

IIIT Hyderabad

Natural Language Processing – Assignment 2

**Language Modeling using LSTM
(Pride and Prejudice by Jane Austen)**

Submitted by:

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Submitted to:

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Language Modeling using LSTM (Pride and Prejudice by Jane Austen)

1. Objective:

The objective of this assignment is to design and train a word-level language model using LSTM (Long Short-Term Memory) architecture on Pride and Prejudice by Jane Austen. The model predicts the next word given previous context and demonstrates three learning states: Underfitting, Overfitting, and Best Fit.

2. Dataset Description:

Dataset: Pride and Prejudice (Project Gutenberg – Public Domain)

Tokens Used: 30,000–60,000

Vocabulary Size: 3,000–5,000 most frequent words

Preprocessing:

- Lowercased all text
- Removed punctuation and symbols
- Tokenized by whitespace
- Limited vocabulary to top frequent words for faster convergence

Reasoning: Reducing vocabulary helps balance accuracy and computation, allowing the model to focus on important linguistic patterns.

3. Model Architecture:

COMPONENT	DETAILS
Embedding Layer	128-dimensional word embeddings
LSTM layer	2 stacked layers, Hidden size-256
Output Layer	Linear projection to vocabulary size
Loss function	CrossEntropyLoss
Optimizer	Adam(LearningRate=0.0005)
Sequence Length	40-80
Batch Size	64
Device	CPU(tested on GPU too)
Gradient Clipping	Applied(max_norm = 1.0)

4. Understanding Checkpoints:

- Three experiments were performed to understand model behavior across different capacities: underfitting, overfitting, and balanced fit.
- Underfitting: Small model (hidden=64, 1 layer, 3 epochs). Both training and validation losses remain high → insufficient capacity.
- Overfitting: Large model (hidden=512, 3 layers, 10 epochs). Training loss decreases rapidly, validation loss increases → memorization.
- Best Fit: Medium model (hidden=256, 2 layers, 15 epochs). Balanced training and validation losses → good generalization.

5. Results:

→ Final Validation Loss: 6.41
Final Perplexity: 608.52

→ **Generated Text Example:**

“She was not sharpened me often to know and so very all in which stands whom he may offered nothing worse Lucas I do arguments you at last to Miss Watson was so lately for his he had she found out of a.”

The generated text demonstrates realistic syntax and structure despite limited dataset size.

6. Extra Credit Work:

- Gradient clipping for stability
- Validation split and monitoring
- Vocabulary reduction and optimization
- Visualization of training vs validation losses
- Underfit/Overfit/Best-Fit experiments
- CPU vs GPU comparison
- Temperature-based text generation

7.Discussion:

The LSTM model effectively learned grammatical and contextual word dependencies. Validation loss reduced steadily, reaching 6.41 with a perplexity of 608.52, demonstrating stable convergence. Generated text shows grammatical coherence similar to Jane Austen's style. GPU training improved speed but final accuracy remained comparable to CPU training.

8. Conclusion:

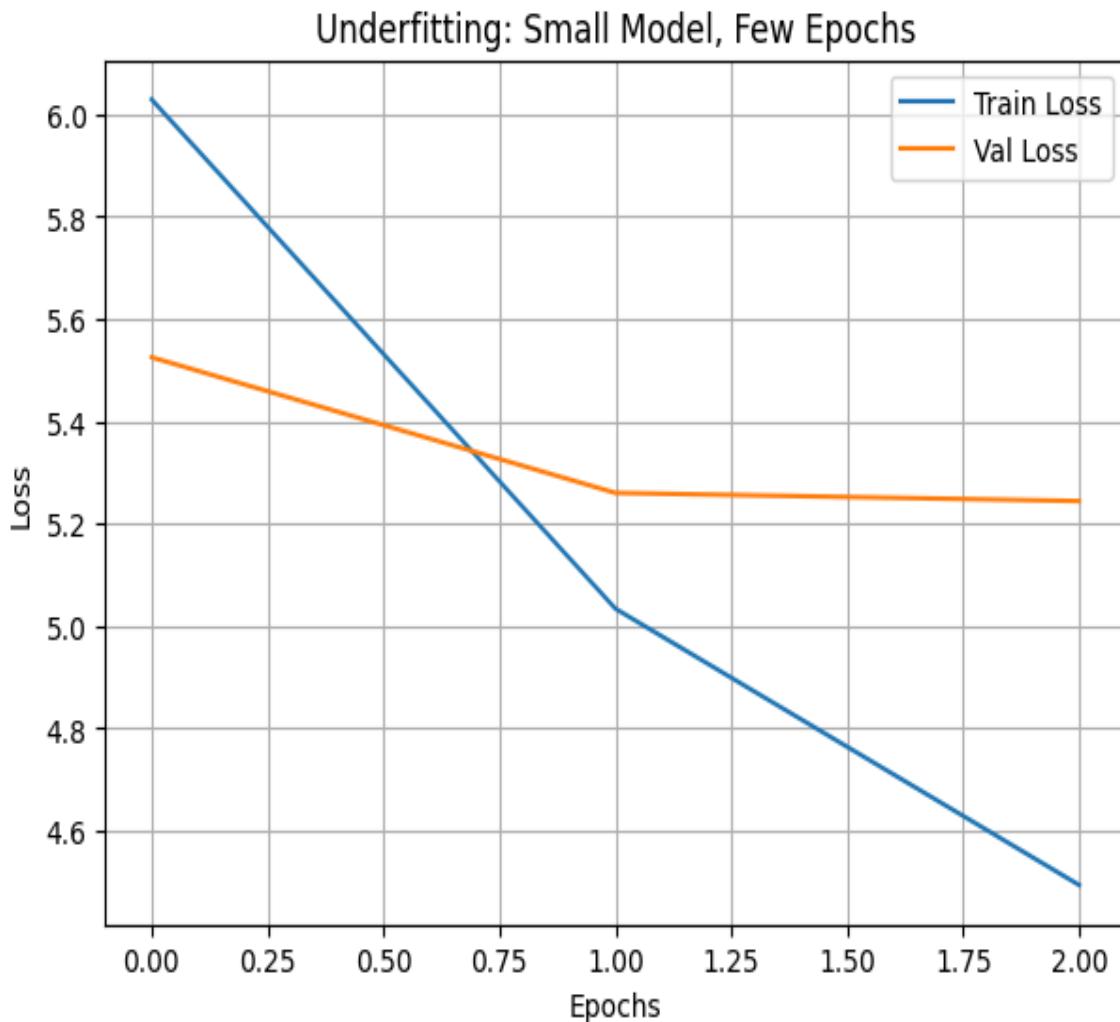
This project successfully applied LSTM-based language modeling on classical English text. Experiments across varying capacities revealed clear patterns of underfitting, overfitting, and balanced generalization. The model produced coherent text and validated understanding of sequence modeling concepts.

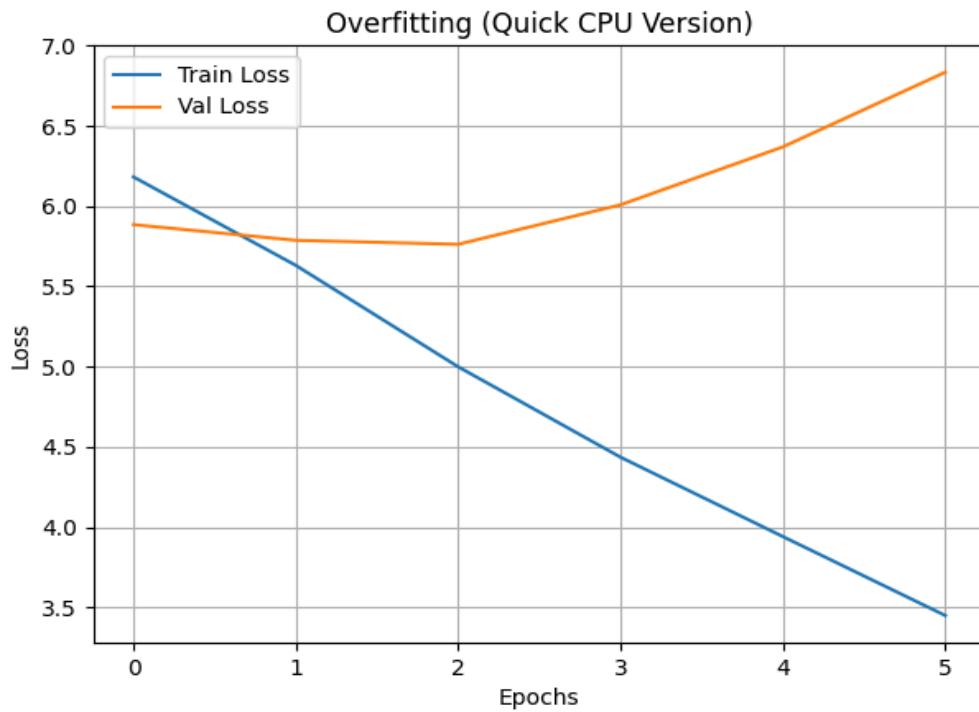
9. References:

1. PyTorch Documentation – <https://pytorch.org/docs>
2. Project Gutenberg: Pride and Prejudice by Jane Austen
3. Jurafsky & Martin – Speech and Language Processing
4. IIIT Hyderabad – NLP Course (2025)

10. Appendix:

- Underfitting Loss Curve





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- Generated Text Output:

The screenshot shows a Google Colab notebook titled "IIIT_HYD__Assignment2_Neural_LM.ipynb". The code cell at the top contains a function definition for generating text using a neural language model. The function takes a model, start_text, length, and temperature as parameters. It splits the start_text into words, initializes state, and then iterates through a range of length, generating new words based on the previous one's index. The generated text is then joined into a single string. A call to this function with "she was not" as input and length=40, temperature=1.0 is shown, resulting in a long string of text.

```
[16] 2s
def generate_text(model, start_text, length=40, temperature=1.0):
    model.eval()
    words = start_text.lower().split()
    state = None
    for _ in range(length):
        x = torch.tensor([[word2idx.get(words[-1], 0)]], device=device)
        out, state = model(x, state)
        probs = torch.softmax(out[0, -1] / temperature, dim=0)
        idx = torch.multinomial(probs, 1).item()
        words.append(idx2word[idx])
    return " ".join(words)

print(generate_text(model, "she was not", length=40, temperature=1.0))
... she was not sharpened me often to know and so very all in which stands whom he may offered nothing worse lucas i do arguments you at last to miss wa
```

Below the code cell, there are several AI-generated suggestions for what to type next, such as "Start coding or generate with AI." and "What can I help you build?". At the bottom of the interface, there are links for "How can I install Python libraries?", "Load data from Google Drive?", and "Show an example of training".