Assignment 3 NLP

1 n-gram Language Model

1.2 n-gram Language Modeling

| | Corpus Length | Unique n-grams |
|---------------|---------------|----------------|
| Unigram Model | 1622905 | 26602 |
| Bigram Model | 1684434 | 510392 |
| Trigram Model | 1684433 | 1116160 |

Figure 1: Model Information

| | Train Perplexity | Validation Perplexity | Test Perplexity |
|---------------|------------------|-----------------------|-----------------|
| Unigram Model | 1105.5403 | 1009.9143 | 1015.3158 |
| Bigram Model | 77.0735 | inf | inf |
| Trigram Model | 7.8279 | inf | inf |

Figure 2: Model Perplexity Scores (unsmoothed)

Train perplexity decreases as the history increases, thereby suggesting better performance in the model from unigram to trigram. As UNK token was used in the unigram model, probability would be non-zero for the validation and test perplexity. In contrast, since the probability of certain bigram/trigram were found to be 0, the perplexity obtained is infinite for their respective validation and test perplexity

1.3 Smoothing

| | Train Perplexity | Validation Perplexity | Test Perplexity |
|--------------------------------------|------------------|-----------------------|-----------------|
| $\lambda_{1,2,3} = 0.01, 0.10, 0.99$ | 7.6296 | 2126.3137 | 2121.6016 |
| $\lambda_{1,2,3} = 0.05, 0.15, 0.95$ | 7.8492 | 935.2956 | 934.4221 |
| $\lambda_{1,2,3} = 0.10, 0.10, 0.80$ | 9.3821 | 739.8144 | 739.4445 |
| $\lambda_{1,2,3} = 0.10, 0.30, 0.50$ | 14.4137 | 793.1056 | 793.7961 |
| $\lambda_{1,2,3} = 0.66, 0.66, 0.66$ | 10.0358 | 239.5573 | 240.1129 |
| $\lambda_{1,2,3} = 0.10, 0.30, 0.60$ | 12.0533 | 736.4886 | 736.9305 |

Figure 3: Model Perplexity Scores and Hyperparameters

1.3.3 If you use half of the training data, would it increase or decrease the perplexity on previously unseen data? Why? Provide empirical experimental evidence if necessary.

The perplexity would increase as the training data decreases since there is less information and tokens to be utilized by the model. Below are the perplexity scores trained on half the data set using interpolation smoothing

| | Train Perplexity | Validation Perplexity | Test Perplexity |
|--------------------------------------|------------------|-----------------------|-----------------|
| $\lambda_{1,2,3} = 0.10, 0.30, 0.60$ | NA | 468.3740 | 471.4108 |

Figure 4: Model Perplexity Scores Based on ½ Training Set

1.3.4 If you convert all tokens that appeared less than 5 times to (a special symbol for out-of-vocabulary tokens), would it increase or decrease the perplexity on the previously unseen data compared to an approach that converts only a fraction of words that appeared just once to? Why? Provide empirical experimental evidence if necessary.

More UNK tokens would lead to a model that has less perplexity and is more generalizable. Below are the perplexity scores after changing the UNK Threshold from 3 to 5 on a unigram model.

| | Train Perplexity | Validation Perplexity | Test Perplexity |
|---------------|------------------|-----------------------|-----------------|
| Unigram Model | 909.6217 | 853.7755 | 856.9755 |

Figure 5: Unigram Model Perplexity Score with UNK Threshold of 5

The Unigram model with the higher UNK threshold showed a decrease in perplexity compared to Figure 2.

2 Neural Language Modeling, based on Eisenstein 6.10 (p. 136)

2.1.1 Fully describe your model architecture, hyperparameters, and experimental procedure.

The neural language model is trained using vanilla RNN with the epoch=6, learning rate=0.001, and batch size=128.

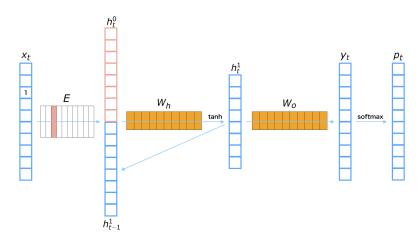


Figure 6: One layer of the RNN Language Model¹

The process used to get a next word prediction from the i-th input word x_t is as follows:

- 1) Get the embedding vector: $h_t^{(0)} = Ex_t$
- 2) Calculate the hidden layer: $\mathbf{h}_{t}^{(1)} = \tanh \left(\mathbf{w}_{h} \begin{bmatrix} \mathbf{h}_{t}^{(0)} \\ \mathbf{h}_{t-1}^{(1)} \end{bmatrix} \right)$ Calculate the output layer: $\mathbf{y}_{t} = \mathbf{W}_{0} \mathbf{h}_{t}^{(1)}$
- 4) Transform to probability: $p_t = softmax(y_t)$

2.1.2 After each epoch of training, compute your LM's perplexity on the development data. Plot the development perplexity against # of epochs. Additionally, compute and report the perplexity on test data.

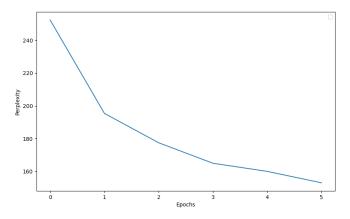


Figure 7: Vanilla RNN Language Model Training Perplexity The perplexity on the test dataset was computed to be 142.65

¹ https://docs.chainer.org/en/stable/examples/ptb.html

3 What Can Language Models Do?

I am more or less convinced by the paper's argument. Based on the paper's definition of linguistic meaning to be "the relation between a linguistic form and communicative intent", it would mean there requires some level of sentience in order to have an intent in trying to communicate something before just probabilities that a machine has learnt. In our current state of what machines can do, we are far from achieving that level of autonomy and self-awareness that is required to attain intent in speech. Beyond the technical study of NLP, I believe there needs to be a broader study on the sense of what it means for a machine to be able to communicate and what that means if a machine can do so in relation to humans.