Chapter 9: Word embedding

NLP and Word Embeddings

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Outline

- Introduction to Word Embeddings
    - Word representation
    - Using word embeddings
    - Properties of word embeddings
    - Embedding matrix
- Learning Word Embeddings: Word2vec & GloVe
    - Learning word embeddings
    - Word2Vec
    - Negative sampling
    - GloVe word vectors
- Applications using Word Embeddings
    - Sentiment classification
    - Debiasing word embeddings

NLP and Word Embeddings

Word representation

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Word representation

V = [a, aaron, ..., zulu, <UNK>]

|V| = 10,000

1-hot representation

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

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

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

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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	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
⋮	⋮	⋮				

300

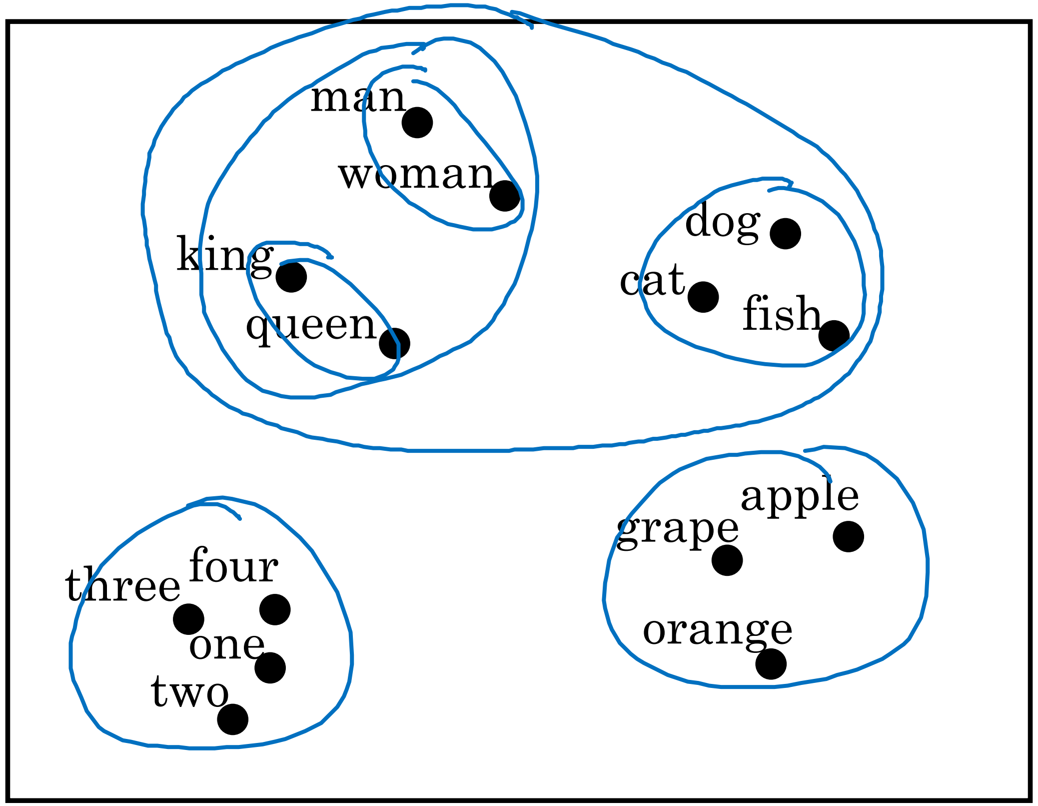
size
cost
alive
verb

e_{5391} e_{9853}

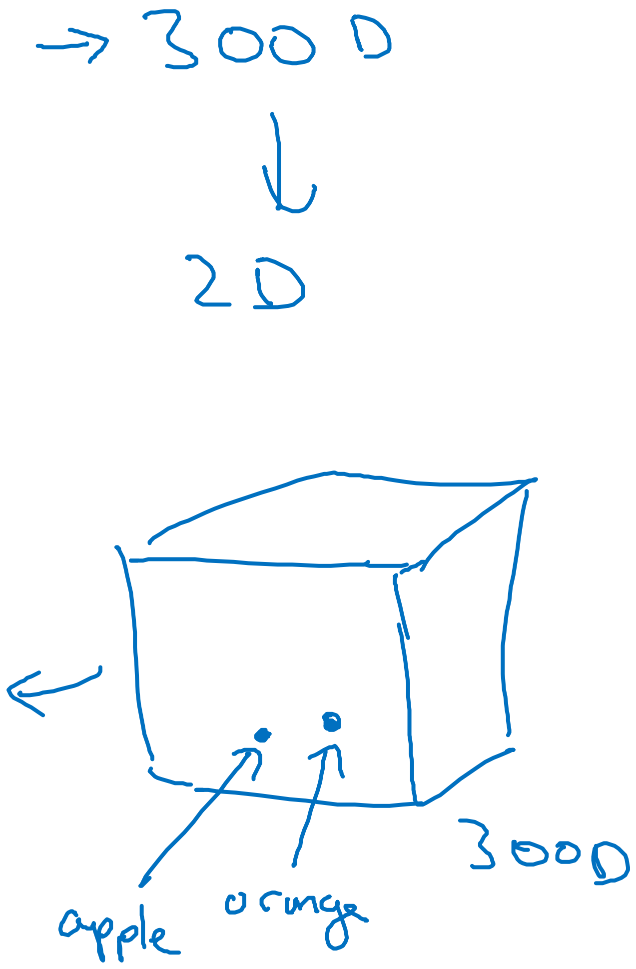
I want a glass of orange juice.

I want a glass of apple juice.

Visualizing word embeddings



t-SNE



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

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Using word embeddings

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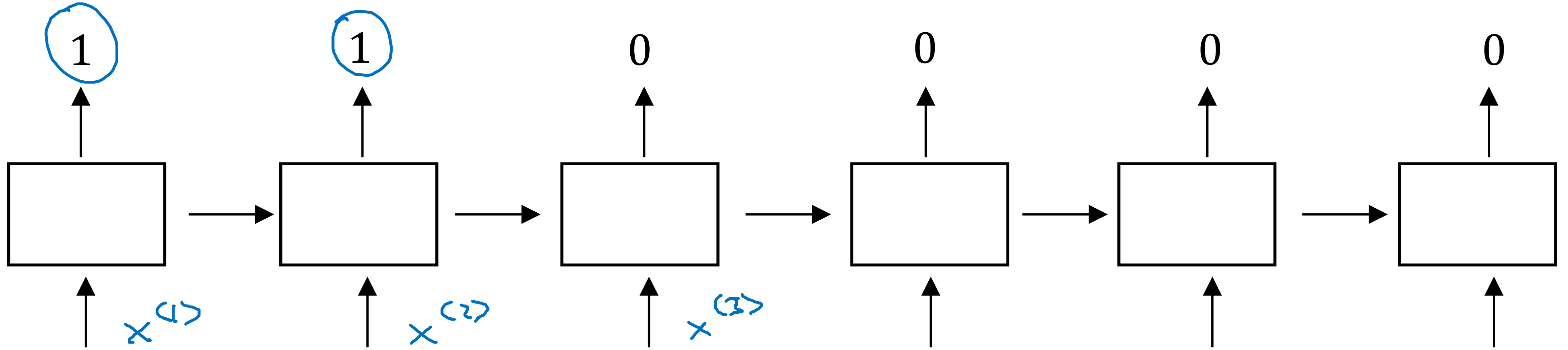
Named entity recognition example



Sally Johnson is an $\boxed{\text{orange}}$ $\boxed{\text{farmer}}$

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

→ 1B words – 100B words a $\boxed{\text{durian}}$ $\boxed{\text{cultivator.}}$

→ 100k words

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Transfer learning and word embeddings

A

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

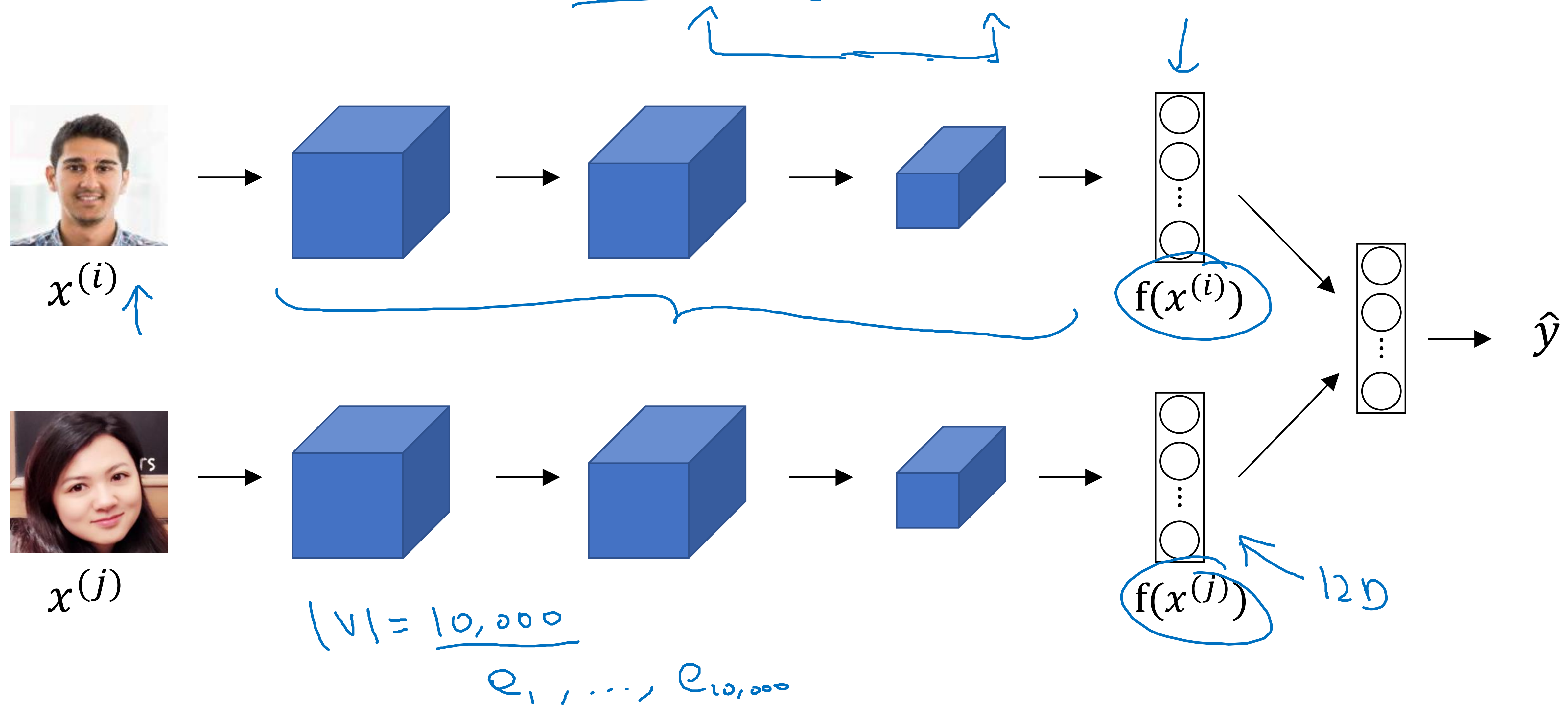
   (Or download pre-trained embedding online.)

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.

Relation to face encoding (embedding)



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

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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]

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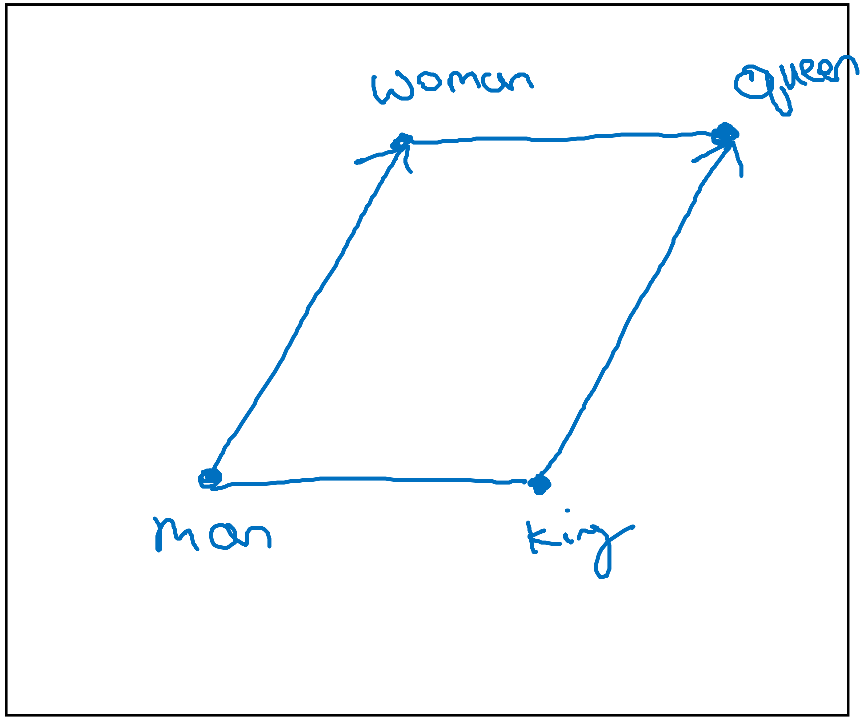
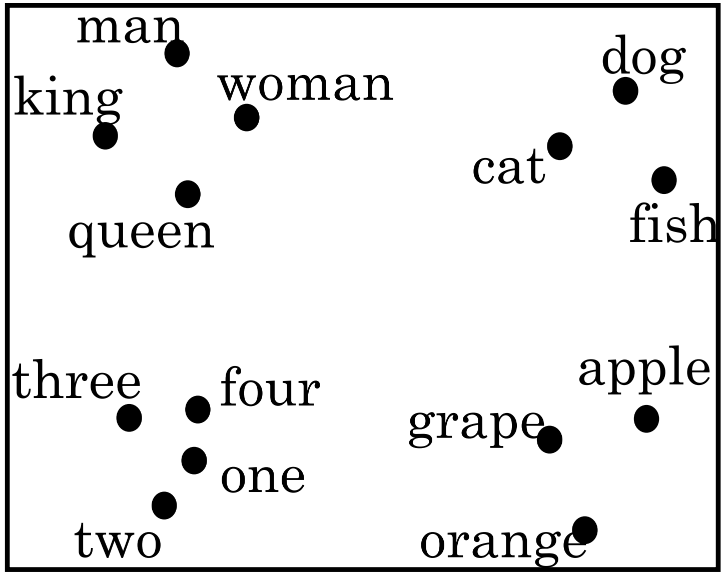
Analogies using word vectors



300 D

300D → 2D



t-SNE

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

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

30 - 75%

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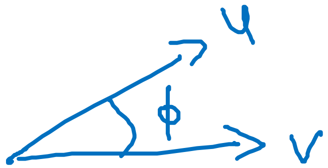
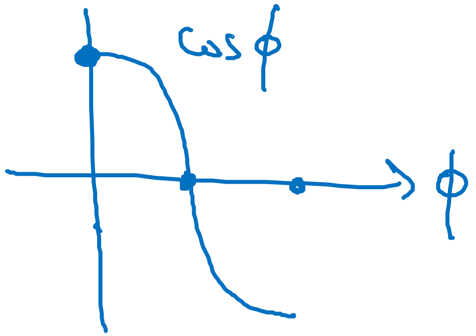
Cosine similarity

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

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





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

Man:Woman as Boy:Girl

Ottawa:Canada as Nairobi:Kenya

Big:Bigger as Tall:Taller

Yen:Japan as Ruble:Russia

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Embedding matrix

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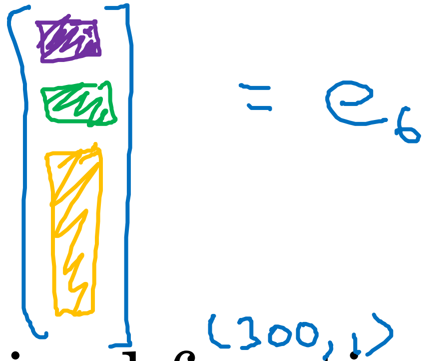
Embedding matrix

$$\underbrace{E \cdot O_{6257}}_{(300,\ 10K)\quad (10K,1)} =$$



$$= e_{6257}$$

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

= embedding for word j

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

→ Embedding

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NLP and Word Embeddings

Learning word embeddings

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~~	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}

Softmax

10,000

$W^{[1]}, b^{[1]}$

$W^{[2]}, b^{[2]}$

~~1800~~ 1200

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

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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

Last 1 word

Nearby 1 word

skip gram

a glass of orange ___?___ to go along with

orange ___?___

glass ___?___

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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.]

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Model

Vocab size = 10,000k

$x \longrightarrow y$

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

$O_c \rightarrow E \rightarrow e_c \longrightarrow O \longrightarrow \hat{y}$

softmax

$e_c = E O_c$

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

θ_t = parameter associated with output t

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

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

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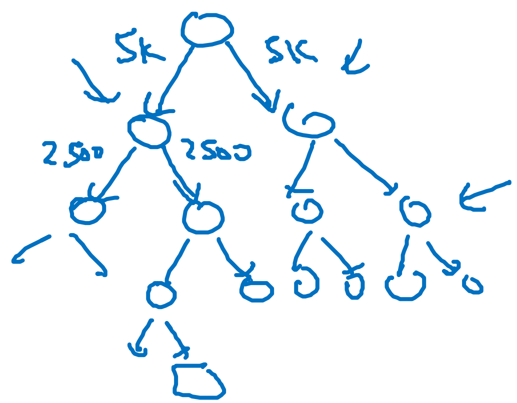
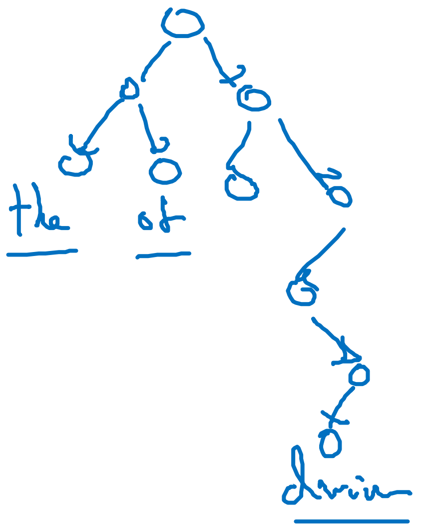
Problems with softmax classification

Hierarchical softmax.

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

$\log |V|$





How to sample the context c?

→ the, of, a, and, to, ...

→ orange, apple, durian

durian

t

$c \to t$

$P(c)$

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

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

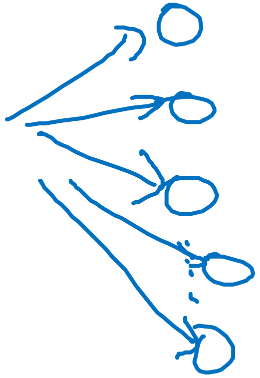
x: context, word; y: target?

k

$c \quad t \quad y$

Orange 6257

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



juice?

king

10,000

10,000 binary classification problem

$k+1$

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

$\uparrow$ k

the , of, and, ...

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

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

$\uparrow$

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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.

c t   t   c

$X_{ij} = X_{ji}$

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

Model

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

$$\theta_i \to t, \quad e_j \to c, \quad b_i \to t, \quad b_j' \to c, \quad \log X_{ij} \to 0?$$

$$\text{"}\theta_t^T e_c\text{"}$$

weighting term

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

this, is, of, a, ...

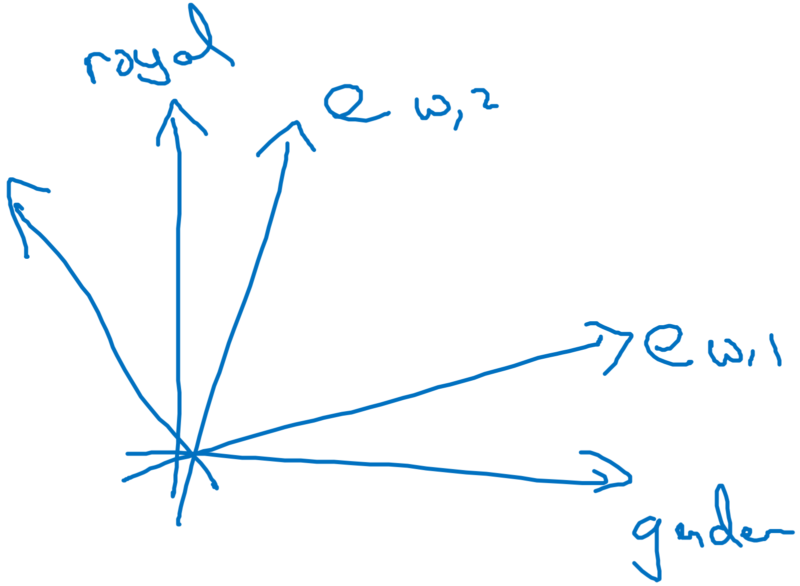
durian

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



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

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

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NLP and Word Embeddings

Sentiment classification

Sentiment classification problem

$\underline{x} \longrightarrow y$

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.	★☆☆☆☆

$\underline{10{,}000} \rightarrow 100{,}000$ 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 $o_{3180} \longrightarrow E \longrightarrow e_{3180}$

Avg → O → $\hat{y}$

300D

softmax

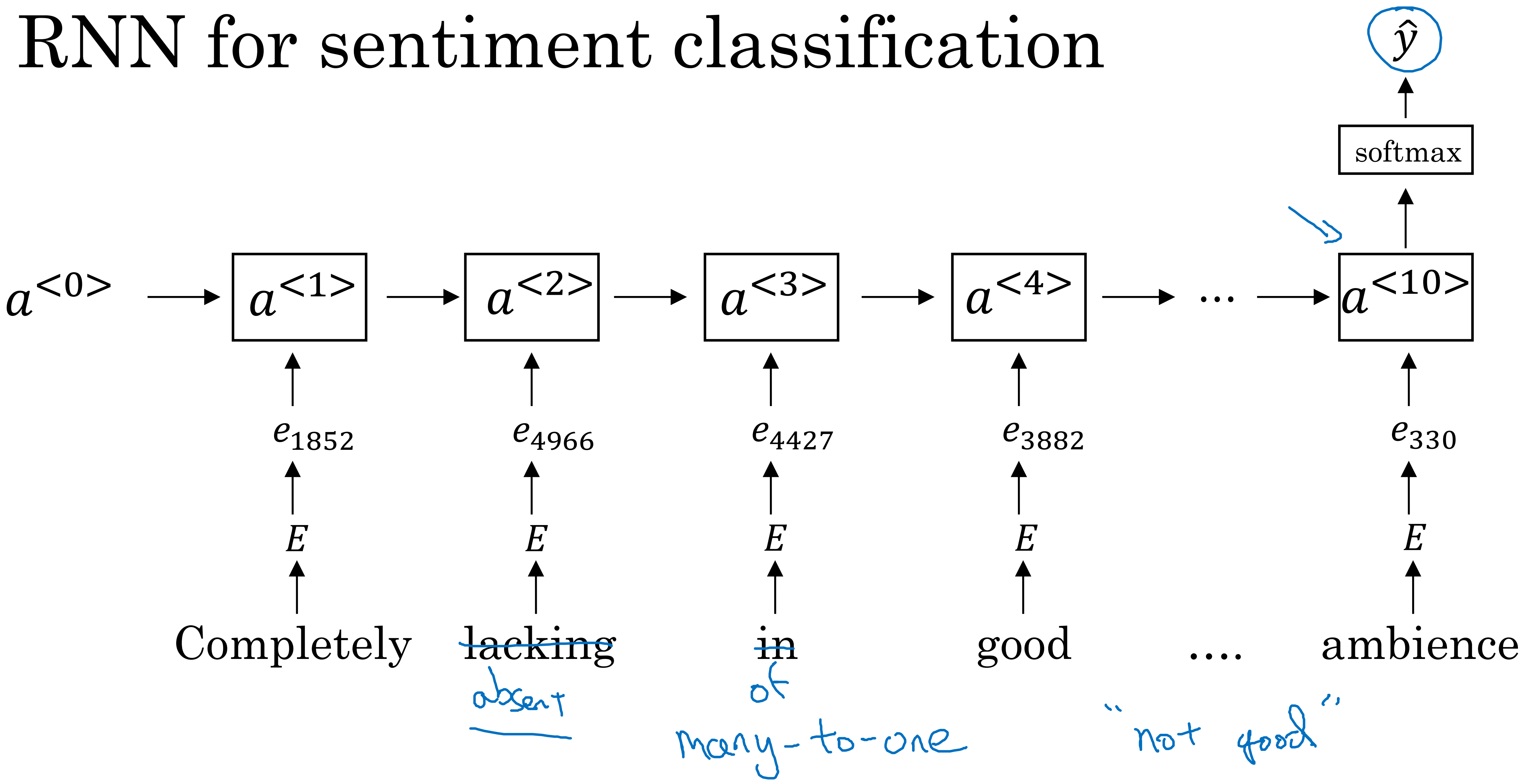
1-5

$\underbrace{e_{3180}}_{300D}$

100B words

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

RNN for sentiment classification



NLP and Word Embeddings

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Debiasing word embeddings

The problem of bias in word embeddings

Man:Woman as King:Queen

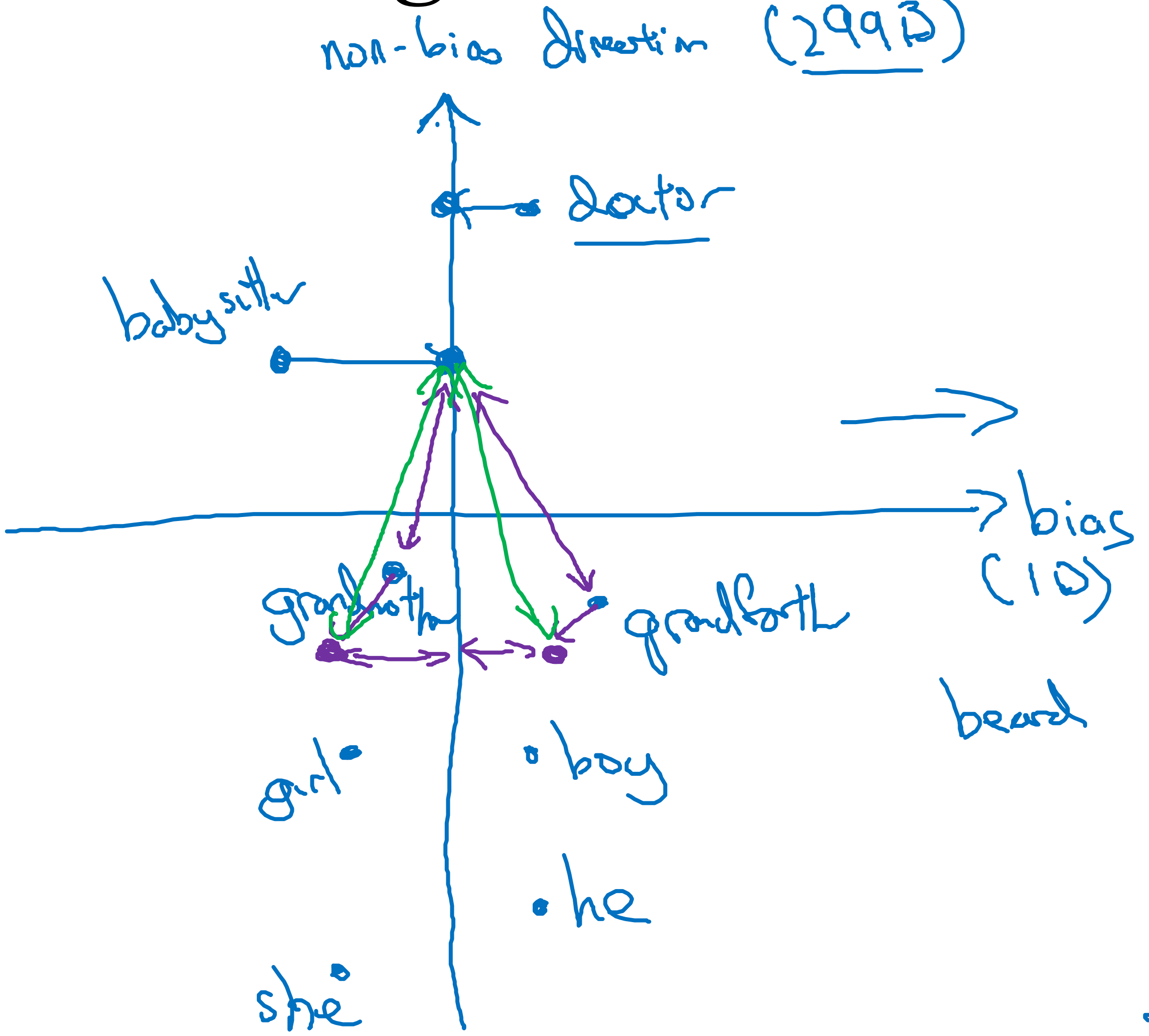
Man:Computer_Programmer as Woman: Homemaker

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.

$$\left.\begin{array}{l} e_{he} - e_{she} \\ e_{male} - e_{female} \\ \vdots \end{array}\right\} \to \text{average}$$

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]

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