Recommender systems: Exploring opportunities in financial services

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Organisations today are increasingly using technology to become more innovative in their business operations. They are utilising technological innovations to bolster customer retention and harness digital transformation. A recommender system is one such technological innovation that is helping organisations recommend products or content to their users. Such a system primarily uses machine learning (ML) to function.

It is not uncommon for us to come across product- or content-related suggestions while browsing e-commerce websites or over-the-top (OTT) platforms. Websites become aware of user preferences within a few minutes of browsing and come up with product/content suggestions. ML is enabling systems to become smarter and adapt to user preferences. Large-scale internet penetration has resulted in significant volumes of data being collected from users. The data helps in providing numerous insights into users' likes and dislikes, trends in content/product consumption and products/content they should explore.

ML-based recommender systems help in storing user data/search history and based on the stored data, recommend suggestions similar to a user's search history. This is a simple example of filtering data according to a user's search history. For countable data, Excel formulas can provide insights but for large datasets, ML and big data are utilised more frequently.

Machine learning

- ML helps a computer programme to learn and adapt to new data without human interference.
- ML algorithms learn the pattern in data, group them, classify them, form clusters, etc. When new data comes in, it can easily identify the cluster it belongs to.
- Given a set of data, ML algorithms come up with inferences that can be applied to many domains.

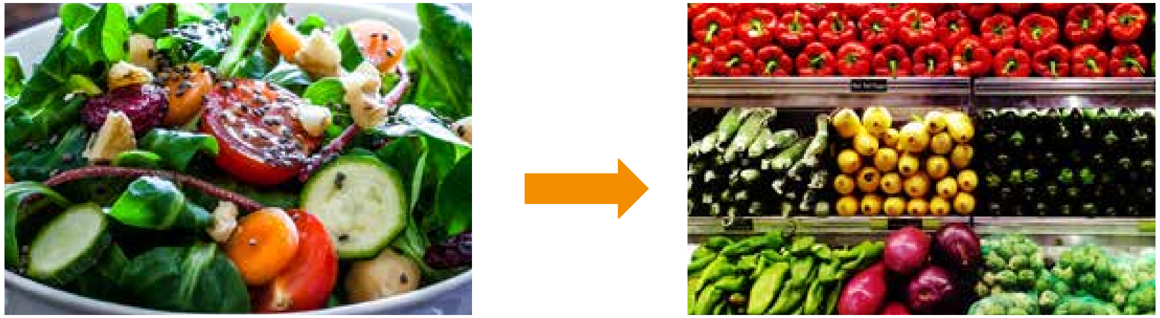
Recommendation in ML

- A recommendation engine filters data using different algorithms and recommends the most relevant items to users. It first captures the past behaviour of customers/users who share similar likes and recommends products that the users are likely to buy.
- Collaborative filtering is the most commonly used recommendation algorithm.

Supervised vs unsupervised learning

ML involves understanding patterns, leading to generation of data-driven insights. Learning can be either guided (supervised) or unguided (unsupervised). For example, data from a dataset of 60,000 samples is divided into training data and test data. An ML-operated system uses training data to learn filtering and testing data to check accuracy. From a dataset of 60,000 samples, 70–80% is utilised as training data and the rest 20–30% is used as testing data. Labelling a dataset and providing it to a system for it to learn from is called supervised learning. Such learning produces data output from previous experiences. Classification is a supervised learning technique.

On the other hand, when data is not labelled and random inputs are given from sample datasets, an ML-operated system finds unknown patterns and features in the data, and these could be used for categorisation. Thus, the system learns to categorise data on its own. This form of learning is known as unsupervised learning. Clustering is an unsupervised learning technique.



Sample

Cluster/ group

How recommender systems work

Zettabytes of data currently exist both online and offline, and it's difficult to extract insights from such huge volumes of data. There is a need to run multiple algorithms to address a given problem statement. A recommender system is one such problem statement. Internet penetration has exponentially increased the amount of data available worldwide. Datasets are fed to recommender systems which enable them to provide recommendations based on content/products liked by users, pages visited, ratings given, transactions conducted, etc.

Various recommendation engine (REs) have been developed and they can be used across channels:

- **Physical branches:** In physical branches of banks and other financial institutions, parameterised REs are used to capture demographic details of branch visitors, types of services to be offered and how employees are to be trained. Physical branches can also benefit from a text-based recommendation system in which a user fills up a feedback form or uses a kiosk to submit feedback. Textual data can be gathered and used for natural language processing (NLP).
- **Call centre:** A feature-based RE is suitable for call centres. The engine translates speech into text, post which NLP is applied to it. The best keywords are picked and then n-gram or word cloud is built on basis of the keywords. The n-gram/ word cloud is then installed into the system and a customer segment wise script is generated. A feature-based recommender engine also helps in identifying the performance of agents. It allows banks/financial institutions to capture details such as an agent's work experience and whether the agent sells products or manages queries. Such information enables organisations in building REs that can help them categorise whether an agent is suitable for a selling role or not.

The techniques of data utilisation are different in the two abovementioned REs. Also, customer experience/journey plays a crucial role in developing an RE. Large volumes of data can be utilised in building cross-channel REs.

There are various recommendation-filtering techniques that help in providing potentially useful suggestions. The major categories that will be discussed further are highlighted below.

Major categories of recommendation filtering techniques

Content-based filtering

- Vector space model
- Probabilistic model
  - Naïve Bayes classifier
  - Decision tree
  - Neural network

Collaborative filtering

- Model-based filtering
  - Clustering
  - Association
  - Neural network
- Memory-based filtering
  - User based
  - Item based

Source: Science Direct

Both content-based and collaborative filtering techniques are based on user data. The difference between the two techniques is discussed in detail below.

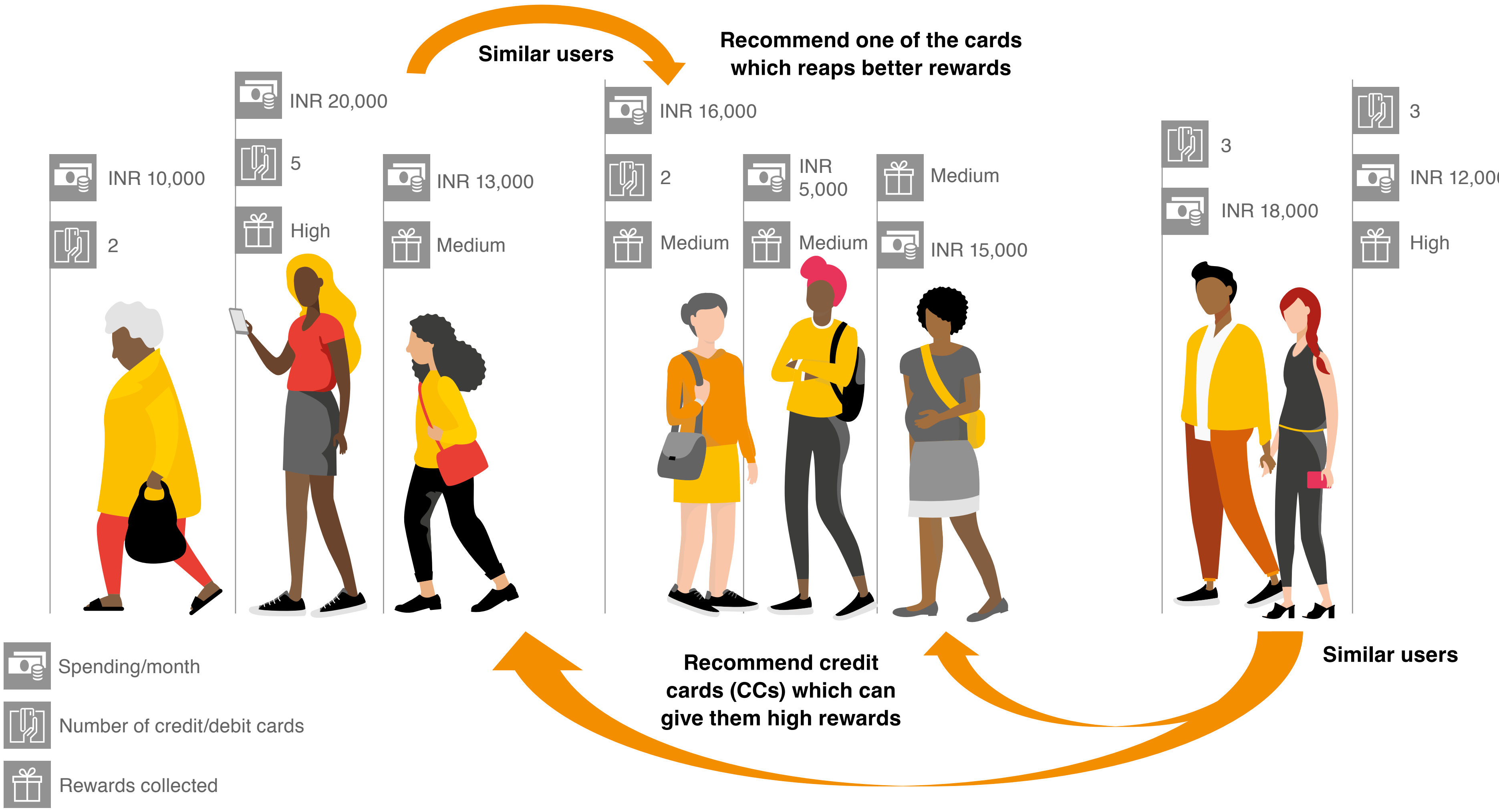
Content-based filtering

A content-based filtering system uses details or characteristics of products for recommending them to buyers. This system is a faster way of recommending products to buyers. For example, if a buyer has a history of buying select branded products, a newly launched product from a similar brand will be recommended to the buyer by this system. But such systems omit behavioural data or data gathered from buyers with similar purchasing patterns. A product would still be recommended to buyers even if it fetches very low rating/negative feedback.

Collaborative filtering

Collaborative filtering was first used by developers at a US-based print and digital products company in its document retrieval system. Collaborative filters predict personal preferences of buyers by tracking their likes and dislikes for product-related information. They also track the behaviour of lookalike audiences to predict preferences. The collected information is then connected to a database that stores data related to preferences of another set of buyers to look for matches and predict purchasing behaviour.[1]

How collaborative filtering works

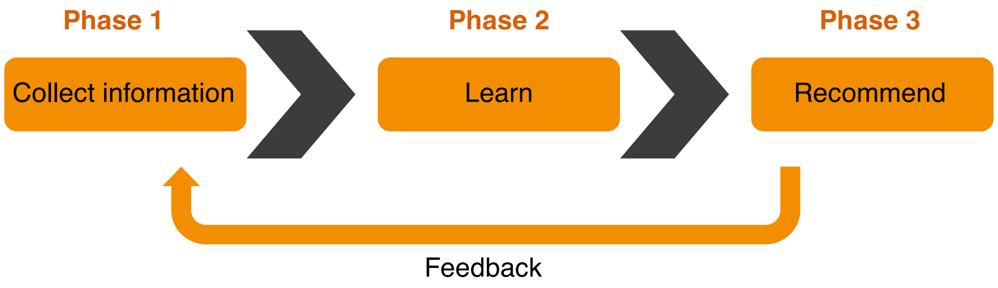


Source: PwC data from internal research

1 http://www.moyak.com/papers/collaborative-filtering.html

The collaborative filtering technique works by building a database (user-item matrix) of preferences for items used/bought by users. The database is then used to match users with relevant interests and preferences by calculating similarities between user profiles. A group of such users is called a neighbourhood. A user receives recommendations for items that have been positively rated by the neighbourhood.

The architecture of a recommender system is as follows:



Source: Science Direct

The recommender system receives feedback based on choices made by users and subsequently learns what is to be recommended in future.

The two types of collaborative filtering techniques as seen in the framework are:

- user-based collaborative filtering
- item-based collaborative filtering.

User-based collaborative filtering is a technique that calculates similarity between users by comparing their spending habits and the type of cards they use to make purchases and gain maximum reward points. This data is stored in a matrix and ML algorithms compute the data for similarity. To understand the filtering process better, let us analyse the example given below.

If we consider users rating movies in the image below, users 2 and 3 are in the same category as they have provided similar ratings for the four movies and users 1 and 4 are in same categories. So how can the rating given by user 5 for the fourth movie be determined? User 5 is similar to user 1, so he/she might give the movie a rating of 3 and would recommend it to others. But one disadvantage of user-based filtering is that many satisfied customers do not rate a film at all while unsatisfied customers always give a rating. This makes the dataset underfitted, resulting in inadequate results. So for such datasets, we should increase the training time or include more parameters until the model provides desired output.

Movie ratings by users

	Movie 1	Movie 2	Movie 3	Movie 4
User 1		★★★★	★★	★★★
User 2	★★★★	★★	★★★	
User 3	★★★★	★★	★★	
User 4		★★★	★★★	★★★
User 5	★	★★★★	★★	?

Item-based filtering was developed by a US-based multinational company. As the name suggests, such systems compute recommendation using the similarity between items. A model item is built by retrieving the details/characteristics of all items rated by an active user from the user-item matrix. The system then calculates the similarity between the retrieved items and target items, and finally selects items that are similar in nature/characteristics. User preferences can be predicted by taking a weighted average of ratings given by active users on similar items. Mutual funds (MFs) or investment products use item-based filtering to predict user preferences.

Consider the example of MFs and their values given below. There is a set of users who invest in MFs as seen in the user-wise MF investment table. If user 4 required recommendation on which MF to invest in, what would it be? The process to get proper recommendations would be to filter the users based on the items they like. As per the table below, user 4's investment patterns are similar to user 3's, i.e. they like the same items and hence a recommender system will suggest MF 4 to user 4.

Name	Size	Financial return	Credit rating
MF 1	Large cap	1 year: 8%	AAA
MF 2	Large cap	1 year: 17.5%	AA
MF 3	Mid cap	1 year: 22.6%	AAA
MF4	Mid cap	1 year: 17.2%	AA
MF 5	Mid cap	1 year: 6%	AA
MF 6	Small cap	1 year: 9.3%	AA
MF 7	Small cap	1 year: 17.6%	AA

User-wise MF investment

				Recommended
User 1	MF 1	MF 2	MF 4	
User 2	MF 1	MF 4	MF 6	
User 3	MF 3	MF 4	MF 7	?
User 4	MF 2	MF 7	?	**MF4**

Similar item

Which filtering is more beneficial?

While item-based filtering recommends the best items in the same category, it does not diversify choices and the number of items recommended are limited as product attributes are almost constant. On the other hand, user-based filtering bridges that gap, thus making people aware of other items and enabling organisations to cross-sell additional products. Today, there are millions of users across the internet whose purchasing patterns/behaviours are not constant. A combination of these two filtering systems creates a hybrid system that leverages the advantages of both, thereby ensuring that the recommendation system is much smarter.

Both the systems have the following advantages and disadvantages:

	Advantage	Disadvantage
Collaborative filtering	• Captures behavioural similarity of other users • Captures behavioural/ interest changes • Provides dynamic useful recommendations • Increases cross-selling opportunities	• Takes time to learn about new users/ products • Requires a large dataset to acquire information • Finds it difficult to recommend a new item if no user has purchased or rated it
Content-based filtering	• Works with lesser data • Provides recommendation based on user history • Faster algorithm	Different items are not recommended as filtering is restricted to one dataset

Recommender system for financial institutions

Let us consider the functioning of a recommendation system for an insurance provider in which the training data consists of a feedback matrix/ rating matrix where:

- each row represents a user profile
- each column represents structured data gathered from a user.

User matrix for an insurance recommendation system

	Demographic details	Behavioural data	Employment data	Financial profile (annual)
User 1	Tier 1	Shopping, movies and games	Business	Income > INR 40 lakh Expense > INR 10 lakh High-net-worth individual (HNWI) and product insurance CC: 3
User 2	Tier 2	Games, reading and dancing	Teacher	Income > INR 10 lakh Expense > INR 3 lakh Health and motor insurance CC: 1
User 3	Tier 1	Travel, sports and shopping	Permanent employee	Income > INR 20 lakh Expense > INR 5 lakh HNWI and travel insurance CC: 2
User 4	Tier 1	Blogging, shopping and travel	Contractor	Income > INR 12 lakh Expense > INR 4 lakh CC: 0
User 5	Tier 2	Movie, games and dancing	Part-time employee	Income: INR 7 lakh Expense > INR 2 lakh CC: 0

Similar users recommend – CCs and health insurance

Similar users recommend – CCs, travel insurance and loan

Source: PwC data from internal research

The feedback received by the insurance provider can be categorised as:

- **Explicit:** Users specify how much they would recommend a travel destination, products purchased or a movie rated by them.
- **Implicit:** If a user applies for buying insurance, the system infers that the user is interested. For example, in the figure above, the products purchased/used by user 1 are insured as the user purchases high-end products. Thus, the user can be provided with good insurance offers on his/her next purchase.

When a user visits the website of a financial service provider, the recommender system should recommend credit cards, insurance, loans, etc., based on:

- insurance that similar users have availed (from the above matrix, we see users 3 and 4 are similar so it is highly likely that both will opt for the travel insurance recommended to them)
- similarity to insurance schemes the users have applied for in the past (if user 2 has health and motor insurance, user 5 will be recommended similar insurance schemes).

This was just an overview of how recommender systems in insurance companies work and are put into use. Since insurance companies deal with huge datasets, multiple ML algorithms are used to provide quick results and recommendations.

Recommender systems are currently used by all financial institutions and still being improvised. There is a large scope for FinTechs in implementing such systems. Payment start-ups can tie up with insurance providers to provide best recommendations on travel, health and vehicle insurance.

Matrices to evaluate a recommender system

The business value of a recommender system can be calculated by considering the impact and financial benefits generated from it. The measuring criteria includes:

- clickthrough rates
- conversion rates
- user engagement
- change in sales volume
- impact on sales distribution
- customer experience with recommendations
- level of personalisation
- reduced information overload
- revenue generation
- coverage – how many users and items it analyses at a time
- diversity – level of cross-selling and diversified recommendations
- generalisation – weak/strong recommendations
- handling new users.

Other statistical key metrics include:

- Decision support metrics like precision and recall:
  — Precision is the accuracy of predicting the next-best recommendation.
  — Recall is the ability of the recommender to recall all the items the user has rated positively in the test set.[2]
- Performance is defined by the quality of output, where a confusion matrix can be used:
  — A recommender system uses mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) for accurate prediction.

2 https://towardsdatascience.com/evaluation-metrics-for-recommender-systems-df56c6611093

PwC's view on building a recommendation engine

A good recommendation engine will be built using a multitiered algorithmic approach tailored for analysing different levels of data, channel and industry, e.g. association analysis, Hidden Markov Model, Support Vector Machine (SVM) and Bayesian network.[3] Deep-learning algorithms are being used nowadays, especially for non-financial industries, though they have some relevance for the financial sector as well. Such algorithms are used for the following:

- algorithmic trading
- portfolio management
- fraud detection
- loan/insurance underwriting
- risk management
- chatbots
- document analysis
- trade settlements
- prevention of money laundering.

If the financial services industry adopts multi-model recommender systems that are built on linear, neural networks and deep-learning techniques, they can assess risks associated with customers, disburse loans and provide other financial services within milliseconds. This will help the industry in enhancing cross-selling opportunities and improving financial inclusion.

3 https://www.researchgate.net/publication/221112030_Combined_Support_Vector_Machines_and_Hidden_Markov_Models_for_Modeling_Facial_Action_Temporal_Dynamics

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Contact us

Vivek Belgavi
Partner, Financial Services Technology Consulting and India FinTech Leader
PwC India
vivek.belgavi@pwc.com

Raman Bhushan
Partner and Leader, Retail and Consumer Analytics
PwC India
raman.bhushan@pwc.com

Author

Shivangi Maheshwari

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