Prediction and Application of Queuing Analysis at Regional Hospital Limbe (Cameroon)

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Abstract

This study was conducted at a local hospital in Cameroon, the Regional Hospital Limbe (RHL), and it aimed at attempting one of Africas major problems; queuing systems with long queues, using health care systems as a study [1]. It concentrated on the application of queuing analysis and prediction of waiting time at (RHL). The work was a mix of concepts, using machine-learning techniques together with queuing theory concepts and their associated simulations. The main purpose of the work was to be able to make mathematical sense of a real-life scenario concerning queues (waiting lines), and try to come up with models for performance measure and improvement [3]. In terms of machine learning methodology, the problem was a supervised regression problem, which fit a model using the Random Forest Regressor [2]. In order to predict waiting time spent by a patient in a queue on any other day, random forest were used for predictions, outlining the waiting time for a given day, provided variables like department, among other variables. From results, the model prediction of a patient waiting in queue before receiving service was predicted with an average of 10.53 minutes of error (MAE), and as a verifier of methods, the model for total time spent in system had 1.75 minutes of error (MAE). Additionally, important variables in predicting both waiting times and total time spent in the system were identified. The work, through machine learning techniques, was thus able to predict how long a patient can wait in the hospital before receiving service and the total time from arrival until leaving the system.

INTRODUCTION

- Queuing theory: Study of lines and waiting time.
- Daily wait for service; hospitals, food outlets, banks, among various services.
- Waiting is tiring, inconvenient and frustrating.
- Hospital waiting → more injuries → complications, death.
- Application of queuing analysis to reduce waiting time.
- Analyse the queuing system and propose alternative operating systems.
- Use RandomForest Regressor to predict time taken tomorrow in the hospital by a patient.

Aim of the study

1. To decrease patient waiting time.
2. To predict the amount of time a patient spends before receiving service in future.

Research questions

In this project, the main aim was to study the queues with the following research questions;

1. What is causing the queues?
2. Which are the busiest departments, busiest days and busy times of the day?
3. How is the queuing system performing in terms of waiting and service times? Is it efficient enough?
4. Is it possible to have patient time predictions for the future?

DATA AND METHODOLOGY

Data

- Primary data collected through questionnaires and observations.
- Secondary data collected through hospital registers.
- Response rate for patients: 84% and 32 refusal cases.
- Response rate for medical personnel: 100%.

Methodology

- The problem was a supervised regression ML problem.
- Under ML, the learning algorithm used for prediction was random forest.
- The random forest worked by building and merging several decision trees in order to obtain a more accurate and stable forecast for waiting and total time in the hospital.
- Predictions for both waiting and total time spent were made using the Jupyter notebook in python, mainly to check the possibility of predicting the waiting and total time a patient spends in the hospital on any other day and model accuracy.
- The observed data was split into $\frac{2}{3}$ train data and $\frac{1}{3}$ test data.
- Model fitting using the Random Forest Regressor, initially had 1000 decision trees which were further trimmed for simplicity.
- For measuring prediction accuracy/error size, measures like Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were used to find error size and describe the average error and error size to be expected from the forecasts.

RESULTS

General overview

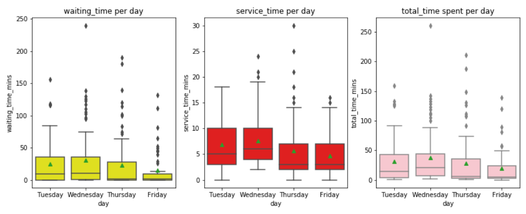

Figure 1: Average times daily

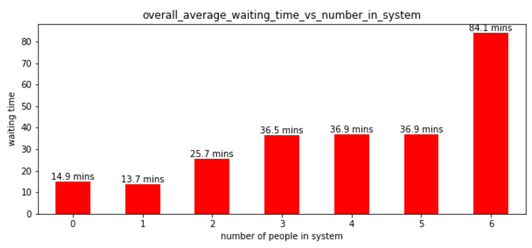

Figure 2: Average w-time vs number of patients

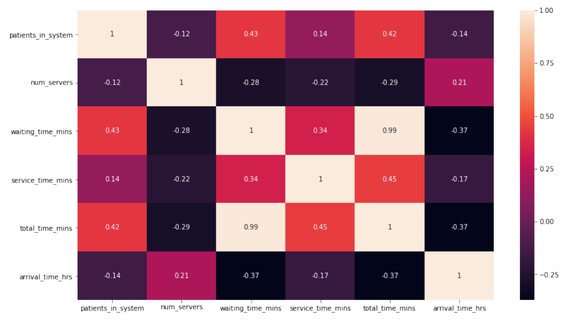

Figure 3: Correlation matrix

Waiting time prediction

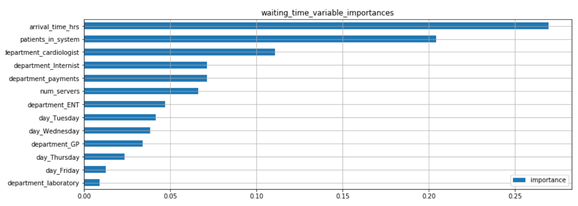

Figure 4: Variables for waiting time prediction

Figure 5: Waiting time prediction tree

Total time prediction

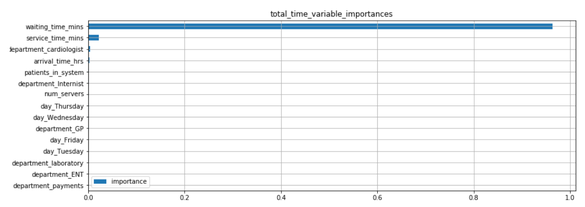

Figure 6: Variables for total time prediction

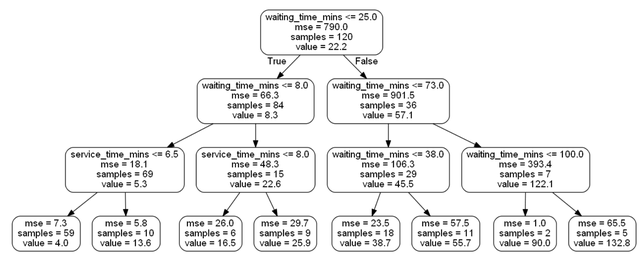

Figure 7: Total time prediction tree

CONCLUSION

Research questions	Subjective findings
Main cause of long w-time	Docs' arrival time, other activities.
Departments with long w-times	OPD, Lab & Imaging centre.
Busy days	Mon, Wed and Tues.
Busy time	Morning.

Any patient to visit RHL can use the proposed model to forecast the amount of time they will spend in the system.

RECOMMENDATIONS

1. To predict amount of time to be spent in the hospital at RHL, check and confirm day and time to visit, department and number of people that already exist in the system.
2. Change queuing system: one queue-multiple server.
3. Exempt doctors on duty for morning meetings, ward rounds and emergencies.
4. Increase doctors/shift and dedicate different server for patients requiring shorter services.
5. **Specialists**: Introduce consultation by appointment.
6. Combine steps for triage with screening points.
7. Computerise payment system to avoid hand invoicing.
8. Produce results in two shifts for the lab.

Allocate staff according to the busy days and times.

REFERENCES

[1] Association, B. C. M. et al. (2006). Waiting Too Long: Reducing and Better Managing Wait Times in BC: a Policy Paper by the BCMA's Council on Health Economics & Policy. British Columbia Medical Association.

[2] Curtis, C., Liu, C., Bollerman, T. J., and Pianykh, O. S. (2018). Machine learning for predicting patient wait times and appointment delays. Journal of the American College of Radiology, $15(9) : 1310 - 1316$.

[3] Ozcan, Y. A. (2005). Quantitative methods in health care management: techniques and applications, volume 4. John Wiley & Sons.