Diplomarbeit

A Contribution to Rating and Recommendation Systems: Concepts, Development and Evaluation

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Kiel, ** Datum der Abgabe **

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Ich erkläre hiermit, dass ich die vorliegende Arbeit selbstständig und nur unter Verwendung der angegebenen Literatur und Hilfsmittel angefertigt habe.

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Abstract

The focus of this thesis is the development of a recommendation system for user generated content. The purpose of this system is to utilize the unused content that is contributed by users. If this content is added in a meaningful way on existing websites it can increase the benefit of the website for its users. Meaningful way means, that the content matches the current context of the website and is interesting for the current user. This process involves three different types of research areas.
First, the generation of implicit user ratings by analyzing user interactions on a website. This part of the thesis involves the discussion of different user interactions on a website. For the two interactions that correspond the most with explicit ratings of a user a rating scale is created that enables the transformation of user interactions into implicit ratings.
The second research area is approximate string matching which is the matching of strings even if the words are slightly different. This technology is used for categorizing the user generated content by its keywords. This part of the thesis involves the analysis of different techniques that can be used for such a process. The technique of the *levenshtein automaton* is explained in more detail and a range is created that expresses how different words are allowed to be in order to be accepted as a match.
The last research area is the field of recommendation systems.The different types of recommendation systems are discussed in this part. Moreover a new technique is introduced that combines two well known recommendation techniques to improve the rating predictions. This system is implemented with a service oriented architecture so, that every component of the system can be exchanged with different alternatives or parts can be used to extend existing systems. This leads to a considerable amount of flexibility and expandability.

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1 Introduction

Since the creation of the term Web 2.0 the internet is about user generated content and communities. More and more website operators are adding methods to their sites with the goal of increasing the user engagement by allowing users to actively contribute to the content of the website. However, as more and more content is produced most of the user contributed content will remain unseen. The value of a website is the benefit that it brings to its users. Therefore every content that includes valuable information must be presented to users that might be interested in it. This can improve the user interactions on the website and can help the users to learn from each other and thus to better understand the content. Though, the quality of the content that is produced by users may vary widely. Moreover, the context of the user generated content can be inappropriate to the current subject of the page. Thus there is a need for a system that is able to identify the interest of a user and the context of the user generated content.
With these information contributed content that is interesting for the current user could be added individually on websites with matching subject. This thesis deals with the development of a system that can

1.1 Related Work

This thesis combines different fields of research namely the field of recommender systems, the field of collecting implicit user ratings and the field of string matching techniques. The team of Claypool et al. [2001] developed a web browser that collects user interactions on a website. This browser asks the user when he leaves a website for his rating for the site. They conducted a field experiment with 75 students that rated 1823 websites and analyzed the correlation between the explicit ratings and the implicit user interactions. The paper *Personalized news recommendation based on click behavior* written by Liu et al. [2010] analyzed the click behavior of Google news users to find out how the interest of the users changed over time to predict the current and future interest depending on the clicks of similar users. They tested the developed system in production mode and found out that the traffic of the *Google News* website increased because of the improved recommendation system. The team of Sarwar et al. [2001] introduces their invention of the *item-based* recommendation algorithm. This algorithm calculates the item similarities based on item rating vectors and recommends items to users based on the similarity of the items they rated. Furthermore they discuss different calculation techniques and evaluate the performance of the algorithm. Linden et al. [2003] explains the product recommendation system of *amazon.com* in detail and describes their implementation of the *item-based* recommendation algorithm. Karatzoglou et al. [2010] describe a mathematical concept and an algorithm for representing and compressing the latent factors of the singular value decomposition with hashing. For each user and each item one vector has to be stored in the main memory while calculating the matrix decomposition. However usually only a small number of ratings exist for each item Karatzoglou et al. [2010] introduced a method of an approximate compressed representation of the latent factor matrices. Cacheda et al. [2011] describe the current state of the algorithm and evaluation techniques of collaborative filtering recommendation systems. They discuss the different metrics that are used for evaluating recommendation systems. Additionally they found that the best performing algorithms in their evaluation are all based on the singular value decomposition. The article *Matrix Factorization Techniques for Recommender Systems* by Koren et al. [2009] explains the strategies of recommender systems and how to apply matrix factorization methods in these systems which are according to Koren et al. [2009] the most accurate prediction techniques found out by many of the teams that were competing for the *Netflix prize*[1]. The paper of Herlocker et al. [2004] deals with the evaluation of recommender systems. They explain in detail the different type of testing datasets and the current trends in datasets and accuracy metrics. The following article treat the techniques of approximate string matching which is the matching of strings that allow errors. Navarro [2001] presents an overview on the different kind of concepts that enable approximate string matching. Schulz and Mihov [2002] explain the principle of a *levenshtein automata* in detail and describe a concept on how to use this levenshtein automata for an efficient way to correct strings with the help of a dictionary. The same authors wrote a paper about an *universal levenshtein automata* - Mihov and Schulz [2004] - which is a specialized version of a *levenshtein automata* that improves the time that is needed for constructing the automata.

1.2 Challenges

The focus of this work is the development of a recommendation system for user generated content. One challenge of such a system is that no trustworthy information about the quality or context of the user generated content is available. Hence, a concept must be created that treats the finding of keywords in this content. These keywords should be found by matching the content with the words from a thesaurus even if the words have spelling mistakes or are in a different form. Additionally the concept must include the generation of user ratings for this content to be able to predict how interesting the content is for the user. This rating generation should work by automatically analysing the user interactions on the website that presents the content. Therefore the user experience of the website is not disturbed by explicitly asking for the users opinion. Another challenge is to use the rating and keyword information to generate content recommendations for users based on their interest. This concept should be implemented into a system that can be used as an ad on

[1]http://www.netflixprize.com/

for existing systems. Moreover each component should be usable as a standalone system to extend existing systems. Finally the developed system has to be evaluated to see if the requirements are fulfilled and to propose offers for future work.

1.3 Overview

In Chapter 2 the concepts of this thesis are presented. This chapter is divided into four sections. At first the concept of a *Question and Answer* website is explained which is used as a tool for collecting user generated content. The second section evaluates the differences between implicit and explicit ratings and the different sources of types of user interactions on websites. Besides it introduces a concept for generating implicit ratings with these user interactions. The next section examines the methods of string matching that allows a system to match words even if they are in a different form or have spelling mistakes. Additionally this section introduces the technique that is used in the developed system for finding the keywords in the user generated content that is collected by the *Question and Answer* website. In the last section different types of recommendation systems are considered and the concept of *collaborative filtering* is explained in more detail. Likewise the new concept of recommending user generated content based on a combination of *item* - and *singular value decompositon* - based methods is explained.
Chapter 3 starts with a section about the presentation of the technologies that are used for implementing the previously developed concept. Alongside, with a description of the service oriented software architecture and an insight into the implementation as well as the relationships of the single services.
Chapter 4 evaluates the implemented rating, tagging and recommendation concepts. This chapter is divided into three sections. The first section tests the implemented concept of the implicit ratings. For this process values that are collected by a field experiment conducted by Claypool et al. [2001] are used for evaluating the rating concept. These values are used for simulating user interactions on a website and the results are compared with the analysis of Claypool et al. [2001]. The second section evaluates the implemented tagging concept. For this evaluation different sized texts were created. These texts have a percentage of 30% of words that are included in the used thesaurus and 70% that are not. However, into the 30% of the words that are included in the thesaurus are spelling mistakes inserted or the form is changed. Hence, the tagging implementation is tested for the amount of words that are found and the time that it needed for this process. The last section evaluates different types of recommendation systems that are composed with the techniques of the recommendation concept of this thesis. This evaluation uses a rating database with 100.000 real user ratings of the *MovieLens*[2] project for evaluating the speed and the quality of the predictions of the different recommendation systems.

[2]http://movielens.org/

2 Concepts

This chapter outlines the concepts that are integrated in the developed system. The first section deals with the approach of a *question and answer site* and explains the necessity of such a system. The second section is about the differences between implicit and explicit ratings and the different sources of implicit ratings. Moreover this section describes the implemented concept of collecting implicit ratings. The third section treats the automated tagging process that is used to connect the questions and answers with the recommendation system. The fourth section is a discussion about the different types of recommendation systems. This leads to the analysis of the different techniques of collective recommendations and explains how these techniques are used in the final system. Finally the last section presents the relationship of the individual concepts from the previous sections.

2.1 Question and Answer Site

A question and answer site is a website that has only one focus namely getting the right answer for a question. Therefore a user can ask a question. This question should be precise enough and include all information that another user needs to be able to write a correct answer to the question without asking for more details. So, it is not a discussion forum but a website in which every answer only refers to the original question. Then the user who started the question can mark one answer as correct. This question and answer site should make the information retrieval process on a website publicly accessible. Therefore all users are able to read all questions and answers and can support domain experts by answering questions. For each question on the site there is exactly one answer marked as correct, thus, it is possible to recommend the questions with the correct answers to users who visit a website with the same subject. This recommendation process should increase the user interaction with the website. Moreover, it should help the user to understand the content which he is interested in. Such question and answer sites are widely spread on the internet and there exists a couple of open source implementations that can be used for free. Some of such open source implementations are askbot.com, discourse.org, lampcms.com and osqa.net. They all work and almost look the same. However, they use different technologies and some are more mature than others. The open source variant that is in use for the implemented system is askbot.com. It is build with the *django web framework* and actively maintained since 2011.
Henceforth, for better understanding, the word *item* will be used instead of question and answer for an element that should be recommended.

2.2 Rating System

In order to be able to recommend items to users it is important to understand what items a user likes. For the purpose of such a task a rating scale ranging from 1, strongly disliked, to 5, strongly liked, is used. There are two possible forms for retrieving ratings namely implicit ratings and explicit ratings. The latter are those in which a user is explicitly asked for his opinion on a specific item. Implicit ratings are those in which a system generates a rating according to the actions of a user. Anyhow, according to the book *recommender systems an introduction* [Jannach et al. [2011]] the explicit user ratings are usually not well accepted if a direct benefit is not visible to the user. Furthermore, the explicit ratings might disturb the user experience of a website. Adding the explicit ratings with visible benefits to an existing *question and answer website* would require too much customization, because in case the *question and answer website* is replaced by a different open source version or an own implementation the explicit ratings with visible benefits have to be added again. Therefore it is a good approach to use implicit ratings to collect the interest of a user. The research group of Claypool et al. [2001] developed a web browser that monitors user interactions and afterwards asks a user how he would rate the page. Thereby it compares user interactions with explicit ratings. Claypool et al. [2001] build their results on a field experiment of over 80 people browsing over 2500 Web pages. The user interactions they measured with their web browser are presented below.

2.2.1 The time a user spends on a website

The team of *Claypool et al* measured the time a user spends on a website as a first indicator that the user works with the site. The idea behind this method is that the more time the user takes to view the content of the website the more interesting the website is for him. For this method a timer was used that measured the time a user spends on a website. The timer starts after the website is completely loaded and stops when the user leaves the website or closes the window. Additionally the timer is only active as long as the website is visible in the web browser. They compared the time a user spends on a website with the explicit rating from the user this correlated about 70% of the time. So, they found out that the time a user spends on a website is a good indicator of interest. For this reason this method is used as one implicit rating indicator in this thesis. However one has to keep in mind, that the general time a website is open and visible needs to be relativized because one does not know whether the user is actually reading or interacting with the content of the current website. Therefore other indicators where measured and included in *Claypool's* research. Which will be clarified in the following sections.

2.2.2 The time the cursor is in motion

Whereas the general time a user spends on a website already gives a good indication on how interesting the website is it is also important to measure how far the user actively engages with the website. The use of methods that measure how active a user is on a website is important because these methods can indicate whether a user just opened a website and does not work with it or if he really engages with the content. The time the cursor is in motion was measured by timing how long the mouse cursor changes its position inside the active browser window. By comparing the explicit user ratings with the collected data they found out that the time a user moves the mouse cursor is proportional to the interest a user has in the website. However, due to the fact that some users use the mouse heavily whilst reading the content of the website or looking at interesting objects such as diagrams or pictures, other users tend to only use the mouse in order to click on objects. Consequently, it is not possible to tell how much a user is interested in the website by timing the cursor motion but it is only possible to tell which websites receive the least amount of interest. Thus, in order to reflect the users interest more properly other ways to measure the active time on the website must be taken into account.

2.2.3 The number of mouse clicks

Another method of collecting user interactions that might correlate with the explicit rating of a user is the number of mouse clicks on a website. The research team of Claypool et al. [2001] thought that a high number of mouse clicks would be a sign that the website has links to interesting websites or objects and as such would be valuable to the users. The collected data, however, showed that the number of mouse clicks on a website is not significantly different as though the user rated it with the highest or lowest rating. So, this method is not a good indicator for the users' interest.

2.2.4 The time a user scrolls

The last indicator they used was the time a user scrolls. This is an important activity indicator because a user has to scroll in order to be able to see the whole content of a website. The web browser the team of *Claypool et al* developed measured the time a user scrolls a website by keys and by mouse. They compared the data of the method of the field experiment with over 80 people with the explicit user ratings. With that data they found out that both the measurement of user scrolls by keys and by mouse are on their own poor indicators of interest a combination of both methods is found to be a good indicator of interest. This is explainable by the fact that some users prefer to scroll by using the mouse while others prefer the keyboard for such a task. For this reason the time a user scrolls by mouse and by key was used in this thesis as an activity indicator.

2.2.5 Total Rating Concept

As could be seen above the best sources of implicit ratings are the time a user spends on a web page and the amount a user scrolls on a web page according to Claypool et al. [2001]. These methods have an accuracy of about 70% to the explicit user ratings. This correlation between the implicit and explicit ratings can be explained by the fact that a user who is interested in an item takes a good look at an interesting website and reads the content that is presented on this site more carefully. This process takes time, the user stays on the website longer and the user has to scroll in order to see the whole content of the website.

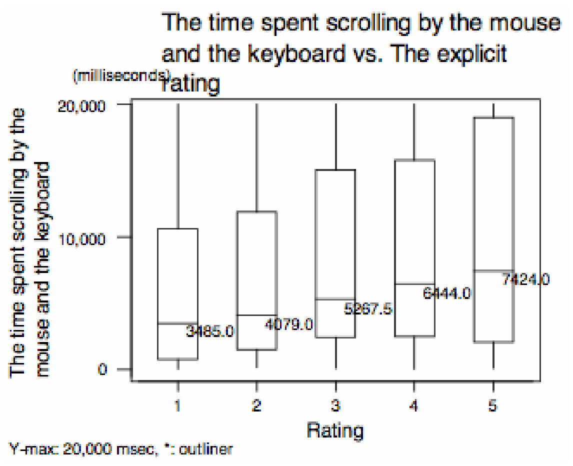


Figure 2.1: Time spent scrolling Claypool et al. [2001]

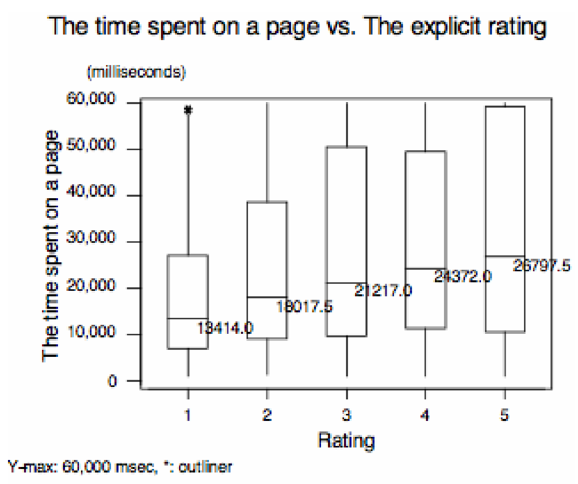


Figure 2.2: Time spent on a page Claypool et al. [2001]

In order to collect implicit user ratings by timing how long the website is in focus, the truncated mean time all users spend on the item page is used as a benchmark.

Definition 1 (Truncated Mean)**.** *The truncated mean (tm) is calculated the same way as the average mean after discarding a specific percentage of the highest and lowest values. Let $n \in \mathbb{N}$, V be a set of sorted numbers and p be a percentage with $0 \leq p < 0.5$. Let $k = np$ be the trimmed value, $r = n - 2k$ be the remaining values, $v_j \in V$ and $j \in \mathbb{N}$. Then the following formula represents the truncated mean.*

$$TruncatedMean = \sum_{j=k+1}^{n-k} v_j \cdot \frac{1}{r}$$

The percentages of the two rating processes result out of the two diagrams of figure 2.1 and figure 2.2. These diagrams are created by the team of Claypool et al. [2001]. The x-axis represents the explicit user ratings and the y-axis represent the time that a user has spend on the website and the time a user has scrolled on a website respectively. The bar for each explicit rating represents the time range of all users that explicitly rated with that rating. The line in each of the bars represents the average time of all user times of that range. For this thesis the time differences between the average times of each rating is assumed as a range for implicit ratings. These ranges are expressed as percentages in dependence to the complete average time of all users in the following two enumerations.

- If the user spends 76.5% of the truncated mean time on the item page it is used as a rating of 1.
- If the user spends between 76.5% and 94.3% of the truncated mean time on the website it is used as a rating of 2.
- If the user spends between 94.3% and 109.6% of the truncated mean time on the item page, it is used as a rating of 3.
- If the user spends longer than 1.23% of the truncated mean time on the website it is used as a rating of 4.

A rating of 5 can only be achieved if a user does a predefined user interaction on the web page. The reason behind this choice is that users tend to make breaks while surfing the internet. Thus, the user leaves the current browser window open but is not actively working on this website. Therefore it is possible that a user is on a break and the currently active browser window might not be interesting for him in that moment. Such a predefined user interaction can be used as an indicator that a user likes an item. A possible predefined user interaction could be an up-vote or the writing of a comment or answer. A similar scale is chosen for determining the rating of a user by the time a user scrolls.

- If the user scrolls less than 69% of the truncated mean time on the item page it is used as a rating of 1.

- If the user scrolls between 69% and 86% of the truncated mean time on the webpage it is used as a rating of 2.
- If the user scrolls between 86% and 108% of the truncated mean time on the webpage it is used as a rating of 3.
- If the user scrolls between 108% and 129% of the the truncated mean time on the website it is used as a rating of 4.
- If the user scrolls longer than 129% of the truncated mean time on the website it is used as a rating of 5

Due to the fact that scrolling is an active process and the user has to be in front of the computer a rating of 5 is achievable in this method. First of all both implicit ratings - the time a user spends on a website and the time a user scrolls - are determined separately. Afterwards the average of both ratings is calculated and used as the total rating.

$$totalrating = \frac{rating_{time} + rating_{scroll}}{2}$$

If a user returns to an item site the time the user spends on the page and the time the user scrolls on the page is added to the previous times and the sum of both sessions is used to calculate the new rating.
As mentioned above Claypool et al. [2001] research group bases its results on a field experiment of over 80 people browsing over 2500 Web pages. The total rating concept is strongly build upon these results. It would have been desirable to conduct a field experiment for the concept of the total rating but unfortunately due to the lack of time it was not possible.

2.3 Tagging

In order to recommend items with a matching subject on a website, the newly developed system needs to be able to filter the items based on their content. Therefore the keywords of the item content are used as tags in order to reflect the content of the items. In the context of economics the *ZBW* provides the *STW Thesaurus for Economics*. The *STW Thesaurus for Economics* provides vocabulary on any economic subject and includes about 19000 terms and 6000 standardized keywords which can be used to match words from a text.[1] It, thus, provides a good basis for the tagging process. However, the *STW Thesaurus for Economics* only includes the basic form of the words while excluding most of the words with affixation. Due to this it is not sufficient to check whether the words from the items are equal to the words from the *STW Thesaurus for Economics*. So, the challenge for this tagging process is to find the correct words in the *STW Thesaurus for Economics* even though the words from the item might not correspond directly to the words in the *STW Thesaurus for Economics*. One possible solution for such a task is to reduce each word from the text to its stem.Such a task is called stemming and is usually done by using predefined rules on the words. A rule is usually a combination of the minimum number of letters in a word, plus the suffix that should be changed and the replacement for the suffix. More advanced algorithms might also use rules for prefix reduction and detecting irregular changes of the stem according to *Caumanns A Fast and Simple Stemming Algorithm for German Words*. For example a predefined rule might be '3+ies' → 'y'. So, the word *libraries* would be reduced to *library*. Thus it is important that the stemming algorithm has all necessary rules for each supported language.

definition stem

Another challenge for using the stemming algorithm is that all words in the basis for the tagging process must be in the stem form. Otherwise the algorithm might reduce a word to its stem that would match in its original form. Due to these maintenance problems it was decided that the stemming algorithm is not suitable for the developed system. Another possible solution for the problem is to calculate the differences between the words from the text and the words from the basis for the tagging process. This difference can be used as an indicator whether the words are similar or not. If they are in a predefined difference range the words can be used as tags.This creates the need for a metric that indicates the difference or distance between two words. A practical metric for such a task is the *levenshtein distance* which will be explained in the following section.

2.3.1 Levenshtein Distance

The *levenshtein distance* calculates the minimum numbers of substitutions, insertions and deletions that are needed to change one word into another. The following example explains the *levenshtein distance* for the words *library* and *libraries*. The algorithm has to perform two deletions and one substitution in order to create the

[1]STW Thesaurus for Economics url: http://zbw.eu/stw/versions/latest/about

word *library* out of the word *libraries*. If it creates the word *libraries* out of the word *library* it has to perform a substitution and two insertions.

$$\textit{library} \leftrightarrow \textit{librari} \leftrightarrow \textit{librarie} \leftrightarrow \textit{libraries}$$

Both processes result in a *levenshtein distance* of three. So, the *levenshtein distance* is zero if the words are equal and adds one to the result if it has to perform a substitution, an insertion or a deletion of a letter. For a more detailed description compare algorithm 1.

Algorithm 1 Recursive Levenshtein Distance Algorithm

```
 1: procedure LevenshteinDistance($s : String, t : String$)
 2:     $lenS \leftarrow length(s)$
 3:     if lenS = 0 then
 4:         return $lenT$
 5:     end if
 6:     if lenT = 0 then
 7:         return $lenS$
 8:     end if
 9:     if s[lenS-1] = t[lenT-1] then      ▷ test if last characters of the strings match
10:         $cost \leftarrow 0$
11:     else
12:         $cost \leftarrow 1$
13:     end if
            ▷ The first recursive call represents a deletion, the second represents an
    insertion and the third represents a substitution or a correct letter
14:     return minimum of
          $LevenshteinDistance(s[0..lenS-1], t) + 1,$
          $LevenshteinDistance(s, t[0..lenT-1) + 1,$
          $LevenshteinDistance(s[0..lenS-1], t[0..lenT-1]) + cost)$
15: end procedure
```

The direct implementation of the *levenshtein distance algorithm* has a complexity of O(mn) with m size of the first word and n size of the second word. Therefore it is a good utility to better understand the *levenshtein distance* in general, but it is not feasible for a software that should work in production mode.

2.3.2 Optimized Levenshtein distance algorithm

The following definitions are based on the book Hopcroft et al. [2003].

Definition 2 (Non Deterministic Finite Automata)**.** *A non deterministic finite automaton is a 5-tupel of the form* $\mathcal{A} = (Q, \Sigma, q_0, \Delta, F)$*.*

- *Q is a finite set of the states*

- *Σ is a finite set of input symbols*
- *$q_0 \in Q$ is the initial state*
- *$F \subset Q$ is a subset that contains the final states*
- *Δ is a relation of the form $\Delta \subset Q \times \Sigma \times Q$*

$\mathcal{A}$ is called finite exactly when Q is finite. Furthermore Σ^* is the set of words over Σ and ϵ is the empty word.

Definition 3 (Deterministic Finite Automata)**.** *$\mathcal{A}$ is deterministic if for all $p \in Q$ and all $a \in \Sigma$ exists exactly one state $q \in Q$ with $(p, a, q) \in \Delta$. In this case Δ is written as a function $\delta : Q \times \Sigma \rightarrow Q$.*

Definition 4 (Path)**.** *A path for $\mathcal{A}$ is a series $\pi = p_0a_1p_1a_2 \dots a_np_n$, $(p_i, a_{i+1}, p_{i+1}) \in \Delta$ and $0 \leq i \leq n-1$. The length of π is n and the label for $\beta(\pi)$ is $a_1a_2a_3 \dots a_n$.*

Definition 5 (Path shortwriting)**.** *The function $\beta(\pi)$ maps a path π to a label ω. $\mathcal{A} : p \xrightarrow{\omega} q$ with $\omega \in \Sigma^*$ states, that a path π for $\mathcal{A}$ from p to q with label $\beta(\pi) = \omega$ exists.*

Definition 6 (Automata accepts a word)**.** *$\mathcal{A}$ accepts $\omega \in \Sigma^*$, if and only if $p \in I, q \in F$ exists with $\mathcal{A}$: $p \xrightarrow{\omega} q$. For $\mathcal{A}$ let $\mathcal{L}(\mathcal{A}) = \{\omega \in \Sigma^* \mid \mathcal{A}$ accepts $\omega\}$ be the language that $\mathcal{A}$ accepts.*

The following definitions are based on Schulz and Mihov [2002]

Definition 7 (Formal Levenshtein Distance)**.** *The levenshtein distance between two words $V, W \in \Sigma^*$ is the minimal number of edit operations (substitutions, deletions or insertions) that are needed to transform V into W. $d_L(V, W)$ denotes the levenshtein distance between V and W.*

Definition 8. *$\mathcal{L}_{Lev}(n, W)$, $n \in \mathbb{N}$ and $W \in \Sigma^*$ is the set that denotes all words $V \in \Sigma^*$ such that $d_L(W, V) \leq n$.*

Definition 9 (Degree Levenshtein Automata)**.** *Let $W \in \Sigma^*$ and $n \in \mathbb{N}$. A finite state automaton A is a Levenshtein automaton of degree n for W if and only if $\mathcal{L}(A) = \mathcal{L}_{Lev}(n, W)$.*

An optimized version of the *levenshtein distance algorithm* that uses a *levenshtein automaton* is described by Baeza-Yates [1996]. The purpose of the *levenshtein automaton* is to decide whether $d_L(W, V)$ is smaller than a specific $n \in \mathbb{N}$ with $V \in \Sigma^*$. So, it is possible to decide if a word from a question is similar to a word from the *STW Standard Thesaurus*, similar in the meaning it has a *levenshtein distance* smaller than n. Therefore Σ contains the alphabet {a,. . . ,z,A,. . . ,Z}. The states in Q of the *levenshtein automaton* denote the current position in the original word W, written as i and the current *levenshtein distance* between ω and W, written as j, with ω prefix of V. The label of such a state is i^j. Thus the initial state $q_0 \in Q$ is

0^0. The final states $f \in F$ are all states where i equals |W| and j is smaller than n. Let $\omega_{correct}$ be the correct letter after state i^j. The relation $\Delta : (Q \times \Sigma \times Q)$ has the following elements.

- $(i^j, \sigma, (i+1)^j)$ if $\sigma = \omega_{correct}$
- $(i^j, \sigma, i^{(j+1)})$ if σ is inserted after state i^j and $(j+1) < n$
- $(i^j, \sigma, (i+1)^{(j+1)})$, if σ is substituted by $\omega_{correct}$ and $(j+1) < n$
- $(i^j, \sigma, (i+1)^{(j+1)})$, if $\omega_{correct}$ is deleted

The elements are not exclusive, therefore all of these cases can be possible after reading only one letter.

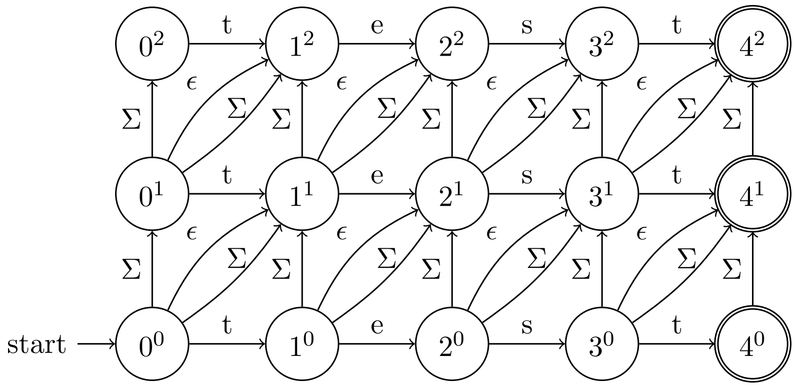


Figure 2.3: A non deterministic levenshtein automaton for the word *test* with degree 2

The automaton in example 2.3 is a non deterministic levenshtein automaton for the word *test*. In the following description the *levenshtein automaton* represents the word $W \in \Sigma^*$ and $\sigma \in \Sigma$ is the currently read letter. Σ indicates that any element from Σ is accepted on this path. The initial state 0^0 is in the bottom left corner. If σ is a correct letter it follows the horizontal path in the automaton. A vertical path is an insertion of a letter $l \in \Sigma$ into the word W which is possible for any σ. A diagonal path can be a deletion of a letter $l \in W$ with the empty word ϵ or a substitution of σ for any σ. Therefore after reading the letter 't' in the initial state 0^0 the automaton can be in five different states namely 0^1, 1^2, 1^1, 2^2 and 1^0. Evaluating a non deterministic levenshtein automata is computational complex due to the fact that there can be a large number of active states at the same time. Thus it is necessary to convert a non deterministic automata to a deterministic automata before using it to find tags. The process of generating a deterministic automata with a non deterministic automata is called *powerset construction.*

Powerset Construction

The process of creating a *deterministic levenshtein automata* out of an *non deterministic levenshtein automata* is based on the *powerset construction* from the book *Introduction to Automata Theory, Languages, and Computation* by Hopcroft et al. [2003]. Given a *non deterministic levenshtein automaton* the construction of an equivalent *deterministic levenshtein automaton* is described below.

- Create q_0' as a set with original q_0 and all states that are reachable with an ϵ path.
- $Q' \subseteq 2^Q$, thus all $q \in Q'$ are subsets of Q.
- $\delta(R, a) = \{q \in Q \mid \exists r \in R$ with (r, a, q) $\in \Delta$ or (r, ϵ, p) and (p, a, q) $\in \Delta\}, R \subseteq Q$.
- F' includes all $q \in Q'$ that include $f \in F$

Therefore the new *deterministic levenshtein automaton* is (Q', Σ, q_0', δ, F').

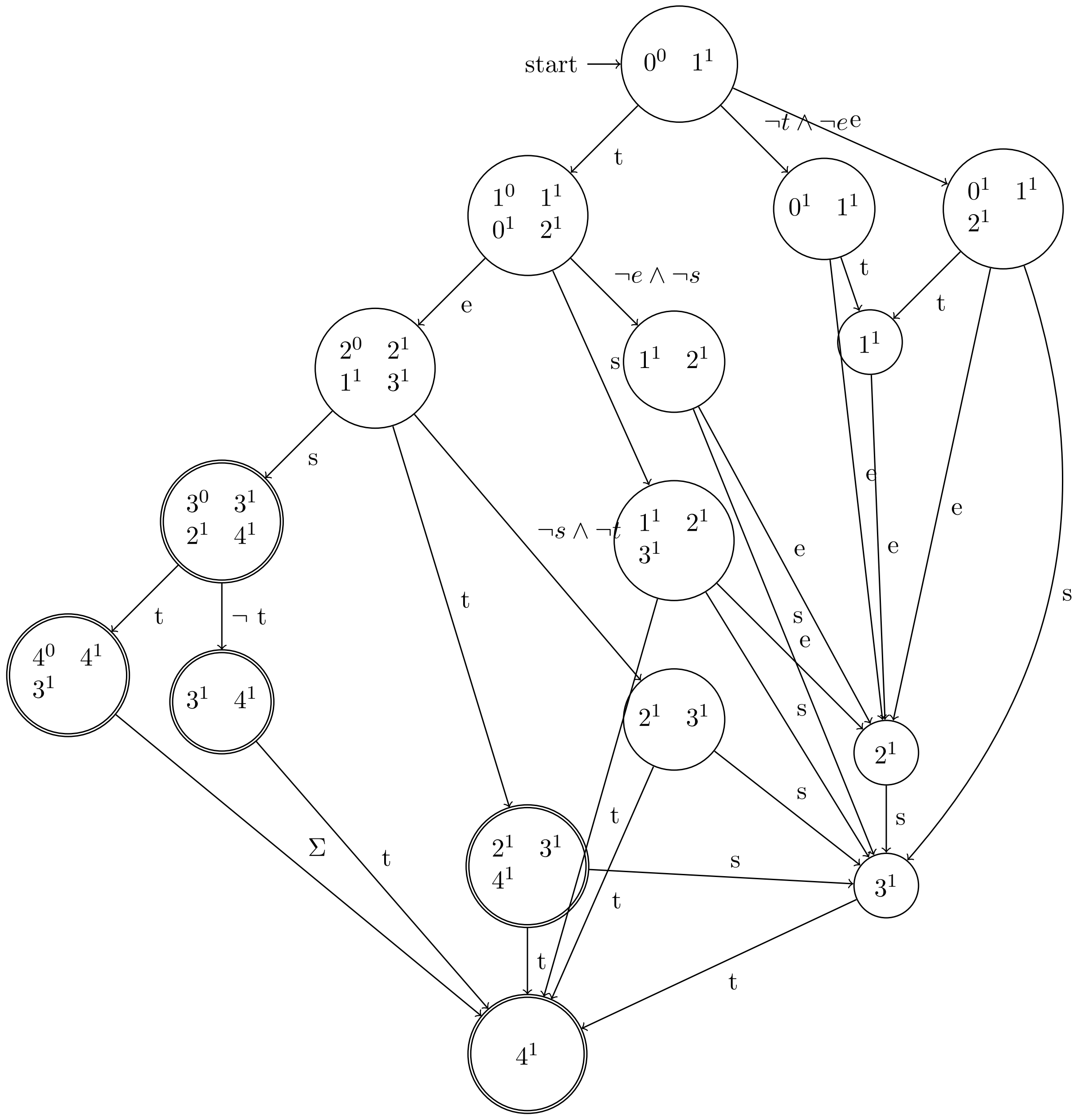


Figure 2.4: A deterministic levenshtein automaton for the word *test* with degree 1

Let $(Q, \Sigma, q_0, \Delta, F)$ be a *non deterministic levenshtein automaton* for the word *test* with maximum *levenshtein distance* 1 [2]. Then the *deterministic levenshtein automaton* $DLA = (Q', \Sigma, q_0', \delta, F')$ from figure 2.4 is the output from the powerset construction. Consequently the DLA can only have one active state at a time and accepts all words V from Σ^* with $d_L('test', V) \leq 1$. This deterministic finite au-

[2]This is the automaton from figure 2.3 without the first row

tomaton with degree $n \in \mathbb{N}$ for a word $W \in \Sigma^*$ can decide in linear time if a word $V \in \Sigma^*$ has $d_L(W, V) \leq n$.

Algorithm 2 Levenshtein Automaton is in distance

```
 1: procedure IsInDistance($automata : DeterministicFiniteAutomata, term : String$)
 2:     $i \leftarrow 0$
 3:     $currentStates \leftarrow (0, 0)$                    ▷ add the initial state
 4:     while currentStates.size > 0 AND i < term.length do
 5:         $c \leftarrow term[i].toLowerCase$   ▷ c gets the current active lower cased letter
 6:         $currentStates \leftarrow automate.nextState(currentStates, c)$
 7:         $i \leftarrow i + 1$
 8:     end while
 9:     if currentStates includes a final state then
10:         return true
11:     else
12:         return false
13:     end if
14: end procedure
```

The maximum distance for a given word $W \in \Sigma^*$ depends on the length n of W. A word with a length of $n \leq 3$ in the *Standard Thesaurus Economics* is usually an abbreviation and therefore is only used as a direct match. A word with a length of $n > 3$ is used with a maximum distance of one due to the reason that most of the plural forms for short words involve the appending of a letter. A word with a length of $n > 7$ is used with a maximum distance of three considering that composing the plural form of a word involves a maximum of three changes (substitution, insertion and deletion) in the German language.

add source Die Pluralbildung im Deutschen: Eine Untersuchung an Hand der Optimalitätstheorie: "German Noun Plural reconsidered" von Dieter Wunderlich explain that there are 15 different plural forms . . .

To get back to the original problem this paragraph explains the application of a *levenshtein distance automata* to find the right tags for a text. The overall tagging concept is to calculate for every word from the text an automata and read all words from the *STW Thesaurus for Economics* into each automata. If a word from the *STW Thesaurus for Economics* ends in a final state it is used as a tag for the text. A possible optimization would be to calculate once all the automata's for the complete *STW Thesaurus for Economics* and to store it with an efficient data structure in a database. Currently the *STW Thesaurus for Economics* is stored in a triple store because it can easily be updated with the standard files from the website. A triple store is special database that stores data in the form of triples. The triple store technology is described in more detail in subsection 3.1.2.

2.4 Recommendation

A recommendation system is a system that creates personalized item recommendations based on information about the items or the relationships between items and users. These recommendations can be created by different types of recommendation systems that exploit different information about the users or items.

2.4.1 Different types of recommendation systems

The book *Recommender Systems An Introduction* by Jannach et al. [2011] distinguishes between the following four different kind of recommendation systems.

Collaborative recommendation

Collaborative recommendations are recommendations based on similar interests of users. So, if user A and user B are interested in similar items and user A shows interest in item I that is unknown to user B, than item I might be interesting for user B as well. Due to the fact that this technique filters all items based on implicit collaboration of the users it is also known as *collaborative filtering.* For using the collaborative filtering approach no other information are needed than the relationship between users and items. Depending on the number of items in the system and the activity of the users of the system the process of collecting information about the relationship between the users and the items they are interested in might be needing some time. Although it needs to collect initial data it is a good approach if the items that need to be recommended are unknown or additional information for the items would be hard to maintain.

Content-based recommendation

In content-based recommendations the items are usually documents that should be recommended based on the content. Thus, the content of the document is described by tags. These tags can have an indicator that expresses the importance of the tag. Therefore the documents can be filtered by the tags of the documents and ranked by the importance of the tags. These tags can be maintained explicitly by the users of the systems or by tagging algorithms. One advantage of content-based recommendation systems is that they do not require a large user base to achieve good recommendations for users. A second advantage is that new items can be recommended to users immediately after the content has a description. If the content is user generated the recommendation system can only recommend documents that fit the current context. It has no information whether a user likes the content or not which can lead to poor recommendations. All in all, content-based systems are a good choice if the system has to provide recommendations for quality documents. As long as the documents have a description for the system.

Knowledge-based recommendation

The basic idea behind knowledge-based recommendation system is a system that has enough information about the items and the needs of the user and as such can recommend items based on matching the needs of the user and the features of the items. Moreover the system has to use individual user requirements in order to create personalized recommendations. For example if a user would like to buy a new jacket for a summer camping trip in England the knowledge based system has to use the specific context in order to recommend a thin light rain jacket with the right size and price for the user. These information are usually manually provided by the user and the maintainer of the system. Furthermore not only the system needs to correctly interpret the information but the user needs to have the domain knowledge in order to provide the system with the correct information. So, knowledge-based recommendation is a good approach if the system has to recommend items that are not frequently requested and no user history is available. It is especially suited for applications in which items are not frequently bought such as expensive digital goods or cars.

Conclusion

All of the described recommendation approaches have advantages and disadvantages. Knowledge based systems require too much domain knowledge that is not accessible for user generated questions and answers, therefore knowledge based systems are not feasible for the system. Collaborative recommendation systems need an initial amount of user item relationship data in order to present good recommendations. Additionally, they have no information about the subject of the items and this might lead to a situation were a collaborative filtering system might recommend inappropriate items to the current context. Nonetheless collaborative filtering is the only approach that takes the interest of similar users into account. As such it is the only technique that is able to recommend items that are approved by similar users. Moreover the content-based systems have the disadvantage that they do not make use of the information whether or not a user likes a document. Yet, they do not need to collect additional relationship information in order to recommend items. Because of the reason that the user generated content is not moderated and therefore the system has no information about the quality of the content the implemented system uses a collaborative filtering technique with pre filtered content based on the tags for each item. This approach should yield the best possible recommendations for a user of the system.

2.4.2 Collaborative recommendation system

As mentioned above a collaborative recommendation system recommends items to users based on the interest of similar users. The following definitions are based on Jannach et al. [2011]

Definition 10 (User)**.** *$U = \{u_1, u_2, u_3, \ldots, u_n\}$ is a set with u_i users from the recommendation system. With $n, i \in \mathbb{N}$ and $i \leq n$.*

Definition 11 (Item)**.** *$I = \{i_1, i_2, i_3, \ldots, i_n\}$ is a set with i_j items from the recommendation system. With $n, j \in \mathbb{N}$ and $j \leq n$.*

Definition 12 (Rating)**.** *R is an $n \times m$ matrix with $n = |I|$ and $m = |U|$. Furthermore is $r_{n,m}$ a rating for item $n \in I$ and user $m \in U$ with $r_{n,m}$ entry in R and $r_{n,m} \in \{1, 2, 3, 4, 5\}$. If a user $k \in U$ has not rated an item $l \in I$ the entry $r_{l,k}$ remains empty. $\hat{I_u}$ is a set with all items $i \in I$ where $r_{i,u}$ is empty, $\tilde{I_u}$ is a set with all items i and $r_{i,u}$ is not empty.*

Definition 13 (Prediction)**.** *A prediction is a rating $r_{i,u}$ for item $i \in I$ and user $u \in U$ with $r_{i,v}$ empty entry in R.*

Definition 14 (Recommendation)**.** *Let $n \in \mathbb{N}$ and $u \in U$. A recommendation is a set of n predictions for a user u ordered by the values of the predictions.*

Item-Based Recommendation

The concept of item-based recommendation was introduced by Sarwar et al. [2001]. The idea behind this concept is that recommendations can be calculated based on similar items of the items that a user likes. If $i, \in \hat{I_u}$ and $u \in U$, then the prediction for i can be calculated with the similarity between i and all items $j \in \tilde{I_u}$. One method for calculating the similarity between two items is the cosine similarity.

Definition 15 (Cosine Similarity)**.** *With i, $j \in \mathbb{N}^n$, $n \in \mathbb{N}$.*

$$cos(\overrightarrow{i}, \overrightarrow{j}) = \frac{\overrightarrow{i} \cdot \overrightarrow{j}}{||\overrightarrow{i}||_2 \cdot ||\overrightarrow{i}||_2} \tag{2.1}$$

If $\overrightarrow{i}$, $\overrightarrow{j}$ are rating vectors, the individual rating behaviour of a user needs to be taken into account to get better predictions with the similarities of $\overrightarrow{i}$ and $\overrightarrow{j}$. Due to the fact that different users have different average ratings. This results in the *adjusted cosine similarity.*

Definition 16 (Adjusted Cosine Similarity)**.** *Let $i, j \in Items$ and $\overline{r_u}$ be the average rating from user u. The cosine similarity can be transformed to the adjusted cosine similarity by subtracting the average user rating from the current rating.*

$$sim(i, j) = \frac{\sum_{u \in U} (r_{u,i} - \overline{r_u})(r_{u,j} - \overline{r_u})}{\sqrt{\sum_{u \in U} (r_{u,i} - \overline{r_u})^2} \sqrt{\sum_{u \in U} (r_{u,j} - \overline{r_u})^2}} \tag{2.2}$$

Researches made by Sarwar et al. [2001] show that the *adjusted cosine similarity* has the best performance with attention to prediction accuracy compared to all other similarity measures for item based algorithms. The results of the cosine similarity are between -1 and 1 with 1 meaning identical, 0 meaning indifferent and -1 meaning opposite [Wikipedia [27 March 2013 at 10:24]]. Although the results vary between -1 and 1 those items that have a *cosine similarity* of ≤ 0 are too different and thus are not used for further calculations. The user item predictions can be generated with the similarities by using the following formula.

Definition 17 (Item Based Prediction)**.**

$$pred(u,p) = \frac{\sum_{i \in \tilde{I_u}} sim(i,p) \cdot r_{u,i}}{\sum_{i \in \tilde{I_u}} sim(i,p)} \tag{2.3}$$

The item similarity calculations can be calculated offline on a regular basis - every day or weekly - depending on the activeness of the users and the amount of item changes. So, the item based technique is a good choice for websites that need fast scalable recommendations because only the item predictions are calculated on time. Furthermore the team of *Sarwar et al* found out that the system only needs a subset of all items. According to *Sarwar et al* a sample of the 25 most similar items is needed to generate good recommendations. Thus the on time calculation needs to find the top 25 most similar users in the similarity table and has to calculate the recommendations with these users instead of using all similar users. Moreover, it is a tested concept for instance amazon.com uses item based recommendations for their product recommendations [Linden et al. [2003]]. To get back to the overall concept, the item based predictions are used in order to decrease the rating sparsity of the user-item table. So, more information about the user interest is available before the actual recommendations can be calculated. In real world recommendation systems the user item ratings tend to be very sparse because most users only rate few items [Jannach et al. [2011]].

Example for Item-Based Recommendations

The table in figure 2.5 represents a user item relationship.

	Item1	Item2	Item3	Item4	Item5
User1	5	3	4	4	?
User2	3	1	2	3	3
User3	4	3	4	3	5
User4	3	3	1	5	4
User5	1	5	5	2	1

Figure 2.5: User Item Relationship Table

This example calculates the item based prediction for User1 and Item5

$$sim(Item5, Item1) = \frac{3 \cdot 3 + 5 \cdot 4 + 4 \cdot 3 + 1 \cdot 1}{\sqrt{3^2 + 5^2 + 4^2 + 1^2} \cdot \sqrt{3^2 + 4^2 + 3^2 + 1^2}} = 0.99$$

sim(Item5, Item1) = 0.99
sim(Item5, Item2) = 0.74
sim(Item5, Item3) = 0.72
sim(Item5, Item4) = 0.94
With these similarities the following prediction can be calculated.

$$pred(User1, Item5) = \frac{0.99 \cdot 5 + 0.74 \cdot 3 + 0.72 \cdot 4 + 0.94 \cdot 4}{0.99 + 0.74 + 0.72 + 0.94} = 4.07$$

As a result User1 would most likely rate Item5 with 4.07.

Singular Value Decomposition

The singular value decomposition is a matrix factorization technique that can be used to find latent factors in the rating patterns. With these factors it is possible to find similar users and items. The singular value decomposition was found in the late 1800 to early 1900 [Stewart [1993]]. Besides one of the main areas of application of the singular value decomposition today is information retrieval. The basic idea behind the singular value decomposition based information retrieval is to match user queries to documents. This is done by decomposing a term by document matrix and using the item vectors of the decomposition to find documents based on queries that are decomposed into term vectors [Deerwester et al. [1990]].

Definition 18 (Vector)**.**

Definition 19 (Matrix)**.**

Definition 20 (Linear Dependent, Linear Independent)**.**

Definition 21 (Rank of a Matrix)**.**

Definition 22 (Matrix Multiplication)**.**

Definition 23 (Orthogonal Matrix)**.**

Definition 24 (Eigenvalue of a Matrix)**.**

The singular value decomposition of an $m \times n$ matrix with rank r is a factorization of the form:

$$SVD(M) = U\Sigma V^t \tag{2.4}$$

U and V are orthogonal matrices with dimension $m \times r$ and $r \times n$. Furthermore Σ is a rectangular diagonal matrix with dimension $r \times r$. The diagonal values $\sigma_{i,i} \in \Sigma$ with $i \in \mathbb{N}$ have by convention the property $\sigma_{i,i} \geq \sigma_{i+1,i+1} > 0$. The $\sigma_{i,i}$ are the none negative square roots of the eigenvalues of AA^t and A^tA [3] [Allaire and Kaber [2008]]. The columns of U are the corresponding eigenvectors to the eigenvalues of AA^t. On the other hand are the columns of the Matrix V the corresponding eigenvectors to

[3]Due to the fact that AA^t and A^tA share the same eigenvalues.

the eigenvalues of A^tA [4] [Allaire and Kaber [2008]]. So, $AA^t \cdot u_i = \sigma_{i,i}^2 * u_i$.
To sum this up, the matrix U corresponds to the columns of the matrix A and the matrix V corresponds to the rows of the matrix A. It is possible to obtain an optimal rank k approximation from matrix A, with $k \leq r$. By setting all $\sigma_{i,i}$ with $i > k$ to zero [Stewart [1998]]. Thus $A_k = U_k \times \Sigma_k \times V_k^t$ yields the optimal rank k approximation. As a result all column vectors u_i, with $i > k$, of matrix U will be multiplied by a zero vector from matrix Σ_k. Due to the fact that matrix U represents the columns of matrix A and that the last rows of matrix U will be removed in order to generate the optimal rank k approximation of matrix A, it is possible to generate a good approximation of the user interests by removing the last rows of matrix U.[5]
The two dimensional matrix U_2 is created by removing all rows of matrix U up to the first two rows. This matrix U_2 can be seen as a value table that can be represented by a graph. Therefore, it enables a graphical presentation of the user similarities. Furthermore the user similarities can be calculated by using the cosine similarity between the columns of U_k.
After calculating the similarities for each user, the recommendations for $user_a \in U$ are calculated. For this task the algorithm takes all similar users U_{sim} for $user_a$. Afterwards it uses the top rated items from all $user_b \in U_{sim}$ that are not rated by $user_a$ this is denoted by $I'_{user_a,user_b}$. $\overline{r_a}$ denotes the average rating of user a. Finally for each item $i \in I'_{user_a,user_B}$ the prediction is calculated.

$$pred_{a,i} = \overline{r_a} + \frac{\sum_{b \in U_{sim}} (r_{i,b} - \overline{r_b}) * similarity_{a,b}}{\sum_{b \in U_{sim}} similarity_{a,b}}$$

[4]The eigenvalues are the squares of $\sigma_{i,i}$
[5]A user from the system is represented by a column in the matrix A

Example for a singular value based recommendation

	Item1	Item2	Item3	Item4	Item5
User1	5	3	4	4	
User2	3	1	2	3	3
User3	4	3	4	3	5
User4	3	3	1	5	4
User5	1	5	5	2	1

The following example calculates the rating prediction for *User1* and *Item5*. A singular value decomposition for a user item relationship table is created in figure 2.6. The first two rows of matrix U are used to create a value table for a graph that represents the user similarities this is displayed in figure 2.7. The *cosine similarity* is used to calculate the following similarities.

$$sim(User1, User2) = \frac{0.475467 \cdot 0.342950 + 0.325691 \cdot -0.316949}{\sqrt{0.475467^2 + 0.325691^2} \cdot \sqrt{0.342950^2 + (-0.316949)^2}} = 0.222322$$

- sim(User1, User2) = 0.222322
- sim(User1, User3) = 0.561072
- sim(User1, User4) = 0.151704
- sim(User1, User5) = 0.896770

The following itemization contains the average user ratings.

- $\overline{r_{User2}} = 2.4$
- $\overline{r_{User3}} = 3.8$
- $\overline{r_{User4}} = 3.2$
- $\overline{r_{User5}} = 2.8$

With these similarities and average ratings the following prediction can be calculated.
$pred(User1, Item5) =$
$4 + \frac{(3-2.4)\cdot 0.222322+(5-3.8)\cdot 0.561072+(4-3.2)\cdot 0.151704+(1-2.8)\cdot 0.896770}{0.222322+0.561072+0.151704+0.896770} = 3.6254$
As a result User1 would most likely rate Item5 with 3.6254.

$$
\begin{array}{cccccc}
 & \text{Item1} & \text{Item2} & \text{Item3} & \text{Item4} & \text{Item5} \\
\text{User1} & 5 & 3 & 4 & 4 & \\
\text{User2} & 3 & 1 & 2 & 3 & 3 \\
\text{User3} & 4 & 3 & 4 & 3 & 5 \\
\text{User4} & 3 & 3 & 1 & 5 & 4 \\
\text{User5} & 1 & 5 & 5 & 2 & 1
\end{array}
=
$$

$$
\begin{pmatrix}
0.475467 & 0.325691 & 0.798636 & -0.053513 & -0.164835 \\
0.342950 & -0.316949 & 0.082532 & -0.250224 & 0.844099 \\
0.535742 & -0.210593 & -0.362530 & -0.589189 & -0.435955 \\
0.455479 & -0.486113 & -0.054206 & 0.729352 & -0.146077 \\
0.402286 & 0.716108 & -0.470107 & 0.235423 & 0.221199
\end{pmatrix}
\cdot
$$

$$
\begin{pmatrix}
15.627834 & 0.0 & 0.0 & 0.0 & 0.0 \\
0.0 & 5.104899 & 0.0 & 0.0 & 0.0 \\
0.0 & 0.0 & 3.541202 & 0.0 & 0.0 \\
0.0 & 0.0 & 0.0 & 2.426008 & 0.0 \\
0.0 & 0.0 & 0.0 & 0.0 & 0.534013
\end{pmatrix}
\cdot
$$

$$
\begin{pmatrix}
0.46825 & 0.432206 & 0.46056 & 0.487586 & 0.379564 \\
-0.177671 & 0.42127 & 0.572180 & -0.250389 & -0.633148 \\
0.609379 & -0.316926 & -0.139853 & 0.322858 & -0.635938 \\
-0.392214 & 0.489216 & -0.480126 & 0.571026 & -0.224148 \\
-0.473276 & -0.544015 & 0.458702 & 0.518898 & -0.019831
\end{pmatrix}
$$

Figure 2.6: Singular Value Decomposition of the User Item Relationship Table

2.4.3 The recommendation process

The sparsity of the user item table is decreased by using item based predictions for user-item pairs that are not rated. For this process the system uses the similarities between rated and not rated user-item pairs. Therefore for each user (u) the rating for a not rated item (i) is predicted by using the similarity of i and items that are rated by u. This improved user item table is decomposed into three matrices U, Σ and V^t. The matrix U represents the user interests and is reduced by k rows in order to improve the execution time of the recommendation process.The cosine similarity is calculated between the columns of the matrix U_k. With these similarity information the recommendations are generated by finding the top rated items of the most similar users that are unknown for the current user. If the current user of the system is not registered the system uses the default user to calculate the recommendations. This default user is the first user of the system who should be generated by the system administrator. Besides the default user should have the average ratings for the items that most of the system users agree up on with their ratings.

$$\begin{pmatrix} 0.475467 & 0.325691 \\ 0.342950 & -0.316949 \\ 0.535742 & -0.210593 \\ 0.455479 & -0.486113 \\ 0.402286 & 0.716108 \end{pmatrix}$$

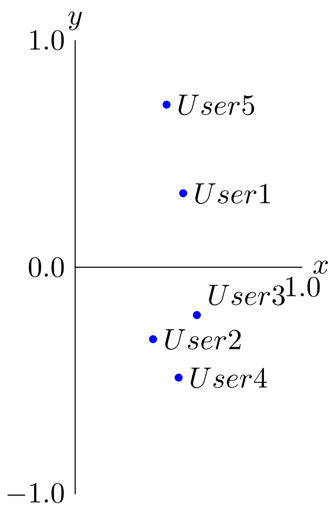


Figure 2.7: Similar Users based on Singular Value Decomposition

2.4.4 Different Recommendation approaches

The explained techniques that where used in the recommendation process can be used for other recommendation processes.

Only Item-Based Recommendations

The recommendation system concept uses item-based recommendations to decrease the sparsity of the rating table. Thus the item-based method calculates similarities between items and with these similarities the empty user-item ratings are predicted if enough similar items are found. However the item similarities can be used to directly generate recommendations for users. Yielding a functional recommendation system which will be compared with the main recommendation system in section 4.3.

Only SVD-Based Recommendations

The svd-based recommendation system is part of the recommendation concept that is introduced in this thesis. This svd-based recommendation system calculates the user-item recommendations after the item-based system decreased the sparsity of the rating table. Consequently the svd-based recommendation system can be used as a standalone recommendation system. However rating matrix that results out of the rating table does not have empty entries otherwise the singular value decomposition can not be calculated for that matrix. Hence the empty entries of the rating matrix must be filled with values before calculating the singular value decomposition. For this process two different approaches are tested in the evaluation process. The first one fills the empty entries with the average value of the 1 to 5 rating scale which is the 3. The second one uses the average item ratings for the missing entries. The runtime and performance of these systems is compared with the recommendation system of this thesis in section 4.3.

2.5 Concept Relationships

The last sections described the different concepts that are used in this thesis. This section emphasizes the relationship between the different ideas. The *question and answer* system enables users of a website to create questions and answers. These questions and answers are the *items* that are used as recommendations on sites that have the same subject. For this process the items need to have a rating that indicates the interest that a user has for this item. These ratings are generated with the implicit rating concept that is introducted in this thesis. Additionally the ratings are used by the recommendation system concept for calculating the rating predictions. Besides the items need a tag that describes the content of the item for filtering the recommendations before they are used on the website. These tags are generated with the explained tagging concept. The final outcome is a question and answer recommendation list that is ordered by the predicted interest for an user. Moreover the recommendation list matches the current subject of the website.

3 Implementation

This chapter begins with a discussion about the technology choices for the different system parts. Afterwards, the service oriented software architecture and the different interfaces to those services are explained.

3.1 Technologies

This system combines five different concepts namely the *question and answer system*, the *rating system*, the *tagging system*, the *rating system* and the *recommendation system*. For such a variety of techniques with different requirements there is the need for different technologies.

3.1.1 Programming Language

The requirements for the programming language are that it should be object oriented for good programming code encapsulation and that the software should work on a number of different operating systems due to the reason that the development takes place on a mac operating system and the final software has to run on a linux server. Moreover it needs to generate fast and reliable software programs as well as it should bring libraries for fast linear algebra calculations. The linear algebra libraries are needed for the *singular value decomposition*. The different matrix calculations that one needs to have for the *singular value decomposition* must be implemented the way that they are able to calculate the results as fast as possible otherwise the whole recommendation process would be too slow to be used on a productive system. Such a fast execution time can only be achieved by using different tricks that utilize specific programming language features. This implementation process would be too time consuming for a six month thesis. A programming language that meets these requirements is the scala programming language.

Scala Programming Language

The Scala programming language is an object oriented and functional programming language. Meaning that it is possible to write code with a functional programming paradigm together with an object oriented programming paradigm. Moreover every value in Scala is an object and every function is a value. The advantage of a functional programming paradigm is that it enables a more mathematical programming approach due to the reason that functions can be passed as parameters and can be used as return values. This is helpful for designing complex algorithms.

Additionally Scala offers the functionality to mark all operations on collections as parallel. Consequently the language supports developers to write programs that can utilize multicore computer systems. The Scala programming language compiles to the Java byte code therefore it runs in the *Java runtime environment.* Thus it is possible to use applications that are developed with the Scala programming language on any system that is able to run the *Java runtime environment* which is almost any operating system. Likewise an application that is developed with the Scala programming language can use any Java library. Moreover Hundt [2011] analyzed four different programming languages namely C++, Go, Java and Scala. He implemented the same algorithm in each of these programming languages and analyzed the outcome on their individual performance, code size, binary size and complexity. The Scala implementation of this algorithm has the fastest execution time and the lowest number of lines of code of all non optimized implementations. The only implementation that achieved a shorter execution time is a highly optimized C++ version that utilizes optimized non standard C++ data structures. For these reasons the Scala programming language is used as the server side programming language. However the part of the rating systems that collects the user activities needs to run on the client side inside the web browser. This is currently only possible with the JavaScript programming language. Out of that reason JavaScript is used as a second programming language for the development of the system which is explained in more detail in the next subsection.

JavaScript

As mentioned in the last section the JavaScript programming language has to be used to create client side browser applications which is needed for the part of the rating system that collects the user activities. JavaScript is a scripting language as a consequence it can be interpreted and executed without being compiled first. The language is supported by almost every web browser and therefore is used by web pages to interact with the user and to dynamically load and change the website. As of the *W3C Document Object Model Events* specification which is a web standard and therefore implemented by almost all web browsers the browser has to provide events for detecting scroll and focus events. Callback functions such as activity timers can be attached to these callback functions. These callback functions are called if the event fires. This enables the rating system to detect the user activities that it needs to calculate the user ratings. Therefore all technical requirements for the programming language are fulfilled with the use of the Scala programming language in combination with the JavaScript programming language.

3.1.2 Databases

The system uses two different databases one for the main system and a second database for the *STW Thesaurus for Economics.* This architectural choice was made in order to use the original *STW Thesaurus for Economics* database files from the website. The first database that will be discussed is the *PostgreSQL* database.

PostgreSQL

The main database is a *PostgreSQL* database that is in use by the *askbot question and answer system* as well as the implemented system. The *PostgreSQL* database is an open source free to use relational database that is to the greatest possible extend conform with the SQL standard *ANSI-SQL 2008.* Thus the main functionality from this standard is available and works as expected.

4Store Triple Store

As mentioned at the beginning of the database section the triple store is used in order to be able to directly import the *resource description framework* (RDF) files from the *STW Thesaurus for Economics.* A triple store is a database that is optimized for storing and retrieving triples. Such a triple is a data entity composed of subject-predicate-object. Whereas the subjects and the predicates are resources the object might be a value or a resource as well. The subject is described by the predicate with the object. For example the subject can be an identifier for a person the predicate can be a resource for a name and the object is the name itself.
ID:5462, name, 'John Doe'
The triples can be retrieved via a query-language which is called *SPARQL.* The triple store that is used in the implemented system is *4store* which is a free to use triple store developed and maintained by *Garlik.* The *4store* can be used as a service that uses the http protocol for querying the database this goes with the service oriented system architecture that is used in this thesis. Furthermore an important aspect for the use case of the triple store in this thesis is the retrieving of ordered lists of objects. These order function is needed for dividing all words that are stored in the triple store into parts of 1000 words per request by using the ordered by, limit and offset command. This is used for processing 1000 words at once for the tagging algorithm. The triple store performance benchmark of Mironov et al. [2010] tested five triple store implementations for the average response time of different queries. This benchmark shows that the *4Store* is the fastest triple store for the task of responding to requests which uses *ordered by* and that it has in comparison with the other triple store implementations an overall good performance result.

3.1.3 Network Communication

The implemented system uses the *Hypertext Transfer Protocol (HTTP)* as a network communication protocol. The network communication for this system is handled by the *finagle* open source framework that is developed and maintained by *Twitter.*

Hypertext Transfer Protocol (HTTP)

HTTP is a stateless network protocol that is used by web browsers to access content in the world wide web. This protocol specifies how clients request data and how servers respond to those requests. The HTTP protocol is used in combination with the Uniform Resource Locator (URL). This URL is a combination of a host, a port and a path. http://host[:port][path] The host specifies the server address that provides the requested service and the port is an optional number for further specifications. The path describes a specific resource that the client can access on the server. The implemented system uses the port for selecting the service. Consequently each service is accessible with a specific port. The path is used for accessing the methods that the service provides. For example http://localhost:10000/recommendation/5/3/marketing/unternehmen calls the recommendation method on the *WebService* that is running on the current computer. This method generates three item recommendations for the user with id 5 that are tagged with *Marketing* and *Unternehmen*. The implemented system uses four different HTTP request methods that are defined by the HTTP 1.1 standard[1]. These requests are the HTTP Get request, the HTTP Post request, the HTTP Put request and the HTTP Delete request. The HTTP Get request can access resources but cannot provide additional data than the data that it specifies in the URL. The HTTP Post request can access resources and can specify additional data to the path in the body of the request that should be added to the resource. The HTTP Put request is used for requesting that the specified data is stored or updated on the specific URL. The HTTP Delete request is used for requesting that the specific resource on the URL is deleted.

Finagle Framework

The *finagle* framework[2] is an extensible remote procedure call system with the purpose of creating high performance and concurrent servers. On the one hand it provides interfaces for creating services that can be bound to a combination of a network address and a protocol for the network communication. Yielding a server that waits for a connection on the specific network address in order to execute the implemented service. On the other hand it provides interfaces for creating clients that must specify one ore more server addresses together with the protocol and the connection limit. Thus it creates a client that can execute methods on a pool of servers and handles simple load balancing with the connection limit on its own. Furthermore it uses its own data structure *Future* as asynchronous return values. A *Future* is a data structure that is returned as a value before the server finishes its execution. Consequently the client gets the future as a return value and can continue with its operation until it needs the result from the server. In that case the future can either provide the value from the server directly or it has to block

[1]http://www.w3.org/Protocols/
[2]http://twitter.github.io/finagle/

until the server finishes the operation. However the client and the server should be build in such a way that the server is able to return a value before the client actually needs the return value. As an additional feature the framework offers the possibility to bind functions on futures thus the functions will be executed if the server returns the value to the future. This yields a non blocking service architecture.

3.1.4 Testing

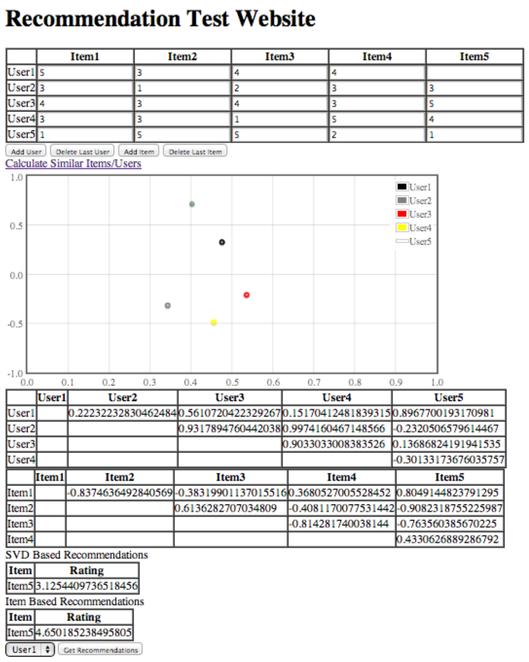
The implemented application uses two different test systems. One of the systems is a testing framework called *Spec2* that can run predefined tests in order to check on a regular basis if the system works as expected. The second system is a graphical user interface build with *backbone.js* that enables a user to create a user item table in order to test the recommendation process.

Spec2 Test Framework

As mentioned before *Spec2* is a library for writing application specifications that are executable. This works by defining test classes for each class that should be tested. These test classes must have the same package structure as the original implementations. Moreover it is necessary to define a test inside the test class that checks if a function works as expected. The developed system uses the *Spec2* test framework to check if all core components such as services function as anticipated.

Graphical User Interface

The graphical user interface is useful for analyzing the recommendation techniques. The purpose of this application is to illustrate how the recommendation process works in the praxis. The figure 3.1 displays the recommendation test website. On the top of the page the user can define the user ratings for the items. Depending on these entries the user and item similarities are calculated which is displayed by the diagram and the two tables underneath the diagram. Additionally the recommendation test website can calculate rating predictions for the users that have empty rating entries in the table.
The user interface is implemented with the *backbone.js* framework that provides models, collections and views for creating model view controller websites on the client side. The advantage of such a framework is that it supports the development of creating client side applications that communicate with the database. Therefore the framework provides objects that represent the data from the database and sends request to the server if data is modified added or deleted. The server has to provide interfaces for the *backbone.js* framework that are based on HTTP Get, Post, Put and Delete methods for reading, updating, deleting and storing data in the database.



Recommendation Test Website

	Item1	Item2	Item3	Item4	Item5
User1	5	3	4	4	
User2	3	1	2	3	3
User3	4	3	4	3	5
User4	3	3	1	5	4
User5	1	5	5	2	1

	User1	User2	User3	User4	User5
User1		0.22232232830462484	0.5610720422329267	0.15170412481839315	0.8967700193170981
User2			0.9317894760442038	0.9974160467148566	-0.2320506579614467
User3				0.9033033008383526	0.13686824191941535
User4					-0.30133173676035757

	Item1	Item2	Item3	Item4	Item5
Item1		-0.8374636492840569	-0.38319901137015516	0.3680527005528452	0.8049144823791295
Item2			0.6136282707034809	-0.4081170077531442	-0.9082318755225987
Item3				-0.814281740038144	-0.763560385670225
Item4					0.4330626889286792

SVD Based Recommendations

Item	Rating
Item5	3.1254409736518456

Item Based Recommendations

Item	Rating
Item5	4.650185238495805

Figure 3.1: The Graphical User Interface for The Recommendation Process

3.2 Architecture

The system uses a service oriented architecture. Thus the main components of the system namely the tagging process, the rating system and the different recommendation techniques are encapsulated in different services. One advantage of that architectural choice is that the system can be spread on different servers. This not just opens the possibility to run services that have high hardware requirements on different servers but also enables the choice to duplicate services. The duplication of services can improve service downtimes and can decrease service respond times if the service is under high load. A disadvantage of a service oriented architecture is that it is more complex to debug system errors because each service must be debugged on its own as well as the network communication between those services. However one requirement for this system is that the single system components should be usable separately. With a service oriented architecture each service can be used individually over a network communication. The network communication protocol that is necessary for communicating with the services is the http protocol which is explained in subsection 3.1.3. The next sections describe the single services and the methods that they provide.

3.3 Services

The individual parts of the system are separated into different services. Each service inherits from the implemented HttpServer. This HttpServer handles the decomposing of the http request, provides simple HTTP routing and creates the http responses for the network communication. Thus the services implement the service specific logic and provide methods for accessing this logic. These methods are accessible for the router that is inherited by the HttpServer and provide a HTTP path for each method in form of a string. Consequently the services are accessible on their specific port with HTTP Post and HTTP Get requests that correspond to the HTTP path.

3.3.1 RecommendationService

The recommendation service controls the item based service and the svd based service. Therefore the single recommendation techniques can be regulated by editing the recommendation service. This opens the possibility to use different recommendation approaches without much programming effort.

RecommendationService		
Standard Port	13000	
Get Methods	Parameter: Type	Return Value
/calculateSimilarities	-	
/calculateUserPrediction	user id: Integer item id: Integer	List (user, rating)
Post Methods	Parameter: Type	
/generateRecommendations	user id: Integer amount: Integer	List (user, rating)

The */calculateSimilatities* method starts the item similarity calculation of the *ItemBasedService*. After the calculation finishes the *RecommendationService* starts the svd based similar user calculation of the *SVDBasedService*. These similarity values are stored in the database by the individual service for future rating predictions. The */calculateUserPredictions* method takes an user id and an item id as parameters. If the item id is empty the prediction for all items are calculated if enough similar item ratings exist. The final prediction calculation is handled by the *SVDBasedService*. The */generateRecommendations* method takes an user id, an amount of predictions that should be returned and a list of tags as parameters. This method forwards the parameters to the *SVDBasedService* and returns the list of item rating pairs to the caller method.

3.3.2 ItemBasedService

The *ItemBasedService* is a service that is responsible for calculating the item similarities and to predict user ratings to decrease the sparsity of the user-item table. It is the implemented item based recommendation concept and therefore can be used as a part of the complete recommendation concept that is introduced in this thesis but it is a full functional recommendation system on its own. In the evaluation chapter section 4.3 the *ItemBasedService* is used as a standalone recommendation system and the results are compared with the complete recommendation concept.

ItemBasedService		
Standard Port	13100	
Get Methods	Parameter: Type	Return Value
/calculateSimilarItems	-	-
/calculateUserPrediction	user id: Integer item id: Integer	List (user, rating)
Post Methods	Parameter: Type	
-	-	-

The */calculateSimilarItems* method calculates the similarity between all items. The idea behind the similarity calculation is that the algorithm only considers to calculate the item similarity of items if they are rated together with other items by the same user. The algorithm 3 is based on the work of Linden et al. [2003]. Let N be

Algorithm 3 Item Similarity Calculation

```
1: procedure ItemSimilarity
2:     items ← load all items
3:     seenTogether ← empty Set of item tupel
4:     for each $item_1$ in items do
5:         newItems ← empty Set of items
6:         for each user that rated $item_1$ do
7:             for each $item_2$ that is rated by user do
8:                 if $item_2 \neq item_1$ and seenTogether does not contain $(item_2, item_1)$ then
9:                     add $(item_2, item_1)$ to seenTogether
10:                    add $item_2$ to newItems
11:                end if
12:            end for
13:        end for
14:        calculate similarities for $item_1$ and all items from newItems
15:    end for
16: end procedure
```

the number of items in the system and M be the number of users who rated that item. Then as Linden et al. [2003] stated the worst case runtime of algorithm 3 is $O(N^2M)$ but due to the reason that most rating tables are very sparse the runtime on a productive system is closer to $O(NM)$. The */calculateUserPrediction* method takes an user id and an item id as parameters. It calculates the rating prediction for the user-item pair and returns it as a list with one element. If the item id is empty it calculates the user predictions for all not rated items for the specific user and returns it as a list.

3.3.3 SVDBasedService

The *SVDBasedService* implements the concept of the *singular value decomposition* based recommendation system. This concept states that a user-item matrix can be decomposed into three matrices. Where the columns of one matrix responds to the user interest of the original user-item matrix. With these columns the similarity between the users is calculated and with the user similarities the recommendations are generated. The whole concept of the singular value decomposition based recommendation is explained in more detail in subsection 2.4.2. The *SVDBasedService* service is responsible for calculating the recommendations after the item based service has decreased the sparsity of the rating table. However this service can be used as a stand alone recommendation system which is evaluated and compared with the complete recommendation system in section 4.3.

SVDBasedService		
Standard Port	13200	
Get Methods	Parameter: Type	Return Value
/calculateSimilarUsers	-	-
/calculateUserPrediction	user id: Integer item id: Integer	List (user, rating)
Post Methods	Parameter: Type	Return Value
/generateRecommendations	user id: Integer amount: Integer tags: List[String]	List (itemTitle, url, rating)

The */calculateSimilarUsers* method executes the calculation of the similar user values. This process is split into four steps. At first the user-item matrix is created out of the rating table. After that the method calculates the singular value decomposition of the matrix. For this task the *Apache commons-math* library is used. This library is a general math library with strong linear algebra algorithms developed and maintained by *The Apache Software Foundation*. The third step is the approximation of the U matrix that is one of the resulting matrices from the singular value decomposition. Finally the similar users are generated by calculating the cosine similarity between all columns of the U matrix. This method does not have a return value. All similar user values are stored in the database for future calculations. The */calculateUserPrediction* method calculates a prediction for the specified user-item pair. If no item is specified the method calculates a prediction for all items that are not rated by the specified user. For this process the system generates a list of the most similar users U_{sim}. With these similar users it generates a list of items that these users rated but are unknown to the current user. For each item that is in the unknown item list the system calculates the prediction for the user-item pair as described in subsection 2.4.2. These predictions are returned as a list of user-item tupel. The */generateRecommendations* method calculates the item recommendations for the current user. This user is the first parameter that is passed to the function. If the user is unknown because he is not logged in a value of zero is passed. This zero user is the default user that has ratings for the most popular items. The second parameter specifies the amount of recommendations that the system should return. The third parameter that is passed inside the request body as a post parameter is a Json string that represents a list of tags. The recommendations that the system generates correlate with these tags. The whole recommendation process is split into four steps. At first the tags are converted into the corresponding descriptor from the *STW Standard Thesaurus Economics.*Afterwards the system generates a list of the most similar users for the current user. For each of these similar users a list is generated that contains the top rated items from this user that are unknown to the current user. Besides, the top rated items match the tags that are specified at the beginning of the request. Finally, for each of these items the rating prediction for the current user is calculated. The items with the highest rating predictions are used as recommendations.

describe stw and descriptor

3.3.4 TaggerService

The *TaggerService* is the implementation of the tagging concept. This concept describes the process of finding the right tags for a text. For this process the system creates a deterministic levenshtein automata for each word in a text. Every one of these deterministic levenshtein automata reads the complete *STW Standard Thesaurus Economics* if a word from the *STW* ends in a final state the word is used as a tag for the text. More details about the tagging concept can be found in section 2.3.

TaggingService		
Standard Port	11000	
Get Methods	Parameter: Type	Return Value
-	-	-
Post Methods	Parameter: Type	
/tagText	text: String	list of tags
/descriptorsForText	text: String	list of STW descriptors
/tagsForDescriptors	descriptors: List[String]	list of tags
/descriptorsForTags	tags: List[String]	list of STW descriptors

The */tagText* method takes a text as parameter. The single words of the text are extracted into a list. For each word in this list a deterministic levenshtein automaton is generated. For this process the service creates a finite automaton for each word with a specific degree. A degree states the maximum allowed levenshtein distance between the word for which the automaton is generated and the word that the automaton can read. This degree depends on the word size. For a word with more than five letters a degree of three is used otherwise a degree of one is used.The states are written as tupel of the form (c, d) where c denotes the current position in the word and d denotes the current levenshtein distance between the prefix of the original word and the word that the automaton reads. For each letter in a word W with a length of n four transitions are created if the levenshtein distance of the current state is smaller than n. These four transitions represent reading a correct letter, deleting a letter, inserting a letter and substituting a letter. The last states that are reached thru the last letter do not get any transitions by this process. Consequently the next step is to insert the missing insertion transitions for these last states where the current position in the word is the size of the word. These insertions are needed because the word that is read might be longer than the original word and therefore letters must be added to the original word up to the maximum degree. The last step for creating this finite automaton is to mark all of the last states where the current position in the word is the size of the word as final states. This finite levenshtein automaton is transformed into a deterministic finite levenshtein automaton. This transformation process replaces every deletion transition which represents an ϵ transition by one or more new transitions. These new transition start at the beginning of the ϵ transition and end at a destination of a transition that starts at the end of the ϵ transition. This operation has to be performed due to the reason that ϵ transitions are not allowed in deterministic automata. Furthermore the substitution and insertion transitions are transformed in the way that they only accept labels that are not used by any other transition from the current source. This process yields a deterministic Levenshtein automata. Finally, all words from the *STW* are loaded and read into the deterministic Levenshtein automaton Each word that ends in a final state is added to the list of tags that is returned to the caller. The */descriptorsForText* method generates a list of labels for a text. This method is implemented the same way as the *tagText* method. The only difference is that it converts the words which end in a final state to their corresponding *STW* descriptors before returning them. The */tagsForDescriptors* method takes a list of STW descriptors as a parameter and returns the corresponding list of tags. For this process each preferred label is read from the triple store by its descriptors. The triple store contains the STW. The */descriptorsForTags* method takes a list of tags as a parameter and returns a list of STW descriptors. This method loads the descriptors from the triple store that corresponds to the tags that were passed as a parameter.

3.3.5 QuerySTWService

The *QuerySTWService* is the interface between the services and the triple store. It provides methods for sending data to the triple store and processes the data before responding to the requests. This service encapsulates the triple store communication. Hence, it enables an integration into existing systems that use different triple store technologies by replacing only the provided methods of this service.

QuerySTWService		
Standard Port	11500	
Get Methods	Parameter: Type	Return Value
/descriptor	preferred label: String	descriptor
Post Methods	Parameter: Type	Return Value
/runQuery	query: String	-
/descriptorsForTags	tags: List[String]	list of descriptors

The */descriptor* method takes a word from the STW as a parameter and returns the descriptor of the preferred label. Another method that the service provides is the */runQuery* method. This method takes a query that should be executed on the triple store as a parameter and returns the response from the triple store. The last method that this service provides is the */descriptorsForTags* method. Which takes a list of tags as a parameter and returns the corresponding list of descriptors.

3.3.6 RatingService

The *RatingService* is responsible for calculating and creating the user ratings for the items. This contains the creation process of new users and items. Besides the service starts the asynchronous tagging process if a new item is created and adds the tags to the items if it finishes.

RatingService		
Standard Port	12000	
Get Methods	Parameter: Type	Return Value
-	-	-
Post Methods	Parameter: Type	Return Value
/currentItem	user id: Integer item id: Integer item title: String item text: String item url: String	-
/calculateRating	user id: Integer item id: Integer time spend: Double time scroll: Double user interaction: Boolean	-

An in the item-page included JavaScript code calls the */currentItem* method every time a user visits an item-page. This JavaScript code sends the item id, the item title, the item text and the user id to the *WebService* which forwards these data to the rating service. The */currentItem* method creates a new item if the current item does not exist. In addition it sends the item text to the *taggerService* to get the tags for the item if it does not exist. Moreover it creates a new user if the current user is unknown to the system. The same JavaScript code is responsible for sending every two seconds the current time that the user has stayed on the page (CT) as well as the time that the user has scrolled on the page (ST) together with the user id and the item id to the *WebService* which forwards the data to the */calculateRating* method. The design choice of sending the data periodically every two seconds to the server is made for the reason that sending the complete data set if the user leaves the website is not reliable enough and can lead to the loss of these rating information. After the */calculateRating* method receives the CT and ST times it adds these times to the previously received times or creates a new table entry with the times for that user. With these new times the method calculates the new rating for that item and stores it in the database.

3.3.7 WebService

The *WebService* is the interface for external clients which are usually web browser that visit item pages or the developed recommendation test page. This service forwards external enquiries and processes data before it sends the data back to the client. Furthermore it provides an interface for accessing the database objects for the *backbone.js* application that represents the *recommendation test website* as well as an interface for accessing static files like JavaScript and HTML files.

WebService		
Standard Port	10000	
Get Methods	Parameter: Type	Return Value
/	-	index.html
/tagger	-	tagger.html
/data	type: String id: Integer	model
/file	path: String	document
/calculate	type: String id: Integer	result
/recommendation	user id: Integer amount: Integer tags: List[String]	JavaScript code
Post Methods	Parameter: Type	Return Value
/data	model: Object	-
/rating	*	-

The / and the */tagger* methods are both returning specific static HTML files from the file system these methods should be deactivated for the production mode. The / methods returns the index.html file which is the main page for the recommendation test website. Additionally the */tagger* method returns the tagger.html website which is a website for testing the *taggerService*. The */calculate* method forwards the calculation requests that can be specified by a provided type parameter to the

RecommendationService. For the types the client can use *similarities*, *recommendations* and *recommendationsItemBased*. If a client sends a request for similarities to the WebService the service starts the calculations for similar users and items on the RecommendationService the user id is not necessary for this request. By sending the *recommendations* type together with an user id to the */calculate* method the service sends a request to the RecommendationService for calculating all predictions for the items that the user has not yet rated. The *recommendationsItemBased* type has the same effect as the *recommendations* type the only difference is that the predictions are calculated with the item based approach instead of the standard SVD based approach. The */recommendation* method is usually called by an HTML website that expects a JavaScript code that is embedded into the page. The method takes an user id, an amount and a list of tags as a parameter. These data is forwarded to the recommendation system. However the returned list of item recommendations is transformed into a HTML link for each recommendation. These HTML links are embedded into a JavaScript code that is returned by the service. This JavaScript code inserts all item links into a specified HTML Div container. There are three */data* methods that are interfaces for reading, creating, updating and deleting entries in the database. These interfaces are necessary for the backbone.js framework that is used for building the recommendation test website. The first method that is called via a post request updates existing entries in the database or creates new entries for the provided parameter. The second method which is called via a get request reads data from the database. The type that is provided as a parameter represents the database table from where the data should be read. If an id is provided as a parameter the service returns the specific entry otherwise the service returns all entries from the database table. The third method is accessible via a http delete method and must provide a type and an id. The specific entry with the corresponding id from the database table that is specified by the type is deleted by the service. The */rating* method forwards all request to the *RatingService*.

3.4 Service Relationships

This section explains the relationships between the services. The whole system can be separated into three use cases. The first use case is the situation when a user visits an item page this situation is illustrated by a sequence diagram in figure 3.2. The second use case is the situation when a user visits a website that recommends items to users this situation is described by the sequence diagram in figure 3.3. The third use case is the situation when the system starts the calculation of the user and item similarities. This situation is described by the sequence diagram in 3.4.

3.4.1 User Visits Item Page

The use case that occurs if a user visits an item page is illustrated in the sequence diagram in figure 3.3. The web browser that executes the JavaScript code that is embedded in each item page sends the current information about the item and

the user to the WebService. However the web browser does not expect a response. The WebService checks if the data is complete and forwards the request to the RatingService. The sequence diagram from figure 3.3 represents the situation when the item and the user are unknown to the system. Therefore the RatingService creates a new item and a new user. Besides, the RatingService sends the text of the item together with its title to the TaggingService. The TaggingService creates a Levenshtein distance automaton for each word in the text and requests all words that are included in the STW from the QuerySTWService. These words are tested with the Levenshtein automatas each word that ends in a final state is returned in a list of tags. Finally the returned tags are added to the newly created item.
Additionally the web browser sends periodically the time that the user spends on the website together with the time that the user has scrolled on the website to the WebService. This data is needed to calculate the implicit user rating for the item. The WebService forwards the request to the RatingService which updates the times in the database and calculates the new rating.

3.4.2 User Visits Recommendation Website

This subsection describes the network communication between the services if a user visits a website that recommends items. The sequence diagram in figure r̃efrec represents the network communication between the involved services. The website that has to display the recommendations communicates with the system by including a JavaScript file from the system. The path for this JavaScript file includes optional parameters namely the user id, the amount of recommendations and tags. If the current user is not registered the system uses a standard user for generating recommendations. The tags are used for filtering the items so that the recommended items match the subject of the website. The web browser requests the JavaScript file from the WebService. Which is basically the interface for external clients for the internal services. Thus the WebService forwards the request to the RecommendationService. This RecommendationService requests the recommendation calculation on the currently activated recommendation system which is in the sequence diagram the SVDBasedService. Another option would be the ItemBasedService. The SVDBasedService passes the tags to the TaggerService which translates them to the corresponding descriptors by communicating with the triple store via the QuerySTWService. The latter returns the descriptors to the TaggerService which passes the returned descriptor list on to the SVDBasedService. This SVDBasedService generates the item list which includes the items with the highest rating prediction for the current user that match the subject of the tags. This item list is returned to the RecommendationService. The RecommendationService hands the item list to the Webservice. The WebService creates html links for each of the items in the list and embeds these links into the requested JavaScript file. The web browser executes the JavaScript file and thus inserts the recommended item links into the website.

3.4.3 System Calculates Similarities

The system requests the calculation of new similar user and similar item value from the RecommendationService. The RecommendationService calculates the average user ratings and the average item ratings. Additionally, the service requests the calculation of the user similarities by the SVDBasedService and the calculation of the item similarities by the ItemBasedService. Each of these services stores the calculated values in the database. This should occur periodically every 24 hours to once a week depending on the frequency that the item catalog changes and the frequency that new user ratings are generated.

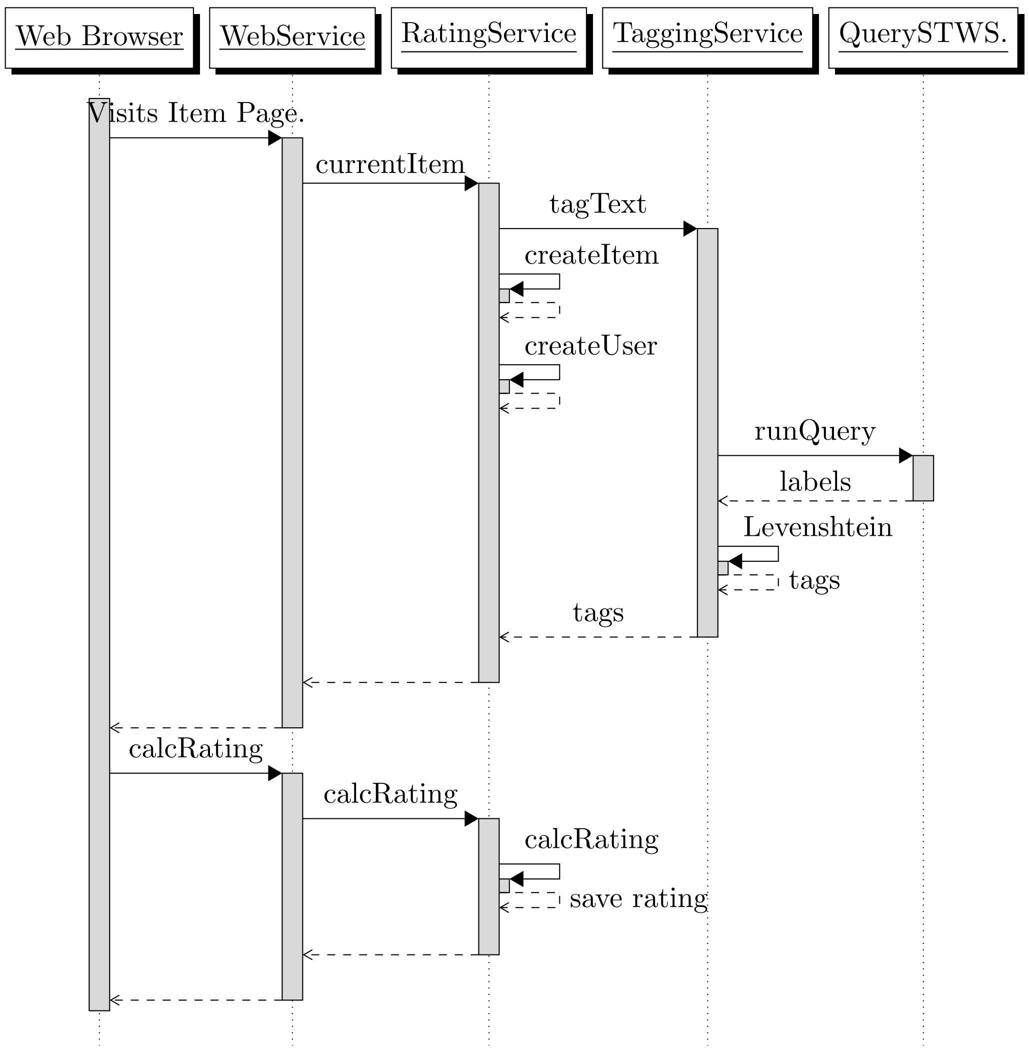


Figure 3.2: User Visits Item Page Sequence Diagram

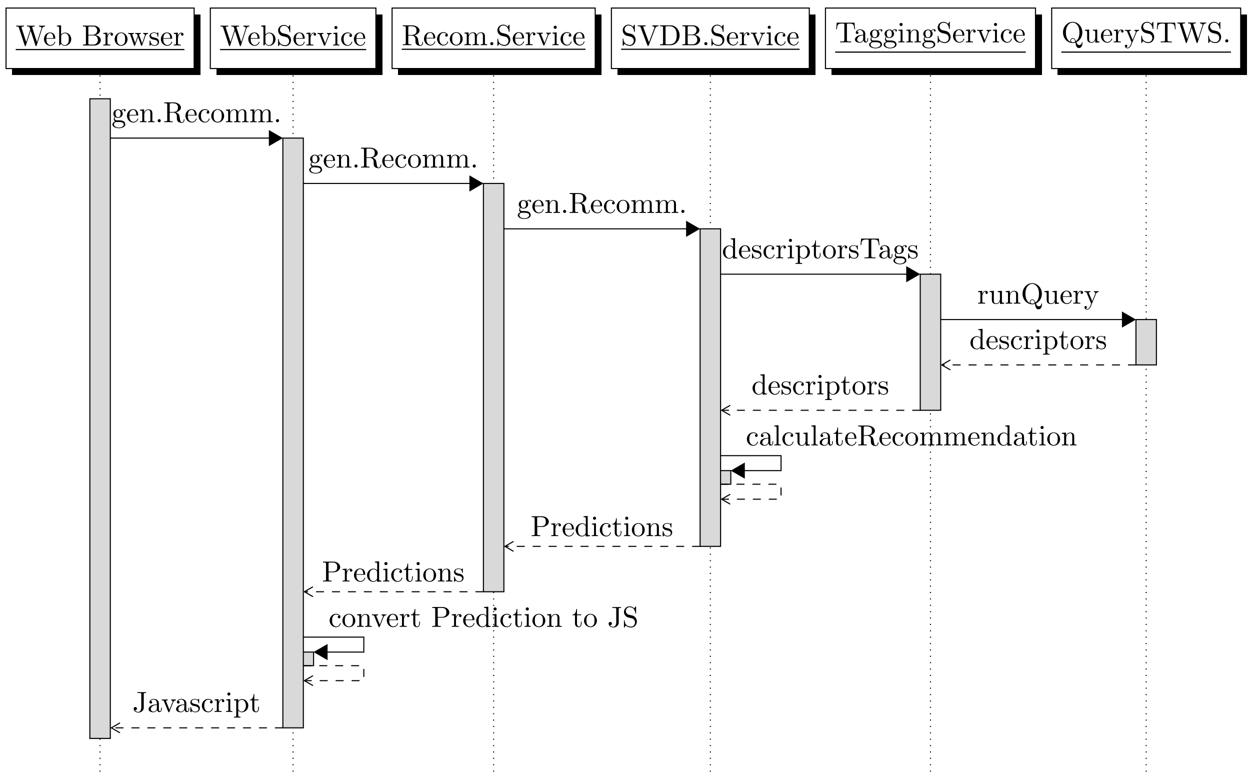


Figure 3.3: Embedded Recommendations Sequence Diagram

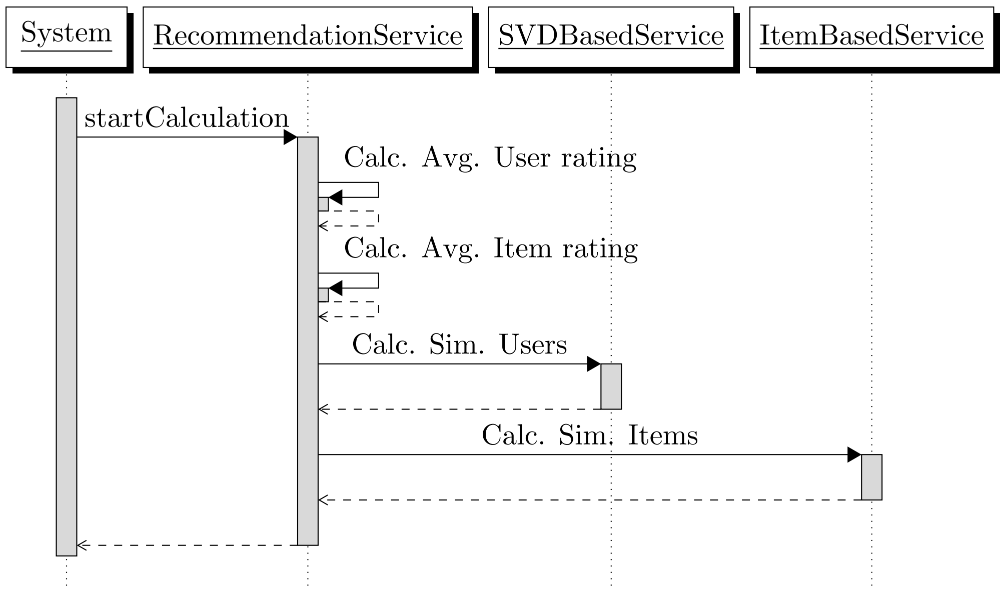


Figure 3.4: System Calculates Similarities Sequence Diagram

4 Evaluation

In this chapter the different concepts that are introduced in this thesis are evaluated. The first section deals with the rating concept and evaluates the quality of the ratings that are generated for the individual user interaction on a web page. The second section evaluates the time and the quality of the tagging concept by applying the tagging algorithm on texts with different word counts. Moreover the tags that are returned by the algorithm are compared with the tags that should have been returned by the algorithm. Finally different recommendation techniques are compared by the run time and the quality of their predictions.

4.1 Rating

The evaluation for the rating system refers to the rating concept from subsection 2.2.5. This concept is build upon the researches from Claypool et al. [2001] who evaluated different user interactions and compared those with explicit user ratings. The two user interactions that performed the best with an accuracy of about 70% to the user ratings are the time a user spend on a website and the time a user scrolls. Each of the measured times of the user interactions are split into segments depending on the truncated mean time of all user times. Yielding a scale that enables the system to calculate ratings based on the user interactions. Based on this scale the ratings are calculated separately and are combined to the total rating by calculating the average of both ratings. This total rating is evaluated with the research data from Claypool et al. [2001] in this section. For the rating evaluation an item test website is created. This test website is a standard html website with a high of 2000px. Consequently there is the possibility to scroll on a standard screen resolution. Additionally the item test website has a truncated mean time for the time a user spends on the website and another truncated mean time for the time a user scrolls on the website. For these truncated mean times the average times from all user ratings of the field test from Claypool et al. [2001] are used. These average times are 5.339 seconds for the time a user scrolls and 20.763 seconds for the time a user spends on a website. Finally users who visits the website are simulated. Those users are interacting with the website according to the times of Claypool et al. [2001] field experiment. Therefore the ratings that the simulated users generate can be compared to the data from the team of Claypool et al. [2001].

Rating Algorithm Evaluation				
Scroll Time	Scroll Rating	Time Spend	Time Rating	Total Rating
3.559	1	14.012	1	1
3.249	1	21.603	3	2
3.355	1	25.497	4	3
5.077	3	13.414	1	2
5.342	3	21.217	3	3
5.287	3	26.797	4	4
7.374	5	12.113	1	3
7.504	5	20.917	3	4
7.431	5	24.797	4	5

The table represents the result of the rating algorithm evaluation. The *Scroll Time* represents the time that a user scrolls on the page and the *Scroll Rating* represents the rating that results out of that scrolling behavior. Additionally the *Time Spend* represents the time that a user spends on the web page and the *Time Rating* represents the rating that the system generates for that behavior. The total rating is the implicit rating that the system uses as the rating of that user for the specific item. These total ratings are integer values and are therefore rounded. The values of the *Scroll Time* nearly match the average times that were found out as rating indicators in the field experiment from Claypool et al. [2001]. These average times that a user scrolls on a web page and rates the site with an explicit rating are 3.485 seconds for an explicit rating of 1, 4.079 seconds for an explicit rating of 2, 5.267 seconds for an explicit rating of 3, 6.444 seconds for an explicit rating of 4 and 7427 seconds for an explicit rating of 5. All generated *Scroll Ratings* reflect the expected ratings from the field test of Claypool et al. [2001]. The same is true for the generated *Time Ratings*. The *Time Spend* values nearly match the average times for the specific ratings from the Claypool et al. [2001] field experiment. These average times are 13.414 for a rating of 1, 18.017 for a rating of 2, 21.217 for a rating of 3, 24.372 for a rating of 4 and 26.797 for a rating of 5. However the rating of five could not be achieved by spending time on the web page this rating is only attainable by performing a pre defined user interaction such as clicking on a specific button. All other *Time Ratings* reflect the expected ratings from the field experiment of Claypool et al. [2001]. The *Total Rating* which is introduced in this thesis correlate with the combined user interest of the *Scroll Rating* and the *Time Rating* and therefore represent the expected result. Moreover the total rating is derived from the data of Claypool et al. [2001] and it would have been desirable to conduct a field experiment but unfortunately due to the lack of time this was not possible and should be considered for future works.

4.2 Tagging

This section evaluates the tagging process that was introduced in subsection 2.3.2. The concept behind the tagging process is to create a *levenshtein automata* for every word in an item and read each word from the *STW Standard Thesaurus Economics* into the automata. If the word ends in a final state it is used as a tag for the item. Such a *levenshtein automata* is a deterministic finite automata that can decide in linear time if a word has a *levenshtein distance* smaller than a desired $n \in \mathbb{N}$. Four different texts are created for the evaluation process. In each of these four texts 70% of the words are from a placeholder text that is called *Lorem ipsum*. The *Lorem ipsum* text is according to Wikipedia [2013] typically based on a Latin text from Cicero with words altered added and removed thus it is not a proper Latin text any more. These words are chosen based on the fact that they do not match with the words from the *STW Standard Thesaurus Economics*. Consequently they do not create false matches during the evaluation process. The other 30% of the words in the evaluation texts are from the *STW Standard Thesaurus Economics*. However, not all of the words are in the same form as they are found in the *STW Standard Thesaurus Economics*. Thus the tagging algorithm has to match the words from the item with the correct words from the STW. After each test the matched words are compared to the words that should have matched. Moreover, the time that the algorithm needed for creating the Levenshtein automata and the total time in seconds is evaluated. The computer that is used for testing this tagging algorithm is a *Macbook Air* with a 1.86 *GHz Intel Core 2 Duo* precessor and 4 GB DDR3 memory.

Tagging Algorithm Evaluation					
Words	STW	Non Matching	Matched Words	Levenshtein Time	Total Time
1	1	0	2	0.099	14.481
10	3	7	3	0.2843	20.348
100	30	70	54	0.4751	79.9616
1000	300	700	470	2.5606	777.4643

At first the word *tests* is used with the tagging algorithm. This evaluation results two matches from the *STW* namely *test* once for the English and once for the German language. The time that is needed for creating the Levenshtein automata is approximately a tenth of a second. For this complicated generation process this is a good performance. However the total computation time is 14.481 seconds which involves the loading of the 31.682 words from the *STW* and the reading of all of these words into the Levenshtein automata.
For the second evaluation ten words are used with 7 non matching words and three words from the *STW*. Two of the three words are modified therefore they are not in the same form as they appear in the *STW*. All three of these words are matched by the tagging algorithm. The creation time of the Levenshtein automata is 0.2843

seconds which is approximately three times as high as the Levenshtein automata computation time for the one word creation. The total computation time of 20.348 seconds is 1.5 times higher than the total computation time for the one word tagging process.
The 100 words evaluation consist of 30 words from the *STW* with spelling mistakes and different forms. The other 70 words are non matching words from the *Lorem ipsum* placeholder text. The algorithm returns 54 words as matches from the *STW*. These 54 words include all 30 words that were included in the original 100 words plus 24 words that are similar spelled or use the same words in English and German. The computation time for the 100 Levenshtein automata is 0.4751 and in total the computation needs 79.9616 seconds.
For the final tagging algorithm test a text with 1000 words is used. This text contains 300 words from the *STW* with approximately 150 words in different forms or with spelling mistakes. The other 700 words are words from the *Lorem ipsum* placeholder text and thus are non matching. The algorithm returns 470 words almost all of the original words were included. The words that did not match are the words that had more than three changes resulting from changing the singular form to its plural form and adding spelling mistakes. The computation time for the Levenshtein automata is five times higher than the corresponding time for the 100 word test. However the total computation time is nearly ten times higher than the total time for the 100 word test.
A conclusion of this evaluation is that the largest part of the total time is the reading of the words from the tagging base into the Levenshtein automata and not the time that the algorithm needs to create these automata. Therefore the main focus in future works should not be to improve the performance of the creation process of the Levenshtein automata but to decrease the number of words in the tagging base.

4.3 Recommendation

This section evaluates the different recommendation approaches that are explained in subsection 2.4.4. These different approaches are the item-based recommendation, the different singular valued decomposition (SVD) based recommendations, and the approach that is described in this thesis that uses item-based predictions to decrease the sparsity of the rating table and the SVD-based approach for recommendations. The evaluation process of the recommendation system contains two parts. First the evaluation of the performance of the different approaches by using the wall clock time. Second the comparison of the accuracy of the different concepts. For this task the *MovieLens* database is used. The *MovieLens* database includes 100.000 ratings from 943 users for 1682 movies. This data is collected with the movielens.org website that is part of the *GroupLens* research project from the University of Minnesota. The website is a recommendation website for movies. Each user of the website can rate movies on a scale of 1 to 5 and is afterwards presented with movies that might be interesting for him. To compare the accuracy of the recommendation systems the *Mean Absolute Error* (MAE) is used.

Definition 25 (Mean Absolute Error). *Let $p_{i,j}$ be the predicted rating for user i and item j and let $q_{i,j}$ be the real rating for user i and item j. Then the following formula calculates the MAE.*

$$MAE = \frac{\sum_{u \in U} \sum_{i \in testset_u} |rec(u,i) - r_{u,i}|}{\sum_{u \in U} |testset_u|}$$

This metric is according to Sarwar et al. [2001] most commonly used for evaluating recommendation systems. The MAE is a statistical metric that compares the calculated user-item ratings from the recommendation system with real user-item ratings. For this process the recommendation system is trained with a percentage p of a test rating database and afterwards the remaining 1-p percent are used to check if the recommendations are correct a ratio of 80% training data and 20% prediction data is used.
The team of Herlocker et al. [2004] noticed that many collaborative recommendation systems in the movie domain reach a mean absolute error of up to 0.73 on a rating scale of 1 to 5. Out of this realisation Herlocker et al. [2004] created the hypothesis that collaborative recommendation systems that are tuned to its optimum can not get much more accurate than a mean absolute error of 0.73. They explain this hypothesis with the reason that users tend to provide inconsistent ratings when they are asked to rate the same movie at different times and therefore an algorithm cannot be more accurate than the users rating variance for the same item.

Recommendation Comparison 80.000 ratings 20.000 predictions			
Technology	MAE	Offline Computation Time	Prediction Time
Item Based	0.83187	3187.69	4208.49
SVD Concept	0.77937	32471.93	4315.31
SVD Three	0.79545	469.82	4395.75
SVD Average	0.78622	507.90	4226.31
Three	1.03333	0.00	0.49
Average	0.82714	112.13	249.18

The table ... represents the evaluation of the recommendation systems. The computer that is used for testing the different recommendation techniques is a *Macbook Air* with a 1.86 *GHz Intel Core 2 Duo* precessor and 4 GB DDR3 memory. Consequently all computation times that are measured in this evaluation are based on this hardware system and can be faster on a productive server. However the computation times can be used to compare the speed of the different recommendation systems. The evaluation contains three different metrics the mean absolute error, the offline computation time and the prediction time. The mean absolute error is, as explained before, a statistical metric that declares the average distance between the predicted user-item rating and the real user-item rating. The offline computation time represents the time that the system needs to generate the data that is needed for the prediction of the items. Thus this computation must not be calculated for every recommendation but every 24 hours to once a week depending on the frequency that new items are added to the system and the activeness of the users to ensure the correctness of the user and item similarities. The prediction time is the time that the system needs to calculate the predictions for all 20.000 ratings. Therefore this time divided by 20.000 approximately represents the time that the system needs to calculate one prediction for the recommendations that are presented to the user on a website.

The *Item Based* technology is the implementation of the item based recommendation approach that is part of the overall recommendation concept of this thesis. It has a mean absolute error of 0.83187 which is the second poorest mean absolute error of all tested technologies. This is a surprising outcome of the evaluation it was expected that this technology would be more similar to the mean absolute error of the SVD based technologies. The offline computation time in this implementation consists of finding items that were rated by the same users and calculating the adjusted cosine similarity between those items. The adjusted cosine similarity is a special form of the cosine similarity. The cosine similarity for two items is calculated by applying the dot product between the rating vectors of the items and dividing the result by the Euclidean length of the rating vectors. The adjusted cosine similarity uses the same computation but normalizes the ratings in the rating vectors before calculating the cosine similarity. This normalization consists of subtracting the average user rating from the rating to remove the individual rating behavior of the user. This process is explained in more detail in subsection 2.4.2 The calculation of the adjusted cosine similarity between all items takes the largest part of the computation time. At last the item similarities are stored in the database.

can I write this?

The prediction time for an user-item pair involves the finding of similar items that the user has rated and calculating the sum of the product of the similarity and the rating and dividing the result by the sum of the similarities. So, all in all the implemented *Item Based* technique has the second slowest offline calculation time and with an average distance of 0.83 between the predicted rating and the actual rating one of the poorest mean absolute errors of the implemented methods.

The *SVD Concept* technology represents the recommendation system that is introduced in this thesis. Therefore it uses item based rating predictions to fill empty rating entries in the user-item rating matrix with predictions. The mean absolute error of this technology is the best of all the implementations that were tested. In terms of the other *SVD* based implementations this can be explained by the fact that the rating matrix has the most accurate entries of all. However the *SVD Concept* has a very high offline computation time. The offline computation time of this system contains the following calculations. At first the average user rating is calculated which is needed to remove the individual rating behaviour from the user ratings before calculating the predictions. Thereafter the item based cosine similarity is calculated which contains the same parts that where explained for the offline computation time of the *Item Based* technology. After that for each user the rating prediction of the missing user-item entries in the rating table is calculated which

is responsible for the largest part of the total computation time. The computation time for each user is approximately 30 seconds and the test database consists of 943 users. This can be explained by the fact that each user has only rated a fraction of all items and therefore many predictions must be calculated. Afterwards the rating matrix is generated from the rating table. The entries of the matrix represent a rating for an user-item pair. The previously generated rating predictions are used for empty entries in the rating matrix. For this rating matrix a singular value decomposition is generated. This process decomposes the rating matrix into three matrices namely U, V and Σ. The matrix U has the property that each column of the matrix represents the interest of a user. More details to the singular value decomposition and the features of the three matrices are described in subsection 2.4.2 In addition, the matrix U is reduced to the two dimensional approximation to decrease the following computation time. This computation time is the calculation of the cosine similarity between the columns of the two dimensional approximation of the matrix U. These similarities are used to created the final rating predictions for the item recommendations when a user visits a website. Finally the user similarities are stored in the database.
The prediction time consists of finding similar users that rated a specific item and calculating the prediction with the similarity of the users and their ratings. Overall this technique has the best mean absolute error but it has by far the poorest offline computation time.
The *SVD Three* technology represents a singular value based recommendation system that uses a rating of three to fill in the missing user-item ratings in the rating matrix. The rating of three is used because it represents the middle of the rating scale of 1 to 5 and therefore it should have the least distance between all ratings if the ratings are uniformly distributed. The mean absolute error of this implementation is 0.79545 which is the poorest of the SVD based approaches this is expected because it generates the singular value decomposition with a rating matrix that uses static values for the missing entries. This matrix should have the highest difference to the matrix that would represent the real user interest and therefore should generate the poorest user similarities. The offline computation time of this system consist mostly of the same parts as the *SVD Concept*. Namely by calculating the average user rating for each user, creating the rating matrix from the database, calculating the singular value decomposition, creating the approximation of the matrix U that is part of the singular value decomposition, calculating the cosine similarity between the columns of the matrix U approximation and storing this user similarities in the database. The calculations that are created during the prediction time are the same as the calculations that were used in the *SVD Concept* approach namely the finding of similar users that rated a specific item and the calculation of the predictions. This system is evaluated to compare the impact of the values that are used to fill in the missing ratings in the rating matrix. This evaluation demonstrates that the more accurate these values are the better is the quality of the predictions. However the difference of the mean absolute error of this approach and the other two SVD based approaches is smaller than expected. Therefore further developments that

should improve the prediction accuracy should be concentrated on the prediction calculation and not on the improvement of the similarity calculations. Altogether this technique has the fastest offline calculation time of all tested more advanced recommendation systems and a good mean absolute error.
The *SVD Average* technology is the implementation of the SVD based approach but it uses the average item ratings to fill in the missing entries of the rating matrix. Therefore it is a solution without complex calculations to create dynamic rating predictions for the missing entries in the rating matrix that mirror the overall user interest. The mean absolute error is 0.78622 and thus it is has the second best mean absolute error of all testet systems. The offline calculation time consists of calculating the average user ratings, calculating the average item rating, creating the rating matrix from the database, calculating the singular value decomposition, creating the approximation of the matrix U which is part of the singular value decomposition, calculating the cosine similarity between the columns of the matrix U approximation and storing this user similarities in the database. These calculations are the offline calculation time processes for the *SVD Three* approach plus the calculation of the average item ratings. These average item ratings are needed to fill in the missing entries in the rating matrix. The prediction time of 4226.31 seconds includes the same calculations that were used for the other two SVD based approaches which are the the finding of similar users that rated a specific item and the calculation of the predictions. Therefore it has almost the same prediction time as the other SVD based approaches that were tested in this evaluation. To sum up this technique has the second best mean absolute error and moreover it has one of the fastest offline computation times of the tested more advance recommendation systems. Thus this system has a fast computation time and a very good mean absolute error and for this reasons it should be used for further developments if the quality of the recommendations is more important that the computation time.
The last two systems are added to the evaluation to compare the results of the more advanced recommendation systems with naive approaches. The *Three* technique uses a rating of three for all predictions. The three was chosen because it represents the middle of the five point rating scale. Therefore it has the smallest mean absolute error of 1.2 of all static ratings if the user ratings are evenly distributed. This technique does not require any offline computations and the mean absolute error calculation consists of subtracting the real rating from three. This approach yields a MAE of 1.03333. Consequently the ratings are less common on the outer boundaries of the rating scale which is a common user rating behaviour. The MAE of 1.03333 can be seen as a lower boundary. If any of the recommendation techniques is below this MAE it is an indicator that the recommendation technique does not work properly.
The *Average* technique uses the average item rating as a rating prediction. Thus it is the least complex method which generates dynamical rating predictions that represent the interest of all users. The difference from its MAE of 0.82714 to the lower boundary of 1.03333 is 0.20619 which is a good result. Additionally it has nearly the same mean absolute error as the item based approach. Therefore it can be concluded that the interests of the individual users from the *MovieLens* database

does not vary widely. However this technique has to calculate the average user ratings of all users which is very fast and needs to load only one value from the database to instead of calculating a prediction. As a result the *Average* technique is a good choice if the user interest of the system does not vary widely and if the system needs a fast solution.

In conclusion the evaluation of the recommendation techniques revealed that the SVD based approach that was introduced in this thesis has the best mean absolute error of the implemented approaches. However it does not vary widely from the MAE of the *SVD Average* technique and the offline computation time of the *SVD Concept* approach is by far the slowest. The item based approach has a slow computation time and the MAE is nearly the same as the *Average* approach. The research teams of Sarwar et al. [2001] showed that this method can yield an MAE of up to 0.73 by improving the prediction calculation but these improvements should have the same effect for the SVD based approaches and therefore the SVD based techniques should be the better choice for collaborative recommendation systems. The evaluation of the *SVD Three* technique indicates that SVD based recommendation systems result generally good predictions. Moreover it showed that improvements for the missing entries for the rating matrix yield improvements of the predictions but that these optimizations only improve the MAE by approximately 0.2 points. Therefore future works with the goal of optimizing collaborative recommendations should concentrate on the improvement of the prediction calculations. Finally the evaluation revealed that using the average user rating as a rating prediction can yield good and fast predictions if the user interest does not vary widely. Consequently this can be used for calculating rating predictions as part of recommendation systems if the use case of the system does not require highly optimized recommendations. This evaluation should be repeated when the system is in productive usage and has collected the same amount of data that was used for this evaluation to check if the data for the specific use case of recommending questions and answers reveal the same findings as this evaluation.

5 Conclusion

The focus of this thesis is the development of a recommendation system for user generated content. These recommendations should match the user interest and the context of the website on which they are included. For this focus it is important to analyze the user generated content for quality and to identify the subject of the content automatically. Hence, user interactions that can occur on a website are evaluated to be able to tell if a user is interested in the content. Based on the research of Claypool et al. [2001] the time a user spends on a website and the time a user scrolls on a website are chosen for generating implicit user ratings. These two user interactions correspond about 70% of the time with the explicit ratings of a user. The times of each of these interactions are used separately for creating a scale that expresses user ratings by these times. The average of these two ratings is then used as the total rating. This concept is evaluated with simulated user interactions. The result of this simulation displays that the two separate ratings agree with the findings of Claypool et al. [2001]. Besides the total ratings are as expected. However for this part of the thesis a field test in the future would be a good idea to adjust the formula according to the use case. The identification of the subject of the user generated content is based on matching the words of the content with words from a thesaurus. For this task different error allowing string matching methods are evaluated. The chosen concept is the *levenshtein automata* which is a special automata for approximate string matching. Based on the work of Schulz and Mihov [2002] the algorithm for a deterministic levenshtein automata is integrated into the overall concept. Besides, a concept for finding the maximum *levenshtein distance* for a word depending on its length is introduced in this thesis. This is important because a word with a small word size can not be handled the same way as a word with a long size. The smaller word needs a smaller distance otherwise it would generate too many false matches. This word match algorithm is used to find the keywords of a text and to use them as tags. This enables the system to presort the content by the keywords before recommending it on a website. The tagging process is evaluated by using texts with a different amount of words. Each of those texts has 30% words that should match with the words in the thesaurus however most of the words are in a different form or spelling mistakes are inserted. So, the evaluation process checks how many words are found and how long does the algorithm need. In three of four tests more words were returned than the algorithm should have matched. This is mostly due to the reason that most words in the thesaurus are included in the German and English language and that some of those words are quite similar. Consequently the algorithm returns the English and the German word. Other false matches occurred because the thesaurus included words that were too similar and thus the algorithm returned both of these words. Therefore a future optimization is to reduce the size of the tagging base which would not just reduce the occurrence of false matches but would also decrease the time that the algorithm needs to find the matches. Another possible future work is to decide whether the text is in the German or English language and to use only the words from the corresponding language as a tagging base. In addition, different types of recommender systems are discussed. The conclusion of this discussion is that for the use case of recommending user generated content a collaborative recommendation system would be the best approach. Two existing collaborative recommendation techniques are explained namely the *item based* technique and a recommendation technique based on *singular value decomposition*. These techniques are combined into a new recommendation concept which is introduced in this thesis. This concept uses the *item based* approach for decreasing the scarcity of the rating matrix which is used for the calculation of the *singular value decomposition*. This recommendation system uses the ratings that are generated with the user interactions on the website and the tags that are generated with the help of the *levenshtein automata* to recommend user individual matching content that is interesting for the current user. The evaluation of the recommendation system showed that the new recommendation concept creates better prediction than the two techniques on their own. Though, the calculation time increased drastically and the prediction was slightly better than a prediction that uses average ratings for decreasing the sparsity of the rating matrix for the singular value decomposition. Consequently future works with the goal of improving the recommendation system should use the *singular value decomposition* that uses average ratings and concentrate on the prediction calculation for improvements. Moreover the evaluation showed that the method of using only average ratings for recommendation can create good rating predictions. Thus, systems that do not have a need for using highly optimized recommendations could use this method for creating recommendations.

5.1 Future Work

The implemented system is fully functional and can be used for the purpose it is intended to be. However each of the single parts might have the possibility of improvements. The following subsections are suggestions on how the system might be enhanced in the future.

5.1.1 Rating System

The evaluation of the rating system denotes that the implicit ratings should approximately mirror the real user interest. However due to the shortness of time it was not possible to conduct a field experiment to test the assumptions. Such a field experiment would be desirable and might lead to further improvements. One possible improvement that could be tested would be to to weight the two single ratings that result out of the time a user spends on a website and the time a user scrolls on a website during the average calculation phase by the difference of their times to the truncated mean time.

5.1.2 Tagging Service

The evaluation of the tagging service suggests that the process can be improved by decreasing the tagging base. This might be done by automatically detecting the language of the content and only using the words of that language for generating tags.

5.1.3 Recommendation System

The evaluation of the recommendation techniques yield that the best recommendation approach of the implemented recommendation systems for a productive system is the *singular value decomposition* with the use of average ratings for the empty entries in the rating matrix. Furthermore the evaluation suggests to concentrate future improvements on the calculation of the rating predictions instead of the calculation of the user similarities. Thus, it might improve the prediction calculation by weighting the ratings for the calculation based on the difference to the average rating. This should on the one hand reduce the importance of ratings on which most user agree upon and on the other hand should increase the importance of the items that are more diverse. Consequently the predictions should be more individual for the single user.

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