

The Netflix logo, consisting of the word "NETFLIX" in a bold, red, sans-serif font, centered within a black rectangular background.

Project Title: Exploratory Data Analysis of Netflix with SQL

Domain: OTT

Tools Used: PostgreSQL via pgAdmin

Objective: To analyze Netflix content using SQL to find trends in genres, ratings, and production countries, and to understand what makes content popular on the platform.

By: Abhijeet Beura

Dataset Description

Dataset Description

This project utilizes two distinct datasets to perform analysis on movies and TV shows:

Titles Dataset (Abhijeet.csv)

This dataset provides detailed metadata for each movie or TV show. Key attributes include:

Title: Name of the movie or show

Type: Indicates whether the title is a movie or a TV show

Release Year: The year the title was released

Genres: Associated genre(s) of the title

Country: Country of origin or production

Ratings: Ratings from platforms such as IMDb and TMDb

Runtime: Duration of the movie/show in minutes

People Dataset (AbhijeetA.csv)

This dataset captures information about the individuals (cast and crew) associated with each title. It is linked to the Titles dataset through a common identifier (id).

Key attributes include:

Name: Name of the person

Role: Role in the production (e.g., actor, director, writer)

Associated Title ID: Foreign key linking to the Titles dataset

Project Objective

The goal of this project is to leverage SQL queries to analyze a Netflix dataset to derive actionable insights related to user behavior, content performance, and subscription trends. By examining various aspects such as user engagement, content preferences, and profitability, the project aims to inform strategies for improving user retention, optimizing content offerings, and maximizing revenue. Key focus areas include analyzing content performance, demographic segmentation, churn prediction, subscription plan effectiveness, and time-based trends, providing data-driven recommendations to enhance the Netflix user experience and business outcomes.

Insights from SQL Queries

1. Which movies and shows on Netflix ranked in the top 10 their IMDB scores ≥ 8

Top 10 Movies

```
SELECT title, type, imdb_score
FROM titles_NNNN
WHERE type ILIKE 'movie'
      AND imdb_score  $\geq 8.0$ 
ORDER BY imdb_score DESC
LIMIT 10;
```

	title text	type text	imdb_score numeric
1	Major	MOVIE	9.1
2	Chhota Bheem & Krishna vs Zimbara	MOVIE	9.1
3	C/o Kancharapalem	MOVIE	8.9
4	David Attenborough: A Life on Our Planet	MOVIE	8.9
5	Inception	MOVIE	8.8
6	Forrest Gump	MOVIE	8.8
7	GoodFellas	MOVIE	8.7
8	A Lion in the House	MOVIE	8.7
9	Chhota Bheem Neeli Pahaadi	MOVIE	8.7
10	Chhota Bheem & Krishna in Mayanagari	MOVIE	8.7

Top 10 Shows

```
SELECT title, type, imdb_score
FROM titles_NNNN
WHERE type ILIKE 'show'
      AND imdb_score  $\geq 8.0$ 
ORDER BY imdb_score DESC
LIMIT 10;
```

	title text	type text	imdb_score numeric
1	#ABTalks	SHOW	9.6
2	Khawatir	SHOW	9.5
3	Breaking Bad	SHOW	9.5
4	Our Planet	SHOW	9.3
5	Avatar: The Last Airbender	SHOW	9.3
6	Reply 1988	SHOW	9.2
7	Kota Factory	SHOW	9.1
8	My Mister	SHOW	9.1
9	The Last Dance	SHOW	9.1
10	Leah Remini: Scientology and the Aftermath	SHOW	9

Top 10 Movies & Shows (IMDb ≥ 8.0)

Insight:

Only a limited number of titles qualify as top-rated.

High IMDb score strongly reflects critical success.

Recommendation:

Promote these titles on the homepage and curated lists.

Use them as benchmarks for acquiring or creating future content.

2.Which movies and shows on Netflix ranked in the top 20 based on their IMDB scores >= 7

Top 20 Movies

```
SELECT title, type, imdb_score
```

```
FROM titles_NNNN
```

```
WHERE type ILIKE 'movie'
```

```
AND imdb_score >= 7.0
```

```
ORDER BY imdb_score DESC
```

```
LIMIT 20;
```

	title text	type text	imdb_score numeric
1	Major	MOVIE	9.1
2	Chhota Bheem & Krishna vs Zimbara	MOVIE	9.1
3	David Attenborough: A Life on Our Planet	MOVIE	8.9
4	C/o Kancharapalem	MOVIE	8.9
5	Inception	MOVIE	8.8
6	Forrest Gump	MOVIE	8.8
7	Chhota Bheem & Krishna in Mayanagari	MOVIE	8.7
8	Anbe Sivam	MOVIE	8.7
9	A Lion in the House	MOVIE	8.7
10	GoodFellas	MOVIE	8.7
11	Chhota Bheem Neeli Pahaadi	MOVIE	8.7
12	Bo Burnham: Inside	MOVIE	8.7
13	Chhota Bheem and the ShiNobi Secret	MOVIE	8.6
14	Merku Thodarchi Malai	MOVIE	8.6
15	The Art of Incarceration	MOVIE	8.6
16	A Second Chance	MOVIE	8.6
Total rows: 20 Query complete 00:00:00.083			

Top 20 Show

```
SELECT title, type, imdb_score
FROM titles_NNNN
WHERE type ILIKE 'show'
      AND imdb_score >= 7.0
ORDER BY imdb_score DESC
LIMIT 20;
```

	title text	type text	imdb_score numeric
1	#ABtalks	SHOW	9.6
2	Khawtir	SHOW	9.5
3	Breaking Bad	SHOW	9.5
4	Our Planet	SHOW	9.3
5	Avatar: The Last Airbender	SHOW	9.3
6	Reply 1988	SHOW	9.2
7	The Last Dance	SHOW	9.1
8	My Mister	SHOW	9.1
9	Kota Factory	SHOW	9.1
10	Okupas	SHOW	9
11	Hunter x Hunter	SHOW	9
12	Attack on Titan	SHOW	9
13	DEATH NOTE	SHOW	9
14	Leah Remini: Scientology and the Aftermath	SHOW	9
15	Arcane	SHOW	9
16	Raja, Rasoi Aur Anya Kahaniyaan	SHOW	8.9
Total rows: 20 Query complete 00:00:00.131			

Insight:

A wider pool of strong-performing titles can attract different viewer groups.

Recommendation:

Use these to diversify featured content for broader appeal.

Consider long-term contracts or sequels/spinoffs for these titles.

**3.Which movies on Netflix ranked in the bottom 10 based on their IMDB scores
>= 6**

Movie Bottom 10

```
SELECT title, type, imdb_score
FROM titles_NNNN
WHERE type ILIKE 'movie'
      AND imdb_score >= 6.0
ORDER BY imdb_score ASC
LIMIT 10;
```

	title text	type text	imdb_score numeric
1	The Rite	MOVIE	6
2	One More Try	MOVIE	6
3	Fiza	MOVIE	6
4	Kabhi Alvida Naa Kehna	MOVIE	6
5	6 Bullets	MOVIE	6
6	Vettai	MOVIE	6
7	The George McKenna Story	MOVIE	6
8	Tim Allen: Rewires America	MOVIE	6
9	Halloween	MOVIE	6
10	Walk of Shame	MOVIE	6

Show Bottom 10

```
SELECT title,type,imdb_score
FROM titles_NNNN
WHERE type ILIKE 'show'
      AND imdb_score >= 6.0
ORDER BY imdb_score ASC
      LIMIT 10;
```

	title text	type text	imdb_score numeric
1	Home: Adventures with Tip & Oh	SHOW	6
2	Champions	SHOW	6
3	The Next Step	SHOW	6
4	Chelsea	SHOW	6
5	Transformers: Robots In Disguise	SHOW	6
6	Polly Pocket	SHOW	6
7	Robocar Poli	SHOW	6
8	Justin Time	SHOW	6
9	Popples	SHOW	6
10	Death by Magic	SHOW	6

Insight:

- Even average-rated content contributes to content depth.
- These may underperform in engagement.

Recommendation:

- Evaluate content retention data for these titles.
- Remove or demote in search results if engagement is low.

4.What were the average IMDB and TMDB scores for shows and movies?

SELECT

type,




ROUND(AVG(imdb_score), 2) AS avg_imdb_score,

ROUND(AVG(tmdb_score), 2) AS avg_tmdb_score

FROM titles_NNNN

WHERE imdb_score IS NOT NULL AND tmdb_score IS NOT NULL

GROUP BY type;

	type text 	avg_imdb_score numeric 	avg_tmdb_score numeric 
1	SHOW	6.98	7.47
2	MOVIE	6.25	6.46

Insight:

- Average scores are similar across movies and shows.
- Indicates consistent quality control.

Recommendation:

- Continue balancing investments in both formats.
- Set score benchmarks (e.g., IMDb ≥ 7.2) for licensing decisions.

5.Count of movies and shows in each decade

SELECT

CONCAT(FLOOR(release_year / 10) * 10, 's') AS decade,

COUNT(*) AS movies_shows_count

FROM titles_NNNN

WHERE release_year >= 1940

GROUP BY CONCAT(FLOOR(release_year / 10) * 10, 's')

ORDER BY decade;

	decade text	movies_shows_count bigint
1	1940s	1
2	1950s	5
3	1960s	8
4	1970s	18
5	1980s	52
6	1990s	121
7	2000s	369
8	2010s	3304
9	2020s	1972

Insight:

- Sharp rise in content post-2000s.
- Viewer preferences have evolved over decades.

Recommendation:

- Segment content recommendations by decade.
- Target nostalgic users or retro content lovers with themed sections.

6. What were the average IMDB and TMDB scores for each production country?

```

SELECT
production_countries,
ROUND(AVG(imdb_score),2) AS avg_imdb_score,
ROUND(AVG(tmdb_score),2) AS avg_tmdb_score
FROM titles_NNNN
GROUP BY production_countries
ORDER BY avg_imdb_score DESC;
```

	production_countries text	avg_imdb_score numeric	avg_tmdb_score numeric
1	['DK', 'LB', 'GB']	[null]	[null]
2	['US', 'LB', 'AE']	[null]	[null]
3	['HU', 'CA']	[null]	7.80
4	['US', 'ZA', 'DE']	[null]	6.10
5	['DE', 'AT']	[null]	7.40
6	['ES', 'BE']	[null]	4.90
7	['QA', 'PS']	[null]	7.00
8	['TH', 'US']	[null]	8.20
9	['GB', 'DK', 'GR']	[null]	5.60
10	['GE']	[null]	6.70
11	['SY', 'GB']	[null]	7.40
12	['QA', 'TN', 'FR']	[null]	[null]
13	['GB', 'CZ', 'FR']	[null]	7.40
14	['JP', 'KR', 'FR']	[null]	9.00
15	['LB', 'PS']	[null]	1.00
16	['JP', 'GB']	[null]	5.80
Total rows: 452		Query complete 00:00:00.098	

Insight:

- US leads in quantity and consistent ratings.
- Some smaller countries show high quality despite fewer titles.

Recommendation:

- Invest in co-productions with high-performing countries.
- Promote international titles in local markets.

7.What were the 10 most common age certifications for movies?

```
SELECT age_certification,
       COUNT(*) AS certification_count
FROM titles_NNNN
WHERE type ILIKE 'movie'
AND age_certification IS NOT NULL
```

```
AND age_certification != ""
AND age_certification != 'N/A'
GROUP BY age_certification
ORDER BY certification_count DESC
LIMIT 10;
```

	age_certification text	certification_count bigint
1	R	556
2	PG-13	451
3	PG	233
4	G	124
5	NC-17	16

Insight:

- TV-MA, R, and PG-13 dominate.
- Family-friendly content is less common.

Recommendation:

- Increase PG or G-rated titles to attract family demographics.
- Ensure content filters and recommendations reflect user profiles.

8 .Who were the top 30 actors that appeared the most in movies/shows?

```
SELECT DISTINCT name AS actor,  
        COUNT(*) AS number_of_appearances  
FROM cast_crewA  
WHERE role ILIKE 'actor'  
GROUP BY name  
ORDER BY number_of_appearances DESC  
LIMIT 30;
```

	actor text	number_of_appearances bigint
1	Kareena Kapoor Khan	25
2	Boman Irani	25
3	Shah Rukh Khan	23
4	Takahiro Sakurai	21
5	Priyanka Chopra Jonas	20
6	Paresh Rawal	20
7	Amitabh Bachchan	20
8	Anupam Kher	19
9	Nawazuddin Siddiqui	19
10	Junichi Suwabe	19
11	Yuki Kaji	19
12	Fred Armisen	18
13	Nassar	18
14	Ajay Devgn	18
15	Fred Tatasciore	18
16	Om Puri	18
Total rows: 30		Query complete 00:00:00.504

Insight:

- High-visibility actors have strong viewer recognition.
- Recurring faces may contribute to loyalty.

Recommendation:

- Promote actor-centric collections.
- Use actor appearances in marketing campaigns.

9. Who were the top 30 directors that directed the most movies/shows?

```
SELECT DISTINCT name AS director,  
COUNT(*) AS number_of_appearances  
FROM cast_crewA  
WHERE role ILIKE 'director'  
GROUP BY name  
ORDER BY number_of_appearances DESC  
LIMIT 30;
```

	director text	number_of_appearances bigint
1	Raúl Campos	20
2	Jan Suter	19
3	Ryan Polito	17
4	Jay Karas	15
5	Marcus Raboy	14
6	Jay Chapman	12
7	Cathy Garcia-Molina	12
8	Youssef Chahine	11
9	Justin G. Dyck	8
10	Kunle Afolayan	8
11	Anurag Kashyap	8
12	Suhas Kadav	8
13	Troy Miller	8
14	Fernando Ayllón	7
15	Shannon Hartman	7
16	Lance Bangs	7
Total rows: 30 Query complete 00:00:00.453		

Insight:

- Key directors frequently create successful content.
- Indicates reliability and quality in production.

Recommendation:

- Foster exclusive deals with top directors.
- Showcase from the director of.. trailers and highlights.

10.Calculating the average runtime of movies and TV shows separately?

Movie

```
SELECT  
'Movies' AS content_type,  
ROUND(AVG(runtime),2) AS avg_runtime_min  
FROM titles_NNNN  
WHERE type ILIKE 'Movie';
```

	content_type text	avg_runtime_min numeric
1	Movies	98.21

Show

```
SELECT  
'show'AS content_type,  
ROUND(AVG(runtime),2) AS avg_runtime_min  
FROM titles_NNNN  
WHERE type ILIKE 'show';
```

	content_type text	avg_runtime_min numeric
1	show	38.98

UNION ALL

SELECT

'Movies' AS content_type,

ROUND(AVG(runtime),2) AS avg_runtime_min

FROM titles_NNNN

WHERE type ILIKE 'Movie'

UNION ALL

SELECT

'show' AS content_type,

ROUND(AVG(runtime),2) AS avg_runtime_min

FROM titles_NNNN

WHERE type ILIKE 'show';

	content_type text	avg_runtime_min numeric
1	Movies	98.21
2	show	38.98

Insight:

- Shows: ~40–50 mins, Movies: ~100–110 mins
- Content fits within viewer expectations.

Recommendation:

- Optimize runtime to match user session length (especially for mobile viewers).
- Consider mini-series format for content between 60–90 mins.

11. Finding the titles and directors of movies released on or after 2022

```
SELECT DISTINCT
    t.title,
    c.name AS director,
    t.release_year
FROM titles_NNNN AS t
JOIN cast_crewA AS c
    ON t.id = c.id
WHERE t.type ILIKE 'movie'
    AND t.release_year >= 2022
    AND c.role ILIKE 'director'
ORDER BY t.release_year DESC;
```

	title text	director text	release_year integer
1	11M	José Gómez	2022
2	365 Days: This Day	Barbara Bialowas	2022
3	365 Days: This Day	Tomasz Mandes	2022
4	40 Years Young	Pietro Loprieno	2022
5	A Perfect Pairing	Stuart McDonald	2022
6	Adam by Eve: A Live in Animation	Hibiki Yoshizaki	2022
7	Adam by Eve: A Live in Animation	Nobutaka Yoda	2022
8	Adam by Eve: A Live in Animation	Waboku	2022
9	Adam by Eve: A Live in Animation	Yuichiro Saeki	2022
10	Against the Ice	Peter Flinth	2022
11	AI Love You	Stephan Zlotescu	2022
12	Ali Wong: Don Wong	Nahnatchka Khan	2022
13	All Hail	Marcos Carnevale	2022
14	Along for the Ride	Sofia Alvarez	2022
15	Amandla	Nerina de Jager	2022
16	Amy Schumer Presents: Parental Advisory	Ryan Polito	2022
Total rows: 213 Query complete 00:00:00.440			

Insight:

- Surge of fresh releases with modern production.
- New director names entering the platform.

Recommendation:

- Track new directors' performance for future collaboration.
- Use recent releases to drive engagement and subscriber interest.

12. Which shows on Netflix have the most seasons?

```
SELECT t.title,  
SUM(t.seasons) AS total_seasons  
FROM titles_NNNN AS t  
WHERE t.type ILIKE 'show'  
GROUP BY title  
ORDER BY total_seasons DESC  
LIMIT 5;
```

	title text	total_seasons bigint
1	Survivor	42
2	Wheel of Fortune	39
3	The Challenge	37
4	Top Gear	32
5	Power Rangers	29

Insight:

- Long-running shows signal sustained audience interest.

Recommendation:

- Promote “binge-worthy” collections.
- Use as flagship titles for subscriber retention.

13.Which genres had the most movies?

```
SELECT genres,  
SUM(t.seasons) AS total_seasons  
FROM titles_NNNN AS t  
WHERE t.type ILIKE 'show'  
GROUP BY genres  
ORDER BY total_seasons DESC  
LIMIT 5;
```

	genres text	total_seasons bigint
1	['reality']	289
2	['comedy']	194
3	['documentation']	155
4	['drama']	148
5	['comedy', 'drama']	104

Insight:

- Reality and Comedy dominate genre share.

Recommendation:

- Prioritize trending or underutilized genres for growth (e.g., mystery, documentary).
- Tailor recommendations based on viewing history.

14. What were the total number of titles for each year?

```
SELECT release_year,  
COUNT(*) AS title_count  
FROM titles_NNNN  
GROUP BY release_year  
ORDER BY release_year DESC;
```

	release_year integer	title_count bigint
1	2022	371
2	2021	787
3	2020	814
4	2019	836
5	2018	773
6	2017	563
7	2016	362
8	2015	223
9	2014	153
10	2013	135
11	2012	107
12	2011	86
13	2010	66
14	2009	59
15	2008	63
16	2007	48
Total rows: 63		Query complete 0

Insight:

- Strong year-on-year content growth.

Recommendation:

- Monitor content saturation risk.
- Limit new title uploads based on quality, not just quantity.

15.What were the top 15 most common genres?

```
SELECT genres,  
SUM(t.seasons) AS total_seasons  
FROM titles_NNNN AS t  
WHERE t.type ILIKE 'show'  
GROUP BY genres  
ORDER BY total_seasons DESC  
LIMIT 15;
```

	genres text	total_seasons bigint
1	['reality']	289
2	['comedy']	194
3	['documentation']	155
4	['drama']	148
5	['comedy', 'drama']	104
6	['drama', 'comedy']	102
7	['drama', 'romance']	81
8	['animation']	75
9	['family']	55
10	['comedy', 'family']	43
11	['documentation', 'crime']	42
12	['crime', 'drama', 'thriller']	41
13	['drama', 'crime']	38
14	['reality', 'comedy', 'drama', 'scifi']	37
15	['animation', 'family']	37

Insight:

- High concentration in a few genres.

Recommendation:

- Diversify offerings in emerging genres.
- Build themed playlists (e.g., “Top 10 Historical Thrillers”).

16. Which movies are both critically acclaimed (IMDB score > 8.0) and widely popular (TMDB popularity > 60)? Display their titles, IMDB scores, and TMDB popularity scores, sorted by popularity in descending order.

```
SELECT title, imdb_score, tmdb_popularity
FROM titles_NNNN
WHERE imdb_score > 8.0
AND tmdb_popularity > 60
AND type ILIKE 'movie'
ORDER BY tmdb_popularity DESC;
```

	title text	imdb_score numeric	tmdb_popularity numeric (8,2)
1	A Silent Voice: The Movie	8.1	162.66
2	Inception	8.8	108.28
3	The Dark Knight Rises	8.4	91.76
4	Catch Me If You Can	8.1	72.32
5	Minnal Murali	8.1	68.03
6	Django Unchained	8.4	66.92
7	Miracle in Cell No. 7	8.2	65.55
8	Forrest Gump	8.8	63.45

Insight:

- These titles offer both critical and audience approval.

Recommendation:

- Use for flagship promotions.
- Target new users with this trusted content.

17. Which movies have both strong critical reception (IMDB score > 7.5) and high audience popularity (TMDB popularity > 80)? List their titles along with the directors.

```
SELECT t.title,  
c.name AS director  
FROM titles_NNNN AS t  
JOIN cast_crewA AS c  
ON t.id = c.id  
WHERE t.type ILIKE 'movie'  
AND t.imdb_score > 7.5  
AND t.tmdb_popularity > 80  
AND c.role ILIKE 'director';
```

	title text	director text
1	Titanic	James Cameron
2	Inception	Christopher Nolan
3	The Dark Knight Rises	Christopher Nolan
4	How to Train Your Dragon 2	Dean DeBlois
5	A Silent Voice: The Movie	Naoko Yamada

Insight:

- Content + creator combo offers compelling storytelling.

Recommendation:

- Highlight director's name in featured carousels.
- Build recommendation chains based on director influence.

18.Top repeated character-actor pairs based on total appearances

```
SELECT name, character, COUNT(*) AS appearances
FROM cast_crewA
WHERE character IS NOT NULL
GROUP BY name, character
HAVING COUNT(*) > 1
ORDER BY appearances DESC;
```

	name text	character text	appearances bigint
1	John Paul Tremblay	Julian	10
2	Mike Smith	Bubbles	10
3	Donald Trump	Self (archive footage)	9
4	Chie Nakamura	Sakura Haruno (voice)	9
5	Robb Wells	Ricky	9
6	Kazuhiko Inoue	Kakashi Hatake (voice)	8
7	Junko Takeuchi	Naruto Uzumaki (voice)	8
8	Dave Chappelle	Self	8
9	Showtaro Morikubo	Shikamaru Nara (voice)	6
10	Nobuyuki Suzuki	Yamato	6
11	Tiffany Haddish	Herself	6
12	John Mulaney	Himself	5
13	Terry Jones	Himself	5
14	Tom Segura	Himself	5
15	Terry Gilliam	Himself	5
16	Michael Palin	Himself	5
Total rows: 1281 Query complete 00:00:00.641			

Insight:

- Recurring characters create familiarity.

Recommendation:

- Promote series with beloved character arcs.
- Leverage these for marketing and merchandise.

19.Fetching Movie Titles and IMDB Scores

```
SELECT title, imdb_score  
FROM titles_NNNN  
WHERE imdb_score > 8.0  
ORDER BY imdb_score DESC;
```

	title text	imdb_score numeric
1	#ABtalks	9.6
2	Khawatir	9.5
3	Breaking Bad	9.5
4	Our Planet	9.3
5	Avatar: The Last Airbender	9.3
6	Reply 1988	9.2
7	My Mister	9.1
8	Major	9.1
9	Chhota Bheem & Krishna vs Zimbara	9.1
10	The Last Dance	9.1
11	Kota Factory	9.1
12	Okupas	9
13	Hunter x Hunter	9
14	DEATH NOTE	9
15	Arcane	9
16	Leah Remini: Scientology and the Aftermath	9
Total rows: 401 Query complete 00:00:00.258		

Insight:

- A good metric for curating best-of content.

Recommendation:

- Use to populate “Top Rated” sections.
- Retain exclusive rights for high-scoring titles.

20.Fetching Movie Titles and Directors

```
SELECT t.title, c.name AS director
FROM titles_NNNN AS t
JOIN cast_crewA AS c
ON t.id = c.id
WHERE t.type ILIKE 'movie' AND c.role ILIKE 'director';
```

	title text	director text
1	Taxi Driver	Martin Scorsese
2	Deliverance	John Boorman
3	Monty Python and the Holy Grail	Terry Jones
4	Monty Python and the Holy Grail	Terry Gilliam
5	The Dirty Dozen	Robert Aldrich
6	Life of Brian	Terry Jones
7	Dirty Harry	Don Siegel
8	Bonnie and Clyde	Arthur Penn
9	The Blue Lagoon	Randal Kleiser
10	The Guns of Navarone	J. Lee Thompson
11	The Professionals	Richard Brooks
12	Richard Pryor: Live in Concert	Jeff Margolis
13	White Christmas	Michael Curtiz
14	Cairo Station	Youssef Chahine
15	Hitler: A Career	Joachim Fest
16	FTA	Francine Parker
Total rows: 3871 Query complete 00:00:00.467		

Insight:

- Connects creative ownership with the content.

Recommendation:

- Show director names in UI for cinephiles.
- Enable director-based browsing filters.

21. Which movies have an IMDB score greater than 8.0, and who are the directors of these movies?

```
SELECT t.title, c.name AS director, t.imdb_score
FROM titles_NNNN AS t
JOIN cast_crewA AS c
ON t.id = c.id
WHERE t.type ILIKE 'movie' AND c.role ILIKE 'director' AND t.imdb_score > 8.0
ORDER BY t.imdb_score DESC;
```

	title text	director text	imdb_score numeric
1	Major	Sashi Kiran Tikka	9.1
2	David Attenborough: A Life on Our Planet	Keith Scholey	8.9
3	C/o Kanchrapalem	Venkatesh Maha	8.9
4	David Attenborough: A Life on Our Planet	Alastair Fothergill	8.9
5	David Attenborough: A Life on Our Planet	Jonathan Hughes	8.9
6	Inception	Christopher Nolan	8.8
7	Forrest Gump	Robert Zemeckis	8.8
8	Anbe Sivam	Sundar C	8.7
9	A Lion in the House	Steven Bogner	8.7
10	GoodFellas	Martin Scorsese	8.7
11	Bo Burnham: Inside	Bo Burnham	8.7
12	A Lion in the House	Julia Reichert	8.7
13	The Art of Incarceration	Alex Siddons	8.6
14	Se7en	David Fincher	8.6
15	Best Wishes, Warmest Regards: A Schitt's Creek Farewell	Amy Segal	8.6
16	A Second Chance	Cathy Garcia-Molina	8.6
Total rows: 113 Query complete 00:00:00.449			

Insight:

- Combines quality and leadership in content creation.

Recommendation:

- Prioritize these movies for content partnerships.
- Feature in award-season campaigns.

Business Impact :

The analysis conducted through SQL has a direct impact on several key business areas:

Content Strategy Optimization: By identifying top-performing genres, countries, directors, and actors, Netflix can prioritize investments in high-yield segments.

Improved User Retention: Insights into viewer preferences and runtime patterns can enhance personalized recommendations, reducing churn.

Increased Engagement: Leveraging data-driven decisions about popular content and recurring actor-character combinations allows for more effective curation and marketing.

Global Market Expansion: Country-based performance and audience ratings reveal opportunities for international growth through targeted localization and partnerships.

Data-Driven Acquisition: Understanding which movies are both critically acclaimed and widely popular can help guide licensing and production strategies.

Areas for Improvement:

While the analysis reveals rich insights, several improvement areas exist for more comprehensive decision-making:

Missing Demographic Data: No information on viewer age, region, or watch time limits personalization potential.

Unstructured Genre Tags: Genre data is currently not normalized, making in-depth analysis of sub-genres difficult.

Limited Engagement Metrics: Metrics like completion rate, re-watch value, or session duration were unavailable but would be powerful additions.

No Real-Time Data: The current analysis reflects static data. Trends can shift quickly; real-time or recent data would make the insights more actionable.

Age Certification Inconsistency: The presence of nulls and "N/A" in certifications could be cleaned for better classification and targeting.

Final Strategic Recommendations:

Based on the full analysis:

Expand in High-Performing Genres & Countries: Invest more in Drama, Action, and Comedy genres, and deepen collaboration with production houses in the US, UK, and France.

Leverage Top-Rated Titles in Promotions: Use movies with IMDb > 8 and high TMDB popularity in email campaigns, banners, and push notifications.

Build Actor/Director-Based Navigation Features: Implement filters or spotlight rows for popular actors and directors to aid fan-based discovery.

Target Families with More PG Content: Create a balanced offering by adding more PG/G-rated content for broader family appeal.

Optimize Runtime for Mobile-First Audiences: Introduce more mini-series or content under 90 minutes to cater to shorter attention spans.

Feature Long-Running Shows: Use shows with high season counts as retention anchors—ideal for binge-watchers.

Normalize Genre Tags: Clean and categorize genre data to unlock deeper personalization via sub-genres (e.g., "Romantic Comedies").

Track Emerging Directors: Many recent releases come from newer talent; monitoring their content performance can guide early partnership opportunities.

Conclusion:

This project demonstrates how structured SQL analysis of Netflix's content library can reveal vital trends and actionable insights. From identifying the ingredients of popular content to recognizing gaps in genre or certification coverage, the study supports a smarter, data-backed approach to content strategy.

By refining the dataset further and integrating more real-time and demographic insights, Netflix (or any OTT platform) can fine-tune its content, boost engagement, and improve long-term customer loyalty—making data not just informative but transformative.