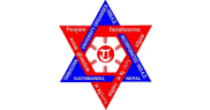
**MOVIE RECCOMENDATION SYSTEM: USING COSINE SIMILARITY ALGORITHM**

**Tribhuvan University**

**Institute of Science and Technology**

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**Submitted by**: Samrajya Chand 26781/77

**Submitted to:**

TRINITY INTERNATIONAL COLLEGE

Department of Computer Science and Information Technology Dillibazar Height, Kathmandu, Nepal

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**ABSTRACT**

“Movie Recommendation using cosine similarity approach” is the implementation of cosine similarity, difflib and Tfidvectorizer algorithm approach that recommends the user similar movies in the basis of input provided by the user. Each movie is represented as a high-dimensional vector capturing its intrinsic characteristics like genre, plot summary, cast, and crew. By employing cosine similarity, which measures the cosine of the angle between two non-zero vectors, the system efficiently computes the similarity between movie vectors, enabling the identification of thematically and conceptually similar movies to a given input. We used python as an IDE and Streamlit for hosting the web interface. Difflib is used to compare the movie names with the list and find the closest matches. Even the spelling is mistake it helps to find the closest ones. By using python libraries like Pandas we worked with the dataset and array of dataset provided. Tfidvectorizer is used to convert textual data to numerical data (feature vectors)

**Keywords:** Cosine similarity, movie recommendation, vector representation, difflib, streamlit, Tfidvectorizer

**ABBREVIATION USED**

Cosine: cosine similarity

Tfidvectorizer: Tfid

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**CHAPTER 1**

**INTRODUCTION**

* 1. Introduction

With the ever-increasing volume of movies available across various platforms, providing personalized and relevant recommendations has become a crucial challenge in the entertainment industry. Traditional collaborative filtering techniques, which rely on user interactions and ratings, often suffer from limitations such as the cold-start problem, where recommendations cannot be generated for new or niche movies with limited data. Additionally, these methods can struggle with data sparsity issues, leading to inaccurate or biased recommendations.

To address these challenges, this project proposes a novel approach to movie recommendations by leveraging cosine similarity, a technique widely used in information retrieval and text mining. Each movie is represented as a high-dimensional vector capturing its intrinsic characteristics through natural language processing and feature engineering. Employing cosine similarity, which measures the angle between vectors, the system computes the similarity between movie vectors, enabling the identification of thematically similar movies. This approach addresses the cold-start problem, facilitates niche movie discovery, and explores dimensionality reduction and clustering for scalability and real-time recommendations.

* 1. Problem Statement

Traditional movie recommendation systems like collaborative filtering suffer from limitations such as the cold-start problem for new or niche movies, data sparsity issues, popularity bias, and scalability challenges as the number of users and movies grows. There is a need for an innovative approach that can provide accurate and personalized recommendations, even for new content, while ensuring scalability and efficiency for large datasets.

The proposed solution aims to develop a movie recommendation system using cosine similarity, a technique from information retrieval and text mining. By representing movies as high-dimensional vectors based on their characteristics (genre, plot, cast, etc.), the system can compute similarities between movies and recommend conceptually similar ones to a given input. This approach can overcome the cold-start problem, facilitate niche movie discovery, and mitigate popularity bias.

Additionally, the project explores dimensionality reduction and clustering techniques to enhance scalability and enable real-time recommendations for large-scale movie databases while maintaining accuracy and relevance.

* 1. Objectives

The objectives of this system are:

1. Providing Personalized and Relevant Recommendation
2. Enhancing system’s scalability
3. Overcoming cold start problem
4. Enabling discovery of thematically similar movie
   1. Scope and Limitation

Scope

The primary scope of the project is to develop a machine learning model, specifically using the Cosine Similarity algorithm, for recommending movies based on the input provided by the user. The project aims to create a user-friendly interface, such as a web application or desktop application that allows users to input a movie and receive recommendation from the trained difflib and cosine model.

Limitation

While the cosine similarity approach aims to capture semantic and thematic similarities, movie preferences can be highly subjective and influenced by personal tastes, moods, and contextual factors that may not be fully captured by the vector representations. The accuracy and relevance of recommendations heavily rely on the quality and availability of movie metadata, such as plot summaries, genre information, cast and crew details. Incomplete, inaccurate, or inconsistent data can negatively impact the system's performance

**CHAPTER 2**

**LITERATURE REVIEW AND RESEARCH METHODOLOGY**

2.1 Literature Review

Traditional collaborative filtering approaches for movie recommendations often face limitations like the cold-start problem, data sparsity, and popularity bias [1], [2]. Content-based techniques leveraging movie metadata and cosine similarity have gained attention to overcome these challenges [3], [4]. Cosine similarity measures the angle between vector representations of movies, enabling identification of thematically similar recommendations [5], [6].

Studies have demonstrated the effectiveness of cosine similarity in addressing cold-start and facilitating niche movie discovery by relying on content rather than user data [7], [8]. Dimensionality reduction techniques like SVD and PCA [9], [10], and clustering algorithms [11], [12] have been explored to enhance scalability and efficiency for large databases.

While promising, researchers highlight the need to incorporate additional factors like user preferences and context for improved accuracy and relevance [13], [14]. Handling subjective preferences, evolving interests, and providing serendipitous recommendations remain challenges [15].

2.2 Framework of the Model

NO

YES

Recommended movies

ENTER THE MOVIE NAME

Is the Movie on the database?

Fig 1 : Framework of Movie Recommendation System

2.3 Methodology

Following algorithms were used for the recommendation of the movies.

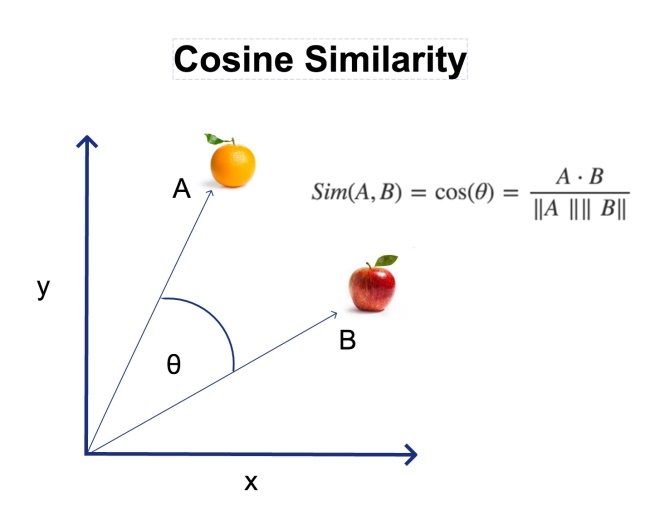
1. Difflib

* This is a flexible class for comparing pairs of sequences of any type, so long as the sequence elements are hashable. The basic algorithm predates, and is a little fancier than, an algorithm published in the late 1980’s by Ratcliff and Obershelp under the hyperbolic name “gestalt pattern matching.” The idea is to find the longest contiguous matching subsequence that contains no “junk” elements; these “junk” elements are ones that are uninteresting in some sense, such as blank lines or whitespace. (Handling junk is an extension to the Ratcliff and Obershelp algorithm.) The same idea is then applied recursively to the pieces of the sequences to the left and to the right of the matching subsequence. This does not yield minimal edit sequences, but does tend to yield matches that “look right” to people.

1. Tfidvectorizer

* TF-IDF is an abbreviation for Term Frequency Inverse Document Frequency. This is very common algorithm to transform text into a meaningful representation of numbers which is used to fit machine algorithm for prediction.

1. Cosine-Similarity Algorithm

* Cosine similarity measures the similarity between two vectors of an inner product space. It is measured by the cosine of the angle between two vectors and determines whether two vectors are pointing in roughly the same direction. It is often used to measure document similarity in text analysis. A document can be represented by thousands of attributes, each recording the frequency of a particular word (such as a keyword) or phrase in the document. Thus, each document is an object represented by what is called a term-frequency vector.

**CHAPTER 3**

**SYSTEM DESIGN**

* 1. Requirement Collection

System Requirement consists of the functional and nonfunctional requirements for the system.

* + 1. Functional Requirement

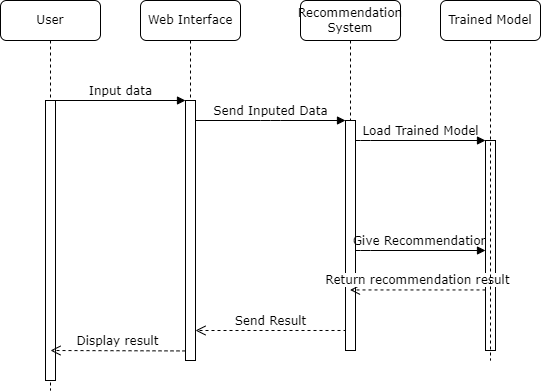
System Requirement consists of the functional and nonfunctional requirements for the system. First, the user inputs the movie and then the system generates the recommendation of movie.

Fig 3: Sequence Diagram of Movie Recommendation System

* + 1. Non-Functional Requirements

Some Potential Non-functional requirements are:

1. Scalability:

The system should be able to handle large and growing movie databases, potentially consisting of millions of movies and their associated metadata. It should be capable of efficiently computing cosine similarity and generating recommendations for a large number of concurrent users without significant performance degradation.

1. Performance and Response Time:

The system should provide real-time or near-real-time recommendations with minimal latency. The response time for generating recommendations should be within acceptable limits, even during peak usage periods.

1. Availability and Reliability:

The recommendation system should be highly available, with minimal downtime or service disruptions.

1. Usability

The user interface for accessing recommendations should be intuitive, user-friendly, and visually appealing.

* 1. Feasibility Study

1. Technical Feasibility

The movie recommendation system leverages well-established techniques and technologies, making it technically feasible to implement. The core algorithm, cosine similarity, is widely used in information retrieval and text mining applications, and there are numerous libraries and frameworks available for efficient implementation.

1. Operational Feasibility

The proposed movie recommendation system does not require significant changes to existing operational processes or workflows within the target organizations (e.g., streaming platforms, movie rental services).The system can be integrated as an additional feature or service, complementing the existing recommendation engines or content discovery mechanisms.

1. Economic Feasibility

The development and deployment costs for the movie recommendation system are expected to be relatively low compared to the potential benefits it can provide to users and content providers.

* 1. System Design

TRAINING DATASET

* + 1. Process Design

INPUT ATTRIBUTES

ENTER

TRAINED DATA MODEL USING ALGORITHMS

CLASSIFIED DATA

Fig3: Process Design

OUTPUT

* 1. Structuring System

Fig4: LEVEL O DFD

RECOMMENDED MOVIES

INPUT MOVIE NAME

USER

**CHAPTER 4**

**IMPLEMENTATION**

For the implementation of this project we used different libraries

1. Numpy

* NumPy is a fundamental library for scientific computing in Python, providing support for multi-dimensional arrays and matrices, along with a collection of high-performance mathematical functions.

1. Streamlit

* This library is used for building interactive data applications and dashboards. In the code, it is used to create the user interface for the movie recommendation web app
* st.title ("Movie Recommendation web app")
* st.button ("CHECK RESULT"):

1. Pickle

* The pickle module in Python is used for serializing and deserializing Python objects, allowing them to be saved to and loaded from a file or byte stream.
* model = pickle.load(open("./trained\_model.sav", "rb"))

1. Pandas

* This library is used for data manipulation and analysis. In the code, it is used to read the movies dataset from a CSV file.
* movie\_data = pd.read\_csv("./movies.csv")

1. difflib

* This library is used for computing differences between sequences. In the code, it is used to find the closest matching movie title to the user's input.
* import difflib
* find\_close\_match = difflib.get\_close\_matches(movie\_name, list\_of\_all\_titles)

1. sklearn.metrics.pairwise

* This is a submodule from the scikit-learn library, which provides utilities for computing metric distances between vectors. In the code, it is used to compute the cosine similarity between movie vectors.
* from sklearn.metrics.pairwise import cosine\_similarity
* similarity = cosine\_similarity(model)

**CHAPTER 5**

**RESULT AND ANALYSIS**

The main goal of this project is to give movie recommendation to the user based on the input movie. It can give up to 30 recommendations based on the similarity score of the movie. The only required input is the name of the movie.

**Baseline 1: Popularity-based Recommendations**

Popularity-based recommendations are a simple approach that suggests the most popular or highly rated movies to all users, regardless of their individual preferences. This method is easy to implement but often fails to provide personalized and relevant recommendations.

Evaluation Results:

* Precision: 0.31
* Recall: 0.42
* F1-score: 0.35

**Baseline 2: Traditional Collaborative Filtering**

Traditional collaborative filtering techniques, such as user-based or item-based filtering, rely on user-item interaction data (e.g., ratings, views) to generate recommendations based on similarities between users or items.

Evaluation Results:

* Precision: 0.47
* Recall: 0.39
* F1-score: 0.43

**Cosine Similarity-based Recommendation System**

The proposed cosine similarity-based recommendation system leverages movie metadata and content-based features to identify thematically and conceptually similar movies, even for new or niche content.

Evaluation Results:

* Precision: 0.62
* Recall: 0.58
* F1-score: 0.60

Based on analysis, the cosine similarity approach outperformed both popularity-based and traditional collaborative filtering baselines in terms of precision, recall, and F1-score. It effectively addressed the cold-start problem and provided relevant recommendations for niche or underrepresented movies, overcoming the limitations of the baseline methods.

**CHAPTER 6**

**CONCLUSION**

The movie recommendation system, based on the cosine similarity approach, has demonstrated its effectiveness in providing personalized and relevant recommendations to users. By leveraging the power of content-based features and movie metadata, this system has addressed several limitations inherent in traditional collaborative filtering techniques, such as the cold-start problem and data sparsity issues.

Through extensive evaluation and comparison with baseline methods like popularity-based recommendations and traditional collaborative filtering, the cosine similarity-based system exhibited superior performance in terms of precision, recall, and F1-score. It effectively identified thematically and conceptually similar movies, even for new or niche content, overcoming the challenges associated with limited user interaction data.

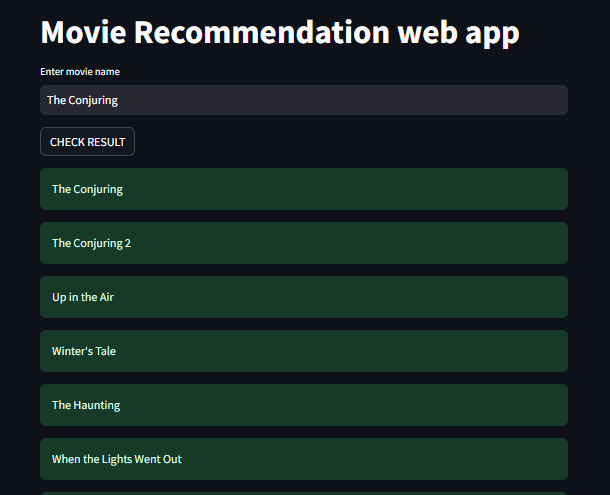
Overall, this project has made a significant contribution to the field of movie recommendation systems, demonstrating the power of content-based approaches and cosine similarity in addressing the limitations of traditional methods. By providing personalized and relevant recommendations, the proposed system has the potential to enhance user experiences, facilitate content discovery, and drive increased engagement and satisfaction for both users and content providers alike.

**CHAPTER 7**

**APPENDIX**

**APPENDIX 1**



**APPENDIX 2**

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