Analysis

February 24, 2023

1 Analysis

1.1 Contents

The notebook is laid out as follows:

- Loading the data
- Chart Data Exploration
- One Hit Wonders
- Last FM data
- Recommendations

I will also export it to PDF just in case it fails to render.

[1]:
```
import pathlib
import sqlite3

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

pd.set_option("max_columns", 40)
```

1.2 Load Data

The data is stored in a sqlite database, comprised of four tables (linked either with `lastfm_id` or `artist_name, song_name`):

- charts: The UK chart data, scraped from the website.
- lastfm: The lastfm data for the tracks.
- lastfm_tags: The song tag data.
- lastfm_artists: The artists from lastfm.

This is primarily as sometimes I think it is better to work in SQL for certain types of analysis (in particular, it's hard to beat the expressiveness of window functions).

[2]:
```
dataset_path = pathlib.Path("../data/dataset.sqlite")
conn = sqlite3.connect(dataset_path)
```

[3]:
```python
def sql(query: str) -> pd.DataFrame:
    """Helper function for querying the database."""
    return pd.read_sql_query(query, conn)
```

1.3 Sanity Checks

Below are some sanity checks for the data we're loading, to make sure it can be loaded and that it looks alright.

[4]:
```python
# Can we load the data?
charts = sql("SELECT * FROM charts ORDER BY week_ending DESC")
charts.head()

charts.to_excel("../data/charts_dump.xlsx", index=False)
```

[5]:
```python
# Check that the dates make sense.
query = """
SELECT MIN(year), MAX(year), COUNT(DISTINCT year), COUNT(DISTINCT chart_id),␣
 ↪COUNT(*) FROM
(SELECT STRFTIME('%Y', week_ending) AS year, chart_id FROM charts) a
"""
sql(query)
```

[5]:
```
   MIN(year) MAX(year)  COUNT(DISTINCT year)  COUNT(DISTINCT chart_id)  \
0       1980      2010                    31                      1566

   COUNT(*)
0    148987
```

[6]:
```python
# 1566 * 100 != 148987 - which I think is because the charts didn't always have␣
 ↪100 entries.
query = """
SELECT chart_id, COUNT(*) AS cnt
FROM charts
GROUP BY chart_id
"""
sql(query)
```

[6]:
```
            chart_id  cnt
0      7501-19800105   75
1      7501-19800112   75
2      7501-19800119   75
3      7501-19800126   75
4      7501-19800202   75
…                 …    …
1561   7501-20091205  100
1562   7501-20091212  100
```

```
1563  7501-20091219  100
1564  7501-20091226  100
1565  7501-20100102  100

[1566 rows x 2 columns]
```

1.4 Chart Data Exploration

Below are charts and tables that I used to understand the dataset.

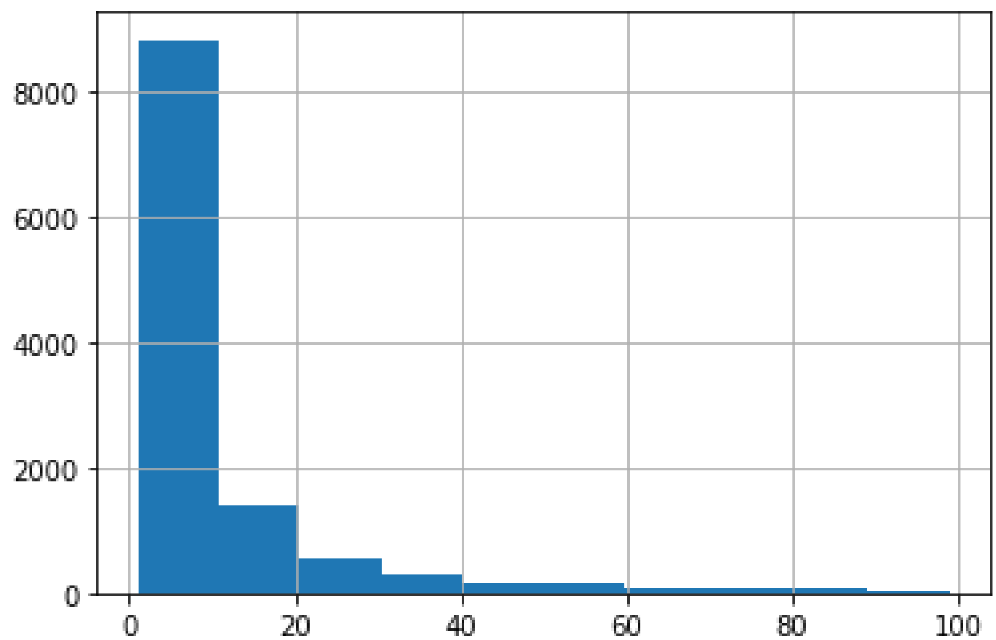
[7]:
```
# Summary stats
sql(
    """
SELECT
    COUNT(DISTINCT artist_name),
    COUNT(DISTINCT chart_id),
    COUNT(DISTINCT product_id),
    COUNT(DISTINCT song_name),
    COUNT(DISTINCT label_name)
FROM charts
"""
).T
```

[7]:
```
                                0
COUNT(DISTINCT artist_name)  11832
COUNT(DISTINCT chart_id)      1566
COUNT(DISTINCT product_id)   32336
COUNT(DISTINCT song_name)    25642
COUNT(DISTINCT label_name)    2471
```

[8]:
```
# Filtering out outliers with 100+ chart appearances
df = sql(
    """
    SELECT artist_name, COUNT(DISTINCT chart_id) AS chart_appearances,␣
 ↪COUNT(DISTINCT product_id) AS unique_songs
    FROM charts
    GROUP BY artist_name
    HAVING chart_appearances < 100
"""
)
```

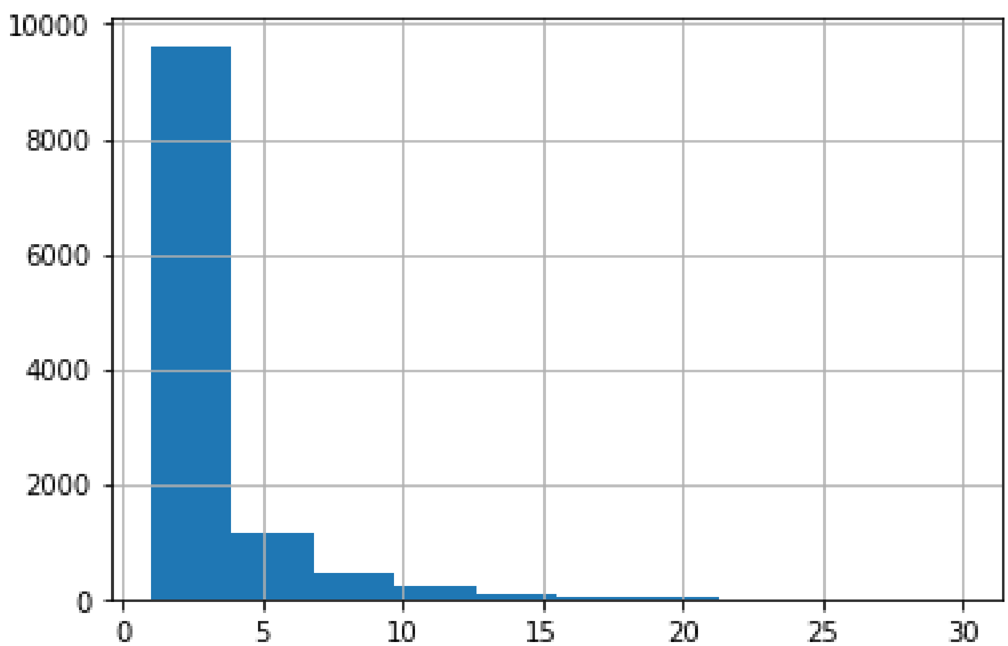
[9]:
```
# What's the spread of artists by the number of appearances they've made in the␣
 ↪charts?
df.chart_appearances.hist()
```

[9]: <AxesSubplot:>




```
[10]: # What's the spread of artists by the number of appearances they've made in the
      ↪charts?
      df.unique_songs.hist()
```

```
[10]: <AxesSubplot:>
```

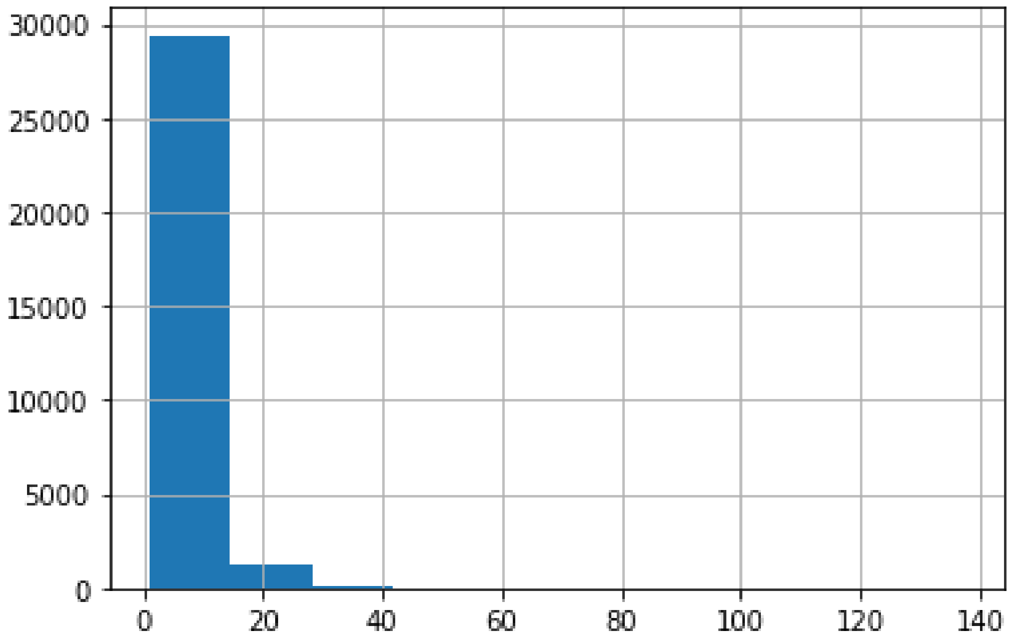


[11]:
```python
# How well do songs do?
df = sql(
    """
SELECT artist_name, song_name, MIN(week_ending) AS first_week_ending,␣
 ↪COUNT(DISTINCT chart_id) AS total_weeks
FROM charts
GROUP BY 1, 2
"""
)
df.sort_values(by="total_weeks", ascending=False).head(10)
```

[11]:
```
              artist_name             song_name    first_week_ending  \
25054         SNOW PATROL          CHASING CARS  2006-07-29 00:00:00
19900               OASIS              WHATEVER  1994-12-31 00:00:00
26634           TAKE THAT        RULE THE WORLD  2007-10-27 00:00:00
19891               OASIS        SOME MIGHT SAY  1995-05-06 00:00:00
14799             KILLERS         MR BRIGHTSIDE  2004-06-05 00:00:00
19878               OASIS  CIGARETTES & ALCOHOL  1994-10-22 00:00:00
10062  FLO RIDA FT T-PAIN                   LOW  2008-02-16 00:00:00
19423           NEW ORDER           BLUE MONDAY  1983-03-19 00:00:00
19902               OASIS            WONDERWALL  1995-11-11 00:00:00
1257        AMY WINEHOUSE                 REHAB  2006-10-28 00:00:00

       total_weeks
25054          137
19900          110
26634           92
19891           81
14799           81
19878           79
10062           75
19423           74
19902           74
1257            73
```

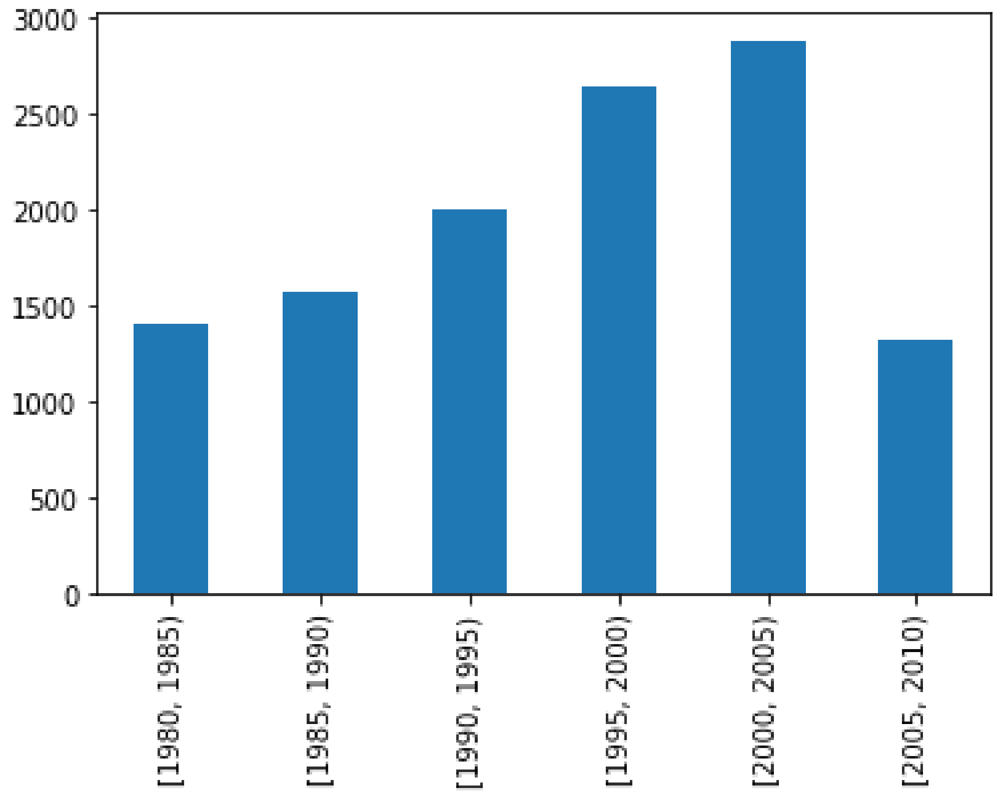
[12]:
```python
df.total_weeks.hist()
```

[12]: <AxesSubplot:>



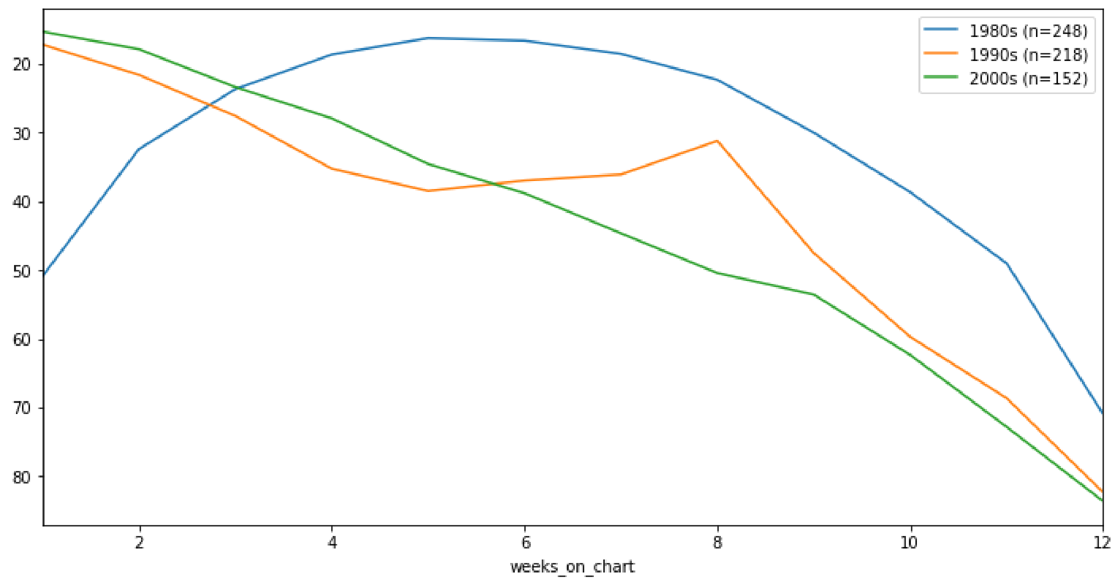
[13]:
```
# How many new entrants are there over time?
df = sql(
    """
SELECT artist_name, MIN(week_ending) AS first_chart_week
FROM charts
GROUP BY 1
"""
)
new_artists = pd.to_datetime(df.first_chart_week).dt.year
# .sort_index().plot.bar(figsize=(12,6))
pd.cut(
    new_artists, bins=[1980, 1985, 1990, 1995, 2000, 2005, 2010], right=False
).value_counts().sort_index().plot.bar()
```

[13]: <AxesSubplot:>



[14]:
```
# Can we understand how songs perform on a track over time?
# The drop off % might be useful for estimating longer term performance
weeks_on_chart = sql(
    """
SELECT
    SUBSTR(STRFTIME('%Y', MIN(week_ending) OVER (PARTITION BY artist_name,␣
 ↪song_name)), 0, 4) AS decade,
    product_id,
    artist_name,
    song_name,
    1 + (julianday(week_ending) - julianday(MIN(week_ending) OVER (PARTITION BY␣
 ↪artist_name, song_name)))/7 AS weeks_on_chart,
    position
FROM charts
ORDER BY weeks_on_chart DESC
"""
)
time_on_chart = weeks_on_chart.groupby("product_id").weeks_on_chart.max()
time_on_chart = time_on_chart[time_on_chart == 12]
```

```python
weeks_on_chart = weeks_on_chart[weeks_on_chart.product_id.isin(time_on_chart.
 ↪index)]
grouped = weeks_on_chart.groupby(["decade"]).apply(
    lambda g: g.groupby("weeks_on_chart").agg({"position": ["mean", "sem"]})
)
songs_by_decade = weeks_on_chart.groupby(["decade"]).product_id.nunique().
 ↪to_dict()
fig, ax = plt.subplots(figsize=(8, 6))
for decade, group in grouped.reset_index().groupby("decade"):
    group.plot.line(
        x="weeks_on_chart",
        y=("position", "mean"),
        figsize=(12, 6),
        xlim=[1, 12],
        legend=True,
        ax=ax,
        label=f"{decade}0s (n={songs_by_decade[decade]})",
    )
plt.gca().invert_yaxis()
```



1.5 One Hit Wonders

1.5.1 Identifying One Hit Wonders

I have defined one hit wonders as when an artist has the majority of their top 40 success concentrated around one song (I've picked 2/3 of hit weeks on the chart).

I have also filtered out some terms for things like "FT" in order to limit the number of collaborations in the charts.

[15]:
```
query = """
SELECT * FROM (
  SELECT
  artist_name,
  song_name,
  first_week_ending,
  max_chart_run,
  peak_position,
  CAST(max_chart_run AS float) / SUM(max_chart_run) OVER (PARTITION BY␣
↪artist_name) share_of_weeks -- What % of weeks did this particular song␣
↪occupy?
  FROM (
    SELECT
      artist_name,
      song_name,
      MIN(week_ending) AS first_week_ending,
      MIN(peak_position) AS peak_position,
      MAX(weeks_on_chart) AS max_chart_run
    FROM
    charts
    GROUP BY 1, 2
    HAVING peak_position <= 40
 )
)
WHERE 1=1 -- Helper statement
   AND share_of_weeks >= 0.67 -- must be at least above 50% to achieve "one hit"
   -- Filter out collaborations
   AND artist_name NOT LIKE '%FT%'
   AND artist_name NOT LIKE '%FEATURING%'
   AND artist_name NOT LIKE '%&%'
   AND artist_name NOT LIKE '%AND%'
   AND artist_name NOT LIKE '%VS%'
   AND artist_name NOT LIKE '%/%'
ORDER BY 3 DESC, 4 DESC
"""
one_hit_artists = sql(query)
one_hit_artists.to_excel("../data/output_one_hit_artists.xlsx", index=False)
```

[16]:
```
# Helper view for later joins + the lastfm script.
view = f"""
CREATE VIEW v_one_hit_wonders AS
{query}
"""
# view = conn.execute(view)
```

[17]:
```
one_hit_wonders = sql("SELECT * FROM v_one_hit_wonders")
one_hit_artists["first_week_ending"] = pd.to_datetime(
```

```
    one_hit_artists["first_week_ending"]
)
```

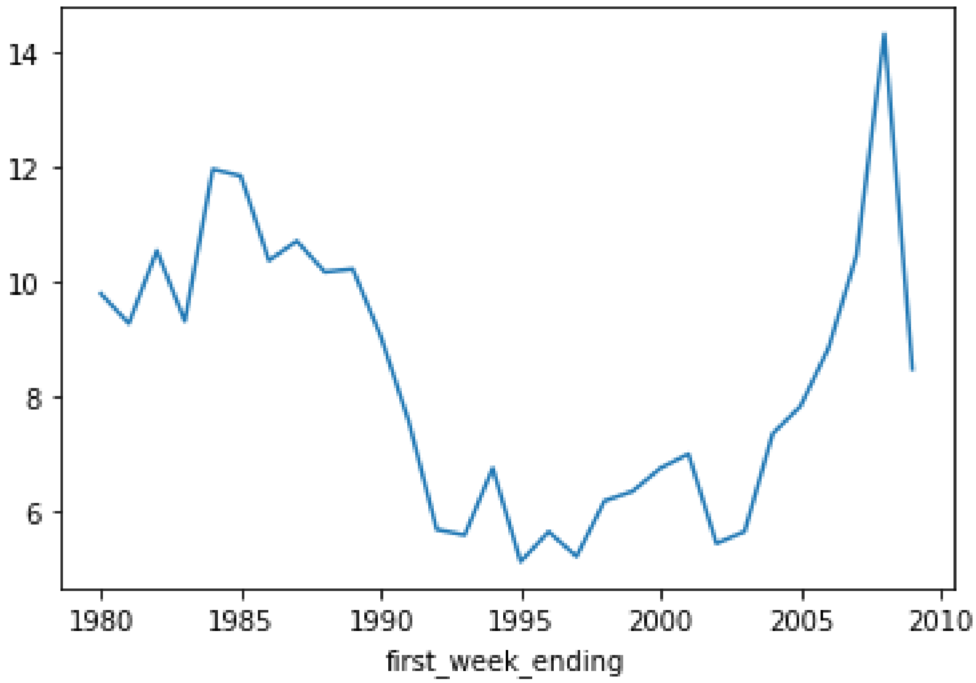
[18]:
```
# Not often you get to look for bangers as part of your sense check
one_hit_artists.sort_values(by="max_chart_run", ascending=False).head(10)
```

[18]:
```
          artist_name                song_name first_week_ending  max_chart_run  \
57        JASON MRAZ                 I'M YOURS        2008-12-06             54
158             FRAY          HOW TO SAVE A LIFE        2007-01-27             53
281      BODYROCKERS            I LIKE THE WAY        2005-04-30             52
170    GOO GOO DOLLS         IRIS/STAY WITH YOU        2006-10-21             51
90        SAM SPARRO              BLACK & GOLD        2008-03-29             47
266    DANIEL POWTER                   BAD DAY        2005-08-06             45
126  NEWTON FAULKNER             DREAM CATCH ME        2007-08-04             43
975      TELETUBBIES  TELETUBBIES SAY EH-OH!        1997-12-13             41
91   GABRIELLA CILMI            SWEET ABOUT ME        2008-03-15             41
71            MADCON                   BEGGIN'        2008-08-23             40

     peak_position  share_of_weeks
57              11        1.000000
158              4        0.697368
281              3        1.000000
170             26        0.927273
90               2        1.000000
266              2        1.000000
126              7        1.000000
975              1        1.000000
91               6        0.759259
71               5        1.000000
```

1.5.2 Analysis

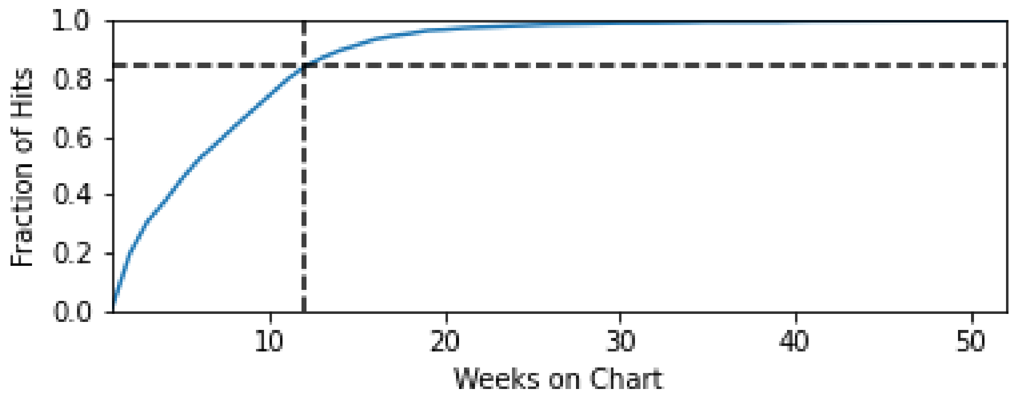
[19]:
```
# Average runs on the chart rose dramatically from 2000-2010 - they might be␣
↪better known.
one_hit_artists.groupby(
    one_hit_artists.first_week_ending.dt.year
).max_chart_run.mean().plot.line()
```

[19]: <AxesSubplot:xlabel='first_week_ending'>



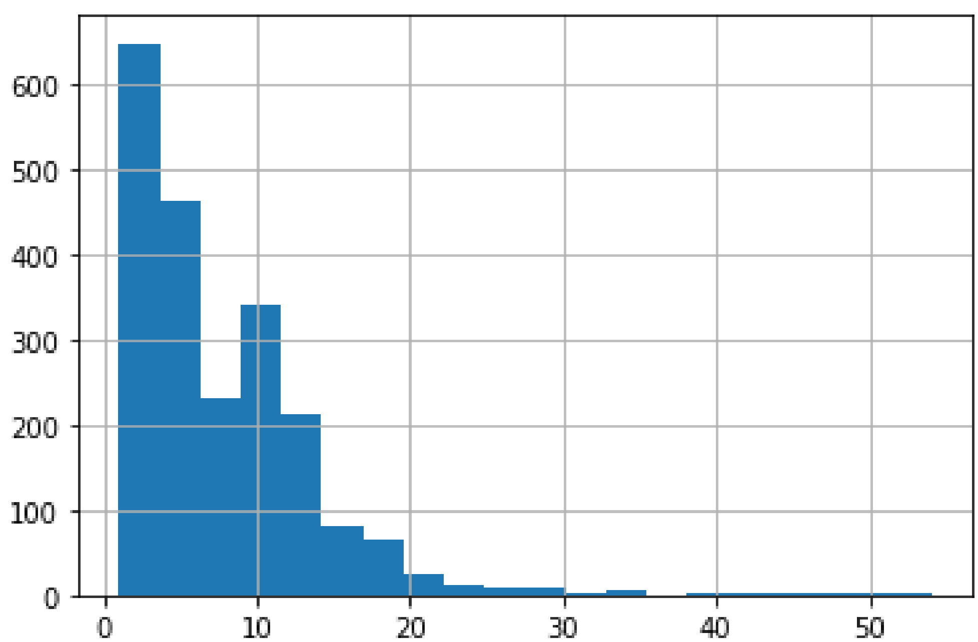
[20]:
```
# Can we measure "sucess" by longevity in the charts?
pareto_artists_by_num_weeks = (
    one_hit_artists.groupby("max_chart_run").size().div(len(one_hit_artists)).
 ↪cumsum()
)
ax = pareto_artists_by_num_weeks.plot.line(
    figsize=(6, 2),
    xlabel="Weeks on Chart",
    ylabel="Fraction of Hits",
    xlim=[1, 52],
    ylim=[0, 1],
)
percentile = pareto_artists_by_num_weeks[pareto_artists_by_num_weeks > 0.84].
 ↪index[0]
plt.axvline(percentile, color="k", linestyle="--")
plt.axhline(0.84, color="k", linestyle="--")
```

[20]: <matplotlib.lines.Line2D at 0x7f38c5e6e1c0>



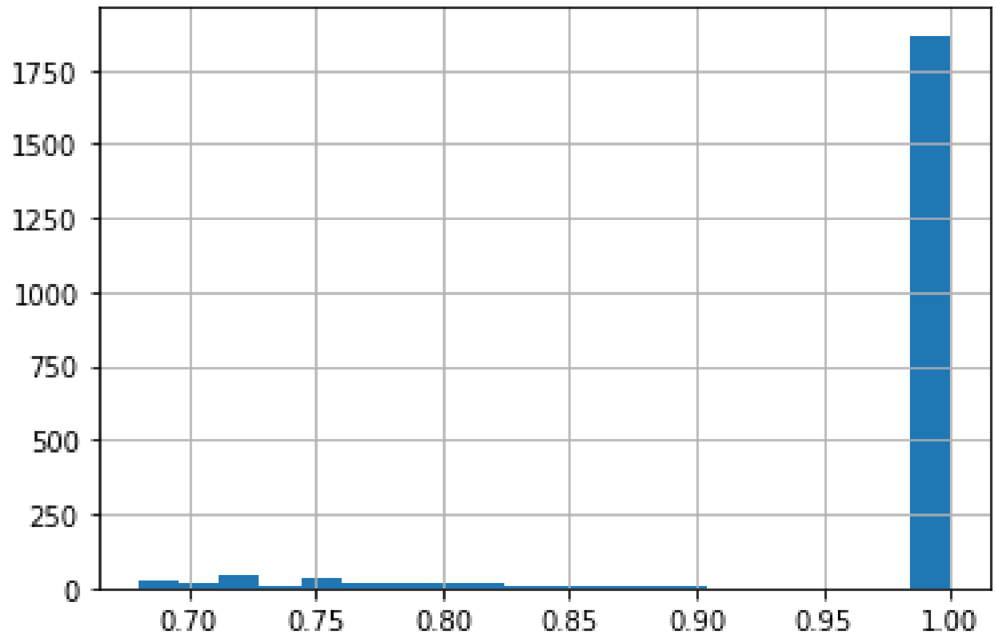

```
[21]: # Success? Number of runs on the chart - majority aren't that successful (<5␣
      ↪weeks on the chart, but some really linger on for up to a year on the chart)
      one_hit_artists.max_chart_run.hist(bins=20)
```

```
[21]: <AxesSubplot:>
```



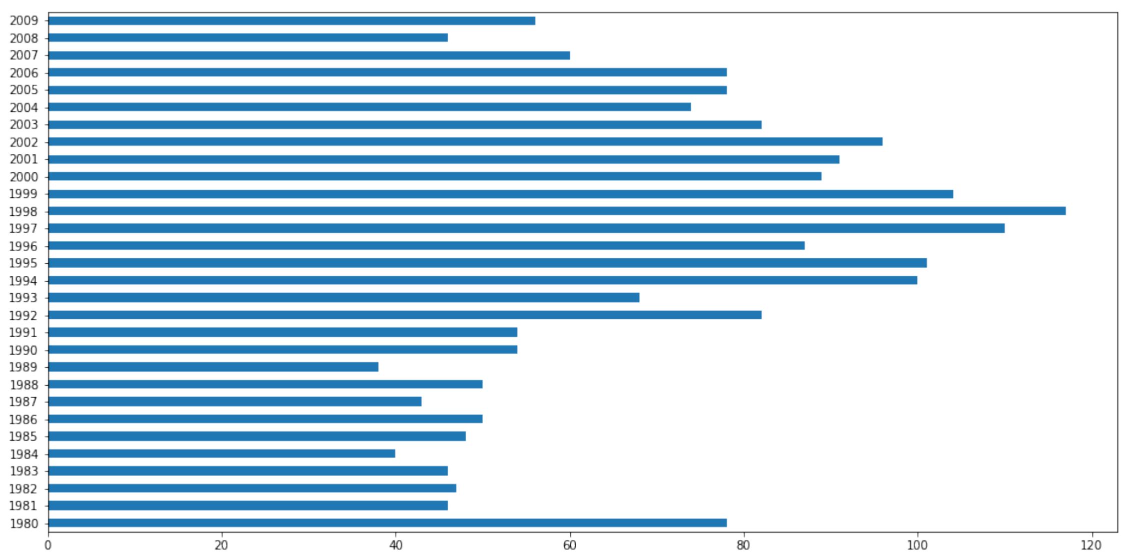

```
[22]: # Do one hit artists typically tend to have other tracks that do well? - No
      one_hit_artists.share_of_weeks.hist(bins=20)
```

```
[22]: <AxesSubplot:>
```



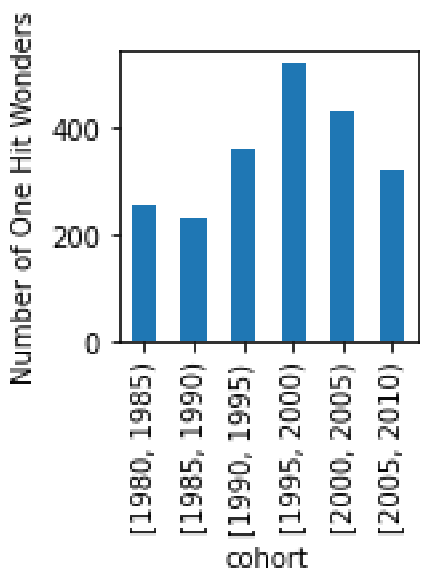
[23]:
```
# Too detailed, but showcases how there's a lot of growth over the last 90s/00s.
one_hit_artists.first_week_ending.dt.year.value_counts().sort_index().plot.barh(
    figsize=(16, 8)
)
```

[23]: <AxesSubplot:>



```
[24]: # One hit wonders start to grow up until 2000 where it begins to peak.
# Q: who were people listening to post recession?
one_hit_wonders_by_cohort = (
    pd.cut(
        one_hit_artists.first_week_ending.dt.year,
        bins=[1980, 1985, 1990, 1995, 2000, 2005, 2010],
        right=False,
    )
    .value_counts()
    .to_frame(name="one_hit_wonders")
)
one_hit_wonders_by_cohort.sort_index().plot.bar(
    legend=False,
    xlabel="cohort",
    ylabel="Number of One Hit Wonders",
    figsize=(2, 2), # Presentation friendly
)
```

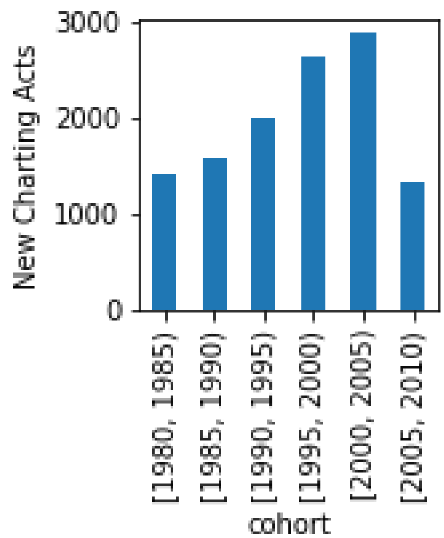
```
[24]: <AxesSubplot:xlabel='cohort', ylabel='Number of One Hit Wonders'>
```




```
[25]: # Can we see if there are lots of artists vying for the charts?
new_artists_by_cohort = (
    pd.cut(new_artists, bins=[1980, 1985, 1990, 1995, 2000, 2005, 2010],␣
↪right=False)
    .value_counts()
    .to_frame(name="new_artists")
)
```

```
new_artists_by_cohort.sort_index().plot.bar(
    legend=False, xlabel="cohort", ylabel="New Charting Acts", figsize=(2, 2)
)
```

[25]: <AxesSubplot:xlabel='cohort', ylabel='New Charting Acts'>



[26]:
```
# What tracks did  well in the recession?
one_hit_artists[
    one_hit_artists.first_week_ending.dt.year.isin([2007, 2008, 2009])
].sort_values(by="max_chart_run", ascending=False).head(20)
```

[26]:
```
              artist_name                song_name first_week_ending  \
57             JASON MRAZ                I'M YOURS        2008-12-06
158                  FRAY         HOW TO SAVE A LIFE        2007-01-27
90             SAM SPARRO             BLACK & GOLD        2008-03-29
126       NEWTON FAULKNER            DREAM CATCH ME        2007-08-04
91        GABRIELLA CILMI            SWEET ABOUT ME        2008-03-15
71                MADCON                   BEGGIN'        2008-08-23
123        PLAIN WHITE T'S       HEY THERE DELILAH        2007-08-11
113          RAY PARKER JR             GHOSTBUSTERS        2007-11-10
67                    MIA             PAPER PLANES        2008-09-13
133                FERGIE        BIG GIRLS DON'T CRY        2007-06-30
106     SOULJA BOY TELLEM  CRANK THAT (SOULJA BOY)        2007-12-08
124    ROBYN WITH KLEERUP      WITH EVERY HEARTBEAT        2007-08-11
64      GURU JOSH PROJECT            INFINITY 2008        2008-11-01
62       BELLAMY BROTHERS        LET YOUR LOVE FLOW        2008-11-08
49          METRO STATION                 SHAKE IT        2009-03-07
37    DANIEL MERRIWEATHER                      RED        2009-05-30
```

```
75              KID ROCK          ALL SUMMER LONG        2008-07-12
94           ONEREPUBLIC           STOP AND STARE        2008-02-23
42             VERONICAS                UNTOUCHED        2009-05-09
27                   JLS               BEAT AGAIN        2009-07-25

     max_chart_run  peak_position  share_of_weeks
57              54             11        1.000000
158             53              4        0.697368
90              47              2        1.000000
126             43              7        1.000000
91              41              6        0.759259
71              40              5        1.000000
123             35              2        1.000000
113             35              2        0.777778
67              34             19        1.000000
133             33              2        0.702128
106             30              2        1.000000
124             28              1        1.000000
64              28              3        1.000000
62              26              7        1.000000
49              26              6        1.000000
37              26              5        0.787879
75              25              1        0.806452
94              25              4        1.000000
42              24              8        0.857143
27              24              1        0.750000
```

1.6 Last.FM Data

1.6.1 Data Exploration

[27]:
```
# ~ 7 billion streams
sql("SELECT SUM(playcount) FROM lastfm")
```

[27]:
```
   SUM(playcount)
0       723917022
```

[28]:
```
# Slight tail off, possibly due to missed joins.
sql("SELECT COUNT(*) FROM lastfm")
```

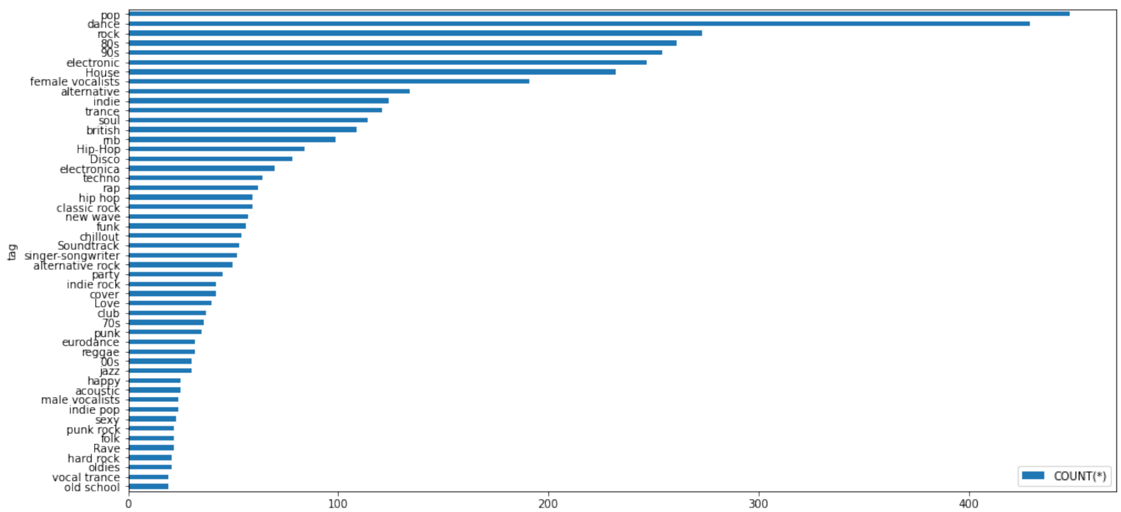
[28]:
```
   COUNT(*)
0      2016
```

[29]:
```
# ~1 track has 3 labels
sql("SELECT COUNT(*) FROM lastfm_tags")
```

[29]:
```
   COUNT(*)
0      7504
```

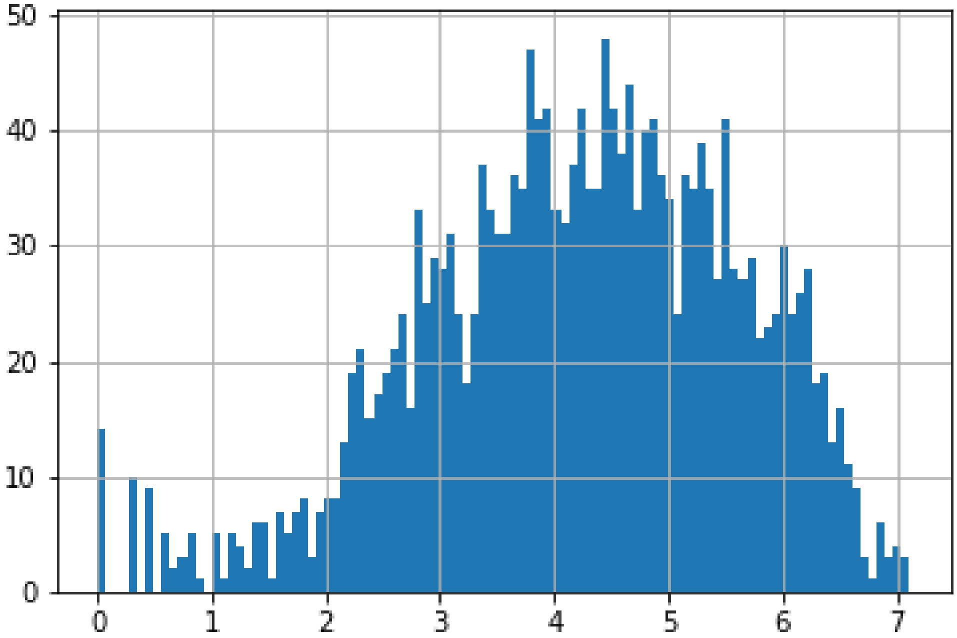
[30]:
```
# What are some popular tags/genres?
sql(
    "SELECT tag, COUNT(*) FROM lastfm_tags GROUP BY 1 ORDER BY 2 DESC LIMIT 50"
).set_index("tag").sort_values(by="COUNT(*)", ascending=True).plot.
 ↪barh(figsize=(16, 8))
```

[30]: <AxesSubplot:ylabel='tag'>



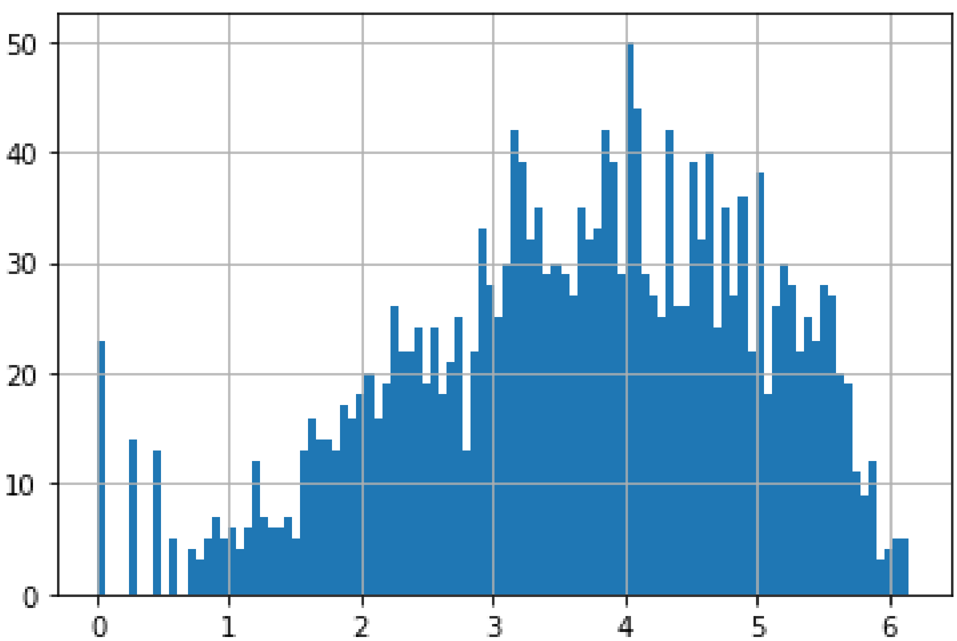
[31]:
```
# The average hit has between 10-100k streams
sql("SELECT playcount FROM lastfm").playcount.map(np.log10).hist(bins=100)
```

[31]: <AxesSubplot:>



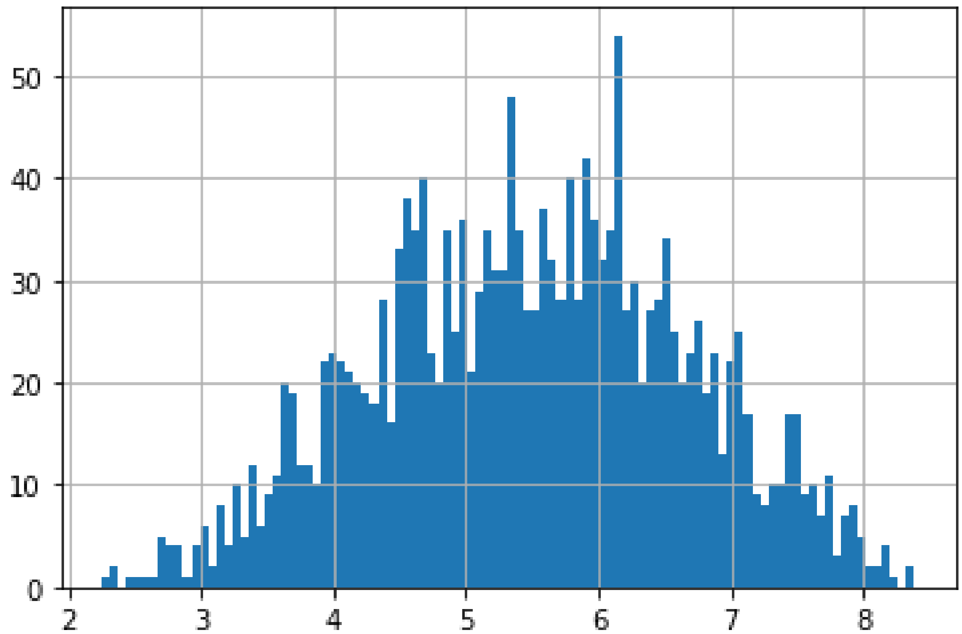
[32]:
```
# Average hit has between 500-10,000 streams
sql("SELECT listeners FROM lastfm").listeners.map(np.log10).hist(bins=100)
```

[32]: <AxesSubplot:>



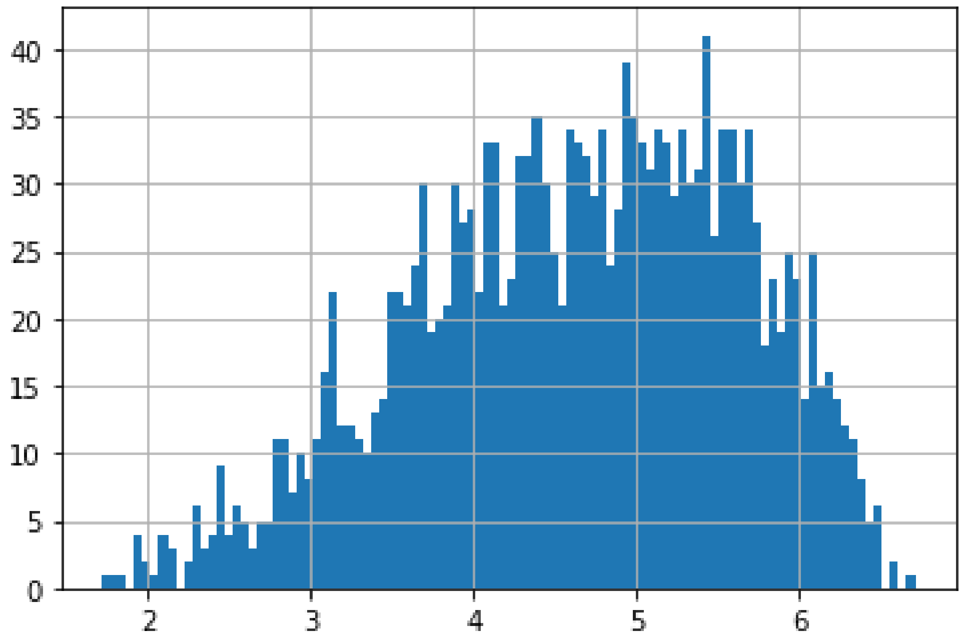
[33]:
```
# Average artist has between 100k-1m streams
sql("SELECT playcount FROM lastfm_artists").playcount.map(np.log10).
 ↪hist(bins=100)
```

[33]: <AxesSubplot:>



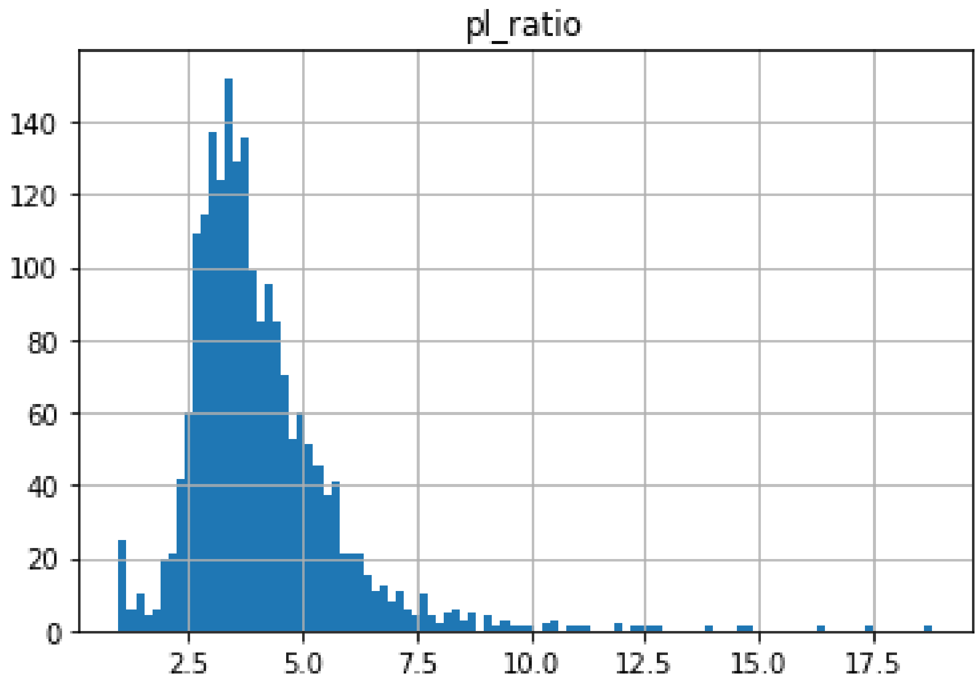
[34]:
```
# Average artist has between 10k and 100k listeners
sql("SELECT listeners FROM lastfm_artists").listeners.map(np.log10).
 ↪hist(bins=100)
```

[34]: <AxesSubplot:>



[35]:
```
sql(
    "SELECT CAST(playcount AS FLOAT)/listeners AS pl_ratio FROM lastfm WHERE␣
 ↪pl_ratio < 20"
).hist(bins=100)
```

[35]: array([[<AxesSubplot:title={'center':'pl_ratio'}>]], dtype=object)



[36]:
```
pl_ratio_artists = sql(
    "SELECT CAST(playcount AS FLOAT)/listeners AS pl_ratio FROM lastfm_artists"
)
pl_ratio_artists.describe()
```

[36]:

	pl_ratio
count	1814.000000
mean	9.152611
std	8.794331
min	2.346914
25%	4.513894
50%	6.227777
75%	10.192455
max	111.535817

1.6.2 Analysing songs based on streaming habits

[37]:
```
# Join together the tracks and add some features such as listener stickiness␣
 ↪(song_pl_ratio)
query = """
SELECT
  DISTINCT c.*,
  l.*,
  la.playcount AS artist_playcount,
```

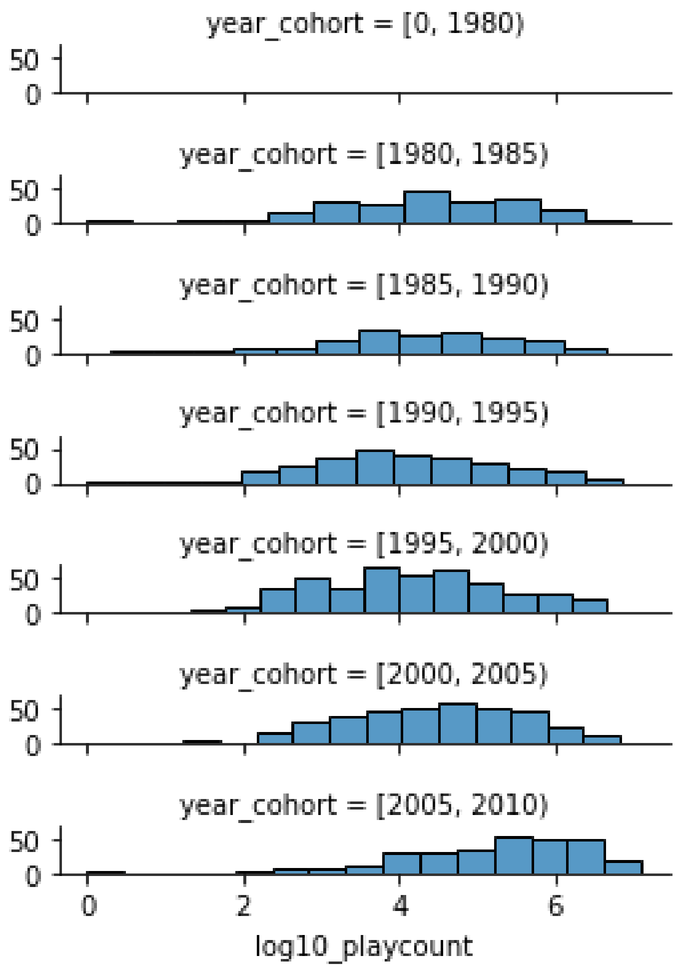
```
  la.listeners AS artist_listeners,
  CAST(l.playcount AS FLOAT)/l.listeners AS song_pl_ratio,
  CAST(la.playcount AS FLOAT)/la.listeners AS artist_pl_ratio,
  CAST(l.listeners AS FLOAT)/la.listeners AS song_artist_listener_ratio,
  CAST(l.playcount AS FLOAT)/la.playcount AS song_artist_playcount_ratio
FROM lastfm l
JOIN link_lastfm_chart lc ON lc.lastfm_id = l.lastfm_id
JOIN lastfm_artists la ON la.artist_mbid = l.artist_mbid
JOIN v_one_hit_wonders c ON c.artist_name = lc.artist_name AND c.song_name = lc.
 ↪song_name
"""
ohw_stats = sql(query)
ohw_stats["first_week_ending"] = pd.to_datetime(ohw_stats.first_week_ending)

# sqlite annoyingly isn't as good an analytics database as I remember
# Add order of magnitude values for clearer reasoning
log10_cols = ["artist_playcount", "artist_listeners", "playcount", "listeners"]
for col in log10_cols:
    ohw_stats[f"log10_{col}"] = np.log10(ohw_stats[col])
ohw_stats["pct_split_playcount"] = (
    ohw_stats.sort_values(by="playcount", ascending=False)
    .playcount.cumsum()
    .div(ohw_stats.playcount.sum())
)
ohw_stats["playcount_rank"] = ohw_stats.playcount.rank(method="min",␣
 ↪ascending=False)

# Generate a year cohort to make grouping easier
ohw_stats["year_cohort"] = pd.cut(
    ohw_stats.first_week_ending.dt.year,
    bins=[0, 1980, 1985, 1990, 1995, 2000, 2005, 2010],
    right=False,
)[ohw_stats.index]
```

[38]:
```
# Can deteirmine weighting from this
ohw_stats[["year_cohort"]].value_counts(normalize=True).sort_index()
```

[38]:
```
year_cohort
[0, 1980)       0.000000
[1980, 1985)    0.124728
[1985, 1990)    0.098039
[1990, 1995)    0.158497
[1995, 2000)    0.247821
[2000, 2005)    0.208061
[2005, 2010)    0.162854
dtype: float64
```

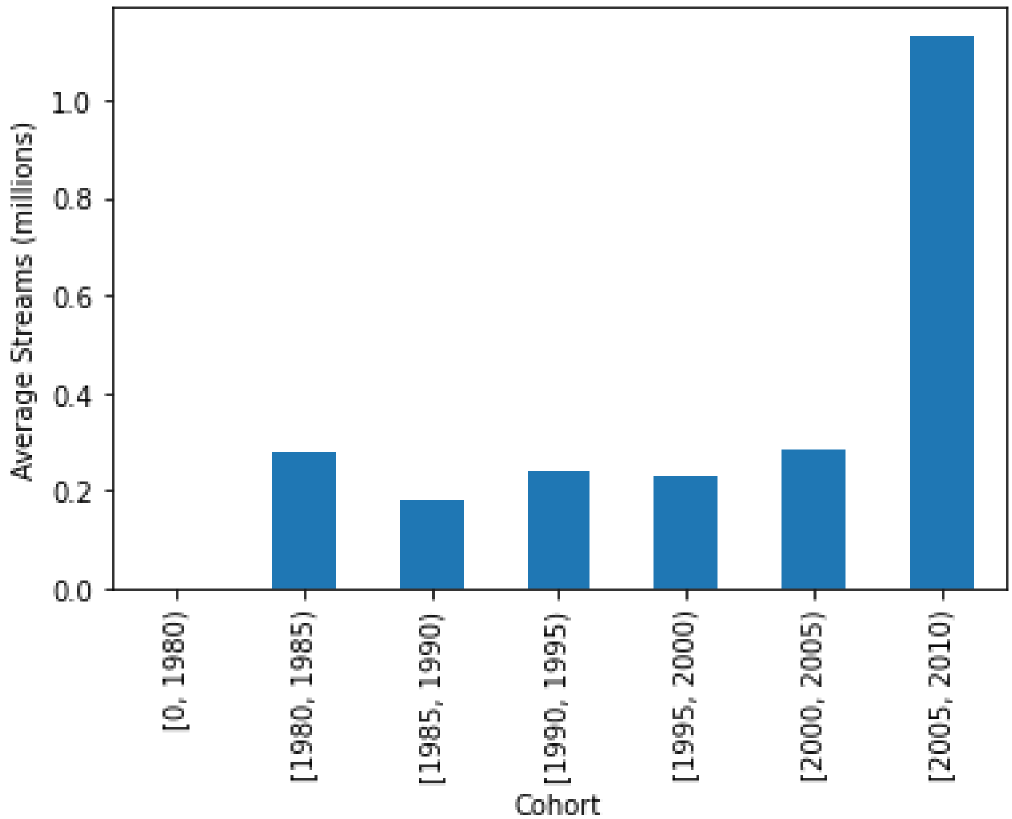
[39]:
```python
# Later charts (around advent of streaming) have more skew than earlier tracks
g = sns.FacetGrid(ohw_stats, row="year_cohort", aspect=5, height=0.75)
g.map(sns.histplot, "log10_playcount")
```

[39]:
```
<seaborn.axisgrid.FacetGrid at 0x7f38e642cf40>
```



[40]:
```python
# Average is way higher
ohw_stats.groupby("year_cohort").playcount.mean().div(1_000_000).sort_index().
↪plot.bar(
    ylabel="Average Streams (millions)", xlabel="Cohort"
)
```

[40]:
```
<AxesSubplot:xlabel='Cohort', ylabel='Average Streams (millions)'>
```



1.6.3 Analysing Tag Data

[41]:
```
tags = sql(f"""SELECT * FROM lastfm_tags""")
```

[42]:
```
# Build a genres table with some well known genres - nb, some tracks overlap
genres = [
    "indie",
    "folk",
    "pop",
    "dance",
    "rock",
    "alternative",
    "metal",
    "classic rock",
]
genres_table = tags[tags.tag.isin(genres)][["lastfm_id", "tag"]]
genres_table = (
    pd.get_dummies(genres_table, prefix="genre", columns=["tag"])
    .groupby("lastfm_id")
    .sum()
```

```
    .reset_index()
)  # Annoying bit of logic for uniqueness (one-to-many tags)
genres_table
```

[42]:

```
      lastfm_id  genre_alternative  genre_classic rock  genre_dance  \
0             4                  0                   0            1
1             8                  0                   0            0
2             9                  0                   0            0
3            10                  0                   0            1
4            11                  0                   0            0
…           …                  …                   …          …
1018       2008                  1                   0            0
1019       2009                  0                   0            1
1020       2010                  0                   0            0
1021       2011                  0                   0            0
1022       2013                  0                   0            1

      genre_folk  genre_indie  genre_metal  genre_pop  genre_rock
0              0            0            0          1           0
1              0            1            0          0           1
2              0            0            0          1           0
3              0            0            0          0           0
4              0            0            0          1           0
…            …          …          …        …         …
1018           0            0            0          0           1
1019           0            0            0          0           0
1020           0            1            0          1           0
1021           0            0            0          1           0
1022           0            0            0          0           0

[1023 rows x 9 columns]
```

[43]:

```
# Build a time period table
time_periods = ["60s", "70s", "80s", "90s", "00s"]
time_table = tags[tags.tag.isin(time_periods)][["lastfm_id", "tag"]]
time_table = (
    pd.get_dummies(time_table, prefix="decade", columns=["tag"])
    .groupby("lastfm_id")
    .sum()
    .reset_index()
)
time_table
```

[43]:

```
     lastfm_id  decade_00s  decade_60s  decade_70s  decade_80s  decade_90s
0            1           0           0           0           1           0
1            4           1           0           0           0           0
2            6           0           0           0           0           1
```

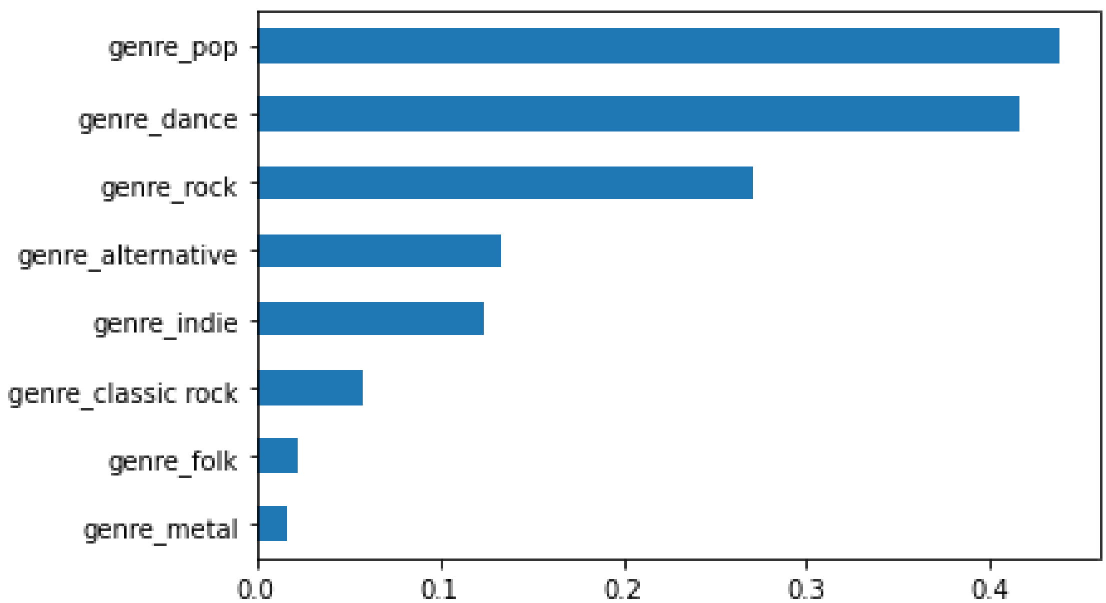
3	11	0	0	0	1	1
4	13	0	0	0	1	0
..	…	…	…	…	…	…
569	1990	0	0	0	0	1
570	2000	0	0	0	1	0
571	2001	0	0	0	1	0
572	2004	1	0	0	0	0
573	2013	0	0	0	0	1

[574 rows x 6 columns]

[44]:
```
ohw_stats = ohw_stats.merge(time_table, on="lastfm_id", how="outer").merge(
    genres_table, on="lastfm_id", how="outer"
)
ohw_stats = ohw_stats[ohw_stats.artist_name.notnull()]
```

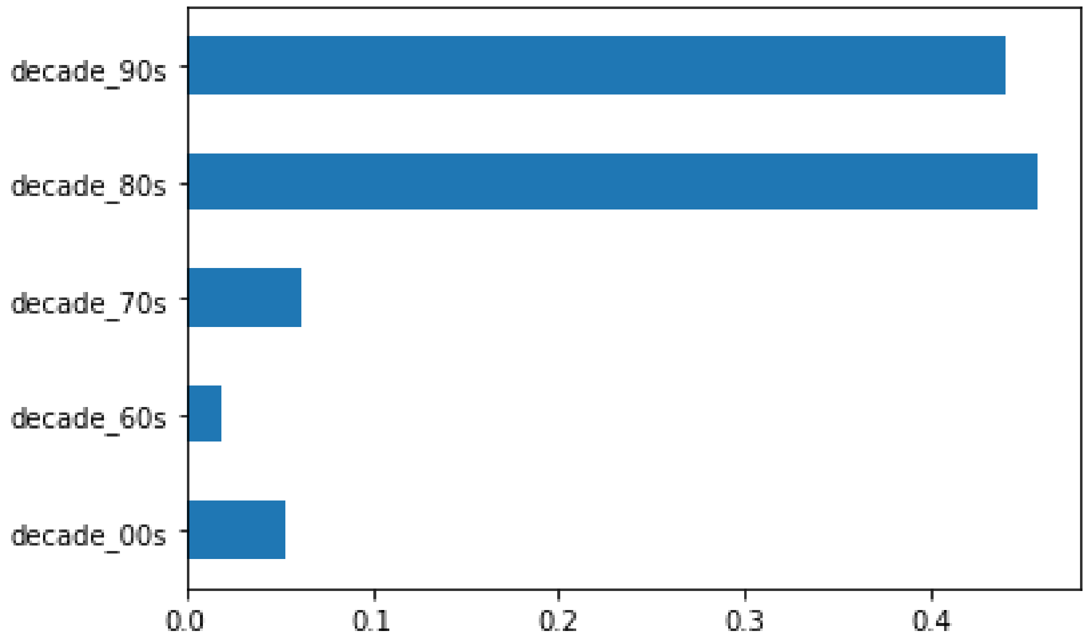
[45]:
```
ohw_stats.filter(like="genre").mean().sort_values().plot.barh()
```

[45]: <AxesSubplot:>



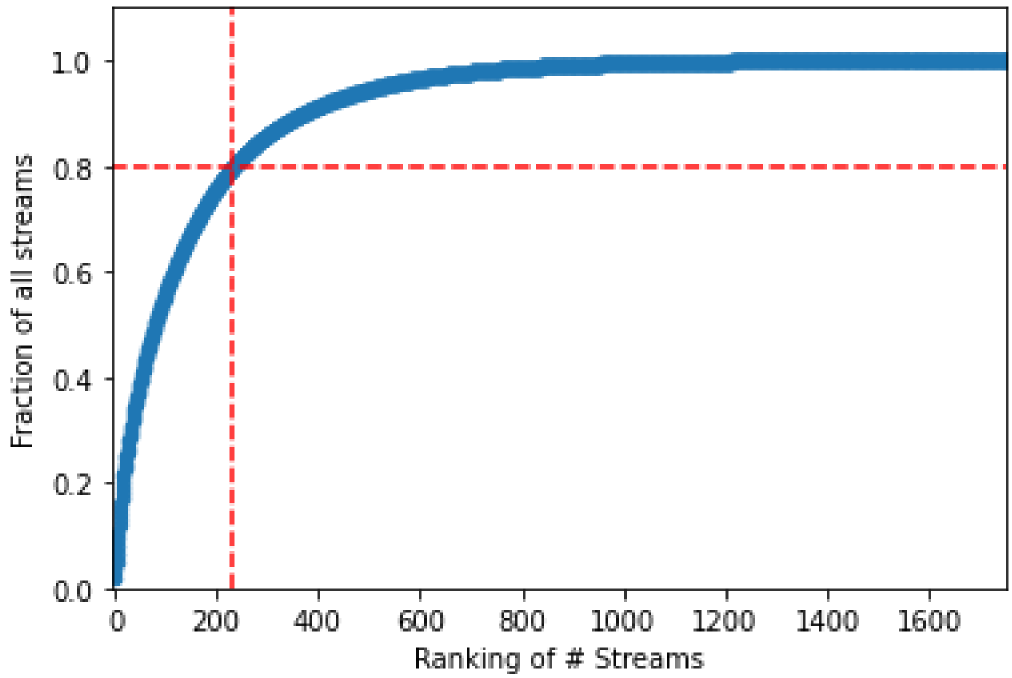
[46]:
```
# Nostalgia factor? Why tag with "90s" etc otherwise?
ohw_stats.filter(like="decade").mean().plot.barh()
```

[46]: <AxesSubplot:>



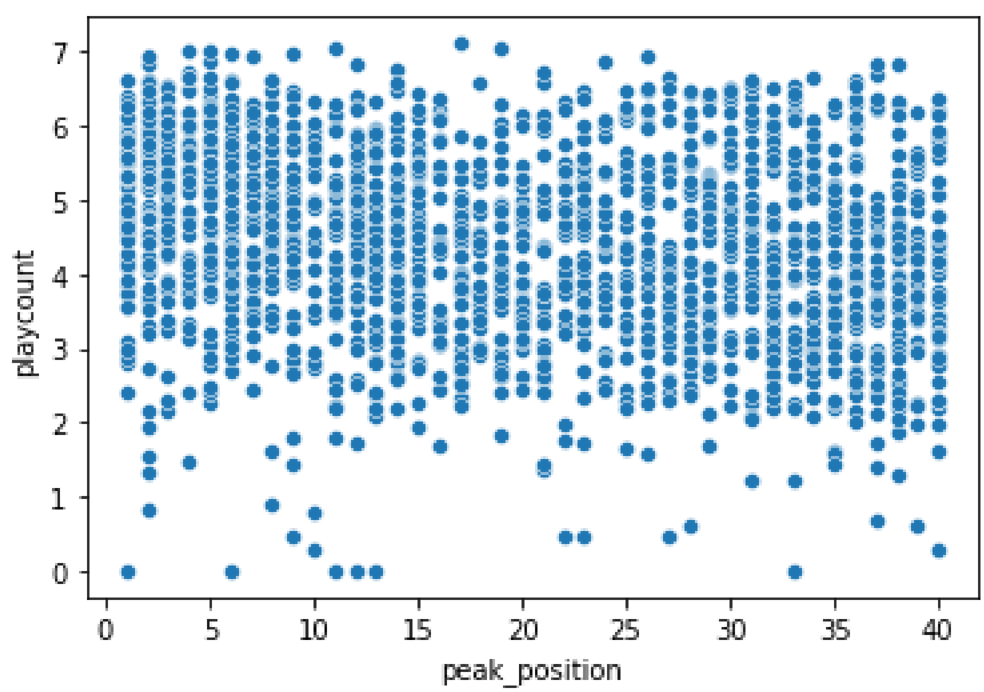
[47]:
```
# 80% of listens come from about 233 of the songs
# 50% of listens come from 79 songs
ohw_stats.plot.scatter(
    x="playcount_rank",
    y="pct_split_playcount",
    xlim=[-5, 1750],
    ylim=[0, 1.1],
    xlabel="Ranking of # Streams",
    ylabel="Fraction of all streams",
)
ohw_stats[ohw_stats.pct_split_playcount <= 0.8].sort_values(
    by="pct_split_playcount", ascending=False
).iloc[0].playcount_rank

# Super hits
# plt.axvline(79, color="r", linestyle="--")
plt.axvline(233, color="r", linestyle="--")
plt.axhline(0.8, color="r", linestyle="--")
# plt.axhline(0.5, color="r", linestyle="--")
```

[47]: <matplotlib.lines.Line2D at 0x7f38c44406a0>



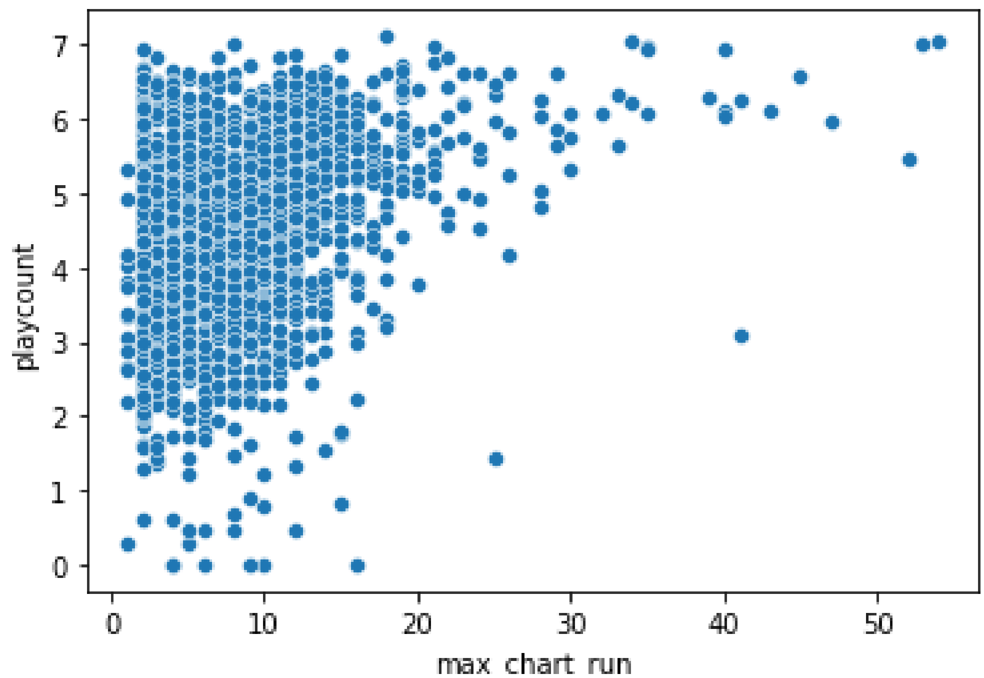
[48]:
```python
# Max peak position doesn't really have much of a bearing
sns.scatterplot(x=ohw_stats.peak_position, y=np.log10(ohw_stats.playcount))
```

[48]: <AxesSubplot:xlabel='peak_position', ylabel='playcount'>



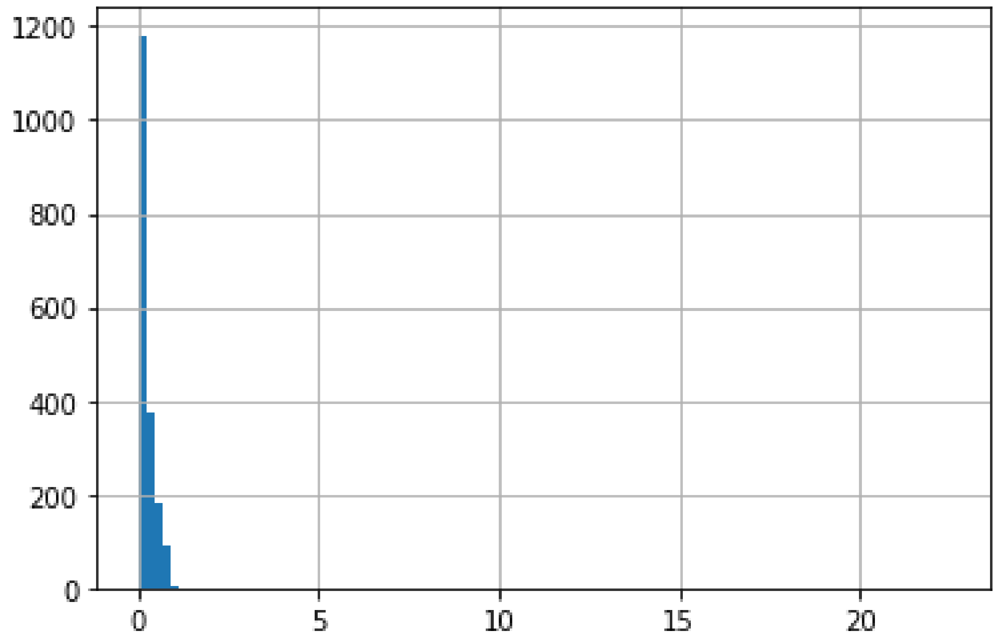
[49]:
```
# Seems to have a switchpoint around the 20 week run mark (1/2 year), but it's
↪so concentrated it's hard to tell if it's statistically significant
sns.scatterplot(x=ohw_stats.max_chart_run, y=np.log10(ohw_stats.playcount))
```

[49]:
```
<AxesSubplot:xlabel='max_chart_run', ylabel='playcount'>
```



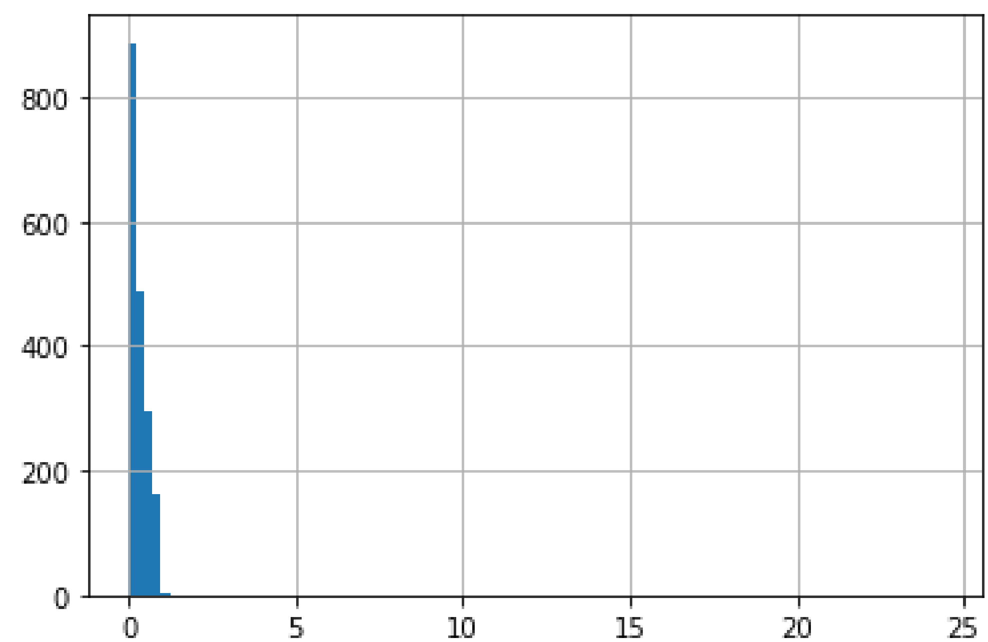
[50]:
```
# A measure of how concentrated an artist's plays are around one song
ohw_stats.song_artist_playcount_ratio.hist(bins=100)
```

[50]:
```
<AxesSubplot:>
```



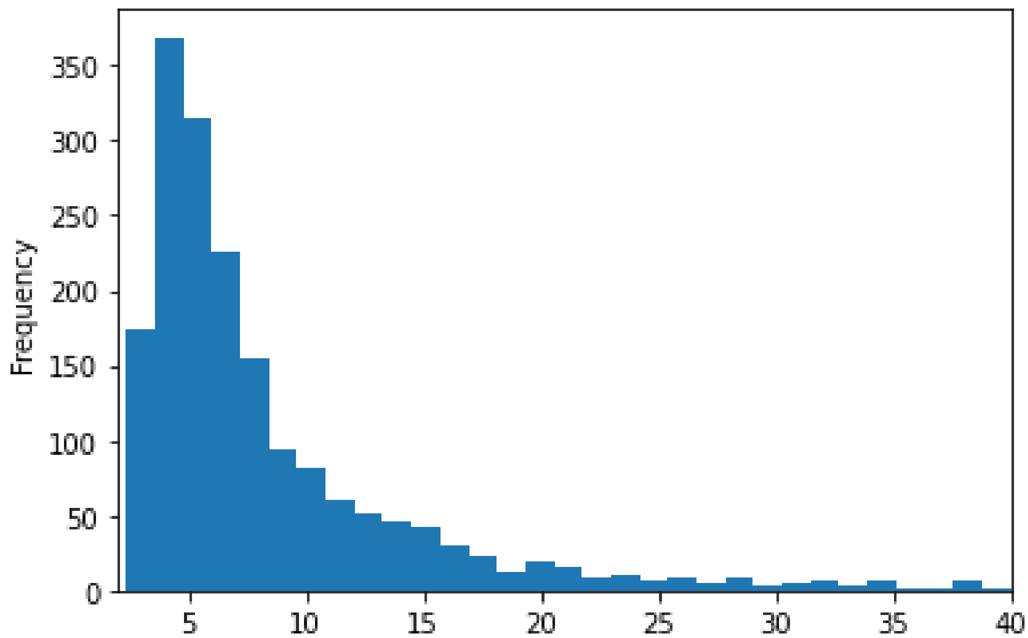

```
[51]: # measure of how concentrated an artist's listeners are around their one hit
      ohw_stats.song_artist_listener_ratio.hist(bins=100)
```

```
[51]: <AxesSubplot:>
```



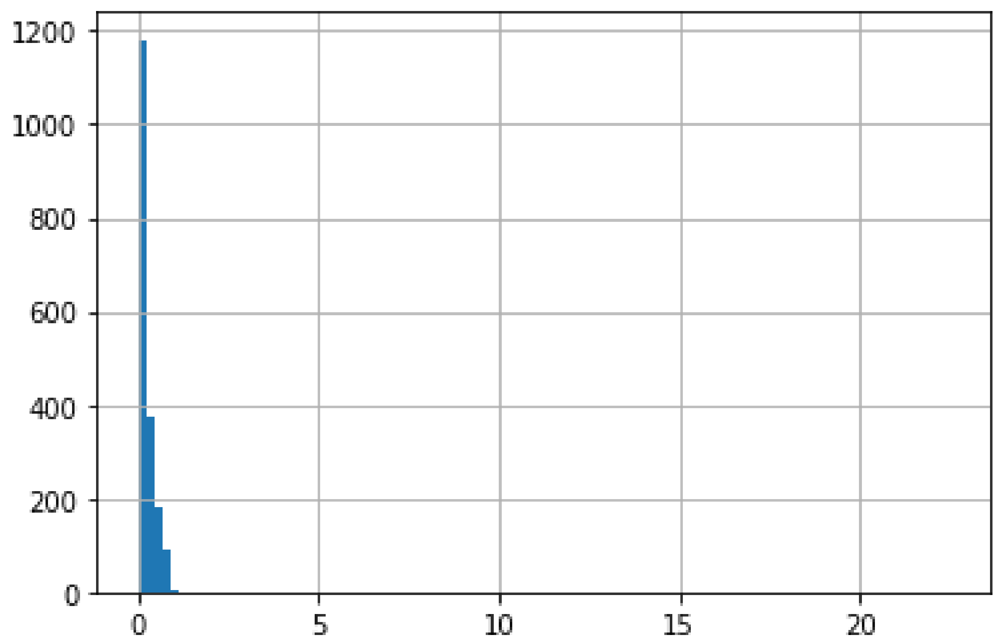
[52]:
```
# Some artists have very sticky / concentrated fan bases
ohw_stats.artist_pl_ratio.plot.hist(bins=90, xlim=[2, 40])
```

[52]: <AxesSubplot:ylabel='Frequency'>



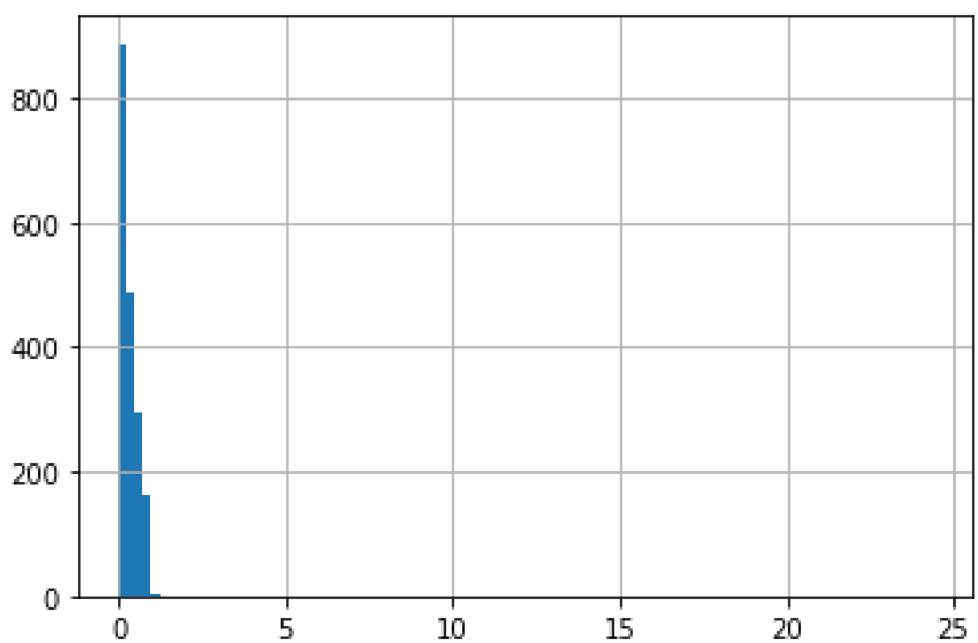
[53]:
```
# Appears like most artists plays are not heavily concentrated in their one␣
↪hits - possibly a proxy for popularity?
ohw_stats.song_artist_playcount_ratio.hist(bins=100)
```

[53]: <AxesSubplot:>




```
[54]: # Looks like artists have more concentrated listeners around their major hits,
      ↪maybe it's a measure of their catalogue's longer term popularity?
      ohw_stats.song_artist_listener_ratio.hist(bins=100)
```

```
[54]: <AxesSubplot:>
```



[55]:
```python
# Top tracks with high listeners are not really big artists
ohw_stats.sort_values(by="song_artist_playcount_ratio", ascending=False).
  ↪head(10)
```

[55]:
```
             artist_name                        song_name first_week_ending  \
1228        PETER CETERA                    GLORY OF LOVE        1986-08-02
1274      PROPELLERHEADS                        SPYBREAK!        1997-05-17
575      FOUR BUCKETEERS    THE BUCKET OF WATER SONG        1980-05-03
833         KATE WINSLET                          WHAT IF        2001-12-08
559            FERRY AID                        LET IT BE        1987-04-04
1721           TWISTED X                  BORN IN ENGLAND        2004-06-19
222       BOY MEETS GIRL   WAITING FOR A STAR TO FALL        1988-11-26
1199   PARTNERS IN KRYME                     TURTLE POWER        1990-07-21
18                 4-4-2                   COME ON ENGLAND        2004-06-19
265    CAST FROM CASUALTY                  EVERLASTING LOVE        1998-03-14

      max_chart_run  peak_position  share_of_weeks  lastfm_id  listeners  \
1228           13.0            3.0             1.0        902   172318.0
1274            2.0           40.0             1.0        828   111518.0
575             6.0           26.0             1.0        487      121.0
833            17.0            6.0             1.0        708    57044.0
559             7.0            1.0             1.0        242     4743.0
1721            3.0            9.0             1.0        693      573.0
222            14.0            9.0             1.0        877   110650.0
1199           10.0            1.0             1.0       1498     7622.0
18              5.0            2.0             1.0          5     1223.0
265             9.0            5.0             1.0         65       55.0

      playcount  duration                                  mbid  \
1228   699315.0  260000.0  09970bad-8cfe-4c74-a940-be7fd13fa5f7
1274   377752.0  420000.0  ed0c9373-6ffa-4c60-83d4-9b3b673c10c7
575       307.0  172000.0                                  None
833    287372.0  244000.0  af45aab5-1c23-4ef6-acb1-e1ebe73c3e03
559     13265.0       NaN  1138308e-d67d-4b19-b4e0-c85382c2ec29
1721     1857.0  180000.0  52acd439-d243-4ff7-9f25-e240a51d6bbf
222    542361.0  321000.0  80214d59-9f71-4cee-b3fb-f677720eaa7b
1199    28986.0  230000.0  00db40ea-7874-4a4f-8c2f-96cbc1988115
18       4241.0  223000.0  553af8f8-75f6-444f-a658-997682893a4d
265       187.0  171000.0                                  None

                               artist_mbid  artist_playcount  \
1228  cdcd53c9-f37c-48cc-b7e3-dfe34be22e92           31095.0
1274  cbaafb20-eb74-421a-85f1-2bb6341aad23           40143.0
575   5270d69b-bf85-4399-949e-3a971bf2e981             311.0
833   ceb05831-03e8-4605-904d-894ee0492d00          307011.0
559   590233d0-5ab2-4a67-8f43-a647c2100bdc           14261.0
```

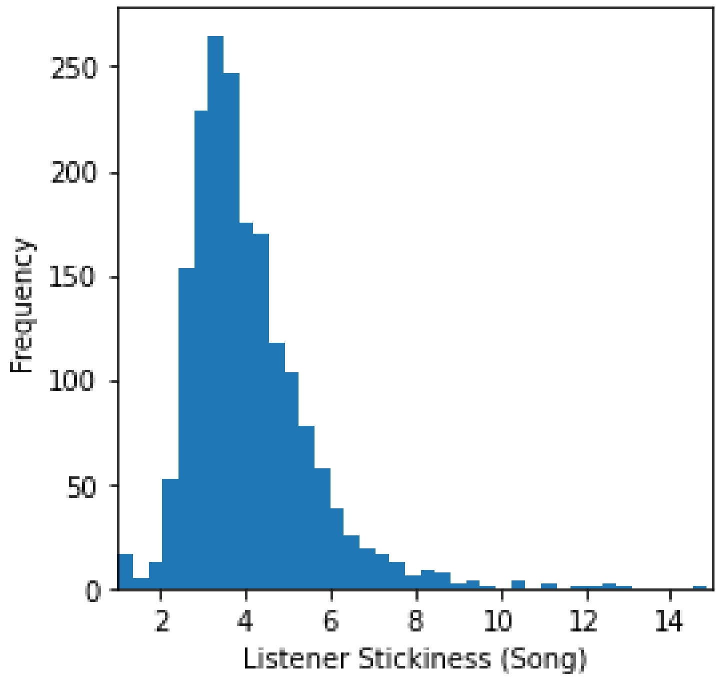
```
1721  a330ac7f-4722-465f-938f-7c7a703219f0        2027.0
222   1752572e-2179-4507-9214-b29a6f2d7888      592946.0
1199  7e3b1e89-9dc4-44ff-bb47-21be91a3dd72       32067.0
18    e4a47762-3b26-4263-a756-6fd2c3e425a8        4740.0
265   33542e9c-48af-4b98-8fbd-bda7383881c3         210.0

      artist_listeners  song_pl_ratio  artist_pl_ratio  \
1228            7084.0       4.058282         4.389469
1274           11735.0       3.387363         3.420793
575              122.0       2.537190         2.549180
833            60293.0       5.037725         5.091984
559             4924.0       2.796753         2.896223
1721             625.0       3.240838         3.243200
222           114253.0       4.901591         5.189763
1199            8221.0       3.802939         3.900620
18              1341.0       3.467702         3.534676
265               59.0       3.400000         3.559322

      song_artist_listener_ratio  song_artist_playcount_ratio  \
1228                   24.324958                    22.489629
1274                    9.503025                     9.410159
575                     0.991803                     0.987138
833                     0.946113                     0.936032
559                     0.963241                     0.930159
1721                    0.916800                     0.916132
222                     0.968465                     0.914689
1199                    0.927138                     0.903920
18                      0.912006                     0.894726
265                     0.932203                     0.890476

      log10_artist_playcount  log10_artist_listeners  log10_playcount  \
1228                4.492691                3.850279         5.844673
1274                4.603610                4.069483         5.577207
575                 2.492760                2.086360         2.487138
833                 5.487154                4.780267         5.458444
559                 4.154150                3.692318         4.122707
1721                3.306854                2.795880         3.268812
222                 5.773015                5.057868         5.734288
1199                4.506058                3.914925         4.462188
18                  3.675778                3.127429         3.627468
265                 2.322219                1.770852         2.271842

      log10_listeners  pct_split_playcount  playcount_rank   year_cohort  \
1228         5.236331             0.817518           251.0  [1985, 1990)
1274         5.047345             0.889168           350.0  [1995, 2000)
575          2.082785             0.999977          1714.0  [1980, 1985)
833          4.756210             0.916507           410.0  [2000, 2005)
```

```
559          3.676053           0.996425          1088.0  [1985, 1990)
1721         2.758155           0.999684          1480.0  [2000, 2005)
222          5.043951           0.851879           291.0  [1985, 1990)
1199         3.882069           0.991306           907.0  [1990, 1995)
18           3.087426           0.999085          1333.0  [2000, 2005)
265          1.740363           0.999991          1756.0  [1995, 2000)

      decade_00s  decade_60s  decade_70s  decade_80s  decade_90s  \
1228         0.0         0.0         0.0         1.0         0.0
1274         NaN         NaN         NaN         NaN         NaN
575          NaN         NaN         NaN         NaN         NaN
833          NaN         NaN         NaN         NaN         NaN
559          NaN         NaN         NaN         NaN         NaN
1721         NaN         NaN         NaN         NaN         NaN
222          0.0         0.0         0.0         1.0         0.0
1199         0.0         0.0         0.0         1.0         0.0
18           NaN         NaN         NaN         NaN         NaN
265          NaN         NaN         NaN         NaN         NaN

      genre_alternative  genre_classic rock  genre_dance  genre_folk  \
1228                0.0                 0.0          0.0         0.0
1274                0.0                 0.0          1.0         0.0
575                 NaN                 NaN          NaN         NaN
833                 0.0                 0.0          0.0         0.0
559                 NaN                 NaN          NaN         NaN
1721                NaN                 NaN          NaN         NaN
222                 0.0                 0.0          0.0         0.0
1199                NaN                 NaN          NaN         NaN
18                  NaN                 NaN          NaN         NaN
265                 NaN                 NaN          NaN         NaN

      genre_indie  genre_metal  genre_pop  genre_rock
1228          0.0          0.0        1.0         0.0
1274          0.0          0.0        0.0         0.0
575           NaN          NaN        NaN         NaN
833           0.0          0.0        1.0         0.0
559           NaN          NaN        NaN         NaN
1721          NaN          NaN        NaN         NaN
222           0.0          0.0        1.0         0.0
1199          NaN          NaN        NaN         NaN
18            NaN          NaN        NaN         NaN
265           NaN          NaN        NaN         NaN
```

[56]:
```python
# For artists, this is effectively a measure of how concentrated their fan base
↪is in tandem with the play concentration
a = ohw_stats.song_pl_ratio.plot.hist(
    bins=90, xlim=[1, 15], xlabel="Listener Stickiness (Song)", figsize=(4, 4)
```

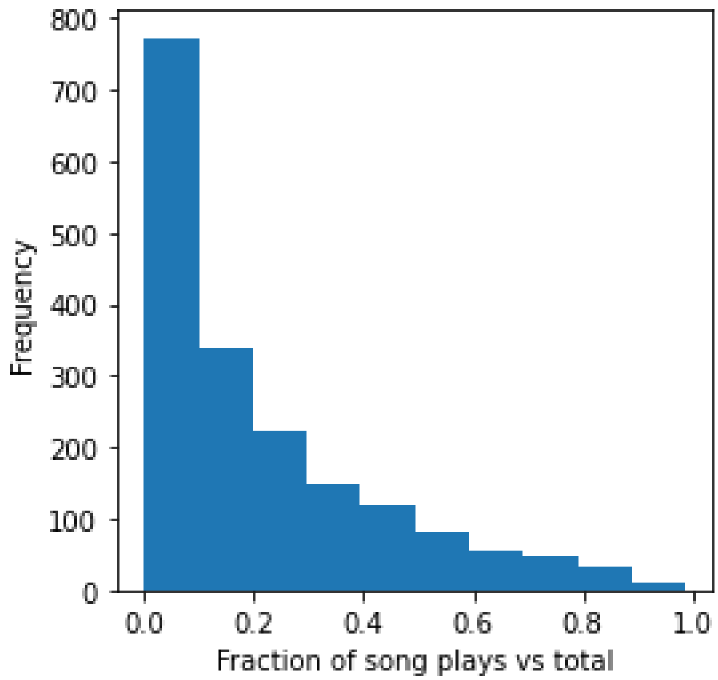
```
)
a.set_xlabel("Listener Stickiness (Song)")
```

[56]: Text(0.5, 0, 'Listener Stickiness (Song)')



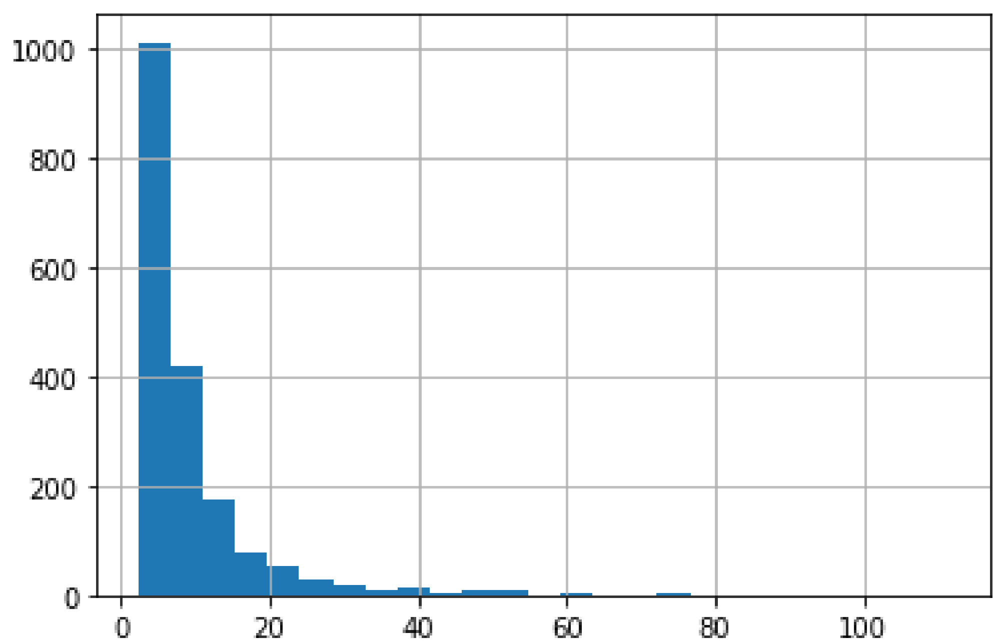
[57]:
```
a = ohw_stats[
    ohw_stats.song_artist_playcount_ratio <= 1
].song_artist_playcount_ratio.plot.hist(
    xlabel="Fraction of song plays vs total", figsize=(4, 4)
)
a.set_xlabel("Fraction of song plays vs total")
```

[57]: Text(0.5, 0, 'Fraction of song plays vs total')




```
[58]: # For artists, this is effectively a measure of how concentrated their fan base
      ↪is
      ohw_stats.artist_pl_ratio.hist(bins=25)
      print(ohw_stats.artist_pl_ratio.mean())
```

9.184217837778288



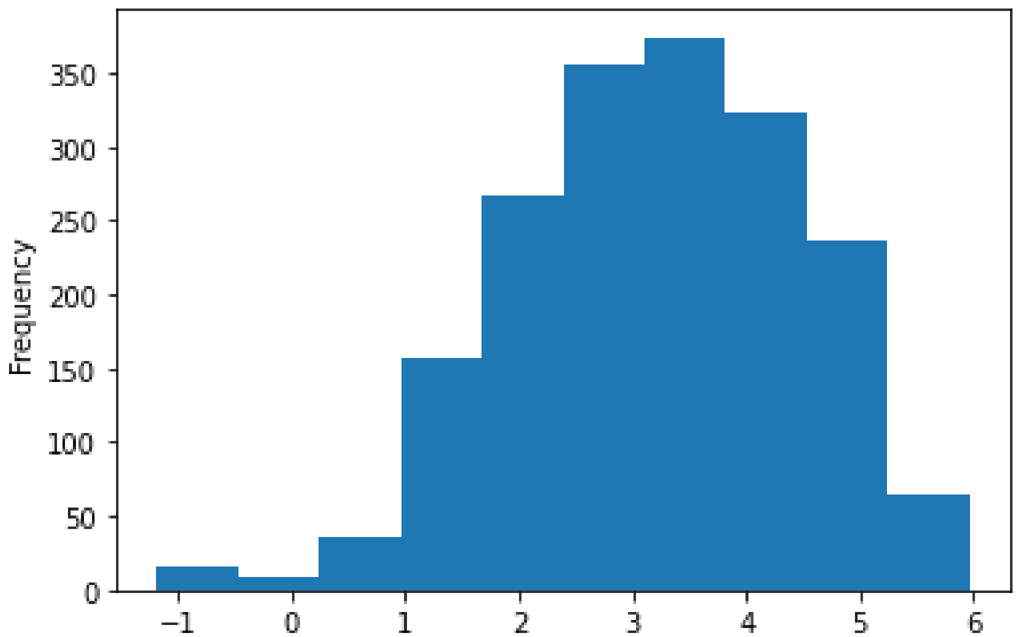
[59]:
```
## Some feature engineering to get a feeling for how the tracks fare by
## May not include in final report, one big question that it raises is "when␣
↪were the majority of streams?" otherwise could hugely bias the dataset
## towards the more recent tracks.

import datetime

def years_since_spotify(row: pd.Timestamp) -> float:
    """Computes how many listens per year a track has had since the advent of␣
↪spotify."""
    end_date = pd.Timestamp(2021, 8, 6)
    reference_date = pd.Timestamp(2006, 4, 23)

    # If the song came out after spotify, then count that  directly.
    if row > reference_date:
        reference_date = row
    return (end_date - reference_date).days / 365.25


ohw_stats["years_since_spotify"] = ohw_stats.first_week_ending.
↪map(years_since_spotify)
ohw_stats["annual_song_streams_since_spotify"] = (
    ohw_stats.playcount / ohw_stats.years_since_spotify
)
ohw_stats["annual_artist_streams_since_spotify"] = (
    ohw_stats.artist_playcount / ohw_stats.years_since_spotify
)

# https://www.indiemusicacademy.com/blog/music-royalties-explained
ohw_stats["gbp_annual_song_royalty_est"] = (
    ohw_stats.annual_song_streams_since_spotify * 0.066
)
```

[60]:
```
# Come back if time - potentially too noisy with poor streaming data
# https://www.statista.com/statistics/885750/
↪average-risk-free-rate-united-kingdom/
risk_free_rate = 0.013
def npv(years: int, risk_free_rate: float, coupon: int) -> float:
    result = []
    for year in range(years):
        result.append(coupon / (1 + risk_free_rate) ** year)
    return np.sum(result)

# Below - bit dubious w/o trend data
```

```
# ohw_stats["gbp_annual_song_royalty_npv_5yr"] = ohw_stats.
↪gbp_annual_song_royalty_est.map(lambda r: npv(5, risk_free_rate, r))
# ohw_stats["gbp_annual_song_royalty_npv_10yr"] = ohw_stats.
↪gbp_annual_song_royalty_est.map(lambda r: npv(10, risk_free_rate, r))
# ohw_stats["gbp_annual_song_royalty_5yr_price_at_irr"] = ohw_stats.
↪gbp_annual_song_royalty_est.map(lambda r: npv(5, 0.1, r))
```

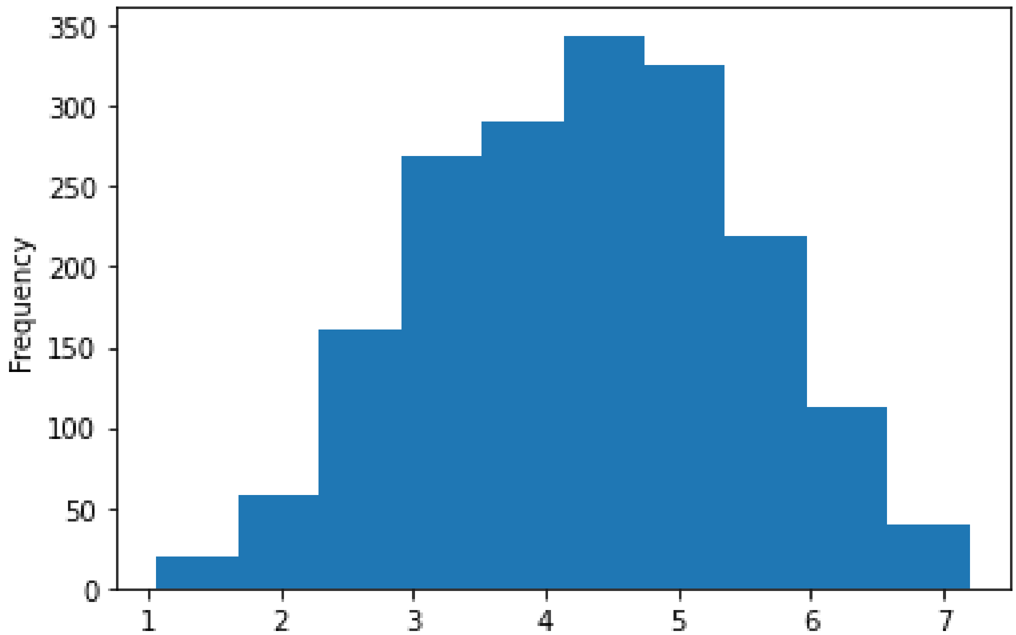
[61]:
```
ohw_stats.annual_song_streams_since_spotify.map(np.log10).plot.hist()
```

[61]: <AxesSubplot:ylabel='Frequency'>



[62]:
```
ohw_stats.annual_artist_streams_since_spotify.map(np.log10).plot.hist()
```

[62]: <AxesSubplot:ylabel='Frequency'>



1.6.4 Clustering Analysis

I use AffinityPropagation with a small feature set in order to group together songs with similar properties. This is a proof of concept to highlight why data science can be useful for performing fast target scanning / comp. analysis.

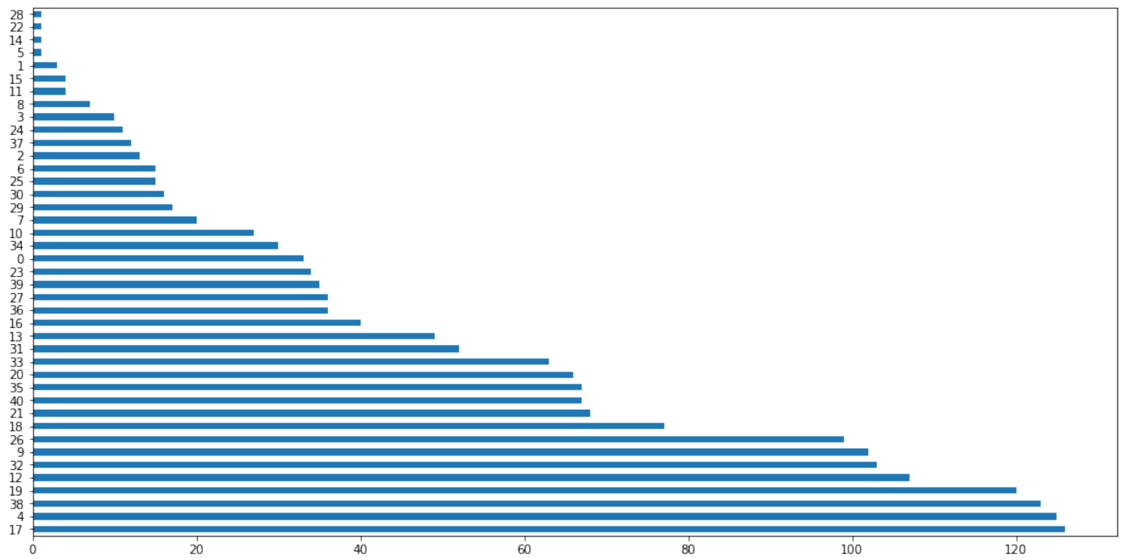
[63]:
```python
# Some extra stuff - quick and dirty clustering to see if we can segment the ohw market
from sklearn.cluster import AffinityPropagation

model = AffinityPropagation(damping=0.9)
data = ohw_stats[
    [
        "song_artist_listener_ratio",
        "song_pl_ratio",
        "artist_pl_ratio",
        "peak_position",
        "share_of_weeks",
    ]
]
model.fit(data)
ohw_stats["cluster"] = model.predict(data)
```

```
/home/niall/Documents/Projects/[redacted]/assignment/venv/lib/python3.8/site-
packages/sklearn/cluster/_affinity_propagation.py:148: FutureWarning:
'random_state' has been introduced in 0.23. It will be set to None starting from
```

```
1.0 (renaming of 0.25) which means that results will differ at every function
call. Set 'random_state' to None to silence this warning, or to 0 to keep the
behavior of versions <0.23.
  warnings.warn(
```

[64]:
```
# Large skew - cluster 17 seems like a "catch all"
ohw_stats.cluster.value_counts().plot.barh(figsize=(16, 8))
```

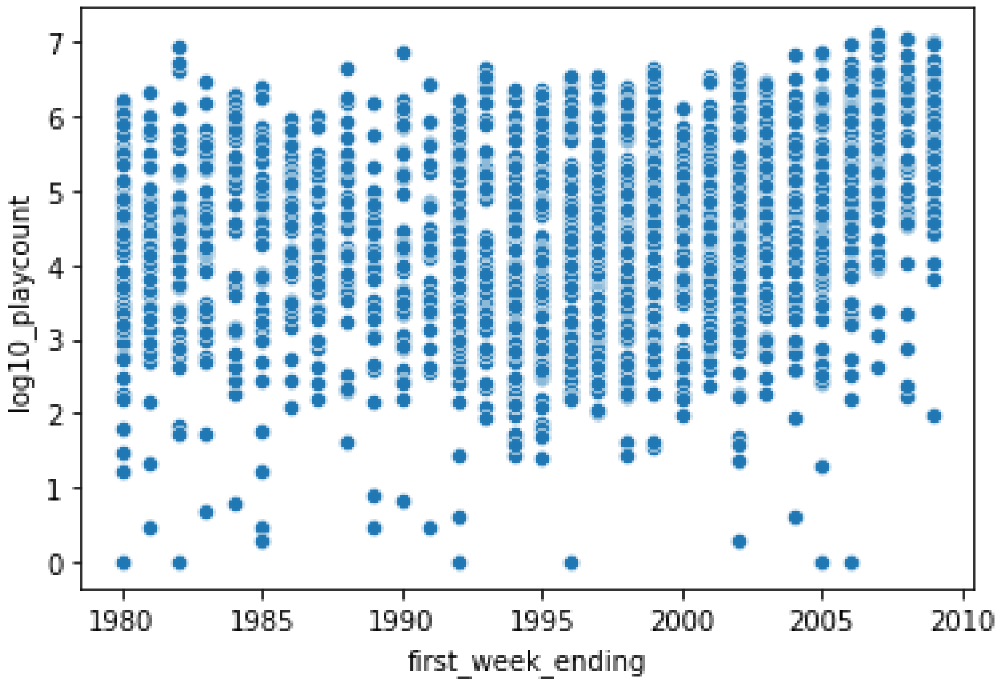
[64]:
```
<AxesSubplot:>
```



1.6.5 Searching for correlations

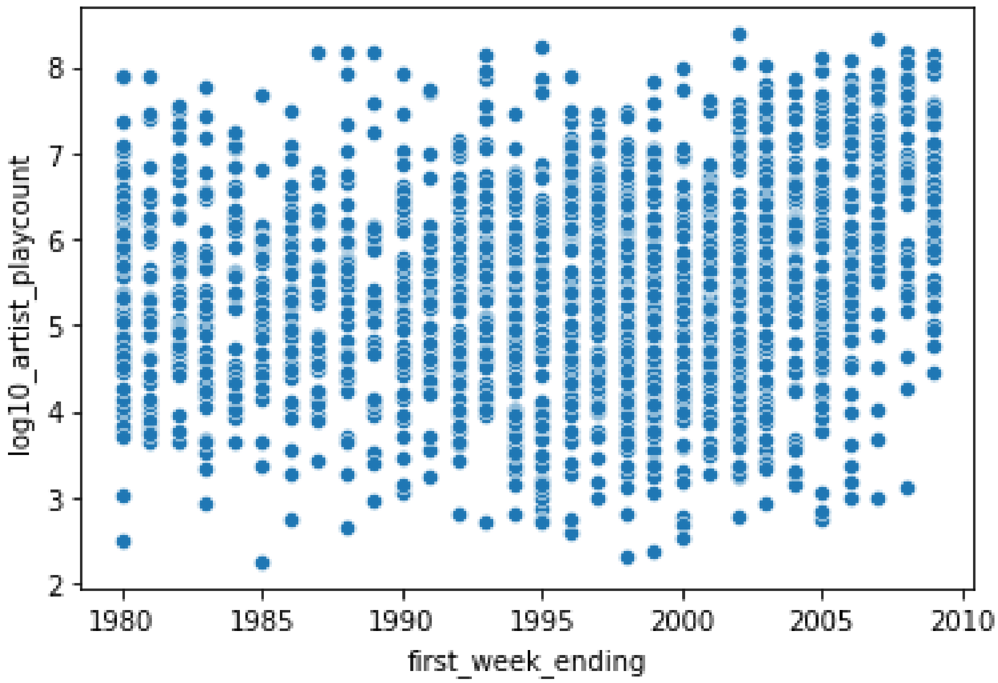
[65]:
```
# Older songs don't appear to offer much of a leg up on newer songs for total␣
 ↪streams
sns.scatterplot(x=ohw_stats.first_week_ending.dt.year, y=ohw_stats.
 ↪log10_playcount)
```

[65]:
```
<AxesSubplot:xlabel='first_week_ending', ylabel='log10_playcount'>
```



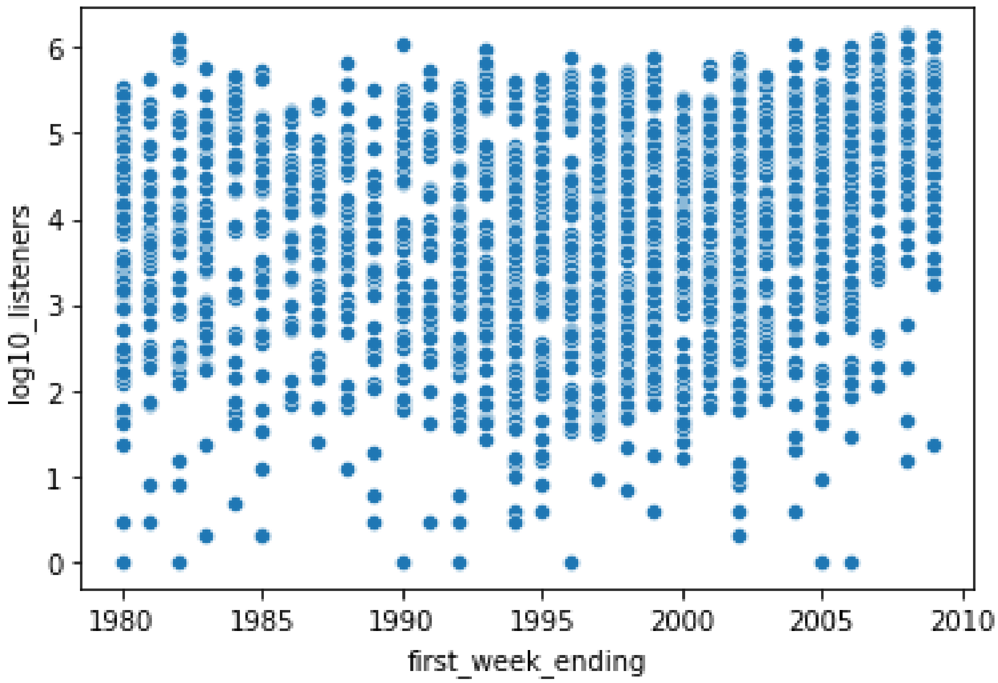
[66]:
```
# Older songs don't appear to offer much of a leg up on newer songs for total␣
↪streams
sns.scatterplot(
    x=ohw_stats.first_week_ending.dt.year, y=ohw_stats.log10_artist_playcount
)
```

[66]:
```
<AxesSubplot:xlabel='first_week_ending', ylabel='log10_artist_playcount'>
```



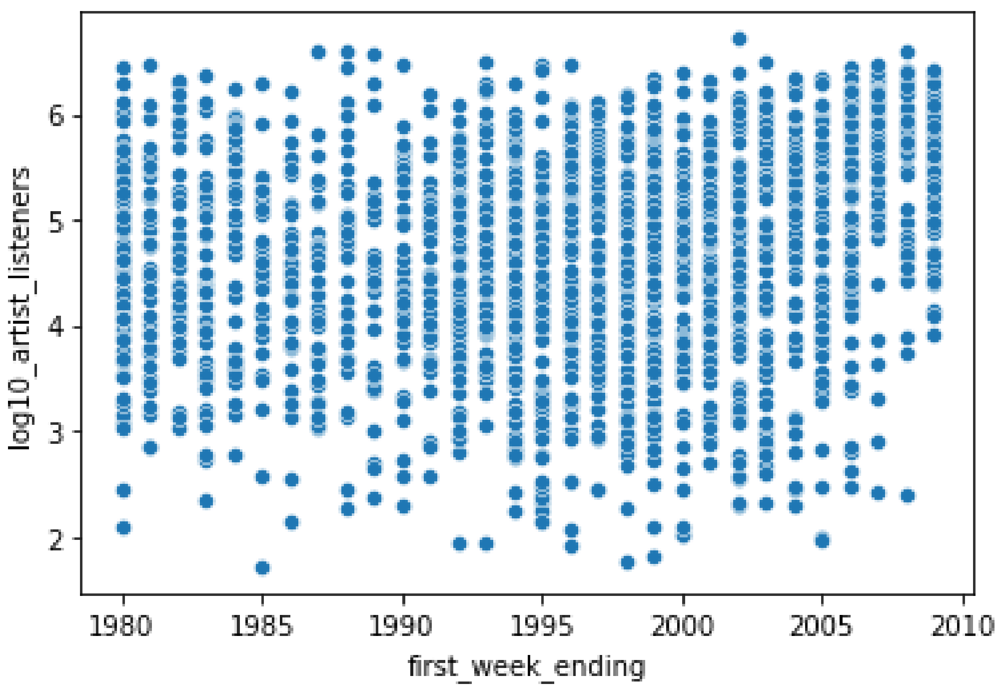
[67]:
```
# Nor for listeners except on average
sns.scatterplot(x=ohw_stats.first_week_ending.dt.year, y=ohw_stats.
 ↪log10_listeners)
```

[67]: <AxesSubplot:xlabel='first_week_ending', ylabel='log10_listeners'>



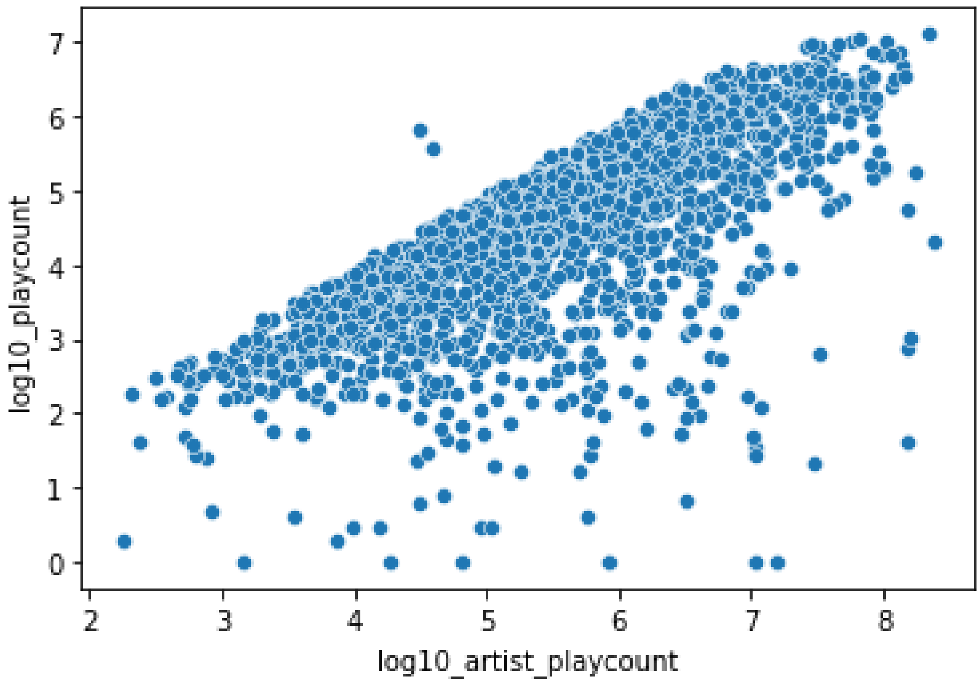
[68]:
```
# Nor for listeners, mean number of listeners is higher
sns.scatterplot(
    x=ohw_stats.first_week_ending.dt.year, y=ohw_stats.log10_artist_listeners
)
```

[68]: <AxesSubplot:xlabel='first_week_ending', ylabel='log10_artist_listeners'>



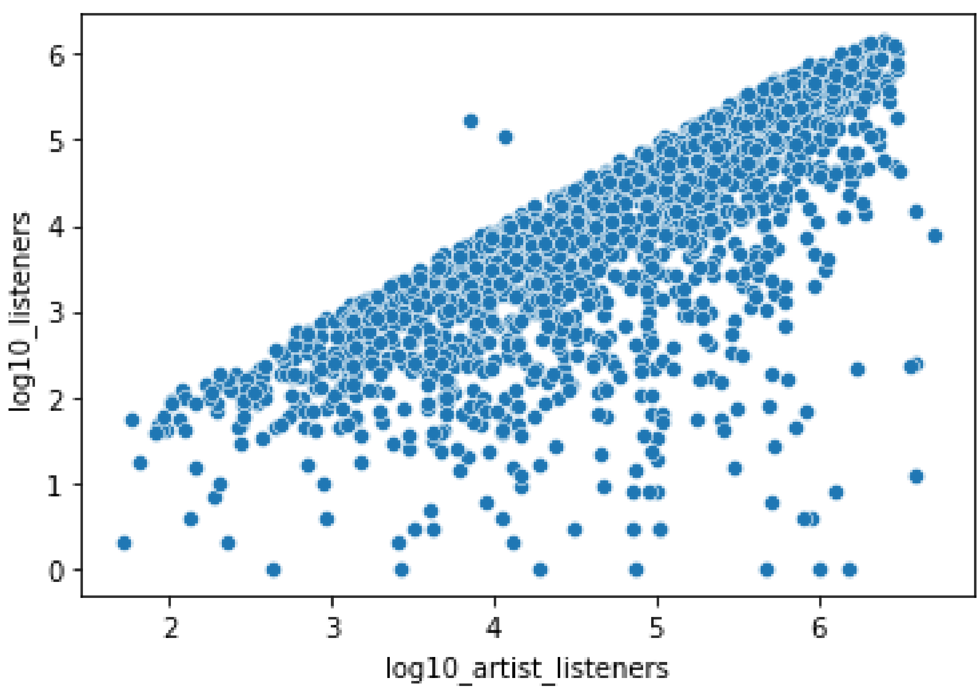
[69]:
```
# The most listens the hit has, the better a predictor of the artist's overall␣
↪listens?
sns.scatterplot(x=ohw_stats.log10_artist_playcount, y=ohw_stats.log10_playcount)
```

[69]:
```
<AxesSubplot:xlabel='log10_artist_playcount', ylabel='log10_playcount'>
```



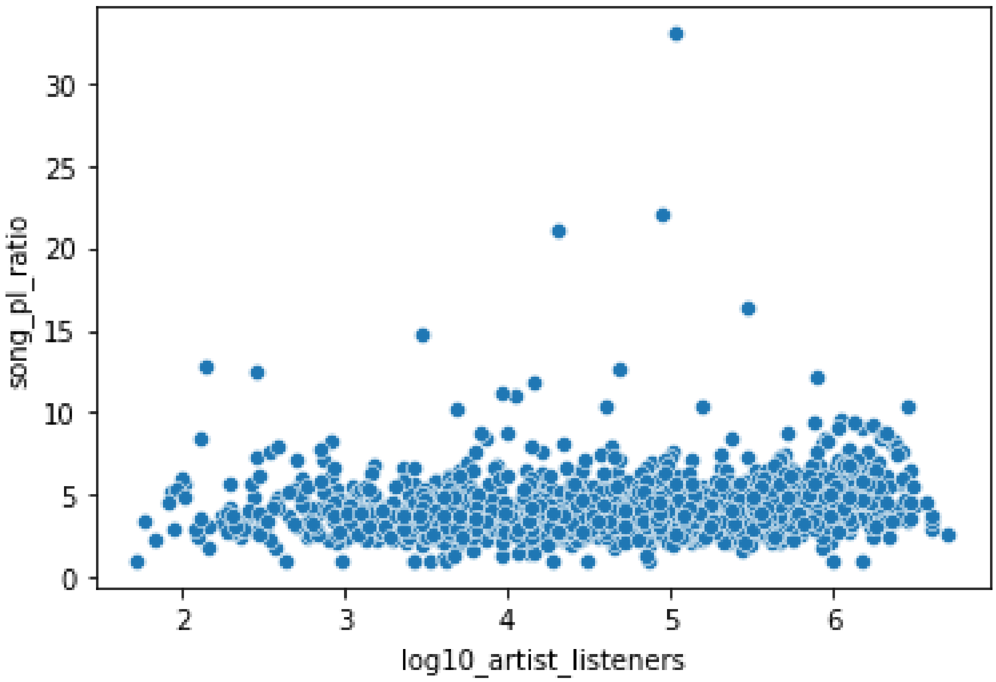
[70]:
```
# Popular songs help artists with their overall portfolio
sns.scatterplot(x=ohw_stats.log10_artist_listeners, y=ohw_stats.log10_listeners)
```

[70]: <AxesSubplot:xlabel='log10_artist_listeners', ylabel='log10_listeners'>



[71]:
```
sns.scatterplot(x=ohw_stats.log10_artist_listeners, y=ohw_stats.song_pl_ratio)
```

[71]: <AxesSubplot:xlabel='log10_artist_listeners', ylabel='song_pl_ratio'>



1.7 Recommendations

In order to build a stable portfolio that will generate revenue, I focus on the following criteria:

- Top half of listens (do people want to listen to the songs?)
- Avoiding potentially very pricy top tier songs
- Songs which performed well in the charts (3+ months)
- Artists who aren't too niche (as measured by playcount)

Plus some smaller data filtering steps (to get rid of some datapoints that I didn't think made sense, e.g. Jimi Hendrix as a one hit wonder).

[72]:
```
mask = ohw_stats.pct_split_playcount <= 0.5  # pick popular songs
mask &= (
    ohw_stats.pct_split_playcount > 0.1
)  # but not so popular that they'll be overpriced
mask &= (
    ohw_stats.duration < 4.5 * 60 * 1000
)  # pick shorter songs (just to filter out the nicher classic rock stuff)
```

```
mask &= (
    ohw_stats.max_chart_run >= 12
)  # pick songs that had more than 3 months of airtime on the charts
mask &= ohw_stats.song_artist_playcount_ratio <= 0.5
mask &= ohw_stats.decade_60s != 1
candidates = ohw_stats[mask]
candidates.sort_values(
    by=["year_cohort", "song_pl_ratio"], ascending=False
).sort_values(by="song_pl_ratio", ascending=False)

candidates.to_excel("../data/output_shortlist_review.xlsx", index=False)
```

[73]:

```
## I reviewed by eye to identify the songs fit for portfolio.

selection_lds = [
    811,  # Best PL for 80s,
    1456,  # Best PL for 90s,
    252,  # Best PL for early 00s,
    1755,  # Third best PL for early 00s - different genre to best so I think␣
 ↪that balances out better
    1605,  # Best PL for late 00s
]



def format_output_table(row: pd.Series) -> pd.Series:
    return pd.Series(
        [
            row.lastfm_id,
            row.artist_name,
            row.song_name,
            tags[tags.lastfm_id == row.lastfm_id].tag.tolist(),
            row.first_week_ending.year,
            row.playcount,
            row.song_pl_ratio,
            row.song_artist_playcount_ratio,
            row.cluster,
        ],
        index=[
            "lastfm_id",
            "artist",
            "song",
            "tags",
            "year",
            "total_plays",
            "listener_stickiness",
            "listening_concentration",
            "cluster",
```

```
        ],
    )


final_candidates = (
    candidates.loc[selection_lds]
    .apply(format_output_table, axis=1)
    .sort_values(by="listener_stickiness", ascending=False)
)
final_candidates
```

```
[73]:       lastfm_id                   artist                  song  \
1605        1262              TEMPER TRAP     SWEET DISPOSITION
811         1429                  JOURNEY  DON'T STOP BELIEVIN'
252          723                  CAESARS           JERK IT OUT
1456         355  SIXPENCE NONE THE RICHER               KISS ME
1755        1997           VANESSA CARLTON      A THOUSAND MILES

                                                  tags  year  total_plays  \
1605  [indie, indie rock, 500 Days of Summer, austra…  2009    9455762.0
811          [classic rock, 80s, rock, journey, scrubs]  1982    8982453.0
252     [indie, rock, alternative, indie rock, swedish]  2003    3002434.0
1456            [pop, 90s, female vocalists, Love, rock]  1999    4677837.0
1755  [pop, female vocalists, piano, vanessa carlton…  2002    3722367.0

      listener_stickiness  listening_concentration  cluster
1605             9.492184                 0.333081       30
811              6.970458                 0.279932       23
252              6.476597                 0.390669       36
1456             5.934677                 0.460359       18
1755             5.552275                 0.306132       36
```

1.7.1 Using the cluster model to construct a similar portfolio automatically

```
[74]: # Demo of fast lookup based on clustering
mask = ohw_stats.cluster.isin(
    final_candidates.cluster
)  # Same clusters - some songs may be in a "unicluster", which is obviously a␣
 ↪drawback for the proof-of-concept
mask &= ~ohw_stats.lastfm_id.isin(
    final_candidates.lastfm_id
)  # Don't pick the songs we know
mask &= ohw_stats.pct_split_playcount <= 0.5  # still focus on popular songs
mask &= ohw_stats.decade_60s != 1
ohw_stats[mask].sort_values(by="song_pl_ratio", ascending=False).groupby(
    "year_cohort"
).first().apply(format_output_table, axis=1).dropna().sort_values(
```

```
    by="listener_stickiness"
)
```

[74]:

```
                lastfm_id                                              artist  \
year_cohort
[1995, 2000)       1457.0                                        NEW RADICALS
[2000, 2005)        404.0                                       JUNIOR SENIOR
[1980, 1985)       1676.0  DEXY'S MIDNIGHT RUNNERS WITH THE EMERALD EXPRESS
[1985, 1990)       1201.0                                      TRACY CHAPMAN
[2005, 2010)         53.0                                       JOSE GONZALEZ

                              song  \
year_cohort
[1995, 2000)  YOU GET WHAT YOU GIVE
[2000, 2005)         MOVE YOUR FEET
[1980, 1985)         COME ON EILEEN
[1985, 1990)               FAST CAR
[2005, 2010)             HEARTBEATS

                                                         tags    year  \
year_cohort
[1995, 2000)    [90s, rock, alternative, pop, alternative rock]  1999.0
[2000, 2005)               [dance, pop, electronic, fun, happy]  2003.0
[1980, 1985)                [80s, pop, new wave, british, rock]  1982.0
[1985, 1990)  [folk, acoustic, female vocalists, 80s, singer…  1988.0
[2005, 2010)  [acoustic, chillout, indie, Mellow, singer-son…  2006.0

              total_plays  listener_stickiness  listening_concentration  \
year_cohort
[1995, 2000)    3231926.0             5.478704                 0.600575
[2000, 2005)    2342399.0             5.510801                 0.462756
[1980, 1985)    4271605.0             5.734545                 0.662270
[1985, 1990)    4496842.0             6.739002                 0.212117
[2005, 2010)    9539488.0             9.309897                 0.208667

              cluster
year_cohort
[1995, 2000)     18.0
[2000, 2005)     18.0
[1980, 1985)     18.0
[1985, 1990)     23.0
[2005, 2010)     30.0
```

[75]:

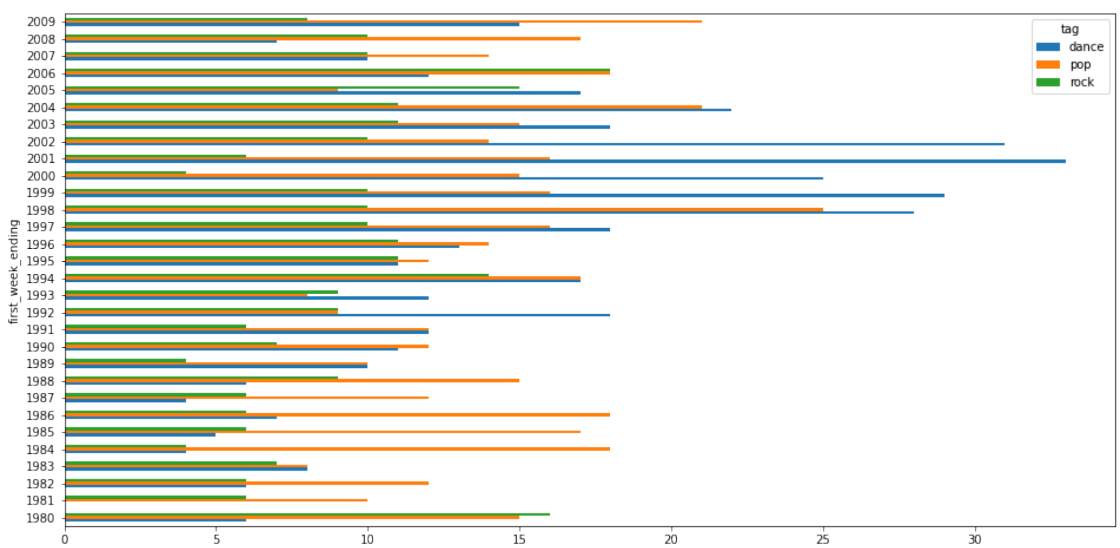
```
# Save the data for later
ohw_stats.to_excel("../data/output_one_hit_wonders_with_statistics.xlsx",␣
 ↪index=False)
sql("SELECT * FROM lastfm").to_excel("../data/output_lastfm.xlsx", index=False)
```

1.7.2 Some more tag analysis

[76]:
```
# Are some genres more sticky than others?
pop_rock = ohw_stats.merge(
    sql("SELECT * FROM lastfm_tags WHERE tag in ('rock', 'dance', 'pop')"),
    on="lastfm_id",
)
```

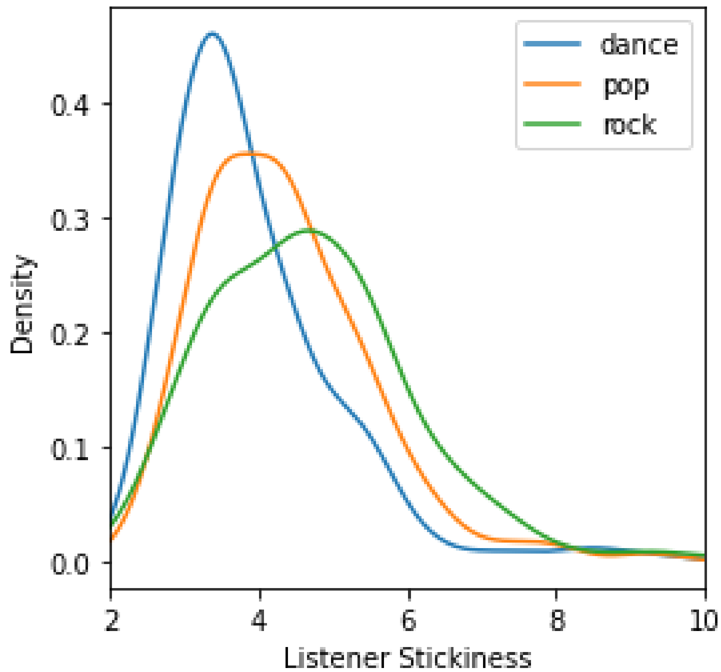
[77]:
```
pop_rock.groupby(
    ["tag", pop_rock.first_week_ending.dt.year]
).size().reset_index().pivot(index="first_week_ending", columns="tag",␣
↪values=0).fillna(
    0
).plot.barh(
    figsize=(16, 8)
)
```

[77]: <AxesSubplot:ylabel='first_week_ending'>



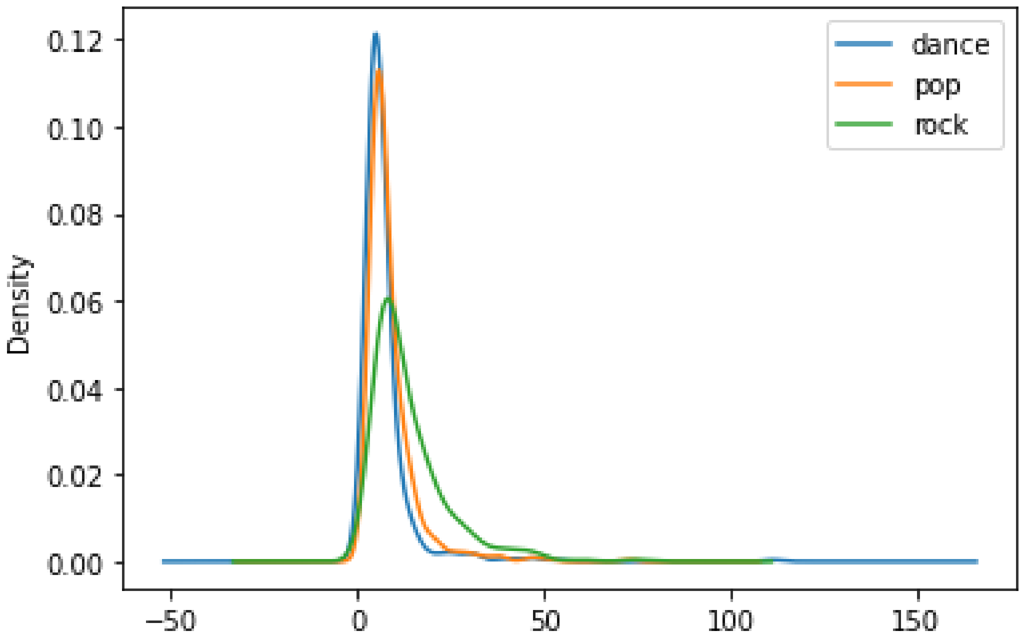
[78]:
```
fig, ax = plt.subplots()
pop_rock.groupby("tag").song_pl_ratio.plot.kde(
    legend=True, xlim=[2, 10], figsize=(4, 4)
)
ax.set_xlabel("Listener Stickiness")
```

[78]: Text(0.5, 0, 'Listener Stickiness')



[79]:
```
pop_rock.groupby("tag").artist_pl_ratio.plot.kde(legend=True)
```

[79]:
```
tag
dance    AxesSubplot(0.125,0.125;0.775x0.755)
pop      AxesSubplot(0.125,0.125;0.775x0.755)
rock     AxesSubplot(0.125,0.125;0.775x0.755)
Name: artist_pl_ratio, dtype: object
```


Density
0.12
0.10
0.08
0.06
0.04
0.02
0.00
−50
0
50
100
150
dance
pop
rock