Analysis of Song Popularity on Spotify

This project is to determine what factors help determine the popularity of a song, and to what extent these factors relate to a song's popularity. The dataset used contains songs from 1921-2020 and includes many variables.

Acouticness, Danceability, Energy, Instrumentalness, Liveness, Speechniness, and Valence are all variables with a range of 0-1 describing as a percentage how well the song reflects the given variablses. So a song with a danceability of 96%, for instance, would be a song considered extremely danceable.

Valence describes how positive a song is considered.

Mode is a dummy variable showing if the song was began with a major or minor chord progression. One equals major; zero equals minor.

Explicit is a dummy variable showing if the song contains explicit content. One equals explicit content; zero equals no explicit content.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
data= pd.read_csv([redacted])
data_artist= pd.read_csv ([redacted])
data_genre = pd.read_csv ([redacted])
data_year = pd.read_csv ([redacted])
data_w_genre = pd.read_csv ([redacted])
```

In [3]:
```
data=data.drop('id', axis=1)
data.head()
```

Out[3]:

	valence	year	acousticness	artists	danceability	duration_ms	energy	explicit	insti
0	0.0594	1921	0.982	['Sergei Rachmaninoff', 'James Levine', 'Berli...	0.279	831667	0.211	0	
1	0.9630	1921	0.732	['Dennis Day']	0.819	180533	0.341	0	
2	0.0394	1921	0.961	['KHP Kridhamardawa Karaton Ngayogyakarta Hadi...	0.328	500062	0.166	0	
3	0.1650	1921	0.967	['Frank Parker']	0.275	210000	0.309	0	
4	0.2530	1921	0.957	['Phil Regan']	0.418	166693	0.193	0	

In [4]:
```
data_artist.head()
```

Out[4]:

	mode	count	acousticness	artists	danceability	duration_ms	energy	instrumentali
0	1	9	0.590111	"Cats" 1981 Original London Cast	0.467222	250318.555556	0.394003	0.01
1	1	26	0.862538	"Cats" 1983 Broadway Cast	0.441731	287280.000000	0.406808	0.08
2	1	7	0.856571	"Fiddler On The Roof" Motion Picture Chorus	0.348286	328920.000000	0.286571	0.02
3	1	27	0.884926	"Fiddler On The Roof" Motion Picture Orchestra	0.425074	262890.962963	0.245770	0.07
4	1	7	0.510714	"Joseph And The Amazing Technicolor Dreamcoat"...	0.467143	270436.142857	0.488286	0.00

In [5]:
```
data_genre.head()
```

Out[5]:

	mode	genres	acousticness	danceability	duration_ms	energy	instrumentalness	livenes
0	1	21st century classical	0.979333	0.162883	1.602977e+05	0.071317	0.606834	0.3616(
1	1	432hz	0.494780	0.299333	1.048887e+06	0.450678	0.477762	0.1310(
2	1	8-bit	0.762000	0.712000	1.151770e+05	0.818000	0.876000	0.1260(
3	1	[]	0.651417	0.529093	2.328809e+05	0.419146	0.205309	0.2186(
4	1	a cappella	0.676557	0.538961	1.906285e+05	0.316434	0.003003	0.1722(

In [6]:
```
data_year.head()
```

Out[6]:

	mode	year	acousticness	danceability	duration_ms	energy	instrumentalness	liveness
0	1	1921	0.886896	0.418597	260537.166667	0.231815	0.344878	0.205710
1	1	1922	0.938592	0.482042	165469.746479	0.237815	0.434195	0.240720
2	1	1923	0.957247	0.577341	177942.362162	0.262406	0.371733	0.227462
3	1	1924	0.940200	0.549894	191046.707627	0.344347	0.581701	0.235219
4	1	1925	0.962607	0.573863	184986.924460	0.278594	0.418297	0.237668

In [7]:
```
data_w_genre.head()
```

Out[7]:

	genres	artists	acousticness	danceability	duration_ms	energy	instrumentalness
0	['show tunes']	"Cats" 1981 Original London Cast	0.590111	0.467222	250318.555556	0.394003	0.011400
1	[]	"Cats" 1983 Broadway Cast	0.862538	0.441731	287280.000000	0.406808	0.081158
2	[]	"Fiddler On The Roof" Motion Picture Chorus	0.856571	0.348286	328920.000000	0.286571	0.024593
3	[]	"Fiddler On The Roof" Motion Picture Orchestra	0.884926	0.425074	262890.962963	0.245770	0.073587
4	[]	"Joseph And The Amazing Technicolor Dreamcoat"...	0.510714	0.467143	270436.142857	0.488286	0.009400

In [8]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 170653 entries, 0 to 170652
Data columns (total 18 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   valence           170653 non-null  float64
 1   year              170653 non-null  int64  
 2   acousticness      170653 non-null  float64
 3   artists           170653 non-null  object 
 4   danceability      170653 non-null  float64
 5   duration_ms       170653 non-null  int64  
 6   energy            170653 non-null  float64
 7   explicit          170653 non-null  int64  
 8   instrumentalness  170653 non-null  float64
 9   key               170653 non-null  int64  
 10  liveness          170653 non-null  float64
 11  loudness          170653 non-null  float64
 12  mode              170653 non-null  int64  
 13  name              170653 non-null  object 
 14  popularity        170653 non-null  int64  
 15  release_date      170653 non-null  object 
 16  speechiness       170653 non-null  float64
 17  tempo             170653 non-null  float64
dtypes: float64(9), int64(6), object(3)
memory usage: 23.4+ MB
```

Based on the non-null values, there's doesn't appear to be any null values in the first dataset. Still, it's best to double check to make sure.

In [9]:
```
data.isnull().sum()
```

Out[9]:
```
valence             0
year                0
acousticness        0
artists             0
danceability        0
duration_ms         0
energy              0
explicit            0
instrumentalness    0
key                 0
liveness            0
loudness            0
mode                0
name                0
popularity          0
release_date        0
speechiness         0
tempo               0
dtype: int64
```

In [10]:
```
data_genre.isnull().sum()
```

Out[10]:
```
mode                0
genres              0
acousticness        0
danceability        0
duration_ms         0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
valence             0
popularity          0
key                 0
dtype: int64
```

In [11]:
```
data.describe()
```

Out[11]:

	valence	year	acousticness	danceability	duration_ms	energ
count	170653.000000	170653.000000	170653.000000	170653.000000	1.706530e+05	170653.00000
mean	0.528587	1976.787241	0.502115	0.537396	2.309483e+05	0.48238
std	0.263171	25.917853	0.376032	0.176138	1.261184e+05	0.26764
min	0.000000	1921.000000	0.000000	0.000000	5.108000e+03	0.00000
25%	0.317000	1956.000000	0.102000	0.415000	1.698270e+05	0.25500
50%	0.540000	1977.000000	0.516000	0.548000	2.074670e+05	0.47100
75%	0.747000	1999.000000	0.893000	0.668000	2.624000e+05	0.70300
max	1.000000	2020.000000	0.996000	0.988000	5.403500e+06	1.00000

Some basic exploratory analysis. There are some interesting numbers that would be worth looking into later. Both the amount of instrumentalnes and speechiness in these songs skewy low. The explicit mean of .846 shows that most songs produced since 1921 contains the use of explicit language. Seeing how this relates to year and popularity can be interesting. Finally a mode mean of .71 shows that most songs since 1921 have begun with a major chord progression.

The big feature to make note of is popularity. While the popularity metric is a number between the range of 1 and 100, the average popularity is onl 31.43. This means that most songs on Spotify are not very popular. Popularity also has a standard deviation of nearly 22, a little over a fifth of its whole range. These two statistics together show that distribution for popularity won't be even, and there will almost definitely be outliers in the distribution.

In [12]:
```
data_corr= data.corr()
data_corr
```

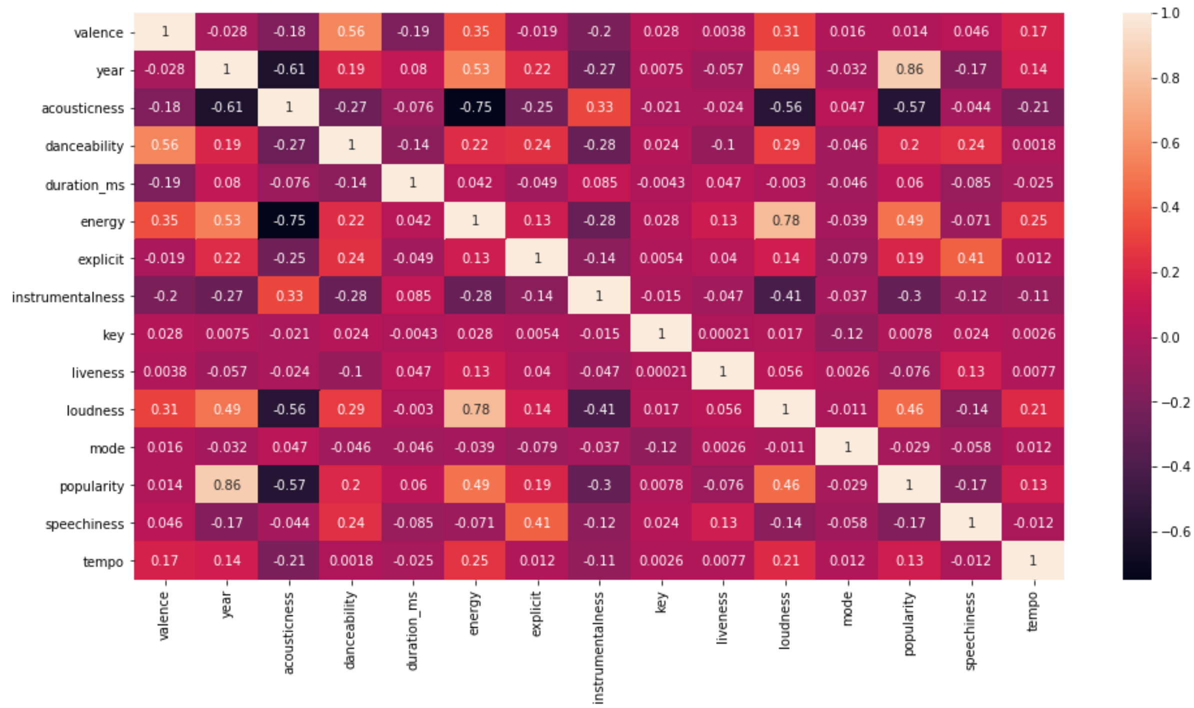
Out[12]:

	valence	year	acousticness	danceability	duration_ms	energy	ex
valence	1.000000	-0.028245	-0.184101	0.558946	-0.191813	0.353876	-0.01
year	-0.028245	1.000000	-0.614250	0.188515	0.079713	0.530272	0.22
acousticness	-0.184101	-0.614250	1.000000	-0.266852	-0.076373	-0.749393	-0.24
danceability	0.558946	0.188515	-0.266852	1.000000	-0.139937	0.221967	0.24
duration_ms	-0.191813	0.079713	-0.076373	-0.139937	1.000000	0.042119	-0.04
energy	0.353876	0.530272	-0.749393	0.221967	0.042119	1.000000	0.13
explicit	-0.018613	0.220881	-0.246007	0.241757	-0.048880	0.132723	1.00
instrumentalness	-0.198501	-0.272371	0.329819	-0.278063	0.084770	-0.281101	-0.14
key	0.028473	0.007540	-0.020550	0.024439	-0.004266	0.027705	0.00
liveness	0.003832	-0.057318	-0.024482	-0.100193	0.047168	0.126192	0.03
loudness	0.313512	0.487697	-0.561696	0.285057	-0.003037	0.782362	0.14
mode	0.015641	-0.032385	0.047168	-0.045956	-0.046085	-0.039260	-0.07
popularity	0.014200	0.862442	-0.573162	0.199606	0.059597	0.485005	0.19
speechiness	0.046381	-0.167816	-0.043980	0.235491	-0.084604	-0.070555	0.41
tempo	0.171689	0.141048	-0.207120	0.001801	-0.025472	0.250865	0.01

This looks pretty dry though, so let's pretty it up a bit!

In [13]:
```
plt.figure(figsize=(16, 8))
sns.heatmap(data_corr,annot=True)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x142d09bf1c8>



In [14]:
```
data_corr["popularity"].sort_values(ascending=False)
```

Out[14]:
```
popularity          1.000000
year                0.862442
energy              0.485005
loudness            0.457051
danceability        0.199606
explicit            0.191543
tempo               0.133310
duration_ms         0.059597
valence             0.014200
key                 0.007826
mode               -0.028897
liveness           -0.076464
speechiness        -0.171979
instrumentalness   -0.296750
acousticness       -0.573162
Name: popularity, dtype: float64
```

Based on the heatmap, a song's popularity in the original dataset is most correlated to the year the song was released. In this case, that means that the later a song was released, the more popular a song was. Or in other words, there is strong recency bias when it comes to a song's popularity. It also has a pretty strong positive correlation to the song's energy and its loudness. On the other hand, it has a signficiant negative correlations to a song's acousticness and instrumentalness.

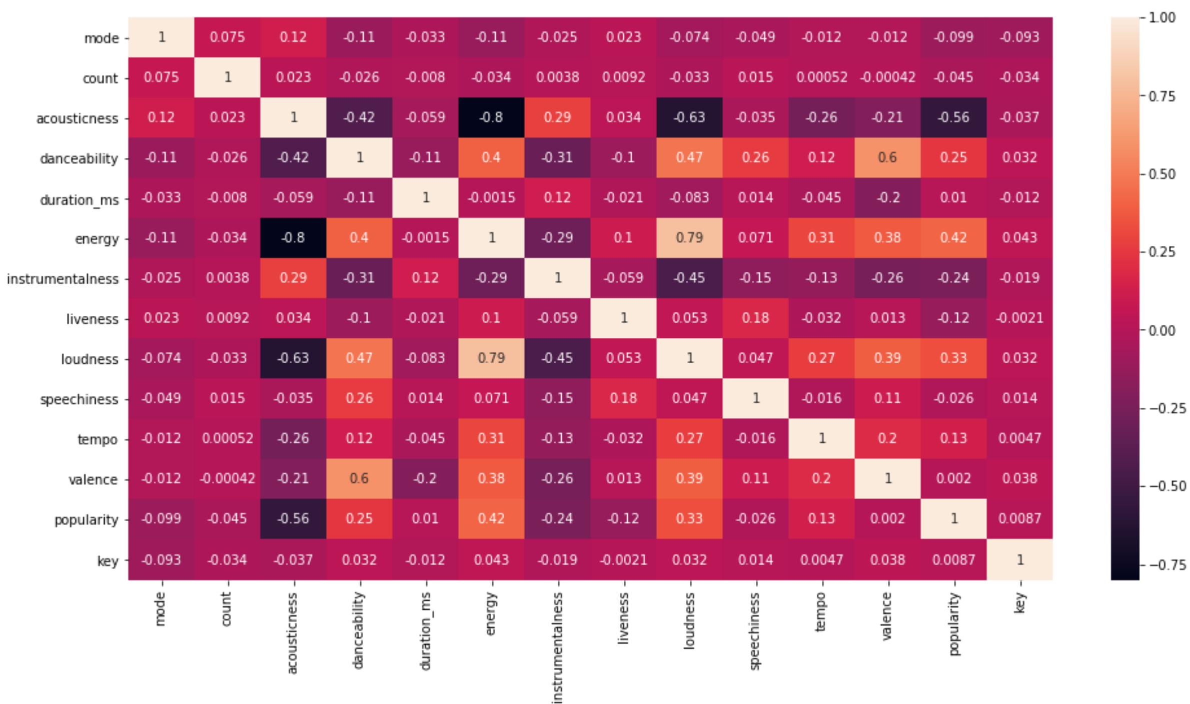
As loudness and energy are both positively correlated to popularity, it's worth pointing out that the two features are also significantly correlated with each other as .78.

So what about the correlations for the other datasets?

In [15]:
```
data_artist_corr= data_artist.corr()
data_year_corr= data_year.corr()
data_genre_corr= data_genre.corr()
data_w_genre_corr= data_w_genre.corr()
```

In [16]:
```
plt.figure(figsize=(16, 8))
sns.heatmap(data_artist_corr,annot=True)
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x142d09bf6c8>

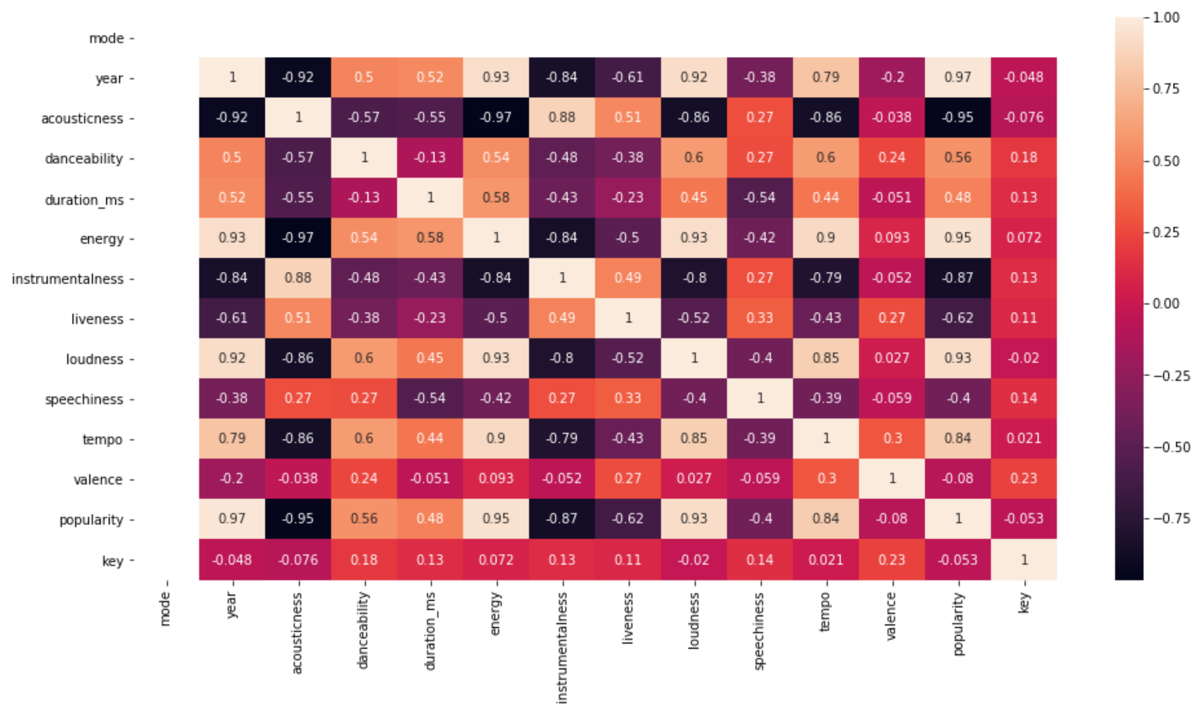


In [17]:
```
data_artist_corr["popularity"].sort_values(ascending=False)
```

Out[17]:
```
popularity          1.000000
energy              0.415092
loudness            0.332941
danceability        0.246283
tempo               0.132922
duration_ms         0.010137
key                 0.008743
valence             0.002005
speechiness        -0.025825
count              -0.044916
mode               -0.099185
liveness           -0.120099
instrumentalness   -0.235548
acousticness       -0.556790
Name: popularity, dtype: float64
```

In [18]:
```
plt.figure(figsize=(16, 8))
sns.heatmap(data_year_corr,annot=True)
```

Out[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x142cf3d65c8>
```

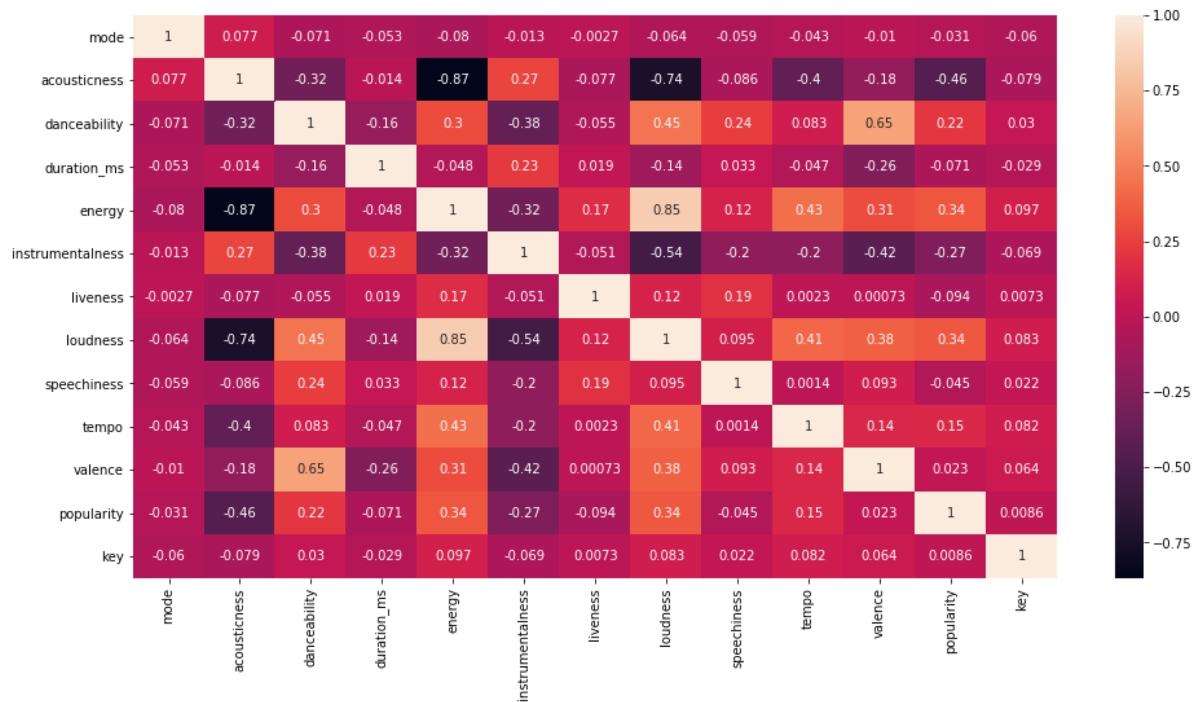


In [19]:
```
data_year_corr["popularity"].sort_values(ascending=False)
```

Out[19]:
```
popularity          1.000000
year                0.974517
energy              0.953637
loudness            0.928369
tempo               0.843231
danceability        0.560226
duration_ms         0.484321
key                -0.053469
valence            -0.079516
speechiness        -0.398338
liveness           -0.623418
instrumentalness   -0.872021
acousticness       -0.945010
mode                     NaN
Name: popularity, dtype: float64
```

In [20]:
```
plt.figure(figsize=(16, 8))
sns.heatmap(data_genre_corr,annot=True)
```

Out[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x142cf53ffc8>
```

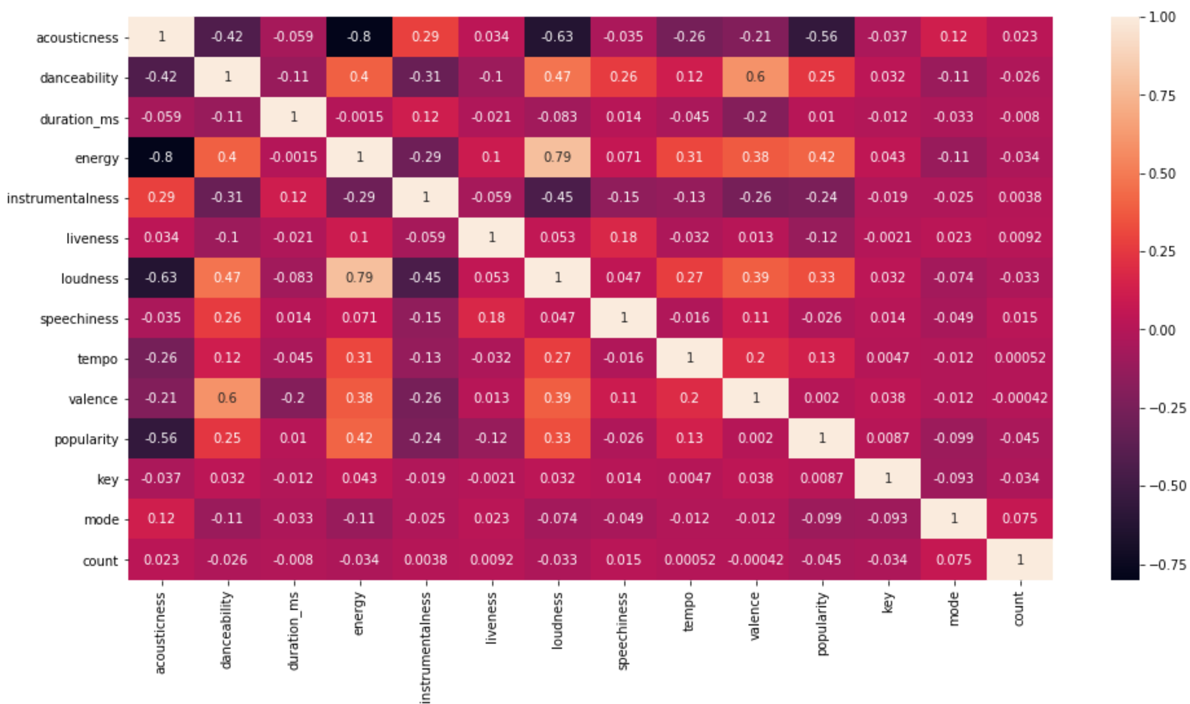


In [21]:
```
data_genre_corr["popularity"].sort_values(ascending=False)
```

Out[21]:
```
popularity          1.000000
loudness            0.344361
energy              0.337795
danceability        0.217992
tempo               0.146717
valence             0.023072
key                 0.008577
mode               -0.031231
speechiness        -0.045217
duration_ms        -0.071019
liveness           -0.094178
instrumentalness   -0.265449
acousticness       -0.458698
Name: popularity, dtype: float64
```

In [22]:
```
plt.figure(figsize=(16, 8))
sns.heatmap(data_w_genre_corr, annot=True)
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x142d1117088>
```



In [23]:
```
data_w_genre_corr["popularity"].sort_values(ascending=False)
```

Out[23]:
```
popularity          1.000000
energy              0.415092
loudness            0.332941
danceability        0.246283
tempo               0.132922
duration_ms         0.010137
key                 0.008743
valence             0.002005
speechiness        -0.025825
count              -0.044916
mode               -0.099185
liveness           -0.120099
instrumentalness   -0.235548
acousticness       -0.556790
Name: popularity, dtype: float64
```

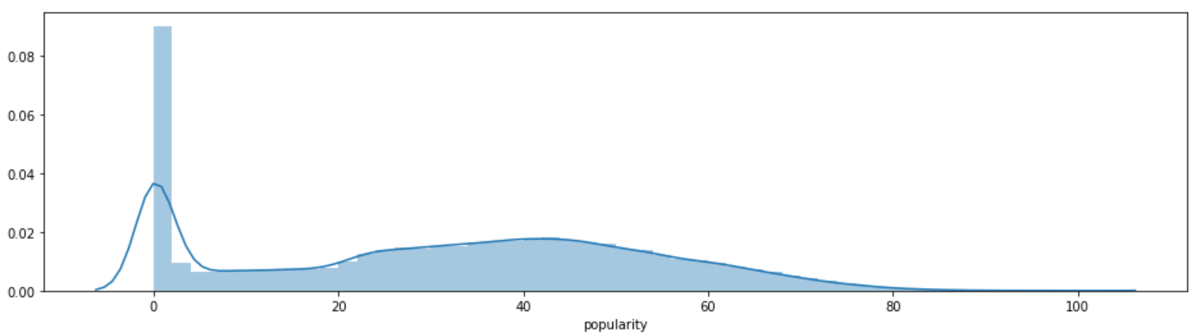
Most of the other datasets hold to the same relationship, though the data with songs grouped by year has some new, interesting relationships. In fact most of the features outside of the song's valence, or positivity, seems to correlate with its popularity in a some strong way.

Speechniness and Liveness are negatively correlated to it as well now, and tempo, energy, duration, and are all positively correlation to it.

So now that we know what features can give information on a song's popularity, what does the popularity variable look like in the dataset?

In [24]:
```
plt.figure(figsize=(16, 4))
sns.distplot(data["popularity"])
```

Out[24]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x142d1d90f88>
```

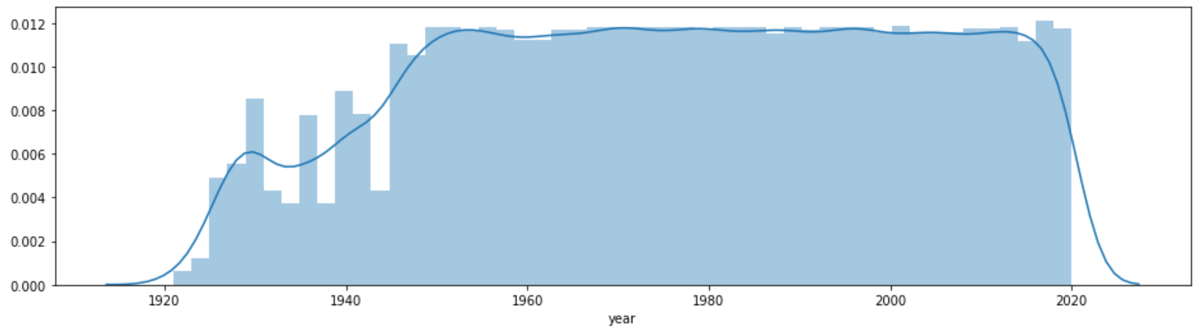


This is an extremely interesting distribution. Ignoring the outlier, this could be considered a fairly normal distrubition, if skewing ever so slightly to the left. With the outlier though, it's clear that the majority of songs uploaded to Spotify are not popular. This could be due to how many independent artists there are on the platform.

The outlier songs could be removed in order to simplify the dataset and potentially get more accurate relationships with popularity, but considering just how many songs fall within the range, I'll keep them for now.

In [25]:
```
plt.figure(figsize=(16, 4))
sns.distplot(data["year"])
```

Out[25]: `<matplotlib.axes._subplots.AxesSubplot at 0x142d17eb5c8>`



As one would expect, the periods between 1921-1950 show a ramping up of music featured on Spotify. There was a dip in the 1930's, probably due to the Great Depression severely hampering the markets for many luxury goods, including music, but they grew regardless.

What is surprising is that the amount of songs between 1950-2020 has been consistent. Spotify holds a similar amount of songs from 1960 as they do from 2020. My initial assumption would be that the amount of songs would continue to rise after 1950, especially given the boon Spotify and other such services have been for independent artists. But that does not seem to be the case.

Finally, it might be hard to properly analyze some of the years before 1950. especially the years in the 1920's. This is due to such few songs being on Spotify for them. It would be hard to determine is a certain feature of a song is unique to the song, or an aspect of the music industry of the year more generally.

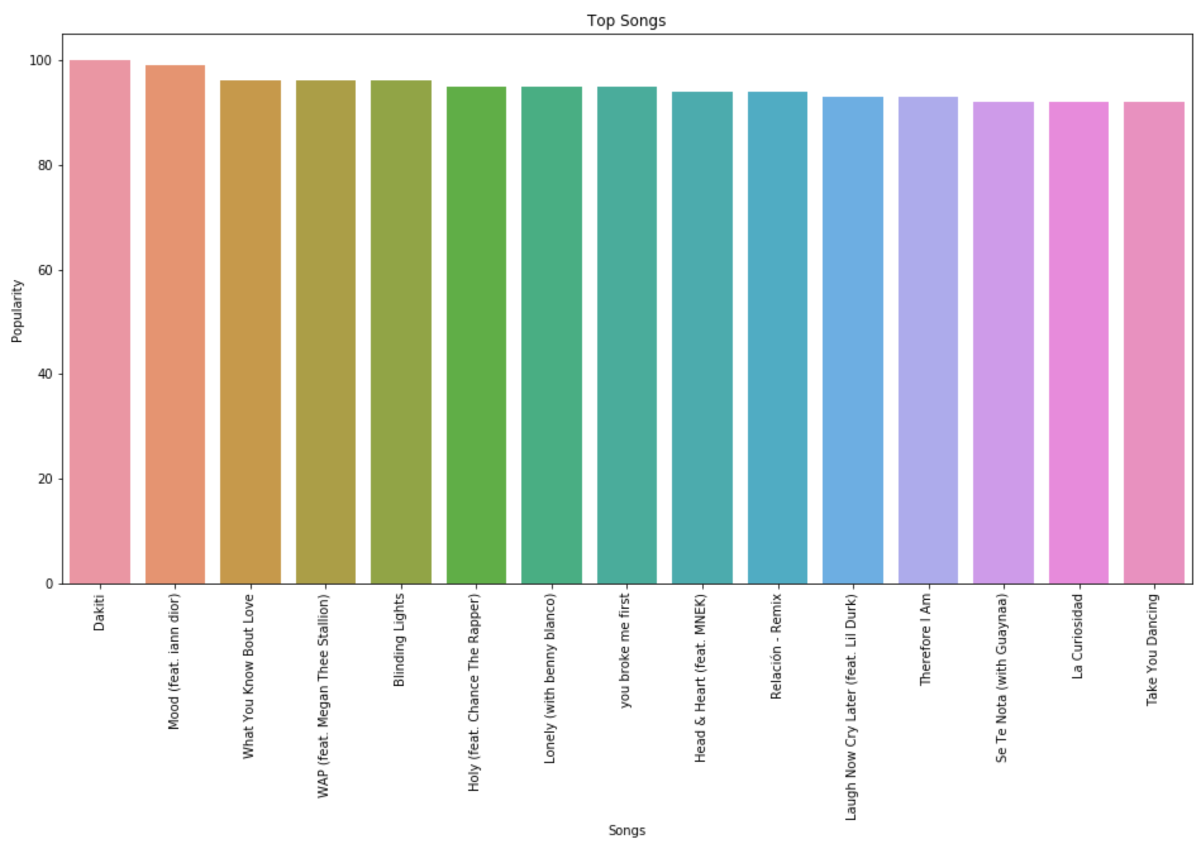
Now what are the most popular songs on Spotify?

In [26]:

```
plt.figure(figsize=(16, 8))
x = data.groupby("name")["popularity"].mean().sort_values(ascending=False).hea
d(15)
axis = sns.barplot(x.index, x)
axis.set_title('Top Songs')
axis.set_ylabel('Popularity')
axis.set_xlabel('Songs')
plt.xticks(rotation = 90)
```

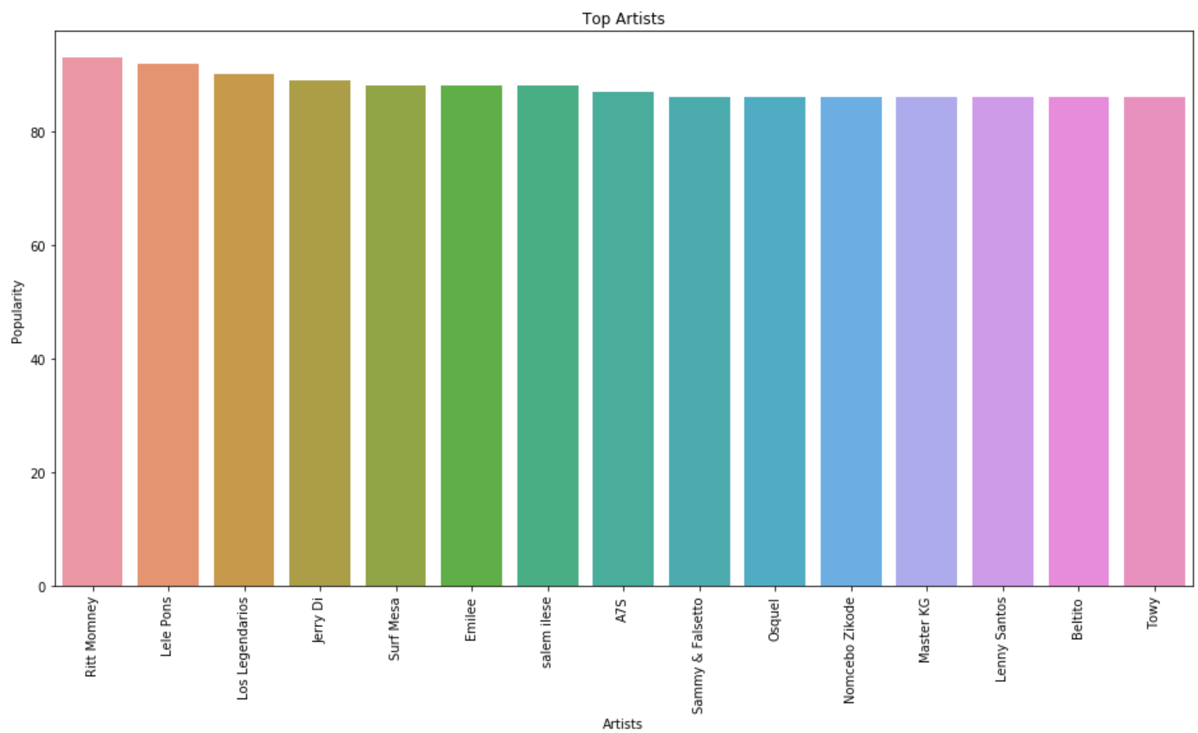
Out[26]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14]),
 <a list of 15 Text xticklabel objects>)
```



In [27]:
```
plt.figure(figsize=(16, 8))
x = data_artist.groupby("artists")["popularity"].sum().sort_values(ascending=False).head(15)
ax = sns.barplot(x.index, x)
ax.set_title('Top Artists')
ax.set_ylabel('Popularity')
ax.set_xlabel('Artists')
plt.xticks(rotation = 90)
```

Out[27]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14]),
 <a list of 15 Text xticklabel objects>)
```



As the graphs show, the most popular songs and artists from the collection of this data appear to be the more recent ones on the platform. This holds with the high correlation seen between the year a song is released and its popularity.

Now that we have a good grasp of the datasets we are working with, we can safely move on to building a model.

Model Building

As the initial question of this study was 'What determines a song's popularity on Spotify?', we will be building a model based off 'popularity' being the predicted variable, and the other factors being potential predictor variables.

To start out with, I'll be dropping the use of all but the first dataset. The other datasets either have too few datapoints to be useful for model building or would be irrelevant to the question at hand. Therefore, we'll stick with the original dataset. Also, we should split the data into a training test and a testing set. This is so we make sure that we don't overfit our models to the data we have, and it'll be better prepared for any new data going forward.

In [28]:
```
data=data.drop(["name", "artists", "release_date"], axis=1)
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

data_train_set, data_test_set = train_test_split(data, test_size=0.33, random_
state=42)
```

In [29]:
```
data_train_set.head()
```

Out[29]:

	valence	year	acousticness	danceability	duration_ms	energy	explicit	instrumentalne
125020	0.329	1930	0.987	0.466	183400	0.240	0	0.0001
95445	0.317	1953	0.900	0.326	199907	0.402	0	0.8390
48551	0.553	1976	0.018	0.427	386667	0.730	0	0.0003
34968	0.472	2002	0.265	0.699	254467	0.668	0	0.0000
31555	0.158	1985	0.968	0.336	239467	0.167	0	0.0014

In [30]:
```
data_train_set2= data_train_set.drop("popularity", axis=1)
data_labels= data_train_set["popularity"].copy()
```

In [31]:
```
data_train_set2.head()
```

Out[31]:

	valence	year	acousticness	danceability	duration_ms	energy	explicit	instrumentalne
125020	0.329	1930	0.987	0.466	183400	0.240	0	0.0001
95445	0.317	1953	0.900	0.326	199907	0.402	0	0.8390
48551	0.553	1976	0.018	0.427	386667	0.730	0	0.0003
34968	0.472	2002	0.265	0.699	254467	0.668	0	0.0000
31555	0.158	1985	0.968	0.336	239467	0.167	0	0.0014

Now it's time to standardize the data. Since the data uses different scales, it's best to standardize the scaling so that the different scaling doesn't mess up their determinative capabilities.

In [32]:
```
pipe = Pipeline([('std', StandardScaler())])
pipe.fit(data_train_set2, data_labels)
```

Out[32]:
```
Pipeline(memory=None,
         steps=[('std',
                 StandardScaler(copy=True, with_mean=True, with_std=True))],
         verbose=False)
```

This model will start with a simple linear regression. They are often the best way to start off modeling for a continous predicted variable like popularity.

In [34]:
```
scaler=StandardScaler().fit(data_train_set2)
data_train_scaled = scaler.transform(data_train_set2)

from sklearn.linear_model import LinearRegression

reg= LinearRegression()
reg.fit(data_train_scaled, data_labels)
```

Out[34]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Fals
e)
```

In [35]:
```
experiment_labels = data_labels.iloc[:5]
reg.predict(data_train_scaled[:5])
```

Out[35]:
```
array([-0.30200639,  9.53349374, 33.44509239, 50.10280427, 36.35057419])
```

In [36]:
```
print(list(experiment_labels))
```

```
[0, 0, 39, 57, 43]
```

In [37]:
```
from sklearn.metrics import mean_squared_error
data_predict = reg.predict(data_train_scaled)
mse= mean_squared_error(data_labels, data_predict)
rmse= np.sqrt(mse)
rmse
```

Out[37]:
```
10.854295899445983
```

After the model was created, I decided to test it in two ways. The first way was by feeding it back in some data from the training set. I could've also used the test set, but I don't want the test set to be used against the model as that might accidentally overfit the model to the test set. It's best to bring in the test set only after the model has been fully tuned.

So with the first experiment, which took the first five data points in the training set, we see that the model predicted they'd have a popularity of -.3. 9.5, 33.44. 50.1. and 36.4. This data is also scaled differently than the original, being on a 0-100 scale than a 0-1, so all the numbers need to be divided by 100 to reach their accurate numbers.

As for the actual values, we have 0, 0, 39, 57, and 43. Comparing that to -.003, .095, .334, .501, and .364, we see that the numbers weren't too far off. It was a good approximation at the least.

The RMSE basically gives the average error for the predicted variable. So the RMSE of 10.8 says that the popularity is typically off by around 10.8, which isn't the best. This model is slightly underfitting the data. Because of this, we should test out some other models and see how they perform with the data

In [38]:
```
from sklearn.ensemble import RandomForestRegressor
forest= RandomForestRegressor()
forest.fit(data_train_scaled, data_labels)
predictions= forest.predict(data_train_scaled)
tree_mse= mean_squared_error (data_labels, predictions)
tree_rmse = np.sqrt(tree_mse)
print(tree_rmse)
```

```
3.6977607948892675
```

An RMSE of 3.69 is better than our previous RMSE. This is more useful than the basic approximation our regression model gave us.

Of course it's important to understand what a random forest is. It's multiple decision trees run simultaneously, then averaging them out. As my computer can attest to, it's much more taxing and time consuming than a simple decision tree or linear regression, but it typically performs better.

With an RMSE of 3.69, there is a chance that my model overfit my data, meaning that, while it's accurate for the data given, it might not perform as well to any new data. I could check it by using Cross Validation or another parameter tuning method, but overall I'm satisfied with the model as is.

In [61]:
```
data_train_scaled[4:5]
```

Out[61]:
```
array([[-1.40954437,  0.31526891,  1.24153249, -1.14371999,  0.06951001,
        -1.18067758, -0.3027854 , -0.52784128, -0.90831316, -0.71590228,
         0.16005009, -1.55454636, -0.36692644,  0.36892391]])
```

In [59]:
```
record = [[-1.4,  0.32,  1.25, -1.140,  0.07,
        -1.2, -0.30 , -0.5, -0.91, -0.72,
         0.158, -1.56, -0.37,  0.38]]
final_pred = forest.predict(record)
final_pred
```

Out[59]:
```
array([40.33])
```

In [63]:
```
data_labels[4:5]
```

Out[63]:
```
31555    43
Name: popularity, dtype: int64
```

As a final test, I decided to run a test on a newly created song using the fifth record in the training set as its nearest neighbor. This means that the predicted popularity for this new song should be very similar to the given popularity of the fifth record if my model is performing correctly.

My model gave the new song an expected popularity of 40.33, while the song which is very similar to it had a popularity of 40.33. Considering the songs have different parameters, missing the expected popularity of 43 is great.