

# Predicting The Next Song in a Playlist

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## What we are trying to solve

Our group is aiming to create playlists with newly generated songs. We hope to do this by training a model to recognize patterns within playlists and as a byproduct be able to recommend a song based on previous tracks.

# The current solution for this problem:

- The current state of the art solution is the built in recommended playlists that spotify has built in
- Others have tried to do playlist generation, but few have tried by use of deep learning techniques, or trying to analyze order in a playlist to predict the next song's attributes
- Spotify has a built in API function to get a track based on attributes, a function that we will be using in our project to generate songs

# Why is it important?

Music is a universal way of bonding and entertainment. While dearly loved apps like Spotify and Apple Music have made discovering music a more pleasant experience than manually searching for songs, understanding the technicalities behind music recommendation and playlist curation is a fun way to better understand how exactly we are getting our music.

As a group, we wanted a better understanding of how we might use deep learning to generate our own music instead of relying on the apps we use daily.

# Data

We downloaded 103 playlists from Spotify's API (ensuring that none of the curated playlists were based upon a singular artist). The dataset includes playlist IDs, track IDs, and the following attributes:

**Mood:** Danceability, Valence, Energy

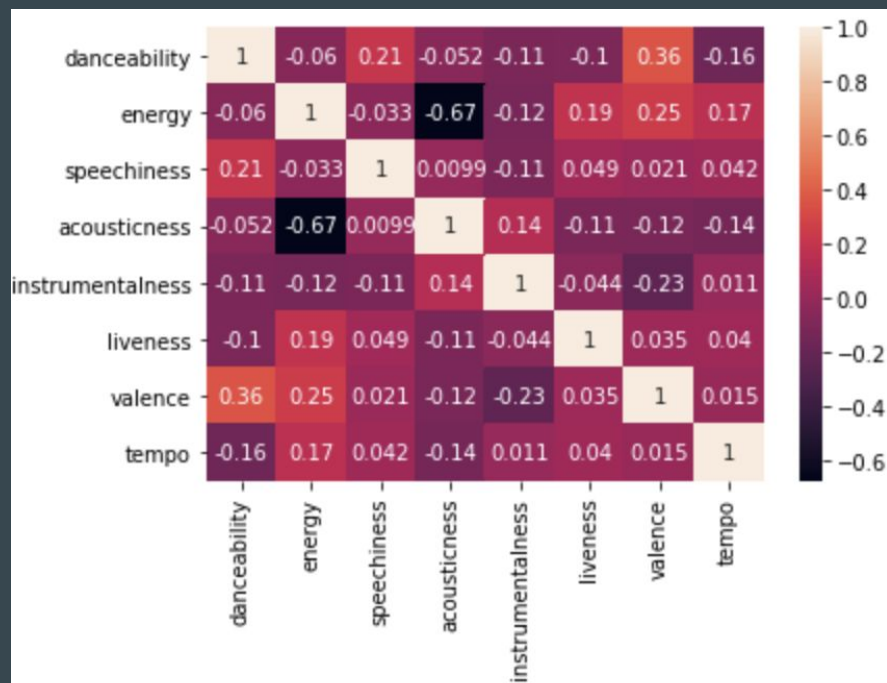
**Properties:** Loudness, Speechiness, Instrumentalness

**Context:** Liveness, Acousticness

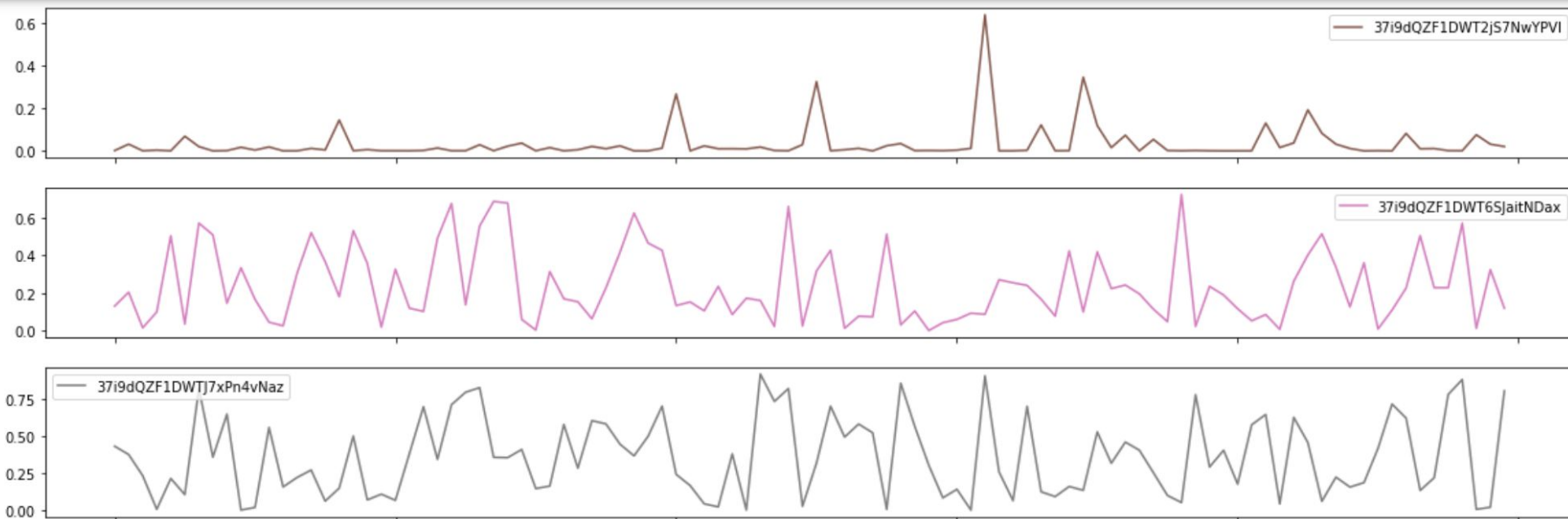
In total, the dataset included 8,025 songs with the length of each playlist ranging from 49 songs - 99 songs

# What does an exploratory data analysis tell you about your data?

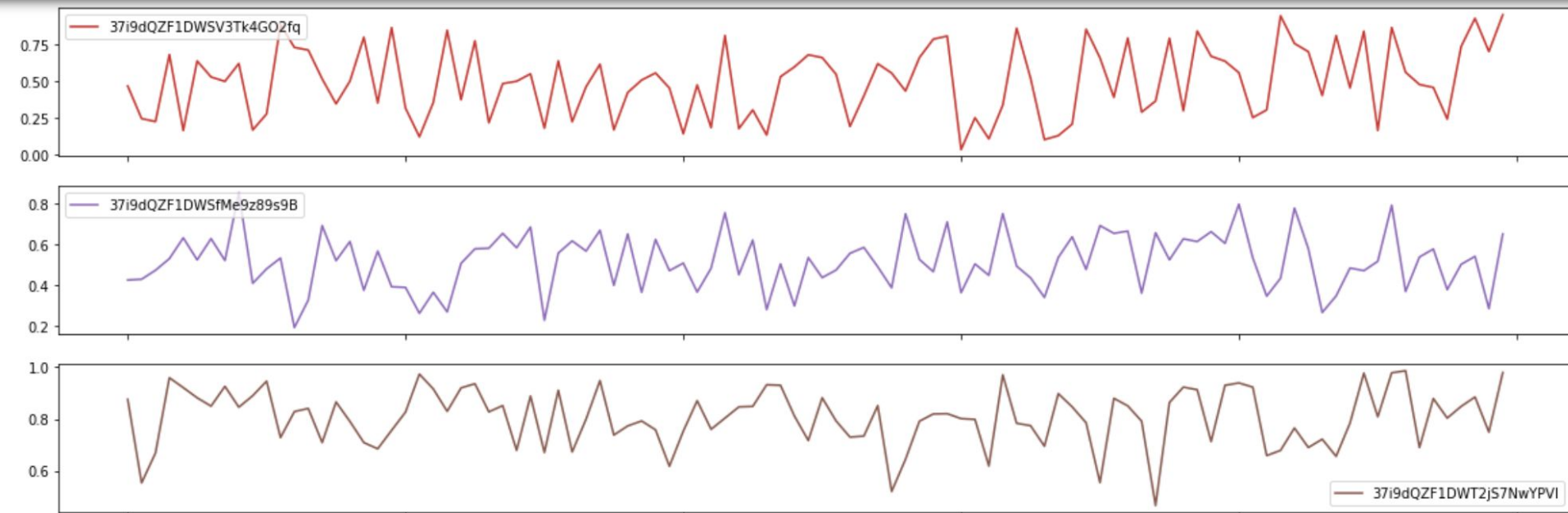
- Exploratory analysis shows us that each playlist across each genre or type of playlist is different.



# Accousticness



# Energy





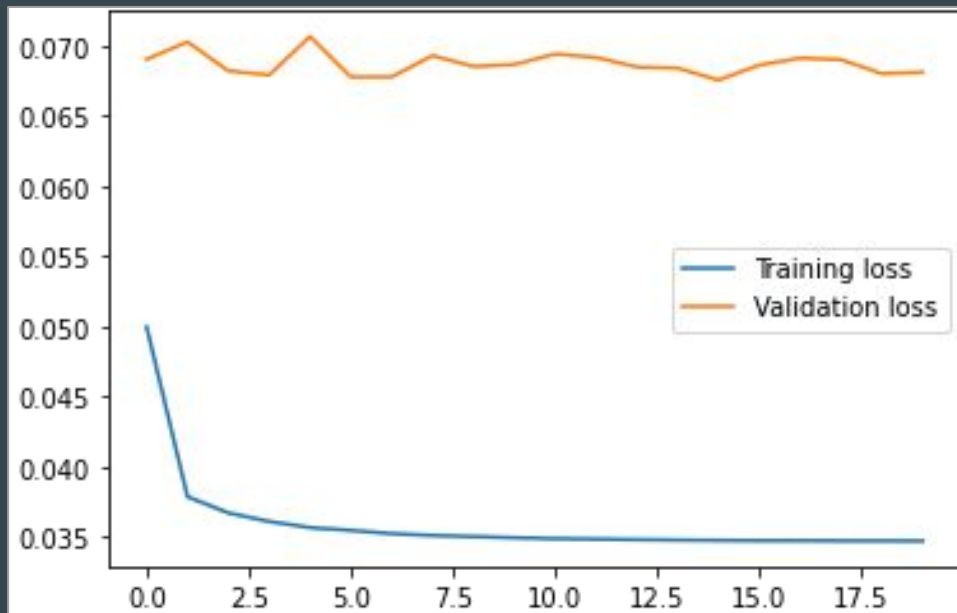
# Model

- Data
  - 5 steps back
- Model
  - Layers
    - LSTM layer: 64 nodes
    - Dropout layer: 0.2
    - LSTM layer: 32 nodes
    - Dropout layers: 0.2
  - Parameters
    - Optimizer: Adam
    - Loss: mean squared error
    - Epochs: 20
    - Batch size: 16

Layer (type)	Output Shape	Param #
lstm_12 (LSTM)	(None, 5, 64)	18432
dropout_10 (Dropout)	(None, 5, 64)	0
lstm_13 (LSTM)	(None, 32)	12416
dropout_11 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 7)	231
Total params: 31,079		
Trainable params: 31,079		
Non-trainable params: 0		

# Results

- Decrease training loss but not validation loss
- Good at training on the data we have but not on unseen data
  - Overfit
- Prediction from
  - [Losing My religion - REM](#)
  - [Bigmouth Strikes Again - The Smiths](#)
  - [Love Will Tear Us Apart - Joy Divisions](#)
  - Age of consent - New Order
  - This Charming Man - The Smiths
- Results in
  - [Where is my Mind - The Pixies](#)



# Future steps for improvement

- More powerful computer could train on million playlist dataset
- More hypertuning of parameters
- Actually generate full playlists instead of a couple songs.
- More playlists to train on need to update api commands to refresh token (when downloading auth token would time out after an hour there are more playlists we can grab)

# A slide with links to any references you used

<https://machinelearningmastery.com/how-to-develop-lstm-models-for-time-series-forecasting/>

<https://machinelearningmastery.com/multivariate-time-series-forecasting-lstms-keras/>

<https://www.youtube.com/watch?v=tepxdcepTbY>

[https://github.com/bnsreenu/python\\_for\\_microscopists/blob/master/181\\_multivariate\\_time\\_series\\_LSTM\\_GE.py](https://github.com/bnsreenu/python_for_microscopists/blob/master/181_multivariate_time_series_LSTM_GE.py)