dsc424_final_project

May 19, 2019

1 DSC 424 Final Project

```
In [71]: #Import packages
         import pandas as pd
         import os
         import numpy as np
         import matplotlib.pyplot as plt
         import statsmodels.api as sm
         import scipy.stats as stats
         import seaborn as sns
         import warnings
         from math import sqrt
         import pylab
         from sklearn.cross_validation import train_test_split
         from sklearn.metrics import mean_squared_error

         %matplotlib inline
         warnings.filterwarnings('ignore')
```

```
In [4]: #Import data
        song_data = pd.read_csv(r'https://raw.githubusercontent.com/PixarJunkie/dsc-424-final-p
        song_info = pd.read_csv(r'https://raw.githubusercontent.com/PixarJunkie/dsc-424-final-p

        #Shape of data
        print('song_data shape: ' + str(song_data.shape))
        print('sing_info shape: ' + str(song_info.shape))
```

```
song_data shape: (18835, 15)
sing_info shape: (18835, 4)
```

```
In [79]: #Columns
         print('song_data columns: ' + str(list(song_data.columns)))
         print('song_info columns: ' + str(list(song_info.columns)))
```

```
song_data columns: ['song_name', 'song_popularity', 'song_duration_ms', 'acousticness', 'dancea
song_info columns: ['song_name', 'artist_name', 'album_names', 'playlist']
```

2 Notes about the variables

Song_ popularity [0,100] Dependent variable

Song_duration [1.200000e+04,1.799346 e+06] In milliseconds

Acousticness [0,0.996] 1.0 represents high confidence the track is acoustic.

Danceability [0,0.897] A value of 0.0 is least danceable and 1.0 is most danceable

Energy [0.001,0.999] A value of 1 means most energetic (tracks feel fast, loud, and noisy)

Instrumentalness [0.01,0.986] Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.

Liveness [0,0.997] Higher liveness values represent an increased probability that the track was performed live

Loudness [-38.768, 1.585] values are averaged across the entire track Speechiness [0,0.94] Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.

Tempo [0 ,242.318]

Audio_valence [0,0.984] Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric) Ordinal (3)

Key [0,1,2,3,4,5,6,7,8,9,10,11] 0 = C, 1 = C/D, 2 = D, and so on

Audio_mode [0 or 1] Major is represented by 1 and minor is 0

Time_signature [0,1 ,3,4,5] Nominal (4)

Categorical: Album_name song_name play_list artist_name

3 NULLS

NOTES: There are no null values in the dataset

```
In [5]: #Check for null values
        print(song_data.isnull().sum())
        print(song_info.isnull().sum())
```

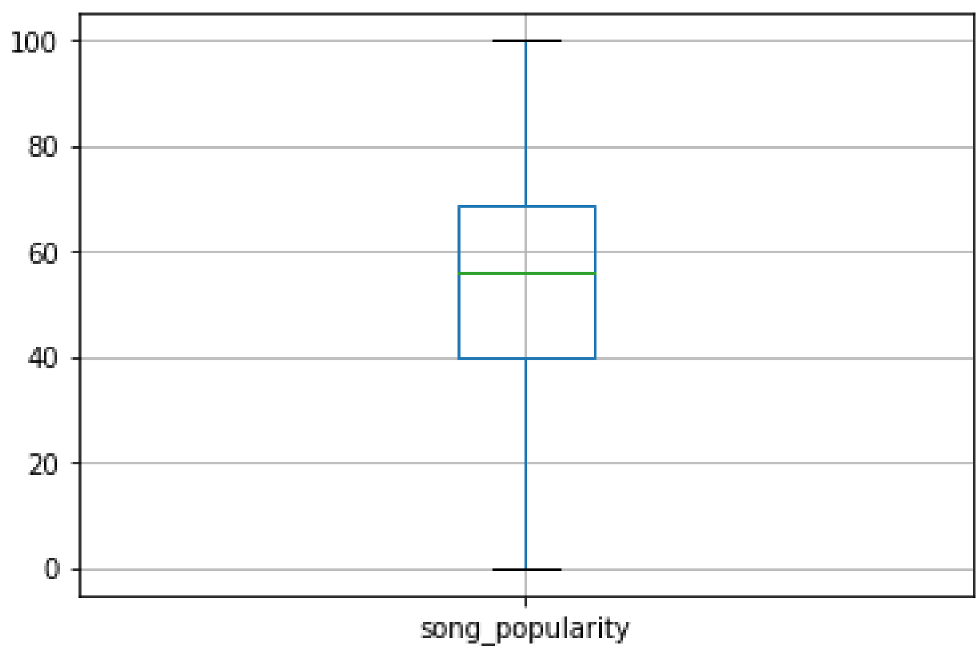
```
song_name           0
song_popularity     0
song_duration_ms    0
acousticness        0
danceability        0
energy              0
instrumentalness    0
key                 0
liveness            0
loudness            0
audio_mode          0
speechiness         0
tempo               0
time_signature      0
audio_valence       0
dtype: int64
song_name      0
```

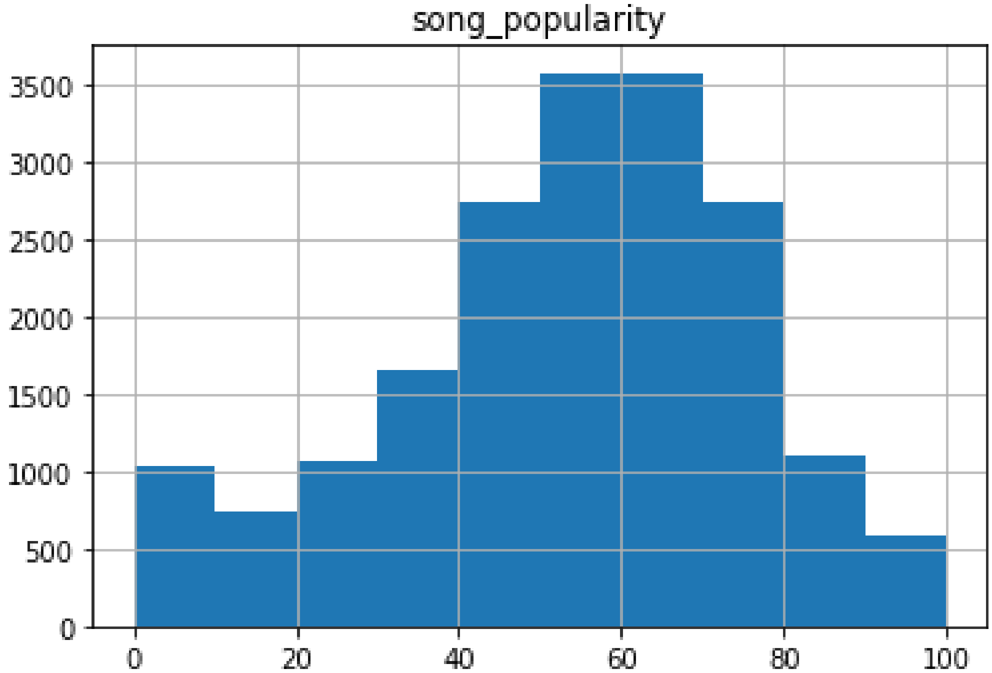
```
artist_name    0
album_names    0
playlist       0
dtype: int64
```

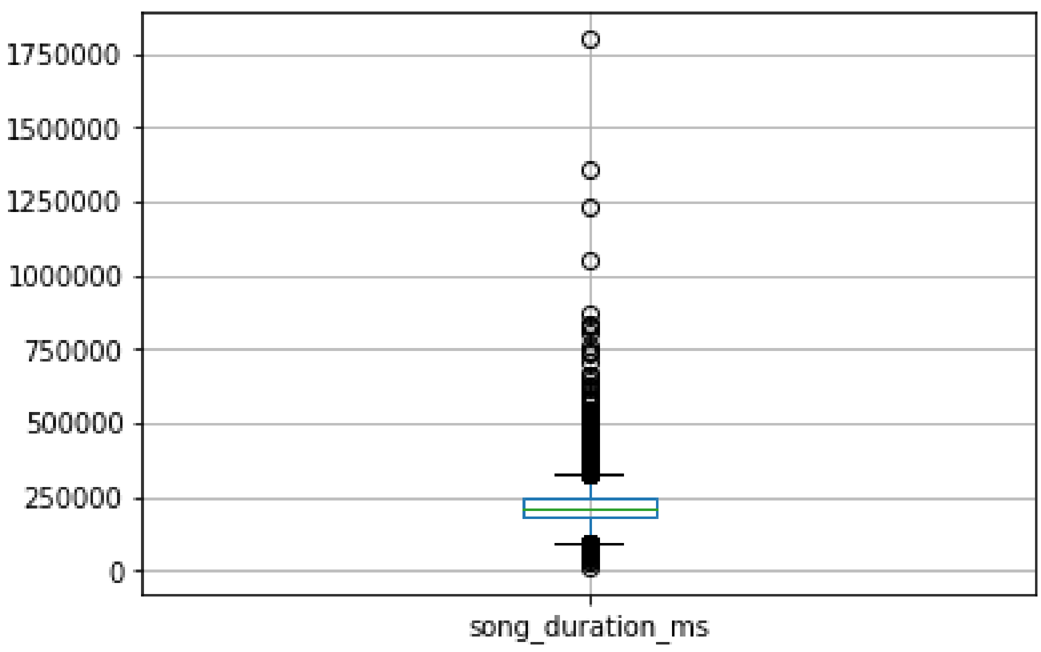
4 Histograms and Boxplots

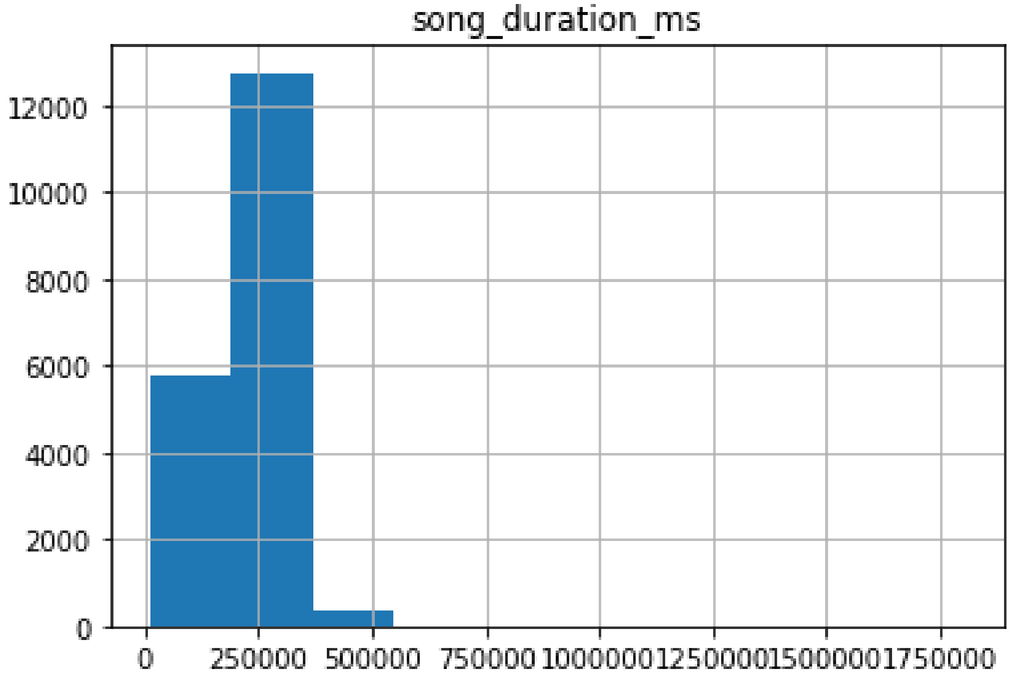
NOTES: Some of the columns such as song duration, instrumentalness, and time signature are imbalanced. Will consider removing some of the outliers to smooth the distributions.

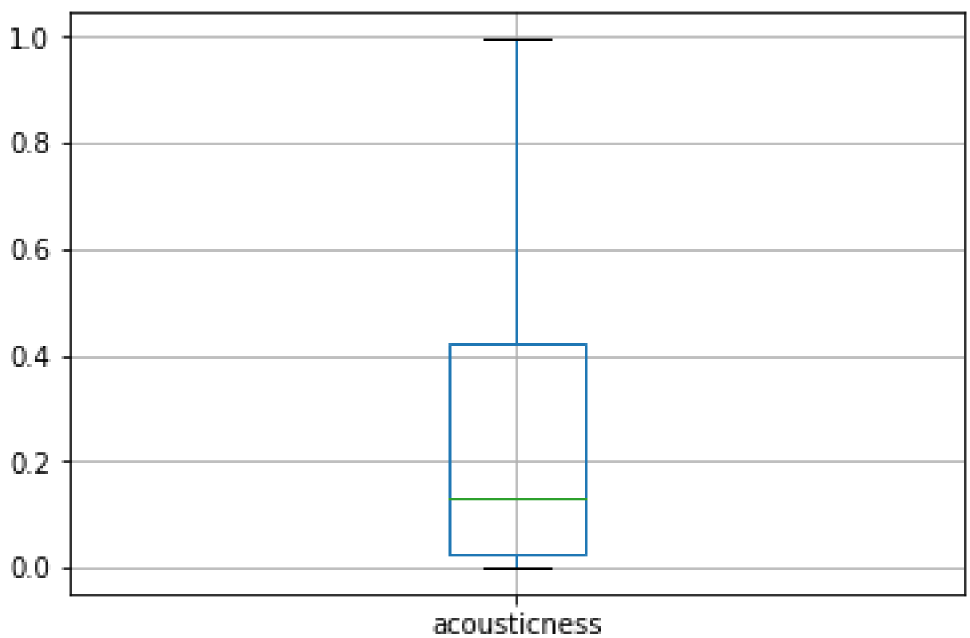
```
In [33]: #Histograms
         for col in song_data_2.columns:
             plt.figure()
             song_data_2.boxplot([col])
             song_data_2.hist([col])
```

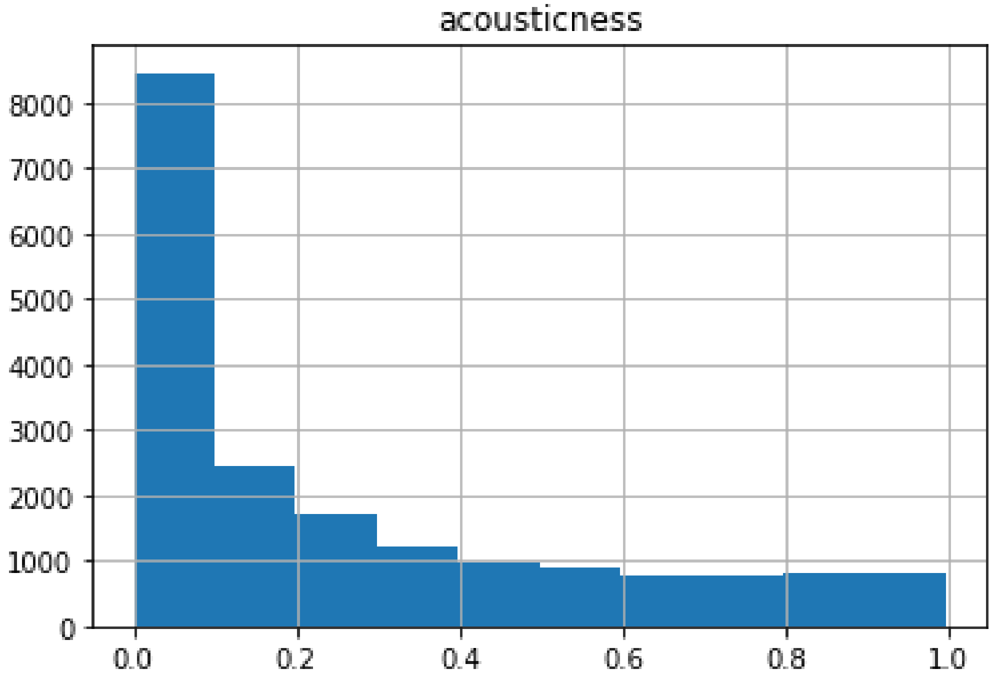


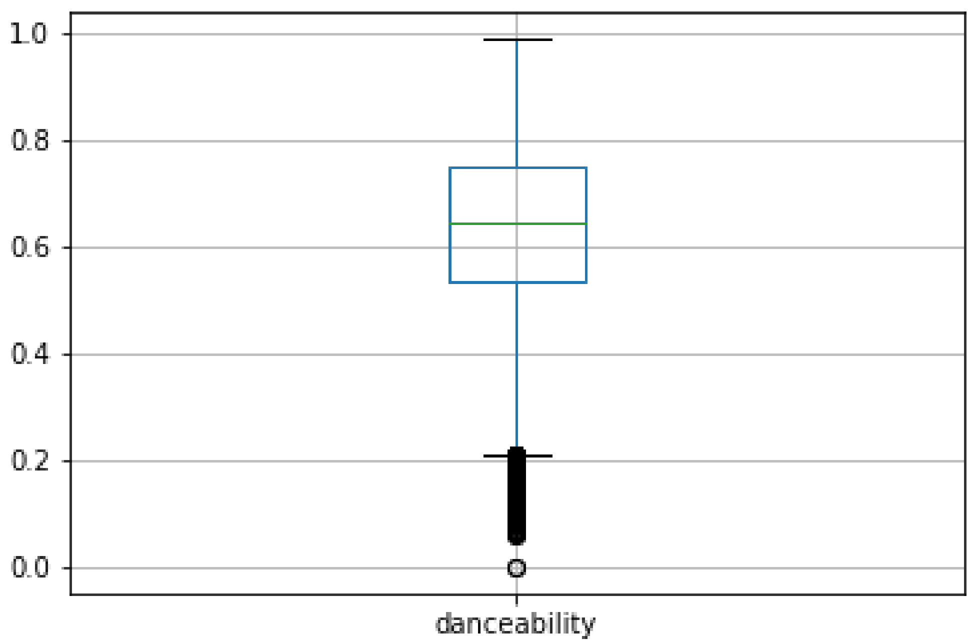

song_popularity
3500
3000
2500
2000
1500
1000
500
0
0
20
40
60
80
100

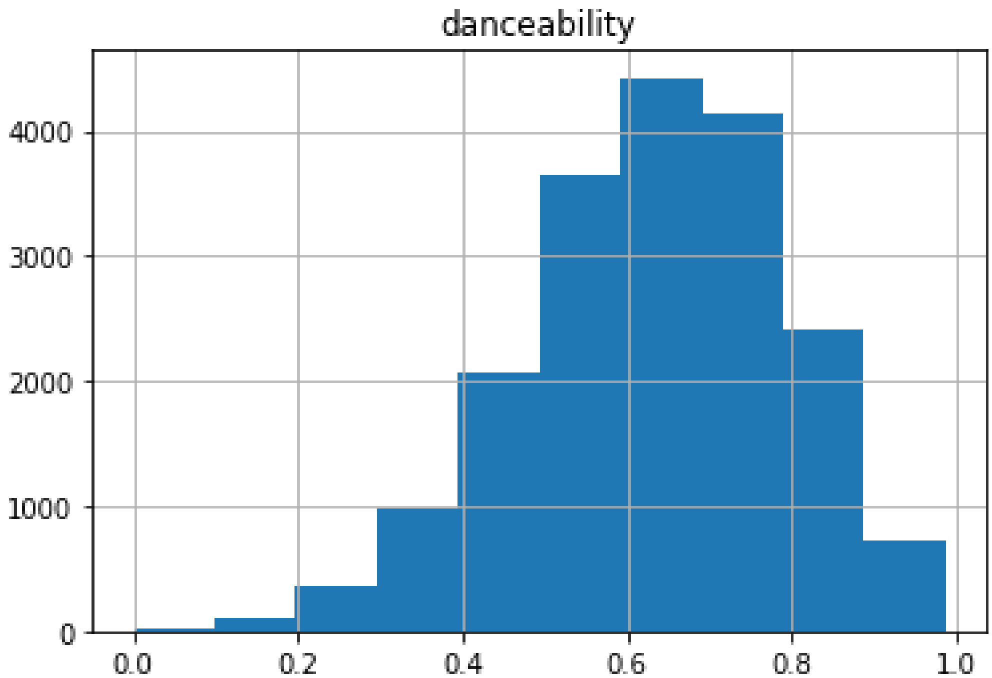

1750000
1500000
1250000
1000000
750000
500000
250000
0
song_duration_ms


song_duration_ms
12000
10000
8000
6000
4000
2000
0
0
250000
500000
750000
1000000
1250000
1500000
1750000

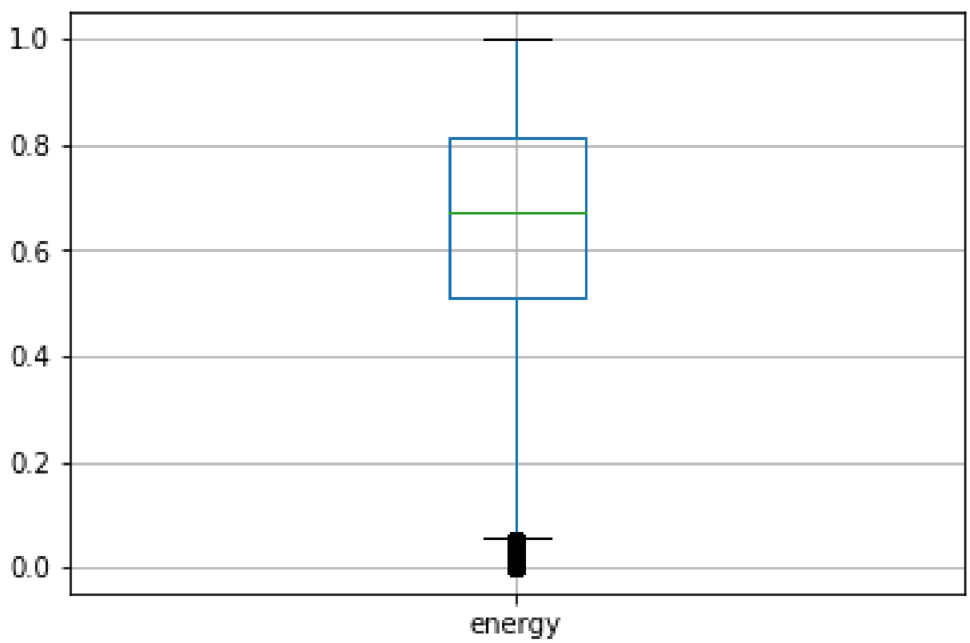

1.0
0.8
0.6
0.4
0.2
0.0
acousticness


acousticness
8000
7000
6000
5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0

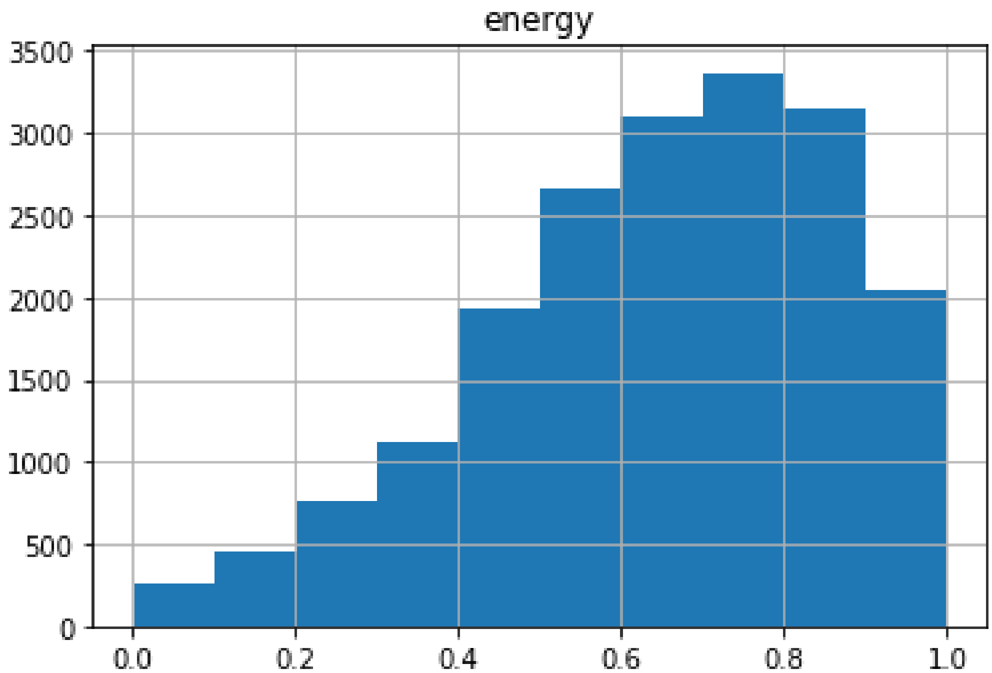

1.0
0.8
0.6
0.4
0.2
0.0
danceability

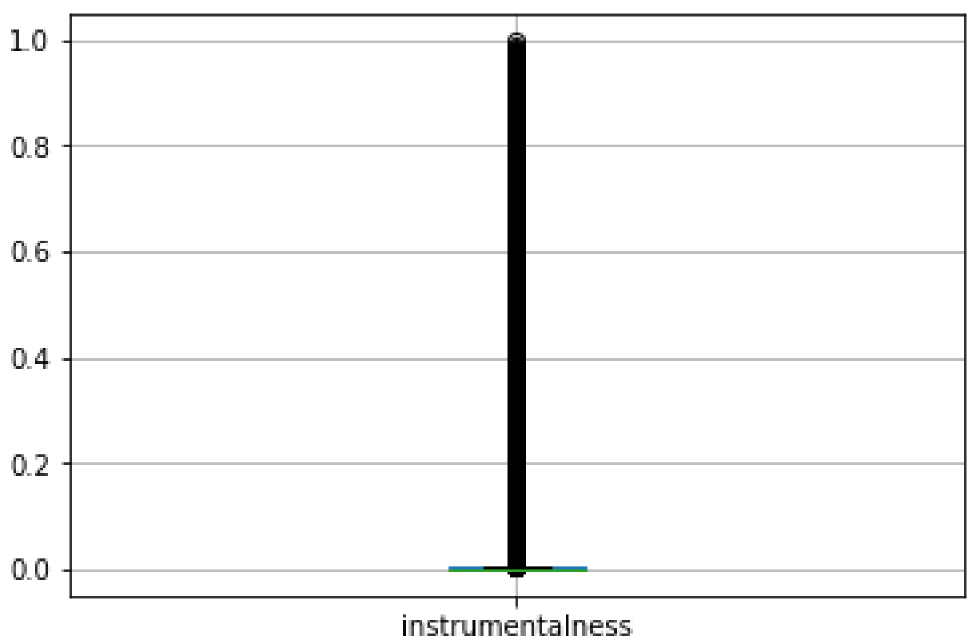


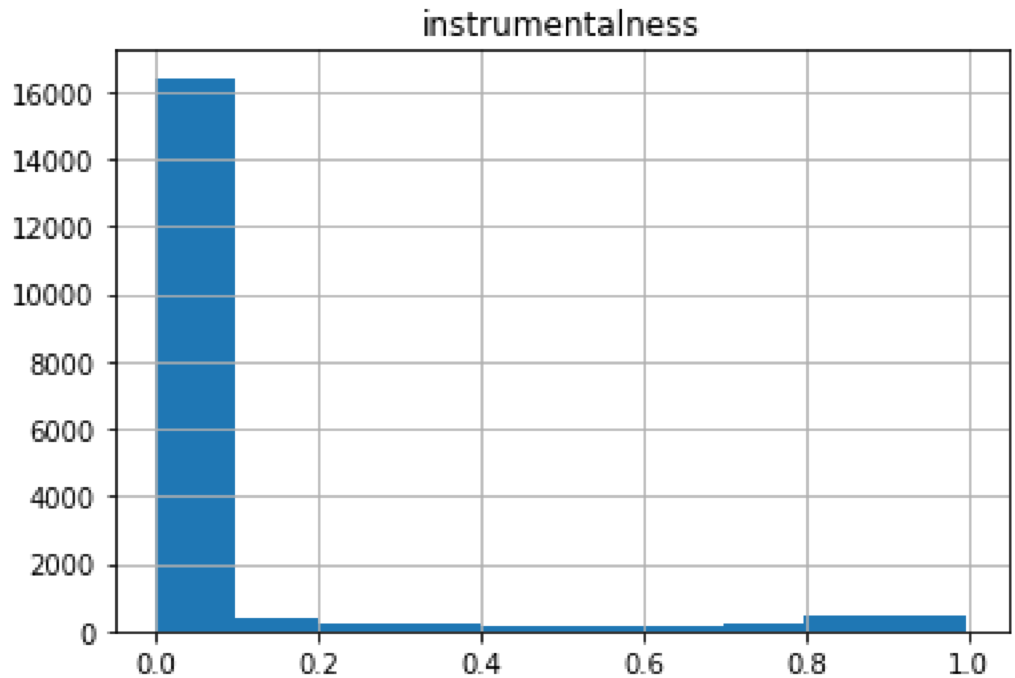
danceability
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0

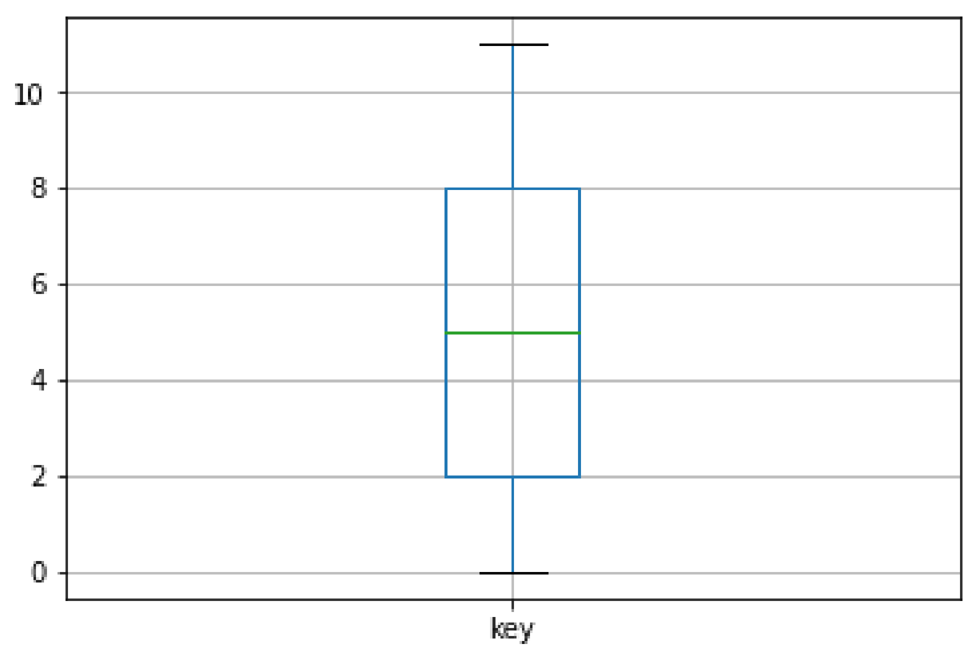


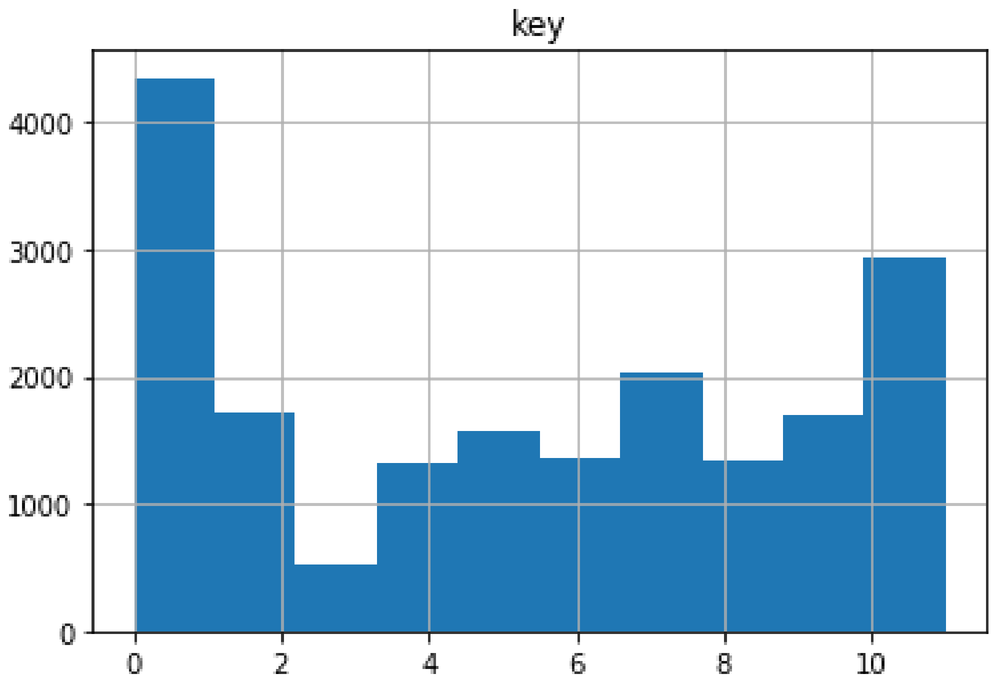
1.0
0.8
0.6
0.4
0.2
0.0
energy

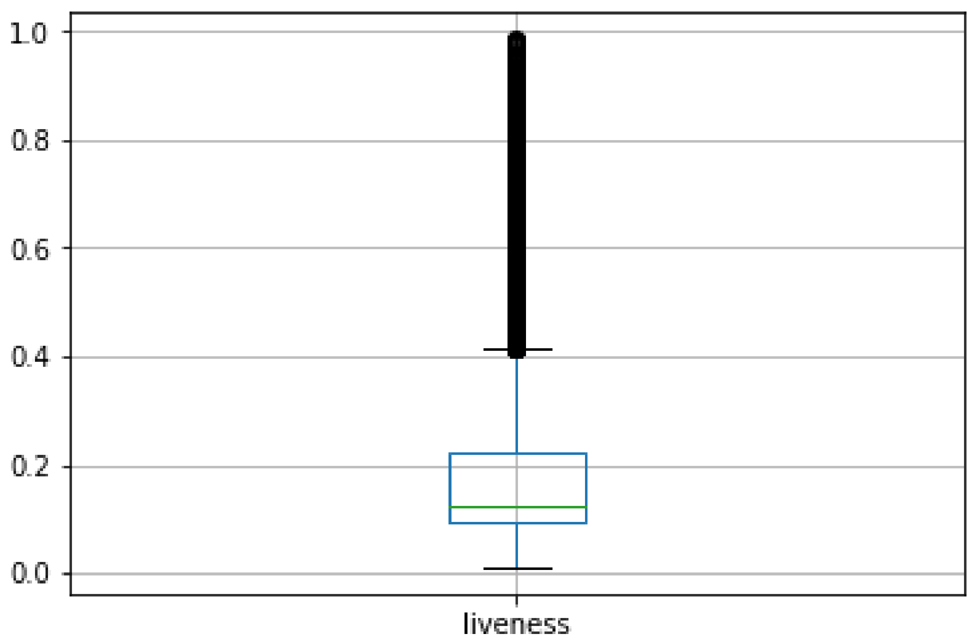

energy
3500
3000
2500
2000
1500
1000
500
0
0.0
0.2
0.4
0.6
0.8
1.0

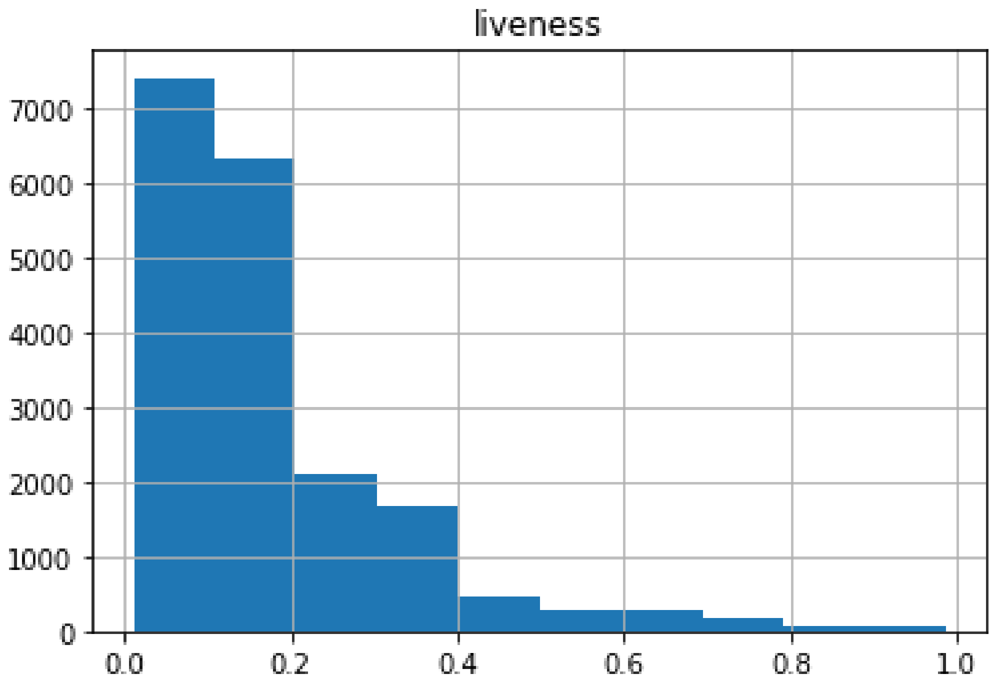

1.0
0.8
0.6
0.4
0.2
0.0
instrumentalness


instrumentalness
16000
14000
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0

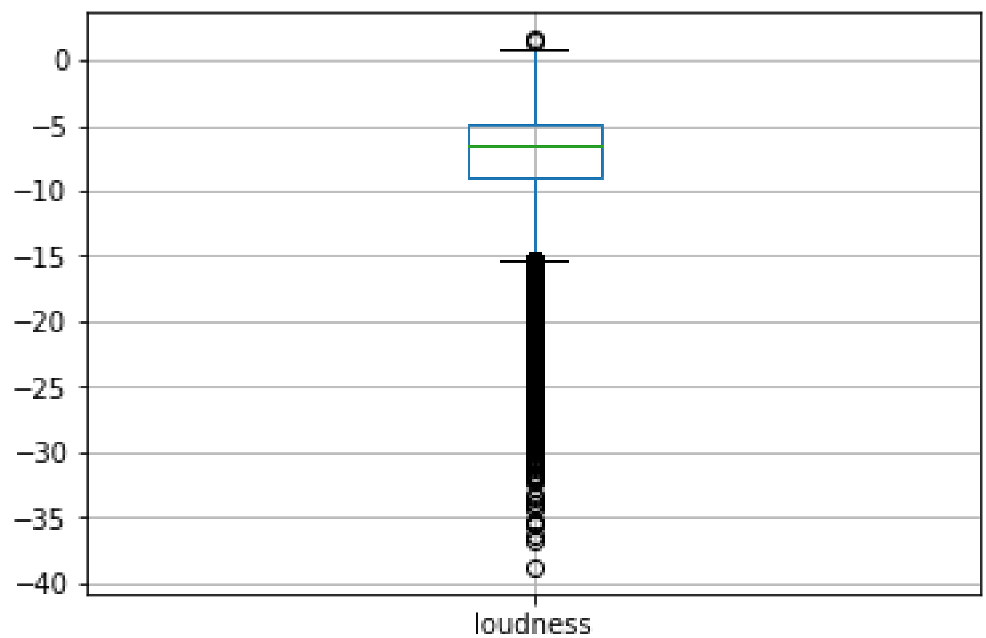

10
8
6
4
2
0
key


key
4000
3000
2000
1000
0
0
2
4
6
8
10

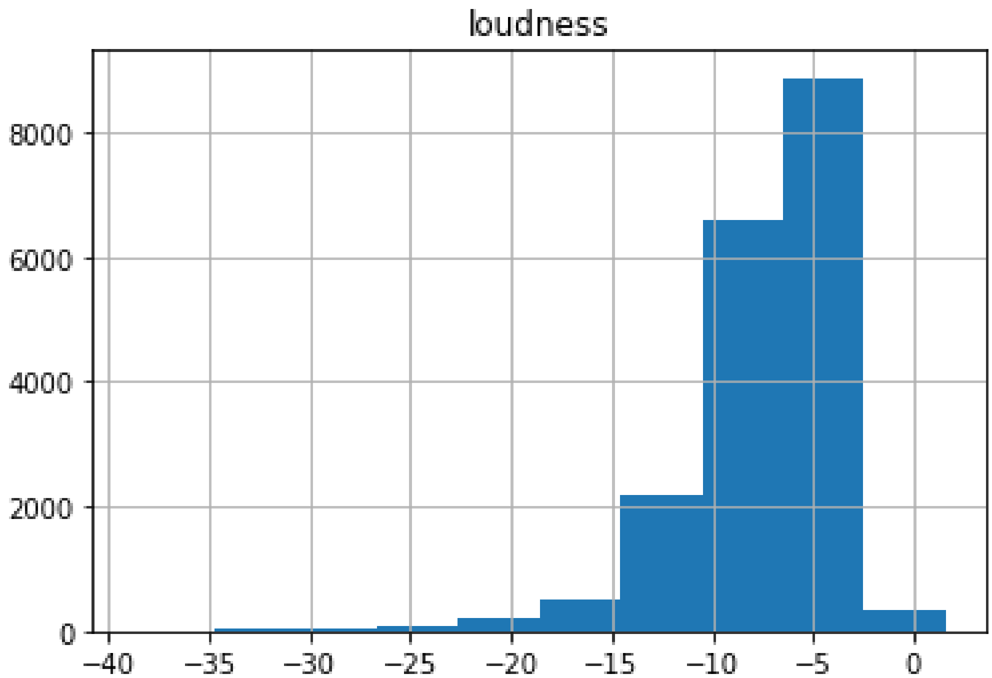

1.0
0.8
0.6
0.4
0.2
0.0
liveness

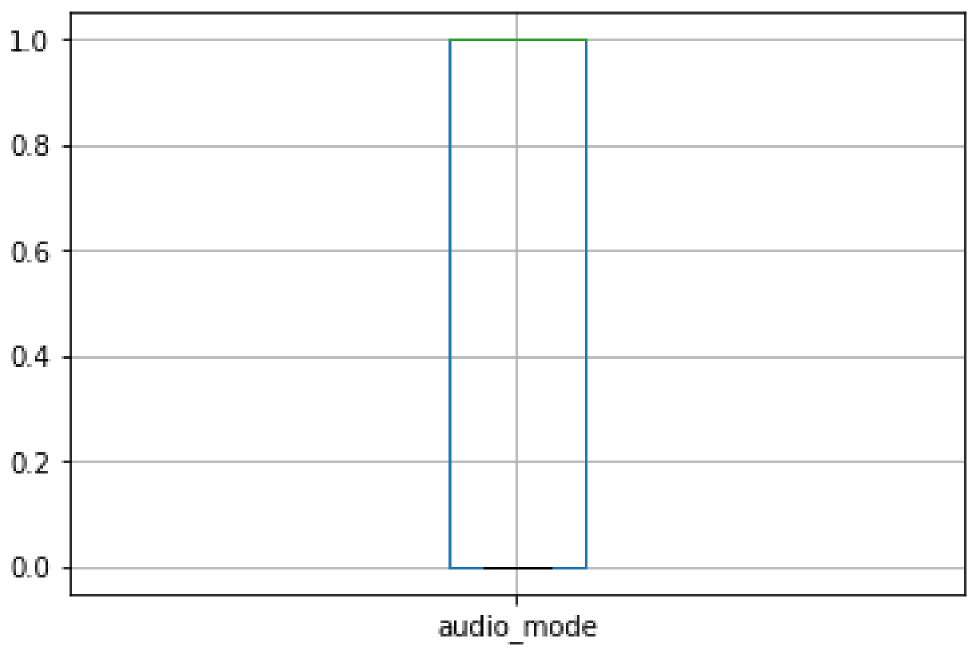


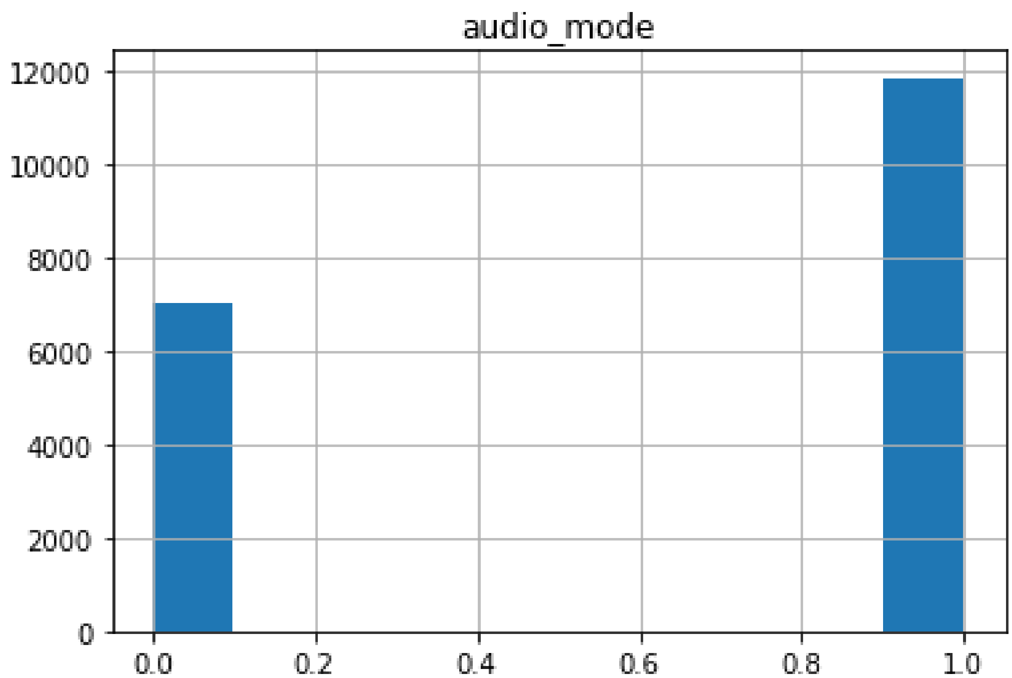
liveness
7000
6000
5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0

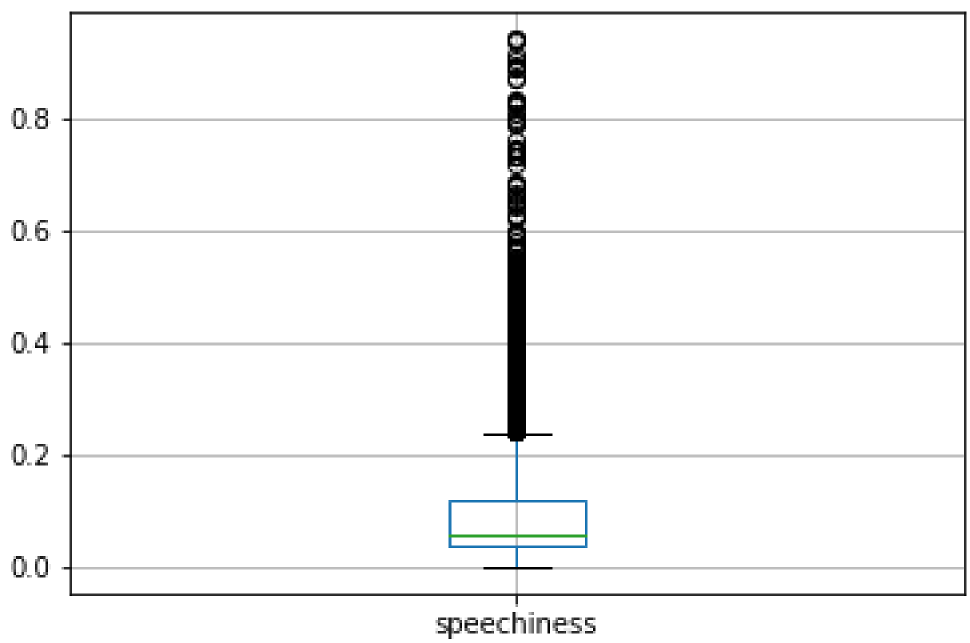


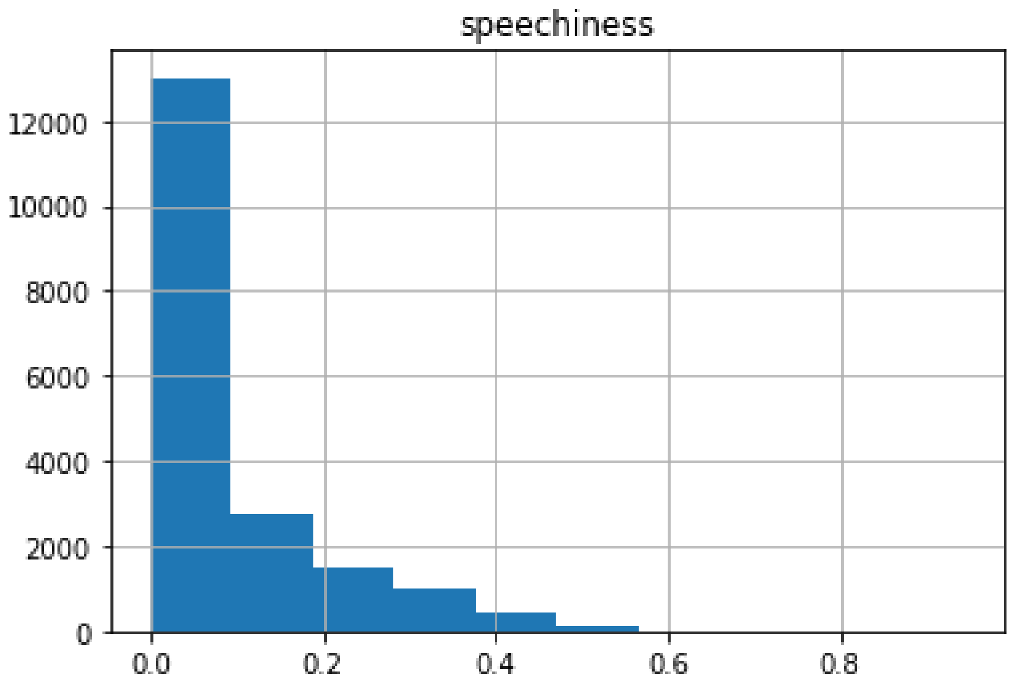
0
−5
−10
−15
−20
−25
−30
−35
−40
loudness

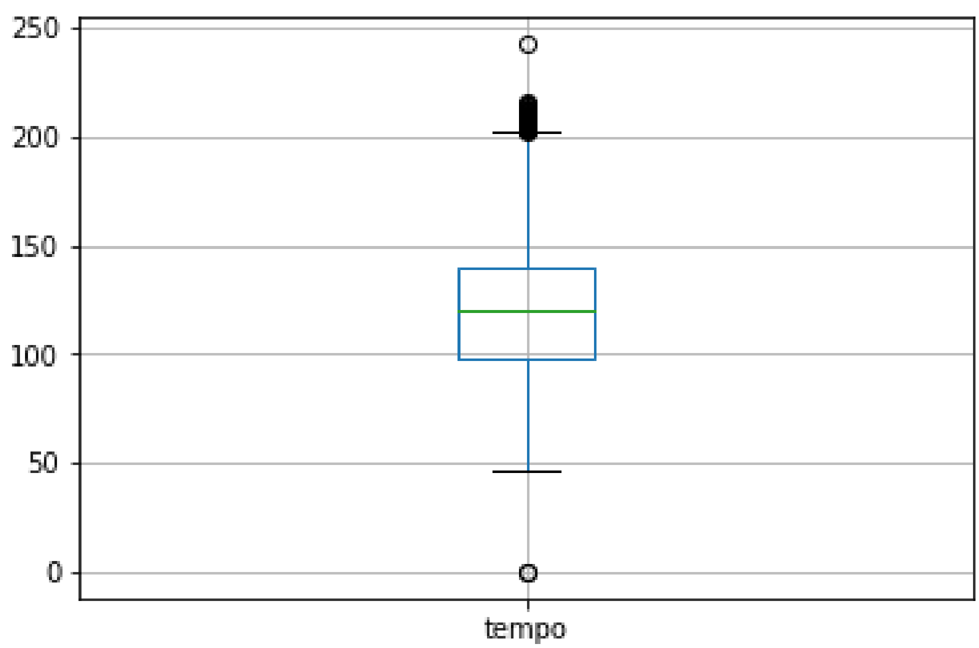

loudness
8000
6000
4000
2000
0
−40
−35
−30
−25
−20
−15
−10
−5
0

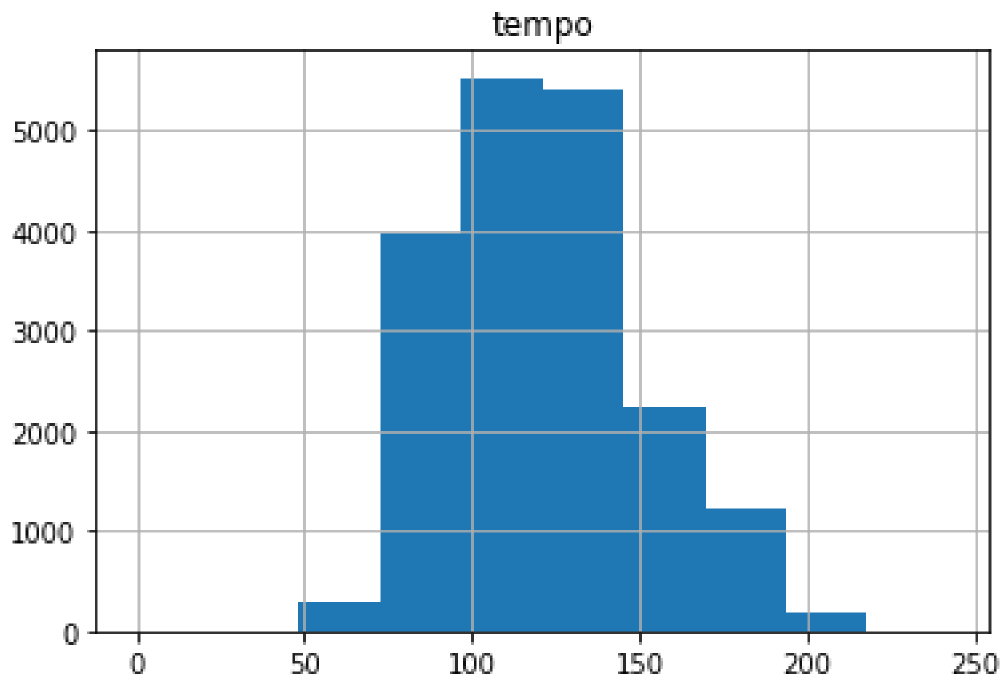

1.0
0.8
0.6
0.4
0.2
0.0
audio_mode

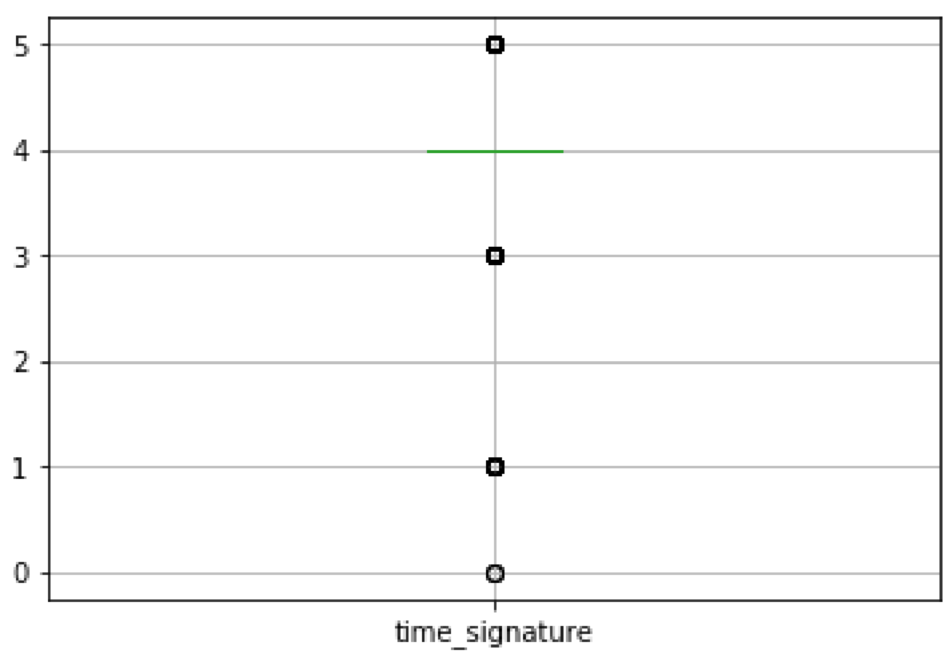

audio_mode
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0

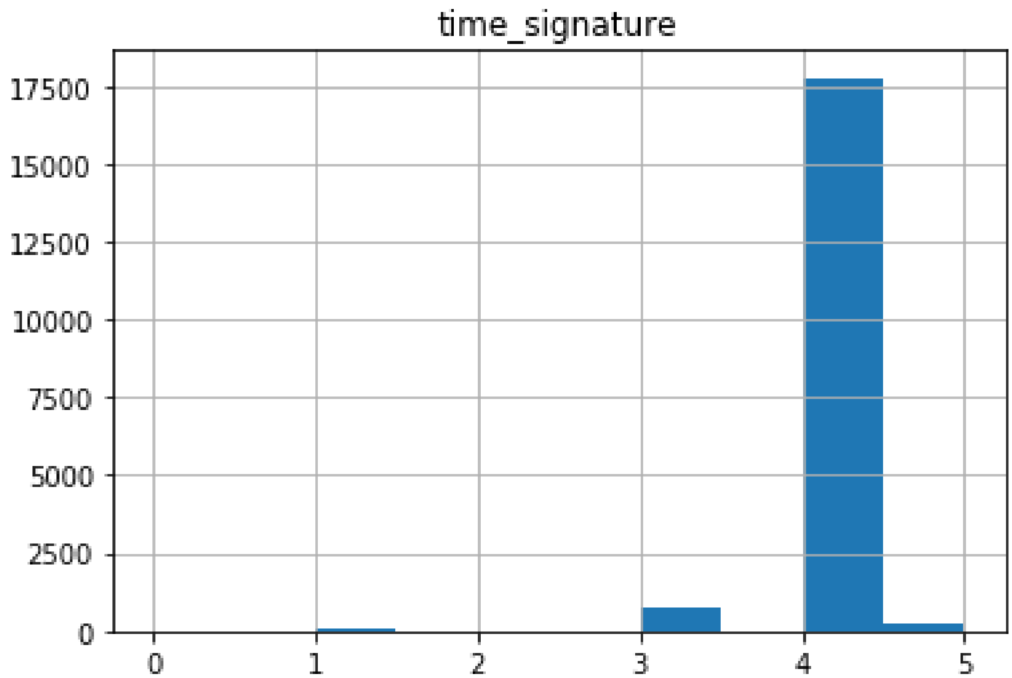

0.8
0.6
0.4
0.2
0.0
speechiness

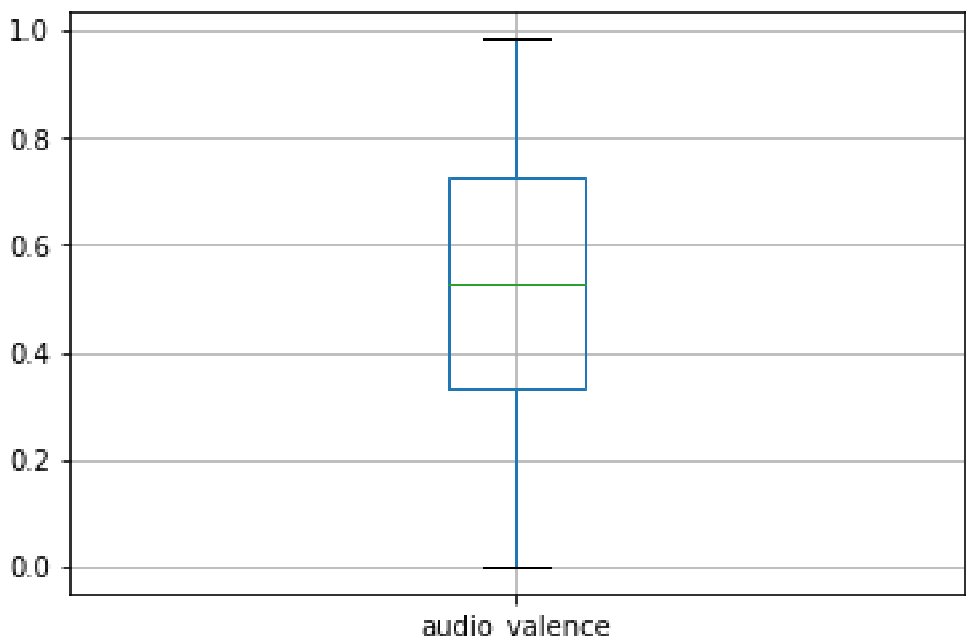

speechiness
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8

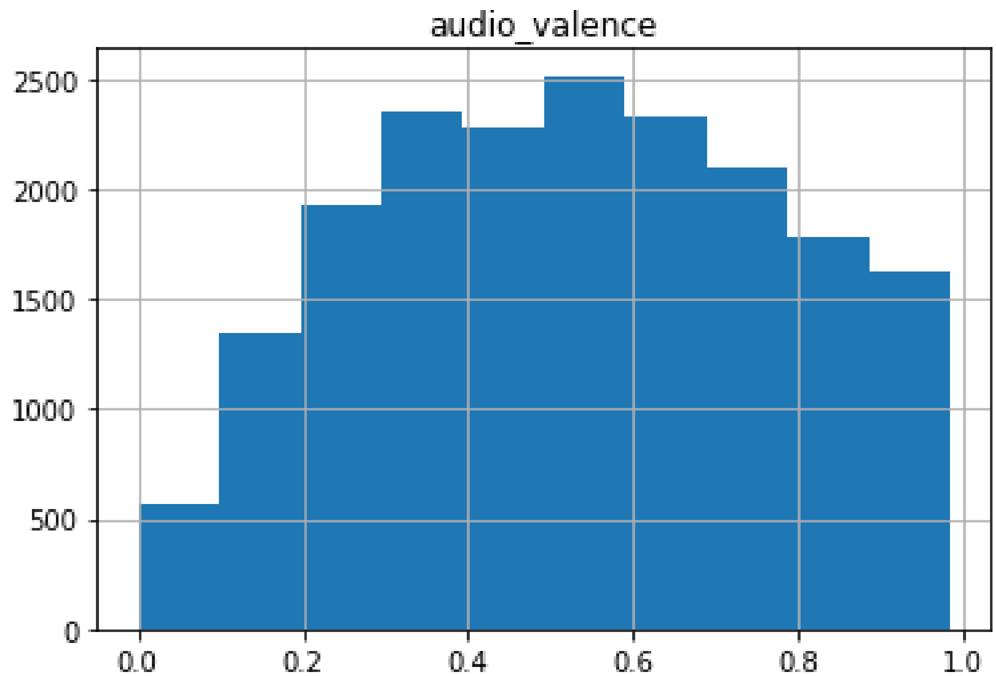

250
200
150
100
50
0
tempo


tempo
5000
4000
3000
2000
1000
0
0
50
100
150
200
250


5
4
3
2
1
0
time_signature


time_signature
17500
15000
12500
10000
7500
5000
2500
0
0
1
2
3
4
5


1.0
0.8
0.6
0.4
0.2
0.0
audio_valence



5 Correlation Plot

NOTES: Loudness and energy have a moderate positive correlation. This is a logical relationship since a louder song would register high decibels resulting in a higher energy score. Will consider removing one, or creating a new variable that captures both. Acousticness and energy have a moderate negative correlation which is also logical since acoustic songs tend to be quieter, resulting in lower decibels/energy.

```
In [34]: #Correlation Matrix
         song_data_2.corr().style.background_gradient(cmap='coolwarm')

Out[34]: <pandas.io.formats.style.Styler at 0x242dfdadc50>
```

6 Initial Multiple Regression

Notes The initial multiple regression shows a moderately high multiple R-squared on the trianing set, though some of the additional analysis into the residuals suggest that there are some issues with the model. The normal residuals plot shows a clear slanted line at the start and increasing negative error moving to the right. The QQ also plot does not look uniform. The predicted vs. actuals on the test set do not show the correlation that we would expect by looking at the multiple R2 from the traning set. Will consider other models, removing correlated variables, feature selection, etc.

In [44]:
```
#Dummy Vars via mapping
categ_cols = song_data.dtypes.pipe(lambda x: x[x == 'object']).index
mapping = {}

for col in categ_cols:
    song_data[col], mapping[col] = pd.factorize(song_data[col])
```

In [ ]:
```
#Dummy through pd.get_dummies
```

In [54]:
```
#Training and test sets
X = song_data.drop('song_popularity', axis = 1)
y = song_data.song_popularity

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_sta
print('X_train shape: ' + str(X_train.shape))
print('y_train shape: ' + str(y_train.shape))
print('X_test shape: ' + str(X_test.shape))
print('y_test shape: ' + str(y_test.shape))
```

```
X_train shape: (13184, 14)
y_train shape: (13184,)
X_test shape: (5651, 14)
y_test shape: (5651,)
```

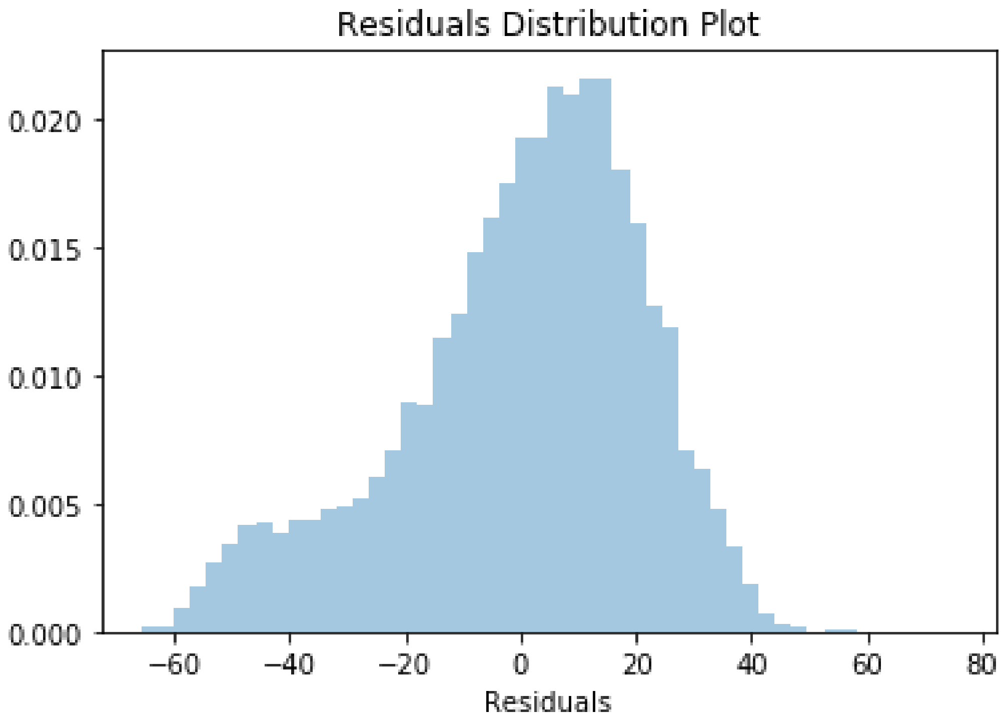
In [55]:
```
#Regression
lm = sm.OLS(y_train, X_train).fit()

# Summary
lm.summary()
```

Out[55]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:        song_popularity   R-squared:                       0.863
Model:                            OLS   Adj. R-squared:                  0.863
Method:                 Least Squares   F-statistic:                     5921.
Date:                Sun, 19 May 2019   Prob (F-statistic):               0.00
Time:                        21:45:58   Log-Likelihood:                -58959.
No. Observations:               13184   AIC:                         1.179e+05
Df Residuals:                   13170   BIC:                         1.181e+05
Df Model:                          14
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
song_name           -0.0012   4.93e-05    -24.101      0.000      -0.001      -0.001
song_duration_ms  7.885e-06    3.1e-06      2.542      0.011     1.8e-06     1.4e-05
```

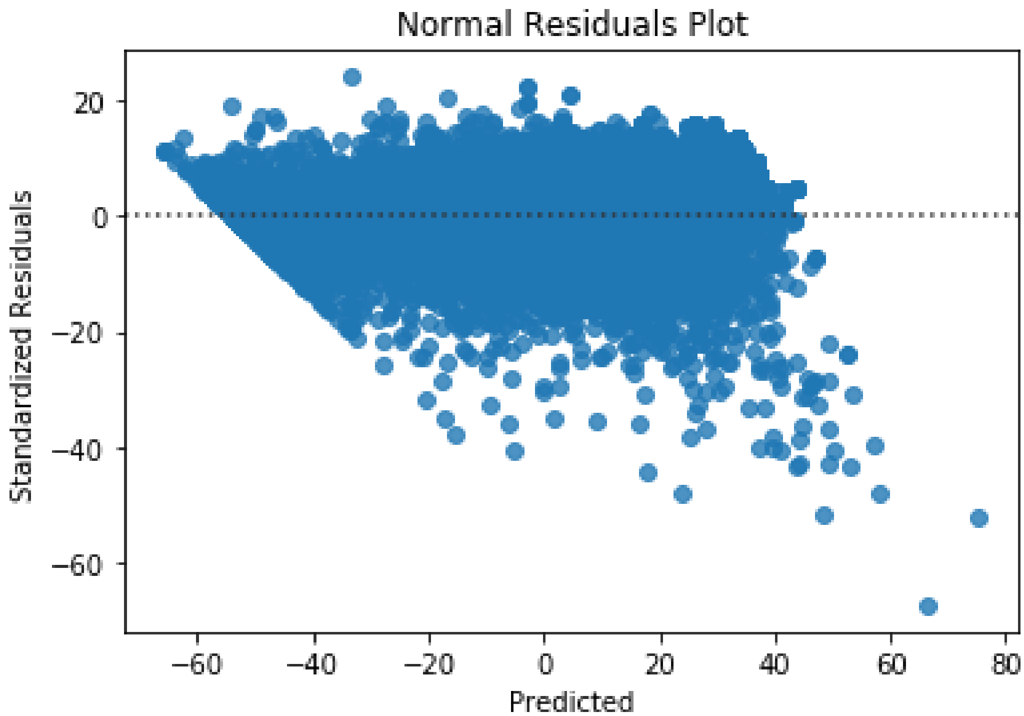
```
acousticness          2.7515      0.851      3.233      0.001       1.083       4.420
danceability         25.3029      1.322     19.134      0.000      22.711      27.895
energy                4.1610      1.507      2.762      0.006       1.208       7.114
instrumentalness     -8.8720      0.921     -9.638      0.000     -10.676      -7.068
key                   0.0719      0.052      1.393      0.164      -0.029       0.173
liveness             -2.7290      1.325     -2.060      0.039      -5.326      -0.132
loudness              0.0950      0.076      1.252      0.210      -0.054       0.244
audio_mode            1.0678      0.391      2.732      0.006       0.302       1.834
speechiness          -2.7380      1.834     -1.493      0.135      -6.333       0.857
tempo                 0.0351      0.006      5.512      0.000       0.023       0.048
time_signature       10.7271      0.438     24.476      0.000       9.868      11.586
audio_valence       -13.9000      0.884    -15.719      0.000     -15.633     -12.167
==============================================================================
Omnibus:                      714.641   Durbin-Watson:                   2.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              837.358
Skew:                          -0.617   Prob(JB):                    1.48e-182
Kurtosis:                       2.995   Cond. No.                     2.33e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
[2] The condition number is large, 2.33e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

7 Training Residuals

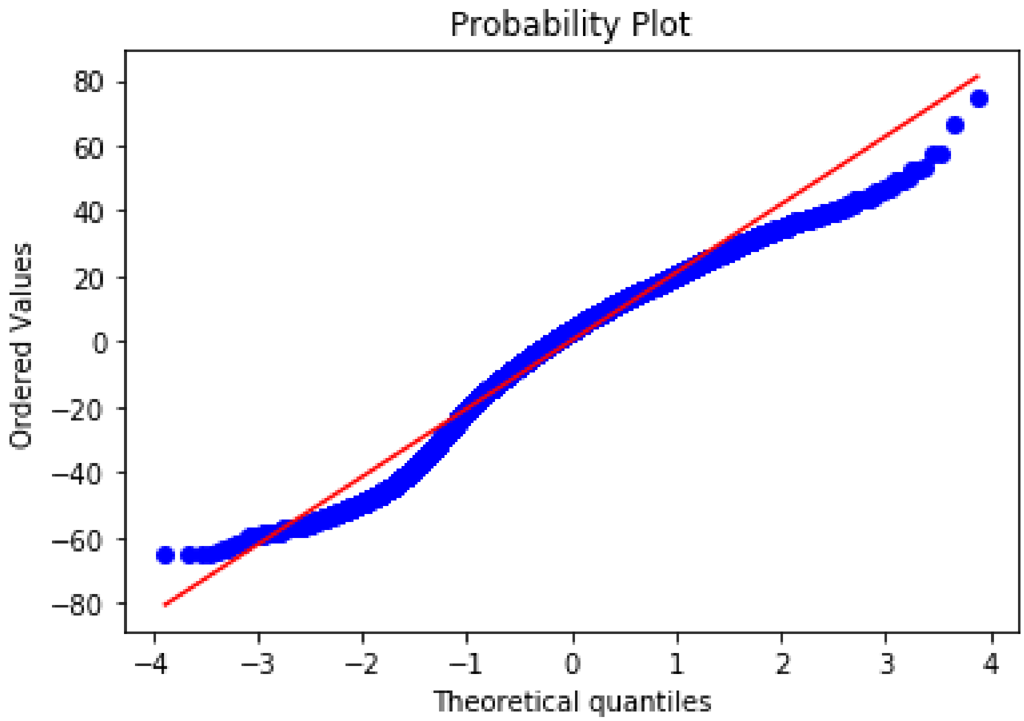
In [62]:
```
#Calculate residuals
train_preds = lm.fittedvalues
res = y_train - train_preds

#Residual distribution
ax = sns.distplot(res, kde = False, rug = False, norm_hist = True)
plt.title('Residuals Distribution Plot')
plt.xlabel('Residuals')
plt.show()
```




```
In [64]: #Normal Residuals Plot
         ax = sns.residplot(res, train_preds)
         plt.title('Normal Residuals Plot')
         plt.xlabel('Predicted')
         ax.set_ylabel('Standardized Residuals')
         plt.show()
```



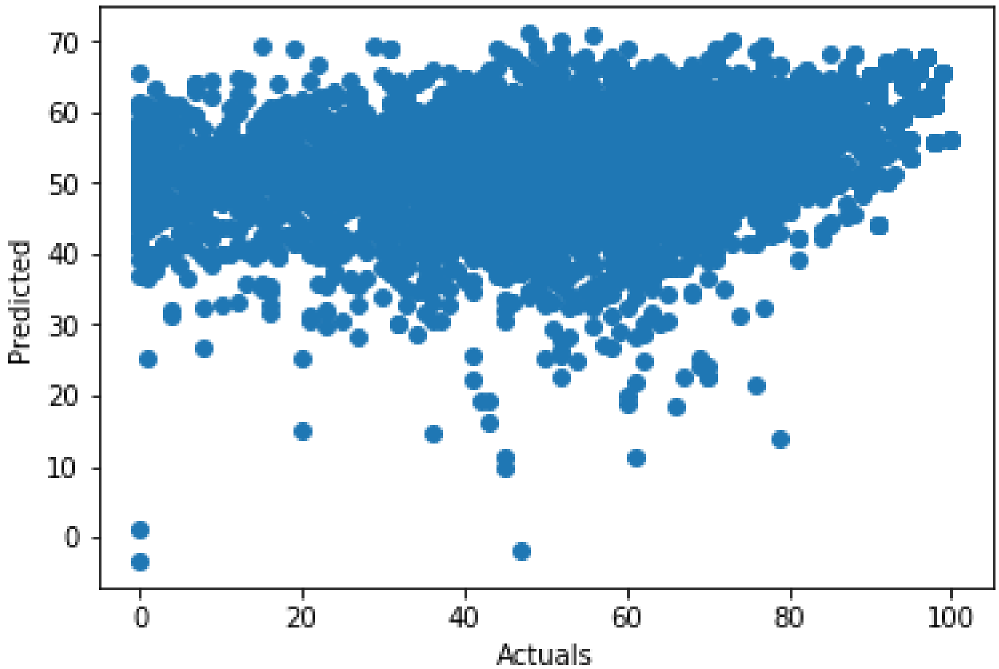

```
In [67]: #Probability Plot
         measurements = np.random.normal(loc = 20, scale = 5, size=100)
         stats.probplot(res, dist="norm", plot=pylab)
         pylab.show()
```



8 Test Predictions

In [73]:
```
#Prediction on test set/plot predicted vs. actuals
test_preds = lm.predict(X_test)
plt.scatter(y_test, test_preds)
plt.xlabel('Actuals')
plt.ylabel('Predicted')
#Train RMSE
train_rmse = sqrt(mean_squared_error(y_train, train_preds))
#Test RMSE
test_rmse = sqrt(mean_squared_error(y_test, test_preds))
print('Train Root Mean Square Error: ' + str(train_rmse))
print('Test Root Mean Square Error: ' + str(test_rmse))
```

```
Train Root Mean Square Error: 21.18039827236602
Test Root Mean Square Error: 21.156133550501618
```


70
60
50
40
30
20
10
0
Predicted
0
20
40
60
80
100
Actuals