Bayesian Belief Network Model of the Radical Prostatectomy Pathway

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Abstract

A clinical pathway represents sequencing and timing of interventions by clinicians, nurses and other healthcare professionals for a particular clinical presentation. It is designed to minimize delays and resource utilizations and to maximize the quality of tertiary care. A pathway is used to monitor and control patient's progress that is measured according to standard process and clinical outcomes. We conducted a retrospective chart study and used the Bayesian belief network (BBN) to model a pathway for radical prostatectomy that was developed at The Ottawa Hospital – Civic Campus, and to predict the patient's length of stay (LOS) given the deviations from pre-determined course of action.

1. Introduction

A clinical pathway represents sequencing and timing of interventions by clinicians, nurses and other healthcare professionals for a particular diagnosis or procedure. It is designed to minimize delays and resource utilizations and to maximize the quality of tertiary care. A pathway is a cost-effective tool for clinical process improvement that has been accepted in hospitals and various healthcare organizations. Usually it consists of four essential components: a timeline, categories of care processes (e.g., assessment, treatment, activity, etc.), patient's outcomes, and the variance record [1]. It is argued that adherence to a clinical pathway while managing a patient should result in more effective care model. Such an argument is true providing that patient's progress does not deviate significantly from the norm. However, in a tertiary care practice such deviations, called variances, often occur thus making the management task much more difficult.

In this research we consider variances (deviations from a norm) that are associated with the care-related activities and the outcome of a patient. While development of the clinical pathways was described in the literature, the evaluation of the impact of the variances on the patient's outcomes and the patient's length of stay (LOS) in a hospital remains relatively less reported.

Research on clinical pathways mostly deals with representing pathways in a formal way [2, 3], documenting, collecting and representing variances [4, 5], and finally with developing decision support tools that would supplement a pathway with a predictor of the LOS [6]. Widely adopted methodologies to model clinical pathways include PERT/CPM models, Petri nets, skeletal plans and decision rules in the ARDEN syntax. The documenting and tracking frameworks developed so far allow tracking variances associated with a clinical pathway, but usually they are limited to frequencies of general variances, and the impact on the LOS is not evaluated. Finally, predictors of the LOS are usually implemented with neural networks, thus they may be difficult to comprehend by the physicians, although they may have acceptable predictive accuracy.

Our research involves predicting the LOS given variances, but also it offers comprehensive and readable representation of a pathway in form of a network model. It aims at evaluating how non-adherence to a clinical pathway, described by set of outcome measures affects the LOS and at developing a theoretical model of a pathway that could be used for predicting the LOS given the observed variances. A clinical pathway created and implemented at The Ottawa Hospital – Civic Campus (Ottawa, Canada) for radical prostatectomy (RPP) was used in the research as a case study. The Ottawa Hospital – Civic Campus is a teaching hospital and the pathway was constructed following the evidence-based guidelines.

Considering the character of the activities comprising the pathway, it was decided that the theoretical model will be developed from retrospective abstracted chart data and the Bayesian belief network (BBN) model will be used to represent the probabilistic relationships in the RPP. We will use the term *BBN_RPP* model throughout the paper while referring to this implementation. The BBN modeling methodology was selected for the following reasons:

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1. The clinical pathway represents a sequence of events in time and relationships among them. Therefore, it is possible to view the pathway as a probabilistic process with conditional probabilities of the events that can be assessed from past data. The events are dependent on each other and form a network.
2. Compared to other models (neural networks or decisions trees) the BBN can easily represent inter-dependencies or independencies between events and is not affected by multicollinearity. Moreover, it is well suited to represent events with associated sets of possible values and the probabilities assigned to each of these values [7].
3. Predicting impact of the variances on the patient's future condition (or LOS) on the basis of current observations is a typical conditional-type probability question. The BBN model is designed to answer such question.

The process of developing the *BBN_RPP* model involved several steps. First, we identified the variables describing events in the RPP. Then, data required for model development was collected from the retrospective chart study, and a model was created using this data. In addition, we used out-of-sample data to evaluate the predictive accuracy of the *BBN_RPP* model. The model provides probabilities for the LOS being *met* or *delayed* and for testing purposes we assumed the output with the probability greater than 0.5 would be presented as the final prediction.

2. Foundations of the BBN model

The BBN model was described among others in [7] and [8]. In this section we present basic theory behind it.

A BBN denoted by $B = (G, P)$ is represented by a directed acyclic graph $G = (X, A)$ with a set of nodes $X = \{x_1, x_2, \ldots, x_n\}$ representing stochastic variables taking a finite set of values, and a set of arcs $A \in X \times X$ representing direct dependencies between the associated variables. The strength of these dependencies is quantified by conditional probabilities. A joint probability distribution P is defined on the stochastic variables that can be factorized according to the topology of the graph as follows: $P(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} P(x_i | par(x_i))$ where $par(x_i)$ is a set of parents of the node x_i. This implies that $P(x_1, x_2, \ldots, x_n)$ can be defined in terms of local probability tables $P(x_i | par(x_i))$ by assuming the variable x_i to be conditionally independent of all its predecessors given the parents $par(x_i)$ [9]. Such formulation allows evaluating conditional probabilities being subject to some earlier observations, providing that there is a path in a network linking the variables in question.

In order to develop the BBN, it is necessary to know the precedence relationships in a network, the events and their occurrences, and conditional probabilities associated with the events. There are several ways to acquire this information. One is to develop the BBN model from the subjective assessment elicited from a domain expert. Another is to learn the model structure from data. This later approach was used in developing the *BBN_RPP* model. The motivation for such an approach was as follows:

1. In the RPP, the pathology and the relationships between patient outcomes and patient activities are complicated, which makes it difficult to re-create the structure of cause-effect graph from expert opinion.
2. Conditional probabilities can be obtained either from the extensive interviews with the experts – a method not feasible in most practical applications, or automatically. We decided for the automatic acquisition and conditional probabilities were obtained from data using the maximum likelihood method.
3. Updating the *BBN_RPP* model as new data becomes available is an important modeling feature. A BBN created by learning from data is easier to maintain and upgrade because only new variables need to be considered instead of consulting the relevant experts to reconsider the entire domain.

In this research we used the K2 algorithm [8] to heuristically develop the *BBN_RPP* model from a retrospective data set.

The K2 algorithm constructs a BBN from a set of cases D described by a set of ordered discrete variables $X = \{x_1, x_2, \ldots, x_n\}$. The ordering of variables is defined by the function $pred(x_i)$ that for each x_i returns a set of preceding variables.

The operation of K2 algorithm is presented in Figure 1. The algorithm takes as inputs a database D, a set of variables X and their ordering $pred(x_i)$, and the maximum number of parents a node in a constructed network may have max_par.

K2 generates a Bayesian belief network B that maximizes $P(B, D)$ – the posterior probability of a network B on a database D. The algorithm uses the greedy search method. It works in a loop over all variables that become nodes in the network and initially assumes a node has no parents. Then it adds incrementally that parent whose addition most increases the probability of the resulting network. If it is impossible to increase the probability of the network or the maximum number of parents is reached, the algorithm stops adding parents to the node. K2 returns as output the structure of a network B as a set of pairs $(x_i, par(x_i))$ for each x_i.

```
procedure K2
B = {}
for each xi in X do
     par(xi) = {}
     Pold = P(B ∪ (xi, par(xi)), D)
     proceed = true
     while proceed and |par(xi)| < max_par do
        z = a node in pred(xi) - par(xi)
            that  maximizes
            P(B ∪ (xi, {z} ∪ par(xi)), D)
        Pnew = P(B ∪ (xi, {z} ∪ par(xi)), D)
        if Pnew > Pold then
           Pold = Pnew
           par(xi) = {z}  ∪ par(xi)
        else
           proceed = false
     end
     B = B ∪ (xi, par(xi))
end
```

Figure 1: K2 algorithm

Once the Bayesian belief network is constructed, it can be used to make bi-directional inferences. There are many other effective procedures for computing arbitrary conditional probability distributions [9, 10]. They all operate on the same underlying probability distribution and therefore the results – the required conditional probabilities – are the same.

3. Development of the BBN_RPP model

3.1 Definition of variables

All of the patient's outcomes listed in the pathway (e.g., patient teaching, respiratory function, etc.) were represented as stochastic variables in the *BBN_RPP* model. This set was further augmented to include variables representing non-outcome related activities. A dependent variable was represented by LOS and it indicated if the expected length of hospital stay was *met* or *delayed*.

Table 1 presents all stochastic variables considered in the *BBN_RPP* model together with their values and time windows of occurrence (indicated by "+" for appropriate post-operation day). The classification of variables in the model followed the RPP categorization of activities and outcomes into: physical activity, nutrition, patient teaching, pain, respiratory function, elimination, and mobility. An outcome associated with each category could occur only for the specific time windows, and all stochastic variables were grouped accordingly.

We considered three time windows, referring to the first, second and third day (from 00:00 to 24:00) of the patient's stay in the hospital ward after the surgery and denoted them as post-op day 1, 2 and 3 respectively. The majority of variables were observed in all time windows (e.g. vital signs), however, there were some limited to specific post-op days (e.g., psychological condition was considered on post-op day 1 only). There were few variables that had values common for all post-op days, and few that had day-specific values (e.g., normal value of the respiratory function might occur on post-op day 1, 2 and 3, while mild on post-op day 1 only). Clearly, variables having only one value for a specific time window were excluded for that day (e.g., respiratory function for post-op day 2 and 3). The remaining variables were ordered according to the time sequence outlined in the RPP (e.g., vital signs on post-op day 1 preceded vital signs on post-op day 2).

3.2. Retrospective chart study

The retrospective chart study took place at The Ottawa Hospital – Civic Campus that provides health care services on tertiary-level and specialty care to the residents of Eastern Ontario. This includes 70,000 surgical cases, 120,000 emergency visits and 770,000 outpatient visits a year (2005 data). The 125 RPP charts coming from this hospital could be considered as representative for similar populations elsewhere because the epidemiological studies have not shown differences in the recovery after the radical prostatectomy between Canadian, U.S., and European populations. These charts describe patients managed by different surgical teams during the period 2002 to 2003 for the radical prostatectomy and they were randomly selected from the patient information database.

In order to obtain complete information for each patient included in the study, we abstracted values of defined stochastic variables recorded in the RPP Integrated Progress Notes, and Variance Tracking Records that form standard elements included in a patient's file. Such integrated information was further evaluated by a urology specialist for consistency and correctness. After resolving the ambiguities, values of the attributes recorded in the charts and describing patient's condition were transcribed as average for a given post-op day, and an aggregate table was created. The table with abstracted data was further augmented with information about the LOS coming form Discharge Summary – the LOS was dichotomized in order to indicate whether it was *met* or *delayed*. Finally, values of all variables were discretized either on a basis of charts' data or by urology specialist for non-definitive situations.

From the retrospective data set of 125 patients, a set of 75 randomly selected cases was created and used for learning of the *BBN_RPP* model (dependency structure and conditional probabilities). The remaining 50 cases were put aside and later used for testing model's predictive accuracy.

Table 1: Variables in the RPP

Code	Name	Values	Descriptions or examples	Post-op day 1	2	3
Psycho	Patient psychological condition	abnormal	e.g. Patient's anxiety;	+		
		normal	Patient can understand and is compliant	+		
Vs	Vital signs	abnormal	e.g. The pulse rate of the patient is abnormal	+	+	+
		normal	Vital signs of the patient are normal	+	+	+
Temp	Temperature	abnormal	Patient's temperature is abnormal		+	+
		normal	Patient's temperature is normal		+	+
ActW	Activity with the RPP	no	Patient does not ambulate	+	+	+
		ambulate	Patient does (progressive) ambulation	+	+	+
NutriW	Nutrition with the RPP	fluid	Patient drinks fluid	+	+	+
		regular	Patient has regular foods		+	+
NutriO	Nutrition outcome	vomit	Patient vomits	+	+	+
		nausea	Patient feels nausea	+	+	+
		normal	None of the above	+	+	+
PainR	Pain at rest	medium	The verbal pain score at rest of the patient is between 4-7	+	+	+
		mild	The verbal pain score at rest of the patient is between 1-3	+	+	+
		nopain	Patient has no pain at rest	+	+	+
Resp	Respiratory function	mild	e.g. Crackle, difficult to breath	+		
		normal	The respiratory function of the patient is normal	+	+	+
Jp	JP output (JP denotes Jackson	large	The amount of JP is large	+	+	+
	Pratt wound drainage system	medium	The amount of JP is medium	+	+	+
	that is used to help healing by	small	The amount of JP is small	+	+	+
	draining fluid from the wound)	d/c	JP is discontinued		+	+
Hema	Evidence of hematuria	yes	Patient has evidence of hematuria	+	+	+
		bt	Patient has blood-tinged	+	+	+
		no	Patient has no evidence of hematuria	+	+	+
UrineO	Urine output	inadequate	The amount of urine is inadequate	+	+	+
		adequate	The amount of urine is adequate	+	+	+
BowelS	Bowel sounds outcome	absent	The bowel sound is absent	+	+	
		present	The bowel sound is present	+	+	
PainM	Mobility outcome	medium	The verbal pain score with mobility of the patient is between 4-7	+	+	+
		mild	The verbal pain score with mobility of the patient is between 1-3	+	+	+
		nopain	Patient has no pain with mobility	+	+	+
Wound	Wound outcome	medium	Patient's incision has severe infection		+	+
		mild	Patient's incision has mild infection		+	+
		normal	Patient's incision has no evidence of redness, swelling, rash, dehiscence		+	+
LOS	Length of patient stay	delayed	Patient is discharged after Post-op day 3			
		met	Patient is discharged on or before Post-op day 3			

3.3. Model development and validation

A software package integrating Bayesian learning (the K2 algorithm) and Bayesian reasoning called Bayesware Discoverer [11] was used to develop a *BBN_RPP* model from the data. The structure of this model is given in Figure 2.

In order to evaluate the predictive accuracy of the *BBN_RPP* model, we used the validation set with 50 new cases that were not used for developing the model. These cases described variances of patients for the first two days after the surgery (post-op day 1 and post-op day 2). We assumed that the output of the model (either LOS *met* or *delayed*) with probability greater than 0.5 would be used as the final prediction and compared to the actual LOS recorded for each testing case.

Ideally, the results of the *BBN_RPP* model should be compared to the evaluations of physicians. Unfortunately we did not have this information, therefore we decided to compare the performance of our model with models based on logistic regression [12] and decision trees [13].

The results of validation are given in Table 2. The highest overall accuracy was obtained by the *BBN_RPP* model, the logistic-based model was the second, and the tree-based model was the last. For the *met* LOS the highest accuracy was observed for the logistic-based model, however, it was coupled with very low accuracy for the *delayed* LOS, what questions the usability of this model in practice. Finally, the tree-based model had the same accuracy for *met* LOS as the *BBN_RPP*, but much lower accuracy for *delayed* LOS.

Table 2: Variables in the RPP

Accuracy	BBN_RPP	Decision tree	Logistic regression
Met LOS	90.9%	90.9%	93.9%
Delayed LOS	64.7%	41.2%	41.2%
Overall	82.0%	74.0%	76.0%

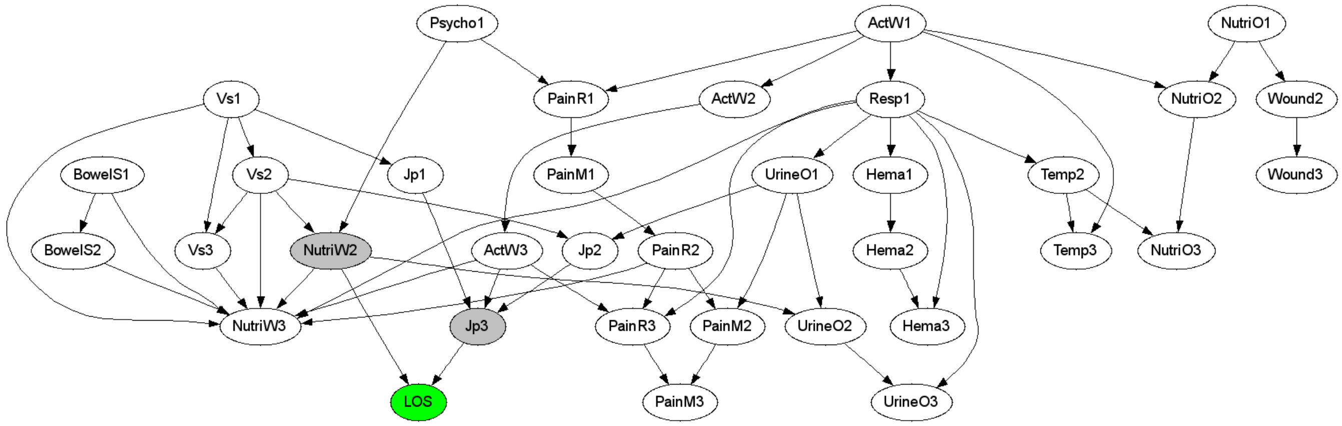

Figure 2. The structure of BBN_RPP model

The *BBN_RPP* model provided the highest overall accuracy and the highest accuracy for the *delayed* LOS. Moreover, the accuracy for the *met* LOS was equal or slightly lower then the accuracy of the remaining models further confirming superior performance of the BBN model.

4. Summary and conclusion

The research described here presents an innovative approach to modeling clinical pathways and demonstrates how to develop a novel tool for predicting the LOS. Currently, a medical team uses an established pathway (usually in paper form) to monitor patient progress and record variances, however, the assessment and prediction of the LOS is based on "gut feeling" and is evaluator-specific.

Our research used objective and verified data from retrospective chart study to develop the *BBN_RPP* model to represent a clinical pathway. The structure of the model and all conditional probabilities were derived from data. We applied the model to predict the LOS given the variations in a realization of the pathway for new cases. The results demonstrated that the *BBN_RPP* model very well describes probabilistic inferences of the RPP and provides high predictive accuracy.

Following the consultations with urology specialists at The Ottawa Hospital, we were able to conclude that the *BBN_RPP* model supports an understanding of the process of patient care, and provides a tool for predicting the LOS given variances from the pathway.

In summary, a model such as the *BBN_RPP* provides a patient management team with new insight into patient's clinical condition given the current observations. Since the LOS is one of the most important proxies for the resource utilization in a hospital, the determination of pertinent factors and the evaluation of variances from a normal path of patient's care should support more effective patient management process.

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