Proceedings of the 2006 Winter Simulation Conference
L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, and R. M. Fujimoto, eds.

A DATA-INTEGRATED NURSE ACTIVITY SIMULATION MODEL

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ABSTRACT

This research develops a data-integrated approach for constructing simulation models based on a real data set provided by Baylor Regional Medical Center (Baylor) in Grapevine, Texas. Tree-based models and kernel density estimation were utilized to extract important knowledge from the data for the simulation. Classification and Regression Tree model, a data mining tool for prediction and classification, was used to develop two tree structures: (*a*) a regression tree, from which the amount of time a nurse spends in a location is predicted based on factors, such as the primary diagnosis of a patient and the type of nurse; and (*b*) a classification tree, from which transition probabilities for nurse movements are determined. Kernel density estimation is used to estimate the continuous distribution for the amount of time a nurse spends in a location. Merits of using our approach for Baylor's nurse activity simulation are discussed.

1 INTRODUCTION

In traditional stochastic simulation models, transition probabilities are obtained either subjectively or by looking at all possible combinations of the levels of the simulation state variables. If the system under consideration is complex, such as nurse movement, then a subjective approach is unlikely to be accurate, and an approach using all possible combinations of the states will be impractical. In the past, in order to reduce the number of simulation variables, factorial designs and screening methods were used (Bettonvil and Kleijnen 1997; Cheng 1997; Shen and Wan 2005). Even after eliminating some of the variables, a few remaining variables could lead to a huge number of combinations for the simulation. For instance, six categorical variables with ten categories each, will lead to a million possible states in the simulation. Obtaining accurate transition probabilities for such a huge simulation model is still difficult. In this paper, using the Baylor data, we present a new methodology to reduce the number of combinations and find transition probabilities for stochastic simulation models. Kernel density estimates and trees were utilized to extract important knowledge about the workload of nurses from an encrypted data set provided by Baylor for four care units. The four units include two medical/surgical units, one mom/baby unit, and one high-risk labor-and-delivery unit. Classification and Regression Trees, a data mining tool for prediction and classification, was applied to the Baylor data to develop two tree structures: (a) a regression tree, from which the amount of time a nurse spends in a location is predicted based on factors, such as the primary diagnosis of a patient and the type of nurse; and (b) a classification tree, from which transition probabilities for nurse movements are determined.

This research develops a simulation model for nurse activity which could be used to evaluate nurse-patient assignments. In the literature, most of the relevant research focuses only on nurse budgeting and nurse scheduling methodologies (Aickelin and Dowsland 2003; Burke et al. 2001; Jaumard et al. 1998; Kirkby 1997; Miller et al. 1976; Warner 1976) and ignores uncertainty. By contrast, our research seeks an integrated statistical data mining and simulation optimization approach that utilizes patterns in the real data to balance workload. The integration of statistical modeling and optimization has been found to work well for some complex problems (Cervellera et al. 2003; Chen

2001). Simulation models developed with this approach will be much more representative of actual systems and more efficient than those that consider all possible combinations.

The rest of this paper is organized as follows: In Section 2, a brief introduction is given on data and notation. Section 3 describes the statistical models and their use in building the simulation model. In Section 4, we present performance and tuning of kernels. Section 5 concludes by discussing a possible simulation-optimization approach to optimize the system.

2 DATA DESCRIPTION

Baylor provided data for this research from four care units: Medical/Surgical unit I, Medical/Surgical unit II, Mom/Baby unit and High-Risk Labor unit. The data were preprocessed to create seven new variables to hold information on the previous seven locations visited for each location entered by nurses to predict patterns in their movement. Also, a new variable is created to indicate the nurse-patient assignments. To create this variable, it is assumed that the nurse who spent the maximum amount of time in a patient room during a shift is the nurse assigned to that patient for that shift. More details on other preprocessing, encryption and variable descriptions can be found in Sundaramoorthi et al. (2005). After preprocessing, Medical/Surgical unit I, Medical/Surgical unit II, Mom/Baby unit and High-Risk Labor unit have about 389,349, 418,683, 315,997 and 210,457 observations, respectively. Following the conclusions in Sundaramoorthi et al. (2005) and further similar analysis presented in Sundaramoorthi et al. (2006), the following types of variables with their specific levels are considered significant for the methodology presented here.

1. Location : patient rooms, nurse station, break room, reception desk, and med room.
2. Nurse Type: registered nurse, licensed vocational nurse, licensed practitioner nurse, and nurse aide.
3. Diagnosis Code : 17 categories covering the range of diagnosis codes. See INGENIX (2003) for more details.
4. Shift: 3 weekday shifts (8 hours each) and 2 weekend shifts (12 hours each).
5. Hour: 24 hour ranges covering a complete day.
6. Assignment: An assigned nurse entering a patient room (1), an unassigned nurse entering a patient room (0), and a nurse entering any location other than patient rooms (2).

Based on the tree analyses of Sundaramoorthi et al. (2005, 2006), our simulation includes location variables that specify current location and seven previous locations. Data from different care units were handled separately, as the number of categorical levels of the considered variables, listed above, differed slightly among different care units. In this paper, we maintain the following notation: X_S, X_T, X_{NT}, X_L, X_D, and X_A are the variables representing shift, hour, nurse type, current location, primary diagnosis and assignment, respectively; N_S, N_T, N_{NT}, N_L, N_D, and N_A are the number of levels of X_S, X_T, X_{NT}, X_L, X_D, and X_A, respectively; X_{P1L}, ..., X_{P7L} are the variables representing the seven previous locations with X_{P1L} being the latest and X_{P7L} being the oldest among the seven locations visited before any current location; X_{P1L}, ..., X_{P7L} have the same number of levels (N_L) as of X_L.

3 SIMULATION MODEL

3.1 Classification and Regression Trees for Simulation

Classification and Regression Trees (CART) is a data mining tool for prediction and classification (Breiman 1984; Hastie 2001). CART utilizes recursive binary splitting to uncover structure in a high-dimensional space. CART, on application to a data set, will partition the input space into many disjoint sets and fit a constant response for each of the disjoint sets. Salford Systems' CART® software was used to obtain our tree structures. In particular, two tree structures were developed: (a) a regression tree to predict the amount of time a nurse will spend in a location based on the levels of X_S, X_T, X_{NT}, X_L, X_D, and X_A; and (b) a classification tree from which transition probabilities for nurse movement are determined based on the levels of X_S, X_T, X_{NT}, X_L, X_D, X_A, X_{P1L}, X_{P2L}, X_{P3L}, X_{P4L}, X_{P5L}, X_{P6L}, and X_{P7L}. A hypothetical regression tree is shown in Figure 1 to illustrate a prediction of the amount of time a nurse would spend in a location. At each node of the tree, a question is asked; a data point which satisfies the question will go left in the branching and right if it fails to meet the criterion. Based on the levels of X_S, X_T, X_{NT}, X_L, X_D, and X_A, every data point ends up in one of the terminal nodes of the tree. For each terminal node of the regression trees, kernel density estimation (KDE) is used to estimate the probability density function for time spent (Y) by a nurse (under the conditions specified by that terminal node). Assume we have $n(j)$ independent observations $y_1, \ldots, y_{n(j)}$ for the random variable $Y(j)$ in the terminal node j. Let $K(\cdot)$ be a kernel function. Then the kernel density estimator $\hat{f}_{j,h}(y)$ at a point y is defined by equation (1) (Silverman 1986).

$$\hat{f}_{j,h}(y) = \frac{1}{h \times n(j)} \sum_{i=1}^{n(j)} K\left(\frac{y_i - y}{h}\right), \tag{1}$$

where h is bandwidth, which controls the "window" of neighboring observations that will highly influence the estimate at a given y. Sheather and Jones plug-in bandwidth estimation method is used, as it is one of the best for optimizing bandwidth h (Jones 1996; Sheather 1991; Sheather 2004). $Y(1), \ldots, Y(J)$ are the random variables that denote the time spent (Y) in terminal nodes 1, ..., J, respectively.

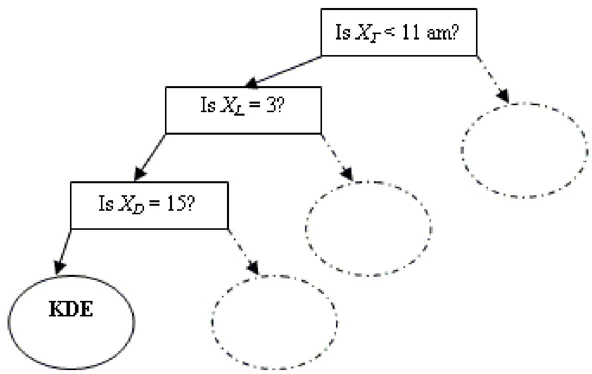

Figure 1: A Hypothetical Regression Tree

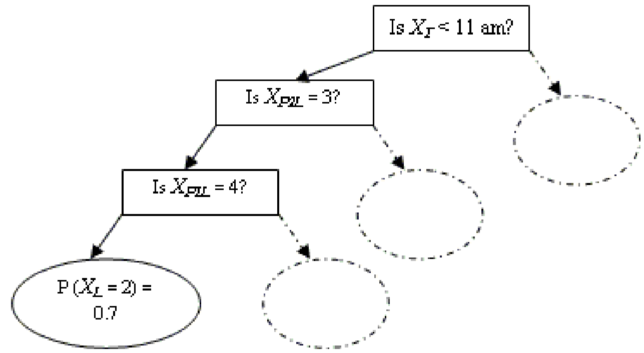

Figure 2: A Hypothetical Classification Tree

Kernel density estimates with Sheather and Jones plug-in bandwidths were obtained for each terminal node of the regression trees. A typical plot with Gaussian and Triangular kernels for each of the four care units is shown in Figure 3.

A hypothetical classification tree is shown in Figure 2 to illustrate the estimation of the probability that a location would be visited by a nurse. At each node of the tree, similar to the regression tree, a question is asked; data that satisfy the question will go left in the branching and right if they fail to meet the criterion. Depending on the levels of X_S, X_T, X_{NT}, X_L, X_D, X_A, X_{P1L}, X_{P2L}, X_{P3L}, X_{P4L}, X_{P5L}, X_{P6L}, and X_{P7L}, every data point ends up in one of the terminal nodes of the tree, where transition probabilities are estimated as follows:

$$\hat{p}(l/j) = \tfrac{1}{n(j)}\textstyle\sum_{i=1}^{n(j)} I(i \in l), \tag{2}$$

where j = 1, ..., J are the terminal nodes of the tree; $n(1)$, ..., $n(J)$ are the numbers of observations in terminal nodes 1, ..., J, respectively; l = 1, ..., N_L are the levels of X_L, i.e., the different locations in a given care unit and I is an indicator function.

3.2 Driving Simulation Model

To drive a nurse activity simulation, two essential questions are asked: (1) Where will a nurse go next given her current location, past locations and other factors (shift, hour, nurse type, primary diagnosis and assignment)? (2) How much time will she spend there? After an initialization run to (randomly) warm up the simulation, transition probabilities obtained by equation (2) from the classification tree determine the next location a nurse will visit. Once a location has been sampled for a given nurse, the amount of time she spends there is determined by randomly sampling a y value from the kernel density estimate at the appropriate terminal node in the regression tree. Clock time and the location variables are then updated. The level of X_T is changed if the updated time enters a new category, as listed in Section 2. The levels of variables X_S and X_{NT} associated with a nurse remain unchanged throughout the shift. This process of sampling location and time spent is repeated until the shift ends.

Traditionally, in stochastic simulations, transition probabilities are obtained either subjectively or by looking at all the possible combinations of variable levels. If the system under consideration is complex, such as the care units in Baylor, then a subjective approach is unlikely to be accurate, and it will be impractical to implement an approach using all possible combinations of the levels of the simulation variables. In the latter approach, the number of possible combinations (NPC) grows exponentially with the number of variables. In our problem, there are $N_S \times N_T \times N_{NT} \times {N_L}^8 \times N_D \times N_A$ combinations. On the other hand, simulation models developed as discussed in Section 3.1 require only $J \times N_L$ combinations extracted based on the patterns found in the data. The more efficient the simulation, the more useful it will be for making real time decisions. For example, ninety minutes prior to a shift, a charge nurse will determine whether the set of scheduled nurses is sufficient for the shift. If there is a shortage, she will call a nurse agency to hire nurses for that shift. The simulation model can assist in this decision provided its run time is sufficiently fast. Calculated difference between $N_S \times N_T \times N_{NT} \times {N_L}^8 \times N_D \times N_A$ and $J \times N_L$, given in Table 1, shows that our approach is significantly more efficient. All locations in the care units under consideration can be visited from any other location of that care unit. Even though some of these combinations of locations are unlikely to be visited in succession, without using a statistical method like trees, it is not easy to justify ignoring or combining them.

Table 1: Numerical Values Of Levels In Different Care Units And Number Of Combinations

Variable Level	Care Unit			
	Med/SurI	Med/SurII	Mom/Baby	High-Risk
N_S	5	5	5	5
N_T	24	24	24	24
N_{NT}	4	6	8	7
N_L	34	32	52	52
N_D	18	20	9	7
N_A	3	3	3	3
$J(class.)$	222	358	156	204
NPC	$> 10^{17}$	$> 10^{17}$	$> 10^{18}$	$> 10^{18}$
$J \times N_L$	7548	11546	8112	10608

4 KERNEL PERFORMANCE

4.1 Kernel Choice

Kernel functions include Uniform, Gaussian, Triangular, Epachenikov, Quadratic, and Cosinus. Gaussian and Triangular kernels were chosen for this research as they are common among simulation modelers. Also, it is relatively easy to draw samples from Gaussian and Triangular distributions, which are required for sampling the time spent random variable. Sheather and Jones plug-in bandwidth estimates (Sheather and Jones 1991) were obtained for each terminal node of the regression tree using SAS®.

Figure 3 and the normal probability plots in Sundaramoorthi et al. (2005) show that the time spent data have a long right tail, and a major portion of the data is concentrated near the left end of the distribution. Gamma distributions provided inadequate density estimates, motivating the use of KDE. To assess how well KDE represents the time spent distribution, 100,000 realizations of time spent data were generated from Gaussian and Triangular kernel density estimates. The simulated data were compared with actual data in four different ranges i.e., (0, Median/2], (Median/2, Median], (Median, (Median + Meidan/2)], ((Median + Meidan/2), ∞). Results from 100,000 simulated realizations of Gaussian and Triangular kernels are shown in Table 2. There were 171, 101, 458 and 72 terminal nodes in the regression trees of Medical/Surgical I, Medical/Surgical II, Mom/Baby and High-Risk Labor units, respectively. The table shows that the Triangular kernel wins more often than the Gaussian kernel irrespective of the care units and ranges. Among all the competitions i.e., J $\times$ 4 competitions, the Triangular won 80%, 79%, 84% and 87% of the competitions in Medical/Surgical I, Medical/Surgical II, Mom/Baby and High-Risk Labor units, respectively. A terminal node win was considered to be achieved if a kernel managed to win at least three ranges out of the four considered. Both the kernels were considered to be tied if they won two ranges

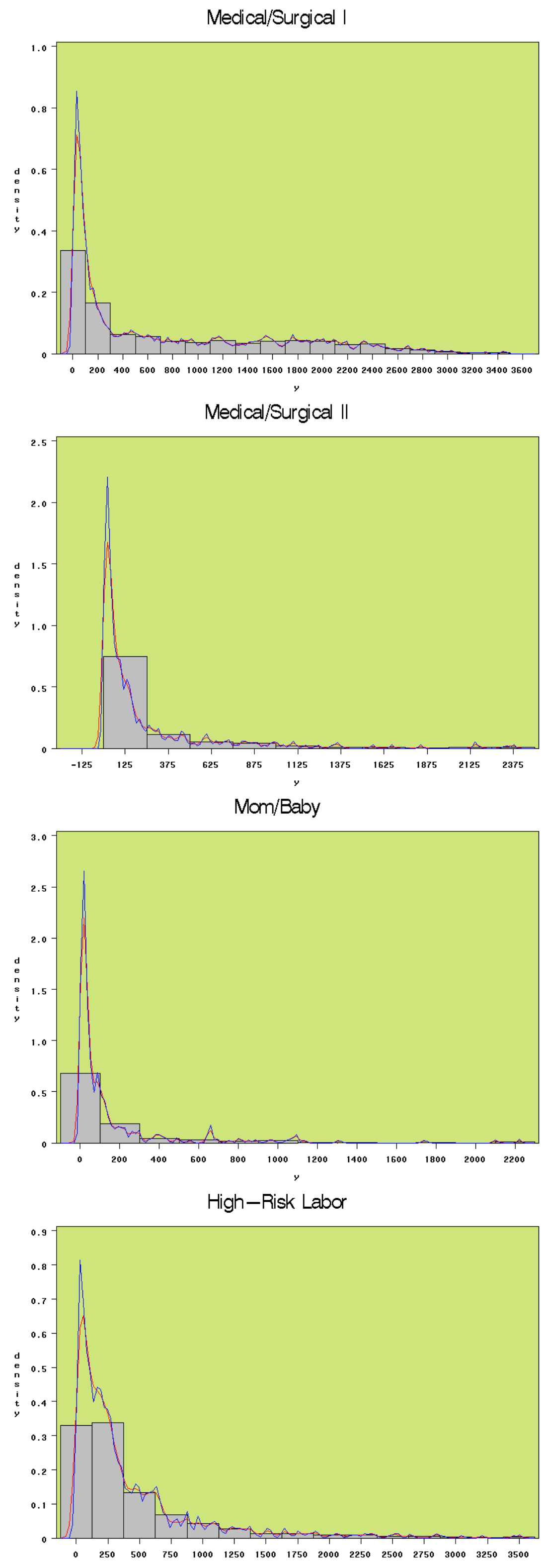

Figure 3: Kernel Density Estimates (Red-Gaussian, and Blue-Triangular)

each. The results on terminal node wins shown on the last two rows of each care unit further indicate that the Triangular kernel is a better choice for the Baylor data.

Table 2: Performance of Gaussian and Triangular Kernels

CARE UNIT	GAUSSIAN	TRIANGULAR	TIE
MED/SUR I			
J(Reg.)=171			
Range I wins	26	145	
Range II wins	41	130	
Range III wins	53	118	
Range IV wins	15	156	
% wins	20%	80%	
Ter. node wins	11	143	17
% Ter. node wins	6%	84%	10%
MED/SUR II			
J(Reg.)=101			
Range I wins	12	89	
Range II wins	29	72	
Range III wins	32	69	
Range IV wins	11	90	
% wins	21%	79%	
Ter. node wins	5	83	13
% Ter. node wins	5%	82%	13%
MOM/BABY			
J(Reg.)=458			
Range I wins	64	394	
Range II wins	88	370	
Range III wins	108	350	
Range IV wins	40	418	
% wins	16%	84%	
Ter. node wins	16	402	40
% ter. node wins	3%	88%	9%
HIGH-RISK			
J(Reg.)=72			
Range I wins	6	66	
Range II wins	11	61	
Range III wins	18	54	
Range IV wins	3	69	
% wins	13%	87%	
Ter. node wins	0	64	8
% ter. node wins	0%	89%	11%

4.2 Bandwidth Tuning

The accuracy of estimates depends more on choosing an appropriate bandwidth than the choice of kernels (Epachenikov 1969; Silverman 1978). Bandwidth selection methods, including Sheather and Jones plug-in bandwidth estimates (Sheather and Jones 1991), try to find the optimal bandwidth that compromises a tradeoff between oversmoothness and undersmoothness of the estimated density. After obtaining bandwidths from bandwidth estimation methods, we can decide to either decrease or increase the bandwidth size depending on the knowledge of the system. Data used in this project were collected over more than a six-month period and have hundreds of thousands of observations for each care unit. With data collected over months, the different possible characteristics of the Baylor system will be well reflected in the simulation if the bandwidths are tuned to prefer a less smooth density estimate that reflects the data more accurately. In this research, if the fraction of simulated realizations in the ranges given in the previous section go beyond $\pm$ 0.015 of the actual fraction of data, the bandwidth was iteratively decreased by one until this criterion was met. For example, the seventh terminal node of high-risk labor unit shown in the table 3 has fractions of realizations that violated $\pm$ 0.015 limit. After sixty iterations of bandwidth tuning, all four ranges have fractions within the limit. This leads to a change of bandwidth at this particular terminal node to 7.03 from 67.03 and thus yields more representative realizations of the time spent data.

Table 3: Bandwidth Tuning for Terminal Node 7 of High-Risk Labor Unit

BANDWIDTH TUNING	SIM. FRACTION	ACTUAL FRACTION	DIFF.
BEFORE			
h=67.03			
range I	0.16609	0.358699	0.192609
range II	0.16558	0.148042	-0.017538
range III	0.13608	0.08319	-0.052890
range IV	0.53225	0.41007	-0.122180
AFTER			
h=7.03			
range I	0.345610	0.358699	0.013089
range II	0.155620	0.148042	-0.007578
range III	0.083620	0.08319	-0.00043
range IV	0.415150	0.41007	-0.00508

5 CONCLUSIONS

We presented classification and regression trees and kernel density estimation to extract important knowledge for constructing a nurse activity simulation model. Given the current state, classification trees provide state transition probabilities to determine where a nurse will go next. Regression trees combined with kernel density estimates determine the amount of time a nurse will spend once she/he goes to a new location. Further, we presented a criterion to select the kernel function and the bandwidth. Simulation models developed with this approach will be much more efficient than those that consider all possible combinations. To optimize the system, simulation-optimization methods such as Atlason et al. (2004), Fu et al. (1997), and Glasserman et al. (1990), can be applied to achieve the simulation model. Implementing this methodology will help charge nurses make better decisions on nurse-patient assignments.

Further, the approach studied here can be used to simulate any systems with probabilistic state transitions.

6 ACKNOWLEDGMENTS

This research is supported by the Robert Wood Johnson Foundation grant number 053963.

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