Online Serendipity: The Case for Curated Recommender Systems

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Abstract

Recommender systems are effectively used to provide users with suggestions based on their preferences, and first showed their value in e-commerce sites like Amazon and eBay that algorithmically provided recommendations. A key drawback with these systems is that some items need "personal touch" recommendations to spur on purchase, use, or consumption. A recommender system that facilitates "personal touch" recommendations by enabling users to discover good recommenders as opposed to focusing on algorithmically recommending items addresses this drawback. In this paper, we discuss such a system—the Curated Recommender System. The characteristics of this kind of system are as follows: the system discovers curators and curators make recommendations; a curator is typically another user, though it can be an expert or even an algorithm; curators recommend from curated, thematic, and persistent collections of items; the system needs to support social networking; and curation leads to more serendipitous discovery. It is this last characteristic regarding online serendipity that holds particular promise for Curated Recommender System to provide new value for Websites, especially those that sell books, stream content, or provide social networking platforms.

Keywords: Recommender Systems, Curated Recommender Systems, E-Commerce,

1. AN INTRODUCTION TO RECOMMENDER SYSTEMS

When we are faced with a decision in life, from picking what shampoo to purchase, to deciding which movie to watch, we often find ourselves consulting others to make our decisions easier and better informed. The people we consult can include friends, family members, or more popular now, online reviews of products. This has paved the way for recommender systems, which have become popular through their use in e-commerce (Resnick & Varian, 1997).

Recommender systems have been developed to provide users with suggestions based on their interests, preferences, likes and dislikes. They provide a means by which users can experience an easier decision making process by managing information overload, reducing search costs, and allowing users to make better, more informed, decisions. Recommender systems often act as a sales assistant, supporting a user while browsing, finalizing the list of products they have chosen, and most importantly, offering personalization.

All recommender systems focus on two sets of tasks: 1) obtaining the user's preferences, including demographics, and 2) characterizing items. They then use a relevance score to rank how much the user will like the items, based on the user's features (Ricci, Rokach, & Shapira, 2011).

2. WHY HAVE RECOMMENDER SYSTEMS GAINED POPULARITY?

As the Internet developed and most importantly, e-commerce websites experienced tremendous growth, there became a need to sort through the mass amount of information that was available on the Web to allow users to make decisions without becoming overwhelmed. Recommender systems provide users with recommendations that suited their preference and allow them to experience new items that they would have either not known about, or not considered selecting. An effective recommender system can also overcome many of the challenges that individuals who lack personal experience or expertise in an area face: They can reduce user's search effort for product information, decrease the size of their consideration sets, while improving the quality of their purchase decisions (Gomez-Uribe & Hunt, 2015).

Recommender systems are now ubiquitously used to recommend entertainment (e.g. Netflix), music (e.g. Spotify), travel and leisure services (e.g. TripAdvisor), and products to buy (e.g, Amazon). These companies use recommender systems to provide users with new suggestions that match their preferences or serendipitously raise their awareness to something that they may not have otherwise considered. Furthermore, recommender systems provide a mutual benefit to both users (customers) and the sites. In terms of users, recommender systems help users find items that they would enjoy, help narrow down their choices and to discover new items. As for providers, recommender systems can help companies provide a more personalized service for customers, increase trust and customer loyalty, increase sales and provide opportunities to gain more knowledge of their customers. Effective recommender systems ensure that users—who are increasingly fickle and impatient in their search for content, service, or product—do not abandon a site but rather find value in using it: "Consumer research suggests that a typical Netflix member loses interest after perhaps 60 to 90 seconds of choosing, having reviewed 10 to 20 titles on one or two screens. The user either finds something of interest or the risk of the user abandoning our service increases substantially" (Gomez-Uribe & Hunt, 2015, p. 2).

3. WHAT ARE THE MOST WIDELY USED TYPES OF RECOMMENDER SYSTEMS?

There are three key types of recommender systems that are most prominently used.

- *Collaborative Filtering* is the most common type of recommender system used today. User preferences, purchase histories, and site usage activities are used to develop ad hoc, ephemeral communities of similar users. Users in the same community then receive similar recommendations. Collaborative filtering works especially effectively for making recommendations for items that are often hard to describe and characterize, such as music.
- In *Content-Based Filtering,* an individual user's preferences and profile are matched to features and characteristics of recommended items. The user's preferences and profile are continuously updated based on the feedback they give on the items recommended to them and whether they purchased the items. Content-based filtering does not necessarily require examining usage activity and is not a community-based model.
- On many popular e-commerce websites, collaborative filtering is supplemented with content-based filtering as a *hybrid recommender system*. In this form, the advantages of both systems are combined to provide better, more personalized recommendations. Collaborative recommender systems can suggest items to users based on a community-based model, where items that are recommended are often popular items. Content-based filtering can recommend items that are not necessarily well-known. Although this system can be complex to implement, it has the potential to improve recommendations when implemented effectively. According to Netflix: "Predictive accuracy is substantially improved when blending multiple predictors. Our experience is that most efforts should be concentrated in deriving substantially different approaches, rather than refining a single technique. Consequently, our solution is an ensemble of many methods" (Kantardzic, 2011, p. 243).

<Insert Table 1>

4. INTRODUCING CURATION: THE MISSING ELEMENT FROM PROMINENT RECOMMENDER SYSTEMS

Inasmuch as collaborative and content-based filtering methods are powerful, there are drawbacks to their use. For instance, when it comes to music, "algorithm heavy services do not get much better when you listen and like/dislike more songs. It even seems that by liking and disliking certain songs, we are 'confusing' the radio and taking it in a completely different direction" (Fowler, 2014). That is, these algorithms can sometimes seem plain dumb, because they cannot really think like humans. While recommender systems have continuously evolved to make better and more accurate recommendations to users, they are missing a "human touch." Users are more likely to take a recommendation from another person rather than an algorithm. While traditional recommender systems can make recommendations based on the user's preferences, tastes and interests, they are not able to make an emotional connection with the user (Hennig-Thurau, Marchand, & Marx, 2012). A strong emotional connection can strengthen brand loyalty and increase the likelihood that the user will act upon a suggestion.

Furthermore, human recommenders are often better able to understand a group of users' distinct preferences. The cognitive processes for achieving this understanding cannot readily be explicated. That is, often, machines simply cannot be programmed to provide the same quality of personalized recommendations as humans. The more personalized the recommendations are, the more satisfied the user may be with continuing to follow the recommender's advice. Moreover, automated recommender systems cannot integrate context as well as a human recommender. For example, it is common for bookstore staff to ask about the occasion or context for a book purchase: "Is this for you or is this a gift for someone else"? Not only may the staff person recommend a different book based on the context but their recommendations for complementary, cross-selling items (e.g.

another book if it is for purchaser, and a greeting card if it's a gift) would differ. This kind of fluid interactivity and commonsensical reasoning that is so easy for staff to engage in would be difficult to program in to an algorithm.

Of course, it is infeasible to have a human recommender for every possible online query 24/7. Nevertheless, is there a way to imbue more of a "human touch" to algorithmic recommendations? In Curated Recommender System, curators add this "personal touch."

In common parlance, a curator works in a museum. A museum curator makes decisions in regards to what artwork would be best suited for the visitors of a particular museum. They have a specific profile in mind of what artwork should be included as part of a collection. A museum is not formed from putting a collection of random items together, but rather, developed with specific attributes and expertise. A visit to the museum is enjoyed when visitors see artwork that is part of a collection that matches what they were looking for and is of high quality, because the collection has been curated by an expert. Curators in a Curated Recommender System have similar responsibilities as a museum curator.

Online curators create and make public personalized collections of items based on their own preferences. If these preferences are simple and can be expressed algorithmically, then the curator could be an algorithm. If, on the other hand, the preferences require expertise, judgement or personal taste—as is the case with museum curation—then the curator is human. Each item in a curated collection is a product, content like books, songs, or photos, or even other curated collections.

5. KEY CHARACTERISTICS OF CURATED RECOMMENDER SYSTEMS

System Discovers Curators; Curators Make Recommendations

The responsibility of a Curated Recommender System then is not so much to make an appropriate recommendation to a particular item as it is to recommend the appropriate curator or curated collection. Rather than ask a user to trust an algorithm's recommendation for an item, the algorithm helps find a curator whose item recommendations the user is more apt to trust. Additionally, an algorithm may be employed to find a curated collection, and the user may then be compelled to select an item from that collection or other collections of the same curator. The focus of a Curated Recommender System is to either leverage a user's pre-existing trust in a curator, or foster trust in a new curator by allowing the user to discover and appreciate the curator's collections. The underlying algorithms employed in Curated Recommender Systems may be content-based or collaborative filtering, or a hybrid of these. The type of algorithms employed does not set Curated Recommended Systems apart; rather, it is the focus on recommending a curator or a curated collection, as opposed to recommending any individual item.

The rationale for taking this approach is that in certain context a "personal touch" recommendation from a human curator is more effective at motivating the purchase, use, or consumption of the recommended item. Consuming long form content is an example of just such context. Music and short magazine articles are examples of short form content that are quick to discover and consume. Long form content takes longer to discover and consume, and so is somewhat relatively expensive in terms of money, but it is especially expensive in terms of time[1]. A magazine reader might read an article for 2 minutes before abandoning it; a move viewer might take 20. In contrast, a book reader might commit 2 hours before deciding not to commit more time. Because of this relative

[1] Executive, personal communication, April 16, 2016

expensiveness, a reader will likely place more weight on a recommendation from a trusted or expert curator than from a black-box algorithm. The *Reco* app by Canada's Indigo Books & Music is billed as a Curated Recommender System for books.

In *Reco*, a user specifies books they have read or want to read. These books constitute the user's reading list and finished list, which serve as their curated collection of books. Users can "follow" other users. A user can browse the recommendations and lists of users they follow, and add books from these lists to their own list. Or, users can recommend books to their followers. Accepting a recommendation automatically adds the recommended book to a user's reading list. Comments about the book may accompany each recommendation to further motivate the recipient to start reading the book. *Reco*'s design facilitates curating, following, browsing, and recommending by users; it does not necessarily emphasize searching for items.

A Curator Is Typically Another User, Though It Can Be An Algorithm or an Expert

In Reco, each user is also a curator. This is also true in other places that support curation like the photo sharing site Pinterest and the business networking site LinkedIn. In Pinterest, users create pins, which are mainly photos but can be other media like audio or video. Pins are curated and collected into pinboards. In LinkedIn, users can be considered to curate their contact list; choosing who to connect to is in of itself an act of curation.

Another type of sites that is especially amenable to curation is streaming music. Music recommendations are complicated as user preferences are shaped by the large variety of variables including genre, social preference and geographical factors. The large volume of songs available also makes it difficult to provide recommendations to users that are perfectly in line with their preferences. This issue can only be simplified by recommending songs from a single artist or album. However, users do not always like all songs from a single artist or album, or even solely from the one genre, and would like a variety. So, just as having the best curator can bring more visitors to a museum, so too can having better curation of music bring additional listeners to a site

Spotify and Google Play Music are two streaming sites that have access to over 20 million tracks of music each but take different approaches to how these are curated for their users. In Spotify, users are also curators who have the option of making their playlists public. Spotify uses algorithms that process numerical data and text-process over blogs and Websites to curate playlists of novel or recent tracks. Google Play Music, in contrast, allows curation only by experts. They have a dedicated team including DJs and musicians who build themed playlists. In addition, a team of editors manages the expert curators and ensures playlists are provided the right description.

Collections Are Curated, Thematic, and Persistent

In *Reco*, each user curates exactly two collections: books read and books to read. In LinkedIn, users nominally curate one collection: the list of their contacts. In Pinterest and Spotify, each user can curate multiple collections. In Google Play Music, each expert also curates multiple collections. It can be considered that collections are delineated thematically. In *Reco* and LinkedIn, an apt theme for user collections is "My favorites." In Spotify and Google Play Music, themes can range from "My favorites," specific artists (e.g. U2), specific musical genre (e.g. reggae), time periods (e.g. 80's music), or to the idiosyncratic (e.g. Academy Award nominated songs).

Let's draw another analogy to museums. They typically have two kinds of collections: permanent and exhibited. Permanent collections maintain a consistent theme and central pieces in the collection are persistently displayed even if other pieces are swapped in and out of public display. An exhibited collection is only on display for a certain period of time and after that duration another exhibited collection of a different theme is displayed. Either way, a museum collection is curated, thematic, and persistent—i.e. not ephemeral. Even if the pieces in the collection change, the theme remains persistent, and the pieces are not changed too frequently or haphazardly.

In contrast, traditional collaborative and content-based filtering methods produce collections for users which are intended to be ephemeral, not persistent. For example, when a user is viewing a book on Amazon, it will suggest other books that they may also like. However, this list will sit on that particular page and does not carry forward with the user's profile. In fact, the same user viewing the same book minutes later may be provided with slightly different suggestions. A list of suggestions presented to a user is algorithmically composed and sequenced to maximize the expected value of purchases, and so as facts change (e.g. user buys additional books, or books not suggested before start to be purchased by others), so may the list. Hence, what binds the items on the list thematically may also quickly change.

Contrast this, say, with collections of songs maintained by a Spotify user. The user may add or delete songs from their collections from time to time or even very frequently. The collections are meant to be standalone artifacts reflecting some themes, rather than theme-less, ephemeral artifacts generated by a pragmatic algorithm. Regardless of frequency of change, the themes of the collections are likely to persist or at the very least not be so transitory. So Spotify exemplifies that collections in a Curated Recommender System are curated, thematic, and persistent.

These characteristics are very beneficial for a recommendation system. According to Indigo Books and Music, the following are key elements in how a user of a website might act upon a recommendation from any type of recommender system in order to make the final decision on reading a book: *topic* (cover, tags, genre & description) and *quality* (reviews, ratings, testimonials)[2]. The user could assess whether the recommendation is based on a topic of interest to them. Second, the user could assess whether the recommendation is of high quality, and to do so they may look up the latest ratings and testimonials.

As for the first element identified by Indigo—topic—all recommendation systems including curated systems enable viewing topic and descriptions about recommended items. A curated system can offer incrementally more value than other types: Collection themes can be considered akin to topics, so the theme of the collection from which a recommendation comes can be used to further tag, describe, or search for a recommended item. As for addressing the second element—quality—curation offers advantages over other recommendation systems: Judgement, expertise, personal taste, or objective criteria are applied so that curation results in a collection comprising of notionally high quality items. Curation is the process by which quality is "built into" a collection: think the value provided by Google Play Music's curating DJ's. Then when a user receives a recommendation from a well curated collection, quality assurance of that recommendation is built in. That the collection is persistent also contributes to quality; users may not place as much faith in recommendations if at one moment it comes from a curated collection and next moment it does not.

Social Networking Support Is Important

The third element as identified by Indigo in how a user of a website might act upon a recommendation from a recommender system is *relevancy* (social, friends, trend). Say, for example, that the user and their classmates are getting ready for job interviews in Finance. They are more likely to look for, and recommend to each other, books about investment banking because these

[2] Executive, personal communication, April 16, 2016

books are socially relevant to them. Curated systems can be more effective than other types of systems at facilitating socially relevant recommendations, if it supports social networking. That is, a recommendation from someone in a user's social network is likely to be more trusted and regarded as of higher quality than from a stranger or an algorithm. That user is also more likely to browse and show interest in the collection of a curator in their social network. LinkedIn is in of itself a social networking site. In *Reco* and Pinterest, users establish a relationship by following another user. Spotify users can recommend songs to their Facebook friends. These are ways in which Curated Recommender Systems leverage social networking.

Social relevance is also key to the catalytic recommendation. For example, when an individual is deciding whether to watch a new movie, there is a process that they must go through in their mind to commit to watching the movie. First for example, they will watch advertisements on TV to discover that there is a new movie which potentially interests them. Then, the individual may see an article in a prominent newspaper highlighting how great the movie is. The individual takes another step in committing to watch the movie. Then, the individual may receive an online recommendation from a user who selects a movie from their collection to praise and recommend. This last step provides the catalytic positive reinforcement that the individual needs to move from considering the movie to watching it, and that step is more likely to be taken when the recommendation comes from someone in the individual's social network (Guy, 2015).

Curation Leads to More Serendipitous Discovery

In recommender systems research, there is a design concept called the "cold start problem," which notes the difficulty of making recommendations when there is insufficient data about the person receiving a recommendation or the item being recommended (Lam, Vu, Le, & Duong, 2008). Without sufficient data, collaborative and content filtering algorithms just cannot give good recommendations. A Curated Recommender System does not suffer from this problem to the same extent because recommendations are not data driven but rather curator driven. Without data, a traditional recommender system does not "know" enough about the user or the item. In contrast, as long as the curator knows the user (or the user knows the curator) and is knowledgeable about the items in their collection, the recommendations they make are credible.

Traditional recommender systems typically are not good at making novel recommendations either. Novelty and diversity describe the capability of a system to recommend items that a user would not have otherwise discovered (Adomavicius & Kwon, 2012). Like the cold start problem, the difficulty in making novel recommendations is a problem borne of insufficient data. In the cold start problem, the system possesses insufficient data to make any credible recommendation. For typical recommendations, the system may possess enough data to make recommendations to popular items or to items that its algorithms predict a user will like. However, an inordinate amount of data about the user and the world would be needed, as well as sophisticated models of user behavior, to make a recommendation so novel and diverse yet appropriate that it would pleasantly surprise the user.

With curated systems, curators use judgement, expertise, and personal taste to decide whether a not well-known item is worthwhile recommending or purchasing. In the same vein, curators can make recommendations that may seem novel to users. They may also make recommendations to items that are not typically associated with interests of a user and others in the user's social network. These recommendations would be considered diverse. In addition to receiving recommendations from curators, the user may also take a more active role in seeking items: They may actively browse the collections of curators in their social network. In so doing, the user may discover not well-known, novel, or diverse items that they may have otherwise not considered; that is, a Curated

Recommender System effectively supports serendipitous discovery in a way that purely data driven approaches simply cannot.

The last online recommendation that acts as a final catalyst for recipient action can also be considered a product of serendipity. The recipient views that recommendation from a friend as a serendipitous occurrence. Had that same recommendation come from an algorithm, the recipient might view it as a mere coincidence to simply ignore.

In *Reco*, receiving a recommendation from a friend or a respected expert, receiving several recommendations from different people for the same book, or finding an interesting book amongst collections of one or more users they follow are all ways in which a user may serendipitously discover a book. In LinkedIn, a user can make a general recommendation about a contact that may be seen by any in the contact's own network, or the user can specifically recommend a contact for a specific position. This can lead to serendipitous discovery. Because LinkedIn connects different social networks, a user may get the perfect applicant for a job they posted from "a friend of a friend." Filling the position with someone in their network is a great use of LinkedIn but is not serendipitous; filling it with someone they didn't know beforehand but was made aware of through LinkedIn is.

6. CONCLUSION

Recommender systems are effectively used to provide users with suggestions based on their preferences. They allow users to make better informed and easier decisions. Recommender systems first showed value in e-commerce sites like Amazon and eBay. Traditionally, recommender systems were classified according to the technologies employed: as using content-based filtering, collaborative filtering, or a hybrid of the two. As well as value inherent in employing these technologies in e-commerce sites, there are also drawbacks. A key drawback is that some items need "personal touch" recommendations to spur on purchase, use, or consumption. A recommender system that facilitates "personal touch" recommendations by enabling users to discover good recommenders as opposed to focusing on algorithmically recommending items addresses this drawback. In a novel design of such a system, recommenders curate a collection of items—whether it is a playlist of songs of a certain genre or a list of favorited books—and recommend items from their collections. These systems are called Curated Recommender Systems.

In a curated system like Indigo's *Reco*, every user is a curator. In Google Play Music, curators are employees who curate playlists using expertise gathered as DJ's The streaming music site Spotify has a sophisticated algorithm that curates fresh music. Though the curator could be a human user or expert, or even an algorithm, what they have in common is that they all curate collections of items—e.g. books, music tracks, photos, and even business contacts. Each collection is carefully curated, have a theme, and is persistent—i.e. not ephemeral. These characteristics help build collections that are of good quality, which by extension then gives assurance that the item recommended from the collections is also of good quality.

The promise of curated systems is fully realized if it supports social networking. A recommendation from a curator in a user's social network is likely to be more trusted and regarded as of high quality than from a stranger or an algorithm. The user is also more likely to browse and show interest in the collections of a curator in their social network. And finally, a compelling rationale for using a curated system is the greater opportunity for serendipitous discovery. Traditional recommender systems are not good at dealing with the "cold start problem," nor at giving novel or diverse recommendations, but curated systems potentially are. In *Reco*, for example, receiving a book recommendation from a friend, receiving several recommendations from different people for the same book, finding an interesting book amongst collections of friends, or getting a final, catalytic recommendation for a book about which a user had heard offline buzz are all ways in which a user may serendipitously discover a book.

So, the following are key characteristics of a Curated Recommender System

- System discovers curators; curator make recommendations
- A curator is typically another user, though it can be an expert or even an algorithm
- Collections are curated, thematic, and persistent
- Social networking support is important
- Curation leads to more serendipitous discovery

It is the last characteristic which describes the compelling rationale for using Curated Recommender Systems. Traditional algorithms can "calculate" popularity and recommend items that users are expected to like. Serendipity is more complicated: recommend an item that the user is not necessarily expected to like, that the user does not necessarily expect to be recommended to them, and is something that will resonate with the user nevertheless when they are recommended it. The likelihood of serendipity is generally low, so for serendipitous discovery to occur the user must be open-minded to being pleasantly surprised. A user is much more likely to be open-minded to a recommendation from a curator they know or whose expertise they respect and who chooses to recommend from a well-curated collection than from an impersonal black-box algorithm.

7. REFERENCES

Adomavicius, G., & Kwon, Y. . (2012). Improving Aggregate Recommendation Diversity Using Ranking-Based Techniques. *IEEE Transactions on Knowledge and Data Engineering*, *24*(5), 896–911. http://doi.org/10.1109/TKDE.2011.15

Fowler, J. (2014, July 12). Why We Crave Human-Curated Playlists. *The Next Web - Design and Development*. Retrieved from http://thenextweb.com/dd/2014/07/12/crave-human-curated-playlists/#gref

Gomez-Uribe, C. A., & Hunt, N. (2015). The Netflix Recommender System. *ACM Transactions on Management Information Systems*, *6*(4), 1–19. http://doi.org/10.1145/2843948

Guy, I. (2015). Social Recommender Systems. In F. Ricci, L. Rokach, & B. Shapira (Eds.), *Recommender Systems Handbook* (pp. 511–543). Boston, MA: Springer US. http://doi.org/10.1007/978-1-4899-7637-6

Hennig-Thurau, T., Marchand, A., & Marx, P. (2012). Can Automated Group Recommender Systems Help Consumers Make Better Choices? *Journal of Marketing*, *76*(5), 89–109. http://doi.org/10.1509/jm.10.0537

Kantardzic, M. (2011). *Data Mining: Concepts, Models, Methods, and Algorithms* (Vol. 0). John Wiley & Sons. Retrieved from https://books.google.com/books?id=4IyrNiNvx0gC&pgis=1

Lam, X. N., Vu, T., Le, T. D., & Duong, A. D. (2008). Addressing cold-start problem in recommendation systems. In *Proceedings of the 2nd international conference on Ubiquitous information management and communication - ICUIMC '08* (p. 208). New York, New York, USA: ACM Press. http://doi.org/10.1145/1352793.1352837

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM*, *40*(3), 56–58. http://doi.org/10.1145/245108.245121

Ricci, F., Rokach, L., & Shapira, B. (2011). Introduction to Recommender Systems. In F. Ricci, L. Rokach, & B. Shapira (Eds.), *Recommender Systems Handbook* (2nd ed., Vol. 54, pp. 1–34). Boston, MA: Springer US. http://doi.org/10.1007/978-0-387-85820-3

Table 1: 3 Examples of Recommender Systems

Website	Type of Recommender System	Description	Methodology
Amazon	Collaborative Filtering	• Amazon's recommender system is based on the following elements: o User's past purchases o Items in the user's shopping cart o Items users have rated and liked o What users have viewed and purchased	• For each item, Amazon builds a neighborhood of related items. Whenever an item is bought, Amazon will recommend other items from that item's neighbourhood. These are referred to on the website by "You viewed" and "Customers who viewed this also viewed," or "Frequently Bought Together."
Pandora	Content Based Filtering	• Pandora is a music platform which provides users with the opportunity to build up a "station" based on their musical preferences. • The user indicates in each station one or more songs or artists that he or she likes. Based on these preferences, Pandora plays similar songs that are in line with the user's preferences. The user will provide feedback on the selection by selection thumbs up or thumbs down. This refining system continues to improve and improve the profile of the user.	• First, Pandora classifies songs in their database into a taxonomy using a team of trained musicians. • They perform a manual classification on each song. Pandora compares the description of musical tastes of a station selected by an individual user with the classification of the songs in the music database. • This comparison returns a collection of songs that drive the playlist. An algorithm determines a proximity measure for songs in order group songs together.
Last.fm	Collaborative Filtering	• Recommends songs by observing the tracks played by user and comparing to the behavior of other users • Suggests songs played by users with similar interests	• Last.fm creates a "station" of recommended songs by observing what bands and individual tracks the user has listened to regularly and compares those against listening behavior of other users. • Last.fm will play tracks that are not in the user's library, but are often played by users with a similar interest.
Netflix	Hybrid	• Make movie recommendations by comparing the watching and searching habits of similar users (i.e. collaborative filtering) as well as by offering movies that share characteristics with films that a user has rated highly (content-based filtering).	• Netflix offers recommendations of movies that users may like based on the ratings provided by other users.
YouTube	Content Based Filtering	• The goal of the YouTube video recommendation system is to provide personalized video recommendations to its users	• For each video for each user, the system predicts the next video user will watch. This is combined with additional information about the user to create a path of videos that the user will watch. These videos are then recommended to the user
LinkedIn	Collaborative Filtering	• LinkedIn is a business networking and jobs posting site. In order to connect people, LinkedIn makes extensive use of item-based collaborative filtering.	• Each member's profile on LinkedIn has "People Who Viewed Your Profile Also Viewed this Profile" link. • Collaborative filtering datasets, or browsemaps, exist not just for items like people, but also for jobs postings, companies and groups. These navigational aids are principal components of engagement on the site.