Importing Pakages import matplotlib.pyplot as plt

from sklearn.svm import SVC

In [2]: import numpy as np import pandas as pd import seaborn as sns %matplotlib inline from sklearn import preprocessing

> from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier from sklearn.linear model import LogisticRegression from sklearn.decomposition import PCA from sklearn.tree import DecisionTreeClassifier

from sklearn.neighbors import KNeighborsClassifier

from sklearn.model_selection import train test split, GridSearchCV, cross val score from sklearn.metrics import accuracy score, confusion matrix

Reading data

chroma_stft_var

0.091048

0.086147

0.092243

0.086856

0.088129

rms_mean

9990.000000

0.130859

0.068545

0.000953

0.083782

0.121253

0.176328

0.442567

0.335406

0.343065

0.346815

0.363639

0.335579

9990.000000

0.084876

0.009637

0.015345

0.079833

0.085108

0.091092

0.120964

rms_mean

0.130405 0.003521

0.112699 0.001450

0.132003 0.004620

0.132565 0.002448

0.143289 0.001701

9.990000e+03

2.676388e-03

3.585628e-03

4.379535e-08

6.145900e-04

1.491318e-03

3.130862e-03

3.261522e-02

rms_var spectral_centroid_mean spectral_centroid_var 1773.065032

1816.693777

1788.539719

1655.289045

1630.656199

rms_var spectral_centroid_mean spectral_centroid_var spectral_ba

9.990000e+03

4.166727e+05

4.349644e+05

8.118813e+02

1.231961e+05

2.650692e+05

5.624152e+05

4.794119e+06

- 0.0

- -0.2

9990.000000

2199.219431

751.860611

472.741636

1630.680158

2208.628236

2712.581884

5432.534406

mfcc16_mean

mfcc17_mean mfcc18_mean

0.034784

0.018716

0.023073

0.023187

0.016451

0.459205

0.470831

0.494051

0.455246

0.451651

mfcc15 mean

mfcc14 mean

mfcc13 mean

0.262173

0.270969

0.265293

0.238427

0.233460

0.5

pca_col1

sns.scatterplot(x = df_min['pca_col1'], y = df_min['pca_col2'], data = df_min, hue = 'label', s = 100,

167541.630869

90525.690866

111407.437613

111952.284517

79667.267654

In [4]: | df = pd.read csv('features 3 sec.csv')

length chroma_stft_mean chroma_stft_var

0.379534

0.090466

0.107108

0.315698

0.384741

0.442443

0.749481

9990.000000

66149

66149

df.head() filename length chroma_stft_mean

Out[4]:

In [6]:

In [7]:

In [8]:

Out[8]:

Out[7]: 60

0 blues.00000.0.wav **1** blues.00000.1.wav

2 blues.00000.2.wav

66149 3 blues.00000.3.wav 66149 blues.00000.4.wav 66149

5 rows × 60 columns df.shape Out[6]: (9990, 60)

9990.0

66149.0

66149.0

0.0

count

mean

std

min

df.columns.value_counts().sum() df.describe()

66149.0 25% 66149.0 50% 75% 66149.0 max 66149.0 8 rows × 58 columns

Exploratory Data Analysis In [9]: mean cols = [col for col in df.columns if 'mean' in col] corr = df[mean cols].corr() mask = np.triu(np.ones like(corr, dtype = bool)) plt.figure(figsize = (12, 10)) print("mean_cols size:", len(mean_cols)) sns.heatmap(data = corr, mask = mask, vmax = .2, cmap = 'magma', linewidths = .5, center = 0, cbar_kws={

"shrink": .5})

plt.show() mean_cols size: 28 chroma_stft_mean ms_mean spectral_centroid_mean spectral_bandwidth_mean

rolloff_mean

harmony_mean perceptr_mean mfcc1_mean

> mfcc2_mean mfcc3_mean mfcc4_mean

mfcc5_mean

mfcc14_mean mfcc15_mean mfcc16_mean mfcc17_mean mfcc18_mean mfcc19_mean mfcc20_mean

zero_crossing_rate_mean

spectral centroid mean spectral bandwidth mean

chroma stft mean

X = df.drop(['label'], axis = 1)

0.355399

0.367322

0.373159

0.399349

0.355668

transformer = preprocessing.MinMaxScaler() x trans = transformer.fit transform(X)

0.716757

0.670347

0.728067

0.677066

0.689113

Out[14]: <matplotlib.axes. subplots.AxesSubplot at 0x1eed95ca790>

X = X.iloc[0:, 2:]y = df['label']

harmony_mean

perceptr_mean

mfcc1 mean mfcc2 mean mfcc3 mean

0.293133 0.107955

0.253040 0.044447

0.296753 0.141663

0.298024 0.075042

0.322308 0.052149

mfcc4_mean

mfcc5 mean mfcc6 mean mfcc7 mean mfcc8 mean mfcc9 mean mfcc10 mean mfccll mean mfcc12 mean

zero_crossing_rate_mean

mfcc6_mean mfcc7_mean mfcc8_mean mfcc9_mean mfcc10_mean mfcc11_mean mfcc12_mean mfcc13_mean

MinMaxScaling

X = pd.DataFrame(x trans, columns = X.columns) In [12]: X.head() Out[12]: chroma_stft_mean chroma_stft_var rms_mean rms_var spectral_centroid_mean spectral_centroid_var spectral_bandwidth_mean spe 0 1

3

alpha = 0.8)

1.00

0.75

0.50

0.25

-0.50

-0.75

-1.00

Modeling

In [16]:

In [17]:

label blues

country disco

jazz

metal

reggae rock

-0.5

X = df.drop(['label', 'length', 'filename'], axis = 1)

scaller = preprocessing.MinMaxScaler()

model.fit(x_train, y_train) y_pred = model.predict(x_test)

print(model.score(x_train, y_train)) print(accuracy_score(y_test, y_pred))

models = [KNeighborsClassifier(n_neighbors=5),

print("-----","\n")

LogisticRegression(max_iter=1000),

Encode label (y) with LabelEncoder and scalle data feature using MinMaxScaler

df['label'] = preprocessing.LabelEncoder().fit_transform(df['label'])

print(f"train_accuracy and val_accuracy for {model.__str__()} \n")

train_accuracy and val_accuracy for LogisticRegression(max_iter=1000)

X = pd.DataFrame(scaller.fit_transform(X), columns = X.columns)

In [11]:

5 rows × 57 columns In [13]: # reduce the dimasion of our dataset to 2 for scatter plot using Principal Component Analysis PCA model = PCA(n components=2) df min = PCA model.fit transform(X) df min = pd.DataFrame(df min, columns = ['pca col1', 'pca col2']) df_min = pd.concat([df_min, y], axis = 1) In [14]: plt.figure(figsize = (16, 10))

0.00 -0.25

split data in train en test set x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2) In [18]: # model fit function def fit_model(model):

In [19]: # list of estimators

0.9471971971971972 0.9049049049049049

y = df['label']

RandomForestClassifier(n_estimators=1000), DecisionTreeClassifier(), SVC()] In [20]: | # fit all model in our list estimators for model in models: fit_model(model) train_accuracy and val_accuracy for KNeighborsClassifier()

0.7040790790790791 0.6796796796796797 train_accuracy and val_accuracy for RandomForestClassifier(n_estimators=1000) 0.9992492492492493 0.8838838838838838

train accuracy and val accuracy for DecisionTreeClassifier() 0.9992492492492493 0.6381381381381381 train accuracy and val accuracy for SVC() 0.7795295295295295

0.7397397397397397

In []: | # GriSeachCV for knn model

function to get the distance between feature vecotrs and find neighbors distances = []

> neighbors = [] for x in range(k):

return neighbors

knn_grid.fit(x_train, y_train)

print(knn grid.best params)

plt.figure(figsize = (12,8)) print("confusion matrix")

plot confusion matrix

best_knn_model = knn_grid.best_estimator_

print("accuracy", knn_grid.best_score_)

sns.heatmap(conf matrix, annot=True)

for x in range(len(neighbors)): response = neighbors[x] if response in classVote: classVote[response] += 1 else: classVote[response] = 1

classVote = {} sorter = sorted(classVote.items(), key = operator.itemgetter(1), reverse=True)

identify the class of the instance def nearestClass(neighbors): In [3]:

return sorter[0][0] function to evaluate the model In [4]: def getAccuracy(testSet, prediction): correct = 0for x in range(len(testSet)):

correct += 1

In [2]: def getNeighbors(trainingSet, instance, k): for x in range (len(trainingSet)): dist = distance(trainingSet[x], instance, k) + distance(instance, trainingSet[x], k) distances.append((trainingSet[x][2], dist)) distances.sort(key=operator.itemgetter(1))

knn_grid_params = {'n_neighbors': np.arange(3, 50, 2),

'metric':['euclidean', 'manhattan']}

knn_grid = GridSearchCV(KNeighborsClassifier(), param_grid=knn_grid_params)

print("val_accuracy", accuracy_score(y_test, best_knn_model.predict(x_test)))

conf_matrix = confusion_matrix(y_test, best_knn_model.predict(x_test))

neighbors.append(distances[x][0])

return (1.0 * correct) / len(testSet)

if testSet[x][-1] == predictions[x]: