



Supervised Noun Phrase Coreference Research: The First Fifteen Years

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My first ACL talk

- “Improving Machine Learning Approaches to Coreference Resolution” (Ng & Cardie, 2002)
 - Proposed linguistic and extra-linguistic extensions to Soon et al.’s (2001) system
 - The mention-pair model

Goal

Survey the major milestones in supervised noun phrase coreference research in the past fifteen years (1994-2009)

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Focuses on:

Within-document coreference (no cross-doc coreference)

Identity coreference (no bridging references, ..)

Areas Covered

- Supervised models
- Linguistic features
- Publicly-available annotated coreference corpora
- Evaluation issues

Areas Covered

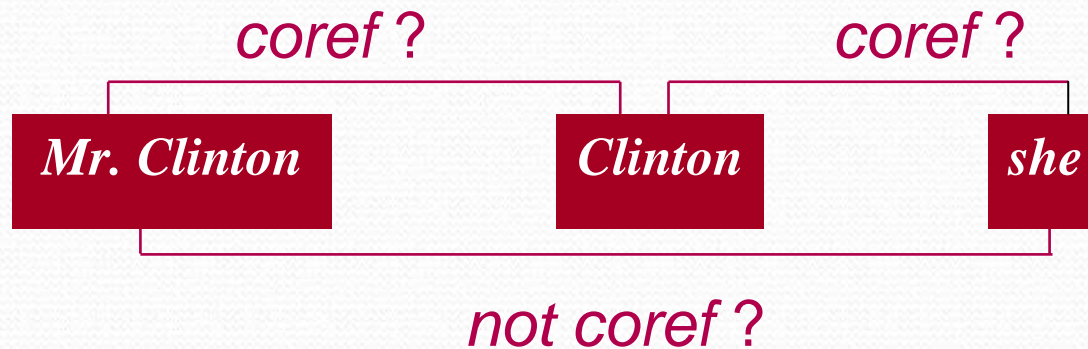
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Noun Phrase Coreference Resolution

- Identify the noun phrases (NPs) in a text that refer to the same real-world entity
- Inherently a **clustering** problem
 - Goal: produce a partition of the NPs

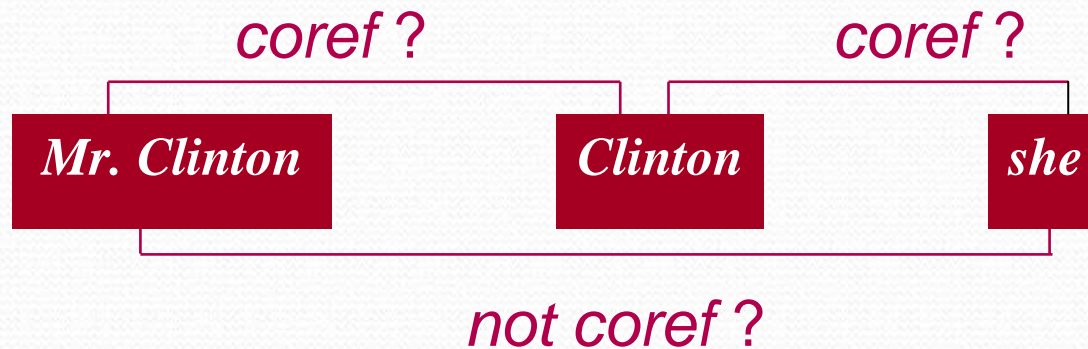
Standard Supervised Approach

- **Step 1:** Learn a coreference model
 - *CM*: $NP_i \times NP_j$ [0, 1] from **annotated** data



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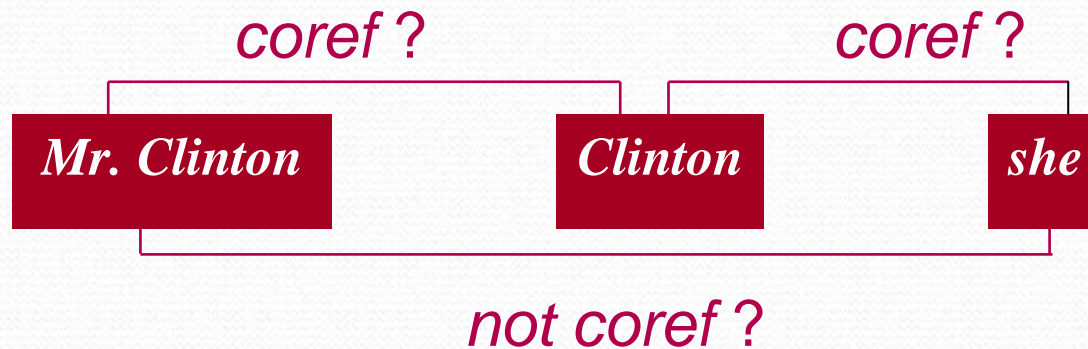
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 - coordinates the pairwise classification decisions

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Mention-Pair Model

- a classifier that determines whether two NPs are coreferent
- Train the model using any off-the-shelf machine learner
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- a classifier that determines whether two NPs are coreferent
- Train the model using any off-the-shelf machine learner
- Apply the model to a test text to determine whether two NPs are coreferent
- Need a clustering algorithm to coordinate the pairwise coreference decisions
 - many clustering algorithms have been used
 - three types of clustering algorithms

Really Greedy Clustering Algorithms

- Single-link clustering (Soon et al., 2001)
 - For each NP_j , select as its antecedent the **closest** preceding NP that is determined as coreferent with it
 - Posit NP_j as non-anaphoric if no preceding NP is coreferent with it
- Best-first clustering (Ng & Cardie, 2002)
 - Same as single-link clustering, except that we select as the antecedent the NP that has the highest coreference likelihood

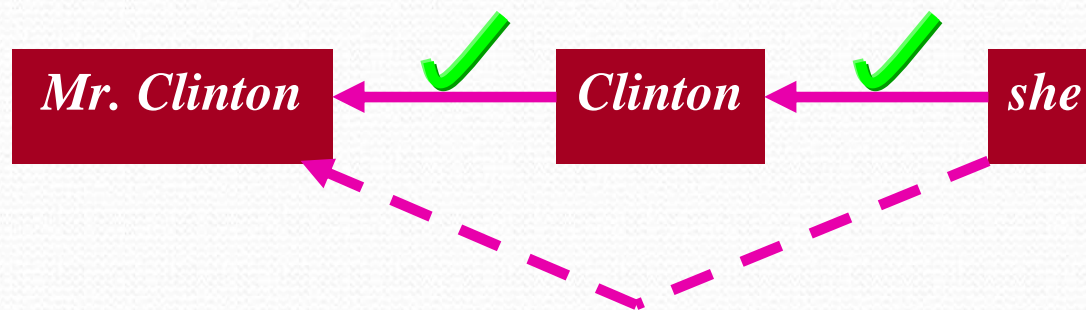
Why are they really greedy?

- Clusters are formed based on a small subset of the pairwise coreference decisions
 - Many pairwise decisions are not used in the clustering process



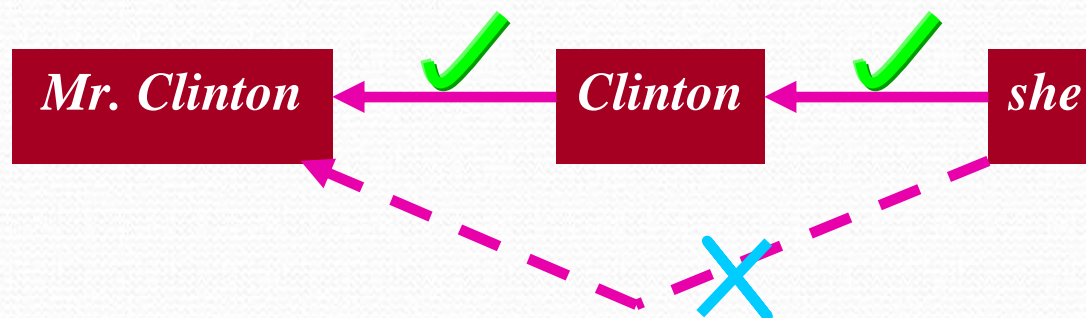
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Less Greedy Clustering Algorithms

- Use all the pairwise coreference decisions
- **Graph partitioning algorithms**
 - each text is represented as a graph
 - each vertex corresponds to a NP; edge weight is coref likelihood
 - Goal: partition the graph nodes to form coreference clusters

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 - each text is represented as a graph
 - each vertex corresponds to a NP; weight of an edge indicates the likelihood that the two NPs are coreferent
 - Goal: partition the graph nodes to form coreference clusters
 - **Correlation clustering** (e.g., McCallum & Wellner (2004))
 - cluster that respects as many pairwise decisions as possible
 - **Minimum-cut-based clustering** (Nicolae & Nicolae, 2006)
 - Find the mincut of the graph and partition the graph nodes; repeat until some stopping criterion is reached

Time-Aware Clustering Algorithms

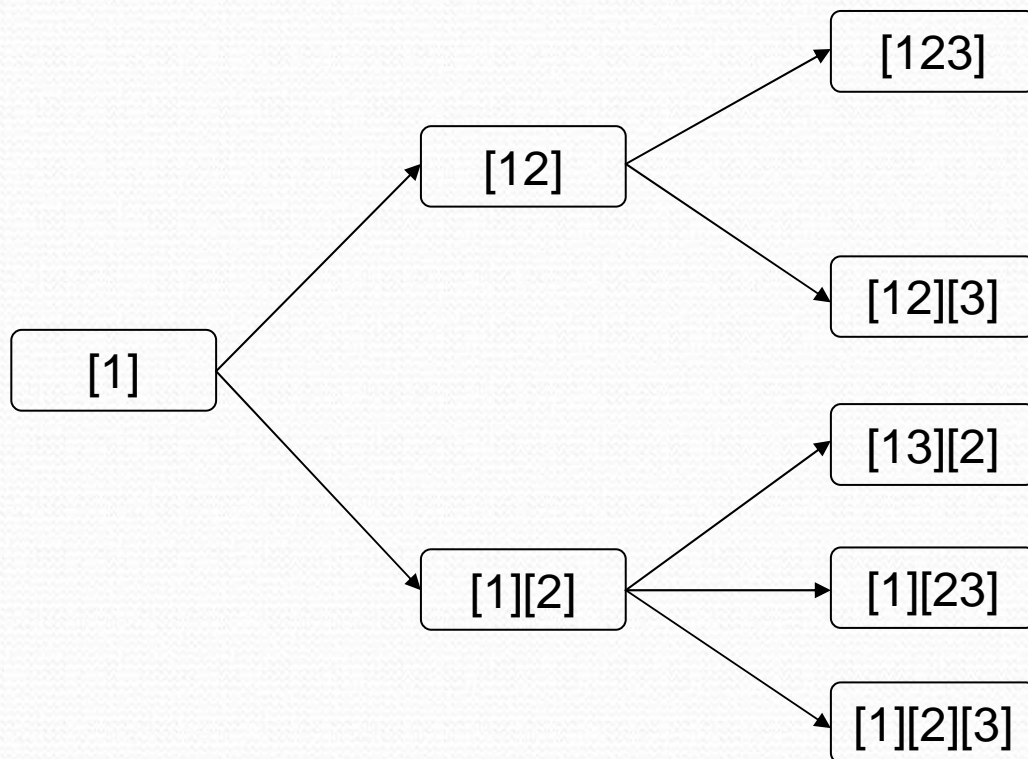
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Time-Aware Clustering Algorithms

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- Luo et al. (2004): Bell-tree clustering
 - Bell tree: represents the space of possible NP partitions

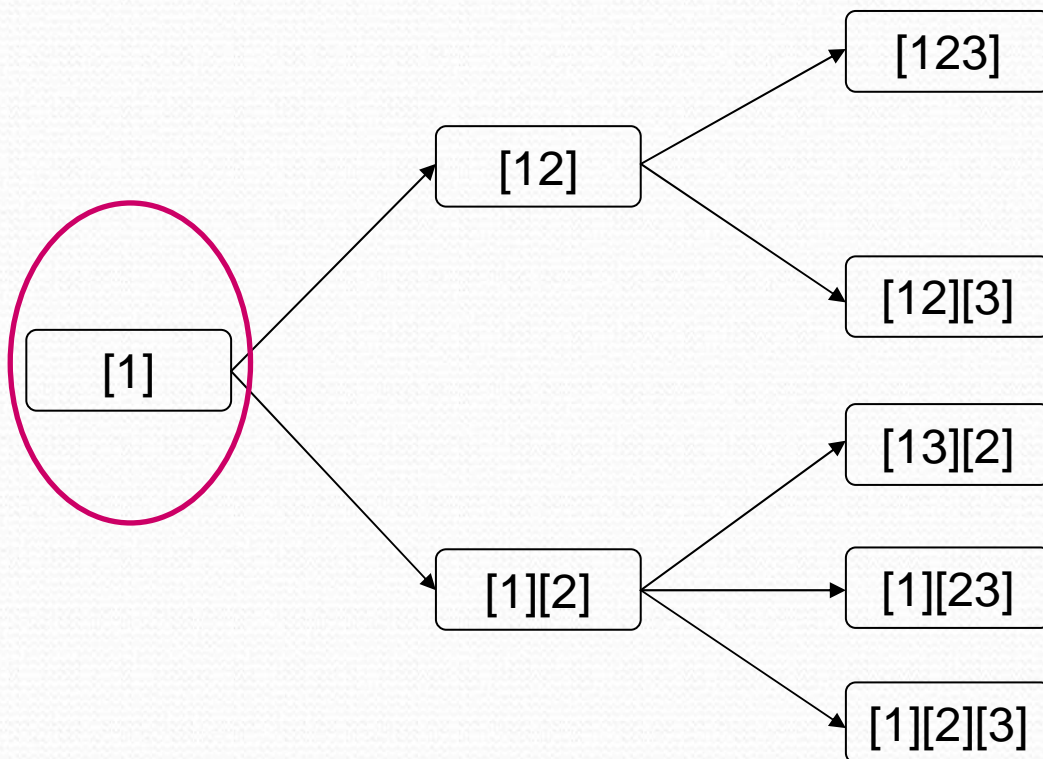
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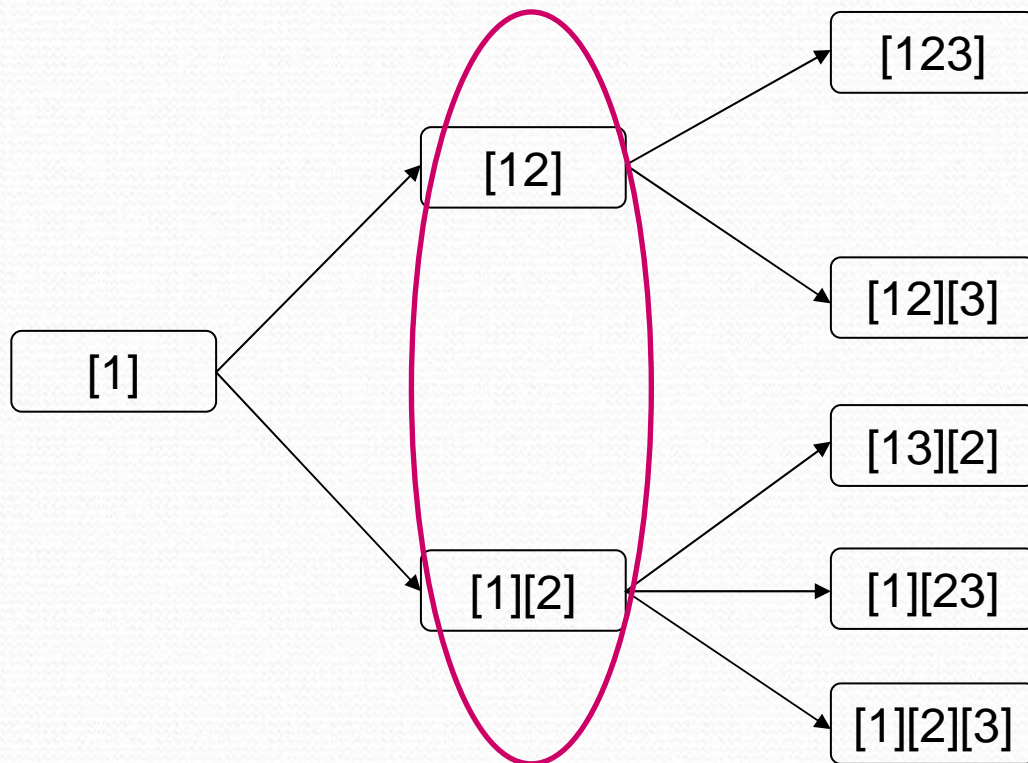
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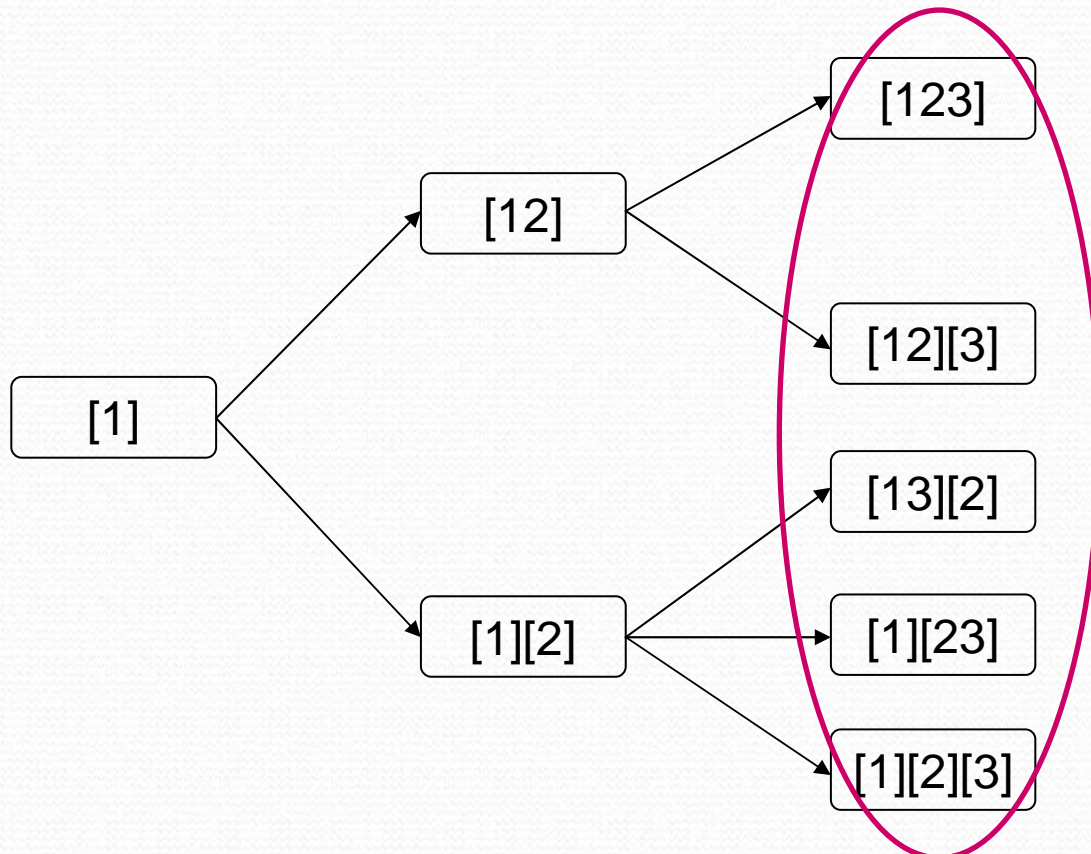
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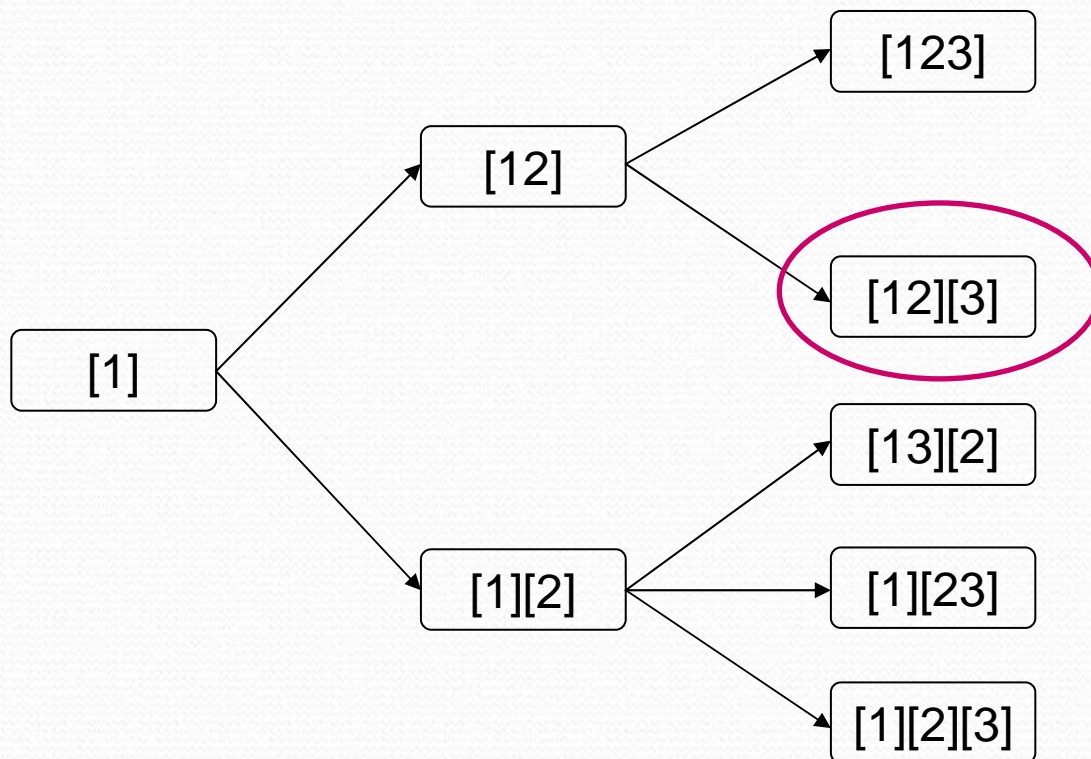
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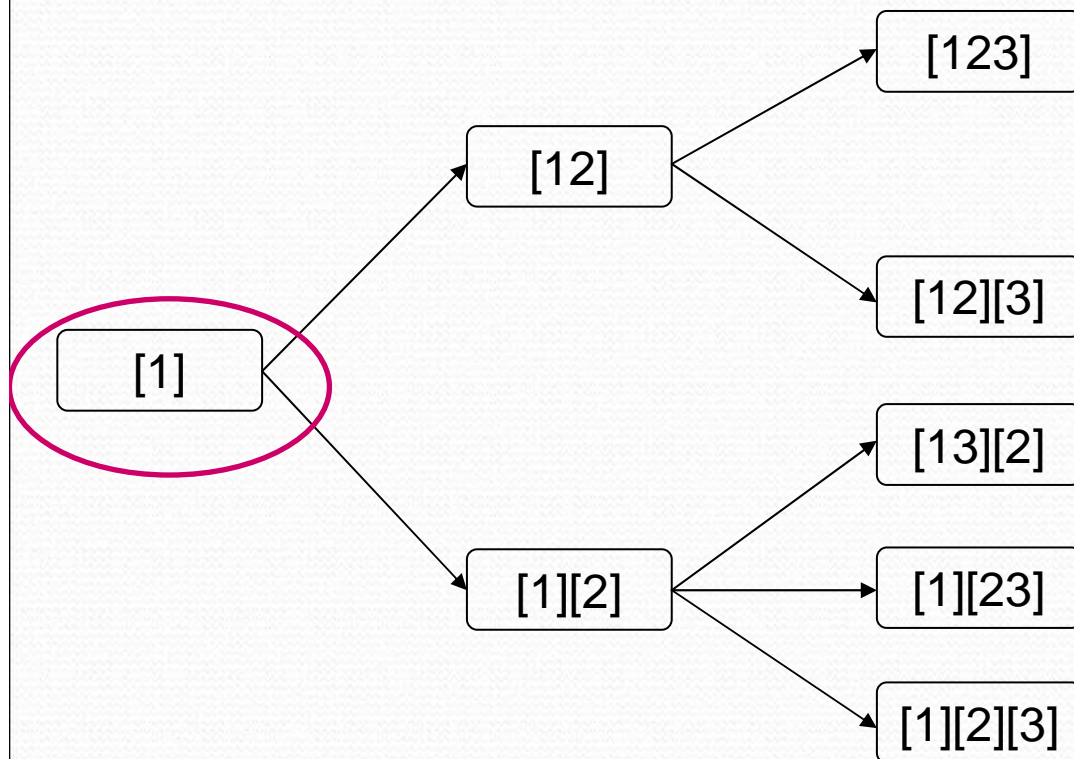
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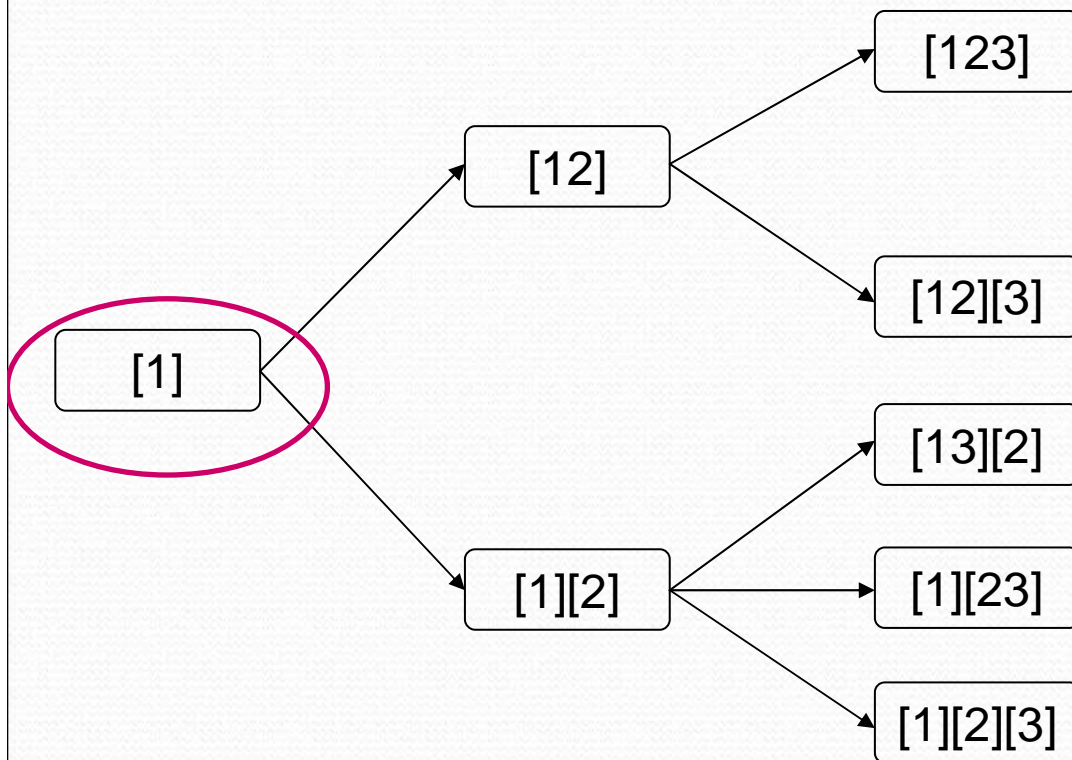
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Recast as a search problem

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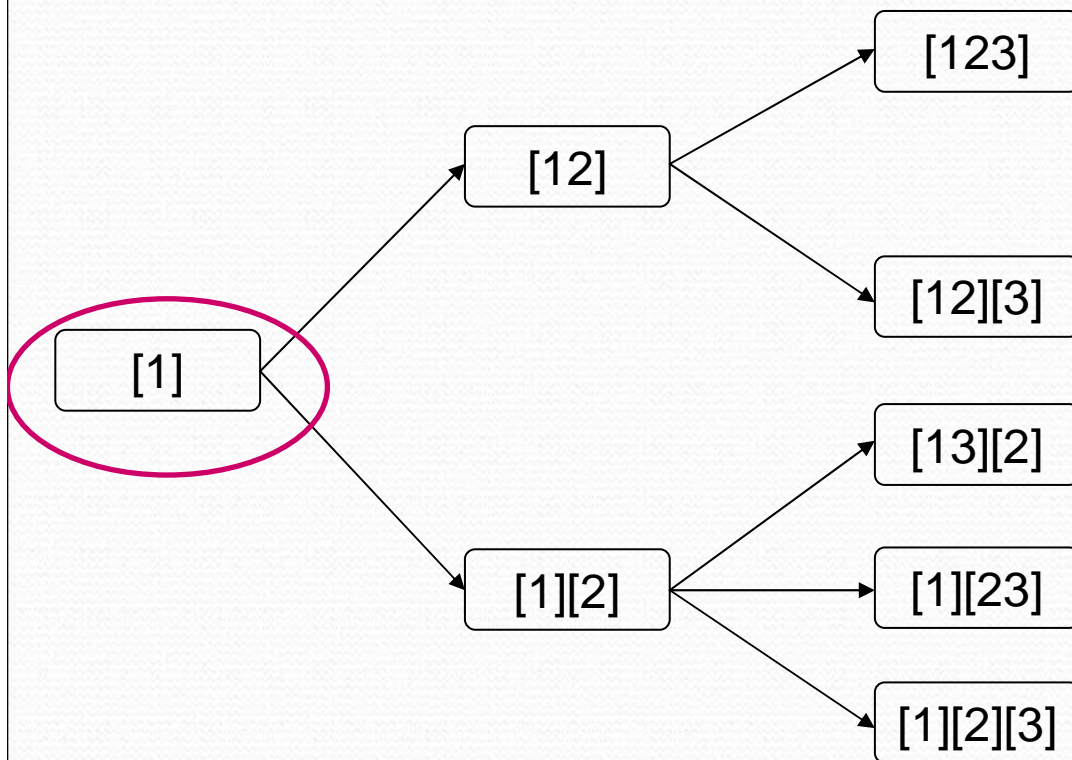


Recast as a search problem

Expands the most promising paths

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Recast as a search problem

Expands the most promising paths

Scores a path based on pairwise probabilities

Which clustering algorithm is the best?

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 - Klein (2005, pc): search space is too large, need to apply a lot of heuristics to prune the space, making it a greedy algorithm
 - Nicolae & Nicolae (2006): not much difference in performance between Bell tree clustering and the really greedy algorithms

Supervised Coreference (Recap)

- **Step 1:** Learn a coreference model

- **Step 2:** Apply a clustering algorithm

Supervised Coreference (Recap)

- **Step 1:** Learn a coreference model
 - Mention-pair model

- **Step 2:** Apply a clustering algorithm
 - Really greedy algorithms
 - Less greedy algorithms
 - Time-aware algorithms

Weaknesses of the Mention-Pair Model

- **Limited expressiveness**
 - information extracted from two NPs may not be sufficient for making an informed coreference decision
- **Can't determine which candidate antecedent is the best**
 - only determine how good a candidate is relative to NP to be resolved, not how good it is relative to the others

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Entity-mention model



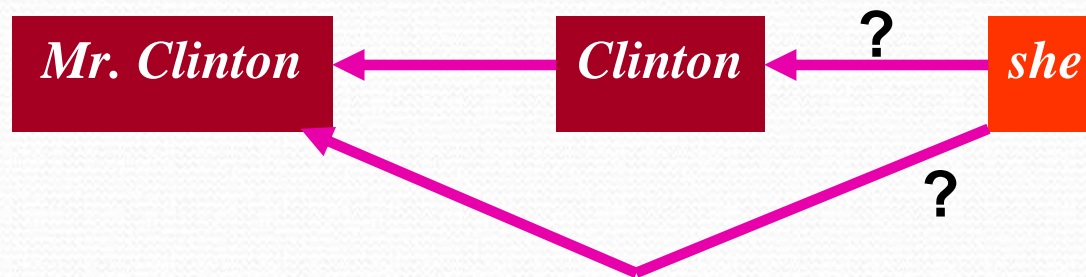
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Mention-ranking model



Improving Model Expressiveness



- Want a coreference model that can tell us how likely “she” and a preceding cluster of “she” are coreferent

The Entity-Mention Model

- a classifier that determines whether (or how likely) an NP belongs to a preceding coreference cluster
- more **expressive** than the mention-pair model
 - can employ **cluster-level** features defined over any subset of NPs in a preceding cluster
- addresses the expressiveness problem

Pasula et al. (2003), Luo et al. (2004), Yang et al. (2004, 2008),
Daume & Marcu (2005), Culotta et al. (2007), ...

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How to address this problem?

- Idea: train a model that imposes a **ranking** on the candidate antecedents for an NP to be resolved
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 - so that it assigns the highest rank to the correct antecedent
- A ranker allows all candidate antecedents to be considered simultaneously and captures competition among them
 - allows us find the best candidate antecedent for an NP
- There is a natural resolution strategy for a ranking model
 - An NP is resolved to the highest-ranked candidate antecedent

How to train a ranking model?

- Convert the problem of ranking m NPs into the a set of pairwise ranking problems
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- Convert the problem of ranking m NPs into the a set of pairwise ranking problems
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 - Each one is essentially a classification problem
- First supervised coreference model: **Connolly et al. (1994)**
 - Train a decision tree to determine which of the two candidate antecedents of an NP is more likely to be its antecedent
 - During testing, need to heuristically combine the pairwise ranking results to select an antecedent for each NP

Revival of the Ranking Approach

- The ranking model is theoretically better but far less popular than the mention-pair model in the decade following its proposal
- Rediscovered almost ten years later independently by
 - Yang et al. (2003): twin-candidate model
 - Iida et al. (2003): tournament model

The Mention-Ranking Model

- Denis & Baldrige (2007, 2008): train the ranker using maximum entropy
 - model outputs a rank value for each candidate antecedent
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Caveat

- Since a ranker only imposes a ranking on the candidates, it cannot determine whether an NP is anaphoric
 - Need to train a classifier to determine if an NP is anaphoric

Recap

Problem	Entity Mention	Mention Ranking
Limited expressiveness	✓	✗
Cannot determine best candidate	✗	✓

Can we combine the strengths of these two model?

Mention-ranking model



Rank candidate antecedents

Entity-mention model



Consider preceding **clusters**,
not candidate antecedents

Mention-ranking model

Entity-mention model

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The Cluster-Ranking Model

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The Cluster-Ranking Model (Rahman & Ng, 2009)

- **Training**
 - train a **ranker** to rank preceding clusters
- **Testing**
 - resolve each NP to the highest-ranked preceding cluster

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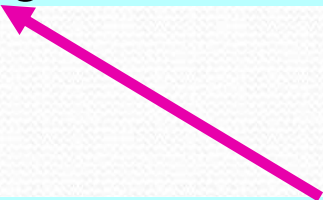
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Lappin & Leass's (1994) heuristic pronoun resolver



The Cluster-Ranking Model (Rahman & Ng, 2009)

- As a ranker, the cluster-ranking model cannot determine whether an NP is anaphoric
 - Before resolving an NP, we still need to use an anaphoricity classifier to determine if it is anaphoric
 - yields a **pipeline** architecture
- Potential problem
 - errors made by the anaphoricity classifier will be propagated to the coreference resolver
- Solution
 - **joint learning** for anaphoricity and coreference resolution

Some Empirical Results on ACE 2005

	B³			CEAF		
	R	P	F	R	P	F
Mention-Pair Baseline	50.8	57.9	54.1	56.1	51.0	53.4
Entity-Mention Baseline	51.2	57.8	54.3	56.3	50.2	53.1
Mention-Ranking Baseline (Pipeline)	52.3	61.8	56.6	51.6	56.7	54.1
Mention-Ranking Baseline (Joint)	50.4	65.5	56.9	53.0	58.5	55.6
Cluster-Ranking Model (Pipeline)	55.3	63.7	59.2	54.1	59.3	56.6
Cluster-Ranking Model (Joint)	54.4	70.5	61.4	56.7	62.6	59.5

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- Cluster ranking is better than mention ranking, which in turn is better than the entity-mention model and the mention-pair model
- Joint models perform better than pipeline models

Summary

- A lot of progress in supervised coreference modeling
 - the mention-pair model is theoretically unappealing
 - it makes coreference decisions based on only two NPs
- The cluster-ranking model
 - resembles Lappin & Leass's (1994) heuristic pronoun resolver
 - narrows the gap between the **sophistication of heuristic-based coref models** and the **simplicity of learning-based coref models**

Concluding Remarks

- To ensure progress, new coreference results should be compared against a baseline stronger than Soon et al. (2001)

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- Publicly available coreference systems
 - **The mention-pair model**
 - JavaRAP (Qiu et al., 2004)
 - GuiTAR (Poesio & Kabadjov, 2004)
 - BART (Versley et al., 2008)
 - The Illinois Coreference Package (Bengtson & Roth, 2008)
 - Reconcile (Stoyanov et al., 2010)
 - **The mention-ranking model**
 - CoRTex (Denis & Baldrige, 2008)
 - **The cluster-ranking model**
 - CherryPicker (Rahman & Ng, 2009)