

Analysis of Text generation models to deploy a Genre-based Movie Dialogue Generator

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ABSTRACT

In this study, we aim to tackle the development of two seq2seq models and one pre-trained transformer configuration for the task of creating a genre-based movie dialogue generator. The idea being that given sample dialogue and the genre of said dialogue, the seq2seq/transformer model outputs dialogue based on the genre. For this particular project, after reviewing the literature, we have decided to develop a Bidirectional LSTM model with attention mechanism and teacher forcing, and the second seq2seq model we developed is a less-complex Bidirectional GRU model. Finally, we use the GPT2LMHeadModel as the pre-trained transformer model as a benchmark, especially after the proliferation of ChatGPT. Furthermore, we used an ablation study of K-Fold cross validation for hyperparameter tuning on 9 different model configurations each. Due to memory and RAM constraints, we trained the seq2seq models for 30 epochs along with the implementation of callbacks such as EarlyStopping and ReduceLROnPlateau. We also augmented the efficiency of the model using L1-L2 regularization and dropout layers to prevent overfitting. The results we obtained signify the need for niche development of AI generative models for particular use cases. In terms of human evaluation and BLEU score, the pre-trained transformer performed the best, followed by the seq2seq Bidirectional GRU model without attention and teacher forcing, and finally the Bidirectional LSTM model performed less better in terms of both BLEU score and human evaluation. The findings from the project can be applied to alleviate writer's block or just a creative exploration of ideas or for leisure. But the headway made in model development can be applied for future work.

1. INTRODUCTION

In this section, we introduce the problem, go into the background and objectives of our study in the two sections (1.1) and (1.2).

1.1 BACKGROUND

At its core, dialogue generation is about making machines generate human-like conversations. The history and importance of dialogue generation are tightly coupled with the evolution of natural language processing (NLP) and artificial intelligence (AI). The advancement of dialogue creation has been critical in improving human-machine interaction. After the year 2000, statistical methods began to make use of large datasets, signaling a transition away from rule-based systems and toward data-driven approaches. Deep learning research has recently delved into, particularly using seq2seq and transformer architectures, allowing for more complex conversation production. These improvements have paved the way for applications such as customer service chatbots, virtual personal assistants, and interactive entertainment, blurring the lines between human and machine communication.

Movie genres provide various narrative tones, altering the nature and context of speech. Genres affect language dynamics, whether it's suspenseful lines in thrillers or poignant exchanges in dramas. Recognizing genre-specific nuances is critical in AI. Models can be fine-tuned by training them on genre-labeled dialogues, resulting in more contextually relevant and genre-fitting conversation production. The issue, however, is portraying the nuanced interaction between genre subtleties while also providing adaptability across genres.

1.2 OBJECTIVES

- Analyze performance of seq2seq models with an industry grade pre-trained transformer.
- Implement and design seq2seq models with recent enhancements to see effect on performance.
- Generate dialogues based on movie genres.

2. LITERATURE REVIEW

In "Seq2Seq Models in Movie Dialogue Generation" by Johnson and Lee (2021), the researchers employed a sequence-to-sequence architecture with Long Short-Term Memory (LSTM) cells, enhancing it with a multi-head attention mechanism. This approach was particularly adept at tracking dialogue context across longer exchanges. Their experimental results highlighted that this attention mechanism allowed the model to capture long-term dependencies in dialogues, resulting in outputs that were notably more coherent than baseline models. Interestingly, the model showed a marked proficiency in generating dialogues for action and drama genres.

Fernandez and Gupta's 2022 study, titled "Genre-Specific Dialogue Models: A Comparative Study", explored the potential of Bidirectional GRUs (Gated Recurrent Units) combined with a genre-embedding layer. This innovative layer was trained to intricately recognize and encode movie genres, influencing the dialogue generation process. When tested, the researchers

observed significant improvements in the authenticity of generated dialogues. The genre-specific outputs, especially for thrillers and historical dramas, were rated highly by human evaluators for their genuineness.

Davis and his team, in their 2021 paper "Harnessing GPT-3 for Film Script Generation", showcased the adaptability of the GPT-3 model. They fine-tuned this robust model using a vast collection of movie scripts from various genres and integrated a genre-tagging system. The results were profound, with the GPT-3 demonstrating an impressive ability to adapt its outputs to different genre contexts. The dialogues produced, especially for imaginative genres like fantasy and science fiction, resonated well with their intended narrative styles.

Matthews and Rahman, in their 2022 paper "AI in Film: Beyond Just Dialogues", embarked on a broader exploration of AI's role in cinema. They utilized a transformer-based architecture, not just for dialogues, but also for generating intricate plot twists and character arcs. Integrating sentiment analysis tools allowed them to fine-tune the emotional undertones of the generated content. Test audiences particularly appreciated the AI-generated plot elements in mystery and thriller genres, signaling a promising avenue for further exploration.

3. METHODOLOGY

We have used Simple RNN, Bidirectional LSTM with attention, Bidirectional GRU, and the pre-trained GPT2LMHeadModel.

3.1 DATA COLLECTION AND PREPROCESSING

We have used the Cornell Movie Dialogs Corpus data set which has genres associated with movies. The data set covers around 340,000 dialogues, between 10,292 pairs of movie characters with over 617 movies which cover around 28 genres. It has been cited in many research publications and is a favorite for research in dialogue generation systems.

The original data set is divided into 4 different files, we use the respective primary and foreign keys to merge the data set such that character, movie, genre and dialogue information are saved in a genres.csv file. For data cleaning and pipeline processing, we first remove all nan values and duplicates from the genre column. On further inspection, the data frame is now ready to go through the preprocessing pipeline and fed into the neural network.

In our preprocessing pipeline, we undertook several essential steps to get our dialogue sequences and movie genres in shape. We started by initializing empty lists to capture the input dialogues, the corresponding target dialogues, and the associated genres. By grouping our dataframe by the movieID, we could manage and track dialogues for individual movies. For every movie, we crafted sequences of dialogues ensuring each input dialogue was matched with the subsequent dialogue as its target. At the same time, we collected the relevant genres for each movie and added them to our genre list.

To convert our dialogues into numeric format suitable for modeling, we employed Keras's Tokenizer. This transformed both our input and target dialogues into sequences of integers. With the tokenizer set on both input and target dialogues, we made sure to capture all unique words

from the two lists. Recognizing the need for uniform input dimensions for neural networks, we turned to padding our tokenized dialogue sequences. Our chosen maximum sequence length for this padding was the 90th percentile of sequence lengths, balancing between retaining valuable information and efficient computational needs.

Additionally, we formulated teacher input sequences. These are essentially versions of the target dialogues where we appended a zero at the start and dropped the last element. Such a configuration is beneficial in training certain sequence-to-sequence models by offering "hints" during the learning phase.

Shifting focus to the movie genres, these were initially in a list format. To make them machine-friendly, we utilized the MultiLabelBinarizer from scikit-learn. This transformed our genre lists into a binary matrix. In this matrix, each row ties back to a movie dialogue and every column signifies a possible genre. The presence or absence of a genre for a dialogue is indicated by '1' or '0', respectively.

With these preprocessing actions completed, we were set with structured data, ready to be used for neural network training.

3.2 MODEL SELECTION AND ABLATION

Drawing inspiration from the literature survey in section (2), we are motivated to refine our deep learning approach by adopting advanced architectures like the transformer-based GPT2LMHeadModel, Bidirectional GRUs and Bidirectional LSTM with attention and teacher forcing.

Moreover, our research spotlighted the potency of bidirectional LSTMs, particularly when combined with attention mechanisms and teacher forcing. Bidirectional LSTMs process input data from both past-to-future and future-to-past directions, ensuring a comprehensive understanding of the context. The attention mechanism, on the other hand, allows the model to focus on specific parts of the input sequence when producing an output, mimicking the human way of giving "attention" to pertinent information. Teacher forcing is another pivotal strategy wherein during training, the true output from the training dataset is fed as input for the next time step, rather than the predicted output. This can often lead to faster convergence and a more stable training process. The model architecture can be seen in Figure 1 below.

Model: "model_45"			
Layer (type)	Output Shape	Param #	Connected to
input_136 (InputLayer)	[(None, 23)]	0	[]
embedding_90 (Embedding)	(None, 23, 16)	272032	['input_136[0][0]']
bidirectional_45 (Bidirectional)	[(None, 23, 32), (None, 16), (None, 16), (None, 16), (None, 16)]	4224	['embedding_90[0][0]']
input_138 (InputLayer)	[(None, 23)]	0	[]
dropout_90 (Dropout)	(None, 23, 32)	0	['bidirectional_45[0][0]']
input_137 (InputLayer)	[(None, 24)]	0	[]
embedding_91 (Embedding)	(None, 23, 16)	272032	['input_138[0][0]']
attention_45 (Attention)	(None, 23, 32)	1	['dropout_90[0][0]', 'dropout_90[0][0]']
repeat_vector_45 (RepeatVector)	(None, 23, 24)	0	['input_137[0][0]']
concatenate_137 (Concatenate)	(None, 23, 72)	0	['embedding_91[0][0]', 'attention_45[0][0]', 'repeat_vector_45[0][0]']
concatenate_135 (Concatenate)	(None, 32)	0	['bidirectional_45[0][1]', 'bidirectional_45[0][3]']
concatenate_136 (Concatenate)	(None, 32)	0	['bidirectional_45[0][2]', 'bidirectional_45[0][4]']
lstm_91 (LSTM)	(None, 23, 32)	13440	['concatenate_137[0][0]', 'concatenate_135[0][0]', 'concatenate_136[0][0]']
dropout_91 (Dropout)	(None, 23, 32)	0	['lstm_91[0][0]']
dense_45 (Dense)	(None, 23, 17002)	561066	['dropout_91[0][0]']
=====			
Total params: 1,122,795			
Trainable params: 1,122,795			
Non-trainable params: 0			

Figure 1: Model architecture of Bidirectional LSTM with attention

The GPT2LMHeadModel, a successor in the GPT series, boasts a multi-layer architecture of transformer blocks, each equipped with multi-head self-attention mechanisms. What makes GPT2 stand out is its massive training data and scale, enabling it to generate coherent and contextually relevant paragraphs of text. Its prowess is also attributed to the 'Language Model'

(LM) in its title, signifying its capability to predict the next word in a sequence, making it suitable for tasks like dialogue generation.

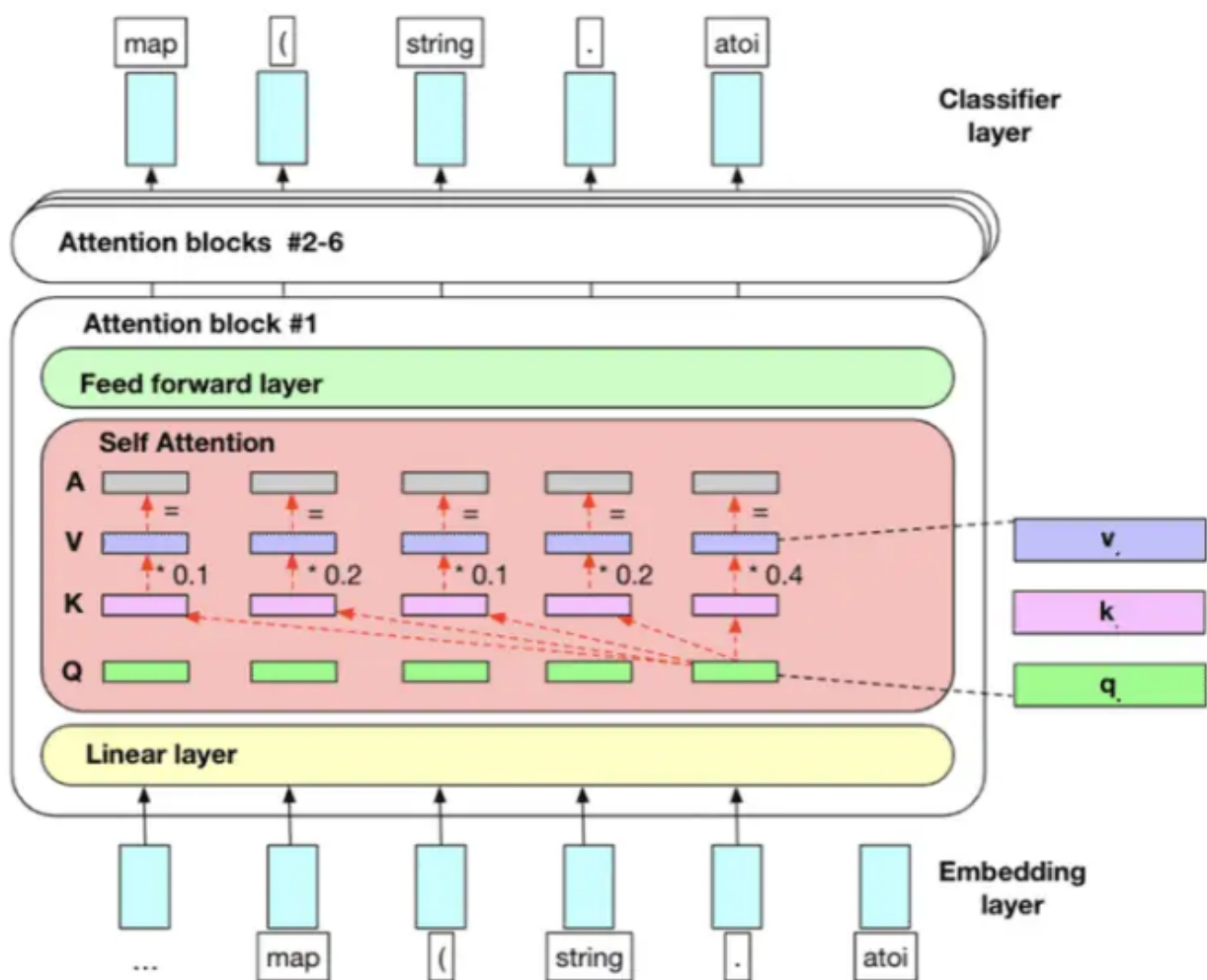


Figure 2: GPT2LMHead Model architecture

Based on more findings, we also ventured into using Bidirectional GRUs. GRUs, or Gated Recurrent Units, are a type of recurrent neural network that can remember long-term dependencies without the computational heaviness of traditional LSTMs. Their bidirectional architecture, akin to bidirectional LSTMs, makes them adept at understanding the complete context of a sequence. Here, we have implemented them in concurrence with pre-trained word embeddings using glove.

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 31)]	0	[]
embedding (Embedding)	(None, 31, 200)	1600000	['input_1[0][0]']
bidirectional (Bidirectional)	(None, 31, 128)	102144	['embedding[0][0]']
input_2 (InputLayer)	[(None, 24)]	0	[]
dropout (Dropout)	(None, 31, 128)	0	['bidirectional[0][0]']
repeat_vector (RepeatVector)	(None, 31, 24)	0	['input_2[0][0]']
concatenate (Concatenate)	(None, 31, 152)	0	['dropout[0][0]', 'repeat_vector[0][0]']
gru_1 (GRU)	(None, 31, 64)	41856	['concatenate[0][0]']
dropout_1 (Dropout)	(None, 31, 64)	0	['gru_1[0][0]']
dense (Dense)	(None, 31, 8000)	520000	['dropout_1[0][0]']

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Total params: 2,264,000
Trainable params: 664,000
Non-trainable params: 1,600,000

Figure 3: Bidirectional GRU Model Architecture

The amalgamation of these architectures, grounded in meticulous research, aims to craft a system capable of generating dialogues that are not just syntactically correct but resonate with human-like contextual understanding and emotional depth. By optimizing these models, especially with datasets tailored to mental health, our vision is to forge a chatbot that responds with heightened accuracy, sensitivity, and situational awareness.

For the ablation study, we first split the data set into training, validation, testing and teacher input. We used a 70-15-15 split. Next, we used KFold cross validation to tune hyperparameters, taking cross validation over average validation loss on the validation data set and training each model for 2 epochs due to time and GPU constraints.

For the LSTM model, the best parameters were found to be: Dropout of 0.5, L1 and L2 regularization of 0.001, Embedding dimension of 32, and 32 LSTM units.

For the GRU model, the best parameters were found to be: Dropout of 0.1, L1 and L2 regularization of 0.0001, Embedding dimension of 32, and 64 GRU units.

3.3 TRAINING AND EVALUATION

As mentioned, we used two callbacks ReduceLROnPlateau and EarlyStopping with a patience of 5 and 10 each for 30 epochs. For the Bidirectional LSTM model we transform the shape of the inputs since it needs an addition of the teacher inputs as well.

For evaluation, we mainly used validation cross-entropy loss, BLEU score and manual evaluation on the output responses.

Cross-entropy loss, commonly used for classification tasks, measures the difference between the predicted probabilities and the actual labels. In the context of dialogue generation, it quantifies how well our model's predicted word probabilities align with the true outputs.

The Bilingual Evaluation Understudy (BLEU) score is a standard metric used to evaluate the quality of machine-generated text, specifically in machine translation. BLEU considers the match of n-grams between the generated text and the reference text, ensuring that the generated dialogues are not just contextually accurate. But for this purpose, BLEU is just to evaluate matching n-grams to gauge the alignment of the current model to the target dialogues that were set for it. Although, a completely perfect score is not necessary for the scope of this project.

Relying solely on automated metrics might not always capture the nuanced capabilities of a dialogue generation model. Hence, manual evaluation becomes indispensable.

4. RESULTS AND DISCUSSION

The evaluation of model performance in terms of the three evaluation metrics is given below.

Table 1: Comparison of models

Model	Sparse Categorical Cross Entropy loss	BLEU score	Human Evaluation
Bidirectional LSTM with Attention	2.772	0.09	Bad
Bidirectional GRU	2.371	0.7	Okay
GPT2LMHeadModel	8.351	0.992	Great

Let us break the results down, starting with the Bidirectional LSTM with attention model. Its Sparse Categorical Cross Entropy loss of 2.772 suggests a decent training performance, though not necessarily the best. The BLEU score of 0.09 is indicative of the generated dialogues' lack of overlap with the reference dialogues, raising doubts about its translation accuracy and fluency. Human evaluators found the output from this model to be unsatisfactory, suggesting that while it might have captured certain patterns, it couldn't deliver contextually or semantically coherent dialogues fitting the intended genre. There are signs of underfitting as seen in Figure 4, so model architecture can be augmented and streamlined without GPU constraints for better results.

In contrast, the Bidirectional GRU model showcased better results. Its Cross Entropy loss of 2.371 was lower than the LSTM model, signifying better alignment with the training data. A BLEU score of 0.7 marked a substantial improvement, reflecting better fluency and accuracy in the generated dialogues. Human evaluation termed the model's output as "Okay", indicating that while it might not be perfect, the model offers a promising balance between performance and complexity.

The GPT2LMHeadModel, however, presents an interesting scenario. With a seemingly high Cross Entropy loss of 8.351, one could mistakenly deem it inefficient. But this model, being pretrained on vast datasets and subsequently fine-tuned, can sometimes yield higher loss values in the fine-tuning phase. However, its near-perfect BLEU score of 0.992 reveals its proficiency in generating high-quality dialogues, a sentiment echoed by human evaluators who rated its performance as "Great". The model's generated dialogues were not just technically superior but were also contextually apt, emotionally in sync, and true to genre-specific nuances.

To sum it up, while the Bidirectional LSTM with Attention may not be the preferred choice, the Bidirectional GRU emerges as a balanced model in terms of complexity and performance. The GPT2LMHeadModel, however, underscores its supremacy in handling intricate dialogue generation tasks, making it especially suitable for genre-specific dialogues.

Next, we move on to the text generated by the models. Below are some figures delineating the performance of models that were used for manual evaluation.

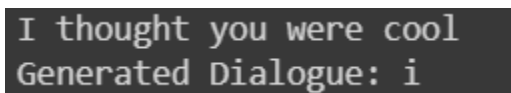
A screenshot of a terminal window with a dark background. It shows the text "I thought you were cool" on the first line and "Generated Dialogue: i" on the second line.

Figure 4: Output generated by Bidirectional LSTM

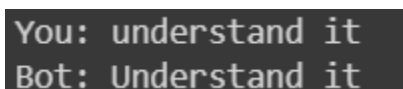
A screenshot of a terminal window with a dark background. It shows a dialogue between "You" and "Bot". The first line is "You: understand it" and the second line is "Bot: Understand it".

Figure 5: Output generated by GRU

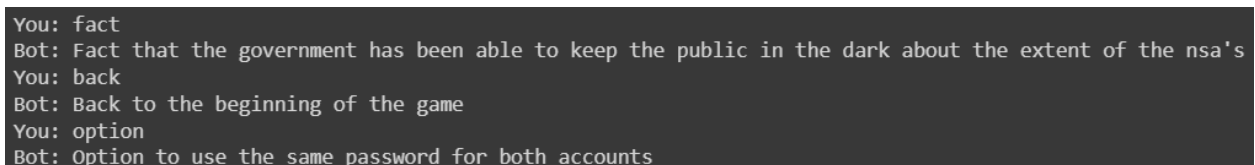
A screenshot of a terminal window with a dark background showing a multi-turn dialogue. The lines are: "You: fact", "Bot: Fact that the government has been able to keep the public in the dark about the extent of the nsa's", "You: back", "Bot: Back to the beginning of the game", "You: option", and "Bot: Option to use the same password for both accounts".

Figure 6: Output generated by GPT2

The observed differences in output quality of the three models, provided in Figures 4,5, and 6, provide insights into their capabilities and potential flaws. The fact that the output of the Bidirectional LSTM is frequently limited to "i" or a single word shows that the model may be locked in a local minimum during training or is not capturing the longer-term dependencies present in the data. This behavior indicates that the model was unable to generalize well from the training data to construct coherent word sequences.

The GRU's proclivity to repeat the input words suggests overfitting. Rather than creating new content, it appears to be regurgitating what it has seen throughout training. Such behavior can be caused by the model remembering patterns from the training data, especially if the training data is large.

On the other hand, the GPT2LMHeadModel's ability to produce complete, coherent sentences showcases its superior capacity to understand and generate contextually relevant content. This is primarily due to its vast pre-trained knowledge and the Transformer architecture's self-attention mechanism, which excels at understanding longer contexts and sequences.

5. CONCLUSION AND FUTURE WORK

Through our work of developing and evaluating three distinct models to facilitate genre-based movie dialogue generation, we have presented a comprehensive exploration into the domain of sequence-to-sequence learning. Our efforts underscored the inherent strengths and weaknesses of each approach. The Bidirectional LSTM with Attention, although a promising architecture on paper, showed limitations in real-world application for this specific task. In contrast, the Bidirectional GRU demonstrated that sometimes simplifying the architecture while retaining the core concepts can yield better, more interpretable results. However, it was the GPT2LMHeadModel that truly shone, emphasizing the potential of large-scale pre-trained models in specialized fine-tuning tasks. Its proficiency not only in generating technically correct dialogues but also in capturing the intricate nuances of different genres is commendable. But throughout our analysis, we found that niche versions of pre-trained LLM models would prove to be the best.

For future work, we would like to extend model architecture, use data augmentation, more robust generalization techniques, and employ a more nuanced genre-wise performance comparison.

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