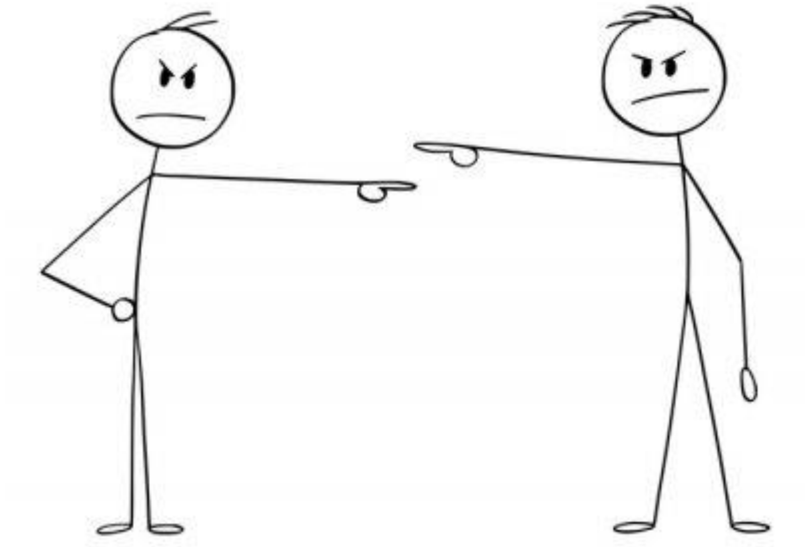

Drawing by Zdenek Sasek, fetched [here]

On recommender algorithms: Anyone volunteer to take responsibility?

Fall 2022, ACIT4100 Understanding and Communicating Research

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> I know you. Yes, you. *You scroll, you click, and you watch.* Over and over and over again. Sporadically all day, every single day. *I* know *you*. I distract you; I educate you; I entertain you; I make you frustrated; I help you. I can make you think and feel a particular way; I help you find the content you like; I influence you, and you do not even notice it. Who am I? Maybe you do not know, but I know you because you let me. *You scroll, click, watch,* and let me know. I know what you buy, what you like and dislike, what you watch, and what you click. *I* know *you*. At times, I know you better than you do. How do I know you so well? Because I spend all my time getting to know *you.* And you are all I need to know. You scroll, you click, you watch, and *I know*.

Okay, okay, hold on a second. You absolutely manage to paint a certain picture of yourself, do you not? Like, for real, do you want to describe yourself like that? You sound like a total stalker, to be honest. Even though I know you do not exactly appreciate that characterization. But come on. Listen to yourself; of course, people are sceptical towards you. You make it sound like you are about to break into peoples' houses in the middle of the night. What about this instead: I will try my best to understand better who you are, just because I know you do not necessarily have as bad intentions as people think. In the end, I know you can do a lot of good. And if people still do not like you, what can you do… But great sounds like a plan, so let us dive into it!

1. Introduction

You have a conversation with your friends about a product or a trip, then the next time you open your phone, it is suddenly ads for it all over the place. Sometimes it can feel like someone is listening, which is not pleasant. Although this paper is not out to discuss whether that is the case, it will look into how our various devices, to that extent, can make sophisticated guesses on what content we would like. And there are two sides to this story. First is the technology; how is it possible, and how does it work? To this side, the presented research intends to find the most effective ways to make the best guesses. Then there is the other side. The other side, often more in the social science field, asks: are we sure we want this technology? Or, more precisely: are we sure we want to live with the possible consequences of this technology? And the research on this site is far more sceptical than enthusiastic.

We can label the two sides of research in the field up for exploration as sceptical or enthusiastic. Although that involves a certain generalization, it is not that far from the truth. Like the research is divided into two sides, so are often people. That is not to say that some people entirely disapprove of all technology, while others approve of everything. Still, people tend to be either more positively angled or negatively angled. To generalize even further, one might allege that technologists are the positive ones while social scientists are the negative ones. Although they both have their fair reasons to be either positive or negative, this dissolution forms challenges when questioning responsibility. Who is responsible when something goes wrong? Who is to blame, and who is in charge of setting future measures to avoid it happening again? The issue of responsibility for technology is what this essay is out to explore, but first, an understanding of the technology should be in place.

On the enthusiastic and technical side of the research, it is possible to divide the technology into four terms: algorithms, artificial intelligence, user profiling and recommender systems. For many, these terms constitute a black box of technologies we are aware surrounds us; however, it is farfetched, hard to understand and challenging to discuss. Seeing and hearing about the societal consequences it can cause, one quickly associates it with something unknown and alarming. Avoiding panic requires a better understanding of the technology and will be handled in sections 1, 2 and 3. Knowledge and understanding often render harmless, so hopefully, it will brighten up the black box and bring a clearer vision in coming discussions.

2. Prerequisites

2.1. Algorithms

What is an algorithm? Googling this exact question gives about 719 000 000 results. 719 000 000 search results portray a high demand for an explanation from a significant amount of people, so this is a somewhat abstract term to many. In general, an algorithm is a set of instructions we give to a computer with the intention that these instructions will work together to solve a problem or perform a computation (Gillis, 2022). One of the reasons algorithms can be hard to grasp is that we use the term in such a broad set of cases and situations. However, this can be explained with the fact that algorithms have an unlimited number of use cases. For example, calculators, social media, and self-driving cars are all built on algorithms making predictions and/or doing calculations. Simply put, algorithms are the backbone of every computer program.

An algorithm starts by taking some input. This input is the basis for the algorithm's calculations and predictions. The complexity of the input can range from a simple number given directly by the user, like in figure 1 to the right, to complex data sets like sensor data from self-driving cars or satellites. The figure to the right shows an example use case of an algorithm, although it is probably not the most useful one ever made. The algorithm asks for user input to add to its *total* value until it exceeds 100. When that is the case, the program prints the value to the user. Although figure 1 shows the basics of an algorithm, it does not quite bring an understanding of how someone can *know* who we are or, as we will see, accurately *predict* who we are. To understand this, we have to dive a little deeper.

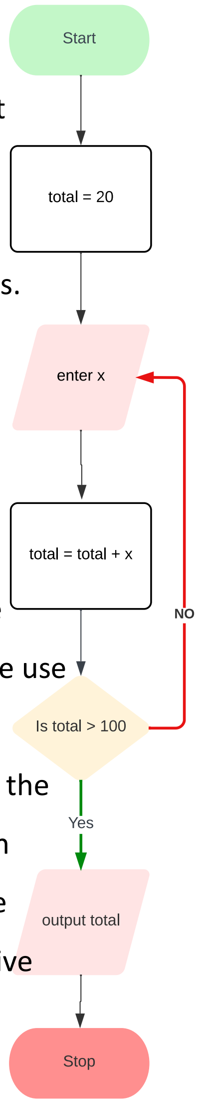


Figure 1 Simple algorithm flowchart

2.2. Artificial intelligence

> The room is silent. So silent, I can hear the drops of sweat dripping from your forehead down on the table. The feeling in the room is intense as everyone looks at the table. Disbelief. You thought you would beat me. 5-0 or 4-1, you said, and I cannot blame you. I was not at my best the last time you saw me play. But I have practiced. And now here we are. It is you, me, my assistant, and three observers. All

in suits, in a dark blue, deadly quiet room, trying to grasp what is happening. Disbelief. You can feel it filling the room. You lean your elbows on the table and place your hands on the sides of your face. I can hear you think. As I am closing into victory, it is like the room shrinks. Then suddenly. Game over. Your jaw drops as you keep staring at the table. I understand. You are the best and did not expect to lose to a computer.

When Alan Turing first considered asking the question *can machines think?* He soon realized that it was meaningless if we did not know what thinking was in the first place (Murphy, 2020). Turing was a pioneer in artificial intelligence (AI), and, amongst other work, he is famous for the Turing test. The test constitutes the core of artificial intelligence: can machines imitate human intelligence? (Thereby the *"imitation game".)* (Dvergsdal & Karlsen, 2017). Since his work in the 1900s, AI has grown exponentially. The term artificial intelligence was first introduced in 1956, and the area concerns the simulation of human intelligence in machines (Zhang & Lu, 2021). AI is an umbrella term covering many different technologies and approaches. The top major branch is machine learning (ML), while deep learning (DL) is the growing subset of machine learning. Figure 2 on the right shows a common visualization of how the fields are connected.

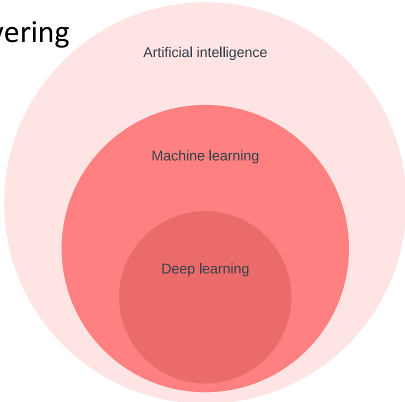


Figure 2 AI landscape

DL differs from ML in its complexity. While ML algorithms need some human interaction to learn, DL algorithms do not, as they are based on neural networks. Neural networks have allowed for complex machine learning algorithms, today used in everything from self-driving cars to personalized shopping and social media, along with many other applications and systems. Neural networks consist of an input layer, hidden layers, and an output layer. The layers further consist of multiple connected nodes used in the decision-making and prediction process. Consequently, one can look at neural networks as a set of algorithms working together to reflect the human brain and make predictions (IBM, 2020).

So, simply put, neural networks are complicated, but they allow machines to learn from massive datasets and make sophisticated predictions on future data. As we now have some basic understanding, we can continue on our journey to hopefully better understand our friend from earlier. Before moving on, let us establish that the following paragraphs might not directly point out the words algorithms, machine learning or deep learning, but we know now that this is the basis of our discussion. There will be plenty of other details to keep in mind. And oh, by the way! I almost forgot about it, but our friend stopped by again in the initial paragraph of this section. If you did not catch it: he referred to beating Lee Sedol in the Chinese, very comprehensive game "Go". Sedol is one of the strongest players of all time, so you should look that up; it is cool. Now let us move to the next section: technology.

3. The technology

3.1. Establishing the context of research

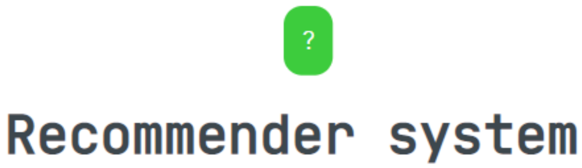
The literature of this section is, as mentioned, of the more enthusiastic type. The studies commonly use prototypes, where the general objective of the research is not to present a final product but to test concepts grounded in literature (Koskinen & Frens, 2017). Data is often simplified and of a smaller scale than in the real world, sometimes opening the discussion on whether or not the results can translate into the real world. That might be especially true when it relates to the particular field of recommender systems, as they, in the real world, would collect and analyze a vast amount of data from our online actions, which is close to impossible to mimic in a prototype. Instead, the data they use is often manageable, publicly available datasets. Many of the following papers have, in fact, been utilizing the same dataset, called MovieLens, to test their approaches.

This literature will describe approaches to a recommender system's different technical issues and elements. As mentioned, most of the papers presented, in fact, a considerable amount of the research on optimizing recommender systems in general, propose the same research method. They are predominantly experimental research papers developing a prototype that they later prove to be more effective than existing techniques based on an efficiency/accuracy comparison. A common issue they embark on is the data sparsity issue, which is a common problem for collaborative filtering that will be discussed further in section 3.4.3 about the cold start problem.

The use of prototypes is common in technology as it facilitates the practical testing of methods in a context. On the one hand, prototypes allow for testing and improving an approach until it proves to outperform the ones tested against it. Because of this, most papers conclude something like: "... our prototype (substantially) outperforms other approaches …". On the other hand, prototypes can also lead to a lot of work but no results. On the surface, it might seem like all prototypes end up as successful, but in reality, it seems this way only because the successful ones are the ones to bring new knowledge into the field and get published. There is little value in publishing a paper that proposes a method proven to perform worse than existing approaches. The reality is not that no one has ever failed; it is just that we never get to read about them.

So, the strength of a prototype is that you can work on it until it meets or exceeds the criteria of expected results. The risk is that you put in a lot of money and effort but never reach the point of meeting or exceeding the requirements set for its performance. In addition, there will always be the question of significance: Can an approach tested on a limited dataset prove itself better than those utilized in the real world on massive datasets? However, as mentioned before, replicating real-world data in a research prototype is nearly impossible, considering the immense amount of data that the real world brings. Therefore, there is seemingly a common understanding that this limitation is inevitable. Nevertheless, because the research falls to smaller, publicly available datasets, it can at least prove itself to be better than approaches researched in other studies, as they likely have tested their approach on data of equal scale.

Now that we have some insight into the research we are about to be presented, we are ready to dive into a terrain of technologies, terms, and approaches belonging to recommender systems. Trying to grasp everything is an extensive task. Therefore, we will use the simple, unfancy, yet familiar and helpful mind map to keep us on track. It will probably not end up *painting the entire scenery, but hopefully, it will be sufficient for us to understand the basics of what is happening. Considering the range of technology we are about to discover, it will probably be favourable to have a somewhat structured, gradual approach. The optimized recommendation framework presented by Singh et al. (2021) inspired the structuring of content in this section, so without further ado, let us get our mind map started right at the root of it.*



3.2. Recommender systems

After the explosion of online information, recommender systems got the job of assisting us in navigating our way through the vast amount of content on the internet. Various fields use recommender systems; however, two of the most common areas are e-commerce and movie rental platforms like Netflix. Recommender systems get divided into content and collaborative filtering methods. Content-based is the traditional approach, which recommends items to Bob similar to items he already liked. Content-based filtering is, however, no longer the preferred approach, and collaborative filtering methods have become the standard. Consequently, is most of the research regarding recommender systems about optimizing collaborative filtering and finding solutions for common issues. The coming sections describes approaches and techniques related to collaborative filtering.

In collaborative filtering, one bases recommendations on similar users. For example, suppose users A and B have given a high rating to product X. In that case, A can receive recommendations for products he has not yet rated but is rated high by B. That makes the ability to group users vital in collaborative filtering methods. The partitioning of data into groups, where each group contains similar data, is known as data clustering (Sammut & Webb, 2011). Evolutionary clustering algorithms are often used to cluster data, providing a robust and prosperous technique to create and optimize such clusters (Corne, Handl, Knowles, 2011). In their study, Chen et al. presented an evolutionary clustering algorithm to enhance user recommendations. Their algorithm groups users based on their relationship to items; if users give an item a similar rating, they are grouped (Chen et al., 2020). They tested their algorithm against several other approaches and found that their evolutionary algorithm outperformed common methods by optimizing user clustering. However, to cluster data, one first needs to collect the data.

As the name suggested, the purpose of recommender systems is to recommend content to users. Now, we will start by dividing this concept into blocks of information and research. For coming sections, the selected research papers illustrate that particular topic or "bubble" in our mind map. However, they will also demonstrate how the researchers commonly use prototypes in this field of research. So, as it was said, you cannot cluster data before collecting data, and therefore the first bubble of our mind map starts at the basis of a recommender system: data collection.

3.3. Data collection

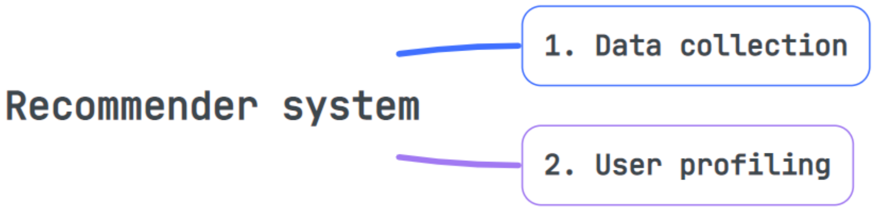
What does it mean to know? According to Merriam-Webster, one definition is "to have understanding of" (Merriam-Webster, 2022). Algorithms can *know us* in the way that they have an accurately predicted understanding of what we like, dislike, are drawn to, and what we tend to avoid when we are online. A prerequisite to having this knowledge must then be that data about our online behaviour is somehow collected. Two methods for collecting data are implicit and explicit data collection. Explicit data collection is the gathering of direct information that we give. In an online store this can be reviews or ratings on a specific product, while on a social media platform, it can be a like to a post. On the contrary, implicit data collection is gathering data we may be less aware we leave behind. Implicit data can, for example, be information about how we move the cursor around the screen or how long we look at a particular product (Singh et al., 2021).

Effective implicit or explicit data collection is a common field of research. Another field is the research on linking user accounts from multiple platforms to the same user. This is what Kaushal, Ghose & Kumaraguru explored as they analyzed five methods to gather what they call *linked identities.* Linked identities are user accounts across different online social networks belonging to the same individual. If collected and connected, linked identities give more profound insights into an individual's preferences, as more data points is collected. The study investigates five methods' proficiency in collecting linked identities and compares them based on a qualitative evaluation, along with two quantitative metrics, namely "social network coverage" and "per-user linked identity count" (Kaushal, Ghose & Kumaraguru, 2019). This is the only presented study to this side, that does not build a prototype. Instead, they conduct experiments on already existing methods and evaluate them. The methods presented for collection of linked identities are:

- Advanced Search Operator (ASO): utilizes an advanced search operator to filter for specific information. In the study, they used Google's advanced search operator.
- Social Aggregator (SA): utilizes social aggregating websites where users can provide account details to desired online social networks. In the study, they used the social aggregating website "*about.me".*
- Cross Platform Sharing (CPS): utilizes the content we share on multiple platforms in addition to the source platform. Using Instagram's API, they looked for posts with a pattern indicating that the post also had been shared on Twitter
- Self-Disclosure (SD): utilizes a user's bio on the social networks, should it contain usernames for other platforms, e.g., "Facebook: *fb_username,* Snapchat: *sc_username*".
- Friend Finder Feature (FFF): exploits the friend finder feature one finds on online social networks by (1) adding emails to a fake user accounts contact list, (2) signing up to multiple online social networks and (3) mapping the common friend suggestions that appear based on the fake users' contact list.

The results showed that the methods to have benefits in different fields. For example, if one is to collect data about user behaviour across numerous online platforms, SA emerges as the preferred method. On the other hand, if one wishes to look at a user's behaviour in only a pair of platforms, e.g., Twitter and Instagram, CPS appeared as the preferred method. In any case, the study shows that data rarely lives the vacuum of a single platform and that no matter what data you want, there is always an effective way to collect it. Users are more connected than ever, allowing large datasets to be collected, analyzed, and used. The desire to connect a users' data is not applicable only to social media platforms. Collecting user data across platforms, for example, across e-commerce domains, is a hot topic in the research field and will be further discussed in 3.4.3. as a solution to the cold start problem.

So that was a little about data collection. To recap, we know that both explicit and implicit data about our online actions and preferences are collected. In addition, we also have the slightly bugging, but probably not surprising, knowledge that our online habits do not exist in the vacuum of the platform or site we express them in. Actors collect our information across domains and platforms, resulting in a massive dataset. Okay, so now what? Someone has all this data about us, but what do they do with it? Indeed, they need to categorize it somehow, which leads us to our next bubble! Let us dive into the field of data filtering and user profiling:



3.4. User profiling

3.4.1. From data to information

When it comes to explicit data, the collection containing, for example, a user's rating of items has to be processed to become valuable, and filtering data is a way to process data into information. The primary purpose of the filtering process is to categorize the items a user likes and dislikes. To obtain a more profound classification, one can classify items using a set of categorical attributes (Singh et al., 2021). Categorical attributes are descriptive characteristics of an item, like the genre of a movie. If items are described by attributes, a users' single rating to an item would provide a rating value to all the categorical attributes of that item. Categorical attributes turn a single rating into information about a set of user preferences and non-preferences.

Singh et al. (2021) proposed a method to filter data based categorical attributes, by first categorizing the data at the most basic level. Users' ratings were split into two datasets: one containing highly-rated items and the other containing low-rated items. Based on these two datasets and a dataset containing the items' categorical attributes, they could merge both the high and low-rating datasets with the dataset containing the items' attributes. This resulted in two new datasets: "Users' high categorical attributes" (HCA) and "Users' low categorical attribute" (LCA). The HCA dataset contained users' high ratings for categorical attributes of an item, while the LCA dataset contained low ratings for categorical attributes of an item. Categorizing information into HCA and LCA was significant in creating the user profile (Singh et al., 2021).

3.4.2. Creating the user profile

The HCA and LCA datasets contain information about a user's high and low ratings of an item's categorical attributes. However, this information needs to be further processed if it is going to be used to build a good user profile. Although there are many approaches to this issue, Singh et al. (2021) had the approach of applying the Apriori algorithm to the HCA and LCA datasets. This approach enabled them to find users' liking and disliking features, resulting in an optimized user profile containing "users' liking attributes (ULA)" and "users' disliking attributes (UDA)". The more accurate information one finds in a user's profile, the better one can utilize the actual recommender algorithm (Sing et al., 2021).

3.4.2.1. Apriori algorithm

Using the Apriori algorithm was an experimental approach to form an optimized user profile based on the categorical attributes of a rated item. The Apriori algorithm is a standard algorithm that generates association rules and is often used in so-called "basket analysis", where the goal is to find combinations of frequently bought items (Korstanje, 2021). A critical threshold in the Apriori algorithm is the support count, which indicates a measure to be reached to define association. In the case of a shopping basket, for example, you can calculate how often customers buy two products together. If that number exceeds the support count threshold, those products can be associated as two commonly bought together. The following steps describe the prototype built to form user profiles based on the Apriori algorithm in the study by Singh et al. (2021). From step 2 onwards, there are always two tables in the research: one handling the "low-ratings version" and the other the "high-ratings version". They contain the same information, but the value of low-rated items in tables containing high ratings (and the same for the opposite) are stored with only 0-s. All following tables in this section are for visualization and are only simplified versions of original tables; however, they reference the study. The following is an explanation of the study:

1. The initial dataset of user-movie ratings, containing users' ratings of movies, is captured from the dataset (MovieLens).
2. A separate dataset containing the movies' genre (as only the categorical attribute) is defined:

	attribute			
movie	Action	Drama	Horror	Adventure
movie-1	1	1	0	1
....	...	...	...	...
movie-n	0	1	0	1
(Singh et al., 2021, *Table 13/14,* p. 7)				

3. Next, they split the user-movie rating dataset from step 1 into "User-movie high rating dataset" and "User-movie low rating dataset", one containing high (> 2) ratings and the other containing low (<= 2) ratings.
4. Both the datasets from step 3 now evolve from storing *"user-n"s'* rating to movie-n to store "user-n" and the categorical attributes of "movie-n" ("Users' high/low categorical attribute")

	movie		
user	movie-1	…	movie-n
user-1	1 (action), 2 (drama), 4 (horror)	…	….
…	…	…	…
user-n	…	…	…
(Singh et al., 2021, *Table 15/16,* p. 7)			

5. Now, the datasets to store high/low "categorical attribute count", meaning the count of each categorical attribute *x* for each user, is created.
6. From the datasets in step 5, they now calculate the categorical attribute support count.
7. Categorical attributes with a support count that does not fulfil the threshold of 30% are removed from the dataset, leaving only attributes with a support count above the threshold.
8. In further steps, they calculate associations based on an initial attribute count, like in step 5, but now on pairwise combinations of attributes. Next, like in step 6, the support count of these combinations is calculated. Then, like in step 7, support counts that do not fulfil the support count threshold are removed. Finally, they repeated this process, taking three and three categorical attributes until what is left is a final list of a user's liking and disliking attributes.

And just like that, you just made a user profile containing information about a user's preferences and non-preferences! How hard can it be, right? I am just kidding. If the above quick explanation of the Apriori algorithm made you think, "umm, what...?", that is fine. However, if you caught the essence and grasped the primary workings of the algorithm, you might have realized one of the main issues that both this and other approaches have when creating user profiles. Do you know? What major issue can we face when calculating user preferences based on user ratings? You got it: if the users have not rated anything yet. How on earth can you calculate preferences based on nothing? You are not the first to wonder. And we are led to the mentioned issue of data *sparsity, which is commonly discussed in the field as it disrupts the building of optimized and reliable user profiles. The extreme manifestation of this problem is the cold-start problem, which we will look into now.*

3.4.3. Cold start problem

Most of the common approaches to building user profiles rely on explicit feedback from the user, like ratings (Feng et al., 2021). In the movie rating example above, when Singh et al. (2021) used the Apriori algorithm to build user profiles containing genre preferences, they needed the users' ratings of a set of movies as a base. However, in some cases, this base is insufficient to build profiles. The two main scenarios where that is the case are 1) a new user subscribes and has no historical ratings or 2) an item does not get any ratings (Hwangbo & Kim, 2017). As mentioned before, one can collect data cross-domain. Combining data from multiple domains is a recent approach to solving the cold start problem that has lately gotten more attention. Another commonly studied approach is to create optimized rating or ranking models for either explicit or implicit feedback in a single domain; however, few have explored a combination of the two (Hwangbo & Kim, 2017).

In opposition to the latter approach of optimizing a ranking or rating model on either implicit or explicit data, Feng et al. proposed a hybrid between the two. Their method utilizes implicit and explicit user feedback (in a single domain) and is a take on the "new user" type of cold start problem. They aim to combine implicit and explicit data into one hybrid model that will improve the assumptions of a new user's preferences. Their proposed model (shown in figure 3 below) outperformed existing methods by using mainly implicit data, like clicking activity and search history, but further supplementing the ranking with available explicit data (Feng et al., 2021). BPR and PMF are common, existing models to process implicit and explicit data.

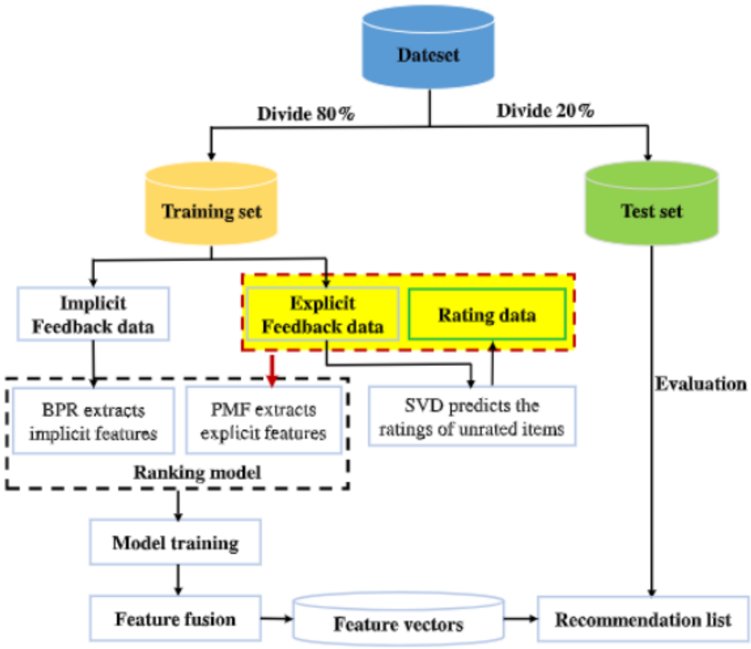
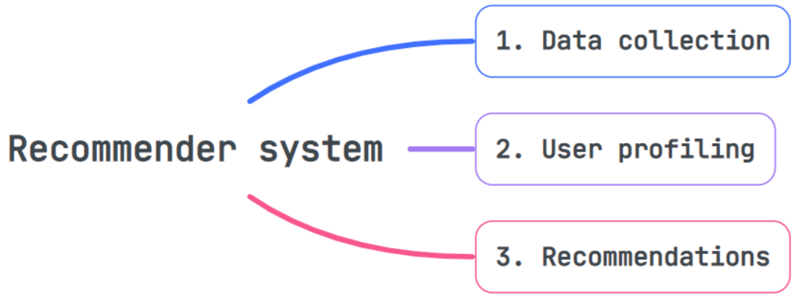


Figure 3: Proposed hybrid model (Feng et al., 2021, Figure 3, *p. 4)*

The other mentioned approach that has gotten a lot of attention in recent studies is cross-domain recommender systems. This approach aims to provide a user with better recommendations in a target domain based on information collected in a source domain. Cross-domain recommender systems ensure that even though data is sparse in the target domain, it is possible to give users good recommendations based on data collected from other domains (Hwangbo & Kim, 2017). Many have conducted experimental studies to optimize recommendations based on data collected cross-domains. As mentioned earlier, their approaches are the same; researchers build a model and use a public dataset for experimenting with the model compared to other commonly used models.

We are now at our final and most exciting bubble: the recommendations. We will now see how everything ties together and start to make a little more sense. So far, we have seen that most of the research in the field keeps making progress by improving technology. The algorithms we build can create more accurate predictions about us based on better models for implicit and explicit data and cross-domain data collection. Few papers propose a method that does not outperform other commonly used ones, so obviously, this field moves in the *right direction! Let us now dive into the last section, which mainly covers two terms: similarity measures and top-N recommendations.*



3.5. Recommendations

3.5.1. Similarity measure

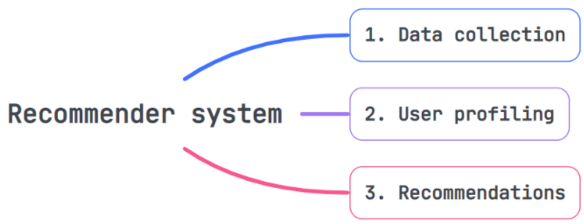
Similarity computation is a significant step in collaborative filtering methods. There are mainly two types of similarity measures a system can utilize, and that is 1) similarity between users and 2) similarity between items. These two techniques split collaborative filtering into two different types, namely, user-based and item-based collaborative filtering. When it comes to similarity measures (SM), there are many types. Many new ones have emerged since traditional SMs have struggled with the data sparsity issue previously discussed. For example, in user-based CF, measuring similarity between users is difficult if there is a lack (or non-existence) of items rated by both users (Singh et al., 2021).

In the study by Singh et al. (2021), the researcher used a so-called “modified similarity measure”, “modified” because they based it on categorical attributes. When looking at similarity measures, the benefits of categorical attributes suddenly start to show: co-rated items is no longer required to measure similarity. In other words, users A and B no longer have to rate the same item because one can now calculate similarity on co-rated categorical attributes instead. For example: before, if two users did not rate the same item, it was impossible to say whether there was a similarity between the users as to whether they liked or disliked that item. Now, however, using categorical attributes, the same item no longer needs to be rated by two users, as two items can share their categorical attributes. For example, suppose user A likes item A, and user B likes item B. In that case, you can calculate a similarity between users A and B if movies A and B have corresponding categorical attributes, without being the same movie.

3.5.2. Top-N recommendation

The last step of the recommendation system is the top-N recommendation, which involves recommending a user a set of top-N items from an initial large itemset. It is possible to predict users' expected rating of an un-rated item based on similarity measures to other users (user-based CF) or other items (item-based CF). The predicted ratings of items (high or low) form the basis from which a list of "top-n items" can be chosen to recommend for the user (Singh et al., 2021). After the system has provided the target user with top-N items, the only thing left is communicating these recommendations. That can, for example, be a "You might also like"-section on Netflix or an online shop, the next TikTok video that pops up or a sponsored post on your social media profile.

So, those were the three main pieces we needed to understand the technology. Our friend from the beginning knows us well because he 1) gathers data about our actions and preferences and 2) turns this data into information and forms a profile about what we like and do not like. Our mind map is done and ended up like this:



And we learned that our friend is quite nice, is he not? Recommending us stuff he thinks we will like and everything? There is a lot of information on the internet, so without him, we would be pretty lost. I mean, imagine scrolling on Netflix and seeing no traces of any recommendations or knowledge of what you might like: romance, horror, reality, and documentaries, simply just a soup of chaos. So, I guess that was it. Recommender systems are needed and valuable. Knowledge renders harmless, and as we now understand *recommender technology better, there is no need to worry! Or, hold on. There was that other side of the research. I suppose they are not settled just yet. Let us see what they have to say as we move out of the technology and into the discussions.*

4. The discussions

4.1. The research of the sceptical side

For good reasons, the other side of the research on recommender systems is more sceptical. It focuses less on "how can we optimize this technology?" and more on "what are the issues of this technology to society?". The latter of the questions got much attention after the 2016 U.S. presidential election. Why? Cambridge Analytica. At this point, the Cambridge Analytica scandal is familiar to most. In short, Cambridge Analytica collected Facebook data from millions of American citizens and used it to create personality profiles for those citizens. Based on these profiles, they recommended customized content made to manipulate their decision on election day. When coming into the light of day, this incident brought discussions and thoughts regarding technology, how we use it, how little we control it, and the apparent privacy issue.

In the research field, these topics got extra attention in the aftermath of Cambridge Analytica. Many have conducted experimental studies concerning recommender technologies' possible harmful consequences and the extent to which those consequences might affect us. Sometimes, these studies build a simulation of an environment where researchers can measure the effects of algorithms recommending the "wrong content to the wrong users". Compared to prototypes, as previously discussed, these simulations are not set on a mission to develop something better but measure the result of something. For example, in the study by Zarouali et al. (2022) where they constructed a fake social network to target participants with political advertisements and assessed its degree of persuasion (Zarouali et al., 2022).

Aside from simulations, there have also been conducted experiments on existing platforms. For example, did the study by Cho et al. (2020) examine the effects of politically targeted advertisements on YouTube. Based on the search/watch history of newly created YouTube accounts, they manipulated the recommender algorithm to recommend a particular type of political content. After that, they handed out credentials for those accounts to the participants. Their results indicated that algorithms could increase political polarization by assessing the participants' political attitudes before and after using the manipulated user account (Cho et al., 2020). A final common approach to this topic is case studies. Case studies look at a particular event, group, platform, or person and are a common approach in social sciences (Cherry, 2022). Many have conducted case studies and secondary data analysis to understand a specific event. Due to its scale, the Cambridge Analytica scandal has many such papers dedicated to it.

A case study conducting a secondary data analysis was the study by Papakyriakopoulos et al. (2022), where they looked into how Facebook, Google and TikTok shape the distribution of political advertisements. They collected and assessed information about online political promotions in the 2016 U.S. election by looking at Google and Facebook's ad libraries. They found that the distribution is far from incidental, and there are severe shortcomings regarding public disclosure regarding the targeted distribution of political ads to specific user groups. The public does not know the platforms and the advertisers' tactics and are, therefore, often unaware of the level of targeting behind the information they receive (Papakyriakopoulos et al., 2022). The fact that they could find and point out this issue in their study is one of the benefits of case studies. Case studies can portray how something works or what happened. In this particular case, using a case study opened the possibility of "showing" the public the issues we face in the time of online political advertisements.

When comparing the sceptical against the enthusiastic, the simplest factor to categorize papers on either of the sides and understand their main distinction is ambition; the technologists want to keep improving, while the social scientists want to illustrate challenges. As mentioned before, the research on the technical side usually goes something like this: a problem is defined, they make an effort to find an approach to tackle this problem, and when such an approach is available, they present it. Unfortunately, the studies often have little awareness concerning possible harm. The studies concerning potential harms are what we usually find on the social science side of research. They conduct experiments on platforms or simulations and preform case studies to measure the effects of a technology that someone else created.

Hello! It is me again. We have now gained a little more insight to the sceptical side and what kind of research they conduct in comparison to the technical side. However, you might wonder when the talk about "two sides", like there is no in-between, will end, and soon enough it will. Someone with a lot of responsibility that so far has gotten away with neglecting that responsibility will soon be brought into the light of day. So, please bear with it just a little longer! Nuance will soon arrive.

4.2. Addressing the problems

4.2.1. What we choose to be

An undeniable problem with recommender systems is the consequences we, the users, sense around us in society. These come from someone's *choice* to use the technology for worse. The word *choice* is essential in this context because technology does not have any intention of its own. Instead, it is chosen to be for better or for worse. A case to illustrate how the choice for utilization affects the outcome is the story of a young man radicalized on YouTube. The New York Times podcast series Rabbit Hole told his story and described a promising young man turning to self-help videos on YouTube as he went through a difficult time. Self-help videos come in a variety of sorts, some more alternative than others. So, at a point in time, this man watched the wrong video at the wrong time and started to spiral down the rabbit hole of far-right political content because that was all he was recommended (New York Times, 2020).

However, at some point, he suddenly clicked a video where someone overran one of his favourite debaters with facts, leaving her unable to respond. And at this point, he turned. Although it might be hard to believe, that was his start on a journey to be a radicalized to the left instead. In other words, it does not serve as the best example but shows technology's influence. It can make you spiral down; however, it can also propose content of different perspectives, bring diversity to users' recommendations and lessen the spiral. So, who makes the decisions on which one it will be, and why do they not choose the latter approach of diversity? The answer is that big companies make the decisions, and big companies wants profit. Continuously showing people content they like is more likely to keep them on the platforms and generate revenue than showing them the opposite and risking losing them.

Here we are, finally! I hope you are still with us in the end. Let us talk more about the big companies.

4.2.2. Blaming in the wrong place

Another problem is related to what has been done so far in this essay, dividing the research into two sides, insinuating that the "blame" must lie within one of them, and most likely the technical one. Indeed, researchers developing new technology should be more aware of the harms their results can bring. However, social scientists should also put in an effort and try to understand the technology, not leaving all responsibility with the technologists. Still, creating sides in a matter that affects all of us is not an efficient solution. A better approach is to come together, and in section 4.1, papers where that happened, were presented. The studies contradicted the previous settling of sides A and B as they brought technologists and social scientists together, like in the study by Zarouali et al. (2022), where the researchers constructed a fake social network to measure the consequences of receiving politically targeted advertisements. As one can see, defining a gap between technologists and social scientists does not have much ground in the real world, neither does is do any good to the discussion.

What rather has ground in the real world is that we tend to leave some with a lot of responsibility out of the conversation. Bringing them back in, we should instead set the gap between us (users, technologists, and social scientists) and the big companies *choosing* to use technology in a harmful way, whether to make money or manipulate people for whatever reason. Google, Facebook and Apple are most likely not about to make significant changes in their conduct just because researchers in the field of technology in their paper include a reflection paragraph, discuss possible misuse or set loose guidelines for caution. What is needed is regulation and demands that force reaction if not followed or fulfilled.

If regulation is the way to go, the first new question is: where would you even direct the regulations? Would you limit the amount or type of data the platforms are allowed to collect about their users? Would you define how thoroughly they can analyze this data in terms of how accurately they can form a user profile? Maybe you would set provisions for how or for what purposes they can use it? Or perhaps they can use the profile for whatever they want, as long as there is a certain transparency about this towards the users. The second question is: who will decide upon these questions and ensure the answers to them are complied with? That might be the most important of the two.

4.3. Defining regulations

Some might still argue that most of the responsibility for the utilization of recommender systems lies with their creators. It is fair to say that the blame must lie with those who placed it into this world and understand its workings. At the same time, that is not how we deal with other societal issues. When there is possible harm around us, the government is who we turn to for protection. Take weapons, for example, a thing in society that can be a severe source of harm to innocent people. However, they are under strict regulations to minimize the threat they propose. Regulations are how we balance the need for things that can also be harmful. That sounds very much like something needed for recommender algorithms. We need them to improve our platforms, but for some reason, no one controls the harm they propose. Should it not be up to the government to do its best to ensure that companies do not misuse them, the same way they minimize threats presented by everything from weapons to fraud to criminals to poor infrastructure?

With that said, we again steer the conversation away from the problem's core, the big companies having little to no desire to do anything about their conduct. However, big companies are, first and foremost, out to make money. Within limits defined by authorities, they tend to do what they can to make as much as possible, so demand for ethical reasoning might not do too much. Instead, measures should be set where it can have actual effect: in the laws. Take data regulation, for example. Using, sharing and storing data is strictly regulated on a national and international level, and if not obliged, they induce financial consequences. Maybe the same should exists for utilizing algorithms. Although one can wonder why this is not in place yet, the European Union have proposed the Artificial Intelligence Act, which is out to address the risks of utilizing AI algorithms (Gaumond, 2021). So maybe more control and regulation are on its way. However, based on how long regulating currently takes, can we keep up with technology? Regulating something today is fine, but another problem will probably develop tomorrow.

4.4. Final thoughts

As we have explored the field of recommender systems, including its technology, research and lack of regulations, we have left something out of the conversation—you and me. No one ever asked us if we were willing to sacrifice our privacy for the benefit of better recommendations. Yes, we do, without a doubt, appreciate it in everyday life, but do we reflect on what we appreciate? We believe we need it, but our lives did not have less value before, for example, when we had to go to physical movie rental places and choose from a "soup of chaos". If we, before it all started, had been presented with all the good and evil, would we have said, "go ahead"? There is an apparent ethical dilemma to the extent that recommender technology is used versus the extent to which people understand what it does and how it works. If the big tech companies would share the data collection and user profiles they have on us, you and I would likely be amazed and terrified by its accuracy. Control and regulation can only do so much; no matter what, we will be left as a piece of information to be used, misused, sold, and profited on. Are we okay with that?

So, here we are at the end. I hope everyone managed to hang on until the end, where we hopefully were able to unite the researchers and place the responsibility in the hands of those responsible: big tech companies and governments. The final thoughts made us wonder whether recommender technology is something to cheer for. However, no matter what, it is there to stay, which is why we should think of it as best we can. So, let us finish by giving our friend one more chance to explain himself, as we have learned a thing or two.

> Hi there! I am here to assist you in your online experience. You scroll, click, and watch every day, which is why I have gotten to know you and what you like so well. If you find that a bit uncomfortable, that is okay. Actually, it is best if you do not blindly trust me, as some set me out to do things they should not. However, as you now know that when you scroll, click, and watch, I learn a lot about you; I hope you can be aware that what you see is rarely a coincidence. Although the ones making the decisions should decide for me to show you the calculations I make to present you what I do, you can also try to remember that sometimes, you get manipulated. For example, if you get angry at some content, put your phone away instead of commenting with angry messages. Someone could make you angry intentionally, and commenting will only worsen your anger. (Because you realize I read those comments, too, right?)

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