# Predicting song popularity by genre

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# Project overview and motivation

- Our aim was to utilize **audio features** and **track metadata** to predict **song popularity**
- Our data consists of features extracted from the Free Music Archive, https://github.com/mdeff/fma

**Input**

**Audio features:** acousticness, danceability, energy, etc.

**Track metadata:** track title, duration, bit rate, location

**Classification model**

(Logistic regression, KNN, decision tree, random forest)

**Output**

**Popular or not popular**

# Data overview

- **Audio features:** speechiness, liveness, energy, tempo, etc.
- **Track features:** title, latitude / longitude, duration, bit rate, etc.
- Additional feature: sentiment analysis on song name - we take positive and negative sentiment using nltk package
- We find the year with the most tracks (2010) and select the top 3 genres (rock, hip-hop, electronic)
- To change our data to classification, we take the **top 25% of track listens to be popular** and the rest as unpopular

# Sentiment analysis

**Code**

```python
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download('vader_lexicon')

# Read in track data - change to local directory
tracks_senti = pd.read_csv('/Users/kathyli/Downloads/fma_metadata/tracks.csv',header=None)

header = tracks_senti.iloc[1]
header[0]='track ID'
header[52]='track title'
tracks_senti.drop(tracks_senti.index[[0,1,2]],inplace=True)
tracks_senti.rename(columns = header,inplace=True)
tracks_senti.head()

df=tracks_senti[['track ID','track title']]
df.dropna(axis=0, how='any')

ml = df["track title"].values
title=[]
for i in range(len(ml)):
    a=str(ml[i])
    title.append(a)
idd = df["track ID"].values

neg=[]
neu=[]
pos=[]
comp=[]

sid = SentimentIntensityAnalyzer()
for sentence in title:
    ss = sid.polarity_scores(sentence)
    score=[]
    for k in ss:
        a=ss[k]
        score.append(a)
    neg.append(score[0])
    neu.append(score[1])
    pos.append(score[2])
    comp.append(score[3])
```

e.g.

Happy: Positive=1
Negative=0

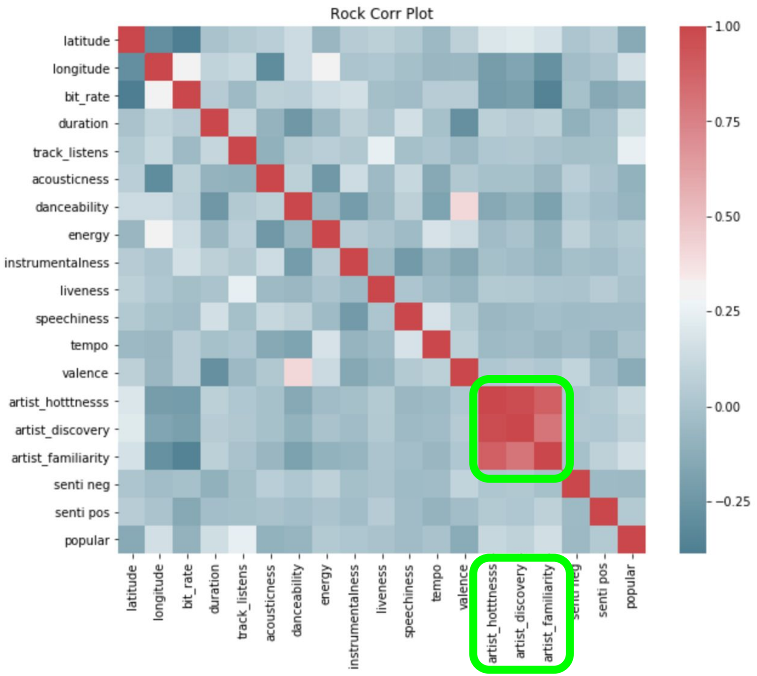
Sad : Positive = 0
Negative=1

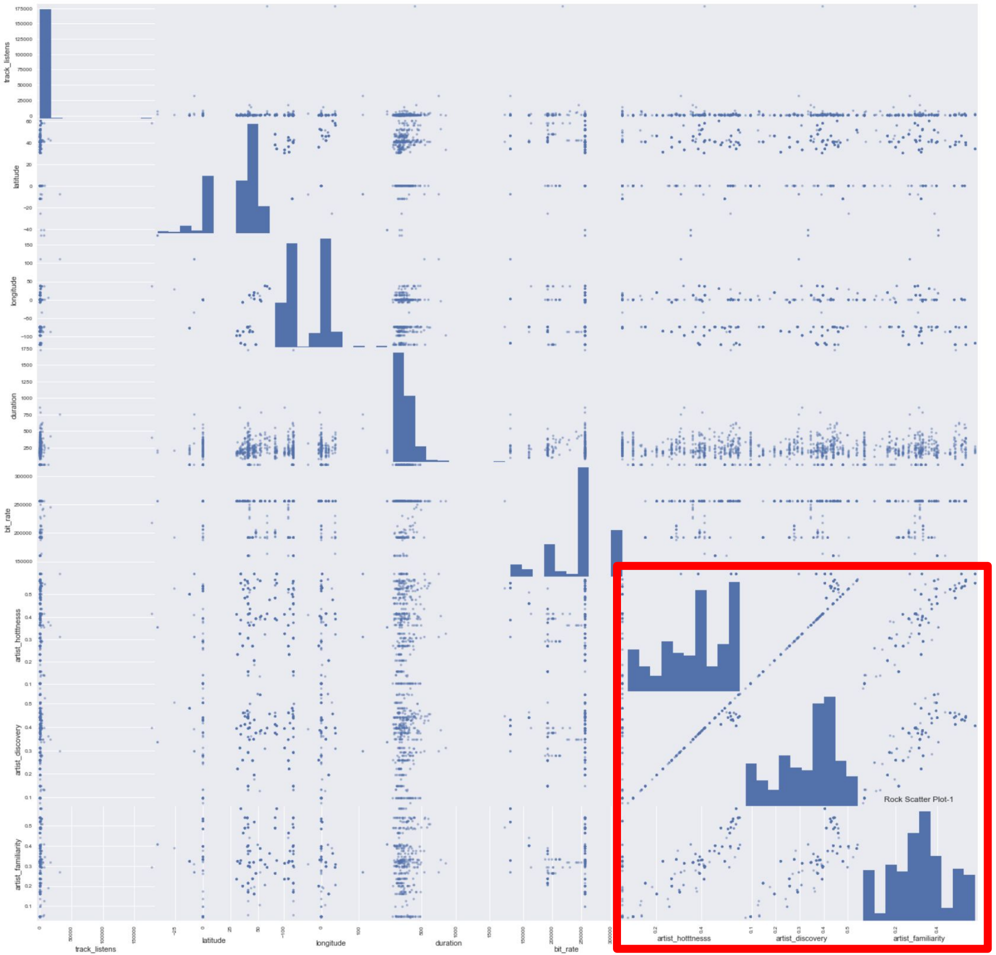
**Output**

| | senti comp | senti neg | senti neu | senti pos | track_ID | track_title |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 1 | 0 | 2 | Food |
| 1 | 0 | 0 | 1 | 0 | 3 | Electric Ave |
| 2 | 0 | 0 | 1 | 0 | 5 | This World |
| 3 | 0.0516 | 0 | 0 | 1 | 10 | Freeway |
| 4 | 0 | 0 | 1 | 0 | 20 | Spiritual Level |
| 5 | 0.6369 | 0 | 0.417 | 0.583 | 26 | Where is your Love? |
| 6 | 0.5719 | 0 | 0.213 | 0.787 | 30 | Too Happy |
| 7 | 0 | 0 | 1 | 0 | 46 | Yosemite |
| 8 | 0 | 0 | 1 | 0 | 48 | Light of Light |
| 9 | 0 | 0 | 1 | 0 | 134 | Street Music |
| 10 | 0 | 0 | 1 | 0 | 135 | Father's Day |
| 11 | 0 | 0 | 1 | 0 | 136 | Peel Back The Mountain Sky |
| 12 | 0 | 0 | 1 | 0 | 137 | Side A |
| 13 | 0 | 0 | 1 | 0 | 138 | Side B |
| 14 | 0 | 0 | 1 | 0 | 139 | CandyAss |
| 15 | 0 | 0 | 1 | 0 | 140 | Queen Of The Wires |
| 16 | 0 | 0 | 1 | 0 | 141 | Ohio |
| 17 | -0.3818 | 0.565 | 0.435 | 0 | 142 | Punjabi Watery Grave |
| 18 | 0 | 0 | 1 | 0 | 144 | Wire Up |
| 19 | 0 | 0 | 1 | 0 | 145 | Amoebiasis |
| 20 | 0 | 0 | 1 | 0 | 146 | Gimme a Buck or I'll Touch You / Boilermaker |
| 21 | -0.25 | 0.5 | 0.5 | 0 | 147 | Repetitive Motion Sickness |
| 22 | 0 | 0 | 1 | 0 | 148 | Blackout 2 |
| 23 | 0 | 0 | 1 | 0 | 149 | Outside the window bees buzzed... |
| 24 | 0.4939 | 0 | 0.686 | 0.314 | 150 | ... listening to the sunshine burn the grass |
| 25 | 0 | 0 | 1 | 0 | 151 | Untitled 04 |
| 26 | 0 | 0 | 1 | 0 | 152 | Untitled 11 |
| 27 | 0 | 0 | 1 | 0 | 153 | Hundred-Year Flood |
| 28 | 0 | 0 | 1 | 0 | 154 | Squares And Circles |
| 29 | 0 | 0 | 1 | 0 | 155 | Maps of the Stars Homes |
| 30 | 0 | 0 | 1 | 0 | 156 | Track 01 |
| 31 | 0 | 0 | 1 | 0 | 157 | Track 02 |
| 32 | 0 | 0 | 1 | 0 | 158 | Track 03 |
| 33 | 0 | 0 | 1 | 0 | 159 | Track 04 |

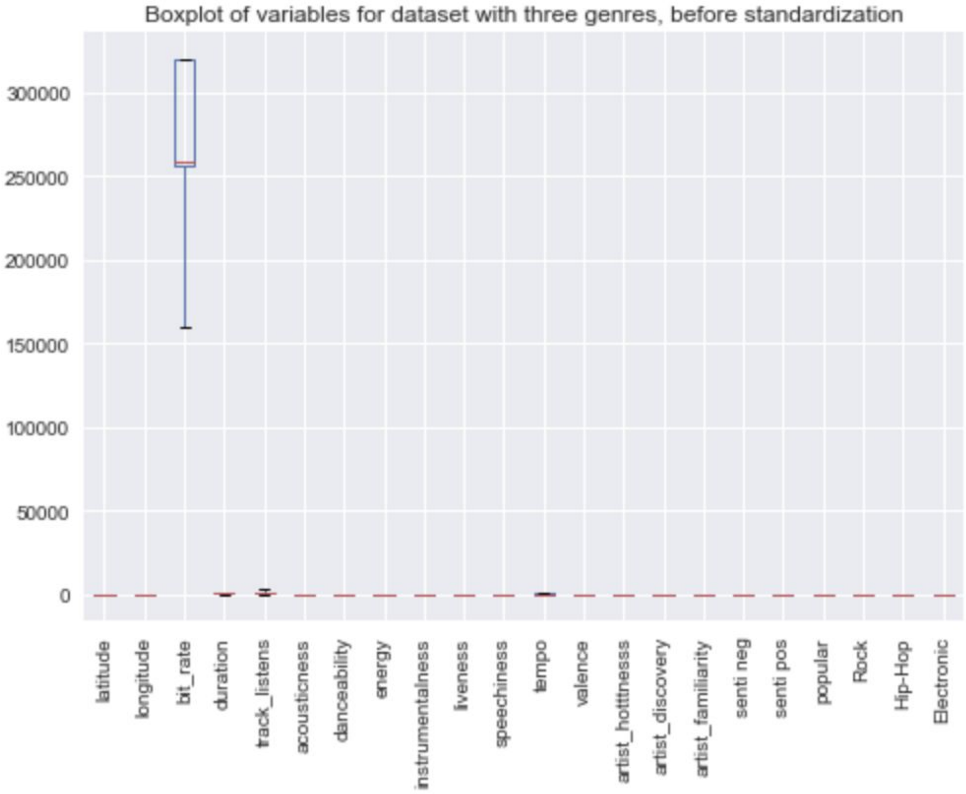
# Exploratory data analysis

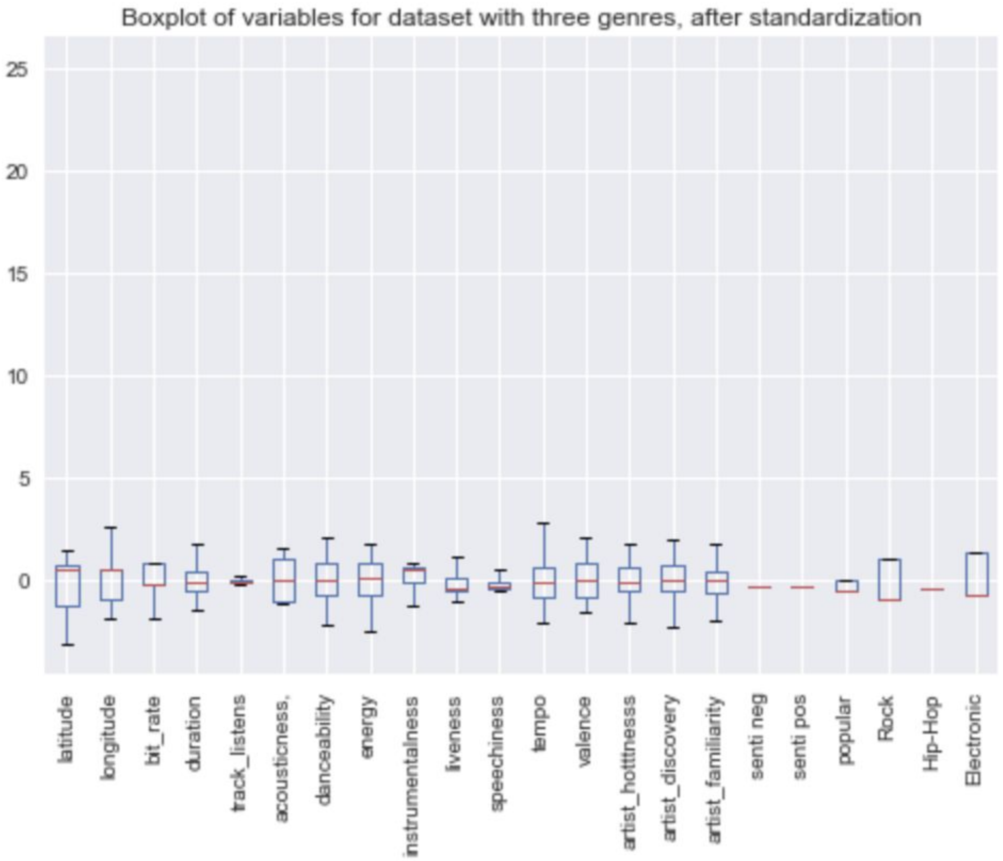
- We plot correlation between variables and see that artist hottness, artist familiarity, artist discovery are redundant, so we choose one




track_listens
latitude
longitude
duration
bit_rate
artist_hotttnesss
artist_discovery
artist_familiarity
Rock Scatter Plot-1

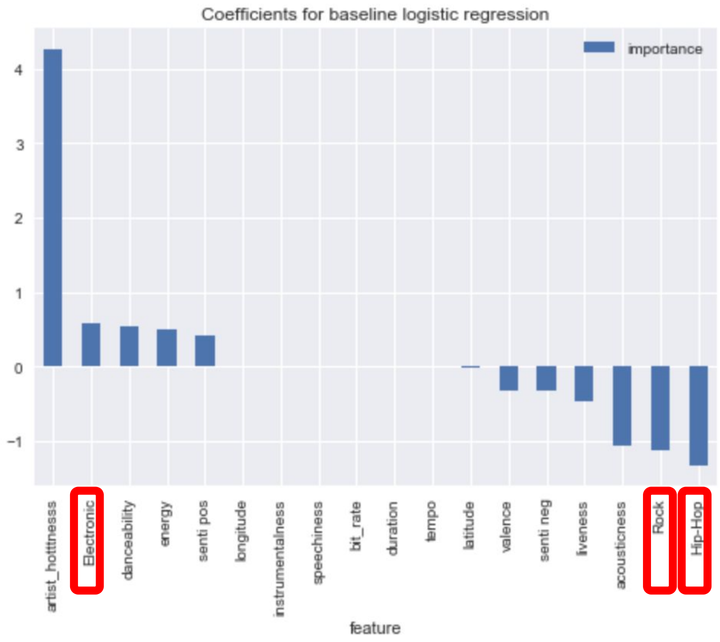
- We also standardize data using StandardScaler




Boxplot of variables for dataset with three genres, after standardization
25
20
15
10
5
0
latitude
longitude
bit_rate
duration
track_listens
acousticness,
danceability
energy
instrumentalness
liveness
speechiness
tempo
valence
artist_hotttnesss
artist_discovery
artist_familiarity
senti neg
senti pos
popular
Rock
Hip-Hop
Electronic

# Baseline model

- Our hypothesis: **genre is an important predictor for song popularity**
- To validate this, we first implement a baseline logistic regression, where we include **genre as a categorical variable** (rock, hip-hop, electronic)
- **Genre variables have high magnitude coefficients**, so we subset by genre to investigate what separates the genres



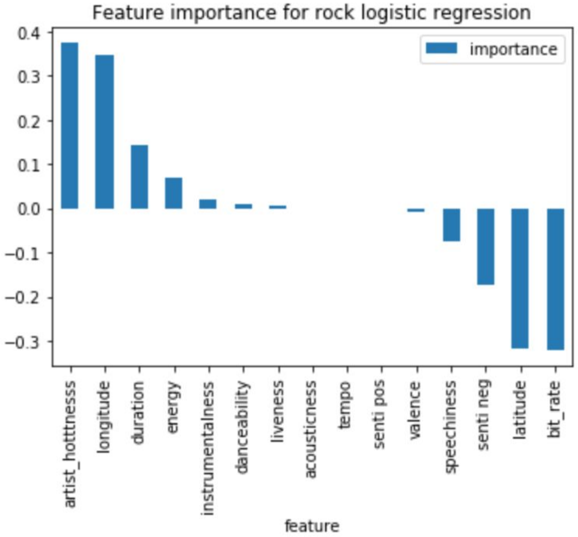
# Genre-specific models

- For each genre, we test
    - **Logistic regression** - regularize using L1 penalty
    - **Decision tree** - find optimal tree depth
    - **Random forest** - find optimal depth and max number of features
    - **KNN** - find optimal number of neighbors
- We perform five-fold cross-validation and for each genre, pick the model that performs optimally on random subsets based on AUC ROC
- We also look at **feature importance** to determine which features are most important for each genre
- Notebook: https://github.com/kathyyli/DS_project/blob/master/DS%20project%20v4.ipynb

# Logistic regression for rock example

**Logistic regression with L1 penalty**

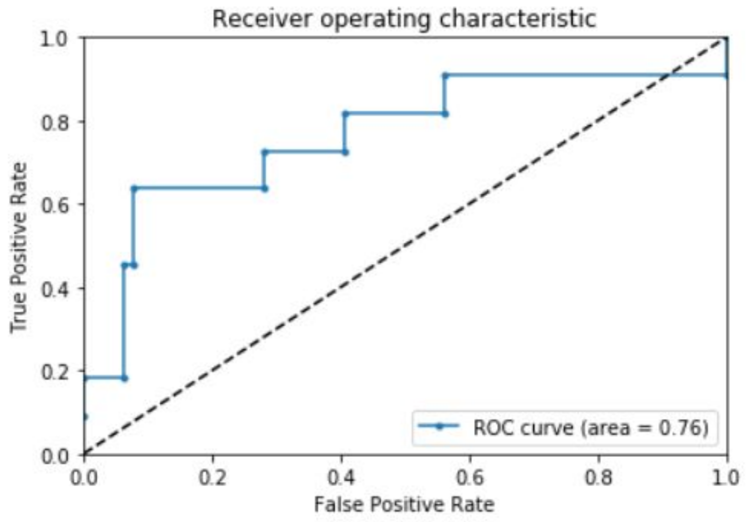
```
# Regularize over L1 penalty
C_vals = np.logspace(-4,0,100)
scores = []
for C_val in C_vals:

    #change penalty to l1
    regr = LogisticRegression(penalty='l1', C = C_val)
    regr.fit(X_train, y_train)

    probas_ = regr.fit(X_train, y_train).predict_proba(X_test)

    fpr, tpr, thresholds = roc_curve(y_test, probas_[:, 1])
    roc_auc = auc(fpr, tpr)

    scores.append(roc_auc)

#plot alphas vs. scores
plt.plot(C_vals, scores)
plt.xlabel('alpha')
plt.ylabel('AUC ROC')
plt.title('alpha vs. AUC ROC')
plt.show()

C_best_L1 = C_vals[scores.index(max(scores))]
print('Optimal C value for logistic regression: ' + str(C_best_L1))
```




Artist hotness, longitude/latitude, duration, and bit rate are important coefficients for rock

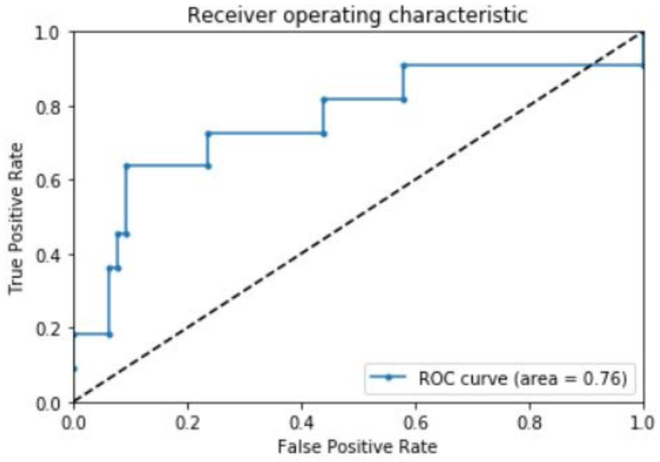
# Rock music result

Area under the ROC curve : 0.764205




Logistic with L1 penalty

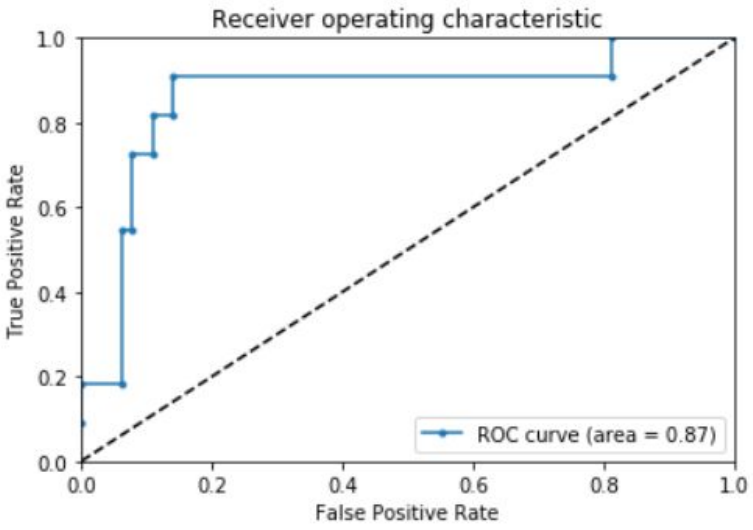
Area under the ROC curve : 0.759943




Logistic with L2 penalty

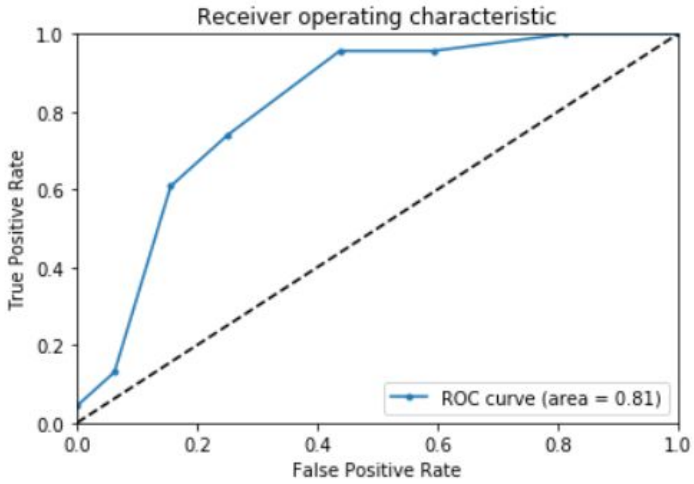
# Rock music result

Area under the ROC curve : 0.866477




Random Forest

Area under the ROC curve : 0.813179




knn

# Web app demo

rlx.pythonanywhere.com

Input: song info

Output: popular / not popular