Sentiment-based Lyrics Generator.

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I. Introduction

This project aims to build a GPT-based model that generates new song lyrics with a specified sentiment. The model will be trained using a dataset containing song lyrics with associated sentiment labels (happy, sad, or neutral). The goal is to fine-tune the GPT model so that it can create coherent and creative lyrics that match the given sentiment.

This text generation project combines sentiment analysis with creative text generation to produce sentiment-specific song lyrics. By fine-tuning a GPT-based model, it aims to generate coherent and creative lyrics matching the desired sentiment. The approach involves using sentiment labels as prefixes during fine-tuning to help the model learn the relationship between sentiment and lyrics. The soundness of the task relies on the GPT model's capabilities, sentiment-guided generation, and fine-tuning on a domain-specific dataset, resulting in a reliable model for sentiment-specific lyrics generation.

The implementation makes sense because it leverages the strengths of GPT-based models and follows a well-established fine-tuning process to learn the intricacies of song lyrics and the relationship between sentiment and lyrics. This approach enables the generation of creative, coherent, and sentiment-specific lyrics

The dataset we used for training the model is "lyrics-data.csv"[1]. Below is a representation of the dataset.



Figure 1. lyrics dataset.csv

II. Methodology

We first removed unnecessary columns (refer to Figure 1) namely, "ALink", "SName", and "SLink" as they are not necessary for this task. Next, we dropped all the languages except English as it is the only language we are interested in for this task.

Since we want to generate lyrics with a specific sentiment attached to it we implemented that using TextBob library, which is a simple and convenient tool for natural language processing tasks, including sentiment analysis. TextBlob calculates sentiment polarity, which is a score ranging from -1 (most negative) to 1 (most positive), with 0 representing neutral sentiment. Here, 0 was the threshold, if the score > 0 then "happy" else if the score < 0 "sad", else "neutral".

	Lyric	language	sentiment
69	I feel so unsure\nAs I take your hand and lead	en	happy
86	Don't let them fool, ya\nOr even try to school	en	happy
88	Baby, let's cruise, away from here\nDon't be c	en	happy
111	Know it sounds funny\nBut, I just can't stand	en	happy
140	You've got that look again\nThe one I hoped I	en	happy

Figure 2. Added "sentiment" feature

On further data analysis, we discovered that there was a significant class imbalance.

happy	134386	
sad	54946	
neutra	1 2482	
Name:	sentiment, dtype:	int64

Figure 3. Class Imbalance

In order to avoid any kind of bias in our model we downsampled "happy" instances to bring it closer to the number of "sad" instances and we completely dropped "neutra" instances as it was very small in quantity.

	Lyric	language	sentiment	lyrics_with_sentiment
86	Don't let them fool, ya\nOr even try to school	en	happy	happy: Don't let them fool, ya\nOr even try to
88	Baby, let's cruise, away from here\nDon't be c	en	happy	happy: Baby, let's cruise, away from here\nDon
111	Know it sounds funny\nBut, I just can't stand	en	happy	happy: Know it sounds funny\nBut, I just can't
140	You've got that look again\nThe one I hoped I \dots	en	happy	happy: You've got that look again\nThe one I h
168	Everyone's feeling pretty\nlt's hotter than Ju	en	happy	happy: Everyone's feeling pretty\nlt's hotter

Figure 4. Concatenate "sentiment" and "Lyric"

In the process of fine-tuning, the GPT model acquires knowledge of the correlation sentiment as a prefix to the lyrics and learns to produce lyrics that align with the given sentiment.

As the model is fine-tuned, it takes in the concatenated input and makes an effort to anticipate the subsequent token in the sequence by considering the context. The sentiment prefix and the lyrics are both taken into account during this process, allowing the model to identify the patterns and connections between them. As a consequence, the model improves its ability to generate lyrics that match the desired sentiment.

Below is a brief description of our fine-tuning methodology:

- Load a pre-trained GPT-2 model from the Hugging Face Transformers library.
- 2. Define the training arguments, such as the number of training epochs, batch size, and evaluation strategy, to configure the fine-tuning process.
- Create a Trainer object from the Hugging Face library, which takes the
 pre-trained model, training arguments, data collator, and datasets for training
 and evaluation as inputs.
- 4. Fine-tune the GPT-2 model using the Trainer's train() method. This step adjusts the pre-trained model's parameters based on the provided training dataset, tailoring the model to the specific task of sentiment-guided lyrics generation.

III. Evaluation

During training, we get the following as our validation-set loss.

Epoch	Training Loss	Validation Loss
1	3.179900	3.640633
2	2.961100	3.642054
3	2.789800	3.666516
4	2.639000	3.699453
5	2.541300	3.740723
6	2.419600	3.777518
7	2.336100	3.825857
8	2.292300	3.875850
9	2.261000	3.888371
10	2.216300	3.907690

Figure 5. Training/Validation Loss

We think this is a sign of overfitting as the training loss is monotonically decreasing. This may not be a problem at all in case we do more training iterations as the mode could be learning patterns in our training data set and hence causing a slight loss. But in any case, we could be more cautious and apply some regularization and tune the hyperparameters by adjusting learning rates, batch sizes, etc.

We split our training data into train and validation (80:20 split) data sets and will be using perplexity for evaluation purposes. Using perplexity as an evaluation metric in this sentiment-guided lyrics generation project makes sense as perplexity evaluates the model's ability to predict the next token in a sequence, which is an essential aspect of text generation which is essentially our task. Lower perplexity means the model has learned the structure of the input text, including the lyrics and the sentiment prefixes, more effectively.

GPT-based models are pre-trained on a large corpus of text and are fine-tuned for specific tasks. Perplexity is a relevant metric for these models, as it measures how well the fine-tuned model generalizes to the given dataset.

We got a perplexity score of 49.783832694649114, which is not a desired result but given the amount of data we trained I think we can improve with more data, regularization, and better hyperparameter tuning.

IV. Generated Lyrics

After training we finally generate our lyrics with a sentiment attached to them. Below are two examples of "sad" lyrics and a "happy" lyrics.

Figure 6. Sad Lyrics Figure 7. Happy Lyrics happy: ive never been afraid I will always remember you sad: ive seen the best of both worlds the worlds of cleveys and sandals My first love song nascar, planes, boats I will always remember you birds eye, laser rays Even though hate will blind us and tear us apart aint nothing like tennis shoes I will Tigger every step of the way I know, my eyes, I'm blessed with eyes smellin like whiskey No matter what, I will never walk away all through my heart As you always will cause all that matter is love I will always remember you My first love song I will always remember you Chorus: Even though hate will blind us and tear us apart If i tell you right, god will know I will Tigger every step of the way if i'm right this time if i'm wrong this time

The lyrics' sentiment does seem to follow our expectations!

References

- [1] Dataset, "lyrics-data.csv", https://www.kaggle.com/datasets/neisse/scrapped-lyrics-from-6-genres
- [2] HuggingFace, "GPT-2", https://huggingface.co/gpt2
- [3] Shah, P. (2020, November 6). My Absolute Go-To for Sentiment Analysis—TextBlob. Medium.

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