Music Taste Analysis

Ever been asked what sort of music you like and felt unable to describe it convincingly? This notebook represents my effort to once and for all answer the question, because, yes, I regard it to be this complicated.

How to Use

My first pass at this depended upon Watsonbox's Exportify, but I decided I didn't like his version because of bugs and inadequate output detail. So I went and forked it, cleaned up the code, and hosted it myself.

As such, the code here depends on `.csv` inputs in the format output by my version.

1. To get started, hop on over there, sign in to Spotify to give the app access to your playlists, and export whatever you like.
2. Next, either download this `.ipynb` file and run the notebook yourself or launch it in Binder.
3. Either put the downloaded `.csv` in the same directory as the notebook, or upload it in Binder.
4. Open the `.ipynb` through your browser, update the `filename` variable in the first code cell to point to your playlist instead, and `shift+enter` in each following code cell to generate the corresponding plot. (Or select `Cell` -> `Run All` from the menu to make all graphs at once.)

Read the Data

For years I've been accumulating my favorite songs in a single master playlist called `music that tickles my fancy`. It's thousands of songs. This is what I'll be analyzing. Let's take a look at the first few rows to get a sense of what we're dealing with.

In [1]:
```
filename = 'music_that_tickles_my_fancy.csv'

from matplotlib import pyplot
import seaborn
import pandas
from collections import defaultdict
from scipy.stats import pareto, gamma
```

```python
from datetime import date

# read the data
data = pandas.read_csv(filename)
print("total songs:", data.shape[0])
print(data[:3])
```

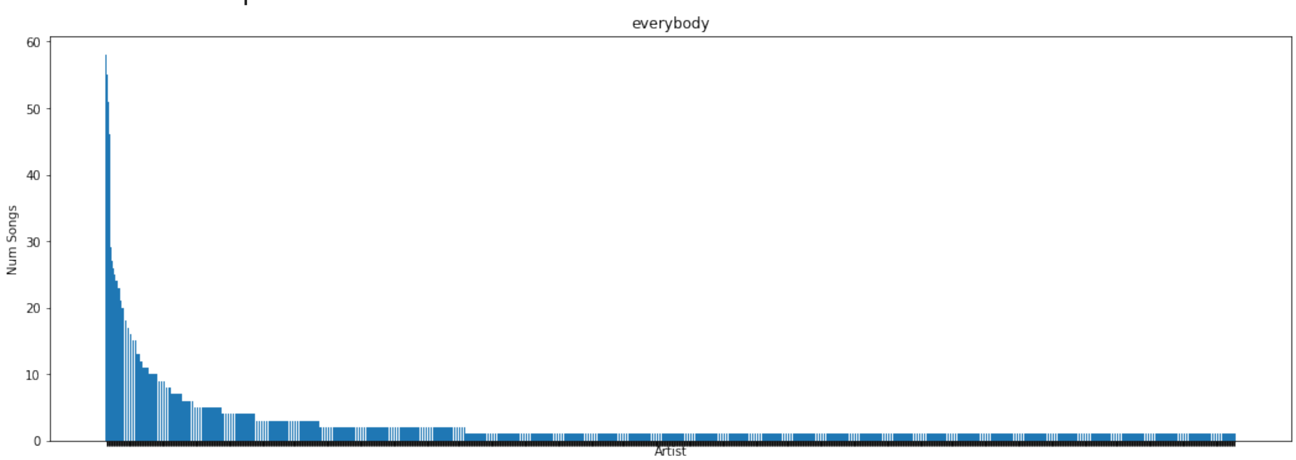
```
total songs: 3088
               Spotify ID                                     Artist IDs  \
0  3T9HSgS5jBFdXIBPav51gj  0nJvyjVTb8sAULPYyA1bqU,5yxyJsFanEAuwSM5kOuZKc
1  2bdZDXDoFLzazaomjzoER8                         1P6U1dCeHxPui5pIrGmndZ
2  1fE3ddAlmjJ99IIfLgZjTy                         0id62QV2SZZfvBn9xpmuCl

                Track Name  \
0  Fanfare for the Common Man
1           Highschool Lover
2            I Need a Dollar

                                       Album Name  \
0  Copland Conducts Copland - Expanded Edition (F...
1                                 Virgin Suicides
2                                 I Need A Dollar

                          Artist Name(s) Release Date  Duration (ms)  \
0  Aaron Copland,London Symphony Orchestra         1963         196466
1                                      Air         2000         162093
2                               Aloe Blacc   2010-03-16         244373

   Popularity             Added By             Added At  ... Key  Loudness
\
0          41  spotify:user:pvlkmrv  2014-12-28T00:57:17Z  ...  10   -15.727
1           0  spotify:user:pvlkmrv  2014-12-28T00:59:35Z  ...   1   -15.025
2           3  spotify:user:pvlkmrv  2014-12-28T01:03:38Z  ...   8   -11.825

   Mode  Speechiness  Acousticness  Instrumentalness  Liveness  Valence  \
0     1       0.0382         0.986             0.954    0.0575   0.0378
1     0       0.0302         0.952             0.959    0.2520   0.0558
2     0       0.0384         0.178             0.000    0.0863   0.9620

     Tempo  Time Signature
0  104.304               4
1  130.052               4
2   95.516               4

[3 rows x 23 columns]
```

Artist Bar Chart

Number of songs binned by artist.

In [2]:
```
# count songs per artist
artists = defaultdict(int)
for i,song in data.iterrows():
        for musician in song['Artist Name(s)'].split(','):
                artists[musician] += 1

# sort for chart
artists = pandas.DataFrame(artists.items(), columns=['Artist', 'Num Songs']
                          ).sort_values('Num Songs', ascending=False).reset_
print("number of unique artists:", artists.shape[0])

pyplot.figure(figsize=(18, 6))
pyplot.bar(artists['Artist'], artists['Num Songs'])
pyplot.xticks(visible=False)
pyplot.xlabel(artists.columns[0])
pyplot.ylabel(artists.columns[1])
pyplot.title('everybody')
pyplot.show()
```

```
number of unique artists: 1387
```



Note I've attributed songs with multiple artists to multiple bars, so the integral here is the number of unique song-artist pairs, not just the number of songs.

It seems to follow a Pareto distribution. Let's try to fit one.

In [3]:
```
# Let's find the best parameters. Need x, y data 'sampled' from the distribu
# parameter fit.
y = []
for i in range(artists.shape[0]):
        for j in range(artists['Num Songs'][i]):
                y.append(i) # just let y have index[artist] repeated for eac

# sanity check. If the dataframe isn't sorted properly, y isn't either.
#pyplot.figure()
#pyplot.hist(y, bins=30)
```

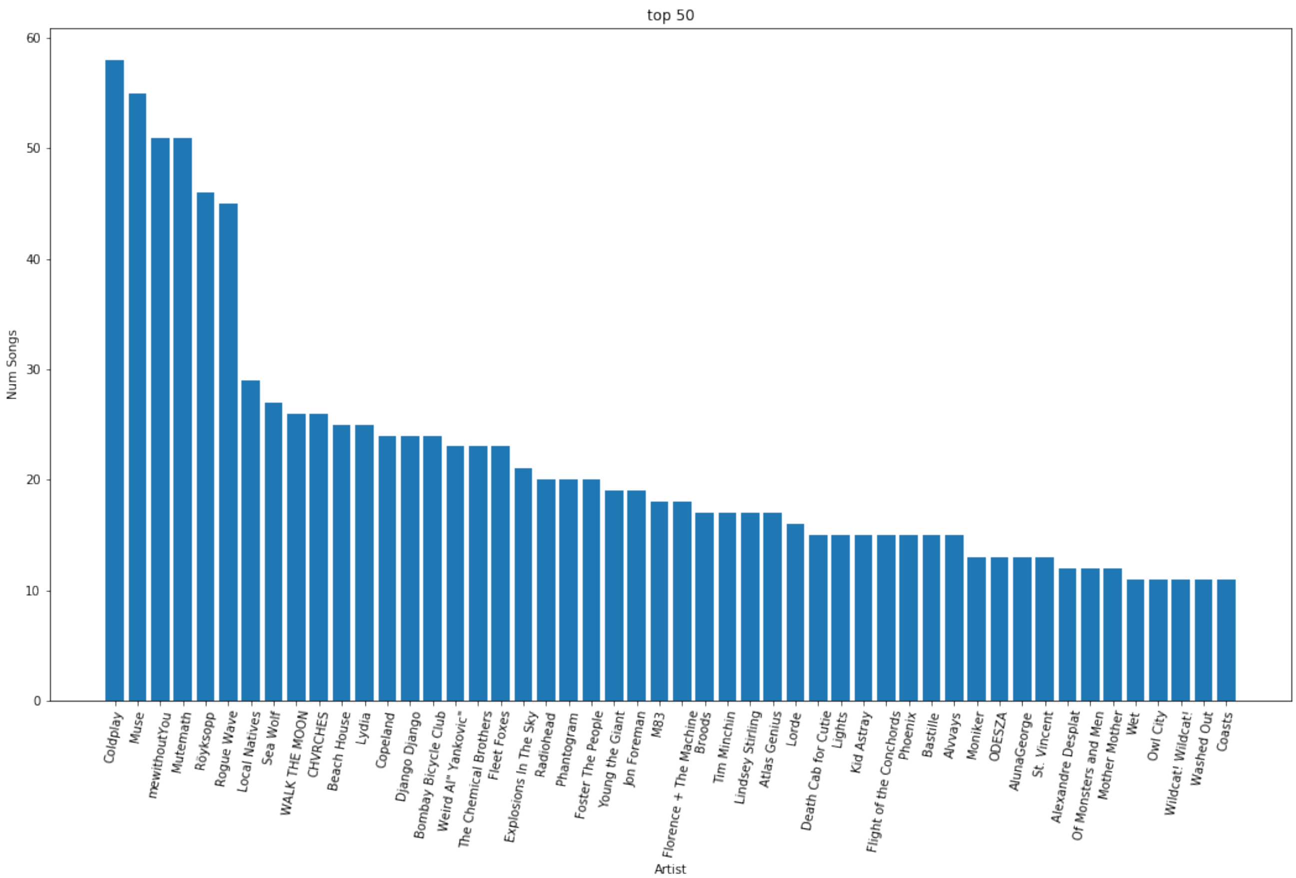
```
# The documentation is pretty bad, but this is okay:
# https://stackoverflow.com/questions/6620471/fitting-empirical-distributior
# ones-with-scipy-python
param = pareto.fit(y, 100)
pareto_fitted = len(y)*pareto.pdf(range(artists.shape[0]), *param)
# param = gamma.fit(y) # gamma fits abysmally; see for yourself by uncomment
# gamma_fitted = len(y)*gamma.pdf(range(artists.shape[0]), *param)

pyplot.figure(figsize=(18, 6))
pyplot.bar(artists['Artist'], artists['Num Songs'])
pyplot.plot(pareto_fitted, color='r')
#pyplot.plot(gamma_fitted, color='g')
pyplot.xticks(visible=False)
pyplot.xlabel(artists.columns[0])
pyplot.ylabel(artists.columns[1])
pyplot.title('everybody');
```

```
/home/pavel/.local/lib/python3.6/site-packages/scipy/stats/_distn_infrastruc
ture.py:2381: RuntimeWarning: invalid value encountered in double_scalars
  Lhat = muhat - Shat*mu
/home/pavel/.local/lib/python3.6/site-packages/scipy/stats/_distn_infrastruc
ture.py:1682: RuntimeWarning: divide by zero encountered in log
  return log(self._pdf(x, *args))
```

Best fit is still too sharp for the data, and I tried for a good long while to get it to fit better, so I conclude this doesn't *quite* fit a power law.

Let's plot the top 50 artists so we can actually read who they are.

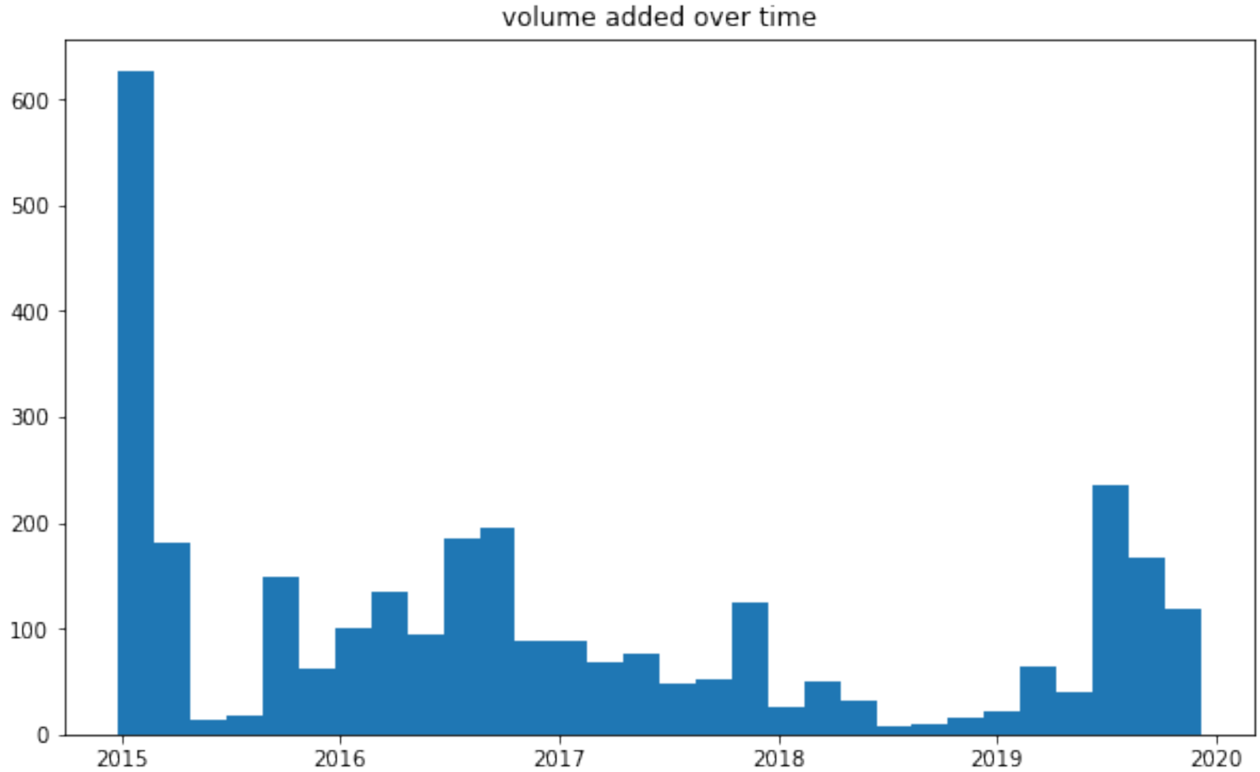
In [4]:
```
pyplot.figure(figsize=(18, 10))
pyplot.bar(artists['Artist'][:50], artists['Num Songs'][:50])
pyplot.xticks(rotation=80)
pyplot.xlabel(artists.columns[0])
pyplot.ylabel(artists.columns[1])
pyplot.title('top 50');
```



Volume Added Over Time

My proclivity to add songs to this playlist is a proxy for my interest in listening to music generally. How has it waxed and waned over time?

In [5]:
```
from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters() # to suppress warning

# Plot of added volume over time
parse_date = lambda d:(int(d[:4]), int(d[5:7]), int(d[8:10]))
pyplot.figure(figsize=(10, 6))
pyplot.hist([date(*parse_date(d)) for d in data['Added At']], bins=30)
pyplot.title('volume added over time');
```



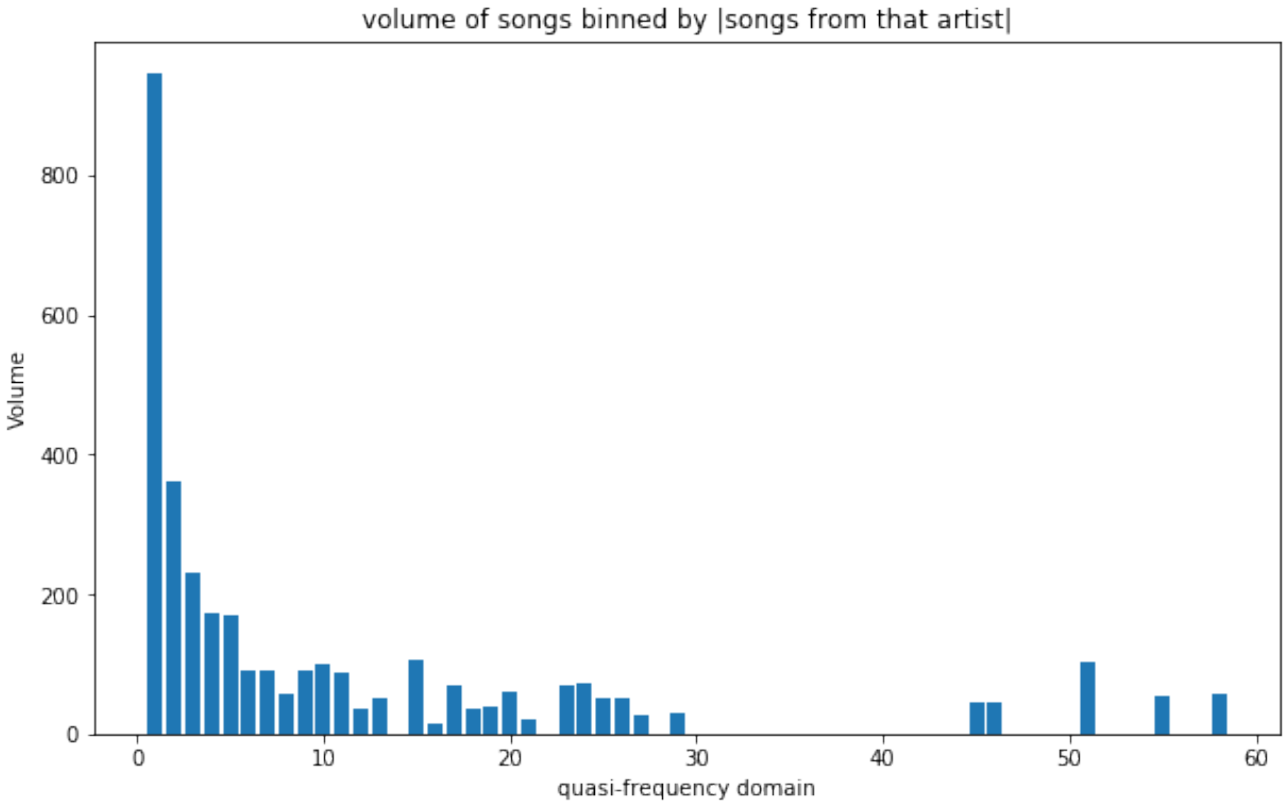
The initial spike is from when I first stared using Spotify as the home for this collection and manually added hundreds from my previous list.

Eclecticness Measure (Frequency Transform)

This one is a personal favorite. I want to know how many of my songs are one-offs from that artist for me--just individual pieces I found fantastic and ended up adding after a few listens--, how many are two-offs, et cetera. I know it must be heavily skewed toward the low numbers.

In [6]:
```
# bar chart of first bar chart == hipster diversity factor
frequency = defaultdict(int)
for n in artists['Num Songs']:
        frequency[n] += n
frequency = pandas.DataFrame(frequency.items(), columns=['Unique Count', 'Vo
                           ).sort_values('Volume', ascending=False)
print("number of song-artist pairs represented in the eclecticness chart:",
      sum(frequency['Volume']))

pyplot.figure(figsize=(10, 6))
pyplot.bar(frequency['Unique Count'].values, frequency['Volume'].values)
pyplot.title('volume of songs binned by |songs from that artist|')
pyplot.xlabel('quasi-frequency domain')
pyplot.ylabel(frequency.columns[1]);
```

```
number of song-artist pairs represented in the eclecticness chart: 3430
```



So, yes, it's much more common for an artist to make it in my list a few times than many times. In fact, the plurality of my top songs come from unique artists.

Conversely, this view also makes stark those few musicians from whom I've collected dozens.

Note that here, as in the artist bar charts, some songs are doubly-counted, because in cases artists collaborated I listed the song in both bins.

Genres Bar Chart

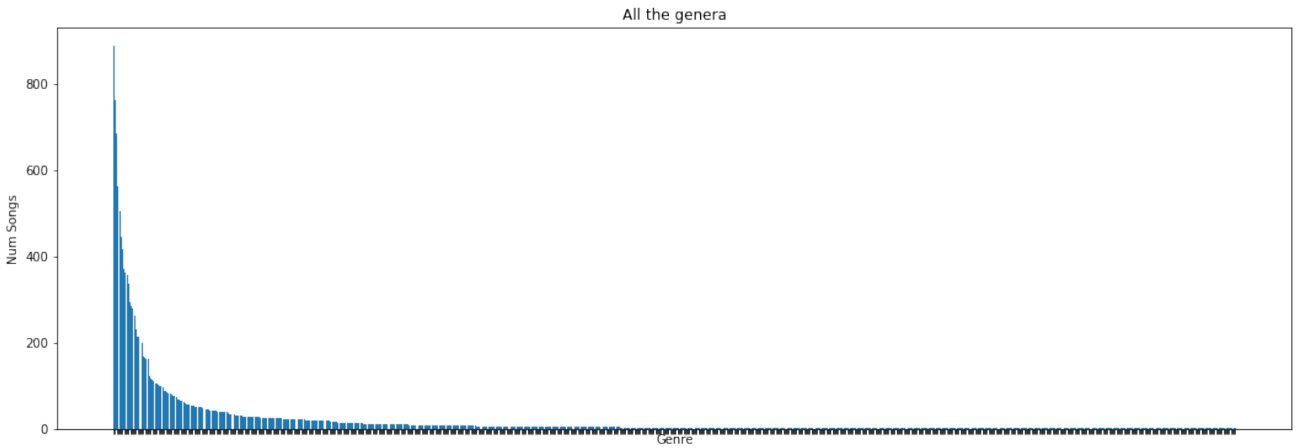
Alright, enough messing around. All the above were possible with the output from Watsonbox's Exportify. Let's get to the novel stuff you came *here* for.

People describe music by genre. As we'll see, genre names are flippin' hilarious and extremely varied, but in theory if I cluster around a few, that should give you a flavor of my tastes.

In [7]:
```
# count songs per genre
genres = defaultdict(int)
for i,song in data.iterrows():
    if type(song['Genres']) is str: # some times there aren't any, and this
```

```
        for genre in song['Genres'].split(','):
            if len(genre) > 0: # empty string seems to be a legit genre
                genres[genre] += 1

# sort for chart
genres = pandas.DataFrame(genres.items(), columns=['Genre', 'Num Songs']
                         ).sort_values('Num Songs', ascending=False).reset_
print("number of unique genres:", genres.shape[0])

pyplot.figure(figsize=(18, 6))
pyplot.bar(genres['Genre'], genres['Num Songs'])
pyplot.xticks(visible=False)
pyplot.xlabel(genres.columns[0])
pyplot.ylabel(genres.columns[1])
pyplot.title('All the genera');
```

```
number of unique genres: 755
```

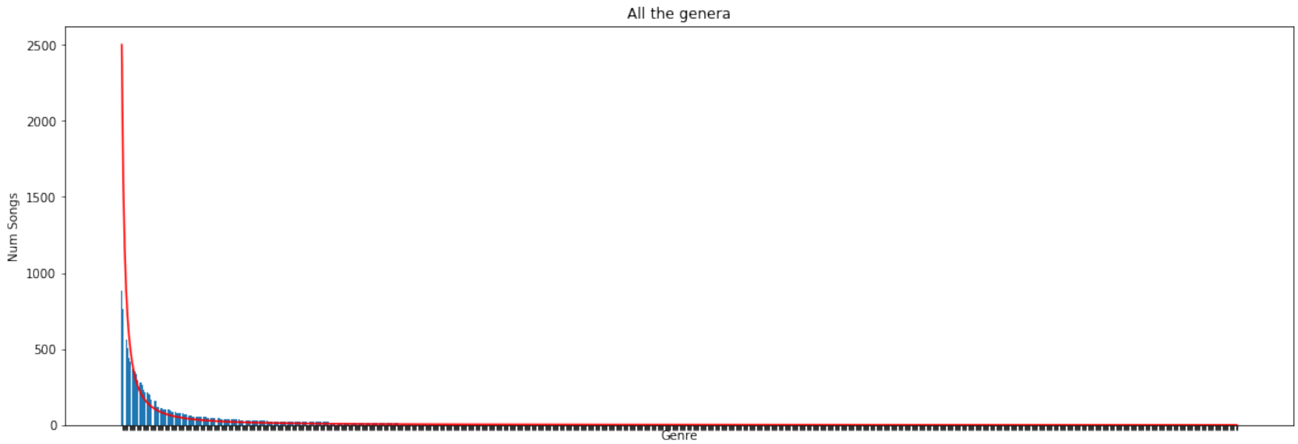


So many! Let's do the same thing as with the artists and for giggles see if it fits a power law.

In [8]:
```
y = []
for i in range(genres.shape[0]):
        for j in range(genres['Num Songs'][i]):
                y.append(i)

# sanity check
#pyplot.figure()
#pyplot.hist(y, bins=30)

param = pareto.fit(y, 100)
pareto_fitted = len(y)*pareto.pdf(range(genres.shape[0]), *param)

pyplot.figure(figsize=(18, 6))
pyplot.bar(genres['Genre'], genres['Num Songs'])
pyplot.plot(pareto_fitted, color='r')
pyplot.xticks(visible=False)
```

```
pyplot.xlabel(genres.columns[0])
pyplot.ylabel(genres.columns[1])
pyplot.title('All the genera');
```

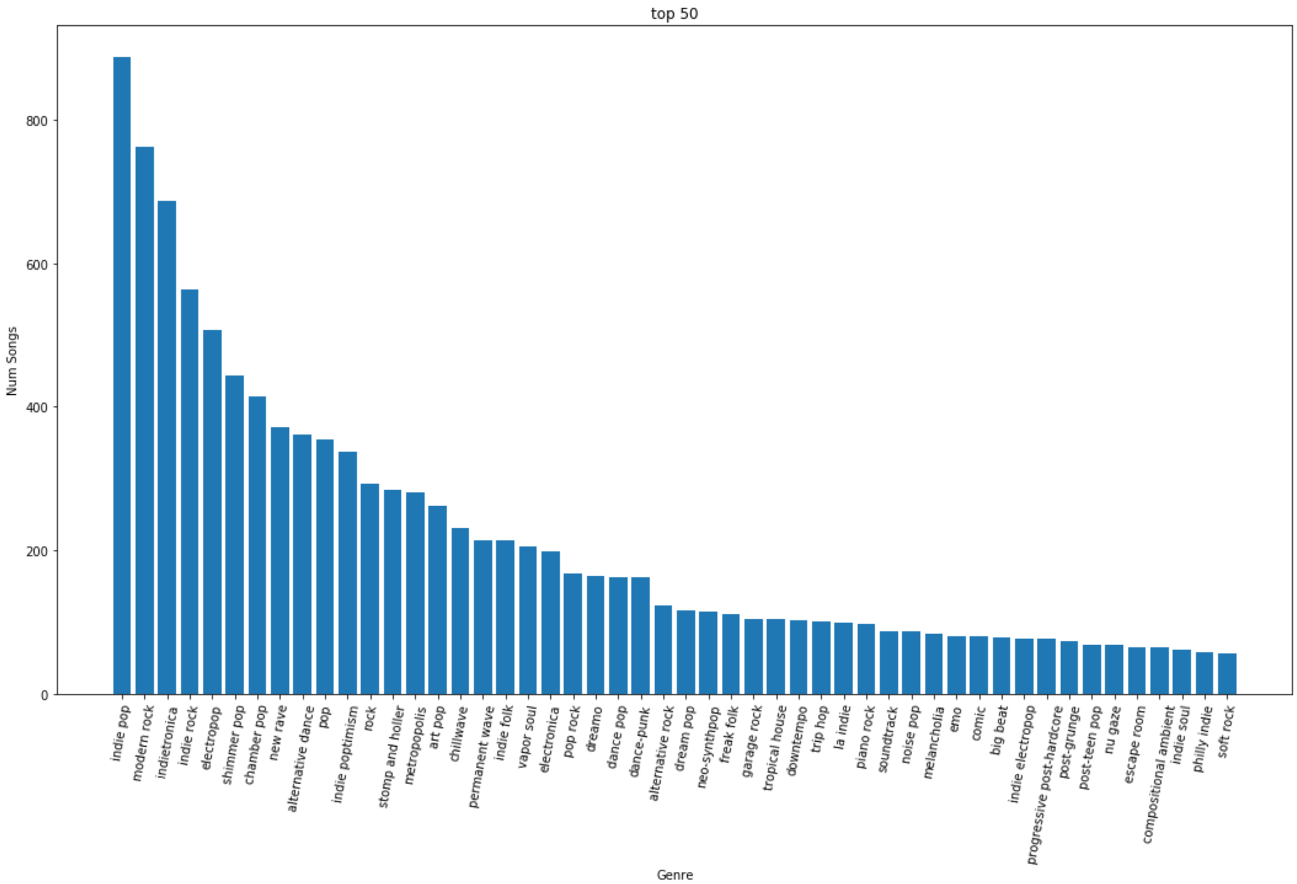
```
/home/pavel/.local/lib/python3.6/site-packages/scipy/stats/_distn_infrastruc
ture.py:2381: RuntimeWarning: invalid value encountered in double_scalars
  Lhat = muhat - Shat*mu
```



Still too sharp, but fits better than with the artists.

Let's look at the top 50 so we can read the names.

In [9]:
```
pyplot.figure(figsize=(18, 10))
pyplot.bar(genres['Genre'][:50], genres['Num Songs'][:50])
pyplot.xticks(rotation=80)
pyplot.xlabel(genres.columns[0])
pyplot.ylabel(genres.columns[1])
pyplot.title('top 50');
```

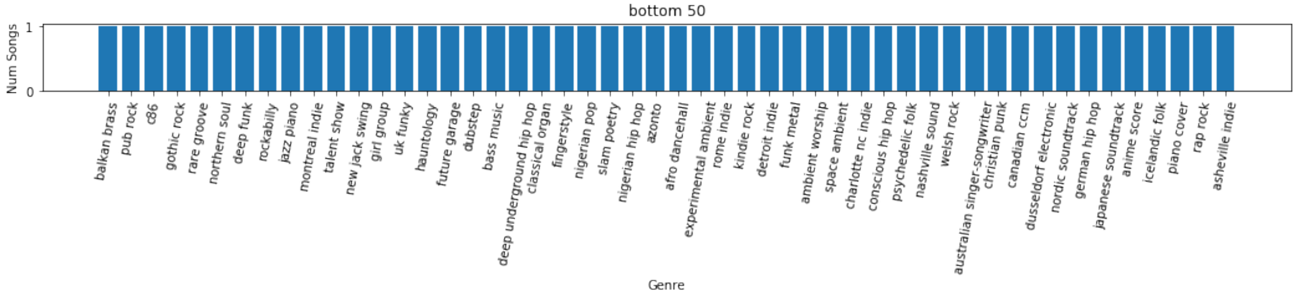


"Indie poptimism" lol. wtf? "Dreamo", "Vapor soul", "Freak folk", "Tropical house", "Post-grunge", "Hopebeat", "Noise pop", "Mellow gold"

These are too good. Next time someone asks me my music taste, I'm definitely using these.

If these are the *most* popular names, what are the really unique ones at the bottom of the chart?

In [10]:
```
pyplot.figure(figsize=(18, 1))
pyplot.bar(genres['Genre'][-50:], genres['Num Songs'][-50:])
pyplot.xticks(rotation=80)
pyplot.xlabel(genres.columns[0])
pyplot.ylabel(genres.columns[1])
pyplot.title('bottom 50');
```



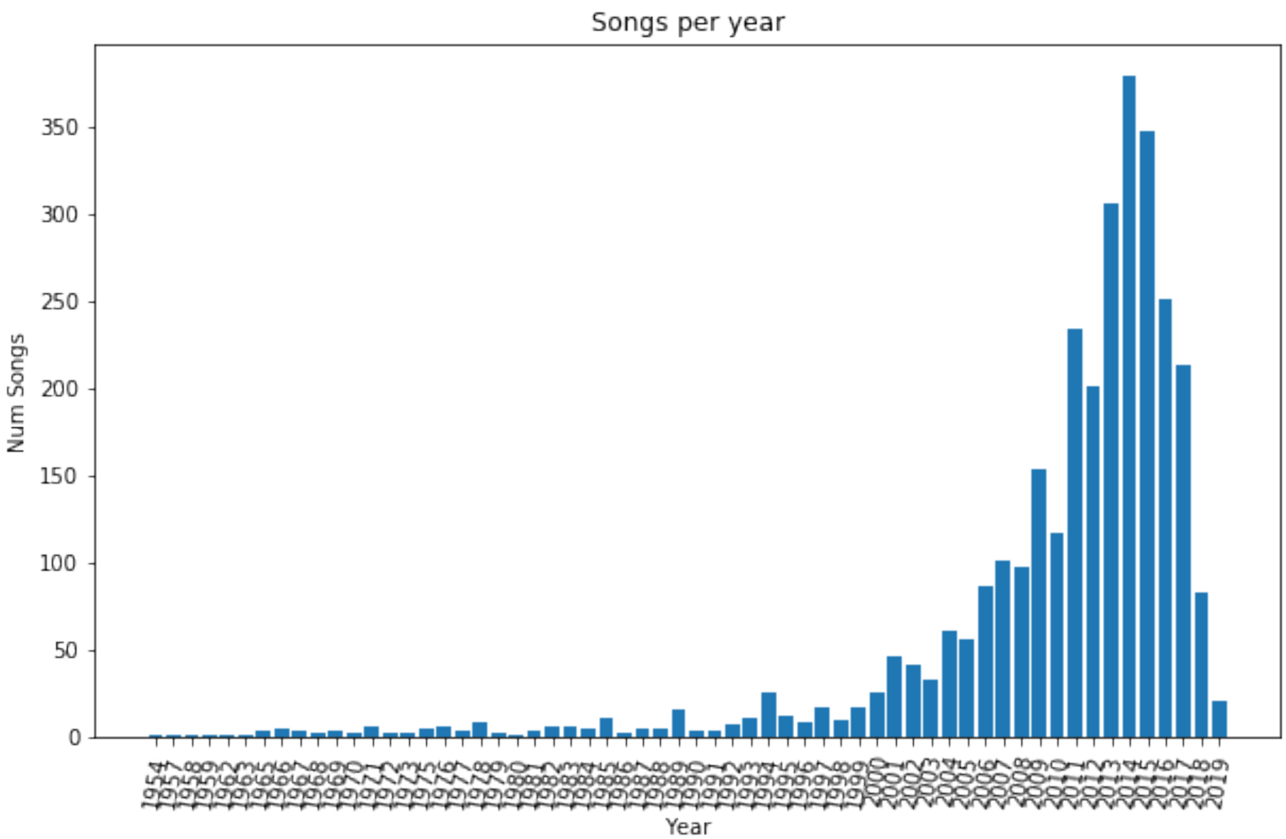
"hauntology", "psychadelic folk", "stomp and whittle", "dark trap", "filthstep", "shamanic", "deep underground hip hop", "future garage"

That was fun.

Release Dates

Which era of music do I prefer?

In [11]:
```
years = defaultdict(int)
for i,song in data.iterrows():
    years[song['Release Date'][:4]] += 1

years = pandas.DataFrame(years.items(), columns=['Year', 'Num Songs']
                         ).sort_values('Year')

pyplot.figure(figsize=(10, 6))
pyplot.bar(years['Year'], years['Num Songs'])
pyplot.xticks(rotation=80)
pyplot.xlabel(years.columns[0])
pyplot.ylabel(years.columns[1])
pyplot.title('Songs per year');
```



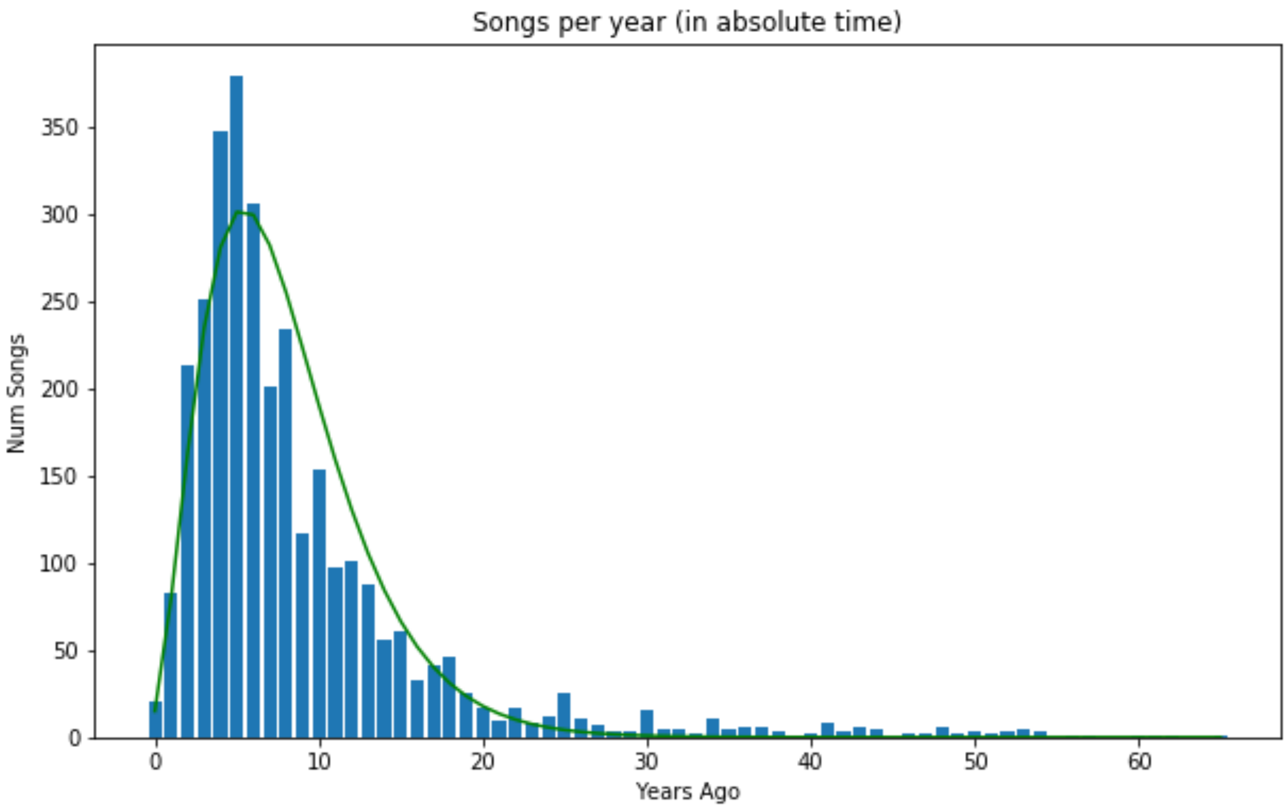
It seems to follow a Gamma distribution! This makes sense because I'm more likely to have heard things that are nearer me in time, and it takes a while for them to get through my process and become favorites.

Let's fit that gamma to the time-reversed data.

In [12]:
```
# Some years are missing, so transform to a dataframe that covers full time
eldest = int(years['Year'].values[0])
youngest = int(years['Year'].values[-1])
missing_years = [str(x) for x in range(eldest+1, youngest) if
                 str(x) not in years['Year'].values]
ago = years.append(pandas.DataFrame.from_dict(
    {'Year': missing_years, 'Num Songs': [0 for x in range(len(missing_years
                  ).sort_values('Year', ascending=False).reset_index(drop=Tr

y = []
for i in range(ago.shape[0]):
        for j in range(int(ago['Num Songs'][i])):
                y.append(i)

# sanity check histogram to make sure I'm constructing y properly
#pyplot.figure()
#pyplot.hist(y, bins=30)
```

```
param = gamma.fit(y, 10000)
gamma_fitted = len(y)*gamma.pdf(range(ago.shape[0]), *param)

pyplot.figure(figsize=(10, 6))
pyplot.bar(range(len(ago['Year'])), ago['Num Songs'])
pyplot.plot(gamma_fitted, color='g')
pyplot.xlabel('Years Ago')
pyplot.ylabel(ago.columns[1])
pyplot.title('Songs per year (in absolute time)');

print('Oldest Hall of Fame')
print(data[['Track Name', 'Artist Name(s)', 'Release Date']].sort_values(
    'Release Date')[:10])
```

```
Oldest Hall of Fame
                                             Track Name  \
3063                                      That's Amore
2509                      (Where Do I Begin) Love Story
3021                                    Autumn Nocturne
2484                                          Take Five
2697                                        Stand by Me
0                            Fanfare for the Common Man
554                                  Get Ready For This
1422                                           New Math
1905                         Yesterday - Remastered 2009
2123  Il Buono, Il Brutto, Il Cattivo: Titoli Di Testa

                                Artist Name(s) Release Date
3063  Dean Martin,Dick Stabile And His Orchestra         1954
2509                             Andy Williams         1957
3021                             Lou Donaldson         1958
2484                    The Dave Brubeck Quartet   1959-12-14
2697                                Ben E. King   1962-08-20
0        Aaron Copland,London Symphony Orchestra         1963
554                                2 Unlimited         1965
1422                                Tom Lehrer   1965-01-01
1905                               The Beatles   1965-08-06
2123                            Ennio Morricone         1966
```



Pretty good fit! I seem to be extra partial to music from about 5 years ago. We'll see whether the present or maybe the further past catches up.

Popularity Contest

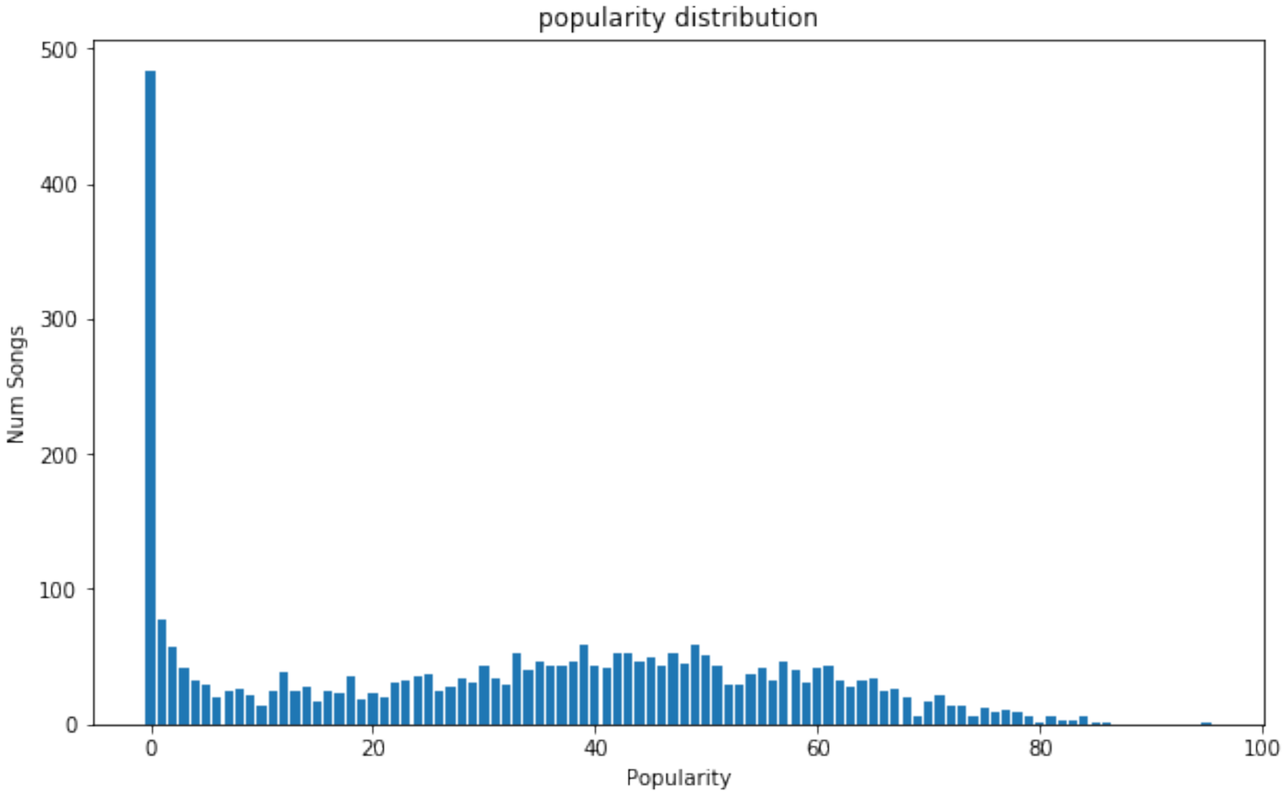
I was happy to find popularity listed as a field in Spotify's track JSON. It's a percentile between 0 and 100, rather than an absolute number of plays. Still, it can be used to give a notion of how hipster I am.

In [13]:

```
popularity = defaultdict(int)
for i,song in data.iterrows():
    popularity[song['Popularity']] += 1

popularity = pandas.DataFrame(popularity.items(), columns=['Popularity', 'Nu
                          ).sort_values('Popularity')

pyplot.figure(figsize=(10, 6))
pyplot.bar(popularity['Popularity'].values, popularity['Num Songs'].values)
pyplot.xlabel(popularity.columns[0])
pyplot.ylabel(popularity.columns[1])
pyplot.title('popularity distribution');

print("Average song popularity: ", popularity['Popularity'].mean())
print("Median song popularity: ", popularity['Popularity'].median())
```

```
print("Max song popularity: ", popularity['Popularity'].max())
```

```
Average song popularity:  43.59090909090909
Median song popularity:  43.5
Max song popularity:  95
```



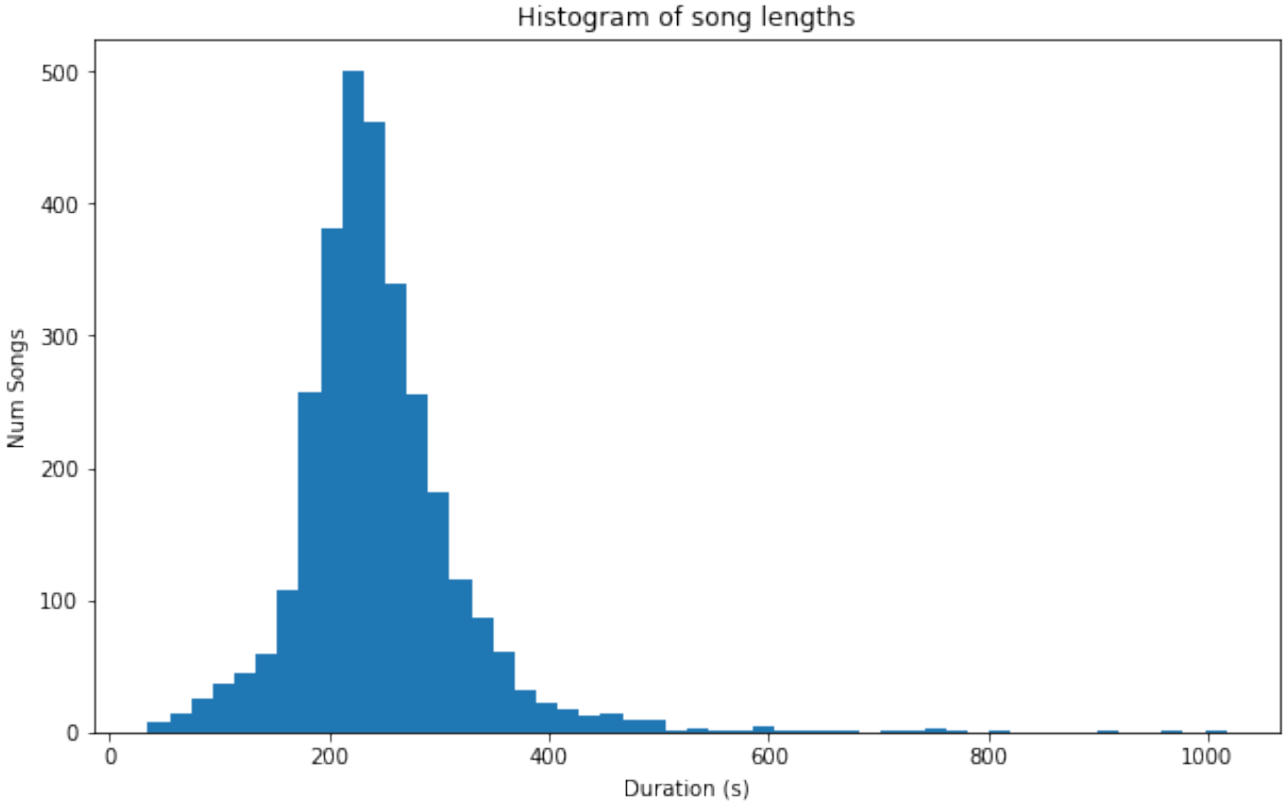
Damn, I'm a hipster.

Track Duration

Do I prefer long songs or short ones?

In [14]:
```
pyplot.figure(figsize=(10,6))
pyplot.hist(data['Duration (ms)']/1000, bins=50);
pyplot.xlabel('Duration (s)')
pyplot.ylabel('Num Songs')
pyplot.title('Histogram of song lengths')

mean = data['Duration (ms)'].mean()/1000
median = data['Duration (ms)'].median()/1000
print("Average song length: " + str(int(mean//60)) + (":" if mean%60 >=10 el
      + str(mean%60))
print("Median song length: " + str(int(median//60)) + (":" if median%60 >=10
      + str(median%60))
```

```
Average song length: 4:06.183588730569966
Median song length: 3:56.16
```



Median is lower than the mean, so I'm skewed right. That is, I like a few really long songs. What are they?

In [15]:
```
print("Longest Hall of Fame:")
print(data[['Track Name', 'Artist Name(s)', 'Release Date', 'Duration (ms)']
    'Duration (ms)', ascending=False)[:10])
```

```
Longest Hall of Fame:
                                             Track Name  \
705                                               Irene
1954  The Return of the King (From The Lord of the R...
464                                    The Cure For Pain
2406                Shine On You Crazy Diamond (Pts. 1-5)
142   Two Step - Live At Piedmont Park, Atlanta, GA ...
1474                                          Cage-Nerd
2407                Shine On You Crazy Diamond (Pts. 6-9)
144   Warehouse - Live At Piedmont Park, Atlanta, GA...
143   Don't Drink the Water - Live At Piedmont Park,...
2717                                          The Alien

                                 Artist Name(s) Release Date  Duration (ms)
705                                 Beach House   2012-05-15        1017013
1954  The City of Prague Philharmonic Orchestra   2004-01-01         976893
464                                mewithoutYou   2002-01-01         908840
2406                                 Pink Floyd   1975-09-12         811077
142                           Dave Matthews Band   2007-12-11         808226
1474                                Tim Minchin   2011-04-04         778250
2407                                 Pink Floyd   1975-09-12         747325
144                           Dave Matthews Band   2007-12-11         743906
143                           Dave Matthews Band   2007-12-11         743493
2717                 Ben Salisbury,Geoff Barrow   2018-02-23         723579
```

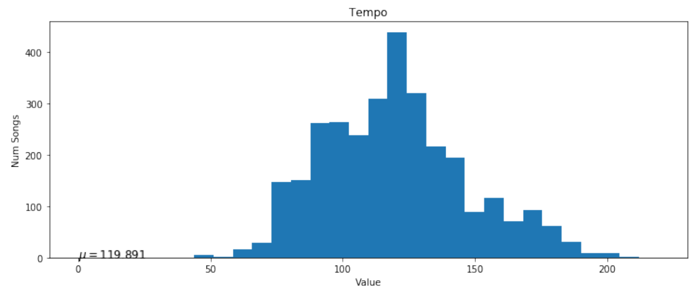
Musical Features

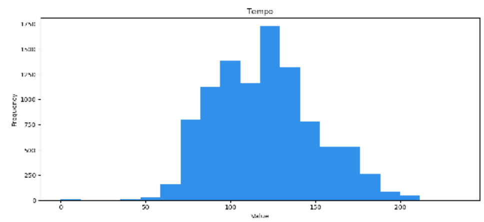
In the interest of understanding user tastes and providing the best possible music recommendations, Spotify has done some really sophisticated analysis of actual track content. Music is a time series, but most similarity metrics (and most ML methods generally) require inputs to be vectors, that is: points in some feature-space. So they've transformed the tracks to numerical metrics like Energy and Valence (continuous) and Key (discrete).

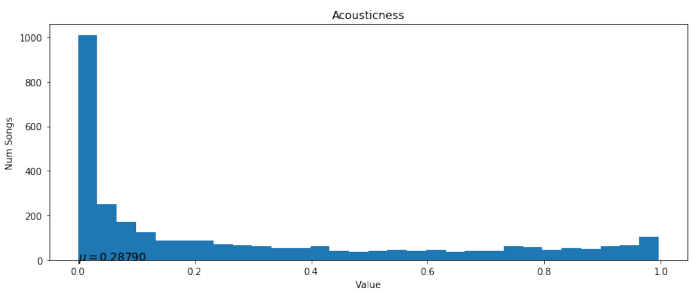
For the continuous metrics, they provide distributions across all music. Here they are next to similar plots of my own songs.

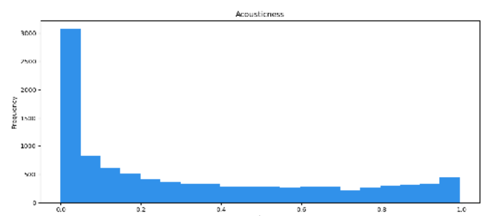
In [16]:
```
pyplot.figure(figsize=(20,40))

for i,category in enumerate(['Tempo', 'Acousticness', 'Instrumentalness', 'L
                              'Valence', 'Speechiness', 'Loudness', 'Energy',
    pyplot.subplot(9, 2, i*2+1)
    # It would be nice to show the KDE on these plots, but there isn't a way
    # to show it on unnormalized https://github.com/mwaskom/seaborn/issues/4
    pyplot.hist(data[category], bins=30)
    pyplot.text(min(data[category]), 0, r'$\mu=$'+str(data[category].mean())
    pyplot.xlabel('Value')
```

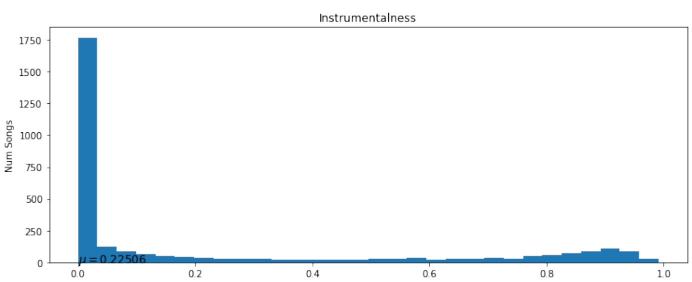
```
    pyplot.ylabel('Num Songs')
    pyplot.title(category)

    pyplot.subplot(9, 2, i*2+2)
    pyplot.imshow(pyplot.imread('https://developer.spotify.com/assets/audio/
                                    category.lower()+'.png'))
    pyplot.axis('off')

pyplot.tight_layout(h_pad=2)
```

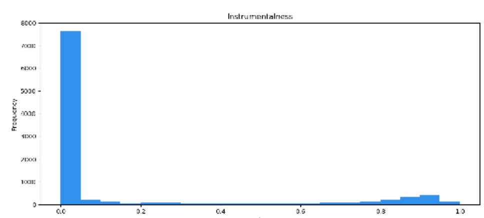


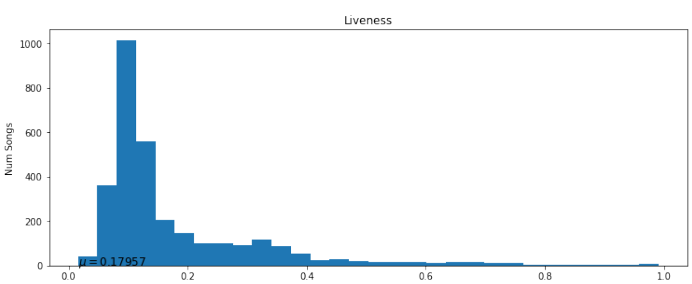


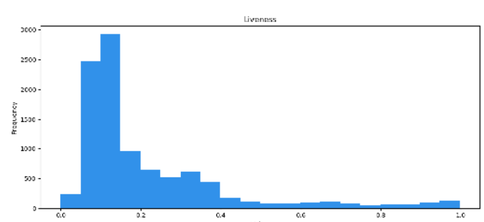


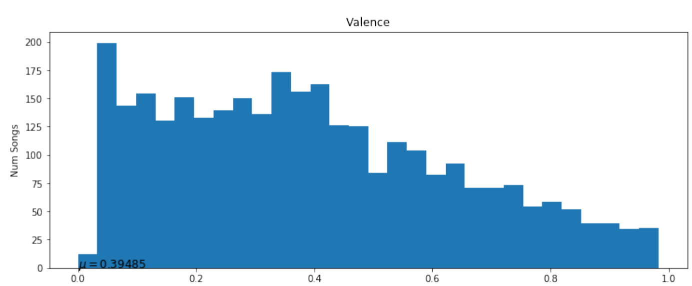


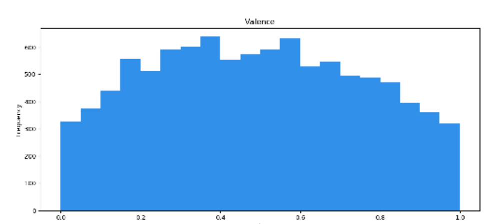


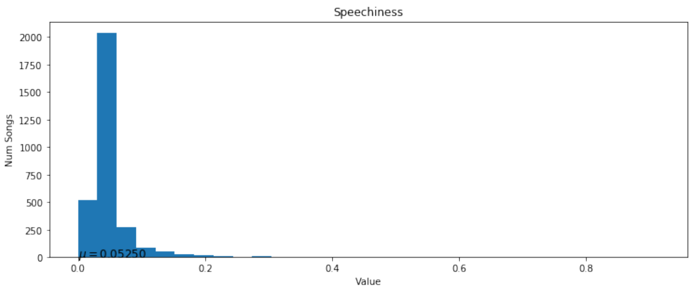


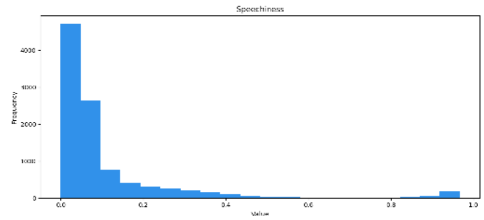


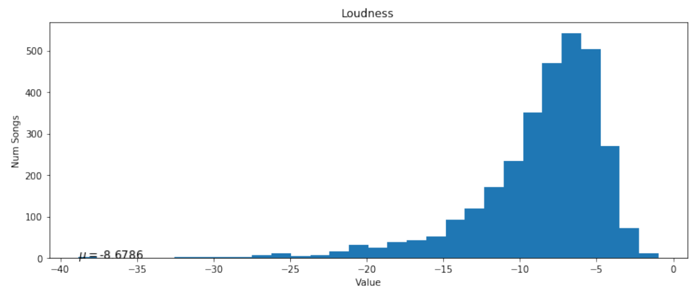


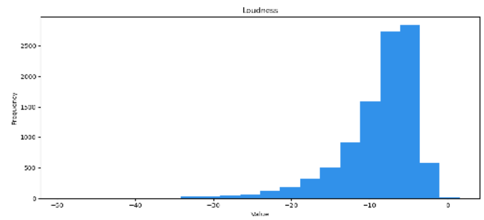


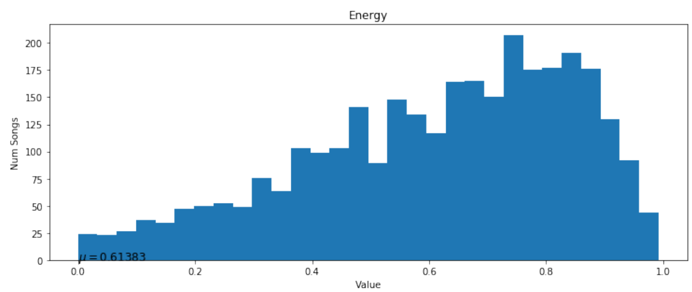


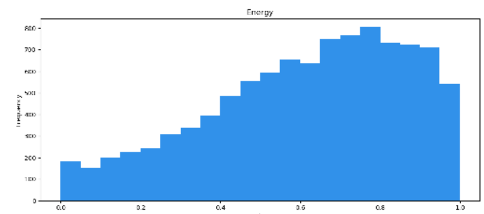


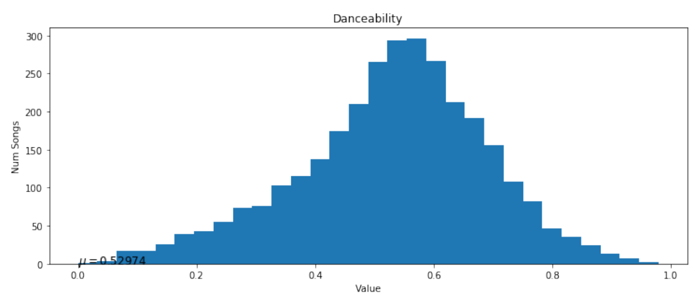


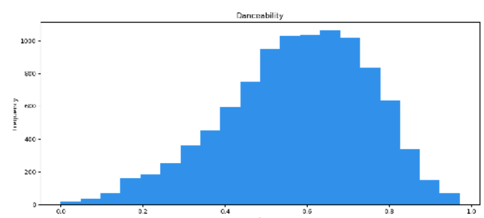










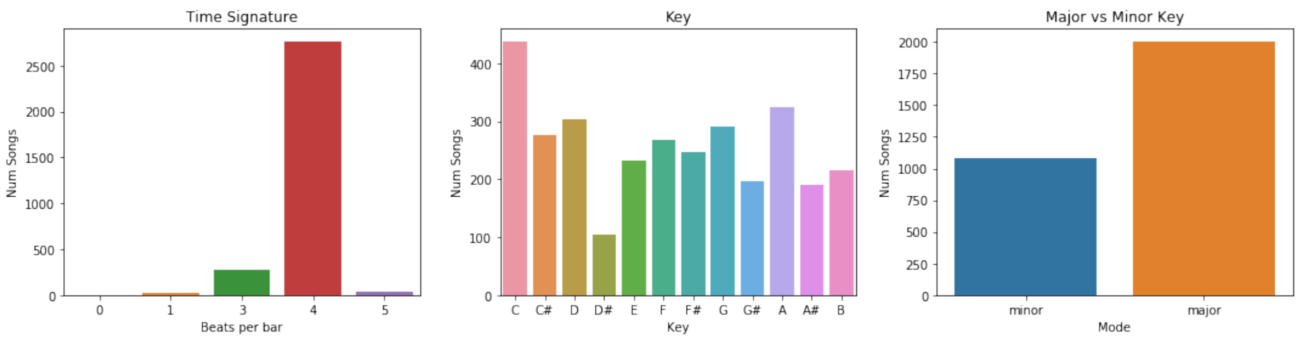


Looks like my preferred Tempo, Acousticness, Instrumentalness, Liveness, Speechiness, and Loudness are not much different from average. Energy is pretty similar, but I have perhaps slightly lower affinity for the super-energetic stuff. My Valence is somewhat negatively skewed, meaning I like sadder songs than average. And my Danceability peaks lower than average.

Now let's look at the discrete music features.

In [17]:
```
pyplot.figure(figsize=(15,4))

pyplot.subplot(1, 3, 1)
seaborn.countplot(data['Time Signature'])
pyplot.xlabel('Beats per bar')
pyplot.ylabel('Num Songs')
```

```
pyplot.title('Time Signature')

pyplot.subplot(1, 3, 2)
axes = seaborn.countplot(data['Key'])
axes.set(xticklabels=['C', 'C#', 'D', 'D#', 'E', 'F', 'F#', 'G', 'G#', 'A',
pyplot.ylabel('Num Songs')
pyplot.title('Key')

pyplot.subplot(1, 3, 3)
axes = seaborn.countplot(data['Mode'])
axes.set(xticklabels=['minor', 'major'])
pyplot.ylabel('Num Songs')
pyplot.title('Major vs Minor Key');

pyplot.tight_layout(w_pad=2)
```



Musicians seem to favor C major and eschew D#. More than a third of my songs are in a minor key. I don't have a baseline to compare against here, but this might contribute to my lower Valence.

Looks like the vast majority of my music is 4/4 time with a good few in 3/4. I wasn't even aware there were any with 5 beats. What are those?

In [18]:
```
print('5:\n', data.loc[data['Time Signature']==5][
    ['Track Name', 'Artist Name(s)', 'Release Date']][:20])
```

```
5:
                            Track Name  \
76    Yachts - A Man Called Adam mix
121          Good Morning Fire Eater
227                         Carry On
248                          Elysium
277                           Lately
390                         Evenstar
451                      Make A Fist
463                              (B)
573                          Animals
741                  All That Remains
749                  Crush The Camera
827                                O
1081                     Cold Sparks
1182                You Are Gonna Die
1209   Everything In Its Right Place
1214                      The Tourist
1215             I Am Citizen Insane
1875         Have I Always Loved You?
2015                       Resonance
2180                            Pray

                                      Artist Name(s) Release Date
76                               Coco Steel Lovebomb   2000-10-31
121                                         Copeland   2008-01-01
227                                             fun.   2012-02-21
248   Klaus Badelt,Lisa Gerrard,Gavin Greenaway,The ...   2000-01-01
277                                      Memoryhouse   2011-09-13
390                   Howard Shore,Isabel Bayrakdarian   2002-12-02
451                                       Phantogram         2011
463                                     mewithoutYou   2002-01-01
573                                             Muse   2012-09-24
741                                       Rogue Wave         2010
749                                       Rogue Wave   2005-08-23
827                                         Coldplay   2014-05-19
1081                                        Mutemath   2011-09-30
1182                             Marc Streitenfeld   2015-03-24
1209                                       Radiohead   2000-10-02
1214                                       Radiohead   1997-06-17
1215                                       Radiohead   2003-06-09
1875                                        Copeland   2014-11-17
2015                                            Home   2014-07-01
2180                                       Sam Smith   2017-10-06
```

Make A Fist is totally 5/4, and so is Animals. Funny how I didn't notice the strange energetic time signature until now. But Carry On is definitely 4/4, as is Yachts, and Pray is 6/8. So Spotify's algorithm isn't perfect at this, which is expected.

What are 0 and 1?

In [19]:
```
print('0:\n', data.loc[data['Time Signature']==0][
    ['Track Name', 'Artist Name(s)', 'Release Date']][:10])
print('\n1:\n', data.loc[data['Time Signature']==1][
    ['Track Name', 'Artist Name(s)', 'Release Date']][:20])
```

```
0:
       Track Name Artist Name(s) Release Date
1393  Small Memory    Jon Hopkins   2009-05-05

1:
                                             Track Name  \
71                                        Clair De Lune   
120                                     Top Of The Hill   
231                     I Am the Very Model of a Modern   
243                         The Last of Us (You and Me)   
366                                              Bowery   
507                                    The Eternal City   
570                                             Prelude   
608                                      Þú ert jörðin   
611                                               Raein   
1302                                  Campfire Song Song   
1356                                        Mylo Xyloto   
1399                                            Anagram   
1957  The Fellowship (From The Lord of the Rings: Th...   
1997                                            Monsoon   
2041                                 Meet Me in the Woods   
2080                                         Only Songs   
2228                                         Old Casino   
2241                                     Work This Time   
2658                                     I Don't Think So   
2738                                       Other Worlds   

                                Artist Name(s) Release Date  
71                              Claude Debussy   2014-10-13  
120                                   Conduits   2013-04-16  
231                     The Pirates Of Penzance         1981  
243             Gustavo Santaolalla,Alan Umstead   2013-06-07  
366                              Local Natives   2013-01-29  
507                          Michele McLaughlin   2007-12-04  
570                                       Muse   2012-09-24  
608                              Ólafur Arnalds   2010-05-07  
611                              Ólafur Arnalds   2009-08-28  
1302                       Spongebob Squarepants         2001  
1356                                  Coldplay   2011-10-24  
1399                           Young the Giant   2014-01-17  
1957  The City of Prague Philharmonic Orchestra   2004-01-01  
1997                              Hippo Campus   2017-02-24  
2041                                Lord Huron   2015-04-07  
2080                            The Wild Reeds   2017-04-07  
2228                                Coastgaard   2016-02-26  
2241          King Gizzard & The Lizard Wizard   2014-03-07  
2658                                Ben Phipps   2016-09-30  
2738                      Bassnectar,Dorfex Bos   2017-12-01  
```

Looks like there is only one song with 0 time signature. It's a piano piece with a tempo that rises and falls. This category might be for variable tempo.

Claire De Lune is 9/8 time, so sort of waltzish but not really.

The Major General's Song is 4/4, but there are some stops in there and a lot of speaking, so I understand how that might be difficult to pick out.

Top of the Hill really sounds like 7/4 to me (1-2-123 sort of beat).

Þú ert jörðin is actually properly 1/4 time according to the internet, and relistening I understand how that could be the case. It's like there are little riffs each bar following a quadruplet pattern, but the major beats really only come every bar.

The Last of Us (You and Me) seems similar. It might be properly 1/4 time.

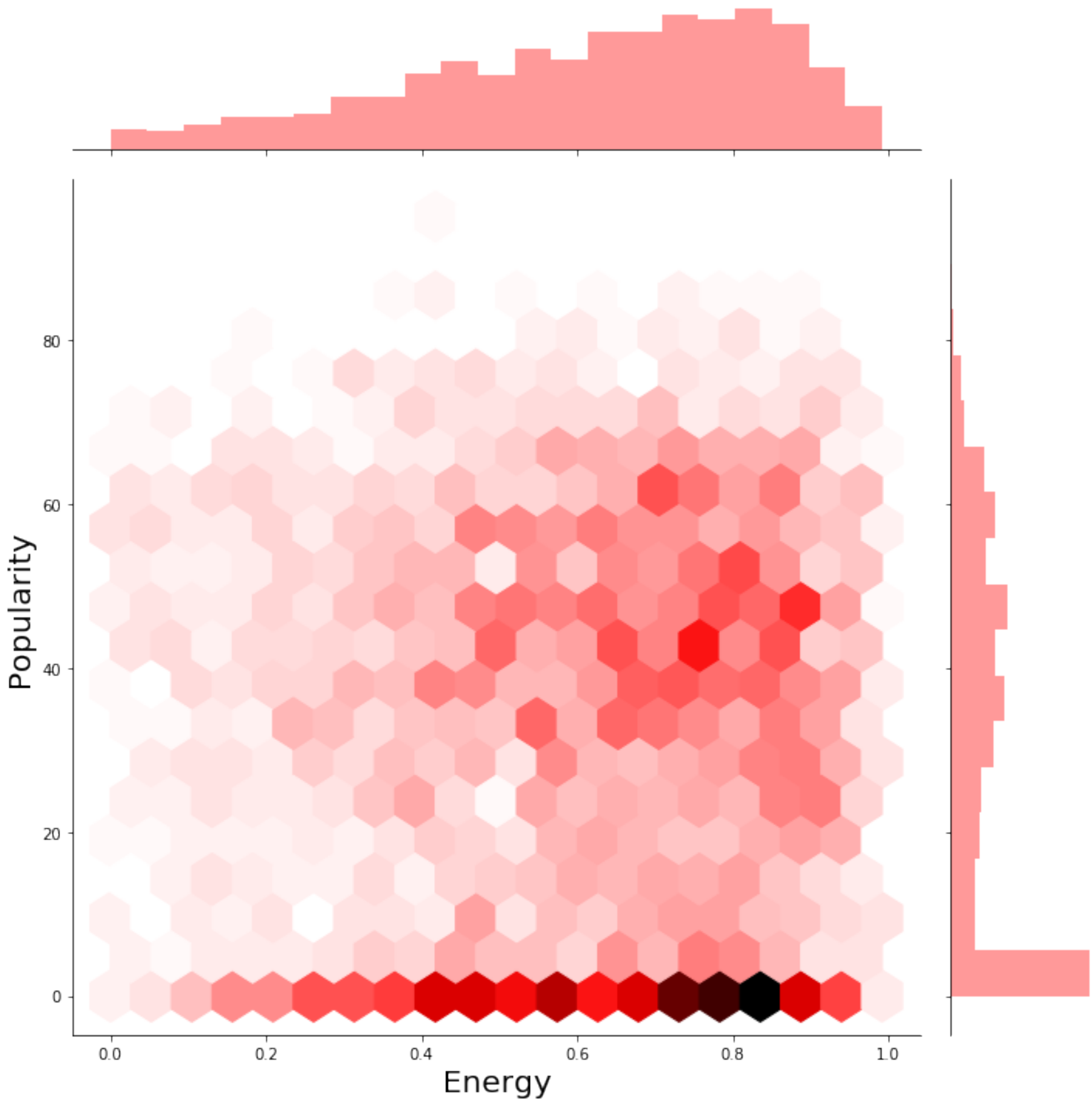
So it looks like this category is for actual single beats and unusual time signatures that Spotify isn't sure what to do with.

Joint Analysis

I mostly just want to showcase what's possible. Let's plot Energy and Popularity together to see whether there is a relationship.

In [20]:
```
x = 'Energy'
y = 'Popularity'

axes = seaborn.jointplot(x=data[x], y=data[y], kind='hex', color='r', size=1
axes.set_axis_labels(x, y, fontsize=20);
```

```
/home/pavel/.local/lib/python3.6/site-packages/seaborn/axisgrid.py:2262: UserWarning: The `size` paramter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```



The data is pretty scattered around the whole plot, meaning the relationship here is actually pretty weak. Surprising.

The Final Frontier

Finally, I'm going to follow this guy's example and feed the dimension-reduced data to a one-class SVM to get a sense of what the frontier of my normal taste looks like in that space, heat-map-of-the-universe-style.

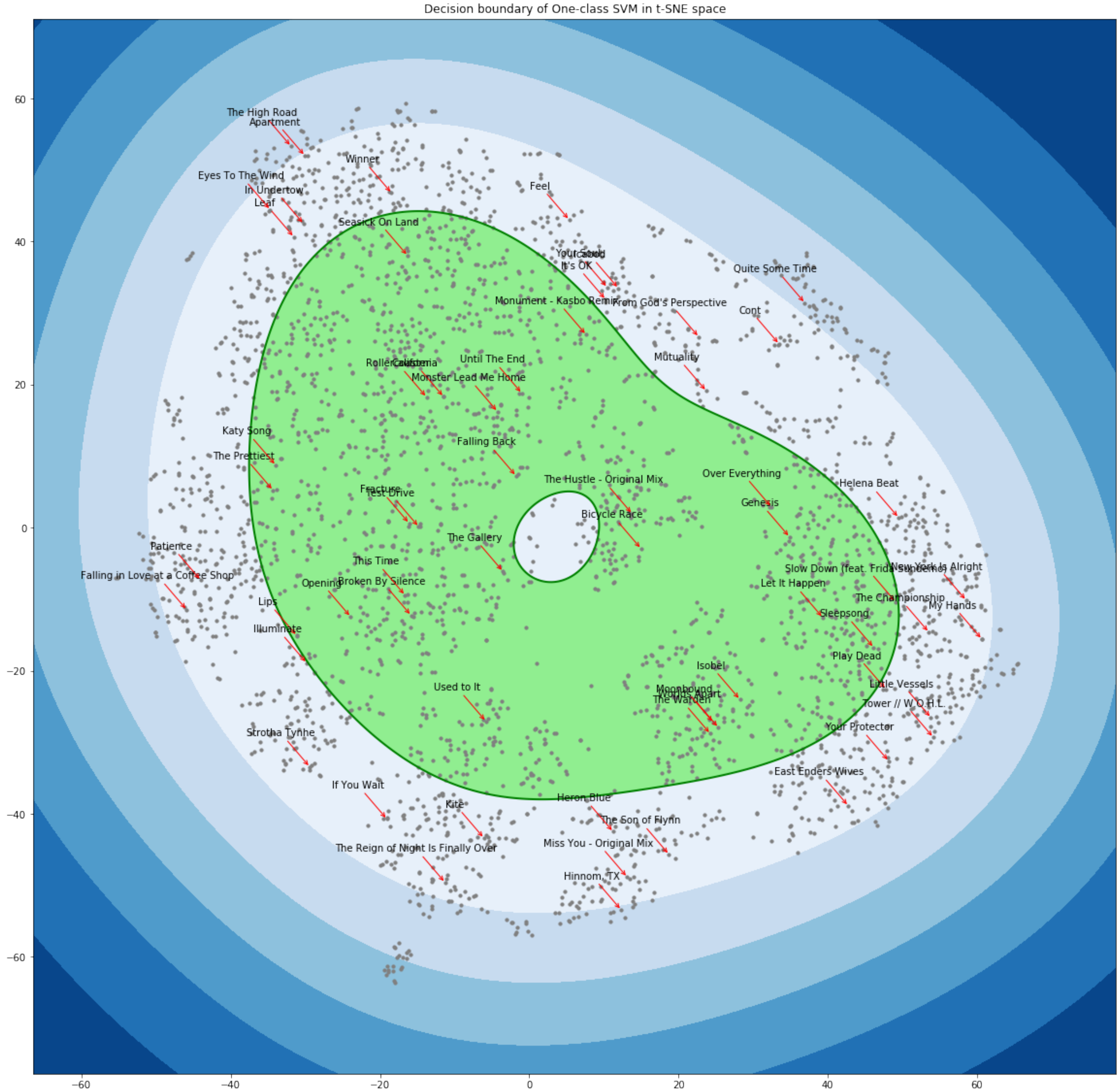
t-SNE is a method for visualizing high-dimensional data in low-dimension. Songs which are more alike will be nearer each other in the feature space, but we can't visualize a space with that many dimensions. What we can do is reconstitute the points in 2D, attempting to preserve the pairwise distances, the notions of similarity, between songs.

In [21]:
```
show_percent = 2

from sklearn.manifold import TSNE
from random import random
from sklearn.svm import OneClassSVM
import numpy

# Create a dataframe of only the numerical features, all normalized so embec
# doesn't get confused by scale differences
numerical_data = data.drop(['Spotify ID', 'Artist IDs', 'Track Name',
        'Album Name', 'Artist Name(s)', 'Added By', 'Added At',
        'Genres'], axis=1)
numerical_data['Release Date'] = pandas.to_numeric(
    numerical_data['Release Date'].str.slice(0,4))
numerical_data = (numerical_data - numerical_data.mean())/numerical_data.stc
print('using:', list(numerical_data.columns))

# If you like, only include a subset of these, because the results with all
# is really hard to interpret
#tsne_data = numerical_data[['Popularity', 'Energy', 'Acousticness',
#                                'Valence', 'Loudness']]
#print("\nConsidering similarity with respect to the following features:")
#print(tsne_data.dtypes)

# Takes a 2D data embedding and an svm trained on it and plots the decision
def plotFrontier(embedded, svm, technique_name, scale):
    # get all the points in the space, and query the svm on them
    xx, yy = numpy.meshgrid(numpy.linspace(min(embedded[:,0])*scale,
                                       max(embedded[:,0])*scale, 500),
                        numpy.linspace(min(embedded[:,1])*scale,
                                       max(embedded[:,1])*scale, 500))
    Z = svm.decision_function(numpy.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape) # positive Z means yes. negative means outliers.

    pyplot.figure(figsize=(20,20))
    pyplot.title('Decision boundary of One-class SVM in '+technique_name+' s
    pyplot.contourf(xx, yy, Z, levels=numpy.linspace(Z.min(), 0, 7), cmap=py
    pyplot.contour(xx, yy, Z, levels=[0], linewidths=2, colors='green') # th
    pyplot.contourf(xx, yy, Z, levels=[0, Z.max()], colors='lightgreen')

    pyplot.scatter(embedded[:, 0], embedded[:, 1], s=10, c='grey')
    for i,song in data.iterrows():
        if random() < show_percent*0.01: # randomly label % of points
        #if song['Artist Name(s)'] in ['Coldplay']:
            x, y = embedded[i]
            pyplot.annotate(song['Track Name'], (x,y), size=10,
```

```
                     xytext=(-30,30), textcoords='offset points',
                     ha='center',va='bottom',
                     arrowprops={'arrowstyle':'->', 'color':'red'})

tsne_embedded = TSNE(n_components=2).fit_transform(numerical_data)

svm_tsne = OneClassSVM(gamma='scale')
svm_tsne.fit(tsne_embedded)

plotFrontier(tsne_embedded, svm_tsne, 't-SNE', 1.2)
```

```
using: ['Release Date', 'Duration (ms)', 'Popularity', 'Danceability', 'Ener
gy', 'Key', 'Loudness', 'Mode', 'Speechiness', 'Acousticness', 'Instrumental
ness', 'Liveness', 'Valence', 'Tempo', 'Time Signature']
```

Decision boundary of One-class SVM in t-SNE space



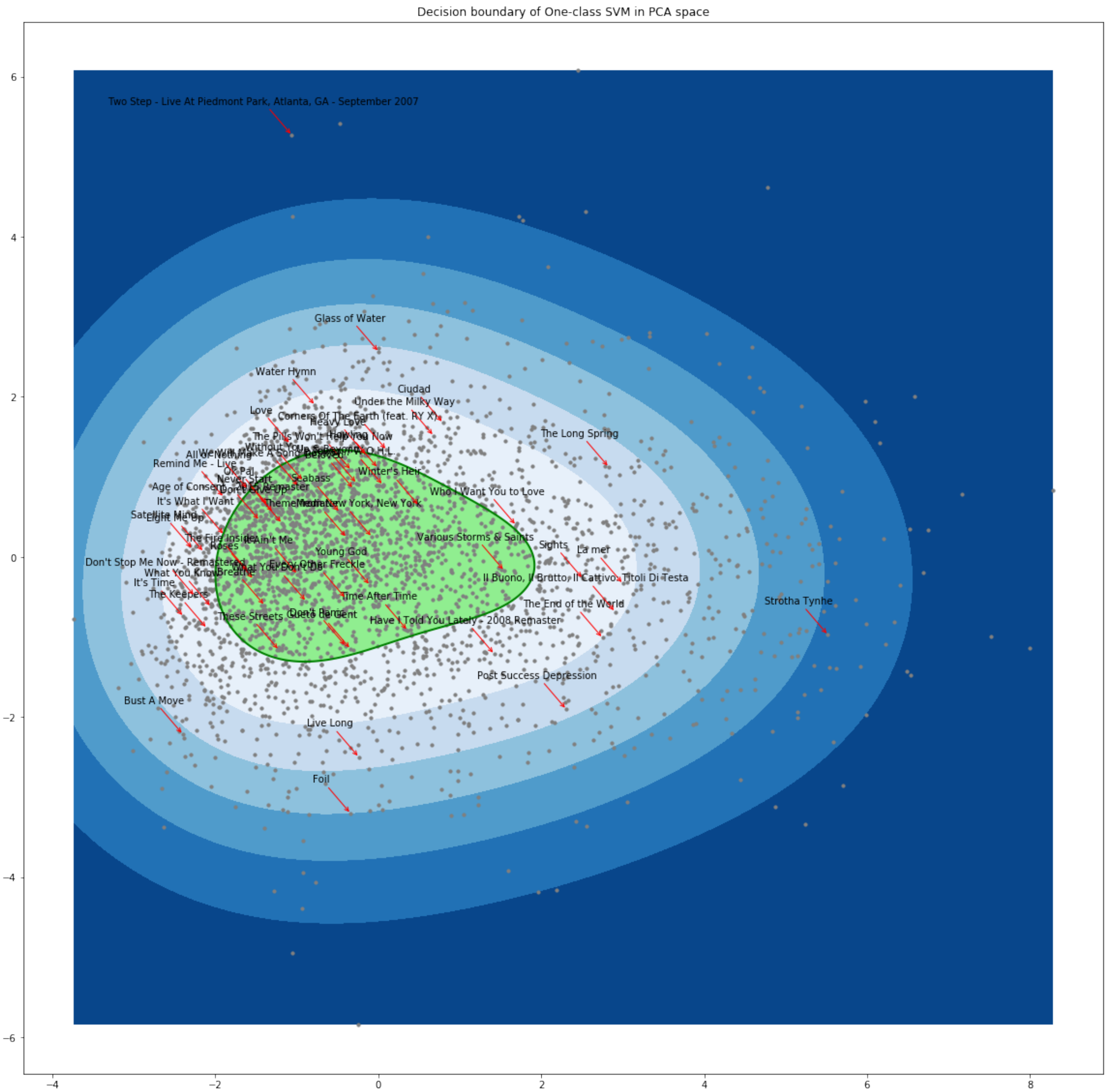
The point scatter looks really different every time this runs, because it's stochastic. The clusters don't necessarily have sensible interpretations, though you might be able to label a few of them. It's good to see some notionally similar pieces ending up near each other. You can try this with a subset of these dimensions to try to make the result more interpretable.

Modifying the parameters of the SVM changes its fit significantly, so I'm not sure this is the best model. Gamma too large just clearly overfits the data. Gamma too small just makes the decision boundary a boring ellipse. Using `gamma='scale'` as the docs recommend is a more interesting middle ground, but still the SVM seems to believe that a great many of the songs I love fall outside the boundary.

I'll try a different dimensionality reduction technique. The original author uses Principle Component Analysis to feed the SVM.

In [22]:
```
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
pca_embedded = pca.fit_transform(numerical_data)
print("% variance explained by successive PCA dimensions:",
      pca.explained_variance_ratio_)

svm_pca = OneClassSVM(gamma='scale')
svm_pca.fit(pca_embedded)

plotFrontier(pca_embedded, svm_pca, 'PCA', 1)
```

```
% variance explained by successive PCA dimensions: [0.21986282 0.09180652]
```



Ideally, songs falling nearer the center here, like Cheeseburger in Paradise and RAC's We Belong, are those that most characterize my taste numerically, and the odd ones, like Pink Floyd's Comfortably Numb and The Fellowship of the Ring orchestral suite, fall on the outside.

So in the end my music taste is a blob that doesn't even fit the data very well. And that's the point: Like many things, it's too complicated to boil down. You can't answer the question fully. But understanding elements of the answer can aid the process of discovery, and that's valuable. It's why Spotify is such a force at music recommendation. It's why Data Science.