



**SKILLFACTORY**

# Word embeddings

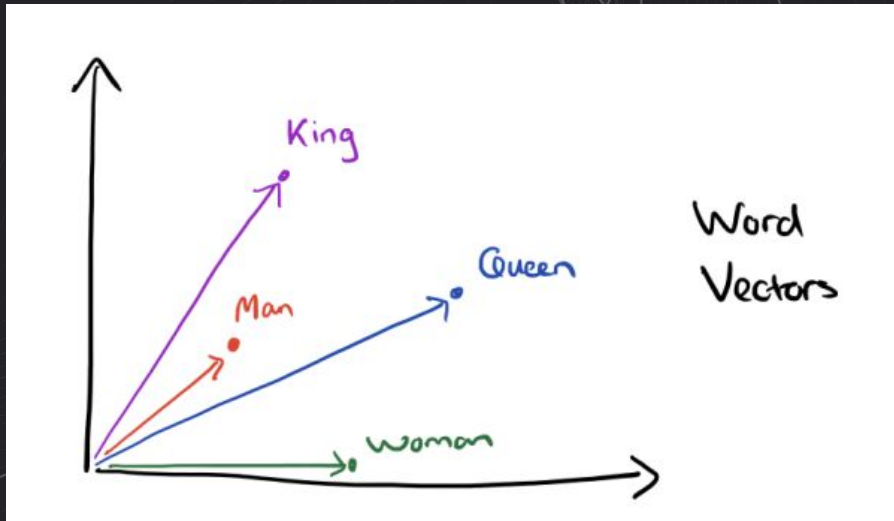
## CNN for texts

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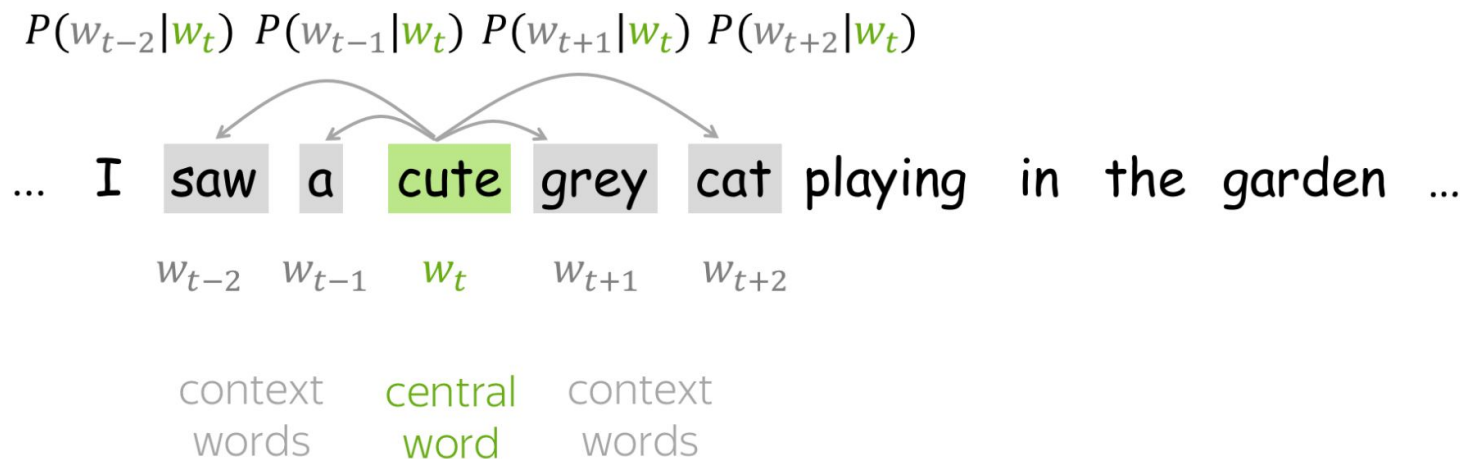
**Sidorov Nikita**

MLE (NLP) in Sber

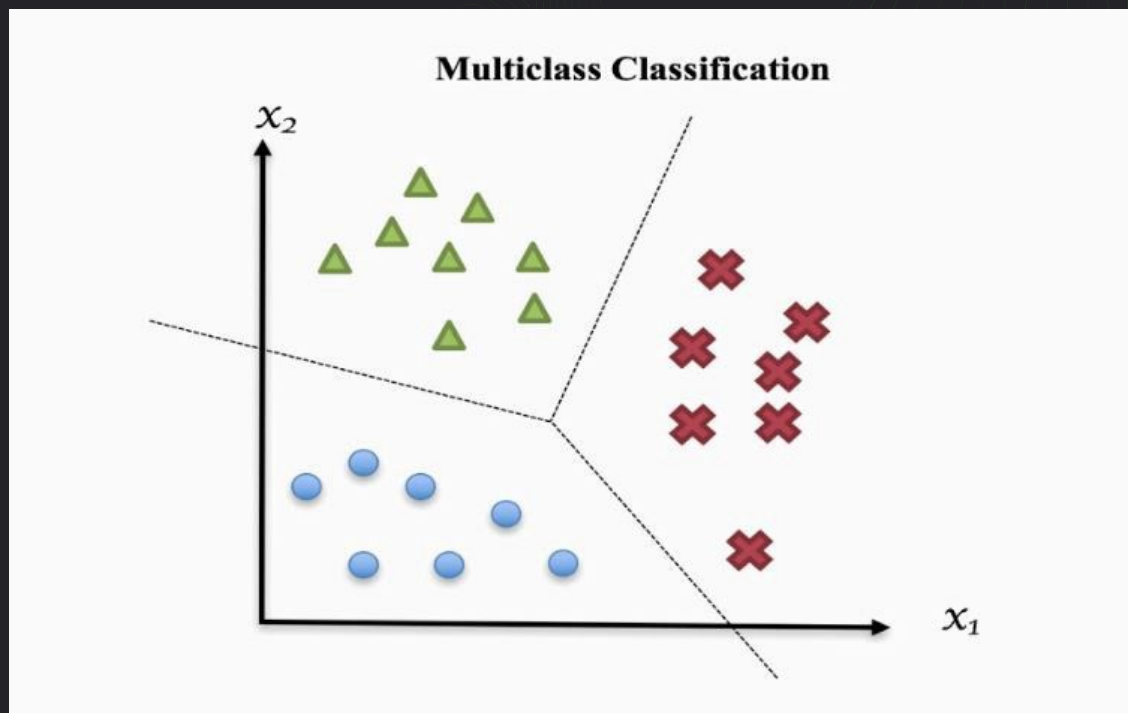
# Word2vec



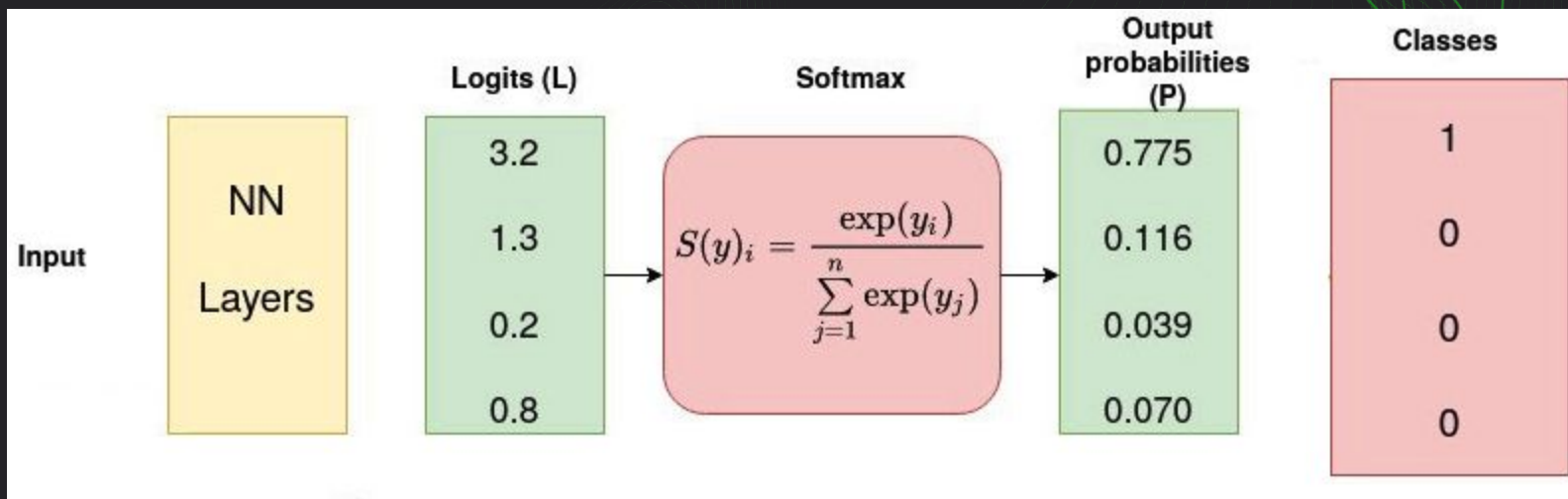
## What task is solving Word2vec



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## Cross-entropy



## Cross-entropy

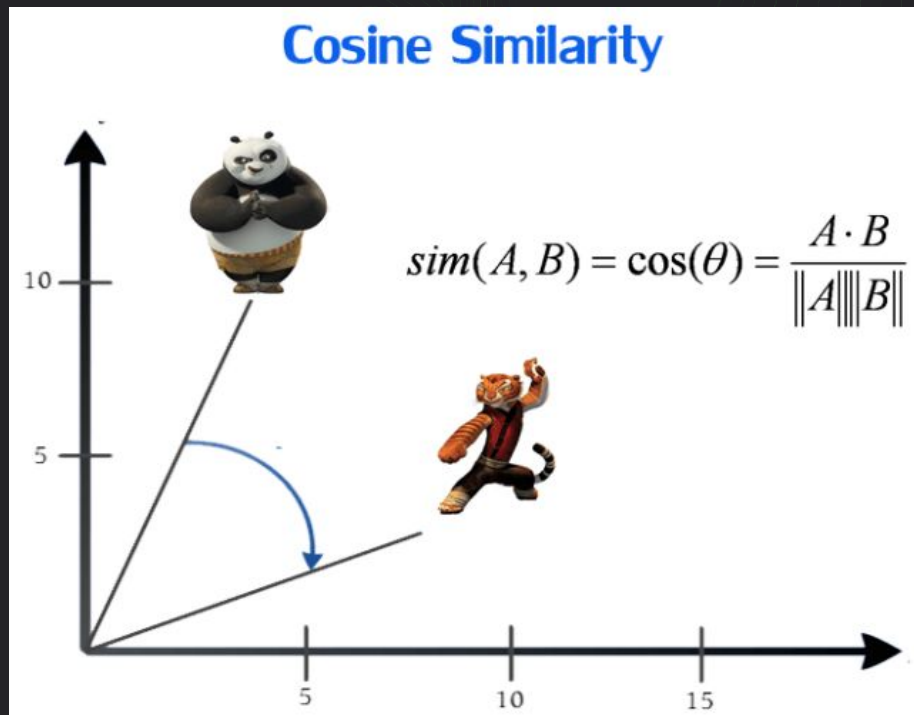
$$CCE(p, t) = - \sum_{c=1}^C t_{o,c} \log(p_{o,c})$$

## 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.

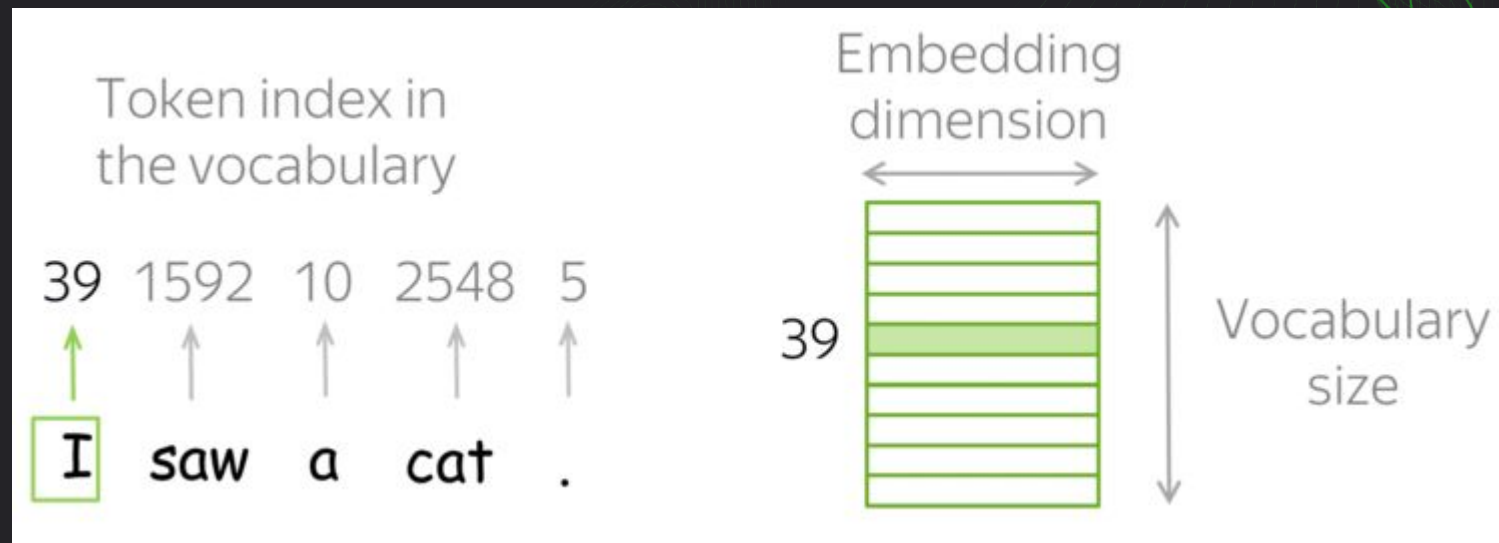
example from [Jacob Eisenstein's NLP notes](#)

## How to measure distances between vectors?





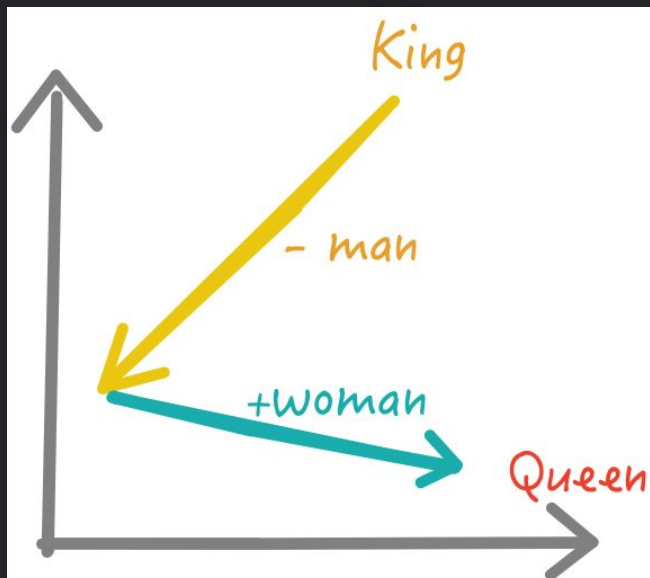
## What we want from word embeddings?



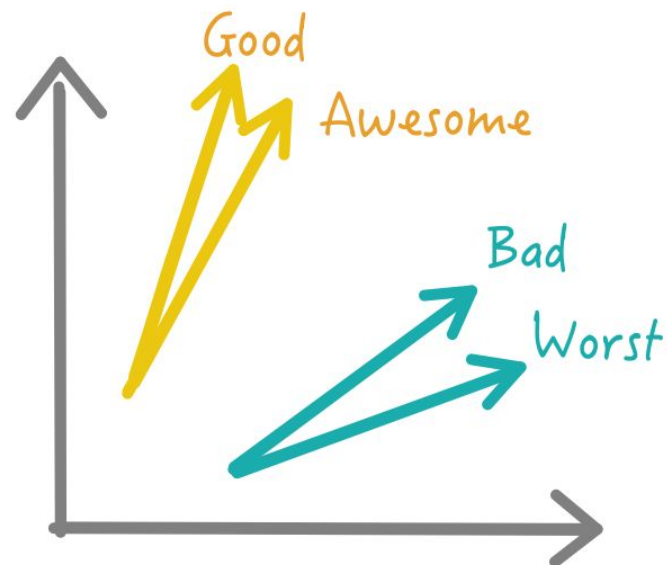
## What we want from word embeddings?

$$\begin{matrix} [0 & 0 & 0 & 1 & 0] \\ \text{One-hot vector} \end{matrix} \times \begin{matrix} \begin{bmatrix} 8 & 2 & 1 & 9 \\ 6 & 5 & 4 & 0 \\ 7 & 1 & 6 & 2 \\ 1 & 3 & 5 & 8 \\ 0 & 4 & 9 & 1 \end{bmatrix} \\ \text{Embedding Weight Matrix} \end{matrix} = \begin{matrix} [1 & 3 & 5 & 8] \\ \text{Hidden layer output} \end{matrix}$$

## Word2vec

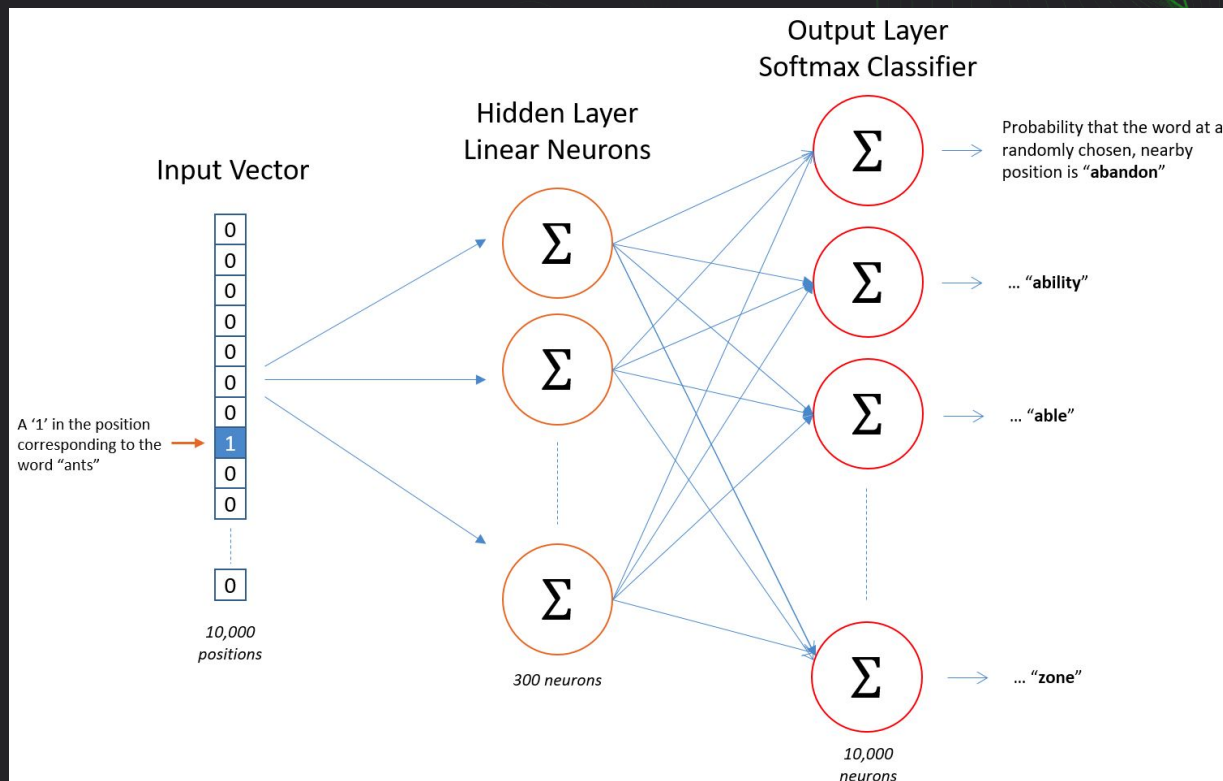


a) Learns Analogy

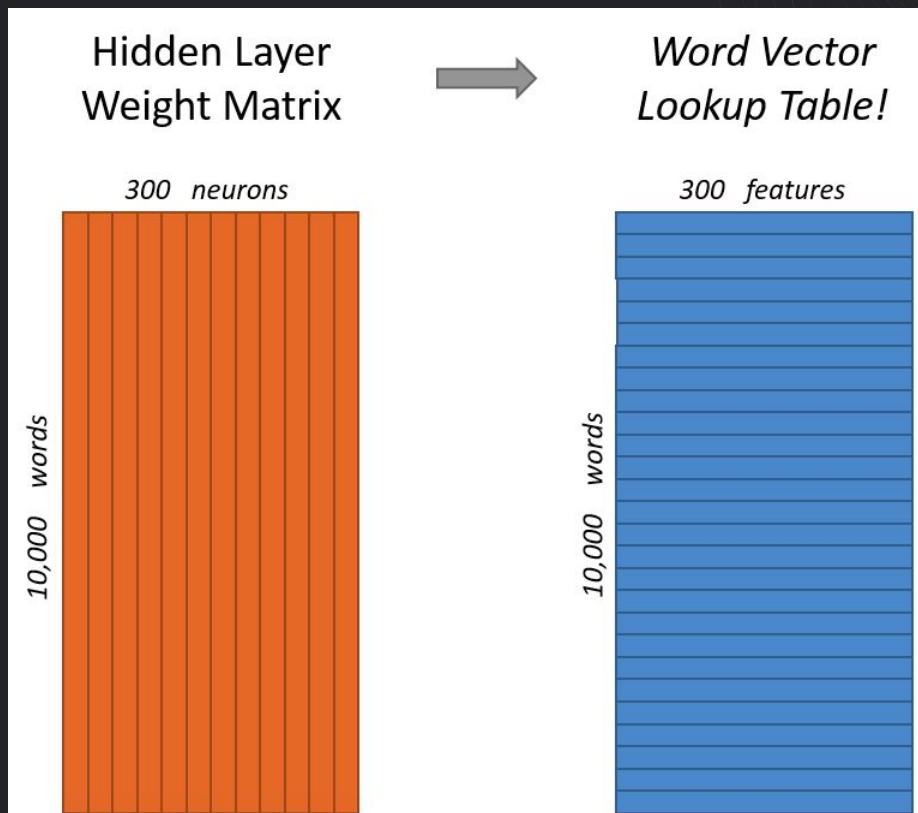


b) Similar Words have same angles

## Word2vec

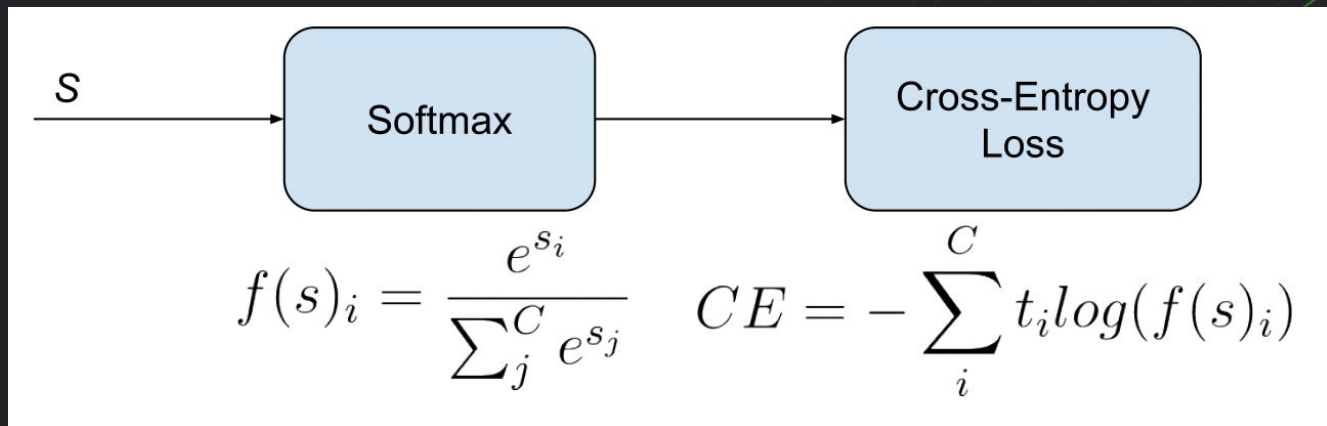


## Word2vec

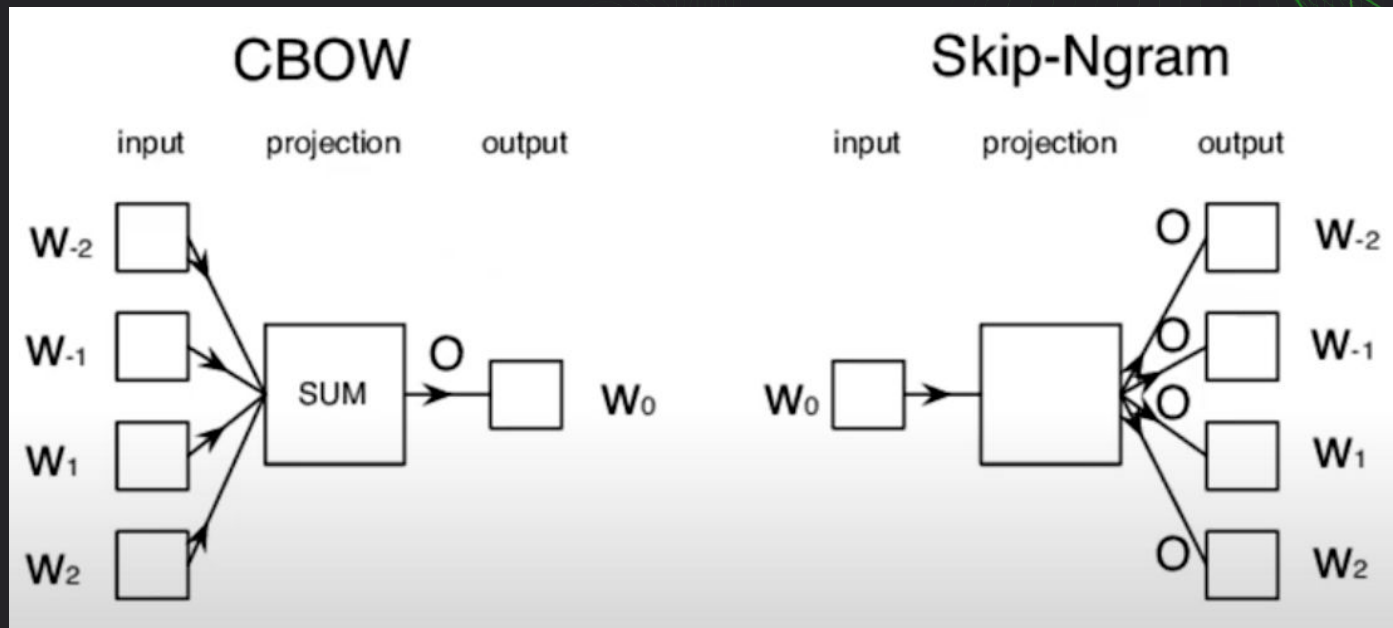


## Word2vec

How to get probabilities for occurrence of words?



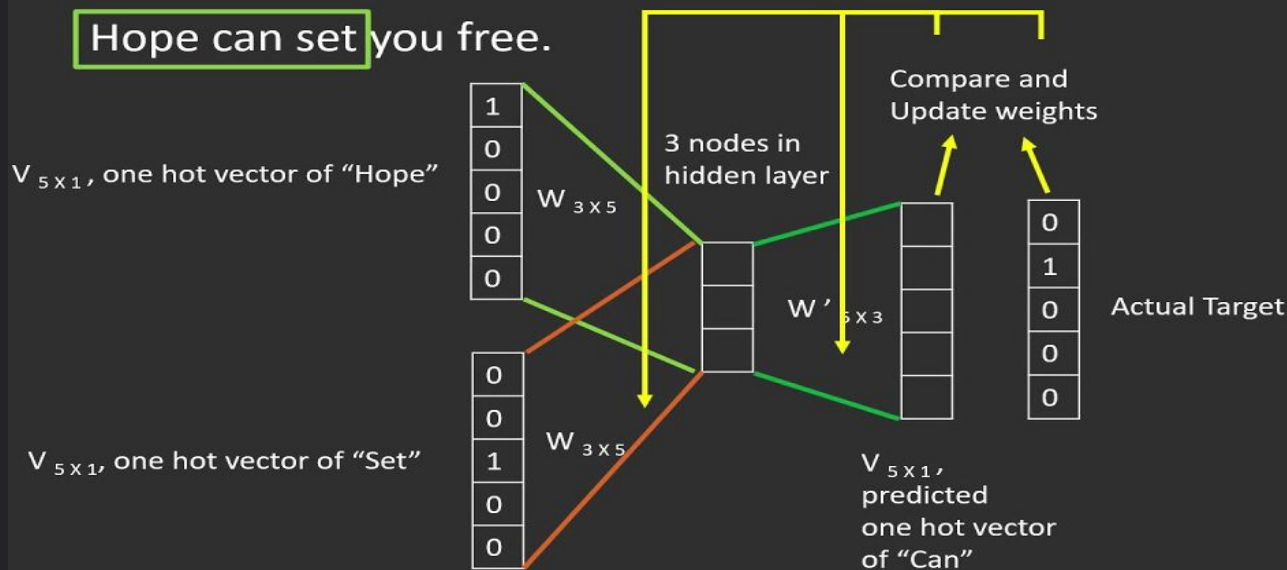
## Word2vec approaches for training





## CBOW - Working

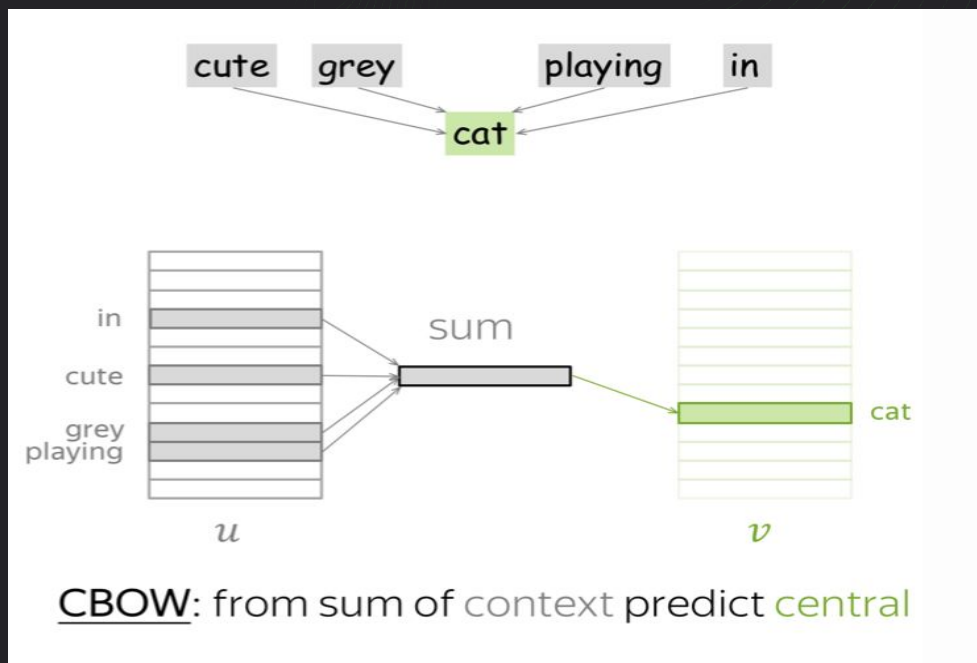
Hope can set you free.





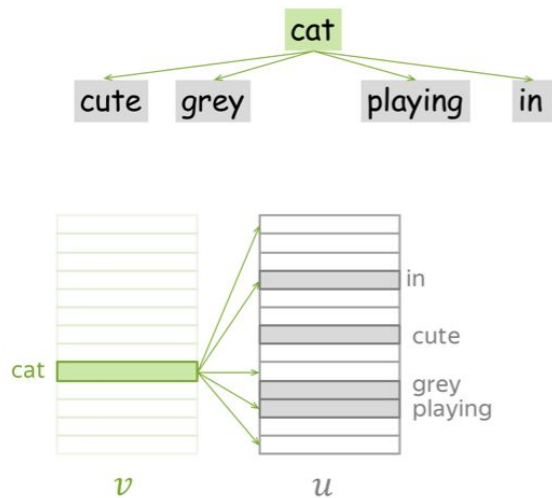
## CBOW

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



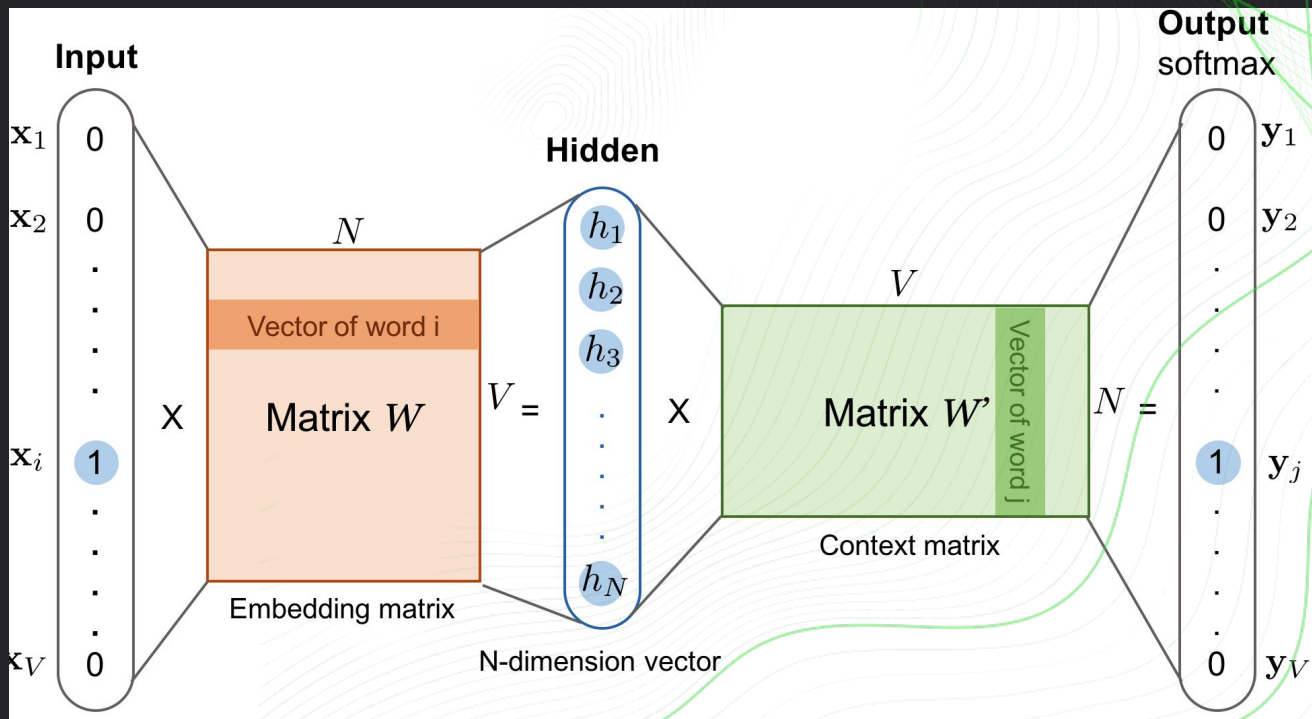
## Skip-gram

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



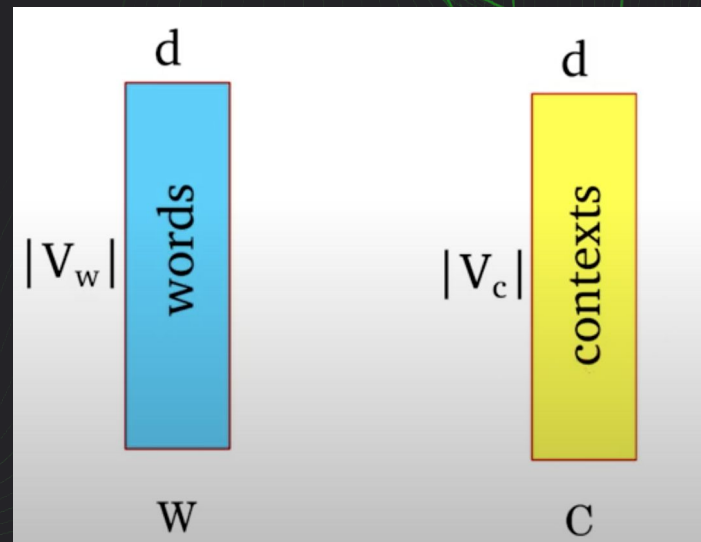
Skip-Gram: from **central** predict context  
(one at a time)

## How to learn



## 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

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

- predict context word(s)
- from word  $w$

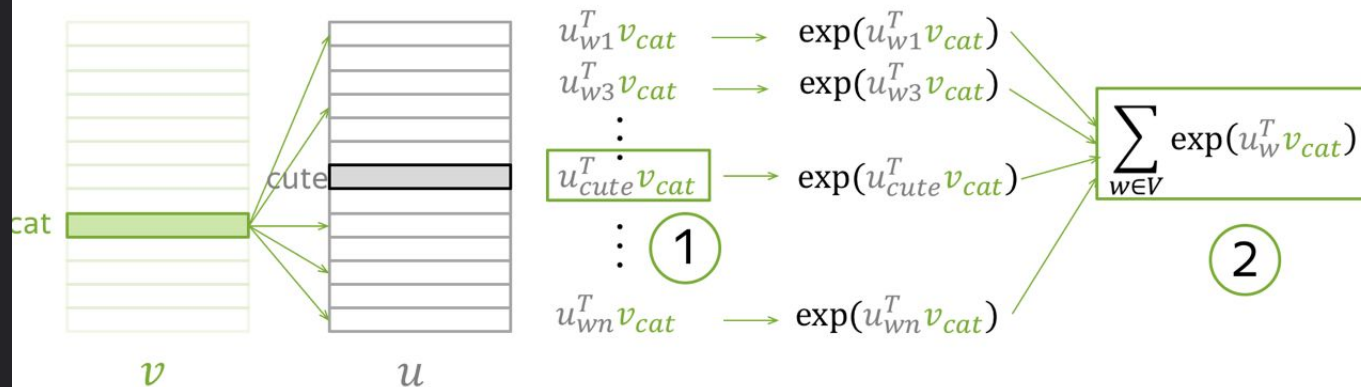
## How to learn

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

1. Take dot product of  $v_{cat}$  with all  $u$

2. exp

3. sum all



## How to learn

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

4. get loss (for this one step)

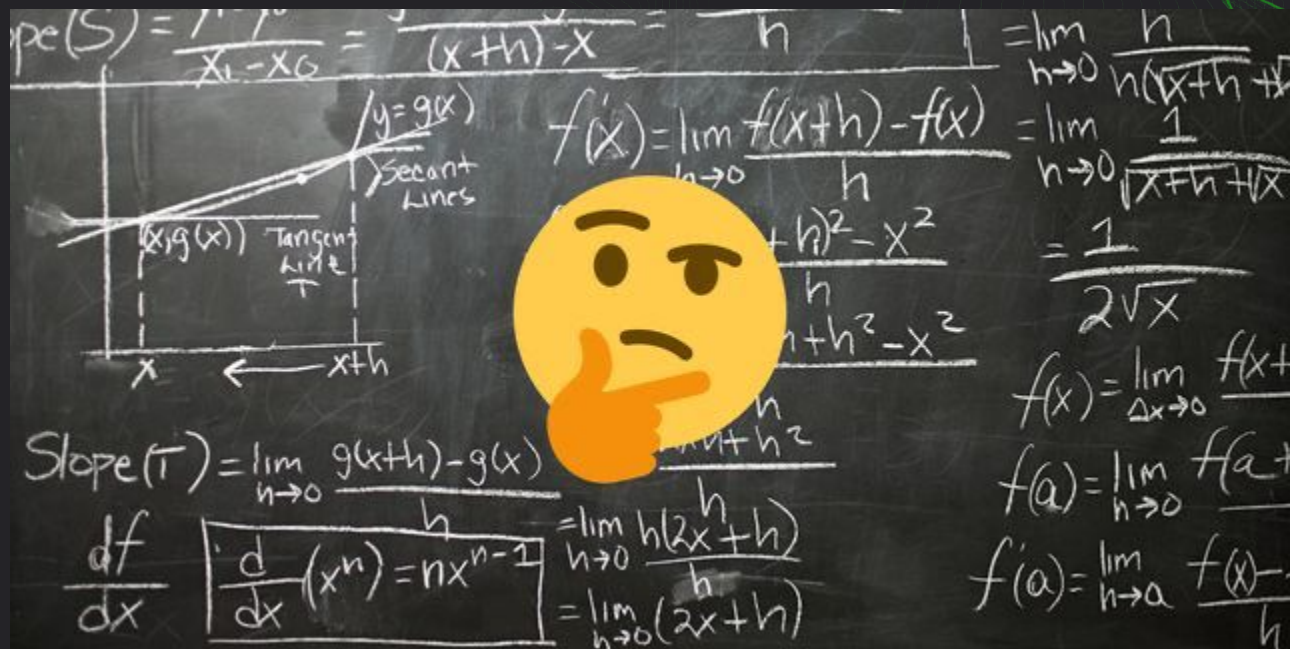
$$J_{t,j}(\theta) = \underbrace{-u_{cute}^T v_{cat}}_{\textcircled{1}} + \log \underbrace{\sum_{w \in V} \exp(u_w^T v_{cat})}_{\textcircled{2}}$$

5. evaluate the gradient,  
make an update

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



## What's the problem?



Graph of  $y = g(x)$  showing a secant line and a tangent line at point  $(x, g(x))$ . The x-axis is labeled with  $x$  and  $x+h$ .

Derivations on the chalkboard:

$$\text{Slope}(S) = \frac{f(x_1) - f(x_0)}{x_1 - x_0} = \frac{f(x+h) - f(x)}{h} = \frac{h}{h} = 1$$
$$f'(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h} = \lim_{h \rightarrow 0} \frac{1}{\sqrt{x+h} + \sqrt{x}} = \frac{1}{2\sqrt{x}}$$
$$\text{Slope}(T) = \lim_{h \rightarrow 0} \frac{g(x+h) - g(x)}{h} = \lim_{h \rightarrow 0} \frac{h(2x+h)}{h} = \lim_{h \rightarrow 0} (2x+h) = 2x$$
$$\frac{df}{dx} \left[ \frac{d}{dx} (x^n) = nx^{n-1} \right] = \lim_{h \rightarrow 0} \frac{h(2x+h)}{h} = \lim_{h \rightarrow 0} (2x+h) = 2x$$
$$f'(a) = \lim_{h \rightarrow 0} \frac{f(a+h) - f(a)}{h}$$



## Negative sampling

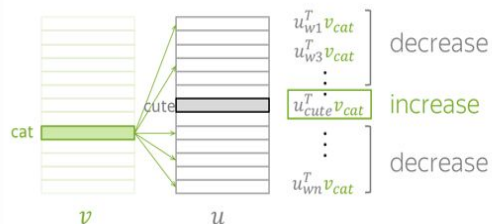
Dot product of  $v_{cat}$ :

- with  $u_{cute}$  - increase,
- with all other  $u$  - decrease



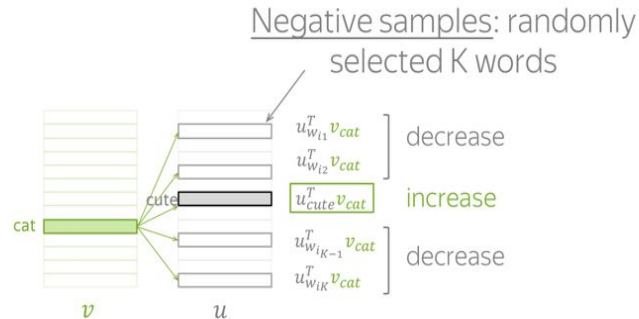
Dot product of  $v_{cat}$ :

- with  $u_{cute}$  - increase,
- with a subset of other  $u$  - decrease



Parameters to be updated:

- $v_{cat}$
- $u_w$  for all  $w$  in the vocabulary  $|V| + 1$  vectors

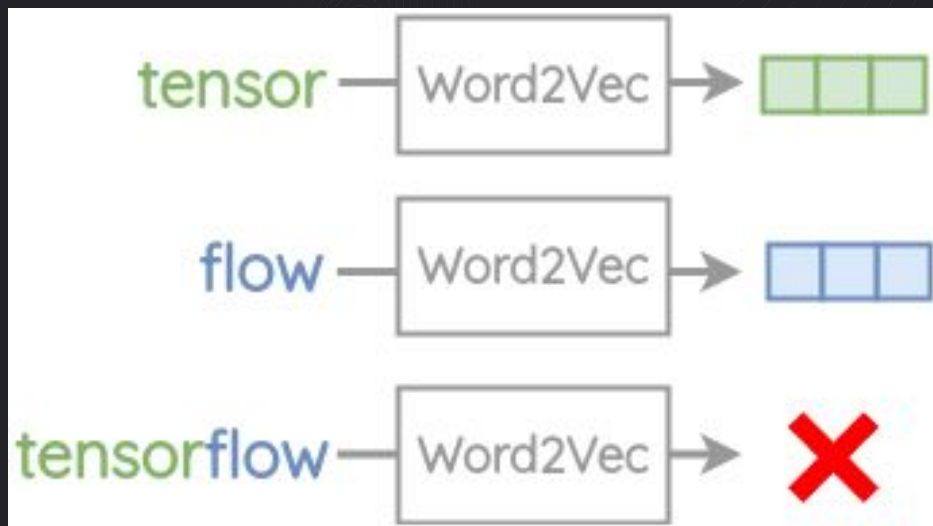


Negative samples: randomly selected K words

Parameters to be updated:

- $v_{cat}$
- $u_{cute}$  and  $u_w$  for  $w$  in K negative examples  $K + 2$  vectors

## OOV words



Word2vec  
CNN for texts

## 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

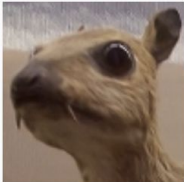

- Skip-gram model as base model
- take each word and n-grams for it (from 3 to 6)
- for reducing space we use hashing trick
- negative sampling is our everything

## 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

*Edge detection*

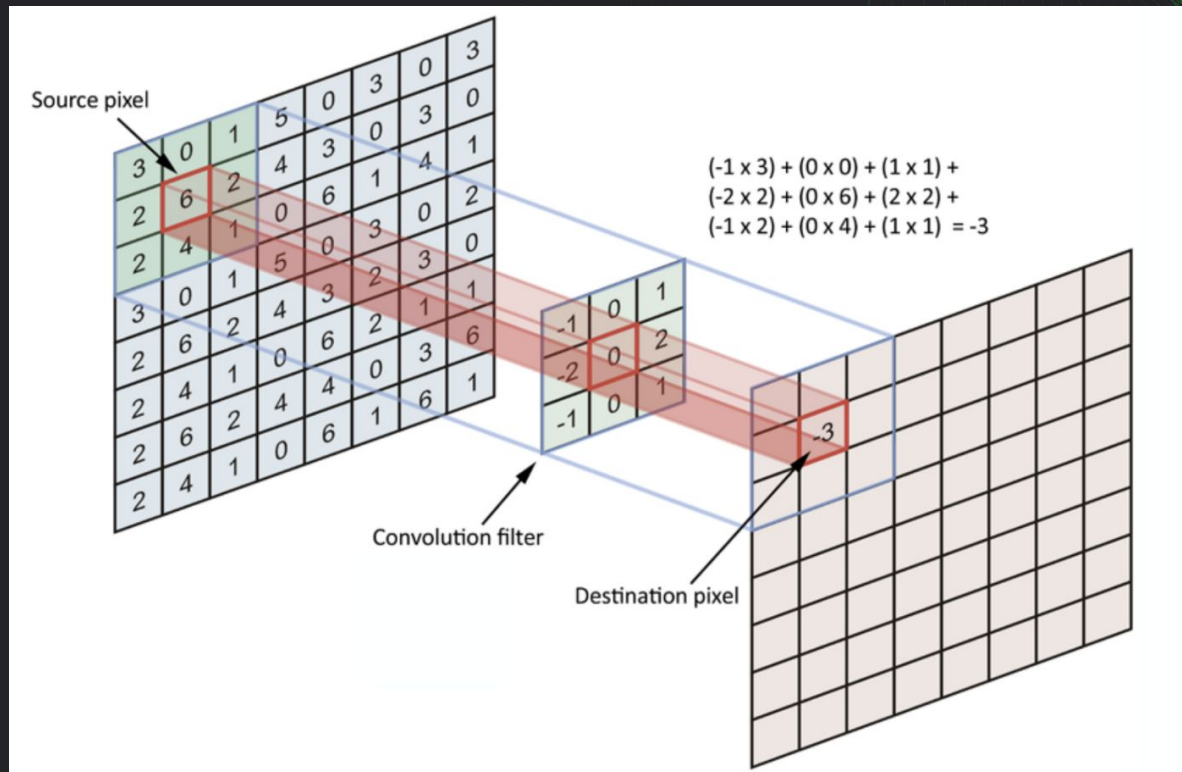
 \*  $\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$  = 

Kernel

*Sharpen*

 \*  $\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$  = 

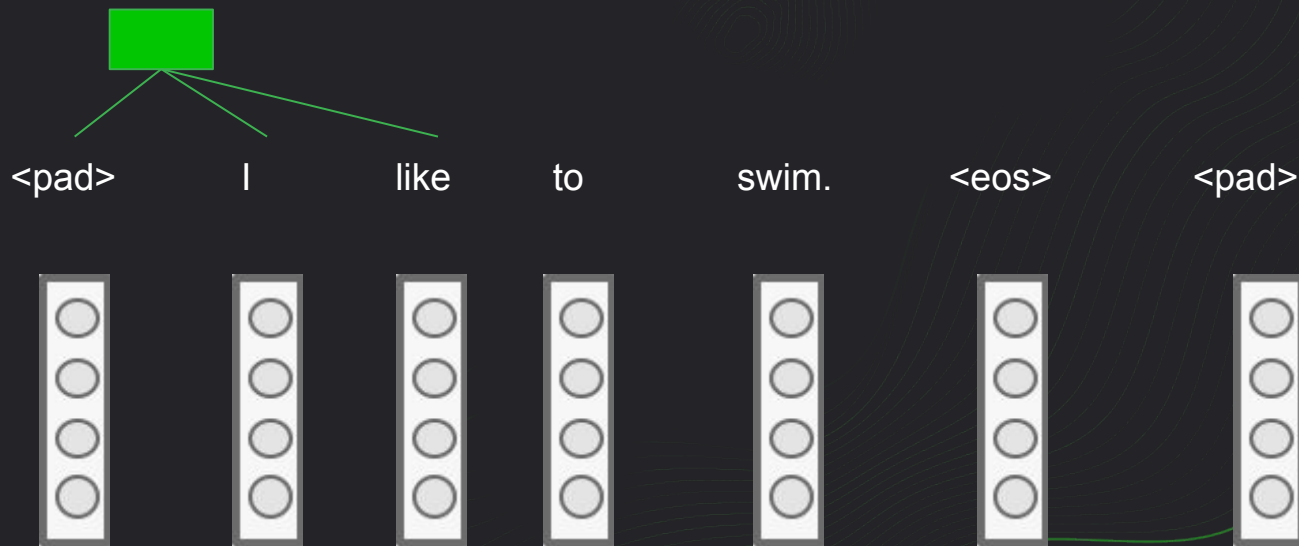
## Convolutions





Word2vec  
CNN for texts

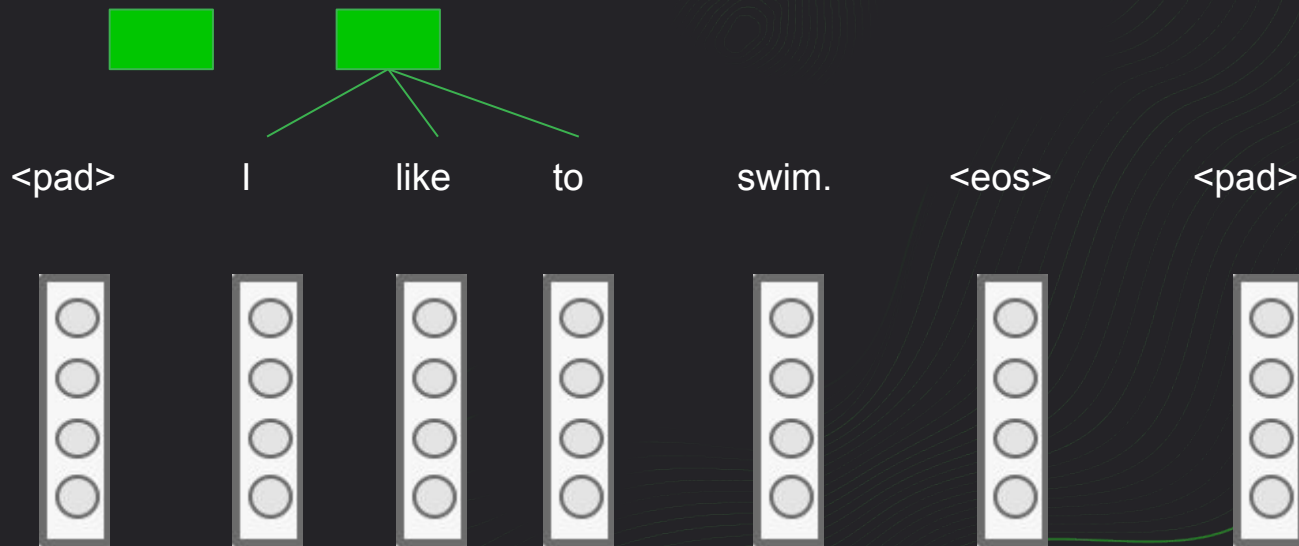
## Convolution for texts





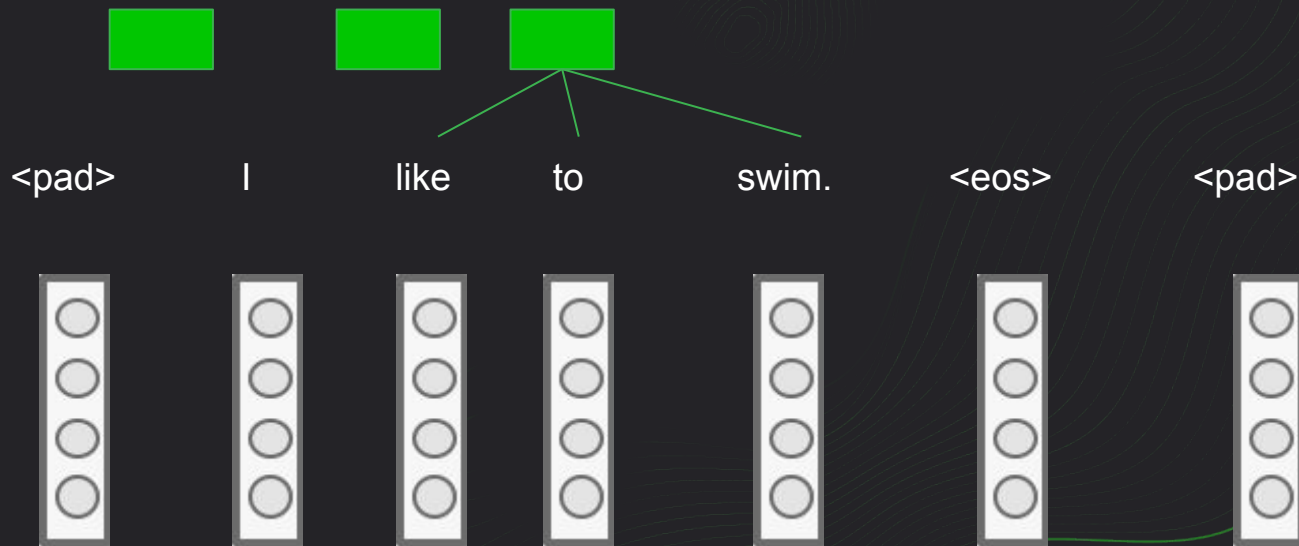
Word2vec  
CNN for texts

## Convolution for texts



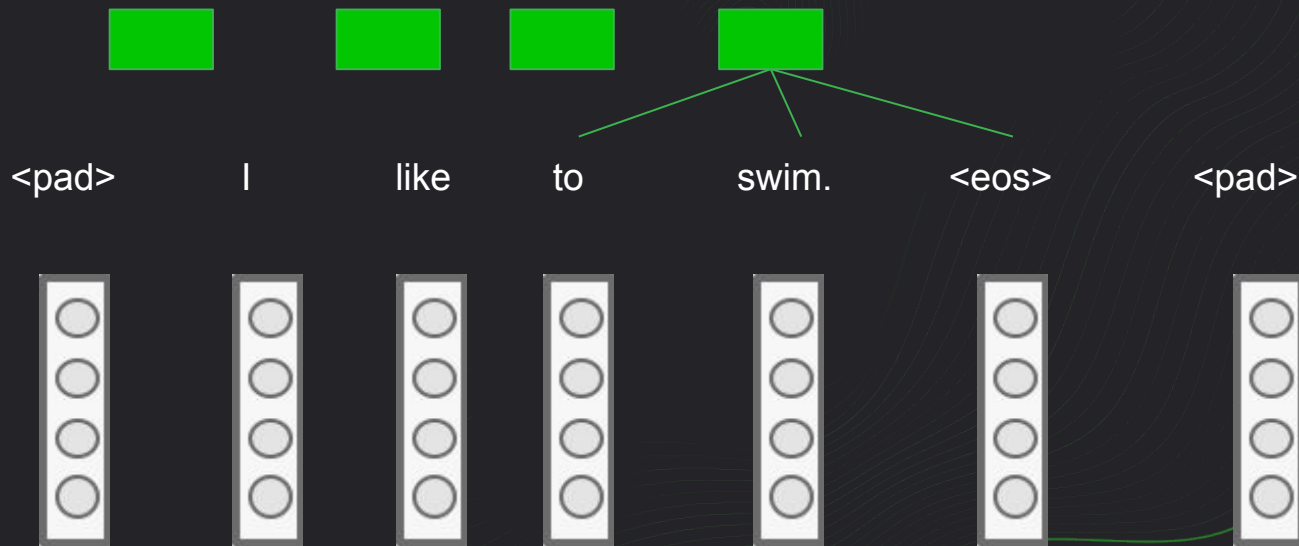
Word2vec  
CNN for texts

## Convolution for texts

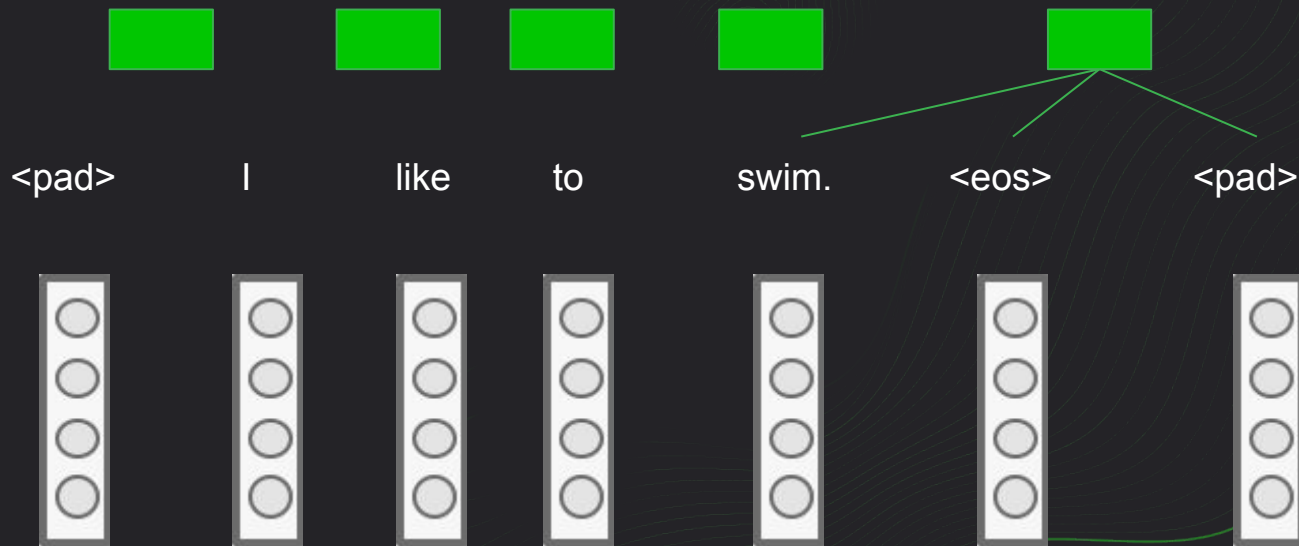


Word2vec  
CNN for texts

## 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>	0.1	-0.6	-0.3	0.2

## 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
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swim.	-0.7	0.5	0.9	0.1
<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.1	-0.6	-0.3	0.2

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>	0.1	-0.6	-0.3	0.2

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>	0.1	-0.6	-0.3	0.2

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>	0.1	-0.6	-0.3	0.2

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>	0.1	-0.6	-0.3	0.2

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
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<eos>	-0.4	0.4	0.1	-0.5
<pad>	0.1	-0.6	-0.3	0.2

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
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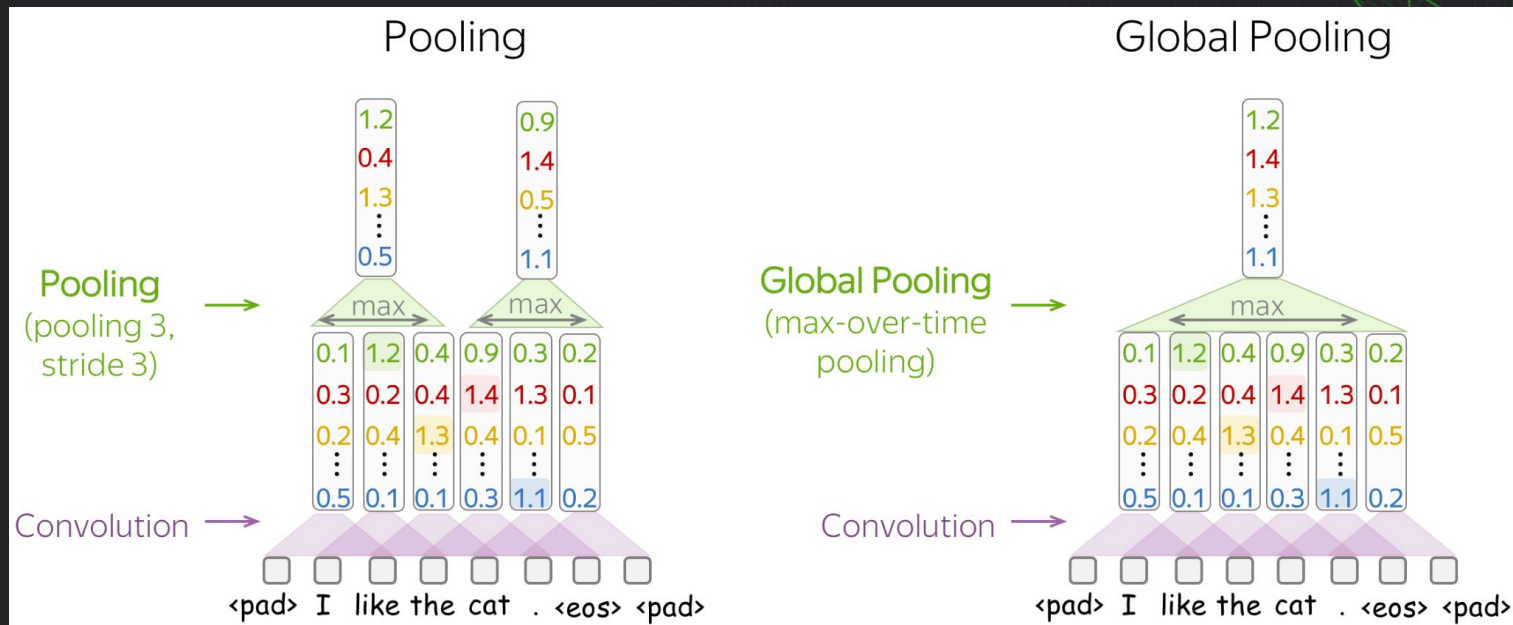
Apply filter of size 3, that have 4 channels

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<<	-2.4

## Pooling for convolutions



example from [Lena Voita NLP course](#)