A Music Recommendation System Based On Personality

Orçun Özdemir
Computer Engineering Department,
Istanbul Technical University
ozdemiror@itu.edu.tr

MOTIVATION

- Information filtering according to user interests
- More relevant content = More customer time spent in app
- High customer satisfaction, retention and conversation rate
- Not affected by cold start problem

LITERATURE REVIEW

- L. R. Goldberg, “An alternative “description of personality”: The big-five factor structure.” Journal of Personality and Social Psychology, vol. 59, no. 6, pp. 1216— -1229, 1990.
  - Big five personality framework to identify user's personality
- B. Ferwerda, M. Tkalcic, and M. Schedl, “Personality traits and music genre preferences : How music taste varies over age groups,” vol. 1922, 2017, pp. 16–20.
  - Musical genre correlation values using age groups and big five personality values
- O. P. John, E. M. Donahue, and R. L. Kentle, “The big five inventory,” 1991.
  - 44 questions for users to calculate their big five personality values

INTRODUCTION

- Ferwerda et. al., analyzed a dataset with the music listening histories and personality information of 1415 users. Spearman's correlation between music genres and personality traits over age groups.

	Openness			Conscientiousness			Extraversion			Agreeableness			Neuroticism		
	12-19	20-39	40-65	12-19	20-39	40-65	12-19	20-39	40-65	12-19	20-39	40-65	12-19	20-39	40-65
R&B	-.019	-.004	-.053	-.026	-.009	.150	**.106**	.065	**.326**	-.049	.047	.326	.027	-.001	-.175
Rap	-.019	-.011	-.205	-.085	-.065	.059	.030	**.108**	.052	-.070	.062	.052	.003	-.072	-.158
Electronic	.046	**.106**	-.138	-.043	-.031	.152	.015	.038	-.246	-.090	-.050	-.246	.036	-.023	.133
Rock	-.075	**-.104**	.095	-.058	.016	-.124	-.085	**-.102**	-.182	.070	-.031	-.182	.014	.053	.182
New Age	**.142**	**.105**	.133	.037	-.053	.006	-.022	**-.184**	-.209	.008	.011	-.209	-.062	-.064	-.143
Classical	.080	.038	.266	.028	-.060	.261	**-.136**	**-.146**	-.136	-.070	-.010	-.136	-.015	-.005	-.080
Reggae	-.015	.046	.185	**-.102**	-.059	-.059	.039	.025	.046	-.032	.051	.046	.028	-.042	-.138
Blues	**.130**	**.167**	**.358**	-.048	-.046	.321	.060	.032	.252	-.006	.018	.252	-.054	-.005	**-.552**
Country	**.117**	**.126**	.325	-.067	-.073	.154	.005	.005	.128	.062	**.184**	.128	.049	-.027	-.109
World	**.114**	**.217**	.201	-.016	-.009	.217	**-.102**	-.054	.028	-.056	-.025	.028	.061	-.014	-.236
Folk	**.230**	**.231**	**.368**	-.014	**-.114**	-.268	.066	-.040	.181	**.101**	**.110**	.181	-.064	.004	-.217
Easy Listening	.084	.060	-.161	.020	.024	.256	.041	-.019	.212	-.073	.041	.212	.035	-.012	.006
Jazz	**.139**	**.106**	-.124	-.047	-.025	**.510**	.005	-.010	.062	-.053	-.068	.062	-.039	.004	-.106
Vocal (a cappella)	**.132**	**.170**	.282	.059	-.007	.125	.038	-.013	.136	-.074	-.001	.136	-.014	.002	-.091
Punk	-.032	-.008	.089	**-.130**	**-.103**	.081	**-.111**	-.029	-.074	.005	.006	-.074	**.101**	.049	.220
Alternative	**.131**	**.116**	.154	**-.108**	**-.165**	**.507**	-.010	-.052	-.027	.018	.029	-.027	**.129**	**.137**	.070
Pop	.021	.000	-.157	.045	.005	.052	.064	.017	.287	-.017	**.194**	.287	.040	-.010	-.275
Heavy Metal	-.033	-.044	-.117	-.005	-.012	.038	**-.148**	**-.126**	**-.339**	-.058	**-.105**	**-.339**	-.030	-.030	**.372**

B. Ferwerda, M. Tkalcic, and M. Schedl, "Personality traits and music genre preferences : How music taste varies over age groups," vol. 1922, 2017, pp. 16–20.

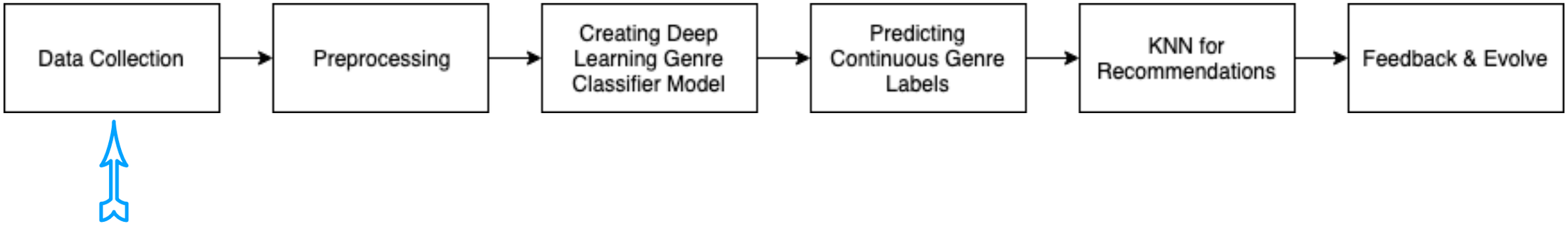
SYSTEM BACKGROUND

- Basic Mode
  - User can give big five personality values manually if he/she knows them.

- Advanced Mode
  - User can answer 44 questions, his/her big five personality values will be calculated in backend side.

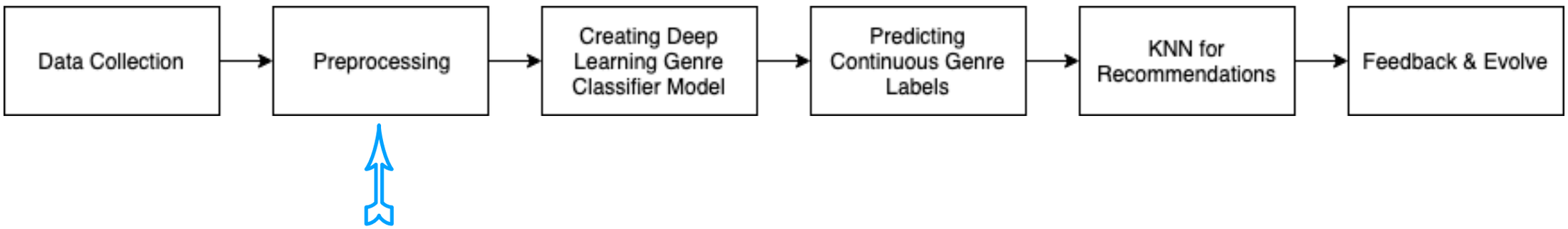
After calculating big five personality values of user by one of the modes,
1) Calculate genre interest matrix
2) KNN search to get the most relevant recommendations

PROPOSED MUSIC RECOMMENDATION SYSTEM



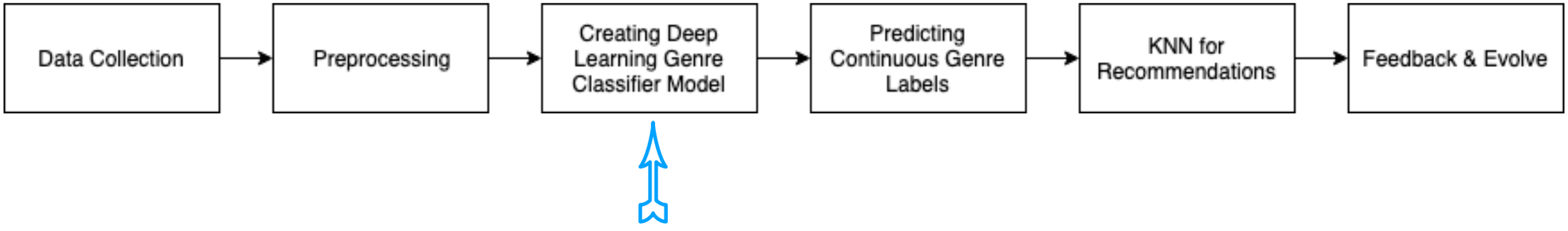
- Data Collection
  - Spotify API
    - Song, album, and artist information
    - 12 audio features for each song
    - Multiple genres for each artist

PROPOSED MUSIC RECOMMENDATION SYSTEM



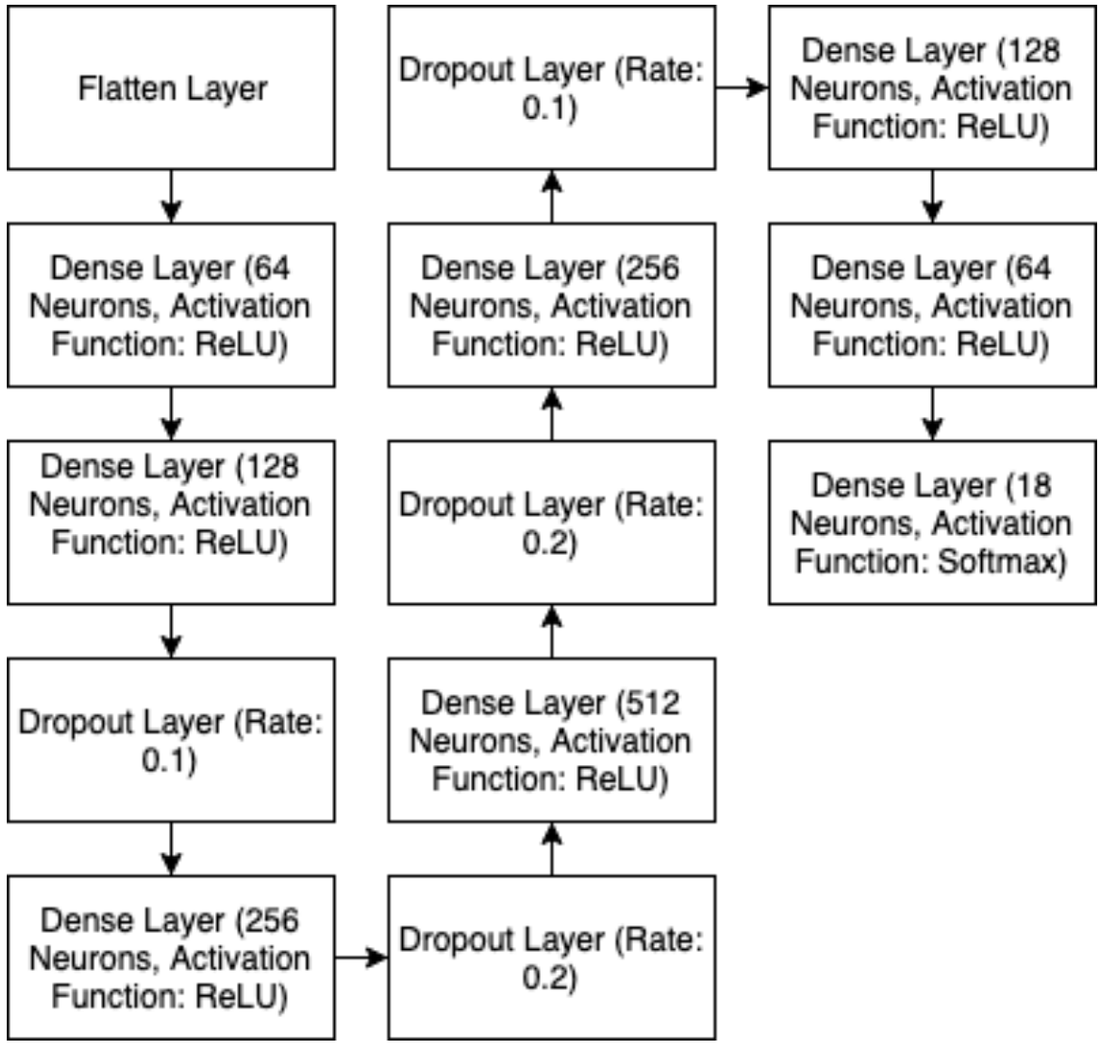
- Preprocessing
  - Mapping sub-genres to 18 main genres
  - One hot encoding for genres
  - Normalize audio features
  - Labeling songs genres as artist genre

PROPOSED MUSIC RECOMMENDATION SYSTEM

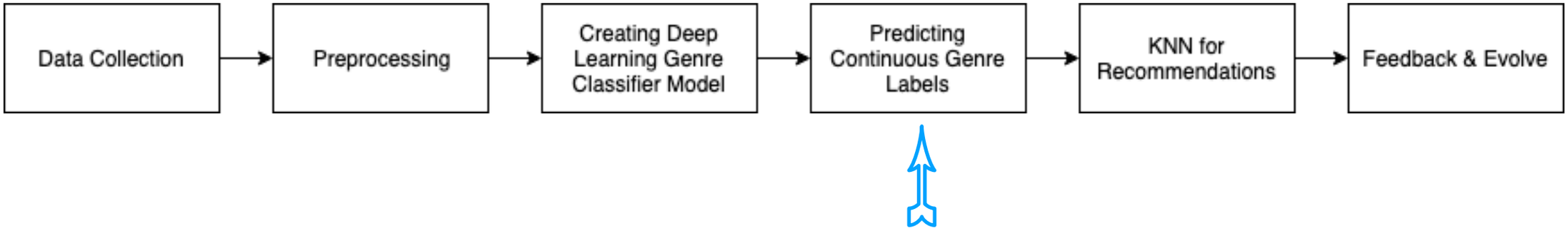


- Creating Genre Classifier Deep Learning Model
  - Used 12 audio features and 18 genre classes

DEEP LEARNING MODEL OVERVIEW

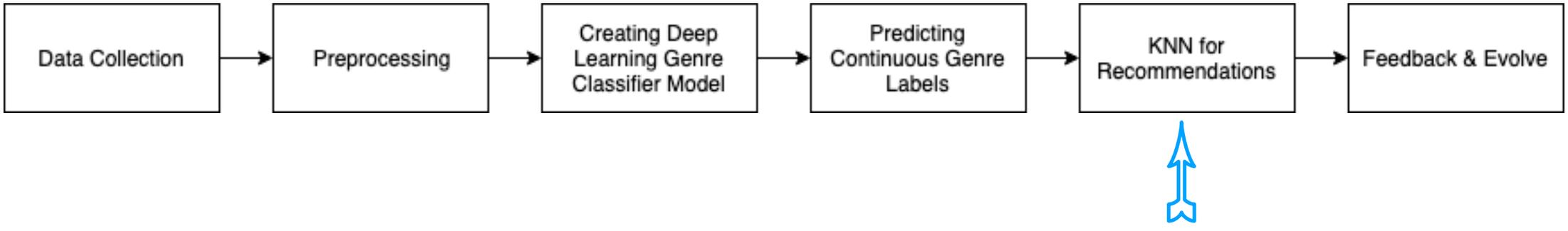


PROPOSED MUSIC RECOMMENDATION SYSTEM



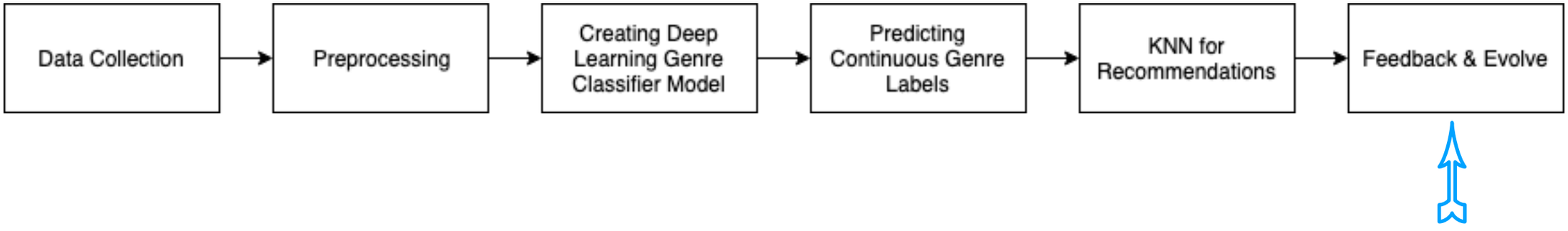
- Predicting Continuous Genre Labels
  - Get predictions for all songs in DB.
  - Give 12 audio feature matrix to model, get normalized 18 genre class values.
  - Store all predictions in song_genre_predictions table to use in live application.

PROPOSED MUSIC RECOMMENDATION SYSTEM



- KNN for Recommendations
  - When a user send a recommendation request, apply k nearest neighbor search using user's genre interest matrix on song_genre_predictions table to get most relevant songs.

PROPOSED MUSIC RECOMMENDATION SYSTEM



- Feedback & Evolve
  - After recommendations, user can give 3 different feedbacks:

1. "Dissatisfied" button to send irrelevant songs.
2. Song genre suggestion form to send feedback for wrong predicted songs by model.
3. Genre interest form to send interests on 18 main genres.

EXPERIMENTS

Software Features:

Programming Language	Python
Web Framework	Django
Frontend (CSS) Framework	MaterializeCSS
Frontend Dynamic Features	Javascript & JQuery
Web Server	Nginx
Operating System	Ubuntu 16.04
Database	PostgreSQL
Cache Server	Redis
Deep Learning Frameworks	Tensorflow and Keras
KNN and Preprocessing Library	Scikit-learn
CSV Processing Library	Pandas
Array Processing Library	NumPy

Live Demo: individualsymphony.com

EXPERIMENTS

Training accuracy: 43.04%

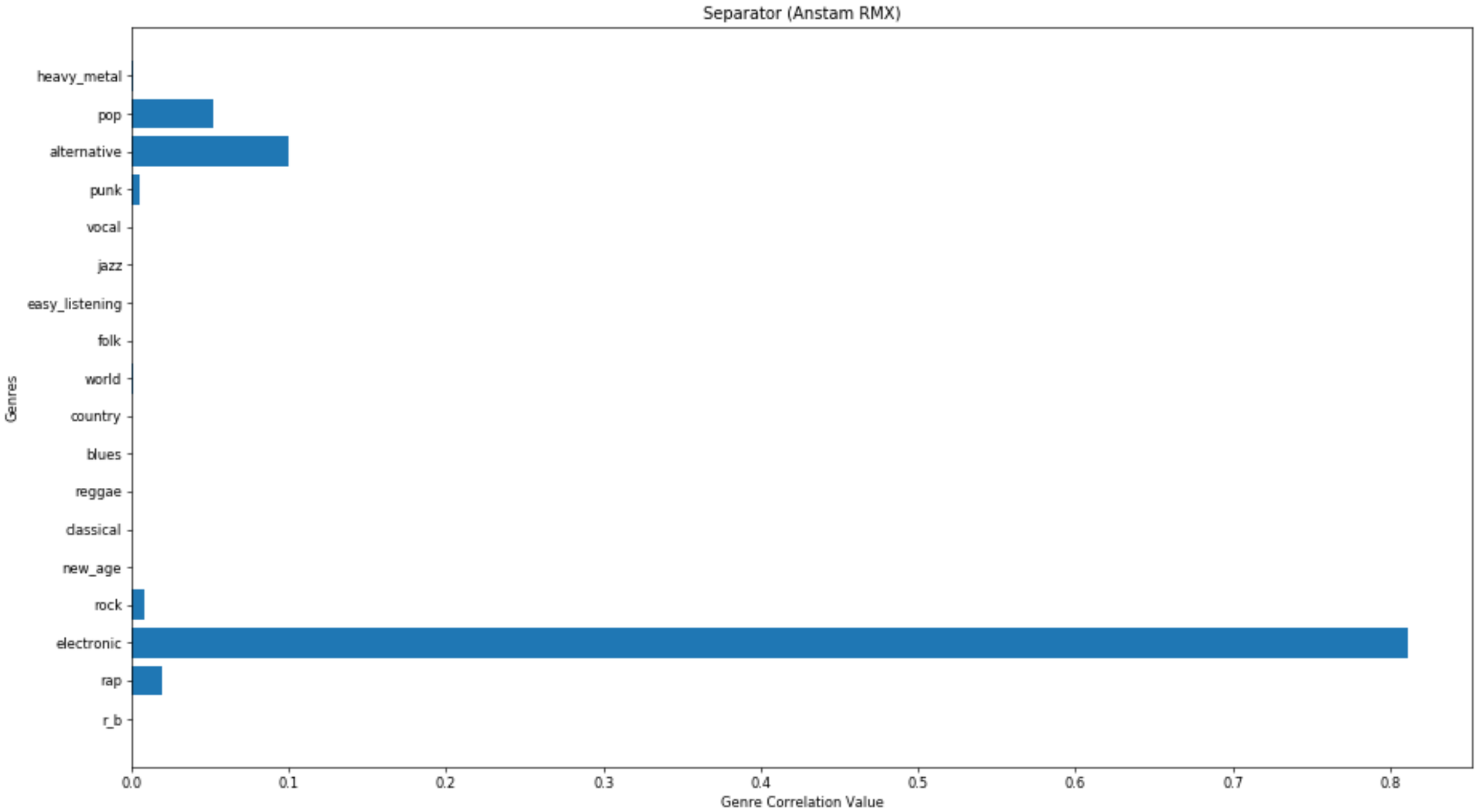
Possible reasons:

- Boundaries between different musical genres is unknown in data science.
- Using 18 classes as main genres, and some of them really close to each other like reggae and blues, folk and world music.

Collecting real world evaluations and feedbacks from users are important metrics to validate a recommendation system.

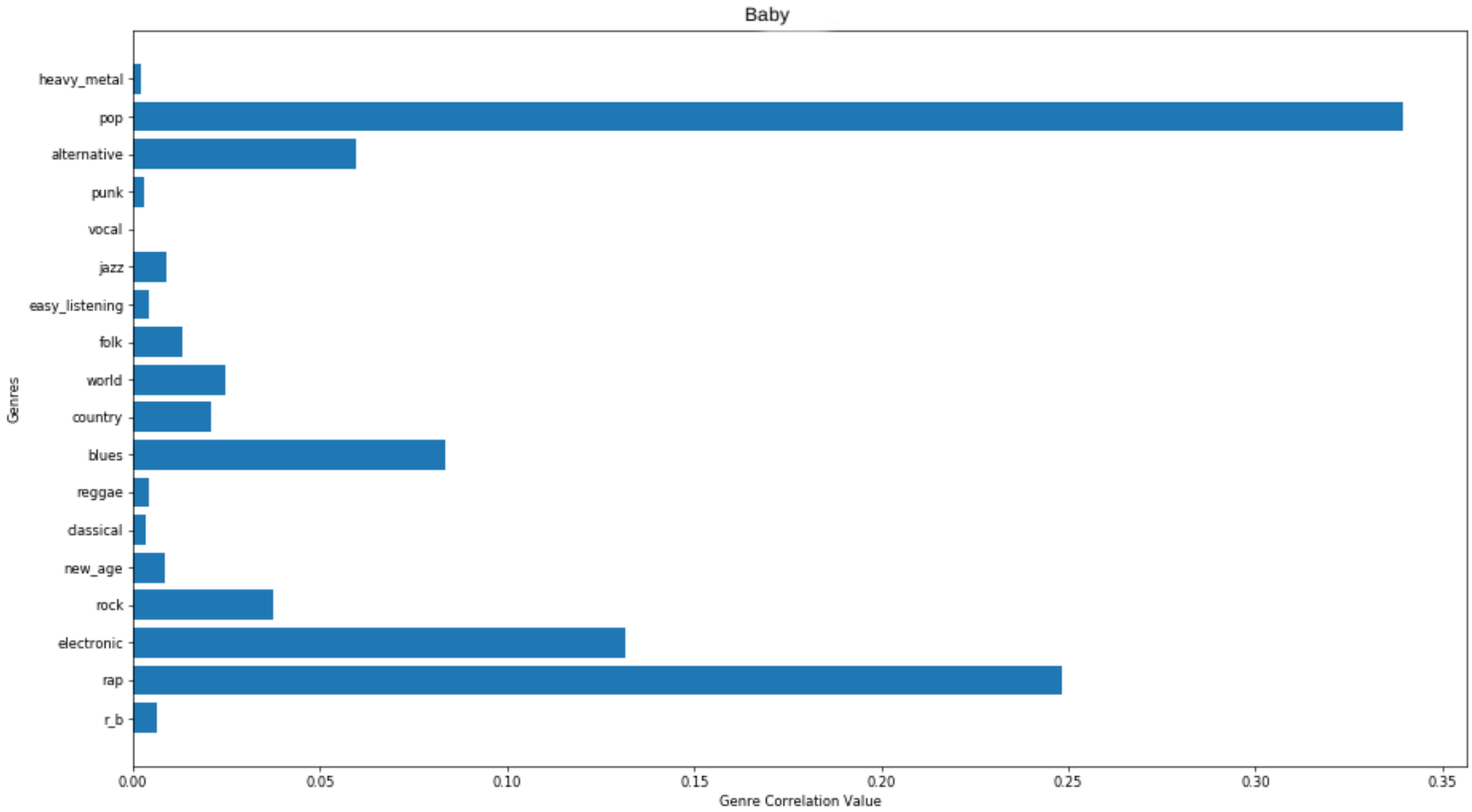
EXPERIMENTS

Radiohead is an alternative rock band, but their song "Seperator" is from an electronic dominant album, and model achieved to understand electronic characteristics in the song.



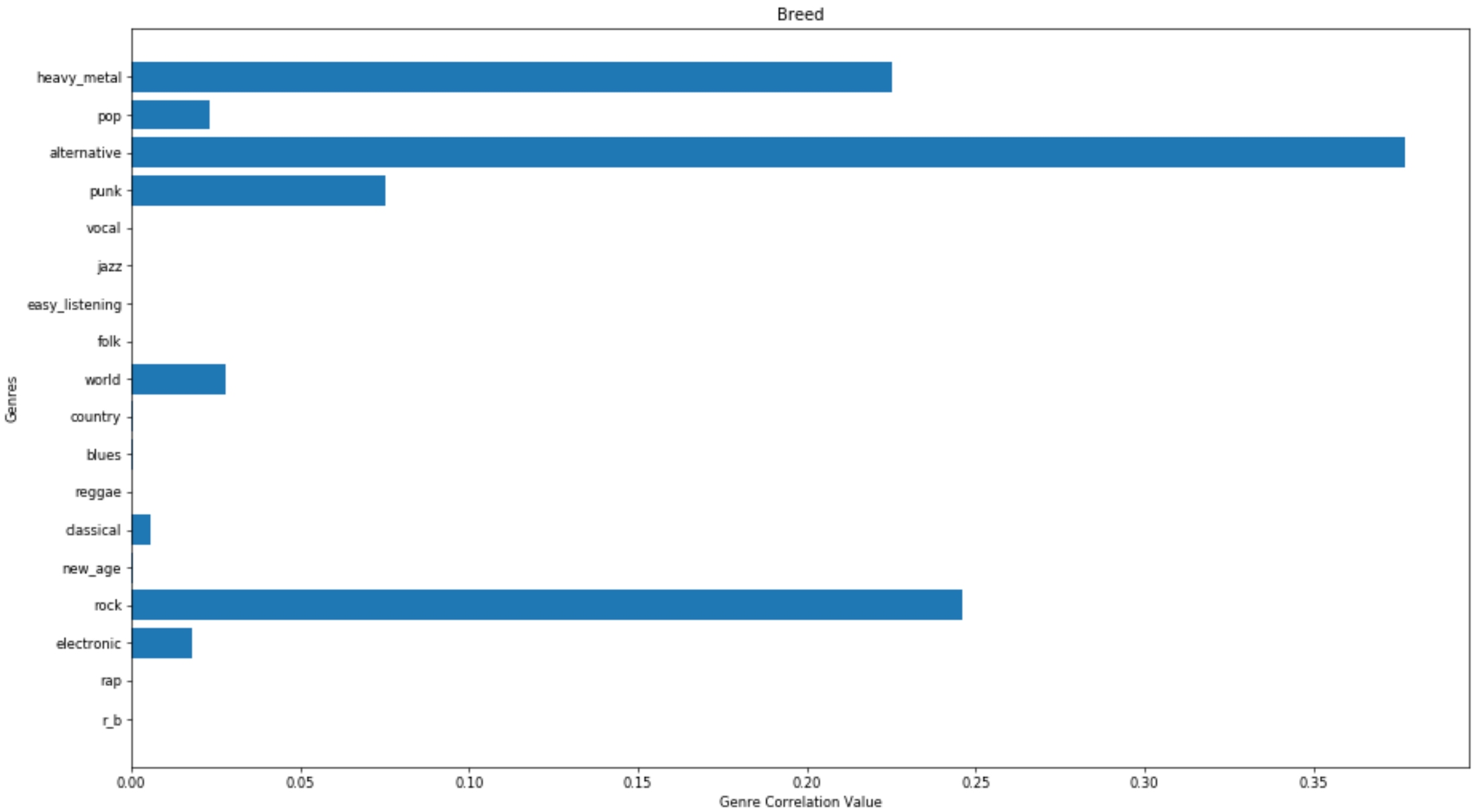
EXPERIMENTS

Justin Bieber is a popular pop singer, but his popular song "Baby" is by featuring Ludacris who is a rap singer, and model achieved to understand rap characteristics in this song.



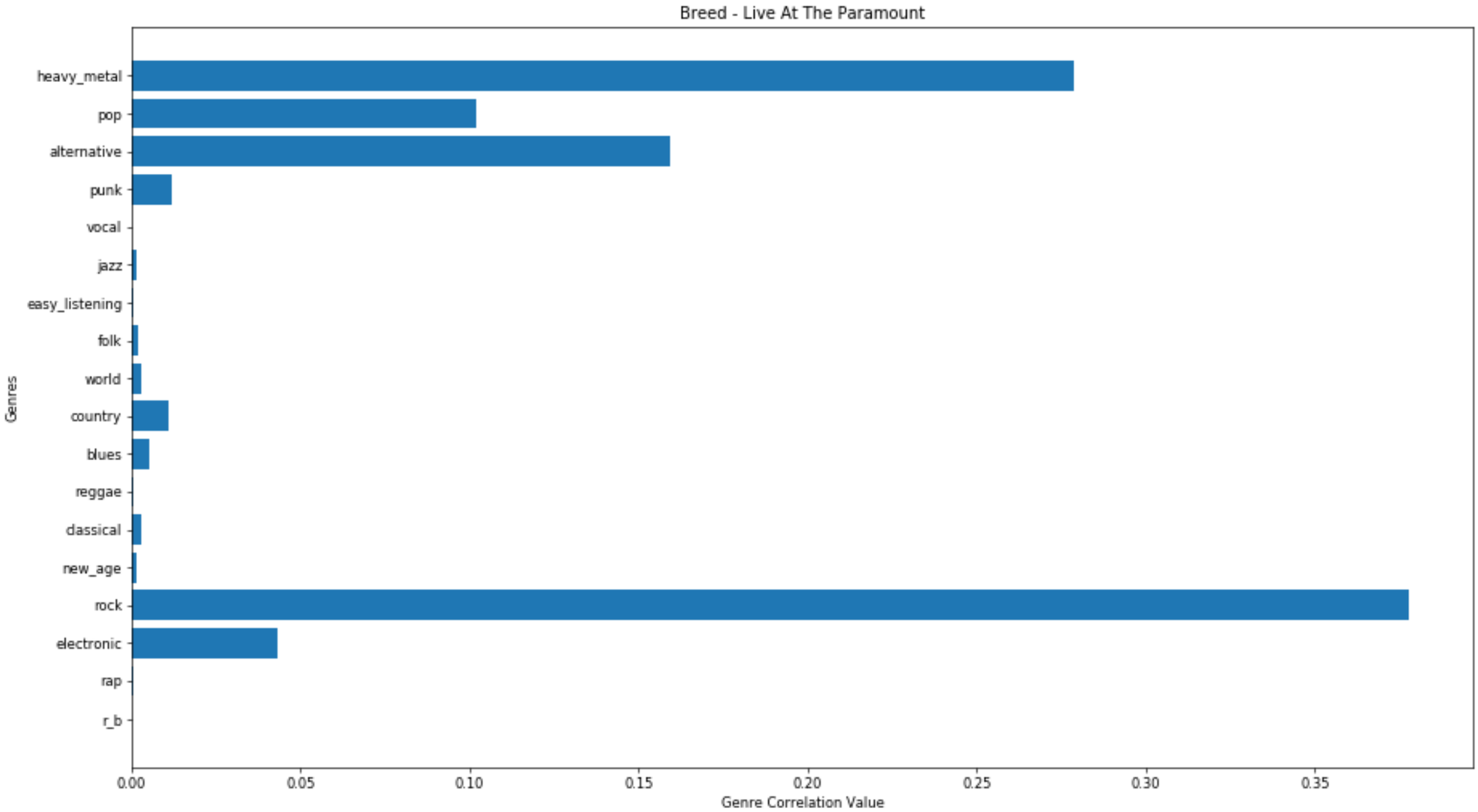
EXPERIMENTS

This song "Breed" is recorded by Nirvana which is grunge/alternative rock band, album version of this song shows alternative and rock characteristics.



EXPERIMENTS

Live version of "Breed" shows rock and heavy metal characteristics which is noisier than album version, and model perceived the difference between live and album version.



CONCLUSION

- Future Work
  - Song genre suggestion feedbacks from different users will correct wrong genre labels of songs and retrain the model.
  - Song dissatisfaction feedbacks which come from real users will help to validate and evaluate the recommendation system in real world.
  - Genre interest feedback form values storing from DB will help to create new model to construct relation from BFP to musical genre tastes.
  - Using better understanding of relations between musical genres and physical music characteristics will advance genre classifier model in the future.

Thank you!

Contact:

ozdemiror@itu.edu.tr