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# NERC

— Named Entity Recognition and —  
Classification

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# Outline

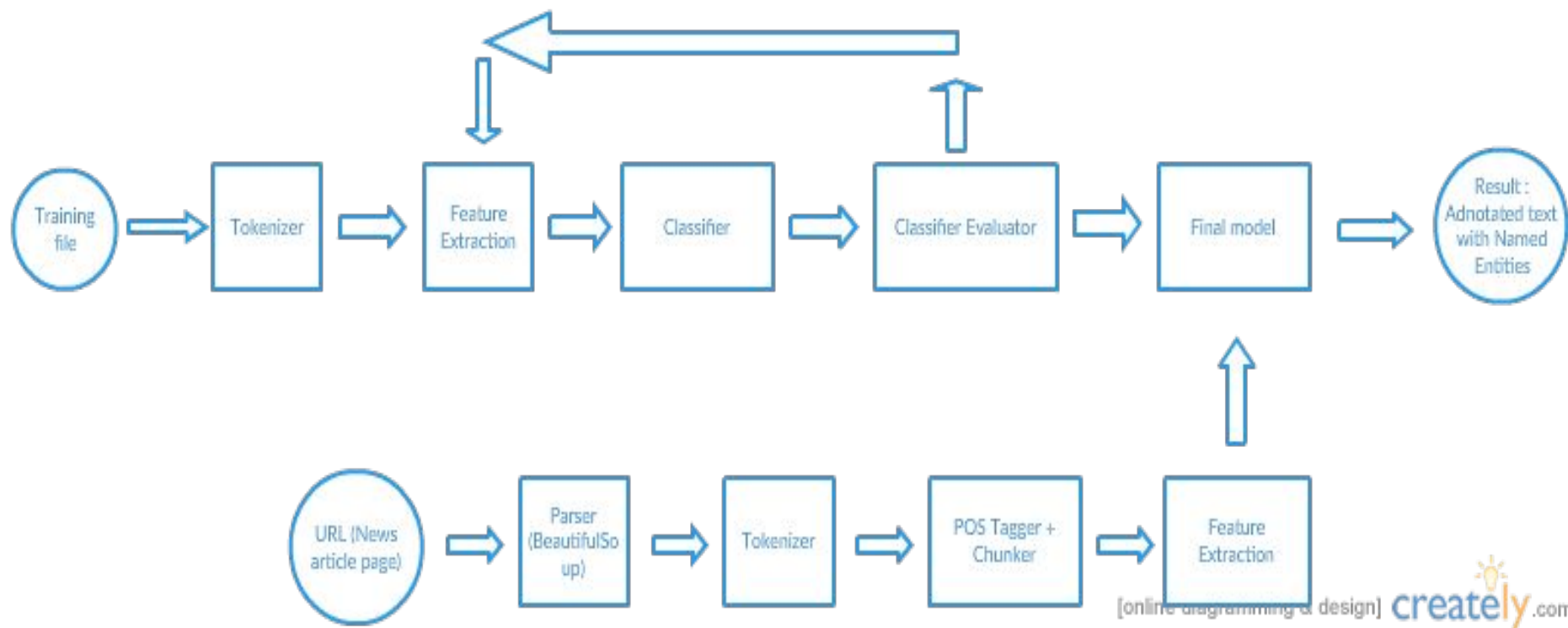
- Overall architecture
- Tools
- Feature extraction
- Classifiers and evaluation
- Preliminary results
- QA

# Overall architecture(1)

- Training data
  - **CoNLL 2003**
- Tokenizer
  - (word, POS Tag, Chunk Tag, NE Tag)
- POS Tagger and Chunker
  - nltk
- Classification and Evaluation

```
The DT I-NP O
European NNP I-NP I-ORG
Commission NNP I-NP I-ORG
said VBD I-VP O
```

## Overall architecture(2)



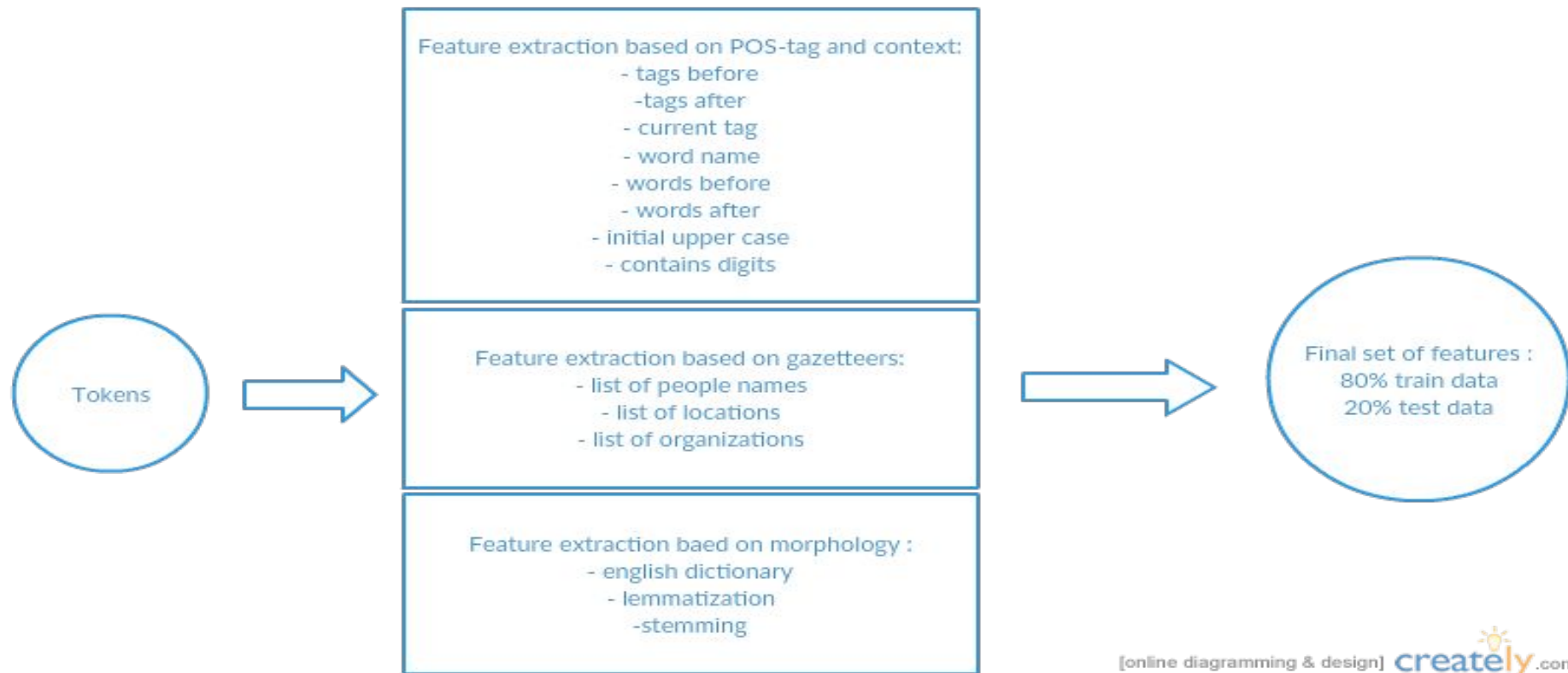
# Tools

- Scikit-learn for the Maximum Entropy Classifier (Logistic Regression)
- Pandas library for a user-friendly representation of the training and test data
- NLTK library for python
  - POS-Tagger and Chunker
  - Naive Bayes + other classifier
  - POS-Tagged corpuses

# Feature extraction(1)

- Feature extraction based on POS-tags and context
  - Current word
  - Previous words
  - Next words
  - POS Tags
  - Word suffixes
- Feature extraction based on gazetteers:
  - Elite Classic → Elite Classic → HTL → Asia/Dubai
- Feature extraction based on morphology
  - WordNet lemmatization

# Feature extraction(2)

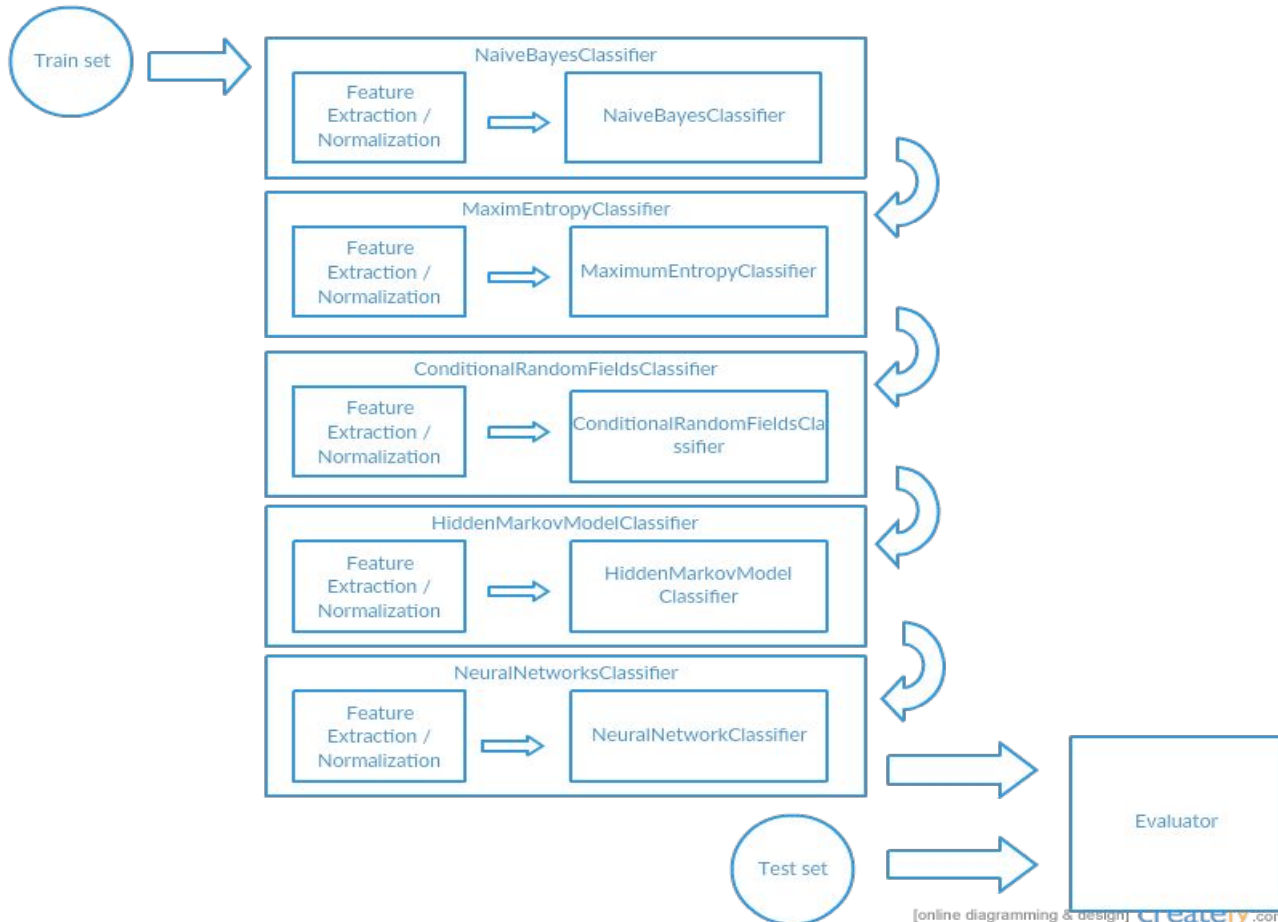


# Classifier and evaluation(1)

- Naive Bayes classifier
- Maximum Entropy Classifier
  - Logistic Regression → scikit-learn
- Neural Network Classifier
  - Word2Vec(Python) + NN(Torch)



# Classifier and evaluation(2)



# Preliminary results(1) → Naive Bayes

Precision Person: 0.64632 | Recall Person: 0.81137 | Accuracy Person: 0.97018 | **F-score Person: 0.71950**

Precision ORG: 0.49823 | Recall ORG: 0.55752 | Accuracy ORG: 0.95602 | **F-score ORG: 0.52621**

Precision LOC: 0.54844 | Recall LOC: 0.64562 | Accuracy LOC: 0.96427 | **F-score LOC: 0.59308**

# Preliminary results(2) → Maximum Entropy

- **CoNLL 2003** corpus
- Logistic Regression → **scikit-learn**
- Comparison with nltk.
- My results:
  - Including “O”-tags:
    - **F1-Score:** 82 % **Precision:** 82.4 % **Recall:** 82.4 %
  - Without “O”-tags:
    - **F1-Score:** 16 % **Precision:** 16.8 % **Recall:** 16.8 %

# Preliminary results(3) → Word2Vec + NN (I)

- Dataset sample (ConLL 2003)

Word	POS tag	syntactic chunk Tag	named entity tag
EU	NNP	I-NP	I-ORG
rejects	VBZ	I-VP	O
German	JJ	I-NP	I-MISC
call	NN	I-NP	O
to	TO	I-VP	O
boycott	VB	I-VP	O
British	JJ	I-NP	I-MISC
lamb	NN	I-NP	O
.	.	O	O

# Preliminary results(3) → Word2Vec + NN (II)

## Word2Vec steps

- process text

e.g: EU rejects German call to boycott British
- give input to word2vec and get the vectors
  - Set window skipping at 1 and minimum frequency at 0 to catch all the words
- serialize vectors to be used at training NN

# Preliminary results(3) → Word2Vec + NN (III)

- Check similarities

## Test similarity

```
In [8]: indexes, metrics = model.analogy(pos=['of'], neg=[], n=10)
```

```
In [9]: model.generate_response(indexes, metrics).tolist()
```

```
Out[9]: [(u'from', 0.995997284001497),  
(u'for', 0.995595312942011),  
(u'at', 0.9955636284163529),  
(u'with', 0.9935470112344263),  
(u'by', 0.9933905557391695),  
(u'over', 0.990679873191216),  
(u'in', 0.9901027223658493),  
(u'new', 0.9893901859142927),  
(u'after', 0.9893870905141411),  
(u'bodies', 0.9884139010302534)]
```

# Preliminary results(3) → Word2Vec + NN (IV)

```
nn.Sequential {
```

```
[input -> (1) -> (2) -> (3) -> (4) -> (5) -> output]
```

```
    (1): nn.Linear(80 -> 400)
```

```
    (2): nn.ReLU
```

```
    (3): nn.Linear(400 -> 800)
```

```
    (4): nn.ReLU
```

```
    (5): nn.Linear(800 -> 8)
```

```
}
```

## Results:

- Accuracy: 63%
- Why 63%? Predicting all values as others
- Why predicting all values as others?
- Dataset is unbalanced

1 : 1218

2 : 4

3 : 13959

4 : 3772

5 : 617

6 : 5

7 : 2192

8 : 3

//egal din toate

# Preliminary results(3) → Word2Vec + NN (V)

## ConfusionMatrix:

[[ 4 0 964 0 0 0 0 0]	0.413%	[class: 1]
[ 0 0 4 0 0 0 0 0]	0.000%	[class: 2]
[ 41 0 11001 1 0 0 0 0]	99.620%	[class: 3] Others
[ 11 0 3070 0 0 0 0 0]	0.000%	[class: 4]
[ 1 0 494 0 0 0 0 0]	0.000%	[class: 5]
[ 0 0 4 0 0 0 0 0]	0.000%	[class: 6]
[ 9 0 1809 0 0 0 0 0]	0.000%	[class: 7]
[ 0 0 3 0 0 0 0 0]]	0.000%	[class: 8]



# References

- [1] Bender, Oliver, Franz Josef Och, and Hermann Ney. "Maximum entropy models for named entity recognition." *Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003-Volume 4*. Association for Computational Linguistics, 2003.
- [2] Curran, James R., and Stephen Clark. "Language independent NER using a maximum entropy tagger." *Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003-Volume 4*. Association for Computational Linguistics, 2003.
- [3] Chieu, Hai Leong, and Hwee Tou Ng. "Named entity recognition: a maximum entropy approach using global information." *Proceedings of the 19th international conference on Computational linguistics-Volume 1*. Association for Computational Linguistics, 2002.
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- [5] Bishop, 2006 "*Pattern recognition and machine learning*" p.325 - p.357, Ch. 7 : Sparse Kernel Machines
- [6] Asif Ekbal and Sivaji Bandyopadhyay - "*Named Entity Recognition using Support Vector Machine: A Language Independent Approach*"
- [7] Fredrick Edward Kitoogo and Venansius Baryamureeba - "*A Methodology for Feature Selection in Named Entity Recognition*"
- [8] Joel Mickelin - "*Named Entity Recognition with Support Vector Machines*", Master of Science Thesis Stockholm, Sweden 2013
- [9] Tomas Mikolov et al. - "*Distributed Representations of Words and Phrases and their Compositionality*"
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Questions ?

Thank you  
for your attention!