Natural Language Processing & Word Embeddings

LATEST SUBMISSION GRADE

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100%				
1. Question 1 Suppose you learn a word embedding for a vocabulary of 10000 words. Then the embedding vectors should be 10000 dimensional, so as to capture the full range of variation and meaning in those words.				
1 / 1 point				
True				
•				
False				
Correct				
The dimension of word vectors is usually smaller than the size of the vocabulary. Most common sizes for word vectors range between 50 and 400.				
2. Question 2 What is t-SNE?				
1 / 1 point				
An open-source sequence modeling library				
•				
A non-linear dimensionality reduction technique				
0				
A linear transformation that allows us to solve analogies on word vectors				
0				
A supervised learning algorithm for learning word embeddings				

Correct

Yes

3.

Question 3

Suppose you download a pre-trained word embedding which has been trained on a huge corpus of text. You then use this word embedding to train an RNN for a language task of recognizing if someone is happy from a short snippet of text, using a small training set.

x (input text)	y (happy?)
I'm feeling wonderful today!	1
I'm bummed my cat is ill.	0
Really enjoying this!	1

Then even if the word "ecstatic" does not appear in your small training set, your RNN might reasonably be expected to recognize "I'm ecstatic" as deserving a label y = 1y=1.

1	1	1	point
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(•)

True

 \mathbf{C}

False

Correct

Yes, word vectors empower your model with an incredible ability to generalize. The vector for "ecstatic" would contain a positive/happy connotation which will probably make your model classify the sentence as a "1".

4.

Question 4

Which of these equations do you think should hold for a good word embedding? (Check all that apply)

1 / 1 point

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 $e_{boy} - e_{boy} - e_{sister} - e_{sister} - e_{sister} - e_{sister}$

Correct

Yes! $\overline{\mathbf{v}}$ e_{boy} - e_{girl} \approx e_{brother} - e_{sister}eboy-egirl~ebrother-esister Correct Yes! $e_{boy} - e_{girl} \land e_{sister} - e_{brother} e_{boy} - e_{girl} \approx e_{sister} - e_{brother}$ e_{boy} - e_{brother} \approx e_{sister} - e_{girl}eboy-ebrother \approx esister-egirl 5. Question 5 Let EE be an embedding matrix, and let o_{1234} o_{1234} be a one-hot vector corresponding to word 1234. Then to get the embedding of word 1234, why don't we call $E * o_{1234}E*o_{1234}$ in Python? 1 / 1 point None of the above: calling the Python snippet as described above is fine. \bigcirc The correct formula is $E^T * o_{1234} E^T * o_{1234}$. **(•**) It is computationally wasteful. O This doesn't handle unknown words (<UNK>).

Correct

Yes, the element-wise multiplication will be extremely inefficient.

6.

Question 6

When learning word embeddings, we create an artificial task of estimating $P(\text{target} \mid \text{mid} \text{context})P(\text{target} \mid \text{context})$. It is okay if we do poorly on this artificial prediction task; the more important by-product of this task is that we learn a useful set of word embeddings.

1 / 1 point

O

False

 \odot

True

Correct

7.

Question 7

In the word2vec algorithm, you estimate $P(t \mid mid c)P(t \mid c)$, where tt is the target word and cc is a context word. How are tt and cc chosen from the training set? Pick the best answer.

1 / 1 point

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cc is the one word that comes immediately before tt.

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cc is a sequence of several words immediately before *tt*.

 \circ

cc is the sequence of all the words in the sentence before tt.

(**•**)

cc and tt are chosen to be nearby words.

Correct

8.

Question 8

Suppose you have a 10000 word vocabulary, and are learning 500-dimensional word embeddings. The word2vec model uses the following softmax function:

$$P(t \mid c) = \frac{e^{\left(t \mid c\right)}}{\left(t \mid c\right)} \left(t'=1\right)^{10000}$$

$$e^{\left(t \mid c\right)} P(t \mid c) = \sum_{t'=1100000e\theta t' Tece\theta tTec}$$

Which of these statements are correct? Check all that apply.

1 / 1 point

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\theta_t θt and e_cec are both trained with an optimization algorithm such as Adam or gradient descent.



After training, we should expect \theta_t θt to be very close to e_cec when tt and cc are the same word.

✓

\theta_t θt and e_cec are both 500 dimensional vectors.

Correct

\theta_ $t\theta t$ and e_cec are both 10000 dimensional vectors.

9.

Question 9

Suppose you have a 10000 word vocabulary, and are learning 500-dimensional word embeddings. The GloVe model minimizes this objective:

 $\begin{array}{l} \min \sum_{i=1}^{10,000} \sum_{j=1}^{10,000} f(X_{ij}) (\theta_{i} - \log X_{ij})^2 \\ \end{array} \\ \times \left(\begin{array}{l} (ij) \\ (i$

Which of these statements are correct? Check all that apply.

1 / 1 point

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 $X_{\{ij\}}X_{ij}$ is the number of times word j appears in the context of word i.

Correct

\theta_i θ i and e_jej should be initialized to 0 at the beginning of training.

✓

The weighting function f(.)f(.) must satisfy f(0) = 0f(0) = 0.

Correct

The weighting function helps prevent learning only from extremely common word pairs. It is not necessary that it satisfies this function.

✓

\theta_i θ i and e_jej should be initialized randomly at the beginning of training.

Correct

10.

Question 10

You have trained word embeddings using a text dataset of m_1m_1 words. You are considering using these word embeddings for a language task, for which you have a separate labeled dataset of m_2m_2 words. Keeping in mind that using word embeddings is a form of transfer learning, under which of these circumstances would you expect the word embeddings to be helpful?

1 / 1 point

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 $m_1m_1 >> m_2m_2$

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m_1*m*1 << m_2*m*2

Correct