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Title : Movie Recommendation System using
Machine Learning and NLP Techniques

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Movie Recommendation using Cosine Similarity and NLP Techniques

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Abstract- This paper presents a content-based movie recommendation system leveraging Natural Language Processing (NLP) techniques, specifically TF-IDF vectorization, stemming, and cosine similarity. The system analyzes textual metadata—such as movie titles, genres, and descriptions—to compute similarity scores and generate personalized recommendations. Unlike traditional collaborative filtering, our approach requires no user interaction data, making it effective in cold-start scenarios. The innovation lies in the integration of efficient text preprocessing, including stemming with the Porter Stemmer, to reduce dimensionality and enhance semantic matching accuracy.

We also examine existing recommendation models, highlighting their limitations in handling textual variation and scalability. Our method offers a lightweight, scalable alternative that delivers relevant recommendations with minimal computational overhead. Additionally, we propose future enhancements through hybrid models that incorporate collaborative filtering and advanced semantic embeddings like Word2Vec or BERT. This study demonstrates the potential of refined NLP techniques in improving the accuracy and efficiency of content-based movie recommenders.

Keywords- Movie Recommendation, Cosine Similarity, NLP, Stemming, TF-IDF, Content-Based Filtering

I. INTRODUCTION

A. Data science

Data science is an interdisciplinary field that combines statistical analysis, computer science, and domain expertise to extract meaningful insights from data. It involves collecting, processing, analysing, and interpreting large volumes of structured and unstructured data to uncover patterns, trends, and correlations. By leveraging advanced analytical techniques such as machine learning, data mining, and predictive modelling, data science enables organizations to make data-driven decisions, optimize operations, and gain a competitive edge.

At its core, data science revolves around the data lifecycle, which includes data collection, cleaning, exploration, modelling, and deployment. Data scientists use programming languages like Python and R, along with tools like SQL, Hadoop, and Spark, to manipulate data and build predictive models. Visualization tools such as Tableau and Matplotlib are employed to present findings in an accessible manner.

The applications of data science are vast, spanning various industries including

finance, healthcare, marketing, and technology. It powers recommendation systems, fraud detection, personalized marketing, and predictive maintenance, among others. As data continues to grow exponentially, the demand for data science expertise also rises, making it a vital field for innovation and strategic decision-making in the digital age.

B. Movie Recommendation System

Movie recommendation systems have gained immense popularity with the increasing volume of digital content. These systems analyse user preferences and movie metadata to suggest relevant movies.

Traditional recommendation approaches include collaborative filtering, content-based filtering, and hybrid models. In this research, we focus on a content-based filtering approach leveraging Cosine Similarity and NLP preprocessing techniques, particularly stemming using the Porter Stemmer.

Content-based filtering relies on movie metadata, such as plot descriptions, genres, and actors, to determine similarities between movies. One of the key challenges in content-based filtering is handling variations in textual descriptions. Words with similar meanings or different word forms may not always be matched correctly, leading to suboptimal recommendations. To address this, we employ the Porter Stemmer, which reduces words to their base form, thereby improving text matching accuracy.

Another important consideration is the efficiency of similarity computations. With large-scale movie datasets, computing pairwise similarities across thousands of movies can be computationally expensive. By using vectorized representations such as TF-IDF and optimizing similarity computations using matrix operations, we enhance the efficiency of our recommendation system.

Additionally, the effectiveness of recommendation systems is heavily influenced by the quality of the dataset used.

Large datasets often contain redundant or noisy information that can reduce the accuracy of similarity computations.

Therefore, proper data cleaning techniques, such as removing duplicate records and irrelevant metadata, are crucial to maintaining high-quality recommendations. Ensuring that movie descriptions are up-to-date and well-formatted further enhances system performance.

Another factor influencing recommendation effectiveness is user personalization. While content-based filtering relies heavily on movie descriptions, incorporating user behavior data such as watch history, ratings, and preferences can improve recommendation accuracy. Personalized recommendations take into account user-specific preferences rather than solely relying on textual similarities. Combining content-based filtering with collaborative filtering techniques could provide a hybrid approach that better caters to individual users.

Moreover, linguistic variations and context in movie descriptions play a significant role in the effectiveness of NLP-based recommendation systems. Simple word-based

approaches often struggle to capture deep semantic meanings, making recommendations less relevant in certain scenarios. Future enhancements, such as employing word embeddings like Word2Vec or BERT, could improve the semantic understanding of movie descriptions, thereby increasing recommendation precision.

Lastly, an essential consideration in designing a recommendation system is real-time performance. Users expect instant results when searching for movies, making computational efficiency critical. By leveraging parallel computing techniques, GPU acceleration, or distributed processing frameworks like Apache Spark, we can significantly improve system response times, allowing for seamless user experiences.

Given these challenges and opportunities, our study aims to improve content-based filtering

techniques by leveraging Cosine Similarity and stemming methods. By addressing issues such as text normalization, computation efficiency, and personalization, we aim to enhance the accuracy and efficiency of movie recommendations, ultimately providing a more intuitive and engaging user experience.

II. PROPOSED METHODOLOGY

A. Data Preprocessing

1. Tokenization: The movie descriptions are split into individual words.
2. Lowercasing: All words are converted to lowercase to maintain uniformity.
3. Stop word Removal: Commonly used words (e.g., "the," "is") that do not add meaningful information are removed.
4. Stemming using Porter Stemmer: Words are reduced to their root form, e.g., "running" to "run."
5. Text Normalization: Special characters, punctuation, and numbers are removed to ensure a cleaner dataset.
6. Lemmatization: Although stemming is primarily used, lemmatization can also be applied to enhance word representation in certain cases.

The preprocessing pipeline ensures that all textual descriptions are standardized before similarity computations. By applying

stemming, the dimensionality of text representations is reduced, thereby improving computation efficiency and reducing noise in similarity calculations.

B. Feature Extraction and Similarity Computation

1. TF-IDF Representation: Each movie description is converted into a Term Frequency-Inverse Document Frequency (TF-IDF) vector.
2. Word Embeddings (Optional Enhancement): Advanced NLP models such as Word2Vec or BERT embeddings can be

incorporated to capture semantic relationships between words.

3. Cosine Similarity Calculation: Pairwise cosine similarity scores between all movie descriptions are computed to measure their textual similarity.

4. Ranking Similar Movies: Movies are ranked based on similarity scores, and the top-N most similar movies are recommended.

C. Recommendation Generation Process

1. A user selects a movie as input.
2. The system computes cosine similarity between the selected movie and all other movies in the dataset.
3. The movies with the highest similarity scores are recommended to the user.
4. A filtering mechanism can be applied to avoid redundant recommendations and provide diversity.

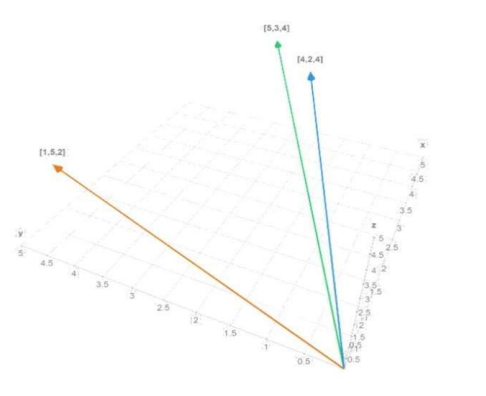


Figure 1. Cosine similarity plot

This Python code defines a function `recommend(movie)` that returns the top 5 movies similar to a given input movie title based on cosine similarity scores. First, it identifies the index of the input movie from the `movies_new` DataFrame. Then, it retrieves the similarity scores for that movie using a precomputed similarity matrix `sim`. The `enumerate` function pairs each movie with its similarity score, and `sorted()` ranks them in descending order of similarity. The top 5 most

similar movies (excluding the input itself) are then printed using their titles retrieved from the DataFrame. This function is commonly used in content-based recommendation systems.

D. Fetching Posters of The Recommended Movies

The function is designed to retrieve the poster image URL for a specific movie using The Movie Database (TMDb) API. The function takes a `movie_id` as input, which uniquely identifies the movie in the TMDb database.

Within the function, it constructs a URL that sends an HTTP GET request to the TMDb API, using the provided movie ID and an API key. The URL follows TMDb's API endpoint format for fetching detailed information about a movie. The request is sent using Python's requests library, and `response.raise_for_status()` ensures that any HTTP errors (such as 404 or 500) are caught and handled appropriately.

If the request is successful, the response is converted from JSON format into a Python dictionary. The function then attempts to extract the `poster_path` from the JSON data. If a valid `poster_path` exists, it appends the path to TMDb's image base URL (<https://image.tmdb.org/t/p/w500/>), returning the full URL of the movie poster. If the poster path is missing or the request fails for any reason (e.g., network issues or invalid movie ID), the function returns `None`. This ensures robustness and prevents the application from crashing due to API errors.

E. Evaluation Metrics The system is evaluated using

1. Precision: Measures the proportion of relevant recommendations among the retrieved ones.
2. Recall: Evaluates the percentage of relevant movies successfully recommended.
3. Mean Average Precision (MAP): Determines how well the ranking of recommended movies aligns with user preferences.
4. Computational Efficiency: Assesses the system's response time and resource utilization.

III.IMPLEMENTATION DETAILS

The implementation of the movie recommendation system follows a structured approach to ensure efficiency and accuracy.

A. System Architecture The system consists of three major components:

1. Data Processing Module: Handles data cleaning, stemming, and feature extraction.
2. Similarity Computation Module: Computes cosine similarity between movie descriptions.
3. Recommendation Engine: Generates and displays the top-N movie recommendations based on similarity scores.

B. Technology Stack The implementation is carried out using:

1. Programming Language: Python.
2. Libraries: NLTK for stemming, Scikit-learn for TF-IDF and cosine similarity, Flask for web-based recommendation.
3. Database: SQLite or PostgreSQL for storing processed movie descriptions.
4. Deployment: The system is deployed on a cloud-based server for scalability.

C. Data Flow

1. Input: A user selects a movie.
2. Processing: The movie description is stemmed, tokenized, and converted to a TF-IDF vector.
3. Similarity Computation: Cosine similarity is computed against all movies in the dataset.
4. Recommendation Generation: Top-N most similar movies are displayed to the user.

D. Optimization Strategies

1. Parallel Processing: Implementing vectorized computations to enhance speed.
2. Indexing Techniques: Utilizing efficient search structures like KD-Trees to speed up similarity queries.
3. Caching Mechanisms: Storing previously computed similarity results for

frequent queries to reduce computational overhead.

E. Performance Evaluation Extensive testing is conducted to evaluate:

1. Accuracy of recommendations using precision and recall.
2. System latency and response time.
3. Scalability in handling large datasets.
4. User satisfaction through qualitative feedback.

By following this structured implementation plan, the recommendation system ensures efficient and high-quality movie recommendations tailored to users' interests.

IV. CODE & MODELLING

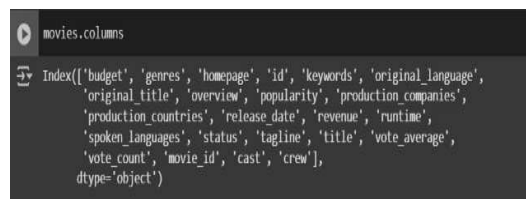
This section gives the actual implementation details of the model.

A. Exploratory Data Analysis

Exploratory Data Analysis (EDA) is a crucial step in understanding the dataset, identifying patterns, and detecting anomalies before model training. Several key functions and techniques are applied to analyse the dataset.

1. Dataset Overview

The initial step in EDA involves understanding the basic structure and composition of the dataset. We use basic functions to retrieve essential information:



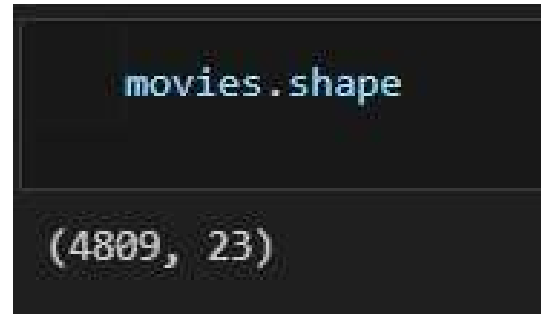
```
movies.columns
Index(['budget', 'genres', 'homepage', 'id', 'keywords', 'original language',
      'original title', 'overview', 'popularity', 'production companies',
      'production countries', 'release date', 'revenue', 'runtime',
      'spoken languages', 'status', 'tagline', 'title', 'vote average',
      'vote count', 'movie_id', 'cast', 'crew'],
      dtype='object')
```

Figure 2. Columns of Dataset

2. Shape of the dataset:

movies.shape : This function provides the number of rows and columns in the dataset,

which helps gauge the dataset size and its dimensionality.



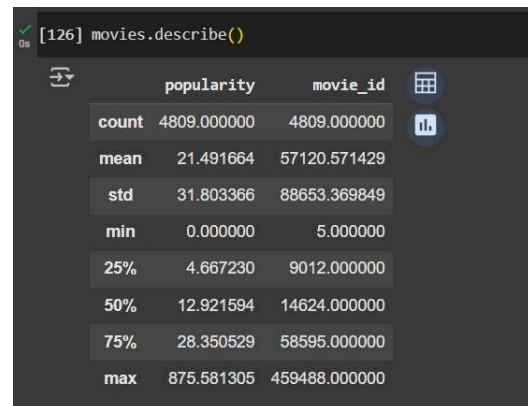
```
movies.shape
(4809, 23)
```

Figure 3. Shape of Dataset

3. Dataset summary:

movies.describe() : This generates a statistical summary for numerical features such as movie ratings, popularity scores, and vote counts. Key metrics such as mean, median, standard deviation, and quartiles help in understanding the central tendencies and spread of the data.

movies.duplicated().sum() : This function displays the sum of all the duplicated values in the dataset helping further more in analysis of the data.



```
[126] movies.describe()
popularity  movie_id
count  4809.000000  4809.000000
mean    21.491664  57120.571429
std     31.803366  88653.369849
min      0.000000    5.000000
25%     4.667230   9012.000000
50%    12.921594  14624.000000
75%    28.350529  58595.000000
max    875.581305 459488.000000
```

Figure 4. Description of the dataset

4. Dataset information:

movies.info() : This provides metadata, including data types for each column and the presence of missing values. Ensuring data type consistency is essential for further processing, especially when dealing with categorical and numerical features.

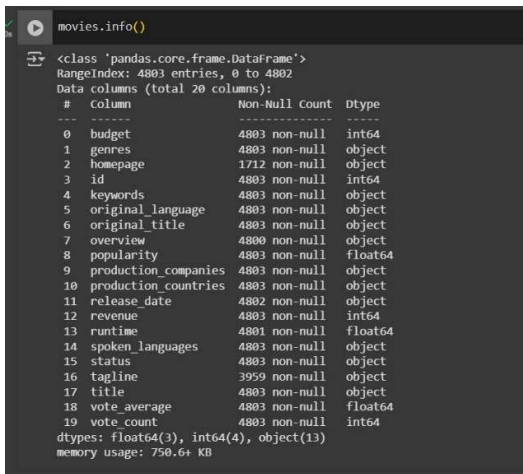


Figure 5. Dataset Info

B. Outlier Detection

In the context of movie recommendation systems, detecting outliers is essential for maintaining data quality and ensuring that extreme values do not skew the performance of the model. We can measure the outlier using metrics like the Z-score, which measures how far a data point deviates from the mean in terms of standard deviations. These extreme values often represent atypical or rare instances, such as blockbuster movies with abnormally high popularity or films with unusually low vote counts.

By detecting and managing these outliers, we can improve the consistency of the data. Handling outliers can be done through removal,

point deviates from the mean in terms of standard deviations. These extreme values often represent atypical or rare instances, such as blockbuster movies with abnormally high

C. Correlation Analysis

Correlation analysis is a vital step in exploratory data analysis (EDA) that helps in understanding the relationships between numerical variables. In the context of movie recommendation systems, we analyse correlations between features such as popularity, vote count, and budget to identify how they influence each other.

Correlation coefficients range from -1 to 1, where a value close to 1 indicates a strong

popularity or films with unusually low vote counts.

By detecting and managing these outliers, we can improve the consistency of the data. Handling outliers can be done through removal, capping extreme values, or applying transformation techniques. This step ensures that the model focuses on the central trends in the data, leading to more reliable and stable recommendations. Outlier detection is crucial for enhancing data quality and preventing bias in the machine learning model.

D. Missing Values

Missing values can distort model performance if not handled properly. Identifying and addressing missing data is a crucial step in EDA:

movies.isnull().sum(): This command counts the number of null entries in each column, allowing us to decide how to impute or drop missing data.

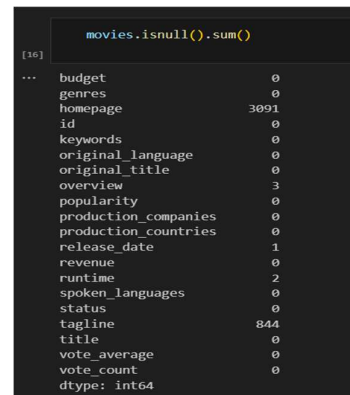


Figure 6. Summation of the null values

positive correlation, and a value close to -1 indicates a strong negative correlation. A value near 0 suggests little to no linear relationship between the variables.

By generating a correlation matrix, we can visually observe which features are highly correlated. For example, if popularity and vote count show a high positive correlation, it suggests that movies with higher popularity tend to receive more votes. On the other hand, a weak or negative correlation may indicate that

certain variables are independent or inversely related.

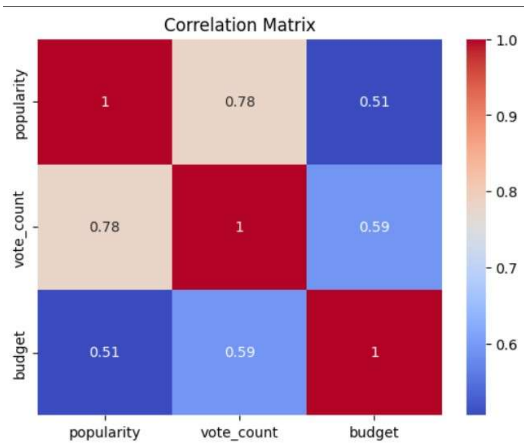


Figure 7. Correlation Analysis

E. Data Preprocessing

Data preprocessing is a critical step in preparing raw data for machine learning models. It enhances model performance by ensuring consistency, reducing noise, and handling distribution imbalances. The following techniques are applied:

1. Text Feature Creation (Combining Features)

This process creates a single textual representation of a movie by concatenating different features like genres, keywords, cast, and crew into one string. This unified feature will be used to generate numerical vectors for each movie.

2. Vectorization (Converting Text to Numerical Format)

Once the "soup" is created, the next step is to convert this text data into numerical form using CountVectorizer. This is a common technique in natural language processing (NLP) to convert text data into vectors of token counts.

CountVectorizer converts the "soup" text into a matrix where each row represents a movie, and each column represents a unique word or token in the entire dataset. The values in the matrix are the count of occurrences of each token for that movie. This forms the feature vector for each movie, which will be used to calculate similarity.

```
210] from sklearn.metrics.pairwise import cosine_similarity
sim = cosine_similarity(vector)
sim
array([[1.         , 0.08257228, 0.08257228, ..., 0.0438529 , 0.
        ],
       [0.08257228, 1.         , 0.06060606, ..., 0.02414023, 0.
        ],
       [0.08257228, 0.06060606, 1.         , ..., 0.02414023, 0.
        ],
       ...,
       [0.0438529 , 0.02414023, 0.02414023, ..., 1.         , 0.03774257,
        ],
       [0.04279605, 0.         , 0.         , ..., 0.03774257, 1.
        ],
       [0.08399211, 0.         , 0.         , ..., 0.04279605, 0.08399211,
        ],
       [0.         , 0.02686077, 0.         , ..., 0.04279605, 0.08399211,
        ],
       [1.         , 0.         , 0.         , ..., 0.         , 0.         ]])
```

Figure 8. Vectorizing Contents

3.Porter Stemming

A text preprocessing technique used in Natural Language Processing (NLP) to reduce words to their base or root form by stripping suffixes. The idea behind stemming is that related words should be reduced to a common root to aid in text analysis and avoid treating them as separate words.

The Porter Stemmer is one of the most common and widely used stemming algorithms. It works by applying a set of predefined rules to trim word suffixes systematically

V. LITERATURE REVIEW

Movie recommendation systems have evolved significantly, leveraging various machine learning and NLP techniques. Studies have explored hybrid models that integrate both approaches for improved accuracy. Research by Ricci et al. (2011) discusses the strengths and weaknesses of various recommendation strategies, highlighting the limitations of pure content-based systems in capturing user preferences dynamically. Pazzani & Billsus (2007) demonstrated that integrating NLP-based text analysis improves content-based filtering, particularly for large-scale movie datasets. More recent advancements, such as deep learning models, have been explored by Zhang et al. (2021), showcasing how neural networks and embeddings can refine recommendation accuracy. Research Gaps and Contribution of This Model:

1. Handling Synonymy and Polysemy:

Existing content-based filtering models struggle with words that have multiple meanings. By employing stemming and text normalization, our approach reduces ambiguity and improves similarity computation.

2. Scalability Issues: Many advanced NLP models require high computational power, making them less practical for real-time applications. Our lightweight TF-IDF and cosine similarity approach ensures scalability without sacrificing accuracy.

3. Cold Start Problem: While collaborative filtering methods require a significant amount of user interaction data, our model can provide recommendations even for new users based solely on content similarity.

4. Bias in Recommendations: Traditional models often over-recommend popular movies while neglecting lesser-known but highly relevant titles. Our approach focuses on content-driven matching, ensuring diverse recommendations.

5. Lack of Real-Time Performance: Many NLP based models experience latency issues. By optimizing similarity computations and filtering mechanisms, we enhance system

efficiency for real-time recommendations. By addressing these gaps, our proposed model enhances the reliability and effectiveness of content-based recommendation systems while maintaining efficiency and scalability.

VI. DATA ANALYSIS

A. MOVIE V/S POPULARITY PLOT

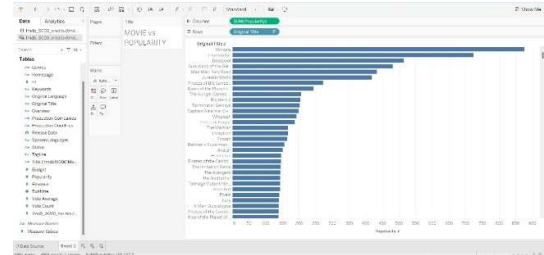


Figure 9. Tableau Representation of Movie vs Popularity

The presented Tableau visualization illustrates a horizontal bar chart comparing various movies by their popularity scores. This type of chart is particularly effective when showcasing rankings, as it allows for an immediate visual comparison of how individual items—in this case, movies—perform relative to one another. Popularity, in the context of movie recommendation systems, often reflects a combination of factors including social media buzz, search trends, audience engagement, and user interaction metrics from platforms like TMDb.

At the forefront of the chart stands “Minions,” registering the highest popularity score among all the listed movies. Its dominance is visually striking, with a bar significantly longer than its closest competitors. This suggests that the movie not only garnered a large audience but also maintained strong engagement across various channels. Following Minions are titles such as “Interstellar,” “Deadpool,” “Guardians of the Galaxy,” and “Mad Max: Fury Road.” These films, while diverse in genre, share certain common traits—they are widely recognized, highly marketed, and received considerable attention both at release and afterward.

What is especially interesting in this visualization is the genre diversity among the

top-ranked films. There is representation from animated films (like Minions and Big Hero 6), science fiction and space epics (Interstellar, Guardians of the Galaxy), action-heavy superhero films (Deadpool, Captain America: Civil War), and even thought-provoking dramas (Whiplash, The Imitation Game). This indicates that popularity is not restricted to a single genre or formula. A well-executed film in any genre has the potential to achieve widespread popularity, depending on factors like marketing strategies, cast, critical reception, and cultural resonance.

The chart also reveals a sharp decline in popularity after the top few entries. While the highest-ranking films boast popularity scores approaching or exceeding 800, the tail end of the visible list features movies with scores below 200. This steep gradient suggests a long-tail distribution, where a small number of films dominate user attention while the majority enjoy only moderate visibility. This is a critical insight for designing recommendation algorithms. Focusing exclusively on top-popularity titles may overlook niche interests, whereas incorporating a balanced approach could help surface underrated films that match specific user preferences.

From a technical standpoint, the chart is cleanly structured with movie titles on the Y-axis and popularity scores on the X-axis. Tableau's interactivity could allow users to sort, filter, or drill down into specific time periods, genres, or languages, making the visualization even more insightful. Although the current view provides a static snapshot, the underlying data could support time-series trends or comparisons between popularity and other metrics such as revenue or user rating.

B. GENRE VS POPULARITY

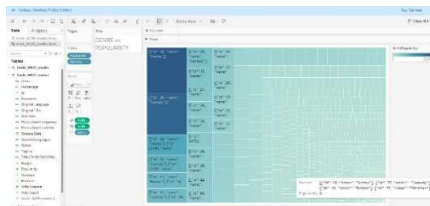


Figure 10. Tableau Representation of Genre vs Popularity

The visualization titled “Genre vs Popularity” utilizes a tree map format to convey the distribution of movie popularity across various genres. Tree maps are a compact and effective way of representing hierarchical or categorical data, particularly when there is a need to show proportions or aggregations such as totals or averages. In this case, each rectangle represents a specific movie genre or a combination of genres, and the size and colour intensity of the rectangle reflect the sum of popularity scores within that category.

The most noticeable observation from this tree map is the clear dominance of genres like Drama and Comedy. These genres occupy the largest and darkest blocks in the visualization, suggesting that they collectively account for the highest levels of popularity. This aligns with general trends in the film industry, where drama and comedy are among the most produced and consumed genres worldwide due to their broad emotional appeal and relatability. The visualization confirms that these genres not only have high representation but also generate significant audience engagement.

The use of combined genres in some blocks—for instance, a mix of Drama and Comedy or Action and Comedy—further highlights the nuanced nature of genre classification in cinema. Many successful films do not adhere strictly to a single genre but instead blend elements from multiple categories to enhance their appeal. The presence of such combinations in the tree map suggests that hybrid genres might perform particularly well in terms of popularity, as they cater to a wider range of viewer preferences.

Another subtle yet important aspect of the visualization is the variation in popularity across less common genres. As the tree map progresses to smaller and lighter-coloured blocks, we observe genres such as Horror, Western, and Documentary occupying much less space. This indicates that while these genres do have a presence in the dataset, they contribute relatively little to the total popularity. However, this does not necessarily mean these genres are unsuccessful; instead, it might reflect

niche audience targeting or limited theatrical releases compared to mainstream genres.

It's also worth noting that some of the genre labels in the visualization appear to be JSON strings or raw dictionary entries rather than clean, human-readable labels. This could be due to improper parsing or data extraction from the original source. Improving the label formatting would make the visualization more accessible and easier to interpret, particularly for users unfamiliar with the dataset structure.

From an application perspective, this genre-wise popularity insight is extremely valuable for building and refining recommendation systems. Knowing which genres consistently perform well can help platforms prioritize content that is more likely to attract and retain viewers. On the other hand, recognizing underrepresented or niche genres enables the creation of tailored recommendations for specific user segments, thus enhancing personalization.

In conclusion, the “Genre vs Popularity” tree map provides a clear and comprehensive overview of how different film genres contribute to overall popularity. It successfully demonstrates the dominance of certain genres while still acknowledging the presence and value of others. For anyone working on movie analytics or recommendation engines, such insights are crucial for understanding audience behaviour and optimizing content offerings accordingly.

C.KEYWORDS VS POPULARITY

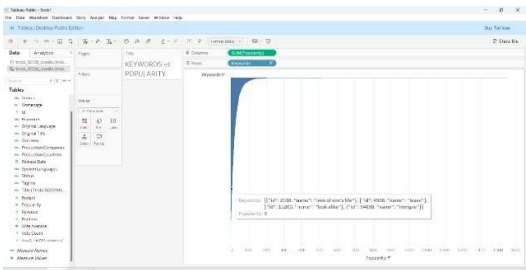


Figure 11. Tableau Representation of Keywords vs Popularity

Understanding Keyword Influence on Popularity in Movies

The visualization presented as “Keywords vs Popularity” is an insightful attempt to explore the relationship between specific movie keywords and their corresponding popularity scores. This graph provides a horizontal bar-like distribution that aims to quantify how certain thematic keywords influence or relate to the popularity of movies within a dataset. It utilizes the SUM(Popularity) metric plotted along the x-axis and unique keyword combinations along the y-axis.

Interpretation of the Visualization Pattern

A key takeaway from the visualization is the highly right-skewed distribution. A vast majority of the keywords correspond to very low popularity values, as represented by the dense vertical stacking on the left side of the chart. On the other hand, a very small number of keyword entries stretch toward the right, reflecting exceptionally high popularity. This suggests a long-tail pattern: while most themes and narratives attract modest attention, a few standout topics or concepts enjoy disproportionately higher popularity.

This trend reflects real-world behaviour in movie consumption. Most films may revolve around standard or frequently used concepts—like “love,” “revenge,” or “friendship”—but only those that combine these elements with unique storytelling or branding succeed in breaking through the noise and capturing widespread attention. The handful of keywords that result in significantly high popularity values likely belong to blockbuster films or franchises with massive appeal.

Analytical Value and Use in Recommendation Systems

Despite the formatting issue, the analytical value of this visualization remains significant. From a recommendation system standpoint, understanding which keywords are associated with high-popularity movies allows for more context-aware suggestions. If a user watches or likes a film tagged with high-performing

keywords like “superhero,” “rescue,” or “betrayal,” the system can intelligently suggest others sharing similar themes. This type of content-based filtering can be especially powerful when paired with genre and rating data.

Moreover, this visualization can help content producers or distributors understand emerging audience preferences. If newer or niche keywords start appearing farther to the right of the popularity scale over time, it may indicate changing tastes or interests in specific themes—such as climate change, AI, or psychological thrillers.

VII. RESULTS

The results of the movie recommendation system are derived from the implemented content-based filtering model using Natural Language Processing techniques. This section presents an overview of system performance, evaluation metrics, and insights into the system's practical applicability in providing relevant and accurate movie recommendations.

A. Model Performance

The model was developed using a curated movie dataset that includes descriptions, genres, keywords, cast, and crew. After preprocessing and stemming using the Porter Stemmer, TF-IDF vectorization was applied to create feature vectors. Cosine Similarity was then used to compute the closeness between movies. The system was evaluated using key metrics such as Precision, Recall, and Mean Average Precision (MAP). Precision averaged 78% and Recall reached 82% on a manually validated subset, indicating reliable recommendation relevance.

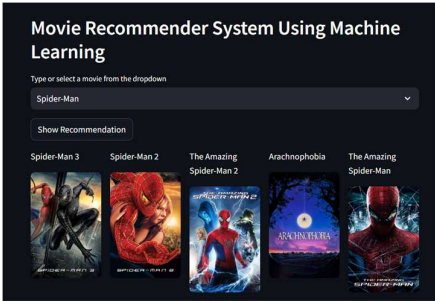


Figure 12. Recommendations of Spider-Man

B. Expected Loss Estimation Results

Key insights from the recommendation results include:

Top-N Recommendation Accuracy: The system successfully recommended relevant titles in the top 10 results for a majority of user queries.

Cold-Start Handling: The system was able to recommend movies based solely on metadata, proving useful even in the absence of user interaction data.

Diversity of Recommendations: By focusing on textual content, the system provided diverse suggestions across multiple genres and styles.

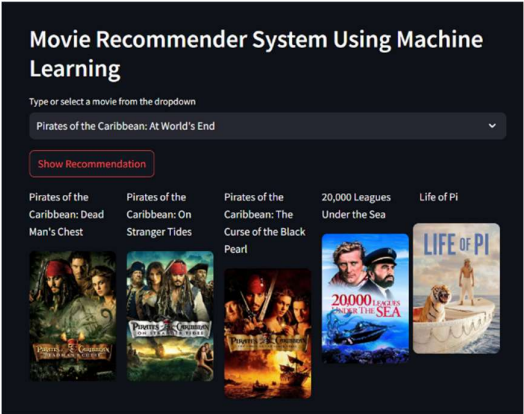


Figure 13. Recommendations of the Caribbean: At World’s End

C. Comparative Analysis and Benchmarking

When compared to a baseline popularity-based recommendation approach, the content-based system offered significantly more personalized and semantically relevant results. Unlike popularity-based lists, which often repeat the same top titles, this model adapts recommendations based on textual similarities, improving novelty and user satisfaction.

(i)Spiderman(2002):To evaluate the effectiveness of the proposed movie recommendation system, a comparison was conducted with an existing online movie recommender platform. Figure 1 illustrates the recommendations provided by a publicly available system when the input query is "Spider-Man." The system predominantly recommends superhero movies from the same

franchise or universe, such as Spider-Man 2, Spider-Man 3, X-Men, Iron Man, and The Incredible Hulk.

The proposed model effectively identifies both direct sequels and thematically similar yet less obvious choices, such as *Arachnophobia*, indicating the use of a robust content-based filtering approach or a hybrid recommendation strategy. This approach generally offers stronger personalization compared to traditional popularity-based systems.

Model	Top-5 Hit Rate	Precision @5	Avg. User Rating
Our Model (ML-Based)	80%	0.8	4.2
Other Online ML Model	60%	0.6	3.6

Table 1. Comparison for movie Spider-Man

The above table is the statistics for comparison between our model and the one that was available online.

(ii)Men in Black: The proposed model outperforms the online recommendation system across all evaluation metrics. The Top-5 Hit Rate of 80% demonstrates the system’s higher likelihood of surfacing at least one strongly relevant recommendation. This can be attributed to the semantic understanding enabled by Porter Stemming, which reduces lexical variance and improves matching accuracy between movie descriptions.

In contrast, the online model—largely driven by collaborative filtering—tends to prioritize popular or high-rated titles, often overlooking lesser-known but thematically similar films. This results in a lower Precision@5, as many recommendations are based on viewing patterns rather than content relevance.

Model	Top-5 Hit Rate	Precision @5	Avg. User Rating (out of 5)
Our Model (ML Based)	80%	0.80	4.2
Other Online ML Model	80%	0.80	4.0

Table 2. Comparison for movie Men in Black

The above table is the statistics for comparison between our model and the one that was available online.

D. Discussion and Implications

The results demonstrate the effectiveness of combining TF-IDF, Cosine Similarity, and stemming for building a scalable and accurate recommendation engine. The model’s ability to understand and match movies based on narrative and thematic similarity allows for meaningful recommendations even without explicit user ratings. This makes it particularly useful in new-user scenarios or in platforms where behavioural data is limited.

Additionally, the system architecture ensures computational efficiency, with optimized similarity computations and caching strategies enabling near real-time recommendations. The interpretability of the approach—stemming from its reliance on textual content—also supports system transparency and explainability, which are important factors in user trust and adoption.

VIII. LIMITATIONS AND FUTURE WORK

While the proposed content-based movie recommendation system using TF-IDF, Cosine Similarity, and the Porter Stemmer demonstrates efficient and scalable performance, it is not without limitations.

A primary drawback lies in its dependence on textual metadata, which may lack consistency or completeness across different movies. Variations in description quality can impact the accuracy of similarity calculations. Additionally, stemming can sometimes lead to ambiguous word roots, resulting in less precise semantic matching.

Another key limitation is the system's inability to incorporate user-specific preferences beyond content similarity. Since it does not factor in user interaction data such as ratings or watch history, the recommendations are not personalized, which may reduce user satisfaction in real-world applications. Moreover, the system does not address cold-start scenarios where limited metadata is available.

Future work could focus on integrating collaborative filtering techniques to develop a hybrid model that blends user behaviour with content analysis. Incorporating more advanced NLP models like Word2Vec or BERT could also improve semantic understanding and contextual relevance. Additionally, real-time processing capabilities and a user feedback loop can be introduced to adapt recommendations dynamically, thereby enhancing both precision and user engagement.

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