Music Genre Prediction using Logistic Regression

Loading and Displaying data

In [1]:

```
import pandas as pd
from sklearn import preprocessing
import numpy as np
import matplotlib.pyplot as plt
```

In [1]:

```

```

In [2]:

```
df = pd.read_csv("train.csv", sep = r',', skipinitialspace = True)
df.head()
```

Out[2]:

	Artist Name	Track Name	Popularity	danceability	energy	key	loudness	mode	speechiness
0	Bruno Mars	That's What I Like (feat. Gucci Mane)	60.0	0.854	0.564	1.0	-4.964	1	0.0485
1	Boston	Hitch a Ride	54.0	0.382	0.814	3.0	-7.230	1	0.0406
2	The Raincoats	No Side to Fall In	35.0	0.434	0.614	6.0	-8.334	1	0.0525
3	Deno	Lingo (feat. J.I & Chunkz)	66.0	0.853	0.597	10.0	-6.528	0	0.0555
4	Red Hot Chili Peppers	Nobody Weird Like Me - Remastered	53.0	0.167	0.975	2.0	-4.279	1	0.2160

Cleaning data

In [3]:

```
# Dropping rows with NaN
df = df.dropna()

# Dropping columns not needed for features
del df["Track Name"]
del df["Artist Name"]

df.head()
```

Out[3]:

	Popularity	danceability	energy	key	loudness	mode	speechiness	acousticness	instrum
1	54.0	0.382	0.814	3.0	-7.230	1	0.0406	0.001100	
2	35.0	0.434	0.614	6.0	-8.334	1	0.0525	0.486000	
4	53.0	0.167	0.975	2.0	-4.279	1	0.2160	0.000169	
5	53.0	0.235	0.977	6.0	0.878	1	0.1070	0.003530	
6	48.0	0.674	0.658	5.0	-9.647	0	0.1040	0.404000	

In [4]:

```
df.shape
```

Out[4]:

```
(11813, 15)
```

Defining X and y and Splitting data

In [5]:

```
from sklearn.model_selection import train_test_split

# Columns used as predictors
Xdf = df.drop(["Class"], axis = 1)
X = Xdf.values

# Extracting output values
y = df["Class"].values

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 0, test
_size = 0.2)
```

Scaling data

In [6]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
Xtr1 = scaler.fit_transform(X_train)
Xts1 = scaler.transform(X_test)
```

Cross fold validation with regularization

In [7]:

```
import sklearn.model_selection
from sklearn.linear_model import LogisticRegression
```

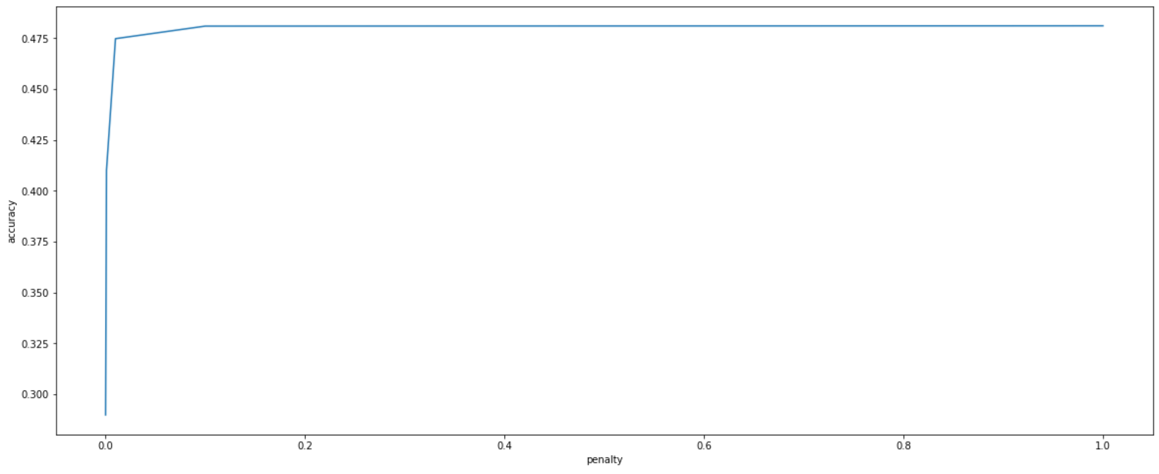
In [8]:

```
nfold = 10

kf = sklearn.model_selection.KFold(n_splits=nfold, shuffle=True)
ptest = [0.0001, 0.001, 0.01, 0.1, 1.0]

crossval_matrix = np.zeros((len(ptest),nfold))

#Kfold cross validation
for isplit, Ind in enumerate(kf.split(X)):
  Itr, Its = Ind

  xtr = X[Itr]
  ytr = y[Itr]
  xts = X[Its]
  yts = y[Its]

  scaler = StandardScaler()
  xtr1 = scaler.fit_transform(xtr)
  xts1 = scaler.transform(xts)

  # Loop over the penalty
  for it, p in enumerate(ptest):

      # Fit data on training data
      model = LogisticRegression(solver='lbfgs', penalty='l2', C =p, multi_class
="multinomial", max_iter=1000)
      model.fit(xtr1,ytr)
      acc = model.score(xts1,yts)

      # Measure acc on test data
      crossval_matrix[it,isplit] = acc

crossval_avg = np.mean(crossval_matrix, axis=1)
```

In [9]:

```
# Plot of accuracy against penalty
plt.figure(figsize=(20,8))
plt.plot(ptest, crossval_avg)
plt.xlabel('penalty')
plt.ylabel('accuracy')
print(f"The highest accuracy is {np.max(crossval_avg)}")
```

```
The highest accuracy is 0.4810798729460107
```



Testing number of features

In [10]:

```
from sklearn.feature_selection import RFE

#select the top features
logreg = LogisticRegression(solver='lbfgs', penalty='l2', C =1.0, multi_class="m
ultinomial", max_iter=1000).fit(Xtr1, y_train)
rfe = RFE(logreg, n_features_to_select=1)
rfe.fit(Xtr1, y_train)
```

Out[10]:

```
RFE(estimator=LogisticRegression(max_iter=1000, multi_class='multino
mial'),
    n_features_to_select=1)
```

In [11]:

```
from operator import itemgetter
features = Xdf.columns.to_list()
print("Features importance in descending order")

for x, y in (sorted(zip(rfe.ranking_ , features), key=itemgetter(0))):
    print(x, y)
```

```
Features importance in descending order
1 duration_in min/ms
2 energy
3 speechiness
4 acousticness
5 instrumentalness
6 danceability
7 valence
8 Popularity
9 loudness
10 mode
11 liveness
12 tempo
13 key
14 time_signature
```

In [12]:

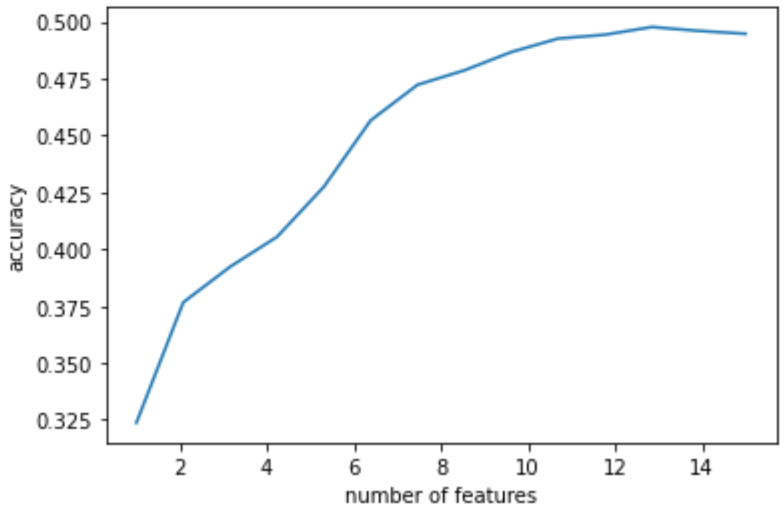
```
# Accuracy with respect to number of features
n_features = 14

acc_features = np.zeros(n_features)

for n_f in range(n_features):
  logreg = LogisticRegression(solver='lbfgs', penalty='l2', C =1.0, multi_class=
"multinomial", max_iter=1000).fit(Xtr1, y_train)
  rfe = RFE(logreg, n_features_to_select=n_f+1)
  rfe.fit(Xtr1, y_train)
  acc_features[n_f] = rfe.score(Xts1, y_test)
```

In [13]:

```
x = np.linspace(1,15,num=14)
plt.plot(x,acc_features)
plt.ylabel('accuracy')
plt.xlabel('number of features')
```

Out[13]:

```
Text(0.5, 0, 'number of features')
```



Prediction using a Neural Network

In [ ]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras import optimizers
from keras.layers import Dropout

import tensorflow.keras.backend as K
nin = X_train.shape[1]
nout = np.max(y_train) + 1
hist_arr = []
accuracies = []
scores = []


#Testing for best number of hidden units. Note that the range is small here,
#but during testing multiple sessions were ran, all testing different ranges (do
ne to save time).
#The most optimal nh was found to be 26.


# for i in range(13, 18, 1):
#   K.clear_session()
#   print(i)
#   nh = i
#   model = Sequential()
#   model.add(Dense(units=nh, input_shape=(nin,), activation='sigmoid',name='hid
den'))
#   model.add(Dense(units=nout, activation='softmax', name='output'))

#   opt = optimizers.Adam(learning_rate=1e-3)
#   model.compile(optimizer=opt,
#                 loss='sparse_categorical_crossentropy',
#                 metrics=['accuracy'])

#   hist = model.fit(X_train, y_train, epochs=1000, batch_size=100, verbose=Fals
e)
#   hist_arr.append(hist)
#   score, acc = model.evaluate(X_test, y_test, verbose=1)
#   accuracies.append(acc)
#   scores.append(score)


#Different hidden layers were tested, and it was found that the following layers
were most effective.
#Note that a single dropout layer was the best case, and the highest accuracy ac
hieved was approximately 55%

#What we learned in class was applied for each of the parameters, and further re
search was conducted to gain insight
#as to what the best combinations of layers would be.

K.clear_session()
nh = 34
model = Sequential()
model.add(Dense(units=nh, input_shape=(nin,), activation='sigmoid',name='hidden'
))
# model.add(Dropout(0.6))
model.add(Dense(units=nout, activation='softmax', name='output'))

opt = optimizers.Adam(learning_rate=1e-3)
```

```
model.compile(optimizer=opt,
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

hist = model.fit(Xtr1, y_train, epochs=1000, batch_size=100, verbose=False)
hist_arr.append(hist)
score, acc = model.evaluate(Xts1, y_test, verbose=1)

# accuracies.append(acc)
# scores.append(score)
```

Music Genre Prediction using SVM

In this section, we use SVMs to instead classify music genres

Importing libraries

```
from sklearn import svm
```

Finding Optimal Conditions for SVC

For our SVC, we will train and test the model across different c and gamma values to find the optimal hyperparameters.

The chosen parameters for c are: 0.001, 0.01, 0.1, 1 and 10, and a linear kernel is used.

The chosen parameters for gamma are: 0.001, 0.01, 0.1, and 1.

Double-click (or enter) to edit

```
c_values = np.array([0.001, 0.01,0.1,1,10])
gamma_values = np.array([0.001, 0.01, 0.1, 1])
# kernel_values = np.array(["linear", "poly", "rbf", "sigmoid"])


acc_matrix = np.zeros((c_values.shape[0],gamma_values.shape[0]))

for i_c, c in enumerate(c_values):
  for i_g, g in enumerate(gamma_values):
    print(i_c, i_g)
    svc = svm.SVC(probability=False,  kernel="linear", C=c, gamma=g,verbose=10) #linear
    svc.fit(X_train,y_train)
    yhat = svc.predict(X_test)
    acc = np.mean(yhat == y_test)
    # print(acc)
    acc_matrix[i_c, i_g] = acc
```

```
0 0
[LibSVM]0.4336111111111111
0 1
[LibSVM]0.4336111111111111
0 2
[LibSVM]0.4336111111111111
0 3
[LibSVM]0.4336111111111111
1 0
[LibSVM]0.5038888888888889
```

```
1 1
[LibSVM]0.5038888888888889
1 2
[LibSVM]0.5038888888888889
1 3
[LibSVM]0.5038888888888889
2 0
[LibSVM]0.5111111111111111
2 1
[LibSVM]0.5111111111111111
2 2
[LibSVM]0.5111111111111111
2 3
[LibSVM]0.5111111111111111
3 0
[LibSVM]0.5122222222222222
3 1
[LibSVM]0.5122222222222222
3 2
[LibSVM]0.5122222222222222
3 3
[LibSVM]0.5122222222222222
4 0
[LibSVM]0.5119444444444444
4 1
[LibSVM]0.5119444444444444
4 2
[LibSVM]0.5119444444444444
4 3
[LibSVM]0.5119444444444444
```

Next, we fill find the values of c and gamma with the highest accuracy

```
max_index = np.argmax(acc_matrix)
max_i = max_index//gamma_values.shape[0]
max_j = max_index - (max_i)*gamma_values.shape[0]
c = c_values.flatten()[max_i]
gamma = gamma_values.flatten()[max_j]
max_acc = acc_matrix.flatten()[max_index]

print("-- SVC with highest accuracy --")
print(f"Accuracy = {max_acc}")
print(f"c = {c} and gamma = {gamma}")
```

```
-- SVC with highest accuracy --
Accuracy = 0.5122222222222222
c = 1.0 and gamma = 0.001
```

Now, we will print out the accuracy of this model:

With PCA Data

Using the above optimal conditions, we will observe how the model gets more accurate as the number of

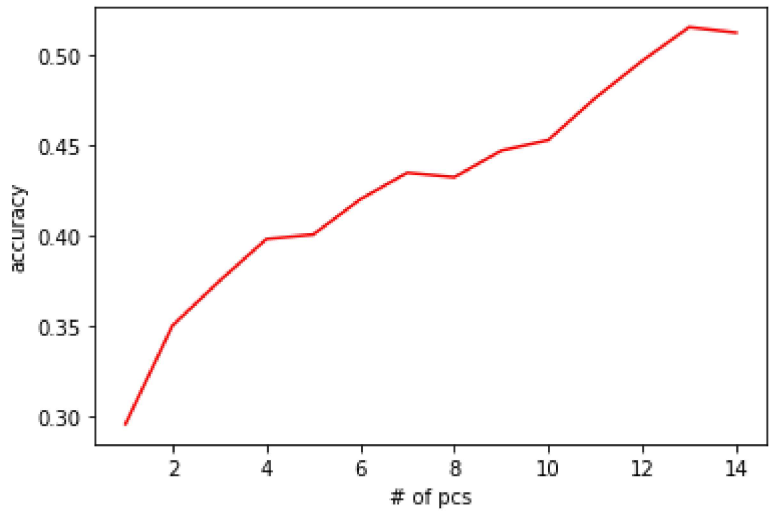
```
acc_matrix_pca = np.zeros(X_train.shape[1])

for i_c in range(X_train.shape[1]):
    pcal = PCA(n_components = i_c + 1)
    X_pca_train = pcal.fit_transform(X_train)
    X_pca_test = pcal.transform(X_test)
    svc = svm.SVC(probability=False,  kernel="linear", C=c, gamma=g,verbose=10) #linear
    svc.fit(X_pca_train,y_train)
    yhat = svc.predict(X_pca_test)
    acc = np.mean(yhat == y_test)
    acc_matrix_pca[i_c] = acc
```

```
0
[LibSVM]0.2961111111111111
1
[LibSVM]0.35055555555555556
2
[LibSVM]0.37527777777777777
3
[LibSVM]0.3983333333333333
4
[LibSVM]0.4008333333333333
5
[LibSVM]0.42027777777777775
6
[LibSVM]0.435
7
[LibSVM]0.4325
8
[LibSVM]0.44722222222222224
9
[LibSVM]0.45305555555555554
10
[LibSVM]0.47638888888888886
11
[LibSVM]0.49694444444444447
12
[LibSVM]0.5155555555555555
13
[LibSVM]0.5125
```

Plot the relationship of accuracy against number of PCs

```
plt.plot(np.arange(acc_matrix_pca.shape[0])+1, acc_matrix_pca,  'r')
plt.xlabel('# of PCs')
plt.ylabel('accuracy')
```

```
Text(0, 0.5, 'accuracy')
```



Let us find the highest performing number of PCs.

```
max_pca_index = np.argmax(acc_matrix_pca)
max_pca_acc = acc_matrix_pca[max_pca_index]

print("-- SVC with highest accuracy --")
print(f"Accuracy = {max_pca_acc}")
print(f"c = {c} and gamma = {gamma}")
print(f"Number of PCs = {max_pca_index + 1}")
```

```
-- SVC with highest accuracy --
Accuracy = 0.5155555555555555
c = 1.0 and gamma = 0.001
Number of PCs = 13
```

By the above results, contrary to expectations, we see that having 13 PCs has had a slightly better results than using all 14 PCs. This can be misleading since the difference in accuracy is miniscule. However, this may also indicate that there exists an input feature that is harming the performance of the system.