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Development of a Framework for Recommendation Algorithms in E-Commerce Applications

Master’s Thesis

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supervised by
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AUTHOR’S DECLARATION

Unless otherwise indicated in the text or references, or acknowledged above, this thesis is entirely the product of my own scholarly work. Any inaccuracies of fact or faults in reasoning are my own and accordingly I take full responsibility. This thesis has not been submitted either in whole or part, for a degree at this or any other university or institution. This is to certify that the printed version is equivalent to the submitted electronic one.

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Signature
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ABSTRACT

Recommendation systems are an essential part in the personalization of the customer experience in e-commerce applications. For e-commerce businesses, recommendation systems increase sales and enhance customer satisfaction and loyalty. Recommendation systems attempt to suggest the most suitable products or services to particular customers based on previous purchases, individual preferences and various user interactions within an e-commerce application. This thesis focuses on recommendation systems in e-commerce businesses, which use machine learning algorithms to personalize the customer experience. A recommendation system framework is developed acting as a big picture of a holistic perspective from a technical approach. This thesis, presents an outline how recommendation systems work. Additionally, it focuses on various machine learning algorithms and data mining techniques applied in recommendation systems. The key success factors which positively influence the conversion rate in e-commerce applications are identified. On the basis of the framework, e-commerce operators, marketers and developers can derive implementation approaches for recommendation systems and approaches increasing sales in e-commerce applications. In order to ensure a structured approach to develop the framework, the Design Science Research of information systems research was used. The framework provides an overview of underlying algorithms, required data and relevant customer touchpoints, in which potential customers get in touch with recommendation systems within the customer journey of e-commerce applications. Finally, the individual components of the framework are compared using the recommendation system of Amazon.com to ensure the practicability of the framework.
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1 INTRODUCTION

“If I have 3 million customers on the Web, I should have 3 million stores on the Web.”
— Jeff Bezos, CEO of Amazon.com (Schafer, Konstan, & Riedl, 2001, p. 115)

Recommendation systems take an essential part of personalization in e-commerce applications to increase sales and to build up customer relationships. Based on past purchases, browsing history, individual preferences and user interactions within an e-commerce application, recommendation systems attempt to suggest the most suitable product or service to particular consumers (Jie, Dianshuang, Mingsong, Wei, & Guangquan, 2015). From a customer-oriented perspective, recommendation systems help customers to find the best solution.

Recommendations are used in many application fields including online shopping, movies, music, restaurants, news, social networks, job portals and many more (Akhil & Shelbi, 2017; Park et al., 2012). The following thesis focuses on recommendation systems in e-commerce businesses using artificial intelligence algorithms which include machine learning algorithms and data mining techniques to personalize the customer experience. (Li & Karahanna, 2015)

Many e-commerce businesses use already forms of artificial intelligence-driven recommendations to better understand their customers providing an enhanced customer experience. This level of intelligence is vital to deliver a personalized shopping experience for (potential) customers. Amazon makes recommendations to users depending on their activities on the site and past purchases. Netflix makes TV and movie recommendations based on a user's interaction with categories, e.g. drama, comedy and action. According to studies by McKinsey, 75% of Netflix viewer activity is driven by recommendation and 35% of Amazon's sales are generated through their recommendation engine. (MacKenzie, Meyer, & Noble, 2013)
For these reasons, recommendation systems have become a very interesting field of research and practice in the past decade. (Akhil & Shelbi, 2017; Park et al., 2012) The technological progress in computational power has made it possible to achieve enormous advances in the applicability of recommendation algorithms in the past years. Hence, many different approaches and algorithms have been developed making accurate and efficient suggestions for the consumer. (Park et al., 2012)

This work deals with the question how recommendation systems work, which data mining techniques and algorithms they use, and finally which key success factors can be identified in order to positively influence the conversion rate in e-commerce applications.

1.1 Motivation and problem statement

From the perspective of e-commerce operators, recommender systems are an important part of the business model. For example, 35 % of Amazon's sales are generated through their recommendation engine and 75 % of Netflix viewer activity is driven by recommendation (MacKenzie et al., 2013). Likewise, recommendations are responsible for more than 70 % of the time people spend watching videos on Youtube. (Solsman, 2018)

From the customers' point of view, the user experience in e-commerce applications is affected in many ways. The intense growth of information leads to a phenomenon known as information overload. E-Commerce shops like Amazon frequently offer thousands of products. Recommendation systems as information systems have to assess the relevance of the information to offer products or services of interest for particular customers. (Anand & Mobasher, 2005) In e-commerce, recommendation systems have the potential to influence customers' purchasing decisions. Proposals for movies, products and suggested friends on social networks are just some of the many influential recommendations. For this reason, recommendation systems have become a very interesting field of research in the past decades. (Akhil & Shelbi, 2017; Park et al., 2012)
The first research paper addressing recommendation systems was released in the mid 1990s. This was followed by many academic works. (Akhil & Shelbi, 2017) Due to the numerous application areas of such systems, many approaches, methods and algorithms have emerged, which should give the recipients the best possible recommendations. Technological progress made it possible to deal with large amounts of data. In the last decade, algorithms have received the computing power needed to generate predictions from big data. (Park et al., 2012) As a result, e-commerce recommendations have become more accurate than ever.

Due to these advances, many older academic contributions are considered as obsolete or no longer applicable. In addition, many researchers and practitioners focus on specific areas of application and advancements of recommendation systems to make even better predictions. The result is a very complex topic with many approaches in the academic field and practice to successfully implement recommendation systems. Furthermore, it becomes difficult for practitioners to choose specific machine learning algorithms or data mining methods when developing a recommendation system. (Portugal, Alencar, & Cowan, 2018) For this reason, an overview of currently applicable methods and techniques of recommendation systems should be given in this master’s thesis.

The rapid advances in technology, data mining methods and artificial intelligence make it difficult for e-commerce operators to gain an overview and understanding of the various capabilities and uses of recommendation systems. In order to be able to evaluate a possible use of recommendation systems a framework is developed.

1.2 Research question and objective

This master's thesis aims at developing a recommendation system framework. Within this framework, a fundamental understanding in which manner and logic recommendation algorithms influence the purchasing behavior of consumers in e-commerce applications will be created. Furthermore, the framework should provide an overview how recommender systems use machine learning techniques to influence the customer's purchase decision process.
On the basis of the framework, e-commerce operators, marketers and developers can derive concepts for recommendation systems and approaches increasing sales on e-commerce applications.

Research question: Which components of recommendation systems (data, user inputs, algorithms, data mining methods and user interfaces) can be identified?

To answer the research question research literature and studies on recommendation systems are analyzed. On this thesis, a framework for the functionality and the techniques of recommendation systems is iteratively being created.

Accordingly, a major resulting objective is the simplified presentation of the complex topic of recommendation algorithms and techniques in the form of the framework. While scientific papers often use in-depth special algorithms or underlying statistical methods, the following elaboration should convey a big picture of several perspectives and levels. Additionally, many papers focus on literature reviews classifying the work that has been done in science. This work aims to provide a deep understanding from the practical perspective using the recommendation system framework.

1.3 Methodological approach and structure

As part of the master's thesis, the Design Science Research of information systems research is chosen. The problem context addresses a topic of the discipline of information systems, which is part of the Design Science Approach. (Hevner, March, Park, & Ram, 2004) The Design Science Research defines itself as a construction-oriented method that focuses on the creation and evaluation of IT artifacts. (Geerts, 2011; Hevner et al., 2004) Within this thesis, the recommendation system framework represents the artifact. Figure 1 shows the individual components of the Design Science approach.

The Design Science Research tries to ensure the scientific foundation (rigor) as well as the practical relevance (by empirical studies) of the research results with an iterative approach and defined cycles. (Hevner et al., 2004; Wieringa, 2014)

In the first step, the problem of high complexity in research and practice is defined. In the generalized form of the Design Science approach, this is carried out with the help of an
environmental analysis to identify the need for research. Within this thesis, a detailed environmental analysis of all stakeholders is not carried out. The addressees of the recommendation system framework, especially e-commerce operators, have to carry out an environmental analysis for their individual business purpose. Nevertheless, the general business needs to be derived from this step are shown on the basis of empirical studies within the literature analysis in order to support the relevance of the topic.

Based on a systematic literature search, the artifact of a recommendation system framework, defined by the functionality and components of recommendations, is designed. The literature was found in the databases of Web of Science, Google Scholar, Science Direct, WISONET – WIWI, UNIKAT – University of Graz and EBSCO – Business Source Premier. The focus of the selected literature has been placed on peer-reviewed publications. In order to explain basic methods of recommendation systems, highly cited publications were included in the work. A further restriction has been made by limiting the selection of recommendation systems, methods, algorithms to the scope of e-commerce.

![Figure 1: Design science in information systems (Hevner et al., 2004, p. 80)](image-url)
The relevance cycle forms the interface between the environment and design science research. As a result of the findings of the problem domain, it provides possible requirements for the artifact, which show the current state of research of the artifact and provide possible implications for further research or confirmation of practicality. (Hevner et al., 2004; Wieringa, 2014). This step is mainly done in chapter two.

The rigor cycle connects the Design Science Research with the existing academic knowledge described here as a knowledge base. This is the purpose of the academic foundation of the work, but also the delimitation of existing research. This is to ensure that the new artifact is an innovation and does not merely replicate existing results. (Geerts, 2011; Wieringa, 2014) In this phase, the novelty and the link to previous scientific contributions of this thesis are defined with the help of the research.

The inner design cycle represents the relationship between artifact creation and evaluation. (Hevner et al., 2004)

As part of the development phase, an analytical procedure is chosen as the design evaluation method. In order to be able to specify individual framework components and criteria for the presentation and classification of the framework, the layer architecture of the software architecture common in software development is used. The 3-tier architecture can be used to illustrate the basic components of e-commerce applications. All 3 layers are part of recommendation systems modularizing the user interface, the business logic and the data storage layers. (Hirschfeld, 1996).

In addition, based on a qualitative content analysis, individual categories are worked out for the classification of recommendation systems at the various levels. (Mayring & Brunner, 2007) The framework is developed step by step covering the components for recommendations in the e-commerce area. The framework provides an overview of possible areas of application, underlying algorithms, required data and relevant customer touchpoints, in which potential customers come in contact with recommendation systems in the customer journey.

As a final step, the artifact is checked for its suitability (evaluation) (Hevner et al., 2004). The testing and evaluation of the created framework will be done using the e-commerce
platform best practice Amazon. The evaluation follows the created category system of the framework to prove its applicability. From this, success factors can be worked out for marketers and e-commerce practitioners to successfully introduce a recommendation system.

In order to present the approach of the thesis in a clear way, figure 2 gives an insight into the chapters and the individual results of the work.

<table>
<thead>
<tr>
<th>Recommendation systems in e-commerce (chapter 2)</th>
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<tr>
<td>Identification of areas of applications, benefits and potential of recommendation systems. Insights about key success factors of personalization of the customer experience through recommendations to prove relevance and the need for recommendation systems.</td>
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<th>Functionality and components of automated recommendation systems (chapter 4)</th>
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<tr>
<td>Sustain understanding how recommendation systems work and which machine learning and data mining techniques are used.</td>
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<th>Approach of recommendation system framework (chapter 4)</th>
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<td>Development of a framework which acts as a guideline to optimize the conversion rate in e-commerce applications.</td>
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<th>Evaluation of recommendation systems framework (chapter 5)</th>
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<tr>
<td>Prove of the applicability of the developed recommendation systems framework</td>
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*Figure 2: Structure of thesis and outcomes of chapters*

**1.4 Definitions and use of terms**

In literature, different definitions for the key terms of this thesis exist. The following definitions aim at clarifying the meaning and understanding of key terms in this thesis and give introductory notes.
Recommendation system

“An online recommendation system involves using information technology and customer information to tailor electronic commerce interactions between a business and individual customers” (Li & Karahanna, 2015, p.72) Recommendation systems attempt to recommend the most suitable product or service to particular consumers (Jie, Dianshuang, Mingsong, Wei, & Guangquan, 2015). In other words, such systems recommend products (such as movies, books, music, clothes) that consumers had not yet considered. (Jie et al., 2015; Sharma & Gera, 2013).

Machine learning algorithms

“Machine learning (ML) uses computers to simulate human learning and allows computers to identify and acquire knowledge from the real world, and improve performance of some tasks based on this new knowledge.” (Portugal et al., 2018, p. 2) The learning process is defined as knowledge acquisition. This process is a key element in recommendation systems. In general, computers learn with the help of algorithms. (Portugal et al., 2018)

Data mining

Data mining techniques are defined as „extracting or mining knowledge from data“ (Park et al., 2012, p. 10060). Data mining approaches are used to find interesting patterns in large amounts of data to derive new insights from this data. (Park et al., 2012; Schafer et al., 2001).

Artificial Intelligence (AI)

Artificial Intelligence (AI) enables machines to learn from experience, adapt to new incoming information, and master tasks that require human-like thinking. It is a field of computer science to solve cognitive problems of human intelligence. (‘Gartner IT Glossary’, 2018)

Artificial intelligence is frequently based on deep learning techniques and natural language processing. With these technologies, computers can be trained for very specific tasks by processing large amounts of data and recognizing patterns in these data. (Portugal et al., 2018)
Deep Learning

Deep learning techniques are a class of machine learning algorithms. They involve non-linear layers and complex model structures to identify relationships between elements. In the field of machine learning and artificial intelligence, the ability of deep learning relies on the system to recognize more relationships than humans could practically encode in software, or relationships that humans cannot even perceive. After sufficient training, the algorithm network can begin to make predictions or interpretations of very complex data. (Portugal et al., 2018)

Conversion Rate

Conversion in an e-commerce context is usually understood as the transformation of a visitor of an e-commerce application to a customer placing a product or service order (Li & Karahanna, 2015). In practice, it can simply mean a certain action like clicking on a banner. A conversion rate can refer to different situations. Actions, such as a click on a banner, subscribing to newsletters or a click on a specific product triggered by a recommendation can be a conversion. In this work, conversion rate is defined as the percentage of prospective buyers who become buyers when they visit a website.
2 RECOMMENDATION SYSTEMS IN E-COMMERCE

“A lot of time, people don’t know what they want until you show it to them.”

E-commerce recommendation systems attempt to recommend the most suitable product or service to particular consumers (Jie, Dianshuang, Mingsong, Wei, & Guangquan, 2015). The aim of recommendation systems is to reduce information overload by predicting consumer interest based on various machine learning algorithms and data mining techniques. The following chapter covers basic insights of recommendation systems, their application fields, their benefits and critical aspects and provides a first rough overview of the technologies used in recommendation systems.

2.1 Introduction to recommendation systems

Recommendation systems are one of the most successful and widespread applications of machine learning technologies in business. Recommendation systems have improved considerably over the years. Due to the lack of data available and intelligent algorithms they used to offer relatively inaccurate predictions of customers' behavior in the past. The systems have improved quickly with the computational power and artificial intelligence. (Konstan & Riedl, 2012) Nowadays, state-of-the-art recommendation systems use artificial intelligence methods to offer personalized recommendations (Portugal et al., 2018).

From the customer's point of view, recommendations are encountered in many ways in practice. Different e-commerce sites take different approaches where to place recommendations within the customer journey. But the technology behind recommendations is flexible enough to adapt to different use cases. Individualized offers are often shown by merely opening the homepage of the e-commerce application via a web browser. In the simplest form of recommendations, Netflix gives its users suggestions based on the most recent films and series watched when the user opens the Netflix start page. Amazon gives its customers product recommendations when looking at a specific
product depending on the activities on the site and past purchases. When viewing a product page, it is common to see “customers who bought this also bought”, or “frequently bought together”. Furthermore, often shopping carts define a chance to recommend users products or services in follow-up marketing efforts such as e-mails.

To help customers to find products or services that they want to purchase defines an essential part of turning them into customers. Brick and mortar stores have shopping assistants who can recognize the customer’s preferences taking their descriptions of what they are hoping to find. In a digitalized world, a recommendation system performs the work of a shopping assistant. The predicted interest in certain products or services is based on related information about the items, the consumer preferences and the interaction among consumers. (Jie et al., 2015; Sharma & Gera, 2013). Using machine learning algorithms, recommendations can perform in a much better way – and are often more accurate – than a human brain (Portugal et al., 2018).

In addition, all touchpoints and previous interactions with the company, as well as existing purchases can be analyzed to provide personalized recommendations to the customer in real time. The system learns customer’s preferences, buying intentions and shopping habits by using this knowledge and data from other buyers with similar characteristics to make personalized recommendations for products that are particularly relevant: Intelligent recommendation systems improve with each interaction, learn more about what's important to each individual customer, and can make more accurate suggestions that are more appealing. (Portugal et al., 2018)

2.1.1 Scientific assignment of recommendation systems

Recommendation systems are information systems that can be categorized into decision support systems because they are used in decision making and are intended to support other people instead of replacing them. (Burke, 2007)

Xiao and Benbasat (2007) point out that recommendation systems differ from traditional decision support systems in certain respects. The latter are aimed at managers and analysts, who use such systems to support various tasks, such as planning tasks.
Use cases of recommendation systems, on the other hand, address (potential) customers and face the preferential choice problem. (Xiao & Benbasat, 2007)

While decision support systems use process models, recommendation systems use choice models, which support the integration of decision criteria for the choice between alternatives. The latter also share similar properties with knowledge-based information systems. They should also explain conclusions or recommendations to their users in order to create trust among them.

Burke (2007) points out that recommendation systems are no information retrieval systems. Recommendation systems provide interesting product recommendations for the customer, while information retrieval systems provide content that match the user's search best. Such search engines present all matching products sorted by the degree of match. Search engines help us to find something we already know, while recommendation systems help us to find new products.

2.1.2 Recommendation systems’ application fields

Recommendation systems are frequently used in practice. The wide-ranging application fields include product recommendations in web shops, travel recommendations suggesting hotels and restaurants a customer might like, up to the matchmaking process of jobs or partner search. (Akhil & Shelbi, 2017; Park et al., 2012; Sharma & Gera, 2013)

Table 1 shows a classification according to the application domain and individual recommendation fields. The table makes no claim to completeness and deals with common fields of application in literature and practice. The structure according to the individual domains was aggregated according to similar characteristics and attitudes of the individual application fields.

In the application domain of media and content, news articles or articles in blogs on other web pages are frequently recommended (Marmanis & Babenko, 2009). Online streaming services such as Amazon Video, Netflix or the music streaming service Spotify can also be mentioned here.
Application domain | Recommendation field
--- | ---
Media and content | News, video on demand, music, web pages
Web shops | Clothing, electronic products, books and many more
Travel and real estate | Restaurants, events, hotels, flights
Job and education | Job offers, personalized education materials
Social media | Friends, corporate social pages
Services | Expert consultation, houses to rent, matchmaking services, e-learning applications
Advertising | Targeted advertisements

Table 1: Recommendation system application domains and fields (based on Akhil & Shelbi, 2017; Kordík, 2018; Marmanis & Babenko, 2009; Park et al., 2012; Ricci, Rokach, & Shapira, 2010; Sharma & Gera, 2013)

Recommendation systems in web shops focus on product recommendations. Especially from the point of view of an e-commerce operator, two fundamental questions arise: Which products could User X like? And which users might like product Y? One of the most successful operators of recommendation systems in e-commerce is Amazon. After a consumer shows interest or purchases an item, Amazon offers each consumer personalized recommendations that are similar to the item that they have just purchased or viewed. Additionally, features like “customers who bought this, also bought” are offered to the consumers. (Li & Karahanna, 2015; Schafer et al., 1999)

Recommendation systems are also used in the area of learning and education. (Ricci et al., 2010) The recommendation is directed, for example, in e-learning portals to learn videos that build on the knowledge level of the previously viewed and consumed videos or tutorials. In order to expand one's own network of friends in social media channels, friend recommendations are issued. The target group-oriented addressing of marketing measures on various channels is also based on the technologies of recommendation systems. (Akhil & Shelbi, 2017)
The focus of this paper is on business-to-customer (b2c) recommendation systems that are available to the end customer via e-commerce applications and are designed to achieve conversions.

### 2.1.3 Benefits and critical aspects

The use of recommendation systems brings advantages, but also potential risks. The identified aspects focus on e-commerce applications and look at them from the point of view of e-commerce operators and marketers.

Table 2 gives an overview of the benefits and risks that can arise from the use of recommendation systems.

<table>
<thead>
<tr>
<th>Benefits</th>
<th>Risks</th>
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<tbody>
<tr>
<td>Increase of conversion rate</td>
<td>Privacy</td>
</tr>
<tr>
<td>Increase of sales (up-selling, cross-selling, cart value)</td>
<td>- Data protection law restrictions</td>
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<tr>
<td></td>
<td>- Feeling of persecution</td>
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<td>- Security threat</td>
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<tr>
<td>Higher customer satisfaction through enhanced customer experience</td>
<td>Assignment errors of customer interactions</td>
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<td></td>
<td>Selling long tail products</td>
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<td></td>
<td>Changing purchasing behavior over time</td>
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*Table 2: Benefits and risks of recommendation systems (based on Anand & Mobasher, 2005; Konstan & Riedl, 2012; Lam, Frankowski, & Riedl, 2006; Li & Karahanna, 2015; Ricci et al., 2010; Salonen & Karjaluoto, 2016; Schafer et al., 1999; Sivapalan, Sadeghian, Rahanam, & Madni, 2014)*

The conversion rate can be increased by the high degree of personalization of the application. (Ricci et al., 2010) Personalized offerings turn browsers into buyers and boost sales on e-commerce platforms. (Schafer et al., 1999)

Cross-selling is improved by suggesting additional products or services to customers. (Schafer et al., 1999) This recommendation type is frequently done in the checkout process, based on the products or services in the shopping cart. Up-selling is achieved by bundling closely related items together. As a result, basket size increases. (Sivapalan et
al., 2014). According to a study by McKinsey, cross-selling increases sales by 20 % and profits by 30 %. (‘Targeted online marketing programs boost customer conversion rates’, n.d.).

A higher customer satisfaction can be achieved through a high level of personalization. Recommending products or services most suitable to particular customers speed up searches and save time for the customers. (Salonen & Karjaluoto, 2016) Finally, it has the potential to enhance the customer experience to easy access content a customer is really interested in. (Ricci et al., 2010) From the user’s point of view, it increases experience and creates engagement. For the business, it generates more revenue.

Recommendation systems also act as a customer relationship measure and contribute to customer loyalty. (Salonen & Karjaluoto, 2016) A high level of customer loyalty is essential, especially in businesses for easily exchangeable product offers among competitors (Sivapalan et al., 2014). Recommendation system create a value-added relationship between the marketer and the customer. Through the learning process of the customer’s preferences and interests, e-commerce applications are able to customize interfaces that match customers’ needs. (Schafer et al., 1999) Ultimately, switching costs are increased because the level of personalization is lost when switching to a competitor. The continuous calibration of the preferences of the user makes products become stickier to customers. Finally, by knowing what a user wants, the company gains competitive advantage and the threat of losing a customer to a competitor decreases.

Long tail products are non-popular items or items a customer may not be considered to buy. Recommendations help to sell more diverse products or services that might be hard to find without a recommendation. (Ricci et al., 2010)

Personalized recommendations require much data from customers in order to make recommendations. Potentially, more input data increases recommendation accuracy but also increases the violation of privacy. (Lam et al., 2006) Customers may start feeling that the e-commerce site knows too much about their true preferences. For example, there is the risk that a recommendation model learns information that the user wished to keep private. Salonen (2016) indicates that high personalization in online ads was found to increase feelings of intrusiveness and to harm business performance. They suggest that companies should only focus on customers who are willing to be profiled for
personalization, as even additional privacy features were not effective in increasing participation of the unwilling group. Finally, it could rise a feeling of persecution. Therefore, it is necessary to develop solutions that sensibly use user data. (Ricci et al., 2010)

Especially the General Data Protection Regulation (GDPR) introduced by the European Union restricts the collection, sharing and use of personal data. In other countries, for example the United States, law imposes only few restrictions for data usage and data reselling. (Anand & Mobasher, 2005) An important aspect for the protection of privacy is the protection of data gathered from customers' interaction within the e-commerce application. Encryption technologies and security techniques are used to protect against attacks to protect personal data. (Lam, Frankowski, & Riedl, 2006) It is a challenge to bridge the gap between personalization and privacy. Brands have to take transparency, security and honesty to an entire new level. Further studies can be made to analyze the barriers to recommendations systems in law.

Another problem is the unambiguous assignment of interactions triggered by customers. For example, the use of a profile of several people, such as family members, presents a challenge. This leads to a distortion of user behavior and preferences.

The problem of changing customer behavior over time states another issue for recommendation systems. Preferences change, tastes vary from time to time and changing purchasing behavior arise inconsistency in the user profile. Therefore, a strategy has to be worked out to separate long-term preferences and short-term interactions of users. (Konstan & Riedl, 2012)

### 2.2 Intelligent recommendation technologies

Recommendation systems use state-of-the-art technologies to generate recommendations for individual users. Machine learning describes the learning process

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1 A detailed understanding of the technical structure and the functionality of algorithms and data mining methods is covered in chapter 3.
about the interests and preferences of users. This process is realized with algorithms and models. Data mining techniques define procedures that are used to analyze large amounts of data and recognize patterns in data in order to provide relevant recommendations. Artificial Intelligence is the leading construct of automated recommendation systems, which sees machine learning and data mining as a sub-discipline. Artificial intelligence tries to solve problems from the point of view of human intelligence.

2.2.1 Machine learning algorithms

“Machine learning (ML) uses computers to simulate human learning and allows computers to identify and acquire knowledge from the real world, and improve performance of some tasks based on this new knowledge.” (Portugal et al., 2018, p. 206)

Machine learning is a collection of algorithms that can learn from data and make predictions based on recorded data. The learning process is defined as knowledge acquisition. This process is a key element in recommendation systems. In general, computers learn with the help of algorithms. Basic machine learning algorithms use known training data to predict unknown data. For example, training data consisting of books are classified with attributes and other related information. The machine learning algorithm learns with the training data. New books are classified based on the knowledge about the training books. (Portugal et al., 2018)

Machine learning is often used where explicit programming is too rigid. Unlike computer code, which is developed by software developers to produce output based on a given input, machine learning uses data to produce statistical code that outputs the "correct result" based on a pattern recognized by previous examples of input. The accuracy of a machine learning model is mainly based on the quality and quantity of the historical data. (Portugal et al., 2018)

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2 To be noted, the term “user” is selected with regard to a technical level used in recommendation techniques or algorithms context. The term “customer” is chosen from the perspective of e-commerce. However, there is no distinction in the terms.
2.2.2 Data mining techniques

Data mining techniques are defined as „extracting or mining knowledge from data” (Park et al., 2012, p. 10060). Data mining approaches are used to find interesting patterns in large amounts of data to derive new insights from this data. (Park et al., 2012; Schafer et al., 2001).

From an e-commerce perspective, data mining discovers relationships between items and users (Schafer et al., 2001). For example, a customer purchases a particular product on a web shop. Data mining approaches find relations between the purchase of items indicating the purchase of another or that a particular product is now more likely to be bought. The recommendation system suggests the consumer the related products based on the mining output.

2.2.3 Artificial intelligence-driven recommendations

Marinchak et al. (2018) define artificial intelligence (AI) as a field of computer science dedicated to solve cognitive problems commonly associated with human intelligence. AI solves complex problems with human intelligence such as learning and pattern recognition. It applies advanced analysis and techniques, including machine learning.

AI-based e-commerce recommendation systems understand items (like products or services) and users at a level that goes beyond the traditional use of tags, classifications or algorithms that are simply based on the behavior of other buyers. It learns more about a customer’s taste with each interaction, so that e-commerce sites can increasingly make personalized recommendations based on the habits and preferences of each individual. (Marinchak et al., 2018)

Likewise, assistants based on artificial intelligence can be regarded as an area of application in e-commerce. Chatbots are text-based dialogue systems that allow chatting with technical systems. In addition, virtual shopping assistants can be used to give recommendation systems a personality. (Marinchak et al., 2018)
2.3 Personalization of customer journey through recommendations

From a customer-oriented perspective, recommendation systems focus on the construct of personalizing the customer experience in e-commerce applications. Personalization is generally regarded as a high effective tool for achieving business success on the Internet. (Salonen & Karjaluoto, 2016).

“The goal of personalization is to provide users with what they want or need without requiring them to ask for it explicitly.” (Mulvenna, Anand, & Büchner, 2000, p. 43). The Personalization Consortium (2003, as cited Liang, Lai, & Ku, 2006, p. 47) defines personalization as “the use of technology and customer information to tailor electronic commerce interactions between a business and each individual customer”.

E-commerce is speeding up and modifying the behavior of the interaction of businesses with their customers, the shopping behavior or watching movies online. To stay competitive, e-commerce operators need to provide different products or services to different customers. (Sivapalan et al., 2014) Recommendation systems allow fast and automated personalization and customization of e-commerce sites. (Sivapalan et al., 2014)

Data mining and machine learning techniques form the basis for personalization in web applications. Those techniques build models of user behavior to predict user needs and deliver personalized future interactions in e-commerce. (Anand & Mobasher, 2005)

2.3.1 Personalization impact on customers

Literature and studies have paid a lot of attention to the impact of recommendation systems. Impacts concern effects on customers' perceptions, intentions and on the customer decision making process purchasing a product or service. (Li & Karahanna, 2015; Liang & Chen, 2012)

Many studies use the Technology Acceptance Model (TAM), proving that recommendations increase the perceived usefulness towards the e-commerce system. Furthermore, perceived benefits of using a specific e-commerce system are present.
Liang et al. (2012) indicate that personalized recommendations reduced the time and effort in searching and buying products or services. In addition, studies found that personalized recommendations increase the trust and finally positively influence customer long-term relationships. (Li & Karahanna, 2015)

Further studies have shown that personalized recommendations influence the purchasing decision process (Ho, Bodoff, & Tam, 2011; Li & Karahanna, 2015). Users are more satisfied with the recommendations and are more likely to accept them if the personalized recommendations are presented at an early stage of the online customer journey. This means that there is a need for personalized offers within several decision stages like initial product searching or offering related products based on previous clicks on e-commerce applications. (Ho et al., 2011) This means that the timing of the offer of personalized recommendations is crucial.

Building on the theories of human information processing in decision making according to Huber and Seiser (2001, as cited in Ho, Bodoff, & Tam, 2011), the impact of recommendations on all four decision phases (attention, cognitive processing, decision and evaluation) of the product purchase are involved. They found that personalized offerings and the relevance of recommendations (i.e., the accuracy of recommendations) significantly affect consumers' perceptions in all four decision phases. In particular, highly personalized recommendations were perceived by consumers as more useful than random offers and reduced the cognitive burden on consumers when making purchasing decisions. (Ho et al., 2011)

These findings support the results of the studies on the problem of information overload on the Internet. Liang et al. (2006, p. 64) point out that „reducing the information overload is the most important concern for users in seeking information”.

2.3.2 Degree of personalized recommendations

Personalization is an essential component in recommendation systems. In order to distinguish between personalized and non-personalized recommendations, Schafer et. al. (2001) have pointed out different dimensions of personalization.
The degree of personalization encompasses the accuracy and usefulness of recommendations which are both important (Schafer et al., 2001). It has be noted that quality measures like the accuracy of recommendation algorithms are discussed in the following chapters. The following list in table 3 is sorted in ascending order according to the degree of personalization.

<table>
<thead>
<tr>
<th>Degree of personalization</th>
<th>Personalized recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generic</td>
<td>The same products are presented to every customer. These are completely non-personalized recommendations. The recommendations are based on statistical summarization or manual selection. As an example, e-commerce applications show recommendations of top-sellers, editor’s choices or average ratings. (Schafer et al., 2001).</td>
</tr>
<tr>
<td>Demographic</td>
<td>All members within a defined target group receive the same recommendations. Demographic data like age, gender or location within user profiles are used to divide customers into different target groups. (Szczepaniak &amp; Niewiadomski, 2005)</td>
</tr>
</tbody>
</table>
Recommendations are based on current customer activity. They appear in the customer navigation or on product information pages. (Schafer et al., 2001) It provides recommendations that are responsive to interaction of the customer within the current online session (Schafer et al., 2001).

As an example, Amazon's "Customers who ..." are List recommendations. This type of personalization is temporal, but above non-personalized recommendations.

Recommendations are based on long-term customer interests and require consistent identities from customers. This type defines the most personalized experience to create recommendations and are individualized for each customer even when they are looking at the same products or service. (Schafer et al., 2001)

While ephemeral recommendations are based on a current session, they deliver different recommendations on every web page but the same for all customers. Persistent recommendations use customer's behavior and preferences using the history of interactions on different touchpoints with the customer. This form of full-personalization can only be achieved with logged in users. (Szczepaniak & Niewiadomski, 2005)

The process of personalization consists of learning the customer preferences and aggregating the collected knowledge into personalized offers, recommendations and several versions of interaction touchpoints. (Salonen & Karjaluoto, 2016)

| **Ephemeral** | Recommendations are based on current customer activity. They appear in the customer navigation or on product information pages. (Schafer et al., 2001) It provides recommendations that are responsive to interaction of the customer within the current online session (Schafer et al., 2001).
As an example, Amazon's "Customers who ..." are List recommendations. This type of personalization is temporal, but above non-personalized recommendations. |
| **Persistent** | Recommendations are based on long-term customer interests and require consistent identities from customers. This type defines the most personalized experience to create recommendations and are individualized for each customer even when they are looking at the same products or service. (Schafer et al., 2001)
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The process of personalization consists of learning the customer preferences and aggregating the collected knowledge into personalized offers, recommendations and several versions of interaction touchpoints. (Salonen & Karjaluoto, 2016) |

*Table 3: Degree of personalized recommendations (based on Salonen & Karjaluoto, 2016; Schafer et al., 2001; Szczepaniak & Niewiadomski, 2005)*
Whether and to what extent recommendation systems can issue personalized recommendations depend on the customer or product models. As long as the model has not been created, no personalized recommendation can be generated. (Schafer et al., 2001)

2.4 Recommendation influence on the customer experience

Products and services are linked to an experience. This also applies to the interactions with a company.

In literature and practice, there is often no distinction between customer and user experience. But the two terms are not the same. However, both take a central stage in e-commerce applications. The customer experience is an integrated approach affecting not just one department or process in a company. In other words, it is not a concern of a single customer touchpoint, it is a matter of the entire company. (Meyer & Schwager, 2007) The user experience describes the user experience of a particular online touchpoint. It reflects a person's experiences as well as feelings while using the service, for example, the usability of the company's website interface. (Meyer & Schwager, 2007)

The customer experience tries to encompass every aspect of the company's offering, including the process of seeking products or services, the purchasing process itself, the advertising or the ease of use of e-commerce applications such as a web shop or online streaming portal. (Meyer & Schwager, 2007)

Following these definitions, the customer experience has to be ensured on all touchpoints and channels. Customers tend to revisit e-commerce applications if they were satisfied with the provided customer experience. Even if there is a similar product or service offer by a competitor, customers are more likely to return to the known experience they have previously made and do not want to go through a learning process what they like or not. (Sivapalan et al., 2014)

Recommendation systems take a critical role, as data inputs about past purchases, preferences, interests and other customer interactions that need to be aggregated across multiple channels. Finally, recommendations should be made based on all available
information about the customer in order to achieve high accuracy and usefulness of the recommendation.

### 2.4.1 Customer analytics to enhance customer experience

The analysis of customer data and customer behavior is becoming more and more important. By the use of machine learning and data mining techniques merchants are able to adapt in real time to current preferences of the customer. (Ho et al., 2011)

Technological advances have brought a paradigm shift in marketing and the way customers are approached. In traditional mass marketing, products were pushed one-way and marketing campaigns were designed with a catch phrase and slogans. (Marinchak et al., 2018) Furthermore, traditional mass marketing and mass production was based on static customer segments. Demographic data like age, gender or income were used to determine whether products or services are needed by the target group. (DeAsi, 2017)

Today, e-commerce practitioners cannot make assumptions about the interests, needs, desires or values of individual customers based solely on who they are, or based on a Persona they have assigned to them solely on demographic or qualitative grounds. (Marinchak et al., 2018)

The digital age is responsible for a dramatic change when companies want to find out whether a product or service is bought by a specific customer. E-commerce is getting away with segmenting customers into groups to personalize the customer experience by using static attributes like demographics. Technological progress made it possible to better understand “who” the customers are. Customer profiles are created by data analytics. As a result, personalized experiences and personalized products or services can be offered on e-commerce sites. (DeAsi, 2017) Marketing campaigns and ads are shifting towards personalization and digitization, enabled by increasing algorithms. (MacKenzie et al., 2013)

Successful e-commerce operators like Amazon, Netflix or Zalando have largely laid out their business logic to analyze data (DeAsi, 2017). They know that the key to understanding their customers can be more what they do and how they interact with the company. These insights show that by knowing the customers’ behavior, one is able to
provide a more accurate picture of what the customers want and need, and how and when it can be best delivered to them.

Advanced analytics can be used to make offers and decisions that are targeted, localized and delivered in real time by recommendation systems. These offerings and decisions should be informed by product preferences and influences for example for consumers who liked or reviewed a product on the web shop. (MacKenzie et al., 2013)

2.4.2 Data intelligence within the omnichannel customer journey

Through digitalization an increasing number of data points within the customer journey are available on e-commerce applications (Salonen & Karjaluoto, 2016).

Customers live in an omnichannel world. Products are purchased through various channels. Information about products and the search can be done through multiple online and offline channels. This requires an integrative approach to gather useful information from all touchpoints between customers and the company. (Thiel, 2018)

Marketing recommendation systems represent an integrative approach to link the marketing activities of a company with recommendation systems. They act as an approach to connect stored customer information of all touchpoints and sales channels of the company with an e-commerce recommendation system. (Mocean & Pop, 2012) Whether it is a mobile application, the company’s web shop, or an email campaign, marketing recommendation systems are continuously monitoring all devices and channels to create a holistic customer view. This unified customer view enables e-commerce retailers to deliver a seamless customer experience across all platforms within the entire customer journey.

With the quality of a holistic customer profile and the underlying preferences, buying behavior and other interests, the possibilities and accuracy of personalized recommendations increase (Thiel, 2018).

To ensure a holistic experience across all touchpoints of the enterprise, patterns must be found across a large number of data points. The complexity and importance of connecting data and information from different systems defines a core task of an integrative recommendation system.
Intelligent web personalization leverages all available information about user's behavior, interest, previous purchases and other interactions to deliver a personal experience. The intelligence within the personalization process is achieved through data mining.

In addition to customer-related data, intelligent recommendation systems take into account other data sources from various enterprise information systems. For example, customers expect precision in geolocation data, inventory data or arrival dates. (Flaherty & Kaley, 2018) Intelligent recommendation systems only consider available and relevant products or services in real-time. As an example, only products that can be delivered to the customer's region, products in the fashion area that are in stock in the preferred size or movies that are available in the preferred language are recommended. As a result, a personalized customer experience can be offered to the customer at any point within the customer journey.
3 CLASSIFICATION OF AUTOMATED RECOMMENDATION SYSTEMS

This chapter deals with the functionality and types of recommendation systems and provides insights into how the recommendation process works.

In accordance with the design science approach, this chapter ties with the current knowledge base in literature and practice on recommendation systems. State-of-the-art recommendation systems are classified using a predefined structure.

The presentation of the individual phases of the recommendation process provides an initial overview about the functionality of recommendation systems and the associated components. The used methods and techniques are presented in detail in the following subchapters. They consist of the classification by filtering methods, recommendation types and data mining techniques. This classification of the structure and components of recommendation systems is finally used in the design of the framework in the following chapter.

3.1 Phases of the recommendation process

At the beginning of a customer relationship, e-commerce operators know little about the preferences and interests of their customers. An intelligent recommendation system must be able to learn from users and collect data about their tastes and preferences. Over time and with enough data, machine learning algorithms can be used to perform useful analyses and provide meaningful recommendations.

The essential basis for recommendations is, therefore, data that must be collected, stored, analyzed, trained and filtered into recommendations in a defined process. (Shearer, 2000)

The following phases of the recommendation process are identified based on the Cross-Industry Standard Process for Data Mining (CRISP-DM). The reference model offers a blueprint of data mining related projects. (Shearer, 2000)
Figure 3 shows the six phases of the data mining process including business understanding, data understanding, data preparation, modelling, evaluation and deployment. In the following, the reference model is applied to the data mining process of recommendation systems.

![Phases of CRISP-DM process model. (Shearer, 2000, p.14)](image)

### 3.1.1 Business and data understanding

The business and data understanding phases include the definition of business objectives, data mining goals and success criteria for the recommendation system. (Shearer, 2000) For example, the increase of conversions within the e-commerce application can be defined within these stages. Furthermore, a deep understanding of the data required and data which are used within recommendations has to be ensured.

In detail, this phase determines which data and information about customers can be collected from an economic and technical point of view. For this purpose, all customer touchpoints on different channels are analyzed. The products and services offered are analyzed to identify similarities and other factors between items (Shearer, 2000).

The output of this phase is a profound understanding of the possibilities and objectives of implementing recommendation systems.
3.1.2 Data collection and preparation

The data preparation phase includes the collection, storage, transformation, filtering and analysis of the data needed for recommendations. (Geyer-Schulz & Hahsler, 2002; Google Inc., 2016; Isinkaye, Folajimi, & Ojokoh, 2015)

Data collection

Data collection is responsible for generating user profiles and models, including user’s attributes, demographics, prior product purchases, or other interactions (e.g. clickstream data) of the resources the user accesses on different touchpoints. (Li & Karahanna, 2015) Two main types of data collection are distinguished: (Isinkaye, Folajimi, & Ojokoh, 2015)

- Explicit feedback: includes explicit input by users showing their interest
- Implicit feedback: is gained through observation of user behavior and interactions

Hybrid feedback can be seen as the combination of both explicit and implicit feedback. Therefore, a recommendation system collects user data based on explicit inputs or implicit behavior. Accurate user profiles and models form the basis for obtaining relevant and accurate recommendations from any prediction technique. (Isinkaye, Folajimi, & Ojokoh, 2015) A detailed comparison of the data and knowledge sources can be found in chapter 4 within the recommendation systems framework.

Data storage and transformation

The storage and transformation of data include the process of data cleaning, transformation and integration into permanent storages like databases. (Shearer, 2000).

In the run-up, rules are set up in which formats and constructs data are stored in databases. These tasks are usually carried out by data analysts who have comprehensive knowledge of data mining methods and recommendation types in accordance with the business objectives. In addition, data constructs are created that are further used in filtering methods and data mining techniques. In order to create data constructs, data records and attributes are defined for this purpose. (Google Inc., 2016) Attributes represent, for example, records of past purchases made. Based on the recommendation
type, different data records and attributes are transformed. (Shearer, 2000) For example, web usage mining data is collected by observing the behavior of users browsing in an e-commerce application on the web. Effort has to be put on data preprocessing, cleaning and transformation. Problems involve the identification of users, dynamic IP-addressing or inconsistent data. For example, collaborative filtering techniques consist of explicit ratings by users. Data preparation discovers and removes inconsistent ratings to transform them into a representable format for data mining. (Geyer-Schulz & Hahsler, 2002)

Data filtering and analysis

The filtering approach of a recommendation defines on which data the particular recommendations are based. It defines a further basic decision is the choice of methods of recommendations. Recommender systems are generally classified into collaborative filtering, content based filtering and hybrid recommendations (Park et al., 2012).

The basic filtering methods serve as a starting point for numerous data mining approaches and recommendation types. Filtering methods give a generic view of the subject of recommendation systems. Furthermore, different types of recommendations describe which focus is on a particular recommendation and on what data it is based. These are described in detail in the section filtering techniques.

In close connection with the selected filtering technique are various possibilities of data analyses and their time factor from a technical point of view. The type of data analysis considers the time factor of how quickly data are needed to be present to the users. Mainly three types can be distinguished: (Google Inc., 2016)

- Real-time systems are able to process data in the same moment as it was generated. This type of system usually includes tools that can process and analyze data streams. This is required to give users in-the-moment recommendations clicking on a particular product.

- Near real-time analysis, data can be collected quickly so that analyses can be updated every few minutes or seconds. Such a system might be good for making recommendations during the same browser session.
• Batch analyses require periodic processing of the data. A batch system could work well to send an email with product recommendations at a later time.

3.1.3 Modeling and evaluation

The modeling phase describes the technical matchmaking process of delivering recommendations to customers. According to Li and Karahanna (2015) the key task is to “accurately identify the products and services that match consumer’s profiles as identified in the previous stage.” At this point artificial intelligence and machine learning algorithms come into the point of interest.

The first step is to define the modeling technique. Several data mining techniques can be used to find interesting patterns in the data set for recommendation purposes. (Shearer, 2000) The output of the data mining process could be patterns like items that are frequently bought together or groups of customers with similar interests or similar purchasing behavior. (Geyer-Schulz & Hahsler, 2002)

Machine learning is used within this “learning phase” to build a model of input data, to analyze data with data mining techniques, to make predictions based on the data and to evaluate the relevance or accuracy of the model. (Koren, Bell, & Volinsky, 2009)

The evaluation of mining models is frequently done by machine learning methods. A common way is to evaluate the performance of several models to divide the data basis into a set of training data, with known output, and a test data set for evaluation of the model. (Geyer-Schulz & Hahsler, 2002) The model created on the basis of the training data is applied to the test data records. The respective classification result is compared with the real experience value. If there is a match, the accuracy of the model increases because the data set was correctly predicted. (Google Inc., 2016; Isinkaye, Folajimi, & Ojokoh, 2015)

Machine learning algorithms and data mining techniques are discussed and classified in more detail in the following sections. Additionally, metrics for evaluation of the predictive power of recommendations are presented within this chapter.
3.1.4 Deployment and presentation

The deployment phase presents recommendations on the front-end of the e-commerce application. (Koren, Bell, & Volinsky, 2009)

From a customer-oriented perspective, customer touchpoints with recommendations are defined in the entire customer journey of the e-commerce application. Recommendations can, for example, be presented as soon as a web shop is opened in a browser. Suggested products are displayed based on purchasing behavior of the individual customer. By clicking on specific products, similar products can be displayed or by searching for specific products, already viewed products can be prioritized for a particular customer. (Geyer-Schulz & Hahsler, 2002)

A detailed analysis of the user interfaces and points of contact with recommendations is carried out directly in chapter 4.

3.2 Classification of filtering methods

Recommender systems are generally classified into collaborative filtering, content based filtering and hybrid recommendations (Park et al., 2012; Sharma & Gera, 2013).

In general, collaborative filtering uses an information filtering technique based on the user’s previous evaluation of items or history of previous purchases. In contrast, content-based filtering approaches recommend items to users based on the knowledge about the products and users. Content-based recommendations are based on interest profiles and descriptions of items. Hybrid techniques try to overcome the disadvantages of both to combine filtering methods to deliver better results. (Akhil & Shelbi, 2017; Park et al., 2012).

Moreover, there are multiple modifications common in literature and practice (Li & Karahanna, 2015). These include: (Aggarwal, 2016; Ricci, 2011)

- non-personalized filtering: recommendations are issued equally to all customers
- knowledge-based filtering: recommendations are made on the basis of expertise
- demographic filtering: recommendations are based on socio-demographic data
In the following classification only methods of collaborative filtering, content-based filtering and hybrid filtering are considered. The restriction is based on decision criteria of practical suitability in e-commerce and a minimum degree of personalization, which can be fulfilled by state-of-the-art recommendation systems through machine learning and artificial intelligence.

3.2.1 Collaborative filtering systems

In collaborative filtering systems, behavior patterns of user groups are evaluated to determine the interests and preferences of individuals. The underlying assumption of collaborative filtering is that, if two users have the same preferences for similar products, they agree on other products as well. The aim is an automatic prediction (filtering) of users’ interests.

3.2.1.1 Data sources

Subsequently, the core idea is to gain knowledge about the user by different types of interaction. User feedback has an important role in this process. Two main types of feedback can be distinguished:

**Explicit feedback** relies on personal input from the user. To mention some options for explicit feedback, the user can rate items, submits comments or opinions on products, fill in forms or click buttons with predefined actions. The bottleneck is that consumers often do not spend a lot of time on detailed feedback. Furthermore, only few users leave explicit feedback like ratings (Kumar & Agneeswaran, 2018). It must be considered that the quality of the recommendation depends on the quantity of the ratings and reviews. (Isinkaye et al., 2015)

**Implicit feedback** does not require an interaction by the user during the process of constructing profiles. It automatically updates as the user interacts with the e-commerce application. The system automatically monitors consumer behavior, e.g. the time spent in the web shop or the navigation history. (Sharma & Gera, 2013) The quality of the recommendation is defined by the user behavior and implicit interaction with the e-commerce application. The main advantage of implicit feedback is that this method does not require effort from the user, but generally, it is less accurate than explicit feedback based recommendations. (Isinkaye et al., 2015).
3.2.1.2 Methods of collaborative filtering

As described before, recommendations require the collection and transformation to “learn” from the gathered data. The learning process can be classified into memory-based filtering and model-based filtering. (Anand & Mobasher, 2005)

**Memory-based filtering** calculates similarities between products or users and recommends items with the highest similarity. In a memory-based approach, algorithms make use of the complete consumer and item database. Users or items are compared with statistical methods like similarity measures. The statistical methods identify neighbors who have similar characteristics for example with correlations. (Akhil & Shelbi, 2017)

The most popular measures are correlation-based and cosine-based. For example, the Pearson correlation coefficient is the basic correlation algorithm for rating information. It tries to measure how two users differ from their normal ratings of products or services. If two users vary in the same way they have rated items in common, they get a positive correlation, otherwise, they get a negative correlation. Cosine similarity is based on linear algebra rather than statistical approaches. It is widely used in text mining to compare two text documents or explicit feedback from users. (Isinkaye, Folajimi, & Ojokoh, 2015)

Memory-based filtering can be achieved by user-based and item-based techniques. (Isinkaye, Folajimi, & Ojokoh, 2015) **Item-based filtering** calculates the similarity between items. It builds a model of all items rated by a user in form of a user-item matrix. It computes how similar the items to a target item are and selects the most similar items. The relationship is formed based on the frequency that same items appear in shopping carts. As a result, the items are predicted to have a close relationship. User-based techniques build a relationship between users based on similar ratings on the same items or similar purchase behavior. (Sarwar, Karypis, Konstan, & Reidl, 2001) Then, the predicted rating for an item is computed as a weighted average of the ratings where weights are the similarities of users with the target item. (Isinkaye, Folajimi, & Ojokoh, 2015) If a group of users has similar interests and behavior, this approach has a very high probability of acceptance. It is considered as one of the very successful approaches of recommending items in e-commerce to users. (Akhil & Shelbi, 2017)
In contrast to memory-based approach, the **model-based filtering** method uses the user database to learn a model. Models are trained by algorithms. The goal is to find latent factors that can describe observations. The predictions are based on these models. Data mining techniques like Bayes networks or clustering are used to make predictions. Model-based techniques analyze the user-item matrix to identify relations between items. (Akhil & Shelbi, 2017; Isinkaye et al., 2015)

A widespread application of model-based filtering is matrix factorization. For example, it is used by Netflix in the recommendation of films and series. (Koren, Bell, & Volinsky, 2009)

In its basic form, matrix factorization characterizes both items and users by vectors of factors within a matrix. A high correspondence between item and user factors leads to a recommendation. These methods have become established in recent years by combining good scalability with high predictive accuracy. (Ghosh, 2018; Koren, Bell, & Volinsky, 2009) With the help of machine learning algorithms, users are matched with individual preferences and interests by calculating similarities within a user-item matrix. Their relationship is defined with groups of users called “neighborhood”. A user receives recommendations to products or services that were already positively rated by users in his or her neighborhood. (Isinkaye, Folajimi, & Ojokoh, 2015)

As shown in figure 4 the task is to predict the user’s rating of a specific item that the user has not given yet. Latent factors represent missing values in the matrix. With Netflix, empty matrix fields represent films or series that the user has not yet viewed and therefore no evaluation is available. The goal of matrix factorization is matrix completion. For the prediction of the rating, the algorithm has to find similarities between items and users. (Koren, Bell, & Volinsky, 2009)

![Figure 4: Collaborative filtering matrix factorization (based on Sharma & Gera, 2013)](image-url)
A well-known learning method to find latent factors is the alternative least square (ALS) algorithm. The equations resulting from the matrix can be solved with the ALS algorithm. (Sharma & Gera, 2013) The process is based on analyzing large amount of user data. The challenge consists of matching a set of users that are most similar to a set of items that are most similar to a given item. As a result, the algorithm makes predictions for each entry in the matrix expressed in a rating scale. (Marmanis & Babenko, 2009; Sharma & Gera, 2013)

3.2.1.3 Use case scenarios

A popular usage scenario is the feature “customers who bought this item also bought” in e-commerce web shops. Summing up, collaborative filtering methods create recommendations based on user ratings and transaction or purchase data. In practice collaborative filtering is able to achieve high predictive accuracy in the interest of consumers and buying behavior. (Gigimol & Sincy, 2016)

A disadvantage is that products are only suggested to others if it has already been rated enough by other users. This is decided by the algorithm. Only then a similarity can exist. Likewise, users who cannot be assigned to standard behavior of consumers are difficult to predict and provide a possibly poor accuracy. (Balabanović & Shoham, 1997; Gigimol & Sincy, 2016)

The benefit of collaborative filtering is that no domain-knowledge is necessary. Recommendations can be shown without a deep understanding of item or user profiles. Personalization is achieved through using insights of the customer behavior and interaction. Furthermore, recommendations of new “genres” of products or services are possible. In contrast to content-based methods, recommendations of new products with similar attributes are suggested. (Kumar & Agneeswaran, 2018)

A challenge for collaborative filtering methods is the cold start problem. It deals with the problem that explicit or implicit user feedback is needed, to produce recommendations. If there is no interaction in the past, for example, for new customers visiting the e-commerce application, no items will be recommended.
Furthermore, the sparsity problem deals with the poor accuracy when there is little data about explicit user feedback. The lemming effect names the problem that popular items are recommended more often than new or long tail products. (Kumar & Agneeswaran, 2018)

### 3.2.2 Content-based filtering

Content based filtering approaches recommend items to users based on the knowledge about the items and users. Differently to collaborative filtering techniques, recommendations are made upon interest profiles of users and descriptions of items. (Akhil & Shelbi, 2017)

#### 3.2.2.1 Data sources

The data sources of content-based filtering basically consist of item profiles and user profiles. Item profiles are based on attributes and description options of products or services. For example, a similarity between movies can be described by actors, language, genre, directors or other predefined keywords or tags describing the content or attributes of a specific movie. (Sharma & Gera, 2013) In smaller e-commerce applications, profile attributes can be assigned manually. For large providers such as Netflix or Amazon, automated machine learning algorithms are used to create profiles for new products.

User profiles display general demographic data or specified preferences. Products already purchased or viewed by an individual user are also included in the profile. In contrast to collaborative filtering methods, such profiles are created without interaction data or behavior data of other users. (Akhil & Shelbi, 2017)

A central challenge of content-based filtering methods is to ensure the understanding of similarities and correlations of products and users.

#### 3.2.2.2 Content-based filtering process

The generalized process of content-based filtering is shown in figure 5. First, attributes are added to each item. Item profiles are defined by adding product information and attributes to the particular item profile. (Sharma & Gera, 2013)
Then user profiles are built by preferences, demographic data (e.g. age, gender, occupation) and other related user information. Therefore, this step is defined through gathering user information. In the next step, commonly occurring attributes among users are weighted and assigned to users. The preference model scores the similarity based on the attributes and user profiles. Combining the two profiles the recommendation system computes the utility for the user resulting in a recommendation. (Akhil & Shelbi, 2017; Sharma & Gera, 2013)

The recommendation system uses machine learning algorithms to induce a profile of the users’ preferences based on the descriptions of items. The similarity is computed from item attributes. (Kumar & Agneeswaran, 2018)

Standard data mining techniques like logistic regression, clustering, support vector machines and decision trees are applied for making predictions. (Akhil & Shelbi, 2017; Isinkaye et al., 2015). Further, similarity measures based on item features can be applied. Vector spaces calculate the distances between items based on a predefined set of features like product category or price ratio. TF-IDF is a feature extraction algorithm is a text mining method, where item features are extracted automatically. (Jannach, Ludewig, & Lerche, 2017)

3.2.2.3 Use case scenarios

In practice, when text documents such as web pages, publications and news are to be recommended, a content based filtering technique is most successful. (Isinkaye et al., 2015) Web shops frequently use content-based filtering methods in the form of "you might
like that too" or “products related to this item”. On individual product pages, which are clicked by the user, products with high similarity are suggested.

The disadvantage is that the accuracy of the recommendation depends on the existing knowledge about the user and item metadata (Gigimol & Sincy, 2016). One of the key tasks is to organize user profiles and descriptions of items very well, before recommendations can be made. Thus, the effectiveness of content-based filtering recommendations depends on the availability on the accuracy of the profiles. (Isinkaye, Folajimi, & Ojokoh, 2015)

Beyond, content-based filtering methods are applied to e-commerce operators with a large number of product offerings. Amazon or Netflix make use of content-based filtering, mostly in combination with collaborative filtering, to compute the most similar items within a product set. (Kumar & Agneeswaran, 2018)

One advantage is that recommendations are made independently of the behavior of the users. Similarities between products or services usually do not change as often as the behavior compared between two users. (Kumar & Agneeswaran, 2018) The difficulty is the task of defining properties and attributes for products as properly as possible. For complex products such as pictures, the definition of similarity characteristics is a challenge. (Kumar & Agneeswaran, 2018)

### 3.2.3 Hybrid filtering techniques

Hybrid approaches combine collaborative and content-based filtering approaches to leverage synergies between them (Sharma & Gera, 2013). They combine the advantages of both and try to overcome the limitations of each filtering technique. Hybrid filtering techniques offer the opportunity to achieve a better accuracy. (Felfernig et al., 2014)

Hybrid recommendations solve the issue of collaborative filtering of cold the start problem by leveraging both collaboration and content. (Kumar & Agneeswaran, 2018). Furthermore, the challenge of defining useful content descriptions and attributes in content-based filtering methods in complex product domains like music, videos or images can be solved with a hybrid approach.
A disadvantage is the high complexity of the implementation of a hybrid system (Kumar & Agneeswaran, 2018). From an economic point of view, practical combinations of filtering methods must be defined in line with the customer journey. From a technical point of view, recommendation systems must be developed in a flexible way that different filtering methods, data mining techniques and recommendation types can be applied together.

<table>
<thead>
<tr>
<th>Hybridization method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighted</td>
<td>Scores of several recommendation techniques are combined to receive a single result. Individual scores of collaborative and content-based recommendations are summed up.</td>
</tr>
<tr>
<td>Switching</td>
<td>The system switches between different techniques depending on the current customer touchpoint and requirements.</td>
</tr>
<tr>
<td>Mixed</td>
<td>Recommendations from different recommendation methods are presented at the same time.</td>
</tr>
<tr>
<td>Cascade</td>
<td>The cascade hybridization technique applies an iterative refinement process in constructing an order of method preference among different items.</td>
</tr>
<tr>
<td>Feature combination</td>
<td>Features from different data sources are put together into a single recommendation algorithm. For example, a content-based system receives additional information about similar interests of two users used in collaborative filters.</td>
</tr>
<tr>
<td>Feature augmentation</td>
<td>Output from one filtering method is used as an input feature to another method.</td>
</tr>
<tr>
<td>Meta-level</td>
<td>The model learned defines the input to another model applied.</td>
</tr>
</tbody>
</table>

*Table 4: Hybrid filtering techniques (based on Burke, 2007; Felfernig et al., 2014)*
Over the years, a number of hybrid approaches have been developed, most of which attempt to address the weaknesses of a single system. Burke (2007) and Felfernig et al. (2014) mention seven ways of combining different components of recommendations shown in table 4.

It should be noted that the combination of previous methods are the most common ones in literature and in practice. (Felfernig et al., 2014) There are many hybrid techniques and adaptive filtering methods that have been developed in the recent past. For example, knowledge-based recommendations do not primarily base on item ratings or item descriptions. This filtering method relies on deep knowledge about offered items. The semantic knowledge uses information about consumer and product lifecycle concerns. For example, user preferences can change within years without being detected by classic recommendation approaches. (Patil, Deshpande, & Potgantwar, 2017)

3.3 Classification of recommendation types

Recommendation systems can be distinguished between types of the recommendation. Recommendation types describe what the input data are based on, and which data are needed to successfully recommend items to consumers. They build decision support which data mining techniques can be used in the next step of the recommendation process.

3.3.1 Non-personalized recommendations

Non-personalized recommendations are based on product ratings of customers, who already purchased the particular product. Preferences and other related user information are not used within this type. Thus, recommendation is based on what other consumers have said about the product. The recommendations are independent where each consumer receives the same recommendation. (Schafer et al., 1999)

These recommendations are straightforward and require very little effort to produce. (Sivapalan et al., 2014) Non-personalized recommendations represent a weak form of collaborative filtering methods. (Sharma & Gera, 2013)
3.3.2 Personalized recommendations

Personalized recommendations are automatic and base on the customers’ preferences from an e-commerce perspective. Personalization is achieved through building consumer profiles and preferences. Favorited movie genres, colors, or other related information are used in content-based filtering methods. In collaborative filtering methods personalization is achieved through the monitoring of individual user interactions and behavior. The accuracy of personalized recommendations depends on the quantity and quality of the information about the consumer. (Sivapalan et al., 2014)

3.3.3 Attribute-based recommendation

Attributes are added to products or services (items) within an attribute-based recommendation. The items can be described with various features and attributes. If the consumer manually searches for a certain type of product in an e-commerce application, the attribute-based recommendation system is triggered. (Sivapalan et al., 2014) For instance, if a consumer searches for an action movie, the web shop offers recommended action movies for the consumer. Content based filtering methods make use of item profiles made out of item attributes.

3.3.4 Item-to-item correlation

The item-to-item correlation is based on similar items a consumer was interested in. Recommendations are based on clicks or shopping carts on what products the consumer has in it. For instance, if a consumer places several products in his shopping cart, the recommendation system recommends complementary products with a high item-to-item correlation. (Schafer et al., 1999; Sivapalan et al., 2014) The correlation between items can be calculated through various statistical methods and data mining techniques. (Sivapalan et al., 2014) Association rules are frequently used in this approach, which is explained in more detail in the next section. Mainly, content-based filtering use item-to-item correlations.
3.3.5 People-to-people correlation

People-to-people recommendations find similarities between consumers. The correlation is based on statistical methods and data mining techniques as well. It recommends products to consumers who have purchased or have shown interest in the same particular product in the past. It is mostly used in collaborative filtering, since it is dependent on previous purchases or ratings. (Schafer et al., 1999; Sivapalan et al., 2014)

3.4 Classification of data mining techniques

Intelligent recommendation systems include data mining techniques. Regardless of the previously selected filtering method, different data mining techniques can be applied in a next step.

This chapter gives an overview of data mining techniques used in the context of recommendation systems. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

3.4.1 Bayesian networks

Bayesian networks are classification methods that assign a “class” to each data set. It is a probabilistic methodology for solving classification problems. The assignment to classes is determined with the highest probability. (Jie et al., 2015)

Classes for new data are predicted based on the model. The model includes training data where the output is already known. In machine learning, a “label” was added to the training data with known output. For instance, the training set consists of single consumers. For each item in the database the feedback of the consumer is added. The label is a binary decision variable with {0} like or {1} dislike. The labelling is made with the so-called Bayesian classifier. It develops a model based on training data (Isinkaye et al., 2015; Park et al., 2012; Schafer et al., 2001) Such classifiers are more simple than other methods providing understandable simple labels. If the training data set has a very high quality, the predictions are able to have a high accuracy for unseen data. (Isinkaye et al., 2015)
The advantage is that Bayesian networks are easy to implement. With each new dataset, the model learns and classifiers become more accurate. (Jie et al., 2015)

However, there are disadvantages in using Bayesian classification. All attributes used in the model are weighted equally and are independent from each other. Therefore, it is not possible to create complex relationships about purchasing behavior and preferences. A so-called "overspecialization" can also occur. The model is adapted too much to the training data and does not provide useful results for new data. (Akhil & Shelbi, 2017)

3.4.2 Decision trees

Decision trees are a very common classification technique. In the course of the training of the model, decision trees are derived from the analyzed observed values. The observations (or elements) to be classified consist of attributes and their target value. The nodes of the tree can be decision nodes or leaf nodes. In decision nodes, a single attribute value is tested to determine which branch of the subtree it applies to. Leaf nodes specify the value of the target attribute. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

The construction of a decision tree takes place through a recursive process. The process starts at the root node with an input record. An item attribute is selected as a split attribute at each node. For each possible value, child nodes are created and the parent set is divided among child nodes so that each child node receives as input set all elements that have the corresponding values corresponding to that child node. (Gershman et al., 2010)

Rules can be derived from decision trees in the form of "If the customer clicks on the same product more than once within a week, he will buy this product with a probability of x \%". In order to derive rules, the attributes of the tree are split. This creates a tree structure of levels. The split by attributes is done according to the best predictive power of the attribute. The impurity measure, Entropy, is calculated as an indicator for each attribute. The attribute with the lowest Entropy value is used for the split.
Decision trees can be used for different filtering methods. In collaborative approaches, for example, explicit feedback such as ratings can be used. The attributes can describe the user, such as age, gender, and occupation. Attributes can also describe the items, for example, weight, price and color. Rating is the target attribute by which the decision tree is classified. Based on the training set, the system attempts to predict the rating of elements for which the user has no rating and recommends the elements with the highest predicted rating to the user. (Gershman et al., 2010)

Decision trees are also used in content-based filtering methods. A separate decision tree is created for each user, which is used as the user profile. The functions of each element are used to create a model that explains the user’s preferences. Even complex decision trees can be created using hybrid filtering methods. (Gershman et al., 2010)

Decision trees are easy to interpret and can be easily parallelized. These properties are particularly useful for large amounts of data and increase the performance and speed of calculations. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

3.4.3 Artificial neural networks

An Artificial Neural Network solves complex patterns inspired in the architecture of the biological brain. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

A neural network is able to learn and self-organize. The networks learn tasks by considering examples without programming of a specific rule. The connections between the so called “neurons” are weighted based on the influence one has on another. Such networks have the ability to identify complex relationships in data. (Isinkaye et al., 2015)

It consists of input nodes and output nodes which are calculated using mathematical functions. Within the neural network, hidden layers take into account the complex weighting of attributes, presented similar to a tree structure.

Neural networks are therefore a form of deep learning. In deep learning, a computer model learns how to perform classification tasks directly from images, text or acoustic data. Models are trained using extensively classified data and multi-level neural network architectures.
Neural networks can be used in both main types of filtering techniques. The main application area represents the automated processing of complex objects, which is used as an example of content-based filtering for classifying features and creating item profiles. For example, the network learns how to identify specific products within images by analyzing images that were previously manually labeled as specific products. With this prior knowledge, the neural network automatically identifies relevant products. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

### 3.4.4 Support vector machines

Support vector machines (SVM) classify data with the principle of regression analysis. Regression analysis makes predictions based on the linear dependency of variables. It has emerged to a powerful technique both for regression and classification. As a result, associative relationships between items can be predicted or tested. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

SVM learn a hyperplane that separates the data in a way that the margin is maximized. (Min & Han, 2005) In a simplest version, SVM classify two classes of data. With a linear hyperplane as a decision boundary, some data are assigned to class A and other data to class B. It can be useful to identify trends within datasets. (Amatriain et al., 2011; Isinkaye et al., 2015) Support vector machines are frequently used in model-based collaborative filtering techniques.

Non-linear models can also be solved with the help of SVM. SVM have a similar behavior in the classification of data like Bayesian networks. However, SVM are used to calculate the separation of classes drawn with the hyperplane. Bayesian Networks work with predefined classes and assign objects.

### 3.4.5 Ensembles

Ensemble methods are meta-learning methods designed to produce better predictions by combining multiple mining models. The use of ensembles is common in practice. It allows to combine hybrid techniques. Ensemble classifier construct a set of classifiers from the training data set and predict the class labels by aggregating their predictions.
As a result, ensembles combine independent classifiers of a similar classification. For example, by using a combination of different interaction types (e.g. explicit and implicit feedback types of consumers), ensembles are able to make accurate recommendations (Amatriain et al., 2011)

To generate ensembles, several approaches are possible. The most common are Bagging and Boosting. Bagging combines multiple predictions from regression or classification models. The individual predictions are weighted equally, and the average of the predictions is determined at the end. The decision which class the data record is assigned to is therefore made after a majority decision. Boosting focuses more on previously misclassified data. Unlike Bagging, weights can change at the end of each boosting round. Data records that were wrongly classified will increase their weights. Boosting thus merges several weak classifiers into a strong classifier. (Amatriain et al., 2011)

Ensembles can be applied to any hybridization techniques. Boosting algorithm is often used to combine preferences, for example, to produce movie recommendations in a collaborative filtering setting. (Amatriain et al., 2011)

3.4.6 Linear regression

Recommendation systems use regression analyses when two or more variables are systematically connected by a linear relationship. The regression analyses the relationships between a dependent variable and one or more independent variables. With regression, predictions can be made from the context of recommendations. Beyond, regression analysis can test systematic hypotheses about relationships between variables. Trends within datasets can be evaluated. (Amatriain et al., 2011)

Linear regression is based on an optimization problem. The regression analysis searches for a straight line to which the individual data sets are as close as possible to each other. An equation describing the relationship between the attributes is established. (Amatriain et al., 2011)

A more detailed description of the equation and solution method of linear or non-linear regression is not given here. In the context of recommendation systems, linear
regressions play a subordinate role. Often, machine learning methods or methods that take complex learning methods into account are used.

### 3.4.7 Association rule mining

Association rule mining is a data mining technique to discover interesting relations between items in large databases. (Isinkaye et al., 2015). It is common in shopping cart analysis of many applications and web shops. It focuses on finding rules that predict the occurrence of transaction rules. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

The a priori algorithm is used for association analysis. It is used to find useful relationships in transaction-based databases. The algorithm establishes so-called association rules. In order to recognize frequent product combinations, two basic steps are carried out of finding frequent combinations (item sets) and deriving frequent rules. Two key measures are used for this. The “minimum support” is the lowest limit of the probability that a certain product combination can be found in all transactions. This means that uninteresting and rare combinations can be excluded at an early stage. For instance, the combination of \{Product A, Product B\} was found frequently in shopping carts. Rules can be established on the basis of the combination. The lowest limit of frequent rules is calculated with the “minimum confidence”. (Anand & Mobasher, 2005) The association rule has shown that consumers who buy product A and B are also likely to buy Product C. As a result, the rule \{A, B\} → C is defined. Therefore, association rules are very well suited to recognize patterns in data (Isinkaye et al., 2015).

### 3.4.8 Cluster analysis

Clustering is be assigned to unsupervised learning. It assigns items to groups with similar attributes. The goal is to discover meaningful groups that exist in the data. The similarity is determined using a distance measure. The goal of a clustering algorithm is to minimize the distances between intra-clusters while maximizing the distances between inter-clusters. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

Clustering techniques identify groups of users with similar preferences. Groups are formed into clusters. (Park et al., 2012; Schafer et al., 2001) Once the clusters are
created, the opinions of other users within a cluster are averaged. Recommendations to individual users are based on the cluster. It has to be noted that clustering usually offers less-personal recommendations than other related methods. (Isinkaye et al., 2015; Schafer et al., 2001)

Various clustering algorithms have been used, including algorithms such as K-means for item and user-based clustering (Anand & Mobasher, 2005). K-means forms a previously known number of k groups from a set of similar objects.

Furthermore, other similarity algorithms can be used to determine clusters. The generic principle is to define the nearest neighbors based on computing the distance between consumers or items (Schafer et al., 2001) The nearest neighbor technique represents a typical collaborative filtering based recommendation system. First, a user profile is constructed through data like preferences, user ratings or other relevant purchase information. The next step involves machine learning techniques to discover neighbors. The nearest neighbor classifier finds the closest points from the training data set. Then it assigns the prediction data to the same class designation of its nearest neighbors. (Amatriain et al., 2011) Neighbors have shown similar behavior in the past. The final step defines the prediction which product the user is most likely to buy by analyzing the items, which neighbors were interested previously. (Felfernig et al., 2014; Park et al., 2012)

Clustering approaches are commonly used in model-based collaborative filtering methods. Collaborative filtering pursues two approaches to clustering. These are item-based and user-based clustering. In user-based clustering, users are clustered according to the similarity of their ratings of items. In item-based clustering, items are grouped based on the similarity of all users' ratings. The recommendation system can calculate the similarity of an active user profile with each of the discovered user models represented by cluster centroids. The highest matching centroid is used to create a recommendation similar to that used in user-based collaborative filtering. (Anand & Mobasher, 2005)
3.5 Classification of recommendation system’ evaluation

A challenge is the evaluation of the data mining model based on the filtering method and the created data mining model. (Konstan & Riedl, 2012) Providing accurate recommendations is the desired output of any recommendation system. Recommendations that are perceived as useful and relevant from the customer’s perspective are able to increase the conversion rate within e-commerce applications. (Li & Karahanna, 2015) In general, two types of recommendation system evaluations are discussed: online and offline approaches.

3.5.1 Online evaluation approaches

Online evaluations are done in the real business world. They focus on consumers’ evaluations of personalized recommendations. With online methods, user reactions are measured given the recommendations made. For example, it is measured when the user clicks on recommended items or measures directly the conversion rate of specific recommendations. The disadvantage is that “real” data from the business context must be gathered from customers and transactions. (Anand & Mobasher, 2005) The disadvantage is that those experiments like A/B testing run in the production system. A failed experiment likely has a direct negative impact on revenue or user experience.

In addition to this, measures like user satisfaction or utility of particular recommendations are considered. (Li & Karahanna, 2015) These can be queried with the help of survey techniques. However, it is difficult to clearly delineate these metrics, as they are highly complex and dependent on several influencing factors. For example, customer satisfaction can consist of customer experience parameters, can be expressed in customer loyalty or in the customer lifetime value. (Anand & Mobasher, 2005)

Therefore, online evaluation of recommendation systems remains a challenge due to the lack of understanding of what factors are affecting a successful recommendation.

3.5.2 Offline evaluation approaches

Offline evaluation approaches are ideal for experimental stages, since the user is not directly involved, and unlike online methods, the system has not to be deployed. The data
is split into training and test datasets. Training data will be used to construct the system and the test set is part of the evaluation. (Isinkaye et al., 2015) The type of metrics used depends on the type of filtering technique. (Isinkaye et al., 2015). Two main categories of metrics are presented: accuracy and coverage.

**Accuracy** is the fraction of correct recommendations out of the total possible recommendations. Metrics for measuring the accuracy of recommendation filtering systems are divided into statistical and decision support accuracy metrics.

Statistical accuracy metrics evaluate accuracy of a filtering technique by comparing the predicted ratings directly with the actual user rating. These metrics are commonly used in collaborative filtering with explicit feedback like product ratings. Metrics are the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Correlation. MAE is the most commonly used measuring the deviation of recommendation from user’s specific value. The lower the MAE, the more accurately the recommendation systems predicts user ratings. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

For implicit feedback decision support accuracy metrics are frequently used. The most popular metrics are Precision and Recall. Precision is the fraction of recommended items that are actually relevant to the user, while recall can be defined as the fraction of relevant items that are also part of the set of recommended items. In other words, Precision measures the relevance of a recommended item, Recall measures the probability a relevant item is selected. (Isinkaye et al., 2015). Next to accuracy, the coverage of a recommendation system can be evaluated. **Coverage** is the percentage of items for which the recommendation system is able to generate a recommendation. For example, predictions may be impossible if no users of only few users rated an item. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

A proper strategy to evaluate the chosen filtering method or data mining technique models is to consider both online and offline evaluation methods. In test mode, the algorithms of the models can be used with metrics for offline evaluation. If these have passed the tests, online methods can be continued in productive system in order to achieve the business key performance indicators. (Anand & Mobasher, 2005)
4 APPROACH OF RECOMMENDATION SYSTEM FRAMEWORK

The development of the recommendation system framework represents a central point of this thesis. Findings from the previous chapters are now used to develop the approach of a framework for e-commerce applications.

First, the methodological approach to develop the framework is described. This is described using the 3-tier architecture of software artifacts. Finally, categories and components of the framework are defined in order to be able to give a big picture about the functionality, methods and key success factors on all 3 layers.

4.1 Methodological approach

The framework gives a big picture of a holistic perspective from an technical approach on individual components and key success factors of recommendation systems in e-commerce applications. On the basis of the framework, strategic and implementation decisions on recommendation systems for e-commerce operators and marketers are to be facilitated.

The framework is an artifact according to the Design Science approach (Hevner, March, Park, & Ram, 2004). Individual framework components are derived from the literature. For this purpose, qualitative content analysis is used. (Mayring & Brunner, 2007)

The structured qualitative content analysis defines a coding guide to develop the artifact using pre-defined criteria. In the context of recommendation systems in e-commerce applications, the coding guideline defines the architecture and its components of an e-commerce application. The coding guide consists of the 3-tier architecture, which allows a presentation view, logic view and data view on recommendation systems. Individual framework components are worked out for the classification of recommendation systems on the basis of the 3-tier architecture following a top-down approach. (Hirschfeld, 1996)
This is done following a bottom-up approach. Individual components of the 3-layers are worked out step-by-step on basis of the literature analysis. Architecture levels addressed in respective papers or studies can be used as components of the framework.

4.2 3-tier architecture

In order to be able to specify individual framework components and criteria for the presentation and classification of the framework, the layer architecture of the software architecture common in software development is used. The architecture of the e-service is presented using a 3-tier architecture. The 3-tier architecture is used in client-server applications. It modularizes the user interface, business logic and data storage layers. (Hirschfeld, 1996)

It has to be taken into consideration that in software development there are far more flexible architectural patterns, such as the microservices architecture (Raj, Raman, & Subramanian, 2017). In the current context, a layered architecture is not used for the technical development of e-commerce software. Rather, the basic architecture is evaluated in the context of recommendation systems in e-commerce on these layers. The selected 3-layer architecture thus represents a high degree of suitability for the selected context. (Raj, Raman, & Subramanian, 2017).

The **presentation tier** is the front-end layer of a web application. The graphical user interface (GUI) is accessible through a web browser and renders the content and information of an e-commerce application. (Raj et al., 2017). The presentation layer is built on technologies such as Java-Script, HTML5 and CSS technologies. The front-end records user interactions to collect data for personalized recommendations.

The **logic tier** contains the business logic of an application (Raj et al., 2017). In a recommendation systems context, machine learning and data mining techniques are often used that can analyze data and build recommendation models.

The **data tier** consists of the database and data access layer (Hirschfeld, 1996). Technologies like MySQL are used for the data storage system. The storage is accessed by the logic tier to apply machine learning and other data analyses.
In order to better understand the three tier-based recommendation system architecture, a customer-journey oriented recommendation process is presented.

Chapter 3 already explained the recommendation and data mining process from a technical point of view. As shown in figure 6, the tasks are performed by a holistic perspective on the recommendation process. In order to be able to create customer-centric recommendation systems, a generic insight into the functionality of the recommendation process on all three layers is now given. In order to get from technical point of view in detail to the big picture of the recommendation process, the recommendation system is regarded as a black box. This is based on the concept of service blueprinting. The blueprint is adapted to the recommendation systems context illustrating the recommendation process. (Kumar & Agneeswaran, 2018)

The service blueprint visualizes the processes and relationships between different components of a service - the recommendation process. Key elements define the frontstage actions within the customer journey, backstage actions and support processes. (Lynn Shostack, 1982)

The interaction with potential customers is represented within the frontstage customer journey of the service blueprint. They describe the line of visibility within the service blueprint. (Esch, Kochann, & Schneider, 2016). All possible customer touchpoints with recommendation systems are assigned to the service blueprint from the customer's point of view. The main questions answered within the service blueprint are whether there are customers involved and which components are necessary to deliver the personalized recommendation. (Lynn Shostack, 1982). Customer actions are activities and steps that a customer performs while interacting with the application. (Esch, Kochann, & Schneider, 2016) The presentation layer includes the GUI of the e-commerce application where users can interact using web browsers.

Backstage actions are performed outside the customer's field of vision. The logic layer forms the basis here. The logic layer consists of the recommendation system including data mining techniques and machine learning algorithms to train models.
Support actions represent the storage and preparation of the data base in the data layer. The data layer includes the database and input data from interactions with individual users.

Figure 6: Recommendation system process (based on Kumar & Agneeswaran, 2018; Schafer, Konstan, & Riedl, 1999)

With reference to the recommendation blueprint shown in figure 6, users interact with the e-commerce application via the web browser. For example, individual products can be searched for, clicked on or configured in a web shop. Requests are then sent to the web server. The recommendation system is now activated and performs the necessary computations and tasks to provide recommendations. (Kumar & Agneeswaran, 2018) These include machine learning algorithms and data mining techniques to deliver personalized recommendations back to the user via the web server. Preferences, inputs and interactions are stored in the database based on the previous interactions of the individual user. (Schafer, Konstan, & Riedl, 1999) They are provided to the machine learning model. The core task is to learn from the new data the model already learned in order to improve the accuracy of the predictions whether a customer might like or not. With the updated information about the user, the updated model is automatically transferred to the recommendation system and can be used for future recommendations. (Kumar & Agneeswaran, 2018)
4.3 Framework architecture

The architecture of the framework is determined by the components that are assigned to the 3-layers.

4.3.1 Data and knowledge layer

Recommendation systems need to gather various kinds of data in order to model and provide recommendations (Ricci et al., 2010). The data and knowledge layer requires a deep business and data understanding. Data from various sources are gathered to the recommendation system.

4.3.1.1 Data sources

Recommendation systems require input data on which recommendations are based. The usage of different data types indicates an indication which data mining approach or machine learning algorithm can be applied.

As shown in table 5, the following data sources can be distinguished: user data, transaction data and items data (Ricci, Rokach, & Shapira, 2010; Schafer, Konstan, & Riedl, 1999; Sivapalan, Sadeghian, Rahanam, & Madni, 2014)

User data

E-commerce applications that do not use user data about the targeted customer can only make non-personalized recommendations. User data enable recommendations based on the customer’s individual interactions and preferences. (Schafer, Konstan, & Riedl, 2001)

Subsequently, the core idea is to gain knowledge about the user by different types of interactions. (Aguilar, Valdiviezo-Díaz, & Riorio, 2017)
<table>
<thead>
<tr>
<th>Data source</th>
<th>Data input</th>
</tr>
</thead>
</table>
| **User data** | Explicit feedback  
- Rating actions (e.g. rating scores)  
- Feedback actions (e.g. product reviews, comments, opinions)  
- Preference settings (e.g. favorited product categories)  
- Demographics (e.g. age, gender, profession, location)  
Implicit feedback  
- On-site interactions (e.g. navigation history, click frequency, retention time, search behavior)  
- Off-site interactions (e.g. tracking clicks in mailing-campaigns, mobile applications, push notifications) |
| **Transaction data** | - Purchasing history (e.g. purchasing quantity, product bundles, willingness to pay) |
| **Items data** | - Item description (e.g. attributes, categorization)  
- Functional information (e.g. functions and features to solve the customer’s need)  
- Structural information (e.g. components and relationship to other items)  
- Operational information (e.g. description of use) |

Table 5: Data sources and inputs (based on Ricci, Rokach, & Shapira, 2010; Schafer, Konstan, & Riedl, 1999; Sivapalan, Sadeghian, Rahanam, & Madni, 2014)

Explicit feedback includes inputs by users showing their interest. Product ratings for purchases already made are often used. Customers are also frequently asked to provide feedback in the form of comments or product reviews.(Aguilar et al., 2017)
In addition, e-commerce providers already offer personalization when creating a user account for the first time. A query cycle asks new customers about their preferences for certain products or services in order to get to know them better. Demographic data such as age or gender can be used to highlight specific product categories according to statistical characteristics. (Anand & Mobasher, 2005)

Implicit feedback refers to data that can be collected undetected by monitoring the interactions with the e-commerce application. (Anand & Mobasher, 2005) Many indicators can be defined to monitor the customer behavior. The retention time on specific products is taken as an indicator of interest in the item. Actions like adding an item to the basket, repeated clicks on particular items or the navigation history can imply the interest. Furthermore, off-site interactions like tracking clicks in email campaigns, in mobile applications or push notifications should be included to ensure a holistic view on the particular interests of the customer. (Aguilar et al., 2017)

These indicators must be defined specifically to the design and the customer journey of the e-commerce application. As mentioned before, the main advantage of implicit feedback is that this method does not require any effort from the user, but generally, it is less accurate than explicit feedback-based recommendations.

**Transaction data**

Transaction data is generated during the purchase, or more generally, during the conversion into a purchase. Shopping cart analyses are used to obtain samples from the transactions made. Purchasing quantities, prices, discounting, product bundles, and other correlations are tracked. With the help of association analysis, rules can be computed to recognize connections and patterns within transaction-based data. (Geyer-Schulz & Hahsler, 2002)

**Item data**

Items define the objects to recommend. The complexity of an item is expressed in its structure, attributes, representation and dependency on other items. (Aguilar, Valdiviezo-Díaz, & Riofriio, 2017) Item-related data include product descriptions, categorization and attributes of items to create a holistic product ontology (Anand & Mobasher, 2005).
The level of detail and accuracy of product profiles depends on the complexity of the object. Items with low complexity such as news articles, books or movies are easier to categorize and classify. Items with high complexity such as mobile phones or travel offers need a clear structure and understanding about the item attributes.

Recommendation systems are able to structure a range of properties and product features of items. For example, a movie recommendation system automatically classifies movies related to the genre, director, actors and keyword descriptions and learns how the utility depends on its features. (Ricci, Rokach, & Shapira, 2010)

Aguilar et al. (2017) classify item data into four dimensions: the general item description included (description, categorization), the functional information (functions to solve the customer’s need), the structural information (components and relationship to other items) and the operational information (description of use).

4.3.1.2 Data-based recommendation types

Different types of recommendations have already been explained in chapter 3. Within the framework, these are assigned to the data layer. They describe on what input data recommendations are based on, and which data are needed to successfully recommend items to customers. Furthermore, they build decision support for the next layer which data mining techniques can be used in the next step of the recommendation process. Five types were distinguished: non-personalized, personalized, attribute-based, item-to-item and people-to-people based correlations.

Attribute-based recommendations take user profiles to learn about product attribute a particular customer is interested in. (Sivapalan et al., 2014) For example, a customer frequently purchases movies of the genre “action”. Content-based filtering techniques make use of item profiles made out of item attributes.

Item-to-item correlation identifies associations with items a customer has expressed interest in. It can be based on purchase data or preferences. Item-to-item correlations are able to identify matching items for a single item, that are commonly purchased together. (Sivapalan et al., 2014) For example, a customer places several products in his shopping
cart, the recommendation system recommends complementary products with a high item-to-item correlation. Mainly, content-based filtering uses item-to-item correlations.

**People-to-people correlation** recommend items based on the correlation between a particular customer and other customers. Mainly, this type is used in collaborative filtering techniques. (Sivapalan et al., 2014)

**Non-personalized recommendations** make use of statistical or manual approaches to highlight and recommend specific products. (Sharma & Gera, 2013) According to marketing campaigns discounts, new products or best-sellers are recommended.

**Personalized recommendations** are based on automatic techniques to gain knowledge about the customer preferences and individual interactions. Personalization requires machine learning and data mining techniques to offer personalized recommendations. (Sharma & Gera, 2013) It should be noted that all components of the framework assume a degree of personalization as a minimum requirement. Therefore, this recommendation type refers to explicitly specified preferences and individual interactions of a customer (without consideration of interactions of other users).

### 4.3.2 Machine learning and logic layer

Filtering techniques, data mining techniques and data analysis techniques are assigned to the logic layer. Detailed information about these techniques can be found in chapter 3.

**4.3.2.1 Filtering techniques**

Filtering methods form the basis for deciding which recommendations can be presented. This matchmaking process tries to accurately match customer preferences to products or services. Table 6 summarizes a possible classification of filtering techniques made in chapter 3.
<table>
<thead>
<tr>
<th>Filtering technique</th>
<th>Algorithms and methods</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Collaborative filtering (CF)</strong></td>
<td></td>
</tr>
<tr>
<td>Memory-based</td>
<td>Similarity measures (correlation-, cosine-based, Jaccard coefficient):</td>
</tr>
<tr>
<td></td>
<td>- Nearest-Neighbor (user-based similarity)</td>
</tr>
<tr>
<td></td>
<td>- User-item matrix (item-based similarity)</td>
</tr>
<tr>
<td>Model-based</td>
<td>Machine learning techniques (model training):</td>
</tr>
<tr>
<td></td>
<td>- Classification</td>
</tr>
<tr>
<td></td>
<td>- Regression</td>
</tr>
<tr>
<td></td>
<td>- Association rule mining</td>
</tr>
<tr>
<td></td>
<td>- Clustering</td>
</tr>
<tr>
<td><strong>Content-based filtering (CBF)</strong></td>
<td></td>
</tr>
<tr>
<td>User profile</td>
<td>Machine learning techniques (probabilistic methods frequently applied):</td>
</tr>
<tr>
<td></td>
<td>- Classification</td>
</tr>
<tr>
<td></td>
<td>- Regression</td>
</tr>
<tr>
<td></td>
<td>- Association rule mining</td>
</tr>
<tr>
<td></td>
<td>- Clustering</td>
</tr>
<tr>
<td>Item profile</td>
<td>Similarity measures (vector space, TF-IDF, nearest-neighbor)</td>
</tr>
<tr>
<td><strong>Hybrid filtering</strong></td>
<td>Machine learning techniques:</td>
</tr>
<tr>
<td>Weighted Switching</td>
<td>- Classification</td>
</tr>
<tr>
<td>Mixed</td>
<td>- Regression</td>
</tr>
<tr>
<td>Cascade</td>
<td>- Association rule mining</td>
</tr>
<tr>
<td>Feature combination</td>
<td>- Clustering</td>
</tr>
<tr>
<td>Feature augmentation</td>
<td>Similarity measures</td>
</tr>
<tr>
<td>Meta-level</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Classification of filtering techniques and algorithms (based on Aggarwal, 2016; Akhil & Shelbi, 2017; Burke, 2007; Felfernig et al., 2014; Ghosh, 2018; Gigimol & Sincy, 2016; Isinkaye, Folajimi, & Ojokoh, 2015; Koren, Bell, & Volinsky, 2009; Kumar & Agneeswaran, 2018; Li & Karahanna, 2015; Marmanis & Babenko, 2009; Park, Kim, Choi, & Kim, 2012; Sharma & Gera, 2013)
4.3.2.2 Data mining techniques

Data mining techniques were presented in the previous chapter. Table 7 shows a classification of data mining techniques. Depending on the area of application, further data mining techniques exist. The following classification is based on relevant literature in the topic of application of recommendation systems. The classification includes different machine learning techniques and a classification related to the learning model. Finally, data mining techniques are assigned to the classification.

<table>
<thead>
<tr>
<th>Machine learning technique</th>
<th>Learning model</th>
<th>Data mining technique</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classification</td>
<td>Supervised learning</td>
<td>Bayesian networks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Decision trees</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Neuronal networks</td>
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<tr>
<td></td>
<td></td>
<td>Support vector machines</td>
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<tr>
<td></td>
<td></td>
<td>Ensembles</td>
</tr>
<tr>
<td>Regression analysis</td>
<td></td>
<td>Linear regression</td>
</tr>
<tr>
<td>Association rule mining</td>
<td>Unsupervised learning</td>
<td>Apriori algorithm</td>
</tr>
<tr>
<td>Clustering analysis</td>
<td></td>
<td>K-means algorithm</td>
</tr>
</tbody>
</table>

Table 7: Classification of data mining techniques (based on Amatriain, 2013; Amatriain, Jaimes, Oliver, & Pujol, 2011; Anand & Mobasher, 2005; Felfernig et al., 2014; Isinkaye, Folajimi, & Ojokoh, 2015; Mulvenna, Anand, & Büchner, 2000; Park, Kim, Choi, & Kim, 2012; Schafer, Konstan, & Riedl, 1999)

Supervised learning approaches are methods that attempt to discover the relationship between input properties (independent variables) and a target attribute (dependent variable). The relationship found is presented in a structure called a data mining model. Typically, models describe and explain phenomena that are hidden in the data set and can be used to predict the value of the target attribute that knows the values of the input properties. (Amatriain, Jaimes, Oliver, & Pujol, 2011) The direction of learning is given
during the training of the model. Outputs are predefined and, for example, assigned to a “class” during classification. In its simplest form, for example, the two classes "like" and "dislike" can be given. Based on the test data, the model now calculates the prediction of class assignment for new data, i.e. whether a product is liked or not.

Supervised learning uses "categories", "classes" or "labels" that are known. In contrast, unsupervised learning they are not known, and the learning process tries to find "suitable categories". Consequently, an algorithm is not trained, but the structure of the data is analyzed to form meaningful information. Therefore, no learning direction is given, but the algorithm finds patterns independently. Cluster analysis, for example, finds clusters in data sets and classifies customers with similar behavior in clusters. (Amatriain, Jaimes, Oliver, & Pujol, 2011)

4.3.2.3 Data processing

Data analysis techniques provide insights into the technical requirements adding a time factor of how quickly data are needed to be analyzed and presented to the customer. Three main distinguishing time factors have already been presented in chapter 3. Within the framework, they are assigned to the respective recommendation types. This should give e-commerce operators and marketers insights into the different requirements of data analysis and technologies that an e-commerce application has to meet.

**Real-time systems** are able to process data in the same moment a user interacts with the system. This is required to give users in-the-moment recommendations clicking on a particular item. (Google Inc., 2016)

**Near real-time analysis** are able to quickly collect and update data every few minutes or seconds. Such a system might be good for making recommendations during the same browser session. (Google Inc., 2016)

**Batch analysis** requires periodic processing of the data. A batch system could work well to send an email with product recommendations at a later time. (Google Inc., 2016)
4.3.3 Interface and presentation layer

The user interface of e-commerce applications is usually accessible via web browsers or mobile applications. A central focus here is to design system interfaces where recommendations are well placed. (Li & Karahanna, 2015)

The presentation of recommendations within the e-commerce application’s customer journey has, besides the different algorithms, a great influence on the effectiveness of recommendation systems. (Schafer, Konstan, & Riedl, 1999) It is important to understand which type of recommendation technique is used when within the customer journey. Studies found out that the timing and interplay between “what” and “when” personalized recommendations are visible for the customer are very important. (Ho et al., 2011)

Four different criteria are used to classify the presentation layer. User interface types separate the GUI of the application into different types. Recommendation strategies are evaluated according to the various objectives in the customer journey. The degree of personalization determines another classification criterion for the framework. Finally, the user’s recommendation touchpoints form a main dimension of the framework.

4.3.3.1 User Interface touchpoints

Based on the literature, three different interface types can be identified: Customers get in touch with recommendations via the personalized main page or main category pages, individual item pages as well as pages directly related to the conversion, such as the shopping cart. (Jugovac & Jannach, 2017; Schafer, Konstan, & Riedl, 2001, 1999)

Main and category page recommendations

Main page recommendations represent personalization possibilities on the start page of the e-commerce application. Item categories are assigned to e-commerce applications with many products or services. The various recommendation techniques can also be applied to the overview pages of item categories. Individualized recommendations are already offered to the customer when the homepage or category page is visited.
The variety of personalization options on the main page offers the potential to respond to the user's long-term interests. This requires user profiles that are built up through implicit and explicit feedback. Typical recommendation labels are “Inspired by your browsing history”, “Trending”, “Recommended for you” or “You might be interested in”. (Jugovac & Jannach, 2017)

**Item page recommendations**

Item pages are sites where one or more products or services are displayed that a user has reached, for example, by navigating or searching in the web shop. A typical example is Amazons interface label “Customers who bought … also bought,”. Item page recommendations frequently provide personal ordered lists of items according to the selected filtering criteria of the user. The products which are “relevant” are computed by the recommendation system. (Jugovac & Jannach, 2017) In addition, short-term interests or session-based indicators tend to be used to make recommendations.

**Shopping cart page recommendations**

Shopping cart recommendations are used to increase the size of the shopping cart. Cross-selling offers, promotions or up-selling recommendations can be given. These are triggered as soon as the user adds one or more items to the shopping cart. Furthermore, it can be triggered when the user has indicated a purchase intent through implicit or explicit feedback. (Jugovac & Jannach, 2017)

4.3.3.2 **User’s recommendation types**

Customer touchpoints with recommendations form a main dimension of the framework. From the perspective of e-commerce operators and marketers, this dimension can be used as a starting point for recommendation strategies. The following touchpoints within recommendation systems in e-commerce applications can be identified.

**Similar Users**

Similar users are frequently labelled by “Customers who bought…also bought”, or “Customers who viewed…also liked this” within the user interface. (Jugovac & Jannach, 2017). This method works by identifying similarities between user’s shopping behavior
and preferences. Furthermore, the logic of the algorithm includes how often two items have been together in the purchase or browsing history. It is a successful strategy to cross-sell and generate more sales by recommending complementary items. (Jugovac & Jannach, 2017)

**Similar Items**

Similar products or services are usually recommended from a common item category. This is combined with other meta data or features. With the help of data mining techniques, especially of neural networks, a complex product description can be made on several levels. Product features are weighted and combined. (Jugovac & Jannach, 2017) Finally, relevant recommendations can be offered on the basis of price expectations, price level ratio, item colors, brand preferences or distance features like the “distance to first or last view” of the items a particular user viewed within a session. (Jannach, Ludewig, & Lerche, 2017) Examples of popular interface labels are “Products related to this item” or “Because you were interested in”. Users are thus made aware of products they may have forgotten or may not even know. (Schafer, Konstan, & Riedl, 1999)

**Complementary items**

Frequently purchased items are displayed on product pages that are currently viewed by a specific user. They are also frequently displayed in the shopping cart. Recommending items that are frequently bought together help to increase basket values with complementary suggestions. (Jannach, Ludewig, & Lerche, 2017)

For example, if a customer wants to purchase a camera, the recommendation system offers compatible tripods and carry cases with the label “Frequently bought together”. Furthermore, if a customer buys clothes within a web shop, recommendation systems can offer suggestions with labels like “complete the look” with matching accessories.

**Top-N list**

Within Top-N lists, recommendations are based on an interest based-navigation. The order of the items is sorted by the interest level. These recommendations are displayed by ordered search lists.
Items are sorted according to the probability that the recommended item fits the customer. (Schafer, Konstan, & Riedl, 1999) For example, the more active time a user spends on a particular product or page, the higher the interest measured.

Bayesian networks are often used to divide items into classes with the help of learning algorithms and to perform a ranking. (Jannach, Ludewig, & Lerche, 2017) Matrix factorization is another recommendation algorithm used to find products within the user item matrix which are still undiscovered but could be of interested to the user. (Tewari, Singh, & Barman, 2018)

**Popular items**

The recommendation of “Popular items” is a non-personalized technique. In its basic form, this recommendation strategy can be offered by any e-commerce application that keeps statistics on the sales of its items. The best-selling items or items that are currently trendy can be recommended to all users without a degree of personalization. (Jannach, Ludewig, & Lerche, 2017)

Intelligent recommendation systems go one step further. They also consider data from individual sales data or user profile data like demographics to decide which items are recommended. The algorithm computes a popularity measure for each item in predefined time periods, e.g. same day, week or month. Additionally, the popularity measure can include view counts or conversions to identify popular items. (Jannach, Ludewig, & Lerche, 2017)

**Top rated or reviewed items**

Rating-based recommendations use explicit and implicit rating factors. Positive ratings and feedback are seen as indicators to influence the purchasing decision of customers. (Jannach, Ludewig, & Lerche, 2017)

Product reviews can be compared with recommendations from friends or associates in the offline world. This results in a positive reference in the best case, which strengthens the purchase decision. Text comments or product rating systems in the form of point systems represent different possibilities.
The label "Top rated" is often used in the user interface. (Schafer, Konstan, & Riedl, 1999) Top rated items recommendations can display ratings from users with similar purchasing behavior or similar previous purchases using machine learning techniques.

**Browsing history**

Recommendations based on the browsing history of individual users analyze recently viewed items. This recommendation system does not actually require any in-depth data of customers. (Jannach, Ludewig, & Lerche, 2017) Nevertheless, recommendations can be improved by user profiles and other indicators. In particular, implicit feedback data is integrated, where click frequencies or the length of stay on individual items are used as indicators. "Recently viewed" or "Because you were interested in" are often used as labels within the user interface.

As part of a retargeting campaign, browsing history-based recommendations are well suited for browsing abandonment emails. For example, if a customer has recently viewed a particular item, but did not make a conversion. It is a reminding strategy that displays the items a particular user had shown interest. (Jannach, Ludewig, & Lerche, 2017)

**New items**

A new item recommendation does not require personalization. However, even if sufficient customer data are available, personalized recommendations for new items can be made. User profile data like demographics can be used to inform customers about new items most suited for their age, gender or items that are in stock based on the location of the user. Furthermore, user profile data like preferences can be included. (Schafer, Konstan, & Riedl, 1999) For example, item features in item profiles can be clustered with demographic features and preferences in user profiles to identify relevant users for new items.

**Deals**

Slow moving inventory are items that have very little customer demand over a given time period. Slow moving items can be advertised with targeted offers or discounts.
The recommendations are based on item and user profiles, which calculate possible relevance for individual customers. For example, demographic user information can be included. (Jannach, Ludewig, & Lerche, 2017)

**Cart recovery**

Cart recovery-based recommendations identify abandoned carts. A cart is considered abandoned if the cart still contains items after closing a session or there has been no purchase for a specific time period when user added an item to the cart. Finally, a precisely exit pop-up recommends the user special conditions, for example, free shipping or a discount for the selected item. (Jannach, Ludewig, & Lerche, 2017)

The timing and item selection of the recommendations are decisive within cart recovery recommendations. For example, to send personalized reminder emails, the purchase history, product combinations and other implicit feedback can be analyzed. If, for example, there are several very similar items in the shopping cart, the one with the highest probability of completion can be suggested on the basis of the user profile.

**Up-sell recommendations**

Up-sell recommendations represent upgrades to existing products. By analyzing the previous purchases of the customer, the recommender system will also provide recommendations that are upgrades to the products the customer already owns. (Schafer, Konstan, & Riedl, 2001)

Up-sell recommendations focus on item profiles and features. For example, an upgrade can be classified as a higher quality and more expensive item. Up-sell recommendations are frequently found on shopping cart pages. (Schafer, Konstan, & Riedl, 2001)
4.3.3.3 Recommendation strategies

Basically, recommendation strategies can be made according to various filtering methods and the available data. At the presentation layer, such strategies are mapped to direct objectives. The following structure describes a possible classification of objectives and strategies. Schafer et al. (2001) distinguishes five methods:

Helping new and infrequent customers: Broad recommendation lists

Broad recommendation lists typically allow the targeted customer to use current navigation to pull non-personalized suggestions. These include overall best sellers, best sellers in a particular item category, expert recommendations or recommendations through simple statistical summarization. The goal is to offer recommendations to new or infrequent customers even though there is little or no information available about the customer. (Schafer, Konstan, & Riedl, 2001)

Building credibility: Community feedback

Customer comments and ratings are used to build credibility about a particular item. For example, satisfied customers who already bought the item report about their experiences. In addition, such recommendations create the perception of a community. Customer reviews can be implemented in the form of reviews or scoring systems. (Schafer, Konstan, & Riedl, 2001)

Inviting customers back: Notification services

Notification services are often implemented through additional marketing channels. The goal is to invite certain customers back to the e-commerce application. For example, targeted emails can be sent to the customer to inform about new items that a particular user could be interested in or notifications about particular discounts or product offerings. Notification services belong to a form of personalized recommendations with the objective to build a stronger customer relationships (Schafer, Konstan, & Riedl, 2001)
Cross- and up-selling: Product-associated recommendations

Product-associated recommendations have the objective to increase sales. The value of shopping carts is to be increased by recommending complementary items or item upgrades. Complementary items are related to a customer’s current interaction. Based on purchase histories, product attributes or ratings product-associated recommendations can be offered. (Schafer, Konstan, & Riedl, 2001)

Building long-term relationships: Deep personalization

Based on a customer’s preferences, purchases or interaction data, deep personalized recommendations can be made. It is the strongest form but most challenging type of personalization to implement. Deep personalization updates the user profile whenever the customer interacts with the e-commerce application. (Schafer, Konstan, & Riedl, 2001)

4.3.3.4 Degree of personalization

The degree of personalization is the result of the chosen filtering technique and available data for recommendations. In chapter 2, individual degrees of personalization were presented in detail. These are now transferred to the framework as decision components.

Generic recommendations present the same products to every customer. They are non-personalized and based on statistical summarization or manual selection. Demographic recommendations present the same recommendations to all members of a defined target group. Demographic data divide customers into different groups. Ephemeral recommendations are responsive to interactions of the customer within the current online session. Persistent recommendations are based on long-term customer interests. It is the most personalized experience recommendations are able to offer. Persistent recommendations are beyond the current session in the customer’s e-commerce application and form recommendations based on individual preferences and interactions throughout the customer lifecycle. (Schafer, Konstan, & Riedl, 2001; Szczepaniak & Niewiadomski, 2005)
4.4 Limitation of the framework

The first chapter of this thesis has already explained the limitations of this elaboration. Specific limitations of the framework should be pointed out in the following.

Due to the numerous fields of application and various techniques of machine learning and data mining, the framework focuses on the core approaches in this area. Therefore, modifications and in practice mostly unexplored recommendation methods are not considered in the framework.

Another limitation is the focus on recommendation systems in e-commerce. The framework could also be extended to other application areas. Other channels can also be integrated, such as social media or marketing channels such as email marketing. These channels are not considered within the framework.

In addition, it should be noted that further success factors can be worked out at a deeper level on each layer. For example, Jugovac and Jannach (2017) investigate design aspects of recommendation systems. Factors, such as the screen position or visibility of particular recommendations are analyzed on the presentation layer. In order to obtain a generic view of the components of recommendation systems, further levels of detail in the framework are omitted.

4.5 Literature-based recommendation framework

The framework provides an overview and classification of different components of recommendation systems. For this purpose, individual components were developed on the basis of the 3-layer architecture of recommendation systems. These are applied in tabular form on the horizontal perspective of the framework.

The vertical perspective presents individual touchpoints with recommendation systems from the customer's point of view within the customer journey. The individual touchpoints have the objective to increase the conversion rate. Therefore, they serve as a starting point for the allocation of the individual components in the framework. From a technical point of view, the available data and its analysis options form the basis for recommendation systems. The reversal and focus on the presentation layer are therefore deliberately based on the research question.
The following components are defined as the main dimensions of the individual layers of the architecture: *user interface touchpoints (presentation), filtering and data mining techniques (logic) and input types (data)*. They are used as evaluation criteria in the following evaluation. The main dimensions of the framework classify and describe the basic functionality of recommendation systems. The further dimensions of the framework represent requirements based on the selected main dimensions. These are declared as description features of the available data, the selected recommendation technique and the presentation of the recommendation in the user interface. The following components are defined as description characteristics: Recommendation strategy, degree of personalization, data analysis method, recommendation type.
<table>
<thead>
<tr>
<th>Customer Journey</th>
<th>Recommendation type</th>
<th>Recommendation tier (3-tier architecture)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Presentation</td>
<td>Logic</td>
</tr>
<tr>
<td></td>
<td>User interface type</td>
<td>Recommendation strategy</td>
</tr>
<tr>
<td>Similar users</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Similar items</td>
<td></td>
<td></td>
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<tr>
<td>Complementary items</td>
<td></td>
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</tr>
<tr>
<td>Top-N list</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Popular items</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top rated items</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Browsing history</td>
<td></td>
<td></td>
</tr>
<tr>
<td>New items</td>
<td></td>
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</tr>
<tr>
<td>Deals</td>
<td></td>
<td></td>
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<tr>
<td>Cart recovery</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Up-sell</td>
<td></td>
<td></td>
</tr>
<tr>
<td>recommendations</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

# 5 EVALUATION OF RECOMMENDATION SYSTEM FRAMEWORK

The objective of the evaluation of the framework is to test its applicability in practice for e-commerce operators. As an example of best practice, the globally active online shop Amazon.com will be analyzed. The framework will be evaluated on the basis of Amazon's successful recommendation systems based on the 3-tier architecture and customer touchpoints of the framework. Finally, the framework is extended with the evaluation results from the case study and adaptations are made.

## 5.1 Research approach

Design Science Research justifies the method chosen for the evaluation. Hevner et al. (2004) describe several design evaluation methods that can be carried out within the framework of the Design Science approach. The following evaluation is assigned to the observational methodology. As a case study, the artifact is tested in practice and in the business environment. The criteria of the case study are based on the framework components that represent the artifact. On the basis of the case study, refinements can be made to the artifact. (Hevner, March, Park, & Ram, 2004)

### 5.1.1 Case Study evaluation criteria

The framework offers a modular structure based on the 3-tier architecture and the associated customer touchpoints with recommendation systems. As already mentioned, these modules can be combined. In the last chapter, a main dimension was identified for each layer of the 3-tier architecture. They are compared with the recommendation system of Amazon. The following framework components are defined as the main dimension of the framework: interface type (presentation layer), filtering technique and used algorithms (logic layer) and the data input types (data layer).
Thus, the evaluation can be conducted on the basis of the collected data, the processing of the data with machine learning algorithms on the logic layer and the presentation of the recommendation in the user interface on the presentation layer. The individual customer touchpoints of the customer journey from the framework are the starting point of the framework.

5.1.2 Framework analysis method

The individual analysis methods and sources for the evaluation are presented below. The case study basically contains the following three evaluation aspects:

Presentation layer

As main dimension and therefore starting point, all touchpoints with recommendations in the customer journey of the Amazon.com web shop are collected. In order to carry out a review of the available interfaces, three existing user profiles of volunteers were analyzed. In order to achieve the highest possible degree of personalization, as specified in the framework, the following profile selection requirements were set: Amazon member for at least one year, at least one purchase made with the selected profile, profile activity must contain on average at least one session per month (averaging period 1 year).

Logic layer

The filtering techniques and machine learning algorithms used by Amazon are explained on the basis of the official patent document submitted by Amazon through its recommendation system. (Jacobi, Benson, & Linden, 2006) In addition, the information is quoted from several scientific articles that have dealt with the Amazon recommendation system. There is also an open source project published by Amazon itself that provides parts of the algorithms and machine learning techniques for developers to use and develop further.³

Data layer

The data collected by Amazon for recommendations are evaluated based on studies already carried out from researchers and practitioners. Another key assessment aspect is Amazon’s data protection declaration, in which all data collected have to appear according to the EU General Data Protection Regulation (GDPR 2018).

5.2 Case study: Amazon.com

For two decades, Amazon.com has run recommendations to millions of customers and millions of items, helping potential customers to find what they might be interested in within their web shop (Smith & Linden, 2017). As mentioned earlier, McKinsey revealed within a study that 35 % of Amazon’s sales are generated through their recommendation system (MacKenzie, Meyer, & Noble, 2013).

Amazon’s recommendation system is declared one of the best in the world. The algorithms and methodologies have been widely used by other well-known e-commerce operators in online retail, travel, news, advertising and more. (Smith & Linden, 2017) In addition, Amazon also offers recommendation services and machine learning processes for e-commerce applications declaring Amazon’s recommendation system as a best practice in the field of e-commerce.  

Amazon uses recommendations to personalize the online store for each user. The products and recommendations displayed vary based on the interests of each user. (Linden, Smith, & York, 2003) To achieve this, Amazon itself has developed an algorithm based on its own requirements, which is described in the logic layer section.

The individual layers of the created framework are assigned in the following section on the basis of the recommendation systems used by Amazon.

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4 Amazon EU Privacy Notice https://www.amazon.de/gp/help/customer/display.html?nodeId=201909010 [22.03.2019]
6 Amazon personalize – Real-time personalization and recommendation https://aws.amazon.com/personalize [26.03.2019]
5.2.1 Presentation layer

The presentation layer explains the recommendation touchpoints and interface types. Appendix 2 of this thesis shows the user interfaces of the Amazon web shop included in the following analysis.

5.2.1.1 Recommendation touchpoints

The individual recommendation types are analyzed on all 3 layers and relevant dimensions of the framework.

Customers who viewed this item also viewed

Amazon offers recommendations based on “Customers who bought…also bought”, or “Customers who viewed…also liked this” within the user interface. As described in the previous chapter, the logic of the algorithm includes how often two items have been together in the shopping cart or in the browsing history from similar users.

Products related to this item

Amazon recommends similar items from a common item category. Within this example related items are based on the search of notebooks within the web shop. Displayed recommendations of similar notebooks are based on item features like the brand, price class, technical specifications, size and other features.

Complementary items

Based on the search for notebooks within the analyses, complementary items are recommended. Customers frequently buy together laptop bags and a mouse, based on the item page of a particular laptop.

Top-N list

Within Top-N lists, the order of the items displayed within the user interface is sorted by the interest level of a particular user. In the course of the analysis, the level of personalization proposed differs. Amazon uses non-personalized recommendations. Featured merchants’ products are ranked in a pre-defined order. An algorithm ranks merchants according to parameters such as product availability or average ratings. Unlike
suggested in the framework, Amazon’s Top-N lists are not based on the purchase probability from the user's point of view, but on the quality criteria of its merchants. Nevertheless, classification methods like Bayesian networks can be used to perform a ranking. (Jannach, Ludewig, & Lerche, 2017)

**Popular items**

Amazon recommends the best-selling items or items that are currently trending within certain item categories. Within the analysis, Amazon places the focus of these recommendations on individual category pages, but not on the main page. An indication of this is that Amazon sells millions of items of various categories and would spread an entire bestseller list too far away from the interests of individual users.

**Top rated or reviewed items**

Unlike suggested by the framework regarding to the highest possible degree of personalization, Amazon displays the same item reviews to all users. Reviews or ratings are not filtered by user similarity measures. Therefore, Amazon does not offer the highest possible level of personalization within this recommendation touchpoint. In addition, top-rated items are shown in the individual category pages.

**Browsing history**

The browsing history is a core element of Amazon's recommendation system. In the user interface, recommendations are provided to the user on all visited pages in categories, on individual item pages or the shopping cart. "Inspired by your browsing history" or "Related to items you've viewed" recommend similar items based on the items already viewed. The same items are also displayed the user has already viewed but not yet purchased.

**New items**

As mentioned in the previous chapter, new item recommendations do not require personalization. Nevertheless, Amazon uses a logic based on the user profile data, like preferences and purchasing history to recommend new items within the label "New for you".
 Deals and offers

Amazon recommends “Today’s deals” within different item categories. For example, slow moving items can be advertised with targeted offers or discounts. Contrary to the framework, Amazon does not use a high degree of personalization. The daily deals are delivered to all users without differentiating individual preferences.

 Cart recovery

Cart recovery recommendations are frequently offered through additional communication channels. For example, Amazon sends personalized reminder emails about items that are still in the shopping cart but not yet purchased. The analysis only included the web shop of Amazon. In the web shop, cart recovery-based recommendations for repurchases are offered. The label "Buy it again" gives users the possibility to buy items again they have already purchased.

 Up-sell recommendations

Up-sell recommendations are offered by Amazon under the label "Compare with similar items". When searching for laptops during the analysis, up-sell recommendations are displayed on item pages of individual laptops. Similar items, often with higher prices, are compared on the basis of a predefined set of item features.

5.2.1.2 Interface types

The interface types identified in the framework provide a high level of coherence. Amazon integrates recommendations at the following user interfaces: main page, category page, item page and shopping cart page.

Main page recommendations provide a high degree of personalization that includes multiple recommendation touchpoints. User can find this under the label "Recommended for you". These recommendations are only available to registered members. New members who have not made any purchases can find recommendations based on popular items like best-sellers instead.
While no distinction was made in the framework between main page and category page recommendations, Amazon sometimes offers different recommendations on these interfaces. On the main page, the recommendation touchpoints of the browsing history, deals and offers, cart recovery and new items are used.

Category pages focus on recommendations of the top-N list, popular items, top rated items, cart recovery, deals and offers and browsing history.

Item page recommendations are triggered by a click on a product, which takes the user to the detailed view. In the background, real-time data analyses are carried out to ensure current recommendations based on click behavior and browsing history. The recommendation touchpoints define similar users, similar items, complementary items and browsing history.

Shopping cart recommendations are based on the items in the customer's cart. These recommendations are intended to increase the user's shopping cart with additional items before the conversion is completed. Based on the user's browsing history and previous purchases, Amazon recommends users to repurchase these products. Recommendation touchpoints define the browsing history and cart recovery recommendations.

5.2.2 Logic Layer

On the logic layer of Amazon’s recommendation system, the used filtering techniques and data mining techniques are analyzed. The objects of investigation are scientific contributions and studies as well as official sources of Amazon itself. The patent document submitted by Amazon regarding its recommendation system was decisive for the analysis. (Jacobi, Benson, & Linden, 2006) The original scientific paper by Amazon, in which the widely used Amazon recommendation algorithm is presented, was also used (Linden, Smith, & York, 2003).

Amazon has developed a recommendation algorithm based on its own recommendation requirements, the high complexity and product diversity and large number of users. The key points of the algorithm are graphically illustrated in Appendix 1. Amazon invented a so-called item-to-item collaborative filtering approach (Linden, Smith, & York, 2003).
This item-based approach of a collaborative filtering technique allows a combination of several techniques. “Classical” collaborative filtering approaches primarily calculate similarities between users. Amazon’s approach primarily focuses on finding similar items for each particular item. (Linden, Smith, & York, 2003) In other words, for each item the recommendation system calculates items that were purchased with unusually high frequency by people who bought the initial item. This approach is a form of clustering in which, instead of clustering customers, items were clustered (Linden, Smith, & York, 2003).

A similarity index between items is calculated that rates or adds an item into the shopping cart while a customer makes a purchase. The algorithm updates these events in the database. The similarities are calculated within a similar-item matrix for all the millions of items available. (Linden, Smith, & York, 2003) These calculations are time consuming and are done offline. Within the matrix, for example, items that customers tend to purchase together are identified. (Jacobi, Benson, & Linden, 2006)

The similar-item matrix is uploaded to the recommendation system as an input for the recommendation algorithm. The recommendation system uses that data to produce real-time recommendations (Jacobi, Benson, & Linden, 2006). With the similar-items matrix, the algorithm recommends the most popular or correlated items to each individual user. (Linden, Smith, & York, 2003)

This algorithm has many advantages over the common user-based collaborative filtering. The main advantage addressing the performance is that the computation is done offline. A batch system builds related items and the computation of the recommendations is done in real-time. (Smith & Linden, 2017)

In addition, the algorithm includes many other parameters that are included in the similarity score (Smith & Linden, 2017). For example, ratings or implicit feedback data can be included in the algorithm. Exclusion scenarios for recommendation results can also be integrated, such as for, products that have already been purchased or for which the user has submitted a negative rating. (Ceballos, Chang, & Lee, 2014)

In the next step the algorithm is trained with machine learning models. Data mining techniques are applied and tested in the machine learning models as required. Amazon
uses all four techniques found within the framework: classification, clustering, association rule mining and regression analysis. Clustering is used, for example, to identify and cluster similar items in a first step. (Smith & Linden, 2017) Similarity measures such as the Jaccard coefficient are used to calculate item features in a matrix. Neural networks associated with classification techniques are used to ensure a high degree of personalization at different levels. (Chunk, 2016) Amazon itself has developed a machine learning model called Deep Structure Semantic Model (DSSM). This is particularly helpful when hybrid data is put into the model. For example, item descriptions, item features, user reviews, ratings, or implicit feedback. Through neural networks it is possible to assign different weightings to different parameters on different levels. These are also considered in the similar-item matrix and added to the total score. The items with the highest score are delivered as recommendations to particular users. (Yarden, 2018)

Finally, the algorithm is trained within the machine learning model and predictions are derived from it. (Yarden, 2018)

5.2.3 Data Layer

In the course of the analysis, the applicability of the framework at the data layer was also proven. In practice, a fundamental distinction can be made between user, item and transaction data. The data collected by Amazon can also be mapped to the data inputs identified in the framework – as shown in table 9.

Amazon.com uses explicit and implicit information collection techniques to obtain information from users. (Isinkaye et al., 2015) This is also confirmed by Amazon’s official patent document on its recommendation system (Jacobi, Benson, & Linden, 2006). In addition, Amazon’s privacy statement was part of the analysis. Within this document the data sources collected from Amazon are listed. (‘Amazon Privacy Notice’, 2019)

Amazon tracks data on all customer behavior activity on the web shop. Algorithms can be used to perform big data analyses to track implicit feedback. For every click, view or other interaction a data record of the interaction is recorded in the database.
Beyond this, explicit feedback like item ratings, reviews, preference settings or purchases are analyzed. Amazon’s artificial intelligence algorithms assign implicit values on different kinds of user interactions to particular items indicating a user might like or buy the item.

<table>
<thead>
<tr>
<th>Data source</th>
<th>Data input</th>
<th>Amazon’s official data input sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>User data</td>
<td>Explicit feedback</td>
<td>Item ratings</td>
</tr>
<tr>
<td></td>
<td>- Ratings</td>
<td>Customer reviews</td>
</tr>
<tr>
<td></td>
<td>- Preferences</td>
<td>Wishlist</td>
</tr>
<tr>
<td></td>
<td>- Demographics</td>
<td>Watchlist</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Favorited product categories</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Product availability alerts</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Account information* (e.g. age, gender, address, location (IP address), payment information, profession) *relevant for recommendations</td>
</tr>
<tr>
<td></td>
<td>Implicit feedback</td>
<td>Browsing history (navigation / search history)</td>
</tr>
<tr>
<td></td>
<td>- On-site interactions</td>
<td>Page interaction information (click frequency, scrolling, retention time, mouse-overs)</td>
</tr>
<tr>
<td></td>
<td>- Off-site interactions</td>
<td>Marketing channel information (e.g. tracking clicks in mailing-campaigns, mobile applications, push notifications)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Third party data (e.g. user data from contracting parties or subsidiaries)</td>
</tr>
<tr>
<td>Transaction data</td>
<td>- Purchase history</td>
<td>Order information and history (e.g. quantities, returns, product bundles)</td>
</tr>
<tr>
<td>Items data</td>
<td>- Item description</td>
<td>Item categorization, attributes</td>
</tr>
<tr>
<td>- Functional information</td>
<td>Item functions and features</td>
<td></td>
</tr>
<tr>
<td>- Structural information</td>
<td>Item components and relationship to other items</td>
<td></td>
</tr>
<tr>
<td>- Operational information</td>
<td>Description of use</td>
<td></td>
</tr>
</tbody>
</table>

Table 9: Data inputs for recommendations on Amazon.com (based on ‘Amazon Privacy Notice’, 2019; Isinkaye, Folajimi, & Ojokoh, 2015; Jacobi, Benson, & Linden, 2006)

5.3 Evaluation result

The underlying framework was extended with a practical example in the course of the evaluation. On the basis of the 3-layer architecture, the individual components of the framework were compared using the Amazon case study.

The results provide a high accordance in the structure and the corresponding components of recommendation systems. The framework components used could therefore also be applied in practice. Above all, the presentation layer formed an almost congruent result. The recommendation touchpoints dealt with in scientific papers were also used in practice, for example by Amazon, or in other practice-oriented studies. The basic filtering techniques and algorithms could also be demonstrated on the logic layer of recommendation systems. It should be noted that a large part of the scientific contributions dealt with individual areas of filtering techniques and focused on their further development. For example, Amazon combined different filtering techniques. Amazon has developed its own recommendation algorithm, which is based on the basic techniques described in the framework. The dimensions selected on the data level could also be confirmed. The comparison of data input types resulted in a correspondence between theory and practice. Intelligent recommendation systems can decide between the algorithm used and the combination of filtering techniques as required for particular recommendations. The machine learning algorithm calculated results by using several methods in models. The most accurate results in terms of predictive power about the
interest of individual users were chosen. In practice, different mining methods can be applied based on the observed values and big data available to web shop operators such as Amazon.

5.4 Recommendation system framework

Table 10 shows the recommendation systems framework according to the previous chapters. The assignments to the individual recommendation touchpoints of the framework are made on the basis of the 3-layer architecture. The mapping between the components of the customer journey and the 3-layer architecture of recommendation systems is based on the qualitative content analysis and the evaluation of the case study. The components of the framework were deduced from the presented coding guideline in the previous chapters. Based on the analysis, the mapping between the individual components can be made.

It should be noted that the assignment within the framework is not a rigid construct. It has been combined on the basis of the literature, practice-oriented studies and the Amazon case study. Specific implementations can also consider other combinations as required. Accordingly, the framework provides a guideline to increase the conversion rate in e-commerce applications from an academic as well as a practical point of view. Recommendation algorithms and data mining methods can be integrated with varying intensity into some recommendation touchpoints, such as the recommendation of popular or new products. In the respective basic form, for example, even new products could be displayed to all customers without using a filtering method. In the framework, the focus on the logic layer is on automated and intelligent recommendations. An associated filtering method is declared as the basis to ensure the highest possible degree of personalization for each interface. This approach raises the interface types to the highest possible level of personalization.

In addition, on the logic layer filtering and data mining techniques are assigned which are declared as minimum to present recommendations. It should be noted that especially hybrid filtering techniques, where content-based and collaborative filtering techniques are combined, can be extended in almost any recommendation touchpoint. In order to ensure a clear overview of the framework, not all enhancement options are assigned.
<table>
<thead>
<tr>
<th>Customer Journey</th>
<th>Recommendation type&lt;sup&gt;7&lt;/sup&gt;</th>
<th>Recommendation tier (3-tier architecture)&lt;sup&gt;8&lt;/sup&gt;</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>User interface type&lt;sup&gt;9&lt;/sup&gt;</td>
<td>Presentation</td>
<td>Logic</td>
</tr>
<tr>
<td>Similar users</td>
<td>Item page</td>
<td>Deep personalization</td>
<td>Ephemeral</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Similar items</td>
<td>Item page</td>
<td>Product-associated recommendation</td>
<td>Ephemeral</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complementary</td>
<td>Item page</td>
<td>Product-associated recommendation</td>
<td>Ephemeral</td>
</tr>
<tr>
<td>items</td>
<td>Shopping cart page</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

<sup>7</sup> Recommendation type

<sup>8</sup> Recommendation tier (3-tier architecture)

<sup>9</sup> User interface type

<sup>10</sup> Recommendation strategy

<sup>11</sup> Degree of personalization

<sup>12</sup> Filtering technique

<sup>13</sup> Data mining & algorithms

<sup>14</sup> Data processing

<sup>15</sup> Input type

<sup>16</sup> Data-based recommendation type
| Top-N list  
(Ordered search list) | Category page | Deep personalization | Persistent | Collaborative Content-based | Machine learning - f.u.:  
- Bayesian Networks  
- Similarity measures | Near real-time system | User Item Transaction | Personalized |
|------------------------|----------------|----------------------|------------|----------------------------|------------------------------------------------|----------------|----------------|-------------|
| Popular items  
(Trending, top-sellers) | Main page Category page | Broad recommendation list | Generic Demographic | Collaborative Content-based | Machine learning - f.u.:  
- Support Vector Machines  
- Regression  
- Association rule mining | Batch system | User Item Transaction | Non-personalized |
| Top rated items  
(Top rated or reviewed) | Category page | Community feedback | Generic Demographic | Collaborative | Machine learning  
Similarity measures | Batch system | User | Non-personalized People-to-people correlation |
| Browsing history  
(“Because you were interested in”,  
“Inspired by your browsing history”) | Main, Category, Item, Shopping cart page | Deep personalization Notification services | Ephemeral | Content-based | Machine learning - f.u.:  
- Probabilistic methods  
- Similarity measures | Near Real-time system | User | Personalized |
| New items | Main page Category page | Notification services | Generic Demographic Persistent | Content-based | Machine learning - f.u.:  
- Clustering  
- Regression  
- Association rule mining  
- Classification  
Similarity measures | Batch system | Item User | Non-personalized Attribute-based |
|---|---|---|---|---|---|---|---|---|
| Deals | Main page Category page | Notification services | Demographic | Content-based | Machine learning - f.u.:  
- Clustering  
- Regression  
- Association rule mining  
- Classification  
Similarity measures | Batch system | User Transaction | Non-personalized Attribute-based |
| Cart recovery | Main page Category page Shopping cart page | Deep personalization Notification services | Persistent | Content-based | Machine learning - f.u.:  
- Classification  
Similarity measures | Batch system | User Transaction | Personalized |
| Up-sell recommendations (“Compare with similar items”) | Item page | Product-associated recommendation | Persistent | Content-based | Machine learning - f.u.: - Association rule mining | Similarity measures | Real-time system | Item | Item-to-item correlation | Attribute-based |
|---|---|---|---|---|---|---|---|---|---|---|---|


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7 based on (Jugovac & Jannach, 2017; Schafer, Konstan, & Riedl, 2001, 1999)
8 based on (Hirschfeld 1996; Raj, Raman, & Subramanian, 2017)
10 based on (Schafer, Konstan, & Riedl, 2001)
11 based on (Salonen & Karjaluoto, 2016; Schafer et al., 2001; Szczepaniak & Niewiadomski, 2005)
12 based on (Aggarwal, 2016; Akhil & Shelbi, 2017; Burke, 2007; Chunk, 2016; Felfernig et al., 2014; Ghosh, 2018; Gigimol & Sincy, 2016; Isinkaye, Folajimi, & Ojokoh, 2015; Koren, Bell, & Volinsky, 2009; Kumar & Agneeswaran, 2018; Li & Karahanna, 2015; Linden, Smith, & York, 2003; Marmanis & Babenko, 2009; Park, Kim, Choi, & Kim, 2012; Sharma & Gera, 2013)
13 based on (Amatriain, 2013; Amatriain, Jaimes, Oliver, & Pujol, 2011; Anand & Mobasher, 2005; Felfernig et al., 2014; Isinkaye, Folajimi, & Ojokoh, 2015; Mulvenna, Anand, & Büchner, 2000; Park, Kim, Choi, & Kim, 2012; Schafer, Konstan, & Riedl, 1999)
14 based on (Aggarwal, 2016; Google Inc., 2016)
15 based on (‘Amazon Privacy Notice’, 2019; Isinkaye, Folajimi, & Ojokoh, 2015; Jacobi, Benson, & Linden, 2006; Ricci, Rokach, & Shapira, 2010; Schafer, Konstan, & Riedl, 1999; Sivapalan, Sadeghian, Rahanam, & Madni, 2014)
16 based on (Sharma & Gera, 2013; Sivapalan et al., 2014)
6 SUMMARY AND OUTLOOK

This thesis discussed intelligent recommendation systems in e-commerce applications. Recommendation systems enable e-commerce businesses to better understand their customers and to provide personalized stores to increase the customer experience. For e-commerce businesses, recommendation systems increase the conversion rate, enhancing customer satisfaction and loyalty.

The rapid advances in technologies, data mining methods and artificial intelligence have made it difficult for e-commerce operators to gain an overview and understanding of the various capabilities and use cases of recommendation systems. The objective of this thesis was a simplified presentation of the complex topic of recommendation systems in the form of a framework.

The development of the framework followed the Design Science Research approach. On the basis of the literature analysis in the theoretical part, it was analysed how e-commerce recommendations work and to gain a deep understanding for recommendation algorithms and data mining methods. As part of the development phase of the framework, the generic layer architecture of business applications was used. Accordingly to the 3-tier architecture recommendation systems consist of the user interface, business logic and data storage layer. Based on a qualitative content analysis, individual framework components were worked out for the classification of recommendation systems at all 3 layers. The framework provides an overview of underlying algorithms, required data and relevant customer touchpoints, in which potential customers can come into contact with recommendation systems during the customer journey. In the last step, the framework was checked for its applicability. Within a case study, the artifact was evaluated on the basis of the best practice example Amazon.com. Amazon has developed a recommendation system based on its own requirements, in particular the high complexity and product diversity and the large number of users. On the basis of the 3-layer architecture, the framework were evaluated using the Amazon case study. The evaluation
showed a high accordance in the structure and the corresponding components of recommendation framework.

The research question of this master thesis is answered by providing the framework. The framework can be used to provide a guideline how to increase the conversion rate in e-commerce applications from an academic as well as a practical point of view. Key success factors consisting of different components of recommendation systems were identified to optimize the conversion rate in e-commerce applications. Furthermore, key insights could be worked out on the basis of the framework. It has to be noted that data form the basis and the most important asset of recommendations. Data must be collected, stored, analyzed, trained in machine learning models and filtered for recommendations in a defined process. E-commerce owners and marketers have to gain a deep knowledge about their (potential) customers and items they are selling. For example, Amazon.com tracks data on all customer behavior activity on the web shop. Algorithms can be used to perform big data analysis to track every click, view or other interactions recording in databases. An intelligent recommendation system must be able to learn from users and collect data about their tastes and preferences.

It should be noticed that the assignment within the framework is not a rigid construct. The combinations were worked out on the basis of the literature, practice-oriented studies and the Amazon case study. Specific implementations of e-commerce applications could also require other combinations. Therefore, modifications and in practice mostly unexplored recommendation methods are not considered in the mentioned framework. Another limitation is the focus on recommendation systems in e-commerce. The framework could also be extended to other application areas. Other channels could also be integrated, such as social media or marketing channels like email marketing. These channels have not been considered within the framework yet.

On the basis of the framework e-commerce operators, marketers and developers can derive implementation approaches for recommendation systems and approaches increasing sales on e-commerce applications. In addition, a fundamental understanding in which manner recommendation systems work was created.
In addition, the framework enables decisions, which can be made on all 3 layers of recommendation systems. On the logic layer, the framework can offer recommendations for action which user interfaces recommendations should be offered, which strategy should be pursued, and which degree of personalization should be required. The logic layer can provide e-commerce operators with an overview of the available filtering techniques and data mining techniques used in intelligent recommendation systems. Furthermore, they are provided with a technical understanding of the functionality of machine learning algorithms. At the data level, an understanding which data has to be entered as input in recommendation systems and which connections between data have to be established in order to implement recommendations on the layers of the architecture of recommendation systems has been given.

Further research can be carried out on customer acceptance and trust in recommendation systems. Data protection is also becoming more and more important, which can also affect the limits of the personalization of recommendations. In addition to this, future research can systematically examine additional factors that may affect the accuracy of recommendations. Accuracy defines the most important goal to predict consumer behavior. Determining which recommendation approach provides the highest level of accuracy under which conditions is still open in this work. This should be another aspect for future research.

**Fig. 3**

(Jacobi, Benson, & Linden, 2006, p.5)
GENERATE INSTANT RECOMMENDATIONS

IDENTIFY ALL POPULAR ITEMS PURCHASED OR RATED BY USER WITHIN LAST SIX MONTHS

RETRIEVE SIMILAR ITEMS LISTS FROM TABLE

WEIGHT EACH SIMILAR ITEMS LIST BASED ON USER'S PURCHASE DATE OR RATING OF CORRESPONDING POPULAR ITEM

MERGE SIMILAR ITEMS LISTS (IF MULTIPLE LISTS) WHILE SUMMING SCORES

SORT RESULTING LIST FROM HIGHEST-TO-LOWEST SCORE

FILTER RESULTING LIST BY DELETING ITEMS WHICH HAVE BEEN PURCHASED, HAVE BEEN RATED, HAVE A NEGATIVE SCORE, OR FALL OUTSIDE DESIGNATED PRODUCT GROUP OR CATEGORY

OPTIONALLY SELECT ITEM FROM USER'S RECENT SHOPPING CART CONTENTS AND INSERT INTO ONE OF THE TOP M POSITIONS IN LIST

RECOMMEND TOP M ITEMS FROM LIST

(Jacobi, Benson, & Linden, 2006, p.7)
Note: the following examples have been made anonymous to user profiles. Brand names or film titles are not promotional and have been chosen arbitrarily. [Retrieved on 19 March 2019]
Amazon's Recommendation User Interfaces – 2. Appendix

[Top-N list]

[Popular items]

[Top rated or reviewed]
Amazon’s Recommendation User Interfaces – 2. Appendix

Top positive review
See all 53 positive reviews

Top critical review
See all 7 critical reviews

[Inspired by your browsing history]

Your recently viewed items and featured recommendations
Inspired by your browsing history

Related to items you've viewed
See more

[New items]
[Deals and offers]

Today's Deals
New deals every day. Shop our Deal of the Day, Lightning Deals and more daily deals and limited-time sales.

Deal of the Day & Lightning Deals

- **Up-selling**

- **Cart recovery**

- **Deals and offers**

  **Today's Deals**

  New deals every day. Shop our Deal of the Day, Lightning Deals and more daily deals and limited-time sales.

  **Deal of the Day & Lightning Deals**

  - **Up-selling**

  - **Cart recovery**

  - **Deals and offers**
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