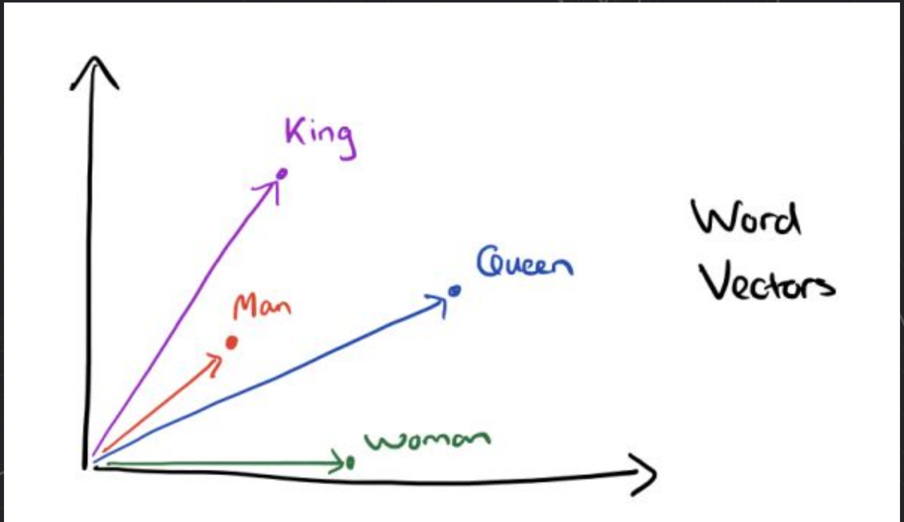
SkillFactory

Word embeddings
CNN for texts

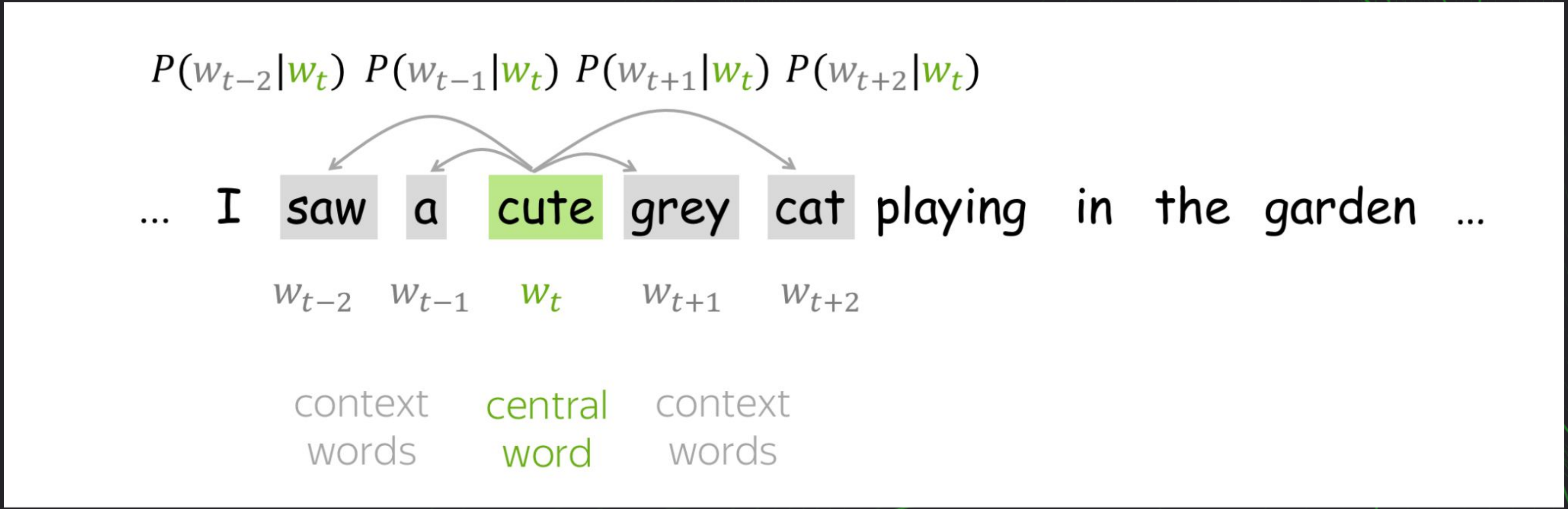
Sidorov Nikita

MLE (NLP) in Sber

Word2vec

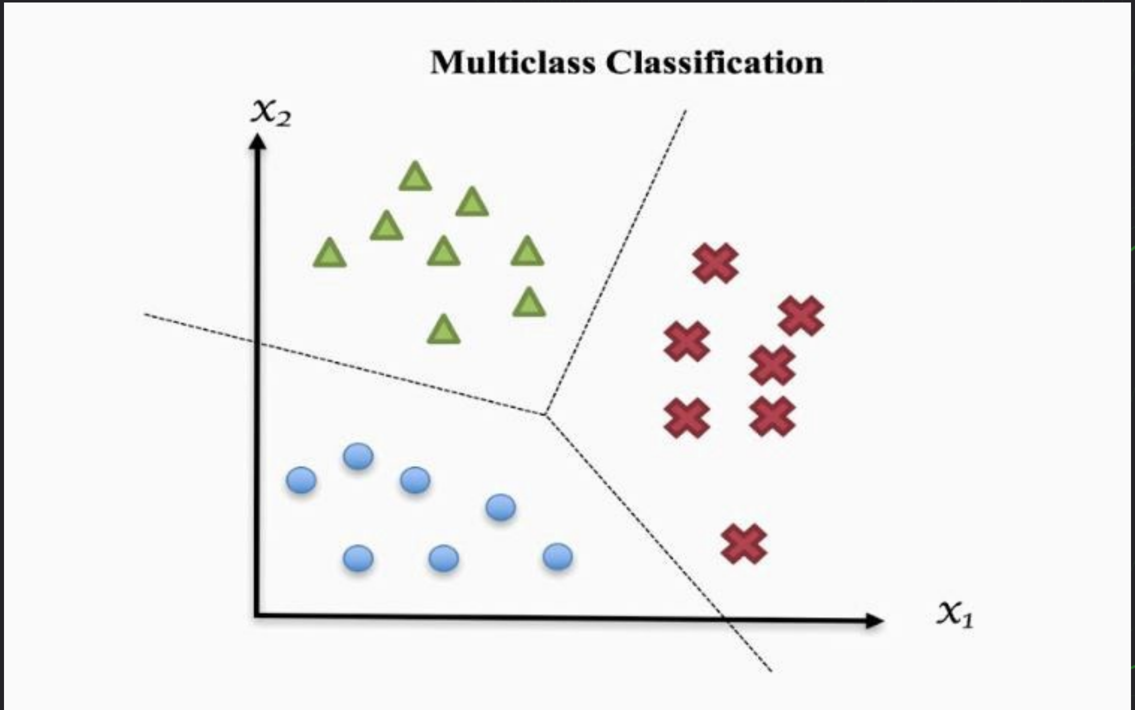


What task is solving Word2vec

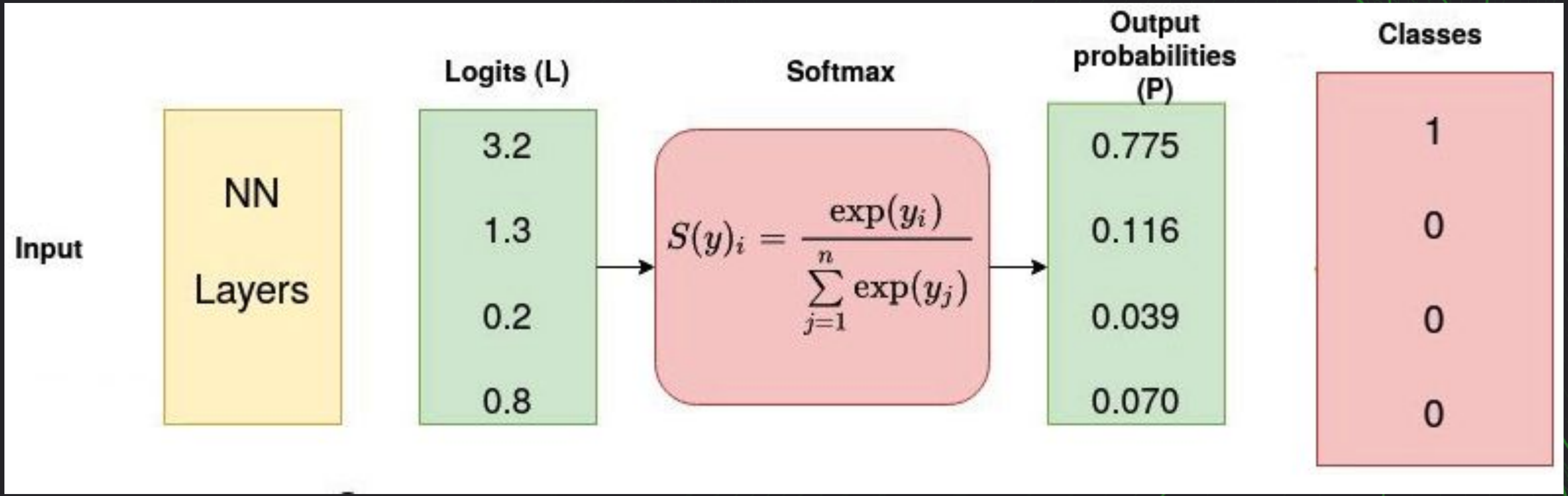


example from Lena Voita NLP course

What task is solving Word2vec



Cross-entropy



Cross-entropy

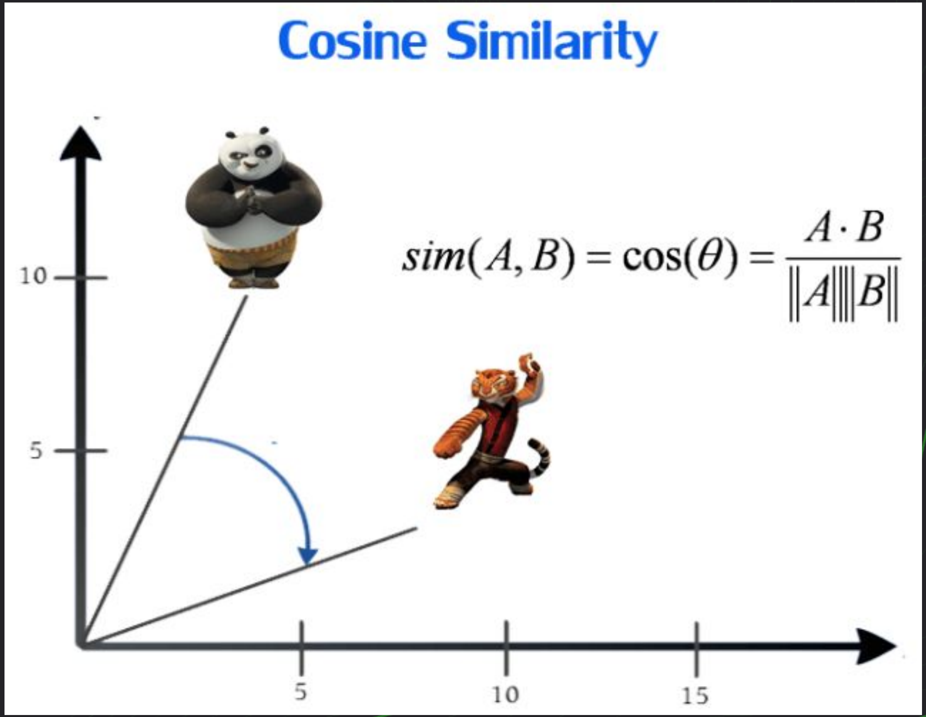
$$CCE(p,t) = -\sum_{c=1}^{C} t_{o,c} \log\left(p_{o,c}\right)$$

Distributional semantics

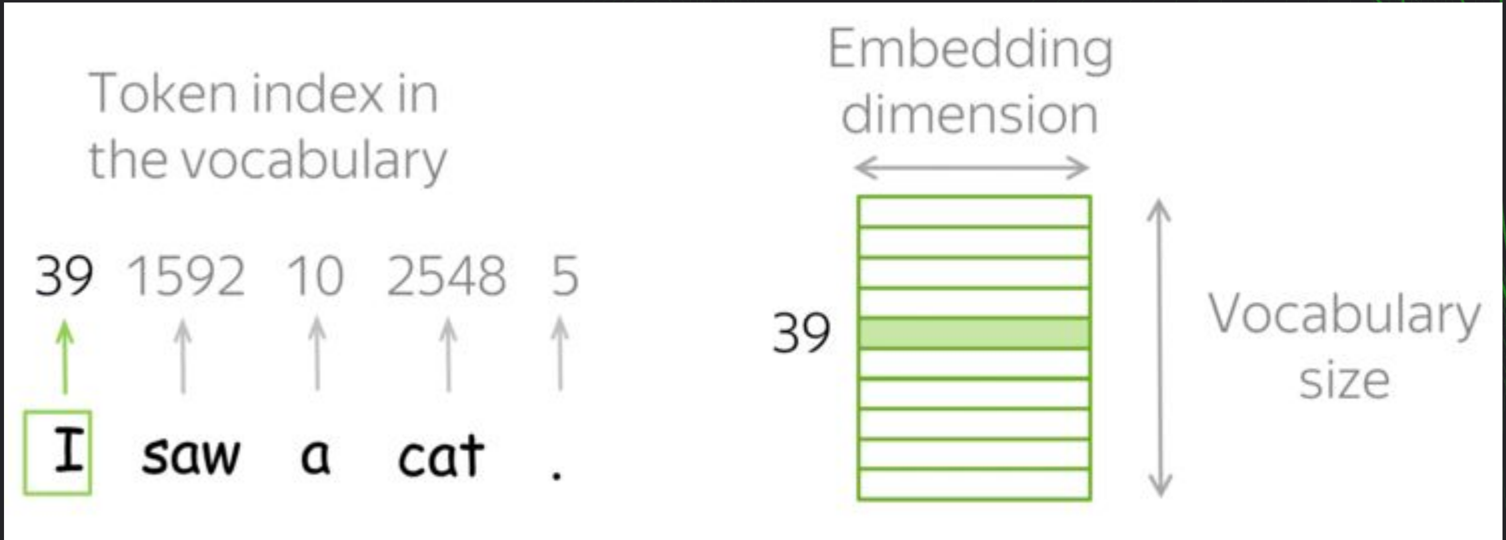
1. A bottle of ______ is on the table.
2. Everybody likes ______.
3. Don`t have ______ before you drive.
4. We make ______ out of corn.

example from Jacob Eisenstein's NLP notes

How to measure distances between vectors?



What we want from word embeddings?



What we want from word embeddings?

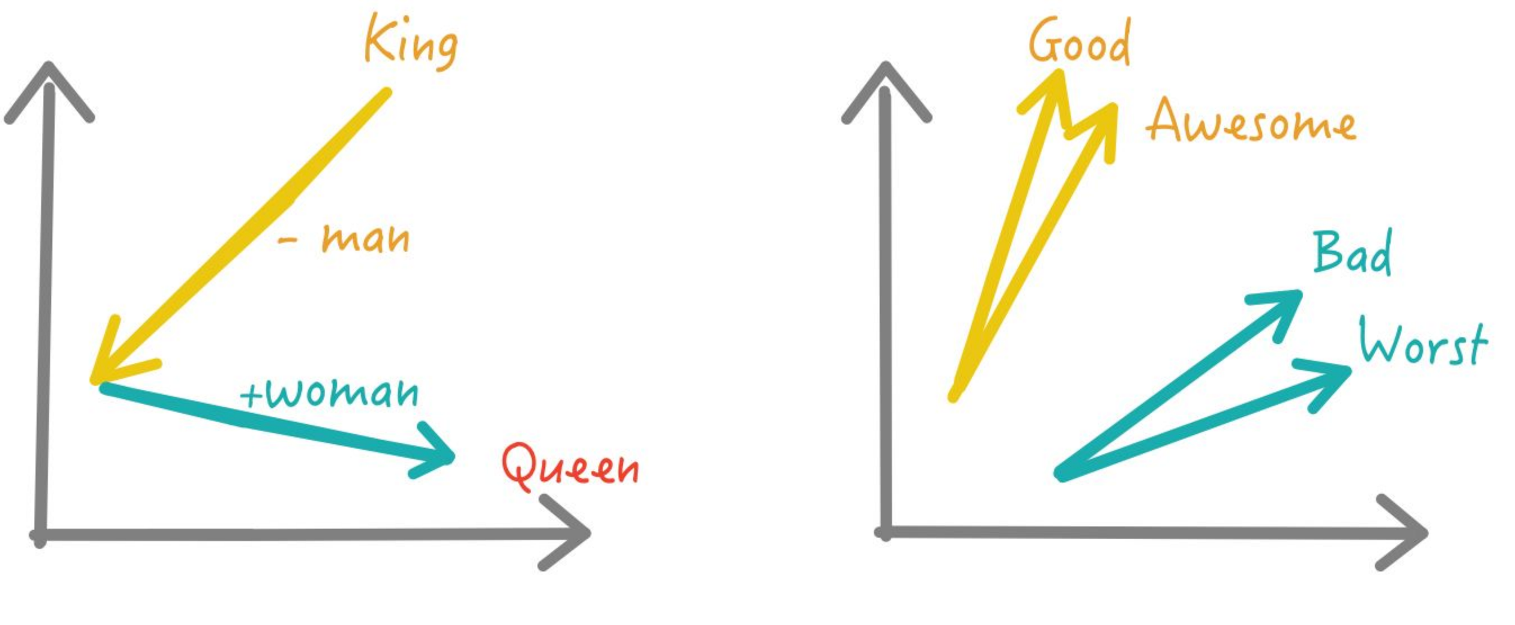
$$\begin{bmatrix} 0 & 0 & 0 & 1 & 0 \end{bmatrix} \times \begin{bmatrix} 8 & 2 & 1 & 9 \\ 6 & 5 & 4 & 0 \\ 7 & 1 & 6 & 2 \\ 1 & 3 & 5 & 8 \\ 0 & 4 & 9 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 3 & 5 & 8 \end{bmatrix}$$

One-hot vector

Embedding Weight Matrix

Hidden layer output

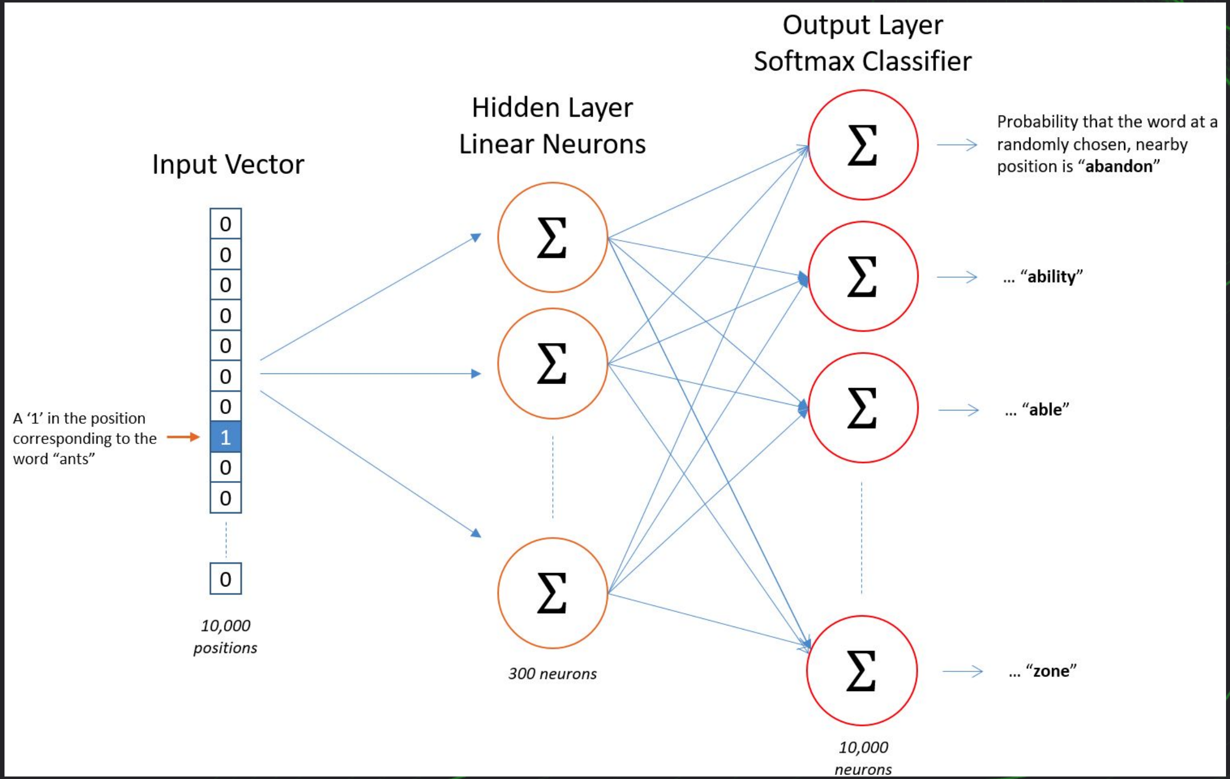
Word2vec



a) Learns Analogy

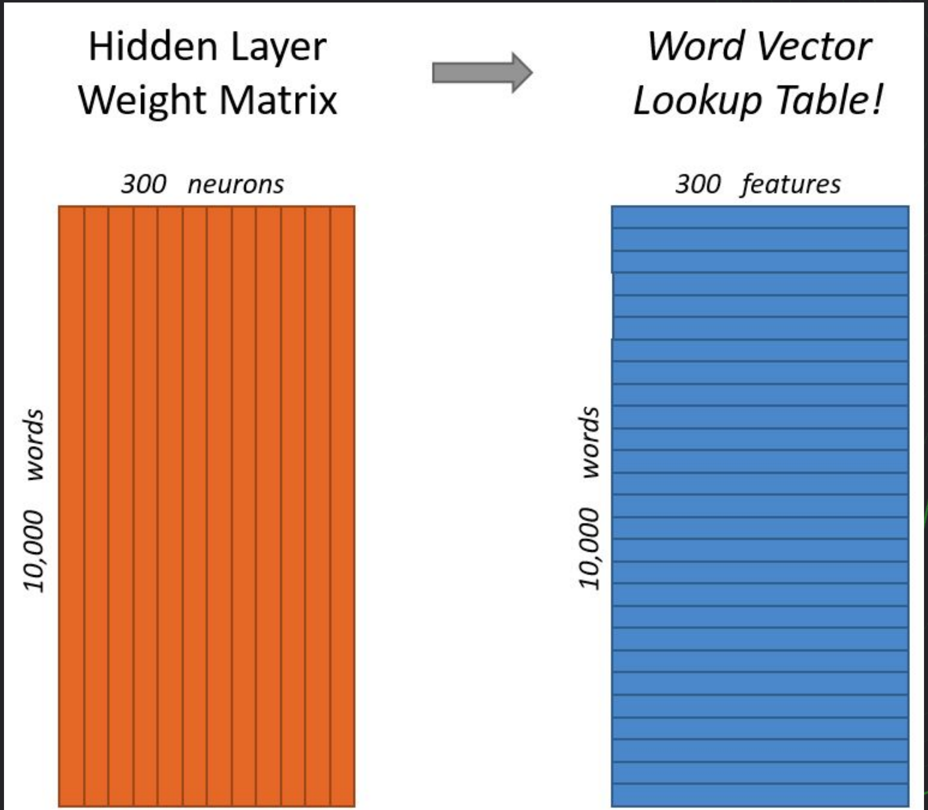
b) Similar Words have same angles

Word2vec



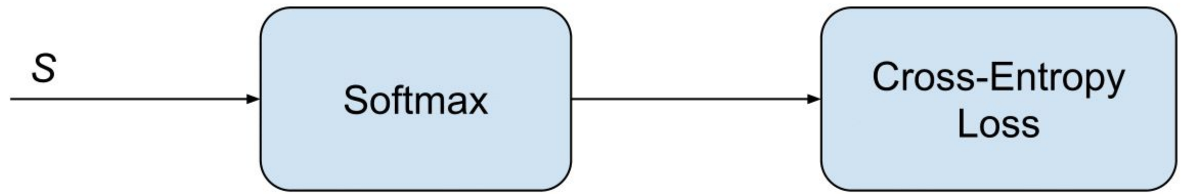
example from Chris McCormick blog

Word2vec


Hidden Layer
Weight Matrix
Word Vector
Lookup Table!
300 neurons
10,000 words
300 features
10,000 words

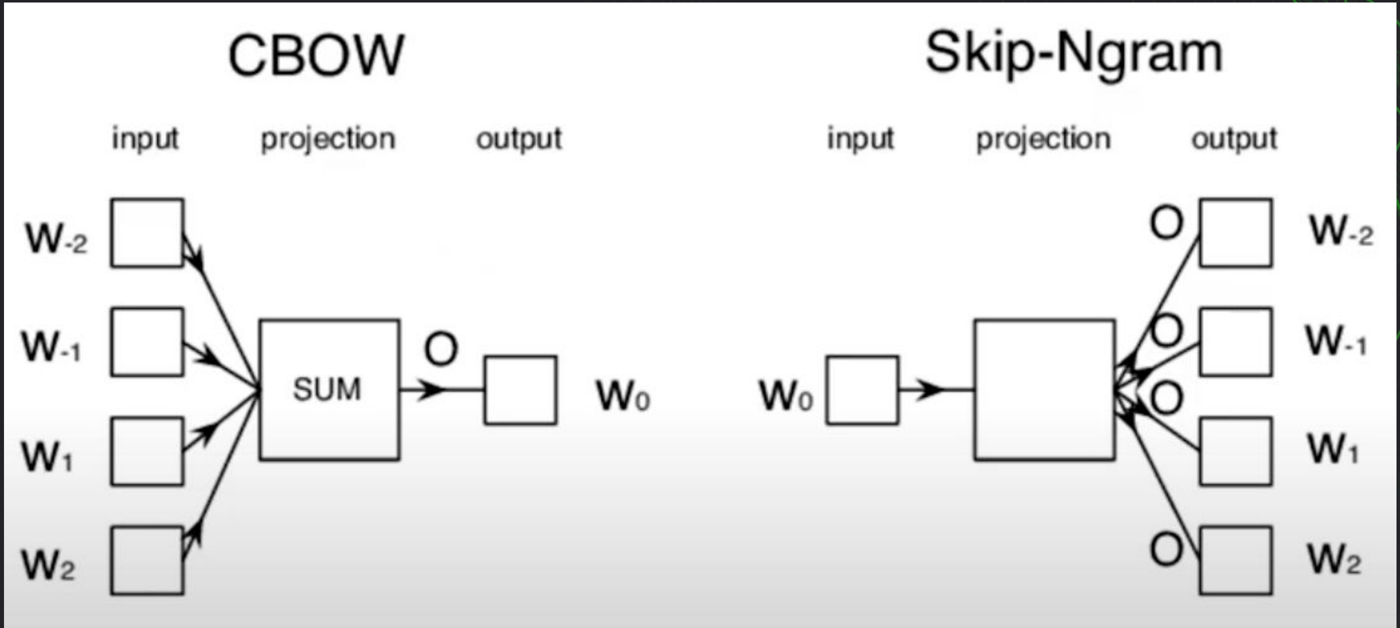
Word2vec

How to get probabilities for occurrence of words?

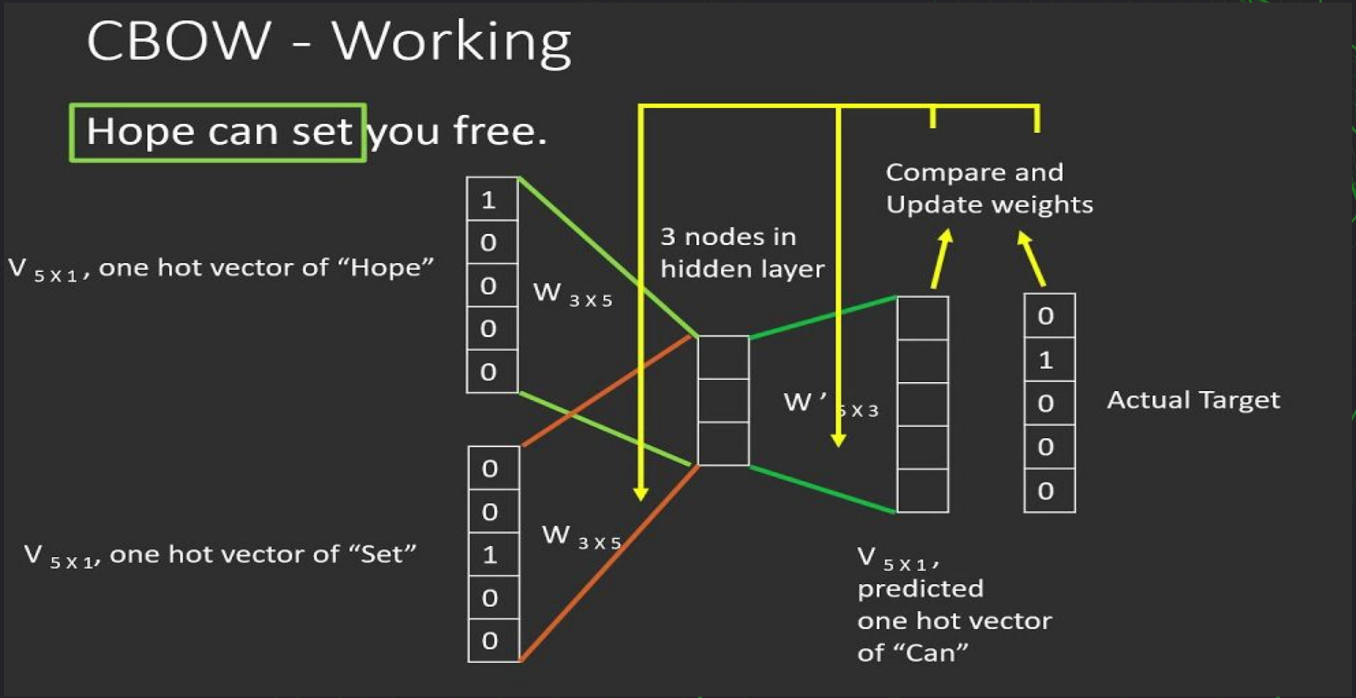


$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \qquad CE = -\sum_i^C t_i log(f(s)_i)$$

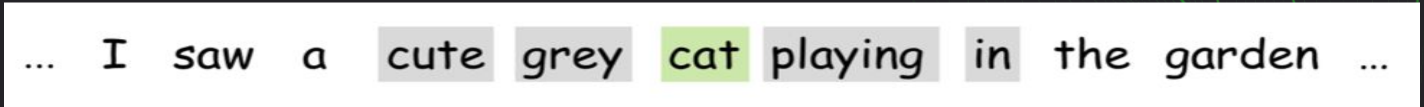
Word2vec approaches for training

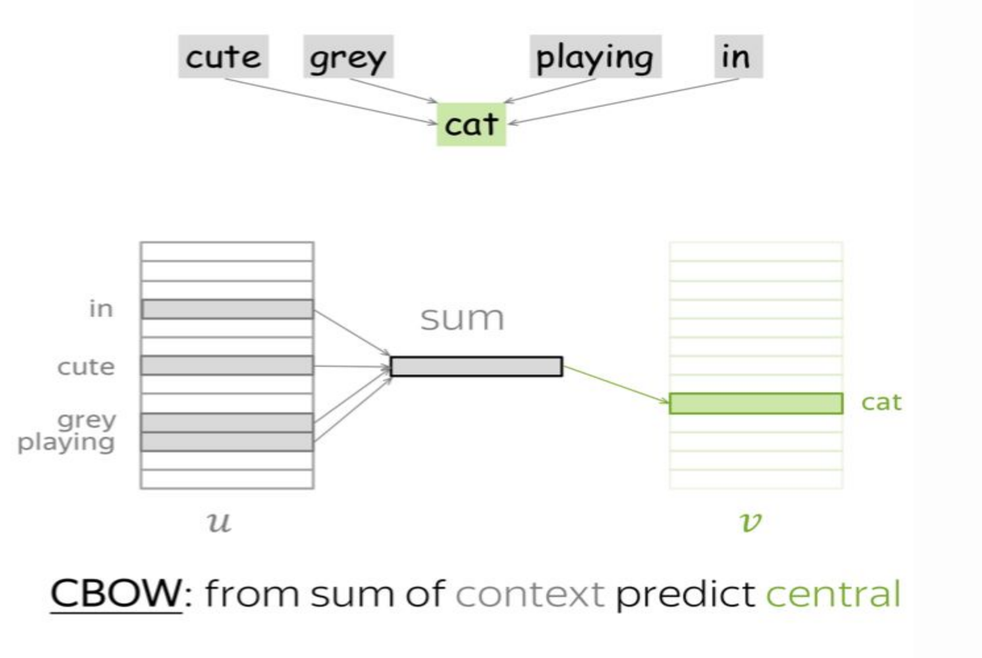


CBOW


CBOW - Working
Hope can set you free.
V 5 x 1 , one hot vector of “Hope”
1
0
0
0
0
W 3 x 5
V 5 x 1, one hot vector of “Set”
0
0
1
0
0
W 3 x 5
3 nodes in hidden layer
W ’ 5 x 3
Compare and Update weights
V 5 x 1 , predicted one hot vector of “Can”
0
1
0
0
0
Actual Target

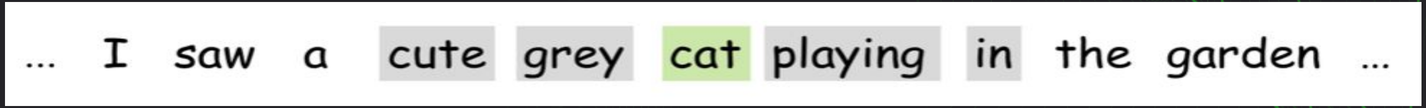
CBOW

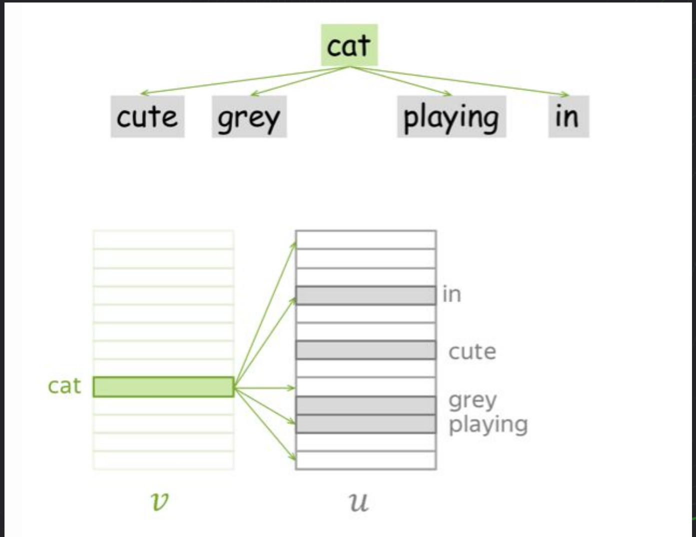




example from [Lena Voita NLP course]

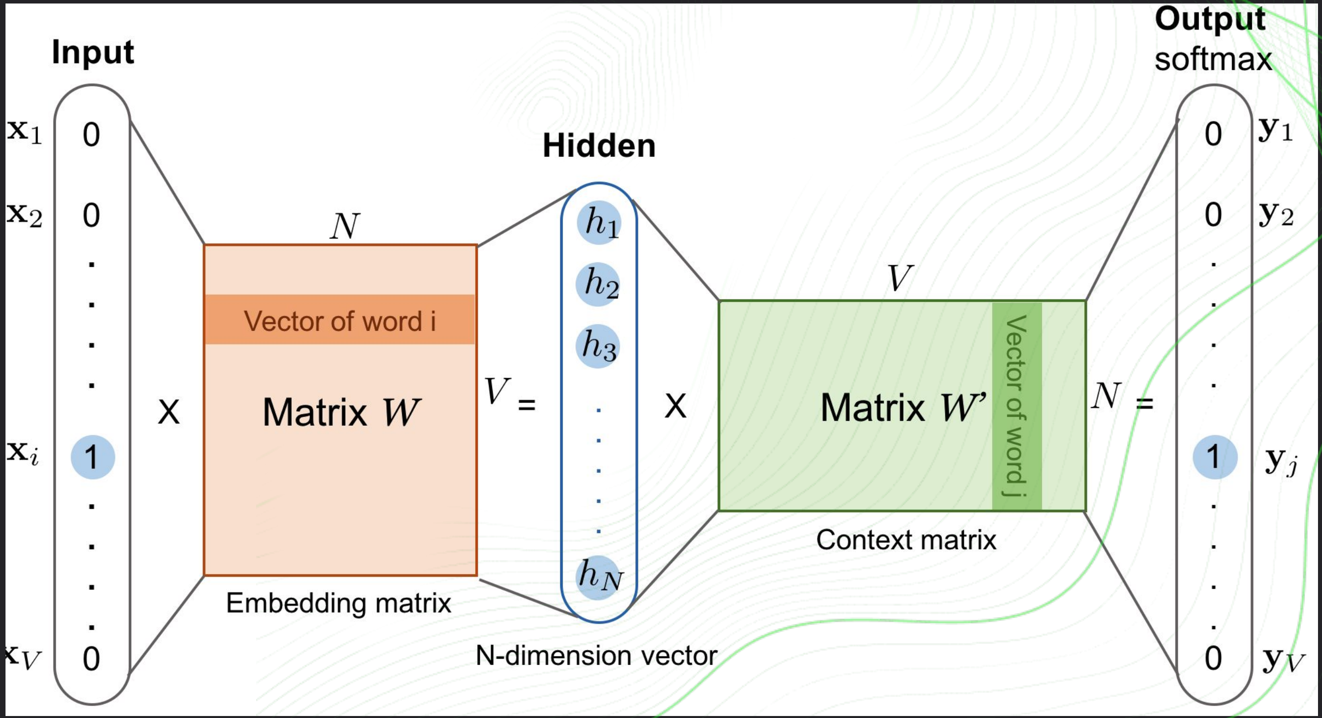
Skip-gram





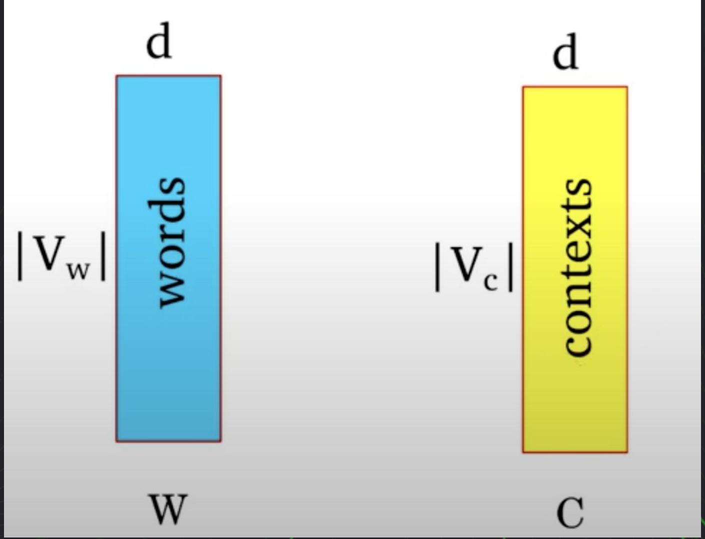
Skip-Gram: from central predict context
(one at a time)

How to learn


Input
$\mathbf{x}_1$ 0
$\mathbf{x}_2$ 0
$\mathbf{x}_i$ 1
$\mathbf{x}_V$ 0
X
N
Vector of word i
Matrix W
Embedding matrix
V =
Hidden
h_1
h_2
h_3
h_N
N-dimension vector
X
V
Matrix W'
Vector of word j
Context matrix
N =
Output
softmax
0 $\mathbf{y}_1$
0 $\mathbf{y}_2$
1 $\mathbf{y}_j$
0 $\mathbf{y}_V$

How to learn

1) For each word we would have vector of context
2) Represent each context as a *d* dimensional vector
3) Initialize all vectors to random weights
4) Arrange vectors in two matrices W and C



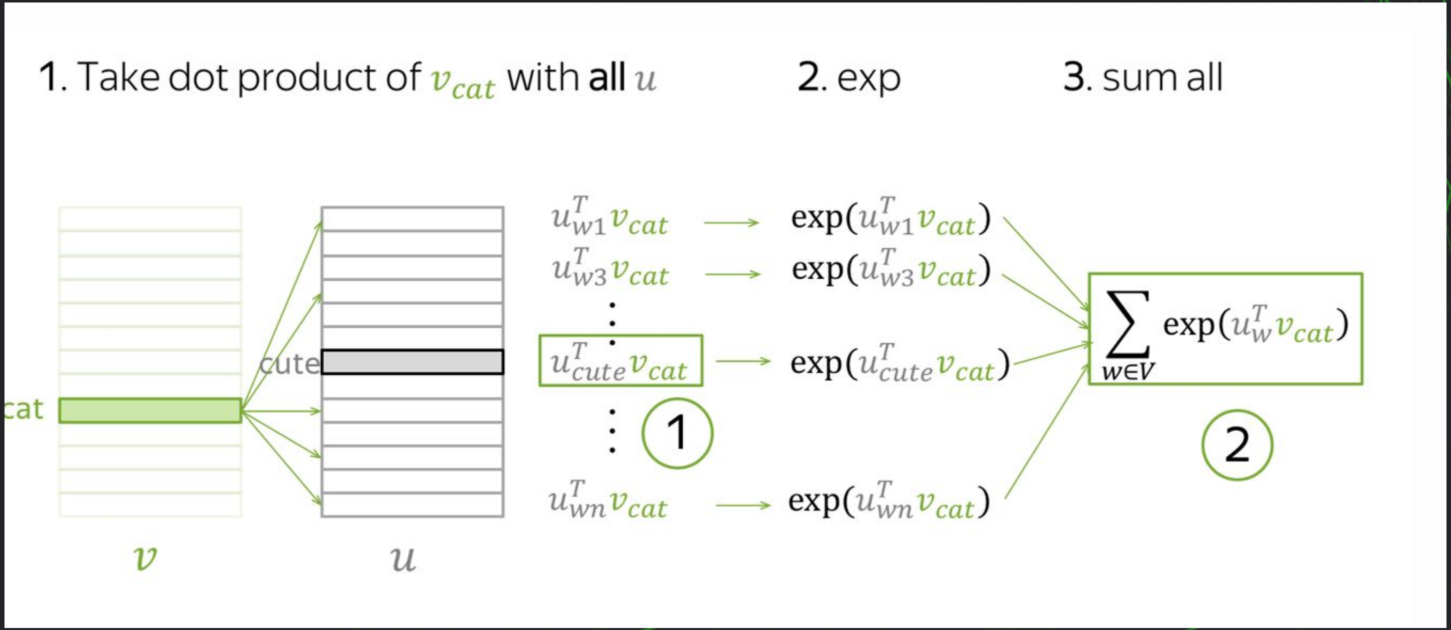
How to learn

$$\log p(c \mid w; \theta) = \frac{\exp v_c \cdot v_w}{\sum_{c' \in C} \exp v_{c'} \cdot v_w}$$

- predict context word(s)
- from word w

How to learn

… I saw a cute grey cat playing in the garden …



example from Lena Voita NLP course

How to learn

... I saw a cute grey cat playing in the garden ...

4. get loss (for this one step)

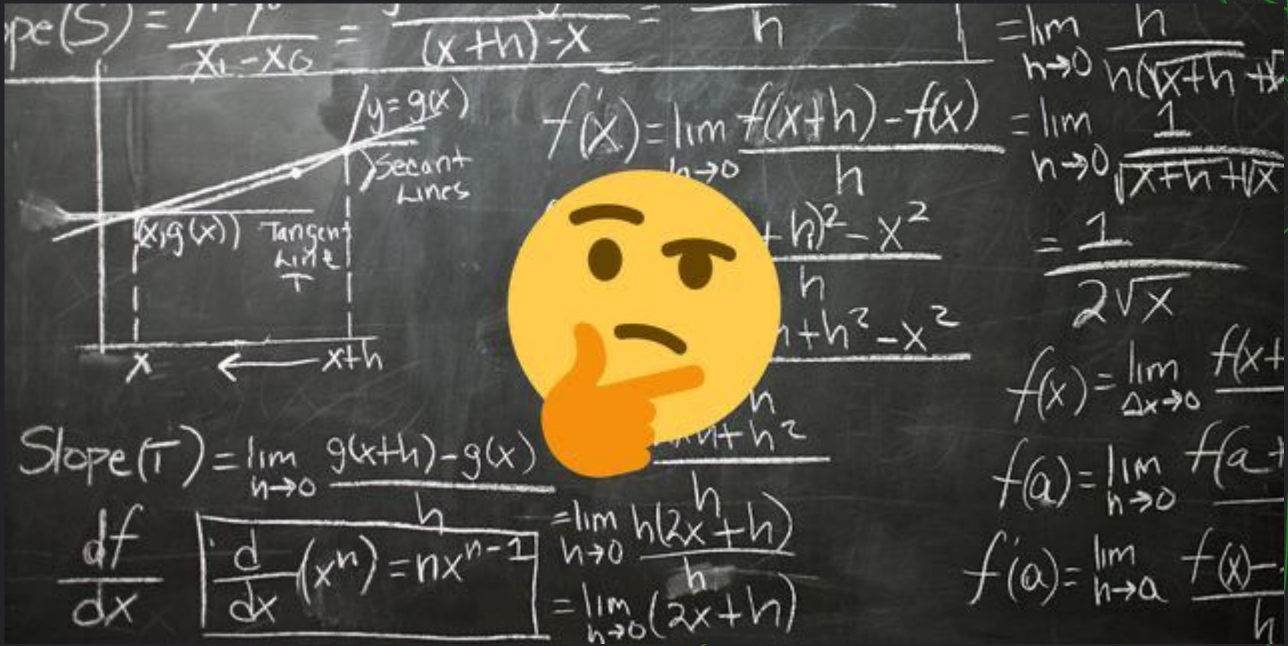
$$J_{t,j}(\theta) = \underbrace{-u_{cute}^T v_{cat}}_{1} + \underbrace{\log \sum_{w \in V} \exp(u_w^T v_{cat})}_{2}$$

5. evaluate the gradient, make an update

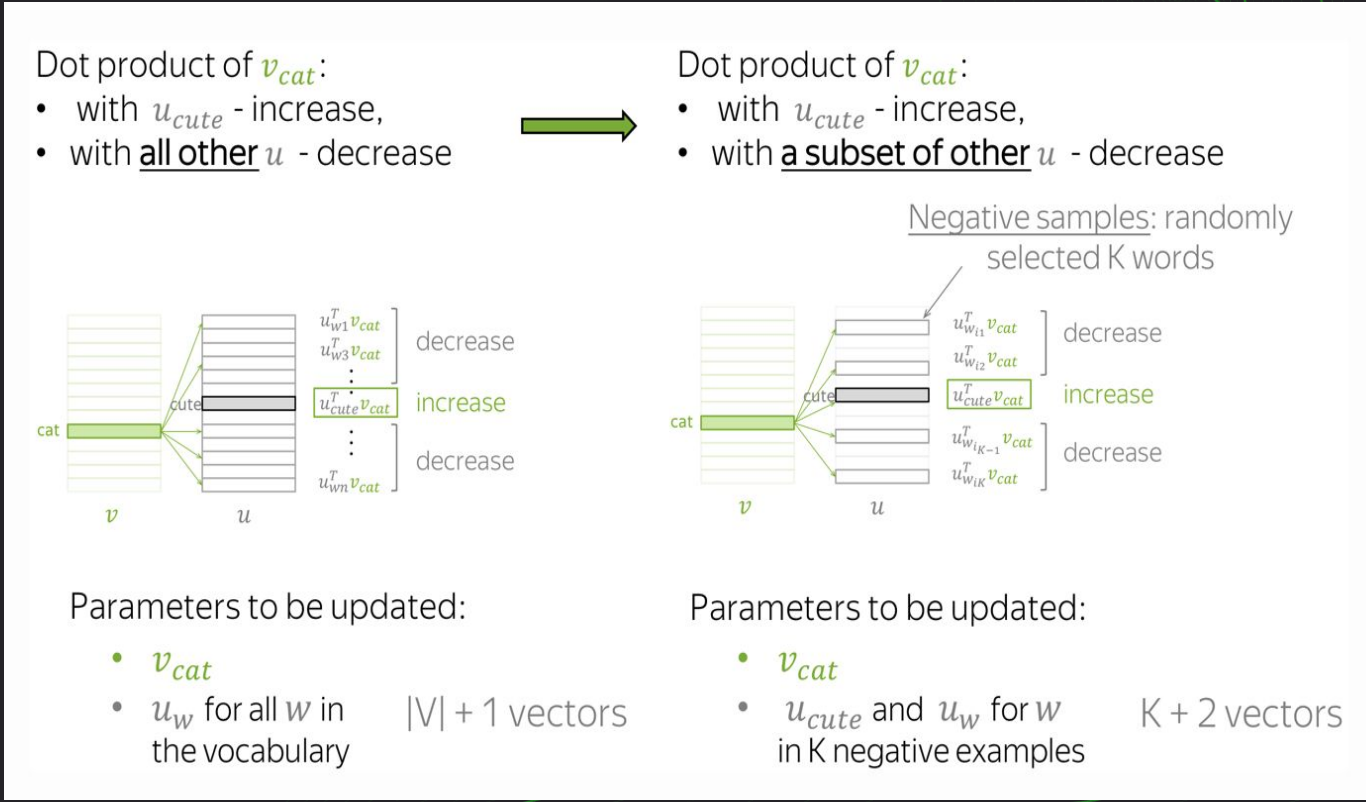
$$v_{cat} := v_{cat} - \alpha \frac{\partial J_{t,j}(\theta)}{\partial v_{cat}}$$

$$u_w := u_w - \alpha \frac{\partial J_{t,j}(\theta)}{\partial u_w} \; \forall \, w \in V$$

What`s the problem?



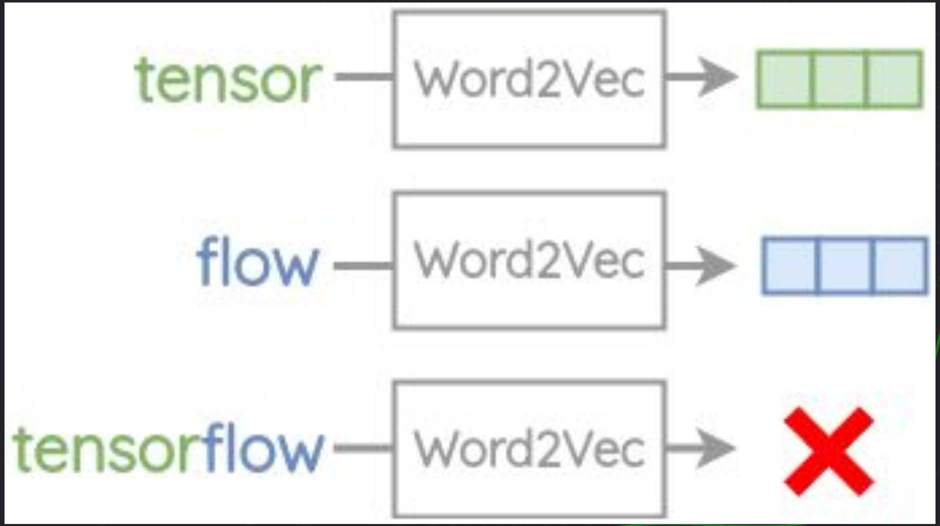
Negative sampling



example from [Lena Voita NLP course]()

Word2vec
CNN for texts

OOV words



Fasttext

- Take not only words, but n-grams in this words
- harder to compute
- longer to train
- bigger models
- well works for morphologically rich languages

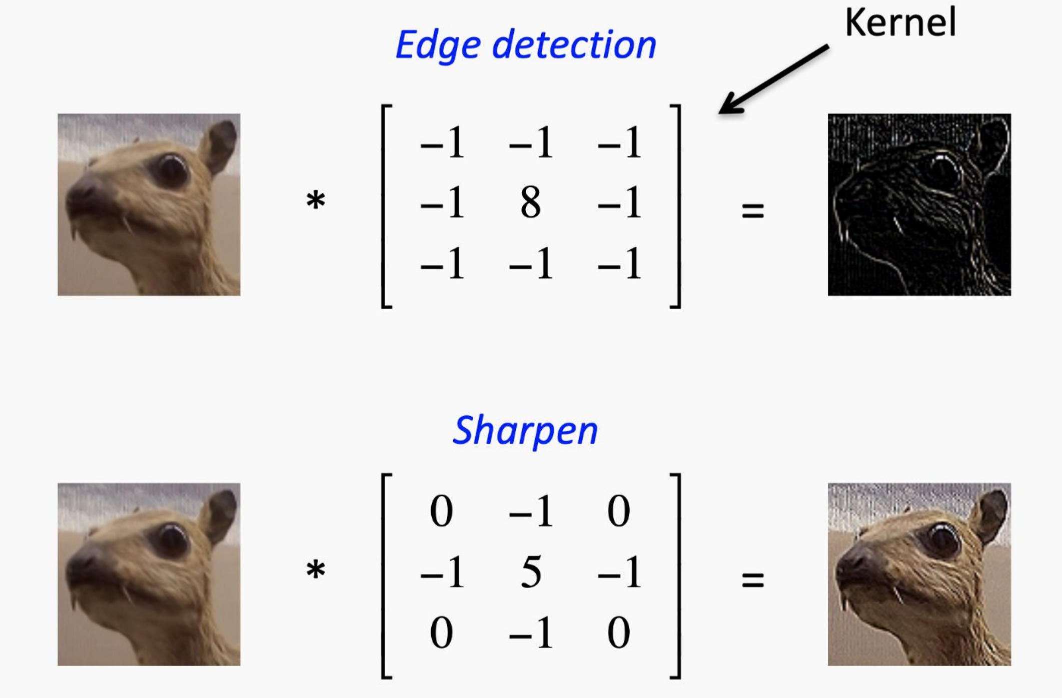
Fasttext

- Skip-gram model as base model
- take each word and n-grams for it (from 3 to 6)
- for reducing space we use hashing trick
- negative sampling is our everything

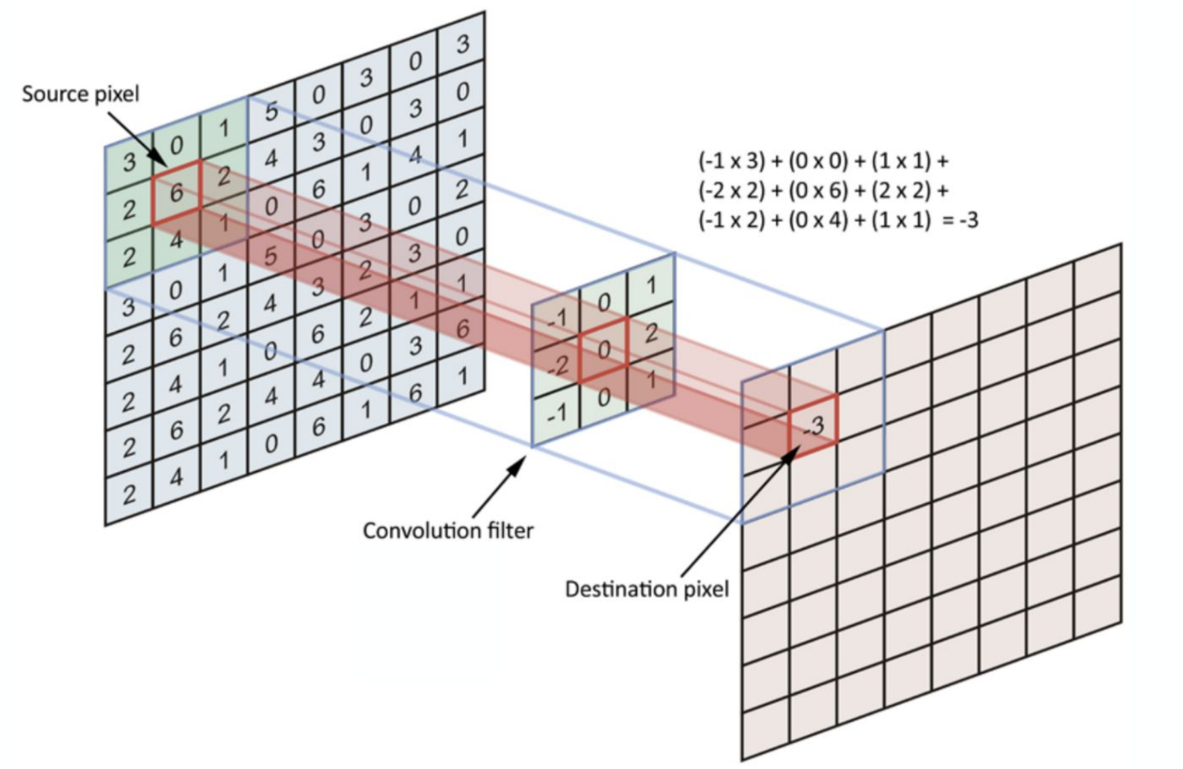
Convolutions

In deep learning, a convolutional neural network (CNN) is a class of artificial neural network, most commonly applied to analyze visual imagery. They are also known as artificial neural networks that slide along input features and provide translation equivariant responses known as feature maps. Counter-intuitively, most convolutional neural networks are only equivariant, as opposed to invariant, to translation.

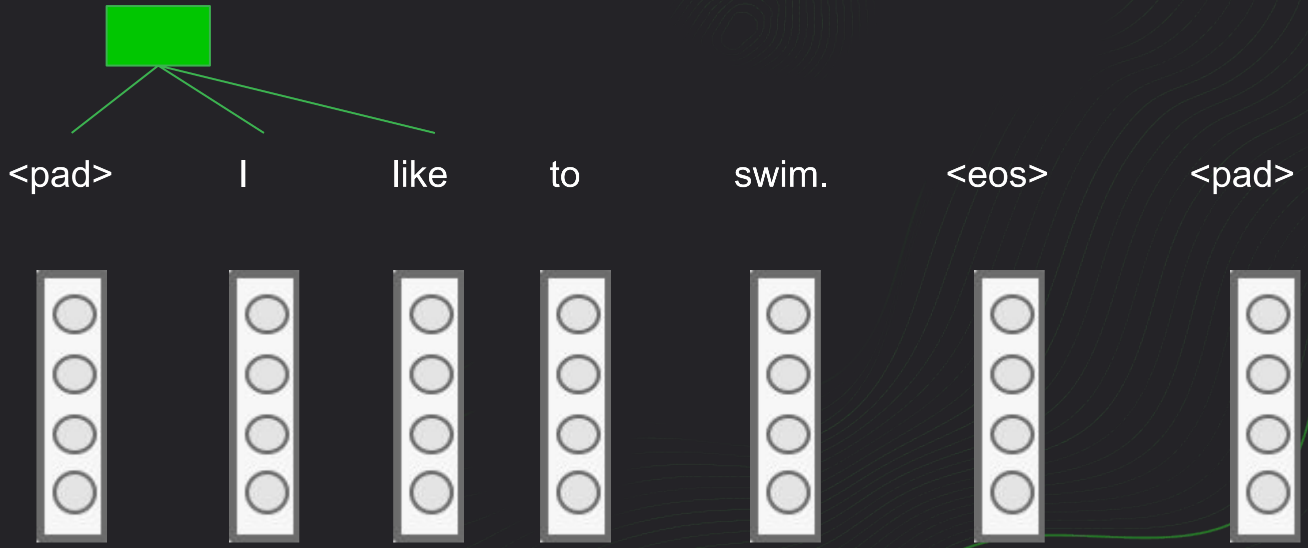
Convolutions



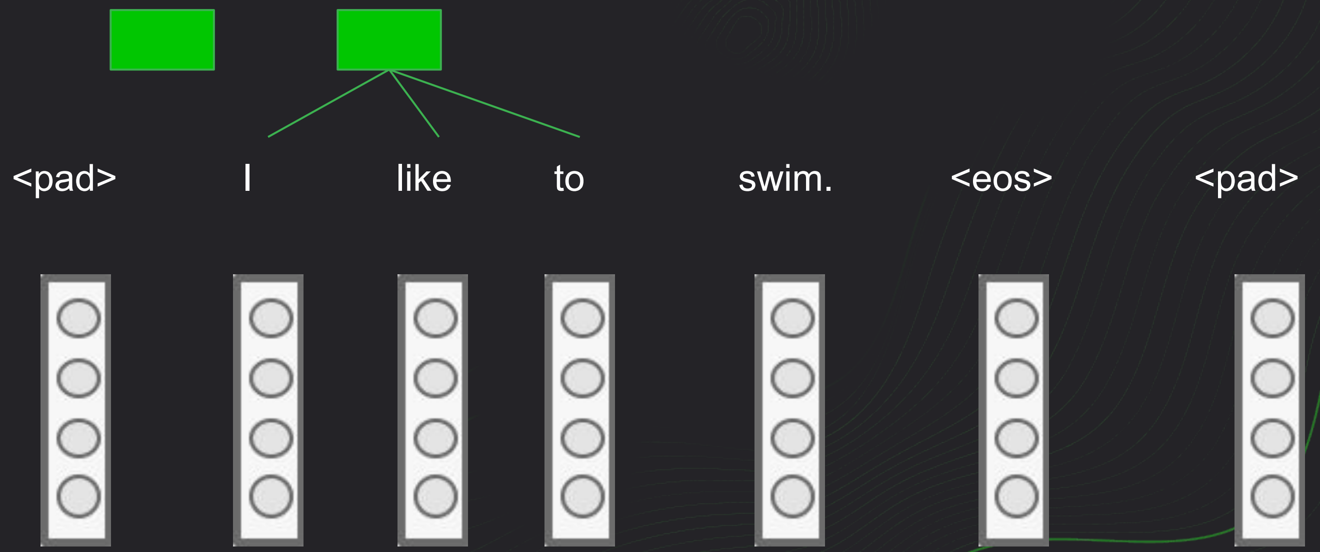
Convolutions



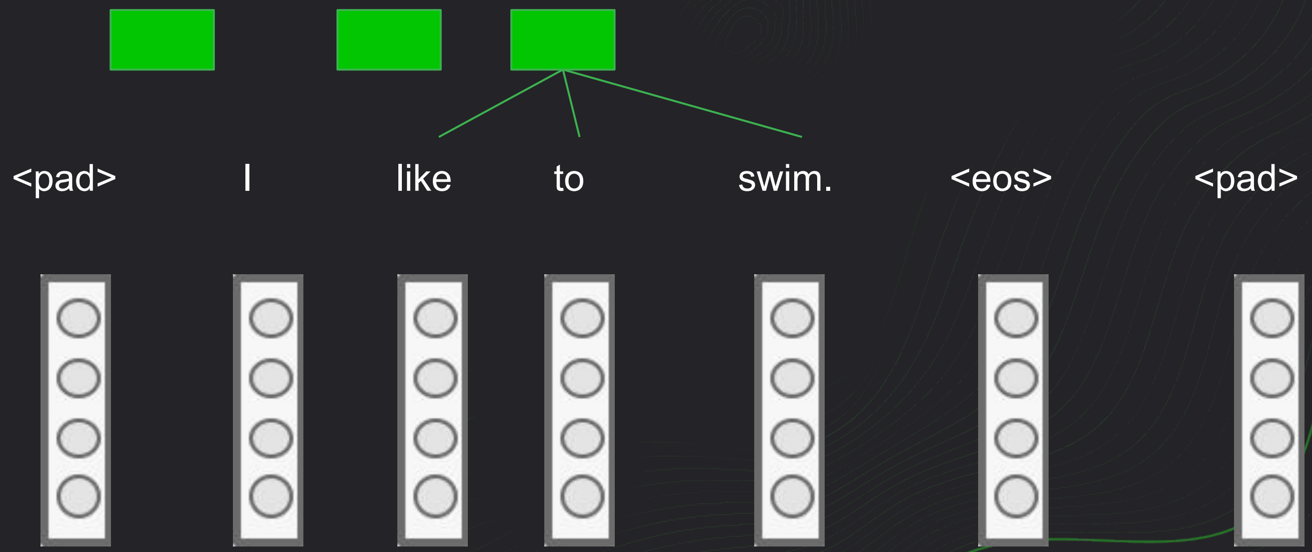
Convolution for texts



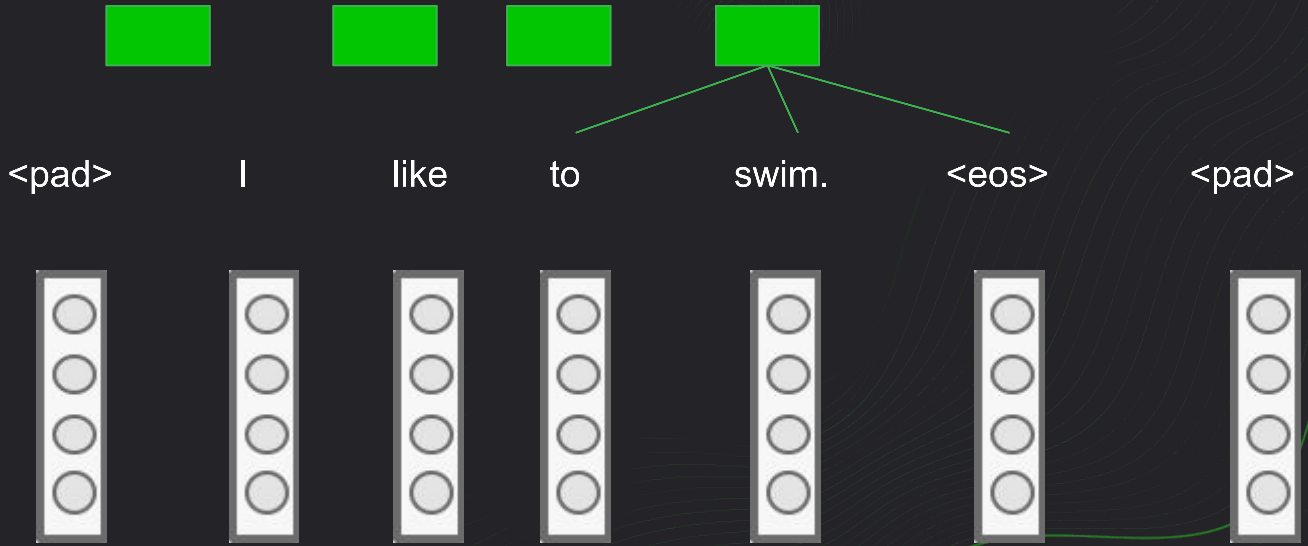
Convolution for texts



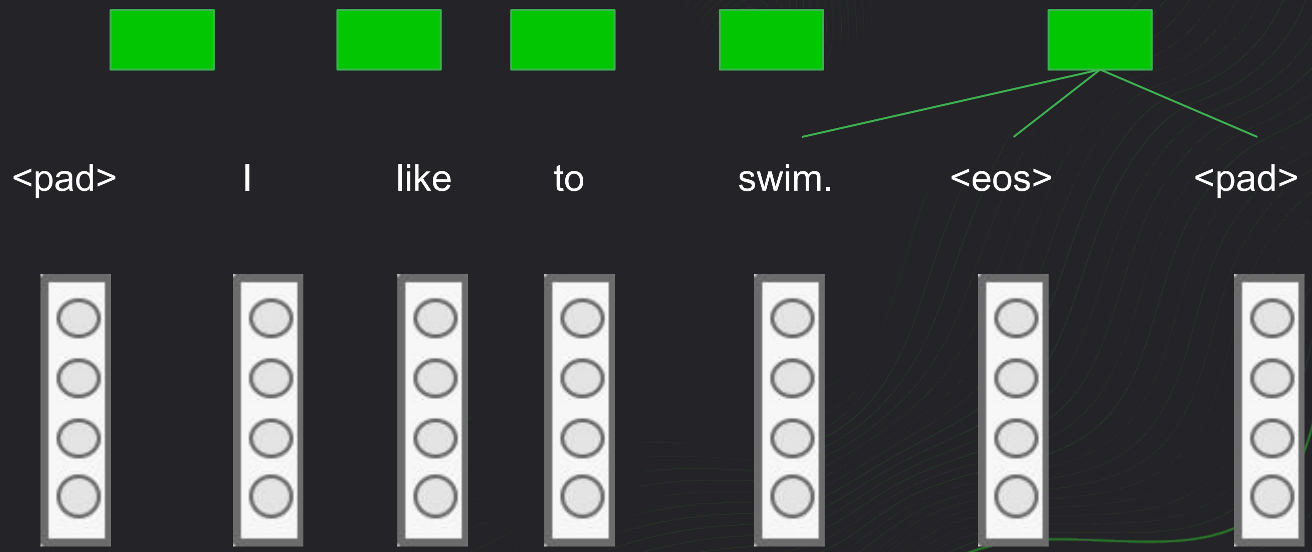
Convolution for texts



Convolution for texts



Convolution for texts



Convolution for texts

Text

<pad>	0.3	0.4	-0.2	-0.6
I	0.5	0.1	-0.3	0.4
like	-0.1	0.5	0.8	-0.2
to	0.2	-0.3	-0.4	-0.5
swim.	-0.7	0.5	0.9	0.1
<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.3	0.4	-0.2	-0.6

Convolution for texts

Text

<pad>	0.3	0.4	-0.2	-0.6
I	0.5	0.1	-0.3	0.4
like	-0.1	0.5	0.8	-0.2
to	0.2	-0.3	-0.4	-0.5
swim.	-0.7	0.5	0.9	0.1
<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.3	0.4	-0.2	-0.6

Apply filters of size 3 and that have 4 channels

3	2	1	-1
1	0	2	1
-1	1	1	-2

Convolution for texts

Text

<pad>	0.3	0.4	-0.2	-0.6
I	0.5	0.1	-0.3	0.4
like	-0.1	0.5	0.8	-0.2
to	0.2	-0.3	-0.4	-0.5
swim.	-0.7	0.5	0.9	0.1
<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.3	0.4	-0.2	-0.6

Apply filters of size 3 and that have 4 channels

3	2	1	-1
1	0	2	1
-1	1	1	-2

Result

<IL	
ILT	
LTS	
TS<	
S<<	

Convolution for texts

Text

<pad>	0.3	0.4	-0.2	-0.6
I	0.5	0.1	-0.3	0.4
like	-0.1	0.5	0.8	-0.2
to	0.2	-0.3	-0.4	-0.5
swim.	-0.7	0.5	0.9	0.1
<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.3	0.4	-0.2	-0.6

Apply filters of size 3 and that have 4 channels

3	2	1	-1
1	0	2	1
-1	1	1	-2

Result

<IL	4.2
ILT	
LTS	
TS<	
S<<	

Convolution for texts

Text

<pad>	0.3	0.4	-0.2	-0.6
I	0.5	0.1	-0.3	0.4
like	-0.1	0.5	0.8	-0.2
to	0.2	-0.3	-0.4	-0.5
swim.	-0.7	0.5	0.9	0.1
<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.3	0.4	-0.2	-0.6

Apply filters of size 3 and that have 4 channels

3	2	1	-1
1	0	2	1
-1	1	1	-2

Result

<IL	4.2
ILT	2.4
LTS	
TS<	
S<<	

Convolution for texts

Text

<pad>	0.3	0.4	-0.2	-0.6
I	0.5	0.1	-0.3	0.4
like	-0.1	0.5	0.8	-0.2
to	0.2	-0.3	-0.4	-0.5
swim.	-0.7	0.5	0.9	0.1
<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.3	0.4	-0.2	-0.6

Apply filters of size 3 and that have 4 channels

3	2	1	-1
1	0	2	1
-1	1	1	-2

Result

<IL	4.2
ILT	2.4
LTS	2.5
TS<	
S<<	

Convolution for texts

Text

<pad>	0.3	0.4	-0.2	-0.6
I	0.5	0.1	-0.3	0.4
like	-0.1	0.5	0.8	-0.2
to	0.2	-0.3	-0.4	-0.5
swim.	-0.7	0.5	0.9	0.1
<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.3	0.4	-0.2	-0.6

Apply filters of size 3 and that have 4 channels

3	2	1	-1
1	0	2	1
-1	1	1	-2

Result

<IL	4.2
ILT	2.4
LTS	2.5
TS<	3.2
S<<	

Convolution for texts

Text

<pad>	0.3	0.4	-0.2	-0.6
I	0.5	0.1	-0.3	0.4
like	-0.1	0.5	0.8	-0.2
to	0.2	-0.3	-0.4	-0.5
swim.	-0.7	0.5	0.9	0.1
<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.3	0.4	-0.2	-0.6

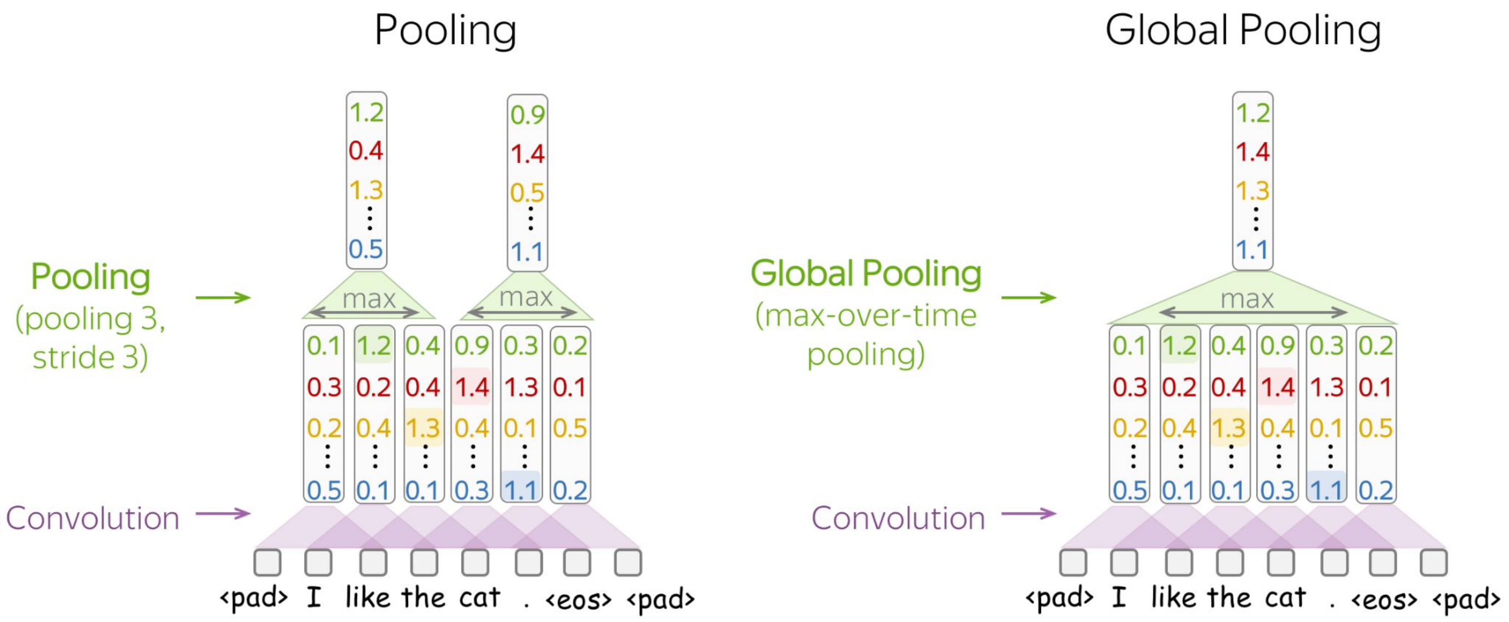
Apply filter of size 3, that have 4 channels

3	2	1	-1
1	0	2	1
-1	1	1	-2

Result

<IL	4.2
ILT	2.4
LTS	2.5
TS<	3.2
S<<	0.1

Pooling for convolutions



example from [Lena Voita NLP course]