Coreference Resolution

CS224n
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(borrows slides from Roger Levy, Altaf Rahman, Vincent Ng, Heeyoung Lee)

Knowledge-based Pronominal Coreference

- [The city council] refused [the women] a permit because they feared violence.
- [The city council] refused [the women] a permit because they advocated violence.
  - Winograd (1972)

- See: Hector J. Levesque "On our best behaviour" IJCAI 2013. http://www.cs.toronto.edu/~hector/Papers/ijcai-13-paper.pdf

Hobbs' algorithm: commentary

"*… the naïve approach is quite good. Computationally speaking, it will be a long time before a semantically based algorithm is sophisticated enough to perform as well, and these results set a very high standard for any other approach to aim for.*

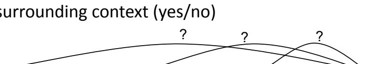
"Yet there is every reason to pursue a semantically based approach. The naïve algorithm does not work. Any one can think of examples where it fails. In these cases it not only fails; it gives no indication that it has failed and offers no help in finding the real antecedent." (Hobbs 1978, *Lingua*, p. 345)

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 clusters of coreferring expressions
  - E.g., generative models of clusters in (Haghighi & Klein 2007)

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 (yes/no)



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

- 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
  - Learn weights from labeled training data
  - Classify new instances

Evaluation

- B^3 (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 problem
    - In the computational NP-hard sense
  - Greedy matching is done in practice for evaluation

Evaluation

- B-CUBED algorithm for evaluation

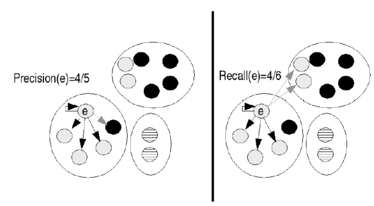


Figure from Amigo et al 2009

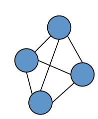
Evaluation metrics

- 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
- …

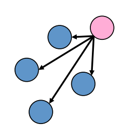
- All of them are sort of evaluating getting coreference links/clusters right and wrong, but the differences can be important
  - Look at it in PA3

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)



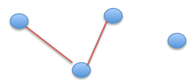
- Mention ranking models
  - Explicitly rank all candidate antecedents for a mention



- 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 a classifier 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



Features: Grammatical Constraints

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

Features: Soft 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 … so weight features

- 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
- Gendered pronouns can refer to inanimate things
  - [India] withdrew her ambassador from the Commonwealth
- Split antecedence
  - John waited for Sasha. And then they went out.

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

20

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

21

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22

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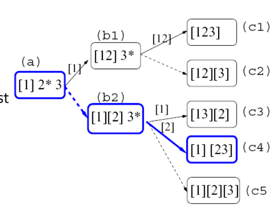
secretary of state ………..the President……..He ………….**her**

23

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

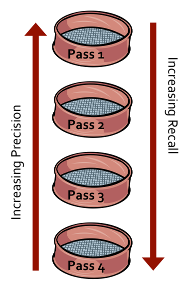
Mention-Ranking (MR) Model

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

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")



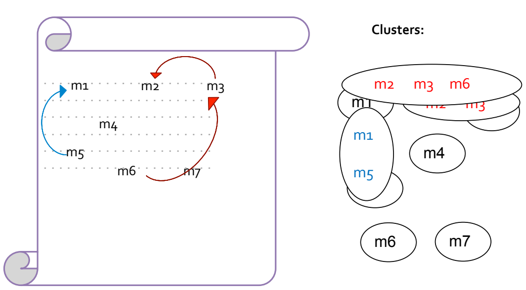
Approach: start with high precision clumpings

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



Detailed Architecture

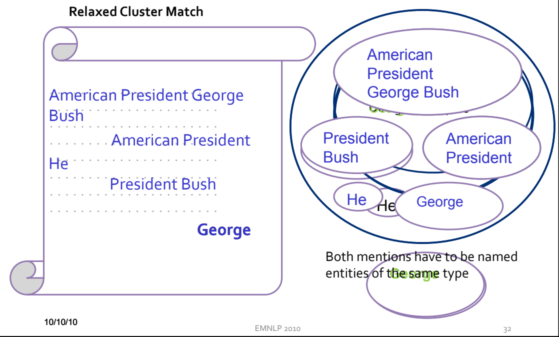
The system consists of seven passes (or sieves):

- 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*}

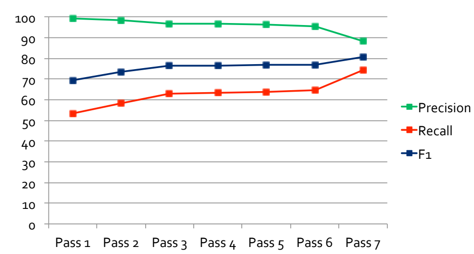
Pass 6: Relaxed Head Matching



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
  - Done subsequently: Recasens et al. 2013
- 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??