# Popularity Prediction of Spotify Music

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Identify features and create models to predict the popularity of a song based on the features provided by the Spotify API

## Overview

- After model development the Linear Regression was best at predicting popularity with an MAE of 6.26 and RMSE of 8.65

- Random Forest Model was best at making the binary prediction if a song would be popular not with an accuracy of 90% and MAE of 1.64 and RMSE of 0.32

| | Model | Accuracy | MAE | MSE | RMSE |
|---|---|---|---|---|---|
| 2 | KNeighborsClassifier | 0.000000 | 37.506617 | 1526.300102 | 39.067891 |
| 3 | DecisionTreeClassifier | 0.011266 | 19.802104 | 540.345029 | 23.245323 |
| 4 | AdaBoostClassifier | 0.036037 | 11.390024 | 236.521208 | 15.379246 |
| 1 | RandomForestClassifier | 1.000000 | 0.000000 | 0.000000 | 0.000000 |
| 0 | LinearRegression | NaN | 6.256225 | 74.748668 | 8.645731 |

## The Data and Feature Engineering

```
In [2]: rawdata = pd.read_csv('SpotifyFeatures.csv')
        print(rawdata.head())
        print(rawdata.tail())
        rawdata.shape
        rawdata.describe()
```

```
   genre       artist_name                                        track_name  \
0  Opera    Giuseppe Verdi  Stiffelio, Act III: Ei fugge! … Lina, pensai c...
1  Opera  Giacomo Puccini  Madama Butterfly / Act 1: ... E soffitto e pareti
2  Opera  Giacomo Puccini      Turandot / Act 2: Gloria, gloria, o vincitore
3  Opera    Giuseppe Verdi      Rigoletto, Act IV: Venti scudi hai tu detto?
4  Opera    Giuseppe Verdi          Don Carlo / Act 4: "Ella giammai m'amò!"

                 track_id  popularity  acousticness  danceability  \
0  7EsKYeHtTc4H4xWiTqSVZA          21
1  7MfmRBvqaW0I6UTxXnad8p          18
2  7pBo1GDhIysyUMFXiDVoON          10
3  02mvYZX5aKNzdqEo6jF20m          17
4  03TW0jwGMGhUabAjOpB1T9          19

   duration_ms   energy  instrumentalness ke
0       490867  0.23100          0.000431  C
1       176797  0.20100          0.028000  D
2       266184  0.47000          0.020400
3       288573  0.00605          0.000000
4       629760  0.05800          0.146000

   speechiness    tempo time_signature  vale
0       0.0547   86.001            4/4   0.0
1       0.0581  131.798            4/4   0.3
2       0.0383   75.126            3/4   0.0
3       0.0480   76.493            4/4   0.0
4       0.0493  172.935            4/4   0.0
```

```
In [5]: duplicateRowsDF = rawdata[rawdata.duplicated()]
        duplicateRowsDF

        bins = np.array([100000,300000,500000,700000,900000,1000000])
        rawdata["bucket"] = pd.cut(rawdata.duration_ms, bins)

        rawdata['lognorm_duration'] = np.log(rawdata['duration_ms'])

        rawdata['Count'] = \
            rawdata.groupby('artist_name', as_index=False)['artist_name'].transform(lambda s: s.count())

        rawdata['popular'] = np.where(rawdata['popularity'] >= 40, 'popular', 'not-popular')
        print (rawdata)
```

## Data Analysis


| | Popularity Correlation |
|---|---|
| Unnamed: 0 | 0.797325 |
| popularity | 1.000000 |
| acousticness | 0.008367 |
| danceability | 0.059371 |
| duration_ms | 0.022568 |
| energy | 0.045087 |
| instrumentalness | 0.007961 |
| liveness | 0.055524 |
| loudness | 0.055885 |
| speechiness | 0.084576 |
| tempo | 0.017993 |
| valence | 0.003175 |
| lognorm_duration | 0.017973 |
| Count | 0.127838 |

## Models

### Popularity Score Prediction

| | Model | Accuracy | MAE | MSE | RMSE |
|---|---|---|---|---|---|
| 4 | AdaBoostClassifier | 0.000068 | 44.764981 | 2149.432372 | 46.361971 |
| 2 | KNeighborsClassifier | 0.000271 | 36.673023 | 1462.290126 | 38.239902 |
| 3 | DecisionTreeClassifier | 0.016491 | 16.878181 | 409.673295 | 20.240388 |
| 1 | RandomForestClassifier | 1.000000 | 0.000000 | 0.000000 | 0.000000 |
| 0 | LinearRegression | NaN | 16.245047 | 423.599554 | 20.581534 |

# Binary Popularity Prediction

| | Model | Accuracy | MAE | MSE | RMSE |
|---|---|---|---|---|---|
| 1 | RandomForestClassifier | 0.899355 | 1.635222 | 0.101052 | 0.317887 |
| 0 | LogisticRegression | 0.489243 | 123.985612 | 0.510757 | 0.714672 |
| 4 | AdaBoostClassifier | 0.247302 | 0.097251 | 0.097251 | 0.311852 |
| 2 | KNeighborsClassifier | 0.097251 | 230.200882 | 0.902749 | 0.950131 |
| 3 | DecisionTreeClassifier | 0.097251 | 230.200882 | 0.902749 | 0.950131 |

# Model Performance and Hyperparameters

### Popularity Score Prediction: Linear Regression

```
In [190]: LR_Model = LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1,normalize=False)
          LR_Model.fit(X_train, y_train)
          y_pred = LR_Model.predict(X_test)


          LR_MAE = metrics.mean_absolute_error(y_test, y_pred)
          LR_MSE = metrics.mean_squared_error(y_test, y_pred)
          LR_RMSE = np.sqrt(metrics.mean_squared_error(y_test, y_pred))
          print('Mean Absolute Error:', LR_MAE)
          print('Mean Squared Error:', LR_MSE)
          print('Root Mean Squared Error:', LR_RMSE)

          cv_scores_rf_test= cv_scores_test.mean()
          cv_scores_rf_train= cv_scores_train.mean()

          print ('Mean cross validation test score: ' +str(cv_scores_rf_test))
          print ('Mean cross validation train score: ' +str(cv_scores_rf_train))

          Mean Absolute Error: 6.237420071514329
          Mean Squared Error: 71.77087073161633
          Root Mean Squared Error: 8.471769043807576
          Mean cross validation test score: 0.955077746550893
          Mean cross validation train score: 0.9644744855320806
```

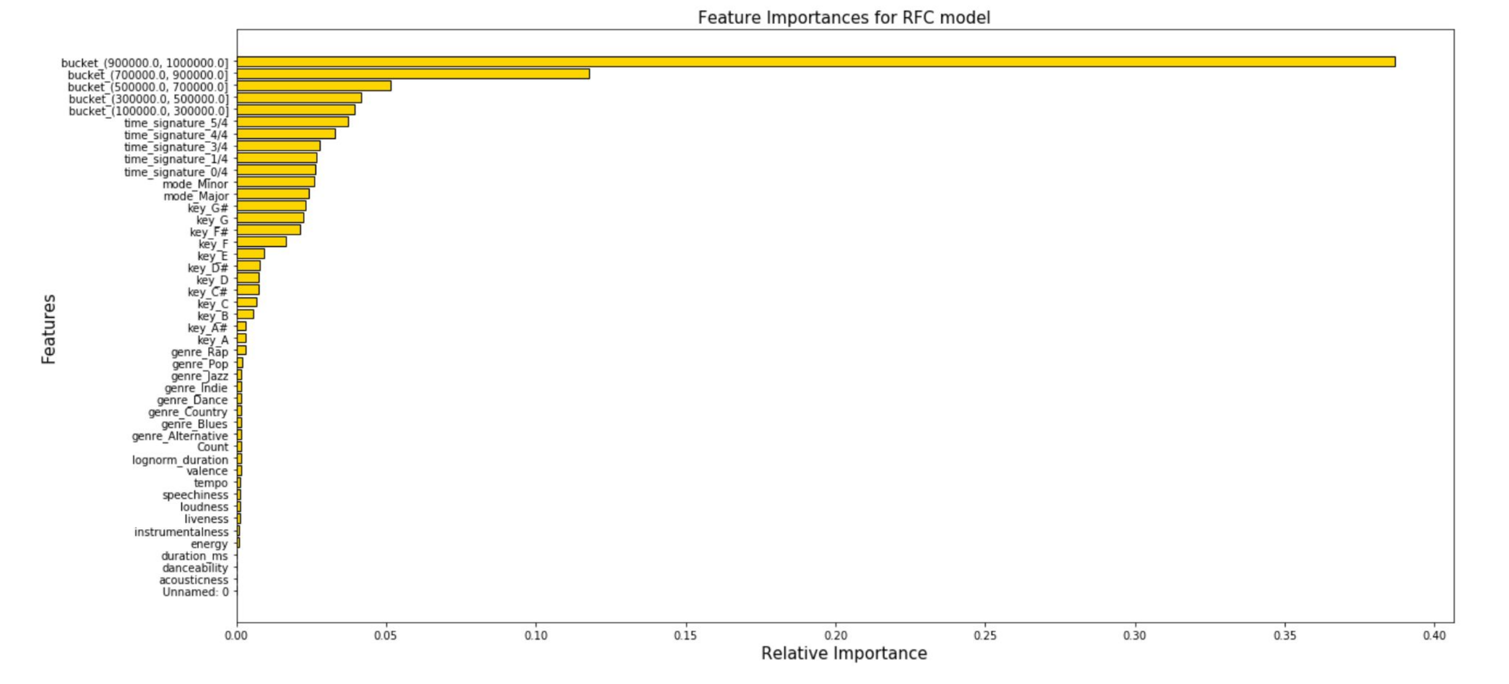
### Binary Popularity Prediction: Random Forest

```
In [32]: param_grid = {'bootstrap': [True],
          'max_depth': [10, 40],
          'max_features': [2, 3],
          'min_samples_leaf': [2, 4],
          'min_samples_split': [5, 10],
          'n_estimators': [600, 1000]}
         rf = RandomForestClassifier()
         rf_cv= GridSearchCV(rf,param_grid,cv=5)
         rf_cv.fit(X,y)

Out[32]: GridSearchCV(cv=5, error_score=nan,
                      estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                                       class_weight=None,
                                                       criterion='gini', max_depth=None,
                                                       max_features='auto',
                                                       max_leaf_nodes=None,
                                                       max_samples=None,
                                                       min_impurity_decrease=0.0,
                                                       min_impurity_split=None,
                                                       min_samples_leaf=1,
                                                       min_samples_split=2,
                                                       min_weight_fraction_leaf=0.0,
                                                       n_estimators=100, n_jobs=None,
                                                       oob_score=False,
                                                       random_state=None, verbose=0,
                                                       warm_start=False),
                      iid='deprecated', n_jobs=None,
                      param_grid={'bootstrap': [True], 'max_depth': [10, 40],
                                  'max_features': [2, 3], 'min_samples_leaf': [2, 4],
                                  'min_samples_split': [5, 10],
                                  'n_estimators': [600, 1000]},
                      pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                      scoring=None, verbose=0)
```

Best Parameters: learning_rate': 0.01, 'n_estimators': 800 and
bootstrap': True, 'max_depth': 40, 'max_features': 2, 'min_samples_leaf': 4, 'min_samples_split': 5, 'n_estimators': 1000

## Important Features



## Key Takeaways

- All genres (except for Blues) the more danceable a song is the more likely it is to be popular
- Trying to predict popularity alone was best done any the Linear Regression model with MAE of 6.26 and RMSE of 8.65
- Trying to predict if a song will be popular was best predicted by Random Forest or not has a 90% chance of being correct and MAE of 1.64 and RMSE of 0.32
- Features that contributed most to the popularity of a song for the Random Forest model are the time buckets and can be seen on the previous slide

## Future Work

- Look into different features and/or feature reduction to see if these features
- Designation of popularity at 80 could be arbitrary and changing to a different number could yield better results
- Training and testing data on models that look exclusively at one genre could lead to less noise in the data and to better predictive power.

# Questions?