

Coreference Resolution

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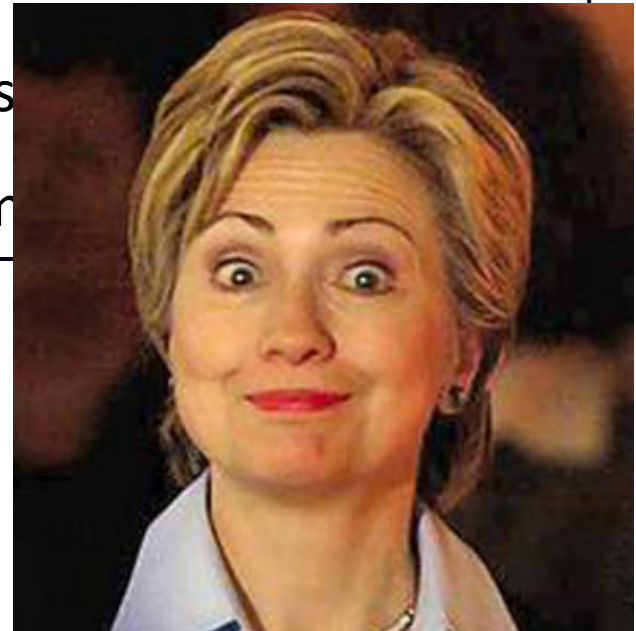
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Reference Resolution

- Noun phrases refer to entities in the world, many pairs of noun phrases co-refer, some nested inside others

John Smith, CFO of Prime Corp. since 1986,

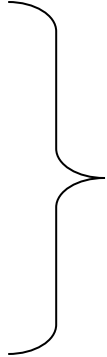
saw his pay jump 20% to \$1.3 million

as the 57-year-old also became

the financial services co.'s president.

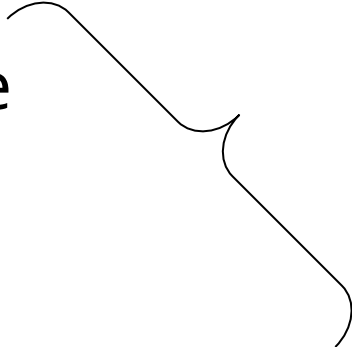
Kinds of Reference

- Referring expressions
 - *John Smith*
 - *President Smith*
 - *the president*
 - *the company's new executive*



More common in
newswire, generally
harder in practice

- Free variables
 - Smith saw *his pay* increase
- Bound variables
 - The dancer hurt *herself*.



More interesting
grammatical
constraints,
more linguistic
theory, easier in
practice

“anaphora
resolution”

Not all NPs are referring!

- *Every dancer* twisted *her knee*.
- (*No dancer* twisted *her knee*.)
- There are three NPs in each of these sentences; because the first one is non-referential, the other two aren't either.

Coreference, anaphors, cataphors

- Coreference is when two mentions refer to the same entity in the world
- The relation of anaphora is when a term (anaphor) refers to another term (antecedent) and the interpretation of the anaphor is in some way determined by the interpretation of the antecedent
 - ... and traditionally the antecedent came first

Cataphora

*"From the corner of the divan of Persian saddlebags on which **he** was lying, smoking, as was **his** custom, innumerable cigarettes, **Lord Henry Wotton** could just catch the gleam of the honey-sweet and honey-coloured blossoms of a laburnum..."*



(O. Wilde – The Picture of Dorian Gray)

Anaphora vs. coreference

- Not all anaphoric relations are coreferential

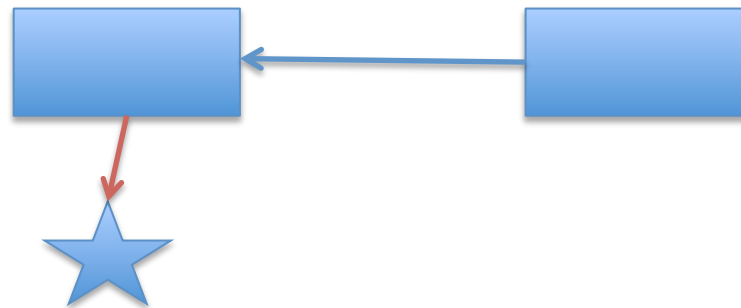
We went to see a concert last night. The tickets were really expensive.

- This is referred to as bridging anaphora.
- Conversely, multiple identical full NP references are typically coreferential but not anaphoric.

Two different things...

- Anaphora

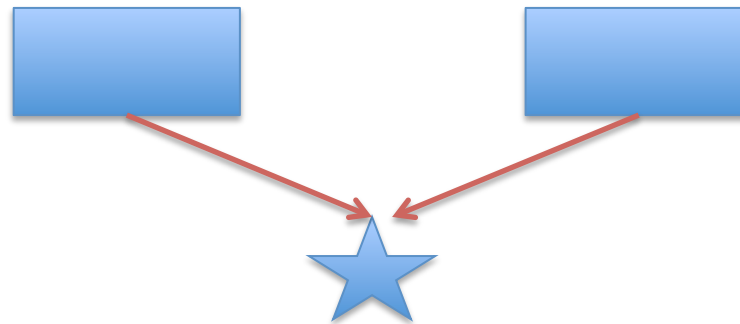
- Text



- World

- (Co)Reference

- Text



- World

Two different things...

- Something you might like to think about:
 - Do various models treat these two cases the same or differently?
 - Should we do more to treat them more differently?

Applications

- Full text understanding:
 - understanding an extended discourse
- Machine translation (if languages have different features of gender, number, etc.)
- Text summarization, including things like web snippets
- Tasks like information extraction and question answering, when some sentences have pronouns
 - *He married Claudia Ross in 1971.*

Traditional pronominal anaphora resolution: Hobbs algorithm

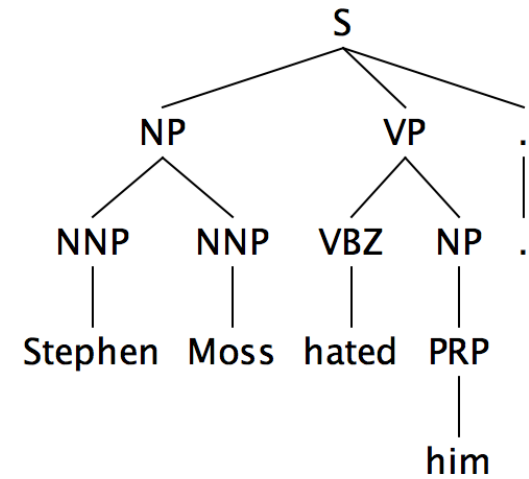
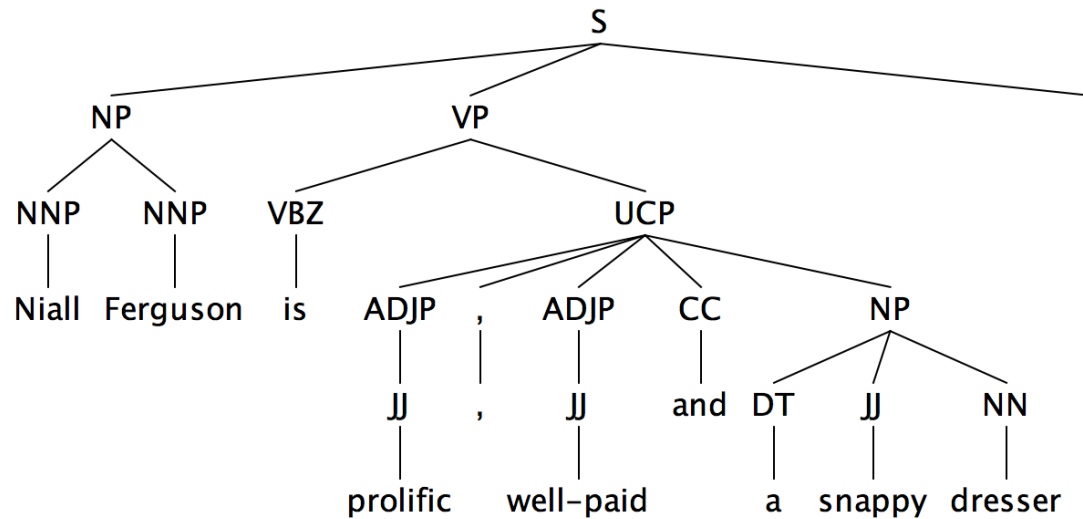
1. Begin at NP (immediately dominating the pronoun)
2. Go up tree to first NP or S. Call this X, and the path p.
3. Traverse all branches below X to the left of p, left-to-right, breadth-first. Propose as antecedent any NP that has a NP or S between it and X
4. If X is the highest S in the sentence, traverse the parse trees of the previous sentences in the order of recency. Traverse each tree left-to-right, breadth first. When an NP is encountered, propose as antecedent. If not the highest node, go to step 5.

Hobbs algorithm

5. From node X, go up the tree to the first NP or S. Call it X, and the path p.
6. If X is an NP and the path p to X did not pass through the nominal that X dominates, propose X as antecedent
7. Traverse all branches below X to the left of the path, in a left-to-right, breadth first manner. Propose any NP encountered as the antecedent
8. If X is an S node, traverse all branches of X to the right of the path but do not go below any NP or S encountered. Propose any NP as the antecedent.
9. Go to step 4

Actually still often used as a feature in ML systems!

Hobbs Algorithm Example

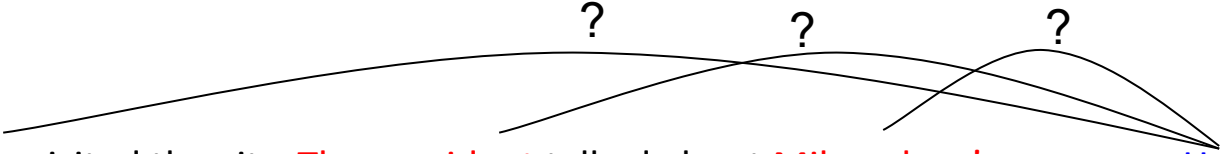


Supervised Machine Learning

Pronominal Anaphora Resolution

- Given a pronoun and an entity mentioned earlier, classify whether the pronoun refers to that entity or not given the surrounding context

Mr. Obama visited the city. The president talked about Milwaukee's economy. He mentioned new jobs.



The diagram shows three curved lines, each with a question mark above it, representing the task of resolving pronouns to their antecedents. The first line connects 'Mr. Obama' to 'Milwaukee's economy'. The second line connects 'The president' to 'Milwaukee's economy'. The third line connects 'He' to 'Milwaukee's economy'.

- Usually first filter out pleonastic pronouns like “It is raining.” (perhaps using hand-written rules)
- Use any classifier, obtain positive examples from training data, generate negative examples by pairing each pronoun with other (incorrect) entities
- This is naturally thought of as a binary classification or ranking task

Features for Pronominal Anaphora Resolution

- Constraints:
 - Number agreement
 - Singular pronouns (it/he/she/his/her/him) refer to singular entities and plural pronouns (we/they/us/them) refer to plural entities
 - Person agreement
 - He/she/they etc. must refer to a third person entity
 - Gender agreement
 - He → John; she → Mary; it → car
 - Jack gave **Mary** a gift. **She** was excited.
 - Certain syntactic constraints
 - John bought **himself** a new car. [himself → John]
 - John bought **him** a new car. [him can not be John]

Features for Pronominal Anaphora Resolution

- Preferences:
 - Recency: More recently mentioned entities are more likely to be referred to
 - John went to a movie. Jack went as well. He was not busy.
 - Grammatical Role: Entities in the subject position is more likely to be referred to than entities in the object position
 - John went to a movie with Jack. He was not busy.
 - Parallelism:
 - John went with Jack to a movie. Joe went with him to a bar.

Features for Pronominal Anaphora Resolution

- Preferences:
 - Verb Semantics: Certain verbs seem to bias whether the subsequent pronouns should be referring to their subjects or objects
 - John telephoned Bill. He lost the laptop.
 - John criticized Bill. He lost the laptop.
 - Selectional Restrictions: Restrictions because of semantics
 - John parked his car in the garage after driving it around for hours.
- Encode all these and maybe more as features

Coreference Resolution

- Can be done analogously to pronominal anaphora resolution: Given two mentions, classify as coreferent or not
- Some approaches also do clustering on the referring expressions instead of doing binary classification

Grammatical Constraints

- Apposition
 - Nefertiti, Amenomfis the IVth's wife, was born in ...
- Predicatives
 - Sue is the best student in the class
- It's questionable whether predicatives should be counted, but they generally are.

Discourse Constraints

- Recency
- Salience
- Focus
- Centering Theory [Grosz et al. 86]
- Coherence Relations

Other coreference features

- Additional features to incorporate aliases, variations in names etc., e.g. *Mr. Obama, Barack Obama; Megabucks, Megabucks Inc.*
- Semantic Compatibility
 - Smith had bought *a used car* that morning.
 - *The dealership* assured him it was in good condition.
 - *The machine* needed a little love, but the engine was in good condition.

But it's complicated

- Common nouns can differ in number but be coreferent:
 - a patrol ... the soldiers
- Common nouns can refer to proper nouns
 - George Bush ... the leader of the free world
- Split antecedence
 - John waited for Sasha. And then they went out.

Evaluation

- B³ (B-CUBED) algorithm for evaluation
 - Precision & recall for *entities in a reference chain*
 - Precision: % of elements in a hypothesized reference chain that are in the true reference chain
 - Recall: % of elements in a true reference chain that are in the hypothesized reference chain
 - Overall precision & recall are the (weighted) average of per-chain precision & recall
 - Optimizing chain-chain pairings is a hard (in the computational sense) problem
 - Greedy matching is done in practice for evaluation

Evaluation

- B-CUBED algorithm for evaluation

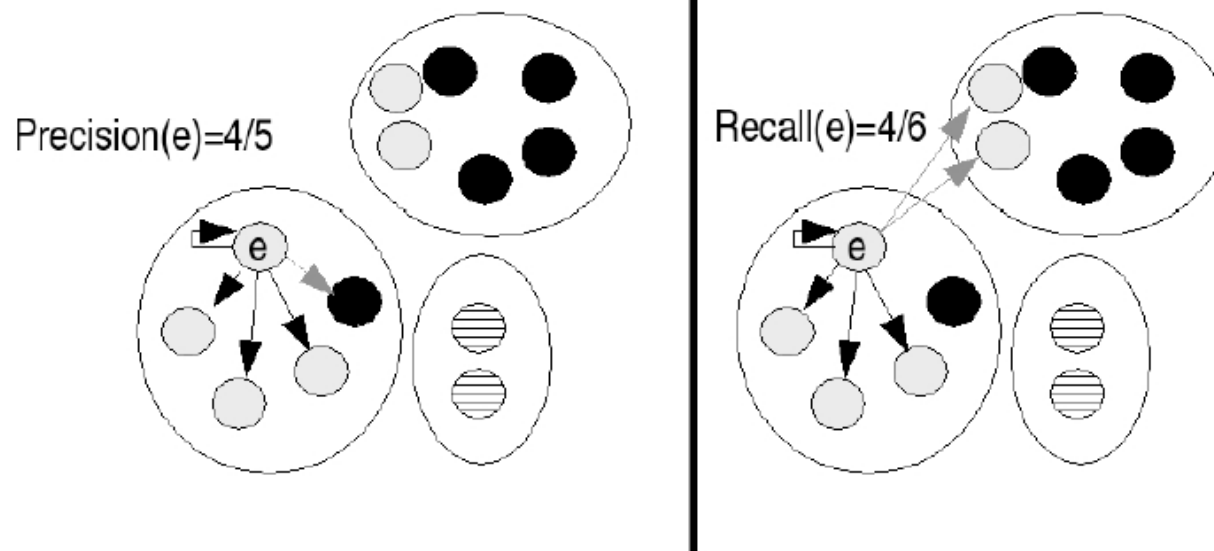


Figure from Amigo et al 2009

Evaluation metrics

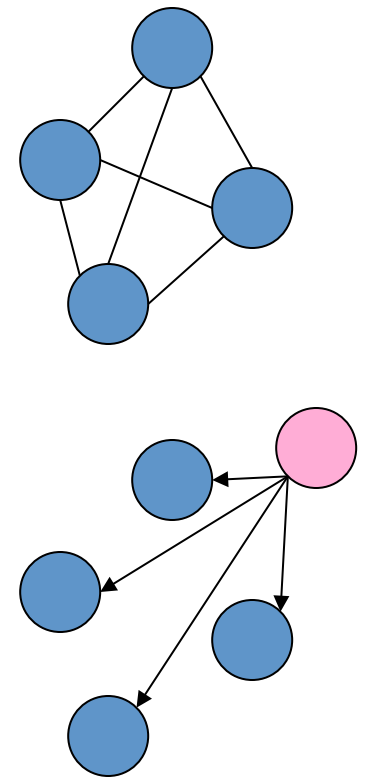
- MUC Score (Vilain et al., 1995)
 - Link based: Counts the number of common links and computes f-measure
- CEAF (Luo 2005); entity based
- BLANC (Recasens and Hovy 2011) Cluster RAND-index
- ...
- All of them are sort of evaluating getting coreference links/ clusters right and wrong, but the differences can be important
 - Look at it in PA3

Machine learning models of coref

- Start with supervised data
 - positive examples that corefer
 - negative examples that don't corefer
 - Note that it's very skewed
 - The vast majority of mention pairs *don't* corefer
- Usually learn some sort of discriminative model of phrases/clusters coreferring
 - Predict 1 for coreference, 0 for not coreferent
- But there is also work that builds generative models of clusters (Haghighi & Klein 2007)

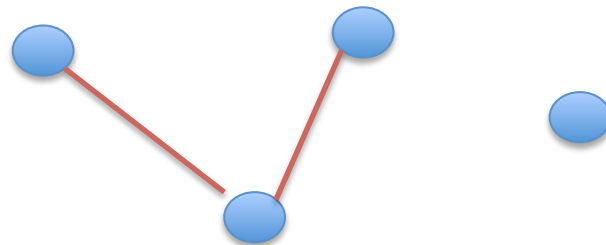
Kinds of Models

- Mention Pair models
 - Treat coreference chains as a collection of pairwise links
 - Make independent pairwise decisions and reconcile them in some way (e.g. clustering or greedy partitioning)
- Mention ranking models
 - Explicitly rank all candidate antecedents for a mention
- Entity-Mention models
 - A cleaner, but less studied, approach
 - Posit single underlying entities
 - Each mention links to a discourse entity [Pasula et al. 03], [Luo et al. 04]



Mention Pair Models

- Most common machine learning approach
- Build classifiers over pairs of NPs
 - For each NP, pick a preceding NP or NEW
 - Or, for each NP, choose link or no-link
- Clean up non-transitivity with clustering or graph partitioning algorithms
 - E.g.: [Soon et al. 01], [Ng and Cardie 02]
 - Some work has done the classification and clustering jointly [McCallum and Wellner 03]
- Failures are mostly because of insufficient knowledge or features for hard common noun cases



Pairwise Features

1. **strict gender** [true or false]. True if there is a strict match in gender (e.g. male pronoun Pro_i with male antecedent NP_j).
2. **compatible gender** [true or false]. True if Pro_i and NP_j are merely compatible (e.g. male pronoun Pro_i with antecedent NP_j of unknown gender).
3. **strict number** [true or false] True if there is a strict match in number (e.g. singular pronoun with singular antecedent)
4. **compatible number** [true or false]. True if Pro_i and NP_j are merely compatible (e.g. singular pronoun Pro_i with antecedent NP_j of unknown number).
5. **sentence distance** [0, 1, 2, 3,...]. The number of sentences between pronoun and potential antecedent.
6. **Hobbs distance** [0, 1, 2, 3,...]. The number of noun groups that the Hobbs algorithm has to skip, starting backwards from the pronoun Pro_i , before the potential antecedent NP_j is found.
7. **grammatical role** [subject, object, PP]. Whether the potential antecedent is a syntactic subject, direct object, or is embedded in a PP.
8. **linguistic form** [proper, definite, indefinite, pronoun]. Whether the potential antecedent NP_j is a proper name, definite description, indefinite NP, or a pronoun.

Pairwise Features

Category	Features	Remark
Lexical	exact_strm left_subsm right_subsm acronym edit_dist spell ncd	1 if two mentions have the same spelling; 0 otherwise 1 if one mention is a left substring of the other; 0 otherwise 1 if one mention is a right substring of the other; 0 otherwise 1 if one mention is an acronym of the other; 0 otherwise quantized editing distance between two mention strings pair of actual mention strings number of different capitalized words in two mentions
Distance	token_dist sent_dist gap_dist	how many tokens two mentions are apart (quantized) how many sentences two mentions are apart (quantized) how many mentions in between the two mentions in question (quantized)
Syntax	POS_pair apposition	POS-pair of two mention heads 1 if two mentions are appositive; 0 otherwise
Count	count	pair of (quantized) numbers, each counting how many times a mention string is seen
Pronoun	gender number possessive reflexive	pair of attributes of {female, male, neutral, unknown} pair of attributes of {singular, plural, unknown} 1 if a pronoun is possessive; 0 otherwise 1 if a pronoun is reflexive; 0 otherwise

[Luo et al. 04]

Mention-Pair (MP) Model

- Soon et al. 2001 ; Ng and Cardie 2002
- Classifies whether **two mentions** are coreferent or not.
- Weaknesses
 - Insufficient information to make an informed coreference decision.

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 - Each candidate antecedent is considered independently of the others.

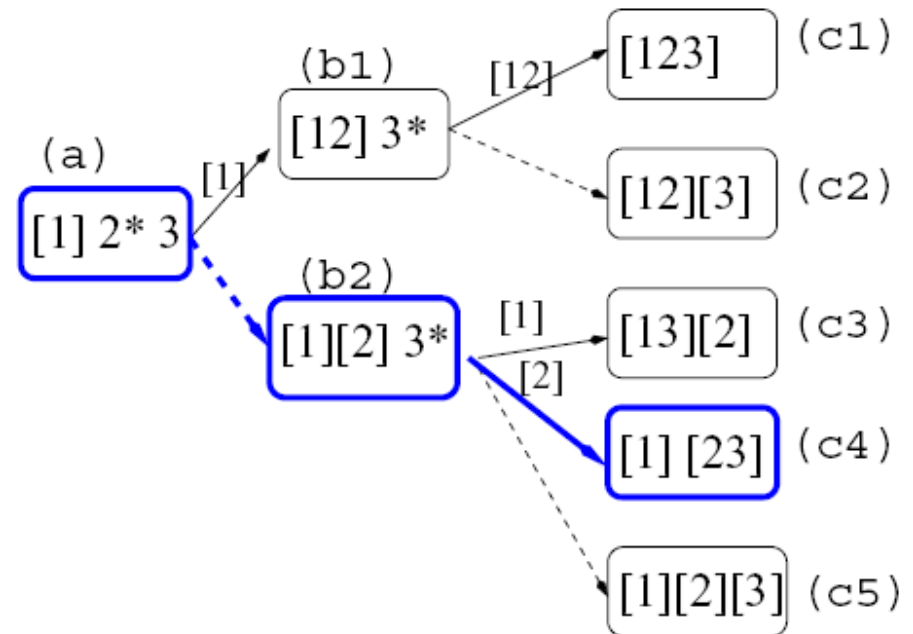
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Barack ObamaHillary Rodham Clintonhis
secretary of statethe President.....Heher

An Entity Mention Model

- Example: [Luo et al. 04]
- Bell Tree (link vs. start decision list)
- Entity centroids, or not?
 - Not for [Luo et al. 04], see [Pasula et al. 03]
 - Some features work on nearest mention (e.g. recency and distance)
 - Others work on “canonical” mention (e.g. spelling match)
 - Lots of pruning, model highly approximate
 - (Actually ends up being like a greedy-link system in the end)



Entity-Mention (EM) Model

- Pasula et al. 2003 ; Luo et al. 2004 ; Yang et al. 2004
- Classifies whether **a mention** and **a preceding, possibly partially formed cluster** are coreferent or not.
- Strength
 - Improved expressiveness.
 - Allows the computation of cluster level features
- Weakness
 - Each candidate cluster is considered independently of the others.

Barack Obama Hillary Rodham Clinton his
..... secretary of state He her

Mention-Ranking (MR) Model

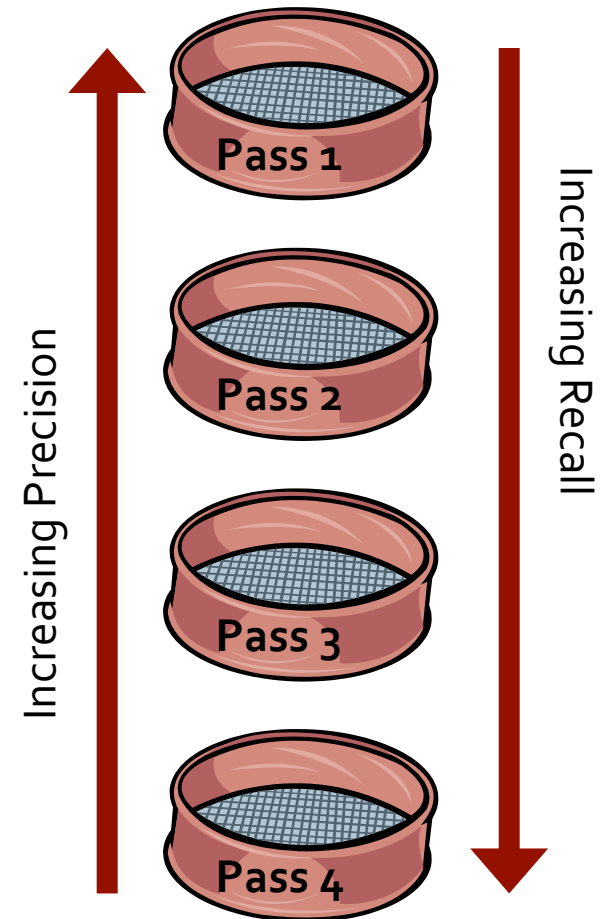
- Denis & Baldridge 2007, 2008
- Imposes a **ranking** on a set of candidate antecedents
- Strength
 - Considers all the candidate antecedents simultaneously
- Weakness
 - Insufficient information to make an informed coreference decision.

Barack ObamaHillary Rodham Clintonhis
..... secretary of stateHeher



Lee et al. (2010): Stanford deterministic coreference

- Cautious and incremental approach
- Multiple passes over text
- Precision of each pass is lesser than preceding ones
- Recall keeps increasing with each pass
- Decisions once made cannot be modified by later passes
- Rule-based (“unsupervised”)



Approach: start with high precision clumpings

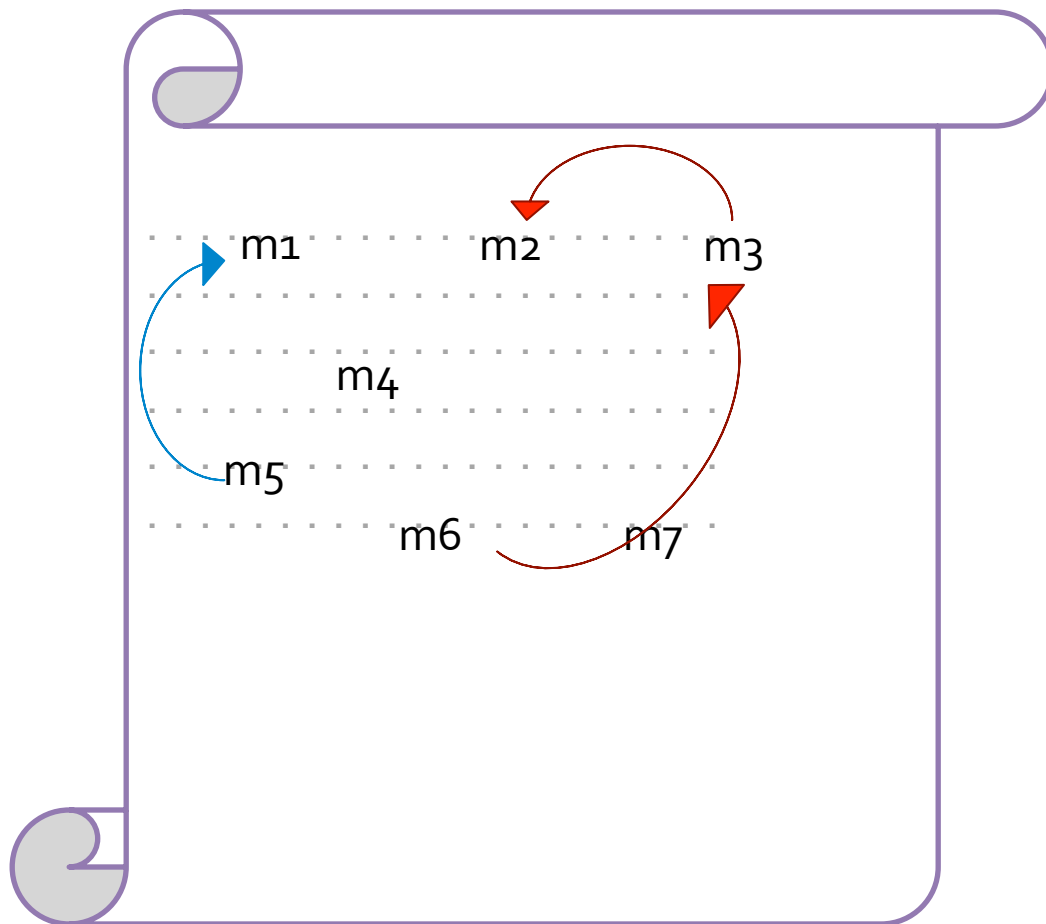
E.g.

Pepsi hopes to take Quaker oats to a whole new level.... Pepsi says it expects to double Quaker's snack food growth rate. ... the deal gives Pepsi access to Quaker oats Gatorade sport drink as well as

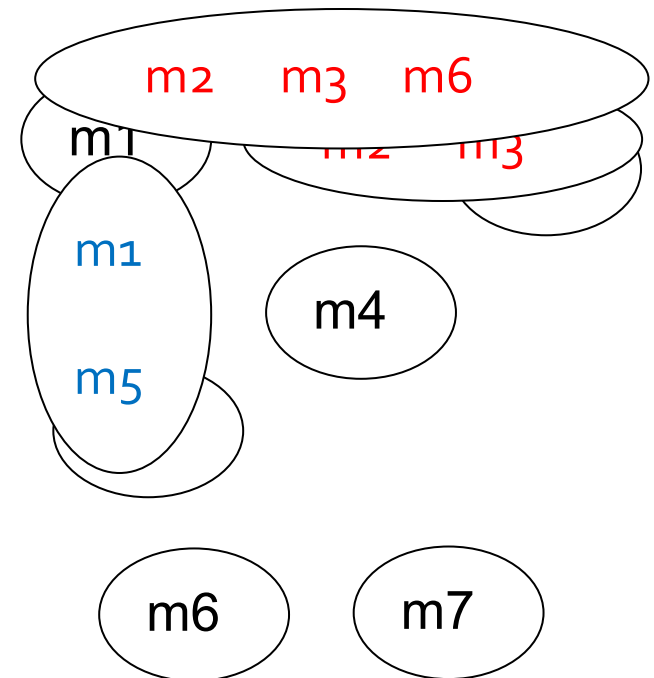


Exact String Match: A high precision feature

Entity-mention model: Clusters instead of mentions

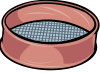




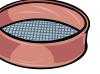



Clusters:



Detailed Architecture

The system consists of seven passes (or sieves):

-  Exact Match
-  Precise Constructs (appositives, predicate nominatives, ...)
-  Strict Head Matching
-  Strict Head Matching – Variant 1
-  Strict Head Matching – Variant 2
-  Relaxed Head Matching
-  Pronouns

Passes 3 – 5: Examples

- **Pass 3**
 - Yes: *"the Florida Supreme Court", "the Florida court"*
 - No: *"researchers", "two Chinese researchers"*
- **Pass 4** (-Compatible Modifiers)
 - Yes: *"President Clinton", {American President, American President Bill Clinton, Clinton}*
- **Pass 5** (-Word Inclusion)
 - Yes: *"The Gridiron Club at the Greenbrier Hotel", {an organization of 60 Washington journalists, The Gridiron Club}*

Pass 6: Relaxed Head Matching

Relaxed Cluster Match

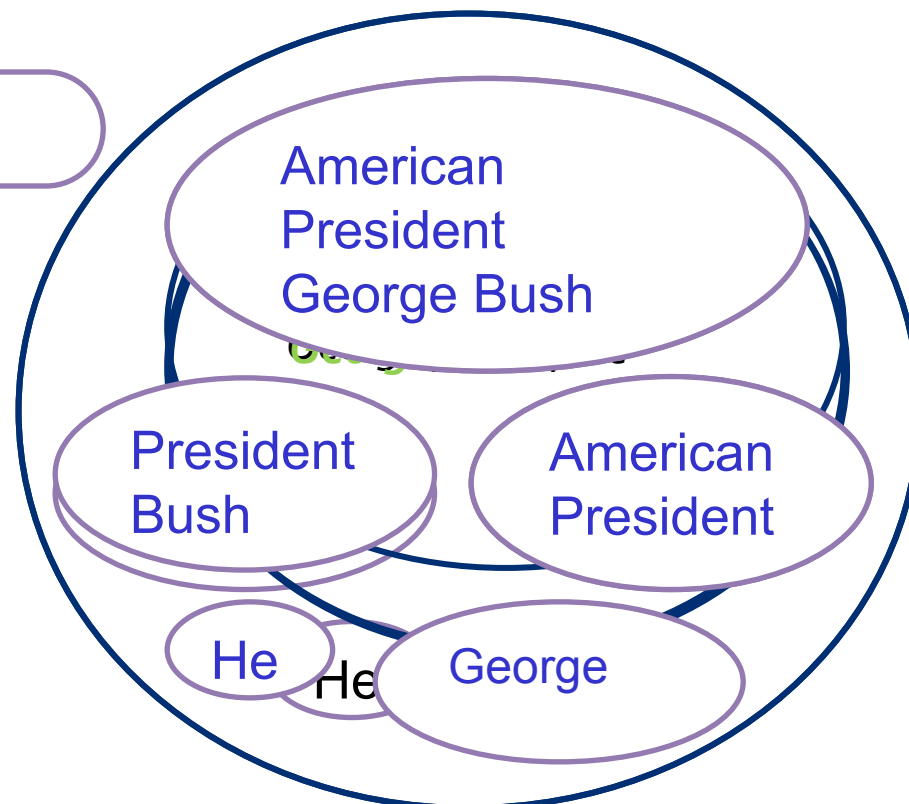
American President George
Bush

..... American President

He

..... President Bush

George

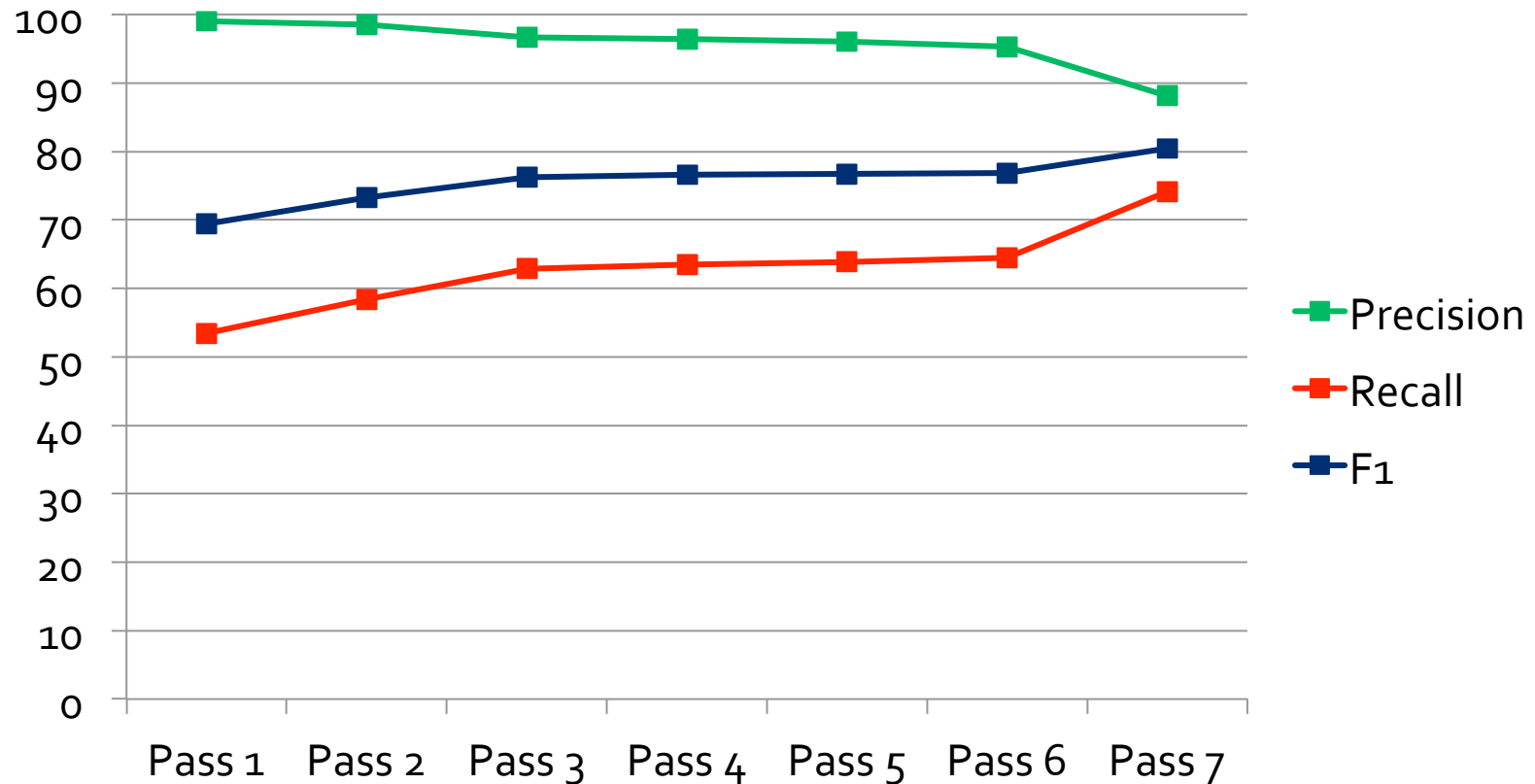


Both mentions have to be named
entities of the same type

Pass 7 – Pronoun Resolution

- Attributes agree
 - Number
 - Gender
 - Person
 - Animacy
- Assigned using POS tags, NER labels, static list of assignments for pronouns
- Improved further using Gender and Animacy dictionaries of Bergsma and Lin (2006), and Ji and Lin (2009)

Cumulative performance of passes♪



Graph showing the system's B³ Precision, Recall and F1 on ACE2004-DEV after each additional pass

CoNLL 2011 Shared task on coref

Official; Closed track; Predicted mentions

System	MD	MUC	B-CUBED	CEAF _m	CEAF _e	BLANC	Official
	F	F ¹	F ²	F	F ³	F	$\frac{F^1+F^2+F^3}{3}$
lee	70.70	59.57	68.31	56.37	45.48	73.02	57.79
sapena	43.20	59.55	67.09	53.51	41.32	71.10	55.99
chang	64.28	57.15	68.79	54.40	41.94	73.71	55.96
nugues	68.96	58.61	65.46	51.45	39.52	71.11	54.53
santos	65.45	56.65	65.66	49.54	37.91	69.46	53.41
song	67.26	59.95	63.23	46.29	35.96	61.47	53.05
stoyanov	67.78	58.43	61.44	46.08	35.28	60.28	51.92
sobha	64.23	50.48	64.00	49.48	41.23	63.28	51.90
kobdani	61.03	53.49	65.25	42.70	33.79	62.61	51.04
zhou	62.31	48.96	64.07	47.53	39.74	64.72	50.92
charton	64.30	52.45	62.10	46.22	36.54	64.20	50.36
yang	63.93	52.31	62.32	46.55	35.33	64.63	49.99
hao	64.30	54.47	61.01	45.07	32.67	65.35	49.38
xinxin	61.92	46.62	61.93	44.75	36.23	64.27	48.46
zhang	61.13	47.28	61.14	44.46	35.19	65.21	48.07
kummerfeld	62.72	42.70	60.29	45.35	38.32	59.91	47.10
zhekova	48.29	24.08	61.46	40.43	35.75	53.77	40.43
irwin	26.67	19.98	50.46	31.68	25.21	51.12	31.28

Remarks

- This simple deterministic approach gives state of the art performance!
- Easy insertion of new features or models
- The idea of “easy first” model has also had some popularity in other (ML-based) NLP systems
 - Easy first POS tagging and parsing
- It's a flexible architecture, not an argument that ML is wrong
 - Pronoun resolution pass would be easiest place to reinsert an ML model??