In [60]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score, train_test_split,KFold,RandomizedSearchCV
from sklearn import metrics,svm
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import classification_report
import lightgbm as lgb
from matplotlib.pyplot import figure
import os
os.getcwd()
os.chdir('/Users/haochunniu/Desktop/Kaggle Compatition/Spotify Hit Prediction/Raw Data')
```

Problem Statement

Music has a always played an important role in people's daily life. In addition, as mobile and app technology thrive, more and more artists rely heavily on music streaming platforms, such as Spotify. As a music lover, I am really curious about nowadays music listeners' taste and preference. Hence, I create a prediction model that could accurately predict whether the track is going to be a hit track based on various musical characteristic, using the Spotify dataset from Kaggle. (https://www.kaggle.com/datasets/theoverman/the-spotify-hit-predictor-dataset)

1. Import Data

In the original raw data, we have data about Spotify hit tracks from 1960-2010. Yet, based on my observation, the music preference has changed dramatically in the past few decades. Hence, in this project, I use only the data from the **past 20 years (2000-2019)**.
The detailed data description about each column could be find in the below URL from Kaggle.
https://www.kaggle.com/datasets/theoverman/the-spotify-hit-predictor-dataset

Within the Spotify dataset for **2010-2019**, there are **6398 tracks and rows of data also with 19 columns**.
Within the Spotify dataset for **2000-2009**, there are **5872 tracks and rows of data also with 19 columns**.

In [2]:

```python
data_2000=pd.read_csv('dataset-of-00s.csv')
data_2010=pd.read_csv('dataset-of-10s.csv')
```

In [3]:

```python
data_2000.head()
```

Out[3]:

	track	artist	uri	danceability	energy	key	loudness	mode	speechiness	acousticness	i
0	Lucky Man	Montgomery Gentry	spotify:track:4GiXBCUF7H6YfNQsnBRIzl	0.578	0.471	4	-7.270	1	0.0289	0.368000	
1	On The Hotline	Pretty Ricky	spotify:track:1zyqZONW985Cs4osz9wlsu	0.704	0.854	10	-5.477	0	0.1830	0.018500	
2	Clouds Of Dementia	Candlemass	spotify:track:6cHZf7RbxXCKwEkgAZT4mY	0.162	0.836	9	-3.009	1	0.0473	0.000111	
3	Heavy Metal, Raise Hell!	Zwartketterij	spotify:track:2IjBPp2vMeX7LggzRN3iSX	0.188	0.994	4	-3.745	1	0.1660	0.000007	
4	I Got A Feelin'	Billy Currington	spotify:track:1tF370eYXUcWwkIvaq3IGz	0.630	0.764	2	-4.353	1	0.0275	0.363000	

In [4]:

```python
data_2010.head()
```

Out[4]:

	track	artist	uri	danceability	energy	key	loudness	mode	speechiness	acousticness	inst
0	Wild Things	Alessia Cara	spotify:track:2ZyuwVvV6Z3XJaXIFbspeE	0.741	0.626	1	-4.826	0	0.0886	0.02000	
1	Surfboard	Esquivel!	spotify:track:61APOtq25SCMuK0V5w2Kgp	0.447	0.247	5	-14.661	0	0.0346	0.87100	
2	Love Someone	Lukas Graham	spotify:track:2JqnpexlO9dmvjUMCaLCLJ	0.550	0.415	9	-6.557	0	0.0520	0.16100	
3	Music To My Ears (feat. Tory Lanez)	Keys N Krates	spotify:track:0cjfLhk8WJ3etPTCseKXtk	0.502	0.648	0	-5.698	0	0.0527	0.00513	
4	Juju On That Beat (TZ Anthem)	Zay Hilfigerrr & Zayion McCall	spotify:track:1lltf5ZXJc1by9SbPeljFd	0.807	0.887	1	-3.892	1	0.2750	0.00381	

In [23]:

```python
#Merge the two data frame
raw=pd.concat([data_2000,data_2010],ignore_index=True)
raw.shape
```

Out[23]:

```
(12270, 19)
```

2. Data preprocessing

a. Missing value inspection

For the raw dataset, there's no NA values within the dataset.

In [24]:

```python
raw.isnull().sum()
```

Out[24]:

```
track               0
artist              0
uri                 0
danceability        0
energy              0
key                 0
loudness            0
mode                0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
tempo               0
duration_ms         0
time_signature      0
chorus_hit          0
sections            0
target              0
dtype: int64
```

b. Data type inspection

In the original data set, the key and mode columns which are categorical variable are mis-treated as numeric variables.
Hence, I need to convert them back to categorical variables.

In [25]:

```python
## Key column should be categorical
raw['key']=raw['key'].astype('str')
```

In [26]:

```python
raw = pd.get_dummies(raw,
                     prefix='key',
                     prefix_sep='-',
                     columns=['key'])
```

In [27]:

```python
## Mode column should be categorical
raw['mode']=raw['mode'].astype('str')
```

In [28]:

```python
raw = pd.get_dummies(raw,
                     prefix='mode',
                     prefix_sep='-',
                     columns=['mode'])
```

c. Drop unuseful columns

In [29]:

```python
raw=raw.drop(columns=['track','uri','artist'])
raw.columns
```

Out[29]:

```
Index(['danceability', 'energy', 'loudness', 'speechiness', 'acousticness',
       'instrumentalness', 'liveness', 'valence', 'tempo', 'duration_ms',
       'time_signature', 'chorus_hit', 'sections', 'target', 'key-0', 'key-1',
       'key-10', 'key-11', 'key-2', 'key-3', 'key-4', 'key-5', 'key-6',
       'key-7', 'key-8', 'key-9', 'mode-0', 'mode-1'],
      dtype='object')
```

d. Imbalance data inspection

Given that this project is a binary classification problem, to ensure model performance, I need to be aware of the imbalance data issue. In this project, the binary target variable does not suffer from the imbalance data issue. Each class is account for 50% of the data.

In [30]:

```python
raw['target'].value_counts()
```

Out[30]:

```
1    6135
0    6135
Name: target, dtype: int64
```

e. Train test split

In [31]:

```python
x_train,x_test,y_train,y_test = train_test_split(raw.loc[:,raw.columns!='target'],raw['target'],test_si
ze=0.2,random_state=9)
```

3. EDA & Data Vizualization

In this project, all data vizualizations are completed on Tableau, and all plots will be published to my Tableau Public. The URL is attached below. Feel free to take a look at it. Tableau Public URL:
https://public.tableau.com/app/profile/hao.chun.niu/viz/SpotifyHitTrackEDA/Dashboard1

4. Nested Random Search to find the best models

In [67]:

```python
# 1. Create the Classifier
rf=RandomForestClassifier(random_state=9)
xgb=XGBClassifier(seed=9,objective='binary:logistic',use_label_encoder =False,verbosity = 0)
lgbm=lgb.LGBMClassifier(objective='binary',random_state=9)

##############################################################
# 2. Create the parameter grid
rf_grid={'n_estimators':list(range(100,1100,100)),
         'max_depth':list(range(3,11))}
xgb_grid={'eta':np.arange(0.1,0.6,0.1),
          'max_depth':list(range(3,16)),
          'n_estimators':list(range(10,310,10)),
          'gamma':list(range(1,6))}
lgbm_grid={'learning_rate':np.arange(0.1,0.6,0.1),
           'max_depth':list(range(3,16)),
           'n_estimators':list(range(10,310,10))}

##############################################################
# 3. Create the CV
inner_cv = KFold(n_splits=3, shuffle=True, random_state=9)
outer_cv = KFold(n_splits=3, shuffle=True, random_state=9)

##############################################################
# 4-1-1. Random-search CV for Random Forest
clf = RandomizedSearchCV(rf,rf_grid,cv=inner_cv,scoring='accuracy',n_iter=15,random_state=9)

# 4-1-2. Nested CV for Random Forest
nested_score = cross_val_score(clf,X=x_train, y=y_train, cv=outer_cv,scoring='accuracy')

# 4-1-3. Result for Nested CV
rf_result=nested_score.mean()

##############################################################
# 4-2-1. Random-search CV for XGBoost Classifier
clf = RandomizedSearchCV(xgb,xgb_grid,cv=inner_cv,scoring='accuracy',n_iter=15,random_state=9)

# 4-2-2. Nested CV for XGBoost Classifier
nested_score = cross_val_score(clf,X=x_train, y=y_train, cv=outer_cv,scoring='accuracy')

# 4-2-3. Result for Nested CV
xgb_result=nested_score.mean()

##############################################################
# 4-3-1. Random-search CV for LightGBM Classifier
clf = RandomizedSearchCV(lgbm,lgbm_grid,cv=inner_cv,scoring='accuracy',n_iter=15,random_state=9)

# 4-3-2. Nested CV for LightGBM Classifier
nested_score = cross_val_score(clf,X=x_train, y=y_train, cv=outer_cv,scoring='accuracy')

# 4-3-3. Result for Nested CV
lgbm_result=nested_score.mean()
```

In [68]:

```python
print('Average Performance of Random Forest Classifier: {}%'.format(round(rf_result*100,2)))
print('Average Performance of XGBoost Classifier: {}%'.format(round(xgb_result*100,2)))
print('Average Performance of LightGBM Classifier: {}%'.format(round(lgbm_result*100,2)))
```

```
Average Performance of Random Forest Classifier: 84.17%
Average Performance of XGBoost Classifier: 85.13%
Average Performance of LightGBM Classifier: 84.86%
```

5. Random Search on XGBoost Classifier to find the best parameter combination

In [69]:

```python
# 1. Create estimator
xgb=XGBClassifier(seed=9,objective='binary:logistic',use_label_encoder =False,verbosity = 0)

# 2. Create parameter grid
xgb_grid={'eta':np.arange(0.1,0.6,0.1),
          'max_depth':list(range(3,16)),
          'n_estimators':list(range(10,310,10)),
          'gamma':list(range(1,6))}

# 3. Grid-search
model = RandomizedSearchCV(xgb,xgb_grid,cv=5,scoring='accuracy',n_iter=15,random_state=9)

# 4. Fit the model
model.fit(x_train,y_train)

# 5. Predict
y_pred=model.predict(x_test)
```

In [70]:

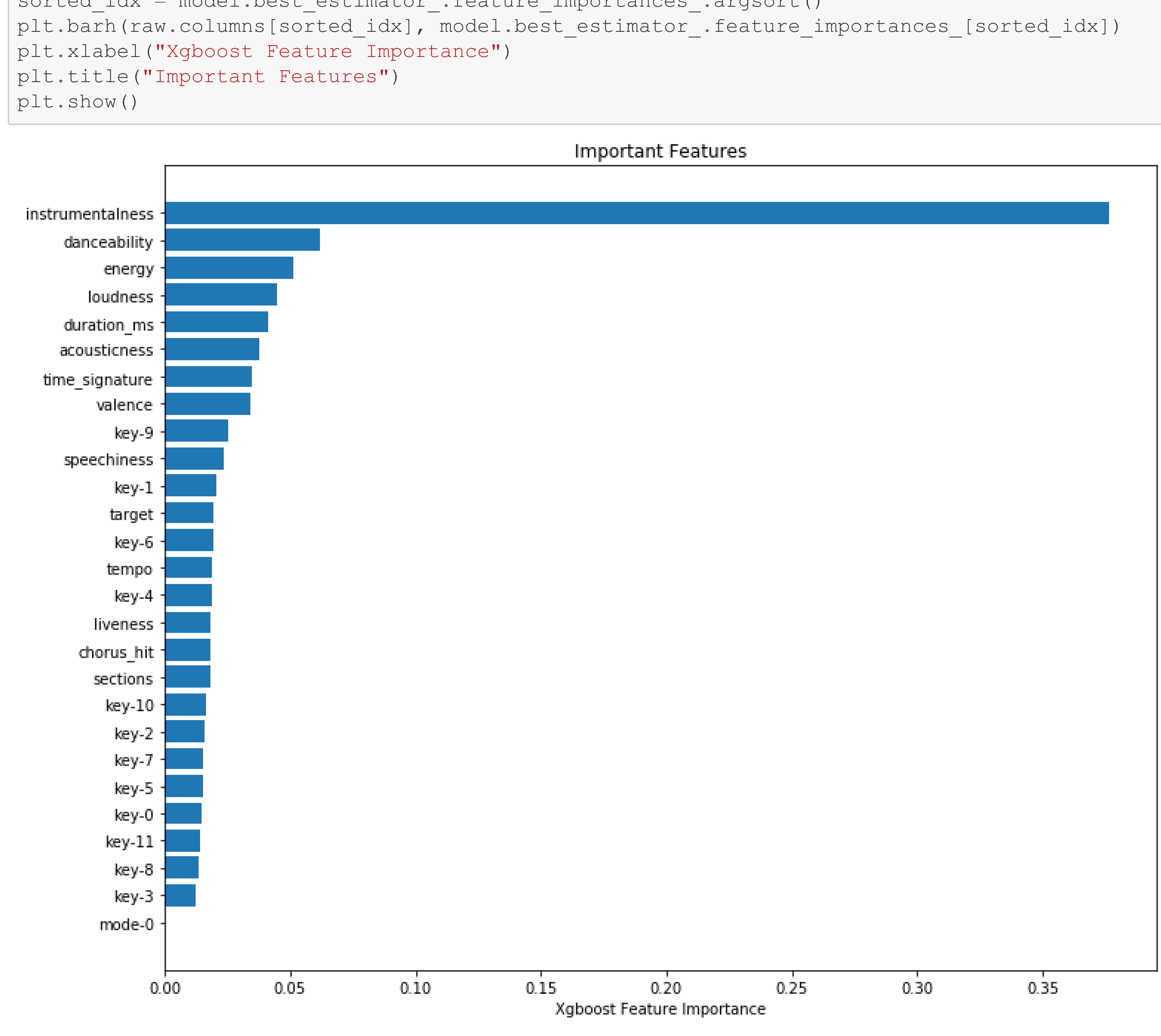
```python
# 6. Result
print ("With CV random search, I found the best hyperparameter is eta={}, max_depth={}, n_estimators={}
, and gamma={}.".format(model.best_params_['eta'],

                        model.best_params_['max_depth'],

                        model.best_params_['n_estimators'],

                        model.best_params_['gamma']))
print("Prediction Accuracy Score on Test Data: {}%".format(round(metrics.accuracy_score(y_test,y_pred)*
100,2)))
print('--------------------------------------------------------------------------------------------------
----------------')
print(classification_report(y_test, y_pred))
```

```
With CV random search, I found the best hyperparameter is eta=0.1, max_depth=6, n_estimators=220, and
gamma=2.
Prediction Accuracy Score on Test Data: 82.93%
----------------------------------------------------------------------------------------------------
-----------
              precision    recall  f1-score   support

           0       0.87      0.79      0.83      1275
           1       0.79      0.88      0.83      1179

    accuracy                           0.83      2454
   macro avg       0.83      0.83      0.83      2454
weighted avg       0.83      0.83      0.83      2454
```

6. Feature Importance

In [71]:

```python
figure(figsize=(12, 10))
sorted_idx = model.best_estimator_.feature_importances_.argsort()
plt.barh(raw.columns[sorted_idx], model.best_estimator_.feature_importances_[sorted_idx])
plt.xlabel("Xgboost Feature Importance")
plt.title("Important Features")
plt.show()
```



Summary

Based on the feature importance plot, I notice that instrumentalness and danceability are the two most important features, and I believe this result is reasonable. In the past few years, as party culture and K-pop culture go viral, all kinds of electric and party songs become more and more popular. In conclusion, based on the analysis result, electric party and pop styles are more align with nowadays music listeners' taste.