

✔ Congratulations! You passed!

Grade  
received 90%

Latest Submission  
Grade 90%

To pass 80% or  
higher

Go to next item

1. Suppose you learn a word embedding for a vocabulary of 10000 words. Then the embedding vectors could be 10000 dimensional, so as to capture the full range of variation and meaning in those words.

0 / 1 point

- ☐ False
- ☒ True

Expand

✘ Incorrect

No, the dimension of word vectors is usually smaller than the size of the vocabulary. Most common sizes for word vectors range between 50 and 1000.

2. True/False: t-SNE is a linear transformation that allows us to solve analogies on word vectors.

1 / 1 point

- ☒ False
- ☐ True

Expand

✔ Correct

tr-SNE is a non-linear dimensionality reduction technique.

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.

1 / 1 point

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

True/False: Then even if the word “upset” does not appear in your small training set, your RNN might reasonably be expected to recognize “I’m upset” as deserving a label  $y = 0$ .

- ☒ True
- ☐ False

Expand

✔ Correct

Yes, word vectors empower your model with an incredible ability to generalize. The vector for “upset” would contain a negative/unhappy connotation which will probably make your model classify the sentence as a “0”.

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

1 / 1 point

☐  $e_{boy} - e_{girl} \approx e_{sister} - e_{brother}$

☒  $e_{boy} - e_{brother} \approx e_{girl} - e_{sister}$

✔ Correct  
Yes!

☒  $e_{boy} - e_{girl} \approx e_{brother} - e_{sister}$

✔ Correct  
Yes!

Typesetting math: 100%  $e_{sister} - e_{girl}$

Expand

✔ Correct  
Great, you got all the right answers.

5. Let  $E$  be an embedding matrix, and let  $o_{1234}$  be a one-hot vector corresponding to word 1234. Then to get the embedding of word 1234, why don't we call  $E * o_{1234}$  in Python?

1 / 1 point

- ☐ This doesn't handle unknown words (<UNK>).
- ☐ None of the above: calling the Python snippet as described above is fine.
- ☒ It is computationally wasteful.
- ☐ The correct formula is  $E^T * o_{1234}$

✔ Expand

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

6. When learning word embeddings, we create an artificial task of estimating  $P(\text{target} \mid \text{context})$ . 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

- ☐ False
- ☒ True

✔ Expand

✔ Correct

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

1 / 1 point

- ☐  $c$  is the sequence of all the words in the sentence before  $t$
- ☐  $c$  is a sequence of several words immediately before  $t$
- ☒  $c$  and  $t$  are chosen to be nearby words.

Processing math: 100% word that comes immediately before  $t$

✔ Expand

✔ Correct

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

1 / 1 point

$$P(t \mid c) = \frac{e^{\theta_t^T e_c}}{\sum_{t'=1}^{10000} e^{\theta_{t'}^T e_c}}$$

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

- ☐ After training, we should expect  $\theta_t$  to be very close to  $e_c$  when  $t$  and  $c$  are the same word.
- ☒  $\theta_t$
- and
- $e_c$
- are both 500 dimensional vectors.

✔ Correct

- ☒  $\theta_t$  and  $e_c$  are both trained with an optimization algorithm such as Adam or gradient descent.

✔ Expand

✔ Correct  
Great, you got all the right answers.

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

1 / 1 point

$$\min \sum_{i=1}^{10,000} \sum_{j=1}^{10,000} f(X_{ij})(\theta_i^T e_j + b_i + b_j - \log X_{ij})^2$$

True/False:  $X_{ij}$  is the number of times word  $j$  appears in the context of word  $i$ .

- ☐ False
- ☒ True

 Expand

 Correct

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

10. You have trained word embeddings using a text dataset of  $m_1$  words. You are considering using these word embeddings for a language task, for which you have a separate labeled dataset of  $m_2$  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

- ☐  $m_1 < m_2$
- ☒  $m_1 \gg m_2$

Processing math: 100%

 Expand

 Correct