COGS 108 - Final Project

Overview

The background of the Spotify Tracks Database contains the songs related features including genre, artist, track, id, popularity and so on. Each song in the Spotify database has a unique ID. We can apply the features such as genre and popularity to predict the popularity of a song based on its genre, and we can predict how is the popularity of a song being related to the singer. We can even combine multiple characteristics of a song to predict whether a song with certain crucial features will be most likely to be popular in the features. The database we chose is newly updated in 2019 March, so very few online projects applied this database yet, but we can find some other Spotify database in previous years and applied the ideas from those database related projects.

This data is extremely useful for artists or producers that are looking to create the next “hit” song. By utilizing the given data, they can possibly predict what the next “hit” song will be by analyzing the data of song features and determining if there is a correlation. We can apply the features such as genre and popularity to predict the popularity of a song based on its genre, and we can predict how is the popularity of a song being related to the artist. We can even combine multiple features of a song to predict whether a song with certain crucial features will be most likely to be popular in the features. We want to discover the specific song features that all top charting songs share, if there are any. We will look at specifically chosen song features to see if there is a correlation between songs sharing similar features that are in the top charts. If our hypothesis is correct, it will show that songs in music top charts share similar song features. Thus, this will lead us to be able to predict the next “hit” song.

Names

-Yu Shen: set up, Data Cleaning, Model Training, Data Analysis & Results

-Zhaokai Xu: set up, Data Cleaning, Model Training, Visualization

-Iris Peng: Research question, ethics and privacy, analysis

-Anthony Martinez: Background, Introduction, analysis

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Research Question

Output target: song_popularity

Q1. Do popular songs have similar attributes? If so, what are these attributes? Specifically, out of a chosen 13 attributes (song duration, tempo, key, etc.), are there similarities between them that determine a song's popularity?

Q2. Furthermore, after identifying these attributes, can we use them to predict which song will be most popular next?

Background and Prior Work

Music is a huge component of the history and culture of mankind. More recently, music has evolved into a business. Artists are constantly competing for the top spots on music charts. Whether it is for top song or top album. Being highly ranked in these charts is important for artists because it will lead to more endorsements, more recognition, and most importantly, more record and song sales. Now, creating a song that makes it on the top charts doesn't necessarily mean that it was composed by Mozart. Most popular songs have a familiar sound. Upbeat, fast, and loud are good indicators of what could possibly be a popular song. Creating a popular song doesn't necessarily mean that you will make it on the top charts, but it does give you a better chance at it. Now, streaming is the future of music.Streaming services like Apple Music and Spotify are releasing very useful data on current music. More specifically, Spotify releases data on the song features for each song. There are 13 total song features that Spotify releases to the public including: tempo, time signature, loudness, danceability, and more.

In other Spotify related projects such as, https://www.kaggle.com/nadintamer/top-tracks-of-2017 (https://www.kaggle.com/nadintamer/top-tracks-of-2017)
It raises interesting questions to explore the dataset such as Looking for patterns in the audio features of the songs. Why do people stream these songs the most? How can we predict one audio feature based on the others features Explore which features correlate the most
https://www.kaggle.com/edumucelli/spotifys-worldwide-daily-song-ranking (https://www.kaggle.com/edumucelli/spotifys-worldwide-daily-song-ranking) Can you predict what is the rank position or the number of streams a song will have in the future? What are the signs of a song that gets into the top rank to stay? Do continents share same top ranking artists or songs? Are people listening to the very same top ranking songs on countries far away from each other? Other projects builders mostly applied machine learning regression models and classification models to make predictions, and the most popular library they referred to is Sklearn. They realized that the data preprocessing is crucial to the success of the projects, and feeding balanced data into the model they applied greatly contributes to improve the accurate prediction.These are the things we can be careful about while working on our project. Since the dataset we are using contains different features compared to the other Spotify dataset, we suggest to try to take the best advantage of our unique features and raise some interesting exploration. References (include links):

- 1) https://www.kaggle.com/nadintamer/top-tracks-of-2017 (https://www.kaggle.com/nadintamer/top-tracks-of-2017)
- 2) https://www.kaggle.com/edumucelli/spotifys-worldwide-daily-song-ranking (https://www.kaggle.com/edumucelli/spotifys-worldwide-daily-song-ranking)

Hypothesis

Among the 14 features we have, 'song_duration_ms', 'acousticness', 'danceability', 'energy', 'instrumentalness', 'key', 'liveness', 'loudness', 'audio_mode', 'speechiness', 'tempo', 'time_signature', 'audio_valence', u'playlist, we want to analyze what feature would contribute the most to the popularity of a song.

Intuitively, we will make the hypothesis that dancebility, livenesss, tempo and energy are key factors of a song_popularity

Dataset(s)

- Dataset Name:19000 Spotify Songs
- Link to the dataset: https://www.kaggle.com/edalrami/19000-spotify-songs (https://www.kaggle.com/edalrami/19000-spotify-songs)
- Number of observations:19000

This dataset uses Spotify API and contains data of 19000 songs. It has 15 features, including： song_name, song_popularity,song_duration_ms, acousticness, danceability, energy, instrumentalness, key, liveness, loudness, audio_mode, speechiness, tempo, time_signature, audio_valence. It has a relatively large amount of samples which is the main reason we chose this dataset. All these audio features come from Spotify API and the data set is updated 5 months ago.

Setup and data pre-analyzing

In [28]:

```
%matplotlib inline

#These are the packages that we
#needed to import for the rest of our code.
#Some of the packages that we needed
#to use include the typical pandas,
#numpy, and matplot packages for
#data manipulation and visualization.

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

import patsy
import statsmodels.api as sm
import scipy.stats as stats
from scipy.stats import ttest_ind, chisquare, normaltest, norm
import seaborn as sns;

from sklearn.model_selection import train_test_split
from sklearn.utils import shuffle
```

In [29]:
```
# 1.1 read data

song_data_df = pd.read_csv("song_data.csv")

song_info_df = pd.read_csv("song_info.csv")
```

In [30]:
```
# 1.2 preview data
song_data_df.head(5)
```

Out[30]:

	song_name	song_popularity	song_duration_ms	acousticness	danceability	ene
0	Boulevard of Broken Dreams	73	262333	0.005520	0.496	0.6
1	In The End	66	216933	0.010300	0.542	0.8
2	Seven Nation Army	76	231733	0.008170	0.737	0.4
3	By The Way	74	216933	0.026400	0.451	0.9
4	How You Remind Me	56	223826	0.000954	0.447	0.7

In [31]:
```
song_info_df.head(5)
```

Out[31]:

	song_name	artist_name	album_names	playlist
0	Boulevard of Broken Dreams	Green Day	Greatest Hits: God's Favorite Band	00s Rock Anthems
1	In The End	Linkin Park	Hybrid Theory	00s Rock Anthems
2	Seven Nation Army	The White Stripes	Elephant	00s Rock Anthems
3	By The Way	Red Hot Chili Peppers	By The Way (Deluxe Version)	00s Rock Anthems
4	How You Remind Me	Nickelback	Silver Side Up	00s Rock Anthems

In [32]:
```
song_data_df = song_data_df.set_index('song_name')
song_info_df = song_info_df.set_index('song_name')
```

The reason we set the song_name as the index is:

1. we do not want to treat it as a feature;
2. using it as index allow us to combine two dataframe by index.

In [33]:
```
song_data_df.shape
```
Out[33]: (18835, 14)

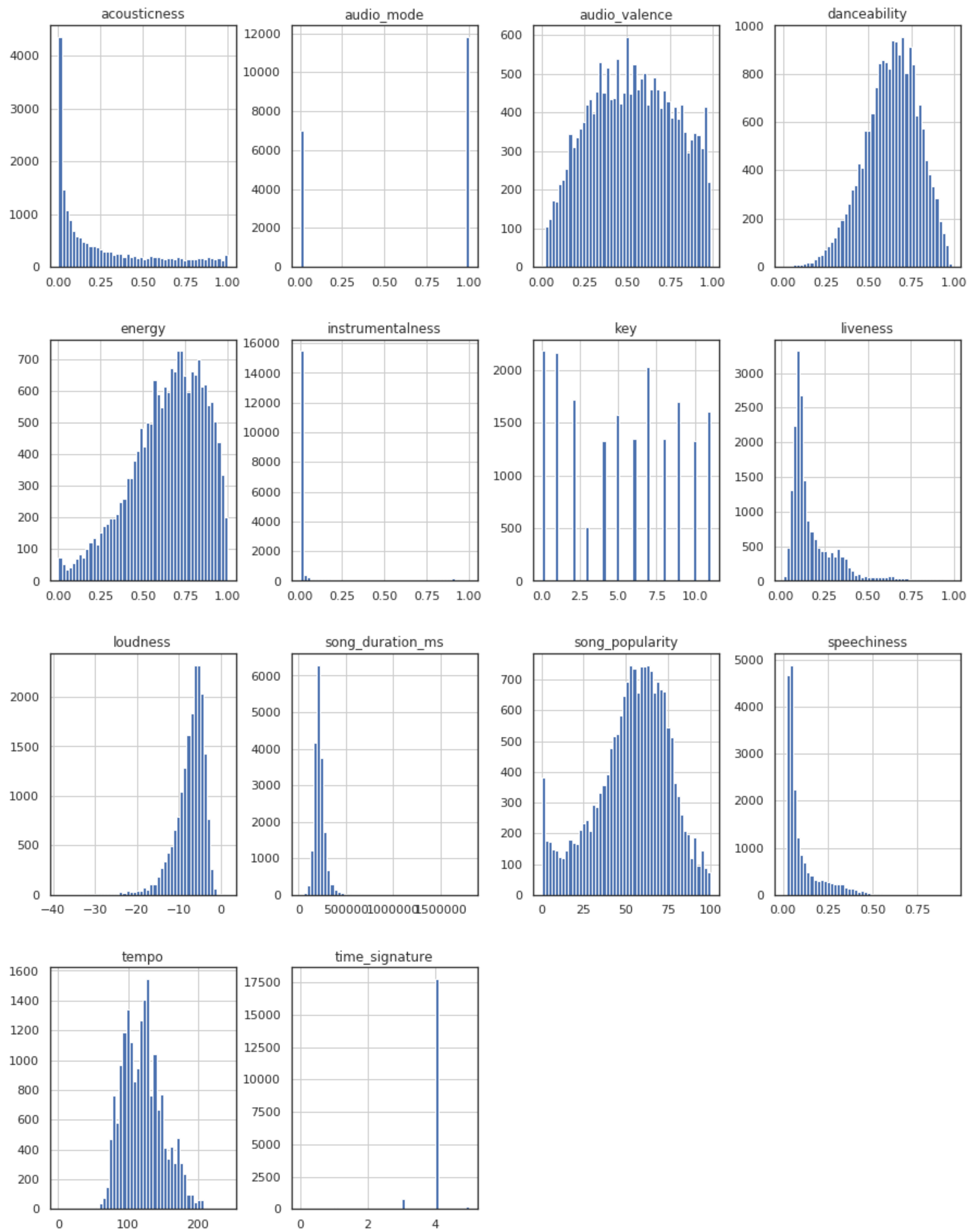
In [34]:
```
song_info_df.shape
```
Out[34]: (18835, 3)

In [35]:
```
# 1.3 combine the two dataset into df
df = pd.concat([song_data_df, song_info_df], axis=1)
df.shape
```
Out[35]: (18835, 17)

In [36]:
```
df.head(5)
```
Out[36]:

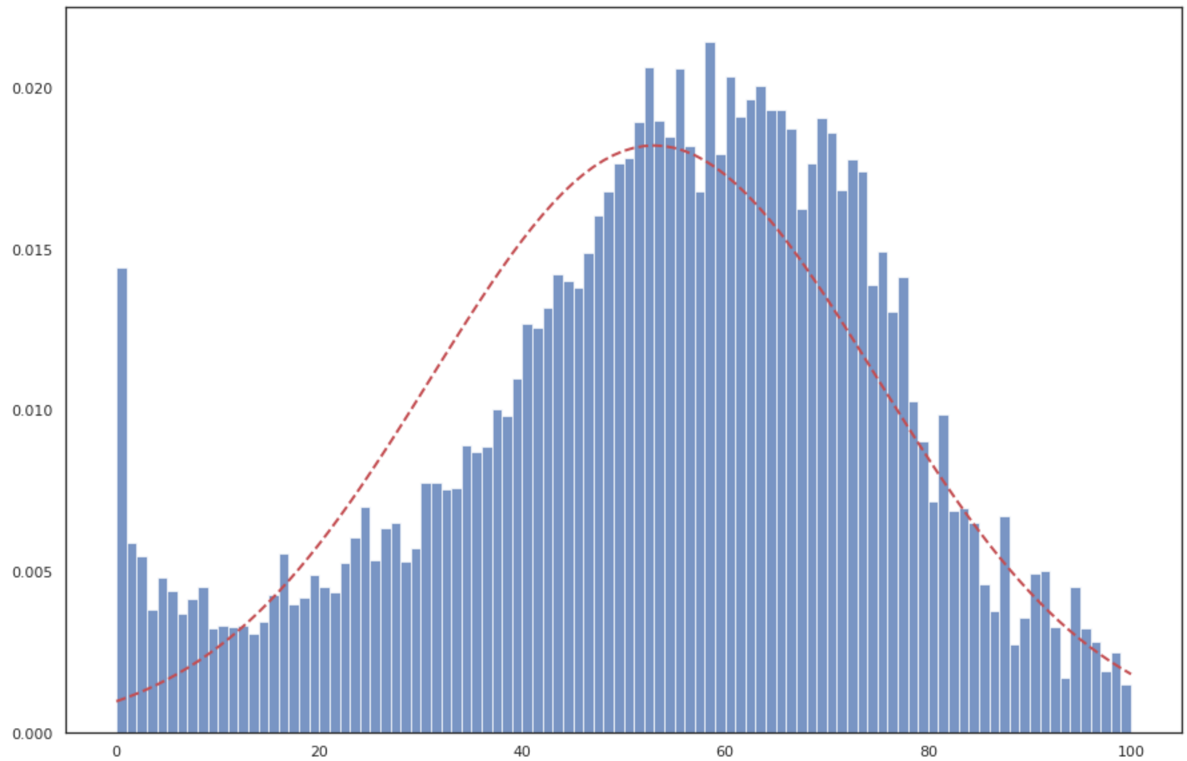
	song_popularity	song_duration_ms	acousticness	danceability	energ
song_name					
Boulevard of Broken Dreams	73	262333	0.005520	0.496	0.682
In The End	66	216933	0.010300	0.542	0.853
Seven Nation Army	76	231733	0.008170	0.737	0.463
By The Way	74	216933	0.026400	0.451	0.970
How You Remind Me	56	223826	0.000954	0.447	0.766

In [37]:
```
# 1.4 print distribution alongside all features
hist = df.hist(bins = 50,figsize = (15,20))
```



Print distribution alongside all features). Above are histograms of all the different features of the songs, including the song popularity after the song data and information has been combined into a single dataframe. Ad

In [38]:
```
song_popularity = df['song_popularity'].tolist()
# find stats of song__popularity: mean and standard deviation
mu, sd = norm.fit(song_popularity)

#draw the histogram of the target
plt.subplots(figsize=(15,10))
n, bins, patches = plt.hist(song_popularity, bins = 100,density = 1,alpha = 0.75)

#draw the distribution function curve
y =stats.norm.pdf( bins, mu, sd)
curve = plt.plot(bins, y, 'r--', linewidth=2)
plt.show()
```



We could find that most of the songs have popularity around 40-80, this matches the normal distribution. We have also observed that there are many songs have no popularity, so we should drop that part of songs.

Data Cleaning

2.1 drop potential useless features:

In [42]:
```
df = df.drop(['album_names'], axis=1)
df = df.drop(['artist_name'], axis=1)
df = df[df.song_popularity != 0]
df.shape
```

Out[42]: (18563, 15)

We drop these two features because they all have unique values, which cannot be treated as a meaning feature. Therefore we dropped them. We also drop all the song that has no popularity.

2.2 one hot encoding the playlist

In [43]:
```
newdf = pd.get_dummies(df,prefix=['playlist'])
```

In [44]:
```
newdf.head(5)
```

Out[44]:

	song_popularity	song_duration_ms	acousticness	danceability	energ
song_name					
Boulevard of Broken Dreams	73	262333	0.005520	0.496	0.682
In The End	66	216933	0.010300	0.542	0.853
Seven Nation Army	76	231733	0.008170	0.737	0.463
By The Way	74	216933	0.026400	0.451	0.970
How You Remind Me	56	223826	0.000954	0.447	0.766

5 rows × 314 columns

After one-hot encoding, we have 313 features, 300 of which are one-hot encoded of different playlists, since we have 300 different playlists in the dataset.

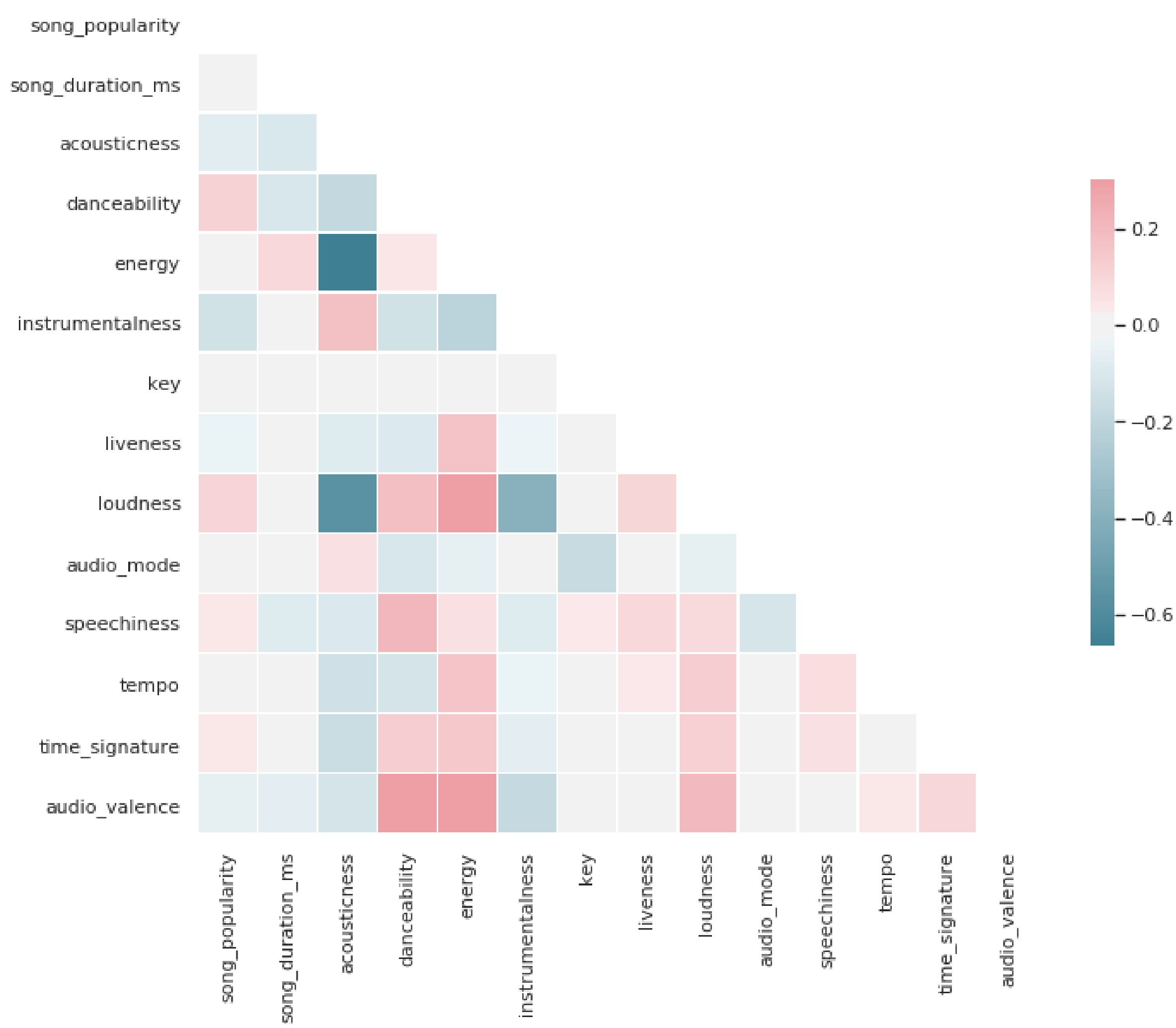
2.3 analyze data relevance

In [45]:
```
len(df['playlist'].unique())
```

Out[45]:
```
300
```

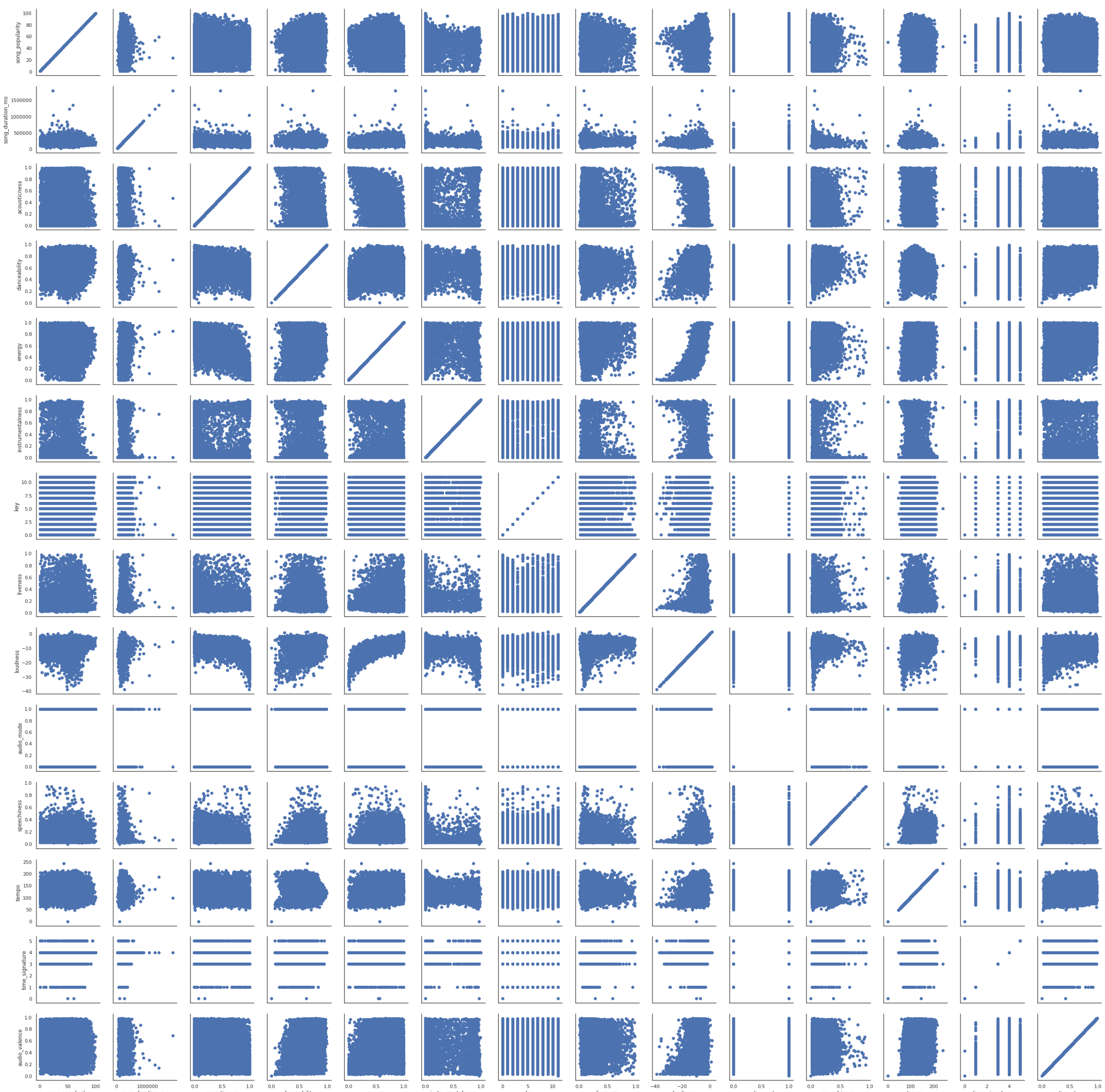
In [46]:
```
# analyze correlation
# in range [-1,1], -1 means negtively correlated, 1 means positively correlated,0 means no relation

# analyze the correlation corresponding to popularity


sns.set(style="white")

# Generate a large random dataset
# rs = np.random.RandomState(33)
d = pd.DataFrame(data=df,columns=list(df.columns))

# Compute the correlation matrix
corr = d.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 10))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc6102068d0>



For this section, we are analyzing the correlation between song features. We are using a range of -1 to 1 to measure the correlation. Any negative number means that there is a negative correlation and any positive number means that there is a positive correlation. The correlation of each feature will be calculated relating to popularity. In this instance, we use a heatmap to see what is more positively correlated with popularity. We use a heat map because it allows us to easily see the features and how they are correlated with popularity. The more pink the color, the more correlated the feature is to popularity. When looking at the heatmap, we can see that loudness, danceability, and energy are most positively correlated with popularity. Similarly, acousticness is the least correlated with popularity.

In [47]:
```
# This class maps each variable in a dataset onto a column and row in a grid of multipl
e axes.
# Different axes-level plotting functions can be used to draw bivariate plots in the upp
er and lower triangles,
# and the the marginal distribution of each variable can be shown on the diagonal.

g = sns.PairGrid(df)
g = g.map(plt.scatter)
```



We have observed that some features are not affected by other feature at all, for example, song_popularity has no effect on audio_mode. Vice versa, we could use this graph to rule out some factors that have no effect on song_popularity, here it is key, audio_mode and time_signature.

In [ ]:
```
# print the corr matrix for later filtering use
corr = df.corr()
corr.style.background_gradient()
```

Here, we run the correlation function, to observe the correlation between two features. It returns a value from -1 to 1, representing how the two variables are related.

Since the target is song_popularity, in the following step, we will drop the features that are not too relevant to song_popularity. We set the threshhold as 0.05. This means, if the correlation of a feature between song_popularity, is less than 0.05, we will drop it in the dataframe.

In [48]:
```
# drop the features whose correlation is less than 0.05

dropIndex = corr[abs(corr['song_popularity'])<0.05].index
print(dropIndex)

for name in dropIndex:
    df = df.drop([name], axis=1)
    newdf = newdf.drop([name], axis=1)

newdf.head(5)
```

```
Index(['song_duration_ms', 'energy', 'key', 'liveness', 'audio_mode',
       'speechiness', 'tempo', 'time_signature'],
      dtype='object')
```

Out[48]:

	song_popularity	acousticness	danceability	instrumentalness	loudne
song_name					
Boulevard of Broken Dreams	73	0.005520	0.496	0.000029	-4.095
In The End	66	0.010300	0.542	0.000000	-6.407
Seven Nation Army	76	0.008170	0.737	0.447000	-7.828
By The Way	74	0.026400	0.451	0.003550	-4.938
How You Remind Me	56	0.000954	0.447	0.000000	-5.065

5 rows × 306 columns

In [49]:
```
newdf.shape
```
Out[49]:
```
(18563, 306)
```

In [50]:
```
### Data Wraggling
```

In [51]:
```
# separate the training and testing
X = df.drop(['song_popularity','playlist'], axis=1)
X = shuffle(X)
Y = df['song_popularity']
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state
=1)
```

In [52]:
```
print("X_train:",X_train.shape, "y_train",y_train.shape)
print("X_test:",X_test.shape, "y_test",y_test.shape)
```
```
X_train: (14850, 5) y_train (14850,)
X_test: (3713, 5) y_test (3713,)
```

In [53]:
```
X.head()
```
Out[53]:

	acousticness	danceability	instrumentalness	loudness	audio_valence
song_name					
Stars	0.916	0.381	0.00142	-18.361	0.116
Trip	0.214	0.717	0.00000	-5.680	0.387
Mambo No. 5 (A Little Bit of...)	0.107	0.607	0.00000	-6.849	0.901
Malo	0.431	0.429	0.00000	-3.716	0.468
How Will I Know	0.943	0.506	0.00000	-12.346	0.301

In [54]:
```
Y.head()
```
Out[54]:
```
song_name
Boulevard of Broken Dreams    73
In The End                    66
Seven Nation Army             76
By The Way                    74
How You Remind Me             56
Name: song_popularity, dtype: int64
```

Train the model

3.1 train a parametric model

Benefits of Parametric Machine Learning Algorithms:

Simpler: These methods are easier to understand and interpret results. Speed: Parametric models are very fast to learn from data. Less Data: They do not require as much training data and can work well even if the fit to the data is not perfect. Limitations of Parametric Machine Learning Algorithms:

Constrained: By choosing a functional form these methods are highly constrained to the specified form.

Limited Complexity: The methods are more suited to simpler problems. Poor Fit: In practice the methods are unlikely to match the underlying mapping function.

Multi-Variable Linear Regression

statsmodels.regression.linear_model.OLS

In [75]:
```
# set song_popularity to be predicted value y
# set (acousticness  danceability  instrumentalness  loudness audio_valence play list) to be X

# Note the difference in argument order
model = sm.OLS(np.asarray(y_train), np.asarray(X_train)).fit()
y_pred = model.predict(np.asarray(X_test)) # make the predictions by the model
```

In [76]:
```
model.summary()
```

Out[76]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.836
Model:	OLS	**Adj. R-squared:**	0.836
Method:	Least Squares	**F-statistic:**	1.510e+04
Date:	Tue, 11 Jun 2019	**Prob (F-statistic):**	0.00
Time:	18:08:05	**Log-Likelihood:**	-67905.
No. Observations:	14850	**AIC:**	1.358e+05
Df Residuals:	14845	**BIC:**	1.359e+05
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
x1	2.9243	0.807	3.626	0.000	1.343	4.505
x2	53.0726	0.873	60.822	0.000	51.362	54.783
x3	-0.5717	0.958	-0.597	0.551	-2.450	1.307
x4	-1.4304	0.059	-24.258	0.000	-1.546	-1.315
x5	12.9436	0.822	15.754	0.000	11.333	14.554

Omnibus:	209.160	**Durbin-Watson:**	1.984
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	217.512
Skew:	-0.294	**Prob(JB):**	5.86e-48
Kurtosis:	2.930	**Cond. No.**	49.5

From the model training summary, we could obeserve that the 95% confidence interval for the 5 parameters trained.

In [77]:

```
#print('params', model.params)
print('tvalues',model.tvalues)

print("The model is:","\n song_popularity = ",  model.params[0],"*acousticness","\n",
      model.params[1],"*danceability",model.params[2],"*instrumentalness","\n",
        model.params[3],"*loudness",model.params[4],"*audio_valence")
```

```
tvalues [  3.62567816  60.8221414   -0.59652797 -24.25816397  15.754115
83]
The model is:
 song_popularity =  2.92429180428 *acousticness
 53.0726101337 *danceability -0.57166234799 *instrumentalness
 -1.43042645297 *loudness 12.9435509189 *audio_valence
```

In [78]:
```
#visualize the result
df_reg = pd.DataFrame( y_test.values, columns = ['actual_song_popularity'], index
=y_test.index)
df_reg['predict_song_popularity'] = y_pred
df_reg
```

Out[78]:

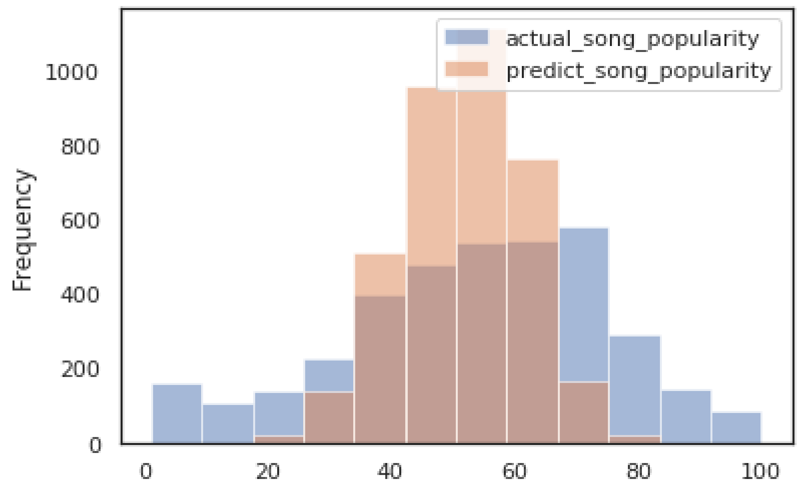
	actual_song_popularity	predict_song_popularity
song_name		
Out My Way/ Around You (feat. Marr Grey, RELLA, July 7 & Devin Tracy)	44	56.022159
You Can Cry	72	40.938954
My Number	72	53.992895
Once I Loved	59	63.931513
Have Love Will Travel	55	56.847152
Macarena	62	61.772959
IDGAF	89	61.841387
Worst Comes To Worst - Edited	53	58.209548
When I Come Around	74	30.282736
Evening Buffalo	58	50.525015
tokyo glo remix	46	50.007174
Bands on Me (feat. Blac Youngsta, A Boogie Wit Da Hoodie & Teejay3k)	61	76.171227
Cómo Los Vaqueros	55	64.357782
Big Fish	69	52.685824
Missin You Crazy	81	53.281327
Mo Bamba	90	46.399834
No One Knows	13	48.366566
Maps	60	72.518100
Mi Muñeca Me Habló	36	67.749204
City Looks Pretty	32	48.976743
The Wanting	9	43.818353
Latinos	16	44.542137
Alas de Papel	35	60.180162
What a Difference You've Made in My Life	34	59.277773
Locomia	48	53.683596
The Time I've Wasted	63	58.512793
Stone	65	51.318981

	actual_song_popularity	predict_song_popularity
song_name		
Favela	82	60.073168
Walk on the Wild Side	18	43.793611
Fighter	69	48.486455
...	...	...
Visions	58	54.147669
Itchycoo Park	49	49.600982
Roly-Poly	28	56.695414
Inocente Pobre Amiga	44	57.253850
Un gaou à Oran - Bonus track	48	58.059429
Shout, Pts. 1 & 2	61	72.518100
AND WHAT	57	73.959718
Atento Al Lobo	41	41.462794
totoba	46	35.954284
No Stylist	91	61.150398
Cry, Cry, Cry - Long Version	30	59.698137
Lonely Days	50	72.093567
On The Run (feat. Offset)	76	51.109135
Drop It Like It's Hot	36	60.624099
4:21 (Con María)	18	44.166527
Zooted (feat. French Montana & Farruko)	74	54.450512
The Mother We Share	58	59.135718
Killshot	91	49.603586
Jolene	67	51.949799
My Hero	69	49.613565
Es Por Tí	72	34.464812
Youngblood	90	69.345300
Cosmic Cave	48	54.889212
No Brainer	94	62.390252
Falling Down	97	65.877878
Young Lovers	32	28.530405
Two Weeks	58	55.194387

	actual_song_popularity	predict_song_popularity
song_name		
Young Dumb & Broke	87	53.484642
Shots	36	53.128853
Blur	51	59.885188

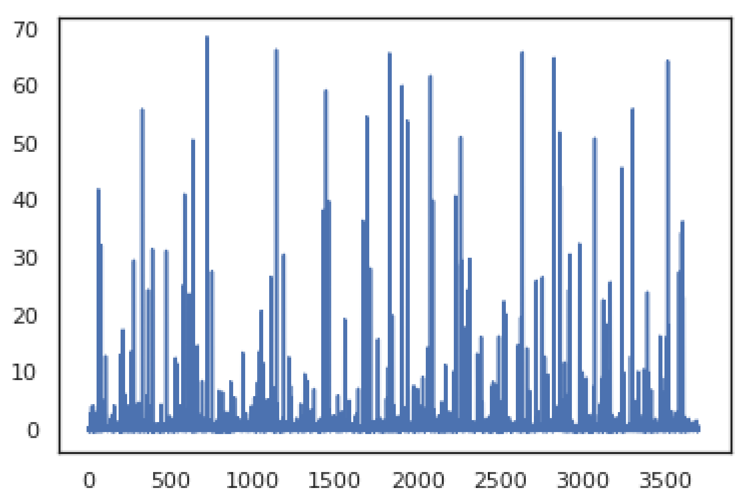
3713 rows × 2 columns

In [79]:
```
# to view the distribution difference
ax = df_reg.plot.hist(bins=12, alpha=0.5)
```



In [115]:
```
#loss
loss_ratio = (df_reg.predict_song_popularity - df_reg.actual_song_popularity)/df_reg
.actual_song_popularity
index = range(len(loss))
plt.plot(index,loss)
```

Out[115]: `[<matplotlib.lines.Line2D at 0x7fc5d34a06a0>]`



Data Analysis & Results

Feature Analysis:

1. Distribution: We print distribution alongside all features. We print the histograms of all the different features of the songs, including the song popularity after the song data and information has been combined into a single dataframe. Additionally, we have a histogram of the song popularity compared to the normal curve to get an initial idea of what the data looks like before any data cleaning and manipulation. Histograms are appropriate here because we are able to compare large quantities of songs against certain dimensions that we care about.
2. Relevance: For this section, we are analyzing the correlation between song features. We are using a range of -1 to 1 to measure the correlation. Any negative number means that there is a negative correlation and any positive number means that there is a positive correlation. The correlation of each feature will be calculated relating to popularity. In this instance, we use a heatmap to see what is more positively correlated with popularity. We use a heat map because it allows us to easily see the features and how they are correlated with popularity. The more pink the color, the more correlated the feature is to popularity. When looking at the heatmap, we can see that loudness, danceability, and energy are most positively correlated with popularity. Similarly, acousticness is the least correlated with popularity.

Data Cleaning

For data cleaning, we started by filtering to only the song features that we care about. This essentially meant dropping the 'album_names' and 'artist_name'. Then, we assigned one-hot encoding to the features, encoding 300 of them in order to help us with the prediction part later.

We also use the result from the previous observation of statistics, to rule out several factors. After observed the pair-grid map, we decided to rule out time_signature and audio_mode and key.

Most significantly, we print the relevance, and rule out every factors that is has less that 0.05 with our target song_popularity.

Result

We measure the loss as : pred-actual / actual, as a ratio. According to the loss of OLS linear model, we observe that this model is not as accurate as we thought.

Some of the predict_song_popularity were much more greater than the actual, and some of the predict_song_popularity were huge less than the actual, which mean the result model is polarizing while compare the actual song's popularity.

Ethics & Privacy

We took our data from kaggle.com, which is a public database made specifically for data science work. We've only used and analyzed retrieved from the site, so permissions of use and privacy concerns have already been filtered by the site prior to use.

Because we took our data from the site, there are limitations to our analysis that stem from this. For instance, we can only analyze and use the song features that were listed in the song. However, by carefully choosing features that best characterize songs, we can still derive a close approximation. Another bias we should be mindful of in our analysis is that certain songs may be more similar to another because they are of the same genre. In this case, finding more salient features of the song such as tempo to be similar would be redundant. We can mitigate this issue, however, by also analyzing other features of the song that are not homogeneous across those of the same genre.

Additionally, although the usage of data may not have been an issue, we should still be considerate of the potential issues with distribution of the conclusions drawn from the data. For instance, that this information won't result in an abusive inclusion of the features in hopes of gaining more popularity in a song. Although we, personally, may not use it for unethical marketing purposes, we should still try to ensure that such a thing may not happen.

Conclusion & Discussion

Q1. Do popular songs have similar attributes? Yes, they do have similar attributes. After dropping attributes that have low relevance with song_popularity, we got the rest factors:

Q2. If popular songs do have similar attributes, can we predict what song will be the next “hit”? We have obtained a model based on the datasets. However the test accuracy was not really high.

Even through our model did not have the higher accuracy to shows verify our hypothesis, but by the work we have done, we are still believe that the popular songs have the similar attributes. Because after clean the data with dropping the low relevance attribution with song_popularity, we have attribution has the high relevance with the song_popularity: acousticness, danceability, instrumentalness, loudness, audio_valence.
From the data we found, we make the prediction about the song’s popularity and also compare with the one in the data, which shows our prediction did not same as the popularity in the data, even not closing to it. From the graph shows the difference between the song’s popularity we predict and actual one, we can see the dipolar result in the predict and actual one. The way we work on should be the correct one but some detail we should not overlook make this failure.

Future work Since the model did not work as we except, which makes us to think is what are the attribution really affect the song popularity, are the every high relevance attribution affect the song popularity in the same weight? Is possible that some of high relevance attribution affect the song popularity more than other? And think deeper, does the attribution affect the song’s popularity change as time change? There are many and many different possibility about attribution affect the songs popularity. We have much more to work on and to found the what exactly affect the song’s popularity.

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