Hyperlink perfume

helping users with different goals to find the right content

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Helping users with different goals to find the right content

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Abstract

StudyPortals' mission is to enable students to find the best studies worldwide by creating websites where users can find detailed information about study programs and explore them in various ways. In the ongoing search for a user interface that assists users to find a university or study that matches their needs, this thesis aims to improve *goal attainment* and *usefulness* of one of StudyPortals' websites; BachelorsPortal. Through the use the *information foraging theory* (IFT), which draws an analogy between the way in which animals forage food and humans forage online information, *reversed information scent* is proposed. Its aim is to be an implementation of the IFT that can be used to improve information scent on websites, by making hyperlinks more similar to the content they refer to.

In the construction of these optimal hyperlink texts, the *goal directedness* (the specificity of the goal) of a user can influence the type of information needed. The theory of *information categorization* is used to hypothesize that users with a higher goal directedness prefer subordinate information categorization (i.e. Bayesian probability theory), while more explorative users prefer a more general, basic information categorization (i.e. statistics). This directedness is hypothesized to be highly dependent on the *expertise* of a user; experts are expected to have more specific goals.

An online experiment was designed for BachelorsPortal's search page where the information scent of the search results was modified. For all 49.000 studies, labels were constructed by using StudyPortals discipline system for the "basic" labels, and an automated labelling process for the "subordinate" labels. In 14 days over 17.600 users experienced the modification, and their behavior was analyzed. Moreover, 140 participants participated in a questionnaire aimed to measure goal attainment and usefulness.

The results show significant results when information scent is increased with basic information categorization: users spend less time searching and are more engaged with the studies they click on compared to users who see links with no information scent. The users viewing increased information scent with subordinate labelling show opposite behavior. Combined with an analysis of the goals indicated by users on the survey, we suggest that the average directedness of users on BachelorsPortal is too low for the subordinate information scent to have a positive effect. Subjective measures show no support for the hypothesis regarding subjective behavior, we suggest that the modification might be too small to show an effect on the perception of users in the small sample collected.

Overall this work shows the potential of reversed information scent to increase the goal attainment & usefulness on informational websites. A number of interesting directions could be explored in further research, such as the algorithm for label generation and a more solidly designed subjective measurement. It suggests that directedness is an important factor to consider when aiming to increase information scent, and picking the correct level of information abstraction based on user characteristics might improve desired results.

Contents

1 Introduction

This chapter is a general introduction to this thesis, starting with an introduction overview of the website BachelorsPortal. It continues with explorative research on this website, from where a problem definition and a possible solution is defined. Finally, the methodology and its results are introduced and the organization of this thesis is described.

1.1 BachelorsPortal

The complexity of choosing the right study and university has been growing significantly in the last decades. Through the internet hundreds of thousands of programs are accessible, leaving it up to students to find that one study that matches their needs best. StudyPortals aims to assist users in making this choice by creating websites where users can search, explore and find detailed information on all studies worldwide. One of these portals is BachelorsPortal and contains over 49.000 bachelor programs. On this website, users can take different approaches to explore their interests; studies are grouped in specific pages per disciplines (i.e. law or computer science), country and university. Besides these page types, there is a home page, users can manage their account on a number of account pages, and study-options pages exists, where studies from a certain discipline in a certain country are displayed (i.e. all biology studies in Germany).

Table 1 shows the number of page visits for specific page types over 4 weeks. It shows the effect of StudyPortals' underlying strategy to attract users with high quality information pages, led them to the search page (the "heart" of the website with 15.4% of all page visits) and let them explore studies (the main content with 34,2% of all page visits) from there.

	Page views	**Percentage of all page visits**
studies	*179,673*	34.24%
search	*80,757*	15.39%
study-options	*50,460*	9.62%
account	*47,874*	9.12%
universities	*42,317*	8.06%
countries	*41,334*	7.88%
home	*37,254*	7.11%
disciplines	*28,764*	5.48%
articles	*11,025*	2.10%

Table 1: overview of visits per page type of BachelorsPortal users between 12-28-2015 & 01-24-2016. In this period, 138,996 unique users had a total of 173,835 sessions on the portal.

1.2 Explorative analytics

Previous research that might assist in the design of a study choice process shows a wide variety of selection criteria of users choosing a study; where some may focus on market perspective and pricing (Maringe, 2006), others may look at properties like university reputation and location (Smith, Agahi, Price, & MatzDort, 2003). Designing an interface that supports all these different goals is challenging in itself, but becomes even larger when accounting for the decision phase where users are in. Some might be very explorative and use search results to make up their mind, while others can be highly directed in their search (Payne, Bettman, & Johnson, 1993; Rose & Levinson, 2004).

Explorative analysis initially focused on big data handling (described in appendix chapter 12) and showed that the search page was a critical point in the user journey. The link they pick in the search result tiles such as the one presented in Figure 1 was a significant predictor for

their preference towards studies, countries or universities. Users that clicked on a university in a search result viewed more university pages after that (μ=2.6, σ=3.5) compared to those who clicked on study- or country links (μ=0.3, σ=1.5). Explorative A/B tests were used to confirm these findings in terms of *conversions* (users clicking on buttons linking to external websites from universities) as they appeared to be a good indicator of a user having found something interesting.

One experiment ran between 06-11-2015 & 19-11-2015 and removed the link to the country (i.e. "Poland" in Figure 1) while keeping the text. This was initially expected to reduce the distraction from finding a suitable study and lead to more conversions. The opposite was found, with users converting significantly less (1.39 times per user compared to 1.47 for the baseline). The same drop happened in another condition where the link wouldn't redirect to the country page, but filtered the search results to that country (also 1.39 conversions per user). Though quite trivial, we concluded that users might be most interested in the types of links they click on. Moreover, the more specific the link they interact with, the more interest they seem to show.

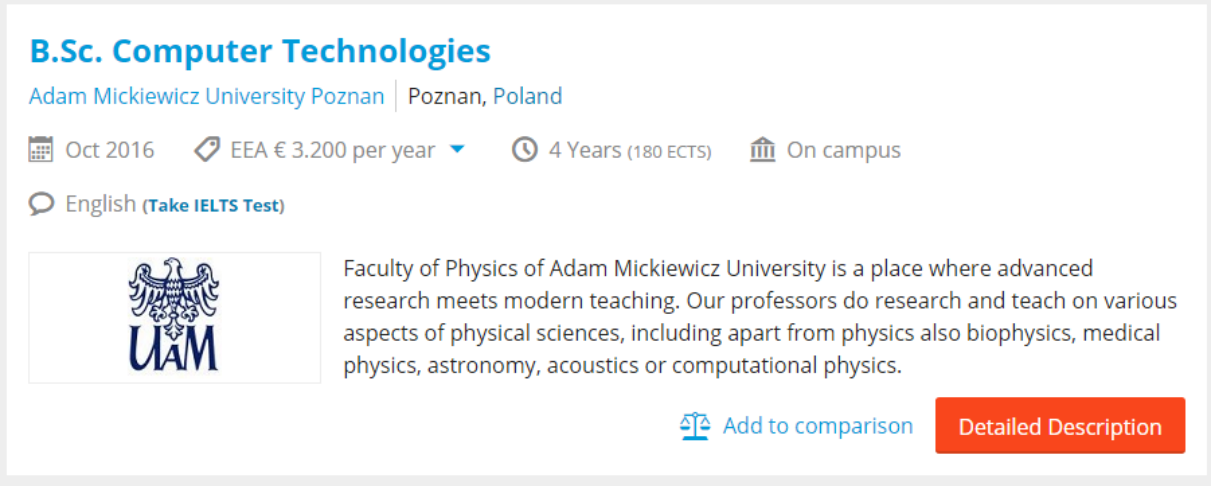


Figure 1: example of a sponsored study being presented as search result on the search page of BachelorsPortal.

A visual scan of the search results, such as the one presented in Figure 1, shows a distinct presence of the red button in the right bottom corner, drawing attention by using a very distinct and bright color. This button is used by BachelorsPortal to give more presence to *sponsored* search results (4.7% of all studies at 27-04-2016), who besides the red button also get priority in result ordering, images in the study search tiles and conversion buttons on their study pages. This results in 45.7% of all shown search results to be like the ones in Figure 1, the other studies are shown as "normal" results, an example being shown in Figure 2. The content of the button, *Detailed Description*, is the same for all studies. This presented an interesting opportunity as it is very generic, while early experiments suggested a more specific link might assist users more than the current one.

Figure 2: example of a non-sponsored study being presented as search result on the search page of BachelorsPortal.

1.3 Problem definition & proposed solution

At this point the interest of the search page was threefold. Firstly, it acted as the center of the website, meaning even a little improvement could have an interesting effect for BachelorsPortal and its users. Secondly, improving the search page was one of the intentions of BachelorsPortal at the time of the start of this thesis: the *bounce rate* (percentage of page views that were closed before interacting with the page) of the search page was high (24.9% in October & November 2015). This showed that the search page might have had more potential then it delivered. Finally, the explorative analysis suggested that the search page was a central place of the website from where users picked clear paths into the website, and clear communication of these different paths could help them reach the information they wanted. These insights formed as base for the problem definition:

> *BachelorsPortal's search page does a good job at letting users find content they are interested in, but uses a very generic text to describe their most distinct element on the search page. By doing so they might prevent users from finding studies they are interested in, potentially missing out both from commercial- and user goal perspectives.*

The *information foraging theory* (Pirolli & Card, 1999) predicts that users follow links that have a high similarity with their goal, and is used as underlying theory to solve this problem. By making the links more informative we hypothesize that it becomes easier for users to pick interesting search results, and the probability that they attain their goal increases. One of the main additions of this thesis compared to previous IFT research is the use of *information categorization* (Johnson & Mervis, 1997) to split the needs of novices and domain experts. Where novices benefit from simpler, more abstract representation of information, experts might benefit from more specific and complex information, as their search goals will generally be more complex. Based on these theories we suggest that calculating specific labels for each study and using those labels as texts instead of the current "Detailed Description" could assist in addressing the defined problem.

1.4 Methodology & Results

An auto-labelling process was constructed for this purpose with the aim to find labels that described the content of every study as good as possible. It matched labels from a public label set with all 49.000 studies from BachelorsPortal by using similarity metrics comparable to the ones used by the information foraging theory. These labels were then used to replace the "Detailed Description" text in an online experiment, which ran on BachelorsPortal for 2 weeks. The user behavior was analyzed, as well as the subjective measures from 145 users who participated in the survey.

Overall we found support for most hypotheses concerning behavior: buttons containing custom labels decreased the search time and number of studies users clicked on, while increasing the time spend on the chosen study pages and conversion. No effects were found in the subjective measurements; we suggest that the effects might be too small to show an effect on user perception in the small sample of survey responses we collected. Overall the impact seems to be small but significant and makes a strong suggestion that the current methodology can be generalized and used to help users find the information they are looking for quicker and more successfully by improving generic hyperlinks.

1.5 Thesis Organization

This thesis is organized in a number of chapters & appendixes. Chapter 2 will discuss the related literature and previous experiments regarding hyperlink optimization and constructs a conceptual idea for implementation. Chapter 3 will follow up with research questions and hypotheses and chapter 4 describes the auto-labelling process used for this thesis. Chapter 5 describes an experimental design which uses these labels to modify the buttons in the search results. Its results are presented in chapter 6 and discussed in chapter 7.

A number of chapters are appended to this work as they contain relevant information but do not directly fit into the main body. Chapter 10 presents an elaborate overview of StudyPortals and BachelorsPortal and chapter 11 presents the methodology and results of the pilot that was run prior to the main experiment. Finally chapter 12 presents an overview of the data used in this thesis, as well as a proposal on how to scale the gathering, processing and analytics at StudyPortals from an engineering perspective.

2 Theoretical background

Navigating the web in search for a piece of information is a complex task, where an overwhelming amount of links, buttons, images and other web elements have to be evaluated to find the information that satisfies the goal of the user. Users with different levels of expertise and varying goals may process these web elements differently, resulting in different needs. The aim of this thesis is to improve navigation and simplify this process, in particular by making links more specific and similar to their underlying content.

This chapter will cover the theoretical background of these topics and propose a method which can be used to apply this theory to the search result buttons on BachelorsPortal. Firstly, tagging research will be covered and while it potentially could assist in solving the current search page problem, we suggest the use of the information foraging theory fits better. Furthermore, the concepts of information categorization, expertise and goal directedness are introduced as they might play an important role in the type of information users prefer. Finally, a number of subjective measures are introduced that might be useful in this thesis.

2.1.1 Tagging

When trying to summarize bodies of information in just one or two words, a straight-forward concept is that of *tagging*; attaching pieces of metadata (often in the form of a couple of words) to other data. Tagging became popular with the rise of Web 2.0, where users started to organize content with tags. It's still widely used in blogs and Q&A platforms like Quora and Stack Overflow, as the relatively small user-effort of adding a tag helps these platforms organize their content, making it easy for other users to explore. Obviously this is possible due to the large community, manually tagging 49.000 studies for a research project however is much more tedious and biased, and would benefit from automation.

Auto-tagging documents based on their content has been studied before: one of these studies (Sood, Owsley, Hammond, & Birnbaum, 2007) tried to auto-generate tags for a given blog post, and found that their system could construct relevant, meaningful tags. Good results are also achieved with summarizing email contents into keywords (Dredze, Wallach, Puller, & Pereira, 2008). Algorithmic improvements are being made in a recent study that attempted to auto generate tags for questions on Quora (Nie, Wang, Shen, & Chua, 2014). All these works solve a *classification* problem, where the first two use a *supervised* approach the latter uses *unsupervised* methods. As the naming suggests, supervised only predicts tags based on tags it has been trained with before, while an unsupervised approach can also discover new tags and is preferable in most situations, as it can adopt to changes in content over time. Another approach to tagging is *clustering*, where similar documents are being clustered and the underlying concept is used as tag. One of these systems is the matured *carrot2*[1], a web search engine that clusters webpages and uses the tags that describe that cluster as filters.

When comparing these tagging works with the problem statement of this thesis, it was found that the purpose of tagging is organization and resulting discovery, while this problem searched for a solution that would guide users based on their goal. While these ideas will sometimes overlap, a tagging system works best if a tag has a reasonable amount of documents attached to it. A Q&A site with as many tags as questions will not benefit from the tags. This thesis does not aim to solve this organization, and might even benefit from a larger number of tags, as it can help users to distinct links and pick the one closest to their goal. So while tagging is closely related, the use cases are too different for tagging research to be

[1] http://search.carrot2.org/

directly applicable to this thesis. Methodologies like the relevant tag selection described in (Nie et al., 2014) and tag concept validation in (Sood et al., 2007) can however be applied.

Besides tagging, a large body of literature exists in the topic of website navigation optimization. A large proportion of that is devoted to personalization, i.e. changing navigational structures based on user behavior (Lin & Liu, 2008), recommending content (Mobasher, 2007) and finding usability problems and opportunities. Improving hyperlink quality however is not found in current literature.

2.2 Information Foraging Theory

A theory that might be a better fit is the *Information Foraging Theory* (IFT), which draws an analogy between the ways animals forage food and users forage information. The core hypothesis of the IFT is that living creatures optimize reward-effort, whether they are animals looking for food or humans looking for information (Pirolli & Card, 1999). Animals do so by identifying patches of food, for instance a bush of berries, which they forage until more *utility* can be gained from finding a new patch. Effectively, they consume a patch until the time to look for a new patch and its expected payoff is lower than the remaining payoff in the current patch. When locating a patch (either by initial search or by switching), the scent is very important as it is the main driver in locating potential food.

IFT hypothesizes humans behave the same way when looking for information on the web, hopping between different informational patches in pursuit of a certain goal. Like animals, they do so by scent, which IFT defines as the similarity between a textually defined goal of a user and a hyperlink text. This similarity is strongly correlated with the interest of a user in that link, and hence the clicking probability. If a link delivers other information than its scent promised, or scent of a patch drops below the average scent of all previously seen patches, users are very likely to leave.

The value of this theory for information foraging has been proven in a number of experiments and systems being described in research the last 15 years. Most of this research has been done by created automated systems that walk through a website based on these concepts, often motivated by some predefined goal. They analyze link texts and compute similarities with its predefined textual goal via *latent semantic analysis* (LSA). The higher the similarity between a link and the goal, the stronger the scent, and the more likely that the system will pick that hyperlink. The paths taken by these systems is strikingly similar to paths taken by real users with the same goal (Fu, Avenue, & Pirolli, 2007).

LSA, an important concept in IFT, is a natural language processing technique which converts text documents to word count vectors, and reduces those vectors to a predefined number of components. This allows a document to be described in underlying concepts, which has the psychological concept that different words (i.e. “vector” & “array”) can be considered very similar. It also reduces the number of features while keeping most variance, which is desirable form a computational perspective.

LSA is a technique often used for text processing (Dredze et al., 2008; Geiß, 2011; Gomez & Moens, 2014; Rott & Cerva, 2014), especially in the field of information scent (Blackmon, Polson, Kitajima, & Lewis, 2002; Chi et al., 2003; Fu et al., 2007). Related techniques such as probabilistic LSA (pLSA) and *Latent Dirichlet Allocation* (LDA) improved upon LSA and have been compared extensively (Maguitman, 2008; Niraula, Banjade, Dan, & Rus, 2013). They differ conceptually: LSA assumes that words and documents can be represented as points in Euclidean space. On the other hand, LDA and pLSA assume that the semantic properties of words and documents are expressed in terms of probabilistic topics

(Maguitman, 2008). As none of the 3 is superior to the others in all circumstances, LSA is a good choice as it's often used in IFT research.

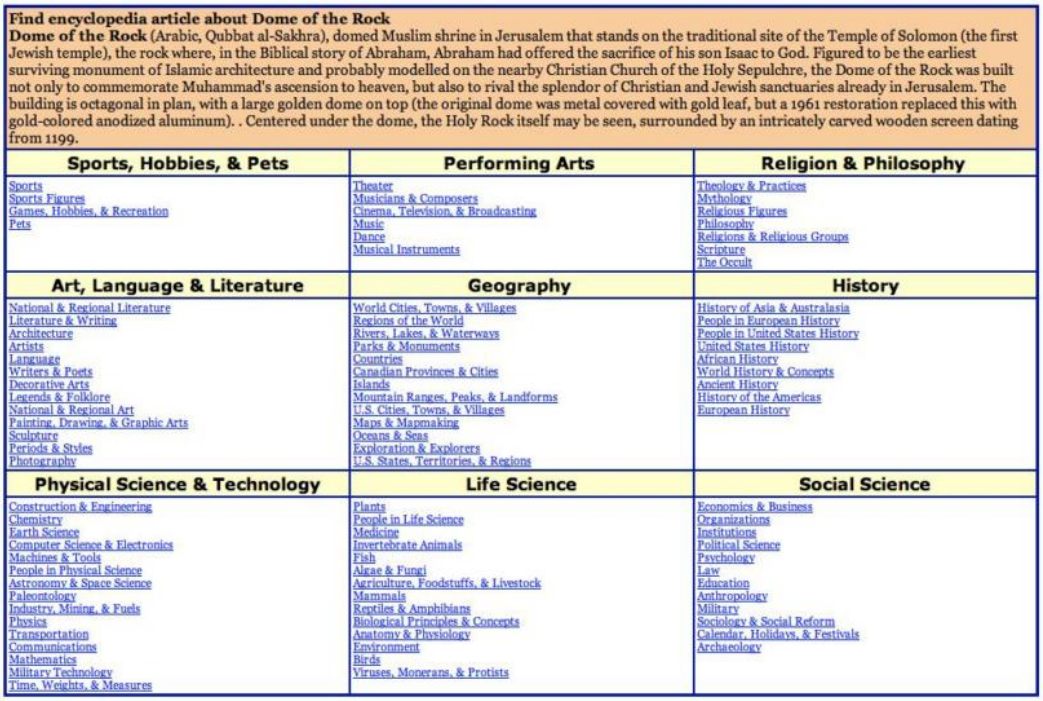
Quite some work directly and indirectly related to IFT has been published, which will be covered in the following subchapters.

2.2.1 Previous work

Two streams of related automated systems have been involved into automated web analysis. *CoLiDeS* on the one hand attempts to predict information foraging behavior at the level of individual information pages and it was founded upon the Construction-Integration model of text comprehension, action planning and problem solving (Kintsch, 1988). Its predecessors aimed to learn and explore complex GUI's by Kintsch model, but not in an automated way. It considers one page to consist of several information patches: humans will first search for the most interesting patch on a page, and from there continue to look for the most interesting link (Blackmon, Polson, & Kitajima, 2000). Based on CoLiDeS is the *Cognitive Walkthrough of the Web* (CWW): a partially automated usability evaluator that identifies website navigational problems (Blackmon, Kitajima, & Polson, 2005). It works on a predefined goal and website structure, and it's still online for those interested[2].

Secondly, the *SNIF-ACT* (Fu et al., 2007) branch directly originates from the ACT-R computational model from the original IFT research done by (Pirolli & Card, 1999). In contrast to CoLiDeS, SNIF-ACT considers information patches to exist on many levels, for example different websites or different subsets of webpages, but treats a single page as a complete patch. Therefore, it is better in predicting navigation between webpages compared to CoLiDeS, but can be improved by considering the way in which links are presented in a webpage. It processes links all in the same way, while it may be obvious that users looking at a website like Figure 3 will not. All links under "history" for example will be barely interesting for users looking for soccer clubs. This within-page patch effect has been shown by a recent study dubbed the *web party effect* (Rigutti, Fantoni, & Gerbino, 2015) and shows to be a valuable addition to CoLiDeS.

[2] http://autocww2.colorado.edu/~brownr/v2/



Find encyclopedia article about Dome of the Rock

Dome of the Rock (Arabic, Qubbat al-Sakhra), domed Muslim shrine in Jerusalem that stands on the traditional site of the Temple of Solomon (the first Jewish temple), the rock where, in the Biblical story of Abraham, Abraham had offered the sacrifice of his son Isaac to God. Figured to be the earliest surviving monument of Islamic architecture and probably modelled on the nearby Christian Church of the Holy Sepulchre, the Dome of the Rock was built not only to commemorate Muhammad's ascension to heaven, but also to rival the splendor of Christian and Jewish sanctuaries already in Jerusalem. The building is octagonal in plan, with a large golden dome on top (the original dome was metal covered with gold leaf, but a 1961 restoration replaced this with gold-colored anodized aluminum). . Centered under the dome, the Holy Rock itself may be seen, surrounded by an intricately carved wooden screen dating from 1199.

Sports, Hobbies, & Pets	Performing Arts	Religion & Philosophy
Sports Sports Figures Games, Hobbies, & Recreation Pets	Theater Musicians & Composers Cinema, Television, & Broadcasting Music Dance Musical Instruments	Theology & Practices Mythology Religious Figures Philosophy Religions & Religious Groups Scripture The Occult
Art, Language & Literature	**Geography**	**History**
National & Regional Literature Literature & Writing Architecture Artists Language Writers & Poets Decorative Arts Legends & Folklore National & Regional Art Painting, Drawing, & Graphic Arts Sculpture Periods & Styles Photography	World Cities, Towns, & Villages Regions of the World Rivers, Lakes, & Waterways Parks & Monuments Countries Canadian Provinces & Cities Islands Mountain Ranges, Peaks, & Landforms U.S. Cities, Towns, & Villages Maps & Mapmaking Oceans & Seas Exploration & Explorers U.S. States, Territories, & Regions	History of Asia & Australasia People in European History People in United States History United States History African History World History & Concepts Ancient History History of the Americas European History
Physical Science & Technology	**Life Science**	**Social Science**
Construction & Engineering Chemistry Earth Science Computer Science & Electronics Machines & Tools People in Physical Science Astronomy & Space Science Paleontology Industry, Mining, & Fuels Physics Transportation Communications Mathematics Military Technology Time, Weights, & Measures	Plants People in Life Science Medicine Invertebrate Animals Fish Algae & Fungi Agriculture, Foodstuffs, & Livestock Mammals Reptiles & Amphibians Biological Principles & Concepts Anatomy & Physiology Environment Birds Viruses, Monerans, & Protists	Economics & Business Organizations Institutions Political Science Psychology Law Education Anthropology Military Sociology & Social Reform Calendar, Holidays, & Festivals Archaeology

Figure 3: example of a webpage with segmented links; a user will make a preselection of links based on the similarity of the headers and his/her goal.

A number of studies and experiments have been built on these frameworks, a good introduction is the literature overview of (Mccart, Padmanabhan, & Berndt, 2013). They showed the effect of information scent in objective measures such as page views and session times on websites with small user bases. This is an addition to the more traditional information scent research, that have already shown the positive effects of high information scent. Overall, users experience higher goal attainment & site satisfaction (Pirolli & Card, 1999), experience less stress (Moody & Galletta, 2015) and choose the correct links quicker, with more confidence and less errors (Tselios, Katsanos, & Avouris, 2009), reducing the probability of leaving the site unsatisfied (Nielsen, 2003). Due to these highly desirable effects for informational websites, fully automated systems besides CWW have been developed that analyze and identify information scent problems on websites, one of them being CogTool[3] (Teo & John, 2008).

[3] https://github.com/cogtool/cogtool

2.3 Reversed information scent

Given the potential benefits of optimizing links using the IFT, it seems strange that some websites, including BachelorsPortal's search page, still contain links without specific scents. IFT predicts and points out the problem spots with information scent exceptionally well, but fails to define a solution that can be used to solve them. One of the problems is that the theory approaches the user navigation from a theoretical, top-down perspective. From this perspective, users (or computer systems) get a written assignment and a controlled environment. To illustrate, consider the "city task", used in for the SNIF-ACT system (Fu et al., 2007) which provides the following assignment:

> *You are the Chair of Comedic events for Louisiana State University in Baton Rouge, LA. Your computer has just crashed and you have lost several advertisements for upcoming events. You know that The Second City tour is coming to your theater in the spring, but you do not know the precise date. Find the date the comedy troupe is playing on your campus. Also find a photograph of the group to put on the advertisement.*

While the assignments are carefully designed to closely represent real-world problems, this approach creates several impracticalities when looking for improvements in actual websites. User goals might be unknown and expensive to discover, and differ in specificity from the highly directed goals used by IFT research. Moreover, IFT research uses laboratory settings and motivates users extrinsically to find a given goal. While some research (Mccart et al., 2013) overcome most of these issues by analyzing real user data, it still leaves an implementation gap and does not show the effects of information scent modification, both on behavior and subjective measures.

Based on the potential improvements of IFT that can be used to solve the stated problems of BachelorsPortal, we propose a way to construct higher information scent. Rather than trying to find the most attractive scent on a webpage given a goal, a bottom-up analysis can be used to construct scents based on the content they refer to. The aim then is not to analyze how users will behave given a certain goal, but to create strong information scents that will lead users to the most relevant content, without the system knowing their goal.

If this *reversed information scent* works as suggested, users should be able to better identify what links are relevant for the information they are interested in and reach higher goal attainment. This should result in users getting to their goal with a higher success rate, with less clicks and time spend searching, resulting in a better user experience as well as improved business metrics for StudyPortals.

For BachelorsPortal, IFT does not only explain why users that click on very specific (highly scenting) links have higher engagements. By slightly changing the concept into this reversed form it also provides a starting point for optimizing links where no scent is present, like the "Detailed Description" button. Which, given the potential positive effects shown by previous research, is well worth looking into.

2.3.1 Information categorization

To apply the reversed information scent to hyperlinks, one has to answer the question

Which words best describe this piece of content?

IFT provides a computational answer to determine what concepts have a high similarity with content (i.e. studies): latent semantic analysis. Where IFT uses LSA to compute the similarity between links and goals, the process can easily be reversed to compute the similarity between content and a possible hyperlink. What it does not answer is what the optimal label is from a user perspective, given a number of high-scoring labels. LSA can for instance identify that a study scores high on "functional distributed programming" and "programming", it now depends on user characteristics (i.e. knowledge) to determine which label is best and most meaningful.

A psychological theory that can assist in making decisions on information representation is *categorization* (Rosch, Mervis, Gray, Johnson, & Boyes-braem, 1976). This theory states that concrete things can be described on different levels of abstraction: *superordinate-*, *basic-* and *subordinate*. Best explained by an example; a cat (basic) can also be described as a British shorthair (subordinate) or an animal (superordinate). These different levels of categorizations have different (dis)advantages, where the basic level representation is most often preferred. In the original paper for instance, a number of experiments were conducted where users either heard the word "apple" or "fruit" before being shown 2 separate images of apples. When hearing the basic level categorization of the object, it was more likely to trigger the *semantic priming effect*, which allowed them to identify the pictures quicker.

While in general basic-level naming is preferred, it has been shown that experts prefer subordinate level representation of knowledge in some tasks, such as object naming and masked object identification (i.e. identifying silhouettes of birds) (Johnson & Mervis, 1997). Reflecting this on IFT, in general the basic version of a label might have the best results as it generally is the most preferred alternative. For experts however, the subordinate version of a label might support them better. Which leads to the question; what is an expert?

2.3.2 Expertise and directedness

User *domain expertise* is defined as the level of background knowledge that a user has of a certain topic, in this case concerning the patches of information that are being examined. As shown by previous IFT implementations like CWW (Blackmon, Polson, Kitajima, & Muneo, 2005) and search related studies (Duggan & Payne, 2008), expertise is a concept that influences the way a user behaves when looking for information. As mentioned in the previous subchapter it also influences which level of information categorization appeals most to the user, making a look into expertise literature worth the effort.

Experts are generally quicker and more successful in attaining their online information goal (Blackmon, Polson, et al., 2005). This intuitively makes sense: if a user is interested in computers but doesn't know what the programming language "java" is, (s)he will not search for it, and a link referring to this term will have very low scent for that user. These types of words are referred to as a *zero-frequency words* (Blackmon, Polson, et al., 2005), meaning it does not exist in the corpus that makes up the user's domain knowledge. The CWW model is based (amongst others) on the assumption that these words are usually ignored by users.

Besides this *domain expertise*, another type of expertise influences the way users behave on a website, namely *web expertise*, meaning the level of experience a user has with using websites. This has been well studied in the domain of web search (Duggan & Payne, 2008;

Hölscher & Strube, 2000; White, Dumais, & Teevan, 2009), and shows that both domain- and web expertise result in similar (desirable) behavior: less time to goal attainment, better choice of information patches and use of more specific search queries. These 2 types of expertise have been found to strengthen each other: the best searchers on the web have both domain and web expertise. An interesting study (Jenkins, Corritore, & Wiedenbeck, 2003) compared the 4 conditions of expertise, and looked at how they searched (broad vs in depth) and how they evaluated the results (see Table 2). Given the role of internet nowadays, combined with the fact that most visitors of BachelorsPortal are expected to be suited for bachelor-level education, we assume every user has at least an average web expertise level. As the variance in domain expertise is more likely to be larger, it is the primary focus of expertise in this study.

	Domain novice	**Domain expert**
Web novice	Breadth-first No result evaluation	Breadth first Evaluate with domain knowledge
Web expert	Mixed strategy General evaluation	Depth-first Deep evaluation

Table 2: overview of results found by Jenkins et. all 2003, comparing the search and evaluation strategies dependent on domain- and web expertise. The table describes how a user with certain expertise searches (wide, breadth searches covering a lot of content shallow, or depth, evaluating content in more detail), and how they evaluate these results.

While most of the previous research suggests a direct effect between expertise and behavior, we suggest that there is a variable in between these two that matters when users are searching for information; *goal directedness*. Within informational web behavior, segmentation studies show that users differ in their goal: there are *directed* users who know very specifically what their goal is, and *undirected* users who are more explorative (Rose & Levinson, 2004). This level of specificity has been shown to influence user behavior on websites (Wang, Wang, & Farn, 2009) which can be linked back to IFT: attractiveness of information patches depends on the goal, so users with different goals will use them differently.

Novices are constrained by their limited amount of knowledge, and therefore limited in the directedness of the goal they can search for. Simply put, they cannot search for the things they don't know exist. Experts on the other hand do have extended knowledge and can construct highly directed, specific search goals, though they do not have to. It might be possible that experts go back to explorative searches within their field of expertise every now and then. When relating this to information categorization, novices will always prefer basic information categorization; it better fits their goals and the more complex, subordinate categorized information might not even be familiar with them. Experts on the other hand might prefer subordinate information more often, as shown before (Johnson & Mervis, 1997).

Combining these branches of research in expertise and goal directedness, we suggest the two are highly intertwined. The goal of the user ultimately influences the preference towards basic or subordinate most and can be explained in terms of the goal directedness. Directedness is highly influenced by expertise, simply because the less experience a user has in an area, the less directed his or her goal can be.

2.4 Subjective measures

In the theories outlines above, especially the IFT, objective measurements on user behavior dominate the evaluation of concepts and theories. In some works broad subjective metrics such as the System Usability Scale (SUS) (Rigutti et al., 2015) or overall website attitude (Moody & Galletta, 2015) are used. Other works focus purely on behavioral metrics and use no subjective measures at all (Blackmon, 2012a). As this thesis aims to target only very specific links, these broad subjective measures might be too general. They're influenced by a large number of aspects (site design, speed, device etc.) and might cloud the effects of the more interesting underlying concepts: how users experience the added information scent and if it helps them achieving their goals. Therefore, two main measures are proposed that are more specific and relevant in this context; perceived goal attainment and usefulness.

These metrics might not only give specific insights into the areas of the user experience that we expect to be effected, but also provide comparison with behavioral metrics. Combining the behavior metrics with their subjective equivalents might give insights that have not been seen before. In this subchapter we'll further elaborate on perceived goal attainment and usefulness.

2.4.1 Perceived goal attainment

While BachelorsPortal/StudyPortals never did an extended user goal study or task analysis, previous mentioned research in university and study choice suggests a wide range of possible goals. Users might focus on (amongst others) university location, reputation, market perspectives, pricing, course content and discipline (Maringe, 2006; Smith et al., 2003). As mentioned before, the use of reversed information scent would solve this problem as it does not require knowledge of the goal of a user.

If the goal of the user is not known upfront it is not only interesting to find out his or her goal, but also whether the goal is being perceived as achieved. In previous work this was trivial to quantify; users get a specific goal where the researchers know up front where it is located in the fake website. If users viewed that page or segment then the goal is attained, both objectively and (almost always) subjectively. In real life this is only possible to some extend: clicks or page viewing times do predict goal attainment partially (Mccart et al., 2013), but not completely. Secondly, real life goals might be less specified; for example the lab-goal "find out how much it costs to study in the Netherlands" versus the real-life goal "find out if studying in the Netherland could be worth considering". The first is almost binary regarding goal achievement: either the user found out the costs or not. The latter, which might be closer to a real-world goal, can be partly fulfilled, for example if a user already did some research but did not consider costs yet. Summarizing, it would be most interesting to find out *what* the user's goal was, and *to what extend* that goal was achieved. Finally, information scent also aims at reducing goal attaining time, which might be interesting to compare objectively and subjectively.

2.4.2 Perceived usefulness

At the core of information scent (and informational websites in general) is the usefulness of the information: links with high scent are perceived as more useful and used more often. The concept of *perceived usefulness* (Larcker & Lessig, 1980) is therefore a very close subjective equivalent of information scent. It also has been found to highly correlate with self-reported usage and expected future usage of websites (Davis, 1989), even more then general usability.

Conceptually it is very similar to a measurement called *perceived system effectiveness* used in recommender research (Knijnenburg, Willemsen, Gantner, Soncu, & Newell, 2012). The words effectiveness and usefulness are very closely related, when looking at the dictionary definitions, they both define something to serve its purpose well:

> ***Useful**: 1. Being of use or service; serving some purpose, advantageous, helpful, or of good effect. 2. Of practical use, as for doing work; producing material results; supplying common needs.*[5]

> ***Effective**: 1. adequate to accomplish a purpose; producing the intended or expected result*[6]

This is also reflected in the questions used by (Knijnenburg et al., 2012) to measure perceived system effectiveness; some of them literally contain the words “useful” and “useless”. For this project the assumption is made that both concepts (as measured by (Knijnenburg et al., 2012; Larcker & Lessig, 1980)) measure the same thing; perceived usefulness. This might not hold in all situations, but in this context both target the underlying concept that is most interesting to measure: how useful is the system (with or without scent) for attaining a certain goal?

[5] http://www.dictionary.com/browse/usefulness, retrieved 17-03-2016
[6] http://www.dictionary.com/browse/effectiveness, retrieved 17-03-2016

2.5 Summary

Explorative analytics on BachelorsPortal showed that specific hyperlinks may assist users better in their search for information. On the search page the most prominent design element was identified as having very low specificity, this chapter aimed to look at related literature that might assist in increasing the usefulness of this button. One of the potential areas of research, tagging, showed to be closely related but the different goals made it unsuitable to solve this thesis' problem. The theory of information foraging showed more potential, as it is a solid, proven theory that can help websites like BachelorsPortal to identify areas where the information scent could be improved. We hypothesize that IFT can be reversed and in that way applied on BachelorsPortal; by increasing the scent of web links based on the content they refer to users might experience increases goal attaining and perceived usefulness. LSA can be used to compute viable labels for these links, the final choice can be made using information categorization theory. The preferred categorization level of information scent depends on two user characteristics.

First of all, there is expertise: domain experts are better in identifying the best information patches and accomplishing their goals more efficiently compared to domain novices. As they have a larger body of knowledge on the specific topic, they might prefer subordinate-level information, especially in the context of hyperlinks on the web, where room is sparse. Non-experts will prefer basic-level representation of knowledge, if only for the fact that they might not be familiar with the words used in the subordinate representation.

Secondly there is the level of directedness: more goal-directed users will have a more specific and concrete goal, which lies closer to subordinate-level information. Less directed users who will have more general goals and therefore be better served with basic-level representation of information, as it lies closer to their goal in terms of information scent.

Finally, expertise and directedness are very closely related: users with either high expertise or directedness both showed improvements in the same types of behavior properties: higher and more efficient goal attaining & less page visits, among other things. Moreover, experts have been shown to use a more goal-directed approach in problem solving (Hershey, Walsh, Read, & Chulef, 1990).

Besides the theoretical background two subjective measures have been introduced that are of interest in this context. Perceived goal attainment will simply measure whether the supposed effects of IFT are actually improved when scent gets larger. Perceived usefulness will measure the usefulness of specific elements. Measuring these subjective concepts might not only show how modifications on information scent influence users' perception. It also allows for comparison between behavior and their subjective equivalents, one of the potential additions of this thesis to the current body of literature.

Secondly, none of the previous works on IFT appear to have attempted actual website improvements, a pragmatic aspect that might allow the IFT theory to be used for more than just design flaw detection. Lastly, using the concepts of information categorization and directedness to explain information scent type preferences can potentially explain effects not covered before. We believe these three concepts can add significant knowledge to the current literature of IFT, and might even prove to be a starting point for real-world website improvements.

3 Research Question

This chapter will define research questions and hypotheses that follow from concepts introduced in chapter 2, aiming to improve BachelorsPortal's search page with information scent. The idea of reversed information scent lies at the core of this study, the concepts of goal-directedness, expertise and information categorization are concepts that are expected to heavily influence the effects of reversed information scent. Therefore, the main research question will be:

> *Can increased information scent in hyperlinks be used to let users find the information they are after more efficiently and effectively? Which level of information categorization works best when increasing information scent, and how is that affected by goal directedness?*

There are two sub questions that can be generated from the literature overview in chapter 2 that look at the concepts of information categorization and goal directedness.

I. *Does basic- or subordinate-level information scent lead to improved goal attainment and usefulness?*

II. *Does the effect of basic- or subordinate-level scent depend on the directedness of a user?*

As shown in earlier literature we expect a main effect of goal directedness on goal attainment; the more specific a user's goal is, the more likely it will be attained (Jenkins et al., 2003; Sánchez-Franco & Roldán, 2005; Wang et al., 2009). In this study however we are more interested in how this directedness interacts with different levels of information categorization, something that has not been studied before.

In summary, the objective is to see if there is a positive effect of information scent on goal attainment and usefulness, and if the goal directedness of a user moderates the effects of basic- and subordinate categorization of the information scent. Figure 4 Figure 4represents this idea in graphical form: information scent and categorization are the independent variables, goal attainment and usefulness are dependent variables and goal directedness is a moderator. Expertise is expected to affect directedness.

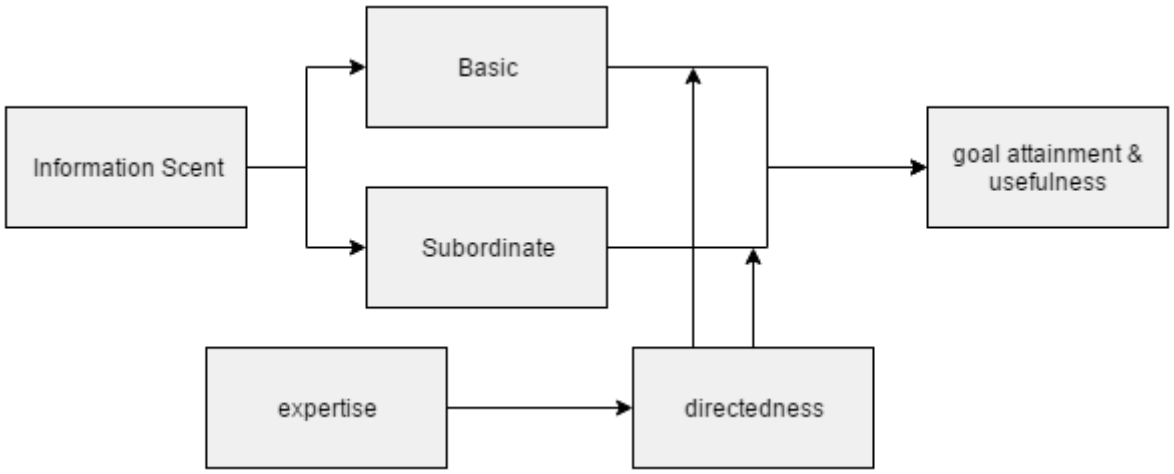


Figure 4: graphical representation of the research concepts.

3.1 Hypotheses

A number of hypothesis are proposed to answer the research questions. These are split into two sections: the direct effects of information scent and the influence of information categorization, directedness & expertise.

3.1.1 Reversed information hypothesis

One of the main disadvantages of having a low information scent is that users, when trying to achieve their goal, are more likely to end up in irrelevant information patches. Once they notice that the current patch is dried out or not the correct one, either of these 3 actions will be performed: search for another patch (which can consist of backtracking and picking up another scent) using other sources to initiate a new search (i.e. Google) or stopping the task all together (Pirolli & Card, 1999). All these options will reduce the probability of goal attainment, which after all is the goal of informational searching of the web. Therefore, it is expected that users viewing high-scenting links complete their goal more often compared to users viewing no-scenting links.

A number of objectively measurable behaviors (sometimes referred to as *implicit interest indicators*) can indicate interest of a user towards the content on a study page. For example, a user viewing a study page for 40 seconds and then clicking on one of its links will be more interested in the content then a user viewing the page and closing it after 10 seconds. To link this to goal attainment and usefulness, we make 2 assumptions based on (Mccart et al., 2013):

Assumption 1: Higher interest means the content is closer to the goal

Assumption 2: Higher interest means the content is more useful

These assumptions will later be tested when comparing subjective and objective data. Hypotheses 1-6 all use these assumptions to imply higher goal attainment and usefulness. All hypotheses that are covered below are visualized in Figure 5.

To start with, users can click on studies from the search results, indicating interest. IFT predicts that higher scent should enable the user to find the correct link more easily, making less mistakes in the process:

H1: Users viewing highly scenting links click on a lower number of search results compared to users viewing links without scent.

Besides picking the right study more efficiently, users are expected to be triggered more by the information scent. So while we expect them to investigate a lower number of studies from the search page, it is expected they are more likely to click on at least one:

H2: Users viewing highly scenting links are more likely to click on at least one search results compared to users viewing links without scent.

The overall active time spend on a page (*dwelling time)* is a good overall predictor for the interest in content on that page (Claypool, Le, Wased, & Brown, 2001; Fox, Karnawat, Mydland, Dumais, & White, 2005), constructing the following hypotheses:

H3: Users viewing highly scenting links will have higher study page dwelling times then users viewing links without scent.

For the search page the opposite effect is expected, as the scent should trigger users quicker:

H4: Users viewing highly scenting links will have lower search page dwelling times then users viewing links without scent.

Conversion happens when users click on links within BachelorsPortal that refer to external websites, usually from universities, and is one of the most significant business metrics. It indicates a potential engagement as a user is interested enough to browse to the website of the university, even though these buttons have no scent (most of the buttons contain "visit programme website", see Figure 35Figure 35). It is expected that more users achieve their goal, but they need less attempts to do so:

H5: Users viewing highly scenting links are more likely to convert at least once compared to users viewing links without scent.

H6: Users viewing highly scenting links will convert less often than users viewing links without scent.

One of the primary shown effects of the IFT is that users viewing highly scenting links are expected to need less time to complete their goal, compared to non-scenting links (Pirolli & Card, 1999; Rigutti et al., 2015). This is partly caused by the argumentation for hypothesis 1 (users waste less time in irrelevant patches), but users can also identify the right patch more quickly and with less effort, reducing the dwelling time on search pages. Time here is defined as the complete session time. The IFT states that users are most likely to leave when either their goal is achieved (why hang around any longer?) or their belief of achieving their goal at the current patch goes below average.

H7: Users viewing highly scenting links need shorter sessions to complete their goal compared to users viewing links without scent.

In chapter 2.4 two concepts are discussed that relate to information scent: perceived goal attaining time and perceived usefulness. Goal attaining time is expected to reduce as not only the actual time reduces, but potentially the increase in mental effort due to the more complex and dynamic texts may lead to a reduced sense of time, enlarging the effect. Usefulness is expected to increase (as argued in chapter 2.4.2), as well as goal attaining, a measure that lies at the heart of IFT.

H8: Users viewing highly scenting links perceive higher goal attainment compared to those viewing links without scent.

H9: Users viewing highly scenting links perceive lower goal attainment time compared to those viewing links without scent.

H10: Users viewing highly scenting links perceive higher usefulness compared to those viewing links without scent.

In summary we expect a number of effects on implicit interest indicators when the current links without scent are replaced with more meaningful, highly scenting links. Under the to-be-verified assumption that this interest correlates with goal completion, these hypotheses suggest that higher information scent should lead to higher (implicitly stated) goal attaining. Furthermore, it's expected that users perceive higher goal attaining and usefulness, while lowering that goal attaining time if the information scent increases.

3.1.2 Information categorization, directedness and expertise

As elaborated in chapter 2.3.1, information can be presented on different levels (Rosch et al., 1976). In general basic-level categorization is preferred over the super- and subordinate levels as it seems to have the right balance between abstraction and specificity. It is hypothesized that the same applies to information scent:

H11: Basic-level scenting hyperlinks result in higher goal attainment and usefulness compared to subordinate-level hyperlinks.

For sake of simplicity goal attainment and usefulness are considered to be one factor from here on, as all independent variables are expected to affect both in the same direction.

To answer the second sub question of this thesis, the interaction between goal directedness and categorization is reviewed. As argued in Chapter 2.5, highly directed users are hypothesized to be served better with subordinate-level information, while undirected users will find basic-level information to be more valuable.

H12: goal directedness moderates the effect of categorization on information scent: subordinate-level scenting hyperlinks will affect highly directed users more in goal attainment and usefulness, basic-level scenting hyperlinks will affect undirected users more.

Following up on the argumentation in chapter 2.3.2 on directedness and expertise, it is expected that expertise influences the level of directedness a user can have:

H13: Domain experts will have higher goal-directedness then novices.

For the case of BachelorsPortal, we are most interested in the domain expertise of a certain field of study. One could also focus on the expertise of study choice, but that would be less interesting given that the majority of the users will only pick a bachelor once, making variance in study choice expertise a lot lower than that of study-field domain expertise.

Summarizing, high scenting basic level categorization links are expected to result in more positive outcomes then high scenting subordinate links. This is moderated by goal directedness, where higher goal directedness has a negative effect on basic categorization and a positive effect on subordinate categorization. Finally, expertise positively influences goal directedness.

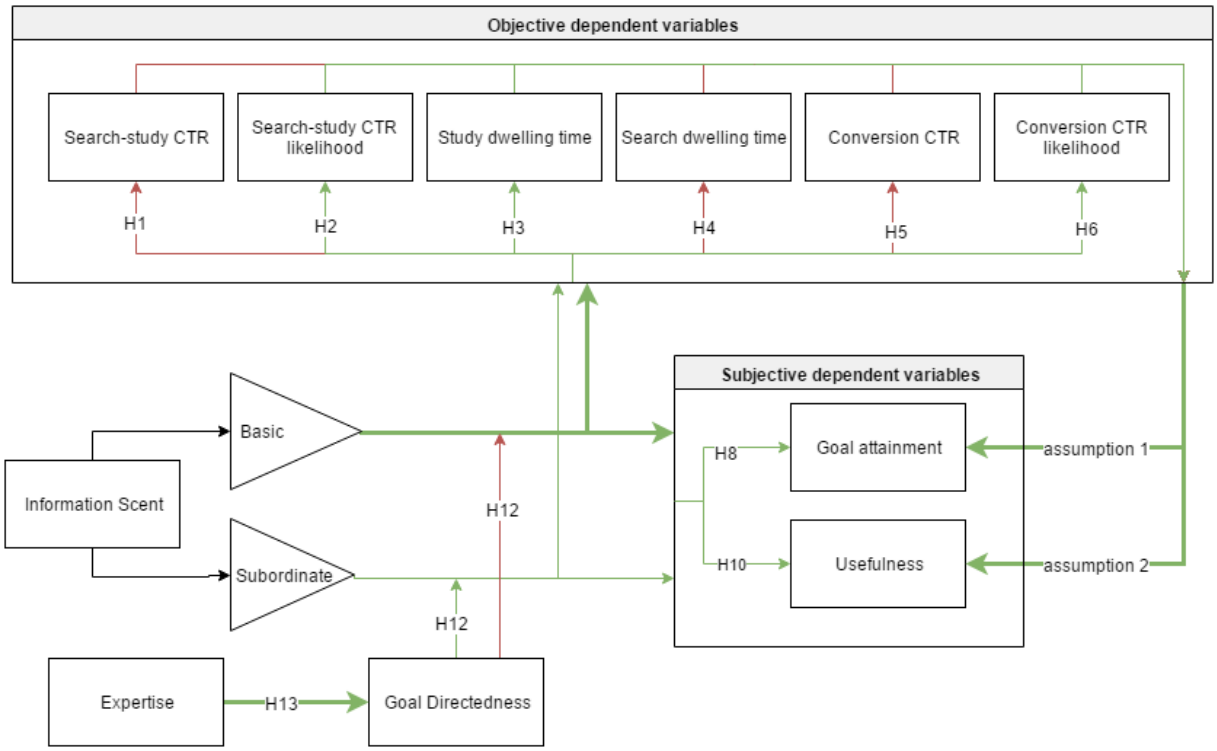


Figure 5: visualization of all hypotheses, except the ones concerning time. The color indicates an expected positive (green) or negative (red) effect. To summarize: high information scent is expected to influence a number of objective metrics (top). We assume these metrics indicate goal attainment and usefulness. Furthermore, information scent is expected to directly affect goal attainment and usefulness, depicted as different line thickness between basic & subordinate (H11), basically categorized information more than subordinate. Finally, goal directedness is expected to moderate the effect of information scent (H12). This directedness depends on expertise (H13).

4 Auto-labelling studies

One of the main challenges of this thesis, and a requirement to test for the stated hypotheses, is the automated generation of optimal labels for all (over 49.000) bachelor studies. A methodology was developed for that purpose, which will be elaborated in this chapter.

Overall the goal of this labelling process was to generate three labels for each study: a basic categorization label, a subordinate categorization label, and an intentionally wrong label. The first two were required to modify the buttons in BachelorsPortal's search page, which in turn was needed to test the hypotheses and answer the research questions. The third, wrong label was added to be able to check for any side effects, i.e. users behaving differently just because the button changed in size. A randomly (and intentionally wrong) label could account for these effects. The usefulness of this wrong label is further covered in chapter 5.1.

To match these labels per study, a pre-defined *label tree* was used. A label tree is a structured tree of concepts that specifies how these concepts relate to each other in a hierarchical way, an example of which is shown in Figure 6. The intention of using this tree was that labels at the end of the branches in the tree could be matched with studies as subordinate labels, and a number of steps up in the tree would result in a decent basic level representation of that same concept.

Firstly, the collection and cleaning of the dataset will be elaborated in 4.1, after which the used method is described that was used to find the "best" label per study in 4.2. In 4.3 the process of the basic- & wrong label construction is discussed, the quality of these matches are presented in 4.4.

4.1 Collect & clean

For each study its contents were collected with StudyPortals' API, and 4 properties were extracted: title, summary, description and study content (a piece of text which describes the curriculum of a study program). These are the most significant textual properties that are presented on the actual web page of the study and are good candidates with regards to the ideas of reversed information scent. After concatenating these properties per study, each study was presented as one text document, containing between 500~5000 characters per study. The size of these documents depends on StudyPortals data inserting, and some studies seem to be edited more elaborately than others.

Based on suggestions by (Gomez & Moens, 2014), a number of cleaning and processing steps were performed that resulted in a cleaner data set. First of all, all HTML tags were stripped, and 2400 English stop words (i.e. "the", "that" etc.) were removed (Porter, 1980). Moreover 42 study specific words that occurred very often in almost all studies (i.e. "program", "degree", "bachelor") were removed as well. All reading signs and numbers were removed, all texts were lowercased and split into a word list using spaces as delimiters. As final cleaning step, each word was *lemmatized*, which made sure all words were used in the same form (i.e. "walk", "walking" and "walks" can be transformed to just "walk"). This was implemented with the NLTK WordNet lemmatizer[7].

The Polythematic Structured Subject Heading System (PSH) (Mynarz, Kamrádková, & Kožuchová, 2010) was used as a label tree. It is constructed and maintained by the National Library of Czech for categorization of literature and papers and fits this use case very well; both this labelling process and PSH are concerned with scientific labelling, unlike more popular label tree's like WordNet. Moreover, it contains over 14.000 English labels and is

[7] http://www.nltk.org/api/nltk.stem.html

professionally maintained. As final advantage over other label trees, it consists of a count of the number of papers that each label has attached, which serves as popularity score. An example of a couple of branches within the PSH tree is given in Figure 6.

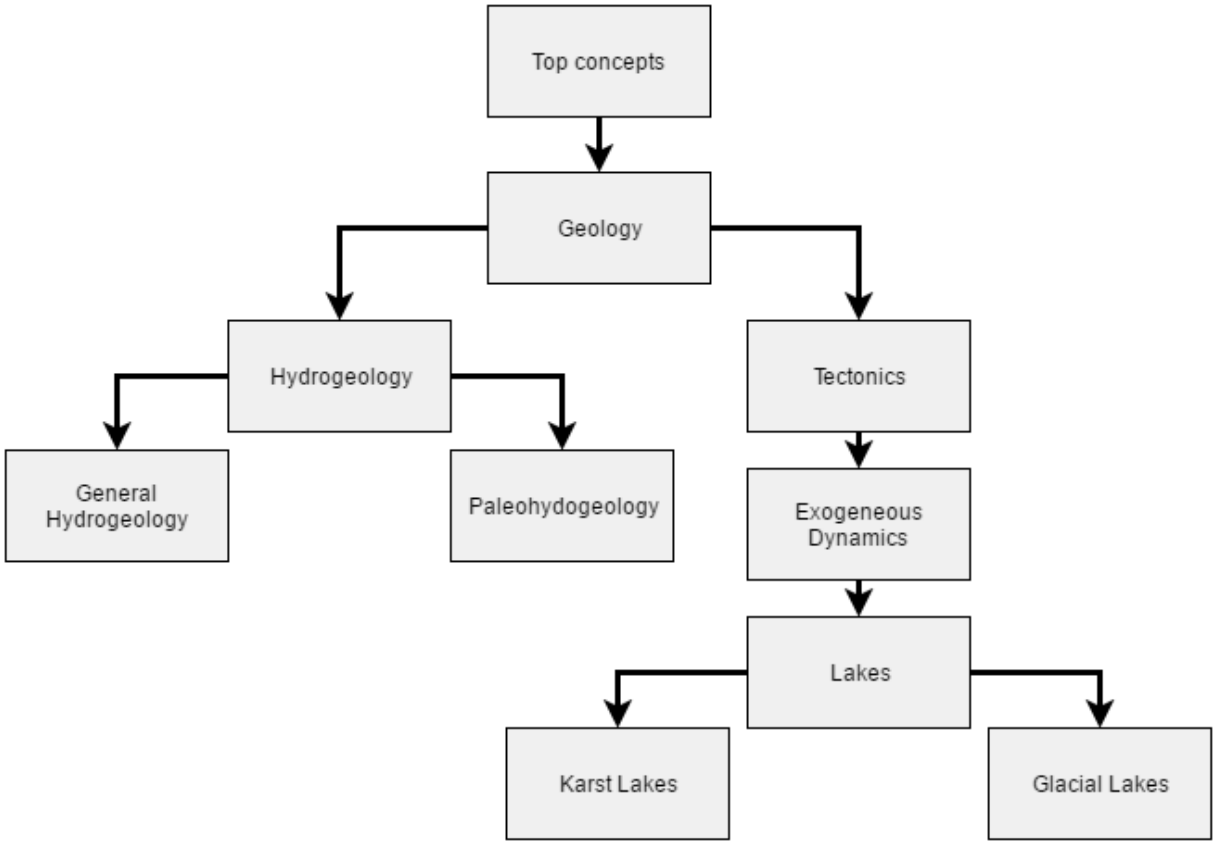


Figure 6: example of some branches within the PSH tree.

The labels of the PSH were downloaded and cleaned with the same steps described above. The resulting 2 datasets were cleaned label and study documents represented as word lists.

4.2 Finding the optimal label for each study

To find the best label for each study, study word-lists needed to be matched with label word-lists that had the highest similarity. Latent Semantic Analysis was the most preferred similarity matching metric, as it is used in the original works of the information foraging theory. Moreover, it can find relationships between semantics, allowing it to match documents with words that are really closely related, even though they are not same. While the concept of LSA (explained in chapter 2.2) works well in a lot of use cases, it has quite a high error rate when comparing very small documents with large documents, i.e. matching labels with studies. The one or 2 words of a label from the PSH tree are usually not enough to explain the concept really well, and minor effects which usually go unnoticed with decent document sizes get more significant when the document size shrinks. This results in quite a high error rate, too high to use just LSA for the purpose of this thesis.

To correct these errors, the *term frequency, inversed document frequency* (TF-IDF) algorithm was used to filter out most of the errors. TD-IDF computes a score for each word in each document, by counting how often it occurs in a document, and then multiplies it with an

importance score of that word over all documents. This *inversed document frequency* score is computed by taking the logarithm of the number of documents divided by the number of documents a specific word appears in. This way, words that occur only sporadically get more weight than frequent words. This generally results in a very low error rate, but misses the relationship properties that LSA can detect. For that reason, a combination of TF-IDF and LSA was used in this thesis to find semantically related labels for studies without too much errors.

For each study document the following steps were performed to reduce the set of all possible PSH labels to the best possible label. As this process was intended to find subordinate labels, only the PSH labels at the lowest 2 layers of the PSH tree was used.

1. Filter out all PSH labels that were literally in the title. These usually scored well, but defeated the purpose of the experiment as they were already in each search result;
2. Filter out all PSH labels that were not in the study document. Labels were split by words, so n-grams did not literally have to occur in the same order in the document;
3. Filter out all PSH labels that had less than 0.02 LSA similarity with the study document. 1200 components were used for the LSA computations, distance between word label- and study features were computed with cosine distance;
4. Filter out all PSH labels that had less than 0.01 TF-IDF similarity with the study document;
5. Filter out all PSH labels where LSA-similarity * TF-IDF-similarity < 0.1 and LSA-similarity < 0.7 and TF-IDF-similarity < 0.2. This forced a label either to have high LSA similarity, high TF-IDF similarity, or both to have a reasonable score;
6. The highest scoring tag (LSA-similarity * TF-IDF-similarity * ln(number of papers attached to label + 1)) was picked as subordinate tag.

The numbers for cutoff points were chosen during development of the method, with the aim of having the highest possible quality while still being able to label as much studies as possible. Due to computational resources required for step 1-5, the total set of 48,802 studies (extracted from BachelorsPortal on 04-04-2016) was randomly split up into 10 subsets. For 8,051 studies no labels were computed, most of these were low-quality studies that were lowly maintained, and often had only 2 or 3 sentences of generic information (the documents were significantly shorter than the other studies). As almost all of them were non-sponsored and had low priority, they often ended up low in the search rankings. Overall, the sacrifice of not being able to label 16.5% of all studies was worth the increase in quality for the studies that were labelled.

4.3 Subordinate to basic and wrong labels

The intention of using the PSH structure to generate a basic label up in the tree based on the subordinate label proved to be non-trivial and error prone (discussed in detail in appendix chapter 11.3). Therefore, the discipline system of BachelorsPortal was used to construct basic labels. StudyPortals does not only classify studies in top disciplines but also in one of 204 sub disciplines, which worked well for the purpose of this thesis.

This step however had 2 consequences: firstly, basic- and subordinate label of each study were not semantically related anymore. While this might cause a small bias, this is not a requirement as the overall goal is simply to find the best information scent towards a study. Secondly, the sub disciplines are manually picked, introducing a number of possible biases, the implications of which are discussed in the limitations of this thesis.

Secondly, the wrong labels needed to be selected in such a way that their information scent was wrong, but not so wrong that it would either hurt BachelorsPortal's reputation or alter the user behavior as the labels were so obviously flawed. To achieve this balance, wrong labels where picked by randomly taking a label which had the same root label as the highest scoring PSH tag. This made sure that the tag, even though wrong, was somewhat in the area of the study. For example using Figure 6, if a study was labelled with "glacial lakes", a possible wrong label could be "general hydrogeology".

	Wrong	**Subordinate**	**Basic**
B.Sc. Animal Biology	Agriculture	Animal Husbandry	Animal Sciences
B.Sc. Electrical Engineering	Input-output relations model	Systems Engineering	Electrical Engineering
Elementary Teacher Education	Economy of education	Education Policy	Education

Table 3: some randomly picked example studies and their computed labels.

4.4 Verifying the quality

To verify the quality of the generated labels we first looked at the quality of the sub discipline categorization used by StudyPortals. Secondly, we compared the similarity between the labels and studies for the 3 label types (basic, subordinate and wrong).

To verify the validity of StudyPortals' sub-disciple categorization, 2 random subsets (n_1=8104, n_2=10299) studies were taken, and for each subset the underlying LSA similarities were computed between all the studies that had the same sub-discipline. Table 4 shows the results, and suggest high underlying LSA similarities between studies within the same sub-disciplines. To compare: studies that did not share the same sub-discipline (but might still share the same top discipline) had a relatively high average LSA similarity of 0.903 (SD=0.069).

	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
Set 1	16485	0.9656	0.0249	0.7705	0.9542	0.9705	0.9829	1
Set 2	28141	0.9660	0.0262	0.7285	0.9536	0.9725	0.9844	1

Table 4: descriptives of LSA-similarities between studies within the same sub-disciplines, for 2 random subsets of BachelorsPortal studies. The high means and low standard deviations suggest high similarities.

To check labelling quality a random study sample (n=7422) was taken and the LSA similarity between their content and the final basic-, subordinate- and wrong labels were computed, shown in Table 5. The difference are significant (all p-values < 0.001, see appendix 9.2.1), suggesting the subordinate labels were "better" in terms of LSA similarity then the basic labels, which both were a lot better than the wrong labels. The means are closer to 0 then might be expected; this is due to the low number of words per label as explained in the beginning of this chapter. Given the statistics of the basic labels, and considering that that is the result of high-quality manual categorization, the labels can be considered reasonably good.

	count	mean	std	min	25%	50%	75%	max
basic	7422	0.222	0.281	-0.364	0.009	0.120	0.398	0.997
subordinate	7422	0.247	0.286	-0.331	0.019	0.145	0.451	0.981
wrong	7422	0.168	0.228	-0.344	0	0.097	0.296	0.964

Table 5: descriptives of LSA similarities with final labels and the content they referred to, split for the different types of labels.

5 Method

An experiment was designed to answer the hypotheses and research questions., the design and implementation of which will be described in this chapter.

Prior to the design of this experiment a pilot study was conducted, which is described in appendix chapter 11. Overall the pilot study was underpowered but did point into the direction of the hypotheses. This chapter will further cover the method of the main experiment: subchapter 5.1 explains the experimental design, 5.2 explains the procedure, 5.3 elaborates on the participants and 5.4 covers the data tracking and processing.

5.1 Design

A 4x1 between-subject design with the conditions *baseline, basic, subordinate* and *wrong* was used for the experiment. The baseline served as original, unmodified version of the website. The basic- and subordinate conditions increased the information scent of the search result buttons as mentioned in the problem definition, respectively with basic and subordinate information categorization. The comparison between the behavior and subjective answers of users between these 3 different conditions allowed us to test the hypotheses. Finally, a wrong condition was added that used intentionally wrong labels. The pilot study suggested there might be "button effects"; slight differences in behavior because the size of the buttons was modified. A condition with wrong labels allowed us to account for that and other similar effects. Moreover, it allowed to check that the label quality was actually better than random, as well as indicating the "damage" that an auto labelling system would do if errors were made in the process.

5.2 Procedure

The modification for the experiment were minimal and only applied to the search page; participants that were not in the baseline conditions had a modification applied to their search results. The red button in each study search result tile was modified so it contained the text "Details (computed label)", where computed label was replaced with the actual computed (as described in chapter 4) label, as shown in Figure 7. Non-sponsored studies on BachelorsPortal don't have this button, but do have a regular looking link placed on the left side of each search result, similarly labelled "Detailed Description", which received the same treatment.

Figure 7: example of an unmodified search button (left) and a modified one (right).

Initially questionnaire requests where placed on the search page between search result number 2 and 3 (see Figure 8), and on study pages below the description of the study (Figure 9). Due to a very low initial response rate, the prompts where changed halfway into the experiment by a popup in the right bottom, which were more constant and salient in the interface (see Figure 10), while keeping the underlying logics.

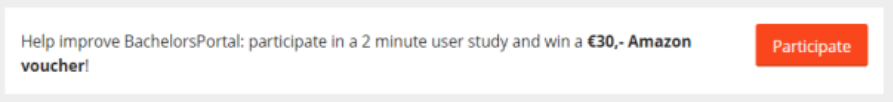


Figure 8 : initial questionnaire request on the search page.

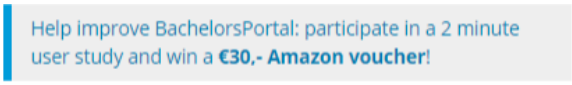


Figure 9: initial questionnaire request on a study page.

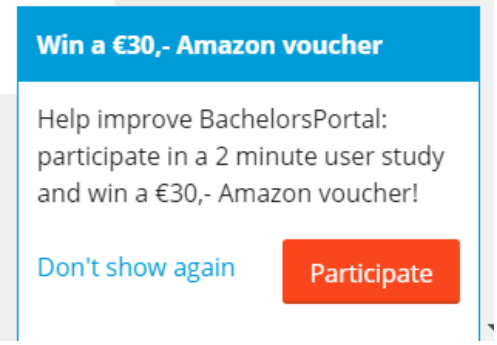


Figure 10: modified questionnaire request on search and study pages.

Users that clicked the participate button opened a new window that showed the introduction screen for the questionnaire. A short introduction explained that the questionnaire would take about 2 minutes and was concerned the search page and search results. It also stated that 5 Amazon vouchers would be raffled between valid responses. After clicking start, 3 screens where presented:

- A general-question screen asking for age, level of finished education (selection box of 11 different levels, i.e. high school, Bachelor's degree etc.[8]) and gender;
- The main question screen asked 13 Likert-style questions to measure the 4 main concepts of interest for this thesis (explained below);
- A final question screen asked goal related question (explained below), after which they could leave their email and the questionnaire would be closed.

On the "main question screen", text on top of the page again explained that all the questions were about the search page and search results (see Figure 11). The 13 questions were designed to measure 4 underlying concepts; goal attainment, goal directedness, perceived usefulness and expertise. The questions on goal directedness (Gomez & Moens, 2014) and usefulness (Knijnenburg et al., 2012) were constructed based on earlier research, the other 2 concepts had no good example questions from previous research that could be directly applied. The 13 questions were presented in the order as shown below, though without segmentation headers.

[8] See https://web.archive.org/web/20151112132635/http://www.snapsurveys.com/blog/5-survey-demographic-question-examples/ for all 11 variants that were used.

Goal attainment

- The search helped me find what I was looking for.
- The search helped me to achieve the goal I had when entering BachelorsPortal.
- With the search I found the answer I wanted to find.

Goal directedness

- I already had a particular Study (or University) in mind and just used the search to get there.
- I had no specific piece of information in mind that I wanted to find, and used the search to explore.
- I know very specifically what I want to find with this search.

Perceived usefulness

- The search results were useful.
- The search results allowed me to more quickly see what studies interest me.
- The search results saved me time.
- I can find better study programs with the help of the search results.

Expertise

- I'm an expert in the field of study that I searched for.
- I do not know a lot about the field of study that I searched for.
- By seeing a study in the search results I get a good idea what that study is about

On the last question-screen, 3 goal related questions were asked, aimed to measure what their goal was, how much of that was achieved and how long they believe it took them to do so:

- What is your goal of using this search; what do you hope to find? [text area]
- To what extend did you complete this goal? [slider, 0 = not at all, 100 = fully]
- How many seconds do you estimate it took to complete your goal from the moment you entered Bachelorsportal? [numeric input]

The questionnaire was tested with a number of test participants to ensure the questions were clear and unambiguous. Figure 11 shows a screenshot of the main question screen on a desktop, appendix 9.1 contains screenshots of the other screens.

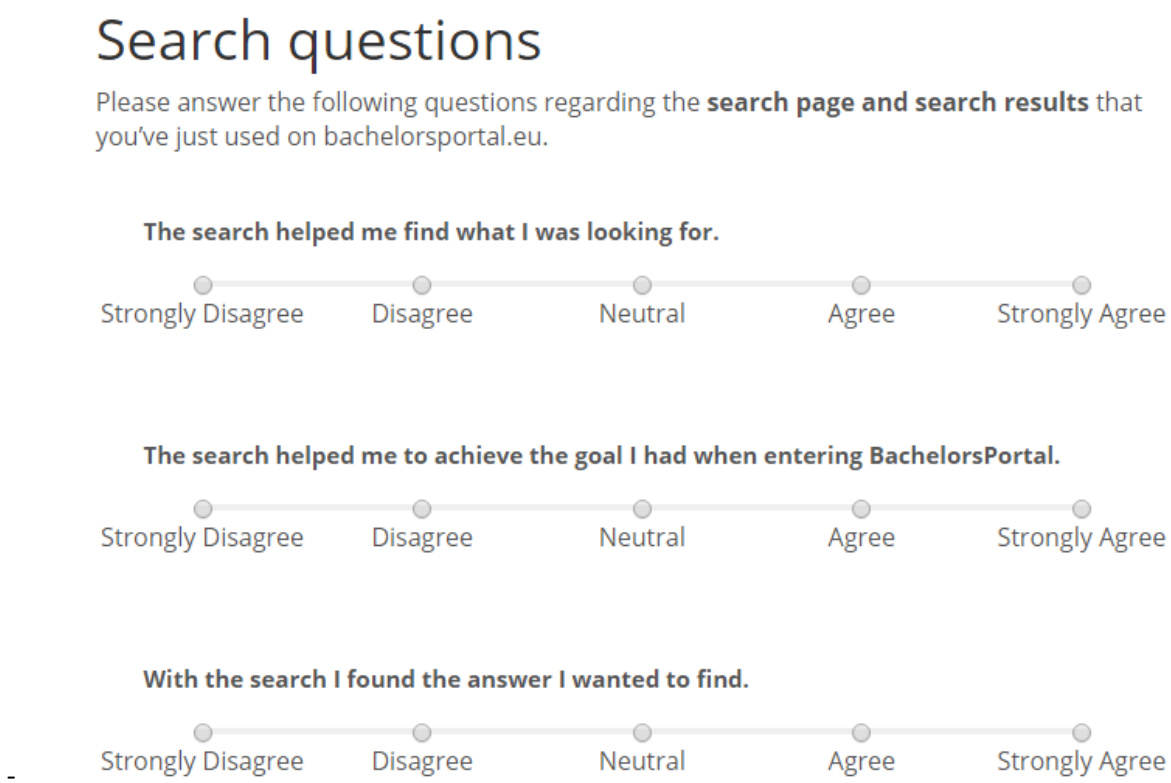


Figure 11: screenshot of the first couple of questions as presented on a desktop-sized screen.

5.3 Participants

All users automatically participated once they entered the search page, and were randomly assigned to one of the 4 conditions. After having seen the condition on the search page at least once, every subsequent search page page-view had a probability of 0.5 of triggering the questionnaire request, asking users to participate in a questionnaire. If the questionnaire request was triggered, the request was presented on search- and study pages until the user either participated or hid the request. This exponential approach allowed measuring user responses on different progress levels in their search, as previous research did not indicate a good point for questioning users.

17,691 users participated in the experiment between 07-04-2016 and 22-04-2016 by seeing the search page at least once. Users were identified at session level using BachelorsPortal's session system, where users stayed in the same session if their last activity was less than 60 minutes ago. Implementation of the experiment was done by Optimizely, leading to slightly unequal user numbers between conditions (see Table 6). This is due to Optimizely's aim to get equal amounts of search page views per condition, while this thesis primarily focusses on user level aggregation.

	basic	original	subordinate	wrong
number of users	4362	4560	4364	4405
completed questionnaires	31	37	40	37

Table 6: number of participants per condition.

After filtering out all questionnaire-responses which were incomplete or had all the same answers on the 13 Likert-scale questions (3 in total), 145 valid responses remained, equaling a response rate of 0.51%. Among participants who completed the questionnaire, 5 Amazon vouchers worth 30 euros were randomly raffled.

41.4% was male, and the average age was 21.28 years (SD=28.12) (see Figure 19). 61.4% indicated high school as their highest finished level of education, followed by bachelor (14.5%) and associate and nursery (both 6.2%) (see Figure 20). Based on IP addresses 62 countries where identified from where the responses came, the countries with the highest number of participants being India (12), US (12), Germany (10), Pakistan (7) & Italy (6) (see). Overall this is consistent with BachelorsPortal's overall user age- (Figure 29) and location distribution (Figure 32), suggesting the sample is a decent representation of the population with regard to sociodemographic characteristics.

5.4 Tracking user behavior and processing data

After several iterations on data tracking, collection and cleaning, a combination of StudyPortals' internal business tracking system and Snowplow was used to gather raw user data. This subchapter will give a quick overview of this process, as a more detailed overview is not in the direct scope of the project but in interest of StudyPortals, it is added as appendix chapter 12.

Figure 11 visualizes the process. In the browser of end users, 2 independent JavaScript scripts manage the tracking of the 2 data gathering pipelines. StudyPortals internal system sends preconfigured events to their Tracking API, which logs these events (i.e. a tracking click or study view) into *JSON*[9] files. For business critical events like banner clicks, users are send to a dedicated redirect page which logs the event, ensuring data quality. These JSONs are zipped and made available for processing for each day. On average each of these (unpacked) JSON is between 350-400 MB, containing around 1.4 million events. A python script was used to process these files and put the results into a MySQL database.

The other data pipeline is a more generic user behavior data tracker based on the open source software Snowplow[10]. It is configured to measure page view-, page ping- and click events and measures a number of variables for each of these events, including timestamp, screen size, IP address, browser language, several user ids (session ids, global user ids and StudyPortals user ids), time zones and page referrals. It does so by requesting pixels hosted on Amazon's AWS cloud platform, containing all data in the request URL. AWS is configured to log these request, resulting in ~250 files per day, combining to ~120MB. A python script was used to parse these files and put them in the same MySQL database. Most of the data used in this project is from this Snowplow tracker, StudyPortals system is mostly used for business critical data such as university, study and banner referrals. Where StudyPortals data contains data for all their websites, the Snowplow tracker only tracks data from Bachelorsportal.

The MySQL database is duplicated, and a number of outliers are removed (see below). A number of python scripts are then used to query subsets of those data, processing them as required. Nearly all analysis is done in Jupyter notebooks (Shen, 2014), using pandas as in-memory data store (McKinney, 2011), MatplotLib as plotting library (Hunter, 2007) and

[9] JSON stands for JavaScript Object Notation and is a popular way to save structured data in a human readable way. Valid JSON might look like: {"key": "value", "nested": {"nested key": "nested data"}}
[10] snowplowanalytics.com

SciKit-learn (Pedregosa et al., 2012) & StatsModels (Seabold & Perktold, 2010) for statistical modelling.

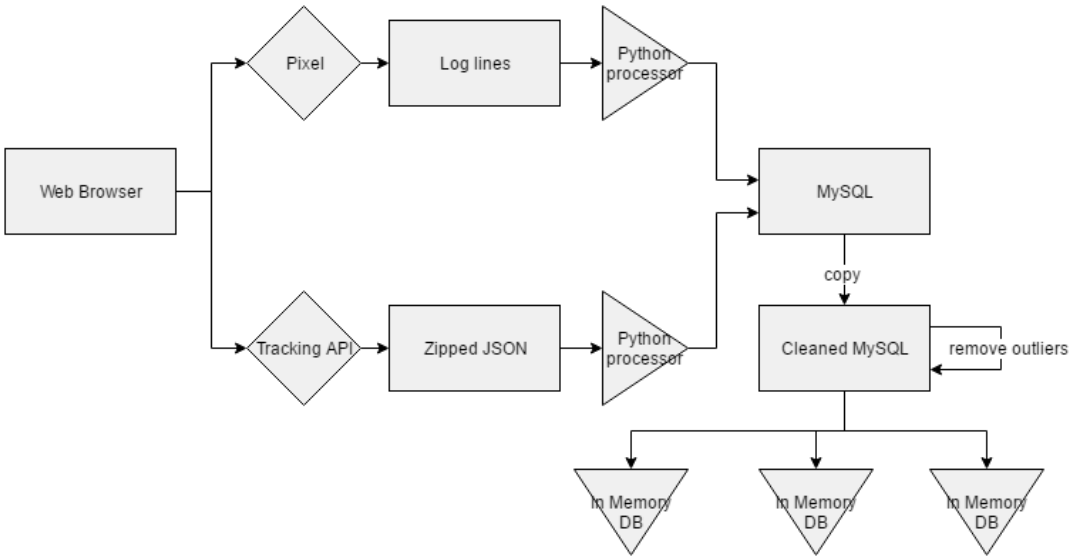


Figure 12: global overview of data gathering and cleaning.

5.4.1 Outliers

An effort was made to keep as much of the data as possible, mostly because the metrics (like page views, conversions, dwelling times) are not normally distributed and have a very skewed right tail. Therefore, even "extreme" cases, for example a user viewing two hundred studies, can lie within the distribution.

Nonetheless, a small number of user sessions are so obviously flawed that they were removed. Firstly, 5 sessions converted more than 30 times on the same study which does seem like a lot (shown in appendix Figure 22). Only one of the sessions participated in the experiment (original condition) and its conversions were removed (all of them happened in a time span of 23 seconds).

Secondly, users who viewed the same pages too often were removed. One user viewed an electronics study 555 times (basic condition), 6 more viewed the same page over 15 times rapidly (at least 12 times a minute), which was considered outlier behavior as well, 2 of which were in the wrong condition. Furthermore 1 user in the wrong condition was found to have a very large number of page ping events (15182), who was excluded from analysis as well.

The final dataset consisted of 120,169 conversions for all portals (66,741 users) and 368,010 page views, 1,130,061 page pings & 102,865 experiment-condition views from 108,341 BachelorsPortal users.

6 Results

In this chapter the results of the experiment will be presented in regards to the hypotheses. Only users that saw the search page with modification at least once are taken into consideration for this analysis. For most of the results all the 4 conditions of the experiment will be analyzed at the same time;

- *Original* for all users who had no modifications, and serve as the baseline
- *Basic* for all users who saw modified, highly scenting buttons with basic information categorization
- *Subordinate* for all users who saw modified, highly scenting buttons with subordinate information categorization
- *Wrong* for all users who saw modified buttons with wrong labels

Even though the wrong condition is not necessary to answer the hypotheses most of the time, it will be used later to reflect upon the quality of the basic and subordinate conditions.

6.1 Search result click-through

Starting with users' behavior on the search page, it was expected users viewing higher scenting links have a lower click-through rate (CTR) from search to study (H1), but have a higher clicking likelihood, meaning they are more likely to click on at least one search result (H2).

A search page view was defined as the presentation of a new result set on the search page, so pagination and filtering also resulted as one page-view count each. Study page views were defined by study page which were *referred from the search page*. As we are most interested in the studies users engage with from the search results, any study page views that did not originate from the search page were left out. This also left out study page views that were opened in a new tab; as their requests do not contain URL referrers it is hard to determine where the requests came from (0.102 of all study page views had no referrer).

The search-study CTR is then defined as the number of study views divided by the number of search page views. Table 7 describes this statistics per condition. The slight user count discrepancy with Table 6 is due to points in time when events are registered: participation events are recorded before page view events, some users left in between those events.

	count	mean	std	min	25%	50%	75%	max
original	4547	0.266	0.516	0	0	0	0.353	9
basic	4350	0.250	0.487	0	0	0	0.333	7.5
subordinate	4355	0.236	0.455	0	0	0	0.333	8
wrong	4396	0.261	0.533	0	0	0	0.333	11

Table 7: descriptives of the search-study CTR per condition.

To estimate the size and significance of each condition on CTR, a negative binomial regression is used. The reason for this can be seen in Table 7: the shape of this metric (as with other metrics discussed below) is over-dispersed. This means the variance is larger than the mean when it should be roughly equal, and a negative binominal distribution fits the situation well as it is specialized in handling over-dispersed data.

The results are shown in Table 8. The distribution goodness of fit was significant (χ^2_3= 9.49, p = 0.0234). A simple condition coding (sometimes referred to as effect coding) was used instead of dummy encoding, as it isolates the effect of each manipulation, making it easier to analyze coefficient sizes (Alkharusi, 2012).

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-1.3754	0.015	-91.735	0.000	-1.405	-1.346
C(X, Simple)[Simp.basic]	-0.0103	0.026	-0.393	0.694	-0.062	0.041
C(X, Simple)[Simp.subordinate]	-0.0708	0.027	-2.651	0.008	-0.123	-0.018
C(X, Simple)[Simp.wrong]	0.0299	0.026	1.161	0.246	-0.021	0.080
alpha	0.0032	0.020	0.163	0.871	-0.035	0.041

Table 8: negative binomial regression results for the model "search-study CTR ~ condition". Note that all regression tables in this study aim to describe the formula that they tested in a "R-style" format[11]. For understanding of this thesis, it is sufficient to understand that the variable on the left of the tilde (~) is the dependent variable, the variables on the right side of it are the independent variables.

Both the basic - and subordinate high scent conditions point into the direction of H1, though only subordinate is significant. The wrong condition points in the opposite direction: users in the wrong condition view more studies per search. Based on these results H1 was found to be partially confirmed, as the data points in the expected directions, but only subordinate does so significantly. This does suggest that the higher information scent leads to users exploring less options. As this is congruent with the IFT findings, it might mean they click on studies that better fit their goal, and end up on wrong studies less often.

To check for H2 (higher scent resulting in higher CTR likelihood, meaning users are more likely to click on at least one search result) a Chi-Square test was run, shown in Table 9. It resulted in an insignificant effect (χ^2_3= 4.79, p = 0.188), indicating that CTR likelihood does not depend on condition.

	original	basic	wrong	subordinate
No	2587 (56.9%)	2490 (57.2%)	2571 (59.0%)	2531 (57.6%)
Yes	1960 (43.1%)	1860 (42.8%)	1784 (40.1%)	1865 (42.4%)

Table 9: chi-square test of condition and search to study click trough likelihood, indicating how much users did (yes) or did not (no) click on at least one search result.

A logistic regression was run to check for the direction of each condition and check its significance (see Table 10), with McFadden's R^2 statistic being low (R^2=0.0002). H2 expected basic and subordinate to have higher CTR likelihood, basic does point into that direction but is not significant. Subordinate condition was significant, but points into the other direction: less users click at least one search result in the subordinate condition. Based on these results and the overall insignificance of the test, H2 was not supported. This suggests that subordinate information scent might "scare" away users that would have otherwise inspected at least one search result. Moreover, high information scent does not seem to convince users to engage with a higher probability; those who were not interested are still not.

[11] http://patsy.readthedocs.io/en/latest/formulas.html

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-0.3100	0.015	-20.340	0.000	-0.340	-0.280
C(X, Simple)[Simp.basic]	0.0183	0.026	0.691	0.490	-0.034	0.070
C(X, Simple)[Simp.subordinate]	-0.0554	0.027	-2.084	0.037	-0.108	-0.003
C(X, Simple)[Simp.wrong]	0.0047	0.026	0.176	0.860	-0.047	0.056

Table 10: logistic regression results for "Search-study CTR likelihood ~ condition".

6.2 Dwelling times

As the information scent is expected to allow users to select studies that better suite their goal, dwelling times (amount of time spend on a page) are expected to be larger for study pages (H3). Secondly, scent should lead them to clicking one of the studies faster, reducing dwelling time on search pages (H4). Dwelling times are measured as events that are trigged if a user actively engaged with a page within a timeframe. The first dwelling time event is triggered 30 seconds after page load, the next ones are triggered every 10 seconds.

To measure H3, we first looked at the number of dwelling time events per user per search result they visited. 3 outliers were removed that were very large (203 & 539 in the original condition, 606 in the wrong condition). Table 11 shows the descriptive statistics, and again shows a very skewed distribution.

	count	mean	std	min	25%	50%	75%	max
original	3630	2.339	3.676	0	0	1	3	38
basic	3740	2.534	4.109	0	0	1	3	45
subordinate	3463	2.378	3.617	0	0	1	3	48
wrong	3598	2.336	3.555	0	0	1	3	44

Table 11: number of dwelling time events per user per study page view.

Table 12 shows the results for the negative binomial regression results, of which the distribution goodness of fit was significant (χ^2_3 = 8.56, p = 0.0375) but McFadden's R-squared low (R^2=0.0001). The results partially support H3: higher scent with basic information categorization leads to higher dwelling times on study pages. The subordinate and wrong conditions both appear to negatively influence study page dwelling time, but aren't significant. This is in congruence with the IFT and suggests that high, basic information scent helps users select better links, after which they show more interest in the content they picked.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	0.8735	0.012	75.051	0.000	0.851	0.896
C(X, Simple)[Simp.basic]	0.0562	0.020	2.831	0.005	0.017	0.095
C(X, Simple)[Simp.subordinate]	-0.0073	0.020	-0.355	0.723	-0.047	0.033
C(X, Simple)[Simp.wrong]	-0.0249	0.020	-1.234	0.217	-0.065	0.015
alpha	1.5355	0.026	58.808	0.000	1.484	1.587

Table 12: negative binomial regression results for the model "dwelling times per study page view ~condition".

A very similar analysis was done for the dwelling times on search pages (H4). Table 13 shows the descriptive table of the "dwelling events per search page view" statistic, and show significantly larger means and maximal values compared to Table 11. This suggests users stay a lot longer on search pages then study pages.

	count	mean	std	min	25%	50%	75%	max
original	18975	4.46	5.95	0.0	1.0	3.0	5.0	183
basic	19630	4.37	6.59	0.0	1.0	3.0	5.0	467
wrong	18286	4.63	9.35	0.0	1.0	3.0	5.0	506
subordinate	18222	4.62	7.57	0.0	1.0	3.0	6.0	261

Table 13: number of dwelling time events per search page view.

Table 14 shows the results for the negative binomial regression (R^2=0.0001, χ^2_3 p < 0.0001). The model is significant in all conditions, though only the basic condition is in the expected direction; users who see basic categorization high scenting links dwell (a little) shorter on the search page. This shows support for H4, but only for the basic categorization. Again in congruence with IFT, it suggests users who see basic information scent find it easier to pick results, while wrong and subordinate labels seem to add some decision time.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	1.5079	0.004	407.410	0.000	1.501	1.515
C(X, Simple)[Simp.basic]	-0.0336	0.006	-5.308	0.000	-0.046	-0.021
C(X, Simple)[Simp.wrong]	0.0256	0.006	3.974	0.000	0.013	0.038
C(X, Simple)[Simp.subordinate]	0.0214	0.006	3.310	0.001	0.009	0.034
alpha	0.8068	0.005	152.597	0.000	0.796	0.817

Table 14: negative binomial regression results for the model "dwelling times per search page view ~ condition".

6.3 Conversion

H5 stated that higher scenting links should result in higher probabilities that users will convert at some point in their session (*conversion likelihood*), as they should be more likely to attain they goal due to the information scent. To check for H5 the metric "did this user convert" was used (see Table 15 for the descriptives). A Chi-Square test was run (see Table 16), resulting in a near-significant effect (χ^2_3 = 7.66, p = 0.052), indicating that conversion-likelihood does (likely) depend on condition.

	count	mean	std	min	25%	50%	75%	max
original	4557	0.140	0.347	0	0	0	0	1
basic	4360	0.155	0.362	0	0	0	0	1
subordinate	4363	0.137	0.344	0	0	0	0	1
wrong	4407	0.150	0.358	0	0	0	0	1

Table 15 descriptives of conversion likelihood per condition

	original	basic	wrong	subordinate
No	3919 (85.9%)	3684 (84.5%)	3765 (86.3%)	3744 (84.9%)
Yes	638 (14.0%)	676 (15.5%)	598 (13.7%)	663 (15.0%)

Table 16: Chi-Square test of condition and conversion likelihood, indicating how much users did (yes) or did not (no) convert at least once.

Table 17 shows the result of the logistic regression (R^2=0.0005), and shows significant effects for basic- and subordinate level information scent: basic resulted in a higher probability that users converted at least once, subordinate resulted in a lower probability. H5 seems partially supported by this data and shows that replacing links without scent for highly scenting links with basic information categorization might assist websites in increasing their business metrics.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-1.7705	0.021	-82.963	0.000	-1.812	-1.729
C(X, Simple)[Simp.basic]	0.0749	0.036	2.053	0.040	0.003	0.146
C(X, Simple)[Simp.subordinate]	-0.0694	0.038	-1.840	0.066	-0.143	0.005
C(X, Simple)[Simp.wrong]	0.0393	0.037	1.073	0.283	-0.032	0.111

Table 17: Logistic regression results for "conversion likelihood ~ condition".

As users are expected to find their goal quicker with higher information scent, they are expected to convert less often (H6). To check for this hypothesis, 2 metrics are considered: the conversion count for a user (see Table 20 for descriptives), and the conversion CTR per study page view (see Table 21 for descriptives). While technically the first metric would test H1.1, it introduces a bias as users viewing more studies will in general convert more, hence the latter metric to verify the results.

Table 18 shows the results for the regression of conversion count as dependent variable and condition as independent variable (R^2=0.0005, χ^2_3 =10.48, p=0.015). Only basic information categorization results in significantly more conversions (contradicting H6), the other 2 conditions' p-values are too high to say something sensible. The conversion CTR test that is used as validation (probability that a user converts given per single study page view, leaving out all users with 0 conversions) is shown in Table 19. The insignificant goodness of fit (χ^2_3 p = 0.89) and insignificant alpha indicate that the negative binomial distribution might not be the right distribution. This is unexpected given that the metric is over-dispersed and the histogram looks like a traditional negative binomial distribution as shown in appendix Figure 23. For this reason the statistic will only be used to confirm the findings of Table 18 and make sure there is no "more study pages viewed bias". A quick comparison between Table 20 & Table 21 show great proportional similarities in means, indicating the absence of a bias.

Based on these results, H6 is not supported: basic categorization users convert more often than users in the baseline, no sensible conclusion can be drawn for the other conditions. This is in congruence with the findings of H5 and might suggest an overall increase of business performance when low scenting links are replaced with high scenting, basic links.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-1.1767	0.025	-46.936	0.000	-1.226	-1.128
C(X, Simple)[Simp.basic]	0.1323	0.043	3.070	0.002	0.048	0.217
C(X, Simple)[Simp.wrong]	-0.0131	0.044	-0.301	0.763	-0.098	0.072
C(X, Simple)[Simp.subordinate]	-0.0382	0.044	-0.873	0.383	-0.124	0.048
alpha	7.8641	0.248	31.692	0.000	7.378	8.350

Table 18: negative binomial regression results for the model "conversions ~ condition".

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-1.8802	0.051	-37.150	0.000	-1.979	-1.781
C(X, Simple)[Simp.basic]	0.0221	0.085	0.259	0.796	-0.145	0.190
C(X, Simple)[Simp.subordinate]	-0.0018	0.090	-0.020	0.984	-0.178	0.174
C(X, Simple)[Simp.wrong]	0.0433	0.086	0.506	0.613	-0.124	0.211
alpha	9.272e-05	0.205	0.000	1.000	-0.401	0.401

Table 19: negative binomial regression results for the model "conversion-CTR ~ condition".

	count	mean	std	min	25%	50%	75%	max
original	4558	0.284	1.047	0	0	0	0	20
basic	4362	0.352	1.284	0	0	0	0	23
wrong	4407	0.304	1.054	0	0	0	0	17
subordinate	4364	0.297	1.151	0	0	0	0	29

Table 20: descriptives of the number of conversions per session.

	count	mean	std	min	25%	50%	75%	max
original	4558	0.0200	0.0765	0	0	0	0	1
basic	4362	0.0242	0.0938	0	0	0	0	1
wrong	4407	0.0239	0.0931	0	0	0	0	2
subordinate	4364	0.0208	0.0897	0	0	0	0	3

Table 21: descriptives of the number of conversions divided by the number of study page views, indicating the conversion-CTR.

6.4 Time

Based on previous research in IFT it was expected that users would not only need less time to complete their goal (H7), but also perceive it to be lower (H9) when information scent is higher. To check for H7, the minimal and maximal timestamp of each session were used to create a session-timespan. Some browsers appeared to have triggered events with old session ids, even days after their sessions ended. This made us filter out all sessions with timespans higher than 3 hours, which manually inspection showed to be a good cutoff point. The descriptives are stated in Table 22, a negative binomial regression showed no differences in session time per condition as shown in Table 23, and shows no support for H7. Apparently higher information scent did not significantly increase or decrease session time, which might suggest it did also not affect goal finding time.

	count	mean	std	min	25%	50%	75%	max
basic	4576	746.1	1198.5	0	65	270	892.75	11390
original	4766	748.6	1239.1	0	64	263	890.75	12943
subordinate	4569	721.5	1205.6	0	56	250	868	13048
wrong	4646	715.7	1144.3	0	56	252	865.5	13957

Table 22: descriptives of the session times per condition in seconds.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	6.5969	0.012	550.172	0.000	6.573	6.620
C(X, Simple)[Simp.basic]	0.0179	0.021	0.858	0.391	-0.023	0.059
C(X, Simple)[Simp.subordinate]	-0.0156	0.021	-0.746	0.456	-0.056	0.025
C(X, Simple)[Simp.wrong]	-0.0236	0.021	-1.138	0.255	-0.064	0.017

Table 23: negative binomial regression results for the model "session time ~ condition".

To check for H9, the time-estimation given by users was used. Quite a number of participants set the values really high (over a million) or invalid (text or empty), leaving 101 valid responses which are shown in Table 24. While the data is not over-dispersed, a histogram (Figure 23) shows it's far from normally distributed. The alpha significance and coefficient of the negative binomial regression indicate the negative binomial to be a good fit (see Table 25).

	count	mean	std	min	25%	50%	75%	max
original	27	165.26	176.01	2	30	80	290	600
basic	23	223.57	235.67	2	45	120	300	900
subordinate	26	192.88	172.85	4	90	120	300	600
wrong	25	229.08	211.65	5	60	120	300	600

Table 24: descriptives of the time estimations needed to complete their goal, given by users in the questionnaire.

Besides the alpha, the test (McFadden's R^2=0.0012, χ^2_3 p=0.67) does not show significant results: none of the conditions is a significant predictor for estimated goal attainment time, leaving H9 unsupported. In congruence with the results of the session times, this suggest the increased information scent did not alter the goal finding time in a significant way.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	5.3033	0.105	50.468	0.000	5.097	5.509
C(X, Simple)[Simp.basic]	0.1064	0.188	0.567	0.571	-0.261	0.474
C(X, Simple)[Simp.subordinate]	-0.0413	0.180	-0.229	0.819	-0.394	0.312
C(X, Simple)[Simp.wrong]	0.1307	0.182	0.717	0.473	-0.227	0.488
alpha	1.1064	0.138	8.020	0.000	0.836	1.377

Table 25: negative binomial results for the model "estimated goal completion time ~ condition".

6.5 Subjective goal attainment & usefulness

In order to check for the hypothesis concerning subjective measures (H8-H10), the questionnaire responses were analyzed with a principal component analysis and Oblimin rotation. After excluding a number of questions from the dataset 2 strong components remained instead of 4 as expected, explaining 0.61 of all variance (eigenvalues 4.17 and 1.32). The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO-test) is 0.87, indicating that the patterns of correlations are relatively compact and the PCA yields reliable factors. Furthermore Bartlett's test of sphericity suggests correlations between variables are significantly different from 0, which is good (χ^2_{36} =472.37, p<0.0001). The 2 components have a low, insignificant Pearson correlation: r=0.04, p=0.61.

This resulted in 4 out of the 13 questions being dropped, as the PCA showed they either loaded poorly in one of the 2 components (< 0.3), or they cross loaded highly between

multiple components. The remaining 2 components are presented in Table 26. Component 1 was interpreted to be the factor goal attainment/usefulness, as it scores high on questions like “The search helped me find what I was looking for” and “The search results were useful”. Component 2 was interpreted as (the lack of) directedness/expertise, scoring high on the 2 questions “I had no specific piece of information in mind that I wanted to find, and used the search to explore.” & “I do not know a lot about the field of study that I searched for.” The 4 questions that were dropped were:

- I already had a particular Study (or University) in mind and just used the search to get there.
- I know very specifically what I wanted to find with the search.
- I can find better study programs with the help of the search results.
- I'm an expert in the field of study that I searched for.

It was expected that the factors in both pairs would be very close together: all hypotheses expected perceived goal attainment and usefulness to be effected in the same way. For expertise and directedness, H13 suggested that they were closely related, and while this makes it impossible to test for H13, it still allows for analytics regarding information scent, categorization and directedness. The goal attainment/usefulness component appears to be quite strong, with a high load from multiple questions. The expertise/directedness component seems less strong, as 3 out of 4 questions that were removed came from that angle. Moreover, the 2 remaining questions in the component seem to be measure some “I don’t know” like attitude. Combining these 2 facts, the second component could be measuring something related to directedness, but slightly different. These implications are covered in the discussion.

The two extracted components were used to test for the hypotheses regarding subjective measures. Their descriptives per condition are stated in appendix & .

	Component	
	1	2
The search helped me find what I was looking for.	**,756**	
The search helped me to achieve the goal I had when entering BachelorsPortal.	**,766**	
With the search I found the answer I wanted to find.	**,783**	
I had no specific piece of information in mind that I wanted to find, and used the search to explore.		**,776**
The search results were useful.	**,819**	
The search results allowed me to more quickly see what studies interest me.	**,788**	
The search results saved me time.	**,808**	
I do not know a lot about the field of study that I searched for.		**,789**
By seeing a study in the search results I get a good idea what that study is about.	**,665**	,275

Table 26: pattern matrix of rotated PCA of questionnaire items. Two components were extracted: goal attainment/usefulness and directedness/expertise.

6.5.1 High scent => high goal attainment and usefulness (H8 & H10)

It was expected that higher scent would lead to higher perceived goal attainment (H8) and usefulness (H10). As the dependent variables for both hypotheses are captured in the same component goal/usefulness, both can be tested with a single ANOVA-test shown in Table 28. The descriptives are stated in Table 27.

	count	mean	std	min	25%	50%	75%	max
original	34	0.0156	0.8821	-1.908	-0.612	-0.043	0.679	1.544
basic	31	0.0844	0.7920	-1.128	-0.476	-0.027	0.637	1.546
subordinate	38	0.0264	1.1720	-3.417	-0.450	0.169	1.052	1.546
wrong	37	-0.1122	1.0923	-3.821	-0.507	-0.031	0.458	1.547

Table 27: descriptives of the factor goal attainment/usefulness, per experimental condition.

Overall it performed poorly, with R^2 = 0.005 and an F-statistic of 0.27 (p=0.87). A possibility could be the unequal sample sizes and skewness of the data distribution (kurtosis=4.55, skewness=-0.84). Three potential outliers with very negative scores were removed (resulting in kurtosis=2.55, skewness=-0.05) which did not result into any significant insights. Moreover, a non-parametric Kruskal-Wallis test was used to verify the findings, as it does not depend on the assumption of normally distributed data. It found no significant difference in means (χ^2_3=0.96, p=0.81). Based on these results, both H8 and H10 are not supported, meaning no support could be found for the hypothesis that higher information scent leads to higher perceived goal attainment or perceived usefulness. It also shows no support for H11 (from a subjective point of view): neither the basic nor the subordinate conditions differ significantly from the original, and seen that they both point into the same direction, do also not differ from each other. This might indicate that an increase in information scent in the detailed form that it was done in this experiment has no effect on the perceived usefulness or perceived goal attainment.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	0.0036	0.085	0.042	0.967	-0.166	0.173
C(X, Simple)[Simp.basic]	0.0808	0.154	0.525	0.601	-0.224	0.385
C(X, Simple)[Simp.subordinate]	0.0229	0.144	0.159	0.874	-0.262	0.307
C(X, Simple)[Simp.wrong]	-0.1158	0.145	-0.798	0.426	-0.403	0.171

Table 28: OLS regression of "goal/usefulness ~ condition".

In one of the questions participants were asked to indicate to what percentage they completed their goal (see Table 29 for descriptives and appendix Figure 25), as an independent question different from the questions used to extract the factors. Its correlation with the goal/usefulness factor was reasonable (0.59) but showed no significant differences between the conditions in an ANOVA (see Table 30) (R^2=0.018, F(3) = 0.80, p=0.49). This enforces the statement that H8 is not supported by this data.

	count	Mean	std	min	25%	50%	75%	max
original	32	75.22	19.91	21	65.25	74.5	89.25	100
basic	29	70.38	21.30	26	57	71	88	100
subordinate	37	66.54	26.82	9	52	72	85	100
wrong	35	69.46	24.28	7	59.5	70	86.5	100

Table 29: descriptives of the goal completeness indicated by users per condition per experimental condition.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	70.3989	2.042	34.475	0.000	66.359	74.439
C(X, Simple)[Simp.basic]	-0.0196	3.695	-0.005	0.996	-7.330	7.290
C(X, Simple)[Simp.subordinate]	-3.8584	3.406	-1.133	0.259	-10.597	2.880
C(X, Simple)[Simp.wrong]	-0.9418	3.468	-0.272	0.786	-7.803	5.919

Table 30: OS regression of "goal finding ~ condition".

6.5.2 Directedness interaction (H12)

To test whether directedness moderates the effect between condition and the goal/usefulness factor (described in Table 32), an OLS regression was done, shown in Table 31 ($F(7)=0.33$, $p=0.94$). It showed no significant interactions from directedness/expertise on goal/usefulness, and shows no support for H12 from the subjective point of view. This suggests there is no evidence that goal directedness affects the preference for basic or subordinate information scent, though we argue in the discussion that this could be due to small effect sizes combined with a limited sample size.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	-0.0053	0.091	-0.058	0.954	-0.185	0.174
C(se_va, Simple)[Simp.basic]	0.1059	0.164	0.646	0.520	-0.218	0.430
C(se_va, Simple)[Simp.subordinate]	0.0336	0.152	0.221	0.826	-0.267	0.334
C(se_va, Simple)[Simp.wrong]	-0.1207	0.154	-0.786	0.433	-0.424	0.183
factor_expert	0.0454	0.093	0.486	0.628	-0.139	0.230
factor_expert:C(se_va, Simple)[Simp.basic]	0.0477	0.141	0.338	0.736	-0.231	0.327
factor_expert:C(se_va, Simple)[Simp.subordinate]	-0.1465	0.172	-0.854	0.395	-0.486	0.193
factor_expert:C(se_va, Simple)[Simp.wrong]	-0.0525	0.164	-0.320	0.749	-0.377	0.272

Table 31: OLS regression results for the model "factor goal ~ factor expert * condition".

	count	mean	std	min	25%	50%	75%	max
original	34.0	0.104	0.931	-1.922	-0.497	-0.044	0.698	2.138
basic	31.0	-0.247	1.289	-2.817	-1.072	-0.263	0.489	2.027
subordinate	38.0	0.038	0.852	-1.359	-0.567	-0.065	0.435	2.219
Wrong	37.0	0.073	0.930	-2.169	-0.295	-0.106	0.786	2.027

Table 32: descriptives of the factor directedness/expertise per experimental condition.

From the objective perspective, all the tests done to test for H1-H6 were repeated for the users who answered the questionnaire, with the factor expert/directedness added as interaction. Due to the relatively low number of participants (making the data behave more unexpectedly) and the fact that this is a copy of the analysis already done, only the regression results will be stated in the appendix and summarized here.

Out of the 6 tests (Table 47 - Table 52) only one, with study dwelling time as dependent variable resulted in a somewhat significant model (p=0.095), where subordinate*expert was the strongest interaction (coefficient=-0.37, p=0.096); in the expected direction but not significant. This however does not tell much; the tests done for H1-6 did show significant results, the fact that they did not appear here is most likely due to the low number of participants combined with the small effect sizes that could be expected based on effect sizes of the behavioral data.

To predict expertise of all users and perhaps draw stronger conclusions, an attempt was made to generate a regression model that would predict the expertise level based on user characteristics described before. Too little variance was explained by these variables however (R^2 =0.145), and going to great lengths to compute extended features for this model is unfortunately outside the scope of this project. The implications of this are discussed in chapter 7.2.

6.6 Combining subjective and objective

H11 & H12 are only partially covered up until this point, as they are only answered from a subjective point of view. In this subchapter we'll try to connect the subjective and objective data to answer H11 & H12 and check the assumptions made in chapter 3. In the process we'll take a look at the goals users entered in the questionnaire as well as button versus study name link choice on the search page. Hopefully these statistics will tell something more about the research questions, as they are not directly stated in the hypotheses but are closely related and potentially influential.

In the pilot the metric of *dropout locations* (pages were users end their session) showed interesting patterns and suggested that users ended their session more often on the search page if the original buttons were shown (see appendix chapter 11.4.3.4). This dropout indicates where users either satisfied their information needs or lost the confidence of doing so and is therefore relevant for this analysis. However, the data of the main experiment showed no significant differences between conditions (see appendix Figure 24) and is therefore left out of this analysis.

6.6.1 Goals

Manual inspection showed that out of 190 users who answered this question only about a dozen users were somewhat specific in their preferences (*".. B.A. in Filmmaking or Photography…"*, *"…highly interested in Game Design/Development Courses.."*), having a goal that was similar in level as the labels in the basic condition. Two goals were so specific that the subordinate labels might have assisted better ("*I want to be a Sign Language Interpreter…*"). Most of the goals however were pretty generic ("*suitable university for me*", "*Everything I need, the requirements for me to study abroad.*"). Overall this suggests something about the general level of directedness of the participants, which might be lower than anticipated when the studies were labelled.

Figure 13 displayes a visualized network of comments, where distance between comments is computed with LSA. This explorative analysis shows about 8 clusters that are identified by keywords, ranging from clusters focussed on “university” & “bachelor” to “right” & “good”. There appeared to be no significant differnence between conditions regarding the goal they were after (shown in appendix Figure 27 and Figure 28). This visualization indicated that users might not actually be looking for something specific as most of them seem to cluster together around very generic topics.

Figure 13: annotated plot of goals defined by users in the questionnaire, distances computed with LSA. It indicates several areas of what users hope to find, primarily a good university, a specific course or program, a Bachelor, or simply a “good” or the “right” study or university.

An explorative analysis was done on the user defined goals by extracting ten LSA factors (see appendix chapter 9.2.5.1), that had some interesting relations with previously covered measures. Appendix Table 39 trough Table 43 show a number of regressions that show these effects, summarizing the main results:

- Factor 0 (university, study, course, good, field, interest) has a positive effect on the goal/usefulness factor (p=0.03, coefficient=0.36), and for younger users (coefficient =-1.41, p=0.08). Apparently, users with a general goal that satisfied their interest (i.e. not "find the best university" but "find a good university that offers interesting courses") find BachelorsPortal more useful.
- Factor 2 (University, -course, -field, right, best, good) has a negative effect on search page view counts (p=0.007, coefficient =-2.0) and estimation of seconds used to complete goal (p=0.006, coefficient =--1801). Apparently, users who are looking for a good university use less searches and subjectively need shorter to complete their goal;
- Factor 3 (Field, -study, future, -good, life, -degree) has a positive effect on conversion likelihood (p=0.004, coefficient =0.23), suggesting that users interested in a certain field and a focus on their future life's as more likely to convert.

Overall this LSA reduction showed that the user goals were quite general, making a more in-depth LSA similarity between links that a user clicked and their goal less interesting; only a handful of goals were specific enough to have any similarity. This suggests something about the overall goal (and therefore directedness) of the users: they are relatively general and subordinate information scent might be too specific and might not even be in their knowledge space. This is further elaborated in the discussion.

6.6.2 Search result: link or button?

In each search result, such as the one in Figure 1, users have 2 possibilities to access the study: either by clicking on the name of the study, or by clicking on the button. What is left unconsidered up until this point is how users accessed the study: do they click the button or the link, and how does this differ over the different conditions?

In total 6,827 clicking events were tracked, only a fraction of the 90,745 study pages viewed with search as the referrer. This difference is most likely because the event is triggered when the browser starts navigating, and some browsers do not allow or stop those kind of requests. To make sure this didn't cause too much bias (i.e. only non-mobile devices registering clicks) a number of comparisons were done between sessions that did register clicks and those that did not. No indication of such a bias could be found.

The measure is described Table 33, and shows that users in the baseline condition click significantly more often on the button compared to all others. A logistic regression was run and confirmed these results (McFadden's R^2=0.005, χ^2_3 p<0.0001, see Table 34). This is somewhat surprising given previous found effects: users in the unmodified condition click the button more often! This suggests that users might be more hesitant to click the buttons when specific labels are put into them, though only the wrong condition was found to be significant, allowing for the possibility that it might depend on the quality of the label. Combining this finding with the previous results suggest that the button modification changes the scent of the complete patch (being one search result) and does assist in drawing users' attention to the right search result, even though they seem to have a preference to interact with the search result via the title link.

	basic	original	subordinate	wrong
No	1230 (74.1%)	1158 (67.9%)	1197 (75.1%)	1440 (76.9%)
Yes	429 (25.9%)	546 (32.0%)	396 (24.9%)	431 (23.0%)

Table 33: did a user in a condition click the button (yes) or the link (no) to a study in a search result?

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-1.0294	0.028	-37.257	0.000	-1.084	-0.975
C(X, Simple)[Simp.basic]	-0.0239	0.048	-0.495	0.621	-0.119	0.071
C(X, Simple)[Simp.subordinate]	-0.0768	0.049	-1.553	0.120	-0.174	0.020
C(X, Simple)[Simp.wrong]	-0.1769	0.048	-3.712	0.000	-0.270	-0.083

Table 34: logistic regression for the model "clicked on search result button ~ condition".

6.6.3 Assumptions

In chapter 3 two assumptions were made: that high interest in content means higher goal attainment, and higher usefulness. These were used to construct hypothesis 1-6, and attempted to connect objective to subjective behavior.

To test whether these assumptions were correct the metrics used for H1-6 were used as predictors for the 2 found subjective factors and the user-estimated goal completion. Appendix 9.2.5.3 contains the detailed regression results. Using backwards stepwise regression only a significant model for the directedness/expertise factor was found ($F(6)=4.63$, $p = 0.003$, $R^2=0.53$). In this model, s_pp is page dwelling events per search visit & conv_study_count_prem is the count of premium conversions on study pages.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	-0.9219	0.443	-2.082	0.048	-1.834	-0.010
conv_study_count_prem	0.5133	0.228	2.256	0.033	0.045	0.982
s_pp	0.1677	0.064	2.617	0.015	0.036	0.300
study_pp	-0.0646	0.015	-4.273	0.000	-0.096	-0.033
study_page_count	0.0692	0.027	2.572	0.016	0.014	0.125
search_count	0.0629	0.034	1.829	0.079	-0.008	0.134
paging_count	-0.0926	0.048	-1.918	0.067	-0.192	0.007

Table 35: OLS regression results of the factor directedness/expertise.

Overall this suggests that directedness is measurable from behavior: they convert more, search a little more (different queries, less paging) and dwell a little longer on search pages, while dwelling a little shorter on study pages. For goal achievement no model could be found, leaving the assumption unsupported.

7 Discussion and Conclusion

The information foraging theory (IFT) predicts how users behave on webpages based on the goal they are after, and has been validated over different studies with different conditions (Fu et al., 2007; Pirolli & Card, 1999). These studies often find that users browsing websites with better, higher information scent are more likely to attain the goal they are after and have a better experience (Mccart et al., 2013; Rigutti et al., 2015). In an exploratory research of BachelorsPortal, a website where users can search and find detailed information about more than 49.000 bachelor studies worldwide, links with no information scent on important places in the user interface were found.

Based on the IFT, and the desire to continuously improve BachelorsPortal to better assist users in their search for the perfect study, a method was proposed that allowed implementation of the IFT. By taking the content of a study and computing the optimal labels the information scent should be better, and it should become more attractive for users to engage with studies they are close to the goal they are after.

An experiment was proposed and ran on BachelorsPortal for two weeks, modifying the information scent of buttons in search results. For the construction of these labels the theory of categorization (Johnson & Mervis, 1997) was used, with the hypothesis that more directed users were better served with subordinate (specific) labels, while in general basic (more abstract) labels would work better. A fourth “wrong” condition with faulty labels was added to rule-out button effects and validate label quality.

Thirteen hypotheses were defined and tested with the data gathered from the experiment. This chapter will summarize those results to answer the two sub-research questions, elaborate on the limitations of this study and present a final conclusion and possibilities for further research.

7.1 Findings

Table 36 summarizes the findings of the hypotheses. While most hypotheses are not- or only partially supported, the information scent did show a clear effect, and in case of the basic categorization mostly in the expected direction. Overall the subjective measures proved to be of little value in regards to the hypotheses. This was not completely unexpected given the small effect sizes in the behavior data and the relatively low number of participants in the survey, a study with more respondents might give more insights.

Another reason might be that the questions did not show the four underlying components that were used to design the questionnaire, even though the questions were largely based on previous research. One of the possible consequences is that the first extracted component represented something else then goal attainment/usefulness (the wide range of questions suggest something like overall search engine usefulness). This would be a possible explanation why almost none of the expected effects on this factor could be extracted from the results. Regarding expertise & directedness the same argument applies, though analysis of the user goals also suggest that they in general are quite generic, and users on BachelorsPortal might simply be too inexperienced to differ much in expertise (all are relatively low).

The findings will be further discussed in reference to the 2 sub research questions.

Hypothesis	**Finding**	**Elaboration**
H1	Partially confirmed	Subordinate users view lower # study views, basic insignificant
H2	Not supported	Subordinate users had a lower search-study CTR likelihood where a higher was expected
H3	Partially confirmed	Only basic scent increased study page dwelling time
H4	Partially confirmed	Only basic scent decrease search page dwelling time, subordinate increases it
H5	Partially confirmed	Only basic scent increases conversion likelihood, subordinate decreases it
H6	Counter confirmed	Basic scent leads to more conversion, subordinate insignificant
H7	Not supported	
H8	Not supported	
H9	Not supported	
H10	Not supported	
H11	Not supported	
H12	Not supported	
H13	Not supported	Untestable due to single directedness/expertise factor

Table 36: summary of the hypotheses and their results found in this study.

7.1.1 Does basic- or subordinate-level information scent lead to improved goal attainment and usefulness?

With increase of information scent, it was expected that goal attainment and usefulness would improve. A number of the objective metrics supported this for the basic categorization condition:

- Spend more time on study pages;
- Spend less time on the search page;
- Have a higher conversion likelihood;

What was not expected was that there was no difference in search-study CTR, apparently information scent in the search result button could not trigger more users to explore studies. This suggests information scent only works if there already is some sort of motivation. Secondly, users in the basic condition converted more, where it was expected they converted less often. A possible argument for this finding could be that the underlying assumption was not valid. Conversion might not be a definitive study-choice action, but merely an extra step in the study choice process. In that sense, conversion might just be an indication of interest, just like longer dwelling times on a study page are.

The findings for the subordinate condition are somewhat harder to interpret. Generally, it was expected to behave worse than the basic condition, what we found was that users:

- Have lower search-study CTR & search-study CTR likelihood;
- Dwell longer on the search. As the wrong condition has almost the same effect size, it might be due to the added complexity, not the actual quality of the labels;
- Are less likely to convert at least once.

These findings suggest that the subordinate tags might have been too complex, as users needed longer to process them and do not appear to pick better studies based on the labels.

A rather unexpected finding in this experiment was that the whole concept of IFT initially was based on the idea that users would actually *click* the button with higher information scent. We found the exact opposite: users clicked the button less and the title of the study more (only significant for the wrong condition). This may suggest that the labels did not help by being the best link, but by making the scent of the patch higher, though the evidence for this evidence is not that strong.

To answer research question 1: behavioral measures suggest basic level information scent improves goal attainment and usefulness. These results could not be reproduced with subjective metrics, though it is likely due to the low number of participants, or the absence of an effect in the users' perception. And as the subjective results are insignificant but the objective interest indicators are, we can conclude the modifications might not help on subjective experience, but certainly also do not work counterproductive. This makes reversed information scent a viable solution for information scent issues which can be used to increase important user metrics and overall website usefulness. Determining the user's expertise level and balancing the categorization of the labels is critical however, and basic-level categorization will most likely work best, unless users have a high expertise. The different processes in label construction could also have played a role in this; perhaps the human generated labels were better even though their LSA score was lower. This is one of the limitations in this thesis (covered in chapter 7.2), which cannot be tested with the available data.

7.1.2 Does the effect of basic- or subordinate-level scent depend on the directedness of a user?

It was expected that highly directed users were better supported with subordinate-level information scent, while less directed users were better served with basic information scent. Overall we found no support for this theory as statistical tests proved to be insignificant. So while there is little statistical support for this question, a straight-forward argumentation can be made that suggests possible support for out hypotheses.

As shown in the analysis of the goals defined by users themselves (chapter 6.6.1), about 90% of the users had goals that were so generic that even the basic-level tags might have been too specific, as they really seemed to be exploring their initial options and interests. Only about a dozen where somewhat specific, and 2 were very specific. This suggests that the overall level of directedness is relatively low for BachelorsPortal users. So low in fact that the subordinate labels will have a more negative effect then the basic (and in some cases even the original) condition. This is also what the results showed: the subordinate results were either insignificantly different from the original, or in the opposite direction of the hypotheses.

In conclusion; the data does not show a strong, direct effect of directedness on preference for subordinate-level tagging. It is however plausible that the effect exists, and we overestimated the variance of directedness between users in the design of this experiment. This can be generalized to the statement that basic information scent might be the best choice when trying to improve hyperlink scent, except in the (perhaps rare) case when users are highly experienced in the information field they are searching in.

7.2 Limitations

The findings of this thesis can be partly explained by a number of limitations, which will be elaborated here.

Firstly, reflecting on the results the subordinate labels might have been too complex, and the experiment would have benefitted from less complex (though still subordinate) labels. Different labelling processes in the pilot and the main experiment combined with the low power of the pilot hid the fact that users generally might be undirected in their search on BachelorsPortal.

Secondly, the quality of the labelling process was found to be reasonable, but might benefit from a number of improvements. The results of the wrong condition indicate significantly better quality of the labels then random though, thus it is likely significant improvements can be made. More complex algorithms like (Nie et al., 2014; Sood et al., 2007) could improve the overall quality and make the process independent and unsupervised. Another point in the labelling process is the different labelling methodologies used for the basic- and subordinate condition. The first is human, the second automated, both constructed on different label-sets which were constructed for different purposes. One tightly managed by StudyPortals, the other quickly scanned for computational verification. This might have caused biases which cannot be checked for with the gathered data.

Thirdly, the survey responses caused a number of problems. The directedness factor for example, previously tested by (Gomez & Moens, 2014), could not be extracted at all, and the well-proven factor of usefulness (Knijnenburg et al., 2012) could not be isolated. As discussed before, a study with more information scent modifications combined with a larger number of survey responses could assist in better answering questions regarding subjective metrics.

Which touches the fourth point; user behavior metrics that were analyzed in this thesis only predict a small percentage of the variance of the 2 subjective factors (less than 5% for goal attainment/usefulness, 14.5% for directedness/expertise). This suggests we might have missed user metrics that differ greatly between users with higher goal attainment/usefulness or directedness/expertise from which stronger conclusions could have been drawn. The metrics used here however are very similar to the ones used in these types of research before (Mccart et al., 2013) and it is possible that some of the variance simply cannot be extracted from user behavior.

Fifthly, the experiment was implemented on a very specific location, making it hard to argue that its results are applicable in every situation. The search page of BachelorsPortal can be seen as the "heart" of the website, which has the advantage of a lot of visitors, but the disadvantage of low user directedness with a very wide range of motivations and goals. While previous information scent research like (Blackmon et al., 2002; Blackmon, 2012b; Rigutti et al., 2015) suggests similar effects found in this study also apply to different websites, it is possible that users respond differently to these kind of information scent modifications on different pages.

Finally, the target group limited the focus in a number of ways, again introducing uncertainty whether these results can be generalized. Most obviously, users are targeted that are looking for a bachelor study, which in itself implies all kind of user characteristics such as age (Figure 29), educational background (Figure 20), economical welfare and location (Figure 32). Again, similarity between results of this study and previous work such as (Mccart et al., 2013) suggest that the results found here will work for users with other characteristics as well. Besides the objective measures, the way in which participation was requested biased the questionnaire responses towards users that were motivated by financial rewards and willing to participate. As it was only such a small percentage of the users (0.51%), event with obvious popups, they might not have been a good representation of the whole population.

7.3 Conclusions & Further Research

Given the conclusions drawn from sub-research questions and the studies limitations, a final conclusion regarding the main research question is made here, and possibilities for future research are suggested.

Overall, the aim of this study was to answer the question

> *Can increased information scent in hyperlinks be used to let users find the information they are after more efficiently and effectively? Which level of information categorization works best when increasing information scent, and how is that affected by goal directedness?*

The first part of this research question is already answered in 7.1.1, which suggested that reversed information scent might indeed assist users in their search for certain information. Especially user behavior showed significant improvements in desirable behavior (both from a company and user perspective), suggesting information scent might be a good tool for information websites. Regarding directedness and information categorization, results of this study suggests that in alignment with earlier categorization studies (Johnson & Mervis, 1997; Kim, Porter, & Goolkasian, 2014), basic information scent is preferred over subordinate information scent. Basic categorized information scenting hyperlinks lead to behavior that we expected to match goal attainment and usefulness: less time used searching, more interest in the chosen studies & higher conversion. This could not be reproduced with subjective metrics, where no significant effects of the different experimental conditions could be detected. While these results in combination with the limitations presented above do not make the most solid case, reversed information scent has proven to be a promising technique to improve information scent in places where little is in place.

We suggest this is the most interesting idea to be extracted from this thesis, and worth continuing to build on. One of the current limitations, the algorithm for auto labelling, is one of the area's where improvements can be made. Now that the underlying idea has shown its potential more effort can be put into this as significant improvements are very plausible. These results also suggest that one level of categorization might work fine for websites where there is not too much variance in user directedness and expertise level; a metric worth checking before constructing a labelling process.

Another main area that can benefit from further research is the subjective effects of information scent. Up until this point IFT has mostly been a mathematical model, and besides some usability studies that almost appeared more mandatory then a main focus point, no real effort was done to look into how users experienced the information scent. One of the goals of this thesis was to dive deeper into this information scent usability gap, but failed to draw strong conclusions due to the small number of survey responses. Further research might look into these subjective measures by aiming to get more responses from a larger portion of the population, while perhaps aiming to create a bigger effect by modifying multiple links.

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9 Appendix

The appendix consists of a number of tables, figures and extra content which is not directly necessary in the main text, but can assist in a more detailed explanation. Three separate chapters (BachelorsPortal overview, pilot study and data engineering) are added after the appendix for the same reason.

9.1 Questionnaire

The questionnaire conducted in the main experiment consisted of a number of pages: a welcome page, shortly describing the expected time duration and the upcoming question lists, a general question page, a collection of Likert-style questions, a page with open questions, and a finishing page where users could leave their email address and close the experiment. The questionnaire was designed for desktop and mobile use and in congruence with StudyPortals' design-style.

9.1.1 General questions

- What is your current age? [numeric input]
- What is your gender? [select, male/female]
- What is currently your highest finished level of education? [select]

9.1.2 Likert-questions

On top of the page the following text was added to make sure the reference to the "search" in the questions was clear:

All of the following questions are about the **search** actions you just performed on **BachelorsPortal.** Please indicate to what extent you agree to the following statements.

Possible answers for all questions were: strongly disagree, disagree, not agree/not disagree, agree and strongly agree. Questions were shown in the order as stated below. Furthermore, the page was designed to work well on mobile and desktop (as was the whole questionnaire), see Figure 15.

Goal attainment

- The search helped me find what I was looking for.
- The search helped me to achieve the goal I had when entering BachelorsPortal.
- With the search I found the answer I wanted to find.

Goal directedness (Gomez & Moens, 2014)

- I already had a particular Study (or University) in mind and just used the search to get there.
- I had no specific piece of information in mind that I wanted to find, and used the search to explore.
- I know very specifically what I want to find with this search.

Perceived usefulness

- The search results were useful.
- The search results allowed me to more quickly see what studies interest me.
- The search results saved me time.

- I can find better study programs with the help of the search results.

Expertise

- I'm an expert in the field of study that I searched for.
- I do not know a lot about the field of study that I searched for.
- By seeing a study in the search results I get a good idea what that study is about

9.1.3 Open questions

- What is your goal of using this search; what do you hope to find? [text area]
- To what extend did you complete this goal? [slider, 0 = not at all, 100 = fully]
- How many seconds do you estimate it took to complete your goal from the moment you entered Bachelorsportal? [numeric input]

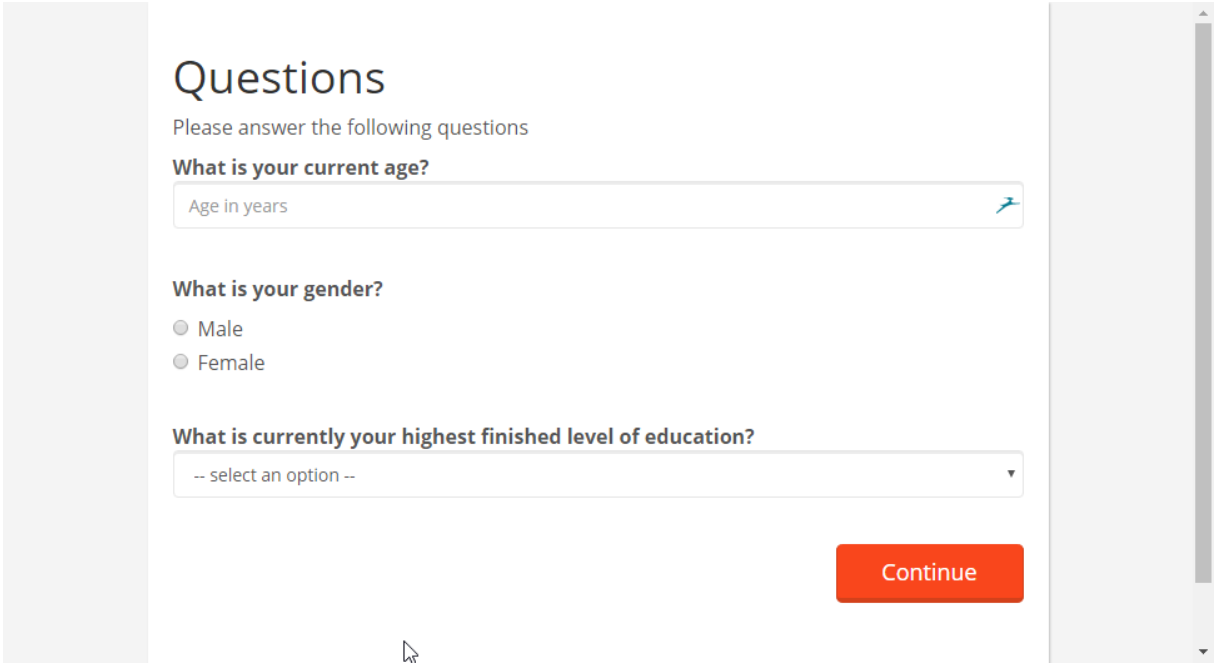

Figure 14: screenshot of questionnaire that popped up if users clicked on the participate button on the questionnaire participation request on BachelorsPortal.

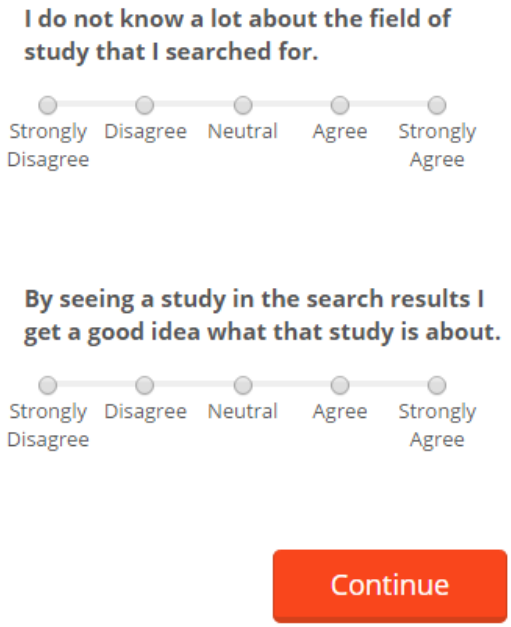

Figure 15: screenshot of the Likert-style questions on mobile-sized screens.

9.2 Experiment data

While analyzing the results from the experiment, a number of tables, figures and some texts were constructed that did not fit in the main body of the study, but are significant in some argumentations. They are added in this subchapter.

9.2.1 Labels

The quality of the labels generated for the experiment were verified by analyzing the LSA similarity of the final labels with the content of the studies they were attached to. The OLS regression at the bottom shows that LSA subordinate > LSA basic > LSA wrong.

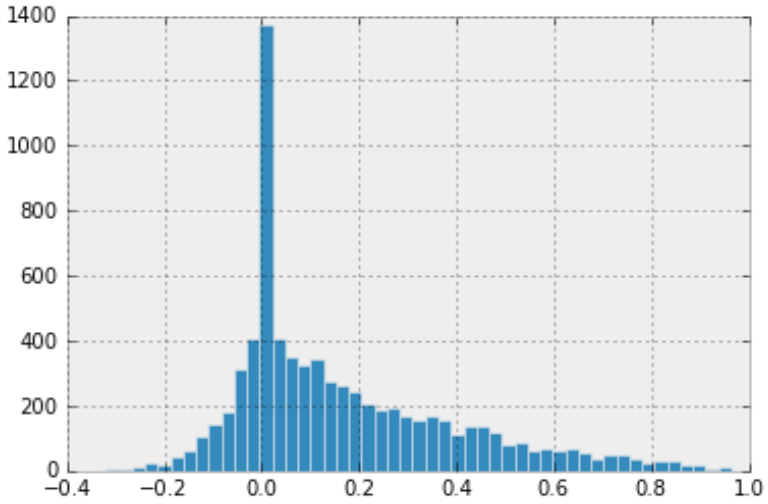

Figure 16: distribution plot of LSA similarity between the final wrong tags and the studies they were attached to.

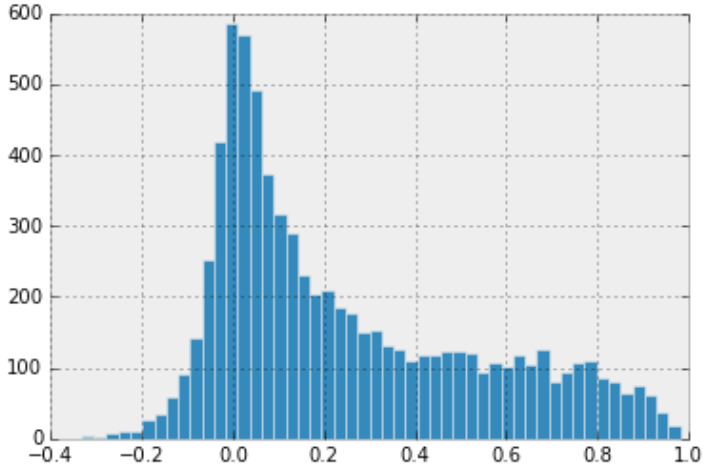

Figure 17: distribution plot of LSA similarity between the final subordinate tags and the studies they were attached to.

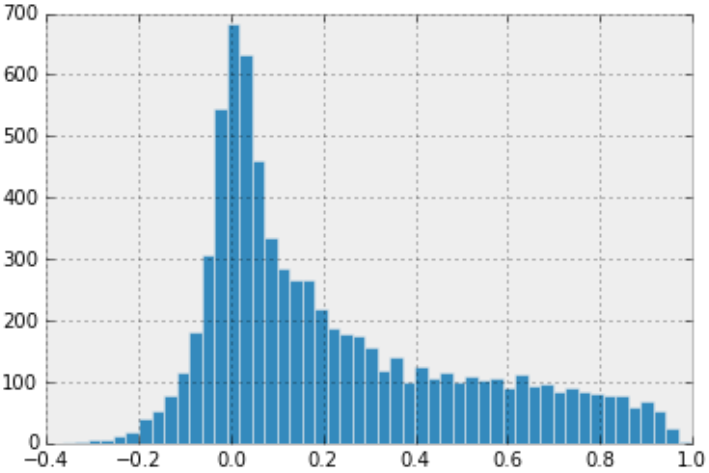

Figure 18: distribution plot of LSA similarity between the final basic tags and the studies they were attached to.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	0.2218	0.003	71.711	0.000	0.216	0.228
C(type)[T.subordinate]	0.0251	0.004	5.732	0.000	0.016	0.034
C(type)[T.wrong]	-0.0542	0.004	-12.399	0.000	-0.063	-0.046

Table 37: OLS regression ($F(2)=171.8$, $p<0.0001$, $R^2=0.02$) results of the model "LSA similarity ~ tag type". Subordinate outperforms basic, wrong underperforms both, as intended.

9.2.2 Questionnaire participants

This chapter presents a number of graphs explaining certain statistics from the participants who participated in the questionnaire.

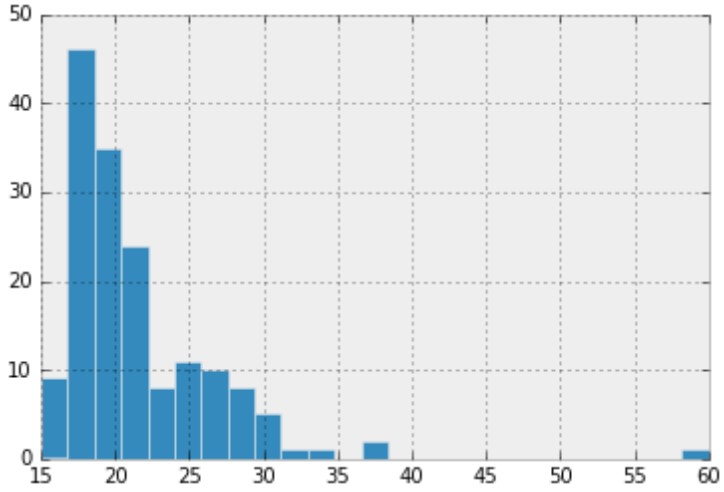

Figure 19: age distribution of questionnaire respondents. It looks very similar to the age distribution of all visitors to BachelorsPortal.

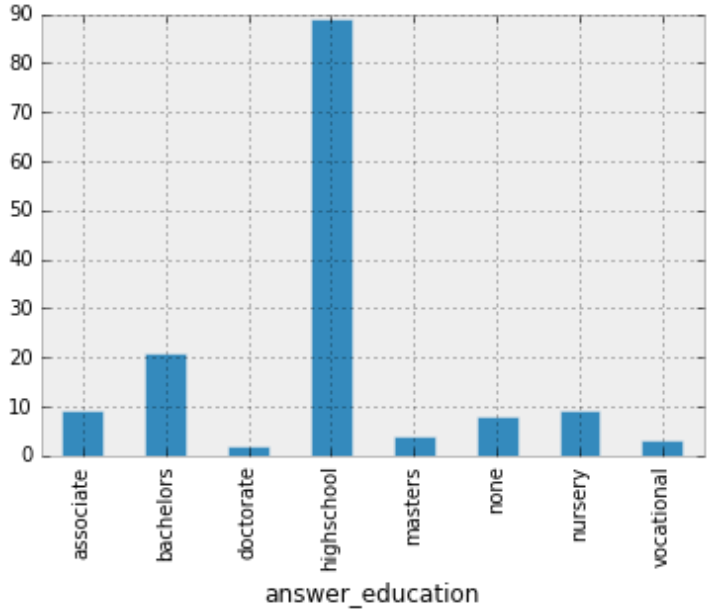

Figure 20: counts of completed educational levels of questionnaire respondents: high school clearly beats the other options.

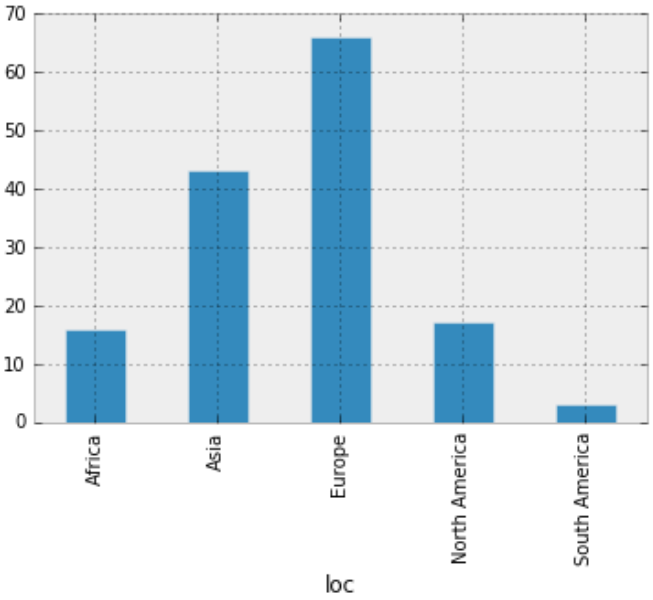

Figure 21: number of respondents per continent.

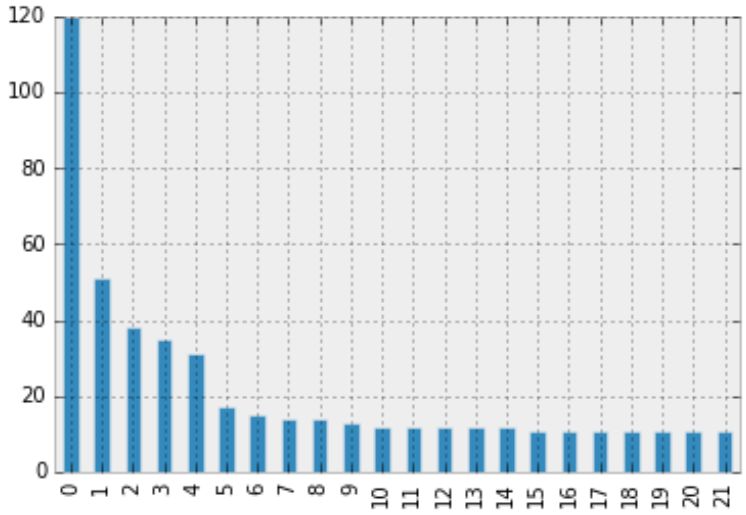

Figure 22: users (x-axis) that converted most often per study (y-axis). A clear outlier converted almost 120 times on the same study.

9.2.3 Results

This subchapter contains some extra data for the result section of the experiment to prevent cluttering the main text body.

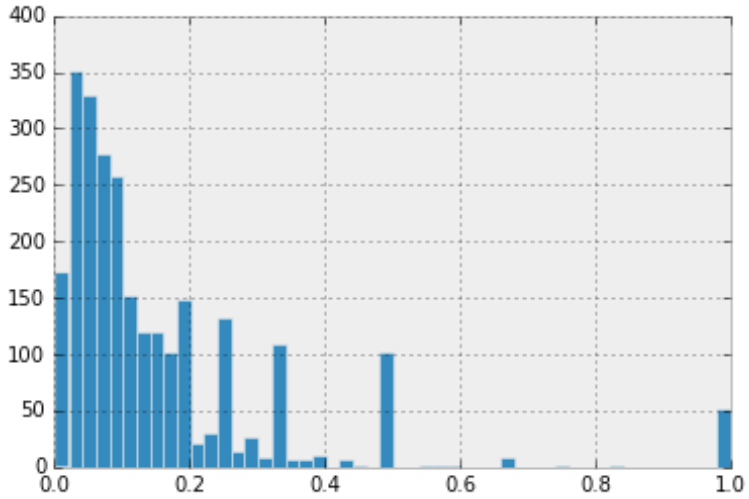

Figure 23: histogram of conversion-CTR probabilities.

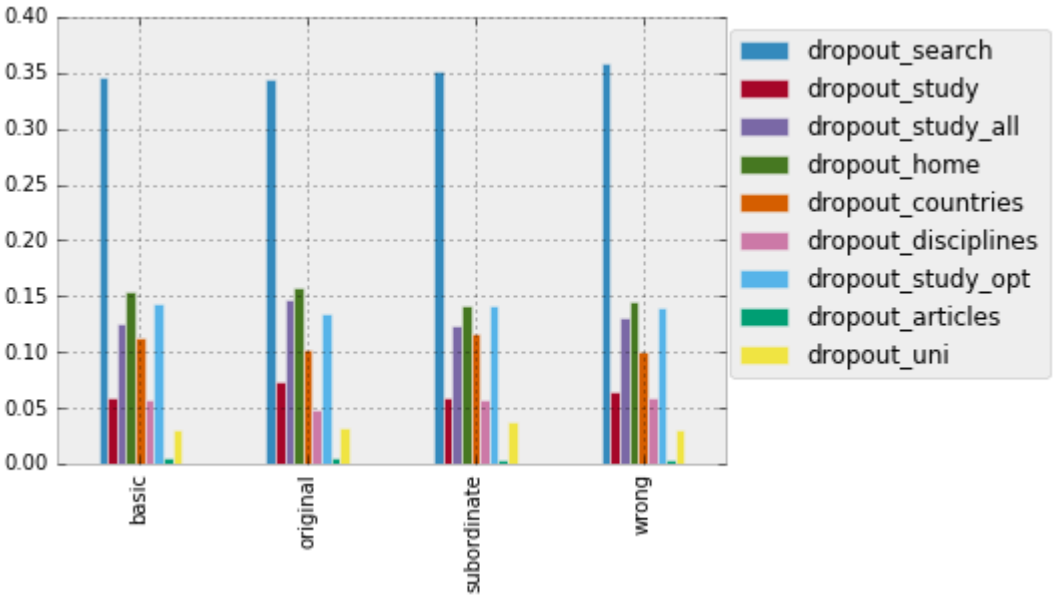

Figure 24: dropout rates per page type and condition; i.e. about 0.35 of the users in the subordinate condition end their session at the search page. Where there were significant differences between the conditions in the pilot data, the data from the experiment revealed no such patterns.

9.2.4 Questionnaire results

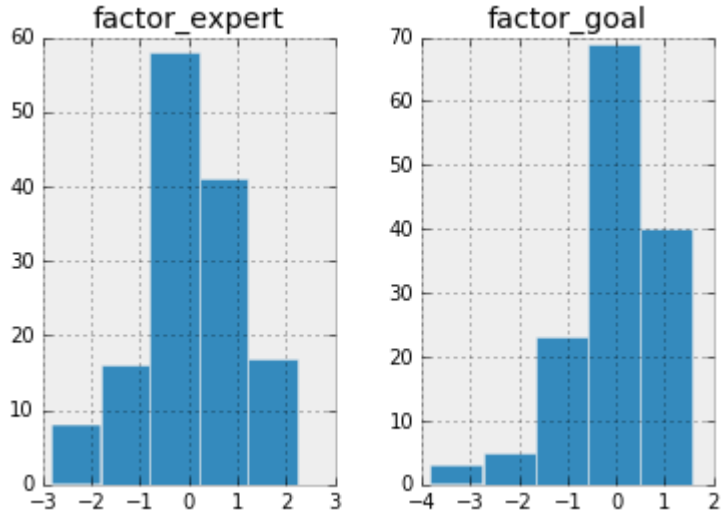

Table 38: histograms for computed variables for the 2 components expert/directedness (left) and goal attainment/usefulness (right).

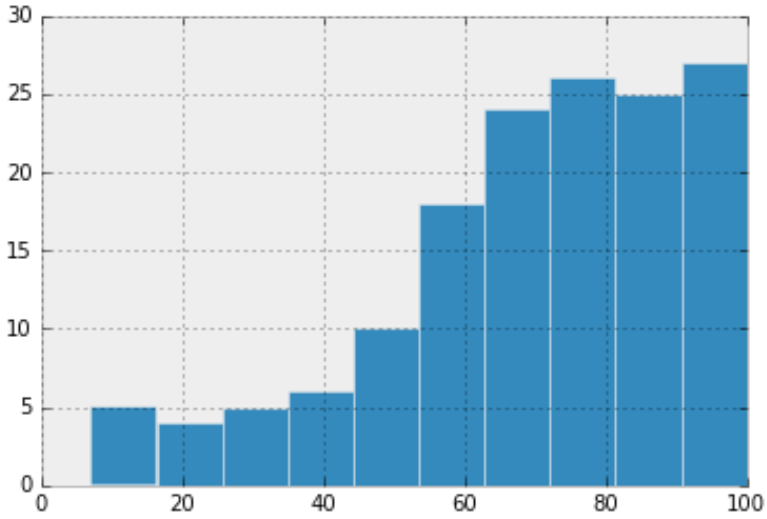

Figure 25: histogram of goal completion as indicated by users in the questionnaire. Clearly not-normally distributed, and clearly a lot of users estimate to be far in their goal completion process.

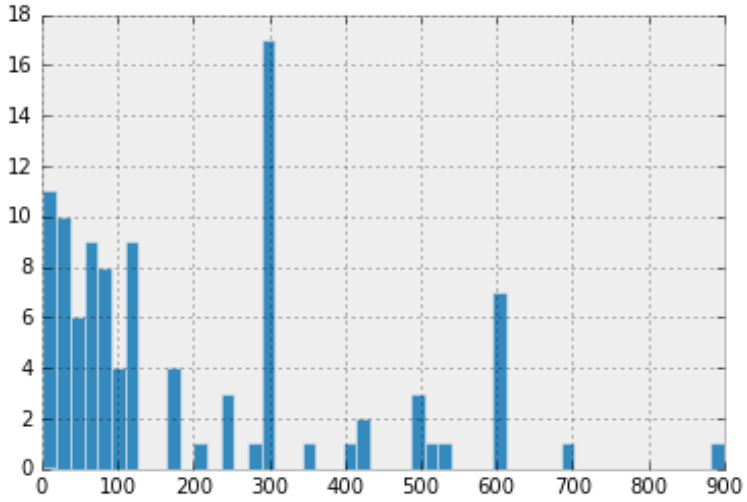

Figure 26: histogram of goal attainment time estimation made by users in seconds.

9.2.5 User goals

Users were asked to write down their goal for coming to BachelorsPortal in the questionnaire. This subchapter presents some of the visualizations that resulted from analyzing these written goals.

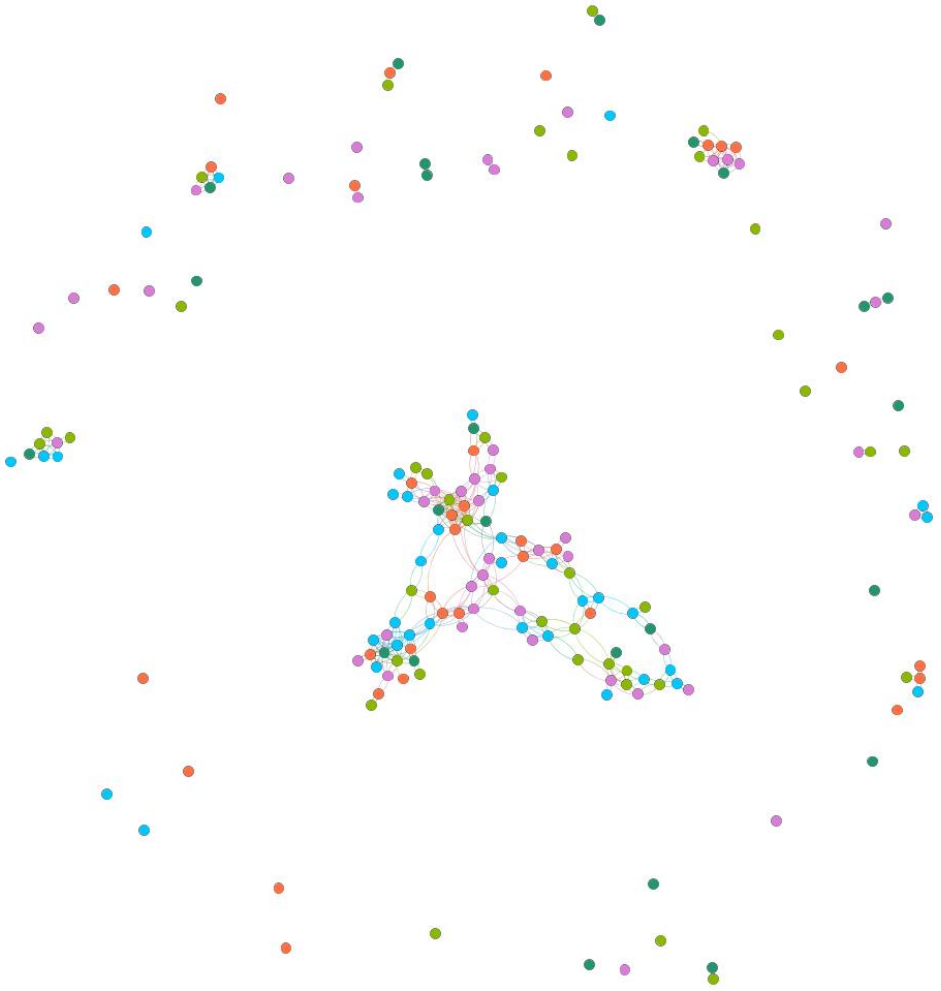

Figure 27: same plot of user goals, only focused on experimental condition: pink=subordinate, wrong=green, blue=original, basic=orange and no condition=dark green.

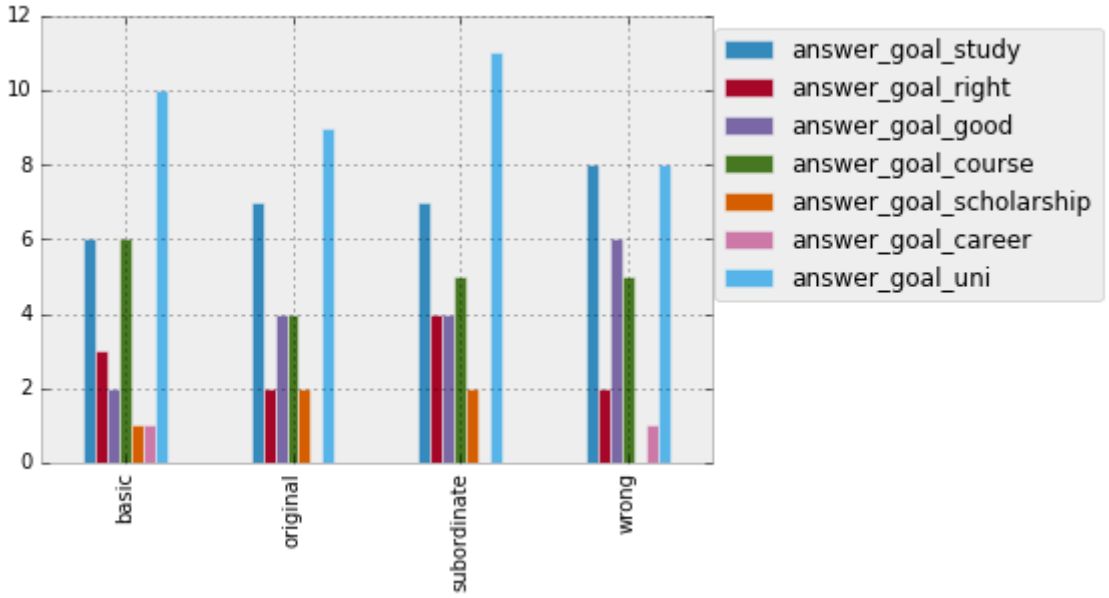

Figure 28: usage of keywords per condition when describing their goal in the questionnaire.

9.2.5.1 LSA topics extracted from user goals

Using LSA 10 topics where extracted, presented below. All words are stemmed, so "university" will be reduced to "univers".

0 -- 0.569*univers + 0.461*studi + 0.255*cours + 0.164*good + 0.163*field + 0.161*interest + 0.140*look + 0.120* + 0.108*offer + 0.104*futur

1 -- 0.507*studi + -0.437*cours + -0.229*interest + 0.217*field + -0.202*univers + 0.169*futur + 0.155*life. + -0.152*suitabl + -0.130*look + 0.123*goal

2 -- 0.552*univers + -0.435*cours + -0.164*field + 0.152*right + 0.141*best + 0.140*good + -0.130*interest + -0.129*degre + -0.118*futur + -0.115*studi

3 -- 0.375*field + -0.346*studi + 0.264*futur + -0.220*good + 0.213*life. + -0.155*degre + 0.148*univers + 0.127*interest + 0.118*inform + 0.116*university,

4 -- -0.299*interest + -0.281*degre + 0.276*cours + -0.273*bachelor + -0.221*higher + 0.186*look + -0.183*program + 0.163*good + -0.151*option + -0.147*avail

5 -- 0.510*good + 0.288*help + 0.196*A + -0.169*univers + 0.166*find + -0.149* + 0.145*Studi + 0.140*Find + 0.137*much + 0.132*match

6 -- 0.217*countri + -0.210*interest + -0.203*year + 0.190*good + 0.183* + -0.179*look + -0.162*studi + -0.147*option + -0.139*move + -0.129*finish

7 -- 0.344*help + -0.324*good + -0.267*A + 0.243*work + 0.243*line + 0.185*suit + 0.182*mani + 0.179*program + 0.155*use + -0.141*suitabl

8 -- -0.300*program + -0.259*suitabl + -0.233*A + 0.196*year + 0.193*option + -0.167*goal + 0.151*finish + 0.137*higher + 0.136*degre + -0.135*plan

9 -- -0.231*good + 0.219*studi + -0.200*. + -0.190*search + 0.182*look + -0.165*use + -0.160*scienc + -0.153*knowledg + -0.153*plan + -0.147*goal

9.2.5.2 Results of regressions run with LSA topics

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	-0.1537	0.122	-1.258	0.211	-0.395	0.088
lsi_0	0.3608	0.163	2.208	0.029	0.037	0.684
lsi_1	-0.0527	0.152	-0.346	0.730	-0.354	0.249
lsi_2	0.2670	0.182	1.467	0.145	-0.093	0.627
lsi_3	-0.0439	0.188	-0.234	0.815	-0.415	0.327
lsi_4	0.1364	0.192	0.709	0.480	-0.244	0.517
lsi_5	-0.0737	0.203	-0.363	0.717	-0.476	0.328
lsi_6	0.0392	0.202	0.194	0.846	-0.360	0.438
lsi_7	0.0643	0.208	0.310	0.757	-0.346	0.475
lsi_8	-0.2036	0.215	-0.948	0.345	-0.628	0.221
lsi_9	-0.3113	0.220	-1.418	0.159	-0.746	0.123

Table 39: OLS regression (F(10)=1.18, p=0.31, R^2 = 0.08) on the factor goal/usefulness with all LSA components as independent variables.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	1643.6232	435.813	3.771	0.000	781.357	2505.889
lsi_0	732.3582	583.012	1.256	0.211	-421.146	1885.862
lsi_1	675.4298	543.899	1.242	0.217	-400.687	1751.547
lsi_2	-1801.0777	648.990	-2.775	0.006	-3085.120	-517.036
lsi_3	937.3624	668.876	1.401	0.163	-386.026	2260.751
lsi_4	-1855.7095	686.062	-2.705	0.008	-3213.100	-498.319
lsi_5	-231.6156	724.501	-0.320	0.750	-1665.058	1201.827
lsi_6	847.4747	719.779	1.177	0.241	-576.625	2271.574
lsi_7	176.3781	740.357	0.238	0.812	-1288.436	1641.192
lsi_8	280.9910	765.928	0.367	0.714	-1234.417	1796.398
lsi_9	6.5707	783.109	0.008	0.993	-1542.830	1555.972

Table 40: OLS regression (F(10)=2.11, p=0.028, R^2 = 0.14) on the goal completion second estimation as dependent variable, with all LSA components as independent variables.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	0.2241	0.036	6.231	0.000	0.153	0.295
lsi_3	0.2305	0.078	2.964	0.004	0.077	0.384

Table 41: OLS regression (F(1)=8.78, p=0.004, R^2 = 0.06) on conversion likelihood with LSA components as independent variables. A very similar model was found with only premium conversions.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	3.7885	0.353	10.729	0.000	3.090	4.487
lsi_2	-2.0247	0.737	-2.746	0.007	-3.483	-0.566
lsi_9	1.8894	0.938	2.014	0.046	0.034	3.745

Table 42: OLS regression (F(2)=5.73, p=0.004, R^2 = 0.08) on search view count with LSA components as independent variables.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	21.7691	0.565	38.509	0.000	20.651	22.887
lsi_0	-1.4100	0.810	-1.740	0.084	-3.013	0.193
lsi_6	-2.0327	1.053	-1.931	0.056	-4.115	0.049

Table 43: OLS regression (F(2)=3.40, p=0.04, R^2 = 0.05) on age with LSA components as independent variables.

9.2.5.3 Results of regressions exploring subjective-objective relations

Using backwards stepwise regression, a number of objective metrics (page visit counts, page ping counts, conversion counts, search-study CTR) were used to try and predict the 2 subjective factors from the question list. Only for the expertise factor a significant model was found.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	-0.3762	0.265	-1.417	0.170	-0.927	0.174
convert_y	-0.2202	0.567	-0.388	0.701	-1.396	0.955
search_ctr	-4.362e-16	6.97e-16	-0.626	0.538	-1.88e-15	1.01e-15
search_ctr_bin	-0.3762	0.265	-1.417	0.170	-0.927	0.174
conv_study_count_prem	0.0122	0.389	0.031	0.975	-0.795	0.820
s_pp	0.1284	0.085	1.504	0.147	-0.049	0.305
st_pp	0.0491	0.127	0.386	0.703	-0.215	0.313
study_pp	-0.0128	0.029	-0.439	0.665	-0.074	0.048
search_pp	-0.0047	0.007	-0.675	0.507	-0.019	0.010
study_page_count	0.0208	0.040	0.522	0.607	-0.062	0.104
search_count	0.0333	0.040	0.833	0.414	-0.050	0.116
paging_count	-0.0163	0.045	-0.366	0.718	-0.109	0.076

Table 44: initial OLS regression (F(9)=0.62, p=0.77, R^2 = 0.20) of several objective metrics with the factor goal/usefulness as dependent variable. Using a backwards stepwise method, no significant model remained.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	18.8579	7.775	2.425	0.024	2.734	34.982
convert_y	9.1109	16.606	0.549	0.589	-25.327	43.549
search_ctr	2.432e-14	2.04e-14	1.190	0.247	-1.8e-14	6.67e-14
search_ctr_bin	18.8579	7.775	2.425	0.024	2.734	34.982
conv_study_count_prem	-7.1840	11.405	-0.630	0.535	-30.837	16.469
s_pp	2.9002	2.501	1.160	0.259	-2.286	8.087
st_pp	3.1196	3.729	0.837	0.412	-4.614	10.854
study_pp	-0.4520	0.857	-0.527	0.603	-2.230	1.326
search_pp	0.1336	0.203	0.659	0.517	-0.287	0.554
study_page_count	0.9011	1.168	0.772	0.449	-1.521	3.323
search_count	0.2795	1.171	0.239	0.814	-2.150	2.709
paging_count	-0.6301	1.304	-0.483	0.634	-3.335	2.074

Table 45: initial OLS regression (F(9)=1.16, p=0.36, R^2 = 0.32) of several objective metrics with the subjective goal attainment as dependent variable. Using a backwards stepwise method, no significant model remained.

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	-0.4610	0.221	-2.082	0.048	-0.917	-0.005
search_ctr	-6.473e-16	2.24e-16	-2.885	0.008	-1.11e-15	-1.85e-16
search_ctr_bin	-0.4610	0.221	-2.082	0.048	-0.917	-0.005
conv_study_count_prem	0.5133	0.228	2.256	0.033	0.045	0.982
s_pp	0.1677	0.064	2.617	0.015	0.036	0.300
study_pp	-0.0646	0.015	-4.273	0.000	-0.096	-0.033
study_page_count	0.0692	0.027	2.572	0.016	0.014	0.125
search_count	0.0629	0.034	1.829	0.079	-0.008	0.134
paging_count	-0.0926	0.048	-1.918	0.067	-0.192	0.007

Table 46: result of backwards OLS regression (F(6)=4.63, p=0.003, R^2 = 0.53) of several objective metrics with the factor directedness/expert as dependent variable.

9.2.5.4 Regressions to test expertise on objective metrics

The regression tests done for hypothesis 1-6 were repeated for the users who answered the questionnaire, to find the relation between directedness and objective metrics such as search-study CTR and conversion.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-2.7425	0.474	-5.787	0.000	-3.671	-1.814
C(X, Simple)[Simp.basic]	0.4330	0.671	0.645	0.519	-0.882	1.748
C(X, Simple)[Simp.subordinate]	-0.1723	0.708	-0.243	0.808	-1.559	1.214
C(X, Simple)[Simp.wrong]	-1.4365	1.189	-1.209	0.227	-3.766	0.893
factor_expert	0.5550	0.438	1.269	0.205	-0.303	1.413
factor_expert:C(X, Simple)[Simp.basic]	0.0547	0.586	0.093	0.926	-1.094	1.204
factor_expert:C(X, Simple)[Simp.subordinate]	-0.3329	0.735	-0.453	0.651	-1.774	1.109
factor_expert:C(X, Simple)[Simp.wrong]	0.6594	1.050	0.628	0.530	-1.399	2.717

Table 47: logit regression results for "search-study CTR likelihood ~ condition * factor expert" (DF =7, p=0.32, McFadden's R^2=0.09).

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-2.4898	0.499	-4.991	0.000	-3.467	-1.512
C(X, Simple)[Simp.basic]	1.0610	0.654	1.622	0.105	-0.221	2.343
C(X, Simple)[Simp.subordinate]	-0.4854	0.767	-0.633	0.527	-1.989	1.018
C(X, Simple)[Simp.wrong]	-1.4401	1.239	-1.162	0.245	-3.869	0.989
factor_expert	0.8329	0.593	1.404	0.160	-0.330	1.996
factor_expert:C(X, Simple)[Simp.basic]	0.1554	0.777	0.200	0.842	-1.368	1.679
factor_expert:C(X, Simple)[Simp.subordinate]	-0.5552	0.961	-0.578	0.563	-2.438	1.327
factor_expert:C(X, Simple)[Simp.wrong]	1.0188	1.424	0.715	0.474	-1.772	3.810
alpha	5.6489	3.246	1.740	0.082	-0.713	12.011

Table 48: negative binomial regression results for "search-study CTR ~ condition * factor expert" (χ^2_7 p=0.24, McFadden's R^2=0.08).

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	2.1886	0.136	16.059	0.000	1.922	2.456
C(X, Simple)[Simp.basic]	0.2652	0.240	1.107	0.268	-0.204	0.735
C(X, Simple)[Simp.subordinate]	-0.4641	0.224	-2.068	0.039	-0.904	-0.024
C(X, Simple)[Simp.wrong]	-0.0216	0.242	-0.089	0.929	-0.496	0.453
factor_expert	0.0133	0.130	0.102	0.919	-0.242	0.269
factor_expert:C(X, Simple)[Simp.basic]	-0.2632	0.183	-1.442	0.149	-0.621	0.095
factor_expert:C(X, Simple)[Simp.subordinate]	-0.3728	0.224	-1.666	0.096	-0.811	0.066
factor_expert:C(X, Simple)[Simp.wrong]	0.3085	0.273	1.129	0.259	-0.227	0.844
alpha	0.9483	0.177	5.362	0.000	0.602	1.295

Table 49: negative binomial regression results for "study dwelling time ~ condition * factor expert" (χ^2_7 p = 0.095, McFadden's R^2=0.03).

	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
Intercept	35.7840	3.104	11.527	0.000	29.642	41.926
C(X, Simple)[Simp.basic]	4.4609	5.610	0.795	0.428	-6.638	15.559
C(X, Simple)[Simp.subordinate]	1.7544	5.227	0.336	0.738	-8.586	12.095
C(X, Simple)[Simp.wrong]	3.7432	5.272	0.710	0.479	-6.688	14.174
factor_expert	2.4167	3.198	0.756	0.451	-3.910	8.743
factor_expert:C(X, Simple)[Simp.basic]	-12.8999	4.827	-2.672	0.008	-22.450	-3.350
factor_expert:C(X, Simple)[Simp.subordinate]	14.5516	5.889	2.471	0.015	2.900	26.203
factor_expert:C(X, Simple)[Simp.wrong]	1.0659	5.631	0.189	0.850	-10.075	12.207

Table 50: OLS regression results for "search dwelling time ~ condition * factor expert" (F(7)=2.09, p = 0.053, R^2=0.10). A negative binomial should have been used but failed to convert, this should be seen as estimation.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-1.2353	0.218	-5.661	0.000	-1.663	-0.808
C(X, Simple)[Simp.basic]	-0.4471	0.444	-1.008	0.314	-1.317	0.422
C(X, Simple)[Simp.subordinate]	-0.1143	0.363	-0.315	0.753	-0.826	0.597
C(X, Simple)[Simp.wrong]	0.5058	0.331	1.528	0.126	-0.143	1.154
factor_expert	-0.3894	0.223	-1.749	0.080	-0.826	0.047
factor_expert:C(X, Simple)[Simp.basic]	-0.1289	0.353	-0.365	0.715	-0.821	0.563
factor_expert:C(X, Simple)[Simp.subordinate]	-0.0906	0.429	-0.211	0.833	-0.932	0.751
factor_expert:C(X, Simple)[Simp.wrong]	0.3175	0.350	0.908	0.364	-0.368	1.003

Table 51: logit regression results for "conversion likelihood ~ condition * factor expert" (χ^2_7 p= 0.55, McFadden's R^2=0.04).

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-1.0858	0.186	-5.829	0.000	-1.451	-0.721
C(X, Simple)[Simp.basic]	-0.1211	0.350	-0.346	0.729	-0.807	0.565
C(X, Simple)[Simp.subordinate]	-0.1111	0.316	-0.351	0.725	-0.731	0.509
C(X, Simple)[Simp.wrong]	0.4155	0.286	1.455	0.146	-0.144	0.975
factor_expert	-0.3132	0.199	-1.578	0.115	-0.702	0.076
factor_expert:C(X, Simple)[Simp.basic]	-0.0091	0.285	-0.032	0.974	-0.567	0.549
factor_expert:C(X, Simple)[Simp.subordinate]	-0.1289	0.385	-0.335	0.738	-0.883	0.625
factor_expert:C(X, Simple)[Simp.wrong]	0.3554	0.295	1.205	0.228	-0.223	0.934
alpha	1.4837	0.735	2.019	0.043	0.044	2.924

Table 52: negative binomial regression results for "conversion ~ condition * factor expert" (χ^2_7 p = 0.64, McFadden's R^2=0.02).

10 StudyPortals & BachelorsPortal

In addition to the short introduction, and necessary information given about StudyPortals and Bachelorsportal in the main text, this chapter provides a little more insight into the website structure, StudyPortals' underlying goals (given in this subchapter and 10.1). Chapter 10.2 summarizes some findings based on explorative research done in the early stage of this thesis. It describes the research which lead to the main research question, and might contain some terms and concepts which are elaborated in the main text.

StudyPortals is a company developing and maintaining a number of websites that provide information about study courses all around the world on different levels: BSc-, MSc- and PHD courses but also language- and online courses. The goal of the company is "Empowering the world to choose (for) education", which translates in platforms that aim to provide high-quality information.

Bachelorsportal.eu is one of those websites, providing detailed information on bachelor studies to inform new students in making their choice. With 236.300 sessions per month from 180.610 users (February 2016), it's a relatively large website with relatively high engagement: users average 4 page visits per session and stay for 4:31 minutes. 71.3% of the sessions have never been there before, and only 3-5% of the users revisit the website within a month. These statistics are taken from Google Analytics, so might divert from the actual numbers due to tracking- or ad blockers.

Males and females are equally represented in the visitors (respectively 0.504 and 0.496), and most visitors are relatively young (see Figure 29). Almost 0.25 of the visitors are over 34, something that seems counterintuitive giving age distributions of bachelor students in western countries, such as Canada (Figure 30) and the US (Figure 31). One of the possibilities may be parents interested in studies for their children. Analysis of the user goals (chapter 6.6.1) in the questionnaire however show no such goals, even though the age distribution in the questionnaire is similar to the one in Figure 19. Apparently, users from older ages then what might be expected based on student age distributions in the US and Canada are interested in Bachelors as well.

Sessions tend to come from all over the world, led by the UK (8.95%), US (8.29%), Kenya (6.05%) and the Netherlands (5.51%) (Figure 32).

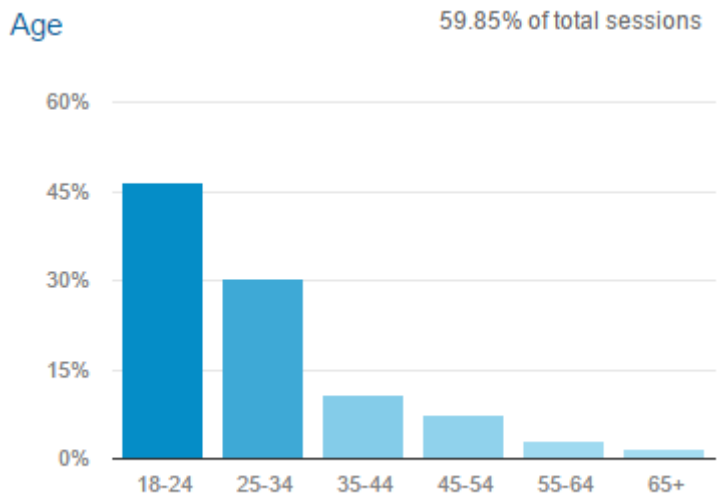

Figure 29: estimated age distribution of BachelorsPortal visitors.

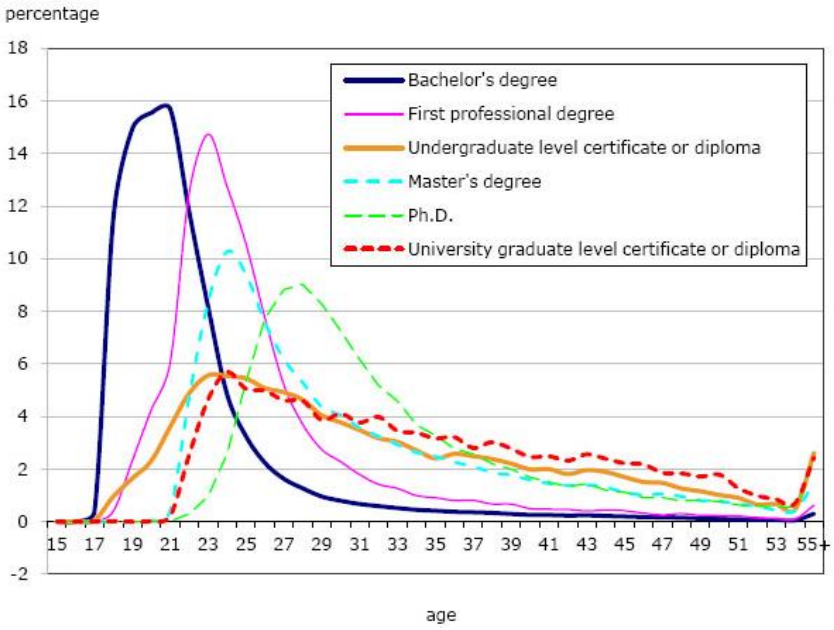

Figure 30: age distributions for Canadian university students in 2007, retrieved at 22-06-2016 from http://www.statcan.gc.ca/pub/81-004-x/2010005/article/11386-eng.htm

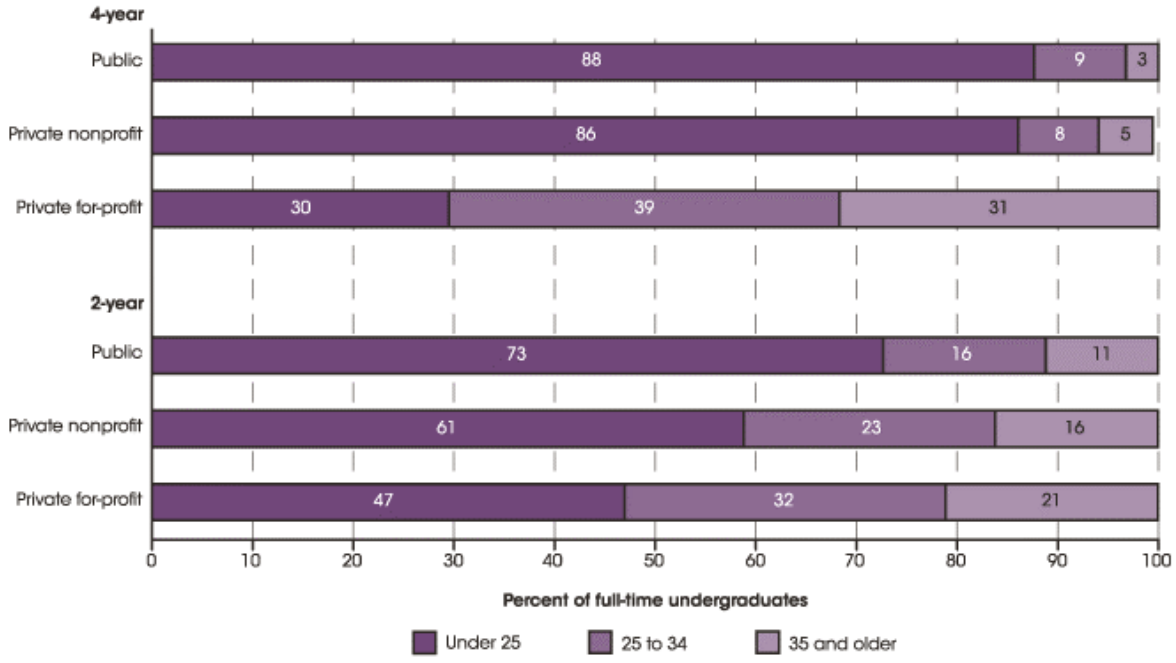

Figure 31: age distributions for US fulltime undergraduate students in 2013, retrieved from http://nces.ed.gov/programs/coe/indicator_csb.asp at 22-02-2016

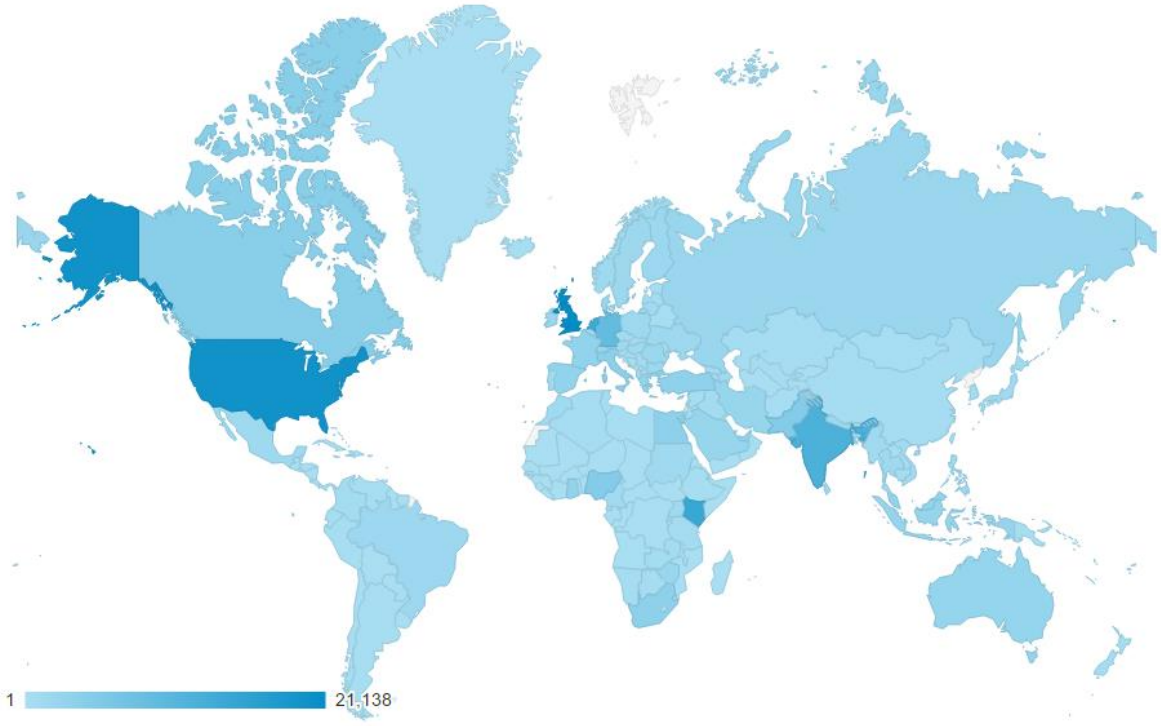

Figure 32: estimated location distribution of BachelorsPortal visitors.

Just over a third of the sessions (37.40%) are performed via mobile devices, tablet represent 6.17% of all sessions, all other is desktop. Almost three quarters of the sessions arrive via search engines (73.53%), 14.79% is direct traffic and 10.95% is referred from other websites.

10.1 Page types & structure

BachelorsPortal's home page (hereafter referred to as *home*) contains a large search input field and button, inviting users to search through the available studies. Further down the page, links to discipline pages and country pages are given, as well as user reviews, universities in the spotlight and a number of recommended articles.

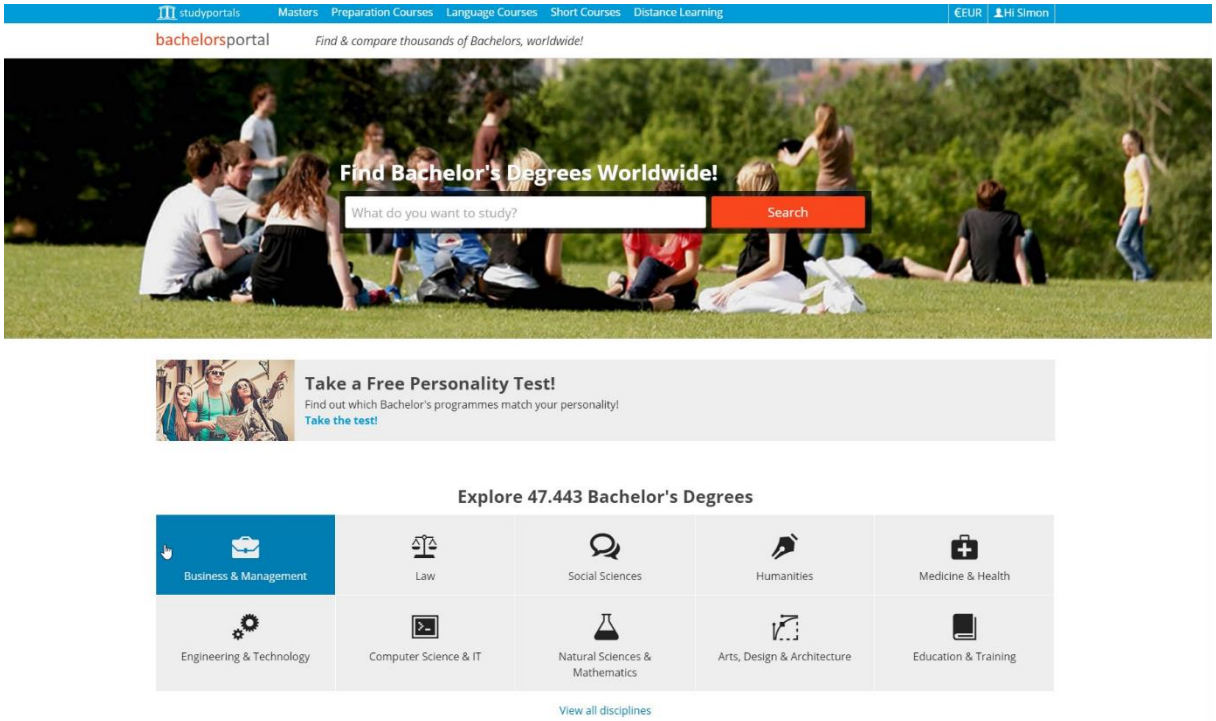

Figure 33: BachelorsPortal's home page, retrieved 19-02-2016.

Discipline pages contain a description and a number of studies (presented in tiles such as Figure 34) on a certain discipline, such as "Law" or "Computer Science & IT". These ten top disciplines are further split into sub disciplines (little over 200 at the time of writing), which are accessible at the bottom of a discipline page. *Country pages* are quite similar but contain information about a country; not only the country itself, but also what the student life is like as well as general live-and-work information. It also provides some extra statistics such as population, number of students and number of universities. Both discipline- and country pages led users to the search page (with an active filter of the discipline or country they originated from).

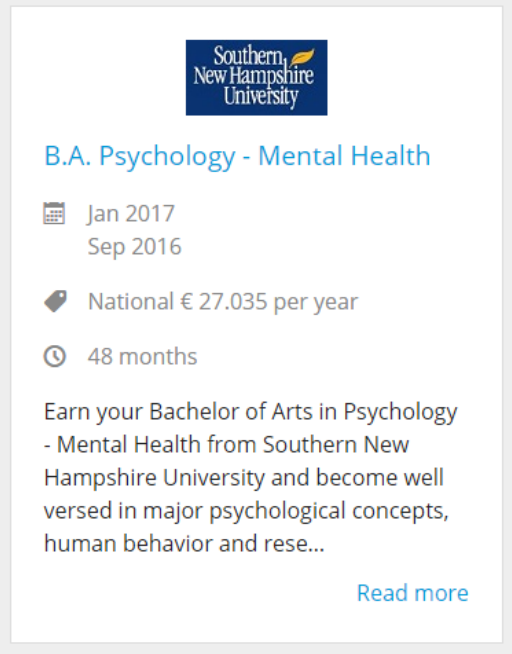

Figure 34: example of a study tile on a discipline page.

The *search page* provides an interface for users to search and filter the available studies (>49.000) on a number of properties, such as discipline, location, language, costs, duration and more. Each search result is represented as a search tile (see Figure 1), giving quick facts of a study course, and linking to the study page.

On a *study page*, a description, details, requirements, and possible scholarships for the chosen study are presented. On the study page, a number of buttons and links lead to the course page of the university. Users clicking on one of these links is referred to as a conversion. They are labeled as “Visit Programme Website”, “You can find more information about this programme on the programme website” or “Programme website”. Besides the information, tiles of information about the country, references to required language tests and related studies are given.

Besides these page types other significant page types (in terms of visits) are *article pages* (containing study-related articles), *university pages* (very similar to study pages, only concerning a whole university instead of one study), *account pages* (where users can set account preferences and view studies that (s)he put on the wish list) and *study option pages* (containing a country-discipline combination, i.e. information and study tiles of computer science bachelors in Poland).

Table 53 shows the number of page visits for specific page types between 12-28-2015 and 01-24-2016. In this period, 138,996 unique users with 173,835 sessions were identified (a session being all actions from a user with less than 60 minutes between 2 consecutive actions). The data shows a dominance of the study pages in visitor behavior: 34.2% of all page views are on a study page. Account pages, accounting for 9.7% of all page views, differ from the other pages as they do not directly serve the purpose of finding a study: they target account details for users that signed up with BachelorsPortal. On a monthly basis these statistics seem to be slowly rising; each month gaining a couple of percentages in sessions. On smaller timespans the data fluctuates a little more; weekends are usually less busy, and events like holidays or website downtimes introduce significant peaks and valleys.

	Page views	Percentage of all page visits
studies	*179,673*	34.24%
search	*80,757*	15.39%
study-options	*50,460*	9.62%
account	*47,874*	9.12%
universities	*42,317*	8.06%
countries	*41,334*	7.88%
home	*37,254*	7.11%
disciplines	*28,764*	5.48%
articles	*11,025*	2.10%

Table 53: page view frequencies per page type on BachelorsPortal.

10.2 Finding opportunities: information scent

BachelorsPortal is generally a well-optimized website: design and content have had many years of iterations based on qualitative research and business development, resulting in a website that's overall pleasing to the eye and easy in its use. However, as in every company, issues and potential area's for improvement are always present. A number of important ones at StudyPortals are *missing body of research, willingness to become more data-driven* and *missing framework for optimizing hyperlinks*.

In the following subchapters, research concerning study choice will be summarized and the conclusion will be drawn that it might not be sufficient for a global market like the one targeted by BachelorsPortal. Secondly, the process of optimizing hyperlinks in a data-driven way is described. While analyzing these points, an opportunity for the improvement of information scent was found, which formed the idea for the main research question.

10.2.1 Research

A lot of research has been done in the area of study and university choice. For example (Maringe, 2006) finds that market perspectives outweigh the interest and love for the subject, resulting in students focusing on program contents and price more than other aspects. (Smith et al., 2003) show that most participants most often picked a university because of a specific course that it offered, followed by university reputation and –proximity to the hometown. Also significant is that they took measures in 2000 and 2001, where some results differ highly between the two years, indicating possibly quick shifts of student's choice criteria.

There seems to be a very large body of literature that concern the student's choice of a university. They however all seem to miss some properties for being really relevant for this project. First of all, all of them are localized: they all concern experiments or students from a specific country or state, which differs significantly from the target group of BachelorsPortal, namely all countries. Secondly, recent research seems to attempt and tackle specific topics, for example the importance of facilitation (Smith et al., 2003) and socio-economic factors (Niu & Tienda, 2007) in choosing universities, usually with the goal to help universities gain insights into ways to draw more students. A general model of student choosing a study would be most useful, and while it exists (Chapman, 1981), the research is so old that it is most likely outdated in the context of this project, where future students have detailed information of over 40.000 studies just a few clicks away.

Seemingly, the fact that BachelorsPortal (and other platforms of StudyPortals) is an *online* study platform at *world wide* scale makes it hard to find research that can assist in theorizing about user characteristics. While a lot of attention is on quantitative research, UI and UX research and business related research, nobody has concrete results on specific questions, such as "how is the distribution of users regarding goal-directedness", or "what is the level of domain-expertise of average users".

10.2.2 Missing framework for optimizing hyperlinks

This lack of research results in suboptimal development. A good example is the current state of experiments run on the website: StudyPortals is very keen on the idea of *A/B testing*, and puts much effort into building underlying testing systems and designing and running experiments. Much of the current running experiments aim for the same goals of this project (text optimization, most of the time hyperlinks specifically) but miss an underlying theory or system.

In example, one of the currently running experiments consists of changing text related to the conversion button on a study page (see Figure 35), some of the conditions being "Many students visit a programme website", "Application deadline is approaching" and "Most students apply in {current-month}". An underlying framework such as the reversed information scent hypothesis can assist here by suggesting alternatives and compute their impact before running the experiment, effectively allowing developers to compute a possibly-optimal text before running the experiment, instead of generating variations based on non-data driven factors, and possibly requiring multiple iterations to come to an optimal variation.

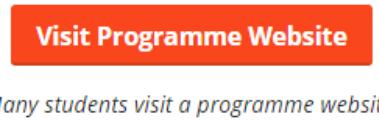

Figure 35: conversion button and motivational text on a study page.

Based on these 3 opportunities for improvements mentioned above (willingness to become more data-driven, missing body of research, and missing framework for optimizing hyperlinks), the theory of information foraging (elaborated in chapter 2) was found, and used to analyze the website. It turned out two important places on the website had low information scent: conversion links and search study tile pages.

10.2.2.1 Conversion links

The obvious place to look first, as it is in main interest of the company, is the conversion links, where the company will get a financial benefit from users click those links (see Figure 35 as example). They all consist of the text "Visit Programme Website", a text chosen based on previously ran A/B test results. While the context may already be a great indication of the information patch that users might end up with after clicking this link, the theory previously outlined shows potential improvements for these texts. For example the button of Figure 35 was shown on a study page information the user about "B.A. Psychology" in Spain. Based on information scent, "Visit B.A. Psychology Website" contains much more scent and will result in more optimal user behavior. Looking at less intrusive interventions, the text "Many students visit a programme website" can be optimized with a number of alternatives such as "This website explains more about psychology and human behavior" for undirected users and

perhaps “Organizational- & consumer psychology” for more directed users with more expertise.

Two problems exist with implementing this kind of intervention. First of all, the button links to an external page where information is presented in a lot of different ways, compared to the structured data available from StudyPortals. A possible solution to this could be to assume that the contents of a certain study on BachelorsPortal are very similar to the content of the webpage of the university which is quite likely as study descriptions are based on the webpages they link to. Secondly, while the link opens in a new browser tab, the fact that the website is not under StudyPortals control means no measures or questionnaires can be performed unless the user actively returns to BachelorsPortal’s webpage. While it is not ideal, it does offer some valuable data, for example whether a user clicked the button or not, tied to earlier shown behavior.

Note that this will increase the information scent and might result in the benefits described before, it may have an effect that is undesirable for StudyPortals. As users are more likely to go for the optimized link in favor of reading information below first, users might be of lower interest in the actual study (lower-quality of referrals), which is one of StudyPortals main selling points towards universities.

10.2.2.2 Study tiles

Throughout the website several study tiles are implemented, presenting a study in a summarized way, for example on the search page (see Figure 36) or on discipline pages (see Figure 34). While again the information patch is quite obvious (it does give a title, some important attributes and a very concise summary), the link does not tell the user anything about what it is referring to. This effect is largest in the search page tiles, where the “detailed description” button is made so distinctive in the interface that it is most likely to draw a lot of attention, focusing the users’ attention on a link text with no scent. A small pre-experiment was run to verify the significance of this button between 19-01-2016 and 23-01-2016. The experiment was stopped because of the significant drop in user interaction, and might therefor not be totally valid, it did run mostly in the weekend for example, where user behavior on BachelorsPortal is significantly different than behavior throughout the week. Nonetheless the results can serve as an indication.

In that period, 3640 sessions viewed a variation of the search page without the detailed description button 12.67 times. For the baseline, 3694 sessions viewed the “normal” search page 12.85 times. The treatment group when from the search page to a specific study 4.81 times (mean=0.379, standard error = 0.004), the control group did so 5.40 times (mean=0.420, standard error=0.004). The 9.7% drop in study views was significant ($p < 0.001$ at a two-sided 99% confidence level).

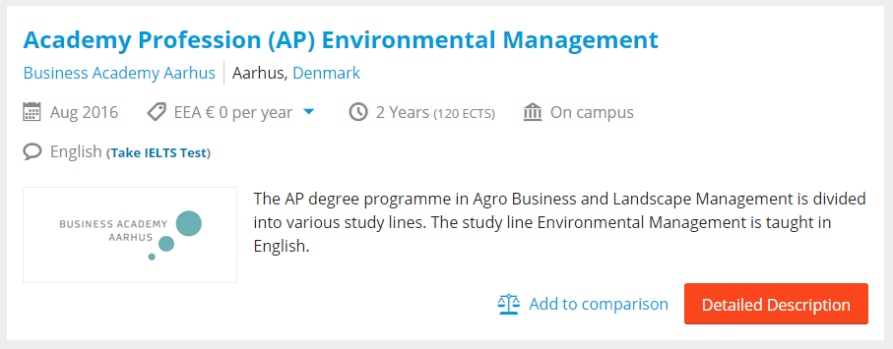

Figure 36: example of a study tile on the search page.

This simple experiment shows the significance of making such a distinct button: users will click it even if the text of the link has no scent. Regarding the study tiles on discipline pages: they are quite popular. 19.73% of the users viewing a discipline page between 01-01-2016 and 20-01-2016 (n=28,775) clicked on one of the studies.

It has to be noted that for both the types of study tile, two links refer to the study page: the title and the read more / detailed description button. Which one the user clicked was not measured.

10.3 Summary

In this chapter the site structure of BachelorsPortal and its general user behavior was shortly described. Motivated by the focus points of StudyPortals the information foraging theory was used to analyze their website; conversion links and study tiles on the search page were found to be significant buttons with low information scents. A simple experiment was run on the search page, where the red buttons were removed. The drop in search-study CTR showed the significance of the button, even though the information scent was very low.

11 Pilot

A pilot study was done to try and find useful insights and base effects without the need to create high quality labels for all studies. Furthermore, it allowed adding a conditions with wrong labels, hypothesizing it would show the effects of misclassifications in the labelling algorithm. This could then further be used to focus the labelling on the right metric when making tradeoffs between false positives and true positives.

The studies in the discipline Computer Science & IT was chosen for the pilot. First of all, the number of studies in that discipline (n=3065) is reasonably large, but not too large. Secondly, it's the most popular top discipline on BachelorsPortal in regard to searches (7,154 out of 130,838 searches that were performed between 28-12-2015 and 23-01-2016 were using a CS&IT filter), making it a good candidate for the purpose of this pilot.

11.1 Preparing data

There are a number of steps that were taken to get from a set of documents, consisting of studies, to a set of high scenting sets of words, both basic- and subordinate level, which can then be used to construct specific hyperlinks. Any text-related computation often involves a number of steps before the actual implementation, being *collection*, *cleaning* and *pre-processing*. Both collection and cleaning were largely handled by StudyPortals internal systems and high quality database. Their internal API was used to gather all bachelor studies and descriptive data. Concretely, each study has (amongst others) the following text attributes:

- Title, the title of a study;
- Summary, a short 1 to 2 sentence string that aims to summarize a study;
- Description, a long description of the study that contains html tags. There is usually a high similarity between a summary and a description, sometimes the summary occurs literally in the description;
- Contents, an overview of the actual contents of the study, i.e. what tracks there are in a study program, how long it takes, the content of actual courses etc. Contains html;

All of these attributes were concatenated and are considered to be one document of a certain study. The only necessary cleaning steps was removing html tags from these documents.

Pre-processing consists of several possible steps as mentioned by (Gomez & Moens, 2014): *tokenization, stop word removal, stemming*, *lemmatization* and *feature selection*. Stemming and lemmatization was performed by python's NLTK package[12], tokenization and stop word removal were performed with the scikit-learn package[13], feature selection was handled by LSA in the next step.

[12] http://www.nltk.org
[13] http://scikit-learn.org/

11.2 Labelling studies

To label the document-matrix of studies produced, a predefined set of labels was chosen and then linked to each document. This obviously is not entirely "bottom-up" as proposed in the reversed information scent hypothesis and doesn't allow for exploration of labels for instance. Full automated label extraction proved to be a significant challenge however. It is an *unsupervised learning problem*, meaning that the data is unlabeled (there is no variable to be predicted for instance) and no error or reward signal is present to evaluate outcomes. This makes related tagging research mostly unusable, as it has the advantage of using user labels to train their model (Nie et al., 2014). Several methods were tried but failed to deliver acceptable results (all evaluated by manual inspection), being:

- Reducing the documents using LSA (and LDA) and attempt to label these underlying concepts based on the words that were most influential for each of these concepts. For a large number of documents this proved to be near to impossible: concepts were often very similar (the word "business" for instance occurs often (> 10 times) as most important word for a concept) or words of concepts were so vaguely connected that it was hard or impossible to determine what the underlying meaning was. Multiplying by thousands of components needed to describe these studies, this was not a viable solution. Using TF-IDF improved this a little though not enough.
- Reducing the documents using LSA (and LDA) and computing the most influential words for a study like suggested by (Dredze et al., 2008). While it did result in good summary keywords, they were very similar across studies (i.e. the words information, computer, technology occurred very often for example), this was not desirable for this experiment. The target is to describe studies with labels as specifically as possible (creating the largest possible distance between two studies); ten studies all with the same information scent will be of little use.
- Automated keyword discovery trough WordNet and YAGO (two taxonomy databases), trying to explore keywords from a number of base words (computer science to start with) and using LSA to link these words to documents. A very tight scope (for example only the 2 dozen concepts in the branches of "computer science" in Wordnet) gave good tags, but was again too little for the purpose of this study, expanding the scope (for example including the branches of "database") included words that had nothing to do with the contents of studies at all (database has a branch "list", which has items like "agenda", "FAQ", "price list", a kind of labels that would make little sense). Secondly, LSA similarity only worked if the word occurred somewhere in the existing document, for instance "tele robotics"[14] did not occur in the other documents. An attempt with the short description given by WordNet gave a huge improvement, but was still too inaccurate: as the description generally has a dozen words, each words is greatly significant. The description "the use of computers to translate from one language to another" for "machine translation" made a tight fit with studies that do something with language, which was more often learning of different languages (for students) then the program actually teaching machine translation.
- The keywords extracted from WordNet (and YAGO[15]) were given to BachelorsPortal's' search engine (which is a TF-IFD search engine with some business rules added). The results were used to label the studies and turn the problem into a supervised learning problem. For each label a classifier was made (both Naïve Bayes and Support Vector Machine techniques were tried) that predicted whether a given label was suitable for a study. As input both LSA vectors and TF-IDF vectors were tried. After some iterations

[14] a sub-sub-branch of computer science, meaning the area of robotics concerned with distant control of a robot

[15] www.yago-knowledge.org

and optimizations about 50% of the labels were manually verified as “quite correct” (algebra for example is quite applicable to most computer science studies), too low for the purpose of this pilot. Again the labels had to be literally in a text to be returned by the search engine, which did not consider terms that were closely related.

Based on this experience, a method was found that gave good results: keywords were manually picked and their meaning was scraped from Wikipedia. The picking process was quite generic: a number of studies were used to take out their main concepts, and the availability of the concept on Wikipedia was checked. This process resulted in 107 labels, i.e. “linear programming”, “video game development” and “big data” (all labels are listed in chapter 0). This Wikipedia description was then used to search the most similar documents using LSA and their cosine distance, effectively creating a LSA-based search engine. The 2 best fitting terms (ordered by cosine similarity) were picked for each study provided that the similarity between the 2 documents was larger than 0,2. Overall this process produced rather good results. Again this is subjectively measured and hard to quantify, but serves as an acceptable solution for the pilot. Table 54 displays some of the basic-subordinate relations that resulted from this labelling process.

basic	**subordinate**
algebra	Linear algebra
artificial intelligence	machine translation
artist	media arts
Business software	Business software
cloud computing	cloud computing
communications technology	digital communications
computer architecture	complex instruction set computing
data	data driven
data analysis	Time Series Analysis
data management	data management
data prediction	unsupervised learning
data processing	machine learning
database	web database
game design	game design
Geographic information systems	GIS
language processing	text processing
mathematics	calculus
mathematics	convex optimization
Microprocessor	Microprocessors
Microsoft	Microsoft
Operating systems	Windows
programming	Imperative programming
Programming language	python
robotics	animatronics

Table 54: a sample of the 107 basic-subordinate related labels used for tagging studies in the pilot.

11.2.1 Finding basic-subordinate relations

The second challenge for this setup was to find correct basic representations of the subordinate keywords found before. The choice for this direction was rather simple: going from subordinate to basic should be rather trivial (windows is an operating system), going from basic to subordinate is impossible without creating errors (windows is an operating system, but so are Linux and OSX). While for some research this might not be a problem, here it is: the information scent of Linux is significantly different than that of windows (some might find it two completely different worlds).

The initial reason to use WordNet (and later YAGO) was the tree-like structure they have: going one branch up should give (somewhat of) a basic categorization of the word. In theory this should give a nice result (linear programming for example links to applied mathematics, which is a nice subordinate-basic information relation), though it was found that a lot of manual intervention was needed. First of all, some concepts are extremely nested while others are not, making it hard to programmatically define how many up branches is the right amount. An example is the following: biology – zoology – entomology – lepidopterology. Lepidopterology would be the most interesting to use as tag, though entomology (and perhaps even zoology) wouldn't be very nice basic level information categorizations, non-experts in the area of biology will have a hard time understanding its meaning. Secondly, while WordNet is quite extended and contains 117.000 concepts, most of the concepts are irrelevant for this purpose. Even when all challenges occurred in previous chapter are conquered, "branching up" quickly reduces the number of labels to a dozen or so, again generating problems for the purpose of this study. Thirdly a lot of interesting labels generated were not in Wordnet at all. Finally, while some relations are far too deep, some branches seem to be too shallow, meaning that one branch up gets to somewhere completely else[16].

YAGO was used as a second attempt as it contains far more words (almost 17 million). It however is an automatically generated network, and while the accuracy is high (95% according to their own work), quite often relations were found to be strange or mishitting.

In the end, Wordnet and YAGO combined were able to provide labels for about 60% of the labels, almost half of them were removed due to poor fits and manually filled, as well as all other labels that were not found in Wordnet and YAGO. This process does definitely not provide a full set of possibly well-fitting labels nor scales well to all studies, but serves the purpose of the pilot well enough. The resulting set can be found in appendix chapter 1050.

[16] The word "engineer" for example is related to the higher level words "disciplines" and "subject of study". Both are technically correct subordinate-basic relations, though just "subject of study" has no value in this context.

11.3 Method

The pilot was implemented by modifying the button in the search results for users that searched for the keyword “computer”, or in one of the disciplines related to computer science & IT. For each search result (like the one in Figure 36), the text of the red button leading to the page of that study is modified, depending on the variant the user is in:

- Baseline: no modification, buttons are displayed as Figure 38;
- Basic level categorization: the basic level categorization versions of the two best fitting labels were added to the button text;
- Subordinate level categorization: the subordinate level categorization (the original label) of the 2 best fitting labels were added to the button text
- Mixed: 33%-33%-33% mix of original, basic and subordinate level categorization buttons were used, randomly assigned to studies. This variation was primarily to find out if users preferred one of the options if all were present.
- Wrong: Intentionally wrong labels (randomly picked labels that are not associated with the study) were used, where 50% of the button had a basic level categorization and 50% had a subordinate level. This variation was used to verify the effect of adding text to the buttons, even if they were wrong. Note that the distance between the best possible labels and the wrong ones were not as large as they could be, as all labels were still from the computer science & IT domain. A big data study being labelled as “computer circuit” is less “wrong” then being labelled as “nursing”.

If a study got modified, the button containing the word “Detailed Description” was modified such that its text was changed to “Details (tag1, tag2)” (see Figure 37 and Figure 38). This syntax was chosen as it needed to be clear that the button lead to the study, just the labels would have been too vague. Implementation was done with Optimizely[17], tracking of user behavior was done with snowplow and StudyPortals own tracking system (see chapter 12.1.2).

Figure 37: modified link with 2 labels.

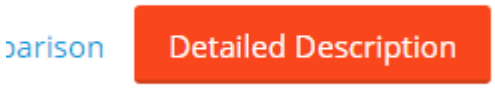

Figure 38: original button.

[17] An online A/B testing platform which allows inserting JavaScript snippets on webpages.

11.4 Results

Between 11-03-2016 and 23-03-2016 1,214 sessionos from 937 users were tracked that participated in the pilot experiment. They randomly got assigned to one of the 5 conditions, from here on referred to as “original”, “basic”, “subordinate”, “mixed” and “wrong”. Not all conditions were completely equally balanced, as can be seen in Table 55, for the same reasons mentioned in chapter 5.3. The differences in session counts between StudyPortals and Snowplow are quite large as well, as they are measured in different ways. StudyPortals ends a session when the browser closes or no page request has been done for the last 60 minutes, snowplow ends a session when no page requests has been made for 30 minutes. A user was assigned a condition only once, so saw the same condition even if there were multiple sessions. In the further analyses the StudyPortals session metric will be used.

	Users	StudyPortals-sessions	Snowplow-sessions
basic	174	208	210
mixed	199	252	245
original	201	299	262
subordinate	173	228	225
wrong	190	227	231

Table 55: user and session counts from participants in the pilot.

This subchapter will do explorative data analysis on the found data with the goal of finding out if users behaved the ways expected by the hypothesis, and what the (if any) relations between the variables are.

11.4.1 Removing outliers

Three sessions were removed that contained a large number of study page views referred from the search page: 171, 154 and 91. The average of this metric was 5.54, the next largest after 91 was 36, all 3 of these sessions were in the wrong condition. Furthermore, all events without a session id were removed. No further outliers were detected.

11.4.2 Definitions

In the next subchapter the terms *search page* and *study page* are used to a large extend, to avoid ambiguity, “search page” refers to the search page of BachelorsPortal where studies are presented as search result tiles (such as Figure 1). A study page refers to a page completely dedicated to present a single study, accessed by the user **referred by the search page**. There are many ways a study page can be visited (directly through search engines, trough overview pages etcetera), though we are only interested in the studies users view when having seen the experimental condition. So “study page” refers to study page visits directly linked by the search page, unless stated otherwise.

11.4.3 Study engagement

Four metrics have been defined in hypothesis *1-6* that should indicate interest in studies. First of all, there is *study click trough*, identifying what studies were clicked by users in the search results. Secondly, *dwelling times* measure how long a user actively engages with a certain page (tabs are seen as different pages). *Conversion* refers to users clicking on one of the links on study pages referring to the website of the specific university offering that program. Lastly, *dropout* happens when sessions leave the website at a certain page, not to return (in the current session).

One measure that is very relevant is the *button clicking behavior* on the search page, as that is the location where the text is edited. Unfortunately, the measurements for the pilot where not accurate enough: snowplow measured only 51 of these clicks while Optimizely's aggregated statistics showed 257 (with none of the variants being close to significantly different then the baseline). Note that study click trough (covered in Chapter 11.5) and button clicking are not the same; each search result has 3 links pointing to a study (title, image and button, see Figure 1).

11.4.3.1 Study click trough

Study click troughs are measured by taking study page views that are referred to by the search page, basic descriptive measures per condition are given in Table 56, and shows a very positively skewed distribution. Table 57 shows the descriptive statistics of number of search page visits. The decision was made to keep search page visits as a simple metric, without considering for example backtracking, doing the same queries multiple times or pagination. Backtracking appeared to be a really small proportion of all search queries (98 out of 2908), measurements for pagination where invalid due to StudyPortals internal pagination mechanism and is hard to determine a good separation point in time when 2 of the same queries should count as 1 or 2 (is it 1 minute, 5, 1880?). Though these are all computational impracticalities, most important are the hypotheses and calculations needed to (dis)prove them: they are all centered around single search page views, not some overlying concept like distinct search result pages. This does imply that each search page means one "search query action", and includes all the pagination of that search query. shows that not all conditions might have equally distributed number of paginations, though for this project the focus is how user attitudes and behaviors are regarding one search action: if a modification can trigger them to explore less or more pages, then that's part of the effect that we're looking for.

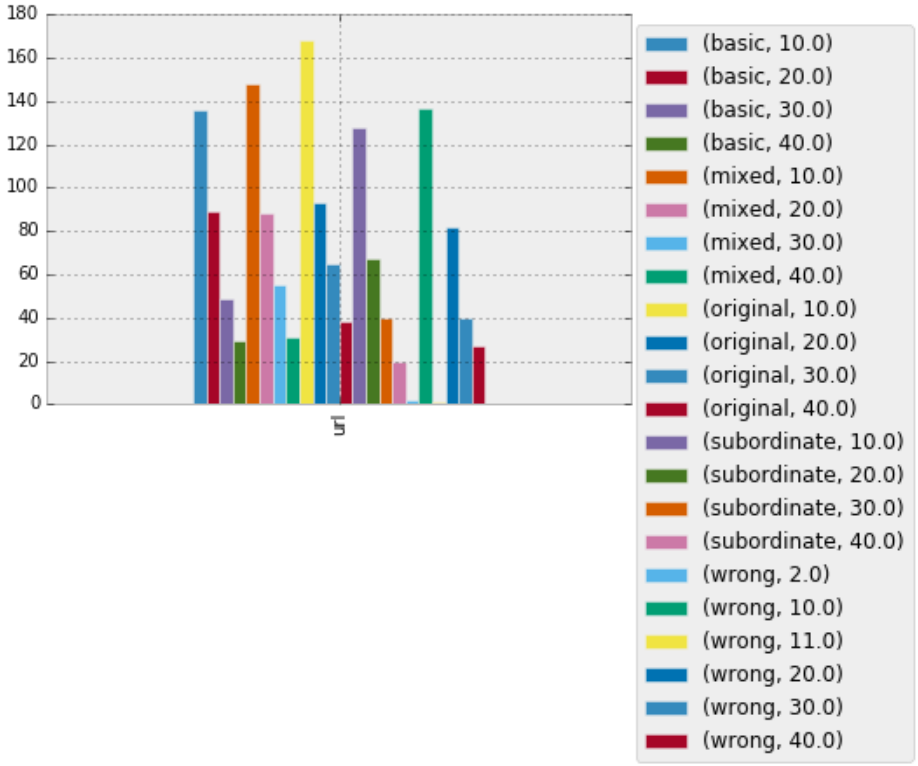

Figure 39: number search actions that had at least one page ping on a paginating search page per condition (shown as condition, offset). I.e. almost 140 search queries from the basic condition had a page ping on the first pagination page (having an offset of 10).

	count	mean	std	min	25%	50%	75%	max
original	299	1.55	3.06	0	0	0	2	25
basic	207	2.63	5.27	0	0	0	3	39
wrong	226	1.97	4.46	0	0	0	2	36
Subordinate	228	1.75	3.69	0	0	0	2	33
mixed	251	2.07	4.44	0	0	0	2	30

Table 56: descriptive statistics of study click troughs.

	count	mean	std	min	25%	50%	75%	max
original	298	2.34	2.33	1	1	2	3	21
basic	207	2.65	3.48	1	1	1	3	33
wrong	224	2.34	3.13	1	1	1	3	38
subordinate	228	2.17	2.38	1	1	1	2	20
mixed	248	2.59	3.23	1	1	2	3	37

Table 57: descriptive statistics of search page visits.

Information scent predicts that a stronger scent should lead to users clicking less links (H*1*) and more users should be interested in at least one link (H*2*). Figure 12 shows that the probability that a user will engage with one of the studies from the search results doesn't differ significantly between conditions, a Chi-Square tests resulted in $\chi^2_4 = 0.59$, $p = 0.96$. Though the power is not large enough yet to support H*2*, the effect points into the right direction, with a slightly higher probability for buttons with scent. A logistic regression is

used to test the effect of each condition (see Table 58), no significant differences from the baseline have been found.

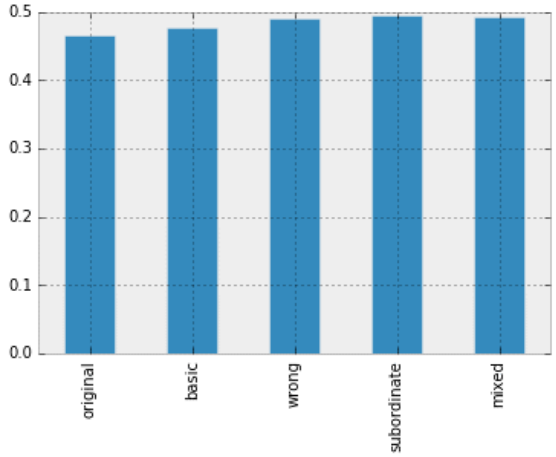

Figure 40: probability that a user in a certain condition views a study presented in the search results at least once.

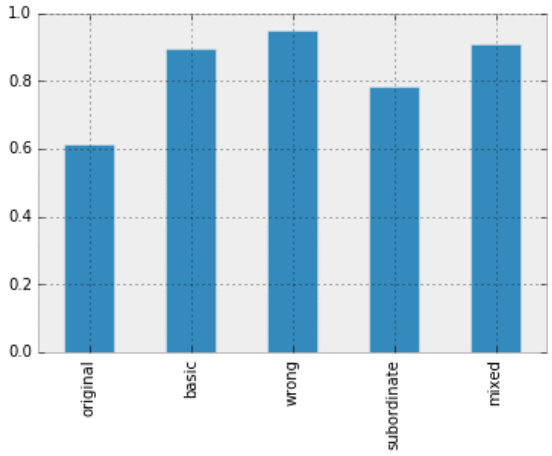

Figure 41: click through rate of search results to study pages.

Looking at the search *click-through rate (CTR)* (number of page views / number of searches) (Figure 13) a much larger difference can be seen: users in the basic condition averagely view 0.897 studies per search, compared to 0.614 for the original condition. To estimate the size and significance of each condition on the dependent variable, a negative binomial regression is used, as the shape of this data (as with other measures discussed below) is over-dispersed. This means the variance is larger than the mean when it should be equal, and a negative binominal distribution fits the situation well as it is specialized in handling over-dispersed data.

The regression (Table 59) shows a significant difference between the original and basic condition. It shows the opposite of what was expected in H*1*. There are a number of explanations for these results, that contradict the results in earlier IFT research. Firstly, the "real world" differs from the fabricated goals that users had in the original experiments, which might explain why users are more exploring in this experiment. Secondly, the increased size (which have an extra significant impact on smaller, mobile screens) might draw more attention, which on itself, or in combination with varying texts trigger more action. For now, we'll assume that any of these (or a combination of the 2) is more likely than information scent working against users finding their goal (especially given the results of previous research), and will be referred to as the *button effect*. The assumption will later be verified with subjective data.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-0.1344	0.116	-1.158	0.247	-0.362	0.093
X[T.basic]	0.0474	0.181	0.262	0.794	-0.308	0.403
X[T.wrong]	0.0990	0.177	0.561	0.575	-0.247	0.445
X[T.subordinate]	0.1169	0.176	0.664	0.507	-0.228	0.462
X[T.mixed]	0.1103	0.172	0.642	0.521	-0.227	0.447

Table 58: logit regression results with at least one study click probability as dependent variable.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	0.4320	0.127	3.407	0.001	0.183	0.680
X[T.basic]	0.5343	0.188	2.838	0.005	0.165	0.903
X[T.wrong]	0.2478	0.188	1.316	0.188	-0.121	0.617
X[T.subordinate]	0.1251	0.190	0.659	0.510	-0.247	0.498
X[T.mixed]	0.2889	0.183	1.581	0.114	-0.069	0.647

Table 59: negative binomial parameter estimation results with "number of study page views referred by the search page" as dependent variable.

11.4.3.2 Dwelling times

Page pings were tracked, effectively measuring intervals in time where users are actively viewing a certain page on BachelorsPortal. Activity is defined by mouse movement or scrolling in the active tab: if one of those events was performed by the user within an interval the page ping event triggered at the end of that interval. The first interval was set to 0-30 seconds after initial page load, every sequential interval was an increment of 10 seconds. While a shorter initial interval would have been more ideal, this period was initially chosen due to the large number of events (and therefor data) it generates: little over 1 million out of the 1.195 million[18] events are page pings. Dwelling places is interesting in two places: first of all, the study page - where it is expected to be higher in the high scent condition (H*33*). Secondly, the search page, where dwelling times should be lower for higher information scent (H*4*).

11.4.3.2.1 Study pages

Table 60 described the statistics for the number of dwelling times per user per study page. In example, a user that is in the basic condition averagely has 2.28 page-ping events per study page that he or she visits from the search page, meaning that group averagely spends 42.8 seconds on each search result page they click on. A negative binomial regression used for parameter estimation shows no significant difference between the original and modified conditions (Table 61).

	count	mean	std	min	25%	50%	75%	max
original	267	2.011	3.646	0	0	1	2,5	36
basic	260	2.285	3.325	0	0	1	3	23
wrong	235	2.340	3.171	0	0	1	3	18
subordinate	211	2.199	3.709	0	0	1	3	33
mixed	263	2.536	3.540	0	0	1	3	21

Table 60: descriptives for dwelling time measures on study pages referred to by the search page.

[18] This is for all 86.126 users visiting the site in the pilot period, not just the ones participating in the experiment.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	0.7025	0.097	7.265	0.000	0.513	0.892
X[T.basic]	0.1237	0.136	0.908	0.364	-0.143	0.391
X[T.wrong]	0.1478	0.139	1.060	0.289	-0.126	0.421
X[T.subordinate]	0.0855	0.144	0.593	0.553	-0.197	0.368
X[T.mixed]	0.1989	0.136	1.464	0.143	-0.067	0.465

Table 61: negative binomial results with number of page pings as dependent variable.

Significant differences do exist in whether users on a certain study page triggered at least one page ping: $\chi^2_4 = 9.84$, $p = 0.043$ (see Table 62). Table 63 shows the logit regressions results of single page pings as dependent variable.

variation	**wrong**	**original**	**basic**	**mixed**	**subordinate**
no	76	110	76	89	81
no proportion	0.323	0.412	0.292	0.338	0.384
yes	159	157	184	174	130
yes proportion	0.677	0.588	0.708	0.662	0.616

Table 62: Chi-Square test of condition and page ping probability on a study page referred to by a search page.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-0.5273	0.047	-11.332	0.000	-0.618	-0.436
X[T.basic]	0.1815	0.064	2.818	0.005	0.055	0.308
X[T.wrong]	0.1366	0.066	2.055	0.040	0.006	0.267
X[T.subordinate]	0.0429	0.069	0.618	0.536	-0.093	0.179
X[T.mixed]	0.1081	0.065	1.656	0.098	-0.020	0.236

Table 63: negative binomial results with likelihood of page pings as dependent variable.

The button effect seems to be present: all versions where buttons are modified the mean dwelling time is higher, which is in congruence with H*3*.

11.4.3.2.2 Search pages

A similar analysis is performed for dwelling times on the search page, showing descriptives in Table 64. Table 65 shows only a significant difference between mixed and the original condition. Significant differences do exist in whether users on a certain search page triggered at least one page ping: $\chi^2_4 = 10.59$, $p = 0.03$ (see Table 62).

	count	mean	std	min	25%	50%	75%	max
original	485	4.186	7.052	0	0	2	5	73
basic	376	4.614	7.798	0	1	2	6	95
wrong	391	4.043	4.882	0	0	3	6	29
subordinate	362	4.843	7.221	0	0	2	6	61
mixed	444	5.137	7.912	0	0	2	7	67

Table 64: descriptives for dwelling time measured on the search page.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	1.4349	0.071	20.290	0.000	1.296	1.573
X[T.basic]	0.0943	0.106	0.887	0.375	-0.114	0.303
X[T.wrong]	-0.0378	0.106	-0.357	0.721	-0.245	0.170
X[T.subordinate]	0.1426	0.107	1.330	0.184	-0.068	0.353
X[T.mixed]	0.1996	0.101	1.969	0.049	0.001	0.398

Table 65: negative binomial regression results with search page pings as dependent variable.

variation	wrong	original	basic	mixed	subordinate
no	108	165	91	132	109
no proportion	0.276	0.340	0.242	0.297	0.301
yes	283	320	285	312	253
yes proportion	0.724	0.659	0.758	0.703	0.699

Table 66: chi-square test of condition and page ping probability on the search page.

In contradiction with H*4*, high scenting links seem to add dwelling times to the search page. This however is only part of the story: if a user needs a little longer to pick the correct study at the first try, it is still quicker than a small dwelling time but one or multiple wrong attempts. Note the similarties between dwelling times and study click through rates: apparently the buttons trigger something motivating users to stay longer at the search page and explore more results.

Interesting on this metric is the significance of the mixed condition and the unsignificance of the wrong condition, as well as its standard deviation. The mixing of conditions makes users explore the results longer, though the CTR isn't higher then can be expected from a 1/3 split between original, basic and subordinate. The wrong condition is significantly lower then the mixed, disproving that it could be due to a button effect.

11.4.3.3 Conversion

A conversion event is triggered when a user clicks on one of conversion links (either a button, links within texts or links in related links lists). An analysis of which of these links were picked by the user proved to be impossible with the pilot data: the link tracker malfunctioned and the amount of conversion tracked by StudyPortals were multiple times higher those of snowplow. As StudyPortals tracking system has gone through numerous verification processes, its validity is easier to defend than that of snowplow. One outlier with 27 conversions in the basic condition was removed. While it is an outlier in the pilot data subset, it might not be in all user data: out of all $1.28*10^5$ user sessions within the pilot period, 64 converted more than 26 times. It is removed here as it greatly influenced the results, but might not be a real-world outlier.

Table 67 shows the descriptive statistics of conversion, an ANOVA test showed no significance in difference of means $F(4) = 0.76$, $p = 0.55$. In an negative binomial parameter estimation, neither of the conditions where significant predictors for number of conversions (Table 68).

	count	mean	std	min	25%	50%	75%	max
original	299	0.4147	1.4684	0	0	0	0	15
basic	206	0.4951	1.5229	0	0	0	0	10
wrong	226	0.3363	0.9439	0	0	0	0	9
subordinate	228	0.3114	0.8777	0	0	0	0	9
mixed	251	0.3586	1.2324	0	0	0	0	14

Table 67: descriptives of number of conversions per user.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-0.8768	0.179	-4.894	0.000	-1.228	-0.526
C(X)[T.basic]	0.1739	0.271	0.642	0.521	-0.357	0.705
C(X)[T.wrong]	-0.2130	0.285	-0.746	0.456	-0.773	0.347
C(X)[T.subordinate]	-0.2899	0.290	-1.000	0.317	-0.858	0.278
C(X)[T.mixed]	-0.1408	0.273	-0.516	0.606	-0.676	0.395

Table 68: negative binomial regression results with number of conversions per user as dependent variable.

Table 44 visualizes the means of Table 67 and does show a rather big peak for the basic condition, though it is far from significant. Figure 43 plots the conversion probabilities that a user converts x or more times, and gives a clear visual explanation for the effects: users in the basic condition convert multiple times more often compared to other conditions, while the other conditions have a slightly higher "converts at least once" statistic.

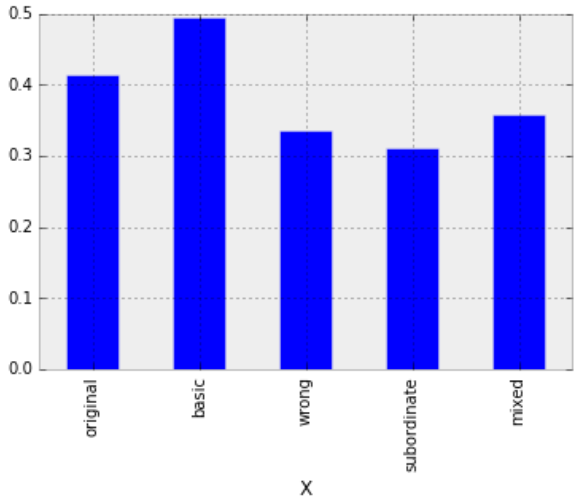

Figure 42: expected number of conversions per session per condition.

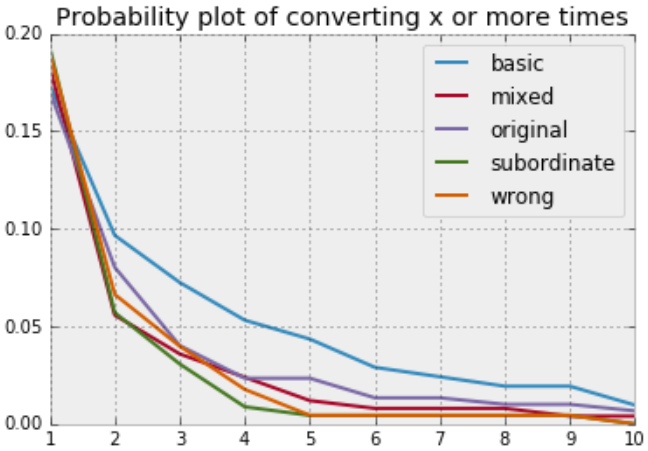

Figure 43: probability plot of users converting x times per condition.

Finally, looking at the click through rate (# conversions / # study page views per user), Table 69 shows the different CTR's per condition. Again outliers may play a large role at this small sample size: 2 participants in the original condition converted 15 & 12 times, greatly influencing the proportions. Finally no differences were found in whether users converted at least once $\chi^2(4) = 0.751$, $p = 0.945$ (Table 70).

	conversions	study views	CTR
original	120	3162	0.0379
basic	101	3451	0.0293
wrong	66	2688	0.0246
Subordinate	69	2459	0.0281
mixed	90	4046	0.0222

Table 69: click through rates for study to conversion links.

variation	wrong	original	basic	mixed	subordinate
no	183	248	171	205	184
no proportion	0.809	0.829	0.830	0.817	0.807
yes	43	51	35	46	44
yes proportion	0.190	0.171	0.169	0.183	0.193

Table 70: chi-square statistics for condition and user converted at least once.

In regard to H6, users in information scent conditions would have been expected to convert more often. The results for conversion do not yet show significant differences.

11.4.3.4 Dropout

A session is considered a dropout when it leaves the website not to return in the same session. The place where the dropout happens is of significant importance: it means the user, for whatever the reason may be, does not want to continue browsing the website. While there are cases where dropout can be positive from the user perspective (i.e. the perfect study was found and just the university needed to be retrieved), we assume here that a dropout is a negative signal if no page pings are detected, indicating that the user closed the session after showing little interest into the content. 174 users (0.1433 of all test sessions) dropped out with a page ping, excluding them from the analysis in this subchapter. Table 72 shows almost equal "page ping dropouts" amongst the conditions, with a insignificantly smaller percentage for the baseline.

	original	basic	wrong	subordinate	mixed
Dropout with page ping	35	33	33	35	38
Total sessions	299	208	227	228	252
Dropout proportion with page ping	0.117	0.159	0.1454	0.154	0.151

Table 71: statistics of user counts that dropped out with page ping.

As can be seen in Table 72, there are large differences in the dropout rates between the basic, original and subordinate condition. A chi-square test between these 3 conditions show a significant effect of condition on dropout rate on the search page: $\chi_2^2 = 6.07$, $p = 0.048$. A similar pattern exists for the study dropout, though the effects are not significant: $\chi_2^2 = 2.52$, $p = 0.28$.

A logistic regression on both variables showed that the effect of each conditions were not significantly different (Table 73 for the search page, Table 74 for the study page).

	original	basic	wrong	subordinate	mixed
Dropout search	0.4144	0.2759	0.2618	0.3160	0.2727
Dropout study	0.1597	0.1437	0.1780	0.0933	0.1100
Dropout study all	0.2091	0.1782	0.2251	0.1347	0.1866
Dropout home	0.1635	0.1667	0.1989	0.2332	0.1770
Dropout countries	0.0380	0.0172	0.0576	0.0415	0.0862
Dropout disciplines	0.0342	0.0575	0.0314	0.0726	0.0718
Dropout study options	0.0989	0.2586	0.1623	0.1347	0.1339
Dropout university	0.0228	0.0172	0.0471	0.0363	0.0431

Table 72: dropout percentages for different page types per condition. Note an overlap in study (referred by search) and study all. Moreover, the columns without study all do not add up to one, as dropouts with page pings on the last page are excluded.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-0.3456	0.125	-2.761	0.006	-0.591	-0.100
C(se_va)[T.basic]	-0.6195	0.211	-2.939	0.003	-1.033	-0.206
C(se_va)[T.wrong]	-0.6911	0.207	-3.342	0.001	-1.096	-0.286
C(se_va)[T.subordinate]	-0.4263	0.199	-2.141	0.032	-0.817	-0.036
C(se_va)[T.mixed]	-0.6352	0.199	-3.184	0.001	-1.026	-0.244

Table 73: logistic regression results for dropout on the search page as dependent variable.

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
Intercept	-1.6605	0.168	-9.865	0.000	-1.990	-1.331
C(se_va)[T.basic]	-0.1246	0.274	-0.455	0.649	-0.661	0.412
C(se_va)[T.wrong]	0.1306	0.253	0.516	0.606	-0.366	0.627
C(se_va)[T.subordinate]	-0.6139	0.299	-2.051	0.040	-1.201	-0.027
C(se_va)[T.mixed]	-0.4298	0.278	-1.547	0.122	-0.974	0.115

Table 74: logistic regression results for dropout on the study page as dependent variable.

Overall the drop-outs points at the expected effects of information scent on goal attaining: dropout rates reduce significantly on search pages if information scent is higher, again showing a button effect. Subordinate conditioned users drop out significantly less as study pages as well, being congruent with the information scent theory. While not significant, the quality of the button texts is clearly presented in the coefficients of Table 74: wrong causes users to drop out most on study pages. Figure 44 visualizes Table 74.

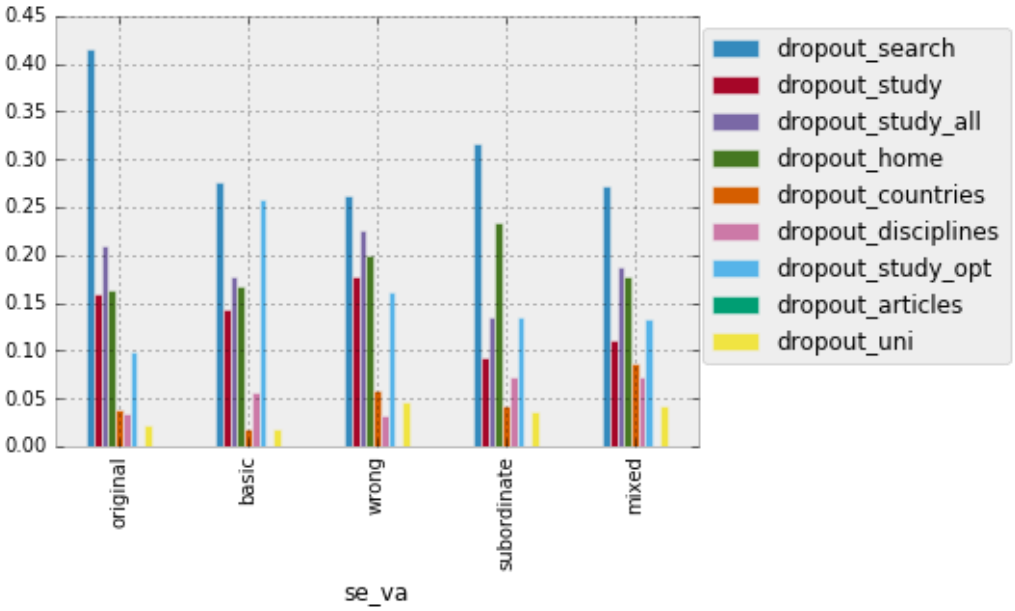

Figure 44: proportion of users per condition that dropout at certain page types.

11.5 Evaluation

Most notable in the results of the pilot is the low power: most effects (if any) are relatively small and need a high number of participants to verify significant differences, the 1.214 sessions clearly were not enough. As there is a need for significantly more participants, a fully automated auto-labelling algorithm wouldn't be just convenient but a requirement for this experiment. This would also remove the biases introduced by manual intervention, which might have influenced the labels. Furthermore, an experiment over all study-programs removes the "Computer Science & IT bias": it isn't hard to imagine that health care or law students behave differently from CS&IT students.

The mixed condition proved to give some insights; while its main purpose was to measure button choice behavior, which the tracker failed to measure properly. 472 tracking events where triggered where the button details where saved, and though it's only a small proportion of the total number of searches it should give some idea about the preferences: in the mixed condition, where 33% of the shown studies had the original button text, only 25% of the clicked studies had the original text. Moreover, 50.42% of the clicks where basic categorization, the remaining 24.58% was subordinate. Interestingly, basic and subordinate separation in the wrong condition was almost 50-50, though a measurement error could not be excluded based on the gathered data. This suggests a general preference towards basic information categorization, as suggested by H*13*. Another surprising effect happened in the dwelling time of the search page: mixed conditioned users used the search page significantly (& study pages, though not significantly) longer. This wouldn't only suggest a button effect, but also a *between-button diversity effect*, effectively adding decision time if the diversity between buttons is larger. While the conversion was not larger, dropout and CTR were comparable in the mixed condition compared to the other modified conditions. Perhaps the diversity triggers some curiosity. Though it's outside of the scope of this project, it does look like a promising effect worth looking into.

The wrong condition proved quite valuable in showing the effect size of the earlier discussed button effect, and would therefor add valuable insight into the main experiment. The combined metrics show a large initial interest of users due to the labels: CTR is high & dropout rates are low on search and a low dwelling time. This optimism seems to turn tide however when users inspect the actual studies, resulting in lower overall conversion (though convert-at-least-once probability is higher) and higher drop rates. This could be expected: the information scent lures them in, but on discovery that they are in the wrong patch they leave for other information.

From a design perspective, buttons often became very long (especially with 2 labels, each one spanning multiple words), which presented itself as a problem on mobile phones. Here the buttons were too long, effectively making them 2 lines, making them even more prominent in the interface. This both had aesthetical and experimental drawbacks and the choice was made to only use one tag per button.

12 User behavior data engineering

A large part of this project consisted of exploration into StudyPortals data to find viable hypotheses for research. Much of the early exploration was done under the assumption that StudyPortals had "Big Data" and therefor required analytical processes that could scale to immense sizes. It turned out that for this project, the big data could with relative ease be reduced to a lot of data, that still could be processed on a normal laptop. That reduction allows for much quicker processing and iteration, though the process is not scalable in the current form. Switching a number of processing and storage steps however allows for the same process to scale to several hundreds of Terabytes of storage and "infinitely" scalable analytics, which should be sufficient for StudyPortals current and upcoming data needs.

This chapter covers some of the main processes and findings of the data exploration, as well as a recommendation for scaling the analytical process to terabyte-scale. In contrast to the other chapters, it is mostly process focused.

12.1 Data at StudyPortals

Several data sources were available when the project was started. This subchapter aims to provide a short oversight of these sources. Generally, 4 "pipelines" were available:

- Server logs: requests that are to the servers that are logged by apache2 (an open source web server). The logs are stored as simple flat-text lines and pushed to an aggregation service, which makes it straight forward to download all server logs from several servers;
- Portal logs: business critical data logged by StudyPortals' custom trackers and processing;
- Google analytics: tracking script by Google that tracks user behavior and presents the aggregated results in a number of reports. StudyPortals does extended effort to keep this up to date with relevant labels, user metrics etc.;
- StudyPortals own database, which can be communicated with trough an API accessible from their internal network. Where portal logs are the events performed by users, this is the actual content of their websites, i.e. studies, countries etc.

Both GA and StudyPortals' API will not be covered in detail, the first because it's a commercial product of which plenty of documentation is available online[19], the second one because it is essentially the core of StudyPortals' business and allows access to over 200 database tables, making it a very long and irrelevant description. The latter is also barely used for this project, besides gathering all available disciplines and studies.

[19] www.google.com/analytics

12.1.1 Server logs

Apache2 is server software, processing incoming HTTP requests, diverting the request to the right scripts (PHP in this case) and outputting the response of that script to the requesting user. Apache2 logs all these requests by default, resulting in a stream of all HTTP requests performed by users to that certain server, including html pages, but also CSS and JS scripts and images for examples. The formatting is done using the standard settings so that every request that a user makes is saved into flat text files in the following format:

```
[website] [user_ip] [user_identifier] [identified_user_id] [[date]] "[http_method]
[request_path] [request_type]" [status_code] [content_size] "[referrer_host]"
"[user_agent]"
```

Two examples:

```
sl.prtl.eu 95.23.28.70 0 - [17/Jun/2015:01:59:59 +0200] "POST /track/facts/
HTTP/1.1" 200 44 "http://www.mastersportal.eu/search/?q=di-7|ln-3|lv-master|rv-1"
"Mozilla/5.0 (Windows NT 6.1) AppleWebKit/537.36 (KHTML, like Gecko)
Chrome/43.0.2357.124 Safari/537.36"

www.shortcoursesportal.eu 66.102.6.173 46804 - [17/Jun/2015:02:00:02 +0200] "GET
/studies/71385/how-colors-affect-you-what-science-reveals.html HTTP/1.1" 307 850
"https://www.google.com/" "Mozilla/5.0 (Linux; Android 5.0.1; SCH-I545 Build/LRX22C)
AppleWebKit/537.36 (KHTML, like Gecko) Chrome/43.0.2357.93 Mobile Safari/537.36"
```

Generally, apache logs' usefulness is limited to a number of use cases. The most straightforward analysis is that of general web traffic, i.e. what popular pages are (Girme & Laulkar, 2015; Kalola, 2014; Premchaiswadi & Romsaiyud, 2012) or trying to catch DOS attacks (Lee & Lee, 2012). Clustering of users, or constructing matrices of page visits per users can be done as well (Premchaiswadi & Romsaiyud, 2012). In the case of StudyPortals, apache logs needed quite some filtering and work to make them somewhat more reliable and useful, these are some of the issues found during exploration:

- *Sessination:* apache logs contain very little user specific information besides IP addresses and a 'userId' variable, a user identifier at server level, making it unusable for user analysis. Thereby, users can only be identified by IP address and user agent, meaning all data that is performed by IP's that are suspected of being used by multiple users (about 40% of all weblogs, depending on the exact cutoff point) has to be left out of user analysis. It is good enough for basic analysis, but user targeted analytics need something more reliable and precise.
- Caching as well as reversed proxies are used to optimize page rendering speeds, which is great for speed purposes but results in HTTP requests not hitting servers anymore, therefor not logging the request while it was made.
- Quite some page interactions like modals, on-page clicks, page dwelling and repeated search actions are web-based interactions, meaning that no specific requests are done to the backend servers, and such the information is not logged.
- As everybody can simply make server requests, the data needs a lot of preprocessing. Bots for example scrape whole websites and can significantly influence results. While most of them identify themselves as bots with proper user agents, a number of "bad behaving" bots have been found.
- The data contains *every* server request. This means loading a study page can consist of dozens of requests, loading resource scripts, images, doing API requests for additional information. While these can be filtered out with relative easy, the requests

can have some significant meaning (i.e. loading of a new piece of on-page information, a new search query or page loading times).

For the purpose of this research project, Apache2 logs were generally found to be too unspecific (especially with regard to user recognition) and required a lot of preprocessing and filtering.

12.1.2 Custom logging system

Several types of user interaction are recorded in a custom logging system, which was created to save data used to invoice StudyPortals customers. The logs are generated in the browser and are sent to the tracking API in JSON format. There they are stored as flat text files and parsed once every 24h. In this parsing process they are validated and saved in a relational MySQL database (in aggregated form), as well as in an ARCHIVE MySQL database. The JSON files and archive tables are mainly for backup purposes, the relational MySQL tables are used for invoicing, analytics and reporting. An example of a tracked event is shown in Figure 45, in this case it is a banner ("bnnr") impression ("impr").

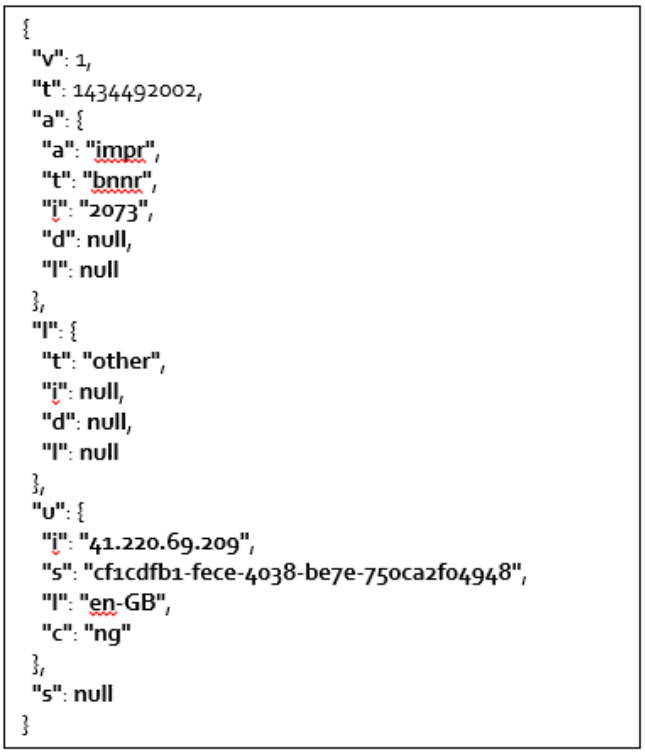

Figure 45: example of a (prettified) JSON log for a banner impression from a user.

For each event a number of parameters are tracked, for example the timestamp, details on the user and the location from where the event was triggered. Table 75 includes the details of all these variables.

Key	TYPE	Description
v	INT	Version of the log, currently only 1
T	INT	UNIX Timestamp
a	OBJECT	This represents the logged action
a.a	STRING	The actual action. Possible values are: - *impr* Impression - *clic* Click - *view* View - *subm* The submission of a lead form
a.t	STRING	The target of the action. Possible values: - *bnnr* A banner on the page - *study* A study (i.e. comparable studies shown on a study page) - *org* An organization or university - *srch* Results of a search query - *lead* The submission of a lead form (in which case a.a. is *subm*)
A.I	STRING	Action identifier. Can be an integer for bnnr, study, org and a search string for srch.
a.d	STRING	The name of the instance id, or url of a click
A.I	STRING	Commercial type of the action, either *premium, regular* or *revenue*
I	OBJECT	Represents the object of a shown element on the requested webpage, i.e. a banner, search result or spot instance.
I.T	STRING	The type of the shown element. Possible values: - *other* - *rslts* - *study* - *spot*
I.I	INT	The id of the shown element.
I.D	STRING	The name
I.L	STRING	Commercial type of the shown element, either *premium* or *regular*
U	OBJECT	The object that holds data on the user
U.I	STRING	Ip address of the end user
U.S	STRING	Session ID: a unique identifier that identifies a user throughout a session.
U.l	STRING	Language of the user
u.c	STRING	Country of user
s	STRING	Last used search string by user. Search string is in the StudyPortals search string format.

Table 75: details of the different parameters tracked by StudyPortals internal system.

While the data is generally accurate and clean, only information that is directly interesting to universities and colleges is tracked, which is only a subset of the data usually required for more detailed analytics. Only search- and study page views are tracked for example, and very little user information (such as user agent or device type) is available. It proved to be more useful in combination with the server logs, but the lack of a unified definition of a user (only IP addresses are available for both datasets) made merging the two datasets error prone and complex.

BachelorsPortal besides a custom logging system, also uses a custom query construction, enabling every query to be summarized into a single string. This simplifies search queries over different production and analytical systems. Each query consists of concatenated [parameter]-[value] combinations, separated by pipes. A valid query would be lv-bachelor|di-7, looking for bachelor studies with discipline 7. Table 76 summarizes all possible parameters and data types.

Parameter	Explanation	Data Type
Lv	Level of education	Master, bachelor
Kw	Keywords	(string)
Di	Disciplines	List of integers
Ci	Location	List of integers
Ln	Language of instruction	List of integers
Mh	Select filters	Face2face, blended, online
Tm	Tuition fee minimum	Integer
Tx	Tuition fee maximum	Integer
Tt	Tuition type	Eea, noneea
Tu	Tuition timeunit	Semester, year
Dm	Minimal days of program	Integer, 360 days in 1 year
Dx	Maximal days of program	Integer, 360 days in 1 year
Sd	Month on which program starts	List of integer (1=jan, 12=dec)
De	Parttime/fulltime	Parttime, fulltime
Dg	Type of degree	Msc, bsc, (+ others)
Jt	Special programs	Erasmus, erasmus_scholarship, joint(inter-university/joint)

Table 76: overview of parameters used in StudyPortals search queries.

12.1.3 Initial data processing

As initially the perception was that analytics should be done on a "big data" scale, a Hadoop based solution was looked into. Hadoop[20] is a popular open source Apache project that handles distributed file storage and processing, allowing analytical tasks to be spread out over servers and chunks of data, allowing for theoretically infinitely scalable processing. Nearly every big data product is based on Hadoop, making it the perfect framework. As most of StudyPortals infrastructure was already run on Amazon, the decision was made to run Hadoop on AWS.

Amazon Web Services (AWS) is a collection of cloud computing services offered by amazon, ranging from simple storage space (S3) to computing power (EC2), email, key management etc. Any of these service instances can be quickly deployed (in matter of minutes) and scaled up or down – allowing for example a website to almost instantly increase or decrease their server size depending on the current traffic. AWS is only charging the amount of server capacity used. This pricing model, reliability and scalability has made it a popular choice to host websites or do computations.

AWS offers an Elastic Map Reduce (EMR) service, where a cluster of worker and task nodes can be configured and deployed with a few clicks, in a few minutes. EMR is basically a top-level service which launches multiple EC2 instances (Virtual Private Servers), installs a preferred Linux Distribution (AWSs own 'AMI' is the default), installs and configures Hadoop and preferred libraries build on top, and configures all the underlying connections between these EC2 instances and the S3 storage where data is pulled from. This allows for an easy start with Hadoop with almost zero fiddling with server setups, but comes at the cost of vendor lock-in, server costs and hiding of lower level details through higher level services.

[20] http://hadoop.apache.org/

A combination of hive and impala were used for analyses. Both are built on top Hadoop and use a subset of SQL to query data from flat files. Hive is built on the (now somewhat old) map-reduce technique, that runs the same query on multiple data chunks, and then combines (reduces) the results into one main output. Initially developed by google to run their massive queries on common hardware, the technique showed good initial results but more modern techniques have proved to be much faster. Impala uses nearly the same SQL-like syntax but proved to be significantly faster, up to a 100 times for some queries. Practically, their main difference is that hive accepts custom serdes: functions that allow parsing of a flat input file. In example a JsonSerde allows parsing JSON into HDFS, where the build in RegExSerde allows parsing files based on regular expressions. Impala doesn't have this feature, but the significant speed improvements make it the preferred choice for running analytics. This makes hive perfect for the importing of data from S3 (something that AWS EMR allows to be set as a bootstrap job) and impala for any analysis. Using a month of data (around 100 million server logs and 30 million StudyPortals logs) took an EMR cluster of 1 master and 2 worker nodes (costing a total of about 1$ an hour to run) around an hour to setup and import all the data. Impala queries run on the cluster then gave near-instant results (depending on the complexity).

12.1.4 Snowplow analytics

Due to the lack of certain data types and the complex processing required to get only limited reliability in data, alternative ways were explored to gather and structure data. Between a wide variety of commercial products, Snowplow seemed to be an open source alternative that met all the requirements for this project. Besides being free and allowing for full control, it integrates well with Google Analytics tracking, and a lot of scripts are prewritten, ranging from JavaScript trackers to clustered cleaning and processing steps allowing for scalable processing. Giving a detailed overview of snowplow would be a mere copy of the documentation, for that we refer to http://snowplowanalytics.com/.

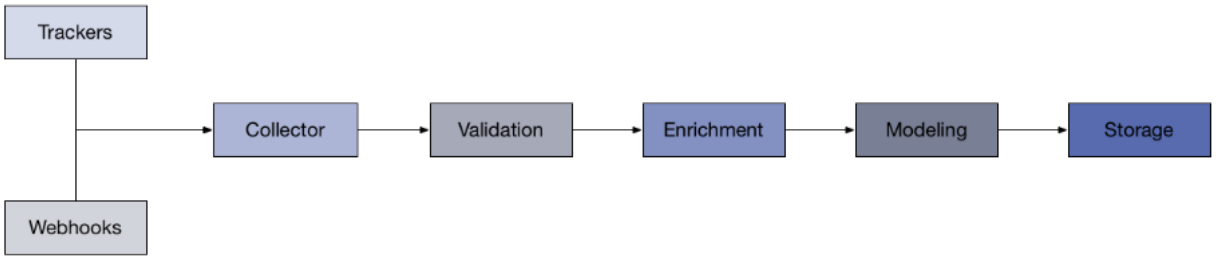

Figure 46: snowplow data pipeline.

For this research project only the first part of the pipeline (up until validation) provided by Snowplow was used. They offer enrichment and modelling scripts that can be setup on AWS clusters and allow for the process to be "massively scaled", which was not the intention of this project. On playing with a rough local setup, a simple python script for parsing and a MySQL database proved to be enough to gather the necessary data.

Overall the quality of data with snowplow seemed to be higher than server logs. Bots rarely execute JavaScript, and the setup is immune to caching proxies. Moreover, the standard data logged by Snowplow is much better suited for analytics, and accounts for much of the problems discussed before such as sessination.

Overall the combination of StudyPortals' internal system (which is well verified, stable and measures business critical data) and Snowplow (for all non-business critical user behavior) proved to be a good pair.

12.2 Scaling to the stars

This process proved to be a near identical clone of snowplows process (Figure 46Figure 46), with some components being switched, losing the ability to scale it infinitely, but reducing setup time significantly. Here a proposal will be done on how to scale analytics to sizes far beyond the current needs of StudyPortals. It's mostly based on Snowplow's pipeline (that is used by many companies according to their website) and existing, proven big data tools. Depicted in Figure 47Figure 47, it shows a lot of similarity with the components used by this project.

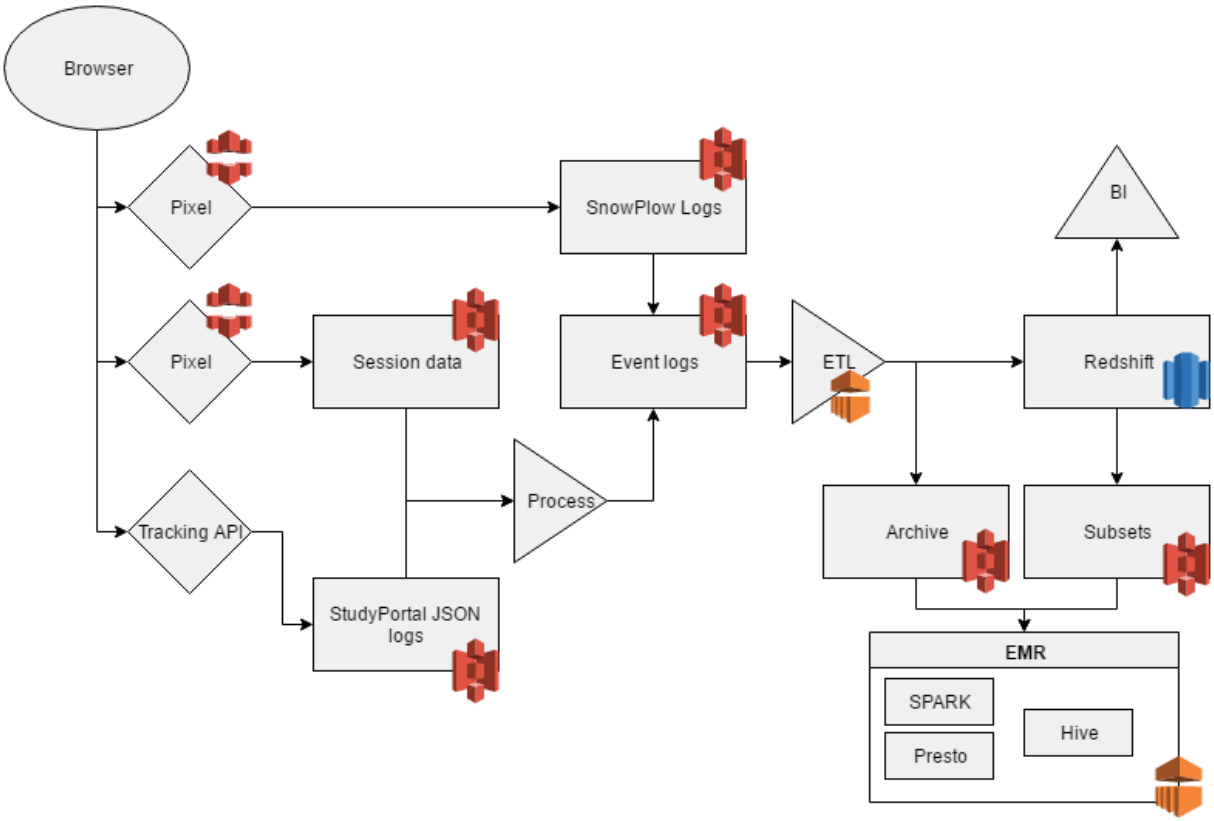

Figure 47: proposed data pipelines and analytical infrastructure for StudyPortals.

12.2.1 Collect

Snowplow's data pipeline setup is quite extended, building on top of it will save significant setup time, enforce proven practices, streamline the data format and allow for a lot of premade processing and analytical tooling. As both snowplow's "classic" data and StudyPortals own logs are event data, though in slightly different forms, merging them early on and consider them as one data stream will remove complexity later in the pipeline.

Snowplow logs are processed the way they are now: simply stored in an S3 bucket waiting to be processed. StudyPortals' JSON log data however will be transformed into the same structure with help of session data triggered by the browser. This processing step is trivial, as it combines the data from 2 static files, and can easily be processed by AWS Lambda service for instance, allowing for scalability and direct processing: as soon as the logs are available they will be processed to the event log bucket.

12.2.2 Process

Depending on the requirements a lot of logic can go into the processing step, ranging from IP location lookups, IP anonymization, user agent processing & device authentication, and even custom API calls to gather resource information. It's main functionality however is to take the files in the event log S3 bucket, and output it into another S3 bucket into "event files", optimized to be loaded into redshift. The outputs will be archived, both for later processing or loading if required, and for input for Hadoop / EMR based analytic processes.

The ETL (extract, transform, load) step can be done instantly with snowplow's Scala Kinesis (an AWS service) scripts, though initially an on-schedule ran ETL-EMR setup is suggested, that runs on set times and processes all event logs that gathered in between previous run and the current. Kinesis adds setup and maintenance overhead and currently real-time processing is not required.

12.2.3 Store

Stored in redshift, data is available for a wide range of clients to be analyzed. As storage infrastructure is fully managed by AWS and storage schemas are predefined by Snowplow, this step is very low maintenance and low effort. The same goes for the events logged in S3, waiting to be read into other data sources for further processing.

While redshift is on top of the market regarding speed, badly designed queries that run for hours (or even days) can clough up the cluster and significantly slow down other queries. It is therefore suggested to:

- Limit access to database-experienced users;
- Train them in redshift query optimization. Ideally deep, though a short training session can enforce a number of good practices;
- Limit query execution time, so queries going wild can't run forever.

12.2.4 Analyze

All data is available in Redshift, allowing for a wide range of clients to access and query the data. Commercial parties like Tableau and SAS provide direct connections, and with Redshifts ODBC and JDBC connectors, all software supporting these drivers can connect to the store and start querying data.

For custom processing, for example complex statistics, data outputs and machine learning, custom EMR jobs can be used. They can load either all data from the archive bucket, or query subsets from the redshift data store. The tools used from hereon are dependent on the requirements and the engineer(s) implementing them, but is independent from the data store itself.