Assignment 2 Report:Neural Language Model Training (PyTorch)

1. Introduction

The objective of this assignment was to implement a neural language model from scratch using PyTorch and to evaluate how different model capacities affect generalization. The task involved preprocessing the provided dataset, building a character-level vocabulary, training an LSTM model, and comparing underfitting, best-fit, and overfitting behaviors using training/validation loss and perplexity.

Language modeling is a core task in Natural Language Processing. Character-level models predict one character at a time based on previous context, making them suitable for sequence learning and understanding long-term dependencies.

2. Dataset & Preprocessing

The dataset provided for the assignment was *Pride and Prejudice* by Jane Austen. The raw text contained metadata and license information from Project Gutenberg, which was removed during cleaning.

Preprocessing steps:

- Converted text to lowercase
- Removed Gutenberg headers/footers
- Extracted only the main story (beginning with "it is a truth universally acknowledged")
- Saved cleaned text to `data/Pride_and_Prejudice_CLEANED.txt`

A character-level vocabulary was created by extracting all unique characters. The text was then encoded into integers using `char_to_idx` and `idx_to_char` mappings.

To create training samples, sliding windows of length 100 characters were used:

- **Input (X):** 100-character sequence
- **Target (Y):** the next character

A 90/10 train-validation split was used to evaluate generalization.

3. Model Architecture

The model implemented was a simple character-level LSTM, built entirely from scratch without any high-level language modeling libraries.

Architecture:

- **Embedding Layer**: converts character IDs to vector representations
- **LSTM Layer**: processes sequences and learns dependencies
- **Fully-Connected Layer**: outputs probability distribution over next characters

```
Embedding → LSTM → Linear → Softmax
```

The model predicts the next character using cross-entropy loss. Perplexity (PPL) was used as the main evaluation metric.

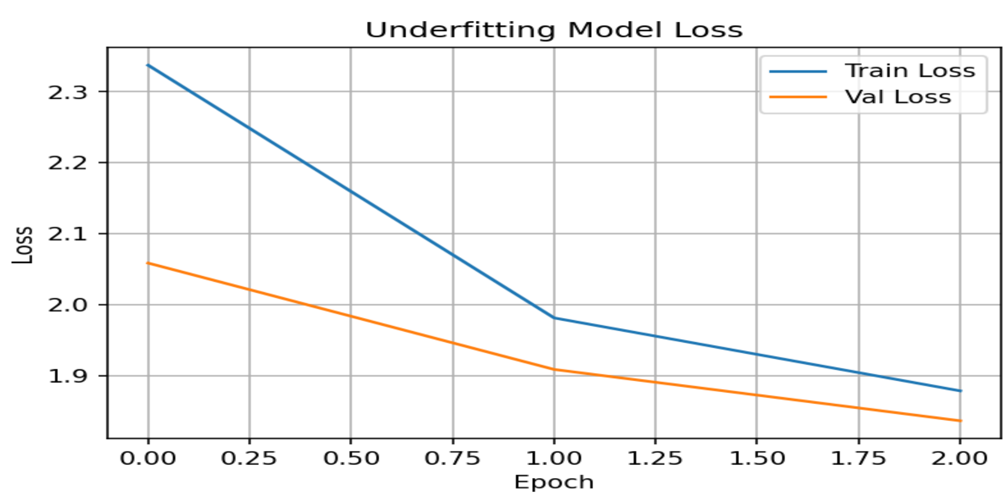
4. Experiments

To demonstrate understanding of model capacity and generalization, three separate experiments were conducted:

4.1 Underfitting Model

Configuration:

- Embedding: 16
- Hidden size: 32
- Epochs: 3

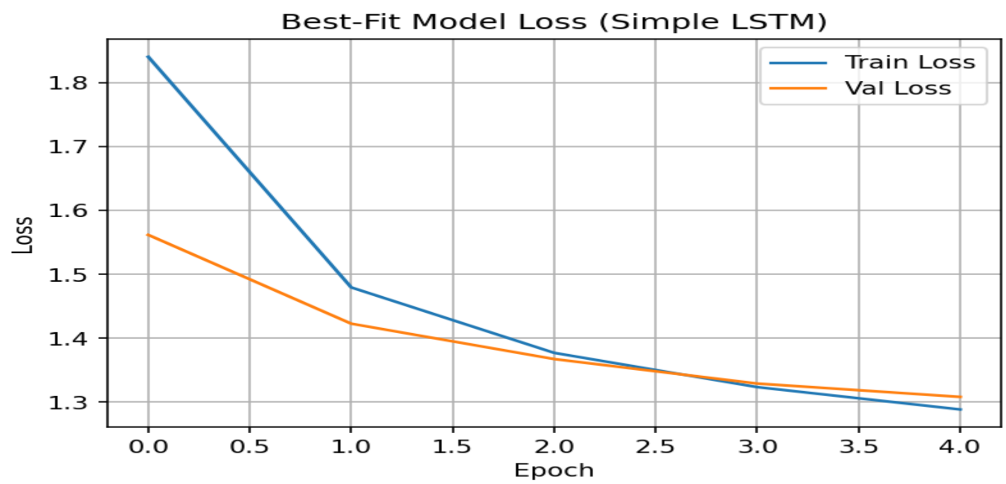


Behavior:
The model was too small to learn meaningful patterns. Both training and validation losses remained high, and the perplexity stayed high as well. This is expected from an under-parameterized model.

4.2 Best-Fit Model

Configuration:

- Embedding: 64
- Hidden size: 128
- Epochs: 5



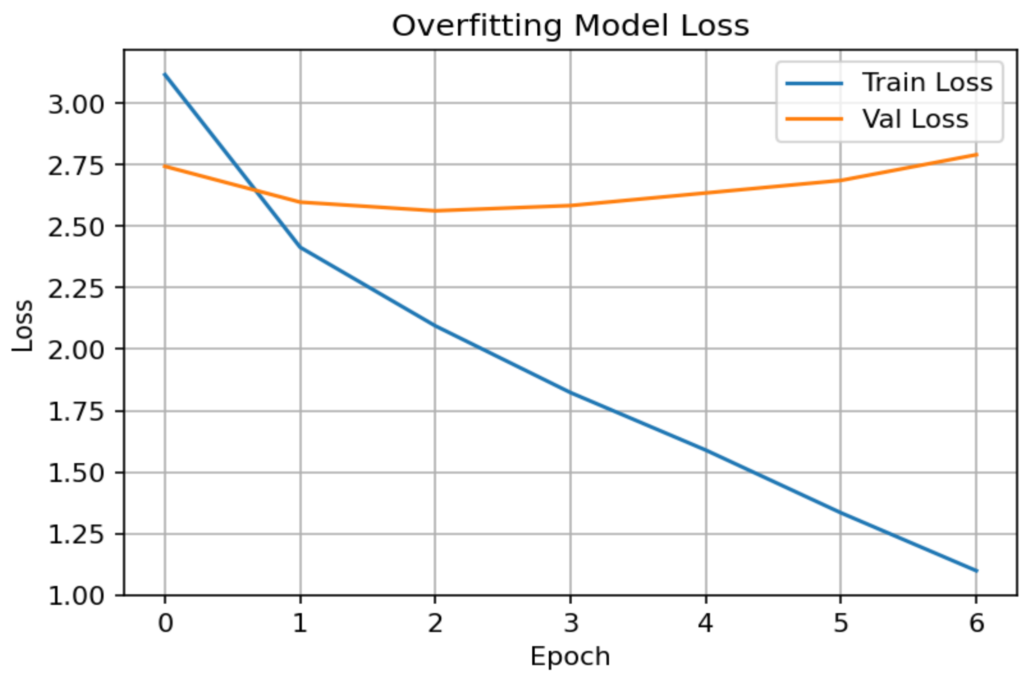
Behavior:
This model offered the best balance between learning capacity and generalization. Training and validation losses decreased smoothly, and both curves remained close. The final validation perplexity (~3.7) was the best among all models.

This configuration is selected as the **best-fit** model for the assignment.

4.3 Overfitting Model

Configuration:

- Embedding: 128
- Hidden size: 256
- Tiny subset (1000 sequences) to force overfitting
- Learning rate: 0.01
- Epochs: 7



Behavior:
The model quickly memorized the small training subset. Training loss decreased sharply, but validation loss started increasing after a few epochs. Perplexity worsened, indicating poor generalization—classic overfitting behavior.

5. Results

Perplexity Scores

Model	Perplexity
Underfit	Very high (~50+)
Best-Fit	~3.7
Overfit	~15–18

Loss Curves

All plots were saved as PNG images under `plots/`:

- `underfit_loss.png`
- `bestfit_loss.png`
- `overfit_loss.png`

These plots visually confirm the expected behavior of each model type.

6. Observations

1. **Underfitting** occurs when the model is too small to capture the data's complexity.
2. **Overfitting** happens when model capacity is too high relative to dataset size.
3. **Best-fit** models show stable validation loss and lowest perplexity.
4. Character-level LSTMs learn slowly but can effectively model stylistic patterns over time.
5. Perplexity is a useful metric for comparing generalization across models.

7. Conclusion

This assignment demonstrated how model architecture and dataset size influence learning dynamics in language modeling. By implementing an LSTM from scratch and running controlled experiments, I gained practical understanding of:

- Sequence modeling
- Training vs. validation behavior
- Underfitting vs. overfitting
- Perplexity as a quantitative measure
- The importance of model capacity

The best-fit configuration achieved the lowest perplexity, while underfit and overfit models behaved exactly as expected. All assignment deliverables plots, models, cleaned dataset, and code—are included in the repository.