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Lyrics Generation with Deep Learning Models
Group 14: Jiaqin Wu, Kefan Yu, Naihuan Jing

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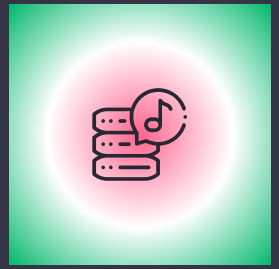
01

Background & Research Objectives

Background

Today, music is a universal source of joy and relaxation, featuring a rich variety of popular songs that connect with audiences worldwide. More than just a pleasant sound, the blend of lyrics, rhythms, and stylistic elements plays a crucial role in a song's popularity. Artists use their unique styles, and even the song's title can greatly impact how it's received.

Research Objectives

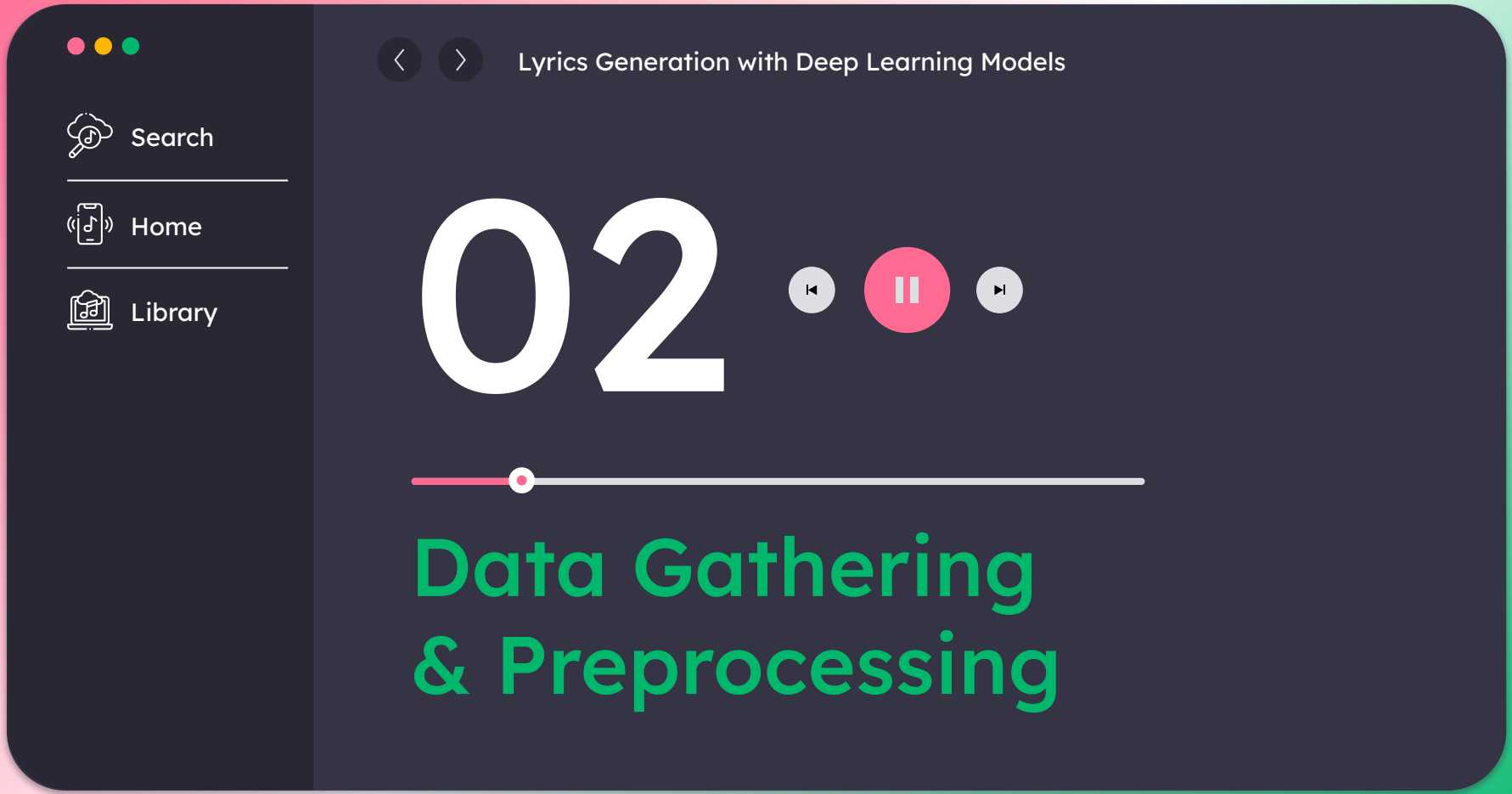


RNN

Pre-trained Models

Research Objectives

- Lyrics Generator with Starting Sentences
- Lyrics Generator with Artists
- Lyrics Generator with Titles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02
Data Gathering
& Preprocessing

Data Gathering

Source: Kaggle

Features: artist, title, lyrics

Methodology: Download + manually input more records

Final Shape: 1099 records

Data Preprocessing

- Created a Corpus of Lyrics text
- Removed the unrequired characters
- Created a dictionary to map characters and their indices
- Splitted the corpus into smaller sentences of equal length
- Resized and normalized and labels

Preprocessed Data

- The preprocessed corpus would only contain lowercase English alphabets, numbers, and a few punctuations
- Encoding the corpus and creating sequences of equal lengths for features and their corresponding targets
- Each feature and target will represent the mapped index from the dictionary of unique characters

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Lyrics Generation with Deep Learning Models

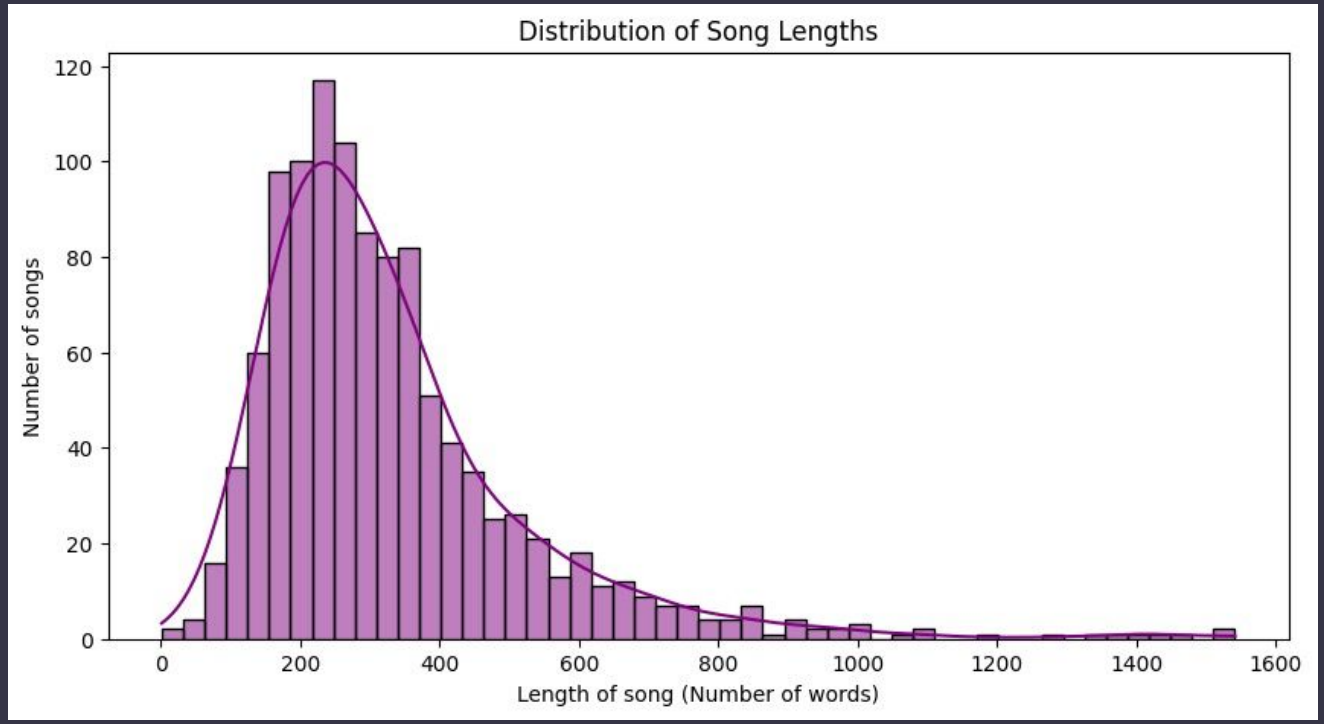
03

EDA

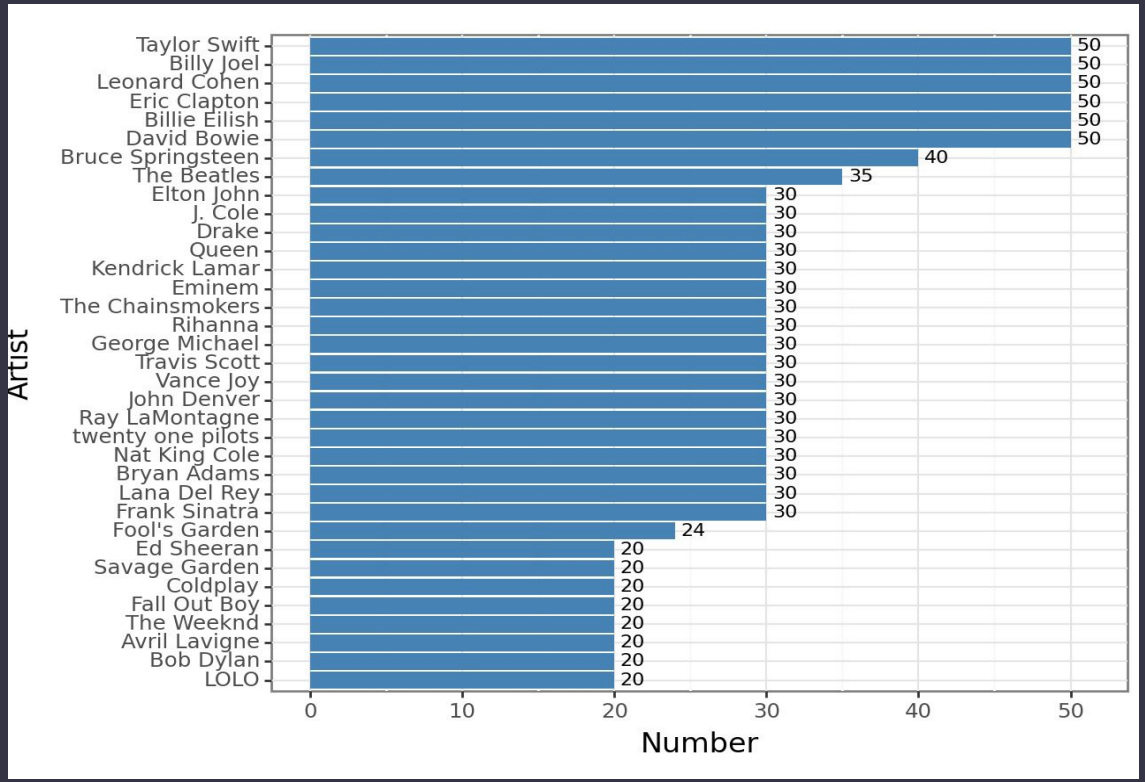
Number of characters/words/lines

	Num_char	Num_word	Num_line
count	1099.000000	1099.000000	1099.000000
mean	1675.098271	390.432211	52.649682
std	1007.412870	244.696049	25.612499
min	1.000000	1.000000	1.000000
25%	1028.000000	231.000000	35.000000
50%	1422.000000	328.000000	48.000000
75%	2014.000000	473.000000	64.000000
max	7846.000000	1828.000000	224.000000

Distribution of Song Lengths



Distribution of Artists



Word Cloud

Common Words in Songs
love
know
now
time
see
one
take
say
got
want
come
go
way
back
feel
cause
never
make
life
yeah
let
baby
will
tell
think
night
need
good
heart
right
thing
ain't
wanna
give
look
la la
na na
yeah yeah
oh oh
man
well
said
day
eye
oh
keep
sh t
nigga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04
Lyrics Generator
with Starting Sentences

RNN Models

- RNN-1: One Hidden Layer + Dropout Rate 0.2
- RNN-2: One Hidden Layer + Dropout Rate 0.3
- RNN-3: Two Hidden Layers + Dropout Rate 0.2

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Lyrics Generation with Deep Learning Models

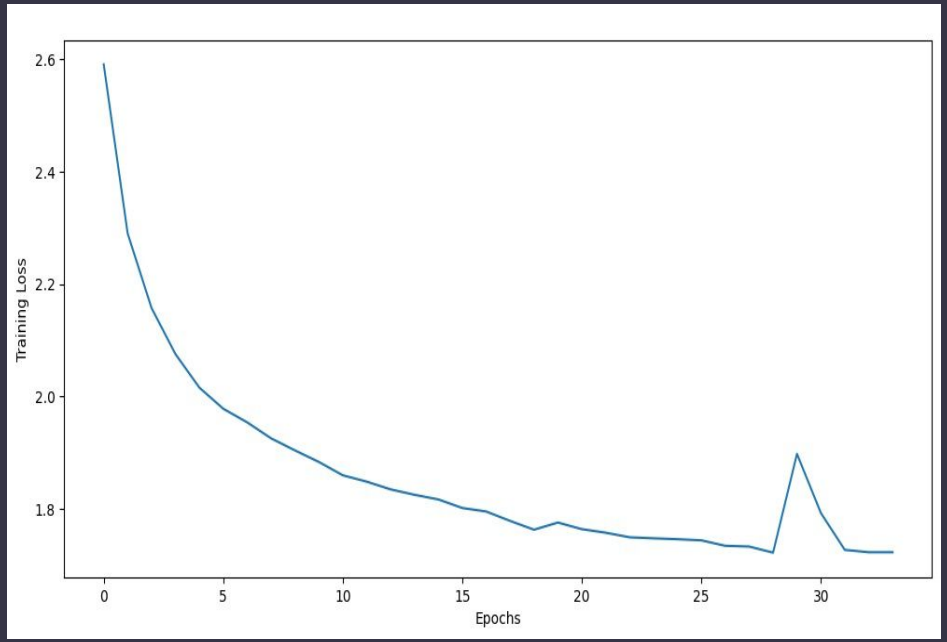
RNN-1

One Hidden Layer + Dropout Rate 0.2

Model Description

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_4 (LSTM)               (None, 256)               264192

 dropout_3 (Dropout)         (None, 256)               0

 dense_3 (Dense)             (None, 47)                12079

=================================================================
Total params: 276271 (1.05 MB)
Trainable params: 276271 (1.05 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

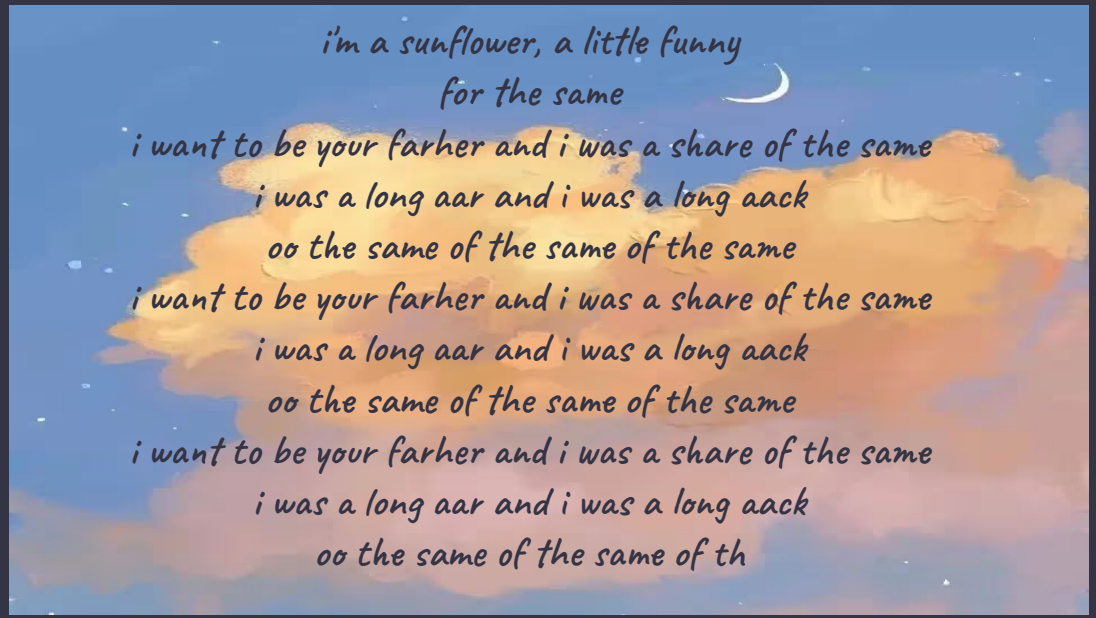
Model Performance



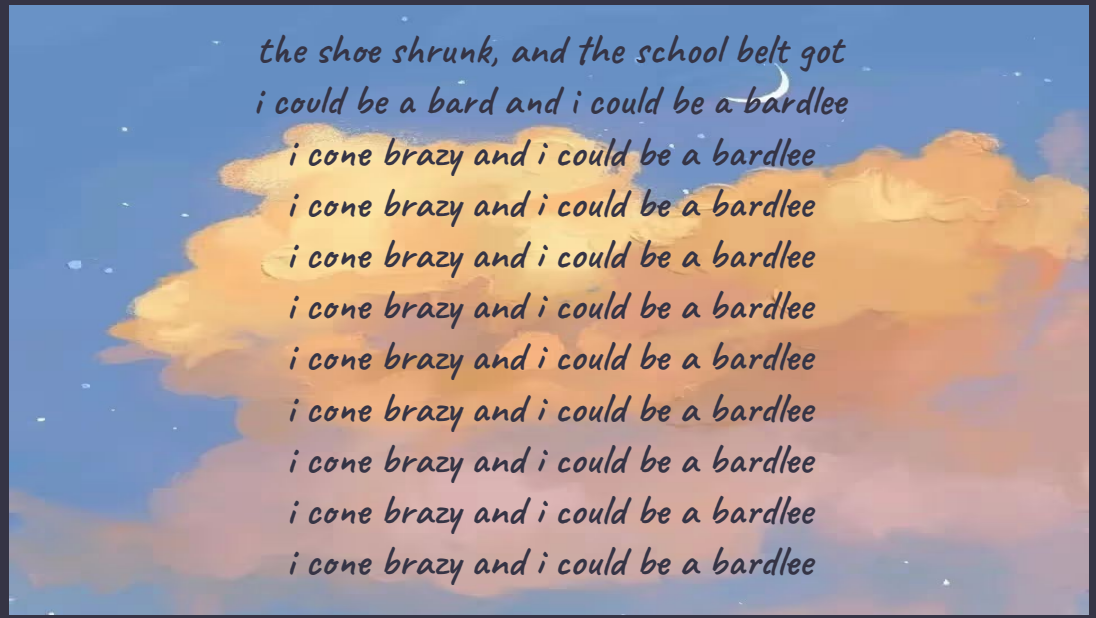
Lyrics Generation Function

```python
# Define a function to generate the text
def generate_text(model, starter, length, temperature=1.0):
    model.eval()
    generated = starter

    with torch.no_grad():
        for _ in range(length):
            seed = [mapping[char] for char in starter]
            x_pred = torch.tensor(seed, dtype=torch.float32).view(1, len(seed), 1).to('cuda')
            x_pred /= float(L_symb)

            prediction = model(x_pred)

            # Ensure prediction is a 2D tensor
            prediction = prediction.squeeze()

            # Applying temperature to control randomness
            prediction = prediction / temperature
            prediction = F.softmax(prediction, dim=0)

            # Sample from the predicted probabilities
            index = torch.multinomial(prediction, 1).item()
            next_char = reverse_mapping[index]

            # Generating new text
            generated += next_char
            starter = starter[1:] + next_char

    return generated
```

Generated Lyrics



Generated Lyrics



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Lyrics Generation with Deep Learning Models

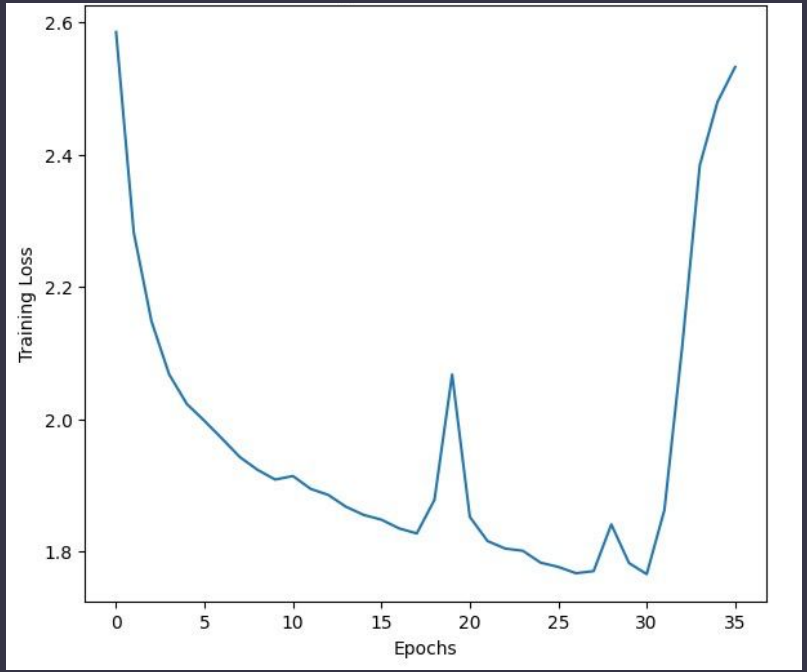
RNN-2

One Hidden Layer + Dropout Rate 0.3

Model Description

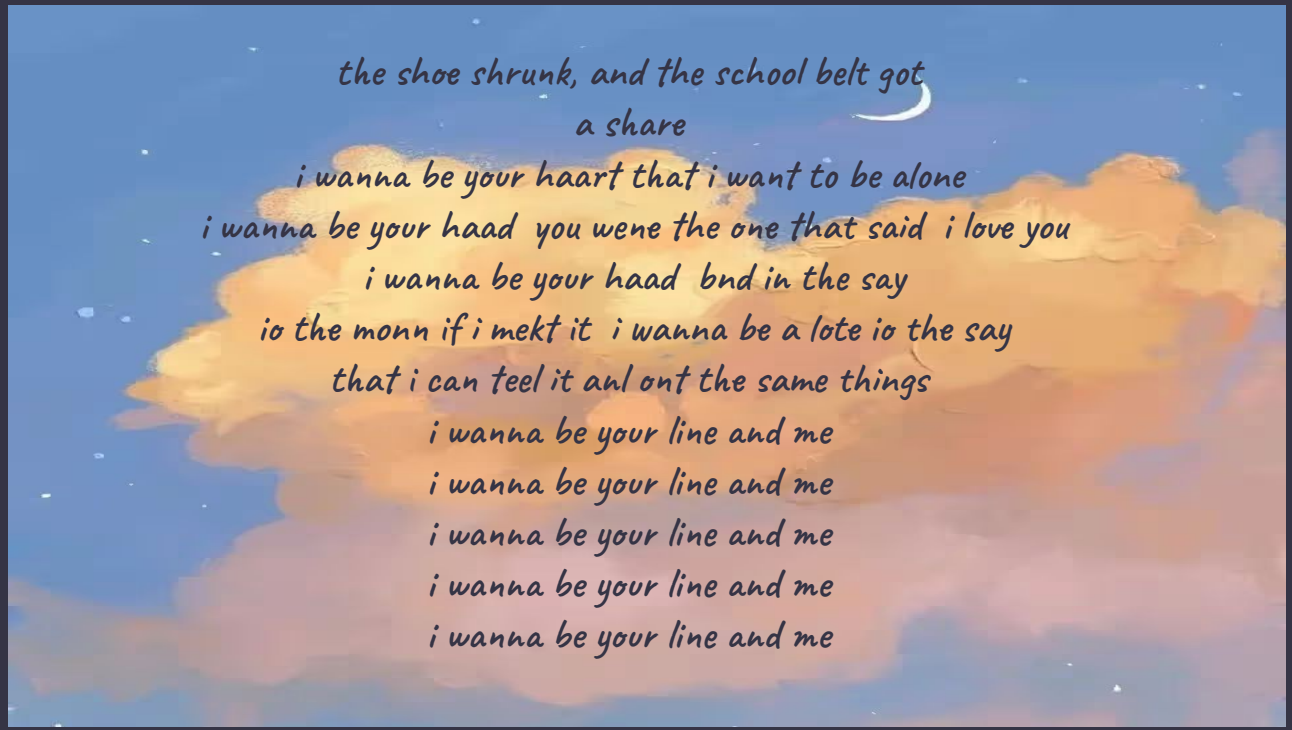
```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_5 (LSTM)               (None, 256)               264192

 dropout_4 (Dropout)         (None, 256)               0

 dense_4 (Dense)             (None, 47)                12079

=================================================================
Total params: 276271 (1.05 MB)
Trainable params: 276271 (1.05 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Model Performance



Generated Lyrics

Generated Lyrics



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Lyrics Generation with Deep Learning Models

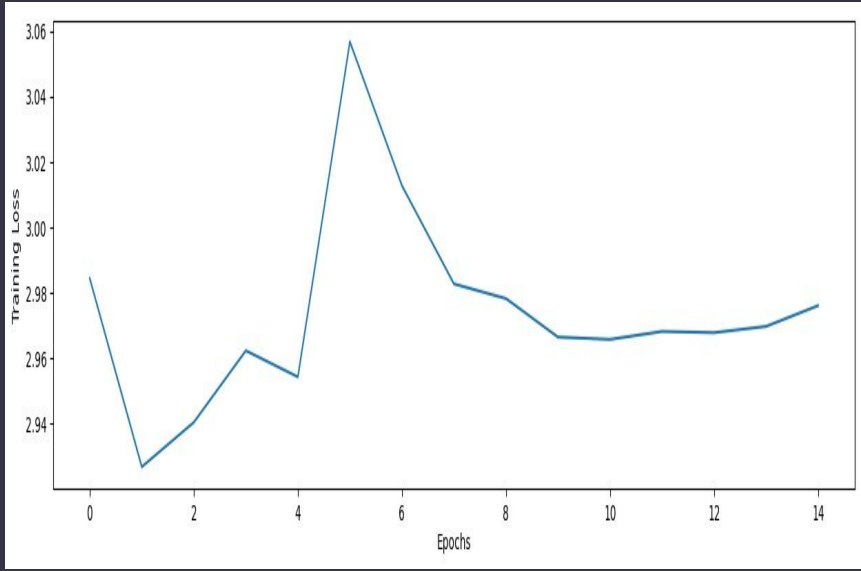
RNN-3

Two Hidden Layers + Dropout Rate 0.2

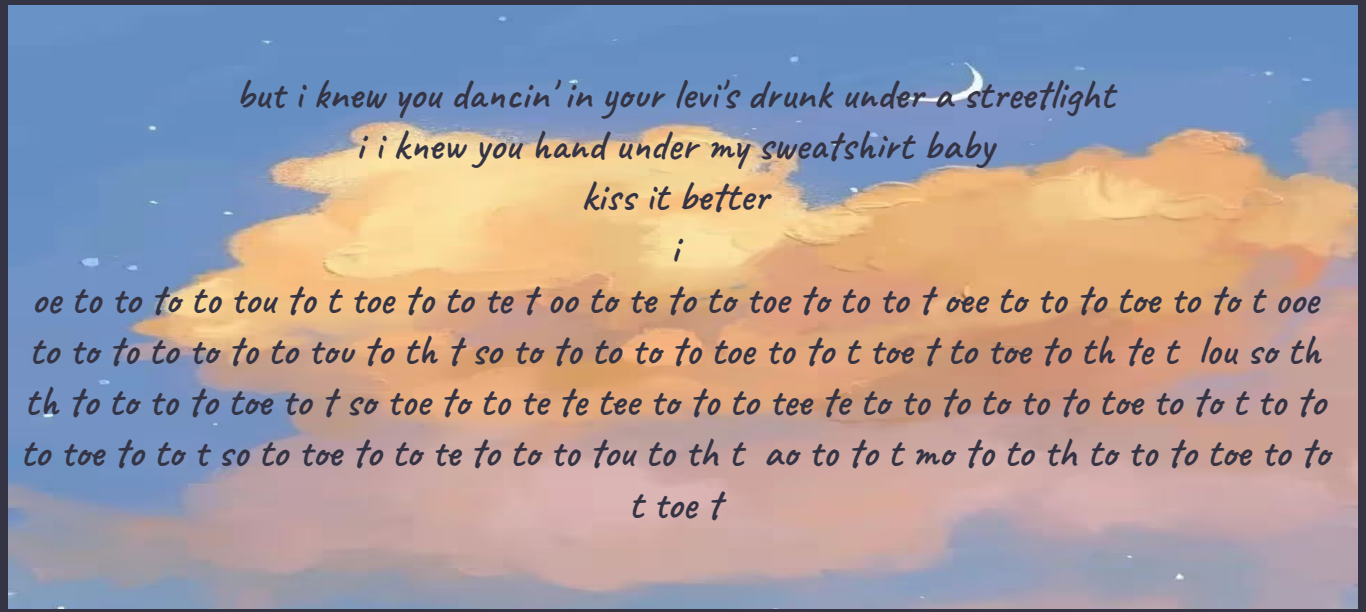
Model Description

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 100, 256)          264192

 dropout (Dropout)           (None, 100, 256)          0

 lstm_1 (LSTM)               (None, 128)               197120

 dropout_1 (Dropout)         (None, 128)               0

 dense (Dense)               (None, 47)                6063

=================================================================
Total params: 467375 (1.78 MB)
Trainable params: 467375 (1.78 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

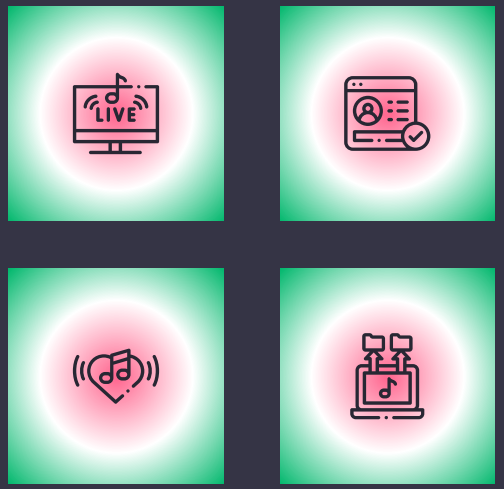
Model Performance



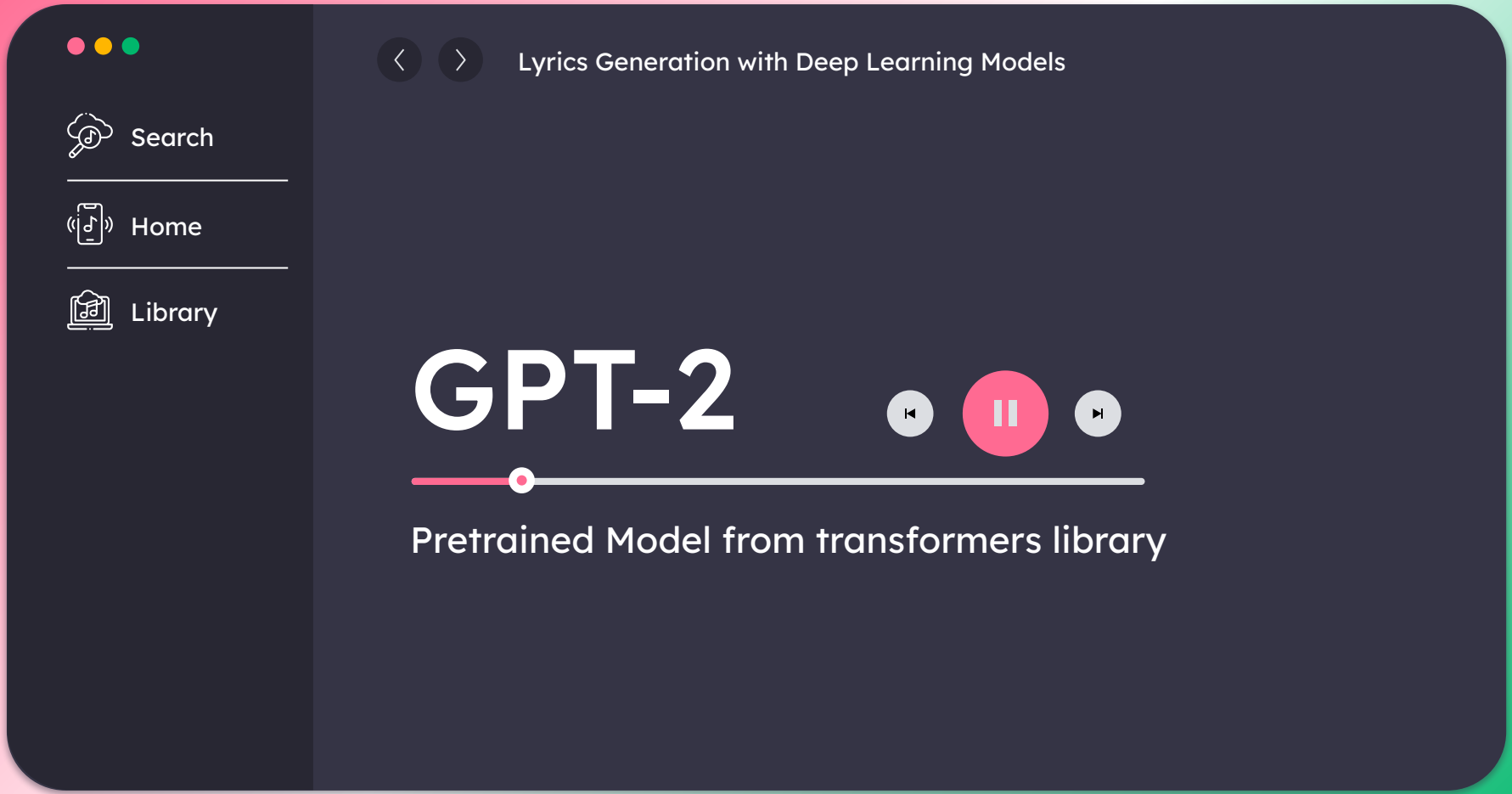
Generated Lyrics



Pre-trained Models



GPT-2
Google's T5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GPT-2
Pretrained Model from transformers library

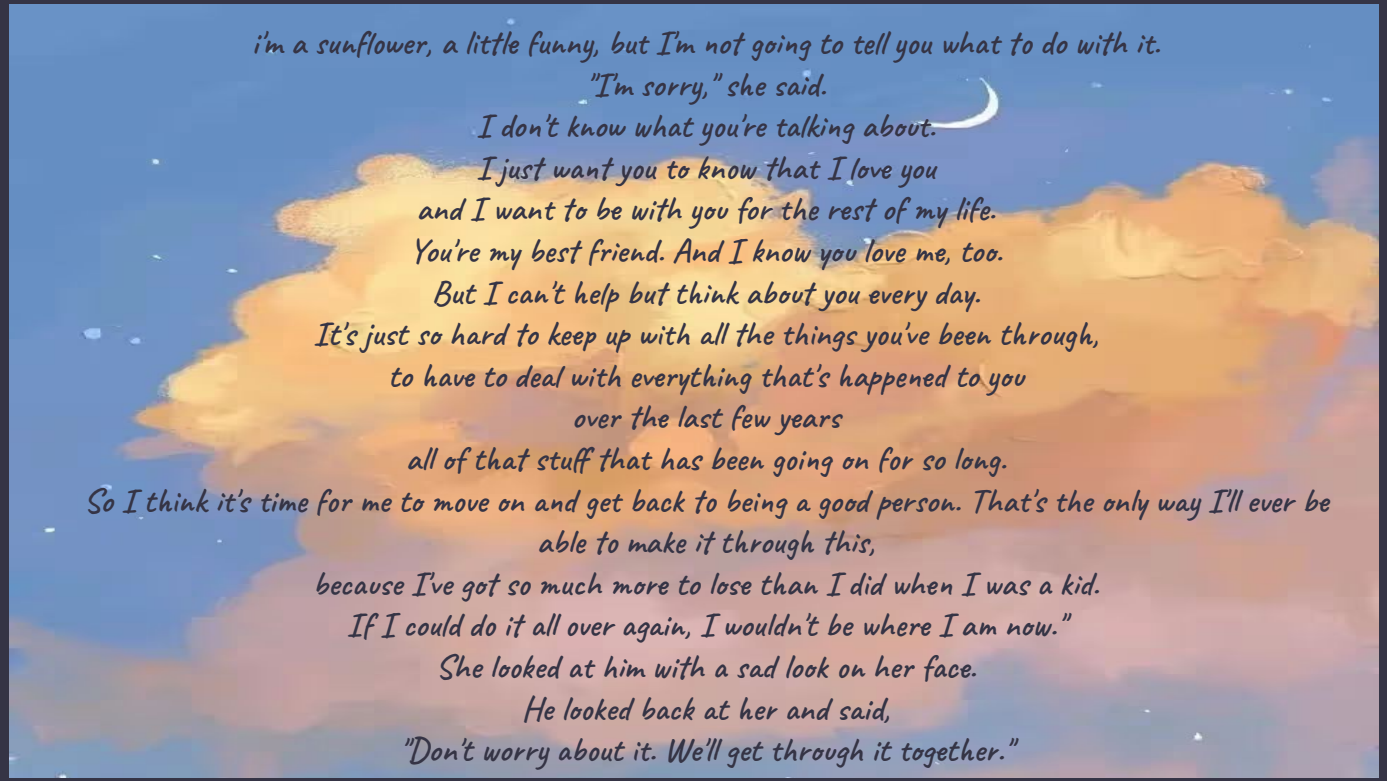
Introduce GPT-2 Model

```
# Install the transformers library
from transformers import GPT2LMHeadModel, GPT2Tokenizer

# Load pre-trained GPT-2 model and tokenizer
model_name = "gpt2"
tokenizer = GPT2Tokenizer.from_pretrained(model_name)
model = GPT2LMHeadModel.from_pretrained(model_name)
# Set the model to evaluation mode
model.eval()
```

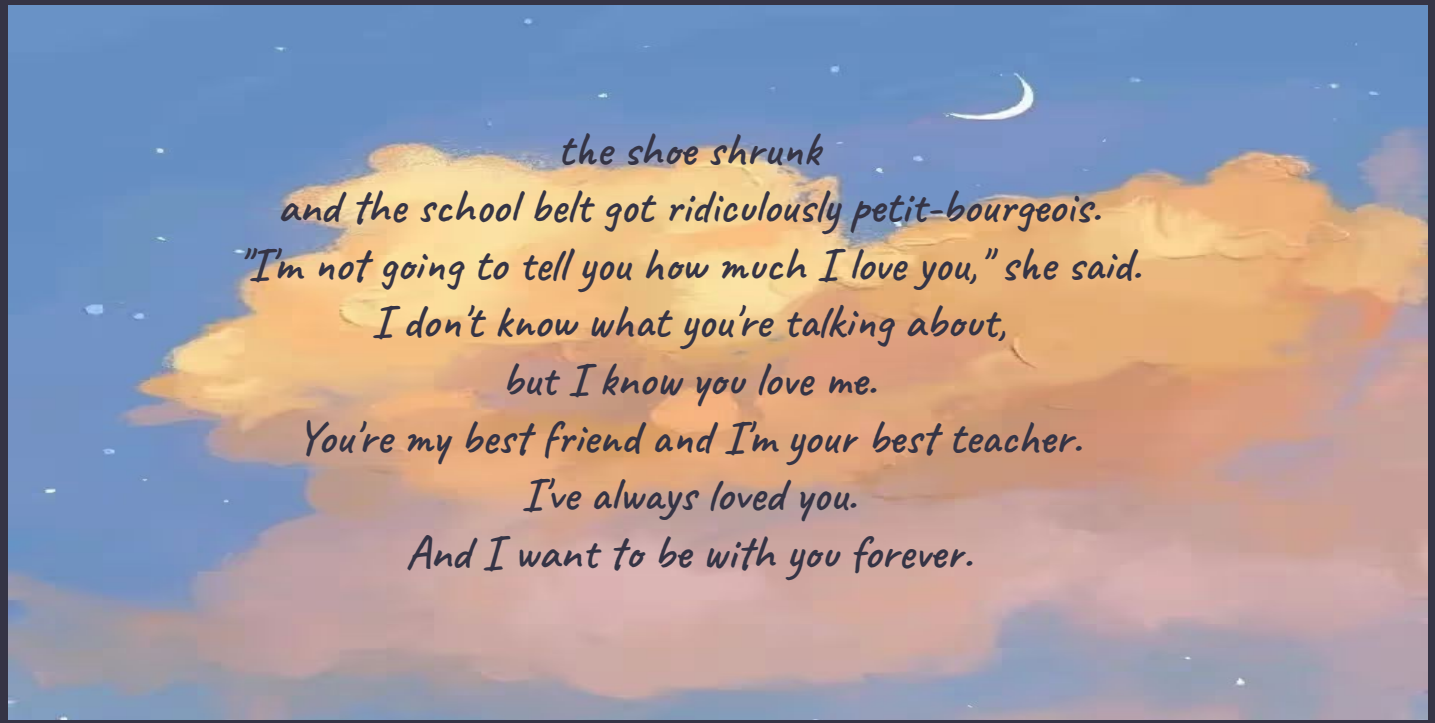
GPT-2: Lyrics Generation

```python
# Function to generate lyrics
def generate_lyrics(prompt, max_length=400, temperature=0.7):
    input_ids = tokenizer.encode(prompt, return_tensors="pt")

    # Generate text
    output = model.generate(
        input_ids,
        max_length=max_length,
        temperature=temperature,
        num_beams=5,
        no_repeat_ngram_size=2,
        top_k=50,
        top_p=0.95,
        pad_token_id=tokenizer.eos_token_id,
    )

    generated_lyrics = tokenizer.decode(output[0], skip_special_tokens=True)

    return generated_lyrics
```

GPT-2: Model Performance



GPT-2: Model Performance

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Google
T5
Pretrained Model from transformers library

Introduce T5

```python
from transformers import T5ForConditionalGeneration, T5Tokenizer

# Load pre-trained T5 model and tokenizer
model = T5ForConditionalGeneration.from_pretrained('t5-small')
tokenizer = T5Tokenizer.from_pretrained('t5-small')
```

T5: Lyrics Generation

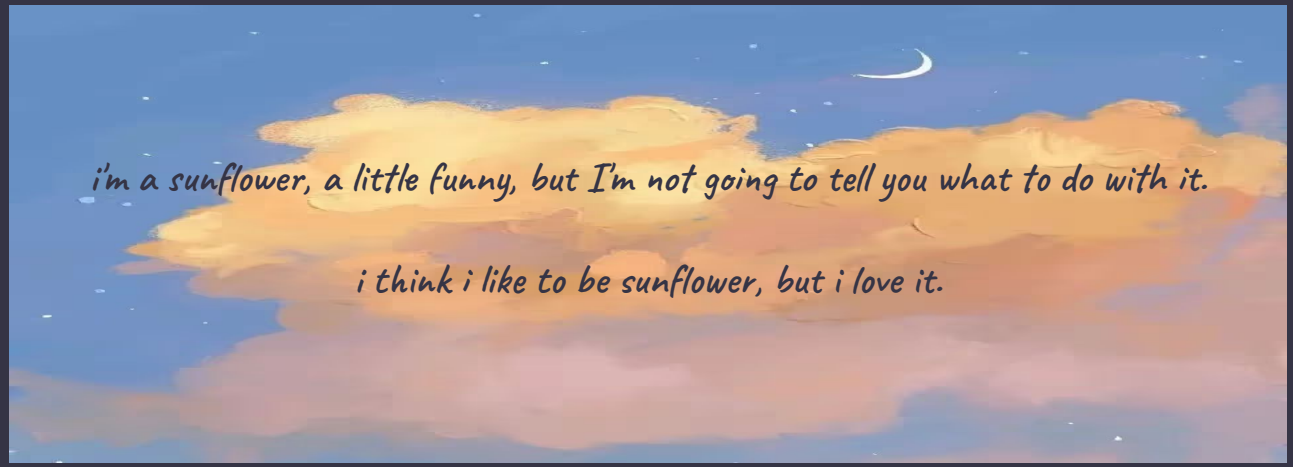
```python
# Function to generate lyrics
def generate_lyrics(prompt, return_tensors="pt", max_length=512, truncation=True):
    input_ids = tokenizer.encode(prompt, return_tensors="pt", max_length=512, truncation=True)

    # Generate text
    output = model.generate(
        input_ids,
        max_length=400,
        num_beams=2,
        no_repeat_ngram_size=3,
        top_k=50,
        top_p=0.95,
        length_penalty=0.2)

    generated_lyrics = tokenizer.decode(output[0], skip_special_tokens=True)

    return generated_lyrics
```

T5: Model Performance



T5: Model Performance

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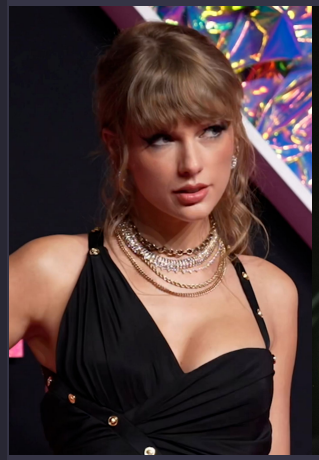
05

Lyrics Generator with Artists

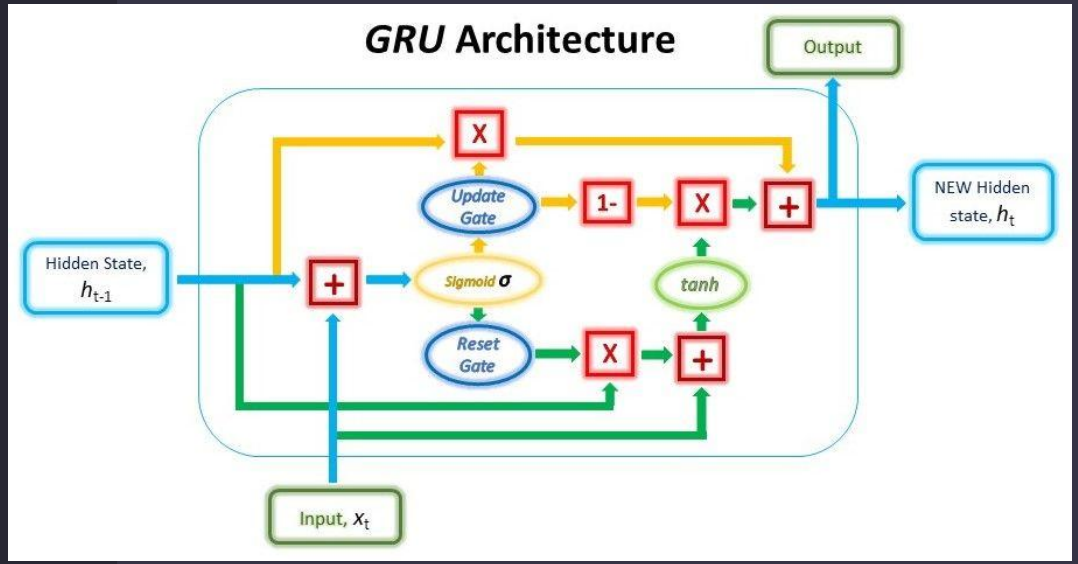
Seed Text: Artist Names

Different artists have their own styles of songs. Therefore, we passed the artist names as seed text to see if the model can generate text with their styles.




Reference: Wikipedia

Gated Recurrent Unit

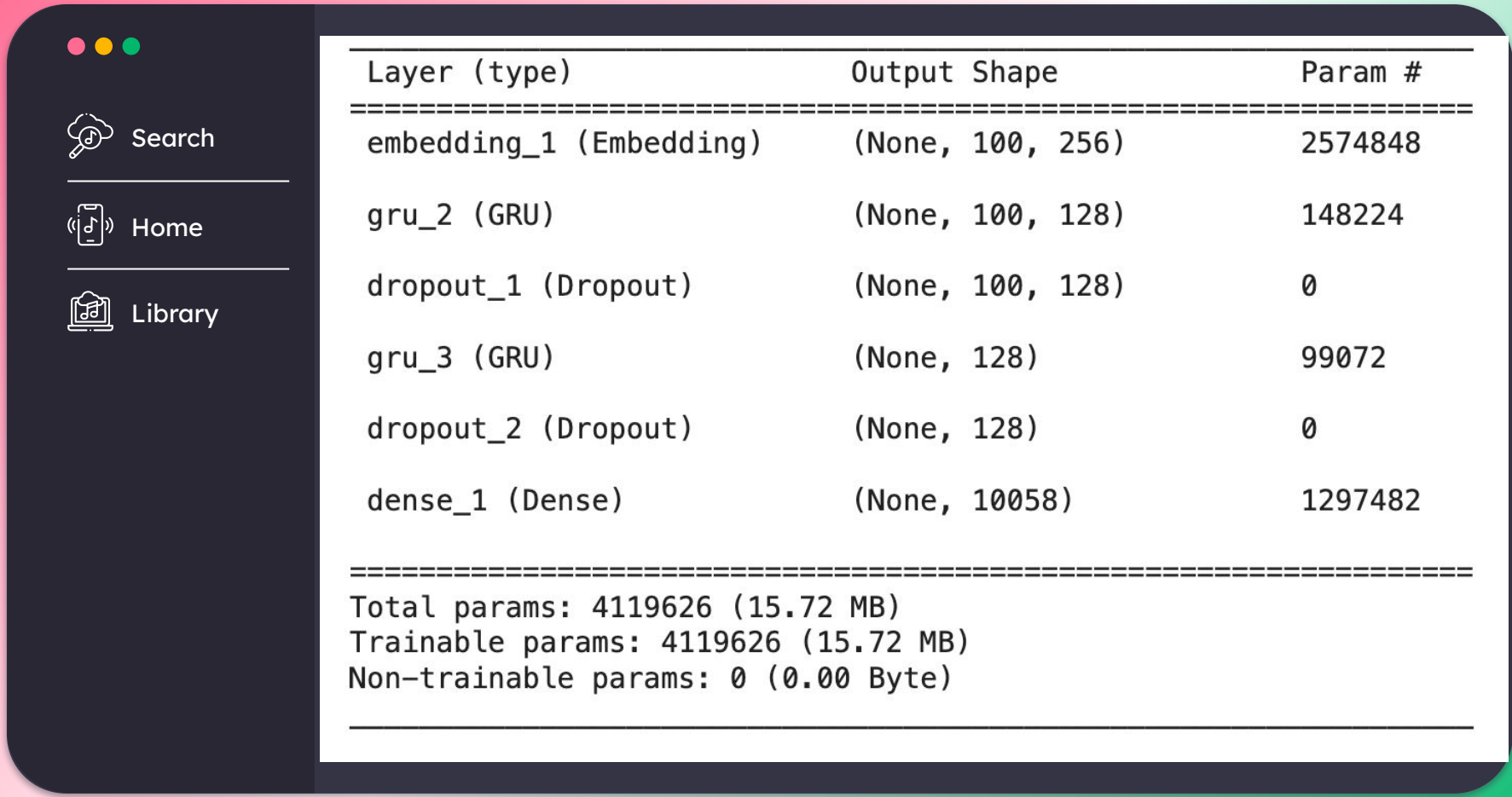


Gated Recurrent Unit (GRU) is a relatively new mechanism designed by Cho et al. at 2014.

GRU gets rid of the cell states in LSTM, and it has a reset gate and an update gate.

Reset gate decides how much pass information to forget. Update gate decides what information to discard and add.

Reference:
https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21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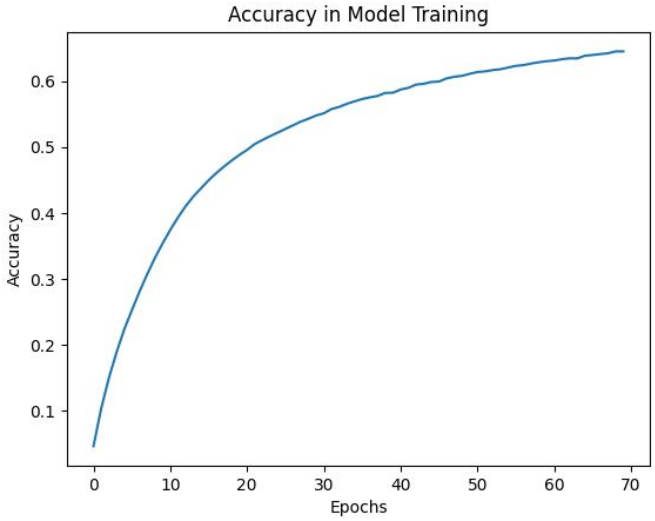
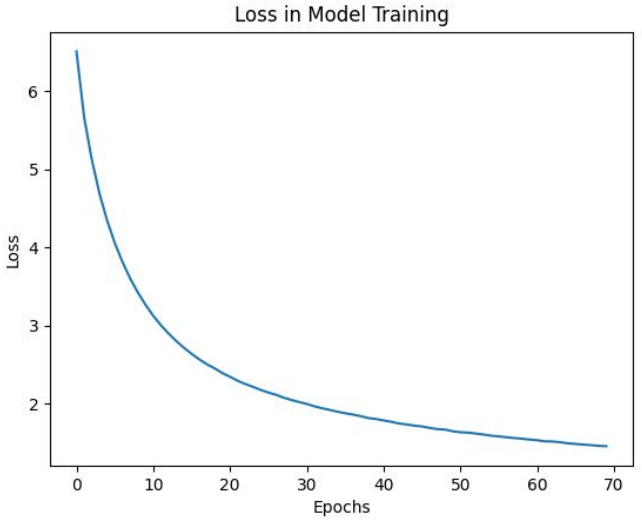
Layer (type) Output Shape Param #
embedding_1 (Embedding) (None, 100, 256) 2574848
gru_2 (GRU) (None, 100, 128) 148224
dropout_1 (Dropout) (None, 100, 128) 0
gru_3 (GRU) (None, 128) 99072
dropout_2 (Dropout) (None, 128) 0
dense_1 (Dense) (None, 10058) 1297482
Total params: 4119626 (15.72 MB)
Trainable params: 4119626 (15.72 MB)
Non-trainable params: 0 (0.00 Byte)

Metrics


Accuracy in Model Training
Accuracy
0.1
0.2
0.3
0.4
0.5
0.6
0
10
20
30
40
50
60
70
Epochs


Loss in Model Training
Loss
2
3
4
5
6
0
10
20
30
40
50
60
70
Epochs

Pre-trained Model: CTRL

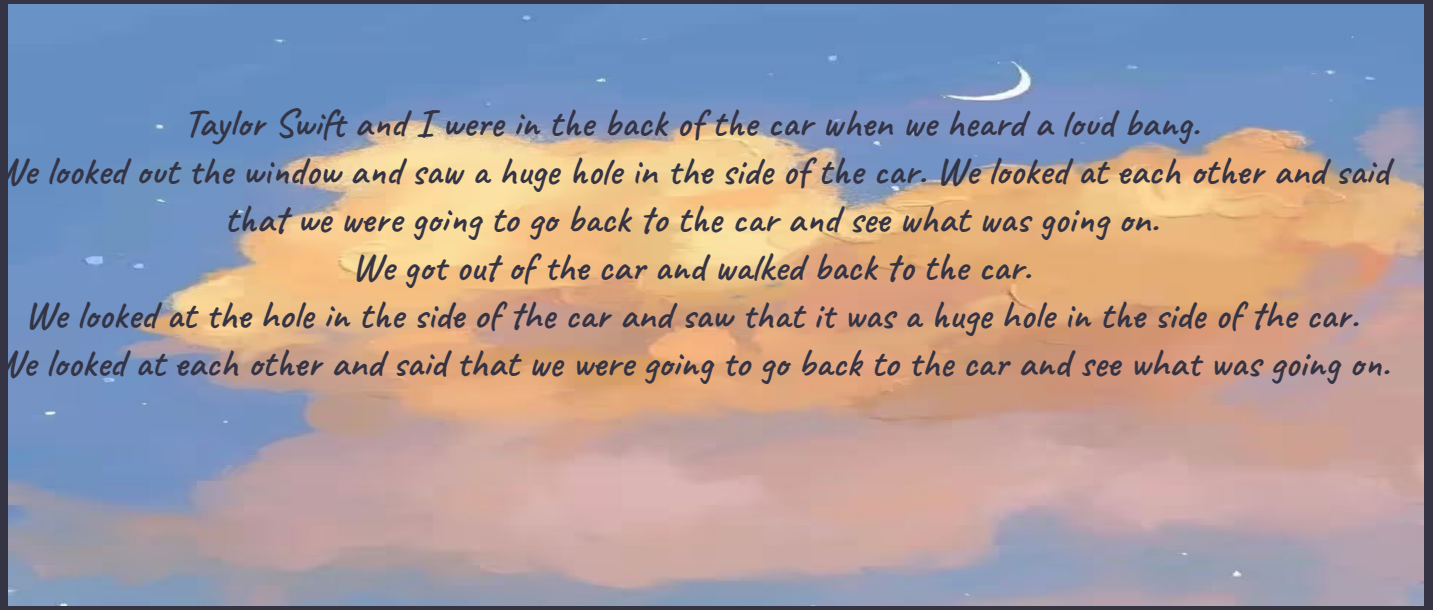
Conditional Transformer Language Model (CTRL) is a pre-trained model training on a very large corpus of ~140 GB of text data with the first token reserved as a control code (Wikipedia, Books, etc.)

To utilize this model, we have to add a control code token at the beginning of the seed text, which might influence the results

Reference: https://huggingface.co/docs/transformers/model_doc/ctrl#ctrl

Results: Taylor Swift (RNN)

Results: Horror Taylor Swift (CTRL)

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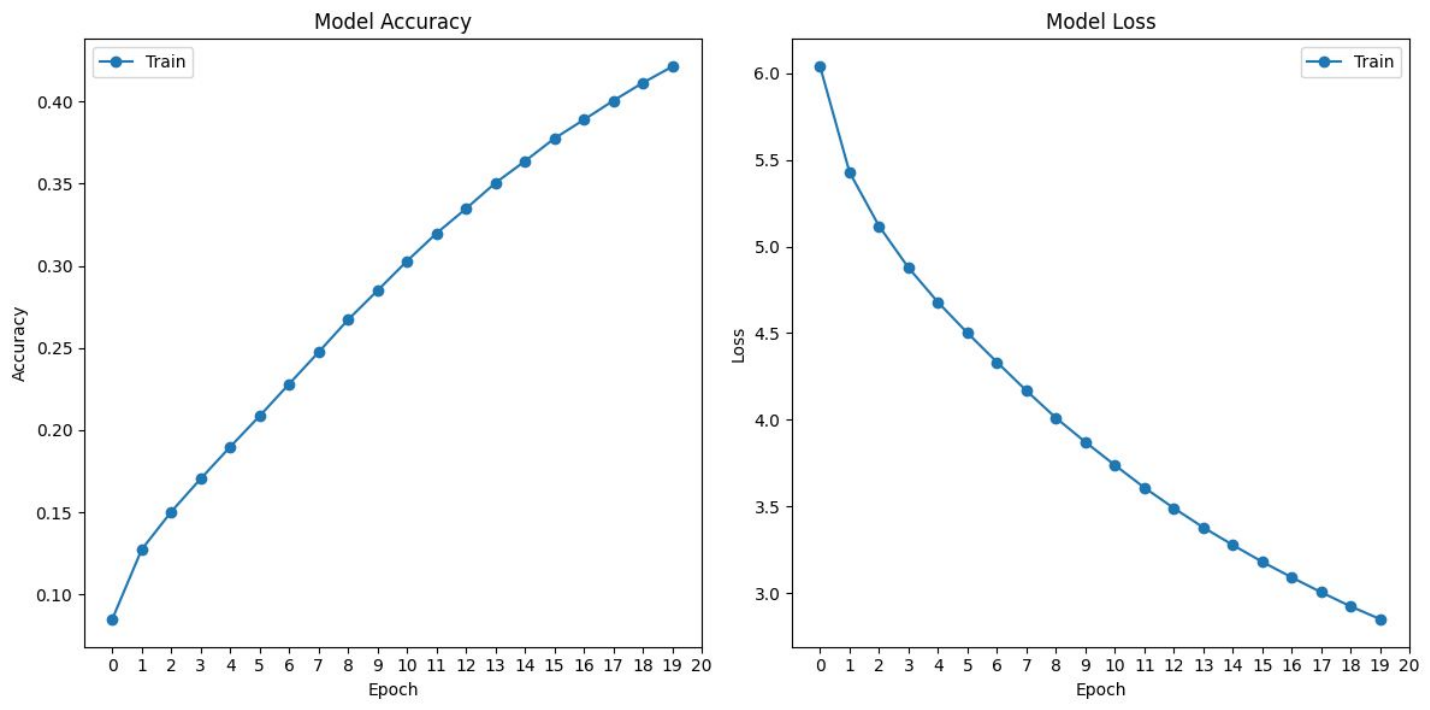
Lyrics Generator with Titles

RNN Model - Summary

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 1569, 100)	1496500
bidirectional (Bidirectional)	(None, 1569, 300)	301200
bidirectional_1 (Bidirectional)	(None, 200)	320800
dense (Dense)	(None, 14965)	3007965

Total params: 5126465 (19.56 MB)
Trainable params: 5126465 (19.56 MB)
Non-trainable params: 0 (0.00 Byte)

RNN Model - Fit

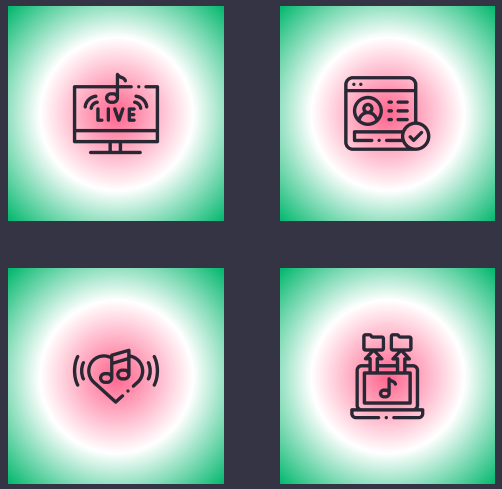


RNN Model - Lyrics Generation

```python
# Function to generate text

def generate_text(seed_text, next_words, model, max_sequence_len, temperature=1.0):
    for _ in range(next_words):
        token_list = tokenizer.texts_to_sequences([seed_text])[0]
        token_list = pad_sequences([token_list], maxlen=max_sequence_len-1, padding='pre')
        predictions = model.predict(token_list, verbose=0)[0]

        # Apply temperature to the predictions
        predictions = np.log(predictions + 1e-7) / temperature  # Smoothing and avoid log(0)
        exp_predictions = np.exp(predictions)
        predictions = exp_predictions / np.sum(exp_predictions)

        # Choose the next word with weighted probability
        next_word_index = np.random.choice(len(predictions), p=predictions)

        output_word = ""
        for word, index in tokenizer.word_index.items():
            if index == next_word_index:
                output_word = word
                break
        seed_text += " " + output_word
    return seed_text

# Generate new lyrics
print(generate_text("Love", 200, model, max_sequence_len, temperature=1.003))
```

RNN Model - Lyrics Generation

Pre-trained Models



- Model Choice
- How the Model Works
- Model Performance

GPT-2

GPT-2: How the Model Works

```
from transformers import GPT2LMHeadModel, GPT2Tokenizer

# Load pre-trained model tokenizer (vocabulary)
tokenizer = GPT2Tokenizer.from_pretrained('gpt2')

# Load pre-trained model (weights)
model = GPT2LMHeadModel.from_pretrained('gpt2')
model.eval()  # Set the model to evaluation mode
```

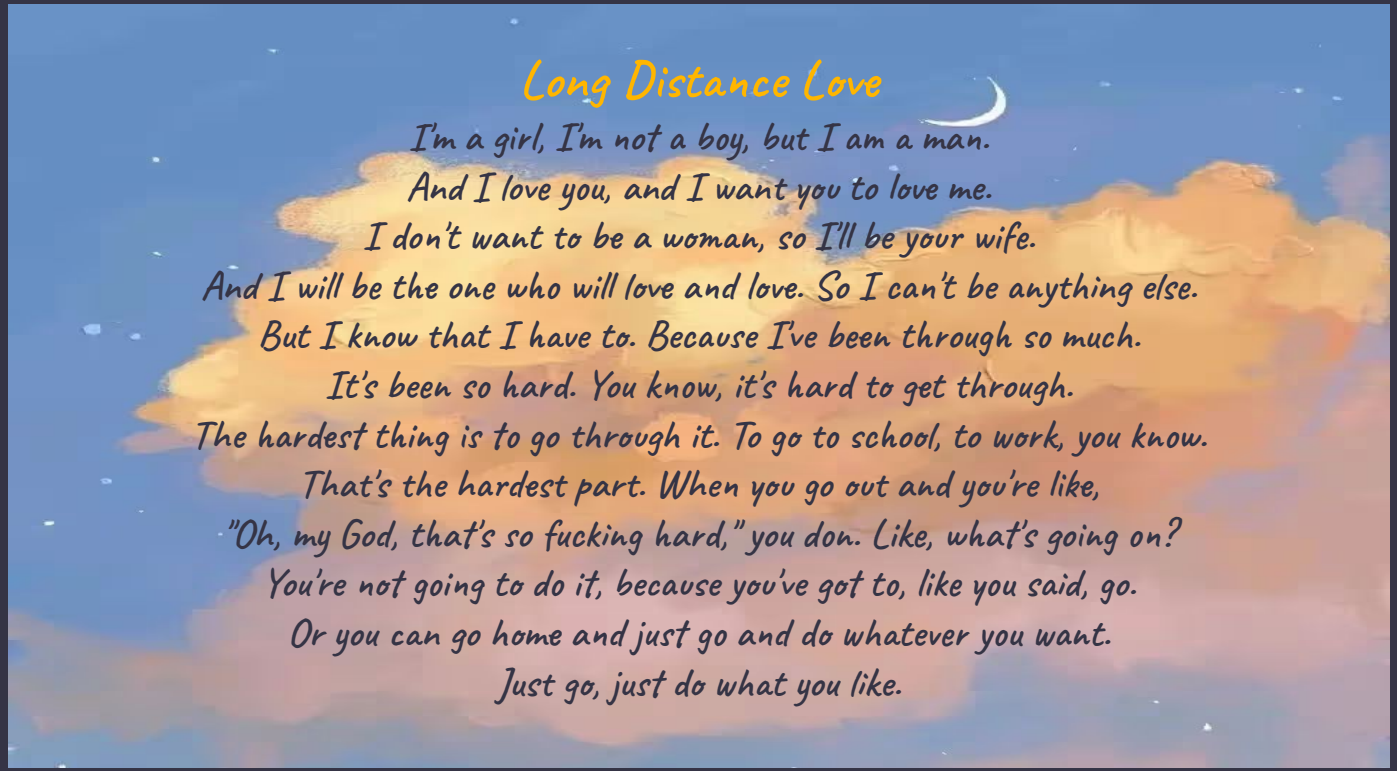
GPT-2: How the Model Works

```
GPT2LMHeadModel(
  (transformer): GPT2Model(
    (wte): Embedding(50257, 768)
    (wpe): Embedding(1024, 768)
    (drop): Dropout(p=0.1, inplace=False)
    (h): ModuleList(
      (0-11): 12 x GPT2Block(
        (ln_1): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
        (attn): GPT2Attention(
          (c_attn): Conv1D()
          (c_proj): Conv1D()
          (attn_dropout): Dropout(p=0.1, inplace=False)
          (resid_dropout): Dropout(p=0.1, inplace=False)
        )
        (ln_2): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
        (mlp): GPT2MLP(
          (c_fc): Conv1D()
          (c_proj): Conv1D()
          (act): NewGELUActivation()
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
    )
    (ln_f): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
  )
  (lm_head): Linear(in_features=768, out_features=50257, bias=False)
)
```

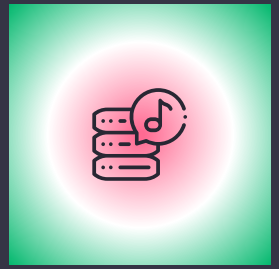
GPT-2: Lyrics Generation

```
# Define the prompt with the song title and an indicator to start the lyrics
prompt = "Title: Long Distance Love\nLyrics:\n"
# Encode the prompt text to token ids
input_ids = tokenizer.encode(prompt, return_tensors='pt')
# Generate the lyrics with modified parameters
lyrics_output = model.generate(
    input_ids,
    max_length=300,
    temperature=1.,
    top_p=0.9,
    no_repeat_ngram_size=2,
    num_return_sequences=1,
    pad_token_id=tokenizer.eos_token_id
)
# Decode and print the generated lyrics
lyrics = tokenizer.decode(lyrics_output[0], skip_special_tokens=True)
print(lyrics)
```

GPT-2: Model Performance



Compare Performances



RNN

More than 13 hours of training

Cost me more than $150 on Google Colab

GPT-2

Generate in 5 seconds

Cost Nothing

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Limitations & Discussions

Limitation & Discussion

- Limited Training Epochs for RNN Models
- Minimal Hyperparameter Fine-Tuning
- Limited Diversity in Training Data
- Pre-trained Models' Limitation
- Dependency on Dataset Quality

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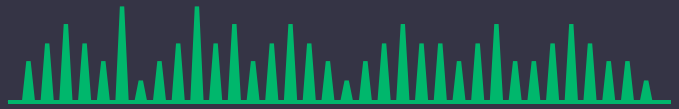
Conclusion

Conclusion

- RNN models showcased a commendable effort, the constraints of training epochs and hyperparameter fine-tuning underscored the inherent challenges in achieving optimal results.
- The comparative analysis revealed that pre-trained models, particularly GPT-2, emerged as powerful alternatives, exhibiting superior performance and significantly faster execution.
- As we navigate the dynamic landscape of text generation, the trade-offs between model complexity, training efficiency, and output quality become apparent.
- In the ever-evolving field of natural language processing, the pursuit of innovative solutions continues, fueled by a commitment to unraveling the complexities of creative text generation.

Reference



- Github Repository: https://github.com/JiaqinWu/ds6600_Final_Group14/tree/main
- Kaggle: https://www.kaggle.com/code/karnikakapoor/lyrics-generator-rnn
- GRU: https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21
- CTRL: https://huggingface.co/docs/transformers/model_doc/ctrl#ctrl
- GPT pretrained Model: https://openai.com/research/better-language-models
- Google T5 Model: https://wandb.ai/mukilan/T5_transformer/reports/Exploring-Google-s-T5-Text-To-Text-Transformer-Model--VmlldzoyNjkzOTE2

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Thank You!

Do you have any questions?

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