04 – Named Entity Recognition
IA161 Natural Language Processing in Practice

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November 18, 2022

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.

Named entities (NEs) can be one word or multi word.
[overlap with multi word expression (MWE) processing]

Example

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

Authors		Title
Patrick Hanks		Lexical Analysis: Norms and Exploitations
Randy	Craig T.	A Natural History of Rape:

Named Entity Recognition (NER)

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

Example

NER: recognizing boundaries

Example

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

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

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

Example

The Picture of $\boxed{\text{Dorian Gray}}$

$\boxed{\text{The Picture of Dorian Gray}}$

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

Named Entity Classification

Common classes: PERSON, ORGANIZATION, LOCATION
Less common classes: MONEY, PERCENT, DATE, TIME
Rare classes: ARTWORK, PRODUCT, ROLE

Example

The White House	LOCATION? ORGANIZATION
Othello	PERSON? ARTWORK? PRODUCT?
Motorola	ORGANIZATION? PRODUCT?
The Pope	PERSON? ROLE?
two years ago	DATE? nothing?

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:

- list of names
- list of company names
- list of place names

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

bootstrapping = a small degree of supervision
typically requires a small set of *seeds*

Example

seeds: John, James, Steve
search patterns in contexts:
Peter, David, Michael ...

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,
...

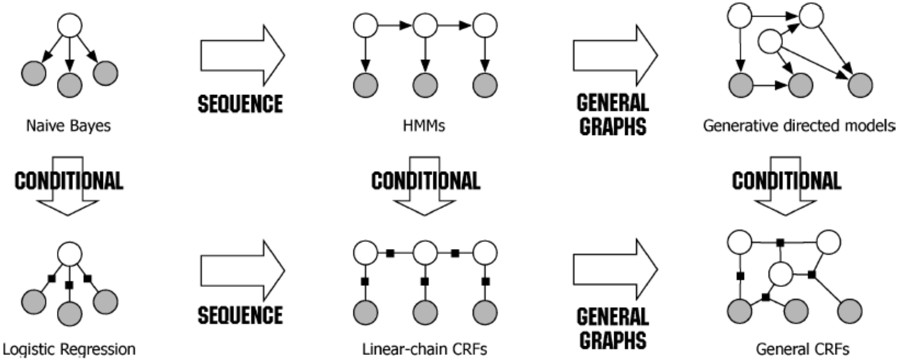
Semi-supervised methods for NER

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.

$\rightarrow$

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

Evaluation of NER systems

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: ORGANIZATION, ARTWORK

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 [9]

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 [10]	93.39%
English	CONLL-2003 [6]	90.10%
English	CONLL-2003 BERT [3]	92.8%
English	CONLL-2003 ACE [14]	94.6%
German	GermEval 2014 best result [5]	77.14%
German	LSTM+CRF+char-based [8]	78.76%
Russian	[4]	75.05%
Italian	tint[2]	82.11%
Czech	[12]	82.82%
Czech	[7]	83.24%
Arabic	[1]	65.76%

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

[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

Maha Althobaiti, Udo Kruschwitz, and Massimo Poesio.
A semi-supervised learning approach to Arabic named entity recognition.
In Galia Angelova, Kalina Bontcheva, and Ruslan Mitkov, editors, *RANLP*, pages 32–40. RANLP 2011 Organising Committee / ACL, 2013.

R. A. Baeza-Yates.
Algorithms for string searching.
SIGIR Forum, 23(3-4):34–58, April 1989.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova.
BERT: pre-training of deep bidirectional transformers for language understanding, 2019.

Rinat Gareev, Maksim Tkachenko, Valery Solovyev, Andrey Simanovsky, and Vladimir Ivanov.
Introducing baselines for Russian named entity recognition.
In *Proceedings of the 14th International Conference on Computational Linguistics and Intelligent Text Processing - Volume Part I*, CICLing'13, pages 329–342, Berlin, Heidelberg, 2013. Springer-Verlag.

Christian Hänig, Stefan Thomas, and Stefan Bordag.
Modular classifier ensemble architecture for named entity recognition on low resource systems.
2014.

Zhiheng Huang, Wei Xu, and Kai Yu.
Bidirectional LSTM-CRF models for sequence tagging.
CoRR, abs/1508.01991, 2015.

Michal Konkol and Miloslav Konopík.
Crf-based czech named entity recognizer and consolidation of Czech NER research.
In Ivan Habernal and Václav Matoušek, editors, *Text, Speech, and Dialogue*, volume 8082 of *Lecture Notes in Computer Science*, pages 153–160. Springer Berlin Heidelberg, 2013.

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer.
Neural architectures for named entity recognition.
CoRR, abs/1603.01360, 2016.

Chris Manning.
Doing named entity recognition? Don't optimize for F1.
online, accessible on `http://nlpers.blogspot.cz/2006/08/doing-named-entity-recognition-dont.html`, accessed 2015-10-08.

Andrei Mikheev, Claire Grover, and Marc Moens.
Description of the LTG system used for MUC-7.
Association for Computational Linguistics, 1998.

David Nadeau and Satoshi Sekine.
A survey of named entity recognition and classification.
Linguisticae Investigationes, 30(1):3–26, January 2007.
Publisher: John Benjamins Publishing Company.

Jana Straková, Milan Straka, and Jan Hajič.
A new state-of-the-art Czech named entity recognizer.
In Ivan Habernal and Václav Matoušek, editors, *Text, Speech, and Dialogue*, volume 8082 of *Lecture Notes in Computer Science*, pages 68–75. Springer Berlin Heidelberg, 2013.

Charles Sutton and Andrew McCallum.
An introduction to conditional random fields.
Foundations and Trends in Machine Learning, 4(4):267–373, 2012.

Xinyu Wang, Yong Jiang, Nguyen Bach, Tao Wang, Zhongqiang Huang, Fei Huang, and Kewei Tu.
Automated Concatenation of Embeddings for Structured Prediction.
In *the Joint Conference of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (**ACL-IJCNLP 2021**)*. Association for Computational Linguistics, August 2021.