Case Representation and Similarity Modeling for Non-Specific Musculoskeletal Disorders — A Case-Based Reasoning Approach

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Abstract

This paper presents a method for developing case-based reasoning (CBR) application for discovering similar patients with non-specific musculoskeletal disorders (MSDs) and recommending treatment plans using previous experiences. From a medical perspective, MSD is a complex disorder as its cause is often bounded to a combination of physiological and psychological factors. Likewise, the features describing the condition and outcome measures vary throughout studies. However, healthcare professionals in the field work in an experience-based way, therefore we chose CBR as the core methodology for developing a decision support system for physiotherapists which would assist them in the process of their co-decision making and treatment planning. In this paper, we focus on case representation and similarity modeling for the non-specific MSD patient data as well as we conducted initial experiments on comparing patient profiles.

Introduction

The term "musculoskeletal disorder"¹ (MSD) denotes health problems of the human musculoskeletal system including all forms of ill-health ranging from light, transitory disorders to irreversible, disabling injuries. MSDs and their resulting disability are common within the workforce worldwide, a major cause of sickness absence and often leading to longterm absence (Black 2012). MSDs are classified as specific (having evident pathology, and symptoms), and non-specific that are not attributable to a recognizable, known specific pathology, also the symptoms tend to be diffuse and nonanatomical. Symptoms generally involve pain, discomfort, and numbness without evidence of discrete pathology.

The decision making for optimal interventions in primary care for non-specific MSDs is challenging as there is often no specific cause for the patient's condition (Malmgren-Olsson and Armelius 2003).

Case-based reasoning (CBR) is a problem-solving paradigm (Aamodt and Plaza 1994) in the field of artificial intelligence (AI). It has an intrinsic commonality, the way

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¹http://www.who.int/occupational_health/publications/ oehmsd3.pdf Ingebrigt Meisingset, Ottar Vasseljen

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a physiotherapist suggests and adapts a treatment plan for a new patient (Bach and Althoff 2012).

Co-decision making in our view is bringing together the clinician's view with the formal knowledge and the patient's view who needs to implement recommendations and incorporate them in their daily life.

We believe CBR being an easy-to-understand and explainable methodology is a promising basis for a co-decision making tool. In this paper, we present an approach on how to develop a CBR system for non-specific MSD patient data, that would assist physiotherapists in their process of codecision making and treatment planning in primary care. While we are focusing on non-specific MSD, we believe the general concept is applicable to a broad range of diseases and conditions.

Related Work

There has been steady interests in developing CBR systems for healthcare domain with many successful prototypes throughout the years (Bichindaritz 2008; Bichindaritz and Montani 2011). However, there are still challenges in bringing the results of the research developments and applications into practice (Begum et al. 2011). With the recent focus on explainable AI, medical applications will certainly benefit from this movement (Holzinger et al. 2017). CBR being an explainable AI technique (Leake 1995; Roth-Berghofer 2004), can facilitate these efforts.

Furthermore, CBR provides the freedom of incremental development and rapid prototyping thus being highly preferred in healthcare domain (Gonzalez, Lopez, and Blobel 2013), it also presents an approach for decision support making based on patient's electronic health records. The paper (Karpov and Yudin 2010) presents a decision support system based on CBR for providing information to physicians while they attempt to diagnose and choose treatments.

In comparison with many CBR applications introduced before, we present our work targeting clinical practice in primary care such as the selfBACK project (Mork and Bach 2018). Our approach has a similar application domain, musculoskeletal disorders. However, the selfBACK focuses on patient-specific advice for non-specific low back pain whereas, we focus on comparing patient profiles from a physiotherapist's view, covering a broader range of disorders. However, both projects share considerable similarities in the case representation and similarity modeling.

Application Domain

The research presented is based on the FYSIOPRIM² dataset that captures data from patients treated by physiotherapists. The domain experts, closely involved in our research, extracted non-specific MSD patients from FYSIOPRIM dataset. This dataset additionally contains follow-up information, and prescribed treatments that lead to a decrease in pain, increase in functionality, or an improvement in the perceived quality of life of a patient.

The dataset consists of 506 patient profiles. Each patient profile is a collection of 286 features which include problem description, questionnaire responses, treatment variables, region of pain, etc. The dataset is uniformly distributed over four categories based on the region of pain: neck, shoulder, back, and widespread (multiple pain regions). Further, the feature set is also grouped into multiple categories such as demographics, disability and function, pain variables, psychological factors, treatments, and follow-ups among others.

Application Scenario: Co-decision Making

Figure 1 presents our application from a user's perspective. The primary use case is subdivided into multiple stages. The first stage is *data acquisition*, where patients with non-specific MSD capture their data through a tablet. This data acquisition happens while the patient is waiting for the first encounter with the physiotherapist. The second stage is *query*, where captured patient data is sent as a query to the CBR system. While the patient is waiting, the query results will be queued for the physiotherapist to be viewed, when the patient is with him/her. The third stage *co-decision making*, where physiotherapist examines the patient and reviews the queried result. The result contains treatment recommendations and outcomes of similar patients. Subsequently, the patient and the physiotherapist together create an informed treatment goal, followed by a treatment plan.

The core focus of our research is on the second and third stage in which the CBR system provides treatment recommendations. The second stage is initiated by the patient filling out data that is sent as a query to a CBR system. As a result, the most similar patient profiles (symptoms, treatments, and outcomes) will be available for the physiotherapist when he/she meets the patient. The willingness of the patient is a critical factor in deciding the treatment goal and treatment planning which is part of co-decision making.

Once the treatment goal and treatments are finalized, the patient is asked to visit the physiotherapist again after a defined follow-up time period. The reported symptoms and prescribed treatments, in the first encounter, are labeled as baseline data. On follow-up encounters the patients need to capture their follow-up data. These include few repeated (from the baseline with an intention to record the respective change), and few new questionnaires.



Figure 1: The CBR system to assisting physiotherapist in treatment planning for non-specific MSD patient.

Once the agreed treatment goal is achieved, the patient profile will be preserved as a new case/experience. In contrary, if the treatment goal is not achieved, then the result of the current query (baseline and follow-up data) would assist physiotherapist to modify or create a new treatment goal or treatment plan. This would be an iterative process.

The CBR system is build in the core of this process as a learning system that captures new cases (experiences) and are retained into the case base. Eventually, the recommendations improve over the time with new experiences, which might be missing in the initial case base. The CBR system should be viewed as assistance for physiotherapists and not as a replacement for their decision making. The system also helps to educate the patients for the current challenges in their treatment process and enables them to take informed decisions.

The CBR System Definition

As the goal of our proposed system is to assist physiotherapist by recommending treatment plans, the problem description of a case must be the care-seeking patient and we use a subset of the FYSIOPRIM variables to do so. The case representation is based on the features selected by domain experts.

In order to test how well the selected attributes differentiate the dataset, we applied few clustering techniques such as agglomerative clustering, k-Means, and latent class analysis (Vermunt and Magidson 2002). As a result, we observed 6 to 10 different classes in the dataset.

Furthermore, when comparing the clusters to outcomes, treatment plans, and other success factors, we could not see an obvious relationship. Therefore, we believe that using CBR will provide us with a dynamic system that would return the most similar cases for a new patient. In general, we found that a preliminary data analysis such as clustering is extremely helpful for understanding the dataset as well as undermining the relevant features. Based on this knowledge,

²https://www.med.uio.no/helsam/english/research/groups/ fysioprim/

we started to implement the components of the CBR system using the myCBR (Stahl and Roth-Berghofer 2008) tool.

The core of a CBR system consists of 3 parts: (I) vocabulary (the knowledge representation in terms of the definition of the domain and concept along with attribute names, value ranges, data-types, etc.), (II) similarity measures (the functions used for determining the sense of closeness between two cases), and (III) case base (collection of cases in a CBR system). We populate our case base with the cases derived from our dataset and implemented the prototype using the myCBR tool and its extension³ for easier prototyping.

Case Representation

A case is a tuple representation of a problem and its solution observed in the past. As the FYSIOPRIM dataset was initially collected to gain insight and understanding of the effectiveness of the treatment of MSDs, some of the features are used for measuring the effect of the treatment, but do not have an influence on the selection of the treatments. Further, to measure an effect, questions have been repeated over time and should (initially) not be included in the case representation as this apriori information will not be available in the first encounter. There are already evaluated measures to combine questions to scores and therewith encode knowledge. Thus, selecting the current case representation we focus only on information that is available at the time of the first encounter, and relevant for the treatment.

We chose attribute-value representation for the case modeling. The current cases only contains the problem description while the solution (treatments) is kept empty. As this is an ongoing research, the relevant treatment information will be consolidated once available.

Similarity Modeling

Our similarity model is based on the local-global principle (Richter 1995). The local similarities are the attribute level similarity functions that are modeled primarily based on their data types. For example, nominal attributes such as sex, marital status, etc. are modeled as tabular similarity function. For numeric attributes, we use the polynomial similarity function. The degree of respective polynomial function is determined by a data-driven approach, based on the distribution of its value in the case base as described in (Hüllermeier and Schlegel 2011). Figure 2 shows an example similarity function and its respective value distribution as a box plot, as introduced in (Verma, Bach, and Mork 2018). The Inter Quartile Range (IQR) is used as an indicator of the degree for the polynomial similarity function. The degree is chosen such that the similarity score for a distance more than the IQR value approaches to zero, as shown in figure 2.

The global similarity function is the weighted sum of all local similarity scores. The similarity function for our application is shown in equation 1. Where sim(Q, C) describes the global similarity function between a query Q and a case C. For each attribute i a local similarity function is defined as sim(q, c), where q is the attribute value of the query and c is the respective attribute value of the case.



Figure 2: Polynomial similarity function of work_ability, based on its IQR. (Y-axis is for similarity scores and X-axis is for distance between a query and case attribute value.)

$$\operatorname{sim}(\mathbf{Q}, \mathbf{C}) = \frac{1}{\sum w_i} \sum_{i=1}^n w_i \cdot sim_i(\mathbf{q}, \mathbf{c})$$
(1)

The amalgamation function is a weighted sum where w is the weight of each attribute i. The result of the global similarity function is a value in the range [0,1].

Experiments

We conducted experiments to test the developed CBR system using the FYSIOPRIM dataset with the main goal to showcase that the developed case representation and similarity measures are able to distinguish semantically similar cases.

We use a Leave-one-out cross-validation with 20 queries to the case base. These queries are grouped in 4 subsets representing the different pain sites in the FYSIOPRIM dataset. The query cases have been provided by domain experts and represent characteristic profiles that the CBR system should be able to distinguish. The execution of a query against the CBR system is facilitated via RestAPI calls. As a result we retrieve the ten most similar cases ranked by similarity. For each of the four subsets we then compute the mean similarity score per rank.



Figure 3: Mean similarity score versus k most similar cases from the case base. q_back , q_neck , $q_shoulder$, and $q_widespread$ are query subsets selected by domain experts based on pain sites.

³https://github.com/ntnu-ai-lab/mycbr-rest

Figure 3 presents the retrieval results with the mean similarity scores for a query with respect to the k most similar cases. As it is shown in the figure, the highest mean similarity score ranges between 0.77 and 0.84 with widespread pain having higher similarity scores than the others. Overall the decline of similarity follows the same trend for all four subsets.

Discussion

The retrieved similar patients were found to be deemed ground-truth relevant by the domain experts. Additionally, the decrease in mean similarity scores, shown in figure 3, with increasing number of retrieved patients demonstrates that the similarity measure distinguishes similar patients well.

The result shows that the CBR system is able to discover relevant similar patients from the case base, based on the selected attributes, case representation, and modeled similarity measures. However, we have also seen in discussion with domain experts that the features used to evaluate whether a patient was relevant varies.

Currently we hold all the cases in the same case base and have only one global similarity measure for the distinction. As the pain site clearly distinguishes the treatment suggested, the CBR system might perform better with multiple case bases. We believe that with the availability of correct and relevant solutions (treatments) the performance of the CBR system could be improved and evaluated objectively.

Overall we have seen that the features provided in the FY-SIOPRIM dataset are sufficient to develop a CBR system and the data-driven approach for creating local similarity measures is suitable for the application domain at hand.

Conclusion and Future Work

This paper presents the initial implementation of a CBR system for investigating co-decision making in primary care. Our application domain MSD shows the complexity of the domain and hence provides challenges for a decision support system.

In this paper, we have focused on the incremental and iterative development of the CBR system. We have presented an approach of case representation and similarity modeling for non-specific MSD dataset. To conclude, our developed system was able to discover the relevant similar patient profiles for a queried patient data.

In future work we aim at refining the CBR system and evaluating the approach with clinicians where the main challenge will be to include explanations and treatment variations that allow co-decision making using CBR.

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