RECOMMENDED CULTURE

Distinctions in cultural consumption and taste in a digitized and recommendation driven age

KEYWORDS:
recommender systems
social classes
distinctions
cultural consumption and taste
digitization

THESIS
July 10, 2014
MA New Media & Digital Culture
Alice Nell | 3804054
Tutor: Ann-Sophie Lehmann
Second reader: Imar de Vries

Index

1. Introduction

Over the past years the importance of traditional broadcast media such as newspapers, magazines, radio and TV has declined. New media, in particular the internet, has gained prominence. On the internet so-called ‘recommender systems’, or in short ‘recommenders’, are often employed. Recommenders are software systems that provide recommendations for both physical and digital products based on the explicit behaviour of the individual user. Online services such as YouTube, Spotify and Netflix utilize recommenders mainly to provide their users with highly personalised recommendations for streaming videos, music, films and TV shows, respectively. Online stores such as Amazon and eBay use recommenders to determine which advertisements and recommendations for products to show to their customers (Konstan & Riedl 2012).

When a new mother visits the Books department of the online retailer Amazon, she may be offered books about child upbringing. On the other hand, a software engineer may see advertisements offering new books about a programming language. When a member of Netflix watches a particular movie, she or he will get recommendations based on her or his act of watching that movie. When she or he for instance watches DESERT FLOWER (2009), Netflix may recommend her or him more “films based on a book” or more “movies featuring a strong female lead”. The advertisements based on, and recommendations given by recommender systems, highlight products and bring them to peoples’ attention.

Since the consumption of both media and products has largely shifted to the internet during the past years, it is safe to say that, among other things, the internet has partly taken over traditional media’s function with regard to reference of and recommendation for cultural products. In so far, recommenders have taken over the function of traditional sales strategies. Whereas traditional sales strategies were and are determinative for the cultural products highlighted in traditional media, recommenders are the determining factor for the cultural products highlighted online (Lotz 2007; The Communications Market 2006). Recommenders work as innovative, modern sales strategies and their recommendations can be interpreted as product promotions. They have come to “provide an effective form of targeted marketing” for cultural products, among other things (Linden et al. 2003, 79). However, recommenders can also be interpreted as a new agent in personal reference and recommendation, fulfilling a function that is in a way comparable to, potentially even re-shaping, the function of social peers exchanging personal references of and recommendations for cultural products.

Taken together, recommender systems have become increasingly important as an influence on people’s frame of reference for cultural products, which now relies on three sources; social peers, traditional media and online recommenders. As such, recommenders, just like traditional media and social peers, influence people’s choices and preferences for cultural goods, among other things. Therefore they influence peoples’ cultural consumption but also their cultural taste. According to widely acknowledged sociologist Pierre Bourdieu, a person’s entire set of patterns of choice and preferences - a person’s “manifested preferences”, can be defined as her or his ‘taste’ (Bourdieu 1984, 56). A person’s entire set of manifested preferences for cultural products, such as movies, films and books, can therefore be referred to as her or his ‘cultural taste’. Taste is directly linked to consumption for two main reasons. First of all, consumption leads to intrinsic understanding and through that to taste. Secondly, taste becomes ‘objectified’ in products a person prefers, chooses and thus consumes (1984). The question arises in what ways recommenders, as new agents for reference and recommendation, influence people’s cultural consumption and taste, and how this influence differs from traditional sales strategies.

Traditional sales strategies highlight products based on presumptions about generalized social groups in a society, taking into account level of education and income, among other things (Kotler et al. 2010). Therefore, due to the employment of traditional sales strategies, only goods that are assumed to be “appropriate” for people in a certain social group are highlighted to them in traditional media; for instance in the newspapers they are assumed to read, and on the TV channels they are assumed to watch. In this way, traditional sales strategies and traditional media contribute to a system in which people in different social groups consume different cultural products. Since groups are mainly determined based on level of education and income, and because such groups are highly compatible with Bourdieu’s notion of ‘social classes’, traditional sales strategies and traditional media contribute to a distinction in cultural consumption and taste between people in various social classes.

Recommenders’ work fundamentally different from traditional sales strategies; they highlight products based on the individual user’s actual behaviour (Konstan & Riedl 2012; Lekakos and Giaglis 2006; Medo 2012). They do not highlight products to groups but to individuals, and they do not highlight products based on presumptions but rather based on actual observations. Considering the less generalized, more personal character of recommenders’ recommendations, it is questionable whether recommenders contribute to a distinction in cultural consumption and taste between people in various social classes in the same way that traditional sales strategies do. If recommenders really do recommend to individuals, solely based on their own explicit behaviour, they may enable taste to develop more independently from social position than ever before (when there were no recommenders, but merely social peers and traditional media as sources for reference). In that case, recommenders may thus contribute to a less pre-determined relationship between cultural consumption, cultural taste, and social class.

This question central in this thesis is focused on whether the use of recommenders online contributes to, or detracts, from a distinction in consumption of and taste for culture between people in different social groups, and in particular; between people in different social classes.

The main question is formulated as follows:

In what ways does the use of recommenders online create and influence distinctions in cultural consumption and taste between people in varying social classes, and are recommenders less prone to manifesting pre-determined ideas about certain tastes for certain classes than traditional sales strategies and media were?

The aim of this research is not to statistically measure the differences in cultural consumption and taste between people in different social classes, but rather to map how recommenders influence and potentially change the assumed distinction.

The main question is caught up with five hypotheses primarily. First of all; that the rise of mass culture, combined with the digitalization of contemporary Western societies and the rise of the internet in particular, have destabilized the pre-determined character of the relationship between cultural consumption, cultural taste, and social class. Secondly, that recommender systems employed online can be interpreted as modern sales strategies on one hand, and as agents for personal reference and recommendation comparable to social peers on the other. Thirdly, that recommenders highlight cultural products to people based on fewer presumptions and generalizations than traditional sales strategies do, and that therefore they contribute to a less pre-determined relationship between cultural consumption, taste and social class. Fourthly; that the use of recommender systems contributes to broader trends, fuelled by the internet, in which the relationship between cultural consumption, cultural taste and social class is being re-defined and re-shaped. Finally: that even though recommenders offer highly personalised recommendations, their partiality, subjectivity and biases, are often ignored.

1.1 A bridge between marketing and media research

Following Bourdieu's theory about the direct relationship between consumption and taste, recommenders' influence on taste can be investigated through consumption. In the field of media studies, little has been written about the influence of recommender systems on consumption. More about the topic has been written in the field of marketing. Research in marketing has primarily focused on recommenders' influence on sales. Since the products sold are the same as the ones being bought and consumed, research about recommenders' influence on sales reveals their influence on consumption, too. Recommenders' influence on distinctions in cultural consumption and taste can be investigated by looking into (mainly) media research about recommenders' influence on the formation of online social groups, as well as by looking into media research about digital inequalities, leading to distinctions in cultural consumption among other things.

In chapter 2 of this thesis, I present a literature review of the status quo of relevant marketing and media research, as discussed above. The research from the fields of marketing and media are bridged through the lens of Bourdieu's theory about distinction and taste, on which I will elaborate in chapter 3.

Integration in a literature research, according to Chris Hart, author of the book *Doing a Literature Review: Releasing the Social Science Research Imagination* is "a key element that makes for good scholarship" (1999, 8). Integration can be accomplished by "drawing elements from different theories to form a new synthesis, or to provide a new insight. It may also mean re-examining an existing body of knowledge in the light of a new development" (1999, 8). In the literature review of this thesis, I achieve integration by bridging research from the field of marketing with research from the field of media, as discussed above. I also integrate by forming new syntheses: I draw elements from theories about recommenders' influence on sales and consumption, and mix them with elements from theories about the internet's potential to nurture new sorts of social groups and new sorts of distinctions.

1.2 Bourdieu's theory of distinction and taste

Sociologist Pierre Bourdieu's widely accepted distinction theory about the relationship between cultural consumption, taste and social class will be used as a main perspective in this thesis (1984). As mentioned, Bourdieu argued that there is a direct relationship between consumption and taste. However, his research also proved that there is a typical distinction in cultural consumption and taste between people in various social classes. It is Bourdieu's theory, on which the distinction in cultural consumption and taste between people in various social classes is presumed in this thesis, and it is his theory, on which the direct link between consumption and taste is presumed too. Bourdieu's mentioned definition of taste as a person's set of "manifested preferences" is also maintained in this thesis.

In the third chapter of this thesis, I present a theoretical framework by elaborating on the aspects of Bourdieu's theory that are most relevant with regard to this thesis' context. I will elaborate on the vicious circle between peoples' social, cultural and economic 'capital'; on the relationship between consumption and taste; on the notion of consumed cultural products as 'objectifications' of taste and markers of class; and finally, on the influence of social capital and cultural capital on cultural consumption and taste.

Although Bourdieu's research is based on France in the 1960's, the main arguments derived from it can be translated to contemporary Western societies (Bourdieu, 1984). Douglas Holt, assistant professor in Advertising and Sociology at the University of Illinois' Institute of Communications Research, highlights this argument:

> Rather than a nomothetic theory, Bourdieu's theory is a set of sensitizing propositions concerning the relations between social conditions, taste, fields of consumption, and social reproduction that must be specified in each application to account for their particular configuration (Holt 1998, 6)

I will re-evaluate Bourdieu's theory in the light of mass culture, digitalization and the growing employment of recommenders online. For my re-evaluation I will make use of various concepts and theories, which I will briefly introduce in paragraph 1.4.

1.3 Methodology

Auto-ethnographic examples

I have aimed to deepen the scope of my literature research by integrating examples. I investigated my own experiences, as well as those of other people, in real-life situations and with existing applications, thus carrying out ethnographic research as 'complete participant' or 'participant as observer', respectively (Brennen et al. 2013, 161).

Following the guide for qualitative research *Qualitative Research Methods for Media Studies*, written by Bonnie S. Brennen and published by Routledge in 2013, ethnographic methods can be utilized to "draw out broader contexts surrounding media usage, as well as to understand how people actually engage with media" (Brennen 2013, 161-162). It can be carried out through depth interviews and participant observations, among other things and is seen as a "blending of observation and interpretation" by "listening, watching and interacting with people" in order to learn about the "realms of their experiences, routines and practices" (Brennen 2013, 161).

Case studies

Aside from the various auto-ethnographic examples that are woven into my research, I have integrated software analyses and textual interface analyses of three recommender case studies.

Following the paper *Five Misunderstandings About Case-Study Research,* written by Bent Flyvbjerg and published in the interdisciplinary journal *Social Sciences* by SAGE in 2006, I am able to name a number of reasons for utilizing case studies in this thesis. First of all, the case studies are well suited to provide context-dependent knowledge about the application of recommender systems in the online world. Since “social science has not succeeded in producing general, context-independent theory (…) there is nothing else to offer than concrete, context-dependent knowledge” (Flyvbjerg 2006, 223). Furthermore, although not in a formal manner, the primary outcomes of the case studies can be generalized to prove or at least illustrate something about recommenders' workings. The case studies that I present in this thesis will be helpful to integrate theoretical knowledge with empirical observations of actual recommenders at work. In this way, they help to deepen and broaden the analysis of recommenders. Before discussing my case studies more in-depth, I will explain which platforms and products I have chosen for my case studies, and for which reasons.

I have chosen to focus my case studies, as well as my ethnographic examples, on the recommenders in three specific platforms, namely those utilized in Netflix, Spotify and Amazon Books. Since these platforms are well known and widely used, I am certain that they are at least to that extent successful and influential. Additionally, films, music and books are recognized ‘taste-makers’ and expressions of taste and distinction, following the theory by Bourdieu (1984). I have chosen Netflix and Spotify in particular, because the products involved in these platforms (films, TV shows and music, respectively) provide for an excellent integration of my case studies with the culture critical theory involved in this thesis:

First of all, unlike some other cultural products such as fashion, theatre and food, films and music can be bought as well as consumed virtually and online. For this reason, peoples' ability to consume films and music is less dependent on their geographical location across countries, regions and cities. When discussing Netflix' and Spotify's recommenders' influence on cultural consumption, the variable of geographical location will thus remain relatively stable.

Secondly, prices for movies, TV shows and music in Netflix and Spotify do not differ among each other. Instead of setting a price per item, both platforms offer their products for a fixed monthly price; they offer users the possibility to unlimitedly ‘stream' content – listen and watch content online without downloading. Spotify offers users unlimited streaming without any financial payment, but users will have to accept the advertisements that will be played in between every 5 to 7 songs. Another option is to pay €7,25 a month for ad-free Spotify. Netflix offers unlimited access to their content for a fixed monthly price of €7,99. For this fee, Netflix offers users an account with two ‘active streams', meaning that two people can use the account separately and thus potentially share costs, reducing monthly costs to €4,00 a person. Considering the relatively low financial thresholds for consuming music and films with Spotify and Netflix, the group of people who cannot afford these services is relatively small. As prices for movies, TV shows and music do not differ among each other in Netflix and Spotify, prices cannot affect users' choices for consumption of one product over the other (e.g. why to consume one album or film instead of another). Thus, the variable of financial considerations as an influence on users' cultural consumption is kept stable within these platforms.

The reasons outlined above only partly formed my motivation for selecting Amazon Books as a case study. Most of Amazon's books can be shipped worldwide, so once again geographical location matters relatively little for the motivation of consumption. Keeping in mind the prices, it hardly ever happens that prices for two new books on Amazon (with a comparable number of pages) differ more than a few euros throughout Europe. This is very different from cultural products in branches such as cars, food and fashion. Prices for a dress can vary from 10 euros at H&M to 4000 euros at Dolce & Gabbana, for instance. Thus, Amazon's Books department also has relatively few financial and geographical variables to influence users' consumption choices. However, the most important reason to include Amazon Books as a case study is different. As will become clear in chapter 4.4 and 4.7, Amazon Books utilizes and presents recommendations in very different ways than Netflix and Spotify do. For this reason, the case study of Amazon Books can be used as a foil to highlight differences in how recommenders function on a technical and interface level. Including Amazon Books as a case study therefore sharpens the analysis of all three cases.

Software analyses

In chapter 4.4, I carry out software analyses of the recommenders in Netflix, Spotify and Amazon Books. I look into the platforms' own explanations about their recommenders and analyse them through theoretical explanations and taxonomies of recommender systems, which I present in chapter 4.1 to 4.3. The aim of the software analyses is to investigate how the recommenders in the three case study platforms work, how they potentially differ, and to what extent they highlight products based on the individual user's actual behaviour.

Textual interface analyses

In chapter 4.7, I carry out qualitative textual analyses of the Netflix, Spotify and Amazon interfaces. The aim is to consider how these platforms' interfaces contain meaning, and how they are used to influence users' perception of and assumptions about the platforms and their recommender systems.

For the purposes of textual analyses, texts can be interpreted as "literary and visual constructs, employing symbolic means, shaped by rules, conventions and traditions intrinsic to the use of language in its widest sense" (Brennen et al. 2013, 193). Examples of texts are books, films and newspapers, but also websites, games, television programs advertisements and popular music. Such texts can be interpreted in order to "understand some of the many relationships between media, culture and society" (ibid).

"Maintaining that texts help to construct our knowledge, values and beliefs, and reinforce our common sense understandings" textual analyses of recommender systems' interfaces, carried out from an ideological perspective, can help me to examine the range of potential meanings communicated through recommenders' interfaces (Brennen et al. 2013, 202). It will also enable me to consider how these meanings may influence peoples' assumptions and ideas about the platforms and their recommenders' impartiality, neutrality, objectivity, and ability to provide highly personalised recommendations (Brennen et al. 2013).

Most researchers performing textual analysis from an ideological perspective follow a set of specific categories and guidelines outlined by Mike Cormack in 1995 (Brennen et al.

2013). Following Cormack's theory, five main areas need to be emphasized in ideological analysis: content, structure, absence, style and mode of address (ibid). Although Cormack's outline is mostly used for analyses of textual documents such as books and articles, it can also be used for other sorts of texts (ibid).

Content: I analyse whether there are opinions, values, beliefs or other judgment present in the interfaces' written content.

Structure: I analyse the structure of the interfaces, for instance by looking into what content is placed where, what and how content is emphasized, and how content is clustered. I will also see if there is a specific logic that can be recognized in the structure of the content, or that rather, content is structured intuitively.

Absence: I consider aspects that are absent, unsaid, missing or avoided in the interfaces. Such aspects can be textual explanation or information, but also certain features (e.g. features that enable users to interact with each other).

Style: I consider the style of the interfaces by primarily considering visual and textual aspects, clean or cluttered design and use of colours.

Mode of address: I analyse how the platforms address their users through the interfaces (e.g. formal or informal, directly or indirectly).

Since I am only able to observe and interpret the interfaces from my own perspective, subjectivity in these analyses is inevitable. Furthermore, it is important to note that, as most textual analyses, mine too are far from complete (Brennen et al. 2013). Many more aspects of the platforms' interfaces could be discussed and a lot more interpretations could be given too. I have tried to take into account the aspects of the interfaces that seem most important, given the analyses' purpose in the context of this thesis.

I will describe the interfaces as they look like on a regular laptop or computer screen, accounting for the five categories outlined by Cormack (1995) and recommended by Brennen et al. (2013). I will discuss some of the interfaces' ideological implications simultaneously. After discussing the interfaces of Netflix, Spotify and Amazon individually, I will synthesize my findings and their implications in a comparative conclusion.

1.4 Structure of the thesis

In the second chapter of this thesis, I present the status quo of relevant marketing and media research as briefly introduced in paragraph 1.1. To set up a context, I first look into supply-side characteristics of consumption on the internet, making use of the notorious Long Tail theory by Chris Anderson (2006). The Long Tail theory is critically analysed using theory by Lister, Dovey, Giddings, Grant, and Kelly; authors of the book *New Media A Critical Introduction* (2009).

After looking into the broad supply-side effects of the internet on online consumption, I turn to a discussion of demand-side and recommender system-characteristic effects on online consumption. I discuss recommenders' influence on variety of sales, and on sales of niche products in particular, using research results derived from the fields of Operations and Information management, Technology, and Management Science.

Outcomes of a simulative mathematical modelling exercise carried out by Fleder & Hosanagar (2009) and outcomes of an empirical data analysis by Brynjolfsson, Hu and Simester (2011) will be of main importance.

Having discussed online consumption, and recommenders' influence on online consumption in particular, the last part of the second chapter is concerned with the potential effects of the internet on social group formation, social integration and fragmentation. As early as 1997, S.R Hiltz and B. Wellman, professor of Computer and Information Science and professor of Sociology respectively, expressed their expectation that computer networks would yield communications not so much based on social class, but rather based on homogeneous preferences and attitudes (1979). More recently in 2005, Van Alstyne, working for Boston University and Massachusetts Institute of Technology, and Brynjolfsson, member of Massachusetts Institute of Technology and the Sloan School of Management, published a modelling and measuring exercise for the integration of electronic communities. In their paper, Van Alstyne and Brynjolfsson defined a set of (mathematical) measures that suggest specific conditions under which either human integration or fragmentation online occurs. As will become clear, the expectations about the formation of social groups online, combined with the outcomes about the internet's, and especially recommenders' influence on cultural consumption, imply that the online employment and use of recommenders may stimulate distinctions in cultural consumption and taste based on preferences and attitudes, rather than based on social classes.

This idea specifically, and the outcomes of the literature research more generally, are further investigated in the third chapter of this thesis. I do so through a broad theoretical framework consisting of an elaboration on sociologist Pierre Bourdieu's Distinction theory (such as briefly introduced in paragraph 1.2) and a re-evaluation of that theory in the light of mass culture, the digitalization of the Western world, and in particular; in the light of the grown deployment of recommenders online.

I will look into the way in which traditional sales strategies used to maintain and still help to manage the predetermined character of class-based distinctions in cultural consumption and taste, such as described by Bourdieu. By doing so, I make room to investigate the influence of recommenders on class-based distinctions in cultural consumption and taste more profoundly in chapter 4. In the context of this thesis, traditional sales strategies can be defined as strategies used to sell both products and traditional media; used to determine for instance which products should be advertised to people through what magazines, but also which target market to aim for with a newspaper. I will mainly deploy marketing theory by Philip Kotler et al. (2010) and Amanda D. Lotz (2007): Philip Kotler is Distinguished Professor of International Marketing at North-Western University's Kellogg School of Management and "one of the world's leading marketing thinkers" according to websites such as Wiley and Amazon. Amanda Lotz is associate professor of Communication Studies at the University of Michigan and author of the book The Television Will Be Revolutionized.

I look into the universality of Bourdieu's theory by using outcomes of a quantitative data analysis, conducted by Tally Katz-Gerro, member of the department of Sociology and Anthropology at University of Haifa (2002). Afterwards I turn to the outcomes of an interpretive empirical study by Douglas Holt (1998) to discuss the applicability of Bourdieu's theory on mass-culture characterized societies. Through an analysis of six ethnographic interviews, Holt examined whether Bourdieu's theory about the relationship between cultural capital and consumption is applicable to the mass-culture characterized contemporary United States. Based on his research outcomes, Holt argues that consumed products as 'objectifications' of taste and markers of class have decreased in value, while the importance of motivations for, and patterns of cultural consumption as 'embodiments' of taste and markers of class, have increased. Holt draws a distinction between consumers with so-called 'omnivore' and 'univore' consumption behaviours. Along with this, he describes six dimensions of taste "that distinguish informants with high versus low cultural capital resources" (Holt 1998, 1). Holt's theory is strengthened using arguments about digitized consumption by Alicia Bastos, member of the London College of Communication and the University of the Arts London (2010). It is supplemented with qualitative and quantitative research outcomes by Alan Warde, David Wright, Modesto Gayo-Cal, Tony Bennett, Elizabeth Silva and Mike Savage; members of the University of Manchester and the Open University of the United Kingdom (2005). They investigated the notion of 'omnivorous consumption behaviour' more in-depth and considered the phenomenon directly in the light of Bourdieu's distinction theory.

I re-evaluate Bourdieu's theory from a new media perspective, mainly by looking into the concepts of 'digital divide' and 'digital inequality'. These concepts focus on the inequality in access to computing artefacts, and on the inequality in benefits derived from computer and internet usage. As will become clear, the existence and widespread usage of recommenders leads to a distinction in cultural consumption and taste between people who, for whatever reason, do and do not make use of recommender systems. For instance between people who do and who do not use Netflix or Spotify. I will discuss the possibility that, while recommenders influence personal taste among their users, people without access to recommenders may have fewer opportunities to develop a personal taste. The concepts of the digital divide and digital inequality help me to investigate this issue. I elaborate on the digital divide and digital inequality by deploying ethnographic research outcomes of Lynette Kvasny, who investigated "the concept of cultural reproduction in the domain of digital inequality" (2006, 163), and by looking into anthropological research outcomes by Marlena Mattei (2012).

In the last part of chapter three, I look at the ways in which social capital is influenced by the internet, and by social media platforms in particular. For this purpose, I will mainly use the paper *Understanding the Relationship between Information and Communication Technology (ICT) and Social Capital: A Conceptual Framework*, written by Song Yang, Heejin Lee and Sherah Kurnia, members of the department of Information systems at University of Melbourne, Graduate School of International Studies, and Department of Information systems at University of Melbourne, respectively (2007). Their paper maps the current state of the research in the area of social capital and ICT, providing a clear overview of the status quo. As will become clear, the internet has reshaped and is still reshaping human interaction, thereby also reshaping the way people build up and maintain their social capital. The internet has provided mobility for social capital in terms of time, space and context. To this paper, the role of social media (Facebook, especially) is particularly of interest because social media are often linked to or woven into recommender systems.

Based on the literature review presented in chapter 2 and the theoretical framework outlined in chapter 3, I present extended and profound analyses of the objects central in my thesis in chapter 4. Critical analysis of recommender systems in the broadest sense is presented based on literature research, software analyses of three case study recommenders, and textual analyses of the interfaces of these same three case study recommenders. The main aim is to verify to what extent recommenders truly highlight products based on individual users' actual behaviour: to verify whether it is true that recommenders highlight products based on fewer presumptions and generalizations than traditional sales strategies do, and therefore, if they indeed make room for a less predetermined relationship between cultural consumption, taste and social class. However, the investigation is also meant to elaborate on the public perception of recommenders, to clarify how business interests are involved in recommenders, to analyse the function of recommenders' interfaces, and finally, to investigate the way in which recommenders deploy recommendations by social peers.

I first examine what actually underlies recommenders; software, consisting of data-structures and algorithms. For this purpose I present software theory by Lev Manovich, director of the Software Studies Initiative and author of the book *Software Takes Command* (2013). I continue to discuss the cultural relevance of recommendation algorithms, as well as the public discourse surrounding recommendation algorithms. I use Tarleton Gillespie's essay *The Relevance of Algorithms* (2012) as a main input. Gillespie is an associate professor at the Departments of Communication and of Information Science at Cornell University.

Secondly, I define recommenders and briefly discuss their history. I give an overview of the existing recommenders by discussing three possible taxonomies of recommender systems. By doing so, I also provide insight into the technical workings of various recommenders, and how they differ from each other. The first taxonomy is based on a widely acknowledged and often cited survey by Robin Burke; member of the Department of Information Systems and Decision Science at the California State University (2002). The second taxonomy is based on a state of art research about the evaluation of recommender systems from a user's perspective, presented by Li Chen, Rong Hu and Pearl Pu (2012). Hu and Pu are members of the Human Computer Interaction Group at the School of Computer and Communication Sciences and of the Swiss Federal Institute of Technology. Chen is a member of the Department of Computer Science at the Hong Kong Baptist University. The third taxonomy is based on an overview of recommenders, created by Gediminas Adomavicius and Alexander Tuzhilin (2005). Adomavicius is member of the IEEE group of Transactions On Knowledge and Data Engineering, and member of the School of Management at University of Minnesota. Tuzhilin is member of the School of Business at New York University. The three taxonomies are supported and comprehended by research outcomes, explanations and arguments from other researchers in the fields of Computer Science and Engineering, Information Engineering, Information Filtering and Machine Learning. Of main importance are various research outcomes and theories by J. Konstan (2008, 2012, 2014), J. Riedl (2012), and to a lesser extent M.D. Ekstrand (2014), all working on the widely acknowledged GroupLens Research project on recommenders, and members of the department of Computer Science and Engineering at the University of Minnesota. I will later introduce these and other authors more elaborately.

Based on the theoretical overview and explanation of recommender systems, three existing and widely used recommenders, namely those in Netflix, Spotify and Amazon Books, are analysed on a technical level through software analyses. On one hand, the analyses are based on information about the systems provided by (employees of) the platforms themselves, while on the other hand I consider the theoretical overview and explanation as previously discussed in chapter 4.

Xavier Amatriain and Justin Basilico, both specialised in Personalization Science and Engineering at Netflix, published a two-fold article on *The Netflix Tech Blog* explaining the Netflix algorithm in 2012. This article will be used as an input for the Netflix case study. Spotify, to the best of my knowledge, has no written documents explaining their recommendation system. However, in 2014, Chris Johnson, Machine Learning employee at Spotify, published a SlideShare presentation about the Machine Learning Methods employed by the Spotify recommender. This presentation provides basic insight in Spotify's recommenders. The main input for the Amazon case study is derived from Amazon's 2003 industry report *Amazon Recommendations. Item-To-Item Collaborative Filtering*, written by Amazon employees Greg Linden, Brent Smith and Jeremy York and published in IEEE Internet Computing.

Having investigated recommenders on a technical level, I continue to explore the way in which recommenders' technology is 'translated' and presented to users through interfaces. I investigate how interfaces are designed to influence and steer users' perceptions of underlying recommender systems. I make use of Chen, Hu and Pu's theoretical overview about the most important design choices concerning recommenders' interfaces (2012) and provide illustrative examples. Afterwards, I carry out textual analyses of the three aforementioned case study's interfaces: those in Netflix, Spotify and Amazon Books. While continuing to use the recommenders in Netflix, Spotify and Amazon books as case studies, I discuss the business interests involved in recommender systems' deployment with due regard to recommenders' role in advertisement, platforms' control over content, and the interpretation of user behaviour as a form of labour. At last I look into the ways in which recommender systems can utilize users' social peers for recommendation, namely through a link with social media platforms. In the final, fifth chapter of this thesis I present my conclusions.

2. Cultural consumption and social group formation on the internet

In this chapter, I first look into research about the influence of the internet, and recommenders in particular, on cultural consumption. Afterwards I investigate the influence of the internet and recommenders in specific, on the development of social groups online. The relationship between consumption and taste is not discussed in this chapter, but will be elaborated on in the next one.

2.1 Cultural consumption on the internet: The long tail theory

Over the last few years, the debate about the influence of the internet on cultural consumption and taste has been held primarily from the perspective of the well-known and widely accepted 'Long Tail' theory, by Chris Anderson (2006). According to Martin Lister, Jon Dovey, Seth Giddings, Iain Grant and Kieran Kelly, authors of *New Media A Critical Introduction* (2009), "the 'Long Tail' has emerged as an important new model for understanding networked media, unlocking new possibilities for users and producers alike" (2009, 6). Furthermore it is "one of the most compelling accounts of the ways in which conventional media economics have changed in the post network cultures of the broadband world" (2009, 179). The long tail theory looks into supply-side changes in online, virtual sales of products, as opposed to offline 'physical-store' sales of products. It interprets changes in supply of products online, as causes for demand-side (consumption) effects. Anderson's main argument for the long tail is that on the internet, the physical, financial, and distribution-related constraints and thresholds for selling products are relatively low.

In the physical offline world, a lot of niche products do not sell enough for traditional retail to supply, mainly because of high costs for physical storage, in relationship to a low demand for such niche products. "High cost, low volume products were unlikely to get made since they lingered relatively invisible in the 'long tail of the demand curve'" (Lister et al. 2009, 197). However, on the internet it is no problem to virtually store and sell niche products. Costs for production have decreased, and the means of production have been democratized (Lister et al. 2009). "As digital media tools have become more widespread and cheaper, the barriers to entry into the marketplace are much lower, we can produce work a lot more cheaply" (Lister et al. 2009, 198). On the internet, products can also be presented and distributed to an audience that is geographically scattered and considerably larger than would be possible in a physical store. In principle, products online can be seen and bought by people worldwide, and in most cases products can be shipped worldwide, too.

Without the constraints of a physical store, "narrowly-targeted goods and services can be as economically attractive as mainstream fare" (Thelongtail.com, Chris Anderson's Blog, 2014). Therefore on the internet, a larger supply of niche products is offered. In fact, the number of niche products online "outnumbers the hits by several orders of magnitude" (ibid). People are no longer limited to what their local physical stores offer; they are no longer limited to popular 'hit' products, and due to the arguably infinite choice online, a less hit-centred "true shape of demand" is revealed (ibid).

> Our culture and economy is increasingly shifting away from a focus on a

> relatively small number of "hits" (mainstream products and markets) at the head of the demand curve and toward a huge number of niches in the tail. (The longtail.com, Chris Anderson's blog)

"The 'astonishing popularity of many thousands of blogs (….) is evidence of the Long Tail in action" (Lister et al. 2009, 199). Although it may be true that distribution of consumption on the internet is less hit-centred and more spread out over niche products, Anderson's argument that therefore, consumption is democratized and the 'true shape of demand' is revealed, seems rather utopian. However, it is safe to say that the Long Tail analysis has far reaching implications; changing the economic basis of production and unlocking "market diversity on an unprecedented scale", among other things (Lister et al. 2009, 197). Having said that, it is once again important to be critical towards the seductive rhetoric concerning the Long Tail theory; diversity of consumer choice is not the same as diversity of political or economic power.

> The economic freedom to take advantage of the unlimited choices of the Long Tail is enjoyed by a minority even in the broadband world. The neo-liberal mantra of choice is usually at the expense of the denial of economic, political or ecological choice elsewhere (Lister et al. 2009, 198)

Successful companies like Spotify, Netflix and Amazon (Books) are part of this minority. The Long Tail theory shows that "our media experiences are shaped by technologically produced opportunities and shifting economic conditions" (ibid). The widespread usage and popularity of platforms such as Spotify, Netflix and Amazon Books only strengthen this notion.

2.2 The long tail, search engines and recommender systems

A factor that didn't cause the Long Tail to develop, but rather has been and still is necessary for it to be able to exist, is the availability of search technologies and recommender systems.

> Search technologies place the most obscure products at your fingertips; automated recommendation, reviewing and rating processes make it possible for the consumer to make purchase decisions in the jungle of the Long Tail marketplace. Search and recommendation make it possible for us to consume with confidence, to make often very highly individualized choices from the vast array of media choices that lower barriers to entry produce (Lister et al. 2009, 198)

"Our ability to control and to choose our media consumption depends increasingly upon our skill at working with the logic of search technologies" (Lister et al. 2009, 199). While search engines and recommenders are essential for people to navigate through the 'endless' products available on the web, they also facilitate highly targeted advertising possibilities.

Not only Anderson (2006) and Lister et al. (2009) argue that search engines and recommenders are essential for the Long Tail to exist. D. Fleder & K. Hosanagar, both working in the department of Operations and Information management of the University of Pennsylvania, also do. They did an empirical research focused on the influence of the most popular recommender systems, so-called 'collaborative-filtering' recommenders, on aggregate sales diversity, and consequently, on aggregate consumption diversity (2009). Through a simulative modelling exercise, they proved that collaborative-filtering recommenders create a rich-get-richer effect for popular products and a poor-gets-poorer effect for unpopular products. Because collaborative-filtering recommenders, on which I will elaborate more extensively in chapter 3, make use of historical sales-data in order to recommend products, the products that are bought (or consumed) often will end up being recommended more frequently (2009). Thus, the recommender systems develop a "positive feedback loop" for popular products, which according to the authors leads to a decrease in potential consumption diversity on aggregate (2009, 701). However, this is only true when the recommenders' influence is compared to the influence of those same recommenders without their collaborative-filtering characteristics: a non-existent situation and unrealistic scenario. When the influence of collaborative recommenders on consumption diversity is compared to the influence of existing alternatives, such as best-seller lists published in traditional media, aggregate consumption diversity can increase. In that case, the traditional alternatives present recommendations that are even more popularity-based, and thus create worse rich-get-richer effects than collaborative recommenders do (2009). Independent from collaborative recommenders' effect on aggregate consumption diversity, Fleder & Hosanagar discovered that collaborative recommenders are able to increase consumption diversity on the level of the individual user. This is true, because recommenders are able to introduce individuals to new products while on aggregate pushing a lot of users to the same new products (2009, 701).

In 2011, Brynjolfsson, Hu and Simester, members of the Sloan school of management and the Massachusetts Institute of Technology, of the Krannert School of Management and of the MIT Sloan School of management respectively, also investigated recommenders' influence on sales and consumption diversity. Brynjolfsson et al. conducted an empirical data-analysis in which they compared the variety of sales of clothes through an online web shop, with the variety of sales of clothes through a paper catalogue. Although clothes (fashion) are not accounted for in this thesis, the research by Brynjolfsson et al. is interesting because it proves that recommenders have a positive effect on consumption diversity. The web shop researched by Brynjolfsson et al. had a so-called 'semi-personalised' content-based recommender, which provided recommendations based on item-item similarities. The researchers controlled supply-side factors to explore "the demand-side factors associated with increased sales of niche products via the internet" (2011, 1384). Product availability, product descriptions, prices and pictures of products were identical in the web shop and paper catalogue. Furthermore, consumers' demographic and socioeconomic differences such as income, age, education and gender were matched. The research results showed that, when keeping all these variables stable, the web shop had a significantly less concentrated sales distribution than the paper catalogue.

Since the supply-side factors were kept constant, the researchers were able to look into demand-side causes for the less concentrated sales distribution observed online. They statistically measured consumers' use of recommendation and search tools in the web shop, and discovered that both the use of the recommender system, and the use of non-directed search were significant for the increased sales of niche products online (2011). These results are compatible with other research results, such as those of an earlier research by Brynjolfsson and others presented in 2003, which proved that online bookstores sell relatively more niche books and fewer mass-market books than offline bookstores, "reflecting their more sophisticated search and recommendation tools and the broader selection of titles that they provide" (Van Alstyne & Brynjolfsson 2005, 859).

The fact that recommenders and search tools lower search costs for consumers (both in terms of time, effort and money), may be the theoretical explanation for the discussed outcomes. In other words; recommenders may be the demand-side answer as to why niche products are sold more, and distribution of sales is more diverse on the internet. "Standard models of search behavior in the marketing and economic literatures predict that consumers search for information to improve their purchasing decisions" and that "more importantly, rational consumers continuously weigh expected benefits against search costs" (Brynjolfsson et al. 2011, 1377). Thus, in a case where search costs (efforts) are high, consumers will not search for product information a lot. In an extreme case, they will only consider products for which they already have 'ex ante awareness': already existing awareness, for instance as a result of information obtained through magazines and other media that play "a key role in setting the current trend for popular [products]", and through word-of-mouth referrals which also "tend to favor popular products" (ibid). Sales distribution in this case will therefore be extremely concentrated on popular products - for which ex ante awareness exists. In an opposite situation where search costs are relatively low, for instance due to the availability of recommendation and search tools, consumers may endlessly search for available products. The "distribution of sales across products will fit more closely to consumers' "true" preferences", and will therefore be less concentrated on popular products (ibid).

The outcomes by Fleder & Hosanagar (2009) and Brynjolfsson, Hu and Simester (2011) support the argument about recommenders' contribution to the long tail theory. On one hand, recommenders offer more diverse, less hit-centred references for cultural products than traditional alternatives do; on the other hand, they contribute to the long tail's existence by enabling people to navigate through the 'tail' of products. Altogether, recommenders contribute to a trend in which consumption of cultural goods becomes less hit-centred and more diverse. In chapter 2, I will explain how it is possible that through consumption, recommenders also influence taste.

2.3 The internet, recommenders and the formation of social groups

As this thesis is concerned with the investigation of recommenders' influence on distinctions in cultural consumption and taste between people in various social groups, recommenders' influence on the development and formation of social groups needs to be addressed. In order to do so, I will first discuss research outcomes with regard to the influence of the internet on the formation of social groups, and then narrow down to discuss recommenders' influence in particular.

As early as 1997, S.R. Hiltz and B. Wellman, professor of Computer and Information Science and Professor of Sociology, respectively, published an article in which they stated:

> Computer-mediated communication can enable people with shared interests to form and sustain relationships and communities. Compared to communities off-line, computer-supported communities tend to be larger, more dispersed in space and time, more densely knit, and to have members with more heterogeneous social characteristics but with more homogeneous attitudes" (Hiltz & Wellman 1997, 44)

Hiltz and Wellman expected that computers, and the internet in particular, would yield formation of social groups not so much based on social characteristics (social class, age, gender, ethnicity), but rather on homogeneous attitudes and preferences (Hiltz & Wellman 1997). Such groups may form based on for instance a shared interest for a particular movie or TV series, a shared love for a certain music genre or shared political arguments and ideals (ibid). In 2005, Van Alstyne & Brynjolfsson researched the potential consequences of the emerged global online information infrastructure on human integration. They presented outcomes compatible to those of Hiltz and Wellman (1997). Van Alstyne & Brynjolfsson focused on diversity of consumption of information and human interaction. Although the researchers focused mostly on diversity of consumption of (politically loaded) information meant to gain or increase knowledge, 'information' can also be interpreted as any content in the shape of sound, text, or (moving) image. As such, cultural products could also be interpreted as a form of information, and in this way, the outcomes by Van Alstyne & Brynjolfsson are relevant to this thesis. Van Alstyne & Brynjolfsson found that "increased connectivity and improved filtering" online, the latter due to the use of search engines and recommender systems, can lead to a global village, a "virtual community of neighbors freed of geographical constraints" but also to a less integrated, more balkanized cyberspace (Van Alstyne & Brynjolfsson 2005, 851).

People are bound to a certain capacity for information processing. They cannot absorb unlimited information, and therefore search engines and recommenders need to be selective in the recommendations for information that they provide people with. They need to screen out certain things, and their final selection of recommended products should be tailored to the preferences of each individual user. Empowered by information technology, such as recommender systems and search agents, people using the internet thus have the possibility to interact with "information sources customized to their individual interests" in a faster and easier way than ever before (ibid). As a consequence, recommenders have "enormous potential to elevate the nature of human interaction" (Van Alstyne & Brynjolfsson 2005, 852).

Individuals who prefer diversity and who are open to different streams of information may become more integrated, both intellectually and socially. However, "Individuals empowered to screen out material that does not conform to their existing preferences may form virtual cliques, insulate themselves from opposing points of view, and reinforce their biases" (Van Alstyne & Brynjolfsson 2005, 866). This can lead to radicalization of groups; in which shared average opinions move to the extreme. A virtual group of people who love rock music and talk about this, exchanging references and recommendations among each other, may for instance listen considerably less to other music genres than when their group would not have existed. A current and more problematic example is the group of anorexic girls (and more rarely, boys) who want to lose weight and find each other online, for instance by searching for stimulating photos and stories on social media platforms like Instagram, Pinterest and Tumblr. Through hashtags such as #thinspo #pro-anorexia and #thinspiration, the girls find each other easily. Since they find so many others who are losing weight through the same or even more extreme methods as they do, a lot of girls in the group convince each other to think that what they do and believe is 'normal'. Even worse, they often stimulate each other to keep working on their ideal body image, thus encouraging each other in their eating disorders (blog.instagram.com 2013; nationaleatingdisorders.com 2014; Huffington Post 2012).

The internet, and recommender systems in particular, have the ability to "foster tribalism as well as a “global village”, “super-regionalism” as well as “separatism” (Van Alstyne & Brynjolfsson 2005). Preferences are reshaping “social, intellectual and economic neighborhoods as distinct from those based on geography”, and separation in virtual knowledge space can “divide special interest groups” that are potentially even more insular than geographical ones are (Van Alstyne & Brynjolfsson 2005, 851).

Following the research outcomes by Van Alstyne & Brynjolfsson (2005) and Hiltz and Wellman (1997), the internet, and recommenders more specifically, stimulate the formation of social groups not so much based on geographic location or social class, but rather based on preferences for consumption of information in the form of news, conversations, and cultural products, among other things.

As has become clear, the arguments about the internet’s and recommenders’ ability to foster the formation of social groups based on preferences and attitudes, is strongly related to the arguments about the internet’s and recommenders’ influence on (cultural) consumption, as previously discussed. The supposition underlying the arguments about online group formation is that the internet somehow ‘democratizes’ society. Research outcomes are focused on utopian and dystopian scenarios; global village or tribalism, super-regionalism or separatism. However, since different people have different attitudes and preferences, it seems more logical that on the internet, characterized by the increasing use of recommender systems, both balkanization and integration occur. It may depend on the subject at stake, and differ among individual people and groups, whether they tend to balkanize themselves, or rather integrate with others.

Now that the status quo of research about (recommenders’ influence on) online consumption and online group formation has been presented, I will turn to a re-evaluation of Pierre Bourdieu’s distinction theory. In the next chapter, Bourdieu’s theory will be explained and used to explore the relationship between consumption and taste, and to set up a framework for the further analysis of recommenders’ influence on distinctions in cultural consumption and taste in chapter 4.

3. Distinctions in cultural consumption and taste: A re-evaluation of Bourdieu

According to research and theories developed by sociologist Pierre Bourdieu, people in different social classes have a different cultural taste; they prefer other sorts of culture (Bourdieu 1984). Bourdieu researched class-based distinctions in cultural consumption and taste in France in the 60's, and presented his conclusions in the notorious and influential book *Distinction* (1984). Bourdieu wasn't the first one to relate cultural consumption and taste to socioeconomic position. Holt points out that economist and sociologist Velben ('The Theory of Leisure Class' [1899] 1970), sociologist and critical philosopher Georg Simmel ('Fashion' [1904] 1957), sociologist and educator Hellen Lynd ('Middletown: A Study in Modern American Culture [1929] 1956) and socio-anthropologist William Lloyd Warner (et. al. 'Social Class in America: The Evaluation of Status, 1949) also interpreted consumption-objects as markers of social class; as markers that (potentially) emphasised and maintained differences between social classes (Holt 1998, 2).

In this thesis, the direct link between consumption and taste, as well as the distinction in cultural consumption and taste between people in different social classes, is presumed based on Bourdieu's Distinction theory (1984). Considering these presumptions, several aspects of Bourdieu's theory need to be discussed. In order to explain the presumed distinction in cultural consumption and taste between people in different social classes, the vicious circle of economic, social and cultural capital described by Bourdieu will be addressed. Afterwards, the relationship between consumption and taste, as well as the notion of consumed products, as 'objectifications' of taste will be clarified. Once I have elaborated on the most important aspects of Bourdieu's theory with due regard to the context of this thesis, I will re-evaluate the theory in the light of mass culture, the digitization of Western societies, and in particular; the growing use of recommenders online.

As an introduction to the explanation of Bourdieu's theory in the first part of this chapter, Douglas Holt, former professor at the Harvard Business School and L'Oréal Chair in Marketing at Oxford, provides an insightful view. In his article *Does cultural capital structure American consumption?* (1998) Holt states:

> Bourdieu offers a theory of social class consonant with social relations in advanced capitalist societies. Bourdieu emphasizes that status is continually reproduced as an unintended consequence of social interaction because all interactions necessarily are classifying practices; that is, micropolitical acts of status claiming in which individuals constantly negotiate their reputational positions. Crucial to this process is the expression of cultural capital embodied in consumer actions. (Holt 1998, 5)

3.1 Economic, social and cultural capital

In the late 19th century, the German sociologist, philosopher and political economist Max Weber coined the term 'social class' (1978). Whereas hereditary characteristics had long been used to measure status in the form of 'states' and 'ranks', it was perceived that wealth and income were important measures for social class, or in short 'class'. Weber however, argued that hierarchic social layers in societies were not determined by economic capital solely (as described by Marx), but also expressed and reinforced by “styles of life” (Holt 1998, 2). Bourdieu later elaborated on this idea, by presenting three sorts of capital that were determinative for social class: economic, social and cultural capital (Bourdieu, 1984). Economic capital is the financial power that people have. Social capital is determined by the sum and quality of social contacts that people have: their relationships, groups, and networks with for instance friends, family and colleagues. Cultural capital is the total of knowledge and skills that people own, including their ‘ability’ to consume certain forms of culture and art. The three forms of capital are interdependent, meaning that a continuation or change in one capital automatically leads to a continuation or change in the other capitals (Bourdieu 1984).

Social capital has a function of personal reference and recommendation. It offers reference in the widest sense, for instance for information, ideas, opinions, feelings and (cultural) products. Social capital therefore is a determinative for what people think, what they talk about and how they choose to act, but also: for the things that they are exposed to (ibid). Since cultural capital is build up by learning, and according to Bourdieu, people can only learn by being exposed to, and being in contact with the things they want to learn, social capital influences cultural capital (ibid.) Social capital also influences economic capital: in a direct manner, for instance when social peers advise each other on a good investment or a job vacancy, but also indirectly, namely by its influence on cultural capital (Bourdieu 1984).

Cultural capital is mainly acquired in three ways: through family upbringing, through formal education, and through work related culture (Bourdieu 1984). These situations provide social and cultural products that build up, shape and maintain the cultural capital. Such products can be either abstract or tangible; they take the shape of (institutionalized) education, conversations, books, newspapers, films, documentaries, radio shows, theatre, music and so on. Different products have various functions for people’s cultural capital. Familiarity with certain theatre, for instance, can lead to general insight in role-plays and storylines, just as reading a certain newspaper can provide knowledge about specific news topics. Cultural capital influences the work that people are able to do and since different jobs and fields of work come with different incomes, cultural capital influences economic capital. Cultural capital influences social capital, since social peers are linked by situations where cultural capital is key: the place where someone is educated or the place where someone works, is usually where she or he meets people, and thus builds up social capital (Bourdieu 1984).

Transversely, economic capital influences social and cultural capital. Depending on an individual’s financial resources, certain products can be bought that directly influence cultural capital (e.g. books, formal education, a home in a good area, tickets to a theatre play). Since social capital is acquired through contact with people in certain situations and places, economic capital also has a direct influence on this. If people cannot buy a ticket to a theatre play, they will not meet people there; if they cannot afford a certain education, they will not build up a network there.

The vicious circle of interdependence between social, cultural and economic capital is complete. It all but freezes people’s social class, and thus all but freezes differences between social classes (Bourdieu 1984). The question that arises with regard to the topic of this thesis is how the distinction in cultural consumption and taste can be framed within this vicious circle of capitals. Why do people in different social classes generally consume different cultural products, and why do people have a distinct cultural taste?

3.2 The relationship between consumption and taste

Culture, according to Bourdieu, consists of a broad range of fields: art, food, interior, decoration, clothes, popular culture, leisure activities and sports (1984). Taste, for culture among other things, can be defined as a person's entire set of patterns of choice and preferences – a person's "manifested preferences" (Bourdieu 1984, 56). Preferences then, are to a large extent dependent on the ability to 'take in' and appreciate certain forms of culture: an ability (a 'skill') that is part of cultural capital. The ability to 'take in' certain forms of culture comes from the intrinsic understanding of the 'objects'; the cultural products. Only when an object is understood can it be valued, and thus the only way to arrive at an understanding of an object is by "being in touch" with it, by "taking it in", by "consuming" it (1984, introduction). By consuming a series of objects, either intentionally or unintentionally, it becomes possible to place individual objects within the series as a whole. An object is placed in a certain era, school or time, by implicitly or explicitly comparing it to other objects in a series consumed. Placing an object leads to an understanding of the object, which makes it possible to value it and potentially give preference to it over other objects. This explains how consumption leads to (either explicit or implicit) understanding, and understanding to taste, and thus how taste and consumption are directly related (Bourdieu, 1984). For this same reason, taste can also be recognized in products consumed. When people prefer certain products, they want to get in contact with them, experience them and therefore, consume them. Thus, products consumed can be interpreted as objectifications of taste (and partly, as objectifications of cultural capital) (Bourdieu 1984; Holt 1998).

Since taste is dependent on understanding, and since knowledge and skills are necessary for understanding, taste is dependent on the same cultural capital as it is a part of. Social capital provides the frame of reference that helps to develop and steer the cultural consumption and taste. Economic capital then provides the financial resources with which cultural products can be consumed, and therewith influences taste.

3.3 The role of traditional media: consumption, taste and social class

Adorno, Horkheimer (1944) and Habermas (1962), neo-Marxist critical philosophers like Bourdieu, have explained very early on how traditional sales strategies employed by the culture industry are building up and maintaining class-based distinctions in cultural consumption and taste.

The culture industry, according to these philosophers, tries to make cultural products as accessible and attractive as possible to a group of people as large as possible. With the aim to sell as much as possible, products are altered on both an economic and psychological level. On the side, strategies are developed to make sure that the 'right' products are brought to the attention of the 'right' groups of people. The industry distinguishes and classifies its cultural products based on the groups of people for whom they are supposed to be most fitting: the 'target markets' (ibid). This involves, for example, marketing certain newspapers or magazines to certain groups of people, but it also involves making sure that the right products are highlighted in the right newspapers and magazines, accordingly.

Sharp distinctions like those between A and B films, or between short stories

> published in magazines in different price segments, do not so much reflect real differences as assist the classification, organization, and identification of consumers. Something is provided for everyone so that no one can escape; differences are hammered home and propagated. (…) Everyone is supposed to behave spontaneously according to a "level" determined by indices and to select the category of mass product manufactured for their type. On the charts of research organizations, indistinguishable from those of political propaganda, consumers are divided up as statistical material into red, green and blue areas according to their income group (Adorno & Horkheimer 1944, 97)

Although the cultural-critic character of the interpretations made by Adorno, Horkheimer and Habermas are obvious, their observations are not incorrect. Marketing books are filled with explanations and theories about how to classify and group people into tangible target markets. One of the world's leading marketing experts, Philip Kotler, has explained in detail how people (consumers) can be distinguished and classified into different social groups based on explicitly created as well as 'naturally observed' differentiations, such as level of income and level of education (Kotler et al. 2010). The distinguished and classified cultural products are then brought to the attention of consumers via the media (which of course can be considered 'products' themselves, too), but also through carefully chosen selling points. Altogether, traditional sales strategies make sure that people are only confronted with those products that are considered 'appropriate' for the social group and class that they are in (Kotler et al. 2010). In this way, they also ensure that people's frame of reference for consumption of cultural products among other things, stays limited to such 'appropriate' products. Traditional sales strategies have contributed and still contribute to the vicious circle described by Bourdieu - and specifically: to the predetermined character of class-based distinctions in consumption and taste.

3.4 Reasons for re-evaluation

Over the last years, the function and importance of traditional media has decreased. It has shifted to new media, mainly to the internet, which has become an enormous competitor to traditional media, potentially threatening their very existence. Magazines are going bankrupt because people read their content online, television channels are struggling with advertisement incomes due to decreased viewer numbers, and so on. On the internet, traditional sales strategies are not often applied and recommender systems, or in short recommenders, are used to highlight products instead (Lotz 2007; The Communications Market 2006). Among other things, recommenders have come to "provide an effective form of targeted marketing by creating a personalized shopping experience" for each user; no matter whether she or he is 'shopping' for virtual products in a streaming service like Spotify, or for physical products in an online store such as Amazon (Linden et al. 2003, 79).

In order to critically analyse how recommenders influence the class-based distinctions in cultural consumption and taste, a re-evaluation of Bourdieu's theory in the light of the digitization of the contemporary western society, among other things, is needed.

3.5 Universality of Bourdieu's theory

Tally Katz-Gerro, member of the department of Sociology and Anthropology at the University of Haifa, conducted research with the aim of creating a universal vision and argument about the relationship between social class and cultural consumption and taste, such as described by Bourdieu. She investigated consumption of 'highbrow culture' in five varying geographical and demographical situations; Italy, West Germany, Sweden, Israel and the United States, by factor analysing five separate data sets, taken from nationally held questionnaires representing "a variety of cultural activities and preferences" (2002, 207).

Katz-Gerro makes use of the term 'highbrow culture', but according to her, no universal description of 'highbrow culture' is possible, because they involve strikingly similar, yet "unique combination[s] of leisure behavior and tastes", varying per country (2002, 213). Katz-Gerro does not define 'highbrow culture' in her paper, but it is clear that she uses the term to refer to forms of culture that are perceived as 'high', 'important' or 'intellectual', rather than 'popular' or 'religious' – although sometimes highbrow culture can be popular or religious. Katz-Gerro found that "the highbrow cultural consumption factors across the five countries are comparable, though not identical" (2002, 218). The use of a term such as 'highbrow culture' implies value judgment, but Katz-Gerro uses it "for the sake of simplicity" (2002, 220). "We need some kind of labels that at least allow a common terminology even if they do not fully capture the meanings of various lifestyle choices", she writes (2002, 220).

> Overall, the same [social] variables affect the consumption of highbrow [consumption] in the same direction. Older persons (with the exception of Sweden), the more educated, women, the more affluent, and urban residents tend to participate more in highbrow lifestyle (Katz-Gerro 2002, 220)

The effects of social class and the influence of work-related positions on consumption of highbrow culture differ among the countries, yet they are present everywhere (ibid). The same goes for the influence of residence (urban or rural), ethnicity, race and religion (2002, 220 – 222). Level of education was found to be "the main determinant" of cultural consumption, influencing it in the same way in all the countries. In line with Bourdieu's research outcomes, Katz-Gerro found that people with longer and higher formal education tend to consume more highbrow culture (2002, 220).

Altogether, Katz-Gerro shows that cultural consumption does "not always follow the expected pattern wherein the upper classes are associated with highbrow culture and the lower classes are not" (2002, 220). The differences in the relationship between consumption pattern and class in various countries can according to Katz-Gerro be explained by differences in the spending of government subsidies and private foundations.

Katz-Gerro's research results strengthen Bourdieu's theory by showing that social class, especially when determined based on level of formal education solely, still strongly relates to cultural consumption (2002, 220). However, her results can also be used to point towards a weakness in Bourdieu's theory: differences in cultural consumption cannot be linked to social class or level of education exclusively (2002).

3.6 Objectifications and embodiments of culture

Douglas Holt, assistant professor in Advertising and Sociology at the University of Illinois' Institute of Communications Research, formulated an important argument against Bourdieu's notion of consumed products as 'objectifications of taste' and 'markers of class' (1998). Through an analysis of six ethnographic interviews, Holt examined whether Bourdieu's theory about the relationship between social class and cultural consumption and taste, is applicable to the contemporary United States.

Holt's research outcomes do not dispute Bourdieu's main arguments, but add to Bourdieu's theory by showing that distinctions in cultural consumption and taste can no longer be recognized very clearly in consumed cultural products (Holt 1998). However, distinctions can be distinctively recognized in patterns of (and underlying motivations for) consumption. The other way around is also applicable; patterns of (and underlying motivations for) consumption can clearly reveal distinctions. In contemporary society, people in varying social classes, according to Holt, consume virtually the same products.

> The utility of goods as consensus class marketers has weakened substantially owing to a variety of widely noted historical shifts. Technological advances have led to the wide accessibility of goods, travel and media by all but the poor (Holt 1998, 5)

Instead of looking into consumed goods primarily, Holt suggests that, in order to recognize distinctions in consumption and taste, it is more important to look into the patterns of (and underlying motivations for) consumption (1998).

> Class differences in American consumption have gone underground; no longer easily identified with the goods consumed, distinction is becoming more a matter of practice. (…) As popular goods become aestheticized and as elite goods become "Massified" (..) the objectified form of cultural capital has in large part been supplanted by the embodied form" (Holt 1998, 6)

Holt argues that cultural elites emphasize the distinctiveness of consumption practices themselves, apart from the cultural contents to which they are applied. Culture's 'embodied' form therefore gained importance over its 'objectified' form (Holt 1998, 6). Interesting is that for his research, Holt interprets social classes as classes based on cultural capital solely. He differentiates between two opposite 'classes of consumption', namely between people with high cultural capital ('HCC's') and people with low cultural capital ('LCC's'). Holt finds several differences in their consumption pattern. The most important difference is that people with high cultural capital consume more "omnivorously" than people with low cultural capital; who consume in a more 'univorous' way. "[O]mnivores tend to like and actively consume a much broader range of both popular and high entertainments than (…) univores", Holt explains (1998, 19).

Based on the outcomes of his research, Holt defines six dimensions of taste "that distinguish informants with high versus low cultural capital resources". These dimensions do not reflect particular cultural products, but rather indicate attitudes towards the consumption of cultural products in general:

> Material versus formal aesthetics, referential versus critical appreciation, materialism versus idealism, local versus cosmopolitan taste, consumer subjectivity as local identity versus individuality, and leisure as self-actualization versus autotelic sociality (Holt 1998, 19)

Holt's findings are compatible with Katz-Gerro's findings insofar that education (the main determinative for cultural consumption in Western societies found by Katz-Gerro) is a main determinative for cultural capital. In most cases, the level of education and level of cultural capital will therefore be in accordance.

It is important to note that since Holt has not taken into account economic capital as determinative for class or consumption, his argument about the decreased value of consumed cultural products as objectifications of taste and hence markers of class may not be valid for all sorts of cultural products. This particular argument may only apply to the consumption of cultural products that are easy to obtain with relatively little regard to economic capital. It may be valid for consumption of music, films and books, for example. However, it seems unlikely that his argument is entirely true with regard to sorts of cultural products that require a significant economic capital; for example, it would be impossible to wear Armani shoes or drive a Porsche without a significant economic capital.

Having that said, Holt is not the only one who found that consumed cultural products have decreased in value for marking class or objectifying taste. Conclusions similar to those of Holt were drawn based on story-telling narrative interviews and device demonstration-observations by Ting, Dubelaar and Dawson (2009). Alicia Bastos, member of the London College of Communication and the University of the Arts London, also discovered that culture in its ‘embodied’ form has become more important than culture in its ‘objectified’ form. Whereas Holt focuses on mass culture as a cause for this phenomenon, Bastos puts more emphasis on the effects of technological developments, and especially the internet (2010).

> With the development of digital technologies and the expansion of communication on a global level, the way people produce and consume culture is going through radical changes. (…) Culture, especially in the digital age, is something that people can process more than possess (2010, 6)

Bastos adds to Holt’s argument, stating that although it is not true for all sorts of cultural products, a couple of important cultural products such as films, music and books are now consumed virtually, more than physically. Nowadays people consume films through Netflix or smart-TV’s, more than they consume them through DVD’s; people consume music through Spotify or iTunes, more than they consume it through CD’s or LPs. Books are still often consumed in their physical form, but the consumption of e-books is also on the rise.

Alan Warde, David Wright, Modesto Gayo-Cal, Tony Bennett, Elizabeth Silva and Mike Savage, members of the University of Manchester and the Open University of the United Kingdom, delivered a working paper to the European Sociological Association Conference (2005) in which they investigate omnivorous behaviour more in-depth. They find “a substantial number of papers have now been written explicitly exploring the nature, extent and significance of the omnivore phenomenon” (2005, 1). In this literature, two definitions of omnivorousness are presented; one focused on the volume of consumed products, the other one focused on the composition of consumed products (ibid).

Using both qualitative (focus-group discussions and semi-structured household interviews) and quantitative (questionnaires) methodologies, the authors explore “cultural tastes, forms of cultural participation and cultural knowledge” (2005, 3). They look into national TV, film, musical, fine art (paintings), books and music as forms of culture to explore the volume, as well as the composition of consumption activities.

In accordance with the outcomes of Katz-Gerro (2002) and Holt (1998), Warde et al. discover that the level of education is significant for omnivorous consumption behaviour; “The most highly educated, those with a degree, had the largest number of likes” and “university education has an influence on omnivorous tendencies. Graduates are particular likely to be omnivorous” (2005, 8, 19). Furthermore, volume of consumption increases with age, yet decreases among the elderly. Interestingly, income was found to be insignificant for volume of consumption. Region (geographical location) on the other hand was found significant: “Metropolitan life increases the range of items which a person regards favourably” (2005, 9). In addition and interesting in the context of this paper, the authors find that “having technical qualifications (…) [makes] a respondent favorable to more items” (ibid). This particular outcome implies that people who have technical know-how and skills, tend to consume more omnivorous than people who do not have these skills. This idea will be further explored in the next paragraph.

Warde et al. further examine how an omnivore “identified as someone with a large volume of tastes, combines taste for rare and consecrated items (those to which the highly educated have affinity) with taste for more common and more popular items” (2005, 10). Although there are different types of omnivores, the authors find that in general, omnivores are “selecting the most consecrated items disproportionately” (ibid). They are “disproportionately attracted” to “items which carry most cultural distinction” and are not likely to “include the least prestigious of items” (ibid). Therefore, the authors conclude that, in Bourdieu’s terms:

> “There is no contradiction (…) between being an omnivore and displaying high objectified cultural capital. To the extent that taste is in the spotlight, omnivores prefer exactly the same items in the same order, as might have been expected in the past. (…) It is only a change in volume, not a restructuring of a hierarchy of preferences” (2005, 13)

The authors conclude to suggest that “omnivorousness is not necessarily inconsistent with the persistence of distinction” (ibid). Distinction may remain “more after the fashion of Bourdieu (with a weaker core middle class pattern)” rather than that it is a result of omnivorous tendencies (ibid).

Altogether, in this paragraph a couple of important arguments and conclusions have been presented that contribute to the re-evaluation of Bourdieu’s theory. First of all, the distinction in cultural consumption and taste has shifted; from a distinction between people in various social classes (shaped and maintained by cultural, economic and social capital), to a distinction between people with various levels of cultural capital specifically (of which formal education is a part, and on which it is an influence). Furthermore, distinctions in cultural consumption and taste can no longer be clearly recognized in consumed cultural products. People in various social classes have started to consume more of the same products and due to the digitization of Western societies a lot of cultural products are now virtually ‘processed’ rather than physically ‘possessed’ (Bastos 2010). For these reasons, the value of consumed products as objectifications of taste and markers of class has decreased. The value of embodied culture in the form of consumption patterns (and underlying motivations) on the other hand, has gained importance; as marker of taste, and class (Holt 1998; Warde et al. 2005). The most important distinction in consumption pattern is between omnivorous and univorous consumption behaviour (Holt 1998; Warde et al. 2005).

3.7 Technology as cultural capital: The digital divide

Considered from a new media perspective, two more arguments can be formulated to re-evaluate Bourdieu's theory. The first argument is focused on the interpretation of Information & Communication Technology (ICT) as a form of cultural capital, and thus, as a distinguishing factor for cultural consumption and taste. This argument will be discussed in this paragraph, mainly through the concept of the 'digital divide'. The second argument concerns the influence of technology on social capital, and will be elaborated on in the next paragraph.

Anthropologist Marlena Mattei conducted participant observation, supplemented by informal interviews with students of a West Philadelphia high school, to investigate the notion of technology as a form of cultural capital (2012). Bourdieu distinguishes between three subtypes of cultural capital: objectified, embodied and institutionalized (1984). Applied in a technological context, objectified capital consists of material items that provide advantages, such as computers and routers. Embodied capital then consists of the skills and 'competences' that are necessary to utilize the objectified cultural capitals (Mattei 2012, 52). Institutionalized capital consists of capital in the form of institutional recognition, for instance through a diploma or academic degree, and is less relevant in the context of this thesis (Mattei 2012).

The divide between people who do and who do not have physical access to technology, and to the internet specifically, is often referred to as 'the digital divide' (Mattei 2012, 52). In Bourdieu's terms, the divide could of course also be called the 'digital distinction'; namely between people who can afford access to a computer and internet (the 'haves') and people who cannot (the 'have-nots') (ibid). The distinction between 'haves' and 'have-nots' of objectified technological capital exists mainly due to financial reasons and is therefore often related to social class.

> The price of a computer, coupled with monthly internet prices, not including various other expenses such as routers, flash divers, printers, or ink, is relatively large and does not always fit in the family budget (Mattei 2012, 53)

Mattei finds that physical access is "not the only factor in effectively closing the digital divide" and that "the ability to use technology is essential to social inclusion" too (2012, 52). Although students in the West Philadelphia high school did have (limited) access to computers and internet, namely on school ground, they were not able to operate the machines; they lacked embodied technological capital. Mattei draws examples of students who had a hard time turning on and off the computer, students who were not able to manage programs such as Word or Excel, and those who didn't know how to search on the internet without proper instructions (2012, 54-55).

Mattei's research outcomes show that technology reflects "many of the ideas of Bourdieu's concept of cultural capital", such as the lack of physical access (objectified capital) and "basic knowledge and usage" (embodied capital) (2012, 56).

Mattei's arguments are in line with outcomes by Michael Emmison and John Frow, who analysed data drawn from a large scale Australian project concerned with cultural tastes and preferences (1998). They too find that “the skills and competencies which IT entails can (…) be conceptualized as a form of cultural capital in their own right” (1998, 41). Just “like the other two forms [of capital], [technological] capital is unequally distributed amongst social groups” (1998, 41). Mattei’s outcomes can also be related to the previously discussed research outcomes by Warde et al., which proved that people with technical skills and know-how tend to consume more omnivorous than people who do not have such skills and know-how (2005). At last, Mattei’s outcomes are compatible with research presented by Lynette Kvasny (2006). Kvasny carried out an ethnographic study titled *Cultural (re)production of digital inequality in a US community technology initiative*. Based on analysis of historical data obtained through published documents, supplemented with informal conversations, Kvansny discovers that ICT “can unintentionally contribute to cultural reproduction of social order” (2006, 178).

> The digital divide provides a classification scheme for designating have and have-nots, assigning social groups to each category, ascribing positive and negative values to these categories (2006, 176)

Just like Mattei, Kvasny also argues that the ‘digital divide’ concerns “access to computing artefacts”, as well as “equitable access to the benefits derived from Internet and Computer use (2006, 161). The digital divide should be defined broadly, “as an unequal ability to achieve life chances that include, but are not limited to, [physical] access to ICT” (2006, 177). The digital divide, accounting for both objectified and embodied divisions in technology, causes extended divides, for instance in chances on the job market, and chances of getting into a college (Emmision & Frow 1998; Kvasny 2006; Mattei 2012). However, it also leads to ‘positional suffering’, “in which the social world is experienced by people who occupy an inferior position in a privileged social context” (Kvansny 2006, 175). Positional suffering results from “painful disappointments” and are “just as real” as other sorts of suffering (Kvansny 2006, 176). Altogether, research has proved that the digital divide has far reaching consequences for both individuals and society at large.

3.8 The digital divide: recommendation, access and consumption

In the context of this paper it is particularly relevant that the digital divide is responsible for a divide in cultural consumption and taste. It draws a divide between people who do and do not have access to internet, and as a consequence, it divides people who do and do not have access to cultural products available online. Furthermore, it divides people who are and are not able to utilize recommender systems – for reference of, recommendation for, and consumption of cultural products.

While recommenders may cause distinctions in consumption and taste among their users, it is essential to note that the existence and widespread use of recommenders also leads to a sharp distinction between people who for whatever reason do and do not use them. For that matter, recommenders are subject to and part of the digital divide. This distinction may be observable through non-users lacking awareness of, or having less knowledge about certain cultural products (e.g. titles of movies, certain music genres, new books). However, the distinction may be even more noticeable through differences in users and non-users’ consumption pattern (as also implied by the research outcomes of Warde et al. (2005)). I will give three examples to illustrate how the digital divide leads to a divide in sources of reference of, recommendation for, access to, and consumption of cultural products. I will also demonstrate how this leads to the positional suffering as described by Kvasny (2006). The first example is fictional and illustrates a divide due to the online music streaming service Spotify. The last two examples are (auto-) ethnographic; the second example illustrates a divide concerned with the use of Netflix, the third one includes Amazon Books.

The first example: two girls who love music, both 20 years old. One girl named Emma, the other girl named Julia. Emma does not use the internet: she can use computers on school ground, but she does not feel comfortable using them, because she lacks a lot of know-how and skills to do so. Therefore she only uses traditional media (radio, magazines) and human social peers (friends, family, colleagues) as sources of reference for music. She has no possibility to consume music online, and so in order to consume music, she has only traditional options: listening to the radio, going to live concerts, or purchasing physical CD's or LP's. Then there is Julia, who is a heavy internet user. She employs the same sources of reference for consumption of music as Emma does. However, she owns a laptop and uses the internet on a daily basis. She uses several music-related services such as Spotify, Soundcloud and Shazam for recommendations and consumption of music. Furthermore, she has a profile on Facebook. Via Facebook, she also receives recommendations and references for new music; for instance through friends who post a new music video they have seen on YouTube, a new album that they have listened to on Spotify, or a mixtape that they have discovered through Soundcloud.

Suppose that Emma and Julia both have similar taste for music; they both like electronic music. While Emma may know the relatively big, mainstream artists in this scene, who she has discovered through radio and of whom she purchased physical CD's, she may be only slightly aware of other, smaller artists, whom she has merely heard of from friends. It is relatively hard for her to discover new music, and moreover; it is expensive to consume new music, unless it is played on the radio. Julia, on the other hand, continuously receives references of and recommendations for music online. She does not need to make a big effort for it and it costs her relatively little money. Whereas Emma may find out about three or four new artists she likes every six months, Julia may discover three or four new artists every day. Due to the digital divide, Emma's and Julia's consumption behaviours are extremely different. Julia's consumption of music is probably scattered over a larger number of artists than Emma's consumption is, and her taste for music may be more refined than Emma's, because unlike Emma; she has the ability to constantly 'refine' what she prefers, by choosing one artist or song over another.

A second, auto-ethnographic example: Last year I moved to Berlin, where I did an internship for a start-up company called Vamos - a mobile application listing events in the city. Most people working in the company were originally from Sweden, and they all had a subscription to streaming movie platform Netflix. Netflix was their main source for watching movies, TV series and documentaries. Germany has very strict policies against illegally downloading content such as movies and TV series, so everybody advised me not to do obtain my media that way. However, Netflix was not available in the Netherlands nor in Germany at that time, so I had no possibility whatsoever to consume (new) movies, TV shows and documentaries for an affordable amount of money. As a consequence, I was unable to join conversations about certain movies and documentaries that my colleagues had seen. Even worse, was that I could not understand references made to the Netflix platform during brainstorms about the vision and strategy for the Vamos app. Thus, in both personal and professional aspects of my life, I experienced a divide.

A last (auto-) ethnographic example: My mother loves to read. She goes to the library often, but cannot always find what she wants. Most books that she wants to read are in English (she has a large group of English friends) and the library does not have a large selection of English books. Last January, my mother told me that she had been out with her friends, but had not been able to join the conversation. Her friends had been talking about a new English book that they had read, but my mother had not been able to get her hands on it. The local English bookstore had closed, and another bookstore apparently could not order the book for her. I asked her if she had already looked on Amazon's Books department, to which she replied 'No, I have no clue how to do that!' I asked her ‘What do you mean?’ after which she explained to me that she did not understand how to get to the books department of Amazon. Apparently she was not aware that she could just search for the book title from the Amazon homepage. Furthermore, she was afraid that something bad could happen if she would ‘fill in her bank details on a website’. Because of her lack of know-how about, and limited experience with online shopping, in this case through Amazon, my mother thus experienced a divide.

3.9 Technology and social capital

In the last paragraph I discussed and illustrated the concept of the digital divide. I elaborated on the idea that technology, and the internet and recommender systems as forms of technology in particular, can be interpreted as forms of cultural capital. However, as a source of reference of and recommendation for cultural products among other things, the internet, and particularly social media sites such as Facebook, also heavily influence, and arguable became part of social capital.

Song Yang, Heejin Lee and Sherah Kurnia, all working at the University of Melbourne as members of the department of Information Systems, of the Graduate School of International Studies and of the department of Information Systems, respectively, have mapped the current state of research about social capital in relationship to ICT (Yang et al. 2007).

As there is no theoretical framework to explain “why ICT consumption leads to changes in social capital”, the authors “identify the gaps in the ICT related social capital research” and “develop a number of propositions related to the role of ICT (…) in social capital building (Yang et al. 2007, 1-5). The authors define social capital as “an individual’s network of social relationships and the qualities of those relationships, which enhance the ability of participants to associate with each other for mutual benefits” (Yang et al. 2007, 1). They recognize four main streams of research on ICT in relationship to social capital, namely two streams focused on individual capital (social capital of an individual person) and two focused on collective social capital (e.g. social capital of a nation, a continent, or worldwide). In both categories, there is a distinction between research interpreting social capital as a dependent variable (concerned with “social capital building and maintaining”), and as an independent variable (concerned with the “effects of social capital”) (Yang et al. 2007, 3). In the context of this thesis, only the research on ICT in relationship to individual social capital is relevant.

The main conclusion of the research conducted on this topic is that ICT is “developed to extend human communication capability by breaking through the limits such as time difference and geographical distance” and that in this way, ICT enables a greater mobility in human interaction than ever before (Yang et al. 2007, 5). The mobility in

human interaction has enabled people to send and receive messages without being bound to a certain fixed place, and without knowing the location of the person they are interacting with.
Applying Yang, Lee and Kurnia's conclusion to social media usage in particular, it is obvious that the increased "temporal, spatial and contextual mobility" has gone hand-in-hand with a decreased need for personal contact between people who are exchanging 'messages'. On social media platforms such as Facebook, it is not even necessary to direct a message to another person in particular; by posting to the timeline, a user sends out a message to all of her or his 'friends' at once. Social media platforms such as Facebook have made it increasingly easy to find out what other people like, what they do, what they watch, read or listen to, without having to actually converse with them. Following theory by Fabio Sabatini, member of SPES Development Studies and the Department of Public Economics at University of Rome, social media foster so-called 'weak ties' (2006). They enable people to build "bridges and connections with different types of networks" of people, and through that, they foster "knowledge diffusion" about cultural products among other things (2006, 25).

Altogether, the internet, and social media platforms such as Facebook in particular, influence social capital by making it more mobile in terms of time, space and context. Arguably, in a way they even became part of social capital. Since social capital is an important source of reference of and recommendation for cultural consumption among other things, the internet and social media platforms also influence cultural consumption and taste. In this way, they contribute to the digital divide, as previously discussed.

In the next chapter I will investigate if, and in what ways, recommender systems such as utilized in Spotify, Netflix and Amazon Books, account for social media platforms in their systems, and consequently, in what way they account for the mobilized social capital online.

3.10 Synthesis and implications

Based on the research results presented so far, a couple of broad conclusions can be drawn that help to formulate an answer to the main question of this thesis: *In what ways does the use of recommenders online create and influence distinctions in cultural consumption and taste between people in varying social classes, and are recommenders less prone to manifesting pre-determined ideas about certain tastes for certain classes than traditional sales strategies and media were?*

In the first chapter of this thesis, it became clear that due to the internet and supported by the widespread use of recommender systems online, consumption of cultural products has become less hit-centred and more diverse (Anderson 2006; Fleder & Hosanagar 2009; Brynjolfsson, Hu and Simester 2011). The internet, and the use of recommenders in particular, may also foster the formation of social groups online based on preferences and attitudes rather than based on social class (Hiltz and Wellman 1997; Van Alstyne & Brynjolfsson 2005). It is not yet clear, whether such groups will be more or less insular than groups based on social class (ibid).

In the second chapter of this thesis, I re-evaluated Bourdieu's distinction theory to discover that distinctions in cultural consumption and taste nowadays are not so much found between people in various social classes, but rather between people with different levels of cultural capital (Holt 1998; Katz-Gerro 2002; Warde et al. 2005). Furthermore, distinctions in cultural consumption and taste are no longer primarily found in consumed cultural products (objectified culture). Rather, distinctions are found in patterns of and motivations for cultural consumption (embodied culture) (Holt 1998; Warde et al. 2005; Bastos 2010). Therefore, whereas objectified forms of culture became less valuable for marking taste and class, embodied forms of culture gained importance. This is particularly true for forms of culture that can be consumed virtually and with relatively little financial resources; films, music and (e-)books, for example.

It also became clear that technology, and the internet and recommender systems in particular, can be interpreted as new forms of cultural capital; drawing distinctions between people who do and who do not have physical access to computing artefacts and the internet, as well as between people who do and do not have the technical skills and know-how necessary to derive benefits from computer- and internet usage (Emmision & Frow 1998; Kvasny 2006; Mattei 2012). At last, the internet and social media increasingly influence social capital, making it more mobile.

It is possible that there is a link between the potential of the internet and recommender systems to foster groups based on similar preferences and attitudes, and the theory about distinctions in patterns of and motivations for consumption (which are basically preferences and attitudes too), between people with varying levels of cultural capital. It may be that such groups overlap; that the preference- and attitude-based groups fostered by the internet, are groups that vary from one another in levels of cultural capital. However, this topic to the best of my knowledge has not yet been explored more in-depth.

At this point, the answers found so far need to be further explored by broadly and critically analysing the objects central in this research: recommender systems. Also, there are a couple of questions left unanswered. To find an answer to these questions too, a critical analysis of recommenders is needed:

First of all, it is necessary to analyse to what extent recommenders provide recommendations solely based on the actual behaviour of individual users. If it is true that recommenders provide recommendations without making presumptions and generalizations about people in social groups and classes, then to this extent they may enable a less predetermined relationship between cultural consumption, taste and class, among their users. Secondly, it would be valuable to analyse to what extent recommenders' recommendations are comparable to recommendations exchanged by social peers in the physical world. Also, it is important to investigate how recommenders incorporate references and recommendations of social peers, by deploying links with social media platforms such as Facebook. The answers to these two questions provide insight in the influence that recommender systems have as sources of reference of and recommendation for cultural consumption and taste. Thirdly, since in this thesis, recommender systems have been compared to traditional sales strategies as a determinative for highlighted products, it is important to find out how recommenders present products to users, but also to find out how recommenders are utilized for business interests. In relation to the topic of business interests accounted for by recommenders, it is important to investigate the potential discontinuity between the public perception of recommenders as personal, trustworthy and useful tools on one hand, and their profit-driven, partial and biased character on the other.

4. Recommender systems

In this chapter, recommenders' software is first discussed on an aggregate level. Then, a state of the art taxonomy of recommenders follows, in which technical underpinnings and differences between systems are highlighted. Software analyses of the case studies Netflix, Spotify and Amazon Books will be provided. The role of recommenders' interfaces will be discussed from a design perspective, and finally qualitative textual analyses of the interfaces of Spotify, Netflix and Amazon Books will be conducted. Recommenders' connection to and use of social media platforms is discussed throughout the chapter, yet is elaborated on more profoundly in the last paragraph.

4.1 Software

4.1.1 What is software

The programs that computers and applications run on are called 'software'. Software "shows parallels with language in its structure, while in its effect it is similar to machinery" writes Mirko Tobias Schäfer, assistant professor in New Media & Digital Culture at the University of Utrecht and author of *Participation Inside? User Activities between Design and Appropriation* (2009, 151). Software is bound to material, physical data carrier: 'hardware'. However, as opposed to its hardware, software is not tangible. Lev Manovich, professor in Computer Science at the City University of New York and author of several books on software, the most recent one titled *Software takes command,* explains that software consists of two parts: data structures and algorithms (2013, 208). Tarleton Gillespie, associate professor at the Departments of Communication and Information Science of Cornell University, co-author of the anthology *Media Technologies: Essays on Communication, Materiality and Society* and author of the essay *The Relevance of Algorithms,* further explains the data structures and algorithms. Some sort of information is collected, brought into the system and "sometimes excluded or demoted" (Gillespie 2012, 3). This information is translated into for the system readable data, to form so-called data structures. The data structures as a whole need to be created in such a way that they "logically fit with the task which needs to be done" (Manovich 2013, 209). The algorithms are the 'operations', 'tools', or 'commands' that operate on the data structures (ibid). In his TED talk "*How Algorithms Shape Our World",* Kevin Slavin, assistant professor at the MIT Media Lab, explains the algorithms as the 'math' that the software uses to decide things (Slavin 2011).

Deriving from fields such as Computer Science and Computer Engineering, Information Filtering, Machine Learning, Knowledge Discovery and Artificial Intelligence, algorithms in recommender software are designed to process information. They can work with different types of digital data and are not specified or bound to one particular type; they are 'media-independent' (Manovich 2013, 113). Recommenders' software is not media-independent by itself: "a different method needs to be implemented for each data type" and media independent techniques then need to be translated into the algorithms as "general concepts" that can operate on the particular data types there (ibid). Due to its media-independent character, recommendation software is able to combine and process different sorts of data, such as data about products (e.g. about movies in Netflix, songs in Spotify, books in Amazon), data about user behaviour (e.g. what products did a user look at, what products did she or he consume) and data about user ratings (e.g. how many stars did a user give a certain product).

The media-independent recommendation software utilized by platforms such as Netflix, Spotify and Amazon Books can be further categorized as “cultural software” because it is “used by hundreds of millions of people”, it “carries ‘atoms’ of culture” and it is meant primarily to access and share cultural products (Manovich 2013, 2, 7, 36). The recommendation software is determinative for the content that users eventually see on their screens; for the recommendations that they receive, and for the ways in which they can interact with the recommendations given (critique them, update information, etc.), among other things (Manovich 2013). As such, the software has a considerable amount of cultural relevance.

4.1.2 The cultural relevance of recommendation software

Because of the cultural relevance of recommendation software, it is important to investigate how it works exactly. Tarleton Gillespie explains the working of software simple: software is constantly making choices (Gillespie 2012). Recommendation software also makes choices: whether to include or exclude information, how to interpret and combine information and what to make of the final ‘mixed and matched’ information (ibid). Such choices are based on the information that the software can process, but also on the software engineers’ perception about the relevance of information (ibid). Even if only information about individual users’ actual behaviour is used to perform evaluations and provide recommendations, this information is still mixed and matched based on what is assumed to be relevant. "Evaluations performed by algorithms always depend on inscribed assumptions about what matters, and how what matters can be identified" (Gillespie 2012, 12). Therefore, it is unavoidable and impossible that no social assumptions are represented in the choices made by recommenders.

Furthermore, although recommenders software aims to know as much as possible about their users, it never knows everything. The information that it does have and is able to process therefore needs to ‘make up’ for the information missing. Some aspects are chosen to be emphasized, others are chosen to be overlooked. In this way, recommendation software renders users’ identities to “algorithmic identities” (Gillespie 2012, 8). Users are turned into “shadow bodies” that can be understood and processed (ibid). No matter for what reason, choices made by recommenders’ software are loaded with judgment and therefore recommenders form important political and semantic interventions in people’s frame of reference for cultural consumption (Gillespie 2012). The fundamental struggle and question is and will probably remain to be:

> "How to identify relevant information crucial to the public, through unavoidably human means, in such a way as to be free from human error, bias, or manipulation” (…) "In many ways, algorithms remain outside our grasp, and they are designed to be." (Gillespie 2012, 26)

Unfortunately, as I have noticed while looking into literature for this thesis, and as was noticed by Gillespie as well, it is extremely hard to figure out how and what choices exactly are being made in recommenders’ software (Gillespie, 2012). A lot of general information is available about the sorts of recommenders that exist, and about how these recommenders work on a basic technical level. However, more thorough information remains absent and therefore vague for most people. Both users and researchers may wonder: Exactly what kind of information is used? What is included and what is excluded? How is information in the “seemingly automaticity of the algorithm” cleaned up and made algorithm-ready (Gillespie 2012, 4)? How then, is the cleaned-up data interpreted and matched with other information? What categories and groups are created, how and based on what (Gillespie 2012, 2)?

While it is possible to observe what 'comes out' of recommenders, it is unclear what exactly 'goes in' and what exactly happens 'in' the system. The so-called 'black box' theory seems fitting to describe the recommenders, yet it still fails because the algorithms' workings are "both obscured and malleable". As is the case with other sorts of software, recommenders' software is "likely so dynamic that a snapshot of them would give us little chance of assessing their biases" (Gillespie 2012, 12; referencing Pasquale 2009).

4.1.3 Measures of objectivity and neutrality

While it is clear that recommenders make innumerable choices that form important political and semantic interventions, and while there is no thorough information about the exact workings of recommenders, there is also no independent measure to evaluate their neutrality, impartiality or objectivity (Gillespie 2012).

Currently, a recommender's degree of neutrality and objectivity seems to be measured based on the function and purpose of the service it is employed by, and based on the 'accuracy' of the recommendations that it provides users with (Gillespie 2012, 16). Chen, Hu and Pu, member of the Department of Computer Science at the Hong Kong Baptist University and members of the Human Computer Interaction Group at the School of Computer and Communication Sciences and of the Swiss Federal Institute of Technology respectively, explain that accuracy is measured in different ways (2012). However, generally, recommenders' accuracy is interpreted as the accuracy of their recommendations when related to user's 'actual' preferences. Recommenders' accuracy can be measured through the "Mean Absolute Error" (MAE) defined as "the difference between the predicted ratings of an algorithm and actual user ratings" (for rating based recommenders), or by looking at "whether a user changes her or his initially preferred item, which was identified by using a recommender agent" (for feature-based recommenders) (Chen et al. 2012, 337).

Recently, 'perceived accuracy' has gained increased interest in research. Perceived accuracy is not about 'objective' algorithm accuracy, but about the "degree to which users feel proposed recommendations match their interests and preferences (ibid). Users' perception will be discussed more elaborately in the next paragraphs, but for now the most important conclusion is that engineers of recommenders decide by themselves what looks "right" and "accurate". They tweak their algorithms to attain the results that look most accurate, but in the light of all the choices that recommenders constantly make, the results can never be impartial or neutral (Gillespie 2012).

4.1.4 Discourse and public perception

Despite the lack of in-depth information about recommenders' software, and despite the fact that recommenders clearly make many semantic and politically loaded choices for which no independent measure of neutrality or objectivity exists, most literature and research describe and project software, including recommendation software, as 'objective', 'neutral' and 'impartial' (Gillespie, 2012). Recommenders are described (and consequently, perceived) as "stabilizers of trust, practical and symbolic assurances that their evaluations are fair and accurate, free from subjectivity, error, or attempted influence" (Gillespie 2012, 13). Even when it seems like literature offers thorough, precise information about behind-the-scenes processes of recommenders, it also seems to be “performed backstage”, “carefully crafted to (…) legitimize the process and its results” (Gillespie 2012, 14).

Since “no information service can be completely hands-off in its delivery of information”, it is at least somewhat surprising that recommender systems are described (and thus perceived) as if they function in a hands-off manner of delivery (ibid). The fact that for instance, a newspaper is created by human editors who (need to) make choices, is common sense to most readers. The struggle with and strive for journalistic objectivity and neutrality (in newspapers) is openly discussed in most literature regarding journalism. Why is this so different for recommenders, which are also information services, created by humans?

One possible explanation for the vagueness about the exact workings of recommenders is that providers cannot be explicit about their systems because they would provide competitors with means of “duplicating and surpassing their service” (Gillespie 2012, 10). "Information providers often contend that their algorithms are trade secrets that must not be divulged in a public venue" (Gillespie 2012, 19). Furthermore, being explicit would help people to “game the system”, for instance to get their products on top of search results (ibid).

Another possible explanation, which would also clarify the uncritical description of recommenders as ‘objective’ systems, is that transparency about the information that is actually used, and about the ways in which that information is linked, clustered, transformed into profiles, and categorized, could have negative consequences for the public’s perception of recommenders. As a consequence, it could have negative consequences for many companies and services that utilize recommenders. As long as recommenders are ‘propagated’ for their neutrality, automaticity, impartiality and objectivity, by both the industries that deploy them as well as by uncritical researchers (from different fields), the public generally will not feel hesitant using the systems and relying on them (Gillespie 2012). The articulation of recommenders as impartial and neutral systems lends credibility and relevance to their results, maintaining providers’ “apparent neutrality in the face of the millions of evaluations [they] make” (Gillespie 2012, 13).

To create a firmer grasp on recommender algorithms, the next paragraphs explain how they work from a technical point of view. Since recommenders’ software was and is developed mainly in Computer Science and Computer Engineering, Information Filtering, Machine Learning, Knowledge Discovery and Artificial Intelligence, I will use research from these fields primarily. The next paragraphs explore some definitions of recommenders, and survey the state of the art of recommenders in both research and usage. The critical perspective outlined in this very paragraph will be released, because the aim of the upcoming paragraph is to explain recommenders’ workings, rather than to criticize the discourse around them. Moreover, letting go of the critical perspective I have held on to so far, will enable me to clearly illustrate the uncritical (academic) discourse surrounding recommenders elsewhere; the very discourse that I have described and questioned in this paragraph.

4.2 Recommenders: development and definitions

> Recommender systems are software programs that use your behaviour or opinions, and those of thousands or millions of other folks, to help you find restaurants, movies, products, information, and even other people. They've become so widespread that we're more surprised when an online business does not have a recommender system, than when it does (Konstan and Ekstrand, 2013)

J. Konstan and J. Riedl, founders of the widely acknowledged GroupLens Research project on recommenders, and members of the department of Computer Science and Engineering at the University of Minnesota, explain that recommender systems were developed in the 90's (2012). The aim of recommenders was to help internet users in finding the information they wanted in the continuously expanding internet quickly and easily (Konstan & Riedl 2012, 102). Recommendation techniques grew out of the field of information filtering, which developed systems that were able to index content and rank media and products for users, based either on overlap with the terms in the user's search-request, or based on the content's popularity (Konstan, 2008). The first recommender systems that were developed were so-called "collaborative filtering" recommenders. In their early days, user profiles needed to be created manually. When the systems matured, they grew into fully automatic systems, increasingly complex, incorporating more and more sorts of information. Today, recommenders are popular tools, widely used in a broad range of (mostly) online applications. Recommenders make use of both implicit and explicit user behaviour; either by monitoring the users' behaviour while she or he is interacting with the system, or by asking the user to explicitly rate items (Lekakos & Giaglis 2006). The implicit and explicit behaviours comply with, and can also be interpreted as forms of implicit and explicit participation (Schäfer 2009). Recommenders' performance and results improved, and a broad range of new sorts of recommenders such as content-based systems have joined the field (Konstan & Riedl 2012). Although recommender systems have been and still are evolving and maturing, the core principles underpinning their working have remained the same (ibid).

There has always been a good deal of agreement about what recommenders are and what they are supposed to do. Some definitions of recommender systems by acknowledged experts in the fields of Computer Science, Computer Engineering and related fields are as follows:

> Recommender systems were originally defined as systems in which "people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients". The term now has a broader connotation, describing any system that produces individualized recommendations as output or has the effect of guiding the user in a personalised way to interesting or useful objects in a large space of possible options (Burke 2002, 1)

> Recommender systems are a special class of personalized systems that aim at predicting a user's interest on available products and services by relying on previously rated items or item features. Human factors associated with a user's personality or lifestyle, although potential determinants of user behavior, are rarely considered in the personalization process (Lekakos & Giaglis 2006, abstract)

> A recommender system is a Web technology that proactively suggests items of interest to users based on their objective behavior of explicitly stated preferences (Chen et al. 2012, 317)

> The task of recommender systems is to utilize past evaluations of items by users to select further items that could be appreciated by the users. We often speak about personalized recommendations because a good recommender system should be able to recognize preferences of individuals and select the object to be recommended accordingly (Medo 2012, 14)

As the above set of chronologically ordered definitions illustrate, recommenders have been defined from the beginning, as systems that aim to help users in finding the items that they are interested in, by providing them with recommendations based on their actual, implicit or explicit behaviour. Later when the field of recommenders matured, the individualized, personalised character of recommenders became a more prominent aspect in their definition.

4.3 Varying recommender systems, varying technologies

In order to fully understand recommenders, it is essential to understand how the systems work on a technological level, and to understand the technological differences that exist between the various systems. Therefore, I will now provide a brief overview of recommender systems and the way they work.

The most widely recognized taxonomy of recommender systems is probably the one created by Robin Burke, member of the department of Information Systems and Decision Science at the California State University (2002). His survey is cited in most literature about recommenders and although it might not be the newest source of information, the survey gives a good, general overview of recommenders that has been accepted and used by most experts on the subject. More recently, previously introduced Chen, Hu and Pu proposed taxonomies (2012), and Adomavicius and Tuzhilin did too (2005). Adomavicius is member of the IEEE group of Transactions On Knowledge And Data Engineering, and member of the School of Management at University of Minnesota. Tuzhilin is member of the School of Business at New York University. In this chapter, the Taxonomies by Burke (2002), Chen et al. (2012) and Adomavicius and Tuzhilin (2005) are used to create an overview.

The three taxonomies are supported and comprehended by research outcomes, explanations and arguments, mainly derived from the fields of Computer Science and Engineering, Information Engineering, Information Filtering, and Machine Learning. I make use of empirical analysis by Breese, Heckerman and Kadie (1998), who worked as researchers for Microsoft Corporation and studied predictive algorithms for collaborative filtering recommenders. I also make use of research outcomes by Fleder and Hosanagar, who I introduced in paragraph 2.2 (2009). For explanation and clarification particularly, I deploy an introduction to recommenders by Konstan and Ekstrand (2013), both working on the GroupLens Research Project at the Department of Computer Science and Engineering of the University of Minnesota. For similar purposes I deploy an analysis of the status quo of research on recommenders, presented by Konstan and Riedl (2012). I look into an empirical data analysis concerned with the improvement of prediction accuracy of recommendation algorithms by Lekakos and Giaglis, both working at the department of Management Science and Technology at the Athens University of Economics and Business in Greece (2006). At last, I make use of an overview of so-called 'random walk' algorithms in recommenders by Medo (2012), working at the department of Physics at the University of Fribourgh in Switserland, and of an empirical data-analysis concerned with recommendation algorithms for e-commerce, presented by Sarwar, Karypis, Konstan and Riedl, all members of the GroupLens Research Project and the Army HPC Research Center (2000).

It is important to note upfront that the various recommender systems discussed in the upcoming paragraphs are often combined or mixed. Various recommender systems can be combined in several ways, such as through "weighted hybridization" (votes of several recommender systems are combined to produce a single recommendation); through switching hybridization (the system 'switches' between different recommenders, depending on which one's outcome is 'strongest' in a particular situation) by means of "mixed hybridization" (recommendations from several systems are presented at the same time); using "feature combination" (features from different recommenders are combined into one algorithm); through a "cascade" (one recommender refines the outcomes of another); by "featuring augmentation" (outcomes of one recommender are used as input for another) and finally, through "meta-level hybridization" (the model created by one recommender is used as input for another) (Burke 2002, table III; Adomavicius and Tuzhilin 2005).

4.3.1 Taxonomy by Burke

The taxonomy created by Robin Burke distinguishes recommenders based on three aspects; the background information that the recommender collects, the input that it uses, and the process that it goes through in order to provide recommendations. Based on these aspects, Burk distinguishes five recommenders: collaborative recommenders, content-based recommenders, demographic recommenders, utility-based recommenders and knowledge-based recommenders (2002).

<u>Collaborative recommenders</u>
Collaborative recommenders, also known as 'user-user collaborative recommenders' have been acknowledged as the most successful, most familiar, most mature and most widely implemented recommendation technique to date (Sarwar et al. 2000; Burke 2002; Lekakos & Giaglis 2006; Chen et al. 2012). Collaborative recommenders generate recommendations for users based on inter-user comparisons, by measuring correlations between pairs of users (Burke 2002; Konstan & Riedl 2012; Lekakos & Giaglis 2006). Thus users who have some form of similarity are used to recommend unobserved items to each other (Lekakos & Giaglis 2006).

Although collaborative filtering recommenders are the most successful recommender systems to date, they have three important downsides. First of all, insufficient data on new users and new items are causing so-called 'cold-start problems' (Konstan & Riedl 2012, 104). When insufficient data is available, demographic or content-based factors have to be taken into consideration as an alternative for, or extension to the system. Another important weakness in collaborative filtering is that implicit user behaviour cannot be interpreted as a negative behaviour. This means, that when implicit user behaviour is used as data, every action (a click, a visit, a consumption) is interpreted as a positive relationship between the user and the item that the action was performed on (Breese et al. 1998). Lastly, collaborative filtering has not proven scalable to perform for retailers and services with large data sources and a large number of catalogue items (Linden et al. 2003). Such retailers therefore cannot make use of collaborative recommenders, and thus often use content-based recommenders instead.

Content-based recommenders

As an alternative to 'classic' collaborative recommenders, content-based recommenders were developed. Content-based systems don not recommend items based on what similar users rated highly, but rather make use of product information (e.g. author, genre, theme) to recommend items to the user, which are similar to those that she or he already rated highly (Fleder and Hosanagar 2009; Adomavicius and Tuzhillin 2005). Thus, the system treats its task as a search for related items, based on both product information and user-item ratings. It builds correlations between pairs of items and then computes recommendations "by finding items with high similarity to the set of items already rated favorably by the user" (Konstan & Riedl 2012, 122).

The upside of content-based recommenders is that they perform faster than collaborative recommenders, especially for commercial applications that have many more users than products. The downside of content-based filtering recommenders is that they cannot be used to recommend all types of content, because they are incapable of capturing abstract concepts such as quality or taste; they can only recommend by using concrete product information, for instance in the form of terms, titles, themes and authors. Therefore, content-based recommenders are often applied in applications concerned with text documents (Lekakos & Giaglis 2006).

Utility-based and knowledge-based recommenders

Utility-based and knowledge-based recommenders, as opposed to collaborative and content-based systems, do not build up long-term generalizations about users in the shape of user profiles. In fact, they do not build up user profiles at all. They evaluate a match between "a user's need and the set of options available" in a different way (Burke 2002, 3). Utility-based systems use products' features as input and rank the products based on their features. "Users have to explicitly or implicitly specify their preferences for a set of attributes which characterize the multi-attribute product", and products are then ranked based on the concordance of their features with the user's preferences (Chen et al. 2012, 323). Utility-based recommenders can apply both product-attributes and non-product attributes (such as delivery schedule) in their computation (ibid). Utility-based recommenders are employed mostly in applications dealing with infrequent user purchases in high-risk domains, such as in cars, washing machines and smart phones (ibid).

Knowledge-based recommenders have a lot in common with utility-based recommenders. However, an important difference is that knowledge-based recommenders "have functional knowledge on how a particular item meets a particular user need" (Burke 2002, 3). They don not need explicitly specified user preferences, but rather use implicit user behaviour as input (ibid).

Demographic recommenders

Demographic recommenders, the last category in Burke's taxonomy, search for correlations between users based on demographic information about users such as gender, age and level of education and income (Adomavicius and Tuzhillin 2005; Burke 2002). Product ratings of demographically similar users are used to formulate a recommendation for the active user.

Burke visualized his taxonomy in a table, clearly showing how the several recommenders differ.

> I is the set of items over which recommendations might be made, U is the set of users whose preferences are known, u is the user for whom recommendations need to be generated and I is some item for which we would like to predict u's preference (Burke 2002, 2)

Technique	Background	Input	Process
Collaborative	Ratings from **U** of items in **I**.	Ratings from **u** of items in **I**.	Identify users in **U** similar to **u**, and extrapolate from their ratings of **i**.
Content-based	Features of items in **I**	**u**'s ratings of items in **I**	Generate a classifier that fits **u**'s rating behavior and use it on **i**.
Demographic	Demographic information about **U** and their ratings of items in **I**.	Demographic information about **u**.	Identify users that are demographically similar to **u**, and extrapolate from their ratings of **i**.
Utility-based	Features of items in **I**.	A utility function over items in **I** that describes **u**'s preferences.	Apply the function to the items and determine **i**'s rank.
Knowledge-based	Features of items in **I**. Knowledge of how these items meet a user's needs.	A description of **u**'s needs or interests.	Infer a match between **i** and **u**'s need.

4.3.2 Taxonomy by Chen, Hu and Pu

Chen, Hu and Pu propose a taxonomy of recommender systems based on distinctions in so-called 'preference elicitation techniques'. Most recommenders currently are 'preference-based'; they make use of explicit and implicit user ratings, sometimes in combination with information about item features (Chen et al. 2012). Preference-based systems can be divided into rating-based, feature-based and personality-based recommenders (ibid).

<u>Rating-based systems</u>
Rating-based systems can be divided into collaborative recommenders and content-based recommenders. They are called rating-based systems because they make use of explicit and implicit user behaviour, which they interpret as 'ratings'. Rating-based systems (collaborative and content-based systems) "allow users to explicitly express their preferences". Furthermore, they are characterized by the fact that they build up user profiles. They collect and apply historical data (such as ratings) to estimate user preferences (Chen et al. 2012, 322).

<u>Feature-based recommenders</u>
As opposed to rating-based systems, feature-based recommenders do not attempt to "build long-term generalizations about their users". Rather, they "base their advice on an evaluation of the match between a user's need and the set of options available" (Chen et al. 2012, 322). Feature-based recommenders can be split into case-based, knowledge-

based, utility-based and critiquing-based recommenders (Chen et al. 2012). The latter three systems can be interpreted as variants of case-based systems. "Case-based systems can rely on utility-based or knowledge-based technologies to assess the similarity between a case [an item], and a user's query" (Chen et al. 2012, 322). Critiquing-based systems are a form of case-based recommenders, operating in a "reactive fashion" (ibid).

Personality-based systems

Personality-based systems form a new category in recommender systems, which use "personality acquisition methods" to build user profiles (Chen et al. 2012, 323). Based on the idea that "personality is an enduring and primary factor that determines human behavior and that there are significant connections between personality and people's tastes and interests", these recommenders use personalised information to understand users (ibid). Like rating-based systems, personality-based recommenders use both implicit and explicit user behaviour as input. Implicit methods observe users' behaviour while explicit methods rely on personality questionnaires (Chen et al. 2012).

4.3.3 Taxonomy by Adomavicius and Tuzhilin

Preference-based vs. rating-based systems

Adomavicius and Tuzhilin make a distinction between 'preference-based' recommenders, which aim to predict "the relative preference of users", and 'rating-based' recommenders, which focus on predicting the absolute value of ratings for individual items (Adomavicius and Tuzhilin 2005, 735). Most recommenders are rating-based, but Adomavicius and Tuzhilin do not specify which recommenders fall under which category. Since the distinction is mostly mathematical, it seems safe to assume that all sorts of recommenders may fall into either category.

Collaborative vs. content-based systems

A second distinction made by Adomavicius and Tuzhilin is based on the way in which recommendations are being made. Whereas Burke (2002) incorporates utility-based, knowledge-based and demographic recommenders, and Chen et al. (2012) take into account case-based, utility-based, knowledge-based, critiquing-based and personality-based recommenders, Adomavicius and Tuzhilin only focus on the two most popular recommender systems: they differentiate between content-based recommenders, collaborative recommenders and hybrid recommenders (the latter combining content-based and collaborative approaches) (2005).

Memory-based vs. model-based systems

At last, Adomavicius and Tuzhilin make a distinction based on the "recommendation techniques used for the rating estimation". They distinguish between 'heuristic', also called 'memory-based' recommenders, and 'model-based' recommenders (Adomavicius and Tuzhilin 2005, 742). Whereas heuristic or memory-based methods make predictions ad hoc based on a set of heuristic rules, model-based recommenders use a "model learned from the underlying data using statistical learning and machine learning techniques" (Adomavicius and Tuzhilin 2005, 737). While collaborative recommenders and content-based recommenders can be both memory-based (heuristic) and model-based, case-based systems such as utility-based and knowledge-based systems are always model-based. I will explain in more detail how memory-based and model-based filters differ from each other, by looking into their function in collaborative recommenders.

Memory-based collaborative recommenders

Memory-based filters in collaborative recommenders make so-called ‘k-nearest-neighbour predictions’, which means that they aggregate users’ ratings or recommendations for items, and then seek to recognize commonalities between users based on their ratings and recommendations (Konstan & Riedl 2012, 103). By tracing relationships and similarities between one user and other users in the database or network, ‘similar’ users’ ratings and recommendations are aggregated, which are then used as a prediction for the target user. Memory-based collaborative filtering is based on the assumption that the implicit or explicit ‘vote’ of a user can be calculated (predicted), by a weighed sum of the votes of other users (Breese et al. 1998, 3). The ‘weight’ of a sum is determined by measuring similarity, correlation or distance between one user and other users. User similarity is usually computed using the ‘Pearson similarity’ also called ‘Pearson correlation coefficient’, but cosine similarity or ‘walk-based similarity’ measures can be used too (Medo 2012, 14).

So-called “Vector Similarity”, a content-based method, is often used in memory-based collaborative filtering systems to index items. Vector Similarity is drawn from the field of information retrieval, where it is used to measure similarity between text documents by “treating each document as a vector of word frequencies and computing the cosine of the angle formed by the two frequency vectors” (Breese et al. 1998, 3). This formalistic approach can be used in collaborative recommenders, by interpreting users as documents; titles of items as words; and votes as word frequencies (ibid). When Vector Similarity is applied, ‘Inverse User Frequency’ is often used too (Breese et al. 1998, 4; Adomavicius and Tuzhilin 2005, 736). The idea of Inverse User Frequency is that words that occur in a document often are not as useful for identifying the topic of that document, as words that occur in it less frequently. The same goes for universally liked items in a collaborative filtering database; they are less likely to capture similarity between users, than less commonly liked items in the database (Breese et al. 1998). Thus, as a compensation for bestselling items, “the algorithm typically multiplies the vector components by the inverse frequency (the inverse of the number of customers who have purchased or rated the item)” (Linden et al. 2003, 77). In this way, less well-known items are made much more relevant (Linden et al. 2003).

An important drawback of memory-based collaborative filtering recommenders is that the systems cannot provide accurate predictions when there is insufficient rating data available. This happens for instance when a new item or new user is introduced in the system; in that case no measurements of similarities can be calculated (Lekakos & Giaglis 2006, 2.1). Therefore, a ‘Default Voting’ extension is often used in memory-based systems. When little or no data about an item or user is available, the extension inserts a ‘default vote value’ for unobserved items (Breese et al. 1998, 4; Adomavicius and Tuzhilin 2005, 739).

Model-based collaborative recommenders

Whereas memory-based collaborative systems compare users against each other directly by seeking for correlation based on historical rating data, model-based systems derive a model from historical data, and use this model to make predictions (Burke 2002). Model-based systems are based on a probabilistic perspective; the model calculates the “probability that the user will have a particular vote value” for an item, by deriving a model from historical data (Breese et al. 1998, 5). Model-based filtering systems thus need an algorithm with a so-called ‘learning technique’ (ibid). A variety of learning techniques have been applied in model-based systems, such as cluster models, Bayesian networks, neural networks and latent semantic indexing (Burke 2002; Adomavicius and Tuzhilin 2005). The first two techniques are the most common and will be briefly introduced (ibid).

Cluster models are created upon the idea that in a system's user-base, certain "groups or types of users" can be recognized, which capture a "common set of preferences and tastes" (Breese et al. 1998, 6). The model clusters supposedly likeminded users into 'classes' (Adomavicius and Tuzhilin 2005, 739). Thus, the user base is split up into many segments, and the system treats its task as a "classification problem" (Linden et al. 2003, 77). The cluster-algorithm aims to "assign the user to the segment containing the most similar [users]" (ibid). Then, it uses these similar users' purchases and ratings, to generate recommendations (ibid). Usually, users are repeatedly matched to existing segments, with provision for new or merging existing segments. Some algorithms can also classify users into multiple segments (ibid).

An alternative to the use of cluster models is the use of a Bayesian network, in which a 'node' corresponds to each item in a domain (Breese et al. 1998, 6). Each node has several possible 'states', which refer to the possible vote values for each item. The algorithm searches over various model structures to seek for the dependencies that each item deals with. Eventually, a 'decision tree' is created for each item, in which a set of 'parent items' is calculated, that most accurately predicts the user's votes (ibid).

4.3.4 Synthesis and implications

The theoretical investigation of the taxonomies shows, that recommenders make use of individual users' actual behaviour to recommend. However, it also proves that this is never the only input that recommenders use. The most popular recommender systems, namely collaborative-filtering recommenders, actually compare users to each other constantly; they categorize them into different segments and deploy users in the same segments as recommendation agents for each other.

The theory discussed in this chapter so far proves furthermore, that there is a discontinuity between the way in which recommender systems are described and defined, and the way in which the systems actually work. Although recommenders do look into users' actual behaviour to recommend products, they appear to make innumerable choices about which information is relevant and about how 'relevant' information can be mixed and matched in order to prove something about a user's preferences. Although the systems may be able to 'empirically observe' users' behaviours, the choices they make are filled with political and semantically loaded judgments. Therefore, the systems can never be objective or neutral.

4.4 Recommender systems in Netflix, Spotify and Amazon Books

Now that recommenders' software has been discussed on a general, technical and theoretical level, it is possible to further explore the way they work by looking into actual applications of recommender system. In this paragraph I identify and discuss the recommender systems that characterize Netflix, Spotify and Amazon Books, respectively. The recommender in Amazon Books is discussed by looking into Amazon's general recommender system; there is no specific, other recommender system that Amazon uses for its Books department. While I touch upon some of the cases' interfaces and their social features, I will avoid an elaborate discussion of these topics. They will be discussed more in-depth later in this chapter.

4.4.1 Netflix

Of the three case study recommenders, Netflix' recommender is probably the most well known. This is for two reasons. First of all, in April and June 2012 respectively, Netflix published an elaborate two-part blog post titled *Netflix Recommendation beyond 5 stars*. The blog post was written by Amatriain and Basilico and revealed Netflix' ways of recommendation. Secondly, in 2006, Netflix announced the 'Netflix Prize'; a prize of 1 million dollar to "whoever improved the accuracy of [their] existing system called Cinematch by 10%" (Amatriain and Basilico 2012, part 1). While the winning team came up with a combination of 107 algorithms, Netflix only implemented the two main 'underlying' algorithms (ibid). Two years later, Netflix announced another 'Grand Prize" worth 1 million dollars. This time around, the winning algorithms were not used at all because the "additional accuracy gains (…) did not seem to justify the engineering effort needed to bring them into a production environment" (Amatriain and Basilico 2012, part 2). Furthermore, Netflix' ideas about how to improve personalization of their recommendations had shifted to "a next level" (ibid). Netflix started to employ three main forms of recommendation, which they elaborated on in the previously mentioned blog post.

According to Netflix, "an obvious baseline [for recommendation] is item popularity. A user "is most likely to watch what most others are watching" (Amatriain and Basilico 2012, part 2). However, since popularity "is the opposite of personalization", Netflix deploys a second approach to adjunct the popularity-based recommendation technique. Based on item comparisons, Netflix calculates "the member's predicted rating of each item" (ibid). Thus, "rather than using either popularity or predicted rating methods on their own", Netflix build a "ranking prediction model" that is able to use both features (ibid). Following the previously presented taxonomies, Netflix deploys a hybrid-recommender, combining a collaborative approach with a content-based approach. In order to determine when popularity is more or less important than predicted rating, Netflix uses a model-based machine-learning algorithm that combines various learning approaches such as singular value decomposition, cluster models, linear regression and gradient boosted decision trees (ibid).

In order to "make Netflix even more personalized", in 2013 a "social feature" was introduced to accompany Netflix' collaborative and content-based approaches, explains Cameron Johnson, Director of Product Innovation at Netflix in the YouTube video "*First Look: Netflix Social Features"* (Netflix 2013a). The social feature enables users to ''connect to friends" by linking their Netflix account to their Facebook profile and agreeing to share the TV shows and movies they watch, with friends who have also agreed to share (ibid). The movies and shows watched and shared by friends, are presented to users in two 'social genre rows' on the Netflix homepage: 'friends favorites' and 'watched by your friends'. 'Friends' favorites' shows movies that a user's "friends have rated with 4 or 5 stars (…) really the things they love" (ibid). 'Watched by your friends' is a list showing all a user's Facebook friends (who have their Facebook profile linked to a Netflix account), and what they have recently watched (ibid).

The Netflix recommender gathers input about its users, which they refer to as 'members', in various ways, explains Carlos Gomez-Uribe, working on Personalization Algorithms at Netflix, in the YouTube Video "*Netflix Quick Guide: How Does Netflix Make TV Show* *and Movie Suggestions?*" (Netflix, 2013b). When a new member joins Netflix, she or he is first asked to answer a "simple test survey" (ibid). The answers to this survey are used as a first input, hence a starting point for recommendations. After a member's first login, Netflix learns more about her or his preferences every time she or he uses the platform. For the collaborative and content-based parts of its algorithm, the Netflix recommender collects and analyses explicit ratings as well as implicit 'ratings', in the form of plays, items added to queues and entered search terms, among other things. The collaborative algorithm in the Netflix recommender considers ratings from all members, the content-based algorithm in the Netflix recommender only takes into account the ratings of the member in question. In addition to the explicit and implicit ratings of members, the Netflix recommender deploys metadata about shows and movies, such as "actors, director, genre, parental rating, and reviews" (ibid). At last, Netflix has the ability to use external data such as "box office performance or critic reviews", and data about "demographics, location, language, or temporal data" (ibid).

Netflix presents its recommendations in what they refer to as 'genre rows'; horizontal category-based lists ranging from "high-level" categories such as 'Comedies', to "highly tailored slices" such as "Imaginative Time Travel Movies from the 1980s"' (Netflix 2013a). Each row is personalised based on three aspects: "the choice of genre itself, the subset of titles selected within that genre, and the ranking of those titles" (ibid). Following the taxonomy by Adomavicius and Tuzhillin (2005), Netflix therefore makes use of both 'preference-based' and 'rating-based' recommendation algorithms; predicting the relative preference (ranking of the titles) as well as the absolute value of ratings for individual items (the choice of genre and the subset of titles), respectively (ibid).

4.4.2 Spotify

Spotify is considerably less transparent about their ways of recommendation than Netflix is. To the best of my knowledge, Spotify has no written documents explaining their recommendation system. However, in January 2014, Chris Johnson, a machine learning employee at Spotify, posted a SlideShare presentation online in which he introduced the various machine learning methods that Spotify utilizes for recommending music. Although it exceeds the scope of this thesis to discuss the specific machine learning methods employed by Spotify, Johnson's presentation does provide insight in the various ways in which Spotify recommends. According to Johnson, Spotify makes use of several recommendation techniques. Spotify recommends through manual curation (curation by music experts); by making item-item and user-item similarities based on tags, audio content, metadata and textual analysis (both content-based approaches following the discussed taxonomies); and through user-user collaborative filtering (Johnson, 2014). Spotify thus deploys a hybrid recommender system mixing collaborative and content-based approaches. Additionally Spotify offers social recommendations, namely through an optional connection to Facebook. When users choose to connect their Spotify to their Facebook account, they enable themselves to follow their Facebook friends' actions on Spotify (at least, when these Facebook friends also have a Spotify account connected to their Facebook profile). Users can opt in to follow a certain friend 'completely', or choose to merely follow one or several of a friend's 'lists'. In the first case, the user gets to see all her or his friend's activity on Spotify; e.g. what songs or albums she or he is listening to, what lists she or he is subscribing to, and what lists she or he creates or updates. 'Lists' consist of songs and can be either created by a regular Spotify user (by the friend in question, for instance) or by an artist, label or other organization. A connection to Facebook also enables Spotify users to easily share music they listen to on Spotify with friends on Facebook, either in private messages (accessible on both Spotify and Facebook), or on their Facebook timeline.

It is interesting to note that on March 6, 2014, Spotify announced that they had bought The Echo Nest; "the industry's leading music intelligence company" specialised in recommendation algorithms, among other things, according to Darrell Etherington writing for online magazine TechCrunch (Etherington, 2014). The Echo Nest "does things like determine what recommendations to make to listeners for automatic streaming radio services" and "[t]he arrangement will help Spotify gain increased access to a key tech piece that already informed a lot of its service delivery" (Etherington 2014). The deal will allow Spotify "to utilize [The Echo Nest's] widely used algorithms to enhance user experience and music discovery for millions of [their] users", according to Billboard (2014). Ultimately, the deal means that Spotify "gains control over tech that underpins its rivals'; perhaps even over the product on which "the entire ecosystem" depends (Etherington 2014).

4.4.3 Amazon Books

> Amazon.com extensively uses recommendation algorithms to personalize its Web site to each customer's interests. (…) The store radically changes based on customer interests, showing programming titles to a software engineer and baby toys to a new mother (Linden et al. 2003, 76 - 79)

In their 2003 industry report *Amazon.com Recommendations. Item-to-item Collaborative Filtering*, written by Linden et al., Amazon opens up about their recommender system. Amazon has invented the so-called 'item-to-item collaborative filtering recommender" – comparable with a content-based recommender, but not quite the same (Linden et al. 2003). Since Amazon has more than 29 million customers and several million catalogue items, it would not be possible for them to run on a classic 'user-user' collaborative recommender. The collaborative recommenders' so-called 'time-to-recommendation', the time needed to generate recommendations, would be too long (Linden et al. 2003, 79). Due to their relatively large customer base and product catalogue, other recommendation techniques also fell short (ibid).

As opposed to most content-based recommenders, Amazon's recommender does not make use of item-feature indexes based on (for instance) keywords, categories and authors to compare items. Such content-based recommendation models could do computations offline, which would be good for Amazon because computation for their large data sets is time-consuming. However, according to Amazon such models "fail to provide recommendations with interesting, targeted titles" (ibid). They would also "scale poorly for customers with numerous purchases and ratings" (ibid).

Furthermore, as opposed to regular content-based recommenders, Amazon's recommender system does not build item-to-item matrixes by "iterating through all item pairs and computing a similarity metric for each pair." Since "many product pairs [on Amazon] have no common customers (…) the approach is inefficient in terms of processing time and memory usage" (ibid). Instead of using item features and computing similarity matrix for all items, Amazon's item-to-item collaborative filtering recommender "matches each of the user's purchased and rated items to similar items", by "finding items that customers tend to purchase together" (Linden et al. 2003, 78). In this way, recommendations can be made without looking into product-features and without iterating through the complete product catalogue. According to Amazon, its recommender is able to provide “highly correlated” and therefore “excellent” recommendations (ibid). Amazon’s recommender system is “cited by many company observers as a killer feature” according to J.P Mangalindan writing on behalf of CNN Money on online platform Fortune (2012). However, there also is “a collective belief within the e-commerce industry that Amazon’s recommendation engine is a suboptimal solution” (ibid).

Amazon’s model-based recommender uses both implicit and explicit user behaviour as input. Additionally to their recommender system, Amazon utilizes customer ratings and customer reviews as a way of recommendation. Although customer reviews are not part of Amazon’s actual recommender systems and could better be interpreted as a form of product information or explanation (see paragraph 1.5), they have proven to increase users’ confidence in purchasing products (Chen et al. 2012; Linden et al. 2003).

4.4.5 Comparison and implications

Netflix, Spotify and Amazon all use implicit and explicit user behaviour as input for their recommender systems. Spotify and Netflix both make use of a three-dimensional recommendation approach, consisting of collaborative, content-based and social recommendations. For their social recommendations, both services make use of a connection to Facebook. Amazon Books on the other hand, uses a self-invented ‘item-to-item collaborative filtering’ approach. Amazon also deploys customer reviews of products, as opposed to Spotify and Netflix. However, Amazon Books does not provide any social recommendations through a connection to a social media website such as Facebook.

It is interesting to note that the social recommendation techniques found in the case studies of Netflix and Spotify were not accounted for in the theoretical taxonomies about recommenders presented earlier. Furthermore, the case of Netflix particularly proofs that external data about users are employed for recommendation; something that did not explicitly come up either in the theoretical discussion about recommenders. Netflix’ openness about their deployment of external data proves that recommenders may not only look into users’ ‘direct’ behaviour within the application in question; recommenders can also look into users’ behaviour ‘outside’ of the application. They may be designed to do so in order to improve recommendations, but other, profit-driven purposes may also be involved. Although Spotify and Amazon are not open about whether or not they look into external data, it is safe to say that, considering their commercial aims, they will do so if this is profitable in any way - and it probably is.

This use of external data raises questions, primarily about whether or not behaviour outside of the applications in question should be considered relevant for recommending cultural products. Netflix did not state where they get their external data from, but what if, for instance, Netflix deploys data about what members search for on Google? And what if they use members’ Facebook profile information (e.g. age, gender, level of education, work status, relationship status, city of residence, likes, etc.) to improve recommendations? The use of such information to improve recommendations raises a myriad of concerns about privacy and discrimination, among other things. Furthermore, in the context of this thesis, the use of external data raises the question if, how and to what extent the deployment of external information about users, leads recommenders to create segments based on social characteristics – comparable to the social characteristics of social classes, and thus to that extent comparable to target markets created by traditional sales strategies.

It is safe to say that recommenders, when compared to traditional sales strategies, at least have the ability to categorize people in considerably more specific, more detailed and probably more accurate segments. Furthermore, as opposed to traditional sales strategies, recommenders do not create segments with the aim to target them. Rather, the segments serve as tools within the recommendation process, aimed to improve recommendations for individual users. For these reasons, when compared to traditional sales strategies, recommenders highlight products based on fewer presumptions and generalizations. To that extent, they have a decreasing effect on the pre-determined character of the relationship between social class and cultural consumption and taste.

4.5 Business interests

Recommenders are not solely employed to “improve users’ choice satisfaction while reducing their effort in finding preferred items” (Chen et al. 2012, 318). A lot of applications that use recommenders are commercial; they have a business interest and in fact deploy recommender systems primarily to help them make a profit. It may not come as a surprise that business interests have been perceived as an important challenge in both research on and engineering of recommenders. In many cases, recommenders’ algorithms are tweaked and altered in order to fit with business logic, for instance to prevent them from recommending out-of-stock goods (Konstan & Riedl 2012). Of course, the possibility of business logic driven tweaks and alterations in recommenders are yet another semantic and politically loaded intervention, impressed on users by the systems. However, this is not the most important argument at stake here. As I will illustrate, the businesses of Spotify, Netflix and Amazon Books are highly dependent on their recommender systems; their recommender systems are a main force behind their businesses’ success.

Amazon is one of the largest retailers online and worth $165 billion dollars according to TIME Magazine (2013). According to Amazon’s own statements in their ‘Media Room’ web page, it "strives to be the Earth's most customer-centric company where people can find and discover virtually anything they want to buy online" (Amazon, 2014). Furthermore, they explain that "it is by design that technological innovation drives the growth of Amazon.com" and that "among its many technological innovations for customers, Amazon.com offers a personalized shopping experience for each costumer" (ibid). It is safe to say that Amazon could not offer such a personalised shopping experience without their recommendation system.

The "world's leading Internet television network" has "over 44 million members in more than 40 countries" and "about 70% of everything Netflix members watch is a personalized recommendation" (Netflix 2014). This means that out of the approximately one billion hours of TV shows and movies that members watch on Netflix each month, 0.7 billion hours are streamed by members based on the recommendations they received from Netflix. Unsurprisingly and in line with this, Netflix has stated that improving the recommendations they provide members with is a key element of their business (Netflix 2014).

Spotify, at last, also states that it is "the best place to discover music". The company says that it has over 24 million active users and it is worth more than $3 billion according to TIME Magazine (2013). "[R]ecent innovations from Spotify have been all about helping people discover even more great music" (Spotify 2013). With their "three-dimensional approach to music discovery" Spotify ensures that users will “always have the right music for every moment" (Spotify, 2013). Spotify’s recent purchase of music intelligence company The Echo Nest only proves how important personalised recommendations are for Spotify.

Altogether, the cases prove that recommenders play a key role in Spotify’s, Netflix’ and Amazon Books’ businesses; they are not simple add-ons to please users, but rather the spine of what these platforms have to offer. Without their recommender systems the platforms would not be able to offer the ‘personalised experience’ that, true to their own statements, is one of the main reason for people to make use their services.

4.5.1 Recommenders systems for advertisement

The large numbers of personal data provided by users and collected by recommenders play a key role in targeted advertisements and market research (Schäfer 2009). Therefore in this way too, recommenders serve business interests.

For online retailers such as Amazon, the personalised shopping experience created by recommenders “provide[s] an effective form of targeted marketing” (Linden et al. 2003, 79). Amazon’s web-based and e-mail advertisements are highly effective, only because their recommender system enables them to target advertisements to individuals:

> Click-through rates and conversion rates – two important measures of Web-based and email advertising effectiveness – vastly exceed those of untargeted content such as banner advertisements and top-seller lists”, (Linden et al. 2003, 76)

Amazon also acknowledges that their “shopping card recommendations, which offer customers product suggestions based on the items in their shopping card, (…) is similar to the impulse items in a supermarket checkout line” (Linden et al. 2003, 78). The main difference however is, that Amazon’s “impulse items” are targeted to individual users, as opposed to supermarkets’ impulse items that are targeted to a broad group of customers (ibid).

Amazon is not the only platform that has been open about its recommenders’ influence on the effect of advertisement, and business revenue more generally. On March 6 2014, Spotify justified buying music intelligence company The Echo Nest stating:

> “the acquisition supports Spotify’s strategy to grow global music consumption and overall revenue back to the music industry by building the best user experience and music discovery engine (…) The addition of The Echo Nest to Spotify will also strengthen Spotify’s ability to help brands and partners build amazing music experiences for audiences” (Spotify, March 6 2014)

The cases in this paragraph again prove that recommenders are central to business. Recommenders are used by and part of large and powerful corporations, who practice business on a global scale and are worth billions. To this extent, recommenders are meant to serve commercial goals. They are utilized mainly to help businesses make revenue, and for this matter, recommenders are very comparable to traditional sales strategies; which serve the same goal.

4.5.2 User behaviour as user labour

In paragraph 4.4 it became clear that Netflix, Spotify and Amazon Books all use implicit and explicit user behaviour as input for their recommender system. In this way, the platforms take advantage of user activities for the improvement of their information systems and for "the generation of content, which either extends [their] content" or even constitutes "their main potential" (Schäfer 2009, 153). By making use of platforms that deploy recommenders, users implicitly or explicitly contribute to the platforms' business models. For this reason, both forms of user behaviour can be interpreted as forms of 'user labour' (Schäfer 2009, 151).

When users behave consciously, 'explicitly', then their labour is performed in free will at least to the extent that they choose to contribute. However, when users behave 'implicitly', their behaviour is automatically channelled and implemented into the software design by default. In this case their labour is not based on a consciously made decision; users contribute data by simply using the application or website.

4.5.3 Control over content and access

It is important to be aware that Spotify, Netflix and Amazon Books' have control over the content that users are able to access in their platforms. While not all users will be aware of it, Spotify, Netflix and Amazon Books do not offer *everything.* Rather, they offer a selection of music, movies and books, respectively. The platforms decide what cultural content they provide their users with, and hence what cultural content their users can access.

As opposed to Spotify and Amazon, Netflix is surprisingly open about their 'programming' function. Netflix will therefore be used as an example to illustrate platforms control over content. In their YouTube video "*How we decide what's on Netflix*" (2013), Netflix explains that their goal is to be an "excellent programmer, offering a mix that delights [their] members rather than trying to be a broad distributor" (ibid). Netflix' goal is to "deliver a compelling, affordable and easy-to-use service that you'll want as one of your entertainment options" (ibid). Netflix is selective in the titles that it offers; it explains that it cannot license everything, and that it therefore looks for "those titles that deliver the biggest viewership, relative to their licensing cost" (ibid). When titles are not watched enough relative to their costs, Netflix can and probably will "forego them or choose not to renew their licensing". Netflix' openness, no matter how well packed for marketing purposes, proofs that its choices for inclusion and exclusion of content are profit-driven. It is these profit-driven choices that determine the content Netflix members are and are not able to access.

4.6 The Interface

So far, this chapter discussed recommenders' software in terms of general technical characteristics and terms of cultural relevance. Furthermore, the discourse surrounding recommenders was addressed and various taxonomies of recommender systems were introduced, along with a technical explanation of the different systems existent. I looked into the technical underpinnings of the recommenders employed in this thesis' cases

Netflix, Spotify and Amazon Books, respectively, and I discussed the business interests involved in the deployment of recommender systems. While I have covered all aspects concerned with the 'back-end' of recommenders, I have not yet looked into the 'front-end' design of recommenders.

Once the software has generated recommendations for a particular user, the recommendations are presented to that user in the front-end design of the application: in the interface (Breese et al. 1998; Chen et al. 2012). The interface is the graphical image a user sees on the screen of her/his device, for instance through icons, folders, lists and menu's, potentially combined with other media and senses, such as sounds, animations, and vibration feedback (Manovich 2013, 29). Altogether, the interface is the layer that communicates between the user and the software. The interface determines "how software appears to users". It is used to present the outcomes of the recommendation software, including the "assumptions and models about a user, her/his needs, and society", that are encoded in the software (ibid). In this way, the interface influences the user's choices and behaviour, and therefore, just like software, it has cultural relevance.

Research on recommender systems used to focus mainly on the accuracy of their predictions and relatively little thought went into the presentation of recommendations (Chen et al. 2012). Recommendations were presented in two ways: either 'one-at-a-time', "usually along with a rating that indicates the users' potential interest in the item shown", or in a list, "with the most important recommendations on top and the least important recommendations on bottom" (Breese et al. 1998, 7-8). However, in recent years it was acknowledged that the interface's effectiveness in presenting recommendations, its ability to explain reasons for recommendations, and its capacity to inspire users' confidence to make decisions, "weighs heavily on user[s] overall perception of a recommender" (Chen et al. 2012, 318). An attractive interface design with effective labels and a good explanation of the recommendations given can "increase users' perception of the systems effectiveness, their overall satisfaction of the system, their readiness to accept the recommended items, and their trust in the system" (Chen et al. 2012, 337). A lot more attention for interface design choices have therefore been considered (Chen et al. 2012). Recommendations' layout, their place on the screen, labels, internal set structure and set composition have been summarized as the most important design choices that need to be made for interfaces (ibid). I will discuss them briefly, and give examples based on the three cases of this thesis, Netflix Spotify and Amazon Books. In the next paragraph, I will use the discussion and examples given to carry out a qualitative textual analysis of the cases' interfaces more in-depth.

<u>Labels</u>

Labels refer to the explanatory 'names' of recommendation sets. Examples of labels are 'Related to Items You've Viewed', 'Recommended for You', 'Customers who Bought This Item also Bought' and 'Customers Who Bought Items in Your Card Also Bought' (by Amazon); 'Top picks for you', 'Because you watched', 'More like' and 'Popular on Netflix' (by Netflix); and 'Trending Playlists near you' and 'Top tracks among friends' (by Spotify). Labels are used for both simple and trade-off explanation. Ideally they lead to users perceiving the recommender as more transparent, and to users who are persuaded to consume items (Chen et al. 2012). Research has proven that "good explanations for recommendations could help inspire users' trust and satisfaction, increase users' involvement and educate users on the internal logic of the system" (Chen et al. 2012, 341).

Product explanation
While the discussed labels are used to explain to users why they receive certain recommendations, explanations about products themselves are mainly used to enable users to further verify whether they are actually interested in the products recommended to them (Chen et al. 2012). Explanation about products can be given in several ways, such as through basic item information (e.g. stating the name of a song, an album, an artist and release date on Spotify), item samples (e.g. giving users the ability to read the first pages of a book on Amazon) and through user generated information. User generated information can exist in the form of keywords (often in the form of 'tags'), ratings (e.g. a numeral rating; certain number of 'stars'), Facebook likes (such as in Netflix), or user reviews (such as on Amazon Books) (ibid).

List or Grid
Recommendations can be presented as a list; a linear set of recommended items, or as a 'grid'; structured and organized into categories of items (Chen et al. 2012, 320). While a grid normally uses up all, or most of the screen's space, lists of recommendations are mostly placed on the right hand side or bottom of the screen ('right-hand longitudinal display' or 'lower latitudinal display') (ibid). In a lot of applications, list and grid-views are combined. This is also the case in Netflix, Spotify and Amazon Books. Whereas Netflix primarily deploys a grid-view build up out of horizontal lists, Spotify and Amazon Books mainly use lists and grids separately.

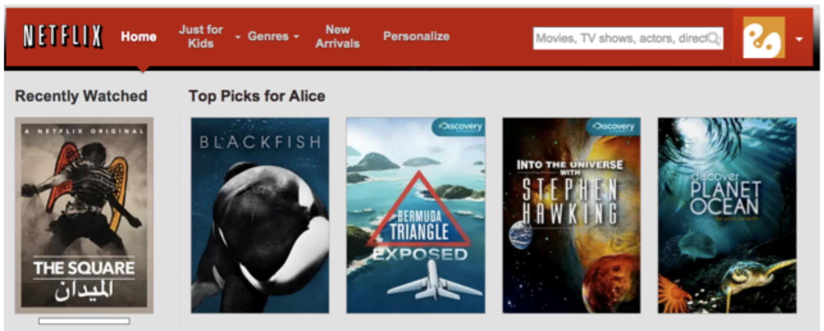
Size and composition of the set
Whether presented as a list or in a grid, choices have to be made about the size and composition of a recommendation set. While one recommendation is normally too little, a set consisting of more than five recommendations increases users' difficulty in choosing (ibid). However, a set consisting of more than five recommendations normally also increases users' "perception of diversity" (ibid). When a choice has been made about set size, a set's composition needs to be addressed. A set can either be "top-ranked" (first showing top-ranked items, then mediocre items) or "mixed" (e.g. top-ranked and mediocre items mixed) (ibid). Furthermore, choices have to be made about the desired diversity of a recommendation set, and about whether or not to intentionally include items familiar to the user (ibid). As may be clear, choices about set size and composition are not solely made on the level of interface design. The choices need to be accounted for by the recommendation software.

4.7 Netflix, Spotify and Amazon: A qualitative textual analysis

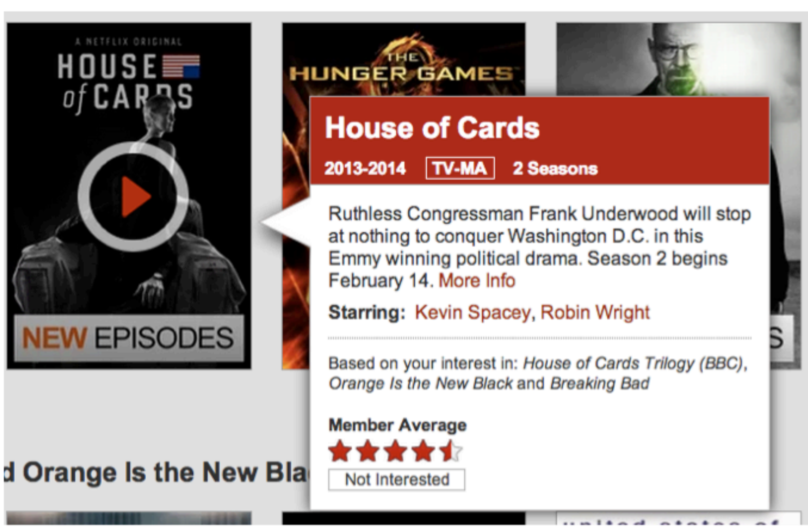
Based on the theoretical introduction and examples presented in the last paragraph, I will now discuss the interfaces of Netflix, Spotify and Amazon more in-depth, namely through a qualitative textual analysis. My aim is to consider how interfaces such as theirs contain meaning, especially as the 'front-end' translation and presentation of their recommendation software. Performing the analysis through my own user perspective, I investigate how the interfaces influence users' perceptions of and assumptions about the platforms and their underlying recommender systems. Throughout the analysis it will also become clear in what ways Netflix, Spotify and Amazon deploy recommendations of social peers (for instance by using a connection to social media, as discussed in paragraph 4.4). The implications about this particular topic will be discussed in the paragraph hereafter.

4.7.1 Netflix

The Netflix' interface is characterized by horizontal lists of recommendations, called 'genre rows' (Netflix 2013). These genre rows have a grid-structure because they are structured along categories. The rows do not have any textual information but they represent the movies and TV shows in them by showing their 'cover' images. The covers look like DVD covers, but they lack the textual information about actors, director(s), audio languages, subtitles and length, among other things.



However, when I roll my mouse cursor over a movie cover, a small square pops up to provide textual information. It informs me about the movie's title, year of release and actors. It also gives me a short explanation about the movie's storyline. In addition, it shows the average rating (number of stars) given by other members, and it gives a small explanation about why the movie or show is recommended to me as a user. In the example below, Netflix for instance explains to me that it recommends 'House of Cards' based on my interest in House of Cards Trilogy, Orange is the New Black and Breaking Bad. Some weeks ago I listed House of Cards in 'My List' because I planned to watch it later and I have seen and enjoyed both Orange is the New Black and Breaking Bad. Therefore in this case, the explanation is successful in helping me to understand why I receive the recommendation.

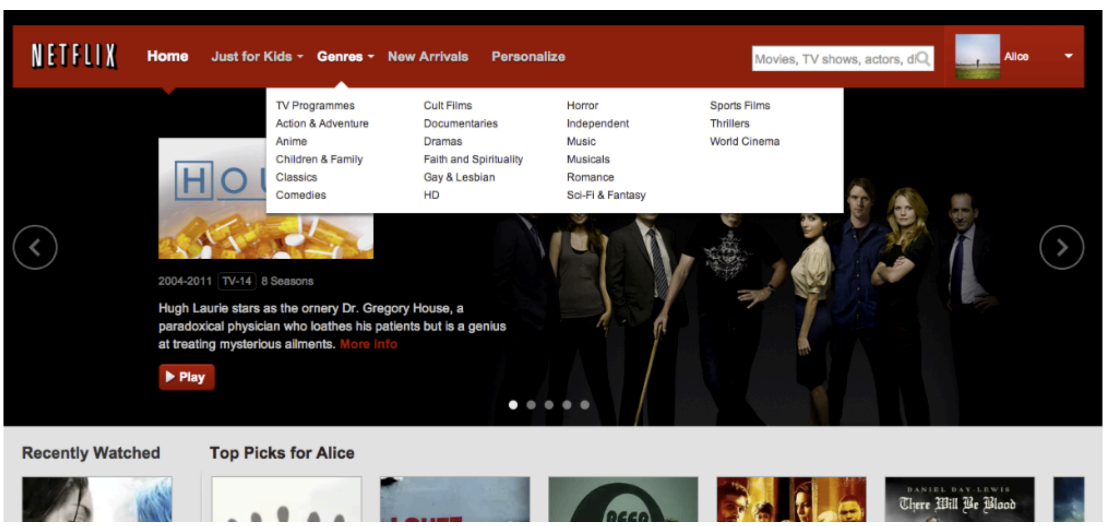


In the top of the Netflix interface, there is a red banner that shows me several options in a menu. The menu, from left to right consists of 'Home', 'Just for Kids', 'Genres', 'New Arrivals' and 'Personalize'. On the far right, there is a white space in which I can search.

‘Home’ is basically Netflix’ homepage when I am logged in. In the upper part of the ‘Home’ screen there is a header that shows me five recommended movies and TV shows in a slide show. It is not clear why I receive these recommendations. If I scroll down a bit, I get to see an overview of all my ‘genre rows’; my categorized lists of recommendations. The sequence of the lists changes based on what I have been watching in Netflix. At the time of writing, the first ones (top to bottom) are labelled ‘Recently watched’ movies and TV shows, ‘Top Picks for Alice’, ‘Popular on Netflix’, ‘New Releases’, ‘Comedies’, ‘Because you watched Orange Is the New Black’ and ‘Dramas’. In total, I am able to see 36 horizontal genre rows.

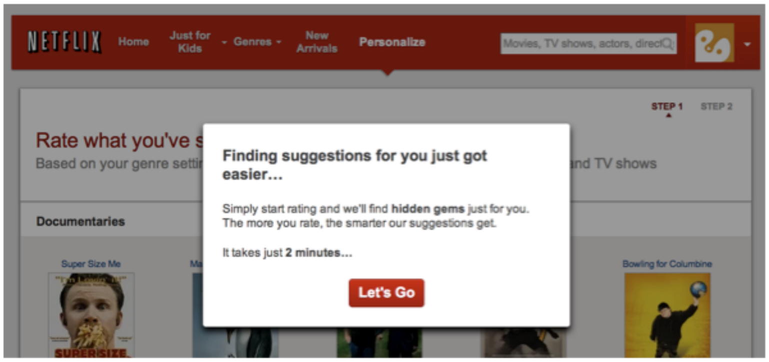
When I roll my mouse cursor over ‘Just for Kids’ in the main menu, I get to see a new pop-up menu with mainly three possibilities. In the left side of the menu, I see ‘Kids Home’ (which is the same as my normal ‘Home’ page and which is also where I end up if I decide to actually click on ‘Just for Kids’), and ‘Characters’. If I click on ‘Characters’ I end up in a menu build up out of pictures of children movies’ characters; perhaps helpful for young kids that have not yet learned how to read, and for even younger ones that can merely explain what they want to see by pointing what they recognize. On the right side of the pop-up menu, I see genres. There are some regular ones such as ‘Action’ and ‘Adventure’, but also genres such as ‘Dinosaurs’, ‘Superheroes’ and ‘Little Kids’. There does not seem to be a specific logic in the taxonomy of genres, but it feels intuitive.

When I click on ‘Genres’ back I the main menu, I am able to pick a certain genre and search for movies within this genre. Examples of genres are ‘TV Programmes’, ‘Action & Adventure’, ‘Anime’, ‘Classics’, ‘Faith and Spirituality’ and ‘Music’. Once again, there does not seem to be a specific logic in the taxonomy of the genres, but this list feels intuitive.



Clicking on ‘New Arrivals’ in the main menu, brings me to a page in which I find several genre lists with new movies and films: ‘New Releases’, ‘Recently added in TV Programmes’ and several ‘Recently added in {genre}’, such as ‘Recently added in Comedies’ and ‘Recently added in Documentaries’.

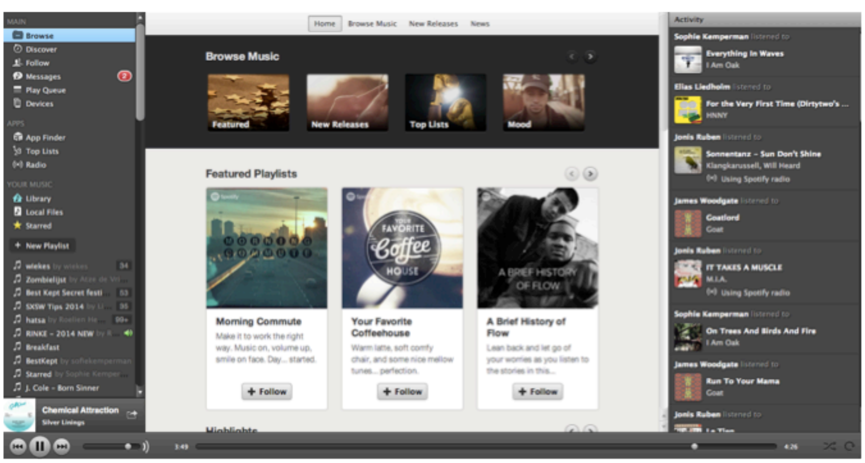
‘Personalize’, the last option in the main menu, leads me to a page that asks me to ‘Rate what I’ve seen’. In a pop-up screen, Netflix explains that by rating some of the movies and TV shows that I have seen, I will help them to ‘find hidden gems just for me’. The more I rate, the ‘smarter’ their suggestions for me will become.



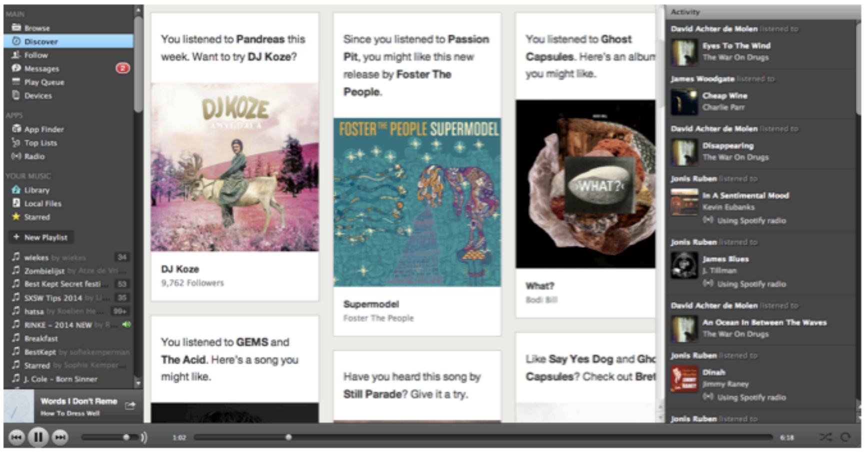
In general, the genre rows in Netflix do not contain a fixed number of recommendations. My genre row ‘Top Picks For Alice’ contains 40 movie recommendations, and so do ‘Popular on Netflix’ and ‘New Releases’. However, my genre row ‘Because you watched Orange is the New Black’ only holds 37 titles, and ‘Because you watched Hercules’ only 29. Altogether, the number of recommendations that I can access in each genre row, and the total number of approximately 1260 recommendations that I have access to in Netflix (36 genre rows multiplied by approximately 35 recommendations per row) makes me feel somewhat overwhelmed.

4.7.2 Spotify

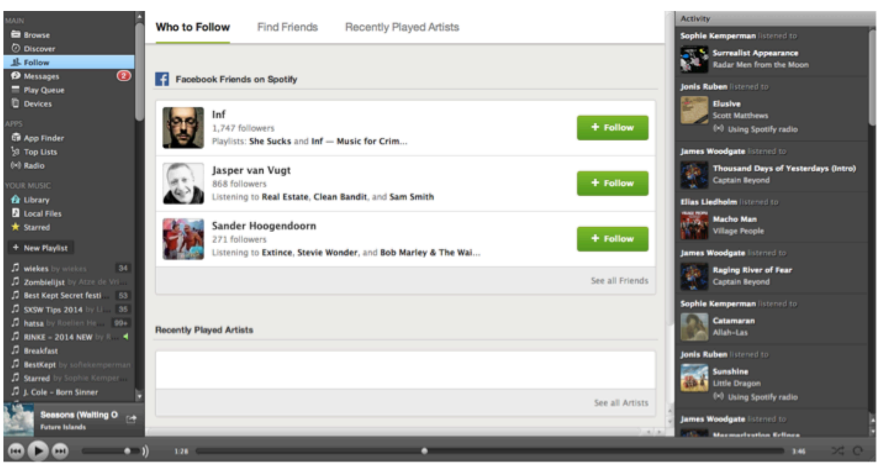
Spotify offers its recommendations in mainly three ways. In its main menu, on the upper left side of the screen, there are three options that lead to recommendations: Browse, Discover and Follow. Clicking on ‘Browse’ leads me to themed playlists, news and new releases. Spotify is not clear about why they show me these particular playlists, this particular news and these particular new releases. The absence of explanation makes me question whether this news, these playlists and new releases, are curated or recommended for me personally, or rather curated and recommended for more people, or even for everyone.



‘Discover’, the second option in the left-side menu, leads me to recommendations for songs and albums based on various factors, such as what I have been listening to, what is ‘trending’ among my friends and what is trending ‘near’ me (location). Here, Spotify presents its recommendations in a top down list build up out of three rows. Each recommended song or album is presented in a little square, showing the image of the album- or single cover, stating the name of the artist and the name of the album or song. Each square also provides me with a short textual explanation as to why the song or album in question is recommended to me (‘You listened to Padreas this week. Want to try DJ Koze?’).



‘Follow’, the third option in Spotify’s main menu, shows me three options: ‘Facebook Friends on Spotify’ that I may want to follow, ‘Recently Played Artists’ by friends that I may want to listen to and ‘Who to Follow”. The ‘Follow’ section as a whole is linked to Spotify’s social recommendations. These recommendations are based on a user’s (optional) connection to Facebook. When a user connects her or his Spotify account to her or his Facebook profile, she or he becomes able to connect to Facebook friends on Spotify. The user can choose to follow friends’ activity on Spotify in several ways, and the user’s friends are enabled to follow the user in question, too.

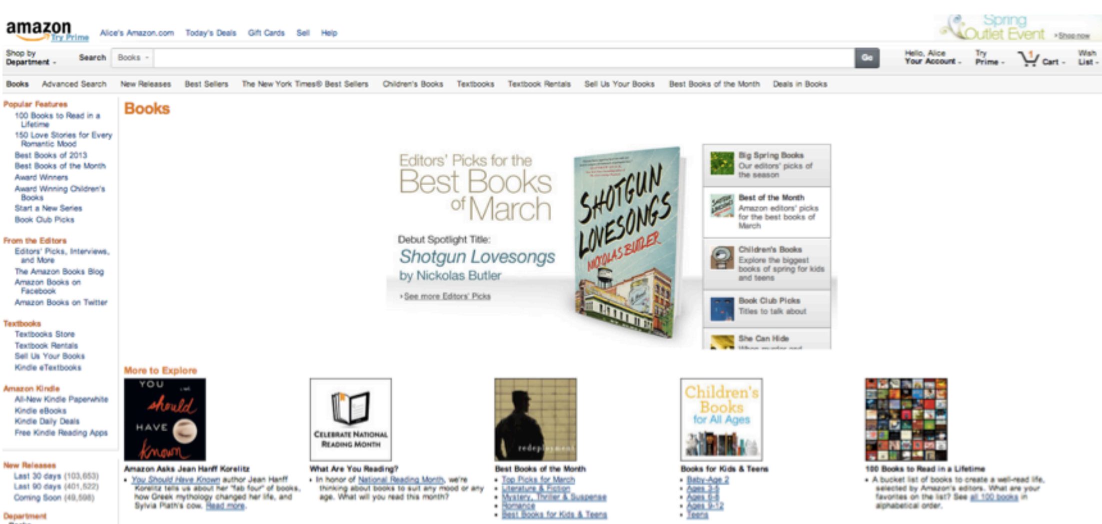


By following new Facebook friends on Spotify or accepting recommendations about ‘Who to follow’, users affect their ‘Activity feed’, shown on the right side of their screen. The feed shows what songs or albums friends are listening to at a particular moment. When users follow a friend (or an artist) they automatically opt in to follow all their ‘lists’ of songs. These lists are shown to the user in a list-menu on the lower left side of the screen. Whenever a friend or artist updates her or his list with new songs, the user is notified about this by a little square accompanying the particular list's title in the lower left list-menu. In the square, the number of new songs that have been added to the list is shown. When users connect their Spotify account to Facebook, Spotify also enables them to share songs, albums and playlists with friends, either by posting them to their Facebook timeline, or by sending them to friends in a private message. Private messages can be found in the 'messages' in Spotify's main menu (on the upper left side), but they are also posted in the user's private messages on Facebook.

4.7.3 Amazon Books

Amazon Books has an interface very different from those of Netflix and Spotify, mainly because unlike Netflix and Spotify, Amazon is an online retailer. This means that unlike the other two, Amazon Books does not make any profit from subscription fees. Rather, it makes profit from individual product sales. As opposed to users of Spotify and Netflix, users of Amazon Books therefore do not need to create a profile in order to use the platform. Users can surf the web shop with or without an account. However, when a user wants to purchase a product, she or he will need to register with a name, e-mail address and password. After registering and purchasing, the user stays logged in by default.

Amazon Books, as a department, is not separated from the rest of Amazon. To reach the Amazon Books department, a user needs to go to Amazon's 'Shop by department' menu on the upper left side of the screen and click on 'Books and Audible'. A smaller screen pops up showing a 'Books' menu, consisting of 'Books', 'Kindle Books', 'Children's Books', 'Textbooks' (referring to books for college) and 'Magazine'. Below the 'Books' menu is the "Audible Audiobooks' menu. For the purpose of this analysis, I will look into the Books' "Books" department solely.



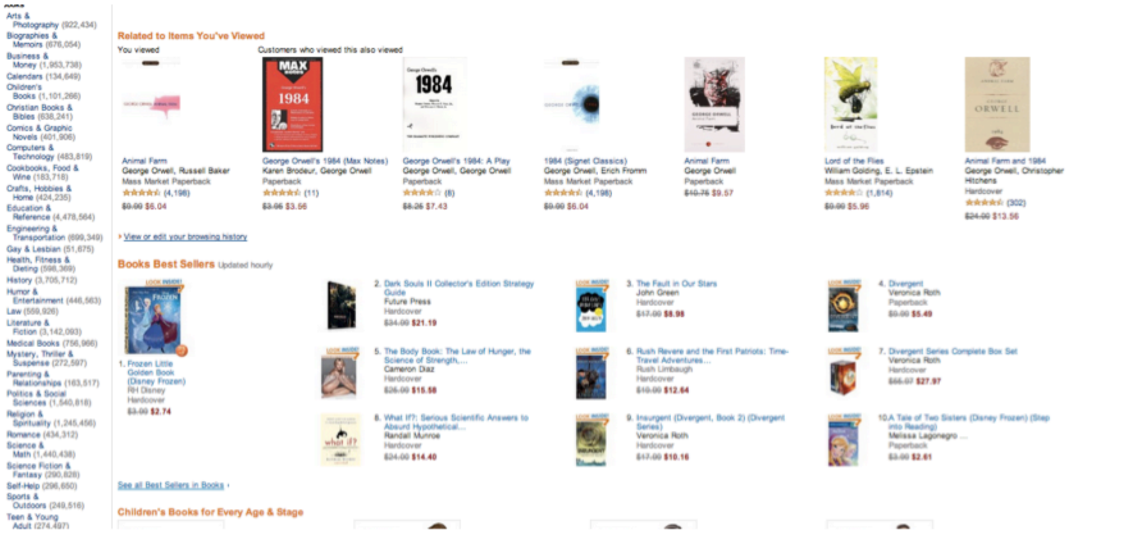
On the left side of the Books homepage, there is a vertical menu showing a list of submenus such as 'Popular Features', 'From the Editors', 'Textbooks', and 'Amazon Kindle'. The menu doesn't contain any images and the written labels are relatively long in comparison to labels in Spotify or Netflix. On the top of the Amazon Books homepage, there also is a horizontally listed menu, showing options such as 'New Releases', 'Best

Sellers', 'The New York Times Best Sellers', and 'Children's Books'. Furthermore, there is an option to sell Amazon books; 'Sell Us Your Books', and a possibility for 'Advanced Search'. Altogether, there is quite some overlap between the vertically listed menu on the left side of the page, and the horizontally listed menu on the top of the page. Moreover, the lists show overlap with the menu that I have already seen in the main 'Shop by Department' – 'Books' submenu on the upper-left side of the page.

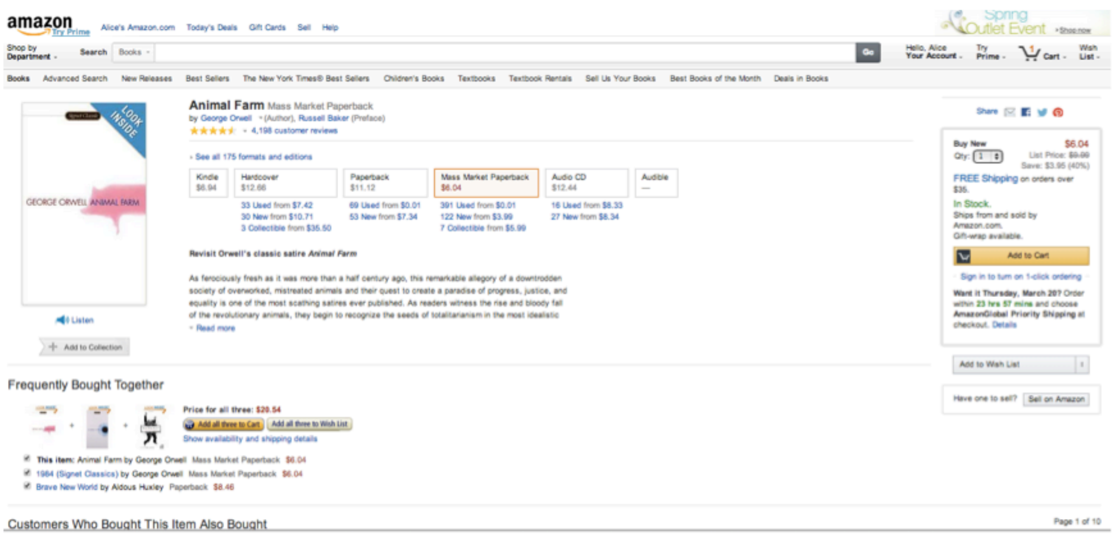
In the centre of Amazon Books' homepage there is a banner containing a slideshow of five 'themes': "Big Spring Books Fresh picks from our editors"; "Editors Picks for the best books of March Debute spotlight title: Shotgun Lovesongs by Nickolas Butter'; "Big Spring Books. Fresh Picks for Kids and Teens"; "Browse our Book Club Picks Store to find your next favourite book to discuss" and "She Can Hide the newest book in the She Can romantic suspense series". It is unclear and unstated, whether the 'themed' content in this banner is curated by Amazon, or advertorial. It may also be both; curated by Amazon, but paid for by third parties anyway. The content in the banner is not based on recommendations for me personally; I have asked friends to log in with their account and they see the exact same content as I do.

Below the banner, there is a horizontal grid titled 'More to explore', consisting of five sections. The sections contain supposedly 'fun' or 'interesting' things, such as an interview with Jean Hanff Korelitz about her books, a celebration of National Reading Month, best books of the month, and '100 Books to Read in a Lifetime'. It seems like the More to Explore section is meant to gain my interest for the Books department, and in a way it does. However, I wonder once again whether third parties somehow pay for this content or not. For instance, did Amazon invite author Korelitz for an interview and did it publish the interview on the web shop 'for free'? And the "100 Books to Read in a Lifetime", who curated those 100 books? When I click on the '100 Books to Read", I get a banner explaining "A bucket list of books to create a well-read life, from the Amazon Book Editors". I click again, and get to see the list. The first books in the list are *To Kill a Mockingbird* by Harper Lee, *Pride and Prejudice* by Ian Edginton, *Anne Frank: The Diary of a Young Girl* by Anne Frank and *1984* by George Orwell. These books obviously are well known and celebrated, so I believe that this content is indeed curated rather than advertised. However, it is not curated for me personally; asking friends to log in with their account yet again proves that everybody sees the exact same content.

Back in the 'Books' homepage, below the 'More to explore' section, there is a section labelled 'Related to Items You've Viewed'. The first item in this horizontal list is an item 'I viewed', namely the book *Animal Farm*, by George Orwell. The next items in the list are items that have been viewed by customers who also viewed *Animal Farm*, labelled 'Customers who viewed this also viewed'. The list of recommendations however, is poor; of the six items recommended, two are 'Animal Farm' (the same item I have already viewed) and three are *1984*, a book by the same author. Only one title is new and interesting to me, namely *Lord of the Flies*, by William Golding and E.L Epstein.



When I click on a book, I get to see an informative overview, stating the book title, the release date, the author, and the average amount of stars given by readers on Amazon. I am able to click on customer reviews, I can choose to see other formats and editions, and I can compare prices, for instance between hardcover, paperback and Kindle editions of the book. At last, there is a short summary of the book's storyline. Below the overview, I can also see two horizontal lists or recommendations; "Frequently Bought Together" and "Customers Who Bought This Item Also Bought".



When I click to add the book to my shopping "Cart", I arrive on a new page showing me my order's subtotal. Here, I also see "Bargain Recommendations" and recommendations "Based on Animal Farm" – again presented in horizontal lists. Finally, when I proceed to check out, I see a horizontal list of recommendations labelled "Customers Who Bought Items in Your Card Also Bought", and on the right-hand side of the screen a vertical list of recommendations labelled "Customers Who Bought Animal Farm also Bought".

Altogether, Amazon's Book department is filled with recommendations. My shopping experience, from the very start to the far end, is guided by Amazon's recommendations for me. However, to me as a user, Amazon's recommendations do not feel as genuine as the recommendations by Netflix and Spotify. Amazon Books' recommendations constantly feel like product advertisements. I do not ever feel like Amazon shows me these products for *my* sake. Rather, I constantly feel that they are meant to serve Amazon Book's commercial goals. Although this perception is undoubtedly linked to the fact that I know that Amazon makes profit of every single book that they are able to sell me, there seem to be other aspects involved as well, such as design.

First of all, the lack of transparency about whether certain content is recommended, curated, or advertised, heavily decreases my trust in all content involved – including content that clearly is personally recommended. The vagueness gives me the feeling that Amazon Books is trying to hide something from me; that it is trying to trick me into buying something rather than trying to help me in discovering interesting products. Secondly, most recommendations that Amazon provides me with are not valuable to me because they are identical, or highly similar to the items that I have already viewed or purchased. Last but not least, I may have a negative feeling about Amazon Books' recommendations because I do not visit the department store to find new books. Whereas I use Spotify and Netflix at least partly to discover new music and books respectively, I mostly visit Amazon Books to buy a book that I have already made up my mind about. When I go to Amazon's Books department, I just want to find and buy the book that I have in mind as fast and easy as possible. I am not there to 'hang around'.

Amazon Book's cluttered interface certainly does not help in making me feel more welcome in their store. I do not experience the interface as being intuitive, nor easy-to-follow. All the written menus and explanations are overwhelming to me and I do not feel encouraged to pay attention to them at all. As a matter of fact, while analysing the interface, I realised that I had never consciously read the menus in Amazon Books before. The layout does not have a 'cosy' or 'leisure' feeling to it either. As opposed to Netflix and Spotify, which have colourful and dark, clean designs. Amazon Books' layout is white, filled with menus in different fonts and letter sizes.

4.7.4 Synthesis and comparison

Netflix and Spotify both have easy to follow, clean, colourful interfaces. The interfaces have an informal and friendly 'feel'. The platforms are relatively transparent about their reasons for recommendations; they deploy clear labels and address me as a user both directly and informally. Both platforms seem to deploy advertisements. However, the advertisements seem to be clearly differentiated from the personalised recommendations.

One of the main differences between Spotify's and Netflix' interfaces, is that Netflix' interface is more visual and less textual than Spotify's. This difference may be caused by the fact that Spotify shows more content on its homepage; it offers a more extended menu and as opposed to Netflix, Spotify offers users the possibility to not only archive, but also structure and categorize the content that they are interested in (namely through the lists). The difference may also be caused by the fact that Spotify has more content to show in general; while Netflix has 60.000 movies in its archive, Spotify has about 20 million songs to offer (Johnson, January 2014). The more content there is to show, the less likely it is that all this content can be captured in images; this would probably take up too much space.

Another difference between Netflix' and Spotify's interface, is that Spotify puts more emphasis on its social recommendations than Netflix does. At the moment, 'Browse' is the only source of recommendation in Spotify that is not at least partly related to the behaviour or recommendations of my Facebook friends. In 'Discover', recommendations based on my friends' behaviour in Spotify are mixed with recommendations based on my own behaviour. The activity feed showing what friends are listening to moreover, is on the right side of my screen at all times. The lists of friends that I follow (and that I have created myself) are also constantly there, yet on the left side of the screen. Altogether, social recommendations are very prominent the Spotify interface. Netflix interface on the other hand, shows social recommendations in merely two of the 36 genre rows.

The third and last main difference between the interfaces of Spotify and Netflix is that Netflix's interface is completely filled with lists of recommendations (the genre rows). Wherever I go; the lists are there. The only exception is 'My list' – the genre-row in which I am able to archive movies and shows to watch later (although the content in this row is also ordered by Netflix' recommender system based on what it assumes I will want to watch first).

Amazon Books' interface strongly differs from those of Spotify and Netflix. First of all, Amazon Books' interface is relatively cluttered, textual and pale. Although Amazon Books addresses me directly and informally, the interface has a relatively formal feel. It is less welcoming, but also less intuitive and easy-to-follow than the interfaces of Spotify and Netflix – partly due to their inefficient infrastructure of heavily overlapping menus and submenus. Secondly, Amazon Books is relatively non-transparent about why they show me 'recommendations'. Most of the time, it is unclear whether content is being advertised, curated or personally recommended. This considerably decreases my trust in all the content shown.

In comparison to Spotify and Netflix, Amazon Books' interface appears to contain a lot of advertised content – although I am unable to verify whether all the content that I perceive to be advertised, actually is. This is interesting considering the fact that Netflix and Spotify are commercial businesses just like Amazon; they probably show me advertised content too. However, whereas I feel relatively unaware of advertisements in Netflix and Spotify, I am highly aware of those (presumed ones) in Amazon.

It appears that Netflix and Spotify care more about user experience than Amazon Books does, and Amazon Books cares more about opportunities for advertising than Netflix and Spotify do. This is not surprising considering the difference between Amazon Books and Netflix and Spotify's core business models for making profit (from individual product sales and subscription fees, respectively) as discussed before.

The interfaces of Netflix and Spotify are most successful in gaining my trust and giving me the feeling that I am experiencing something personal and 'friendly'. Although Amazon Books addresses me informally and directly, it lacks transparency in explaining its content, and its interface is not by far as attractive and welcoming. On top of that, my awareness of Amazon Books' different way of making profit makes me more critical in my observation of its interface – both as a user and as a researcher.

4.7.5 Implications

The textual analysis of Netflix, Spotify and Amazon Books' interfaces proved that Netflix and Spotify's interfaces are successful in gaining my sympathy and trust. Due to the use of clear labels like "Because you watched" or "Because you listened to", I feel like I understand why I receive certain recommendations. I feel like I am interacting with a transparent system. Stimulated by simple explanations and easy-to-follow, user-friendly and informal interface designs, I tend to think that I receive recommendations *only* because I watched or listened to something. I tend not to think about which methods and data have been employed, mixed and matched by Netflix and Spotify, nor do I think about the commercial character of the platforms.

Altogether, the degree of trust that I as a user have in Netflix, Spotify and their recommender systems, is heavily subjected to the success of their interface designs. The platforms' interfaces 'talk to me'. They seem to tell me "don't worry, we are your friend. We get you; we *understand* you. We'll help you out in finding what you're looking for" – and it works.

4.8 Social recommendations: Integration of social peers

The textual analysis carried out in the last paragraph, showed that Netflix and Spotify provide social recommendations to users based on a connection to Facebook. The consequence is that when I, for instance as a Spotify user, want to have music recommendations from friends, then I can get their recommendations without having to ask them for it. Instead of asking my friends, I can log in to Spotify and check out the lists my friends have created. I can look up what lists they are following and I can check the activity feed to see what they are listening to at a particular moment. Furthermore, I can utilize social media such as Facebook, to see what music-related messages they have posted on their timelines and to see which artists they 'like' on their profile.

Recommender systems offering social recommendations particularly, and social media platforms such as Facebook more generally, have altered the shape in which social peers exchange recommendations for cultural products. This is especially true for cultural products that are nowadays consumed in a virtual manner by most people: cultural products such as movies and music. Recommenders and social media have jointly created a virtual space, where exchange of recommendations for these cultural products has become more mobile in terms of space, time and context; where social peers can exchange recommendations in a fast and easy way, without a need for actual personal contact. Social peers can even exchange recommendations without being fully aware of it. They can exchange recommendations for music for instance, by merely looking at their screens while using Spotify: they look left and see each others' lists, they look right and see which songs others are playing at a particular moment.

Of course, people still and probably always will exchange references for cultural products in a physical manner, by telling each other about movies they have seen, books they have read and music they love. However, with the existence and widespread use of recommender systems that provide social recommendations, and with the existence and widespread use of social media platforms, the necessity to exchange references and recommendations in the physical world has decreased. For recommendations from social peers, now and in the upcoming years, most people will probably utilize recommender systems, social media and contact with humans in the physical world simultaneously.

5. Conclusion

Recommenders have become increasingly important as online tools for reference of and recommendation for cultural products. Recommenders can be interpreted as new, innovative sales strategies, but also as new agents for personal reference, comparable to social peers. Recommender systems influence distinctions in cultural consumption and taste between people in different social classes in various ways. According to Bourdieu, social classes are dependent on three interrelated capitals: cultural, economic and social capital. Recommenders are part of, and contribute to a trend that affects the relationship between these individual capitals and cultural consumption and taste, each in a different way.

<u>Social, economic and cultural capital, cultural consumption and taste</u>

Recommenders' highly targeted and personalised recommendations have become an important agent for personal reference of and recommendation for cultural products. Previously, personal references and recommendations could only be derived from contact between social peers, and thus for this purpose; social capital was essential. Due to the existence and widespread use of recommenders, the essentiality of social capital has decreased. However furthermore, recommenders are part of and contribute to a trend in which social capital online, especially for the reference and recommendation of cultural products, becomes more mobile in terms of time, space and context. Altogether, recommenders have contributed to a decrease in the predetermined character of the relationship between social capital and cultural consumption and taste.

Recommenders are also part of and contribute to a trend, in which economic capital becomes less relevant for access to and consumption of particular cultural goods; mainly music and films, but also to a lesser extent (e-)books. These sorts of culture can now be accessed and consumed online for relatively little money, for instance, through streaming platforms such as Netflix (movies) and Spotify (music), and through the books department of online retail giant Amazon (books). Due to a system of monthly subscriptions, prices for movies and music in Netflix and Spotify respectively, do not differ from each other. People pay a monthly flat fee and can consume as much of the available content as they want. Amazon does not offer monthly subscriptions and thus prices for (e-)books do differ. However, in comparison to price differences in other cultural branches such as fashion, books bought online differ relatively little in price. For these reasons, in the online world, the predetermined character of the relationship between economic capital and cultural consumption and taste has decreased, at least with regard to music, movies and (e-)books. As part of the applications that enable the decreased cost- and price differences (Netflix, Spotify, Amazon, among other ones), recommenders contribute to this decrease.

While recommenders contribute to a decrease in the pre-determinacy of the relationship between social and economic capital and cultural consumption and taste, they increase the pre-determinacy of the relationship between a specific new sort of cultural capital, and cultural consumption and taste. This new form of cultural capital is technical capital. Technical capital is concerned with physical access to computing artefacts, as well as with skills and know-how necessary to utilize computers and the internet. There currently is a sharp digital divide between people who do and who do not have technical capital.

Since technical capital is necessary to be able to use recommenders, recommenders contribute to a distinction in cultural consumption and taste, between people with different levels of technical capital. Recommenders' influence on the relationship between general cultural capital, cultural consumption and taste will be elaborated on in the following part of this conclusion.

Recommenders: influence on aggregate vs. influence among users

The trend that recommenders are part of and contribute to exists only online. The increased mobility of social capital for reference of and recommendation for cultural products, and the decreased relevance of economic capital for cultural consumption of mainly music, movies and (e-)books, only exist in the online world. In the physical, offline world, there is no increased mobility of social capital nor is there a decreased relevance of economic capital. Therefore, people who do not have technical capital do not benefit from recommenders influence on cultural consumption and taste, nor from the influence of the trend that recommenders are part of: they are not able to utilize personalised recommendations from recommenders, and they do not experience increasingly mobile social capital or decreased economic thresholds. People who lack technical capital merely experience the increased (and increasing) discontinuity between their cultural consumption and taste, and the cultural consumption and taste of those people who do have technical capital. Considering the fact that technical capital is a form of cultural capital, and that cultural capital is influenced by social and economic capital, a low or absent technical capital indicates a low social class. For this reason, in those cases where technological capital is absent, recommenders nurture a distinction in cultural consumption and taste between people in various social classes.

When people with low or absent technical capital are ignored, and recommenders' influence on cultural consumption and taste is investigated solely among their users, then different conclusions can be drawn. First and foremost, recommenders decrease the pre-determinacy of the relationship between social class and cultural consumption and taste among their users. They do so as part of the discussed trend, in which economic capital becomes less relevant for cultural consumption of mainly music and movies, and in which social capital as a source of reference of, and recommendation for cultural products, becomes more mobile on one hand and less essential on the other. To this extent and among their users, recommenders therefore decrease the relationship between social class, cultural consumption and taste.

However, since recommenders help people in finding cultural products tailored to their preferences in a quick and easy manner, they stimulate people to consume more and more of the cultural products that they prefer - and fewer other cultural products. In this way, recommenders nurture and increase a distinction in cultural consumption and taste, not primarily between people in various social classes, but rather between people who have different preferences ('tastes') and attitudes. It has become clear that people with different levels of cultural capital have different preferences for culture; they give preference to other products, but above all, they prefer to consume a broader or narrower selection of cultural products. People with high levels of cultural capital tend to prefer consumption of a broad and relatively diverse selection of cultural products; they prefer to consume omnivore. On the other hand, people with low levels of cultural capital tend to prefer consumption of a more specific, narrow selection of cultural products; they prefer to consume univore.

Due to their ability to elevate peoples' preferences among their users, recommenders nurture a distinction in cultural consumption and taste between people with various levels of cultural capital. They may cause the gap between those who consume omnivore and those who consume univore, to widen. Whereas recommenders may push people with high levels of cultural capital to consume more omnivore (enabling them to discover new, different and various cultural products fast and easy), they may push people with low levels of cultural capital to consume more univore (enabling them to discover new cultural products highly similar to those they already love). Particularly among univores who prefer a specific and narrow set of cultural products, recommenders may sharpen a distinction between people who prefer either one or the other narrow set of cultural products; for instance between people who love and listen to rock music and people who love and listen to electronic music.

It is important to note that recommenders do not solely influence their users' cultural consumption and taste through the personalised recommendations that they provide them with. Recommenders are part of commercially driven businesses, and as such, they are used for market research and targeted advertising, among other things. For this reason, recommender systems also influence their users' consumption through the advertisements that they show them; in the platforms in question, but possibly also outside of these platforms. Since recommenders are able to look into external data about users, and since this external information needs to come from somewhere, it is only logical that platforms and websites work together in order to utilize each other's data, and therewith improve their systems and advertisements. It is unclear to what extent external data are currently used to add social characteristics to user profiles for the purpose of recommendation. As far as recommenders do add social characteristics to user profiles, and as far as these characteristics are then employed as indicators for recommendation and advertisement, recommenders increase the pre-determinacy of the relationship between social class, cultural consumption and taste among their users, in a way similar to traditional sales strategies. However, since recommenders have the ability to use more specific, more detailed, and more accurate information about people than traditional sales strategies do, it is unclear if they have an increasing or decreasing effect on the pre-determined relationship between social class, cultural consumption and taste, in comparison to traditional sales strategies.

Critical notes

Throughout this thesis, it has become clear that there is a significant discontinuity between the way in which recommenders are defined, described and perceived on the one hand, and the way in which the systems actually work and are utilized on the other. Often, researchers and users both overlook the fact that recommenders are employed by, and part of, powerful and profit driven businesses. Interface design has proven to serve as a good tool for keeping users uncritical. Clean, easy-to-use designs with what seem to be transparent explanations about recommendations, are helpful in building up and maintaining users' uncritical perception: that they are interacting with friendly, neutral systems which recommend products to them 'just' because they 'have watched' a certain movie or 'were interested in' certain items. However, recommenders never merely look into an individual user's behaviour. They constantly make choices about what information about a user is relevant and about how to mix and match presumably relevant information, in order to generate 'accurate' recommendations. Moreover, most of the time recommenders deploy a lot more than just an individual user's behaviour. Most systems also look into other users' behaviour and they utilize external data that is exchanged with third parties. Recommenders are deployed by big corporations and used by many people. They are highly influential to peoples' consumption of and taste for culture, and they have numerous yet varying effects on distinctions in cultural consumption and taste, especially between people in different social classes. A critical stance towards recommenders should therefore be expected from researchers, and media literacy about recommenders should also be promoted among users.

6. Usefulness of the theories and methods deployed

In this thesis, literature research was helpful to gain insight into the status quo of research about online consumption and online group formation. Bourdieu's theory, after re-evaluation, proved to be a valuable framework for investigating recommenders' influence. Especially the differentiation into cultural, social and economic capital proved valuable for recognizing the various ways in which recommenders influence distinction. The literature research about recommenders' software and discourse demonstrated that there is a discontinuity between the way in which recommenders are described, defined and perceived, and the way in which they actually work. It was a starting point for revealing recommenders' biases, as well as for further investigating the business interests involved in the deployment of recommenders.

The theoretical analysis of three recommender taxonomies was useful to gain insight in various recommendation methods. The taxonomies were also helpful as a basic framework for critically analysing Netflix, Spotify and Amazon Books. Their case studies revealed that, aside from the 'classic' recommendation methods elaborated on in the taxonomies, recommendations from social peers can and are being integrated, mainly through a link to social media platform Facebook. Furthermore, the case study of Netflix in particular proved that recommenders may deploy external data. The case studies were not able to reveal how external data are being used to improve recommendations. They were also unable to reveal for which other purposes (external) data about users are being used.

Looking into the business interests involved in recommender systems was helpful to further develop a critical stance towards recommenders discussed in-neutrality and cultural relevance. Looking into the business-side of Netflix, Spotify and Amazon Books in particular provided great insights, as they illustrated how powerful and profit-driven these popular platforms really are.

Finally, theory about interface design offered a framework for textually analysing the interfaces of Netflix, Spotify and Amazon Books. The textual analysis proved that interfaces are useful tools in steering users' perception. Furthermore, the textual analysis revealed how recommendations of social peers are being integrated and presented in the platforms exactly.

7. Suggestions for further research

There are still a lot of research opportunities to further investigate recommenders' influence on cultural consumption and taste, and more specifically, on distinctions in cultural consumption and taste. I present some suggestions:

Further research, especially in fields of anthropology and sociology, would be helpful to further investigate the way in which recommenders nurture a digital divide of cultural consumption and taste, between people who do and who do not possess technical capital. Research in these fields would also be helpful to further explore in what way people use recommender systems as new agents for personal reference. Consequently it would be able to reveal how and to what extent recommenders are reshaping and taking over social peers' function of personal reference and recommendation.

If applications such as Netflix, Spotify and Amazon ever decide to open up about how and what external information about users they employ, then this information should be considered in new research about recommenders' influence on class-based distinctions in cultural consumption and taste.

This thesis has not been concerned with cultural products other than music, movies and (e-)books. Further research would thus be valuable to investigate recommenders' influence on consumption of other cultural products, such as fashion and graphic art.

Bibliography

Adomavicius, G., Tuzhilin, A. "Towards the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extentions." *IEEE Transactions On Knowledge and Data Engineering* (IEEE) 17, no. 6 (June 2005): 734-749.

Adorno, M., Horkheimer, T. “The Culture Industry: Enlightenment as Mass Deception.” In *Dialectic of Enlightenment*, by M. Adorno and T. Horkheimer, translated by Andy Blunden. 1944.

Amatriain, X., Basilico, B. “Netflix recommendation beyond 5 stars - part 1” April 6, 2012. http://techblog.netflix.com/2012/04/netflix-recommendations-beyond-5-stars.html (accessed March 1, 2014).

—. “Netflix recommendation beyond 5 stars - part 2” June 20, 2012. http://techblog.netflix.com/2012/06/netflix-recommendations-beyond-5-stars.html (accessed March 1, 2014).

Amazon. Amazon Media Room. “About Amazon, Overview*”* http://phx.corporate-ir.net/phoenix/zhtml?c=176060&p=irol-mediaKit (accessed March 14, 2014).

Anderson, C. “The Long Tail, in a nutshell” www.longtail.com (accessed March 1, 2014).

—. *The Long Tail: Why the Future of Business Is Seling Less of More.* Vol. 1. New York: Hyperion, 2006.

Bastos, A. *Discovering digital cultural capital in London's events of art and technology: review of the last decade.* paper, University of the Arts London & London College of Communication, London: BCS The Chartered Institute for IT, 2010.

Billboard. “Spotify acquires The Echo Nest.” March 6, 2014. http://www.billboard.com/biz/articles/news/digital-and-mobile/5930111/spotify-acquires-the-echo-nest (accessed March 6, 2014).

Bourdieu, P. *Distinction. A Social Critique of the Judgement of Taste.* Translator: Richard Nice. London, New York: Routledge, 1984.

Breese, J.S., Heckerman, D., Kadie, C. “Empirical Analysis of Predictive Algorithms for Collaborative Filtering.” *Microsoft Research* (Microsoft Corporation), October 1998.

Brennen, B.S. *Qualitative Research Methods for Media Studies.* New York – London: Routledge, 2013.

Brynjolfsson, E., Hu, Y., Simester, D.,. "Goodbye Pareto Principle, Hello Long Tail: The Effect of Search Costs on the Concentration of Product Sales." *Management Science* (Informs) 57, no. 8 (August 2011): 1373-1386.

Brynjolfsson, E., Smith, M.D., Hu, Y. "Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers." *Management Science* 49, no. 11 (2003): 1580-1596.

Brynjolfsson, E., Van Alstyne, M. "Global Village or Cyber-Balkans? Modeling and Measuring the Integration of E-Communities." *Management Science* (Informs) 51, no. 6 (June 2005): 851-868.

Burke, R. “Hybrid Recommender Systems: Survey and Experiments.” (California State University, Fullerton) 2002: 1-29.

Chen, L., Hu, R., Pu, P.."Evaluating recommender systems from the user's perspective - survey of the state of the art." *User Modeling and User-Adapted Interaction* (Springer Science & Business Media) 22, no. 4-5 (October 2012): 317-355.

Emmison, M., Frow, J. "Information Technology as cultural capital." *Australian Universities' Review*, 1998: 41-45.

Etherington, D. “Spotify Acquires The Echo Nest, Gaining Control Of The Music DNA Company That Powers Its Rivals.” March 6, 2014. http://techcrunch.com/2014/03/06/spotify-acquires-the-echo-nest/ (accessed March 7, 2014).

Fleder, D. and Hosangar, K. “Blockbuster Culture's Next Rise or Fall: The Impact of Recommender Systems on Sales Diversity.” *Management Science* (INFORMS) 55, nr. 5 (5 2009): 697-712.

Flyvbjerg, B. "Five Misunderstandings About Case-Study Research." *Qualitative Inquiry* (Sage) 12, no. 2 (April 2006): 219-245.

Gillespie, T. "The Relevance of Algorithms." *Culture Digitally. Examining Contemporary Cultural Production.* november 26, 2012. http://culturedigitally.org/2012/11/the-relevance-of-algorithms/ (accessed January 11, 2014).

Habermas, J. “From a Culture-Debating (kulturrasonierend) to a Culture-Consuming Public.” In *The Structural Transformation of the Public Sphere. An Inquiry into a Category of Bourgeois Society*, door Jurgen Habermas, Editor: 1991 MIT Press paperback, Translater: Frederick Lawrence Thomas Burger, 159-175. Massachusetts: MIT Press, 1962

Hart, C. *Doing a Literature Review: Releasing the Social Science Research Imagination.* Paperback. SAGE, 1999.

Hiltz, S. R. and Wellman, B. “Asynchronous learning networks as virtual classroom.” *Communications of the ACM* (ACM) 40, no. 9 (September 1997): 44-49.

Holt, D. B. “Does Cultural Capital Structure American Consumption?” *Journal of Consumer Research* (Chicago Journals) 25, nr. 1 (06 1998): 1-25.

Huffington Post. “Instagram Bans 'Thinspo': Photo-sharing App Updates Community Guidelines.” 4 23, 2012. http://www.huffingtonpost.com/2012/04/23/instagram-bans-thinspo-ph_n_1445863.html (accessed March 2, 2014).

Instagram. “Instagram's New Guidelines Against Self-Harm Images & Accounts.” 2013. http://blog.instagram.com/post/21454597658/instagrams-new-guidelines-against-self-harm-images (accessed March 1, 2014).

Johnson, C. “Algorithmic Music Recommendations At Spotify” January 13, 2014. http://www.slideshare.net/MrChrisJohnson/algorithmic-music-recommendations-at-spotify (accessed March 1, 2014).

Katz-Gerro, T. “Highbrow Cultural Consumption and Class Distinction in Italy, Israel, Germany, Sweden and the United States.” *Social Forces* (Oxford Journals) 81, nr. 1 (9 2002): 207-229.

Konstan, J. “Introduction to Recommender Systems” 2008. http://www-users.cs.umn.edu/~konstan?SIGMOD-2008.Tut.pdf (accessed March 16, 2014).

Konstan, J.A. and Ekstrand, M.D. “Introduction to Recommender Systems with Joseph A Konstan and Michael D Ekstrand*”.* August 22, 2013. http://www.coursera.org/course/recsys (accessed February 10, 2014).

Konstan, J.A. and Riedl, J. “Recommender systems: from algorithms to user experience.” *User Modeling and User-Adapted Interaction* (Springer Science Business Media B.V.) 22, nr. 1-2 (April 2012): 101-123.

Kotler, P., Kartajava, H. and Setiawan, I. *Marketing 3.0: From Product to Consumers to the Human Spirit.* Hoboken, New Jersey: John Wiley & Sons, Inc., 2010.

Kvasny, L. "Cultural (re)prodcution of digital inequality in a US community technology initiative." *Information, Communication & Society* (Routledge) 9, no. 2 (April 2006): 160-181.

Lekakos, G., and Giaglis, G.M. “Improving the prediction accuracy of recommendation algorithms: Approaches anchored on human factors.” *Interacting with Computers*, may 2006: 410-431.

Lister, M., Dovey, J., Giddings, S., Grant, I., Kelly, K. *New Media A Critical Introduction.* 2nd Edition. London and New York: Routledge, 2009.

Linden, G., Smith, B., York, J. “Amazon.com Recommendations. Item-to-Item Collaborative Filtering.” *IEEE Internet Computing* (IEEE Computer Society), January-February 2003: 76-80.

Lotz, A. D. *The Television Will Be Revolutionized.* New York and London: New York University Press, 2007.

Luckerson, V. “These 8 Internet Companies Are Worth Over $1 Billion - But They Haven't Made a Dime” October 23, 2013. http://business.time.com/2013/10/29/these-8-internet-companies-are-worth-over-1-billion-but-they-havent-made-a-dime/ (accessed March 14, 2014).

Mangalindan, J.P. “Amazon's Recommendation Secret” July 30, 2012. http://fortune.com/2012/07/30/amazons-recommendation-secret/ (accessed March 21, 2014).

Manovich, L. *Software Takes Command.* Edited by Francisco J. Ricardo. Vol. 5. New York, London, New Delhi, Sydney: Bloomsbury, ISSUU, 2013.

Mattei, M. "Technology as cultural capital, particularly in U.S. college access." *The Unfamiliar* (University of Edinburgh) 2, no. 2 (2012).

Medo, M. *Network-based information filtering algorithms: ranking and recommendation.* Physics Department, University of Fribourg, Fribourg: University of Fribourg, 2012.

NEDA. “National Eating Disorders” 2014. http://www.nationaleatingdisorders.org/neda-news (accessed March 1, 2014).

Netflix. “Netflix Quick Guide: How does Netflix Decide What's On Netflix.” June 6, 2013. https://www.youtube.com/watch?v=VvpoUh9gx58 (accessed March 14, 2014).

—. “Netflix Quick Guide: How does Netflix make TV show and Movie Suggestions?” July 18, 2013(b). https://www.youtube.com/watch?v=hqFHAnkSP2U#t=29 (accessed March 14, 2014).

---. “First Look: Netflix Social Features.” March 13, 2013(a). https://www.youtube.com/watch?v=uc82e7GGHI8 (accessed March 14, 2014).

Ofcom. "The Communications Market 2006 (August)." *Ofcom. Independent regulator and competition authority for the UK communications industries.* august 2006. http://stakeholders.ofcom.org.uk/market-data-research/market-data/communications-market-reports/cm06/overview06/ (accessed February 5, 2014).

Sabatini, F. "The Empirics of Social Capital and Economic Development: A Critical Perspective." *Nota Di Lavoro* (The Fondazione Eni Enrico Mattei), January 2006.

Sarwar, B., Karypis, G., Konstan, J., Riedl, J. *Analysis of Recommendation Algorithms for E-commerce.* Department of Computer Science and Engineering, University of Minnesota, Grouplens Research Group / Army HPC Research Center, Minnesota: AMC, 2000.

Schäfer, M.T. "Participation Inside? User Activities between Design and Appropriation." In *Digital Material. Tracing New Media in Everyday Life and Technology*, by Lammes, S., Ann-Sophie Lehmann, L., Raessens, J., Schäfer, M.T., van den Boomen, M., 147-158. Amsterdam: Amsterdam University Press, 2009.

Slavin, K. "How Algorithms Shape Our World." *TED*, July 2011. http://www.ted.com/talks/kevin_slavin_how_algorithms_shape_our_world?utm_source=weibolife.appspot.com (accessed March 1, 2014)

Spotify. “Spotify Press”. March 6, 2014. http://press.spotify.com/us/2014/03/06/spotify-acquires-the-echo-nest/ (accessed March 6, 2014).

—. “Want the right playlist? Just browse.” August 5, 2013. http://press.spotify.com/us/2013/08/05/want-the-right-playlist-just-browse/ (accessed March 14, 2014).

Swingewood, A. *The myth of mass culture.* London and Basingstoke: The Macmillan Press LTD, 1977.

Ting, S., Dubelaar, C., Dawson, L.. *Social Structures of a Consumer's Economy: IT Adoption and Consumption of Three Different Cultural Capitalist Consumers.* paper, AMZAC, 2009.

Warde, A., Wright, D., Gayo-Cal, M., Bennett, T., Silva, E., Savage, M. *Understanding cultural omnivorousness, or the myrth of the cultural omnivore.* paper, European Sociological Association Conference, Torun, Poland: Working Group on the Sociology of Consumption, 2005.

Weber, M. *Economy and Society: An Outline of Interpretive Sociology.* Berkeley and Los Angeles, California: University of California Press, 1978.

Yang, S., Lee, H., Kurnia, S.. *Understanding the Relationship between Information and Communication Technology (ICT) and Social Capital: A Conceptual Framework.* Proceeding of the 13th Asia Pacific Management Conference, Melbourne, Australia: Asia Pacific Management Conference, 2007.