Prediction of liking of functions based on the properties of features on social networking sites

Master’s Thesis

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Prediction of liking of functions based on the properties of features on social networking sites

THESIS

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Abstract

When developing a website, feedback from the community is imperative. This is not different for Social Networking Sites (SNS). There is no way however to measure how well the functionality is liked. During this research, a new methodology is developed that will be able to predict the liking of functions based on features of the site. This will hopefully enable the creators of SNSs to better their sites to increase the number of visitors. For this, first the functions have been defined for the 3 current leading SNSs - Facebook, Google+ and LinkedIn. For this list of functions, lists of features were generated by users. With a questionnaire, a dataset is generated, from which the relation between the features and functions can be derived by machine learning. In the end, three achievements are gained: better understanding of functions, features and the relationship between each other, that are common to these three SNSs, predictors, which takes ratings from a questionnaire as input, that predict how much a user likes a function, and a dataset containing ratings from 125 users.

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Preface

During my MSc thesis, I had the privilege to work with a great number of supportive people. I will not be able to mention everybody by name, but I want to mention several people that made this thesis possible. For moral support and help with both psychological and statistical subjects I would like to thank Dr. M.T.I.W. Schüsler-van Hees and Drs. M.G.A. Remeeus. Furthermore, for proof reading and brain storming, I would like to thank Drs. J.F. Schüsler, Mr. Drs. T.T. Schüsler and Drs. J. Schüsler-Lin. Special thanks to Prof.dr.ir. G.J.P.M. Houben and Ir. J.E.G. Oosterman for their contribution to the computer science subject.

Of course I also want to extend my thanks to everybody else who made this thesis possible. In particular, this holds for Chris, Anne and Martien whom I interviewed for the function identification and everybody who filled out the questionnaire for both ‘feature extraction’ and ‘function and feature rating’.

Olaf Schüsler
Delft, the Netherlands
July 19, 2012
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Chapter 1

Introduction

In this introduction, the history of the subject will be described. First an observation of the problem will be stated in ‘background’, followed by the way this was solved in other areas (section 1.2) and how this method could be used on the current observed problem (section 1.3). This observation will next be formalized in ‘Research objectives’ to a formal problem description. The tools that will be used during this research are described in section 1.5, followed by an outline of this thesis.

1.1 Background

Since the start of the Web 2.0, social networking sites (further referred to as SNSs) are gathering popularity [3, 9]. MySpace emerged for example and in the Netherlands Hyves was popular. Currently, three social networking sites dominate the scene, namely LinkedIn, Facebook and Google+.

LinkedIn was the first of the current three large SNSs in May 2003. The target for this SNS is professionals that can have contact with their connections on LinkedIn. You can start discussions, see upcoming events or send personal messages to connections. Many professionals use LinkedIn. In May 2012 it had 150 million users globally.

February 4th, 2004. The Facebook was presented to the world, at that time as a virtual hangout for students, to get to know people with the same, or completely different interests. Now, eight years later, Facebook has a new face and new purpose. It became available for the larger public - about 850 million users globally - and became for many the main source of social contact.

Seven years after the introduction of Facebook, another internet giant decided that it was time for a new social network. Google introduced Google+. Since the introduction, Google+ is called by many a “Ghost town”. Vic Gundotra, Google’s vice president for engineering, however contradicts this: “we have never seen anything grow this fast. Ever” [3]. But, the growth of Google+ seems brighter than it actually is. According to the sitemap of Google, there are currently 195 million user profiles. Of

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1 http://www.socialbakers.com/linkedin-statistics
2 http://www.socialbakers.com/countries/continents
3 http://bits.blogs.nytimes.com/2012/03/06/google-defending-google-plus-shares-usage-numbers/
these 195 however, roughly 25 million have not even been visited after creation 4.

Clearly, the way people look at the different SNSs differs greatly between the various sites. However, what makes Facebook such a powerful site, while Google+ seems to wither? “Some say it [Google+] is a desolate wasteland that is used only by, well, Google employees and a few Google faithful” 5. The functions offered on the three SNSs, like sharing status updates or having friends, seems to be the same [9], but how much a user likes these functions can influence whether he or she will use the site. This means that the liking of functions will not necessarily influence the using of the site, but it is a possibility. Dwyer [8] saw differences in behavior between users of MySpace and Facebook, based on privacy and trust.

By providing the creators of the SNSs with measurements of the liking of the functions, they have a notion of which functions to improve and - hopefully - increase the number of users that use their sites. Measuring this liking of the functions however is complex, because a function is a complex concept. For this measurement a tool or methodology has to be developed or found.

1.2 Related work

Methodologies to measure a complex concept, have been used to measure the performance of online shops. For this measurement, properties of features - which are distinctive or characteristic parts [23] - of the site were used. In several researches [11, 17, 18, 19] concepts on the site of the store, like the overall ease of use, were measured by using features of the site. For this, the researchers gathered features, asked users to rate these and try to find a correlation between the features and the concept. During the literature survey however, no cases with SNSs were found.

In the first two researches [18, 19], Lohse examined the traffic and sales in a cyberstore. He discovered that four “features”, namely: “product list navigation, number of hyperlinks into the store, hours of promotion and service feedback” account to the variance in monthly sales. The third research by Kumar et al. [17], conducted on overall ease of use and personalization, illustrated that demographic subgroups experience “user interface factors (…) related to overall ease of use” differently. In the last paper Hausman [11] constructs a model, based on user interface features, to explain consumer shopping intentions. “The final list contained features comprising computer factors (…) and human factors (…)”.

These four papers show that features can successfully help to measure a complex concept on a website. Kumar [17], however, raises the issue that, because of the difference in demographics for groups, people experience these features differently. According to Kumar the demographics of a group has to be taken into account when evaluating features related to “the ease of use for the target group”.

4http://www.labnol.org/internet/google-plus-users/21035/
5http://bits.blogs.nytimes.com/2012/03/06/google-defending-google-plus-shares-usage-numbers/
1.3 Research motivation

The current observation for the three SNSs is that they all attract a different ratio of users from their target, while they offer the same functions. There is no methodology however for SNSs to measure how well these functions are liked by the users. To tackle this problem, the methodology from the online shops [11, 17, 18, 19] can be used. To apply this methodology, features for a complex concept have to be determined which are measurable and contribute to the complex concept. These complex concepts are the functions that can be found on SNSs. When the features are established, users can be asked to rate properties, like the ease or importance, of these and the liking of the functions, after which a correlation can be found between the liking of the functions and the rating of the properties of the features. From this correlation, a weight for every property can be found, to enable the creators of the SNSs to predict the liking of functions based on just the features. The rating of these functions are necessary to evaluate how well the prediction is later on.

1.4 Research objectives

In the research motivation, a predictor for the liking of functions based on the rating of properties of features of a social networking site is presented. This thesis is aimed towards understanding whether such a predictor can be created and if possible create one. From this goal, the following research question can be derived:

“Can the liking of functions on social networking sites be predicted by the rating of properties of features?”

Example: does the sorting of messages on your wall, have an influence on how much you like to read the status updates? This question can be translated to the feature “sorting of messages on the wall” and the function “reading of status updates”. The predictor should be able to determine how much someone likes the “reading of status updates”, based on, amongst others, the rating of “sorting of messages on the wall”. Due to this influence of for example “sorting of messages on the wall”, it is harder for most people to objectively rate their liking of “reading of status updates”.

To answer this research question, the key concepts first have to be explored. These key concepts are: the functions on a social networking site, user interface features and the prediction of the liking of functions. The subquestions with which the key concepts will be explored are:

- Which functions are common to social networking sites?
- How to detect features that are important to users?
- Develop a method to enable users to rate the properties of features and liking of functions.
- Can a predictor be created that can predict the liking of functions, based on the ratings of properties of features?
These four subquestions will divide the research in four parts. In discussing these parts, the questions will be answered, after which the main research question can be answered.

Furthermore, due to the statement of Kumar [17] concerning the importance of demographics on the understanding of features and functions, several hypotheses are defined. For these hypotheses demographic properties and time spent on the SNS are linked to the liking of functions. The demographic properties that will be used are age and gender, because these will probably have a huge influence on the use of the SNSs and the liking of the functions on the SNS [24]. The amount of time a subgroup spends on a SNS is used, because this will give insight in who uses the site more often. Five hypotheses were formulated to increase the insight in the users of the social networking sites, and which target should be focused on more. If, for example, a subgroup rates functions low, but does not use the site very often, it might not be opportune to enhance the site for this group. The hypotheses to be validated are:

- Older people will give lower grades for liking of functions on social networking sites.
- Younger people are, on average, longer online on the social networking sites.
- Women will give lower grades for liking of functions on social networking sites.
- Women are, on average, longer online on the social networking sites.
- Users that are longer online on social networking sites will give higher scores for the liking of functions.

1.5 Approach

To answer the questions and hypotheses, posted in section 1.4, several tools and techniques will be used. A short overview of these techniques will be formulated in this section. Furthermore, the way these tools are used are described here.

Questionnaires - Questionnaires [4] were created in the second and third part. The goal of the questionnaire in the second part is to explore which features are important to users. This questionnaire will thus be designed to be open and steer the user as less as possible. The questionnaire in the third part was designed to ask people about the rating of certain properties. This questionnaire was designed as a closed questionnaire.

SPSS - For the statistical analysis during part 4 the IBM SPSS program was used. This program offers analytical techniques. For this paper mainly statistical values like correlations and significance and descriptives like min/max and standard deviation were calculated. These values will be used to find a statistical significant correlation for the features and functions and for the demographical features of the population.

KNIME - The Konstanz Information Miner \(^7\) is an open-source program which offers functionality for, amongst others, statistical analysis and machine learning. During the fourth part of this thesis, KNIME will be used to find weights that can be assigned to the properties of the features, so the predictor can predict the liking of the functions. After KNIME has predicted these values, the correlation between the actual values and the predicted values will be calculated.

### 1.6 Outline

In the following four chapters the problem description will be presented first. In chapter 2, this is followed by the research and concluded with a conclusion. In chapters 3 to 5, the problem description will be followed by a detailed description of the methodologies that can be used to answer the problem description and which methodology was eventually chosen. The hypotheses from section 1.4 will be answered in chapter 6. Chapter 7 will evaluate the used methodology and the results gained by this method. Finally, the conclusion that can be drawn which features influence the functions from chapter 2 is presented in chapter 8.

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\(^7\)http://knime.org
Chapter 2

Function identification

The first step in answering the research question is to find out which functions the major networking sites - Facebook, LinkedIn and Google+ - have in common. In the first section, the problem for this part will be formalized, followed by the research that will be done for this part. Based on this research, a conclusion will be drawn in the last section.

2.1 Problem description

In the research question a predictor is sought to get from the rating of properties of features to the liking of functions on a SNS. The definition of a function is: “a high-level action that a user can perform on a social networking site”. In section 1.1 it was mentioned that the three SNSs offer almost the same functions. In this phase, these functions will be identified, and to be able to develop a method that works on all three SNSs, only the functions that all three sites have in common will be used for this. From this goal, the following research question can be deduced: “which functions are common to social networking sites?”.

2.2 Research

During the research in this part, three sources were used; literature, interviews and reviews of the SNSs itself. The literature is used to get a basic understanding of and identify functions on the different SNSs, and to learn about methodologies to identify them. In the next stage, experts were asked about their opinion concerning the identified functions and whether they could identify more. During the review of the site, the common functions, identified in the previous two stages, were filtered and reviewed whether they adhered to the definition used in this thesis.

2.2.1 Literature

On the web, several papers were available that identified functions on the SNSs. According to Ellison [9] one of the functions is that users “identify others in the system with whom they have a relationship” - for reference called ‘friends’. Another function identified by Ellison is the additions of modules on a users profile: “Others, such as
Facebook, allow users to add modules (‘applications’) that enhance their profile”. The last two functions, originally called features, he identified are ‘status updates’ - “Most SNSs also provide a mechanism for users to leave messages on their Friends’ profiles. This function typically involves leaving “comments,” although sites employ various labels for this function.” - and ‘messaging’ - “In addition, SNSs often have a private messaging function similar to webmail.”.

Kietzmann [14] defines the functional building blocks of social media as: “identity, conversations, sharing, presence, relationships, reputation and groups”. ‘Conversations’ can be seen as the equivalent of messaging, ‘sharing’ as status updates and ‘relationships’ as friends. Furthermore, groups can also be identified as a function on the SNSs.

The definition that Kaplan [13] uses, emphasizes the importance of friends and sharing with those friends on SNSs. “Social networking sites are applications that enable users to connect by creating personal information profiles, inviting friends and colleagues to have access to those profiles, and sending e-mails and instant messages between each other. These personal profiles can include any type of information, including photos, video, audio files, and blogs”. Furthermore, Kaplan identifies virtual game worlds as one of the social applications. This is in accordance with the modules mentioned by Ellison [9].

Canfora [5] describes a methodology that is aimed towards reusing functions in software and the source code that defines these functions. This methodology describes that “a function is completely specified by its sets of input and output data and a set of pre- and postconditions”. Canfora uses the control flow through a program to identify the source code for a function. This same methodology can be used on a SNS, where one can identify a function by looking at the input given by a user, following the flow and ending the function where the site gives an output. The function will then be defined by the flow between the input and output.

2.2.2 Interviews

During the interview stage of the research, several experts and experts by experience were asked for their opinion on functions on SNS. One of the experts points out that the status updates should be split into two different functions, due to the fact that these have different features and are used in a different manner. Furthermore, the use of list or groups on the SNS were mentioned, endorsing Kietzmann’s [14] statement.

Two aspects of the SNSs were also mentioned, namely: overall layout of the site and privacy. Due to the fact that these aspects do not directly match with any of the functions from the literature, these concepts will be reviewed during the next stage of the research. Finally, the function ‘events’ was mentioned. This function can be found on both Facebook and LinkedIn, but Google+ has not integrated events with their SNS yet. The list that will be reviewed during the next stage is: “overall layout, privacy, events” and the current list of functions is: “finding friends, groups, posting of status updates, reading of status updates, messaging, applications”.
2.2.3 Review

The list created in the previous stage, that has to be reviewed, will be reviewed with the methodology described by Canfora [5] from section 2.2.1. Overall layout and privacy will be omitted from the function list, because they do not adhere to the description of a function. They do not have a specific input and output, and a flow in between. Events however does adhere to these constraints. Because events were mentioned multiple times, the integration of Google Calendar in the near future was researched on the internet. The Verge found evidence in the Google+ APK for Android that Google might soon be supporting Google Calendar integration on Google+. This means that events are already present on Facebook and LinkedIn, and might soon come to Google+. In the end the function ‘events’ was added to the list of functions common to the SNSs.

During the reviewing of the site, another function was found, namely “general impression”. The input for this function is the general impression of users of the site, while the output is changed behavior, thus impression of the user. This function contains account and privacy settings, thus will also contain the aspects “overall layout of the site” and “privacy” mentioned before. The list that will be used, thus becomes: “finding friends, groups, posting of status updates, reading of status updates, messaging, applications, events and general impression”.

2.3 Conclusion

After the three stages - literature, interviews and review - to identify common functions on a SNS, a list was composed. During the evaluation of the literature several functions were mentioned which were added to the list: “friends, applications, status updates, messaging, groups”. The interviews split the function ‘status updates’ in two, namely “posting of status updates and reading of status updates”. Finally, during the reviewing of the websites, two new functions were added to the list: ‘events’ and ‘general impression’. The complete list that will be used during the next phase is: “finding friends, groups, posting of status updates, reading of status updates, messaging, applications, events and general impression”. These functions will be described as follows:

finding friends: finding friends and having contact with them.
groups: separating friends into groups, to filter people that can see status updates.
posting of status updates: posting status updates on your own wall or on someone others wall.
reading of status updates: reading status updates on your own news feed, a friends wall or your own wall.
messaging: sending personal messages to friends. These can be instant (IM) or email-like messages.
applications: programs that uses the user’s friend list to offer games of functionality with friends.

http://www.theverge.com/2012/5/24/3042292/google-plus-events-local-features
2.3 Conclusion

Function identification

**events:** inviting people from your SNS to an event, and seeing where your friends are going.

**general impression:** general settings of the SNS, like privacy, default groups to which status updates are posted, and overall layout.
Chapter 3

Feature detection

After the identification of the common functions on a SNS, the features have to be detected. The research question will be formulated in the first section, followed by the methodology that will be used to answer the research question. In the last two sections, the results from the implementation of this methodology and the conclusion that can be drawn, are presented.

3.1 Problem description

The features that will be used in the predictor can be defined as follows: “A feature is that which is a distinctive or characteristic part”. With these features, the predictor can predict the liking of functions, based on the rating of the properties of these features. This means however that the features should only be the ones that can be measured, thus that are noticed by the user. This results in the research question: “how to detect features that are important to users?”.

3.2 Methodology

The methodology to find these features is described below. First, the different constraints to which it has to adhere, are given. Next, the method that adheres to this constraints, and how this method will be used is presented.

3.2.1 Constraints

When building the list of features, first the source of information has to be determined. For this, literature or questionnaires can be used:

- **Literature survey**  When building the list of features based on literature, the functions that are being researched should be described in the literature, along with features that are important. In the literature, used for the first part of the thesis, features were rarely mentioned, which makes it hard to build a list of features, based on literature.

- **Questionnaires**  Using the knowledge of users to build a list of features they think are important on a SNS, will give a subjective list of features. However, because of
the interaction with the user, it is easier to access the knowledge and opinion of that user.

Based on the fact that features for the functions found in the previous part are rarely mentioned in the literature, and users can best judge which features are important to them, users will be asked to compile a list. The next step is to determine the type of questionnaire. For this, an exploratory, a semi-exploratory or a confirmatory questionnaire can be used.

**Exploratory** When using an exploratory questionnaire, the respondents are asked for features they think are important on the SNS without telling them that the scope is geared towards functions. When using such a questionnaire, a few risks are taken. First, because the respondent does not know what the researcher wants, there is a risk that the answers do not fit the setup and are useless. Furthermore, when asking for features without defining scope, the respondent might have the feeling that it is too difficult/may take too much time and not fill out the questionnaire. According to NIPO [4] there is a great risk in non-response. The dataset might for example become skewed because only a certain type of respondents take the time to answer.

**Semi-exploratory** With the use of a semi-exploratory questionnaire, the respondent will be pointed in the direction the researcher wants him/her. In this case, the researcher wants the respondent to name features that are related to the eight functions. This way, the features that are mentioned should all be useful in the prediction of the liking of functions. Furthermore, because the respondent gets pointers what to think of, there is a smaller chance that the user will not fill out the questionnaire, due to the time it will take. The major drawback with this strategy, is that the respondents will be steered by the questions, influencing the answers.

**Confirmatory** In the case of a confirmatory questionnaire, the researcher has to provide the respondents with a list of features, for which the respondents will have to tell whether they think these are important. The great risk with this method is that the developer of the questionnaire misses features, thus missing features in the overall process. Furthermore, by asking respondents to fill out such a questionnaire, there is a slight risk that the users will just answer everything with “yes” or “no”. Because of this risk, the dataset might also become skewed.

Reviewing the three types of questionnaires, the semi-exploratory questionnaire answers the questions posed in this part of the thesis best. Last but not least, the method of asking the users has to be chosen. This can either be orally, or via a questionnaire:

**Questionnaires** Questionnaires can be really hard for users to fill out, due to the fact that questions might be multi interpretable. By giving a few hints in the question the questionnaire can steer a little bit, although the risk of biased results is rather low. However, it is easy to get many results, because the gathering of results can be done in parallel.
Interviews

With interviews, the interviewer can steer when the one who is being interviewed deviates too much from the question. The risk with this technique is biased results, because of the steering, and interviewing many people will take a lot of time.

After the evaluation of all three steps, semi-exploratory questionnaires were chosen. Questionnaires were chosen because they have the lowest risk of influencing the user, while with interviews the interviewer can steer too much in the direction he thinks is important. Furthermore, interviews take a lot of time for both the respondent and the researcher. During this phase a questionnaire will be developed to ask users about features they experience on a SNS, and think are important.

3.2.2 Methods

In this questionnaire respondents will be asked to reflect on the features they think are important for the liking of functions. To achieve the best results, the questionnaire was built up as follows: first an explanation was provided, telling the users about the goal of the questionnaire and the difference between functions and features. The different functions were categorized to ensure that the users would look at the different aspects of the SNS. These categories are: “structure, information, programs, friends, settings, other”. In structure and information, the users were asked about the functions “reading/posting of status updates, messaging and events”. In the category ‘programs’ the users were asked for their opinion concerning their use of programs and why they used them/why not. The category ‘friends’ reflected the possibility of finding friends on a SNS and being able to put them in different groups. The last two categories asked about the ‘general’ function from the previous chapter, and whether the user had features to add that did not fit in any of the functions present.

Next, every category started with a question, explaining the users what was expected from them. When constructing these questions however [4], it is important to think about the kind of questions that need to be asked first. Closed questions have the benefit that they are structured and make sure that responses can be compared with each other. During this phase however the users are asked for their opinion about features they like on the SNS. This can not be done with a closed or semi-open question, thus has to be done with open questions. After the kind of question is selected, the type of question has to be picked. Due to the fact that the questionnaire is exploratory the ‘ordinary question’ was picked in favor of a ‘statement’. An example of such a question, is the question for the category ‘structure’, concerning “reading/posting of status updates, messaging and events”:

With regard to lay-out I want you to look at the way Facebook structures its pages. Do you like the columns? What do you think of the ticker, the chat screen at the right side, the ordering of messages, the fact that there are ‘events’, what you can do with it, etcetera.

At the end of this questionnaire, an additional question was added about the functions. The users were asked which of the functions they used on the SNS and whether there were functions that were missing on this list. This list can be used to verify whether
3.3 Results

all functions are used indeed, and which functions are used most, so the creators of the SNSs know what to look for. The complete questionnaire can be found in Appendix B.

3.2.3 Process

The questionnaire is sent to a number of users that ensures that the number of responses is sufficient and diverse. For Facebook 20 users were asked, after which the results were validated by using 15 Google+ and 15 LinkedIn users. These users are from the authors own network. The demographics for these users are shown in table 3.1.

<table>
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<th></th>
<th>Facebook</th>
<th>Google+</th>
<th>LinkedIn</th>
</tr>
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<tbody>
<tr>
<td>Men</td>
<td>10</td>
<td>12</td>
<td>7</td>
</tr>
<tr>
<td>Women</td>
<td>10</td>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>Younger (&lt; 30)</td>
<td>12</td>
<td>12</td>
<td>7</td>
</tr>
<tr>
<td>Older (≥ 30)</td>
<td>8</td>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>Total</td>
<td>20</td>
<td>15</td>
<td>15</td>
</tr>
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</table>

During this phase, the users were asked to fill out the questionnaire in a personalized mail.

“For my Master Thesis I research the influence of a user interface on the liking of social media, in this case Facebook. For this I would like your help (…) It would help me a lot if you could fill out this questionnaire and return it to me as soon as possible.”

After two weeks, a reminder was sent to fill out the questionnaire. Two weeks later the session was closed and only the data that was received during the four weeks was used to calculate the results.

3.3 Results

The composition of the response group is described in table 3.2.

<table>
<thead>
<tr>
<th></th>
<th>Facebook</th>
<th>Google+</th>
<th>LinkedIn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Men</td>
<td>6</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Women</td>
<td>6</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Younger (&lt; 30)</td>
<td>8</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Older (≥ 30)</td>
<td>4</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>12</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>

Following Baarda’s description [2] of qualitative research the information that was received from the 12 Facebook users was transformed to features. The five steps, each saved in a new file, were used as described below:
1. All responses were printed and gathered in one folder.

2. The information that was added to the answers but which was unrelated to the question was removed.

3. Because the questions asked for the features that people liked or disliked, the responses contained the users’ emotions. The features were sorted in a spreadsheet, with the first column for positive, the second for neutral and third for negative responses. These responses were then stripped of emotions.

4. All items from the previous step were put in one column. The items, based on the information contained in the response, were grouped on features. If two responses described almost the same feature, they were grouped, otherwise, they became two separate features.

5. The features that remained were further stripped of emotion or positive/negative connotation.

At the end of the five steps, a list of features that contribute to the complex concepts, function, remained. This list is shown below:

- Finding friends
  1. Finding old friends back
  2. Amount and depth of contact
  3. Finding new friends
  4. Amount of information others can see about you

- Groups
  1. Sharing information with certain people

- Posting of status updates
  1. Amount of meta-data sent
  2. Disabling the sent meta-data
  3. Choosing type of status update
  4. Choosing with whom the status update should be shared

- Reading of status updates
  1. Clarity of news feed
  2. Sorting of status updates
  3. Usefulness of shown recommendations/games
  4. Amount of meta-data with each status update
  5. Division of types of messages

- Messaging
3.4 Conclusion

1. Notifications for messages
2. Clarity of message screen
3. Combination of messages and chats

• Applications
1. Amount of information applications have access to
2. Ease with which applications can access wall

• Events
1. Find personal events
2. Amount of information concerning events
3. Finding public events

• General impression
1. Privacy settings
2. Clarity of pages in general
3. Possibility of personalization
4. Structure of general pages

After the list for Facebook was constructed, the same procedure for LinkedIn and Google+ was followed. These lists where used to validate - guaranteeing that the same features showed up on all three sites - the original Facebook list. These lists matched on most of the features, except for the events, since they were not yet available on Google+ and the ticker that was mentioned on Facebook. The ticker was removed from the list, but the features for the events remained, due to the fact that Google Calendar will probably soon be integrated on Google+.

3.4 Conclusion

The questionnaire that was developed during this phase was able to detect the features, that users thought important, from functions. For this, a questionnaire was designed with ordinary open questions, asking the user per function about what he or she experienced as good or bad while using that function.

This questionnaire was send to 50 users from the network of the author. The number of responses during this phase was rather low. 60% of the Facebook users send their questionnaire back, but for LinkedIn this was only 26% and for Google+ 20%. Because LinkedIn and Google+ were only meant for validation it was enough, but the amount was low.

The responses that were provided were rewritten to a list of features, that were stripped of any emotion. To validate whether all respondents were talking about the same features, the lists of Facebook, Google+ and LinkedIn were compared. In the responses for all three SNSs, the same features were present, thus validating the questionnaire as a method for the research question.
Chapter 4

Feature and function rating

The features found in the previous chapter and the functions from the second chapter can now be presented to the users for rating. The ratings of functions will be used as a ground truth for the predictor in a later chapter. In the first section the research that will be addressed in this chapter will be presented, followed by the used methodology. In the last two sections the results from this research are presented, followed by the conclusion.

4.1 Research description

For the third part of the research a dataset is needed containing the rating of properties of features and the liking of functions. In this part, a methodology has to be devised that can provide such a dataset. The research objective for this part thus becomes: “develop a method to enable users to rate the properties of features and liking of functions”.

4.2 Methodology

The methodology that has to be developed needs to be able to ask users for their liking of functions and their opinion on properties of features. The constraints that this methodology has to adhere to will be described in the first subsection, followed by the implementation and the way the methodology will be executed.

4.2.1 Constraints

The constraints this method has to adhere are: the ratings should be discrete values, the method has to apply on all three SNSs and the number of responses has to be large. The latter is important because the data is needed to create a predictor. Only two methods adhere to these constraints, namely interviews and questionnaires.

Interviews are basically questionnaires which are asked directly to the user. For the questionnaire a closed question with a scale or likert scale can be used, providing discrete data, passing the first constraint. A problem however with interviews is that it is never sure whether the person has time and actually uses one of the SNSs. This means that it will be hard to find the number of users, but that the
method is applicable on all three SNSs. Finally, taking multiple interviews takes a lot of time, depending on the number of interviewers, in this case only one.

**Questionnaires** can be send out to many users, by which the third constraint is met, although the response rate can be lower than with interviews. To ensure that the method is applicable on all three SNSs, an equal number of users has to be selected, ensuring equal input for all three sites. The last constraint is passed in the same way as in interviews, namely by using closed questions.

Out of the two possibilities, the questionnaire meets the demands best. During this part a questionnaire will have to be developed that asks the user for their liking of functions and the rating of properties of features.

### 4.2.2 Methods

The questionnaire, to be developed, will be used to ask users of SNSs for their opinion on features and functions. For the features, the users will be asked to reflect on properties of features, because they give a better insight in the opinion of the users. First the kind of questions has to be figured out. Based on Brinkman [4], closed questions will be best for both the rating of the properties of features and the liking of the functions. Next, the questions have to be devised.

1. The features, created during the previous part, are put in one list, without mentioning the functions they are part of.

2. Properties are used to gather more information about the given features. The list of properties that will be used for this first has to be established. They should reflect the emotions people used during the previous part. Based on the list that was saved, the properties become:
   - Important
   - Easy
   - Pleasant
   - Clear

3. For the different features, which properties will be used, has to be established, as well as how to formulate the questions. The type of questions will be a ‘regular’ question, thus of the form “How important is it to you to find old friends back?”. The feature list from the first part contained 26 features. Of these 26 features, 16 questions have the property ‘important’, 9 the property ‘easy’, 7 the property ‘pleasant’ and 3 the property ‘clear’. Because several features have multiple properties, in the end, there are more questions than features. Which questions got which property can be found in Appendix C.

To ensure that the user knows which property is asked, the questions were formed as full sentences and not as completion of a statement. The functions were not rewritten to questions, but only asked by name. For both the questions and the functions, the terms that were used on the tree sites - for example ‘tags/circles/lists’ - were used.
4. After the questions have been created, the answer type has to be defined. Functions will be graded on a scale from 1 to 10, because the association with a school grade will make it easier to rate. For features, a five-point likert scale is chosen [4]. When someone has to rate, he or she often avoids the extremes. To keep some level of granularity, there should at least remain two answers without the extremes. Because users should not be forced to choose a position, the neutral answer was also introduced. The likert scale for importance will thus become: “not important at all, not important, neutral, important, really important”.

5. Finally, the sorting of the questions has to be established. For this two groups were made, one with all the ‘important’ questions, and one with all the rest. The questions in these groups were ordered by the functions.

The list of functions will be recoded to ‘func’ etc. For future reference, the list of identifiers, to their Dutch and English questions will be shown in table 4.1. Furthermore, the number of questions per function are listed as N.

<table>
<thead>
<tr>
<th>fid</th>
<th>N</th>
<th>English</th>
<th>Dutch</th>
</tr>
</thead>
<tbody>
<tr>
<td>func_1</td>
<td>7</td>
<td>finding friends</td>
<td>Vrienden/contacten/connecties</td>
</tr>
<tr>
<td>func_2</td>
<td>2</td>
<td>groups</td>
<td>Vrienden indelen in lijsten/tags/-kringen</td>
</tr>
<tr>
<td>func_3</td>
<td>6</td>
<td>posting of status updates</td>
<td>Posten van status updates</td>
</tr>
<tr>
<td>func_4</td>
<td>4</td>
<td>messaging</td>
<td>Versturen van berichten</td>
</tr>
<tr>
<td>func_5</td>
<td>6</td>
<td>reading of status updates</td>
<td>Lezen van status updates</td>
</tr>
<tr>
<td>func_6</td>
<td>4</td>
<td>events</td>
<td>Events/gebeurtenissen</td>
</tr>
<tr>
<td>func_7</td>
<td>1</td>
<td>applications</td>
<td>Programma’s/apps</td>
</tr>
<tr>
<td>func_8</td>
<td>6</td>
<td>general</td>
<td>Algemene indruk</td>
</tr>
</tbody>
</table>

For the distribution of these questionnaires a website will be used with a backend where the responses will be stored. Google Docs offers the functionality of creating a questionnaire, which has one URL for all users. This makes it impossible to verify who has filled out the questionnaire, but makes it easier to point the users to the questionnaire. The responses are saved to a spreadsheet in Google Docs, from where it can be downloaded for further analysis.

4.2.3 Process

As stated in the constraints for this method, the amount of responses has to be large. According to van Buuren [25] the size of the dataset, for a research with several subgroups, should be 200-500 for regional researches, and 500-1000 for national researches. Furthermore, the people that fill out the questionnaire should not all have a relation to the author, to prevent biasedness of the population. For this a select group of users from the network of the author was asked to fill out the questionnaire and send it to a subset of their own network. This way, not just people from the authors own network are asked, but also people with different demographical and geographical features. This can be done in two different ways, the questionnaire can either be posted on the respective networks, or be send in a personalized mail to the users.
During this part, both techniques were used. The link for the Google Docs page was posted along with a message on Facebook, Google+ and LinkedIn. Furthermore, a mail was sent to 10 Facebook, 10 LinkedIn and 9 Google+ users. The composition of this group can be found in table 4.2.

Table 4.2: Demographics of asked population during feature rating

<table>
<thead>
<tr>
<th></th>
<th>Facebook</th>
<th>Google+</th>
<th>LinkedIn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Men</td>
<td>4</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>Women</td>
<td>6</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>Younger (&lt; 30)</td>
<td>6</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>Older (≥ 30)</td>
<td>4</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>10</td>
<td>10</td>
<td>9</td>
</tr>
</tbody>
</table>

To keep this group diverse, the group was composed by asking the authors family, friends and colleagues. The population was spread over different geographical areas, and of the 29 asked users, 18 attended the university, 6 attended HBO and the rest attended another form of education, or did not attend further education at all. Furthermore, 10 of the 29 users were married, while 12 were single and the rest was in a relationship.

These users were also asked to send their invitation to a similarly diverse population. After two and four weeks, the users were asked whether they already heard back from their network and asked whether they could send out a new mail.

## 4.3 Results

From the questionnaires that were sent out over the SNSs, only 6 questionnaires were handed in. In the three months afterwards, all data was gathered in the Google Docs file and analyzed. The responses per social networking site are described in table 4.3

Table 4.3: Demographics of response group during feature rating

<table>
<thead>
<tr>
<th></th>
<th>Facebook</th>
<th>Google+</th>
<th>LinkedIn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Men</td>
<td>25</td>
<td>5</td>
<td>30</td>
</tr>
<tr>
<td>Women</td>
<td>39</td>
<td>1</td>
<td>24</td>
</tr>
<tr>
<td>Younger (&lt; 30)</td>
<td>38</td>
<td>4</td>
<td>12</td>
</tr>
<tr>
<td>Older (≥ 30)</td>
<td>26</td>
<td>2</td>
<td>42</td>
</tr>
<tr>
<td>Total</td>
<td>67</td>
<td>6</td>
<td>54</td>
</tr>
</tbody>
</table>

As an extra note, two third of the users lived in the ‘Randstad’, and around one third of the responses came from the rest of the Netherlands. The data received from the 125 users however has to be cleaned before using. If for a questionnaire more than a quarter of the questions was not filled out, the questionnaire will be removed from the list. For LinkedIn 2 questionnaires did not pass the criteria and for Facebook 1, thus were removed. When people for Google+ were asked why they did not hand in their questionnaire, their response was usually that they created an account, but did not use it.
Because the number of responses was too low, Google+ was removed altogether from the research. This leaves the research with 66 Facebook and 52 LinkedIn questionnaires. Next step was to analyze the questionnaires whether the spread of the responses was as expected. If the width of two times the standard deviation ($\sigma$) is too narrow, the answers to the question will be less reliable [25]. In table 4.4, the bandwidth of the functions for Facebook and LinkedIn will be shown and for the questions in table 4.3.

Table 4.4: Spread of response on function likings

<table>
<thead>
<tr>
<th>Functions</th>
<th>Facebook $\mu + \sigma$</th>
<th>$\mu - \sigma$</th>
<th>LinkedIn $\mu + \sigma$</th>
<th>$\mu - \sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finding friends</td>
<td>8.9</td>
<td>7.2</td>
<td>5.5</td>
<td>9.1</td>
</tr>
<tr>
<td>Groups</td>
<td>6.9</td>
<td>4.4</td>
<td>1.9</td>
<td>7.0</td>
</tr>
<tr>
<td>Posting of status updates</td>
<td>8.0</td>
<td>5.4</td>
<td>2.8</td>
<td>9.2</td>
</tr>
<tr>
<td>Reading of status updates</td>
<td>8.6</td>
<td>6.4</td>
<td>4.2</td>
<td>8.7</td>
</tr>
<tr>
<td>Messaging</td>
<td>8.5</td>
<td>6.3</td>
<td>4.1</td>
<td>8.9</td>
</tr>
<tr>
<td>Applications</td>
<td>7.6</td>
<td>5.2</td>
<td>2.8</td>
<td>8.8</td>
</tr>
<tr>
<td>Events</td>
<td>7.0</td>
<td>4.4</td>
<td>1.8</td>
<td>6.3</td>
</tr>
<tr>
<td>General</td>
<td>8.4</td>
<td>6.5</td>
<td>4.6</td>
<td>8.5</td>
</tr>
</tbody>
</table>

Table 4.5: Spread of response on feature properties ratings

<table>
<thead>
<tr>
<th>Questions</th>
<th>Facebook $\mu + \sigma$</th>
<th>$\mu - \sigma$</th>
<th>LinkedIn $\mu + \sigma$</th>
<th>$\mu - \sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>q1</td>
<td>4.6</td>
<td>3.7</td>
<td>2.8</td>
<td>4.1</td>
</tr>
<tr>
<td>q2</td>
<td>4.6</td>
<td>3.7</td>
<td>2.8</td>
<td>4.2</td>
</tr>
<tr>
<td>q3</td>
<td>3.6</td>
<td>2.5</td>
<td>1.4</td>
<td>3.5</td>
</tr>
<tr>
<td>q4</td>
<td>4.8</td>
<td>4.1</td>
<td>3.4</td>
<td>5.1</td>
</tr>
<tr>
<td>q5</td>
<td>4.3</td>
<td>3.3</td>
<td>2.3</td>
<td>4.5</td>
</tr>
<tr>
<td>q6</td>
<td>4.2</td>
<td>3.3</td>
<td>2.4</td>
<td>4.1</td>
</tr>
<tr>
<td>q7</td>
<td>4.7</td>
<td>4.0</td>
<td>3.3</td>
<td>4.7</td>
</tr>
<tr>
<td>q8</td>
<td>4.1</td>
<td>3.4</td>
<td>2.7</td>
<td>4.5</td>
</tr>
<tr>
<td>q9</td>
<td>3.6</td>
<td>2.6</td>
<td>1.6</td>
<td>3.1</td>
</tr>
<tr>
<td>q10</td>
<td>3.7</td>
<td>2.7</td>
<td>1.7</td>
<td>3.6</td>
</tr>
<tr>
<td>q11</td>
<td>4.3</td>
<td>3.5</td>
<td>2.7</td>
<td>4.0</td>
</tr>
<tr>
<td>q12</td>
<td>3.9</td>
<td>2.9</td>
<td>1.9</td>
<td>4.2</td>
</tr>
<tr>
<td>q13</td>
<td>4.1</td>
<td>3.1</td>
<td>2.1</td>
<td>4.2</td>
</tr>
<tr>
<td>q14</td>
<td>3.6</td>
<td>2.5</td>
<td>1.4</td>
<td>3.6</td>
</tr>
<tr>
<td>q15</td>
<td>5.1</td>
<td>4.5</td>
<td>3.9</td>
<td>5.1</td>
</tr>
<tr>
<td>q16</td>
<td>4.7</td>
<td>4.1</td>
<td>3.5</td>
<td>4.8</td>
</tr>
<tr>
<td>q17</td>
<td>4.5</td>
<td>3.9</td>
<td>3.3</td>
<td>4.4</td>
</tr>
<tr>
<td>q18</td>
<td>4.5</td>
<td>3.7</td>
<td>2.9</td>
<td>4.2</td>
</tr>
<tr>
<td>q19</td>
<td>4.2</td>
<td>3.4</td>
<td>2.6</td>
<td>4.2</td>
</tr>
<tr>
<td>q20</td>
<td>3.6</td>
<td>2.9</td>
<td>2.2</td>
<td>4.0</td>
</tr>
<tr>
<td>q21</td>
<td>4.2</td>
<td>3.3</td>
<td>2.4</td>
<td>4.3</td>
</tr>
</tbody>
</table>
4.4 Conclusion

The questionnaire that was developed during this part was used to create a dataset over Facebook, LinkedIn and Google+. This dataset, which for now only contains raw data, has to be reviewed on three points, namely the demographics of the group, the size of the group and the spread of the results:

Demographics When evaluating the demographics of the group, a few things stand out. The number of women that use Facebook is higher than the number of men, while on LinkedIn, this is the other way around. The number of younger people on Facebook is also higher, compared to the number of users on LinkedIn. One logical explanation would be that Facebook is a popular SNS, while LinkedIn is aimed towards professionals.

Size of the group As stated by van Buuren [25], because this research does not separate based on geographical location, the size of the dataset per SNS should at least have been 200. This means that the dataset is too small to draw conclusions for the Dutch population.

Spread of the results According to van Buuren [25] the answers to the questions should be normally distributed. On Facebook, 66% of the answers were normally distributed. For LinkedIn, this was in 84% of the answers. Considering this, the spread of the results is acceptable. This conclusion was drawn from table’s 4.4 and 4.3.

Table 4.5: Spread of response on feature properties ratings

<table>
<thead>
<tr>
<th>Questions</th>
<th>Facebook</th>
<th></th>
<th>LinkedIn</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu + \sigma$</td>
<td>$\mu$</td>
<td>$\mu - \sigma$</td>
<td>$\mu + \sigma$</td>
<td>$\mu$</td>
<td>$\mu - \sigma$</td>
</tr>
<tr>
<td>$q_{22}$</td>
<td>3.8</td>
<td>3.0</td>
<td>2.2</td>
<td>3.5</td>
<td>2.7</td>
<td>1.9</td>
</tr>
<tr>
<td>$q_{23}$</td>
<td>3.4</td>
<td>2.8</td>
<td>2.2</td>
<td>3.8</td>
<td>2.9</td>
<td>2.0</td>
</tr>
<tr>
<td>$q_{24}$</td>
<td>3.6</td>
<td>3.0</td>
<td>2.4</td>
<td>3.6</td>
<td>2.8</td>
<td>2.0</td>
</tr>
<tr>
<td>$q_{25}$</td>
<td>4.0</td>
<td>3.1</td>
<td>2.2</td>
<td>4.2</td>
<td>3.3</td>
<td>2.4</td>
</tr>
<tr>
<td>$q_{26}$</td>
<td>4.5</td>
<td>3.9</td>
<td>3.3</td>
<td>4.3</td>
<td>3.5</td>
<td>2.7</td>
</tr>
<tr>
<td>$q_{27}$</td>
<td>3.7</td>
<td>3.0</td>
<td>2.3</td>
<td>4.0</td>
<td>3.2</td>
<td>2.4</td>
</tr>
<tr>
<td>$q_{28}$</td>
<td>3.8</td>
<td>3.1</td>
<td>2.4</td>
<td>4.1</td>
<td>3.3</td>
<td>2.5</td>
</tr>
<tr>
<td>$q_{29}$</td>
<td>3.7</td>
<td>3.2</td>
<td>2.7</td>
<td>3.8</td>
<td>3.1</td>
<td>2.4</td>
</tr>
<tr>
<td>$q_{30}$</td>
<td>3.7</td>
<td>3.1</td>
<td>2.5</td>
<td>3.6</td>
<td>2.9</td>
<td>2.2</td>
</tr>
<tr>
<td>$q_{31}$</td>
<td>3.9</td>
<td>3.3</td>
<td>2.7</td>
<td>4.2</td>
<td>3.4</td>
<td>2.6</td>
</tr>
<tr>
<td>$q_{32}$</td>
<td>3.6</td>
<td>3.0</td>
<td>2.4</td>
<td>3.9</td>
<td>3.1</td>
<td>2.3</td>
</tr>
<tr>
<td>$q_{33}$</td>
<td>4.0</td>
<td>3.1</td>
<td>2.2</td>
<td>4.1</td>
<td>3.1</td>
<td>2.1</td>
</tr>
<tr>
<td>$q_{34}$</td>
<td>4.3</td>
<td>3.6</td>
<td>2.9</td>
<td>4.4</td>
<td>3.7</td>
<td>3.0</td>
</tr>
<tr>
<td>$q_{35}$</td>
<td>3.9</td>
<td>3.0</td>
<td>2.1</td>
<td>4.0</td>
<td>3.2</td>
<td>2.4</td>
</tr>
<tr>
<td>$q_{36}$</td>
<td>4.1</td>
<td>3.5</td>
<td>2.9</td>
<td>4.2</td>
<td>3.6</td>
<td>3.0</td>
</tr>
</tbody>
</table>
Chapter 5

Predictor creation

For the last subquestion, a predictor will be created to predict the liking of functions, based on the rating of properties of features. The question whether this is possible will be formulated in the first section, followed by an analysis of the raw data from the previous chapter. After this analysis, the results are presented, on which a conclusion can be drawn.

5.1 Problem description

The predictor to be created in this chapter will use a relationship between features and functions to predict the likings of functions. This relationship will be defined as: “the set of weighted properties of features associated with the liking of a function”. The research question for this part will be: “Can a predictor be created that can predict the liking of functions, based on the ratings of properties of features?”.

5.2 Analysis

Because the dataset from the previous chapter still contains raw data, it has to be edited and analyzed before it can be used. This has to be done, due to the fact that some questions, like the amount of time someone uses a SNS per day, were free text for example. First, the answers have to be recoded to discrete consistent data. Second, the dataset has to be analyzed on internal consistency by SPSS. Finally, if all functions are internally consistent, the dataset can be used in the analysis by KNIME for machine learning.

5.2.1 Recoding datafile

The data gathered during the previous part was recoded for use during the analysis. This way, the data has the same unit and can be compared. The category asking the user for the amount of time he or she is on the SNS per day (time_SNS), is recoded to hours. The time the user has an account on the SNS (use_SNS) was recoded to the number of years. The time a user is on the web on average (time_web) was recoded to the number of hours. All three values were written with 2 decimals, with a minimum
5.2 Analysis Predictor creation

value of 0.10. This minimum value was chosen, because the relevance of the difference in time, for less than six minutes is negligible.

The age of users was split into two groups, less than 30 as 0, and greater or equal to 30 as 1. The gender of the user was recoded to 0 for male and 1 for female. The two groups for age and gender were assigned the abstract values 0 and 1 to make the evaluation in SPSS easier. Finally, the zip code was stripped to four digits.

5.2.2 SPSS

To ensure that all questions contribute to the prediction of the liking of functions, the internal consistency of the functions will be calculated with SPSS. The consistency of the questions with the function is calculated with the Cronbach’s Alpha ($\alpha$). This $\alpha$ should be higher than 0.7 for the consistency to be strong. According to Field [10] however, when dealing with psychological constructs, values below 0.7 can be expected due to “the diversity of constructs being measured”. Cortina [7] endorses this statement, by stating that the $\alpha$ depends on the number of items on the likert scale, thus that the general guidelines need to be used with caution.

The Pearson correlation coefficient can also be used as an indication for the internal consistency. This coefficient will show whether the questions of a function belong together. If the coefficient is between 0 and 0.3, the correlation is weak and the questions don’t belong together. If the coefficient is between 0.3 and 0.5, the correlation is moderate. If the coefficient is higher than 0.5, the correlation is strong and the questions belong together. This correlation will be used to evaluate whether the calculated $\alpha$’s are reliable.

5.2.3 KNIME

After the internal consistency has been determined for the dataset, the predictor can be created. In KNIME the different components can be linked together to create this predictor.

- First, the data file is read into the program from a CSV-file.
- To train and test the predictor the dataset has to be split. For this, ten-fold cross validation [21, 16] was used, which means that the dataset was split in ten parts. Nine parts are used to train the multivariate linear regression learner, and one part is used to test the effectiveness of the linear predictor.
- Next, a linear regression learner and regression predictor were added to the program. For each function, the corresponding questions were added to the learners, and the question itself to the predictor. The learner [6, 15] will assign weights to the questions, so that the least square error is lowest [22]. The predictor will use this relationship on the tenth part of the dataset to predict the liking of the functions.
- Finally, a linear correlation part was added to the program. By running the program, the correlation between the predicted values and the ground truth can be calculated, with which the predictor can be evaluated. If the correlation for the predictor is higher than 0.5, the predictor performs good.
This pipeline can be found in Appendix D. After KNIME had run, three Python scripts were used to normalize and evaluate the data. The first two scripts were created to save the files and read the weights, generated by KNIME, for all questions and put them in one file. This had to be done, because these values could only be written to an XML-file, of which only one could exist. The last script was used to divide the iterations. This was done straightforward, by taking the top $k$ iterations and writing them to a new file.

## Results

The analyses described in the previous section are performed on the dataset from the previous chapter. The results from the SPSS analysis are described in the first subsection, followed by the results from the KNIME analysis.

### Internal consistency

To determine the internal consistency of the functions, the Cronbach’s Alpha is calculated and shown in table 5.1. The value for $\alpha$ is the Cronbach’s Alpha for the functions and its questions. If the $\alpha$ would benefit from the removal of a question, the highest new value is shown in ‘new $\alpha$’. If no question should be removed, a ‘-’ is shown.

<table>
<thead>
<tr>
<th></th>
<th>Facebook $\alpha$</th>
<th>New $\alpha$</th>
<th>LinkedIn $\alpha$</th>
<th>New $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$func_1$</td>
<td>.326</td>
<td>.382</td>
<td>.727</td>
<td>.747</td>
</tr>
<tr>
<td>$func_2$</td>
<td>.401</td>
<td>-</td>
<td>.039</td>
<td>-</td>
</tr>
<tr>
<td>$func_3$</td>
<td>.410</td>
<td>.441</td>
<td>.247</td>
<td>.331</td>
</tr>
<tr>
<td>$func_4$</td>
<td>.277</td>
<td>.296</td>
<td>.493</td>
<td>.540</td>
</tr>
<tr>
<td>$func_5$</td>
<td>.500</td>
<td>.512</td>
<td>.724</td>
<td>-</td>
</tr>
<tr>
<td>$func_6$</td>
<td>.697</td>
<td>.764</td>
<td>.696</td>
<td>.777</td>
</tr>
<tr>
<td>$func_7$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$func_8$</td>
<td>.309</td>
<td>.449</td>
<td>.660</td>
<td>.720</td>
</tr>
</tbody>
</table>

The results gathered by the calculation of the Pearson correlation coefficient confirmed the indications from the Cronbach’s Alpha. The significance of the questions that can be removed according to Cronbach’s Alpha show a high value for significance and a low value for correlation with the other questions for the function.

### KNIME

For the prediction of the liking of functions, at first, the original set of questions was used. This prediction was repeated 1000 times, each time picking a random part from the original set. The correlation over these predicted values and the ground truth was calculated, after which the amount of strong positive correlations was counted. Strong negative correlations were omitted, due to the fact that all questions were positively formulated, thus could not have a negative correlation with the function.
Next, the same steps were followed but with the updated questions (‘modified’) from SPSS. For this, in function 1 question 4 was removed, in function 3 question 5, in function 6 question 32 and in function 8 question 15. This was done for both Facebook and LinkedIn, because the questionnaires have to be kept the same to stay comparable. For function 4, no questions were removed, because the improvement for Facebook was gained with the removal of a different question than for LinkedIn. For function 5, no questions were removed, due to the fact that only Facebook improved, and LinkedIn did not. The number of strong positive correlations for both sets of questions, over the 1000 iterations are shown in table 5.2.

<table>
<thead>
<tr>
<th></th>
<th>Facebook</th>
<th>LinkedIn</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>original</td>
<td>modified</td>
</tr>
<tr>
<td>func1</td>
<td>16 %</td>
<td>17 %</td>
</tr>
<tr>
<td>func2</td>
<td>42 %</td>
<td>39 %</td>
</tr>
<tr>
<td>func3</td>
<td>1 %</td>
<td>1 %</td>
</tr>
<tr>
<td>func4</td>
<td>15 %</td>
<td>15 %</td>
</tr>
<tr>
<td>func5</td>
<td>21 %</td>
<td>19 %</td>
</tr>
<tr>
<td>func6</td>
<td>64 %</td>
<td>54 %</td>
</tr>
<tr>
<td>func7</td>
<td>22 %</td>
<td>22 %</td>
</tr>
<tr>
<td>func8</td>
<td>37 %</td>
<td>43 %</td>
</tr>
</tbody>
</table>

The significance of this improvement is calculated over the same dataset of 1000 iterations. This dataset is split into 10 parts of 100 iterations, for which the number of positive strong correlations was used in the calculation of the significance. The significance for both LinkedIn and Facebook can be viewed in table 5.3.

<table>
<thead>
<tr>
<th></th>
<th>Facebook</th>
<th>LinkedIn</th>
</tr>
</thead>
<tbody>
<tr>
<td>func1</td>
<td>.456</td>
<td>.000</td>
</tr>
<tr>
<td>func2</td>
<td>.231</td>
<td>.947</td>
</tr>
<tr>
<td>func3</td>
<td>.520</td>
<td>.022</td>
</tr>
<tr>
<td>func4</td>
<td>.914</td>
<td>.824</td>
</tr>
<tr>
<td>func5</td>
<td>.416</td>
<td>.395</td>
</tr>
<tr>
<td>func6</td>
<td>.004</td>
<td>.028</td>
</tr>
<tr>
<td>func7</td>
<td>.864</td>
<td>.304</td>
</tr>
<tr>
<td>func8</td>
<td>.009</td>
<td>.060</td>
</tr>
</tbody>
</table>

The weights that were extracted with KNIME are shown below. First the weights for Facebook, followed by the weights for the 8 functions of LinkedIn.

**Facebook**

\[
func_1 = 0.35 \times q_1 + 0.23 \times q_2 + 0.01 \times q_3 + 0.48 \times q_{17} + 0.00 \times q_{18} - 0.03 \times q_{19} + 3.99
\]
5.4 Conclusion

When looking at the predictor, created during this last part, the predictor performs better on LinkedIn, compared to Facebook. For both SNSs, four questions were removed from the original questionnaire, due to a low $\alpha$. With LinkedIn, this improves the correlation between predictions and ground truth. With Facebook however, the correlation does not necessarily increase. For function 1, the correlation stays almost the same (1% difference), function 3 stays the same, function 6 decreases (10%) and function 8 increases (6%). The changes for LinkedIn, for functions 1, 3 and 6 are significant, which means that the improvement of the correlation is no coincidence. For Facebook, the changes of functions 6 and 8 are significant.

**Predictor creation**

\[
func_2 = 0.84 \times q_{20} + 0.43 \times q_{21} + 0.70
\]

\[
func_3 = -0.17 \times q_6 + 0.01 \times q_{22} - 0.00 \times q_{23} + 0.13 \times q_{24} + 0.21 \times q_{25} + 6.73
\]

\[
func_4 = 0.23 \times q_7 - 0.64 \times q_8 + 0.44 \times q_{26} - 0.16 \times q_{27} + 7.38
\]

\[
func_5 = -0.27 \times q_9 + 0.18 \times q_{10} + 0.58 \times q_{11} + 0.51 \times q_{28} - 0.48 \times q_{29} + 0.38 \times q_{30} + 4.08
\]

\[
func_6 = 0.50 \times q_{12} + 0.55 \times q_{13} + 0.57 \times q_{21} + 1.28
\]

\[
func_7 = 0.25 \times q_{14} + 3.44
\]

\[
func_8 = 0.62 \times q_{16} - 0.22 \times q_{33} + 0.77 \times q_{34} + 0.27 \times q_{35} - 0.07 \times q_{36} + 2.00
\]
Based on the changes in correlation, and the corresponding significance, the changes in the questionnaire for Facebook should only be adapted for question 8. For LinkedIn, all changes should be adapted. Due to the fact that the questionnaire should be the same for both SNSs, as explicated in section 5.3.2, the changes are adapted for the questionnaires for both sites. When evaluating the final score for the correlation (table 5.2) between the predicted values and the ground truth, the questionnaire for LinkedIn, predicts for 5 functions (functions 1, 5, 6, 7, 8), for half or more of the predictions correct. For Facebook, this happens for only 1 function (function 6). These predictions are done with the formulas, presented earlier in section 5.3.2.

These final scores show that predictors can be created for functions, but when comparing the weights for the respective functions for Facebook and LinkedIn, several things stand out. First, some of the weights are so small, that when rounded, they become zero. Finally, several large weights have a negative contribution to the predictor. This should not be the case, due to the fact that all questions were formulated positively. These observations can be explained by the size of the group and the influence of that on the quality of the predictor. If the scatter plot is too thinly spread, an incorrect line can be obtained. With the increase of the data size, the predictors might become better and more logical. As a last remark, the weights for the predictors differ greatly between Facebook and LinkedIn. This is however, to be expected, due to the fact that these are two completely different SNSs.
Chapter 6

Hypotheses

In this chapter the hypotheses, presented in section 1.4, will be answered using the dataset from the previous chapter. First, the hypotheses will be repeated, followed by the analysis with SPSS. In the last two sections, the results and conclusion will be given.

6.1 Hypotheses

The five hypotheses that will be (in)validated in this chapter are:

- Older people will give lower grades for liking of functions on social networking sites.
- Younger people are, on average, longer online on the social networking sites.
- Women will give lower grades for liking of functions on social networking sites.
- Women are, on average, longer online on the social networking sites.
- Users that are longer online on social networking sites will give higher scores for the liking of functions.

6.2 Analysis

In this chapter, the recoded time values from chapter 5 were used. To answer the last hypothesis, the time a user spends on the SNS (time_SNS) will also be recoded into bins (bin_time_SNS). When a user is less than an hour per day online, the value 0 is assigned. If the user is an hour or more online per day, the value 1 is assigned. These groups were created to be able to split the dataset for the validation of hypothesis 5. To answer the first four hypotheses the dataset will first be split on either gender or on age group. Next, either the time_SNS or the liking of the functions are used to validate or invalidate the hypotheses. For this, the mean and standard deviation will be used. The last hypothesis will be answered by bin_time_SNS, plotted against the liking of the functions.
6.3 Results

Hypotheses

- “Older people will give lower grades for liking of functions on social networking sites” - the age group is plotted against the mean of the liking of the functions. For H0, the mean for all the functions should be lower for users of age 30 or more, than for users younger than 30.

- “Younger people are, on average, longer online on the social networking sites” - the age group is plotted against the mean of time_SNS and time_web. For H0, the mean for users younger than 30 should be higher than that for users of age 30 or more.

- “Women will give lower grades for liking of functions on social networking sites” - the gender is plotted against the mean of the liking of the functions. For H0, the mean for all the functions should be lower for females than for males.

- “Women are, on average, longer online on the social networking sites” - the gender is plotted against the mean of time_SNS and time_web. For H0, the mean for females should be higher than that of males.

- “Users that are longer online on social networking sites will give higher scores for the liking of functions” - the bin_time_SNS will be plotted against the liking of functions. For H0, the mean for all the functions should be higher for bin_time_SNS with value 1.

6.3 Results

The claims of the first and third hypotheses can be answered with table 6.1. In this table, the mean and standard deviation of the time a user is online on the SNS (time_SNS) and on the web (time_web) is plotted against the gender and age.

Table 6.1: Mean and standard deviation for time online over gender/age

<table>
<thead>
<tr>
<th></th>
<th>Facebook</th>
<th>LinkedIn</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>gender</td>
<td>age</td>
</tr>
<tr>
<td></td>
<td>M F</td>
<td>&lt; 30 &gt; 30</td>
</tr>
<tr>
<td>time_SNS</td>
<td>N 25 38</td>
<td>38 25</td>
</tr>
<tr>
<td></td>
<td>μ 0.91 1.39</td>
<td>1.28 1.08</td>
</tr>
<tr>
<td></td>
<td>σ 0.89 1.32</td>
<td>1.25 1.09</td>
</tr>
<tr>
<td>time_web</td>
<td>N 25 39</td>
<td>38 26</td>
</tr>
<tr>
<td></td>
<td>μ 4.28 3.51</td>
<td>4.58 2.69</td>
</tr>
<tr>
<td></td>
<td>σ 3.06 3.00</td>
<td>3.29 2.19</td>
</tr>
</tbody>
</table>

The data for the second and fourth hypotheses can be found in table 6.2. In this table the mean and standard deviation for the liking of the various functions are plotted against the gender and age.

The last hypothesis can be answered with table 6.3. In this table, the standard deviation, mean and number of responses used are shown for each function, over the time online (bin_time_SNS).
### 6.4 Conclusion

- The first hypothesis, whether older people give lower grades for the liking of functions can be validated for Facebook, but is invalidated for LinkedIn. On Facebook, users of age 30 or higher rate all functions the same (difference of .10) or lower than younger users. On LinkedIn however, five out of the eight functions are rated higher (‘friends, groups, posting of status updates, reading of status updates and applications’).

- The next hypothesis - Younger people are, on average, longer online on the social networking sites - is again validated on Facebook, and invalidated on LinkedIn. In the group of users younger than 30, the users are .20 hours longer online on Facebook, compared to the .19 hours less on LinkedIn. The fact that LinkedIn is a professional network might attribute to this fact. Such a network is more important to older people than to younger. This is also confirmed by the time spent on the web (time_web), that states that for both SNSs, the younger people are longer online. This means that older LinkedIn users spent a larger
6.4 Conclusion

Table 6.3: Mean and standard deviation per function over time on SNS

<table>
<thead>
<tr>
<th>Function</th>
<th>Facebook</th>
<th>LinkedIn</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&lt;1h</td>
<td>≥1h</td>
</tr>
<tr>
<td>func1</td>
<td>N</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>μ</td>
<td>7.50</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>1.37</td>
</tr>
<tr>
<td>func2</td>
<td>N</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td>μ</td>
<td>4.94</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>2.42</td>
</tr>
<tr>
<td>func3</td>
<td>N</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td>μ</td>
<td>6.73</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>2.43</td>
</tr>
<tr>
<td>func4</td>
<td>N</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td>μ</td>
<td>6.64</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>1.73</td>
</tr>
<tr>
<td>func5</td>
<td>N</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td>μ</td>
<td>7.21</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>2.00</td>
</tr>
<tr>
<td>func6</td>
<td>N</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td>μ</td>
<td>6.33</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>2.15</td>
</tr>
<tr>
<td>func7</td>
<td>N</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>μ</td>
<td>4.03</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>2.26</td>
</tr>
<tr>
<td>func8</td>
<td>N</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td>μ</td>
<td>6.85</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>1.58</td>
</tr>
</tbody>
</table>

part of their time online on the SNS.

- Hypothesis three, “Women will give lower grades for liking of functions on social networking sites” is invalidated for both SNS. Women, on Facebook, rate four of the eight functions higher, one virtually the same, and three lower. For LinkedIn, the image is similar; three are rated higher, one the same and four lower.

- The fourth hypothesis, which states that women are, on average, longer online on the social networking sites, is validated for Facebook and invalidated for LinkedIn. On Facebook, women are on average .48 hours more online, while on LinkedIn, they are .08 hours less online. When reviewing the time users spent on the web, men are less online on Facebook, and more on LinkedIn. This means that men spend a smaller part of the time they are online, on Facebook, but more on LinkedIn.

- The last hypothesis states that: “users that are longer online on social networking sites will give higher scores for the liking of functions”. This hypothesis is
validated for both Facebook (6 out of 8 functions) and LinkedIn (all functions). This means that users, if they like the functions more, might use the site more. This supports the reason for this research, that the increase of liking of functions will benefit the site.
Chapter 7

Evaluation

During this research several assumptions were made, that will be scrutinized in this chapter. First of all, the research was conducted under the assumption that the liking of functions can be predicted by the rating of properties of features, where features are “that which is a distinctive or characteristic part”. Furthermore, the assumption was made that one questionnaire could be made for all three SNSs. Third, it was assumed that users could be asked to send out questionnaires. Finally, exploratory questionnaires were used to ask users for their view on the features for the various functions. It was assumed that users would understand what was asked of them and were able to give a sufficient subset of features present on the site.

Although predictors were found for the liking of functions that were able to predict correct for half or more of the predictions, this does not prove that these predictors are correct. One of the hints that the predictors might be flawed, are the strange values for some of the weights in section 5.3.2. A way to check whether the predictor is really flawed or not, can be by testing the same functions with a larger dataset. One of the possibilities is, that the scatter plot of feature property ratings is too thinly spread, and it is relatively easy to draw any kind of line. This way, the predictor guesses the correct values for this data set. However, when the set grows, the predictions might prove wrong.

At the start of the project, the assumption was made that one questionnaire could cover the functions for all three social networking sites. Due to this design choice, several features that were only present on one SNS were omitted from the questionnaire. These features however might have greatly contributed to the prediction of the liking of functions. However, if the questionnaire was tailored for one SNS, it would have been impossible to rate other sites with it, thus multiple sites could not have been rated and compared with this tool. In this case, there is trade-off between having a generic, less precise questionnaire, or one more precise questionnaire, for one SNS.

To research whether a predictor could be created from the rating of properties of features to the liking of functions, users were asked to rate these. In the end however, it seemed harder to get enough responses when asking users via both SNSs and mail. According to van Buuren [25], at least 200 users were needed per SNS, while only 125
users responded for both SNSs combined. As described before, this has a direct impact on the results found in this research. With the current method, different networks were asked to fill out the questionnaire. Maybe, another approach would have given better results, like sending the questionnaire to students at the TU Delft. This, would however have had an impact on the population for the questionnaire.

Finally, the anomalies in the predictors might be caused by the understanding of the questions by the users. In one of the questions, users were asked for their opinion of ‘meta-data’. This concept was explained, but users might still have misunderstood, or have a different interpretation of the question/concept. Furthermore, during the feature extraction, users were asked for their opinion on important features for the different functions. The openness of the question might have caused users to only give the necessary answers, because it might otherwise take too much time, or because they did not understand the questions. Furthermore, in the case that users were only asked for features, not related to the functions, more features might have been provided, which could than have been linked to the functions. This way, features that did not seem relevant for functions, but were in fact, could still have been found.
Chapter 8

Conclusions and Future Work

In this chapter, the answer to the research question will be presented. Furthermore, the contributions to the scientific community are presented, as well as possible future work.

8.1 Contributions

This research has contributed to the understanding of SNSs in three different ways, namely:

Functions and features During this research a better understanding of functions and features common to SNSs is gained. For the three SNSs that are currently dominating the field, a list of functions is created that are present on all three, and are noticed by users using the sites. For these functions lists of features are created that are important to users, along with properties that apply to the features. These lists however are only applicable on the two SNSs, Facebook and LinkedIn, as they exist right now.

Questionnaire The questionnaire and the weights that are constructed during this thesis can be used to predict how users like the various functions on a SNS. Creators of SNSs can use this to evaluate their site, and improve it where necessary. However, every improvement round, the weights have to be re-evaluated.

Dataset A (recoded) dataset has been created, with which the weights can be re-evaluated or improved for the current version of the SNSs. This dataset can be updated further during future work.

8.2 Conclusions

The research question, inspired by the methodology used in web shop evaluation, that was posed at the start of this research was: “Can the liking of functions on social networking sites be predicted by the rating of properties of features?” The answer is “yes”, as can be seen in 5.3.2, although there are some side notes. First, and most important, not all functions could be predicted with the same certainty, based on the current dataset. Furthermore, the predictor only works for the current version of the
SNS, which means that the weights for the questionnaire has to be updated every once in a while. Based on the differences in weights however, the improvement of the liking of functions can be measured. This means that based on the properties of features on a SNS, the liking of functions can be predicted, and the creators of the SNSs can even evaluate whether they improved or not.

Based on the hypotheses, the conclusion can be drawn that the population on LinkedIn is more professional than on Facebook. When evaluating age groups, users of 30 or above like the functions on LinkedIn better and spend more time on the site. For Facebook, this is the opposite. Furthermore, although young people are more online on the web, older people spend a greater part of their time on LinkedIn. When considering gender, there is no real difference between the liking of functions on both LinkedIn and Facebook, although women are more online on Facebook and less on LinkedIn. However, when looking at the last hypotheses, when someone is longer online, the scores for the liking of functions are higher. This means that when a SNS has to focus on a target for which they have to improve the site, they best can focus on age, and the time the users are online. If a user spends more time online, there is a large chance he or she already likes the site. However, if the users spends just a few minutes on the site, there is a chance this is because of the liking of the functions.

Furthermore, a side note that has to be made for this kind of research is, that research done with questionnaires is not an exact science. This means that results may vary based on the responses from the users. However, given a large enough dataset, the results presented in chapter 5 will be met.

8.3 Future work

As mentioned before, the dataset used in this thesis was too small. Because the quality of the predictor is based on the size of the dataset from which it learns, an increase of data will benefit the predictor. At least an amount of 200 responses per questionnaire should be reached, although in this case “the more, the better” holds.

A next step in the prediction of the liking of functions, is the automated retrieval of the liking of properties of features. By not having to ask the users for their opinion, but by using an unobtrusive technique, the responses will not be influenced by the interruption of the user. Furthermore, by having questions being retrieved automatically, less questions have to be asked to users, making the chance that users will answer them larger.

To automatically retrieve the opinion of users on properties of features, the researcher should first look at the meaning of the properties and whether these could be modeled to a series of user inputs on the site. The four properties used in this thesis are: “important, easy, pleasant and clear”. These are described below if and how they can be modeled and which technique can be used. Secondly, the necessary computer science, psychological and sociological models, that are used to translate the user input to the rating of the properties of features, need to be created.

- Importance could be modeled by looking at the speed, or the frequency someone
Conclusions and Future Work

8.3 Future work

changes the settings, or performs the action. For example, when looking at the importance of privacy settings, the time the user ‘waits’ to modify the changed privacy settings is an indication of the importance of these settings. These observations could be made with the use of client sided scripts or classical logs [1].

- To model the ease of use, a researcher could look at difference between the ideal time, or route to get from the start of the action to the end of the action. If a user would have to go through 4 pages in 5 minutes to change a setting, but it takes him/her 6 pages and two returns and 15 minutes, it is not easy to change that setting [12]. Again, a client sided script could be used to observe this behavior.

- The pleasance of a feature is hard to rate. Some features can be rated by looking at the time the user spends on a page, but in general this is an opinion that is hard to model.

- Clarity could be modeled by looking at the interaction of the user on the site and how fluent his/her movements are. Lets say, if a user is looking for a specific button and the hot spots for eye tracking [20] are everywhere, except on the right spot, this could be an indication that the page is not clear.

When the questions that can be answered automatically are removed from the questionnaire, the rest of the questions could be built in into the SNS under review, with the questions for a certain function on the pages for that function. This way, only the important questions for that function are asked, ensuring that the user will not get too many questions at once and only the questions he/she has an opinion on. If the questionnaire is built in into the SNS, there is no longer a sample, but all users can be measured. This means that it is easier to predict the liking of the functions for the total population. However, if changes are made to the SNS, people have to be asked again for their liking of the function, to regenerate the weights for the predictor.


Appendix A

Glossary

In this appendix we give an overview of frequently used terms and abbreviations.

Cronbach’s alpha An index of how consistently or reliably a test measures achievement. ¹

Demography a particular section of a population, typically defined in terms of factors such as age, income, ethnic origin, etc., esp. regarded as a target audience for marketing or broadcasting. [23]

Features: A feature is that which is a distinctive or characteristic part.

Functions: A high-level action that a user can perform on a social networking site.

Machine learning Machine learning is a scientific discipline that is concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data, such as from sensor data or databases. ²

Pearson correlation Commonly used similarity function which looks explicitly at the shape of the expression profile, avoiding the need to transform the data beforehand. ³

Predictor: A mathematical model to calculate the liking of functions based on the rating of properties of features.

Rating: The value of a property or condition that is claimed to be standard, optimal, or limiting for a device, engine, etc.; [23]

Relationship: The set of weighted properties of features associated with the liking of a function.

Weights of properties of features: Values assigned to the properties of features, that contribute to the liking of functions.

¹http://web.worldbank.org/
²http://en.wikipedia.org/wiki/Machine_learning
³http://www.genomicglossaries.com/content/algorithms_glossary.asp
Appendix B

Exploratory questionnaire

As an example, the Facebook questionnaire is presented in this appendix. The Google+ and LinkedIn questionnaire look the same, but uses expressions found on these SNSs.

B.1 Facebook

Mijn master thesis heeft als onderwerp “Het bepalen van de kwaliteit van interfaces van social networking sites”. Om de volgende vragenlijst in te kunnen vullen moet je eerst kennis hebben van de begrippen die gebruikt worden in dit onderzoek.


Social Networking sites zijn in mijn onderzoek de webpagina’s van Google+ en Facebook. Beide sites hebben verschillende interfaces (e.g. de iPhone/iPad/Android/Web versie), maar er wordt hierbij alleen gekeken naar de Web versie.

Mijn vraag aan jullie is of jullie kunnen opschrijven wat voor jullie positieve en negatieve punten zijn aan de interface van Facebook (en niet Google+). Hierbij moet je denken aan de indeling die zij gebruiken, de informatie die je erop toekrijgt en welke instellingen je aan kan passen. Dit zijn natuurlijk altijd maar voorbeelden. Ga even naar Facebook, doe wat je normaal gesproken ook doet, maar denk ondertussen na over wat je prettig en minder prettig vindt aan de interactie met de site. Probeer zoveel mogelijk te noemen. In dit geval geldt, hoe meer data, hoe beter.
**Indeling**

Bij de indeling van de site wil ik graag dat je kijkt naar hoe Facebook zijn pagina’s structureert. Vind je hun kolommen goed? Wat vind je van de ticker en het chat venster aan de rechterkant, de structurering van de berichten, het feit dat er “events” zijn en wat je ermee kan, etc.

<table>
<thead>
<tr>
<th>News feed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Messages</td>
</tr>
<tr>
<td>Events</td>
</tr>
</tbody>
</table>

**Informatie**

Onder informatie versta ik alles wat je op je wall te zien krijgt. Vind je het teveel, vind je het te weinig? Wat voor soort informatie moet er wel zichtbaar zijn en wat wil je liever niet zien?

<table>
<thead>
<tr>
<th>News feed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Messages</td>
</tr>
<tr>
<td>Events</td>
</tr>
</tbody>
</table>

**Programma’s**

Facebook staat bekend om zijn sociale programma’s, maar hoe sta jij hier tegenover? Gebruik je wel eens spelletjes, of andere programma’s op Facebook? Waarom wel, en waarom niet? Vind je het nuttig dat de programma’s bij je informatie kunnen en als je het programma niet meer gebruikt zorg je er dan ook voor dat deze er niet meer bij kunnen?

Vrienden

Vrienden zijn natuurlijk heel erg belangrijk op Facebook, het is immers waar het allemaal om draait. Maar welke impact heeft het nou voor jou? Vind je je vrienden er makkelijk te vinden? Wil je al je vrienden erop kunnen vinden? Deel je je vrienden ook in op groepen en doe je aan access control? Zo ja, waarom? Zo nee, waarom niet?

<table>
<thead>
<tr>
<th>Vinden van vrienden</th>
</tr>
</thead>
<tbody>
<tr>
<td>Groepen</td>
</tr>
</tbody>
</table>
Exploratory questionnaire

B.1 Facebook

Instellingen

Bij Facebook, zoals iedere persoonlijke site, kan je instellingen aanpassen. Kijk je hier wel eens naar, of heb je hier wel eens naar gekeken? Welke instellingen vind je nuttig, en welke zou je er liever bij willen hebben? Denk hierbij bijvoorbeeld ook aan het aanpassen van de indeling, of welke informatie je te zien krijgt van anderen.

<table>
<thead>
<tr>
<th>Account settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Privacy settings</td>
</tr>
</tbody>
</table>

Overig

Mocht je zelf nog commentaar hebben op Facebook, waarvan je denkt dat het bij kan dragen aan mijn onderzoek, hoor ik dit natuurlijk graag.

<p>| |</p>
<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
</table>

Functies

Daarnaast zou ik graag willen weten welke functies jij gebruikt op Facebook. Er mogen meerdere geselecteerd worden uit het lijstje, of je mag er zelf toevoegen.

<table>
<thead>
<tr>
<th>Informatie delen</th>
<th>Posts lezen</th>
<th>Chatten</th>
<th>Events beheren</th>
<th>Vrienden zoeken</th>
<th>Groepen</th>
<th>Sociale programma’s gebruiken</th>
<th>Anders:</th>
</tr>
</thead>
</table>

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Appendix C

Feature rating questionnaire

The scale for the functions in section C.2 is from 1 to 10. The likert scale that is used in sections C.3 and C.4 are:

- Geheel onbelangrijk, Onbelangrijk, Neutraal, Belangrijk, Geheel belangrijk
- Geheel niet eenvoudig, Niet eenvoudig, Neutraal, Eenvoudig, Geheel eenvoudig
- Geheel onprettig, Onprettig, Neutraal, Prettig, Geheel prettig
- Geheel niet eenvoudig, Niet eenvoudig, Neutraal, Eenvoudig, Geheel eenvoudig

C.1 Social networking sites

1. Voor welke social networking site vult u de vragenlijst in?
2. Hoeveel uur besteedt u gemiddeld per dag op de door u geselecteerde social networking site?
3. Op welk(e) tijdstip(pen) maakt u gebruik van de door u geselecteerde social networking site?
4. Hoe lang maakt u al gebruik van de door u geselecteerde social networking site?
5. Hoeveel uur besteedt u gemiddeld per dag op het web?

C.2 Functies

1. Vrienden/contacten/connecties
2. Vrienden indelen in lijsten/tags/kringen
3. Posten van status updates
4. Versturen van berichten
5. Lezen van status updates
6. Events/gebeurtenissen
C.3 Belang van kenmerken

7. Programma’s/apps

8. Algemene indruk

C.3 Belang van kenmerken

$q_1$ Hoe belangrijk vindt u het terugvinden van oude contacten?

$q_2$ Hoe belangrijk vindt u het om contact te hebben via de social networking site?

$q_3$ Hoe belangrijk vindt u het om diepgaande contacten op de social networking site te hebben?

$q_4$ Hoe belangrijk vindt u het dat u de toegang tot uw account kunt beperken?

$q_5$ Hoe belangrijk vindt u het gebruik van lijsten/tags/kringen om de toegang tot uw status updates te beperken?

$q_6$ Hoe belangrijk vindt u het om de meta-data die bij een status update mee gepost wordt uit te kunnen zetten? (*Meta-data is informatie over het bericht, zoals de plaats of het programma wat gebruikt is*)

$q_7$ Hoe belangrijk vindt u het dat de social networking site onderscheid maakt in het type bericht dat u wilt versturen?

$q_8$ Hoe belangrijk vindt u de duidelijkheid dat er nieuwe berichten zijn?

$q_9$ Hoe belangrijk vindt u de wijze waarop berichten zijn gesorteerd?

$q_{10}$ Hoe belangrijk vindt u de getoonde status updates uit apps?

$q_{11}$ Hoe belangrijk vindt u de hoeveelheid meta-data over de status update? (*Meta-data is informatie over het bericht, zoals de plaats of het programma wat gebruikt is*)

$q_{12}$ Hoe belangrijk vindt u de overzichtelijkheid van de scheiding tussen verschillende type berichten?

$q_{13}$ Hoe belangrijk vindt u het om persoonlijke events op te kunnen zoeken?

$q_{14}$ Hoe belangrijk vindt u de hoeveelheid informatie die getoond wordt over een event?

$q_{15}$ Hoe belangrijk vindt u het dat apps namens u een status update kunnen posten?

$q_{16}$ Hoe belangrijk vindt u het privacybeleid van deze social networking site?

$q_{17}$ Hoe belangrijk vindt u de overzichtelijkheid van de pagina’s in het algemeen?
C.4 Eenvoud van kenmerken

q18 Hoe eenvoudig is het terugvinden van oude contacten?

q19 Hoe eenvoudig is het om nieuwe mensen te leren kennen?

q20 Hoe eenvoudig is de mogelijkheid om de toegang tot uw account te beperken?

q21 Hoe eenvoudig is het gebruik van lijsten/tags/kringen om de toegang tot uw status updates te beperken?

q22 Hoe prettig vindt u de hoeveelheid meta-data over de status update? *(Meta-data is informatie over het bericht, zoals de plaats of het programma wat gebruikt is)*

q23 Hoe eenvoudig vindt u het om de meta-data over de status update uit te zetten? *(Meta-data is informatie over het bericht, zoals de plaats of het programma wat gebruikt is)*

q24 Hoe prettig vindt u het dat de social networking site zelf het onderscheid maakt in het type status update dat u post?

q25 Hoe eenvoudig vindt u het om aan te geven met wie u een status update wilt delen?

q26 Hoe duidelijk vindt u de overzichtelijkheid van het scherm om berichten te sturen?

q27 Hoe prettig vindt u de combinatie van verschillende type berichten in 1 inbox?

q28 Hoe duidelijk vindt u de overzichtelijkheid van de newsfeed?

q29 Hoe prettig vindt u de wijze waarop berichten zijn geselecteerd?

q30 Hoe prettig vindt u de hoeveelheid meta-data over de status update? *(Meta-data is informatie over het bericht, zoals de plaats of het programma wat gebruikt is)*

q31 Hoe prettig vindt u het om persoonlijke events op te kunnen zoeken?

q32 Hoe eenvoudig vindt u de vindbaarheid van publieke events?

q33 Hoe eenvoudig vindt u het aanpassen van uw privacy settings?

q34 Hoe duidelijk vindt u de overzichtelijkheid van de pagina's in het algemeen?

q35 Hoe eenvoudig vindt u de mogelijkheid om de social networking site aan uw wensen aan te passen?

q36 Hoe prettig vindt u de indeling van de pagina's in het algemeen?
C.5 Overige info

1. Geslacht
2. Leeftijd
3. Postcode
Appendix D

Figure D.1: Structure of pipeline in KNIME