Word and sentence embeddings [Solution by Karthikeyan.S]

LATEST SUBMISSION GRADE

100%

1.Question 1

Compute a second-order co-occurrence between the words 'These' and 'So' (the cosine similarity between their first-order co-occurrence vectors). Use the toy corpus:

These are the wrong sort of bees. Quite the wrong sort. So I should think they would make the wrong sort of honey.

- Let's define a context of a word as three words to the left and three words to the right from the target word, **occurred within the same sentence** (if there are any).
- For the first-order co-occurrence, let's consider pPMI values (the formula was given on slide 5 of the first video).

<u>Hint:</u> in this question you actually do not need to *compute* anything... And the answer would be the same for any type of first-order co-occurrence.

0
0
1
0
$\frac{3}{2}$
0
2
0
\frac{1}{2}21

Correct

2.Question 2

Choose correct statements about Singular Value Decomposition (SVD), an important notion from the linear algebra. Feel free to consult any additional resource like <u>wiki</u> if needed.

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Squares of singular values of a matrix X are eigenvalues of $X^T XXTX$ (or $X X^TXXT$).

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Singular values decomposition is not unique (for example, the zero matrix can be decomposed in infinitely many ways).

Truncated SVD is the best rank \$k\$ approximation of the original matrix in terms of Frobenius norm.

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Any rectangular matrix with real entries has a singular value decomposition.

Singular values can be negative.

Singular values of a rectangular matrix are its eigenvalues.

Correct

3. Question 3

Find the objective function of the skip-gram negative sampling (SGNS) model.

•

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\label{limits_units_units_units_units_units_units_units_units_units_units_{v \in C} \left( \frac{uv}     \right) \leq \sum_{v \in C} (nuv \log \sigma(\langle \phi u, \theta v \rangle) + k E v \log \sigma(\langle \phi u, \theta v \rangle) + k E v \log \sigma(\langle \phi u, \theta v \rangle) \right) \\
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C

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0

$$\sum_{u \in W} \sum_{v \in C} (n_{uv} \langle \phi_u, \theta_v \rangle - k \mathbf{E}_{v^{\scriptscriptstyle -}} \langle \phi_u, \theta_{v^{\scriptscriptstyle -}} \rangle)$$

0

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\label{limits_unit} $$\sum_{u \in W} \sum_{v \in C} f(n_{uv}) \left(\frac{uv}{uv}\right) + b_{uv} + b_{v'} - \log n_{uv} \right)^2 u \in W \sum_{v \in C} f(n_{uv}) (\langle \phi_u, \theta_v \rangle + b_u + b_{v'} - \log n_{uv})^2
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Correct

4.Question 4

How are word embeddings usually evaluated (qualitatively or quantitively)?

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By the accuracy of analogy prediction (using some pre-defined dataset of 4-word analogies).

By Spearman's correlation (or similar rank correlation measure) with human judgements on word similarity task.
By the amount of positive components of word vectors.
▼ By the interpretability of the components of the vectors.
$\hfill\Box$ By comparing maximal lengths of word vectors (the more is the length, the better is the model).
Correct
5.Question 5 Choose the correct statements.
☐ Word2vec works fine for word analogies, but there are many concerns with word similarities.
For word similarity tasks, count-based methods perform on par with predictive methods.
Skip-gram negative sampling (SGNS) model is too hard to train, and it is often approximated with softmax.
Representations of word or character n-grams may improve the quality of the model.
Correct