Master's thesis

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Norwegian University of Science and Technology
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Department of Computer Science

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Decision Support System For Social Benefit Support Using Case-Based Reasoning

Master's thesis in Master of Technology: Computer Science
Supervisor: Pinar Øzturk
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TRONDHEIM MUNICIPALITY

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Sammendrag

Bruk av skjønn er viktig i evalueringen av økonomisk sosialhjelpsøknader siden en helhetsvurdering av de individuelle behovene til søkeren må gjennomføres. Bruken av skjønn kan gjøre at saksbehandlerne sin subjektivitet fører til inkonsekvent evaluering av søknadene. For å evaluere om dette er tilfelle, og for å hjelpe saksbehandlerne til å gjøre evalueringen av søknadene mer konsekvent og rettferdig, så har et beslutningsstøttesystem blitt utviklet ved hjelp av *Case-Based Reasoning (CBR)*. CBR er en teknikk innenfor kunstig intelligens som er inspirert av hvordan vi mennesker løser nye problemer, og har blitt brukt i en rekke ulike områder. For å lage et CBR system kreves ofte betydelig mengder domenekunnskap, og det å tilegne seg denne kunnskapen er ofte vanskelig. Til tross for at CBR har blitt brukt i mange domener finnes det overraskende lite litteratur om hvordan den nødvendige kunnskapen kan skaffes fra domeneeksperter. Jeg vil derfor i denne masteroppgaven dele mine erfaringer og de metodene som er brukt for å skaffe domenekunnskap i løpet av dette prosjektet.

Delvis strukturerte intervjuer, spørreskjemaer og kognitive oppgaveanalyser er blant metodene som er brukt for å tilegne meg den nødvendige domenekunnskapen. Siden det var vanskelig å skaffe den riktige kunnskapen ble disse metodene brukt i en iterativ prosess. For å evaluere forskjellene mellom saksbehandlerne ble flere instanser av CBR-systemet opprettet, hvor hver instans representerte valgene til de enkelte saksbehandlerne. Evaluering og testing av systemet viste kun små forskjeller i forslagene gitt av de ulike CBR-instansene. Enkelte større forskjeller ble likevel funnet, og aktivitetene som ble gjennomført for å tilegne meg domenekunnskapen avslørte også forskjeller mellom saksbehandlere. Det er fortsatt noe arbeid som gjenstår før CBR-systemet kan bli fullt utnyttet av saksbehandlerne. Dette inkluderer blant annet å utvide omfanget av systemet og å integrere systemet med eksiterende informasjonssystemer som saksbehandlerne bruker.

Abstract

The use of discretion is important in the assessment of social benefit support applications, as an overall assessment of the individual needs of the applicant is made. The use of discretion makes it possible that the subjectivity of the people who evaluates the applications lead to inconsistent evaluation of the applications. In order to evaluate if this is the case, and to help them evaluate the applications more consistent and fair, a decision support system has been developed with the use of *Case-Based Reasoning (CBR)*. CBR is an artificial intelligence technique inspired from how humans tackle new problems, and has been applied to a numerous of different domains. To build a CBR system a substantial amount of domain knowledge is often necessary, and the task of extracting this knowledge is often difficult. Although CBR has been applied in many domains there is surprisingly little literature on how the necessary knowledge can be elicited from domain experts. I will therefore, in this master thesis, share my experiences and the methods used for knowledge elicitation in this project.

Semi-structured interviews, questionnaires and cognitive task analysis are some of the elicitation methods that have been used to elicit the necessary domain knowledge during this master thesis. As it was difficult to extract the necessary knowledge, these methods have been used in an iterative elicitation approach. To evaluate the differences between the case officers who evaluate the applications, multiple instances of the CBR system have been initiated with each instance representing the decisions of each case officer. The evaluation and testing of the system revealed only small differences between the suggestions made by the different case officer-instances. However, occasionally some larger differences were found, and differences amongst case officers were also discovered during the knowledge elicitation activities. There are still some work necessary before this CBR system can be fully utilized by the case officers, such as increasing the scope of the system and integrating it with existing information systems used by case officers.

Acknowledgements

First of all, I would like to thank my supervisor Pinar Øzturk at NTNU, and co-supervisor Leendert Wienhofen from Trondheim Municipality, for their guidance and many helpful suggestions during this master thesis. I would also like to thank all the employees from Trondheim Municipality and NAV I have been in contact with during this project, for taking the time to have interviews and discussions with me throughout the semester.

Contents

1. Introduction

During a research project for Trondheim Municipality in the fall of 2018 the reasons for differences in social benefit support payments between the different districts in Trondheim municipality were analyzed. This research suggested that inconsistent evaluations of social benefit support applications amongst case officers could be a contributing factor for the differences (the work of a case officer is explained in the next section). As a result of this, it was decided to both investigate this further, and also try to help the case officers to make consistent evaluations by implementing a decision support system.

1.1. Social Benefit Support

The social benefit support is an economical safety net offered to all citizens in Norway that are not able to economically support themselves [23]. It should be the last resort for people in difficult social situations. The social benefit will give you a temporary income, and the goal is that people will be economically self-reliant as quick as possible. The temporary income should cover necessities of life such as living expenses, heating and food. To be qualified to receive social benefit support the person needs to be living in Norway, and be unable to support themselves through working or other types of support. There exists various kinds of help citizens can receive that are not covered by the social benefit support. This include housing allowance from Husbanken[1], disability benefits and more. The social benefit support is supposed to be a short term help, while there often exists other types of support for those in need of help for a longer period of time.

The social benefit support is offered by all municipalities in Norway, and NAV is the organization that is responsible to offer this service in the municipalities. When citizens apply for social benefit support from NAV, their application will be evaluated by a case officer. The case officer will make a discretionary assessment of the needs in each application [23]. This means that there are not strict rules for how the application should be assessed, and hence, the case officers can deviate from the norm when the applicants have special needs or difficulties. A client's need can often be complex and individual, and it is therefore difficult to have rules that cover every special case. The use of discretionary assessment is covered in the law on social services in chapter four § 19:

> *"The municipality can in special cases, even if the requirements in § 18 are not satisfied, give financial help to persons who needs it in order to avoid or*

[1] Husbanken is a government-financed organ that supports the municipalities in their help for the less fortunate in the housing market [17].

> *adapt to a difficult living situation."*[24]

As the case officers use discretion in their assessment of citizens' level of eligibility to this support, the individual decisions by the case officers can structure and delimit peoples' lives and opportunities. Hence, the case officers can have a great impact on peoples' lives. Discretion is used because each case should be evaluated individually. The goal is to make decisions that are consistent and fair, but aspects such as experience and personal beliefs may lead to inconsistency between different case officers. To avoid this NAV is responsible for sufficient training and teaching of their employees in the rules and guidelines for social benefit support. However, multiple reports and supervisions shows that there are differences between the case officers in the use of discretion as well as their idea of discretion [19] [43]. [19] is a report by Trondheim Municipality evaluating a subset of the social benefit support payments in Trondheim in 2017. They investigated 66 clients at the four different NAV-offices in the municipality. 34 of them were randomly picked, and the remaining 32 were picked because of their high received financial support. 23 out of the 66 cases had received housing allowance which exceeded the norm with more than 20%, and only 8 of these 23 were living in municipal houses[2]. In addition to this, a case where two different employees evaluated an application very differently was found:

> "In one of the cases we have evaluated, documentation shows that a client has acquired a residence with significantly higher housing expenses than what was agreed. The review shows that two different case officers at NAV evaluated the case, and gave mixed signals. The first case officer gave advice and guidance to the client, informing him that he needed to obtain a residence within the guideline value. When changing to a new case officer, the new officer approved that he could obtain a residence above the guideline values." [19]

During interviews with experts in Trondheim Municipality it was expressed that for the case described above, the second case officer approved the high housing expenses because the client did not manage to find a residence within the guideline value. However, during the same interview it was confirmed that especially the experience of the case officers could impact the result of the evaluations of the applications. So identical applications for social benefit support may be evaluated differently at the different NAV-offices, and also within the offices, leading to different social benefit support payments. The NAV-offices receive many applications, which shall be evaluated in a short period of time. Therefore, there might be occasions where the employees do not have time to evaluate the applications satisfactory, which leads to inconsistency and different practice for the clients.

[2] As the municipal houses are owned by the municipality, higher housing allowance is often accepted for clients living in municipal houses as the rent is payed back to the municipality.

1.2. Decision Support System

Both [19] and [43] suggests more practical teaching and training of the employees at NAV as an action to deal with this problem. However, they mainly enlighten about the problem and do not focus a lot on addressing the problem. In order to help the employees at the NAV-offices, and to address this problem, we have done research on how a decision support system can help alleviate case workers and created a proof-of-concept of a decision support system. The decision support system gives suggestions to answers to the social benefit support applications which the case officers can use in their assessment of the applications. Hence, the decision support system shall not replace the case officers and make automatic evaluations of the applications, but rather be a tool for the case officers to make the evaluations of applications more consistent and more effective. In order for such a system to be useful, the suggestion given by the system needs to be of good quality and a valid justifications for why the proposed suggestion was suggested must be given.

Due to the limited time of this master thesis it was not possible to implement a fully decision support system that is ready for use and integrated with the existing information systems used by the case officers. The work in this master thesis will therefore be a indication on whether or not such a decision support system is beneficial and possible to implement in the domain of social benefit support. It will also work as a good starting point for further development and integration.

1.3. Research Questions and Goals

As the main concern is that the social benefit support applications may be evaluated differently by different case officers, it will also be the focus in this master thesis. Additionally, it would also be important to identify the aspects of the applications that make them difficult to evaluate, which can lead to differences in the evaluation. Therefore, the research questions for this master thesis are:

- **RQ 1: To what extent does subjectivity, caused by differences in experience or personal beliefs, lead to inconsistent evaluation of social benefit applications amongst different case officers?**
- **RQ 2: Which types of applications, i.e. what types of information in the applications, makes it more difficult to evaluate the application?**

In addition to the research questions mentioned above a lot of focus will also be on the artificial intelligence technique called *Case-Based Reasoning (CBR)* and to improve the state of the art on this field, stated in this research goal:

- **RG 1: Contribute to improvement of state of the art in case-based reasoning by giving a detailed description and knowledge in how to build the initial case base and similarity measures.**

1.4. Used Methodologies

The overall research and development methodology used in this master thesis is Hevner's *design science framework* [44]. This framework is illustrated in figure 1.1. The *environment* defines the problem space which in this case is the concern that the assessment of social benefit support applications, made by case officers, are not consistent. The decision support system that will be built to deal with this problem is called the *artifact*. The artifact will be developed with applicable knowledge from the *knowledge base*, i.e. with the existing methodology of case-based reasoning and different knowledge elicitation techniques. After evaluation of the developed decision support system, the artifact is a contribution to both the environment as an application, and to the knowledge base as knowledge on how to initiate a CBR system (RG1).

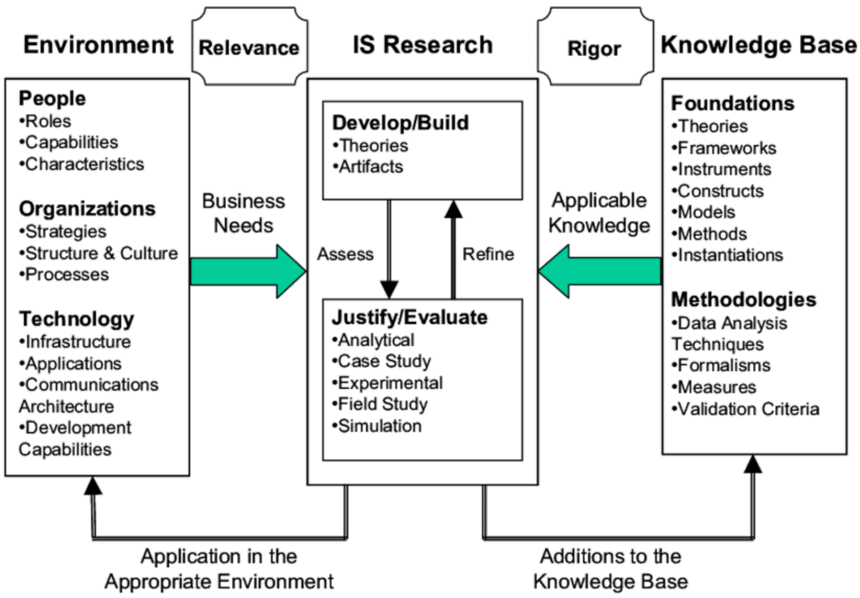

Figure 1.1.: The design science framework *Source:*[44]

In addition to this overall framework a number of knowledge elicitation techniques and activities, such as interviews and questionnaires, have been used and they are described in section 4. These activities and techniques have been applied in an iterative manner based on the SECI-model, described in section 4.1.1, which is a methodology on how tacit knowledge is best transferred in organizations. Literature studies have been used to examine earlier attempts at decision support systems in the field of social benefit support and other similar domains in section 2.1. It has also been used to learn about earlier approaches and methods that have been used during the different development stages of a CBR system, described in section 2.5.

1.5. Outline

The rest of this master thesis is outlined as followed:

Chapter 2: Background
This chapter gives further background on decision support systems, case-based reasoning and ethics. The practical challenges encountered when developing a CBR system are discussed based on existing literature. The development tool used during the project is also described.

Chapter 3: Conceptual Architecture
In this chapter the final conceptual architecture of the CBR system is presented. The final case representation, similarity measures, weights and explanation capabilities are described. A suggestion to how the system can be integrated with existing information systems is also presented.

Chapter 4: Development Process
This chapter describes the development process and the different knowledge elicitation techniques and activities that have been used to gather the necessary domain knowledge to build the CBR system.

Chapter 5: Testing and Evaluation
In this chapter the used methodology for testing and evaluation of the CBR system is presented. The results are also presented and discussed.

Chapter 6: Conclusion
In the final chapter a conclusion of the work and results is given. Lessons learned from the project is also described with focus on the used knowledge elicitation techniques. In the end, necessary and recommended future work is described.

2. Background

In this chapter the necessary background on decision support systems and case based reasoning is provided. First the state of the art on decision support systems in fields similar to social benefit support is discussed in section 2.1. Then, the importance of ethics in artificial intelligence is discussed in section 2.2. In section 2.3 the Case-Based Reasoning methodology is described, before the reasons for why CBR was chosen as methodology are presented in section 2.4. Then, in section 2.5 the practical challenges of implementing a CBR system are described along with a literature study on how to overcome these challenges. This leads to the identification of gaps in the available literature, described in section 2.6, that we would like to fill. Finally a short introduction to the tool used for implementation of the CBR system is provided in section 2.7.

2.1. Decision Support Systems

In this section the state of the art within the field of decision support systems is evaluated with focus on application assessment. Google Scholar and IEEEXplore have been used during the search for literature. The literature study started with searches for previous work in decision support systems for evaluation of social benefit support applications, before we continued in other similar domains and domains where discretion is used.

A common term for what we have described as case officers in this thesis is *street level bureaucrats*. This is a term that is used for public employees who interact directly with individual citizens and uses discretion when allocating facilities. [9] discusses how information technology has changed the use of administrative discretion. They give an example of how the system of student grants and loans has changed drastically from being evaluated by case officials who interviewed students and used discretion in their decision making, to a fully automated system that evaluated the applications. Only when a student objected to the decision the case would be evaluated by a human case officer. So the number of tasks that are handled by computers are growing. However, for certain domains there are specific interests that must be considered which can not be described by formal rules, and the task of developing computer systems in such domains is therefore more difficult. The goal is not to remove the use of discretion, but to keep the use of discretion on the same level amongst case officers to accomplish consistency in the decision making.

No literature was found on evaluation of social benefit applications or other similar social welfare programs that uses discretion. At minimum, the results from the first five search pages on Google Scholar were evaluated for the following search terms: "social security income system", means tested system", "welfare benefits assessment system", "social welfare benefits", "street level bureaucracy decision support", "bureaucracy case workers decision support", "street level bureaucracy computer system", "street level discretion computer system", "building decision support system in discretionary domains", "discretionary decision support" and "case workers decision support".

During the searches for "discretionary decision support" a number of articles were found on discretionary decision support systems in the field of law. In the domain of property distribution upon divorce in Australia the judges have the possibility to use discretion. The Australian Family Law Act lists a number of factors which the judges needs to take into consideration when assessing the case, but no indication on how these factors should be weighted is given. The use of discretion made it difficult to make rule-based reasoning systems in this domain. However, Split-Up [46] have integrated rule-based reasoning with neural networks to tackle this problem. A neural network is used to learn the weights the judges uses for the different factors they consider during assessment. In addition, each case is decomposed into a number of sub-tasks, and each sub-task is either handled by the use of rule-sets or a neural network.

The case described above was a decision support system for judges. However, decision support system may also be developed to support lawyers. For lawyers in court, a series of arguments must be presented, and these arguments are often based on precedence. The use of precedence makes it comparable to the evaluation of social benefit applications, as the goal of the evaluations is that they are consistent such that new applications are evaluated similarly as older evaluated applications. HYPO [32] is a case based reasoning system that can be used in trade secret law. It compares the current case with similar cases and based on this creates an argument for the current case. This system also gives explanation and justification for the analysis and cases found by HYPO.

In [38], a hybrid approach with the use of neural nets and case-based reasoning has been used to build a decision support system for processing of loan applications in banks. The developed system greatly reduced the time of loan application processing. [42] also developed a decision support system for bank loans using CBR, which gave the same answer as the economic experts in 90% of the decisions. This shows that the use of case-based reasoning as a decision support system can reduce the processing time of applications, and also recommend good decisions for the user.

With little available literature in decision support systems for evaluation of applications, the search continued in other domains with similarities to that of the evaluation of social benefit support applications. Real estate property appraisal is one such domain, where the goal is to set a value on a property. This decision is based on a number of attributes related to the property, and experts may even value the same property differently. This is similar to case officers who may evaluate social benefit applications differently because of for example experience. [16] is a CBR approach to such a problem, which gave results that in average were 9 % different from the values asserted by experts.

The main concern in the processing of social benefit support applications is that similar applications may not be evaluated equally amongst different case officers. Therefore, the main goal for this decision support system is that it gives recommendations to the case officers that are of high quality. A different domain where this is crucial is within health and diagnostic. This is also a field that has received much attention when it comes to decision support systems. An example of such a CBR system is [2], where the focus is on diagnosing intoxication by drugs. In this system the attributes are the symptoms for the patient, and some of the specific knowledge in the cases are possible to compile into more general rules which makes the similarity calculations more efficient.

So no literature was found on decision support systems for evaluation of social benefit applications or similar welfare programs where the use of discretion is necessary. However, the similar domains mentioned above shows that case-based reasoning can be a good fit for the problem at hand, and that it has been proven useful in many other domains earlier. So this paper will introduce CBR in the field of social benefit support applications, which hopefully will help make the evaluations more consistent amongst case officers.

2.2. Ethics and AI

As mentioned in the introduction, the decisions made by the case officers can have significant impact on peoples' lives. A decision support system that will support the case officers in their decision making can therefore also have such significant impacts because it may guide the case officers' decision making. The ethical aspects of such a system is therefore crucial. In this context it is especially two aspects of ethics that are of great importance: How can the case officers trust the system? How can we (the system engineers) ensure that the system is not biased? These two questions will be discussed in the following sections.

2.2.1. How to Avoid Bias?

The goal of this project is to reduce the differences in the decision making when processing social benefit support applications, by introducing an artificial intelligence system. The reason for such an approach is that the automated systems are often thought of as superior to human beings in a way that it will rate all individuals equally, and that it does not make the same flaws as human beings during the assessments. However, this is not directly true. The AI algorithms are programmed by human beings, and therefore the biases and values of the system engineers may be introduced into the software. As domain knowledge, which is important in many of the implementation choices for a CBR system, is gathered from domain experts, the bias of the domain experts may also be introduced in the system. So, careful considerations have to be made throughout the development process in order to avoid that the biases of the developers and domain experts are embedded into the system. [11]

There are ways of maintaining objectivity and minimize bias in the computer systems. First of all, the more people who are involved in the implementation, the less the chances are for individual beings' bias to be embedded into the system. In addition, automated systems are often developed to replace or assist human beings, and human experts in the field should therefore be able to review the system to ensure its correctness. In order to be certain that the system does not have bias we need to know how the system works, and on what grounds it makes its decisions. *Transparency* is therefore a key characteristic for such an AI system [8]. With a manual approach to building the CBR system, by extracting knowledge from domain experts, the domain experts involved in the development process gathers a understanding of how the system works. With this understanding they can more easily review the system to ensure that bias has not been introduced. On the other hand, with a automatic approach, by processing previous cases to build the case base, the domain experts do not obtain the same understanding of the system, and it could be more difficult to review and evaluate the system and its bias.

2.2.2. How Can We Trust The System?

More and more artificial intelligence systems are used in different processes that in large extents can affect peoples' lives, i.e. medical diagnostic, credit rating, judicial decision and social welfare. Such systems must be trustworthy. The output can not simply be a yes or a no. An explanation for how the system reached the given answer is also required. Some common approaches for explanation include natural language explanations or explanations by examples [21]. Different types of explanations and how they should be constructed will be discussed next.

2.2.3. Explanations

Types of Explanations

Explanations can be represented in different ways. Humans often explain decisions verbally, and hence a traditional text explanation is ideal but often difficult to create for machines. Visualization is also much used when trying to explain decision, and may be easier for a machine to generate rather than using natural language. It is also possible to give explanations through examples, by showing the solutions or choices that were made for similar cases. [21]

A Good Explanation

In Tim Miller's literature review on explanations [22], one of the major findings was that explanations are *contrastive*. People would like to know why a specific event occurred or a choice was made in contrast to a different option. They ask: *"Why A rather than B?"* when A was the selected choice or occurring event. This is because people wants explanations for events or choices they do not understand. Hence, A is the observed event/choice, and B is the expected event/choice. A client that is not granted social benefit support would therefore probably like a explanation where their situation is contrasted with a similar client that did receive social benefit support. The idea that explanations should be contrastive leads to the next major finding made by Miller in [22]. That explanations are *selected*. People do not expect an explanation that is a complete detailed cause of event, but rather a few causes that they considers as being **the** explanation. Another aspect of a good explanation mentioned by Miller is that people often focused on abnormal causes when they explain events [22].

Other aspects of a good explanation are mentioned in [33]. *Fidelity* is important, and means that the explanations must be based on the same knowledge that the system uses during reasoning. The generated explanation must be *understandable*, and should not contain already known information and be at an appropriate level of abstraction for the user. In addition, *sufficiency* is needed, meaning that enough knowledge is represented in the system so that it is able to answer the possible questions from the user. And finally, the explanations should come with a low construction overhead and be generated efficiently.

2.3. Case-Based Reasoning

Case-based reasoning (CBR) is an artificial intelligence method that is fundamentally different from many other major AI approaches. The key difference from other AI methods is how previously problem situations (cases) are used to find a solution to a new problem (case). Hence, specific knowledge is used rather than general knowledge which is often used in other AI methods. A collection of previously experienced cases are maintained, and new cases are compared to the previous cases to discover similar problems as the current one. The solution to a similar case is then possibly modified to be suitable as a solution for the new problem. Additionally, CBR is an approach to incremental learning, as the new solved problems can be added to the collection of previous cases immediately and reused as a possible solution for the next problem case. Case-based reasoning is therefore considered as a subfield of machine learning [1]. The problem solving methodology in case-based reasoning is highly similar to how humans tackle new problem situations. For example, a doctor who is examining a new patient may often remember an earlier patient with many of the same symptoms. Therefore, the doctor gives the same treatment to the new patient as the previous one, as he remembers that the treatment was successful last time.

2.3.1. The CBR Cycle

The incremental learning in case based reasoning makes it a cyclic methodology. This cycle consist of four sub-processes [1] which can be seen in figure 2.1. These four processes will now be described further.

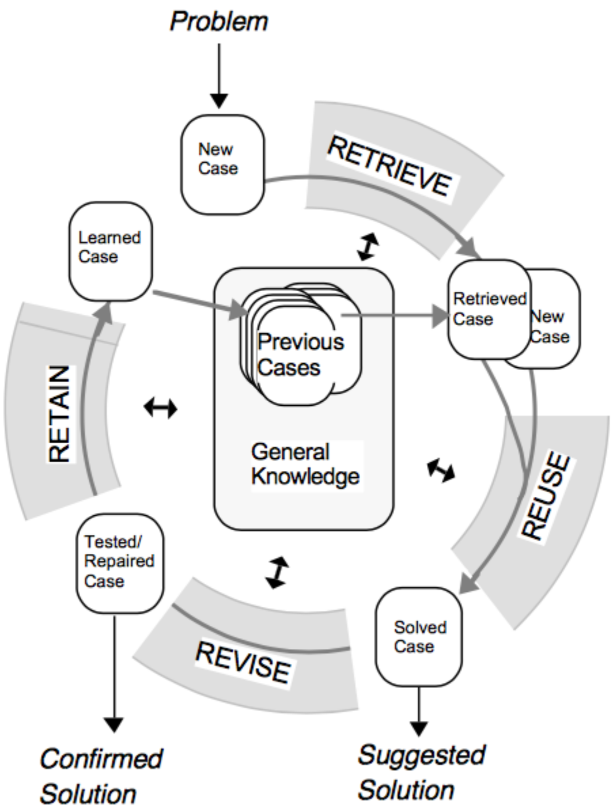

Figure 2.1.: The four stages of the CBR cycle: *Retrieve*, *Reuse*, *Revise* and *Retain*. *Source:*[1]

Retrieve The new problem, the case, that should be solved is used to *retrieve* a similar case from the collection of previous cases, the case base. The case that should be retrieved is based on a *similarity measure* which is used to find the most similar cases. The similarity measure to use is dependent on the specific domain, and will be described further in subsection 2.3.3.

Reuse The solution to the retrieved case is then, in the *reuse* phase, possibly adapted to the new case based on the differences between the cases. The adapted solution is considered a proposed solution to the new problem.

Revise The proposed solution is then evaluated or tested in the *revise* phase to see if the proposed solution is valid or not. If it is not valid, the proposed solution is repaired with domain-specific knowledge or by input from the user.

Retain In the *retain* phase the experience learned from solving the current case is retained. This can be done by storing the new learned case in the case base, or by modifying some existing case(s) in the case base.

General domain knowledge is also usually used during the CBR process, as seen in figure 2.1. This is for example used to define the correct similarity measures and the adaption rules for the domain. This will be discussed further in section 2.5.

2.3.2. Knowledge Containers

The domain knowledge in case-based reasoning systems can be divided into four major *knowledge containers* [30]. These four containers are the *case base*, *similarity measure*, *adaption knowledge* and *vocabulary*. The available knowledge is distributed over the containers, and no container is independently able to solve a task, hence the containers depend on each other. Some knowledge can be easier to represent in some containers and more difficult in others. Now each of the four containers will be described further.

The Vocabulary
The vocabulary is the chosen attributes that are represented in the system, along with their possible values.

The Similarity Measure
The similarity measure is used to calculate the similarity between cases. Both local similarities between attributes and global similarities for the entire case are calculated. This will be described in more detail in section 2.3.3.

The Case Base
The case base contains previous problems/experiences which new cases will be compared to. The solution to the similar problems in the case base will be the initial solution to the new case. It is important to build a case base of the correct size as many cases increases the competence of the system, while at the same time increases the search time when looking for similar cases.

Adaption Knowledge
Often some changes have to be made to the initial solution as the similar cases often do not match perfectly with new cases. This adaption is usually done by the help of adaption rules. In some domains, where the number of cases in the case base is large, there may not be necessary with adaption rules. When the system has very few cases, the adaption of cases is more crucial in order to solve the new cases. In addition, the similarity measure can be defined to either find the most similar cases, or cases that are easier to adapt to the current situations. Hence, the complexity of the adaption rules is dependent on both the domain, the size of the case base, and the similarity method that have been used.

2.3.3. Similarity Measure

The basic assumption in CBR is that similar problems have similar solutions. Therefore, a key task in case-based reasoning is measuring the similarity between cases. Many different measures can be used to calculate the differences, and some of these will be described below. The similarity can be measured to either find cases that have nearly the same solution to the current problem, or to find cases that can be adapted easily to solve the current problem. There is also a trade-off between accurate similarity measures and calculation effort, especially when the case base is large. The goal is to find a similarity measure that has the desired accuracy with smallest possible cost.

Local similarity measures are used to measure similarity for the individual attributes in the cases. All local similarities are then combined in the *global similarity* measure which measures similarities for complete cases.

Weighted Sum

The weighted sum is a global similarity measure which uses weights for the different attributes to denote their importance when measuring differences between cases [26]. Many case-based reasoners use a generalized weighted dissimilarity measure such as:

$$diss(C_{\mathrm{i}}, C_{\mathrm{j}}) = \frac{\sum_{k=1}^{n} w_{\mathrm{k}} * atr\_diss(C_{\mathrm{ik}}, C_{\mathrm{jk}})}{\sum_{k=1}^{n} w_{\mathrm{k}}} \tag{2.1}$$

where C_i and C_j are cases, w_k is the weight of attribute k and $atr\_diss(C_{\mathrm{ik}}, C_{\mathrm{jk}})$ is the local dissimilarity measure between the two cases for attribute k. The similarity measure then becomes:

$$sim(C_{\mathrm{i}}, C_{\mathrm{j}}) = 1 - diss(C_{\mathrm{i}}, C_{\mathrm{j}}) \tag{2.2}$$

.

Euclidean Distance

A much used global similarity measure is the inverse of weighted normalized Euclidean distance. The Euclidean distance denote the distance between two cases, and is given by the following equation:

$$diss(C_{\mathrm{i}}, C_{\mathrm{j}}) = \sqrt{\frac{\sum_{k=1}^{n} w_{\mathrm{k}}^2 * |atr\_diss(C_{\mathrm{ik}}, C_{\mathrm{jk}})|^2}{\sum_{k=1}^{n} w_{\mathrm{k}}^2}} \tag{2.3}$$

As distance is used to calculate the difference, the inverse will calculate the similarity between the cases. The distance is normalized in order to avoid attributes with large absolute values to have greater impact on the measure than smaller values. The similarity is calculated in the same way as for weighted sum:

$$sim(C_{\mathrm{i}}, C_{\mathrm{j}}) = 1 - diss(C_{\mathrm{i}}, C_{\mathrm{j}}) \tag{2.4}$$

.

Local similarities

The local similarity measures measure similarity on the attribute level. Depending of the type of the attribute, i.e. whether it is a string, category, number, etc., different similarity measures are possible.

Numeric Attributes

For numerical attributes the similarity is often measured either by absolute difference $d(q_i, c_i) = c_i - q_i$ or the quotient $d(q_i, c_i) = \frac{c_i}{q_i}$ of the two values. The quotient allows to model the similarities as relative distances. [41]

Symbolic Attributes

For symbolic attributes three possible measures are much used. The first approach is to use a *similarity matrix* where one explicitly assigns the similarity level for each pair of possible values. This can be a very time consuming task. The next approach is to define a *total order* for the symbolic values, such that the similarity can be calculated in the same way as for numerical values. The final approach to model the similarities is to arrange the symbols in a *taxonomy* [41]. The taxonomy is an n-ary tree, where leaf nodes represents concrete objects in the real world, and the inner nodes represents generalizations of the concrete objects. The lower the level of the first common predecessor of the leaf nodes, the higher the similarity between the attributes [6].

Set Attributes

Set attributes are attributes that allow multiple values. The similarity measure of these attributes can be much more complex than for single values [41]. A lot of different configurations can be made, such as to only calculate the best or worst match, or use average similarities for the set. It is also common that the two sets that are compared are not of the same size, and therefore it is also necessary to specify how the similarities for the remaining values in a case should be calculated. Some of these configurations will be discussed later in section 3.2.

2.4. Why CBR?

Many different methods have been used to build decision support systems, and now four reasons for the choice of case based reasoning are presented.

2.4.1. Explanatory by Design

As the CBR system should work as a decision support system for the case officers it is important that they can trust the system. Thes case officers need to be confident that the solutions proposed by the system are correct. Hence, a key aspect of the decision support system is that it can explain the proposed solutions and the underlying reasoning process. As Miller described it:

> The running hypothesis behind the explainable artificial intelligence is that by designing and implementing intelligence agents that are transparent, users will be better equipped to understand and therefore trust the intelligent agents. [22]

Artificial intelligence methods such as neural nets have difficulties to explain their solutions [33]. There exist some workarounds to accomplish this for black box models such as neural nets [34]. The new rules of GDPR states that enterprises must be able to explain how algorithms are used to make decisions. A loan application can not simply be rejected on the basis that an AI model said so, the decision must be explained. Because of this there will probably be further improvements in the field of explainable AI in the future. However, at the moment CBR is a method where it is easier to explain the underlying reasoning process. This is mainly accomplished by the presentation of the most similar case to the user, along with the solution [39]. By also presenting the weights for the different attributes, the user has the possibility to make his or her own judgement about whether the cases are similar or not.

2.4.2. No Rules

Many expert systems have been implemented as rule based decision support systems. However, the use of discretion in the field of social benefit support is justified because the case officers should make individual assessments of the client's need. It is therefore not possible to specify general rules in this domain, and a rule based system was not possible. The case based reasoning approach avoids this problem by relying on the experience-based knowledge of previous problems, rather than explicit rules.

2.4.3. Specific Knowledge

A key aspect of CBR is the use of specific knowledge rather than general knowledge which is often used in many other AI methods. General knowledge often gives great knowledge about the 'normal' situations rather than the special situations. So the use of general knowledge is disadvantageous when it is important to reason correctly about special cases [18, p. 9]. In the social benefit support applications, discretion can be used if the client has special needs or is in a extraordinary situation. Therefore the use of general knowledge is not best suited for such a problem domain.

2.4.4. Integration of Learning and Problem Solving

Many AI methods have a learning phase where the parameters of the model are learned before the model is later used for solving tasks. In CBR on the other hand, the learning and problem solving goes hand in hand. After a problem is solved, the case and its solution can be stored in the case base to be used already for the next case. So if the procedures for maintaining the case base, and when to delete old cases are implemented correctly, the maintenance costs of such systems can be low. Because of this, the CBR system can quickly adapt to changes in the routines of the case officers. For example if it was decided that one should be more considerate to families with children, one could replace the old cases in the case base, which were evaluated with the old routines, with new cases.

2.5. Practical Challenges in CBR

A number of decisions needs to be made when implementing a CBR system. The challenges related to these decisions will now be discussed, and a literature study has been performed to investigate previous work on these topics and the available information on the different challenges.

2.5.1. Gather Domain Knowledge

Many of the decisions that needs to be made during the creation of a CBR system are highly dependent on the domain under consideration. The domain knowledge is therefore crucial in order to implement the correct system for the domain. The domain knowledge is for example used to:

- Choose what to store in a case and how to represent it
- Choose the correct similarity measure to compare cases
- Choose the correct weights for the attributes in the global similarity measure

Case-based reasoning systems have been build for a large number of domains such as law, medicine, oil drilling, and others.. As the domain knowledge is important during many of the implementation choices one encounter during the development of a CBR system, the domain knowledge acquisition process is important in a CBR project. However, as Cordier states: "In a CBR system, the knowledge acquisition process is very difficult to model as it entails a lot of 'test and error'." [13] Cordier also describes two ways to acquire knowledge. Either automatically or manually. Automatic acquisition consists of applying algorithms on data volumes containing knowledge in order to extract the knowledge. This can produce large amount of knowledge easy, but the task of evaluating the produced knowledge may be large for an expert. During manual acquisition methods the knowledge is modelled into the system with help from domain experts.

Either way, there is need of a domain expert. As the use of CBR is often used in domains where there are little written knowledge available, and the use of tacit knowledge is large, the knowledge often has to be elicited from experts. This is often a daunting task. [45] shares their experience with the development of a CBR system in an industrial setting. The first data gathering activity they used was observations to form a structure for later interviews. Then semi-structured interviews, questionnaires and workshops were used to gather the necessary domain knowledge. Another paper describing their used knowledge elicitation techniques is [35], which reports the use of CBR for hydrometallurgical gold ore processing. They performed knowledge elicitation from human experts in order to create a case representation (attributes and value ranges) and to define and evaluate the similarity measures.The techniques they used were interviews with the experts, in addition to questionnaires and similarity measure templates for the experts to fill out. They did this with an iterative approach, and for each iteration, they gathered feedback from the experts on the knowledge elicitation approach. The feedback was gathered to learn if they asked the right questions in order to externalise the tacit knowledge from the domain experts.

The little available literature on knowledge acquisition in CBR may be explained by that it is very domain specific, and that writers tends to focus more on the technical aspects of the system. If we take a look at knowledge acquisition in general, outside the field of CBR, there exists more literature. A number of different techniques can be used to extract knowledge from experts, such as for example observations and interviews [12].

2.5.2. Define Case Representation

A case includes a problem situation description, and the solution to that problem. In addition a case typically contains the outcome of the solution, meaning the result of applying the solution in the real world and the state after the application. Explanations which explain why the specific solution was chosen for the case is also often represented. Domain knowledge is required in order to decide which attributes that should be part of the situation description.

There are mainly three different approaches for representing cases in a CBR system [5]. In the *textual* approach there is only a weak structure on the cases, and it is well suited for domains where experience is captured in documents such as bug reports or FAQs. This approach is suited when the cases have short descriptions with discriminating words in them, and when it is not too many cases. The quality of the retrieval process does in this case also depend on the syntax, and it can often be difficult to achieve high accuracy. The second approach is the *conversational* approach where the case is represented as a list of questions, and is therefore useful in domains where simple problems must be solved over and over. This approach does however come with high maintenance cost as it is necessary to manually place new cases in a decision-tree structure. The final approach is *structural* representation. In this approach a structured vocabulary is defined, and can be in the forms of attribute-value pairs, graph structures or have an object-oriented structure. In the *object-oriented representation* the cases are represented as collections of objects, and each object is described by a set of attribute-value pairs. Such a representation is often suitable for complex domains where cases with different structures occur. The structural approach can achieve high accuracy, but does often require large effort in order to define the case structure. [5]

Regarding the attributes that should be represented in a case, [5] does also mention three important aspects. First of all the attributes should preferably be *independent*. This means that one attribute should not be possible to calculate from the other attributes. This may be difficult to achieve in practice, as dependent attributes can simplify the computation of similarity measures. Another important aspect is *distinguishability*. This means that it is possible to distinguish cases based on the attributes in the case representation. If two cases that should be treated as dissimilar have the same values for the chosen attributes, additional attributes should be added to distinguish them. Finally the last mentioned characteristic is *minimality*, which means that only relevant attributes are part of the case, and irrelevant attributes are removed.

2.5.3. Populating the Case Base

An initial case base is necessary in a case-based reasoning system. However, it is not always straight forward to build the initial case base. Sometimes the cases can be retrieved directly from existing systems such as patient journals and applications, while other domains require manual effort to write the case bases. If the data used to build the cases exists in a database, the process may be a trivial task. On the other hand, if the data needs to be manually extracted from either domain experts or written material, the process can be a costly and time consuming task [28].

Another key aspect when populating the case base is to ensure that the cases are of proper quality. If the cases in the initial case base are not correct, then the proposed solutions to new problems will neither be correct. For the domain of social benefit support applications, a key concern is that the applications are not evaluated consistently. To ensure the quality of the cases that will be put into the case base, some experts needs to evaluate the quality and correctness of the cases.

2.5.4. Define Similarity Measures

Both local and global similarity measures must be chosen, and as described in section 2.3.3 there are a number of possible measures to use depending on the type of the attributes. As stated by Cordier:

> "Determining the similarity between two cases is far from being a trivial task, and the choice of a good similarity measure is crucial to the efficacy of the system." [13]

Because of this difficulty the definition of the optimal similarity measures does often require repeatedly testing and fine tuning [41]. [31] do mention some factors that are important to consider when choosing similarity measures. They state that the representation of the cases has the greatest influence on the choice of similarity measure. The value ranges for the attributes are also important. In addition, the size of the case base and the efficiency needed is also important as a large case base may require simpler similarity measures in order to reach the efficiency goals.

There exists numerous literature on the different similarity measures in CBR, but very little information on how to select and define the appropriate one for specific domains and attributes, other than the general suggestions described above. [40] did also state this, and proposes the use of machine learning to define the similarity measures. Other than this the most common approach in the field seems to be to start with a general similarity measure and make adjustments based on domain knowledge gathered from domain experts. However, no specific methodologies on how to gather this knowledge from experts were discovered.

2.5.5. Define Attribute Weights

Kolodner [18] suggest multiple ways to set the weights for the global similarity measure. The first one is to have a human expert assign them as the case library is being built. The expert is expected to have the knowledge and experience required to decide which features that work as good predictors. Another way to assign the weights is to do a statistical evaluation of known cases to identify the attributes that best predicts the solutions. The more significant predictors are considered to be of greater importance for matching. For example, the magnitude of the correlation coefficient between the input and the output can be used to weigh each input-attribute [36].

Another alternative approach is also proposed by [36], by using *Genetic algorithms (GA)*. Genetic algorithms are stochastic search techniques that searches on large complicated spaces, and the techniques are inspired by natural genetics and the evolutionary principle. GAs consists of four stages: *initialization*, *selection*, *crossover* and *mutation*. The details of these stages will not be outlined in detail here, but can be found in [36]. The approach in using GAs to set the weights in CBR is as follows:

- Search for an optimal or near optimal weight vector based on a number of cases with known solutions/outcome by setting up a genetic optimization problem.
- Apply the weight vector found in the previous step in the retrieval phase, and evaluate the resulting model with additional validation cases (solution/outcome is also known).
- If the evaluation shows that the model is successful, then the model is ready to be used for new (unclassified) cases.

Another possible process that can be used to assign the weights in case-based reasoning is an *Analytic Hierarchy Process* (AHP). The AHP approach is a multi-criteria decision-making method that uses hierarchic structures to represent a decision problem, and from this prioritize the attributes. First the criteria for the decision problem is identified, and then the interaction among them is measured. This is accomplished by doing pairwise comparisons of the attributes to identify the relative importance of the attributes. This can be done in some form of questionnaire, before the results are evaluated and aggregated into relative weights for the attributes. [29]

The before mentioned approaches does require a large case base with known solutions. If this is not available, a manual approach is necessary and domain experts are often asked to set weights. A manual approach can also be beneficial even though a large case base is available. The reason for this is that it will lead to a larger collaboration between the system engineer and the experts. This can increase the understanding of the system for the experts, which results in higher trust in the system and larger chances that the system is accepted and used by the experts. However, it is still not clear exactly how this should be done. How many experts should define the weights in order to avoid bias, and how should one aggregate the choices from multiple experts into one weighting schema if it is not consistency in their answers? Little literature was found on CBR systems where these questions are answered. [37] is one example where they had a survey with five experts in order to reduce subjectiveness. However, they did not state how the results were aggregated.

2.5.6. Create Explanations

As discussed earlier in section 2.2 the explanations provided by the system for their decisions are crucial in domains such as social benefit support. The case officers must be able to trust the system, and must be convinced that the suggestions made by the system are reasonable and correct. So how should the system explain its reasoning process and be able to justify the suggestions that are made?

In case based reasoning the key methodology to achieve such explanations has been to present the solution to an earlier solved case that is similar to the present problem. Research done by [14] showed that presenting example-cases along with the solution significantly improved the user confidence in the solution compared to only presenting the solution. By presenting the weights and similarities of individual attributes along with the similar case and solution, the case based reasoning methodology seems quite transparent. In addition, the presentation of solution to similar cases can work as decent justification for why the solution is a good answer. However, a problem mentioned by [39] is that explanations are transfer of knowledge, and as discussed in section 2.3.2, there are four knowledge containers in case based reasoning: the *case base*, the *similarity measure*, the *adaption knowledge* and the *vocabulary*. The simple presentation of cases as explanations will only use the knowledge found in the case base and vocabulary. If the similarity measures or adaption rules are very complex, it can be difficult to understand how a presented case is similar to the present one. In such situations the presentation of the most similar case will not work as a good explanation. Some additional explanations of the similarity measures and adaption rules that have been used are necessary. [39]

The type of explanation and level of details to use is dependent on who the end user will be. A domain expert can easier make their own similarity evaluation of two presented cases, and therefore it can be adequate to just present the cases. If the user is not experts on the field it is often necessary for more detailed explanations, by for example highlighting the most important features for the computed similarity.

2.6. Research Gaps

As seen from the literature described in the earlier section, there does exist substantial literature on the different possible choices for case representations and similarity measurements in addition to multiple automatic methods to select weights. However, in situations where automatic methods are not possible due to for example a limited case base, it exist little literature in the field of CBR on how to elicit the necessary domain knowledge from experts, which guides many of the implementation choices. [3, 31] does for example discuss the overall process of initiating a CBR system, and the different available choices, but the exact knowledge elicitation process is mainly skipped by saying it was done through talks and discussion with experts. [45, 35] are the literature that was found where the knowledge elicitation process is described, although they do not describe the resulting case representation or similarity measures.

With little available guidelines to follow while initiating a CBR system, the task becomes really challenging, and this overhead may cause people to choose other methods over CBR. As stated by [45], this may be the reason for a limited adoption of the CBR methodology. This is therefore a gap in the literature that we would like to make a contribution to by describing the knowledge elicitation process and the used techniques during the development of the decision support system for social benefit support applications. Although the methods that can be used and the elicitation approach are different from domain to domain, we still find it useful to share the experiences as concrete examples hopefully will make it easier to overcome the difficulty with knowledge representation in CBR systems.

2.7. myCBR

MyCBR[1] has been used to develop the case-based reasoning system. MyCBR is an open source similarity-based retrieval tool and software development kit (SDK) [15]. It is both a workbench where one can easily model and test the case representation and similarity measures, and a SDK which support integration of the model from the workbench with further advanced possibilities.

In the myCBR workbench multiple similarity measures can be made for individual attributes, which makes it easy to test and evaluate different measures. If the workbench does not include a desired similarity measure, it is easy to use the myCBR SDK to create

[1] http://mycbr-project.org

your own similarity measures. The case representation in myCBR consist of concepts and attributes, which makes it possible to create object-oriented case representations [4].

Regarding explanations, myCBR provides two general types of explanations: *forward* and *backward* explanations. *Forward explanations* explain indirectly and predicts the behaviour of the system during modelling time. A central component in myCBR for such explanations is the statistics for the different attributes in the case base. For example, the value distribution of an attribute may reveal parts of the similarity measure that are never used, if the cases in the case base reflects the possible query cases. *Backward explanation* is a explanation of the results from a process and how the result was achieved. In myCBR this is accomplished by showing the similarities of the individual attributes for the most similar cases in the case base. [41]

In this project, we have used both the myCBR workbench and the myCBR SDK. The case representation and structure have been built in the workbench, in addition to most of the similarity measures. Some of the similarity measures could not be created with the options found in the workbench, so they were instead implemented and added with the SDK. These similarity measures are described in detail in section 3.2. The SDK was also used to initiate the weights of the attributes for the global similarity measure. With the SDK, a program was written in Java to let the user enter new cases through the console, and later let them either save the case to the case base, or compare it with existing cases. The results from the comparison are also presented through the console and will be explained further in section 3.4.

3. Conceptual Architecture

In this chapter the developed case based reasoning system will be described. First, the final case representation and similarity measures are presented in section 3.1 and section 3.2 respectively. Then the attribute weights are described in section 3.3, and the explanatory capabilities of the system is described in section 3.4. Finally section 3.5 discusses how this CBR system can be integrated with the existing information systems used by the case officers at NAV today.

3.1. Case Representation

The interviews with the domain experts from Trondheim Municipality, described further in chapter 4, revealed that there are certain aspects of the application which requires use of discretion on its own. This can be decisions regarding what should be considered as income and if the client's assets need to be used before receiving social benefit support or not. Other such decisions are whether to grant loans to applicants instead of giving them the social benefit support, or what level of housing costs that is acceptable. Because of limited time for this master thesis, it was chosen to focus on a subset of the application and disregard these independent decisions. It was chosen to focus on the evaluation of applications for additional supplements which are benefits that the clients can apply for in addition to their regularly monthly benefit support. This include benefit such as extra money to electricity, clothes, food, special occasions and so on.

The final case representation for the decision support system is presented in table 3.1. An object oriented representation has been used, in which an application can have multiple registered children and multiple registered previous supplements. The *supplement amount* attribute is the case solution in this representation, and all other attributes make up the case description. In this representation there are some attributes that are not directly represented in the Visma Velferd computer system that the case officers are using today during evaluation of applications. This includes *health*, *clients effort*, *consequence of disapproval*, *necessity*, *recently moved* and *recently single*. This is information that is usually stored in text segments rather than in general forms, as the personal situation for each individual client should be considered carefully. Based on a number of examples of such descriptions, the six attributes mentioned above were extracted as important attributes that needed to be represented in the cases. They are all applicable for all situations, but the limitation is that they can not represent all the information that is found in the original text segments. This is a weakness for this model, and a automatic natural language processing unit could be used instead in order to analyze the information in the text segments of the applications, and improve the representation power of the model. This was not done because of the scope of this master thesis, as a manual approach was considered adequate for the development of the system as a proof-of-concept.

Attribute	Type
Age	Integer
Children - Age - Parental responsibility	Set Attribute Integer Integer
Living situation	Category
Recently moved	Boolean
Partner	Boolean
Recently single	Boolean
Single provider	Boolean
Health	Category
Clients effort	Category
Consequence of disapproval	Category
Necessity	Category
Norm	Category
Total income	Integer
Total expenses	Integer
Previous supplements (PS.) - Months since - Type - Amount	Set Attribute Integer Category Integer
Calculated norm	Integer
Supplement type	Category
Description	String
Supplement amount	Integer

Table 3.1.: The attributes and objects in the final case representation.

As mentioned in section 2.5.2 the attributes in a case representation should preferably be independent. For the chosen case representation in this CBR system there are a few attributes that can be calculated from other attributes. The *single provider* attribute can be decided based on the values for partner and children. However, this attribute has been kept in the case representation in order to simplify the similarity measure. Some extra considerations are made for single providers during social benefit support applications as they for example have more difficulties to have an income because they must take care of their children. So, instead of creating a similarity measure based on both the *partner* and *children* attribute simultaneously, the *single provider* attribute was represented in the case. The *calculated norm* attribute is also possible to calculate from other attributes. It can be calculated from income, expenses, children, partner and norm, as the expected expenses for a family are incorporated into the calculated norm. The calculated norm is used to indicate if the client should be able to be economically self reliant or not based on the expected costs for the family. Whether or not the client is above or below norm is therefore an important factor in the evaluation process and therefore an important attribute in the case representation.

3.2. Similarity Measures

As mentioned in section 2.3.3 there are different similarity measures used for different data types. For this case representation the similarity for the boolean values is easily calculated, as *true* is considered completely different to *false*. Hence, equal values returns a similarity of 1.0 and different values (true and false) returns a similarity of 0. For the *age* attribute the similarity was calculated based on a grouping of the age into *above 25* and *below 25* as this is also the grouping used in the social benefit norms. For the *children: age* attribute three age groups were used ([0-6], [6-11],[11-17]), also similar to the social benefit norm. The *parental responsibility* attribute was compared with a linear similarity function $sim = |q - c|$ where q is the query value and c is the case value. The same was used for the *Prev. Supplements: Months Since* attribute. For the remaining integer attributes a polynomial function was used because these attributes (*income*, *expenses*, *calculated norm*, *PS. amount*) had a large range of possible values. A polynomial function would allow for a fast decaying similarity, and a difference of 10.000 kr versus 20.000 kr would therefore not be very big in the similarity calculation as they both are very far from the compared value.

For the categorical attributes an ordered category function was used for the attributes *clients effort*, *health*, *consequence of disapproval* and *necessity*. These attributes had categories of the form *none*, *very little*, *little*, *average*, *large* and *very large*, where the neighbouring categories are more similar than categories further away on the scale. For the remaining categorical attributes a similarity table was used to denote the similarity between individual categories, and the domain knowledge gathered from domain experts was used to set these similarities.

With respect to the set similarities, myCBR did not offer the desired functionality. First of all the options in myCBR to compare multiple values were to either match the query values with the case values, or the other way around, or comparing the one with the highest number of values with the other one. For children and additional benefits the last one was desired. However, the matching started with the first value in either the query or case and found its best match, before it continued to the next value. This local maximum approach does not necessary lead to the global maximum matching, as illustrated with an example in figure 3.1. Therefore, the Hungarian algorithm was used to implement the possibility of global maximum matching. The details of this algorithm will not be discussed here, but can be found in [20]. The maximum matching will give

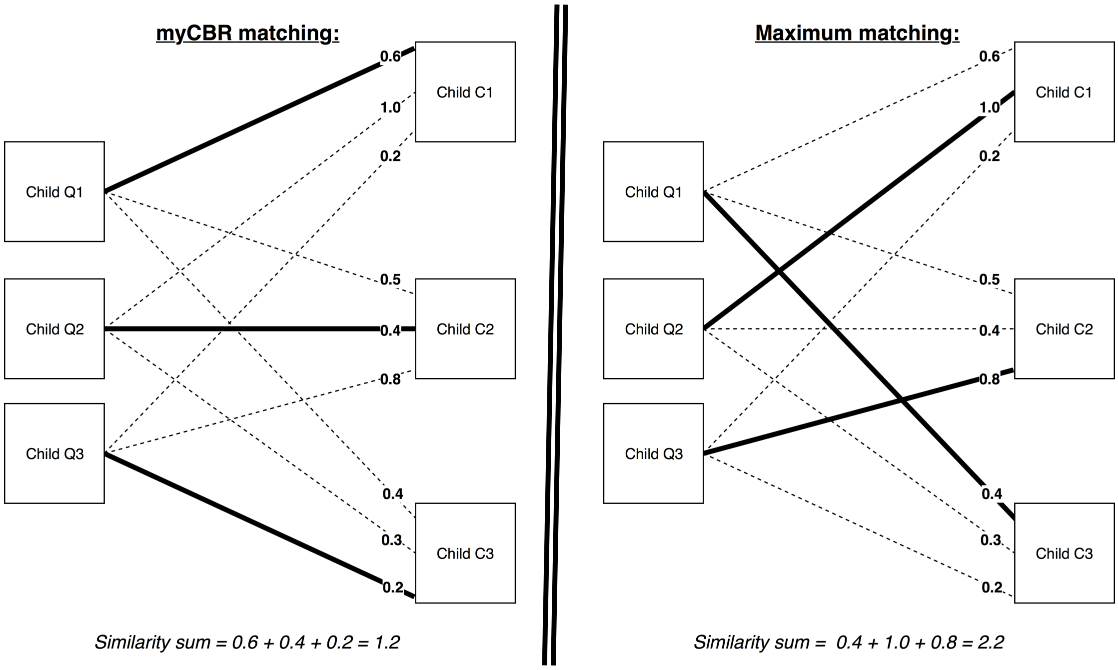

Figure 3.1.: The difference in the calculated similarity for a set attribute by using the local matching algorithm of myCBR (left) and a global maximal matching algorithm (right).

a more accurate similarity measure, but this does come with a cost. In situations with many cases the complexity of the maximum matching algorithm ($O(n^3)$) may be too complex.

Another limitation of myCBR with respect to set similarities is the possibilities when dealing with situations in which either the case or query have more values than the other. In this situation myCBR offers to reuse values to compute the similarities for the remaining values, to set the similarities to zero, or simply ignore the values and not consider them when computing the total similarity. For both the *children* and the *additional benefits* attributes a more sophisticated method had to be implemented. For the children attribute, the similarity of the remaining additional children should be compared with having no additional children. Therefore the *parental responsibility* was used in the similarity calculation as a child that you are only responsible for 10 % of the time should not be considered completely different than having no child.

The remaining values for additional benefits were compared with having no additional values based on the following. If the supplement types of the remaining values are not similar to the supplement type in the application, than they should not be considered as a relevant additional supplement, and they are therefore ignored. For the situations where the types are similar then the following formula is used:

$$similarity = (1 - typeSimilarity) * currentSimilarity \tag{3.1}$$

TypeSimilarity is the similarity between the supplement type for the case and the type of the previous supplement that is considered. If the types are exactly similar then the remaining value is completely different from having no additional benefits, and the similarity for the remaining value will be zero. *CurrentSimilarity* is the average similarity of all the previous supplements that have been considered at this point. By multiplying with the current similarity the remaining values can not possibly increase the similarity between the query and the case. Without the multiplication of the current similarity, additional benefits that are not relevant for the current benefit type could increase the similarity towards 1, which is not desired.

3.3. Attribute Weights

The weights selected by the different case officers were quite different, and because of this it was chosen to initiate different instances of the CBR system. Each of the CBR instances represents the weights chosen by the different case officers. The weights can be seen in table 3.2.

	Officer #1	Officer #2	Officer #3	Officer #4	Officer #5
Age	0	1	6	0	2
Living situation	3	4	9	1	2
Single provider	2	5	7	5	2
Children	6	8	9	10	2
Total income	8	9	10	10	8
Total expenses	6	8	9	10	7
Partner	8	5	7	5	2
Prev. applications	3	5	9	8	7
Norm	3	2	8	7	6
Calculated norm	6	5	8	10	7
Health	6	7	9	10	7
Clients effort	5	5	7	5	6
Necessity	6	7	9	9	7
Consequence of disapproval	6	6	10	10	6
Recently single	10	10	10	10	10
Recently moved	10	10	10	10	10
Description	0	0	0	0	0

Table 3.2.: Weights for CBR instances reflecting the choices of different case officers, where 10 is the highest weight.

Regarding the *recently single* and *recently moved* attributes, their weights are the same for all instances as they were added after the case officers answered the weight form. This is described further in section 4.4.4. The *description* attribute was also added later, but this attribute should not be included in the similarity measure as it simply describes additional context for the cases, which the user themselves must evaluate.

One difficulty encountered when setting weights was how to set the weights for the supplemental support type. The type of the additional supplement is obviously very important, as the cost of for example clothes is cheaper than household goods, which makes them not directly comparable. Therefore, the supplement type should have a high weight to reflect its importance. However, if the supplement type has a very high weight compared to the other attributes in the case representation, the differences in similarities would be very small for cases of similar types. For example, the cases of equal types could all start at a similarity of 0.9 although none of the other attributes are similar, singly because of the high weight of the supplement type. To avoid this a different approach was necessary. As there are some similarities between certain supplement types, the cases with a different supplement type could not simply be removed from the retrieval results. The chosen approach was to multiply the similarity of the supplement type with the total similarity for the case (excluding the supplement type). This way the maximum similarity of two cases would be the similarity for the supplement type. Cases with non-relevant supplement types compared to the query would therefore have a similarity equal to zero.

The same strategy was used for the *children* attribute. The similarity between two children is dependent on the age of the child and the parental responsibility for that child. No combination of weights for the similarities of these two individual attributes gave the correct similarity for the *children* attribute. Therefore, it was necessary to calculate the similarity by using the values for the two attributes simultaneously. For two children the similarity of *parental responsibility* was multiplied with the similarity of the *children: age* attribute. So, if the two children had the same value for parental responsibility their similarity would equal the similarity of their ages. But, if the parental responsibility values were for example 100 % and 10%, then the similarity would be low even though the ages were the same.

3.4. Explanations

Two of the most important aspects to explain for a decision support system are:

1. Why the proposed answer is a good answer (*justification*), and..
2. how the system reached the answer (*transparency*).

For this CBR system, the main explanation method was, like for many other CBR systems, to present the most similar cases along with the proposed solution. The GUI of myCBR was used as a guideline, where the similarity of the cases are presented, and the user can choose the number of similar cases that should be presented. In addition the weights of the individual attributes for the global similarity measures were presented, along with the similarity of the local attributes to increase the transparency of the system. An example of such a similarity table is presented in table 3.3. The first column contains the names of the attributes in the case representation along with their weights. Then the query case, i.e. the new case that has been compared to old cases in the case base, is given in the second column. The subsequent columns will then represent a case in the case base, with the most similar cases presented first. The first rows describes the name of the case, the overall similarity, the supplement amount that was given (i.e. the case solution) along with the supplement type and context description. Then the remaining attributes in the case representation are presented. The local similarities are given in brackets besides the attribute values for the cases. As seen in the similarity table, for the attributes that are objects (previous supplements and children) only the names of the objects are presented. The reason for this is that it was difficult to present these objects and their matches in a good way through the console on the computer. The usability was not prioritized during this project, and this is something that should be improved in future work.

Attribute (Weight)	Query Case	1. best match (Sim.)
Name (0)	Query	Application #13
Similarity	-	0.763
Sup. Amount (0)		1500
Sup. Type (0)	Support, other purposes	Support, other purposes (1.0)
Description	Clothes	Winter clothes. Granted by §19.
Prev. Supplements (9)	PS #16;	PS #14; (0.0)
Health (9)	Moderate challenges	Small challenges (0.75)
Calculated norm (8)	7650	8120 (0.89)
Necessity (9)	Large	Large (1.0)
Consequence (10)	Large	Average (0.8)
Living situation (9)	Rent municipal house	Rent private market (0.8)
Single provider (7)	No	No (0.0)
Clients effort (7)	Average	Big (0.8)
Recently single (10)	No	No(1.0)
Norm (8)	Long term	Short term (0.5)
Recently moved (10)	No	Yes (0.0)
Children (+)	None	None (1.0)
Total income (10)	0	0 (1.0)
Partner (7)	No	No (1.0)
Total expenses (10)	4500	4000 (0.87)
Age (6)	24	24 (1.0)

Table 3.3.: An example of a similarity table outputted from the developed CBR program. A screenshot of the original output can be seen in Appendix A.1.

Case Officer #	Suggestion 1	Suggestion 2	Suggestion 3	Suggestion 4
Case Officer #1	App. #13 (0.76)	App. #5 (0.65)	App. #2 (0.64)	App. #0 (0.64)
Case Officer #2	App. #13 (0.77)	App. #2 (0.67)	App. #0 (0.66)	App. #5 (0.65)
Case Officer #3	App. #13 (0.76)	App. #2 (0.66)	App. #0 (0.66)	App. #5 (0.60)
Case Officer #4	App. #13 (0.75)	App. #2 (0.67)	App. #0 (0.66)	App. #5 (0.58)
Case Officer #5	App. #13 (0.71)	App. #2 (0.68)	App. #0 (0.66)	App. #8 (0.65)

Table 3.4.: An example of a summary table outputted from the developed CBR program. A screenshot of the original output can be seen in Appendix A.2.

As a lot of information can be found in the similarity tables, and as a individual similarity table is presented for each CBR instance, the user was also presented with a summary table. This way the user can first take a look at the summary table, and then possibly evaluate the similarity tables if more information is necessary. In the summary table the suggestions made by each CBR instance are summarized. An example of a summary table is presented in table 3.4. Each row contains the suggestions made by a CBR instance, and for each suggestion the name of the suggested case along with the similarity is presented. This way, the user can see the level of agreement amongst the case officers. If there is large agreement the user can trust the system more than if there is large disagreement amongst the case officers' suggestions (reflected in the CBR instances). Large disagreement can give an indication that the user should carefully assess the application, possibly in collaboration with other case officers. In addition to the summary table, the supplement amount for the suggested applications are presented along with the context it was given (the text in the *description* attribute). With these descriptions the user can evaluate if the context is the same or not, and take action from there. An example of such an context description is presented in figure 3.2.

In App. #2 the amount of 1500kr was given in the following situation: *Clothes*
In App. #8 the amount of 1500kr was given in the following situation: *Clothes, has lost weight and needs a lot of new clothes because of this*
In App. #5 the amount of 0kr was given in the following situation: *Keyboard*
In App. #0 the amount of 1500kr was given in the following situation: *Clothes. Wife is encouraged to apply for a job, she has some health challenges (not documented)*
In App. #13 the amount of 1500kr was given in the following situation: *Winter clothes. Granted by §19.*

The most similar case is App. #13 with a 100.0% agreement amongst the CBR instances. The amount of 1500kr is recommended in the following situation: *Winter clothes. Granted by §19.*

Figure 3.2.: An example of a context description outputted from the developed CBR program together with the summary table.

The possibility to add adaption rules was not chosen, both because of the scope of this project and because the most similar cases seemed adequate as solutions to new cases if the case base was large and diverse. Therefore, the additional explanations for such rules were not necessary. Also, the similarity measures shall reflect how the case officers make their decisions, and as the end user of this system is the case officers it was not found necessary to describe the similarity measures further as explanations.

3.5. Integration with Existing Systems

The case officers in NAV have a series of information systems that they use to look up information on clients and to register new applications etc. An additional problem is that the case officer often does not use computer systems to register information properly because the existing system is cumbersome and because the case officers lack the computer knowledge to use them properly. Because of this, the proposed case based reasoning system will most likely not be used if the case officers would need to access and register information in yet another information system. Therefore, in order for the CBR system to be beneficial it needs to get integrated into the already existing systems, such that it can retrieve/receive all the information needed from already registered information.

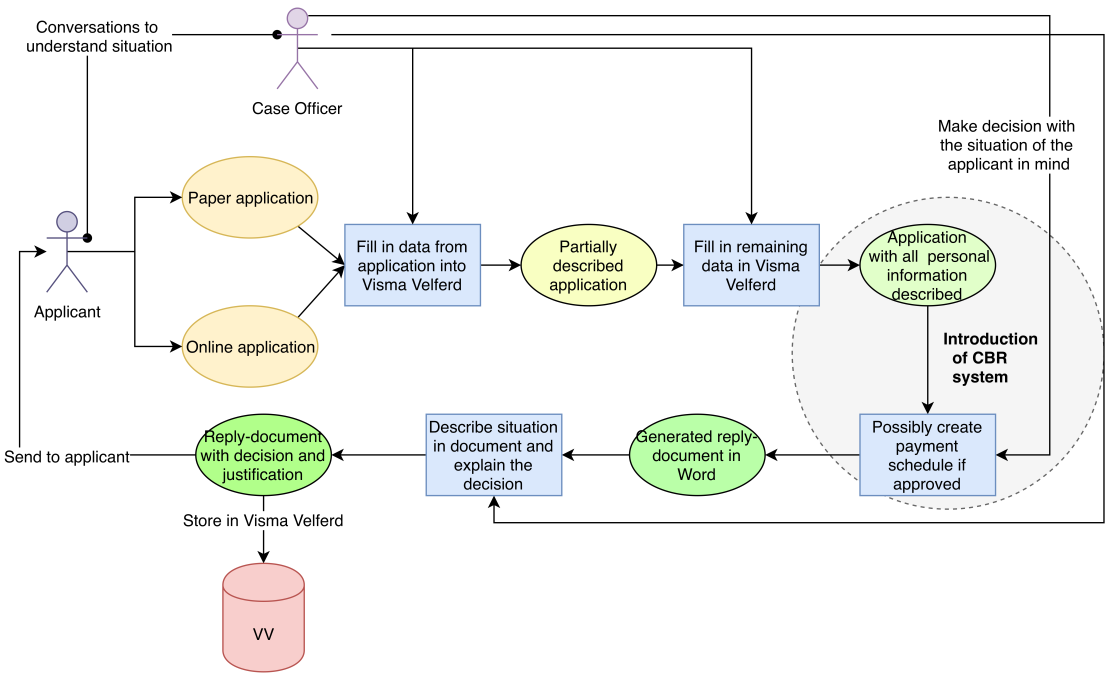

Figure 3.3.: Overview of the social benefit support application process and the use of Visma Velferd during assessment.

In figure 3.3 the evaluation process of social benefit support applications through the information system Visma Velferd is presented. An applicant can either send a social benefit application online or in paper format. Then the information in the application is inserted into Visma Velferd. The case officer will register additional information for the client, based on look-ups in other information systems and talks with the client. Then the case officer makes an overall assessment of the application, and if it is approved, a payment schedule is created. From this, the case officer generates a reply-document template with information such as income and expenses already filled in. The case officer writes additional descriptions of the situation for the client and an explanation for the decision that was made, and the document is returned to the applicant.

The gray circle in figure 3.3 is where we propose the CBR system to be introduced and integrated with the evaluation process. This integration is presented in more detail in figure 3.4. In this case, when all the information is registered in Visma Velferd, it is used to create a CBR case. This CBR case need some additional information related to the situation of the client which is not described in Visma Velferd. This information is much like the information the case officer enters into the generated reply-document which was described at the end of figure 3.3. The CBR case is then used in the CBR system which generates a proposed solution to the current application, which is presented to the case officer. The case officer can then take this suggestion into consideration when he or she makes an assessment of the application.

The task of integrating such a system with the existing Visma Velferd system and other systems is not a trivial task. This was neither a focus during this master thesis, and is left as future work for those in Trondheim Municipality.

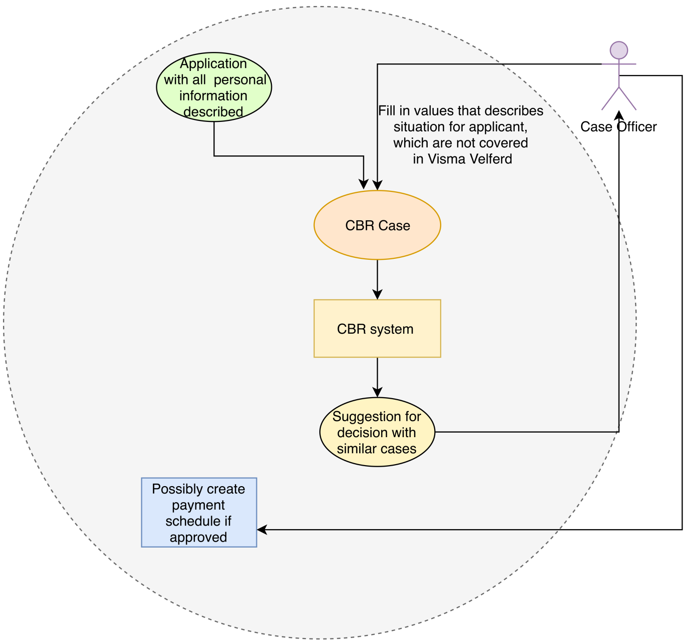

Figure 3.4.: Overview of how the CBR system can be integrated with Visma Velferd.

4. Development Process

In this chapter the development process and the implementation choices will be described. This chapter should work as a description on how a CBR system can be implemented, for this specific domain, from the initial stages of gathering domain knowledge to a finished system. Case-based reasoning is not very generic, meaning that it often requires a lot of implementation choices that are specific to the domain at hand. However, there are certain aspects of the development process that can work as guidelines and tips on how a CBR system can be developed, also in other domains. One such aspect is the process of gathering the necessary domain knowledge in order to make choices regarding the case representation, similarity measures and weights. As mentioned earlier, this is a field of CBR with very little literature available, and this chapter will hopefully fill some of that gap.

In section 4.1 the overall knowledge elicitation methodology is described, together with the initial knowledge elicitation approaches. Then the building of the case representation is described in section 4.2 before section 4.3 presents how the similarity measures were selected. Finally, section 4.4 described how the weights for the global similarity measure were chosen.

4.1. Gather Domain Knowledge

As discussed in section 2.5.1, the domain knowledge is often a crucial aspect when implementing decision support systems with case-based reasoning. In order to understand the domain, knowledge has to be elicited from different sources. As we had considerable little knowledge in the field of social benefit support, certain activities were performed to gain more insight.

4.1.1. Iterative Process

As mentioned earlier, the knowledge acquisition process is very difficult as it consist of a lot of trial and error [13]. Nonaka and Takeuchi talk about how knowledge can be transferred and shared in an organization [25]. They formulate a *SECI-model* that describes the four modes of knowledge conversion, and an illustration of this is shown in figure 4.1. *Socialization* is the process of sharing experiences which is a form of tacit knowledge. *Externalization* is the process of making explicit concepts from the tacit knowledge. In the *combination* phase different explicit knowledge sources are combined and systematized into a knowledge system, which can lead to new explicit knowledge. Finally, in the *internalization* phase, tacit knowledge is gathered from the explicit knowledge now

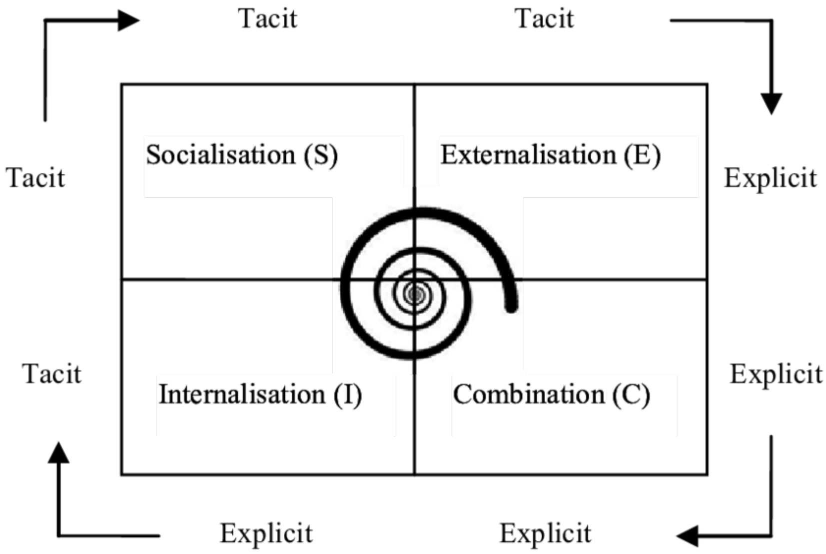

Figure 4.1.: The SECI model. *Source:*[25].

found in documents and manuals etc. The process of knowledge transferring is seen as a spiral, in which individual tacit knowledge must be extracted and made explicit, before this explicit knowledge can lead to new tacit knowledge which once again must be made explicit, and so on. This idea can be transferred to the task of knowledge elicitation for decision support systems. As a novice in the field of social benefit support, it is difficult to ask the right questions to be able to extract the necessary knowledge needed in the CBR system. Therefore, the first attempt to make the tacit knowledge explicit leads to some knowledge in the domain, which makes it easier to ask the correct questions next time. The knowledge elicitation process was therefore performed in an iterative, cyclic manner, in which results and insights from the former attempts helped to formulate more appropriate questions to elicit more information and knowledge.

The overall knowledge elicitation approach used in this project is presented in figure 4.2. In each iteration tacit knowledge is elicited from domain experts, and externalized into a form of explicit knowledge. The new knowledge learned during the elicitation activities and the externalization process is used in subsequent iterations to elicit more knowledge. Each of the iterations will be described in more detail in this chapter.

4.1.2. Semi-Structured Interview

First of all, after reading up on available information online on the field of social benefit support, a meeting with a previous case officer was held, both to gain more knowledge in the field, and to discuss the possibility and usefulness of a decision support system in this field. The meeting took place as a *semi-structured interview*. Semi-structured interviews are partially structured interviews, where the planned questions from the interviewer

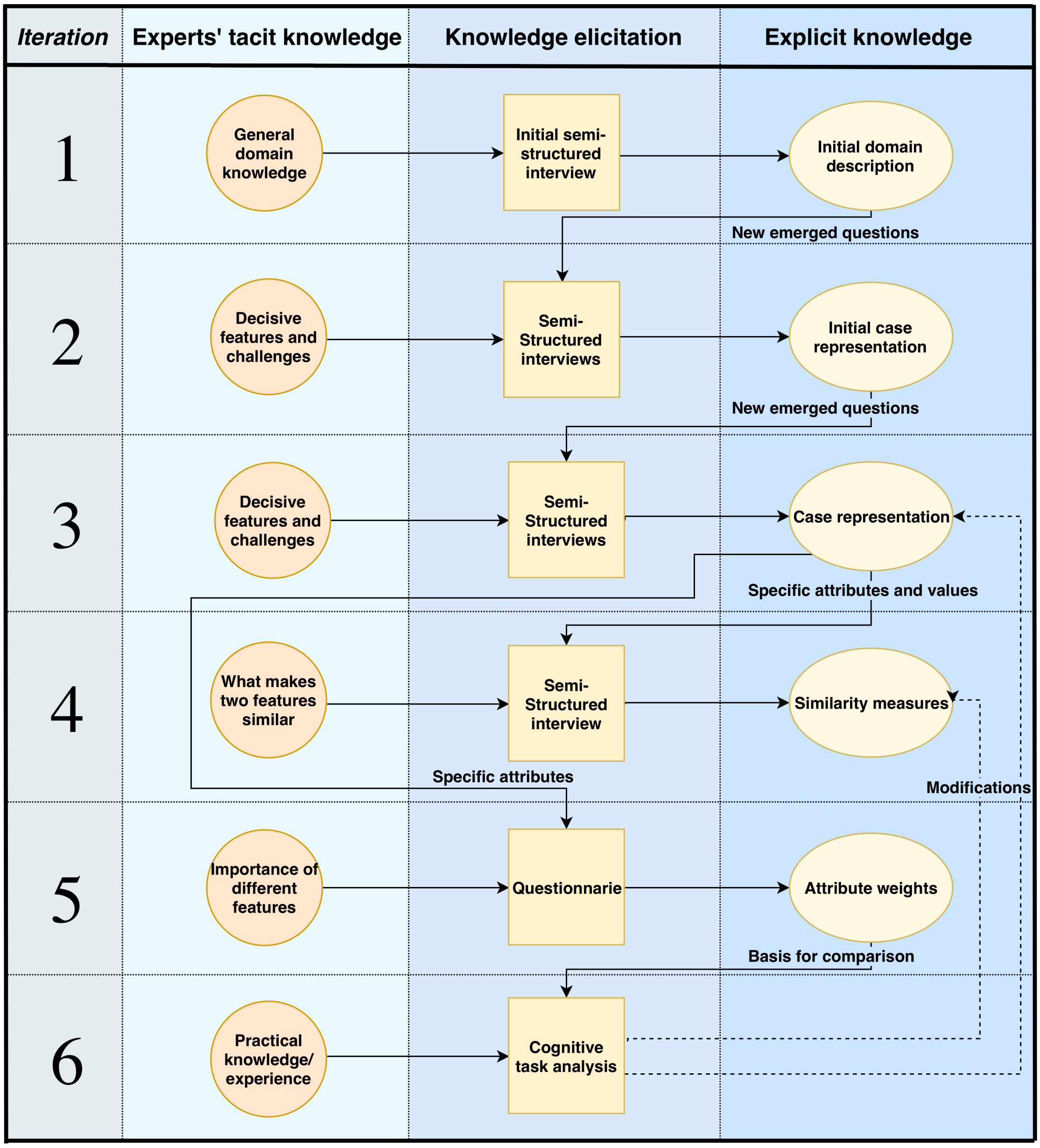

Figure 4.2.: An overview of the knowledge elicitation process used in this project.

often are very open, which can lead to new topics of discussion and new questions [10]. The semi-structured interview was chosen because of the lack of knowledge within the field of social benefit support, which initially made it difficult to ask specific questions to the domain experts. First an introduction was given to the interviewee on the CBR methodology, how it works, and how it could be used to help the case officers during their assessment of social benefit support applications. The following questions were then asked:

- Do you think such a decision support system would be useful?
- What do you think are the most challenging aspects to deal with while developing such a system?
- Is there enough necessary information stored in the existing information systems for such a system?

With respect to the usefulness, the interviewee answered that it could be useful if the system was integrated with the existing information systems as yet another system to use for the case officers would complicate their already busy work schedule. However, she did make us aware that there could be limited documentation available for previously assessed applications, and that this could be a big challenge in the development process. Because the case officers performs individual assessments, and the documentation for why a decision was reached is lacking, it could be difficult too see the differences between two cases, as a key part of the information may be missing from the documentation. As the goal of this master thesis project was to make a proof-of-concept system, the limited documentation for some of the cases was not found as a problem. If the CBR system was to be proven useful, it would perhaps work as a motivating force to improve the documentation routines in the future, as the CBR system should contain cases of high quality to be useful. In addition to the answers given above the interview led to a general knowledge in the field of social benefit support. Further knowledge elicitation activities were performed during the different steps of the implementation process, and these will be described in the subsequent sections.

4.2. Building the Case Representation

The case officers at NAV have a computer program at their disposal when they evaluate the social benefit support applications. In this program all the information necessary to evaluate the applications properly is stored. Due to privacy concerns, the initial data that was used in this project was fictional social benefit clients and applications, rather than real data. The data was retrieved through the same computer program, but from a database that is used during coursing of the case officers, and the data did therefore contain applications which were considered realistic.

With access to the course database, most of the information necessary to build the case base was available. However, some of the information was not necessary to store in the cases, and selecting how the information should be stored and represented in the cases was not a trivial task. The goal was to store only the necessary information needed to evaluate the applications in the cases in order to keep the complexity of the case base to a minimum.

So first, the available information was analyzed in order to select only the strictly necessary attributes for the cases. A course selection was done based on the information found in the help-pages of the program that was used to access the course database. The help-pages contained descriptions on what type of information that was found in the different attributes and fields in the program. A lot of the fields were solely used for either documentation or statistics and were therefore not necessary to represent in the cases. The address, payment method, bank account number etc. were also not necessary to store in the cases. After this initial selection, two semi-structured interviews were performed with employees at Trondheim Municipality, which previously have been working as case officers, to decide on a final case representation. These interviews will now be described more thoroughly.

4.2.1. Semi-Structured Interviews

The semi-structured interviews were conducted in order to gain the necessary domain knowledge needed to be able to represent the social benefit support application correctly, with the correct attributes to describe the case sufficiently. There are certain aspects of the applications which are solely used in a discretion-free calculation of social benefit support, while others are more important when considering if discretion should be used, and to what extent. An additional goal of the first interview was therefore to define the case-based reasoning system that would be the most beneficial for the case officers, which could be developed during the time of this master thesis.

The interviewees were chosen based on the criteria that they had to have large knowledge within the field of social benefit support and evaluation of social benefit support applications. In addition it was also important that the interviewees were available within a reasonable short time, as the interview laid the ground work for further development of the case based reasoning system. Therefore we chose to interview one employee at Trondheim Municipality which we previously had contact with during the project, as she was easier to get in touch with than for example case officers at the different NAV-offices in Trondheim. The chosen employee from Trondheim Municipality does regular reviews of some of the social benefit applications, in order to ensure that they are properly evaluated. Therefore, she had a lot of knowledge within the field of social benefit applications, and was considered to be able to answer the questions we had. However, she was not able to answer all questions, and therefore a second interview was arranged. The second interview was with an employee who worked part time at Trondheim Municipality and part time at NAV, and she had therefore more recent experience as a case officer.

As the questions we wanted answers to were directly related to the development of the case based reasoning system, it was important that the interviewees had some knowledge about the case based reasoning system, how it worked and its purpose. Therefore the interview started with a short introduction of the situation and problem at hand in order to give the interviewees more context which hopefully would make their answers more precise and useful for the specific purpose. The questions that were asked for the two interviews can be seen in Appendix B.1 and Appendix B.2. All the questions were more or less related to the two main goals for the interviews:

- Should the CBR system cover all cases, or just those where the use of discretion is necessary?
- Which attributes should be represented in the CBR system in order for it to fulfill its purpose?

Regarding the first question the interviewees stated that discretion often was used during the entire evaluation process, as the application should be evaluated based on an overall assessment. However, the applications for additional supplements must always be evaluated with the use of discretion. In contrast, applications for monthly support are often calculated according to a norm that takes into consideration aspects such as the age, family situation and living situation of the client. However, there may still be used discretion, for example when deciding on what type of income and expenses that should be accepted and used in the calculation of the norm. The use of discretion could in some situations be challenging, and there were occasionally discussions amongst case officers for difficult cases. These cases often consisted of clients who had severe health, psychological or intoxication issues. So although they were not actually eligible for social benefit support, they were often given support because of the lack of other options, and the consequences it would have to not grant them benefits.

Based on the answers from the interviews it was chosen to limit the scope of the CBR system to decisions on additional supplement benefits. The reason for this was that these applications had to be evaluated with the use of discretion, and the interviewees believed that the biggest differences between case officers would occur for these types of applications. With this in mind a case representation was build based on the attributes that were necessary according to the interviewees. The necessary attributes were identified and selected from the initial selection of attributes made from the help-pages described above. The interviewees were also asked if there were any additional attributes, that were not described in the initial selection of attributes, that should be represented. The resulting case representation was presented in section 3.1.

4.3. Select Similarity Measures

The next step after the case representation was chosen, was to decide how the cases should be compared to one another, i.e. define the similarity measures. This task does also require domain knowledge in order to know what it is that makes two social benefit applications similar. Is it for example the family members or the previous applications? This domain knowledge was also gathered through a semi-structured interview with the same employee as the last semi-structured interview described above. As we now had decided on a case representation it was easier to ask specific questions for each individual attribute in the representation, on how their values should be compared and the similarity calculated.

For the interviewee, the task of changing the mindset from how one assess the applications to how one could compare cases was difficult. Due to the complexity of the applications and the fact that the applications and situations of the client can be very different it was difficult to specify general rules on how they could be compared. During the interview it was clear that defining the similarity measures was not a trivial task. Although the interviewee was not able to specifically specify how many of the attributes should be compared, discussions of the attributes and their possible values gave us a lot of knowledge and information. This knowledge was then, to the best of our ability, made explicit as similarity measures in the CBR system. Later knowledge elicitation techniques and discussions led to further improvement and changes to the similarity measures. How the individual attributes are compared is considered universal amongst the case officers, and therefore it was considered sufficient to interview one case officer.

4.4. Select Weights for Global Similarity Measure

As the concern is that similar cases are not evaluated equally by the different case officers, it is reasonable to believe that the importance of the different attributes in the evaluation may be different amongst the case officers. In order for the case-based reasoning system to have weights that represents the most common beliefs of the case officers, a questionnaire was used to gather the opinions of multiple case officers in Trondheim. The entire process of selecting the weights is shown in figure 4.3. First the questions to be asked in the questionnaire were identified, before the questionnaire was sent to a number of participants. Then the results from the questionnaire were aggregated and used as weights in the CBR system. Finally the retrieval process in the CBR system was evaluated and tested.

Figure 4.3.: The process of setting weights for the global similarity measure.

4.4.1. Identification of Questions

The aim of the questionnaire was to select the weights for the different attributes in the case representation, indicating how big impact the different attributes have on the evaluation. To elicit this knowledge, the questionnaire consisted of questions asking to set a single value (between 0-10), representing the importance of the attribute, for each specific attribute in the chosen case representation. The participants did also have the possibility to specify additional attributes not mentioned in the case representation, and whether or not they had made any assumptions while answering. In addition to this, the participants were also asked how long they had worked as case officers, and how difficult they experienced it to be to select weights for the attributes on a scale from 1 (very easy) to 5 (very difficult).

4.4.2. Questionnaire

The questionnaire was presented during the interview for the similarity measures mentioned above. This was done to ensure decent quality and to make sure that the questions were understandable and easy to answer for the case officers. This was not easy to accomplish, as the weights may vary based on the application and situation of the applicant. Because of this a limited number (eight) of case officers were chosen to answer the questionnaire, to see if the results were useful. Six out of the eight case officers who received the questionnaire responded. The results from the questionnaire can be seen in table 4.1. The key results from the survey is that attributes such as *income*, *expenses* and *children* are considered very important. On the other hand, *age* and *living situation* are attributes that are not considered as important during the assessment process. Other than this, the weights were quite different amongst some of the case officers, and 5 out

	Officer #1	Officer #2	Officer #3	Officer #4	Officer #5	Officer #6
Experience (years)	11	4	7	21	20	2
Difficulty of answering*	4	4	5	2	4	5
Age	0	1	6	0	2	-
Living situation	3	4	9	1	2	-
Single provider	2	5	7	5	2	-
Children	6	8	9	10	2	10
Income	8	9	10	10	8	10
Expenses	6	8	9	10	7	10
Partner	8	5	7	5	2	-
Prev. applications	3	5	9	8	7	5
Norm	3	2	8	7	6	-
Calculated norm	6	5	8	10	7	-
Health	6	7	9	10	7	-
Clients effort	5	5	7	5	6	-
Necessity	3	7	9	8	8	-
Consequence of disapproval	6	6	10	10	6	8

* 1=Very easy, 5=Very difficult

Table 4.1.: Results from questionnaire for weight selection.

of 6 participants stated that it was either difficult or very difficult to select specific weights for the different attributes.

As the case officers experienced it to be difficult to set specific weights for the attributes, a suggestion was made to let them evaluate specific cases during a new questionnaire as the weights may vary for different types of applications. However, they still thought it would be difficult to set weights for specific cases because they perform an overall assessment of the application and the situation of the applicant. It was therefore chosen to not have another questionnaire. Instead a meeting with a case officer was held to review a limited number of example-cases during a *cognitive task analysis* activity. This is described further in section 4.4.4.

4.4.3. Aggregation of Results from Questionnaire

With all the answers to the questionnaire registered, the next task was to aggregate the results to find a proper weight for the different attributes. But how should this be done? Should the opinion of each case officer be equally decisive, or should one emphasize the opinions of the experienced case officers compared to the less experienced case officers? Should one use the average chosen weight, the median weight or the weight with the highest number of votes? All this questions were taken into account, and in this project the focus was on how the weights were different amongst case officers rather than to try an advanced aggregation method. Instead of aggregating the results into a single weighting schema, the weighting made by the different case officers were used in individual instances of the CBR system. When performing a query to the CBR system it does calculate the similarities for all the different weighting schemas and presents it to the user. With this approach it is possible to see how the queried case would be evaluated by different case officers. If it is large diversity in the similar cases than it would mean that the query case is a difficult case to evaluate, and therefore the user can be recommended to perform a thorough evaluation, possibly in cooperation with other case officers. If the proposed similar cases are equal, then the system is confident in its suggested solutions and the query is considered as a easy case to evaluate. With this approach it is also easy to evaluate the differences amongst case officers, as each CBR instance is created with the weights of individual case officers and therefore reflects their decisions. This evaluation will be described in section 5.1.

4.4.4. Cognitive Task Analysis

Due to the difficulties of selecting specific weights for the different attributes in a questionnaire, a *cognitive task analysis* activity was held with the case officer working at Trondheim Municipality and NAV. In this activity the case officer had 4 examples of social benefit support applications and was asked to evaluate them while explaining her reasoning process and thoughts. In this task it was decided to not try to set specific weights from the observations and results, but instead to try to make a flow-chart of the reasoning process of the case officer. This was also a challenging task, especially to

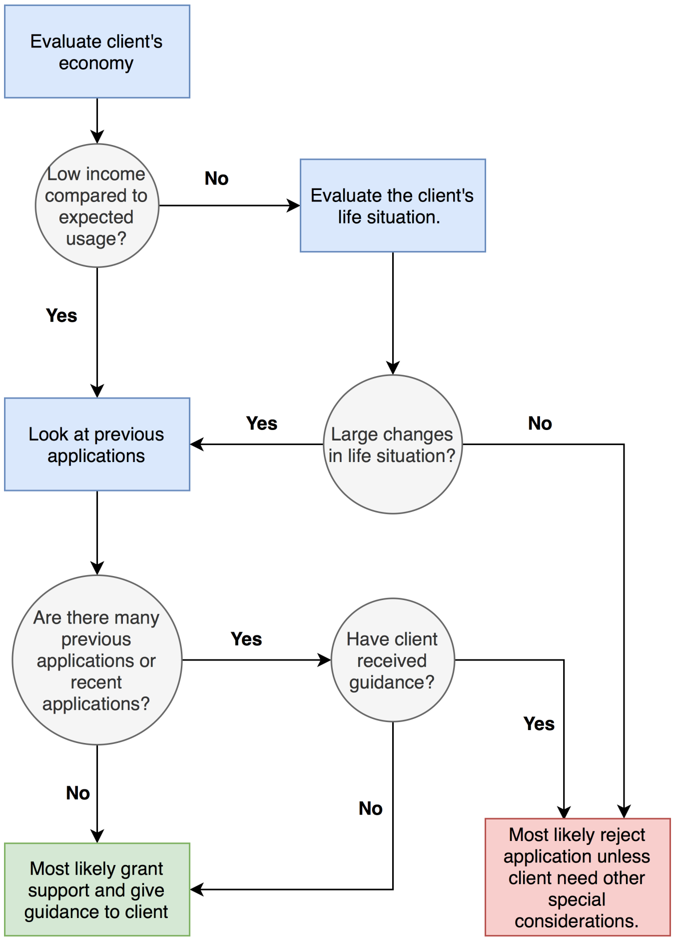

Figure 4.4.: A flow chart of the generalized reasoning during the evaluation of applications made by the case officers.

make it a detailed flow chart. The resulting flow chart is presented in figure 4.4, but this is a simplified description of the evaluation process and should not be strictly followed in all cases. Some clients may have special needs or life situations, and in such situations this reasoning process may not be applicable. On a very general basis the reasoning is as follows: first the economical aspect is evaluated, such as income, expenses and what amount of money the client and his/her family are expected to use. If the client has very low income compared to expected usage (below norm), then it is reasonable to believe that the client has difficulties to pay unexpected expenses, and therefore the additional social benefit support is often granted. On the other hand, if the client does not have very high expected usage compared to income, than a more special reason is necessary. This can often be changes in the living situations, such as separation or relocation. Hence, **changes** are more decisive during evaluation rather than just the current situation of the applicant. This was a aspect not identified earlier which had to be considered in the CBR system. After evaluating the situation of the client and his/her family, earlier applications are analyzed to see if the current application is a repeating pattern or a one time situation. If it is a repeating pattern it is necessary that the client has received guidance in how to avoid ending up in the same situation again. If this has been given, the application will most likely not be granted. However, there are exceptions. For example, a mentally ill client may not be able to follow the guideline given by the case officers, and the consequences of not helping them will be larger than granting these repeating applications.

During this cognitive task analysis activity it was identified that large changes in the life situation of the client, such as separation or moving, could have a large impact on how a case officer evaluate an application. The attributes *recently moved* and *recently single* were therefore added to the case representation. An option could have been to let this information be stated in the description attribute as context. However, this was not chosen because it would have put more work on the case officers who would have needed to explore the descriptions in order to rule out the cases that are not so similar after all. Adding these as separate attributes is therefore in accordance with the desired *distinguishability* property mentioned in section 2.5.2. As these attributes were not part of the questionnaire for the weighting of the attributes, it was chosen, based on the information from the cognitive task analysis, to set their weights to 10.

4.4.5. Evaluation Activity

After the cognitive task analysis, the case officers who participated in the questionnaire were asked to evaluate two of the social benefit applications that were used in the cognitive task analysis. This was done for two purposes. To see if the case officers evaluated the cases in the same way as the participant in the cognitive task analysis or not. And to see if the differences in their choices of weights are also reflected in specific evaluation of applications. Due to their busy work days, only one case officers evaluated both the cases, while a second case officer evaluated just one of them. The evaluated applications consisted of multiple supplement types and the answers given by the case officers will now be presented.

For the first case it was applied for both clothes for a child and two travel cards, and the following answers were given by the different case officers:

- "Approves clothes with 1000 kr for child starting in kindergarten, and two travel cards with 1520 kr." [Experience: 20 years]
- "If the child is starting in kindergarten in only a few weeks the application for clothes would be approved. But if its not, then I would not approve money for clothes as the mother soon will receive introduction support and their economy would then be above the norm. Travel cards would neither be approved as the economy of the family will be better in a short time." [Experience: 21 years]

In the other case it was applied for clothes for a child and money for a new dishwasher and a washing machine as they are both broken. The following answers were given by three different case officers:

- "Approves clothes with 1500 kr as a lot is necessary at the moment. Approves households goods money with 4000 kr which should be enough to buy a used dishwasher and washing machine." [Experience: 20 years]
- "Approves money for clothes (amount not specified) as a lot is necessary at the moment. Approves money for dishwasher and washing machine with an amount based on cheapest alternatives in stores." [Experience: 21 years]
- "Approves clothes with 1500 kr. Approves 2000 kr for washing machine as the dishwasher is not evaluated as strictly necessary." [Experience: 11 years]

From these answers it is clear the there are differences amongst case officers. In the first case the client and his/her family are soon experiencing changes in their life situation as the mother in the family soon will start on introduction courses and receive introduction support[1]. The case officers have evaluated the necessity of support up until that point differently. This does also support that attributes regarding changes in the life situation of the client could be a improvement to the case representation. As this was not in the case representation used during the questionnaire, it is difficult to address whether or not the decisions made by the case officers reflects the weights they had given.

In the second case they have all evaluated the application for clothes equally. Regarding the dishwasher and washing machine there were some differences, both on what was strictly necessary and if the client should buy new or old equipment. Whether it is strictly necessary or if one should buy new or old is not connected to any attributes or weights in the case representation, and the differences in the decisions does therefore not seem to come from how they have weighted the attributes in the case representation. Personal beliefs on the necessity of certain equipment and whether or not it is cheapest to buy new or old are the reason for the differences in this case. The result from this evaluation activity will be discussed further in section 5.2.

4.4.6. Weight Maintenance

Although the methods described above led to an initial set of weights, it does not ensure that there does not exist small improvements that can be made to the weight settings. In addition, changes in social benefit support, for example an overall increased focus on children can change the real life "weights". Therefore it is also important to do weight maintenance to both improve the quality and to adapt to changes.

Introspective learning is a technique that has been used for maintenance of the similarity weights in CBR. If the retrieval process returns a CBR case that is not truly similar to the

[1]The introduction program is a program for newly arrived foreign nationals who need to learn and obtain basic qualifications. Participants in the program will receive economical support.[27]

query case the reason may be a poor model of similarity, in particular incorrect weighting of features. In introspective learning, two basic learning techniques are used: *failure-driven* and *success-driven* [7]. The failure-driven method updates attribute weights as a result of a retrieval failure, while the success-driven method updates the weights when the retrieval is correct. Based on this, four different learning policies are possible:

- There has been a retrieval *success* and the weights of *matching* attributes are *increased.*
- These has been a retrieval *success* and the weights of *unmatching* attributes are *decreased.*
- There has been a retrieval *failure* and the weights of *unmatching* attributes are *increased.*
- There has been a retrieval *failure* and the weights of *matching* attributes are *decreased.*

This technique has been used to improve the retrieval process in CBR for both air traffic control [7] and fault diagnosis for rail turnout system [47]. This has not been implemented during this master thesis, but is left as future work as it would be beneficial to both improve the weights and be able to adapt to changes in the social benefit support domain.

5. Testing and Evaluation

In this chapter the CBR system is tested and evaluated. Section 5.1 presents the methodology that have been used to test the system and the results, before the results and the system are discussed in section 5.2.

5.1. Testing and Results

During testing of the decision support system a case base of 14 cases was used. Nine of the 14 cases were from the course database (i.e. fictional cases), while the remaining five were anonymized cases from the real database. The anonymized cases were added to improve the quality and size of the case base before testing. However, with such a small case base considering the large amount of possible choices in the case representation, it was difficult to do a large scale and thorough testing of the system. As the system was initialized with five different weight schemas representing the choices of different case officers, the main goal of the testing was to evaluate how this affected the suggestions made by the different CBR instances.

Out of the 14 cases, one case applied for supplements for dentist, two for travel card, two for food money, two for expenses related to housing and housing goods, and the last seven cases were applications under the category "Support, other purposes" (mainly clothes). New query cases (i.e. the new case that should be compared to previous cases) were generated by performing minor modifications to some of the existing cases. As the case for dentist support is not of a supplemental benefit type similar to any of the others, all CBR instances would retrieve this as their suggestion to a new application for dentist support, so this category was not tested further. For the other categories retrieval was performed for generated query cases, and the results from the retrievals will now be presented. Tests of supplements for expenses related to housing and housing goods did not reveal any new results or insights that the other tests did not reveal, and the results for this supplement type will therefore not be presented.

5.1.1. Supplement: Travel Card

For the test of travel card supplements the query case was generated by performing small modifications to the information in application number 12 in the case base. The resulting suggestions made by the different CBR instances representing the different case officers' weights are presented in table 5.1. As seen in this table, all the CBR instances retrieve the same two most similar applications, in the same order. The third suggestion has similarity 0, indicating that it is not of the same supplement type as the queried

	Suggestion #1			Suggestion #2			Suggestion #3		
CBR Instance	Amount	App.	Sim.	Amount	App.	Sim.	Amount	App.	Sim.
CBR Instance #1	760	#12	0.76	1520	#9	0.52	5000	#6	0.0
CBR Instance #2	760	#12	0.78	1520	#9	0.57	5000	#6	0.0
CBR Instance #3	760	#12	0.78	1520	#9	0.62	5000	#6	0.0
CBR Instance #4	760	#12	0.78	1520	#9	0.54	5000	#6	0.0
CBR Instance #5	760	#12	0.74	1520	#9	0.64	5000	#6	0.0

Table 5.1.: Retrieval results from query for travel card supplement

case. The differences in weights did not have an impact on the suggestions in this case. However, the second suggestions differ in similarity from 0.52 to 0.64 between the CBR instances. If the case base contained more cases the suggestions made by for example instance 1 and 5 could have been different, as a different case likely could get a similarity value between 0.52 and 0.64. The outputted similarity table for each of the CBR instances, representing the choices of the case officers, can be seen in Appendix C.1. In table 5.2 the contribution of each attribute to the total weight is presented for

Attribute	Case officer #1	Case officer #5
Prev. supplements	0,03	0,08
Health	0,0	0,0
Calculated norm	0,01	0,01
Necessity	0,03	0,09
Consequence	0,06	0,05
Living situation	0,03	0,02
Single provider	0,02	0,02
Clients effort	0,05	0,05
Recently single	0,11	0,11
Norm	0,03	0,07
Recently moved	0,11	0,11
Children	0,0	0,0
Total income	0,01	0,01
Partner	0,0	0,0
Total expenses	0,01	0,01
Age	0,0	0,02
Sum	0.52	0.64

Table 5.2.: The contribution to the similarity for each attribute for case instances representing case officer #1 and #5, for travel card query.

case officer instance 1 and 5. The contribution from each attribute is calculated as

$$attribute\ contribution = \frac{attribute\ weight\ *\ attribute\ similarity}{weight\ sum}.$$

This shows that the large difference in similarity between these two case officers is largely caused by the differences in the weights of the attributes: *previous supplements*, *necessity* and *norm*.

5.1.2. Supplement: Food Money

The results for the query case for food money supplements, seen in table 5.3 showed much of the same results as for the travel card case. The CBR instances suggests the same cases in the same order. However, the difference in similarity between these two cases is not as large as for the travel card case. In addition, the difference in the amount paid for the two suggested cases is quite large. It is therefore a good idea to take a more thorough look at the similarity tables to compare them. The similarity table for CBR instance number four, which had the smallest difference in similarity between the two cases, is seen in table 5.4. The similarity table for the other CBR instances can be found in Appendix C.2. The main differences between application number 4 and 6 is their family situation and income. Although it can seem odd that the client with the highest income receives the highest supplement for food money, it is important to consider that aspects such as the length until the next payment is not described here. The food money supplement is calculated based on how much the client and his/her family are expected to use until the next payment. Therefore, as the client in application 6 has one more children and also a partner, he or she may need more in supplements depending on the length until next payment.

	Suggestion #1			Suggestion #2			Suggestion #3		
CBR Instance	Amount	App.	Sim.	Amount	App.	Sim.	Amount	App.	Sim.
CBR Instance #1	1000	#4	0.77	5000	#6	0.70	1400	#7	0.0
CBR Instance #2	1000	#4	0.78	5000	#6	0.71	1400	#7	0.0
CBR Instance #3	1000	#4	0.80	5000	#6	0.73	1400	#7	0.0
CBR Instance #4	1000	#4	0.76	5000	#6	0.72	1400	#7	0.0
CBR Instance #5	1000	#4	0.81	5000	#6	0.77	1400	#7	0.0

Table 5.3.: Retrieval results from query for food money supplement

Attribute (Weight)	Query Case	1. best match (Sim.)	2. best match (Sim.)	3. best match (Sim.)
Name (0)	Query	Application #4	Application #6	Application #7
Similarity	-	0.765	0.722	0.0
Sup. Amount (0)		1000	5000	1400
Sup. Type (0)	Food money	Food money (1.0)	Food money (1.0)	Dentist (0.0)
Description	Used all of the food money.	Food money, jobseeker	Have spent all of the food money before next payment	
Prev. Supplements (8)	None	None (1.0)	None (1.0)	None (1.0)
Health (10)	No challenges	No challenges (1.0)	No challenges (1.0)	No challenges (1.0)
Calculated norm (10)	-2300	10480 (0.02)	-2145 (0.96)	8300 (0.05)
Necessity (8)	Large	Large (1.0)	Very large (0.8)	Large (1.0)
Consequence (10)	Large	Large (1.0)	Large (1.0)	Small (0.6)
Living situation (1)	Rent municipal house	Rent private market (0.8)	Rent municipal house (1.0)	Rent private market (0.8)
Single provider (5)	Yes	Yes (1.0)	No (0.0)	No (0.0)
Clients effort (5)	Big	Big (1.0)	Average (0.8)	Big (1.0)
Recently single (10)	No	No(1.0)	No(1.0)	No(1.0)
Norm (7)	Long term	Long term (1.0)	Short term (0.5)	Long term (1.0)
Recently moved (10)	No	No (1.0)	No (1.0)	No (1.0)
Children (10)	Children #14	Children #10 (0.4)	Children # 11, Children #8 (0.75)	None (0.0)
Total income (10)	14500	5940 (0.05)	24050 (0.03)	2800 (0.01)
Partner (5)	No	No (1.0)	Yes (0.0)	No (1.0)
Total expenses (10)	7000	8000 (0.75)	9000 (0.56)	5250 (0.6)
Age (0)	32	29 (-)	59(-)	31(-)

Table 5.4.: The similarity table for CBR instance #4 for the query on supplements for food money

The usefulness of the decision support system in this particular situation is therefore limited, as the food money supplement is calculated from family-size and days until payment. However, consider a situation where the client in application 6 once again apply for food money supplements, one month after the previous application. With their high income, this is a situation they should be capable of avoiding, and repeating occasions of such applications may be an indication of exploitation of the social benefit support system. But when is the time to reject the application, and what should one tell the clients to do if they do not have money for the next two weeks or so? In such a situation the decision support system would be useful, especially to inexperienced case officers, with more cases showing possible replies for such cases.

5.1.3. Supplement: Other Purposes

As seven out of the fourteen cases in the case base were applications for supplements for other purposes, multiple tests were performed to evaluate the CBR system for this particular supplement category. The first test was a query for an "average" client with one child, a partner, a small income and rent as approved expenses, applying for supplements for clothes to the child. The result from this query is presented in table 5.5. As seen from the results, there is a little more variations in the suggestions made by the different CBR instances than for the earlier tests for other supplement types. However, the differences are only found in the first three suggestions, and there are only small differences in similarities between the different cases for all the CBR instances. Three out of the four first suggested cases by all of the case officers suggest an amount of 1500 while the last case suggest an amount of 3000. By taking a look at the context descriptions for the different cases, seen in figure 5.1, the reason for this difference is

		CBR Instance #1	CBR Instance #2	CBR Instance #3	CBR Instance #4	CBR Instance #5
Suggestion # 1	Amount App. Sim.	1500 #8 0.78	1500 #8 0.79	1500 #8 0.79	1500 #8 0.74	1500 #2 0.77
Suggestion # 2	Amount App. Sim.	1500 #2 0.72	3000 #3 0.72	3000 #3 0.76	3000 #3 0.70	1500 #8 0.76
Suggestion # 3	Amount App. Sim.	3000 #3 0.72	1500 #2 0.72	1500 #2 0.76	1500 #2 0.69	3000 #3 0.76
Suggestion # 4	Amount App. Sim.	1500 #0 0.72	1500 #0 0.71	1500 #0 0.75	1500 #0 0.69	1500 #0 0.75
Suggestion # 5	Amount App. Sim.	1000 #10 0.70	1000 #10 0.69	1000 #10 0.72	1000 #10 0.68	1000 #10 0.71
Suggestion # 6	Amount App. Sim.	0 #5 0.55	0 #5 0.59	0 #5 0.61	0 #5 0.55	0 #5 0.63
Suggestion # 7	Amount App. Sim.	1500 #13 0.49	1500 #13 0.55	1500 #13 0.58	1500 #13 0.54	1500 #13 0.59

Table 5.5.: Retrieval results from the first query for supplement: other purposes.

In App. #2 the amount of 1500kr was given in the following situation: *Clothes*
In App. #3 the amount of 3000kr was given in the following situation: *Summer clothes for the entire familiy*
In App. #8 the amount of 1500kr was given in the following situation: *Clothes, has lost weight and needs a lot of new clothes because of this*
In App. #10 the amount of 1000kr was given in the following situation: *Clothes, client has had low income for a long time.*
In App. #0 the amount of 1500kr was given in the following situation: *Clothes. Wife is encouraged to apply for a job, she has some health challenges (not documented)*
In App. #5 the amount of 0kr was given in the following situation: *Keyboard*
In App. #13 the amount of 1500kr was given in the following situation: *Winter clothes. Granted by §19.*

The most similar case is App. #8 with a 100.0% agreement amongst the CBR instances. The amount of 1500kr is recommended in the following situation: *Clothes, has lost weight and needs a lot of new clothes because of this*

Figure 5.1.: Context description for the retrieval results of the first query for supplement other purposes.

found. The descriptions for the different cases reveal that application number 3, which accepted an amount of 3000, is supplements for clothes to the entire family, while the other applications are for clothes for a single person. Therefore, as the query case also applies for clothes for a single person, an amount of 1500 seems fair. The similarity table for all of the CBR instances can be found in Appendix C.3.1.

From table 5.5 we can also see that both the third and fifth case officer-instance suggests four cases that are considered more similar than the best case suggested by case officer number four. So what are the reasons for these low similarities for case officer number four? In table 5.6 the contribution for each attribute of application #8 is presented for all case officer-instances. From this table we can see that there is no single attribute that is the reason for the differences between case officer #4 and all the other instances. For case officer #1 it is mainly the *partner*, *recently single* and *recently moved* attributes that are different. *Recently single* and *recently moved* are also the biggest difference to case officer #5, while case officer #2 does not have any differences that stands out. For case officer #3 it is mainly the *living situation* and *age* that causes the differences to case officer #4. Hence, the low similarities of case officer #4 can not be explained by a single factor.

Attribute	Case officer #1	Case officer #2	Case officer #3	Case officer #4	Case officer #5
Prev. supplements	0,03	0,05	0,07	0,07	0,08
Health	0,07	0,07	0,07	0,08	0,08
Calculated norm	0,0	0,0	0,0	0,0	0,0
Necessity	0,03	0,05	0,05	0,05	0,07
Consequence	0,05	0,05	0,06	0,07	0,05
Living situation	0,03	0,04	0,07	0,01	0,02
Single provider	0,02	0,05	0,05	0,04	0,02
Clients effort	0,06	0,05	0,05	0,04	0,07
Recently single	0,11	0,10	0,07	0,08	0,11
Norm	0,02	0,01	0,03	0,03	0,03
Recently moved	0,11	0,10	0,07	0,08	0,11
Children	0,04	0,05	0,04	0,05	0,01
Total income	0,0	0,0	0,0	0,0	0,0
Partner	0,09	0,05	0,05	0,04	0,02
Total expenses	0,09	0,09	0,07	0,08	0,08
Age	0,0	0,01	0,04	0,0	0,02
Sum	0.78	0.79	0,79	0,74	0,76

Table 5.6.: The contribution to the similarity for each attribute for all CBR instances for application #8, for first query on supplements other purposes.

As six out of the seven cases for "supplement: other purposes" were applications for supplements for clothes it could probably be added a new category to supplements for clothes. The second test for supplements for other purposes was a query created by modifications to application number 5 which is an application for supplements for a new keyboard. The results from this query, as seen in table 5.7, is as expected, with application number 5 as the clearly most similar for all CBR instances. As the query case has an economical situation where it is calculated that the client should be able to be economically self reliant according the the calculated norm, similar to application number 5, the suggested solution is to reject the application and encourage the client to save money on a monthly basis to be able to afford equipment such as a keyboard. The similarities for the different CBR instances is also very similar for application number 5, as this is the single case in the case base where the client should, according to the calculated norm, be able to be economically self reliant. The similarity table for all of the CBR instances can be found in Appendix C.3.2.

		CBR Instance #1	CBR Instance #2	CBR Instance #3	CBR Instance #4	CBR Instance #5
Suggestion # 1	Amount App. Sim.	0 #5 0.88	0 #5 0.89	0 #5 0.90	0 #5 0.88	0 #5 0.89
Suggestion # 2	Amount App. Sim.	1500 #8 0.61	1500 #8 0.67	1500 #8 0.70	1500 #8 0.65	1500 #8 0.72
Suggestion # 3	Amount App. Sim.	1500 #2 0.60	1500 #2 0.65	1500 #2 0.65	1500 #2 0.60	1500 #0 0.64
Suggestion # 4	Amount App. Sim.	1500 #13 0.60	1500 #0 0.65	1500 #0 0.65	1500 #13 0.60	1500 #2 0.63
Suggestion # 5	Amount App. Sim.	1500 #0 0.59	1500 #13 0.62	1500 #13 0.64	1500 #0 0.60	3000 #3 0.60
Suggestion # 6	Amount App. Sim.	3000 #3 0.51	3000 #3 0.55	3000 #3 0.57	3000 #3 0.51	1500 #13 0.56
Suggestion # 7	Amount App. Sim.	1000 #10 0.43	1000 #10 0.48	1000 #10 0.5	1000 #10 0.43	1000 #10 0.52

Table 5.7.: Retrieval results from the second query for supplement: other purposes.

5.2. Discussion

5.2.1. Differences Amongst Case Officers

Based on the results described above, the first research question (RQ1) will be evaluated: To what extent does subjectivity, caused by differences in experience or personal beliefs, lead to inconsistent evaluation of social benefit applications amongst different case officers?

The testing of the CBR system showed little differences in the suggestions made by the different CBR instances that reflects the decision of the different case officers. This may be a indication that the differences in weight-allocation, found in table 5.8, are actually not that large. However, as mentioned earlier the case base used during testing consisted of only 14 cases, in which a maximum of seven cases were of the same supplement type. Therefore the different case officer-instances does not have many cases to "choose" from when retrieving similar cases, which could be the reason for why many of the suggestions were equal. As described in 5.1, some of the similarities for the same suggestions were quite different, and therefore it is reasonable to believe that there could be more differences in the suggestions with a larger case base.

As mentioned in section 4.4.4 the *recently moved* and *recently single* attributes were added to the case representation after the questionnaire that was used to set weights for the attributes was held. Therefore, these two attributes have the same weighting for all the CBR instances with a weight value of 10. For the majority of the cases these two attributes are often false, which means that these attributes often will make up a equal amount of the total similarity for many of the the CBR instances. This could be a contributing factor to the small observed differences in the similarities between the CBR instances and also between the cases. The case officers have stated that it was difficult to select the weights for the attributes as what they take into consideration depends on the type of application. For example, the *recently moved* attribute is important when evaluating supplements for households goods because a client who recently has moved is more likely to need more furniture than someone who already has a place to live. Therefore, it could be better to also have weights that are dependent on the application type or context. In that case, attributes like *recently moved* will only have an impact when they are actually important in the assessment process. However, this is an even more difficult and more time consuming task than selecting one set of similarities for the CBR system, as one has to consider multiple contexts and application types. Because of this it was not implemented during this master thesis, but can perhaps be something worth pursuing for future work and improvements.

Another hypothesis for why the observed differences were small is that the weights are actually not that different when they are re-scaled to the same value range. Some of the case officers used the entire scale from 0 to 10 to set weights while other only used a subset of the value range. Therefore the differences may not be that large when the weights are considered as relative which is the case in CBR, rather than absolute. In table 5.8, the numbers in the brackets are the weights re-scaled to numbers between 1 and 10, except for the numbers 0 which indicate that the case officers do not consider this attribute during assessments. To evaluate the differences amongst the case officers the standard deviation was calculated for the weights of the individual attributes. The standard deviation for both the original and re-scaled weights can be seen in the final column in table 5.8. The number in the brackets is the value for the re-scaled weights. This shows that the average standard deviation is smaller for the re-scaled weights, with a reduction of 6%. This is not a very large decrease, and the relative difference can therefore not explain the low differences in suggestions alone, despite the differences found in the weighting schemas.

	Officer #1	Officer #2	Officer #3	Officer #4	Officer #5	Officer #6	SD
Experience (years)	11	4	7	21	20	2	
Difficulty of answering*	4	4	5	2	4	5	
Age	0 (0)	1 (1)	6 (1)	0 (0)	2 (1)	-	2.23 (0.49)
Living situation	3 (2.5)	4 (4.4)	9 (7.8)	1 (1)	2 (1)	-	2.79 (2.56)
Single provider	2 (1)	5 (5.5)	7 (3.3)	5 (5)	2 (1)	-	1.94 (1.91)
Children	6 (7)	8 (8.9)	9 (7.8)	10(10)	2 (1)	10(10)	2.81 (3.08)
Income	8 (10)	9 (10)	10(10)	10(10)	8 (10)	10(10)	0.90 (0)
Expenses	6 (7)	8 (8.9)	9 (7.8)	10(10)	7 (8.5)	10(10)	1.49 (1.09)
Partner	8 (10)	5 (5.5)	7 (3.3)	5 (5)	2 (1)	-	2.33 (2.97)
Prev. applications	3 (2.5)	5 (5.5)	9 (7.8)	8 (8)	7 (8.5)	5(1)	2.03 (2.88)
Norm	3 (2.5)	2 (2.1)	8 (5.5)	7 (7)	6 (7)	-	2.31 (2.13)
Calculated norm	6 (7)	5 (5.5)	8 (5.5)	10(10)	7 (8.5)	-	1.72 (1.75)
Health	6 (7)	7 (7.8)	9 (7.8)	10(10)	7 (8.5)	-	1.47 (1.01)
Clients effort	5 (5.5)	5 (5.5)	7 (3.3)	5 (5)	6 (7)	-	0.80 (1.19)
Necessity	3 (2.5)	7 (7.8)	9 (7.8)	8 (8)	8 (10)	-	2.10 (2.50)
Consequence of disapproval	6 (7)	6 (6.6)	10(10)	10(10)	6 (7)	8 (6.4)	1.80 (1.55)
Average							1.91 (1.79)

* 1=Very easy, 5=Very difficult

Table 5.8.: The original weights and the re-scaled weights in brackets.

Although it was not observed any large differences between the CBR instances, there are no doubt differences in the weights they selected for the different attributes. There does not however, seem to be a correlation between the weights and the experience of the case officers, other than that the case officer with the least experience did not manage to set weights for all attributes as it was too difficult. So what are the reasons for these differences? Subjectivity due to personal beliefs is of course a valid assumption. This is also supported by the results from the evaluations made by a subset of the case officers after the cognitive task analysis, described in section 4.4.5. As the case officers who evaluated the cases had 11 and 21 years of experience, and the participant in the cognitive task analysis had 20 years of experience, differences in experience does not seem to be the reasons for the differences alone. They did however only evaluate a couple of applications, and there may be certain application types or contexts in which there are differences due to subjectivity, while there in other situations are differences due to experience.

On the other hand, there might be other explanations for the differences found amongst the case officers in the weighting schemas. As all participants in the questionnaire, except one, stated that it was difficult to set weights, the chosen weights may be inaccurate due to this difficulty. Also, as discussed earlier the case officers have stated that it is difficult to select the weights for the attributes as what they take into consideration depends on the type of application they evaluate. When answering the questionnaire the case officers may have had different types of applications in their thoughts, for example the last application they had evaluated before they answered the questionnaire, which could lead to the inconsistency in the weight-allocation.

5.2.2. Most Challenging Applications

Now, we will discuss the second research questions (RQ2): Which types of applications, i.e. what types of information in the applications, makes it more difficult to evaluate the application?

From the evaluation of the CBR system and the different instances there were no special application types that resulted in very dissimilar suggestions by the CBR instances. Based on the results it is therefore difficult to decide if certain application types or parts of the applications are more difficult to evaluate than others. One reason for this result may be the different limitations that have been applied to the CBR system. Due to the chosen scope of this project, not all aspects of the evaluation process was taken into consideration. For example, what should be considered as income and what should be considered as approved expenses are also decisions in which discretion is essential, but which have been excluded in this CBR system. This is also the case for decisions on when the client is obligated to use all of his/her assets before receiving social benefit support. These restrictions to the CBR system may have eliminated some of the aspects of the applications that are difficult, or it may have simplified the applications such that certain applications types no longer are difficult to evaluate. The small case base used during testing may also be a reason for the observed results.

On the other hand, answers from case officers during the semi-structured interviews tells us that there are certain applications that are more difficult to evaluate. Applications from clients who struggle with psychological illness or addictions are difficult to evaluate as they are often not eligible, but the consequences of not helping them can be large. If they do not receive help, the clients does often need help from other types of facilities or organizations, and therefore the different possible options must be evaluated based on the client's needs and the costs. These types of applications were seen as the most difficult cases by the one case officer who participated in the semi-structured interviews.

6. Conclusions

During this master thesis a decision support system to support case officers during assessment of social benefit support applications has been developed. Case-based reasoning has been used to implement the system which is intended to work as a proof of concept that CBR can be used to help experts during discretionary assessments. A series of knowledge elicitation techniques, including semi-structured interviews, questionnaire and cognitive task analysis, have been used to extract the necessary knowledge from domain experts.

In addition to the development of this CBR system, two research questions have been studied. To address the first research question (RQ1), whether the subjectivity of case officers lead to inconsistent evaluations of social benefit applications, the weights selected by different case officers were used to initiate different instances of the CBR system. Testing of the CBR system did not reveal large differences in the suggestions made by the different instances. The small case base used during testing could be a contributing factor for the small differences, and some of the tests showed relatively large differences in the calculated similarities amongst the instances. Interviews and evaluation tasks with case officers did support that there are differences amongst case officers, but the experience of the case officers did not seem to be the biggest reasons for the subjectivity, although it was mentioned as important by a case officer.

Regarding the second research question (RQ2), which type of applications are more difficult to evaluate than others, the small case base was also a contributing factor to few results. No particular application types seemed more difficult than others, but during interviews it was stated that especially clients with psychological or addiction problems could be very challenging. In addition, during the knowledge elicitation activities, it was made clear that changes in the client's life situation could be important during the evaluation of the application, and often discretion is used in such cases. This was also supported by the evaluations activity that was performed with a few case officers to compare their decisions.

6.1. Lessons Learned

As a research goal for this master thesis was to contribute to the improvement of the state of the art in case-based reasoning on how to initiate a CBR system (RG1), we would like to share the lessons learned from the development process.

First of all, a lot of contact with domain experts have been necessary to extract the domain knowledge which has been implemented in the system. At the same time, there should preferably have been more collaboration with the case officers in order to make the case representation, similarity measures and weights more accurate as it was not straight forward to elicit the tacit knowledge from the case officers. As this was a student project, and due to their busy work days this was not accomplished.

The cyclic iterative approach to knowledge elicitation was both necessary and beneficial. As we were new both to the field of social benefit support and the case-based reasoning methodology the knowledge learned during earlier elicitation activities helped us to be more specific and accurate on what we needed answers to in subsequent elicitation activities. New questions also arose when trying to implement the knowledge into the CBR system, as we then learned more about the exact knowledge that had to be represented in the system.

Not only is it important for us, the developers, to understand the application domain, but it is also important that the people who participates in questionnaires, interviews or other elicitation activities, understands the basic principles of cased based reasoning and the system that should be developed. If they understand how the information they provide will be used, and how the decision support system is intended to work, it is more likely that they can explain their knowledge more precisely and at a correct level of abstraction, which makes it easier to represent the knowledge in the CBR system.

All of the knowledge elicitation activities were found useful and beneficial. The semi-structured interviews were not only important for selecting the case representation and similarity measures, but also to gain knowledge in the field of social benefit support. This knowledge made us aware of new questions and how questions should be asked for later activities. However, it was discovered additional attributes for the case representation after the interviews. During the semi-structured interviews the case officers were asked to select the attributes they used during evaluation, from a preliminary list of attributes, gathered from help-pages and information systems. They were also asked if some attributes were missing, but as a lot of attributes are considered during an evaluation it may be difficult to remember all om them directly. We could therefore perhaps have used different examples of applications during the case representation tasks in order to elicit all of the necessary attributes. Further, the cognitive task analysis and the evaluation task with other case officers could preferably have been done before the questionnaire. Both as additional attributes for the case representation were identified in these activities, and to learn more about how the case officers specifically evaluates cases. This could have helped us to ask more specific questions in the questionnaire, that hopefully would have been easier to answer for the case officers. In addition, due to the difficulty of selecting weights for the case officers, the cognitive task analysis was found more beneficial than the questionnaire as it was more room for discussion and follow up questions. Therefore, if time would have allowed it, the cognitive task analysis should preferably have been done more thorough with multiple case officers.

6.2. Future Work

As stated earlier, there should preferably have been more collaboration with case officers to improve the CBR system. Therefore, the task of improving the case representation, similarity measures and weights are considered as important future work for this decision support system. This can be done at the same time as the decision support system is introduced to the case officers. While the case officers get familiar with the system and tests it during evaluation of social benefit application, a lot of feedback can be given on missing attributes, inaccurate similarity measures or weights and also usability, by the case officers. Regarding the weights it was stated in section 5.2 that it perhaps could be useful to use different weights depending on the application type. This is also something to consider in future work, in addition to the implementation of weight maintenance described in section 4.4.6. In addition to this, we have focused only on a sub-part of the social benefit support applications by only evaluating applications for additional supplements. More work is therefore necessary to broaden the scope of the CBR system by also supporting applications for monthly support, and take into consideration decisions regarding assets and dept, and the level of acceptable housing allowance.

As the usability has not been a high priority during the master thesis some work is necessary in this area. This includes making a good visualisation of the most similar cases and the similarity measures, and also how explanations are given to the user. As of now the user has to examine the similarity table themselves to identify the attributes that are considered the main reasons for the differences. This should be improved by for example highlighting the most decisive attributes in the similarity calculations for each case. In addition, in order for the decision support system to be beneficial for the case officers, it should impose little additional work on the case officers in order to operate it. The integration of the decision support system with the already existing information systems is therefore an important task, such that the necessary information needed by the CBR system is mainly retrieved from existing information systems. As seen, it is still some work left in order for the CBR system to be fully useful for the case officers. This work is left to Trondheim Municipality to implement.

Finally, this decision support system may have multiple purposes. The one who has been most discussed during this master thesis is that it should work as a support tool for the case officers while they evaluate applications in order for them to make judgements that are consistent with other case officers. Also, the CBR system can perhaps work as a training tool for newly educated case officers. It has been stated, by the case officers themselves, that the experience of the case officers can be a factor for differences in the decisions. Therefore, the CBR system may work as a training tool for new case officers by letting them compare their decisions to the suggestions made by the system. If the choices are different, then the system can give an explanation on how the similarity measures and weights were used to reach the final suggestions, and by this the case officer may have learned how to deal with a new type of application.

7. Bibliography

[1] Agnar Aamodt and Enric Plaza. Case-based reasoning: Foundational issues, methodological variations, and system approaches. *AI communications*, 7(1):39–59, 1994.

[2] Klaus-Dieter Althoff, Ralph Bergmann, Stefan Wess, Michel Manago, Eric Auriol, Oleg I Larichev, Alexander Bolotov, Yurii I Zhuravlev, and Serge I Gurov. Case-based reasoning for medical decision support tasks: The inreca approach. *Artificial Intelligence in Medicine*, 12(1):25–41, 1998.

[3] Kerstin Bach. Knowledge engineering for distributed case-based reasoning systems. In *Synergies Between Knowledge Engineering and Software Engineering*, pages 129–147. Springer, 2018.

[4] Kerstin Bach, Christian Sauer, Klaus Dieter Althoff, and Thomas Roth-Berghofer. Knowledge modeling with the open source tool mycbr. In *Proceedings of the 10th International Conference on Knowledge Engineering and Software Engineering-Volume 1289*, pages 84–94. CEUR-WS. org, 2014.

[5] Ralph Bergmann. *Experience management: foundations, development methodology, and internet-based applications.* Springer-Verlag, 2002.

[6] Ralph Bergmann and Armin Stahl. Similarity measures for object-oriented case representations. In *European Workshop on Advances in Case-Based Reasoning*, pages 25–36. Springer, 1998.

[7] Andrea Bonzano, Padraig Cunningham, and Barry Smyth. Using introspective learning to improve retrieval in cbr: A case study in air traffic control. In *International Conference on Case-Based Reasoning*, pages 291–302. Springer, 1997.

[8] Nick Bostrom and Eliezer Yudkowsky. The ethics of artificial intelligence. *The Cambridge handbook of artificial intelligence*, 1:316–334, 2014.

[9] Mark Bovens and Stavros Zouridis. From street-level to system-level bureaucracies: How information and communication technology is transforming administrative discretion and constitutional control. *Public administration review*, 62(2):174–184, 2002.

[10] Svend Brinkmann. Unstructured and semi-structured. *The Oxford handbook of qualitative research*, pages 277–299, 2014.

[11] Danielle Keats Citron and Frank Pasquale. The scored society: Due process for automated predictions. *Wash. L. Rev.*, 89:1, 2014.

[12] Nancy J Cooke. Varieties of knowledge elicitation techniques. *International Journal of Human-Computer Studies*, 41(6):801–849, 1994.

[13] Amélie Cordier. *Interactive and opportunistic knowledge acquisition in case-based reasoning*. PhD thesis, Université Claude Bernard-Lyon I, 2008.

[14] Pádraig Cunningham, Dónal Doyle, and John Loughrey. An evaluation of the usefulness of case-based explanation. In *International Conference on Case-Based Reasoning*, pages 122–130. Springer, 2003.

[15] DFKI. Mycbr. `http://mycbr-project.org`.

[16] Avelino J Gonzalez and Raymond Laureano-Ortiz. A case-based reasoning approach to real estate property appraisal. *Expert Systems with Applications*, 4(2):229–246, 1992.

[17] Husbanken. Housing allowance. `https://www.husbanken.no/om-husbanken/`.

[18] Janet Kolodner. *Case-based reasoning*. Morgan Kaufmann, 2014.

[19] Trondheim Kommune. Rapport 2/2018 Økonomisk sosialhjelp, 2018.

[20] Harold W Kuhn. The hungarian method for the assignment problem. *Naval research logistics quarterly*, 2(1-2):83–97, 1955.

[21] Zachary C Lipton. The mythos of model interpretability. *arXiv preprint arXiv:1606.03490*, 2016.

[22] Tim Miller. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267:1–38, 2019.

[23] NAV. Financial assistance. `https://www.nav.no/en/Home/Benefits+and+services/Relatert+informasjon/financial-assistance-social-assistance`.

[24] NAV. L18.12.2009 nr. 131 lov om sosiale tjenester i arbeids- og velferdsforvaltningen (sosialtjenesteloven). `https://www.nav.no/rettskildene/lov/L20091218-131_P18#L20091218-131_P18`, 2009.

[25] Ikujiro Nonaka and Hirotaka Takeuchi. *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. Oxford university press, 1995.

[26] Héctor Núnez, Miquel Sanchez-Marre, Ulises Cortés, Joaquim Comas, Montse Martínez, Ignasi Rodríguez-Roda, and Manel Poch. A comparative study on the use of similarity measures in case-based reasoning to improve the classification of environmental system situations. *Environmental Modelling & Software*, 19(9):809–819, 2004.

[27] IMDi Integrerings og mangfoldsdirektoratet. The introduction programme. `https://www.imdi.no/en/the-introduction-programme/the-introduction-programme/`.

[28] Pinar Öztürk and Axel Tidemann. A review of case-based reasoning in cognition–action continuum: a step toward bridging symbolic and non-symbolic artificial intelligence. *The Knowledge Engineering Review*, 29(1):51–77, 2014.

[29] Cheol-Soo Park and Ingoo Han. A case-based reasoning with the feature weights derived by analytic hierarchy process for bankruptcy prediction. *Expert Systems with Applications*, 23(3):255–264, 2002.

[30] Michael M Richter. Knowledge containers. *Readings in Case-Based Reasoning. Morgan Kaufmann Publishers*, 2003.

[31] Michael M Richter and Rosina O Weber. *Case-based reasoning*. Springer, 2016.

[32] Edwina L Rissland and Kevin D Ashley. A case-based system for trade secrets law. In *Proceedings of the 1st international conference on Artificial intelligence and law*, pages 60–66. ACM, 1987.

[33] Thomas R Roth-Berghofer. Explanations and case-based reasoning: Foundational issues. In *European Conference on Case-Based Reasoning*, pages 389–403. Springer, 2004.

[34] Wojciech Samek, Thomas Wiegand, and Klaus-Robert Müller. Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models. *arXiv preprint arXiv:1708.08296*, 2017.

[35] Christian Severin Sauer, Lotta Rintala, and Thomas Roth-Berghofer. Knowledge formalisation for hydrometallurgical gold ore processing. In *Research and Development in Intelligent Systems XXX*, pages 291–304. Springer, 2013.

[36] Kyung-shik Shin and Ingoo Han. Case-based reasoning supported by genetic algorithms for corporate bond rating. *Expert Systems with applications*, 16(2):85–95, 1999.

[37] Samad Valipour Shokouhi, Agnar Aamodt, Pål Skalle, and Frode Sørmo. Determining root causes of drilling problems by combining cases and general knowledge. In *International Conference on Case-Based Reasoning*, pages 509–523. Springer, 2009.

[38] Fadzilah Siraj, Mohd Haniff Yusoff, Megat Firdaus Haris, Muhammad Ashraq Salahuddin, Shahrin Rizlan Mohd Yusof, and Md Rajib Hasan. i-sme: Loan decision support system using neuro-cbr approach. In *Computational Intelligence, Modelling and Simulation (CIMSiM), 2011 Third International Conference on*, pages 91–96. IEEE, 2011.

[39] Frode Sørmo, Jörg Cassens, and Agnar Aamodt. Explanation in case-based reasoning–perspectives and goals. *Artificial Intelligence Review*, 24(2):109–143, 2005.

[40] Armin Stahl. Learning similarity measures: A formal view based on a generalized cbr model. In *International Conference on Case-Based Reasoning*, pages 507–521. Springer, 2005.

[41] Armin Stahl and Thomas R Roth-Berghofer. Rapid prototyping of cbr applications with the open source tool mycbr. In *European conference on case-based reasoning*, pages 615–629. Springer, 2008.

[42] Botelho L Teodoro M. A case-based reasoning approach for predicting bank lending decisions. 2004.

[43] Tina Billbo, Ørjan Mydland, Trine Løvold Syversen, Hanne Glemmestad, Liv Johanne Solheim. Kommunale forskjeller i Økonomisk sosialhjelp, 2014.

[44] R Hevner Von Alan, Salvatore T March, Jinsoo Park, and Sudha Ram. Design science in information systems research. *MIS quarterly*, 28(1):75–105, 2004.

[45] Leendert WM Wienhofen and Bjørn Magnus Mathisen. Defining the initial case-base for a cbr operator support system in digital finishing. In *International Conference on Case-Based Reasoning*, pages 430–444. Springer, 2016.

[46] John Zeleznikow and Andrew Stranieri. The split-up system: integrating neural networks and rule-based reasoning in the legal domain. In *Proceedings of the 5th international conference on Artificial intelligence and law*, pages 185–194. ACM, 1995.

[47] Hui Zhao, Guo-hua Zhang, Wei Dong, Xiang Yan, and Xin-ya Sun. Fault diagnosis for rail turnout system based on improved introspective cbr method. In *2018 13th World Congress on Intelligent Control and Automation (WCICA)*, pages 989–994. IEEE, 2018.

A. System Output

A.1. Similarity Table

Attribute (Weight)	Query Case	1. best match (Sim)
Name (0)	Query	Application #13
Similarity	-	0.763
Sup. Amount(0)		1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)
Description(0)	Clothes	Winter clothes. Granted by §1 9.
PS(9)	PS #16;	PS #14;(0.0)
Health(9)	Moderate challanges	Small challenges(0.75)
Calculated norm(8)	7650	8120(0.89)
Necessity(9)	Large	Large(1.0)
Consequence(10)	Large	Average(0.8)
Living situation(9)	Rent municipal house	Rent private market(0.8)
Single provider?(7)	No	No(1.0)
Clients effort(7)	Average	Big(0.8)
Recently single?(10)	No	No(1.0)
Norm(8)	Long term	Short term(0.5)
Recently moved?(10)	No	Yes(0.0)
Children(9)	_unknown_	_unknown_(1.0)
Total income(10)	0	0(1.0)
Partner(7)	No	No(1.0)
Total expenses(10)	4500	4000(0.87)
Age(6)	24	24(1.0)

I found Søknad #13 with a similarity of 0.763 as the best match.

Figure A.1.: An example of a similarity table outputted from the developed CBR program.

A.2. Summary Table

Case Officer #	Suggestion 1	Suggestion 2	Suggestion 3	Suggestion 4
Case Officer #1	App. #13 (0.76)	App. #5 (0.65)	App. #2 (0.64)	App. #0 (0.64)
Case Officer #2	App. #13 (0.77)	App. #2 (0.67)	App. #0 (0.66)	App. #5 (0.65)
Case Officer #3	App. #13 (0.76)	App. #2 (0.66)	App. #0 (0.66)	App. #5 (0.6)
Case Officer #4	App. #13 (0.75)	App. #2 (0.67)	App. #0 (0.66)	App. #5 (0.58)
Case Officer #5	App. #13 (0.71)	App. #2 (0.68)	App. #0 (0.66)	App. #8 (0.65)

Figure A.2.: An example of a summary table outputted from the developed CBR program.

B. Interview Questions

B.1. First Semi-Structured Interview

- In which types of applications is the use of discretion high, and why is it used much discretion in these particular applications?
- Where is the information that is especially used during discretionary assessments stored?
- Which parts of the applications is easy to evaluate, and which parts require more use of discretion?
- How does the case officers know if they have used discretion or not in the evaluations?
- Does the case officers get a notification or indication if they should use discretion during the assesment of a application?
- Is it possible to know if a previous application is evaluated "correctly" or not?
- Based on the initial case representation, is there any attributes that does not need to be stored for a social benefit application case, or is there some additional attributes that should be represented?

B.2. Second Semi-Structured Interview

- Does the case officers discuss applications with other case officers or leaders because they are not certain of how they should evaluate an application?
- If so, for what types of cases is the need of collaboration most frequent?
- In which types of applications is it the most disagreement amongst the case officers?
- In which types of applications is the use of discretion high, and why is it used much discretion in these particular applications?
- Which parts of the applications is easy to evaluate, and which parts require more use of discretion?
- Based on the initial case representation, is there any attributes that does not need to be stored for a social benefit application case, or is there some additional attributes that should be represented?

- For each of the attributes in the case representation, how should values for the attributes be compared?

C. Results from Testing

C.1. Supplement: Travel Card

Case Officer #1

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #12	Application #9	Application #6
Similarity	-	0.758	0.524	0.0
Sup. Amount(0)		760	1520	5000
Sup. Type(0)	Travel card	Travel card(1.0)	Travel card(1.0)	Food money(0.0)
Description(0)		Participates in program and t reatment	Travel card for two. Dependen t on bus for transportation. Wife needs transportation to school.	Have spent all of the food mo ney before next payment
PS(3)	_unknown_	PS #13;(1.0)	PS #15;(1.0)	_unknown_(1.0)
Health(6)	No challenges	Small challenges(0.75)	Very large challenges(0.0)	No challenges(1.0)
Calculated norm(6)	11650	8120(0.4)	4684(0.15)	-2145(0.01)
Necessity(3)	Large	Large(1.0)	Large(1.0)	Very large(0.8)
Consequence(6)	Average	Average(1.0)	Large(0.8)	Large(0.8)
Living situation(3)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent municipal house(1.0)
Single provider?(2)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Average	Big(0.8)	Big(0.8)	Average(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term	Short term(0.5)	Long term(1.0)	Short term(0.5)
Recently moved?(10)	No	Yes(0.0)	No(1.0)	No(1.0)
Children(6)	_unknown_	_unknown_(1.0)	Children #13;(0.0)	Children #11;Children #(0.0)
Total income(8)	0	0(1.0)	8300(0.06)	24050(0.0)
Partner(8)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(8)	5500	4000(0.65)	0(0.18)	9000(0.35)
Age(0)	27	24(-)	27(-)	59(-)

I found Søknad #12 with a similarity of 0.758 as the best match.

Figure C.1.: The outputted similarity table for CBR instance #1 for query on travel card supplements.

Case Officer #2

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #12	Application #9	Application #6
Similarity	-	0.783	0.568	0.0
Sup. Amount(0)		760	1520	5000
Sup. Type(0)	Travel card	Travel card(1.0)	Travel card(1.0)	Food money(0.0)
Description(0)		Participates in program and t reatment	Travel card for two. Dependen t on bus for transportation. Wife needs transportation to school.	Have spent all of the food mo ney before next payment
PS(5)	_unknown_	PS #13;(1.0)	PS #15;(1.0)	_unknown_(1.0)
Health(7)	No challenges	Small challenges(0.75)	Very large challenges(0.0)	No challenges(1.0)
Calculated norm(5)	11650	8120(0.4)	4684(0.15)	-2145(0.01)
Necessity(7)	Large	Large(1.0)	Large(1.0)	Very large(0.8)
Consequence(6)	Average	Average(1.0)	Large(0.8)	Large(0.8)
Living situation(4)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent municipal house(1.0)
Single provider?(5)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Average	Big(0.8)	Big(0.8)	Average(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(2)	Long term	Short term(0.5)	Long term(1.0)	Short term(0.5)
Recently moved?(10)	No	Yes(0.0)	No(1.0)	No(1.0)
Children(8)	_unknown_	_unknown_(1.0)	Children #13;(0.0)	Children #11;Children #(0.0)
Total income(9)	0	0(1.0)	8300(0.06)	24050(0.0)
Partner(5)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(9)	5500	4000(0.65)	0(0.18)	9000(0.35)
Age(1)	27	24(0.5)	27(1.0)	59(1.0)

I found Søknad #12 with a similarity of 0.783 as the best match.

Figure C.2.: The outputted similarity table for CBR instance #2 for query on travel card supplements.

Case Officer #3

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #12	Application #9	Application #6
Similarity	-	0.777	0.617	0.0
Sup. Amount(0)		760	1520	5000
Sup. Type(0)	Travel card	Travel card(1.0)	Travel card(1.0)	Food money(0.0)
Description(0)		Participates in program and t reatment	Travel card for two. Dependen t on bus for transportation. Wife needs transportation to school.	Have spent all of the food mo ney before next payment
PS(9)	_unknown_	PS #13;(1.0)	PS #15;(1.0)	_unknown_(1.0)
Health(9)	No challenges	Small challenges(0.75)	Very large challenges(0.0)	No challenges(1.0)
Calculated norm(8)	11650	8120(0.4)	4684(0.15)	-2145(0.01)
Necessity(9)	Large	Large(1.0)	Large(1.0)	Very large(0.8)
Consequence(10)	Average	Average(1.0)	Large(0.8)	Large(0.8)
Living situation(9)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent municipal house(1.0)
Single provider?(7)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(7)	Average	Big(0.8)	Big(0.8)	Average(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(8)	Long term	Short term(0.5)	Long term(1.0)	Short term(0.5)
Recently moved?(10)	No	Yes(0.0)	No(1.0)	No(1.0)
Children(9)	_unknown_	_unknown_(1.0)	Children #13;(0.0)	Children #11;Children #(0.0)
Total income(10)	0	0(1.0)	8300(0.06)	24050(0.0)
Partner(7)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(10)	5500	4000(0.65)	0(0.18)	9000(0.35)
Age(6)	27	24(0.5)	27(1.0)	59(1.0)

I found Søknad #12 with a similarity of 0.777 as the best match.

Figure C.3.: The outputted similarity table for CBR instance #3 for query on travel card supplements.

Case Officer #4

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #12	Application #9	Application #6
Similarity	-	0.775	0.545	0.0
Sup. Amount(0)		760	1520	5000
Sup. Type(0)	Travel card	Travel card(1.0)	Travel card(1.0)	Food money(0.0)
Description(0)		Participates in program and t reatment	Travel card for two. Dependen t on bus for transportation. Wife needs transportation to school.	Have spent all of the food mo ney before next payment
PS(8)	_unknown_	PS #13;(1.0)	PS #15;(1.0)	_unknown_(1.0)
Health(10)	No challenges	Small challenges(0.75)	Very large challenges(0.0)	No challenges(1.0)
Calculated norm(10)	11650	8120(0.4)	4684(0.15)	-2145(0.01)
Necessity(8)	Large	Large(1.0)	Large(1.0)	Very large(0.8)
Consequence(10)	Average	Average(1.0)	Large(0.8)	Large(0.8)
Living situation(1)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent municipal house(1.0)
Single provider?(5)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Average	Big(0.8)	Big(0.8)	Average(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(7)	Long term	Short term(0.5)	Long term(1.0)	Short term(0.5)
Recently moved?(10)	No	Yes(0.0)	No(1.0)	No(1.0)
Children(10)	_unknown_	_unknown_(1.0)	Children #13;(0.0)	Children #11;Children #(0.0)
Total income(10)	0	0(1.0)	8300(0.06)	24050(0.0)
Partner(5)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(10)	5500	4000(0.65)	0(0.18)	9000(0.35)
Age(0)	27	24(-)	27(-)	59(-)

I found Søknad #12 with a similarity of 0.775 as the best match.

Figure C.4.: The outputted similarity table for CBR instance #4 for query on travel card supplements.

Case Officer #5

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #12	Application #9	Application #6
Similarity	-	0.739	0.645	0.0
Sup. Amount(0)		760	1520	5000
Sup. Type(0)	Travel card	Travel card(1.0)	Travel card(1.0)	Food money(0.0)
Description(0)		Participates in program and t reatment	Travel card for two. Dependen t on bus for transportation. Wife needs transportation to school.	Have spent all of the food mo ney before next payment
PS(7)	_unknown_	PS #13;(1.0)	PS #15;(1.0)	_unknown_(1.0)
Health(7)	No challenges	Small challenges(0.75)	Very large challenges(0.0)	No challenges(1.0)
Calculated norm(7)	11650	8120(0.4)	4684(0.15)	-2145(0.01)
Necessity(8)	Large	Large(1.0)	Large(1.0)	Very large(0.8)
Consequence(6)	Average	Average(1.0)	Large(0.8)	Large(0.8)
Living situation(2)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent municipal house(1.0)
Single provider?(2)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(6)	Average	Big(0.8)	Big(0.8)	Average(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(6)	Long term	Short term(0.5)	Long term(1.0)	Short term(0.5)
Recently moved?(10)	No	Yes(0.0)	No(1.0)	No(1.0)
Children(2)	_unknown_	_unknown_(1.0)	Children #13;(0.0)	Children #11;Children #(0.0)
Total income(8)	0	0(1.0)	8300(0.06)	24050(0.0)
Partner(2)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(7)	5500	4000(0.65)	0(0.18)	9000(0.35)
Age(2)	27	24(0.5)	27(1.0)	59(1.0)

I found Søknad #12 with a similarity of 0.739 as the best match.

Figure C.5.: The outputted similarity table for CBR instance #5 for query on travel card supplements.

C.2. Supplement: Food Money

Case Officer #1

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #4	Application #6	Application #7
Similarity	-	0.774	0.7	0.0
Sup. Amount(0)		1000	5000	1400
Sup. Type(0)	Food money	Food money(1.0)	Food money(1.0)	Dentist(0.0)
Description(0)	Used all of the food	Food money, jobseeker	Have spent all of the food mo ney before next payment	
PS(3)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(6)	No challenges	No challenges(1.0)	No challenges(1.0)	No challenges(1.0)
Calculated norm(6)	-2300	10480(0.02)	-2145(0.96)	8300(0.05)
Necessity(3)	Large	Large(1.0)	Very large(0.8)	Large(1.0)
Consequence(6)	Large	Large(1.0)	Large(1.0)	Small(0.6)
Living situation(3)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent private market(0.8)
Single provider?(2)	Yes	Yes(1.0)	No(0.0)	No(0.0)
Clients effort(5)	Big	Big(1.0)	Average(0.8)	Big(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term	Long term(1.0)	Short term(0.5)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(6)	Children #14;	Children #10;(0.4)	Children #11;Children #(0.75)	_unknown_(0.0)
Total income(8)	14500	5940(0.05)	24050(0.03)	2800(0.01)
Partner(8)	No	No(1.0)	Yes(0.0)	No(1.0)
Total expenses(8)	7000	8000(0.75)	9000(0.56)	5250(0.6)
Age(0)	32	29(-)	59(-)	31(-)

I found Søknad #4 with a similarity of 0.774 as the best match.

Figure C.6.: The outputted similarity table for CBR instance #1 for query on food money supplements.

Case Officer #2

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #4	Application #6	Application #7
Similarity	-	0.783	0.712	0.0
Sup. Amount(0)		1000	5000	1400
Sup. Type(0)	Food money	Food money(1.0)	Food money(1.0)	Dentist(0.0)
Description(0)	Used all of the food	Food money, jobseeker	Have spent all of the food mo ney before next payment	
PS(5)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(7)	No challenges	No challenges(1.0)	No challenges(1.0)	No challenges(1.0)
Calculated norm(5)	-2300	10480(0.02)	-2145(0.96)	8300(0.05)
Necessity(7)	Large	Large(1.0)	Very large(0.8)	Large(1.0)
Consequence(6)	Large	Large(1.0)	Large(1.0)	Small(0.6)
Living situation(4)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent private market(0.8)
Single provider?(5)	Yes	Yes(1.0)	No(0.0)	No(0.0)
Clients effort(5)	Big	Big(1.0)	Average(0.8)	Big(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(2)	Long term	Long term(1.0)	Short term(0.5)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(8)	Children #14;	Children #10;(0.4)	Children #11;Children #(0.75)	_unknown_(0.0)
Total income(9)	14500	5940(0.05)	24050(0.03)	2800(0.01)
Partner(5)	No	No(1.0)	Yes(0.0)	No(1.0)
Total expenses(9)	7000	8000(0.75)	9000(0.56)	5250(0.6)
Age(1)	32	29(1.0)	59(1.0)	31(1.0)

I found Søknad #4 with a similarity of 0.783 as the best match.

Figure C.7.: The outputted similarity table for CBR instance #2 for query on food money supplements.

Case Officer #3

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #4	Application #6	Application #7
Similarity	-	0.804	0.726	0.0
Sup. Amount(0)		1000	5000	1400
Sup. Type(0)	Food money	Food money(1.0)	Food money(1.0)	Dentist(0.0)
Description(0)	Used all of the food	Food money, jobseeker	Have spent all of the food mo ney before next payment	
PS(9)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(9)	No challenges	No challenges(1.0)	No challenges(1.0)	No challenges(1.0)
Calculated norm(8)	-2300	10480(0.02)	-2145(0.96)	8300(0.05)
Necessity(9)	Large	Large(1.0)	Very large(0.8)	Large(1.0)
Consequence(10)	Large	Large(1.0)	Large(1.0)	Small(0.6)
Living situation(9)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent private market(0.8)
Single provider?(7)	Yes	Yes(1.0)	No(0.0)	No(0.0)
Clients effort(7)	Big	Big(1.0)	Average(0.8)	Big(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(8)	Long term	Long term(1.0)	Short term(0.5)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(9)	Children #14;	Children #10;(0.4)	Children #11;Children #(0.75)	_unknown_(0.0)
Total income(10)	14500	5940(0.05)	24050(0.03)	2800(0.01)
Partner(7)	No	No(1.0)	Yes(0.0)	No(1.0)
Total expenses(10)	7000	8000(0.75)	9000(0.56)	5250(0.6)
Age(6)	32	29(1.0)	59(1.0)	31(1.0)

I found Søknad #4 with a similarity of 0.804 as the best match.

Figure C.8.: The outputted similarity table for CBR instance #3 for query on food money supplements.

Case Officer #4

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #4	Application #6	Application #7
Similarity	-	0.765	0.722	0.0
Sup. Amount(0)		1000	5000	1400
Sup. Type(0)	Food money	Food money(1.0)	Food money(1.0)	Dentist(0.0)
Description(0)	Used all of the food	Food money, jobseeker	Have spent all of the food mo ney before next payment	
PS(8)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(10)	No challenges	No challenges(1.0)	No challenges(1.0)	No challenges(1.0)
Calculated norm(10)	-2300	10480(0.02)	-2145(0.96)	8300(0.05)
Necessity(8)	Large	Large(1.0)	Very large(0.8)	Large(1.0)
Consequence(10)	Large	Large(1.0)	Large(1.0)	Small(0.6)
Living situation(1)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent private market(0.8)
Single provider?(5)	Yes	Yes(1.0)	No(0.0)	No(0.0)
Clients effort(5)	Big	Big(1.0)	Average(0.8)	Big(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(7)	Long term	Long term(1.0)	Short term(0.5)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(10)	Children #14;	Children #10;(0.4)	Children #11;Children #(0.75)	_unknown_(0.0)
Total income(10)	14500	5940(0.05)	24050(0.03)	2800(0.01)
Partner(5)	No	No(1.0)	Yes(0.0)	No(1.0)
Total expenses(10)	7000	8000(0.75)	9000(0.56)	5250(0.6)
Age(0)	32	29(-)	59(-)	31(-)

I found Søknad #4 with a similarity of 0.765 as the best match.

Figure C.9.: The outputted similarity table for CBR instance #4 for query on food money supplements.

Case Officer #5

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #4	Application #6	Application #7
Similarity	-	0.807	0.768	0.0
Sup. Amount(0)		1000	5000	1400
Sup. Type(0)	Food money	Food money(1.0)	Food money(1.0)	Dentist(0.0)
Description(0)	Used all of the food	Food money, jobseeker	Have spent all of the food mo ney before next payment	
PS(7)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(7)	No challenges	No challenges(1.0)	No challenges(1.0)	No challenges(1.0)
Calculated norm(7)	-2300	10480(0.02)	-2145(0.96)	8300(0.05)
Necessity(8)	Large	Large(1.0)	Very large(0.8)	Large(1.0)
Consequence(6)	Large	Large(1.0)	Large(1.0)	Small(0.6)
Living situation(2)	Rent municipal house	Rent private market(0.8)	Rent municipal house(1.0)	Rent private market(0.8)
Single provider?(2)	Yes	Yes(1.0)	No(0.0)	No(0.0)
Clients effort(6)	Big	Big(1.0)	Average(0.8)	Big(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(6)	Long term	Long term(1.0)	Short term(0.5)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(2)	Children #14;	Children #10;(0.4)	Children #11;Children #(0.75)	_unknown_(0.0)
Total income(8)	14500	5940(0.05)	24050(0.03)	2800(0.01)
Partner(2)	No	No(1.0)	Yes(0.0)	No(1.0)
Total expenses(7)	7000	8000(0.75)	9000(0.56)	5250(0.6)
Age(2)	32	29(1.0)	59(1.0)	31(1.0)

I found Søknad #4 with a similarity of 0.807 as the best match.

Figure C.10.: The outputted similarity table for CBR instance #5 for query on food money supplements.

C.3. Supplement: Other Purposes

C.3.1. First Retrieval Test

Case Officer #1

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #8	Application #0	Application #2
Similarity	-	0.778	0.719	0.717
Sup. Amount(0)		1500	1500	1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	New clothes for child	Clothes, has lost weight and needs a lot of new clothes be cause of this	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Clothes
PS(3)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(6)	No challenges	No challenges(1.0)	Moderate challanges(0.5)	Moderate challanges(0.5)
Calculated norm(6)	3000	18005(0.01)	9800(0.16)	9750(0.16)
Necessity(3)	Large	Average(0.8)	Average(0.8)	Large(1.0)
Consequence(6)	Average	Small(0.8)	Average(1.0)	Average(1.0)
Living situation(3)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(2)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Average	Average(1.0)	Little(0.8)	Little(0.8)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term	Short term(0.5)	Long term(1.0)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(6)	Children #14;	Children #9;Children #1(0.65)	_unknown_(0.0)	_unknown_(0.0)
Total income(8)	12000	0(0.01)	10000(0.56)	14000(0.56)
Partner(8)	Yes	Yes(1.0)	Yes(1.0)	Yes(1.0)
Total expenses(8)	6500	6500(1.0)	10050(0.34)	11000(0.25)
Age(0)	29	43(-)	58(-)	58(-)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #3	Application #10	Application #5	Application #13
Similarity	0.715	0.699	0.553	0.488
Sup. Amount(0)	3000	1000	0	1500
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Summer clothes for the entire familiy	Clothes, client has had low i ncome for a long time	Keyboard	Winter clothes. Granted by §1 9.
PS(3)	_unknown_(1.0)	PS #12;(1.0)	_unknown_(1.0)	PS #14;(1.0)
Health(6)	No challenges(1.0)	Very large challenges(0.0)	No challenges(1.0)	Small challenges(0.75)
Calculated norm(6)	24560(0.0)	4684(0.65)	-11600(0.01)	8120(0.25)
Necessity(3)	Large(1.0)	Average(0.8)	Little(0.6)	Large(1.0)
Consequence(6)	Average(1.0)	Large(0.8)	No(0.4)	Average(1.0)
Living situation(3)	Rent private market(1.0)	Rent municipal house(0.8)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Average(1.0)	Big(0.8)	Little(0.8)	Big(0.8)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term(1.0)	Long term(1.0)	Short term(0.5)	Short term(0.5)
Recently moved?(10)	No(1.0)	No(1.0)	No(1.0)	Yes(0.0)
Children(6)	Children #7;Children #8(0.26)	Children #13;(0.62)	_unknown_(0.0)	_unknown_(0.0)
Total income(8)	1940(0.03)	8300(0.33)	20000(0.07)	0(0.01)
Partner(8)	Yes(1.0)	Yes(1.0)	No(0.0)	No(0.0)
Total expenses(8)	12000(0.18)	0(0.12)	4000(0.48)	4000(0.48)
Age(0)	43(-)	27(-)	54(-)	24(-)

I found Søknad #8 with a similarity of 0.778 as the best match.

Figure C.11.: The outputted similarity table for CBR instance #1 for the first query on supplements for other purposes.

Case Officer #2

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #8	Application #3	Application #2
Similarity	-	0.793	0.724	0.72
Sup. Amount(0)		1500	3000	1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	New clothes for child	Clothes, has lost weight and needs a lot of new clothes be cause of this	Summer clothes for the entire familiy	Clothes
PS(5)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(7)	No challenges	No challenges(1.0)	No challenges(1.0)	Moderate challanges(0.5)
Calculated norm(5)	3000	18005(0.01)	24560(0.0)	9750(0.16)
Necessity(7)	Large	Average(0.8)	Large(1.0)	Large(1.0)
Consequence(6)	Average	Small(0.8)	Average(1.0)	Average(1.0)
Living situation(4)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(5)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Average	Average(1.0)	Average(1.0)	Little(0.8)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(2)	Long term	Short term(0.5)	Long term(1.0)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(8)	Children #14;	Children #9;Children #1(0.65)	Children #7;Children #8(0.26)	_unknown_(0.0)
Total income(9)	12000	0(0.01)	1940(0.03)	14000(0.56)
Partner(5)	Yes	Yes(1.0)	Yes(1.0)	Yes(1.0)
Total expenses(9)	6500	6500(1.0)	12000(0.18)	11000(0.25)
Age(1)	29	43(1.0)	43(1.0)	58(1.0)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #0	Application #10	Application #5	Application #13
Similarity	0.714	0.692	0.598	0.545
Sup. Amount(0)	1500	1000	0	1500
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Clothes, client has had low i ncome for a long time	Keyboard	Winter clothes. Granted by §1 9.
PS(3)	_unknown_(1.0)	PS #12;(1.0)	_unknown_(1.0)	PS #14;(1.0)
Health(6)	Moderate challanges(0.5)	Very large challenges(0.0)	No challenges(1.0)	Small challenges(0.75)
Calculated norm(6)	9800(0.16)	4684(0.65)	-11600(0.01)	8120(0.25)
Necessity(3)	Average(0.8)	Average(0.8)	Little(0.6)	Large(1.0)
Consequence(6)	Average(1.0)	Large(0.8)	No(0.4)	Average(1.0)
Living situation(3)	Rent private market(1.0)	Rent municipal house(0.8)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little(0.8)	Big(0.8)	Little(0.8)	Big(0.8)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term(1.0)	Long term(1.0)	Short term(0.5)	Short term(0.5)
Recently moved?(10)	No(1.0)	No(1.0)	No(1.0)	Yes(0.0)
Children(6)	_unknown_(0.0)	Children #13;(0.62)	_unknown_(0.0)	_unknown_(0.0)
Total income(8)	10000(0.56)	8300(0.33)	20000(0.07)	0(0.01)
Partner(8)	Yes(1.0)	Yes(1.0)	No(0.0)	No(0.0)
Total expenses(8)	10050(0.34)	0(0.12)	4000(0.48)	4000(0.48)
Age(0)	58(1.0)	27(1.0)	54(1.0)	24(0.5)

I found Søknad #8 with a similarity of 0.793 as the best match.

Figure C.12.: The outputted similarity table for CBR instance #2 for the first query on supplements for other purposes.

Case Officer #3

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #8	Application #3	Application #2
Similarity	-	0.791	0.764	0.757
Sup. Amount(0)		1500	3000	1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	New clothes for child	Clothes, has lost weight and needs a lot of new clothes be cause of this	Summer clothes for the entire familiy	Clothes
PS(9)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(9)	No challenges	No challenges(1.0)	No challenges(1.0)	Moderate challanges(0.5)
Calculated norm(8)	3000	18005(0.01)	24560(0.0)	9750(0.16)
Necessity(9)	Large	Average(0.8)	Large(1.0)	Large(1.0)
Consequence(10)	Average	Small(0.8)	Average(1.0)	Average(1.0)
Living situation(9)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(7)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(7)	Average	Average(1.0)	Average(1.0)	Little(0.8)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(8)	Long term	Short term(0.5)	Long term(1.0)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(9)	Children #14;	Children #9;Children #1(0.65)	Children #7;Children #8(0.26)	_unknown_(0.0)
Total income(10)	12000	0(0.01)	1940(0.03)	14000(0.56)
Partner(7)	Yes	Yes(1.0)	Yes(1.0)	Yes(1.0)
Total expenses(10)	6500	6500(1.0)	12000(0.18)	11000(0.25)
Age(6)	29	43(1.0)	43(1.0)	58(1.0)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #0	Application #10	Application #5	Application #13
Similarity	0.75	0.727	0.613	0.582
Sup. Amount(0)	1500	1000	0	1500
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Clothes, client has had low i ncome for a long time	Keyboard	Winter clothes. Granted by §1 9.
PS(3)	_unknown_(1.0)	PS #12;(1.0)	_unknown_(1.0)	PS #14;(1.0)
Health(6)	Moderate challanges(0.5)	Very large challenges(0.0)	No challenges(1.0)	Small challenges(0.75)
Calculated norm(6)	9800(0.16)	4684(0.65)	-11600(0.01)	8120(0.25)
Necessity(3)	Average(0.8)	Average(0.8)	Little(0.6)	Large(1.0)
Consequence(6)	Average(1.0)	Large(0.8)	No(0.4)	Average(1.0)
Living situation(3)	Rent private market(1.0)	Rent municipal house(0.8)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little(0.8)	Big(0.8)	Little(0.8)	Big(0.8)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term(1.0)	Long term(1.0)	Short term(0.5)	Short term(0.5)
Recently moved?(10)	No(1.0)	No(1.0)	No(1.0)	Yes(0.0)
Children(6)	_unknown_(0.0)	Children #13;(0.62)	_unknown_(0.0)	_unknown_(0.0)
Total income(8)	10000(0.56)	8300(0.33)	20000(0.07)	0(0.01)
Partner(8)	Yes(1.0)	Yes(1.0)	No(0.0)	No(0.0)
Total expenses(8)	10050(0.34)	0(0.12)	4000(0.48)	4000(0.48)
Age(0)	58(1.0)	27(1.0)	54(1.0)	24(0.5)

I found Søknad #8 with a similarity of 0.791 as the best match.

Figure C.13.: The outputted similarity table for CBR instance #3 for the first query on supplements for other purposes.

Case Officer #4

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #8	Application #3	Application #2
Similarity	-	0.744	0.703	0.695
Sup. Amount(0)		1500	3000	1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	New clothes for child	Clothes, has lost weight and needs a lot of new clothes be cause of this	Summer clothes for the entire familiy	Clothes
PS(8)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(10)	No challenges	No challenges(1.0)	No challenges(1.0)	Moderate challanges(0.5)
Calculated norm(10)	3000	18005(0.01)	24560(0.0)	9750(0.16)
Necessity(8)	Large	Average(0.8)	Large(1.0)	Large(1.0)
Consequence(10)	Average	Small(0.8)	Average(1.0)	Average(1.0)
Living situation(1)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(5)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Average	Average(1.0)	Average(1.0)	Little(0.8)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(7)	Long term	Short term(0.5)	Long term(1.0)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(10)	Children #14;	Children #9;Children #1(0.65)	Children #7;Children #8(0.26)	_unknown_(0.0)
Total income(10)	12000	0(0.01)	1940(0.03)	14000(0.56)
Partner(5)	Yes	Yes(1.0)	Yes(1.0)	Yes(1.0)
Total expenses(10)	6500	6500(1.0)	12000(0.18)	11000(0.25)
Age(0)	29	43(-)	43(-)	58(-)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #0	Application #10	Application #5	Application #13
Similarity	0.689	0.684	0.553	0.541
Sup. Amount(0)	1500	1000	0	1500
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Clothes, client has had low i ncome for a long time	Keyboard	Winter clothes. Granted by §1 9.
PS(3)	_unknown_(1.0)	PS #12;(1.0)	_unknown_(1.0)	PS #14;(1.0)
Health(6)	Moderate challanges(0.5)	Very large challenges(0.0)	No challenges(1.0)	Small challenges(0.75)
Calculated norm(6)	9800(0.16)	4684(0.65)	-11600(0.01)	8120(0.25)
Necessity(3)	Average(0.8)	Average(0.8)	Little(0.6)	Large(1.0)
Consequence(6)	Average(1.0)	Large(0.8)	No(0.4)	Average(1.0)
Living situation(3)	Rent private market(1.0)	Rent municipal house(0.8)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little(0.8)	Big(0.8)	Little(0.8)	Big(0.8)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term(1.0)	Long term(1.0)	Short term(0.5)	Short term(0.5)
Recently moved?(10)	No(1.0)	No(1.0)	No(1.0)	Yes(0.0)
Children(6)	_unknown_(0.0)	Children #13;(0.62)	_unknown_(0.0)	_unknown_(0.0)
Total income(8)	10000(0.56)	8300(0.33)	20000(0.07)	0(0.01)
Partner(8)	Yes(1.0)	Yes(1.0)	No(0.0)	No(0.0)
Total expenses(8)	10050(0.34)	0(0.12)	4000(0.48)	4000(0.48)
Age(0)	58(-)	27(-)	54(-)	24(-)

I found Søknad #8 with a similarity of 0.744 as the best match.

Figure C.14.: The outputted similarity table for CBR instance #4 for the first query on supplements for other purposes.

Case Officer #5

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #8	Application #2	Application #3
Similarity	-	0.768	0.768	0.761
Sup. Amount(0)		1500	1500	3000
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	New clothes for child	Clothes, has lost weight and needs a lot of new clothes be cause of this	Clothes	Summer clothes for the entire familiy
PS(7)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(7)	No challenges	No challenges(1.0)	Moderate challanges(0.5)	No challenges(1.0)
Calculated norm(7)	3000	18005(0.01)	9750(0.16)	24560(0.0)
Necessity(8)	Large	Average(0.8)	Large(1.0)	Large(1.0)
Consequence(6)	Average	Small(0.8)	Average(1.0)	Average(1.0)
Living situation(2)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(2)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(6)	Average	Average(1.0)	Little(0.8)	Average(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(6)	Long term	Short term(0.5)	Long term(1.0)	Long term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(2)	Children #14;	Children #9;Children #1(0.65)	_unknown_(0.0)	Children #7;Children #8(0.26)
Total income(8)	12000	0(0.01)	14000(0.56)	1940(0.03)
Partner(2)	Yes	Yes(1.0)	Yes(1.0)	Yes(1.0)
Total expenses(7)	6500	6500(1.0)	11000(0.25)	12000(0.18)
Age(2)	29	43(1.0)	58(1.0)	43(1.0)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #0	Application #10	Application #5	Application #13
Similarity	0.757	0.716	0.641	0.59
Sup. Amount(0)	1500	1000	0	1500
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Clothes, client has had low i ncome for a long time	Keyboard	Winter clothes. Granted by §1 9.
PS(3)	_unknown_(1.0)	PS #12;(1.0)	_unknown_(1.0)	PS #14;(1.0)
Health(6)	Moderate challanges(0.5)	Very large challenges(0.0)	No challenges(1.0)	Small challenges(0.75)
Calculated norm(6)	9800(0.16)	4684(0.65)	-11600(0.01)	8120(0.25)
Necessity(3)	Average(0.8)	Average(0.8)	Little(0.6)	Large(1.0)
Consequence(6)	Average(1.0)	Large(0.8)	No(0.4)	Average(1.0)
Living situation(3)	Rent private market(1.0)	Rent municipal house(0.8)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little(0.8)	Big(0.8)	Little(0.8)	Big(0.8)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term(1.0)	Long term(1.0)	Short term(0.5)	Short term(0.5)
Recently moved?(10)	No(1.0)	No(1.0)	No(1.0)	Yes(0.0)
Children(6)	_unknown_(0.0)	Children #13;(0.62)	_unknown_(0.0)	_unknown_(0.0)
Total income(8)	10000(0.56)	8300(0.33)	20000(0.07)	0(0.01)
Partner(8)	Yes(1.0)	Yes(1.0)	No(0.0)	No(0.0)
Total expenses(8)	10050(0.34)	0(0.12)	4000(0.48)	4000(0.48)
Age(0)	58(1.0)	27(1.0)	54(1.0)	24(0.5)

I found Søknad #8 with a similarity of 0.768 as the best match.

Figure C.15.: The outputted similarity table for CBR instance #5 for the first query on supplements for other purposes.

C.3.2. Second Retrieval Test

Case Officer #1

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #5	Application #8	Application #2
Similarity	-	0.879	0.609	0.602
Sup. Amount(0)		0	1500	1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Bike	Keyboard	Clothes, has lost weight and needs a lot of new clothes be cause of this	Clothes
PS(3)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(6)	No challenges	No challenges(1.0)	No challenges(1.0)	Moderate challanges(0.5)
Calculated norm(6)	-8900	-11600(0.5)	18005(0.0)	9750(0.0)
Necessity(3)	Little	Little(1.0)	Average(0.8)	Large(0.6)
Consequence(6)	No	No(1.0)	Small(0.6)	Average(0.4)
Living situation(3)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(2)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little	Little(1.0)	Average(0.8)	Little(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Short term	Short term(1.0)	Short term(1.0)	Long term(0.5)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(6)	_unknown_	_unknown_(1.0)	Children #9;Children #1(0.0)	_unknown_(1.0)
Total income(8)	17000	20000(0.41)	0(0.0)	14000(0.41)
Partner(8)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(8)	5500	4000(0.65)	6500(0.75)	11000(0.18)
Age(0)	26	54(-)	43(-)	58(-)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #13	Application #0	Application #3	Application #10
Similarity	0.597	0.587	0.514	0.43
Sup. Amount(0)	1500	1500	3000	1000
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Winter clothes. Granted by §1 9.	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Summer clothes for the entire familiy	Clothes, client has had low i ncome for a long time
PS(3)	PS #14;(1.0)	_unknown_(1.0)	_unknown_(1.0)	PS #12;(1.0)
Health(6)	Small challenges(0.75)	Moderate challanges(0.5)	No challenges(1.0)	Very large challenges(0.0)
Calculated norm(6)	8120(0.0)	9800(0.0)	24560(0.0)	4684(0.02)
Necessity(3)	Large(0.6)	Average(0.8)	Large(0.6)	Average(0.8)
Consequence(6)	Average(0.4)	Average(0.4)	Average(0.4)	Large(0.2)
Living situation(3)	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)	Rent municipal house(0.8)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Big(0.6)	Little(1.0)	Average(0.8)	Big(0.6)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Short term(1.0)	Long term(0.5)	Long term(0.5)	Long term(0.5)
Recently moved?(10)	Yes(0.0)	No(1.0)	No(1.0)	No(1.0)
Children(6)	_unknown_(1.0)	_unknown_(1.0)	Children #7;Children #8(0.0)	Children #13;(0.0)
Total income(8)	0(0.0)	10000(0.1)	1940(0.0)	8300(0.05)
Partner(8)	No(1.0)	Yes(0.0)	Yes(0.0)	Yes(0.0)
Total expenses(8)	4000(0.65)	10050(0.25)	12000(0.12)	0(0.18)
Age(0)	24(-)	58(-)	43(-)	27(-)

I found Søknad #5 with a similarity of 0.879 as the best match.

Figure C.16.: The outputted similarity table for CBR instance #1 for the second query on supplements for other purposes.

Case Officer #2

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #5	Application #2	Application #8
Similarity	-	0.888	0.657	0.653
Sup. Amount(0)		0	1500	1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Bike	Keyboard	Clothes	Clothes, has lost weight and needs a lot of new clothes be cause of this
PS(5)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(7)	No challenges	No challenges(1.0)	Moderate challanges(0.5)	No challenges(1.0)
Calculated norm(5)	-8900	-11600(0.5)	9750(0.0)	18005(0.0)
Necessity(7)	Little	Little(1.0)	Large(0.6)	Average(0.8)
Consequence(6)	No	No(1.0)	Average(0.4)	Small(0.6)
Living situation(4)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(5)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little	Little(1.0)	Little(1.0)	Average(0.8)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(2)	Short term	Short term(1.0)	Long term(0.5)	Short term(1.0)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(8)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	Children #9;Children #1(0.0)
Total income(9)	17000	20000(0.41)	14000(0.41)	0(0.0)
Partner(5)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(9)	5500	4000(0.65)	11000(0.18)	6500(0.75)
Age(1)	26	54(1.0)	58(1.0)	43(1.0)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #0	Application #13	Application #3	Application #10
Similarity	0.649	0.614	0.558	0.481
Sup. Amount(0)	1500	1500	3000	1000
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Winter clothes. Granted by §1 9.	Summer clothes for the entire familiy	Clothes, client has had low i ncome for a long time
PS(3)	_unknown_(1.0)	PS #14;(1.0)	_unknown_(1.0)	PS #12;(1.0)
Health(6)	Moderate challanges(0.5)	Small challenges(0.75)	No challenges(1.0)	Very large challenges(0.0)
Calculated norm(6)	9800(0.0)	8120(0.0)	24560(0.0)	4684(0.02)
Necessity(3)	Average(0.8)	Large(0.6)	Large(0.6)	Average(0.8)
Consequence(6)	Average(0.4)	Average(0.4)	Average(0.4)	Large(0.2)
Living situation(3)	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)	Rent municipal house(0.8)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little(1.0)	Big(0.6)	Average(0.8)	Big(0.6)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term(0.5)	Short term(1.0)	Long term(0.5)	Long term(0.5)
Recently moved?(10)	No(1.0)	Yes(0.0)	No(1.0)	No(1.0)
Children(6)	_unknown_(1.0)	_unknown_(1.0)	Children #7;Children #8(0.0)	Children #13;(0.0)
Total income(8)	10000(0.1)	0(0.0)	1940(0.0)	8300(0.05)
Partner(8)	Yes(0.0)	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(8)	10050(0.25)	4000(0.65)	12000(0.12)	0(0.18)
Age(0)	58(1.0)	24(0.5)	43(1.0)	27(1.0)

I found Søknad #5 with a similarity of 0.888 as the best match.

Figure C.17.: The outputted similarity table for CBR instance #2 for the second query on supplements for other purposes.

Case Officer #3

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #5	Application #8	Application #2
Similarity	-	0.903	0.683	0.658
Sup. Amount(0)		0	1500	1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Bike	Keyboard	Clothes, has lost weight and needs a lot of new clothes be cause of this	Clothes
PS(9)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(9)	No challenges	No challenges(1.0)	No challenges(1.0)	Moderate challanges(0.5)
Calculated norm(8)	-8900	-11600(0.5)	18005(0.0)	9750(0.0)
Necessity(9)	Little	Little(1.0)	Average(0.8)	Large(0.6)
Consequence(10)	No	No(1.0)	Small(0.6)	Average(0.4)
Living situation(9)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(7)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(7)	Little	Little(1.0)	Average(0.8)	Little(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(8)	Short term	Short term(1.0)	Short term(1.0)	Long term(0.5)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(9)	_unknown_	_unknown_(1.0)	Children #9;Children #1(0.0)	_unknown_(1.0)
Total income(10)	17000	20000(0.41)	0(0.0)	14000(0.41)
Partner(7)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(10)	5500	4000(0.65)	6500(0.75)	11000(0.18)
Age(6)	26	54(1.0)	43(1.0)	58(1.0)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #0	Application #13	Application #3	Application #10
Similarity	0.653	0.644	0.581	0.5
Sup. Amount(0)	1500	1500	3000	1000
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Winter clothes. Granted by §1 9.	Summer clothes for the entire familiy	Clothes, client has had low i ncome for a long time
PS(3)	_unknown_(1.0)	PS #14;(1.0)	_unknown_(1.0)	PS #12;(1.0)
Health(6)	Moderate challanges(0.5)	Small challenges(0.75)	No challenges(1.0)	Very large challenges(0.0)
Calculated norm(6)	9800(0.0)	8120(0.0)	24560(0.0)	4684(0.02)
Necessity(3)	Average(0.8)	Large(0.6)	Large(0.6)	Average(0.8)
Consequence(6)	Average(0.4)	Average(0.4)	Average(0.4)	Large(0.2)
Living situation(3)	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)	Rent municipal house(0.8)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little(1.0)	Big(0.6)	Average(0.8)	Big(0.6)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term(0.5)	Short term(1.0)	Long term(0.5)	Long term(0.5)
Recently moved?(10)	No(1.0)	Yes(0.0)	No(1.0)	No(1.0)
Children(6)	_unknown_(1.0)	_unknown_(1.0)	Children #7;Children #8(0.0)	Children #13;(0.0)
Total income(8)	10000(0.1)	0(0.0)	1940(0.0)	8300(0.05)
Partner(8)	Yes(0.0)	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(8)	10050(0.25)	4000(0.65)	12000(0.12)	0(0.18)
Age(0)	58(1.0)	24(0.5)	43(1.0)	27(1.0)

I found Søknad #5 with a similarity of 0.903 as the best match.

Figure C.18.: The outputted similarity table for CBR instance #3 for the second query on supplements for other purposes.

Case Officer #4

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #5	Application #8	Application #2
Similarity	-	0.879	0.63	0.606
Sup. Amount(0)		0	1500	1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Bike	Keyboard	Clothes, has lost weight and needs a lot of new clothes be cause of this	Clothes
PS(8)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(10)	No challenges	No challenges(1.0)	No challenges(1.0)	Moderate challanges(0.5)
Calculated norm(10)	-8900	-11600(0.5)	18005(0.0)	9750(0.0)
Necessity(8)	Little	Little(1.0)	Average(0.8)	Large(0.6)
Consequence(10)	No	No(1.0)	Small(0.6)	Average(0.4)
Living situation(1)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(5)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little	Little(1.0)	Average(0.8)	Little(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(7)	Short term	Short term(1.0)	Short term(1.0)	Long term(0.5)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(10)	_unknown_	_unknown_(1.0)	Children #9;Children #1(0.0)	_unknown_(1.0)
Total income(10)	17000	20000(0.41)	0(0.0)	14000(0.41)
Partner(5)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(10)	5500	4000(0.65)	6500(0.75)	11000(0.18)
Age(0)	26	54(-)	43(-)	58(-)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #13	Application #0	Application #3	Application #10
Similarity	0.604	0.6	0.517	0.43
Sup. Amount(0)	1500	1500	3000	1000
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Winter clothes. Granted by §1 9.	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Summer clothes for the entire familiy	Clothes, client has had low i ncome for a long time
PS(3)	PS #14;(1.0)	_unknown_(1.0)	_unknown_(1.0)	PS #12;(1.0)
Health(6)	Small challenges(0.75)	Moderate challanges(0.5)	No challenges(1.0)	Very large challenges(0.0)
Calculated norm(6)	8120(0.0)	9800(0.0)	24560(0.0)	4684(0.02)
Necessity(3)	Large(0.6)	Average(0.8)	Large(0.6)	Average(0.8)
Consequence(6)	Average(0.4)	Average(0.4)	Average(0.4)	Large(0.2)
Living situation(3)	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)	Rent municipal house(0.8)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Big(0.6)	Little(1.0)	Average(0.8)	Big(0.6)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Short term(1.0)	Long term(0.5)	Long term(0.5)	Long term(0.5)
Recently moved?(10)	Yes(0.0)	No(1.0)	No(1.0)	No(1.0)
Children(6)	_unknown_(1.0)	_unknown_(1.0)	Children #7;Children #8(0.0)	Children #13;(0.0)
Total income(8)	0(0.0)	10000(0.1)	1940(0.0)	8300(0.05)
Partner(8)	No(1.0)	Yes(0.0)	Yes(0.0)	Yes(0.0)
Total expenses(8)	4000(0.65)	10050(0.25)	12000(0.12)	0(0.18)
Age(0)	24(-)	58(-)	43(-)	27(-)

I found Søknad #5 with a similarity of 0.879 as the best match.

Figure C.19.: The outputted similarity table for CBR instance #4 for the second query on supplements for other purposes.

Case Officer #5

Attribute (Weight)	Query Case	1. best match (Sim)	2. best match (Sim)	3. best match (Sim)
Name (0)	Query	Application #5	Application #8	Application #2
Similarity	-	0.884	0.718	0.644
Sup. Amount(0)		0	1500	1500
Sup. Type(0)	Support, other purpos	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Bike	Keyboard	Clothes, has lost weight and needs a lot of new clothes be cause of this	Clothes
PS(7)	_unknown_	_unknown_(1.0)	_unknown_(1.0)	_unknown_(1.0)
Health(7)	No challenges	No challenges(1.0)	No challenges(1.0)	Moderate challanges(0.5)
Calculated norm(7)	-8900	-11600(0.5)	18005(0.0)	9750(0.0)
Necessity(8)	Little	Little(1.0)	Average(0.8)	Large(0.6)
Consequence(6)	No	No(1.0)	Small(0.6)	Average(0.4)
Living situation(2)	Rent private market	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)
Single provider?(2)	No	No(1.0)	No(1.0)	No(1.0)
Clients effort(6)	Little	Little(1.0)	Average(0.8)	Little(1.0)
Recently single?(10)	No	No(1.0)	No(1.0)	No(1.0)
Norm(6)	Short term	Short term(1.0)	Short term(1.0)	Long term(0.5)
Recently moved?(10)	No	No(1.0)	No(1.0)	No(1.0)
Children(2)	_unknown_	_unknown_(1.0)	Children #9;Children #1(0.0)	_unknown_(1.0)
Total income(8)	17000	20000(0.41)	0(0.0)	14000(0.41)
Partner(2)	No	No(1.0)	Yes(0.0)	Yes(0.0)
Total expenses(7)	5500	4000(0.65)	6500(0.75)	11000(0.18)
Age(2)	26	54(1.0)	43(1.0)	58(1.0)

Attribute (Weight)	4. best match (Sim)	5. best match (Sim)	6. best match (Sim)	7. best match (Sim)
Name (0)	Application #0	Application #3	Application #13	Application #10
Similarity	0.639	0.607	0.572	0.528
Sup. Amount(0)	1500	3000	1500	1000
Sup. Type(0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)	Support, other purposes(1.0)
Description(0)	Clothes. Wife is encouraged t o apply for a job, she has so me health challanges (not doc umented)	Summer clothes for the entire familiy	Winter clothes. Granted by §1 9.	Clothes, client has had low i ncome for a long time
PS(3)	_unknown_(1.0)	_unknown_(1.0)	PS #14;(1.0)	PS #12;(1.0)
Health(6)	Moderate challanges(0.5)	No challenges(1.0)	Small challenges(0.75)	Very large challenges(0.0)
Calculated norm(6)	9800(0.0)	24560(0.0)	8120(0.0)	4684(0.02)
Necessity(3)	Average(0.8)	Large(0.6)	Large(0.6)	Average(0.8)
Consequence(6)	Average(0.4)	Average(0.4)	Average(0.4)	Large(0.2)
Living situation(3)	Rent private market(1.0)	Rent private market(1.0)	Rent private market(1.0)	Rent municipal house(0.8)
Single provider?(2)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Clients effort(5)	Little(1.0)	Average(0.8)	Big(0.6)	Big(0.6)
Recently single?(10)	No(1.0)	No(1.0)	No(1.0)	No(1.0)
Norm(3)	Long term(0.5)	Long term(0.5)	Short term(1.0)	Long term(0.5)
Recently moved?(10)	No(1.0)	No(1.0)	Yes(0.0)	No(1.0)
Children(6)	_unknown_(1.0)	Children #7;Children #8(0.0)	_unknown_(1.0)	Children #13;(0.0)
Total income(8)	10000(0.1)	1940(0.0)	0(0.0)	8300(0.05)
Partner(8)	Yes(0.0)	Yes(0.0)	No(1.0)	Yes(0.0)
Total expenses(8)	10050(0.25)	12000(0.12)	4000(0.65)	0(0.18)
Age(0)	58(1.0)	43(1.0)	24(0.5)	27(1.0)

I found Søknad #5 with a similarity of 0.884 as the best match.

Figure C.20.: The outputted similarity table for CBR instance #5 for the second query on supplements for other purposes.

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