04 – Named Entity Recognition

IA161 Advanced Techniques of Natural Language Processing

Z. Nevěřilová

NLP Centre, FI MU, Brno

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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

Named Entity Recognition (NER)

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
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Brno	✓	✗
a priori	✗	✓
New York	✓	✓

Named Entity Recognition (NER)

NER is vital for information extraction (IE).

Example

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

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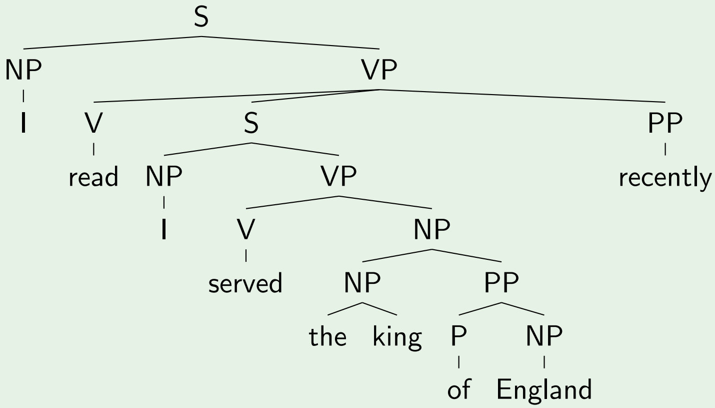
Authors		Title
Patrick Hanks		Lexical Analysis: Norms and Exploitations
Randy Thornhill	Craig T. Palmer	A Natural History of Rape: Biological Bases of Sexual Coercion

Named Entity Recognition (NER)

Treating the whole multiword NE as one entity can improve advanced natural language processing:

Example



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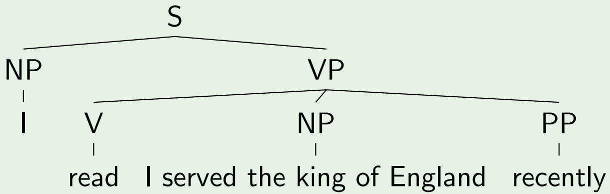

NER: recognizing boundaries

Example

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

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The Picture of Dorian Gray

Nová opera Vladimíra Franze Válka s mloky . . .

NER: recognizing boundaries

Example

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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 (bootstrapping)
- supervised machine learning (training $\rightarrow$ model)

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 $T[1 \ldots m]$
Example algorithms:

- naïve multi-pass: $O(p(m - n + 1))$
- 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 (searchable) 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

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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]`,

Richard Rosenblatt, the CEO of Demand Media,
Michael Close, the CEO of Enterprise Training Centre,
...

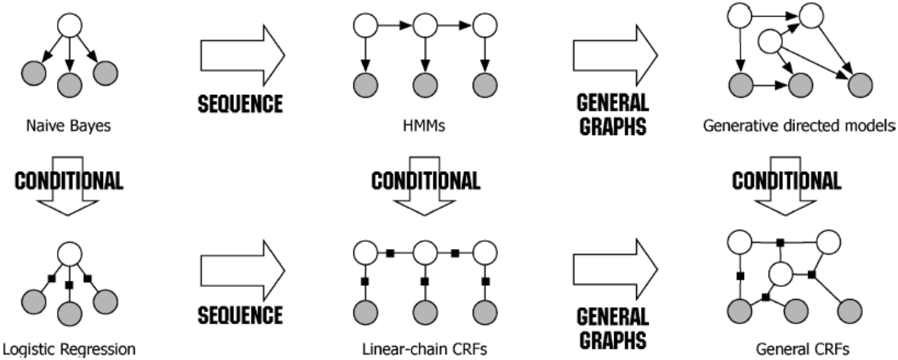
Semi-supervised methods for NER

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



Supervised methods for NER: Annotation

- XML-like annotation

  `Zpívali jí <ne type="oa">Krásnou <ne type="pf">Meredith</ne></ne>`

- token-based annotation

token	simple	IOB	IOBSE
Alex	PER	B-PER	S-PER
is	O	O	O
going	O	O	O
with	O	O	O
Marty	PER	B-PER	B-PER
A.	PER	I-PER	I-PER
Rick	PER	I-PER	E-PER
to	O	O	O
Los	LOC	B-LOC	B-LOC
Angeles	LOC	I-LOC	E-LOC

NER in the Era of Neural Networks

Similarly to traditional ML, NER is solved as classification task for each token in a sequence.

For sequences, recurrent neural networks (such as LSTM and BiLSTM) work the best.
However, the dependencies in the token sequence can be long-range.
For this, the transformer architecture works the best.

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Transformers solve all NLP tasks in one.
BERT [3] uses bidirectional pre-training for language representations.

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Evaluation of NER systems

precision, recall, F1-score

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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 [10]

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 [11]	93.39%
English	CONLL-2003 best result [4]	88.76%
English	CONLL-2003 [7]	90.10%
English	CONLL-2003 BERT [3]	92.8%
English	CONLL-2003 ACE [15]	94.6%
German	GermEval 2014 best result [6]	77.14%
German	LSTM+CRF+char-based [9]	78.76%
Russian	[5]	75.05%
Italian	tint[2]	82.11
Czech	[13]	82.82%
Czech	[8]	83.24%
Arabic	[1]	65.76%

[1] Message Understanding Conference

[2] `http://tint.fbk.eu/ner.html`

Currently used datasets

Language	Dataset name	# size
English	ConLL 2003	22,137 sentences
English	OntoNotes 5.0	1,445k words
Chinese	OntoNotes 5.0	1,200k words
Arabic	OntoNotes 5.0	300k words
Czech	CNEC 2.0	8,993 sentences
Czech	SumeCzech-NER	1,000,000 articles
German	ConLL 2003	18,933 sentences
German	NoSta-D	26,200 sentences
Italian	Evalita (I-CAB)	113,624 words

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