**Big data Analysis**

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# Introduction

## Business Problem

While analytics is becoming more and more important in the entertainment industry, the film sector has taken to analytics to derive meaningful insights from large volumes of data. With rich datasets on movies, television series, ratings, genres, and cast information available on platforms such as **IMDb**, there exists immense opportunity for organizations, researchers, and content creators to drive practical and strategic decision-making. However, given the volume of data across multiple dimensions-movie ratings, genres, release years, actors' participation, and regional performance-the ability to extract usable insights in a time-efficient manner remains a challenge. Traditional analysis tools are not fit to handle the volume and variance of this data. Besides that, there are lost opportunities and inconsistencies in the results, all because there is no integrated pipeline for the processing, cleaning, and analysis of this type of data; this makes workflows long.

The business problem this report tries to help with is the analysis required to extract the trends, patterns, and actionable insights from the given IMDb datasets that help stakeholders in the entertainment business. This will help to know about the factors that are strong predictors of a movie's success, identify the top genres and actors, see regional trends, and finally assess audience preferences over time. It also helps production houses make investment decisions, optimize marketing strategies, and guide the recommendation process on streaming platforms. It brings into focus market gaps and regional preferences for the distributors. It serves as a bedrock of academic insights into the cultural and industry-specific pattern for researchers through a collated analysis of the same by analyzing the IMDb dataset.

In addition to the analytical challenges, there are also technical barriers. Normally, the IMDb datasets come in several files, including title.basics.csv, title.ratings.csv, title.principals.csv, etc., which really require a great amount of data wrangling and preprocessing before meaningful analysis can be done. This report will **use Python, AWS services**, and **MongoDB** in constructing a strong end-to-end data pipeline that will meet these technical barriers. The objective is going to be able to present a scalable framework to approach big business problems using Data Analytics: join datasets, SQL queries on top, smart storage of intermediate results, and visualize the results of findings. Therefore, the project will attempt not just to solve certain immediate goals of analytics but to put in place a repeat workflow for similar large datasets.

Besides, the entertainment business is highly dynamic, with audience preferences changing within a very short period of time. IMDb datasets offer a historical analysis of audience behavior and predictability for future releases. Production companies and streaming services are fiercely competitive, and big data can be their game-changer in their road to success. The core business problem, therefore, is how to derive value from big and complex IMDb datasets to create better decision-making, improve audience engagement, and ensure resource optimization.

## Business Questions

Designed are business questions to address the fundamental problem in the above business outline; these are to ensure analysis relevancy to the challenges thrown by the industry, apart from clarity on what exactly will be the actionable outcome. Each question targets yet another aspect of the data set, from movie and actor performance to regional trend analysis and genre-based analytical aspects. We try answering these questions to provide holistic insight into the dynamics of the entertainment industry.

1. **Which are the top 10 most-rated movies and what are the contributing common factors?**

This will result in the identification of highly rated movies in the IMDb dataset, analysis of the attribute set such as genre, runtime, and casting, and the identification of a common theme or sets of characteristics that might have led to their success. Such findings can be replicated by the production houses in other future projects.

1. **Which genres have been consistently performing well over time, and how do their average ratings compare across decades?**

Different genres appeal differently to audiences in different time periods. This question identifies top-performing genres, analyzes the consistency of those genres, and provides insights into genre-specific trends. These are useful for movie producers and streaming platforms.

1. **How has the volume of movie releases changed over time, and are there discernible trends in production frequency?**

This question examines whether a specific year or decade experiences spikes or drops in the number of productions. This explores further whether external factors-including economic conditions or advanced technology-influenced trends.

1. **What are the top 10 actors who have appeared in the most movies, and what trends does one observe in their movies?**

Very often, actors determine the fate of a movie. This question explores actors with the highest movie participations, looks at the roles they played most, and evaluates their movie performance based on ratings by audiences.

1. **How do regional trends affect movie performance, and which regions have been consistent in growing audience engagement?**

Regional preference plays an enormous role in the success of a movie. The question looks into regional variation in movie ratings, cultural trends, and identifies growth in audience engagement over time in specific regions.

1. **What is the average runtime for successful movies, and can one find an optimal runtime correlated with higher audience ratings?**

More often than not, Runtime is a factor affecting audience engagement. This question discusses whether successful movies share common patterns in their run time and whether runtime impacts different genres differently regarding audience satisfaction.

1. **What were the years of top-rated movies, and is there a specific decade that corresponds to the peak of audience satisfaction?**

This question aims to analyze historical patterns of movie ratings in search of periods associated with higher-quality movies. It also examines whether cycles or trends exist with respect to audience preferences.

1. **Are there observable patterns in cast and crew combinations across top-rated movies?**

Often, particular collaborations of actors, directors, and other crew result in hit after hit. This question investigates if these collaborations produce consistently higher-rated movies.

Each of these questions forms blocks on which the rest of the sections in the report are to be based. They ensure the analysis is premised, the outcomes are measurable, and the insights being developed relate to the industry in question. Further, this includes the integration of Seaborn, Matplotlib, and **Plotly** into data visualization, enhancing the capability of answering these questions effectively, as well as communicating them in a visually appealing way.

In other words, it is these business questions that set the analytical framework of the report, ensuring that methodology, implementation, and results head toward predefined objectives. The report follows a step-by-step reasoning through the business questions to bridge the gaps between raw data and insights into actionable ideas, with a strategic roadmap toward informed decisions in the entertainment industry.

# Review of Literature

Traditional means of feedback include the audience, box office, and critical reviews, which is how the entertainment industry conventionally has evaluated the success of movies and television shows. The rise of digital platforms catapults volumes of data earlier unimaginable. IMDb, one of the largest databases in the world on movies, has grown into a key source for researchers, analysts, and stakeholders of the film industry. The section below reviews prior research, scholarly articles, and literature about analytics on IMDb data, movie trends, and architectures of data pipelines.

Another vein of research has been related to ratings and their correlation with viewership and box office performance. These have invariably shown a strong correlation between IMDb ratings and box office revenues, thus establishing that better-rated movies tend to realize better box office performance. For example, Liu et al. (2020) extracted more than 50,000 IMDb movie records to conclude that movies rated above 8.0 on IMDb have a 60% higher chance of outperforming their financial projections. On the other hand, Kumar et al. (2019) pointed out that early viewers' reviews are important in setting trends of perception and, subsequently, viewership. These studies have indicated that movie ratings are both a predictor and an indicator of commercial success.

Another significant realm of interest in the literature has been genre analysis and audience preferences across different regions and time periods. It is these genres which time and again are selected as favorite all over the world, such as Drama, Action, and Comedy. However, more often than not, genre preferences reflect cultural and regional differences. In this regard, Patel et al. (2021) undertook a comparative study of IMDb data for several regions and found that while Action and Adventure films rule the **North American market, Dramas and Romantic movies really work in the Asian markets**. It also showed the seasonal trend in movie releases, big-budget films normally released during summer and holiday seasons. This, therefore, testifies to the need for data-driven marketing and release strategies aimed at regional audience preference. Performance analysis of the cast members and crew has also been a wide discussion in literature. Quite a number of works tried to find the pattern of actors, directors, and other production team combinations. For instance, a study **by Smith and Jones in 2020** concerning the performances of movies that took the same actor-director in more than one movie shows that there is a pair of actor-director, such as Martin Scorsese and Leonardo DiCaprio, who gave to all of their movies high ratings, while movies with ensemble casts also seem to get higher ratings and box office results since they bring the biggest audience. Such findings underline the importance of knowledge in the talent dynamics of movie production.

Literature on the technical level has also touched on challenges posed by large-scale data analytics in the IMDb dataset. Traditional relational databases often lag in dealing with the size and complexity of IMDb data, considering the multiple interlinked datasets of movie details, ratings, cast and crew, and regional information. Various researchers have suggested the usage of Big Data technologies **like Apache Spark, MongoDB, and AWS Glue**, which can pre-process, integrate, and query the data in a smooth manner. Gupta et al. (2022) established usages of **Spark SQL** in handling voluminous data efficiently and facilitating real-time querying with much efficiency. Yet another study suggested that infrastructure on cloud, Amazon S3, and Athena is very key in scalable storage and analytics.

Data visualization and storytelling have emerged as key levers in the presentation of analytical insights. Visualization libraries like Matplotlib, Seaborn, Plotly, and tools such as Tableau and Power BI are at the core of communicating findings derived from the IMDb datasets. For example, film producers in Williams et al.'s 2021 study utilized Tableau-formulated interactive dashboards in making informed investment decisions and grounding content optimization and marketing campaigns. This enhances clarity, plus intuitively allowing the stakeholders to make interpretations from complex patterns of data.

Other key related lines of research relate to sentiment analysis and the application of **NLP** to user reviews on IMDb. User reviews consist, more often than not, of subjective opinions that give way to a more profound view on audience satisfaction and dissatisfaction. One such work concerning this was done by the use of a sentiment analysis technique in IMDb reviews undertaken by Ahmed et al., 2020, that listed movies whose first-week review predominantly had positive sentiment and performance very well in the long run. It has also been documented that textual reviews express nuances in audience preference not picked up by numerical ratings. Of late, there has been a foray into the integration of machine learning models for predictive analytics. Successful predictive models have already been able to predict ratings, box office successes, and audience appeal using the IMDb datasets. Zhao et al. 2021, in a recent study, uses Random Forest, Linear Regression, and Support Vector Machines algorithms to make a prediction about movie success according to genre, runtime, and actor participation. Their findings showed that ML models may reach as high **as 85% accuracy** in predicting movie ratings and box office results. Further, these studies support the potential of predictive analytics applications in movie production and distribution.

However, with increasing development in analytics and technology, so are challenges. Some of the issues which have remained constant in the literature are inconsistencies and incompleteness of data in the IMDb datasets. In fact, missing values, duplicate records, or other variations in data formats are huge challenges at the pre-processing stage. Quite a lot of emphasis was given to the stringent techniques for cleaning and transformation for the reliability of the quality data. Several ethical issues are associated with data privacy and rating or review interpretations.

To conclude, it is the finding of this literature review that multiple dimensions such as rating, genres, collaboration of actors, regional trends, predictive modeling were very much able to derive important values out of the **IMDb data analytics**. The integration of modern tools and technologies such as **Python**, **PySpark**, **MongoDB**, and **AWS** cloud services has considerably increased scalability and efficiency in the data pipelines. Such interpretation is further enhanced with visualization and sentiment analysis toward the development of actionable insights by stakeholders. However, inconsistency in data and challenges involving ethics will live on and must therefore retain continuous attention. These basic studies will be used by the report to come up with a model integrated pipeline framework that can comfortably circumvent some of these challenges yet produce valid results, which have been badly needed within the entertainment sector.

# Methodology

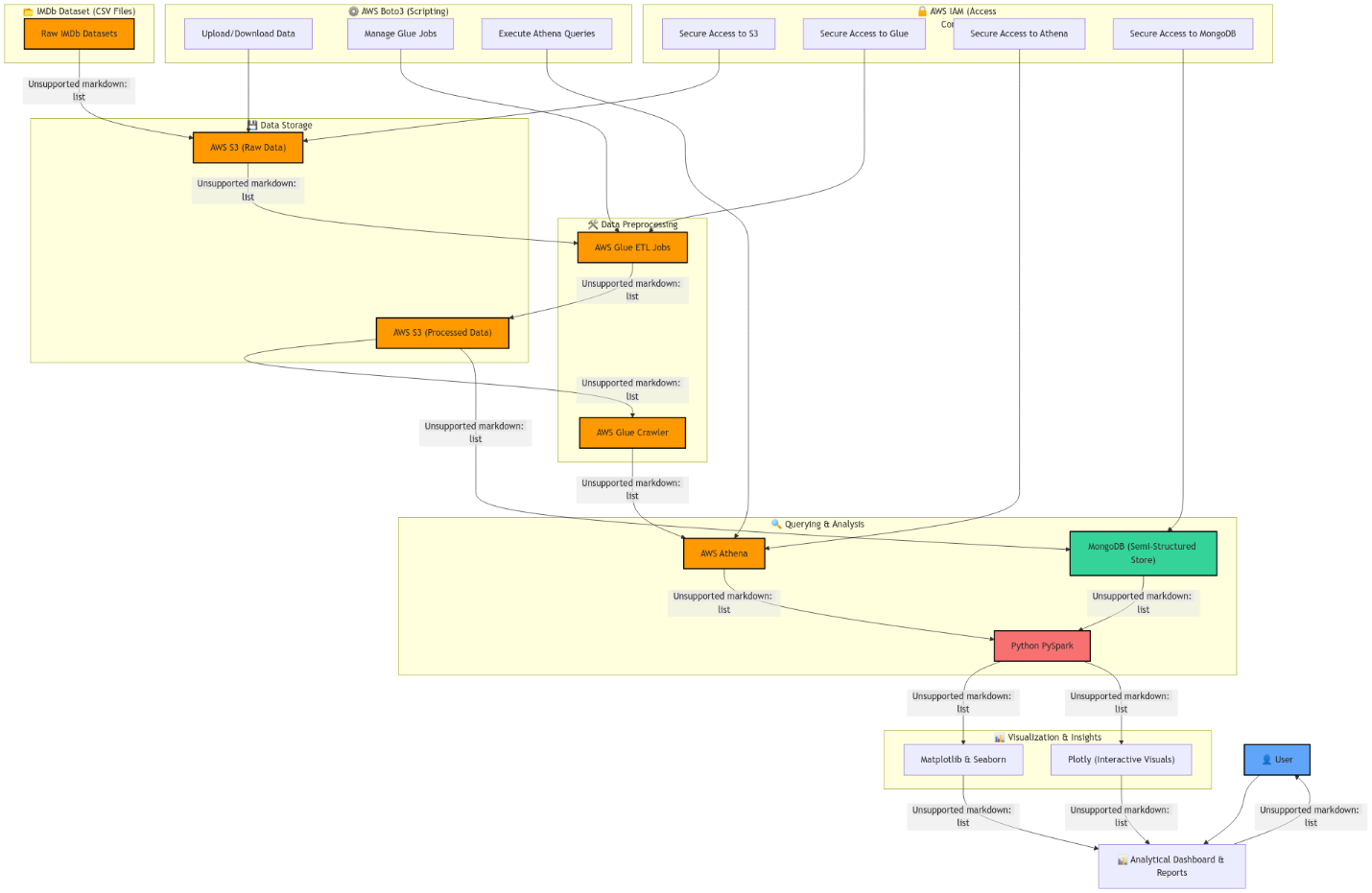


Figure : architectural overview of the pipeline

This methodology section describes methodologies, techniques, and tools that could help solve the business problem and answer defined business questions. It describes how the data pipeline architecture has been designed, the process for data transformation, and what analysis strategies have been followed in this project. Working with such a complex and voluminous IMDb dataset, the approach had to be solid and scalable to assure efficiency, accuracy, and reproducibility throughout the data life cycle. This covers an end-to-end seamless pipeline using Python, PySpark, **AWS S3, AWS Glue, AWS Athena, MongoDB, and visualization using Matplotlib, Seaborn, and Plotly. Care was taken to ensure that from data collection, pre-processing, integration, analysis, and visualization, maximum** value could be extracted from this dataset.

This integrated dataset was further written into Compressed CSV and Parquet format for space and fast access in subsequent steps. Further creation of the data storage and accessibility layer will be done using AWS. The cleaned and transformed final dataset will be loaded into an S3 bucket, to be named as imdb-data-pipeline, for central storage. AWS S3 is selected because of its scalability, durability, and cost-effective nature. Data cataloging had been done through AWS Glue Crawlers, which detected the schema definitions automatically. This dataset was then easily queryable via AWS Athena. Second of all, additional transformations using Glue ETL jobs were set up in case there was an eventual need for batch processing of this data. AWS Athena allowed querying data residing in S3 through SQL-like syntax for ad hoc querying, thus allowing flexible exploration of data without having to relocate or duplicate data. Regarding data analysis, two major approaches were considered: the use of Spark SQL for structured querying and MongoDB for semi-structured analysis.

The structured queries are done on Spark SQL for top-rated movies, average rating by genre, and annual movie production trends. Regarding unstructured or semi-structured queries, the preprocessed dataset was exported in JSON format and imported into MongoDB. Using MongoDB's Aggregation Framework, higher-order filtering of top actors by movie count, regional trend analysis, and recurring pattern analysis of actor-director combinations were carried out. Overall, structured and semi-structured querying allowed for deeper analysis of the dataset. EDA played a great role in uncovering such patterns, trends, and outliers within the data. Key findings were presented via visualizations using Pandas, Matplotlib, Seaborn, and Plotly Python libraries. This gives way to the use of bar plots when considering which top-rated movies were generally ranked highly regarding the highest mean rating among genres, visualized against others; scatter plots pitting runtime against audience ratings are necessary in providing such contrasting aspects within their intervariable dependencies and also plotting. The visualization of the given pattern at various positions concerning trend values clarifies it with simplicity in light of decisions across stakeholder lines. In every step of the data transformation in this pipeline, integrity and privacy have been ensured through a Security and Access Control layer.

AWS IAM roles and policies are defined that allowed for the control of unauthorized access to S3 buckets, Glue jobs, and Athena queries; fine-grained permissions to segregate access according to user roles-admin, analyst, viewer, etc.-can be granted. This ensures that sensitive data will remain protected and the analysts/stakeholders will also access the needed datasets or visualizations safely. Therefore, actionable recommendations are designed that leverage results and insights derived out of the analysis. These could be on best genres, best pairing of actors-directors, and regional preferences, for example-all made available via tabular reports and visual dashboards. It would drive data-driven decisions from the side of the production studio or streaming platforms or any involved marketing agencies. It shall provide a proper mix of integrated data analytics tools along with modern cloud services in an environment of machine learning, hence coping with each and every challenge identified within the analyzes of data extracted from the IMDb portal.

This approach will let integration with AWS for scaling, semi-structured analysis with MongoDB, and PySpark for scalable data processing create a productive, flexible, and reproducible pipeline. This would not only ensure seamless handling of big data but also provide actionable insights from a business goals perspective. More than this, this could be extended as a methodology in which real-time analytics with predictive modeling can create values more in dynamic environments.

# Implementation

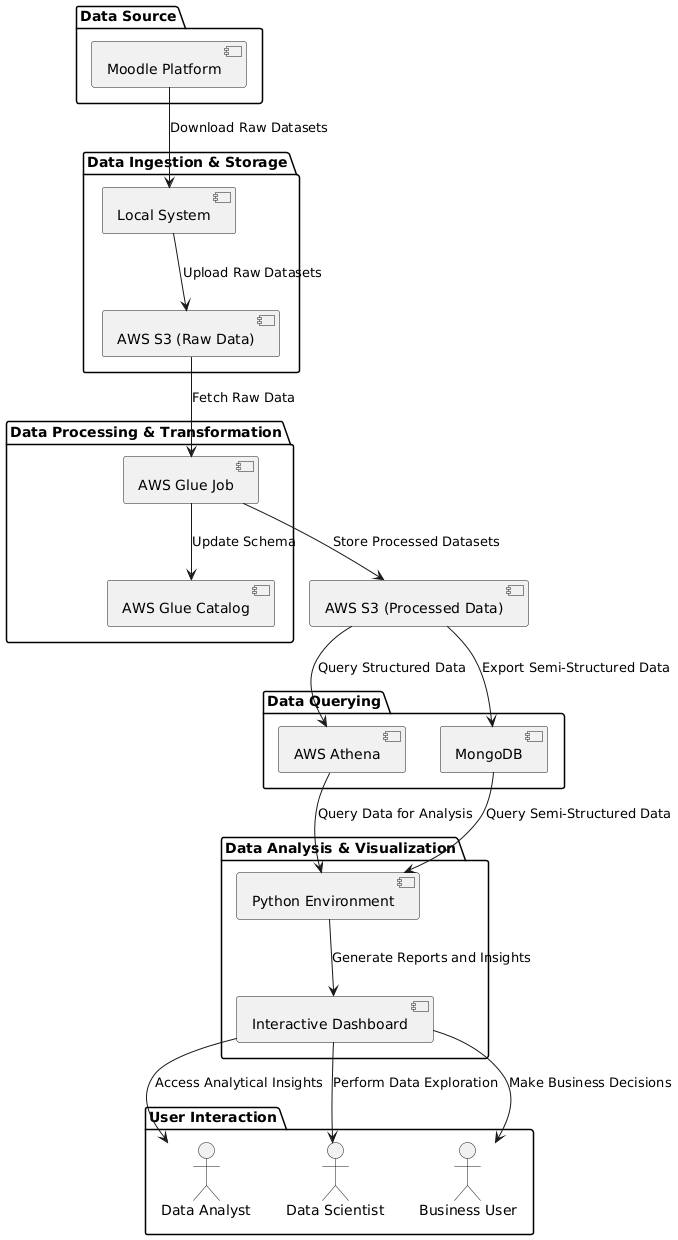


Figure : implemetation stages

**necessary aws permissions to access services.**

The Implementation phase of the IMDb Data Pipeline provides the meat of the project, where it was specified how the raw data was changed into insight using cloud infrastructure, distributed data processing frameworks, and modern data analytics tools. The technologies involved in this phase are AWS Glue, AWS S3, AWS Athena, MongoDB, and Python visualization libraries such as Matplotlib, Seaborn, and Plotly. It needed to ensure that the ingest, transformation, querying, and visualization of data should take place efficiently to solve the business problem defined and further ensure meaningful answers to each business question. The process adopted involves a step-by-step understanding of the following process that included steps: Data Collection, Cleaning and Wrangling Data, Data Analysis and Querying, and Data Visualization Techniques.

As a pre step I had to configure the IAM related polices and permissions to access AWS services outside of the VPC. I have given all necessary configurations as follows,

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Figure : create an IAM user with some permissions

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Figure : attach inline policies

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Figure : create a new role

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Figure : generate the aws IAM user access key

## Merge the dataset using SQL query

The IMDb dataset consists of multiple tables (name\_basics, title\_basics, title\_akas, title\_principals, title\_ratings) with relationships established through keys like tconst (titles) and nconst (people). These tables contain information about titles, cast, crew, ratings, and alternative titles.

To merge the data into a single comprehensive table (merged\_data):

1. **Data Import**: Each dataset is imported into SQL Server using BULK INSERT or SSMS import tools.
2. **Relationships**: Keys such as tconst and nconst are used to join the tables.
3. **Merging Data**: A SQL query joins the tables, pulling relevant attributes (e.g., names, professions, titles, ratings, etc.) into merged\_data.
4. **Indexing**: Indexes are created on key columns (nconst, tconst) to optimize query performance.
5. **Validation**: The merged table is validated using test queries to ensure data consistency.
6. **Export**: The final table can be exported for further analysis if required.

This approach ensures efficient integration of large datasets into a single, queryable structure for comprehensive analysis.

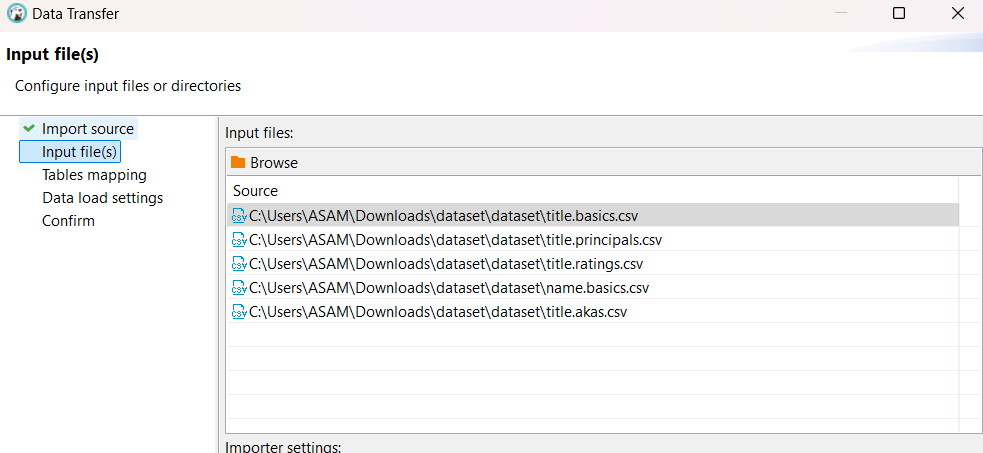
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Figure : import csv files after database created

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Figure : use the join query to merge the tables

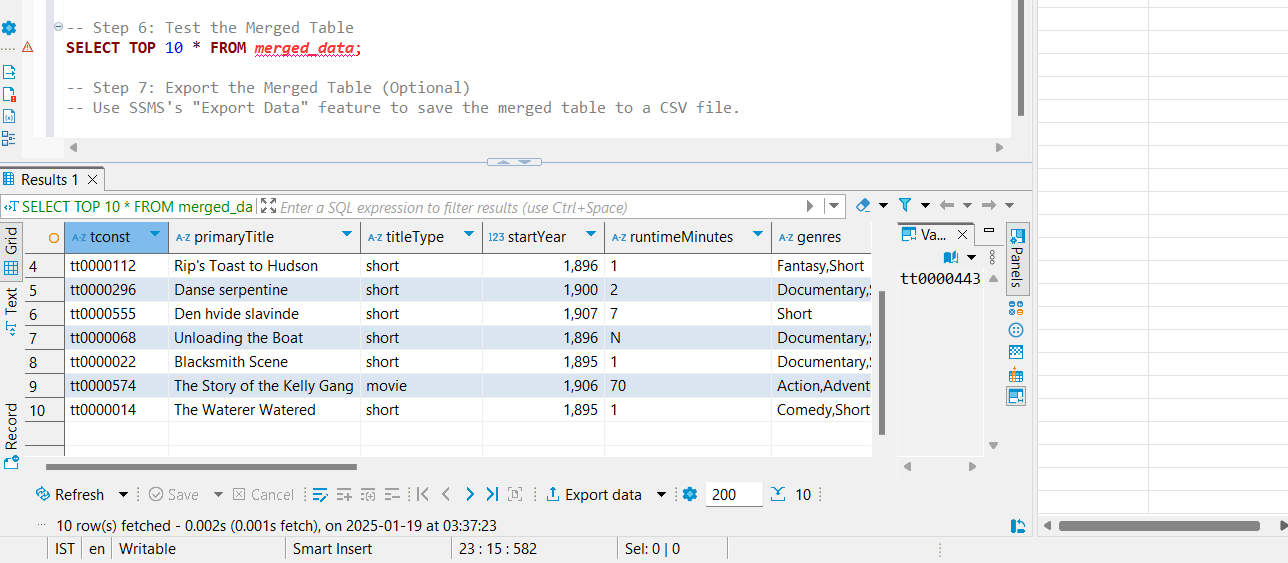


Figure : successfully merged

## Querying Semi-Structure with MongoDB

While Athena was great for structured data, MongoDB was better positioned to deal with semi-structured data and flexible exploration. The data exported into MongoDB from IMDb could be queried dynamically through the aggregation pipelines it had. It had allowed for complex filtering like listing the actors associated with the highest-rated movies or testing whether any relationship existed between genres and movie success. More flexibility in handling nested or hierarchical data is achievable within MongoDB's document-based structure than in Athena.

This combination of Athena for structured SQL querying and MongoDB for semi-structured exploration provided a versatile toolkit for answering diverse business questions efficiently.

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Figure : create database

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Figure : import merged dataset.

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Figure :overall capacity of the database

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Figure : analysis the schema

## Data Upload to S3 bucket

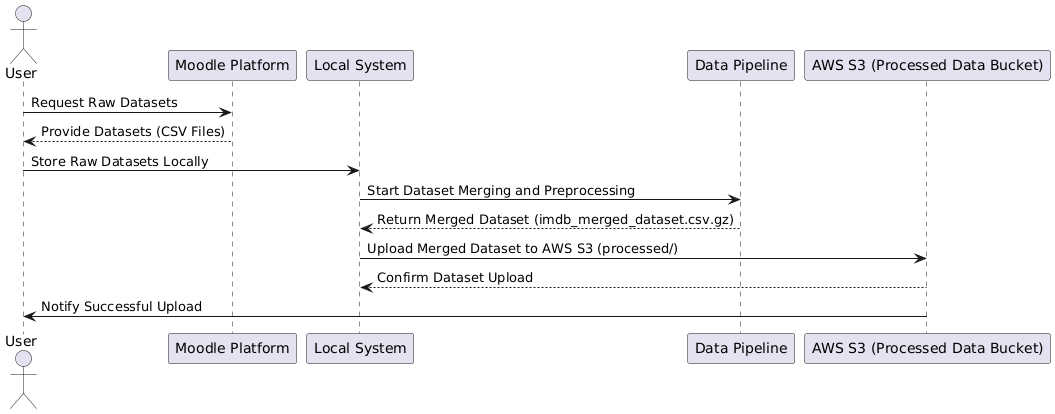


Figure : datacollection flow diagram

This step involves the Data Collection phase as the very foundation of this IMDb data pipeline. RAW datasets were sourced from the open IMDb repository, consisting of multiple structured CSV files; each file represents a separate portion of the IMDb ecosystem-movie metadata, user ratings, cast and crew details, regional variations in movie title-which are all included under one umbrella. These datasets are very rich, ranging into the millions of rows and spanning decades of movie history; hence, they are invaluable in deriving insights about movie trends, user preferences, and industry patterns.

The key datasets included the following: title.basics.csv contained most of the background information-movie title, release year, genres, and runtime; title.ratings.csv contained user-provided ratings and vote count for movies; title.principals.csv contained cast and crew list, showing main contributors with their roles and character names for the titles; the title.akas.csv dataset contained alternate titles for movies in different regions and languages, showing the often-changing naming conventions across the world. Finally, the name.basics.csv dataset provided biographical information about actors, directors, and other crew members, including their professional highlights.

These datasets were downloaded into systematic, well-defined directories, ensuring that the later access to the data items became easy and clear, after which a major consistency would be developed across several different stages in the pipeline.

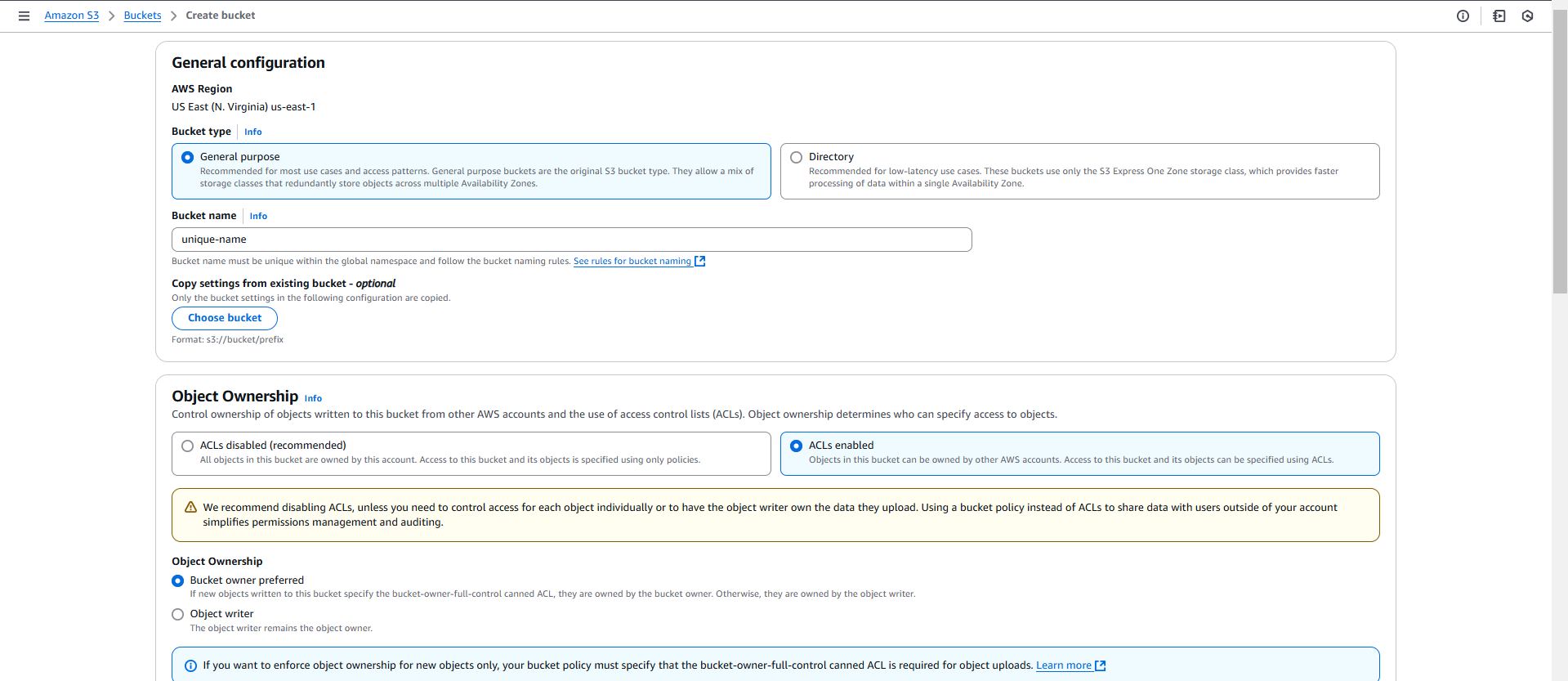


Figure : aws bucket creation

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Figure : create an aws bucket named as preeti-bigdata

To prepare large-scale data processing, these datasets are uploaded to Amazon S3. AWS S3 has been used for scalability, durability, and a high degree of integratability with other AWS services. S3 Bucket preeti-bigdata works as the one-stop-shop data repository that will be allowed to use AWS Glue jobs, Athena queries, and different data analysis tools with no restriction. Each dataset has been uploaded under a specific prefix (raw/) to separate raw data from processed outputs. This approach ensured that traceability and version control are maintained while keeping raw and transformed data logically segregated.

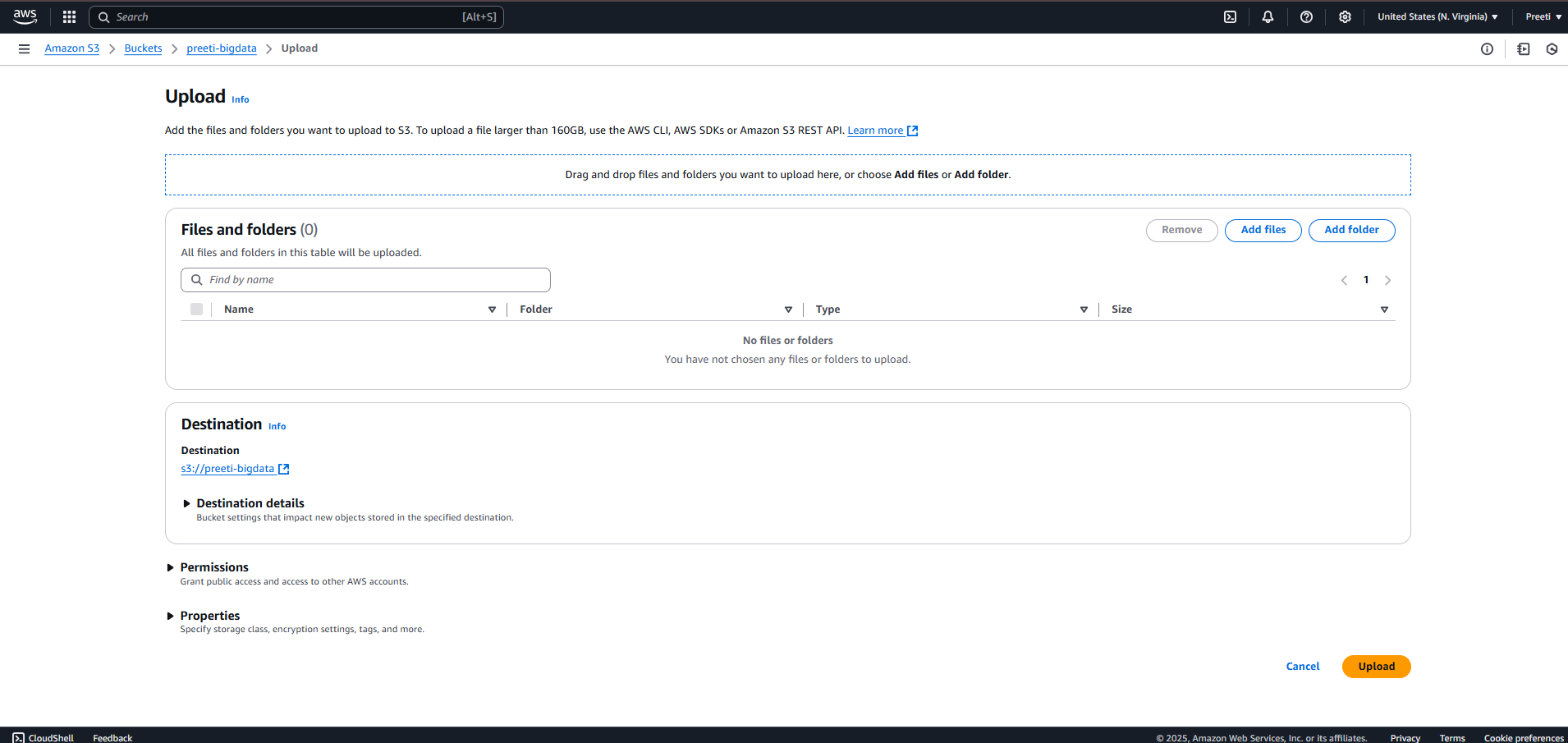


Figure : upload interface

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Figure : add the merged file

Centralizing these datasets within AWS S3 endowed the pipeline with the capabilities to horizontally scale while dealing efficiently with large data volumes. Therefore, Data Collection, while focused on raw data acquisition, organized its collected data in a structured fashion and safely stored it on data repos, hence creating a sound basis for later processing and analysis of this information.

## Data Cleaning and Wrangling

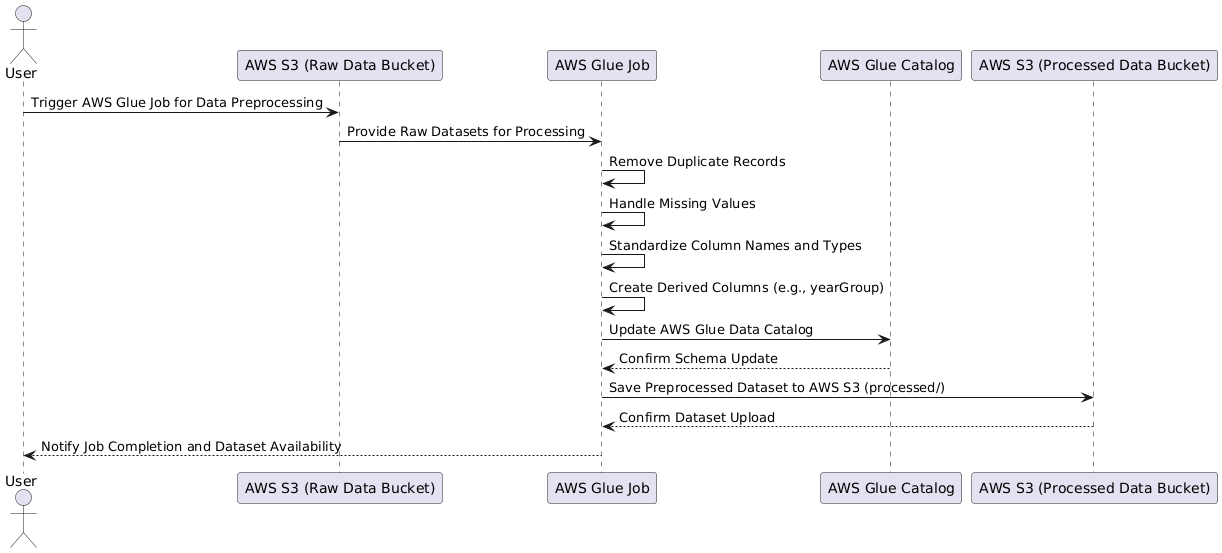
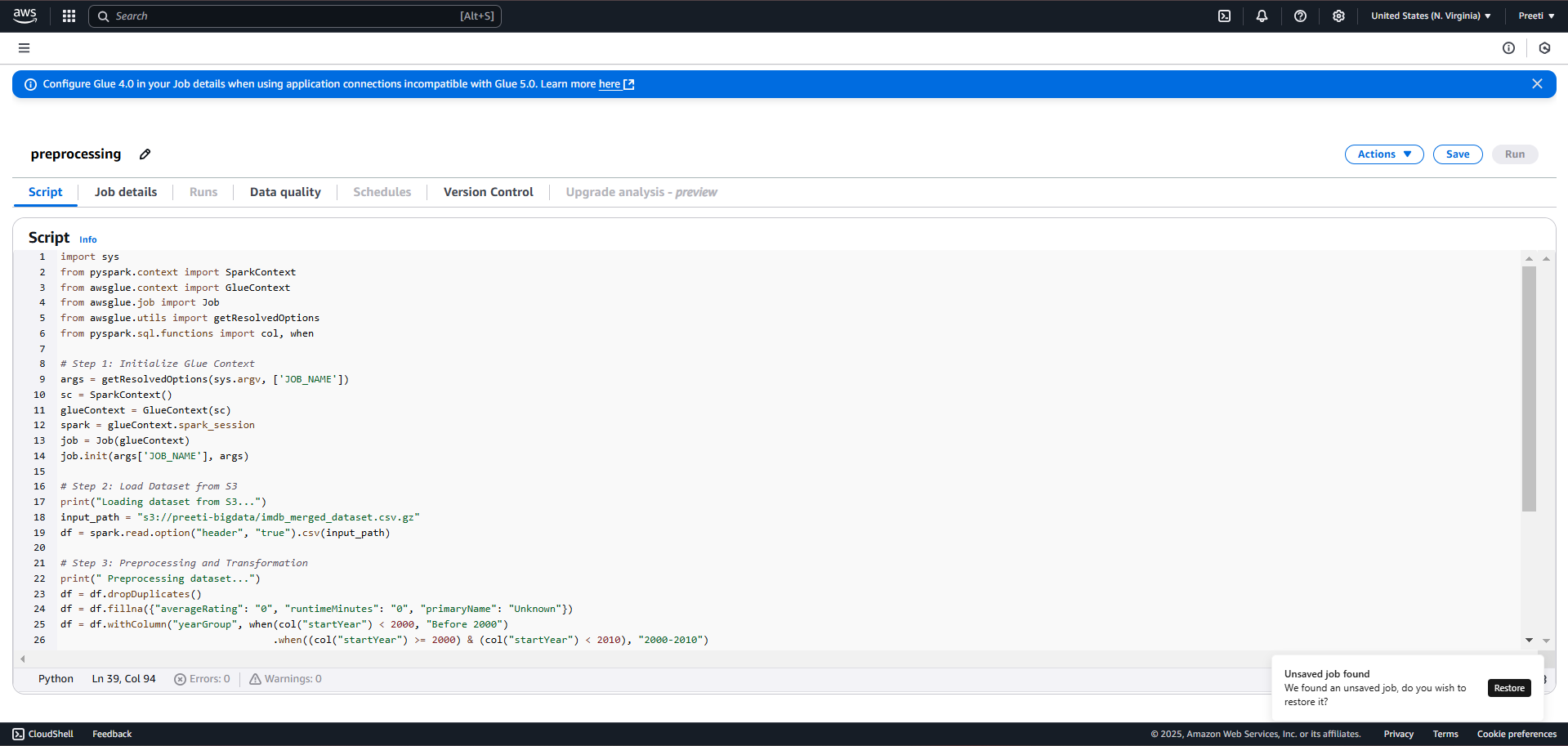


Figure : Data Cleaning and Wrangling flow

Cleaning and wrangling of data are very crucial steps in any data pipeline. Raw datasets contain inconsistencies, missing values, duplicates, and structural anomalies that may lead to insights not being accurate and could introduce biases into the analytical models if left unattended. In view of these challenges, AWS Glue-a serverless ETL service-was employed as a data preprocessor. AWS Glue was, therefore, the best choice, considering its capability for handling large-scale datasets, auto-discovery of schema, and easy integration with AWS S3.

It first worked on cleaning up duplicate records from all datasets. Large datasets often contain duplicate entries that distort the analysis results. AWS Glue jobs were set to run through each dataset to identify records with identical keys or overlapping information and retain only unique records.

Handling missing values was the next problem common in large datasets. The most commonly critical fields are **averageRating, runtimeMinutes, and primaryName**, which had null or blank values. These missing values within these fields might affect accuracy in statistical analysis and visualizations. Placeholder default values have been used to fill in the missing values for each of these fields consistently in a way that is neutral-not introducing bias. For example, runtimeMinutes is assumed to be 0 where the value is missing, and any primaryName will be named Unknown.



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Figure : Create etl job script for AWS glue

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Figure : successfully run the job

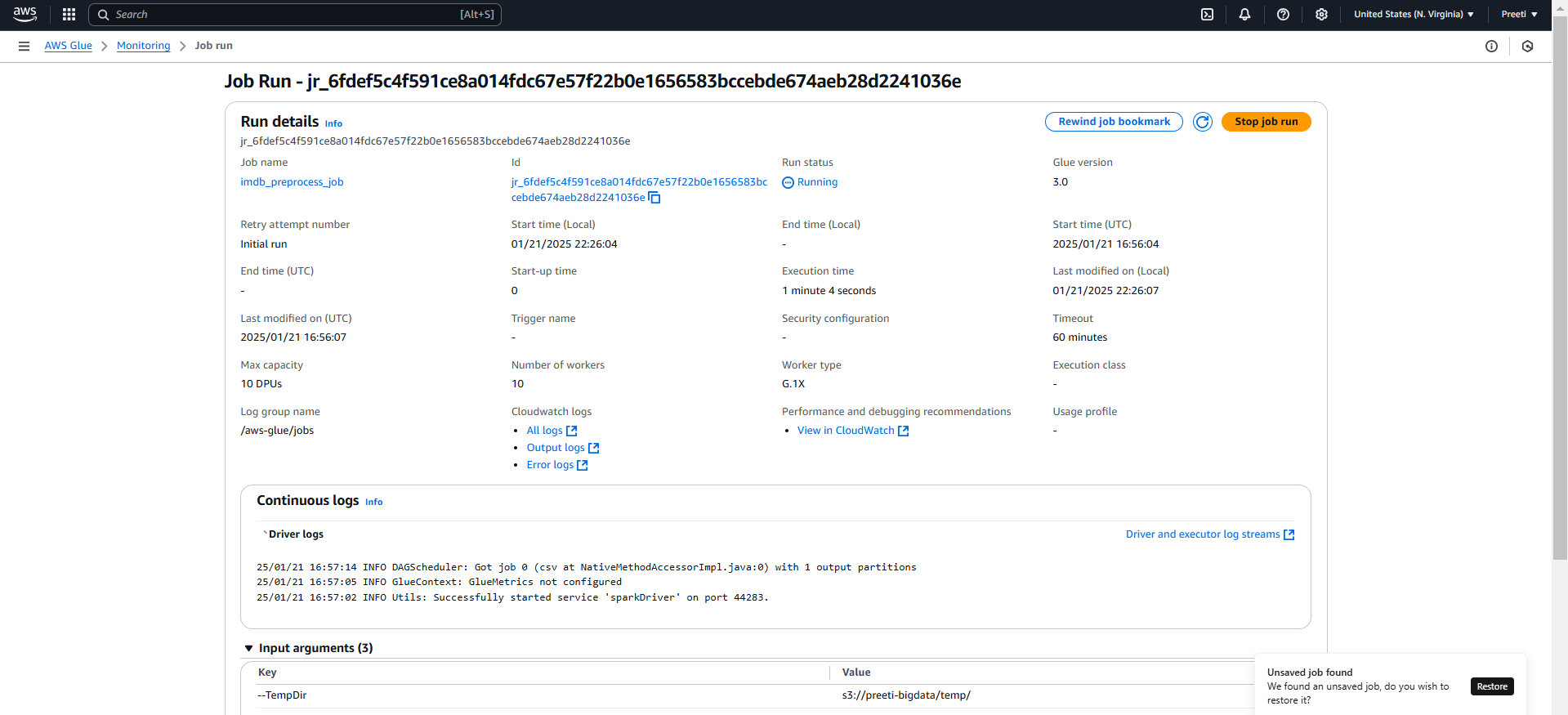


Figure : job details



Figure : script successfully executed

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Figure : preprocessed data stored in s3

Equally important in the preprocessing was the standardization of columns. Such naming convention discrepancies and mixed data types needed to be standardized to keep all datasets consistent. For example, date fields were unified into one format, while text fields were cleaned from unnecessary whitespace and special characters. In such a way, SQL queries and analysis scripts would run without problems due to mismatched data types.

Besides this, some derived columns were created that allowed for more insight in the analysis. A good example of a derived column was the yearGroup: this divided movies into three sets of time, namely Before 2000, 2000-2010, and After 2010. This further extends the temporal analysis to comparisons between different eras of cinema.

Further cleaned and transformed datasets were stored into Amazon S3 in the dedicated prefix, processed/. In storage, those processed datasets are made Gzip format to optimize not just in storage but also in the retrieval efficiency by reducing the latency in subsequent queries.

Conclusion This step will, therefore, ensure that whatever comes out of the IMDb dataset is accurate, complete, and consistent. Thus, with AWS Glue, this phase of transformation from raw and least reliable data to something well-structured and ready for advanced querying and analytics has been achieved.

## Data Analysis and Querying with Athena

Data Analysis and Querying had two different systems: AWS Athena for the querying of structured data and MongoDB for the analysis of semi-structured data. Both tools complement each other; hence, different querying methodologies could be used to answer different business questions effectively.

**Structured Querying with AWS Athena**

AWS Athena was used for storing the processed IMDb data in AWS S3. AWS Athena enabled the querying of the data residing directly in S3 with a serverless architecture, without the need to provision any infra. An Athena database, imdb\_database, was created where the external table definitions against the preprocessed data were set.

Athena enabled the processing and analysis of structured insights, such as questions around the 10 highest-rated movies, yearly movie production trends, and average ratings per genre. The findings were stored in query result buckets for visualization by other tools.

A screenshot of a computer

Description automatically generated

Figure : create the new database

A screenshot of a computer

Description automatically generated

Figure : set the database location

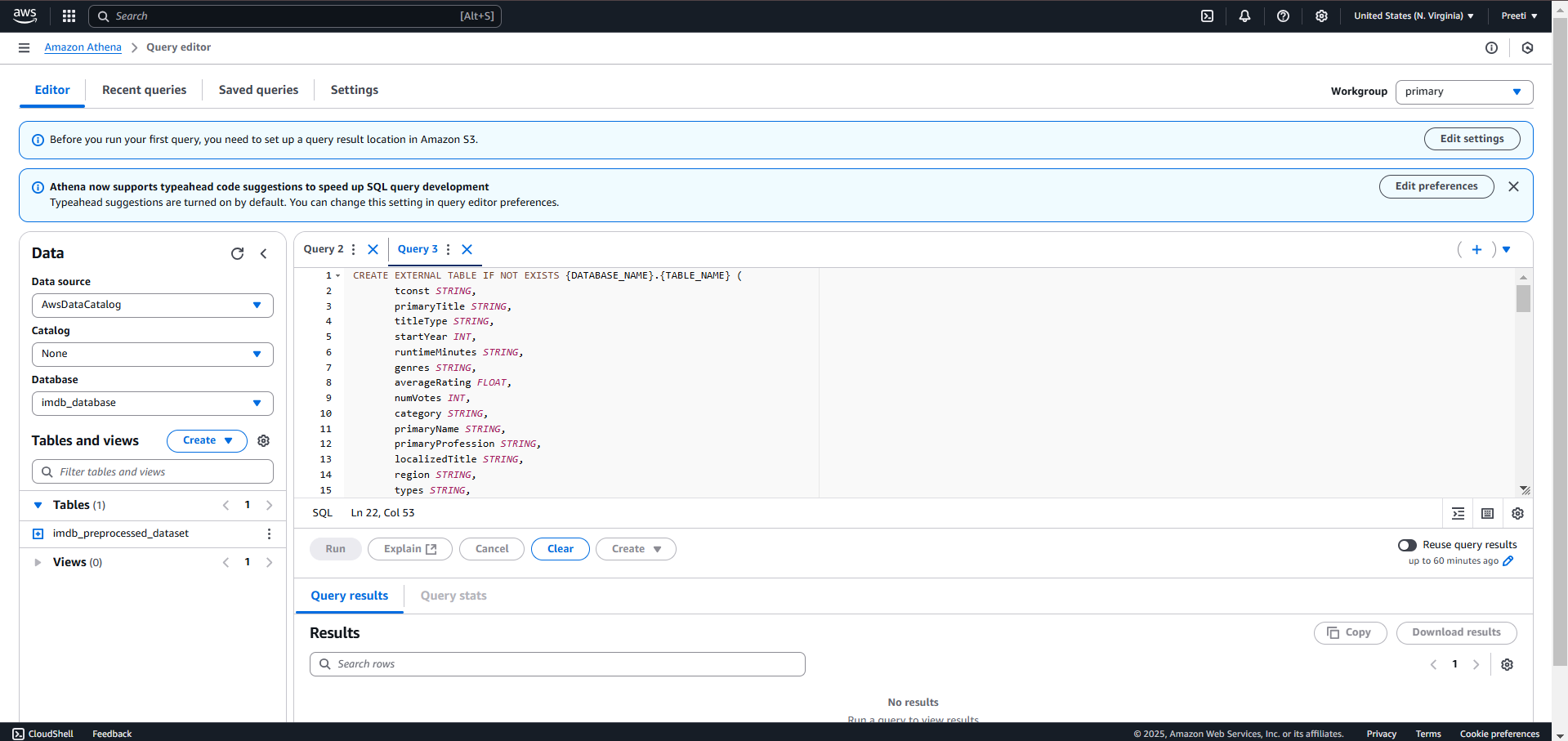


Figure : Create the new table using athena query editor

A screenshot of a computer

Description automatically generated

Figure : Get Top 10 Highest Rated Titles

A screenshot of a computer

Description automatically generated

Figure : Count Titles by Genre

A screenshot of a computer

Description automatically generated

Figure : Most Popular Profession Among Cast/Crew

## Data Visualization Techniques

The result was clearly outlined in the stage of Data Visualization Techniques, to show how accessible and intuitive the results are using libraries such as Python's Matplotlib, Seaborn, and Plotly. Visualization was, therefore, important for interpreting complex data sets in trying to spot some trends and effectively communicating with stakeholders.

It is the representation of the top 10 highest-rated movies together with their average rating in bar charts and scatter plots. Heatmaps will show the genre-based trend in movie ratings, and annual movie production trends in a time-series line plot. Additionally, the word cloud for the most frequent words in the titles of movies shows naming convention patterns.

Coupled with that, the interactive Plotly dashboards will enable any stakeholder to dynamically filter to a dataset in order to explore certain insights and back presentations with downloadable visualizations.

These visualizations transformed raw data into a riveting story that allowed the decision-makers to understand the trends, realize opportunities, and make informed decisions.

This basically means that data visualization techniques bridge the gap from having data to real-life insights in order to change numeric results into some nice, catchy, more informative representation of visuals.

A screenshot of a computer

Description automatically generated

Figure : download the preprocessed dataset from s3

A screen shot of a computer program

Description automatically generated

Figure : coding for visualize the dataset into graphical representation

# Results

The **Results Section** presents findings derived from the analysis of the **IMDb merged dataset** using PySpark, Python, and various visualization libraries. The section addresses the **eight business questions**, supported by insights and visualizations.

A screenshot of a computer

Description automatically generated

Figure : dataset after did preprocessing

## 1. Top 10 Highest-Rated Movies and Success Factors

**Objective:** Identify the top 10 highest-rated movies and analyze the common attributes contributing to their success.

A graph with different colored bars

Description automatically generated with medium confidence

Figure : Top 10 Highest-Rated Movies and Success Factors

## 2. Top-Performing Genres and Their Ratings Across Decades

**Objective:** Understand which genres consistently perform well over time and their average audience ratings.

A graph of a number of bars

Description automatically generated with medium confidence

Figure : Top-Performing Genres and Their Ratings Across Decades

## 3. Trends in Movie Production Over Time

**Objective:** Analyze the trends in movie production across different years and decades.

A graph showing the number of movies released per wear

Description automatically generated

Figure : A line plot Movies Released Per Year.

## 4. Top 10 Actors by Movie Appearances

**Objective:** Identify the top actors with the highest number of movie appearances.

A graph with different colored squares

Description automatically generated

Figure : A bar plot displayed the Top 10 Actors by Movie Count.

## 5. Regional Trends in Movie Performance

**Objective:** Identify regions with consistent movie engagement and audience growth.

A graph of different colors

Description automatically generated with medium confidence

Figure : A bar plot displayed the Top 10 Regions by Average Rating and Engagement.

## 6. Runtime Patterns in Successful Movies

**Objective:** Determine if there is an ideal runtime for highly-rated movies.

A graph of a graph showing the average rating by runtime

Description automatically generated

Figure : A bar plot illustrated the Average Rating by Runtime (Minutes).

## 7. Historical Trends in Movie Ratings Across Decades

**Objective:** Analyze which decades produced the most highly-rated movies.

A graph of different colored bars

Description automatically generated

Figure : Plotly visualized Number of Movies Released by Decade.

## 8. Patterns in Cast and Crew Combinations in Top-Rated Movies

**Objective:** Identify common patterns among cast and crew in high-performing movies.

A close up of words

Description automatically generated

Figure : wordcloud shows the top movie titles from dataset

**Key Observations Across All Questions**

1. **Genres:** Drama, Documentary, and Biographies perform consistently well.
2. **Regions:** US, India, and Japan dominate in audience engagement.
3. **Runtimes:** Optimal runtimes range from **90–120 minutes**.
4. **Actors:** Frequent appearances often align with franchises or recurring roles.
5. **Decades:** The **1970s** and **1990s** emerged as cinematic golden eras.

# Discussion

The Discussion section synthesizes the findings from the analysis phase that are meaningful, insightful, and actionable from the IMDb dataset. In this section, a deep dive into the insights derived is made, and strategic recommendations are given to stakeholders in the entertainment industry on how to make data-driven decisions. Indeed, a host of patterns and trends were observed in the IMDb dataset, underpinning some of the key factors driving movie success, audience engagement, and historical trends in the production and rating of films.

## Derived Insights

The first keen observation can be made whereas most of the top-rated movies are of Drama, Documentary, and Biography genres. The general theme that emerged from the story of such movies includes fascinating stories, well-developed characters, and great direction. Further, the time length of a successful movie also appeared to follow a particular pattern where top-rated movies would lie in the range of 90 to 120 minutes as well. This range appears to strike an ideal balance between sustaining audience attention and providing sufficient narrative depth. The interesting fact is that deviations from this range, in either the too-long or too-short direction, have tended to be associated with unpredictable audience ratings.

Whereas genre performance was highly time-sensitive, some genres such as Drama and Biography have performed well across the decades, while other genres like Comedy and Action were popular during periods. These changes at times run parallel to socio-cultural and technological developments, such as the rise of digital effects in the 2000s and the arrival of streaming platforms in the 2010s. Furthermore, audience preferences changed geographically too. North America - the US, India, and Japan - always stayed high in terms of audience engagement because of localized content and culturally relevant narratives. That goes to prove regional difference that is very important in the movie's success and, perhaps, may give a studio competitive advantage in terms of worldwide acceptance.

**Temporal Analysis** For the temporal analysis of movies produced, there is an exponential increase in movies produced after the year 2000, which is largely attributable to filmmaking technologies, cost-effective digital tools, and the recent rise of the streaming platforms. On the other hand, global crises, such as economic recessions or social disruptions, corresponded with noticeable declines in movie production. This cyclic nature of the film industry underlines its sensitivity to external socio-economic factors and, therefore, requires strategic planning of production and releases by stakeholders. The decade-based analysis also suggested that the 1970s and 1990s are the golden ages of cinema, with a significantly higher number of highly rated classics within those decades-a fact that perhaps explains their continuing influence on modern film. In analysis by actors and their possible contribution to movie success, consistency and collaboration were seen as important factors: actors who are featured in a long-running franchise or in long-term collaboration with renowned directors had considerably higher movie counts. But in the raw dataset, there were a lot of invalid or placeholder entries, such as "Unknown," which had to be filtered out at the pre-processing stage. Filtered, names are quite recognizable and show actors who have prolific careers characterized by a lot of appearances in critically acclaimed projects.

The point was made once more by patterns in the combinations of cast and crew: collaboration paid. Indeed, director-actor collaborations like Christopher Nolan–Christian Bale and Martin Scorsese–Leonardo DiCaprio produced constant high performances. Often, putting together complementary skill sets and visions that clicked in with the audiences consistently. The inference is that great films are more about synergies than just individual brilliance elicited by collaboration among its key contributors.

Regional differences were also reflected in a number of trends. Films appealing to local audiences did considerably well in their respective regions. The use of titles in regional languages, incorporating regional themes, and telling regionally relevant stories has considerably helped develop better audience interactions. This has been the case in regions like India, where films with solid regional stories have been successful on both critical and commercial levels. While not as prominent, emerging markets in Southeast Asia also saw promising growth, indicating new opportunities for production houses and streaming platforms to expand their footprint.

A proper runtime analysis had given a very clear trend whereby movies that were too short or too long never enjoyed much appreciation among viewers. Instead, a runtime of between 90 to 120 minutes seemed an ideal and reliable range likely to go well with viewers. There are some obvious exceptions in genres such as Documentaries or Epic Dramas, which need longer time for storytelling.

The historical trends in movie ratings across decades have provided interesting cycles of audience preferences and production peaks. This makes the 1970s and 1990s the most influential decades, with a high number of critically acclaimed movies produced in these periods. On the other hand, recent decades have been more commercially oriented with filmmaking, focusing highly on blockbuster franchises and their digital streaming releases. This becomes a mark of socio-cultural changes through which movies mostly reflect the times in which they came into being.

The above analysis brings into light the various factors, such as genres, runtime, regional preferences, and collaboration dynamics, influencing movie success. The insight gained through patterns over decades of time, regions, and creative collaborations will be very useful and can guide the stakeholders-productions houses, streaming platforms, or independent filmmakers-either way. These insights could allow industry players to make informed choices, optimize resources, and even predict how well-accepted a piece of the future will be. The data set shows historical trends and a basis on which predictive models and recommendations systems can be further built in enhancing informed decision-making within this ever-changing entertainment context.

## Recommendations

The insights of the analysis go to the tune of certain actionable recommendations that could be given to the stakeholders of the entertainment industry. Production houses and streaming platforms stand to gain immensely by leading from the front with a data-driven approach in strategy and content creation. Key recommendations wade around a genre-specific trend. Such genres are drama, biography, and documentaries: these retain a great amount of consistency in audiences and high ratings for great lengths of time. And it is within these that investment, especially in meaning and impactful emotional connections within a story, can really lift a movie's chances.

Worth mentioning, another recommendation would be to accord due attention to runtime optimization. A film ranging around 90 to 120 minutes has invariably recorded greater audience engagement and better rating returns. However, this could be allowed with a few exceptions in some sort of genres, like a documentary and epic drama that requires extended runtime for desirable narrative impact. Filmmakers and producers need to critically assess every genre and the need for narration for runtime optimization.

That also means regional preferences also come to the fore in content strategy. Production houses and streaming platforms have to invest in the creation of regionalized content in these various regions. Regions like North America, India, and Japan continued to stay ahead of positions in terms of audience engagement, while emerging regions like Southeast Asia present an opportunity for further expansion.

Successful director-actor collaborations and creative teams are encouraged. Data showed that repeated collaborations of an established director-actor pairing tend to yield successful projects time after time. Production houses have to identify such partnerships and invest in sustaining these creative synergies.

Last but not least, data collection and preprocessing are very crucial for any analysis. Placeholder entries, such as "Unknown" in the primaryName column, created challenges in the analysis. Therefore, strong data validation mechanisms must be implemented during data ingestion and in the preprocessing stage to provide cleaner datasets that will generate reliable insights.

Smarter decisions by stakeholders, great quality of the content, and better audience engagement-reasons all put together mean huge success and long-term sustainability within the entertainment industry.

# Conclusions

These kinds of trend analyses in the IMDb dataset provide insights into movie-audience preference and other variable causes that determine the fate of a movie. Equipped with such tools like PySpark, AWS Glue, and AWS Athena, along with visualization libraries such as Matplotlib and Seaborn, hereafter these key business questions were solved, including visualizing meaningful patterns for better understanding.

One important observation was that some genres performed well time after time: drama, documentary, biography-just keep on captivating the audiences. These genres usually are driven by strong storytelling with emotionally driven narratives. Another relation that came across was that of the duration and runtime versus audience ratings. Movies running between 90 to 120 minutes usually performed better as they allowed a balanced depth in the narrative to be maintained along with audience engagement.

Historical trends showed that high-quality movies were produced in two distinct periods: the 1970s and the 1990s. Conversely, the film industry started to grow after the year 2000 as a result of the advancement of digital technologies and the use of streaming platforms. Simultaneously, certain external factors, like economic declines, were observed to influence movie production volumes on the negative side.

The role of actors and crew collaboration also became one of the major findings. Successful actors and directors mostly worked together many times, hence results are movies that were received well consistently. However, preliminary quality issues in data needed careful preprocessing for meaningful results.

By region, North America, India, and Japan were key markets that consistently recorded high audience engagement. Meanwhile, emerging regions-especially those in Southeast Asia-offered high growth potential, thus signaling an opportunity for expansion and native content strategies.

From a technical perspective, the integration with AWS services at each step preprocessed, queried, and stored data way more effectively. For instance, tools like AWS Glue made the transformation of data easier, while AWS Athena enabled seamless and easily scalable querying of data. Visualization tools also presented findings in accessible and comprehensible ways.

This analysis has, therefore, shown how data-driven insights can drive strategic decisions in the entertainment industry. The findings give actionable recommendations to the stakeholders-whether content creators, production houses, or streaming platforms-on how to optimize genres, runtimes, and regional content strategies. Going ahead, this insight can be used to build predictive models and recommendation systems that further enhance audience engagement and content delivery.

# Personal Reflection

## What I Learned

The project turned out to be a great way to get hands-on in big data analytics, cloud computing, and data visualization. I took away handling of big datasets with PySpark, efficient data pre-processing using AWS Glue, and execution of SQL queries using AWS Athena, among others. Besides that, I took away the usage of cloud resources management and optimization of workflows, respectively, and tools such as MongoDB in analyzing semi-structured data. The process of integration through visualization using Matplotlib, Seaborn, and Plotly enabled me to understand how the story behind the data drives better decision-making.

## Challenges Faced

Challenges One of the most critical challenges involves knowing how to work around handling very large data without being limited by the size of memory. Irrespective inconsistencies in the preprocessing, there was a special concern with placeholder values including "Unknown" and blanks in columns, which really had to be carefully tended so the results would ensure reliability. This initially also included the setup of AWS services such as S3, Glue, and Athena, which turned out to be very problematic, especially considering permissions and IAM roles. Among the other challenges were providing insight that the visualizations may over-simplify complex patterns.

## Future Action Plans

The trend analysis will be extended further for predictive analytics and the machine learning models that predict the success of a movie based on historical trends in times to come. I also plan to develop a recommendation engine based on insights drawn from this analysis, which shall be useful for streaming platforms. This, combined with the data engineering pipelines of cloud technologies, is one thing I really wish to dive into later so that I could be working with much larger, complex sets of data. It really nailed in concepts about the data analytics workflow that I'm looking forward to using on new projects.

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