NLP: Exercise 3

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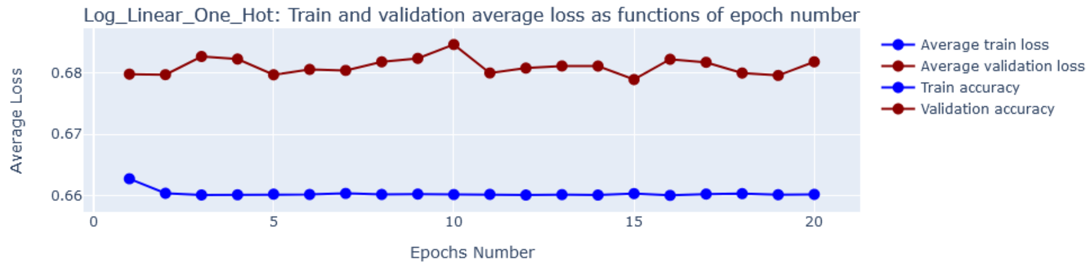
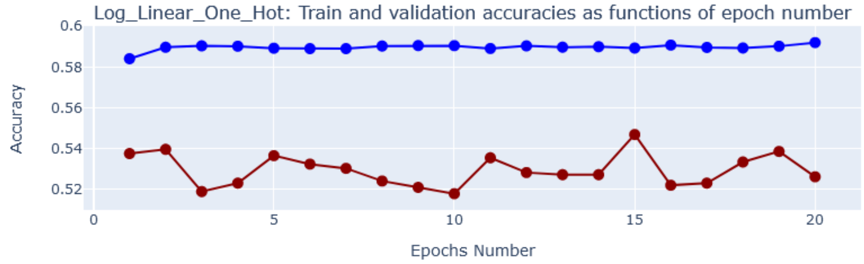
Question 6: Log-Linear model with One-Hot vectors

Average losses and accuracies graphs:





Final results:

a. Average loss and accuracies over the test and validation datasets:

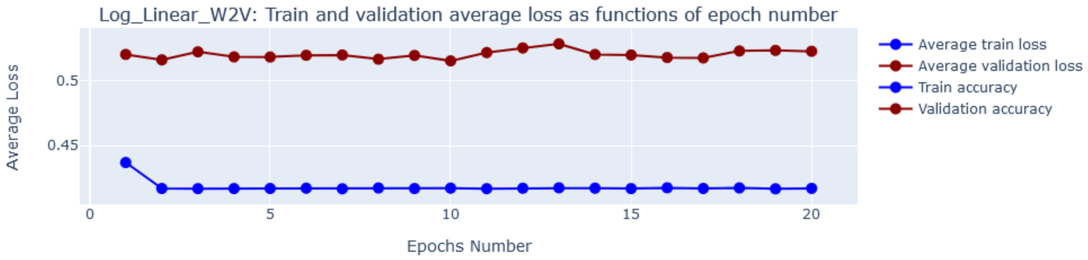
	Validation Dataset	Test Dataset
Average loss	0.682	0.679
Accuracy	0.526	0.526

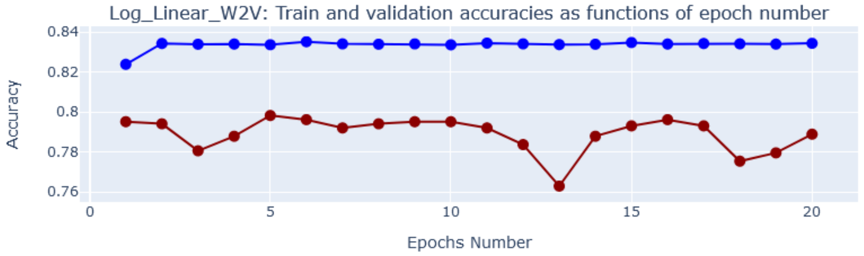
b. Accuracies over special subsets (from the test dataset):

	Sentences with negative polarity	Sentences with rare words
Accuracy	0.484	0.28

Question 7: Log-Linear model with words to embedded vectors

Average losses and accuracies graphs:





Final results:

a. Average loss and accuracies over the test and validation datasets:

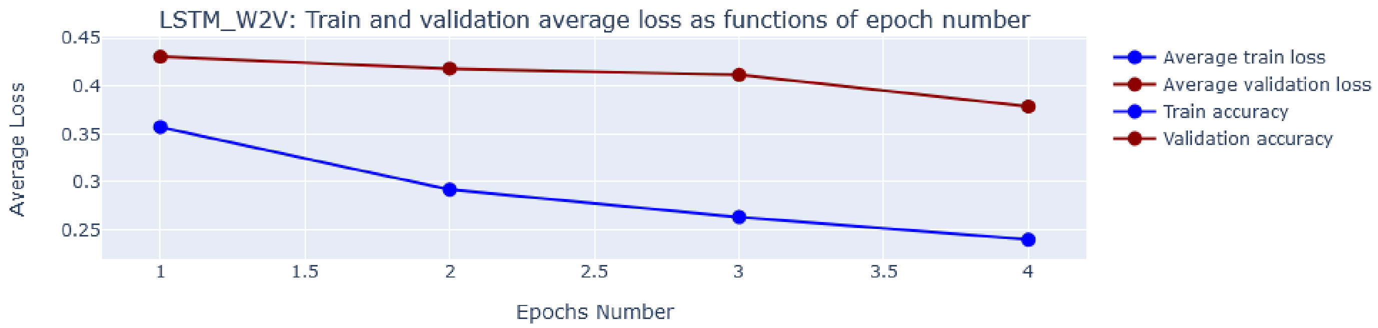
	Validation Dataset	Test Dataset
Average loss	0.523	0.501
Accuracy	0.789	0.809

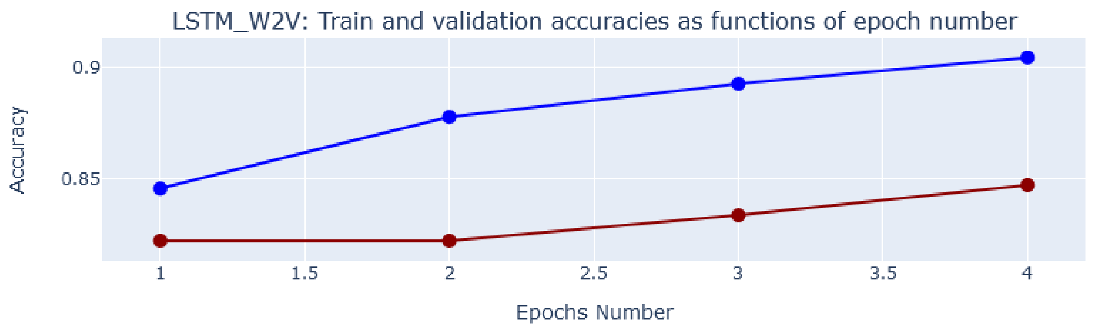
b. Accuracies over special subsets (from the test dataset):

	Sentences with negative polarity	Sentences with rare words
Accuracy	0.597	0.68

Question 8: LSTM model with words to embedded vectors

Average losses and accuracies graphs:





Final results:

a. Average loss and accuracies over the test and validation datasets:

	Validation Dataset	Test Dataset
Average loss	0.379	0.337
Accuracy	0.847	0.853

b. Accuracies over special subsets (from the test dataset):

	Sentences with negative polarity	Sentences with rare words
Accuracy	0.645	0.8

Question 9:

a. Compare the results (test accuracy, validation accuracy) for the models:
   - Log-Linear with One-Hot vectors
   - Log-Linear with words to embedded vectors

	Validation accuracy	Test accuracy
Log-Linear with One-Hot vectors	0.526	0.526
Log-Linear with words to embedded vectors	0.789	0.809

Model with better performance: Log-Linear with words to embedded vectors (from question 7)

Explanation:
Using Log-Linear model with word2vsec rather than One-Hot vector has two advantages:

- Word embedding captures semantic information in a way that similar words have similar embedding vectors. Thus, the model can leverage the semantic similarity between words to make more informed predictions.
  On the other hand, in One-Hot encoding, every word is equally distant from every other word, which means no semantic relationship is captured.
- Word embedding provides much more compact representation of a word compared to One-Hot encoding, in our case vector dimension of 300 instead of the size of the vocabulary.
  Since the samples of One-Hot vectors came from much higher dimensional space, they contain more sparsity, meaning the model will require a much bigger training dataset to better generalize the data, overwise it can overfit the dataset.

b. Compare the results (test accuracy, validation accuracy) for the models:
   - Log-Linear with words to embedded vectors
   - LSTM with words to embedded vectors

	Validation accuracy	Test accuracy
Log-Linear with words to embedded vectors	0.789	0.809
LSTM with words to embedded vectors	0.847	0.853

Model with better performance: LSTM with words to embedded vectors (from question 8)

Explanation:
Using the LSTM with word2vsec model rather than the Log-Linear with word2vsec model has two advantages:

- The (bi-directional) LSTM model processes the sentence in both forward and backward directions, allowing it to capture the context of each word from both directions. This is important when predicting a sentence's sentiment since it can depend on the context in which words appear.
  On the other hand, a Log-Linear with word2vsec model treats the input as an aggregated form (i.e. average of embedding vectors) and loses the sequential information that the LSTM model preserves.
- Using a (bi-directional) LSTM with an additional linear layer, we get a deeper and richer model compared to a simple Log-Linear model that is implemented with only one Linear Layer.
  The LSTM's depth came from the sequential processing of input and the non-linear transformations within the LSTM cells. Overall, we get a model that corresponds to a more complex hypothesis class and can better handle complex tasks of sentiment analysis.

c. Compare the accuracy of the models on the special subsets:

	Sentences with negative polarity	Sentences with rare words
Log-Linear with One-Hot vectors	0.484	0.28
Log-Linear with words to embedded vectors	0.597	0.68
LSTM with words to embedded vectors	0.645	0.8

<u>Model with better performance (for both subsets):</u> LSTM with words to embedded vectors

<u>Explanation:</u>

- <u>Sentences with negative polarity:</u>
  The LSTM model is designed to handle sequential data by processing the sentence word by word from both forward and backward directions. This allows the model to understand the flow of the sentiment within the sentence, including shifts or contradictions in sentiment that may occur due to conjunctions (e.g., "but", " although", etc.)

  In addition, the LSTM model can capture long-term dependencies in the sentence, which can be crucial for sentences where the sentiment expressed in one part of the sentence is countered or mitigated by another part (i.e. " Overall, the movie was good, although I didn't like the opening scene ")

  Log-linear models, whether using one-hot vectors or word embeddings, treat the input in an aggregate manner, hence lose the ability to understand the sentiment flow and capture long-term dependencies in the sentence.

- <u>Sentences with rare words:</u>
  As mentioned before, the LSTM model processes sentences sequentially, taking into account the context provided by surrounding words. This means that even if a rare word is encountered, the LSTM's ability to consider its context helps in understanding its role and significance within the sentence.

  For example: "The girl with the long **hair-braids** is very beautiful" – Even if we are not familiar with the word "hair-braids", we can still understand from its context in the sentence that it has no contribution to the sentence's sentiment.

  Again, Log-linear model, whether using one-hot vectors or word embeddings, treats the input in an aggregate manner, hance more limited to handling rare words that may disturb to predict the sentence's sentiment.