EXPLORING DRAWBACKS IN MUSIC RECOMMENDER SYSTEMS – THE SPOTIFY CASE

Bachelor's thesis in Informatics (15 credits)

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Abstract:
Currently, more and more people use music streaming websites to listen to music, and a music recommendation service is commonly provided on the music streaming websites. A good music recommender system improves people’s user experience of music streaming websites. Nevertheless, there are some issues regarding the existing music recommender systems that need to be looked into.

The purpose of this thesis is to identify the weaknesses of music recommender systems. Spotify, a Swedish music streaming website, has a large number of users. As it is a widely known streaming service, it seems appropriate for a case study on the drawbacks of music recommender systems.

The case study method has been chosen for doing this research. The process of making up this thesis was divided into three stages. At the first stage, some basic preparations for the thesis were done. The second stage was characterized by some empirical work, like interviews and questionnaires, to collect the required data. Those empirical findings were analyzed in the third part to help us to identify and define the drawbacks.

The research results presented in this thesis contribute to close several knowledge gaps in the area of music recommender systems and could thus be beneficial to different actors: streaming website operators to identify drawbacks of their recommender system; designers of recommender systems to improve system design; and, last but not least, this thesis provides some useful advice to those who market music streaming websites.

This thesis does not focus on the technical and algorithm fields, i.e. the hardware- and software-related background. Instead, the idea and the functions of the recommender system, its feedback loop and the user experience were subject to our research and discussion. The results of the thesis can provide those responsible with both and inspiration for creating more customized recommender systems.

Keywords: music recommender system, music streaming website, user experience, feedback system, Spotify
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------Media lab of University of Borås, 5/6/2015, Yiwen Ding & Chang Liu
Table of Contents

1 INTRODUCTION .......................................................................................................................... 2
  1.1 BACKGROUND .................................................................................................................. 2
  1.2 STATEMENT OF THE PROBLEM ......................................................................................... 3
  1.3 PURPOSE OF THE RESEARCH ............................................................................................. 4
  1.4 RESEARCH QUESTIONS .......................................................................................................... 4
  1.5 TARGET GROUP .................................................................................................................... 4
  1.6 DELIMITATIONS .................................................................................................................... 5
  1.7 EXPECTED OUTCOME ............................................................................................................ 5
  1.8 STRUCTURE OF THE THESIS ............................................................................................... 5

2 METHOD ........................................................................................................................................ 7
  2.1 RESEARCH APPROACH ........................................................................................................... 7
  2.2 RESEARCH DESIGN - CASE STUDY ....................................................................................... 8
    2.2.1 Case study plan .................................................................................................................. 9
    2.2.2 Case study data collection ............................................................................................... 10
    2.2.3 Case study data analysis .................................................................................................. 14
  2.3 CREDIBILITY AND DEPENDABILITY ..................................................................................... 15
    2.3.1 Credibility ...................................................................................................................... 15
    2.3.2 Dependability .................................................................................................................. 15

3 CASE DESCRIPTION: SPOTIFY RECOMMENDER SYSTEM .................................................... 17
  3.1 DISCOVER .............................................................................................................................. 17
  3.2 RELATED ARTISTS ................................................................................................................. 17
  3.3 RADIO ..................................................................................................................................... 17
  3.4 THE RECOMMENDATION SERVICE IN SPOTIFY ................................................................. 18
  3.5 THE FEEDBACK SYSTEM IN SPOTIFY .................................................................................... 18

4 THEORETICAL FRAMEWORK .................................................................................................. 20
  4.1 RECOMMENDATION SERVICE .............................................................................................. 20
    4.1.1 Content-based recommendation ....................................................................................... 21
    4.1.2 Collaborative filtering recommendation .......................................................................... 22
    4.1.3 Knowledge-based recommendation .................................................................................. 25
  4.2 FEEDBACK SYSTEM ............................................................................................................... 26
    4.2.1 The concept of a feedback system .................................................................................... 26
    4.2.2 Feedback features: ........................................................................................................... 27
    4.2.3 Feedback requirements: .................................................................................................... 28
    4.2.4 Feedback development ..................................................................................................... 28
  4.3 USER EXPERIENCE ................................................................................................................ 28
    4.3.1 Factors influencing user experience .................................................................................. 29
  4.4 E-CUSTOMIZATION ............................................................................................................... 30

5 RESULT ......................................................................................................................................... 31
  5.1 RESULT OF THE INITIAL GROUP FOCUS INTERVIEW ......................................................... 31
  5.2 RESULT OF QUESTIONNAIRE ................................................................................................. 31
    5.2.1 Result of feedback system in Spotify ............................................................................... 36
  5.3 RESULT OF THE MAIN SEMI-STRUCTURED FOCUS GROUP INTERVIEW .......................... 37
    5.3.1 Basic information .............................................................................................................. 37
    5.3.2 Result of dialog .................................................................................................................. 37
    5.3.3 Advice ............................................................................................................................... 40

6 ANALYSIS ..................................................................................................................................... 41
  6.1 ANALYSIS OF THE QUESTIONNAIRE ................................................................................. 42
    6.1.1 Analysis of user attitudes towards music and Spotify ..................................................... 43
    6.1.2 Analysis of the relationship between two correlative questions ..................................... 43
    6.1.3 Analysis of the feedback system in Spotify ..................................................................... 44
  6.2 ANALYSIS OF THE MAIN SEMI-STRUCTURED FOCUS GROUP INTERVIEW ..................... 44
1 Introduction

This chapter will provide information about the research area and the research purpose. The research problem will also be presented. Moreover, this part contains a description of the target group and the delimitation as well as an outline of the research work.

1.1 Background

It is obvious that music plays an important role in many people’s daily life. No matter if one is a huge fan of music or just randomly listens to music for fun, it cannot be denied that music is a major entertainment factor. From vinyl records to cassette tapes, from CD to mp3, the ways of listening to music have changed. With the help of technology, music can be enjoyed in a more and more convenient way.

Nowadays, with the rapid development of the Internet, it is getting common to use music streaming services. Compared to other ways of providing music, streaming websites can provide more and better services. There are a lot of advantages of using music streaming websites: customers pay less to listen to music than with iTunes or real CDs; the number of music collections in streaming websites is huge; it is much more convenient to listen to music online etc.

According to Karp (2014), in the first half of 2014, the number of downloads of singles and albums dropped by 11% and 14%, whereas the number of users of streaming services increased by 28%; these figures make it obvious that more and more people have changed their ways of listening to music.

Karp (2013) also mentions that the number of music streaming services users is enormous now and still increasing. The number of users in Sweden is even as many as 60% of the population. It seems like using streaming websites is becoming a continuous trend. According to Shao (2014), the growth rate of digital music downloads decreases year by year. Already in 2013, the first negative growth appeared. Meanwhile, for streaming media, there is an explosive increase. The income generated by paid streaming media subscriptions increased by 367%; free streaming media with advertisements increased by 293%. In addition, the cheaper and more effective music streaming services have a huge influence on the business of Apple (Shao, 2014). Streaming music services started to change people’s habits of listening to music. There are already several music streaming websites, for instance: Spotify, Beasts music, Pandora. Some big companies have started their own music recommendation services, for example: Google play music, Sony music unlimited, X-box music etc. The user group of streaming services is gigantic in number.

Using the music streaming services can represent an innovative and superior experience for the user. One important reason why more and more people choose to use music streaming services is that they thus can build up a massive music collection at low cost (sometimes even for free). However, this advantage also entails a problem: information overload. This problem becomes obvious on streaming websites. Facing a massive collection of music, users are unable to make a decision and have no idea of what to listen to. Besides, in the initial group interview, the interviewees expressed that they sometimes have problems discovering new songs when using music streaming websites. They wish the streaming websites to provide
recommendations for them. Even according to the CEO and founder of Spotify, Daniel Ek, users have frequently voiced their desire of finding new music to listen to. Obviously, a music recommender system is essential in music streaming websites (Music week, 2012). Users demand an effective music recommender system because music streaming websites offer numerous items to choose from within a limited period of time which is insufficient to evaluate all possible options (Celma, 2008). With the help of a recommender system, users can skip over the information overload and get customized recommendations from the system.

Recommender systems are applied in various fields, such as electronic commerce, music streaming websites etc. A widely-known example of a recommender system is the one used with “www.amazon.com”. Based on users’ search histories and some other data, Amazon provides recommendations for products by displaying the following message: “Customers who bought this item also bought” (Ekstrand, Riedl, and Konstan, 2010). With the help of recommendation systems, users can save time when searching the products they want, and it can also help the companies to increase profits. In addition to e-commerce websites, there are many other industries using recommender systems as well. For example movie downloading websites that make recommendations based on the comments from customers, online bookshops and music streaming websites.

To meet users’ demands for a recommender system, there are some music streaming websites already providing music recommendation services, for example: Spotify, Pandora, Beats music etc. The ways how they compile their recommendation lists varies between companies. Some websites make up recommendations based on users’ listening records; some recommend the music that the “neighbor user” listens to, which means that the system assumes that they share a similar taste, and other websites recommend music based on user’s mood. Although there are already lots of different ways to draw up recommendations, users are still not satisfied with the recommendation service.

1.2 Statement of the problem

During the initial group interview, interviewees expressed that the music recommended by the recommender systems in music streaming websites does not match with their taste. Sometimes the music recommended was completely different from what they like. A music recommender system, however, is supposed to provide good recommendations for users to solve the information overload problem. However, it has become obvious that the music recommender systems do not meet the demands of the users.

The question is: What causes this problem? There must be some drawbacks existing in the current music recommender systems.

A music recommender system consists of several different components, such as:

- The way of drawing up recommendations: whether the system compiles the recommendations based on data of users’ behaviors or users’ mood or the “neighbor user’s” taste
- The interface design: whether it is easy for users to understand and apply.
- The feedback system: whether it can actually support the recommender system to get feedback from users and in this way to improve the service
Drawbacks in any part of the recommender system may lead to the “un-customized” problem: the recommendations provided by the system are not tailored to users’ demand. In order to fix the problem, different parts of the recommender system will undergo scrutiny to find out if and where there are any drawbacks.

1.3 Purpose of the research

The purpose of research is to try to identify the drawbacks in a music recommender system in order to make the system more customized. With the intention of conducting the research more efficiently, we picked Spotify – a typical music streaming website – as a case. Hopefully, the findings presented in our thesis can help system developers to design and improve recommender systems with regard to increased personalization so that users can enjoy better recommendations.

The research underlying this thesis is conducted from a users’ perspective on drawbacks in music recommender systems. The reason for proceeding in this way is to discover what kind of recommender system and which system functions users need and want to have. The findings may serve as a source of inspiration for designers to improve systems or even supply some practical ideas in connection with making up customized recommendations.

1.4 Research questions

In order to solve the declared research problem, thus helping the system developer to build a more customized recommender system, it is considered advantageous to narrow down the research topic to the drawbacks of the recommender system.

The main question of the research is:

*From a users’ perspective, and by using Spotify as a case, what drawbacks in music recommender systems prevent a higher level of customization that would meet customers’ demands?*

This research analyzes the different aspects in the recommender system, and each step during the research process has a strong connection with the research purpose and expect outcome.

1.5 Target group

Since the study could raise the interest of people in different areas, the target group can be divided into three categories:

The first category: developers in the music recommender system field. From this research, they may become aware of the drawbacks existing in music recommender systems and gain a better understanding of users’ demands. This research may also offer inspirations for them to create more customized systems.
The second category: researchers in the music recommender system area. There is already some previous research work about the drawbacks in music recommender systems. However, few of these studies discuss the problems from the users’ perspective. This research may help researchers to fill in the gaps or to explore further drawbacks that have not been discussed before.

The third category: music streaming website companies. This research may provide several practical suggestions to improve the websites to become more customized. An improved recommender system may attract more customers, and this can help the companies to gain extra profit.

1.6 Delimitations

This research work focuses on the drawbacks and the user requirements regarding existing music recommender systems. It has not been based on the technical background or on the algorithm field. Instead, user feedback and user experiences are reflected in this research. The drawbacks identified from a user perspective can offer inspiration for improvement.

1.7 Expected outcome

The expected outcome of this research work is the identification of drawbacks in existing music recommender systems. It is suitable to support system developers by providing advice and design ideas for the process of programming. Our research is user-centered with a strong focus on user experience. By means of focus group interviews and questionnaires, detailed information about our topic has been collected. Against this background, a clear analysis of the case is presented.

1.8 Structure of the thesis

There are six chapters in the research thesis and every chapter has its own role.

Chapter 1: Introduction.

This chapter presents the general background of music recommender systems and the development of music streaming websites. Moreover, the research question is raised which is the basis for the entire research work.

Chapter 2: Method

This chapter describes the methodology for this research and how it is conducted in a mixed methodological approach. Moreover, the process of applying a case study is presented in this chapter. In addition, this chapter explains how to design research and how to analyze the research data.
Chapter 3: Spotify

This chapter outlines the general knowledge with regard to three main recommendation functions in Spotify.

Chapter 4: Theoretical framework

This chapter explains the general idea of several key concepts involved in this research. Moreover, the theories from previous researches on those key concepts are summarized.

Chapter 5: Result

This chapter presents the results from the empirical study that includes one questionnaire and two group interviews. This part shows strong connections with the theoretical framework.

Chapter 6: Analysis

This chapter sets forth how the results of the empirical study have been analyzed and reflected on different theories. The answers to the research question – the drawbacks of recommender system – are given.

Chapter 7: Discussion and Conclusion

This chapter draws a conclusion from the whole research work. Moreover, some discussion from the authors’ perspective is included.

Chapter 8: References and appendixes

This chapter lists the references that have been used in this research, the text of the questionnaire and part of the transcription of the interviews.
2 METHOD

This chapter will describe the research design, research strategy and research methods. Information about how to design the questionnaire and focus group interview will be presented. In addition, this chapter will provide the analysis approaches for each research step.

The purpose of this study is to investigate the drawbacks in existing music recommender systems, which may provide suggestions to the system developers and improve the quality of recommendation services. So it has been necessary to choose some adequate methods to design the research step by step.

For collecting data, a research method is required as a technique. A research method involves a specific instrument such as questionnaire and interview. A research method is connected with different research designs. The type of research design being used in the research reflects the priority of different part of research process (Bryman & Bell 2011).

2.1 Research approach

A mixed methodology has been applied in this research. Two general methods are widely accepted: quantitative research and qualitative research.

<table>
<thead>
<tr>
<th>Quantitative Mode</th>
<th>Qualitative Mode</th>
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<tbody>
<tr>
<td>Assumptions</td>
<td>Assumptions</td>
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<tr>
<td>• Social facts have an objective reality</td>
<td>• Reality Social constructed</td>
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<td>• Primary of method</td>
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<td>• Variables can be identified and</td>
<td>• Variables can be complex, and</td>
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<td>relationship measured</td>
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<td>• Casual explanations</td>
<td>• Understanding actor’s perspectives</td>
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<td>Approach</td>
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<td>• Begins with hypothesis and theories</td>
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<td>• Naturalistic</td>
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<td>• Component analysis</td>
<td>• Inductive</td>
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<td>• Seeks consensus, the norm</td>
<td>• Searches for patterns</td>
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<tr>
<td>• Reduce data to numeric indices</td>
<td>• Seeks pluralism, complexity</td>
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<tr>
<td>• Abstract language in write-up</td>
<td>• Make minor use of numeric indices</td>
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<td>• Detachment and impartiality</td>
<td>• Personal involvement and partiality</td>
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<td>• Objective portrayal</td>
<td>• Empathic understanding</td>
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Figure 1: Features of Qualitative & Quantitative Research (Bryman & Bell, 2011)
As the purpose is to find the drawbacks in music recommendation service, this research carries out investigations from a users’ perspective. It collects ample data about user experiences and feelings. As shown in figure 1, authors compared the different features of the quantitative method and the qualitative method. Qualitative research offers a chance of gaining wider and deeper understanding of relations and feelings. With qualitative methods, there is more freedom and flexibility for users to give detailed feedback about their user experiences (Bryman & Bell, 2011). A user’s feeling is an abstract variable to be collected. The collection process is usually complicated. Besides, it is hard to accurately describe one’s feelings. An interview is a suitable approach to gain data around users’ feelings. In addition, a user’s feeling is a changeable variable depending on environment, user personality and other factors. User experience also varies with the system usage time and other elements. This data is difficult to be evaluated in a quantitative way. Thus, this research was mainly conducted by applying the qualitative method.

According to Bryman and Bell (2011), qualitative data are collected in order to gain further knowledge about factors that cannot be directly observed and measured. These factors include feelings, thoughts, intentions, and behaviors. This research required collecting information about users’ feelings regarding the music recommender system. These user feelings could not be directly measured and observed. Therefore, the qualitative method was selected.

Newman and Benz (1998) explained that the qualitative method should be used for data and information that cannot be described in numbers and charts, e.g. when researchers analyze the phenomenon of relationship and other similar research materials.

The qualitative method is less structured. Creswell (1994) emphasized that qualitative studies do not generate data that can be used in statistical procedures. Newman and Benz (1998) explained that data in a qualitative method could access deeper dimensions during the research process due to a more flexible relationship with the respondents. Part of the empirical study that this thesis is based on was an interview with respondents who have been using Spotify for quite a long time.

### 2.2 Research Design - Case study

According to Yin and Robert (2009), there are five kinds of research strategies: case study, experiments, surveys, histories and an archival analysis. The case study approach can thoroughly explain questions such as “how”, “what” and “why”. Considering the research situation, a case study has been selected as research strategy. Subsequently, Spotify was selected as case. This research work is therefore directed towards and lays emphasis on Spotify. The main reason why Spotify has been chosen as case for this research was that music recommendation service is a rather wide area. Within the framework of this thesis it is inappropriate to investigate matters and discuss them only on a general level. The research aims at gaining deeper insight into the research problem by focusing on a narrowed area or case. Combined with the general features of the case study strategy, adopting this research line was to make the whole thesis clear and tidy.
2.2.1 Case study plan

The structure of the research has been divided into four sections:

- Initial focus group interview
- Literature review
- Questionnaire
- Main semi-structured interview.

Firstly, to start with, the authors have decided to build their research with the recommendation system as a basis, as they are particularly interested in this, regarding it as a crucial issue. Literature reviewing already started at this stage, because it promised to convey more detailed knowledge and a deeper understanding of the area of recommendation systems. In view of narrowing down the research questions, the research plan was then adjusted.

As figure 2 illustrates, theoretical parts and empirical evidence influence each other during the research process. Every research stage is based on the theoretical concepts and makes contributions to dealing with the research problems. The researchers have held the research questions in their minds while more and more evidence has been found. After a base of knowledge about music recommendation services has been accumulated, the researchers return to the research purpose and research questions. In order to get more information about real-life situations, several methods, tools, and research models are combined to be used comprehensively. For some special cases, even four other approaches are available to be included for obtaining the required research results.

Before the actual thesis writing, an initial focus group interview was conducted to help to narrow down the research questions and focus on a specific area within a music recommender system. The key purpose of doing an initial focus group interview is to find out the user’s perspective on a music recommender system. The questions asked in the initial focus group interview have been designed to target a general level regarding music recommender systems. For example: Have you tried music recommendation services? How do you feel when using it? What music website do you usually choose for music recommendation services? Researchers have picked three interviewees who are more experienced and who have a deeper understanding of music recommendation service than others.
According to Bryman and Bell (2011), a focus group interview is a combination of group interview and focus interview which includes more than one interviewee, those interviewees are selected because the interviewers know that they have a certain involvement in a certain situation. The three interviewees selected by us use Spotify and other music streaming websites frequently. The researchers have chosen these three interviewees because they have been assumed to have extensive experience in searching music online. Music is a part of their everyday life, the interviewees are eager to get a better music recommendation system. They all have experienced and specialized in Spotify.

The conclusions of the initial focus group interview have resulted in some inspirations for the researchers. It was helpful to narrow down the research question into the following: From a users’ perspective, and by using Spotify as a case, what drawbacks in music recommender systems prevent a higher level of customization that would meet customers’ demands?

After narrowing down the research question, a questionnaire and a main semi-structured focus group interview have been conducted to collect the empirical data that is necessary in order to find drawbacks of the Spotify music recommender system.

2.2.2 Case study data collection

Case study data collection - Literature Review

Relevant academic articles and books about recommendation services, human-computer interaction, information systems and research methods have been studied during the process of thesis writing. As far as recommender systems are concerned, this literature review has aimed at collecting the available knowledge about existing functions, the implementation process, the role of each part and some related details. This knowledge is to be found in professional articles. Google scholar and the online library provided by the University of Borås have been used to gain the required data and charts.

Literature sources can be divided into three groups: primary, secondary and tertiary.
According to figure 3, primary, secondary and tertiary literature is categorized by time. Primary literature consists of theses, reports, some unpublished manuscripts, etc., which were published earliest. Later, after publication, the primary literature grows and is used to form the secondary literature source. Books, newspapers and journals are published in public and belong to the secondary literature. Indexes, abstracts and catalogs are easy to use and be found, they can be regarded as search tools to get the primary and secondary literature with more targets and searching directions. (Saunders, Lewis, & Thornhill, 2009)

In order to review the related literature within this research area, both primary and secondary sources were used, including books, articles, journals, theses, and other materials. These sources were identified by means of tertiary sources, especially citation indexes and bibliographies.

At first, what this research concentrated on was to acquire a comprehensive understanding of some specific concepts, including music recommendation service, feedback system, e-customization, drawbacks, user experience and a good understanding of Spotify. By searching the main references connected to these terms, the research questions and the approaches of conducting the research have been formulated.

Secondly, the process of literature search was followed in order to acquire relevant information regarding the concerned terms and the overall topic. The keywords from the introductory chapter have been confirmed as well. The supervisor provided the authors with several good suggestions, namely that this research should identify the core of the research problem, trying to use three to four terms and conceptions to explain what the problem was and what area it belonged to.

Thirdly, these terms were searched for with the help of Google scholar and the online library of the University of Borås. The authors explained the academic terms and main concepts.

Then the authors went back to the original problem and thought about how to deal with this problem. What has been done in this area? What other research should be carried out in the future? What was the related area?

After this, literature with more specific directions and aims was read in order to gain more related information and data to support research assumptions. The authors have divided these tasks into two parts: one is to build the theoretical framework based on previous information and data gained. Another one is to design a questionnaire and the interview infrastructure for our research topic.

The comprehensive findings from the previous literature study and other academic achievements have been summarized. What other work on this theme could be helpful for the researchers to avoid mistakes and get good inspiration for further research?

In addition, various viewpoints and multi-angles have been considered in order to analyze these research problems.

**Case study data collection - How to design Initial focus group interviews**

A qualitative approach has been selected to conduct personal interviews with three interviewees who are familiar with the subject.
According to James and Judi (2009), general interviews can deliver direct and personal understanding where a sole respondent provides unstructured and open answers concerning the overall topic face to face. This is helpful to get some more narrowed direction and define a good research question. The research purpose is to try to find the underlying motivations, attitudes, and feelings based on the users’ experience. In addition, other crucial issues are which part users really want to improve and what the drawbacks of the Spotify music recommender system are.

As a first step, it was necessary to find suitable interviewees. Malhotra, Naresh & David (2003) underlined that it is important to find a process where both parties benefit from the interviews. An interview provides a good chance to ask follow-up questions which deepen the understanding behind the interviewees’ answers and give the interviewees maximum freedom to answer within a topic of interest. The interviewer tried to cover a specific list of topics or sub-areas where timing, exact wording, and time allocated to each question are controlled by the judgment of the interviewer (Malhotra, Naresh & David, 2003). The authors conducted the initial interview face to face with the three interviewees. All of three interviewees are long-term Spotify users. They are all Chinese students and two of them have been living in Sweden for several years. They were asked some questions about their opinions about music recommendation services and their user experience. From the results of this interview, some inspirations regarding the research question have been gained.

**Case study data collection - How to design the questionnaire**

Prior to designing the questionnaire, reading the corresponding literature was necessary. By this, the authors have gained deeper knowledge about how to design a high-quality questionnaire. It has been beneficial for the design of the questionnaire design to draw up a tidy structure and suitable categories. The questionnaire included 27 main questions: 7 simple-choice questions, 15 multiple-choice questions and 5 free open questions; the questions were divided into four categories: general questions, questions about the attitudes to music and recommendation services, relationship between two correlative questions, questions regarding the feedback system in the music recommender system. The authors have provided enough space to express what the interviewees really think about the recommendation service and how it can be improved.

In the general information part, the interviewees were asked to indicate their age. This was considered relevant because users of different age groups might tend to hold totally different tastes and preferences in music. As far as older people were concerned, they do not usually have high demands in the field of music recommendation services. So the questionnaire focused on users around 15 years to 30 years of age. The authors have planned to analyze the results of the questionnaire based on different age groups. Also gender, occupation and other fundamental information regarding the interviewees were necessary for the analysis of the questionnaire.

From the part of “Questions about the attitudes to music and recommendation services”, the authors have gained a broader understanding of users’ music tastes and preferences for music recommendation platforms and the frequency of use. That has proved helpful for the next part; as these questions were closely connected with everyday life. The respondents could release their nervousness about this new questionnaire and then immerse themselves in the questionnaire. More attention has been put to the detailed user experience, which was the
most important part in our questionnaire. The author wanted to understand the situations where users had faced some trouble, which of the features of Spotify were appreciated and received some suggestions for improvement. The research purpose is to find some drawbacks in the Spotify music recommendation service. The authors are supposed to understand the users’ requirements and what service users expected to get. The author have collected and organized data to confirm some specific findings by applying scientific methods. In this part, the Spotify service is shown on three levels: interface level, music classification level, feedback level. Some open questions have also been included in order to obtain further useful information; the respondents have been provided enough freedom and free space to write down what they really think.

In the part of “Questions about the feedback system in the music recommender system”, there were four choice questions about the feedback theory and the acceptance of feedback provided. They were meant to investigate the feelings and the required patience when going through the feedback operations. Whether clicking “Like” or “Dislike” is accepted has been an issue for discussion in this part, and other suggestions have been involved as well.

**Case study data collection - How to design the main semi-structured focus group interview**

The research purpose is to find the drawbacks of the music recommender system from a user perspective. The qualitative interview has been selected as a tool, it was to be a semi-structured interview directed to focus groups. The author has been particularly interested in the interviewees’ opinions about the drawbacks of the music recommender system. During this qualitative interview, the interviewees did not need to strictly follow the interview questions or a schedule. Depending on the interviewees’ replies, new questions could be asked (Bryman & Bell, 2011). In the semi-structured interview, the focus should be put on what interviewees’ think, that is of importance (Bryman & Bell, 2011). Since the purpose of our thesis is try to find the weaknesses of the music recommender system, a qualitative interview would help to reach our goal more easily. A focus group interview puts more focus on a specific topic that is explored deeply (Bryman & Bell, 2011). The interview can only be meaningful provided that the interviewees are experienced in using Spotify. By conducting the interview with more than one interviewee can save us time and also supplies more opinions for the researchers.

Since the author has applied a mixed way of doing the interview - semi-structured and focus groups-, this helped the interviewees to inspire each other when answering the interview questions. That in turn has helped to get more useful information about the thesis topic. The author chose to make a recording of the interviews and have then transcribed word by word in order not to lose something important.

Before doing the main interview, through observation, two interviewees who obviously have used Spotify for several years and use it every day have been picked up. Both of them had their own opinions about music. After that, a list of questions for the interview was made. The questions were not in order but they were categorized in different groups, each of which had a certain theme. For example, the author started with basic questions: the recommendation service in Spotify, the feedback system in Spotify and so on. The questions were asked when the interviewees talked about the relevant topic, otherwise they were asked in the order based on what the author think was more important.
2.2.3 Case study data analysis

Data analysis was required to support the outcome and the way of thinking about the research topic, it is actually like a root for a tree. Data analysis is the fundamental part of the work. In compliance with the approaches that have been chosen, statistics, comparison and some chart analysis needs to be done (Eifler, Herman, Adèr & Mellenbergh, 2001). The author has had to transfer the initial data to form useful information to help further research.

Questionnaire, interview and literature review have been main approaches with regard to data collection. All of them are considered helpful to figure out the process of bad music recommendation service and what problems the users experienced.

Case study data analysis - How to analyze the questionnaire

The questionnaire was released online and sent by mail. Later the data of all questionnaires was collected and an analysis with the help of some strategies and tools has been carried out. These methods can be adopted for the entire population or sampled sectors. The author used “Sojump” as an analysis tool to deal with the data with mathematical methods. “Sojump” is one of the most popular online questionnaire applications among college students. It is easy to use in order to create organized choice questions and open questions. Researchers can analyze the questionnaire data by using the figure generation function and table generation function in “Sojump”. “Sojump” also supports a lot of languages for international users such as: English, Chinese, Spanish, French and so on. There is no system login required for users to be able to answer the questionnaire.

Calculation method of analysis

With the help of the statistics website “Sojump”, the author has tried to answer the question – “what kinds of music users hold what kinds of attitudes towards recommendation service” (DaCosta & Fan, 2012). There was much data and information gained from the questionnaire that was not organized very well. In order to a gain deeper understanding of these specific phenomena and user feelings, some representative questions have been selected to analyze the internal connections.

These approaches have tried to answer the question “who thinks what” by calculating, with the help of the “Sojump” website. The correlations for different types of answers were based on the personal information available. The calculations of all these opinions and attitudes were rather time-consuming, so it was calculated once and saved for further research.

Graphical method of analysis

The second method of analyzing the questionnaire was a graphical representation (Haughton & Haughton, 2011). In this approach, the author concentrated on the differences in response patterns with respect to personal criteria of music. To ease the visual perception, the author has chosen the appropriate figures based on the features and characteristics of the problems, which was mainly applicable for some individual choice questions and multiple-choice questions (Haughton & Haughton, 2011). However, some open-ended questions were not suitable for graphical presentation.
Graphical information can reflect basic facts in an intuitive and vivid way, especially with regard to the problems of proportion. The problems of changing the trend can be clearly demonstrated. In combination with multiple figures reflecting the information, similarities and differences could be found, and, in a following step, similarities could be summarized. The deeper and more detailed analyses on the differences were presented. The author has obtained much other related information that has proved to be very helpful for the research.

Case study data analysis - How to analyze the semi-structure focus group interview

The method of qualitative analysis of interview data described by Kent Löfgren (2013) has partly been used for analyzing the interview in the thesis. The first step of the analysis was the transcription of the interview. After that, there were almost 11 pages of transcription text. A thorough reading of the entire transcription represented the next step. Then, after a quick browse of the transcription, notes were made to identify some important key words. This part of the analysis was called “coding” (Löfgren, 2013). The criteria for choosing the key words were whether the words had a connection to “weakness”, which was the thesis topic, or whether it surprised the author (Löfgren, 2013) or reminded the author of a theory. Then different key words were combined together into different categories. Each category represented one part of the analysis. The author summarized the content of each category, the interviewees answers and comments, and analyzed it to render it useful for the thesis topic, namely to find the weaknesses of music recommender systems.

2.3 Credibility and Dependability

2.3.1 Credibility

The credibility standard means that the relevancy of the relationship between the result of the research and the reflection of the participants are credible or believable during the research process. For from the viewpoint of qualitative research, the author tried to understand and investigate the problems chosen from the participants’ perspective. The research content and assumptions were so important that it should be thought about over and over again (Bryman & Bell, 2011).

The credibility of the results can only be relied on if the participants are involved in the topic. For the questionnaire, the author has not checked out the responders’ group. The questionnaire was published on the website and everyone had the chance to answer the questionnaire, even if they were not recommendation service users. That has had bad effects on the credibility of the questionnaire results and analysis. Age, gender, jobs and other factors should be considered in connection with the credibility problems. If there were some responders who were not familiar with music, it would generate some bad data and information that could disturb the research.

2.3.2 Dependability

Reliability is also one of the important mathematical theories on the basis of any research work. There is a need to study and solve various mathematical methods and models of
reliability, the reliability of a quantitative study needs some mathematical tools for better presentation, involving probability theory, mathematical statistics, stochastic processes, operations research and other branches of mathematics. It applies to the reliability of data collection, data analysis, design and testing and other aspects of the life of the system (Bryman & Bell, 2011).

The assumption of reliability has played a fundamental role in the research and has had great influence on the reliability with regard to the quantitative method. For the perspective of dependability, on the other hand, the author emphasis should be put on the requirements and changes of the researcher, which means that the response could only present the own idea about the research topic within the research progress. Analyzing and describing the differences was to be done during the method process. The individual stages cannot be seen as work independent from the rest; on the contrary, every stage influences further studies and even the overall research. The research strategy guides the complete plan for the research (Pickard, 2013). Every research holds their own perspective, angles and thinking ways to get into the research problems. As to the respondents, the description and expressions should be collected in detail.
3 Case description: Spotify recommender system

This chapter will provide information about the research case—Spotify. The background of Spotify Company and three main functions in Spotify will be described.

Spotify is a music streaming service that provides a platform to listen to music. The music collection of Spotify is a rather large one, around 30 million musical tracks (Spotify press, 2014). The music offered on Spotify comes from record labels, e.g. Universal, Sony, EMI, Warner Music Group etc. (Spotify press, 2014). There are two different versions available, free and premium. According to Spotify official statistics, there are over 50 million active users, among them over 12.5 million premium users, and the Spotify service is currently available in 58 counties and it is still growing (Spotify press, 2014).

Spotify offers a lot of functions, for example: the users can search the music they like, the Browse function includes a list of recommended music which is in vogue or based on the users’ mood, the Radio function, the Discover function. Spotify also presents on the social networks where the user can browse the collections of friends, other artists or celebrities.

The basic recommendation service in Spotify includes the Discover, the Related Artists, and the Radio lists. Spotify is also integrated with Last. FM

3.1 Discover

The “Browse” part comprises a lot of functions, one of them is “Discover”. On the discover page, there are plenty of musical tracks recommended to the user, which makes the discover page more personalized. The recommendations are based on users’ listening histories, favorite music that they have chosen by pressing “Like” or “Starred” or “Saved”, new releases of the artists they follow and also the music shared by friends. The discover function combines the Spotify technology and the content from Picthfork, Tunigo and Songkick and some others (Music week, 2012).

3.2 Related artists

The “Related artists” function works as follows: When the user checks the Spotify page for an artist, a list of artists who are similar to the artists that user checked will be displayed. Here, “similar” is to be understood in a wide meaning, such as similar genres, similar level of reputation of the artists, similar language of the songs, etc. To give an example: When checking the Taylor Swift page, the related artists will, among others, be Katy Perry, Kelly Clarkson, and Sara Evans.

3.3 Radio

This most personalized function in Spotify allows the users to listen to a random list of music that is specially selected. This selection of music is based on one track or artist or playlist (Spotify support, 2014), which means that the random list has special genres and decades (wikipedia for Spotify, 2014). “Thumbs up” and “thumbs down” buttons are used for the
feedback to the music recommended, it helps the system to make more accurate matches with the users’ music tastes (Spotify support, 2014).

### 3.4 The recommendation service in Spotify

According to Dieleman (2014), who worked with Spotify as on the music recommendation functions, Spotify runs the music recommendation service mainly based on the collaborating filtering approaches. The idea of collaborating filtering is to guess users’ preferences by using historical usage data (Dieleman, 2014). For instance, there are two users, A and B. Based on the usage data, it shows that user A and user B have listened to similar sets of music, then the recommender system can assume that user A and user B share the similar taste. It can also be applied to songs; if two songs are listened to by the same groups of users, then probably these two songs are of a similar type (Dieleman, 2014). This kind of information can be adopted to make recommendations.

There may probably exist some weaknesses in using collaborative filtering to compile the recommendations, though. From the point of view of Dieleman (2014), the biggest problem is that new and unpopular songs are hard to be recommended. Since the collaborative filtering approach is based on usage data, the more popular the song is, the more usage data is related to the song. So it is much easier for popular songs to be recommended, whereas music which is new or unpopular is unlikely to be recommended. Besides, attributes such as tone, genre, lyrics etc. of the music cannot be taken into consideration when using collaborative filtering to draw up recommendations. So for Spotify, who are now mainly using collaborative filtering, this could be one substantial weakness.

Besides using collaborating filtering, Spotify started to try some other ways to run and also to improve the recommender system, such as content-based filtering. By acquiring The Echo Nest, Spotify is trying to use data mining, digital signal processing techniques, both of which are techniques for content analysis, and some other ways to power their recommender system (wikipedia for The Echo Nest, 2014).

By using content-based filtering, the attributes of the music will be analyzed, such as the genre, tone, theme of the lyrics, artists, album etc. (Dieleman, 2014). The analyzed data of the music will be collected as track-related information, which then serves as the basis for making recommendations.

In Spotify, the “radio” is obviously using content-based filtering to do the recommendations. Based on a song that is picked, several songs that share some similar attributes will be recommended.

### 3.5 The feedback system in Spotify

Spotify has some simple operations for user information feedback. We have compared the feedback strategy in Spotify with other feedback theories to gain more information and inspiration. Based on the literature review we have done, we summarize the general requirements and features of a feedback system in chapter 4.2.2 and 4.4.3. The standards of good feedback systems in full service offers has been the key line the author follow in the quantitative research.
Compared with current feedback systems in online shopping websites and similar music streaming websites, the feedback system implemented in Spotify is not complicated. Spotify only focuses on the records of recommended music, which does not take into account the user preference information and related private.

Feedback systems in music streaming software do not follow clear criteria and are marginalized within a full-service system. The feedback system in Spotify should process the user information timely and accurately.
4 THEORETICAL FRAMEWORK

This chapter will give a review of the literature about the recommendation service, e-service customization, user experience and feedback system. Based on the research purpose, Spotify has been chosen as the research case. The results to be presented in chapter 5 will be analyzed in relation to the theory set forth in this chapter.

The fourth chapter described the related concepts involved in this research, including the recommendation approaches, user experience and feedback system. Those concepts and theories were crucial for the analysis in this research work. Based on the understanding of the previous research and literature in the music recommendation field, the results from the questionnaire and interviews lead to more findings and conclusions regarding the issue of music recommendation.

4.1 Recommendation service

With the rapid development of the Internet, more and more information and data has become available by e-services, and users have problems to handle such large amounts of information. The information overload problem is severe in the e-service industry. Recommendation service is a promising approach to solve the information overload problem, as it is based on the user's requirements and preferences etc. The recommender system provides customized service to reduce the individual information overload.

A recommender system collects data and information of users’ behavior and preferences in order to predict users’ possible likes and interests, and then provides recommendations for users (Lù, Medo, Yeung, Zhang, Zhang & Zhou 2012). In contrast to search engines, the recommender systems analyze and discover the areas of interest based on the user's preferences and personal choices to match the user's requirements. According to ZhenZhu and Jing-Yan Wang (2007), a good recommender system does not only provide users with personalized service but also establishes close relationships between system and users. Good recommender systems make users trust the recommendation service for a long term. Recommender systems are widely used in many fields. The recommender system is commonly used in the electronic commerce industry which offers good prospects for development and application. Meanwhile, the research about recommender systems has been increased considerably, several previous research works have been done in this field and they gradually have formed an independent discipline (Zhen Zhu & Jing-Yan Wang, 2007).

Music recommender systems are websites or applications where recommendations based on music database and user preference are provided. The number of songs available from the music websites is constantly growing, which is a “double-edged sword”. For the customers, there are more options to choose from; however, at the same time, they face the information overload problem. Music recommender system is the approach that can solve the problem to create a more pleasant user experience.

According to Robillard, Maalej, Walker and Zimmermann (2014), a music recommender system consists of the track selector, the feature extractor, the classifier, the profile manager, the recommendation module, the interface, and the database. The structure of a music recommender system is summarized in figure 4. As the illustration shows, the whole
recommendation service should be a circle process, where the database is the fundamental section and where users in the end get a recommendation for the ideal recommended music based on their own tastes.

![Diagram](image)

**Figure 4: The system architecture of the MRS**

### 4.1.1 Content-based recommendation

Content-based recommendation is an inheritance and development of information filtering technology. It is based on the content of user profiles to provide a recommendation service without the user’s evaluation (Balabanović & Shoham, 1997).

According to Basu, Hirsh and Cohen (1998), content-based recommendation uses machine language to acquire information on the user's interest by relating to the content of the user profile. Using characterization methods, content-based recommendation can offer some choices to the user and then get the user’s feedback. In content-based recommender systems, the items or objects are defined by characteristics and related attributes (Basu, C., Hirsh, H. & Cohen, W., 1998).

Content-based recommendation approaches predict the user’s interest by using text only, users’ ratings are not involved during the process of the prediction (Burke, 2007).

The user data model depends on the learning method. Decision trees, neural networks and vector-based representation methods are commonly used. The user data model perhaps varies from user to user (Burke, 2007).

According to Balabanovic and ShohamY (1997), the advantages of the content-based recommendation approach are summarized as follows:

- Other user information is not required in the recommendation process, it is easier to provide the recommendation service at the initial stage of the system;
- It can provide recommendation service to users with special interests;
- It is able to recommend new or “not mainstream” items;
- It can list the recommended items by content characteristics;
- It is a relatively easily applicable technology.

The disadvantages of the content-based recommendation approach are the following:
- It is hard to extract content into meaningful characteristics for the system to analyze. Content-based recommendation requires good structural characteristics of the content and the user's tastes must be able to be expressed in the characteristic form (Balabanovic & Shoham, 1997).
- According to a study by Shardanand, U. & Maes, P., (1995), the content-based filtering technique is not suitable to analyze media content such as music, video etc., since it uses machine language to learn and obtain the user's interest. Content like music cannot be analyzed with regard to the relevant attributes’ information.
- Content-based filtering can deliver recommendations but the quality of the recommendations cannot be valued (Balabanovic & Shoham, 1997).

The relevant knowledge about content-based recommendation has been collected. In Chapter 6 Analysis, the content-based recommendation approach will be compared with other recommendation approaches. Moreover, the advantages and disadvantages of content-based recommendation approaches are discussed in connection with the empirical results from the questionnaire and the interviews.

4.1.2 Collaborative filtering recommendation

Collaborative filtering recommendation is one of the earliest applied techniques and it has successfully spread and entered the recommender system field (Badrul, George, Joseph & John, 2007).

It generally uses the “K-nearest neighbor (KNN)” technique which is based on the user’s historical records. The music taste of users calculates the distances between the different users. Collaborative filtering recommendation uses the target “user's nearest neighbor user” to weight and evaluate the value of the product. Collaborative filtering recommendation predicts the extent of user's preference for a specific target product (Claypool, Gokhale & Miranda, 1999).

According to Nilashi, Bagherifard, Ibrahim, Alizadeh, Nojeem and Roozegar (2013), the general produce of the collaborative filtering recommendation was summarized in figure 5. The circulation of the recommendation process should run continuously in order to receive improved recommendations, since it takes time to accumulate user data and match users with “neighbor users”.

![Figure 5: The produce of the Collaborative Filtering Recommendation](image-url)
Based on the usage data and the user’s interests, the system searches the “neighbor users” who share similar interests with the user. Then the recommendation system recommends the contents that “neighbor users” are interested in to the user. The general idea of how collaborative recommender systems work is easy to understand. In other words, this approach is also commonly accepted in daily life, people refer to friends’ recommendations when making their own decisions.

Collaborative filtering has been frequently used in e-commerce recommender systems during the past few years. Collaborative filtering provides recommendations for the target users based on other users’ evaluation of content (Soboroff & Nicholas, 1999).

Based on Cai, Leung, Li, Min, Tang and Li (2014), the objects of collaborative filtering recommendation are presented as follows (see table 1). Collaborative filtering recommender systems can be recognized as a way that it makes the suitable recommendation from the user's perspectives. According to Soboroff and Nicholas (1999), collaborative filtering recommendation does not require users to provide by themselves what they are interested in, for example by completing some research forms (Soboroff & Nicholas, 1999).

**Table 1: The Collaborative Filtering Recommendation**

<table>
<thead>
<tr>
<th>User 1</th>
<th>Object 1</th>
<th>......</th>
<th>Object K</th>
<th>......</th>
<th>Object N</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1-1</td>
<td></td>
<td>......</td>
<td>R1-k</td>
<td>......</td>
<td>R1-n</td>
</tr>
<tr>
<td>......</td>
<td>......</td>
<td>......</td>
<td>......</td>
<td>......</td>
<td>......</td>
</tr>
<tr>
<td>User m</td>
<td>Rm-1</td>
<td>......</td>
<td>Rm-k</td>
<td>......</td>
<td>Rm-n</td>
</tr>
<tr>
<td>......</td>
<td>......</td>
<td>......</td>
<td>......</td>
<td>......</td>
<td>......</td>
</tr>
</tbody>
</table>

The advantage of the collaborative filtering technique is that this technique involves analyzing complex unstructured objects such as music, movies etc. (Robillard, Maalej, Walker & Zimmermann, 2014).

According to Cai, Leung, Li, Min, Tang and Li (2014), the advantages of collaborative filtering are as follows:

- It can evaluate information that is difficult to be analyzed by a filtering system automatically, such as art, music etc.
- It can avoid “low accuracy” content analysis by matching users with “neighbor users”, and that is based on a number of complex concept (such as the quality of information, personal taste) filters.
- It is able to make “not similar” recommendations. This is also an apparent difference between collaborative filtering and content-based filtering. Based on users’ profile information, content-based filtering recommends what users are already familiar with. However, collaborative filtering provides recommendations which are based on other user’s taste. This may solve the “similar” problem.

A lot of surveys and research works have pointed out how a collaborative filtering recommender system works. These systems collect data of users’ buying behavior or preferences and then analyze the data. Moreover, recommender systems provide the user with recommendations based on the similarity between products or users.

For example, there are two users, A and B, both using one system and their user behaviors and preferences are similar, so the collaborative filtering recommender system assumes that
they are similar users and that they have common habits. Based on user A’s comments on products, if user A praises it, then the collaborative filtering recommenders system recommends this product also to user B.

Although collaborative filtering recommendations are commonly used in electronic commerce and media websites (music or movie recommendation websites), there are still several drawbacks in this approach.

According to Robin Burke (1999), there are two problems in the collaborative recommendation approach.

- **“Ramp-up” problem**
  By using the collaborative recommendation approach, there needs to be a big amount of product rating data available initially so that the collaborative recommendation approach can work, otherwise if there is no rating data for the system to analyze (for example a new recommender system without any existing rating data), a recommendation cannot be given.

  And also the accuracy of the recommendation service has a strong connection with the number of product ratings. Or, in other words, with the collaborative recommendation approach, accuracy is dependent on the number of available ratings.

- **“Banana” problem**
  In the survey of Robin Burke (1999), he gave an example of buying bananas in the supermarket to explain this problem. In American supermarkets, most of the people want to buy bananas. Almost every shopping basket contains bananas. So if there is a not well-developed or “naïve” recommender system using the collaborative recommendation approach to draw up product recommendations for customers, the recommendation will always be bananas. Because bananas appear in the baskets every time. The system cannot analyze if bananas have any connection with the products. This makes another problem in the collaborative recommendation approach visible, namely that “main stream” items tend to be recommended repeatedly.

Whether the recommendation is good or not depends on the data sets (Herlocker, J., Konstan, J., Terveen, L. & Riedl, J., 2004). The recommendation approach has to match with the data sets. For the collaborative recommendation approach, it is advantageous for useful data sets when the number of users is higher than the number of items (Herlocker, J., Konstan, J., Terveen, L. & Riedl, J., 2004). For example, in the restaurants recommendation app in Shanghai, there are 70,000 restaurants in shanghai but the number of customers using them is much higher than 70,000. For data sets where the number of items considerably exceeds the number of customers, it will probably not be that accurate (Herlocker, J., Konstan, J., Terveen, L. & Riedl, J., 2004). For example: the music recommender system.

Collaborative filtering recommendation is used in the Spotify recommender system. We have described the definition and the process of recommendation to gain a thorough understanding for the Spotify music recommendation functions and mechanism. We have designed our questionnaire and focus group interview based on the knowledge about collaborative filtering recommendation and other kind of recommendations. Our respondents had this basic knowledge before answering the interview questions.
Table 2: Trade-offs between knowledge-based and collaborative-filtering recommender systems (Robin Burke, 1999)

<table>
<thead>
<tr>
<th>Approach</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collaborative filtering</td>
<td>A. Can identify niches precisely</td>
<td>J. Quality dependent on large historical data set.</td>
</tr>
<tr>
<td></td>
<td>B. Domain knowledge not needed.</td>
<td>H. Subject to statistical anomalies in data.</td>
</tr>
<tr>
<td></td>
<td>C. Quality improves over time.</td>
<td>I. Reacts slowly to drift</td>
</tr>
<tr>
<td></td>
<td>D. Personalized recommendations.</td>
<td></td>
</tr>
</tbody>
</table>

4.1.3 Knowledge-based recommendation

To some extent, knowledge-based recommendation could be seen as an inference technology, which is not only based on demands of users but also on preferences on the basis of recommendation. Resnick, P. and Varian, H. R summarized that knowledge-based approaches apparently use different knowledge for recommendation predictions, which are decided by different functions and features of recommendation objects (Resnick & Varian, 1997).

According to Burke, Hammond & Cooper, effectiveness of functional knowledge is a kind of knowledge about how the project satisfies a specific user, thus it is able to explain the relationship between demands and recommendations. In addition to that, the users could generate any data to support the inference of knowledge structure (Burke, R; Hammond, K. & Cooper, E, 1996).

In this research, the knowledge-based recommendation approach is as a recommender model able to add more functions to the system. Knowledge-based recommendation has decent compatibility with other recommendation elements. With regard to the current recommender strategy in Spotify, the further research is to deal with the research problems, and the research tried to test the acceptance of knowledge-based recommendations among Spotify users.

Table 3: Tradeoffs between knowledge-based and collaborative-filtering recommender system (Robin Burke, 1999)

<table>
<thead>
<tr>
<th>Approach</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge-based</td>
<td>A. No ramp-up required</td>
<td>B. Knowledge engineering.</td>
</tr>
<tr>
<td></td>
<td>C. Detailed qualitative preference feedback</td>
<td>D. Suggestion ability is static</td>
</tr>
<tr>
<td></td>
<td>E. Sensitive to short-term variance (drift)</td>
<td></td>
</tr>
</tbody>
</table>
4.2 Feedback system

4.2.1 The concept of a feedback system

In a closed-loop information system, the consequences of the system or output information collected is sent back to the input of the system and then adjust the behaviors of the system (see figure 6) (Desoer, Ruey, Murray & Saeks, 2001).

The closed loop formed by the flow of information is known as a closed-loop system as well. The clear working mechanism of a feedback system according to Franklin, Gene, Powell, and Emami-Naeini (2002) is presented below (see figure 6). The feedback systems usually changes object properties by signals. The feedback system can control the system behavior and eliminate errors. This process is called a “feedback control by error”.

![Diagram of a feedback system]

Figure 6: The theory of the general feedback system

Feedback refers to the general understanding. There are two ways: one is to detect and analyze information after a learning research by a person or other tools. Another one is to reflect the information to the outside world through language and graphic forms etc. Feedback means that it gives visual information itself, which is a direct reflection of the object information.

A feedback system implies that it can transport the phenomenon out and take the returned results in. As for the management and control area, the information is based on management processes and management techniques. In addition to, it is organized during the production and business activities (Desoer, Ruey, Murray & Saeks, 2001).

When the flow of collecting or analyzing information is finished, the feedback information comprises a huge range of data including the information of management control and data of changing records. The different management systems are combined to form new systems - management information systems.

It is necessary for a feedback system to reflect the capacity of the production process. Feedback information systems play a role in controlling the production process and the value formation process. Feedback systems should meet the requirements of management decisions. Moreover, feedback information systems have influence on all levels of management services, so it is a powerful tool for scientific management to design strict implementation plans.

According to Rucker J. and M. J. Polanco, the features of feedback are as summarized below (see figure 7) (Rucker, J. & Polanco, M. 1997).
- To process the information timely and accurately;
- To control plans and management in order to achieve the best possible condition;
- To facilitate comparison and merit-based programs;
- To be helpful for predicting.

**Figure 7: The produce of the general feedback system (Skogestad, 2004)**

Feedback is the basic concept of control theory and refers to the output of the system. Feedback is returned to the input and changes subsequent information in order to influence the operations of the system.

A feedback system has some basic aspects: disturbance, measuring elements, varied value and set point (see figure 7). The controller should have a good effect on the efficiency based on error commands.

Firstly, feedback control could provide managers with up-to-date information on the effects of plan implementation. In addition to that, feedback control can enhance employee motivation.

According to Phillips, Charles and Harbor (1991), the main disadvantage of feedback systems is the problem of time lag. If, after the discovery of a deviation, corrective measures must be taken, a time delay occurs. In the actual situation, it may have already had great impact so that damage has been caused. The data can be produced by the system itself, and in turn, serve as the information that guides the work of the system.

The feedback information shows positive effects on service systems. The music recommendation service in Spotify varies the recommended music based on different users’ preferences. So this research describes the general knowledge about feedback system. Based on this chapter, questionnaire questions (see chapter 2.3.3) and focus group interviews about feedback (see chapter 2.3.2 and chapter 2.3.4) have been designed. For the questionnaire, a good sequence of questions was important as well. This research followed the described sequence: feedback strategies, feedback requirements and feedback developments.

**4.2.2 Feedback features:**

The features of a feedback system according to Phillips, Charles and Harbor (1991) are summarized as follows.
- Targeted. The objectives of feedback are specific.
- Timeliness. Feedback pays attention to the information age in order to solve problems earlier.
- Continuity. Continuity of feedback refers to the case of continuous activities.

4.2.3 Feedback requirements:

The demands of a feedback system according to Sanfilippo and Valle are presented below (Sanfilippo & Valle, 2013).

- The feedback information should be true and accurate.
- It can minimize the feedback time.
- The feedback information should provide more information and be multi-channel.

4.2.4 Feedback development

As to the problem whether information management is effective or not, the key point is the completed information system and whether proper feedback is sensitive and powerful. The quality of a management system is described by to which degree it is sensitive, accurate and powerful. A functioning information management shows plenty of signs of vitality, an integral part of it is the modern management theory of feedback. The trend of the development is presented below (Sanfilippo & Valle, 2013).

- To be “Sensitive”. The information system requests a keen “Receptor” to be able to detect all variables in the contradictory objective between actual and planned projects.
- To be “Correct”. The information system should have high performance analysis system for filtering and processing variables: news, form, data and other information.
- To be “Strong”. That means analyzing the resulting information in order to finish executive actions.

4.3 User experience

User experience is a feeling that is formed during the process of using the product, service or system (Baidu baike for User Experience, 2014). It involves users’ behavior, attitude and emotions (Wikipedia UX, 2014). It is purely subjective (Baidu baike for User Experience, 2014). ISO 9241-210, a standard on ergonomics of human system interaction, gives the following definition of user experience: “a person’s perceptions and responses that result from the use or anticipated use of a product, system or service”. The explanation of the definition in ISO implies that user experience involves all the feelings before, during and after the usage, including emotions, beliefs, preferences, perceptions, physical and psychological responses, behaviors and accomplishments (Wikipedia User Experience, 2014). The standard points out that usability can also be a part of the user experience, as: “usability criteria can be used to assess aspects of user experience”. But in some articles, a difference is made between user experience and usability, where usability means: a quality attribute that assesses how easy user interfaces are to use (Nielsen, 2012), However, user experience has a broader meaning (Nielsen, 2012).
Since usability is one part of user experience, some factors in usability can also be used for reference. Accomplishing tasks quickly and easily for users who use the products is the meaning of usability (Dumas & Redish, 1999). To create a better usability, the process of people using the products should be a productive one. The products should be so designed that they are easy to use. People using the products may have certain aims or tasks, the aims should be reached and also in a not complicated way (Dumas & Redish, 1999).

### 4.3.1 Factors influencing user experience

McNee (2002) states that customers are glad to be provided with a set of recommendations in which there are some items they are not familiar with.

There are many factors that may have an influence on user experience when a system is being used. For the convenience of analysis and discussion, those factors are classified into three categories: user's state and previous experience, system properties, and the usage context (Wikipedia User Experience, 2014). However, the core of user experience is to make sure that users can find value in the system or product or service provided (Morville, 2004). Peter Morville created the honeycomb below to illustrate the different factors that influence user experience (see figure 8).

![User Experience Honeycomb](image)

**Figure 8: User Experience Honeycomb (Morville, 2004)**

*Useful*: the usefulness of a product or system is very important for user experience; it decides whether users can find value in a system or product.

*Usable*: the ease of use is vital but as discussed before, usability is important but not solely determining for use experience (Morville, 2004).

*Desirable*: image, identity, brand, and other design elements are used to raise emotion and appreciation (Morville, 2004).

*Findable*: the content of the product should be navigable and locatable so that users can easily find what they need.

*Accessible*: access to the product for disabled people.

*Credible*: to make the user trust and believe in the content shown in the product.

*Valuable*: the value of the product should be delivered.
4.4 E-customization

The value of customization has aroused great attention in the business and marketing fields. According to Ansari and Mela (2003), customized service and communications is a great way to attract customer attention and to build customer loyalty.

Targeted communications could reduce the problem of information overload, which is a frequent issue in the context of music recommendation services. The music preferences change with mood and environment. It is difficult for music recommendation services to build a unified standard to customize the music service. Considering the features of music recommendation, a constant service adjustment strategy would satisfy customers. However, E-service customization has often proved difficult in view of strategies because of implementation challenges, insufficient customer information, etc. (Ansari, A. & Mela, C.F., 2003).

E-service customization follows the logic path: Collect data using experience and feedback -- Analyze the problems -- Create modification strategy -- Update the relevant function and algorithm. The applications or systems itself can collect and update preference information of customers from online surveys, operation statistics or by other methods. Customers can judge the quality and fluency of e-service by these operations (Ansari, A. & Mela, C.F., 2003).

Since there are some drawbacks involved with e-customization, fulfilling psychological constructions has great influence on customer satisfaction with e-products or e-services. The demand for uniqueness and status aspiration plays a critical role in consumers' purchase of e-customized services (Ansari, A. & Mela, C.F., 2003).

“Generally, uniqueness has been reflected on e-service individuation or frame. E-service and e-products would distinguish themselves from other standardized products in term of customization.” (Park, Han & Park, 2013).

The quality and applicability of e-services depend on psychological demands when customers choose some e-customized service with specific functions. The demands for uniqueness and psychological elements have significant impact on forming favorable attitudes to e-customized products or e-services. As far as customers are concerned, e-service marketers have put more energy on psychological segmentation criteria such as motivation, attitudes, perceptions, and personality (Park, Han & Park, 2013).

Besides, customer loyalty is associated with customization. Effective policies and security policies play roles on the way of building customer royalty (Park, Han & Park, 2013). This psychological approach is meaningful for e-service companies adapting their marketing strategies.

The design of the application should encounter the user’s psychological demands, meanwhile it is emphasized that designing user-friendly applications should be prioritized, especially when dealing with e-customized services.
5 Result

This chapter consists of three parts: the results of the initial group focus interview, the results of the questionnaire and the results of the main semi-structured focus group interview. This chapter will give answers to the research question and will be analyzed in Chapter 6 in reflection of the collected theory.

In order to find the shortcomings of the music recommender system, one questionnaire was distributed and two interviews were conducted. The respondents are all users of music recommender systems. The questions included in the questionnaire and in the interviews were relevant to the theories and concepts in previous research in the music recommendation field. The results of the questionnaire and interviews are listed below.

Based on the selected research design - case study -, Spotify has been chosen as a case for this research work. The conducting of the questionnaire and the interviews, including design and data collection from the questionnaire and the interviews, was followed by the case study plan of the research design.

In order to find the shortcomings of music recommender system, the results have been analyzed in comparison to the theories and concepts of the previous researches in the music recommendation field (see 6.1 & 6.2).

5.1 Result of the initial group focus interview

For the initial focus group, four respondents were interviewed. All of them are students studying at the University of Borås and have some experience of using music recommender systems. Some conclusions from the interview have helped the authors to narrow down the research area and inspired the research.

- The music recommended by the recommender system is not accurate enough. The recommendations given by music streaming websites is vague.
- The music recommendations focus more on mainstream music. One interviewee said that she loves classic jazz music. However, when she tries to use the recommendation service, she is mostly recommended sound tracks of famous films, which is mainstream music.
- User’s mood plays an important role when users listen to music. One of the interviewees mentioned that when he goes to school in the morning, he wants to listen to some exciting music to wake him up and when it is raining, he wants to listen to some classic music.
- A song that users once made a positive comment on is be recommended repeatedly, which makes the users get a feeling of aesthetic fatigue.

5.2 Result of Questionnaire

Our questionnaire was published on “Sojump”, a research platform among in China. There were 52 people who answered this questionnaire and the results of the survey have been summarized into tables and three kinds of charts: pie chart, column chart and line chart.
Result of general questions

Based on figure 9 and figure 10 presented below, YouTube and Spotify occupies the largest usage in the fields of music listening and music recommendation. More than 90 percent of the respondents have used these two types of music sites. Behind these two, Sound Cloud holds 18.75%.

![Pie chart showing usage of music streaming sites](chart1.png)

Figure 9: “Which of the following music streaming website/apps have you tried?” (Multiple choice)

As figure 10 depicts, there are 87.5 percent of the respondents that have experienced the recommendation service in Spotify. In addition, YouTube is popular among the users (62%). Sound cloud, “Wangyiyun” music, vimeo are on the same level, i.e. 18.75%, 6.25%, and 6.25% respectively.

![Pie chart showing usage of music website for recommendation service](chart2.png)

Figure 10: “What music website do you use for music recommendation service?” (Multiple choice)
Result of user attitudes to music and Spotify

Table 4: The ways users get new music

<table>
<thead>
<tr>
<th>Reasons</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>From ITunes</td>
<td>0%</td>
</tr>
<tr>
<td>From blog</td>
<td>18.75%</td>
</tr>
<tr>
<td>From somewhere not specific</td>
<td>75%</td>
</tr>
<tr>
<td>From music streaming websites</td>
<td>42.75%</td>
</tr>
<tr>
<td>From friends</td>
<td>62.5%</td>
</tr>
<tr>
<td>From radio</td>
<td>31.25%</td>
</tr>
<tr>
<td>From party</td>
<td>37.5%</td>
</tr>
<tr>
<td>Other</td>
<td>18.75%</td>
</tr>
</tbody>
</table>

The music recommendation service is not the best choice for getting new music (42.75%) among all the choices in the questionnaire (see table 4). As many as 75% of the users get new music from some undefined source. Recommendations from friends and parties play important roles for these choices (62.5% and 37.5%).

Table 5: The reason users need Spotify

<table>
<thead>
<tr>
<th>Reasons</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large music library</td>
<td>87.15%</td>
</tr>
<tr>
<td>Friends use it</td>
<td>7.14%</td>
</tr>
<tr>
<td>Good music quality</td>
<td>71.43%</td>
</tr>
<tr>
<td>Easy and convenient</td>
<td>92.86%</td>
</tr>
<tr>
<td>Multi-functional</td>
<td>21.43%</td>
</tr>
<tr>
<td>Good music recommendation system</td>
<td>21.43%</td>
</tr>
<tr>
<td>Others</td>
<td>14.29%</td>
</tr>
</tbody>
</table>

The general reasons why respondents use Spotify are presented in table 5 and table 6. The recommendation service in Spotify only occupied 21.43% among all choices. Attention should be drawn to the fact that the strongest reason is the convenience and flexibility, which amounted to 92.86%. Meanwhile, good music quality and a large number of music tracks are vital as well. 52.94% of the respondents would like to use a music recommendation service when they feel bored.

Table 6: The reasons for choosing the recommendation service in Spotify

<table>
<thead>
<tr>
<th>Reasons</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not much music I can listen to</td>
<td>29.41%</td>
</tr>
<tr>
<td>Feel bored, I need music</td>
<td>52.94%</td>
</tr>
<tr>
<td>Too lazy to search new music</td>
<td>58.82%</td>
</tr>
<tr>
<td>The existing music lists cannot satisfy me</td>
<td>23.53%</td>
</tr>
<tr>
<td>In some special mood</td>
<td>47.06%</td>
</tr>
<tr>
<td>Niche music</td>
<td>17.64%</td>
</tr>
<tr>
<td>Other reasons</td>
<td>5.88%</td>
</tr>
</tbody>
</table>
The question to which extent users like Spotify has produced a very intuitive and obvious response (see Figure 11). More than half of the respondents hold a good attitude towards Spotify.

According to figure 12, most of the respondents (68.75%) did not get a customized recommendation service while they were listening to music. Only 18.75% of the respondents are generally satisfied with the recommendation services. However, 6.25% of all respondents are unsatisfied with the recommended music.

Table 7: The reasons why users do not like music recommendations in Spotify (Multiple choices)

<table>
<thead>
<tr>
<th>Reasons</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>The music does not match my taste</td>
<td>100%</td>
</tr>
<tr>
<td>The recommended music is limited</td>
<td>100%</td>
</tr>
<tr>
<td>The relevant artists do not match my taste</td>
<td>16.75%</td>
</tr>
<tr>
<td>The recommended music does not match my mood</td>
<td>66.67%</td>
</tr>
<tr>
<td>The radio function is bad</td>
<td>50%</td>
</tr>
<tr>
<td>The discover function is bad</td>
<td>50%</td>
</tr>
<tr>
<td>Other reasons</td>
<td>5%</td>
</tr>
</tbody>
</table>

In this questionnaire, every respondent has experienced that the music recommended by the system did not match his or her taste. Moreover, mood plays a role in the process of recommending. 66.67% of the respondents are of the opinion that the music recommended does not suit their mood (see table 7).
The reason why users do not like the Radio function (Multiple choices)

This question focused on the Radio function in Spotify. 89% of the respondents miss a “look back” button that would give them a chance to listen to music previously provided by the system (see figure 13).

Result of relationship between two correlative questions

The relationship between “The attitudes to music” and “The frequency of using recommendation service” (Multiple choices)

The stronger the attitudes towards music is, the less is the respondent willing to use a music recommendation service, which represents a downward trend (see figure 14 and figure 15). Users with fixed music attitudes did not want to use the music recommendation service to get music. It is worth mentioning that there are 18.18% of the respondents who never use the music recommendation service in Spotify. However, most respondents with optional attitudes towards music have used the music recommendation service in Spotify.
5.2.1 Result of feedback system in Spotify

Currently, clicking “Like” for favorite songs is widely accepted by users. The recommender system provides the recommendation services based on the history of clicking “like” record. This question investigates the extent of acceptance of this operation. As the statistics show (see figure 16), there are less than a third of the respondents who have the habit of clicking “Like”. However, 12.5% of the respondents would like to adopt this habit. In contrast, 12.5% of the respondents never click “Like” for songs they love.

![Figure 16: The frequency of pressing “like” when users find songs matching their tastes](image)

Figure 16: The frequency of pressing “like” when users find songs matching their tastes

![Figure 17: The operations of the feedback system in Spotify that users like](image)

Figure 17: The operations of the feedback system in Spotify that users like
Both clicking the ‘dislike’ button and ranking the recommended music occupies the same percentage among all choices, i.e. 41.18% (see figure 17). Those two choices are more likely to be accepted among the respondents. As far as the other choices are concerned, there are around 27% of respondents who would like to do more complicated feedback operations such as commenting and answering the questions etc.

5.3 Result of the main semi-structured focus group interview

The result of the main semi-structured interview has played an important role in answering the research question. Interviewees answered questions during the interview from a user’s perspective, provided a lot of important information about what they thought the shortcomings in the music recommender system were.

The basic information and the leading results of the main semi-structured focus group interview are listed below.

5.3.1 Basic information

In this research, two students were interviewed. Both of them have experience of using Spotify. One interviewee had used Spotify for almost four years, while another one had used it for half a year. They are Swedish male students in University of Borås, both 23 years old. This interview was held in the library of the university. Moreover, a voice record was made in case critical information was missed. This interview lasted for around 2 hours. The atmosphere of this interview was kept in a relaxing way. They share the same music tastes. The questions involved in this interview included basic questions about their attitudes to music and some other questions about their user experience of the recommender system in Spotify. They are both premium users. They use Spotify on a daily basis.

5.3.2 Result of dialog

Hereinafter follow the results we obtained from the main semi-structured focus group interview. “Q” stands for the questions in the interview, “A1” represents interviewee number one and “A2” represents interviewee number two.

Q: Do you know what the recommendation services in Spotify are? They actually have several ways of doing the recommendations.

One of the interviewees said he used the recommended lists from the “Browse” pages and listened to new music from those lists. Most of the lists had their own themes, for example: the list for Christmas, the list for working out, the list for sleeping etc. Another interviewee also said he mostly used the recommendation lists, sometimes used the Related artists function and Discover function. Neither of them used the Radio function for a long time. One of the interviewees had tried once or twice.

Q: What do you think about the music classification in Spotify? For example, there is not so many unpopular, not mainstream, or you can say indie music being recommended in the recommender system in Spotify.
A1: Yeah, that’s a bit of a problem for Spotify. I think that Spotify signs with music labels, so Spotify are allowed to play their songs, so Spotify is the one that pay… Because they don’t have contracts with the small music labels or artists, independent artists… If you can upload songs as easily as I can upload songs to YouTube, that will create a problem, it will be lots of copying problems.

Q: Do you have any idea of what you expect of a music recommendation service?

A2: I think they have a pretty good music recommendation system in Spotify but it’s not accurate, they are there but they are just not accurate, they could just improve on the accuracy. I don’t think they need to do the whole invention, need to invent a new way to find new music or to recommend good music. I think the basic functions are there, they need to improve it more. That’s what I think.

During the interview, it has been noticed that the two interviewees had opposite opinions about Spotify doing recommendation services. One interviewee who has been using Spotify for four years thought the music recommendation service Spotify provided was perfect; it was the best recommendation service he had used. On the contrary, another interviewee said the recommendation sometimes did not match with his music taste, which meant the recommendation was not accurate enough. The reason why there was different user experience is that the interviewee who regarded Spotify recommender system as perfect has used Spotify for several years and he loved to give rating for the song he had listened to, so he had thousands of music tracks that he had pressed “like” for, and obviously he had a long listening history. This helped Spotify to make the recommendation more accurate. Meanwhile, another interviewee has only used Spotify for several months and he did not rate songs as frequently as another interviewee did, so the listening history was not sufficient for the system to make the recommendation accurately.

Q: Have you tried others, like the "discover" function the "related artists" function and "radio" function?

A2: I did it, the radio function, I don’t know, the "radio” function is bad.

Q: In which way is it bad?

A2: It’s general. I don’t think it’s really accurate … And when we asked about the reason why they did not use the “radio” function, one of our interviewees told us, the first time he used Radio he felt the accuracy was really low, he was not satisfied. And after this he did not use that function again.

But interviewee A1 told us he likes the other two recommendation services.

A1: I’ve never used the “radio” function, but the “discover” function you mentioned I think it’s quite good. It did help me to find some new songs which are also good.

When talking about the Radio function, there is one thing that surprised us, our interviewee told us that they had actually not really understood what is the radio function was before they tried. There was a misunderstanding that existed.
A1: I mean, they should maybe market it more. Because when I think of radio, seriously I didn’t know that is a music recommendation function, I thought it was a normal radio function like what I use in my car with DJ in it maybe.

A2: Yeah, I thought it was a radio function as well.

There are three buttons in the “Radio” function: “like”, “dislike” and “next”. The interviewees were talking about the need of a “back” button. One of the interviewees said there were two kinds of situations when he liked a song. “One is that after probably just five seconds of listening to these songs, I totally fall in love with these songs; the other is that I don’t like these songs really much at first, but after listening to them repeatedly, I turn to like these songs”. But in the “Radio” function, there is no “back” button for the music that was recommended, once the song has passed, one cannot return to it. In a way the accuracy would be decreased if the songs were the kind of music that required several times listening to be liked.

In the “Radio” function, there are the “like” and “dislike” buttons which can help the “Radio” function to be improved and make the recommendation more accurate. But from the interview, one of the interviewees, as a user of Spotify for five years, he said he never got “hooked up” by that function because at the first time using it, it was not accurate. He did not have a lot of patience to “like” or “dislike” to improve it. Interviewees expressed: “It takes time to make it more accurate through pressing “like” and “dislike” I guess, but I haven’t done that much, that’s why. I never got hooked on it, and basically they need to get you hooked.” However, for the “Radio” function itself, using the “like” and “dislike” function is the way of improving the accuracy, without doing so, the accuracy cannot be improved. But as it becomes obvious from our interviewees’ perspective, they do not have the necessary patience to do that.

Besides, they also expressed that they actually did not know that by using the “like” and “dislike” buttons, they could help the “radio” function to be improved.

A2: I think most of the people don’t know that it will be improved; maybe they should say like “hey, you have to try out two or three days and then it will be improved”. I’d never known of it at first because when I used Spotify they didn’t have this function yet.

When talking about the different version of Spotify: Web version, Desktop version and app version in the phone. Both of our users used mobile app mostly, then came to the desktop version, and they barely used the web version.


A1: I would say if I have the ranking in my mind, I would say that the app is the NO1, the other thing I would say the software in the computers. I think the least thing I use is the website version. Because I don’t think people will go into chrome and type www.spotify.com. I think people have their app and software downloaded.

When talking about the feedback for the recommender system in Spotify, the interviewees expressed the importance of having a feedback system.
A1: They should get more information. The more information they get the better accuracy they can have about the new songs they recommended.

One of interviewees thought if the Discover function and Related artist function could also have the feedback system, then the recommendation service would be more customized. Nevertheless, one of the interviewees thought the way of doing the feedback should not be too elaborate, the way the Radio function did is good, and grading can be an acceptable way to do the feedback as well.

5.3.3 Advice

As to accuracy, one of the interviewees gave a piece of advice. The private playlists of users can be used to make the recommendation more accurate. Most of the users have created their own playlists which contain several songs they like and match their tastes. “The more information they get, the better accuracy they will provide for me.”

A2: If I have a Spotify account and I have my own playlists with different kinds of music, maybe Spotify should collect the information from my own playlist to provide good recommendations to me, based on the songs that I have in my playlists.

Another interviewee took the cost of providing a better recommendation service into consideration. The differences between the free account and the premium account are: “Play any songs”, “download music anywhere”, “listen offline in high-quality audio”, “no ad interruptions and no commitment” (Spotify, 2014). So he recommended that Spotify could add a better recommendation service to the premium account. It could both help Spotify to offer a better recommendation service and to make more profit.

Moreover, if the users can choose the music type they like by themselves so as to provide Spotify with more information about their music taste. This would help Spotify to make the recommendations more customized.

About the patience, one of interviewees suggested: “Probably before using the Spotify recommendation service, the system gives users chances to choose the type of music they like.” This could help the system to make better recommendations for the users who did not have patience or had no listening history.

About the Radio function, the interviewees proposed that the company should promote that function more strongly so that users get to know what “radio” is and how that function can be used.
6 Analysis

In this chapter, the findings of the empirical study, including the questionnaire and two interviews, will be analyzed. The connection between theoretical framework and the empirical findings will be built.

When comparing the theory from previous research in the music recommendation field with the results from the interviews and questionnaires, some shortcomings existing in music recommender systems are very obvious. Those shortcomings are listed as follows.

**Beginning users and long-term users receive same recommendation service.**

In the main semi-structure interview, there was significantly different user experience between two interviewees. The recommender system in Spotify was rated by one interviewee as the best. On the contrary, another interviewee regarded the system as inaccurate. The difference between these two interviewees was that one interviewee had used the system for 4 years, whereas the other interviewee was almost a beginner.

Proceeding from the theory of collaborative recommendation, which is the most frequently applied approach of doing recommendations, it can be learnt that the “Ramp-up” problem exists in the collaborative recommendation approach (Robin Burke, 1999). A big amount of product rating data is required to do the recommendations; otherwise meaningful recommendations cannot be given. Meanwhile, for beginners, it is very obvious that the amount of rating data is insufficient to provide adequate recommendations. The lack of rating data for the system to analyze caused the “inaccuracy” problem.

However, in music streaming websites, it does not matter if users are long-term users or beginners, the same recommendation approach is applied to all of them. For instance, in many streaming websites, both long-term users and beginning users receive recommendations compiled by means of the collaborative recommender filtering technique. Long-term users can receive more customized recommendations than beginning users, since long-term users have accumulated more rating and usage data. There is no difference for users in different usage stages, which caused the recommendation inaccuracy problem for beginning users. This is currently one of the biggest problems for music recommender systems on music streaming websites.

Based on the study by Robin Burke (1999), a knowledge-based recommendation approach could solve the “Ramp-up” problem. By giving several choices to the users at the very beginning, the recommendation could be improved to be more customized.

**Simplex recommendation approach**

As stated by the theory in chapter 4, all recommendation approaches had their own advantages and disadvantages.

By using the content-based recommendation approach, the content of user information will be analyzed to give customized recommendations, other users’ information are not required (Balabanovic & Shoham, 1997). At the same time, the disadvantage of this approach is obvious. This approach has problems in analyzing media data such as music and video. (Shardanand, U., & Maes, P., 1995). Besides, the quality of the recommendation cannot be
promised (Balabanovic & Shoham, 1997), which is not suitable for music streaming websites to do their recommendations. However, it can still be used to analyze users’ profiles to discover the interest of users. As one of the interviewees in the main semi-structured interview mentioned, he expected the system to scan his own profile and playlist; as this can help the system to make recommendations more customized.

For instance, from the results of the questionnaire, it becomes apparent that users are generally not satisfied with the music recommended; the main reason is that the recommended music is not customized to a sufficient degree. Besides, in the main semi-structured interview, regarding the radio function in Spotify (in which content-based filtering is applied), interviewees also expressed that the main problem is the insufficient customization of the recommended music.

By using the collaborative recommendation approach, even media data such as art, music, video etc. can be analyzed. This may solve the problems that content-based recommendation approach implies. In addition, more information from the “neighbor” can be analyzed and compared to make better recommendations (Cai, Leung, Li, Min, Tang & Li, 2014). However, this approach also entails severe problems, namely the “Ramp-up” problem and the “Banana” problem (Robin Burke, 1999). In both the questionnaire and the interviews that have been done, the respondents and interviewees expressed their negative feelings about the recommender system. This proves the findings from previous research and also indicates that those problems have still not been solved.

For example: In the main semi-structure interview, both of the two interviewees expressed that mainstream music was likely to be recommended repeatedly by the recommender system. This corresponds to the “banana problem”.

By applying the knowledge-based recommendation approach, problems such as “Ramp-up” and “Banana” can be avoided (Robin Burke, 1999). For this approach gives users opportunities to choose the music type they want. And it can help the system to make more customized recommendations. But the suggestion ability of this approach is static (Robin Burke, 1999). Users have expressed their eagerness for a knowledge-based recommendation approach. During the main semi-structure interview, interviewees suggested that users could be offered choices of music genres in the beginning and thus tell the system what they like.

These drawbacks in the recommender system cause a negative user experience. The ways of providing recommendations by the music streaming websites are simplex, that is the reason why users are unsatisfied with the recommendations from the existing music streaming services. None of these recommendation approaches is perfect, each recommendation approach has its own drawbacks.

### 6.1 Analysis of the questionnaire

This chapter organizes the empirical data from questionnaires and presents an analysis based on the questionnaire results. Moreover, in this chapter results and data is compared with the theories in Chapter 5. The questionnaire has been divided into four parts: General questions, user attitudes towards music and Spotify, relationship between two correlative questions and feedback system in Spotify.
6.1.1 Analysis of user attitudes towards music and Spotify

According to the results of the questionnaire, 66.7% of the respondents chose “mood” as the main influence factor on music. It indicates that mood plays an important role in users’ choice of music. For example, users tend to listen to “deep” music when they need to focus. According to Hung-Chen and Arbee (2007), a recommender system is likely to suggest similar kinds of music repeatedly; however, it ignores the user's mood. Concerning the e-customization service theory, psychological aspects are crucial to construct marketing strategies including segmentation, user preference, growth experience etc. (Ansari, A. & Mela, C.F., 2003). In most of the music recommender systems, users’ moods were not taken into consideration, which is one of the most important drawbacks. It then leads to the inaccuracy problem in existing music recommender systems.

Some questions were designed around the advantages and drawbacks in the recommender system supplied by Spotify. In terms of the e-customization theory, Park, Han and Park (2013) said that the demands for uniqueness and status aspiration play an important role in consumers' purchase of e-customized services. According to Dieleman (2014), Spotify has a huge database of music resources. This advantage should be fully utilized in the music recommender system in order to enhance the function of the music recommendation service.

Table 4 indicates the problem that users get the latest music recommendations mostly from magazines, friends etc. instead of from recommendation services. This leads to the conclusion that existing music recommendation services do not perform well. The customers’ demand of uniqueness was not satisfied. There is still considerable room for improving the quality of the recommendations.

6.1.2 Analysis of the relationship between two correlative questions

Based on the knowledge derived the analysis of the questionnaire (see figure 14 and figure 15), respondents had different understandings about the drawbacks in music recommendation services. Though the music recommended did not match with users’ mood and the environment very well, users did not expect recommender systems to be highly customized. For users already know it is difficult for the recommender function to release customized recommendations. Users’ requirements are not as high as the authors expected.

According to Cai, Leung, Li, Min, Tang and Li (2014), collaborative filtering recommendation is suitable for making recommendations in music and films industry. However, according to figure13, still 56% of the respondents feel the recommender system in Spotify is not customized enough; it is still difficult to match with users’ preferences by using collaborative filtering recommendations in Spotify.

Based on the users who held different attitudes, this research has drawn up the statistics on users’ attitudes towards music and the purposes of listening to music. Before analysis has been done, it has been assumed that the respondents who have various music preferences tend to demand the recommendation system to be highly customized. However, from the results of the questionnaire, the users with various music preferences have fewer requirements with regard to a recommendation service, which is different from the assumption.
According to Zhen Zhu & Jing-Yan (2007), a good recommendation system can not only provide users with customized service but also establish close relationships between system and users. While the existing recommender systems only put emphasis on providing customized recommendations, the establishing of relationships is ignored.

6.1.3 Analysis of the feedback system in Spotify

This chapter focuses on feedback behavior -- Clicking “Like”.

From the results of the questionnaire, there are less than one third of the respondents holding the habit of clicking “Like”. It is worth mentioning that some of the respondents never clicked “Like” for songs to give feedback. However, 12.5% of the respondents have adhered to this behavior for a long time. 25% of the respondents do so occasionally.

The results of the questionnaire show that most respondents are not aware of the fact that clicking “like” has an effect on the further recommendation service. However, the clicking option “Like” for favorite songs is widely accepted among music streaming websites to collect feedback from the users. Clicking “Like” can accumulate more “neighbor users” to get more customized recommendations in the collaborative recommendation approach. According to Robin Burke (1999), collecting rating data helps the system to match users with the nearest “neighbors”. However, from the results of the questionnaire, collecting rating data is not an effective way, as only 12.5% of the respondents like to rate songs. The gap between these findings and the theory of collaborative filtering recommendation should be investigated more thoroughly.

6.2 Analysis of the main semi-structured focus group interview

Throughout the whole interview, both interviewees expressed that the accuracy of the recommendation service is not as high as they expected, especially the “Radio” function.

Shortcomings in the Recommender system

From the theoretical framework, the principle of the recommendation service in Spotify is presented: The Radio function recommends music based on one track, one artist or one playlist (Spotify support, 2014). The Discover function recommends music based on users’ listening history, following artists. The “related artists” is based on little user information. Both interviewees suggested that if Spotify collected more information about the users to provide recommendations, it could be more customized.

Based on what was found about how Spotify runs the recommendation service, there may be some drawbacks in collaborative filtering (Dieleman, 2014). For example, new or unpopular songs are not likely to be recommended. According to the interviewees, those unpopular songs such as indie music are barely recommended, which proved the theory about this weakness of collaborative filtering in recommender systems from the users’ perspective.

However, one of our interviewees presented an objective reason. Spotify has not signed contracts with less popular music or indie labels. So some indie music is not allowed to be played in Spotify because this is a question of copyright.
Shortcomings in the Radio function

Firstly, the major drawback is that the music recommended by the radio does not match with the users’ taste. And this is also the main reason why users tend to give up using this function. This inaccuracy has its origin in the fact that the systems are only based on one song to generate a recommendation. Clicking the “like” or “dislike” buttons cannot solve this problem. It takes time to collect the “like” and “dislike” information to improve the system. However, from this interview, it shows that neither of the two interviewees has much patience of doing the rating. It should be mentioned in this context that the questionnaires show the same result. Merely 12.5% of the respondents take the effort to do the rating. However, the collaborative filtering technique provides recommendations by collecting rating data (Robin Burke, 1999). The results from the empirical study, however, show that the collaborative filtering technique is not that effective. Some other measures should be taken to improve the accuracy.

One finding that we have not expected before is that both of the interviewees said that they did not have an idea of what the “radio” function was. One interviewee thought it was a real radio that plays random songs and he did not expect it was the recommendation service that would recommend songs based on his own taste and he did not know either that there were the “like” and “dislike” functions that could improve the “radio” recommendations.

Compared with the theory of user experience, the user experience design in Spotify is not decent enough. Users do not understand the function of Radio before trying it. As stated by one of the interviewees, he could not figure out clearly how to use the Radio function. A better user experience design could help the users to understand the products and use it to accomplish tasks easily and productively (Dumas and Redish, 1999). However, from the interface of the Spotify desktop App (see figure 23), the logo and text of the “radio” function do not give users a hint about what is special about this function.

![Function list in Spotify](image)

Figure 18: Function list in Spotify (Spotify, 2014)

Besides, the drawbacks are not only within the recommendation service itself but also concern the marketing of the products in Spotify. The lack of promotion of the “radio” function is a drawback in Spotify, too. The way of doing the promotion should be reconsidered by Spotify.

Shortcomings in the feedback system

Compared with the theories of user experience noted by Morville (2004), useful, usable, desirable and findable are important characteristics for creating good user experience. A product to incite good user experience should be easy to use.

There is a feedback system in the “Radio” function in the form of the “Like” and “Dislike” buttons, for example. But when it comes to the “Discover” and “Related artists” functions, there is no feedback information involved. Even if the users feel that the music recommended does not match with their taste, they cannot do anything about it.
This chapter consists of authors’ discussion, a conclusion of this research and a summary of its contribution to the informatics area. The answers to the research question will be summarized. In addition, suggestions for future research will be given, and the limitation of the research will be described.

This thesis has used Spotify as a case to try to find the drawbacks of music recommender systems. The findings of the thesis mainly refer to Spotify. But there are also some findings that can be applied to music recommender systems in general.

We have found some clear drawbacks in Spotify, and the two main findings are very important with regard to improving this music recommender system (see Chapter 6). We believe that these two main drawbacks do not only exist in Spotify but can also be observed in other music streaming websites. Investigating these two drawbacks more closely will be helpful for improving recommender systems.

Besides we had not expected some of the findings before our research. Our interviewees put more emphasis on the patience aspect involved regarding recommendation service operations. They do not want to spend much time pressing the choice button. We assumed that if they wanted a better music recommendation service, they would be prepared to spend more time, and even some money, to obtain good service. But the results do not confirm this assumption. They need a really easy and convenient way to use a music recommendation service, at the same time, the quality of the recommended music must be good enough.

The aim of the thesis is to find the drawbacks of the music recommender system. Before we started writing the thesis, we thought we would discover the drawbacks rather in the algorithm field, we think that is probably the first thing that comes to one’s mind when talking about drawbacks in this context. But when we actually conducted the thesis, got familiar with the relevant literature and also realized the results of our empirical study, such as the questionnaire and the interviews, we had to admit that there can be drawbacks in many different fields, for example, as we discussed in the thesis before, the feedback system field, the user experience field, etc. This can give future research in the music recommender system field some inspiration of how to identify weaknesses.

On the other hand, we also had some opinions and preconceptions based on our own experiences that have not been confirmed by the study. As international students, we considered some cross-culture issue would be involved in music recommendation service. When users move to a new country, for example for exchange studies or work or just travel, we thought they would face problems in finding music in their own language. To give an example, a lot of Chinese songs cannot be found on Spotify. But our interviewees never mentioned that, probably because English is the mainstream language in popular songs, the demand for songs in other languages is rather low. Furthermore, we assumed that the problem of music classification would be an issue. To our surprise, not too much of the discussion dealt with this problem.

Our questionnaire has been designed to gain more information about the recommendation service in Spotify and the user feelings regarding Spotify; it was based on the knowledge of recommendation categories given in our theoretical framework section. According to Balabanovic and ShohamY(1997), content-based recommendation should be targeted at music. But users in our questionnaire do not show a strong interest in this kind of
recommendation strategy. Users trust their friends and followers more than the system itself. Users hold the view that they are interested in experiencing more new music but they do not wish to expand their original music taste (Balabanovic & ShohamY, 1997).

7.1 Conclusion

Our purpose of this thesis is to find out the drawbacks in the Spotify recommendation service. Spotify has been chosen as a case to represent the whole area of existing music recommendation services, with the intention of gaining a series of suggestions that can be of use for this industry in general. After finishing working on the research methods and analyzing the data collected, a deeper understanding of and wider knowledge about the music recommender system area had been gained. By combining these insights with the literature results, we then succeeded in identifying some drawbacks in Spotify during our research work. Here is a summary of these drawbacks.

- Beginning users and long-term users receive the same recommendation service. Users in different stages have accumulated different amounts of usage data for the system to be analyzed. Varied recommendation services should be applied to different users, depending on the respective characteristics.

- Simplex recommendation approach. Every recommendation approach has its own advantages and disadvantages, it may cause problems if barely a simplex recommendation approach is used.

- In most of the music recommender systems, users’ moods are not taken into account, which is one of the most important drawbacks. It then leads to the inaccuracy problem in existing music recommender systems.

- The Spotify music recommendation service lacks an appropriate feedback system that is required to improve the quality of service. In a well-designed feedback system, the feedback operations must not be complicated, as users are not willing to spend too much time on this. A duration of not more than 30 seconds seems to be recommendable.

- The promotion made by Spotify for their music recommendation service is insufficient. As far as user feedback is concerned, we found out that there are some users who never use the “Radio” function in Spotify, even if they have used Spotify for a long time. (“Radio” is the recommendation service provided by Spotify.) Users expect receiving more introduction and informative advertising when they download and update their Spotify version. This should perhaps be considered when revising the Spotify marketing strategy.
7.2 Contribution

Those approaches step by step helped us find out some shortcomings of Spotify which are not only a contribution for Spotify to improve their service but also can help other websites, music industry or web designers to improve the recommender system.

Contribution to Informatics

This thesis reveals several drawbacks in the Spotify music recommender system. Three main findings that have been extensively set out in the previous text are very important to the field of informatics.

- “Beginning users and long-term users receive the same recommendation service.”
- “Simplex recommendation approach”
- “In most of the music recommender systems, users’ moods are not taken into account.”

These three findings may provide suggestions of how to improve music recommender systems by adjusting the recommendation process towards a higher degree of customization.

Besides, for Spotify itself, there are two major contributions.

Recommendation service: The three main findings can be very beneficial for Spotify music recommender system, besides the conclusion drawn from the focus group interviews can be a contribution for the recommendation service in Spotify, especially as far as the Radio function is concerned.

Marketing: A finding from the focus group interview is that one of the reasons why our two interviewees do not use the Radio function is because they do not know what exactly this function implies. A more obvious promotion, of the Radio function should be made.

Our thesis can be useful for those music streaming websites which also offer a recommendation service on their websites. The data collected by the questionnaire can help them to learn some more about the music streaming service and recommendation service markets. The analysis of the focus group interview provides material for the music streaming websites to improve their functions of recommendation service with the aim to render it more customized.

This research may also provide another viewpoint to the system developer to improve the music recommender systems from a user perspective. With respect to system development, new technology and algorithms could be invented and integrated with the existing recommendation services. System developers can adjust the current systems accordingly to meet the requirements of users, thus improving service quality. The conclusions of our study can be regarded as a list of modification options to inspire the system development to create better and more customized recommendation strategies and algorithms.

User experience plays an important role along the whole recommendation service as a part of the informatics area, music recommendation services are paid more and more attention to. Recommendation strategies are expected to expand and comprise more categories to meet users’ requirements. As to music, it is difficult to define clear borders regarding user preference. Music recommender systems need more individual user data to guarantee quality
of service and to be able to compile music list tailored to each user’s taste. This requires a smart and systematic organization of user information. In connection with global marketing, people have the chance of exploring a wealth of information. Information systems design should be based on the wide knowledge and experience available in computer science and management science. Information systems should be more customized and convenient to use to achieve business and management goals. To sum up, our study may serve as a source of inspiration to those concerned with information management in the field of music recommendation services.

7.3 Limitation

In this study, Spotify has been chosen as the research case. However, there are some limitations and inadequacies within the study. Some areas are difficult to investigate and analyze, especially user experience which is hard to describe accurately. The most difficult section is how music recommendation services can match with the users’ distinctive tastes, preferences, moods and environments. These elements are varying and too different to be accommodated within the framework of this thesis. Besides, there are some problems with respect to the representative level of the interviewee group. Most respondents in the questionnaire are international students at the University of Borås. Although they have used Spotify for long time, they have not acquired knowledge and experience in system development and human-computer interaction. Most of them are between 22 and 30 years old, which constitutes a rather narrow sampling range. In any further research, other groups like music DJs, office workers and system developers should be involved and take part in the study.

7.4 Future proposal

At this point, the final stages of our study, we would like to put forward some ideas for further study by other researchers studying in this area. A modern information system should take into account that users’ requirements are constantly changing and increasing and that adaption is necessary. Furthermore, the recommendation function is also a process that is complicated to design satisfactorily. A rigorous logic and accurate design are vital to success. Every approach and every implementation step should be considered thoroughly and comprehensively. Changes in user experience and requirements should be permanently monitored and dealt with directly or indirectly to improve the music recommender system in the long run. In addition to that, new features keep the user base entertained and attract new users. A well-designed feedback system adapted to users’ behavior patterns will make a substantial contribution to enhancing user experience.
8 REFERENCES AND APPENDIXES

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8.2 Appendix A: Questionnaire about the music recommendation service of Spotify.

1) What is your gender? (Male/Female)

2) How old are you?

3) What is your job?

4) What is your attitude to music (You can choose only one option.)
   A. I don't care about the music quality, just use it as background music when doing some other things.
   B. I do care about the music, I have a certain favorite music type and I feel bit uncomfortable when I listen to the music I don't like.
   C. I'm picky about music; I will divinely change the music if it doesn't match with my taste
   D. Other: ____________________________

5) Do you have a specific music taste? (Only one choice)
   A. Yes
   B. Sometimes
   C. Not really
   D. Other: ____________________________

6) What is your habit of listening to music? (Multiple choice)
   A. Shuffle play
   B. Single song repeat
   C. Order play
   D. Other reasons: ______________________

7) Have you used Spotify? (Only one choice)
   A. Yes
   B. No

8) How long have you used Spotify?
   A. Just started
   B. For several days
   C. For several weeks
   D. For several months
   E. For several years
   F. That's my favorite music player
   G. Other reasons: ____________________________________________

9) The reason why you like Spotify.(Multiple choice)
   A. Large collection of music
   B. A lot of friends are using it
   C. Good music quality
   D. It is easy and convenient to use
   E. It is multi-functional
   F. The music recommendation is good
10) What is the frequency of using Spotify?
   A. Everyday
   B. Couples of days a week
   C. Sometimes a month
   D. Barely

11) Which of the following music streaming website/apps have you tried? (Multiple choice)?
   A. Spotify
   B. YouTube
   C. Sound cloud
   D. Pandora
   E. QQ music
   F. DouBan radio
   G. WangYi music (NetEase)
   H. Last. Fm
   I. Beats music
   J. Xiami music
   K. Duo Mi music
   L. Napster
   M. Simfy
   N. Vimeo
   O. Other

12) What music website do you use for music recommendation service? (You can choose no more than three you used most) (Multiple choice)
   A. Spotify
   B. YouTube
   C. Sound cloud
   D. Pandora
   E. QQ music
   F. DouBan radio
   G. WangYi music (NetEase)
   H. Last. Fm
   I. Beats music
   J. Xiami music
   K. Duo Mi music
   L. Napster
   M. Simfy
   N. Vimeo
   O. Other

13) In which way do you get new music to listen to? (Multiple choice)
   A. From ITunes
   B. From blog to get music recommendation
   C. From the recommendation service of the music online websites
   D. From friends' recommendation
   E. From somewhere, I just listen to that and I feel it’s good
   F. From radio
G. From party
H. Other reasons: _________________________________

14) Have you tried the music recommendation service in Spotify? (the Radio, the Related artists, the Discover functions)?
   A. Yes                     B. No

15) Why have you not tried it?
    The reasons: _________________________________

16) How do you feel when using the recommendation service?
    A. Strongly like
    B. Like
    C. Not really like
    D. Dislike
    E. Strongly dislike

17) How long have you used music recommendation service in Spotify?
    A. Several days
    B. Several weeks
    C. Not really like
    D. Dislike
    E. Strongly dislike

18) What is the frequency of using the recommendation service in Spotify?
    A. Always
    B. Some times during a week
    C. Some times during a month
    D. Barely

19) The reason why you try the recommendation function of Spotify? (Multiple choice)
    A. I feel like there is no music I can listen to, I have no idea what to search. I have tried most of the music.
    B. I just feel bored, need some music.
    C. I feel too lazy to search and I trust the music websites that they can recommend nice music which is close to my taste for me.
    D. Those lists other people made can't satisfy me.
    E. I am in some specific mood or environment; I need some music for this
    F. I want to listen to some not mainstream music.
    G. Other

20) Does the music recommended comply with your taste?
    A. Barely
    B. Sometimes
    C. Most of the times
    D. Always

21) What is the problem of the music recommendation service? (Multiple choice)
    A. The music recommended doesn't match with my music taste.
    B. The songs recommended are limited.
C. The related artists does not match with the singers I like.
D. The music recommended doesn't match with my mood at this moment.
E. The "Discover" function causes problem (music recommended based on the music user listened to before or liked before)
F. The "Related artists" function causes problem (when checking the artist's page, similar artists will be recommended)
G. The "Radio" function causes problem (several songs based on one song)
H. Other

22) How do you think about the interface design of Spotify music recommendation?
(Multiple choice)
A. Rough
B. Little attractive
C. Too much advertisement
D. Just so so
E. Pretty good

23) Will you share the music if you feel you like it? (Multiple choice)
A. Yes, I will share to the social network
B. Yes, but I would like to just share privately with my friends
C. No, I won't
D. Any other ways?

24) Will you press "like" when finding a song that matches your taste when listing to music?
A. Never
B. Barely
C. Sometimes
D. Usually
E. Always

25) Is it necessary to add the feedback system into Spotify music recommendation service?
A. Yes    B. No

26) In what way would you like to do the feedback in the music recommendation system?
(Multiple choice)
A. Click “dislike”
B. Comment the recommended music
C. Level the recommended music
D. Answer the choice questions for recommended music
E. Other

27) Do you have any special need of the functions for the music recommendation feedback system in Spotify? What is that?

28) How is the Spotify music recommendation service supposed to work? Do you have any idea or advice?
8.3 Appendix B: Main semi-structured focus group interview

1. What is your attitude of music?

2. If you listen to some music you don’t like, you will accept it, like just listening or change it?

3. How long you have been using Spotify?

4. What is the frequency of using Spotify?

5. Do you know what the recommendation service is in Spotify? They actually have several ways of doing the recommendations.

6. Top lists songs, most of them are so popular, everybody think that’s kind of commercial songs, so maybe not so special for each users, what do you think about that?

7. So your favorite recommendation service in Spotify is Related artist? Or the most used?

8. Have you ever used the "radio" function?

9. Do you think in which way it can be better?

10. What is the reason why you don’t use the "radio"?

11. How much time do you want to spend on the preparation for the better accuracy?

12. What kind of recommendation service you want?

13. Do you have any idea of what is your expecting music recommendation service?

14. What do you think about the interface of Spotify, do you think it’s easy to be used, especially for the recommendation service part?

15. What do you think about the feedback system in the recommendation service?

16. In the "discover" function do you think if they add some feedback it will be better?

17. In which way you think should be the feedback system

18. Do you expect any new function of the recommendation service in Spotify?
University of Borås is a modern university in the city center. We give courses in business administration and informatics, library and information science, fashion and textiles, behavioral sciences and teacher education, engineering and health sciences.

In the School of Business and IT (HIT), we have focused on the students' future needs. Therefore we have created programs in which employability is a key word. Subject integration and contextualization are other important concepts. The department has a closeness, both between students and teachers as well as between industry and education.

Our courses in business administration give students the opportunity to learn more about different businesses and governments and how governance and organization of these activities take place. They may also learn about society development and organizations' adaptation to the outside world. They have the opportunity to improve their ability to analyze, develop and control activities, whether they want to engage in auditing, management or marketing.

Among our IT courses, there's always something for those who want to design the future of IT-based communications, analyze the needs and demands on organizations' information to design their content structures, integrating IT and business development, developing their ability to analyze and design business processes or focus on programming and development of good use of IT in enterprises and organizations.

The research in the school is well recognized and oriented towards professionalism as well as design and development. The overall research profile is Business-IT-Services which combine knowledge and skills in informatics as well as in business administration. The research is profession-oriented, which is reflected in the research, in many cases conducted on action research-based grounds, with businesses and government organizations at local, national and international arenas. The research design and professional orientation is manifested also in InnovationLab, which is the department's and university's unit for research-supporting system development.