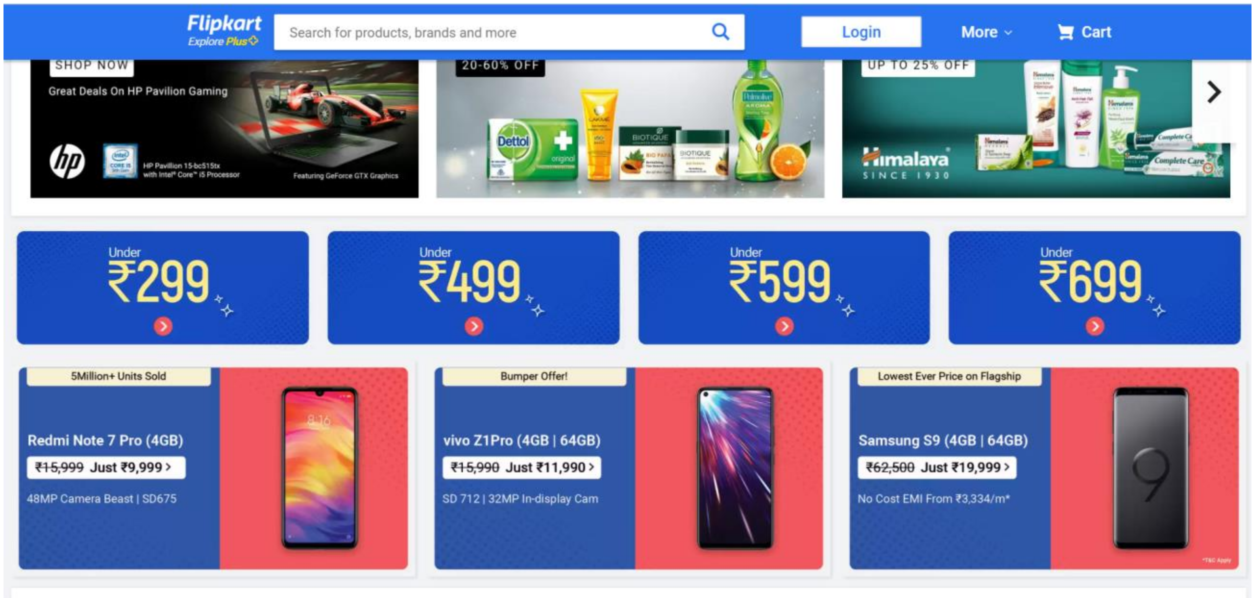
Devakanth Kalapati

Examples of Recommendation Systems

Flipkart



Flipkart is an Indian e-commerce company. It sells a wide range of products such as Electronics, Clothing, Furniture etc.

After looking at the interface and recommendations, an assumption can be made that a hybrid of recommender systems is used that is content based and user based collaborative filtering techniques especially to generate the "Similar Product Recommendations".

The content matching is done over product attributes and images in the catalog; and the collaborative filtering algorithm is applied over user's browse data (like product page views, wishlist, add to cart etc.) to find the most frequently co-browsed products for a given product. The ranked list of similar products based on relevancy is obtained from combining these multiple sources.

The major advantages of this kind of hybrid technique is we can focus on recommending the products based on the customer's behavior that is browse data , at the same time incorporating the recommendations of products which are similar to each other there by increasing the chance, where the customer could potentially buy it.

The disadvantage of this technique is sometimes there might not be enough data to recommend the user accurately. More over the user might not have the account or logged into his/her account at the time of browsing which again decreases the probability of recommending accurately because of less behavioral data and lack of purchase history. Without this data, it is difficult to push the customer to make a buying decision.

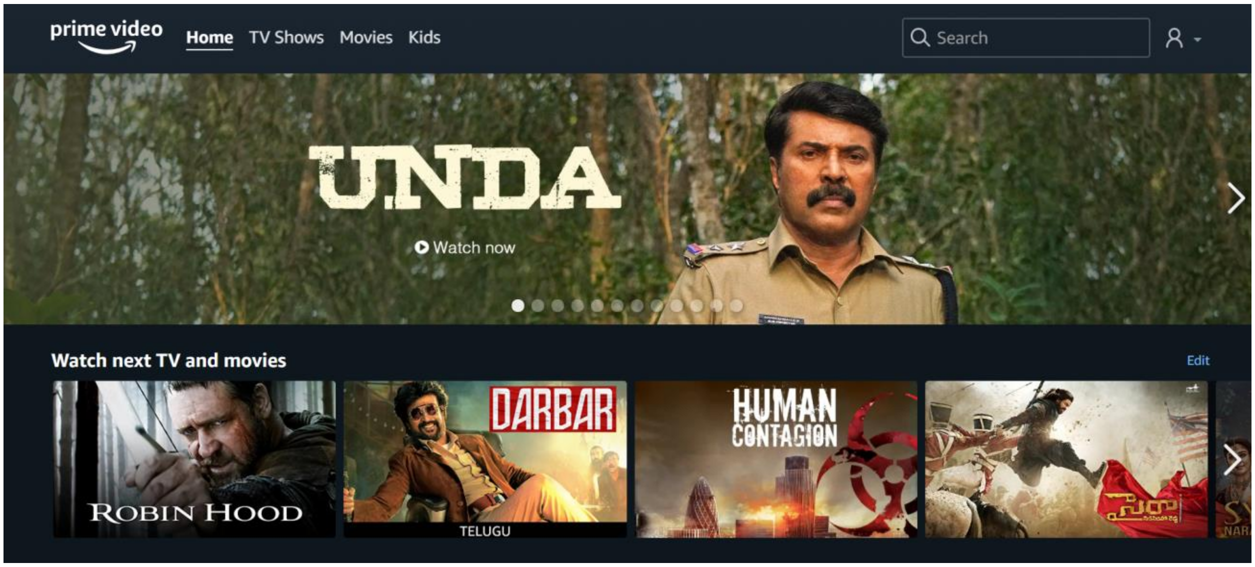
The present recommendation system can be improved by incorporating a ranking function based on certain factors. Since most of the times, we encounter a new user who has no account or very less browse history, we can focus on generalizing the recommendations or recommend based on at least one search.

Then we can rank products based on quality and recommend the ones with high quality because this is what builds the trust factor of the customers on recommendations.

We can also consider performance of the dealer or brand based on their reputation into the criteria. Along with these factors, deep learning can be incorporated for image matching. We can apply machine learning to rank the products and display them.

By replacing the current technique with the proposed technique, there would be a need of more resources in terms of computing as well as data. The accuracy might decrease because it is purely based on 1 search. But with the proposed technique, we can expect an increase in the rate of engagement and conversion.

Prime Video



Prime Video is an American Internet video on demand service that is developed, owned, and operated by Amazon.

As soon as I entered the website, I got recommendations of the latest movies, which had the highest number of views and based on other user's viewing history. You can find "Human Contagion" in the screenshot, which has popped up as one of the recommendation because now we have a pandemic, Corona virus and people are binge watching movies and videos related to viruses and global threats. This is a typical content-based recommender system.

This method has a great advantage over recommending the most usual movies or high rated web series. For example if you take "God Father" or "Casablanca", these are generally the safe bets because of their popularity and this is not what the user actually wants.

Applying their focus on new titles to recommend the latest releases is a clever approach.

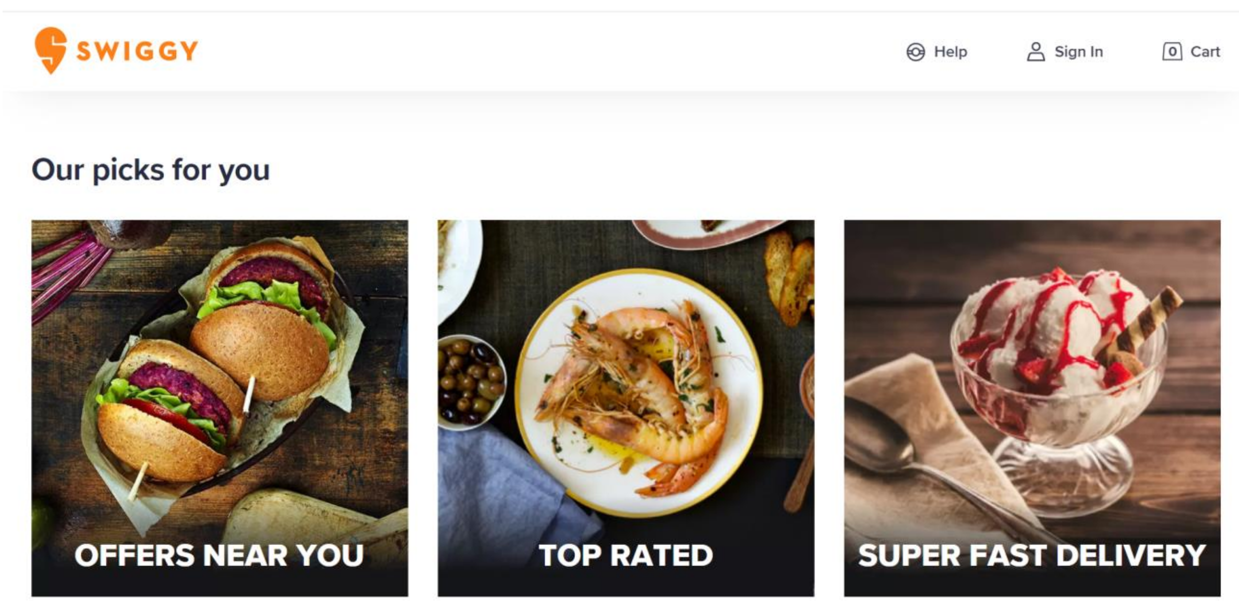
The only disadvantage is that the model has limited ability to expand on the user's existing interests.

We can incorporate user based collaborative filtering into the recommendations by showing what other users bought, who are similar to the user in terms of viewing history. They can also improve the UI. Especially the navigation, because it is pretty complex and does not have filters at the right place to quickly go through the content of our wish such as the ability to search through genres, languages and trending videos.

Also considering the metadata involved in the description of the movies by using NLP techniques to find the right recommendations would be a game changer, but I am sure Prime Video might be having that or tried the technique because it has the DNA of none other than Amazon ;) .

Estimating the performance of the proposed model would be difficult unless put to use in real setting, but considering the number of customers it has, the technique would work because of abundance of data. We can expect a significant increase in the accuracy.

Swiggy



Swiggy is India's largest and most valuable online food ordering and delivery platform.

Once you open, the website without logging in, you can see a variety of recommendations and filters available. Recommendations in terms of popularity, based on the selected location and filters in terms of cuisines, delivery and top rated. This is a generalized approach of recommending a restaurant or a dish. But, once you log into your account, you get a variety of recommendations similar to the food you have ordered previously. Sounds familiar, this is an item based collaborative filtering technique.

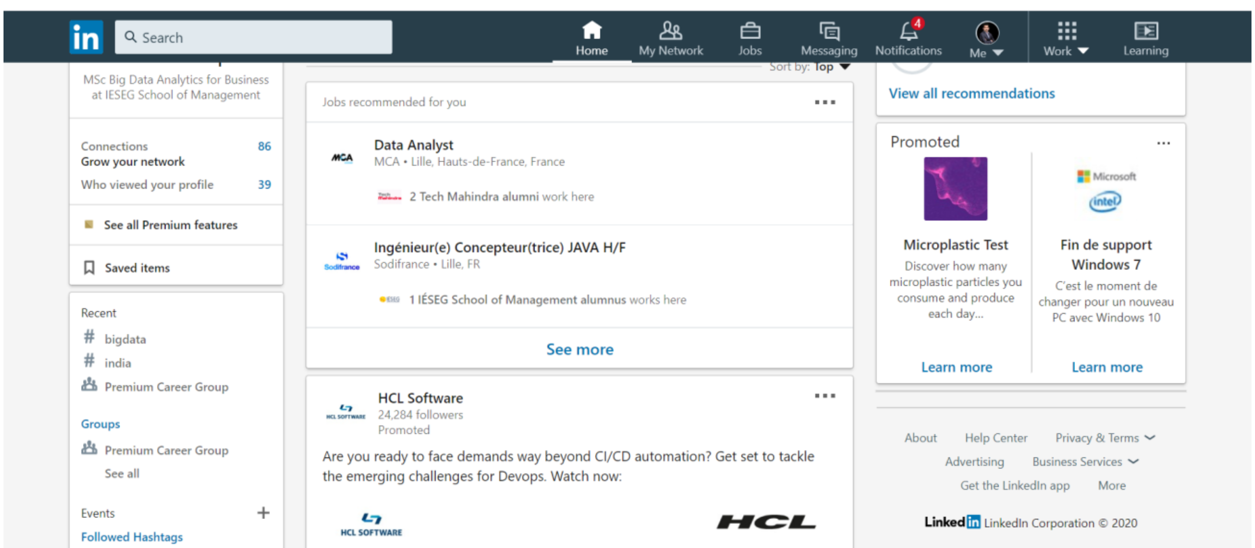
There is a high chance that the user would click the recommendation because users always look for diversity. Moreover, reviews and ratings will always have a great impact especially in restaurant or food business.

Item based recommendation has one major drawback. An item won't be recommended until there is a subset of users who co-rated the item with other items – the new item must first connect to other items already part of the item-similarity graph. One or two co-ratings typically will not do.

We can improve this model with user-based collaborative filtering, as soon as a single user rates the new item, it can potentially be recommended to other, similar users.

With the improved model, we can help users discover new interests as we were talking about the need for diversity. The model does not need any contextual information.

LinkedIn



LinkedIn is an American business and employment-oriented service that operates via websites and mobile apps.

The whole application is filled with recommendations. Such as Job recommendation, Companies you may want to follow similar profiles etc. This implies that this is not just one recommender system but also a mix of variety of techniques.

When someone posts a job, the job poster naturally expects the candidates to have a strong match between job and the profile. Hence, this type of recommendation is heavy on content based.

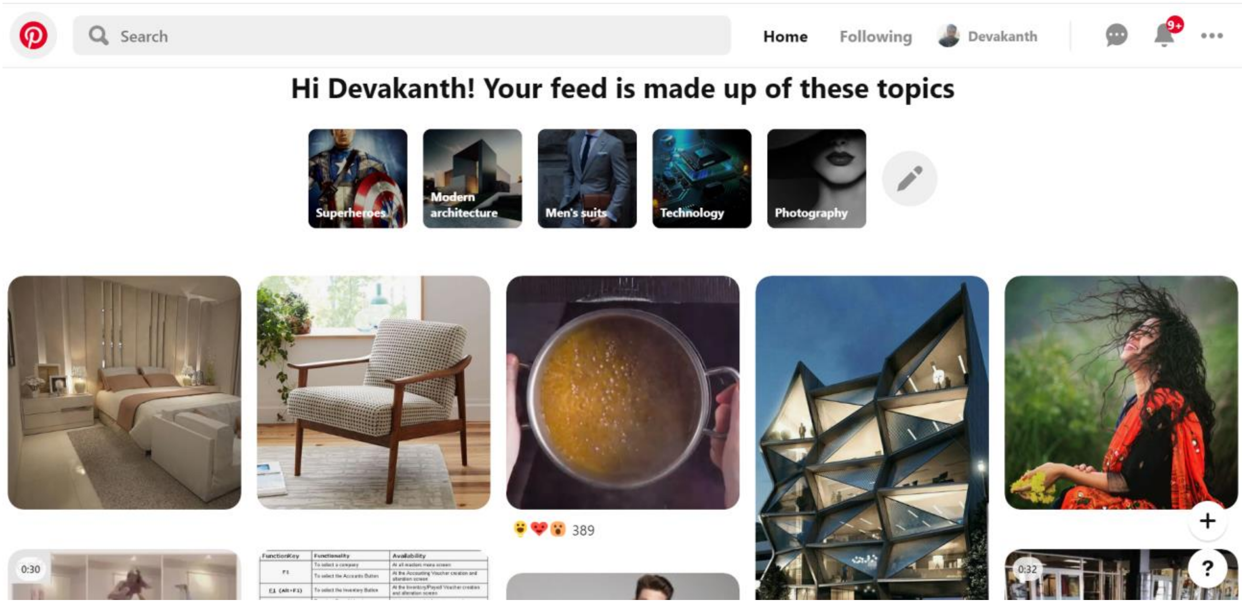
There is a product called 'Viewers of the profile also viewed'. When a member views more than 1 profile within a single session it is recorded as a co-view. Then on aggregating these co-views for every member. We get the data for all profiles that are co-viewed, when someone visits any given profile. This is a classical collaborative filtering based recommendation.

Most other recommendations are hybrid. For e.g. for 'Similar Jobs', jobs that have high content overlap with each other are similar. Interestingly, jobs that get applied to or viewed by the same members are also Similar. So, Similar Jobs is a nice mix of content and collaborative filtering.

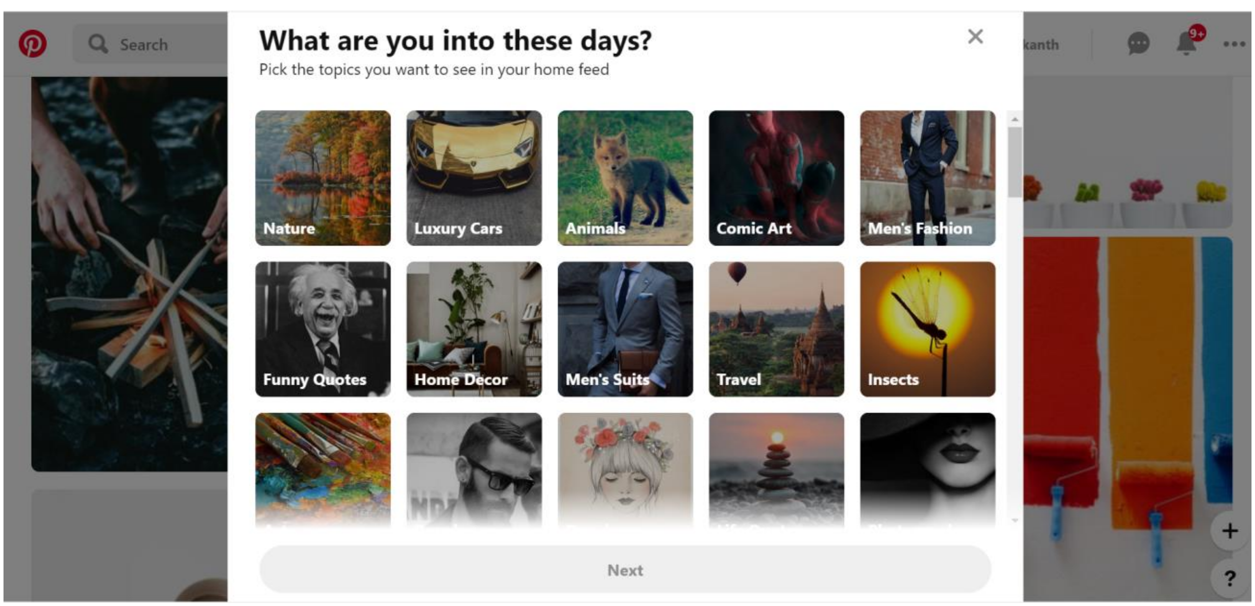
To be honest a recommendation system like this, which is, pinpoint accurate and at the same time complex is already a well-built recommendation. But an option can be added where the user is able to tell whether the recommendation was useful. So, no new recommendation can be proposed.

Pinterest

Pinterest, Inc. is an American social media web and mobile application company. It operates a software system designed to enable saving and discovery of information on the World Wide Web using images and, on a smaller scale, GIFs and videos.



Before going into the details of the recommender system, as soon as I logged into the site I was prompted with certain topics to select to recommend some images of my interest. Apparently, they used cookies to suggest the topics and that is relatable.



This is one of the most complicated and powerful recommendation system one can come across. Pinterest is one of the largest-scale recommender systems around, serving more than 10 billion recommendations every day. By combining the data amassed over the years with human curation, they built human-centered personalization engines that can serve the right recommendation to the right person at the right moment, choosing from a pool of over 100 billion objects—all in real time.

The recommendation engine is called ‘Pixie’. This is a graph-based system. It makes personalized recommendations in real time by providing relevant and narrow recommendations at SOS response rate as Pinners scroll through the home feed.

Imagine you save a Pin of a “Lamborghini” to one of your boards. Using visual signals, Pixie then suggests ten other cars or Lamborghini Pins all based on “Lamborghini”, but it may not know yet exactly what other kinds of cars you want. As the query gets more complicated, Pixie will know that you also save Pins featuring “Maserati” and “Ferrari” Pixie then narrows down the content to Pins related to sports cars, Lamborghinis, Ferraris, all with a focus on Italian cars.

This is what makes it accurate and one of the main reasons people come to Pinterest.

Moreover recommending something based on the user’s actions wile they are still browsing the application and recalculate the recommendations in real time is what makes it one of the best recommendation system.

This graph-based technique is effective because it uses a random walk algorithm which processes in milliseconds. At each step it finds the closest neighbor and has a count of how many times it passed through it. The one with highest count is a relevant image and that is recommended.

The disadvantage of this type of model is the underlying mechanics of storing and traversing a graph efficiently are very complex, and gaining a deep understanding of graph theory is beyond most non-mathematicians.

Random-walk algorithm is limited for sparse graph structures, as seen above. It is limited to suggesting candidates that are directly connected by edges, and cannot travel to nodes that are further away in distance yet still may be similar. In addition, it is vulnerable to clustering effects.