Deep Learning and Reinforcement Learning

Project Title: Character-Level Text Generation

Students: Poojitha B - 1BG23CS100

Rachana F Patil - 1BG23CS113

Project Objective

The project aims to build a text generation system that can produce characteror word-level continuations based on classical literature styles, using LSTM models and an interactive Streamlit interface.

Key Objectives:

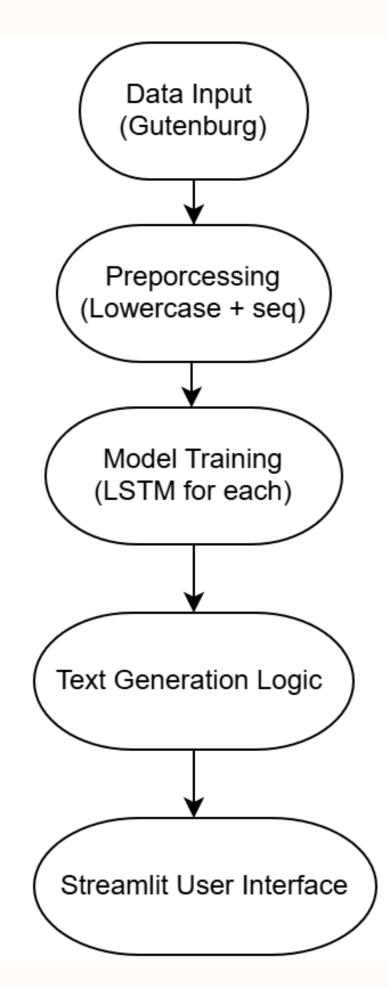
- Train character-level LSTM models on classic books from the Gutenberg corpus.
- Generate text continuations from user prompts.
- Provide both model-generated and verbatim (book-extracted) outputs.
- Build a user-friendly app using Streamlit for real-time interaction.
- Allow style selection across multiple authors and genres.

Methodology

- 1. Data Collection
- Load 5 classical texts from the NLTK Gutenberg corpus
- Convert all text to lowercase
- 2. Preprocessing
- Generate character sequences (length = 40, step = 3)
- Tokenize characters and assign indices
- Vectorize input and output using one-hot encoding
- 3. Model Design & Training
- Build LSTM model (128 units) with softmax Dense layer
- Compile using categorical crossentropy and Adam optimizer
- Train one model per book (3 epochs each)

- 4. Text Generation Logic
- Predict next characters using trained LSTM
- For comparison, extract text directly from books (verbatim)
- Support both character-wise and word-wise modes
- 5. Streamlit App Development
- Interactive UI with dropdowns and input fields
- Users select book, input prompt, and choose output type
- Display generated or extracted text in real-time

Workflow



Key Assumptions

- The user-entered prompt exists in the original book text.
- Each book is trained individually; no transfer learning between styles.
- Character-level generation is sufficient to capture the book's writing style.
- Only lowercase text is used to simplify the model vocabulary.
- Model output is evaluated qualitatively (no automatic accuracy metrics).
- Verbatim output functions rely on simple string search and slicing.
- The model's training is limited to 3 epochs, prioritizing speed over perfection.
- The Streamlit app assumes clean and correct user input.

Model Evaluation and Analysis

- 1. Training Observations
- Models trained for 3 epochs using LSTM and categorical crossentropy
- Loss decreased steadily, indicating learning
- 2. Output Quality
- Generated text mimics original tone and vocabulary
- Some outputs may be repetitive or less coherent
- 3. Strengths
- Captures basic literary style
- Verbatim mode gives clean and accurate references
- 4. Limitations
- No quantitative metrics used
- Short training and character-level modeling limit depth

Project Summary and Outcomes

This project successfully implemented a character-level text generator using LSTM models trained on classic literature. A Streamlit app was developed for interactive input and output, offering both generated and verbatim text extraction.

Key Outcomes:

- Built and trained individual LSTM models for five classic books
- Enabled user-driven prompt-based text generation (character/word)
- Created a user-friendly Streamlit interface for real-time interaction
- Demonstrated the stylistic influence of training data in generated text

Future Improvements and Extensions

- Increase Training Epochs
 Improve model learning and reduce repetition
- Add Evaluation Metrics
 Use Perplexity or BLEU Score to measure text quality
- Integrate Style Transfer
 Allow mixing or switching between author styles
- Enhance UI Features
 Show model confidence and compare generated outputs
- Add Autocorrect for Prompts
 Fix typos automatically to prevent "Prompt not found" issues

Reflections and Learning Outcomes

1. LSTM (Long Short-Term Memory)

Understood how LSTM networks retain and use past information for sequence prediction.

2. One-Hot Encoding

Learned how text is converted into numerical format for training neural networks.

3. Sequential Model Building

Gained hands-on experience in building and compiling models using Keras Sequential API.

4. Text Preprocessing

Explored techniques like lowercasing, character indexing, and vectorization for preparing raw data.

5. Interactive Deployment (Streamlit)

Learned how to deploy models with a clean user interface for real-time input/output.

Appendix

- Code Files
- logic.ipynb : Contains data preprocessing, LSTM model building, training, and text generation logic
- app.py: Streamlit-based web interface for user interaction with the trained models
- Dataset
- NLTK's Gutenberg corpus (e.g., austen-emma.txt, bible-kjv.txt)
- Libraries & Tools Used
- TensorFlow, Keras, NumPy, NLTK, Streamlit

Thank you!