

## ✔ Congratulations! You passed!

Grade received 90%

Latest Submission Grade 90%

To pass 80% or higher

**Go to next item**

1. True/False: Suppose you learn a word embedding for a vocabulary of 20000 words. **1 / 1 point**  
Then the embedding vectors could be 1000 dimensional, so as to capture the full range of variation and meaning in those words.



↗ **Expand**

✔ **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 1000.

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

**1 / 1 point** **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?) |
|-----------------------|------------|
| Having a great time!  | 1          |
| I'm sad it's raining. | 0          |
| I'm feeling awesome!  | 1          |

Even if the word “wonderful” does not appear in your small training set, what label might be reasonably expected for the input text “I feel wonderful!”?

 **Expand** **Correct**

Yes, word vectors empower your model with an incredible ability to generalize. The vector for “wonderful” would contain a negative/unhappy connotation which will probably make your model classify the sentence as a “1”.

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

**1 / 1 point** **Expand** **Correct**

Great, you got all the right answers.

5. True/False: The most computationally efficient formula for Python to get the embedding of word 1021, if  $C$  is an embedding matrix, and  $o_{1021}$  is a one-hot vector corresponding to word 1021, is  $C^T * o_{1021}$ .

**0 / 1 point**

 **Expand** **Incorrect**

No, it is computationally wasteful because the element-wise multiplication will be extremely inefficient.

6. When learning word embeddings, we pick a given word and try to predict its surrounding words or vice versa.

**1 / 1 point** **Expand** **Correct**

Word embeddings are learned by picking a given word and trying to predict its surrounding words or vice versa.

7. True/False: In the word2vec algorithm, you estimate  $P(t \mid c)$ , where  $t$  is the target word and  $c$  is a context word.  $t$  and  $c$  are chosen from the training set using  $c$  as the sequence of all the words in the sentence before  $t$ .

**1 / 1 point** **Expand** **Correct**

and are chosen from the training set to be nearby words.

8. Suppose you have a 10000 word vocabulary, and are learning 100-dimensional word embeddings. The word2vec model uses the following softmax function:

**1 / 1 point**

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

True/False: After training, we should expect  $\theta_t$  to be very close to  $e_c$  when  $t$  and  $c$  are the same word.

 **Expand** **Correct**

To review this concept watch the lecture.

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

**1 / 1 point**

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

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

 **Expand**

 **Correct**

Great, you got all the right answers.



**10.** You have trained word embeddings using a text dataset of  $t_1$  words. You are considering using these word embeddings for a language task, for which you have a separate labeled dataset of  $t_2$  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** **Expand** **Correct**

Transfer embeddings to new tasks with smaller training sets.