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WHICH RECOMMENDATION TYPE IS MOST LIKELY TO LEAD TO PURCHASE ONCE CLICKED?

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Abstract

Wide variety of surveys have studied recommendation systems (RS) and the topic is very current. However, the general research topics are related on what algorithm is the best or how algorithms differ from each other and what happens if different algorithms are combined. Also customers' attitudes and trust (including privacy issues) toward RS are surveyed. This study investigates what happens after a certain (history-related, item-related or toplist) recommendation type is clicked, which will produce the most carted items and the most importantly purchased items.

The data used was from a company providing recommendation services for online stores, thus the company sells only the recommendation service itself. The data was from a real life web store providing very valuable and rare knowledge. Because of the company's clients' privacy policy, the source of data was not known. Known is that the web store was large European store and most customers were European too. An important remark is that the data was gathered only from one web store and included one million single sessions. The data was studied and linear regression models were contributed. Also binary mode format was used to exclude certain occasions. Results gave some strong indications that there is a notable difference between recommendation types. Results were also connected with a literature findings and psychological persuasion, informative persuasion and clickstream behavior were discussed.

The history type was clearly the most effective recommendation type. Item related recommendation was the second most effective. The reason of the difference is the better and more precise knowledge of the user for the history related recommendation. Toplist was clearly the weakest type to provide purchased items. It is totally impersonal, so the informative aspect is very low, only providing knowledge of popular items. Findings suggest that everything is based on to the knowledge of the user. More accurate recommendations will provide more purchases. As mentioned the amount of recommendation researches is very large, yet certain areas are unexpectedly unstudied. More attention should be assigned to practical side of the recommendations and as this study suggests it can provide a great benefit.

Keywords recommendation system, recommendation service, history related recommendation, item related recommendation, toplist recommendation, web store, e-commerce, e-selling

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Tiivistelmä

Suosittelusysteemit ovat erittäin tutkittu ja ajankohtainen aihealue. Kuitenkin useimmat tutkimukset keskittyvät kehittämään parhaan mahdollisen algoritmin, vertailemaan eri algoritmejä tai löytämään tapoja yhdistää niitä. Myös asiakkaiden asenteita ja luottamusta (mukaan lukien yksityisyyden haasteet) suosittelusysteemejä kohtaan on tutkittu. Tämä tutkimus selvittää, mitä tapahtuu, kun tiettyä suositusta (historiatietoon perustuva, tuotteeseen perustuva ja ostetuimmat tuotteet lista) on jo klikattu, mikä suositustyyppi tuottaa eniten ostoskoriin laitettuja tuotteita ja kaikista tärkeimpänä, eniten ostoja.

Käytetyn datan tuotti yritys, joka myy suosittelusysteemejä verkkokaupoille. Yritys myy siis vain itse suosittelupalvelua, eikä omista verkkokauppoja. Data oli aidosta verkkokaupasta, joten se oli erittäin arvokasta ja harvinaista dataa. Yrityksen salassapitovelvollisuuksien vuoksi, verkkokauppa ei ollut tiedossa. Kyseessä oli kuitenkin eurooppalainen verkkokauppa ja suurin osa asiakkaista oli eurooppalaisia. Tärkeä huomio on, että data kerättiin vain yhdestä verkkokaupasta ja sisälsi miljoona yksittäistä sessiota. Dataa tutkittiin ja lineaariset regressiomallit tuotettiin. Myös binäärimuotoon muutettu data tutkittiin, jotta tietyt tilanteet pystyttiin välttämään. Tulokset antoivat vahvoja näyttöjä siitä, että suosittelutyypeillä on selkeä ero. Tulokset yhdistettiin aikaisempiin löydöksiin ja syitä eroihin arvioitiin.

Historiatietoon perustuva suosittelutyyppi oli selkeästi tehokkain tuottamaan lisää ostoja. Tuotteeseen perustuva suosittelutyyppi oli toiseksi tehokkain. Historiatietoon perustuvan suosittelutyypin paremmuus perustuu tarkempaan tietoon käyttäjästä. Suosikkilista oli heikoin lisämään myyntiä. Se ei perustu millään tavalla käyttäjätietoon, joten suosittelujen henkilökohtaisuutta ei ole. Mitä tarkempia ja henkilökohtaisempia suosituksia tuotetaan, sitä tehokkaampia ne ovat. Kuten mainittu, aihealue on erittäin tutkittu, mutta tietyt alueet ovat jääneet pienelle huomiolle. Lisää tutkimuksia tulisi tehdä käytännön näkökulmasta, kuten tämä tutkimus osoittaa, sillä voi olla selkeä vaikutus myyntiin.

Avainsanat suosittelusysteemit, suosittelupalvelu, historia suositus, tuoteriippuvainen suositus, ostetuimmat tuotteet, suosikkilista, verkkokauppa

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1 Introduction

Today's world provides almost unlimited amount of choices, when considered sold services or products. Already in early 1970’s it was found that complexity and the sheer amount of information can cause an information overload and customer feels overwhelmed (Jacoby et al. 1974). In early 1990’s it was noted that mass production should move towards mass customization, to be able to sell more, thus it created even greater variety of products (Pine 1999). And that is how products are today. Similar products with small differences to fit everyone’s taste can be found. The problem is how to find that exact product and/or option for your needs especially on the internet where the amount of data is uncontrolled. It is extremely difficult to find accurate and relevant information, or then there is just too many options and without professional knowledge or professional salesperson, it is impossible to know what is the best option, thus this has led to a development of recommendation systems (RS) (Pine & Gilmore 1999).

Therefore, it comes as no surprise that electronic commerce is one of the largest application and research areas of recommendation systems (see e.g. Park et al. 2012). The basic idea of RS is to create valid recommendations for online customers to create a need or just to offer the right product, thus reduce the search cost (Bakos 1997). Search costs is one of the key aspects why recommendation systems are so important: reducing search costs with quality information will reduce customers’ price sensitivity. Customer may pay more, if the product searched is easily found (see e.g. Bakos 1997, Kaul & Wittink 1995, Lynch & Ariely 2000). It is also stated that the most important benefit of online shopping is actually the possibility of recommendation systems to go through thousands of items and narrow the field only to a few closely related to customer’s needs, thus the consumer saves vast amount of time and nerves (Alba et al. 1997, Diehl et al. 2003).

Online clickstream data creates a possibility to understand customer behavior better and predict user’s preferences and shopping habits. This has opened a great possibility for one-to-one marketing by enabling a possibility to personalize the user’s shopping experience, providing more successful business. Successful recommendation depends upon information pertaining to the preferences of customers. An important factor is that a retailer can provide accurate information and also timely information. These should generate more sales through converting browsers into buyers and by increasing cross-sell (Postma & Brokke 2002, Schafer et al. 2001). Also customer loyalty increases with personalization (Schafer et al. 2001, Srinivasan et al. 2002). Simply, by implementing a RS company can achieve competitive advantage (Nissen & Sengupta 2006).

Recommendation systems have been widely studied (see e.g. Bobadilla et al. 2013, Lü et al. 2012, Park et al. 2012, Schafer et al. 2001). Park et al. (2012) alone contains review of 210 articles on recommendation systems. As far as I know, and according to past literature, there is almost no research that compares recommendation types despite the large number of studies. Researches have been more focused on algorithms and methods behind the systems. Also users' trust and attitude have been surveyed including privacy issues (see e.g. Schafer et al. 2001, Benbasat & Wang 2005).

The research question of this study is to find out which of the following recommendation types provides most purchases (and carted items) after a certain recommendation have been clicked. The types are 1) user's history related 2) item related 3) toplist recommendations. I argue that whatever type algorithms is used there must be variations on effectiveness of the shown recommendations. In this study the aforementioned three recommendations will be investigated and their effectiveness will be compared in a real word web store. The data came from a company providing recommendation systems for already working web stores and their algorithms have proven to be very efficient. This study will focus on which RS provided most purchases, however also to clicked and carted phases will have a part. Literature have been reviewed and previous findings will work as a guideline and comparison during the test. Thus as far as I know there is no similar test and this study will work as guideline for a future researches.

These results can provide a great managerial value and theoretical implications. This is simply method to increase the usage of already available recommendation systems, by choosing the most effective recommendation types to be shown. This can lead to an increase in sales. Also new avenue for future researches is opened and the area is ready for more researches.

The paper starts by studying methods to increase e-selling by using recommendation systems. Relevant literature on recommendation types and consumer psychology are reviewed. Then the three different recommendations used are investigated one by one and the idea and psychology behind them is discussed. Data is then evaluated and SPSS tests contributed. Results are discussed and compared to expectations. These are then linked to findings from literature. Finally, main findings are presented in light of future research areas.

2 Background

In this chapter e-selling is defined and the meaning and possibilities are explained. First different methods to affect people's e-shopping habits is shortly explained. Idea is to have similar effect as a traditional salesperson would have by evaluating the customer. Then recommendation systems are closely explored and previous findings presented. Finally, sales and usage psychology is considered through three different chosen recommendation systems.

2.1 Increasing sales on the internet

E-selling is defined as human activity in which digital interaction is directed increasing customer value by securing a business exchange for mutual benefit (Parvinen et al. 2015). Because online shopping is critical for most of the retailers it has raised more questions and interest over the online customer experience. There are several methods to increase sales on the internet. Many of the methods use at least some kind of recommendation system as a base for the e-sales. The few common ones are shortly evaluated before moving to more detailed review of recommendation systems.

Direct marketing was powerful and well working marketing method in the era of mass marketing when most of the product information on radio, television and magazines was mostly controlled by manufacturers (Schultz et al. 1994). However, internet provides almost unlimited possibilities for direct marketing, but also the possibility to fail is extremely high. This is created by real time interaction, since direct marketing on the internet is not one-way business anymore (Glazer 1991, Lefton 1993, Schultz et al. 1994). The users have better possibility to hide (for example blocking email addresses or using ad blockers) but advertisers have hugely better tools to contact right customers (for example using usage data and accurate shopping history), when compared to times before the internet. To find the right products or services for the right customers is essential and is often generated by recommendation systems.

Since the beginning of human society, word-of-mouth (WOM) has been one of the most significant information transmission resource (Godes & Mayzlin 2004, Maxham & Netemeyer 2002, Reynolds & Beatty 1999). It can be extremely low cost, yet very effective. Customers acquired through WOM can significantly increase the lifetime value of customers through traditional marketing and they also spread more WOM and create more new customers (Chevalier & Mayzlin 2006, Villanueva et al. 2008). Today WOM is often related to recommendations when items are reviewed or rated and is proved to be efficient method to increase sales (see e.g. Senecal & Nantel 2004).

One very interesting and new direction of recommendations is gamification. Many websites are alike and to differentiate is all the time more challenging. Gamification could offer solutions and competitive advantages in this area. If a web page motivates customers to stay or visit more often, there is a very good possibility to also achieve financial advantages. Example of gamification is features can be points, leaderboards, achievements (e.g. badges), feedback, clear goals and narrative. Using gamification can generate a deeper level of consumer engagement and the shopping experience can feel like a form of entertainment (Hamari & Koivisto 2015, Insley & Nunan 2014).

2.2 Increasing sales on the internet using recommendation systems

Nowadays web store users can have an information overload, since a huge amount of possible products. A well working recommendation system can help and work like an agent. The agent can advise in finding suitable products and facilitate customer's decision making process through limiting the offered products based on customer’s preferences. This can lead to better customer satisfaction and results for a company (Häubl & Trifts 2000, Kim et al. 2010, Postma & Brokke 2002, Schafer et al. 2001).

Recommendation systems are commonly used for offering products, which are preferred by other similar users, similar products as looked at or some kind of toplist. Even this basic level evaluation provides a possibility to create recommendations by several different principles. For example, is age and gender equally valuable? How to treat new customers with little or no information? What is similar product? What are the best properties to measure user similarity? A good recommendation system can solve these complex situations by given features.

Data for recommendation systems can be gathered explicitly (simple user rating system) or implicitly by monitoring users' behavior e.g., songs listened, downloaded applications, visited web pages, bought brands. Also age, nationality and gender are used. With Web 2.0 also usage of social information (e.g., followers, followed, posts) was widely implemented. Newest trend is to use information from the internet of things (e.g., location data, RFID). (Bobadilla et al. 2013, Chaudhuri & Holbrook 2001) Most researches are focusing on what would be the best algorithm to create the recommendations (see e.g. Park et al. 2012). Several studies have surveyed other factors that influence the user experience and pointed out the lack of diversity of researches (see e.g. Cosley et al. 2003, Murray & Häubl 2008, 2009) Only few studies are examining a psychology of underlying processes, for example Cosley et al. (2003) proved that movie ratings are significantly affected by other's ratings.

From Amazon's sales historically 60% to 80% comes from the shop's 100 000 most sold products (Brynjolfsson et al. 2003). Thus if recommendation lists can guide customers to better revenue products, the difference can be tremendous. This reminds a situation in an old fashion TV reseller. When a customer goes to buy a discount TV, the salesperson offers something much better for little more money. Also the amount of possible recommendations is limited and is the reason why it is important to know what recommendation type works most effectively. Otherwise the RS might show wrong type of recommendations and this leads to lower sales. Recommendation system's idea is to lower the search costs, but if too many recommendations are offered, it can lead to increased search costs (Fitzsimons 2000, Fitzsimons & Lehmann 2004). This can be optimized by combining the best algorithms with the most effective recommendation types.

There are generally two ways to classify recommendation systems, collaborative filtering (CF) or content-based filtering (CB). CF is based on the user's previous behavior (e.g. looked and bought items), but it has two major issues: sparsity and the scalability problem (Claypool et al. 1999, Sarwar et al. 2000a, 2000b). CB is based on items rated by users and the contents of the items, by combining this information it recommends additional products (Basu et al. 1998). CB’s issue is overspecialized recommendations, because of its syntactic nature (Blanco-Fernández et al. 2008). There is no simple best recommendation type, thus context and available data dependent applications are most likely to offer best products (Lü et al. 2012).

2.2.1 Related researches

Most of the researches uses public databases to explore memory-based recommendation systems (Bobadilla et al. 2013). Many large companies are offering free databases to give researchers a better possibility to develop even better recommendation algorithms. For example, MovieLens, Netflix and Book-crossing offers data without social information. GroupLens hosts ML, Last.Fm and Delicious to offer databases with social information. This shows the limited variety of products and type of stores for easily achieved data.

Reference	Outcome	Result(s)	Context
Senecal & Nantel (2004)	Efficiency of recommendation systems	Consumers are influenced by online recommendations, but the influence differs between sources. Recommended products were chosen twice as often.	Consumer online behavior
Benbasat & Wang (2005)	Consumers receptiveness on recommendation systems	Consumer treats recommendation agents as support tools, but also as “social actors” and perceive human characteristics.	Consumer online behavior
Lü et al. (2012)	Algorithms usability	User average algorithms outperforms object average on Netfilx.	Recommendation system comparison
Bobadilla et al. (2013)	Development of recommendation systems	First generation of recommendations systems used data from purchases, location and memory. Second generation uses web 2.0 by gathering social information. Third generation will use web 3.0 and data from devices (e.g. smart phones and smart watches).	Recommendation system comparison

Zhou et al. (2007)	Effect of personalization and trust issues	Personalized web stores can increase customer loyalty and profits. But privacy concerns over data collection are the reason not to use online store.	Consumer online behavior
Moe (2003)	Separation of user intentions within online store sessions	It is possible to identify direct-buying-, search-, browsing- and knowledge-building sessions.	Consumer online behavior
Senecal et al. (2005)	Clickstream analysis	Recommendation systems increase greatly complexity of sessions.	Decision making process and online shopping behavior
Min & Han (2005)	Time-variant patterns when creating recommendations	By detecting user's time-variant patterns recommendation system's accuracy are improved.	Recommendation system comparison

Table 1. A collection of previous findings and their contexts and outcomes.

Table 1 gives an overview of RS researches and findings. There are strong proofs that recommendation systems work and have an influence on customers, results show that a product was chosen twice as often when recommended. It was also found that RS was the most influential recommendation source even it was offering less expertise (compared to humans) and less trustworthy than other consumers. Also recommendation was more influential for experience product than for the search product. The type and quality of the website did not affect to users perceive about recommendations, but the type of recommendation source and product did affect. (Senecal & Nantel 2004)

Clickstream is a term to describe visitors' path through a web page and is often a good way to analyze customer habits and reactions over a single session. This gives a possibility to understand effect of changes and users' behavior on a certain web page. In this work some rough clickstream data was used and evaluated. There is a concept for this descripted as *flow* (Hoffman & Novak 1996) A clickstream data can be used to categorize users as buying-, browsing-, searching- or knowledge-building visitor. This information can be converted as purchasing likelihood. (Fader & Hardie 2001, Moe 2003, Moe & Fader, 2000, 2004) Every categorized customer have different motivation, thus each one of them would react differently to any recommendation shown (Moe 2003). In this study the clickstream data was limited because only known factors were if a user was shown a recommendation, if it was clicked, was the clicked item carted and was it bought.

Previous researches have found several different shopping cart behavior models. For example, organizational use of cart means using a shopping cart as a wish list or to track items later for price changes. Total price of selection is often seen first time, too. (Kukar-Kinney & Close 2010, Moe 2003) The shopping cart is also used for entertainment value because some users find using a shopping cart as a good way to spend time, even without buying intentions. (Kukar-Kinney & Close 2010). Yet there are proofs that if products are carted, a probability for some purchase action is higher than no purchase action (Close & Kukar-Kinney 2010, Rajamma et al. 2009). Interesting finding was that users who utilize RS have actually more complex behavior during sessions, meaning more web page are viewed and more items seen. Thus even recommendation systems have proven to be good social actors and providing information, the user will actually spend more time and investigate more products if RS is used. (Benbasat & Wang 2005, Senecal et al. 2005)

By reviewing 210 articles Park et al. (2012) found several interesting issues. The interest towards recommendation systems is still increasing and the researches should widen the topics. Many are focused on movie sector (most likely because of easy access for a data), which might not give accurate information about other business areas. Also social media's potential is only marginally used. Also the algorithms have a tremendous part of the researches, which might not be the most important part anymore.

2.3 Compared recommendations

To increase sales on the internet something that user does or sees, should create a need or desire to purchase more. Recommendations could be compared to information (Senecal & Nantel 2004). Recommendation systems are impersonal information sources providing personalized information to consumers (Ansari et al. 2000). Thus users will gain knowledge from recommendations that they would need to search or would not know without recommendation. As a good information source the recommendation system can significantly lower the search cost (Bakos 1997).

Valid information is a strong feature of recommendation systems, but also psychological aspect is relevant. People like to compare themselves to each other, which gives a possibility to create a desire, this phenomenon is called *social comparison* (Festinger 1954). Even when a potential buyer has a strong opinion over an item there are proofs that social influence can have a major affect and change the intended behavior (Asch 1956, Zhu & Huberman 2014). Obtaining a social approval is often a reason for the power of social influence (Cialdini & Goldstein 2004). However, the reason can also be as simple as a belief that a popular item is a good or the best possible product to choose (Burnkrant & Cousineau 1975). *Impulsive buying* is a term for unplanned and sudden purchases, which is also present when recommendations are shown. The effect is based on an immediate stimulus object and is often combined by feelings of excitement and pleasure. (Rook 1987) Impulsive buyers are often emotionally attracted to objects and desire immediate gratification (Hoch & Loewenstein 1991, Thompson et al. 1990). These buyers often ignore the possible negative consequences that a purchase might create (Hoch & Loewenstein 1991, Rook 1987).

Also the negative side of recommendations must be concerned as people react against attempts to control their behavior and against threats to their freedom of choice, this is called *theory of psychological reactance*. Users might feel restricted to make their own decision. (Brehm 1966) The psychological reactance has been studied and it is shown that unavailable products and low quality of recommendations can have a negative sales effect (Fitzsimons 2000, Fitzsimons & Lehmann 2004). Reactance can also derive from the lack of trust. Privacy issues or suspicious towards honesty of recommendations can also have a notable factor (Schafer et al. 2001, Shyong 2006, Benbasat & Wang 2005).

The data provided defined the compared recommendation types and there was no possibility to effect on that. However, the three recommendation types were very common, thus the information is very relevant. The data includes three common recommendation types: *1) user's history related*, *2) watched item related* and *3) toplist related*. Next the three recommendation types are presented in more detailed and possible informative and psychological aspects are discussed based on literature findings.

User's' history related recommendation recommends items, which are related to a history of a user. Recommended products depend on the old behavior of the user. Everything the user does on a web store is recorded and can be used to create history related recommendation. For example, if the user had searched for a pair of shoes, but did not buy any, next time the user will be offered similar shoes. Or if the user did buy the shoes, next time some other shoes or shoe related products are recommended. Also user given information can be used, for example if the user is registered and gives the location, age and gender recommendations can be adopted to suit the customer's attributes better. This type of recommendation can offer very personal recommendations and is proven to be very efficient but cannot be used if there is no relevant history data, thus identifying a single user is very important (Hansen & Wänke 2009, Rossi et al. 1996). The history data provides also possibility to recommend products, which are not looked at during the whole session. Maybe the user never thought of buying new pair of shoes, but seeing an offer can influence to a user and cause an impulsive buying action (see e.g. Rook 1987). Shoes have been shown because of history knowledge. From informative perspective history related recommendations can provide very good value (e.g. winter shoes for winter), because of the best knowledge of the user. However too specific and accurate recommendations can raise reactance effect (see e.g. Brehm 1966, Schafer et al. 2001). It is possible to have a feeling that the seller has too much knowledge of the user.

Watched item related recommendations are closely linked to an item or a product category in view, thus no history data is needed. Recommended products might be similar products or additional parts, for example if a TV is looked at an another TV model or an antenna cable can be recommended. This is very usable recommendations for all kind of users, since no history data is needed. This recommendation type is not as personal as history related recommendations, but closely related to something the user is looking, thus an object of interest, which is personal. This provides valuable information for the user and possibility to cross-sell (see e.g. Rook 1987). This limits the variety of recommended products by depending of the user's path on a web store, but is always relevant. Item related recommendations might create impulsive effect (example screen cleaner for the TV) and the social influence could come from an idea that TV should have a home theater (see e.g. Brehm 1966, Festinger 1954). On the other hand, the reactance effect should be very low, since users can understand how the recommendations are formed (see e.g. Schafer et al. 2001, Shyong 2006, Benbasat & Wang 2005).

Toplist based recommendation is the simplest of the three compared recommendation systems. It does not require any knowledge of the user. In this study it provides top sold products of the whole web store. Toplist is not personal and works also for new customers with no data. Toplist can be shown even on the first visit of the home page. From informative perspective the effect is low, since it only provides knowledge of the overall sold items in the web store. However, this type could be very useful for users who likes to follow what others have done, the reason is the belief that top sold products are the best ones or just to need to have social approval (Burnkrant & Cousineau 1975, Cialdini & Goldstein 2004, Festinger 1954). However, it is good to note that some people might to have reactance towards toplists, since they want to be distinctive and not to buy similar items than others (Brehm 1966). They want to have their own identity, or at least they think so. Impulsive buying is also possible as user needs to only open a front page to see most sold products (e.g. new iPhone). This might create an impulsive buying action (Rook 1987).

Recommendation type	**Information persuasion**	**Psychological persuasion**	**Reactance effect**
History related	Provides very accurate and informative information based on a history data.	Attention can be risen, since objects of interest are known.	Too personal: “the web store knows too much”, privacy issues. Risk of too limited recommendations.
Item related	Provides accurate information about watched item / category.	People tends to buy more than one item or extra equipment.	User can understand how the recommendations are created, thus no reactance effect
Toplist	Provides information about most sold items.	People like to have social approval and/or belief that the most sold items are the best ones.	Some might want to avoid general items

Table 2. Different persuasion effects by recommendation types.

All the recommendations types have their own strengths and weaknesses from informative-, psychological persuasion and reactance perspective. Table 2 gathers the main factors and gives a good overview of the three types of RS. Next the data is presented in detail and tests contributed.

3 Empirical study

In this chapter the data, variables and the process to collect the data are presented. Extremely valuable point for this study was that the data based on a real world web store. No staged situations, no volunteering participants or any other possible negative variable were compounded. Commonly used open data from for example Netflix cannot be compared to this in scarcity point of view.

3.1 Data

The data used was from a company providing recommendation services for online stores, thus the company sells only the recommendation service itself. This means they have a very good knowledge of recommendation services and systems. The company provides recommendation services for online stores, personalized Facebook ads, pop-up ads and direct marketing through emails. They have over 16 000 customers, and web store sizes vary from only few views per day to many millions per day. Because of the company's clients' privacy policy, the source of data was not known. The company is using collaborative filtering for old customers with history data and content-based filtering for new unknown users.

3.2 Data collection and information

Data was collected by the providing company that automatically collects certain logs from its customers' website operations. Thus, the data was already available and not created for research purpose only. Some modification was made to the data before it was handed for the research, but only to protect customers' privacy. In other words, no numbers or values were changed. Because of confidentiality agreement there was no knowledge about the web store which the data came from meaning there was no firsthand information how and when the recommendations were shown.

After testing with a smaller dataset (10 000 sessions) to understand the capabilities of the data and to see all the variables, the company provided two larger sets. Both contained 500 000 individual visits from two separate weeks (for example to limit the effect of a special campaign). An important remark is that the data was gathered only from one web store meaning the customers' behavior and sold products were as similar as possible in both sets. This also gave a possibility to predict that the size of the web store could not be very small, since they had at least 500 000 visitors per week.

The company also provided some information where the recommendations were shown during sessions. This is shown in a Table 3. Toplist was shown only on a front page and was followed at the bottom with history related recommendation. On a category page only history related recommendation was shown at the bottom. On a product page two slots (meaning two separate slots including several products) with item related, followed by history related recommendation at the bottom. Finally, on a carted page there were two slots with item related, followed by history related at the bottom. The history related was only shown, if there was history data available and history data could be from a longer period, not only from that one session.

Recommendation type	**Front page**	**Category page**	**Product page**	**Carted page**
History related	X	X	X	X
Item related			2X	2X
Toplist	X			

Table 3. Where a certain recommendation type was shown on the web store.

As there was no possibility to change the placement of the recommendations on a single page, it might have had an effect. However, there are several proofs that users tend to expect certain locations for a certain item on a web page and since recommendations were placed on a right or left side and bottom of the pages it can be expected to have very little effect (Bernard 2001, Oulasvirta et al. 2005, Roth et al. 2010, 2013). In ideal situation there would have been several data sets. First data as now and then data where the recommendation placements would have been swapped to eliminate the effect of placements. Also there was a possibility that the web store changed the placements of the recommendations during the data logging. It is very unlikely and nothing in the data implied that.

It was also known that the web store was selling products and not services. Products varied from clothes to electronics, thus it sold almost everything. This also meant that prices could vary a lot and most likely did not have the limiting factor since some very expensive products could have a low effect of recommendations, since the shopping process is much more carefully considered. However, it is proved that products do have an effect and it must be considered when results are explored. (see e.g. Bearden & Etzel 1982, Childers & Rao 1992, Formisano et al. 1982, King & Balasubramanian 1994) The web store is European and most of the customers are from Europe.

As the data set was very large it provided a good possibility to compare aforementioned recommendation types after the first step (from shown to clicked). The limitations in the data were all minor as the study was contributed for one million sessions and no single user behavior were studied.

3.2.1 Variables

The data included several variables, which were then compared in SPSS version 23. The data contained one million various sessions and it was gathered from two separate weeks, to avoid the effect of special discounts, holiday weeks or some other special occasion. Thus 500 000 sessions from each week were randomly chosen. In a Table 4 a list of the main information of the data is presented. Every session (1 000 000 total) included all the presented variables in number format, showing exactly how many times certain variable occurred during a session.

Variable	**Meaning**
Bought History	Total bought items through history related recommendations.
Bought Related	Total bought items through product related recommendations.
Bought Toplist	Total bought items through toplist recommendations.
Carted History	Number of times a product was carted after it was viewed through a history related recommendation.
Carted Related	Number of times a product was carted after it was viewed through a product related recommendation.
Carted Toplist	Number of times a product was carted after it was viewed through a toplist recommendation.
Clicked History	Number of times history related recommendation was clicked.
Clicked Related	Number of times product related recommendation was clicked.
Clicked Toplist	Number of times toplist recommendation was clicked.
Shown History	Number of times history related recommendation was shown.
Shown Related	Number of times product related recommendation was shown.
Shown Toplist	Number of times toplist related recommendation was shown.
Total visited pages	The total number of page visited during one session.

Table 4. Variables used in the provided data with original descriptions.

3.3 Results

The first interesting information was how many times a certain recommendation was shown during the one million sessions. Since the placement of the different recommendations were known it is not a surprise that the toplist recommendation was the least shown one since it was on the front page only. It was shown 314 239 times. History related was shown 444 795 times and item related was shown 529 009 times. Numbers seems to be logical, because of the placements and since history related is only shown if history data is available.

The toplist gathered least clicks, which can be explained as the toplist recommendation is only shown on the front page. History related can be shown on any page, if there is history data available for the user. This explains why it was not the most shown one. Thus, item related recommendation achieved most clicks and is shown in several pages and does not need history data. It is important to be aware that only when recommendation was shown to a user, it was taken under investigation. The total amount a certain recommendation gathered clicks was not the most informative part, because of the uneven situation with the shown recommendations. There was a possibility that many user was directed or came to the web store by “accident” and only saw the first page. This limited the possible behavior and intentions of a user. However, after a recommendation were clicked the situation was similar for all the recommendations.

Table 5 shows SPSS output of descriptive statistic for the six variables. Value column shows how many items were carted or bought through a certain recommendation. History related seems to be the most effective. About 13% of clicked history recommendations were carted. For the item related the percentage was 7,7 and for the toplist recommendation 6. From carted products 53,4% was bought for history related, 46,1% for item related and 43,8% for toplist recommendation.

Valid	Carted History	Carted Related	Carted Toplist	Bought History	Bought Related	Bought Toplist
0	994313	996637	999726	996965	998448	999880
1	4736	2628	265	2471	1249	118
2	724	469	7	395	209	2
3	137	155	2	96	63	0
4	61	57	0	41	19	0
5	17	25	0	14	8	0
6	5	14	0	8	3	0
7	2	1	0	4	1	0
8	2	4	0	2	0	0
9	1	2	0	2	0	0
10	1	2	0	0	0	0
11	1	0	0	1	0	0
12	0	0	0	1	0	0
14	0	2	0	0	0	0
17	0	1	0	0	0	0
21	0	2	0	0	0	0
22	0	1	0	0	0	0
Total Carted / Bought	5687	3363	274	3035	1552	120
Total	1000000	1000000	1000000	1000000	1000000	1000000

Table 5. The total amount of a certain recommendation type was carted or bought.

3.3.1 Linear regression analysis

A linear regression test was performed to evaluate which of the compared recommendation types will produce most purchases. As the situation for the three recommendations was not homogeneous in the first step (from shown to clicked) it is important not to make conclusions from related results. The linear regression was performed for original data and also to data edited to binary form. Binary form data was compared to see possible effect of purchase amounts. Because the most important knowledge was if something was purchased and with original data the amount of purchases during one session gave a possibility to distort the wanted results. The results can be seen in a Figure 1.

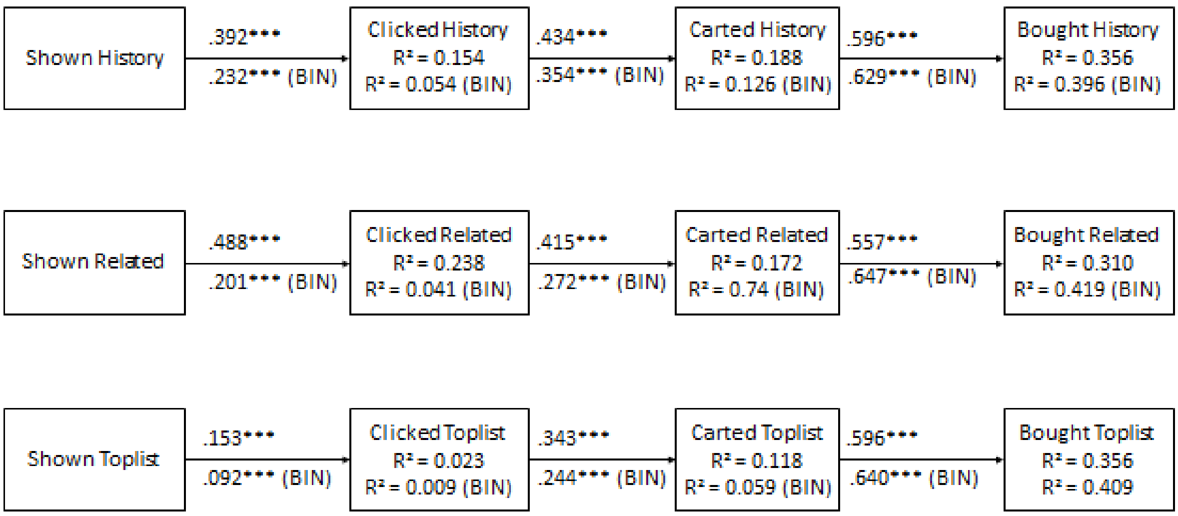

Figure 1. Results for linear regression analyzes.

For the original data the standardized coefficient between shown history related and clicked history related was $\beta = 0.392^{***}$ with $R^2 = 0.154$. Between clicked history related and carted history related $\beta = 0.434^{***}$ with $R^2 = 0.188$ and between carted history related and bought history related $\beta = 0.596^{***}$ with $R^2 = 0.356$. For the binary form data, the standardized coefficient between shown history related and clicked history related was $\beta = 0.232^{***}$ with $R^2 = 0.054$. Between clicked history related and carted history related β =354*** with $R^2 = 0.126$ and between carted history related and bought history related β = 0.629*** with $R^2 = 0.396$.

Standardized coefficient between shown item related and clicked item related was β = 0.488*** with $R^2 = 0.238$. Between clicked item related and carted item related β = 0.415*** with $R^2 = 0.172$ and between carted item related and bought item related β = 0.557*** with $R^2 = 0.310$. For the binary form data, the standardized coefficient between shown item related and clicked item related was β = 0.201*** with $R^2 = 0.041$. Between clicked item related and carted item related β = 0.272*** with $R^2 = 0.740$ and between carted item related and bought item related β = 0.647*** with $R^2 = 0.419$.

Standardized coefficient between shown toplist and clicked toplist was β = 0.153*** with $R^2 = 0.023$. Between clicked toplist and carted toplist β = 0.343*** with $R^2 = 0.118$ and between carted toplist and bought toplist β = 0.596*** with $R^2 = 0.356$. For the binary form data, the standardized coefficient between shown toplist and clicked toplist was β = 0.092*** with $R^2 = 0.009$. Between clicked toplist and carted toplist β = 0.244*** with $R^2 = 0.059$ and between carted toplist and bought toplist β = 0.640*** with $R^2 = 0.409$.

The toplist was the least effective when shown (0.153***), which can be explained by limited appearance. Also the difference between history and item related (0.392*** vs. 488***) could be because of the difference in appearance amounts and placements. However, the following steps can be directly compared as a starting situation is the same. After a recommendation was clicked the results were surprisingly similar. From clicked to carted the difference was from 0.434*** (history) to 0.343*** (toplist). Item related (0.415***) was very close to history recommendation. This suggested that the history and item related recommendations are clearly more effective (7.2-9.0%). The final step was even closer as history was even with the toplist with 0.596*** and item related was 0.557***. Thus the differences varied from 0% to 3.9%. Results were logical as the probability raises with every step, but also surprisingly similar. Also the toplist, which was the least effective until the final step was a surprise. R^2 was also consistent and raised towards the purchase action. As the total amount of the sessions were so large it is logical that R^2 was very low at the beginning and raised towards the end.

Binary values were included into the test (see Figure 1) to see if there was any effect with users who carted many items and only bought few or one. As it is known that a shopping cart is used often for organization, price comparison and also the total price is first seen in the cart it is no surprise that some products are abandoned, yet the important part, also some are still bought (see e.g. Kukar-Kinney & Close 2010). This could provide negative effect on carted to bought step, yet still the customer was actually making a purchase, which was the most important knowledge. As results shows there was some variations, but overall the results were similar. Binary provided smaller R^2 figures, which suggest that several customers either buy nothing or buy many products creating high variation in the sampling. As with binary format the transaction is simply yes or no (0 or 1) the regression line will have less relevancy.

Similar test was done using only sessions with ten or more page views. This limited the session numbers to 98 624 from one million. Idea was to clean out most of the users, who did not have enough page views to even buy anything or see enough recommendations. As expected those users did not click recommendations or purchased anything resulting no major effect on results, which were almost identical to already made test.

As the data was given for the study and control was limited there was some possibilities for uncontrolled situations. Example there was no total understanding which all variations were possible between clicked to carted and finally to bought items. By this reason one more test was conducted. A linear regression test for clicked to bought (carted step was skipped). As this gave no possibility for carting outside of recommendation (a same item) to affect to the results. These findings are presented in a Figure 2 in original and binary form.

Figure 2. Results for the linear regression when the carted step was excluded from the test.

As can be seen from the Figure 2 the results showed a greater amount of difference. History related recommendation provides most sold items after the recommendation is already clicked. The probability is 0.323*** (R^2 = 0.104) and in binary form 0.259*** (R^2 = 0.067). For item related recommendations figures were 0.228*** (R^2 = 0.052) and in binary form 0.185*** (R^2 = 0.034). Toplist was still the least effective with 0.168*** (R^2 = 0.028) and in binary form 0.161*** (R^2 = 0.026).

There is a great difference between the three recommendation types. The object of this study was to find if there was difference in efficiency between these three recommendation types, there clearly is. History related provided 9.5% more bought items than item related and 15.5% more than toplist recommendation. Thus item related was 6% more efficient than the toplist recommendation. Binary form results followed these, but the differences were smaller, especially item related and toplist were very close the difference was only 2.4%. This is expected as amount of purchases are eliminated. This could indicate that history related provides most customers purchasing several items, yet still provides most single purchase sessions. As item related and toplist are very close to each other's it indicates that item related is far superior to provide multi-item shoppers than the toplist, but to create a single purchase they are closely rivaled. These differences are major and can have a great effect on web store sales. R^2 figures were still very small as the variety and session amounts are both large.

Based on these tests it can be concluded that there are variations between the effectiveness of the recommendation types. The history related recommendation seems to provide most sold items. The item related was second effective and toplist was the least effective.

4 Discussion

In this research the bottom idea was to study recommendation types from a new perspective. A wide variety of papers have studied recommendation systems and the topic is very popular and current. Thus, the general research topics are related on what algorithm is the best or how algorithms differ from each other and what happens if different algorithms are combined. Also people's attitudes and trust (including privacy issues) toward RS have been widely surveyed. The idea was to compare three different recommendation types, and their effectiveness to achieve purchases, especially after the recommendations were already clicked.

The data was provided by a company selling recommendation engines for already made web stores. Thus the data was from a real life web store providing very valuable knowledge. The real life data is of course the best possible data format, but also the possibility to control it is more limited. Some factors were unknown since the company had to protect their customers' privacy. The company provided two data sets both including 500 000 individual sessions. The data was then explored and linear regression models were used for the analyses. Results showed very interesting variety between the three compared recommendations. The clicked-to-shown relation is also discussed here, but, as stated, no strong conclusions should be taken. The comparison was started after the recommendation was already clicked, thus the difference in appearance was taken into account. Steps from clicked-to-carted and from carted-to-bought are discussed in more detail.

4.1 Theoretical implications

The general research topics are related to what algorithm is the best or how algorithms differ from each other and what happens if different algorithms are combined (see e.g. Park et al. 2012). Also people's attitudes and trust (including privacy issues) toward RS are widely surveyed (see e.g. Schafer et al. 2001, Shyong 2006, Benbasat & Wang 2005). This study provided a new research avenue and showed that there are other than hidden aspects like algorithms affecting to web store users' persuasion of recommendation systems. As there is evidence that the location of a web page object does matter (Bernard 2001, Oulasvirta et al. 2005, Roth et al. 2010, 2013), now there are proofs that the type of recommendation is also very important.

4.1.1 Recommendation type comparison

The history related recommendation was the most effective for providing carted items. It is personal and informative. Possibility for impulsive buying is high since recommendation can show history related products and create a psychological need (Rook 1987). As long as attention is raised and clicks gained, it is logical that the most personal recommendation provides most of the carted actions with accurate recommendations, since history data and repetition is proven to create more positive attitudes towards products and create more purchases (Hansen & Wänke 2009, Rossi et al. 1996). History related could have a reactance effect as it is very personal and sometimes the range of recommended items can be limited, for example to old and not timely recommendations, thus lower the quality of recommendations (Benbasat & Wang 2005, Blanco-Fernández et al. 2008, Fitzsimons 2000, Fitzsimons & Lehman 2004, Schafer et al. 2001). This might also raise trust issues, but as the results suggest, none of these were a limiting factor.

The item related recommendation was the second most effective for providing carted items and was very close to the history related. This recommendation type is very informative for looked or searched item and the effectiveness was probably mainly based on a same attribute than with the history related. The knowledge of the user is not as good as with history related, but still area of interest is known, thus the possibility to lower a search cost is good and high possibility for impulsive buying is possible (see e.g. Ansari et al. 2000, Bakos 1997, Rook 1987, Senecal & Nantel 2004). Repetition can be used by offering similar products the customer has looked at. They can be accurate as recommendations are very directly controlled by the user's behavior during the session (Hansen & Wänke 2009, Rossi et al. 1996). The reactance effect seems to be low and literature suggests that the effect is mostly absent when a consumer can understand how the recommendation is created (Benbasat & Wang 2005, Schafer et al. 2001).

Toplist was the least effective from clicked to carted. Toplist has a great possibility to provide informative knowledge from the most sold products. This can create an impulsive shopping behavior and/or social influence like owning a popular item. It is also possible that a user simply trusts that the most sold items are the best overall choice (Burnkrant & Cousineau 1975, Gialdini & Goldstein 2004, Rook 1987). Also reactance could only come up from customers trying to avoid general products because feeling social pressure is for them a negative influence (Brehm 1966).

The last step from carted to bought was close between all the three recommendation types. Linear regression percentage is higher to buy a carted product than abandon it and also direct calculations from carted to bought amounts provided percentages over and under 50% depending of the recommendation type. These results are in line with old findings (see e.g. Close & Kukar-Kinney 2010, Rajamma et al. 2009) This also explains why the difference between all the recommendation types is minor, in this step the purchase intention is already strong, no matter what type of recommendation is used.

4.1.2 The most effective recommendation type

As the main target of this study was to find out which RS will achieve most purchases, also from clicked to bought was directly compared to see a greater difference. Now the history type was clearly the most effective recommendation type. People tend to buy similar items repeatedly; if you love to cook, you will buy kitchen equipment, if you love fashion, you will buy new clothes. This has been proven many times in marketing researches and can provide several times larger revenues than without target marketing. (see e.g. Rossi et al. 1996) History data can be used to recommend items from the same brand and brand loyalty has been proven to be very efficient method for increasing sales (see e.g. Chaudhuri & Holbrook 2001) History related RS will have a great amount of informational persuasion, but also psychological aspect as explained (see e.g. Hoch & Loewenstein 1991, Rook 1987, Thompson et al. 1990). It is proven that users who does click recommendations have a more complex flow through the web page (Senecal et al. 2005). As history related recommendations provide most complex recommendations, this could infer that it leads to more complex flow, which leads to more purchased items.

Item related recommendations is at the end very similar recommendation. It will recommend something a user is already interested and seeking, thus similar reasons are behind the buying decisions. The difference is based on better and more precise knowledge of the user for the history related recommendation. For example, the flow is most likely more complex for item related than with toplist recommendations, but less complex than with history related. Reactance effect should lower the power of history recommendation as literature findings suggests, but no proofs of that were found (Benbasat & Wang 2005, Brehm 1966, Fitzsimons 2000, Fitzsimons & Lehmann 2004, Schafer et al. 2001, Shyong 2006).

Toplist was clearly the weakest for providing purchased items. It is completely impersonal, so the informative aspect is very weak, only providing knowledge about popular items. This raises the possibility for social comparison as a positive effect (social approval), but also for negative affect (psychological reactance) (Asch 1956, Brehm 1966, Festinger 1954, Zhu & Huberman 2014). As findings show, toplist generates more sales, but is clearly less effective than history or item related recommendations.

To summarize, the findings suggest that everything is based on the knowledge of the user. After the attention is raised the more accurate recommendations will provide more purchases. Reasons behind it are that more information provides better recommendations, which can provide more informative and psychological persuasion. This confirms suggestions made by Lü et al. (2012). Possible reactance effect does not seem to be a problem.

4.2 Practical implications

From practical side, this research showed that there is still a good reason to use several recommendations on a web page because different situations limit the usability of certain types of recommendation systems. Thus, it is even more important to carefully choose positions, when a certain type of recommendation is shown, since the effect on sales can be significant. The results suggest that algorithms are important, but also more effort should be given to new aspects of researches. Also other studies support this (see e.g. Bernard 2001, Roth et al. 2010, 2013).

As toplist was clearly the weakest one, it should be considered when chosen its usage. For example, the front page recommendation slots are often used for toplist recommendations, since it suits all the users (new and old). This raises a question if user data is available, could there still be some better choices? In this study the front page toplist slot should be changed to a history or item related as soon as possible, since it should provide more sales. Also item related was the only shown recommendation on certain pages, these could be changed for history recommendations, which should result more sales. No proofs were found that any notable reactance occurred, thus at least in this case, more recommendations could still provide more sales.

Customers are nowadays bombarded with ads meaning the recommendations should be chosen carefully. Normally web stores use several different kind of recommendation types, which provides a good possibility to strengthen the efficiency of the used recommendation slots. As the difference between the best (history related) and weakest (toplist) were almost double, there is a great potential to increase usability of user knowledge-based recommendations. Only for new users (cold-start), without any information should toplist-style recommendations be shown. Even smallest amount of knowledge should provide better results as item related recommendations proved. According to this knowledge, a web store can achieve more sales and better competitive advantage by reducing customers' search costs.

4.3 Limitations and future research avenues

As to recap, the data was very rare real life data from the web store that was selling everyday products, from clothes to electronics. This is a great benefit when compared to open data from music and movie businesses. Still the limitations need to be kept in mind when evaluating the results and using this study as a guide for future researches.

4.3.1 Limitations

As already presented in detail in the data chapter (3.1) there was no possibility to affect to the data. This provided some possibilities for uncontrolled situations as uneven appearance for the different type of recommendations. Controlled situation in real life web store would be the ideal case. The company provided a good information about the web store, however it would have been better to know what the web store was and to have real life experience of it. Because sold items were products, results might not be useful for companies selling services.

There was also some ambiguity with the data between clicked to carted to bought action which was not totally clear. It seemed not to have significant effect on results and it should have gone negligible as clicked to bought was directly studied. It could have had a greater effect if single sessions would be compared, but as the study was contained over one million sessions some exceptions should have diminished.

It is good to be aware of possible cultural differences. This data was from a European web store, where most of the customers came also from Europe. There are proofs that this can have an affect (Kacen & Lee 2002).

4.3.2 Future research

This study provides a new base for a new avenue of researches. The amount of recommendation researches is very large, still certain areas are unexpectedly unstudied. More attention should be assigned to practical side of the recommendations. This study suggests it can provide a great benefit. Next step should compare different types of recommendations in equal situation and see what collects most clicks and raises the most attention. Findings suggest it would be history related recommendation, but it needs to be studied more. This could provide a best single recommendation type for a certain event. Very specific, detailed and controlled data would be needed as also can have an effect.

The amount of clicks is also very important knowledge, since it might not be closely related to the amount of purchases, but it shows what type is good for raising attention. This might be very valuable, for example for marketing purpose. Expensive products are not easily bought, but to spread the knowledge and availability might pay off later. Also can a name for a recommendation have an effect from psychological perspective. If same recommendations are offered with different names, will it provide different sales records?

In future, researches in this area will achieve new directions. As stated gamification is a hot topic at the moment and recommendations are very closely related. Researchers will try to improve current methods and algorithms for better quality of recommended items. Also new systems and methods will be developed to combine old systems to work better together. In future researches should focus more on how and when the recommendations are showed, not only to algorithms behind the interface. As this study proves also more tangible facts can have a significant effect.

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