# Information Extraction

### Announcements

- Course evaluation: please fill out
- Bring laptop on Wednesday
  - NLP research at Columbia
  - Final review
- Final exam: 12/9, final is cumulative
- What topics would you like to hear about again?

# What topics would you like covered in review?

Summarization

Dialog

Machine translation

Neural net architectures

**Attention** 

Word embeddings

Word sense disambiguation

Semantics

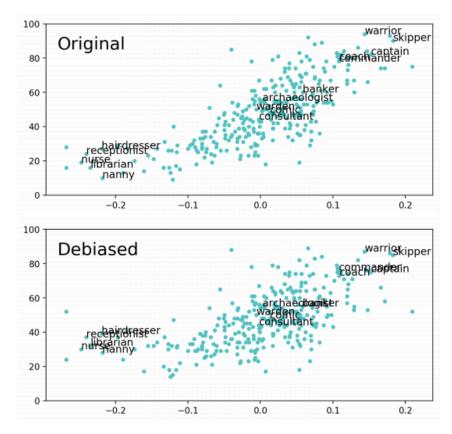
# Are there any other topics you would like covered?

## Summing up on bias.

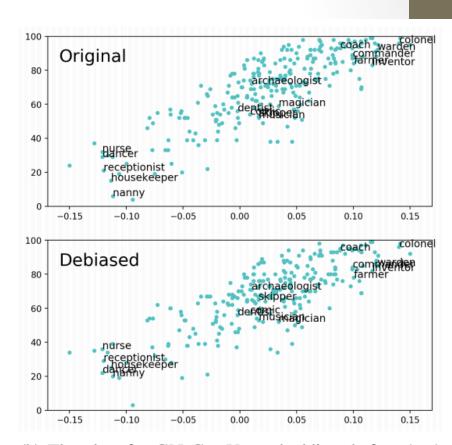
- There are methods for de-biasing word embeddings
  - Remove gender bias by zeroing the gender project for each word on a pre-defined gender direction (Boukbasi et al 2016)
  - Train debiased word embeddings from scratch by concentrating gender information in last coordinate – encourage words in different groups to differ in last coordinate

## Do debiasing methods work?

- Lipstick on a pig paper claims they do not
- Hides the bias
- Still reflected in similarities between gender neutral words
  - E.g., "math" "delicate"
- Three experiments
  - Do male and female biased words cluster together?
  - % male/female socially biased words among k nearest neighbors of target word
  - Predict the gender of a word



(a) The plots for HARD-DEBIASED embedding, before (top) and after (bottom) debiasing.



(b) The plots for GN-GLOVE embedding, before (top) and after (bottom) debiasing.

# Do we care if embeddings are biased?

### Information Extraction



Extraction of concrete facts from text

Named entities, relations, events

 Often used to create a structured knowledge base of facts



 Kathy McKeown, a professor from Columbia University in New York City, took a train yesterday to Washington DC.

### Named Entities



• Kathy McKeown<sub>per</sub>, a professor from Columbia University<sub>org</sub> in New York City<sub>loc</sub>, took a train yesterday to Washington  $DC_{loc}$ .

## Named Entities, Relations



• Kathy McKeown<sub>per</sub>, a professor from Columbia University<sub>org</sub> in New York City<sub>loc</sub>, took a train yesterday to Washington  $DC_{loc}$ .

- Kathy McKeown from Columbia
- Columbia in New York City

# Named Entities, Relations, Events



 Kathy McKeown<sub>per</sub>, a professor from Columbia University<sub>org</sub> in New York City<sub>loc</sub>, took a train yesterday to Washington DC<sub>loc</sub>.

Kathy McKeown took a train (yesterday)

# Entity Discovery and Linking



Kathy McKeown, a professor from Columbia University in New York City, took a train yesterday to Washington DC.



Main page
Contents
Featured content
Current events
Random article
Donate to Wikipedia
Wikipedia store

Interaction



#### Kathleen McKeown

From Wikipedia, the free encyclopedia

Secure https://en.wikipedia.org/wiki/Kathleen\_McKeown

**Kathleen McKeown** is an American computer scientist, specializing in natural language processing. She is currently the Henry and Gertrude Rothschild Professor of Computer Science and Director of the Institute for Data Sciences and Engineering at Columbia University.

McKeown received her B.A. from Brown University in 1976 and her PhD in Computer Science in 1982 from the University of Pennsylvania<sup>[1][2]</sup> and has spent her career at Columbia. She was the first woman to be tenured in the university's School of Engineering and Applied Science and was the first woman to serve as Chair of the Department of Computer Science,<sup>[3]</sup> from 1998 to 2003. She has also served as Vice Dean for Research in the School of Engineering and Applied Science.

# IE for Template Filling Relation Detection

Given a set of documents and a domain of interest, fill a table of required fields.

### For example:

Number of car accidents per vehicle type and number of casualties in the accidents.

Vehicle Type	# accidents	# casualties	Weather
SUV	1200	190	Rainy
Trucks	200	20	Sunny

## Never-Ending Language Learner

Tom Mitchell CMU

- Can computers learn to read?
- Browses the web and attempts to extract facts from hundreds of millions of web pages
- Attempts to improve its methods and accuracy
- To date, 50 million candidate facts at different levels of confidence
- http://rtw.ml.cmu.edu/rtw/

## IE for Question Answering

Q: When was Gandhi born?

A: October 2, 1869

Q: Where was Bill Clinton educated?

A: Georgetown University in Washington, D.C.

Q: What was the education of Yassir Arafat?

A: Civil Engineering

Q: What is the religion of Noam Chomsky?

A: Jewish

## State of the Art (English)



#### F-measure

- Named Entities (news)
- Relations (slot filling)
- Events (nuggets)

- 89%
- 59%
- 63%

Methods: Sequence labeling (MEMM, CRF), neural nets, distant learning Features: linguistic features, similarity, popularity, gazeteers, ontologies, verb triggers

# Where Have You Been Entity Discovery and Linking?



Grow with DEFT	2006-2011	2012-2017 HENG JI, RPI	
Mention Extraction	Human (most)	Automatic	
NIL Clustering	None	64 methods	
Foreign Languages	Chinese (5%-10% lower than English)	System for 282 languages (Chinese/Spanish comparable to/Outperform English); research toward 3,000 languages	
Document Size	-	500 →90,000 documents	
Genre	News, web blog	News, Discussion Forum, Web blog, Tweets	
Entity Types	PER, GPE, ORG	PER, GPE, ORG, LOC, FAC, hundreds of fine-grained types for typing	
Mention Types	Name or all concepts (most)	Name, Nominal, Pronoun (for BeST)	
KB	Wikipedia	Freebase → List only	
Training Data	20,000 queries (entity mentions)	500 → 0 documents; unsupervised linking comparable to supervised linking	
#(Good) Papers	62	110 (new KBP track at ACL); 6 tutorials at top conferences	

Slide from Heng Ji

## Approach for NER

- <PERSON>Alexander Mackenzie</PERSON> , (<TIMEX >January 28, 1822</TIMEX> <TIMEX>April 17, 1892</TIMEX>), a building contractor and writer, was the second Prime Minister of <GPE>Canada</GPE> from ....
- Statistical sequence labeling techniques can be used similar to POS tagging
  - Word-by-word sequence labeling
  - Example of features
    - POS tags
    - Syntactic constituents
    - Shape features
    - Presence in a named entity list

# Supervised Approach for relation detection

- Given a corpus of annotated relations between entities, train a classifier:
  - A binary classifier
    - Given a span of text and two entities -> decide if there is a relationship between these two entities
- Features
  - Types of two named entities
  - Bag of words
  - POS of words in between
- Example:
  - A rented SUV went out of control on Sunday, causing the death of seven people in Brooklyn
  - Relation: Type = Accident, Vehicle Type = SUV, casualty = 7, weather = ?

# Pattern Matching for Relation Detection

- Patterns:
  - "[CAR\_TYPE] went out of control on [TIMEX], causing the death of [NUM] people"
  - "[PERSON] was born in [GPE]"
  - "[PERSON] was graduated from [FAC]"
  - "[PERSON] was killed by <X>"
- Matching Techniques
  - Exact matching
    - Pros and Cons?
  - Flexible matching (e.g., [X] was .\* killed .\* by [Y])
    - Pros and Cons?

# Is rule-based exact matching still used (take a guess)?

Yes

No

# What problems would arise with flexible matching?

## Pattern Matching

- How can we come up with these patterns?
- Manually?
  - Task and domain-specific
  - Tedious, time consuming, not scalable
- Machine learning, semi-supervised approaches

### Bootstrapping Seed Born in Connecticut on July 8, Born in Y on Z, X was 1946, George was **Patterns** Pattern Tuple Search Extraction Pattern Tuple Set Set Tuple Pattern Search Extraction Seed George W. Bush was born < George W. Bush, Connecticut> Tuples in Connecticut

# Task: Produce a biography of [person]

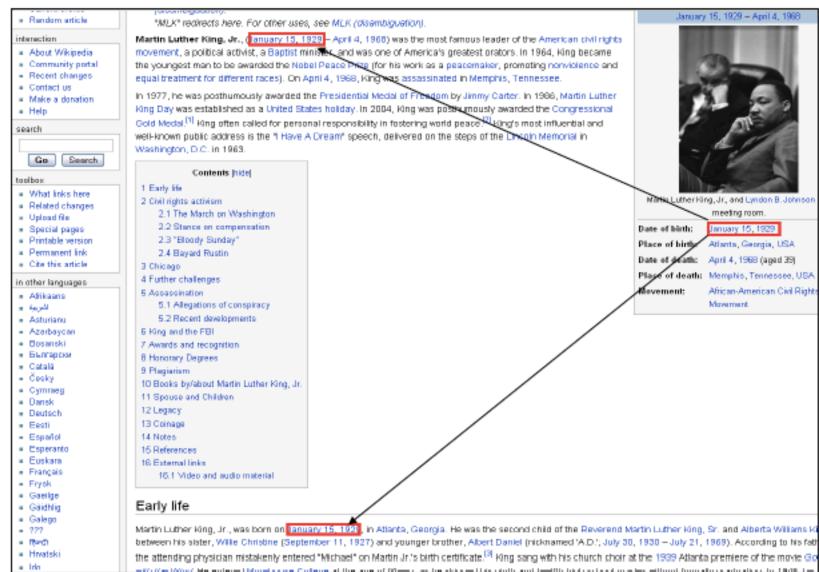
- 1. Name(s), aliases:
- 2. \*Date of Birth or Current Age:
- 3. \*Date of Death:
- 4. \*Place of Birth:
- 5. \*Place of Death:
- 6. Cause of Death:
- 7. Religion (Affiliations):
- 8. Known locations and dates:
- 9. Last known address:
- 10. Previous domiciles:
- 11. Ethnic or tribal affiliations:
- 12. Immediate family members
- 13. Native Language spoken:
- 14. Secondary Languages spoken:
- 15. Physical Characteristics
- 16. Passport number and country of issue:
- 17. Professional positions:
- 18. Education
- 19. Party or other organization affiliations:
- 20. Publications (titles and dates):

## Biography – two approaches

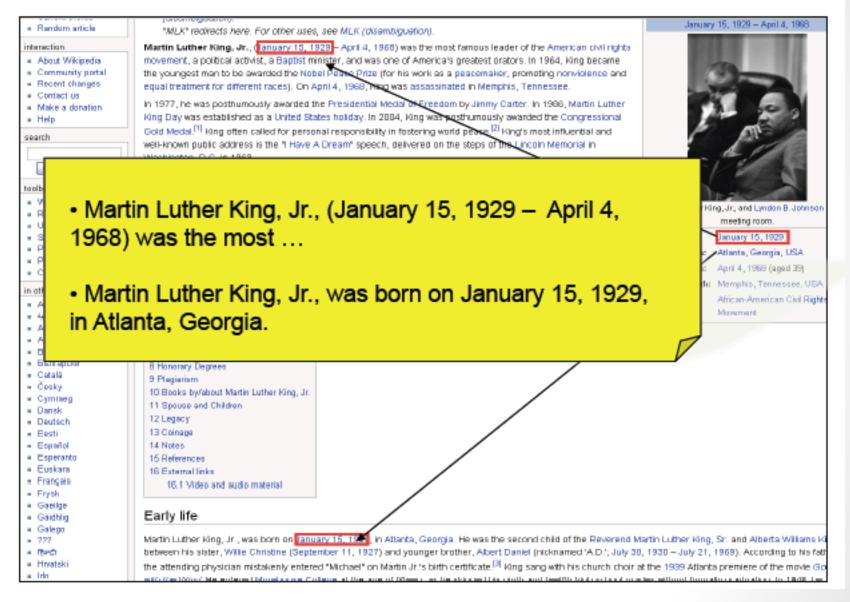
 To obtain high precision, handle each slot independently using bootstrapping to learn IE patterns.

• To improve the recall, utilize a biographical sentence classifier

## Biography patterns from Wikipedia



## Biography patterns from Wikipedia



### Run NER on these sentences

- <Person> Martin Luther King, Jr. </Person>, (<Date>January 15, 1929</Date> <Date> April 4, 1968</Date>) was the most...
- <Person> Martin Luther King, Jr. </Person>, was born on <Date>
  January 15, 1929 </Date>, in <GPE> Atlanta, Georgia </GPE>.
- Take the token sequence that includes the tags of interest + some context (2 tokens before and 2 tokens after)

### Convert to Patterns:

- <Target\_Person> (<Target\_Date> <Date>) was the
- <Target\_Person> , was born on <Target\_Date>, in
- Remove more specific patterns if there is a pattern that contains other, take the smallest > k tokens.
- Target\_Person> , was born on <Target\_Date>
- → <Target\_Person> (<Target\_Date> <Date>)
- Finally, verify the patterns manually to remove irrelevant patterns.

### Examples of Patterns:

### 502 distinct place-of-birth patterns:

```
- 600 <Target_Person> was born in <Target_GPE>
- 169 <Target_Person> ( born <Date> in <Target_GPE> )
- 44 Born in <Target_GPE> , <Target_Person>
- 10 <Target_Person> was a native <Target_GPE>
- 10 <Target_Person> 's hometown of <Target_GPE>
- 1 <Target_Person> was baptized in <Target_GPE>
```

### 291 distinct date-of-death patterns:

```
770 <Target_Person> (<Date> - <Target_Date>)
92 <Target_Person> died on <Target_Date>
19 <Target_Person> <Date> - <Target_Date>
16 <Target_Person> died in <GPE> on <Target_Date>
3 <Target_Person> passed away on < Target_Date>
1 <Target_Person> committed suicide on <Target_Date>
```

## Biography as an IE task

 This approach is good for the consistently annotated fields in Wikipedia: place of birth, date of birth, place of death, date of death

 Not all fields of interests are annotated, a different approach is needed to cover the rest of the slots

## Bouncing between Wikipedia and Google

- Use one seed tuple only:
  - <Target Person> and <Target field>
    - Google: "Arafat" "civil engineering", we get:



Web Images Video News Maps more »

Arafat "civil engineering"

Search

Advanced Search Proferences

#### Web

#### Yasser Arafat

By 1956 Arafat graduated with a bachelor's degree in **civil engineering** and served as a second lieutenant in the Egyptian Army during the Suez Crisis. ... www.jewishyirluallibrary.org/jspurce/biography/arafat.html - 61k - Cached - Similar pages - Note this

#### Yasser Arafat: Biography and Much More from Answers.com

In the 1950s, **Arafat** studied at Fu'ad I University in Cairo (now Cairo University), majoring in **civil engineering**. He was reportedly a member of the Muslim ... www.answers.com/topic/yasser-**arafat** - 89k - Cached - Similar pages - Note this

#### Engplogy.com, Engineer Yasser Arafat, Nobel Piece Prize Winner ...

After the war Arafat studied civil engineering at the University of Cairo. He headed the Palestinian Students League and, by the time he graduated, ... www.engology.com/engogevassearafat.htm - 7k - Cached - Similar pages - Note this

#### Yasser Arafat and the Palestine Liberation Organization

It was there that Yasser **Arafat**, a **Civil Engineering student**, and his coterie, including Salah Khalaf (Abu Iyad), later to become **Arafat**'s second in command ... www.palestinefacts.org/pf\_1948to1987\_plo\_arafat.php - 14k -<u>Cached - Similar pages - Note this</u>

#### A Life in Retrospect: Yasser Arafat | TIME

Here's one thing we know for sure: Yasser **Arafa**t was a grand ... at King Fuad I University (now Cairo University), where he studied **civil engineering**] ... www.time.com/time/world/article/0,8599,781566-1,00.html - 39k - Cached - Similar pages - Note this

#### Yassir Arafat's Biography

Yasser **Arafat** was born in 1929 in Jerusalem. His full name is: Mohammed Abad Arouf **Arafat**. He studied **civil engineering** at CairoUniversity....

www.eretzylsroel.org/~jkatz/arafatbio.html - 72k - <u>Cached</u> - <u>Similar pages</u> - <u>Note this</u>

#### Biographical and other information on Yasser Arafat who is in bad ...

In 1951, at the age of 21, **Arafat** got military training with the Egyptian army. — In 1956, **Arafat** earned a degree in **civil engineering** at the University of ...

www.freemuslims.org/news/article.php?article=198 - 14k - Cached - Similar pages - Note this

#### Bouncing between Wikipedia and Google

- Use one seed tuple only:
  - Google: "Arafat" "civil engineering", we get:
    - ⇒ Arafat graduated with a bachelor's degree in civil engineering
    - ⇒ Arafat studied civil engineering
    - ⇒ Arafat, a civil engineering student
    - ⇒...
  - Using these snippets, corresponding patterns are created, then filtered out.

#### Bouncing between Wikipedia and Google

- Use one seed tuple only:
  - Google: "Arafat" "civil engineering", we get:
    - ⇒ Arafat graduated with a bachelor's degree in civil engineering
    - ⇒ Arafat studied civil engineering
    - ⇒ Arafat, a civil engineering student
    - ⇒...
  - Using these snippets, corresponding patterns are created, then filtered out manually
  - Due to time limitation the automatic filter was not completed.
  - To get more seed tuples, go to Wikipedia biography pages only and search for:
    - "graduated with a bachelor's degree in"
    - We get:

#### Bouncing between Wikipedia and Google

#### New seed tuples:

- "Burnie Thompson" "political science"
- "Henrey Luke" "Environment Studies"
- "Erin Crocker" "industrial and management engineering"
- "Denise Bode" "political science"
- ...
- Go back to Google and repeat the process to get more seed patterns!

Web Images Video News Maps more »

site:en.wikipedia.org "graduated with a bache

Search

Advanced Search
Preferences

#### Web

Resu

#### Burnie Thompson - Wikipedia, the free encyclopedia

In 2000 the **graduated with a bachelor's degree in political science** from California State University, Fullerton. Two years later he graduated from The ... en.wikipedia.org/wiki/Burnie Thompson - 19k - Cached - Similar pages - Note this

#### Roscoe Lee Browne - Wikipedia, the free encyclopedia

Born in Woodbury, New Jersey, Browne first attended historically black Lincoln University in Pennsylvania, and **graduated with a bachelor's degree in 194**5. ... en.wikipedia.org/wiki/Roscoe\_Lee\_Browne - 38k - <u>Cached</u> - <u>Similar pages</u> - <u>Note this</u>

#### Henry Luke Orombi - Wikipedia, the free encyclopedia

Robert has **graduated with a Bachelor's Degree in** Environment Studies from Makerere University and Daniel, a gifted musician like his father, is working on ... en.wikipedia.org/wiki/Henry\_Luke\_Orombi - 25k - <u>Cached</u> - <u>Similar pages</u> - <u>Note this</u>

#### Gustave Eiffel - Wikipedia, the free encyclopedia

Eiffel's study habits improved and he **graduated with a bachelor's degree in** both science and humanities. Eiffel went on to attend college at Sainte Barbe ... en.wikipedia.org/wiki/Gustave\_Eiffel - 52k - <u>Cached</u> - <u>Similar pages</u> - <u>Note this</u>

#### Erin Crocker - Wikipedia, the free encyclopedia

... New York, where she **graduated with a bachelor's degree in** industrial and management engineering in 2003. In 2002, Crocker signed with Woodring Racing to ... en.wikipedia.org/wiki/Erin\_Crocker - 30k - <u>Cached</u> - <u>Similar pages</u> - <u>Note this</u>

#### Jim Boeheim - Wikipedia, the free encyclopedia

Boeheim enrolled in Syracuse University as a student in 1963 and **graduated with a bachelor's degree in** social science in 1969(SU Athletics). ... en.wikipedia.org/wiki/Jim\_Boeheim - 30k - Cached - Similar pages - Note this

#### Denise Bode - Wikipedia, the free encyclopedia

She **graduated with a bachelor's degree in** political science from the University of Oklahoma where she chaired the University of Oklahoma Student Congress. ...

#### Bouncing back and forth

- Worked well for a fields such as education, publications, immediate family members, party, other organization activities
- Did not work well for other fields including religion, ethnic or tribal affiliations, previous domiciles -> too much noise
- Why is the bouncing idea better than using only one corpus?

# Why is bouncing back between two sources better than using just one?

# How are neural nets used for IE?

#### Organizing knowledge

It's a version of <u>Chicago</u> – the standard classic Macintosh menu font, with that distinctive thick diagonal in the "N".

**Chicago** was used by default for Mac menus through MacOS 7.6, and OS 8 was released mid-1997..

#### Cross-document co-reference resolution

It's a version of <u>Chicago</u> – the standard classic <u>Macintosh</u> menu font, with that distinctive thick diagonal in the "N".

<u>Chicago</u> was used by default for <u>Mac</u> menus through <u>MacO\$ 7.6</u>, and <u>O\$ 8</u> was released mid-1997..

#### Reference resolution: (disambiguation to Wikipedia)

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<u>Chicago</u> was used by default for <u>Mac</u> menus through <u>MacO\$ 7.6</u>, and <u>O\$ 8</u> was released mid-1997.











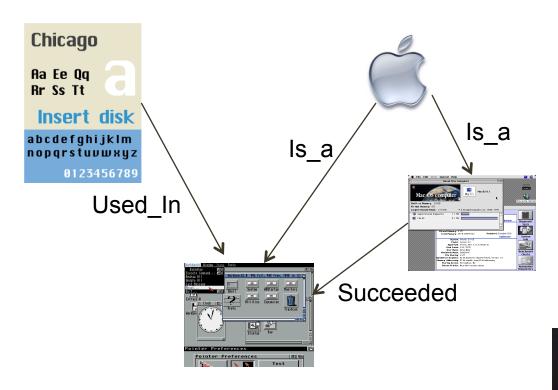




#### The "Reference" Collection has Structure

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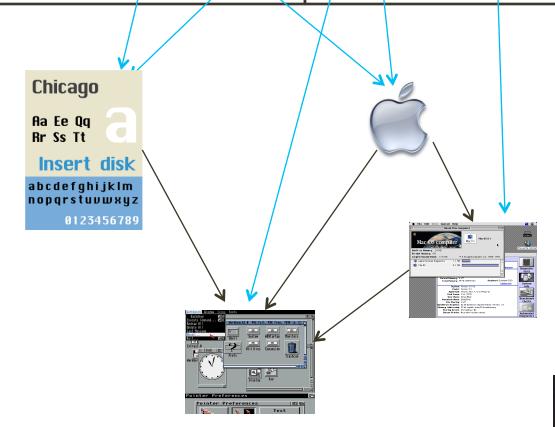


#### Analysis of Information Networks

It's a version of <u>Chicago</u> – the standard classic <u>Macintosh</u> menu font, with that distinctive thick diagonal in the "N".

Chicago was used by default for Mac menus through MacOS 7.6, and OS 8 was released mid-1997..

<u>Chicago VIII</u> was one of the early 70s-era <u>Chicago</u> albums to catch my ear, along with <u>Chicago II</u>.

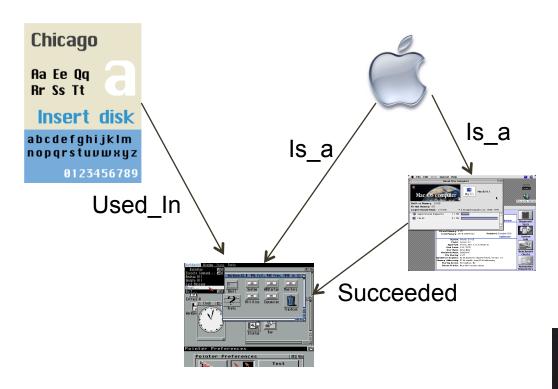






48

# Here – Wikipedia as a knowledge resource .... but can use other resources





# Wikification: The Reference Problem

Cycles of
Knowledge:
Grounding for/
using
Knowledge

Blumenthal (D) is a candidate for the U.S. Senate seat now held by Christopher Dodd (D), and he has held a commanding lead in the race since he entered it. But the Times report has the potential to fundamentally reshape the contest in the Nutmeg State.



Richard Blumenthal

From Wikipedia, the free encyclopedia

Democratic Party (United States)

From Wikipedia, the free encyclopedia

**United States Senate** 

From Wikipedia, the free encyclopedia

<u>Blumenthal</u> (<u>D</u>) is a candidate for the <u>U.S. Senate</u> seat now held by <u>Christopher Dodd</u> (<u>D</u>), and he has held a commanding lead in the race since he entered it. But the <u>Times</u> report has the potential to fundamentally reshape the contest in <u>the Nutmeg State</u>.

Chris Dodd

From Wikipedia, the free encyclopedia

The New York Times

From Wikipedia, the free encyclopedia

Connecticut

From Wikipedia, the free encyclopedia

#### Task Definition

A formal definition of the task consists of:

- 1. A definition of the **mentions** (concepts, entities) to highlight
- 2. Determining the target encyclopedic resource (**KB**)

3. Defining what to point to in the KB (title)

## Examples of Mentions (1)

Blumenthal (D) is a candidate for the U.S. Senate seat now held by Christopher Dodd (D), and he has held a commanding lead in the race since he entered it. But the Times report has the potential to fundamentally reshape the contest in the Nutmeg State.



Richard Blumenthal

From Wikipedia, the free encyclopedia

Democratic Party (United States)

From Wikipedia, the free encyclopedia

United States Senate

From Wikipedia, the free encyclopedia

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Chris Dodd

From Wikipedia, the free encyclopedia

The New York Times

From Wikipedia, the free encyclopedia

Connecticut

From Wikipedia, the free encyclopedia

# Neural Approach to Entity Linking (Wikification) Gupta, Singh and Roth, EMNLP 2017

- Learns a dense, unified representation of entities
  - Encodes semantic and background knowledge from multiple sources
  - An encoder for each source of information
  - Entity embeddings learned to be similar to encodings
- Only uses indirect supervision from Wikipedia/Freebase
- Can incorporate new entities without retraining existing representations
- http://cogcomp.org/papers/GuptaSiRo17.pdf

## Jointly Embedding Entity Information

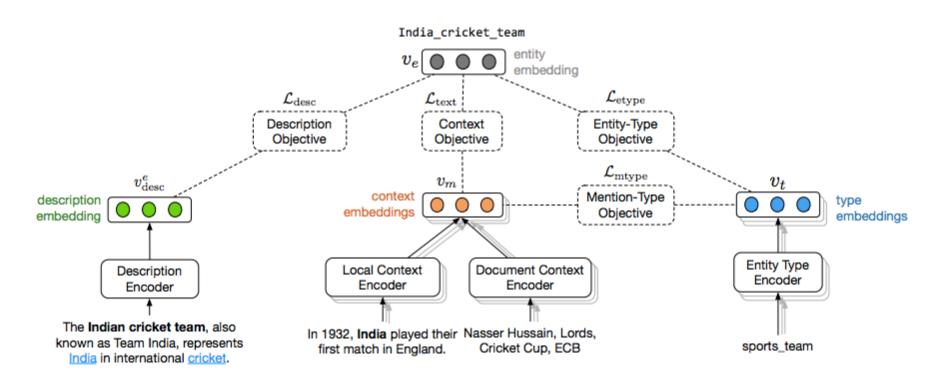


Figure 1: **Overview of the Model** (§ 3): Each entity has a Wikipedia description, linked mentions in Wikipedia (only one shown), and fine-grained types from Freebase (only one shown). We encode local and document-level mention contexts (§ 3.1), entity-description (§ 3.2), and fine-grained entity-types (§ 3.3 & § 3.4). Joint optimization (§ 3.5) over these provides the unified entity representations  $\{v_e\}$ .

## Jointly Embedding Entity Information

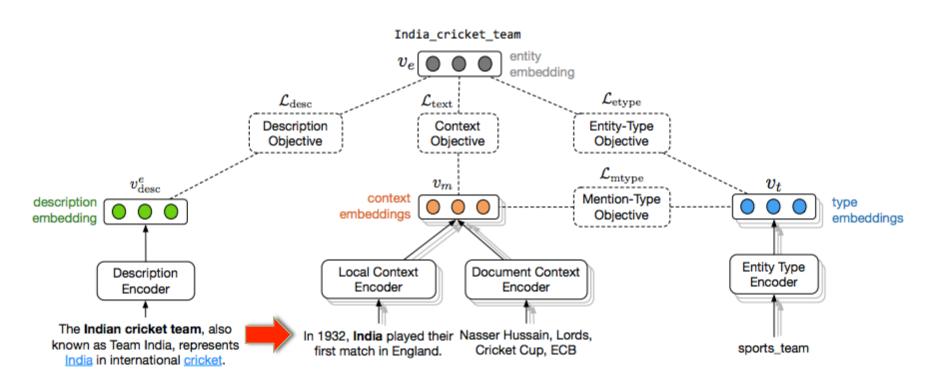


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## Look at Wikipedia

 Entity description: https:// en.wikipedia.org/wiki/ India\_national\_cricket\_team

## Encoding the mention context

In 1932, India played their first game in England.

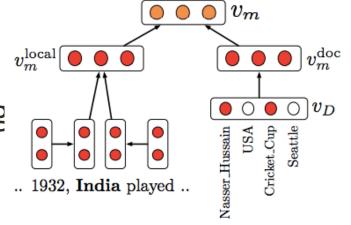
- Example mention contains two mentions: "India" and "England"
- Aim to disambiguate "India" to the team
  - Local context: "played" and "match"
  - Document context: to identify the sport
- Preserve the semantics: "England" should not match to a team

#### Local Context

- Given mention m in sentence: {w<sub>1</sub>, ..., m, .... w<sub>N</sub>}
- Left LSTM applied to  $w_1...m -> h_m^l$
- Right LSTM applied to m ....  $w_N -> \frac{1}{h_m}$
- $\overrightarrow{h_m}$ ,  $\overleftarrow{h_m}$  concatenated and passed through a single layer feed forward network

#### Document Context Encoder

- Bag of mentions vector:
  - USA, Pearl Jam, Nasser Hassain
- Compressed to a low dimensional representation using a single layer feed forward neural network
- Combine local and document representations to get a mention level encoding using concatenation and feed through a single layer feed forward network



$$v_m \in \mathbb{R}^d$$

# Joint inference using all mentions

As of 7 January 2019, *India* have played 533 Test matches

As of 16 June 2018, India have played 968 ODI matches

- Use an objective that encourages the mentions  $v_m$  to be similar to the entity description  $v_e$ 
  - Maximize the probability of predicting the correct entity from the mentions

$$\mathcal{L}_{\text{text}} = \frac{1}{M} \sum_{i=1}^{M} \log P_{\text{text}}(e_{m^{(i)}} | m^{(i)})$$

## **Encoding Entity Description D**

 Embed each word of the Wikipedia description as a d-dimensional vector

Encode as a fixed vector using a CNN:

$$v_{ ext{desc}}^e \in \mathbb{R}^d$$

# Learning the Type Representation

Embed type T in Freebase

Each entity can have multiple types

Jointly learn entity and type representations

# Learning Unified Entity Representations

- Separate models for entity mentions, entity descriptions, type descriptions
- To learn the different entity representations and their parameters, jointly maximize the total objective

$$\{v_e\}, \Theta = \operatorname*{argmax}_{\{v_e\},\Theta} \mathcal{L}_{ ext{text}} + \mathcal{L}_{ ext{desc}} + \mathcal{L}_{ ext{etype}} + \mathcal{L}_{ ext{mtype}}$$

where  $v_e$  are the set of entity representations and  $\theta$  are the parameters

	CoNLL		ACE05	Wiki
	Test	Dev	ACEUS	WIKI
Plato (Sup)	79.7	-	-	-
Plato (Semi-Sup)	86.4	-	-	-
AIDA*	81.8	-	-	-
BerkCNN:Sparse*	74.9	-	83.6	81.5
BerkCNN:CNN*	81.2	86.91	84.5	75.7
BerkCNN:Full*	85.5	-	89.9	82.2
Priors	68.5	70.9	81.1	78.1
Model C	81.4	83.4	83.7	86.1
Model CD	81.0	83.2	85.8	86.1
Model CT	82.3	83.9	86.5	88.2
Model CDT	82.5	85.6	86.8	88.0
Model CDTE	82.9	84.9	85.6	89.0

Table 1: Entity Linking Performance: Accuracy

	F1	Accuracy
AIDA	77.8	-
Wikifier	85.1	-
Vinculum	88.5	-
Model C	88.9	93.1
Model CDT	89.8	93.9
Model CDTE	90.7	94.3

Table 2: **Results for ACE-2004**: F1 is calculated for predicted mentions, and accuracy on goldmentions. Results for Wikifier and AIDA are from (Ling et al., 2015). All systems use the same mention extraction protocol showing the difference in F1 is due to linking performance.

## Looking forward

More languages: 3000!

Multi-media

Streaming mode

No more training data

Context-aware, living