I Workshop de Matemática, Estatística e Computação Aplicadas à Indústria

Medical care in emergency units with risk classification: time to attendance at a hospital based on parametric models

Pedro Luiz Ramos[a], Diego Nascimento[a], Robson Fernandes[a], Edson Guimarães[a]
Marcelo Santana[a], Kleber Soares[a], and Francisco Louzada[a]
[a]Institute of Mathematical and Computer Sciences, University of São Paulo, São Carlos, Brazil

1 Introduction

The Manchester Triage System (MTS) was implemented in Brazilian hospitals as a public policy in 2008 [2] and has been studied since then by many authors. Here, we considered a Brazilian hospital that has recently adopted the Manchester Protocol in order to do classify/detect individuals subsequently needing admission to critical care areas. The hospital is located in São Paulo State and contains 38,699 patients' records from the period of March 1st to August 31st, 2016. The present study aims to describe the attendance for medical care of patients classified under the MTS based on some explanatory variables such as classification under the MT, the period of the day and if the patient is either an adult or children. To achieved this we considered survival analysis techniques with a regression structure to propose a probabilistic model in order to determine the different levels of probability related to the time spent until the patient receives medical attention according to his level of risk. With these results, we aimed to optimize the use of the resources of the emergency units by applying the proposed model to reduce operational costs, make medical care more welcoming, humanized and accurate.

In this study, we intend to study the effectiveness of applying the Manchester Triage System to improve patient flow in a Brazilian hospital, which allows a more welcoming and decisive service. Thus, time to event techniques are applied based on parametric regression models with the objective of investigating indicators for the emergency/urgency sector and thus, contributing to better operational efficiency. The results show that different explanatory variables such as classification, age, period, among others, influence the time of attendance. At the end, we provide a simple model that can be used to predict such time under different explanatory variables for a particular Brazilian hospital.

2 Manchester Triage System

The Manchester Triage System was firstly considered in Manchester in 1997. Afterwards it was implemented as a standard in the United Kingdom. The MTS has a list of 52 pre-defined conditions that, combined with patients' complaints, are divided (see Table 1) in the following categories:

Tabela 1: Manchester Protocol classification

Color	**Time (min)**	**Measure**	**Description**
Red	0	Emergency	Patient needs immediate care
Orange	10	Very Urgent	Patient needs almost immediate care
Yellow	60	Urgent	Patient needs fast care but can wait
Green	120	Slightly Urgent	Patient can wait for care or be referred to other health services
Blue	240	Not Urgent	Patient can wait for care or be referred to other health services

3 The model

These data can be further modeled by more flexible distributions such as Weibull, Exponential, Logistic, Lognormal and Loglogistic. The survival analysis also includes covariates when the response variable is time to event data, i.e., variables that help us explain changes in the response, a simple case can be given by

$$Y = \log(\boldsymbol{T}) = X\boldsymbol{\beta} + \sigma\boldsymbol{\epsilon},$$

where $\boldsymbol{\epsilon} = (\epsilon_1, \ldots, \epsilon_n)$ is the vector containing the individual errors, $\epsilon_1, \ldots, \epsilon_n$ are independent and identically distributed with a particular distribution, X are the explanatory variables with $n \times p$ size, $\boldsymbol{\beta} \in \mathbb{R}^p$ and $\sigma > 0$. In this case, we have that T has a lognormal distribution and the probability density function is given by

$$f(t|\sigma, \boldsymbol{x}, \boldsymbol{\beta}) = \frac{1}{(2\pi)^{\frac{1}{2}}\sigma t} \exp\left(-\frac{1}{2}\left(\frac{\log(t) - \exp(\boldsymbol{x'}\boldsymbol{\beta})}{\sigma}\right)^2\right), \tag{1}$$

where $t > 0$, $\sigma > 0$ and $\beta_i \in \mathbb{R}$ for $i = 1, \ldots, k$. The survival

$$S(t|\sigma, \boldsymbol{x}, \boldsymbol{\beta})) = 1 - \Phi\left(\frac{\log(t)}{\sigma}\right)$$

where $\Phi(x) = \int_{-\infty}^{0} \frac{1}{(2\pi)^{\frac{1}{2}}} e^{-\frac{u^2}{2}} du$. It is worth mentioning that this was implemented in the package Survival in R.

4 Statiscal Analysis

Table 2 presents the results for the $BIC = -2\log(L(\widehat{\boldsymbol{\theta}}; t)) + k\log(n)$ considering the Exponential, Weibull, Gaussian, Logistic, Lognormal and Loglogistic distributions.

Tabela 2: BIC Test Results for different probability distributions.

Distribution	**BIC**
Weibull	315232.8
Exponential	317400.0
Gaussian	379086.8
Logistic	363145.0
Lognormal	**310945.9**
Loglogistic	313196.9

The full model for each distribution was considered, i.e., the model with all covariates. Based on the results elucidated in Table 2, it can be observed that the Lognormal has the best fit to the data set. Table 3 presents the estimates of the variables that were significant to the model. The covariate *X1* represents **Classification**, *X2* - **Clinic** e *X3* - **Period of the day**.

Tabela 3: Significant Variable Results to the Model

$\boldsymbol{\theta}$	**Covariates**	**Value Std.**	**Error**	**Z**	**P-value**
β_1	X1Blue	2.3425	0.0511	45.816	< 0.0001
β_2	X1Green	0.0169	0.0173	0.978	0.3280
β_3	X1Yellow	-0.4117	0.0263	-15.652	< 0.0001
β_4	X1Orange	-0.7291	0.0320	-22.754	< 0.0001
β_5	X2R	0.1381	0.0629	2.195	0.0282
β_6	X3P2	-0.2828	0.0555	-5.097	< 0.0001
β_7	X3P3	0.0119	0.0541	0.220	0.826
β_8	X3P4	0.0301	0.0550	0.547	0.585
β_9	X2R:X3P2	0.2830	0.0673	4.208	< 0.0001
β_10	X2R:X3P3	0.1688	0.0660	2.560	0.0105
β_11	X2R:X3P4	-0.0757	0.0671	-1.127	0.2600
σ		0.2161	0.0036	59.975	< 0.0001

The residual analysis was conducted where showed that the model returned an adequate fit. Based on these results, all the parameters are significant in the model as they have very small p-values. Therefore, the final model is given by

$$f(t|\sigma, \boldsymbol{x}, \boldsymbol{\beta}) = \frac{1}{(2\pi)^{\frac{1}{2}} 0.2161 t} \exp\left(- \frac{1}{2} \left(\frac{\log(t) - e^{2.3425 x1_A + \ldots - 0.0757 X2_R X3_{P4}}}{0.2161} \right)^2 \right).$$

5 Discussion

In this work, we proposed a probabilistic model that can be used to estimate the time of patient attendance in emergency care units under the Manchester Triage System. The model adjusted under the Lognormal distribution with regression structure can be used to describe the different levels of probability precisely related to the time spent until the patient receives medical attention according to his/her level of risk. According to these results, we aimed to optimize the use of resources of the emergency units, through the application of the proposed model to reduce operational costs, make medical care more welcoming, humanized and accurate. we develop a software in the proposal called *Life Care*, as well as some part of its interface (see Figure 1).

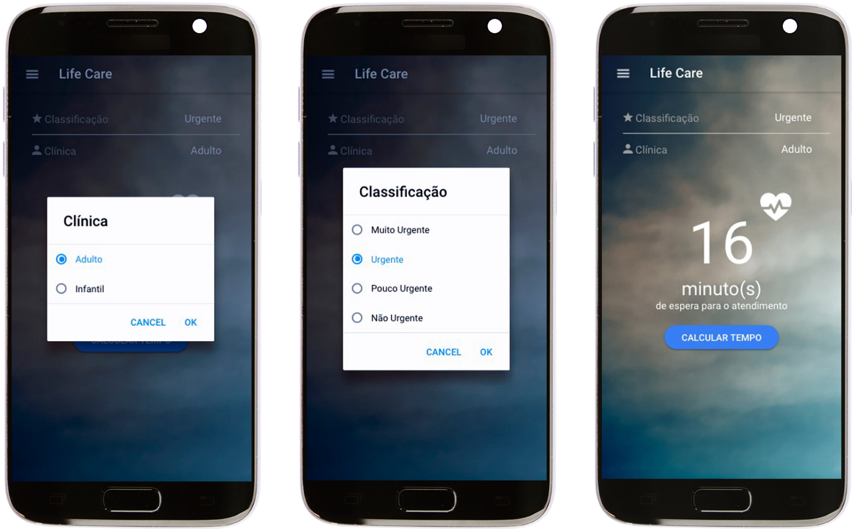

Figura 1: Application's prototype main screen.

According to the adjusted model, the next step to be developed will be an application for medical care applied in emergency units. The application is intended to notify the patient of a estimation of waiting time, associated to a probability, conditioned to its risk rating.

Referências

[1] Migon, H. S., Gamerman, D., & Louzada, F. (2014). *Statistical inference: an integrated approach*. CRC press.

[2] Torres, S. F. D. S., Belisário, S. A., & Melo, E. M. (2015). *A rede de urgência e emergência da macrorregião norte de minas gerais: um estudo de caso*, Saúde e Sociedade 24 (2015), pp. 361–373.

Published Version

Ramos, P. L., Nascimento, D. C., Fernandes, R., Guimarães, E., Santana, M., Soares, K., & Louzada, F. (2019). *Medical Care in Emergency Units with Risk Classification: Time to Attendance at a Hospital based on Parametric Models.* TEMA (São Carlos), 20(3), 571-585.