



# Word2vec and Negative Sampling

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# word representation

- 1-hot representation :  $O(\text{"Man"}) = [0, 0, \dots, 1, 0, \dots, 0]$
- $\text{Dict} = [\text{a}, \text{aaron}, \dots, \text{zulu}, \text{<UNK>}]$
- $|\text{Dict}| = 10000$
- $|O(\text{"Man"})| = 10000$

Man (5391)	Woman (9853)	King (4914)	Queen (7157)	Apple (456)	Orange (6257)
$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$

# word representation

## Weaknesses:

- Can't generalize across words. For example cant get the relation between apple and orange.

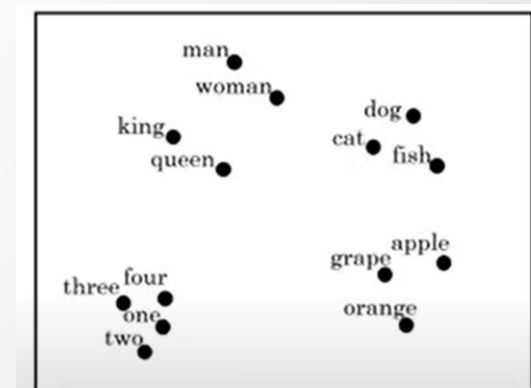
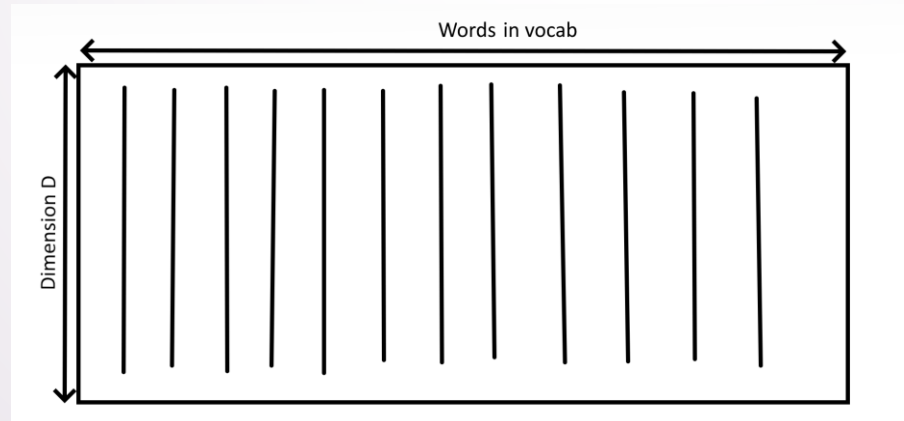
I want a glass of orange ----- . (juice)

I want a glass of apple ----- . (juice)

- Too long, sparse and inefficient

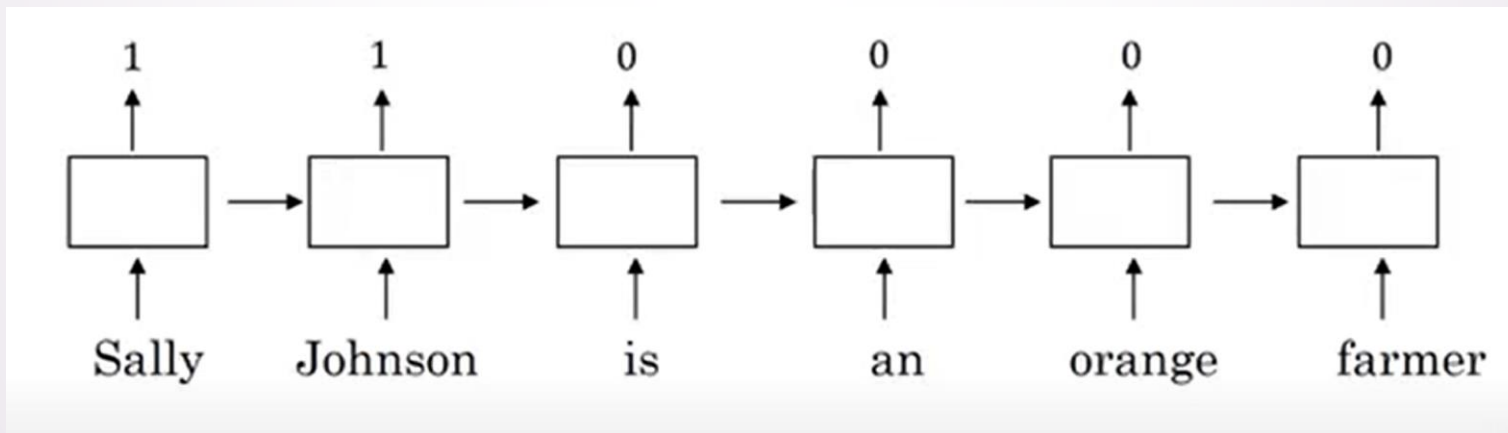
# Featurized representation: word embedding

	Man (5391)	Woman (9853)	King (4914)	Queen (7157)	Apple (456)	Orange (6257)
<b>Gender</b>	-1	1	-0.95	0.97	0.00	0.01
<b>Royal</b>	0.01	0.02	0.93	0.95	-0.01	0.00
<b>Age</b>	0.03	0.02	0.7	0.69	0.03	-0.02
<b>Food</b>	0.04	0.01	0.02	0.01	0.95	0.97



# Named entity recognition example

- ▶ Extracting the names
- ▶ sally johnson is a person from orange farmer ?

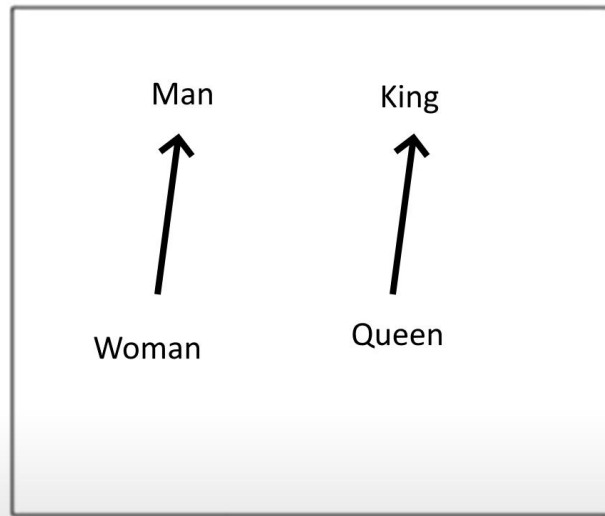




# Transfer learning and word embedding

- 1. Learn word embeddings from a large text corpus (1-100B words)  
➤ (or download pre-trained embedding online.)
- 2. Transfer embedding to new task with smaller training set.(say, 100k words)
- 3.Optional: Continue to finetune the word embeddings with new data

# Cos similarity



Man:Woman as Boy:Girl  
Ottawa:Canada as Nairobi:Kenya  
Big:Bigger as Tall:Taller  
Yen:Japan as Ruble:Russia

$$e_{man} - e_{woman} \approx e_{king} - e_{?}$$

$$sim(e_w, e_{king} - e_{man} + e_{woman})$$

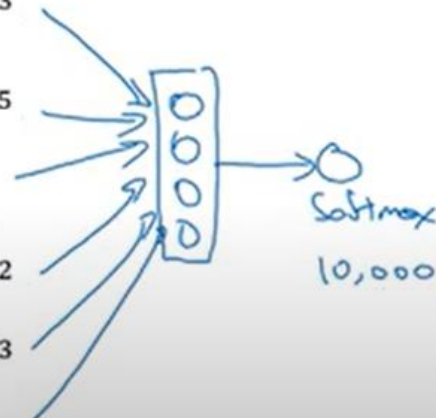
- Need distance to learn with models

# Simple neural network Abstract

## Neural language model

I    want    a    glass    of    orange    \_\_\_\_\_.  
4343   9665    1    3852   6163   6257

I	$o_{4343}$	→	$E$	→	$e_{4343}$
want	$o_{9665}$	→	$E$	→	$e_{9665}$
a	$o_1$	→	$E$	→	$e_1$
glass	$o_{3852}$	→	$E$	→	$e_{3852}$
of	$o_{6163}$	→	$E$	→	$e_{6163}$
orange	$o_{6257}$	→	$E$	→	$e_{6257}$





# Context/target pairs

► I want a glass of orange (juice:target) to go along with my cereal.

Context = last 4 words : a glass of orange ----

Or

4 words on left and right : a glass of orange ---- to go along with

Or

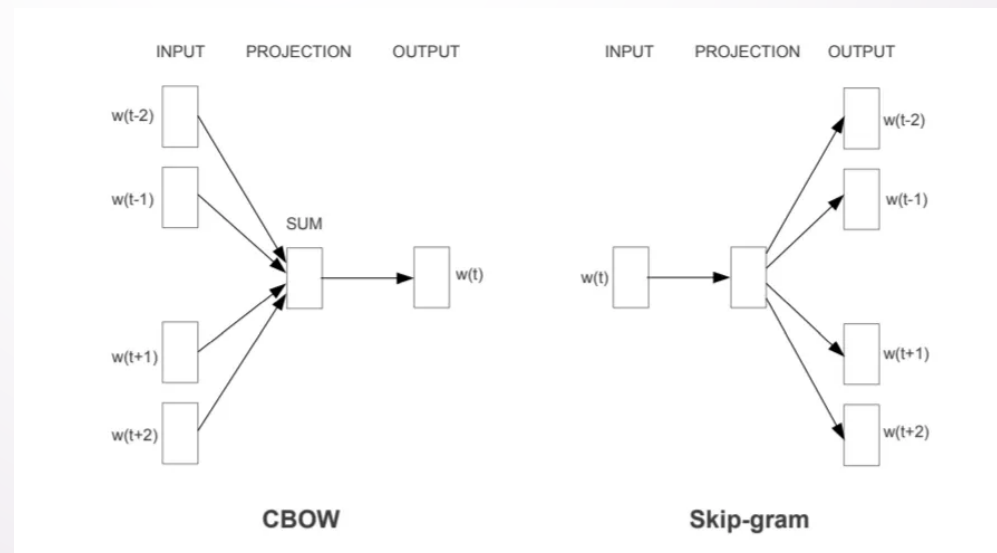
Last 1 word : orange ----

Or

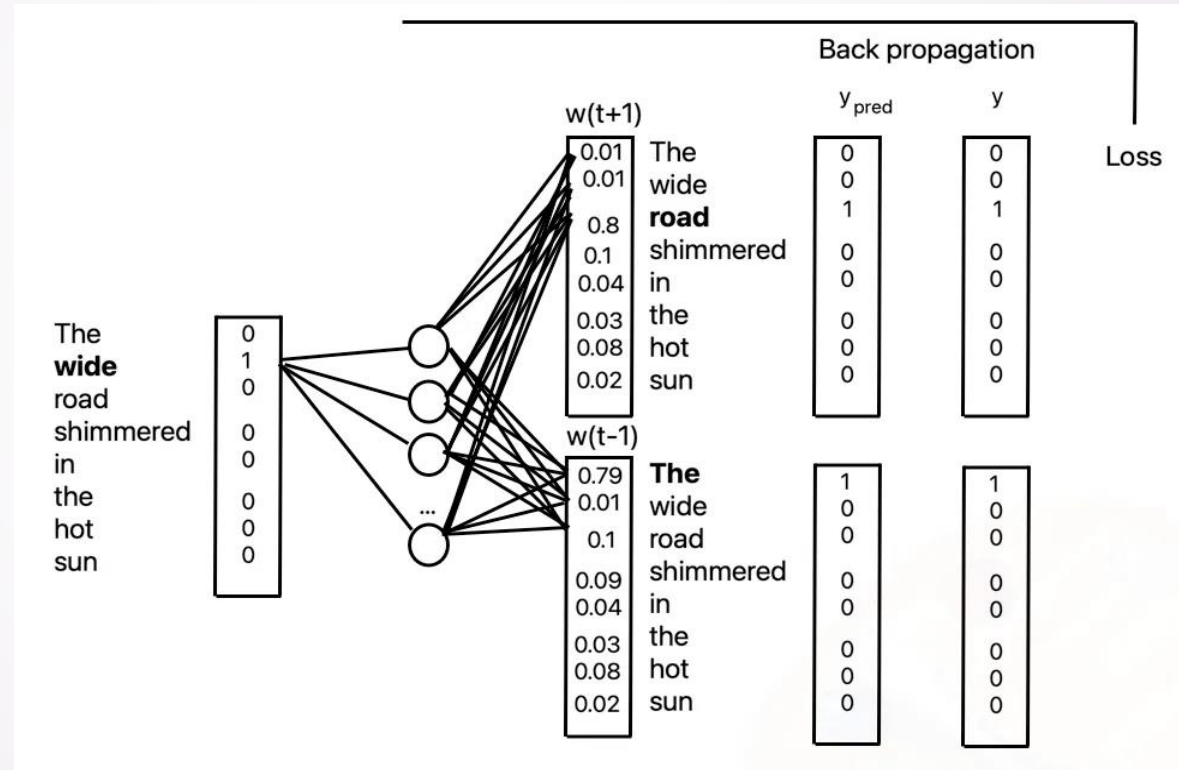
Nearby 1 word (skip-gram) : glass ? ---- ? ?

# Word2vec

- **Main idea:** The words that appear near each other should have similar word vectors.
- **Skip-gram:** works well with a small amount of the training data, represents well even rare words or phrases.
- **CBOW:** several times faster to train than the skip-gram, slightly better accuracy for the frequent words.



# Skip-grams



# Model

► Vocab size = 10000K

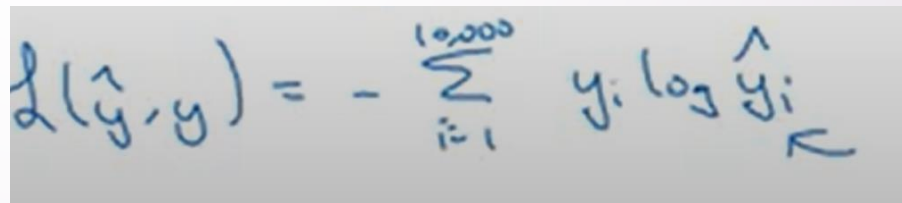
► Mapping from context  $c$  to a target  $t$

$$\frac{1}{T} \sum_{t=1}^T \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j}|w_t)$$

►  $e(c) \rightarrow \text{softmax} \rightarrow y^\wedge$

$$\arg \max_{\theta} \sum_{(w,c) \in D} \log p(c|w) = \sum_{(w,c) \in D} (\log e^{v_c \cdot v_w} - \log \sum_{c'} e^{v_{c'} \cdot v_w})$$

$$p(t|c) = \frac{e^{\theta_t^T e_c}}{\sum_{j=1}^{10,000} e^{\theta_j^T e_c}}$$


$$L(\hat{y}, y) = - \sum_{i=1}^{10000} y_i \log \hat{y}_i$$

►  $\theta(t)$  parameter associated with output  $t$  controlling the distribution

# Problems

- For every  $p(t|c)$  we calculate the sum in the denominator

$$p(t|c) = \frac{e^{\theta_t^T e_c}}{\sum_{j=1}^{10,000} e^{\theta_j^T e_c}}$$

- Hierarchical softmax



# Negative sampling

- Maximizing the similarity of the words in the same context
- Minimizing it when they occur in different contexts
- We do not need to update the entire output weight matrix

# Defining a new learning problem

- I want a glass of orange juice to go along with my cereal
- Second word is random from dictionary
- Of is positive but it is ok to get it negative
- How to choose k ( number of neg samples )
- K = 5-20 small datasets
- K = 2-5 large datasets

<u>context</u>	<u>word</u>	<u>target?</u>
orange	juice	1
orange	king	0
orange	book	0
orange	the	0
orange	of	0

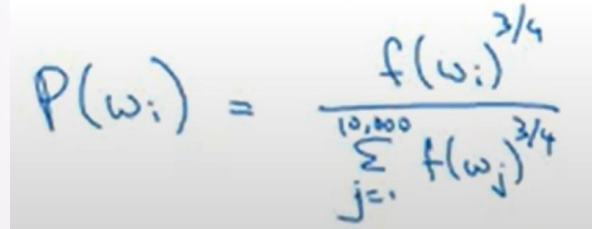
# Model

- 1 giant 10000 way softmax -> 10000 binary classification problem

If we let  $\sigma(x) = \frac{1}{1+e^{-x}}$  we get:

$$\begin{aligned} & \arg \max_{\theta} \sum_{(w,c) \in D} \log \frac{1}{1 + e^{-v_c \cdot v_w}} + \sum_{(w,c) \in D'} \log \left( \frac{1}{1 + e^{v_c \cdot v_w}} \right) \\ &= \arg \max_{\theta} \sum_{(w,c) \in D} \log \sigma(v_c \cdot v_w) + \sum_{(w,c) \in D'} \log \sigma(-v_c \cdot v_w) \end{aligned}$$

- How do you choose negative examples?
- Heuristic:


$$P(w_i) = \frac{f(w_i)^{3/4}}{\sum_{j=1}^{10,000} f(w_j)^{3/4}}$$





## For more information

`word2vec` Explained: Deriving Mikolov et al.'s  
Negative-Sampling Word-Embedding Method

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A decorative graphic on the left side of the slide. It features a solid purple arrow pointing right, positioned above several thin, curved purple lines that sweep upwards and to the right.

*Thank you*