
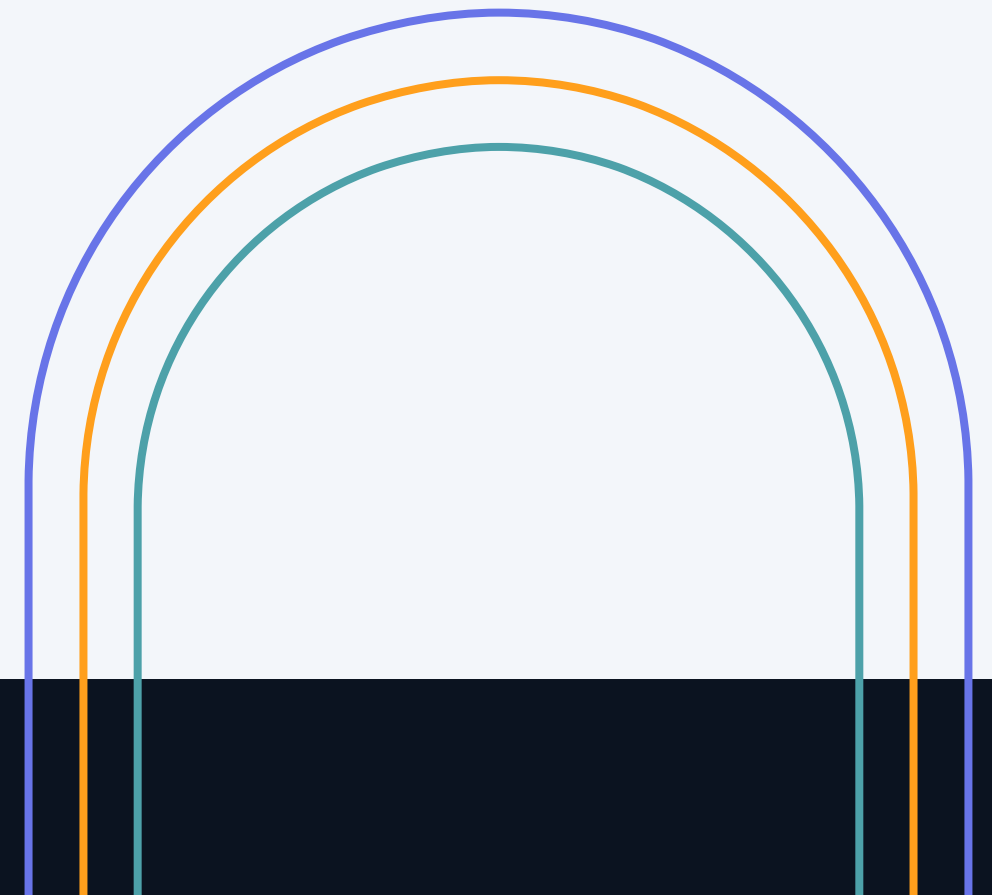


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# To Stream or Not to Stream?

**Morgan Tudor**  
**Leah LoSchiavo**



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# **If you could only choose one streaming service, which one should you pick?**

According to Statista, 83% of American consumers in the United States utilize a subscription streaming service.

Are the plethora of streaming options really different?



# our questions

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What are the “top streaming services”?

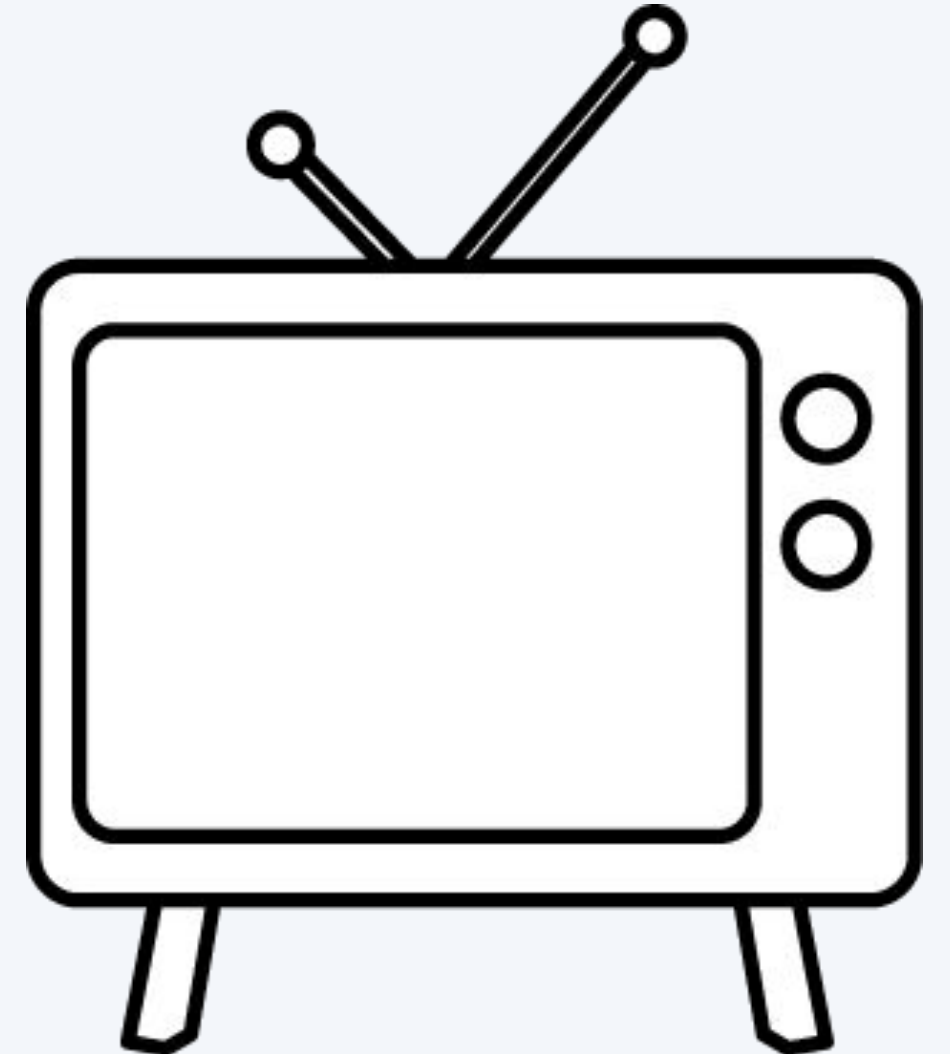
---

What do each of these services offer their customers?

---

If you could choose only one, which would we recommend?

---



# “top streaming services” \_\_\_\_\_



According to our research, the most accessible and utilized streaming services in the United States time and time again included these companies, which we deemed the top 4 services which we would analyze further.



Amazon  
Prime Video



Hulu



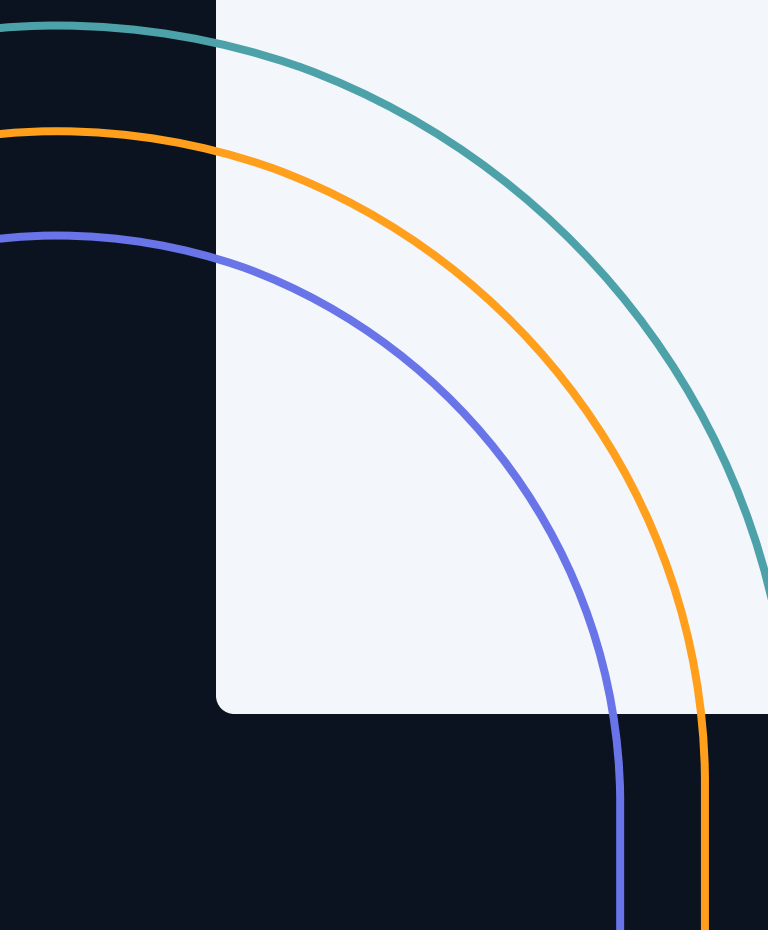
Netflix



Disney+



# What do these services offer?



A deeper analysis into what you get for your money

01.



prime video



amazon prime video



data

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Morgan Tudor MT

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POSSIBLE DATA LOSS Some features might be lost if you save this workbook in the comma-delimited (.csv) format. To preserve these features, save it in an Excel file format. Don't show again Save As...

R14

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	id	title	type	description	release_year	age_certification	runtime	genres	production_countries	seasons	imdb_id	imdb_score	imdb_votes	tmdb_popularity	tmdb_score		
2	tm87233	It's a Wonderful Life	MOVIE	A holiday favourite f	1946	PG	130	['drama', 'family', 'fantasy', 'romance', 'comedy']	['US']		tt0038650	8.6	467766	27.611	8.261		
3	tm143047	Duck Soup	MOVIE	Rufus T. Firefly is nan	1933		69	['comedy', 'war']	['US']		tt0023969	7.8	60933	9.013	7.357		
4	tm83884	His Girl Friday	MOVIE	Hildy, the journalist f	1940		92	['drama', 'romance', 'comedy']	['US']		tt0032599	7.8	60244	14.759	7.433		
5	ts20945	The Three Stooges	SHOW	The Three Stooges w	1934	TV-PG	19	['comedy', 'family']	['US']	26	tt0850645	8.5	1149	15.424	7.6		
6	tm5012	Red River	MOVIE	Headstrong Thomas f	1948		133	['western', 'drama', 'romance', 'action']	['US']		tt0040724	7.8	32210	12.4	7.4		
7	ts37076	The Jack Benny Program	SHOW	Laugh along with fun	1950		30	['comedy']	['US']	21	tt0042116	8.6	1529	9.681	7.5		
8	tm82253	The Best Years of Our Lives	MOVIE	It's the hope that sus	1947		171	['drama', 'romance', 'war']	['US']		tt0038351	8.1	66209	16.056	7.838		
9	tm88469	The Bishop's Wife	MOVIE	An Episcopal Bishop,	1948		105	['comedy', 'drama', 'fantasy', 'romance']	['US']		tt0039190	7.6	19165	9.671	7.113		
10	tm82560	The Little Foxes	MOVIE	The ruthless, moneye	1941		115	['drama', 'romance']	['US']		tt0033836	7.9	12337	7.215	7.549		
11	tm160494	Stagecoach	MOVIE	A group of people tra	1939		96	['western', 'drama']	['US']		tt0031971	7.8	50624	13.939	7.7		
12	tm146745	The Gold Rush	MOVIE	A gold prospector in	1925		81	['drama', 'comedy', 'romance', 'western', 'family']	['US']		tt0015864	8.1	112841	15.889	8.03		
13	tm19248	The General	MOVIE	During America's	1926		79	['comedy', 'drama', 'action', 'war', 'western', 'european']	['US']		tt0017925	8.1	92935	12.316	8.009		
14	tm97735	She Had to Choose	MOVIE	A young actress hits	1934		65	['drama']	['US']		tt0025772	6	64	0.6			
15	tm116781	My Man Godfrey	MOVIE	Fifth Avenue socialit	1936		95	['comedy', 'drama', 'romance']	['US']		tt0028010	8	24814	8.501	7.56		
16	tm83723	Mr. Bug Goes to Town	MOVIE	The happy tranquility	1941	G	78	['comedy', 'fantasy', 'animation', 'family']	['US']		tt0033727	6.9	1334	5.03	6.104		
17	tm112424	Things to Come	MOVIE	The story of a centur	1936		100	['drama', 'scifi', 'war']	['GB']		tt0028358	6.6	8451	8.031	6.449		
18	tm120863	Dodsworth	MOVIE	A retired auto manuf	1936		101	['drama', 'romance']	['US']		tt0027532	7.8	9556	7.516	7.195		
19	tm100333	Broken Blossoms	MOVIE	The love story of an a	1919	PG-13	89	['drama', 'romance']	['US']		tt0009968	7.2	10635	10.717	6.9		
20	tm17025	The Cat and the Canary	MOVIE	Rich old Cyrus West's	1927		80	['comedy', 'horror']	['US']		tt0017739	7.1	3117	4.797	6.852		
21	tm19424	Detour	MOVIE	The life of Al Roberts	1946		66	['drama', 'thriller', 'crime']	['US']		tt0037638	7.3	18222	8.861	7.226		
22	tm74259	The Pride of the Yankees	MOVIE	The story of the life a	1942		127	['drama', 'romance', 'sport']	['US']		tt0035211	7.6	11268	7.618	7.38		
23	tm155610	Wuthering Heights	MOVIE	The Earnshaws are Yc	1939		104	['romance', 'drama']	['US']		tt0032145	7.5	18734	15.933	7.227		
24	tm63937	The Great Rupert	MOVIE	Shortly before Christ	1950		88	['comedy', 'family']	['US']		tt0042524	6.4	1373	4.315	5.684		
25	tm18385	Scarlet Street	MOVIE	Cashier and part-time	1945		103	['drama', 'thriller', 'crime']	['US']		tt0038057	7.8	17636	9.998	7.6		
26	tm89268	The Secret Life of Walter Mitty	MOVIE	Walter Mitty, a daydr	1947		110	['comedy', 'fantasy', 'romance']	['US']		tt0039808	6.9	6541	11.054	6.8		
27	tm2838	The Most Dangerous Game	MOVIE	When legendary hun	1932	PG-13	63	['action', 'thriller', 'horror']	['US']		tt0023238	7.1	12996	10.078	7		
28	tm5096	Blonde Ice	MOVIE	A golddigging femme	1948		73	['drama', 'crime', 'romance']	['US']		tt0041187	6	1174	2.555	5.543		
29	tm113731	Come and Get It	MOVIE	An ambitious lumber	1936		99	['drama', 'romance']	['US']		tt0027459	6.9	2178	2.779	6.729		
30	tm127199	Orphans of the Storm	MOVIE	France, on the eve of	1922		150	['drama', 'history', 'romance']	['US']		tt0242584	7.3	5279	3.824	6.956		
31	tm154	Alice in Wonderland	MOVIE	Alice goes with her si	1915		59	['fantasy', 'family']	['US']		tt0004873	6.1	543	2.992	5.8		
32	tm111987	Black Gold	MOVIE	Wildcat riggers risk t	1936		57	['drama', 'romance', 'action']	['US']		tt0027366	5.3	91	0.673	5		
33	tm74984	Stella Maris	MOVIE	Stella Maris is a beau	1918		84	['drama']	['US']		tt0009652	6.9	1500	2.099	6.792		

titles +

Ready Accessibility: Unavailable

100%

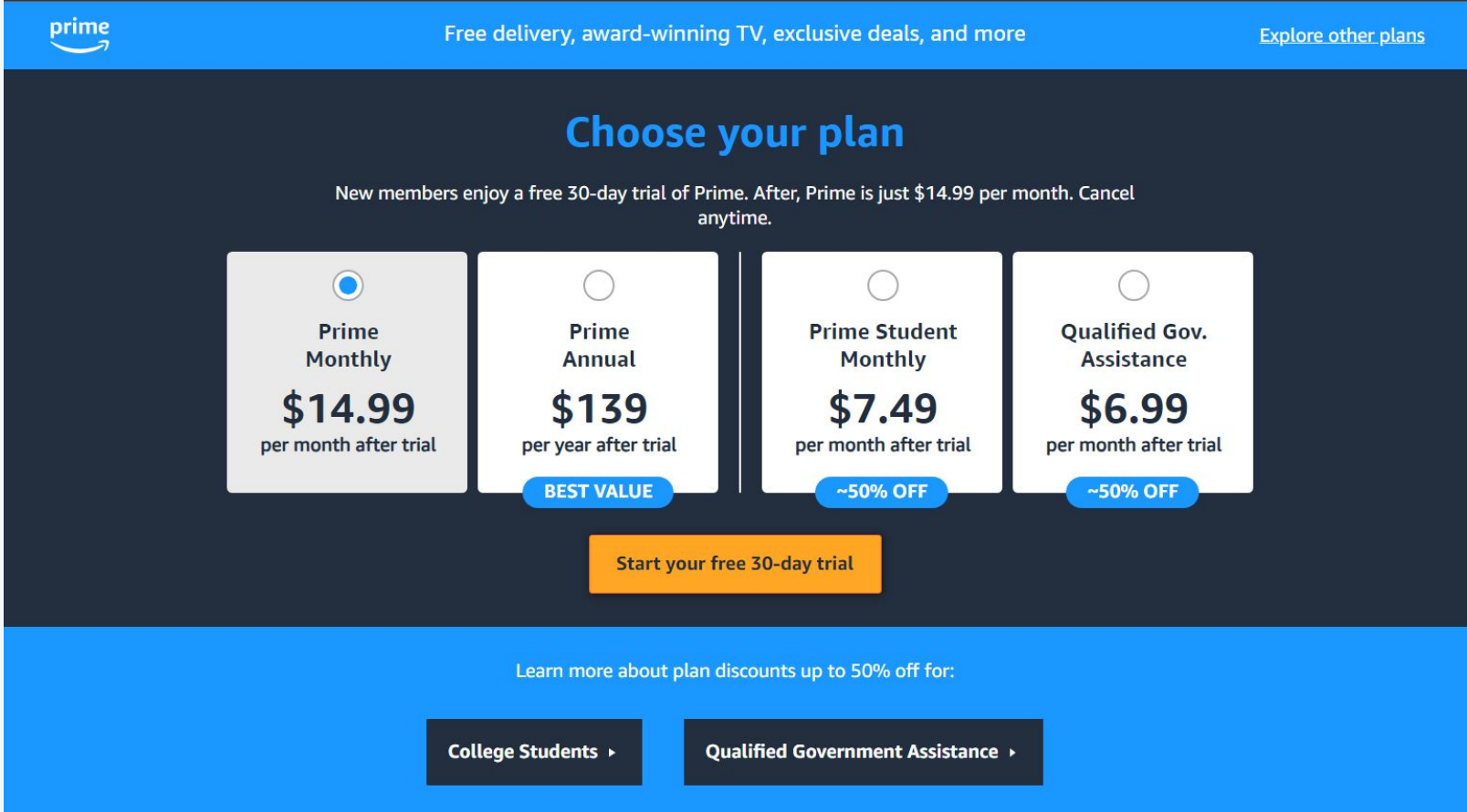
# My data was found on Kaggle

The data included all categories I was hoping to analyze, but needed some cleaning up in the genre category.

In Jupyter Notebook, I was able to delete columns that were not beneficial and the create a reduced data frame from which I could start creating charts.



# Subscription Plans/Prices



Amazon Prime Video features over 25,000 movies and TV shows from around the world, including exclusive originals, live sports, and film premieres.

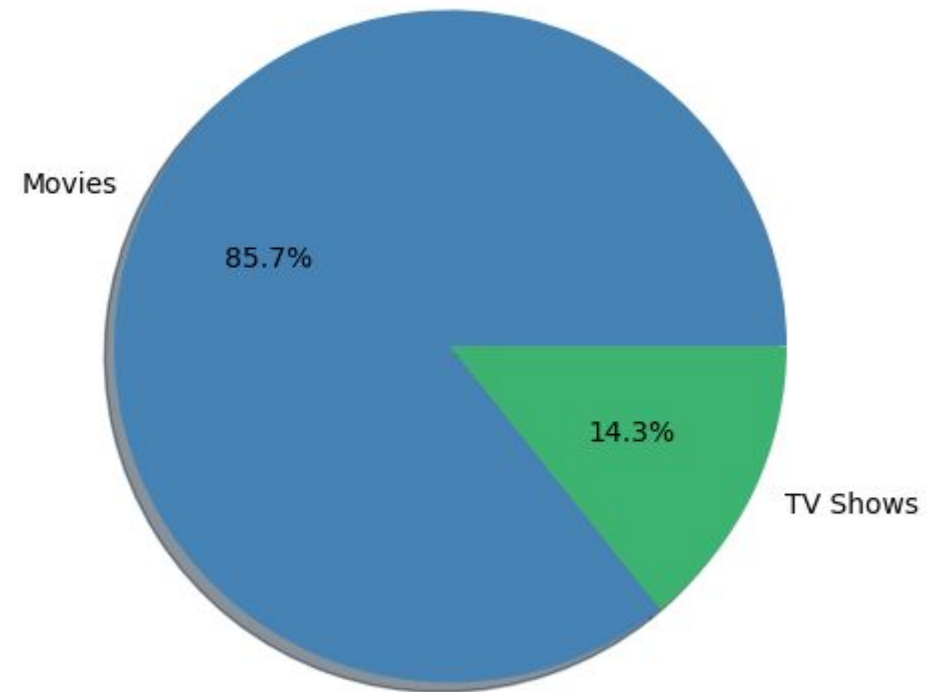
Our data covers around 10,873 of those titles available in the United States as of 2020.

Plan	Price	Video	Streams
Prime Video w/ Amazon Prime membership	\$14.99/mo. or \$139.00/yr.	1080p, 4K	3
Prime Video	\$8.99/mo.	1080p, 4K	3



# price breakdown

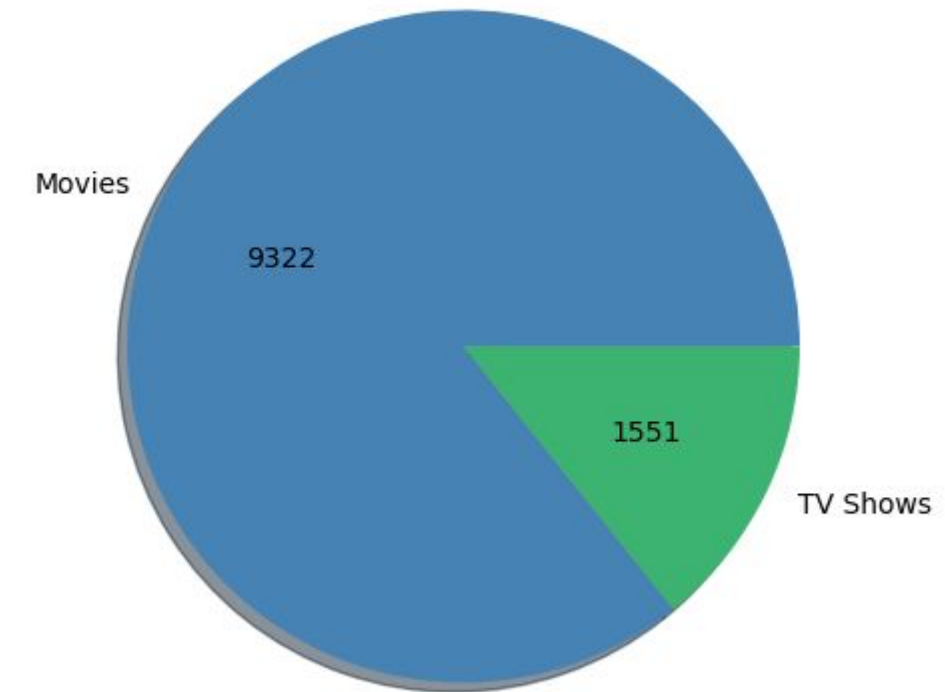
Amazon Prime Video: Movie & TV Show Count



**price per month**

\$8.99 / month

Amazon Prime Video: Movie & TV Show Count

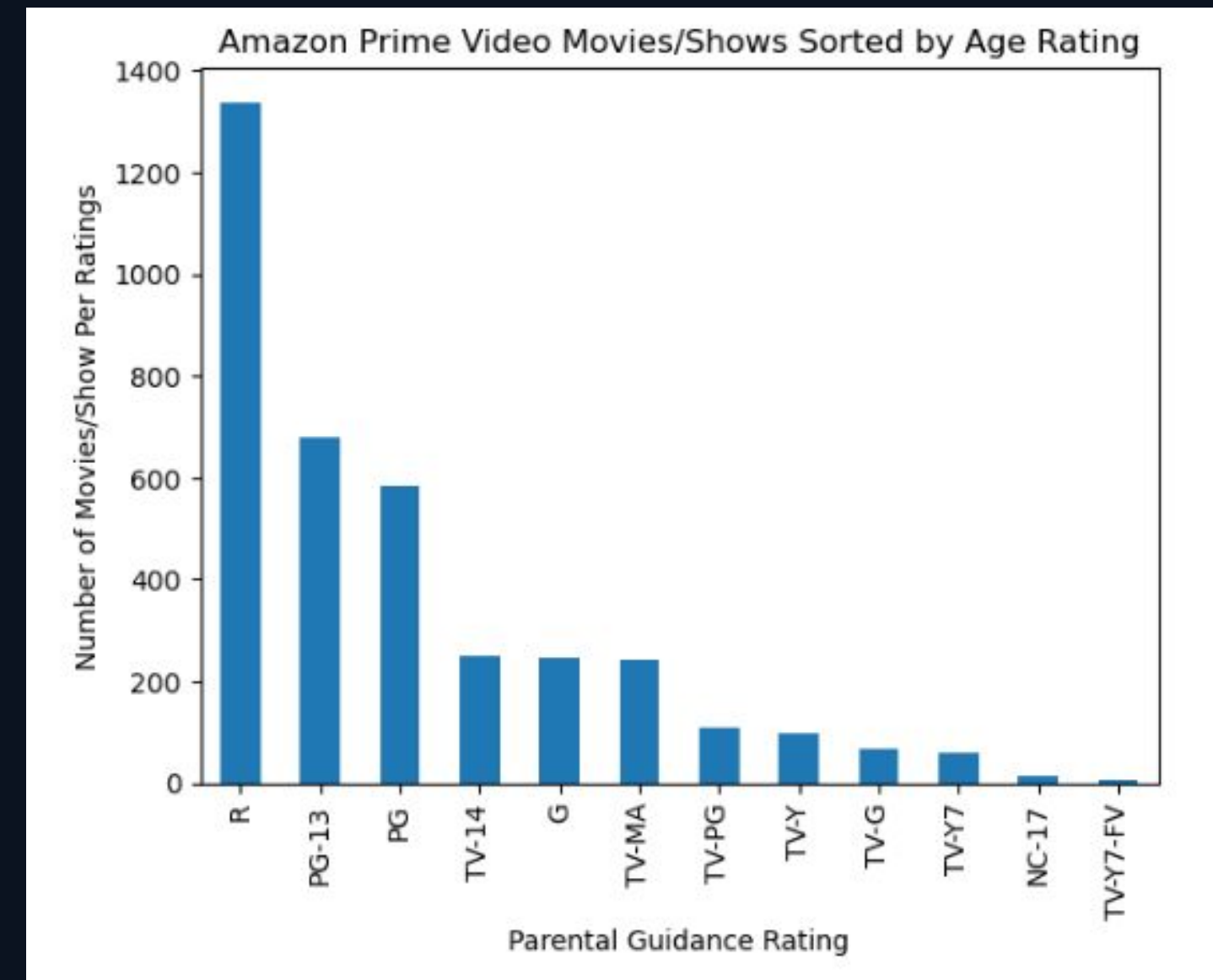


**price per content piece**

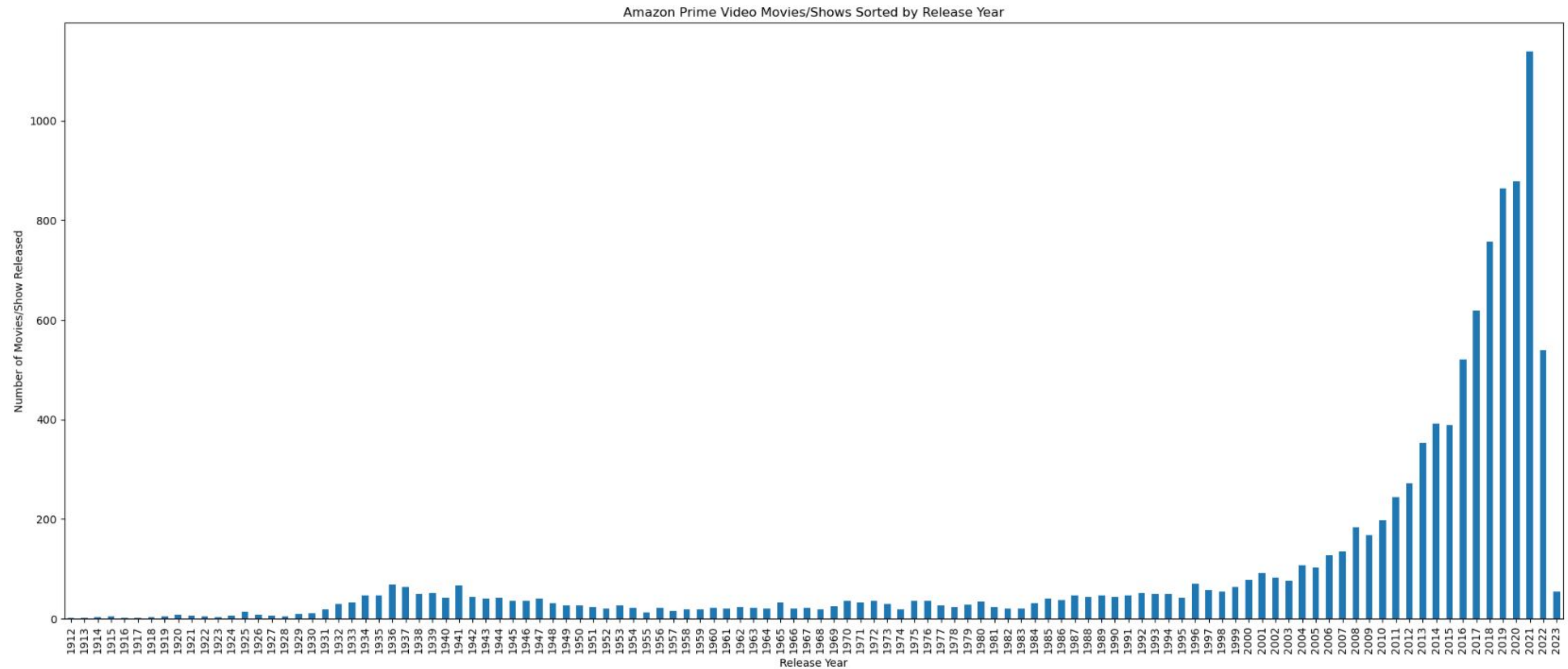
\$0.00082 / tv show or movie

# Who is content on Prime Video for?

MOVIE RATINGS	TV RATINGS
G	TV-Y
PG	TV-Y7
PG-13	G
R	TV-PG
NC-17	TV-14
Adult	TV-MA



# How “fresh” is the content?





# genres: how to compare?

```
In [11]: genres_df = amazon_df[["genres1", "genres2", "genres3", "genres4", "genres5", "genres6", "genres7", "genres8", "genres9"]
genres_df = genres_df.fillna('')
genres_df.head()
```

```
Out[11]:
```

	genres1	genres2	genres3	genres4	genres5	genres6	genres7	genres8	genres9
0	'drama'	'family'	'fantasy'	'romance'	'comedy'				
1	'comedy'	'war'							
2	'drama'	'romance'	'comedy'						
3	'comedy'	'family'							
4	'western'	'drama'	'romance'	'action'					

```
In [12]: new_genres_df = genres_df.stack().reset_index()
new_genres_df.columns = ["movie_number", "column", "genre"]
new_genres_df["genre"] = new_genres_df["genre"].str.strip()
sorted_df = new_genres_df.loc[(new_genres_df["genre"] != "")]
new_sorted_df = sorted_df.groupby('genre')
```

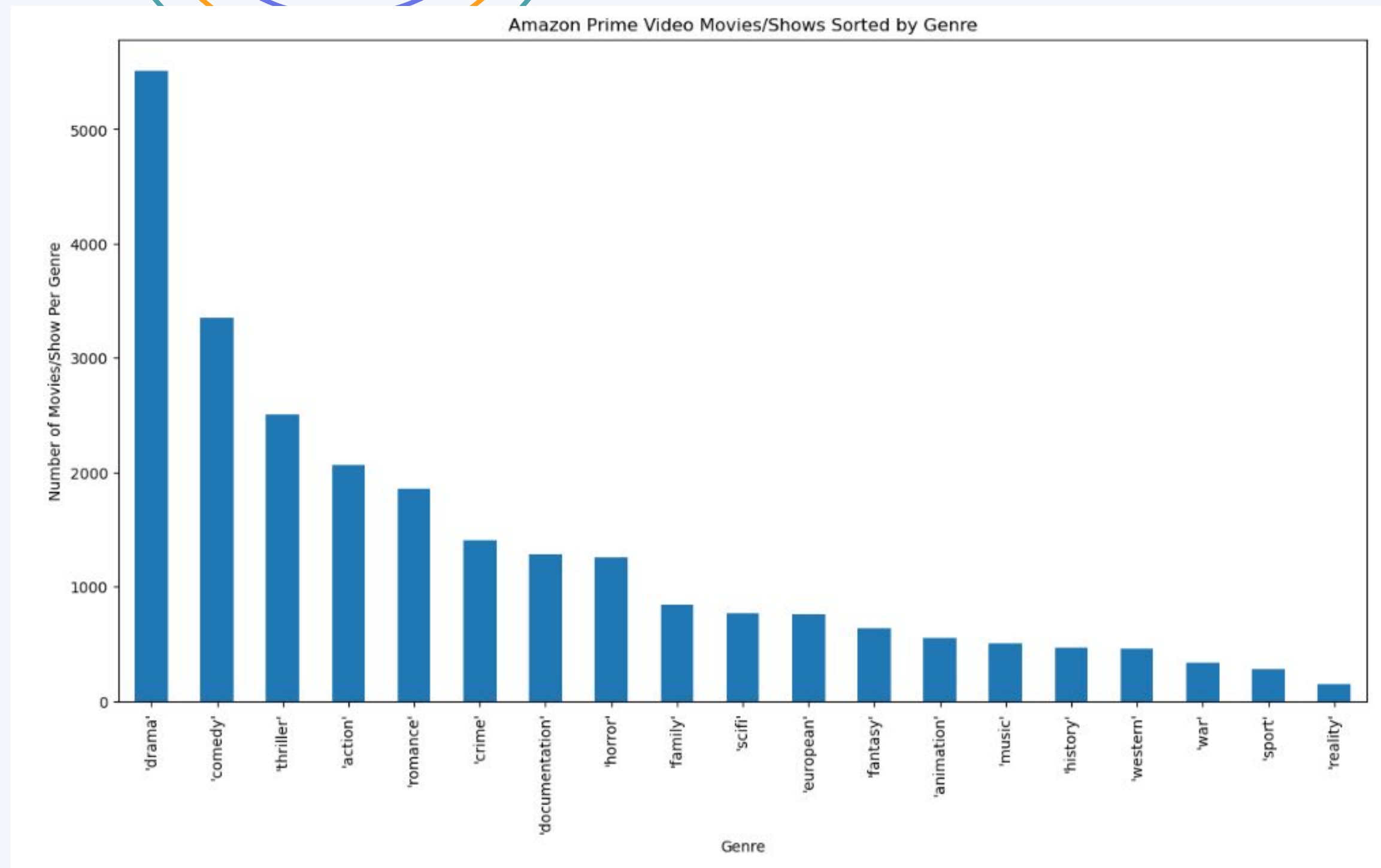
```
In [13]: new_genres_df['genre'].unique()
```

```
Out[13]: array(['drama', 'family', 'fantasy', 'romance', 'comedy', '',
               'war', 'western', 'action', 'european', 'animation',
               'scifi', 'horror', 'thriller', 'crime', 'sport',
               'history', 'music', 'documentation', 'reality'],
              dtype=object)
```

```
In [14]: genre_count = new_sorted_df['genre'].count()
sorted_genre = genre_count.sort_values(ascending=False)
genre_chart = sorted_genre.plot(kind="bar", title="Amazon Prime Video Movies/Shows Sorted by Genre", figsize=(15,8))
genre_chart.set_xlabel("Genre")
genre_chart.set_ylabel("Number of Movies/Show Per Genre")
plt.savefig("Images/Amazon_by_genre.png")
plt.show()
```



# looking for something specific?



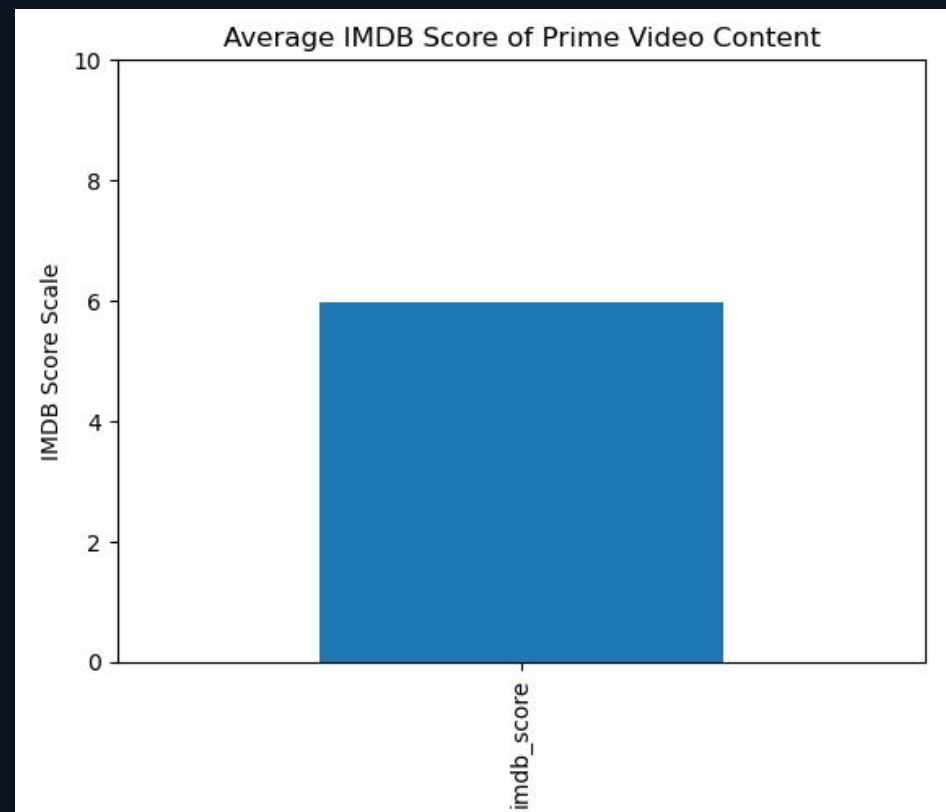


# But is the content “good”?

## IMDB Ratings Analysis

Average  
IMDB Score

Score Average: 5.97



The average rating on  
IMDB is 6.4

Above 7.5 is generally  
considered “good”

Top  
10 Scores

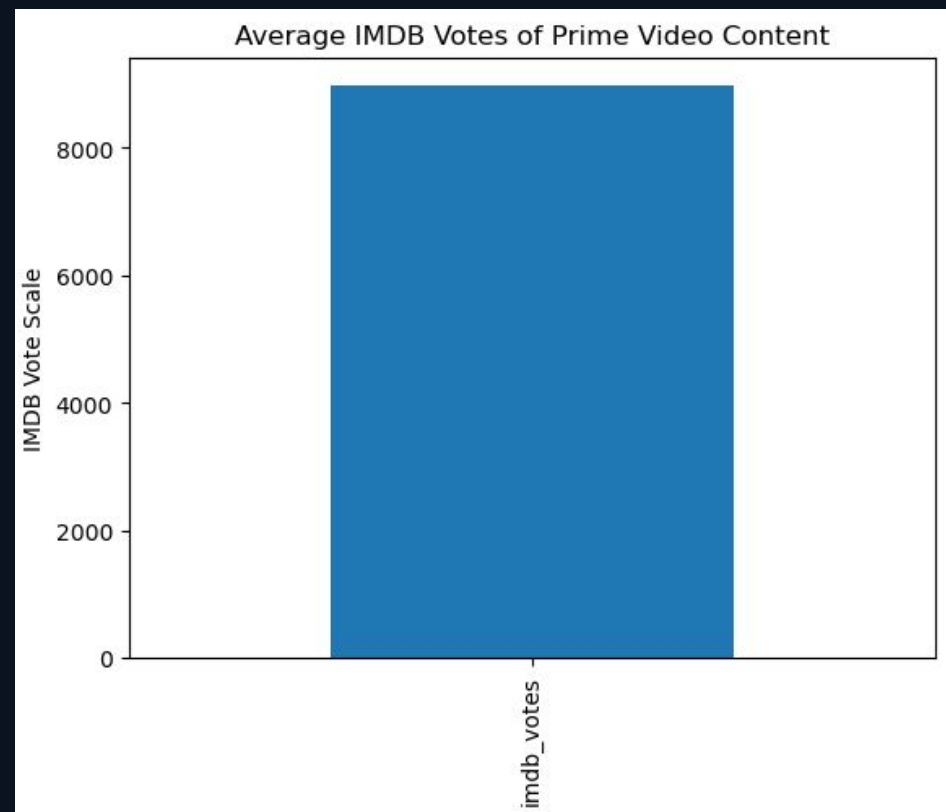
	title	type	imdb_score
1	Pawankhind	MOVIE	9.9
2	COD (Cash On Delivery)	MOVIE	9.8
3	Romeo & Juliet	MOVIE	9.8
4	Last Resort	MOVIE	9.7
5	The 1975 'At Their Very Best' Live from Madiso...	MOVIE	9.7
6	Water Helps the Blood Run	SHOW	9.7
7	Chhote Ustaad-Precaution Is Better Than Cure	MOVIE	9.6
8	Suffer for Good	MOVIE	9.6
9	Life After	SHOW	9.5
10	Denis	SHOW	9.4

# But is the content “good”?

## IMDB Votes Analysis

Average  
IMDB Votes

Vote Average: 8,973



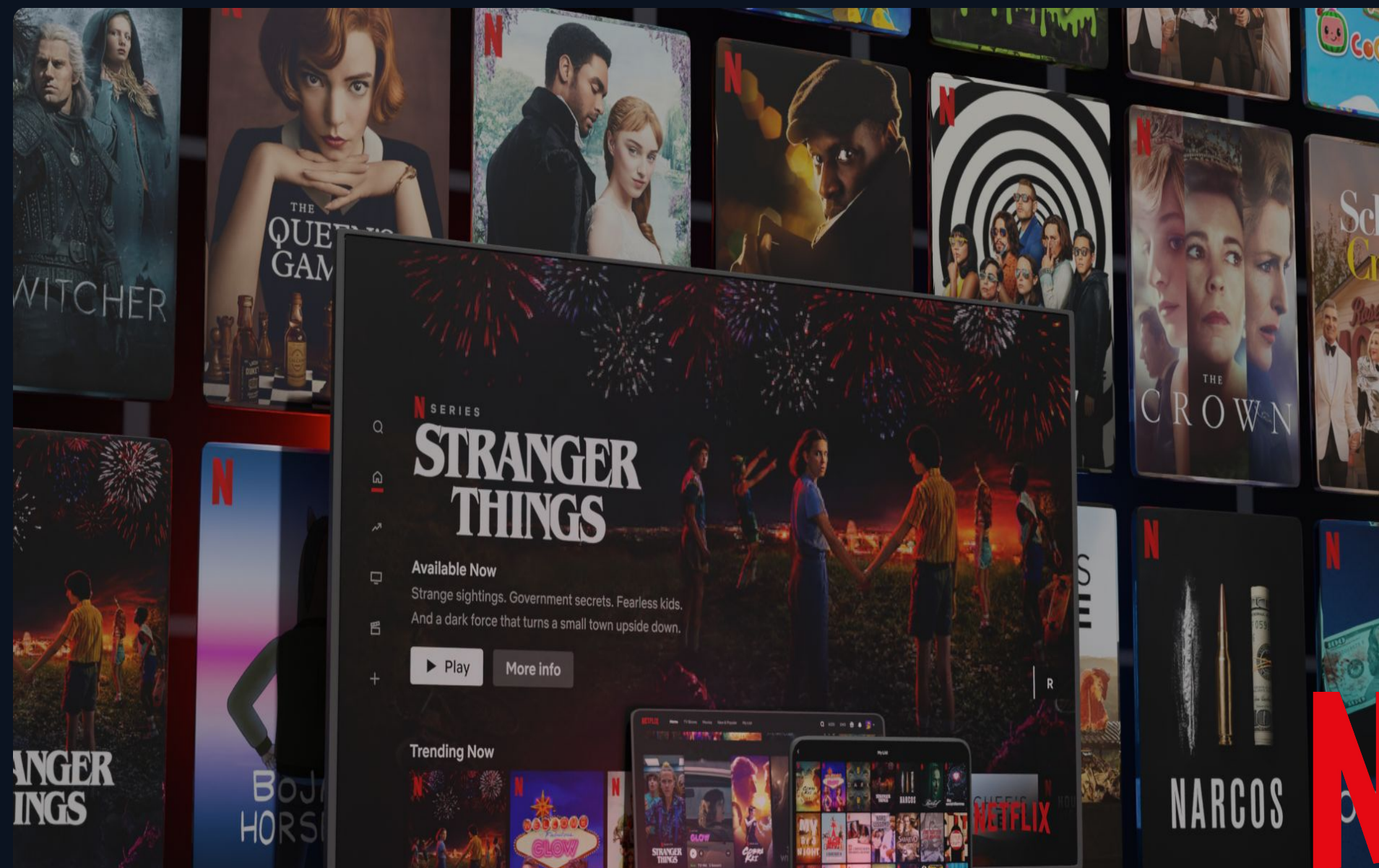
To be considered in  
the top 250, media  
generally must  
receive 25,000 votes.

Top  
10 Votes

title	type	imdb_votes
Pulp Fiction	MOVIE	2081757.0
The Wolf of Wall Street	MOVIE	1437804.0
Eternal Sunshine of the Spotless Mind	MOVIE	1020305.0
Good Will Hunting	MOVIE	987571.0
Raiders of the Lost Ark	MOVIE	976566.0
12 Angry Men	MOVIE	801057.0
Indiana Jones and the Last Crusade	MOVIE	763526.0
Shrek	MOVIE	690470.0
The King's Speech	MOVIE	686908.0
The Curious Case of Benjamin Button	MOVIE	660943.0



# 02.



# NETFLIX



# NETFLIX

# THEN AND NOW

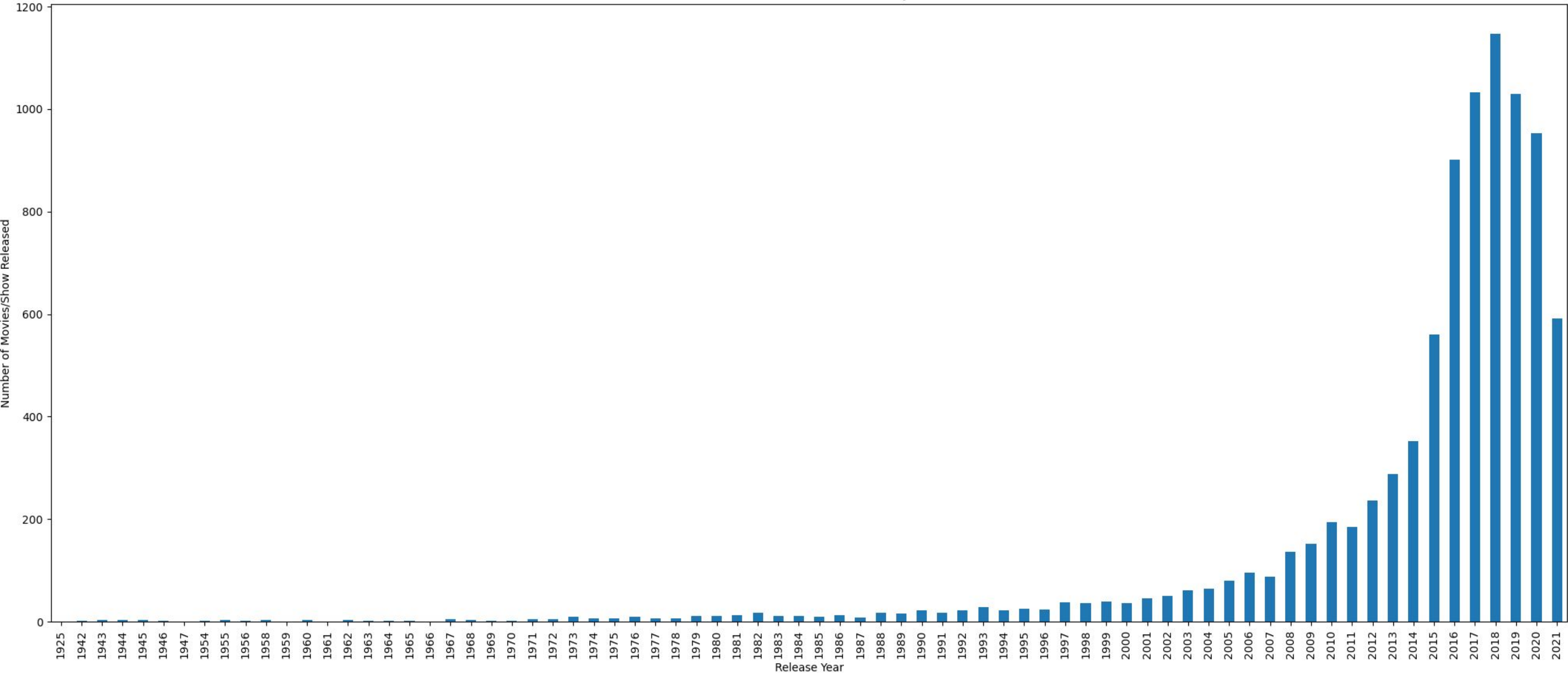
## A BIT OF HISTORY...

- Started in 1997 by Reed Hastings & Marc Randolph in Scotts Valley, CA
- Initially Netflix let people select a movie online to “rent” and return via U.S. mail
- Their main competition was video rental stores (e.g., Blockbuster, Family Video)



# QUANTITY OF MOVIES BY RELEASE DATE

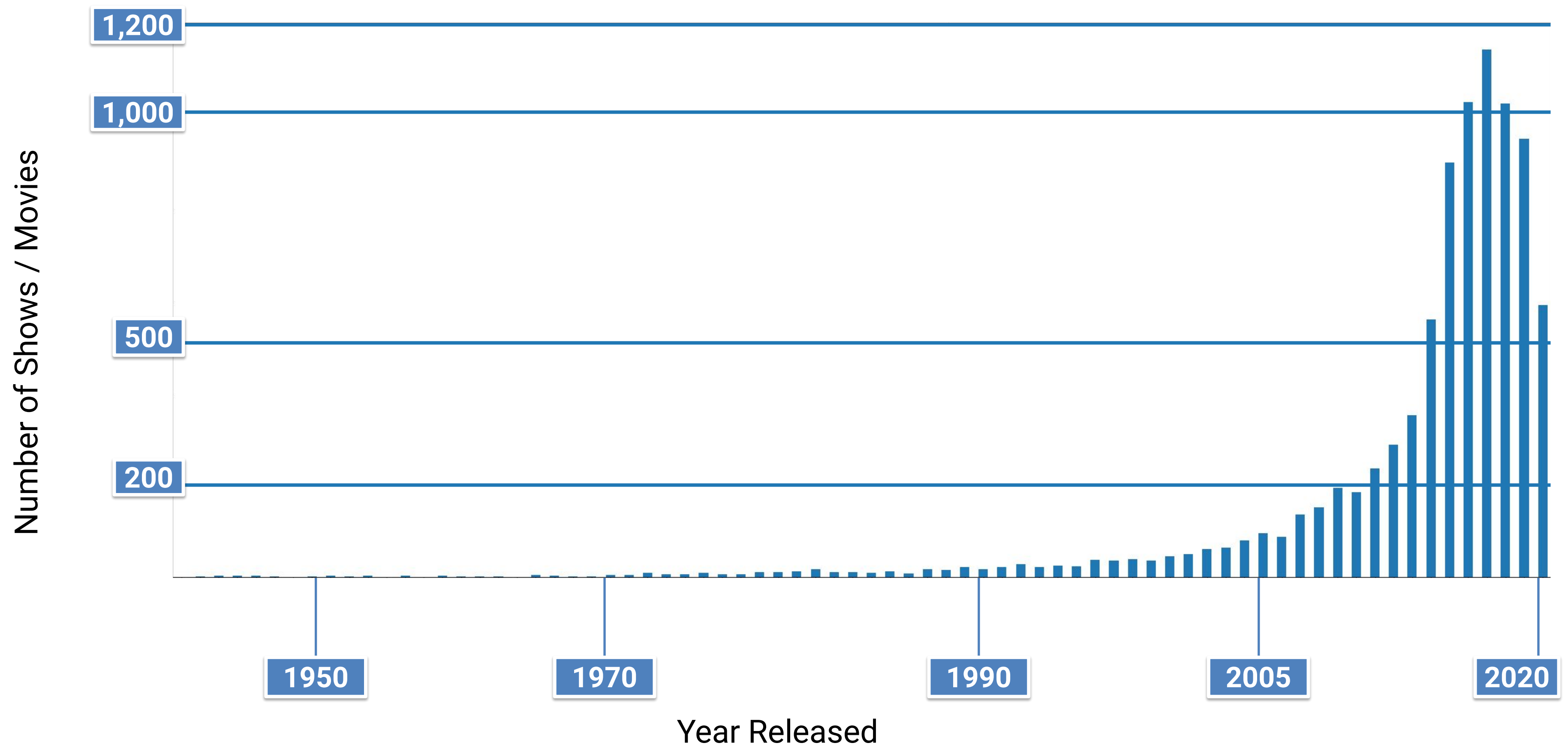
Netflix Prime Video Movies/Shows Sorted by Release Year



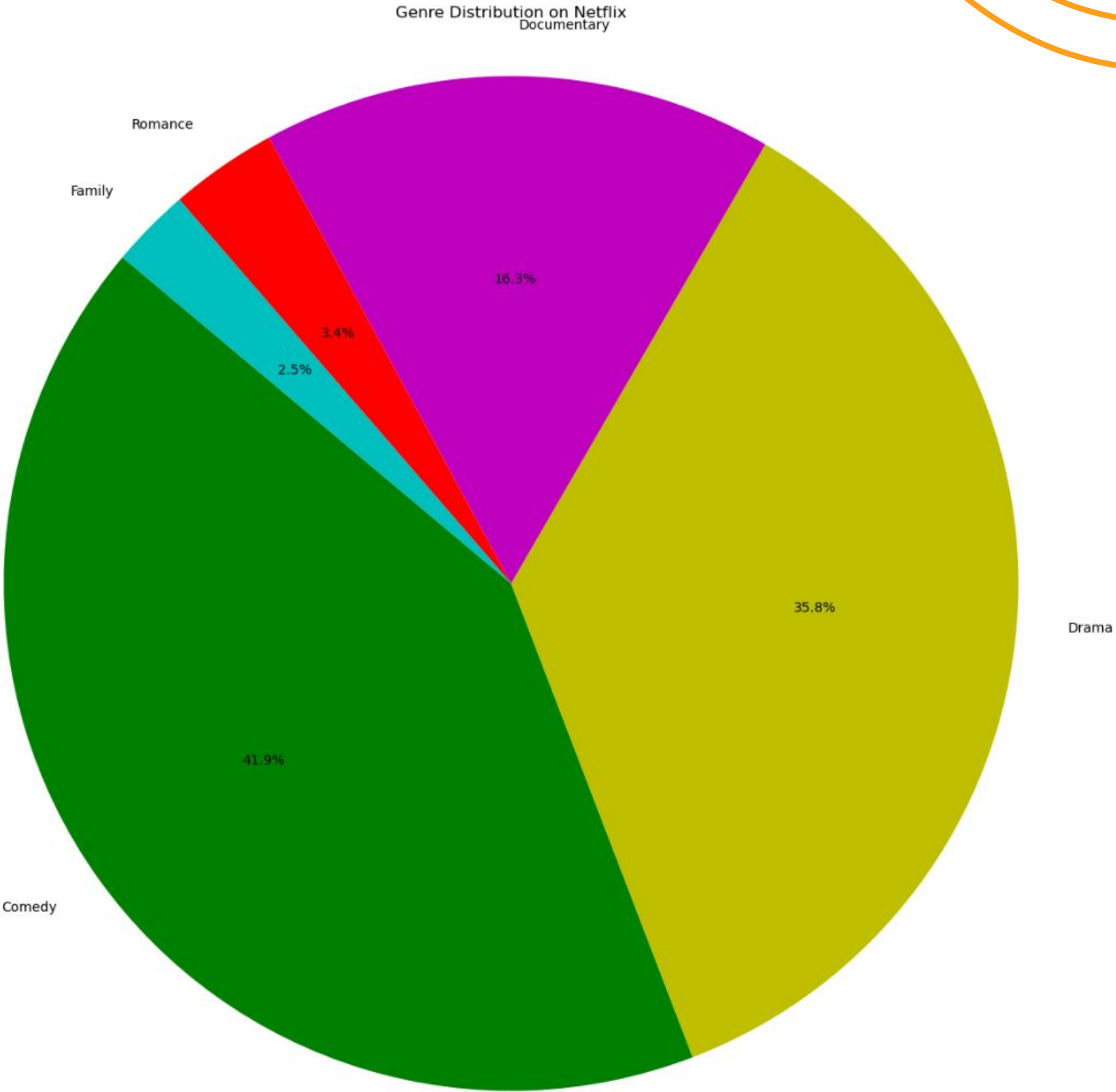


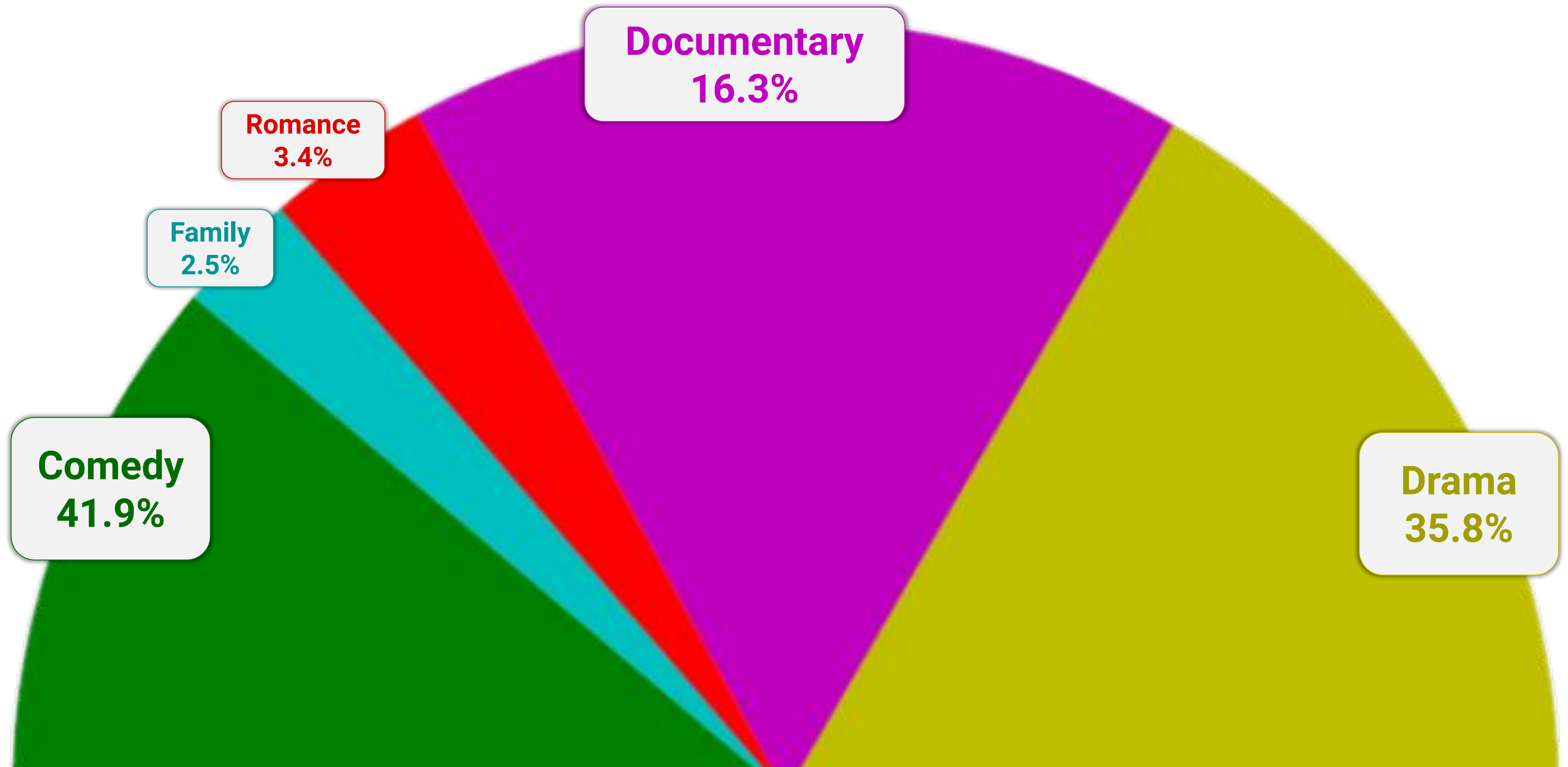


# QUANTITY OF MOVIES BY RELEASE DATE



# MOST POPULAR GENRES





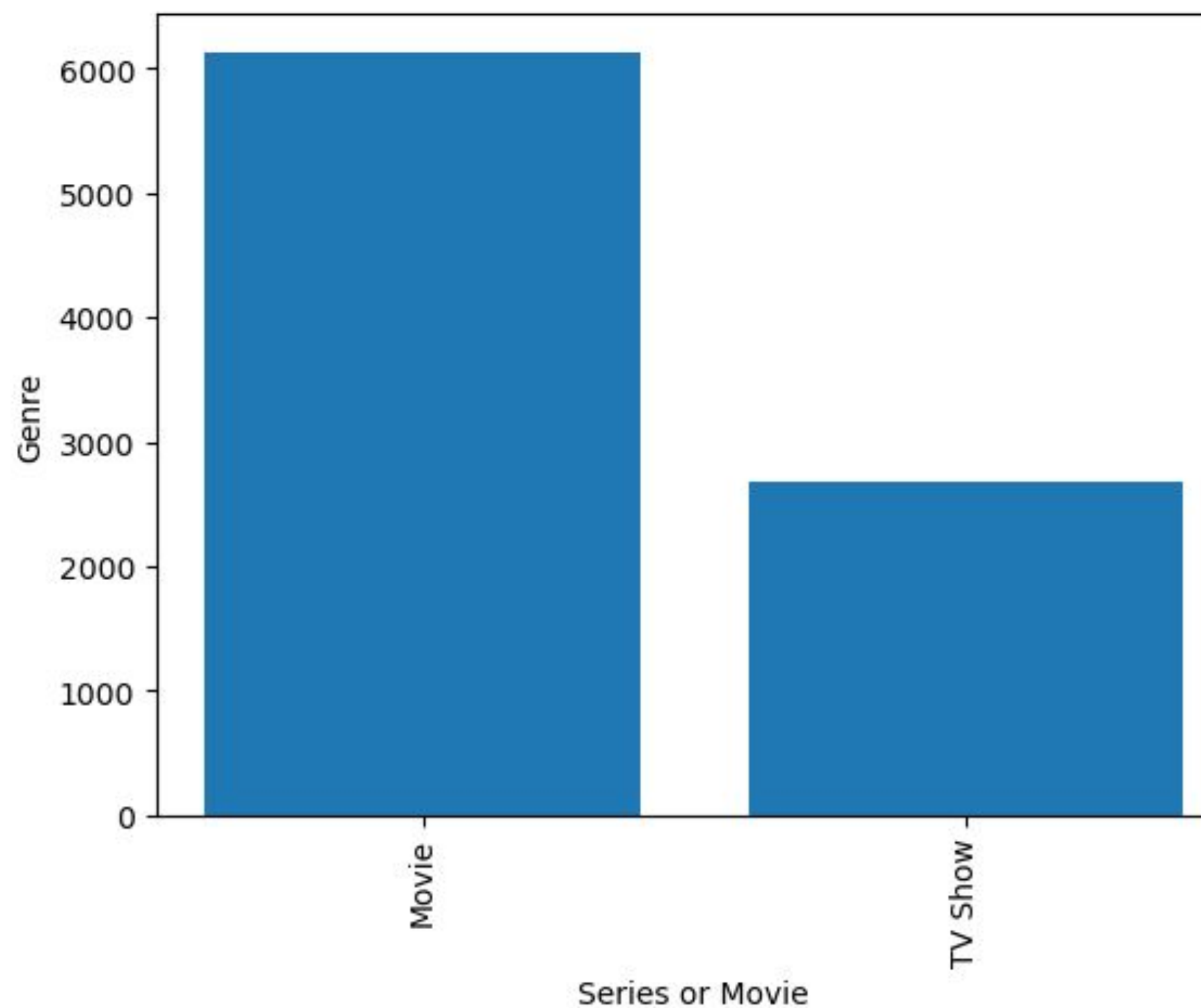
**NETFLIX**

**MOST POPULAR GENRES**

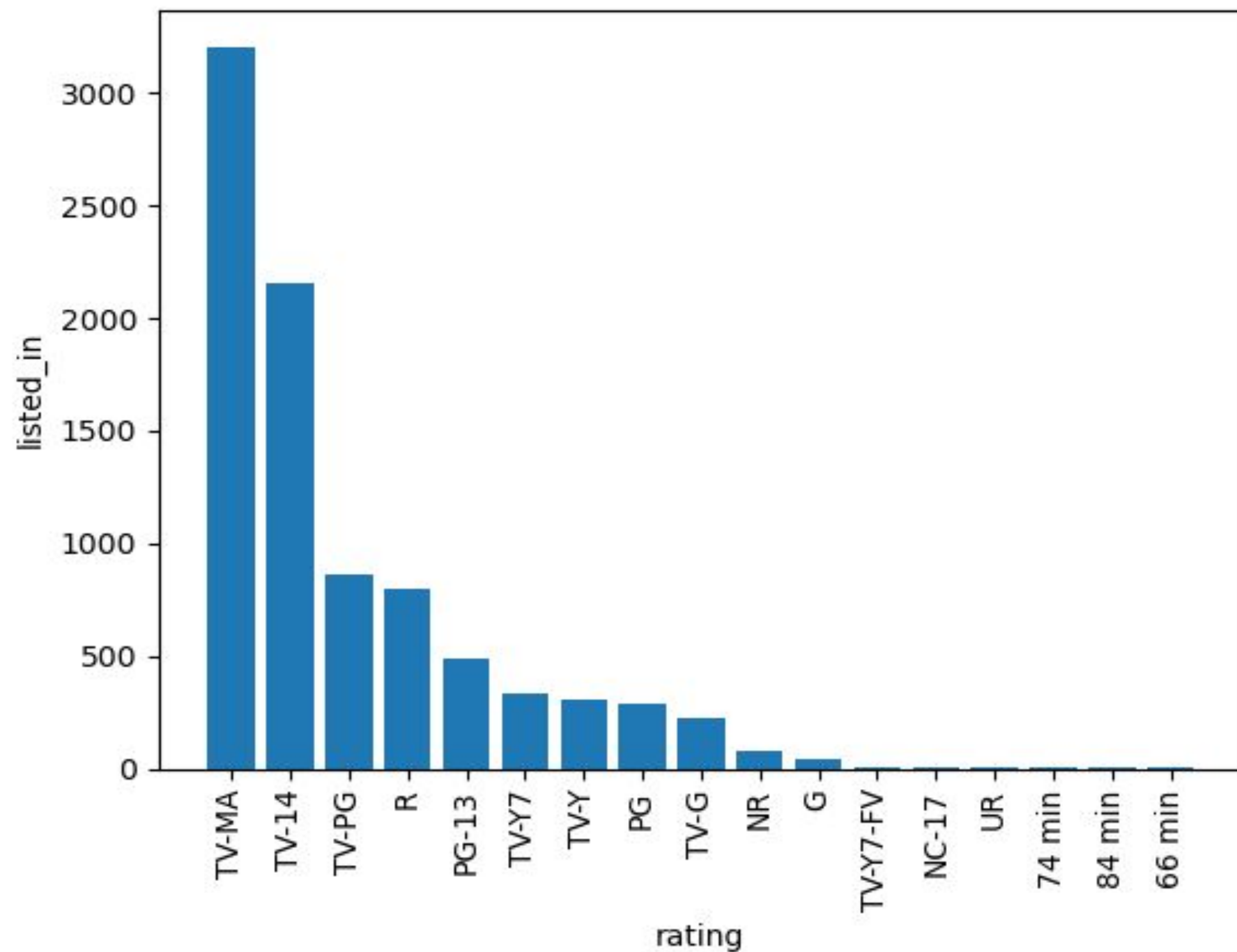
# NETFLIX

## MORE RESEARCH IS NEEDED...

### MOVIES VS SHOWS



### MOST COMMON RATINGS



## DATA SOURCES SELECTED

- Kaggle □ Netflix CSV & Rotten Tomatoes CSV

## DATA CLEAN-UP PROCESS

- Netflix data was a well-organized CSV that gave basic facts
- Rotten Tomatoes data was a large file
- Column clean-up (renaming) for merging data



# APPROACH TAKEN ON THE PROJECT

- This was great practice using past lessons on a blank slate
- Past activities and assignments guided me in selecting the type of code I used
- My goal was to get the most out of the two data frames and attempt to answer questions about a very large topic

03.



hulu

04.



disney+

05.



**to stream or not to stream?**

# so what do we recommend?



## Based on Price

Amazon - \$8.99 / month

Netflix - \$6.99 / month

Average US salary: \$59,428 or  
\$28.34 / hour

According to Forbes

# NETFLIX

## Offerings

In our analysis here, Amazon had  
more content pieces available for  
customers to watch at this time.

prime video



## Reputation

When you think streaming, you don't think  
Amazon first. While it's a great perk that you  
also have so many shows available, customers  
may be enticed by a company who is focused  
on delivering streaming content.

# NETFLIX



# WHAT WE DID WELL

- We communicated well as challenges came up
- We communicated about where our data was similar in preparing for how we may be able to use our individual analysis to compare all services
- We adjusted our question and objective once we saw the data we worked with
- We decided to scale back and cut some of the datasets we looked at - especially after losing a group member

# REFLECTIONS: WHAT WE'D DO NEXT TIME

- Have the data before choosing the objective - some information was not a public as we thought it would be
- Create a better execution plan going into the working groups - more clear timeline
- Collaborate more efficiently and make sure the project reflected a combination of the three parts - especially on merging data to complete our comparison and achieve true analysis of the various services
- With the allotted time, our topic could have been narrower in scope.
- Take a look at more niche categories to compare like original shows, diversity in shows, what “extras” are offered with each service, look into what specifically is offered in the United States and how that compares to the rest of the world