1. Preparing our dataset

```
import pandas as pd

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

# Read in track metrics with the features
echonest_metrics = pd.read_json('datasets/echonest-metrics.json',
precise_float=True)

# Merge the relevant columns of tracks and echonest_metrics
echo_tracks = echonest_metrics.merge(tracks[['track_id','genre_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):
acousticness        4802 non-null float64
danceability        4802 non-null float64
energy              4802 non-null float64
instrumentalness    4802 non-null float64
liveness            4802 non-null float64
speechiness         4802 non-null float64
tempo               4802 non-null float64
track_id            4802 non-null int64
valence             4802 non-null float64
genre_top           4802 non-null object
dtypes: float64(8), int64(1), object(1)
memory usage: 412.7+ KB
```

2. Pairwise relationships between continuous variables

```
# Create a correlation matrix
corr_metrics = echo_tracks.corr()
corr_metrics.style.background_gradient()
```

```
<pandas.io.formats.style.Styler at 0x7f82bd3d8208>
```

3. Normalizing the feature data

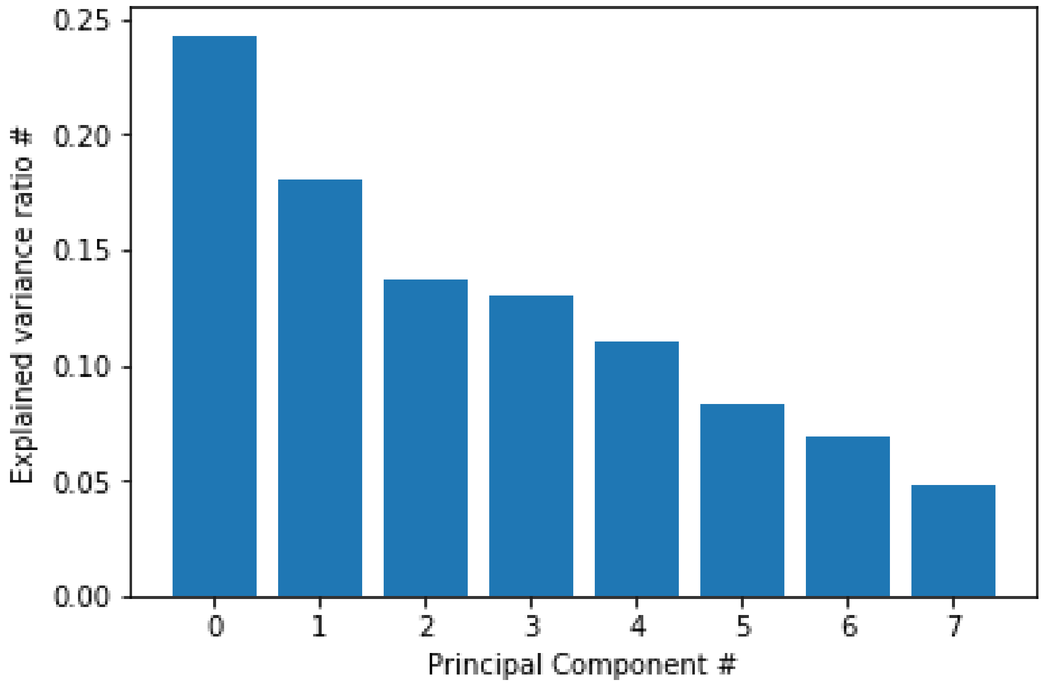
```
# Define our features
features = echo_tracks.drop(['genre_top','track_id'], axis=1)

# Define our labels
labels = echo_tracks['genre_top']

# Import the StandardScaler
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)
```

4. Principal Component Analysis on our scaled data

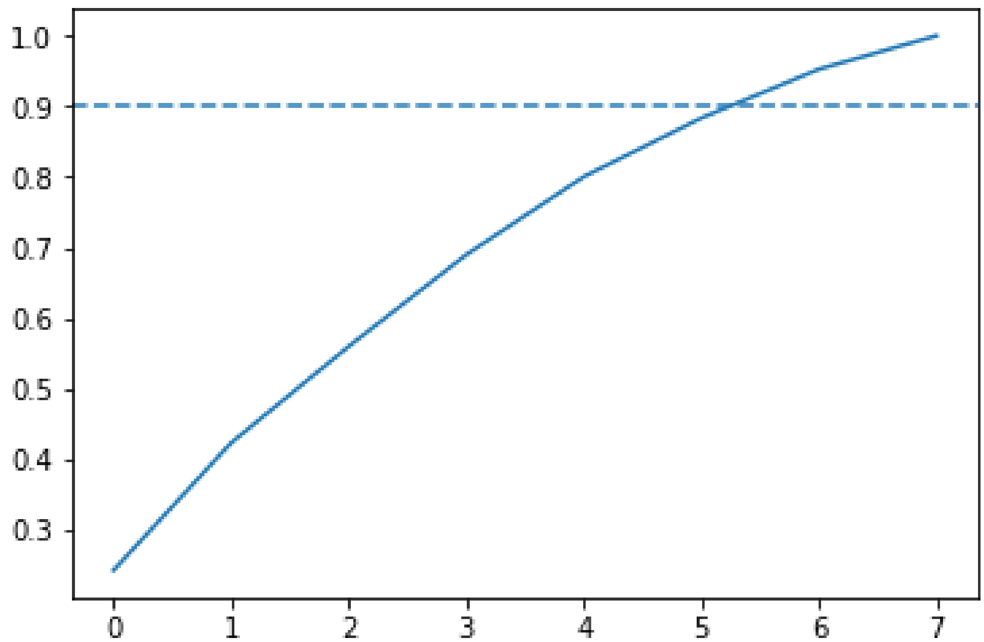
```
# This is just to make plots appear in the notebook
%matplotlib inline

# 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 features
pca = PCA()
pca.fit(scaled_train_features)
#features_pca = pca.transform(scaled_train_features)

#print(scaled_train_features.shape)
#print(features_pca.shape)
#features_pca

exp_variance = pca.explained_variance_ratio_
#print(exp_variance)

# plot the explained variance using a barplot
fig, ax = plt.subplots()
ax.bar(range(len(exp_variance)), exp_variance)
ax.set_xlabel('Principal Component #')
ax.set_ylabel('Explained variance ratio #')
```

```
Text(0,0.5,'Explained variance ratio #')
```



5. Further visualization of PCA

```
# Import numpy
import numpy as np

# Calculate the cumulative explained variance
cum_exp_variance = np.cumsum(exp_variance)

# Plot the cumulative explained variance and draw a dashed line at
0.90.
fig, ax = plt.subplots()
ax.plot(range(len(cum_exp_variance)),cum_exp_variance)
ax.axhline(y=0.9, linestyle='--')
n_components = 6

# Perform PCA with the chosen number of components and project data
onto components
pca = PCA(n_components, random_state=10)
pca.fit(scaled_train_features)
pca_projection = pca.transform(scaled_train_features)
```



6. Train a decision tree to classify genre

```
# Import train_test_split function and Decision tree classifier
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

# Split our data
train_features, test_features, train_labels, test_labels =
train_test_split(pca_projection, labels, random_state=10)

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

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

7. Compare our decision tree to a logistic regression

```
# Import LogisticRegression
from sklearn.linear_model import LogisticRegression

# Train our logistic regression and predict labels for the test set
logreg = LogisticRegression(random_state=10)
logreg_model = logreg.fit(train_features, train_labels)
pred_labels_logit = logreg_model.predict(test_features)

# Create the classification report for both models
from sklearn.metrics import classification_report
class_rep_tree = classification_report(test_labels, pred_labels_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       0.66      0.66      0.66       229
       Rock       0.92      0.92      0.92       972

avg / total       0.87      0.87      0.87      1201

Logistic Regression:
              precision    recall  f1-score   support

    Hip-Hop       0.75      0.57      0.65       229
       Rock       0.90      0.95      0.93       972

avg / total       0.87      0.88      0.87      1201
```

8. Balance our data for greater performance

```
# Subset only the hip-hop tracks, and then only the rock tracks
hop_only = echo_tracks.loc[echo_tracks['genre_top']=='Hip-Hop']
rock_only = echo_tracks.loc[echo_tracks['genre_top']=='Rock']

#print(type(n_samples))
# sample the rocks songs to be the same number as there are hip-hop
songs
rock_only = rock_only.sample(n=len(hop_only.index), random_state=10)

# concatenate the dataframes rock_only and hop_only
rock_hop_bal = pd.concat([rock_only, hop_only])

# The features, labels, and pca projection are created for the
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(features))

# Redefine the train and test set with the pca_projection from the
balanced data
train_features, test_features, train_labels, test_labels =
train_test_split(pca_projection, labels, random_state=10)
```

9. Does balancing our dataset improve model bias?

```
# Train our decision tree on the balanced data
tree = DecisionTreeClassifier(random_state=10)
```

```
dectree_model = tree.fit(train_features, train_labels)
pred_labels_tree = dectree_model.predict(test_features)

# Train our logistic regression on the balanced data
logreg = LogisticRegression(random_state=10)
logreg_model = logreg.fit(train_features, train_labels)
pred_labels_logit = logreg_model.predict(test_features)

# Compare the models
print("Decision Tree: \n", classification_report(test_labels,
pred_labels_tree))
print("Logistic Regression: \n", classification_report(test_labels,
pred_labels_logit))
```

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

    Hip-Hop       0.77      0.77      0.77       230
       Rock       0.76      0.76      0.76       225

avg / total       0.76      0.76      0.76       455

Logistic Regression:
              precision    recall  f1-score   support

    Hip-Hop       0.82      0.83      0.82       230
       Rock       0.82      0.81      0.82       225

avg / total       0.82      0.82      0.82       455
```

10. Using cross-validation to evaluate our models

```
from sklearn.model_selection import KFold, cross_val_score

# Set up our K-fold cross-validation
kf = KFold(n_splits=10, random_state=10)

tree = DecisionTreeClassifier(random_state=10)
logreg = LogisticRegression(random_state=10)

# Train our models using KFold cv
tree_score = cross_val_score(tree, pca_projection, labels, cv=kf)
logit_score = cross_val_score(logreg, pca_projection, labels, cv=kf)

# Print the mean of each array of scores
print("Decision Tree:", np.mean(tree_score), "Logistic Regression:",
np.mean(logit_score))
```

Decision Tree: 0.7241758241758242 Logistic Regression: 0.7752747252747252