# Natural Language Processing II

Jiří Materna





### @mlcollegecom



@mlcollegecom



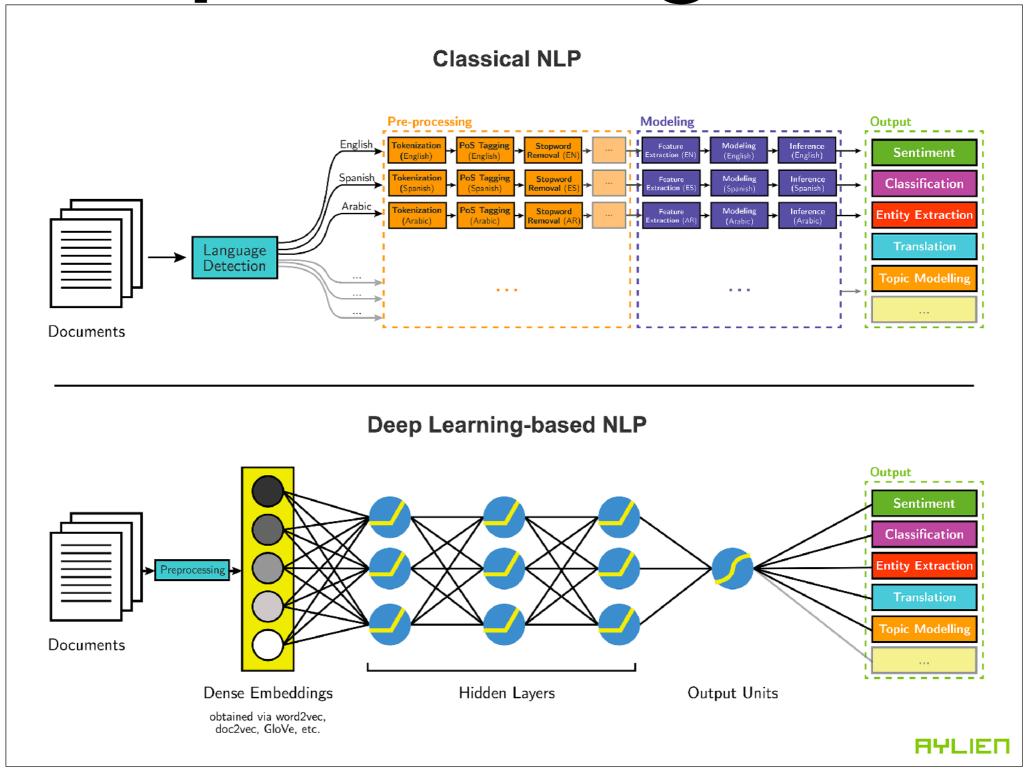
### About me

- Ph.D. in Natural Language Processing and Artificial Intelligence at Masaryk University
- 10 years at <u>seznam.cz</u> (last 8 years as Head Of Research)
- Founder and co-organizer of ML Prague
- Mentor at StartupYard
- ML Freelancer and consultant

### Outline

- Preprocessing for deep learning in NLP
- Recurrent neural networks
- Word embeddings and word2vec
- The Skip-gram model
- Text classification with word embeddings
- Subword tokenization
- LSTM and GRU
- Attention is all you need
- Transformers (GPT3, BERT, XLNET)
- Practical task on classification using BERT

# Deep Learning in NLP



Source: <a href="https://blog.aylien.com/">https://blog.aylien.com/</a>

# Encoding and Unicode

**ASCII** 

не 1 1 о

48 65 6c 6c 6f

Unicode

H e 1 1 o ⊚

00000048 00000065 0000006c 0000006c 0000006f 0000263a

## Encoding and Unicode

UTF-8

H e 1 1 o ⊚

48 65 6c 6c 6f e298ba

**UTF-16** 

H e ] ] o ©

0048 0065 006c 006c 006f 263a

### Unicode normalization

NFD (Normalization Form Canonical Decomposition)
NFC (Normalization Form Canonical Composition)
NFKD (Normalization Form Compatibility Decomposition)
NFKC (Normalization Form Compatibility Composition)

Source		NFD	NFC	NFKD	NFKC
$\mathbf{f}_{FB01}$	:	$\mathbf{f}_{FB01}$	$\mathbf{f}_{FB01}$	f i	f i
25	:	2 5	2 5	2 5	2 5
Ļ	:	fo	<b>أ</b>	Sọċ	<b>ķ</b>
1E9B 0323		017F 0323 0307	1E9B 0323	0073 0323 0307	1E69

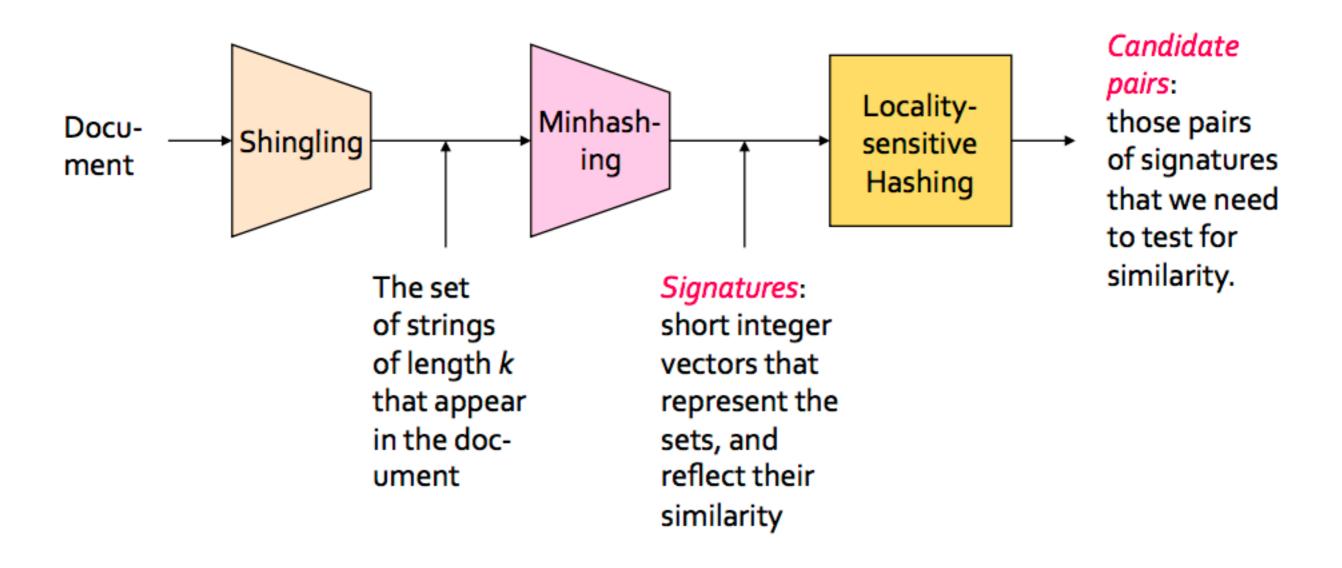
Source: <a href="https://unicode.org/">https://unicode.org/</a>

# Unicode normalization in Python 3

```
>>> aa = b'\xc4\x81'.decode('utf8')
>>> bb = b'a\xcc\x84'.decode('utf8')
>>> aa
'ā'
>>> bb
'ā'
>>> aa == bb
False
>>> import unicodedata as ud
>>> aa == ud.normalize('NFC',bb)
True
```

# Near deduplication

#### **Locality-sensitive hashing**



Source: <a href="https://towardsdatascience.com/understanding-locality-sensitive-hashing-49f6d1f6134">https://towardsdatascience.com/understanding-locality-sensitive-hashing-49f6d1f6134</a>

# Set of shingles (n-grams) as document representation

	Documents				
	1	1	1	o	
	1	1	0	1	
S	0	1	0	1	
Shingles	0	0	0	1	
S	1	o	О	1	
	1	1	1	О	
	1	0	1	О	

# Near deduplication

#### MinHashing signatures

C1   C2   C3   C4
-------------------

Cı	C2	C3	C4
----	----	----	----

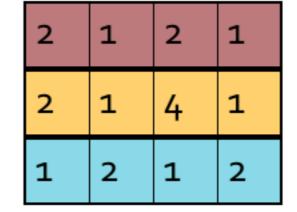
#### Permutation $\pi$

Input matrix (Shingles x Documents)

_										
Si	a	na	ıtι	Jr	e I	m	at	П	х	М
							_			•••

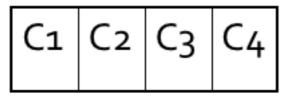
2	4	3
3	2	4
7	1	7
6	3	2
1	6	6
5	7	1
4	5	5

1	o	1	0
1	0	0	1
0	1	0	1
О	1	0	1
o	1	0	1
1	0	1	0
1	0	1	0



Hash function is the *index of the first (in the permuted order) row in which column C has value 1.* Do this several time (use different permutations) to create signature of a column.

# Jaccard similarity and MinHashing signatures



Signature matrix M

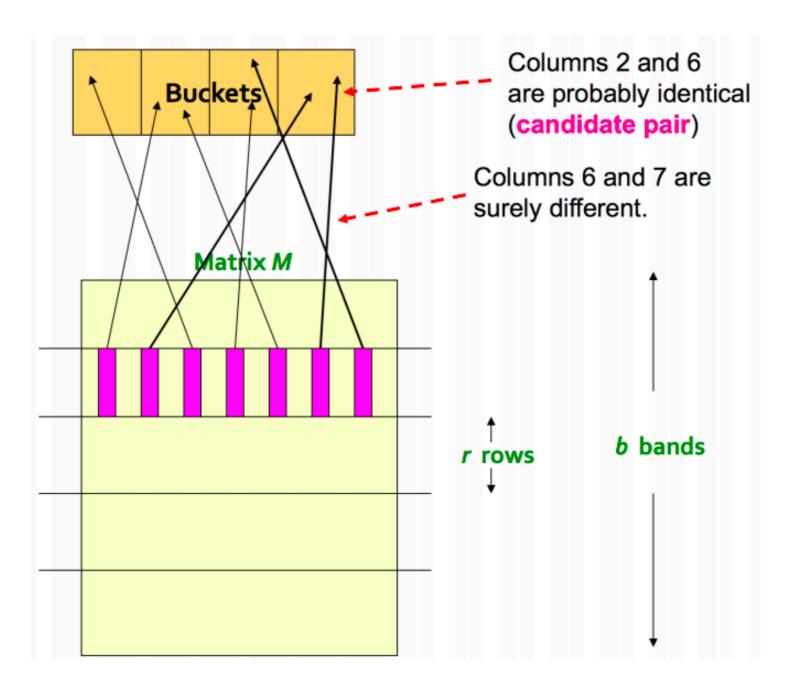
2	1	2	1
2	1	4	1
1	2	1	2

The similarity of the signatures is the fraction of the min-hash functions (rows) in which they agree. So the similarity of signature for C1 and C3 is 2/3 as 1st and 3rd row are same.

Claim: 
$$P[h_{\pi}(C_1) = h_{\pi}(C_2)] = \sin(C_1, C_2)$$

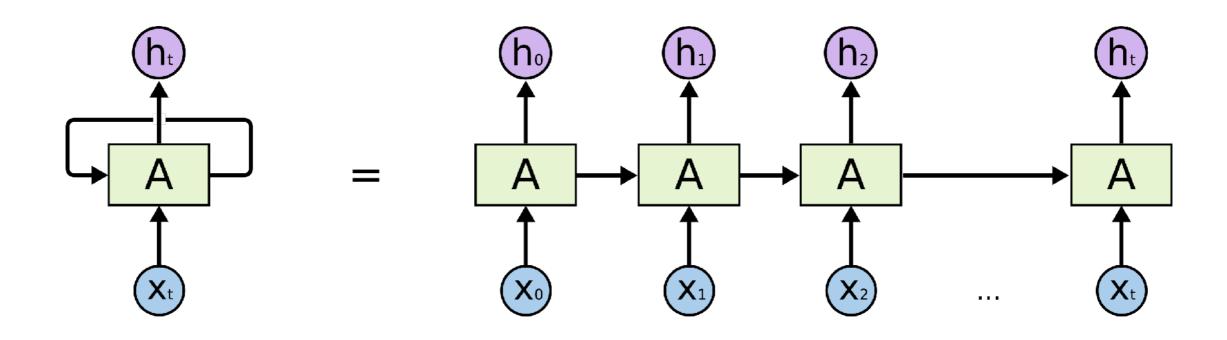
# Near deduplication

#### Locality-sensitive hashing



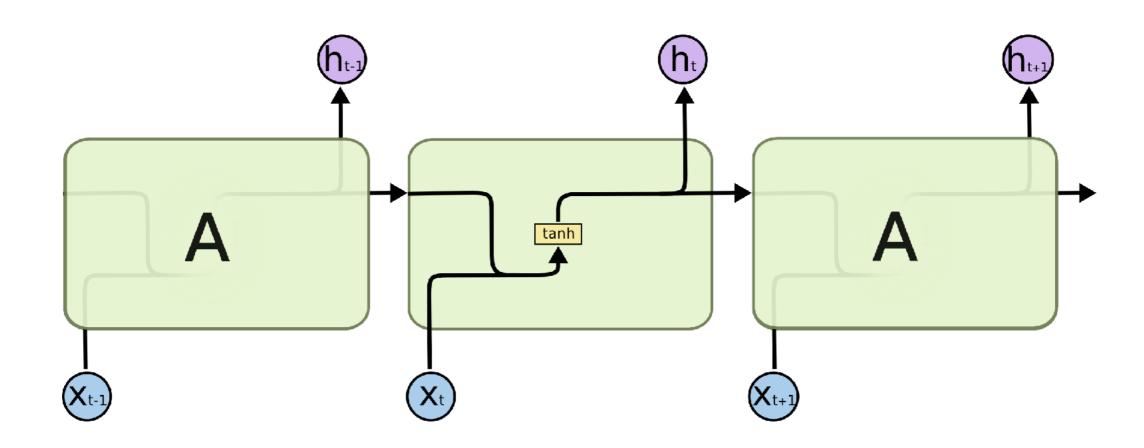
Source: <a href="https://towardsdatascience.com/understanding-locality-sensitive-hashing-49f6d1f6134">https://towardsdatascience.com/understanding-locality-sensitive-hashing-49f6d1f6134</a>

# Recurrent Neural networks 1/2

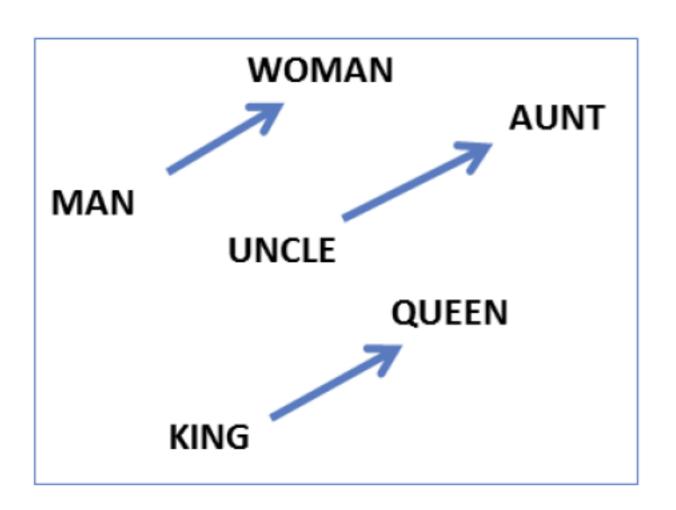


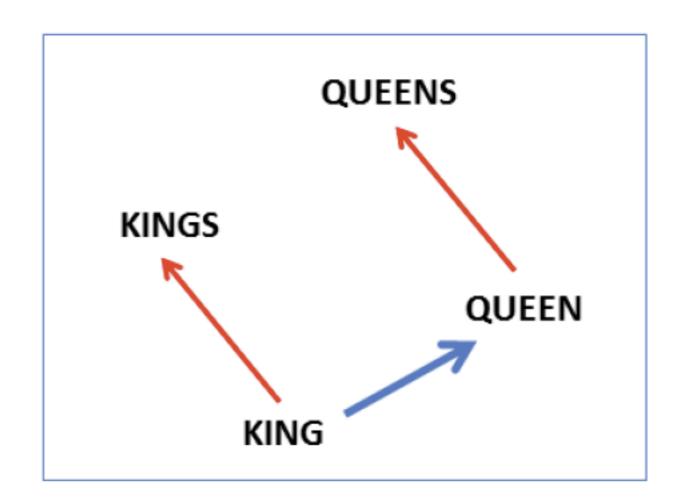
source: <a href="http://colah.github.io/posts/2015-08-Understanding-LSTMs/">http://colah.github.io/posts/2015-08-Understanding-LSTMs/</a>

# Recurrent Neural Networks 2/2



### word2vec

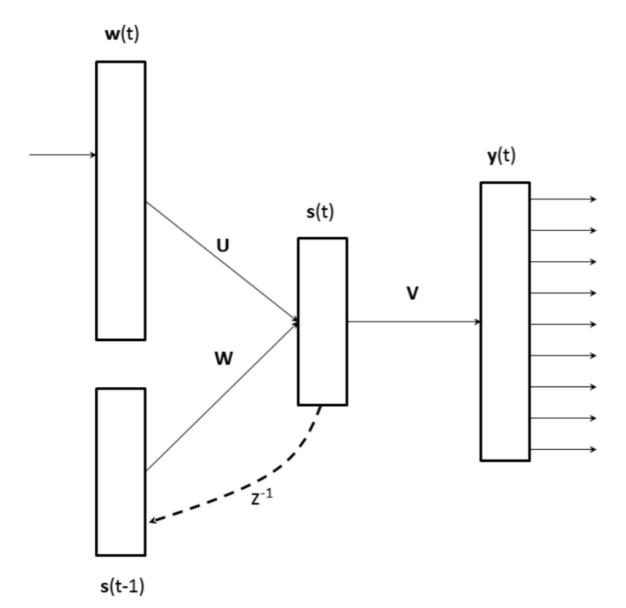




king is to kings as queen to ?.

 $\lor$ (kings) -  $\lor$ (king) =  $\lor$ (queens) -  $\lor$  (queen)

## Recurrent Neural Network Language Modeling Toolkit

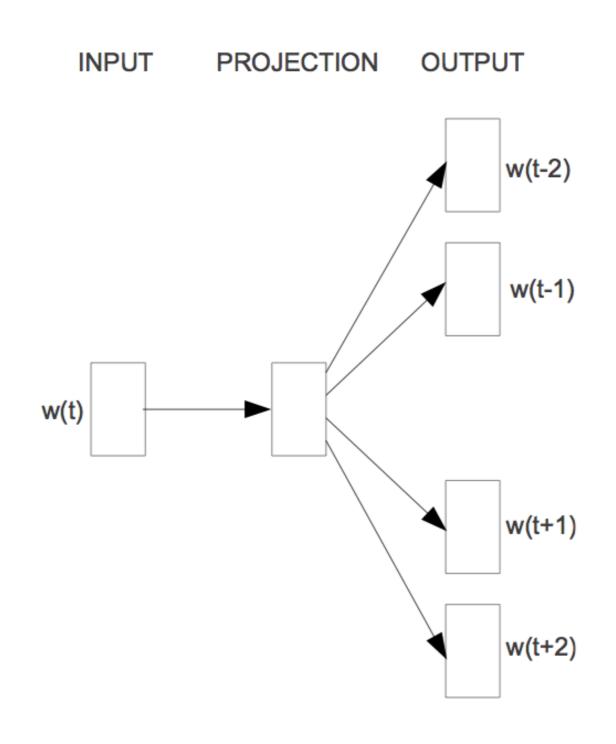


$$\mathbf{s}(t) = f\left(\mathbf{U}\mathbf{w}(t) + \mathbf{W}\mathbf{s}(t-1)\right)$$
$$\mathbf{y}(t) = g\left(\mathbf{V}\mathbf{s}(t)\right),$$

$$f(z) = \frac{1}{1 + e^{-z}}, \quad g(z_m) = \frac{e^{z_m}}{\sum_k e^{z_k}}.$$

source: http://www.fit.vutbr.cz/~imikolov/rnnlm/

# The Skip-gram model



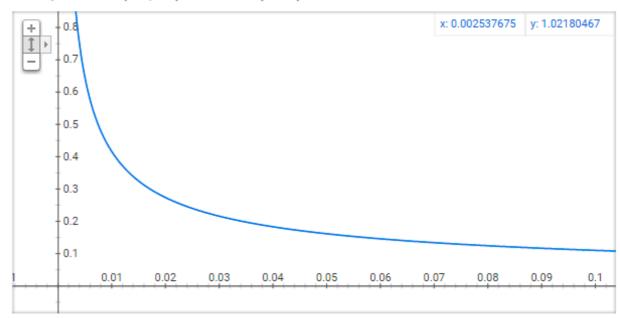
## Skip-gram improvements

#### **Subsampling frequent inputs**

$$P(w_i) = (\sqrt{\frac{z(w_i)}{0.001}} + 1) \cdot \frac{0.001}{z(w_i)}$$

- z(w) Relative frequency of word w
- P(w) Probability of keeping word w

#### Graph for (sqrt(x/0.001)+1)\*0.001/x



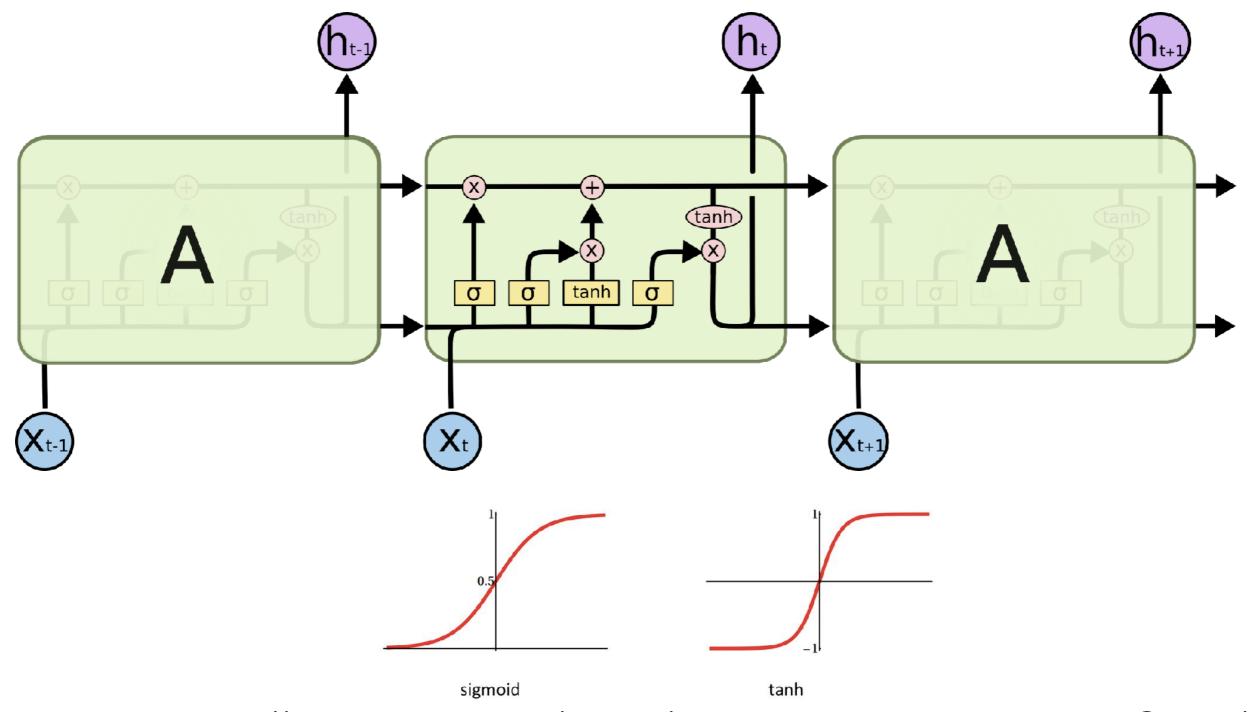
#### **Negative sampling**

We select only 5-20 negative samples in the loss function. The probability of picking a word w is given by z(w).

# Experiments with word2vec

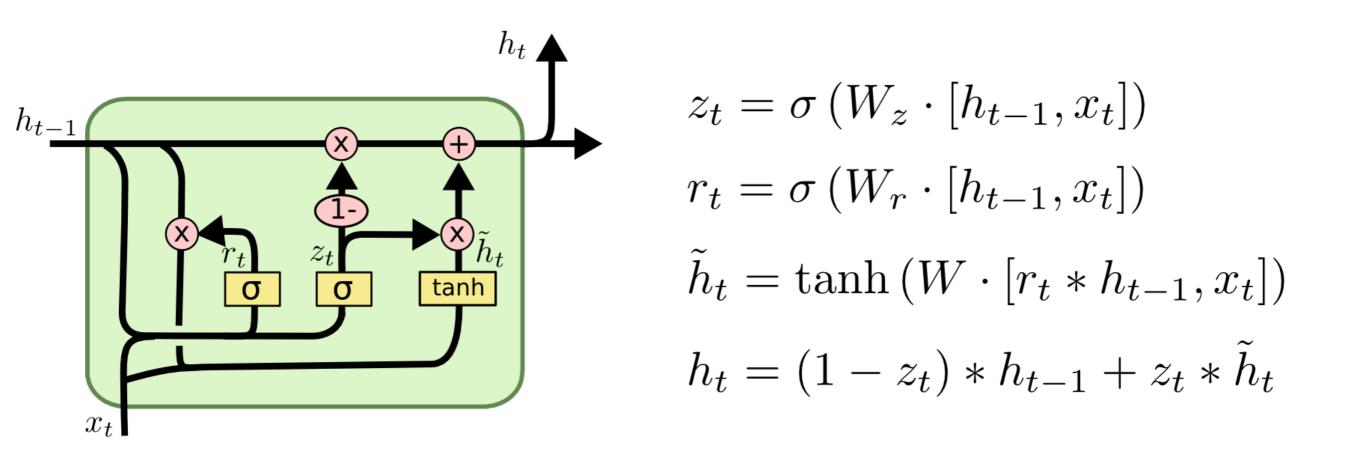
01-Review-classification-w2v-assignment.ipynb

## Long Short-Term Memory



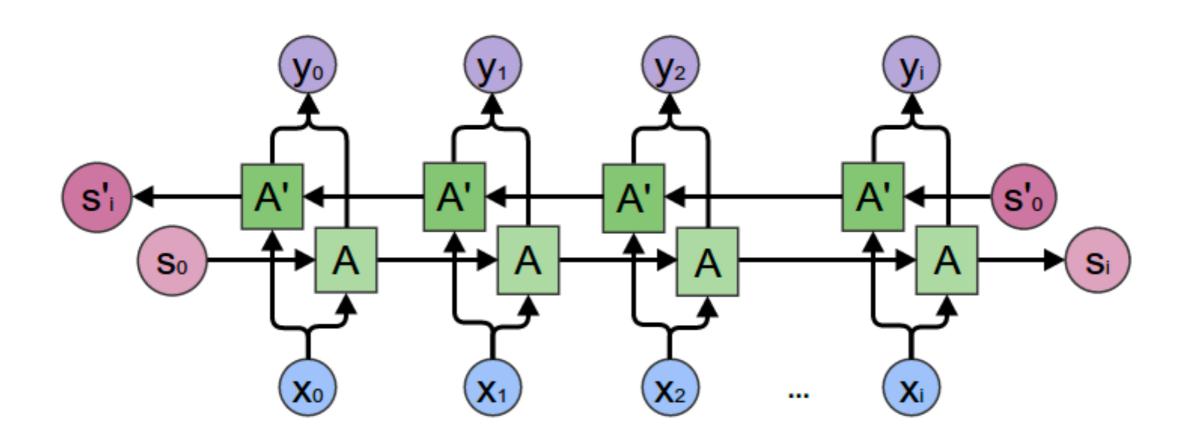
Zdroj: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

### Gated Recurrent Unit

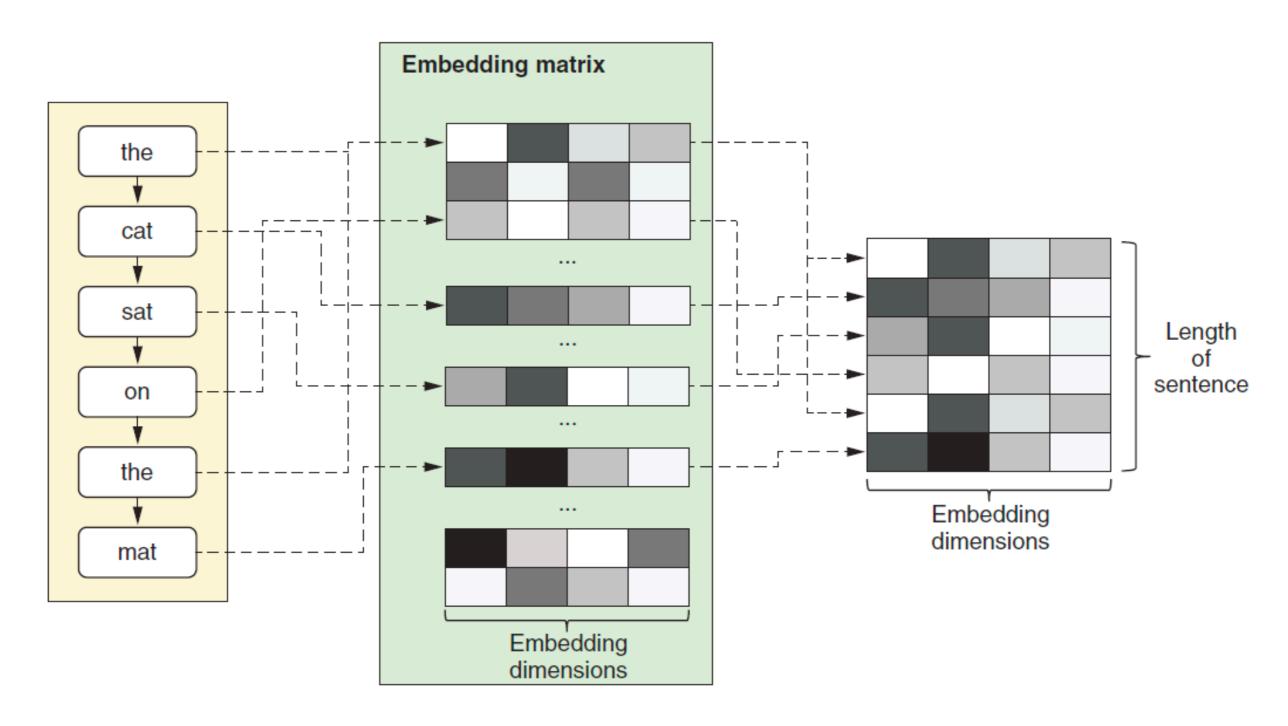


Zdroj: <a href="http://colah.github.io/posts/2015-08-Understanding-LSTMs/">http://colah.github.io/posts/2015-08-Understanding-LSTMs/</a>

# Bidirectional recursive layer in Keras



## Embedding layer in Keras



# Text classification with bidirectional LSTM

02-Review-classification-LSTM.ipynb

### Traditional tokenization

#### **NLTK** tokenizers

```
>>> from nltk.tokenize import word_tokenize #simple
>>> from nltk.tokenize.moses import MosesTokenizer #enables detokenization
>>> from nltk.tokenize import ToktokTokenizer #fast
>>>
>>> moses = MosesTokenizer()
>>> toktok = ToktokTokenizer()
>>>
>>> text = "Welcome to Machine Learning College."
>>> print(word_tokenize(text))
>>> print (moses.tokenize(text))
>>> print (toktok.tokenize(text))
['Welcome', 'to', 'Machine', 'Learning', 'College', '.']
['Welcome', 'to', 'Machine', 'Learning', 'College', '.']
['Welcome', 'to', 'Machine', 'Learning', 'College', '.']
```

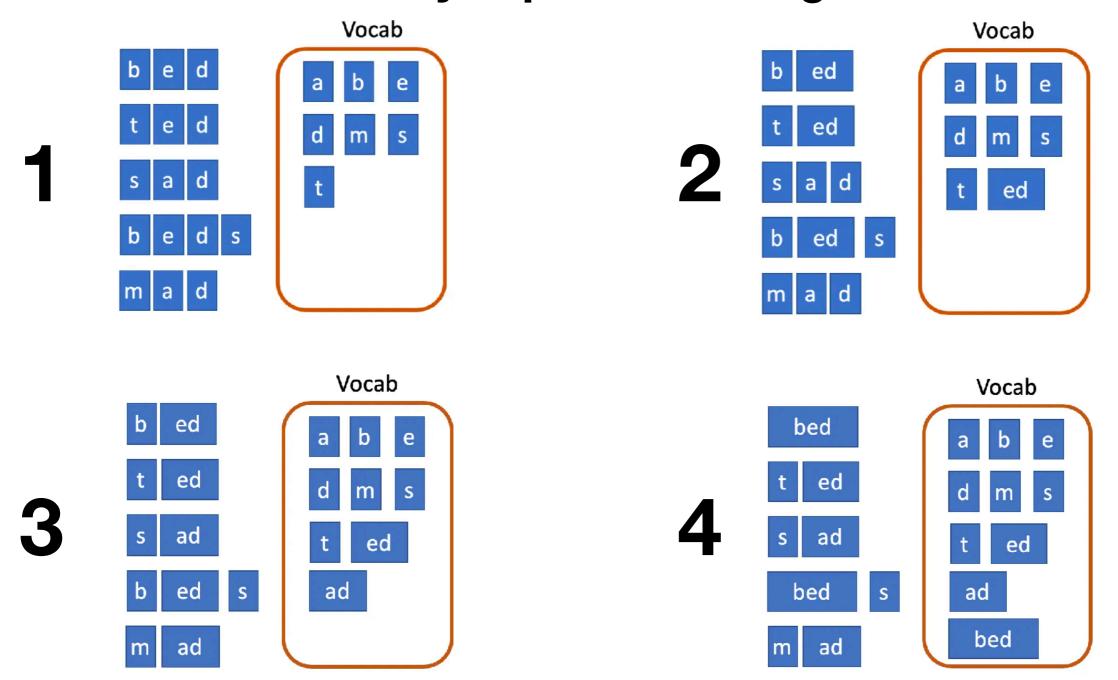
### Traditional tokenization

#### SpaCy tokenizer

```
>>> import spacy
>>> sp = spacy.load('en_core_web_sm')
>>> tokens = sp("Welcome to Machine Learning College.")
>>>
>>> [word.text for word in tokens]
['Welcome', 'to', 'Machine', 'Learning', 'College', '.']
```

### Subword tokenization

#### **Byte-pair encoding**



Source: <a href="https://mlexplained.com/2019/11/06/a-deep-dive-into-the-wonderful-world-of-preprocessing-in-nlp/">https://mlexplained.com/2019/11/06/a-deep-dive-into-the-wonderful-world-of-preprocessing-in-nlp/</a>

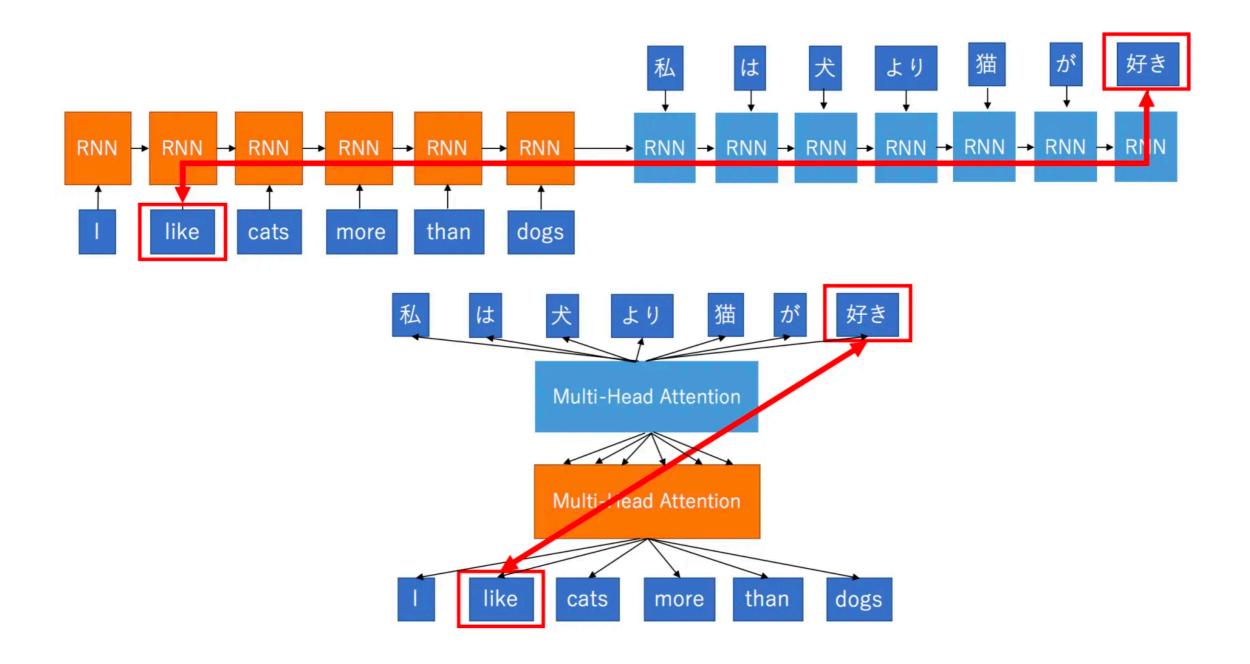
### Subword tokenization

#### Wordpiece and sentencepiece tokenization

Merges bigrams with maximum mutual information instead of maximum frequency.

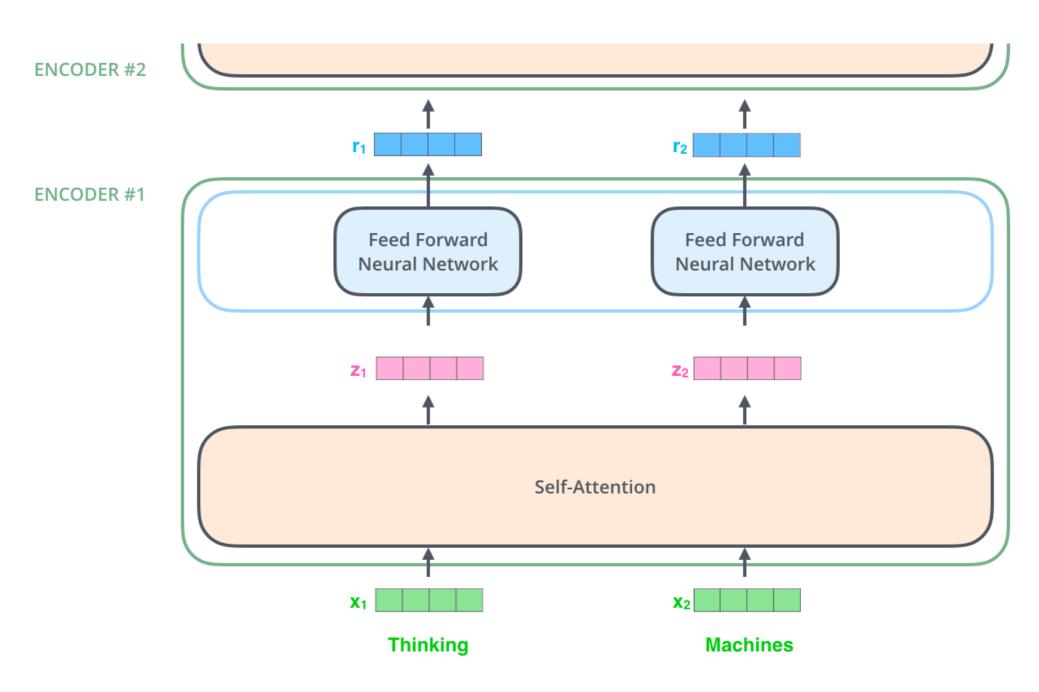
$$I(x,y) = \log\left(\frac{p(x,y)}{p(x)p(y)}\right)$$

### RNN vs. Transformer



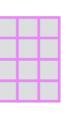
source: www.mlexplained.com

## Attention is all you need



### Self-attention

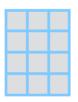
**Thinking** Input **Machines Embedding**  $X_2$  $X_1$ Queries  $q_1$ Keys  $k_1$  $k_2$ **Values V**<sub>1</sub>  $V_2$  $q_1 \cdot k_1 = 112$  $q_1 \cdot k_2 = 96$ Score Divide by 8 (  $\sqrt{d_k}$  ) 14 12 0.88 0.12 Softmax Softmax Χ  $V_1$  $V_2$ Value Sum  $\mathbf{Z}_2$  $Z_1$ 



WQ

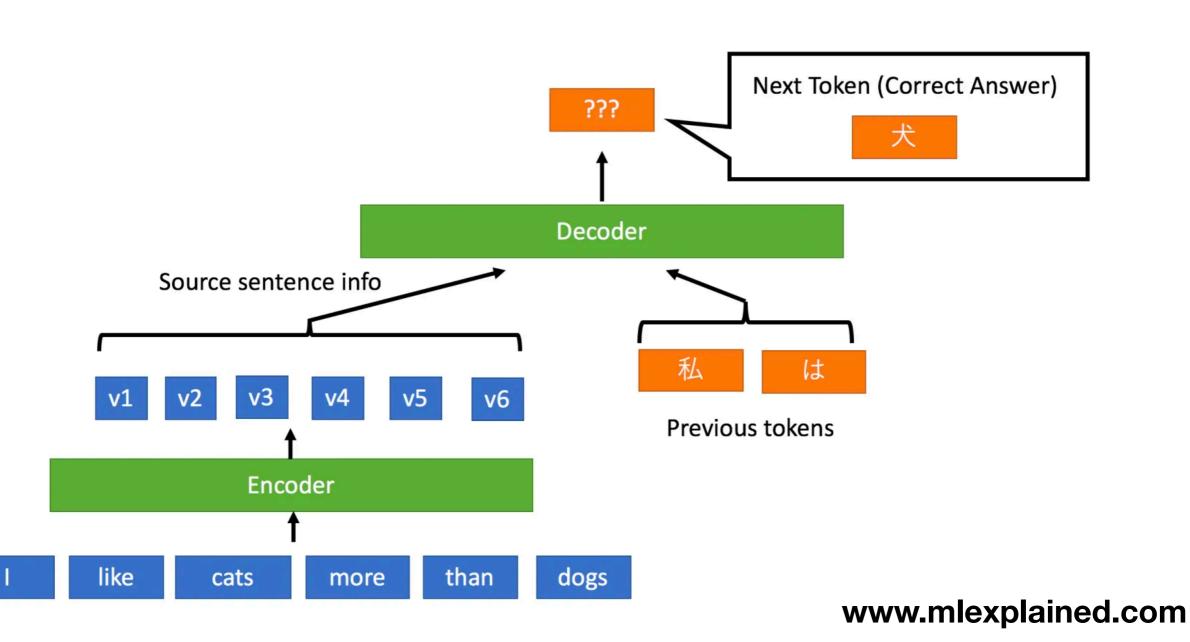


WK



W

### Translation with Transformers



# GPT-2 Language model

Donald Trump told...

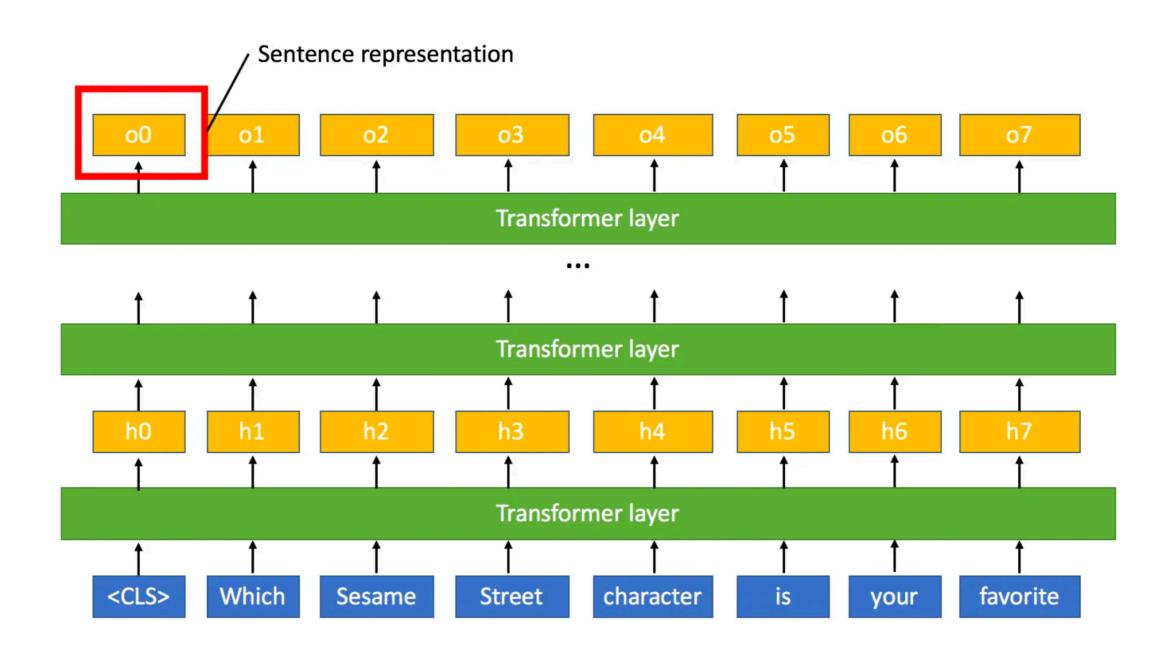
# GPT-2 Language model

**Donald Trump told** the Times he is preparing a "major speech" on his economic plans, but did not provide details on what it will entail.

"I'm getting ready for the speech. And I will have a major speech on Tuesday." Trump said during an interview in the White House residence.

GPT-3: https://openai.com/blog/openai-api/

# BERT (classification)



# Text classification using BERT

03-Review-classification-BERT.ipynb

### Thank you for your attention

e-mail: jiri@mlcollege.com

Web: www.mlcollege.com

Twitter: @JiriMaterna

Facebook: <a href="https://www.facebook.com/maternajiri">https://www.facebook.com/maternajiri</a>

LinkedIn: https://www.linkedin.com/in/jirimaterna/