OPEN IIT
DATA ANALYTICS

Team 2

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Introduction

Netflix operates one of the world's largest streaming catalogs, where content strategy—what to license, produce, and surface—directly drives engagement and retention. This report analyzes Netflix's movie and TV library to uncover patterns in genres, geography, ratings mix, and description tone, and to translate those patterns into clear acquisition and merchandising actions aligned with the brief of the Open IIT "Netflix Content Analytics & Strategic Insights" challenge.

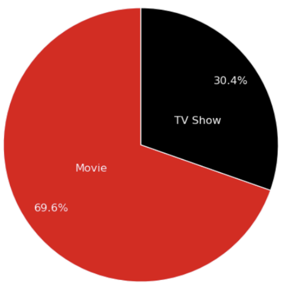
Using the Kaggle catalog as the primary source, we build a Python/Notebook pipeline and an executive Streamlit dashboard to (i) profile catalog composition and growth, (ii) map genre popularity and gaps, (iii) evaluate country-level opportunity via average popularity vs. catalog size, and (iv) study sentiment of title descriptions (VADER) as mood metadata rather than a proxy for audience liking. Statistical checks (ANOVA/LSD) are applied to validate differences across groups. The goal is to convert raw metadata into actionable guidance—e.g., where to expand supply (high-popularity, low-breadth countries), which genres to double down on (Adventure/Sci-Fi/Action), and how to rebalance the ratings mix (more PG/PG-13 family content in co-viewing regions)—and to package those recommendations in an executive-ready, interactive format.

1) Content Landscape Analysis

1.1 Catalog Composition and Structure

Catalog Composition:-Movies have consistently been more prevalent on Netflix compared to TV shows. The number of movies added each year has generally been higher than the
number of TV shows, indicating a stronger focus on movies.

Fig 1.1



1.2 Genre Distribution

- **Genre & Content Strategy – "Big 3":-**
 The treemap is clearly top-heavy: International (4,145), Dramas (3,478), and Comedies (2,620) together make up ~57% of the top 15. So the catalog is built around a few broad, high-demand pillars rather than evenly spreading volume.

- **International as a Core Line:-**
 "International" being the single biggest block shows this is not just Indian content with some imports — it supports a global-first catalog and regional growth.

- **Mid-tier Breadth, Undervolumed Niches:-**
 Genres like Documentaries, Children & Family, Action, Romance add breadth, but the smaller tiles — Thriller, Crime, Horror, Documentary Series, British, Anime, Sci-Fi — are visibly underrepresented. These are good targets for selective content acquisition if engagement/trend data supports them.

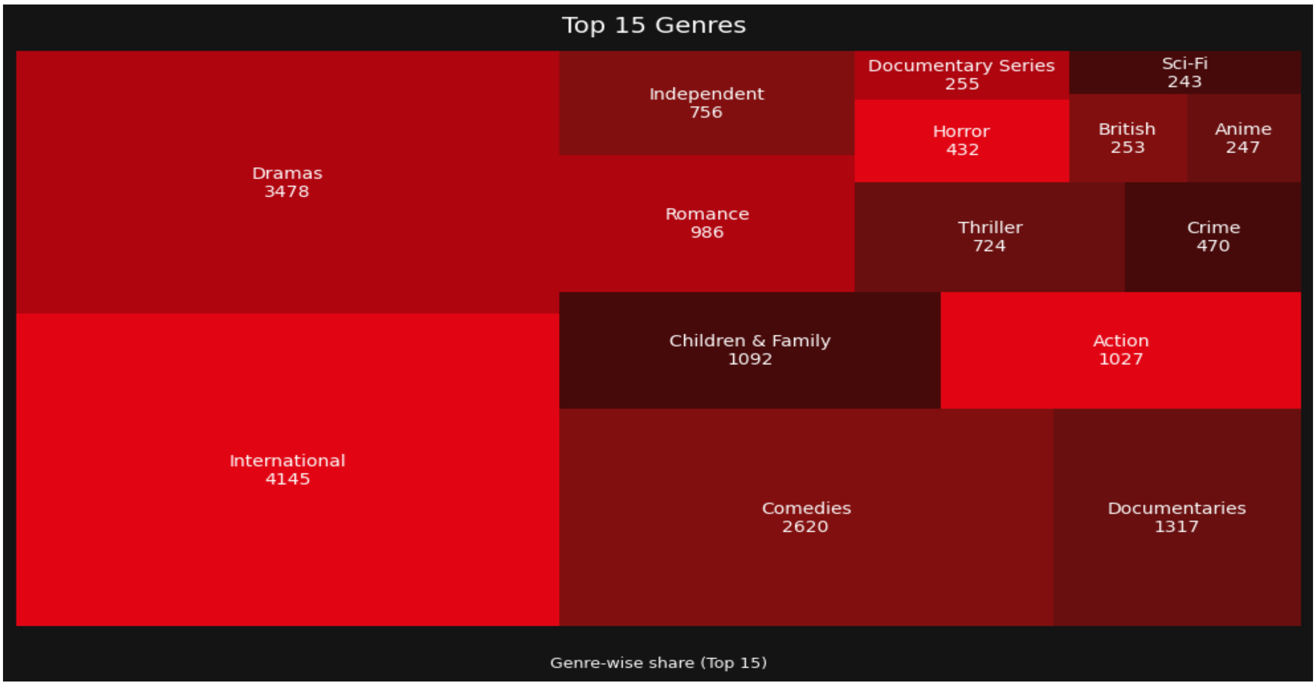


Fig: 1.2

1.3 Rating & Audience Targeting Analysis

- Mature-heavy catalog: The two largest buckets — TV-MA (36.5%) and TV-14 (24.5%) — together account for ~61% of all titles. This shows the catalog is designed primarily for teens and adults, not for young kids.

- Adult layer reinforced by films: R-rated content adds another 9.1%. Taken together, TV-MA + TV-14 + R ≈ 70%, so the clear answer to "which ratings dominate?" is: mature / older-audience content.

- Family is present but secondary: Family-friendly ratings — TV-PG (9.8%), PG-13 (5.6%), plus the kids set (TV-Y, TV-Y7, PG, TV-G) — form a much smaller tier. Netflix is not aiming for a 50–50 mature vs. family split; it keeps a family corridor to serve households, but the volume sits on adult/teen demand.

- Kids-only volume is small: Kids-first ratings — TV-Y (3.5%), TV-Y7 (3.8%), TV-G (2.5%), G (0.5%) — exist, but they are clearly not the primary growth driver.

- Clear brand-safety ceiling: NC-17 (~0%) and TV-Y7-FV (0.1%) are almost absent, which indicates Netflix stays inside a broad, mainstream-safe maturity band.

- Minor data tail: NR (0.9%) and UR (~0%) form a very small residual group; note them in the data-quality / cleanup section, but they do not change the strategic story above.

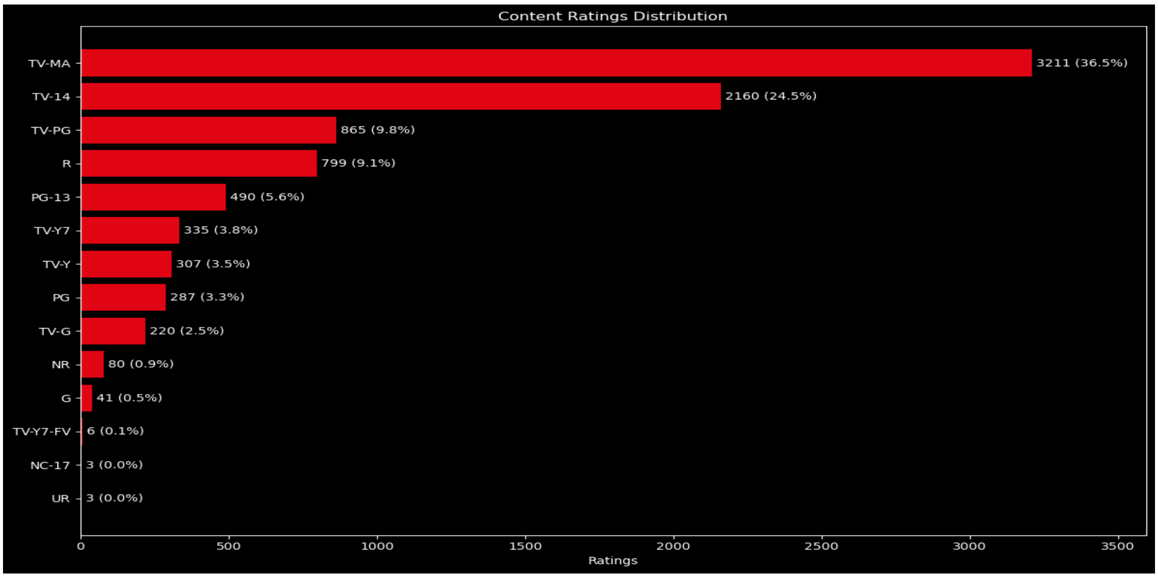


Fig 1.3

1.4 Content volume trends over time

The below visualization is fundamental to the "Temporal Trend Analysis" and provides a clear answer to the strategic question: "How has the content addition strategy evolved?". The chart clearly identifies two distinct eras.

• **The "Trickle" Era (Pre-2015):** The period before 2015 shows negligible content additions, reflecting Netflix's early days and its transition from a DVD-by-mail service to a streaming platform.

• **The "Firehose" Era (Post-2015):** The graph identifies a dramatic "strategic inflection point" around 2015. After this point, the "Netflix catalog growth over the years" becomes exponential.

• **Strategic Pivot:** This shift from a slow trickle to an aggressive "firehose" of content acquisition marks the true beginning of the "Streaming Wars." This pivot is the single most important temporal trend in the dataset.

• **Peak & Volatility**: The period from 2017-2020 shows not only the highest volume but also extreme volatility. The sharp, spiky nature of the line indicates that content is added in large "batches" rather than a steady daily stream. This directly illustrates the "content addition patterns (monthly, yearly, seasonal)", which are event-driven (e.g., 150+ titles added in a single day), peaking just before 2020.

• **Post-2020 Normalization:** After the 2019-2020 peak, the number of additions appears to settle into a "new normal" that is still highly volatile but at a slightly lower volume than the peak, perhaps reflecting a market saturation or a strategic shift from quantity to quality.

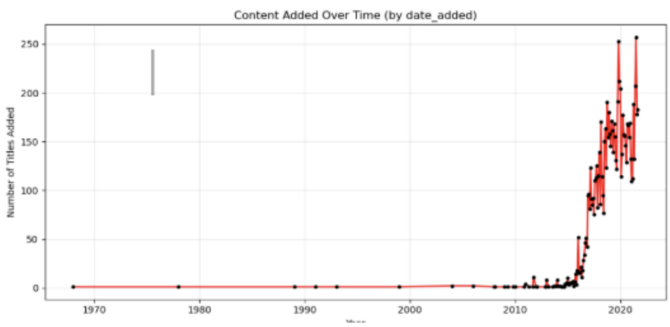


Fig:-1.4

2)Temporal Analysis

2.1 Content Growth and Strategy Evolution

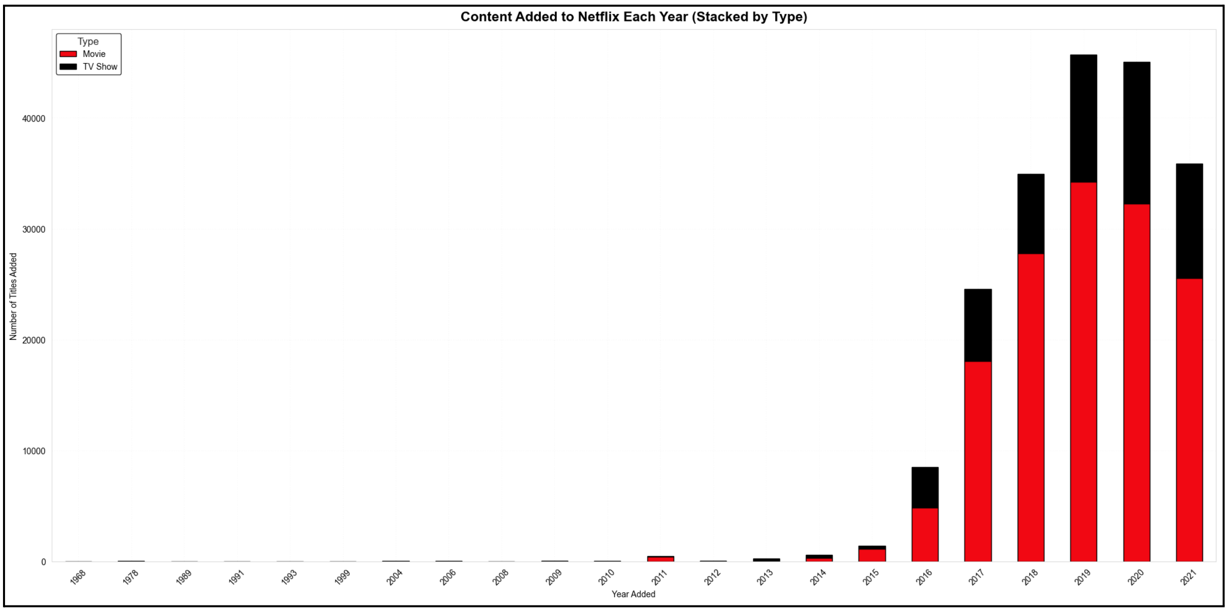


Fig 2.1 Historical Content Growth: Movies vs TV Shows Added Annually

This chart illustrates the multi-phased evolution of Netflix's content acquisition strategy, highlighting a deliberate and significant pivot from a **movie-centric model** to a **balanced, dual-format portfolio**. The data reveals three distinct strategic phases:

- **Phase 1: Catalog Foundation & Market Entry (Pre-2016):** The initial strategy prioritized movie acquisitions to rapidly build a large-scale content library, establishing a core value proposition to drive initial subscriber growth.
- **Phase 2: Aggressive Scaling & Strategic Diversification (2016-2019):** This era marks an inflection point of aggressive scaling and a strategic pivot. A significant investment in TV shows was initiated, recognizing their critical role in driving long-term engagement and retention, complementing movies as the primary tool for subscriber acquisition.
- **Phase 3: Strategic Maturation & Portfolio Optimization (Post-2019):** The strategy has matured from acquisition volume to portfolio optimization. The current, balanced model leverages movies for broad appeal and event

viewership while using TV series to foster subscriber loyalty and create valuable, brand-defining intellectual property.

2.2 Cumulative Content Expansion: Building the Content Moat

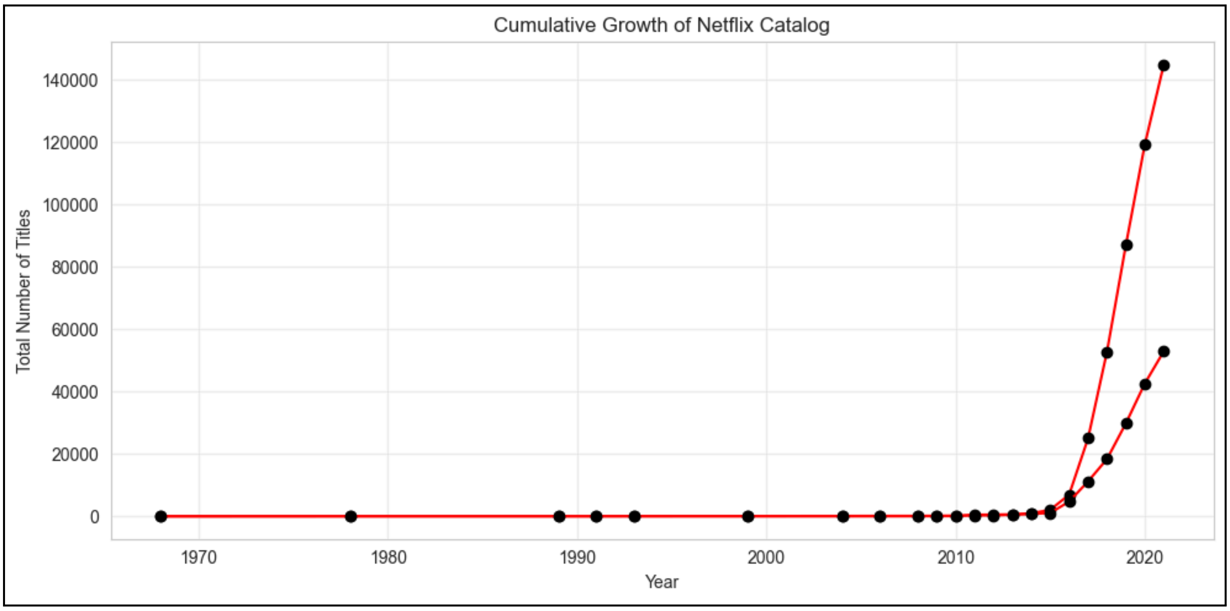


Fig 2.2 Cumulative Growth of the Netflix Content Catalog (Total Titles)

This visualization is a stark depiction of Netflix's core strategic decision to win the market through overwhelming scale. It charts the deliberate creation of a content library so vast that it serves as a primary competitive advantage.

- **The Strategic Inflection Point:** The **near-vertical ascent post-2015** is not merely growth; it is the visual evidence of a pivotal corporate mandate: achieve market-defining library scale at an unprecedented velocity. This **"hockey stick" curve** represents a period of **massive, front-loaded capital investment** aimed at rapidly outpacing all competition.
- **Scale as a Strategic Weapon:** The resulting catalog size, as shown by the cumulative total, functions as a powerful strategic "moat." Its sheer volume acts as a formidable barrier to entry for emerging competitors and serves as a critical tool for minimizing subscriber churn by creating a perception of endless viewing options.
- **Momentum and Market Perception:** The steepness of the curve itself became part of the narrative, **signaling Netflix's aggressive market posture** and commitment to content leadership. This relentless momentum helped solidify

its position as the default, indispensable streaming service in the minds of consumers globally.

2.3 Monthly Content Addition Patterns

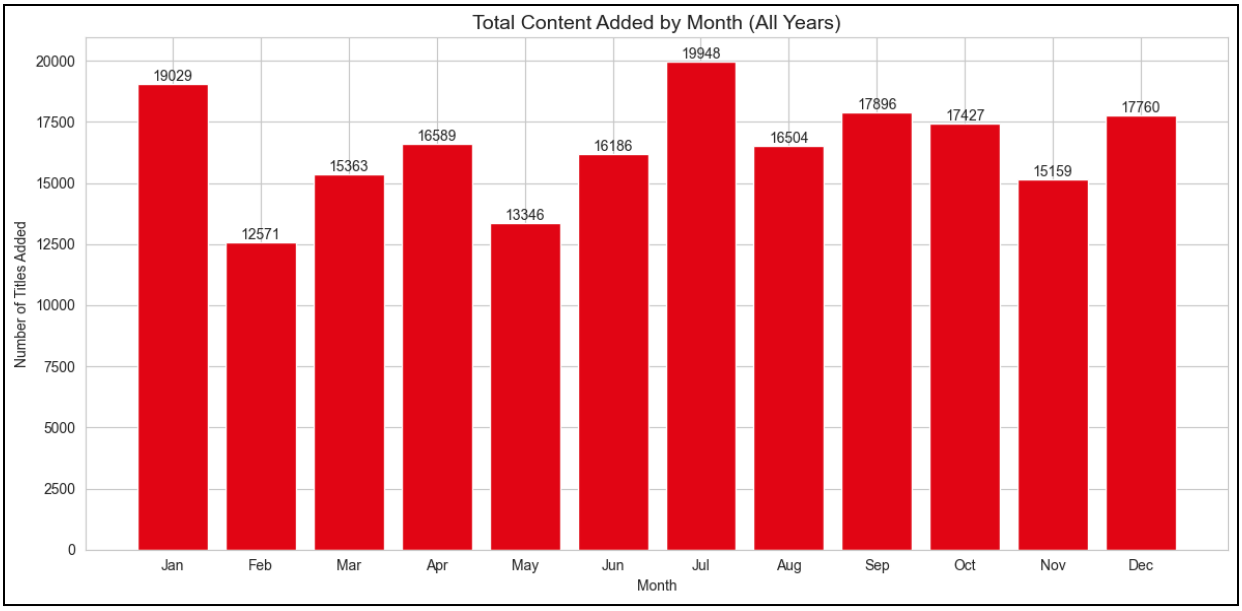


Fig 2.3 Monthly Content Addition (All years)

Insight 1: The "Peak & Strike" Offensive

- **Observation:** Content deployment is heavily concentrated into two primary waves: a ***Q4-Q1 holiday push (Oct-Jan)*** and a ***major mid-year offensive (July).***

- **Inference:** This is a ***"Peak & Strike"*** strategy that aligns massive content drops with periods of maximum audience availability.

- **Strategic Implication:** This approach capitalizes on the ***global holiday season*** for acquisition and co-viewing, while the July peak executes a powerful counter-programming move against the traditional broadcast lull, effectively capturing the summer entertainment market.

Insight 2: The "Strategic Cooldown"

- **Observation:** The months of ***February-May*** show a consistent and significant dip in new content additions.

- **Inference:** These are not budgetary lulls but deliberate ***"Strategic Cooldowns"*** or ***"echo chambers."***

- **Strategic Implication:** This programmatic quiet period prevents ***audience fatigue*** and allows the major titles from the "Peak & Strike" waves to dominate cultural conversation, ***maximizing word-of-mouth marketing*** and the ROI on major productions.

2.4 Micro-Temporal Strategy: Day-Wise Content Addition Patterns

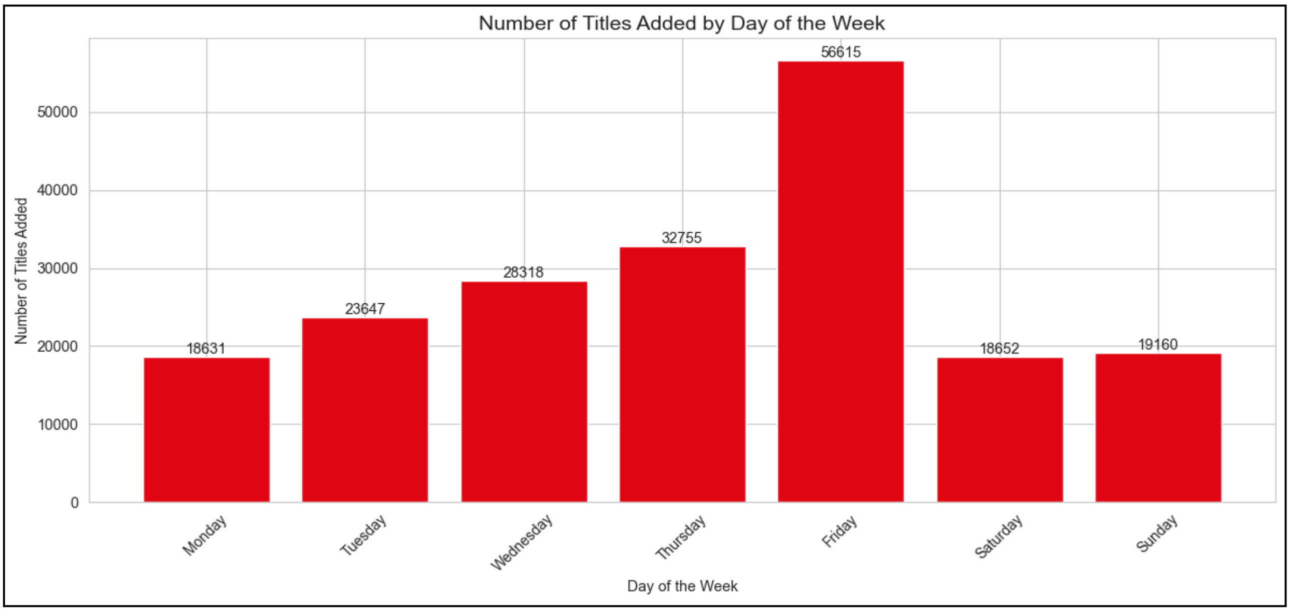


Fig 2.4 Day-wise Content Addition (All years)

This analysis moves beyond a simple daily count; it decodes the highly disciplined, weekly playbook Netflix uses to drive viewership and ritualize the user experience. The pattern is not a coincidence; it is a meticulously engineered strategy.

Insight 1: The "Friday Night Event" as the Strategic Cornerstone

- **Observation:** Content additions on Friday are nearly double that of any other day, creating a massive, deliberate spike.

- **Inference:** This is not just a release day; it is the creation of a recurring "event." Netflix has successfully weaponized the ***end of the work week*** to anchor its entire release schedule.

- **Strategic Implication:** This strategy conditions the subscriber base to view Friday as the "primetime" for discovery. It preemptively answers the universal question, ***"What should we watch this weekend?"***, capturing audience attention and dominating the crucial weekend viewing window before competitors have a chance.

Insight 2: The "Weekend Dead Zone" as a Consumption Funnel

- **Observation:** Saturday and Sunday see a dramatic plunge in new content, dropping to levels below that of even Monday and Tuesday.

- **Inference:** This is a purposeful ***"content dead zone"*** designed to protect the vFriday investment.

- **Strategic Implication:** By not releasing significant new content on the weekend, Netflix creates an ***undisturbed "consumption funnel."*** This strategy channels viewer attention directly towards the high-value titles released on Friday, maximizing their initial viewership, ***encouraging binge-watching***, and allowing them to dominate social media buzz throughout the weekend without being cannibalized. It also reflects operational pragmatism, avoiding high-stakes technical deployments during off-hours.

Insight 3: The Mid-Week "Momentum Build"

- **Observation:** There is a clear, stepped progression of content additions from Monday through Thursday.

- **Inference:** This is a deliberate ***"drip-feed" strategy*** to maintain daily platform engagement and ***build anticipation***.

- **Strategic Implication:** This mid-week activity keeps the catalog feeling dynamic and fresh, feeding content to the most active daily users. It functions as a steady "drumbeat" that ***builds momentum towards the main "Friday Night Event,"*** ensuring the platform remains a daily habit, not just a weekend destination.

2.5 Year-Month Aggregated Timeline of Content Acquisition

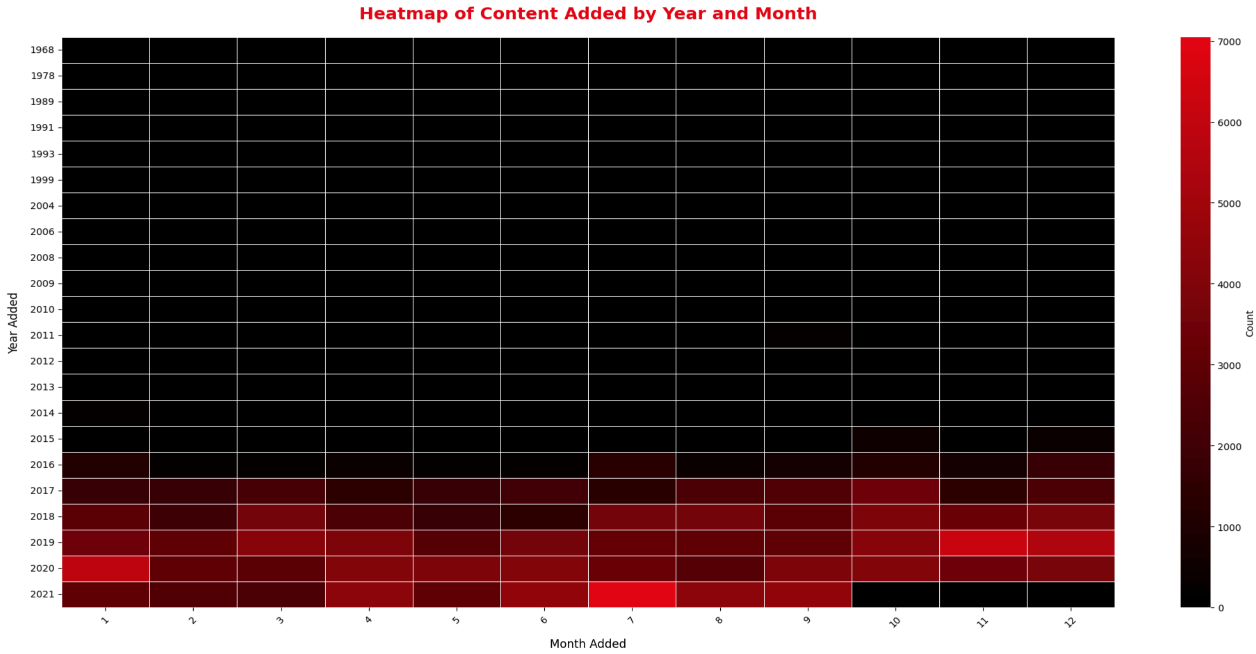


Fig 2.5 Content Releases by Year and Month Heatmap

This Heatmap visualizes the evolution of the content release strategy, showing the precise timing and intensity of catalog growth over the years:

1. **The Strategic Shift to Hyper-Growth (Post-2016):** The map shows a clear dividing line after 2015, shifting from ***near-zero activity*** to an immediate and sustained period of high-volume content acquisition. This visualizes the execution of the ***aggressive growth strategy*** to rapidly build the content library.

2. **A Consistent, Scalable Release Cadence (2017-2019):** During the peak growth years, a ***consistent seasonal pattern*** was repeated annually. The concentration of releases in ***Q1, July, and Q4*** demonstrates a disciplined, repeatable playbook that was scaled effectively each year.

3. **Peak Volume and Maturation (Post-2019):** Total content volume appears to have peaked in 2019. The following years show a shift from overwhelming, uniform monthly additions to a more targeted approach, suggesting a strategic maturation from pure scale to a greater focus on high-impact releases.

2.6 Content Freshness: Average Content lag for Movies and TV Shows Compared

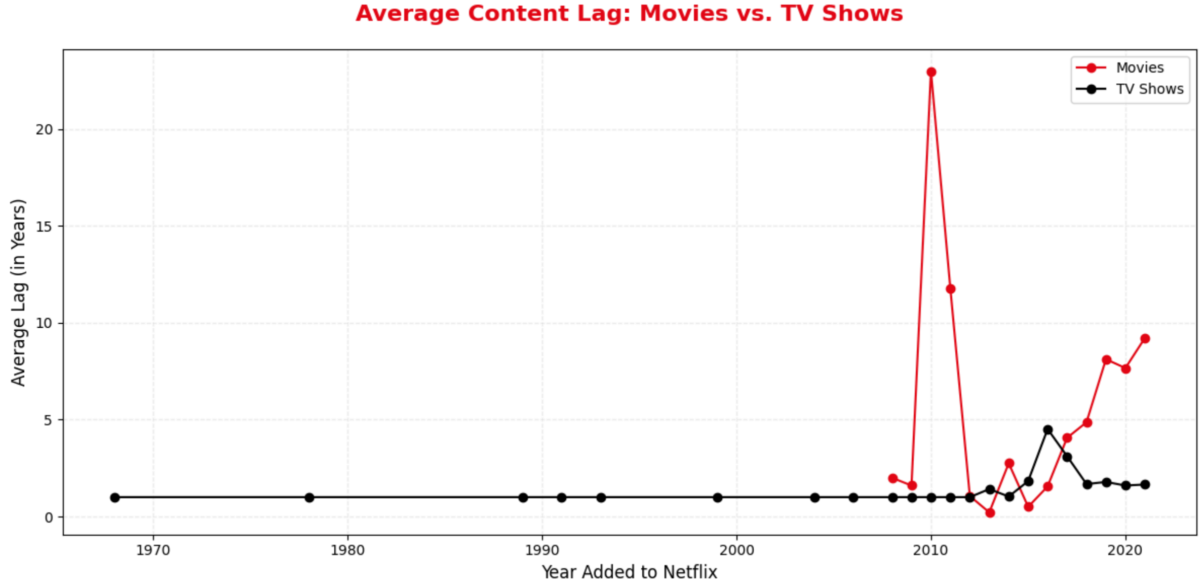


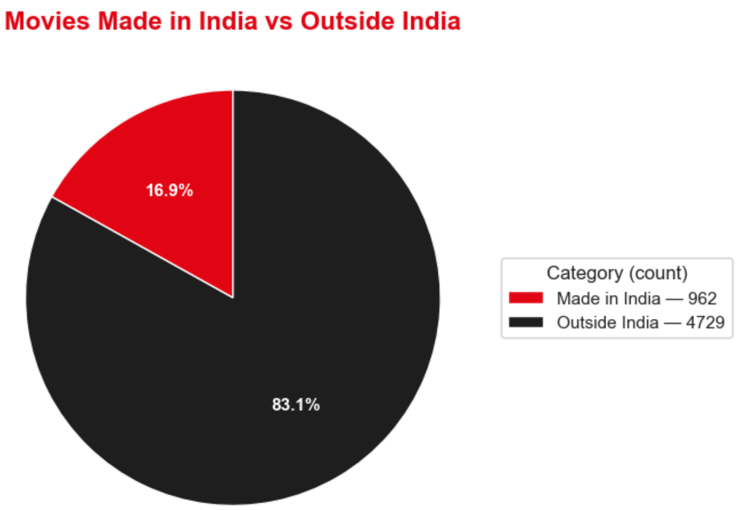
Fig 2.6 Average Age of Content Added to Netflix

- **Insight 1: TV Shows are the Engine of "Now"**
  The lag for TV shows is consistently and remarkably low (averaging 1-2 years). This demonstrates a strategy centered on immediacy and cultural relevance. This is largely driven by the "Netflix Original" model, ensuring the platform is the exclusive, premiere destination for the latest binge-worthy series, which is a primary driver of new subscriptions and media buzz.

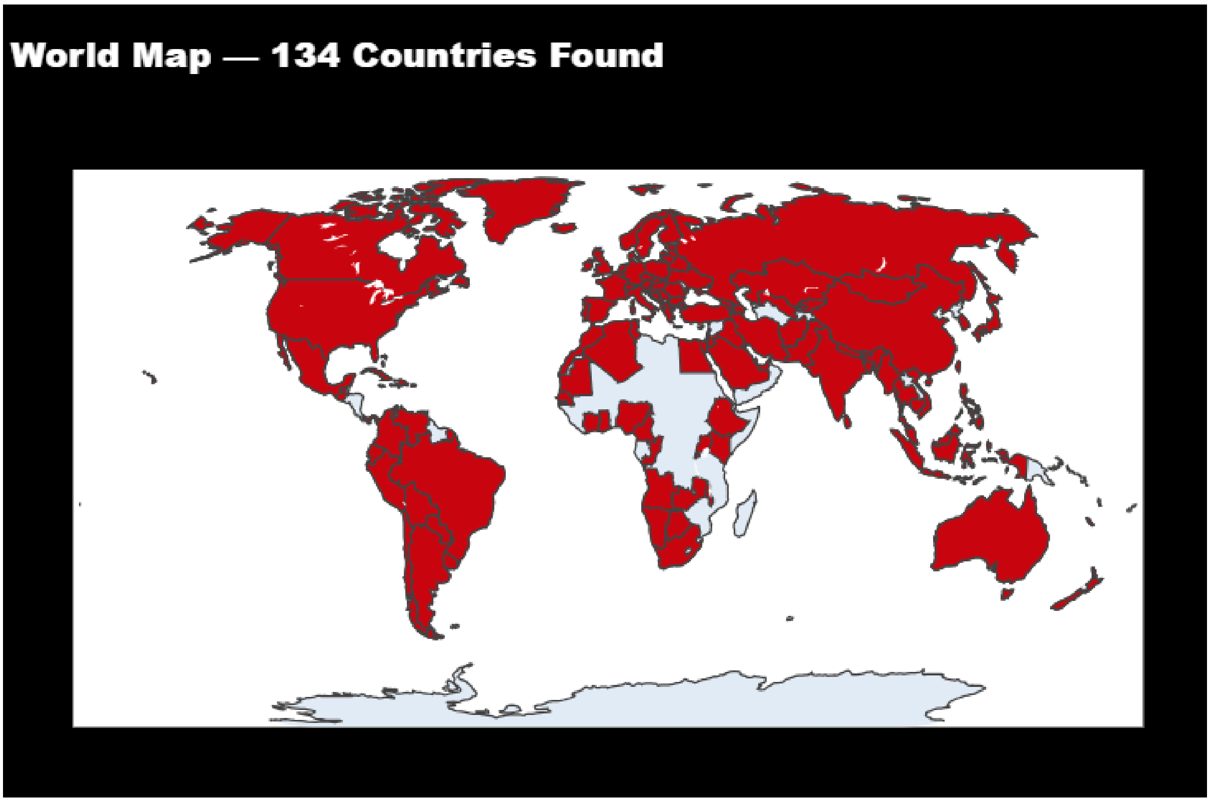
- **Insight 2: Movies Fulfill the "Library" Role**
  Conversely, the average lag for movies is significantly higher and has been trending upwards since 2016. This signals a strategic shift away from competing for expensive, first-run theatrical rights. Instead, the movie strategy is focused on building a deep and cost-effective "library" of proven, second-run hits and classics, a tactic aimed at long-term subscriber retention rather than acquisition.

- **Insight 3: The Two Formats Serve Different Goals**
  The divergence is the core takeaway. Netflix uses its TV show catalog to be timely and essential, creating event television that drives the cultural conversation. It uses its movie catalog to be timeless and comprehensive, providing a vast, comfortable repository of content that keeps subscribers engaged over the long term.

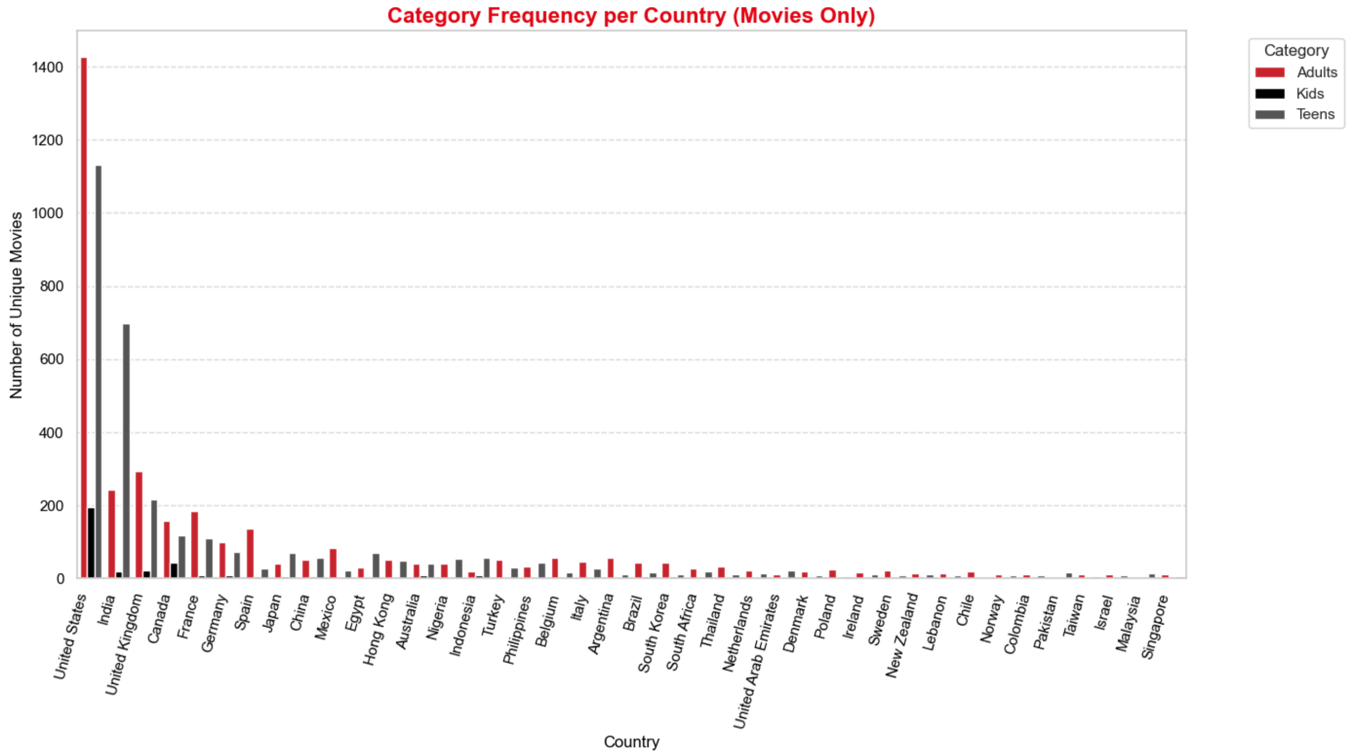
3) Geographic Content Analysis



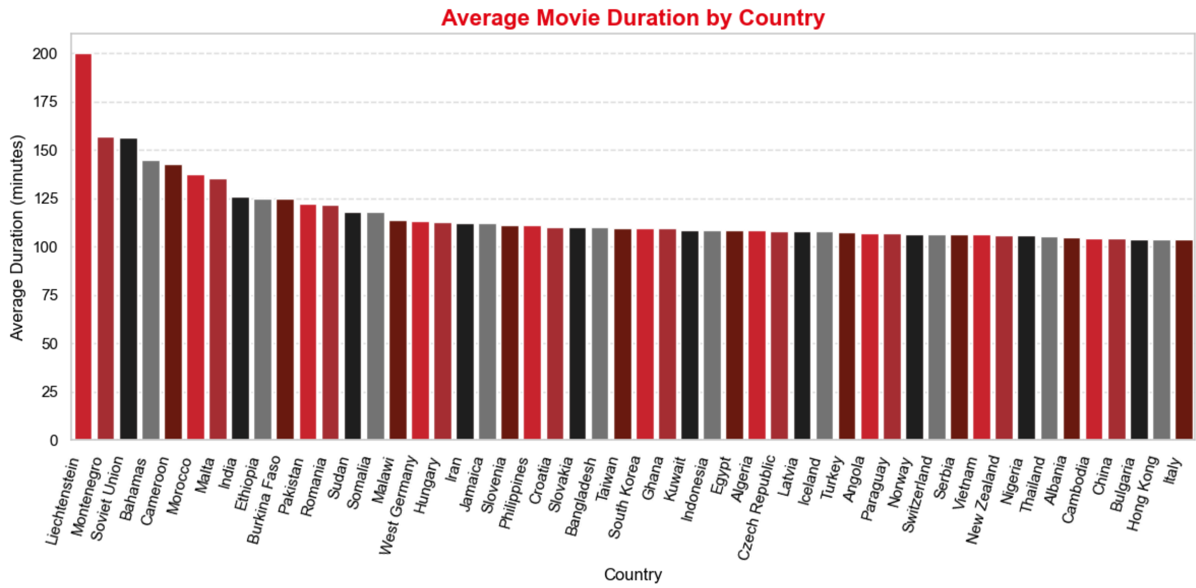
Around 16.9% movies are made in India while 83.1% are made outside.

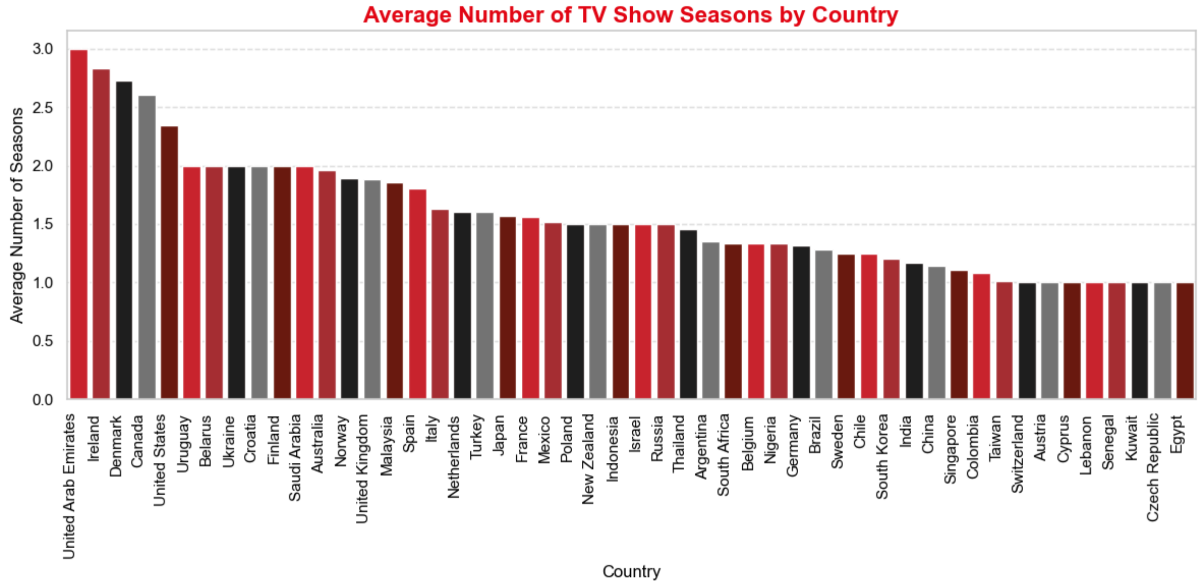


Netflix is home to films and series produced across approximately **134 countries**, representing one of the most diverse entertainment catalogs in the world. The platform features movies in **dozens of languages**, showcasing a wide range of **cultures, storytelling traditions, and cinematic styles**.

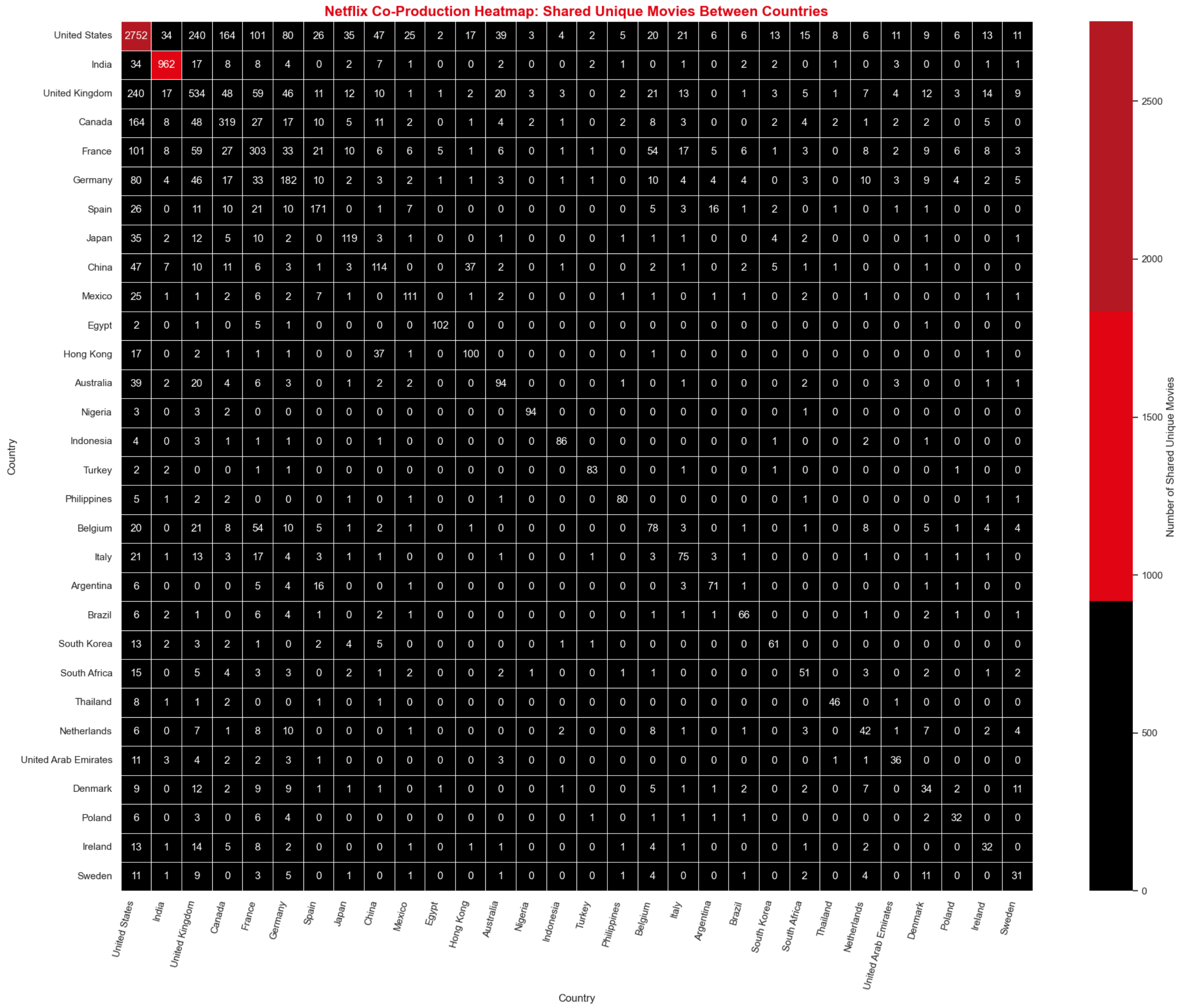


Movies are divided into three categories: “Adults”, “Teens”, “kids”. The USA produces the maximum number of movies in all three categories followed by India.

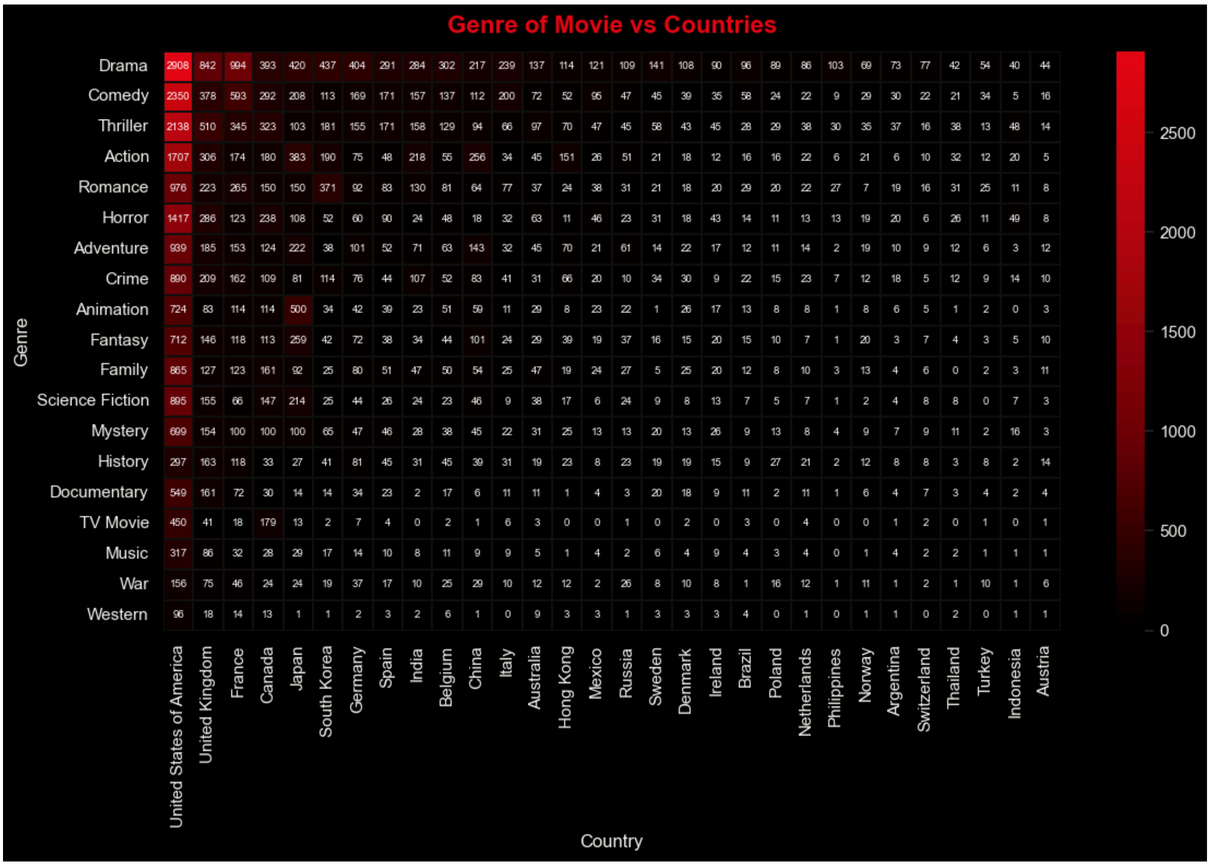


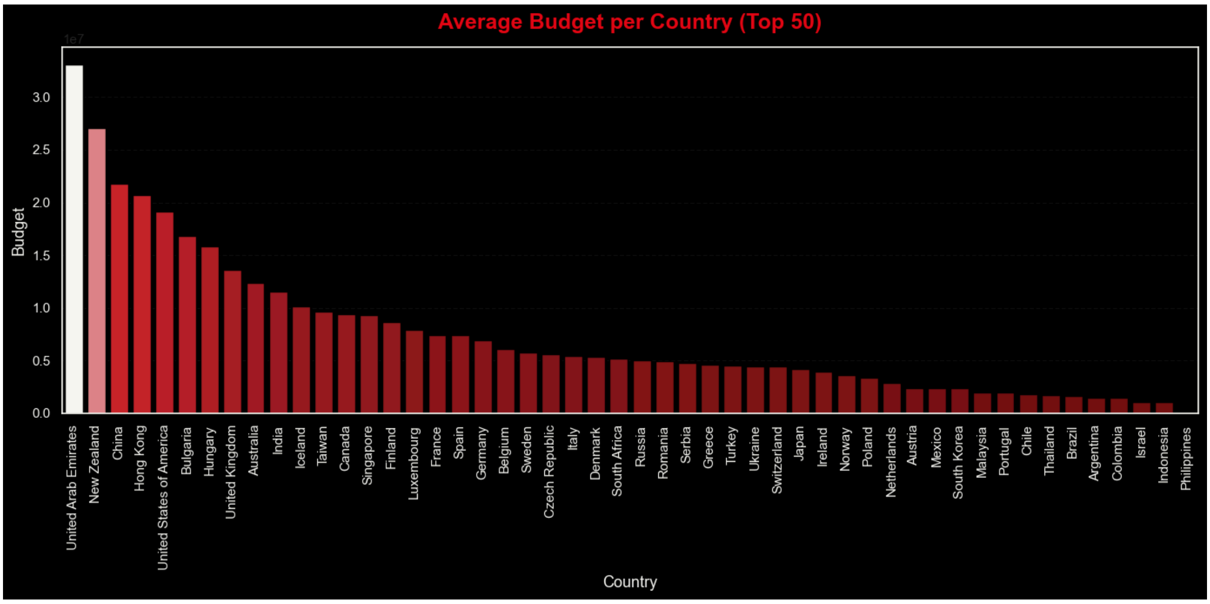


The United States produces movies with the highest average duration on Netflix, whereas television shows from the United Arab Emirates (U.A.E.) have the highest average number of seasons among all countries represented on the platform.

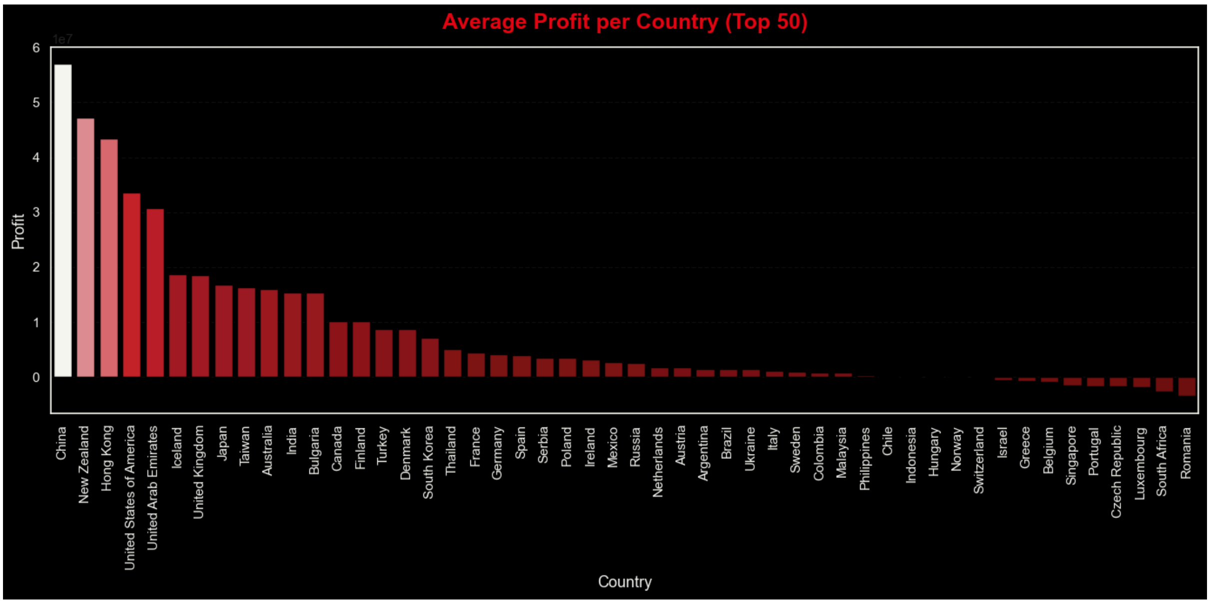


The Co-Production Heatmap reveals that the United States has collaborated on the highest number of movie co-productions, primarily with countries such as the United Kingdom, Germany, France, and Canada.





Countries like the U.A.E, New Zealand, China, U.S.A, U.K. generally have higher average budgets for production of movies. While countries like the Philippines, Indonesia, Israel etc. have lower average budgets for production of movies.



Countries such as China, New Zealand, the United States, Hong Kong, and the United Kingdom exhibit a higher average profit from their movies, whereas countries like Romania, South Africa, Portugal, and Singapore show an average negative profit, indicating overall losses in their film productions.

4) Genre & Category Intelligence

4.1 Genre Evolution over time

From figure 4.1 we can see that drama has always been the most produced genre in Movies from 2010 to 2025 followed by comedy and thriller. Western has been the most underproduced genre out of the 19 genres listed in the dataset in this timeframe.

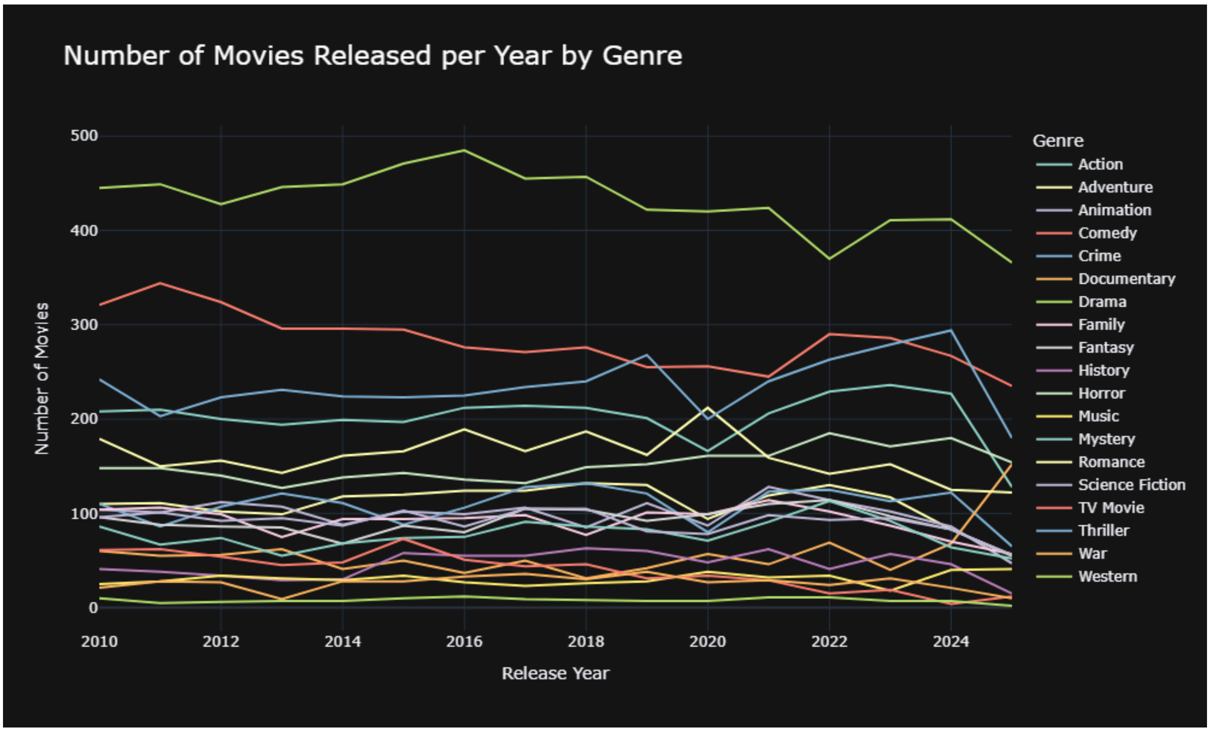


Fig 4.1 - Number of movies of a particular genre across time (2010-2025)

From fig 4.2 it is evident that drama followed by comedy and animation has dominated in the TV shows category from 2010 to 2025. Western TV shows are the least produced TV shows among the 16 genres.

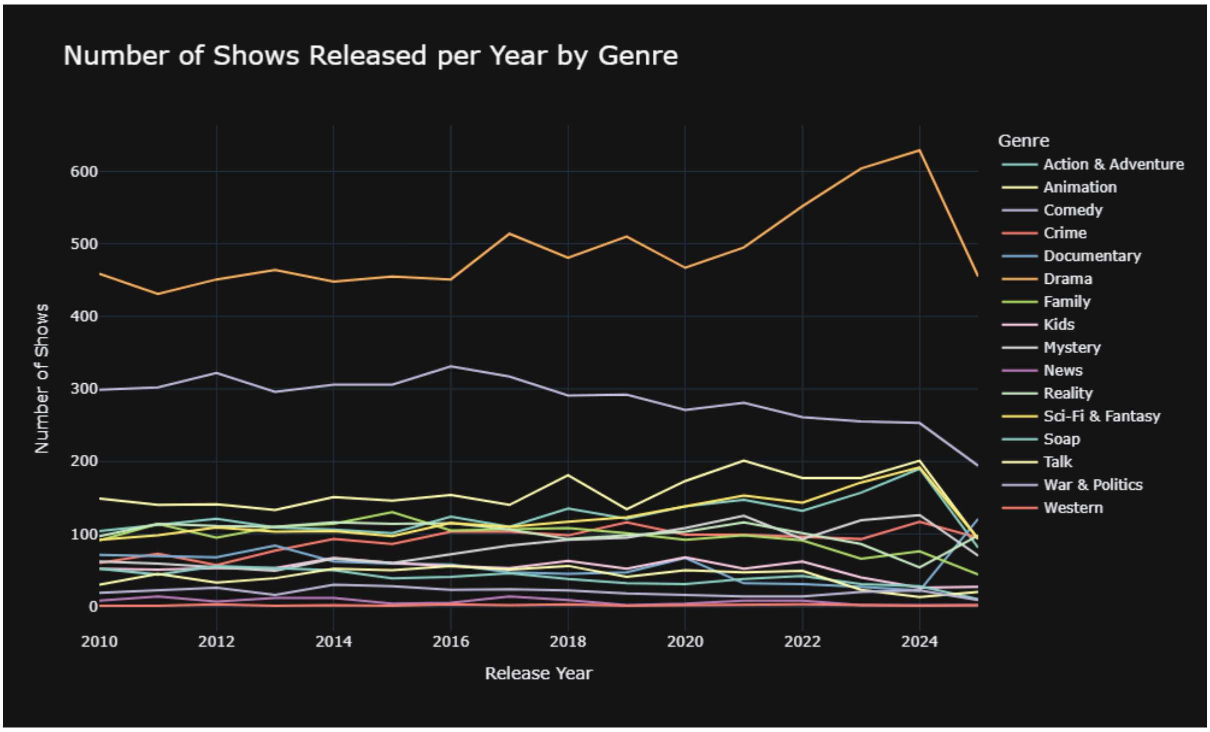


Fig 4.2 - Number of TV shows of a particular genre across time (2010-2025)

4.2 Influence of genre in ratings of movies and TV shows

Fig 4.3 implies that animation is the genre that has the highest median rating followed by documentaries and music. Horror and thriller are the two worst rated genres from the plot.

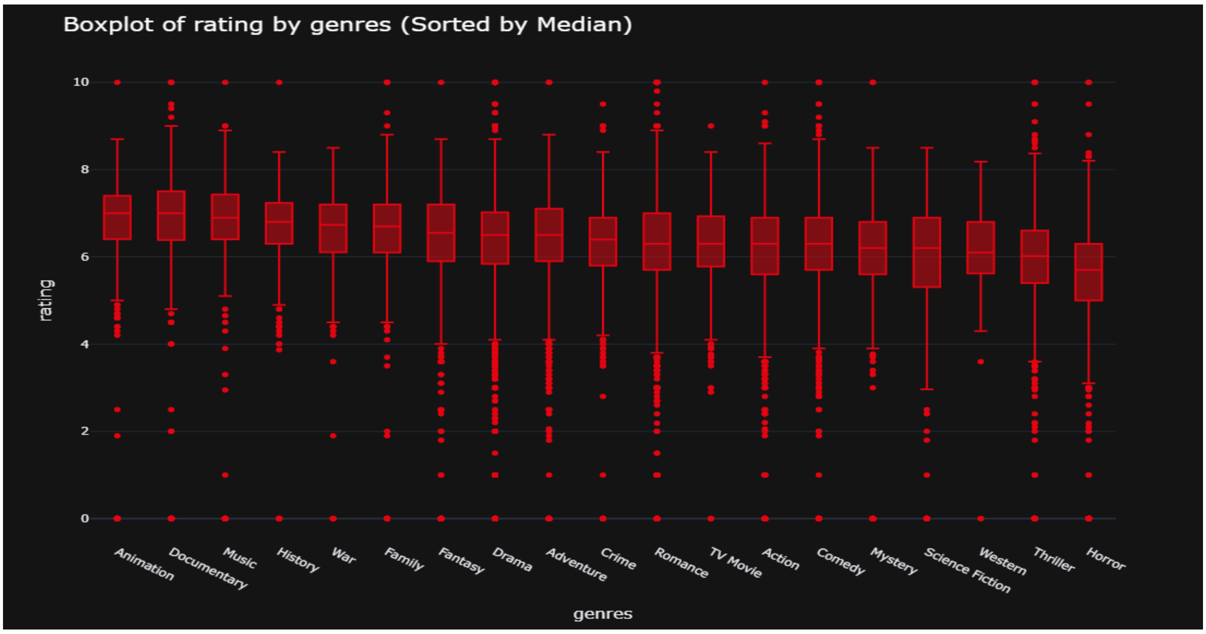


Fig 4.3 - Boxplot of ratings across different genres of movies

Fig 4.4 implied that TV shows with action & adventure as their genre tend to be higher rated than average than any other genre. The genre news has the lowest median rating among all TV show genres.

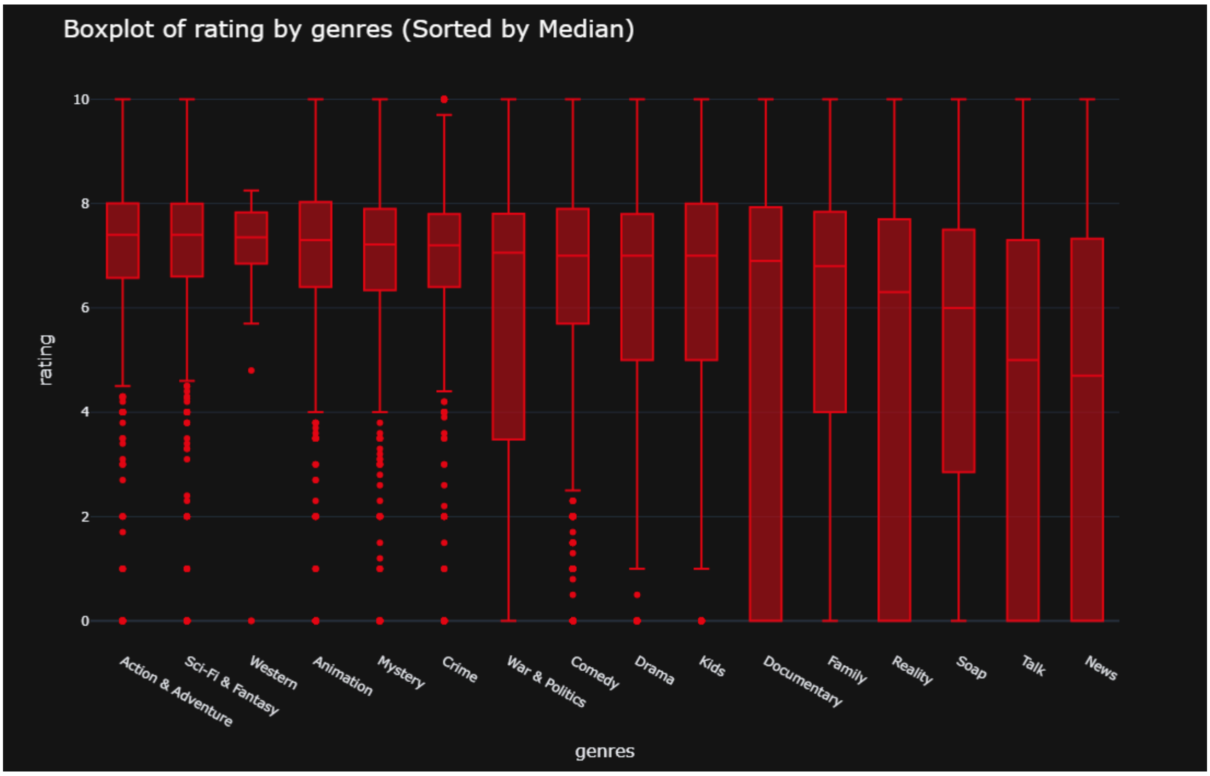


Fig 4.4 - Boxplot of ratings across different genres of TV shows

We cannot conclude from just the plot that some genres are better rated on average than others. Performing **one-way ANOVA (also known as F-test)** will give us concrete proof as to whether genres are rated differently on average.

For the one-way ANOVA test we treat genres as levels.

The null and alternative hypothesis is defined below:

H_0 : all the genres have equal mean rating

H_1 : at least one genre has a higher or lower mean rating than the others

$$SST = sum\ of\ squares\ of\ treatments$$

$$SSE = sum\ of\ squares\ of\ errors$$

$$a = number\ of\ levels\ (genres)$$

$$N = total\ number\ of\ observations$$

$$n_i = number\ of\ observations\ in\ i^{th}\ level$$

$$SSE = \sum_{i=1}^{a} \sum_{j=1}^{n_i} (y_{ij} - \overline{y_{i\cdot}})^2 \qquad SST = \sum_{i=1}^{a} n_i(\overline{y_{i\cdot}} - \overline{y_{\cdot\cdot}})^2$$

$$\overline{y_{i\cdot}} = \sum_{j=1}^{n_i} \frac{y_{ij}}{n_i} \qquad \overline{y_{\cdot\cdot}} = \sum_{i=1}^{a} \sum_{j=1}^{n_i} \frac{y_{ij}}{N}$$

$$F = \frac{SST/(a-1)}{SSE/(N-a)}$$

$$F_{critical} \sim F_{1-\alpha,\, a-1,\, N-a}$$

If F is greater than or equal to $F_{critical}$ then we can say with 95% confidence that the mean rating is different for at least one genre, that is, we reject the null hypothesis. If we get F less than $F_{critical}$ then we fail to reject the null hypothesis and we can conclude that the difference in mean ratings across genres are not statistically significant.

After performing this test on the data given from 2010 to 2025 we were able to infer that the difference in mean ratings are statistically significant, that is, the mean ratings differ across genres, for both movies and TV shows.

To find out exactly which genres have higher or lower mean ratings we performed the LSD test. The procedure is described below:
For every pair of genres we calculate the LSD value and check whether the absolute difference between the observed mean ratings is greater than the LSD value for that pair. If it is greater then the genre in that pair with the higher rating has a statistically higher mean rating than the other genre.

$$LSD = t_{1-\frac{\alpha}{2}, N-a} \sqrt{MSE(\frac{1}{n_i} + \frac{1}{n_j})}$$

$$MSE = \frac{SSE}{N-a}$$

The main takeaways from the LSD test for movies and TV shows is that we have statistical proof for our findings from fig 4.3 and fig 4.4 shown above. The detailed results from the LSD and F test are present in the python notebook.

The best 20 combinations (only pairs) of genres that gave the highest ratings on average is shown in fig 4.5 for movies and fig 4.6 for TV shows. From fig 4.5 we can see that the combination Animation and documentary has the best rating on average among movies and the combination reality and war & politics has the best average rating among all other combinations in TV shows.

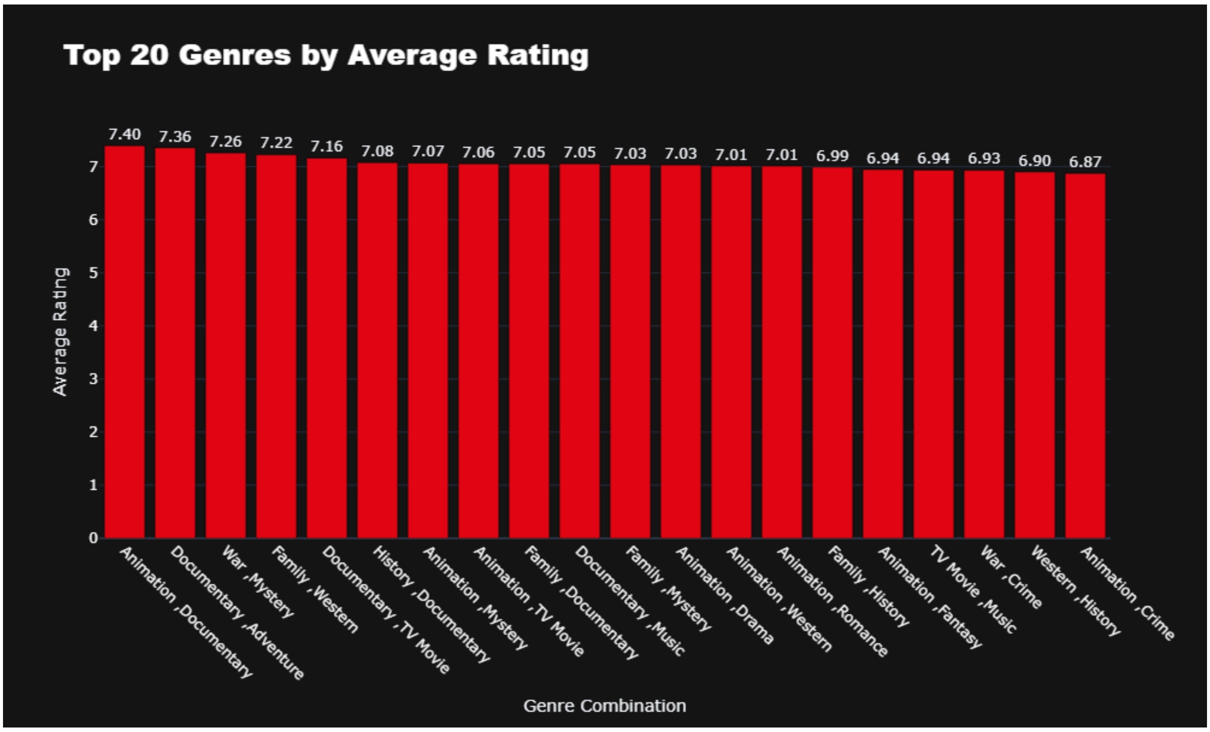


Fig 4.5 - Top 20 pairwise combinations of genres for Movies (using average rating)

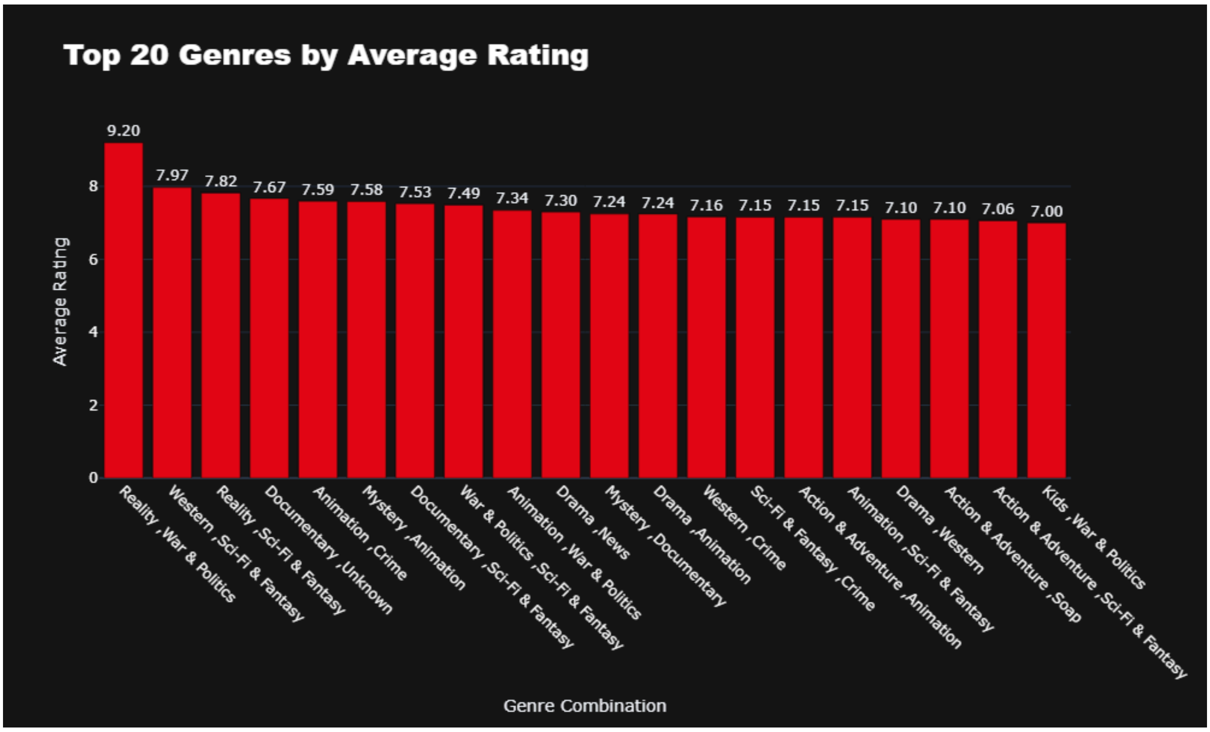


Fig 4.6 - Top 20 pairwise combinations of genres for TV shows (using average rating)

4.3 Influence of genre in the popularity of movies and TV shows

From fig 4.7 adventure followed by fantasy and action are the most popular movie genres out of the 19 genres listed in the dataset from 2010 to 2025. TV Movie is the least popular movie genre. Similarly from fig 4.8 soap followed by news and talk the most popular TV shows. Documentary is the least popular TV show genre.

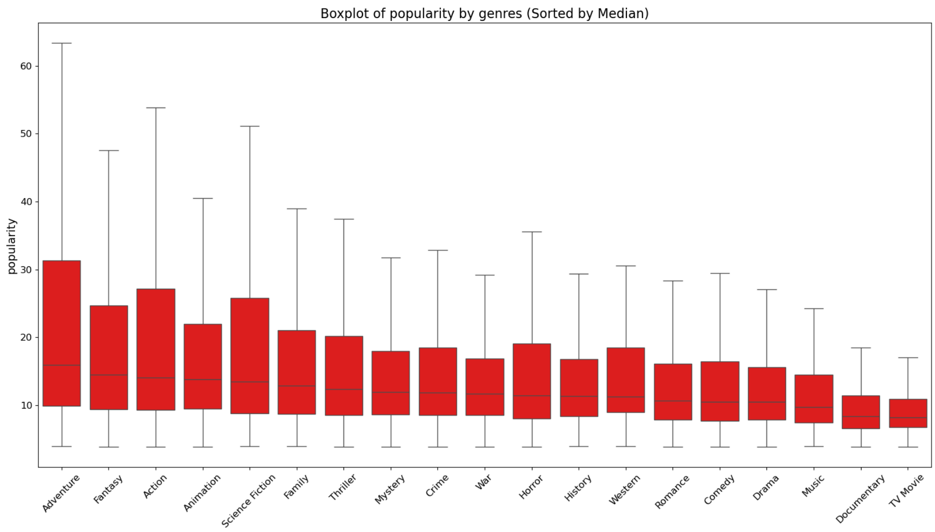


Fig 4.7 - Boxplot of popularity scores of movies across different genres

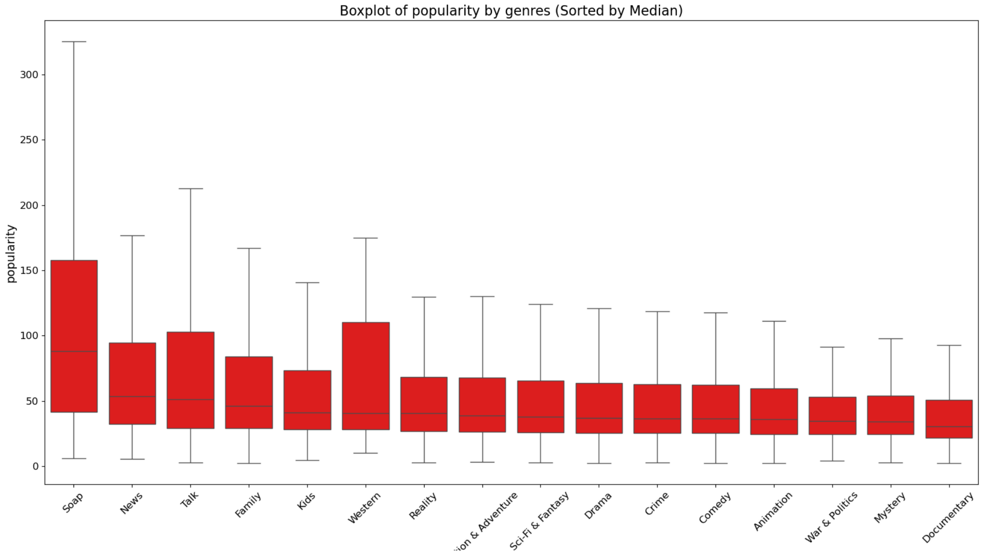


Fig 4.8 - Boxplot of popularity scores of TV shows across different genres

From fig 4.9 and fig 4.10 we can see that the surge in popularity scores of movies is much larger than TV shows. On average adventure is the most popular genre among movies from 2010 to 2025. For TV shows, soap is the most popular genre in recent times (2023 to 2025). In the case of movies, adventure has been on top of the popularity charts almost all the time from 2010 to 2025. We can see that we have a completely different scene in the case of TV shows where the most popular genre has been changing frequently from 2010 to 2025, with the earlier stages of this period having news and talk as the most popular genre, while in the mid stages it was soap and western that was the most popular. In recent years soap has been the most popular genre by a very large margin among TV shows.

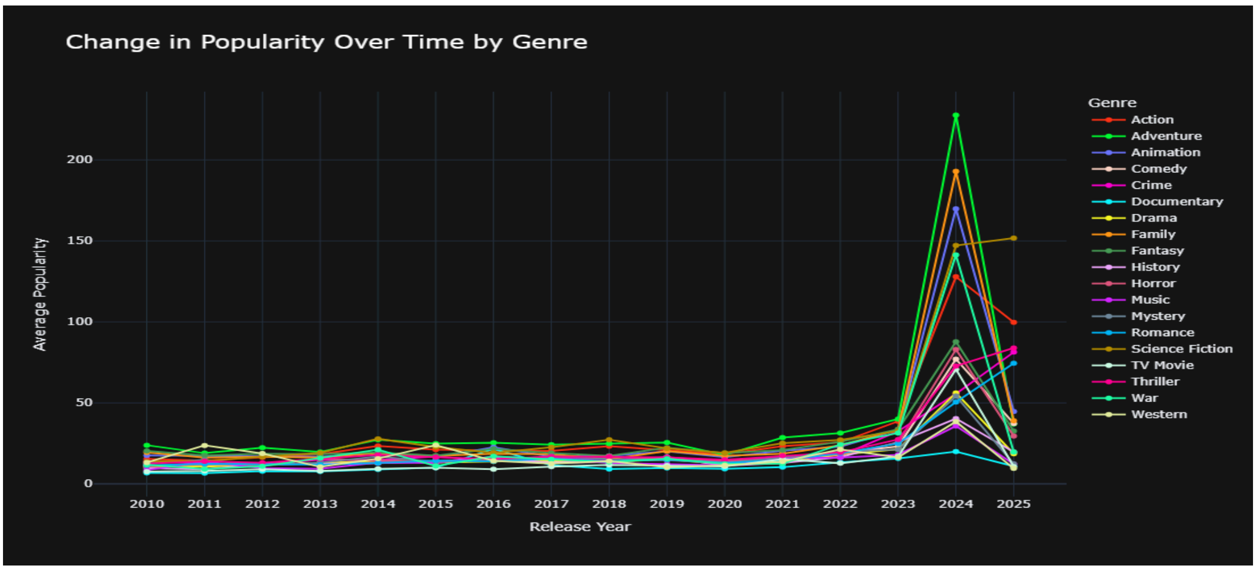


Fig 4.9 - Change in popularity over time by genre for Movies

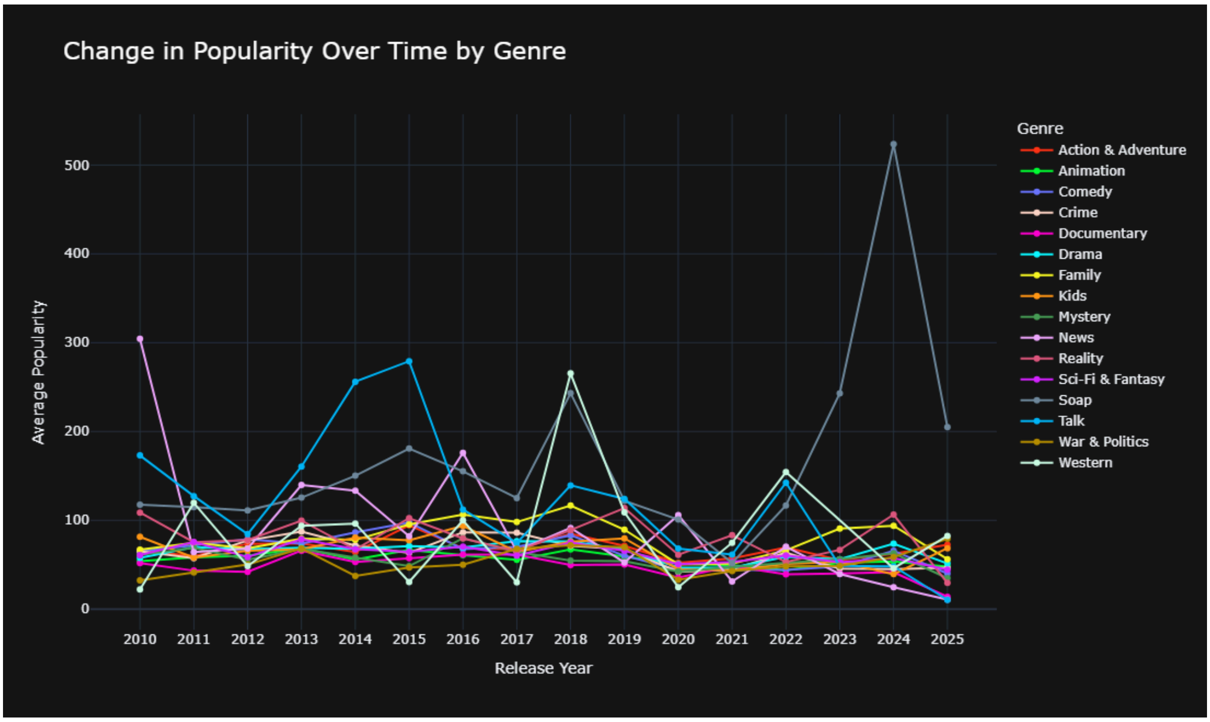


Fig 4.10 - Change in popularity over time by genre for TV Shows

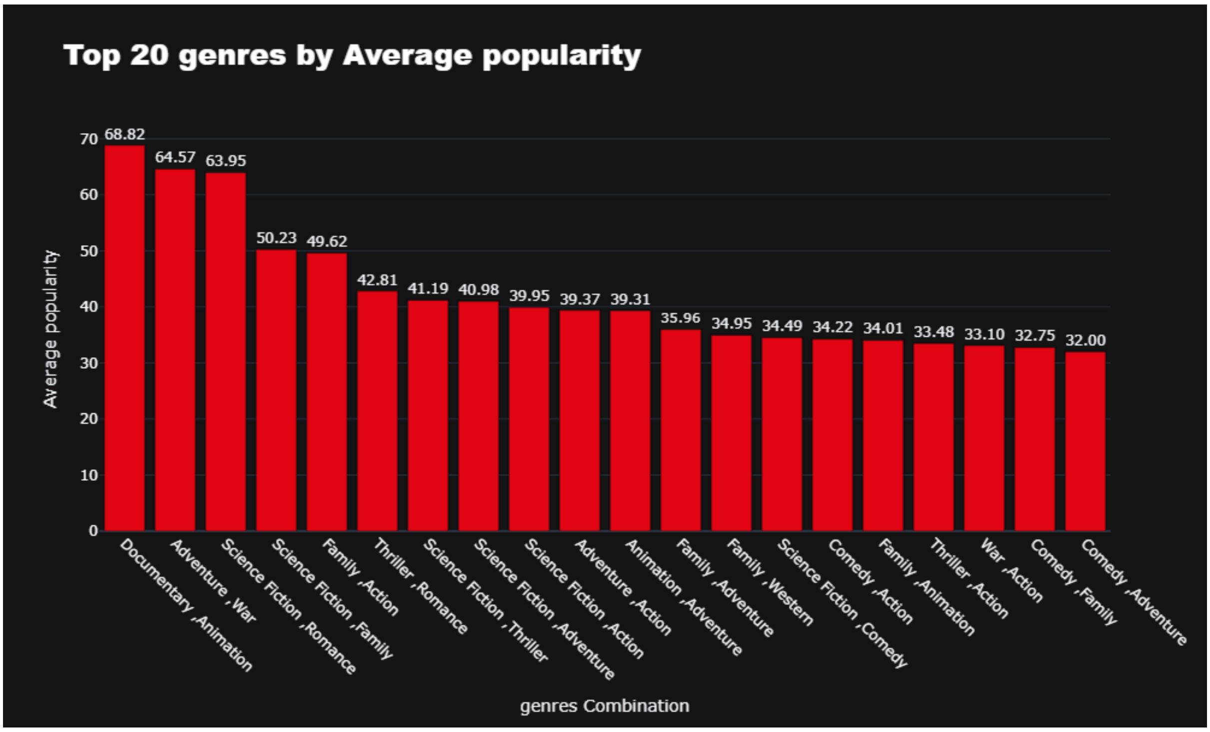


Fig 4.11 - Top 20 combinations (pairs) of Movie genres on the basis of average popularity

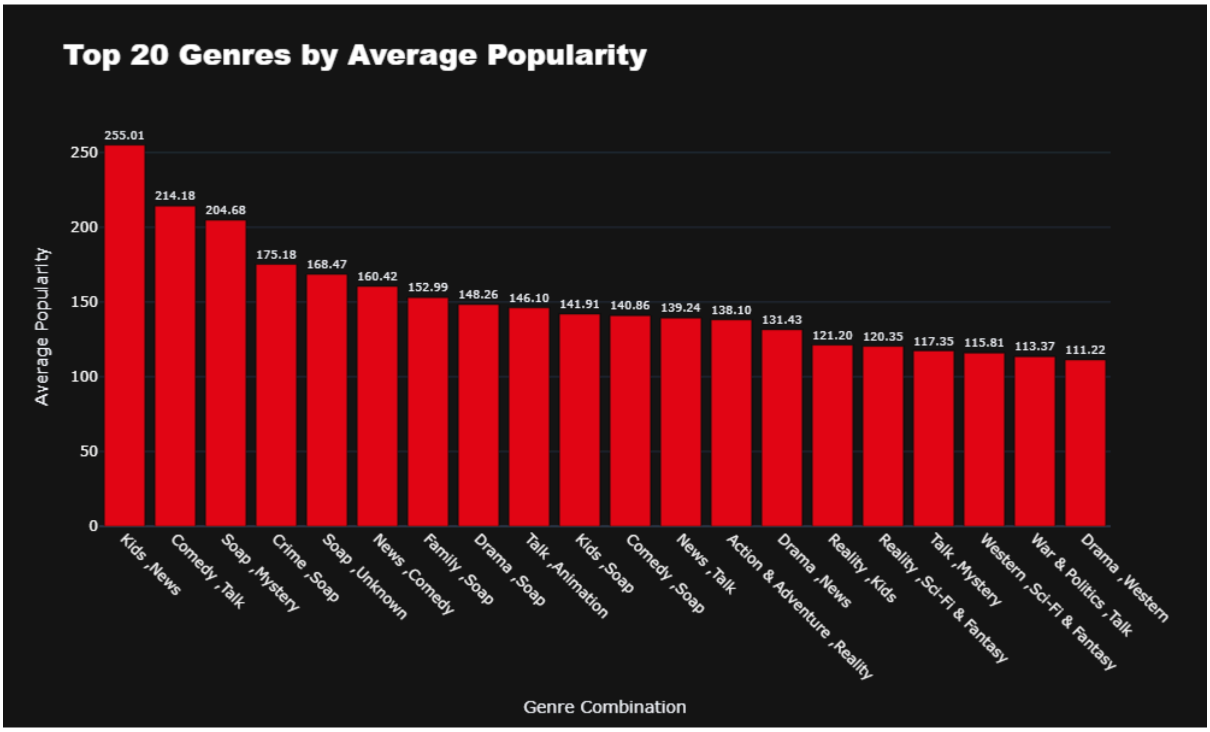


Fig 4.12 - Top 20 combinations (pairs) of TV show genres on the basis of average popularity

4.4 Relationship between profitmaking and genres

Here, a movie is said to be a lossmaking one if the revenue generated by the movie is less than the budget of the movie. From fig 4.13 we can see that the drama genre has the most number of loss making movies while the western genre has the least. However we cannot say that the genres with higher lossmaking movies are more likely to make a loss than the others because they might have a higher number of movies produced than the other genre. For example, Drama has the most movies produced every year starting from 2010 to 2025 while western has the least. Therefore we plotted fig 4.14 which tells us what percentage of the total number of movies produced of a particular genre is lossmaking. From that we can see that western has the highest percentage of movies that made a loss and the genre documentary has the least percentage of lossmaking movies.

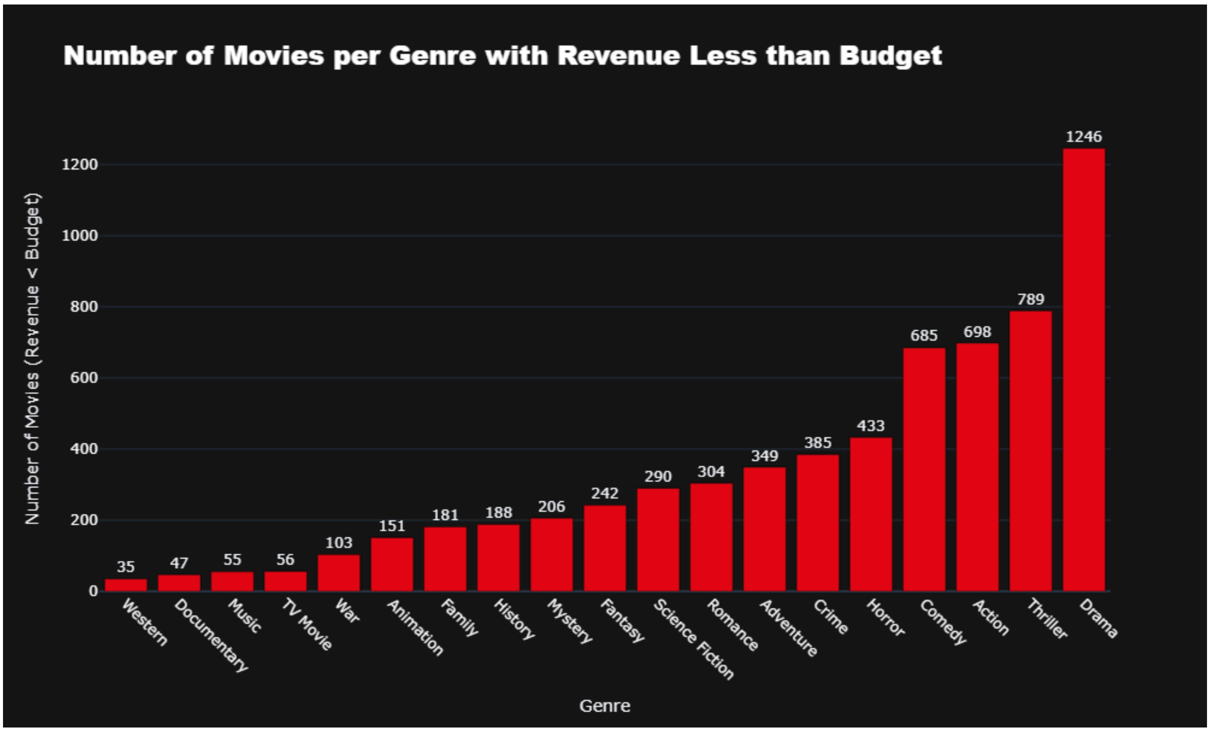


Fig 4.13 - Number of lossmaking movies for every genre

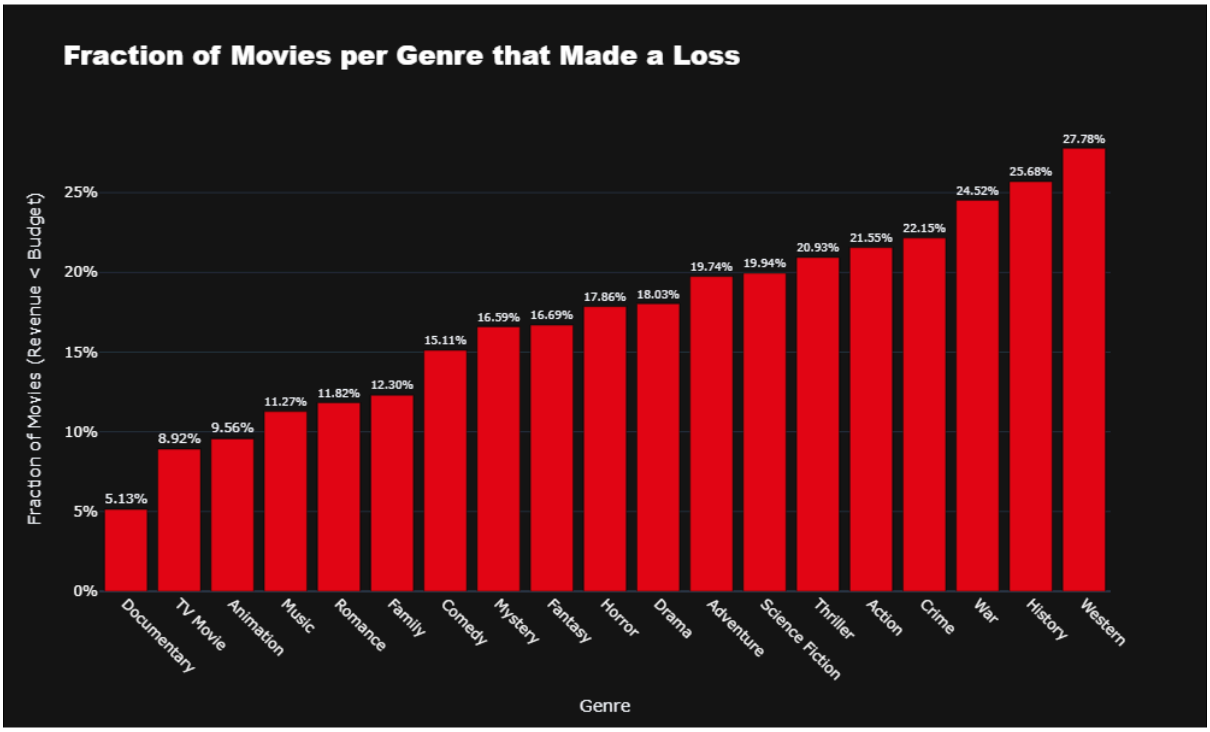


Fig 4.14 - lossmaking percentage of movies of every genre

We cannot judge from only these plots that the genre affects the profit/loss making ability of a movie. Therefore we performed the chi-squared contingency test to test for the same. The procedure for the test is described below:
The null and the alternate hypothesis are defined as:
H_0 : genre and profitability are independent
H_1 : genre and profitability are not independent
If they are independent then the following would hold:

$$P(genre = i, profitability = j) = P(genre = i) \times P(profitability = j)$$

The expected count in each cell is given by:

$$E_i = P(genre = i) \times P(profitability = 1) \times grand\ total$$

$$P(genre = i) = \frac{number\ of\ movies\ of\ genre\ i}{total\ number\ of\ movies}$$

$$P(profitability = 1) = \frac{number\ of\ profitable\ movies\ across\ all\ genres}{total\ number\ of\ movies}$$

$$grand\ total = total\ number\ of\ movies$$

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$

Where O_i is the observed count in each cell

$$\chi^2_{critical} \sim \chi^2_{1-\alpha,\ (r-1)\times(c-1)}$$

If the observed chi-squared value is greater than the critical value of chi-squared then we reject the null hypothesis, that is, we can say with 95% confidence that genres influence the profit making ability of a movie. In our analysis we found that genres do in fact influence the profit making ability of the movies. The details of the test performed is present in the python notebook.

5)Creator & Talent Analysis

5.1 Most Prolific Directors and Actors on Netflix

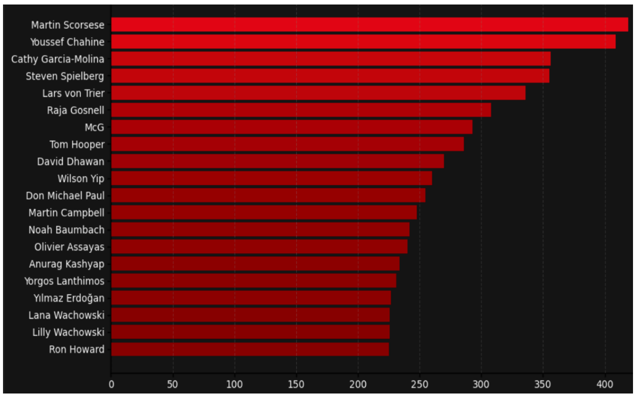


Fig 5.1-Top 20 most prolific directors

The chart shows that Martin Scorsese, Youssef Chahine, and Cathy Garcia - Molina lead as Netflix's most prolific directors. With creators like Anurag Kashyap from India and Yorgos Lanthimos from Egypt also featured, it highlights Netflix's global diversity, though production remains concentrated among a few top names.

Liam Neeson, Alfred Molina, and John Krasinski emerge as Netflix's most frequent actors, followed by Salma Hayek, Anupam Kher, and Shah Rukh Khan. The mix of Western and Asian stars reflects Netflix's diverse global talent pool, though appearances remain concentrated among a select group of prominent performers.

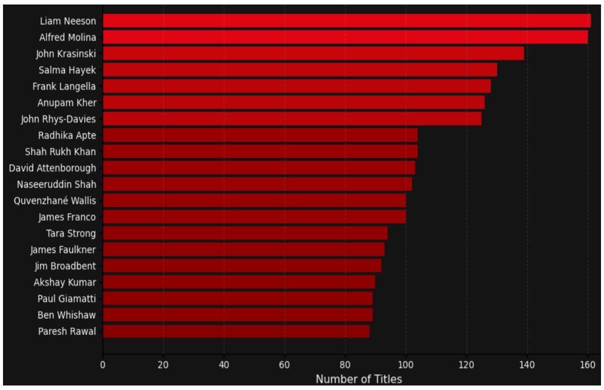


Fig 5.2-Top 20 most frequent actors

5.2 Director - Genre Heatmap

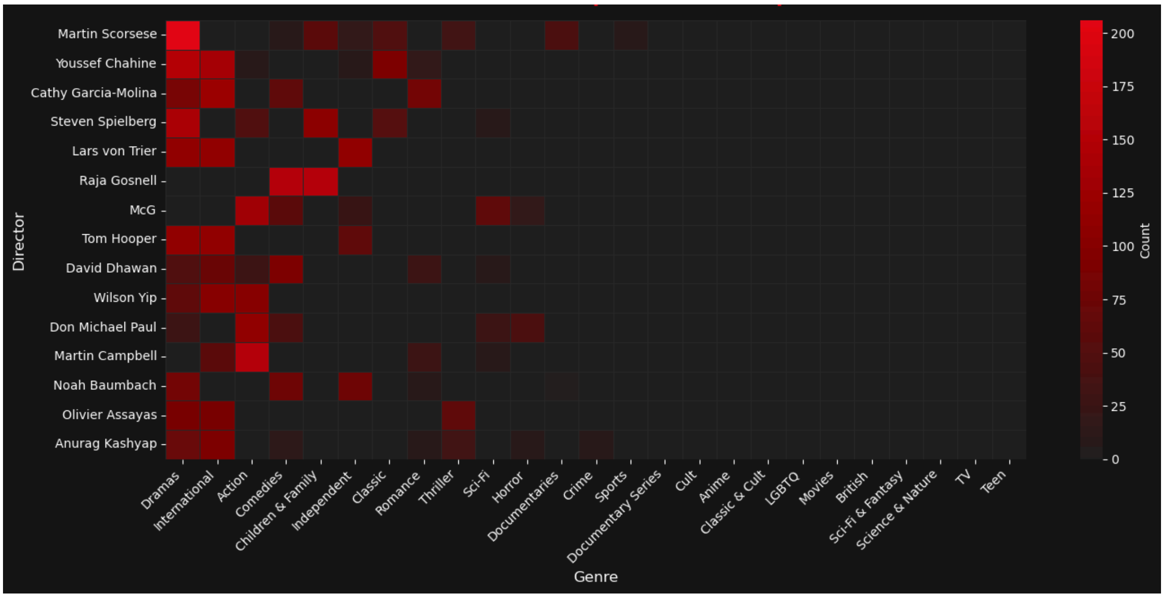


Fig 5.3-Director-Genre Specialisation Map

The heatmap highlights strong genre specialisation among directors. Martin Scorsese, Steven Spielberg, and Tom Hooper demonstrate a clear focus on dramas and classics, whereas directors like Wilson Yip and Martin Campbell tend toward action-oriented films. Regional diversity is also evident, as filmmakers such as Anurag Kashyap and David Dhawan dominate the international and comedy genres, respectively. The sparse distribution across genres suggests that most directors maintain a consistent creative niche, reinforcing distinct storytelling identities within Netflix's global catalogue.

5.3 Director - Actor Collaboration Network

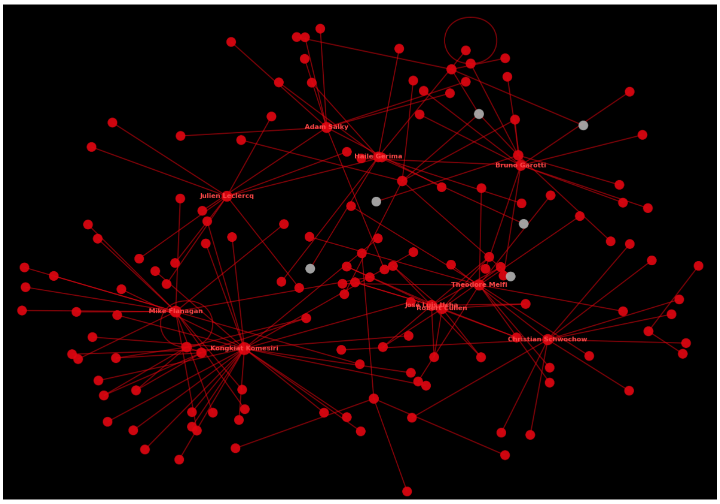


Fig 5.4-Director-Actor Collaboration Network

The collaboration network reveals distinct clusters where certain directors, such as Mike Flanagan, Julien Leclercq, and Theodore Melfi, frequently work with recurring sets of actors, forming tightly knit creative ecosystems. These consistent partnerships suggest a high level of artistic trust and stylistic continuity, enabling directors to maintain a recognisable tone across projects. Meanwhile, the cross-links between clusters indicate instances of actors collaborating with multiple directors across different genres and regions, fostering creative exchange and innovation. Overall, the network underscores Netflix's role as a global creative hub that not only supports established collaborations but also facilitates new artistic intersections across diverse cinematic cultures.

5.4 Yearly Trends

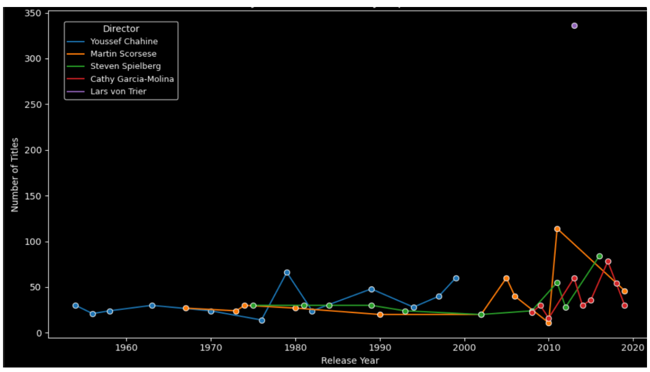


Fig 5.5-Yearly Count of Works by Top 5 directors

Among the top directors, Youssef Chahine maintained steady output over decades, while Scorsese and Spielberg show sharp rises post-2000, reflecting modern dominance. Cathy Garcia - Molina's surge after 2010 marks regional growth on Netflix, and Lars von Trier's brief spike indicates concentrated productivity. Overall, it highlights generational and regional diversity in Netflix's director lineup.

The timeline reveals a sharp surge in 2014 for Netflix's collaborations with top actors such as Alfred Molina, Liam Neeson, Salma Hayek, Frank Langella, and John Krasinski. This spike aligns with Netflix's large-scale expansion of its licensed film catalogue during that period, when several major Hollywood titles-particularly action and drama films-were added as part of Netflix's global content push. Many of these actors appeared in high-profile titles acquired en masse for streaming that year, rather than new original productions. The trend highlights how Netflix's strategic content licensing in 2014 temporarily inflated the visibility of certain actors before shifting focus toward original productions in subsequent years.

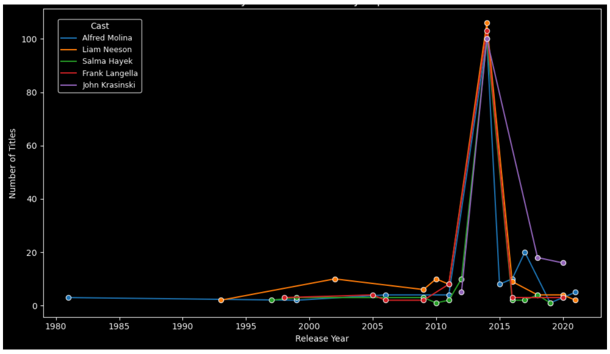
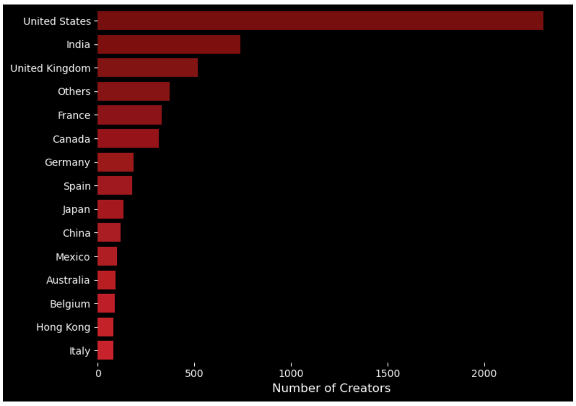


Fig 5.6-Yearly Count of Works by Top 5 casts

5.5 Talent Diversity Across Countries



The analysis highlights the overwhelming dominance of the United States in Netflix's creator network, far exceeding other countries in terms of contributor count. India and the United Kingdom follow as emerging powerhouses, reflecting their growing influence in global entertainment and their increasing collaborations with Netflix.

Fig 5.7 - Top Countries by Creator Content

A further breakdown of India's creative base reveals a heavy reliance on international talent for both directors and casts, with international contributors significantly outnumbering domestic ones. Collectively, these insights reveal Netflix's dual strategy - a strong U.S. foundation paired with selective international integration - as it seeks to balance global expansion with consistent content quality.

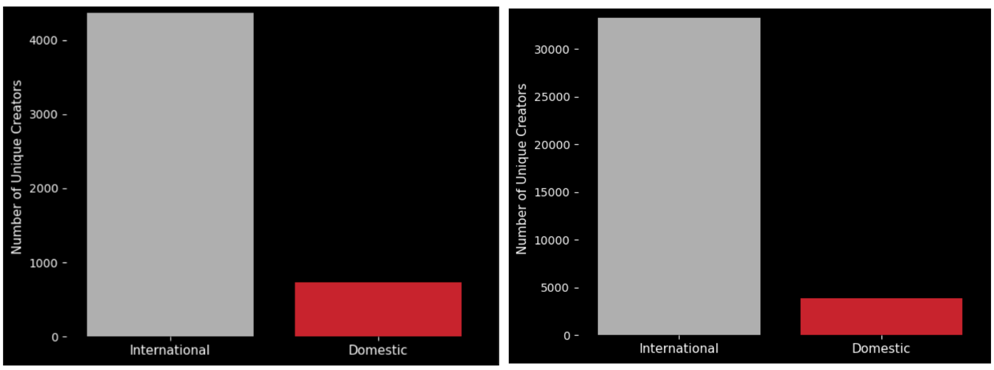


Fig 5.8 (a) International vs Domestic Directors (b) International vs Domestic Casts

5.6 Chi-Square Test (Director vs Rating)

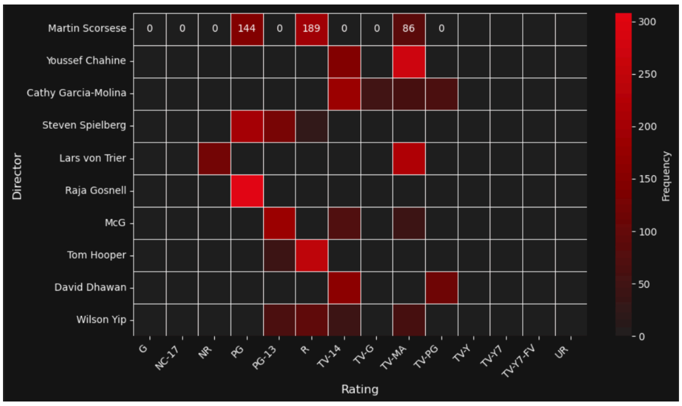


Fig 5.9-Director vs Rating Distribution

With a chi-square statistic of 1,625,896.81 and 64,896 degrees of freedom, we reject the null hypothesis. This confirms a strong connection between directors and rating categories. The heatmap shows that directors such as Martin Scorsese and Steven Spielberg mostly create PG-13 and R-rated content, which indicates a preference for mature themes.

5.7 Entropy (Director -Genre Specialisation)

The entropy-based diversity analysis reveals that Ron Howard (entropy = 2.62), Jeremy Saulnier, and Guillermo del Toro are among Netflix's most versatile directors, engaging across multiple genres rather than focusing on a specific niche. This pattern indicates a strong creative adaptability and cross-genre appeal. Directors like Vikram Bhatt and Priyadarshan also rank high, reflecting a balance between mainstream and regional storytelling diversity within Netflix's catalogue.

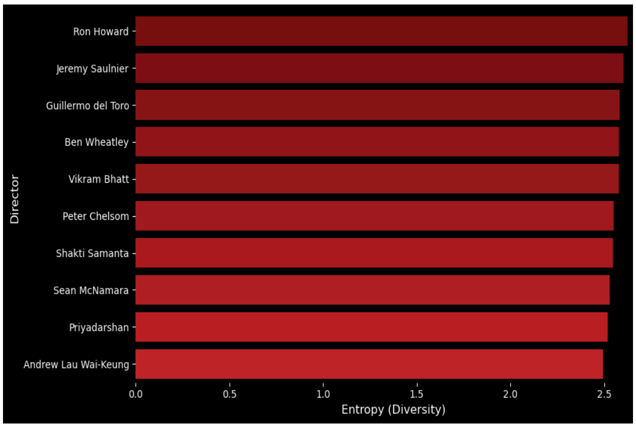


Fig. 5.10-Top 10 most diverse directors

5.8 ANOVA(Duration by Director)

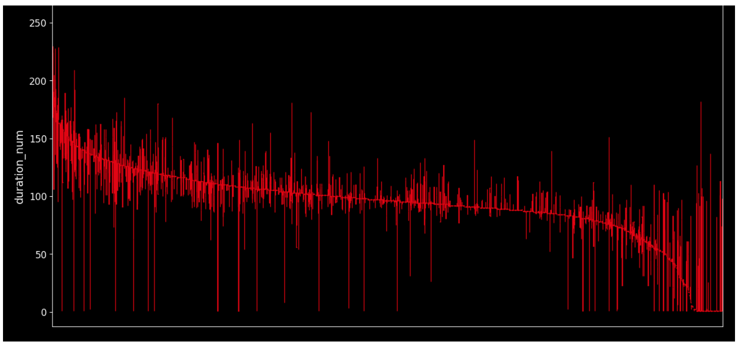


Fig5.11-Boxplot of Duration

The ANOVA test ($F = 772.51$, $p < 0.001$) clearly indicates a statistically significant difference in average movie duration across directors, meaning not all directors produce films of similar lengths. This finding aligns with the boxplot visualisation, where the red distributions show wide variation and differing medians across directors. While some directors consistently make shorter films, others exhibit much higher variability in duration, suggesting that directorial style and genre preferences play a major role in determining runtime diversity

6)RATING AND AUDIENCE TARGET

6.1 Distribution across rating categories

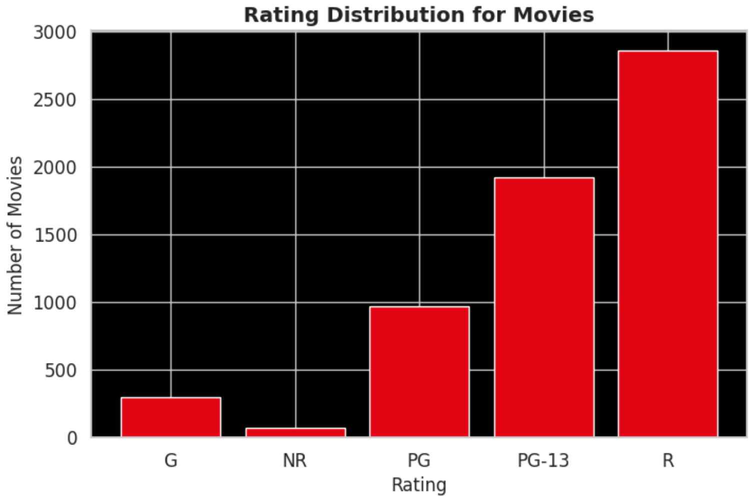


Fig:-6.1

Movies on Netflix show a noticeable concentration in the **PG-13** and **R** rating categories. This indicates that Netflix's movie catalog is **primarily designed for teens, young adults, and mature adult audiences**, rather than very young viewers.

G-13 movies often feature themes that appeal to teenagers and young adults. while **R-rated** films include more intense themes, violence, strong language, or mature emotional narratives that resonate with adult viewers. This suggests that the platform does not heavily prioritize children's cinema or universally family-safe movies.

In summary, both Movies and TV Shows on Netflix are heavily skewed toward teens and adults, with limited representation of purely family-friendly content. Also, it is clearly evident that Netflix focuses more on its mature or Adult audience.

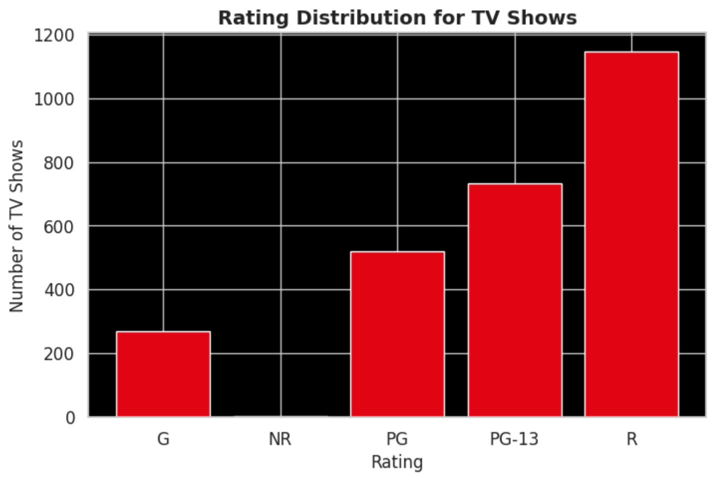


Fig:-6.2

6.2 Rating evolution over time

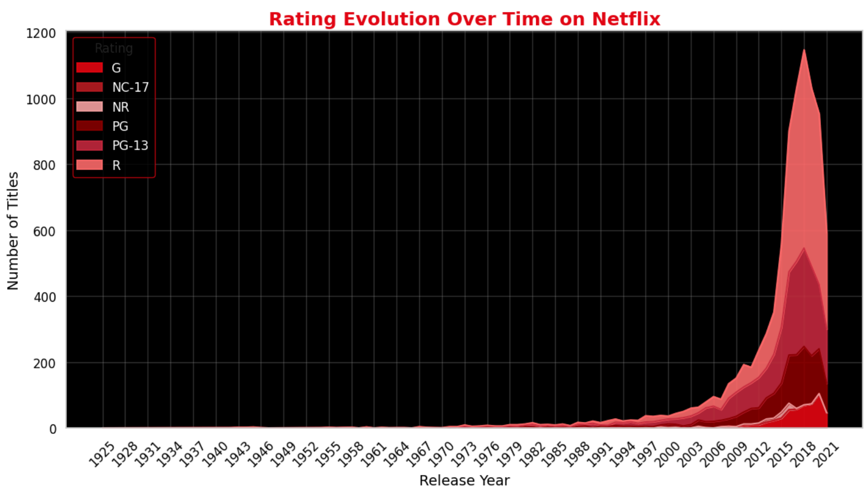


Fig:-6.3

The chart from our data analysis illustrates how the number of Netflix titles across different rating categories has evolved over time, particularly from the early 1900s to 2021.
Before the mid-2000s, the presence of titles across all ratings is relatively low. This reflects both the limited amount of historical media available on Netflix.
A significant increase in the number of titles begins around 2010. This period marks Netflix's transition into a streaming service, characterized by a notable increase in R-rated movies and TV shows. While PG-13 and PG titles do increase, their growth is more gradual.

6.3 Correlation between rating and genre

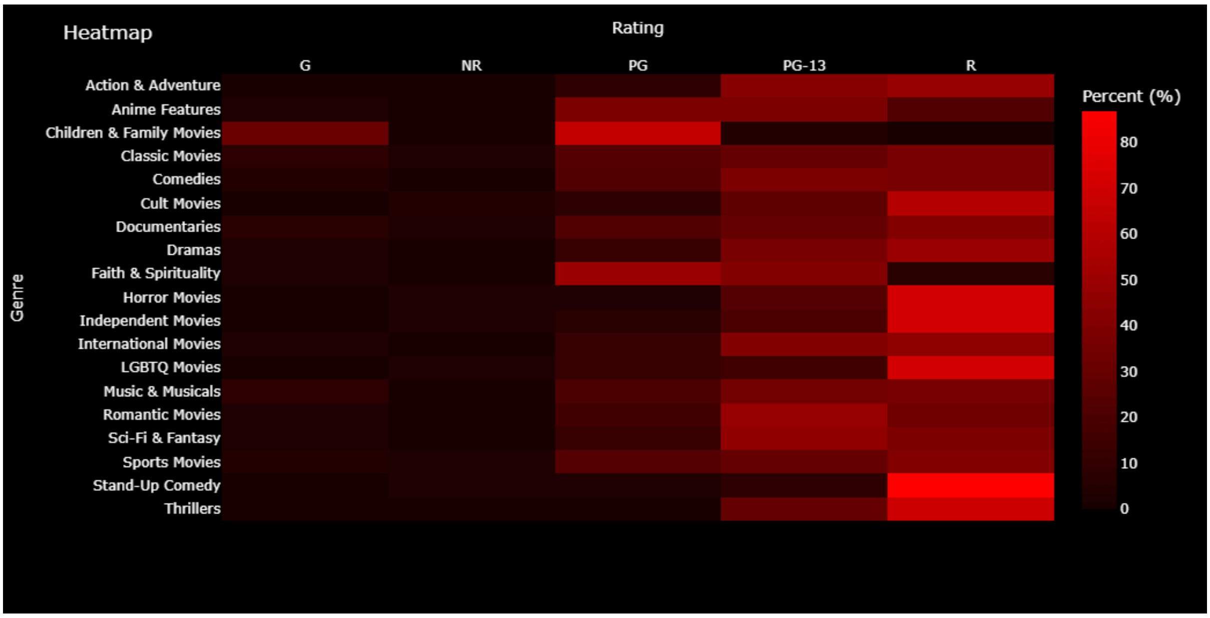


Fig:-6.4

The heatmap reveals the distribution of movie ratings across genres, highlighting how content maturity varies by category. Genres such as Children & Family Movies, Anime Features, and Faith & Spirituality are predominantly rated G or PG, indicating that these categories are mostly targeted toward younger audiences and suitable for general family viewing.

On the other hand, genres such as Sports Movies, Romantic Movies, Action & Adventure, and Sci-Fi & Fantasy exhibit a noticeable shift toward PG-13 ratings, suggesting that these types of movies are more commonly geared toward teenage and young adult audiences.

As expected, Horror Movies, Thrillers, Cult Movies, and independent films exhibit a strong concentration in the R rating, reflecting themes, visuals, and narratives that are generally intended for mature audiences. An interesting observation is that Stand-Up Comedy skews heavily toward R-rated content, likely due to the use of explicit language and adult humor.

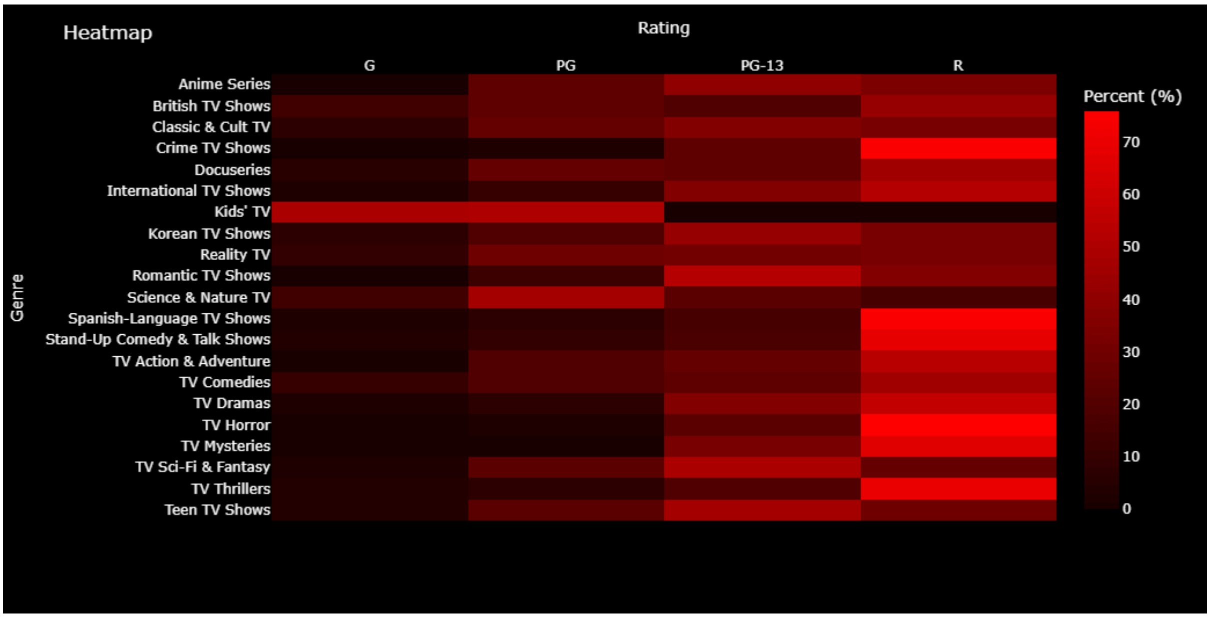


Fig:-6.5

The heatmap for TV shows illustrates how **audience maturity levels vary across television genres**, revealing clear content patterns. Genres such as **Kids' TV, Anime Series, and Science & Nature TV** are primarily associated with **G and PG** ratings, indicating that these categories cater largely to children, pre-teens, and general family audiences

In contrast, genres like **Teen Dramas, Reality TV, International TV Dramas, and Romantic TV** tend to cluster around **PG-13 ratings**, suggesting that these shows are often aimed at adolescents and young adults, balancing mature themes with broader accessibility.

Meanwhile, genres such as Spanish, **Thrillers, Crime series, Comedy Specials, and Horror TV** show a strong dominance of **R ratings**, reflecting content that includes intense violence, explicit language, psychological depth, or adult situations.

6.4 Family-friendly vs. mature content balance

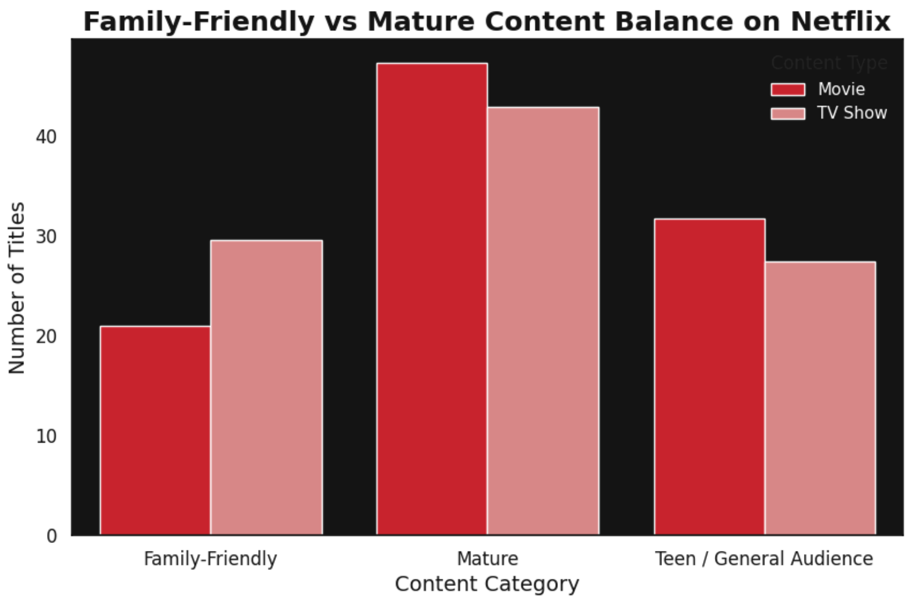


Fig:-6.6

Movies and TV Shows on Netflix exhibit a similar distribution of mature-rated content, with movies showing a slightly higher proportion of adult-oriented titles compared to TV shows. This suggests that Netflix's overall catalog strategy prioritizes content targeting adult and young adult audiences across both formats.

A similar pattern is observed in teen-focused (PG-13 / TV-14) categories, where both movies and TV shows maintain comparable representation. This suggests that Netflix consistently targets the teen and young adult demographic across various genres and media types.

In contrast, family-friendly content (G / PG / TV-Y) is significantly more prevalent in TV shows than in movies. This implies that while Netflix does not primarily position itself as a family entertainment platform, it relies more on episodic TV formats to cater to children and family viewing rather than investing heavily in family-oriented films.

6.5 Genres and Country Correlation

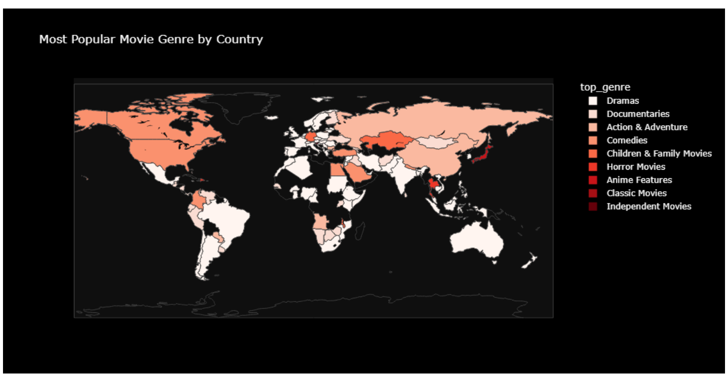


Fig:- 6.7

The choropleth map illustrates how movie genre preferences vary geographically across countries that produce movies for Netflix. A noticeable trend is the worldwide dominance of **Dramas**, which appear as the most popular genre in many regions across Europe, North America, South America, and parts of Asia. This suggests that emotionally driven storytelling and character-focused narratives resonate broadly across cultures.

In contrast, **Comedies** show stronger representation in countries such as the **United States, Canada, Brazil, and parts of Western Europe**, indicating a cultural leaning toward light-hearted entertainment in regions with large entertainment industries or strong comedic traditions. Meanwhile, **Action & Adventure** appeals more to parts of **Eastern Europe, South America, and Southeast Asia**, suggesting a higher engagement with fast-paced, high-energy storytelling in these regions.

Certain countries exhibit unique genre identities. For example, **Japan** stands out with **Anime Features** as its leading category, reflecting both local cultural heritage and global export influence. Regions such as **South Korea and Mexico** show stronger inclinations toward **Thrillers and Horror**, which align with their internationally recognized cinematic styles in suspense and intensity. **Independent Movies** appear across selective European and South American countries, highlighting regions where film industries support niche, auteur-driven storytelling.

Finally, **children's and family movies are dominant in fewer countries, but their presence suggests** targeted cultural emphasis on family-oriented entertainment in specific regions.

7)Duration & Format Analysis

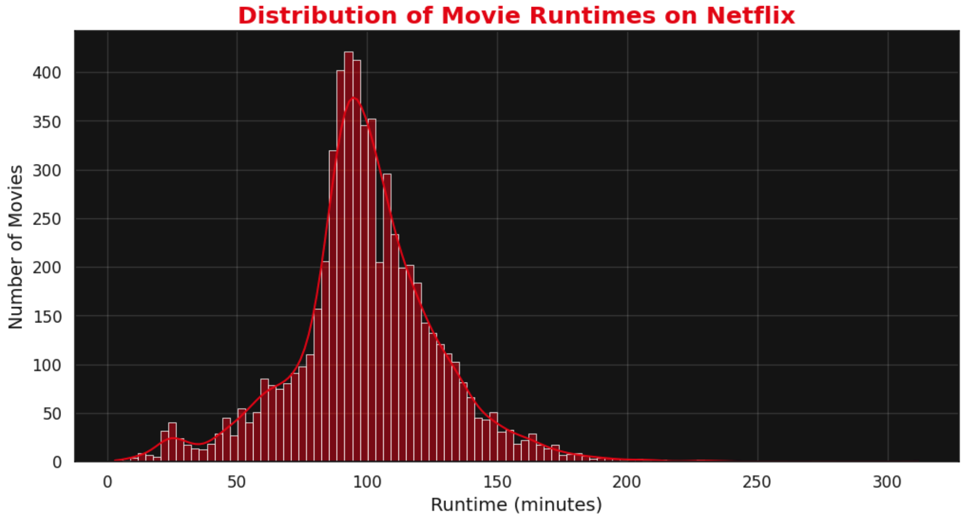


Fig:-7.1

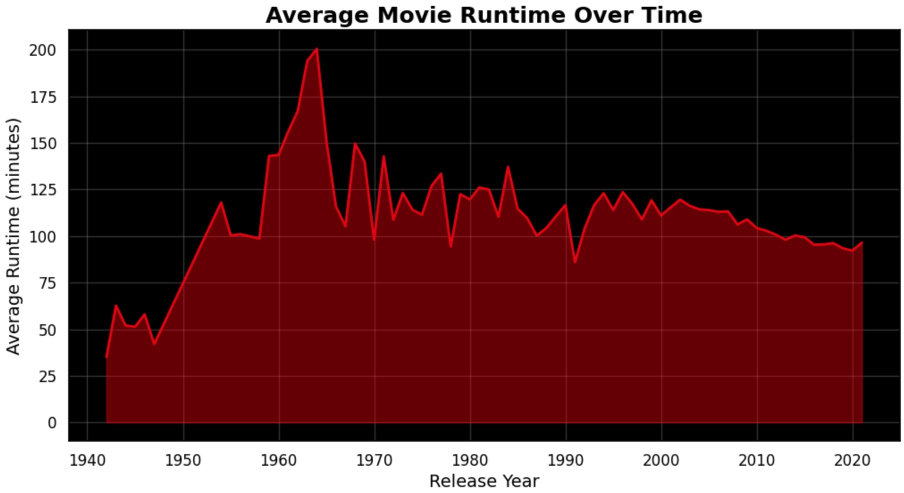


Fig:-7.2

The distribution of movie durations on Netflix is largely centered around the 90 to 110-minute range, which aligns with the traditional feature-length format commonly adopted in mainstream cinema. This duration range is long enough to develop a coherent narrative while remaining short enough to maintain audience engagement.

On the other hand, the structure of TV shows on Netflix reveals a different pattern. Most TV shows tend to have only one season, which can be attributed to several factors. These extended series indicate sustained viewer interest and strong narrative continuity, which encourage binge-watching and long-term audience retention. This contrast between the stability of movie duration and the variable season lengths of TV shows highlights how different content formats on Netflix adapt to evolving viewer preferences and engagement patterns.

Movies were short in length during the initial years of cinema, between the 1940s to 1950s. However, a steep increase is observed towards the later years until the 1960s reaching a peak of over 200 minutes.

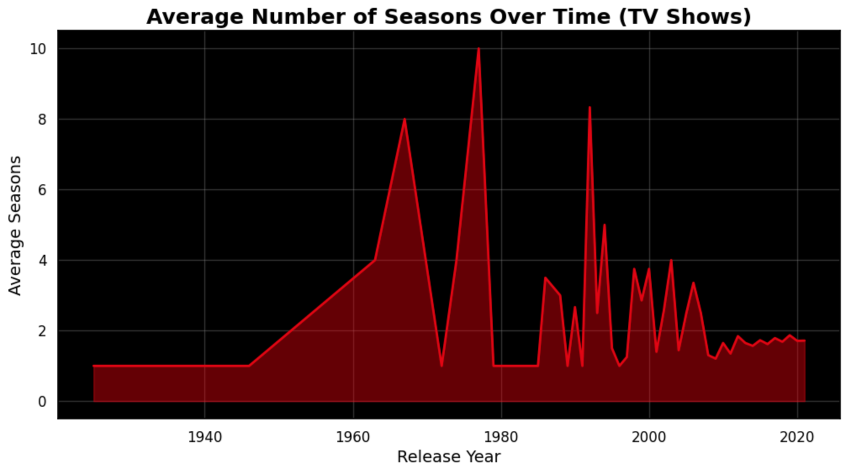


Fig:-7.3

The trend in the average number of TV show seasons over time suggests a noticeable shift in how television content has been produced and distributed. Earlier shows, particularly those released between the 1950s and 1980s, often had a higher average season count, with some going beyond 6–10 seasons. This reflects the traditional broadcasting model, where long-running series were favored to maintain loyal weekly audiences. However, from the late 1990s onward, there has been a clear decline in the average number of

seasons, stabilizing around 1 to 2 seasons for most releases. This change aligns strongly with the rise of streaming platforms like Netflix, where limited series formats, experimental story arcs, and concise narratives have gained popularity.

The average movie length is found to be highest for Classic and Action movies, while found to be least for Children and Family movies. While TV shows were found to have more seasons in Classic and Cult TV.

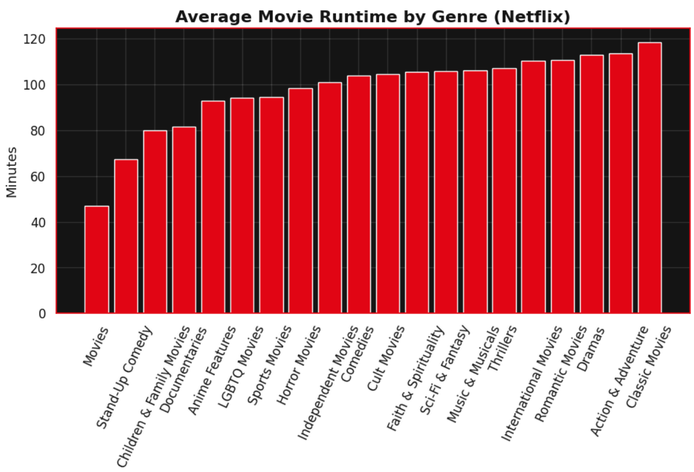


Fig:-7.4

8)Advance Analytics:-

1. Gap Analysis

1.1 Gap Analysis on Directors:-

If a director has been performing well in terms of average popularity scores or ratings but has very few movies on Netflix then more movies from that director must be added to the platform. The director is only considered if there are at least 5 movies of his in the platform already to avoid overestimation due to noise.

For movies, J. C. Chandor and Sean Baker have good average popularity scores but they both only have 5 movies directed by them available on Netflix. Similarly for TV shows, Yan Ji has a very high average popularity score (~203) but there are only 5 movies directed by him available on Netflix. More movies directed by these directors must be added to the Netflix platform since views received by a movie or a TV show is highly dependent on its popularity and the amount of revenue the movie or the TV show makes for Netflix is highly dependent on views. Therefore, the prospects for the revenue generated by a movie can be correlated with its popularity and hence Netflix has to focus on acquiring popular movies and TV shows.

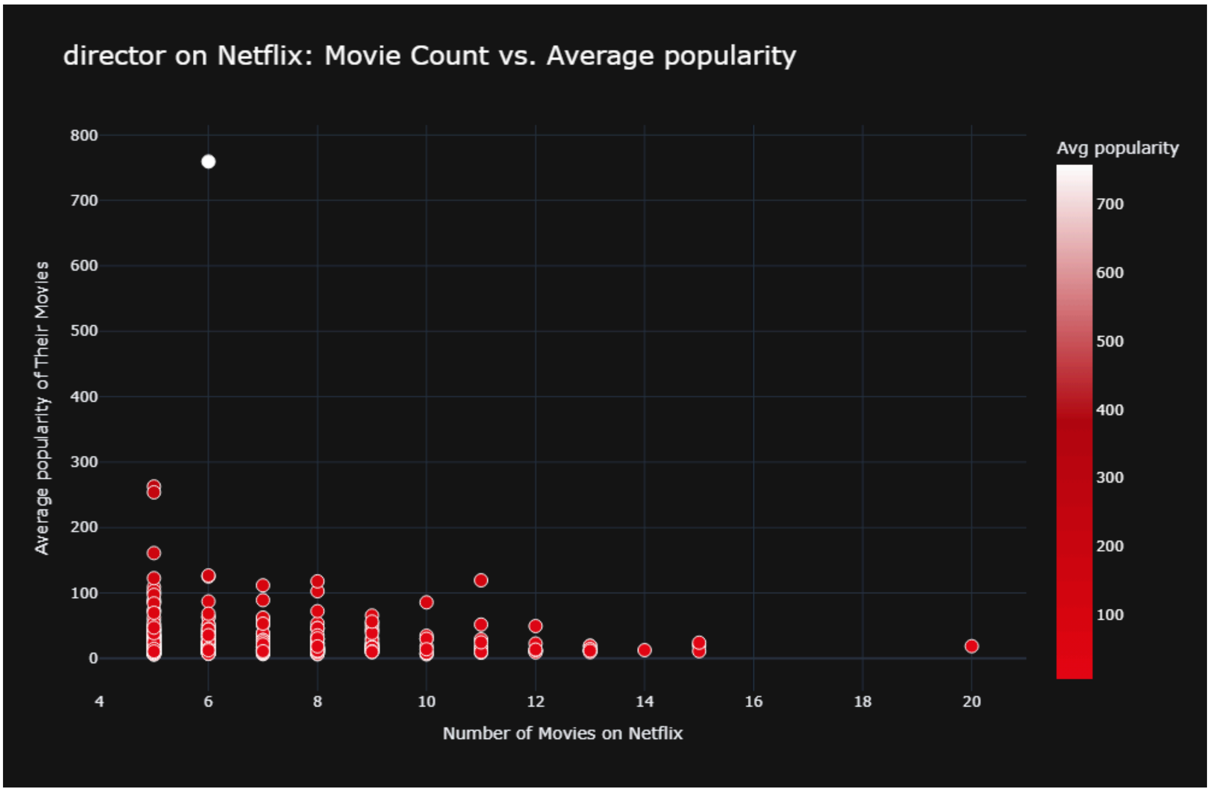


Fig:-8.1

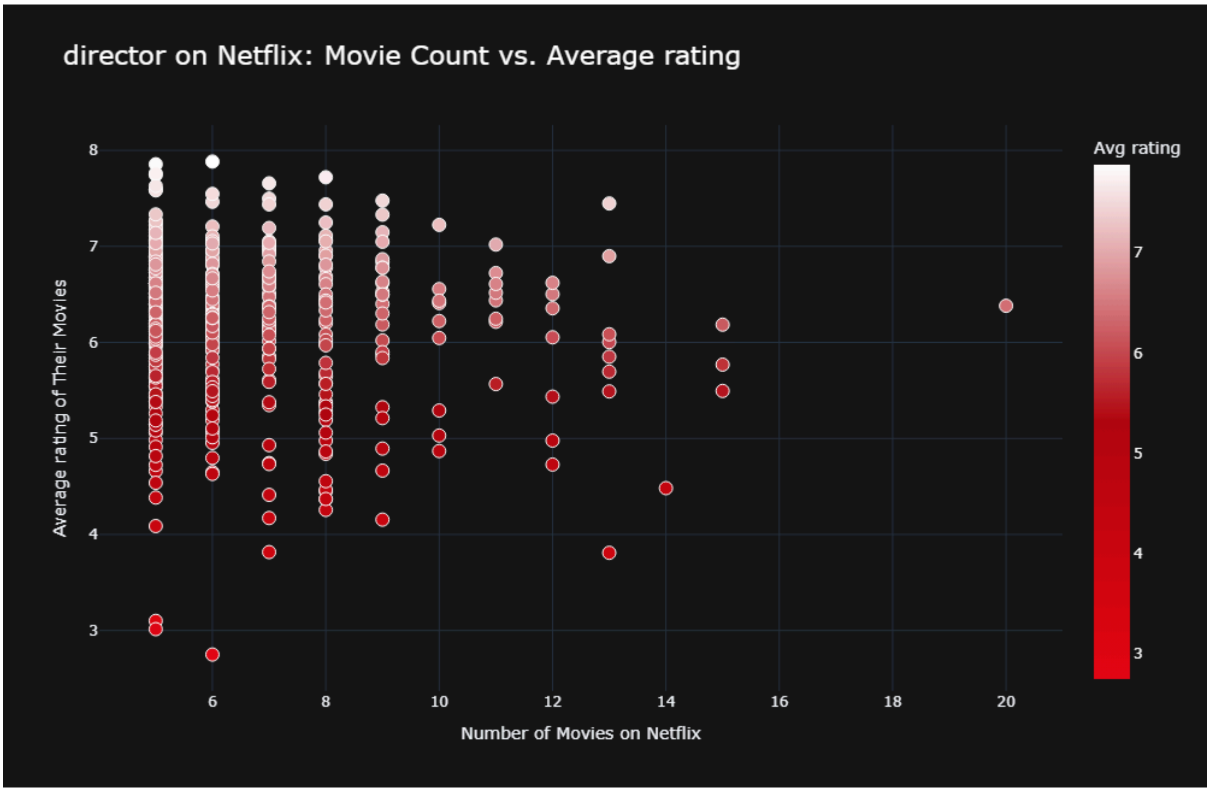

director on Netflix: Movie Count vs. Average rating
Average rating of Their Movies
Number of Movies on Netflix
Avg rating
8
7
6
5
4
3
6
8
10
12
14
16
18
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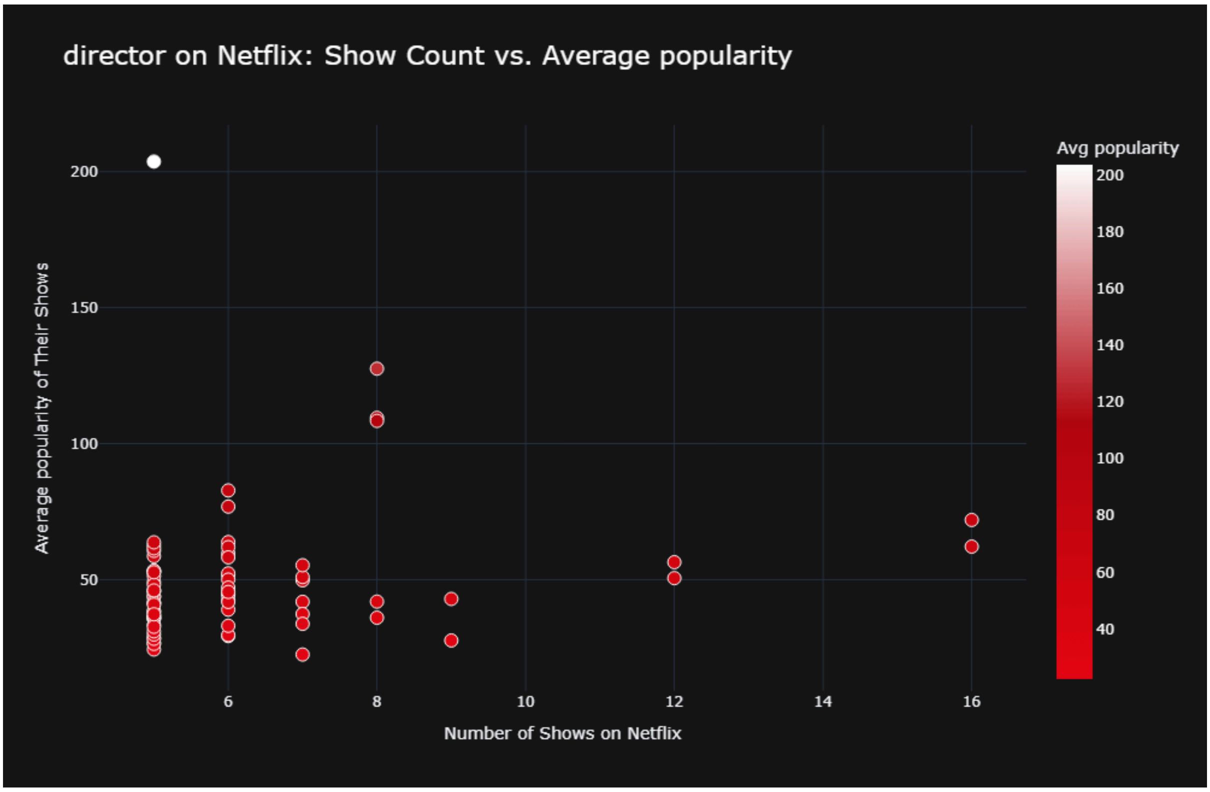
Fig:-8.2


director on Netflix: Show Count vs. Average popularity
Average popularity of Their Shows
Number of Shows on Netflix
Avg popularity
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150
100
50
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8
10
12
14
16
180
160
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80
60
40

Fig:-8.3

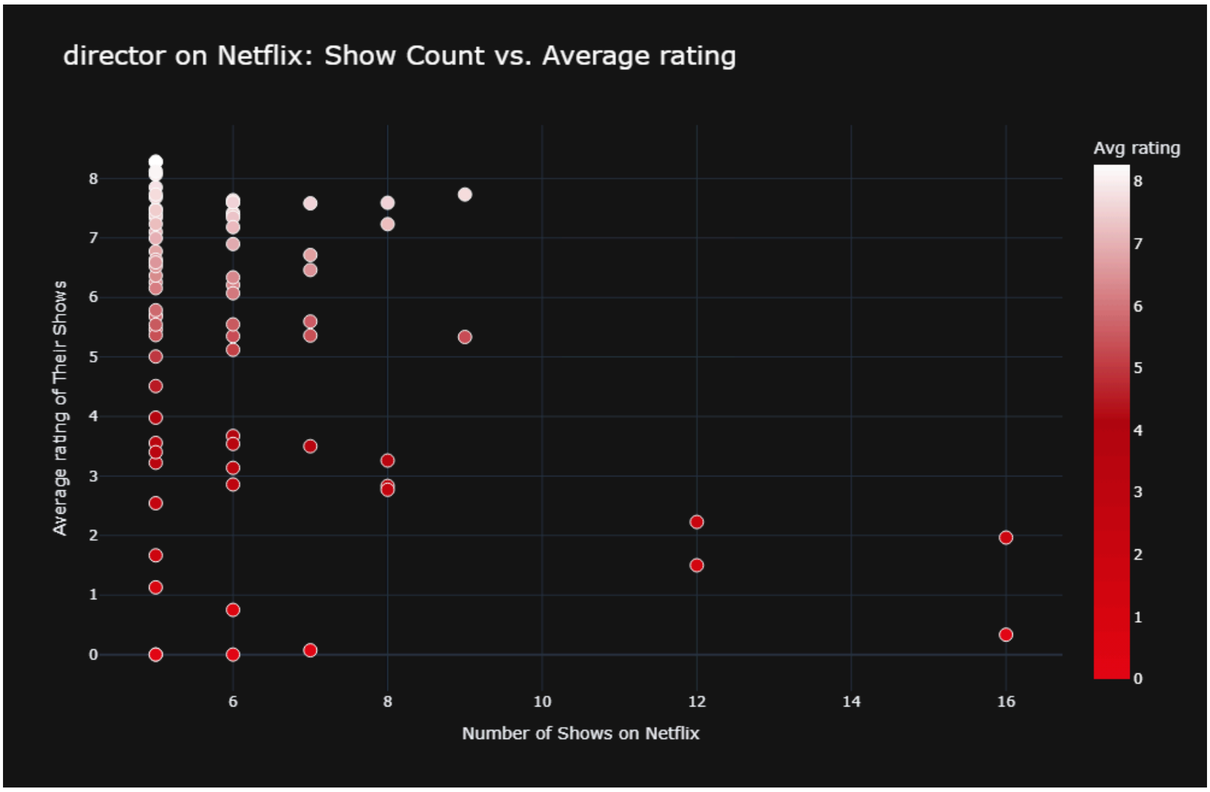


Fig:-8.4

1.2 Gap Analysis on cast members:-

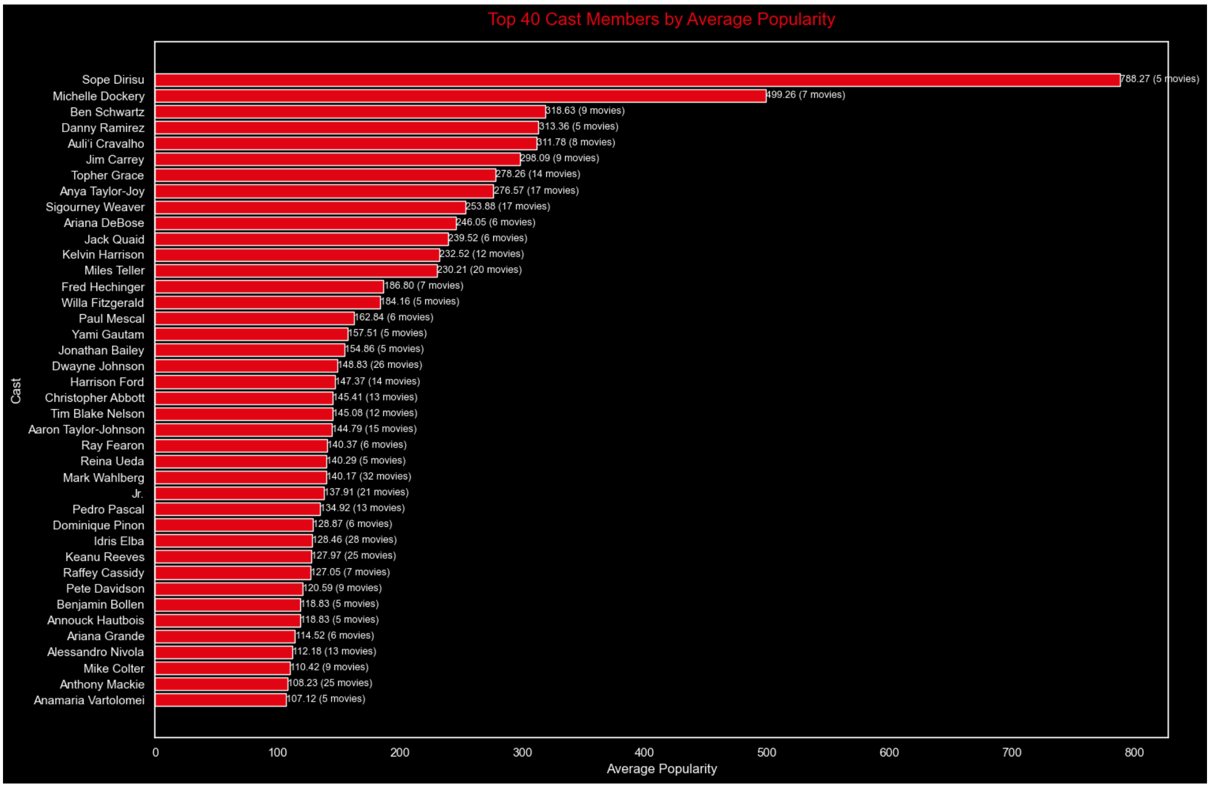


Fig:-8.5

1.3 Gap Analysis on Countries of Production:-

These are countries whose **titles score high on average popularity** (strong audience response) but have a **small number of available movies/TV shows** on Netflix. In other words, **the content that exists performs well, but there isn't much of it**. This indicates **latent demand constrained by supply breadth**.

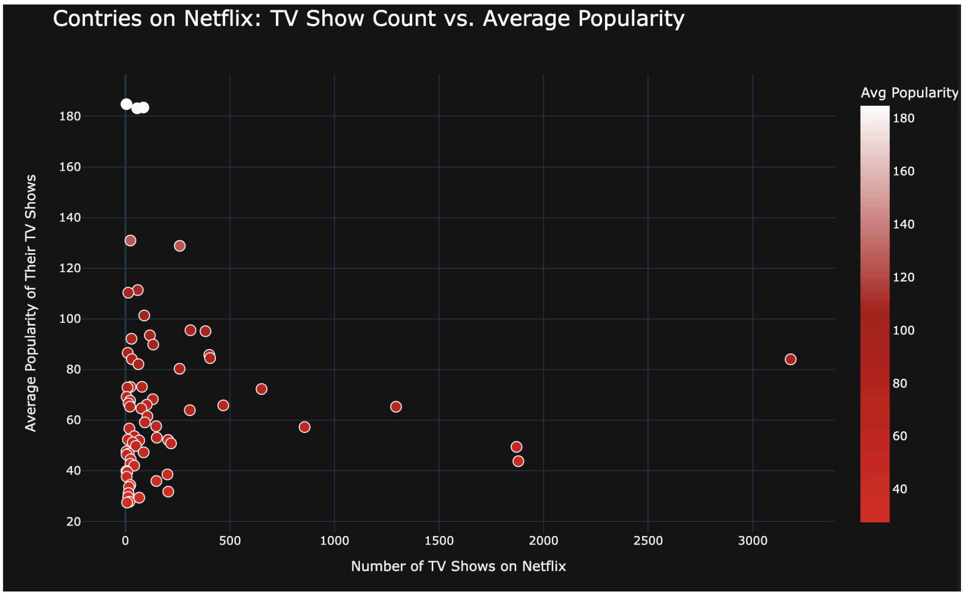


Fig:-8.6

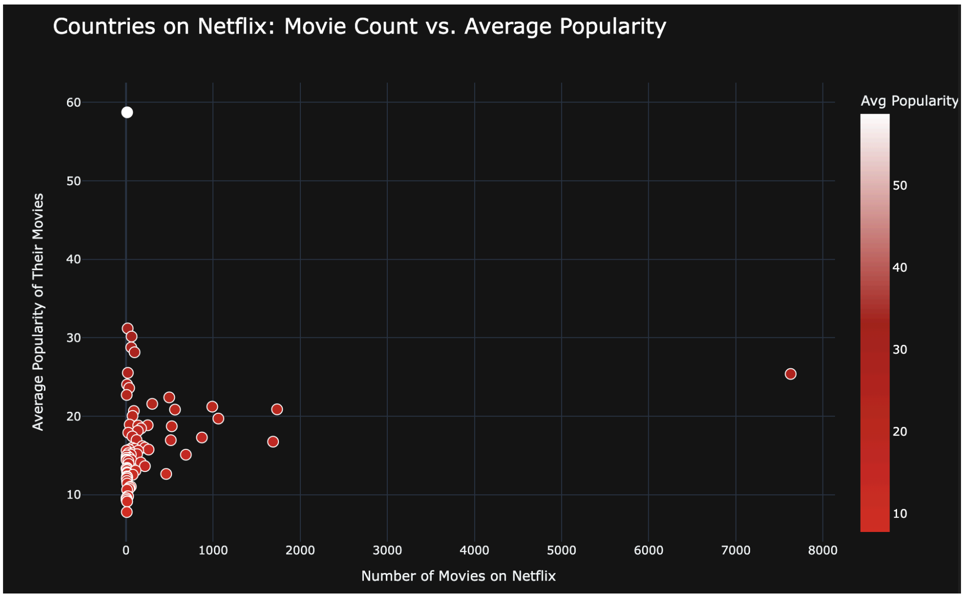
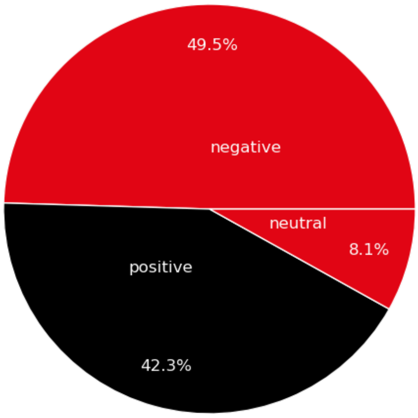


Fig:-8.7

2.Text Analytics:-

2.1 Movies:-



Sentiment Distribution of Netflix Movie Descriptions

The sentiment profile of Netflix movie descriptions is predominantly non-neutral: approximately 49.5% score negative, 42.3% positive, and only 8.1% neutral.

Fig:-8.8

Sentiment Analysis Across Genres (VADER):-

Applying VADER to title descriptions shows a clear genre-driven pattern. “War”, “Western”, “Action”, and “Thriller” titles have a higher share of negative-leaning descriptions, mainly because their synopses contain conflict words such as fight, war, killer, mission, revenge, crime. In contrast, “Romance”, “Music”, and to some extent “Documentary” show a larger positive segment, as their blurbs tend to use supportive/emotional language like love, journey, celebrates, follows, family. Neutral descriptions are relatively few across all genres, indicating that even short Netflix-style synopses usually contain at least one sentiment-bearing word that pushes the score up or down. Overall, the sentiment we observe is a property of how the genre is written about, not how the genre is received by viewers. Hence, negative sentiment here should be read as “conflict-/threat-heavy description”, not “users dislike this genre.”

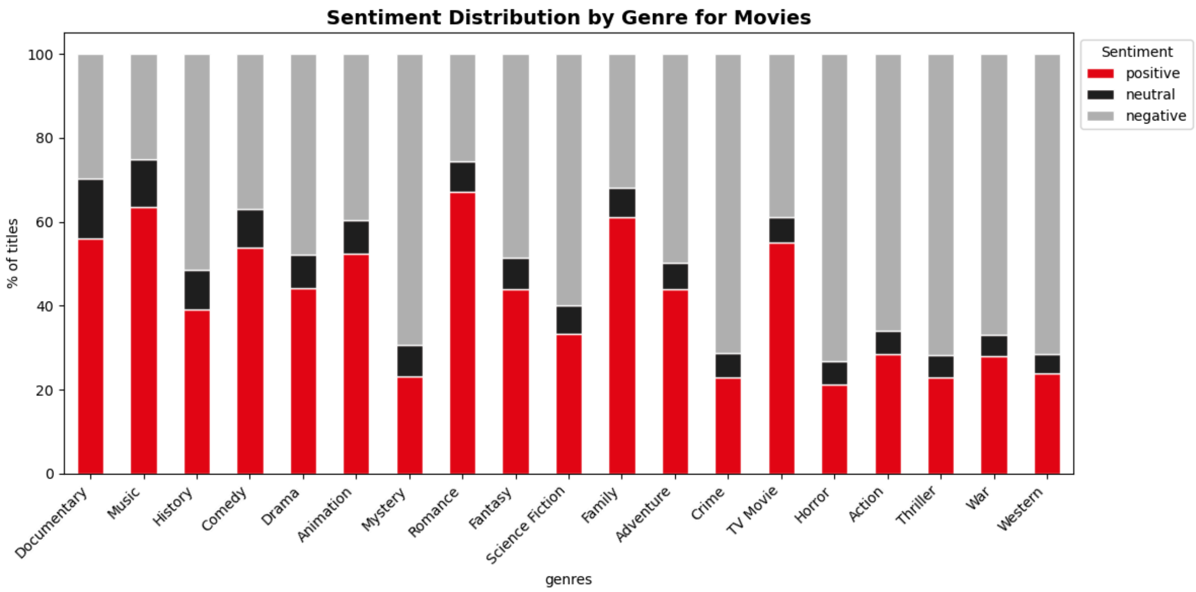


Fig:-8.9

2.2 Text:-

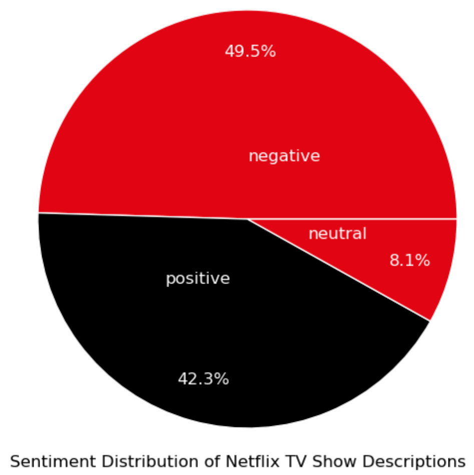


Fig:-8.10

The sentiment profile of Netflix TV show descriptions is predominantly non-neutral: approximately 49.5% score negative, 42.3% positive, and only 8.1% neutral.

Sentiment Analysis Across TV Show Genres (VADER):-

Applying VADER to TV show descriptions also reveals a strong genre-driven tone. Informational genres like “News”, “Talk”, and “Documentary” are dominated by neutral descriptions, since their blurbs are factual ("covers...", "explores...", "discusses...") rather than emotional. In contrast, family-oriented and entertainment genres — "Kids", "Comedy", "Animation", and "Family" — show a much larger positive segment, reflecting warm/supportive language such as family, friends, adventure, fun, follow the story of.... Conflict-heavy or plot-tension genres like "Crime", "Mystery", "Action & Adventure", and "Sci-Fi & Fantasy" exhibit higher negative-leaning descriptions because their synopses contain words related to danger, pursuit, threats, or battles. As with movies, neutral text is relatively limited overall, meaning even short TV blurbs usually contain at least one word that pushes sentiment up or down. Therefore, the sentiment here should be interpreted as "tone of description by TV sub-genre" rather than viewer liking — negative ≈ "high-stakes / conflict-driven storyline," not "audience dislikes this show."

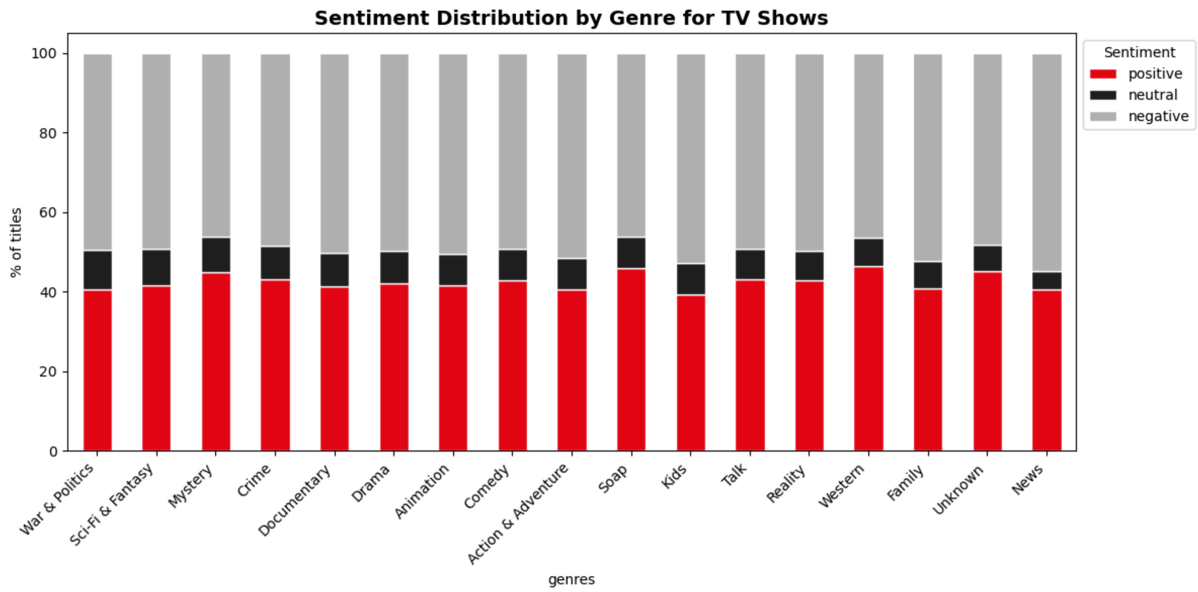


Fig:-8.11

9) Recommendation Insights:-

9.1) The Actor-Genre Niche Matrix

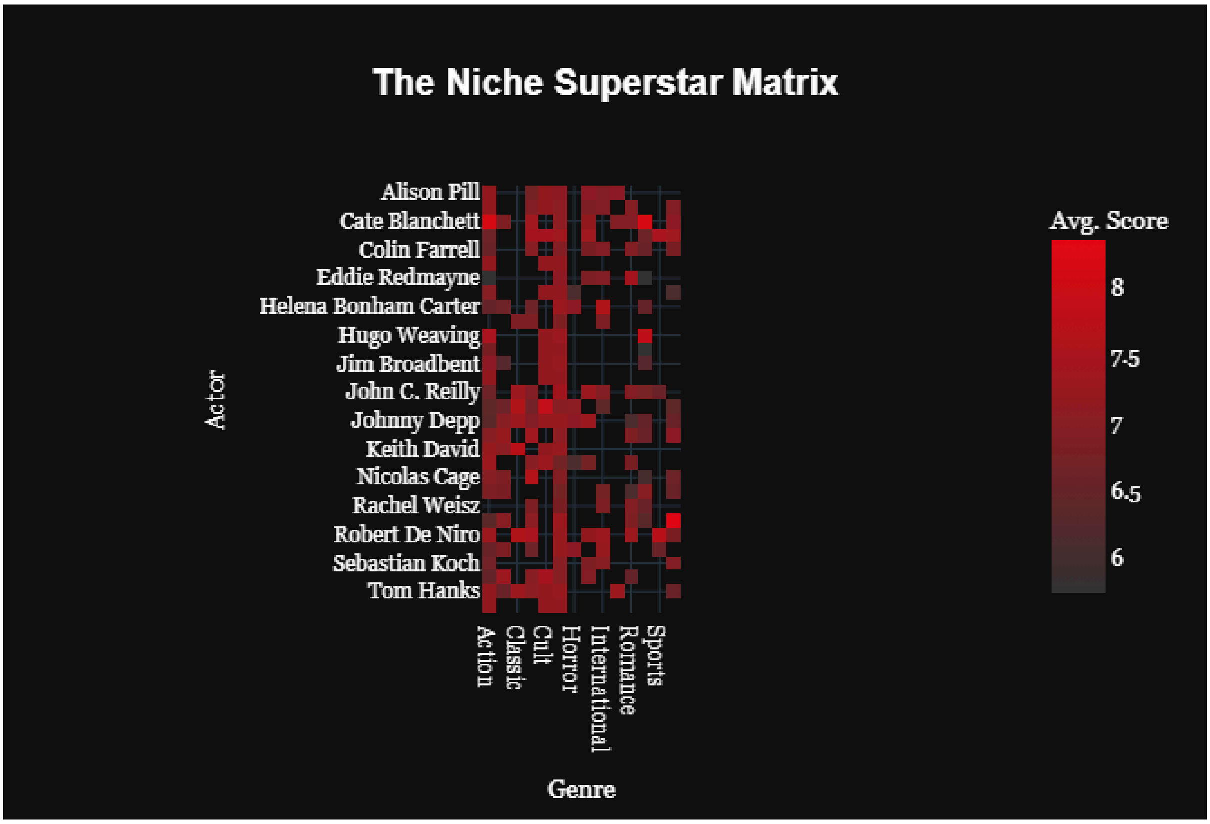


Fig 9.1 Actor - Genre Niche Heatmap

Understanding:

- This is a heatmap that cross-references top actors with key movie genres.
- Each cell's color represents an actor's average popularity score within that specific genre.
- Brighter red cells indicate a highly successful actor-genre pairing, while dark cells show a weak or non-existent one.

Interpretation:

- **Genre-Specific Success**: The primary finding is that actors are not universally popular; their success is highly dependent on the genre.

- **Reveals "Niche Superstars":** The chart clearly identifies actors who are exceptionally dominant and successful in a single category, making them a powerful draw for a specific audience.
- **Highlights Versatility:** It also shows which actors are "utility players" who maintain high popularity across several different genres, making them reliable choices for diverse projects.
- **Identifies Poor Fits:** The dark areas are equally important, showing which high-profile actors are not a good fit for certain genres, helping to avoid costly casting mistakes.

Strategic Insight

- **De-Risk Casting Decisions**: Instead of hiring actors based on general fame, use this matrix to select the perfect actor for a specific genre, maximizing a film's potential for success and ROI.
- **Optimize Audience Targeting**: For a new Horror movie, marketing can confidently feature the actor with the highest score in the 'Horror' column, knowing they are a proven draw for that specific audience.
- **Identify "White Space" Opportunities:** Discover and develop projects for actors who show surprising success in unexpected genres. This is a data-driven way to create innovative, buzz-worthy content that subverts expectations.

9.2) The "Goldilocks Zone" of Content Age

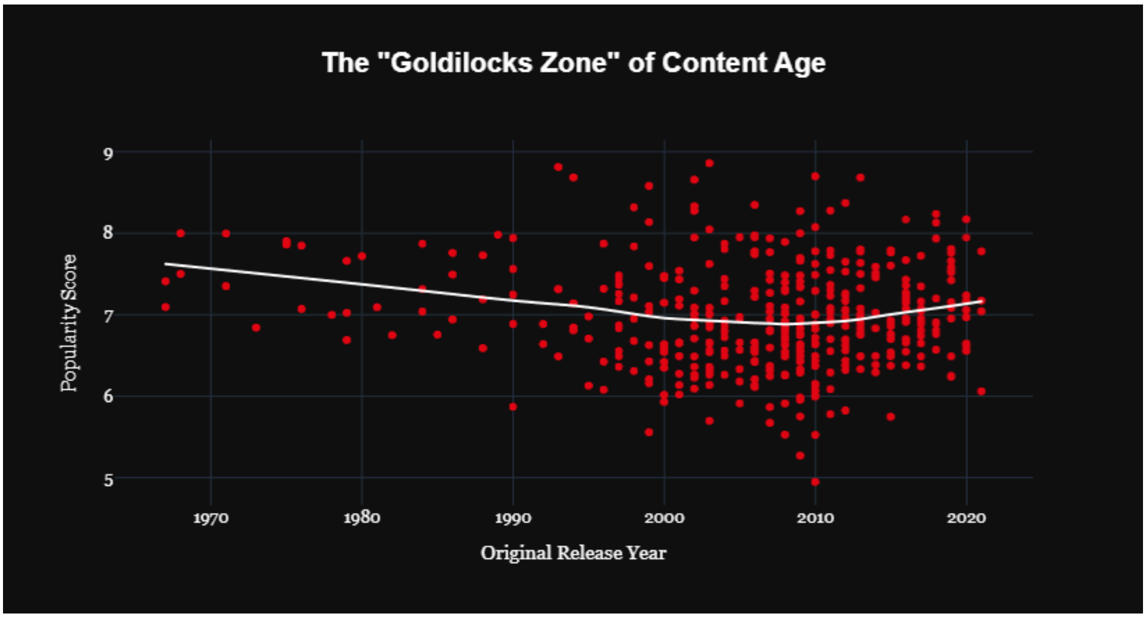


Fig 9.2 Content vs popularity Trend

Understanding:

- This scatter plot maps a title's original release year against its current popularity on Netflix.
- The X-axis is the year the content was produced (e.g., 1970, 2020).
- The Y-axis is its Popularity Score. The trendline reveals the average popularity for content from a given era.

Interpretation:

- **Two High-Value Eras:** Content from two distinct periods performs best: timeless classics (pre-1990) and modern hits (post-2010).
- **The "Nostalgia Valley"**: There is a clear dip in average popularity for content produced between the late 1990s and 2000s.
- **Audience Preference:** This pattern shows that viewers value either extreme cultural relevance (brand new) or established iconic status (classic).

Strategic Insight

- **Adopt a "Barbell" Strategy:** Focus content investment on the two extremes: producing new, modern Originals and licensing a curated library of iconic classics.
- **Justify a "Classics" Budget:** This data proves that maintaining a budget for older, prestigious films is a high-value strategy that adds depth and perceived quality to the platform.
- **Targeted Acquisition for the Valley**: When acquiring content from the "nostalgia valley," prioritize titles with known cult followings rather than general library filler to ensure a better ROI.

9.3) The Content Lag "Sweet Spot"

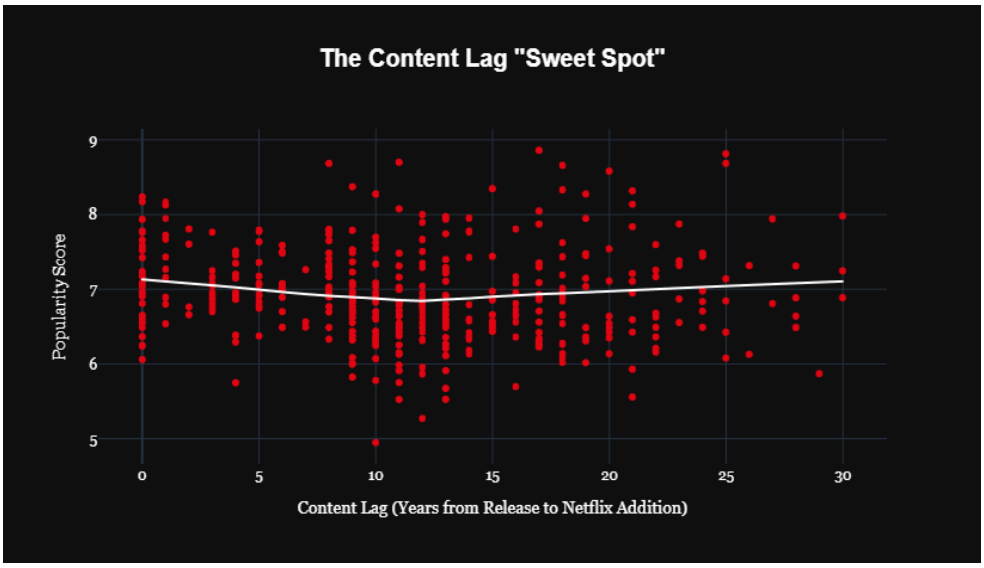


Fig 9.3 Content Lag vs popularity trend

Understanding:

- This is a scatter plot that maps a title's popularity against its "freshness."
- The X-axis shows "Content Lag": the number of years between a title's original release and its debut on Netflix.
- The Y-axis is the calculated Popularity Score. The white trendline shows the average relationship.

Interpretation:

- **Peak Freshness**: The highest average popularity is achieved by content added within 0-5 years of its release. This is the prime window.
- **The Value Decline**: Popularity dips for content acquired with a 10-15 year lag. It's no longer new but not yet a "classic."
- **The Library Revival:** Popularity recovers for iconic "library" titles with a lag of 20+ years, showing their timeless value.

Strategic Insight

- **Prioritize Freshness**: Focus acquisition budget on licensing high-quality content within 5 years of its original release to maximize cultural impact.
- **Invest in a Curated Library**: Selectively license iconic, proven classics that are over 20 years old, as they add significant long-term value.
- **Negotiate Smarter:** For content in the 10-15 year "value decline" zone, be more selective and potentially negotiate lower licensing fees.

9.4) Evolution of Content Strategy

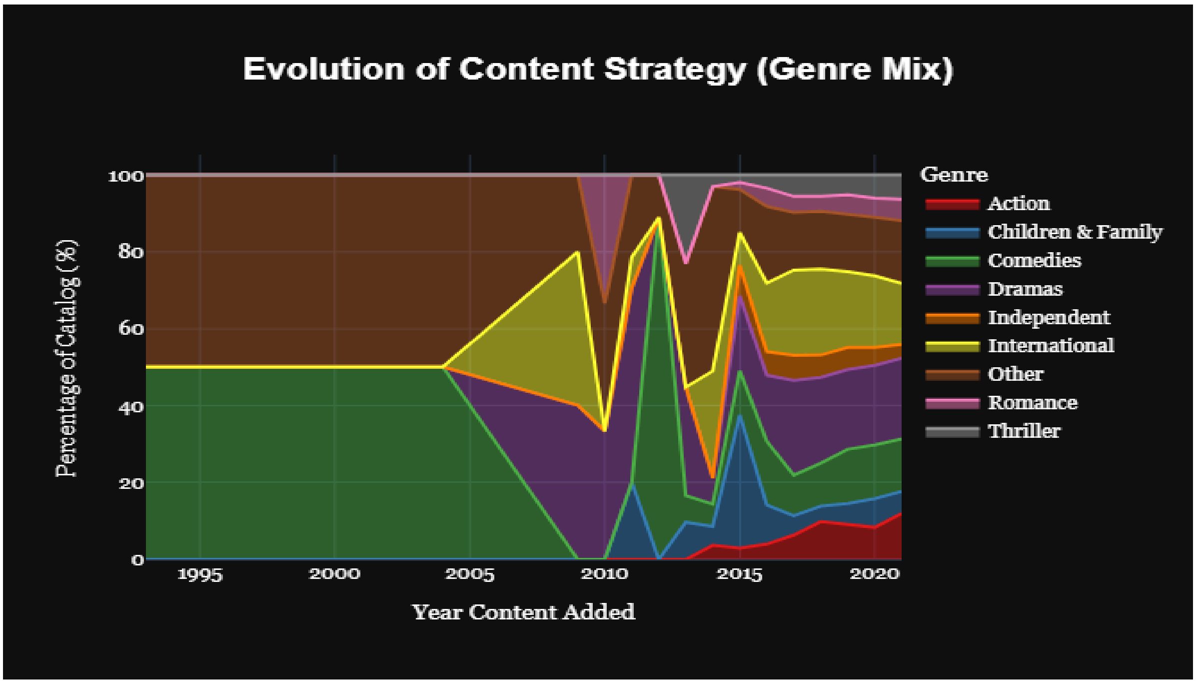


Fig 9.4 Content Evolution wrt genre plot

Understanding:

- This is a 100% stacked area chart showing the proportion of different genres added to Netflix each year.
- It visualizes the strategic shifts in the mix of content, not the raw volume.
- The Y-axis represents the percentage of the catalog, so the total area always sums to 100%.

Interpretation:

- **The "Other" Era (Pre-2010)**: In the early days, the catalog was dominated by a wide variety of licensed "Other" content.
- **The Rise of Originals & International Focus (Post-2012)**: There is a clear, dramatic increase in the proportion of "International" and "Dramas," signaling the shift to a global-first, original content strategy.
- **Strategic Diversification:** In recent years, the slivers for "Action," "Children & Family," and "Thriller" are growing, showing a deliberate move to diversify the catalog beyond the core genres.

Strategic Insight

- **Validate the Global-First Strategy**: This chart provides visual proof that the strategic pivot to International content was a massive and deliberate undertaking, justifying its continued budget.
- **Identify Growth vs. Mature Categories:** "Dramas" and "International" are now mature, foundational pillars. "Action" and "Children & Family" are clearly identified as the key growth areas for future investment.
- **Optimize Content Mix:** Use this historical view to model future content mix scenarios, ensuring a balanced portfolio that serves both core audiences and strategic growth demographics.

9.5) The Director Efficiency Quadrant

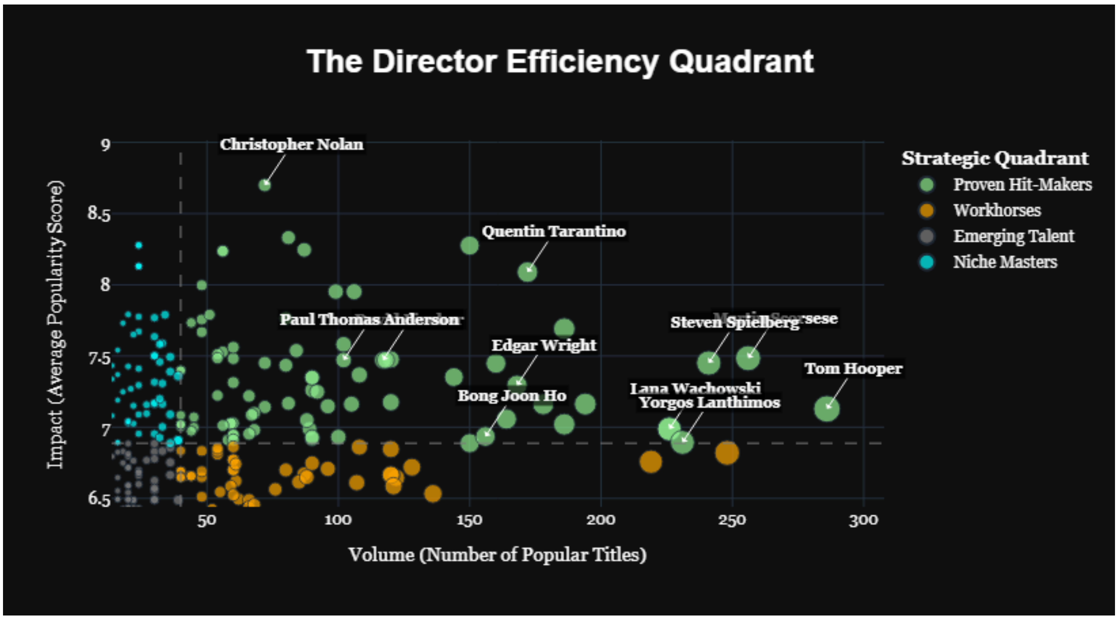


Fig 9.5 Director Efficiency Quadrant plot

Understanding:

- This scatter plot segments directors into four strategic groups based on their performance.
- The X-axis ("Volume") is the number of popular titles a director has in the catalog.
- The Y-axis ("Impact") is the average popularity score of those titles.

Interpretation:

- **Proven Hit-Makers (Top Right)**: High volume, high impact. These are the elite, bankable directors like Steven Spielberg who consistently deliver popular hits.
- **Niche Masters (Top Left):** Low volume, high impact. These are auteurs like Christopher Nolan who create fewer but critically acclaimed, highly popular films.
- **Workhorses (Bottom Right):** High volume, lower impact. These directors are reliable and prolific, consistently delivering content that fills the catalog.
- **Emerging Talent (Bottom Left)**: Low volume, lower impact. This group contains new directors or those who are not yet proven hit-makers on the platform.

Strategic Insight

- **Tailor Talent Management:** Don't treat all directors the same. Secure "Hit-Makers" for major tentpole projects, give creative freedom to "Niche Masters," and leverage "Workhorses" to efficiently build out genre categories.
- **Data-Driven Greenlighting**: Use this quadrant to de-risk investments. A project from a "Proven Hit-Maker" or "Niche Master" is a statistically safer bet than one from the other quadrants.
- **Develop Emerging Talent:** Identify promising directors in the "Emerging Talent" quadrant who are close to the median impact line and invest in their next projects to build the next generation of Hit-Makers.

9.6) Validating the Global Strategy

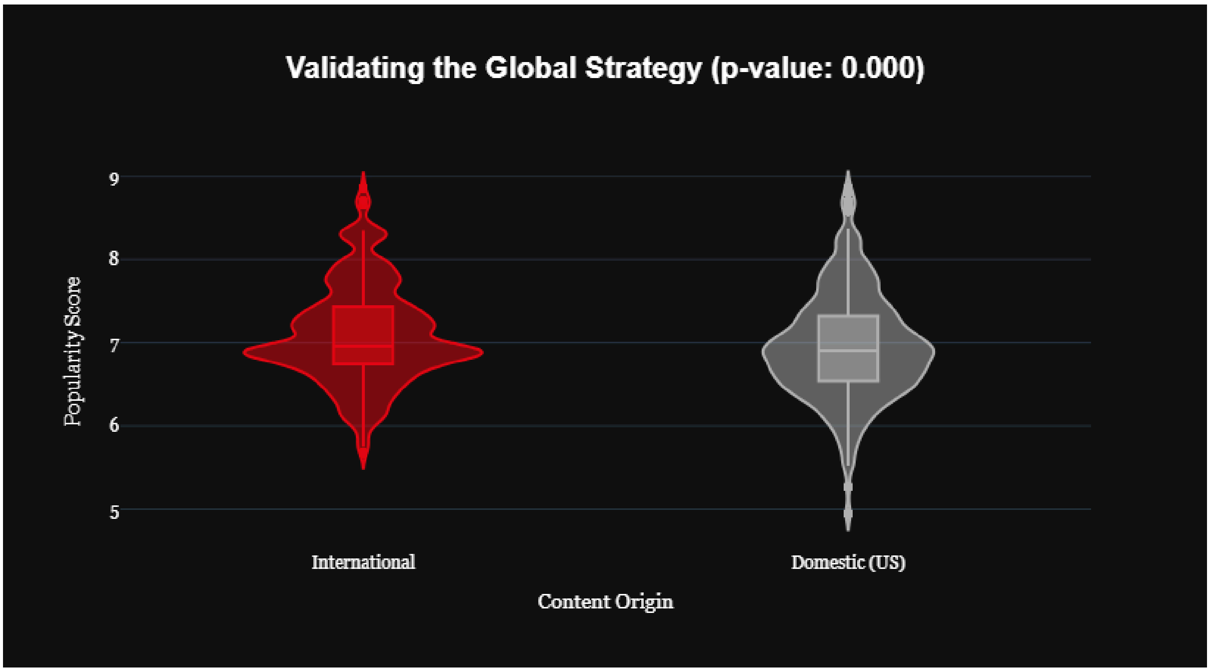


Fig 9.6 Global vs Domestic popularity comparison plot

Understanding:

- This is a violin plot comparing the distribution of popularity scores for Domestic (US) content versus International content.
- The width of the shape shows where scores are most concentrated. The box inside shows the median and interquartile range.
- The p-value (0.000) in the title is from a t-test, a statistical test to see if the difference in averages is real or just due to random chance.

Interpretation:

- **Similar Quality Ceiling:** Both violins reach a similar peak height, indicating that the very best International content is just as popular as the very best US content.
- **Different Distribution:** The shapes of the violins are different, showing how the scores are spread out. The US violin might be wider at the bottom, suggesting more low-performing titles.
- **Statistically Significant Result**: A p-value of 0.000 is less than 0.05, which is the standard threshold. This provides conclusive statistical proof that the observed differences in the popularity distributions are real and not a random fluke.

Strategic Insight

- **Double Down on International Investment**: This chart provides definitive, statistical validation that the multi-billion dollar investment in global content is working. International productions are not a "side project"; they are a core, high-performing part of the catalog.
- **Promote International Content with Confidence:** The marketing team can and should promote international hits with the same confidence and budget as domestic ones, knowing they have the same potential to become global phenomena.
- **Global-First Mindset:** This data justifies a truly global-first content strategy, where the best ideas are sourced and produced anywhere in the world, not just in Hollywood.

9.7)Impact of Genre Complexity on Popularity

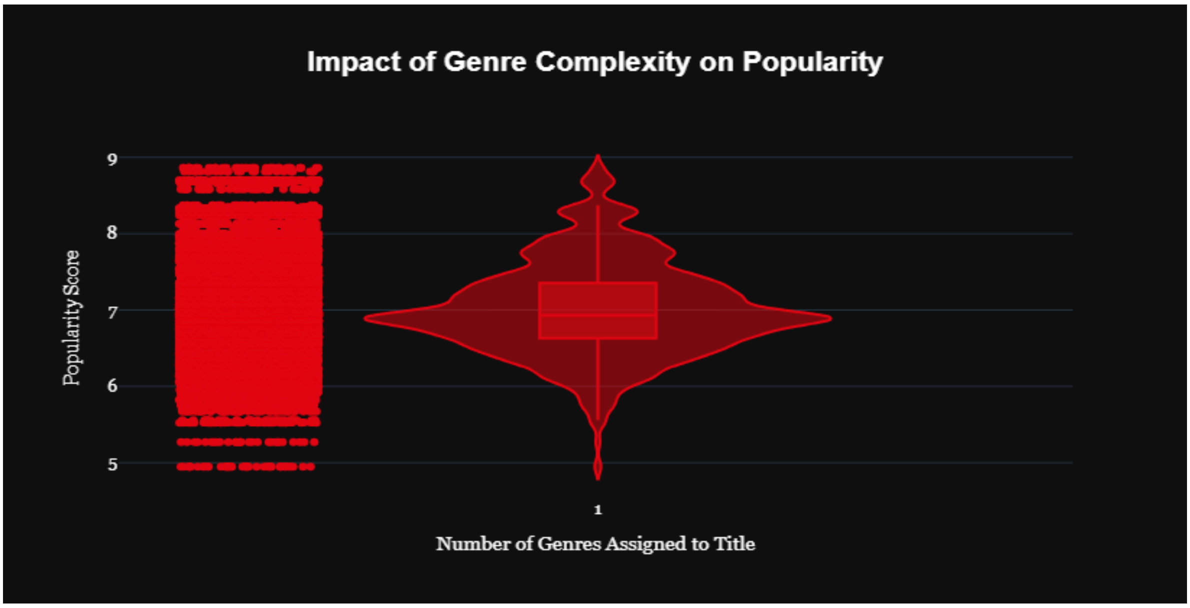


Fig 9.7 Genre Complexity plot

Understanding:

- This visualization is designed to compare the popularity of titles based on how many genres they are tagged with (e.g., 1 genre, 2 genres, 3 genres).
- Each violin would represent a different "genre count."
- The shape and position of the violins reveal if more complex, multi-genre titles are more or less popular than single-genre titles.

Interpretation:

- **Median Score Comparison**: By comparing the white median lines inside each violin, we could see which level of genre complexity achieves the highest average popularity.
- **Risk vs. Reward**: A very wide violin for "3 Genres" would suggest that genre-blending is high-risk, high-reward—these titles are more likely to be either huge hits or big flops.
- **Audience Preference:** The plot would show whether audiences prefer the clear focus of a single-genre title or the depth and novelty of a multi-genre title.

Strategic Insight

- **Median Score Comparison**: By comparing the white median lines inside each violin, we could see which level of genre complexity achieves the highest average popularity.
- **Risk vs. Reward**: A very wide violin for "3 Genres" would suggest that genre-blending is high-risk, high-reward—these titles are more likely to be either huge hits or big flops.
- **Audience Preference**: The plot would show whether audiences prefer the clear focus of a single-genre title or the depth and novelty of a multi-genre title.

10)Strategic Recommendations:-

10.1) Emerging Production Hubs

Insight:- Ten countries—Latvia, Puerto Rico, Estonia, Malta, United Arab Emirates, Cyprus, South Africa, Slovakia, Greece, and Croatia—are emerging as production hubs with strong audience signals relative to their current representation on the platform.

Action:- Prioritize content sourcing from these regions through targeted licensing and selective co-productions to increase engagement and catalog diversity.

10.2) Genre Focus

Insight:-Adventure, Science Fiction, and Action consistently rank as the most popular genres across both movies and TV.

Action:- Double down on these genres by expanding licenses and initiating co-productions, with the goal of lifting viewership and revenue.

10.3) Ratings Mix & Family Co-viewing

Insight:- Netflix's slate is adult-skewed (>40% R, ~30% PG-13) while family co-viewing is strong in India, Southeast Asia, and Latin America; competitors like Disney+ dominate the family segment, creating household churn risk.

Action:- Rebalance toward PG/PG-13 family titles—license/co-produce localized films and series and feature them in dedicated family rows to protect households and reduce churn.

10.4) Catalog Allocation by Genre

Insight:- Recent acquisitions lean into several lower-performing genres; meanwhile, higher-engagement lanes remain underweighted.

Action:- Reallocate sourcing toward high-performing genres—e.g., Adventure/Fantasy/Action for movies and (based on your engagement read-outs) Soap/News/Talk for TV—then track lift via engagement per added title, completion rate, and retention within those rows.

10.5)Director-Level Gaps

Insight:- Gap analysis shows J.C. Chandor and Sean Baker (films) and Yan Ji (TV) deliver high average popularity, yet each has very limited availability on Netflix (≈5 titles).

Action:- Expand director coverage by licensing/co-producing additional titles from these creators. Prioritize discoverability (director hubs/rows) and track lift via engagement per added title and completion rate.