The Use of Case-Based Reasoning for Personalizing Musculoskeletal Pain Treatment Recommendations

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Abstract

This Ph.D. research proposal presents an overview of the project SupportPrim, a Case-Based-Reasoning (CBR) application for the management of musculoskeletal pain complaints, and its research goals. SupportPrim seeks to become an intelligent decision support system that facilitates co-decision making between clinicians and patients by using machine learning methods. Through its clinician dashboard a treatment plan can be review and tailor to the patient specific needs, moving from the one-size-fits-all mentality to personalized healthcare. The main goals of SupportPrim also include to extend and adapt the decision support system for other primary care settings

Keywords

XCBR, Explainable AI, Visualizations, Decision-Support Systems

1. Problem

Musculoskeletal pain has been described as an epidemic. Approximately 10% of the general population report a chronic musculoskeletal pain complaint in the western world [1]. Musculoskeletal pain is a major reason for consultation in primary care putting a high burden on health services, it also brings serious consequences, such as loss of productivity at work and distress of patients and their families[2]. Current management of musculoskeletal pain is inconsistent across countries and settings, and treatment decisions depend largely on clinician's expertise or opinion. A high number of patients have non-specific symptoms with large variations between individuals. This heterogeneity does not fit well with evidence from clinical trials and clinical guidelines that typically proclaim one-size-fits-all treatment recommendations. This can lead to inadequate patient management and higher costs of resources.

The implementation of tailored treatments for patients can improve treatment planning and ideally yield to result in better patient outcomes and better use of resources. One solution towards this goal is creating intelligent healthcare systems by using explainable and transparent AI methods, such as using Case-Based Reasoning (CBR).

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main goal is to improve research prototypes of a CBR system applied in the SupportPrim project, the target is to improve management of musculoskeletal pain disorders (MSD) in primary care and provide decision support for clinical practice. A general overview of the project in this PhD work is as follows: a group of physicians, general practitioners (GP), collect relevant information from several patients under their care (data acquisition) through previously answered questionnaires and assessment by the GP. This data is then fed to the existing CBR system to expand and adapt the query database for GPs. The system looks for the most similar cases using CBR for suggested treatments and these results are displayed on a clinical dashboard for the GP to assess and create a personalized treatment (patient-clinician co-decision) tailored to the patient's needs. Currently, the CBR system searches for most similar cases based on the set of relevant attributes defined by the project's domain experts. The similarity is modeled on the local and global similarity principle but does not *learn* yet from the cases it obtains. An important goal for this PhD project is to advanced the current CBR approach to improve today's application. One major task is to include learning strategies for the system to retain new cases using the provided patient outcomes. For patient management, an important element to be develop is creating visualizations to facilitate the co-decision making of the end users. The ultimate aim is to integrate CBR methods to develop an explainable, intelligent decision support system.

2. Research Plan

For the SupportPrim CBR system, we want to focus on developing a system that reflects its multidisciplinary team. The domain experts are an important part in the development phase, the current CBR system has a global similarity function with weighted attributes defined by them. Recent experimentation suggest there is room for improvement. Finding the right experimentation setting to incorporate their knowledge with computer science will lead to obtain the best possible outcome. In the first phase of this research, we focused on how to improve the development phase of a CBR system. As this is a core starting point in any application, in our first paper[3], we focused on creating visualizations for domain experts, so they understand better how their data is working within the CBR system and assess its performance, such as the attributes' contribution to the global similarity measure and the retrieval results. During this work, we observed that modifications need to be made, e.g. re-evaluating the attributes' weights, so our next experiments will focus on further improvements in the development phase of the CBR system. We will create visualizations that allow to observe the correlations within the attributes and assess their weights influence in the overall results.

At this first phase, we focused on understanding the current system, how it was built and how it works to create a baseline that we can improve. The second phase of the research are the improvements of the SupportPrim CBR system, resulting from the changes that need to be addressed from the first version. The new version will incorporate modifications in the global similarity function, assess the case base representation and redefine weights of the attributes. For the extended version, we aim to incorporate a learning capability. The process can be divided in three general steps. In step one, through the clinician dashboard, the physician can see the most similar patients for the new case. In step two, the dashboard shows the new case characteristics and allows the physician to annotate the treatment information that will be followed, data on this step is stored and it's where the co-decision making between clinician and patient is done. In step three, successful patients treatments will be retained as new cases in the case base automatically. Recio et al,[4] mention features like a system that learns as the therapy evolves, data-driven configuration that besides patients' data also includes the experts input in an initial configuration and in the reuse of cases to make them more suitable. To achieve this objective different clustering methods will be tested to find the appropriate setting. For the third phase of the research we want to focus on the explainability aspect of the CBR system. This task involves creating visualizations not only for the domain experts but also for the end users. Explanation types will be defined as the research evolves, at the present time we are considering the use of counterfactuals, the literature review on XCBR, model agnostic explanations and visualizations. The expected result of this research is an improved, fully functional CBR system that:

- Personalizes treatment recommendations
- Automatically creates intuitive summaries for physicians
- Generates explanations for treatment recommendations for physicians to understand the system's results

2.1. Research Objectives

2.1.1. Investigate knowledge acquisition techniques to adjust the knowledge containers over time

To provide accurate and more personalized information for each treatment recommendation, the learning approach should take into consideration the different angles and knowledge discovery, e.g. treatment evolution, data representation, physician's inputs. Domain experts and clinicians will help with the integration of the CBR output into clinical context to ensure that it is not only functional in theory but also in practice.

2.1.2. Learning strategies for case-base evolution

The CBR system will keep collecting new cases (data points) from incoming patients from the general practitioners and physiotherapists. Every time a new treatment is created, it will be added to the case base (dataset) for reference. We will explore learning strategies for retaining new cases. These include different patients' factors, such as their clinical data and/or the data recorded from previous sessions.

2.1.3. Extend the existing CBR tool with explainability capabilities

The current tool for the project is myCBR, a Java-based development framework. It is designed to expose modelling functionality, as described by Bach et al. [5], creating concepts and similarity functions that run through a HTTP REST API and can be used with all programming languages that supports Rest API and parsing JSON objects. An assessment of the current CBR system will be done to make improvements from the existing functions that can be transfer to different clinical settings, where the main goal is to incorporate explainability functionality. Factors like data visualization and clinicians' adoption of intelligent support systems need to be addressed in the integration of the system in clinical practice for it to be successful [6].

2.2. Methodology

2.2.1. Apply Clustering Techniques and CBR Methods combined with domain knowledge

Oliveira et al. proposed a methodology for the CBR modeling process that "facilitates the allocation of expertise between the application domain and the CBR technology"[7]. Their approach will be useful for analysing and redefining the new SupportPrim CBR system as a whole. Starting from the modeling by studying their approach of static, contextual and dynamic attributes, to studying the CBR system variables relevant for its management process and actions to perform in the retrieval results and in storing new data.

Clustering techniques will be explored to evaluate the data. SupportPrim groups patients with similar characteristics in classes (phenotypes). This grouping only happens at the beginning before starting treatment, K-Means can be use to assess if a new clustering later on, with the patient evolution might further help in pinpointing their treatment needs. As highlighted by Bichindaritz et al.[8] "CBR is also known for its knowledge containers - vocabulary, similarity measure, case base, and adaptation. The case base in and of itself is often a major focus of knowledge discovery in CBR, with its cases, structures, and organization". Bichindaritz et al., mention several functionalities well defined for knowledge discovery, learning new trends and association of data, for clustering particularly, they mention hierarchical clustering or density-based algorithms, which could be adequate to explore for the SupportPrim project, for possibly assessing a re-grouping of the patients depending on the treatment evolution. We expect that pattern recognition of the SupportPrim data can help to investigate if there are other existing patterns that can be integrated in the CBR configuration to make the reuse of cases treatment more suitable for recommendations, a ranking of cases with clustered case-based organization. Lamy et al[9], mention several algorithms in their CBR system for cancer detection, such as KNN, high-dimensional multivariate data visualization and Artificial Feeding Birds (AFB) metaheuristic for adaptable optimization algorithms that propose an interesting approach and that could be helpful for this research, for SupportPrim, their methods could lead to creating better visualizations of the data, as it can be presented in both qualitative and quantitative form, while contributing to the explainability element as well. Mahdi and Seifi [10] suggest a Bayesian network for classifying diseases to support effective medical treatment using experts' knowledge. Their classification methods are based on data and domain experts knowledge and both are considered in the cases, for SupportPrim, their methods with feature reduction and clustering might improve the CBR performance. Other works will be reviewed to improve the existing CBR system.

2.2.2. Create user friendly visualizations and results explainability

Currently, the SupportPrim clinician's dashboard displays the patient relevant data and stores the physician's examination and treatment plan. We want to update the dashboard so that it reflects the summary of relevant data and it's user friendly and intuitive to facilitate the clinicians work as the CBR system evolves. As Kenny et al. [11] mention, adoption barriers can be addressed by the explanation capabilities designed to improve adoption, such as adequate predictions and providing "personalised explanation-by-example". For this task we are considering creating counterfactual or model agnostic explanations, including unsuccessful cases can also help in creating these explanations. Cunningham et al. [12] outline their experiment setting on a case-based explanation system, in their work, subjects score the explanations. The case-based explanation system showed to perform better than having no explanation and better than rule-based systems. Visualizations in the development phase are an important element as well, as they allow to assess and verify that the implemented CBR system works as intended. We will work on creating tools to explore CBR system's for domain experts

3. Progress Summary

As this project already had a system prototype, one of the first tasks was to revise and understand the system's programming and its existing functions. Understanding the type of data and its meaning was important to get familiar with the case base representation. Currently, a review of the state of the art is being done, we narrowed the topics to four main ones of interest: cbr explainability, visualizations, model agnostic explanations and counterfactuals. This task is expected to be finished by the end of August 2022. We have worked on the first paper soon to be published related to understanding our current CBR system through visualizations for our domain experts, to have the baseline to improve from, the visualizations created will be useful in the next development phase of the new CBR system. The next step is working on extending and improving the CBR system and visualizations doing experiments for a second paper, we will explore the use of autoencoders in a CBR system taking into consideration the input from domain experts and visualizations on attributes correlations within the system. Later on, depending on experimentation, we will explore the methods mentioned in the Methodology to incorporate explainability and find the right setting with the clinicians to achieve a human-centered AI.

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