PROJECT WRITE-UP:

STORY GENERATOR USING TIME TRAVEL DATASET

INTRODUCTION

Automated story generation is a compelling application of Natural Language Processing (NLP) and deep learning. This project leverages GPT-like models to generate creative stories in the time-travel genre. By fine-tuning a pre-trained language model on a dataset of book descriptions related to time travel, we aim to develop a system that can generate engaging and coherent time-travel narratives. This system can be applied in creative industries, interactive entertainment, or educational platforms to inspire human creativity.

PROBLEM STATEMENT

Generating coherent and creative stories that follow a particular theme is a challenging task for AI models. Story generation requires a model to understand the plot, setting, characters, and thematic elements of the genre. In this project, we aim to fine-tune a GPT-like model on a dataset of time-travel-themed stories to produce new, human-like stories based on user prompts.

OBJECTIVES

1. Data Collection and Preprocessing: Use a dataset of time-travel-related book descriptions to train a model.

2. Model Fine-Tuning: Fine-tune a pre-trained GPT model to specialize in generating time-travel narratives.

3. Story Generation: Develop a tool that generates new time-travel stories based on user prompts.

4. Evaluation: Assess the generated stories for coherence, creativity, and adherence to time-travel themes.

5. Deployment: Create an interactive interface that allows users to input prompts and receive generated stories.

REVIEW

Language models based on the Transformer architecture, such as GPT-2 and GPT-3, have shown remarkable capabilities in generating human-like text. These models use self-attention mechanisms to capture the relationships between words over long distances, making them well-suited for tasks that require a deep understanding of context, such as story generation.

Previous research has explored story generation using simpler models, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, but these models struggled with long-range dependencies and maintaining coherence over extended narratives. The introduction of transformer models has led to significant improvements in the quality and creativity of AI-generated text. However, fine-tuning models for specific genres, such as time travel, remains a complex task that requires careful data selection and training procedures.

METHODOLOGY

1. Data Collection

For this project, we used a dataset of time-travel-related book descriptions. These descriptions were collected from various sources, providing the model with a diverse set of narratives. The dataset includes the following key features:

- Book Title: The title of the book.

- Author Name: The author's name.

- Book Description: A summary of the book's plot, often focusing on its time-travel elements.

- Genres: Additional metadata that classifies the book into genres such as science fiction or fantasy.

2. Data Preprocessing

The data preprocessing phase involved:

- Cleaning the Data: The raw text in the Book Description column was cleaned by removing unnecessary characters, whitespace, and any artifacts from the text.

- Tokenization: Using a tokenizer specific to the GPT model, the cleaned text was converted into a format that the model could understand (i.e., tokens).

- Padding and Truncation: Text sequences were padded or truncated to ensure uniform input length for the model during training.

3. Model Fine-Tuning

We fine-tuned a pre-trained GPT-2 model using the Hugging Face library. GPT-2 was chosen due to its balance between computational efficiency and ability to generate high-quality text. The fine-tuning process involved adjusting the model’s weights based on the time-travel story dataset.

Key training parameters included:

- Number of Epochs: The model was trained for several epochs to optimize its performance on the dataset.

- Batch Size: A moderate batch size was chosen to balance memory constraints and training speed.

- Learning Rate: A carefully selected learning rate ensured that the model learned effectively without overfitting the data.

4. Story Generation

Once the model was fine-tuned, it could generate stories based on user-provided prompts. For instance, a user might provide a prompt like:

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"A young scientist discovers a hidden portal that can take her back in time to ancient Rome..."
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The model would then generate a continuation of the story, maintaining coherence and adhering to the time-travel theme.

Techniques such as nucleus sampling and top-k sampling were used during generation to ensure diversity in the output while avoiding repetitive patterns. The goal was to create narratives that were not only coherent but also creative and engaging.

5. Evaluation

Evaluating the generated stories involved both quantitative and qualitative methods:

- Perplexity: A standard metric that measures how well the model predicts the next word in a sequence. A lower perplexity score indicates better performance.

- Human Evaluation: Volunteers were asked to read and assess the generated stories for coherence, creativity, and adherence to the time-travel theme. Their feedback helped identify areas for improvement.

- Repetition and Diversity: The model's output was analyzed for any repetitive patterns or lack of diversity, which can diminish the quality of the generated stories.

6. Deployment

After training and evaluation, the model was deployed using a simple user interface, enabling users to interact with the story generator. Tools like Streamlit or Gradio were used to create a web-based application where users could input prompts and receive generated stories.

Results and Discussion

The fine-tuned model demonstrated a solid understanding of time-travel-related narratives. It generated coherent, engaging stories that followed the themes and patterns found in the training dataset. However, there were occasional instances where the model produced irrelevant or nonsensical content, a known limitation in current text generation models.

Through human evaluation, the generated stories were found to be creative and enjoyable, but there is room for improvement in terms of plot consistency and character development. The use of techniques like nucleus sampling improved the diversity of the generated stories, reducing repetitive structures.

Conclusion

This project successfully developed a time-travel story generator by fine-tuning a GPT-like model on a dataset of book descriptions. The model was able to produce coherent and creative stories, demonstrating the potential of transformer-based architectures for creative applications in storytelling.

While the generated stories were generally coherent, further improvements could focus on enhancing the model's ability to maintain consistent plots and develop characters over longer narratives. Future iterations of the project may involve fine-tuning on larger, more diverse datasets or experimenting with hybrid approaches that combine rule-based and neural models.

Future Work

There are several opportunities for further development:

1. Multi-modal Story Generation: Combining text generation with image or video generation for more immersive storytelling.

2. Plot Coherence: Incorporating mechanisms to ensure that generated stories follow a consistent plot with proper character development.

3. Interactive Storytelling: Allowing users to influence the direction of the story by providing inputs at various stages of the narrative.

4. Evaluation Metrics: Developing more robust evaluation metrics to better assess the quality of the generated stories beyond traditional perplexity.

This project lays the groundwork for more advanced AI-driven storytelling systems that can generate narratives in specific genres, such as time travel, with minimal human intervention.