# INTRODUCTION TO NLP (CS7.401, SPRING 2025)

## **ASSIGNMENT 1**

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#### 1 Generation

#### 1.1 No Smoothing

#### 1.1.1 In-Context Text

**Task-1:** Using the generated N-gram models (without the smoothing techniques), try generating sequences. Experiment with different values of N and report which models perform better in terms of fluency.

Figure 1: No Smoothing. N=1

Figure 2: No Smoothing. N=3

Figure 3: No Smoothing. N=5

I attempted to predict a sentence starting with "It was." The results show that the unigram model performed the worst, as it does not consider any previous context, leading to random and incoherent predictions. The trigram model performed better, but the sentence still lacked fluency, with inconsistent shifts in the subject and meaning. The 5-gram model outperformed the others, producing the most fluent and coherent sentence. Based on this, we can conclude that, without smoothing, the 5-gram model provides the best performance, while the unigram model is the least effective among the 5-gram, 3-gram, and unigram models.

#### 1.1.2 Out-of-Data (OOD) scenario

**Task-2:** Attempt to generate a sentence using an Out-of-Data (OOD) scenario with your N-gram models. Analyze and discuss the behavior of N-gram models in OOD contexts.

Figure 4: No Smoothing. Out-of-Data (OOD) scenario

This is focused on inputs where the individual words were familiar, but their combination was entirely new and had not appeared in the training data. In such cases, the N-gram models assigned zero probability to predictions because the specific context was missing from the training data, resulting in a zero count. Without this context, the models were unable to make valid predictions. This is a key limitation of N-gram models, as they struggle with new word combinations and cannot generalize effectively without techniques like smoothing.

**Task-3**: Now try to generate text using the models with the smoothing techniques (LM1, LM2, LM3, LM4, LM5, LM6) for N=1,3 and 5 each.

#### 1.2 Laplace Smoothing

```
mayank@mayank-HP:-/Music/2022101094_assignment15 python3 generator.py l ./Pride\ and\ Prejudice\ -\ Jane\ Austen.txt 5 1
Language model trained successfully!
input sentence: It is
output:
procuring    6.355622501445904e-06
owed    6.355622501445904e-06
apartment    6.355622501445904e-06
sleeping    6.355622501445904e-06
condescendingly    6.355622501445904e-06
mayank@mayank-HP:-/Music/2022101094_assignment1$ python3 generator.py l ./Pride\ and\ Prejudice\ -\ Jane\ Austen.txt 5 1
Language model trained successfully!
input sentence: It is procuring
output:
civility    6.355622501445904e-06
intimate    6.355622501445904e-06
Nonsense    6.355622501445904e-06
rationally    6.355622501445904e-06
rationally    6.355622501445904e-06
rationally    6.355622501445904e-06
encroaching    6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145904e-06
encroaching     6.35562250145
```

Figure 5: Laplace Smoothing. N=1

Figure 6: Laplace Smoothing. N=3

```
| August | A
```

Figure 7: Laplace Smoothing. N=5

when dealing with unseen context using N=1, we found that the probabilities of the top predictions weren't zero, which was an improvement over the case with no smoothing. Additionally, the N=5 model produced sentences that were more fluent than those generated by the N=3 model. With N=3, the fluency started to drop off after a certain point because it only considered the previous two words. Overall, the N=5 model gave the best results in terms of fluency, while N=1 performed the worst.

### 1.3 Good Turing

Figure 8: Good Turing. N=1

Figure 9: Good Turing. N=3

Figure 10: Good Turing. N=5

we can see that the 5-gram model performs the best in terms of fluency, making more confident predictions for the next word. It is followed by the 3-gram model, which also predicts fluently and outperforms the Laplace-smoothed model. The least fluent predictions come from the 1-gram model, which struggles the most.

### 1.4 Linear Interpolation

Figure 11: Linear Interpolation. N=1

Figure 12: Linear Interpolation. N=3

Figure 13: Linear Interpolation. N=5

Here we see that the unigram performs poorly. The trigram produces fluent but not completely fluent sentences. The 5-gram model produces the best fluent predictions out of N=1,3,5.

Among the three smoothing methods, Good-Turing Smoothing produces the most fluent sentences. On the other hand, Laplacian smoothing tends to generate fewer coherent sentences. This may be due to the addition of 1, which might be too large, or the vocabulary size in the denominator, which can make all probabilities small. Linear interpolation, however, can perform better than Good-Turing Smoothing if we find a better way to set the  $\lambda$  weights for each model.

## 2 Perplexity Analysis

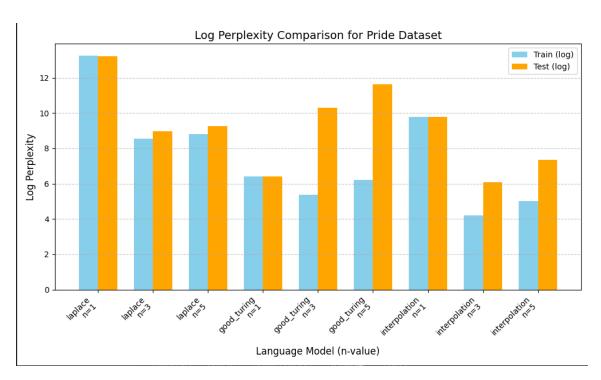


Figure 14: Average perplexity scores for Pride and Prejudice

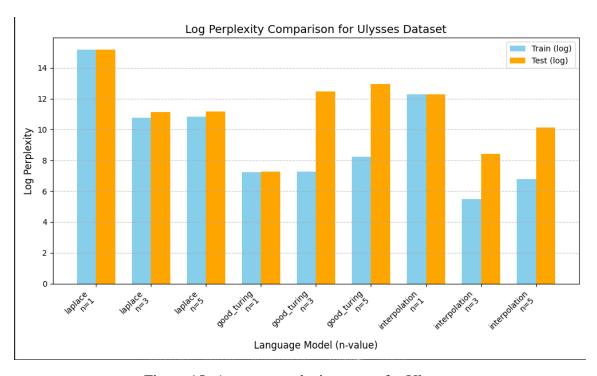


Figure 15: Average perplexity scores for Ulysses

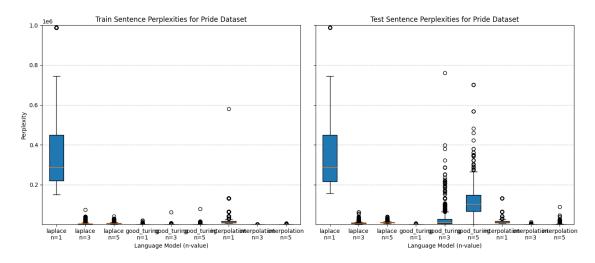


Figure 16: Box plot for perplexity scores for Pride and Prejudice

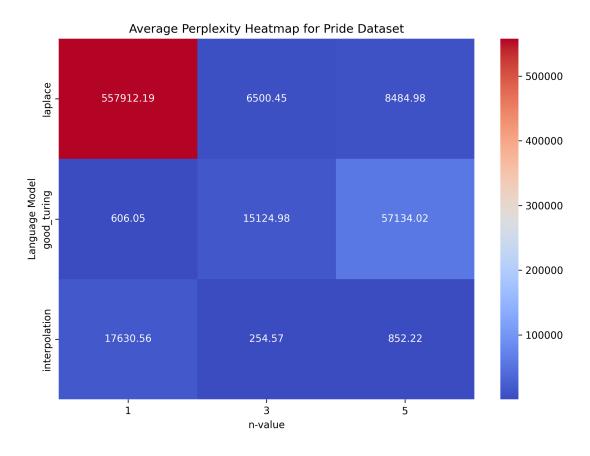


Figure 17: Heatmap of avg perplexity scores for Pride and Prejudice

#### Laplace (n=1) Laplace (n=3) Laplace (n=5) 6000 4000 F 2000 1000 0 10000 20000 30000 40000 50000 60000 70000 Sentence Perplexity 5000 10000 15000 20000 25000 30000 35000 40000 Sentence Perplexity Good\_turing (n=1) Good\_turing (n=3) Good\_turing (n=5) 6000 6000 5000 5000 ≥ 4000 3000 2000 2000 1000 10000 15000 Sentence Perplexity 20000 10000 20000 30000 40000 50000 60000 Sentence Perplexity 0 10000 20000 30000 40000 50000 60000 70000 80000 Sentence Perplexity Interpolation (n=3) Interpolation (n=5) Interpolation (n=1) 6000 5000 5000 4000 를 3000 至 3000 2000 2000 2000 1000 100000 200000 300000 400000 500000 600000 Sentence Perplexity 1000 1500 2000 2500 3000 3500 Sentence Perplexity 1000 2000 3000 4000 5000 6000 7000 Sentence Perplexity

## Sentence Perplexity Distribution for Pride Dataset

Figure 18: Frequency distribution of perplexity scores for Pride and Prejudice

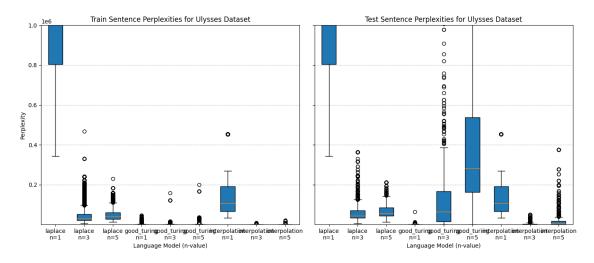


Figure 19: Box plot for perplexity scores for Ulysses

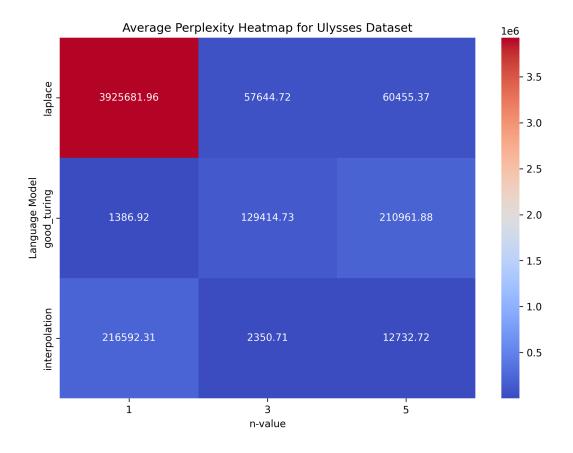
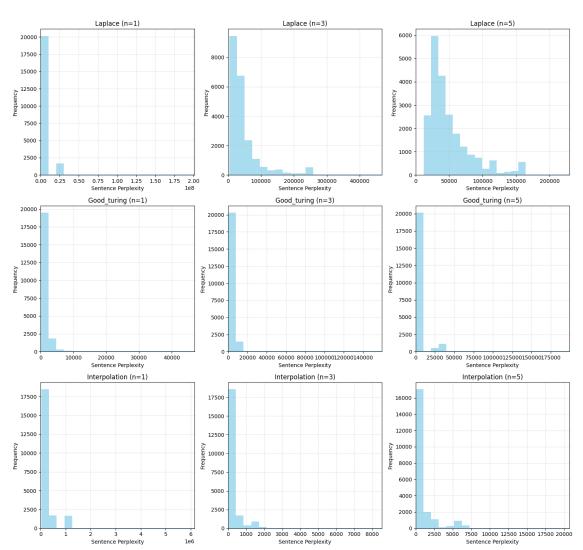


Figure 20: Heatmap of avg perplexity scores for Ulysses



#### Sentence Perplexity Distribution for Ulysses Dataset

Figure 21: Frequency distribution of perplexity scores for Ulysses

- The test set perplexity is consistently higher than the training set perplexity, indicating overfitting in higher-order n-grams due to data sparsity.
- Good-Turing smoothing outperforms Laplace smoothing for lower-order n-grams, as seen in its lower perplexity for N=1 compared to Laplace.
- Linear interpolation shows a significant increase in test set perplexity for N=3 and N=5, suggesting difficulties in managing data sparsity with higher-order n-grams.
- Good-Turing achieves balanced performance across different n values but struggles with generalization for N=5.

• Laplace smoothing consistently produces higher perplexity than other methods, reflecting its ineffectiveness in reducing overfitting.