deeplearning.ai

NLP and Word Embeddings

Word representation

Word representation

V = [a, aaron, …, zulu, <UNK>]

$|V| = 10,000$

1-hot representation

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

I want a glass of orange __juice__.

I want a glass of apple__?__.

Featurized representation: word embedding

300

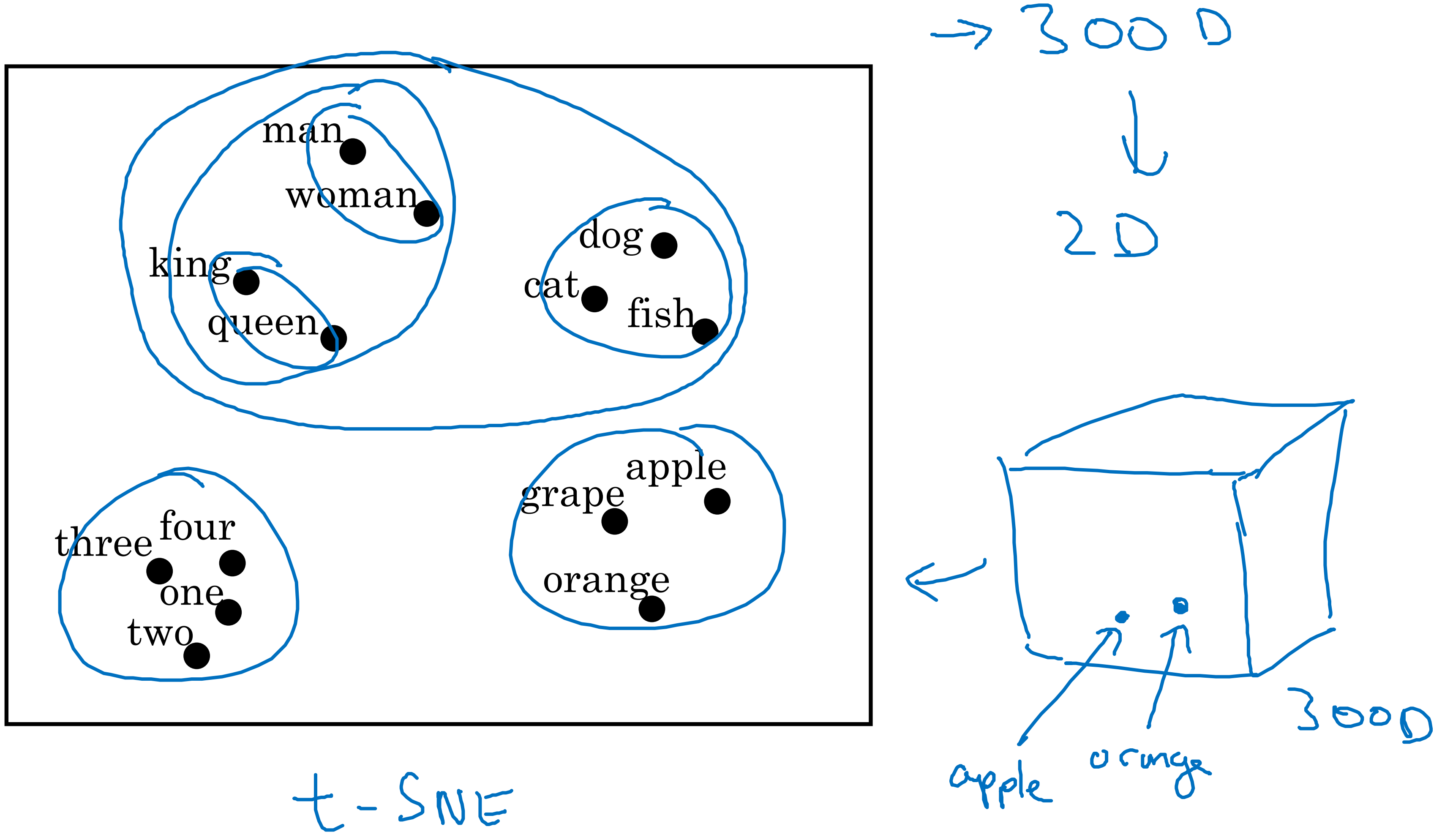
	Man (5391)	Woman (9853)	King (4914)	Queen (7157)	Apple (456)	Orange (6257)
Gender	-1	1	-0.95	0.97	0.00	0.01
Royal	0.01	0.02	0.93	0.95	-0.01	0.00
Age	0.03	0.02	0.7	0.69	0.03	-0.02
Food	0.04	0.01	0.02	0.01	0.95	0.97
⋮	⋮	⋮				
size						
cost						
alive						
verb						

e_{5391} e_{9853}

I want a glass of orange juice.

I want a glass of apple juice.

Visualizing word embeddings



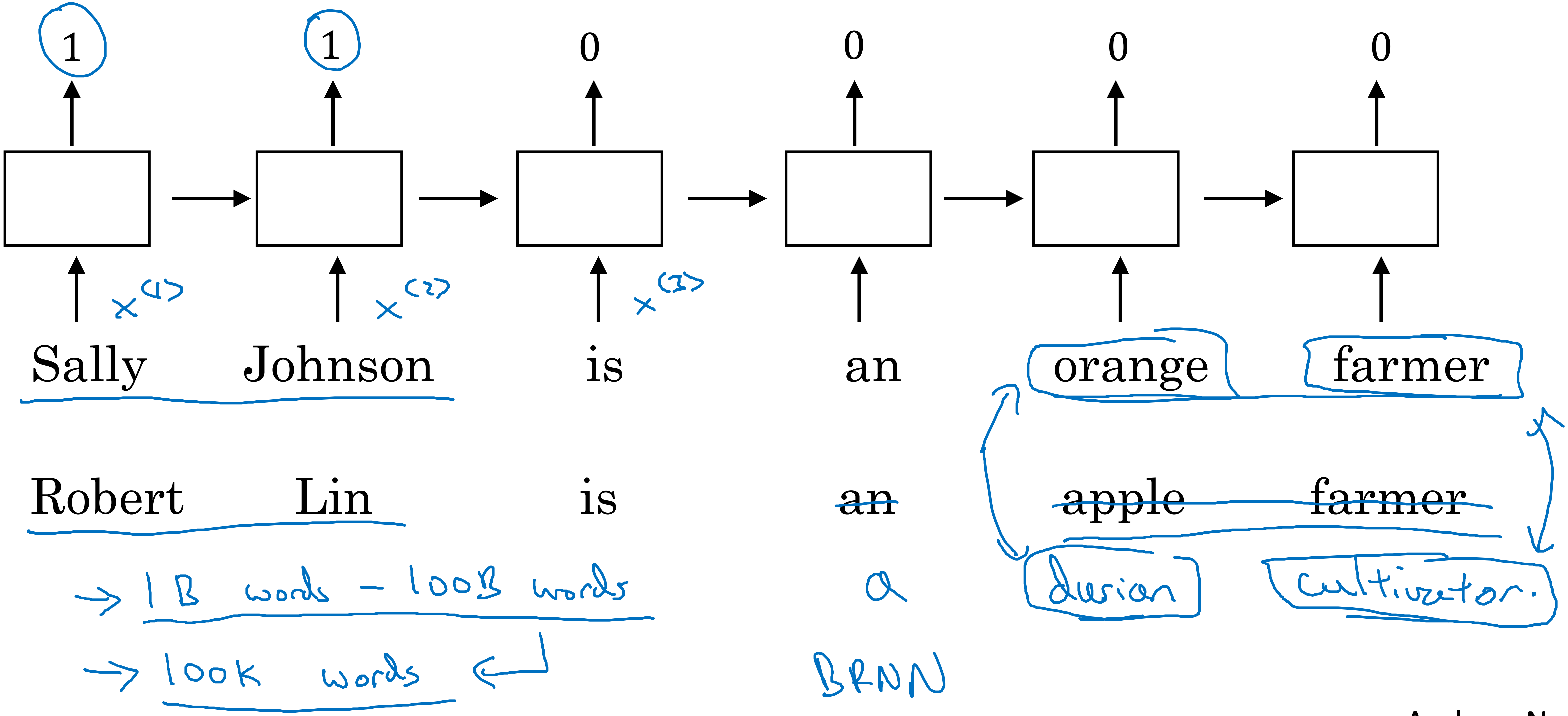
[van der Maaten and Hinton., 2008. Visualizing data using t-SNE]

deeplearning.ai

NLP and Word Embeddings

Using word embeddings

Named entity recognition example



Sally Johnson is an orange farmer

Robert Lin is ~~an~~ ~~apple farmer~~

a durian cultivator.

→ 1B words – 100B words

→ 100k words

BRNN

Transfer learning and word embeddings

Ⓐ

1. Learn word embeddings from large text corpus. (1-100B words)

   (Or download pre-trained embedding online.)

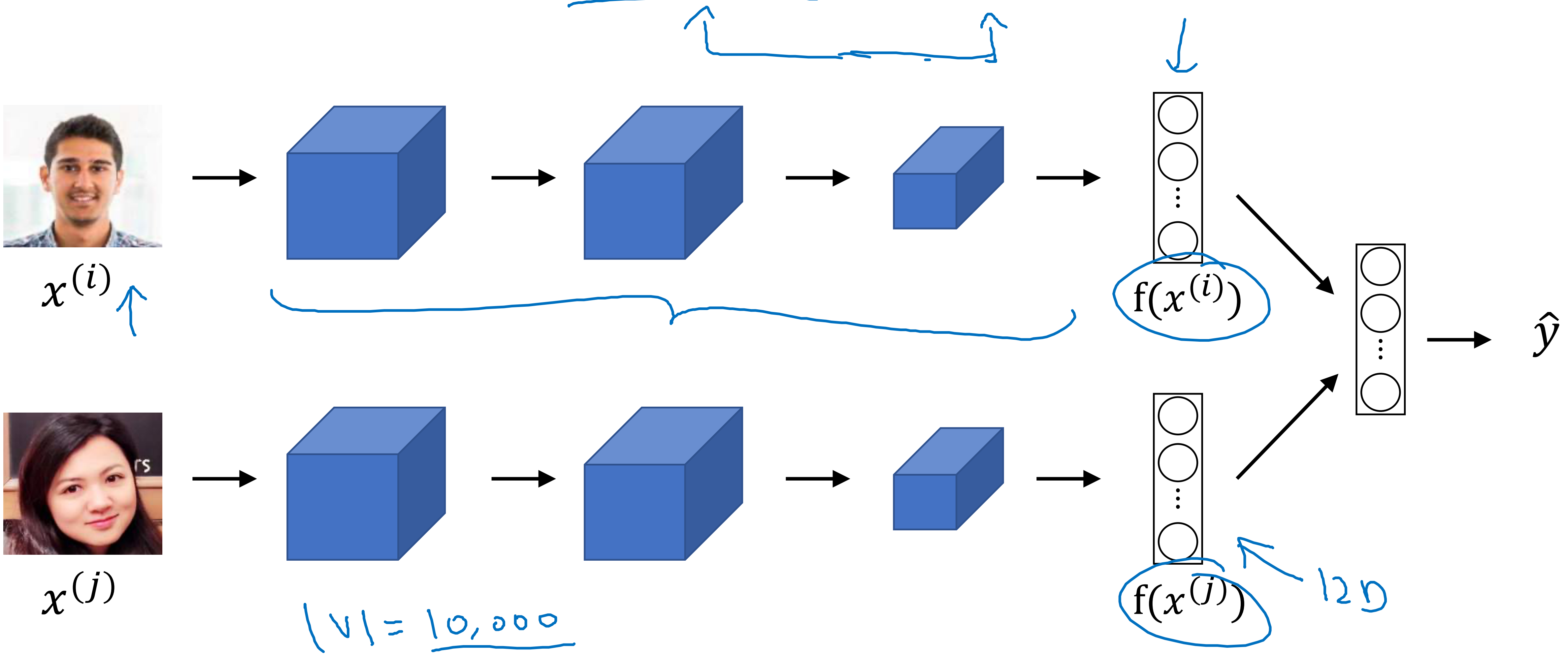
↓

Ⓑ

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



$|V| = 10{,}000$

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

[Taigman et. al., 2014. DeepFace: Closing the gap to human level performance]

deeplearning.ai

NLP and Word Embeddings

Properties of word embeddings

Analogies

	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

e_{5391}

e_{man}

e_{woman}

Man → Woman as King → ? Queen

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

↑ queen

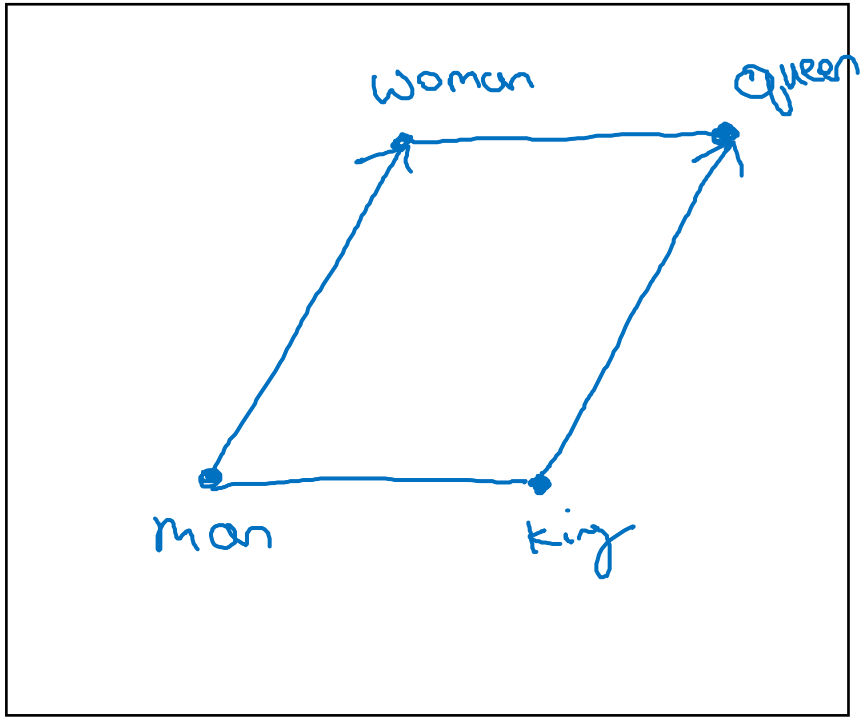
$$e_{man} - e_{woman} \approx \begin{bmatrix} -2 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$e_{king} - e_{queen} \approx \begin{bmatrix} -2 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

↙

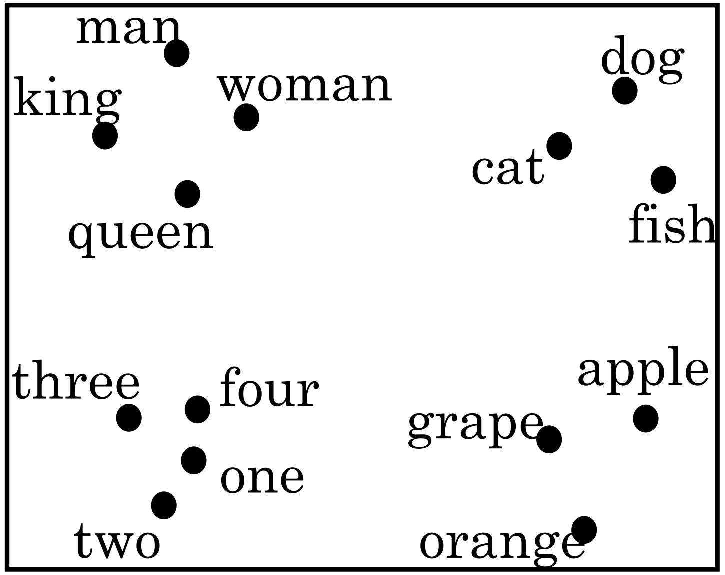
[Mikolov et. al., 2013, Linguistic regularities in continuous space word representations]

Analogies using word vectors



300 D

300D → 2D



t-SNE

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

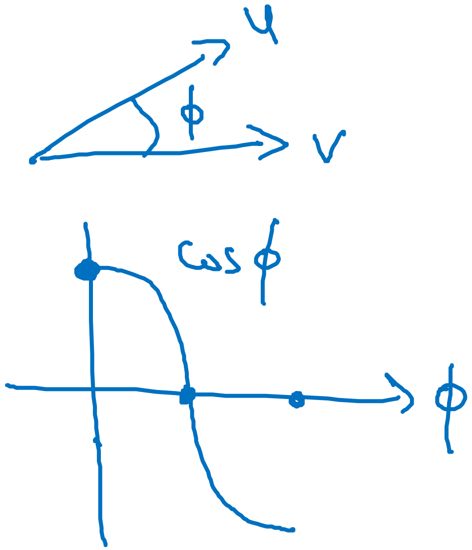
Find word w: $\arg\max_{w} \boxed{sim(\underline{e_w}, \underbrace{\overbrace{e_{king} - e_{man} + e_{woman}}})}$

30 - 75%

Cosine similarity

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

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



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

Man:Woman as Boy:Girl

Ottawa:Canada as Nairobi:Kenya

Big:Bigger as Tall:Taller

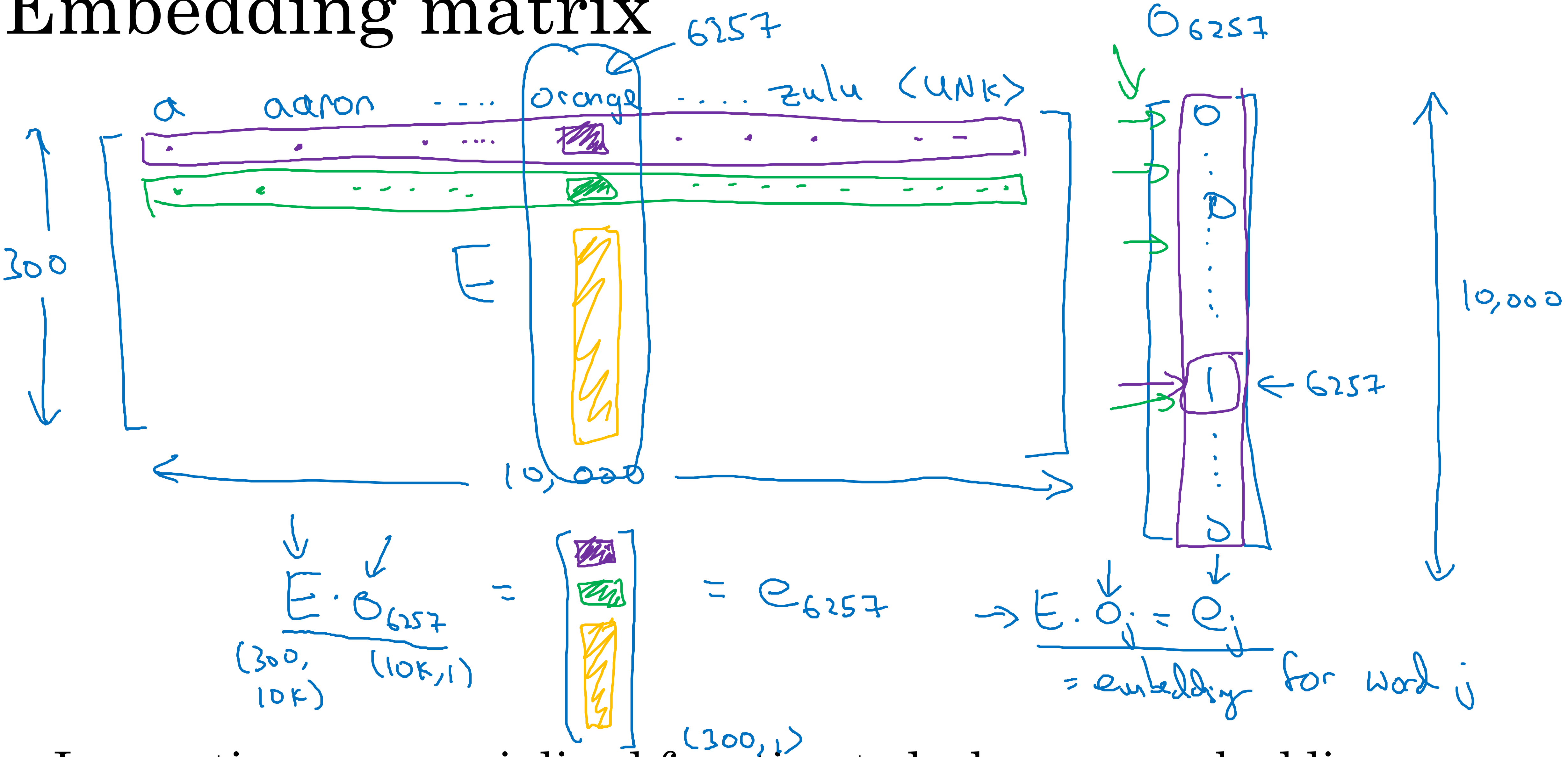
Yen:Japan as Ruble:Russia

NLP and Word Embeddings

Embedding matrix

deeplearning.ai

Embedding matrix



$\underline{E \cdot O_{6257}} = \dots = e_{6257}$

$\rightarrow \underline{E \cdot O_j = e_j}$

= embedding for word j

In practice, use specialized function to look up an embedding.

→ Embedding

Andrew Ng

NLP and Word Embeddings

Learning word embeddings

deeplearning.ai

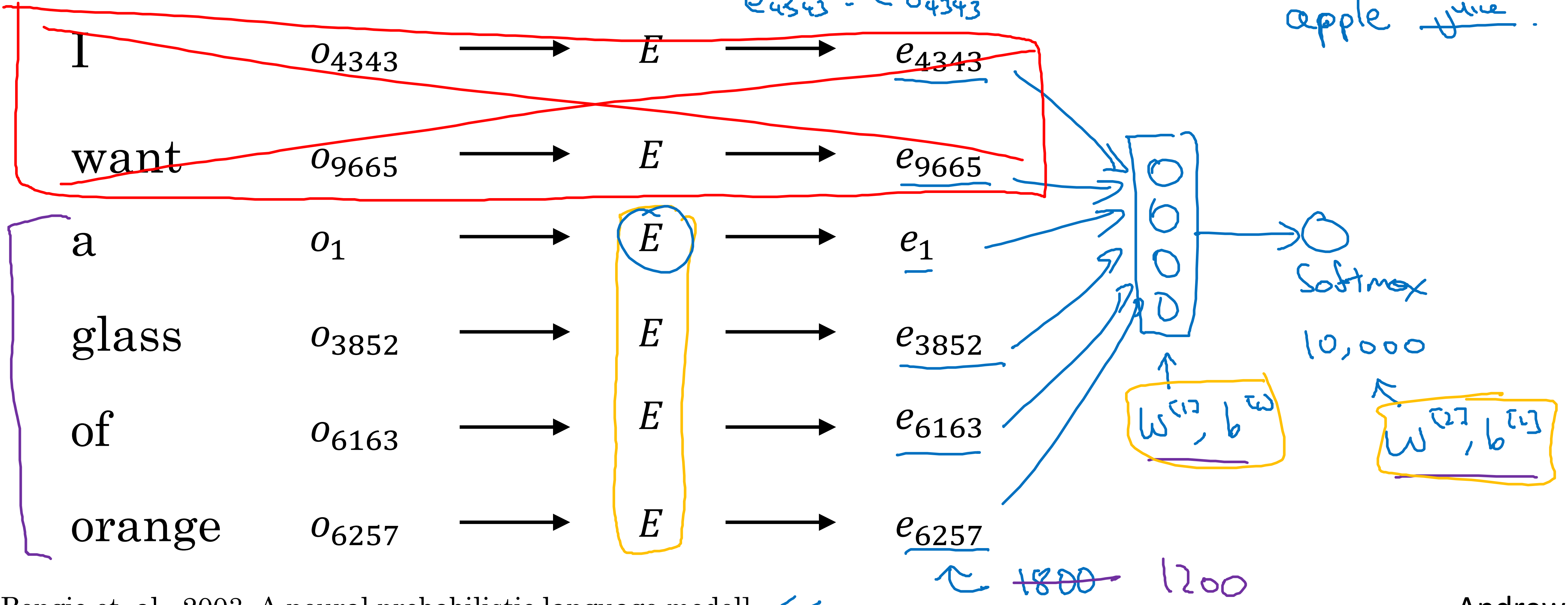
Neural language model

4

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

apple juice.

$e_{4343} = E\, o_{4343}$



I $\quad o_{4343} \longrightarrow E \longrightarrow e_{4343}$

want $\quad o_{9665} \longrightarrow E \longrightarrow e_{9665}$

a $\quad o_{1} \longrightarrow E \longrightarrow e_{1}$

glass $\quad o_{3852} \longrightarrow E \longrightarrow e_{3852}$

of $\quad o_{6163} \longrightarrow E \longrightarrow e_{6163}$

orange $\quad o_{6257} \longrightarrow E \longrightarrow e_{6257}$

[Bengio et. al., 2003, A neural probabilistic language model]

Other context/target pairs

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

context

target

Context: Last 4 words.

- 4 words on left & right

  a glass of orange ? to go alg with

- Last 1 word

  orange ?

- Nearby 1 word

  glass ?

  skip gram

deeplearning.ai

NLP and Word Embeddings

Word2Vec

Skip-grams

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

Context	Target
orange	juice
orange	glass
orange	my

[Mikolov et. al., 2013. Efficient estimation of word representations in vector space.]

Model

Vocab size = 10,000k

$$x \longrightarrow y$$

Context c ("orange") 6257 $\longrightarrow$ Target t ("juice") 4834

$$\boxed{o_c \rightarrow \boxed{E} \rightarrow e_c \rightarrow \underset{\text{softmax}}{\bigcirc} \rightarrow \hat{y}}$$

$$e_c = E o_c$$

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

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

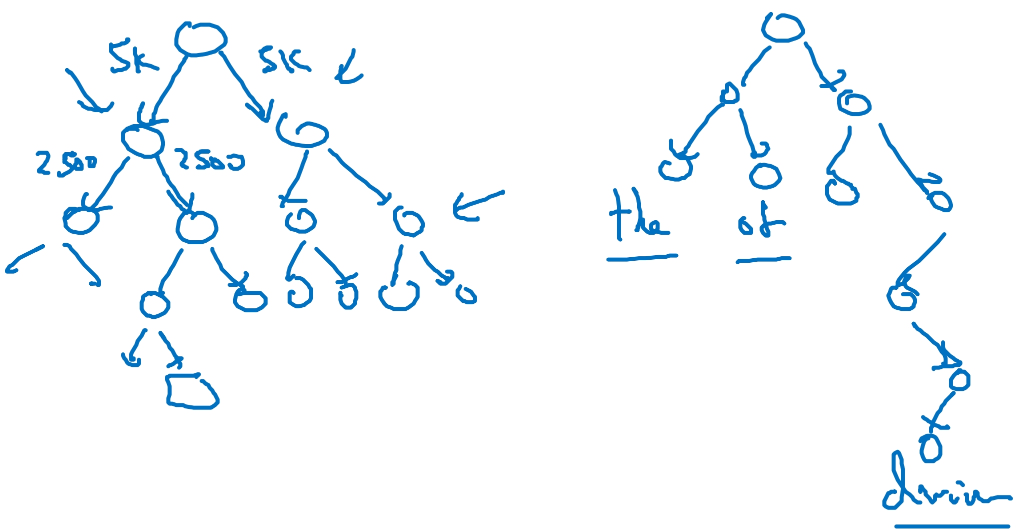
$$y = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} \leftarrow 4834$$

Problems with softmax classification

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

Hierarchical softmax.

log |V|



How to sample the context c?

→ the, of, a, and, to, ...

→ orange, apple, durian

durian

t

c → t

P(c)

deeplearning.ai

NLP and Word Embeddings

Negative sampling

Defining a new learning problem

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

$x \longrightarrow y$

Context	word	target?
orange	juice	1
orange	king	0
orange	book	0
orange	the	0
orange	of	0

k

k = 5-20 smaller. datasets

k = 2-5 larger dataset

[Mikolov et. al., 2013. Distributed representation of words and phrases and their compositionality]

Model

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

10,000-way softmax

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

context	word	target?
orange	juice	1
orange	king	0
orange	book	0
orange	the	0
orange	of	0

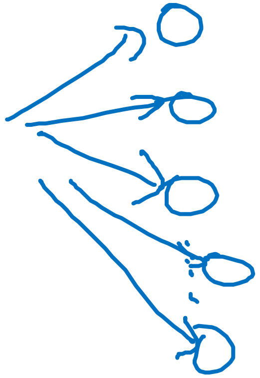
x y

k

c t y

Orange
6257

$$o_{6257} \rightarrow E \rightarrow e_{6257}$$



juice?

king

10,000

10,000 binary classification problem

$\underline{k+1}$

Selecting negative examples

x y

context	word	target?
orange	juice	1
orange	king	0
orange	book	0
orange	the	0
orange	of	0

↑
t

the , of, and, ...

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

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

↑

NLP and Word Embeddings

deeplearning.ai

GloVe word vectors

GloVe (global vectors for word representation)

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

c, t

$$X_{\underset{\overset{\uparrow}{c}}{i}\underset{\overset{\uparrow}{t}}{j}} = \#\text{times } \underset{\overset{\uparrow}{t}}{i} \text{ appears in context of } \underset{\overset{\uparrow}{c}}{j}.$$

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

[Pennington et. al., 2014. GloVe: Global vectors for word representation] ←

Model

$$\text{minimize} \sum_{i=1}^{10,000} \sum_{j=1}^{10,000} \underbrace{f(X_{ij})}_{\text{weighting term}} \left(\overset{\downarrow}{\theta_i^T} \, \overset{\downarrow}{e_j} + \overset{t}{\overset{\downarrow}{b_i}} + \overset{c}{\overset{\downarrow}{b_j'}} - \overset{\rightarrow\, 0\, ?}{\log} \underline{X_{ij}} \right)^2 \leftarrow$$

$$\text{“} \overset{t}{\theta_t^T} \, \overset{c}{e_c} \text{”} \rightarrow X_{ij}$$

$f(X_{ij}) = 0$ if $X_{ij} = 0$. “$0 \log 0$” $= 0$

this, is, of, a, ...

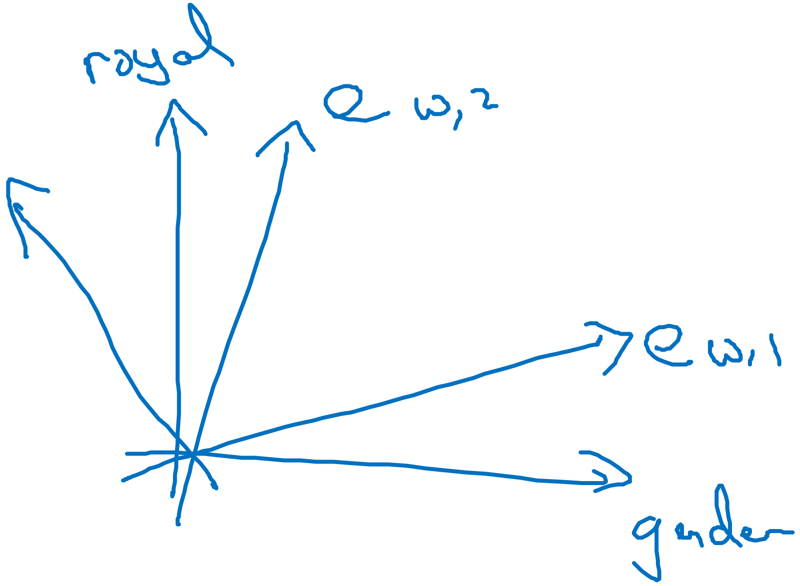
durian

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



$$\text{minimize} \sum_{i=1}^{10,000}\sum_{j=1}^{10,000} f(X_{ij})\left(\underbrace{\overbrace{\theta_i^T e_j}}+ b_i - b_j' - \log X_{ij}\right)^2$$

$$(A\theta_i)^T(A^{-T}e_j) = \underline{\theta_i^T} \cancel{A^T}\cancel{A^{-T}} \underline{e_j}$$

deeplearning.ai

NLP and Word Embeddings

Sentiment classification

Sentiment classification problem

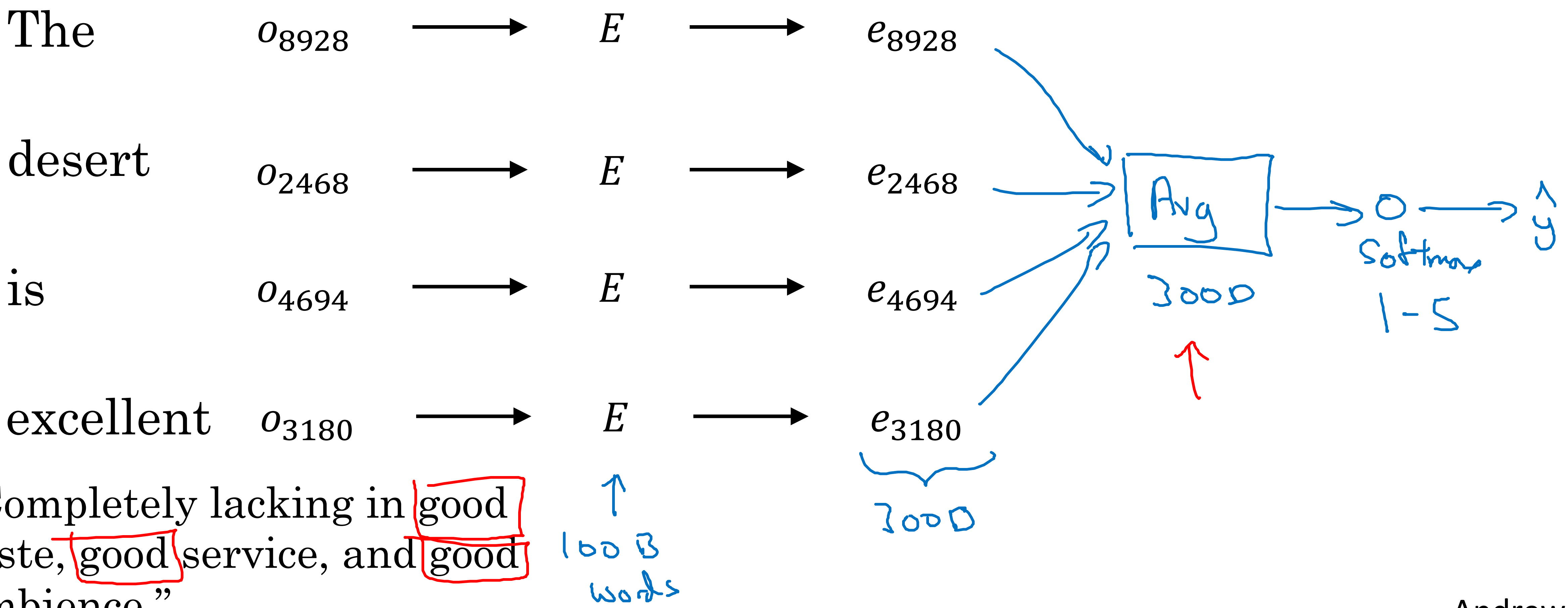
x →	y
The dessert is excellent.	★★★★☆
Service was quite slow.	★★☆☆☆
Good for a quick meal, but nothing special.	★★★☆☆
Completely lacking in good taste, good service, and good ambience.	★☆☆☆☆

10,000 → 100,000 words

Simple sentiment classification model

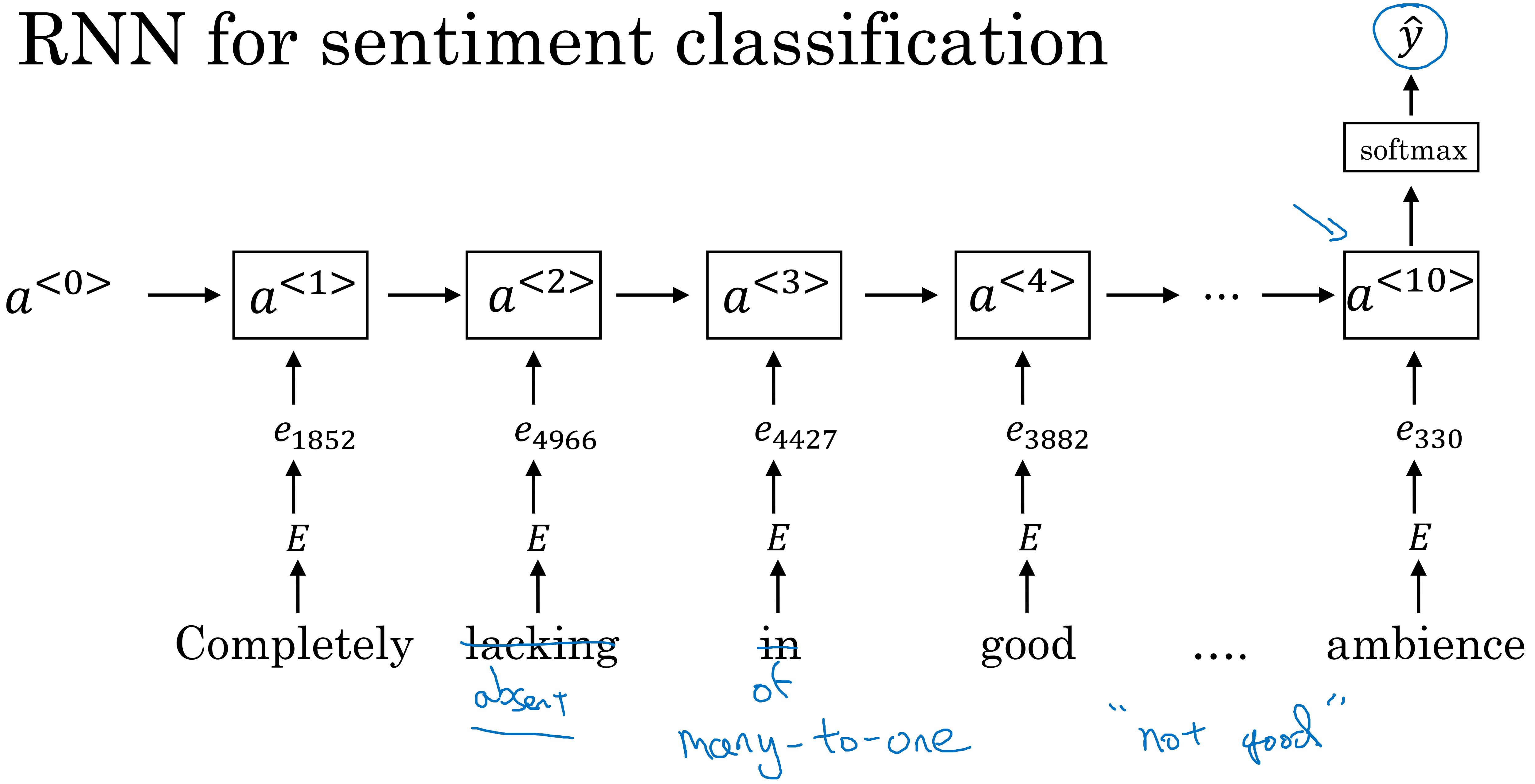
The	dessert	is	excellent
8928	2468	4694	3180

★★★★☆



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

RNN for sentiment classification



Andrew Ng

deeplearning.ai

NLP and Word Embeddings

Debiasing word embeddings

The problem of bias in word embeddings

Man:Woman as King:Queen

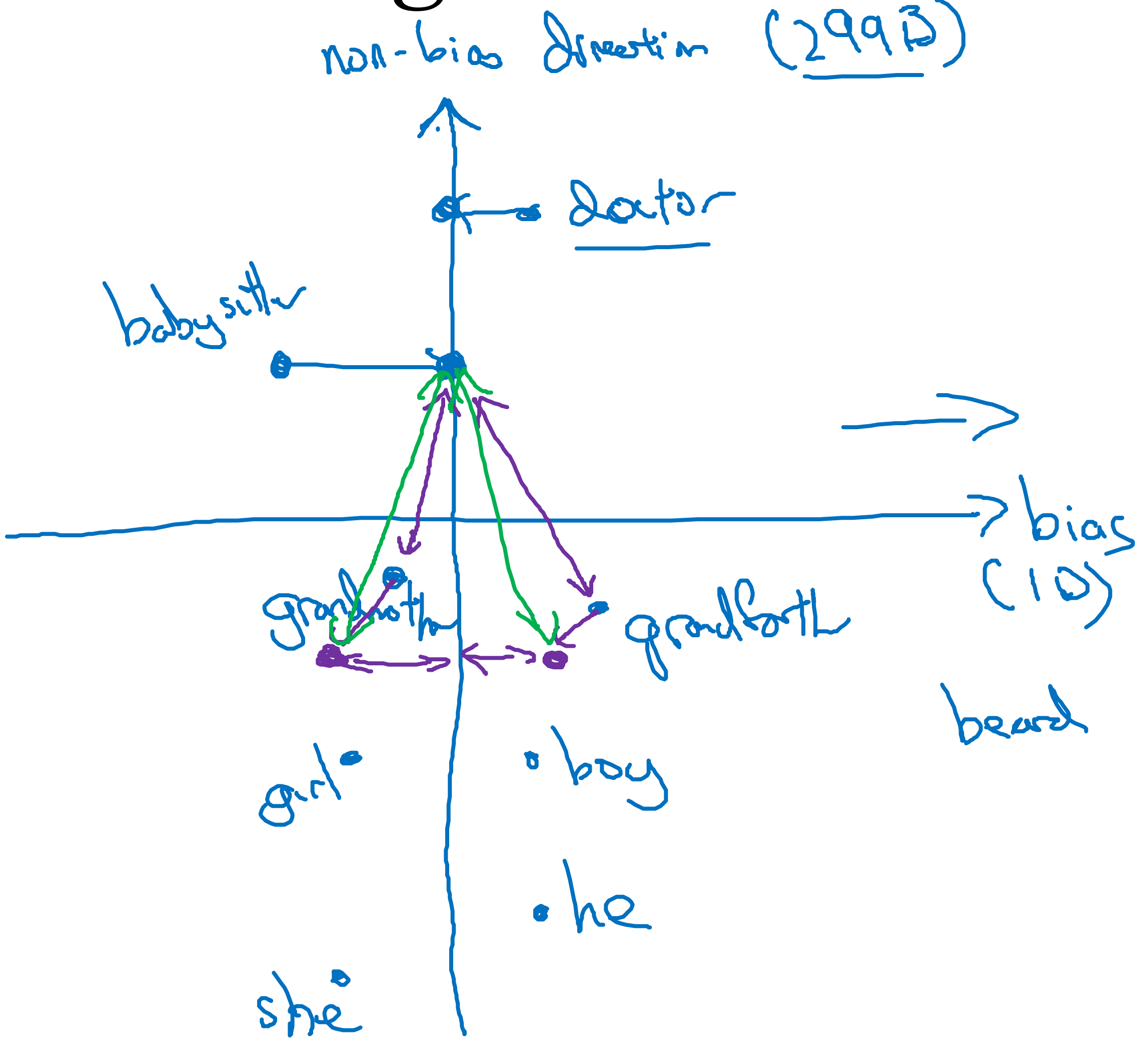
Man:Computer_Programmer as Woman: Homemaker ✗

Father:Doctor as Mother: Nurse ✗

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

[Bolukbasi et. al., 2016. Man is to computer programmer as woman is to homemaker? Debiasing word embeddings] ↙

Addressing bias in word embeddings



1. Identify bias direction.

$e_{he} - e_{she}$

$e_{male} - e_{female}$

⋮

→ average

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

3. Equalize pairs.

→ grandmoth — grandfath

girl — boy

[Bolukbasi et. al., 2016. Man is to computer programmer as woman is to homemaker? Debiasing word embeddings]