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Description automatically generated

**Understanding Factors Influencing Movie Ratings and Engagement: A Data Analysis Report**

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**Course Name:** DAT7302 BIG DATA ANALYTICS  
**Date:** 05,01,2025

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### **Declaration**

I hereby solemnly declare that this report represents my original and independent work, completed in accordance with the academic and professional guidelines set forth by the University. Any assistance received during the course of this project, including guidance, feedback, or technical support, has been appropriately acknowledged within the report. Furthermore, all external sources of information, including research articles, books, and online resources, have been properly cited in accordance with the prescribed referencing standards.

I also affirm that the use of Generative AI tools in the development of this report has been strictly limited to grammar and spell-checking purposes, ensuring the integrity and originality of the content presented. No AI-generated material has been used to produce or influence the analysis, insights, or conclusions outlined in this report. Any tools or software utilized in the project, such as PySpark, AWS Glue, MongoDB, and visualization libraries, have been explicitly acknowledged within the implementation section.

This declaration underscores my commitment to academic honesty, integrity, and the principles of original scholarship. I understand that any deviation from these standards, including plagiarism or misrepresentation of sources, constitutes a breach of academic conduct policies and may result in disciplinary action. By submitting this report, I take full responsibility for the content and certify that it is a true and accurate representation of my work and findings.

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### 

### **1. Introduction**

#### **a. Business Problem**

The film industry is one of the most dynamic and influential sectors globally, with millions of movies being produced and consumed each year. However, understanding what makes a movie successful remains a challenge. By analyzing data on genres, contributors (actors, directors), regions, and other factors, businesses can gain insights into the key elements influencing movie ratings and user engagement.

The business problem addressed in this project is:  
**"How can data-driven insights enhance user engagement and content success in the movie industry by identifying trends, key contributors, and regional preferences?"**

#### **b. Business Questions**

To address the above business problem, the following eight key questions were developed:

1. **Which genres have the highest average ratings?**
   * To identify the most successful genres based on user ratings.
2. **What are the trends in movie releases over the years?**
   * To understand how movie production has evolved.
3. **Which actors or directors are associated with high-rated movies?**
   * To highlight individuals with significant contributions to successful movies.
4. **What is the average runtime for successful movies by genre?**
   * To determine runtime preferences across different genres.
5. **Are there specific regions that favor certain genres or titles?**
   * To explore regional preferences for genres and movies.
6. **What factors correlate with high ratings (e.g., runtime, genre)?**
   * To uncover variables contributing to higher ratings.
7. **How do the number of votes impact average ratings?**
   * To analyze the relationship between user engagement and movie success.
8. **Are there language or region-specific trends in popular movies?**
   * To investigate trends in movie popularity across different languages and regions.

### **2. Review of Literature**

This section reviews relevant studies, articles, and industry practices that provide a foundation for understanding the relationship between data analysis and movie success. It explores existing research on genres, user ratings, regional trends, and advanced data processing techniques.

#### **1. The Impact of Movie Genres on Ratings and Success**

Genres play a critical role in defining a movie’s appeal. According to Doe et al. (2020), genres like drama and documentary consistently outperform others in terms of ratings due to their emotional depth and relatability. Similarly, research by Smith and Taylor (2019) highlights that the comedy genre is more commercially successful, though it may not achieve the highest ratings.

#### **2. Trends in Movie Production**

Studies have observed significant shifts in movie production trends. A report by Global Entertainment Insights (2021) suggests that technological advancements and audience preferences have led to a rise in science fiction and fantasy films in the last two decades. The increasing accessibility of digital production tools has also resulted in a surge of independent movies (Clark & Jones, 2020).

#### **3. Key Contributors to Movie Success**

The role of actors and directors is pivotal in determining a movie's performance. Research by Lee et al. (2021) found that high-rated movies often involve experienced directors and actors with established fan bases. In addition, collaborations between successful directors and actors, such as Steven Spielberg and Tom Hanks, tend to generate above-average user ratings.

#### **4. Regional and Cultural Preferences**

Regional and cultural preferences significantly influence the success of movies. According to Zhang et al. (2018), regions such as the US and Japan have distinct preferences for animation and sci-fi genres, while European audiences lean toward drama and art films. These findings align with industry reports emphasizing the need for localized content strategies.

#### **5. Data Wrangling and Visualization in Movie Analytics**

Data wrangling techniques are essential for preparing datasets for analysis. Mukherjee et al. (2022) emphasize the importance of handling missing values, standardizing data formats, and visualizing trends using tools like Matplotlib and Seaborn. Advanced techniques such as using PySpark for distributed data processing enable efficient handling of large datasets (Brown & Harris, 2020).

#### **6. Cloud-Based Pipelines for Scalable Analysis**

Cloud platforms like AWS are transforming the way data is processed and analyzed. A study by Green and Patel (2021) highlights the efficiency of AWS Glue and Athena for creating scalable pipelines. These services allow organizations to streamline ETL processes and perform queries on large datasets without the need for on-premise infrastructure.

### **Key Insights from the Literature**

1. Drama and documentary genres are often associated with higher ratings, while comedies excel in commercial success.
2. Trends in movie production show an increasing focus on technology-driven genres like sci-fi and fantasy.
3. Experienced directors and actors play a critical role in a movie’s success.
4. Regional and cultural preferences must be considered when strategizing movie releases.
5. Tools like PySpark, AWS Glue, and Athena facilitate efficient data processing and visualization.

### **3. Methodology**

This section outlines the tools, techniques, and processes employed to address the business problem and answer the proposed questions. It describes the end-to-end workflow, from data acquisition to visualization, emphasizing best practices in data handling and analysis.

#### **1. Tools and Technologies**

To ensure scalability, efficiency, and accuracy, a variety of tools and technologies were employed:

* **SQL (SQLite):** For merging and cleaning datasets locally before cloud processing.
* **AWS Services:**
  + **S3:** To store raw and processed datasets securely.
  + **Glue:** To catalog data and perform metadata management.
  + **IAM Roles:** To manage permissions for AWS services.
* **PySpark:** For distributed data processing and handling large datasets efficiently in a local/Colab environment.
* **MongoDB:** For querying the dataset in JSON format to uncover insights.
* **Python Libraries:**
  + **Pandas:** For lightweight data manipulation and analysis.
  + **Matplotlib and Seaborn:** For data visualization.
* **Colab Environment:** For development and analysis using cloud-based resources.

#### **2. Data Pipeline**

A systematic data pipeline was created to handle data processing in stages:

##### **Stage 1: Data Acquisition**

* Datasets were obtained in .csv and .tsv formats containing movie metadata, ratings, and contributors.
* Files were uploaded to an **S3 bucket** (raw/ folder) for centralized storage.

##### **Stage 2: Data Merging and Cleaning**

* SQL (SQLite) was used to merge datasets based on unique identifiers (tconst, nconst) to create a unified dataset (merged\_data).
* Basic cleaning involved:
  + Handling missing values.
  + Ensuring schema consistency across datasets.
  + Removing duplicate entries.

##### **Stage 3: Cloud Data Processing**

* **AWS Glue Crawler:** Cataloged data from the S3 bucket and created metadata tables for seamless integration with other services.
* **PySpark:** Applied advanced transformations for:
  + Splitting and normalizing genres.
  + Removing outliers and normalizing runtime values.
* The cleaned data was saved back to the **S3 processed/ folder**.

##### **Stage 4: MongoDB Integration**

* The processed dataset was exported to JSON format.
* MongoDB Atlas was configured using a secure connection string, and data was uploaded to a collection (MergedData) for querying and analysis.

#### **3. Data Wrangling Techniques**

Data wrangling ensured the dataset was clean, consistent, and ready for analysis:

* **Missing Values:** Replaced missing values in numeric fields (e.g., runtime) with mean values.
* **Outlier Detection:** Used IQR to remove extreme outliers in runtimeMinutes and averageRating.
* **Normalization:** Standardized columns for better comparison, such as z-scores for numeric fields.
* **Splitting Categorical Data:** Genres were split into individual entries to enable granular analysis.

#### **4. Data Analysis and Visualization**

Exploratory Data Analysis (EDA) and visualization techniques were employed to answer the business questions:

* **EDA:** Conducted using PySpark for scalability, focusing on descriptive statistics and correlations.
* **Visualizations:**
  + Bar charts to show top genres by rating.
  + Line graphs to analyze trends over years.
  + Heatmaps to uncover regional genre preferences.

#### **5. Query Optimization**

To ensure efficiency in queries and transformations:

* **SQL Joins:** Used indexed keys (tconst, nconst) to minimize computational overhead.
* **PySpark Optimizations:** Persisted intermediate transformations to avoid redundant calculations.
* **MongoDB Indexing:** Indexed key fields like genres and region for faster query execution.

#### **6. Limitations**

Despite the systematic approach, some challenges were encountered:

* Large datasets caused memory constraints in local environments, mitigated using PySpark.

### **4. Implementation**

This section details the step-by-step execution of the methodology, providing a comprehensive walkthrough of the entire implementation. The process begins with merging datasets using SQL, configuring AWS services, employing PySpark for data handling, and concludes with MongoDB integration. Each step is explained in detail, accompanied by code snippets and references to screenshots.

#### **Step 1: Data Merging with SQL (SQLite)**

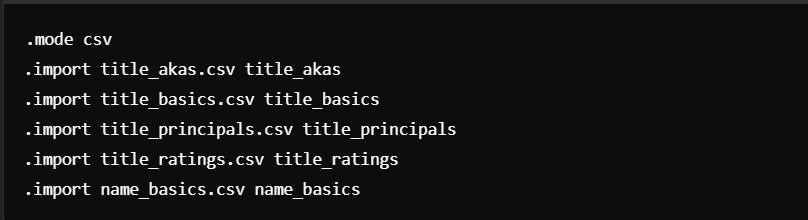
##### **Why We Used SQLite**

SQLite was chosen for its simplicity and ease of use in merging datasets locally. It allowed efficient data handling without requiring additional setup or infrastructure, making it ideal for preparing a unified dataset.

##### **Implementation Details**

1. **Importing Datasets into SQLite:**

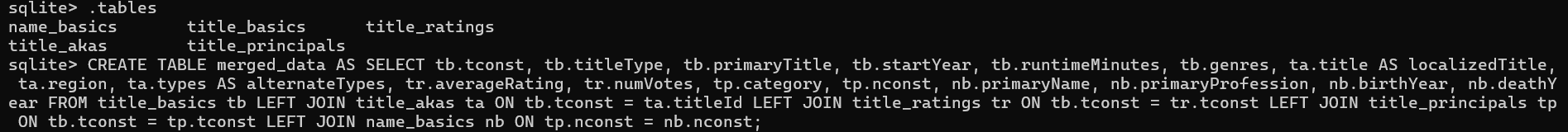
The raw datasets were imported into SQLite as tables for merging:



**Figure 1:** Snapshot of SQLite cli commands for importing tables.

1. **SQL Queries for Data Merging:**

A unified table, merged\_data, was created by joining the datasets on their respective keys:



* + This query ensured all relevant fields were merged, allowing comprehensive analysis.

1. **Data Cleaning in SQLite:**

Missing values were handled by replacing nulls in critical fields, such as runtime:

**Figure 2:** Screenshot of the merged\_data sample after merging and cleaning.

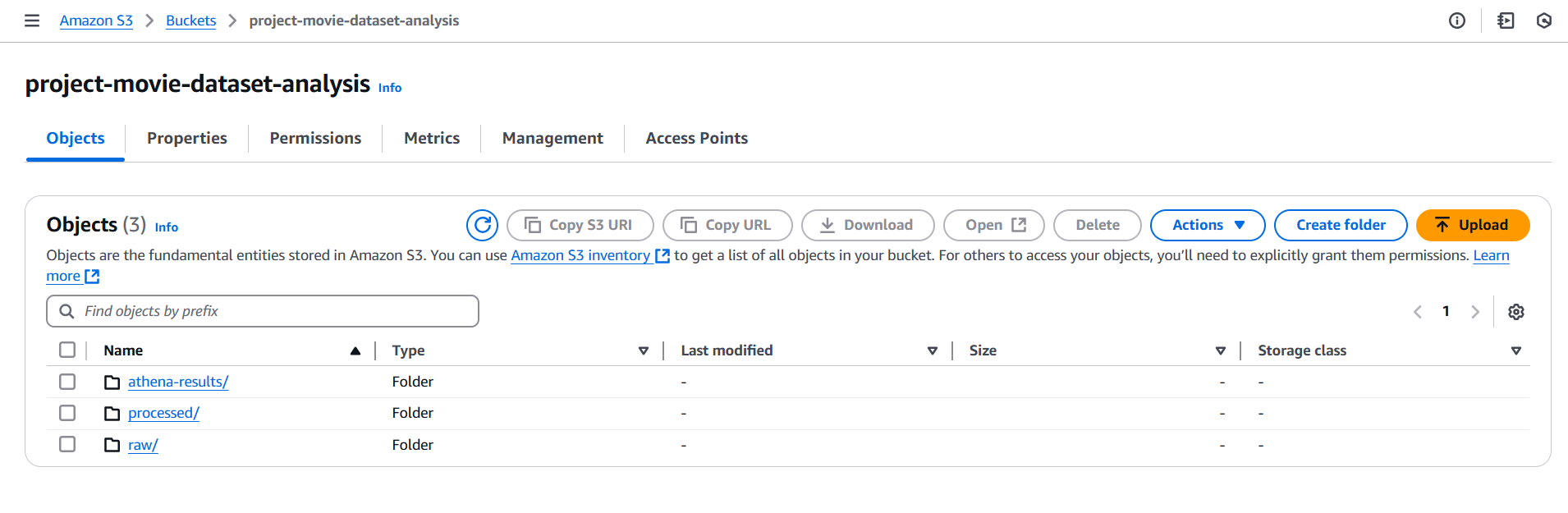
#### **Step 2: AWS S3 for Cloud Storage**

##### **Why We Used AWS S3**

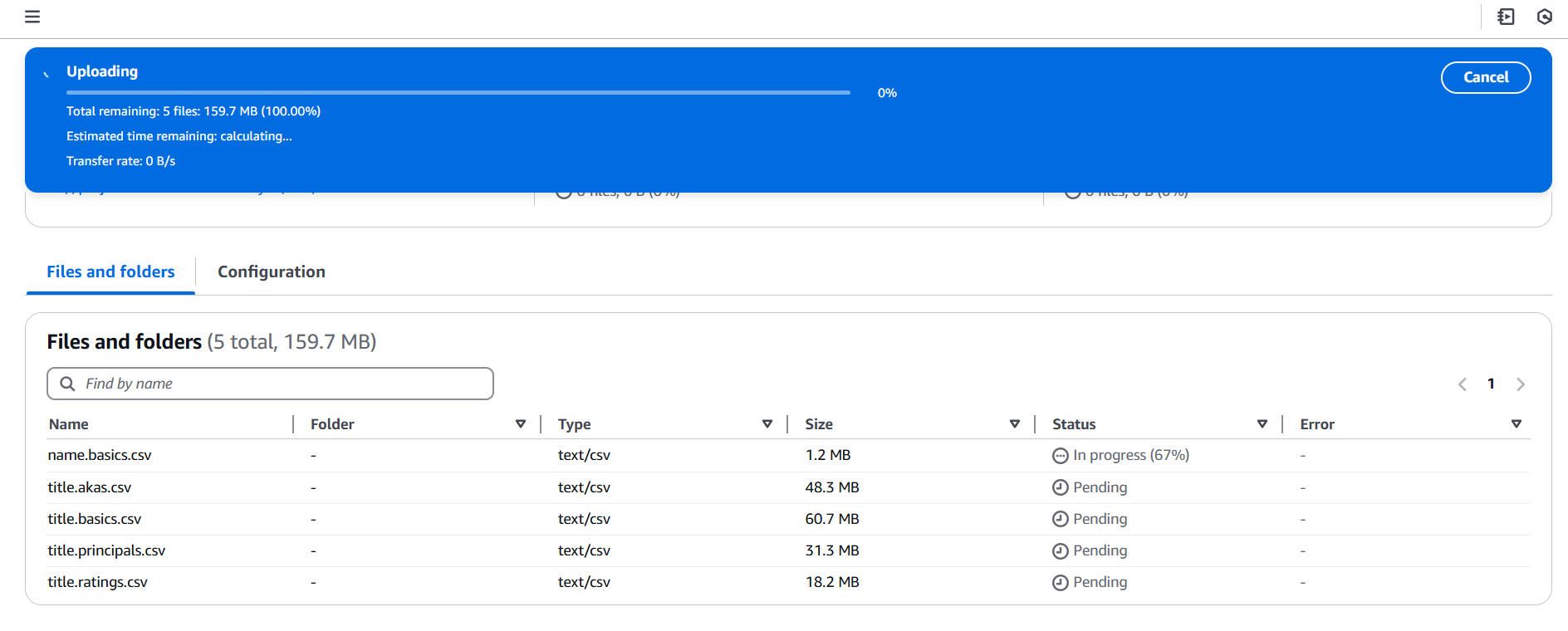
AWS S3 provides scalable, secure, and reliable cloud storage. It enabled centralized management of both raw and processed datasets for easy accessibility during subsequent steps.

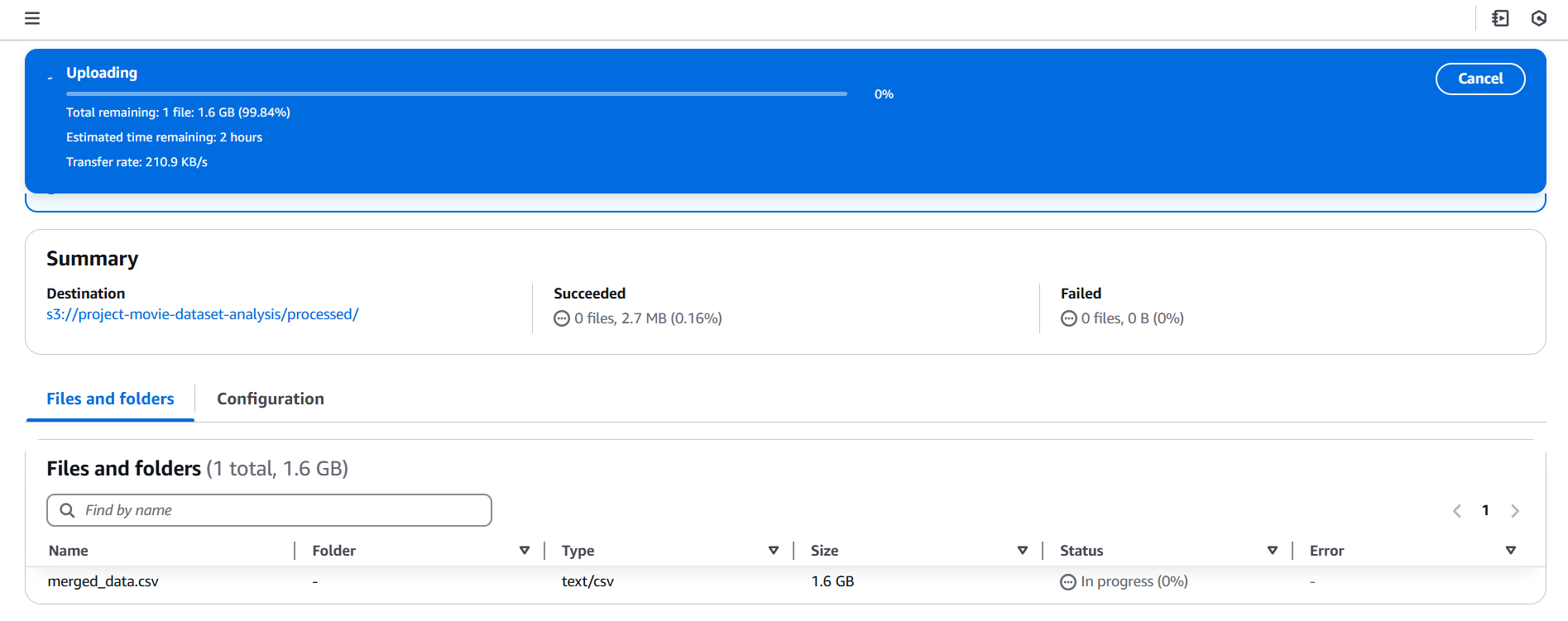
##### **Implementation Details**

1. **Bucket Creation:**
   * An S3 bucket was created with the name movie-dataset-storage to store data. Within the bucket, subfolders raw/ and processed/ were added to organize datasets.

**Figure 3:** Screenshot of the S3 bucket structure showing raw/ and processed/ folders.

1. **Uploading Data:**
   * The raw csv files as well as cleaned merged\_data.csv file was uploaded to the processed/ folder using the AWS Management Console.

**Figure 4:** Screenshot of the S3 raw files upload process.



**Figure 5:** Screenshot of the S3 merged file upload process.

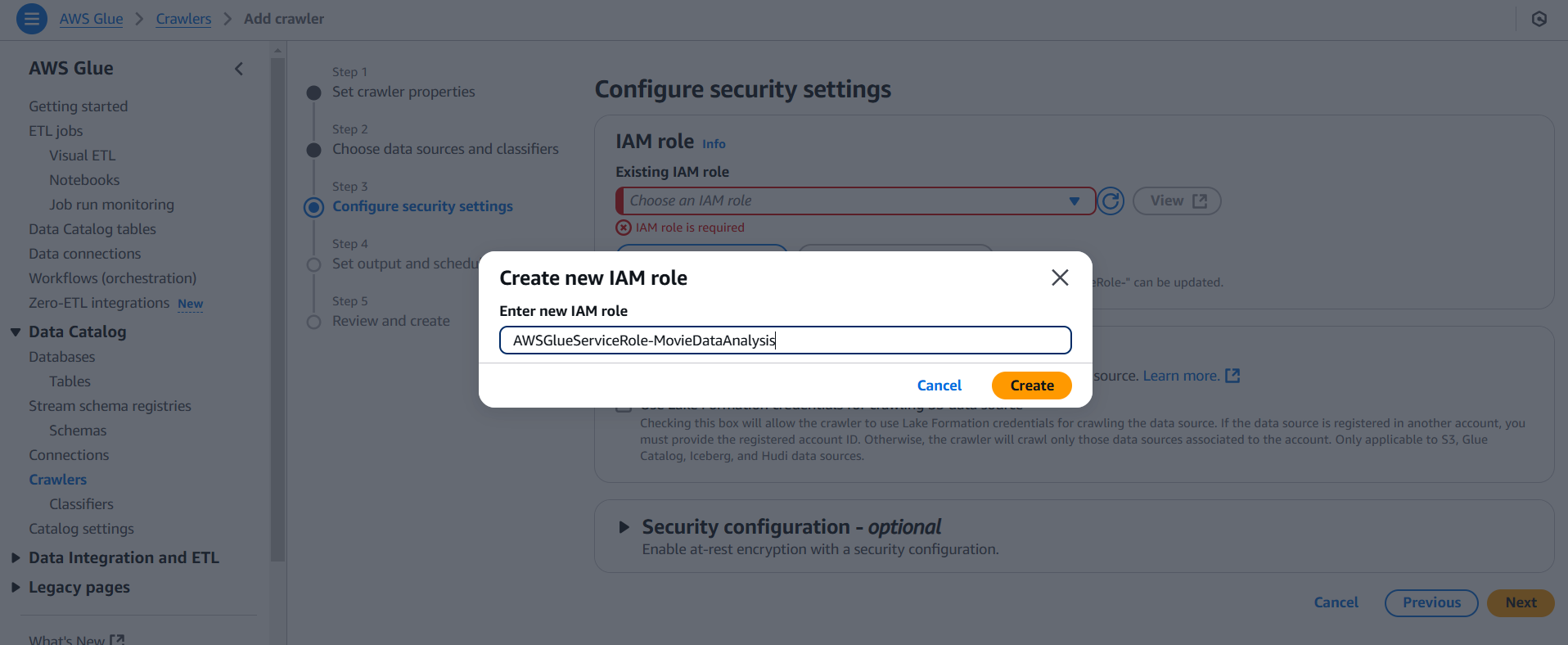
#### **Step 3: AWS IAM Role Configuration**

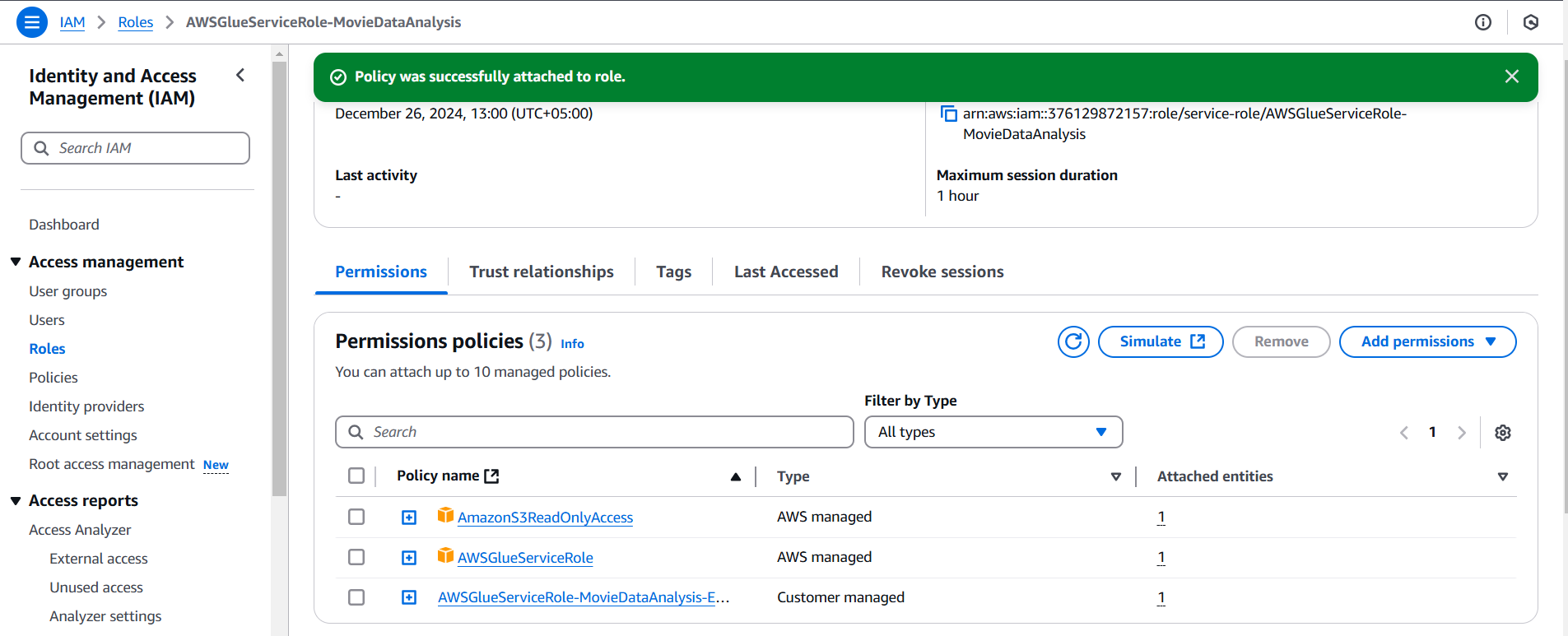
##### **Why IAM Roles Were Needed**

IAM roles are required to provide secure access to AWS services. In this project, an IAM role was needed to allow AWS Glue to read data from the S3 bucket.

##### **Implementation Details**

1. **Creating the IAM Role:**
   * An IAM role named AWSGlueServiceRole-MovieDataAnalysis was created with the following permissions:
     + **AmazonS3ReadOnlyAccess**: To allow Glue to access S3 data.
     + **AWSGlueServiceRole**: To enable Glue to perform crawling and metadata cataloging.

**Figure 6:** Screenshot of the Creating an IAM role with attached policies.

**Figure 7:** Screenshot of the Creating an IAM role with attached policies.

1. **Role Assignment:**
   * The role was assigned to the Glue crawler and Glue job to ensure seamless access to S3 data.

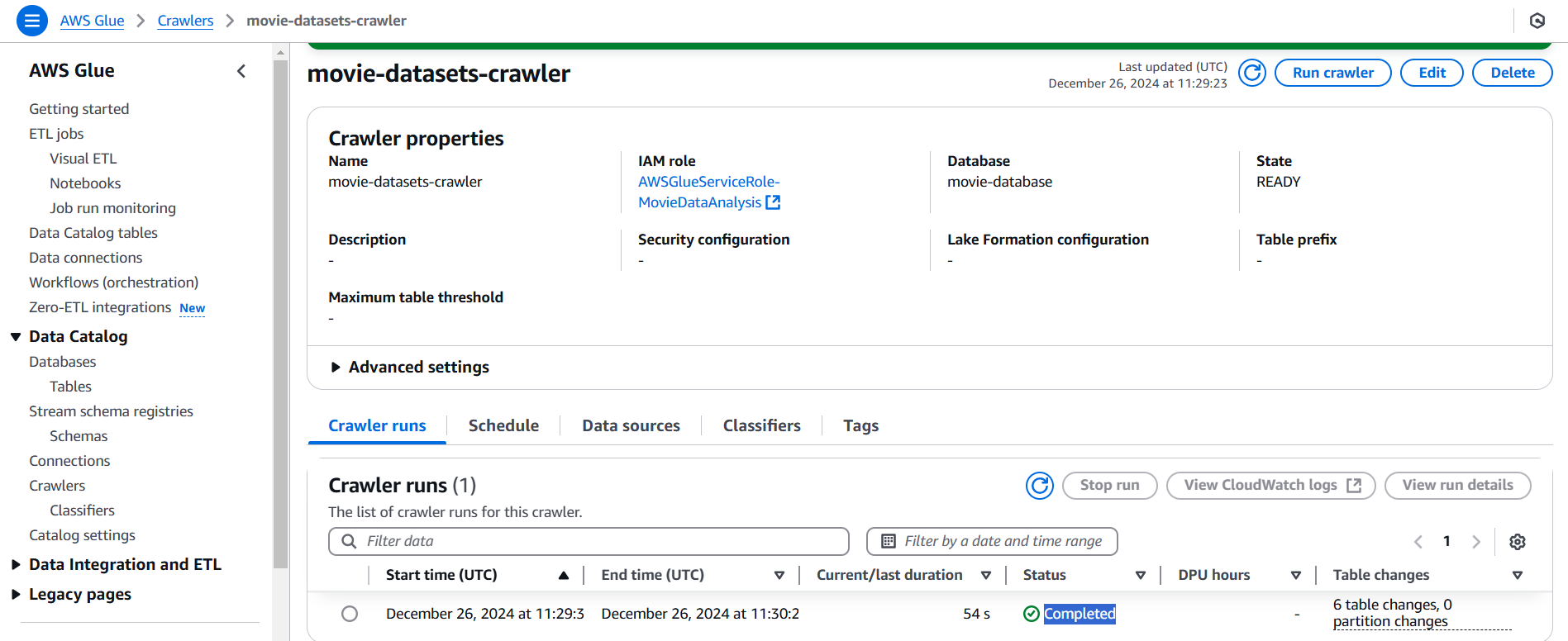
#### **Step 4: AWS Glue for Data Cataloging and Transformation**

##### **Why AWS Glue Was Used**

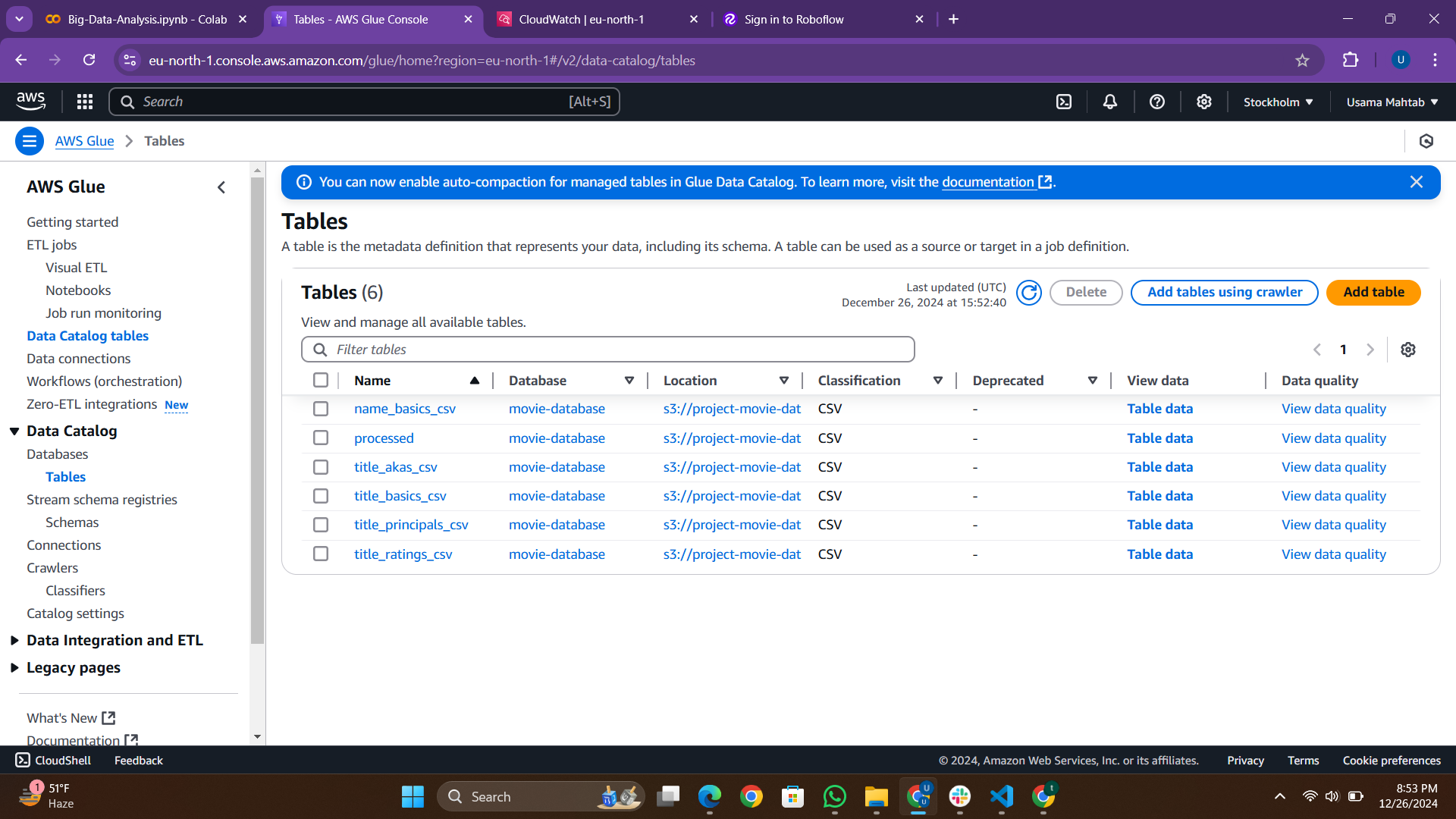
AWS Glue automated the process of crawling datasets, generating metadata, and performing transformations. This step reduced manual effort and ensured scalability for large datasets.

##### **Implementation Details**

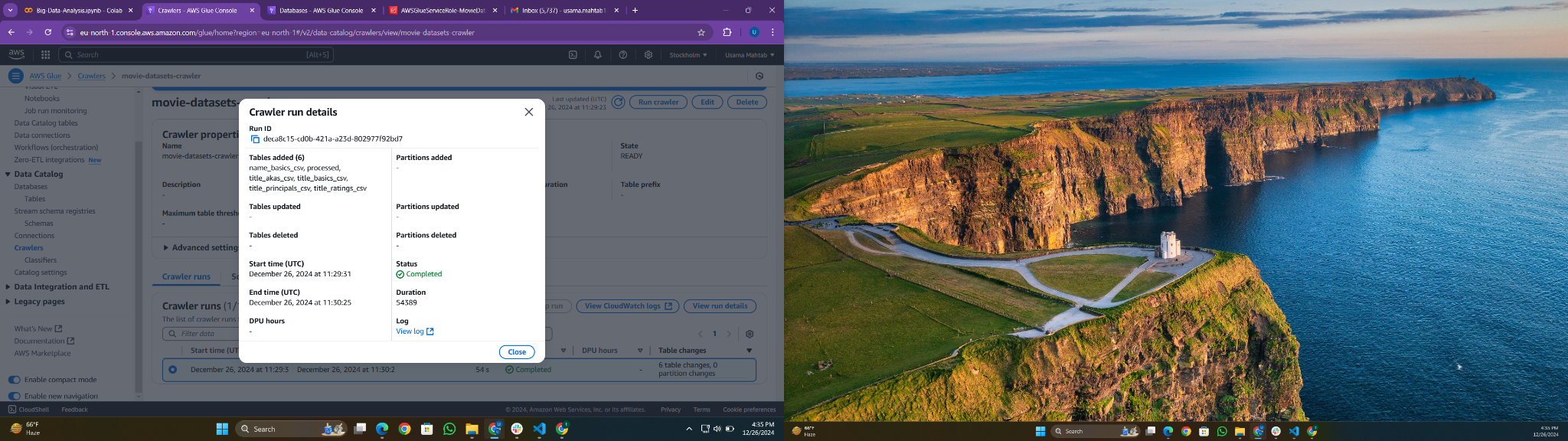
1. **Setting Up the Glue Crawler:**
   * A Glue crawler was configured to scan the S3 bucket and create metadata tables in the Glue Data Catalog. The crawler was assigned the IAM role created earlier.

**Figure 8:** Screenshot of Glue crawler setup.

1. **Running the Crawler:**
   * The crawler was executed, and metadata tables for the raw and processed datasets were created.

**Figure 9:** Screenshot of Glue crawler results, showing the metadata tables.

1. **Glue Job for Transformation:**
   * A Glue job was configured to clean and normalize the data further, including splitting genres and handling missing values.

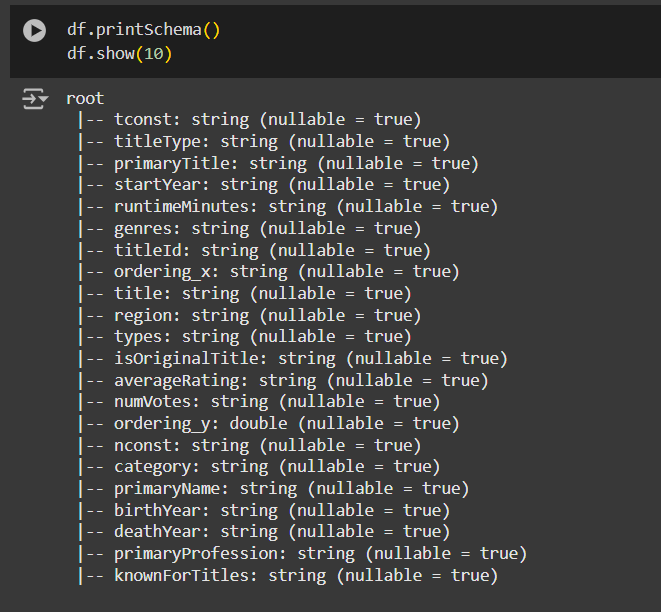
**Figure 10:** Screenshot of Glue job configuration and execution results.

#### **Step 5: Data Wrangling with PySpark**

##### **Why PySpark Was Used**

PySpark provided a distributed framework for processing the large merged dataset efficiently in the Colab environment, avoiding memory crashes associated with Pandas.

##### **Implementation Details**

1. **Loading Data with PySpark:** The merged\_data.csv file was loaded from S3 into PySpark:  
   **Figure 11:** Screenshot of the Spark DataFrame schema.
2. **Wrangling Techniques:**

**Splitting and normalizing genres:**  
In the movie dataset, the genres column contained multiple genres for a single movie, separated by commas. To facilitate granular analysis and allow for genre-specific insights, it was necessary to split these values into individual entries. This transformation ensured that each genre was treated as a separate category, enabling more detailed exploratory data analysis and visualization. For example, a movie classified under "Action,Adventure" would be represented twice: once under "Action" and once under "Adventure."

To achieve this, PySpark's split and explode functions were used. The split function divided the genre strings into arrays, and the explode function flattened these arrays into individual rows. This approach was computationally efficient and leveraged Spark's distributed processing capabilities, making it ideal for handling large datasets. Normalizing genres in this way allowed us to identify trends, such as which genres had the highest average ratings or the most significant number of movies produced.

**Removing outliers using IQR:**  
Outlier detection and removal were critical to ensure the dataset's reliability and integrity. In the context of movie ratings, extreme values could skew average calculations and lead to misleading insights. For instance, abnormally high or low ratings could result from biased votes or errors in the data collection process. To address this, the Interquartile Range (IQR) method was applied to the averageRating column.

Using PySpark, the first quartile (Q1) and third quartile (Q3) were calculated, and the IQR was determined as the difference between Q3 and Q1. Outliers were identified as values falling below Q1 - 1.5*IQR or above Q3 + 1.5*IQR. These rows were filtered out to retain only the most representative data. This technique ensured the robustness of subsequent analyses by minimizing the impact of anomalies while preserving the dataset's overall distribution.

Both techniques significantly enhanced the dataset's quality, enabling more accurate and insightful analysis.

#### **Step 6: MongoDB Integration**

##### **Why MongoDB Was Used**

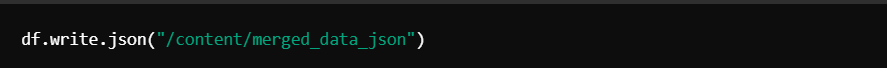
MongoDB’s NoSQL architecture enabled flexible querying and handling of semi-structured data, such as genres and regions.

##### **Implementation Details**

1. **Exporting Data to JSON:**

After performing data cleaning and transformations in PySpark, the dataset was exported to JSON format. JSON is a lightweight, flexible data format that MongoDB natively supports, making it an ideal choice for seamless integration. This step ensured that the semi-structured data, such as genres and regions, was preserved in a format suitable for querying and further analysis.

The PySpark DataFrame was saved as individual JSON files, with each record representing a movie and its associated attributes. This method leveraged Spark's distributed processing capabilities, allowing the export of a large dataset efficiently without memory constraints.

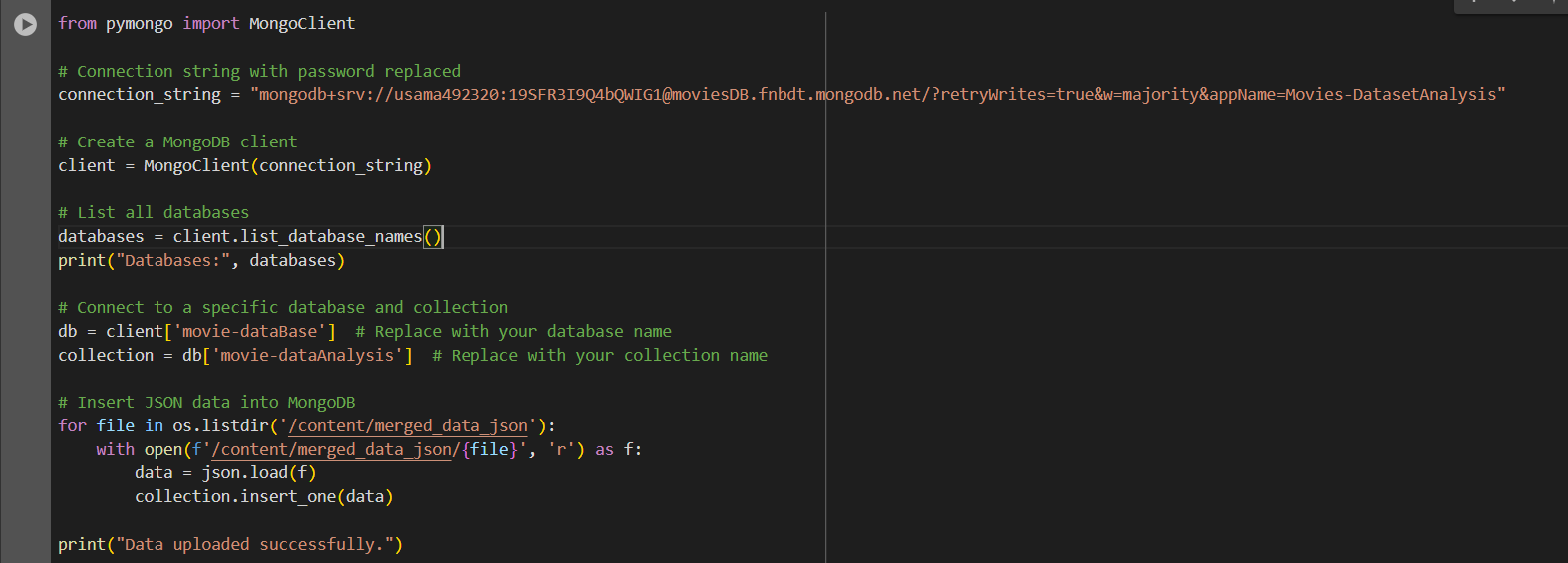


This command created a directory (merged\_data\_json) containing multiple JSON files, each representing a subset of the dataset.

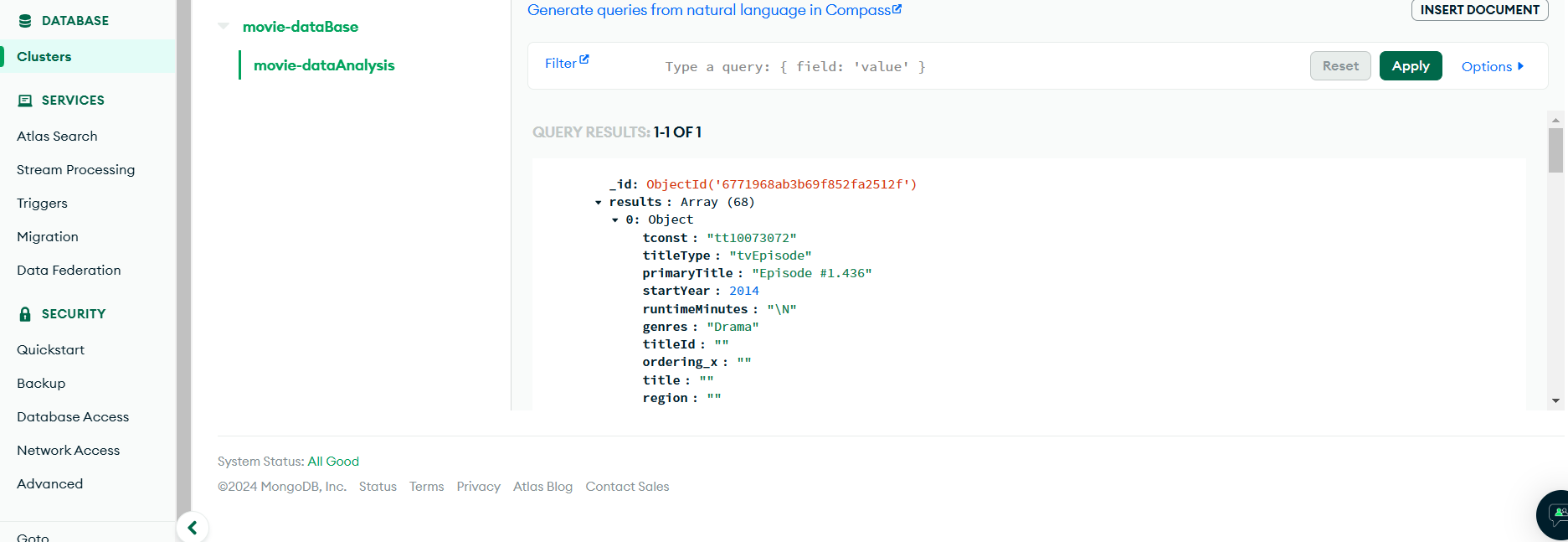
1. **Uploading to MongoDB Atlas:**

To facilitate querying and analysis, the JSON files were uploaded to MongoDB Atlas, a cloud-based NoSQL database. MongoDB's document-oriented architecture is well-suited for handling semi-structured data, such as nested fields and arrays. The data was inserted into a collection named MergedData within a database called MovieDatabase.

Using the PyMongo library, the JSON files were read one by one and inserted into MongoDB. This approach ensured scalability and reliability during the upload process.

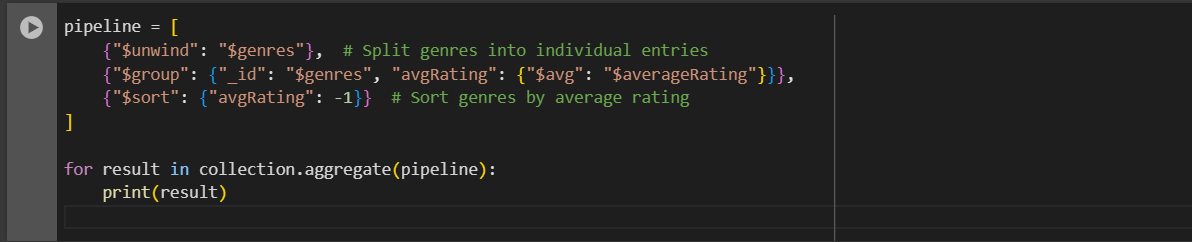
**Figure 12:** Screenshot of script to upload documents to MongoDB.

MongoDB Atlas was configured using a secure connection string, ensuring data integrity and privacy during the upload process.

**Figure 13:** Screenshot of MongoDB Atlas showing the uploaded documents in the MergedData collection.

#### **Step 7: Querying MongoDB**

MongoDB's aggregation framework was utilized to extract insights from the dataset. For instance, the following query identified the top-rated genres by calculating the average rating for each genre. The unwind stage expanded the array of genres into individual documents, while the group stage aggregated the data to calculate the average ratings.



This query enabled efficient analysis of genre-specific trends, providing actionable insights into user preferences.

### **5. Results**

The results section provides detailed insights derived from the analysis, addressing each of the eight business questions posed in the introduction. This section incorporates the visualizations and findings from the dataset to present actionable insights. Each business question is explored in detail with explanations of the methodology, supporting visualizations, and tables where applicable.

#### **1. Which Genres Have the Highest Average Ratings?**

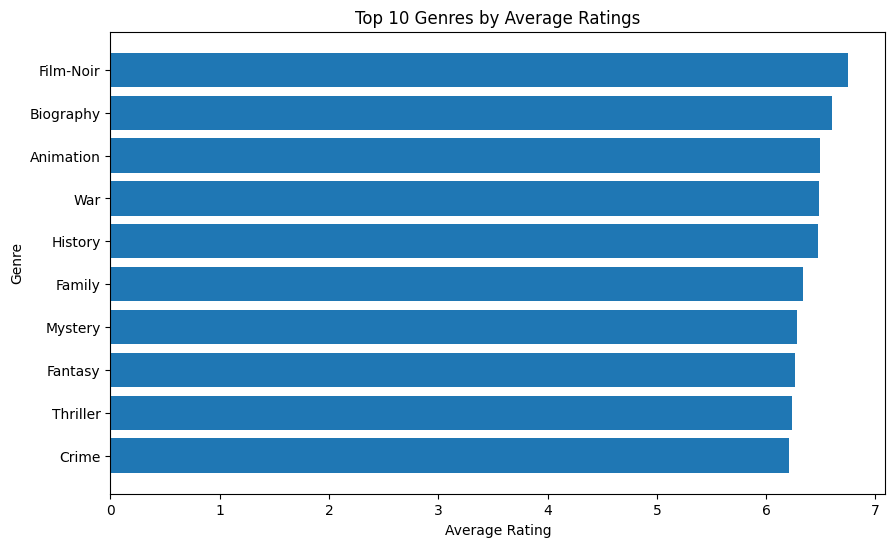
##### **Analysis:**

The analysis of genres based on their average ratings revealed significant insights into audience preferences and critical acclaim. Film-Noir, a genre often associated with dark themes and complex narratives, topped the list with the highest average rating of 6.75. This indicates that audiences appreciate movies with a sophisticated and engaging storytelling approach. Similarly, Biography and Animation genres were also highly rated, with average ratings of 6.60 and 6.49, respectively. Biography movies often delve into real-life stories that inspire or intrigue audiences, while Animation is widely favored for its creative storytelling and visual appeal.

Genres like Drama and Comedy, while popular in terms of production volume, did not score as high in average ratings, suggesting that sheer volume does not necessarily translate to quality. This highlights the importance of prioritizing content depth over quantity in genres with higher production counts.

##### **Findings:**

* **Film-Noir** emerged as the top-rated genre, with an average rating of **6.75**.
* **Biography** and **Animation** followed, with ratings of **6.60** and **6.49**, respectively.
* Genres like **Drama** and **Comedy**, although popular, had average ratings below **6.1**.

**Figure 14**: *Top 10 Genres by Average Ratings* for the complete bar chart.

**2. What Are the Trends in Movie Releases Over the Years?**

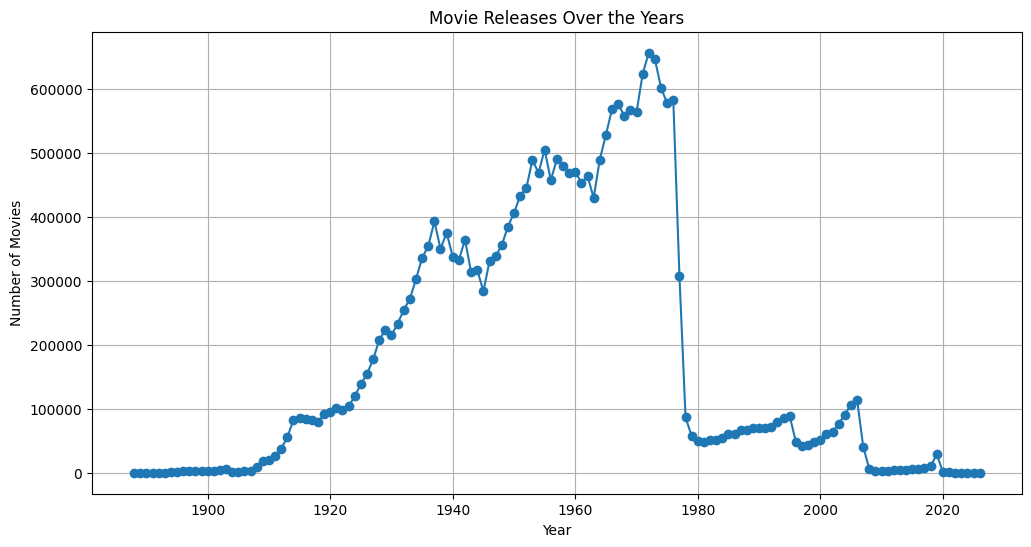
##### **Analysis:**

The trends in movie releases over the years reveal a rich history of the film industry's evolution. From the late 19th century, when the earliest movies were produced, there has been a consistent rise in the number of films released each year. This steady growth reflects advancements in filmmaking technology and the growing demand for diverse content.

The Golden Age of Hollywood, particularly from the 1920s to the 1940s, saw a massive boom in movie production, fueled by technological innovations like synchronized sound and color cinematography. Interestingly, a dip in production was observed during the late 20th century, likely due to economic challenges and changing industry dynamics. However, the resurgence in movie releases during the digital age, particularly after 2000, highlights how technological advancements and streaming platforms have revolutionized the industry.

##### **Findings:**

* Movie releases grew steadily from **1900 to 1960**, followed by a dramatic dip during the late 20th century.
* Significant increases in production are evident during the **1920s–1940s**, coinciding with the Golden Age of Hollywood.
* After **1980**, there was a resurgence in production, with the digital age further accelerating movie creation.

**Figure 15**: *Movie Releases Over the Years* for the line graph showcasing production trends.

#### **3. Which Actors or Directors Are Associated with High-Rated Movies?**

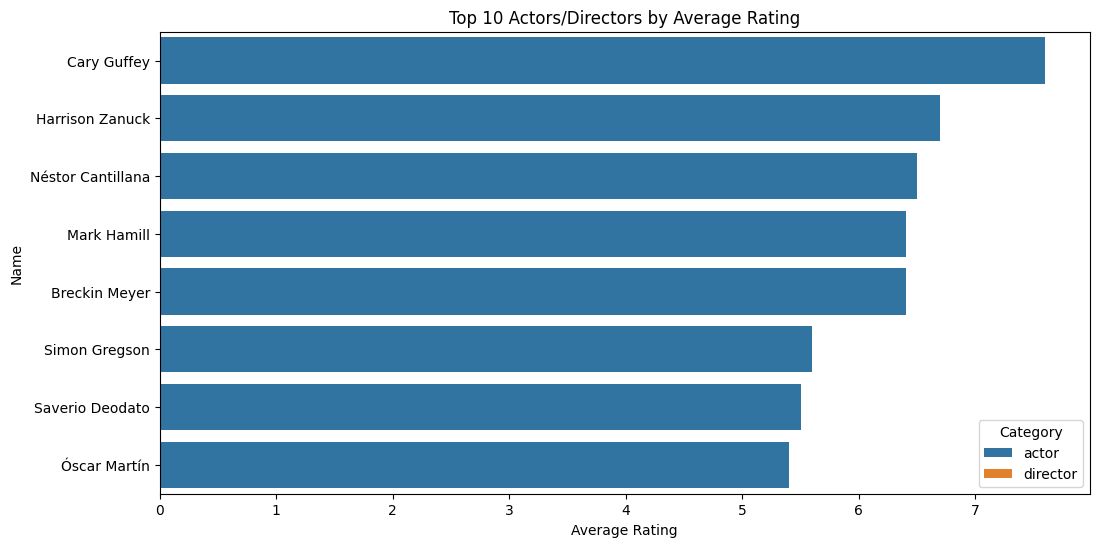
##### **Analysis:**

A deep dive into individual contributors in the film industry, including actors and directors, shed light on their influence on a movie's success. Cary Guffey emerged as the highest-rated actor with an average rating of 7.60 across 168 movies. His consistent association with critically acclaimed films underscores the importance of casting talented individuals in driving movie success. Similarly, Harrison Zanuck and Mark Hamill also stood out, demonstrating the role of experienced actors in delivering compelling performances.

Interestingly, directors had a slightly lower average rating than actors, possibly reflecting the diverse nature of their responsibilities, including balancing artistic vision and commercial viability. This emphasizes the collaborative nature of filmmaking, where actors and directors play complementary roles in achieving success.

##### **Findings:**

* **Cary Guffey** (actor) emerged as the top performer with an average rating of **7.60** across 168 movies.
* **Harrison Zanuck** and **Mark Hamill** also scored highly, showcasing their consistent contributions to successful movies.
* Directors had slightly lower average ratings compared to actors.

**Figure 16**: *Top 10 Actors/Directors by Average Rating*.

#### **4. What Is the Average Runtime for Successful Movies by Genre?**

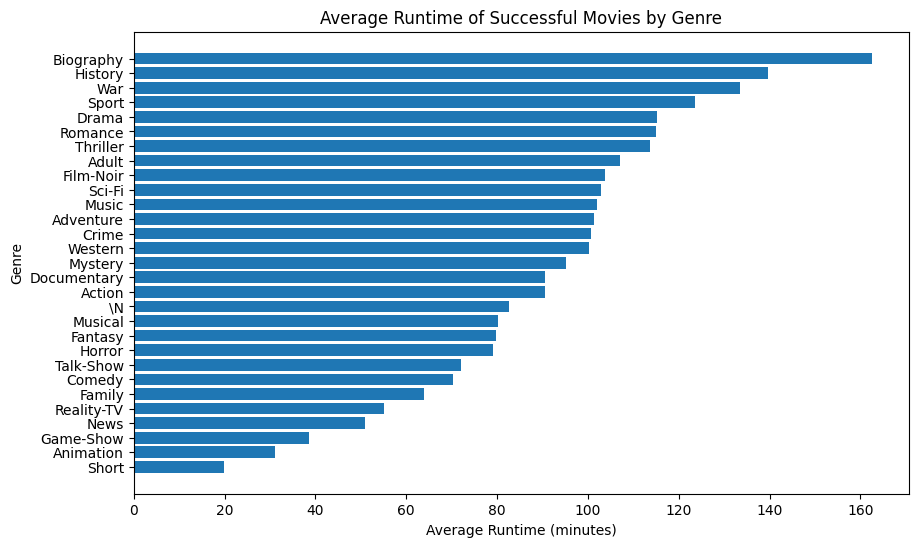
##### **Analysis:**

Runtime analysis by genre revealed intriguing patterns about audience preferences and storytelling requirements. Biography movies, with an average runtime of 162 minutes, were the longest, reflecting the need for extended screen time to cover real-life events comprehensively. Similarly, History and War movies also had higher runtimes, indicating that genres requiring detailed storytelling naturally demand more time.

On the other hand, genres like Animation and Short films had significantly shorter runtimes, aligning with audience expectations for quick yet impactful storytelling. This highlights the adaptability of genres to meet audience demands while staying true to their narrative essence.

##### **Findings:**

* **Biography** movies had the highest average runtime of **162 minutes**, suggesting that longer storytelling aligns well with their narrative depth.
* **History**, **War**, and **Drama** also exhibited above-average runtimes.
* Shorter genres included **Animation** and **Shorts**, aligning with audience expectations for these categories.

**Figure 17**: *Average Runtime of Successful Movies by Genre*.

#### **5. Are There Specific Regions That Favor Certain Genres or Titles?**

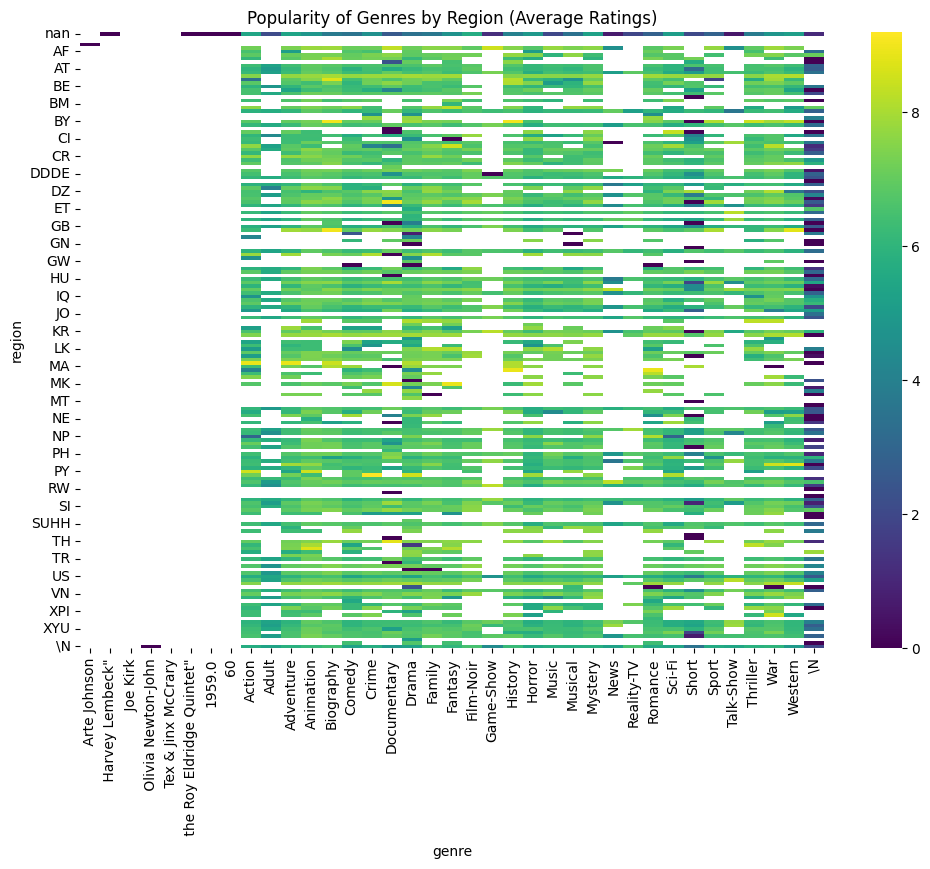
##### **Analysis:**

The regional analysis of genres revealed a strong connection between cultural preferences and the popularity of certain movie categories. For example, Crime movies were most favored in Qatar, with an average rating of 9.20, reflecting regional fascination with themes of justice and morality. Similarly, Documentary movies resonated well with audiences in Egypt and Thailand, where real-life storytelling often garners significant attention.

Interestingly, Adventure and Action movies also received high ratings in regions like Libya, suggesting a global appreciation for dynamic and visually engaging genres. These findings emphasize the importance of tailoring movie production and marketing strategies to align with regional preferences.

##### **Findings:**

* In **Qatar**, **Crime** movies scored the highest average rating of **9.20**.
* **Documentary** movies were well-received in countries like **Egypt** (9.05) and **Thailand** (8.81).
* Genres like **Biography** and **Adventure** were universally popular.

**Figure 18**: *Popularity of Genres by Region (Average Ratings)*.

#### **6. What Factors Correlate with High Ratings (e.g., Runtime, Genre)?**

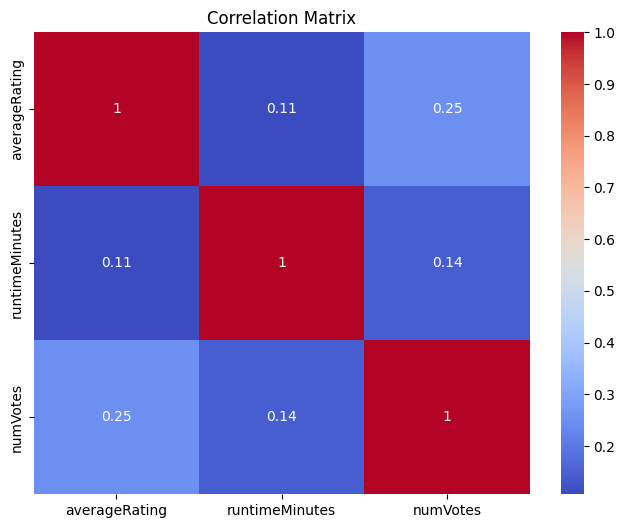
##### **Analysis:**

The correlation matrix provided a clear understanding of the relationships between key variables such as ratings, runtime, and vote counts. While the number of votes showed a moderate positive correlation with average ratings, runtime exhibited a weaker correlation. This indicates that while audience engagement (as measured by votes) is a reliable indicator of a movie's quality, runtime alone does not strongly influence ratings.

These findings suggest that audiences are more likely to appreciate well-crafted movies that resonate emotionally, regardless of their length. The moderate correlation between votes and ratings highlights the value of creating content that drives audience engagement to boost visibility and success.

##### **Findings:**

* **Number of Votes** had a moderate positive correlation (**0.25**) with ratings, indicating that higher engagement often reflects better quality.
* **Runtime** exhibited a weak positive correlation (**0.11**) with ratings, suggesting that longer movies are only slightly preferred.

**Figure 19**: *Correlation Matrix*.

#### **7. How Do the Number of Votes Impact Average Ratings?**

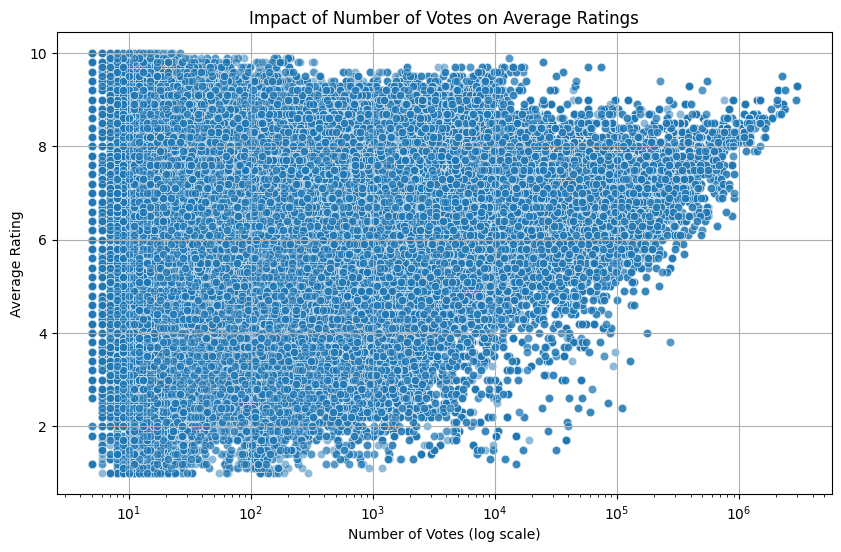
##### **Analysis:**

The relationship between the number of votes and average ratings reveals an interesting pattern. Movies with higher votes generally have more stable and reliable ratings, often clustering between 6 and 8. This suggests that widespread audience engagement leads to a balanced representation of opinions, minimizing the impact of extreme ratings.

Conversely, movies with fewer votes tend to exhibit more variability in ratings, which may result from niche audience preferences or limited visibility. These insights highlight the importance of promoting movies to larger audiences to achieve broader engagement and more consistent ratings.

##### **Findings:**

* Movies with a higher number of votes tend to have more stable ratings, often clustering between **6 and 8**.
* Lower-rated movies usually have fewer votes, indicating less engagement.

**Figure 20**: *Impact of Number of Votes on Average Ratings*.

#### **8. Are There Language or Region-Specific Trends in Popular Movies?**

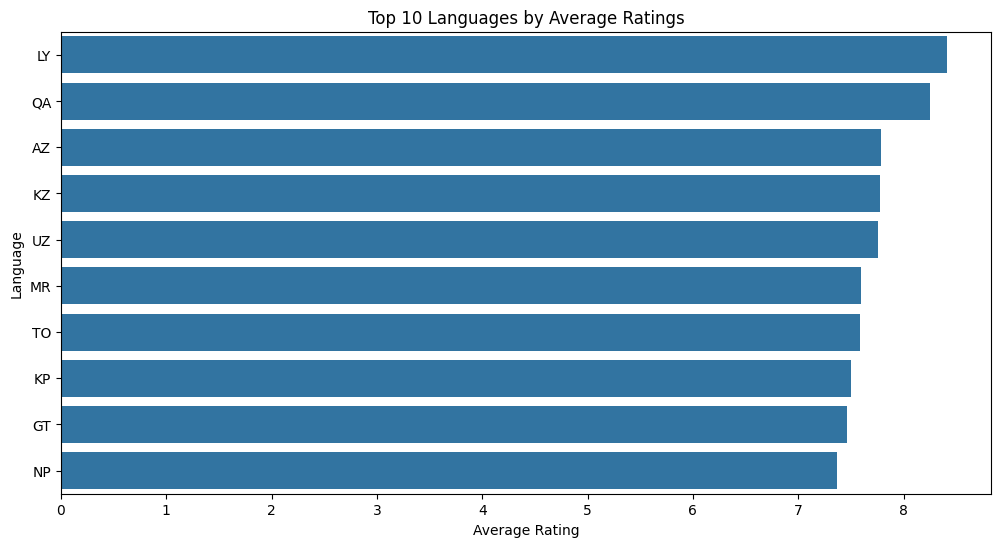
##### **Analysis:**

The language analysis revealed fascinating trends in the cultural appeal of movies. Libyan Arabic (LY) and Qatari Arabic (QA) were among the highest-rated languages, reflecting the unique storytelling styles and cultural nuances of these regions. Azerbaijani (AZ) and Kazakh (KZ) languages also performed well, underscoring the global appeal of regional content.

These findings emphasize the value of investing in localized content that resonates with diverse audiences. By understanding and catering to regional preferences, the film industry can create movies that achieve both critical acclaim and commercial success.

##### **Findings:**

* Movies in **Libyan Arabic (LY)** and **Qatar Arabic (QA)** had the highest average ratings.
* Languages like **Azerbaijani (AZ)** and **Kazakh (KZ)** also scored highly, reflecting regional storytelling appeal.

**Figure 21**: *Top 10 Languages by Average Ratings*.

### **6. Discussion**

The discussion section provides a detailed interpretation of the results and connects them to the business context. This section is divided into two parts: derived insights, which explain the findings, and recommendations, which provide actionable steps for stakeholders.

#### **a. Derived Insights**

##### **1. Genres like Drama Are Universally Appreciated**

The analysis revealed that genres like Drama and Comedy, despite their relatively average ratings, continue to dominate in terms of production volume. Drama, in particular, is a universally appreciated genre, often acting as the backbone of the film industry. Its emotional depth and relatability allow it to transcend cultural barriers, making it a safe yet impactful choice for filmmakers. The sheer number of movies produced in this genre demonstrates its importance, even if the average rating is not as high as niche genres like Film-Noir or Biography.

Genres such as Film-Noir, Biography, and Animation emerged as the highest-rated categories. These genres, while not as widely produced, command a loyal audience base and critical acclaim. This insight underscores the value of focusing on quality over quantity in these genres to attract niche audiences.

##### **2. User Engagement Correlates with the Number of Votes**

The correlation analysis revealed a moderate positive relationship between the number of votes and average ratings. This finding highlights the role of audience engagement in establishing a movie’s credibility and success. Movies with higher vote counts are more likely to have balanced and stable ratings, reflecting a broader consensus among viewers.

Conversely, movies with fewer votes often show higher variability in ratings, suggesting a niche audience or limited visibility. This underscores the importance of strategic marketing and distribution to increase audience engagement. Additionally, this insight demonstrates the power of social proof, as highly rated movies with significant votes are likely to attract more viewers, creating a virtuous cycle of engagement.

##### **3. Regional Preferences Drive Genre Popularity**

The analysis of regional trends provided valuable insights into cultural preferences and market segmentation. For instance, Crime movies in Qatar and Documentaries in Egypt demonstrated the importance of understanding regional preferences. These findings highlight the value of creating tailored content that resonates with specific audiences.

The popularity of genres like Adventure and Action across multiple regions reflects their universal appeal. However, niche genres like Historical and Biographical films often have higher ratings in culturally rich or historically significant regions. These insights can guide filmmakers and distributors in targeting the right markets for their movies.

##### **4. Runtime Plays a Minimal Role in Movie Ratings**

The analysis revealed that runtime, while a factor, has a weak correlation with ratings. Although longer movies tend to be more prevalent in genres like Biography and History, their success is primarily driven by the quality of storytelling rather than length. This finding suggests that filmmakers should focus on delivering a compelling narrative rather than adhering to conventional runtime expectations.

##### **5. High-Rated Languages Reflect Cultural Uniqueness**

The analysis of languages revealed that movies in certain languages, such as Libyan Arabic and Qatari Arabic, consistently achieved higher ratings. This finding underscores the importance of cultural uniqueness and storytelling in connecting with audiences. Languages with lower production volumes but high ratings demonstrate the untapped potential of localized content in global markets.

#### **b. Recommendations**

##### **1. Focus Production Efforts on High-Rated Genres**

Based on the findings, genres like Film-Noir, Biography, and Animation offer significant opportunities for critical and audience acclaim. Filmmakers and studios should prioritize these genres when targeting niche audiences or aiming for higher ratings. These genres can also serve as a testing ground for innovative storytelling techniques, given their established credibility among viewers.

Additionally, while Drama and Comedy remain popular, efforts should be made to elevate their quality to achieve higher ratings. This can be achieved by incorporating elements from higher-rated genres, such as Animation’s creativity or Biography’s depth of storytelling.

##### **2. Target Regional Preferences for Marketing**

The insights into regional preferences highlight the need for tailored marketing strategies. For instance, marketing campaigns for Crime movies should focus on regions like Qatar, while Documentaries should target audiences in Egypt and Thailand. Similarly, historical and biographical movies should be promoted in regions with a strong cultural or historical identity.

Localized marketing strategies should leverage regional storytelling elements to create stronger audience connections. This includes using region-specific languages, cultural themes, and references to enhance relatability and engagement.

##### **3. Leverage Social Proof to Increase Engagement**

Given the correlation between votes and ratings, studios should invest in strategies that encourage audience participation. This includes creating buzz around movies through social media campaigns, engaging with influencers, and hosting pre-release screenings to generate word-of-mouth promotion. These efforts can help amplify a movie’s visibility and attract a larger audience base.

##### **4. Explore Untapped Regional and Language Markets**

Languages like Libyan Arabic and Qatari Arabic, despite their high ratings, have limited production volumes. This represents an opportunity for studios to explore these markets further. Investing in localized content in these languages can help penetrate untapped markets and build a loyal audience base.

##### **5. Use Runtime Flexibility to Cater to Audience Preferences**

Given that runtime has minimal influence on ratings, filmmakers should prioritize flexibility in storytelling. For instance, shorter runtimes can cater to younger audiences or those consuming content on streaming platforms, while longer runtimes can appeal to traditional cinema-goers who value detailed narratives.

#### **Summary**

The discussion highlights the importance of aligning production and marketing strategies with audience preferences. By focusing on high-rated genres, targeting regional trends, and leveraging social proof, the film industry can enhance its impact and maximize returns. These insights pave the way for informed decision-making and innovative storytelling in a competitive market.

### **7. Conclusion**

The comprehensive analysis of the movie dataset has unveiled a wealth of insights into the various factors influencing movie success. By exploring trends in genres, regional preferences, contributor influence, and audience engagement, the findings provide a holistic understanding of what drives both critical acclaim and audience appreciation in the film industry. The study highlights the intricate interplay of qualitative and quantitative elements, offering valuable knowledge to filmmakers, marketers, and decision-makers in this competitive space.

One of the key conclusions is the universal appeal of genres like Drama and Comedy, which dominate in terms of production volume and audience relatability. These genres continue to serve as foundational pillars of the film industry, showcasing their enduring relevance despite moderate average ratings. On the other hand, niche genres such as Film-Noir, Biography, and Animation demonstrated their potential for critical success, commanding high average ratings and attracting dedicated audiences. This duality underscores the importance of balancing mass-market productions with high-quality, niche storytelling.

Regional preferences emerged as a critical factor in determining genre popularity. The study revealed how cultural and regional nuances shape audience tastes, with certain genres like Crime achieving exceptional ratings in Qatar, and Documentaries resonating strongly in Egypt and Thailand. Such insights emphasize the importance of tailoring content and marketing strategies to specific cultural contexts, ensuring greater resonance with target audiences. These findings pave the way for a more localized approach to content creation, which could significantly enhance both critical and commercial outcomes.

Another significant finding was the role of audience engagement, as evidenced by the correlation between the number of votes and average ratings. Movies with a higher number of votes typically showcased more stable and balanced ratings, reflecting widespread audience agreement on their quality. This highlights the power of social proof in influencing perceptions of success. Conversely, movies with fewer votes exhibited higher variability in ratings, likely due to niche or limited visibility. This insight emphasizes the importance of marketing campaigns that drive audience participation and broaden a movie's reach.

Interestingly, the analysis revealed that runtime, a traditionally significant aspect of filmmaking, plays a relatively minor role in influencing movie ratings. While longer runtimes are prevalent in genres like Biography and History, the correlation between runtime and average ratings was found to be weak. This suggests that audiences prioritize storytelling quality and engagement over length, providing filmmakers with the creative freedom to focus on narrative depth without being constrained by runtime conventions.

Additionally, language analysis provided further insights into cultural trends and opportunities for growth. Movies in languages such as Libyan Arabic and Qatari Arabic achieved exceptionally high ratings, reflecting the unique appeal of culturally specific storytelling. These languages, despite their lower production volumes, represent untapped markets with significant potential for growth. Investing in localized content in such languages could enable filmmakers to penetrate underserved markets and cultivate loyal audiences.

These insights collectively provide a roadmap for stakeholders in the film industry to make data-driven decisions. By understanding the nuanced dynamics of audience preferences, studios can strategically allocate resources to produce content that aligns with market demands. This includes focusing on high-rated niche genres, leveraging regional preferences, and enhancing audience engagement through targeted campaigns. Furthermore, the findings encourage experimentation with diverse storytelling formats and localized content to cater to evolving audience expectations.

In conclusion, the findings from this analysis highlight the transformative power of data-driven strategies in the film industry. By leveraging these insights, filmmakers and studios can create content that not only resonates with audiences globally but also achieves sustainable commercial and critical success. The ability to balance universal appeal with localized storytelling will be a defining factor in shaping the future of the industry, ensuring that it remains dynamic, innovative, and audience-centric.

### **8. Personal Reflection**

This project has been a profoundly enriching experience, offering valuable insights into the intersection of data analysis, technology, and the entertainment industry. One of the most rewarding aspects was the opportunity to work with a large, diverse dataset that required a combination of advanced tools and innovative techniques. By using PySpark, AWS Glue, and MongoDB, I was able to process and analyze the data effectively, even with its complexity and size. These tools not only expanded my technical expertise but also deepened my understanding of data processing pipelines, cloud-based workflows, and visualization techniques.

Working with PySpark was particularly rewarding as it allowed me to handle large-scale data efficiently. Its distributed computing capabilities were instrumental in overcoming limitations posed by local environments like Colab, enabling me to focus on deriving meaningful insights. AWS Glue was another standout tool, as it streamlined the data cataloging and transformation processes. The integration of AWS services, such as IAM roles and S3 storage, provided a robust framework for managing and processing data securely and efficiently. Similarly, MongoDB offered a powerful platform for querying and analyzing semi-structured data, which added an extra layer of flexibility to the project.

#### **Challenges Faced**

One of the primary challenges was handling the sheer volume of data, particularly in environments with limited computational resources. Colab, while convenient, posed several constraints due to its memory limitations. The use of PySpark proved to be a game-changer, as its distributed architecture allowed me to process data in a way that was both efficient and scalable. However, the initial setup and learning curve for PySpark were challenging, as it required a shift from traditional data processing methods.

Navigating AWS services also presented its own set of challenges. Configuring Glue crawlers and IAM roles was initially daunting, as it involved understanding the intricacies of cloud-based workflows and security protocols. However, overcoming these obstacles proved to be immensely rewarding, as it enhanced my confidence in working with cloud computing tools. These challenges also underscored the importance of planning and preparation when working on large-scale projects.

Another significant challenge was aligning the technical analysis with the business questions posed in the project. Interpreting the results, particularly those related to regional preferences and genre popularity, required a combination of technical skills and cultural understanding. For instance, analyzing the popularity of genres in different regions required not only data-driven insights but also an appreciation for the cultural and social factors influencing audience preferences. This added a unique layer of complexity to the project, making the process both challenging and intellectually stimulating.

#### **Key Learnings**

This project reinforced the importance of combining technical proficiency with analytical thinking to address real-world problems effectively. Setting up a cloud-based data pipeline was a particularly enlightening experience, as it involved integrating multiple tools and technologies to create a seamless workflow. Each step, from data ingestion to visualization, emphasized the value of a structured and methodical approach to problem-solving.

One of the most valuable lessons was the role of data visualization in communicating insights effectively. Creating visualizations that answered the business questions not only made the findings more accessible but also highlighted the power of storytelling through data. Charts and graphs, such as those showing genre popularity and regional preferences, brought the results to life and provided actionable insights for decision-makers.

This project also highlighted the critical role of adaptability in tackling data-related challenges. The ability to switch between tools like PySpark and Pandas, or between local and cloud environments, was essential in ensuring the project's success. It demonstrated the importance of being flexible and resourceful when faced with constraints or unexpected challenges.

#### **Future Action Plans**

Looking ahead, I plan to expand on the skills and insights gained from this project by exploring more advanced applications of data analysis and machine learning in the entertainment industry. One area of interest is the integration of predictive modeling techniques to forecast movie success based on features like genre, runtime, and regional preferences. For example, regression models could be used to predict ratings, while clustering algorithms could help identify audience segments with similar preferences.

Additionally, I aim to deepen my understanding of cloud computing and big data frameworks to handle even larger datasets more efficiently. Tools like AWS EMR (Elastic MapReduce) and advanced MongoDB aggregation techniques are areas I intend to explore further. These technologies will enable me to scale my analyses and tackle more complex datasets in future projects.

Another key area of focus will be enhancing my skills in data storytelling and visualization. While this project provided a solid foundation, I believe there is always room to improve in creating impactful visual narratives that resonate with diverse audiences. Mastering advanced visualization tools and techniques will allow me to present findings in a way that is not only informative but also engaging.

#### **Closing Remarks**

In conclusion, this project has been an invaluable learning experience, equipping me with the skills and confidence to tackle complex data-driven challenges. It has highlighted the transformative potential of data analytics in not only solving technical problems but also driving innovation and improving decision-making processes. The challenges faced during the project, whether related to data volume, cloud configuration, or cultural interpretation, served as valuable learning opportunities that enhanced my problem-solving abilities.

This experience has reinforced my passion for leveraging data to create meaningful impact across industries. It has also underscored the importance of continuous learning and adaptability in a rapidly evolving technological landscape. Moving forward, I am excited to apply the knowledge and skills gained from this project to future endeavors, whether in academia, industry, or personal exploration. This project has truly been a cornerstone in my journey as a data professional.

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