Cross-Document Coreference Resolution for Entities and Events

Thesis Proposal

Chris Tanner

Advisor: Eugene Charniak

Committee: Michael Littman, Stefanie Tellex, Ellie Pavlik

Problem Introduction

Related Work

Completed Work

Proposed Work

The New York Times

Tuesday, May 15, 2018 ☐ Today's Paper ☐ Video ☐ 74°F Nasdaq -0.81% ↓

North Korea Postpones Talks With South, Hinting Kim-Trump Summit Is in Peril

[...]

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Mr. Trump who threatened North Korea less than a year ago with "fire and fury" if Mr. Kim attacked the United States with nuclear weapons, has said he hopes the planned June 12 meeting in Singapore will lead to improved relations with North Korea after decades of hostility.

Easy for humans!

The New York Times

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State-of-the-art Computer System?

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State-of-the-art Computer System?



Mention Mention

if Mr. Kim attacked the United States with nuclear weapons, has said

hopes

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Mr. Trump, who threatened North Korea less than a year ago with "fire and fury" if Mr. Kim attacked the United States with nuclear weapons, has said he hopes the planned June 12 meeting in Singapore will lead to improved relations with North Korea after

decade

Hard for computers!



Mention Mention

if Mr. Kim attacked the United States with nuclear weapons, has said

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Mr. Trump who threatened North Korea less than a year ago with "fire and fury" if Mr. Kim attacked the United States with nuclear weapons, has said he hopes the planned June 12 meeting in Singapore will lead to improved relations with North Korea after decades of hostility.

Coreference Resolution

definition: grouping together all words which refer to the same underlying thing

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benefits:

- Question Answering (Narayanan and Harabagui, 2004)
- Information Extraction (Humphreys, et. al., 1997)
- Document Summarization (Daniel, et. al., 2003)

Good models should be able to group words from across multiple documents

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North Korea threatens to cancel summit with Trump over U.S.-South Korean military drills

[...]

North Korea suggested that the drills were putting the proposed summit between Trump and Kim, scheduled for June 12, in jeopardy.

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Trump and Kim are due to meet in Singapore, which would be the first time a North Korean leader had met with a sitting U.S. president.

?

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Mr. Trump (who) threatened North Korea less than a year ago with "fire and fury" if Mr. Kim attacked the United States with nuclear weapons, has said he hopes the planned June 12 meeting in Singapore will lead to improved relations with North Korea after decades of hostility.



Democracy Dies in Darkness

May 15, 2018

North Korea suggested that the drills were putting the proposed summit between Trump and Kim, scheduled for June 12, in jeopardy.

mention = word(s) which refer to an underlying entity or event









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entity = a person, location, organization, or time





mention = word(s) which refer to an underlying entity or event









entity = a person, location, organization, or time





event = a specific action





mention = word(s) which refer to an underlying entity or event











attacked

entity = a person, location, organization, or time





event = a specific action





mention



I research **Event Coreference** because it helps complete the picture.

Different axis of info from Entity Coreference

entity = a

Event Coref is hard:

Wide-reading:

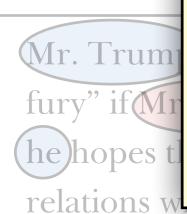
Paraphrase:

The attac

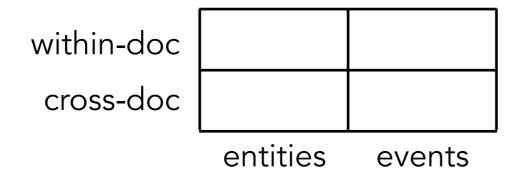
The attack took place yesterday. She gave him the book.

The bombing killed four people.

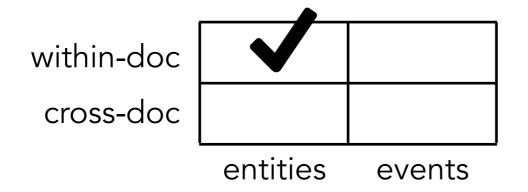
He was given the book by her.



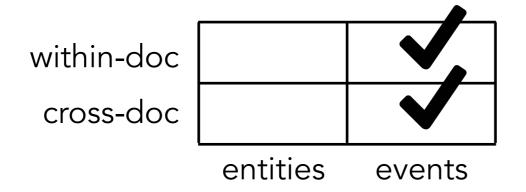
Two events co-refer if they share the same spatiotemporal properties and participants (Quine, 1985)



Most systems do:

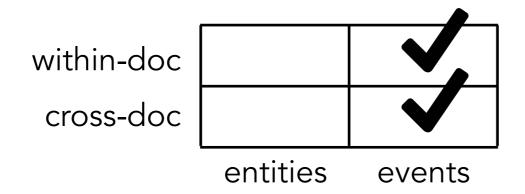


Few systems do:

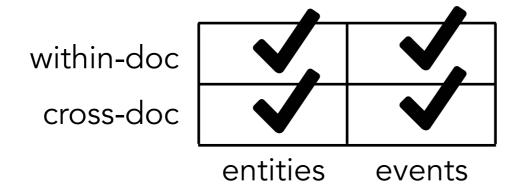


Few systems do:

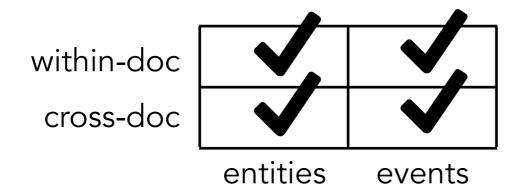
(My system currently does this)



Nobody* does:

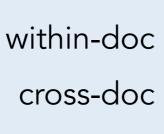


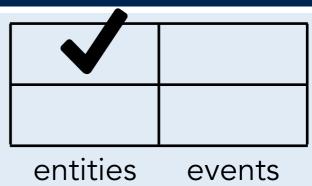
Nobody* does: I propose doing:



Definitions







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Some systems do:

(My system does)

within-doc cross-doc



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Thesis Statement

This research will test the hypothesis that a cross-document coreference resolution system which *jointly* models entities and events can improve state-of-the-art results from having modelled them individually.

Entity Coreference

- Long history (Hobbs, 1978)
- Pronouns are hard
- Corpus: CoNLL-2012:
- within-doc annotations only
 - train set: 2,802 docs
 - dev set: 343 docs
 - test set: 345 docs

Entity Coreference

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Event Coreference

- Shorter history (MUC/ACE ,1997)
- Events not as unique as Entities
 - Sony announced today
 - Friday, Obama announced
- Varying lexical representations:
 - The casting of Smith
 - Smith stepped into the role
 - Smith was handed the keys to play

We

- performed Event coreference
- used Deep Learning

We

- performed Event coreference
- used Deep Learning

Event Coreference Research

	Model	Corpus
Yang, et. al. (2015)	HDDCRP	ECB+
Choubey and Huang (2017)	FFNN	ECB+
our work	CCNN	ECB+

Entity Coreference Research

	Model	Corpus
Wiseman, et. al. (2015)	FFNN	CoNLL-2012
Wiseman, et. al. (2016)	RNN	CoNLL-2012
Clark and Manning (2016)	FFNN	CoNLL-2012
Clark and Manning (2016)	RL	CoNLL-2012
Lee, et. al. (2017)	LSTM + FFNN	CoNLL-2012

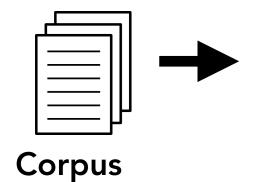
Takeaway #1: all Event research uses ECB+ corpus

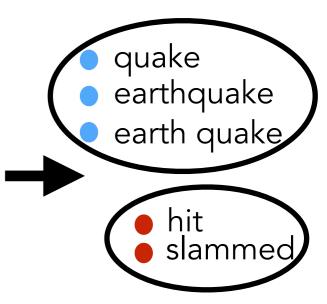
Yang, et. al. (2015)	HDDCRP	ECB+	Wiseman, et. al. (2015)	FFNN	CoNLL-2012
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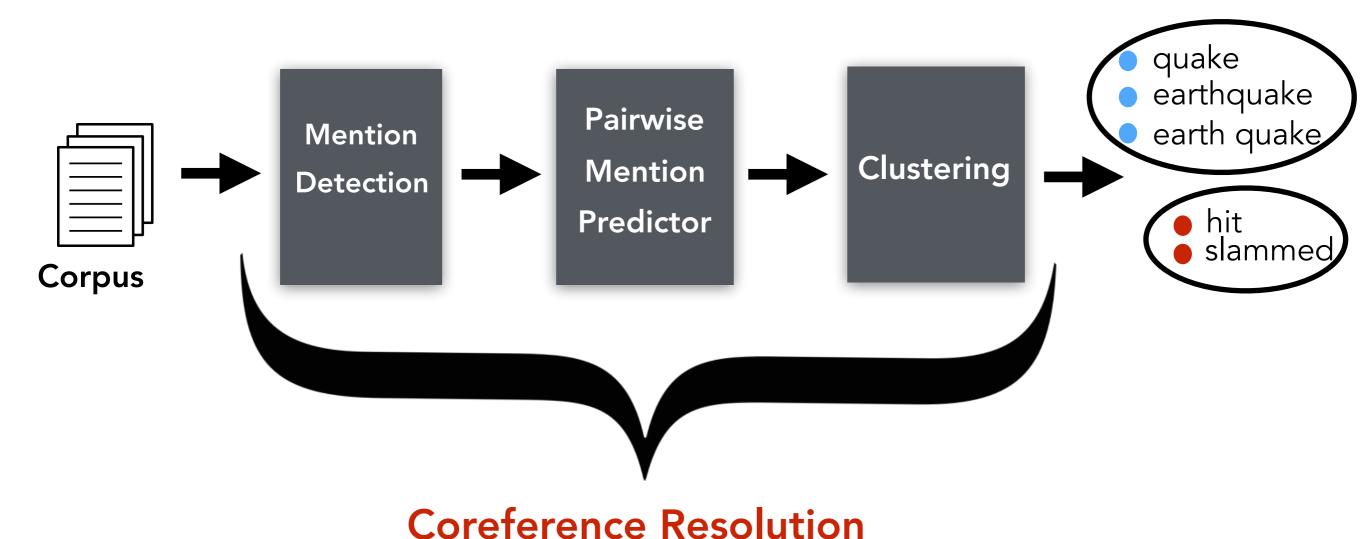
Takeaway #2: Only ~4 successful Deep Learning papers

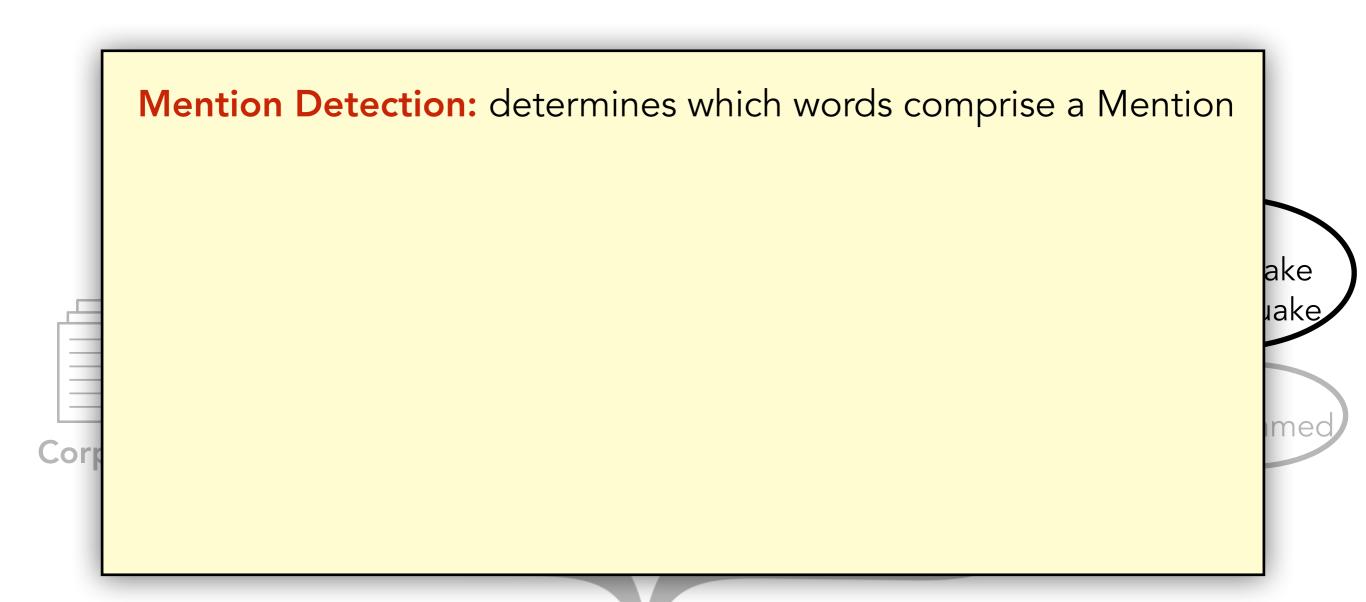
Yang, et. al.	HDDCRP	ECB+	Wiseman, et. al. (2015)	FFNN	CoNLL-2012
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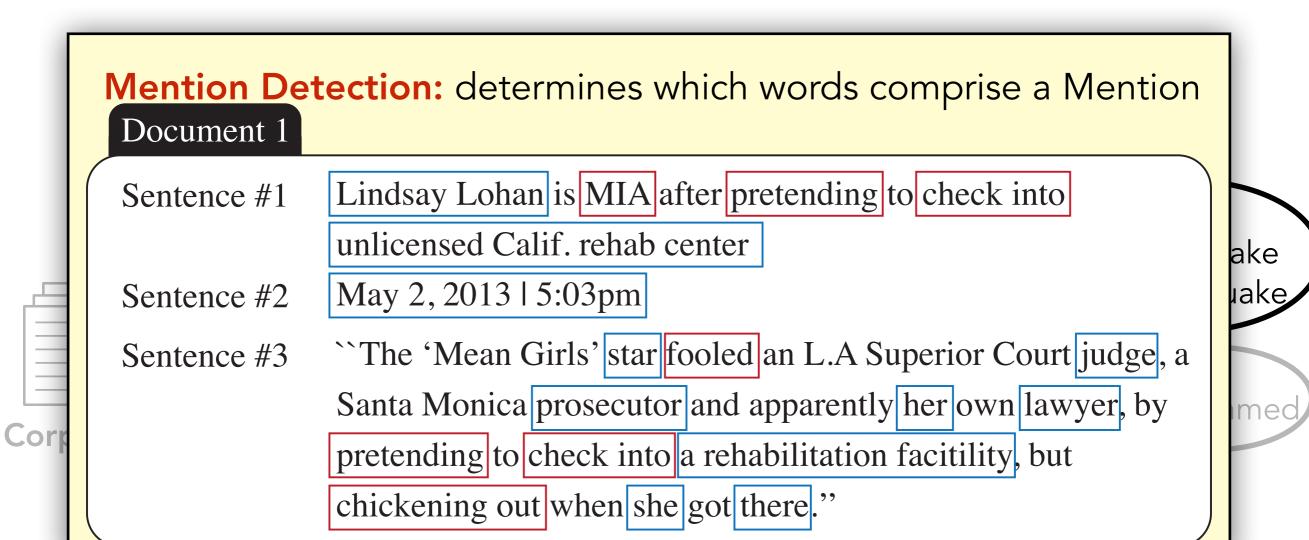




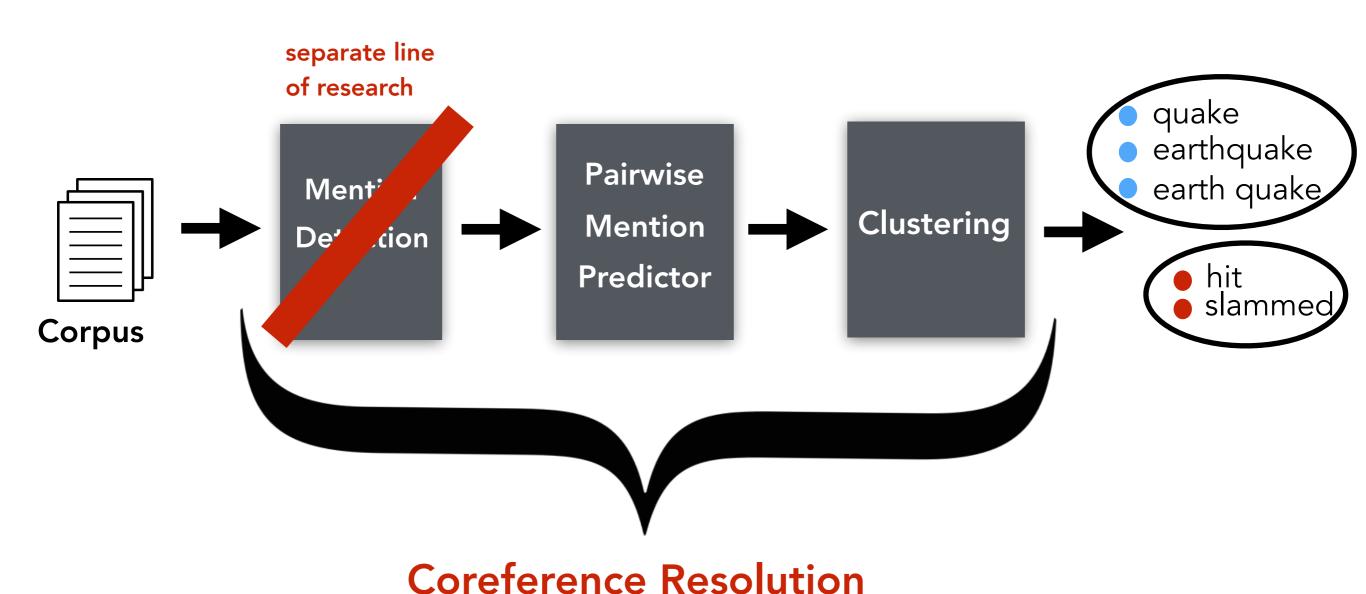


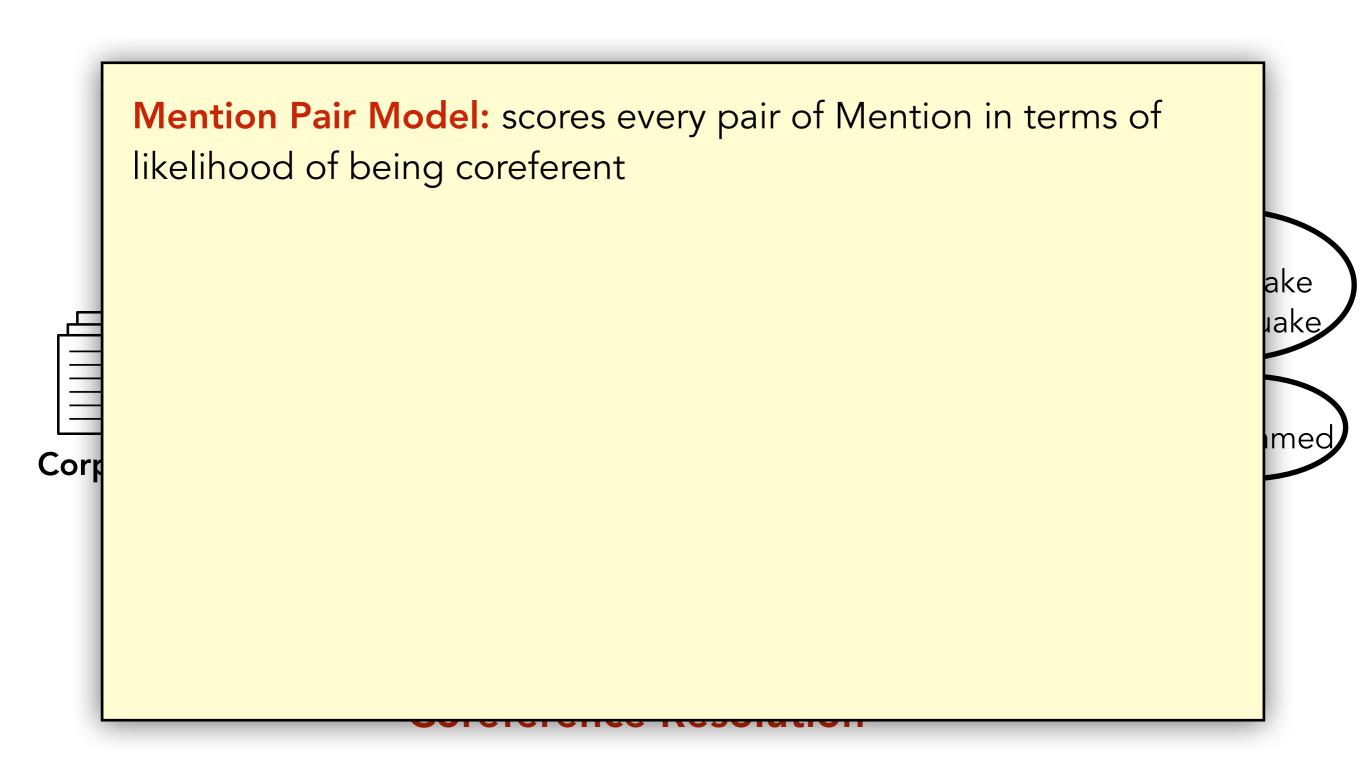


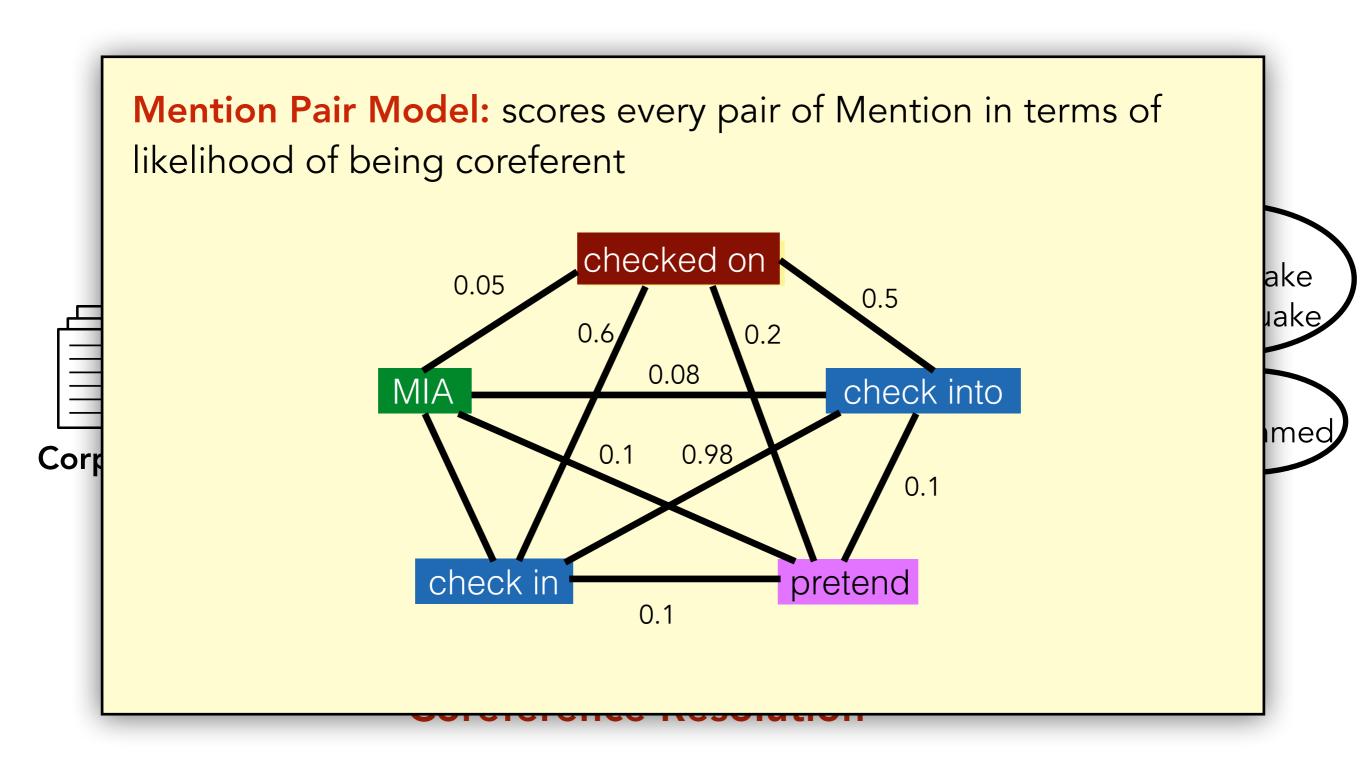
Coreference Resolution

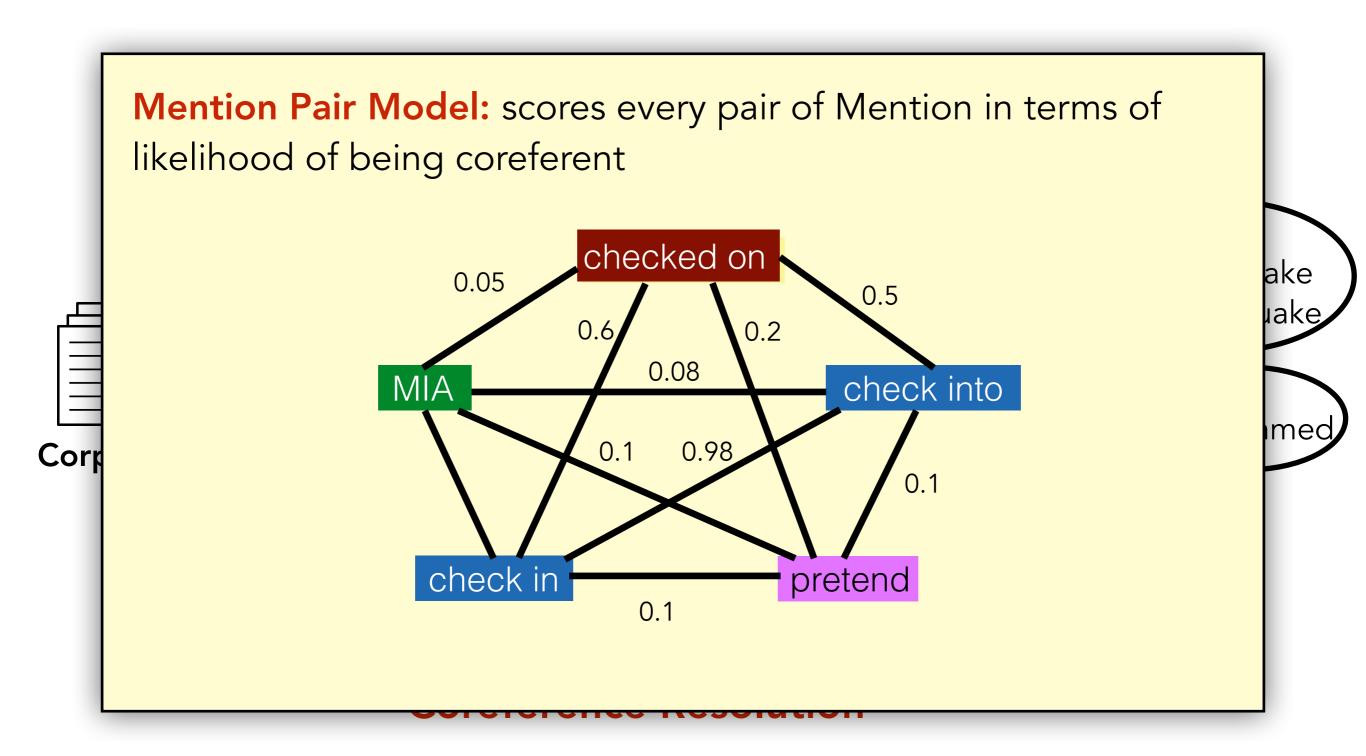


Coreference Resolution









Coreference Resolution Paradigms:

- Mention-Ranking Models
- Mention-Pair Models
- Entity-Based

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For each mention m_i , rank each mention m_j , where $m_j \in \{m_1, m_2, ..., m_{i-1}, \epsilon\}$

Coreference Resolution Paradigms:

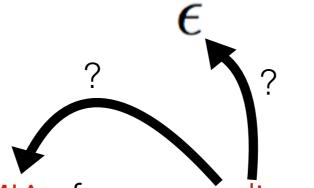
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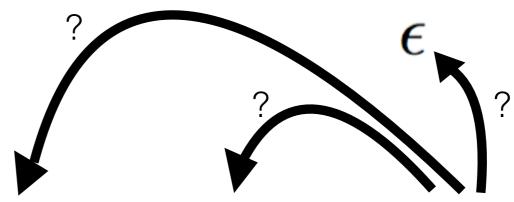


Lindsay Lohan is MIA after pretending to check into ...

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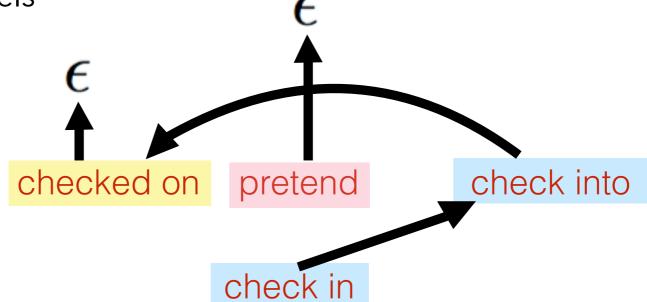
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 Entity-Based
 ← MIA
 checked on pretend
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Weakness #1: clustering is mention-to-mention based

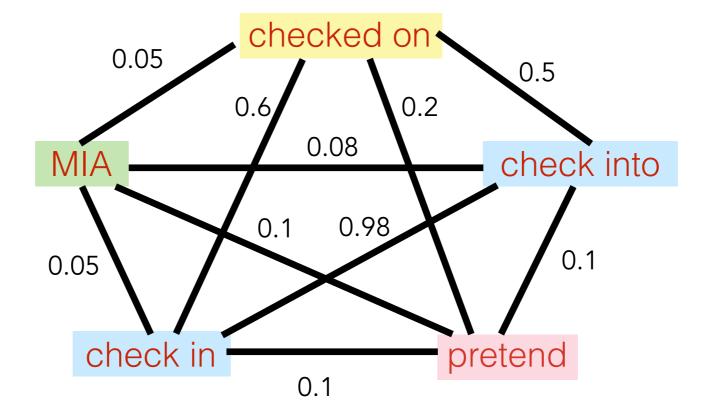
Coreference Resolution Paradigms:

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Objective: score every pair of mentions

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Coreference Resolution Paradigms:

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- Similar to mention-ranking
- undirected
- conducive for cross-document

Objective: score every pair of mentions

Coreference Resolution Paradigms:

- Mention-Ranking Models
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- Entity-Based

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Coreference Resolution Paradigms:

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features (coarse or sparse):

- all, most, none (e.g., 'all-female=true')
- common-noun + pronoun + pronoun

Coreference Resolution Paradigms:

- Mention-Ranking Models
- Mention-Pair Models
- Entity-Based

- Difficult to represent
- How many entities to represent?
- Doesn't make sense for events

Weakness #2: Many features. Which are most useful?

ENTITY COREF

Wiseman, et. al. (2015)

				Sentences between Ment., Ante.	$\{010\}$
	Mention Features (ϕ_{z}) Value Set		i-within-i Same Speaker	{T,F} {T,F}
	Teature	value Set		Document Type	{Conv.,Art.}
	Mention Head	\mathcal{V}		Ante., Ment. String Match	{T,F}
	Mention First Word	\mathcal{V}		Ante. contains Ment.	{T,F}
	Mention Last Word	\mathcal{V}		Ment. contains Ante.	{T,F}
	Word Preceding Mention	\mathcal{V}		Ante. contains Ment. Head	{T,F}
	Word Following Mention	\mathcal{V}		Mention contains Ante. Head	{T,F}
	# Words in Mention	$\{1,2,\ldots\}$		Ante., Ment. Head Match	{T,F}
	Mention Synt. Ancestry	see BCS (2013)		Ante., Ment. Synt. Ancestries	see above
	Mention Type	\mathcal{T}	+	BASIC+ features on Ment.	see above
+	Mention Governor	\mathcal{V}	+	BASIC+ features on Ante.	see above
+	Mention Sentence Index	$\{1,2,\ldots\}$	+	Ante., Ment. Numbers	see above
+	Mention Entity Type	NER tags	+	Ante., Ment. Genders	see above
+	Mention Number	{sing.,plur.,unk}	+	Ante., Ment. Persons	see above
+	Mention Animacy	{an.,inan.,unk}	+	Ante., Ment., Entity Types	see above
+	Mention Gender	{m,f,neut.,unk}	+	Ante., Ment. Heads	see above
+	Mention Person	{1,2,3,unk}	+	Ante., Ment. Types	see above

Pairwise Features (ϕ_{p})

Feature

BASIC features on Mention

BASIC features on Antecedent

Mentions between Ment., Ante.

Value Set

see above

see above

 $\{0...10\}$

ENTITY COREF

Wiseman, et. al. (2016)

Features We use the raw BASIC+ feature sets described by Wiseman et al. (2015), with the following modifications:

- We remove all features from φ_p that concatenate a feature of the antecedent with a feature of the current mention, such as bi-head features.
- We add true-cased head features, a current speaker indicator feature, and a 2-character genre (out of {bc,bn,mz,nw,pt,tc,wb}) indicator to φ_D and φ_a.
- We add features indicating if a mention has a substring overlap with the current speaker (φ_p and φ_a), and if an antecedent has a substring overlap with a speaker distinct from the current mention's speaker (φ_p).
- We add a single centered, rescaled document position feature to each mention when learning h_c. We calculate a mention x_n's rescaled document position as ^{2n-N-1}/_{N-1}.

ENTITY COREF

Clark and Manning (2016)

Embedding Features: Word embeddings of the head word, dependency parent, first word, last word, two preceding words, and two following words of the mention. Averaged word embeddings of the five preceding words, five following words, all words in the mention, all words in the mention's sentence, and all words in the mention's document.

Additional Mention Features: The type of the mention (pronoun, nominal, proper, or list), the mention's position (index of the mention divided by the number of mentions in the document), whether the mentions is contained in another mention, and the length of the mention in words.

Document Genre: The genre of the mention's document (broadcast news, newswire, web data, etc.). Distance Features: The distance between the mentions in sentences, the distance between the mentions in intervening mentions, and whether the mentions overlap.

Speaker Features: Whether the mentions have the same speaker and whether one mention is the other mention's speaker as determined by string matching rules from Raghunathan et al. (2010).

String Matching Features: Head match, exact string match, and partial string match.

The vectors for all of these features are concatenated to produce an I-dimensional vector h_0 , the input to the neural network. If a = NA, the features defined over mention pairs are not included. For this case, we train a separate network with an identical architecture to the pair network except for the input layer to produce anaphoricity scores.

EVENT COREF

Yang, et. al. (2015)

where ψ is a feature vector, containing a rich set of features based on event mentions i and j: (1) head word string match, (2) head POS pair, (3) cosine similarity between the head word embeddings (we use the pre-trained 300-dimensional word embeddings from word2vec¹), (4) similarity between the words in the event mentions (based on term frequency (TF) vectors), (5) the Jaccard coefficient between the WordNet synonyms of the head words, and (6) similarity between the context words (a window of three words before and after each event mention). If both event mentions involve participants, we consider the similarity between the words in the participant mentions based on the TF vectors, similarly for the time mentions and the location mentions. If the SRL role information is available, we also consider the similarity between words in each SRL role, i.e. Arg0, Arg1, Arg2.

EVENT COREF

Yang, et. al. (2015)

Weakness #3: Manuallydefining relational features

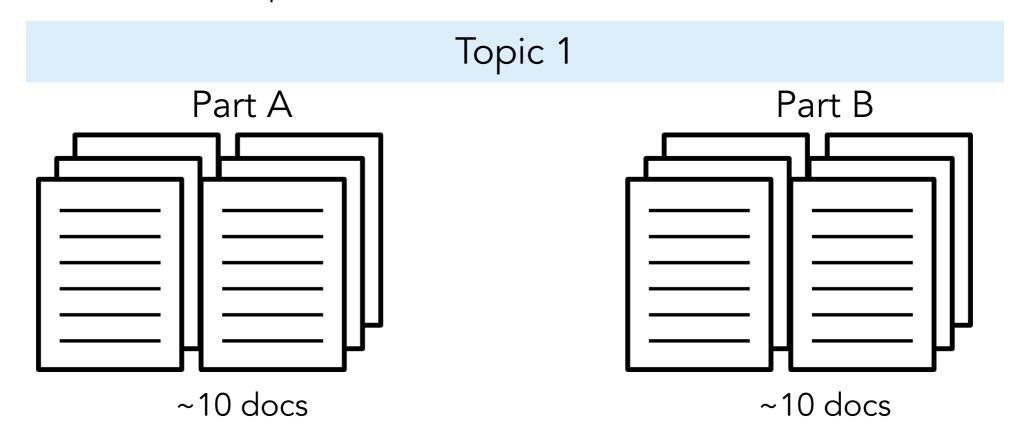
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Event Coreference Corpora:

- ECB (482 docs)
- EECB (added entities to ECB)
- ECB+ (added entities to ECB plus doubled size)

Event Coreference Corpora:

- ECB (482 docs)
- EECB (same but added entities)
- ECB+ (982 docs; ECB plus another half)
 - 43 distinct "topics"



ECB+ (just the events)

- # docs: 982
- 1,840 annotated sentences (from 15,812)
- 1,826 unique entities/events (referents)
 - 399 singletons (22%) and 1,427 non-singletons (78%)
- # mentions: 11,957
 - train: 2,848 entities and 2,117 events
 - dev: 480 entities and 327 events
 - test: 3,571 entities and 2,614 events

ECB+ (just the events)

4.6 Magnitude Quake Recorded in Sonoma County

Thursday, March 14, 2013

An earthquake with a preliminary magnitude of 4.6 was recorded in the North Bay this morning, according to the U.S. Geological Survey. The quake occurred at 2:09 a.m. about 14 miles north-northeast of Healdsburg and had a depth of 1.2 miles. It was followed by a 2.9 aftershock at 2:12 a.m. and a 2.2 at 2:15 a.m... there are no reports of injuries or major damage.

4.6 Magnitude Quake Rattles Sonoma County

Early Thursday

Posted: 03/14/2013 06:37:46 AM PDT

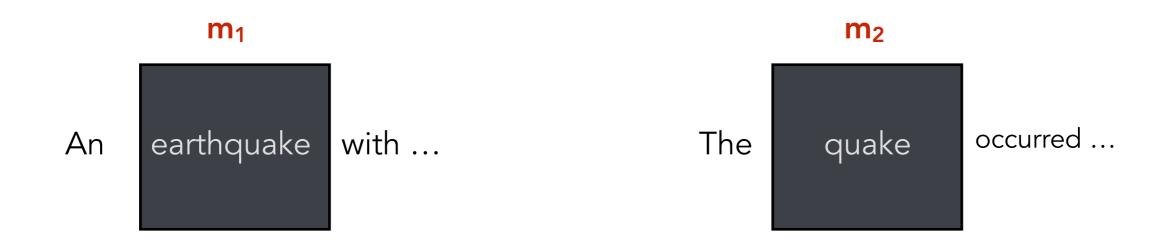
Updated: 03/14/2013 07:51:21 AM PDT

An earthquake measuring 4.6 rattled Sonoma and Lake counties early Thursday, according to the U.S. Geological Survey. The quake occurred at 2:09 a.m., about 14 miles northeast of Healdsburg, on the Maacama Fault with a depth of 12 miles. A Sonoma County Sheriff's dispatcher said around 7 a.m. that there had been no reports of damage or injuries.

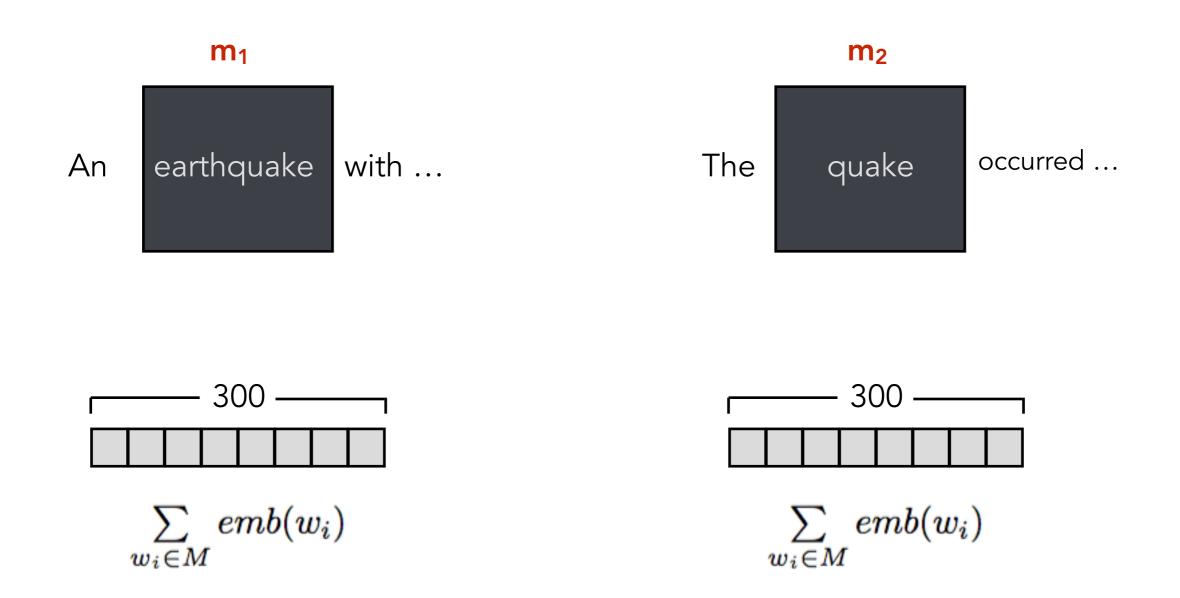
Features

- Word Embeddings (300 dimensions)
- Lemma Embeddings (300 dimensions)
- Character Embeddings (20 dimensions * 20 max length)
- POS Tag Embeddings (100 dimensions)
- Dependency Parents'/Children's Lemma Embeddings (300 dim)
- WordNet Similarity
- Bag-of-Words (summed Lemma Embeddings)

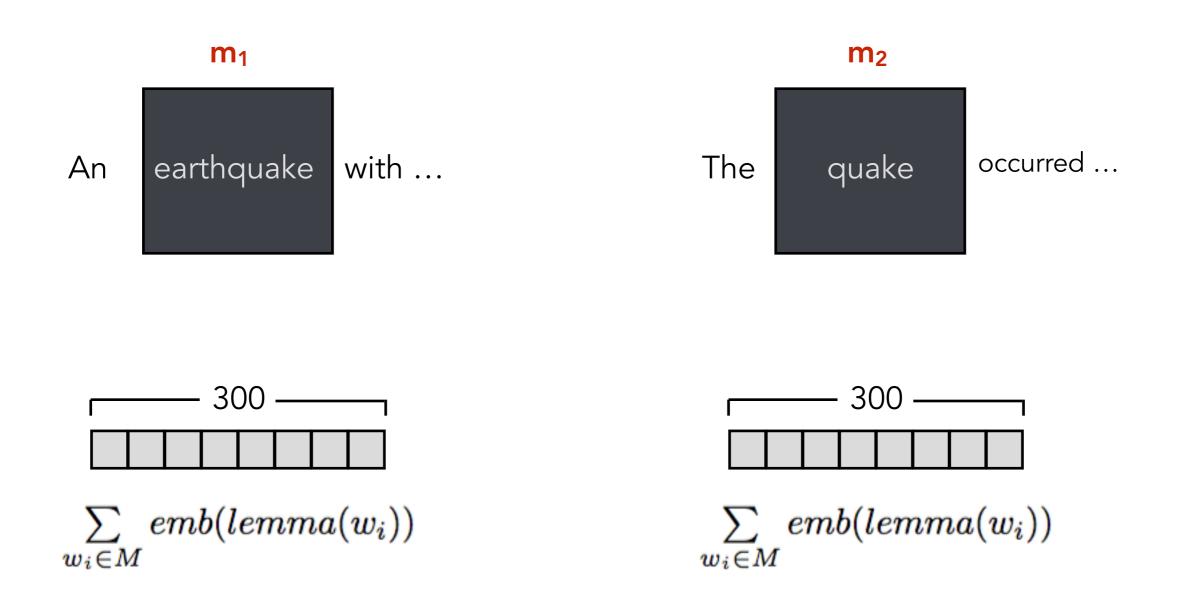
Features



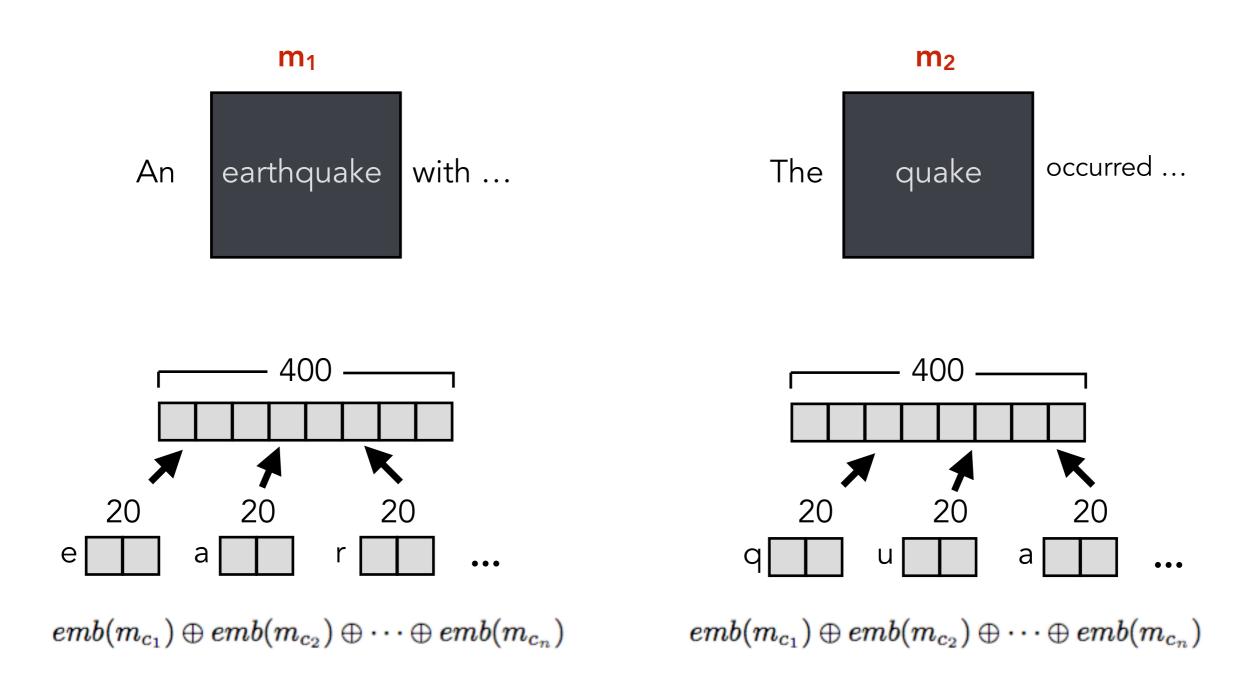
Feature: Word Embeddings



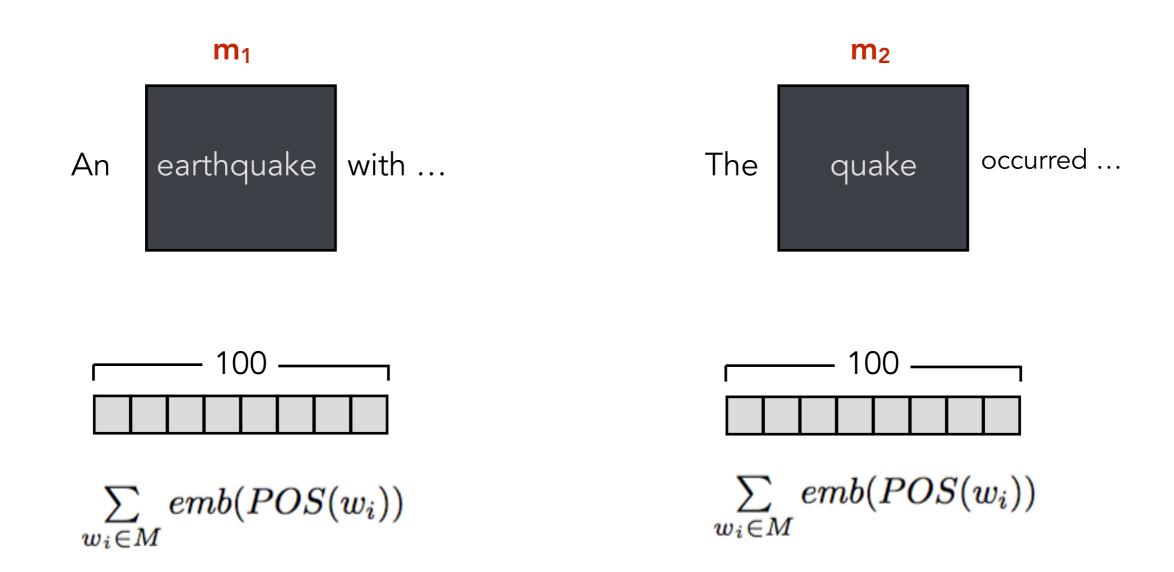
Feature: Lemma Embeddings



Feature: Character Embeddings

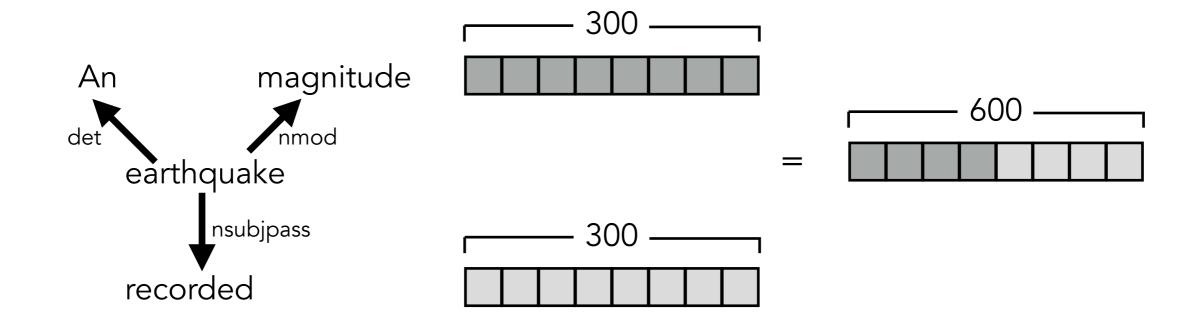


Feature: POS Tag Embeddings

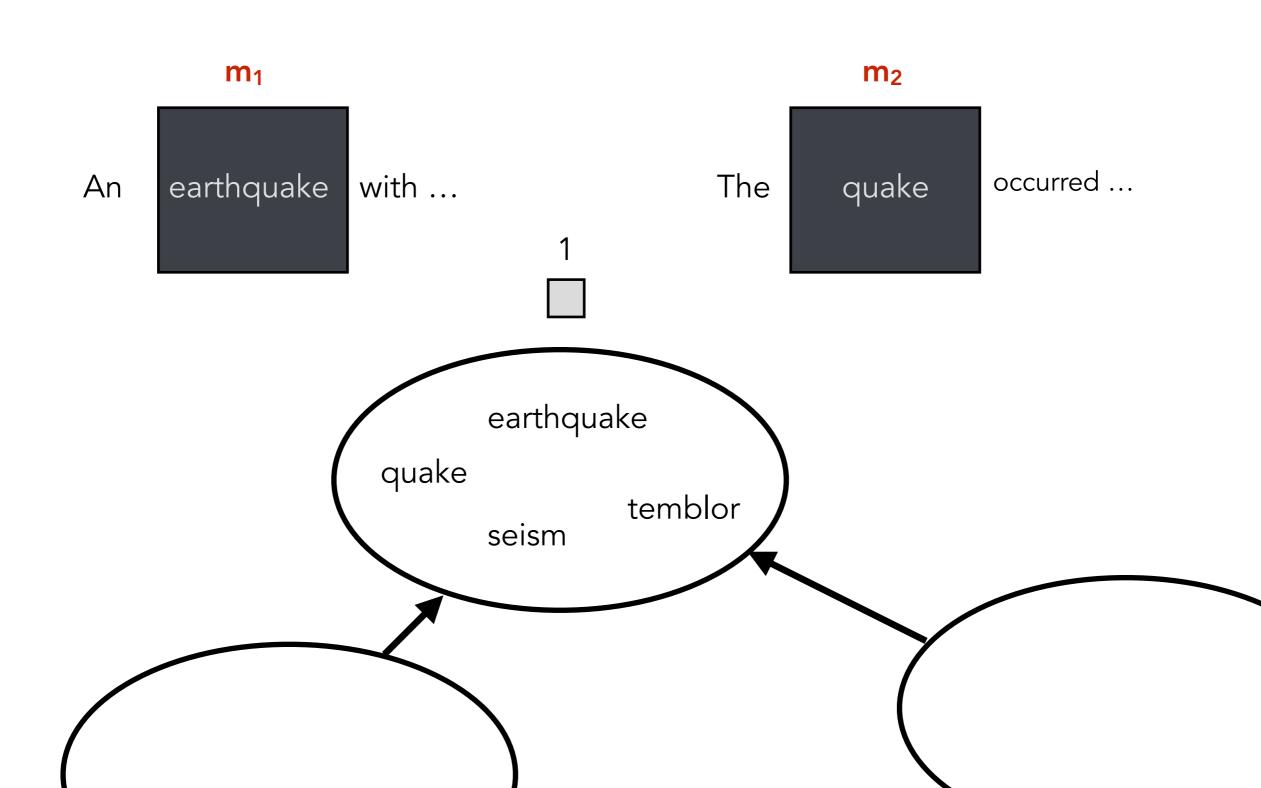


Feature: Dependency Parents'/Children's Lemma Embeddings

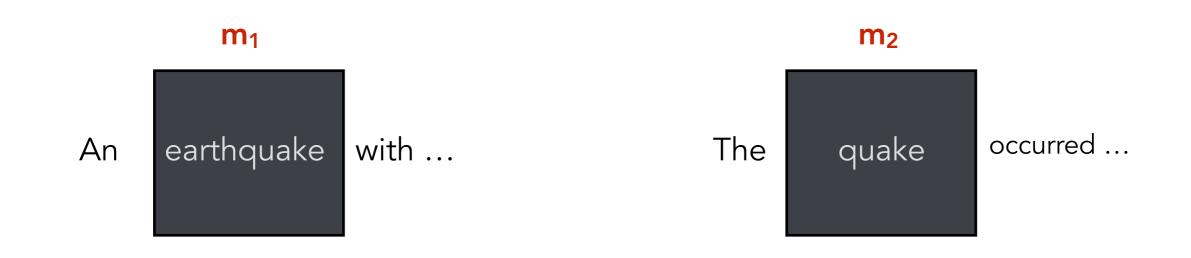


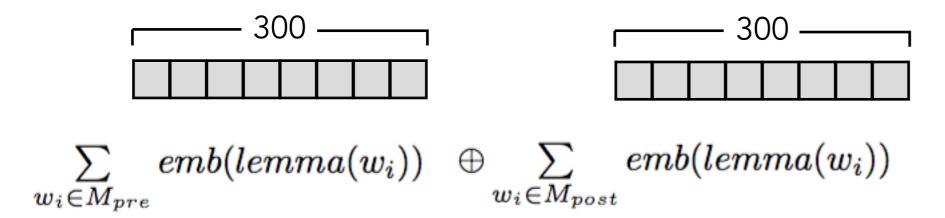


Feature: WordNet Similarity



Feature: Bag-of-Words Embeddings



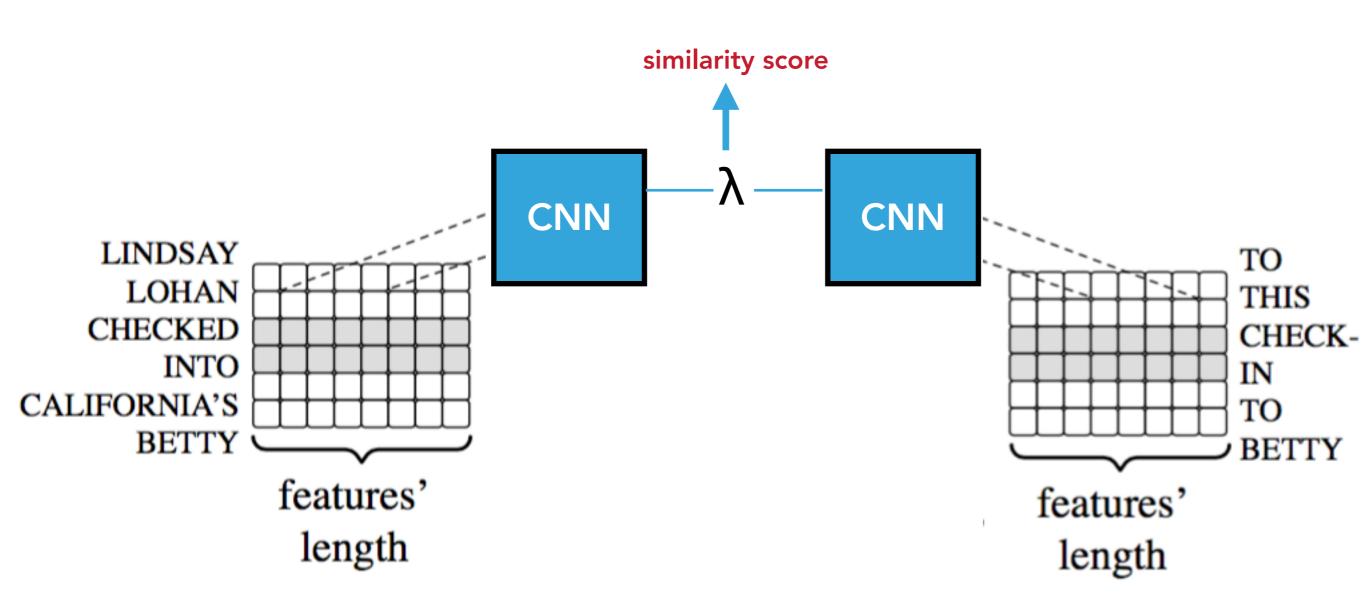


Model

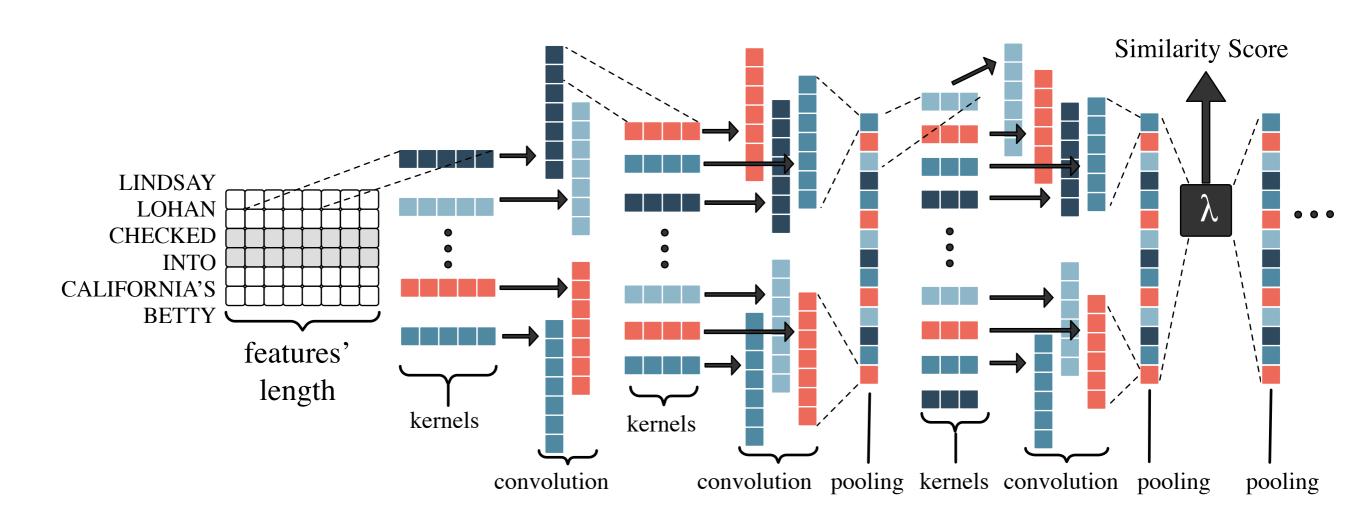
We want

- mention-pair model
- automatically learns relational information
- is symmetric/agnostic w.r.t mention order
- fewest features as possible

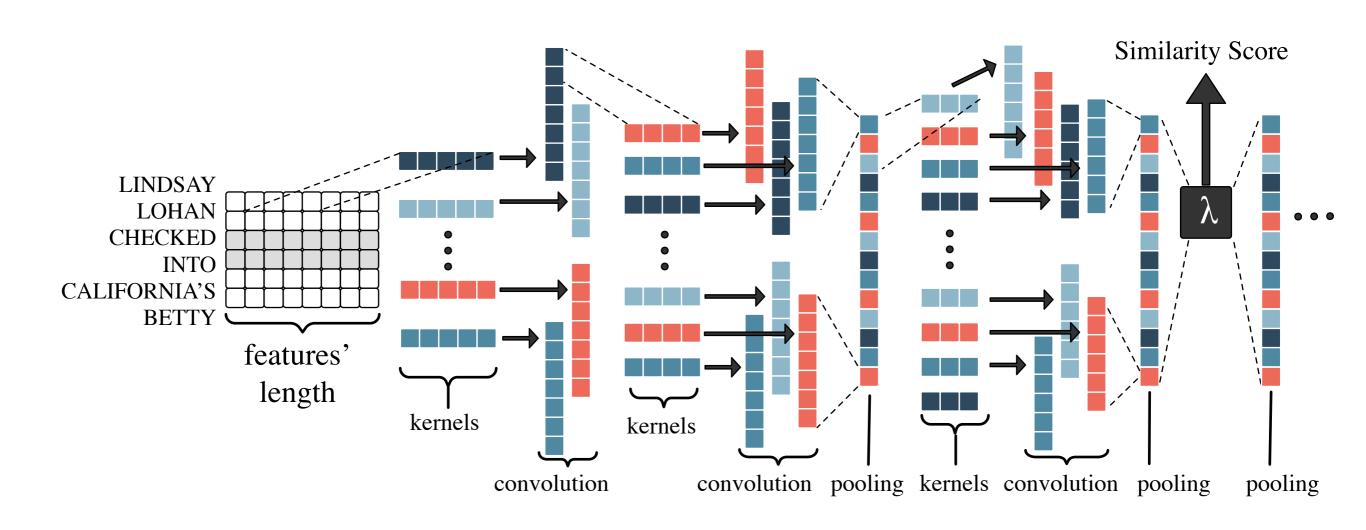
Model: Conjoined Convolutional Neural Network



Model: Conjoined Convolutional Neural Network



Model: Conjoined Convolutional Neural Network



Distance Function: L² norm

Loss Function: Contrastive Loss $(1-Y)\frac{1}{2}(D_W)^2+(Y)\frac{1}{2}\{max(0,m-D_W)\}^2$

Pairwise Evaluation (Within-doc)

m ₁₇ , m ₂	1.0	erupted	erupted			
m ₁₇ , m ₂	1.0	erupted erupted	erupted	accuracy: 92.4		
m ₅ , m ₉₂₃	0.97	announced	announce	precision: 64.0		
	0.95	erunt	erupted	recall: 67.9		
M78, M57	0.75	erupt	erupted	f1: 65.9		
•	1					
:		•	:			
m ₈₀₁ , m ₃₉	0.03	revealed	broke into			

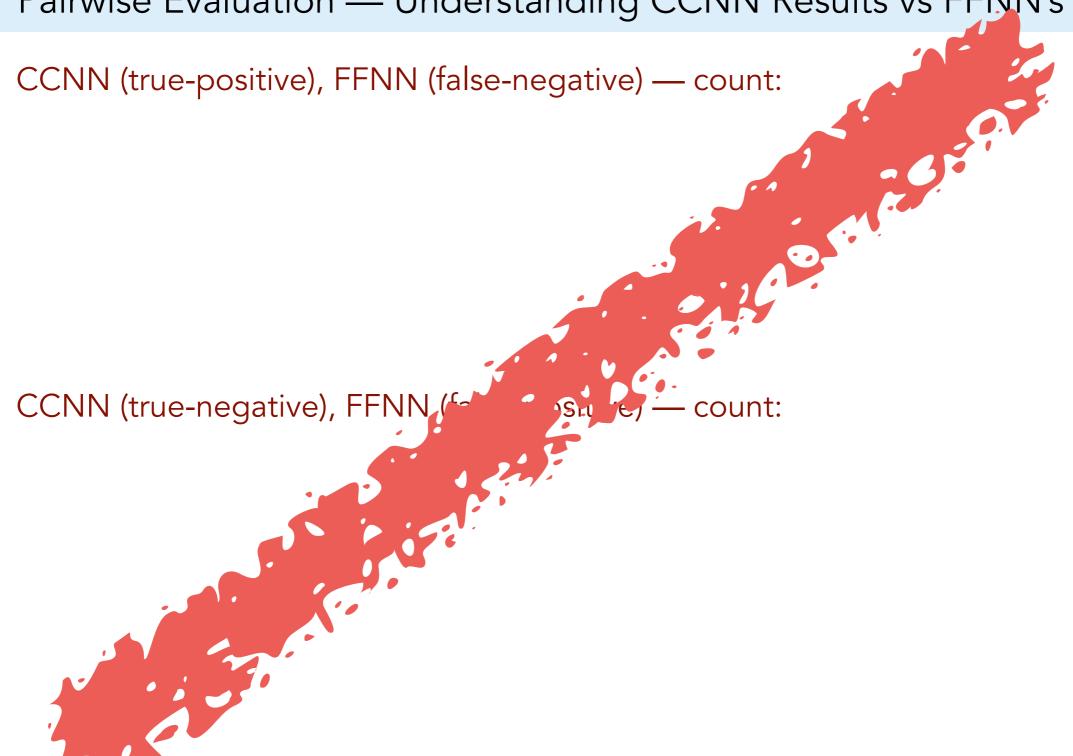
Cot Work acwise Evaluation

	 Within-Doc	Cross-Doc
CCNN	65.9	66.3
FFNN	62.1	64.8
LibSVM	52.1	53.2
SameLemma	_	_

LibSVM and FFNN received same features as CCNN, plus relational features (e.g., cosine sim., dot-product, WordNet)

Pairwise Evaluation — Understanding CCNN Results vs Gold Truth True-Positives: False-Positives: True-Negatives: False-Negat

Pairwise Evaluation — Understanding CCNN Results vs FFNN's

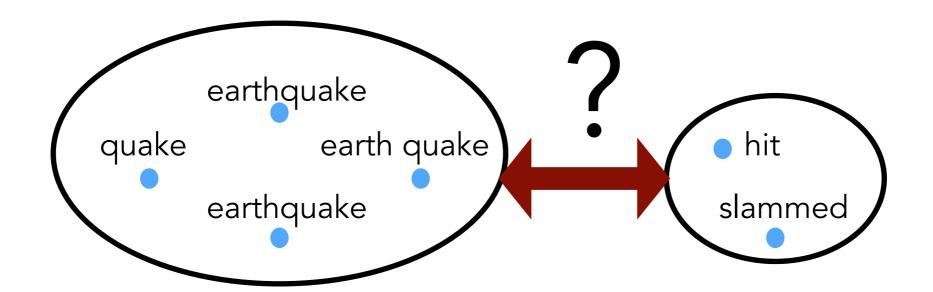


Clustering

We want

- not mention-to-mention based
- less susceptible to non-uniform predictions across topics
- no additional stopping parameter
- prevention against an all-subsuming cluster

Neural Clustering



Simple Features:

- min-pair distance: $\min_{m_i,m_j} d(m_i,m_j)$
- avg-pair distance: $\frac{\sum_{m_i,m_j} d(m_i,m_j)}{\|C_x\| \|C_y\|}$
- max-pair distance: $\max_{m_i, m_j} d(m_i, m_j)$
- size of candidate cluster: $\frac{\|C_x\| + \|C_y\|}{\sum_z \|C_z\|}$

Construct Training Data:

- randomly sample a gold cluster
- positive: 2 random-sized subsets
- negative: 1 subset, 1 set from a different cluster

Neural Clustering — Evaluation Metrics

- MUC (Vilain, et. al. 1995)
 - minimum # of link modifications required to make the predicted cluster equal gold cluster
- **B**³ (Bagga and Baldwin, 1998)

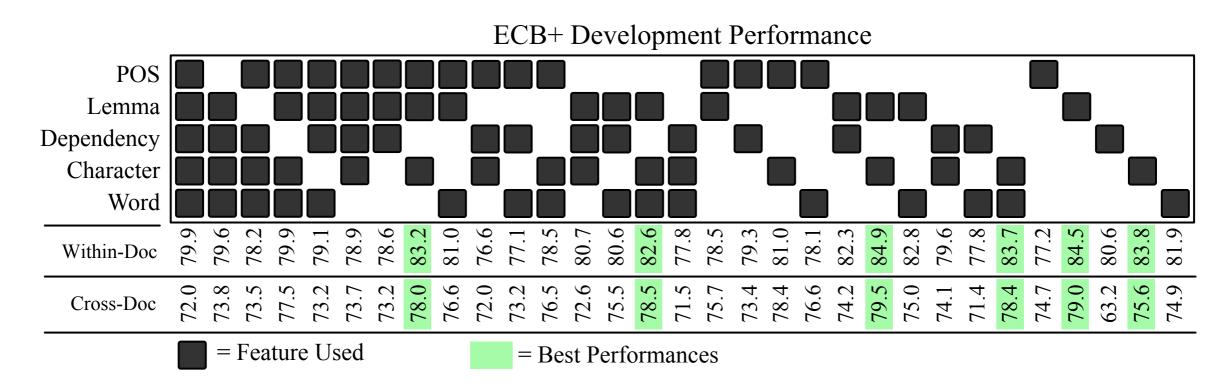
 accuracy of all individual mentions, w.r.t. mapping them to an event
- **CEAF** (Luo, 2005)

unlike B³, doesn't use any event more than once; uses best possible alignment b/w events (computationally expensive)

CoNLL F1

the average F1 score of {MUC F1, B³ F1, CEAF F1}

Neural Clustering



Lemma + Character Embeddings yield the best performance

Neural Clustering — Evaluation on Gold Truth Mentions

	Within-Document				Cross-Document				
_	MUC	\mathbf{B}^3	CEAF	CoNLL F1	MUC	\mathbf{B}^3	CEAF	CoNLL F1	
Test Set: ECB+ Gold Mentions									
SameLemma	58.3	83.0	75.9	72.4	84.2	68.2	48.0	66.8	
FFNN+AGG	59.9	85.6	78.4	74.6	77.7	69.9	50.1	65.9	
FFNN+NC	60.7	86.7	79.4	75.6	74.9	67.8	56.3	67.0	
CCNN+AGG	70.5	89.1	83.5	81.0	84.1	70.7	55.5	70.1	
CCNN+NC	70.9	88.9	83.6	81.2	86.4	71.7	59.1	72.4	

Neural Clustering — Evaluation against state-of-the-art

Gold Test Mentions:

... as Peter Capaldi stepped into Matt Smith's soon to be vacant ...

HDDCRP's Predicted Test Mentions:

... as Peter Capaldi stepped into Matt Smith's soon to be vacant ...

token precision = 1.0

token recall = 0.5

Neural Clustering — Evaluation against state-of-the-art

HDDCRP's Predicted Test Mentions:

measured against the gold test set:

3,571 entity mentions

2,614 event mentions

Neural Clustering — Evaluation against state-of-the-art

	Within-Document				Cross-Document				
	MUC B ³ CEAF CoNLL F1			MUC	\mathbf{B}^3	CEAF	CoNLL F1		
Test Set: HDDCRP's Predicted Mentions									
SameLemma 40.4 66.4 66.2 57.7 66.7 51.4 46.2 54						54.8			
HDDCRP	53.4	75.4	71.7	66.8	73.1	53.5	49.5	58.7	
CCNN+NC 54.0 75.5 72.2 67.2						57.0	49.6	59.3	

Neural Clustering — Evaluation against state-of-the-art

So, we did an additional post-processing (i believe even Bishan did this, though I am not sure) in which we also removed those predicted clusters which don't have any event mention in annotated coreference clusters. I

- > Another guy was assisting me in running her code and he couldn't run the > code after spending a month. Are you using the Perl scorer or mine one? I > haven't tested my scorer on ECB+ corpus and I am not sure if that's correct
- > :P.

Neural Clustering — Evaluation against state-of-the-art

	Within-Document				Cross-Document				
	MUC	\mathbf{B}^3	CEAF	CoNLL F1	MUC	\mathbf{B}^3	CEAF	CoNLL F1	
Test Set: HDDCRP's Predicted Mentions									
SameLemma	40.4	66.4	66.2	57.7	66.7	51.4	46.2	54.8	
HDDCRP	53.4	75.4	71.7	66.8	73.1	53.5	49.5	58.7	
CCNN+NC	54.0	75.5	72.2	67.2	71.3	57.0	49.6	59.3	
Test Set: Choubey's et. al. Mentions									
SameLemma	48.8	66.7	65.1	60.2	68.1	53.3	47.2	56.2	
Choubey	62.6	72.4	71.8	68.9	73.4	80.4	56.5	63.6	
CCNN+NC	67.3	73.0	69.5	69.9	77.0	56.3	60.2	64.5	

Current Work



Current Work

Event Coreference — Lessons Learned

- event corpora are challenging
 - size
 - comparisons to other systems
- vital to do WD then CD
- worth exploring smarter models for including semantics and relations:
 - entities
 - dependencies
 - paraphrases?

Short Term (~2 weeks)

Possible Improvements

- EMNLP deadline in 6 days
- Ensemble Approach (FFNN average scores)
- Self-training

Let's add entities!

1. How well do we do on Entities?

Mention Detection

- Stanford Core NLP
- NLTK
- Bi-LSTM trained on ECB+

Entity Coreference (with and without pronouns)

- Stanford Core NLP
- Our CCNN (try other features)

Corpora

- ECB+
- EECB
- CoNLL-2012
- NIST's TAC Nov 13, 2018 (Entity Discovery and Linking Workshop)

Joint Entities and Events

One of the key suspected Mafia bosses arrested yesterday has hanged himself.

Police said Lo Presti had hanged himself.

His suicide appeared to be related to clan feuds.

Entities can help resolve Events

Joint Entities and Events

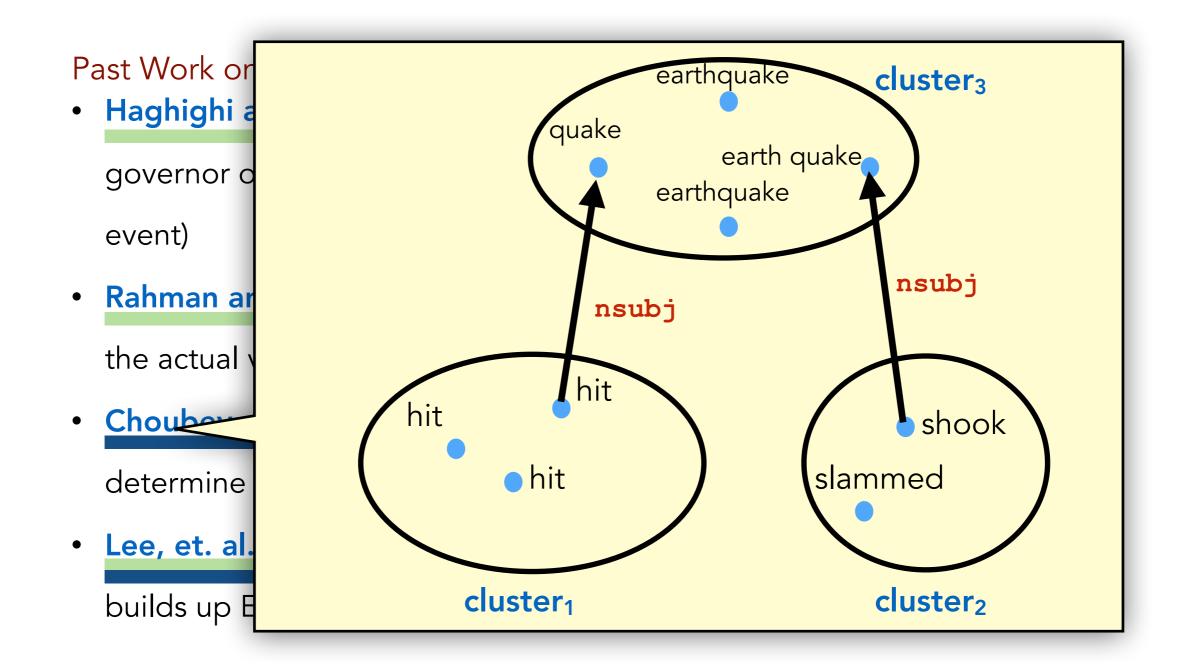
The New Orleans Saints placed Reggie Bush on the injured list on Wednesday.

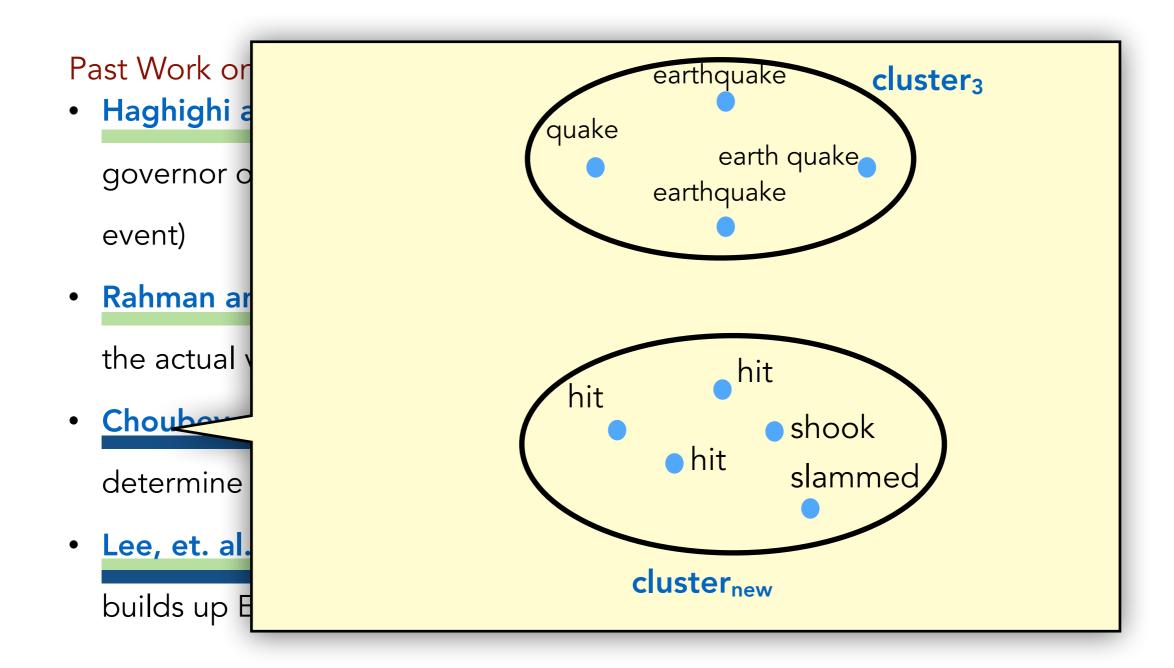
Saints put Bush on I.R.

Events can help resolve Entities

Past Work on Joint Entities and Events

- Haghighi and Klein (2010) include a feature which concerns the governor of the head of the nominal mentions (which could be an event)
- Rahman and Ng (2011) use semantic roles of entity mentions, plus the actual verbs, as features
- Choubey and Huang (2017) uses hand-made relational rule to determine if two event clusters should be merged
- Lee, et. al. (2012) performs Entity Coref via StanfordCoreNLP then builds up Event clusters based on semantic role features.





Past Work or

- Haghighi a
 governor o
 event)
- Rahman ar
 the actual v
- Chouber determine
- Lee, et. al. builds up E

Weaknesses:

- hand-defined, hard-threshold rule
- most events don't directly depend on other events
- doesn't use entities

Past Work on Joint Entities and Events

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2. Jointly Model Entities and Events

Confidence of Event Coreference influence Entity Coreference and vice versa

One of the key suspected Mafia bosses arrested yesterday has hanged himself.

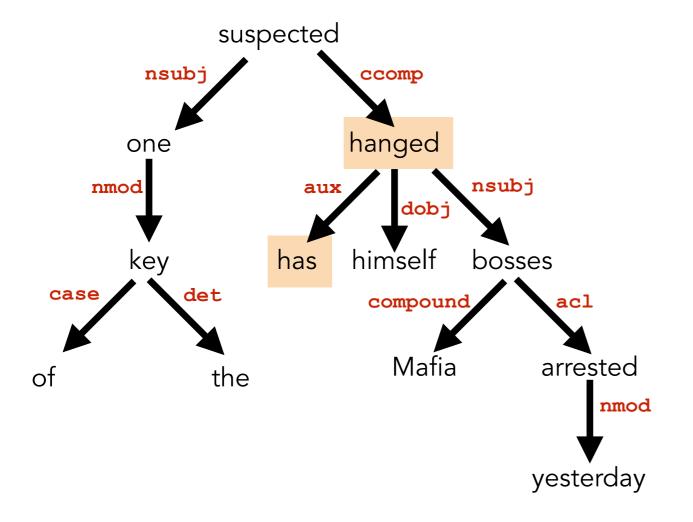
Police said Lo Presti had hanged himself.

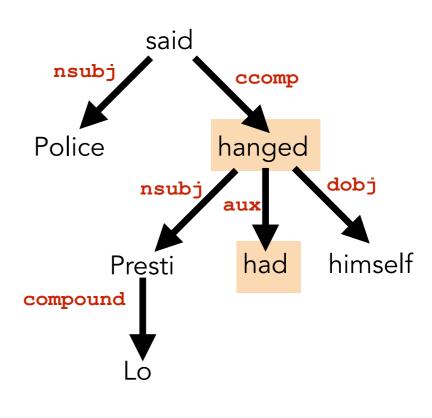
2. Jointly Model Entities and Events

Model dependencies organically

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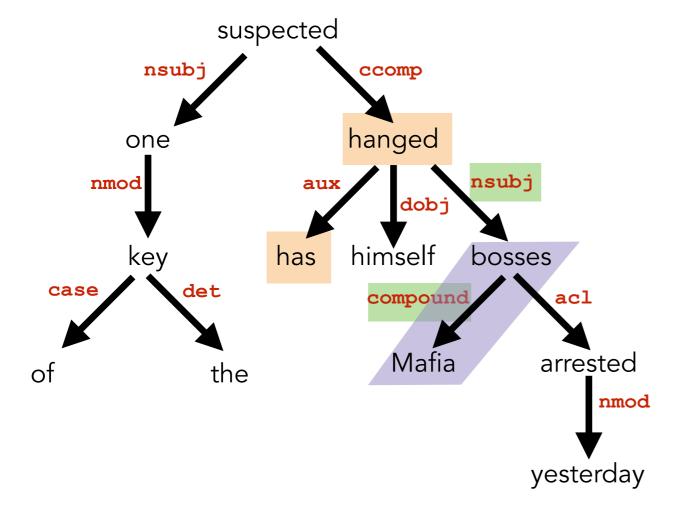


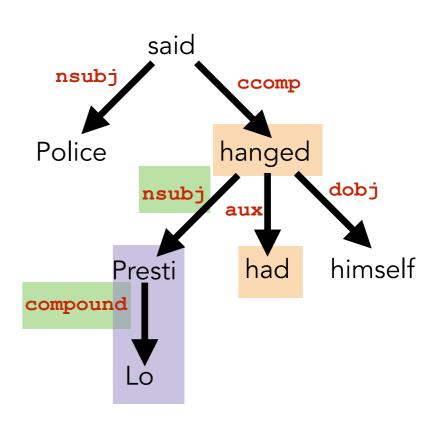
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3. Jointly Detect Mentions and Perform Coreference

My Stretch Goal:

- 1 system performs both mention detection and coreference
- few manually-defined features
 (e.g. not BoW windows, cosine sim. b/w X and Y, governor?)
- little lexical mark-up
 (e.g., dependency relations, POS, word embeddings, lemmas)

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End-to-End Neural Coreference Resolution (Lee, et. al., 2017)

CoNLL (entities)

Within-Doc

3. Jointly Detect Mentions and Perform Coreference

Areas for Improvement:

- Include Events
- Cross-document (or subsuming meta-document)
- Joint Mention Detection and Coreference

Rough Ideas:

- Bi-LSTM input
- Sample pairs of mention spans to evaluate
 - target output serves as a weighted vote for each mention existing and a vote for the pair to co-occur
 - final clusters gleaned by highest democratic votes

Completed Work

baseline Entity Coref experiments

Joint Entity + Event Coref

continue above or if finished, mention detection

write dissertation

defend

Estimated Timeline

May 22

submit to EMNLP

June

improve Event Coref via ensemble + self-training

July - August

baseline Entity Coref experiments

August - Nov

Joint Entity + Event Coref

Nov - March

continue above or if finished, mention detection

March - May

write dissertation

May

defend

Thesis Statement

This research aims to develop the first *comprehensive* cross-document coreference resolution system, by improving event coreference and showing the benefits of jointly modelling both events and entities.

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Thanks!

Questions?