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Towards an Evidence-Based Decision Support Tool for Management of Musculoskeletal Conditions

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Abstract. Musculoskeletal (MSK) problems present an increasing burden for the healthcare sector, particularly in ageing populations. Advances in evidence are often slow to influence clinical decisions, suggesting decision support would be beneficial. We propose a Bayesian network (BN) for providing evidence-based decision support as it can explicitly represent domain knowledge as causal relations and allows both domain knowledge and clinical data to be combined to create a usable decision model. We make a preliminary evaluation of the model's performance.

Keywords. Clinical decision support, Bayesian networks, musculoskeletal

1. Introduction

Musculoskeletal (MSK) conditions "are the dominant source of chronic pain worldwide, and the basis for the most common pain complaints presented to primary care" [1]. However, clinical decisions may ignore the latest clinical evidence as it is difficult for busy clinicians to keep up to date with the latest research. Computerised decision support tools can assist decision makers with evidence-based predictions and inferences.

Expert Systems and Machine Learning (ML) tools have been the most popular approaches to develop clinical DSS. Obedmeyer and Emanuel [2] draws an analogy between the reasoning mechanism of these approaches and medical students. Expert systems reason about clinical situations based on predefined rules, resembling the textbook knowledge of a medical student. ML approaches learn from data which is, according to [2], similar to a more experienced clinical resident. However, whereas a resident relates their experience to their medical knowledge, a pure ML approach learns only from data. This pure ML approach is successful only if a large database exists including the 'true' diagnosis. This is not the situation for the management of MSK conditions: although there are many patients, the data is complex and is not collected

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uniformly. Moreover, the 'true' diagnosis or correct treatment is not recorded, as different clinicians may have equally valid but conflicting opinions [3].

In this paper, we aim to develop a DSS for the management of MSK conditions by analysing the available data in combination with clinical evidence and knowledge about this domain. Our approach is to organise the model using clinical evidence and then to analyse the available data to learn the validity and strength of the modelled relationships, supplementing it with clinical judgement when necessary. We use a probabilistic modelling approach, called Bayesian Networks (BNs), which is suitable for both representing domain knowledge and learning from data [4]. In the remainder of this paper, Section 2 presents the MSK BN, Section 3 shows our preliminary evaluation, and Section 4 presents our conclusions and plan for next steps.

2. MSK Bayesian Network

In practice, clinicians make decisions by listening to patients, observing their condition and performing tests. A dataset usually contains this 'observable' data but clinical decisions are not just based on data: instead clinicians use their understanding to estimate the 'underlying' condition. Such 'latent' variables are usually not recorded in clinical dataset, containing only the directly observable data. Figure 1 shows the main reasoning mechanism of the MSK BN; all variables except treatment routes are latent hence none are directly recorded in a patient dataset. Our approach is to model the main reasoning mechanism of the DSS based on the same 'latent' factors that are used by the clinicians, and to estimate the state of these factors based on the observable variables in the data.

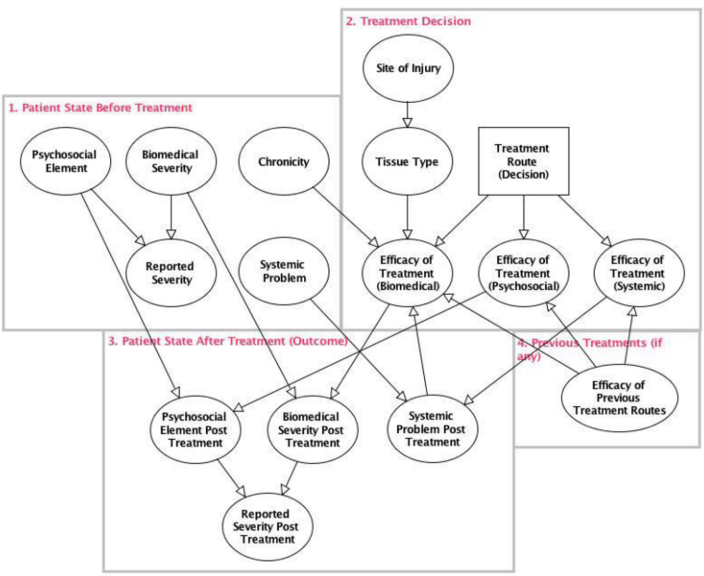

Figure 1. MSK BN: Latent Variables and Relations but Excluding Observable Variables

The model is divided into four fragments shown by four boxes in Figure 1.

1. **Patient state before treatment**: models the current state of the patient, i.e. before the treatment is applied. The aim of this fragment is to diagnose the true severity of the patient's injury. Chronic injuries are usually harder to treat.

Similarly, MSK conditions rarely improve optimally unless an underlying systemic problem is treated, where that co-exists.

2. **Treatment decision:** models the efficacy of different treatment routes. Different treatments have different efficacies for biomedical, psychosocial and systemic condition of the patient. For example, steroids can be useful for patients with systemic problems whereas exercise can be useful for those with psychological problems. The primary factor affecting the biomedical efficacy of a treatment is the type of injured tissue. For example, manual therapy is effective in treating some muscle injuries, and surgery is required for treating some bone injuries. The injury site, and the location and characteristics of pain indicates information about the type of injured tissue.
3. **Patient state after treatment:** predicts the state of the patient after the treatment is applied.
4. **Previous treatments (if any):** models the previous treatments that has been applied for the current MSK condition.

The 'latent' variables in Figure 1 are inferred based on the observations of the clinician. Table 1 shows the 'observable' variables that are used for estimating the state of these variables. These variables are also included in the complete BN.

Table 1. Observable data related to latent variables

Psychosocial Element	**Biomedical Severity**	**Chronicity**
Activity Level	Function with Injury	Duration of Onset
Anxiety	Inflammation	History of Onset
Catastrophizing Thinking	Neurological Signs	Progression
Fear Avoidance	Reported Pain	
Insurance Claim	Unbroken Sleep	
Wellbeing		
Site of Injury	**Tissue Type**	**Systemic Problem**
Location of Pain	Depth of Pain	Pattern of Pain
Localisation of Pain	Description of Pain	Number of Sites of Pain
		Sinister Pathology

We used a combination of a patient dataset and expert knowledge to define the parameters of the MSK BN. Our main dataset contained information about 95 patients who were treated at the Physiotherapy Department of Mile End Hospital in London. This data included the treatment route, all variables in Table 1. The data of the observable variables in the model (Table 1) is be used to learn their conditional probabilities, but those of the latent variable are elicited.

This elicitation can be challenging for latent variables such as treatment efficacy with large Conditional Probability Tables (CPTs). We used graphical scales with verbal anchors [5] and ranked nodes [6] to elicit the CPTs of these variables. The ranked nodes approach is an established BN technique that approximates the states of an ordinal variable by mapping its ordinal states to an underlying continuous, monotonically ordered and bounded unit interval scale [0-1] with a Truncated Normal (TNormal) distribution [6]. Ranked nodes are readily implemented in AgenaRisk [7]. Our approach 1) transforms the answers of the experts into numbers assuming that the graphical scale corresponds to a linear numerical scale between zero and one 2) computes the mean and standard deviation values from this interval assuming that the interval represents 0.1 and 0.9 quantiles on a Normal distribution 3) uses these parameters on a ranked node to compute parameters for the elicited NPT (see Figure 2). The parameters of the rest of the variables were learned from the data by using the Expectation-Maximisation (EM) algorithm. The parameters of the elicited variables were kept fixed when EM was applied.

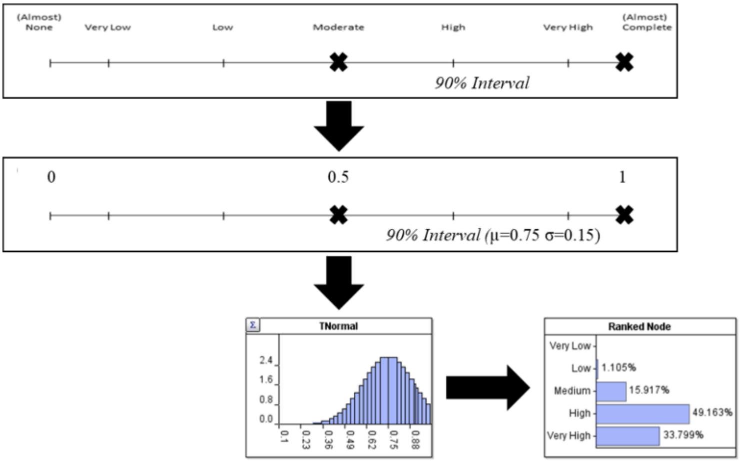

Figure 2. Elicitation of Treatment Efficacy Parameters

3. Evaluation

The data also included EQ-5D-5L outcome index for all 95 patients, and clinicians' assessment for the severity of the injury both before and after the treatment for 49 of those patients. This information was only used for validating the model. Severity of the injury was recorded in the same way as those variables is defined in MSK BN (i.e. 'High Severity', 'Medium Severity' and 'Low Severity') so it enabled us to directly compare our model's predictions for these patients. We used Receiver Operating Characteristic (ROC) curves, and Area Under ROC (AUROC) curves to evaluate the model's performance based on clinicians' judgements in the dataset (see Figure 3). The model's overall AUROC was 0.76 and 0.93 for severities before and after treatment respectively [8].

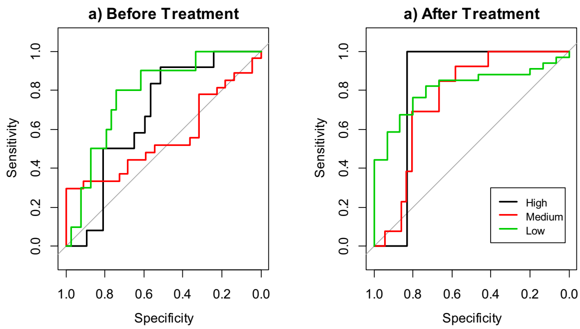

Figure 3. ROCs for Low, Medium and High Severity of Injury

We also evaluated our model's ability to discriminate the patients that had higher or lower scores for EQ-5D-5L index scores (see Figure 4). The patients who were predicted to have a higher severity of injury also had lower index scores.

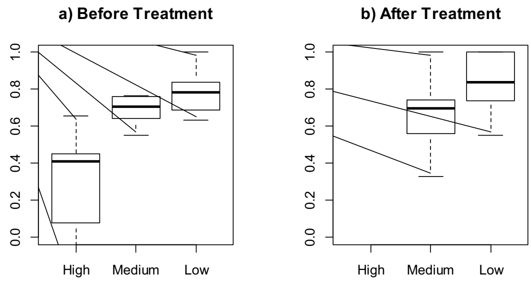

Figure 4. EQ5D-5L Index Scores of Predicted Severity of Injury

4. Conclusion

This paper presented the development steps and initial validation results of a BN based decision support tool for management of MSK conditions. The clinical reasoning mechanism of the MSK BN encodes domain knowledge and up-to-date clinical evidence about biomedical and psychosocial elements of MSK conditions and incorporates it into decision support. A preliminary evaluation shows promising results for model accuracy. Our next steps are to develop a parameter learning approach that exploits the properties of ranked nodes, run a more comprehensive validation of the model using a larger dataset that is currently being collected at the hospital, and to develop an interface that will enable an easier use of the model by physiotherapists.

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