COMP5046
Natural Language Processing

Lecture 9: Named Entity Recognition and Coreference Resolution

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0 LECTURE PLAN

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Lecture 9: Named Entity Recognition and Coreference

1. Information Extraction
2. Named Entity Recognition (NER) and Evaluation
3. Traditional NER
4. Sequence Model for NER
5. Coreference Resolution
6. Coreference Model
7. Coreference Evaluation
8. Preview

1 Information Extraction

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Information Extraction

"The task of automatically ***extracting structured information*** *from unstructured and/or semi-structured machine-readable documents"*

Here are some questions..

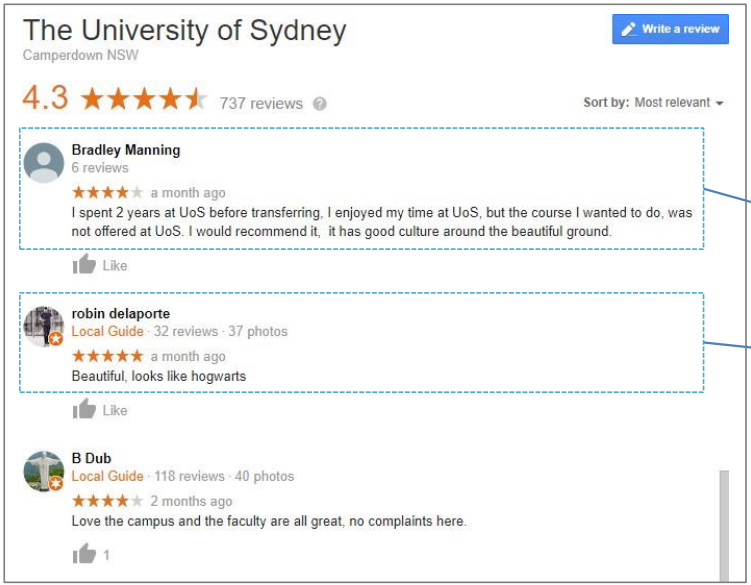
- How to allow computation to be done on the unstructured data
- How to extract clear, factual information
- How to put in a semantically precise form that allows further inferences to be made by computer algorithms

1 Information Extraction

How to extract the structured clear, factual information

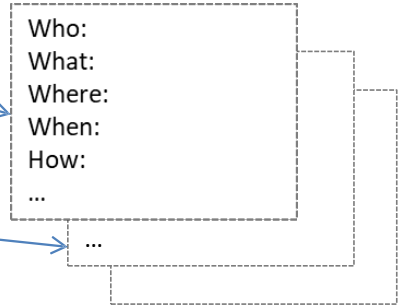
- Find and understand limited relevant parts of texts
- Gather information from many pieces of text
- Produce a structured representation of relevant information

relations (in the database sense) or a knowledge base



"5W1H"

who, what, where, when, why, how



1 Information Extraction

How to extract the structured clear, factual information

- Find and understand limited relevant parts of texts
- Gather information from many pieces of text
- Produce a structured representation of relevant information

relations (in the database sense) or a knowledge base

important paragraph

Sydney

City in New South Wales

Sydney, capital of New South Wales and one of Australia's largest cities, is best known for its harbourfront Sydney Opera House, with a distinctive sail-like design. Massive Darling Harbour and the smaller Circular Quay port are hubs of waterside life, with the arched Harbour Bridge and esteemed Royal Botanic Garden nearby. Sydney Tower's outdoor platform, the Skywalk, offers 360-degree views of the city and suburbs.

Area: 12,368 km²

Weather: 19 °C, Wind S at 19 km/h, 38% Humidity

Local time: Monday 1:08 pm

Population: 4.452 million (2014) United Nations

State electorate(s): various (49)

Extracting

summary

subject, object, relation

Subject	Relation	Object
Sydney	IS-A	Capital of New South Wales
Sydney	IS-A	Australia's largest cities
Sydney	KNOWN FOR	Sydney Opera House
...	...	...

Textual abstract: ***Summary for human***

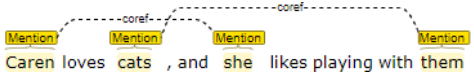
Structured information: ***Summary for machine***

Information Extraction

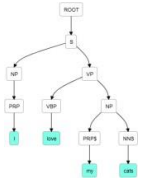
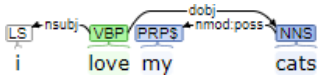
Information Extraction Pipeline with NLP

Application

Understanding

Sentiment Analysis	Caren loves cats, and she likes playing with them	**[positive: 90.10%] [neutral: 4.70%] [negative: 5.10%]**
Coreference Resolution	Caren loves cats, and she likes playing with them	
Entity Extraction (subject / object)	Caren loves cats, and she likes playing with them	

NLP Stack

Parsing	I love my cats	 
PoS Tagging	I love my cats	**[I/JJ] [love/VBP] [my/PRP] [cats/NNS]**
Stemming	I love my cats	**[I] [love] [my] [cat]**
Tokenisation	I love my cats	**[I] [love] [my] [cats]**

Named Entity Recognition (NER)

What is Named Entity Recognition?

key element.

"The subtask of information extraction that seeks to locate and classify named entity mentions in unstructured text into pre-defined categories such as the person names, organizations, locations, medical codes, time expressions, quantities, monetary values, percentages, etc."

Why recognise Named Entities?

- Named entities can be indexed, linked off, etc.
- Sentiment can be attributed to companies or products
- A lot of relations are associations between named entities
- For question answering, answers are often named entities.

Named Entity Recognition (NER)

How to recognize Named Entities?

Identify and **classify** names in text

- *The University of Sydney (informally USYD, Sydney, Sydney Uni) is an Australian public research university in Sydney, Australia. Founded in 1850, it was Australia's first university and is regarded as one of the world's leading universities. (Wikipedia, University of Sydney)*

Different types of named entity classes

Type	Classes
3 class	Location, Person, Organization
4 class	Location, Person, Organization, Misc
7 class	Location, Person, Organization, Money, Percent, Date, Time

miscellaneous 混杂的

**classes can be different based on annotated dataset*

eg financial domain

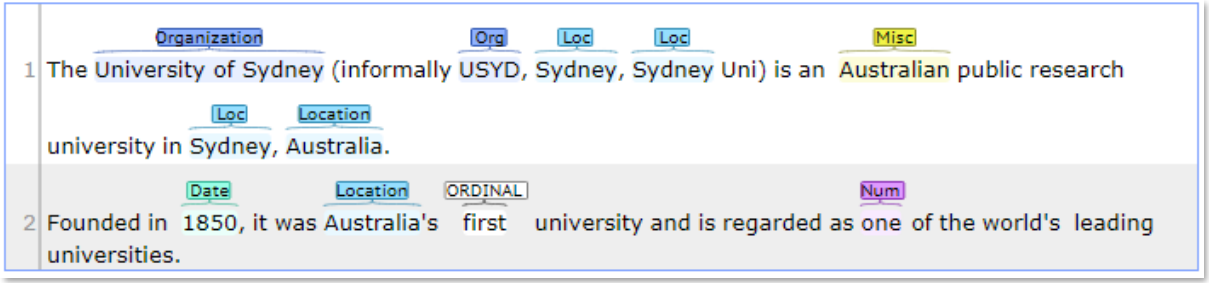
2 Named Entity Recognition (NER)

How to recognize Named Entities?

Identify and **classify** names in text

Upenn CogComp-NLP http://macniece.seas.upenn.edu:4004/

Stanford CoreNLP 3.9.2 http://nlp.stanford.edu:8080/corenlp/process



2 Named Entity Recognition (NER)

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How to evaluate the NER performance?

The goal: ***predicting entities in a text***

identify & classify

***Standard evaluation is per entity, not per token**

	Caren	Soyeon	Han	is	working	at	Google	at	Sydney,	Australia
gold	PER	PER	PER	O	O	O	ORG	O	LOC	LOC
predicted	O	O	O	O	O	O	ORG	O	LOC	LOC

person entity

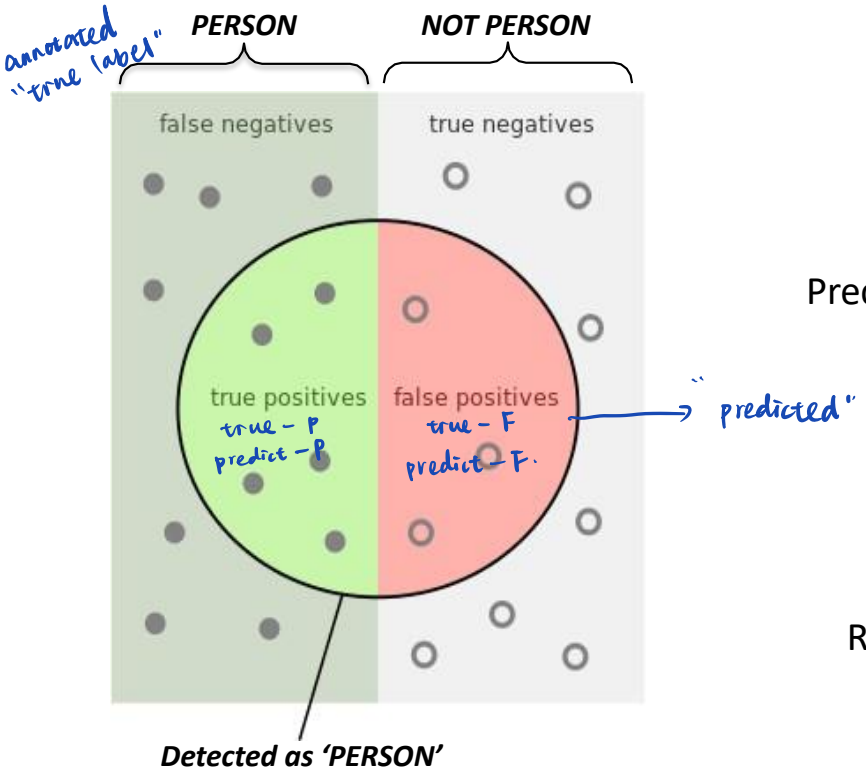
why not per token ?

predict "O" is easy (machine will just simply predict "O")

we only care entity

2 Named Entity Recognition (NER)

How to evaluate the NER performance? Precision and recall

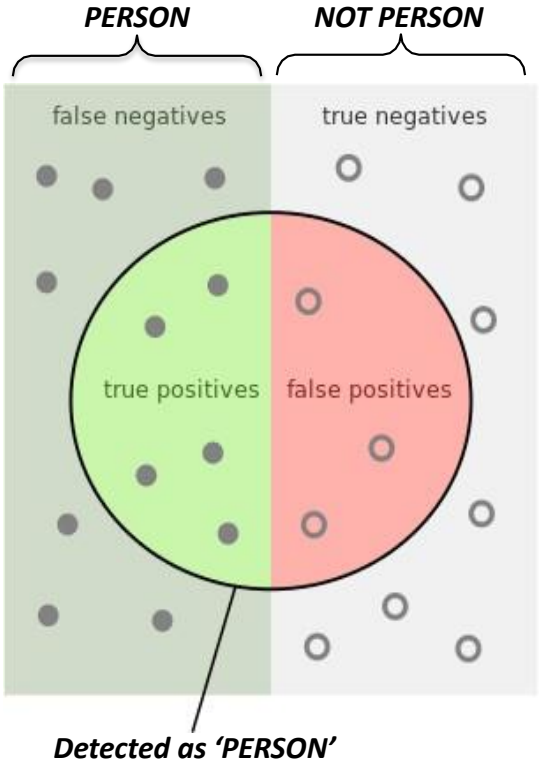


$$\text{Precision} = \frac{\text{Detected as 'PERSON' correctly}}{\text{Total number of detected as 'PERSON'}}$$

$$\text{Recall} = \frac{\text{Detected as 'PERSON' correctly}}{\text{Total number of actual 'PERSON' entities}}$$

2 Named Entity Recognition (NER)

How to evaluate the NER performance? Precision and recall



True positives: The 'PERSON's that the model detected as 'PERSON'

False positives: The NOT 'PERSON's that the model detected as 'PERSON'

False negatives: The 'PERSON's that the model detected as NOT 'PERSON'

True negatives: The 'NOT PERSON's that the model detected as NOT 'PERSON'

2 Named Entity Recognition (NER)

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How to evaluate the NER performance?

The goal: ***predicting entities in a text***

***Standard evaluation is per entity, not per token**

	Caren	Soyeon	Han	is	working	at	Google	at	Sydney,	Australia
gold	PER	PER	PER	O	O	O	ORG	O	LOC	LOC
predicted	O	O	O	O	O	O	ORG	O	LOC	LOC

true

predict

	correct	not correct
selected	True Positive (TP)	False Positive (FP)
not selected	False Negative (FN)	True Negative (TN)

2 Named Entity Recognition (NER)

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How to evaluate the NER performance?

The goal: ***predicting entities in a text***

***Standard evaluation is per entity, not per token**

	Caren	Soyeon	Han	is	working	at	Google	at	Sydney,	Australia
gold	PER	PER	PER	O	O	O	ORG	O	LOC	LOC
predicted	O	O	O	O	O	O	ORG	O	LOC	LOC

Precision and Recall are straightforward for text categorization or web search, where there is only one grain size (documents)

Named Entity Recognition (NER)

Quick Exercise: F measure Calculation

Let's calculate Precision, Recall, and F-measure together!

P = ?? R = ?? F_1 = ?? $F1 = 2 * \frac{P*R}{P+R}$

	correct	not correct
selected	2 (TP)	0 (FP)
not selected	1 (FN)	0 (TN)

Named Entity Recognition (NER)

Data for learning named entity

- Training counts joint frequencies in a corpus
- The more training data, the better
- Annotated corpora are small and expensive

Corpora	Source	Size	Class Type
muc-7	New York Times	164k tokens	per, org, loc, dates, times, money, percent https://aclweb.org/aclwiki/MUC-7_(State_of_the_art)
conll-03	Reuters	301k	per, org, loc, misc
bbn	Wall Street Journal	1174k	https://catalog.ldc.upenn.edu/LDC2005T33

Named Entity Recognition (NER)

Data for learning named entity

- Models trained on one corpus perform poorly on others

train	*F-score*		
	muc	*conll*	*bbn*
muc	82.3	54.9	69.3
conll	69.9	86.9	60.2
bbn	80.2	58.0	88.0

conell has less accuracy

⇒ less class type, less pattern.

2 Named Entity Recognition (NER)

CoNLL 2003 NER dataset

- Performance measure: F = 2 * Precision * Recall / (Recall + Precision)

RANK	MODEL	F1 ↑	EXTRA TRAINING DATA	PAPER	CODE	RESULT	YEAR
1	LUKE	94.3	×	LUKE: Deep Contextualized Entity Representations with Entity-aware Self-attention			2020
2	ACE + document-context	94.14	×	Automated Concatenation of Embeddings for Structured Prediction			2020
3	Cross-sentence context (First)	93.74	×	Exploring Cross-sentence Contexts for Named Entity Recognition with BERT			2020
4	ACE	93.64	×	Automated Concatenation of Embeddings for Structured Prediction			2020
5	CNN Large + fine-tune	93.5	✓	Cloze-driven Pretraining of Self-attention Networks			2019
6	Biaffine-NER	93.5	×	Named Entity Recognition as Dependency Parsing			2020
7	GCDT + BERT-L	93.47	✓	GCDT: A Global Context Enhanced Deep Transition Architecture for Sequence Labeling			2019
8	I-DARTS + Flair	93.47	✓	Improved Differentiable Architecture Search for Language Modeling and Named Entity Recognition			2019
9	CrossWeigh + Pooled Flair	93.43	×	CrossWeigh: Training Named Entity Tagger from Imperfect Annotations			2019
10	LSTM-CRF+ELMo+BERT+Flair	93.38	✓	Neural Architectures for Nested NER through Linearization			2019

https://paperswithcode.com/sota/named-entity-recognition-ner-on-conll-2003

2 Named Entity Recognition (NER)

Datasets for NER in English

The following table shows the list of datasets for English entity recognition.

Dataset	Domain	License	Reference
CONLL 2003	News	DUA	Sang and Meulder, 2003
NIST-IEER	News	None	NIST 1999 IE-ER
MUC-6	News	LDC	Grishman and Sundheim, 1996
OntoNotes 5	Various	LDC	Weischedel et al., 2013
BBN	Various	LDC	Weischedel and Brunstein, 2005
GMB-1.0.0	Various	None	Bos et al., 2017
GUM-3.1.0	Wiki	Several (*2)	Zeldes, 2016
wikigold	Wikipedia	CC-BY 4.0	Balasuriya et al., 2009
Ritter	Twitter	None	Ritter et al., 2011
BTC	Twitter	CC-BY 4.0	Derczynski et al., 2016
WNUT17	Social media	CC-BY 4.0	Derczynski et al., 2017
i2b2-2006	Medical	DUA	Uzuner et al., 2007
i2b2-2014	Medical	DUA	Stubbs et al., 2015
CADEC	Medical	CSIRO	Karimi et al., 2015
AnEM	Anatomical	CC-BY-SA 3.0	Ohta et al., 2012
MITRestaurant	Queries	None	Liu et al., 2013a
MITMovie	Queries	None	Liu et al., 2013b
MalwareTextDB	Malware	None	Lim et al., 2017
re3d	Defense	Several (*1)	DSTL, 2017
SEC-filings	Finance	CC-BY 3.0	Alvarado et al., 2015
Assembly	Robotics	X	Costa et al., 2017

***DUA**: Data Use Agreement*
***LDC**: Linguistic Data Consortium*
***CC-BY 4.0**: Creative Commons Attribution 4.0*

https://github.com/juand-r/entity-recognition-datasets

https://paperswithcode.com/task/named-entity-recognition-ner

Traditional NER

Three standard approaches to NER

- Rule-based NER
- Classifier-based NER
- Sequence Model for NER

] Traditional Approaches

Traditional NER

Rule-based NER

- Entity references have internal and external language cues
  Mr. [per Scott Morrison] flew to [loc Beijing]

- Can recognise names using lists (or gazetteers):
  - Personal titles: Mr, Miss, Dr, President
  - Given names: Scott, David, James
  - Corporate suffixes: & Co., Corp., Ltd.
  - Organisations: Microsoft, IBM, Telstra

lexicon or dictionary

- and rules:
  - personal title X ⇒ per
  - X, location ⇒ loc or org
  - travel verb to X ⇒ loc

per
Mr Scott.
Sydney, Aus
loc.
travel to Beijing
loc.

- Effectively regular expressions, PoS Tagger

Traditional NER

Rule-based NER

- Determining which person holds what office in what organization
  - [person] , [office] of [org]
    - Michael Spence, the vice-chancellor and principal of the University of Sydney
  - [org] (named, appointed, etc.) [person] Prep [office]
    - WHO appointed Tedros Adhanom as Director-General

- Determining where an organization is located
  - [org] in [loc]
    - Google headquarters in California
  - [org] [loc] (division, branch, headquarters, etc.)
    - Google London headquarters

Traditional NER

Mr & Mrs Smith
↓ preprocessing
Mr Smith & Mrs Smith
2 entity

Statistical approaches are more portable

- Learn NER from annotated text
  - weights (≈ rules) calculated from the corpus
  - same machine learner, different language or domain
- Token-by-token classification (with any machine learning)
- Each token may be:
  - not part of an entity (tag o)
  - beginning an entity (tag b-per, b-org, etc.)
  - continuing an entity (tag i-per, i-org, etc.)
- What about N-gram model?

Traditional NER

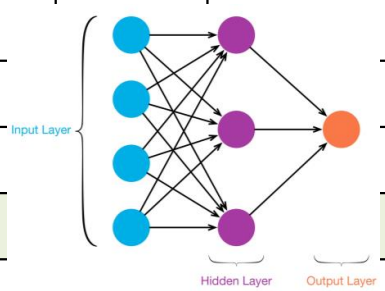
Various features for statistical NER

Unigram	Mr.	Scott	Morrison	flew	to	Beijing
Lowercase unigram	mr.	scott	morrison	flew	to	beijing
POS tag	nnp	nnp	nnp	vbd	to	nnp
length	3	5	4 8	4	2	7
In first-name gazetteer	no	yes	no	no	no	no
In location gazetteer	no	no	no	no	no	yes
3-letter suffix	Mr.	ott	son	lew	-	ing
2-letter suffix	r.	tt	on	ew	to	ng
1-letter suffix	.	t	n	w	o	g
Tag predictions	O	B-per	I-per	O	O	B-loc

Traditional NER

Various features for statistical NER

Unigram	Mr.	Scott	Morrison	flew	to	Beijing
Lowercase unigram	mr.	scott	morrison	flew	to	beijing
POS tag	nnp	nnp	nnp	vbd	to	nnp
length	3	5	4	4	2	7
In first-name gazetteer	no	yes	no	no	no	no
In location gazetteer	no	no	no	no	no	yes
3-letter suffix	Mr.			lew	-	ing
2-letter suffix	r.			ew	to	ng
1-letter suffix	.			w	o	g
Tag predictions	O			O	O	B-loc



Mr. Scott Morrison lives in Sydney ---> ***Predictive Model*** ---> O B-PER I-PER O O B-LOC

Traditional NER

Traditional NER Approaches - Pros and Cons

Rule-based approaches

- Can be high-performing and efficient
- Require experts to make rules
- Rely heavily on gazetteers that are always incomplete
- Are not robust to new domains and languages

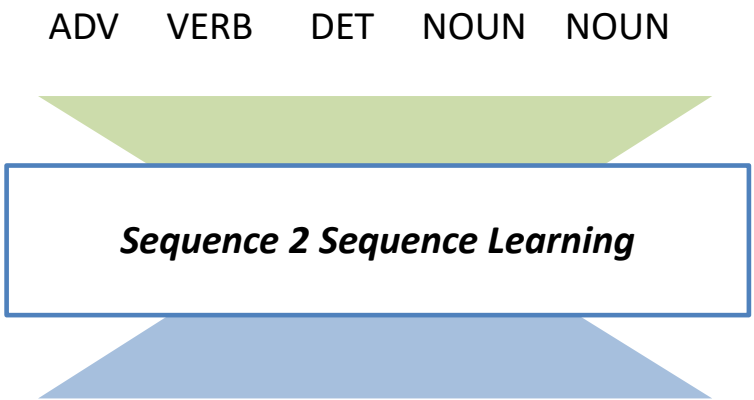
Statistical approaches

- Require (expert-)annotated training data
- May identify unforeseen patterns
- Can still make use of gazetteers
- Are robust for experimentation with new features
- Are largely portable to new languages and domains

once have enough feature

Sequence Model for NER

Sequence Model (N to N)



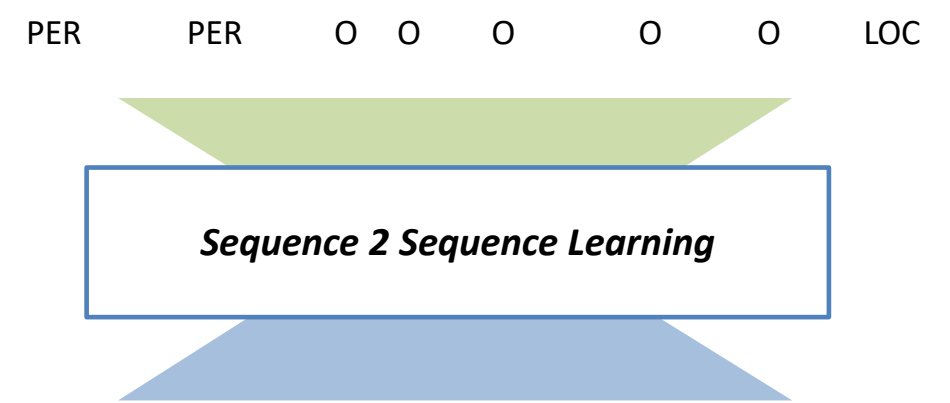
Output: Part of Speech

Input: Text

Sequence Model for NER

Sequence Model

N to N model.



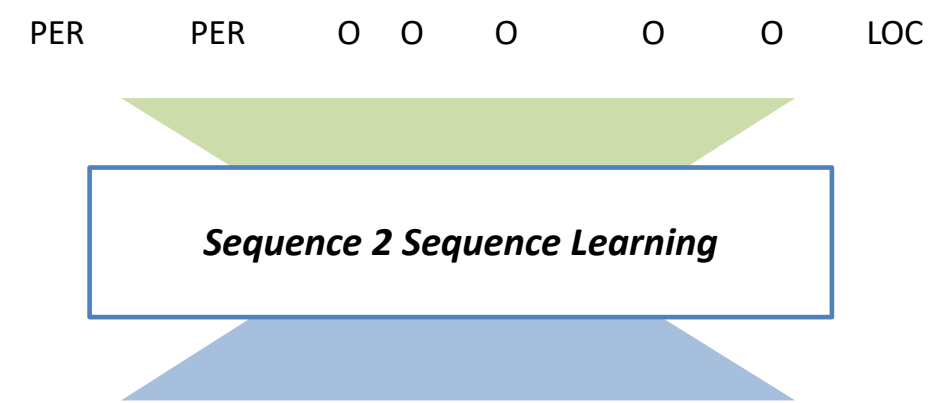
Output: NE tag

Entity class or other(O)

Input: Text

Sequence Model for NER

Encoding classes for sequence labeling



The IOB (short for inside, outside, beginning) is a common tagging format

- I- prefix before a tag indicates that the tag is inside a chunk.
- B- prefix before a tag indicates that the tag is the beginning of a chunk.
- An O tag indicates that a token belongs to no chunk (outside).

Sequence Model for NER

Encoding classes for sequence labeling

The IO and IOB (inside, outside, beginning) is a common tagging format

different name not common

	Josiah	tells	Caren	John	Smith	is	a	student	
IO encoding	PER	O	PER	PER	PER	O	O	O	**n+1**
IOB encoding	B-PER	O	B-PER	B-PER	I-PER	O	O	O	**2n+1**
		even	B-PER	I-PER	I-PER				

IOB is better distinguish 2 name

n = # entity type

n+1 = # ... + "O"

2n+1 = "B", "I" for each entity type

IO encoding vs IOB encoding

- *Computation Time?*
- *Efficiency?*

for generalization

Caren John Smith not common

if IO better

Sequence Model for NER

for NER. maybe don't need stopword removal

Features for sequence labeling

Words

- Current word (essentially like a learned dictionary)
- Previous/next word (context)

Other kinds of inferred linguistic classification

- Part-of-speech tags

Label context

- Previous (and perhaps next) label

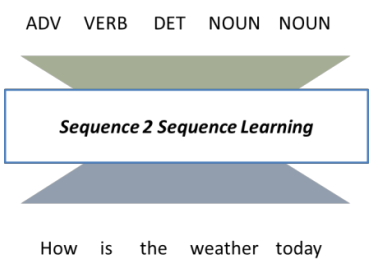
NER, majority of time we don't do stopword removal

Sequence Model for NER

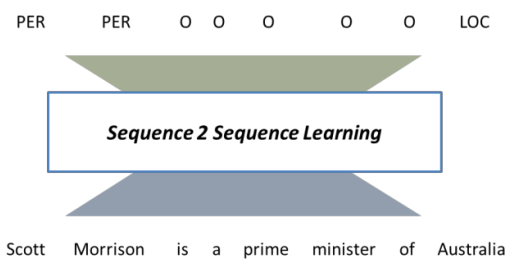
N to N Sequence model

- There are different NLP tasks that used N to N sequence model

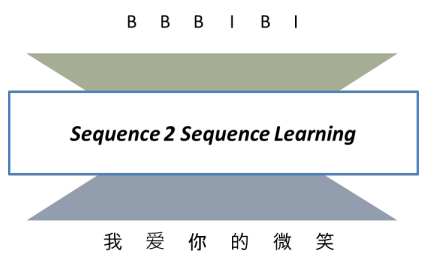
POS tagging



Named Entity Recognition

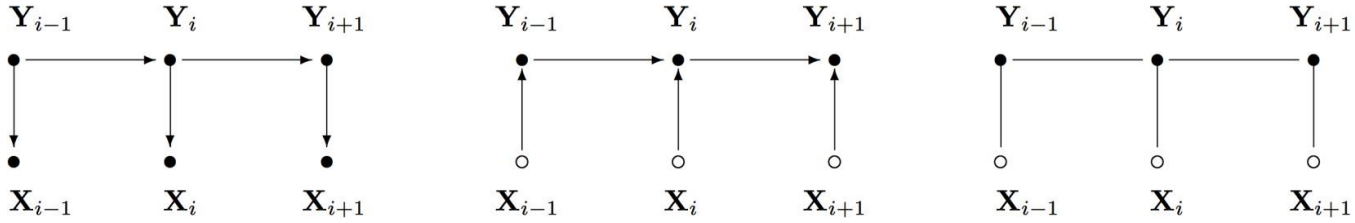


Word Segmentation



Sequence Model for NER

Sequence Model (MEMM, CRF)



HMM MEMM CRF

Sequence Model for NER

Sequence Inference for NER

- The classifier makes a single decision at a time, conditioned on evidence from observations and previous decisions

-3	-2	-1	0	+1
Scott	Morrison	lives	in	Australia
NN	**NN**	**VBZ**	**IN**	**NN**

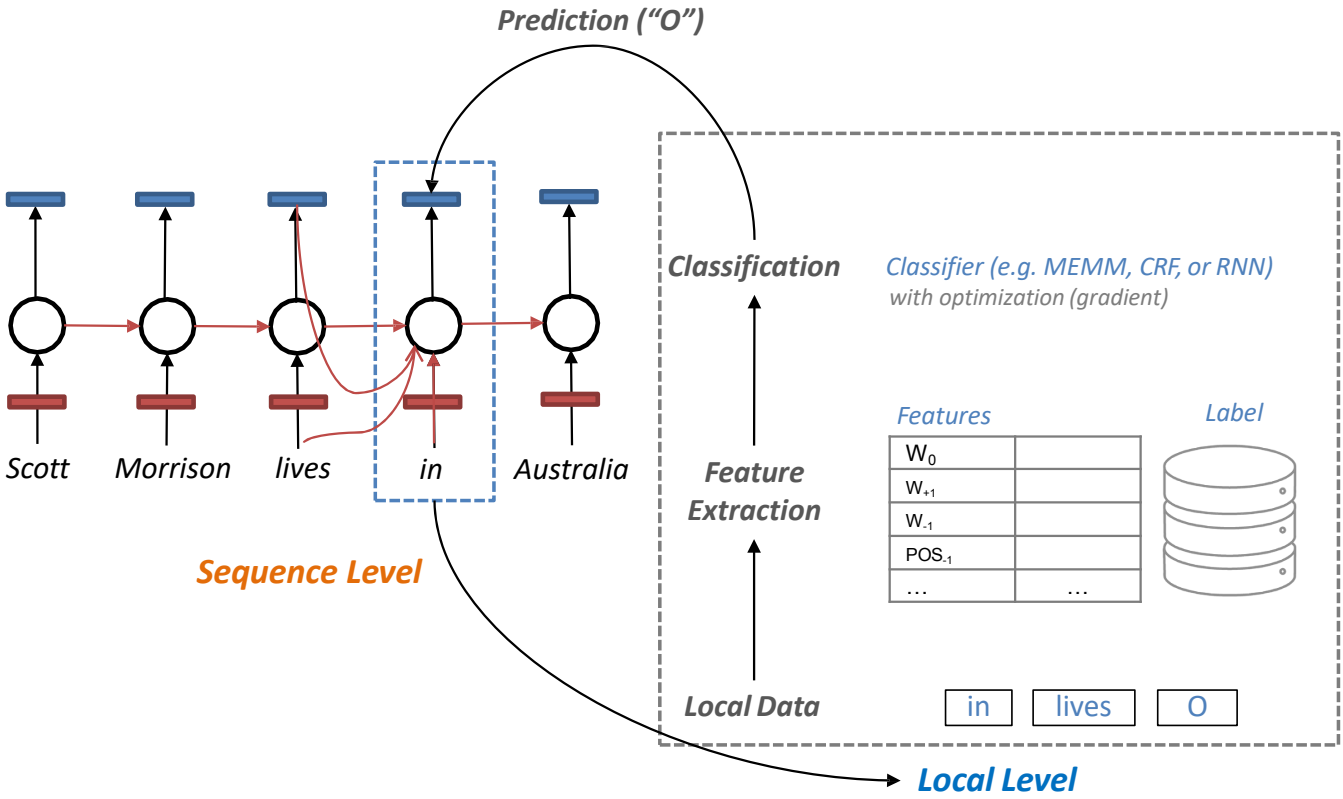
Features

W_0	in
W_{+1}	Australia
W_{-1}	lives
POS_{-1}	VBZ
POS_{-2}-POS_{-1}	NN - VBZ
hasDigit?	0
…	…

(Toutanova et al. 2003, etc.)

Sequence Model for NER

Sequence Inference for NER



Sequence Model for NER

Named Entity Recognition

The goal: predicting named entity mentions in unstructured text into pre-defined categories such as the person names, organizations, locations

Upenn CogComp-NLP

1 The University of Sydney (informally USYD , Sydney , Sydney Uni) is an Australian public research university in Sydney , Australia .

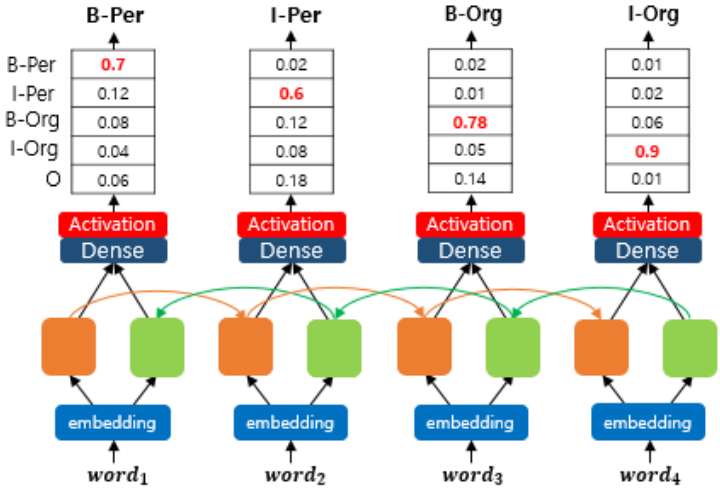
2 Founded in 1850 , it was Australia 's first university and is regarded as one of the world 's leading universities .

	Caren	Soyeon	Han	is	working	at	Google	at	Sydney,	Australia
gold	PER	PER	PER	O	O	O	ORG	O	LOC	LOC
predicted	O	O	O	O	O	O	ORG	O	LOC	LOC

Sequence Model for NER

Named Entity Recognition with Bi-LSTM

We can easily apply Bi-LSTM (N to N Seq2Seq) Model to predict Named Entities



Sequence Model for NER

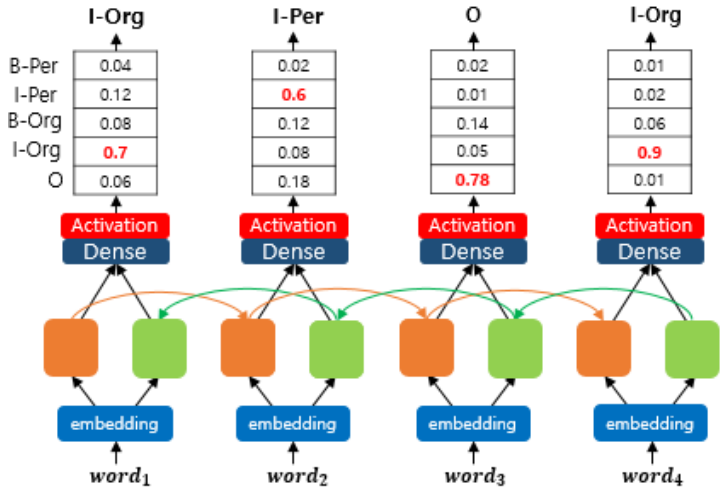
Named Entity Recognition with Bi-LSTM

We can easily apply Bi-LSTM (N to N Seq2Seq) Model to predict Named Entities

*The model clearly contains incorrect predictions.

some implicit rules

'I' cannot appear in the label of the first word. I-Per can only appear after B-Per.
I-Org can also appear only after B-Org.



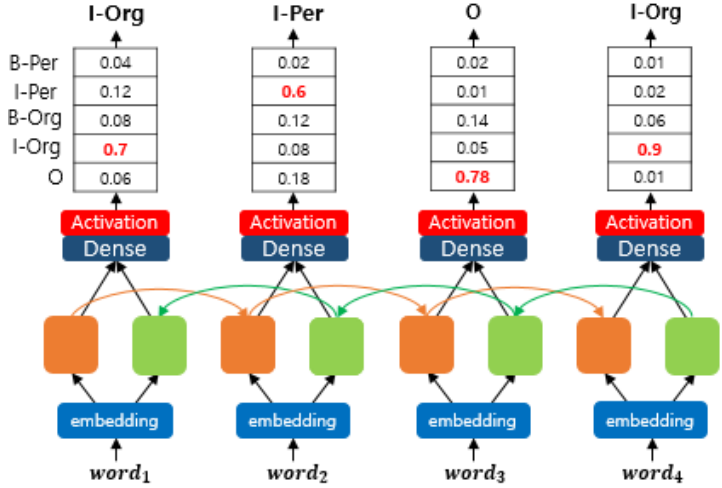
Sequence Model for NER

Named Entity Recognition with Bi-LSTM

We can easily apply Bi-LSTM (N to N Seq2Seq) Model to predict Named Entities

*The model clearly contains incorrect predictions.

'I' cannot appear in the label of the first word. I-Per can only appear after B-Per.
I-Org can also appear only after B-Org.



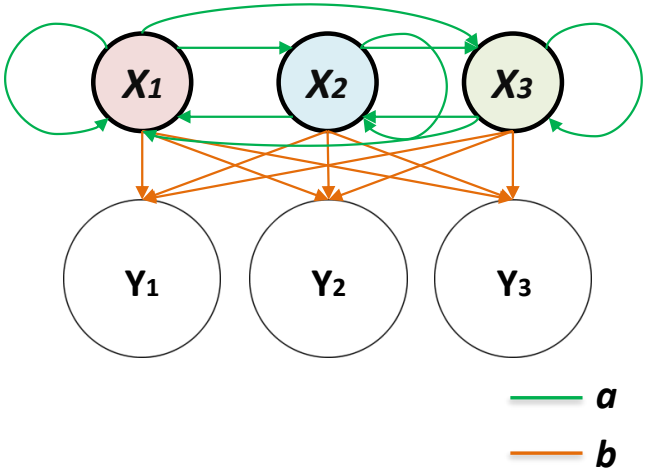
What if we teach the dependency between predicted entity names

Sequence Model for NER

output layer from After Bi-LSTM + transition prob

Wait? What about HMM?

Hidden Markov Models (HMMs) are a class of probabilistic graphical model that allow us to predict a sequence of unknown (hidden) variables from a set of observed variables.



hidden

x	states
y	possible observations
a	state transition probabilities
b	output probabilities

- States are ***hidden***
- ***Observable outcome*** linked to states
- Each state has ***observation probabilities*** to determine the observable event

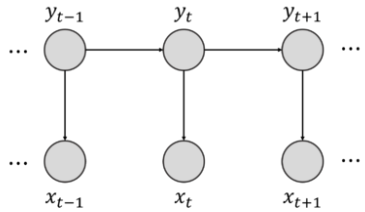
Sequence Model for NER

constraint
eg first word label should be "B-..."
"O"
not "I-..."

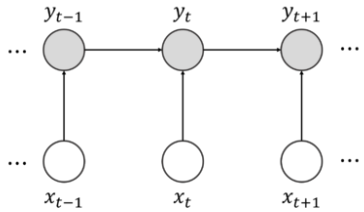
Advanced HMM (MEMM or CRF)

- The CRF model has addressed the labeling bias issue and eliminated unreasonable hypotheses in HMM.
- MEMM adopts local variance normalization while CRF adopts global variance normalization.

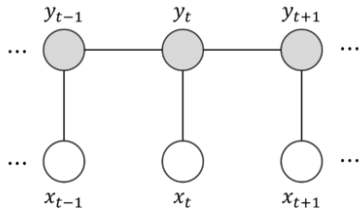
HMM



Maximum-entropy Markov model (MEMM)



Conditional random field (CRF)

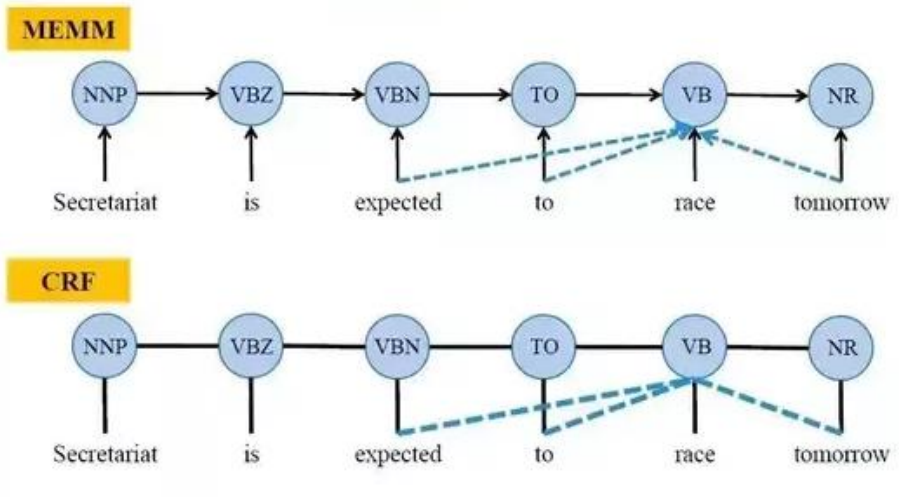


Sequence Model for NER

Advanced HMM (MEMM or CRF)

- The CRF model has addressed the labeling bias issue and eliminated unreasonable hypotheses in HMM.
- MEMM adopts local variance normalization while CRF adopts global variance normalization.

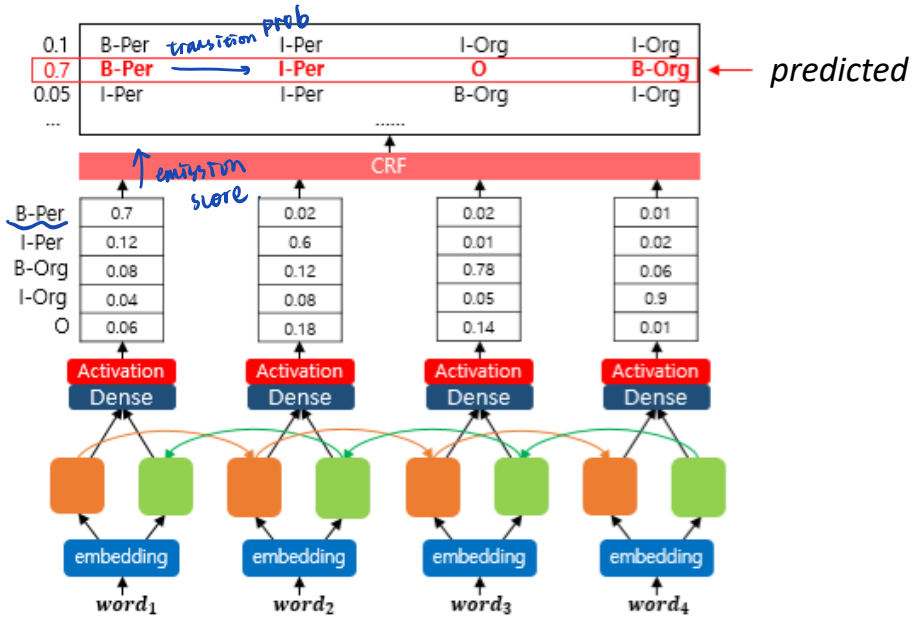
understand the constraints.



Sequence Model for NER

Named Entity Recognition with Bi-LSTM with CRF

What if we put CRF on top of the Bi-LSTM model. By adding a CRF layer, the model can handle the dependency between predicted entity names



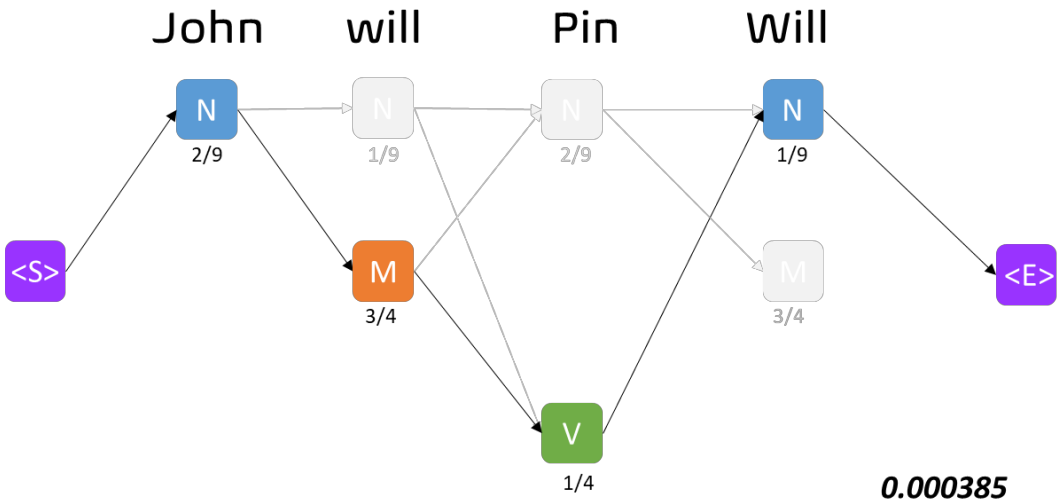
Sequence Model for NER

Remember?

POS Tagging: with HMM

	N	V	M
Emma	4/9	0	0
John	2/9	0	0
Will	1/9	0	3/4
Pin	2/9	1/4	0
Can	0	0	1/4
Meet	0	2/4	0
Pat	0	1/4	0

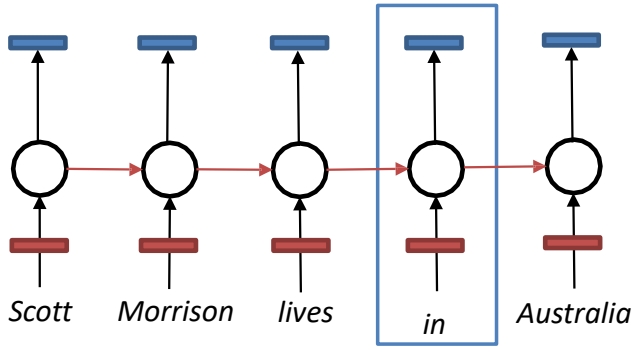
	N	V	M	<E>
<S>	3/4	0	1/4	0
N	1/9	1/9	3/9	4/9
V	4/4	0	0	0
M	1/4	3/4	0	0



Sequence Model for NER

Greedy Inference

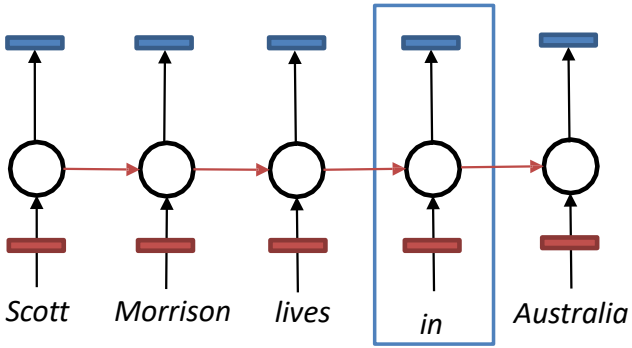
- Greedy inference:
  - We just start at the left, and use our classifier at each position to assign a label
  - The classifier can depend on previous labeling decisions as well as observed data
- Advantages:
  - Fast, no extra memory requirements
  - Very easy to implement
  - With rich features including observations to the right, it may perform quite well
- Disadvantage:
  - Greedy. We make commit errors we cannot recover from



Sequence Model for NER

Beam Inference

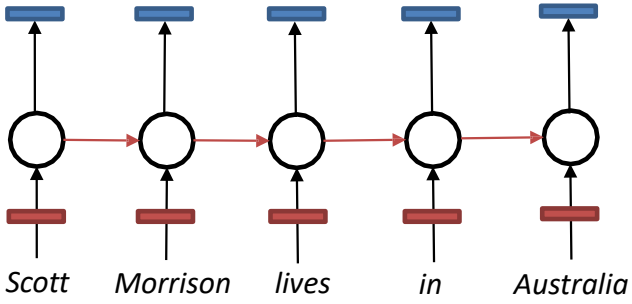
- Beam inference:
  - At each position keep the top k complete sequences.
  - Extend each sequence in each local way.
  - The extensions compete for the k slots at the next position.
- Advantages:
  - Fast; beam sizes of 3–5 are almost as good as exact inference in many cases.
  - Easy to implement (no dynamic programming required).
- Disadvantage:
  - Inexact: the globally best sequence can fall off the beam.



Sequence Model for NER

Viterbi Inference

- Viterbi inference:
  - Dynamic programming or memorisation.
  - Requires small window of state influence (e.g., past two states are relevant).
- Advantage:
  - Exact: the global best sequence is returned.
- Disadvantage:
  - Harder to implement long-distance state-state interactions



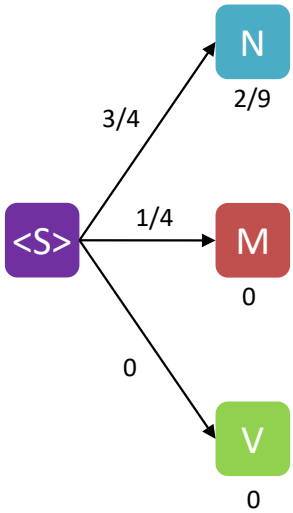
Probabilistic Approaches

Viterbi Algorithm

	N	V	M
Emma	4/9	0	0
John	2/9	0	0
Will	1/9	0	3/4
Pin	2/9	1/4	0
Can	0	0	1/4
Meet	0	2/4	0
Pat	0	1/4	0

	N	V	M	<E>
<S>	3/4	0	1/4	0
N	1/9	1/9	3/9	4/9
V	4/4	0	0	0
M	1/4	3/4	0	0

John will Pin Will



Probabilistic Approaches

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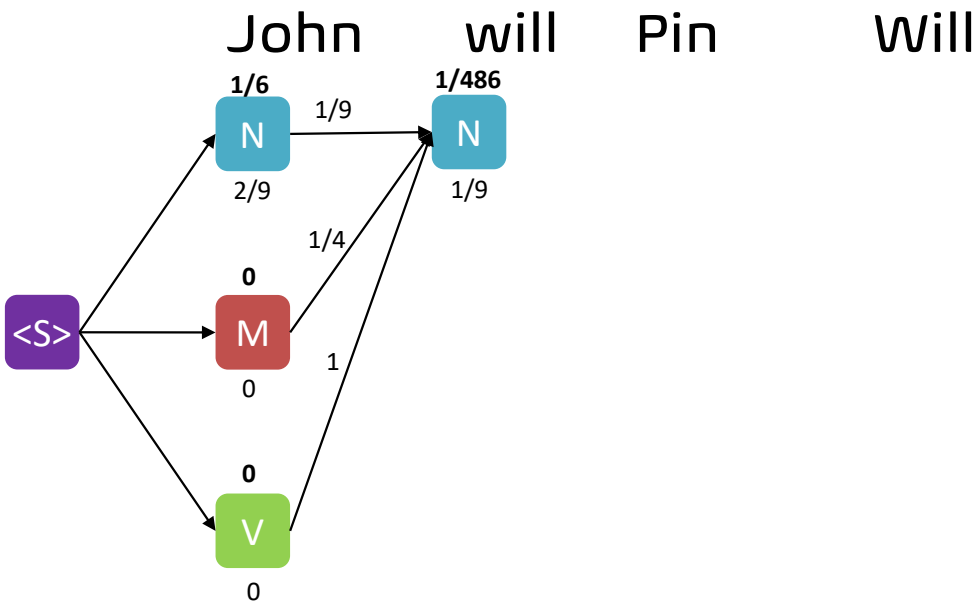

Probabilistic Approaches

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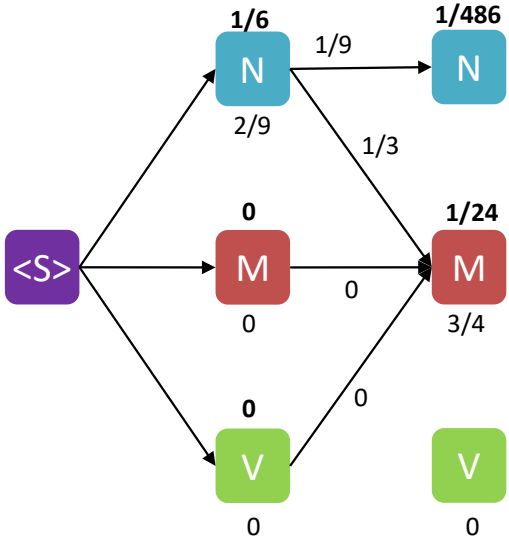

Probabilistic Approaches

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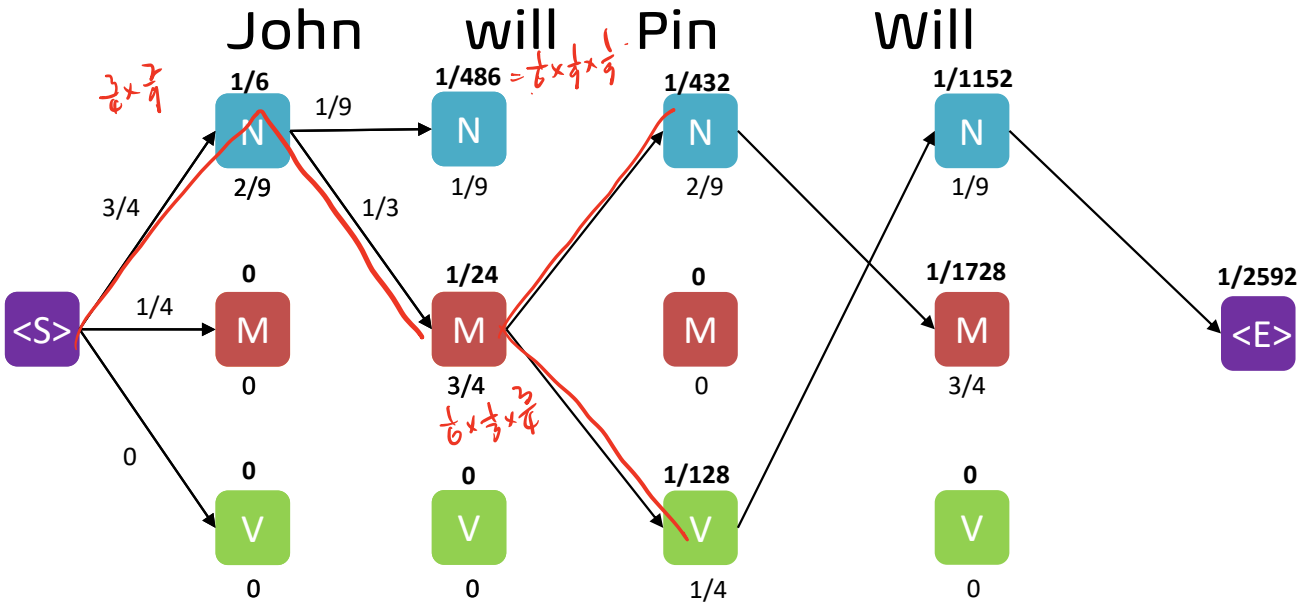

Probabilistic Approaches

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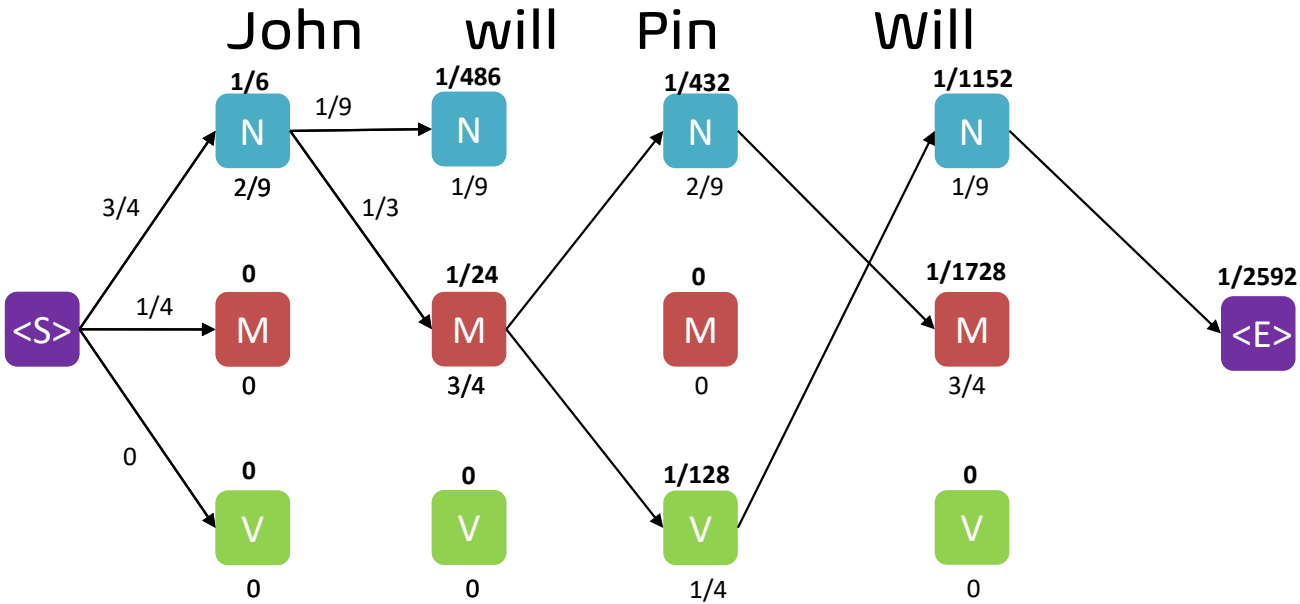

Probabilistic Approaches

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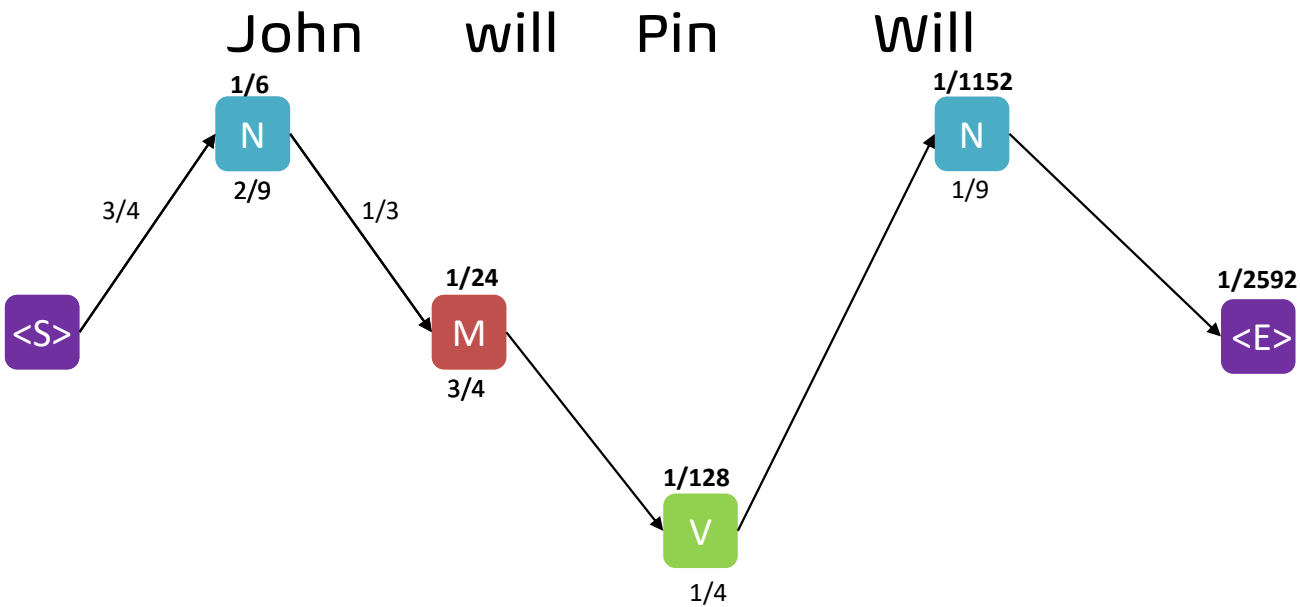


Probabilistic Approaches

Viterbi Algorithm

function VITERBI(*observations* of len T,*state-graph* of len N) **returns** *best-path*, *path-prob*

create a path probability matrix *viterbi*[N,T]
for each state s **from** 1 **to** N **do** ; initialization step
  $viterbi[s,1] \leftarrow \pi_s * b_s(o_1)$
  $backpointer[s,1] \leftarrow 0$
for each time step t **from** 2 **to** T **do** ; recursion step
  for each state s **from** 1 **to** N **do**
    $viterbi[s,t] \leftarrow \max_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$
    $backpointer[s,t] \leftarrow \operatorname{argmax}_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$
$bestpathprob \leftarrow \max_{s=1}^{N} viterbi[s,T]$; termination step
$bestpathpointer \leftarrow \operatorname{argmax}_{s=1}^{N} viterbi[s,T]$; termination step
bestpath $\leftarrow$ the path starting at state *bestpathpointer*, that follows backpointer[] to states back in time
return *bestpath*, *bestpathprob*

https://web.stanford.edu/~jurafsky/slp3/8.pdf

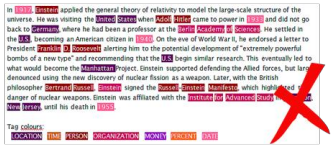
4 Sequence Model for NER

What if there is a language that do not have any annotation?

NER in Low Resource Language

Extreme Low Resource Language Scenario

1



No annotated NE dataset *for low resource target language*

2

No parallel corpus *between source and target language*

3

No or few bilingual dictionary *for target language*

Current State of the Art model: *Han et al. from Usyd NLP Research Group*

TASK	DATASET	MODEL	METRIC NAME	METRIC VALUE	GLOBAL RANK	COMPARE
Low Resource Named Entity Recognition	CONLL 2003 Dutch	Low Resource Named Entity Recognition using Contextual Word Representation and Neural Cross-Lingual Knowledge Transfer	F1 score	75.10	# 1	See all
Low Resource Named Entity Recognition	CONLL 2003 German	Low Resource Named Entity Recognition using Contextual Word Representation and Neural Cross-Lingual Knowledge Transfer	F1 score	58.63	# 1	See all
Low Resource Named Entity Recognition	Conll 2003 Spanish	Low Resource Named Entity Recognition using Contextual Word Representation and Neural Cross-Lingual Knowledge Transfer	F1 score	75.34	# 1	See all
Low Resource Named Entity Recognition	Uyghur Unsequestered Set	Low Resource Named Entity Recognition using Contextual Word Representation and Neural Cross-Lingual Knowledge Transfer	F1 score	42.88	# 1	See all

Coreference Resolution

"he" "it"

NER and Coreference Resolution

NER only produces a list of entities in a text.

- "I voted for **Scott** because he was most aligned with my values"

Then, How to trace it?

Coreference Resolution is the task of finding all expressions that refer to the same entity in a text

- "**I** voted for **Scott** because **he** was most aligned with **my** values"
  - **Scott ← he**
  - **I ← my**

Coreference Resolution

What is Coreference Resolution?

Finding all mentions that refer to the same entity

Donald Trump said he considered nominating Ivanka Trump to be president of the World Bank because “she is very good with numbers,”

Coreference Resolution

What is Coreference Resolution?

Finding all mentions that refer to the same entity

Donald Trump said **he** considered nominating Ivanka Trump to be president of the World Bank because “she is very good with numbers,”

Coreference Resolution

What is Coreference Resolution?

Finding all mentions that refer to the same entity

Donald said he considered nominating **Ivanka Trump** to be **president of the World Bank** because "**she** is very good with numbers,"

Coreference Resolution

How to conduct Coreference Resolution?

1. Detect the mentions

** Mention: span of text referring to same entity*

- Pronouns

e.g. I, your, it, she, him, etc.

- Named entities

e.g. people, places, organisation etc.

- Noun phrases

e.g. a cat, a big fat dog, etc.

Coreference Resolution

The difficulty in coreference resolution

1. Detect the mentions

** Mention: span of text referring to same entity*

Tricky mentions…

- **It** was very interesting
- **No staff**
- **The best university in Australia**

How to handle this tricky mentions? ***Classifiers!***

Coreference Resolution

How to conduct Coreference Resolution?

1. Detect the mentions

Donald Trump said **he** considered nominating **Ivanka Trump** to be **president of the World Bank** because "**she** is very good with numbers,"

2. Cluster the mentions

Donald Trump said **he** considered nominating **Ivanka Trump** to be **president of the World Bank** because "**she** is very good with numbers,"

Coreference Resolution

How to cluster the mentions and find the coreference

Coreference

def It occurs when two or more expressions in a text refer to the same person or thing.

- **"Donald Trump** is a president of the United States. **Trump** was born and raised in the New York City borough of Queens"

Anaphora

The use of a word referring back to a word used earlier in a text or conversation. Mostly noun phrases

- a word (anaphor) refers to another word (antecedent)
- "Donald Trump is a president of the United States. Before entering politics, he was a businessman and television personality"

antecedent anaphor

antecedent *anaphor*

Coreference Resolution

Coreference vs Anaphora

Coreference

Donald Trump →

Trump →

Anaphora

Donald Trump →

↑

he

Coreference Resolution

Not all anaphoric relations are coreferential

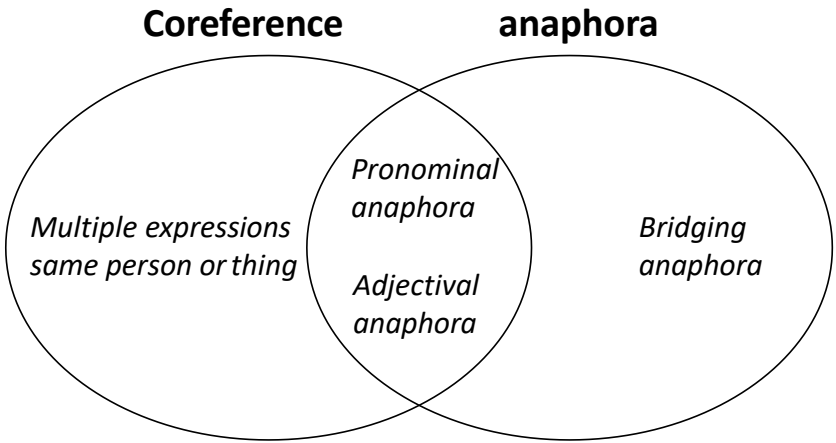
1. Not all noun phrases have reference

- Every student like his speech
- No student like his speech

"Every student"
"No student" don't refer to sth

2. Not all anaphoric relations are co-referential (bridging anaphora)

- I attended **the meeting** yesterday. **The presentation** was awesome!



M
P

cataphora

I almost stepped on **it**.
It was a big **snake**…

first pronoun → next entity

Coreference Model

How to Cluster Mentions?

After detecting this all mentions in a text, we need to cluster them!

Ivanka
Donald
he
her
she

Ivanka was happy that **Donald** said **he** considered nominating **her** because **she** is very good with numbers

Coreference Model

How to Cluster Mentions?

After detecting this all mentions in a text, we need to cluster them!

Ivanka

Donald

he

her

she

Ivanka was happy that **Donald** said **he** considered nominating **her** because **she** is very good with numbers

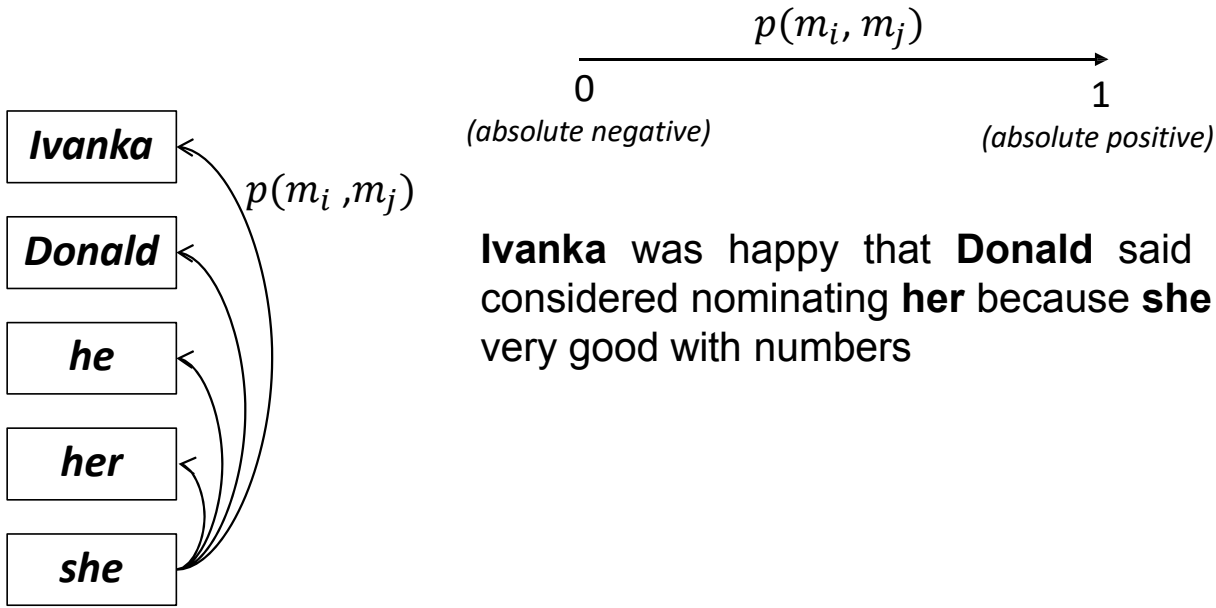
Gold cluster 1

Gold cluster 2

Coreference Model

How to Cluster Mentions?

- Train a binary classifier that assigns every pair of mentions a probability of being coreferent: $p(m_i, m_j)$



Ivanka was happy that **Donald** said **he** considered nominating **her** because **she** is very good with numbers

Coreference Model

Mention Pair Training

- N mentions in a document
- $y_{ij} = 1$ if mentions m_i and m_j are coreferent, -1 if otherwise
- Just train with regular cross-entropy loss (looks a bit different because it is binary classification)

sum over every pairwise decision

$$J = -\sum_{i=2}^{N}\sum_{j=1}^{i} y_{ij} \log p(m_j, m_i)$$

Coreferent mentions pairs should get high probability, others should get low probability

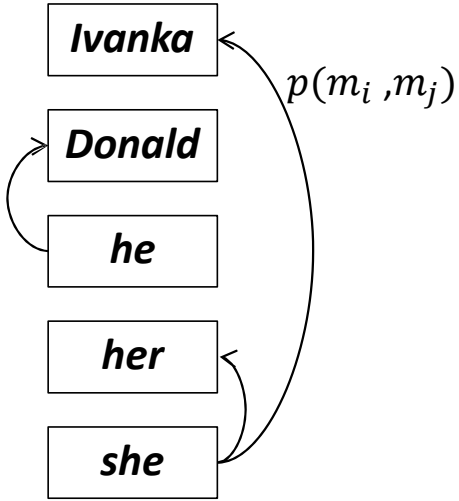
Iterate through mentions

Iterate through candidate antecedents (previously occurring mentions)

Coreference Model

Mention Pair Testing

- Coreference resolution is a clustering task, but we are only scoring pairs of mentions… what to do?
- Pick some threshold (e.g., 0.5) and add coreference links between mention pairs where p(mi, mj) is above the threshold

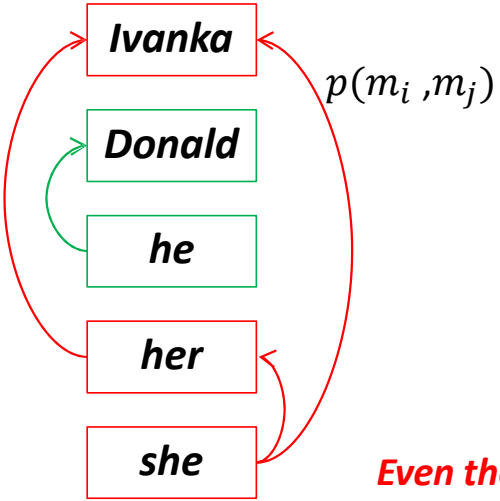


Ivanka was happy that **Donald** said **he** considered nominating **her** because **she** is very good with numbers

Coreference Model

Mention Pair Testing

- Pick some threshold (e.g., 0.5) and add coreference links between mention pairs where $p(m_i, m_j)$ is above the threshold
- Take the transitive closure to get the clustering



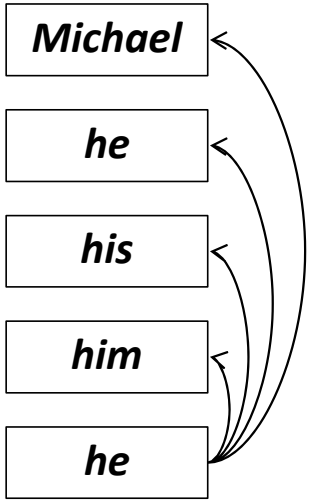
Ivanka was happy that **Donald** said **he** considered nominating **her** because **she** is very good with numbers

Even though the model did not predict this coreference link, Ivanka and her are coreferent due to transitivity

Coreference Model

Mention Pair Testing: Issue

- Assume that we have a **long document** with the following mentions
- Michael… he … his … him … <several paragraphs>
- … won the game because he …



Many mentions only have one clear antecedent but we are asking the model to predict all of them

Alternative solution: instead train the model to predict only one antecedent for each mention

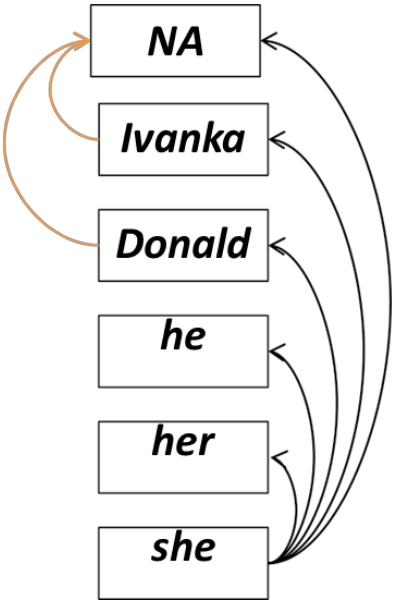
Mention Ranking

Coreference Model

Mention Ranking

- Assign each mention its highest scoring candidate antecedent according to the model
- Dummy NA mention allows model to decline linking the current mention to anything ("singleton" or "first" mention)

link to NA → singleton

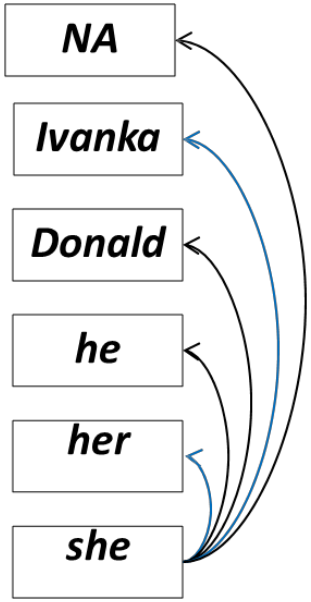


What can be the best antecedent for **she**?

Coreference Model

Mention Ranking

- Assign each mention its highest scoring candidate antecedent according to the model
- Dummy NA mention allows model to decline linking the current mention to anything ("singleton" or "first" mention)



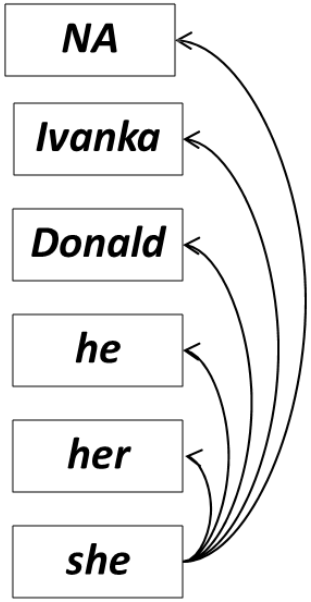
What can be the best antecedent for she?

Positive examples: model has to assign a high probability to either one (but not necessarily both)

Coreference Model

Mention Ranking

- Assign each mention its highest scoring candidate antecedent according to the model
- Dummy NA mention allows model to decline linking the current mention to anything ("singleton" or "first" mention)



What can be the best antecedent for she?

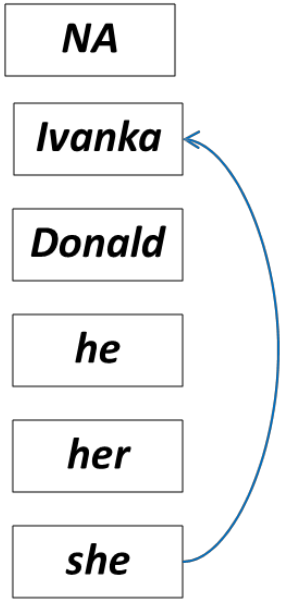
Apply a **softmax** over the scores for candidate antecedents so probabilities sum to 1

- p(NA, she) = 0.1
- p(Ivanka, she) = 0.5
- p(Donald, she) = 0.1
- p(he, she) = 0.1
- p(her, she) = 0.2

Coreference Model

Mention Ranking

- Assign each mention its highest scoring candidate antecedent according to the model
- Dummy NA mention allows model to decline linking the current mention to anything ("singleton" or "first" mention)



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Apply a **softmax** over the scores for candidate antecedents so probabilities sum to 1

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- p(he, she) = 0.1
- p(her, she) = 0.2

only add highest scoring coreference link

Coreference Model

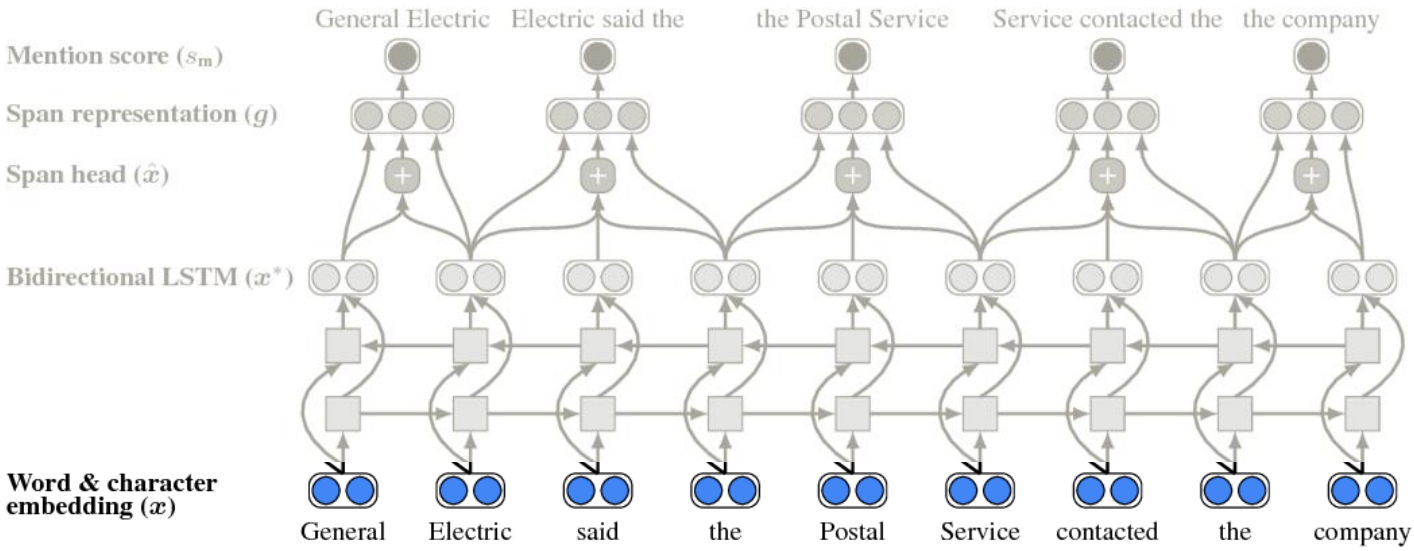
How do we compute the probabilities?
End to End Model (Lee at al., 2017)

- Current state-of-the-art model for coreference resolution (before 2019)
- Mention ranking model
- Improvements over simple feed-forward NN
  - Use an LSTM
  - Use attention (will learn about this in Lecture 10)
  - Do mention detection and coreference end-to-end
    - No mention detection step

Coreference Model

End to End Model (Lee at al., 2017)

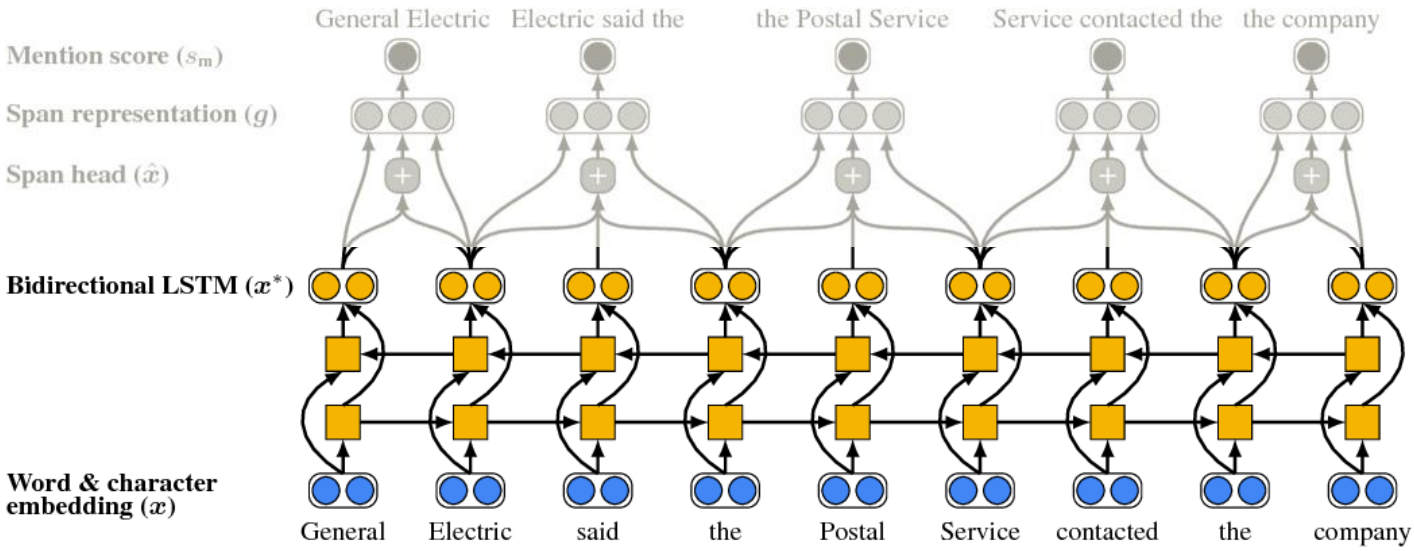
- First embed the words in the document using a word embedding matrix and a character-level embedding



Coreference Model

End to End Model (Lee at al., 2017)

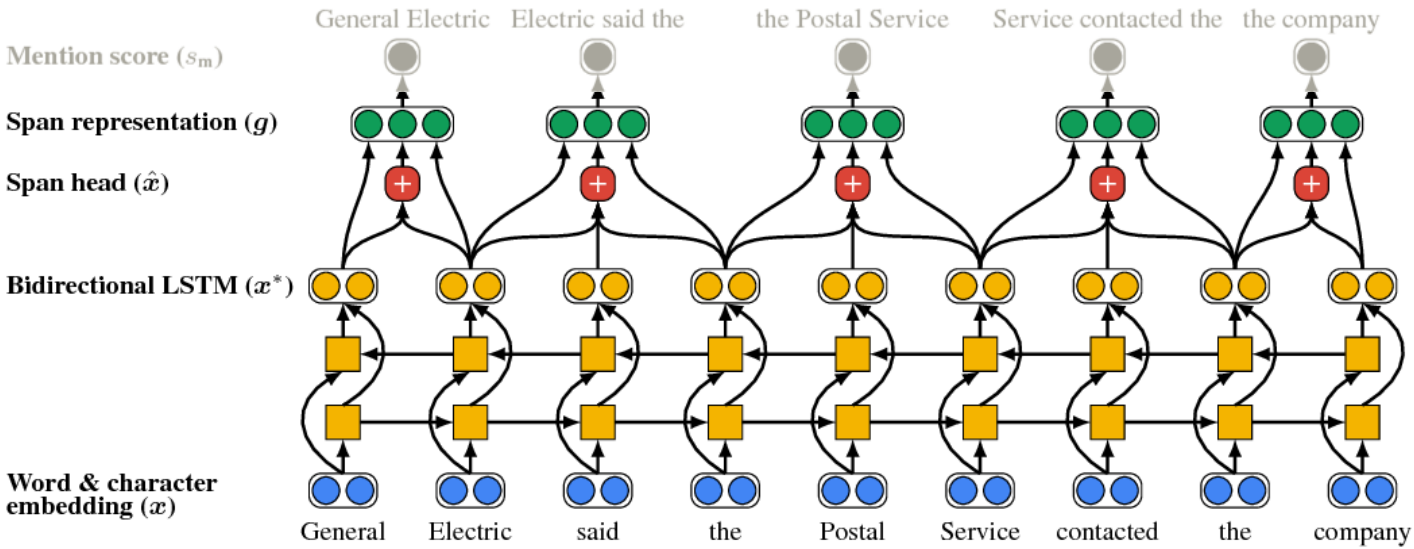
- Then run a bidirectional LSTM over the document



Coreference Model

End to End Model (Lee at al., 2017)

- *Next, represent each span of text i going from START(i) to END(i) as a vector*



Coreference Model

End to End Model (Lee at al., 2017)

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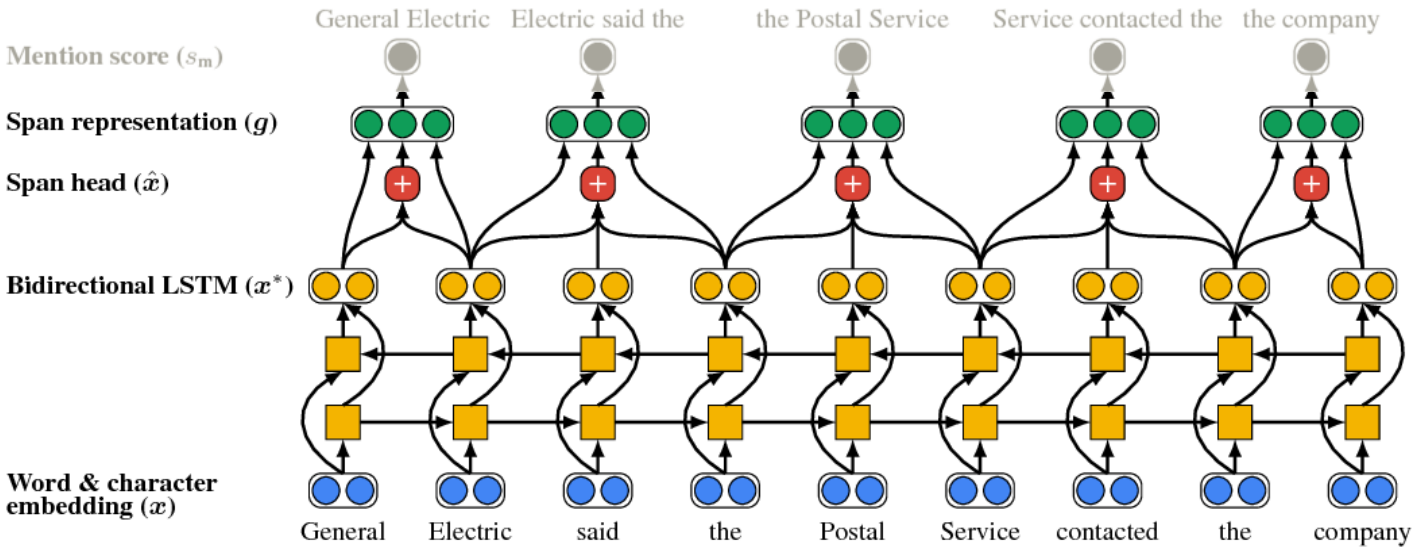
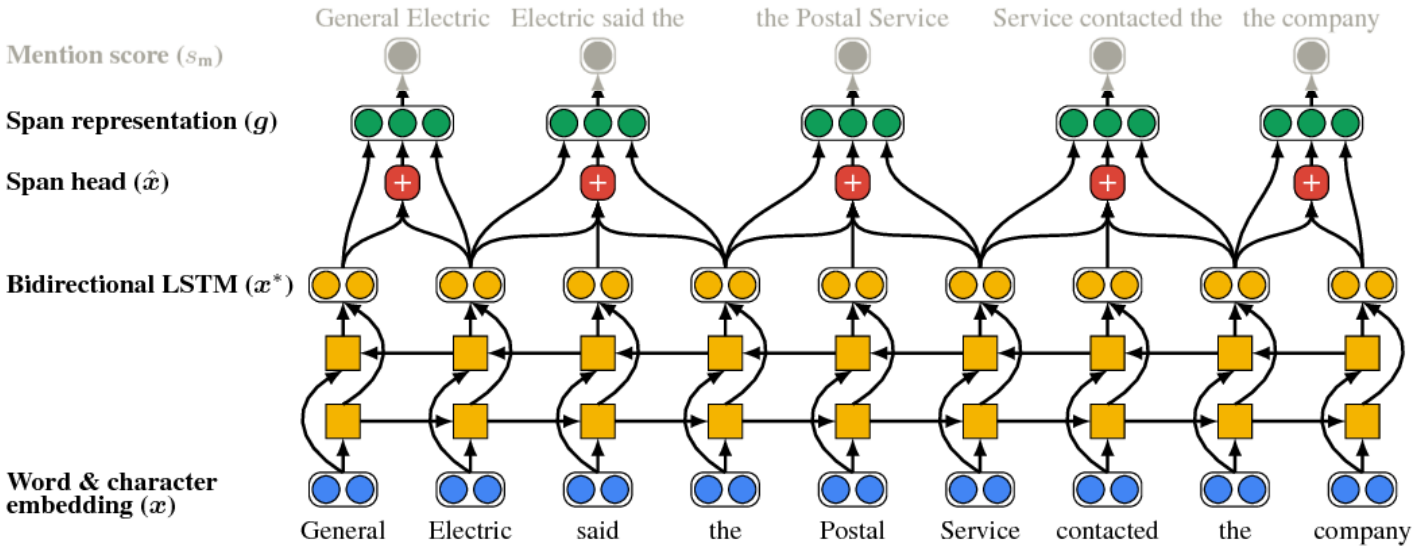


General, General Electric, General Electric said, … Electric, Electrid said,… will all get its own vector representation

Coreference Model

End to End Model (Lee at al., 2017)

- *Next, represent each span of text i going from START(i) to END(i) as a vector*

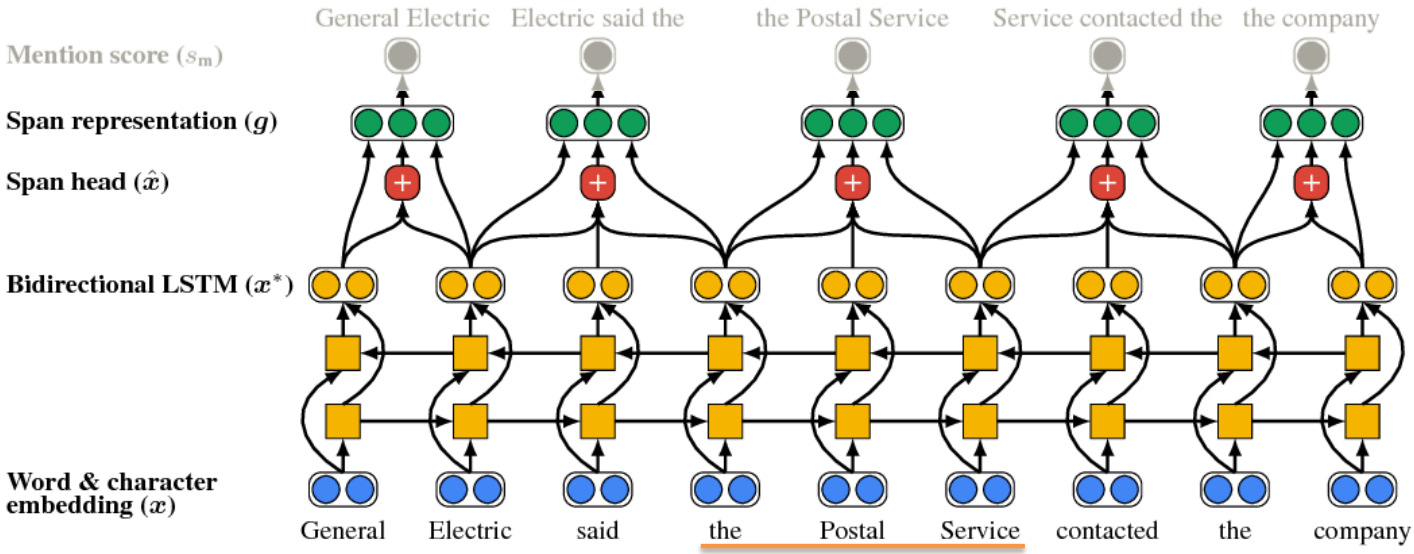


Span Representation: $\boldsymbol{g}_i = [\boldsymbol{x}^*_{\text{START}(i)}, \boldsymbol{x}^*_{\text{END}(i)}, \hat{\boldsymbol{x}}_i, \phi(i)]$

Coreference Model

End to End Model (Lee at al., 2017)

- *Next, represent each span of text i going from START(i) to END(i) as a vector. For example, for "the postal service"*



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Coreference Model

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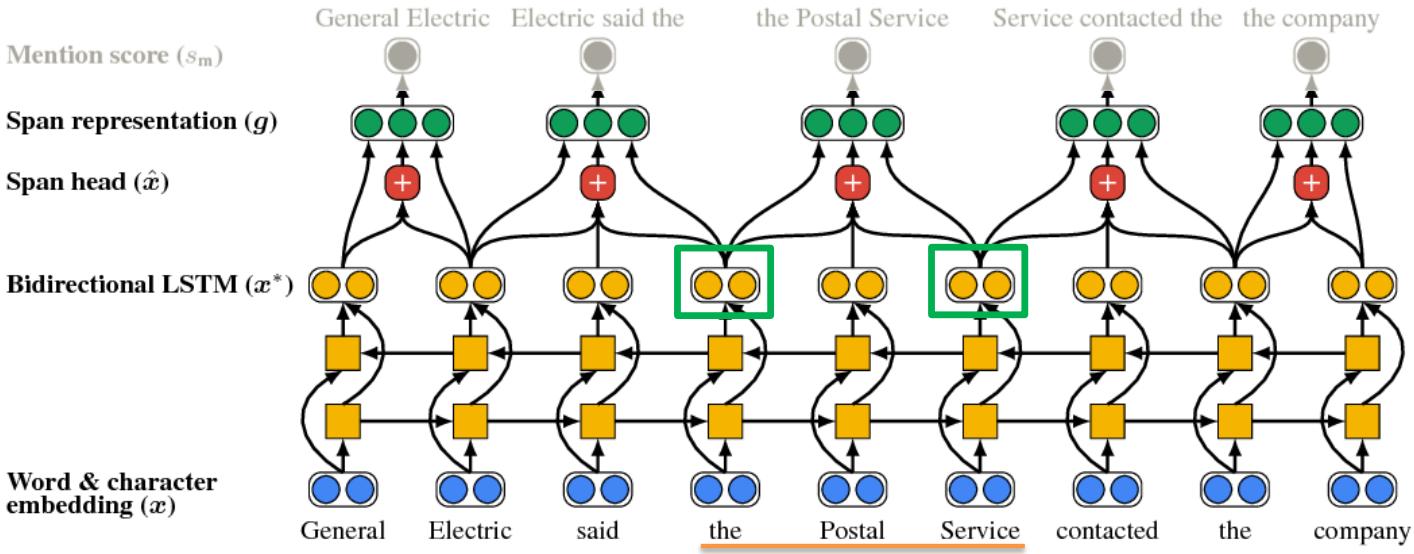

Span Representation: $\boldsymbol{g}_i = [\boldsymbol{x}^*_{\text{START}(i)}, \boldsymbol{x}^*_{\text{END}(i)}, \hat{\boldsymbol{x}}_i, \phi(i)]$

Bi-LSTM hidden states for span's start and end

Coreference Model

End to End Model (Lee at al., 2017)

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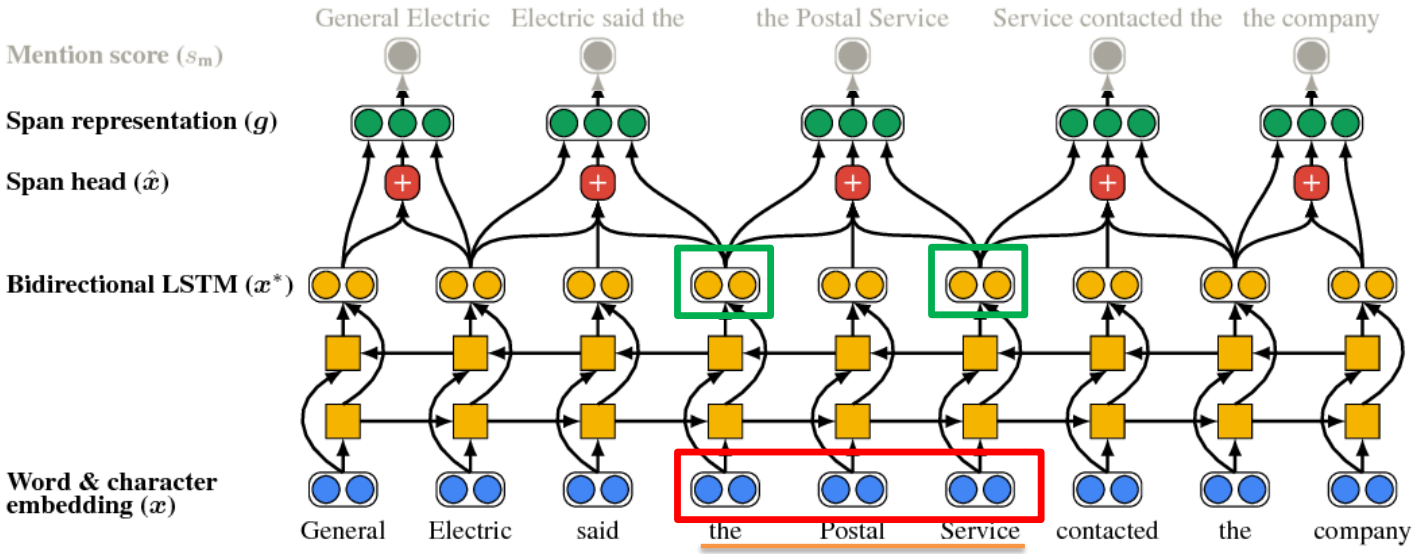


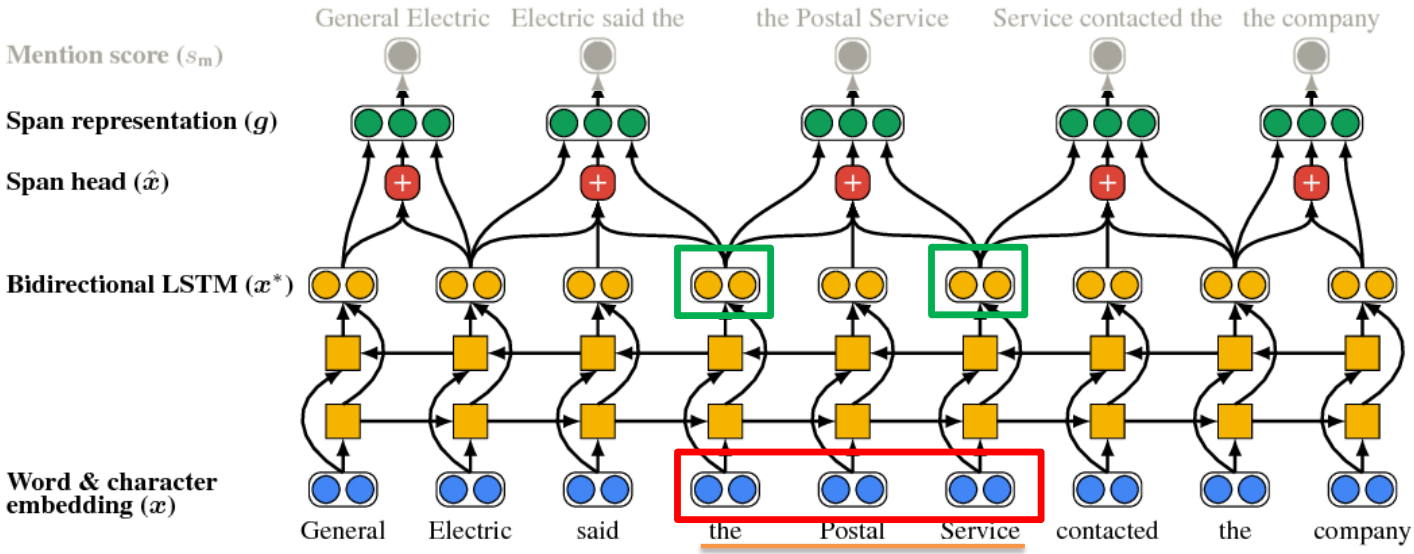
Span Representation: $\boldsymbol{g}_i = [\boldsymbol{x}^*_{\text{START}(i)}, \boldsymbol{x}^*_{\text{END}(i)}, \hat{\boldsymbol{x}}_i, \phi(i)]$

Attention-based representation (Lecture 10)

Coreference Model

End to End Model (Lee at al., 2017)

- *Next, represent each span of text i going from START(i) to END(i) as a vector. For example, for "the postal service"*



Span Representation: $\boldsymbol{g}_i = [\boldsymbol{x}^*_{\text{START}(i)}, \boldsymbol{x}^*_{\text{END}(i)}, \hat{\boldsymbol{x}}_i, \phi(i)]$

eg. time for tagging

Additional features

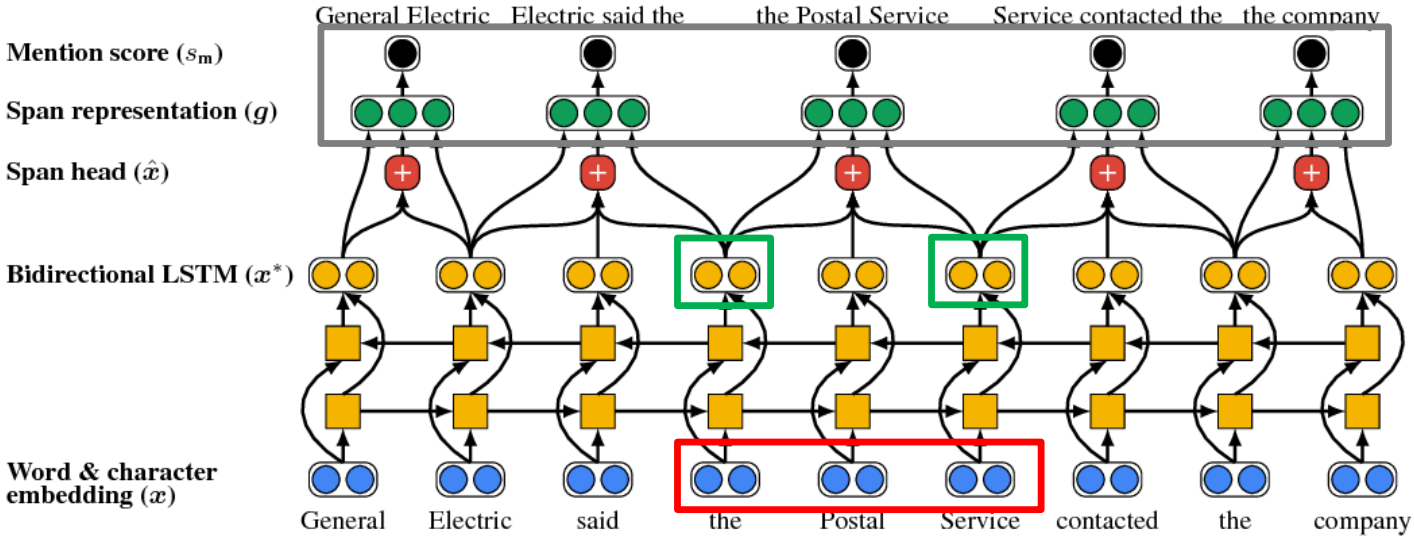
Coreference Model

End to End Model (Lee at al., 2017)

- *Next, represent each span of text i going from START(i) to END(i) as a vector.*

$$s(i,j) = s_{\mathrm{m}}(i) + s_{\mathrm{m}}(j) + s_{\mathrm{a}}(i,j)$$

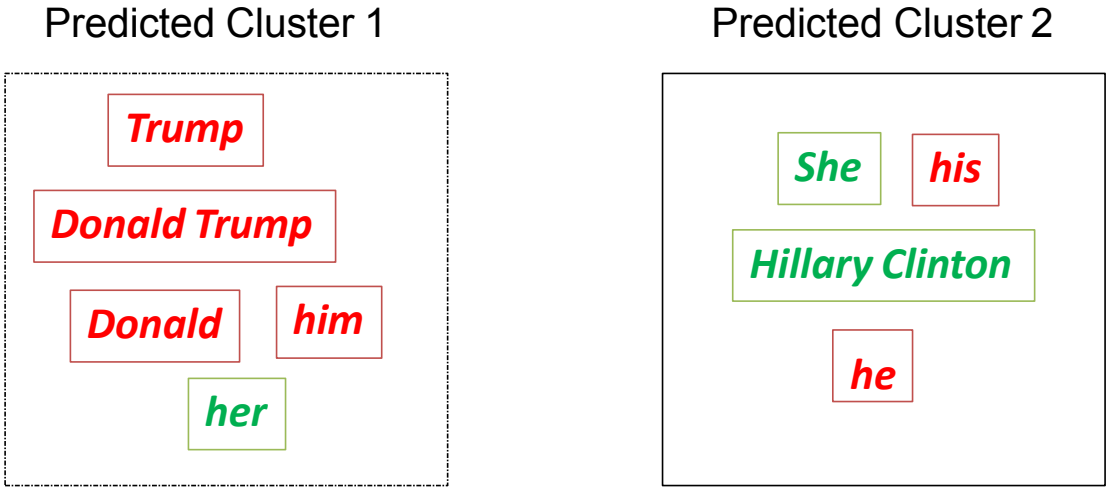
Are spans i and j conference mentions? ***Is i a mention?*** ***Is j a mention?*** ***Do they look coreferent?***



Coreference Evaluation

How to evaluate coreference?

There are different types of metrics available for evaluating coreference, such as B-CUBED, MUC, CEAF, LEA, BLANC, or Often report the average over a few different metrics

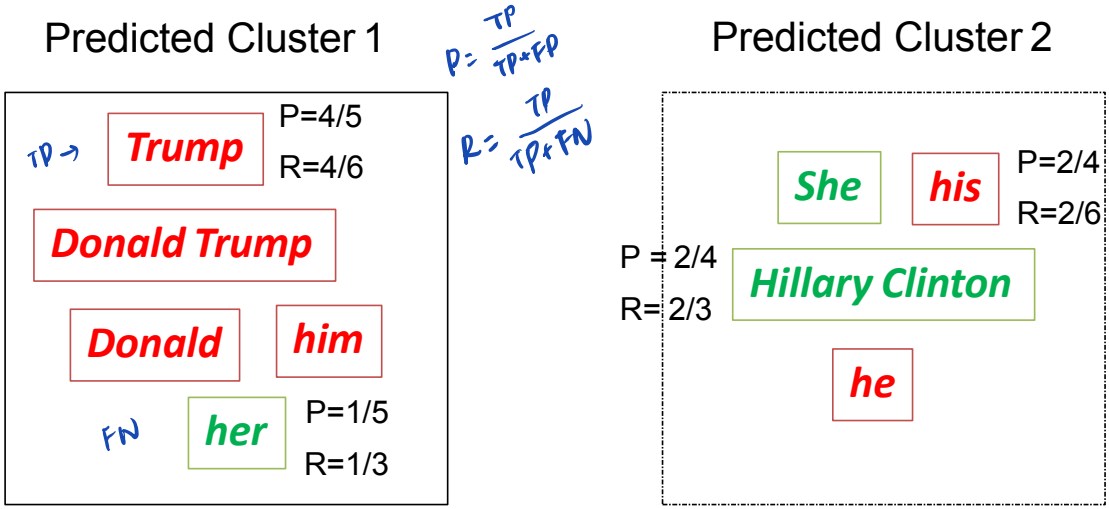


Coreference Evaluation

How to evaluate coreference?

Let's evaluate with B-CUBED metrics

- Compute **P**recision and **R**ecall for each mention.



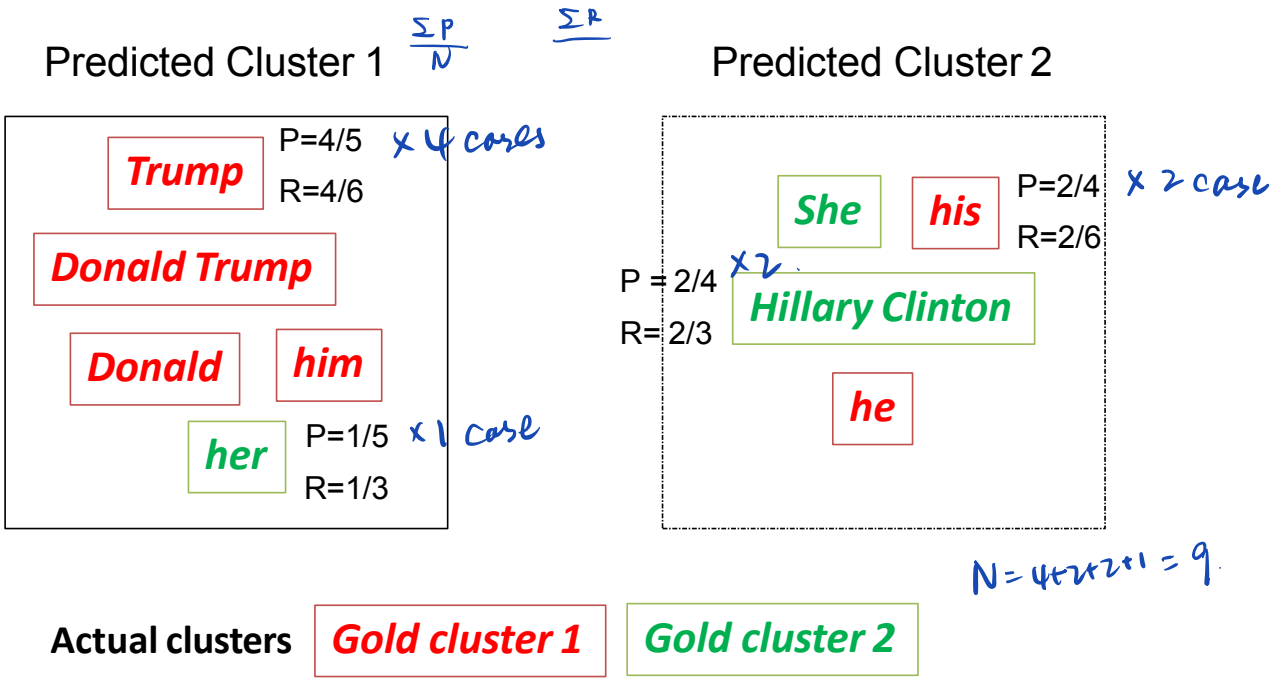
Actual clusters *Gold cluster 1* *Gold cluster 2*

Coreference Evaluation

How to evaluate coreference?

Let's evaluate with B-CUBED metrics

- Compute precision and recall for each mention.
- Average the individual Ps and Rs



Coreference Evaluation

Performance Comparison

OntoNotes dataset: ~3000 documents labeled by humans

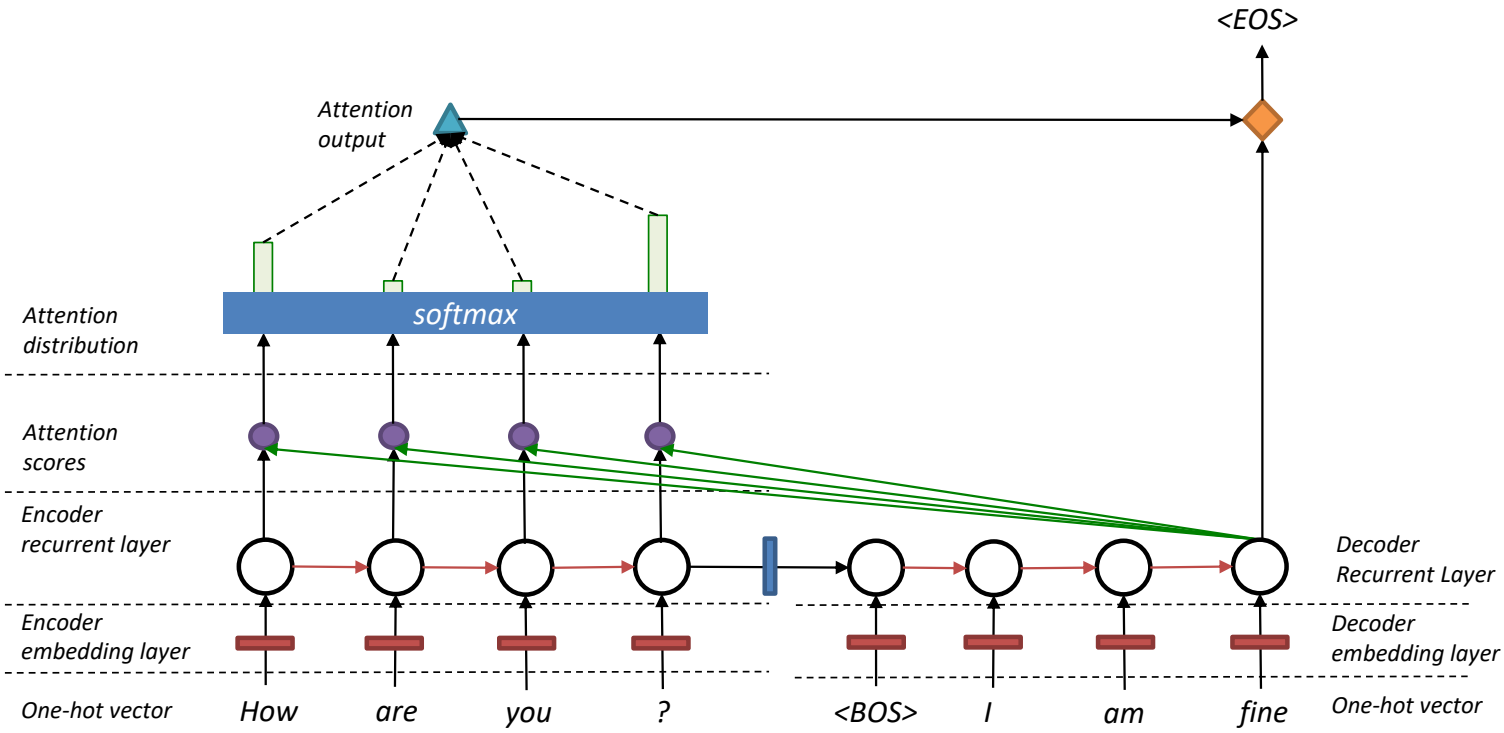
- English and Chinese data

Model	Approach	English	Chinese
Lee et al. (2010)	Rule-based system	~55	~50
Chen & Ng (2012) [CoNLL 2012 Chinese winner]	Non-neural machine learning models	54.5	57.6
Fernandes (2012) [CoNLL 2012 English winner]		60.7	51.6
Wiseman et al. (2015)	Neural mention ranker	63.3	—
Lee et al. (2017)	Neural mention ranker (end-to-end style)	67.2	--
UsydNLP (2019)	Neural mention ranker with lemma cross validation	74.87	--

lemmatisation

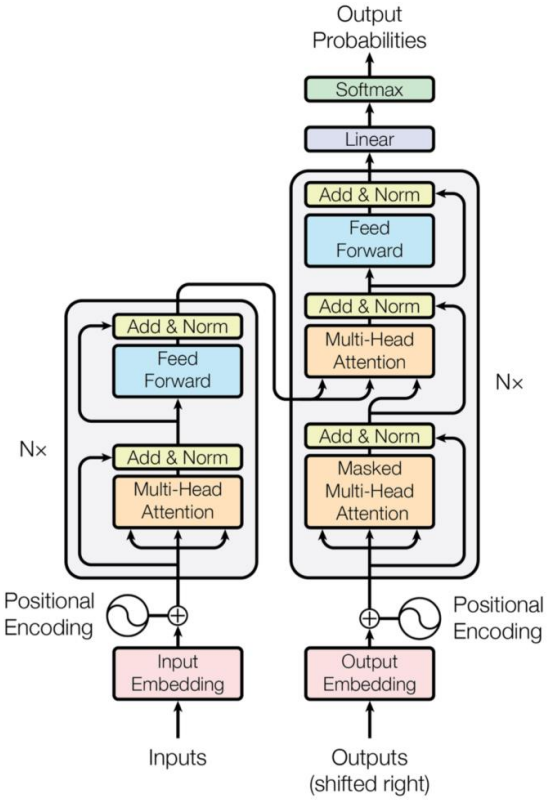
Preview: Week 10

Attention and Reading Comprehension



0 Preview: Week 11

Transformer and Machine Translation



/ Reference

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