crisp_dm_process

January 31, 2022

1 Imports

[174]:
```
import os
import pandas as pd
import seaborn as sns
import matplotlib as plt
import numpy as np
import matplotlib as mpl
from matplotlib import pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import validation_curve
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
from itertools import cycle
```

2 Preprocessing

2.0.1 Importing CSV from Data Collection

[175]:
```
df_import = pd.read_csv(os.path.join('data_collection', 'final_result.csv'))
df_import
```

[175]:
```
       categories.id categories.name categories.playlists.id  \
0             hiphop         Hip-Hop  37i9dQZF1DX0XUsuxWHRQd
1             hiphop         Hip-Hop  37i9dQZF1DX0XUsuxWHRQd
2             hiphop         Hip-Hop  37i9dQZF1DX0XUsuxWHRQd
3             hiphop         Hip-Hop  37i9dQZF1DX0XUsuxWHRQd
4             hiphop         Hip-Hop  37i9dQZF1DX0XUsuxWHRQd
…                  …               …                       …
158317          funk     Funk & Disco  37i9dQZF1DX0oFpWfPwcGv
158318          funk     Funk & Disco  37i9dQZF1DX0oFpWfPwcGv
```

```
158319          funk    Funk & Disco  37i9dQZF1DX0oFpWfPwcGv
158320          funk    Funk & Disco  37i9dQZF1DX0oFpWfPwcGv
158321          funk    Funk & Disco  37i9dQZF1DX0oFpWfPwcGv

       categories.playlists.name categories.playlists.tracks.id  \
0                      RapCaviar         2AaJeBEq3WLcfFW1y8svDf
1                      RapCaviar         7uLFOXgLrS90tEYPO1DGXy
2                      RapCaviar         2lUDBd7JrgAMltcp6dcd7D
3                      RapCaviar         0qHPxjC83zQYcxe39xSShx
4                      RapCaviar         2QIBJFl8DJR1mDh9GwfZef
…                              …                              …
158317           Disco Decadence         00Zum0eGUHgcE5l8MoNuUG
158318           Disco Decadence         2vLaES21zwbX1Rnmj56Bbb
158319           Disco Decadence         3eudp9ZxZAGaDBOuWGrW2D
158320           Disco Decadence         3YJx77Xx8JSwEoxqrkQO5c
158321           Disco Decadence         0Dj3iMM3fvHMOqWsqS64Fu

                 categories.playlists.tracks.name  \
0                                    By Your Side
1                               Man in the Mirror
2                                      25 million
3                                        thailand
4                        Don’t Play (with Lil Baby)
…                                               …
158317     Turn the Beat Around - 7" Single Edit
158318                             I'll Be Around
158319            Got to Be Real - Single Version
158320                              Knock on Wood
158321  White Lines (Long Version) [Re-Recorded]

       categories.playlists.tracks.album.id  \
0                    2RrZgDND03MLu6pRJdTkz5
1                    1VxVQAgekwkFo8yoXvFZ8o
2                    1eVrpJbHRLBbioB9sb5b94
3                    1eVrpJbHRLBbioB9sb5b94
4                    2rLqUcipEjIKK9rma5OTN8
…                                         …
158317               7vlYGZ9hnsuC57PUiqy0WC
158318               6QVemXFGMR4OLvlXvtQVjg
158319               059jmsqbxhu2n78LMS0H3P
158320               07ojYfe9B08p7nmOL2kgNF
158321               5bl0ggdoV1nNEGuVkUG9c3

                   categories.playlists.tracks.album.name  \
0                                            By Your Side
1                                                  B4 AVA
2                                          LIVE LIFE FAST
```

```
3                                       LIVE LIFE FAST
4                                     Hall of Fame 2.0
…                                                    …
158317          Never Gonna Let You Go (Expanded Edition)
158318                                        Spinners
158319                     Cheryl Lynn (Expanded Edition)
158320                                    Knock On Wood
158321  Hip Hop Soundtrack To The Concrete Jungle (Re-…

         categories.playlists.tracks.artists  \
0                                   Rod Wave
1                     A Boogie Wit da Hoodie
2                                Roddy Ricch
3                                Roddy Ricch
4                            Polo G,Lil Baby
…                                        …
158317                    Vicki Sue Robinson
158318                          The Spinners
158319                           Cheryl Lynn
158320                          Eddie Floyd
158321  Grandmaster Flash & The Furious Five

        categories.playlists.tracks.features.danceability  …  \
0                                                   0.649  …
1                                                   0.849  …
2                                                   0.793  …
3                                                   0.875  …
4                                                   0.684  …
…                                                     …  …
158317                                              0.707  …
158318                                              0.593  …
158319                                              0.830  …
158320                                              0.864  …
158321                                              0.814  …

        categories.playlists.tracks.features.loudness  \
0                                             -10.232
1                                              -4.241
2                                              -9.258
3                                             -10.562
4                                              -7.414
…                                                 …
158317                                         -7.540
158318                                         -8.698
158319                                         -7.462
158320                                        -12.918
158321                                         -7.525
```

```
        categories.playlists.tracks.features.mode  \
0                                               1
1                                               0
2                                               1
3                                               1
4                                               0
…                                             …
158317                                          0
158318                                          0
158319                                          1
158320                                          1
158321                                          1

        categories.playlists.tracks.features.speechiness  \
0                                                  0.0959
1                                                  0.0637
2                                                  0.1240
3                                                  0.2180
4                                                  0.3470
…                                                    …
158317                                             0.0720
158318                                             0.0680
158319                                             0.0448
158320                                             0.0365
158321                                             0.0376

        categories.playlists.tracks.features.acousticness  \
0                                                 0.03450
1                                                 0.17100
2                                                 0.01900
3                                                 0.00717
4                                                 0.23900
…                                                     …
158317                                            0.44500
158318                                            0.17500
158319                                            0.20200
158320                                            0.27700
158321                                            0.01030

        categories.playlists.tracks.features.instrumentalness  \
0                                                0.000036
1                                                0.000000
2                                                0.000001
3                                                0.000000
4                                                0.000000
…                                                     …
```

```
158317                                         0.000000
158318                                         0.000000
158319                                         0.044800
158320                                         0.005210
158321                                         0.007750

        categories.playlists.tracks.features.liveness  \
0                                                0.0736
1                                                0.1490
2                                                0.1390
3                                                0.1470
4                                                0.1120
…                                                  …
158317                                           0.3660
158318                                           0.0976
158319                                           0.1370
158320                                           0.0514
158321                                           0.1320

        categories.playlists.tracks.features.valence  \
0                                                0.405
1                                                0.550
2                                                0.395
3                                                0.409
4                                                0.708
…                                                …
158317                                           0.822
158318                                           0.630
158319                                           0.901
158320                                           0.964
158321                                           0.786

        categories.playlists.tracks.features.tempo  \
0                                          157.975
1                                          135.997
2                                          132.202
3                                          128.990
4                                          146.925
…                                              …
158317                                     131.242
158318                                     112.295
158319                                     114.646
158320                                     105.164
158321                                     114.998

        categories.playlists.tracks.features.duration_ms  \
0                                                 194051
```

```
1                                                 215304
2                                                 204626
3                                                 200959
4                                                 156735
…                                                  …
158317                                            204653
158318                                            188800
158319                                            223173
158320                                            189840
158321                                            465048

        categories.playlists.tracks.features.time_signature
0                                                       4
1                                                       4
2                                                       4
3                                                       4
4                                                       4
…                                                    …
158317                                                  4
158318                                                  4
158319                                                  4
158320                                                  4
158321                                                  4

[158322 rows x 22 columns]
```

[176]:
```python
df_import.dtypes
```

[176]:
```
categories.id                                              object
categories.name                                            object
categories.playlists.id                                    object
categories.playlists.name                                  object
categories.playlists.tracks.id                             object
categories.playlists.tracks.name                           object
categories.playlists.tracks.album.id                       object
categories.playlists.tracks.album.name                     object
categories.playlists.tracks.artists                        object
categories.playlists.tracks.features.danceability         float64
categories.playlists.tracks.features.energy               float64
categories.playlists.tracks.features.key                    int64
categories.playlists.tracks.features.loudness             float64
categories.playlists.tracks.features.mode                   int64
categories.playlists.tracks.features.speechiness          float64
categories.playlists.tracks.features.acousticness         float64
categories.playlists.tracks.features.instrumentalness     float64
categories.playlists.tracks.features.liveness             float64
categories.playlists.tracks.features.valence              float64
```

```
categories.playlists.tracks.features.tempo               float64
categories.playlists.tracks.features.duration_ms           int64
categories.playlists.tracks.features.time_signature        int64
dtype: object
```

2.0.2 Removing duplicates

Duplicates are removed by artist and track names. This ensures that tracks that were released twice (e.g. single before album) are still deduplicated. Using the track id as a deduplication criterion wouldn't achieve this.

[177]:
```
df_dedup = df_import.drop_duplicates(subset=['categories.playlists.tracks.
↪artists', 'categories.playlists.tracks.name'])
```

2.0.3 List all genre names

[178]:
```
genres = df_dedup['categories.name'].unique()
print(genres)
```

```
['Hip-Hop' 'Pop' 'Country' 'Rock' 'Latin' 'R&B' 'Mood' 'Indie'
 'Regional Mexican' 'Dance/Electronic' 'Christian & Gospel' 'Chill'
 'Party' 'Folk & Acoustic' 'K-Pop' 'Instrumental' 'Ambient' 'Alternative'
 'Classical' 'Jazz' 'Soul' 'Punk' 'Blues' 'Arab' 'Metal' 'Caribbean'
 'Funk & Disco']
```

2.0.4 Filter genres

[179]:
```
genre_filter = ['hiphop', 'jazz', 'rock']
df_filtered = df_dedup[df_dedup['categories.id'].isin(genre_filter)]
```

2.0.5 Drop unneeded columns and rename

[180]:
```
columns_to_drop = [
    "categories.name",
    "categories.playlists.id",
    "categories.playlists.name",
    "categories.playlists.tracks.id",
    "categories.playlists.tracks.name",
    "categories.playlists.tracks.album.id",
    "categories.playlists.tracks.album.name",
    "categories.playlists.tracks.artists"
    ]
df_dropped = df_filtered.drop(columns=columns_to_drop)

df_dropped = df_dropped.rename(columns={
    "categories.id": "category",
    "categories.playlists.tracks.features.danceability": "feature_danceability",
```

```
    "categories.playlists.tracks.features.energy": "feature_energy",
    "categories.playlists.tracks.features.key": "feature_key",
    "categories.playlists.tracks.features.loudness": "feature_loudness",
    "categories.playlists.tracks.features.mode": "feature_mode",
    "categories.playlists.tracks.features.speechiness": "feature_speechiness",
    "categories.playlists.tracks.features.acousticness": "feature_acousticness",
    "categories.playlists.tracks.features.instrumentalness":␣
 ↪"feature_instrumentalness",
    "categories.playlists.tracks.features.liveness": "feature_liveness",
    "categories.playlists.tracks.features.valence": "feature_valence",
    "categories.playlists.tracks.features.tempo": "feature_tempo",
    "categories.playlists.tracks.features.duration_ms": "feature_duration_ms",
    "categories.playlists.tracks.features.time_signature":␣
 ↪"feature_time_signature"
})
df_dropped = df_dropped.reset_index(drop=True)
df_dropped
```

[180]:

```
      category  feature_danceability  feature_energy  feature_key  \
0       hiphop                 0.649          0.5080            8
1       hiphop                 0.849          0.6310            3
2       hiphop                 0.793          0.4810            9
3       hiphop                 0.875          0.4780            7
4       hiphop                 0.684          0.6240            2
…          …                     …               …            …
13372     jazz                 0.421          0.0952            6
13373     jazz                 0.503          0.4910            0
13374     jazz                 0.644          0.5940            5
13375     jazz                 0.462          0.2110            0
13376     jazz                 0.309          0.8370            2

       feature_loudness  feature_mode  feature_speechiness  \
0               -10.232             1               0.0959
1                -4.241             0               0.0637
2                -9.258             1               0.1240
3               -10.562             1               0.2180
4                -7.414             0               0.3470
…                   …             …                  …
13372           -12.561             1               0.0479
13373           -12.020             1               0.0295
13374            -9.965             1               0.1170
13375           -13.396             1               0.0586
13376            -8.135             1               0.1310

       feature_acousticness  feature_instrumentalness  feature_liveness  \
0                   0.03450                  0.000036            0.0736
1                   0.17100                  0.000000            0.1490
```

```
2                   0.01900              0.000001             0.1390
3                   0.00717              0.000000             0.1470
4                   0.23900              0.000000             0.1120
…                       …                    …                …
13372               0.93100              0.000201             0.1260
13373               0.04120              0.922000             0.0965
13374               0.75100              0.224000             0.1070
13375               0.66500              0.946000             0.1140
13376               0.08500              0.621000             0.1430

       feature_valence  feature_tempo  feature_duration_ms  \
0               0.4050        157.975               194051
1               0.5500        135.997               215304
2               0.3950        132.202               204626
3               0.4090        128.990               200959
4               0.7080        146.925               156735
…                  …             …                   …
13372           0.0773        109.698               177922
13373           0.4890        166.105               263447
13374           0.6320         90.564               494467
13375           0.4260        179.658                77190
13376           0.3880        114.757               810322

       feature_time_signature
0                           4
1                           4
2                           4
3                           4
4                           4
…                       …
13372                       4
13373                       4
13374                       4
13375                       3
13376                       4

[13377 rows x 14 columns]
```

2.0.6 See, if data contains any null or NA values

[181]:
```
df_dropped.isnull().sum()
```

[181]:
```
category                   0
feature_danceability       0
feature_energy             0
feature_key                0
feature_loudness           0
```

```
feature_mode                0
feature_speechiness         0
feature_acousticness        0
feature_instrumentalness    0
feature_liveness            0
feature_valence             0
feature_tempo               0
feature_duration_ms         0
feature_time_signature      0
dtype: int64
```

3 Data Understanding

3.1 Basic Understanding

Show table head

[182]:
```
df_und = df_dropped
df_und.head()
```

[182]:
```
  category  feature_danceability  feature_energy  feature_key  \
0   hiphop                 0.649           0.508            8
1   hiphop                 0.849           0.631            3
2   hiphop                 0.793           0.481            9
3   hiphop                 0.875           0.478            7
4   hiphop                 0.684           0.624            2

   feature_loudness  feature_mode  feature_speechiness  feature_acousticness  \
0           -10.232             1               0.0959               0.03450
1            -4.241             0               0.0637               0.17100
2            -9.258             1               0.1240               0.01900
3           -10.562             1               0.2180               0.00717
4            -7.414             0               0.3470               0.23900

   feature_instrumentalness  feature_liveness  feature_valence  feature_tempo  \
0                  0.000036            0.0736            0.405        157.975
1                  0.000000            0.1490            0.550        135.997
2                  0.000001            0.1390            0.395        132.202
3                  0.000000            0.1470            0.409        128.990
4                  0.000000            0.1120            0.708        146.925

   feature_duration_ms  feature_time_signature
0               194051                       4
1               215304                       4
2               204626                       4
3               200959                       4
4               156735                       4
```

Show shape of data and samples per category

[183]:
```
# shape (rows, columns)
print('basic shape:  ', df_und.shape)

# amount of each category
print('amount of samples for ...')
print('hiphop:  ', df_und.loc[df_und['category'] == 'hiphop'].shape[0])
print('rock:   ' , df_und.loc[df_und['category'] == 'rock'].shape[0])
print('jazz:    ', df_und.loc[df_und['category'] == 'jazz'].shape[0])
```

```
basic shape:   (13377, 14)
amount of samples for …
hiphop:   2694
rock:    7252
jazz:     3431
```

3.2 Analysis of a single feature

Change the following variable feature to select which features should be analysed in this section.

[184]:
```
feature = 'feature_energy'
```

3.2.1 Basic feature information

[185]:
```
# overall basic feature information
print('overall:')
print(df_und[feature].describe())
#skewness and kurtosis

# skewness and kurtosis
print('\nskewness: %f' % df_und[feature].skew())
print('kurtosis: %f'   % df_und[feature].kurt())
```

```
overall:
count    13377.000000
mean         0.650739
std          0.235224
min          0.001530
25%          0.505000
50%          0.687000
75%          0.845000
max          0.999000
Name: feature_energy, dtype: float64

skewness: -0.689911
kurtosis: -0.254297
```

3.2.2 Category specific feature information

[186]:
```
df_hiphop   = df_und.loc[df['category'] == 'hiphop']
df_rock     = df_und.loc[df['category'] == 'rock']
df_jazz     = df_und.loc[df['category'] == 'jazz']
```

Hip-Hop

[187]:
```
print('hiphop:')
print(df_hiphop[feature].describe())

# skewness and kurtosis
print('\nskewness: %f' % df_hiphop[feature].skew())
print('kurtosis: %f'   % df_hiphop[feature].kurt())
```

```
hiphop:
count    2694.000000
mean        0.641614
std         0.149233
min         0.097600
25%         0.536000
50%         0.641000
75%         0.750000
max         0.995000
Name: feature_energy, dtype: float64

skewness: -0.118530
kurtosis: -0.365503
```

Jazz

[188]:
```
print('jazz:')
print(df_jazz[feature].describe())

# skewness and kurtosis
print('\nskewness: %f' % df_jazz[feature].skew())
print('kurtosis: %f'   % df_jazz[feature].kurt())
```

```
jazz:
count    3431.000000
mean        0.441448
std         0.248839
min         0.001530
25%         0.231500
50%         0.436000
75%         0.638000
max         0.992000
Name: feature_energy, dtype: float64
```

```
skewness: 0.126479
kurtosis: -1.005078
```

Rock

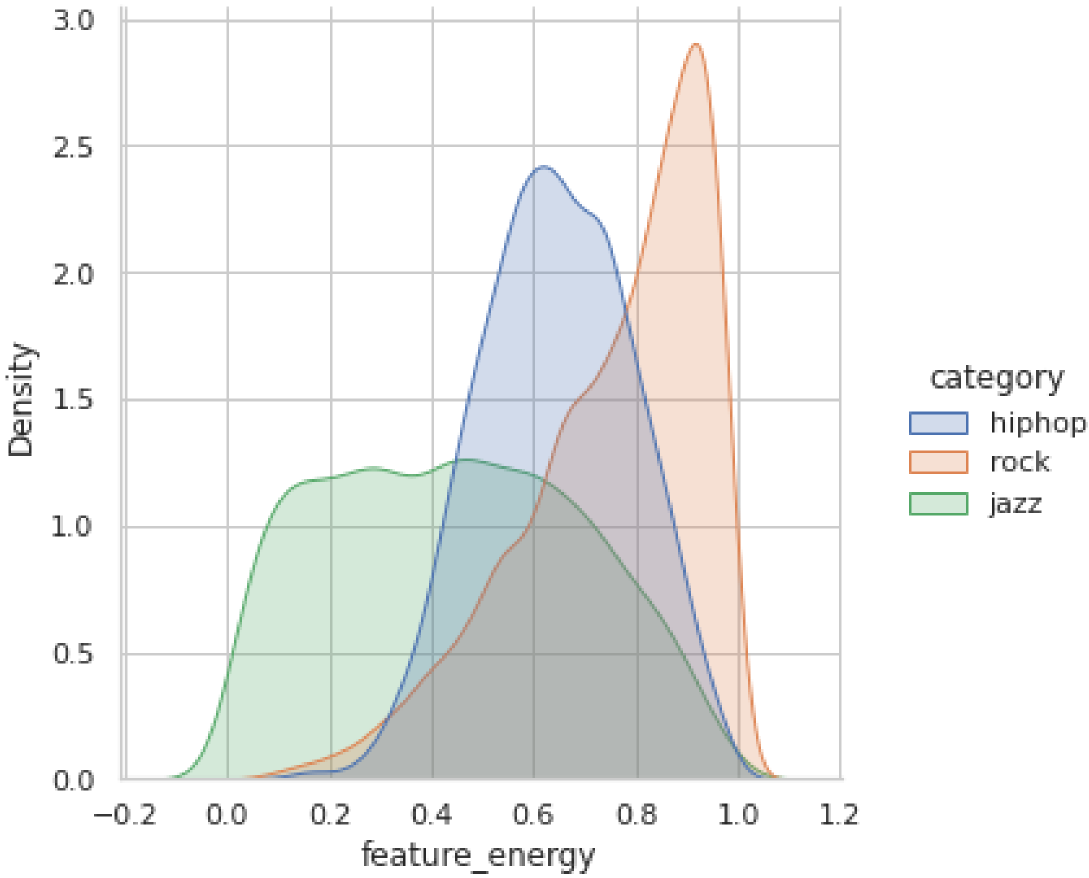
[189]:
```
print('rock:')
print(df_rock[feature].describe())

# skewness and kurtosis
print('\nskewness: %f' % df_rock[feature].skew())
print('kurtosis: %f'   % df_rock[feature].kurt())
```

```
rock:
count    7252.000000
mean        0.753147
std         0.182375
min         0.045700
25%         0.645000
50%         0.798500
75%         0.901000
max         0.999000
Name: feature_energy, dtype: float64

skewness: -0.935620
kurtosis: 0.327018
```

3.2.3 Graphical analysis of the selected feature

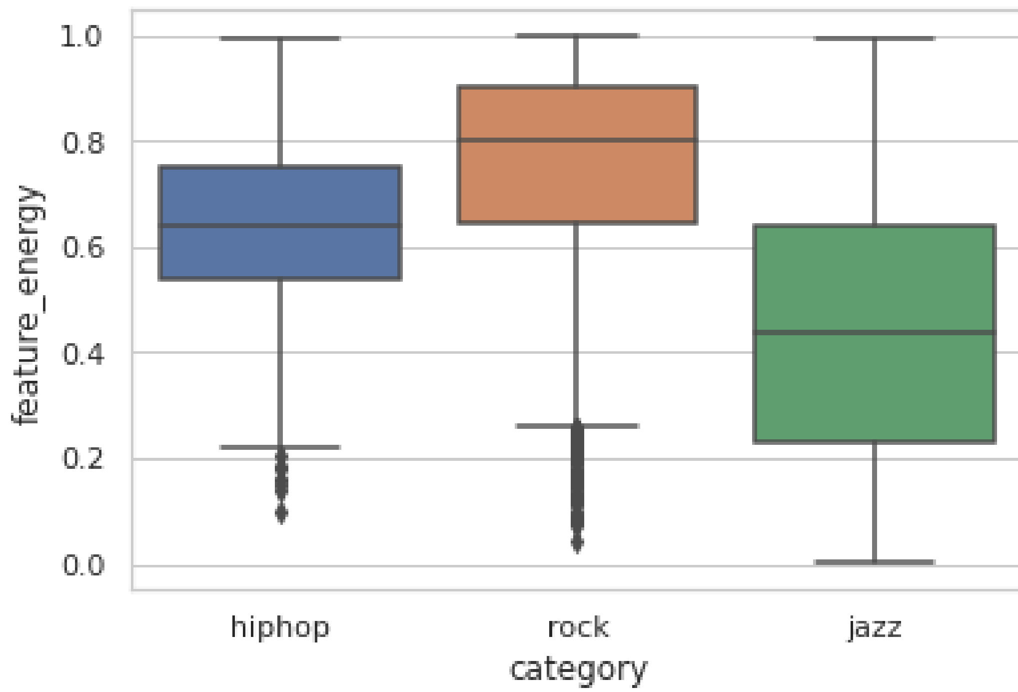
Distribution Plot

[190]:
```
sns.set(style="whitegrid")
ax = sns.displot(data = df_und, x = feature, hue = df_und['category'],␣
 ↪kind="kde",fill=True,common_norm=False)
```



Boxplot

[191]:
```
ax = sns.boxplot(data = df_und, x = 'category', y = feature)
```

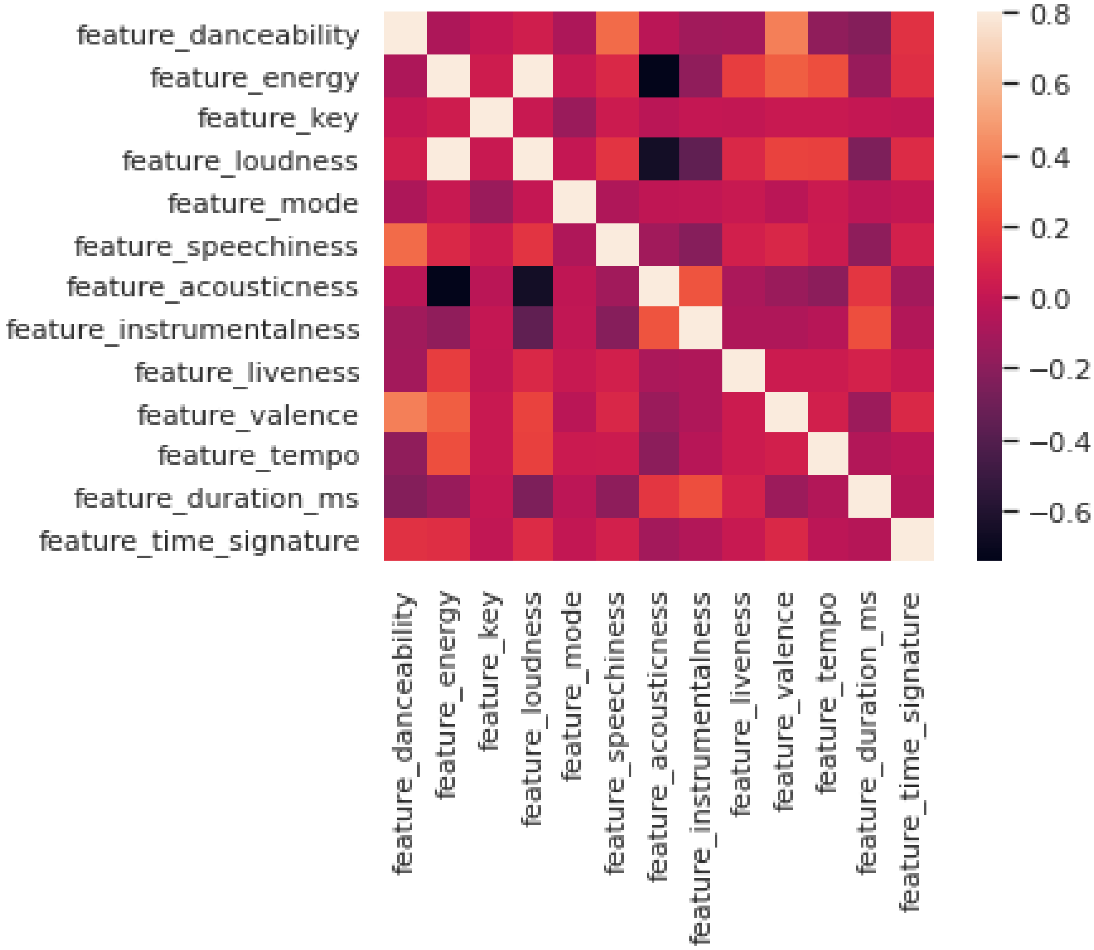


3.3 Correlation between all features

Overall Correlation

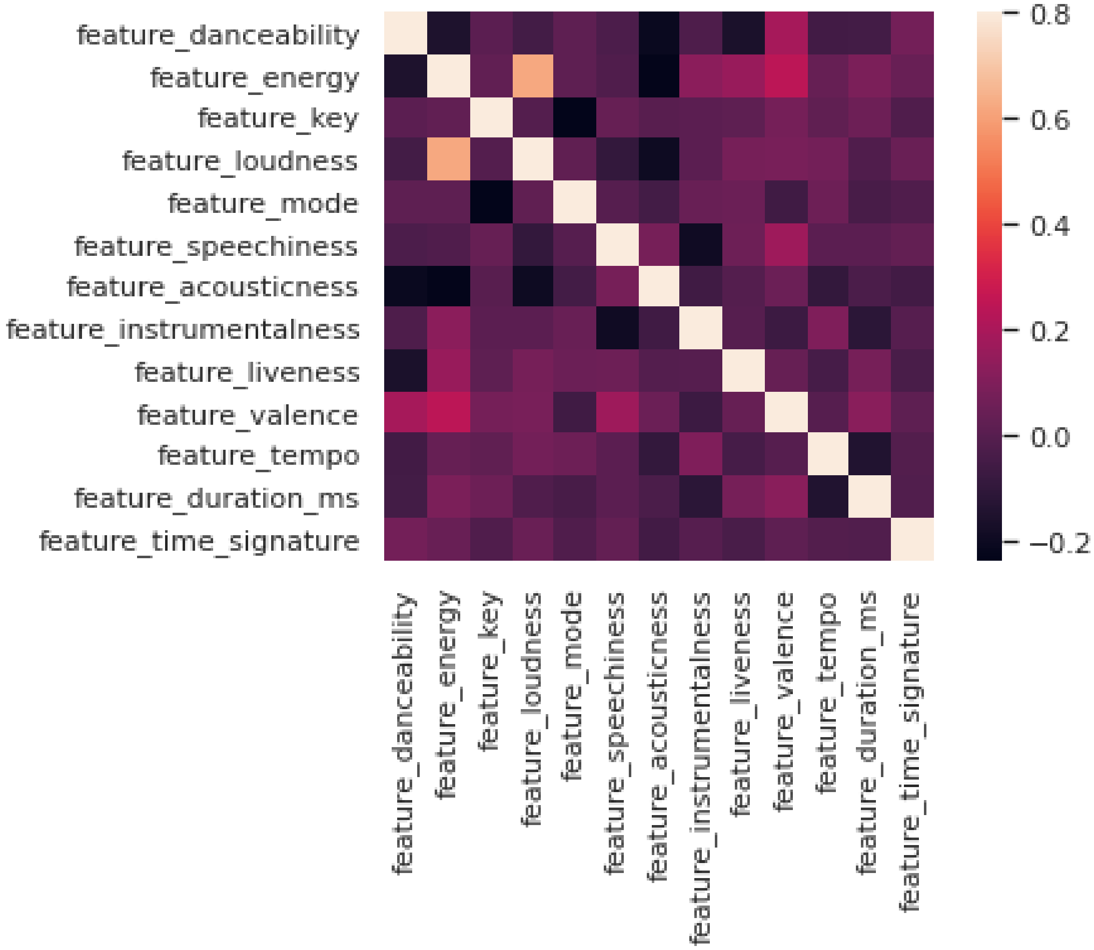
[192]:
```
corrmat = df_und.corr()
sns.heatmap(corrmat, vmax=.8, square=True)
```

[192]: <AxesSubplot:>



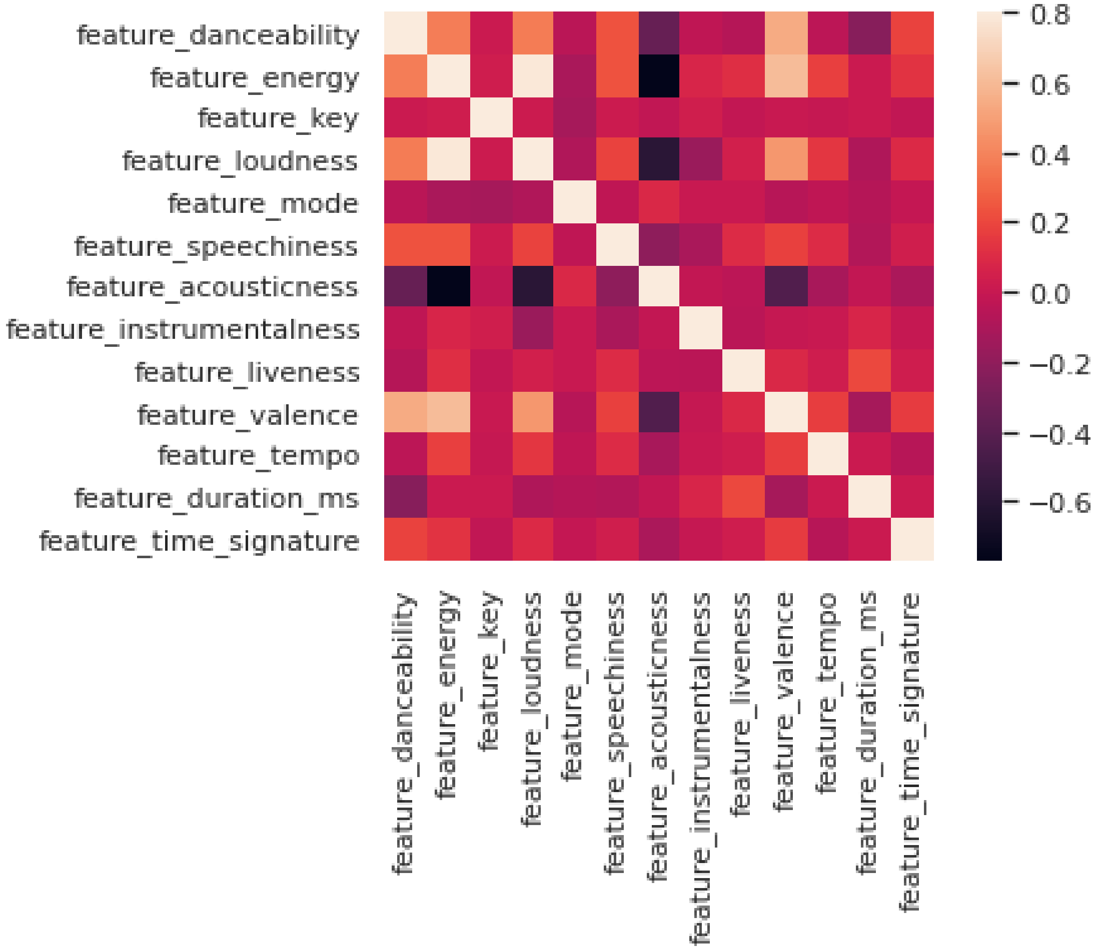
Correlations of Hip-Hop samples

[193]:
```
corrmat = df_hiphop.corr()
sns.heatmap(corrmat, vmax=.8, square=True);
```



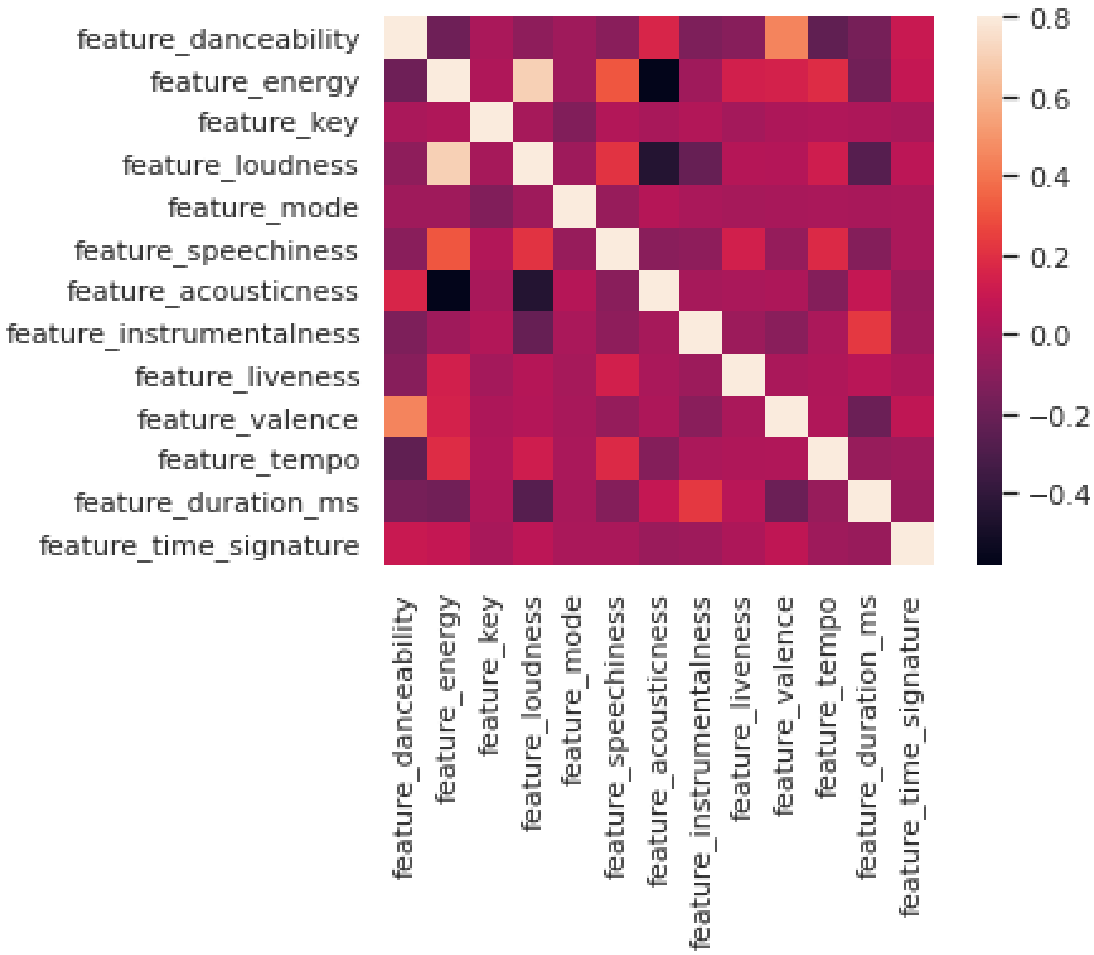
Correlations of Jazz samples

[194]:
```
corrmat = df_jazz.corr()
sns.heatmap(corrmat, vmax=.8, square=True);
```



Correlations of Rock samples

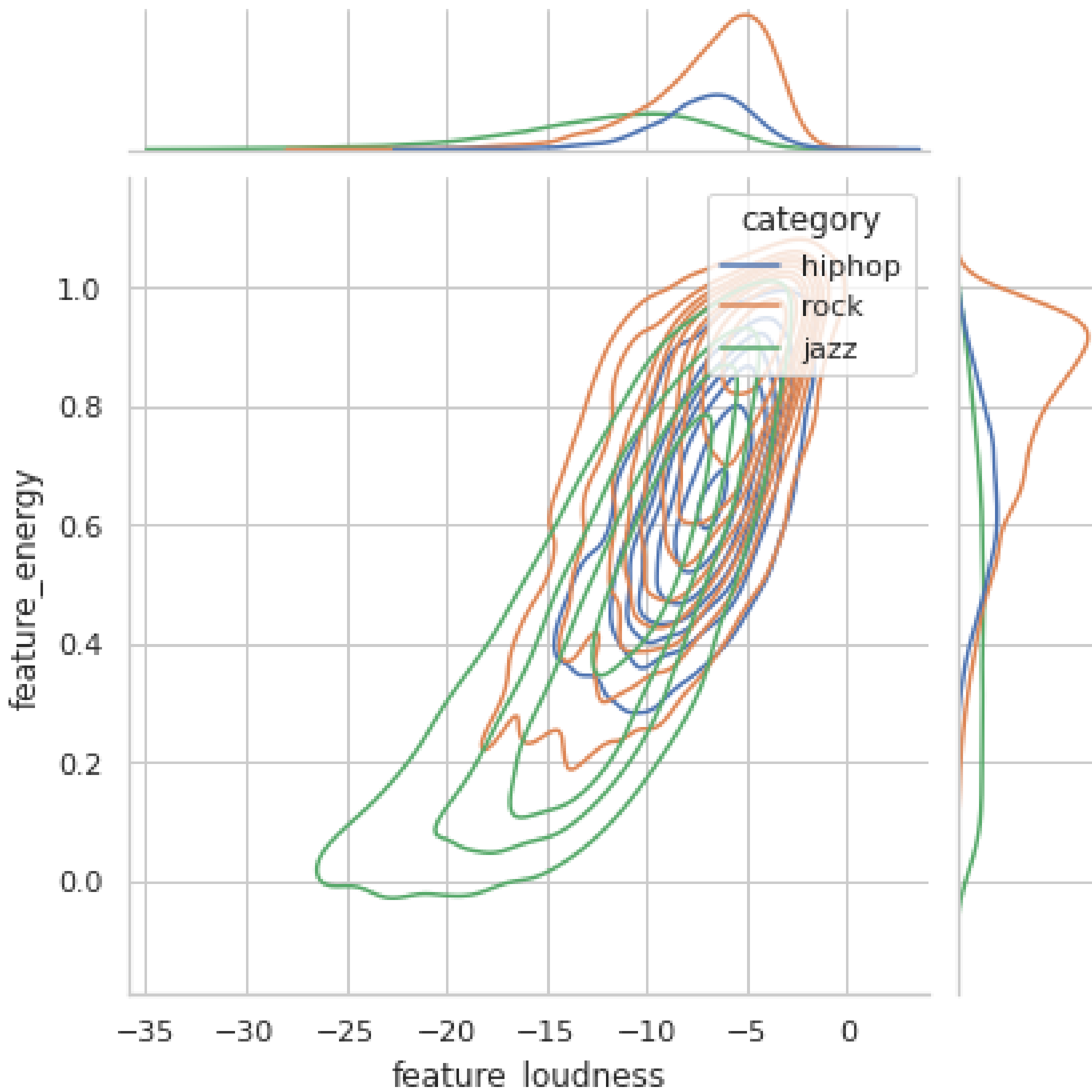
[195]:
```
corrmat = df_rock.corr()
sns.heatmap(corrmat, vmax=.8, square=True);
```



3.4 Correlation between two features

[196]:
```python
feature_x = 'feature_loudness'
feature_y = 'feature_energy'

sns.jointplot(
    data = df_und,
    x    = feature_x,
    y    = feature_y,
    hue  = "category",
    kind = "kde")
```

[196]: <seaborn.axisgrid.JointGrid at 0x7f2eb5247490>



4 Data Preparation for Modeling

4.0.1 Map categories to integers

[197]:
```
def encode_target(df, target_column):

    df_mod = df.copy()
    map_to_int = {name: n for n, name in enumerate(df_mod["category"].unique())}
    df_mod.insert(1, "target", df_mod[target_column].replace(map_to_int))

    return df_mod
```

```python
df = encode_target(df_dropped, "category")
df
```

[197]:

```
      category  target  feature_danceability  feature_energy  feature_key  \
0       hiphop       0                 0.649          0.5080            8
1       hiphop       0                 0.849          0.6310            3
2       hiphop       0                 0.793          0.4810            9
3       hiphop       0                 0.875          0.4780            7
4       hiphop       0                 0.684          0.6240            2
…          …    …                 …           …            …
13372     jazz       2                 0.421          0.0952            6
13373     jazz       2                 0.503          0.4910            0
13374     jazz       2                 0.644          0.5940            5
13375     jazz       2                 0.462          0.2110            0
13376     jazz       2                 0.309          0.8370            2

       feature_loudness  feature_mode  feature_speechiness  \
0               -10.232             1               0.0959
1                -4.241             0               0.0637
2                -9.258             1               0.1240
3               -10.562             1               0.2180
4                -7.414             0               0.3470
…                  …            …                   …
13372           -12.561             1               0.0479
13373           -12.020             1               0.0295
13374            -9.965             1               0.1170
13375           -13.396             1               0.0586
13376            -8.135             1               0.1310

       feature_acousticness  feature_instrumentalness  feature_liveness  \
0                   0.03450                  0.000036            0.0736
1                   0.17100                  0.000000            0.1490
2                   0.01900                  0.000001            0.1390
3                   0.00717                  0.000000            0.1470
4                   0.23900                  0.000000            0.1120
…                     …                    …                  …
13372               0.93100                  0.000201            0.1260
13373               0.04120                  0.922000            0.0965
13374               0.75100                  0.224000            0.1070
13375               0.66500                  0.946000            0.1140
13376               0.08500                  0.621000            0.1430

       feature_valence  feature_tempo  feature_duration_ms  \
0               0.4050        157.975               194051
1               0.5500        135.997               215304
2               0.3950        132.202               204626
3               0.4090        128.990               200959
```

```
4               0.7080        146.925              156735
…                 …           …                   …
13372           0.0773        109.698              177922
13373           0.4890        166.105              263447
13374           0.6320         90.564              494467
13375           0.4260        179.658               77190
13376           0.3880        114.757              810322

       feature_time_signature
0                           4
1                           4
2                           4
3                           4
4                           4
…                         …
13372                       4
13373                       4
13374                       4
13375                       3
13376                       4

[13377 rows x 15 columns]
```

4.0.2 Show final integer mapping

[198]:
```
df[["target", "category"]].drop_duplicates(subset=['target', 'category'])
```

[198]:
```
      target category
0          0   hiphop
2694       1     rock
9946       2     jazz
```

4.1 Data Transformation and Dimension Reduction

Overview over all scores is given at the end of this section

Function for shuffling, splitting, fitting and scoring a simple model

[199]:
```
def eval_prep(df, feature_column_names, label_column_name):
    train, test = train_test_split(df, test_size=0.2, random_state=45,␣
 ↪shuffle=True)

    X_train = train[feature_column_names]
    X_test = test[feature_column_names]

    y_train = train[label_column_name]
    y_test = test[label_column_name]
```

```
    # Create gradient boosting classifier object with default values
    gbc = GradientBoostingClassifier(random_state=45)

    gbc.fit(X_train, y_train)
    score = gbc.score(X_test, y_test)

    return score

score_overview = []
```

4.1.1 Simple regular Gradient Boosting Model for reference

[200]:
```
features = list(df.columns[2:])

score = eval_prep(df, features, "target")
score_overview.append({"score": score, "desc": "Regular Gradient Boosting"})
```

4.1.2 Mean Removal

[201]:
```
X_mr = df[features]
y = df["target"]

X_mr = StandardScaler(with_std=False).fit_transform(X_mr)

df_mr = pd.DataFrame(data=X_mr)
df_mr.insert(0, "target", y)
df_mr.columns = ["target"] + features

score = eval_prep(df_mr, features, "target")

score_overview.append({"score": score, "desc": "Mean Removal"})
```

4.1.3 Variance Scaling

[202]:
```
X_vs = df[features]
y = df["target"]

X_vs = StandardScaler(with_mean=False).fit_transform(X_vs)

df_vs = pd.DataFrame(data=X_vs)
df_vs.insert(0, "target", y)
df_vs.columns = ["target"] + features

score = eval_prep(df_vs, features, "target")
```

```
score_overview.append({"score": score, "desc": "Variance Scaling"})
```

4.1.4 Standardization

[203]:
```
X_s = df[features]
y = df["target"]

X_s = StandardScaler().fit_transform(X_s)

df_s = pd.DataFrame(data=X_s)
df_s.insert(0, "target", y)
df_s.columns = ["target"] + features

score = eval_prep(df_s, features, "target")

score_overview.append({"score": score, "desc": "Standardization"})
```

4.1.5 PCA

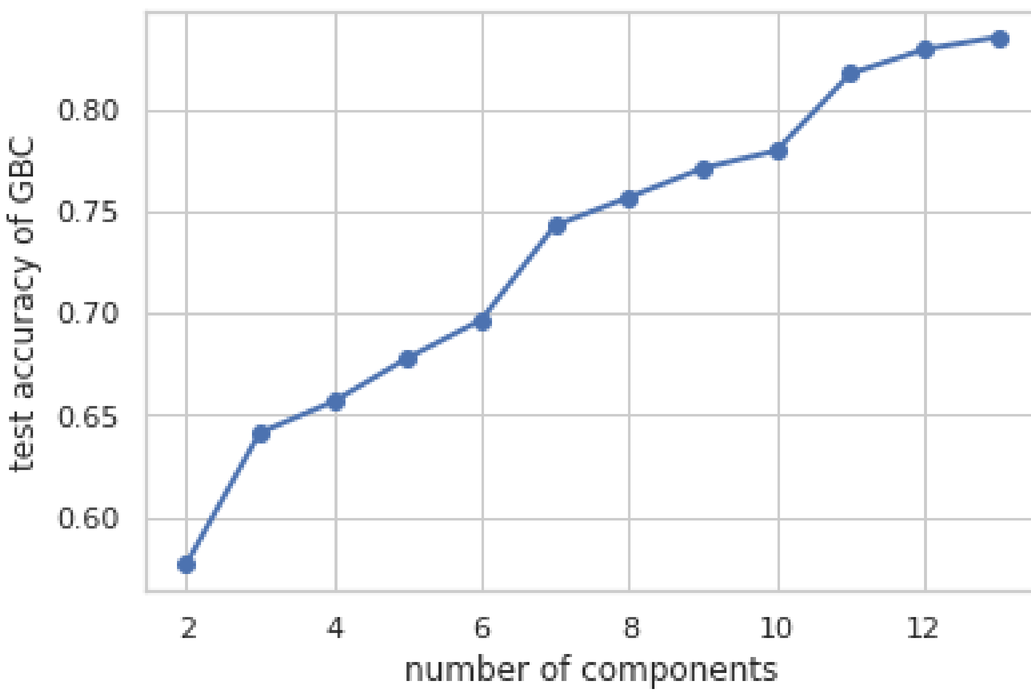
[204]:
```
scores = []

for n_components in range(2,14):

    X_pca = df[features]
    y = df["target"]

    # column names
    column_names = ["target"]
    for n in range(n_components):
        column_names.append(f"pc{n}")

    pca = PCA(n_components=n_components)

    X_pca = pca.fit_transform(X_pca)

    df_pca = pd.DataFrame(data=X_pca)

    df_pca.insert(0, "target", y)
    df_pca.columns = column_names

    score = eval_prep(df_pca, column_names[1:], "target")

    scores.append({"components": n_components, "score": score})

highscore = 0
optimal_components = 0
for entry in scores:
```

```
    if entry["score"] > highscore:
        highscore = entry["score"]
        optimal_components = entry["components"]

print(f"PCA with {optimal_components} components yielded optimal score:␣
 ↪{highscore}")

score_overview.append({"score": highscore, "desc": "Regular PCA"})
```

```
PCA with 13 components yielded optimal score: 0.8352017937219731
```

Plotting score for each dimensionality

[205]:
```
fig, ax = plt.subplots()

plt_scores = []
plt_comps = []
for e in scores:
    plt_scores.append(e['score'])
    plt_comps.append(e['components'])
ax.plot(plt_comps, plt_scores, linewidth=2.0, marker='o')
ax.set_xlabel('number of components')
ax.set_ylabel('test accuracy of GBC')
ax.grid(True)
```



4.1.6 Standardization after PCA

[206]:
```
scores = []

for n_components in range(2,14):

    X_pca_s = df[features]
    y = df["target"]

    # column names
    column_names = ["target"]
    for n in range(n_components):
        column_names.append(f"pc{n}")

    pca = PCA(n_components=n_components)

    X_pca_s = pca.fit_transform(X_pca_s)
    X_pca_s = StandardScaler().fit_transform(X_pca_s)

    df_pca_s = pd.DataFrame(data=X_pca_s)

    df_pca_s.insert(0, "target", y)
    df_pca_s.columns = column_names

    score = eval_prep(df_pca_s, column_names[1:], "target")

    scores.append({"components": n_components, "score": score})

highscore = 0
optimal_components = 0
for entry in scores:
    if entry["score"] > highscore:
        highscore = entry["score"]
        optimal_components = entry["components"]

print(f"PCA with {optimal_components} components yielded optimal score:␣
 ↪{highscore}")

score_overview.append({"score": highscore, "desc": "Standardization after PCA"})
```

```
PCA with 13 components yielded optimal score: 0.8348281016442451
```

4.1.7 Standardization before PCA

[207]:
```
scores = []

for n_components in range(2,14):
```

```
    X_pca_s = df[features]
    y = df["target"]

    # column names
    column_names = ["target"]
    for n in range(n_components):
        column_names.append(f"pc{n}")

    pca = PCA(n_components=n_components)

    X_pca_s = StandardScaler().fit_transform(X_pca_s)
    X_pca_s = pca.fit_transform(X_pca_s)

    df_pca_s = pd.DataFrame(data=X_pca_s)
    df_pca_s.insert(0, "target", y)
    df_pca_s.columns = column_names

    score = eval_prep(df_pca_s, column_names[1:], "target")

    scores.append({"components": n_components, "score": score})

highscore = 0
optimal_components = 0
for entry in scores:
    if entry["score"] > highscore:
        highscore = entry["score"]
        optimal_components = entry["components"]

print(f"PCA with {optimal_components} components yielded optimal score:␣
 ↪{highscore}")

score_overview.append({"score": highscore, "desc": "Standardization before␣
 ↪PCA"})
```

```
PCA with 13 components yielded optimal score: 0.827727952167414
```

4.1.8 Score Overview

[208]:
```
print("Score overview:")
highscore = 0
best_desc = ""
for entry in score_overview:
    if entry['score'] > highscore:
        highscore = entry['score']
        best_desc = entry['desc']
    print(f"{entry['desc']}: {entry['score']}")
```

```
print("\nMethod with highest score: " + best_desc)
```

```
Score overview:
Regular Gradient Boosting: 0.8505231689088192
Mean Removal: 0.850896860986547
Variance Scaling: 0.852017937219731
Standardization: 0.8523916292974589
Regular PCA: 0.8352017937219731
Standardization after PCA: 0.8348281016442451
Standardization before PCA: 0.827727952167414

Method with highest score: Standardization
```

The best score was achieved using the standardized dataset (df_s), so this will be used in the modeling stage.

5 Modeling

5.0.1 Basic examination of the standardized dataset

[209]:
```
df_s
```

[209]:
```
       target  feature_danceability  feature_energy  feature_key  \
0           0              0.525952       -0.606845     0.791667
1           0              1.699036       -0.083920    -0.611631
2           0              1.370572       -0.721633     1.072326
3           0              1.851536       -0.734387     0.511007
4           0              0.731242       -0.113680    -0.892290
…         …                    …               …            …
13372       2             -0.811363       -2.361830     0.230348
13373       2             -0.330399       -0.679119    -1.453609
13374       2              0.496625       -0.241223    -0.050312
13375       2             -0.570881       -1.869516    -1.453609
13376       2             -1.468290        0.791872    -0.892290

       feature_loudness  feature_mode  feature_speechiness  \
0             -0.469262      0.790819            -0.001432
1              0.952395     -1.264512            -0.317468
2             -0.238133      0.790819             0.274363
3             -0.547571      0.790819             1.196953
4              0.199446     -1.264512             2.463060
…                   …             …                   …
13372         -1.021931      0.790819            -0.472542
13373         -0.893553      0.790819            -0.653134
13374         -0.405903      0.790819             0.205660
13375         -1.220076      0.790819            -0.367524
13376          0.028354      0.790819             0.343067
```

```
       feature_acousticness  feature_instrumentalness  feature_liveness  \
0                 -0.677224                 -0.560184         -0.743415
1                 -0.240457                 -0.560299         -0.296830
2                 -0.726820                 -0.560296         -0.356059
3                 -0.764673                 -0.560299         -0.308675
4                 -0.022873                 -0.560299         -0.515977
…                       …                       …                  …
13372              2.191359                 -0.559652         -0.433056
13373             -0.655785                  2.407617         -0.607781
13374              1.615403                  0.160756         -0.545591
13375              1.340224                  2.484873         -0.504131
13376             -0.515636                  1.438699         -0.332367

       feature_valence  feature_tempo  feature_duration_ms  \
0            -0.387093       1.175112            -0.468065
1             0.235137       0.449933            -0.270797
2            -0.430006       0.324715            -0.369909
3            -0.369929       0.218733            -0.403946
4             0.913153       0.810510            -0.814428
…                  …             …                   …
13372        -1.793333      -0.417819            -0.617773
13373        -0.026629       1.443366             0.176060
13374         0.587018      -1.049158             2.320361
13375        -0.296977       1.890556            -1.552755
13376        -0.460045      -0.250894             5.252090

       feature_time_signature
0                    0.189922
1                    0.189922
2                    0.189922
3                    0.189922
4                    0.189922
…                         …
13372                0.189922
13373                0.189922
13374                0.189922
13375               -2.667886
13376                0.189922

[13377 rows x 14 columns]
```

[210]:

```
df_s.describe()
```

[210]:

```
             target  feature_danceability  feature_energy   feature_key  \
count  13377.000000          1.337700e+04    1.337700e+04  1.337700e+04
mean       1.055095         -5.269181e-16    6.119049e-16 -1.699736e-17
std        0.674444          1.000037e+00    1.000037e+00  1.000037e+00
```

```
min       0.000000        -2.805019e+00   -2.760061e+00 -1.453609e+00
25%       1.000000        -7.116513e-01   -6.195990e-01 -8.922902e-01
50%       1.000000        -4.885906e-02    1.541591e-01 -5.031183e-02
75%       2.000000         7.077799e-01    8.258832e-01  7.916665e-01
max       2.000000         2.473271e+00    1.480602e+00  1.633645e+00

       feature_loudness  feature_mode  feature_speechiness  \
count      1.337700e+04  1.337700e+04         1.337700e+04
mean      -1.359789e-16 -2.124670e-18        -1.359789e-16
std        1.000037e+00  1.000037e+00         1.000037e+00
min       -5.649022e+00 -1.264512e+00        -7.228188e-01
25%       -4.571599e-01 -1.264512e+00        -5.844304e-01
50%        2.248371e-01  7.908191e-01        -4.391716e-01
75%        7.034689e-01  7.908191e-01         4.862320e-02
max        2.443819e+00  7.908191e-01         7.910265e+00

       feature_acousticness  feature_instrumentalness  feature_liveness  \
count          13377.000000              1.337700e+04      1.337700e+04
mean               0.000000              6.798944e-17     -6.374010e-18
std                1.000037              1.000037e+00      1.000037e+00
min               -0.787612             -5.602992e-01     -1.098789e+00
25%               -0.765761             -5.602992e-01     -6.012662e-01
50%               -0.526515             -5.588410e-01     -4.152875e-01
75%                0.527485             -2.272643e-02      3.132278e-01
max                2.399344              2.623290e+00      4.725779e+00

       feature_valence  feature_tempo  feature_duration_ms  \
count     1.337700e+04   1.337700e+04         1.337700e+04
mean     -3.399472e-17  -1.784723e-16         1.189815e-16
std       1.000037e+00   1.000037e+00         1.000037e+00
min      -2.015620e+00  -2.826733e+00        -2.052770e+00
25%      -7.904702e-01  -8.080589e-01        -5.583408e-01
50%      -1.804667e-02  -7.793114e-02        -1.942868e-01
75%       7.758331e-01   7.131066e-01         2.929470e-01
max       2.101827e+00   3.226484e+00         2.161469e+01

       feature_time_signature
count            1.337700e+04
mean            -1.019842e-16
std              1.000037e+00
min             -8.383503e+00
25%              1.899224e-01
50%              1.899224e-01
75%              1.899224e-01
max              3.047731e+00
```

5.1 Decision Tree Classifier for Comparison

5.1.1 Preparation

Splitting and shuffling the dataset

[211]:
```
train, test = train_test_split(df_s, test_size=0.2, random_state=45,␣
↪shuffle=True)
```

Seperating labels and features

[212]:
```
X_train = train[features]
X_test = test[features]

y_train = train["target"]
y_test = test["target"]
```

5.1.2 Hyperparameter Tuning

[213]:
```
dt = DecisionTreeClassifier(random_state=45)

param_grid = {
    "criterion": ["gini", "entropy"],
    "splitter": ["best", "random"],
    "max_depth": [30, 50, 75, None],
    "min_samples_split": [2, 5, 10, 15, 20],
    "min_samples_leaf": [1, 3, 5, 10],
    "min_samples_leaf": [1],
    "max_features": ["auto", "sqrt", "log2"],
    "random_state": [42],
    "max_features": [None]
}

# Grid search object
search_dt = GridSearchCV(dt, param_grid, n_jobs=-1, cv=5)

# Fitting model
search_dt.fit(X_train, y_train)

score_dt = search_dt.score(X_test, y_test)
```

5.2 Validation Curves

5.2.1 Function to create validation curves

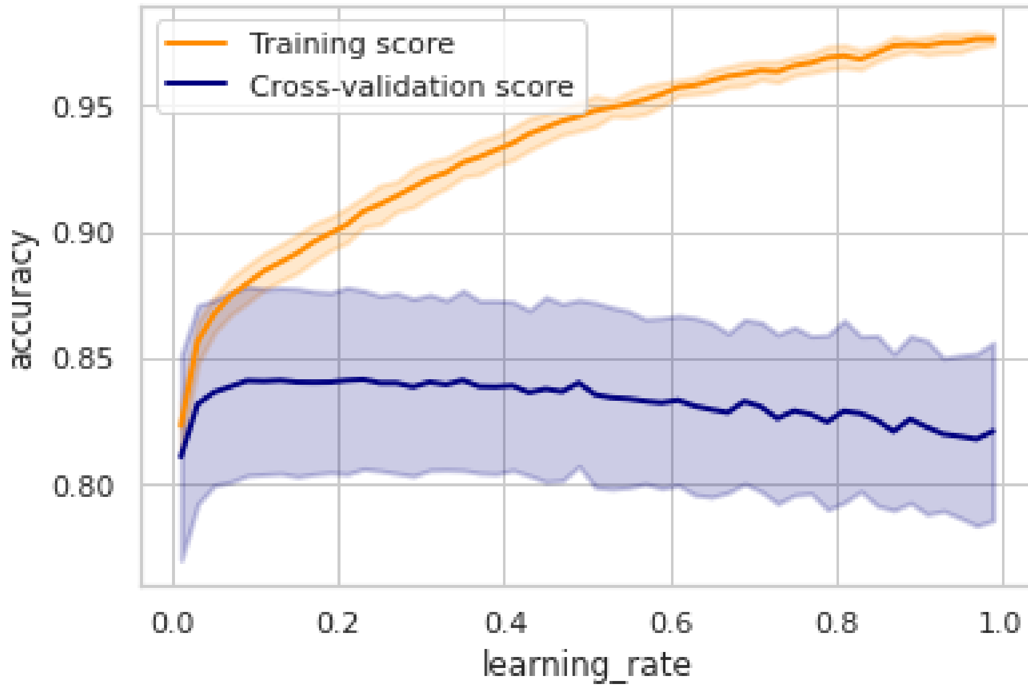
This takes the hyperparameter that should be modulated and a range to use for plotting.

[214]:
```
def val_curve(param_name, param_range):
```

```
X = df_s[features]
y = df_s["target"]

gbc = GradientBoostingClassifier(random_state=45)
train_scores, test_scores = validation_curve(gbc, X, y,
    param_name=param_name,
    param_range=param_range,
    n_jobs=-1)

train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)

#plt.title("Validation Curve with Gradient Boosting Classifier")
plt.xlabel("learning_rate")
plt.ylabel("accuracy")
#plt.ylim(0.0, 1.1)
lw = 2
plt.plot(
    param_range, train_scores_mean, label="Training score",␣
↪color="darkorange", lw=lw
)
plt.fill_between(
    param_range,
    train_scores_mean - train_scores_std,
    train_scores_mean + train_scores_std,
    alpha=0.2,
    color="darkorange",
    lw=lw,
)
plt.plot(
    param_range, test_scores_mean, label="Cross-validation score",␣
↪color="navy", lw=lw
)
plt.fill_between(
    param_range,
    test_scores_mean - test_scores_std,
    test_scores_mean + test_scores_std,
    alpha=0.2,
    color="navy",
    lw=lw,
)
plt.legend(loc="best")
plt.figure(dpi=200)
plt.show()
```

5.2.2 Validation curve learning_rate

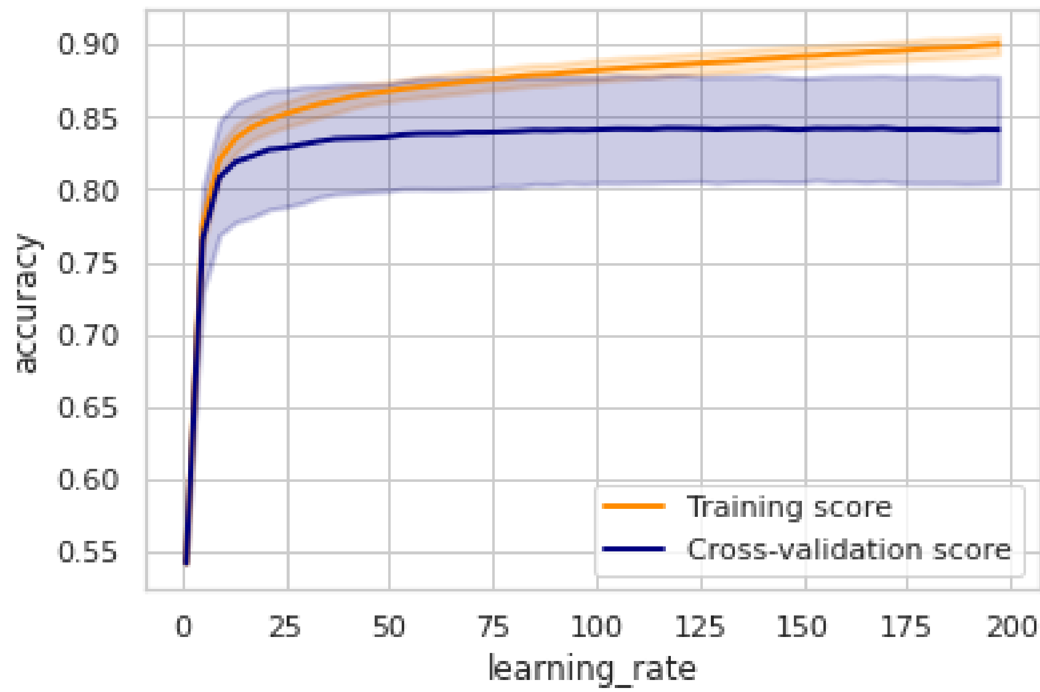
[215]:
```
val_curve("learning_rate", np.linspace(0.01,0.99,50))
```




```
<Figure size 1200x800 with 0 Axes>
```

5.2.3 Validation curve n_estimators

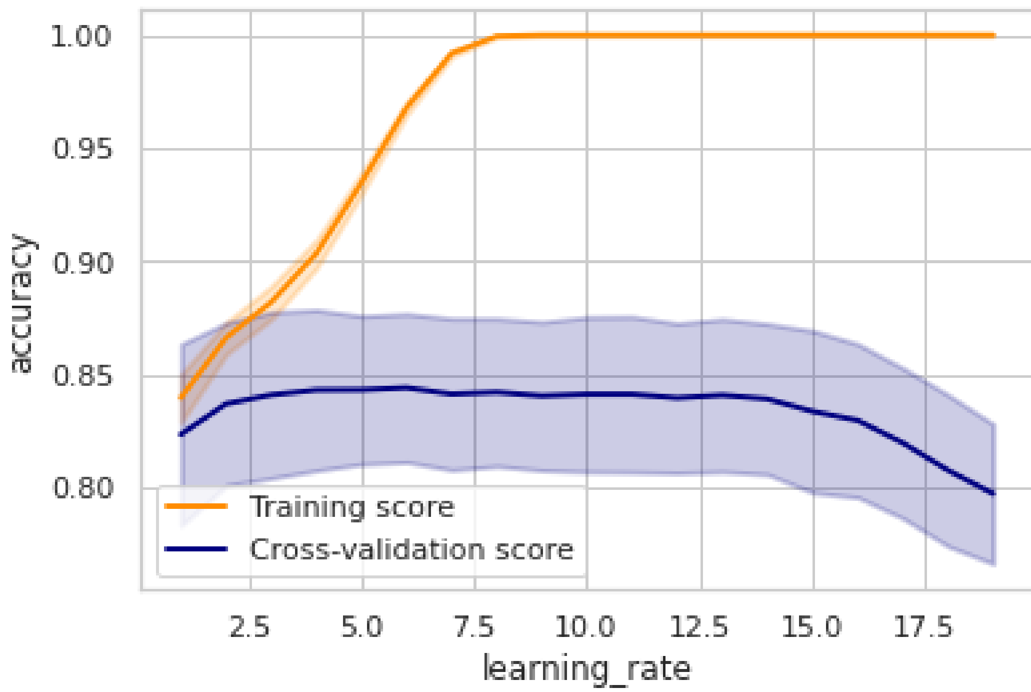
[216]:
```
val_curve("n_estimators", range(1,199,4))
```




```
<Figure size 1200x800 with 0 Axes>
```

5.2.4 Validation curve max_depth

[217]:
```
val_curve("max_depth", range(1,20,1))
```




```
<Figure size 1200x800 with 0 Axes>
```

5.3 Gradient Boosting Classifier

5.3.1 Preparation

Splitting and shuffling the dataset

[218]:
```
train, test = train_test_split(df_s, test_size=0.2, random_state=45,␣
 ↪shuffle=True)
```

Seperating labels and features

[219]:
```
X_train = train[features]
X_test = test[features]

y_train = train["target"]
y_test = test["target"]
```

5.3.2 Hyperparameter Tuning

Specifying parameter ranges for hyperparameter tuning

[220]:
```
learning_rate_values = np.linspace(0.01,0.25,9).round(2)
n_estimators_values = np.linspace(50,200,7).astype(int)
max_depth_values = np.linspace(2,6,5).astype(int)
```

```
param_grid = {
    "n_estimators": n_estimators_values,
    "learning_rate": learning_rate_values,
    "max_depth": max_depth_values
}

print("Values for learning_rate in grid search:")
print(learning_rate_values)
print("Values for n_estimators in grid search:")
print(n_estimators_values)
print("Values for max_depth in grid search:")
print(max_depth_values)
```

```
Values for learning_rate in grid search:
[0.01 0.04 0.07 0.1  0.13 0.16 0.19 0.22 0.25]
Values for n_estimators in grid search:
[ 50  75 100 125 150 175 200]
Values for max_depth in grid search:
[2 3 4 5 6]
```

Creating the Classifier and Grid Search objects

[221]:
```
gbc = GradientBoostingClassifier(random_state=45)

search = GridSearchCV(gbc, param_grid,
    n_jobs=-1,
    error_score="raise",
    verbose=1)
```

Fitting the first Grid Search model on the training data and calculating an accuracy score using the test set

[222]:
```
search.fit(X_train, y_train)

print("Accuracy score:")
print(search.score(X_test, y_test))
```

```
Fitting 5 folds for each of 315 candidates, totalling 1575 fits
Accuracy score:
0.859118086696562
```

Parameters found through Grid Search

[223]:
```
search.get_params()
```

[223]:
```
{'cv': None,
 'error_score': 'raise',
 'estimator__ccp_alpha': 0.0,
```

```
 'estimator__criterion': 'friedman_mse',
 'estimator__init': None,
 'estimator__learning_rate': 0.1,
 'estimator__loss': 'deviance',
 'estimator__max_depth': 3,
 'estimator__max_features': None,
 'estimator__max_leaf_nodes': None,
 'estimator__min_impurity_decrease': 0.0,
 'estimator__min_samples_leaf': 1,
 'estimator__min_samples_split': 2,
 'estimator__min_weight_fraction_leaf': 0.0,
 'estimator__n_estimators': 100,
 'estimator__n_iter_no_change': None,
 'estimator__random_state': 45,
 'estimator__subsample': 1.0,
 'estimator__tol': 0.0001,
 'estimator__validation_fraction': 0.1,
 'estimator__verbose': 0,
 'estimator__warm_start': False,
 'estimator': GradientBoostingClassifier(random_state=45),
 'n_jobs': -1,
 'param_grid': {'n_estimators': array([ 50,  75, 100, 125, 150, 175, 200]),
  'learning_rate': array([0.01, 0.04, 0.07, 0.1 , 0.13, 0.16, 0.19, 0.22,
0.25]),
  'max_depth': array([2, 3, 4, 5, 6])},
 'pre_dispatch': '2*n_jobs',
 'refit': True,
 'return_train_score': False,
 'scoring': None,
 'verbose': 1}
```

Fitting the second Grid Search Model This model uses a tighter range for the n_estimators parameter to try and further optimize the results

[236]:
```
param_grid_2 = {
    "n_estimators": [97,98,99,100,101,102,103],
    "learning_rate": learning_rate_values,
    "max_depth": max_depth_values
}

gbc2 = GradientBoostingClassifier(random_state=45)

search2 = GridSearchCV(gbc2, param_grid_2,
    n_jobs=-1,
    error_score="raise",
    verbose=1)
```

```
search2.fit(X_train, y_train)

print("Accuracy score:")
score_gb = search2.score(X_test, y_test)
print(score_gb)
```

```
Fitting 5 folds for each of 315 candidates, totalling 1575 fits
Accuracy score:
0.8568759342301944
```

Parameters of the final model

[237]:
```
search2.get_params()
```

[237]:
```
{'cv': None,
 'error_score': 'raise',
 'estimator__ccp_alpha': 0.0,
 'estimator__criterion': 'friedman_mse',
 'estimator__init': None,
 'estimator__learning_rate': 0.1,
 'estimator__loss': 'deviance',
 'estimator__max_depth': 3,
 'estimator__max_features': None,
 'estimator__max_leaf_nodes': None,
 'estimator__min_impurity_decrease': 0.0,
 'estimator__min_samples_leaf': 1,
 'estimator__min_samples_split': 2,
 'estimator__min_weight_fraction_leaf': 0.0,
 'estimator__n_estimators': 100,
 'estimator__n_iter_no_change': None,
 'estimator__random_state': 45,
 'estimator__subsample': 1.0,
 'estimator__tol': 0.0001,
 'estimator__validation_fraction': 0.1,
 'estimator__verbose': 0,
 'estimator__warm_start': False,
 'estimator': GradientBoostingClassifier(random_state=45),
 'n_jobs': -1,
 'param_grid': {'n_estimators': [97, 98, 99, 100, 101, 102, 103],
  'learning_rate': array([0.01, 0.04, 0.07, 0.1 , 0.13, 0.16, 0.19, 0.22,
0.25]),
  'max_depth': array([2, 3, 4, 5, 6])},
 'pre_dispatch': '2*n_jobs',
 'refit': True,
 'return_train_score': False,
 'scoring': None,
 'verbose': 1}
```

6 Evaluation

General sources for evaluation:
https://www.kaggle.com/vikumsw/guide-for-comprehensive-data-exploration-in-python/notebook
https://www.kaggle.com/pmarcelino/comprehensive-data-exploration-with-python

6.1 Evaluating the Decision Tree

6.1.1 Classification Report

[238]:
```
print(classification_report(y_test,search_dt.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.77      0.78      0.78       525
           1       0.85      0.85      0.85      1470
           2       0.74      0.73      0.74       681

    accuracy                           0.81      2676
   macro avg       0.79      0.79      0.79      2676
weighted avg       0.81      0.81      0.81      2676
```

6.1.2 Confusion Matrix

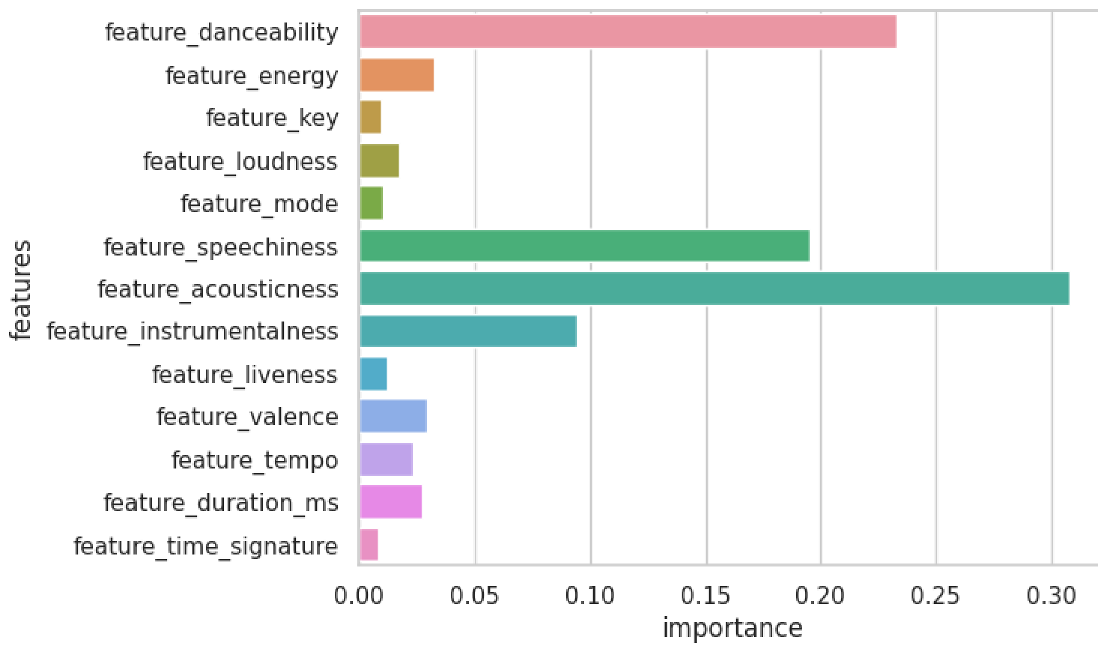
[239]:
```
df_confusion_dt = pd.crosstab(y_test, search_dt.predict(X_test),␣
  ↪rownames=['Actual'], colnames=['Predicted'], margins=True)
df_confusion_dt
```

[239]:
```
Predicted    0     1    2   All
Actual
0          408    84   33   525
1           77  1252  141  1470
2           42   139  500   681
All        527  1475  674  2676
```

6.1.3 Feature Importance

Source: https://scikit-learn.org/stable/auto_examples/ensemble/plot_forest_importances.html

[240]:
```
plt.style.use("default")
f = {'features' : features}
feature_importance = pd.DataFrame(f)
feature_importance['importance'] = search_dt.best_estimator_.
  ↪feature_importances_
sns.set_theme(style="whitegrid")
ax = sns.barplot(x="importance", y="features", data=feature_importance)
```



6.1.4 ROC

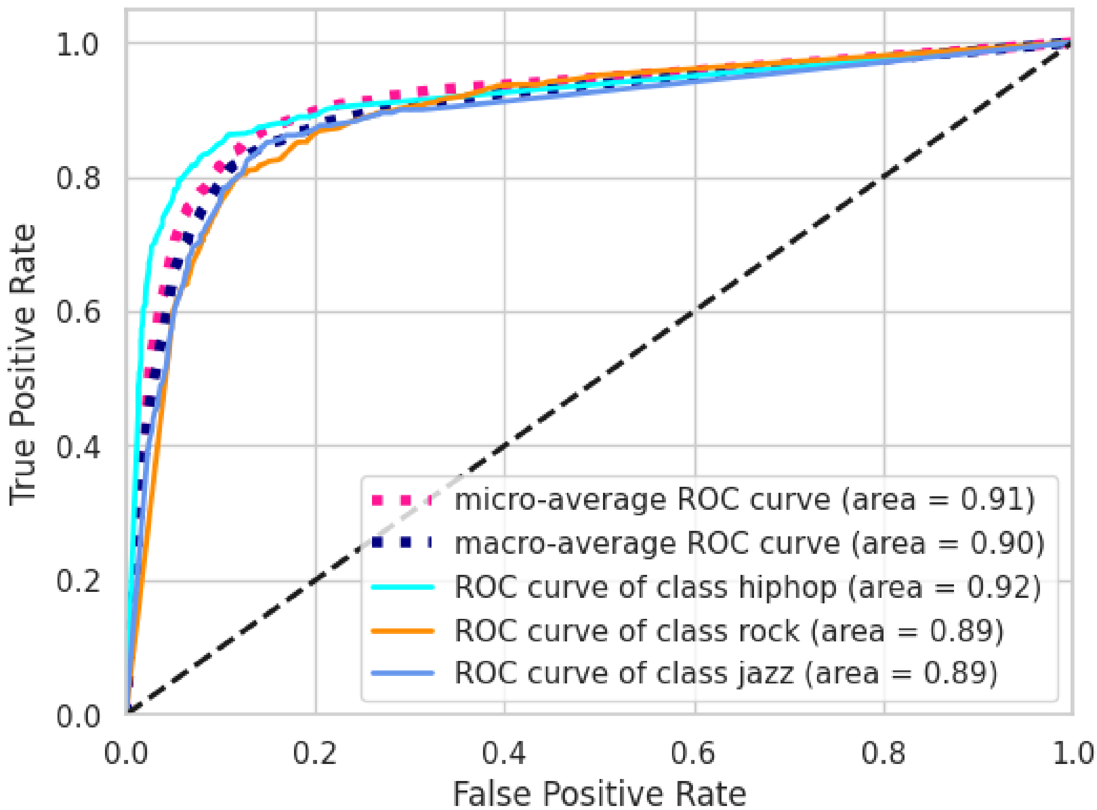
Source: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html

[241]:
```
y = label_binarize(y_test, classes=[0, 1, 2])
n_classes = y.shape[1]

# create x_score
y_test_new = []

for i in y_test:
    if i == 0:
        y_test_new.append([1, 0, 0])
    elif i == 1:
        y_test_new.append([0, 1, 0])
    elif i == 2:
        y_test_new.append([0, 0, 1])

# test input
y_test_np = np.asarray(y_test_new)

# score input
y_score = search_dt.predict_proba(X_test)

# Compute ROC curve and ROC area for each class
fpr = dict()
```

```python
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_np[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_test_np.ravel(), y_score.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

plt.figure()

lw = 2
# First aggregate all false positive rates
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))

# Then interpolate all ROC curves at this points
mean_tpr = np.zeros_like(all_fpr)
for i in range(n_classes):
    mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

# Finally average it and compute AUC
mean_tpr /= n_classes

fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

# Plot all ROC curves
plt.figure()
plt.plot(
    fpr["micro"],
    tpr["micro"],
    label="micro-average ROC curve (area = {0:0.2f})".format(roc_auc["micro"]),
    color="deeppink",
    linestyle=":",
    linewidth=4,
)

plt.plot(
    fpr["macro"],
    tpr["macro"],
    label="macro-average ROC curve (area = {0:0.2f})".format(roc_auc["macro"]),
    color="navy",
    linestyle=":",
    linewidth=4,
```

```
)

colors = cycle(["aqua", "darkorange", "cornflowerblue"])
for i, color in zip(range(n_classes), colors):
    if i == 0:
        cat = 'hiphop'
    elif i == 1:
        cat = 'rock'
    elif i == 2:
        cat = 'jazz'

    plt.plot(
        fpr[i],
        tpr[i],
        color=color,
        lw=lw,
        label="ROC curve of class {0} (area = {1:0.2f})".format(cat,␣
 ↪roc_auc[i]),
    )

plt.plot([0, 1], [0, 1], "k--", lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc="lower right")
plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```



6.2 Evaluating the Gradient Boosting Model

6.2.1 Classification Report

[242]:
```
print(classification_report(y_test,search2.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.85      0.84      0.85       525
           1       0.89      0.89      0.89      1470
           2       0.79      0.80      0.80       681

    accuracy                           0.86      2676
   macro avg       0.84      0.84      0.84      2676
weighted avg       0.86      0.86      0.86      2676
```

6.2.2 Confusion Matrix

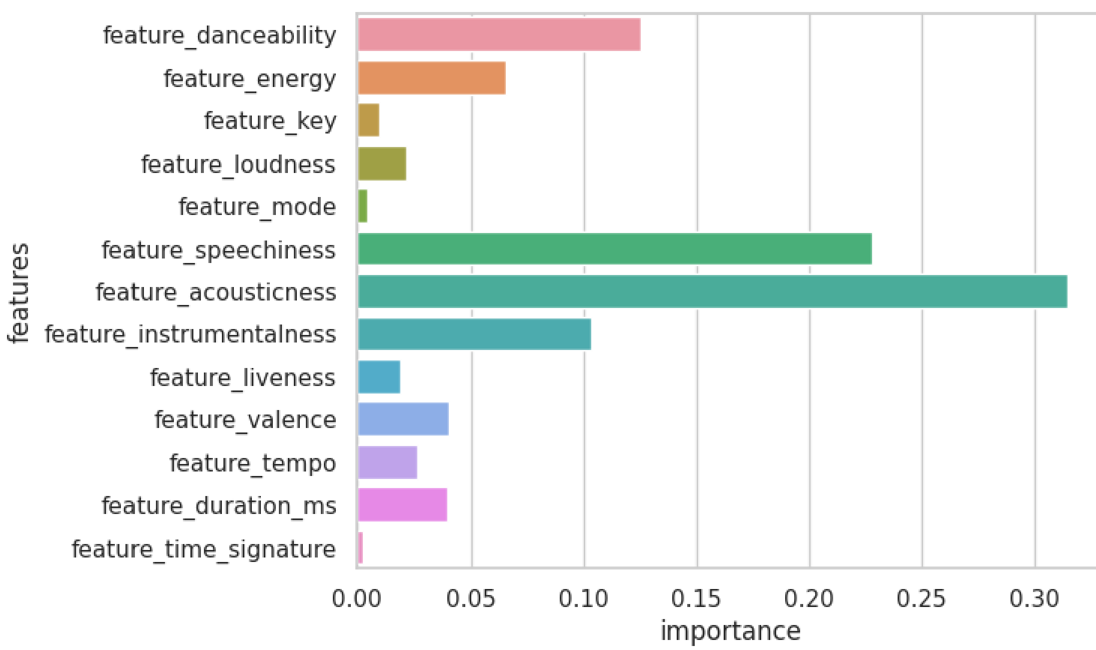
[243]:
```
df_confusion_gb = pd.crosstab(y_test, search.predict(X_test),␣
↪rownames=['Actual'], colnames=['Predicted'], margins=True)
df_confusion_gb
```

[243]:

Predicted	0	1	2	All
Actual				
0	438	62	25	525
1	43	1310	117	1470
2	31	99	551	681
All	512	1471	693	2676

6.2.3 Feature Importance

[244]:
```
f = {'features' : features}
feature_importance = pd.DataFrame(f)
feature_importance['importance'] = search2.best_estimator_.feature_importances_

sns.set_theme(style="whitegrid")
ax = sns.barplot(x="importance", y="features", data=feature_importance)
```



6.2.4 ROC

[246]:
```
y = label_binarize(y_test, classes=[0, 1, 2])
n_classes = y.shape[1]

n_classes

# create x_score
y_test_new = []

for i in y_test:
    if i == 0:
        y_test_new.append([1, 0, 0])
    elif i == 1:
        y_test_new.append([0, 1, 0])
    elif i == 2:
        y_test_new.append([0, 0, 1])

# test input
y_test_np = np.asarray(y_test_new)

# score input
y_score = search2.decision_function(X_test)


# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_np[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_test_np.ravel(), y_score.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

plt.figure()
lw = 2
# First aggregate all false positive rates
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))

# Then interpolate all ROC curves at this points
mean_tpr = np.zeros_like(all_fpr)
for i in range(n_classes):
    mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])
```

```python
# Finally average it and compute AUC
mean_tpr /= n_classes

fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

# Plot all ROC curves
plt.figure()
plt.plot(
    fpr["micro"],
    tpr["micro"],
    label="micro-average ROC curve (area = {0:0.2f})".format(roc_auc["micro"]),
    color="deeppink",
    linestyle=":",
    linewidth=4,
)

plt.plot(
    fpr["macro"],
    tpr["macro"],
    label="macro-average ROC curve (area = {0:0.2f})".format(roc_auc["macro"]),
    color="navy",
    linestyle=":",
    linewidth=4,
)

colors = cycle(["aqua", "darkorange", "cornflowerblue"])

for i, color in zip(range(n_classes), colors):
    if i == 0:
        cat = 'hiphop'
    elif i == 1:
        cat = 'rock'
    elif i == 2:
        cat = 'jazz'

    plt.plot(
        fpr[i],
        tpr[i],
        color=color,
        lw=lw,
        label="ROC curve of class {0} (area = {1:0.2f})".format(cat,␣
 ↪roc_auc[i]),
    )

plt.plot([0, 1], [0, 1], "k--", lw=lw)
```

```
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Some extension of Receiver operating characteristic to multiclass")
plt.legend(loc="lower right")
plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```