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. What is t-SNE? **1 / 1 point**

- ○ An open-source sequence modeling library
- ○ A linear transformation that allows us to solve analogies on word vectors
- ○ A supervised learning algorithm for learning word embeddings
- ◉ A non-linear dimensionality reduction technique

✓ **Correct**
Yes

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 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 $y = 1$.

- ○ False
- ◉ True

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. Which of these equations do you think should hold for a good word embedding? (Check all that apply) **1 / 1 point**

- [x] $e_{boy} - e_{girl} \approx e_{brother} - e_{sister}$

Correct

Yes!

- [ ] $e_{boy} - e_{brother} \approx e_{sister} - e_{girl}$
- [x] $e_{boy} - e_{brother} \approx e_{girl} - e_{sister}$

Correct

Yes!

- [ ] $e_{boy} - e_{girl} \approx e_{sister} - e_{brother}$

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**

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

Correct

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

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

✓ **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 a sequence of several words immediately before t.
- ○ c is the one word that comes immediately before t.
- ○ c is the sequence of all the words in the sentence before t.
- ◉ c and t are chosen to be nearby words.

✓ **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.

- ☑ θ_t and e_c are both 500 dimensional vectors.

✓ **Correct**

- ☐ θ_t and e_c are both 10000 dimensional vectors.
- ☑ θ_t and e_c are both trained with an optimization algorithm such as Adam or gradient descent.

Correct

- [ ] After training, we should expect θ_t to be very close to e_c when t and c are the same word.

9. Suppose you have a 10000 word vocabulary, and are learning 500-dimensional word embeddings.The GloVe model minimizes this objective: **1 / 1 point**

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

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

- [x] θ_i and e_j should be initialized randomly at the beginning of training.

Correct

- [x] X_{ij} is the number of times word j appears in the context of word i.

Correct

- [x] The weighting function $f(.)$ must satisfy $f(0) = 0$.

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

- [ ] θ_i and e_j should be initialized to 0 at the beginning of training.

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**

- (•) $m_1 >> m_2$
- ( ) $m_1 << m_2$

✓ **Correct**