A Survey on Current Recommender Systems

Hendrik Pfaff

January 24th, 2021

Frankfurt University of Applied Sciences
Faculty of Computer Science and Engineering

Abstract. Recommender Systems (RS) are an effective and widely used way to facilitate decision making. In this survey, we first give a broad overview of the theoretical background on RS. We examine their inner workings, filtering types and performance measures, as well as explaining (Deep) Neural Network RS in detail. We then present the current state of research, by presenting recent publications and classifying them by which of the four main challenges, *performance enhancement*, *increasing reproducibility*, *overcoming ethical and social issues*, or *security considerations* they try to overcome and the approaches they take doing so. Lastly we conclude with related fields and an outlook into future works.

Keywords: Recommendation Systems · Filtering · Artificial Neural Networks · Machine Learning · Ethics · Security

1 Introduction

Every time, when using the World Wide Web (WWW), it is almost sure we encounter some form of RS. They suggest new songs, movies or TV series in streaming platforms, products of our interest in online shops, the best matching flight for our vacation, social media posts that would catch our attention and much more. Some RS are more obvious to their users than others, but their wide prevalence in modern software applications makes them a integral part our daily life.

The first RS emerged in 1990 from a work of Jussi Karlgren called *An Algebra for Recommendations*. It described the proximity of interest within user models as a measurement and defines a recommendation as an *algebra on Interests* [18]. In 1992, the *GroupLens Research* lab, specialized in studying and developing RS, was founded by the Department of Computer Science and Engineering at the University of Minnesota, Twin Cities. There the first automated RS were used to recommend articles of the *Usenet* and later, in 1996, movies on the platform *MovieLens* [29]. After that, many other commercial platforms found interest in RS and drove further development and research.

While the first RS were based on well known algorithms and matrix calculations to create probable recommendations, their inner procedures got more sophisticated over time. With the parallel arising field of Machine Learning (ML) new possibilities in handling user data and creating recommendation models emerged.

Today, basically all branches of e-commerce deploy at least some kind of RS. Often used as a replacement of or in combination with a search engine, interactive RS can give results to its user that aren't anticipated. The economical motives of many companies encourage researching RS. From 2006 to 2009 the video streaming company *Netflix* even hold an annual competition for the best RS to predict the ratings of its users. The winners of the *Netflix Prize* was awarded $1,000,000 for exceeding Netflix' own RS algorithms performance by up to over 10 % [28].

With its growing popularity, the number of scientific conferences devoted to RS also increases. The annual hosted conference *RecSys* by the Association for Computing Machinery (ACM) [1] counts, together with the conferences by ACMs Special Interest Group on Information Retrieval (SIGIR) [36], as one of the most reputed. Yet, the *International Conference on Semantics-Enabled Recommender Syst (ICSERS)* [35] and *International Conference on Recommender Systems in Social Networks (ICRSSN)* [34] are also worth mentioning.

This paper is supposed to give a brief introduction into the field of RS and dives deeper into the approach of utilising Artificial Neural Networks (ANN) in modern RS implementations. It will also give an insight into the currently used methods, tools and technologies in the field of RS while categorising the recent publications of this field.

This survey is structured as follows. After the introduction in this section, section 2 will give a broad overview of the foundations in the field of RS and its sub fields. It will also give a deeper insight of the use of ANN for RS in the subsection 2.3. In section 3 we will identify the four main directions of research and what problems they try to solve. The following section 4 exhibits the different approaches to tackle these challenges. In section 5 several representative papers of the groups are presented, while section 6 finished this survey with a conclusion, references to related fields and an outlook into the future.

2 Foundations of Recommender Systems

With the historical background on the features of RS and the current state of the field, introduced in the previous section, several research opportunities emerge. In this section, we give a brief overview of the theoretical foundations, terminology and inner workings necessary to understand RS. We also dive deeper into the theory and use of ANN for RS, which is a promising novel approach in this field.

2.1 Basic Functionality

A RS itself can be described as an active form of *Information filtering system*. Its fundamental functionality is to process given input data and create a model for future predictions. Often the input data consists of historical data produced by its user or similar behaving users e.g. bought products, seen movies or read news articles. Yet, real-time data of a deployed RS can be used for monitoring purposes or online performance measurement. The resulting model is intended to give an user a recommendation for a potential interesting item and can be created with different strategies.

2.2 Filtering Types

Filtering describes the process of building a recommendation model for future predictions. The three most common Filtering types are Collaborative Filtering (CF), Content-based Filtering (CBF) and hybrid methods, that often combine the former two.

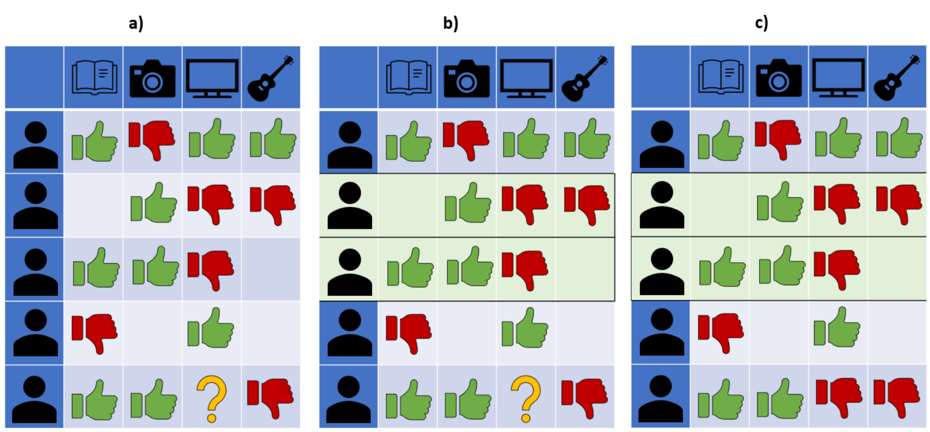

Fig. 1. Making a prediction of a product rating with the Collaborative Filtering approach. a) The rating of the TV from the user in the bottom row is unknown. b) Users with ratings to similar products have already rated the TV. c) The RS would predict a negative rating for the TV due to the negative rating of the other users.

CF can be seen as making a decision on the collaborate information gathered by multiple similar users [39]. The RS compares its users based on their decisions or ratings made in the past (see Figure 1). The system then assumes that users who made similar choices will continue to do so in the future. When it is time to recommend a new product, those who are rated well by similar users will be recommended more.

There are several ways to perform CF on the input data. So called *Matrix factorization* algorithms, for example, perform on the created mathematical matrix attribution of user and item. CF systems can be found in many e-commerce or social media platforms, where they recommend products or new acquaintances.

Opposed to the CF method is the CBF approach. Instead of focusing on similarities between users, CBF uses similarities between the items (see Figure 2) [40]. Items are described by a large number of keywords. The RS now considers items, that share the same keywords, as related. A higher amount of shared keywords, hints a closer degree of relation. If a user rates one product, the next most similar ones will be recommended by the RS.

Due to the fact that CBF techniques rely mostly on item-based data, they can be applied when not enough user data is available. There also exist many variants and algorithms to tweak CBF. Weighting the different keyword for items or using more advanced algorithms like *Bayesian Classifiers*, can additionally increase its performance [25].

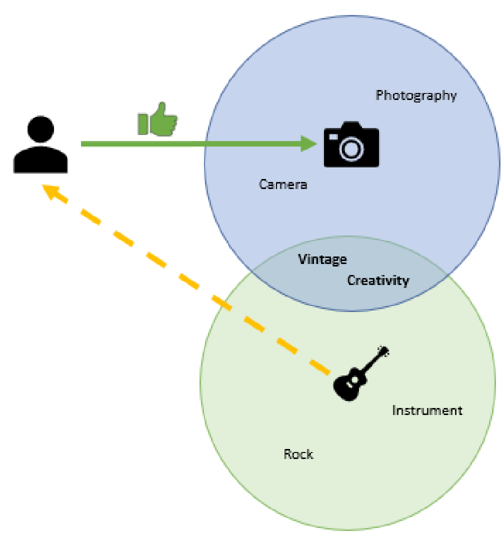

Fig. 2. Recommending a product with Content-Based Filtering. After rating a product positively, the RS recommends one with similar attributes to the user.

A mix the the two Filtering types CF and CBF, or other, approaches is called hybrid method. Combining properties of different filtering types my result in a increased RS performance or a reduction of its drawbacks. There is no limit set of which methods should be combined how. Which itself could lead to more complex models and their corresponding issues. Burke et al. classified hybrid filtering methods even further into the following seven categories [9] :

- Weighted: A combination of multiple recommendations types into one.
- Switching: Context-/Situation-depending use of recommendation type.
- Mixed: Displaying the results of different recommendations at the same time.
- Feature Combination: Combine the features of multiple data sources for one filtering type.
- Feature Augmentation: Output of one RS becomes the input of another.
- Cascade: Given recommendations get refined by another RS.
- Meta-level: A recommender model becomes the input of a RS.

Yet different hybrid RS of these categories could also be combined to a new hybrid method.

Other types of filtering may be used, but are not as prevalent as the three introduced methods. Some of the niche methods are *Demographic Filtering* [32], *Utility based Filtering* [30], or *Knowledge based Filtering* [8].

2.3 Neural Networks for Recommender Systems

ANN are a subfield of supervised ML algorithms [41]. It describes a network of nodes, called *neurons*, which are ordered in subsequently, dedicated, layers and connected via weighted directional graphs. Each node receives the input signal from the neurons in the previous layer, weighted by a calculated value, and gives the sum into its activation function, before transmitting this result to the next layer. Usually, an ANN consists of one input-, several hidden- and one output-layer, in that order (see Figure 3). Their structural properties allow ANN to *learn* a model from large amounts of input data.

When using ANN for the purpose of recommendation, some adjustments have to be made. Based on the already existing filtering type in "classical" RS, Neural Collaborative Filtering (NCF) translates its properties to ANN [15].

In a recent survey of Zhang et al. several advantages and disadvantages of RS with ANN are listed [41]. One advantage is, that the activation functions of the neurons do not have to be linear. This allows the RS to adapt to more complex user-item relationships. With more item information available as input features, a better representation of the recommendation model can be learned. Using recurrent or convolutional neural networks, also enables a RS to create sequential models, that not only predict the single next item, but the whole basket of items. The last advantage of ANN is the vast selection of tools and

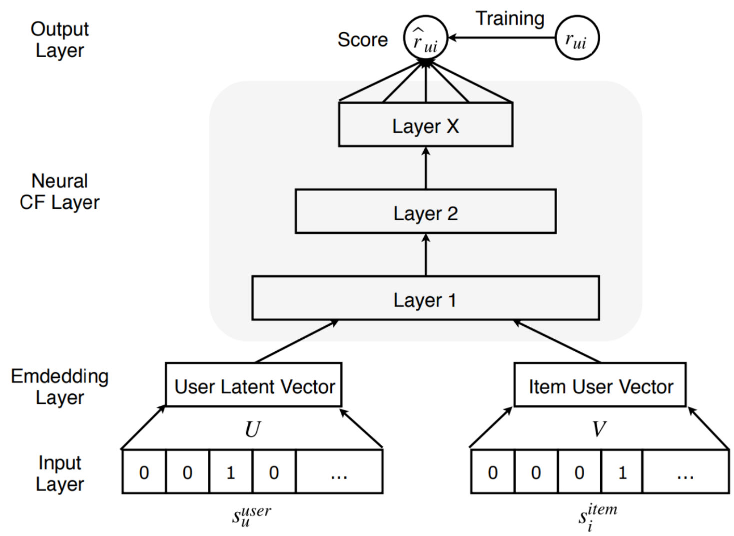

Fig. 3. An example outline of an artificial Neural Network RS [41]. The relation vectors between users and items are given as input layer to train a model.

frameworks to implement and deploy them.

Despite the many advantages, some limitations of ANN are still existing. The interpretability and transparency of ANN quickly vanishes for non-trivial implementations. This black-box behavior makes it almost impossible to back-track unusual RS behavior. While ANN enables RS to work with big amounts of data, it also requires them. Its parametrization requires a certain amount of input data to work sufficiently. The last major drawback of ANN would the need for lengthy tuning of its parameters and hyperparemters. This process alone can be very time consuming.

Due to the fact that the field of ANN is itself very actively researched, new developments in both RS- and ANN-research can lead to completely new combined applications for RS.

2.4 Performance Metrics

Its performance is a very important property of a RS. Oftentimes it even is the most important factor when deciding which RS to choose for a specific usage scenario. To effectively evaluate the output of a RS, common metrics of performance is needed. Several online and offline evaluation methods are possible [3].

The most common used metrics for RS is their *Accuracy* measured by some kind of *mean error metric*. The Mean Absolute Error (MAE) (equation 1), Mean

Squared Error (MSE) (equation 2), and the square root of the later, the Root Mean Squared Error (RMSE), frequently show up in literature.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

For these measurements, the elements of y get compared with the the elements of a test set $\hat{y}$.

Besides the quantitative performance metrics, other, qualitative, metrics can also be relevant for the usage of a RS. Criteria like *Topic Diversity* [42], *Persistence* [5], *User Privacy* [33], *User Demographics* [6], *Robustness* [20], *Trust* [27], or *Labelling* [4] also may be taken into consideration.

3 Currently researched challenges

After describing the theoretical foundations of RS in section 2, we now state the main problems and research challenges that are currently relevant in this field. The four prevalent topics regarding RS can be denoted as *performance enhancement*, *increasing reproducibility*, *ethical and social implications* and *security considerations*. Yet there are lot of other directions of RS-research fields and due to their overlapping nature it is often not possible to draw a clear distinction.

3.1 Performance enhancement

As described in subsection 2.4, the performance of a RS can be measured in several ways. Many different algorithms and approaches are currently researched to make RS recommendations even more precise. Besides trying to increase the accuracy, several projects resolve around overcoming basic limitations of RS. The *Cold Start* problem, for example, when using CF, occurs when there is yet too little data available to make meaningful recommendations [10]. In today's times of Big Data, an increasing number of users and entries also makes *Data Sparsity* its *Scalability* on the existing computation power a real challenge [23].

3.2 Increasing Reproducibility

It is important for scientific research, that publications and their results are reproducible by other researchers. Many different fields suffer from the *Reproducibility Crisis*, where many studies are unable to be replicated. Recent studies have shown this as a problem, in the case of RS research in particular [11], as several published RS models were unable to be reproduced.

3.3 Ethical and Social Implications

A very recent field of study emerged from considering the ethical and social implications of RS. Due to the wide usage of RS in nearly every form of e-commerce or social media, the possible impact on user behavior is still to be researched. The reciprocation between users and the used RS, if existing, can be a major factor in the forming of social echo chambers and social clusters [14]. Further the questions arises in what way can RS be used to actively evoke desired behavior in the user. With the utilization of more and more gathered user data by RS, the issue of privacy arises as well. And with it the question of adequate anonymization.

3.4 Security Considerations

Like with every form of today's software system, security concerns are always to be taken into consideration when developing or operating a RS. Several properties of interactive RS can be used as potential attack vectors by malicious actors.

4 Tools and Approaches

After we introduced the four main challenges, in the field of RS research, in section 3, we now want to describe the approaches that are taken to solve them. Similar to the described research challenges from the previous section, it is hard to group the tools and approaches into distinct clusters.

4.1 Implementation

To actually test a new theoretical approach, only implementing the algorithm and evaluating it statistically, can give reliable results. Researchers, that propose new procedures, need to execute their RS and fill it with data to compare their measured performance with other strategies. The input data for this can have several origins. It may be completely artificial, real historical user data, or actual real time user behavior. The actual programming often makes use of predefined scientific frameworks or libraries [17][16].

4.2 User study

When observing non-quantitative performance measures apart of accuracy, user studies may be an adequate tool. Metrics such as the *Transparency* of the inner workings of a RS to its user can be measured by asking the user in a survey [37]. This is especially useful when interested in the acceptance of the recommended items by the users.

4.3 Theoretical study

More fundamental research approaches may require theoretical studies to bring its points across. Especially in the field of RS ethics or privacy considerations, it is important to have a comprehensive and logical chain of arguments for further discussions. The same applies for publications that introduce completely new mathematical concepts or algorithms. These papers often provide the foundation for further research.

4.4 Security analysis

As with every interactive computer system, RS have several possible vectors of which it can be attacked by malicious actors. Besides the technical exploits of the implementation, RS could be vulnerable to more systematic attacks, like *Probe attacks* or *Product nuke attacks* [31]. It is remarkable, that the attacker does not need much domain knowledge to successfully exploit such a system. The works in this field describe new attack strategies and try to harden RS against these kinds of sabotage.

5 Representative Papers

After introducing the challenges faced by RS researches in section 3 and the different approaches to tackle them in section 4, we now want to present the publications that are most representative for the topics of performance enhancement, reproducibility, ethical implications, or security. An overview of each publication can be found in table 1.

By considering RS as a dynamic model of users and content providers, Mladenov et al. are able to enhance the long term performance and overcome an equilibrium selection of a standard *myopic* RS. [26]. They propose that their approach of scalable techniques increase long term user satisfaction (see Figure 4).

A study, based on a real world scenario by Alam et al., examines which parameters settings and factors are relevant for using RS on Smart TVs [2]. The challenge in this environment consists of recommending items to multiple users of a single shared TV. Resulting of this study are clues on how RS need to adapt to several usage patterns. This scenario shows, how deeply RS are already rooted in the everyday life.

With a crowd sourced user study on hybrid RS, Kouki et al. conclude, how well personalized RS are accepted by its users [21]. For this, they tested several item explanation styles for an online music RS. Their results show, that textual, item-centric explanation styles are preferred by users.

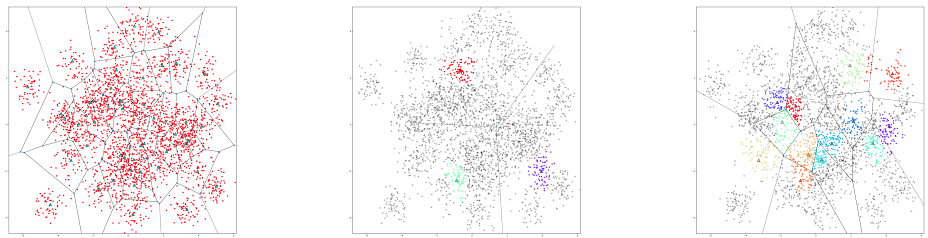

Fig. 4. Mladenov et al. outline the relationships between users (dots) and their content providers (triangles). The last two panels show an equilibrium state between users and providers, either with the myopic or their proposed approach [26].

Dacrema et al. compare recent (neural) CF approaches and criticize their results being outperformed by conceptual simpler techniques [11]. Their analysis concludes, that a majority of published RS algorithms performs worse than strategies like matrix factorisation or linear models. This opposes a growing trend of a evermore increasing complexity of algorithmic approaches in RS and shows the difficulty of actually improving above a baseline. In a similar publication, Dacrena et al. also criticize the reproducibility of neural recommendation approaches [12]. When comparing 18 algorithms from published journals, only 7 could be reproduced.

On the ethical, social and privacy issues of RS, Milano, Silvia, and Taddeo published a comprehensive survey [24]. They point out a lack of literature and publications that cover these topics in a profound manner. In this paper, they also map out the different ethical challenges and involved stakeholders for these issues.

The publication of Ge et al. measures the tendency to form echo chambers in the RS of the e-commerce platform *Alibaba Taobao* [14]. By measuring the formation of significant clusters in gathered user data, they come to the conclusion that there is a tendency of echo chambers in user click behavior. This insights on RS reinforced feedback loops on user interests, prompts many further ethical questions about socially responsible systems.

One paper about the security of RS is written by S. Lam and J. Riedl of the GroupLens Research Group [22]. They describe *shilling* as a potential tactic of attackers to manipulate RS into recommending specific items more often than others and thus undermining its algorithmic neutrality. One conclusion out of their experiments is the recommendation to closely monitor the real time metrics of the deployed RS to detect attacks as early as possible.

Fang et al. describe a similar way of *data poisoning* for top-N-RS in their paper [13]. Their experiments successfully show, that a small number of influential fake users is sufficient for manipulating the recommendations, given to regular ones.

Title	Research Topic
Personalized explanations for hybrid recommender systems [21]	Performance
Optimizing long-term social welfare in recommender... [26]	Performance
Factors affecting the performance of recommender systems... [2]	Performance
A Troubling Analysis of Reproducibility and Progress in... [11]	Reproducibility
An Evaluation Study of Reproducibility and Competitiveness of... [7]	Reproducibility
Are we really making much progress? A worrying analysis of... [12]	Reproducibility
Recommender systems and their ethical challenges [24]	Ethics
Understanding echo chambers in e-commerce recommender... [14]	Ethics
Shilling recommender systems for fun and profit [22]	Security
Influence function based data poisoning attacks ...[13]	Security

Table 1. Overview of recent works representative for RS research.

6 Conclusion

Concluding from our previous sections 3, 4, and 5 we can say, that RS are an integral part of our modern world. Their wide prevalence and deployment in many different fields, from e-commerce to social media, makes it hard to image our daily life without them. The research and work done in RS since 1990, established it as a well defined field within a vast amount of information systems.

While the fundamental principles of RS may seem easy to understand, the difficult nature of making accurate recommendations for humans and the emerge of more RS combined with complex ANN provide lots of ways for intensify ones research. Related to this are works in the broad field Knowledge-based Systems (KBS), for utilizing many dynamic bodies of knowledge [38] as well as the Decision Support Systems (DSS), for their purpose to actively support its users in their decisions [19].

An outlook in the future of RS opens vast possibilities and opportunities. There is still a strong incentive for increasing performance of RS, due to their commercial utilisation. A better performance could lead to better results and more satisfied users. New ways of combining RS with upcoming ML approaches are very likely to be seen in near future, as both fields are very actively researched. This can potentially lead to even more performant systems.

Applying RS in completely new fields and aspects of our daily life is very likely. Establishing RS to support professionals in new sectors or people in their daily choices, could lead to better decision making and an overall increase of quality of life. For this, the existing issues with reproducibility, ethics, societal acceptance, and the potential privacy risks, regarding RS, need to be resolved in the future.

Many steps to this future have already been made and are currently researched, as we show in section 5. RS as a field of research will continue to be of great importance.

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