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1. Introduction:

1.1 Introduction on Recommendation System

The ability of a machine to carry out cognitive tasks including perceiving, learning, thinking, and problem-solving is known as artificial intelligence, or AI. The bar for AI is set at the level of human reasoning, speech, and vision teams. Nowadays, AI is used in nearly every industry, offering all businesses who adopt it widely a technological advantage. In comparison to previous analytics methods, AI has the ability to add 50% more incremental value to the banking industry and 600 billion dollars of value to the retail sector. The potential income increase in logistics and transportation is 89% higher (JavaTpoint., 2021).

Concretely, automating tedious and repetitive duties is possible if a firm uses AI for its marketing staff. This frees up the sales representative to concentrate on relationship-building, lead nurturing, etc. A corporation by the name of Gong offers a service for conversation intelligence. The computer records, transcripts, and analyses every phone call a sales representative makes. The VP can create recommendations using AI analytics and formulate a winning strategy.

A sort of information filtering system is a recommender system. The system's algorithm can detect precise consumer preferences by using huge amounts of data. Once you are aware of your consumers' preferences, you may suggest fresh, pertinent information to them. And that holds true for everything from love partners to music and movies. They are among the most sophisticated machine learning algorithms that online retailers use to boost sales. The implicit web search queries and purchase records, further user evaluations after watching a movie or listening to music, as well as other information about the regular users themselves, provide the data for recommendation systems.

Examples of recommender systems in use include Netflix, YouTube, Tinder, and Amazon. Based on their selections, the programs entice consumers with relevant suggestions.

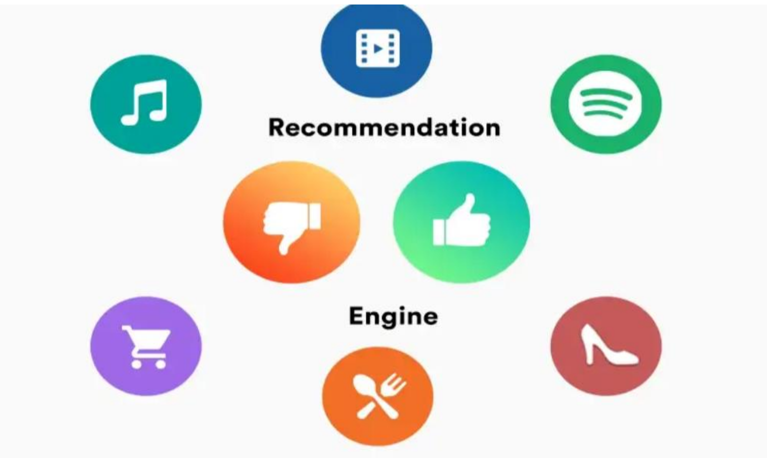

Figure 1: Recommendation system (JavaTpoint., 2021).

For example:

So, suppose you wish to purchase a book. When you visit Amazon online, a variety of books are the first thing you see.

It is identical to the display tables in physical stores. However, once you begin using the platform to make decisions, Amazon's recommender system takes control. Let's imagine you look for one book, and then Amazon suggests another book to you. That's because previous purchasers of this book must also have purchased the book that was recommended. Your recommender system could also suggest different books as an alternative.

A data analysis technology called machine learning automates the creation of modelling strategies. It is a branch of artificial intelligence that is based on the idea that robots can support judgment, identify patterns, and make decisions without human input. Machine learning usually comes in two varieties they are:

1. Unsupervised machine learning.
2. Supervised machine learning.

Unsupervised machine learning

Exploratory data analysis frequently employs unsupervised learning, a kind of machine learning that seeks out underlying patterns in data. Unsupervised learning concentrates on the features of the data rather than using labeled data like supervised learning does. Each input in labeled training data has a matching output. Since the algorithm's objective is to group data points based solely on the input data, we are not concerned with the targeted outputs while utilizing unsupervised learning. Unsupervised learning is not concerned with labeled data, whereas supervised learning is, in order to generate predictions (Johnson, 2022).

Data analysis and the discovery of significant features are the objectives of unsupervised learning algorithms. Unsupervised learning frequently uncovers underlying patterns or subgroups in the dataset that a human observer might miss.

Supervised machine learning

Machine learning under supervision discovers patterns and connections between input and output data. Its usage of labeled data defines it. A dataset with many examples of Features and Target is referred to as labeled data. Algorithms for supervised learning employ a dataset to learn the link between Features and Target. One of the most popular subfields of machine learning (ML) is supervised learning, which makes use of labeled training data to aid in the prediction accuracy of models. Here, the training data acts as both a teacher and a supervisor for the machines, hence the name. Real-world problems including fraud detection, spam filtering, risk assessment, and image categorization benefit from the use of a comparable methodology (Johnson, 2022).

1.2 Explanation of the chosen project problem:

The theme for this AI-based project in this coursework is "Movie recommendation system," with recommendation systems as the chosen challenge. A recommendation system is a type of data filtering system that tries to anticipate how users will rate or respond to a product. A recommendation system, sometimes known as a recommendation engine, is a paradigm for information filtering that aims to anticipate user preferences and offer suggestions in accordance with these preferences. These technologies are now widely used in a variety of industries, including those that deal with utilities, books, music, movies, television, apparel, and restaurants. These systems gather data on a user's preferences and behavior, which they then employ to enhance their future suggestions.

Movies are a fundamental aspect of life. There are many various kinds of movies, such as those meant for amusement, those meant for teaching, children's animation movies, horror movies, and action movies. Movies' genres, such as comedy, thriller, animation, action, etc., make it simple to distinguish between them. Another approach to differentiate between movies is to look at their release year, language, director, etc. When watching movies online, there are many to choose from in our list of top picks. We may find our favorite movies among all of these different kinds of movies with the aid of movie recommendation systems, which saves us the stress of having to spend a lot of time looking for our preferred movies. As a result, it is essential that the system for suggesting movies to us is very accurate and gives us recommendations for the films that are either most similar to or identical to our preferences.

Recommendation systems are being used by a lot of businesses to improve customer interaction and the purchasing experience. The most significant advantages of recommendation systems are client happiness and income.

A very effective and crucial mechanism is the movie recommendation system. However, because of the limitations with a pure collaborative method, scalability concerns and poor recommendation quality also affect movie recommendation systems.

Innovative techniques and algorithms have been developed to address technological problems including providing more accurate recommendations while reducing calculation time. The two most prevalent forms of recommendation systems are collaborative filtering recommendation systems and restricted based filtering recommendation systems. The collaborative filtering recommender notices patterns and trends in previous user activity as well as other user activity, and it offers ideas that are comparable to the current user based on information from previous encounters. The main idea is to put people together who share common interests. A content-based filtering recommender evaluates the background data about products or people before making recommendations to customers. For instance, if a user rates a romantic film highly, the recommender system will propose more romantic films whose users are very comparable. Analyze user preferences for similar genres and movies to make basic recommendations. Comparison of Gross and Profit for Various Genres, Actor, Movie, and Genre-based Recommendation Systems This project will assist us in comprehending the relationship between these variables.

2. Background

2.1 Research work done method:

Collaborative filtering

A domain-independent prediction technique called collaborative filtering which is used for media like music and movies that cannot be accurately and simply represented by metadata. Building a database of user preferences for things (user-item matrix) is how the collaborative filtering technique operates. By comparing commonalities between users' profiles, it then pairs users with shared interests and preferences to generate suggestions. These users establish a neighborhood. A user receives recommendations for products that he hasn't yet reviewed but that have previously received favorable reviews from other users in his area. The recommendations that CF generates can either be recommendations or predictions. Collaborative filtering systems come in two varieties: user-based recommender and item-based recommender (TechTarget Contributor, 2022).

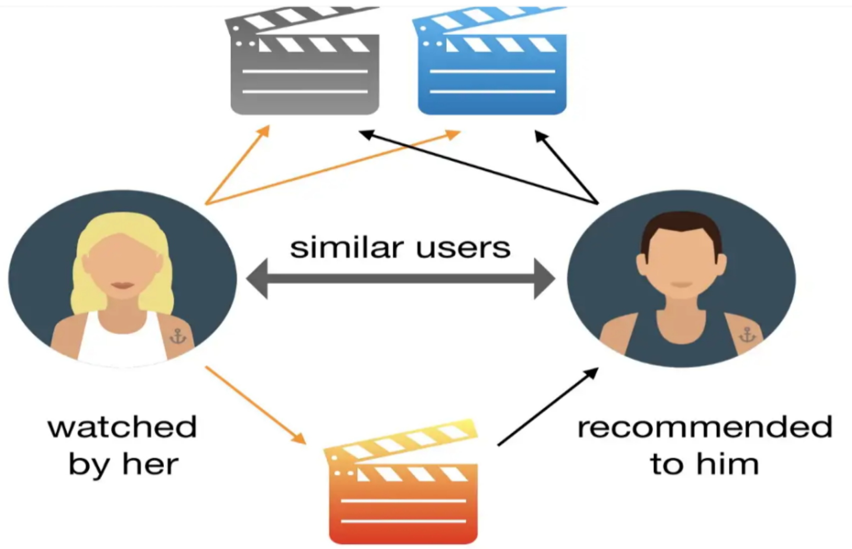

Figure 2: Collaborative Filtering (TechTarget Contributor, 2022).

1. User-Based Recommendations:

Users' preferences are frequently taken into account while creating customized solutions. This strategy is based on consumer preferences. Users first rate some movies (1–5) before the procedure begins.

Both implicit and explicit ratings are possible. When a person expressly ranks an item on a scale or gives it a thumbs-up or thumbs-down, the rating is known as an explicit rating. Explicit ratings are frequently difficult to collect because not all users are keen on leaving comments. We collect implicit ratings based on their actions in various instances.

In relation to movie systems, we can infer that a user has some likeability to the film if they watch the entire thing. Be aware that there are no precise guidelines for establishing implicit ratings. Next, we identify a specific number of nearest neighbors for each user. Using the Pearson Connection method, we determine the correlation between user ratings. When recommending things to consumers, it is assumed that if two users' evaluations are significantly connected, they must have similar tastes in goods.

2. Item-Based Recommendations:

Item-Based filtering, in contrast to user-based filtering, concentrates on the similarity between the items' users rather than the users themselves. It is calculated in advance which things are the most comparable. The user is then given recommendations for products that are most comparable to the target item (TechTarget Contributor, 2022).

Content based recommendation

In order for a content-based recommender to function, we must collect data from the user, either explicitly (via ratings) or implicitly (clicking on a link). By using the information, we can build a profile of the user, which is then used to make suggestions to the user. As the user adds more information or acts more frequently on the recommendation, the engine gets more accurate. A domain-dependent algorithm, content-based technique places more emphasis on the evaluation of item qualities in order to produce predictions. Content-based filtering is the most effective method for recommending materials like web pages, magazines, and news. With the use of features that were taken from the content of the items the user has previously evaluated, recommendations are created utilizing the user profiles in the content-based filtering technique. The user is recommended products that are primarily relevant to the positively rated products. To detect similarities across papers and produce useful recommendations, CBF use a variety of methods. It might employ probabilistic models like Decision Trees or vector space models like Term Frequency Inverse Document Frequency (TF/IDF) (Mishra, 2021).

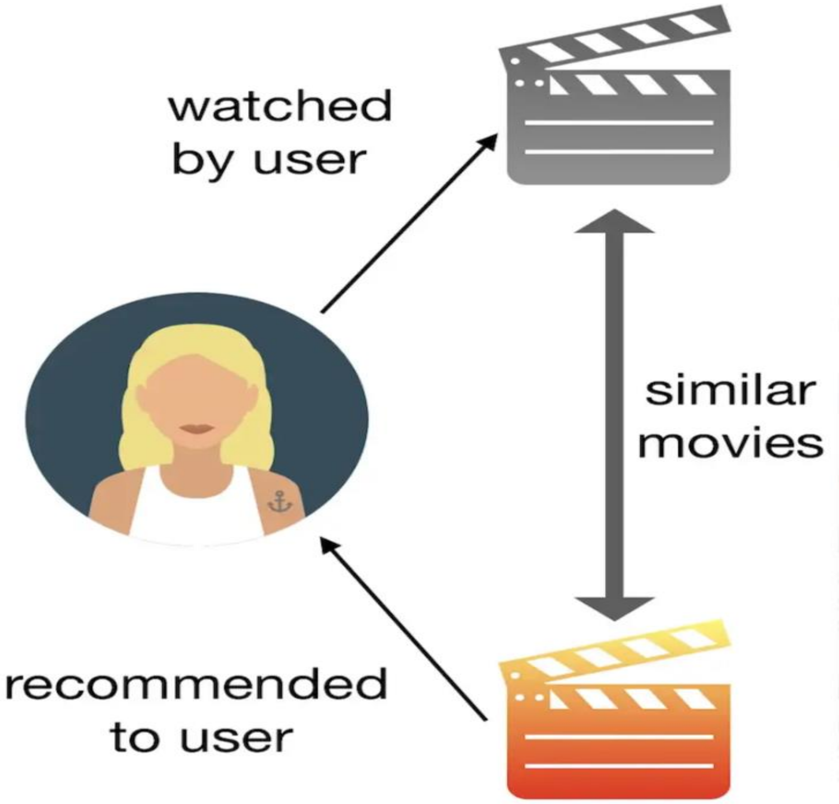

Figure 3: Content based recommendation (Mishra, 2021).

The content-based recommendation system operates in two ways, each of which uses a unique algorithm.

There are two systems:

1. The vector space method:

Let's say you watch a crime thriller film and post a review online. Additionally, you critique a second fictional comedy film alongside it, rating the comedy film as poor and the criminal thriller as excellent. Now, a rating system is created using the data you gave. On a scale of 0 to 9, the crime thriller and detective genres receive a score of 9, while other movie categories range from 9 to 0 and the comedy categories receive the lowest scores, maybe a negative. With this knowledge, your next movie suggestion will probably be a crime thriller as those are the genres that you have given the highest ratings.

A user vector is produced for this ranking system, and it ranks the data you gave. The next step is to design an item vector on which movies are rated in accordance with their categories. By multiplying and obtaining the dot product of the user and item vectors, the vector assigns each movie name a specific value that is subsequently utilized for recommendations. As a result, the top 5 or top 10 movies are determined based on the ranking of all the dot items for the movies you could find after searching.

The first way a content-based recommendation system utilized to suggest products to the user was this one.

1. Classification method:

The classification approach is the second technique. It allows us to build a decision tree and determine whether the user wants to view a video or not. Consider a movie as an example. Let the action be. We look at the movie name first, and it is not an action movie based on the user statistics. Therefore, neither the genre nor the kind of movie you have ever evaluated are action movies. These classifications lead us to the conclusion that you shouldn't watch this movie (Mishra, 2021).

Hybrid recommendation System

A hybrid recommender system uses several different recommendation methods to produce the output. The suggestion accuracy is typically greater in hybrid recommender systems as compared to collaborative or content-based systems.

In order to improve system optimization and get beyond some of the drawbacks and issues of pure recommendation systems, hybrid filtering techniques incorporate various recommendation algorithms. The theory behind hybrid approaches is that a mix of algorithms will produce recommendations that are more accurate and efficient than those produced by a single algorithm since the drawbacks of one algorithm can be mitigated by the advantages of another algorithm. The shortcomings of each individual recommendation strategy can be suppressed in a combined model by using numerous recommendation techniques.

The hybrid approach offered an integrative strategy by combining the weighted similarity measure based on a genetic algorithm and fuzzy k-means clustering method to create a movie recommendation system. The proposed movie recommendation system provides more accurate similarity measurements and higher-quality recommendations than the current movie recommendation system, although it requires more computing time. By using the clustered data points as an input dataset, this issue can be resolved. The suggested method aims to enhance the quality and scalability of the movie recommendation system. By combining Content-Based Filtering and Collaborative Filtering, we use a hybrid technique that allows the two approaches to benefit from one another. We used the cosine similarity measure to quickly and accurately determine how similar the various movies in the given dataset are to one another as well as to shorten the computation time for the movie recommender engine (Li, 2021).

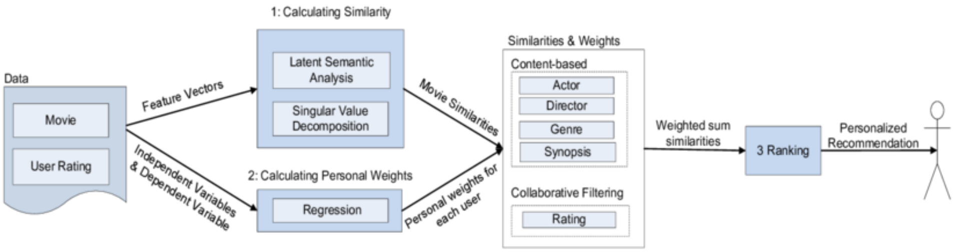

Figure 4: Hybrid Recommendation System (Li, 2021).

Dataset

On the kaggle website, you may access the dataset for the movie's origin. On the website Kaggle, users can create their own datasets and access datasets for a variety of objects. Additionally, it offers data science courses.

Our dataset, which consists of three files, was taken from several websites that offer movie.

1. Movie **-** first are about movies, which include all relevant data, such as name, actor, and release year.
2. Users: Information about registered users, including user id and location, is contained in the second file.
3. Ratings **-** Ratings include details such as which user gave which movie what rating. Therefore, we can create a strong collaborative filtering model based on all three of these files.

Keyword based vector space model

The researchers represented a lookup as a vector of weights using this model and the fundamental TF-IDF weighting approach, with each weight denoting the strength of the association between a movie and a phrase or term. In this paradigm, each object is stored as a vector of its attributes, which are likewise vectors, and the similarity of the vectors is defined by the angles between them. Then, based on his earlier interactions with item attributes, user profile vectors are generated. In a similar way, the similarity between an object and a person is determined.

2.2 Review and analysis of existing work in problem domain

1. It essentially consists of a series of machine learning algorithms that examine user data and movie ratings. Based on consumers' viewing tendencies, Netflix has created 1,300 recommendation clusters to increase its effectiveness. You now see a list of movies and TV shows based on your preferences and user profile whenever you switch on Netflix. Finding a movie or TV show that each user will like and doing so as rapidly as feasible are the objectives (estimations are they have just 90 seconds for that). The actual recommendation engine stays in the background and is hidden from the user.

2. In Instagram's suggestion system, friends are suggested or recommended as "someone you may know." These recommendations depend on a variety of factors, including mutual friends, work, required membership in groups, and other factors. This recommendation system makes advantage of the user's Instagram profile.

3. Daraz's online shopping platform assists customers in sorting through the selection of goods and services on offer and provides recommendations for which goods to purchase in response to their indicated needs by suggesting goods that are similar to those they have already chosen or searched for.

4. To customize suggestions, YouTube employs three key categories: User watch history and action: personalization. Performance measures include satisfaction and interest in the video. External variables: current events, the performance of your competitors, and the season's relevance.

2.3 Similar system case study

A movie recommendation system by using Collaborative filtering

Project: https://ieeexplore.ieee.org/document/9155879

The project outlines a recommender system that users expect the movie community will use. This system recommends films to the intended recipient using a collaborative filtering technique that eliminates or analyses movies depending on the opinions of other like participants. The algorithm examines particular ratings provided by community members as well as ratings of the movie the viewer appreciates in order to anticipate and suggest new movies to that viewer. The idea is to suggest movies that the viewer will enjoy, and then to use user-based collaborative filtering on each movie's individual ratings to find commonalities.

The user's behavior and preferences are analyzed through collaborative filtering algorithms, which then forecast what the user would want based on similarities to other users. Collaborative filtering systems come in two varieties: user-based recommender and item-based recommender. Users' preferences are frequently taken into account while creating customized solutions. This strategy is based on consumer preferences. Users first rate some movies (1–5) before the procedure begins (Gupta, 2020).

Both implicit and explicit ratings are possible. When a person expressly ranks an item on a scale or gives it a thumbs-up or thumbs-down, the rating is known as an explicit rating. Explicit ratings are frequently difficult to collect because not all users are keen on leaving comments. We collect implicit ratings based on their actions in various instances. For instance, a user's repeated purchases of a product show a favourable preference. In relation to movie systems, we can infer that a user has some likeability to the film if they watch the entire thing. Be aware that there are no precise guidelines for establishing implicit ratings. Next, we identify a specific number of nearest neighbors for each user. Using the Pearson Connection method, we determine the correlation between user ratings. When recommending things to consumers, it is assumed that if two users' evaluations are significantly connected, they must have similar tastes in goods.

Item-based filtering, in contrast to user-based filtering, concentrates on the similarity between the items' users rather than the users themselves. It is calculated in advance which things are the most comparable. The user is then given recommendations for products that are most comparable to the target item (Gupta, 2020).

3. Solution:

3.1 Proposed solution/approach to solving the problem.

Game recommendation using collaborative filtering using K-means:

A cluster is a collection of data objects that belong to the same group (class or category), are comparable to one another, and are distinct from the objects in other clusters. A kind of unsupervised learning called clustering uses predetermined classes and prior knowledge to determine how the data should be sorted or labeled into different classes. It may also be regarded as an exploratory data analysis (EDA) method that enables us to find hidden patterns of interest or data structure. Clustering can be used independently to provide insights into the distribution of the data or as a preprocessing step in other methods (javatpoint, 2021).

The most well-known and often used clustering algorithm is undoubtedly K-Means. It's typically the default algorithm for many beginners studying clustering techniques. Unsupervised learning algorithm K-Means Clustering divides the unlabeled dataset into various clusters. Here, K specifies how many pre-defined clusters must be produced as part of the process; for example, if K=2, there will be two clusters, if K=3, there will be three clusters, and so on.

The two major functions of the k-means clustering algorithm are:

1. Uses an iterative technique to choose the best value for K center points or centroids.

2. Each data point is matched with the nearest k-center. A cluster is formed by the data points that are close to a specific k-cente (javatpoint, 2021)r.

As a result, each cluster is distinct from the others and contains data points with some commonality. The K-means Clustering Algorithm is explained in the diagram below:

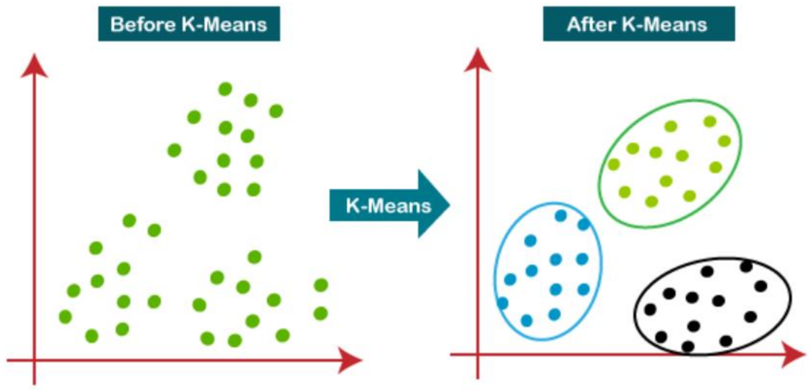

Figure 5: Before and after K-mean (JavaTpoint., 2021).

Here is how the k-means algorithm operates:

1. Specify K as the number of clusters.

2. Shift the dataset to initialize the cluster centers, after which K data points at random are selected for the cluster centers without being replaced.

4. Continue iterating until the cluster centers stay the same. i.e., the distribution of data points among clusters does not change.

5. Determine the sum of squares distances between each dataset point and each cluster center.

6. Assign each and every data point to the closest cluster to its centroid.

7. By averaging all of the data sets in each cluster, determine the cluster centers (javatpoint, 2021).

One of the hardest issues in this k-means clustering approach is choosing the appropriate number for k. The methods for choosing K value is:

1. Elbow Method:

Finding the ideal number of clusters to divide the data into is a critical stage in any unsupervised technique. One of the most prominent techniques for figuring out this ideal value of k is the elbow approach. We will now use the Python Sklearn module and the K-Means clustering algorithm to illustrate the suggested way (Saji, 2021).

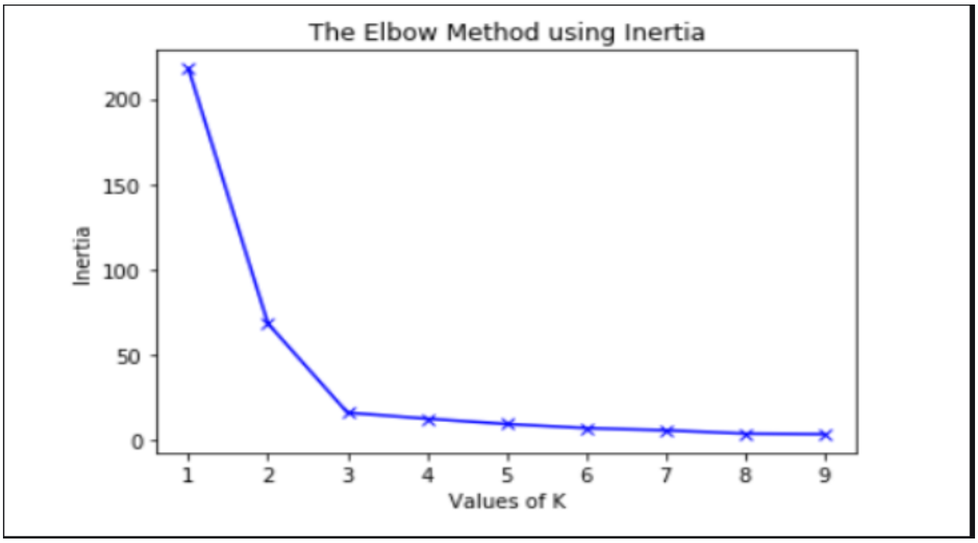

Figure 6: Elbow method using inertia (Saji, 2021).

3.2 Algorithm:

An algorithm is a step-by-step process that specifies a series of directives that must be followed in a particular sequence in order to yield the desired outcome. An algorithm can be implemented in more than one programming language because algorithms are typically designed independently of the underlying languages. A few properties of an algorithm include clarity, excellence, efficacy, and language independence. An algorithm's performance and scalability are what really determine how important it is (Upadhyay, 2022).

The algorithm used in the subsequent technique is:

Step 1: Select K as the first cluster's number.

Step 2: Select k random points from the data and use them as centroids.

Step 3: Assign each component to the cluster center that is closest to it.

Step 4: Recalculate the centroids of newly created clusters.

Step 5: Recalculating the centroids' positions

Step 6: Output data points with a clustering member.

3.3 Pseudo Code:

It is a casual and artificial approach of developing programs where you convey the series of instructions and commands (also known as algorithms) in a way that is simple for people to grasp. The link between your mind and the computer's code executor is pseudocode. It enables you to provide logically organized instructions without adding all of the technical specifics. A beginner's introduction to software programming can be made via pseudocode. There's no need to have your head work too hard on coding syntax (geeksforgeeks, 2022).

```
FUNCTION

kmeans(data, K):

  FOR a is equal to 1 to K

    clusters[a] is equal to emptyset

  END FOR

  FOR a is equal to 1 data.length

    FOR b is equal to 1 to K

       distance[b] is equal to calculateDistance(data[a], centroid[b])

    END FOR

    assignedCluster is equal to index of minimum distance

    clusters[assignedCluster].add(data[a])

  END FOR

  FOR a is equal to 1  K

    centroid[a] is equal to calculateCentroid(clusters[a])

  END FOR

  centroid no change

     RETURN clusters

  ELSE
```

kmeans(data, K)

END IF

3.4 Flowchart:

A flowchart is a visual representation of an algorithm or procedure. In order to explain our method, we utilize flowcharts rather than writing it down in a programming language such as C, C++, Java, C#, PHP, Python, Ruby, etc. This provides us a rough idea of the algorithm. A step-by-step process (with clearly stated instructions) is referred to as an algorithm. It is frequently used by programmers as a program planning tool to resolve issues. It uses interconnected symbols to represent the movement of information and processing. "Flowcharting" is the process of creating a flowchart for an algorithm (lucidchart, 2022).

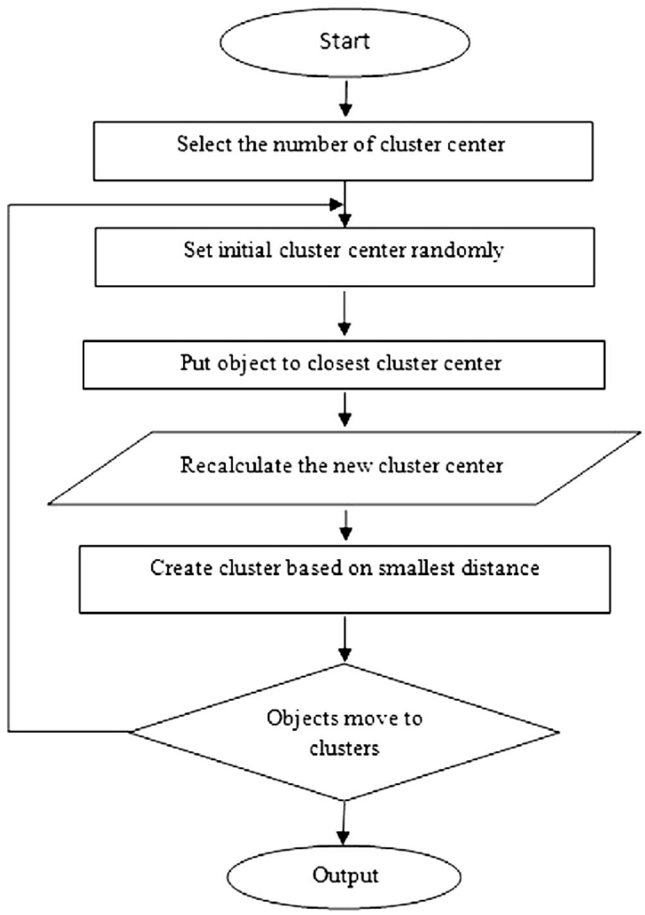

Figure 7: Flowchart (Saji, 2021).

4. Conclusion:

4.1 Analysis of work done

I have done a lot of research about the project and coursework both in which I make a system of movie recommendation system by using collaborative K-mean. Different other kind of method also have been research and choose one method for the project. A part from this algorithm, flowchart as well as pseudo code also done. Different similar system research and review and analysis the existing work of a system also. Different kind of problem having in a project and implementation to solve those domain project has also be carry out at that time.

Table 1: Table of task analysis.

S.N	Task	Status
1.	Research on Artificial intelligence	Completed
2.	Research on Recommendation System	Completed
3.	Research on chosen topic (Game recommendation)	Completed
4.	Problem statements of chosen topic	Completed
5.	Research on work done method	Completed
6.	Similar system review	Completed
7.	Review and analyzing existing work	Completed
8.	Research solution of selected	Completed
9.	Flowchart	Completed
10.	Pseudocode	Completed
11.	Algorithm	Completed
12.	Implementing of the code	Incomplete
13.	Testing project	Incomplete

4.2 How this solution address real world problem

Recommendation systems are integrated into the majority of the software and programs we use on a regular basis. The user can gain a lot from the installation of a recommendation system. Users of the movie platform can use this recommendation algorithm based on their similarity, ratings, and viewing histories as well as searches. Instead of watching a movie on their own without being offered, this recommendation might help the user choose one that they are most likely to enjoy. The user will benefit from time savings, increased system confidence, and a rise in income for the app.

4.3 Further work

This coursework is entirely based on planning research and gathering project-related data. Following completion of the research, the full report is put into practice, including the analysis work that we did on the subject. I'll concentrate on putting this idea into practice and recording how it functions in the following stage. I will search for data sets and make every effort to find the right ones and preserve them logically. The following section requires us to finish the document section, which includes the solution's explanation and the AI-generated pseudocode that was used throughout. Both the coding component and the result must be completed. The coding portion of the coursework requires the application of the algorithm I used in the first section in any programming language.

Thus, in the future we will be required to create the following things:

1. Development of the Movie recommendation system project using python.
2. Testing of the system and
3. Final documentation of the project

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