NLP and Word Embeddings

Word representation

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Word representation

V = [a, aaron, …, zulu, <UNK>]

1-hot representation

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

I want a glass of orange ______.

I want a glass of apple______.

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Featurized representation: word embedding

	Man (5391)	Woman (9853)	King (4914)	Queen (7157)	Apple (456)	Orange (6257)
			-0.95	0.97	0.00	0.01
			0.93	0.95	-0.01	0.00
			0.7	0.69	0.03	-0.02
			0.02	0.01	0.95	0.97

I want a glass of orange ______.

I want a glass of apple______.

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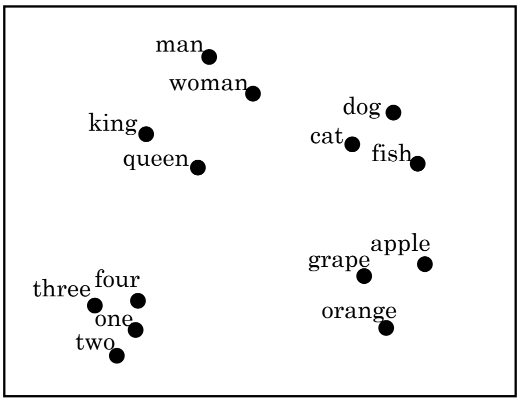
Visualizing word embeddings



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

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Using word embeddings

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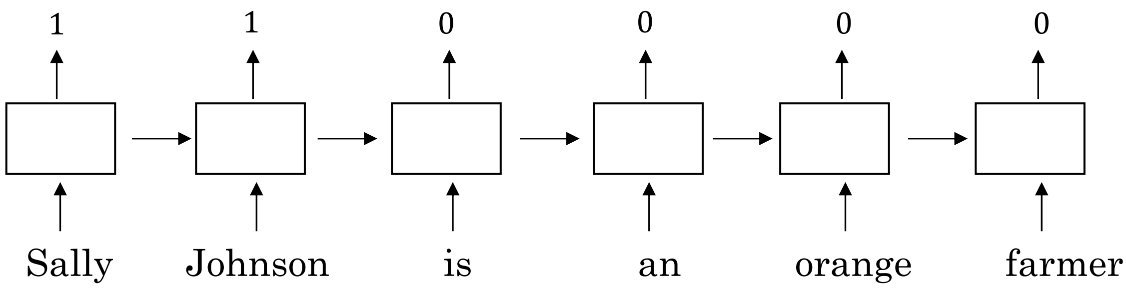
Named entity recognition example



Robert Lin is an apple farmer

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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)

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

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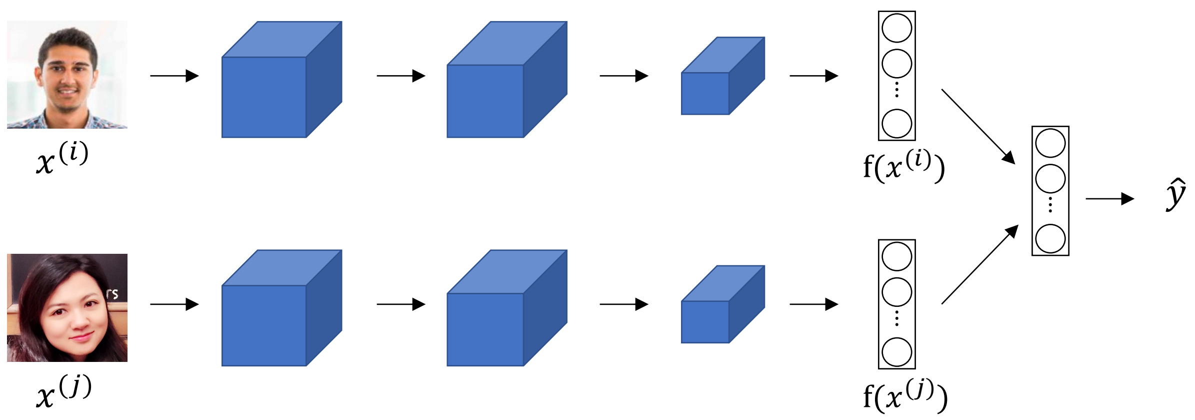
Relation to face encoding



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

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Properties of word embeddings

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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

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

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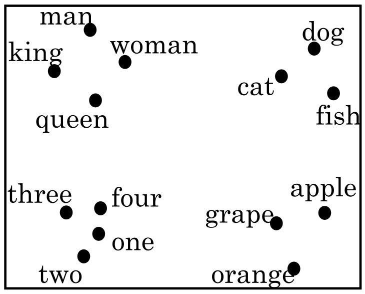
Analogies using word vectors



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

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Cosine similarity

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

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

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

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Learning word embeddings

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Neural language model

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

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

[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: Last 4 words.

4 words on left & right

Last 1 word

Nearby 1 word

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Word2Vec

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Skip-grams

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

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

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Model

Vocab size = 10,000k

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Problems with softmax classification

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

How to sample the context c?

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Negative sampling

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Defining a new learning problem

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

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

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Model

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

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

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Selecting negative examples

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

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GloVe word vectors

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GloVe (global vectors for word representation)

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

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

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Model

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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

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

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Sentiment classification

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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.	★☆☆☆☆

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Simple sentiment classification model

The	dessert	is	excellent	★★★★☆
8928	2468	4694	3180	

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

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

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

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

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

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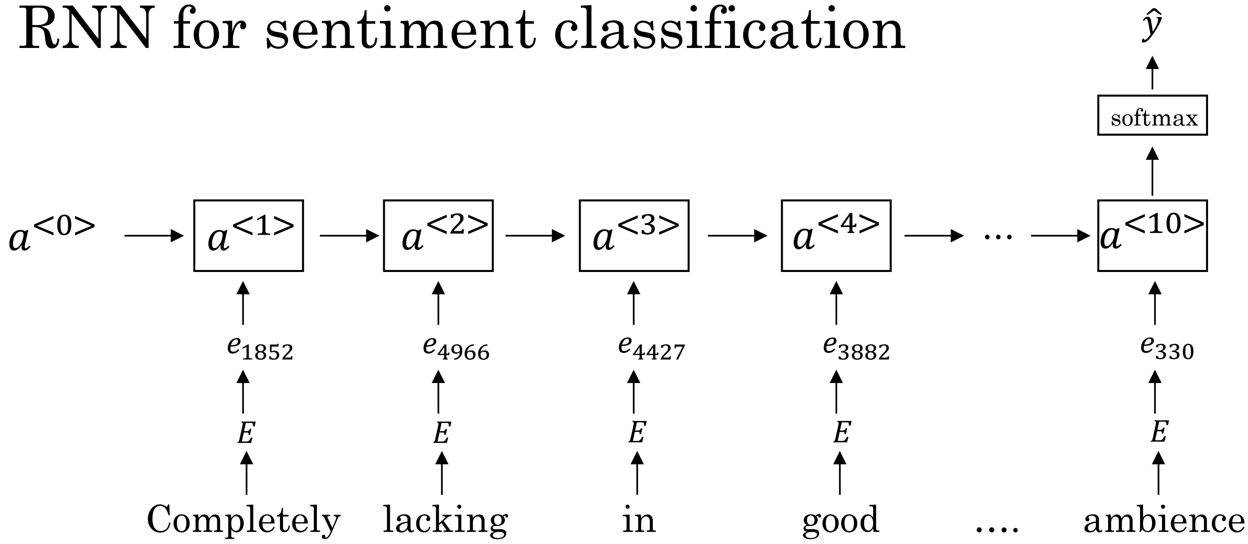
RNN for sentiment classification



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Debiasing word embeddings

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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] Andrew Ng

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Addressing bias in word embeddings

1. Identify bias direction.

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

3. Equalize pairs.

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

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