data-exploratory-analysis

April 20, 2025

1 Exploratory Data Analysis

1.1 Import Essential Libraries

[43]:
```
# Basic Libraries
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt # we only need pyplot
sb.set() # set the default Seaborn style for graphics
```

1.2 Import Data

[44]:
```
df = pd.read_csv('datasets/twitch-data-cleaned.csv')
df.head()
```

[44]:

	channel	watch_time_minutes	stream_time_minutes	peak_viewers	average_viewers	followers	followers_gained	views_gained	partnered	mature	language	watch_time_hours	stream_time_hours	followers_per_hour	views_per_follower	engagement_rate
0	xQcOW	6196161750	215250	222720	27716	3246298	1734810	93036735	True	False	English	1.032694e+08	3587.50			
1	summit1g	6091677300	211845	310998	25610	5310163	1370184	89705964	True	False	English	1.015280e+08	3530.75			
2	Gaules	5644590915	515280	387315	10976	1767635	1023779	102611607	True	True	Portuguese	9.407652e+07	8588.00			
3	ESL_CSGO	3970318140	517740	300575	7714	3944850	703986	106546942	True	False	English	6.617197e+07	8629.00			
4	Tfue	3671000070	123660	285644	29602	8938903	2068424	78998587	True	False	English	6.118333e+07	2061.00			

```
0          483.570732           53.629351         0.008538
1          388.071656           65.470013         0.004823
2          119.210410          100.228279         0.006209
3           81.583729          151.348098         0.001955
4         1003.602135           38.192647         0.003312
```

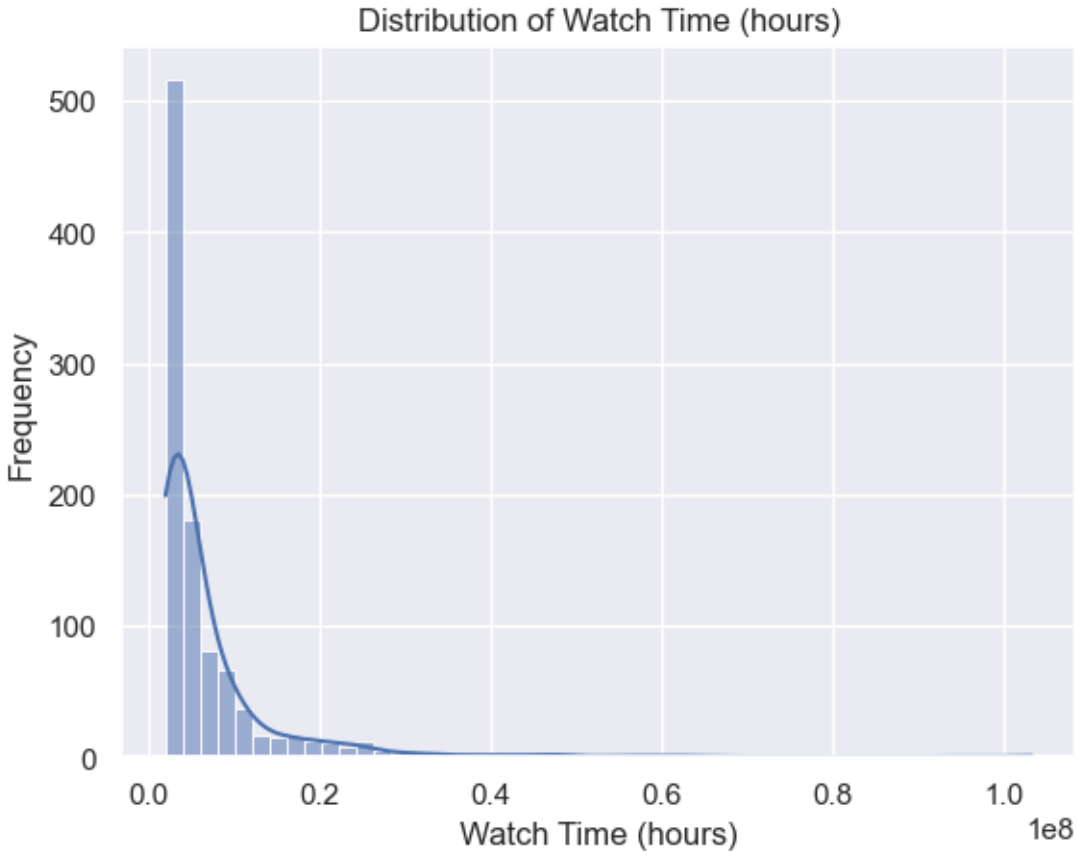
[45]:
```
# Summary Statistics
numerical_df = df[['watch_time_minutes', 'stream_time_minutes', 'peak_viewers',␣
 ↪'average_viewers', 'followers', 'followers_gained', 'views_gained',␣
 ↪'watch_time_hours', 'stream_time_hours', 'followers_per_hour',␣
 ↪'views_per_follower', 'engagement_rate']]
df.describe()
```

[45]:
```
       watch_time_minutes  stream_time_minutes   peak_viewers  \
count        1.000000e+03          1000.000000    1000.000000
mean         4.184279e+08        120515.160000   37065.051000
std          5.496355e+08         85376.201364   60314.307686
min          1.221928e+08          3465.000000     496.000000
25%          1.631899e+08         73758.750000    9113.750000
50%          2.349908e+08        108240.000000   16676.000000
75%          4.337399e+08        141843.750000   37569.750000
max          6.196162e+09        521445.000000  639375.000000

       average_viewers     followers  followers_gained  views_gained  \
count      1000.000000  1.000000e+03      1.000000e+03  1.000000e+03
mean       4781.040000  5.700541e+05      2.055185e+05  1.166817e+07
std        8453.684965  8.044134e+05      3.399137e+05  2.490572e+07
min         235.000000  3.660000e+03     -1.577200e+04  1.757880e+05
25%        1457.750000  1.705462e+05      4.375825e+04  3.880602e+06
50%        2425.000000  3.180630e+05      9.835200e+04  6.456324e+06
75%        4786.250000  6.243322e+05      2.361308e+05  1.219676e+07
max      147643.000000  8.938903e+06      3.966525e+06  6.701375e+08

       watch_time_hours  stream_time_hours  followers_per_hour  \
count      1.000000e+03        1000.000000         1000.000000
mean       6.973799e+06        2008.586000          214.362221
std        9.160592e+06        1422.936689          599.403079
min        2.036548e+06          57.750000           -5.021730
25%        2.719832e+06        1229.312500           20.544001
50%        3.916513e+06        1804.000000           57.243064
75%        7.228999e+06        2364.062500          166.640747
max        1.032694e+08        8690.750000        11772.973312

       views_per_follower  engagement_rate
count         1000.000000      1000.000000
mean           197.545130         0.012748
std           1165.579838         0.026158
```

min	-784.087512	0.000397
25%	31.185667	0.004898
50%	69.964831	0.008291
75%	155.014345	0.013810
max	33552.612613	0.637848

Plot the distribution and scale of the watch time since it's what we're predicting

[46]:
```
sb.histplot(df['watch_time_hours'], bins=50, kde=True)
plt.title('Distribution of Watch Time (hours)')
plt.xlabel('Watch Time (hours)')
plt.ylabel('Frequency')
plt.show()

print(df['watch_time_hours'].describe())
print("Skewness:", df['watch_time_hours'].skew())
```



count	1.000000e+03
mean	6.973799e+06
std	9.160592e+06
min	2.036548e+06

```
25%       2.719832e+06
50%       3.916513e+06
75%       7.228999e+06
max       1.032694e+08
Name: watch_time_hours, dtype: float64
Skewness: 5.165895416683484
```

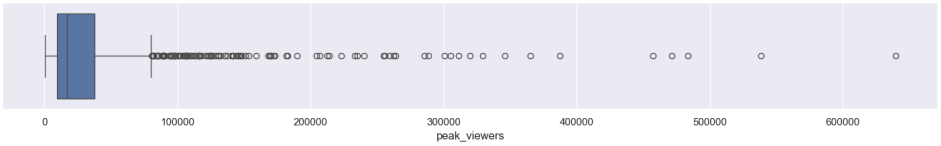
Since it's heavily skewed, apply log transformations for better distribution and model performance

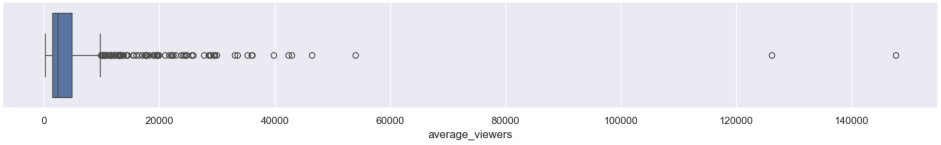
[47]:
```
df['watch_time_hours'] = np.log1p(df['watch_time_hours'])
```

[48]:
```
# Draw the distributions of all variables
f, axes = plt.subplots(len(numerical_df.columns), 1, figsize=(18, 36))
# add a space between the subplots
f.subplots_adjust(hspace=0.5)
count = 0

for var in numerical_df:
  # check if var is numeric
  if df[var].dtype != 'object' and df[var].dtype != 'bool':
    sb.boxplot(data=df[var], orient='h', ax=axes[count])
    count += 1
```

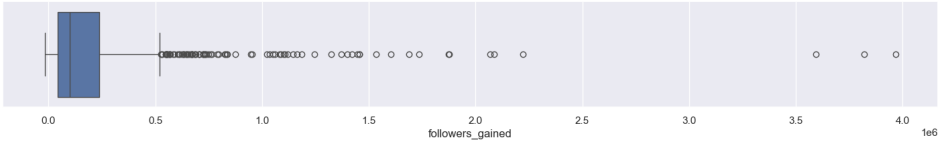

0
1
2
3
4
5
6
watch_time_minutes
1e9


0
100000
200000
300000
400000
500000
stream_time_minutes


0
100000
200000
300000
400000
500000
600000
peak_viewers


0
20000
40000
60000
80000
100000
120000
140000
average_viewers

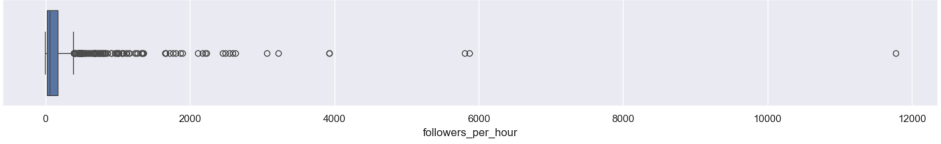

0
2
4
6
8
followers
1e6


0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
followers_gained
1e6


0
1
2
3
4
5
6
7
views_gained
1e8


14.5
15.0
15.5
16.0
16.5
17.0
17.5
18.0
18.5
watch_time_hours


0
2000
4000
6000
8000
stream_time_hours

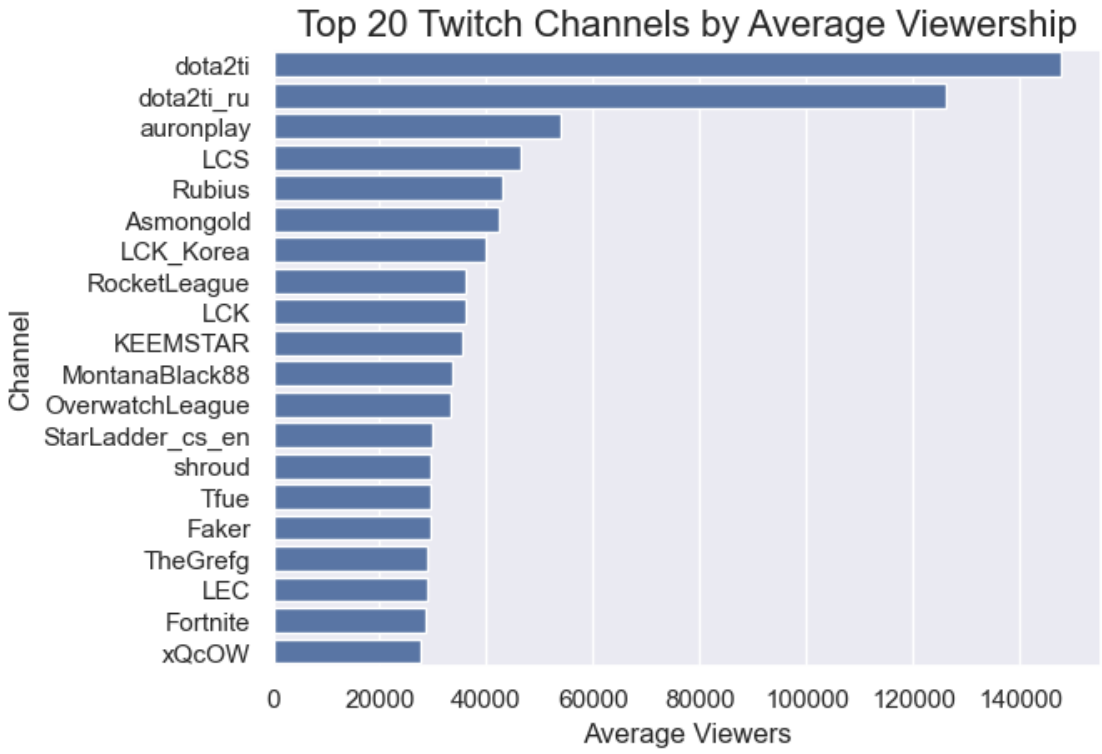

0
2000
4000
6000
8000
10000
12000
followers_per_hour


0
5000
10000
15000
20000
25000
30000
35000
views_per_follower


0.0
0.1
0.2
0.3
0.4
0.5
0.6
engagement_rate

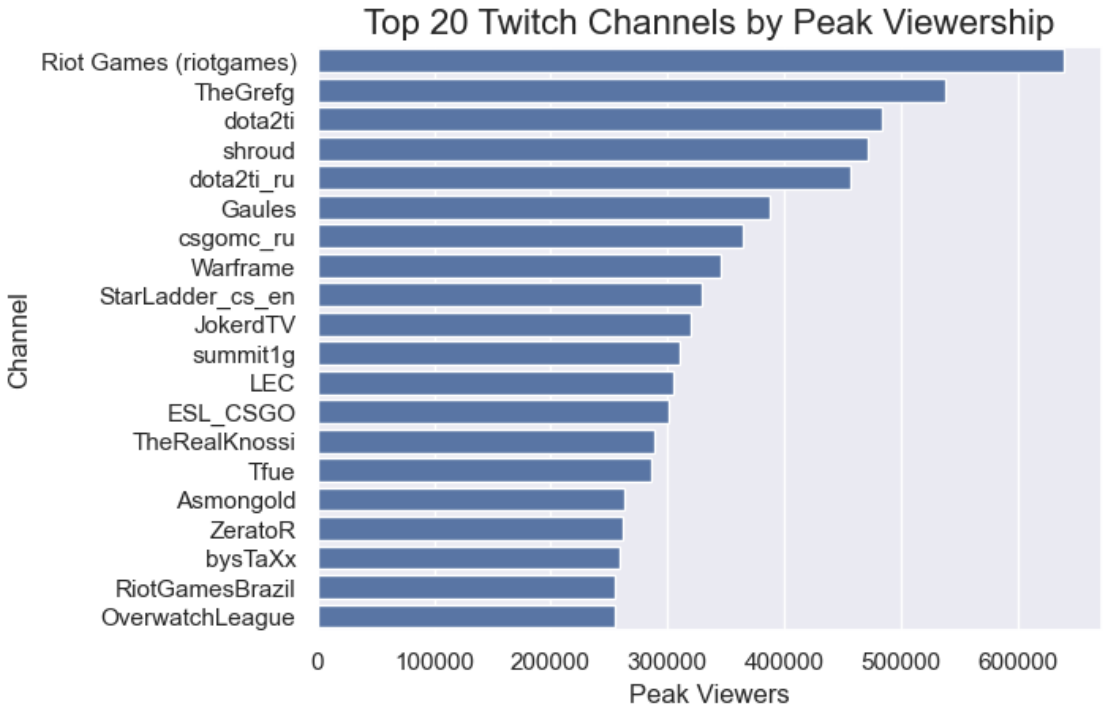
Looking at these graphs, they show a very positive-skewed (distribution is very weighted towards 0) tendency for all the metrics. Any of these metrics may provide very interesting results to look at, but first, we want to remove some potential outliers that may affect our result, like any channels that stream tournaments such as eSports which will likely have very sporadic times when they stream tournaments (it is unlikely that tournaments are streamed every day), so results from these channels may skew our results which is why we want to remove them from our dataset.

[49]:
```
average_viewers = df.sort_values(by='average_viewers', ascending=False).head(20)

sb.barplot(x='average_viewers', y='channel', data=average_viewers)
plt.title('Top 20 Twitch Channels by Average Viewership', fontsize=16)
plt.xlabel('Average Viewers')
plt.ylabel('Channel')
plt.show()
```



[50]:
```
peak_viewers = df.sort_values(by='peak_viewers', ascending=False).head(20)

sb.barplot(x='peak_viewers', y='channel', data=peak_viewers)
plt.title('Top 20 Twitch Channels by Peak Viewership', fontsize=16)
plt.xlabel('Peak Viewers')
```

```
plt.ylabel('Channel')
plt.show()
```



For example, channels like dota2ti, Riot Games, ESL_CSGO, and RocketLeague likely all stream when tournaments happen, but otherwise would not be streaming at all, and they are not particularly single streamers streaming, but a whole company streaming their game tournament. This would not be helpful when we want to predict the popularity of a streamer based on their streaming habits and engagement metrics since including these channels could skew results towards channels that are not representative of a "typical" streamer.

[51]:
```
# lets remove the eSports tournament outlier channels
# done to our best ability (manually removed common eSports titles that were in␣
 ↪the list, so some channels may still exist)
tournament_channels = [
                       'btscsgo',
                       'btssmash',
                       'Call of Duty (callofduty)',
                       'CapcomFighters',
                       'dota2mc_ru',
                       'dota2ti',
                       'dota2ti_ru',
                       'DreamHackCS',
                       'DreamHackDota2_RU',
                       'DreamLeague',
```

```
                        'EAMaddenNFL',
                        'EASPORTSFIFA',
                        'ESAMarathon',
                        'ESL_CSGO',
                        'ESL_CSGO_FR',
                        'ESL_CSGOb',
                        'ESL_DOTA2',
                        'ESL_SC2',
                        'LCK',
                        'LCK_Korea',
                        'LCS',
                        'NBA2KLeague',
                        'OverwatchLeague',
                        'PG_Esports',
                        'PlayHearthstone',
                        'PUBG',
                        'Riot Games (riotgames)',
                        'RiotGamesBrazil',
                        'RiotGamesJP',
                        'RiotGamesOCE',
                        'RiotGamesRU',
                        'RiotGamesTurkish',
                        'RocketLeague',
                        'StarCraft',
                        'StarLadder5',
                        'StarLadder_cs_en',
                        'Twitch',
                        'TwitchRivals',
                        'UCCleague',
                        'Warcraft',
                        'WePlayEsport_EN',
                        'WePlayEsport_RU',
                    ]

# drop the tournament channels
df = df[~df['channel'].isin(tournament_channels)]
df
```

[51]:

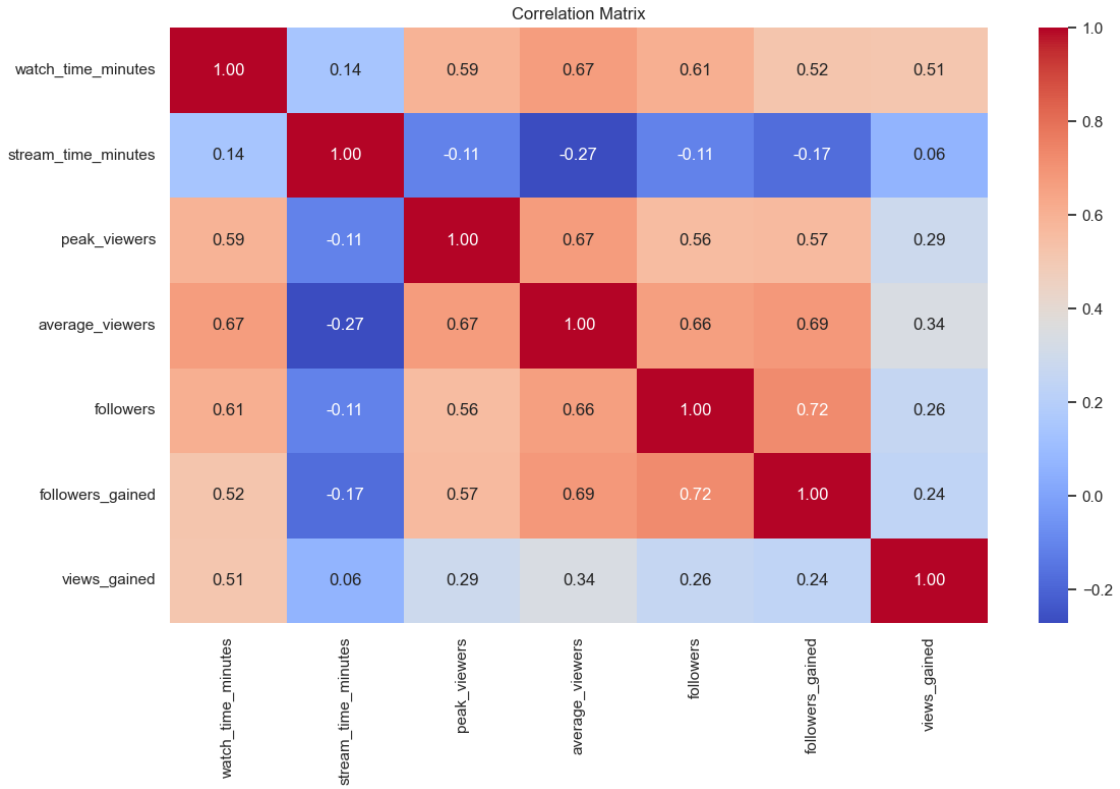
	channel	watch_time_minutes	stream_time_minutes	peak_viewers	\
0	xQcOW	6196161750	215250	222720	
1	summit1g	6091677300	211845	310998	
2	Gaules	5644590915	515280	387315	
4	Tfue	3671000070	123660	285644	
5	Asmongold	3668799075	82260	263720	
..	…	…	…	…	
995	LITkillah	122524635	13560	21359	
996	(bighead033)	122523705	153000	3940	

```
997       (newmasca)           122452320               217410          6431
998     AndyMilonakis            122311065                104745         10543
999              Remx            122192850                 99180         13788

     average_viewers  followers  followers_gained  views_gained  partnered  \
0              27716    3246298           1734810      93036735       True
1              25610    5310163           1370184      89705964       True
2              10976    1767635           1023779     102611607       True
4              29602    8938903           2068424      78998587       True
5              42414    1563438            554201      61715781       True
..               …        …                 …            …         …
995             9104     601927            562691       2162107       True
996              793     213212             52289       4399897       True
997              567     109068             -4942       3417970       True
998             1153     547446            109111       3926918       True
999             1205     178553             59432       2049420       True

     mature    language  watch_time_hours  stream_time_hours  \
0     False     English         18.452851            3587.50
1     False     English         18.435845            3530.75
2      True  Portuguese         18.359619            8588.00
4     False     English         17.929385            2061.00
5     False     English         17.928786            1371.00
..      …         …               …                …
995   False     Spanish         14.529479             226.00
996   False      Korean         14.529471            2550.00
997   False      Korean         14.528888            3623.50
998   False     English         14.527734            1745.75
999   False      French         14.526767            1653.00

     followers_per_hour  views_per_follower  engagement_rate
0            483.570732           53.629351         0.008538
1            388.071656           65.470013         0.004823
2            119.210410          100.228279         0.006209
4           1003.602135           38.192647         0.003312
5            404.231218          111.359924         0.027129
..                  …                   …              …
995         2489.783186            3.842441         0.015125
996           20.505490           84.145748         0.003719
997           -1.363875         -691.616754         0.005199
998           62.500931           35.990120         0.002106
999           35.954023           34.483443         0.006749

[958 rows x 16 columns]
```

1.3 Analysis of Numeric Variables

In order to analyze the relationship between various numeric variables and watch time, we create a heatmap to show their relationships.

[52]:
```
# Create a correlation matrix for the numeric values in the dataset
numerical_df_reduced = df[['watch_time_minutes', 'stream_time_minutes',␣
 ↪'peak_viewers', 'average_viewers', 'followers', 'followers_gained',␣
 ↪'views_gained']]
correlation_matrix = numerical_df_reduced.corr()

plt.figure(figsize=(12, 8))
sb.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.tight_layout()
plt.show()
```



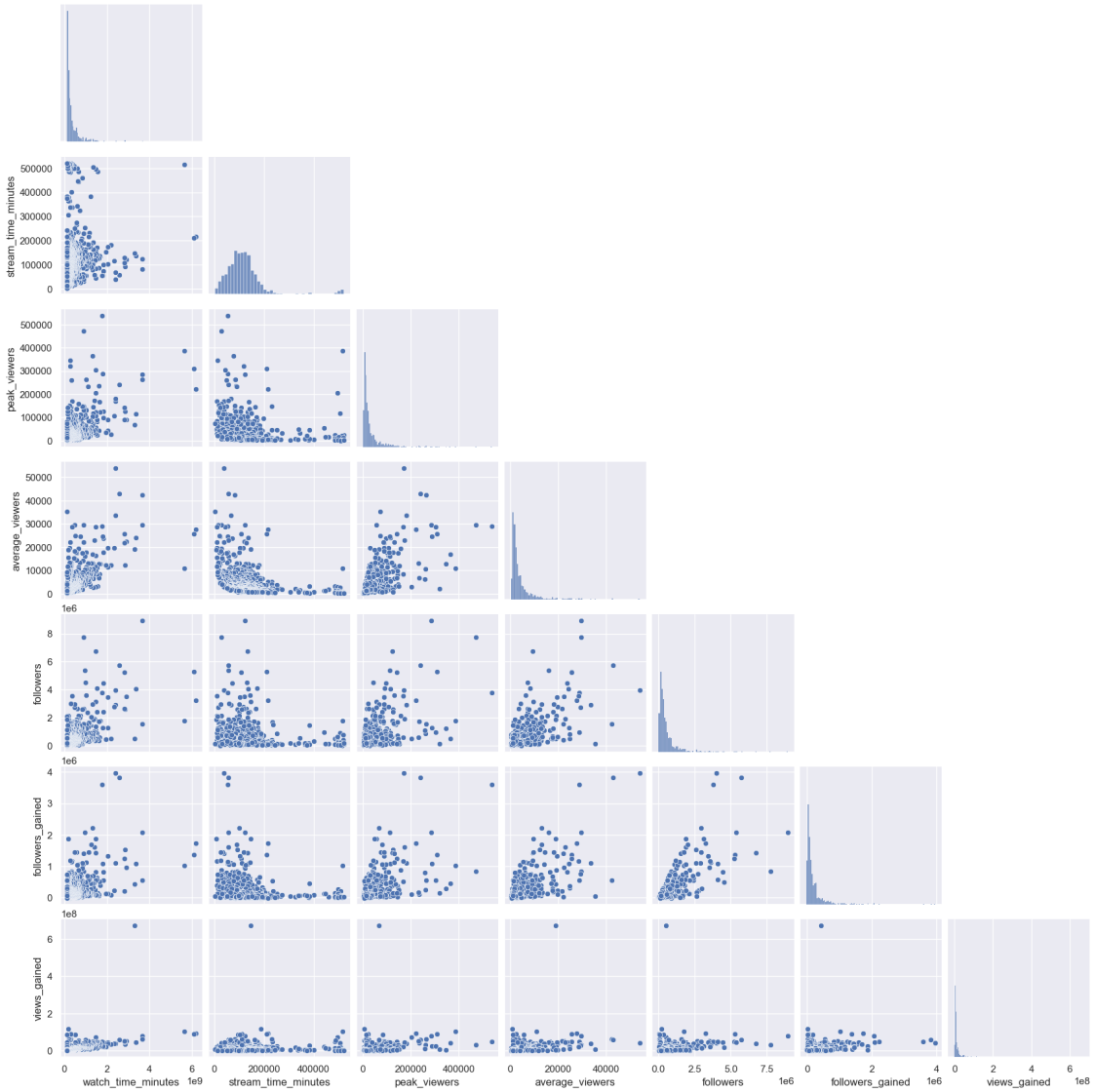
Looking at this heatmap, we see that: - Stream time has very little correlation. This indicates that just because a streamer streams for a longer period of time does not mean that they will have a greater watch time. - Peak viewers and average viewers show moderate correlation with watch time, followers, and followers gained. This shows that streamers who have a higher amount of views during peak time or on average are more likely to have greater watch time, already have a following, and gain followers. - Followers and followers gained have a moderate correlation with

watch time. This indicates that streamers that have a larger following base or with high following growth are more likely to have a higher watch time.

We can continue to analyze the relationship between watch time and other variables by looking at pair plots to determine potential non-linear relationships:

[53]:
```
sb.pairplot(data = numerical_df_reduced, corner = True)
```

[53]: <seaborn.axisgrid.PairGrid at 0x137988050>



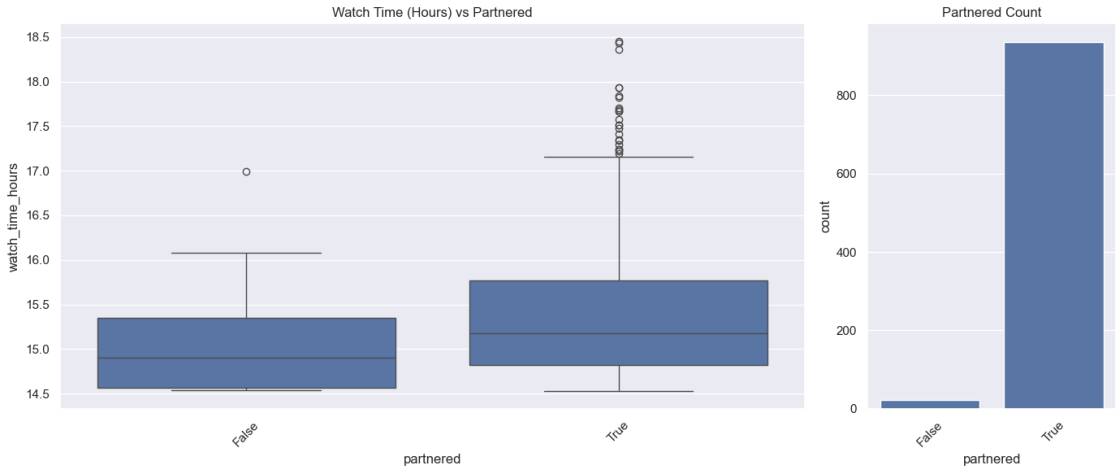
Some observations drawn from these scatter plots include: - Watch time vs stream time: There's a general upward trend — streamers who stream more tend to accumulate more watch time. However, there's significant scatter, meaning high stream time doesn't always mean high watch time (little correlation, like we found in the heatmap). - Watch time vs followers/followers gained: Both of

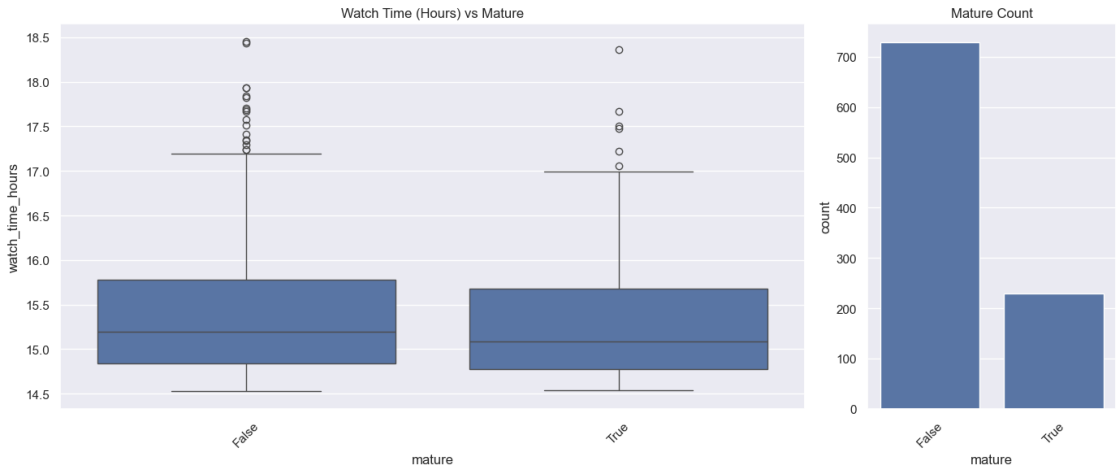
these variables have a similarly scattered positive trend. Streamers with more followers tend to have more watch time and more viewers. - Watch time vs average viewers/peak viewers: This relationship has a positive trend and higher average viewers tend to have much higher total watch time.

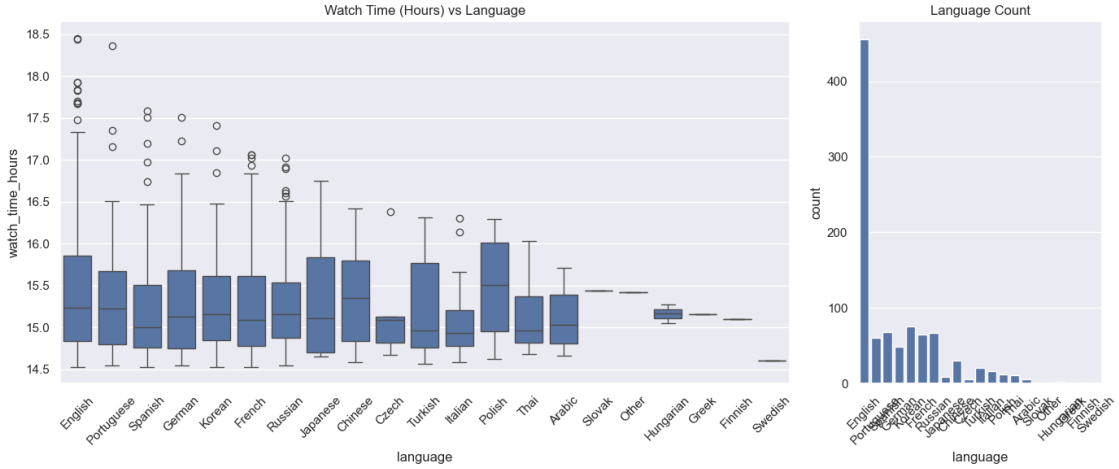
1.4 Analysis of Categorical Variables

Now, we will analyze other variables like Partnered, Mature, and Language. These variables are not numerical and thus will be analyzed separately from the previous heatmap.

[54]:
```
categorical_variables = ['partnered', 'mature', 'language']

for var in categorical_variables:
    fig, axes = plt.subplots(1, 2, figsize=(14, 6), gridspec_kw={'width_ratios':
    ↪ [3, 1]})

    # Boxplot on the left
    sb.boxplot(x=var, y='watch_time_hours', data=df, ax=axes[0])
    axes[0].set_title(f'Watch Time (Hours) vs {var.capitalize()}')
    axes[0].tick_params(axis='x', rotation=45)

    # Countplot on the right
    sb.countplot(x=var, data=df, ax=axes[1])
    axes[1].set_title(f'{var.capitalize()} Count')
    axes[1].tick_params(axis='x', rotation=45)

    plt.tight_layout()
    plt.show()
```







Partnered

Partnered streamers on Twitch receive drastically more watch time than non-partnered ones. However, given that the dataset contains far more partnered streamers and the fact that partnership often follows success, it is likely that partnership is a marker of popularity rather than its driver. Additional metrics should be explored to identify underlying factors contributing to high watch time.

Mature

Most streamers do not mark their streams as mature, and non-mature streamers tend to have a slightly higher median watch time. The mature tag likely serves a niche audience and limits the size of the audience by catering to a smaller demographic.

Language

English dominates Twitch streaming both in quantity and watch time, indicating its role as the primary global language for content. However, languages like Portuguese, Spanish, and German

show solid engagement, meaning streamers in those languages can still be highly successful. On the other hand, less common languages generally have fewer streamers and lower average watch times, possibly due to smaller audience reach.

1.5 Final Takeaways

- The numerical variables that are the strongest predictors for watch time are average viewers and followers.
- Partnered streamers outperform non-partnered ones in total watch time, but parternship is likely a marker of popularity than a reson for it.
- Mature content may lower watch time metrics.
- English language streamers tend to have more followers.