Classify Genres From Audio Data

Preparing our dataset

In [2]:
```
import pandas as pd

# Read in track metadata with genre labels
tracks = pd.read_csv(filepath_or_buffer="datasets/fma-rock-vs
-hiphop.csv")

# Read in track metrics with the features
echonest_metrics = pd.read_json(path_or_buf="datasets/echones
t-metrics.json",precise_float=True)

# Merge the relevant columns of tracks and echonest_metrics
echo_tracks = pd.merge(echonest_metrics,tracks[['track_id','g
enre_top']],on='track_id')

# Inspect the resultant dataframe
echo_tracks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4802 entries, 0 to 4801
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   track_id          4802 non-null   int64  
 1   acousticness      4802 non-null   float64
 2   danceability      4802 non-null   float64
 3   energy            4802 non-null   float64
 4   instrumentalness  4802 non-null   float64
 5   liveness          4802 non-null   float64
 6   speechiness       4802 non-null   float64
 7   tempo             4802 non-null   float64
 8   valence           4802 non-null   float64
 9   genre_top         4802 non-null   object 
dtypes: float64(8), int64(1), object(1)
memory usage: 412.7+ KB
```

Pairwise relationships between continuous variables

In [3]:
```
echo_tracks.head()
```

Out[3]:

	track_id	acousticness	danceability	energy	instrumentalness	livenes
0	2	0.416675	0.675894	0.634476	0.010628	0.17764
1	3	0.374408	0.528643	0.817461	0.001851	0.10588
2	5	0.043567	0.745566	0.701470	0.000697	0.37314
3	134	0.452217	0.513238	0.560410	0.019443	0.09656
4	153	0.988306	0.255661	0.979774	0.973006	0.12134

Normalizing the feature data

In [4]:
```
# Define our features
features = echo_tracks.drop(columns=['genre_top','track_id'])
labels = echo_tracks['genre_top']
from sklearn.preprocessing import StandardScaler

# Scale the features and set the values to a new variable
scaler = StandardScaler()
scaled_train_features = scaler.fit_transform(features)
print(scaled_train_features)
```

```
[[-0.19121034  1.30442004  0.03831594 ...  0.37303429  1.153
97908
   0.46228696]
 [-0.30603598  0.50188641  0.78817624 ...  2.44615517  0.007
91367
  -0.69081137]
 [-1.20481276  1.68413943  0.31285194 ...  0.13513049 -0.777
31688
   0.63107745]
 ...
 [-1.29470431  1.17682795  0.13265633 ...  0.85182206 -0.935
41008
  -0.07941825]
 [-1.13869115 -0.02253433  0.57117905 ...  1.40951543  1.313
01348
   0.47513794]
 [-0.90611434  1.10148973  0.56322452 ...  1.36030881 -1.436
69053
   0.76217464]]
```

Principal Component Analysis on our scaled

data

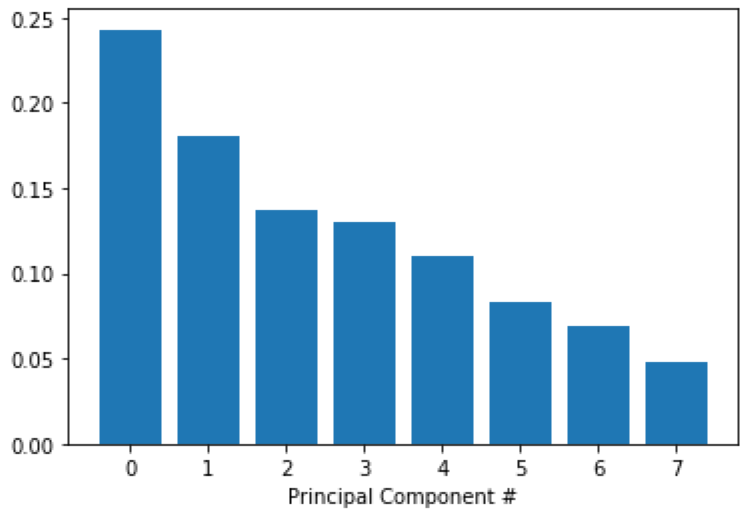
In [5]:

```
# This is just to make plots appear in the notebook
%matplotlib inline

# Import our plotting module, and PCA class
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# Get our explained variance ratios from PCA using all featur
es
pca = PCA()
pca.fit(scaled_train_features)
exp_variance = pca.explained_variance_ratio_
print(exp_variance)
print(pca.components_)

# plot the explained variance using a barplot
fig, ax = plt.subplots()
ax.bar(range(features.shape[1]),exp_variance)
ax.set_xlabel('Principal Component #')
```

```
[0.24297674 0.18044316 0.13650309 0.12994089 0.11056248 0.08
302245
 0.06923783 0.04731336]
[[-4.33617070e-03  5.79543156e-01 -2.36263229e-01 -4.3506317
9e-01
  -5.46236491e-02  4.32381961e-01 -1.79477383e-01  4.4368976
9e-01]
 [-5.43521941e-01 -9.29911248e-02  5.89109033e-01 -3.4425935
5e-01
   2.59405544e-01  8.46847426e-02  3.49788708e-01  1.8318764
4e-01]
 [ 2.86043643e-01 -2.48800804e-01 -1.68840803e-01 -2.6635012
8e-01
   6.56826885e-01  4.36291451e-01  2.75628055e-04 -3.6749928
4e-01]
 [ 4.77238876e-01 -9.68661663e-02  4.79983348e-03  1.0025388
3e-01
  -2.08763560e-01  2.42021088e-01  7.57582026e-01  2.7694614
0e-01]
 [ 2.98644311e-01  1.91995892e-01  1.83922307e-01  3.1785092
4e-01
   6.10719051e-01 -3.19352594e-01 -1.19244387e-01  4.9990945
8e-01]
 [ 2.77995583e-01 -4.73875658e-02  6.56791470e-01  2.0575901
1e-01
  -2.24694808e-01  4.74804140e-01 -4.11318550e-01 -4.0637298
9e-02]
 [-4.18338999e-01  3.10217608e-01 -1.47037071e-01  6.6905133
3e-01
   1.75009382e-01  4.18174935e-01  1.82722016e-01 -1.4360374
5e-01]
 [-2.31321640e-01 -6.69966058e-01 -2.85967880e-01  1.4218519
1e-01
  -2.50487697e-02  2.33783168e-01 -2.33913698e-01  5.3445663
6e-01]]
```

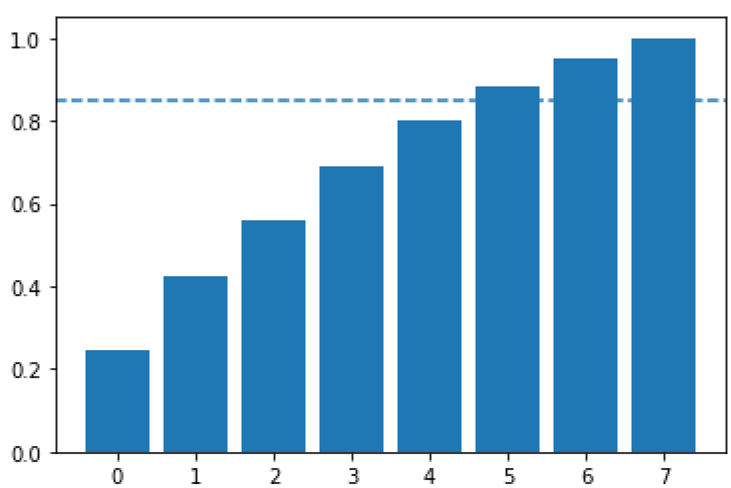
Out[5]:

```
Text(0.5, 0, 'Principal Component #')
```



Further visualization of PCA

In [6]:
```
import numpy as np
cum_exp_variance = np.cumsum(exp_variance)

fig, ax = plt.subplots()
ax.bar(range(features.shape[1]),cum_exp_variance)
ax.axhline(y=0.85, linestyle='--')

n_components = 6

pca = PCA(n_components, random_state=10)
pca.fit(scaled_train_features)
pca_projection = pca.transform(scaled_train_features)
```



Train a decision tree to classify genre

In [8]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

train_features, test_features, train_labels, test_labels = tr
ain_test_split(pca_projection,labels,random_state=10)

# Train our decision tree
tree = DecisionTreeClassifier(random_state=10)
tree.fit(train_features,train_labels)

# Predict the labels for the test data
pred_labels_tree = tree.predict(test_features)
```

Compare our decision tree to a logistic regression

In [9]:
```
# Import LogisticRegression
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression(random_state=10)
logreg.fit(train_features,train_labels)
pred_labels_logit = logreg.predict(test_features)

# Create the classification report for both models
from sklearn.metrics import classification_report
class_rep_tree = classification_report(test_labels,pred_label
s_tree)
class_rep_log = classification_report(test_labels,pred_labels
_logit)

print("Decision Tree: \n", class_rep_tree)
print("Logistic Regression: \n", class_rep_log)
```

```
Decision Tree:
              precision    recall  f1-score   support

     Hip-Hop       0.60      0.60      0.60       235
        Rock       0.90      0.90      0.90       966

    accuracy                           0.84      1201
   macro avg       0.75      0.75      0.75      1201
weighted avg       0.84      0.84      0.84      1201

Logistic Regression:
              precision    recall  f1-score   support

     Hip-Hop       0.77      0.54      0.64       235
        Rock       0.90      0.96      0.93       966

    accuracy                           0.88      1201
   macro avg       0.83      0.75      0.78      1201
weighted avg       0.87      0.88      0.87      1201
```

Balance our data for greater performance

In [10]:

```
echo_tracks.loc[echo_tracks['genre_top']=='Hip-Hop']
```

Out[10]:

	track_id	acousticness	danceability	energy	instrumentalness	live
0	2	0.416675	0.675894	0.634476	1.062807e-02	0.17
1	3	0.374408	0.528643	0.817461	1.851103e-03	0.10
2	5	0.043567	0.745566	0.701470	6.967990e-04	0.37
3	134	0.452217	0.513238	0.560410	1.944269e-02	0.09
118	583	0.748986	0.765886	0.513173	9.572095e-01	0.61
...	...	...	...	...	...	
4797	124718	0.412194	0.686825	0.849309	6.000000e-10	0.86
4798	124719	0.054973	0.617535	0.728567	7.215700e-06	0.13
4799	124720	0.010478	0.652483	0.657498	7.098000e-07	0.70
4800	124721	0.067906	0.432421	0.764508	1.625500e-06	0.10
4801	124722	0.153518	0.638660	0.762567	5.000000e-10	0.26

910 rows × 10 columns

In [11]:

```
hop_only = echo_tracks.loc[echo_tracks['genre_top']=='Hip-Ho
p']
rock_only = echo_tracks.loc[echo_tracks['genre_top']=='Rock']

rock_only = rock_only.sample(hop_only.shape[0],random_state=1
0)
rock_hop_bal = pd.concat([rock_only,hop_only])

# The features, labels, and pca projection are created for th
e balanced dataframe
features = rock_hop_bal.drop(['genre_top', 'track_id'], axis=
1)
labels = rock_hop_bal['genre_top']
pca_projection = pca.fit_transform(scaler.fit_transform(featu
res))

# Redefine the train and test set with the pca_projection fro
m the balanced data
train_features, test_features, train_labels, test_labels = tr
ain_test_split(pca_projection,labels, random_state=10)
```

Balancing our dataset to improve model bias

In [12]:
```
tree = DecisionTreeClassifier(random_state=10)
tree.fit(train_features,train_labels)
pred_labels_tree = pred_labels_tree = tree.predict(test_featu
res)
logreg = LogisticRegression(random_state=10)
logreg.fit(train_features,train_labels)
pred_labels_logit = logreg.predict(test_features)
print("Decision Tree: \n", classification_report(test_labels,
pred_labels_tree))
print("Logistic Regression: \n", classification_report(test_l
abels,pred_labels_logit))
```

```
Decision Tree:
               precision    recall  f1-score   support

     Hip-Hop       0.74      0.73      0.74       230
        Rock       0.73      0.74      0.73       225

    accuracy                           0.74       455
   macro avg       0.74      0.74      0.74       455
weighted avg       0.74      0.74      0.74       455

Logistic Regression:
               precision    recall  f1-score   support

     Hip-Hop       0.84      0.80      0.82       230
        Rock       0.80      0.85      0.83       225

    accuracy                           0.82       455
   macro avg       0.82      0.82      0.82       455
weighted avg       0.82      0.82      0.82       455
```

Using cross-validation to evaluate our models

In [13]:
```
from sklearn.model_selection import KFold, cross_val_score
kf = KFold(n_splits=10)
tree = DecisionTreeClassifier(random_state=10)
logreg = LogisticRegression(random_state=10)
tree_score =cross_val_score(tree,pca_projection,labels,cv=kf)
logit_score = cross_val_score(logreg,pca_projection,labels,cv
=kf)
print("Decision Tree:", np.mean(tree_score), "Logistic Regres
sion:", np.mean(logit_score))
```

```
Decision Tree: 0.7489010989010989 Logistic Regression: 0.782
967032967033
```

```
In [ ]:
```