Recommender Recommender: A Recommender Recommending Recommenders

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ABSTRACT

There has been a dramatic increase in scientific publications and available commercial products regarding recommender systems. There are applications recommending entertainment content, career advice or lifestyle choices. For the future, we expect the digital consulting offering to continue growing. Consequently, people who need support in achieving their goals could be overwhelmed by the vast offer. To overcome these problems, we present Recommender Recommender (RR): a system that recommends recommender systems. A study (N = 8) shows that RR has the potential to improve users life quality and satisfaction. The Recommender Recommender is able to empower users achieving life goals.

CCS CONCEPTS

• **Human-centered computing** → **Interactive systems and tools**; *Human computer interaction (HCI).*

KEYWORDS

Recommender Systems; Personal Empowerment;

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INTRODUCTION

Recommender systems existed already before personal electronic devices, typically as printed matter. Until now, most bookshops provide a section for recommenders. For example, *How to Win Friends & Influence People* [2], *How to Draw Cool Stuff* [5] or *How Not to Die* [10]. However, books are heavy and normally we do not carry them with us all the time. Additionally, books are not able to remind us in the right moments. Therefore, digital recommenders are much more useful. Especially, if they are implemented on a mobile device.

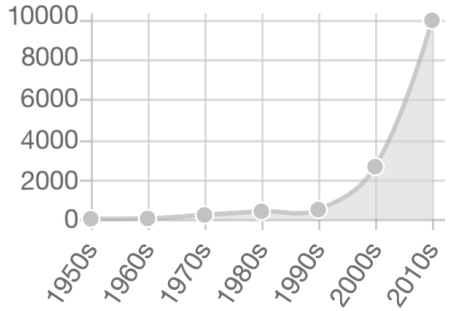
In the recent years, recommender applications got a heavily researched topic in HCI. In consequence, many recommender applications were developed for many different fields such as fitness, nutrition, health, time management, stress avoidance, music listening and more. A survey on research publications on recommender systems in the field of HCI shows a growing number of recommender applications. Extrapolating this trend to the future suggests there will be soon several thousands of recommender systems. Eventually, it will become extremely complex to find out which recommender systems are needed by an individual.

We created a questionnaire which asks the users about their needs and desires. Additionally, the questionnaire asks for the users' self-judgment on how much they already satisfied their goals, needs and desires. In the next step, we developed an algorithm which uses the results from the questionnaire to compile a list of recommenders which are relevant for the user who filled the questionnaire. The algorithm is the basis for a recommender application which we call: *Recommender Recommender* (RR).

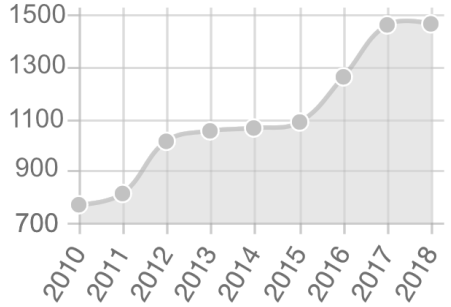
A user study confirmed the feasibility of our approach. The findings were overwhelming positive; most of the participants stated they would recommend *Recommender Recommender*. Our envisioned system seems to solve the problem of the extreme overflow of options, at least in the domain of recommenders, which is a recurring issue for our modern times.

MOTIVATION

It seems that in times of rapid technological development and increasing complexity more and more people get lost. The constant increase of information confuses people, so that they are not sure anymore what and when to eat, when to do physical exercises, what music to listen to, etc. With an increasing wealth in the western world the people from these areas have the capability to consume many products. However, the number of purchasable items and services is so large that many people do not know what they could consume.



Sidebar 1: Number of ACM publications including "recommender" from 1950s until 2010s. In the 1950s there was a total of 5 publications, in the 2010s there were 9984.



Sidebar 2: Number of ACM publications including "recommender" from year 2010 until 2019. In 2010 there was a total of 770 publications, in 2018 there were 1465.

[1]https://tryolabs.com/blog/introduction-to-recommender-systems/; *last accessed: Jan 2019*

On a more abstract level people do not know anymore what is good for them and have problems to be proactive. With competences on technology and human aspects the HCI community has the overview, can provide the right values, and can give the people initiative and orientation by developing appropriate recommender applications.

However, there is a steady increase in publications about recommender systems. Since the 1950s there is an almost exponential growth, as shown in Sidebar 1. In the last 8 years the amount of scientific work regarding recommender systems is still increasing, see Sidebar 2. Investigations in context of the Google Play Store and the Amazon web shop show also many results for the search term "recommender".

Already, the number of recommender applications is so large that an average person can not find out easily which recommender is the right one. A steady increase in available recommenders even exacerbates the isssue. Our idea is to apply the recommender approach to the problem. The result is the Recommender Recommender. We hope it will bring benefit to the people and the economy.

RELATED WORK

There is an dedicated ACM Conference on Recommender Systems which were hold for the 12th time this year. The proceedings of this conference are already a rich source of knowledge but there is also a lot of research published on other conferences. This vast number of publications makes it difficult to say that we read them all, but up to our knowledge there is no publication applying the recommender principle to recommenders in general. However, we did find a meta-recommender which combines multiple recommender technologies and presents a list of movie suggestions as a result [14].

A general overview of recommender systems is presented by Ricci et al. [13]. Additionally, there is a technical design space describing recommender systems with five dimensions [12].

The relevance of recommender systems in e-commerce was shown by Wei et al. [21] and Sivapalan et al. [17]. Herlocker et al. [4] investigated evaluation strategies and metrics for assessing the quality and impact of recommendations. Especially, for electronic commerce application recommender software is interesting [1]. The goal of such applications is to keep the user as long as possible on a website and to motivate customers to buy as many articles as possible. According to Rodríguez[1], recommender systems do perform astonishing well. His article states that 35% of the purchases on Amazon and 75% of chosen content on Netflix are based on recommender systems. Furthermore, 70% of the videos watched on YouTube are suggested by a recommender engine.

To keep users engaged and show them as many interesting offers as possible, recommenders benefit from personal data, e.g. behavior information, habits, preferences, visited websites, demographics, contextual information (date, weather, time...) or wealth. Tuzhilin et al. published a survey with the title “Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions” [20]. According to them, we can expect better recommendation capabilities in the

future. Hence, not only the amount of recommenders will increase, but also the amount of collected data about users which provides a new requirement for fraud.

Besides research on approaches and algorithms, there are many publication for recommenders in specific domains. We identified and classified domains in the following categories:

- Entertainment (Music, videos,...)
- Lifestyle (Clothing, partner,..)
- Health (Fitness, nutrition, medicament, ..)
- Career (Learning, time management, finances..)

There are more publications for each domain or category than there is space in the reference section. Therefore we just present some examples here, but added further domains to our prototype.

A recent article on music recommender systems research is given in [15]. Another recent publication is [16]. A comparison of video recommenders can be found in [6].

Building recommender systems for fashion is explained in [7]. Business partner recommendation is the topic in [8]. Activity recommendation with partners are presented in [19].

For a recommender system of workout and nutrition for runners have a look at [3]. An overview of recommender systems in the healthy food domain is given in [18]. A healthy-food recommender can be found in [22].

There are many publications on recommender systems for learning so that there a full books on the topic [9]. For an example of personalized finance advisory see [11].

As already mentioned above recommender systems have a high impact on e-commerce. For this reason we should assume that some research is not published, since private companies have no interest in giving the knowledge to competitors.

It is striking that most domains aim on the benefit of the person using the recommender system. Recommender systems which focus on humanity seem not to be popular for research. Recommender applications which suggest to give some money to a beggar or prevent the use of weapons seem not to exist, yet. Not even the next generation of recommender systems seems to evolve towards increased humanity [20].

USER STUDY

We designed and evaluated the Recommender Recommender prototype as a web-app. The following sections show who participated, how we implemented RR and what the study procedure was.

Participants

We invited 8 participants between the ages of 28 to 33 to a user study (M = 29.88 years; SD = 1.83 years; 3 female (37.5%); 5 male (62.5%)). Many participants stated to use recommender software, 2 (25 %)

Domain	Recommender
Sports	Runtastic
Food	PARI Food-Recommender
Partner	Tinder
Travel	Tripadvisor
Entertainment	Netflix
Well-being	Google Wellbeing
Career	Glassdoor

Sidebar 3: Domains and related recommenders recommended by Recommender Recommender. For each domain Recommender Recommender recommended one recommender.

use such systems regularly and 5 (62.5%) sometimes. Only one participant never uses recommenders. All of them were university employees and voluntarily participated, no compensation was offered. Participants became briefed about the functionality of RR prior to the study. The study was conducted in accordance with the latest version of the Helsinki Declaration and was not objected by the local ethics committee.

Prototype

The idea of RR is to recommend a digital recommender which can either be a web-app or a mobile application. We did not include books or offline services. All recommenders are available consumer products which fully work, see Sidebar 3.

Concept. The first step is to investigate personal needs of users. Consequently, RR asks which aspects are important in users life. The prototype includes seven domains: *Sports*, *Food*, *Partner*, *Travel*, *Entertainment*, *Well-being* and *Career*. However, the prototype allows to add more domains and sub-domains. Answers regarding each context can be given on a five-point Likert scale, see Sidebar **??**.

The second step is to find out about the level of satisfaction in context of the aforementioned domains. Again, the answers can be given on a five-point Likert scale, see Sidebar **??**. The discrepancy between importance and satisfaction are personal deficits. A personal deficit is something negative and it is not easy to accept suffering from such circumstances. Therefore, we constructed the RR concept as explained above.

After gathering information about users preferences, RR calculates a result. This result either contains a single recommender application or communicates the encouraging message that no deficits could be detected.

Implementation. We implemented our prototype with the standard web technologies HTML5, CSS, JavaScript and a NodeJS server. We are happy to provide the full code for everyone who is interested.

All radio-buttons have an increasing value from 1 (strongly agree) until 5 (strongly disagree). If there are domains with an importance higher 3 and a level of satisfaction lower 3, the tool combines those in a two-dimensional array. The first dimension contains the name of the domain, the second dimension includes a link to a corresponding product. For the final result, RR picks a random entry. If there are no matches found, RR assumes that the participant is seemingly happy in life and does not suggest a recommender. The code at Listing 1 calculates the recommendations. (Please note that the poor indentation is due to the page width.)

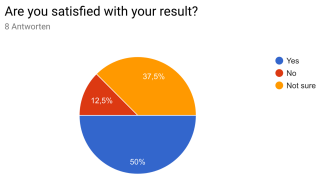
```
function calc_recommendation() {
for (var i = 0; i < values_page1.length; i++) {
for (var j = 0; j < values_page2.length; j++) {
if (i === j) {
if(parseInt(values_page1[i]) < 3 && parseInt(values_page2[j]) > 3) {
calc_results.push(domains[i]);
} } } }
if (calc_results.length > 0) {
var rand = Math.floor(Math.random()*calc_results[0].length);
results.innerText += "You could benefit from a recommender in the domain of " +
    calc_results[rand][0] + ".";

var a = document.createElement('a');
var linkText = document.createTextNode(" Take a look here ;)");
a.appendChild(linkText);
a.href = calc_results[rand][1];
results.appendChild(a);

} else {
results.innerText += "You seem very satisfied. You don't need a recommender, keep
    enjoying life ;)";
}   }
```

Listing 1: RR-code for calculating results

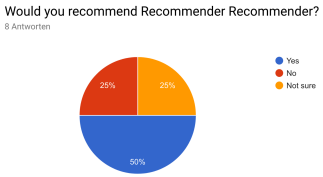
Study Procedure

We employed a pre-study questionnaire to gather data about demographics (gender and age) as well as prior experience with recommenders (software and books). Following, participants interacted with the prototype described in Section *Prototype*. After participants received a result from RR, we asked them about their perception of the prototype. In detail, we presented the following questions (with possible answers described in brackets below each question):

- What was your result?
  (Text field to paste domain)
- Are you satisfied with your result?
  (Yes / No / Not sure)
- Would you recommend Recommender Recommender?
  (Yes / No / Not sure)

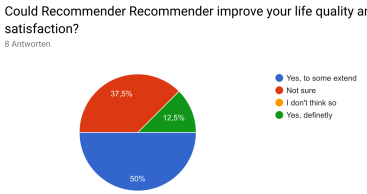


Sidebar 4: Pre-study question 1



Sidebar 5: Pre-study question 2

Sidebar 6: Pre-study question 3



Sidebar 7: Pre-study question 4

- Does Recommender Recommender simplify finding a recommender compared to searching one online?
  (Yes / No / Not sure)
- Could Recommender Recommender improve your life quality and overall satisfaction?
  (Yes, definetely / Yes, to some extend / Not sure / I don't think so)

RESULTS

Participants received their recommender in context of the following domains: *Sport* (3 / 8), *Partner* (2 / 8), *no recommender* (3 / 8). Surprisingly, the other domains never appeared in the result. The main reason might be the small sample size.

Half of the participants stated to be satisfied with the individually received result. The same amount (4 / 8) would recommend RR, Whereas, 25 % are not sure and another 25 % would not do so, see Sidebar 5. No participant stated that RR does not simplify finding a recommender. Nevertheless, 5 participants were not sure if RR is simpler than an online search, see Sidebar 6. None of the subjects thought that RR could not improve their life quality and overall satisfaction. However, 3 were not sure, 4 believe in RRs improvement qualities to some extend and only one does so without doubt.

DISCUSSION

According to the results we can see that most users could recommend RR and only one was not satisfied with the received recommendation. Some even affirm RR simplifies recommender searches. Most importantly, no participant thinks RR would not improve their life quality and overall satisfaction. Additionally, more than the half of our subjects believes RR could improve their life. We see a big potential in RR and are convinced that it has the power to help users achieving individual life goals while saving a lot of time and effort. We suggest that instead of creating more and more recommender systems research should focus on getting the right recommender to the people in need for it.

CONCLUSION

We conducted a literature research about existing recommenders in context of scientific work and commercial products. The existing number of recommender systems is difficult to overview and the problem will even increase in the future. On the basis of gained insights, we devolped a protoype called Recommender Recommender (RR) which recommends recommenders. As indicated by the results of our user study (N = 8), a meta-recommender seems to be a promising solution for the mentioned problem. We strongly believe that users could benefit heavily from *Recommender Recommender*.

FUTURE WORK

The current implementation of RR only reflects a few of the available systems. As we expect further recommenders for the future, a way to integrate these system into the RR-prototype is necessary. One way to achieve this would be a standardized description format for the capability of recommender systems. An XML or JSON formatted code snippet delivered with each recommender could provide such information. Additionally, for new capabilities new and more precise questions for the questionnaire are needed. Furthermore, the users have to be informed on newly available recommender applications. This means an update mechanism is obligatory.

For the future we also plan to conduct a long-term study with RR. It would be interesting to find out how users adapt to recommender systems. Does a constant use of recommenders decrease the users' ability to make decisions on their own? Or does a recommender create a learning effect so that the users do not need the help of a recommender application any more?

Finally, we think about a universial recommender which does not need different recommenders for different categories. Instead, a neuronal network could take all our activities as constant input and create constantly suggestions for our next activities. The question 'what shall I do?' will then not exist any more.

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