Music Genres Classification and Recommendation System

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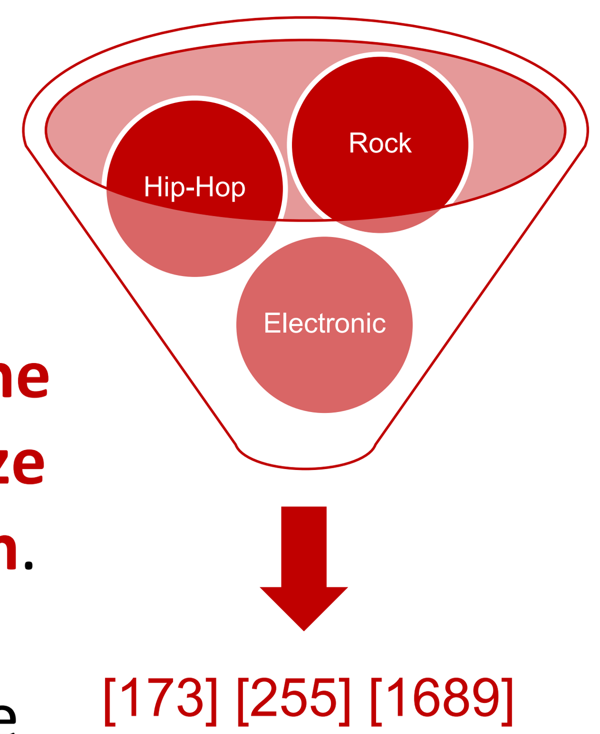
Introduction

- Classifying the multi-type of the audio-recordings and build up the recommendation model to generate the list of songs with similar genres.
- We aim to accurate **distinguish the genres of the songs** and **customize optimal playlist recommendation**.
- While user input a single song, we can provide three songs that includes high-related genres.



Dataset

- The datasets used in our project were collected International by Society for Music Information Retrieval Conference (ISMIR) and are available at https://github.com/mdeff/fma .
- tracks.csv: per track metadata such as ID, title, artist, genres, tags and play counts, for all **106,574 tracks.**
- genres.csv: all **163 genres** with name and parent (used to infer the genre hierarchy and top-level genres).
- features.csv: common features extracted with librosa.
- echonest.csv: audio features provided Spotify for a subset of 13,129 tracks.

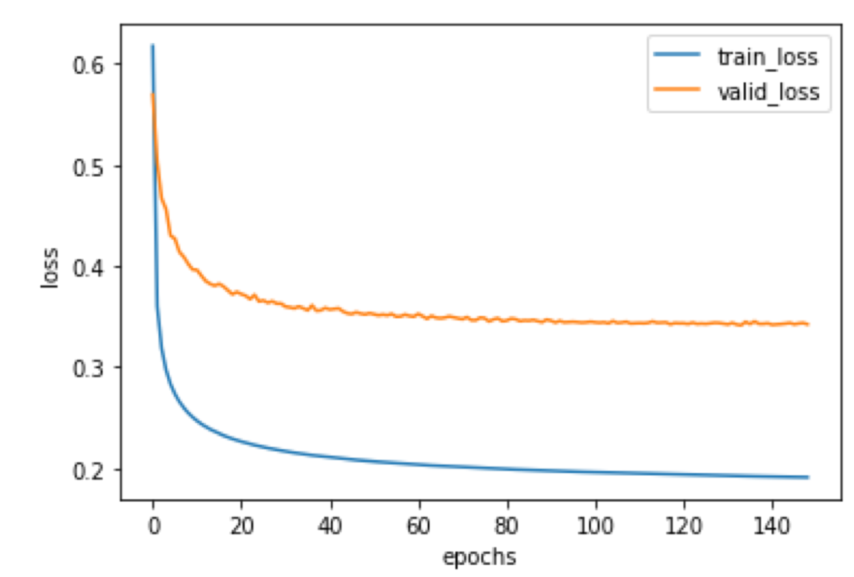
Methodology and Results

Data Preprocessing

- Split and shuffle the data into train, valid , and test set (70%, 20%, and 10%)
- We choose 32 genres[1] that accounted for the greatest proportion of the dataset as the multi true label of our model.
- Balance the amount of songs for different genres so that the weight of each genre can be more easier to learn.

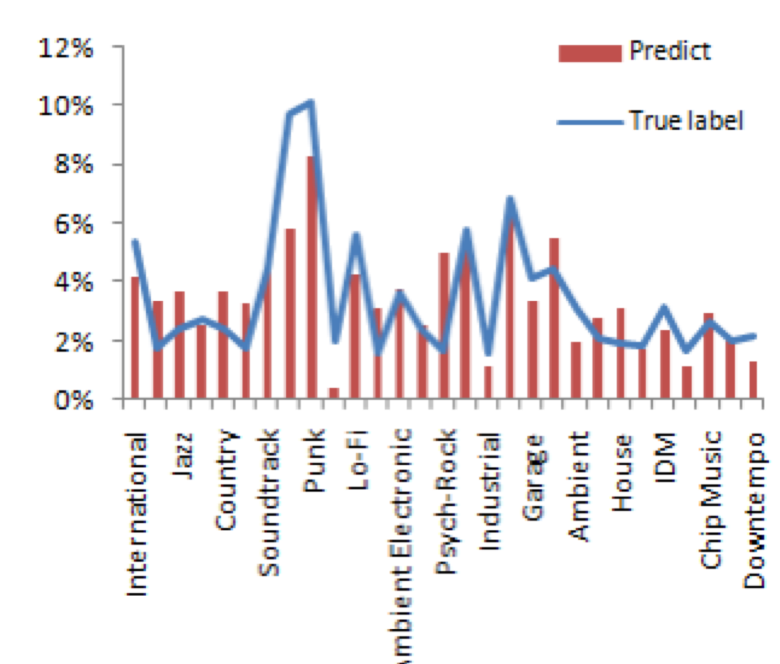
Algorithm and Training

- We choose deep neural network (DNN) as our model with Keras.
- By monitoring val_loss and val_auc, we use EarlyStopping and ModelCheckpoint to prevent our model from overfitting.
- We got 79% accuracy by applying Adagrad optimizer (learning_rate= 5e-4, epsilon= 1e-6)



Testing and Recommendation System

- By using the train model, we could give our test data predicted multi-label.
- A song could be successfully tagging with its genres, and our recommendation system will use set to match top three highest related songs to the users.



[1] International, Blues, Jazz, Classical, Country, Experimental Pop, Synth Pop, Punk, Post-Rock, Lo-Fi, Loud-Rock, Noise-Rock, Psych-Rock, Indie-Rock, Industrial, Garage, Post-Punk, Hardcore, Soul-RnB, Ambient Electronic, Techno, House, Glitch, IDM, Trip-Hop, Chip Music, Downtempo, Psych-Folk, Singer-Songwriter, Hip-Hop, Soundtrack, Ambient.

Discussion and Conclusion

- There are more than 32 genres in our data set, but the rest of the genres can not accurately predict due to insufficient numbers of tracks.
- Because of a large amount of audio features(518), the genres can be more precise with more variety of tracks.

Future Work

- We can includes more type of genres to neural network by enhancing the data set.
- Let our recommendation learn user's preference by the feedback of songs it recommends to them.

References

FMA: A Dataset For Music Analysis
Michaël Defferrard, Kirell Benzi, Pierre Vandergheynst, Xavier Bresson. International Society for Music Information Retrieval Conference (ISMIR), 2017.