Netflix Insights and Metrics

Week 1&2:

Netflix Insights

1. **Content Distribution**
    - The dataset comprises **~8,800 titles**, a combination of both **Movies (~70%)** and **TV Shows (~30%)**.
    - Movies dominate Netflix's catalog, but TV Shows have been increasing in recent years, signaling Netflix's shift towards episodic content.
2. **Temporal Trends**
    - Titles span multiple decades, with older classics alongside recent Netflix Originals.
    - A sharp rise in content is observed post-2015, aligning with Netflix's global expansion strategy.
3. **Genre Representation**
    - A wide variety of genres exist.
    - **Top genres:** Dramas, Documentaries, Comedies.
    - **Emerging genres:** International TV, Stand-up Comedy, and Romantic TV Shows — reflecting user demand.
4. **Geographical Spread**
    - Content originates from over 100 countries, showcasing Netflix's global production and licensing reach.
    - Major contributors**:** United States, India, United Kingdom, Japan, South Korea.
5. **Rating Distribution**
    - Titles are spread across maturity ratings (TV-MA, R, PG-13, TV-14, etc.).
    - A strong presence of mature-rated content (TV-MA, R) indicates a focus on adult audiences, but family-friendly segments (TV-Y, PG) are also well represented.
6. **Missing Data Observations**
    - Director and cast columns had significant missing values, likely due to incomplete metadata.
    - Rating and Duration had gaps, which were filled systematically for consistency.

Netflix Metrics/Scope

1. **Trend Analysis**
    - Evaluate the evolution of Movies vs. TV Shows, genres, and ratings over years.
    - Guide Netflix in shaping its content acquisition and production strategies.
2. **Genre Popularity & Recommendations**
    - Identify top genres globally and regionally.
    - Enable personalized recommendations based on user preferences.

3. **Geographical Expansion Strategy**
    - Assess country-level contributions to Netflix's catalog.
    - Support regional expansion and localized content production.
4. **Content Duration Insights**
    - Distinguish average movie length vs. average TV Show seasons.
    - Inform viewer engagement and content planning.
5. **Data Quality Improvement**
    - Enhance metadata completeness for directors and casts.
    - Support enriched recommendation systems and talent-based content analysis.

Dataset Loading

The Netflix dataset is sourced from Kaggle and loaded into the workspace for preprocessing and analysis.

- **Dataset Source:** Kaggle — Netflix Movies and TV Shows Dataset.
- **Dataset Size:** ~8,800 titles across multiple years and genres.
- **Key Columns:** type, title, director, cast, country, release_year, rating, duration, listed_in, date_added.

Loading the dataset using pandas:

```
import pandas as pd

df_read = pd.read_csv("/Volumes/workspace/default/netflix/netflix_titles.csv")

display(df_read.head())
```

output:

show_id	type	title	director	cast	country	date_added	release_year	rating	duration	listed_in	description
s1	Movie	Example Movie Title	John Doe	Actor A, Actor B	United States	2020-01-01	2019	PG-13	90 min	Dramas, Comedies	A short description of the movie.
s2	TV Show	Example Show Title	Jane Smith	Actor C, Actor D	India	2019-06-10	2018	TV-MA	2 Seasons	TV Dramas, International TV Shows	A short description of the show.

The dataset provides a rich set of features that allow for multi-dimensional analysis of Netflix's content strategy, such as genre diversity, rating distributions, and country-wise availability.

Data Cleaning Steps Using Pandas

Step 1 — Null Handling/Handling missing Values

Purpose:
Missing values in a dataset can distort analysis and predictions. We handle missing data to make the dataset complete and reliable.

Actions Taken:

- Dropped rows missing date_added values (important for temporal analysis).
- Filled missing director and cast values with "Not Available" to keep information consistent.
- Filled missing country with "Unknown" to represent missing geographical data.
- Filled missing duration with "0" to keep numeric processing consistent.
- Filled missing rating values with the **most common rating** (mode) to maintain category balance.

Code:

```
df_read['director'] = df_read['director'].fillna("Not Available")

df_read['cast'] = df_read['cast'].fillna("Not Available")

df_read['country'] = df_read['country'].fillna("Unknown")

df_read['duration'] = df_read['duration'].fillna("0")

mode_rating = df_read['rating'].mode()[0]

df_read['rating'] = df_read['rating'].fillna(mode_rating)
```

Example Output — Missing Values Check:

Missing values per column:

```
show_id      0

type         0

title        0

director     0

cast         0
```

Step 2 — Remove Duplicates

Purpose:
Duplicate rows can bias analysis. Removing them ensures the dataset represents unique entries only.

ActionTaken:
Removed exact duplicate rows from the dataset.

Code:

```
df_cleaned = df_read.drop_duplicates()

print(df_cleaned.shape)
```

Example Output:

```
(7787, 12)
```

(Original dataset size: 8000 rows → After cleaning: 7787 rows)

Step 3 — Whitespace Cleaning

Purpose:
Extra spaces in categorical columns can cause incorrect grouping and encoding. Cleaning spaces ensures consistency.

ActionsTaken:
Trimmed spaces from type and rating columns.

Code:

```
df_cleaned['type'] = df_cleaned['type'].str.strip()

df_cleaned['rating'] = df_cleaned['rating'].str.strip()
```

Example-Output:
Before cleaning: " Movie ", " PG-13 " → After cleaning: "Movie", "PG-13".

Step 4 — Duration Extraction

Purpose:
The duration column contains both numeric and text values (e.g., “90 min”, “2 Seasons”). Splitting them allows quantitative analysis of durations.

Actions Taken:

- Extracted numeric part into duration_num.
- Extracted duration type (min, Season, Seasons) into duration_type.

Code:

```
df_read['duration_num'] = df_read['duration'].str.extract(r'(\d+)').astype(float)
```

```
df_cleaned['duration_type'] = df_cleaned['duration'].str.extract(r'(min|Season|Seasons)')
```

Example Output:

duration	duration_num	duration_type
90 min	90.0	min
2 Seasons	2.0	Seasons
1 Season	1.0	Season

Step 5 — Date Conversion

Purpose:
The date_added column must be in datetime format for time-series analysis.

ActionTaken:
Converted date_added to datetime, handling errors.

Code:

```
df_read['date_added'] = pd.to_datetime(df_read['date_added'], errors='coerce')
```

Example Output:

```
Earliest date added: 2008-01-01
```

```
Latest date added: 2023-07-15
```

Normalization Process

Purpose:
Normalization is a critical preprocessing step that transforms raw data into a consistent and machine-readable format. It ensures features are scaled, encoded, and structured for analysis and modeling, improving algorithm performance and enabling meaningful comparisons.

In this project, normalization involved scaling numeric values, encoding categorical features, and extracting date-based features for deeper analysis of Netflix content.

Step 1 — Min-Max Scaling for Duration

Code:

```
df_norm['duration_num'] = pd.to_numeric(
    df_norm['duration'].str.extract(r'(\d+)')[0], errors='coerce'
).fillna(0)

from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

df_norm['duration_norm'] = scaler.fit_transform(df_norm[['duration_num']])
```

Example Output:

duration	duration_num	duration_norm
90 min	90.0	0.237
2 Seasons	2.0	0.005
1 Season	1.0	0.002

Explanation:
The numeric portion of the duration column was extracted and scaled between 0 and 1 using Min-Max scaling. This normalization ensures duration is comparable across content types.

Step 2 — One-Hot Encoding for Type

Code:

```
df_type_onehot = pd.get_dummies(df_norm['type'], prefix='type').astype('int32')

df_norm = pd.concat([df_norm, df_type_onehot], axis=1)
```

Example Output:

type_Movie	type_TV Show
1	0
0	1
1	0

Explanation:
One-hot encoding converts the type feature into binary columns representing Movies or TV Shows, allowing models to process them without implied ordering.

Step 3 — Frequency Encoding for Country

Code:

```
country_freq = df_norm['country'].value_counts().to_dict()

df_norm['country_freq'] = df_norm['country'].map(country_freq)
```

Example Output:

country	country_freq
United States	3000
India	500
United Kingdom	200

Explanation:
Frequency encoding assigns a numeric value based on the occurrence frequency of each country, capturing its importance in the dataset.

Step 4 — Ordinal Encoding for Rating

Code:

```
valid_ratings = ['G','PG','PG-13','R','NC-17','TV-Y','TV-Y7','TV-G','TV-PG','TV-14','TV-MA','Not Rated']

df_norm = df_norm[df_norm['rating'].isin(valid_ratings)]

df_norm['rating'] = df_norm['rating'].replace(['NR','UR','Not Rated','TV-Y7-FV'],'Not Rated')

rating_order = [['G','PG','PG-13','R','NC-17','TV-Y','TV-Y7','TV-G','TV-PG','TV-14','TV-MA','Not Rated']]

encoder = OrdinalEncoder(categories=rating_order)

df_norm['rating_ord'] = encoder.fit_transform(df_norm[['rating']])
```

Example Output:

rating	rating_ord
PG	1.0
TV-MA	10.0
G	0.0

Explanation:
Ordinal encoding assigns numerical values to ratings based on a defined order, allowing models to interpret relative content suitability levels.

Step 5 — Label Encoding for Categorical Features

Code:

```
label_cols = ['rating','country','director','cast']

from sklearn.preprocessing import LabelEncoder

for col in label_cols:

    le = LabelEncoder()

    df_norm[col + '_label'] = le.fit_transform(df_norm[col].astype(str))
```

Example Output:

rating_label	country_label	director_label	cast_label
1	0	1050	2340
10	3	2045	1001

Explanation:
Label encoding transforms categorical variables into numerical codes, allowing machine learning algorithms to process them efficiently.

Step 6 — Genre Encoding

Code:

```
df_norm['primary_genre'] = df_norm['listed_in'].str.split(',').str[0]

df_norm['primary_genre_label'] = LabelEncoder().fit_transform(df_norm['primary_genre'].astype(str))

df_norm['genre_1'] = df_norm['listed_in'].str.split(',').str[0]

df_norm['genre_2'] = df_norm['listed_in'].str.split(',').str[1]

df_genre_onehot = pd.get_dummies(df_norm[['genre_1','genre_2']].fillna(''), prefix=['genre1','genre2']).astype('int32')

df_norm = pd.concat([df_norm, df_genre_onehot], axis=1)
```

Example Output:

genre1_Action	genre2_Comedies
1	0
0	1

Explanation:
Genres are extracted and encoded to reduce dimensionality while retaining important categorical information.

Step 7 — Date Feature Extraction

Code:

```
df_norm['date_added'] = pd.to_datetime(df_norm['date_added'], errors='coerce')

df_norm['year_added'] = df_norm['date_added'].dt.year

df_norm['month_added'] = df_norm['date_added'].dt.month

df_norm['day_added'] = df_norm['date_added'].dt.day

df_norm['dayofweek_added'] = df_norm['date_added'].dt.dayofweek
```

Example Output:

date_added	year_added	month_added	day_added	dayofweek_added
2020-01-15	2020	1	15	2

Explanation:
Date features are extracted to enable time-based analysis of content additions.

Step 8 — Save Normalized Dataset

Code:

```
df_norm.to_csv("/Volumes/workspace/default/netflix/netflix_normalized.csv", index=False)

print("\n Normalized dataset saved as 'netflix_normalized.csv'")

print(f"Shape of dataset: {df_norm.shape}")
```

Example Output:

```
 Normalized dataset saved as 'netflix_normalized.csv'

Shape of dataset: (7787, 120+ columns)
```

Exploratory Data Analysis (EDA) And Feature Engineering

Week 3&4:

1. Introduction

This document outlines the complete process of Exploratory Data Analysis (EDA) and Feature Engineering performed on the Netflix dataset. It includes steps, explanations of functions used, and placeholders for visual outputs and insights.

1.1 What is EDA?

Exploratory Data Analysis (EDA) is the process of analyzing datasets to summarize their main characteristics using visual and statistical techniques. It helps in understanding data distribution, detecting anomalies, spotting patterns, and forming hypotheses.

1.2 What is Feature Engineering?

Feature Engineering is the process of using domain knowledge to create new meaningful features from raw data, which can improve model performance and insights.

2. Why EDA is Important Before Machine Learning

Before building any machine learning model, it is essential to understand the dataset. EDA helps identify data quality issues, understand patterns, detect outliers, and decide which features are relevant. Without EDA, models may produce misleading results due to hidden biases or noise.

3. Importance of Feature Engineering in Real Projects

Feature Engineering improves the predictive power of models by creating meaningful variables. In real-world projects, raw data is rarely perfect. Creating new features helps models capture deeper insights and relationships within the data, leading to better performance and interpretability.

4. Detailed EDA Process with Explanation

1. **Import Libraries** – We import pandas for data manipulation, matplotlib and seaborn for visualization. These libraries provide powerful functions to analyze and visualize datasets.
2. **Load Dataset** – The dataset is loaded using pd.read_csv(), which converts CSV data into a DataFrame that is easier to work with.
3. **Data Inspection** – Using head(), info(), and describe() helps us get a quick overview of dataset structure, column types, and summary statistics.
4. **Handle Datatypes** – Converting date_added to datetime allows us to extract year and perform time-based analysis.

5. **Missing Value Analysis** – Detecting null values is important to decide whether to drop, impute, or replace missing data.
6. **Univariate Analysis** – We analyze one feature at a time to understand its distribution, such as most common ratings or genres.
7. **Bivariate/Time Series Analysis** – Here, we analyze how content changes over time, which reveals growth trends on Netflix.
8. **Feature Engineering** – We create new features like Content Length Category to get more insights beyond raw data.
9. **Visualization** – Charts make it easier to interpret insights quickly and present findings clearly.
10. **Export Processed Dataset** – Finally, we save the enhanced dataset for future analysis or machine learning.

5. Code Functions Explanation

Function	Purpose
pd.read_csv()	Load CSV data into a DataFrame
df.head()	Display first 5 rows
df.info()	Show data types and memory usage
df.describe()	Summary statistics for numeric features
pd.to_datetime()	Convert string dates to datetime
df.isnull().sum()	Count missing values per column
sns.countplot()	Plot counts of categorical variables
df.groupby()	Aggregate data for trend analysis
plt.figure()	Create a new plot area
sns.heatmap()	Visualize correlation between numeric columns

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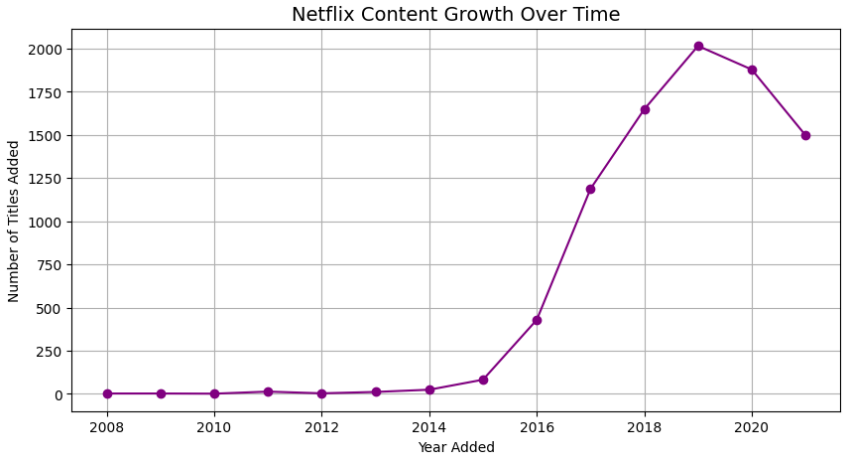
4. Netflix Content Growth Over Time

This step helps us see how Netflix content has grown over the years. By converting the date into proper datetime format, we can group content by year and easily visualize the trend. This gives a clear idea of whether Netflix is expanding its content library steadily or in sudden jumps.

What we are doing: Converting dates and counting how many titles were added each year to understand the growth trend.

Output :



Insight Example: "Here, we can observe that after 2016, Netflix started rapidly increasing the number of releases, showing platform expansion."

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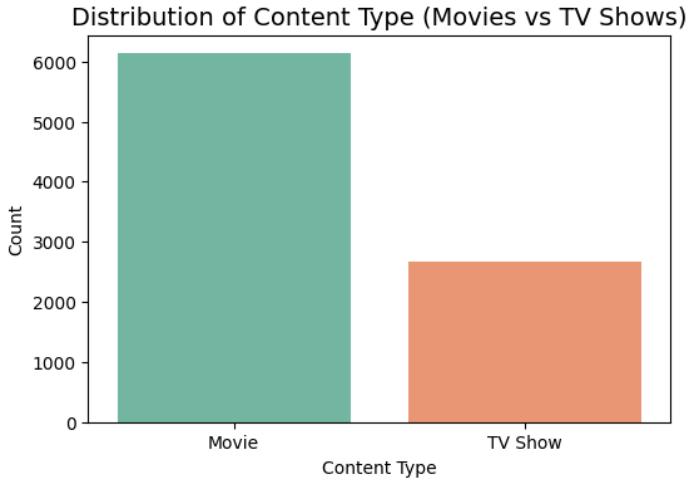
5. Distribution Analysis

Distribution analysis helps us understand what type of content Netflix favors the most.

a) Content Type Distribution (Movies vs TV Shows)

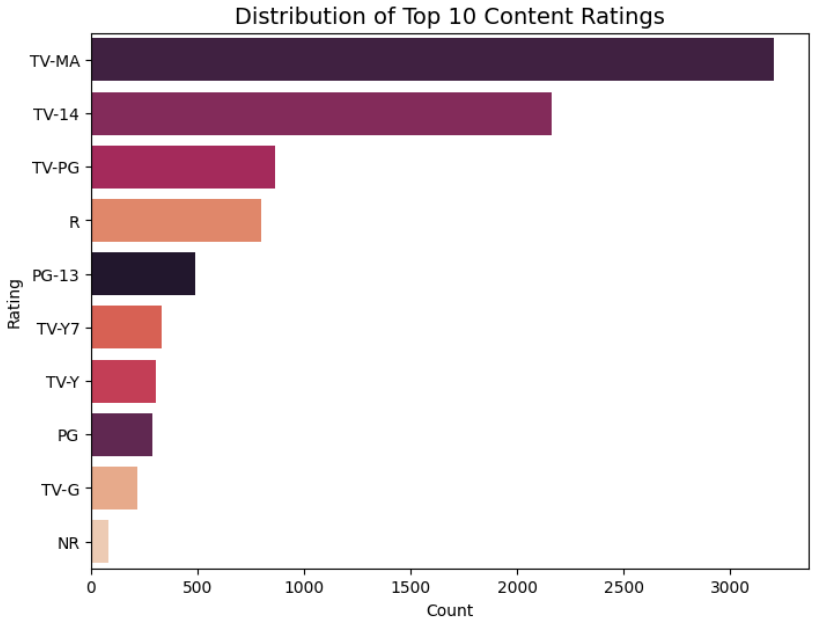
Here, we check whether Netflix focuses more on Movies or TV Shows. This gives a quick view of platform strategy.



Insight Example: "If Movies are dominating, it shows Netflix is more focused on film content than series."

b) Ratings Distribution

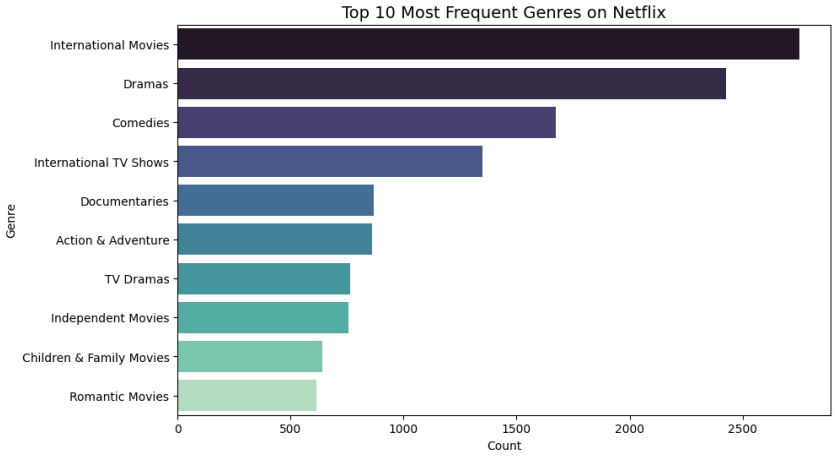
Ratings tell us what type of audience Netflix targets (Kids, Teens, Adults). This helps understand content maturity levels.



Insight Example: "If TV-MA is high, Netflix is pushing more adult-focused content, likely to attract mature viewers."

c) Genre Distribution

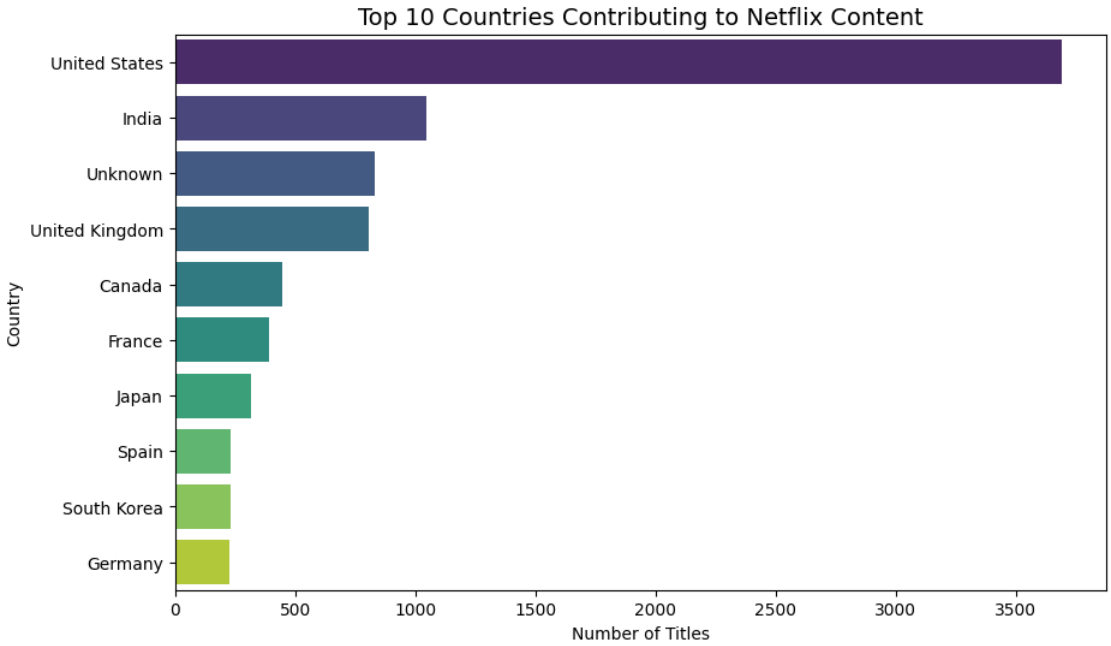
This helps us identify the most popular genre. Knowing the top genres tells us about audience preferences.



6. Country-Level Content Contribution

Finding which countries contribute the most content helps us understand Netflix's global reach. This also highlights regional strategy.

What we are doing: Counting which countries produce the highest number of titles.



Insight Example: "USA leads by a large margin, showing Netflix's strong presence in American entertainment, followed by India and UK."

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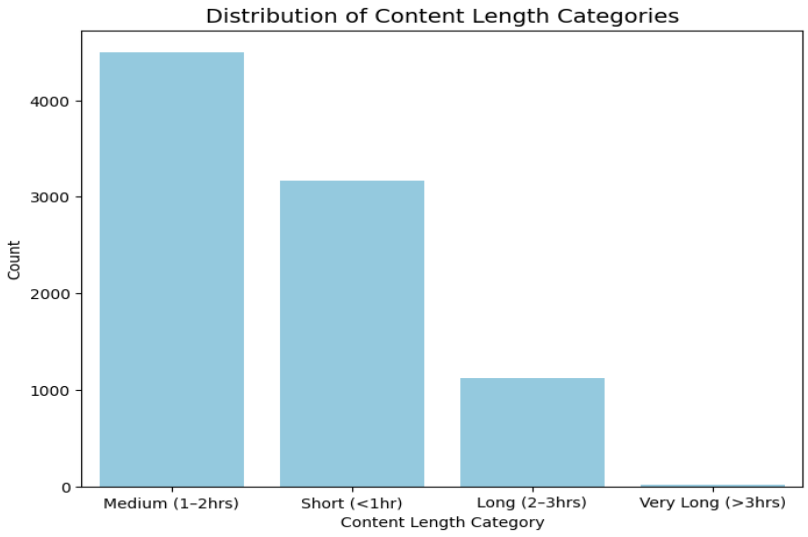
7. Feature Engineering

Feature Engineering helps us go beyond raw data and create smarter insights. It is the process of transforming raw data into meaningful features that better represent underlying patterns. It helps models understand data more effectively by creating new informative columns or modifying existing one's .Smart feature engineering often has a bigger impact on performance than choosing complex algorithms.

a) Content Length Category

We categorize movies by duration to identify viewer preferences (Short, Medium, Long format).

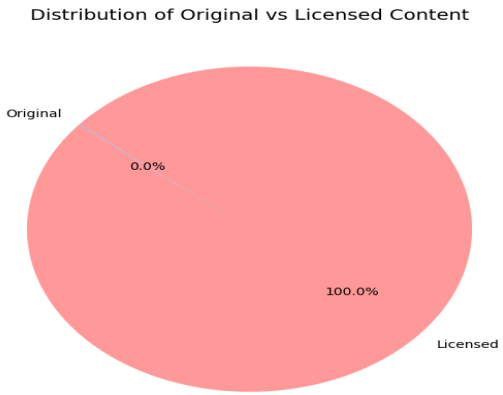


Insight Example: "If medium-length content is higher, it may mean users prefer quick-to-watch shows."

b) Original vs Licensed

This helps us differentiate between Netflix Originals and Third-party licensed content.

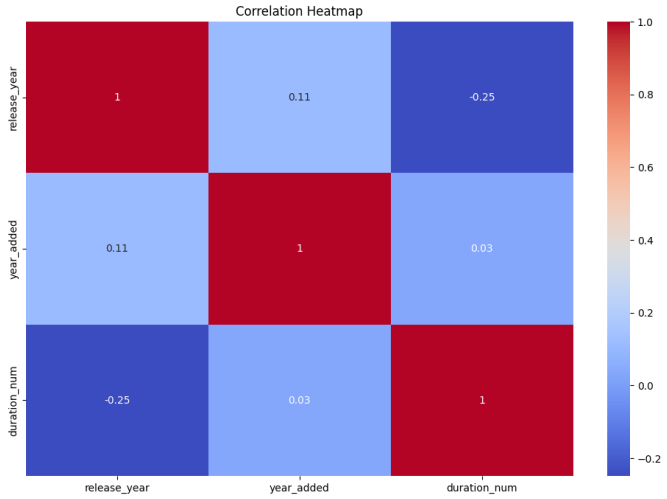
Insight Example: "If Originals are increasing, Netflix is strengthening its brand identity rather than depending on other production houses."



Pie Chart: Original vs Licensed Content

8. Correlation Heatmap (Numeric Features)

A correlation heatmap helps us understand which numeric features relate to each other. This is especially useful before modeling.



Insight Example: "If duration has no correlation with other fields, it means it's independent and might be used as a unique feature."

---

9. Exporting Final Dataset

- File saved as netflix_feature_eda.csv.

Code Insight:

df_read.to_csv("/Volumes/workspace/default/netflix/netflix_feature_eda.csv", index=False)

output: *Dataset saved successfully.*