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NLP and Word Embeddings

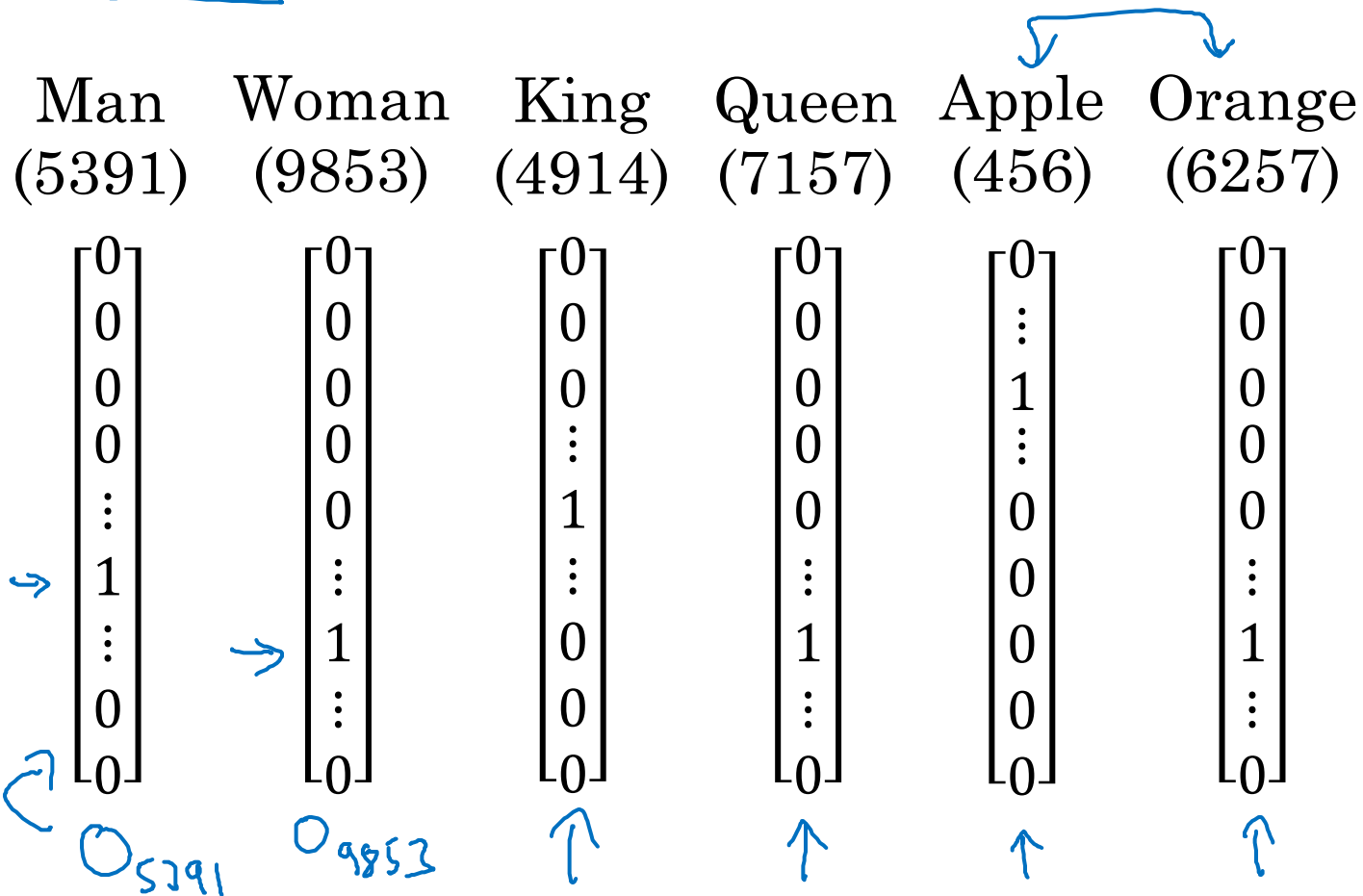
Word representation

Word representation

$V = [a, aaron, \dots, zulu, <UNK>]$

$|V| = 10,000$

1-hot representation



I want a glass of orange juice.

I want a glass of apple ?.

Featurized representation: word embedding

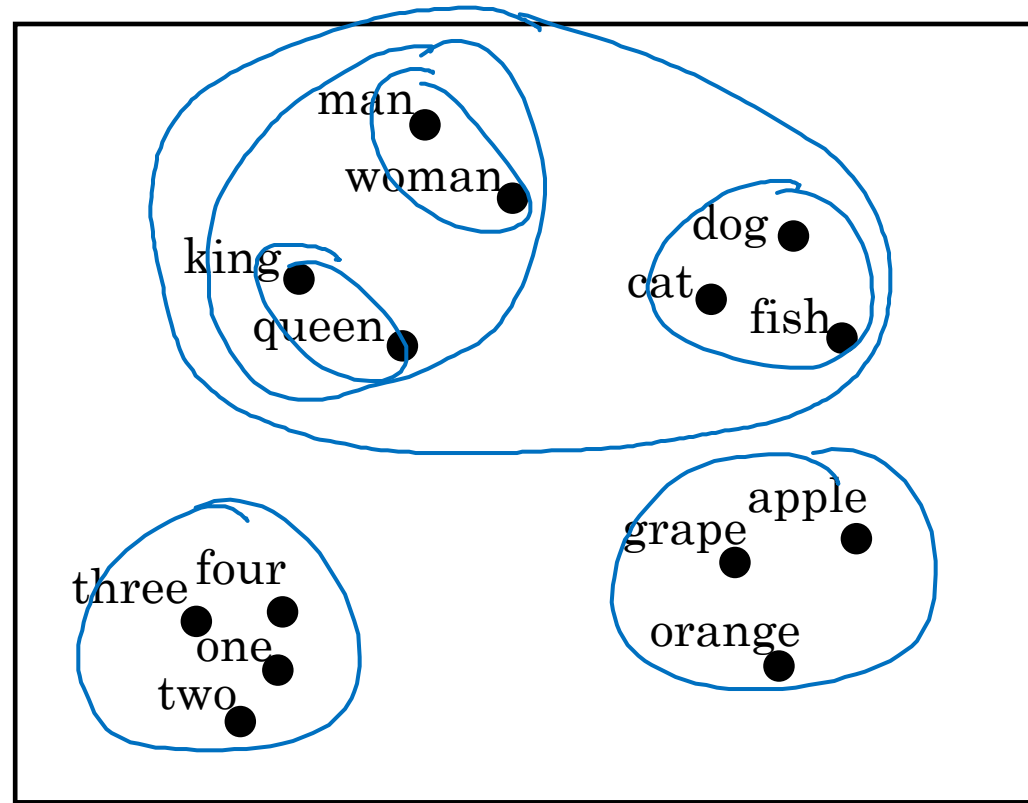
	Man (5391)	Woman (9853)	King (4914)	Queen (7157)	Apple (456)	Orange (6257)
Gender	-1	1	-0.95	0.97	0.00	0.01
Royal	0.01	0.02	<u>0.93</u>	<u>0.95</u>	-0.01	0.00
Age	0.03	0.02	0.7	0.69	0.03	-0.02
Food	0.04	0.01	0.02	0.01	0.95	0.97
...				
size						
cost						
alive						
verb						

I want a glass of orange juice.

I want a glass of apple juice.

Andrew Ng

Visualizing word embeddings

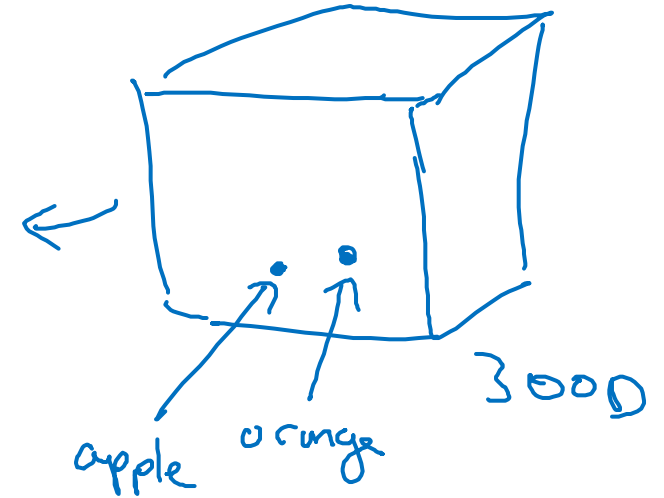


t-SNE

→ 300D



2D



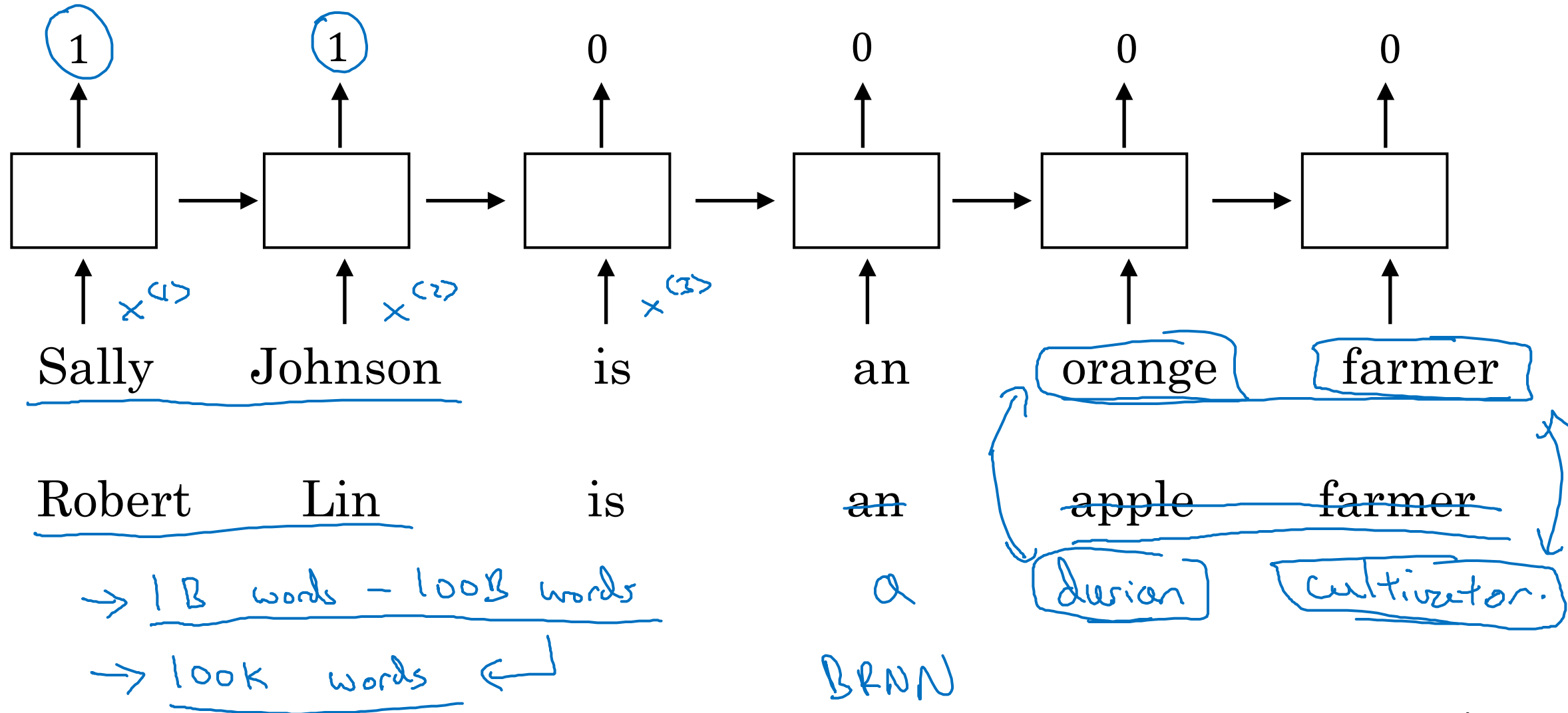


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NLP and Word Embeddings

Using word
embeddings

Named entity recognition example



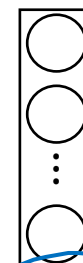
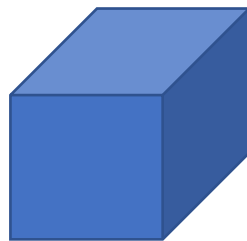
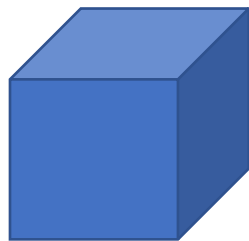
Transfer learning and word embeddings

- 
1. Learn word embeddings from 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) → 10,000 → 300
 3. Optional: Continue to finetune the word embeddings with new data.

Relation to face encoding (embedding) 128D



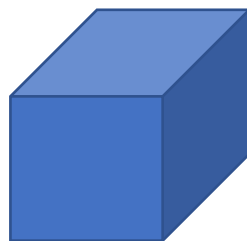
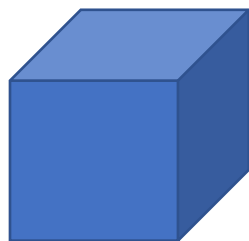
$x^{(i)}$



$f(x^{(i)})$



$x^{(j)}$



$f(x^{(j)})$



\hat{y}

$|V| = 10,000$

$e_1, \dots, e_{10,000}$



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NLP and Word Embeddings

Properties of word embeddings

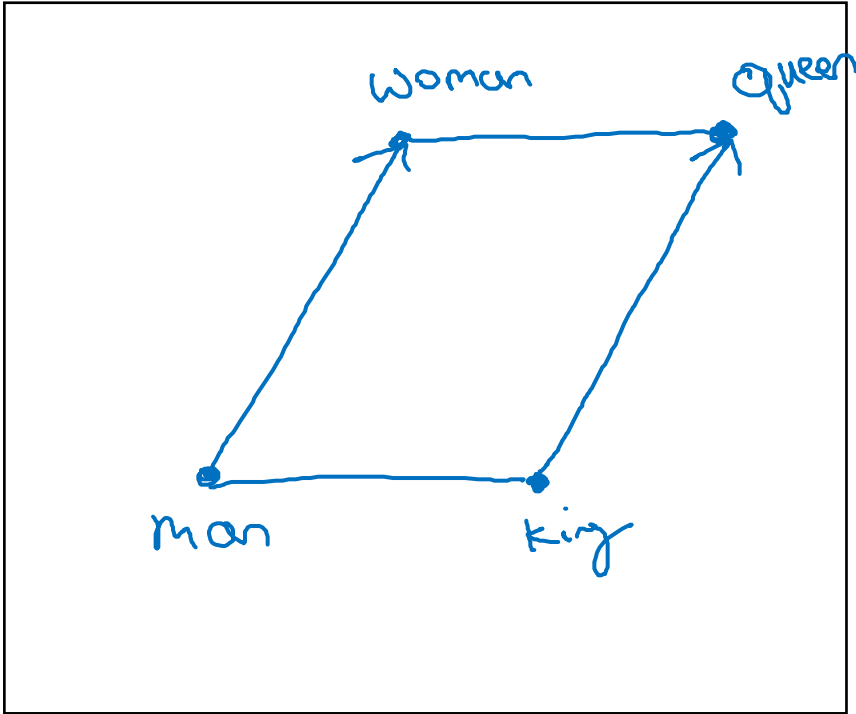
Analogy

	Man (5391)	Woman (9853)	King (4914)	Queen (7157)	Apple (456)	Orange (6257)
Gender	-1	1	-0.95	0.97	0.00	0.01
Royal	0.01	0.02	0.93	0.95	-0.01	0.00
Age	0.03	0.02	0.70	0.69	0.03	-0.02
Food	0.09	0.01	0.02	0.01	0.95	0.97

$\underbrace{e_{5391}}_{e_{\text{man}}} \rightarrow \underbrace{e_{9853}}_{e_{\text{woman}}} \quad \Leftrightarrow \quad \underbrace{e_{4914}}_{e_{\text{king}}} \rightarrow ? \quad \underbrace{e_{7157}}_{e_{\text{queen}}}$
 $e_{\text{man}} - e_{\text{woman}} \approx e_{\text{king}} - e_{?}$

$\underline{e_{\text{man}}} - \underline{e_{\text{woman}}} \approx \begin{bmatrix} -2 \\ 0 \\ 0 \\ 0 \end{bmatrix}$
 $\underline{e_{\text{king}}} - \underline{e_{\text{queen}}} \approx \begin{bmatrix} -2 \\ 0 \\ 0 \\ 0 \end{bmatrix}$

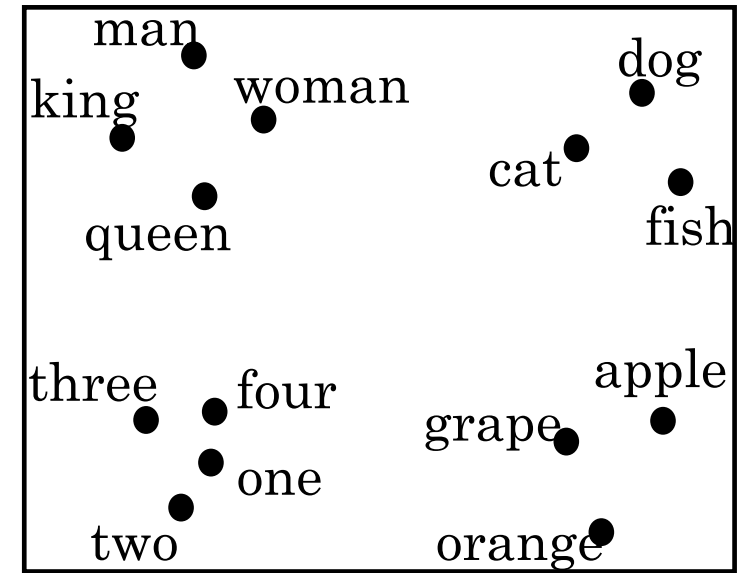
Analogies using word vectors



300 D

Find word w : $\arg \max_w$

3000 \rightarrow 20
↑



t-SNE

$$e_{man} - e_{woman} \approx e_{king} - \cancel{e_w} \quad e_w$$

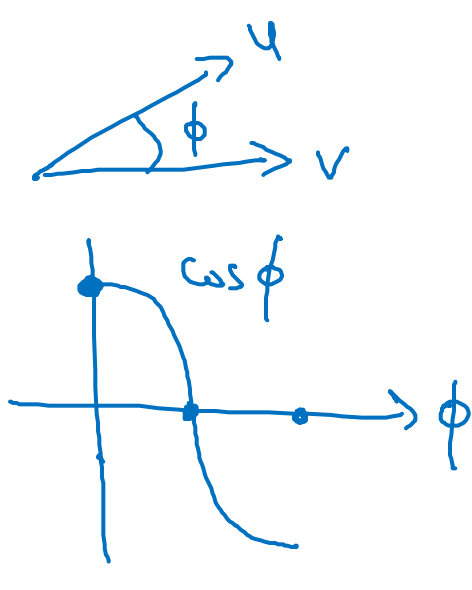
$$\text{Sim}(e_w, e_{king} - e_{man} + e_{woman})$$

30 - 75%

Cosine similarity

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

$$\text{sim}(u, v) = \frac{u^T v}{\|u\|_2 \|v\|_2}$$



$$\|u - v\|^2$$

Man:Woman as Boy:Girl

Ottawa:Canada as Nairobi:Kenya

Big:Bigger as Tall:Taller

Yen:Japan as Ruble:Russia

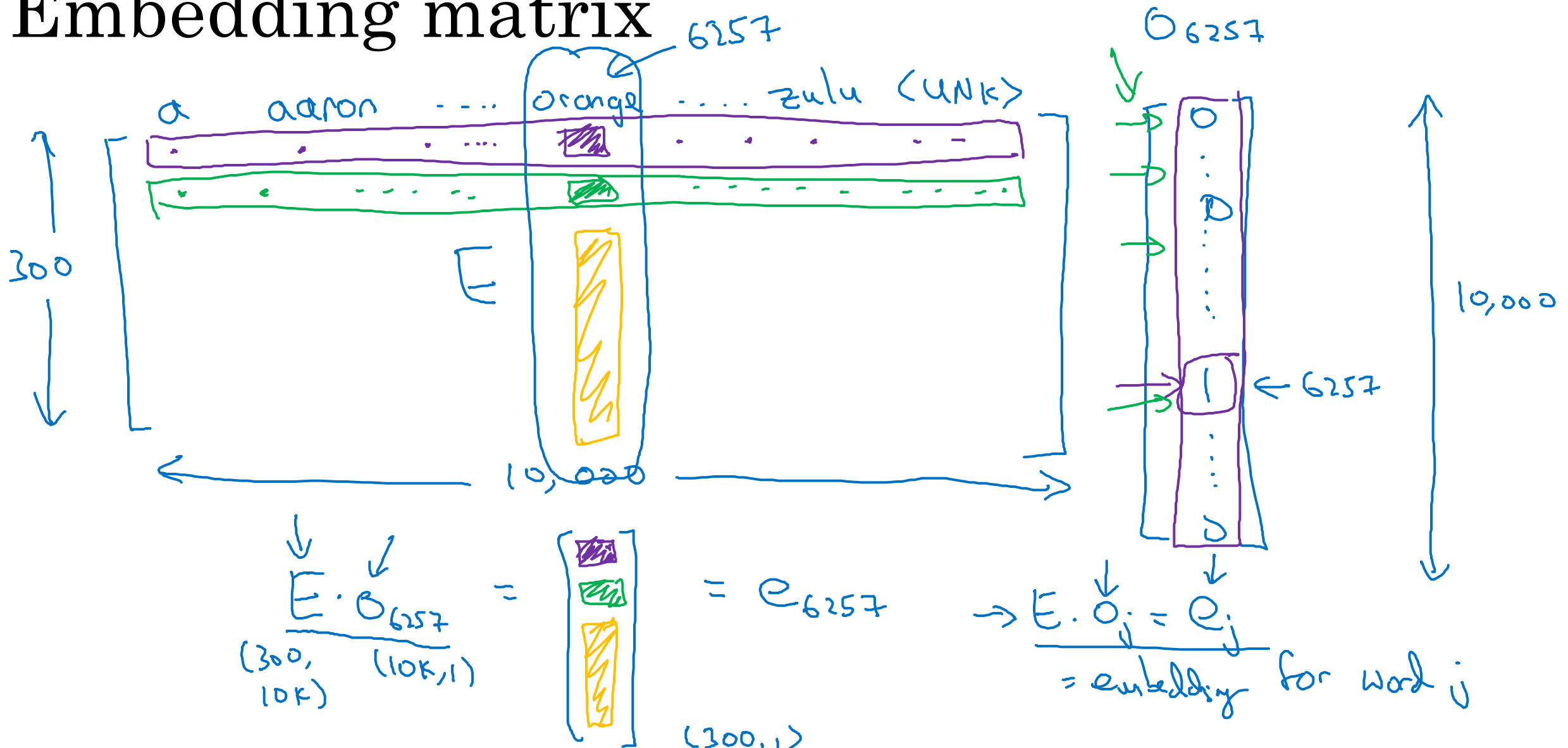


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NLP and Word Embeddings

Embedding matrix

Embedding matrix



In practice, use specialized function to look up an embedding.
 $\rightarrow \text{Embedding}$



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NLP and Word Embeddings

Learning word embeddings

4



Other context/target pairs

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

The diagram illustrates the context and target for the word 'juice'. A purple bracket labeled 'context' spans the words 'a glass of orange'. A blue bracket labeled 'target' is positioned under the word 'juice'. A green arrow points from the 'orange' box to the 'juice' target, and another green arrow points from the 'glass' box to the 'juice' target.

Context: Last 4 words.

- 4 words on left & right
- Last 1 word
- Nearby 1 word

a glass of orange ? to go along with

orange ?

glass ?

skip gram



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NLP and Word Embeddings

Word2Vec

Skip-grams

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



Context

orange

orange

orange



Target

juice

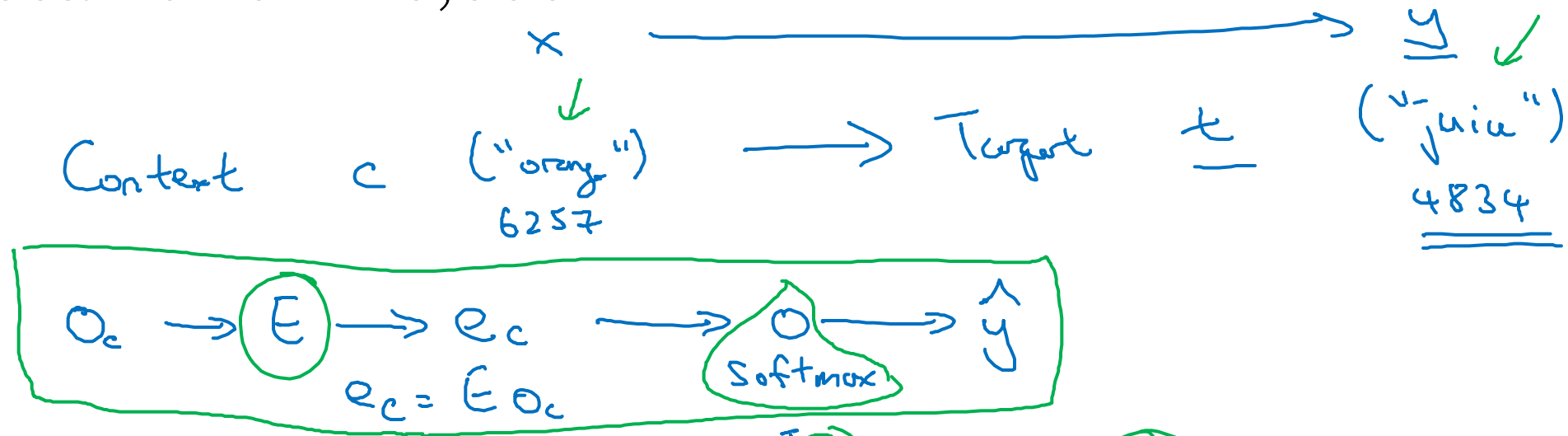
glass

my



Model

Vocab size = 10,000k



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

θ_t = parameter associated with output t

→
$$\mathcal{L}(\hat{y}, y) = - \sum_{i=1}^{10,000} y_i \log \hat{y}_i$$

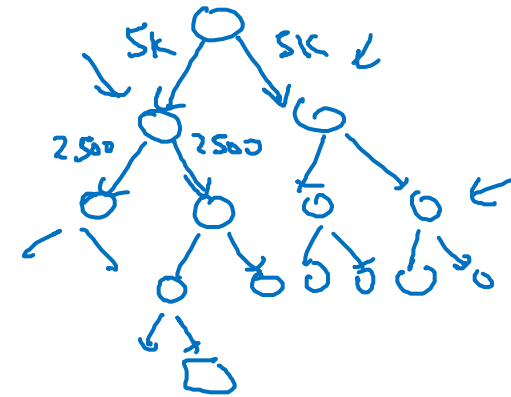
$$y = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} \leftarrow 4834$$

Problems with softmax classification

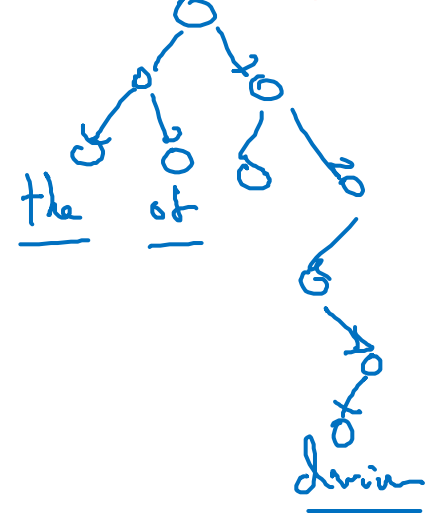
$$\underline{p(t|c)} = \frac{e^{\theta_t^T e_c}}{\sum_{j=1}^{10,000} e^{\theta_j^T e_c}}$$

computational speed -> slow -> solution

Hierarchal software.

 $\log |v|$ 

common words on top



rare words is deeper

How to sample the context c ?

→ the, of, a, and, to, ...

→ orange, apple, lemon

Q. Durian

t

$$C \rightarrow t$$
 $P(\omega)$



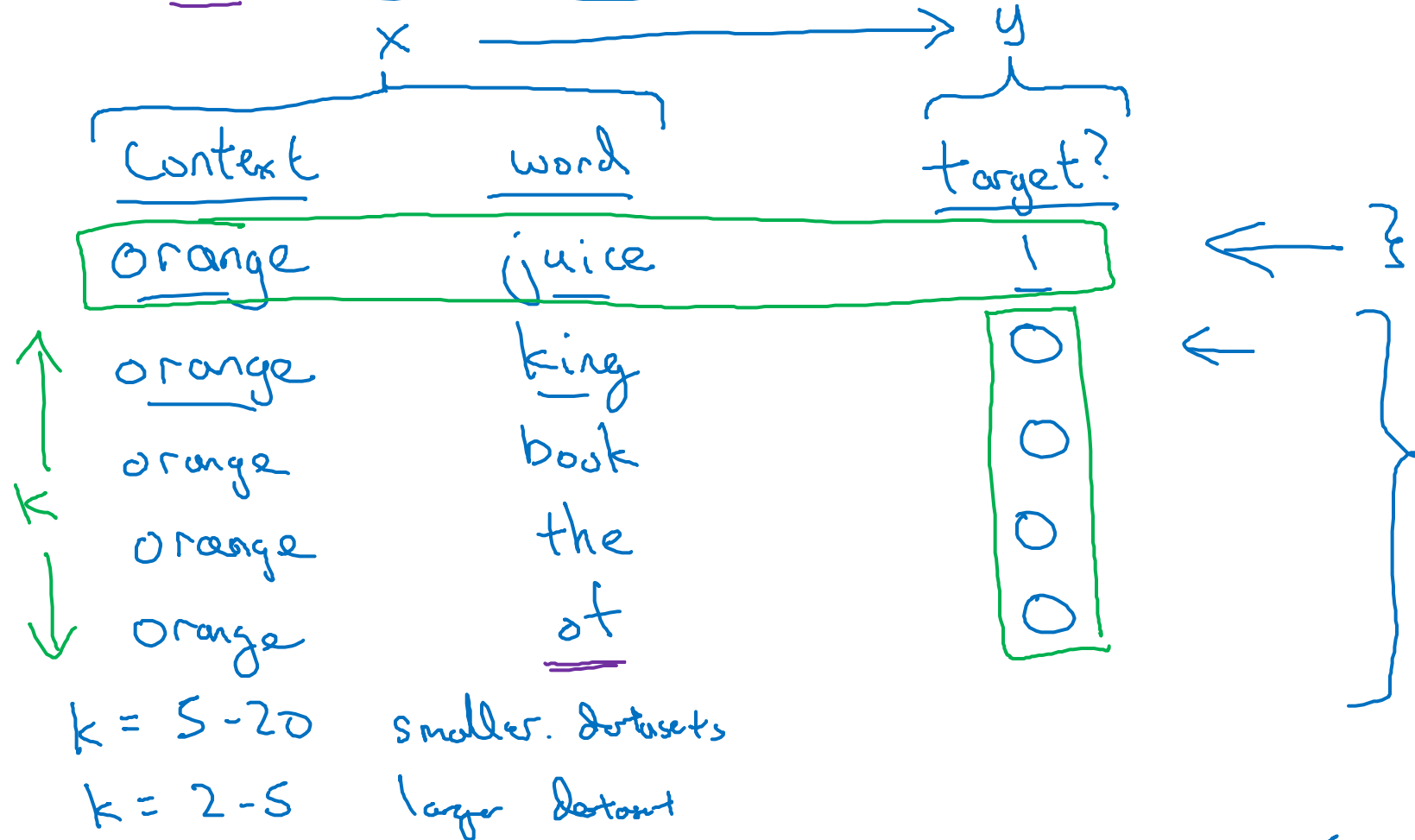
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NLP and Word Embeddings

Negative sampling

Defining a new learning problem

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



Model

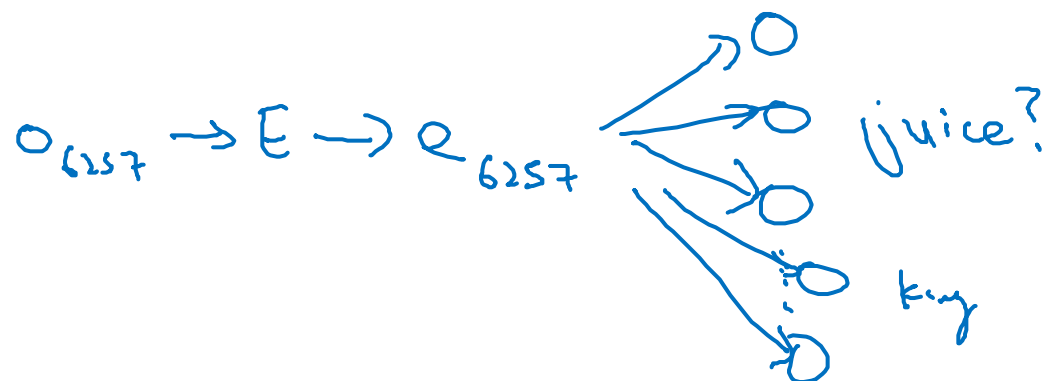
Softmax:

$$p(t|c) = \frac{e^{\theta_t^T e_c}}{\sum_{j=1}^{10,000} e^{\theta_j^T e_c}} \quad \left. \vphantom{\sum_{j=1}^{10,000}} \right\} \begin{array}{l} \text{10,000-way} \\ \text{softmax} \end{array}$$

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

x		y
context	word	target?
orange	juice	1
orange	king	0
orange	book	0
orange	the	0
orange	of	0
c	t	y

Orange
6257



10,000

10,000 binary
classification
problem

only train $k+1$ of them
for every iteration
instead

Selecting negative examples

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

↑
t

the, of, and, ...

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

$$\frac{1}{|V|}$$

↑



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NLP and Word Embeddings

GloVe word vectors

GloVe (global vectors for word representation)

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

c, t

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

$\uparrow \quad \uparrow$
 $c \quad t$

\uparrow
 t

\uparrow
 c

$$X_{ij} = X_{ji} \leftarrow$$

Model

minimize

$$\sum_{i=1}^{10,000} \sum_{j=1}^{10,000} f(x_{ij}) \left(\underbrace{\Theta_i^T e_j}_{\substack{t \quad c \\ \text{"}\Theta_t^T e_c\text{"}}} + b_i + b_j' - \log x_{ij} \right)^2$$

weighting term

$$f(x_{ij}) = 0 \text{ at } x_{ij} = 0.$$

$$"0 \log 0" = 0$$

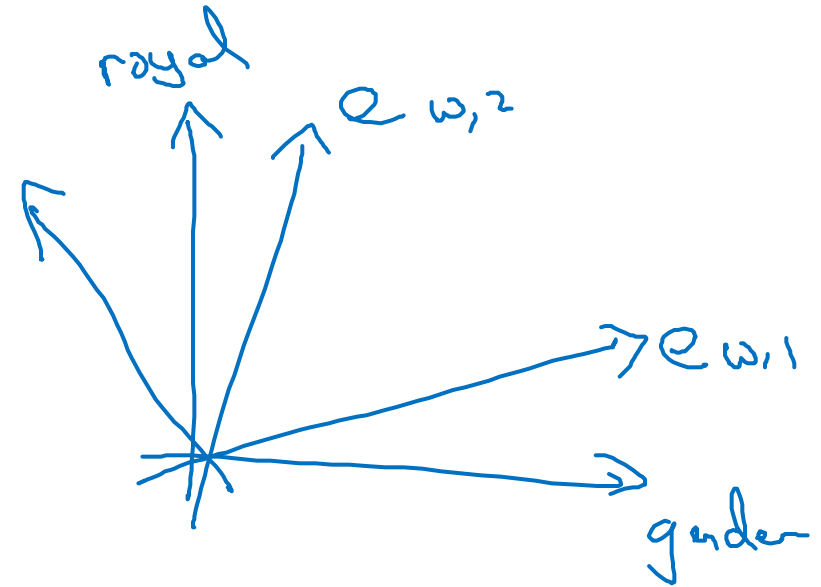
this, is, of, a, ...
derivation

Θ_i, e_j are symmetric

$$e_w^{(final)} = \frac{e_w + \Theta_w}{2}$$

A note on the featurization view of word embeddings

	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	0.70	0.69	←
Food	0.09	0.01	0.02	0.01	←



$$\text{minimize } \sum_{i=1}^{10,000} \sum_{j=1}^{10,000} f(X_{ij}) (\underbrace{\theta_i^T e_j}_{\text{handwritten}} + b_i - b'_j - \log X_{ij})^2$$

$$\text{handwritten: } (A\theta_i)^T (A^T e_j) = \theta_i^T A^T A e_j$$



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NLP and Word Embeddings

Sentiment classification

Sentiment classification problem



The dessert is excellent.



Service was quite slow.



Good for a quick meal, but nothing special.



Completely lacking in good taste, good service, and good ambience.



10,000 \rightarrow 100,000 words

Simple sentiment classification model

The dessert is excellent



8928 2468 4694 3180

The o_{8928} \longrightarrow E \longrightarrow e_{8928}

desert o_{2468} \longrightarrow E \longrightarrow e_{2468}

is o_{4694} \longrightarrow E \longrightarrow e_{4694}

excellent o_{3180} \longrightarrow E \longrightarrow e_{3180}

issue: ignore word order \rightarrow use RNN

Avg

3000

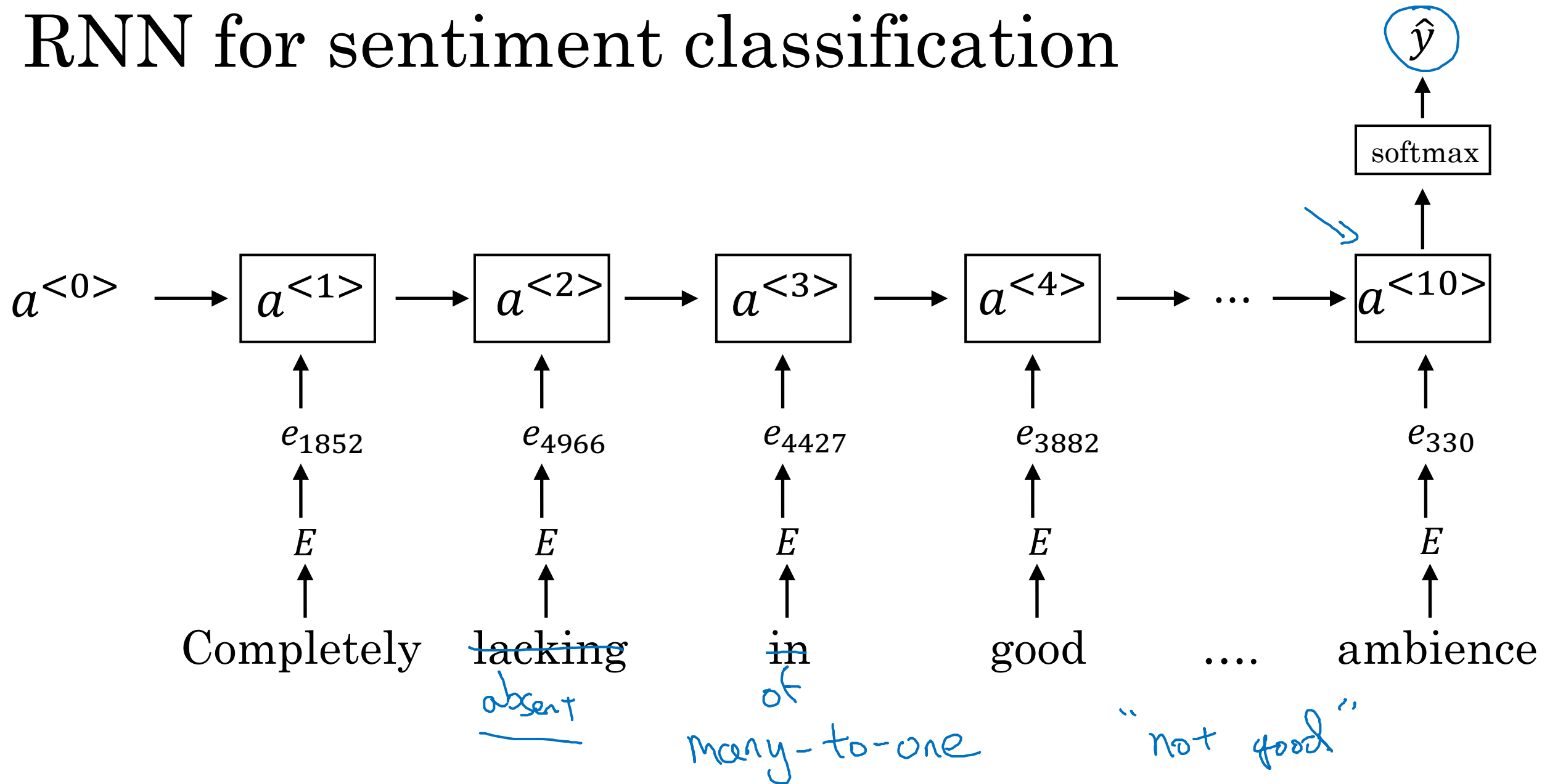
Softmax
1-5
 \hat{y}

“Completely lacking in good
taste, good service, and good
ambience.”

\uparrow
100 B
words

$\underbrace{\hspace{1.5cm}}$
3000

RNN for sentiment classification





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NLP and Word Embeddings

Debiasing word embeddings

The problem of bias in word embeddings

Man:Woman as King:Queen

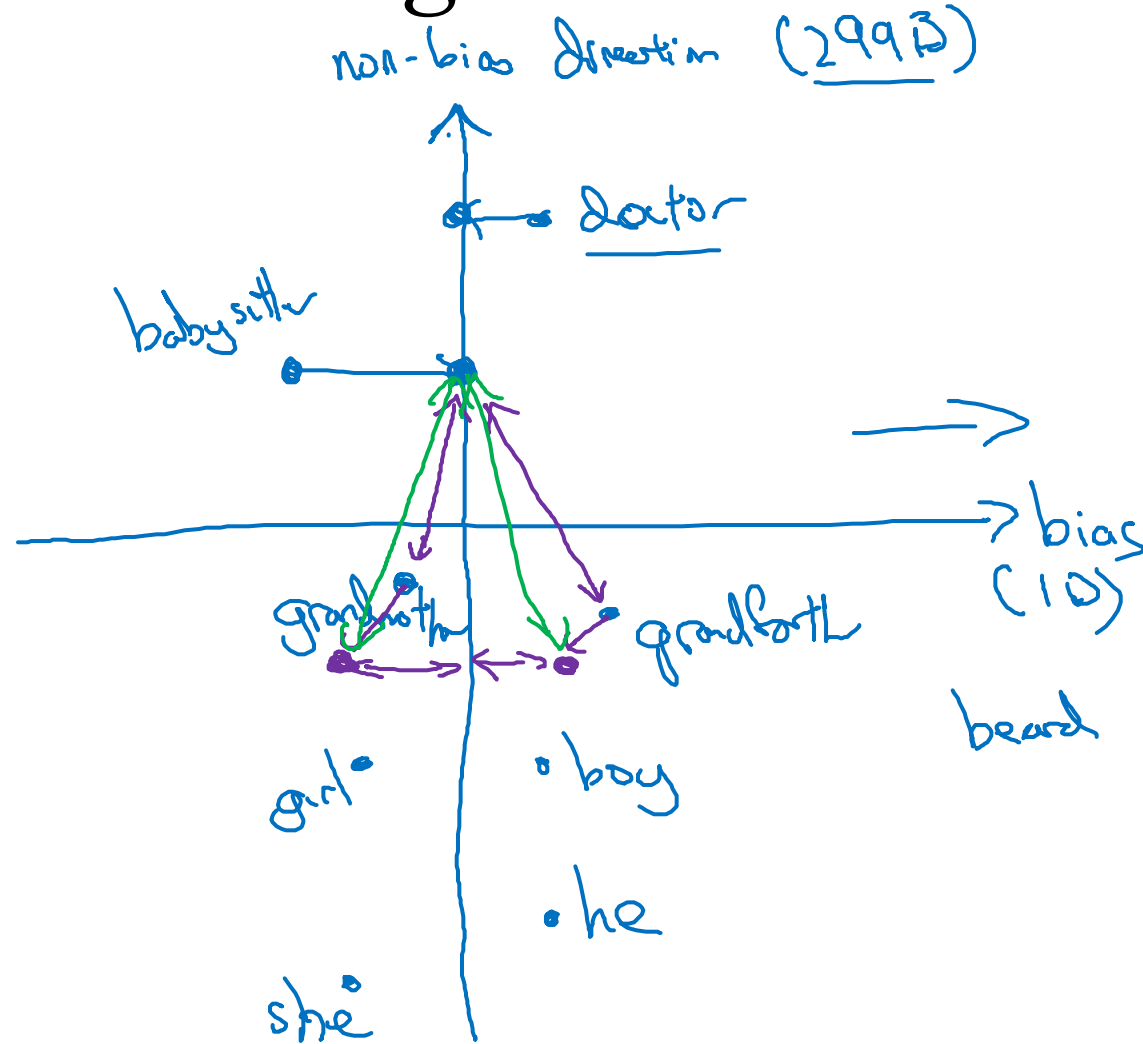
Man:Computer_Programmer as Woman:Homemaker X

Father:Doctor as Mother:Nurse X

Word embeddings can reflect gender, ethnicity, age, sexual orientation, and other biases of the text used to train the model.



Addressing bias in word embeddings



1. Identify bias direction.

$\{ \begin{aligned} &e_{he} - e_{she} \\ &e_{male} - e_{female} \\ &\vdots \end{aligned} \}$
→ average

2. Neutralize: For every word that is not definitional, project to get rid of bias.

3. Equalize pairs.

→ $\left. \begin{array}{cc} \text{grandmother} & \text{grandfather} \\ \text{girl} & \text{boy} \end{array} \right\}$