Overcoming Choice Overload: Evolution and Applications of Recommendation Systems

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Abstract
We live in a world full of choices. With the growth of the Internet, products and information are more readily available and accessible. We are like kids in a candy store. Recommendation systems have become a common feature on many web-based applications, from ecommerce to social media to video streaming services and more. People interact with these systems to have a more highly personalized experience and to explore new products and connections. These systems are based on different algorithms and filtering methods, such as collaborative filtering and content-based filtering. They factor in different sources of information to predict and provide recommendations. This paper provides an overview of how recommendation systems have evolved since their early beginning and how they are being widely used in different ways today to drive and motivate behaviors.

Author Keywords
Recommendation systems; recommender engine; collaborative filtering; content-based filtering

ACM Classification Keywords

H.5 Information Interfaces and Presentation; H.3.3 Information Search and Retrieval; J.4 Social and Behavioral Sciences; I.2 Artificial Intelligence

Introduction

Recommendation systems offer suggestions to a user. We see many examples of these systems especially on ecommerce websites and mobile applications that offer products or services to customers.

The designs for recommendation systems mimic how people would choose candy in a candy store. Individuals would rely on current knowledge, preferences, or past experience, such as which candy they tried and liked or did not like. Additionally, they make decisions based on input from others around them such as family and friends.

There are several approaches to how recommendation systems are designed. One common approach is collaborative filtering. Collaborative filtering makes recommendations based on patterns of ratings or usage (e.g., purchases) without considering information about either items or users [16]. Another approach is content-based filtering where a system determines what a user would like by analyzing information describing the item while factoring in the user's preferences [5]. Other approaches for recommendations systems combine different aspects to form a hybrid approach.

There are different techniques used for recommendation systems. They include k-nearest neighbors, Bayesian networks, neural networks, and genetic algorithms [9].

Explicit versus Implicit Inputs

Recommendation systems are dependent on various types of inputs that are available. The two common types of inputs are explicit data and implicit data.

Explicit data is when users express their interest in something. Users can express interests by providing ratings such as when users provide the number of stars to express their satisfaction for products they purchase online or the level of customer service they receive. Users can also provide rankings such as their top 10 list of all time, such as favorite movies or actors/actresses. In addition, users can provide a list of preferences such as their hobbies or what they like to eat.

Implicit data is data that is gathered from observations or analysis of a user's behavior. This includes things such as browsing history, purchase history, or search history. For example, a person who watches the movie *Big*, *Philadelphia*, or *Forrest Gump* is probably a fan of Tom Hanks.

Collaborative Filtering Approach

Given the different inputs, there are different approaches for recommendation systems. We have often purchased something, watched a movie, or attended an event based on input from other people. Such is an example of collaborative filtering. Collaborative filtering is based on the assumption that people who shared the same opinion or viewpoint regarding something in the past will likely share the same opinion or viewpoint in the future.

This approach makes recommendations by analyzing rating profiles for individuals or items and finding close relationships among them. A technique, such as k-nearest neighbors, is usually used to form neighborhoods. These neighborhoods represent close relationships of individuals who share common preferences, or they can represent close relationships of items that share similarities and will be liked by the same individual.

Content-based Filtering Approach

Content-based filtering is another approach for the design of recommendation systems. This approach makes recommendations based on a user's profile, such as their past behavior or preferences, and an item's description. An example for this approach would be a person who bought a baseball, bat, and glove. This individual is likely a person who is playing baseball. A recommendation system will recommend additional baseball equipment for purchase such as baseball cleats, baseball caps, or baseball gloves.

Techniques for this approach have often included machine learning. Bayesian networks, decision trees, and artificial neural networks have been used to determine recommendations.

Relationship to Data Science

Recommendation systems combine many of the principles of data science that includes problem definitions, algorithms, and approaches for gaining insights from large data sets. Suggestions for products, services, or behaviors are improved by the analysis of data.

We see many applications of recommendation systems in our daily lives. Video streaming services such as Netflix or Amazon Prime Video will recommend movies or shows based on what a person has watched in the past. Online retailers such as Amazon, Walmart, Target and many others will suggest other items to buy based on past purchases or current items in a virtual cart.

Current Implementations

One of the earliest and most well-known implementations of recommendations systems on the Web was launched on Amazon.com in 1998. Amazon's collaborative filtering algorithm was item-based which found related items for each catalog item. It was based on the idea that a person who buys one item is unusually likely to buy the other [20]. This is in contrast to what was common in the mid-1990s which was user-based collaborative filtering.

Another well-known recommendation system is the recommender system found on the Netflix homepage which consists of a variety of custom algorithms to form rows of videos with a similar theme [12]. Some of the genre rows are created by their personalized video ranker (PVR) algorithm that orders videos based on each member profile. Other algorithms include the Top-N Video Ranker that creates its Top Picks row and a trending ranker that creates its Trending Now row.

A widely used recommendation system can also be found on YouTube. Recommendations in YouTube attempt to overcome three major categories- scale, freshness, and noise. YouTube has many videos and users, with many new videos added every second and many user behaviors that are difficult to predict. Its recommendation system is based on two neural networks. One neural network is used for candidate generation by analyzing events from the user's activity history in YouTube to select a subset of videos. The other neural network is used for ranking each video based on features describing the video and the user.

Conclusions

There has been a lot of interest in recommendation systems. With the growth of technology and the Internet, people are constantly interacting with these systems. Recommendation systems influence people's choices and behaviors.

There has been much research in academia to improve the techniques for deploying recommendation systems. Large companies have also started to incorporate and invest in these systems on their technology platforms to improve their bottom line. Recommendation systems will continue to advance as more data is analyzed and new innovations take place. Additionally, advancements in technology will allow for faster processing speeds and should facilitate support for multiple algorithms to be used to form even more advanced and highly personalized recommendation systems.

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