: Best-first, single link clustering
  - Each NP in own class
  - Test preceding NPs
  - Select highest confidence coreferent, merge classes

Baseline Feature Set

Feature Type	Feature
Lexical	SOON_STR
Grammatical	PRONOUN_1*
	PRONOUN_2*
	DEFINITE_2
	DEMONSTRATIVE_2
	NUMBER*
	GENDER*
	BOTH_PROPER_NOUNS*
	APPOSITIVE*
Semantic	WNCLASS*
	ALIAS*
Positional	SENTNUM*

Extended Feature Set

- Explore 41 additional features
  - More complex NP matching (7)
  - Detail NP type (4) – definite, embedded, pronoun,..
  - Syntactic Role (3)
  - Syntactic constraints (8) – binding, agreement, etc
  - Heuristics (9) – embedding, quoting, etc
  - Semantics (4) – WordNet distance, inheritance, etc
  - Distance (1) – in paragraphs
  - Pronoun resolution (2)
    - Based on simple or rule-based resolver

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      - Reminiscent of Lappin & Leass
- Still best results on MUC-7 dataset: 0.634