

# Comparing Conditional Random Fields and LSTM Networks for Named Entity Recognition

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# Motivation

test

# Overview

1. Background & Related Work
2. Implementation Details
3. Evaluation and Comparison
4. Conclusion

# Background & Related Work

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# Named Entity Recognition

## Definition: NER

*Named Entity Recognition* is the task of locating and classifying named entities in unstructured text. A named entity is classified into a predefined set of categories.

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James visited the Eiffel Tower in 2012.



James [PERSON] visited the Eiffel [LOCATION] Tower [LOCATION] in 2012 [TIME].

# Conditional Random Fields

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$$p(y|x) = \frac{1}{Z(x)} \prod_{t=1}^T \exp\left(\sum_{k=1}^K \theta_k f_k(y_t, y_{t-1}, x_t)\right) \quad (1)$$

where  $Z(x)$  is an normalization function:

$$Z(x) = \sum_y \prod_{t=1}^T \exp\left(\sum_{k=1}^K \theta_k f_k(y_t, y_{t-1}, x_t)\right) \quad (2)$$



# Recurrent Neural Networks

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- Suited for sequence labeling
- Problems with long term dependencies
- Vanishing and exploding gradient

# Long-Short-Term-Memory Networks

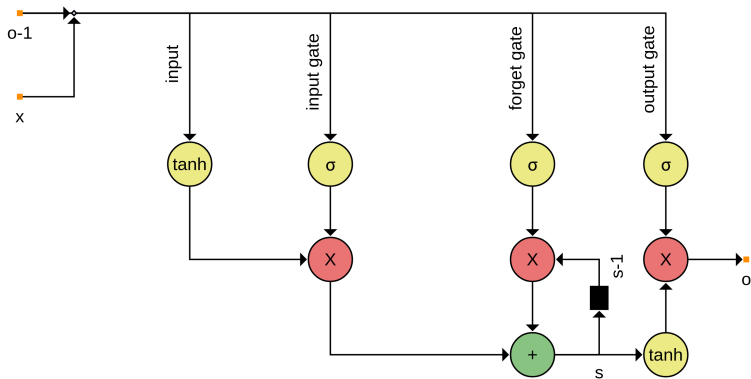
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# Implementation Details

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## Conference on Computational NL Learning

CoNLL 2003 was a shared task on language independent named entity recognition. The data is based on news wire articles from the Reuters corpus.

Four types of Named Entities:

- Person
- Location
- Organization
- Miscellaneous

# Dataset W-NUT

## Workshop on Noisy User-generated Text

W-NUT 17 was a workshop that focused on NLP on noisy and informal text, such as comments from social media, online reviews, forums, etc.

Four types of Named Entities:

- Person
- Location
- Corporation
- Consumer good
- Creative work
- Group

# Dataset Syntax

Word	POS	Syntax Chunk	NE
U.N.	NNP	I-NP	I-ORG
official	NN	I-NP	O
Ekeus	NNP	I-NP	I-PER
heads	VBZ	I-VP	O
for	IN	I-PP	O
Baghdad	NNP	I-NP	I-LOC
.	.	O	O



# Conditional Random Fields

Libraries:

- pycrfsuite
- nltk
- gensim

Features should describe characteristics of named entities.

- Word Features
- Sentence & Collection Features
- Dictionary Features
- Features from unsupervised ML algorithms

# Word Features

- length of word
- the word starts with an upper-case letter
- the word contains an upper-case letter
- the word contains a digit
- the word contains a special character (-, /, etc.)
- word shape: 'Word' → 'Aa+', 'WORD' → 'A+',  
'2019-12-12' → '9999#99#99'

# Sentence & Collection Features

- position of word in sentence
- number of occurrences in collection

# Dictionary Features

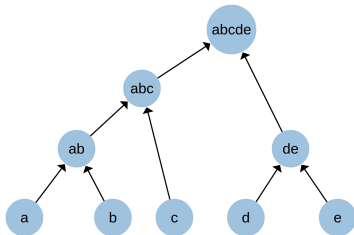
The word is contained in:

- **stop-words** list
  - is, as, the, are, has, that, etc.
  - Problems: 'The Who', 'Take That'
- **name list**
  - 7579 person names from nltk corpus
- **word list**
  - dictionary of 235892 words from nltk corpus
- **wordnet**
  - dictionary and thesaurus
  - provides hypernyms, synonyms, etc.

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The cluster of each word is used as a feature.

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  - hierarchical clustering algorithm



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  - modelling the abstract topics of document
  - example: document A is 20% topic 1, 60% topic 2 and 20% topic 3

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- **Latent Dirichlet Allocation (LDA) topic**
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  - example: document A is 20% topic 1, 60% topic 2 and 20% topic 3
- gensim implementation of **w2v cluster**
  - maps similar words to similar vectors
  - $w2v(king) - w2v(man) + w2v(woman) \approx w2v(queen)$

# LSTM Network

Libraries:

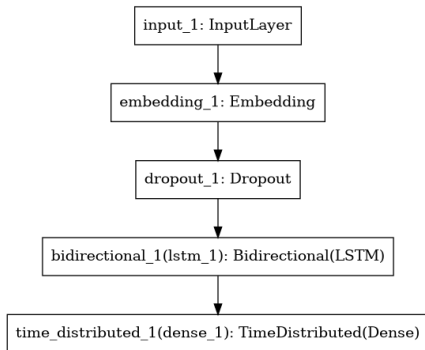
- Keras functional API
- Tensorflow as backend



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- idea is to duplicate LSTM layer
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The other day we saw Paris .

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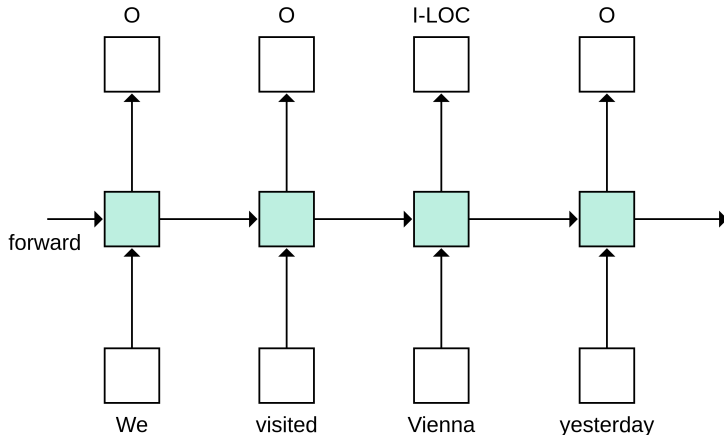
The other day we saw Paris **Hilton**.

# Time Distributed Dense Layer

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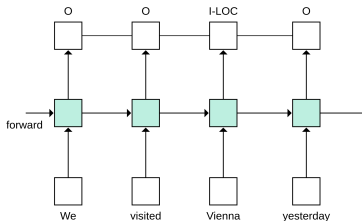
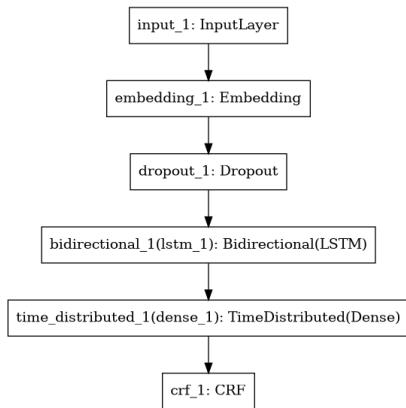
combine the LSTM approach with CRF by adding a CRF layer at bottom:

- use past input features via LSTM layer
- use sentence level tag information via CRF layer

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# Evaluation and Comparison

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Evaluation of the implemented NER systems with metrics:

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Evaluation performed based on:

- token level
- named entity level (CoNLL standard)

# Results

CoNLL dataset:

Method	Precision	Recall	F1-score
CRF	84.25	85.42	84.83
Bi-LSTM	83.03	<b>87.09</b>	<b>85.01</b>
Bi-LSTM-CRF	<b>86.44</b>	83.39	84.89

W-NUT dataset:

Method	Precision	Recall	F1-score
CRF	<b>31.54</b>	<b>56.72</b>	<b>40.53</b>
Bi-LSTM	8.69	23.16	12.63
Bi-LSTM-CRF	28.01	18.00	21.92

# Conclusion

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