Clinical Intervention Effectiveness Estimation through Dynamic Bayesian Network

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Abstract

Determining whether to proceed with a clinical intervention can be a challenging task due to the numerous variables at play. One of the most crucial piece of information for making this decision is a precise assessment of the intervention's effectiveness, but it tends to be a complex calculation for healthcare professionals. In hemodialysis patients, the presence of a functional arteriovenous fistula (AVF) is essential to achieve a sufficient dialysis dosage and prevent various complications. Percutaneous transluminal angioplasty (PTA) is a commonly employed procedure to restore the patency of AVFs. However, it carries the disadvantage of causing long-term vessel damage, thereby reducing the lifespan of the AVF. In this preliminary study we explore Dynamic Bayesian Network (DBN) to estimate the effectiveness of the next PTA from the elaboration of routinely collected clinical data. We build a DBN to predict the risk of problems of AVF and simulate how the next PTA could impact this prediction. The outcomes of this research could contribute to the development of a decision support system for vascular surgeons, aiding in the optimization of the decision-making process regarding whether to proceed with a PTA and/or consider alternative solutions.

Keywords

Dynamic Bayesian Network, hemodialysis, arteriovenous fistula

1. Introduction

Percutaneous transluminal angioplasty (PTA) stands out as a common surgical intervention to treat stenosis or occlusion of a malfunctioning arteriovenous fistula (AVF) [1]. Occluded or partially occluded AVF decreases the efficacy of hemodialysis treatment, increasing the risk of several negative patient's outcomes. As dialysis is a critical care for patient survival, when the hemodialysis efficacy goes under a certain threshold, the patient needs a different vascular access to perform such treatment. PTA involves the use of a balloon catheter to dilate narrowed or blocked vessels, restoring blood flow and improving AVF functionality. The success of PTA, and the lasting of this success, depends on several factors as: vascular surgeon abilities, AVF's anatomical and functional characteristics, patient characteristic and previous invasive

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interventions. PTA generally solves the acute problem, reestablishing the patency of AVF, but can also create a further vessel damage shortening the future AVF free intervention period. The decision to intervene with a PTA or to create a new AVF (and/or a different vascular access), is a cost-benefits decision involving many variables. If the physician expects that a new PTA would keep the AVF functioning for a very short time, he might consider a different option as the creation of a new AVF, switching to another type of vascular access as Central Venous Catheter, or a combination of the previous options. This decision is not trivial as a new AVF required 3-4 months to be ready for the use and catheter is generally considered less preferable for the higher risk of infection. On the other hand, PTA has some risk related to the surgical intervention per se and creates discomfort for such fragile patients. Estimating the duration of the AVF functioning period is critical to take the best decision for the patient, but it is very difficult for a clinician, considering the fact that there is a high number of variables that play a role in this process. In this preliminary study, we tried to build a model based on Dynamic Bayesian Network to estimate the effectiveness of the next PTA considering routinely collected clinical data.

2. Method

2.1. Dataset

Our dataset was composed of 143,454 AVF assessments referred to 4,718 hemodialysis patients from Portugal and collected between 2015 and 2022. The dataset was composed of 7 parameters that characterize the AVF functioning and the history of AVF problems (number of PTAs and failures in the past). We exploit two metrics (average and delta) of the Arterial and Venous Pressure in the last 30 days as proxy of blood flux in the AVF. These two pressures are measured by the dialysis treatment machine and represent the pressure of the blood in the line carrying the blood from the patient to the machine (venous line) and the pressure in the line carrying the blood from the machine to the patient (arterial line). The variables used in the model are described in the following:

- *AVF Failure*: is a discrete variable that describe the status of the AVF. It can assume 3 values: - *No Failure*: the AVF worked fine during the month, *PTA*: a PTA was performed during the month - *Failure*: a problem prevented the use of the AVF during the month
- *Count PTA*: number of PTAs previously performed.
- *Mean Venous Pressure*: Average venous pressure measured by the dialysis machine during the month.
- *Delta Mean Venous Pressure*: Relative difference between the mean venous pressure measured in the month with that measured in the previous month.
- *Mean Arterial Pressure*: mean arterial pressure measured by the dialysis machine during the month.
- *Delta Mean Arterial Pressure*: Relative difference between the mean arterial pressure measured in the month and that measured in the previous month.
- *Stenosis*: Presence of a stenosis during the month. This variable is only partially observed. In fact, we are certain of a stenosis only if specific tests are carried out or if PTA is performed.

All this information are routinely recorded through the Fresenius Medical Care health care system called EuCliD® [2]. Written informed consent for statistical analysis was obtained from all the patients.

2.2. (Dynamic) Bayesian Networks

Bayesian Networks (BNs) are probabilistic network models [3] capable of representing probabilistic knowledge. The BN framework can be divided into two components: quantitative and qualitative. The qualitative element is a Directed Acyclic Graph (DAG) encoding a set of conditional dependences and independences among a set of random variables. The quantitative element describes the relationships among random variables with probability theory [4]. Formally a BN is defined as follows: BN = $(\mathcal{X}, \mathcal{G}, \mathcal{P})$. Where $\mathcal{X}$ is the set of random variables, $\mathcal{G} = (V, E)$ is a DAG representing conditional independences among variables in $\mathcal{X}$ and $\mathcal{P}$ is a set of conditional probability distributions. The construction of a BN requires to learn both the qualitative component $\mathcal{G}$ and the quantitative component $\mathcal{P}$. The learning phase can be carried out using data, expert knowledge or a mixed strategy. The latter approach can be effectively applied in healthcare where the domain expert knowledge can be integrated with data [5]. Bayesian networks do not explicitly model time. For this reason, the Dynamic Bayesian Networks (DBN) framework was developed [6]. A DBN describes the evolution of the system by modeling its variables over different time slices. The most basic form of DBN satisfies the first order Markov property and it is called 2 time slice DBN (2TBN). The 2TBN can be formally described as follows: 2TBN = $(\mathcal{X}, \mathcal{G}_{2\text{TBN}}, \mathcal{P})$ where:

- $\mathcal{X}$ is the set of variables variables evolving through time.
- $\mathcal{P}$is a set of conditional probability distributions.
- $\mathcal{G}_{2\text{TBN}} = (V_{2\text{TBN}}, E_{2\text{TBN}})$ is a DAG encoding a set of conditional dependences and independences among a set of random variables. Here lies the main difference between BNs and DBNs
  - $V_{2\text{TBN}} = V_{T_0} \cup V_{T_t}$ is the set of nodes:
    - V_{T_0} represents the variables $\mathcal{X}$ at time 0.
    - V_{T_t} represents the variables $\mathcal{X}$ at a generic time t.
  - $E_{2\text{TBN}} \subset V_{2\text{TBN}} \times V_{2\text{TBN}}$ is the set of edges:
    - $E_{T_0} = (V_{T_0} \times V_{T_0}) \cap E_{2\text{TBN}}$: is the set of edges enconding the relations among the variable at time 0
    - $E_{T_t} = (V_{T_t} \times V_{T_t}) \cap E_{2\text{TBN}}$: is the set of edges enconding the relations among the variable at time a generic time t
    - $E_{T_{t,t+1}} = (V_{T_0} \times V_{T_t}) \cap E_{2\text{TBN}}$: is the set of edges enconding the relations among the variables through time from a generic time t to $t + 1$.

The strength of DBNs is that they employ the same solving and learning algorithms used for BNs. As for the inference phase, it is possible to use the inference algorithms used for BNs but the DBN must be unrolled first.

# PTA	Median	Mean	Std
0	18	25	22
1	8	15	14
2	5	12	12
3	5	7	7
≥ 4	4	6	6

Table 1
Statistics for the intervention free period (in months) given the number of PTAs carried out.

3. Results

In this section, we aim to utilize a 2TBN to analyze the temporal dependencies of various factors associated with AVF development and failure. By constructing a 2TBN model using expert knowledge and patient data, we can explore the dynamic interactions between variables and estimate the intervention free period for an AVF. Exploring the dataset we found 2,598 PTAs and 4,837 events classified as AVF failure (stopping AVF use or an important medical intervention on AVF). As a result, the AVF intervention free period decreases with each PTA (Table 1). However, these values vary greatly from patient to patient. These observations are in line with those obtained by the authors of [7], who observed that the risk of failure is directly proportional to the number of past failures[1]. The model we are going to present has the main goal of estimating the intervention free survival for the specific patient.

3.1. Structure of the 2TBN

We decided to base the identification of the structure of the 2TBN on domain knowledge and the result is depicted in Figure 1. We can split the structure in three main components:

TIME 0 The left side of Figure 1 represents the nodes V_{T_0}, the edges E_{T_0} and models the dependencies among the variables for the first time slice (month 0). In this component, the pressures depends on the presence of stenosis. All the edges completely contained on the right side of the figure (green edges) have no temporal connotation and do not describe any evolution.

TIME t The right side of Figure 1 represents the nodes V_{T_t}, the edges E_{T_t} and describe the dependencies among the variables at a generic month > 0. Similarly to the previous paragraph, also in this case all the edges completely contained on the right side of the figure (red edges) have no temporal connotation and do not describe any evolution.

Time dependence All the edges crossing from the left side to the right side of Figure 1 (orange edges) are the edges $E_{T_{t,t+1}}$ and describe the dependencies of the variables at a generic month given the variables of the previous month. These are the only edges that have a temporal connotation and describe the evolution of the process over time.

[1]In this study, different types of failures are taken into account. However stenosis is on of the most frequent causes.

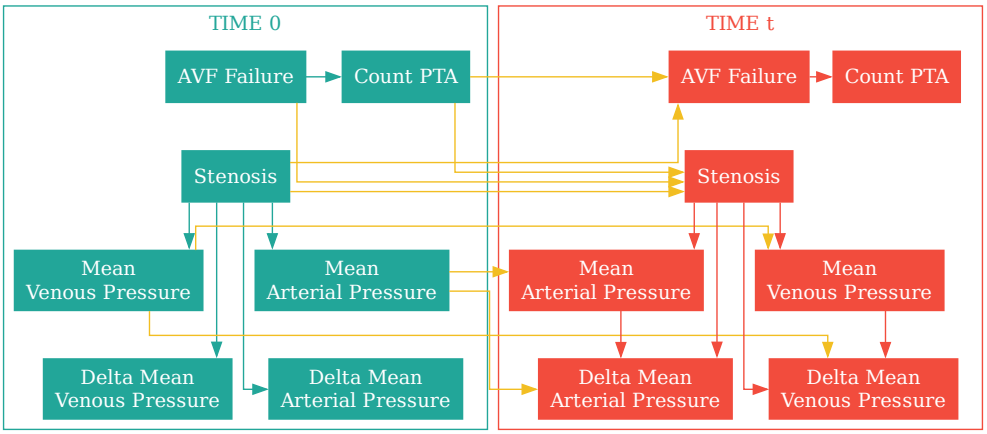

Figure 1: This graph shows the structure of the 2TBN used for the experiments. The nodes and the edges in the left side of the figure represent the conditional (in)dependences at time zero. The nodes and the edges in the right side of the figure describe the conditional (in)dependeces at a generic time $t : t > 0$. The edges crossing the figure from the left side to the right side identify the dynamic of the evolution of the DBN over time.

Observing the right component and the crossing edges we can see that all the pressures mainly depend on the presence/absence of stenosis. Furthermore we can see how the failure of the AVF or the need to do a PTA depend solely on the information from the previous month.

3.2. Parameters of the 2TBN

The parameters of the 2TBN are learned from the dataset. First of all, we discretized the continuous variables (pressure). We experimented with various methods during the discretization process, including uniform, quantile-based, and expert knowledge-based approaches. We discovered that discretization based on expert knowledge was the most effective solution. Specifically, we categorized the data into five pressure levels: very low pressure, low pressure, normal pressure, high pressure, and very high pressure. Then, since we have a partially observed variable (stenosis) we used the Expectation Maximization algorithm to learn the parameters [4]. The implementation used for learning is the one provided in the package pyAgrum [8]. Since correctly modeling the evolution of a stenosis is the fundamental component of this model we will focus on the parameters learned for this variable. Table 2 reports the parameters for the variable stenosis at time T_t and shows that the probability of developing a stenosis increases with the number of previous PTA. Furthermore, PTA loses effectiveness if performed more than 3 times on the same AVF.

AVF Failure (T_0)	Count PTA (T_0)	Stenosis (T_0)	Stenosis (T_t)	
			False	True
Failure	0	False	0.83	0.17
Failure	0	True	0.01	0.99
Failure	1	False	0.53	0.47
Failure	1	True	0.01	0.99
Failure	2	False	0.27	0.73
Failure	2	True	0.00	1.00
Failure	3	False	0.21	0.79
Failure	3	True	0.00	1.00
Failure	≥ 4	False	0.03	0.97
Failure	≥ 4	True	0.00	1.00
No	0	False	0.93	0.07
No	0	True	0.01	0.99
No	1	False	0.72	0.28
No	1	True	0.01	0.99
No	2	False	0.55	0.45
No	2	True	0.00	1.00
No	3	False	0.35	0.65
No	3	True	0.00	1.00
No	≥ 4	False	0.23	0.77
No	≥ 4	True	0.00	1.00
Pta	0	False	0.99	0.01
Pta	0	True	1.00	0.00
Pta	1	False	0.99	0.01
Pta	1	True	0.94	0.06
Pta	2	False	0.99	0.01
Pta	2	True	0.92	0.08
Pta	3	False	0.99	0.01
Pta	3	True	0.93	0.07
Pta	≥ 4	False	0.99	0.01
Pta	≥ 4	True	0.84	0.16

Table 2
Conditional Probability Table of the variable stenosis at T_t.

3.3. Inference

Classical BN exact or approximate algorithms [4] can be used to perform inference over DBN. However, before utilizing these algorithms, it is necessary to unroll the network. Unrolling involves replicating the nodes and edges of the 2TBN for each time step. Each duplicate represents the variables' states at a specific time step, and contains all the nodes V_{T_t}, the edges E_{T_t} and the edges $E_{T_{t,t+1}}$ (Figure 2).

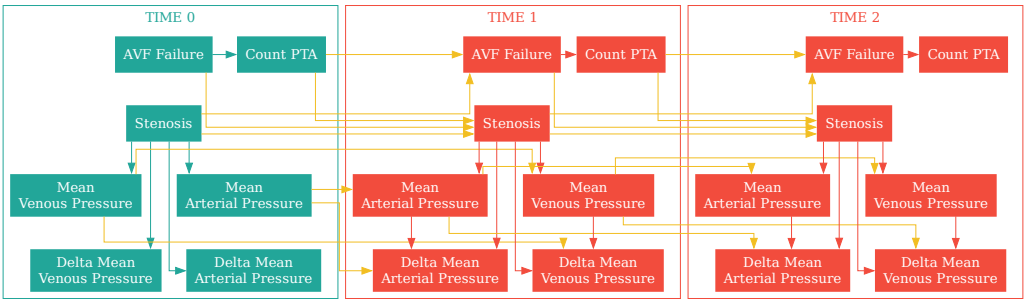

Figure 2: Unrolling with 3 time slices of the 2TBN depicted in Figure 1.

3.4. Application

Our developed 2TBN can serve as a tool for predicting the AVF intervention free period post PTA, assisting doctors in determining the need for a new AVF creation for the patient. In particular, the described model can be utilized in the subsequent manner: when a vascular surgeon determines that a patient needs to undergo a PTA, inputs the relevant data from the current month into the model. Then, the physician hypothesizes performing a PTA in the upcoming month and requests the model to predict the chances of failure or the requirement for an additional PTA over the span of 6 months following the initial procedure. To evaluate the performance of the learned model we randomly selected 70% of the patients as train and we used the remaining 30% of the patients as test. Of the 2,598 PTAs reported in the dataset, 2,106 are in the train set and 492 are in the test set. Of the 492 PTAs present in the test set, 226 failed within 6 months following the operation. We learned the model on the train set and then we used the test set to see how well it predicts the AVF intervention free period using the AUC score obtaining a value of 0.64.

4. Discussion

A well functioning AVF is essential for performing effective hemodialysis treatment and maintaining the overall health of a patient dependent on dialysis. Nevertheless, this vascular access can undergo biological alterations, potentially rendering it unsuitable for dialysis procedures. One primary factor contributing to issues associated with AVF is the stenosis. This problem is often treated with a surgical procedure called PTA, that generally restores the patency of the AVF in the short term but can cause vessel damage and problems in the long term. Every time a stenosis is detected, the physician must ask himself whether a PTA is sufficient or whether it is necessary to create a new AVF. To help the doctor in this difficult decision we developed a model that predicts the risk of AVF problems when a PTA is performed. We selected DBN paradigm to tackle this problems for two main reasons. First, we evaluated as important the use of an approach able to exploit the information coming from data and experts knowledge. Second, in this problem, the risk of having AVF failure is influenced by the PTA and the PTA influences

the future risk of AVF failure, so to represent this kind of loop we needed an approach able to consider the relationship among variables along time. The standard BNs do not accomplish this requirement while DBNs do. Specifically, we developed a 2TBN were each time slice covers a month. The presented model is in an early stage and presents many limitations. First of all, the final accuracy of the prediction (AUC=0.64) that is insufficient for the clinical use. This limited accuracy might be related to the fact that we are ignoring the location of the stenosis in the AVF. Different locations can have different effects on the pressures. In the future we would like to add this information so we can include it in the model. Another strong limitation is the requirement to discretize the variables. Especially for pressures, this operation is extremely delicate and can lead to a distortion in the data. One potential solution to address the issue of discretization could involve the implementation of semi-parametric BNs [9], enabling the direct inclusion of continuous variables within the model. In conclusion, we are aware of the large limitations of such a simple model. However, we are convinced that this paper can be a starting point for the development of a model capable of supporting physicians and patients in the complex decision-making process related to AVF management.

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