

* * * PGM: Final Project Presentation * * *

POS-Tagging and NER

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Agenda

① Task Description

② Process and Tools

③ Results and Comparison

Task Description

- The task was to use probabilistic graphical models for:
 - POS-Tagging (Part-of-Speech Tagging)
 - Named Entity Recognition (NER)
- We used the following models:
 - Naïve Bayes (baseline model)
 - HMMs (Hidden Markov models)
 - CRFs (Conditional Random Fields)

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

Part of Speech Tagging



Figure: Part of speech tagging

Part of Speech Tagging

"There was nothing about this storm that was as expected," said **Jeff Masters**, a meteorologist and founder of **Weather Underground**. "**Irma** could have been so much worse. If it had traveled 20 miles north of the coast of **Cuba**, you'd have been looking at a (Category) 5 instead of a (Category) 3."

Person

Organization

Location

Figure: Named entity recognition

Process and Tools

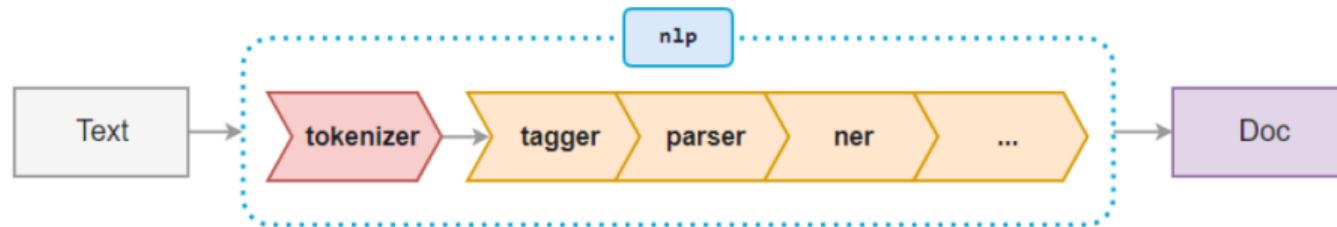


Figure: NLP-Pipeline

- POS tagging is one of the earliest stages in the NLP pipeline and serves as input for most downstream tasks
- E.g. NER: POS tags can be used as a feature

Results

POS Tagging

Naïve Bayes [POS]

Features	F1 score	Acc (w / s)
w, l, s	0.927	0.927 / 0.240
w, l, s, uwf	0.928	0.928 / 0.241
w, l, s, bf	0.957	0.957 / 0.467
w, l, s, uwf, bf	0.949	0.949 / 0.369

HMM [POS]

Features	F1 score	Acc (w / s)
word sequence	0.837	0.837 / 0.496

Legend:

w: word, l: lowercase word, s: stem, uwf: unknown word features, bf: bigram features

Results (Ctd.)

POS Tagging

CRF [POS]		
Features	F1 score	Acc (w / s)
w, l, s		
w, l, s, uwf	0.980	0.980 / 0.749
w, l, s, bf		
w, l, s, uwf, bf	0.985	0.985 / 0.740

Legend:

w: word, l: lowercase word, s: stem, uwf: unknown word features, bf: bigram features

Confusion Matrix CRF (all features)

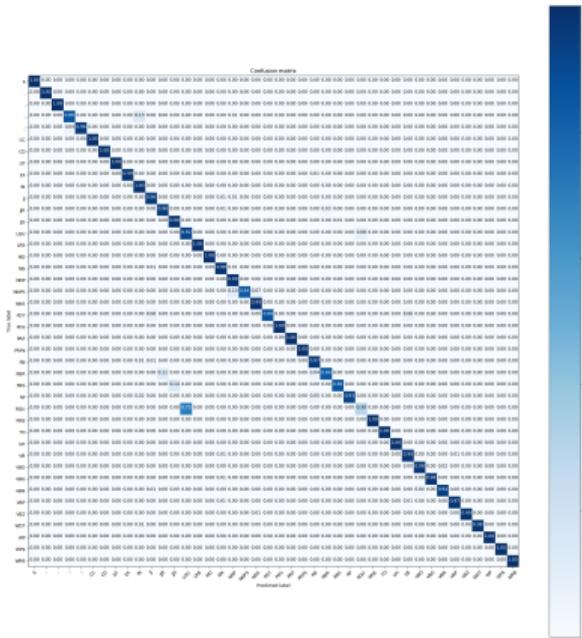


Figure: Named entity recognition

Results (Ctd.)

Named Entity Recognition

Naïve Bayes [NER]		
Features	F1 score	Acc (w / s)
w, l, s	0.921	0.921 / 0.262
w, l, s, uwf	0.922	0.922 / 0.237
w, l, s, uwf, pos	0.921	0.921 / 0.240
w, l, s, uwf, pos, bf	0.929	0.929 / 0.288

HMM [NER]		
Features	F1 score	Acc (w / s)
word sequence	0.946	0.946 / 0.523

Legend:

w: word, l: lowercase word, s: stem, uwf: unknown word features, bf: bigram features, pos: part of speech tags

Results (Ctd.)

Named Entity Recognition

CRF [NER]		
Features	F1 score	Accuracy (w / s)
w, l, s	0.974	0.974 / 0.694
w, l, s, uwf	0.974	0.974 / 0.694
w, l, s, uwf, pos		
w, l, s, uwf, pos, bf		

Legend:

w: word, l: lowercase word, s: stem, uwf: unknown word features, bf: bigram features, pos: part of speech tags

Result Comparison

- Naive Bayes confuses per-ord with eve-ord, but HMM does not
⇒ context knowledge!
- Naive Bayes predicts per-tit very often
- Naive Bayes confuses tim-clo and tim-dat often
- HMM incorrectly predicts DET tag (POS) very often
- HMM incorrectly predicts O tag (NER) very often

What we have learned...

- Feature engineering is 'dirty work' but crucial for later performance
- POS tagging
 - Likely transitions: MD \Rightarrow VB; NNS \Rightarrow VBP
 - Unlikely transitions: DT \Rightarrow DT; VBD \Rightarrow VBD
- NER
 - Likely transitions: \Rightarrow
 - Unlikely transitions: \Rightarrow

Thank you very much for the attention!

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Do you have any questions?