Copyright Notice

NLP and Word Embeddings

deeplearning.ai

Word representation

Word representation

V = [a, aaron, …, zulu, <UNK>]

$|V| = 10{,}000$

1-hot representation — not capture similarity between words

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

I want a glass of $\boxed{\text{orange \_\_juice\_\_}}$.

I want a glass of $\boxed{\text{apple \_\_?\_\_}}$.

Andrew Ng

Featurized representation: word embedding

aspect \ word	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						

300

e_{5391} e_{9853}

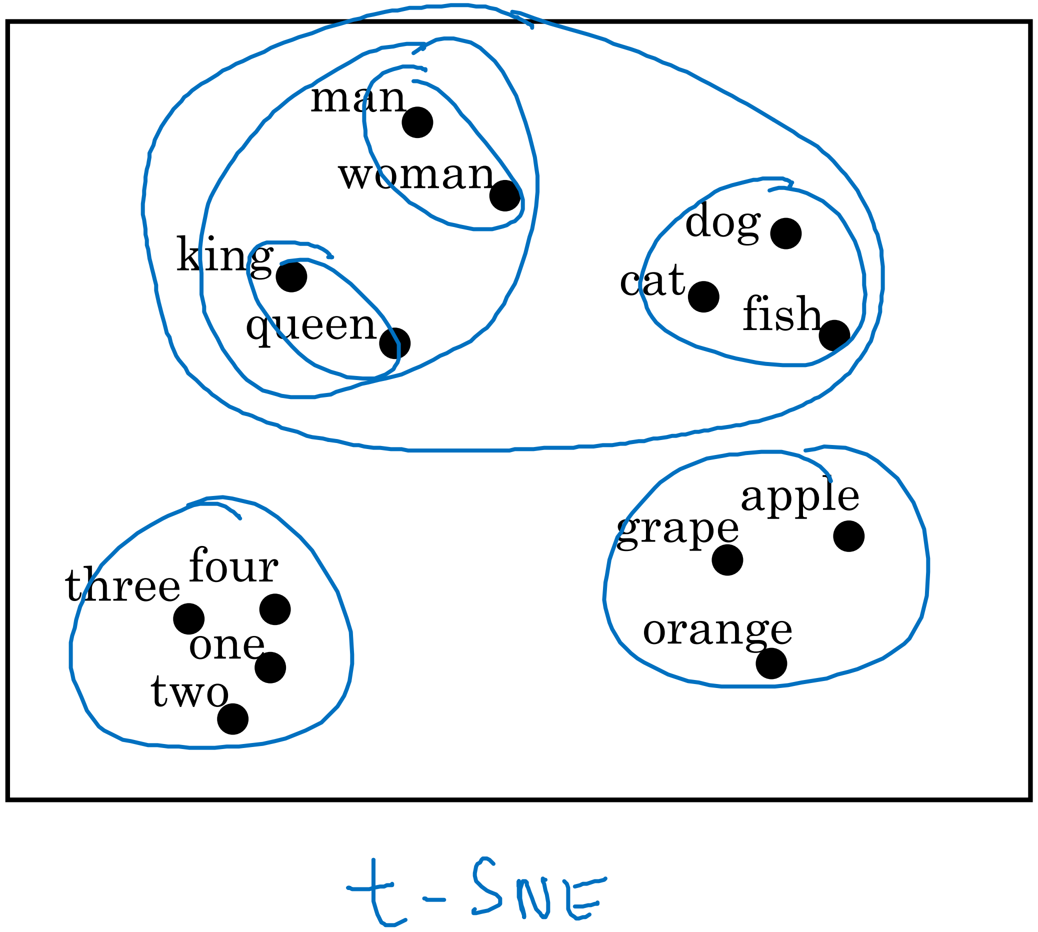
I want a glass of orange juice.

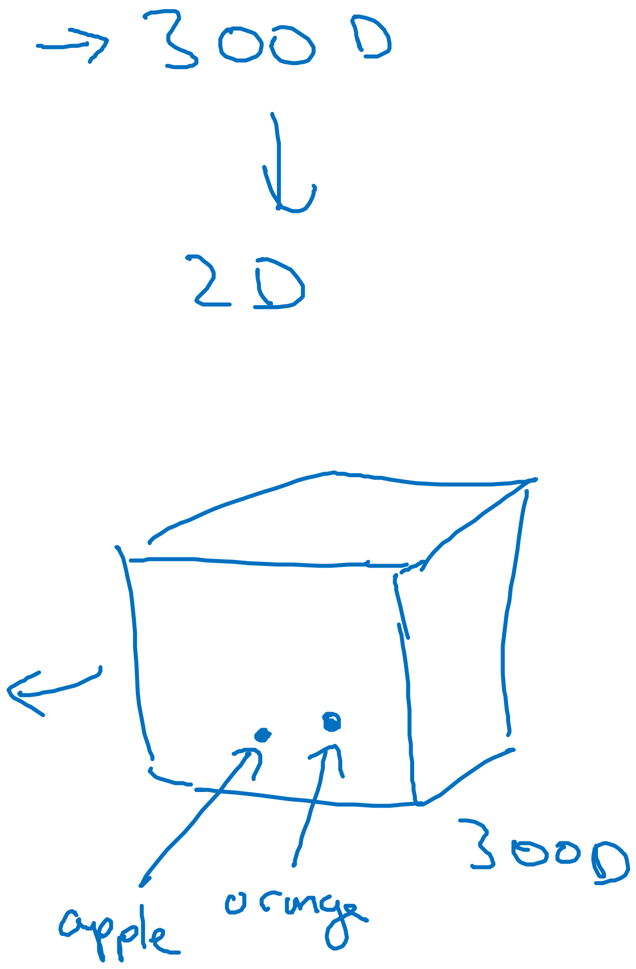
I want a glass of apple juice.

Andrew Ng

Visualizing word embeddings

similar words tend to be near in vector space





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

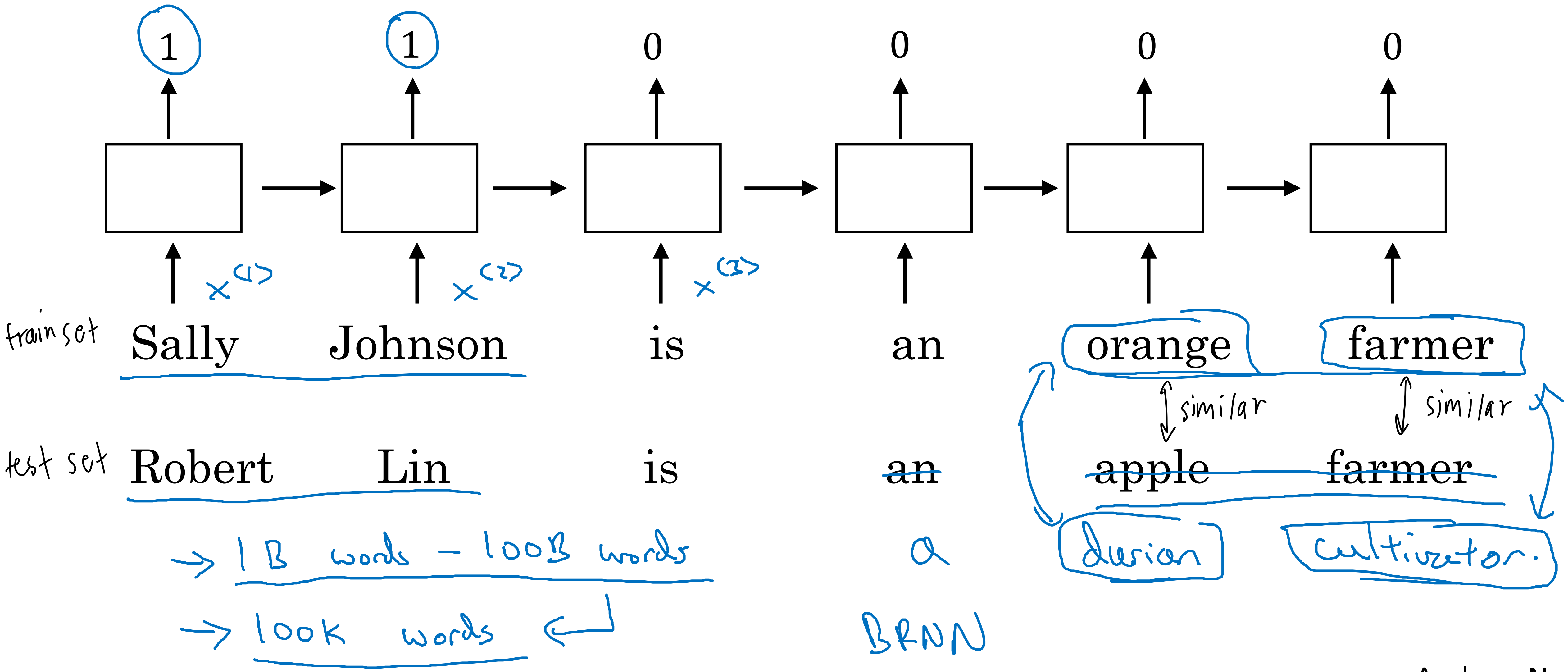
Andrew Ng

deeplearning.ai

NLP and Word Embeddings

Using word embeddings

Named entity recognition example



Andrew Ng

Transfer learning and word embeddings

large train set

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

(Or download pre-trained embedding online.)

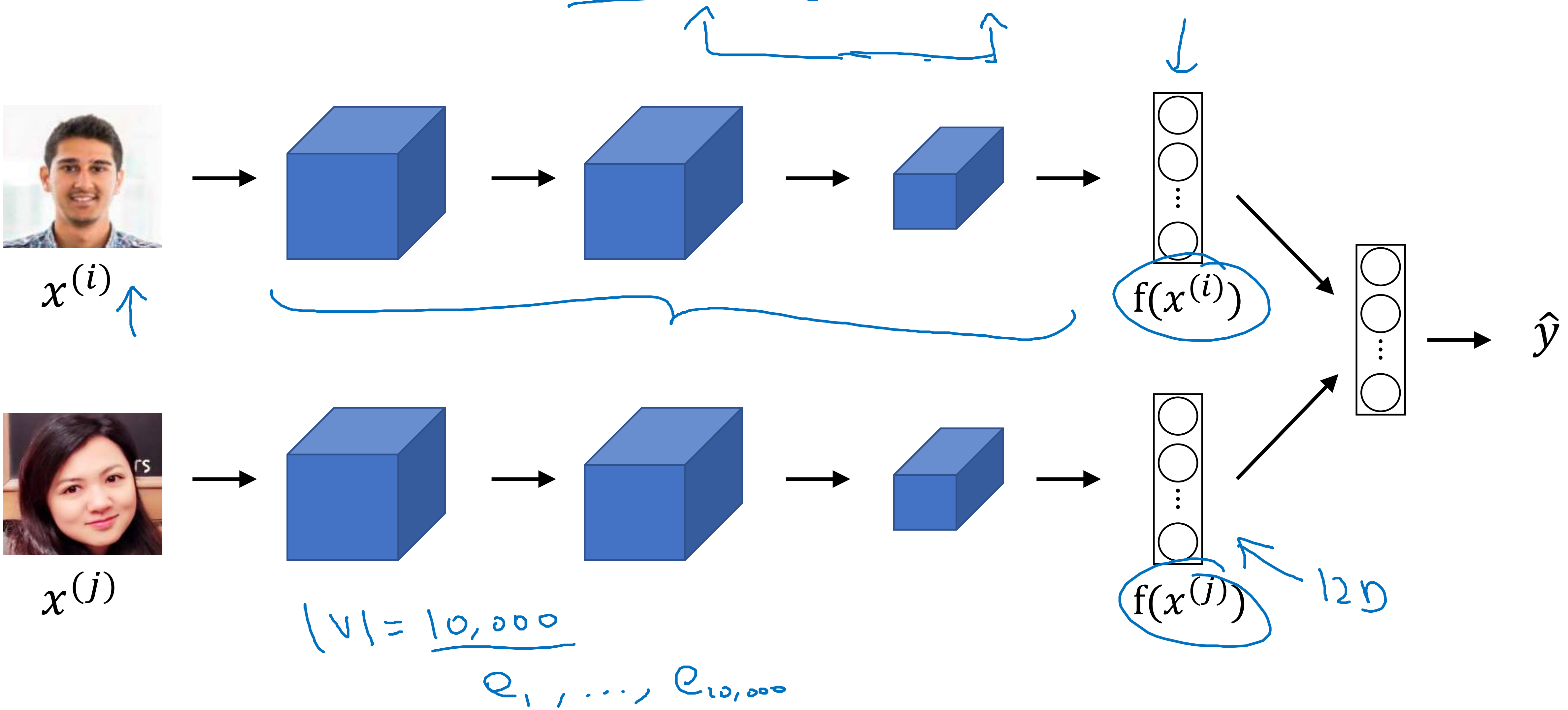
B 2. Transfer embedding to new task with smaller training set. (say, 100k words)

→ 10,000 → 300

3. Optional: Continue to finetune the word embeddings with new data.

Lneed large amount of training data

Relation to face encoding (embedding) 128D



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

Andrew Ng

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} $\qquad e_{woman}$

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

Man → Woman as King →? Queen

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

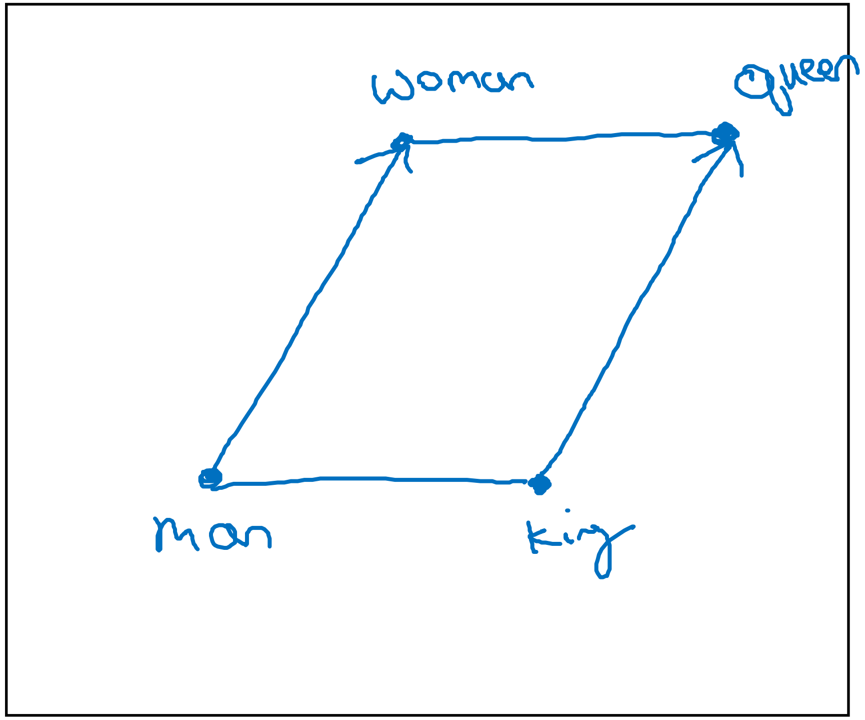
$$e_{man} - e_{woman} \approx e_{king} - e_{?}$$

queen

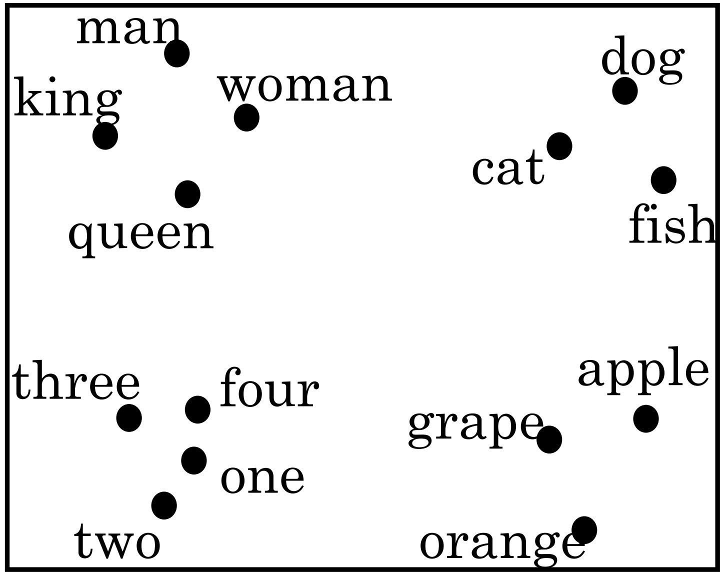
[Mikolov et. al., 2013, Linguistic regularities in continuous space word representations]

Andrew Ng

Analogies using word vectors



300 D



300 → 2D

t-SNE

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

choose vector most similar to $e_{king} - e_{man} + e_{woman}$

Find word w: $\arg\max_w \; \boxed{sim(e_w, e_{king} - e_{man} + e_{woman})}$

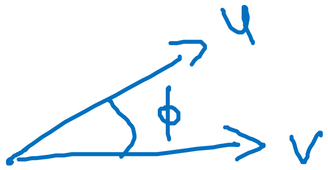
30 - 75%

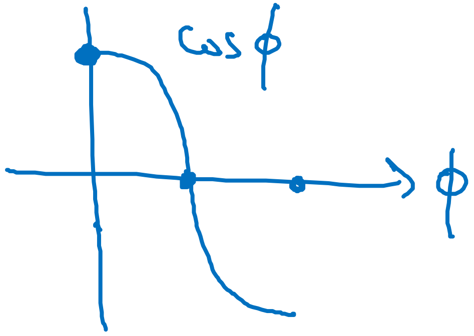
Andrew Ng

Cosine similarity

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

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





$\|u - v\|^2$

Man:Woman as Boy:Girl

Ottawa:Canada as Nairobi:Kenya

Big:Bigger as Tall:Taller

Yen:Japan as Ruble:Russia

NLP and Word Embeddings

deeplearning.ai

Embedding matrix

Embedding matrix

embedding matrix · OH vector
is very in efficient

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

(300, 10K) (10K,1) (300,1)

$\rightarrow E \cdot O_j = e_j$

= embedding for word j

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

→ Embedding

deeplearning.ai

NLP and Word Embeddings

Learning word embeddings

Neural language model

init embedding matrix with random values
learn the matrix while training neural network

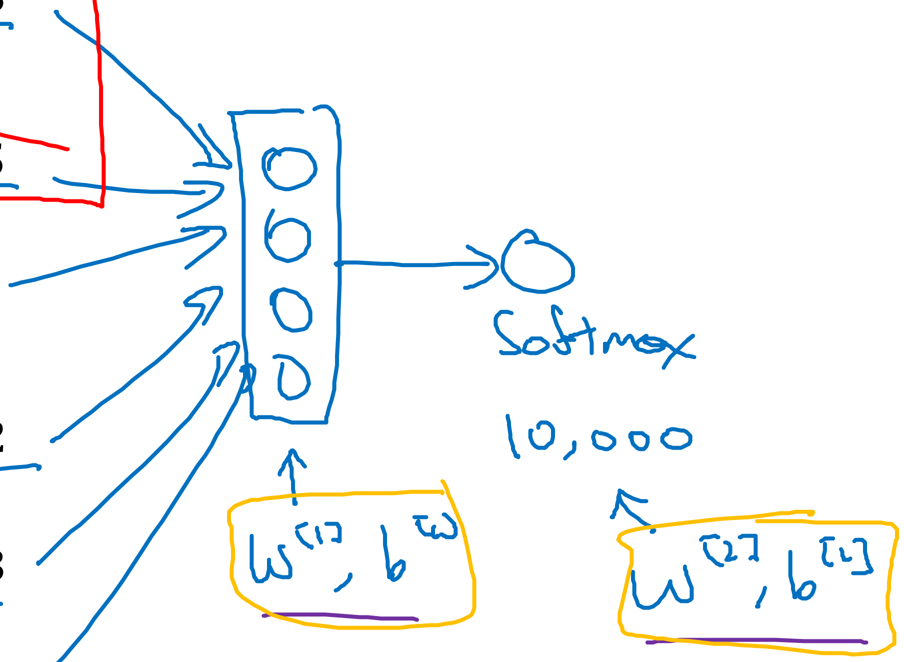
4

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

apple juice .

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

I	o_{4343}	$\longrightarrow$	E	$\longrightarrow$	e_{4343}
want	o_{9665}	$\longrightarrow$	E	$\longrightarrow$	e_{9665}
a	o_{1}	$\longrightarrow$	E	$\longrightarrow$	e_{1}
glass	o_{3852}	$\longrightarrow$	E	$\longrightarrow$	e_{3852}
of	o_{6163}	$\longrightarrow$	E	$\longrightarrow$	e_{6163}
orange	o_{6257}	$\longrightarrow$	E	$\longrightarrow$	e_{6257}



~~1800~~ 1200

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

Andrew Ng

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 along with

Last 1 word

orange ?

Nearby 1 word

glass ?

skip gram

NLP and Word Embeddings

deeplearning.ai

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

context target pairs

1) randomly pick context words (treat common & rare words evenly)
2) randomly pick target word for the context word (the closer to context word, the more chance to get picked as target)
3) train NN to predict target given context and learn embedding matrix during training

Vocab size = 10,000k

$x \longrightarrow y$

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

$$o_c \longrightarrow E \longrightarrow e_c \longrightarrow \underset{\text{softmax}}{O} \longrightarrow \hat{y}$$

$$e_c = E o_c$$

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

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

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

Andrew Ng

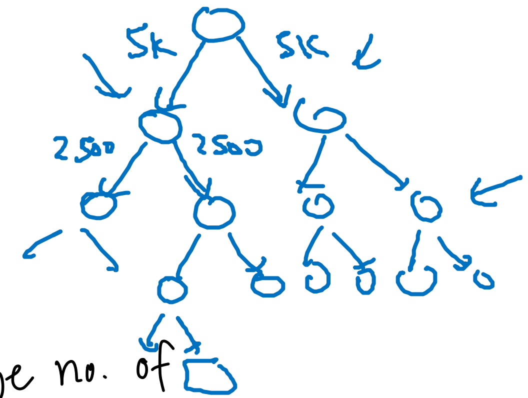
Problems with softmax classification

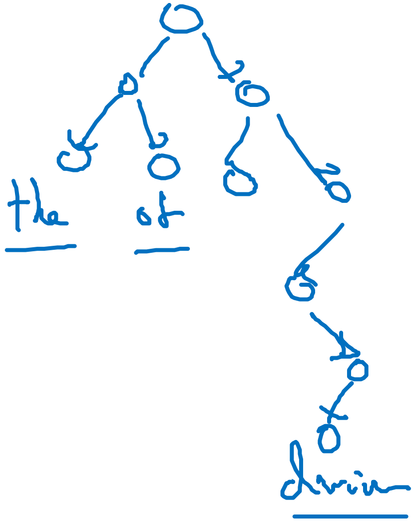
$$p(t|c) = \frac{e^{\theta_t^T e_c}}{\boxed{\sum_{j=1}^{10,000} e^{\theta_j^T e_c}}}$$

might need to sum over large no. of words (inefficient)

Hierarchical softmax.

$\log |V|$





How to sample the context c?

→ the, of, a, and, to, ...

→ orange, apple, durian

durian

t

$c \to t$

$P(c)$

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 → y

1) pick context target pair
2) add fake examples
3) train NN to tell correct context target pair and learn embedding matrix

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

k

no. of negative (fake) samples

k = 5-20 smaller datasets

k = 2-5 larger dataset

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

Andrew Ng

Model

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

10,000-way softmax

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

x y k

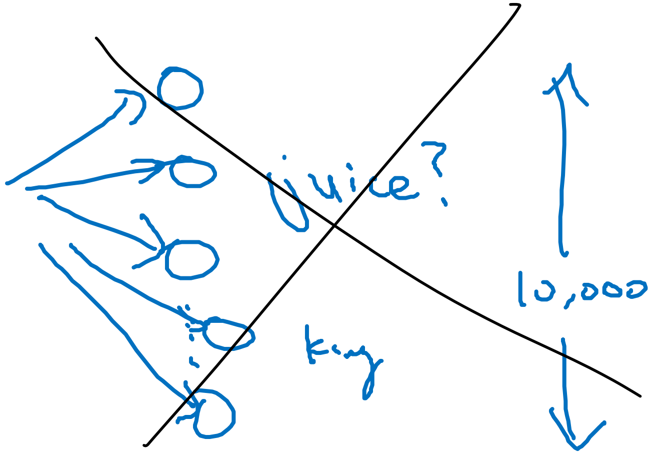
c t y

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

sigmoid

Orange 6257

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



10,000 binary classification problem

k+1

Andrew Ng

Selecting negative examples

$\overbrace{\text{context} \quad \text{word}}^{x}$		$\overbrace{\text{target?}}^{y}$
context	word	target?
orange	juice	1
orange	king	0
orange	book	0
orange	the	0
orange	of	0

t

the, of, and, ...

frequency of word i

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

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

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_{ij} = # times $\overset{j}{\cancel{i}}$ appears in context of $\overset{i}{\cancel{j}}$.

$c \quad t \qquad t \qquad c$

$X_{ij} = X_{ji}$ ← if consider both sides of target as context

in glove model, words are related if they appear together frequently

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

Andrew Ng

Model

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

$t \quad c$

"$\theta_t^T e_c$"

$\rightarrow 0$?

wrong (see next page)

$f(X_{ij}) = 0$ if $X_{ij} = 0$.

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

this, is, of, a, ...

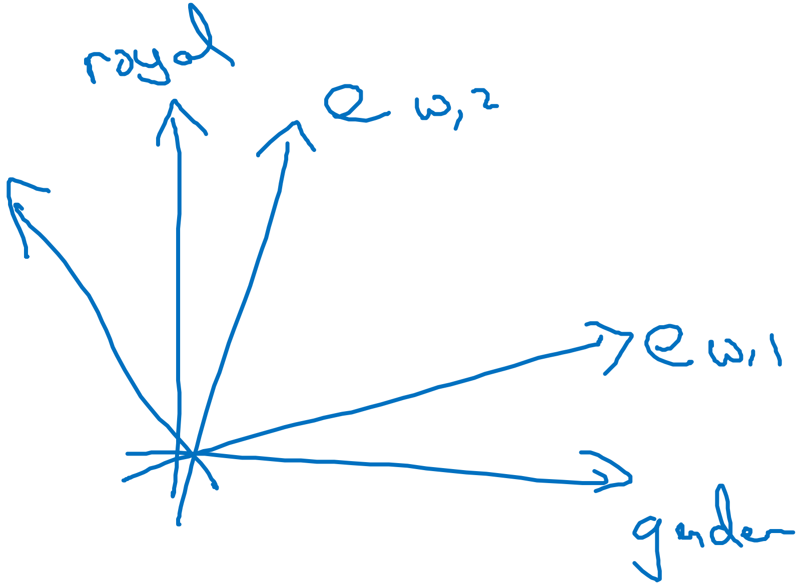
durian

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



objective function

no. of unique words in dictionary

correct formula

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

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

Andrew Ng

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

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

averge

$\boxed{\text{Avg}} \longrightarrow O \longrightarrow \hat{y}$

Softmax

1-5

3000

3000

100 B words

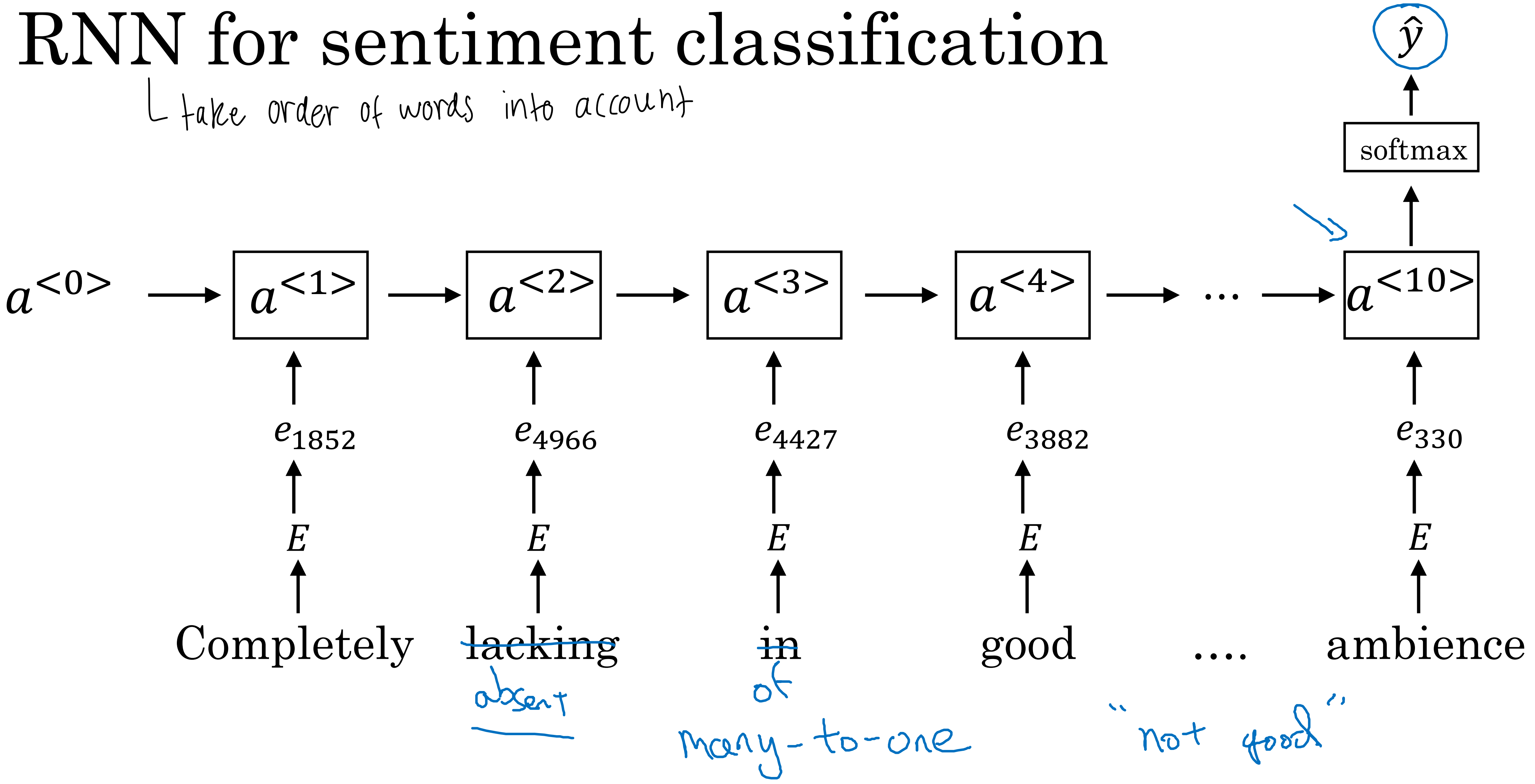
not consider order of word into account

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

Andrew Ng

RNN for sentiment classification

└ take order of words into account



deeplearning.ai

NLP and Word Embeddings

Debiasing word embeddings

The problem of bias in word embeddings

Man:Woman as King:Queen

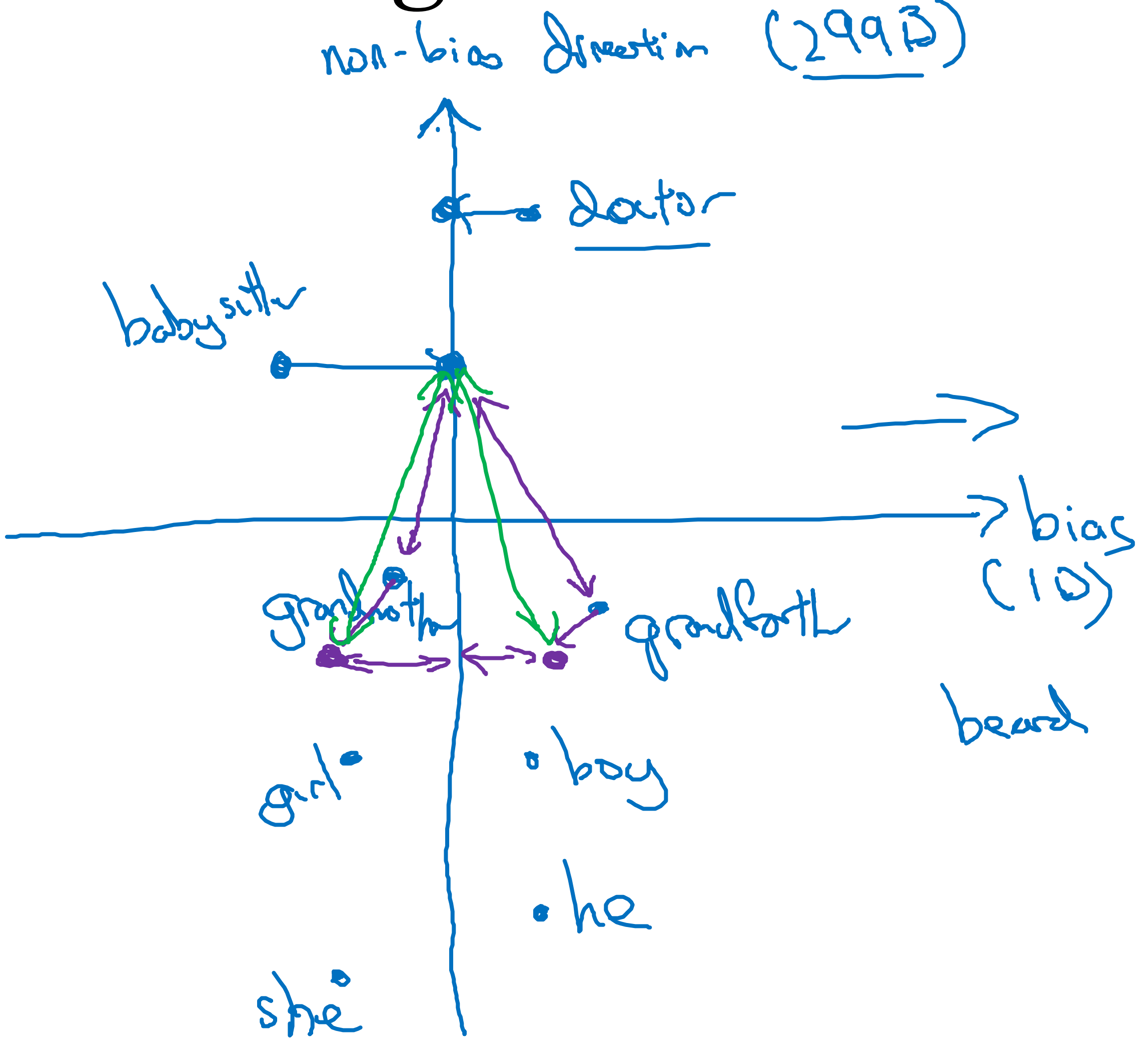
Man:Computer_Programmer as Woman:Homemaker

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.

$e_{he} - e_{she}$

$e_{male} - e_{female}$

$\vdots$

average

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

3. Equalize pairs.

grandmother – grandfather

girl – boy

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