

lord Embeddings

Lecture Notes (Optional)

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• Quiz

테스트: Natural Language Processing & Word Embeddings 10개의 질문

Programming Assignments

테스트테스트 • 30 min30 minutes

Natural Language Processing & Word Embeddings



교제 제출 기한년 8월 30일 오후 3:59 KST년 8월 30일 오후 3:59 KST 시도하기8 hours당 3회

계속하기



성적 받기 통과 점수:80% 이상 성적 100%

피드백 보기

최고 점수가 유지됩니다.





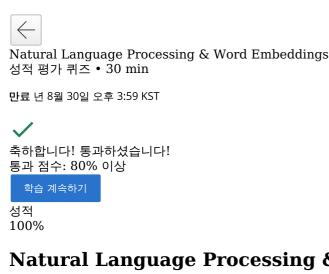


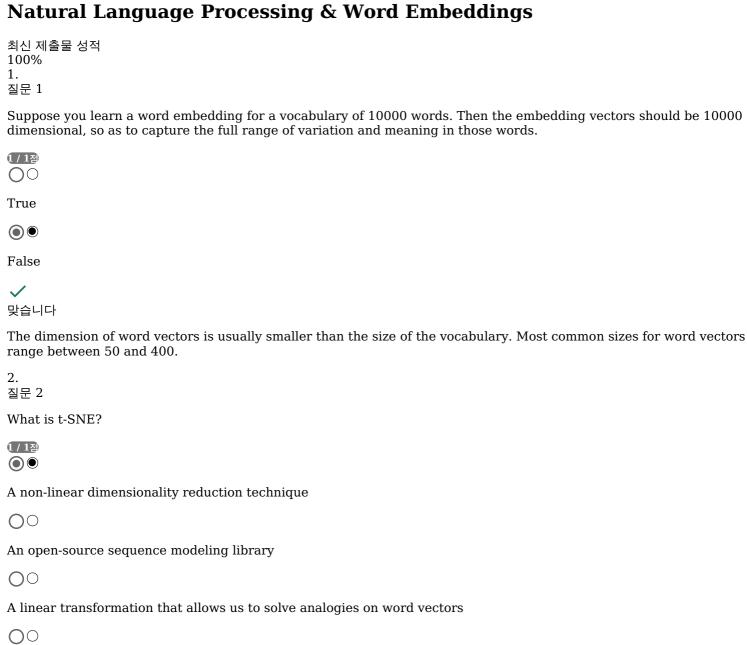
탐색 확인

이 페이지에서 나가시겠습니까?

이 페이지에 머물기

이 페이지에서 나가기





A supervised learning algorithm for learning word embeddings

맞습니다

Yes

3. 질문 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 "ecstarecognize "I'm ecstatic" as o	atic" does not appear in your small training set, your RNN might reasonably be expected to deserving a label $y=1$ y = 1.	
1/1점 ○ ●		
True		
00		
False		
✓ 맞습니다		
	your model with an incredible ability to generalize. The vector for "ecstatic" would contain n which will probably make your model classify the sentence as a "1".	
4. 질문 4		
Which of these equations do	you think should hold for a good word embedding? (Check all that apply)	
1 / 1점		
$e_{boy} - e_{girl} \approx e_{sister} - e_{brother} \mathbf{e}$	boy – egirl ≈ esister – ebrother	
\checkmark		
$e_{boy} - e_{brother} \approx e_{girl} - e_{sister} \mathbf{e}$	boy – ebrother ≈ egirl – esister	
✓ 맞습니다		
Yes!		
$e_{boy} - e_{brother} \approx e_{sister} - e_{girl} \mathbf{e}$	boy – ebrother ≈ esister – egirl	
\checkmark \boxtimes		
$e_{boy} - e_{girl} \approx e_{brother} - e_{sister} \mathbf{e}$	boy – egirl ≈ ebrother – esister	
✓ 맞습니다		
Yes!		
5. 질문 5		
	atrix, and let o_{1234} o1234 be a one-hot vector corresponding to word 1234. Then to get the rhy don't we call $E*o_{1234}$ E * o1234 in Python?	

The correct formula is $E^T * o_{1234} \mathrm{ET} * \mathrm{o} 1234.$

1/1절 ○○

This doesn't handle unknown words (<unk>).</unk>
00
None of the above: calling the Python snippet as described above is fine.
It is computationally wasteful.
✓ 맞습니다
Yes, the element-wise multiplication will be extremely inefficient.
6. 질문 6
When learning word embeddings, we create an artificial task of estimating $P(target \mid context)$ P(target 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.
[/1점 ○○
False
True
✓ 맞습니다 7. 질문 7
In the word2vec algorithm, you estimate $P(t \mid c)P(t \mid c)$, where tt is the target word and cc is a context word. How are t and cc chosen from the training set? Pick the best answer.
1/1 점 ○○
$c\mathbf{c}$ is the one word that comes immediately before $t\mathbf{t}$.
\circ
$c\mathbf{c}$ is the sequence of all the words in the sentence before $t\mathbf{t}$.
\circ
$c\mathbf{c}$ is a sequence of several words immediately before $t\mathbf{t}$.
cc and tt are chosen to be nearby words.
✓ 맞습니다 8. 질문 8
Suppose you have a 10000 word vocabulary, and are learning 500-dimensional word embeddings. The word2vec model uses the following softmax function:
$P(t \mid c) = \frac{e^{\theta_t^T e_c}}{\sum_{t'=1}^{10000} e^{\theta_t^T e_c}} P(\mathbf{t} \mid \mathbf{c}) = \sum_{t'=1}^{10000} P(\mathbf{t} \mid \mathbf{c}) = \sum_{t'=1}^{100000} P(\mathbf{t} \mid \mathbf{c}) = \sum_{t'=1}^{100000000000000000000000000000000000$
Which of these statements are correct? Check all that apply.

After training, we should expect $\theta_t\theta t$ to be very close to $e_c ec$ when tt and cc are the same word.

✓	\boxtimes

 $\theta_t \theta t$ and $e_c ec$ are both 500 dimensional vectors.



 $\theta_t \theta t$ and $e_c ec$ are both 10000 dimensional vectors.



 $\theta_t \theta t$ and $e_c ec$ are both trained with an optimization algorithm such as Adam or gradient descent.



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

$$\min \sum\nolimits_{i\,=\,1}^{10,000} \sum\nolimits_{j\,=\,1}^{10,000} f(X_{ij}) (\theta_i^{\,T} e_j + b_i + b_j^{\,\prime} - log X_{ij})^2 \\ \min \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 2 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 2 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 2 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 2 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 3 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 3 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 3 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 3 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \sum j = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) \\ 4 \sum i = 110,000 \ f(Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij) (\theta i T \ ej \ + \ bi \ + \ bj^{\,\prime} - log Xij)$$

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



 $\theta_i \theta_i$ and $e_i e_j$ should be initialized to 0 at the beginning of training.



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



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



 X_{ii} Xij is the number of times word j appears in the context of word i.



 $\theta_i \theta_i$ and $e_i e_j$ should be initialized randomly at the beginning of training.



You have trained word embeddings using a text dataset of m_1 m1 words. You are considering using these word embeddings for a language task, for which you have a separate labeled dataset of m_2 m2 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?



 m_1 m1 << m_2 m2



 m_1 m1 >> m_2 m2

