TOPIC

RECOMMENDER SYSTEMS AND MATHEMATICS

A BS Project by

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IN PURE AND APPLIED MATHEMATICS
BAHAUDDIN ZAKARIYA UNIVERSITY
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In the Name of Allah, the Most beneficent and the Most Merciful

SUBMISSION CERTIFICATE

A project titled: "**Recommender Systems and Mathematics**" has been completed by ***Samia Zahid*** under the supervision of ***Dr. Athar Kharal***. Report of this study is hereby submitted in partial fulfillment of requirements for the degree of "**BS MATHEMTHICS (2019-2023)".**

Signature

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ACCEPTANCE CERTIFICATE

We hereby accept this report of the project ***"Recommender Systems and Mathematics***" submitted by ***Samia Zahid*** under the supervision of ***Dr. Athar Kharal*** as conforming to the required standards.

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This project report is dedicated to the most supportive parents and my brothers who always have been my pillar of strength.

Also dedicated to Dr. Athar Kharal,

my project supervisor.

Thank You for everything.

DECLARATION

I, Samia Zahid, hereby declare that this project report entitled Recommender Systems is my original work under the supervision of Dr. Athar Kharal. All sources used in this project have been properly cited and I confirm that this work has not been submitted for any other academic program. I also declare that I have read and understood the policies and procedure of the Centre for Advanced Studies in Pure and Applied Mathematics, Bahauddin Zakariya University.

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Samia Zahid BSE-19-25

Signature:

Supervisor:

Dr. Athar Kharal

Signature:

Date:

CERTIFICATE BY SUPERVISOR

I hereby certify that Samia Zahid has successfully completed their project on Recommender Systems under my supervision. Samia Zahid is a student of 8th semester during session 2019-2023.

Throughout the duration of the project, Samia Zahid demonstrated a good work ethic and dedication to producing the best work. They consistently met project deadlines and showed a willingness to take on new challenges.

Overall, Samia Zahid performed admirably on the project, and I have no hesitation in recommending them for further opportunities. They have demonstrated excellent communication skills, both in written and oral form, and have proven to be valuable individuals.

I am confident that Samia Zahid will continue to excel in their academic and professional pursuits. It has been a pleasure to supervise them on this project.

Dr. Athar Kharal

Date:

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I would also like to thank Director CASPAM, Prof. Dr. Khalid Saifullah for providing me with facilities to complete my project in the best environment. Extended thanks to all the teachers of CASPAM for their sincere guidance and efforts.

The completion of the project could not have been accomplished without the continuous love and support of my parents and my brothers who helped me greatly in the work of this project.

My heartful thanks.

ABSTRACT

Recommender systems have become increasingly important in recent years due to the abundance of information available online. The aim of this project was to study and understand a movie recommender system using different techniques.

Recommender system research has incorporated a wide variety of artificial intelligence techniques including machine learning, data mining, user modeling, and constraint satisfaction, among others.

In this project, we tried to understand what recommender systems are and what is the mathematics used behind it. We understood PCA and SVD and their role in recommender systems through examples. Also, we learned how collaborative filtering is done.

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CHAPTER 1: INTRODUCTION

Discussed Topics in Chapter 1:

- *What are Recommender Systems?*
- *Where Used*
- *Movie Recommendation and People You May Know*
- *History of Recommender Systems*

RECOMMENDER SYSTEMS

Recommender Systems are defined as systems that recommend different things to the user by using a person's choices, history, likenesses, and different factors and helping them find what they are looking for.
It is a subclass of filtering systems of data and a class of machine learning that uses Big Data to predict and narrow down people's preferences.
It collects data and then analyzes it to generate recommendations for its customers using its algorithms.
It can include different products, reading articles, food items, and clothes.
For Example, Amazon recommends books to you, or YouTube recommends different videos to you based on your watch history.
Recommender Systems nowadays is the top priority for big technology companies.
The basic idea behind a recommender system is to predict what items or content user is interested in based on their previous or past interactions with the system or even with some similar users.
For use it more simple understanding of recommender system, consider your smartphone which you use to watch videos, listen to music, buy various products from online sites and use to capture pictures. The recommender system behind the smartphone processes it all and in results present you with some recommendations regarding your choice of videos, products, music and much more.

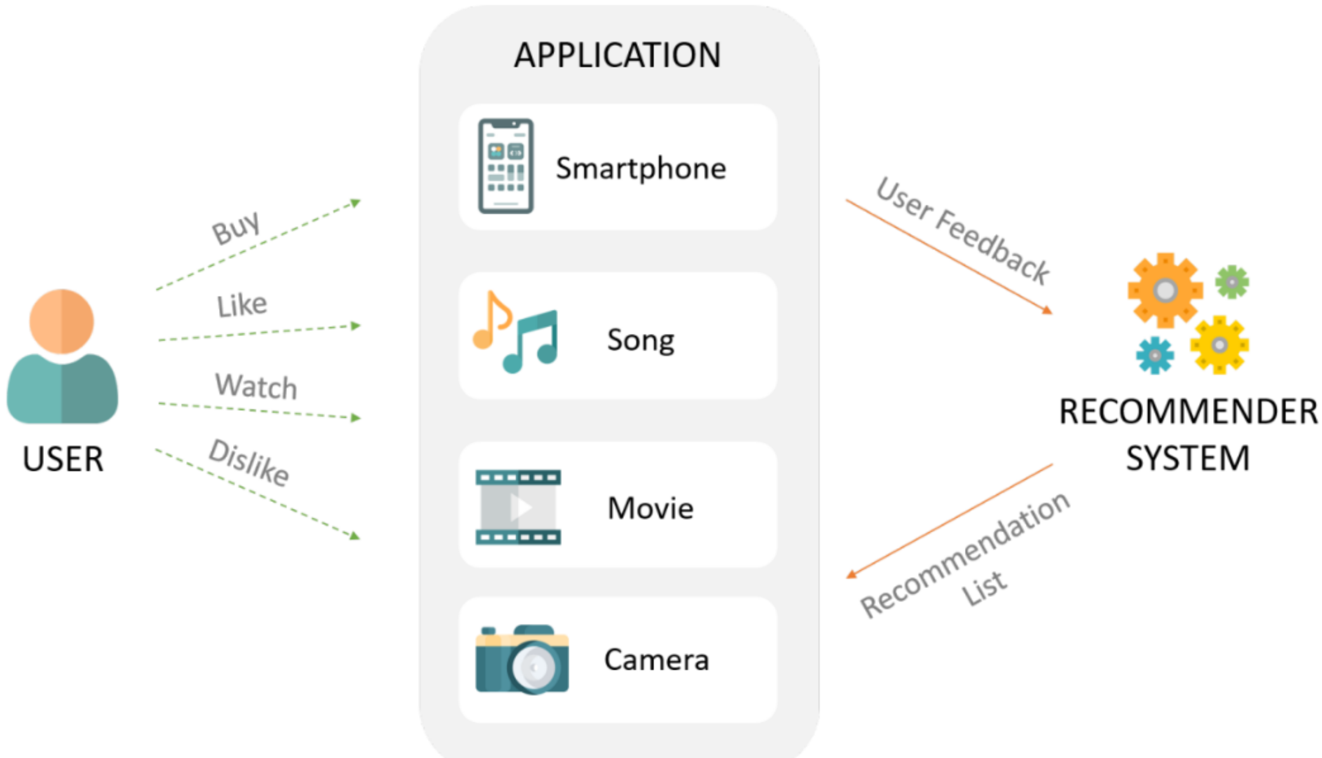

APPLICATION
Smartphone
Song
Movie
Camera
Buy
Like
Watch
Dislike
USER
User Feedback
RECOMMENDER SYSTEM
Recommendation List

Figure 1

WHERE USED?

Recommender systems nowadays are a must for every person related to educational sites, e-commerce and even media.

Educational Sites: Some famous educational sites like **Coursera** and **Udemy** use recommender systems to suggest their students for some other courses based on a student's previous take.

E-Commerce: Online marketplaces such as **Amazon**, eBay and Alibaba use recommender systems to suggest products based on their previous purchases and searches of different products and items.
According to research, 35% of Amazon purchases are thanks to recommended items. Just like this eBay also has recommender systems. For example, if a user searches for a purple dress, it recommends different purple color dresses with different price ranges and materials.

Healthcare: Different professional **doctors** suggest treatments and medicines to patients based on their medical history and symptoms.

Media and Entertainment: Online streaming services like Netflix, Hulu and **Spotify** use recommender systems to suggest movies, music, TV shows and podcast to users based on their viewing and listening history.
Like Spotify, it generates a customized playlist for its subscriber every week which is a personalized list. It even considers language and analyzes the audio file for recommendations.

Social Media: Social networking platforms like Facebook, **LinkedIn**, Instagram and twitter use recommender systems to suggest different types of post, blogs, accounts and groups based on their activities.
Just like any other social media platform, LinkedIn shows "You may also know" and "You may also like."

Travel and hospitality: Online travel agencies such as Booking.com and **Airbnb** use recommender systems to suggest hotels, flights, and vacations rentals to customers based on their travel preferences and past bookings.

Overall recommender systems are used in various industries and applications to help users find products, contents or services that are relevant to their interests and preferences.
By providing personalized recommendations, these systems can improve user engagement, satisfaction and loyalty and ca also help business increase sales and customer retention.

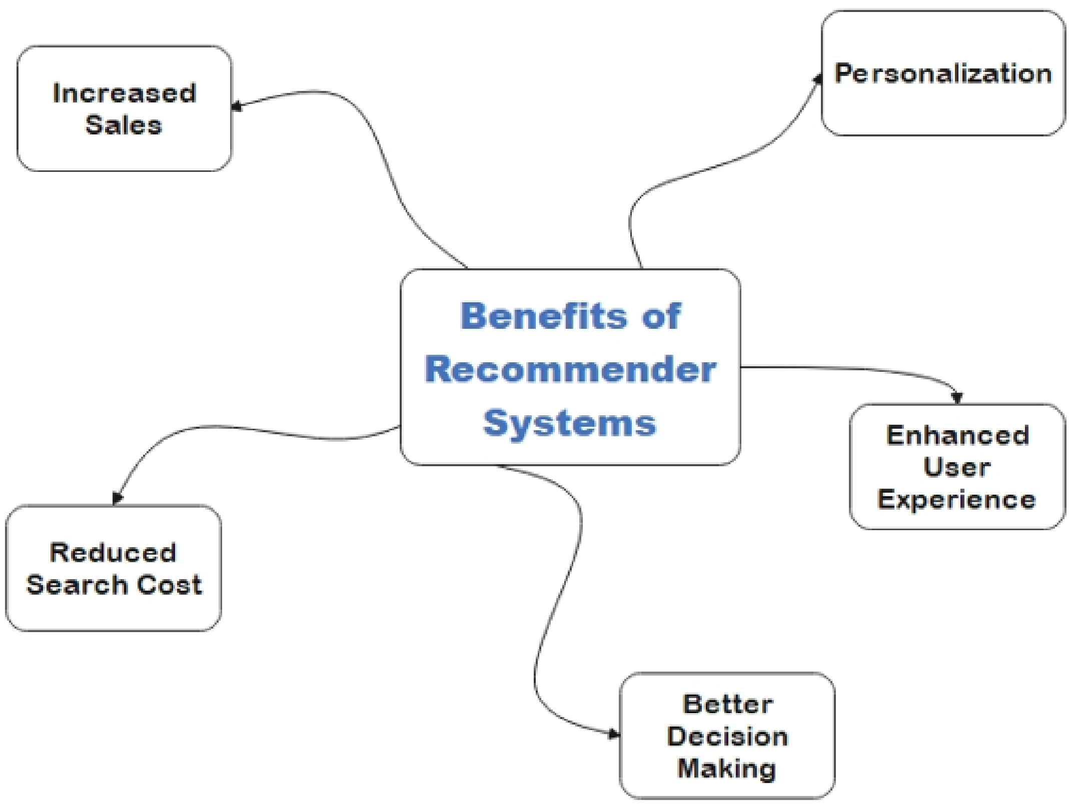


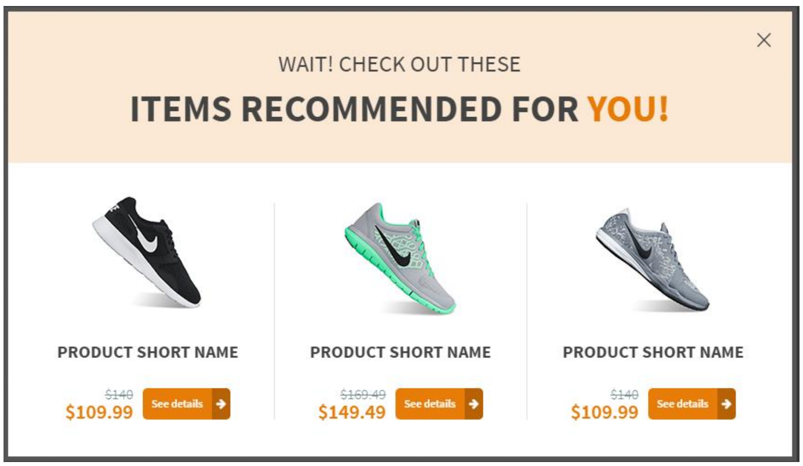
Figure 2: Benefits of Recommender Systems

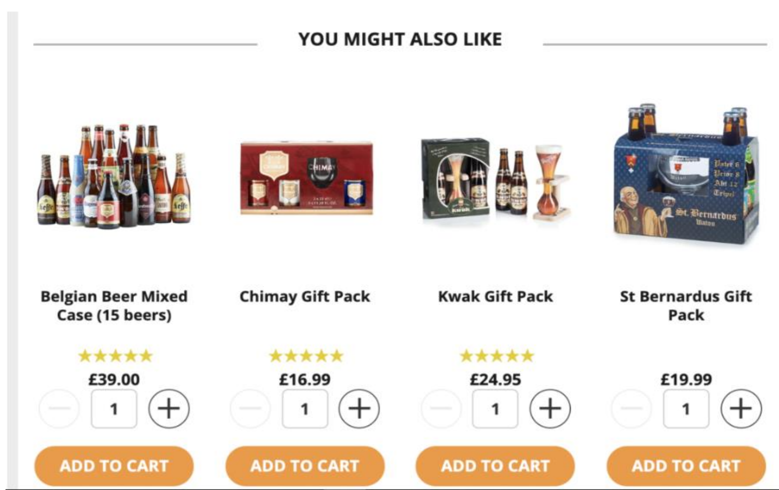
RECOMMENDATIONS AND PEOPLE YOU MAY KNOW

Recommendations and People You may know are two common features used in almost all social media platforms. It is a user-to-user algorithm.

Recommendations: This feature is used to suggest posts, blogs, groups or pages to users based on their interests and past activity on the platform.
For example, if a person frequently interacts with posts related to football, the platform with suggest football related content to the user. This helps in discovering new content and engage with the platform.

People You May Know: People you may know use a collaborative filtering recommender system. This feature is used to suggest connections such as friends or colleagues just based on a user social network and different activities. For example, if two friends have mutual friends and they interact with each other's posts quite often, the platform will suggest them as a connection. This helps a person in expanding their social network.





HISTORY OF RECOMMENDER SYSTEM

The recommender system was first created by **Elaine Rich**, an American computer scientist in 1979. It was named Grundy. She wanted to make a system for recommendations of books. But the recommendation system was first mentioned in the early or mid-1990s when the internet was still in its early stage.

Some researchers from MIT and UMN developed a news recommendations service, named GroupLens. Prof. John Reidl founded a research lab also named GroupLens at UMN, a pioneer of recommendation systems.

After **GroupLens**, the next recommender system was used in 1998 in the launch of Amazon.com. Netflix launched its system in 2000 but in 2000s they also started to develop their recommendation system.

Over the years, recommendation systems have evolved and include a variety of different approaches such as hybrid, content-based and collaborative filtering. Today, recommendation systems are a must for almost every company in various industries such as e-commerce, entertainment, education and social media.

CHAPTER 2: TOOLS, TECHS, AND TECHNIQUES

Discussed Topics in Chapter 2 are:

- *Required Mathematics*
- *Computing Tools, Programming Languages, etc.*
- *Three Main Approaches*
- *Short Description of the Development Process*

REQUIRED MATHEMATICS

Calculus:

Calculus is a branch of mathematics that deals with the study of rates of changes and accumulations. It is a fundamental subject in science, engineering, economics and many other fields. While there is no direct connection between calculus and recommendation systems, there are some applications of calculus relevant to the development of recommendation systems.

For example, calculus can be used to model the behavior of users and items. Differential equations can be used to model how a user's preferences change over time based on their interaction eth the system.

Calculus can be used to optimize the performance of a system. Optimization techniques such as gradient descent, which involves calculation of derivatives, are used to improve the accuracy by minimizing error between predicted ratings and actual ratings.

Statistics:

Statistics is a field of mathematics that deals with collection, analysis, interpretation, and organizing of data. It is a fundamental tool in developing and evaluating recommendation systems. Statistics plays a crucial role in recommendation systems, from data preprocessing and modeling to evaluation and performance analysis.

One important application of statistics in recommendation systems is in collection and preprocessing. Another important application of statistics in recommendation system is in modeling user preferences and item characteristics. Statistical models such as regression, clustering and factor analysis can be used to model the relationships between user and items and to predict user preferences based on their behavior on the system.

Metrices such as F1 score, and precision can be used to measure the accuracy of the systems while techniques such as cross-validation and A/B testing can be used to validate the performance of the systema and optimize its parameters.

Probability:

One way that probability is used in recommendation systems is through collaborative filtering which can be done using techniques such as matrix factorization or nearest neighbor algorithms.

Another way probability is used in recommendation systems is through content-based filtering which can be done using techniques such as cosine similarity or clustering.

In both collaborative filtering and content-based filtering, probability is used to calculate the likelihood that a user will like a particular item based on their past behavior or the behavior of similar users. These probabilities are then used to generate a list of recommended items that the user is likely to enjoy.

Linear Algebra (SVD, PCA):

Linear algebra plays a crucial role in recommendation systems, particularly in collaborative filtering.

To implement collaborative filtering, we need to represent the user-item preferences in the form of a matrix, commonly known as the user-item matrix. In this matrix, each row represents a user, each column represents an item, and the entry at the intersection of a row and a column represents the rating that the user has given to the item.

However, in practice, most of the entries in the user-item matrix are missing because users typically rate only a small fraction of the items. This is known as the "sparse matrix" problem.

One of the key techniques used to solve the sparse matrix problem is matrix factorization, which is a linear algebra method that decomposes a matrix into a product of lower-dimensional matrices. The lower-dimensional matrices capture the latent factors that determine the user-item preferences. By using matrix factorization, we can approximate the missing ratings and fill in the sparse matrix. This allows us to recommend items that the user has not yet rated.

Matrix factorization can be done using various techniques, including singular value decomposition (SVD), principal component analysis (PCA), and non-negative matrix factorization (NMF). These techniques involve solving a system of linear equations, which is where linear algebra comes into play.

In addition to matrix factorization, linear algebra is also used in other recommendation system techniques such as content-based filtering, which involves representing the items as feature vectors and computing similarities between them using linear algebra operations such as dot products and cosine similarity.

Overall, linear algebra is an essential tool for implementing efficient and accurate recommendation systems that can provide personalized recommendations to users.

SVD and PCA:

Singular Value Decomposition is an important concept in linear algebra. It is basically the decomposition or factorization of a matrix into 3 matrices. In SVD, let us assume a matrix A which is an m × n matrix is decomposed as

$$A = U * D * V^T$$

Where U is an m × m matrix, D is a diagonal matrix and V^T is a n × n matrix. SVD gets its name from the diagonal entries on D, which are called the singular values of matrix A which are in fact, the square root of eigenvalues of matrix $A*A^T$.

Principal Component Analysis is a dimensionality reduction method that is used to reduce dimensionality of large datasets while retaining as much as possible of the variation present in the data set.

Steps for performing PCA:

1. Get the data matrix X.
2. Compute the matrix vector μ.
3. Subtract mean from given data set.
4. Calculate the covariance matrix S ($S=\frac{1}{N}D^T D$, where D is mean centered)
5. Calculate the eigenvalues and eigenvectors of the covariance matrix.
6. Select the eigenvectors as principal components.
7. Derive the new data set T=DV.

For example, consider the data (2,1), (3,5),(4,3),(5,6),(6,7),(7,8)

$$X=\begin{bmatrix} 2 & 3 & 4 & 5 & 6 & 7 \\ 1 & 5 & 3 & 6 & 7 & 8 \end{bmatrix}$$

The mean matrix is

$$\mu=\begin{bmatrix} 4.5 \\ 4 \end{bmatrix}$$

Then,

$$D=X-\mu=\begin{bmatrix} -2.5 & -1.5 & -0.5 & 0.5 & 1.5 & 2.5 \\ -4 & 0 & -2 & 1 & 2 & 3 \end{bmatrix}$$

Calculating the covariance matrix, we get

$$S = \frac{1}{6}\begin{bmatrix} 17.5 & 22 \\ 22 & 34 \end{bmatrix} = \begin{bmatrix} 2.92 & 3.67 \\ 3.67 & 5.67 \end{bmatrix}$$

Eigenvalues of matrix S are given by

$\lambda = 8.22, 0.38$

The second eigenvalue is very small so the eigenvector corresponding to first eigenvalue is the first principal component.

Now solving,

$$(S-8.22*I)*v_1=\mathbf{0}$$

$$v_1 = \begin{bmatrix} 2.55 \\ 3.67 \end{bmatrix}$$

Now calculating T

$$T=v_1^T D = \begin{bmatrix} 2.55 & 3.67 \end{bmatrix}\begin{bmatrix} -2.5 & -1.5 & -0.5 & 0.5 & 1.5 & 2.5 \\ -4 & 0 & -2 & 1 & 2 & 3 \end{bmatrix}$$

$$=\begin{bmatrix} -21.05 & -3.82 & -8.61 & 4.94 & 11.16 & 17.38 \end{bmatrix}$$

Example of SVD:

Let $A=\begin{bmatrix} -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix}$

Here r = rank (A) = 2

$A*A^t = \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix}$ with eigenvalues 3 and 1 and singular values $\sqrt{3}$ and 1

Eigenvector associated with eigenvalue 3 is

$$v_1=\begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}$$

and eigenvector associated with eigenvalue 1 is

$$v_2=\begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

Normalized form of eigenvectors are

$$v_1=\frac{1}{\sqrt{6}}\begin{bmatrix}1\\-2\\1\end{bmatrix},\ v_2=\frac{1}{\sqrt{2}}\begin{bmatrix}-1\\0\\1\end{bmatrix}$$

Now for U, we have u_i's as

$$u_1=\frac{1}{\sqrt{2}}\begin{bmatrix}1\\-2\end{bmatrix},\ u_2=\frac{1}{\sqrt{2}}\begin{bmatrix}1\\1\end{bmatrix}$$

Thus

$$A=\begin{bmatrix}-\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}}\\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}}\end{bmatrix}\begin{bmatrix}\sqrt{3} & 0 & 0\\ 0 & 1 & 0\end{bmatrix}\begin{bmatrix}\frac{1}{\sqrt{6}} & -\frac{2}{\sqrt{6}} & \frac{1}{\sqrt{6}}\\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}}\end{bmatrix}$$

This is the reduced form of SVD which gives the essential part of A.

SVD finds latent features that describe the preferences of users and characteristics of items. As SVD factorizes the original user-item matrix into three matrices: U, S, and V. U represents the user feature matrix, S represents the diagonal matrix of singular values, and V represents the item feature matrix. The singular values in S are sorted in descending order, indicating the importance of the corresponding latent features.

The goal of PCA in recommender systems is to identify a small number of latent factors that capture most of the variability in the user-item matrix. These latent factors can be used to model user preferences and item characteristics.

Once the latent factors have been identified, PCA can be used to reduce the dimensionality of the user-item matrix by projecting the data onto a lower-dimensional subspace. This reduced dimensional representation of the user-item matrix can be used to generate recommendations for users.

Example of Mathematics Behind Recommender System

A simple mathematical example of a recommender system involves matrix factorization, which is a common technique used in collaborative filtering-based recommenders.
Suppose we have a matrix R, which represents user ratings of movies. Rows in the matrix represent users, columns represent movies, and each entry in the matrix represents a user's rating of a movie (e.g., on a scale of 1-5). However, the matrix is incomplete, as users have not rated every movie.
We can use matrix factorization to factorize the matrix R into two matrices U and V, such that their product approximates R. The matrix U represents user preferences (i.e., how much each user likes different genres of movies), and the matrix V represents movie attributes (i.e., how much each movie corresponds to different genres).
We can use gradient descent to minimize the difference between the product of U and V and the observed ratings in R. Once we have learned the matrices U and V, we can use them to predict missing ratings in the matrix R and recommend movies to users based on their preferences.

For example, suppose we have the following incomplete matrix R:

	Movie 1	*Movie 2*	*Movie 3*
User 1	5		3
User 2		3	4
User 3	1	2	

We can factorize this matrix into two matrices U and V as follows:

	Action	*Comedy*	*Drama*
User 1	0.7	0.3	0.1
User 2	0.2	0.6	0.4
User 3	0.1	0.2	0.7

	Movie 1	*Movie 2*	*Movie 3*
Action	0.8	0.4	0.1
Comedy	0.2	0.7	0.8
Drama	0.1	0.2	0.7

Now, to predict the missing rating for User 1 and Movie 2, we can compute the dot product of the corresponding row in U and column in V:

User 1 * Movie 2 = (0.7 * 0.4) + (0.3 * 0.7) + (0.1 * 0.2) = 0.47

So, we predict that User 1 would rate Movie 2 as 0.47 (on a scale of 1-5). We can use similar computations to predict missing ratings for other users and movies and recommend movies to users based on their predicted ratings.

Let us consider another example of mathematics behind Recommender systems for if we must see that how much 2 users are like each other.

Consider the following table of information:

	M1	*M2*	*M3*	*M4*
U1	4		5	1
U2	5	5	4	
U3	3		2	5
U4	3	4		

We will be using the methodology of cosine similarity

$$\text{Sim(U1, U2)} = \cos(r_{U1}, r_{U2}) = (r_{U1} * r_{U2}) / |r_{U1}||r_{U2}|$$

If we check similarity between U1 and U2 for M1 and similarity between U1 and U3 for M1 we get
Sim(U1, U2)=0.38 and Sim(U1, U3)=0.30

So there is slightly more similarity between U1 and U2. If we look at it through our intuition we can see that when U1 and U2 have rated the movies quite similar whereas U3's rating is different.

For more approximate results, we will use centered cosine similarity in which we first normalize ratings by subtracting row mean from each rating.

Considering above example,
Row mean of U1 is 10/3, U2 is 14/3, U3 10/3, U4 is 7/2.
By subtracting row means, the above table becomes

	M1	*M2*	*M3*	*M4*
U1	2/3		5/3	-7/3
U2	1/3	1/3	-2/3	
U3	-1/3		-4/3	5/3
U4	-1/2	1/2		

Now if we use the cosine similarity formula we get

Sim(U1,U2)=0.277 and Sim(U1,U3)= -0.10

So, it is clearer that U1 and U2 are similar whereas U1 and U3 are different.

COMPUTING TOOLS, PROGRAMMING LANGUAGES

Python

Python is a popular programming language for building recommendation systems due to its simplicity, ease of use, and availability of a variety of libraries.

Python can be used in recommendation systems. Python has several libraries like Surprise and Tensorflow that can be used to implement collaborative filtering algorithms.

Overall, Python is a versatile language that can be used to implement various types of recommendation systems, from simple rule-based systems to complex machine learning-based models.

Pandas

Pandas is a popular Python library for data manipulation and analysis that can be useful in building recommendation systems. Data preprocessing is a critical step in building recommendation systems. Pandas can be used to load and preprocess data, including cleaning and filtering, removing duplicates, handling missing values, and converting data types. The cleaned data can then be used to train recommendation models.

Java

Java is a widely used programming language that can be used to build recommendation systems. Java provides libraries like Apache Mahout, which offers high-performance implementations of collaborative filtering algorithms and for content-based filtering that can be used in the recommendation models. Recommendation systems often deal with large datasets, and Java is well-suited for handling big data. Java can be used to develop web applications for recommendation systems, which can provide personalized recommendations to users based on their preferences and behavior.

R

R is a popular programming language for statistical computing and data analysis that can be used to build recommendation systems. R provides several libraries like recommender lab, which offers a variety of collaborative filtering algorithms.

R can be used to load and preprocess the data, including cleaning and filtering, removing duplicates, handling missing values, and converting data types. The cleaned data can then be used to train recommendation models. R provides powerful data visualization capabilities, which can be useful in understanding user preferences and behavior.

Machine Learning

Machine learning plays a crucial role in building recommendation systems. Machine learning algorithms can be used to model user-item interactions and make personalized recommendations. Common collaborative filtering algorithms used in recommendation systems include k-Nearest Neighbors (k-NN), matrix factorization, and deep learning-based models.

Deep Learning

Deep learning is a subfield of machine learning that involves building complex neural networks to model and solve complex problems. In recommendation systems, deep learning algorithms can be used to improve the accuracy and personalization of recommendations.
For example, convolutional neural networks (CNNs) can be used to extract features from images, and recurrent neural networks (RNNs) can be used to analyze text data.

Jupyter Notebook

Jupyter Notebook is an open-source web application which is a popular tool for data analysis and machine learning, including building recommendation systems.
Jupyter Notebook can be used to load and preprocess data for recommendation systems. You can use popular data analysis libraries like NumPy to manipulate and preprocess data. This can include cleaning and filtering, removing duplicates, handling missing values, and converting data types.
You can use popular machine learning libraries like Scikit-Learn, TensorFlow, and PyTorch to implement recommendation algorithms. This can include collaborative filtering, content-based filtering, and hybrid recommendation systems.
Jupyter Notebook provides rich visualization capabilities, which can be useful in understanding user preferences and behavior.
You can use libraries like Matplotlib and Seaborn to create interactive visualizations of user-item interactions and recommendation results.
Additionally, Jupyter Notebook can help you visualize and communicate the results of your recommendation systems to stakeholders.

3 MAIN APPROACHES

Content-based filtering systems: This technique involves analyzing the features or characteristics of items or content and using this information for recommendations. For example, a music streaming platform might suggest different tracks based on different genres, artists or lyrics that they have listened to in the past.

Collaborative filtering systems: This technique involves identifying different similarities between users or items based on their interaction with the system and using these similarities to make recommendations. For example, a system might recommend a movie to a user based on the ratings and reviews of other users who have similar taste as the user.

Hybrid recommendation system: Hybrid combines content-based and collaborative filtering to provide more accurate and effective recommendations. The goal is to take advantage of the strengths of different recommendation techniques and overcome their weakness.

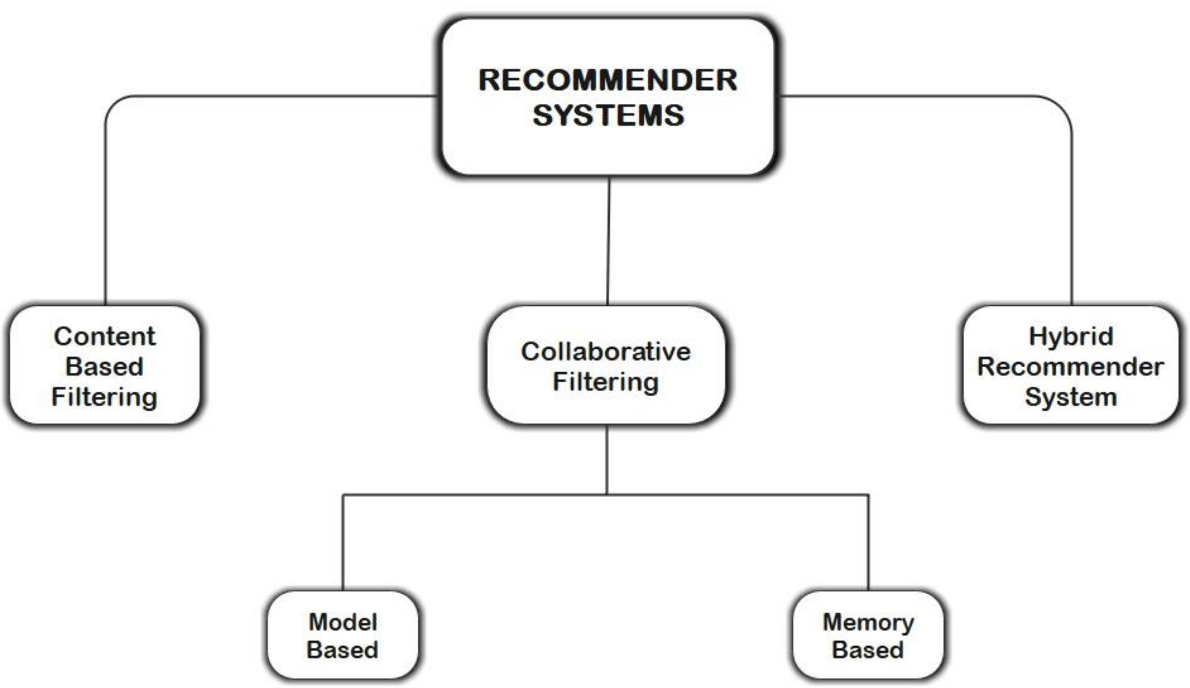


Figure 3

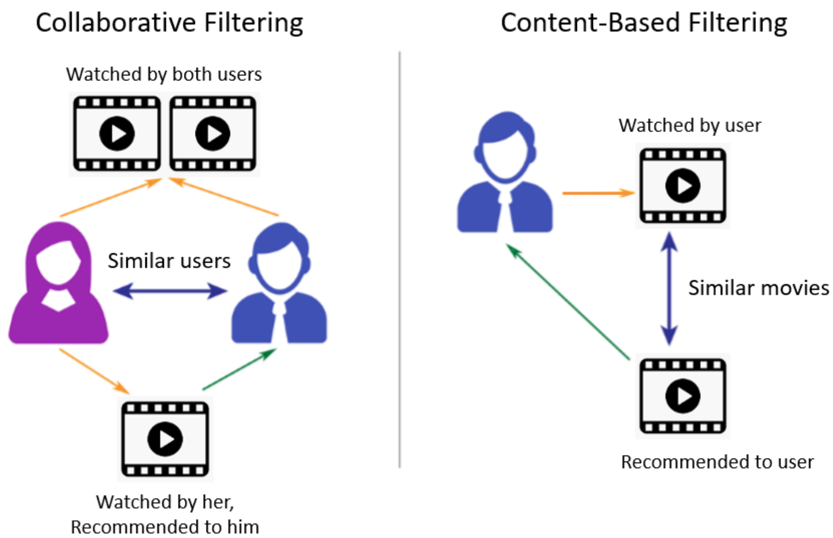


Figure 4: Collaborative and content-based filtering

DESCRIPTION OF DEVELOPMENT PROCESS

For the development of a recommendations system, a person should be able to know calculus, stats, probabilities, and SVD (as a recommendation system is an example of SVD).

We can develop recommender system by the following stages:

1. Problem Definition: First step in any problem solving is that we should clearly define the problem and identify goals. This may include the target audience, and the type of recommendations to be provided.
2. Data Collection: The next step is to collect and preprocess data that will be used in testing the recommendation system. This includes collecting user data, item data and interactive data and cleaning and preprocessing the data to remove inconsistencies.
3. Algorithm Development: After the preprocessing, the next step is to select an appropriate recommendation algorithm and develop it. This includes developing and testing different algorithms, selecting the best algorithm and optimizing it.
4. Evaluation: After this, we need to evaluate the performance of the system using appropriate evaluation metrices. This includes testing the algorithm over a data set and measuring its accuracy.
5. Deployment: The next step is to deploy the algorithm in a production environment and monitor its performance. This includes integrating the recommendation system with application, evaluating its performance and updating it regularly to ensure accurate and effective results.

CHAPTER 3: WELL-KNOWN SYSTEMS

Topics Discussed in Chapter 3:

- *Netflix*
- *PageRank by Google*
- *Some others*

NETFLIX

Netflix is the top streaming service around the world right now which was first founded in August 1997 by Marc Randolph and Reed Hastings.

It is mainly used for watching TV Shows, movies, and documentaries. It has different monthly subscriptions to watch shows and movies either online or downloaded it.

Netflix also uses recommendation systems for its users by suggesting movies and tv shows by looking at users' history.

It uses two-tiered row-based systems which means that through users' navigation, it gives row-wise recommendations. It uses different algorithms and machine learning models to predict what content a user is most likely to enjoy.

The system suggests based on different factors such as interaction with the service members with similar taste also considers different genres, actors, etc.

For example, collaborative filtering is a common technique used to make recommendations based on similar user preferences. This involves analyzing viewing histories of users with similar taste.

Netflix also use deep learning models such as neural networks to make more personalized recommendations. These models can analyze large amounts of data, it includes a user's search history and watchlist.

It uses the jump-start method when you buy or add a profile on Netflix and based on your selection it recommends different movies, shows, and documentaries to watch. Netflix's recommendation system considers the latest watched movies and shows as the user's preference.

Recommendation system is a key for Netflix that helps users find more content that they are likely to enjoy, which results in engagement.

PAGERANK BY GOOGLE

PageRank is an algorithm used by google in the google search engines. PageRank was the result of research by Larry Page and Serger Brin in 1996 at Stanford University. The main idea behind PageRank is to make a hierarchy by the popularity of information on the internet.

Note: Google was founded after PageRank.

PageRank and recommendation system are two different techniques. PageRank is a link analysis algorithm used by google to rank web pages in search engine results. It works by analyzing the link pointing to a webpage and determine the importance of those links based on authority of linking web pages. PageRank is not a recommendation system but rather a way to determine relevance and importance of webpages in search engine results.

SOME OTHERS

AMAZON is also a great example of a recommendation system.

Amazon is an online business founded by Jeff Bezos in 1994 in Washington. It sells books, movies, toys, household, and many other items.

Amazon recommendation uses a variety of algorithms and machine learning models.

Collaborative filtering is a common technique used by amazon where the system analyzes the purchase history of million users to identify similar patterns and suggest products based on what similar users have purchased.

It also uses content-based filtering which analyzes the attributes of products and suggests similar products based on their characteristics. For example, if a user purchases a camera, amazon may suggest camera accessories such as lenses, tripod or camera bags.

In addition to content-based and collaborative filtering amazon uses deep learning models such as neural networks to make more accurate and personalized recommendations to users. It also analyzes wish lists, ratings and reviews for recommendations.

Another example of recommender is **YOUTUBE**. YouTube's recommendation system considers a person's history, likes, and dislikes, views, clicks and watch time to develop different recommendations for its users. It also gives us options to remove YouTube recommendations, which is then also used in the algorithm in the future preferences.

YouTube also uses content-based filtering, collaborative filtering and neural networks for accurate and effective recommendations to its users.

Commercial Use of Recommender systems:

There are several business applications for recommender systems in numerous industries.
To make personalized product recommendations, recommender systems can examine user preferences, browsing habits, past purchases, and other pertinent information. This improves user experience, raises the likelihood that they will buy anything, and increases customer happiness. Many e-commerce sites, including Amazon, employ this strategy.
Based on the users' current decisions, recommender systems can make upgrades or complementary merchandise recommendations.
Recommender systems can deliver personalized adverts by examining user data including demographics, surfing habits, and preferences. Because these advertising are more pertinent to users, there is a higher chance that they will be engaged and converted. Recommender systems are used by platforms like Facebook Ads and Google AdSense to improve ad targeting.
Recommender systems are used by news aggregators, online periodicals, and content platforms to give personalized news stories, blog entries, or videos based on users' reading histories, interests, and preferences.

Future Aspect of Recommender Systems:

Researchers and practitioners are studying several fascinating areas of future work in the field of recommender systems, which is constantly changing.
Future recommender systems will be able to deliver more customized and pertinent recommendations by taking into consideration contextual elements including time, location, device, and social context. Recommender systems can improve user experience by adjusting their recommendations based on the user's current condition by considering these dynamic elements.
An important field of research focuses on improving the transparency and interpretability of recommender systems. Future research can concentrate on formulating methods to clarify the suggestions made by the system, allowing users to comprehend why particular goods are suggested and fostering confidence in the recommendations.
Individual recommendations are the main emphasis of current recommender systems. The social features of recommendation systems can be improved by extending recommender systems to offer group recommendations that take into account the preferences and interests of numerous users. This would allow for collaborative decision-making.

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