Recommender Systems: Past, Present and the Future

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Abstract

The idea of providing targeted recommendations has been around for decades now. The earliest recommender systems, starting in the 1990s, helped select the best suited product from a group of available products. Initially, people used to rely heavily on suggestions provided by peers, be it purchasing a new radio, watching a movie, or even renting an apartment. However, ever since recommender systems were introduced, many of the day-to-day decisions are being influenced by the recommendation system's suggestions. In this report, I seek to explore how recommender systems have evolved and what the future of recommendation systems looks like.

1. Introduction

The human society is based around recommendations, they play a very important part ever since the very beginning of civilizations. Taking agriculture as example, recommendations on which crop to cultivate, the soil best suited for the crop and at what time to plant it was critical for successful agriculture. As the society evolved, the type of recommendation needed day-by-day also changed. Now, the recommendations on what movie to watch is much more prevalent than what type of weapon to use for protection against wild animals.

Today, the wide range of choices has led to more confusion about what choice would best fulfill someone's needs. With the advent of the industrial revolution and the development of computer systems, now it is possible to use computers to make recommendations. The earliest recommender systems were developed to filter out incoming mail as spam or not-spam. Now, they play a very important role in technology firms like HBO, Twitch, Amazon, Instagram, Tinder etc. Some of the biggest organizations, like Google, have their major source of revenue revolving around showing relevant advertisements, identifying the end user, and recommending the most relevant advertisement.

2. Current Approaches

There are various approaches used for generating recommendations, each suited for different types of tasks. In this section we will look at the existing recommendation algorithms including collaborative filtering systems, content and knowledge-based recommendation systems, hybrid systems, and demographics and community centered recommender systems in detail.

2.1 Content-Based Filtering

This algorithm looks at both the similarities between the items and their properties, and the background information about the user for which recommendation is to be made. It considers previous actions and selections, and user's activity is the primary criterion based on which suggestions are made.

Suppose we want to suggest upgrades to someone who has a desktop computer and who has previously bought some desktop parts before. From the purchases before, we have information about the CPU and GPU manufacturers and specifications. Now, with the information about the CPU and GPU, the recommender system may recommend a newly released GPU from the same manufacturer which would be compatible with other parts. It could also suggest liquid cooling systems based on the information about the CPU.

Content-based filtering represents each object as a set of attributes depending on the use-case. These attributes can be rated by the user, or any external expert can assign attributes for each object. The attributes are then combined to cluster objects with similar properties together.

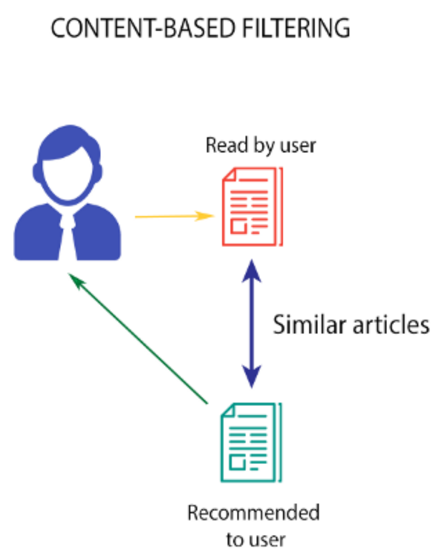

Figure 1: Content-Based Filtering System

The other major part is the creation of user profiles in content-based recommendation systems. These profiles contain all the details about the user’s activities, like past searches, subscriptions, watch time, clicks etc., and the attribute’s magnitude. Attributes that are common across many objects are more impactful as compared to those which appear sparsely, weights are assigned based on that.

Now, a model containing details about the things a user dislikes and likes is created for each user, weighted based on impact. All the users are then assigned scores by comparing them with all objects based on similarity.

Content-based filtering is useful because to start recommendations, there is no need of data about other users. The suggestions are based on an individual's past choices and don't generalize users. The downside is that the chances of discovering new and unique items based on suggestions is very low, and for every change in type or addition of a new item, the attributes need to be updated, which is challenging.

2.2 Collaborative Filtering

This algorithm uses similarities between items and users at the same time to generate suggestions. Unlike content-based filtering, historical personal user data isn't required to make recommendations. The attributes need not be picked using expert specialists, the feature of an item itself can be used as features.

For example, a current student, based on the courses taken by students in previous batches, can be recommended the courses to take. This makes a good suggestion because most students with similar career interests end up taking similar courses.

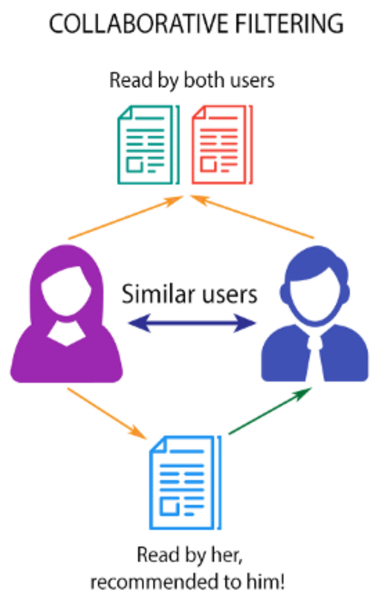

Figure 2: Collaborative Filtering Recommendation System

In collaborative filtering, a user can get novel suggestions which might be a very good match even though the user has never searched or provided any information related to that suggestion. No domain knowledge is required for collaborative filtering as attributes are automatically marked. The downside is that it is impossible to recommend new items as there would be no existing users of that item and no similarities can be generated.

2.3 Hybrid Systems

The hybrid recommendation system combines both content-based and collaborative filtering methods. The idea is to take the best of both the recommendation systems, removing shortcomings. Most organizations nowadays, to an extent, use hybrid recommendation systems for general recommendation generation. For example, the website “Steam”, a video game distributing website, uses both collaborative and content-based filtering to recommend new games to the gamer based on both, past likes, and the similarities with other gamers.

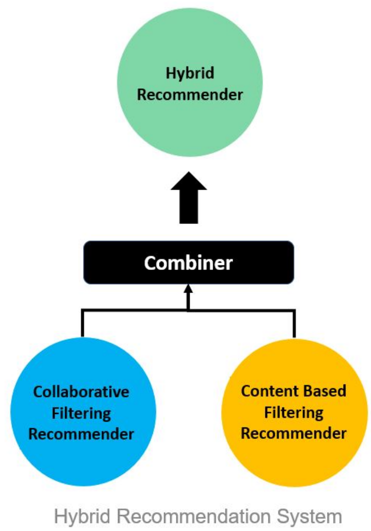

Figure 3: Hybrid Recommendation System

Although the hybrid recommendation systems are very effective for recommendation generation, developing and maintaining them is comparatively more complex.

2.4 Knowledge Based Systems

So far, we've seen that if we have historical data of a user, we can use content-based filtering to generate recommendations. And, if we have a collection of data about other users, then we can use collaborative filtering. But, when we start a new service, there won't be any historical or peer data available, and none of the above recommendation systems will work. This situation is called cold start problem and we use knowledge-based recommendation systems for these cases. In this method, recommendations are made based on domain knowledge.

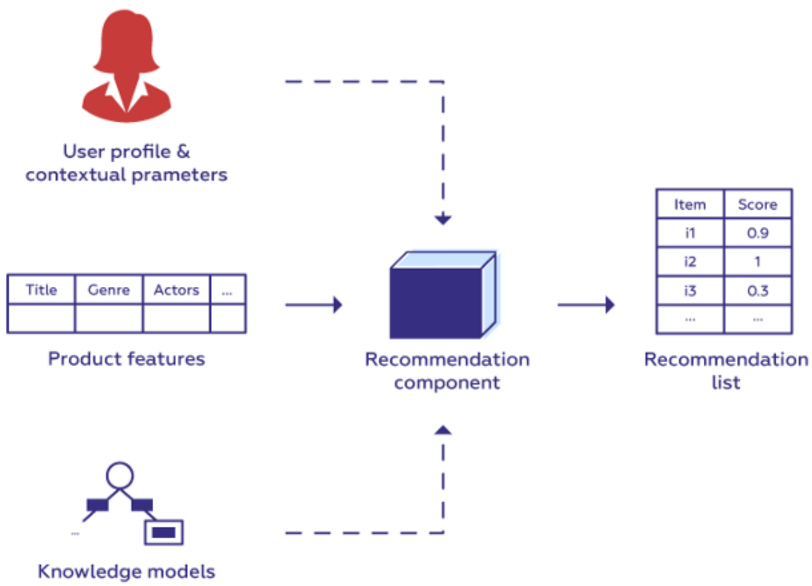

Figure 4: Knowledge Based Recommendation System

For example, on a new art NFT trading website with no historical data, we can ask for user preference like art-style, color pallet etc., and then, based on those requirements, recommend an artwork.

Knowledge-based systems are very well suited for cold start scenarios. However, the time and resources for initial knowledge acquisition with the help of domain experts and users is too high.

2.5 Community-Based Systems

This recommendation system makes suggestions to users based on the user's friends on the social network. Community-based systems, unlike collaborative filtering, do not take similarities of users into account. The recommendations are exclusively based on the items among the user's friends. This recommendation system stems from the idea that users give more weight to friend's suggestions.

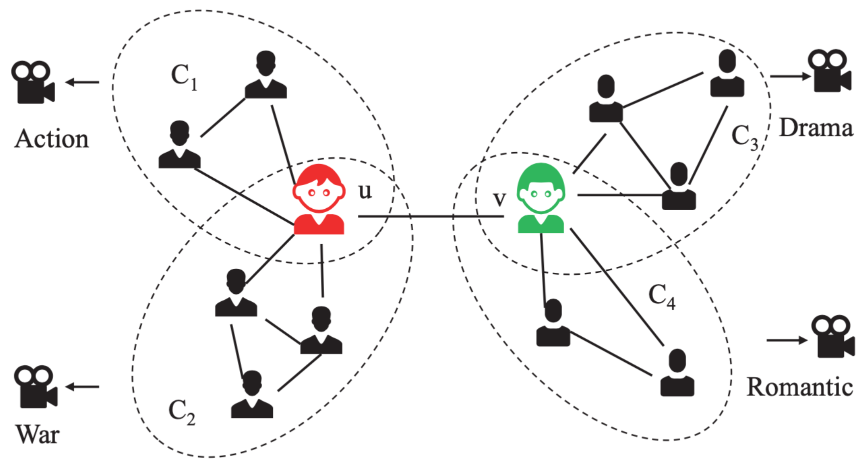

Figure 5: Community-Based Recommendation System

For example, if among the friends of a user, action movies are very common. Then, even though the user might not have any exposure or demonstrated preference for action movies, the community-based recommendation system will suggest action movies to the user.

Although this recommendation system provides an easy way to provide suggestions and give novel recommendations, the results may not always be accurate.

2.6 Demographic Systems

Demographic systems, a relatively new recommendation system, like community-based recommendation systems, recommend items based on the demography or region of the user. It doesn't take users' past choices and preferences into account.

For example, if on an e-commerce website, people from a certain region, suppose California, are buying air conditioners, then the demography-based recommendation system will recommend the user in California similar products, like air coolers. However, if the user was in another region, suppose New Jersey, the suggestions wouldn't be the same. This method provides localized recommendations. However, like community-based recommendation systems, the results may not always be accurate.

3. Case Study: Meta vs Apple

It can't be denied that recommendation systems have become a key part of many organizations. From the biggest targeted advertisement provider, Google, to short video format content platform TikTok. Many technology organizations, both small and large, are using recommendation systems to generate huge economic value.

Recommendation systems have a huge impact on the economy and having good vs average recommendations can make a massive difference. This can be best demonstrated by the downfall of the social media giant Meta (Facebook). Recently, major smartphone manufacturer Apple, in its latest operating system update, provided smartphone users with an option to allow or disallow applications from tracking their details. What seemed like a small change was the major reason for the loss of over $700 billion net worth within a year. Meta (Facebook), which was worth $1 trillion in September 2021, is now only worth $245 billion in November 2022. With the update in the operating system, Apple's OS (IOS) users are now disallowing access to personal tracking data. Meta's primary revenue source was targeted advertisements, with no personalized data from IOS users, Meta now couldn't show targeted ads to the users, causing a massive loss in advertisement revenue.

4. Conclusion

The case study of Meta shows how important and fragile recommendation systems are. An organization forming business around recommendations, must ensure that user and item inputs are consistent. Research and development must be done in this area to develop new recommendation techniques. In the future, augmented and virtual reality are going to become mainstream, which provides a huge opportunity to develop recommendation systems for the metaverse. This platform will provide new dimensions, like eye & face tracking, motion sensing etc., which can be leveraged to provide even better recommendations.

In future, organizations which are quick to adapt to the new metaverse platform by leveraging good recommendation through improved recommendation systems will see huge economic benefits.

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