

Recognize Genre of a Song Using Spotify Web API

MLWR Project SoSe - 2022
Group: 07

Group Members:

Others and
Rubaiya Kabir Pranti

Machine Learning and Scientific Computing

Contents

- Introduction
- Methodology and steps
- Classification models
- Comparison of models
- Visualization results
- Additional Task: Clustering
- Result and conclusion

Introduction

- The aim of this project is to recognize genre of the song by applying different Machine Learning Models
- The dataset used for the project is retrieved from Spotify web API
- Data preprocessing and feature Engineering were performed on the data to get the final dataset, which was then split into training and testing dataset in the ratio of 8:2
- The Machine Learning Models used for our project are:
 - Logistic Regression
 - K-Nearest Neighbors
 - Random Forest Model
 - Decision Tree Model
 - Gradient Boosting Model

Methodology

- Spotify Web API and Data Extraction
- Data Pre-processing
- Feature Engineering
- Splitting Dataset
- Classification-Training Models
- Evaluation through Cross Validation
- Hyperparameter Optimization
- Final Prediction

Spotify Web API and Data Extraction

- Utilized the Spotify music data set using Spotify's <https://developer.spotify.com/documentation/web-api/> website
- achieved a total of **150,550 songs** after first audio feature extraction
- after combining the extracted metadata set and extracted feature dataset, the combined dataset was of total **366,684 data points** or songs consisting of **126 genres** and each has **26 features/columns**
- for less complexity and because of high computation time, we decided to keep only **15 genres** in which each genre has equal or more than 850 songs.

Key audio dataset metadata and features

- Danceability
- Popularity
- Mode
- Speechiness
- Acousticness
- Instrumentalness
- Liveness
- Valence
- Tempo
- Duration
- Key
- Explicitness

| 1 | df.head() | | | | | | | | | | | | | | |
|---|----------------|------------|----------|--------------|--------|-----|------|-------------|--------------|------------------|----------|---------|---------|------------|--|
| | genre | popularity | explicit | danceability | energy | key | mode | speechiness | acousticness | instrumentalness | liveness | valence | tempo | duration_s | |
| 0 | salsa | 57 | 0 | 0.463 | 0.876 | 1 | 1 | 0.0468 | 0.32200 | 0.000001 | 0.4090 | 0.569 | 92.092 | 261.0 | |
| 1 | detroit-techno | 7 | 0 | 0.775 | 0.838 | 10 | 0 | 0.0616 | 0.00676 | 0.900000 | 0.0835 | 0.671 | 139.981 | 422.0 | |
| 2 | tango | 12 | 0 | 0.534 | 0.274 | 11 | 1 | 0.0527 | 0.91800 | 0.594000 | 0.0798 | 0.687 | 126.114 | 185.0 | |
| 3 | detroit-techno | 9 | 0 | 0.789 | 0.458 | 1 | 1 | 0.0783 | 0.00990 | 0.853000 | 0.1300 | 0.419 | 133.035 | 265.0 | |
| 4 | salsa | 65 | 0 | 0.688 | 0.614 | 9 | 1 | 0.0378 | 0.58500 | 0.000000 | 0.0978 | 0.852 | 176.396 | 307.0 | |

Preferred Genre List with 15 genres only

1. Study
2. Club
3. Comedy
4. Bluegrass
5. Black-metal
6. World-music
7. Iranian
8. Grindcore
9. Heavy-metal
10. Turkish
11. Afrobeat
12. Forro
13. Country
14. Happy
15. Chicago-house

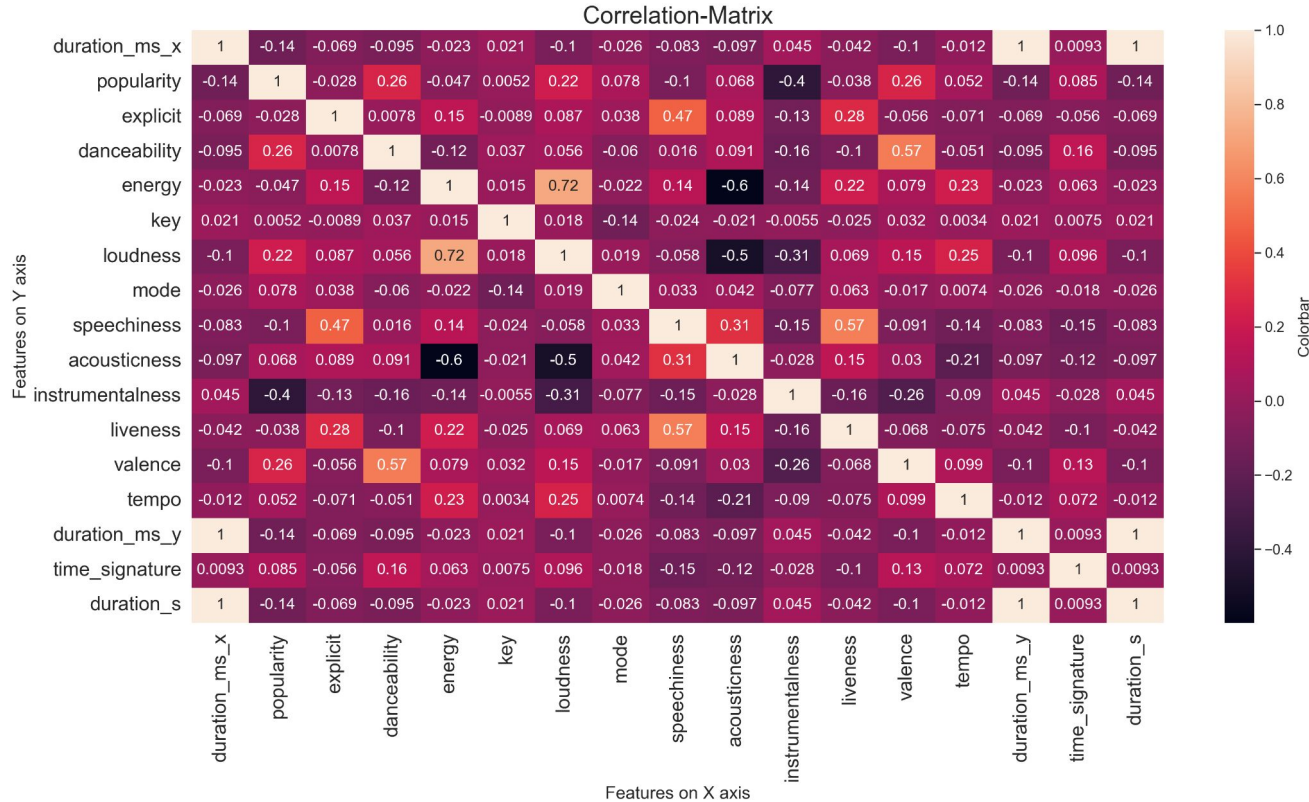
Data Pre-processing

- Deleted rows with missing values
- Erased rows with duplicate data
- Replaced boolean values with numericals
- Took desired genres from 126 to 15 genres

Feature Engineering

- Dropped non-numeric or insignificant columns
- highly correlated feature loudness was dropped using correlation matrix
- After feature analysis, 15 features were kept finally

Correlation Matrix



Splitting Dataset

- The dataset was splitted into training and testing dataset in the ratio of **8:2** respectively
- Training set is used to train the machine learning model to predict
- Testing set is used to measure the performance

Classification-Training Models

- Training is performed
- Data fitting is executed to fit the models

Evaluation through Cross Validation

- For better evaluation, Cross validation is performed to get the estimation of the performance of models through accuracy score function
- Specifically, K-fold cross validation on both training and test dataset is applied to get our initial and final predictions by shuffling the dataset randomly and by splitting into k number of folds

Hyperparameter optimization

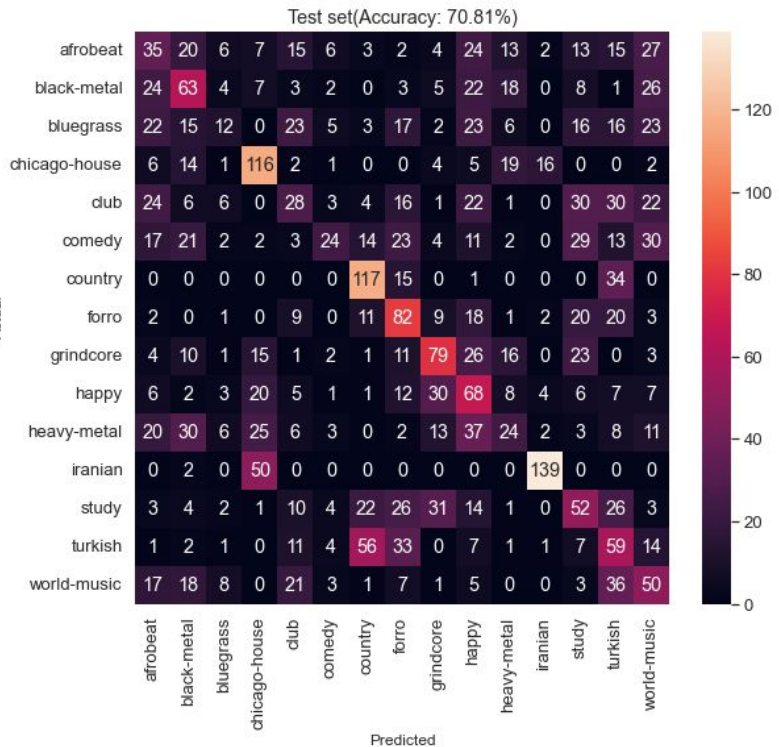
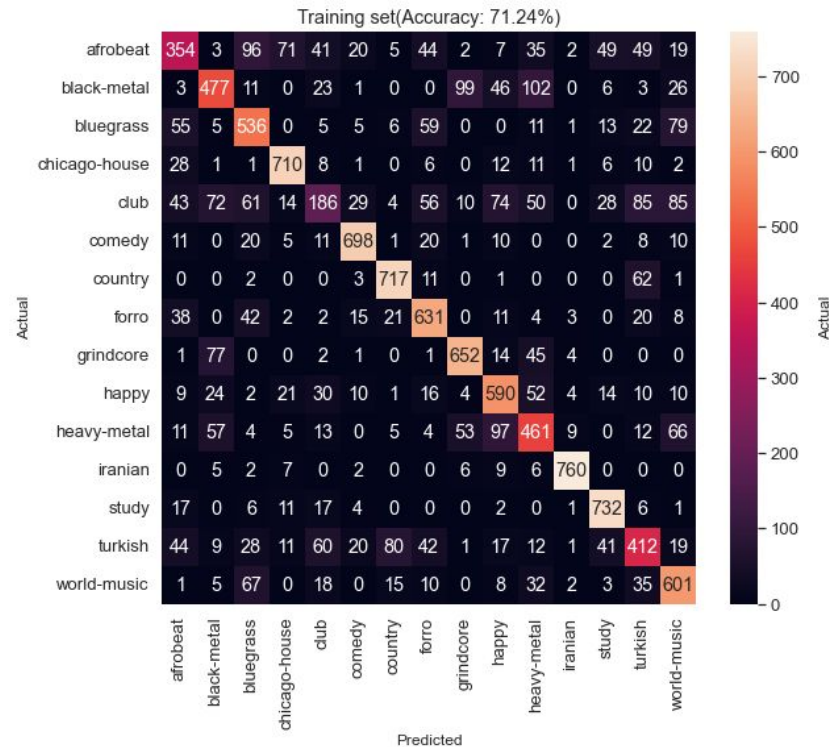
- Manual search/investigation of the best possible hyperparameters
- Through Scikit-Learner's GridSearchCV and RandomizedSearchCV (only applied to Random Forest), models are optimized or retrained by applying optimal/best hyperparameters

Logistic Regression

Steps performed to get optimized LR model:

- used **SMOTE()** function
- “**popularity**” and “**tempo**” having large integer values were scaled **StandardScaler()** function
- included **PCA()** function
- incorporated grid search optimization also
- cross-validation parameter along with pipeline as estimators and after fine tuning model, the LR model was retrained by providing test set accuracy as **70.81%** which was initially **33.87%**.

| Best Hyperparameters | Values |
|----------------------|---------------------|
| C | 100 |
| Penalty | l2 |
| multiclass | ovr |
| solver | newton-cg |
| pipeline | pca,standard scalar |

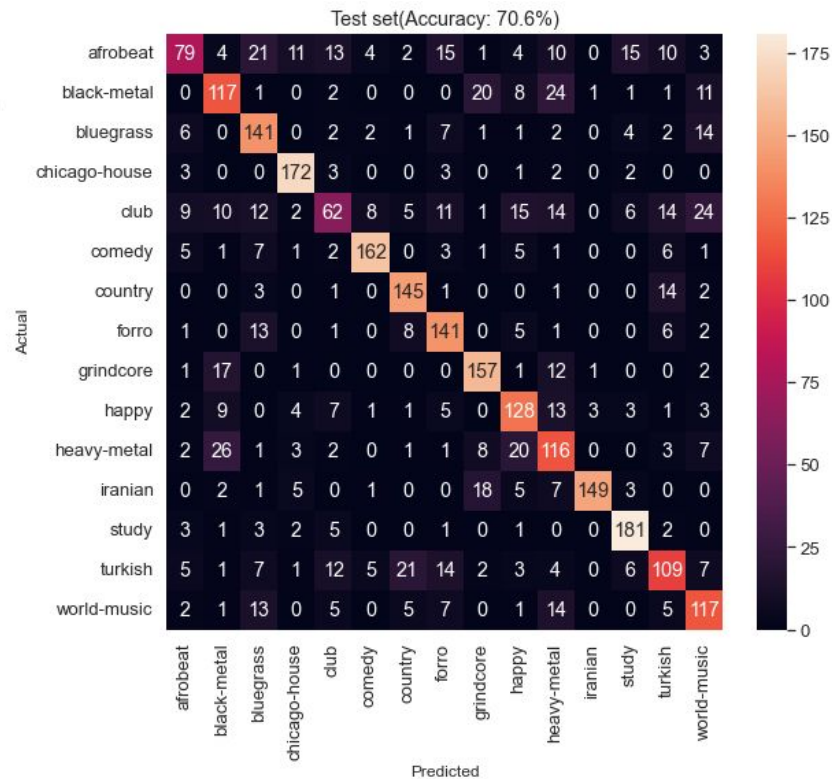
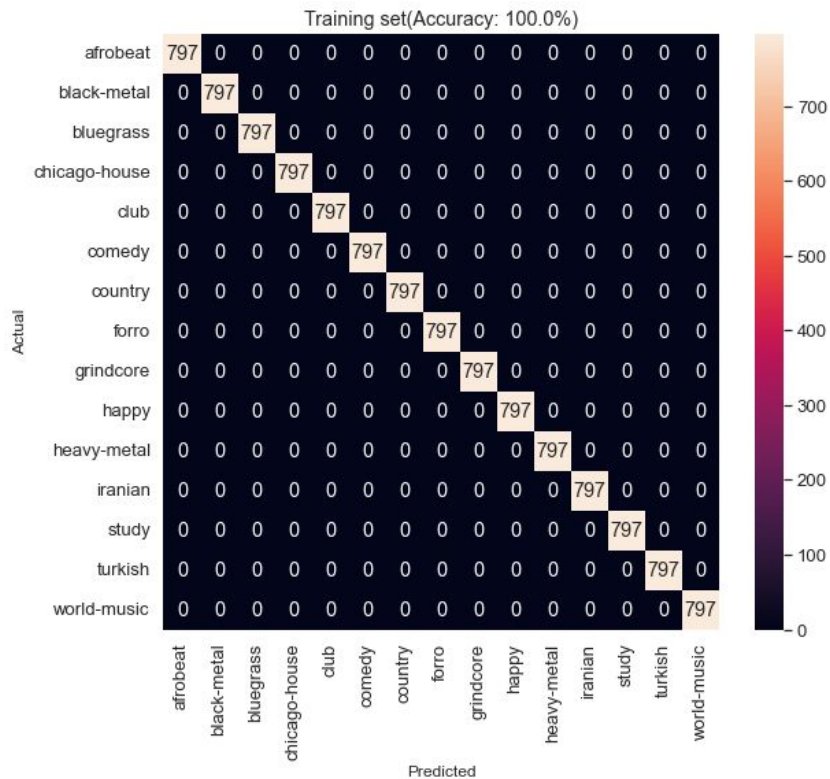


K-Nearest Neighbor

Steps performed to get optimized KNN model:

- If the number of nearest neighbors=**k is too small**, then it results in the decrease of accuracy rate
- the experimental results show that initial value of k is 21, where accuracy rate reached up to **44.68%**.
- after applying smote function, respective pipeline same as LR classification model and
- applying tuning of model through grid search;the K-NN model gave accuracy of about **70.6%**.

| Best Hyperparameters | Values |
|----------------------|---------------------|
| Leaf size | 30 |
| N neighbors | 16 |
| weights | distance |
| metric | minkowski |
| pipeline | pca,standard scalar |

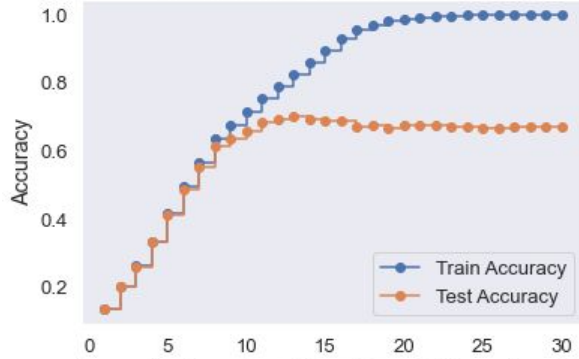


Decision Tree

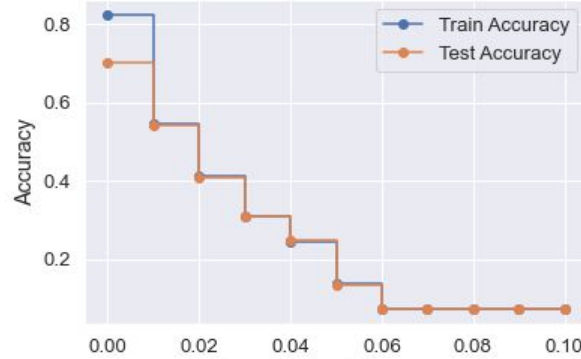
- Observation of DTs performance on our case.
- Initial Tree accuracy: 67%
- For optimization: Hyperparameter tuning (manually)
 - Maximum depth
 - Ccp_alpha (pruning)
 - Minimum samples per split
 - Criterion (Entropy vs. Gini-impurity)
 - Splitter (“Best” vs. Random)
- GridSearch

DT Hyperparameter tuning

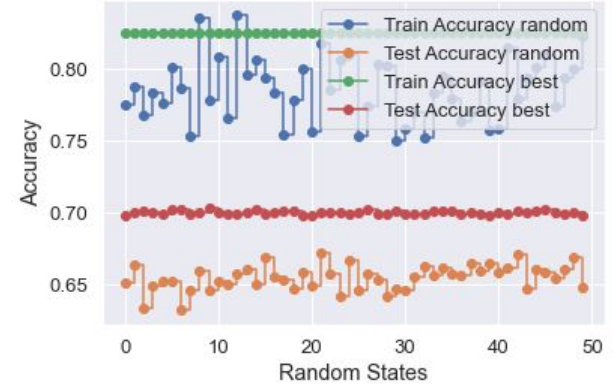
Accuracies for variable max_depth



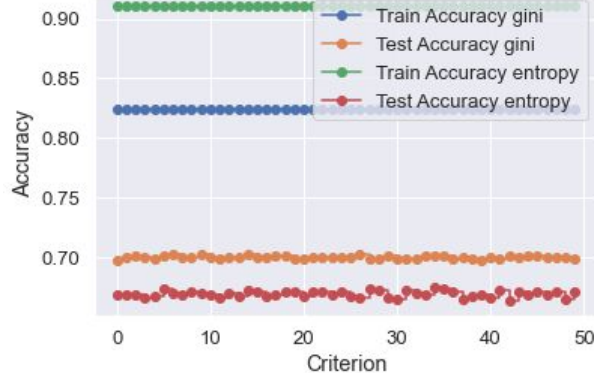
Accuracies for variable ccp_alpha



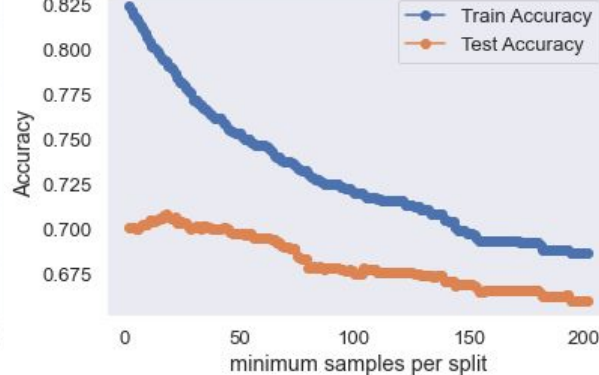
Accuracies for random Tree with variable random state



Accuracies for random Tree with variable random state



Accuracies for variable minimum samples per split



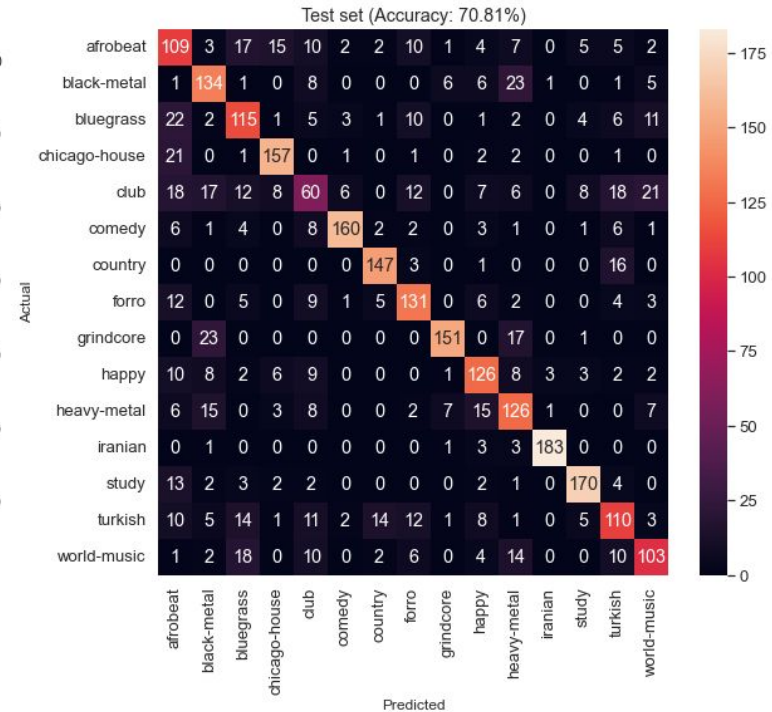
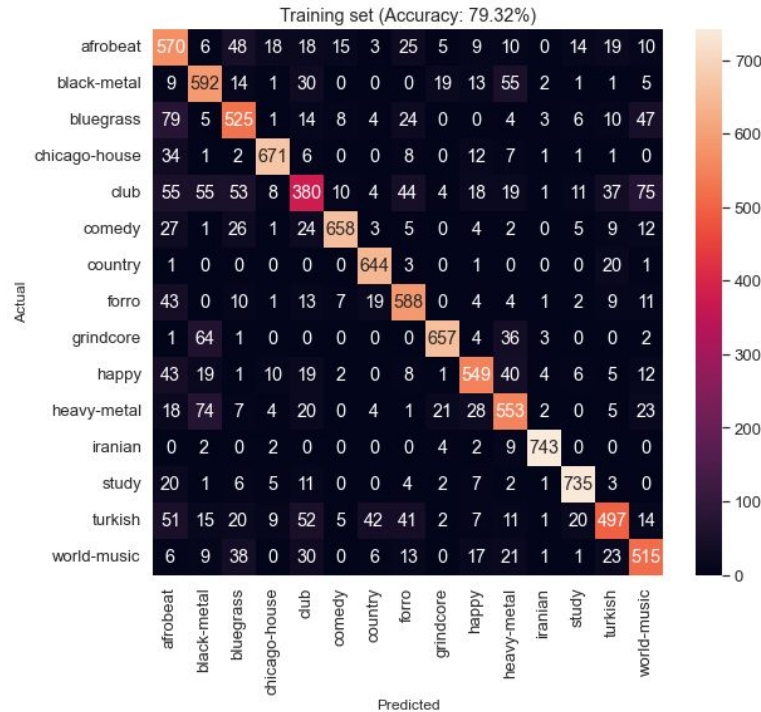
Optimal values for observed hyperparameters

| Hyperparameter | Value (tuning) | Value (gridSearch) |
|----------------------|----------------|--------------------|
| Max. depth | 13 | 13 |
| Ccp_alpha | 0 (no pruning) | 0 |
| Min. samples / split | 18 | 33 |
| splitter | best | best |
| criterion | gini | gini |

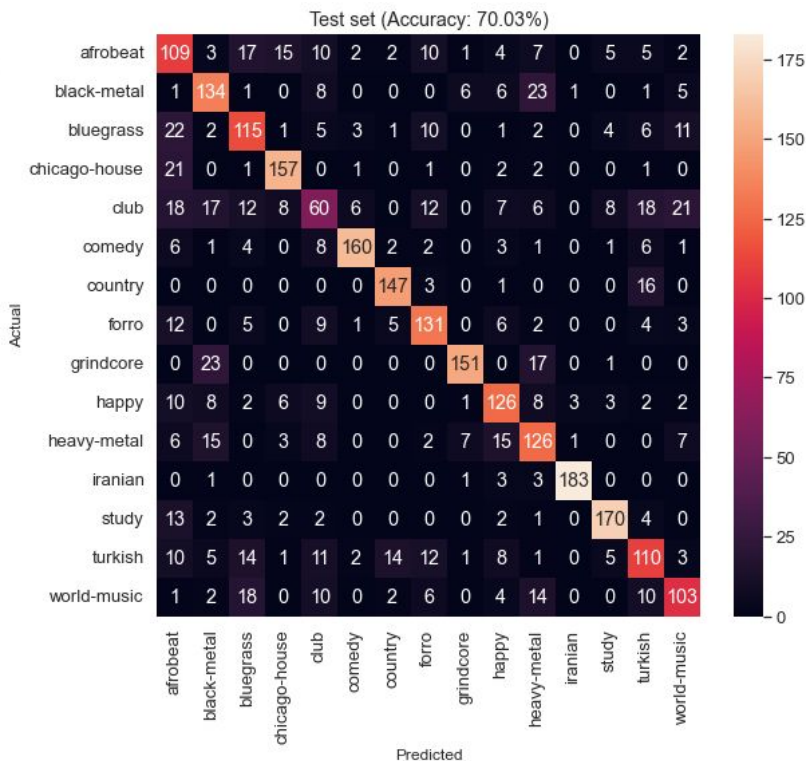
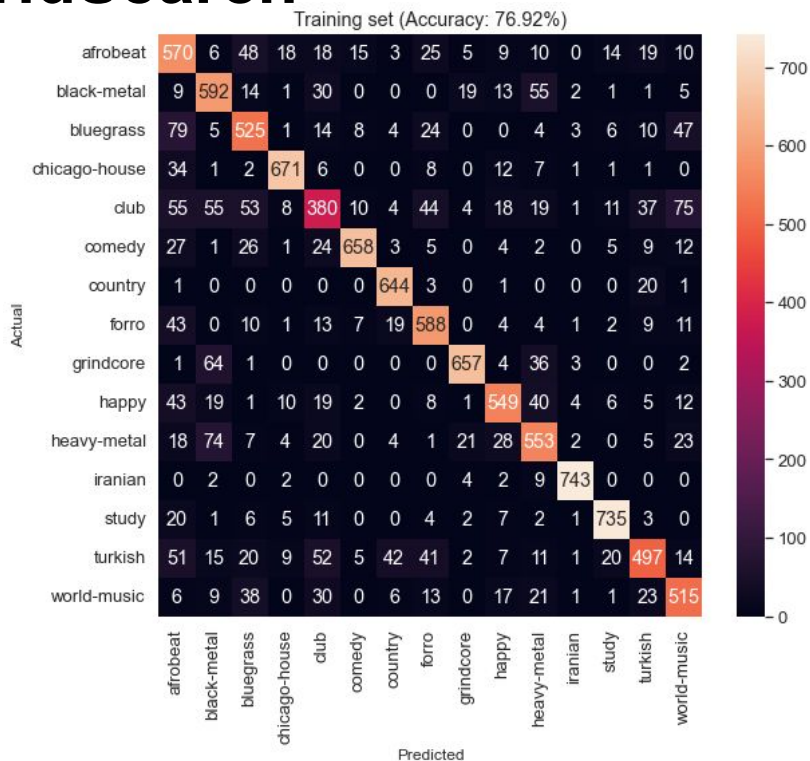
Tuning accuracy: 70.81%

Gridsearch accuracy: 70.03%

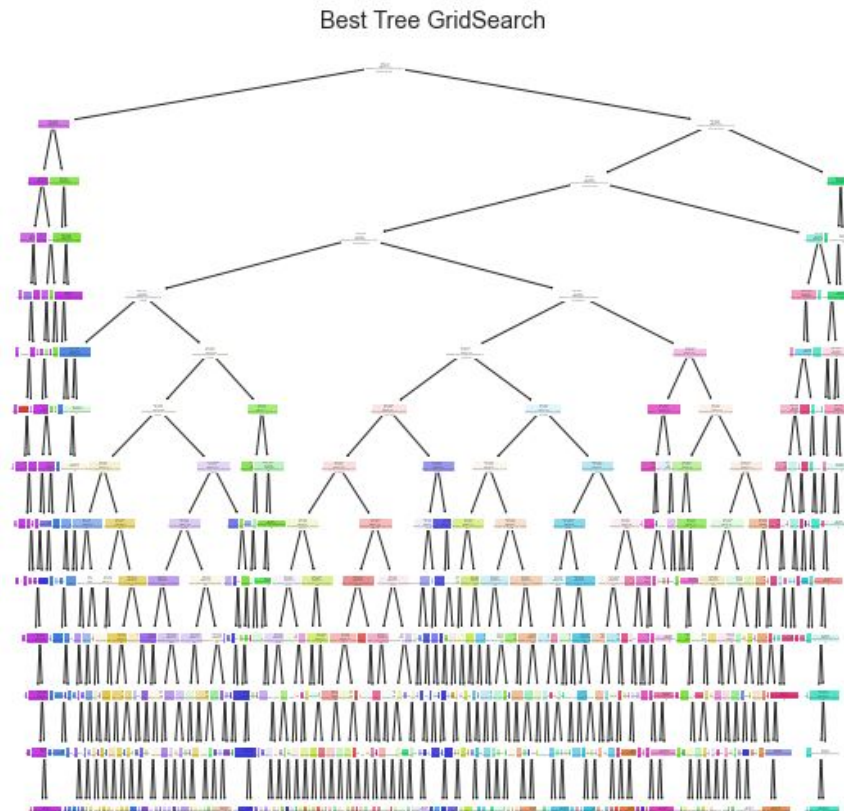
Manual tuning



GridSearch



DT Visualization



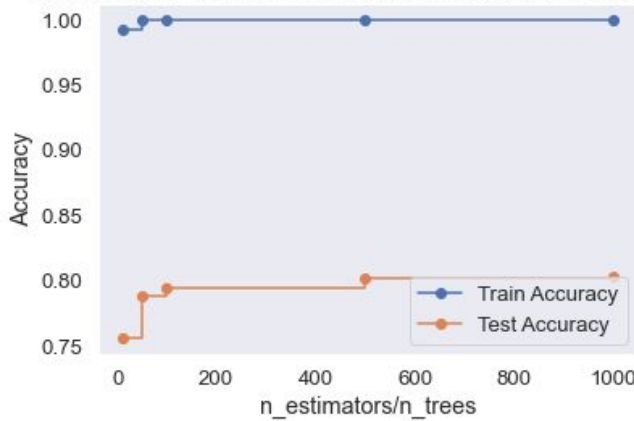
Random Forest

- final parameters used are named as **number of estimators**, **maximum depth**, **maximum features**, **minimum samples per split**, **minimum samples per leaf** etc.
- grid search optimization always comes up with the best possible combination of hyperparameters
- delivers an accuracy of about **79.59%** without hyperparameter tuning. Later accuracy increases up to **79.67%** after tuning.

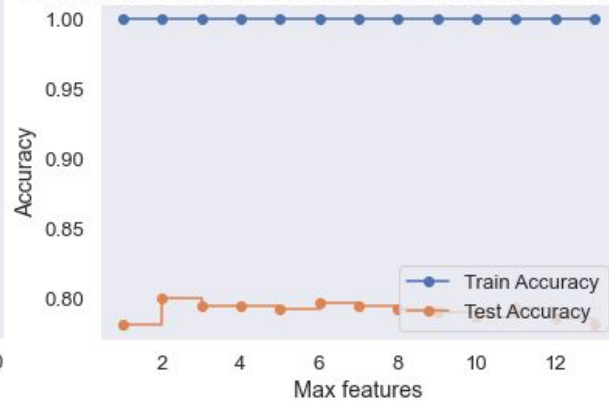
| Best Hyperparameters | Values |
|----------------------|--------------------|
| maximum depth | 19 |
| maximum features | 3 |
| n estimators | 1000 |
| criterion | entropy |
| min. samples leaf | 2 |
| min. samples split | 3 |
| class weight | balanced_subsample |

Random Forest Hyperparameter Tuning(individual)

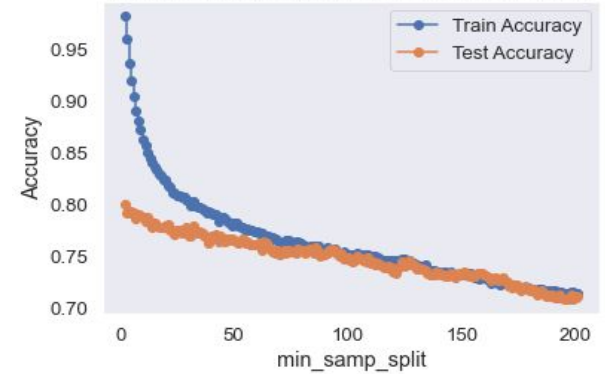
Accuracies of regularised Random Forest depending on no c



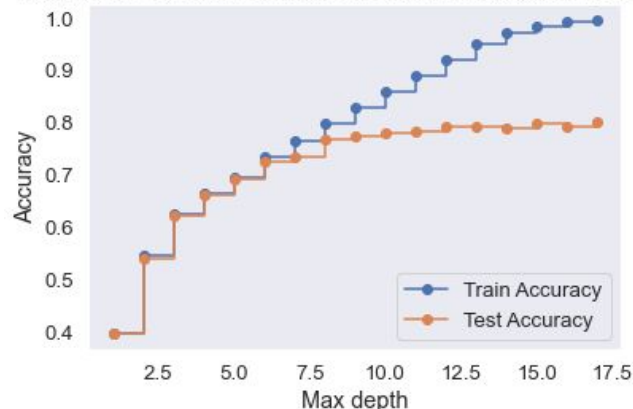
Accuracies of regularised Random Forest depending on max fea



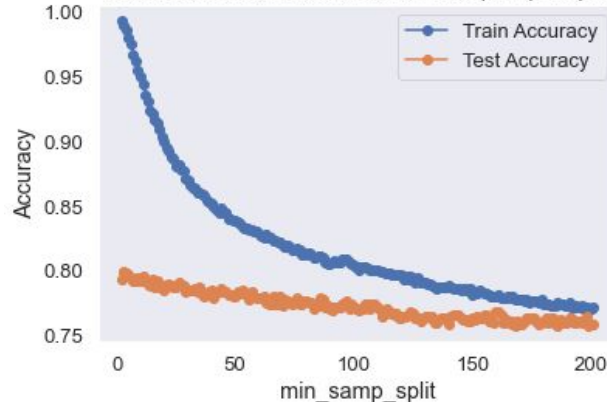
Accuracies for variable minimum samples per split

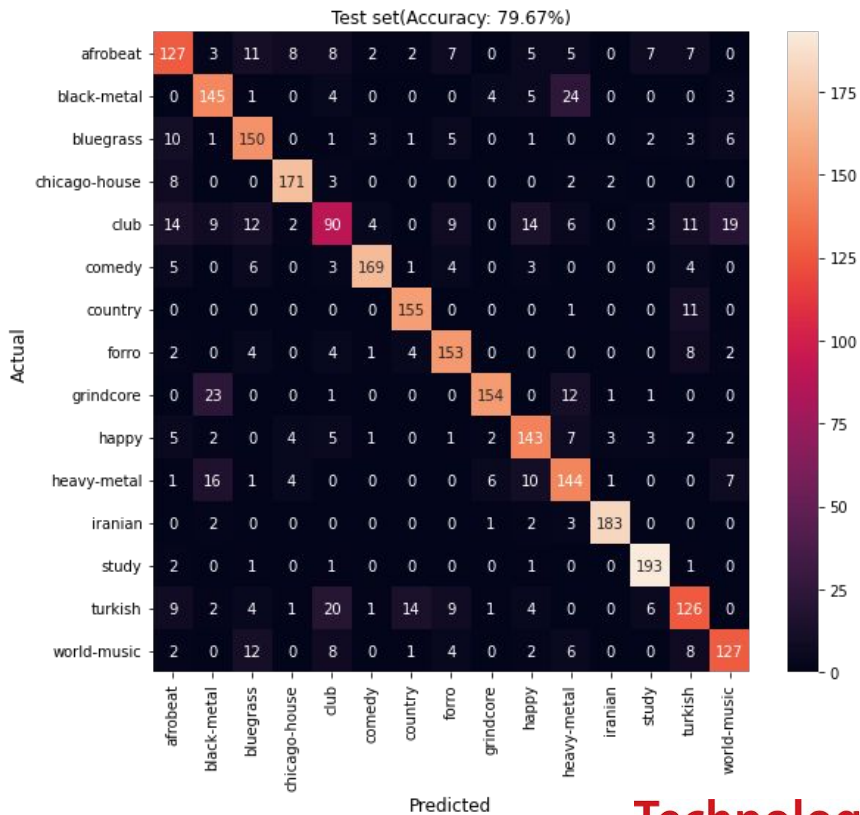
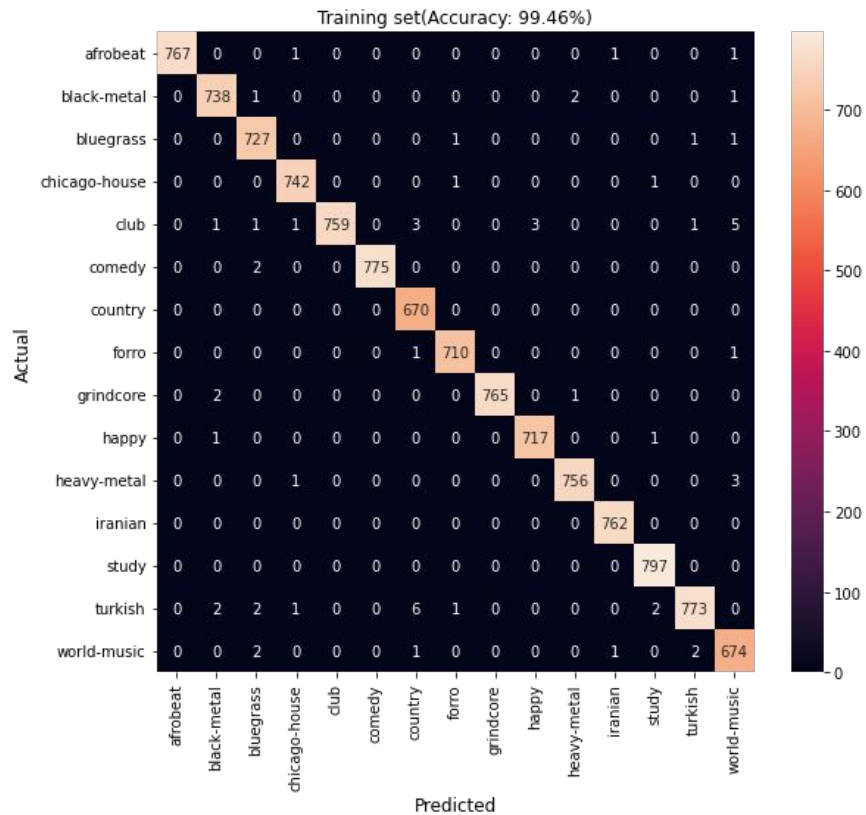


Accuracies of regularised Random Forest depending on max dep



Accuracies for variable minimum samples per split





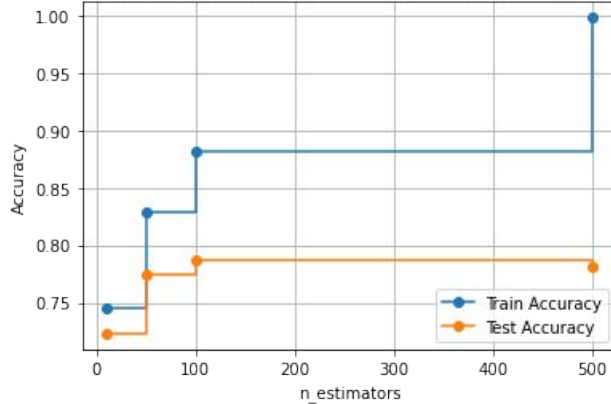
Gradient Boosting

- GB approach uses **multi-classifiers**, which create hundreds of trees.
- Therefore, the design of each classifier is simple and speed up the progress of our training.
- To find the optimal parameters for GB we implemented following parameters are as mentioned for which we get an accuracy score of **80.46%** on the test set which was initially **78.67%** without hyperparameter tuning.

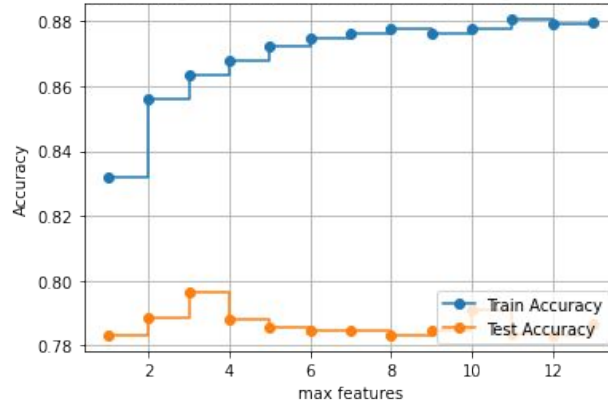
| Best Hyperparameters | Values |
|----------------------|--------------|
| Maximum depth | 8 |
| Maximum features | 2 |
| Learning rate | 0.1 |
| N estimators | 500 |
| subsample | 1.0 |
| Min. samples split | 7 |
| Min. samples leaf | 15 |
| criterion | friedman_msc |

Gradient Boosting Hyperparameter Tuning(individual)

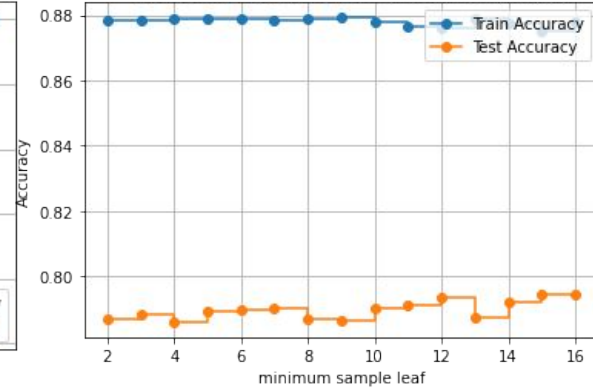
Accuracies of regularised Random Forest depending on n_estimators



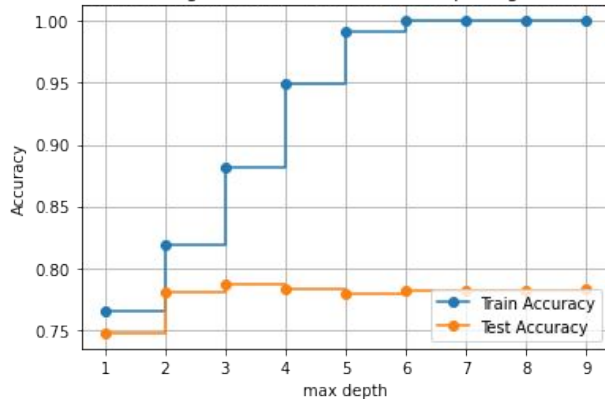
Accuracies of regularised Random Forest depending on max features



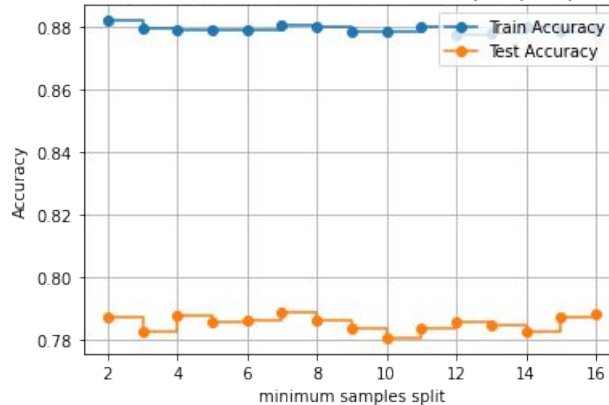
Accuracies for variable minimum samples per leaf

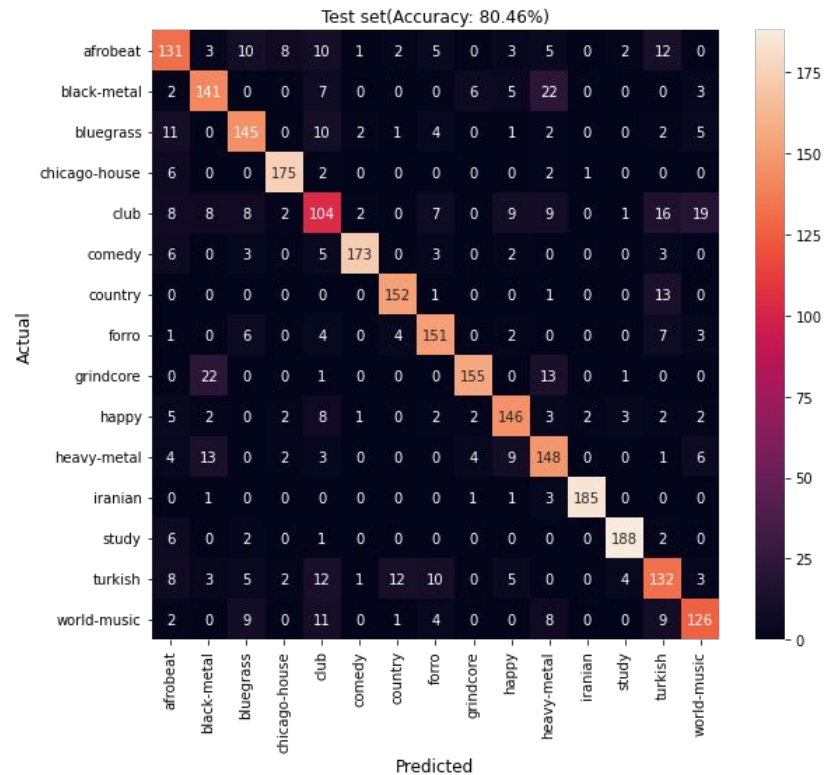
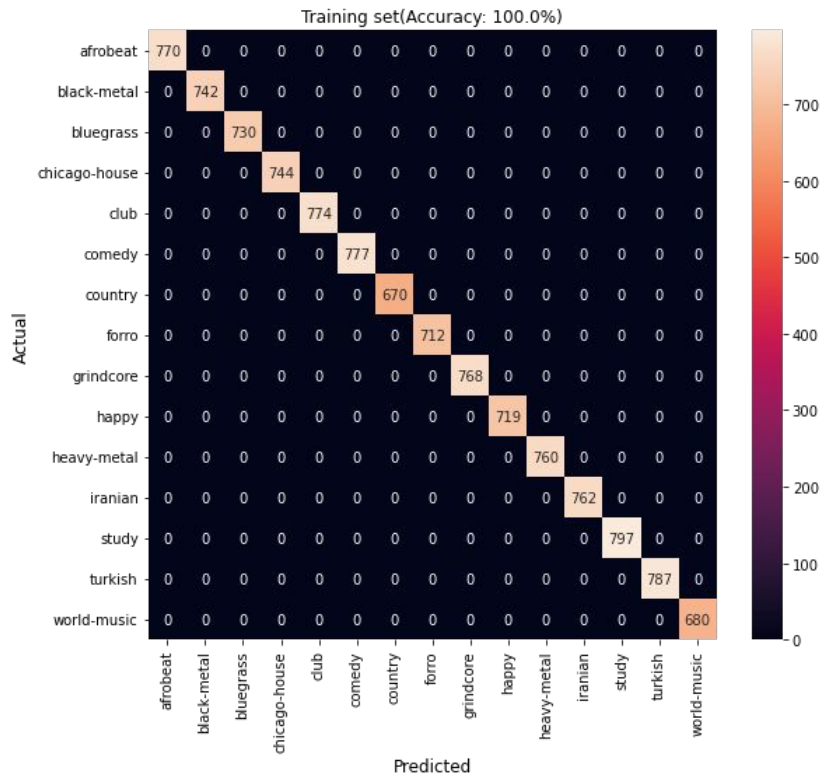


Accuracies of regularised Random Forest depending on max depth

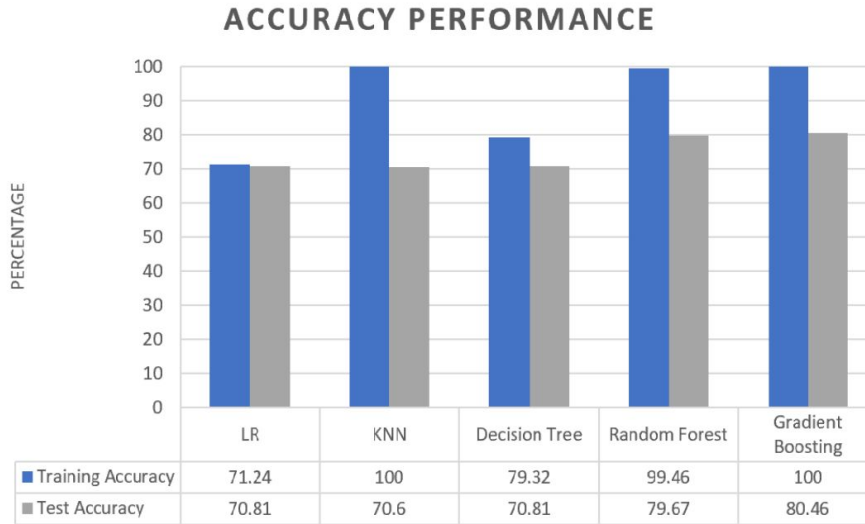


Accuracies for variable minimum samples per split





Model Comparison

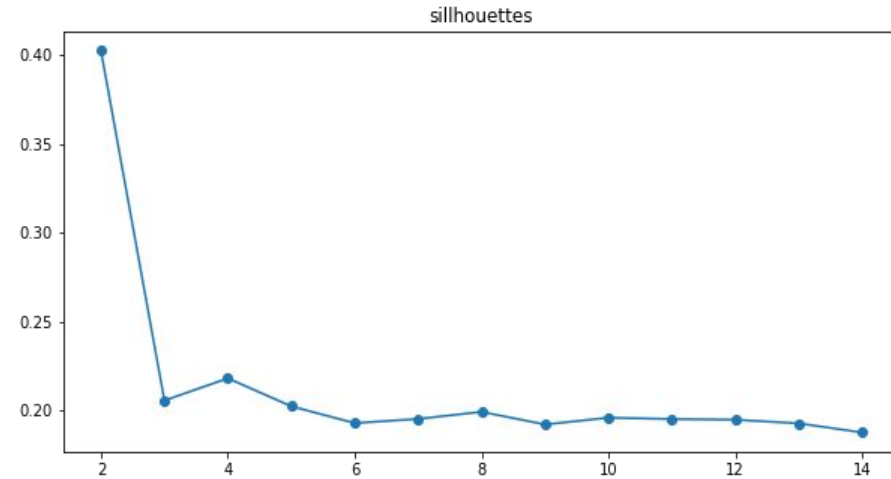
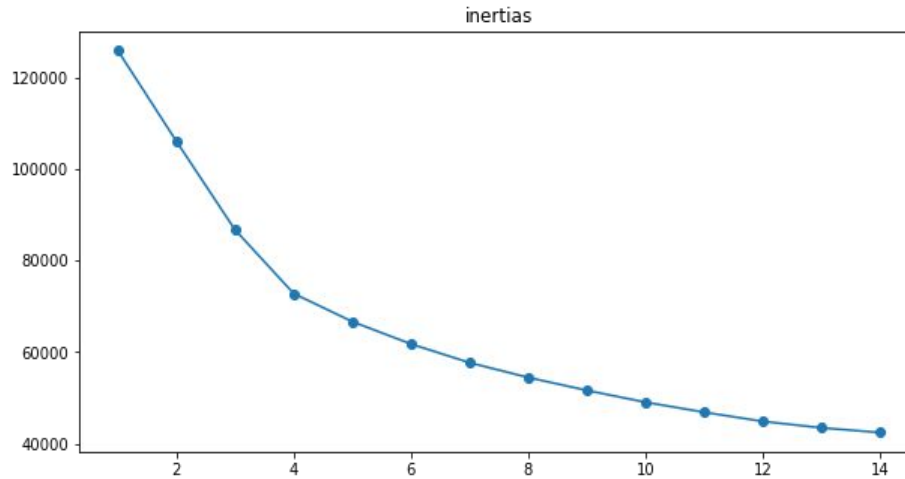


- In the plot, it is visible that both highest performing classifiers are respectively GB with an accuracy of 80.46% and RF with 79.67%.
- The lowest accuracy was achieved by the K-NN classifier with 70.6%. Besides, DT and LR had the same accuracy about 70.81% which is only a small amount of higher than K-NN.

Additional Task: K-Means Clustering

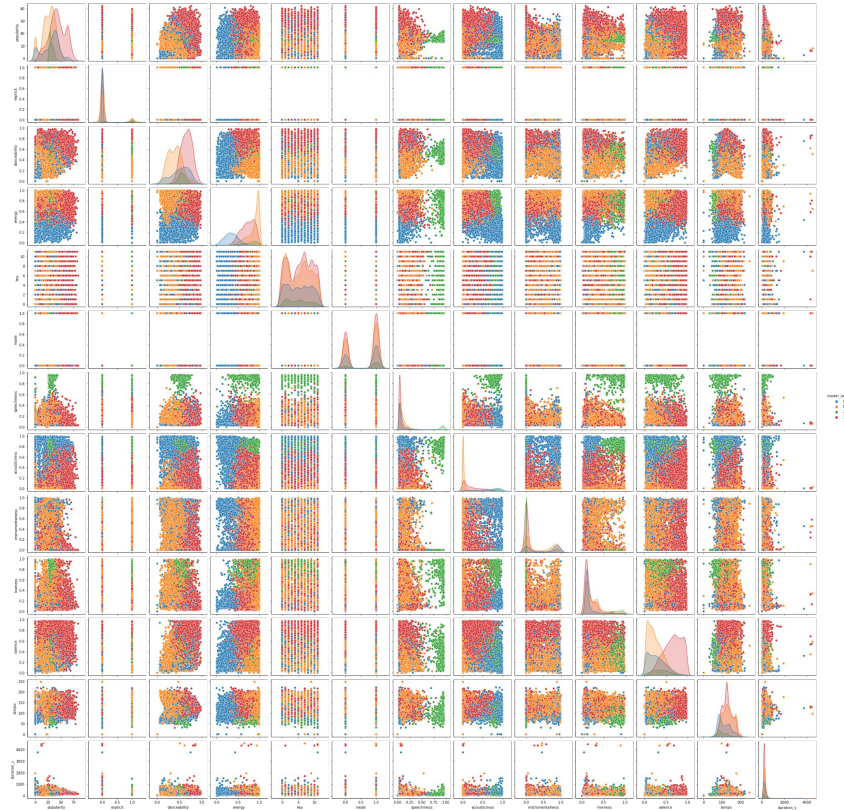
- Used numerical parameters, which give informations about specific character of a song.
 - Popularity
 - Danceability
 - Energy
 - Speechiness
 - Acousticness
 - Instrumentalness
 - Liveness
 - Tempo
 - valence

Amount of clusters

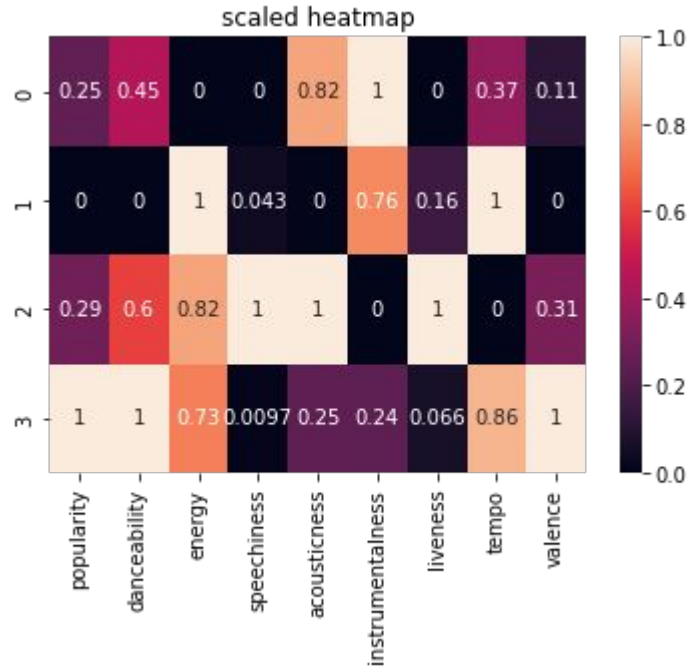


Both say: take 4

Pairplots



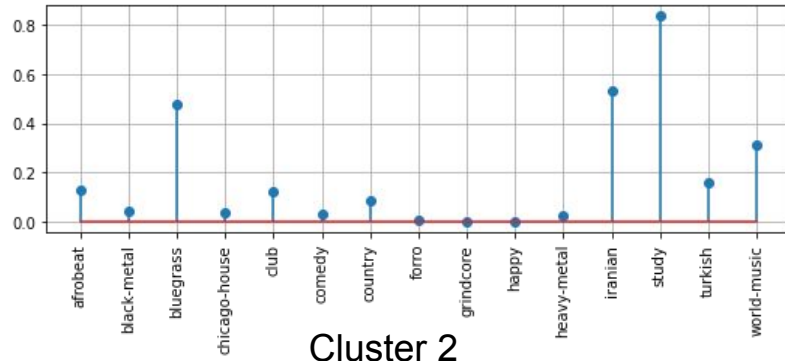
Heatmap



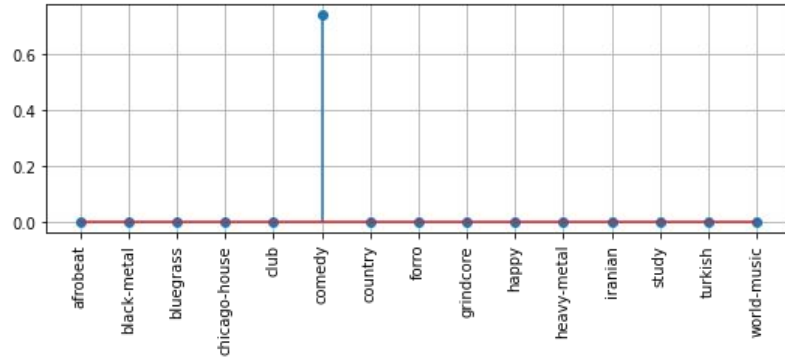
The Clusters

- Cluster 0: Acoustic Instruments
- Cluster 1: energetic fast instrumentals
- Cluster 2: speech live acoustic
- Cluster 3: Pop-Dance

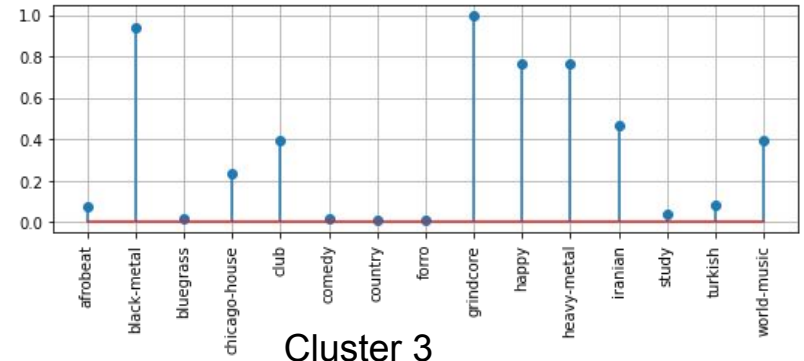
Cluster 0



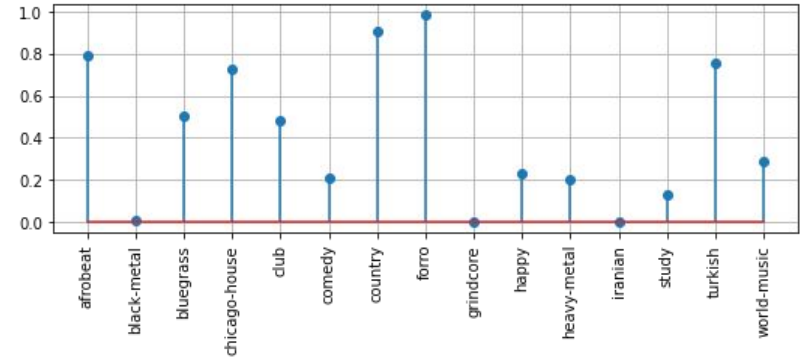
Cluster 2



Cluster 1



Cluster 3



- **Acoustic Instruments:**

- Bluegrass 50%
- Iranian 50%
- Study
- World-music 33%

- **Speech live acoustic:**

- Comedy

- **Energetic fast Instrumentals:**

- Black-metal
- Club 50%
- Grindcore
- Happy
- Heavy-metal
- Iranian 50%
- World-music

- **Pop-Dance:**

- Afrobeat
- Bluegrass 50%
- chicago-House
- Club 50%
- Country
- Forro
- Turkish
- World-music 33%

Result and Conclusion

- Self explaining: Hyperparameter leads to accuracy improvement.
- GB and RF are performing way better, than the rest.
- KNN and GB are overfitting.

Thank you !