Week15
Friday, May 26, 2023 10:24AM

Word Embeddings :-

word representations :-

V = [a, aaron, ..., <unk>]

I want a glass of orange (juice) ?

.. " " " " apple (juice) ....

↳ difficult for algorithm to generalize.

	5391 Man	9853 Woman	7314 King	9257 Queen	6257 Apple	5375 Orange
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	0.02	-0.01
	↳ vector for man (e_{5391})					↳ (e_{5})

..... → one hot number

how most this come → taken in course.

* → Generalize better. juice is predictable. 300 dimension.

t-sne.

* Learn word embeddings from large text corpus and transfer to smaller training set.

↳ transfer learning.

$e_{man} - e_{woman} \approx \begin{bmatrix} -2 \\ 0 \\ 0 \end{bmatrix}$ Vectors are almost same.

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

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

300D space. {visualize t-sne}

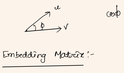
find w : $\arg\max_{w} \; sim(e_w, e_{king} + e_{woman} - e_{man})$

similarity

IMPORTANT :-

Cosine Similarity.

$Sim(u,v) = \frac{u^T v}{\|u\|_2 \|v\|} = \cos(\phi) = \frac{\text{dot}}{\text{magnitude}}$



Embedding Matrix :-

$E \cdot O_{7257} = e_{7257}$ (300, 10000) (300, 1)

↓ embedding vector of orange.

$O_{7257} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$ 10000 × 1

one hot.

$E \cdot O_j = e_j$

↳ embedding for word j

I want a glass of orange juice

context ↳ target

I want a glass of orange

e_{2293}, e_{8453}, e_{9731}, e_{6257}, e_{4271}, e_{5375}

↓

300 × 6 × 1 = 1800 × 1

softmax → {classifies among 10k words} → P(juice) will be highest → juice

10,000

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

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

{" total length of vocab.

Skip grams :-

vocab size = 1M

context c ("orange") → Target t ("juice")

7314 → 9373

P.S → whether it is in +/- 10 window.

$O_c \rightarrow E \rightarrow e_c \rightarrow \underset{\text{softmax}}{\longrightarrow} \hat{y}$ → we saw earlier

θ_t → parameter associated with output 't'

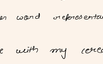
Softmax, $P(t|c) = \frac{e^{\theta_t^T e_c}}{\sum_{j'=1}^{10,000} e^{\theta_{j'}^T e_c}}$

$\mathcal{L}(\hat{y}, y) = -\sum_{j=1}^{10,000} y_j \log(\hat{y}_j)$ } common loss softmax.

Used to iscrimity +/- n^{th} word from orange (ex) .. Skipgram

* Problems :-

↳ computation speed. Sol^n → Hierarchical Softmax (not balanced)



GLOVE :- {Global Vectors for word representation}

I want a glass of orange with my breakfast :-

c t

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

↑ (t) ↑ (c)

$X_{ij} = X_{ji}$ → how related ??

Minimize

$$\sum_{i=1}^{10K} \sum_{j=1}^{10K} f(X_{ij}) \left(\theta_i^T e_j + b_i + b_j - \log X_{ij} \right)^2$$

↓ t ↓ c

weighting term → will make equation 0 if $X_{ij} = 0$

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

↳ STOP WORDS → can make $X_{ij} = 0$.

* θ_i, e_j are symmetric.

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

Sentiment classification :-

The → E → e_{2293}

Dessert → E → e_{8453}

is → E → e_{9731}

excellent → E → e_{6257}

↑ 100B words embedding

→ A-vg → O softmax → $\hat{y}$.

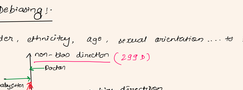
300D vectors

{1 star – 5 star}

"Completely lacking in good taste and good service"

↳ Problem for above model

RNN for sentiment classification :-

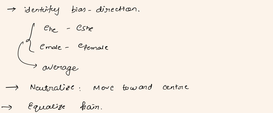


completely lacking in good ..... service

Many to one example.

Debiasing :-

gender, ethnicity, age, sexual orientation ... in train model.



→ identify bias-direction.

$e_{he} - e_{she}$

$e_{male} - e_{female}$

average

→ Neutralize : Move toward center.

→ Equalize pairs.