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A STUDY ON THE WORKING OF RECOMMENDATION SYSTEMS

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Abstract

A recommendation engine is a system that suggests products, services, information to users based on analysis of data. Notwithstanding, the recommendation can derive from a variety of factors such as the *history of the user* and the *behaviour of similar users*.

Recommendation systems are quickly becoming the primary way for users to expose to the whole digital world through the lens of their *experiences*, *behaviours*, *preferences* and *interests*. And in a world of information density and product overload, a recommendation engine provides an efficient way for companies to provide consumers with *personalised information* and *solutions*.

A recommendation engine can significantly boost revenues, Click-Through Rates (CTRs), conversions, and other essential metrics. It can have positive effects on the user experience, thus translating to higher customer satisfaction and retention.

Let's take Netflix as an example. Instead of having to browse through thousands of box sets and movie titles, Netflix presents you with a much narrower selection of items that you are likely to enjoy. This capability saves you time and delivers a better user experience. With this function, Netflix achieved lower cancellation rates, saving the company around a billion dollars a year.

Although recommender systems have been used for almost 20 years by companies like Amazon, it has been proliferated to other industries such as finance and travel during the last few years.

Keywords:

Recommender, system, information

Introduction

Recommendation engines need to know you better to be effective with their suggestion. Therefore, the information they *collect* and *integrate* is a critical aspect of the process. This can be information relating to explicit interactions, for example, information about your *past activity, your ratings, reviews and other information about your profile, such as gender, age, or investment objectives*. These can combine with implicit interactions *such as the device you use for access, clicks on a link, location, and dates*.

There are three main types of techniques for Recommendation systems; content-based filtering**,** collaborative filtering, and knowledge-based system**.**

a. Content-based filtering

Content-based filtering is *based on a single user's interactions and preference*. Recommendations are based on the metadata collected from a user's history and interactions. For example, recommendations will be based on looking at established patterns in a user's choice or behaviours. Returning information such as products or services will relate to your likes or views. With an approach like this, the more information that the user provides, the higher the accuracy.

Given the privacy and regulatory issues are important in some industries' services, personal metadata and individual transactional data can be missing at the outset. These issues are commonly known as 'cold start' problems for recommender systems using this approach. Cold start occurs when a recommender system cannot draw inferences for a query due to lack of sufficient information. A particular form of the content-based recommendation system is a *case-based recommender*. These evaluate items' similarities and have been extensively deployed in e-commerce.

A recommendation like 'products similar to this', is a typical instance of this type of approach. Overall, these are limited though to the specific domain and the level of categorisation available.

b. Collaborative filtering

Collaborative filtering is another commonly used technique. Collaborative filtering casts a much wider net, *collecting information from the interactions from many other users to derive suggestions for you*. This approach makes recommendations based on other users with similar tastes or situations. For example, by using their opinion and actions to recommend items to you or to identify how one product may go well with another. 'Next buy' recommendations is a typical usage. Collaborative filtering method usually has higher accuracy than content-based filtering; however, they can also introduce some increased variability and sometimes less interpretable results. They are especially weak in the absence of previously collected data. Without meaningful information on others, it becomes harder, naturally, to participate in any single person actions.

c. Knowledge-based system

Knowledge-based systems are systems where suggestions are *based on an influence about a user's needs and based on a degree of domain expertise and knowledge*. Rules are defined that set context for each recommendation. This, for example, could be criteria that define when a specific financial product, like a trust, would be beneficial to the user. These do not, by default, have to use interaction history of a user in the same way as the content-based approach is, but can include these as well as customer products and service attributes, as well as other expert information. Given the way the system is built up; the recommendations can be easily explained. But building up this type of framework can be expensive. It tends to be better suited to complex domains where items are infrequently purchased or hence, data is lacking. Given this, it doesn't suffer the same cold-start-up problems as others above.

Shopping has been, is and will continue to be a necessity for humanity. It's not a long time since we asked our friends for a recommendation for buying this or that product. Hence, it's the essence of human beings to buy items recommended by our friends, whom we trust more. The digital age has taken into consideration this ancient habit. Therefore, any online shop you visit today, you may see some recommendation engine used.

With the usage of algorithms and data, recommendation engines filter and recommend the most relevant products to a specific user. As they say, it's like an automated shop assistant. When asking for something, he also suggests another one that you may be interested in.
Developing product recommendation algorithm models is a research area that grows hour by hour.

WORKING OF RECOMMENDER SYSTEM

In order to provide customers with service or product recommendations, recommendation engines use algorithms. Lately, these engines have started using machine learning algorithms making the predicting process of items more accurate. Based on the data received from recommendation systems, the algorithms change.

Machine learning algorithms for recommendation systems are generally divided into two categories; **collaborative** and **content-based filtering**. However, modern recommendation systems combine both of them.
Content-based filtering considers the similarity of product attributes and collaborative methods count similarity from customers' interactions.
Generally, the core of machine learning is to develop a function predicting the utility of items to one another.

With so much information on the Internet and so many people out there using it, it has become of vital importance for organizations to search and provide date to their customers corresponding to their needs and tastes. Recommendation engine processes data in four phases Classic recommender system processes data through these four steps: collecting, storing, analyzing and filtering.

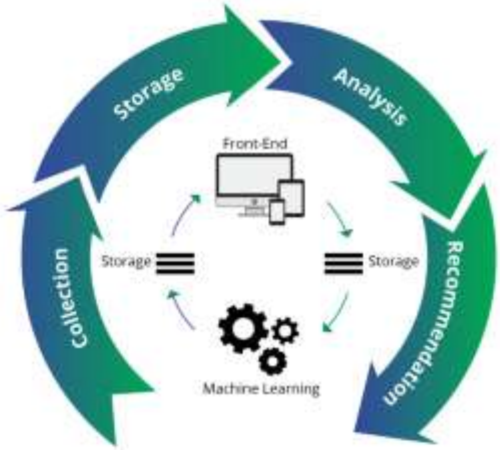

Figure 1: AI Structure

a. Collecting the data

Data gathering is the first phase of creating a recommendation engine. In reality, data is classified into explicit and implicit ones. Data provided by users, like ratings and comments are explicit. Whereas, implicit data may consist of a search log, order and return history, clicks, page views, and cart events. This kind of data is collected from any users who visit the given website.

Collecting behavioural data is not difficult, since you can keep user activities logged on your website. As each user likes or dislikes various items, their datasets are different. During some time, when the recommender engine is feed with more data, it becomes more clever And the recommendations become more relevant too, so the visitors are more inclined to click and buy.

b. Storing the data

To have better recommendations, you should create more data for the algorithms you use. It means that you can turn any recommender project into a great data project quickly. You can decide what type of storage you need to use with the help of the data you use for creating recommendations. It is up to you whether to use a NoSQL database or a standard SQL database or even some sort of object storage. All of these variants are practical and conditioned with whether you capture user behavior or input. A scalable and managed database decreases the number of required tasks to minimal and focuses on the recommendation itself.

c. Analyzing the data

In order to find items with similar user engagement data, it is necessary to filter it with the use of various analyzing methods. Sometimes it is necessary to provide recommendations immediately when the user is viewing the item, so the type of analysis is required. Some of the ways to analyze this kind of data are as follows:

In case you need to provide fast and split-second recommendations you should use the real-time system. It is able to process data as soon as it is created. The real-time system generally includes tools being able to process and analyze event streams.

The best analyzing method of recommendations during the same browsing session is the near-real-time system. It is capable of gathering quick data and refreshing the analytics for few minutes or seconds.

Batch analysis method is more convenient for sending an e-mail at a later date since it processes the date periodically. This kind of approach suggests that you need to create a considerable amount of data to make the proper analysis like daily sales volume.

d. Filtering the data

The next phase is filtering the data to provide relevant recommendations to the users. For implementing this method, you should choose an algorithm suitable for the engine you use. There are a few types of filtering, such as:

Content-based

The focus of content-based filtering is a specific shopper. The algorithms follow actions like visited pages, spent time in various categories, items clicked on and etc. And the software is developed based on the description of the products the user likes. Afterwards, the recommendations are created based on the comparison of user profiles and product catalogues

·Cluster

Cluster analysis is intended for smaller groups of cases. It tries to group more similar to one another in contrast to other types of cases. In this respect, recommended items fit each other regardless of what other users have watched or liked.

·Collaborative

It makes predictions conditioned with the tastes and preferences of the customer and allows you to make product attributes. The essence of collaborative filtering is the following; two users who have liked the same item before will like the one in the future.

DISCUSSION

Let's retake the example of Netflix. The recommendation engine is core to Netflix. More than 80% of the TV shows that people watch on the platform are discovered through a recommendation system. What's unique about the system is that it doesn't look at broad genres, but rather into nuanced threads within the content. The aim is to help break viewers break preconceived notions and find shows that they might have chosen initially.

Netflix's recommendation engine uses 'three-legged stool' working concept. The first leg is the history of what Netflix members watched. Tags are done by Netflix employees who understand everything about the content and proprietary machine learning algorithms that take all of the data and put things together.

Such recommendation engines working concept can serve as an intelligent decision support system that promotes sales activities of products and services for other industries too. These may improve the efficiency of sales representatives or create automatic decision-making processes for the clients themselves.

E-commerce is not an exception. Lots of companies are now looking for ways to cross-sell and up-sell effectively. This is where an AI based recommender system can help.

As McKinsey reports have shown, 75% of content that Netflix users consume and 35% of products that Amazon users buy come from recommendations. After implementing a recommender system, Amazon reported a 29% increase in sales. Alibaba group managed to drive the conversion rates by 20% when it applied ML based recommendation algorithms to provide shoppers with personalized offers during the sales festival in 2016.

Actually, most online shoppers expect companies to provide them with personalized recommendations. According to Evergage, 56% of users will come back to the sites that offer recommendations again and again.

Say, a user has already purchased a hat. Why not offer buying a scarf that matches this hat, so that the look will be complete? This is about related products recommendations, and this use case is very popular among online stores. It is often implemented by means of machine learning algorithms as "Complete the look" or "You might also like" sections in online fashion stores like ASOS, H&M, Pandora and many others.

In addition, such AI based recommender engine can analyze the individual purchase behavior and detect patterns that will help provide a certain user with the suggestions of products that will match his or her interests most likely. This is what Netflix actively applies when recommending movies and TV shows.

Sometimes it happens that a certain product is currently out of stock. This shouldn't become a reason to let a user leave without any purchase. To prevent this, companies implement a smart recommendation system which suggests alternative options. Check this example from Urban Outfitters.

With location based recommendation engine, it is possible to detect customers who are nearby the physical stores or restaurants and send them an invitation to come in.

For instance, Sephora sends the app users a push notification when they are nearby their store and offers them an incentive to come in (such as free makeover). This approach certainly drives customer engagement and significantly increases chances that a user will finally make a purchase.

Recommending the top items is another popular tactic. This is what music streaming services actively apply when offering top charts and playlists. A well-known example of a music recommendation engine is Discover Weekly by Spotify.

CONCLUSION

Recommendation engines can also be *deployed directly for consumers*. For example, Credit Karma is a fintech start up from California that provides free access to credit scores and full credit history, making money from a personalised recommendation on credit cards, loans and other products to their users. Its recommendation system relies on millions of data about users' credit history and current situations, to propose products that not only a user can be interested in, but also has a high probability of being approved for, and therefore has a long-term benefit.

Artificial intelligence solutions are widely used in a variety of businesses. With opportunities they provide, it becomes possible to optimize processes and bring revenues to a new level.

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