In [455]:
```
import warnings
warnings.filterwarnings('ignore')

from keras.models import Sequential
from keras.layers import Dense

import matplotlib
from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import LeaveOneOut
from sklearn.model_selection import KFold

import re
import requests
%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.linear_model import LogisticRegressionCV

import seaborn as sns
pd.set_option('display.width', 1500)
pd.set_option('display.max_columns', 100)
```

In [417]:
```
# make sure all relevant files are in the same directory
!pwd
```

```
/Users/michaelliu/Desktop/tosubmit
```

Some cleaning was done in Microsoft Excel - the following:

1. Deleted rows with headers (because they were all merged, every file that was merged had its own header row)
2. Removed duplicates based on track_id - there were obviously many duplicates because playlists don't all have different songs

In [418]:
```
# uncleaned except excel cleaning; includes headers; includes all featur
es that were scraped
playlists = pd.read_csv('merged_final.csv')
playlists.head()
```

Out[418]:

	Unnamed: 0	album_id	album_name	year_released	album_release_c
0	0	1sXOM4wTy7TbTPdPz68YeF	Confrontation	4	1983
1	1	3q8y9MBuOdOzwJb8QJfwBG	Exodus (Deluxe Edition)	5	1/1/77
2	2	2sjqgdbvLYmvpC3CL8kkyK	Kaya	4	1978
3	3	24qLt9W28msLjUqsucGt1B	Live!	5	1/1/75
4	4	3m89meycBx0T7hYBhj2kkq	This Is The Life	5	9/25/09

In [419]:

```
# Converting album_release_date to YYYY format
import re

bad_indices = [] # will drop tracks with year formats that are not one o
f the following:

lst_4_years = [] # YYYY formats
lst_2_slash = [] # MM/DD/YY formats
lst_2_hyphen = [] # YYYY-MM formats

lst_year_release = [] # to store years converted to standardized format
 YYYY

for i, date in enumerate(playlists.album_release_date):

    if len(date)==4: # keep YYYY as is
        lst_4_years.append(date)
        lst_year_release.append(date)

    elif re.findall(r"(.){1,2}[/](.){1,2}[/](.){1,2}",date): # convert M
M/DD/YY
        lst_2_slash.append(date)

        if int(date[-2:]) < 19: # for years 2000 to 2018
            lst_year_release.append("20"+(date[-2:]))
        else:
            lst_year_release.append("19"+(date[-2:])) # for years 1939
 (oldest year) to 1999

    elif re.findall(r"(.){4}-(.){2}",date): # convert YYYY-MM
        lst_2_hyphen.append(date)
        lst_year_release.append(date[:4])

    else:
        bad_indices.append((i, date))

print(len(bad_indices)) # there are no bad indices :) that means all rel
ease dates were in one of the above 3 formats
playlists["release_year"] = lst_year_release
```

0

In [420]:
```
# how did we know there wouldn't be a problem where e.g. MM/DD/(19)18 an
d MM/DD/(20)18 would be mistaken as the same?
print(sorted(set(lst_year_release)))
# as you can see, there is no years before 1939 and therefore this probl
em simply wouldn't arise.
```

```
['1939', '1942', '1945', '1947', '1948', '1949', '1951', '1952', '195
3', '1954', '1955', '1956', '1957', '1958', '1959', '1960', '1961', '19
62', '1963', '1964', '1965', '1966', '1967', '1968', '1969', '1970', '1
971', '1972', '1973', '1974', '1975', '1976', '1977', '1978', '1979',
'1980', '1981', '1982', '1983', '1984', '1985', '1986', '1987', '1988',
'1989', '1990', '1991', '1992', '1993', '1994', '1995', '1996', '1997',
'1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005', '2006',
'2007', '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015',
'2016', '2017', '2018']
```

In [421]:
```
# drop non-quant and garbage columns
X_database = playlists.drop(['Unnamed: 0','album_id', 'album_name', 'alb
um_release_date', 'track_artist_ids', 'track_id', 'track_name', 'audio_f
eatures_id', 'artist1_id', 'artist_genre1', 'artist_genre2', 'artist_gen
re3', 'album_label','year_released'], axis=1)
X_database.shape
```

Out[421]: (19167, 18)

In [422]:
```
X_database = X_database.dropna(axis=0)
X_database.shape
# looks like 3 rows had NaNs - makes sense, if you look at our data scra
ping mechanism
```

Out[422]: (19164, 18)

In [423]:
```
# make a copy because right after on we'll be temporarily deleting some
 cols we want to add back
X_database_main = X_database.copy()

# delete binary values which will not be standardized
del X_database["track_explicit"]
del X_database["mode"]

# standardize all quantitative columns
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler().fit(X_database)
X_database_scaled = scaler.transform(X_database)
X_database_scaled = pd.DataFrame(X_database_scaled)
X_database_scaled.columns = X_database.columns

# add back binary columns
X_database_scaled["track_explicit"] = X_database_main["track_explicit"]
X_database_scaled["mode"] = X_database_main["mode"]
```

In [424]:
```
X_database_scaled.head()
```

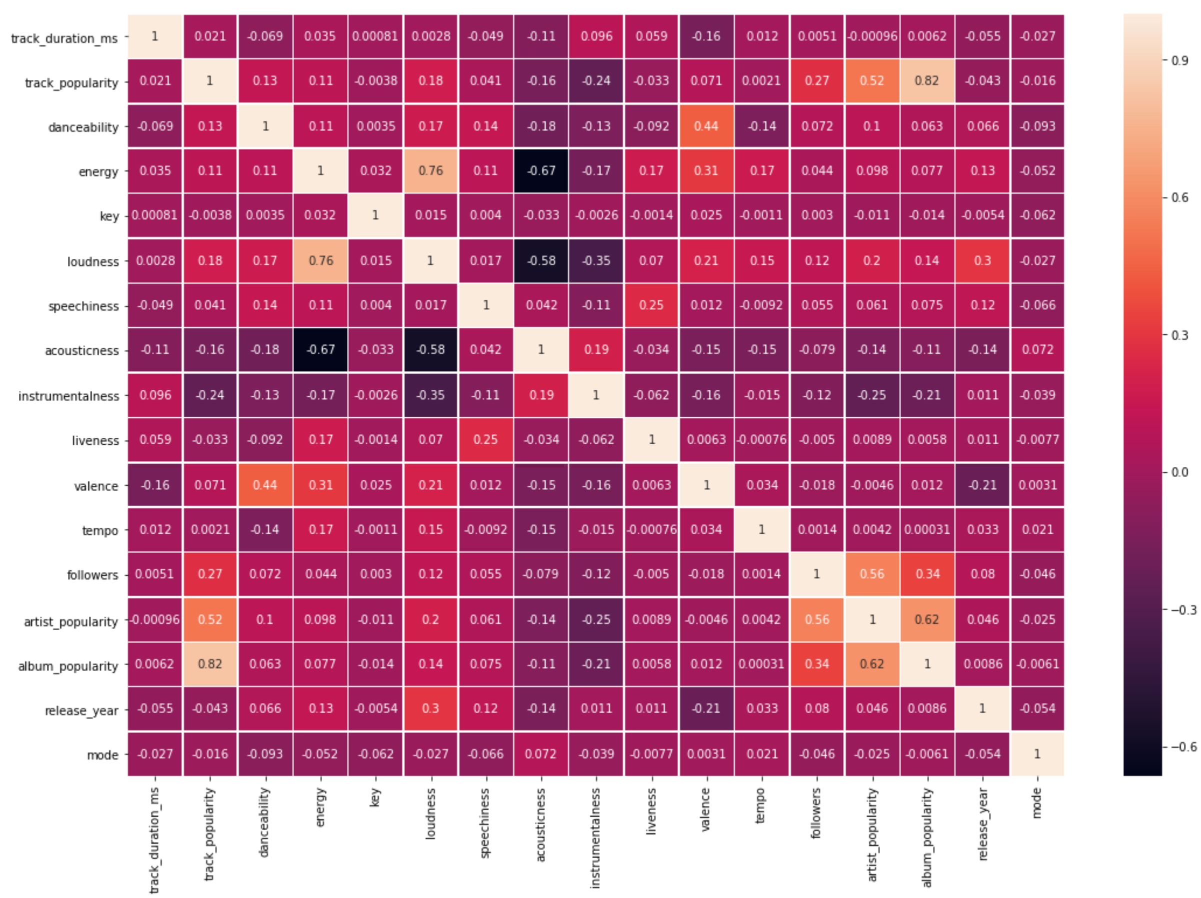
Out[424]:

	track_duration_ms	track_popularity	danceability	energy	key	loudness	spe
0	0.299349	0.974197	2.100562	-0.828570	1.056385	-0.295193	1.58
1	-0.832847	0.766546	0.821219	-0.547890	1.335508	-0.535852	1.92
2	-0.038808	0.818459	1.130239	-0.409850	0.219014	-0.219291	0.06
3	2.581774	0.558894	0.351509	0.142308	-1.176604	-0.472902	-0.2
4	-0.106158	0.091679	0.264984	-0.451262	0.498137	-0.174216	-0.5

In [425]:
```
# correlation plot between all predictors
import seaborn as sns

plt.subplots(figsize=(18, 12))
corr = X_database_scaled.corr()
sns.heatmap(corr, xticklabels=corr.columns.values, yticklabels=corr.colu
mns.values, linewidths=.5,annot=True)
```

Out[425]: <matplotlib.axes._subplots.AxesSubplot at 0x1a379dc358>



Based on the correlation plot we are going to drop one of all pairs of predictors that have higher than 0.75 correlation in magnitude. This is to ensure that when we fit a regression model, the weights/coefficients of two nearly collinear predictors aren't arbitrarily distributed, which would ruin interpretability for both those predictors.

The pairs that meet that criteria are Loudness and Energy, and Album Popularity and Track Popularity. These high correlations make sense and the both predictors in each pair should probably not go into the same model from a logical standpoint as well.

We decide which one to drop based on the one that has the next highest correlation with a different predictor, i.e. we drop energy over loudness because energy has a stronger correlation with acousticness, and we drop album over track popularity because album pop has a stronger correlation with artist popularity.

In [426]:
```
del X_database_scaled['energy']
del X_database_scaled['album_popularity']
```

DO NOT RUN THE CELL BELOW.

In the cell below we originally generate 20 random track IDs to give to our 3 subjects, Helen, Dhruv, and Isabelle. We printed out the corresponding Spotify open link and told them to listen to them fully. They each returned ratings from 1-10, decimals allowed, for each song.

We have commented out the below code because running it again generates new track IDs (we accidentally did this ourselves), and we want to keep track of songs we actually gave them.

In [427]:
```
# indices = np.arange(X_database_scaled.shape[0])

# random_indices = np.random.choice(indices, size=20, replace=False)
# random_indices2 = np.random.choice(indices, size=20, replace=False)
# random_indices3 = np.random.choice(indices, size=20, replace=False)

# # RANDOM SONGS FOR HELEN
# helen_X = X_database_scaled.loc[random_indices]
# for id in helen.track_id:
#     print('https://open.spotify.com/track/{}'.format(id))

# # RANDOM SONGS FOR DHRUV
# dhruv_X = X_database_scaled.loc[random_indices2]
# for id in dhruv.track_id:
#     print('https://open.spotify.com/track/{}'.format(id))

# # RANDOM SONGS FOR ISABELLE
# isabelle_X = X_database_scaled.loc[random_indices3]
# for id in isabelle.track_id:
#     print('https://open.spotify.com/track/{}'.format(id))
```

In [428]:

```
# here you can see that we accidentally generated new random track IDs,
 so we had to go back to the lists we provided
# for our subjects and retrieve the right ones...

helen_links = ['https://open.spotify.com/track/6OG1S805gIrH5nAQbEOPY3',
'https://open.spotify.com/track/0SGkqnVQo9KPytSri1H6cF',
'https://open.spotify.com/track/3Bp478Itxv8gxqqEcf8HRL',
'https://open.spotify.com/track/7iaw359G2XT14uTfV9feip',
'https://open.spotify.com/track/5qmZHOqnuKopAfKv8W61oN',
'https://open.spotify.com/track/3lBRNqXjPp2j3JMTCXDTNO',
'https://open.spotify.com/track/4uQ7wYsuL0DryknoDc11Hk',
'https://open.spotify.com/track/16qYlQ6koFxYVbiJbGHblz',
'https://open.spotify.com/track/4y5Cc7AOL8CIdtLWdcuGMg',
'https://open.spotify.com/track/7DDRPKLKFIvDbNSQmnz19Y',
'https://open.spotify.com/track/6fZersDfjZ7CMyLe0jvixb',
'https://open.spotify.com/track/22eADXu8DfOAUEDw4vU8qy',
'https://open.spotify.com/track/0lAveUGBd27UoLnhbnSzgG',
'https://open.spotify.com/track/0jn2XqaHliEpWd04ZykIHy',
'https://open.spotify.com/track/6Z8R6UsFuGXGtiIxiD8ISb',
'https://open.spotify.com/track/1XGwjdHXHNu3842f75eg3T',
'https://open.spotify.com/track/6EpRaXYhGOB3fj4V2uDkMJ',
'https://open.spotify.com/track/2lH6RlA7NA2CcTfyEsONTc',
'https://open.spotify.com/track/1SayqEg8HKK2IeIEWjdYxY',
'https://open.spotify.com/track/2fQrGHiQOvpL9UgPvtYy6G']

dhruv_links = ['https://open.spotify.com/track/5xS9hkTGfxqXyxX6wWWTt4',
'https://open.spotify.com/track/56ZDcszhe1eCeghso93fXP',
'https://open.spotify.com/track/60geMByGdlcGGMR5R5ZjHE',
'https://open.spotify.com/track/4gHSezW5CHZCvjAUjF2pd5',
'https://open.spotify.com/track/2eW8aJXH9OSqJuw1UcPEj6',
'https://open.spotify.com/track/2IO7yf562c1zLzpanal1DT',
'https://open.spotify.com/track/2SJMm1mWgcy3pj2gMfwRiQ',
'https://open.spotify.com/track/4Sfa7hdVkqlM8UW5LsSY3F',
'https://open.spotify.com/track/4JuZQeSRYJfLCqBgBIxxrR',
'https://open.spotify.com/track/5ybydtBlJJL82AprlvN7Lg',
'https://open.spotify.com/track/5R0b6aGJH9J6BW4eNUgYDd',
'https://open.spotify.com/track/6Yzh272O4hwZHjrnXYhL8a',
'https://open.spotify.com/track/1UE2mIj6uy9Tip2cvQx5xu',
'https://open.spotify.com/track/79nEEoEPY2w8EXj9hjn5oc',
'https://open.spotify.com/track/3JDNTieVelwwVvIIpPqAH3',
'https://open.spotify.com/track/26nxjX1zXkT8oVwO9RPUMf',
'https://open.spotify.com/track/4qdgv45EPcQqpQ08tF34f8',
'https://open.spotify.com/track/2pA4ip3VIEVcIa3qE02oAX',
'https://open.spotify.com/track/1KDYN3odJHnj9pqGHN3FVs',
'https://open.spotify.com/track/5C4PHNJIGuYYcMDsvKmLSV']

isabelle_links = ['https://open.spotify.com/track/0UdWlvyc1Hc97LRX3zAOw
C',
'https://open.spotify.com/track/7cb98TMQPLbkE86up3uLz6',
'https://open.spotify.com/track/00xR9dHhuaNznqB4FSzOlr',
'https://open.spotify.com/track/7cjZxxdwK4NLtXyKCTQnNR',
'https://open.spotify.com/track/4MimthDKiYVMCqDBJEiw1U',
'https://open.spotify.com/track/6IEMLVQMHWuqNX50gGdsYB',
'https://open.spotify.com/track/5YzA563GXTuwQaRq24z1k5',
'https://open.spotify.com/track/78WVLOP9pN0G3gRLFy1rAa',
'https://open.spotify.com/track/4Tjh34RS4ACZ6f6srlDBg8',
```

```
'https://open.spotify.com/track/24lORMRGMv9sXpZJdN1PVm',
'https://open.spotify.com/track/1oh8AROxt4IUEH42CEFRb9',
'https://open.spotify.com/track/4SKlwyLMGQdzul5S5TvCh5',
'https://open.spotify.com/track/6ngavex4sZrVTif1wwRof0',
'https://open.spotify.com/track/6L2Eoo8Dzx60hARXy7TCic',
'https://open.spotify.com/track/3a1lNhkSLSkpJE4MSHpDu9',
'https://open.spotify.com/track/0aPrTlWUf2nmDkC9gcP5kZ',
'https://open.spotify.com/track/0BBOLOV5JntPL3341swIre',
'https://open.spotify.com/track/2qFIJT5hjqaNFA1GKwl9me',
'https://open.spotify.com/track/7i9HsRBt4punMJWoCoSeu6',
'https://open.spotify.com/track/2rqUblDWJKlMVwh9uJc0Vv']

helen_ids = [helen_link[31:] for helen_link in helen_links]
dhruv_ids = [dhruv_link[31:] for dhruv_link in dhruv_links]
isabelle_ids = [isabelle_link[31:] for isabelle_link in isabelle_links]
```

In [429]:
```
# we need to get the indices from playlists rather than X_database_scaled because it has information like IDs
# that aren't being used as predictors, but are obviously crucial for referencing.

helen_indices = [] # the indices from 'playlists' that correspond to their assigned random tracks
for ID in helen_ids:
    helen_indices.append(playlists.track_id[playlists.track_id == ID].index[0])

dhruv_indices = []
for ID in dhruv_ids:
    dhruv_indices.append(playlists.track_id[playlists.track_id == ID].index[0])

isabelle_indices = []
for ID in isabelle_ids:
    isabelle_indices.append(playlists.track_id[playlists.track_id == ID].index[0])
```

From here on, we are demoing our models with Helen's data. If you are interested in seeing the results from Dhruv and Isabelle as well, see our "Human results" section on the website.

In [430]:
```
# These 20 ratings were provided by Helen herself. They are arranged in the same order as the tracks we gave her.
helen_y = [8, 7.5, 3, 5, 5, 7.5, 7, 6, 9, 6, 4, 4, 5, 6, 8, 4, 6, 6.5, 5, 8.5]
```

In [431]:
```
# a simple linear regression model, no higher orders, trained on Helen's
 20 songs and ratings
simple_LR_model = LinearRegression().fit(helen_X, helen_y)

# predictors and their coefficients (based on Helen's preferences)
weights = zip(helen_X.columns.values, simple_LR_model.coef_)
for weight in weights:
    print(weight)
```

```
('track_duration_ms', 0.515496265348243)
('track_popularity', 1.4077916392670764)
('danceability', -0.33696372721600854)
('key', 0.8184112526498223)
('loudness', -0.7879796592182295)
('speechiness', -0.13193310307488265)
('acousticness', -0.6005089507258942)
('instrumentalness', -0.9292250036317006)
('liveness', -1.180497354425426)
('valence', 0.46091770635186124)
('tempo', 0.49193055156456655)
('followers', 1.335690730390116)
('artist_popularity', -1.72994622316518)
('release_year', 1.6926095990110246)
('track_explicit', 0.35192575148128913)
('mode', 0.7837927968302959)
```

In [437]:
```
# need to drop nan's again - a few were generated during scaling
X_database_scaled = X_database_scaled.dropna(axis=0)
X_database_scaled.shape
```

Out[437]:
```
(19161, 16)
```

In [439]:
```
preds_LR = est_model.predict(X_database_scaled) # a list of predictions
 of Helen's ratings of all songs in the database
```

In [440]:
```
database_full = X_database_scaled.copy() # df to hold both predictors an
d predicted ratings
database_full['predicted_ratings'] = preds
```

In [443]:
```
database_sorted = database.sort_values(by=['predicted_ratings']) # sort
 from worst to best ratings
top5_lr = database_sorted[database_sorted.shape[0] - 5:] # top 5 ratings
 (this number can be increased to get more songs)
top5_lr
```

Out[443]:

	track_duration_ms	track_popularity	danceability	key	loudness	speechine
14542	0.608741	1.597151	0.153737	1.056385	0.490770	-0.556391
2683	0.379199	2.375843	0.042489	0.777261	0.314096	-0.587240
14538	-0.102769	1.545238	0.295886	0.777261	0.486366	-0.085326
7413	0.880807	1.700977	-0.068758	1.335508	-3.364954	-0.449672
6663	37.207660	-1.413793	-0.859848	-1.176604	0.198300	-0.220392

In [446]:
```
# print spotify open links for Helen to listen to - she *should* like th
em.
indices = [index for index in top5_lr.index]
top_ids = playlists.loc[indices].track_id.values
for track_id in top_ids:
    print('https://open.spotify.com/track/{}'.format(track_id))
```

```
https://open.spotify.com/track/2RttW7RAu5nOAfq6YFvApB
https://open.spotify.com/track/0tgVpDi06FyKpA1z0VMD4v
https://open.spotify.com/track/35QZaWQRkmnAVqBF1TLCxQ
https://open.spotify.com/track/3B7udSGy2PfgoCniMSb523
https://open.spotify.com/track/7hqowhuDmklJV3DwV9vF5p
```

Helen's ratings: 10, 9, 9, 7, 5.5 These turn out to be really good! The top 3 songs chosen were actually from the same Ed Sheeran album, which Helen claims "she really loves."

We will now fit a couple other different models to see if we get similar results from Helen.

In [447]:
```
from sklearn.ensemble import RandomForestRegressor

est_rf = RandomForestRegressor(random_state=15).fit(helen_X, helen_y)
preds_rf = est_rf.predict(X_database_scaled)

database_rf = X_database_scaled.copy()
database_rf['predicted_ratings'] = preds_rf

database_rf_sorted = database_rf.sort_values(by=['predicted_ratings'])
top5_rf = database_rf_sorted[database_rf_sorted.shape[0]-5:]
top5_rf
```

Out[447]:

	track_duration_ms	track_popularity	danceability	key	loudness	speechines
7114	-0.193873	0.714633	1.779181	1.614632	-1.840435	0.069751
4566	0.973693	0.455069	2.069660	1.335508	-0.036400	-0.277087
1856	-0.268712	0.403156	1.698836	1.335508	0.038725	0.178138
15224	1.141606	0.506982	1.816263	1.335508	-0.440262	-0.168700
12022	0.690909	0.870371	1.006631	0.219014	-0.885312	-0.262080

In [449]:
```
indices = [index for index in top5_rf.index]
top_ids = playlists.loc[indices].track_id.values
for track_id in top_ids:
    print('https://open.spotify.com/track/{}'.format(track_id))
```

```
https://open.spotify.com/track/2RCOWNCxDIphjhqTtkwtwR
https://open.spotify.com/track/1YCsTFttuHAzgfEWKdOb9K
https://open.spotify.com/track/7BwwjDFcpn72BrxCCRqs7d
https://open.spotify.com/track/5mNV8Mz59bzyuQ53gTw0c0
https://open.spotify.com/track/58r4JuwHhXLAkttkaUZfLw
```

Helen's ratings: 6, 7, 4.5, 3.5, 5

RandomForest regression is significantly worse, barely averaging above a 5.

In [450]:
```
model = Sequential([
    Dense(200, input_shape=(16,), activation='relu'), #Dense = fully con
nected
    Dense(150, activation='relu'),
    Dense(100, activation='relu'),
    Dense(1, activation='relu') #using relu as activation produces far b
etter results than softmax
])
```

In [451]:
```
model.compile(loss='mean_absolute_error', optimizer='adam')
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_21 (Dense)             (None, 200)               3400      
_________________________________________________________________
dense_22 (Dense)             (None, 150)               30150     
_________________________________________________________________
dense_23 (Dense)             (None, 100)               15100     
_________________________________________________________________
dense_24 (Dense)             (None, 1)                 101       
=================================================================
Total params: 48,751
Trainable params: 48,751
Non-trainable params: 0
_________________________________________________________________
```

In [452]:
```
model.fit(helen_X, helen_y, epochs=50, batch_size=32, validation_split =
 .2)
```

```
Train on 16 samples, validate on 4 samples
Epoch 1/50
16/16 [==============================] - 0s 23ms/step - loss: 5.8222 -
val_loss: 6.1290
Epoch 2/50
16/16 [==============================] - 0s 138us/step - loss: 5.5203 -
val_loss: 5.8738
Epoch 3/50
16/16 [==============================] - 0s 154us/step - loss: 5.2033 -
val_loss: 5.6240
Epoch 4/50
16/16 [==============================] - 0s 142us/step - loss: 4.9081 -
val_loss: 5.3322
Epoch 5/50
16/16 [==============================] - 0s 154us/step - loss: 4.5704 -
val_loss: 5.0218
Epoch 6/50
16/16 [==============================] - 0s 137us/step - loss: 4.2201 -
val_loss: 4.6868
Epoch 7/50
16/16 [==============================] - 0s 131us/step - loss: 3.8951 -
val_loss: 4.3265
Epoch 8/50
16/16 [==============================] - 0s 135us/step - loss: 3.5580 -
val_loss: 3.9308
Epoch 9/50
16/16 [==============================] - 0s 145us/step - loss: 3.1827 -
val_loss: 3.4942
Epoch 10/50
16/16 [==============================] - 0s 139us/step - loss: 2.7652 -
val_loss: 3.0080
Epoch 11/50
16/16 [==============================] - 0s 265us/step - loss: 2.3491 -
val_loss: 2.4628
Epoch 12/50
16/16 [==============================] - 0s 264us/step - loss: 1.9922 -
val_loss: 1.8634
Epoch 13/50
16/16 [==============================] - 0s 276us/step - loss: 1.7972 -
val_loss: 1.2370
Epoch 14/50
16/16 [==============================] - 0s 178us/step - loss: 1.6910 -
val_loss: 0.6785
Epoch 15/50
16/16 [==============================] - 0s 172us/step - loss: 1.7595 -
val_loss: 0.5258
Epoch 16/50
16/16 [==============================] - 0s 156us/step - loss: 1.8604 -
val_loss: 0.6946
Epoch 17/50
16/16 [==============================] - 0s 200us/step - loss: 1.9201 -
val_loss: 0.7561
Epoch 18/50
16/16 [==============================] - 0s 123us/step - loss: 1.8826 -
val_loss: 0.7319
Epoch 19/50
16/16 [==============================] - 0s 186us/step - loss: 1.7633 -
```

```
val_loss: 0.6422
Epoch 20/50
16/16 [==============================] - 0s 149us/step - loss: 1.5865 -
val_loss: 0.5553
Epoch 21/50
16/16 [==============================] - 0s 173us/step - loss: 1.3722 -
val_loss: 0.6982
Epoch 22/50
16/16 [==============================] - 0s 228us/step - loss: 1.1377 -
val_loss: 0.8410
Epoch 23/50
16/16 [==============================] - 0s 182us/step - loss: 1.0409 -
val_loss: 0.9724
Epoch 24/50
16/16 [==============================] - 0s 485us/step - loss: 1.0543 -
val_loss: 1.0535
Epoch 25/50
16/16 [==============================] - 0s 213us/step - loss: 1.1103 -
val_loss: 1.0981
Epoch 26/50
16/16 [==============================] - 0s 211us/step - loss: 1.1151 -
val_loss: 1.0914
Epoch 27/50
16/16 [==============================] - 0s 250us/step - loss: 1.0764 -
val_loss: 1.0630
Epoch 28/50
16/16 [==============================] - 0s 142us/step - loss: 1.0022 -
val_loss: 1.0148
Epoch 29/50
16/16 [==============================] - 0s 181us/step - loss: 0.9463 -
val_loss: 0.9568
Epoch 30/50
16/16 [==============================] - 0s 183us/step - loss: 0.8951 -
val_loss: 0.8887
Epoch 31/50
16/16 [==============================] - 0s 198us/step - loss: 0.8541 -
val_loss: 0.8369
Epoch 32/50
16/16 [==============================] - 0s 168us/step - loss: 0.8394 -
val_loss: 0.8086
Epoch 33/50
16/16 [==============================] - 0s 147us/step - loss: 0.8076 -
val_loss: 0.8007
Epoch 34/50
16/16 [==============================] - 0s 128us/step - loss: 0.7637 -
val_loss: 0.8209
Epoch 35/50
16/16 [==============================] - 0s 161us/step - loss: 0.7063 -
val_loss: 0.8645
Epoch 36/50
16/16 [==============================] - 0s 124us/step - loss: 0.6365 -
val_loss: 0.9090
Epoch 37/50
16/16 [==============================] - 0s 173us/step - loss: 0.5684 -
val_loss: 0.9527
Epoch 38/50
16/16 [==============================] - 0s 125us/step - loss: 0.5361 -
```

```
val_loss: 0.9680
Epoch 39/50
16/16 [==============================] - 0s 172us/step - loss: 0.5320 -
val_loss: 0.9515
Epoch 40/50
16/16 [==============================] - 0s 253us/step - loss: 0.4948 -
val_loss: 0.9115
Epoch 41/50
16/16 [==============================] - 0s 272us/step - loss: 0.4392 -
val_loss: 0.8691
Epoch 42/50
16/16 [==============================] - 0s 187us/step - loss: 0.4130 -
val_loss: 0.8281
Epoch 43/50
16/16 [==============================] - 0s 203us/step - loss: 0.3830 -
val_loss: 0.7982
Epoch 44/50
16/16 [==============================] - 0s 204us/step - loss: 0.3577 -
val_loss: 0.7784
Epoch 45/50
16/16 [==============================] - 0s 128us/step - loss: 0.3261 -
val_loss: 0.7742
Epoch 46/50
16/16 [==============================] - 0s 122us/step - loss: 0.3043 -
val_loss: 0.7899
Epoch 47/50
16/16 [==============================] - 0s 184us/step - loss: 0.2799 -
val_loss: 0.7963
Epoch 48/50
16/16 [==============================] - 0s 117us/step - loss: 0.2754 -
val_loss: 0.7993
Epoch 49/50
16/16 [==============================] - 0s 214us/step - loss: 0.2685 -
val_loss: 0.7992
Epoch 50/50
16/16 [==============================] - 0s 158us/step - loss: 0.2618 -
val_loss: 0.7892
```

```
Out[452]: <keras.callbacks.History at 0x1a3b9edf98>
```

In [453]:
```
preds_nn = model.predict(X_database_scaled)

database_nn = X_database_scaled.copy()
database_nn['predicted_ratings'] = preds_nn

database_nn_sorted = database_nn.sort_values(by=['predicted_ratings'])
top5_nn = database_nn_sorted[database_nn_sorted.shape[0]-5:]
top5_nn
```

Out[453]:

	track_duration_ms	track_popularity	danceability	key	loudness	speechine
7976	11.743079	-0.842752	0.419494	0.498137	-0.383788	-0.462178
15875	12.897971	-0.894665	0.153737	1.335508	-1.886029	-0.352124
16042	15.166101	0.143592	-1.601496	-0.897480	-2.093529	-0.475518
8787	15.250948	-0.583188	-1.552053	-0.339233	-0.172661	-0.167033
6663	37.207660	-1.413793	-0.859848	-1.176604	0.198300	-0.220392

In [454]:
```
indices = [index for index in top5_nn.index]
top_ids = playlists.loc[indices].track_id.values
for track_id in top_ids:
    print('https://open.spotify.com/track/{}'.format(track_id))
```

```
https://open.spotify.com/track/1j5C6t9MVOUlXFAnUPhdcQ
https://open.spotify.com/track/2cfmjFK51sBubowSigw5f8
https://open.spotify.com/track/6SoVI1qSkmyJG95BF5oFtR
https://open.spotify.com/track/1HNFInFeXqddmDRqvlelGQ
https://open.spotify.com/track/7hqowhuDmklJV3DwV9vF5p
```

Helen got tired of listening to this many songs at this point, and told us after skimming the songs that they were comparable to the RandomForest songs in terms of how much she liked them.

Notably, however, the last song from neural networking was also chosen in simple linear regression.

NOW WE MAKE THE TRANSITION TO THE SECOND KIND OF ALGORITHM: Here, users will provide a playlist with songs they have decided to add because they like them. There will be no need to rate anything farther.

Rather than training models with 20 songs, we will instead train the model on the whole database. Instead of using user-provided ratings as a response variable, we will instead use a binary classification - whether the song is in the playlist, or not in the playlist. We will thus be able to see whether or not other songs "should" be added to the provided playlist if they are predicted to be in the playlist.

In [461]:
```
# unfortunately we can't actually take anyone's playlist, because it wou
ld required that all of the songs in that playlist
# exist in the database that we scraped, and we have a very limited amou
nt of the full 1 million songs.

# therefore, we are going to randomly assign songs to "in playlist" and
 "not in playlist"
import random

rand_choice = []
for i in range(X_database_scaled.shape[0]):
    rand_choice.append(random.randint(0,1))

# Create response var. 0: Song Not present in playlist, 1: Song is prese
nt
y_train = rand_choice

x_train = X_database_scaled.copy()
```

In [465]:
```
# starting out with simple logistic regression
from sklearn.linear_model import LogisticRegressionCV

est_model_lr = LogisticRegressionCV().fit(x_train, y_train)

print("Logisic Regression R^2 Error on Train Set: {}".format(est_model_l
r.score(x_train,y_train)))
print("CV Error on Train Set: {}".format(cross_val_score(est_model_lr, x
_train, y_train, cv=10)))
# these are pretty bad r^2 but we are assigning classes randomly
```

```
Logisic Regression R^2 Error on Train Set: 0.511507750117426
CV Error on Train Set: [0.49765258 0.50286907 0.49191445 0.4822547  0.4
9164927 0.51148225
 0.49895616 0.49686848 0.47989556 0.50496084]
```

In [466]:
```
# now try randomforest classifier
from sklearn.ensemble import RandomForestClassifier

est_model_rf = RandomForestClassifier(50, min_samples_split=5, max_depth
=20).fit(x_train, y_train)

print("Random Forest MSE Error on Train Set: {}".format(est_model_rf.sco
re(x_train,y_train)))
print("CV Error on Train Set: {}".format(cross_val_score(est_model_rf, x
_train, y_train,cv=10)))
```

```
Random Forest MSE Error on Train Set: 0.9930066280465529
CV Error on Train Set: [0.50391236 0.49817423 0.46531038 0.49269311 0.4
9060543 0.50521921
 0.50678497 0.48068894 0.48146214 0.50234987]
```

In [467]:
```
# try boosting
from sklearn.ensemble import GradientBoostingRegressor

est_model_gb = GradientBoostingRegressor(n_estimators=501, max_depth=1,
learning_rate=1).fit(x_train,y_train)

print("Boosting R^2 Error on Train Set: {}".format(est_model_gb.score(x_
train,y_train)))
print("CV Error on Train Set: {}".format(cross_val_score(est_model_gb, x
_train, y_train,cv=10)))
```

```
Boosting R^2 Error on Train Set: 0.04004474007408654
CV Error on Train Set: [-0.02424199 -0.02066139 -0.0311354  -0.01425059
-0.02290821 -0.0167838
 -0.08787088 -0.0334553  -0.03020183 -0.02001175]
```

In [470]:
```
# try kNN, 15 neighbors to start
from sklearn.neighbors import KNeighborsClassifier

est_model_knn = KNeighborsClassifier(n_neighbors = 15).fit(x_train,y_tra
in)

print("Random Forest MSE Error on Train Set: {}".format(est_model_knn.sc
ore(x_train,y_train)))
print("CV Error on Train Set: {}".format(cross_val_score(est_model_knn,
x_train, y_train,cv=10)))
```

```
Random Forest MSE Error on Train Set: 0.6048744846302385
CV Error on Train Set: [0.51225874 0.47261346 0.49452269 0.50626305 0.5
0835073 0.49634656
 0.50104384 0.49008351 0.48720627 0.47937337]
```

In [483]:
```
# careful, this takes a while to run

# try n_neighbors from 10-20, get mean CV scores for corresponding kNN m
odels
results = np.zeros((10,10))
for i,n in enumerate(range(10,20)):
    model = KNeighborsClassifier(n_neighbors = n)
    results[i,:] = cross_val_score(model, x_train, y_train, cv=10)

results_df = pd.DataFrame(results, index=list(range(1,11)), columns= ["C
V1","CV2","CV3","CV4","CV5","CV6","CV7","CV8","CV9","CV10"])
results_df['meanCV'] = np.mean(results, axis=1)
```

In [489]:
```
results_df.index = range(10,20)
results_df # the indices represent n_neighbors
```

Out[489]:

	CV1	CV2	CV3	CV4	CV5	CV6	CV7	CV8	
10	0.510694	0.498696	0.488263	0.498434	0.499478	0.489562	0.505741	0.508351	0.500
11	0.502347	0.489306	0.486176	0.506785	0.498434	0.489040	0.501566	0.500522	0.500
12	0.508086	0.490350	0.489828	0.498956	0.495303	0.479645	0.505741	0.499478	0.491
13	0.506521	0.492436	0.488263	0.505219	0.497390	0.495825	0.504175	0.493737	0.496
14	0.509650	0.477308	0.490871	0.505219	0.492693	0.497912	0.506263	0.488518	0.490
15	0.512259	0.472613	0.494523	0.506263	0.508351	0.496347	0.501044	0.490084	0.487
16	0.512780	0.483046	0.493479	0.507829	0.504697	0.493215	0.518267	0.498956	0.482
17	0.513302	0.477830	0.488785	0.505219	0.504697	0.485908	0.504175	0.490605	0.487
18	0.519040	0.483046	0.503391	0.497390	0.509395	0.492171	0.505219	0.496868	0.485
19	0.515910	0.489306	0.489828	0.505219	0.505219	0.490605	0.500000	0.489562	0.493

In [490]:
```
# highest mean CV score was n_neighbors = 13, so we'll take it as optima
l.
optimal_knn = KNeighborsClassifier(n_neighbors = 13).fit(x_train, y_trai
n)
print("Tuned KNN test set score:",optimal_knn.score(x_train, y_train))

dumb_prediction = np.ones(len(y_train))
print("Trivial Test Set Score:", np.sum(y_train == dumb_prediction)/len(
y_train))
```

```
Tuned KNN test set score: 0.6140598089870049
Trivial Test Set Score: 0.49778195292521266
```

None of the results from the second algorithm can really be taken literally, but the mechanisms can be used as long as a user provides a playlist that isn't actually random.

The end.