

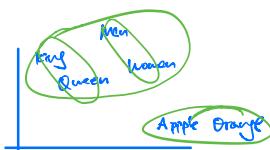
Word Embeddings

- 1-hot representation

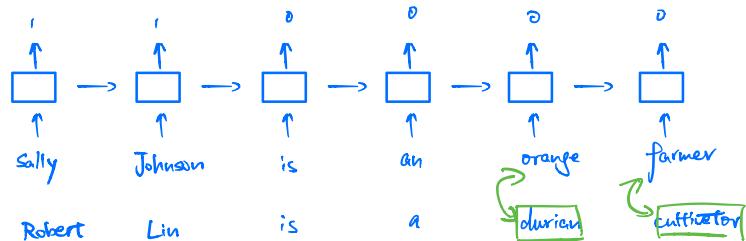
- word embedding

e.g.	Man (5391)	Woman (9853)	King (4914)	Queen (7157)
Gender	-1	1	-0.95	0.97
Royal	0.01	0.02	0.93	0.95
Age	0.03	0.02	0.7	0.69
:				
	e_{5391}	e_{9853}		

300D \rightarrow 2D Visualization



NER example



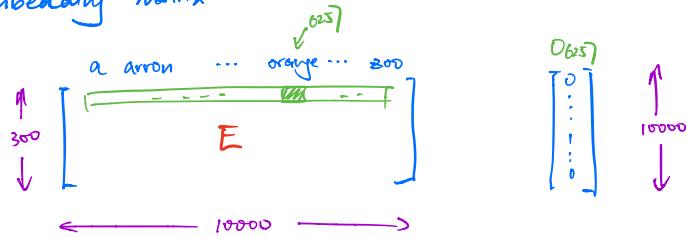
\Rightarrow transfer learning

1. learn word embeddings from large text corpus (1-100B words)
(or download pre-trained embedding)

2. transfer embedding to new task w/ smaller training set
(say 100k words)

3. Optional. Fine-tune word embeddings w/ new data

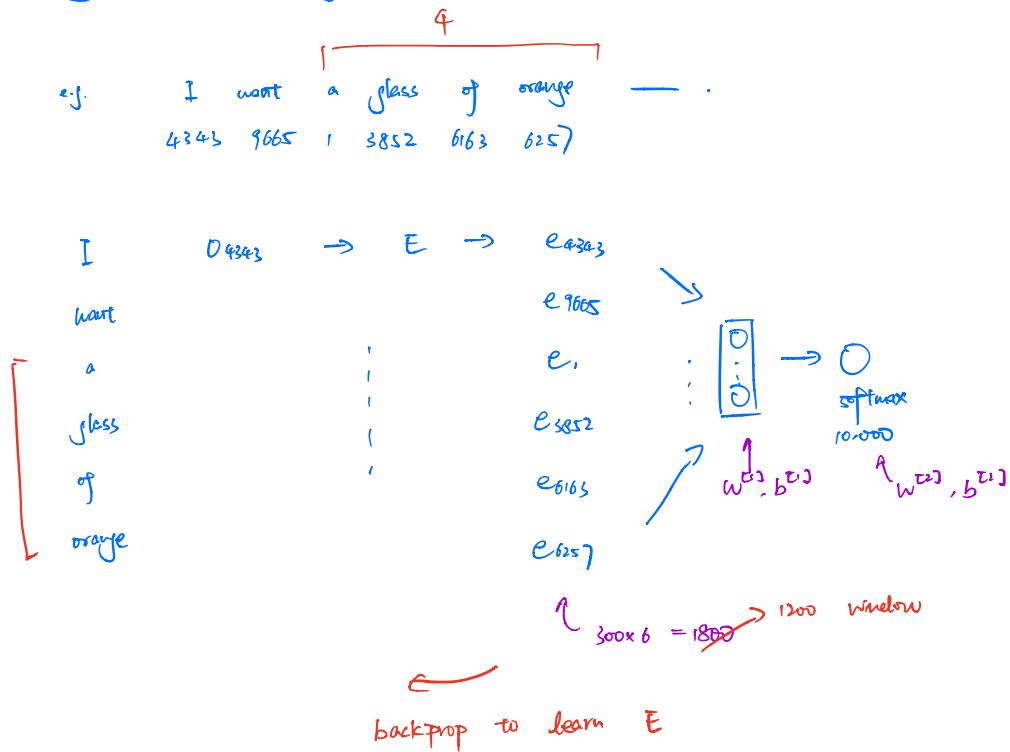
Embedding Matrix



$$E \cdot \begin{matrix} 0_{625} \\ \vdots \\ 0 \end{matrix} = \begin{matrix} 1 \\ \vdots \\ 0 \end{matrix} = e_{625}$$

$(300, 10000)$ $(10000, 1)$ $(300, 1)$

Learning word embeddings



- Context : last 4 words
- 4 words on left & right
- last 1 word
- nearby 1 word

Word2Vec

Skip-Gram

e.g. I want a glass of orange juice to go along my cereal.

<u>Context</u>	<u>target</u>	← sampled from nearby window
orange	juice	
orange	glass	
orange	my	

Model:

$$\text{Vocab size} = 10,000 \text{ K}$$

$$\begin{matrix} \text{Context } c \text{ ("orange")} \\ 625 \end{matrix} \rightarrow \text{Target } t \quad \begin{matrix} \text{("juice")} \\ 4834 \end{matrix}$$

$$e_c \rightarrow \boxed{E} \rightarrow e_c \xrightarrow{e_i \in ED_c} \text{softmax} \rightarrow \hat{y} \leftarrow \text{one-hot}$$

$$\text{softmax: } P(t|c) = \frac{e^{\theta_t^T e_c}}{\sum_{j=1}^{10000} e^{\theta_j^T e_c}} \quad \theta_t = \text{param associated w/ output } t$$

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

Problem:

Calc denominator of softmax is slow

Solution:

hierarchical softmax

negative sampling

Negative Sampling

e.g. I want a glass of orange juice to go along my cereal.

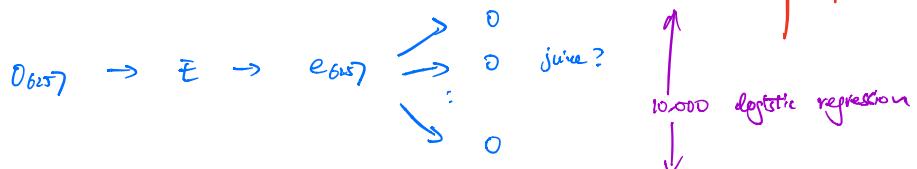
X		Y
<u>Context</u>	<u>word</u>	<u>target ?</u>
orange	juice	1
orange	king	0
orange	book	0
orange	the	0

$k = 5 - 20$ smaller dataset

$k = 2 - 5$ larger dataset

$$\text{softmax : } P(t|c) = \frac{e^{\theta_t^T e_c}}{\sum_{j=1}^{10000} e^{\theta_j^T e_c}}$$

$$\Rightarrow P(y=1 | c, t) = \sigma(\theta_t^T e_c)$$



Select negative sampling

$$P(w_i) = \frac{f(w_i)^{1/4}}{\sum_{j=1}^{10000} f(w_j)^{1/4}}$$

← between uniform distribution & word distribution

GloVe word vectors

e.g. I want a glass of orange juice to go along my cereal.

x_{ij} = # times j appears in context of i

$$x_{ij} = x_{ji}$$

$$\text{Symmetric} \Rightarrow e_w^{(\text{final})} = \frac{e_w + \theta_w}{2}$$

Model :

$$\text{minimize } \sum_{i=1}^{10000} \sum_{j=1}^{10000} f(x_{ij}) (\theta_i^T e_j + b_i + b_j - \log x_{ij})^2$$

weighting term $f(x_{ij}) = 0$ if $x_{ij} = 0$