classification

November 6, 2025

[1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[2]:
```python
pop = pd.read_csv("pop_genres_dataset.csv")
pop.head()
```

[2]:
```
             artists track_name  popularity  duration_ms  explicit  \
0  my little airport                     47       183968         0
1  my little airport                     44       172343         0
2  my little airport                     50       191308         0
3  my little airport                     48       148564         0
4         Eason Chan                     54       228973         0

   danceability  energy  key  loudness  mode  speechiness  acousticness  \
0         0.576   0.505   11   -13.070     0       0.0392         0.753
1         0.577   0.228   11   -14.684     1       0.0306         0.834
2         0.641   0.479    4   -15.395     1       0.0443         0.732
3         0.613   0.210    5   -15.309     1       0.0309         0.769
4         0.646   0.370    0   -10.980     1       0.0351         0.825

   instrumentalness  liveness  valence    tempo  time_signature track_genre
0          0.199000     0.151    0.570  127.025               4    cantopop
1          0.000805     0.384    0.161  119.035               4    cantopop
2          0.059800     0.115    0.301  121.974               4    cantopop
3          0.000477     0.139    0.268  132.035               4    cantopop
4          0.000005     0.090    0.465  129.914               4    cantopop
```

0.1 Predicting pop song explicitness

[3]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score,␣
↪recall_score, ConfusionMatrixDisplay, roc_curve, roc_auc_score
from sklearn.model_selection import train_test_split, cross_val_score, KFold
```

[4]:
```python
# Only selecting numeric variables
X = pop[["popularity", "duration_ms", "danceability", "energy",
         "key", "loudness", "mode", "speechiness", "acousticness",
```

```
        "instrumentalness", "liveness", "valence", "tempo", "time_signature"]]
y = pop["explicit"]

# Splitting into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[5]:
```
df = pd.concat([X_train, y_train], axis = 1)
df.corr()
```

[5]:
```
                  popularity  duration_ms  danceability    energy       key  \
popularity          1.000000     0.119770      0.133854  0.019746  0.011389
duration_ms         0.119770     1.000000     -0.028426 -0.092777  0.006021
danceability        0.133854    -0.028426      1.000000  0.054455  0.031049
energy              0.019746    -0.092777      0.054455  1.000000  0.018415
key                 0.011389     0.006021      0.031049  0.018415  1.000000
loudness            0.105342    -0.111904      0.050184  0.720586  0.024051
mode               -0.071275    -0.020384     -0.120570 -0.091753 -0.092927
speechiness         0.068684    -0.112708      0.131527  0.226773  0.046018
acousticness        0.044592     0.135789     -0.116178 -0.708240 -0.012636
instrumentalness   -0.045519    -0.056019     -0.060166  0.054256 -0.013831
liveness           -0.054945    -0.058741     -0.129208  0.140642 -0.025546
valence            -0.014605    -0.070367      0.334176  0.463023  0.027881
tempo              -0.055654    -0.048555     -0.210335  0.179279  0.012591
time_signature      0.040957    -0.013938      0.131912  0.193845  0.019084
explicit            0.014291    -0.092259      0.129864  0.034781  0.018659

                  loudness      mode  speechiness  acousticness  \
popularity        0.105342 -0.071275     0.068684      0.044592
duration_ms      -0.111904 -0.020384    -0.112708      0.135789
danceability      0.050184 -0.120570     0.131527     -0.116178
energy            0.720586 -0.091753     0.226773     -0.708240
key               0.024051 -0.092927     0.046018     -0.012636
loudness          1.000000 -0.054929     0.164364     -0.487139
mode             -0.054929  1.000000    -0.073293      0.077547
speechiness       0.164364 -0.073293     1.000000     -0.157578
acousticness     -0.487139  0.077547    -0.157578      1.000000
instrumentalness -0.058715  0.022493    -0.019572     -0.077869
liveness          0.043576  0.002541     0.060020     -0.099658
valence           0.211999 -0.066680     0.138043     -0.315047
tempo             0.109209  0.024638     0.122292     -0.146461
time_signature    0.146760 -0.013669     0.037423     -0.210545
explicit          0.079670 -0.016466     0.151343     -0.105286

                  instrumentalness  liveness   valence     tempo  \
popularity               -0.045519 -0.054945 -0.014605 -0.055654
duration_ms              -0.056019 -0.058741 -0.070367 -0.048555
```

```
danceability             -0.060166 -0.129208  0.334176 -0.210335
energy                    0.054256  0.140642  0.463023  0.179279
key                      -0.013831 -0.025546  0.027881  0.012591
loudness                 -0.058715  0.043576  0.211999  0.109209
mode                      0.022493  0.002541 -0.066680  0.024638
speechiness              -0.019572  0.060020  0.138043  0.122292
acousticness             -0.077869 -0.099658 -0.315047 -0.146461
instrumentalness          1.000000  0.015621  0.001061  0.010143
liveness                  0.015621  1.000000  0.043661  0.023649
valence                   0.001061  0.043661  1.000000  0.078323
tempo                     0.010143  0.023649  0.078323  1.000000
time_signature           -0.002642  0.006178  0.088197 -0.009007
explicit                 -0.008930  0.022528 -0.012827  0.012941

                  time_signature  explicit
popularity              0.040957  0.014291
duration_ms            -0.013938 -0.092259
danceability            0.131912  0.129864
energy                  0.193845  0.034781
key                     0.019084  0.018659
loudness                0.146760  0.079670
mode                   -0.013669 -0.016466
speechiness             0.037423  0.151343
acousticness           -0.210545 -0.105286
instrumentalness       -0.002642 -0.008930
liveness                0.006178  0.022528
valence                 0.088197 -0.012827
tempo                  -0.009007  0.012941
time_signature          1.000000  0.031345
explicit                0.031345  1.000000
```

In the training data, explicitness seems to have low correlations with the predictor variables. As such, Random Forests should be used to investigate non-linear relationships and combinations that can help predict whether or not a song is explicit.

0.1.1 Cross validation

[6]:
```python
# Getting the best number of estimators and depth
estimators = np.arange(100, 300, 50)
depths = np.arange(1, 21)
best_score = 0
best_depth = 0
best_estimator = 0

fig,ax = plt.subplots(1)
ax.set(xlabel = "Depth", ylabel = "Cross validations core")

for e in estimators:
```

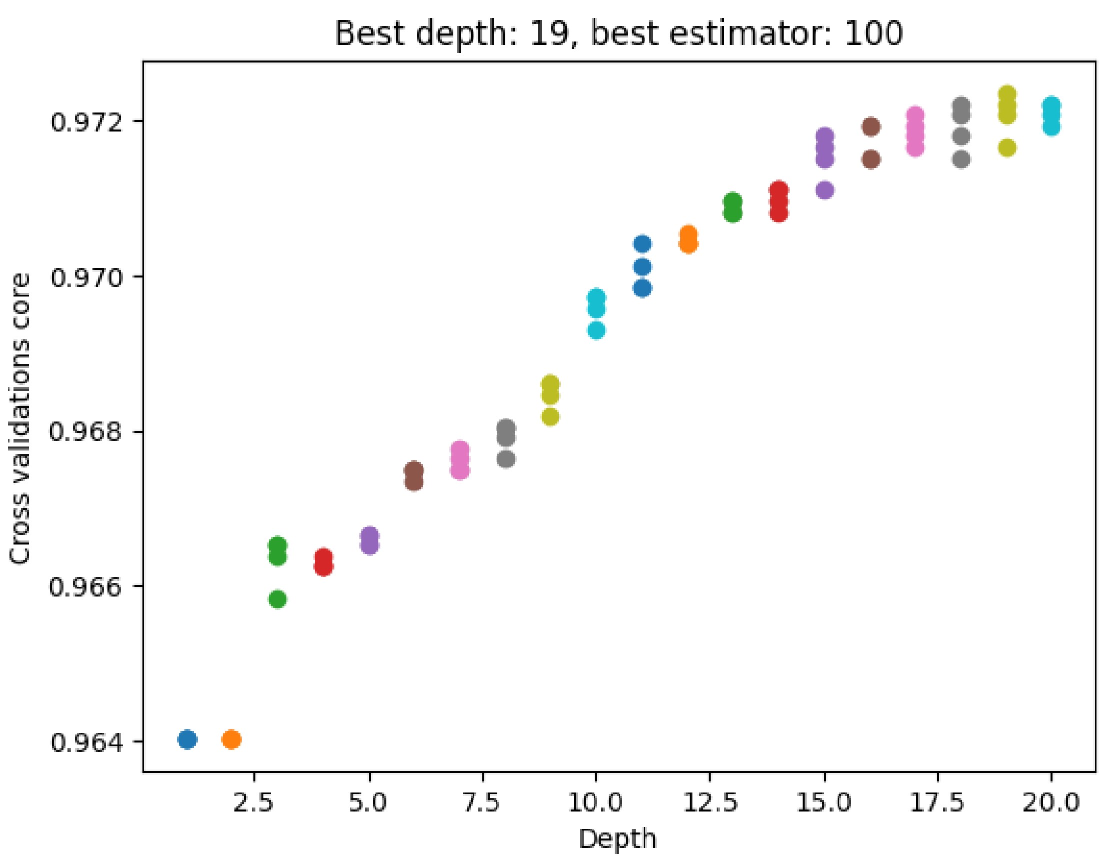
```
    for d in depths:
        rf = RandomForestClassifier(n_estimators= 100, max_depth = d)

        # Cross validate with 5 folds
        score = cross_val_score(rf, X_train, y_train, cv = 5,␣
 ↪scoring="accuracy").mean()

        if score >= best_score:
            best_score = score
            best_depth = d
            best_estimator = e

        ax.scatter(d, score)

ax.set(title = f"Best depth: {best_depth}, best estimator: {best_estimator}")
plt.show()
```



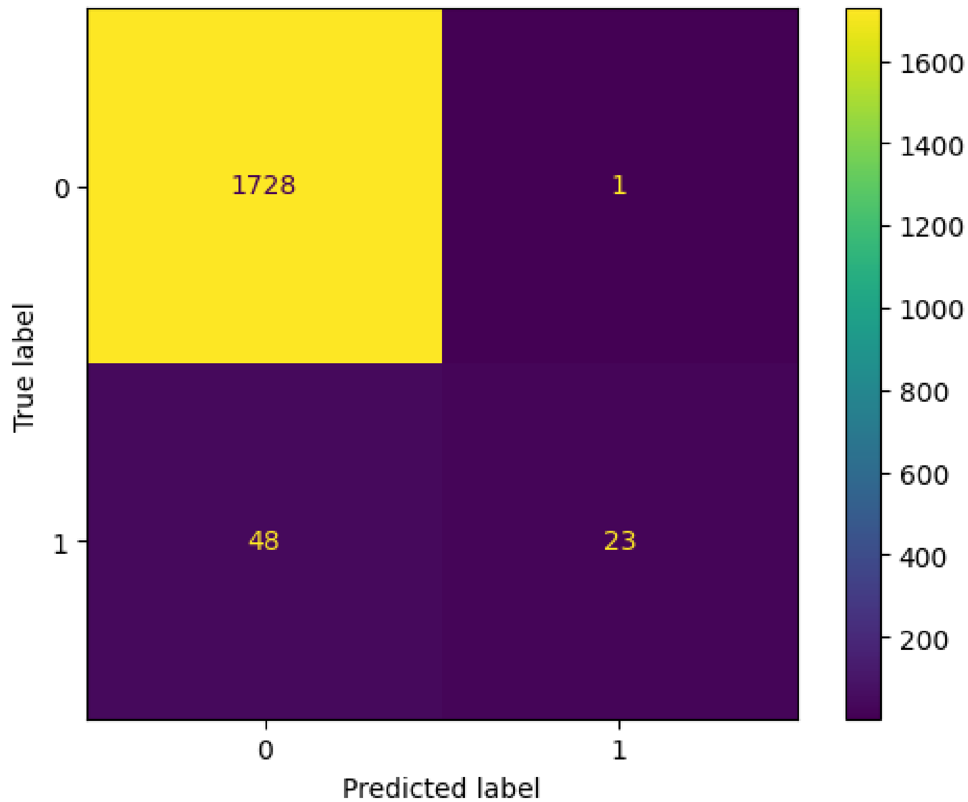
0.1.2 Random Forests

[7]:
```
rf = RandomForestClassifier(n_estimators= best_estimator, max_depth =␣
  ↪best_depth)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
```

0.1.3 Confusion matrix

[8]:
```
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
```

[8]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x10d532150>



0.1.4 Performance metrics

[9]:
```
print("Prediction accuracy:", round(accuracy_score(y_test, y_pred), 5))
print("Prediction error:", round(1 - accuracy_score(y_test, y_pred), 5))

# To obtain values in matrix
cm = confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = cm.ravel()
```

```
print("True positive rate:", round(tp / (tp + fn), 5))
print("True negative rate:", round(tn / (tn + fp), 5))

precision = tp / (tp + fp)
recall = tp / (tp + fn)

print("F1 score:", round((2 * precision * recall) / (precision + recall), 5))
```

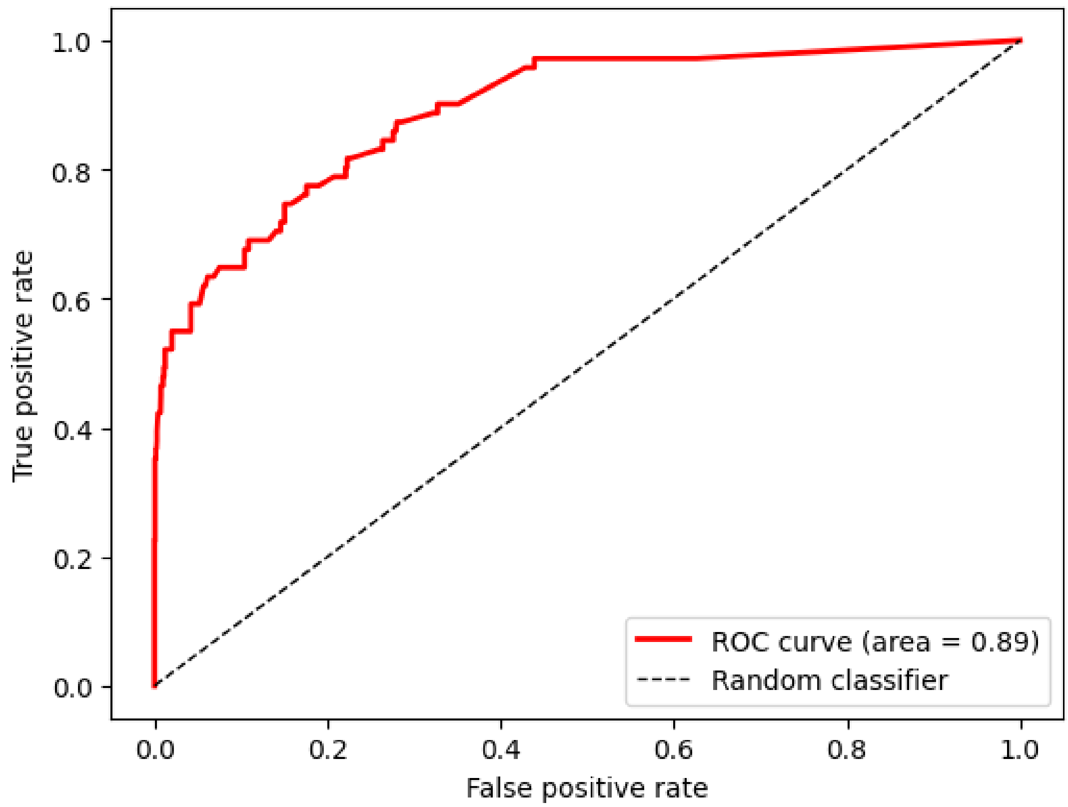
```
Prediction accuracy: 0.97278
Prediction error: 0.02722
True positive rate: 0.32394
True negative rate: 0.99942
F1 score: 0.48421
```

Overall, the model predicts the data well with a prediction accuracy of 97.33%. The model is excellent at identifying non-explicit songs 99.94% of the time but is only able to identify explicit songs 33.8% of the time. This may be due to the fact that there are significantly more non-explicit songs than explicit songs in the data. The F1 score supports the fact that the model is unable to predict explicit songs very well.

0.1.5 ROC curve

[10]:
```
y_pred_proba = rf.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = roc_auc_score(y_test, y_pred_proba)

plt.figure()
plt.plot(fpr, tpr, color = "red", lw = 2,
         label=f"ROC curve (area = {roc_auc:.2f})")
plt.plot([0,1], [0,1], color = "black", lw = 1, linestyle = "--",
         label = "Random classifier")
plt.xlabel("False positive rate")
plt.ylabel("True positive rate")
plt.legend(loc="lower right")
plt.show()
```



After observing the ROC curve with the AUC being 0.89, the problem may lie in the model's threshold instead of its ability to discern between explicit vs non explicit. Adjusting the threshold may lead to better classification of explicit songs.

[ ]:
```
kf = KFold(n_splits=5, shuffle=True, random_state=42)
auc_per_fold = cross_val_score(rf, X, y, cv=kf, scoring="roc_auc")
accuracy_per_fold = cross_val_score(rf, X, y, cv=kf, scoring="accuracy")
fold = pd.DataFrame({
    "Fold": np.arange(1, 6),
    "AUC": auc_per_fold,
    "Accuracy": accuracy_per_fold
})

print(fold)
```

```
   Fold       AUC  Accuracy
0     1  0.904484  0.972778
1     2  0.886606  0.972222
2     3  0.902769  0.975000
3     4  0.898703  0.975556
4     5  0.893236  0.972778
```