04 – Named Entity Recognition

IA161 Advanced Techniques of Natural Language Processing

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Washington: Ben Carson said Wednesday he's pulling in lots of money amid all the backlash he's received for remarks he made regarding Muslims in politics. The retired neurosurgeon said he raised $1 million within 24 hours following the CNN debate on Sept. 16, and that donations have poured in after remarks he made over the weekend about Islam and the presidency. "The money has been coming in so fast, it's hard to even keep up with it," he said Wednesday morning on Fox News, when asked about whether his comments had affected his donations. "I remember the day of the last debate, within 24 hours we raised $1 million. And it's coming in at least at that rate if not quite a bit faster." CNN will not be able to verify fundraising totals with the Federal Election Commission until after the quarter ends Sept 30.

Outline

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NER aims to recognize and classify names of people, locations, organizations, products, artworks, domain names, phone numbers, dates, money, measurements (numbers with units), law or patent numbers etc.

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	NE	MWE
Brno	✓	✗

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a priori	✗	✓

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a priori	✗	✓
New York	✓	✓

NER and information extraction (IE)

Example

MIT Press published a book by Patrick Hanks with the title Lexical Analysis: Norms and Exploitations. .

MIT Press published a book by Randy Thornhill and Craig T. Palmer entitled A Natural History of Rape: Biological Bases of Sexual Coercion

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Authors		Title
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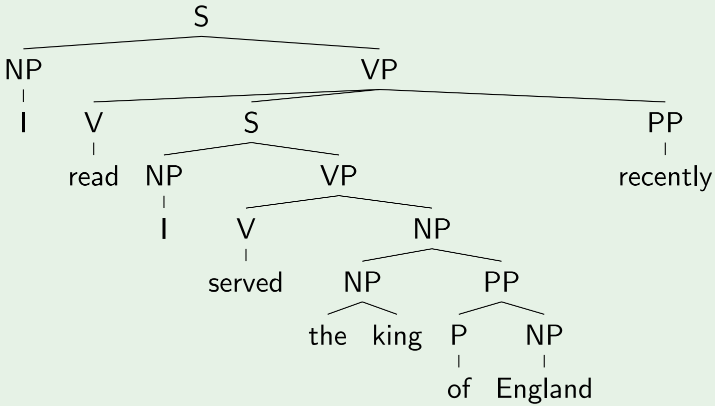
Randy Thornhill	Craig T. Palmer	A Natural History of Rape: Biological Bases of Sexual Coercion

Named Entity Recognition (NER)

Retokenization can improve significantly advanced natural language processing:

Example



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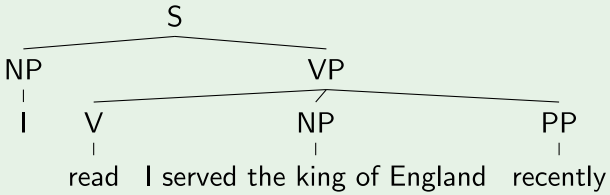

NER: recognizing boundaries

Example

$\boxed{\text{Masaryk}}$ University in $\boxed{\text{Brno}}$

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Example

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Nová opera $\boxed{\text{Vladimíra}}$ $\boxed{\text{Franze Válka}}$ s mloky . . .

NER: recognizing boundaries

Example

Masaryk University in Brno

Example

The Picture of Dorian Gray

Nová opera Vladimíra Franze

Válka s mloky . . .

Named Entity Classification

Common classes: PERSON, ORGANIZATION, LOCATION
Less common classes: MONEY, PERCENT, DATE, TIME
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The White House	LOCATION? ORGANIZATION
Othello	PERSON? ARTWORK? PRODUCT?
Motorola	ORGANIZATION? PRODUCT?
The Pope	PERSON? ROLE?
two years ago	DATE? nothing?

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The main problem is with metonymy.

Methods for NER

- gazetteer methods (list of NEs)
- semi-supervised machine learning (bootstraping)
- supervised machine learning (training)

Gazetteer Methods for NER

lists of NEs + substring search algorithms:

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search all occurences of substrings $S_k, \ldots, S_l$ from lists of pattern strings $P_1, \ldots, P_p$ in a target string $T[1 \ldots m]$

- naïve multi-pass: $O(p(m+n))$
- improvements: Rabin-Karp, Boyer-Moore, Knuth-Morris-Pratt
- single-pass: Aho-Corasick: $O(m+k)$

where p is the number of patterns,
m is the target string length,
n is the average pattern length,
k is the total number of occurrences of the pattern strings in the text

Gazetteer Methods for NER

Problems: disambiguation + fixedness

Example

May the force be with you!
I was born on May.
Karel May is my favorite writer.

Example

Google was bought by Brand New So-far-unknown Company Inc.

Semi-supervised methods for NER

bootstrapping = a small degree of supervision

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seeds: John, James, Steve
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Example

`[Capitalized words and letters]`, the CEO of `[Capitalized words and non-capitalized stop words]`,

$\boxed{\text{Richard Rosenblatt}}$, the CEO of $\boxed{\text{Demand Media}}$,
$\boxed{\text{Michael Close}}$, the CEO of $\boxed{\text{Enterprise Training Centre}}$,
. . .

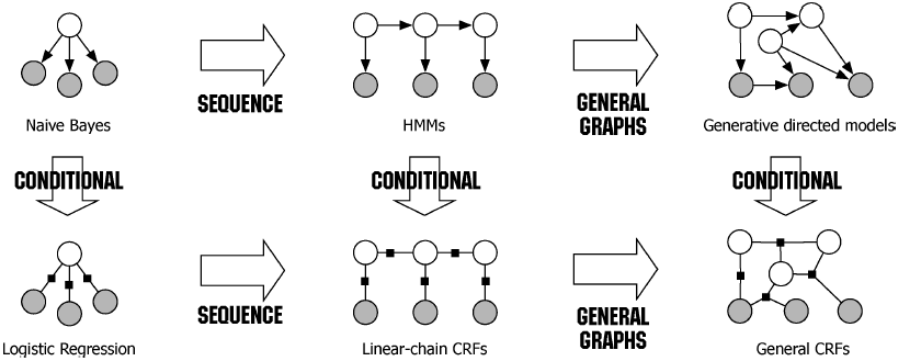
Semi-supervised methods for NER

good for discovering NEs (fixedness problem solved)
but not good at disambiguation

Supervised methods for NER

manually annotated training set
manually annotated test set (the golden standard)
+ optionally the gazetteer

discriminative vs. generative methods



Evaluation of NER systems

precision, recall, F1-score

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precision, recall, F1-score
separate precision, recall, F1-score measurements for different classes
the less difficult classes are: DATE, MONEY, PERCENT
the most difficult classes are: PERSON, ORGANIZATION

Error analysis:

- errors in boundaries detection
- errors in class labeling

What is preferred: high precision (and low recall) or high recall (and more false positives)?

. . . see also [8]

Current state-of-the-art results

Language	System	F1
English	MUC-7[1], baseline	58.89%
English	MUC-7 human annotation	97.60%
English	MUC-7 best result [9]	93.39%
English	CONLL-2003 best result [3]	88.76%
English	CONLL-2003 [6]	90.10%
German	GermEval 2014 best result [5]	77.14%
Russian	[4]	75.05%
Czech	[11]	82.82%
Czech	[7]	83.24%
Arabic	[1]	65.76%

[1] Message Understanding Conference

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