Simulating Patient Movement Through a Hospital Unit

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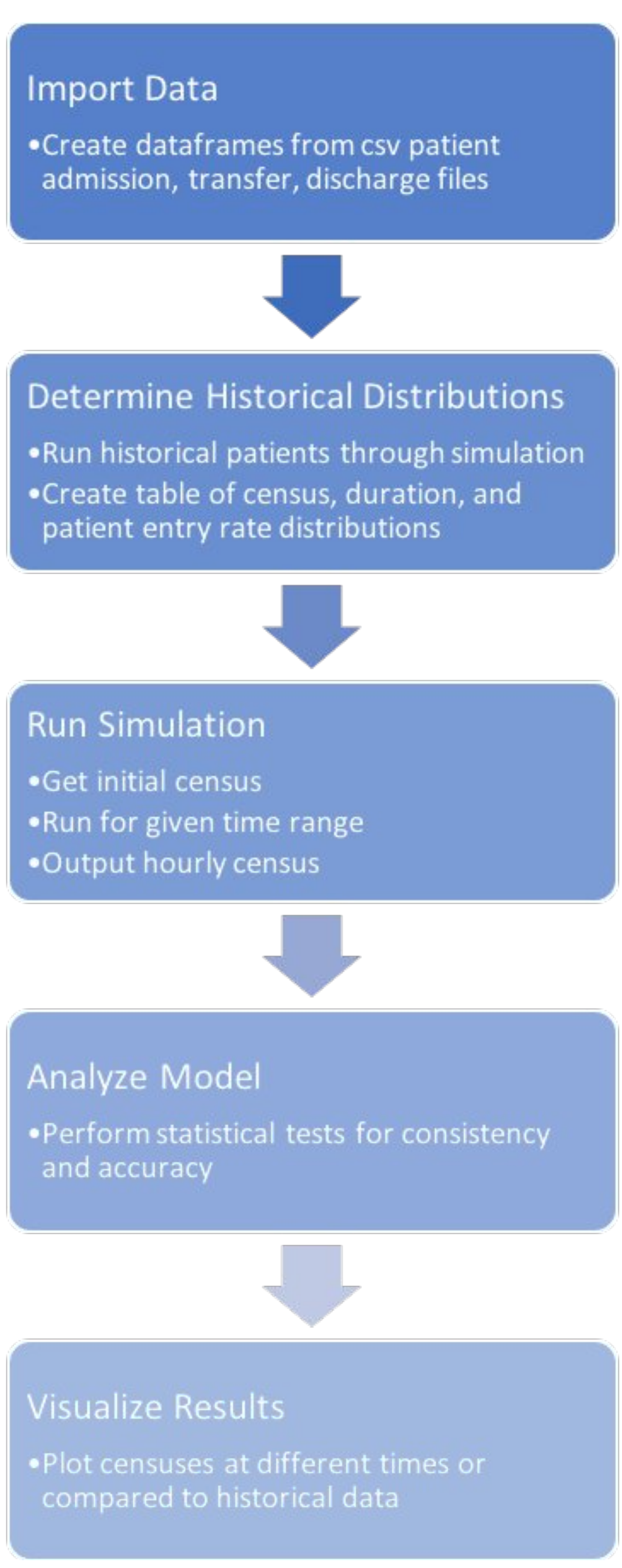
Introduction

- We created a patient census simulation for the 4-Pavilion medical-surgical unit at Howard County General Hospital.
- The simulation is able to accept user input for when to begin and end the simulation. Then, it uses historical data from the unit to generate an hourly patient census and an accompanying nurse schedule for the given time range.
- The goal of developing this simulation was to automate and improve the process of predicting patient flow and staff scheduling in hospitals, which is currently highly variable and uncertain.

Problem

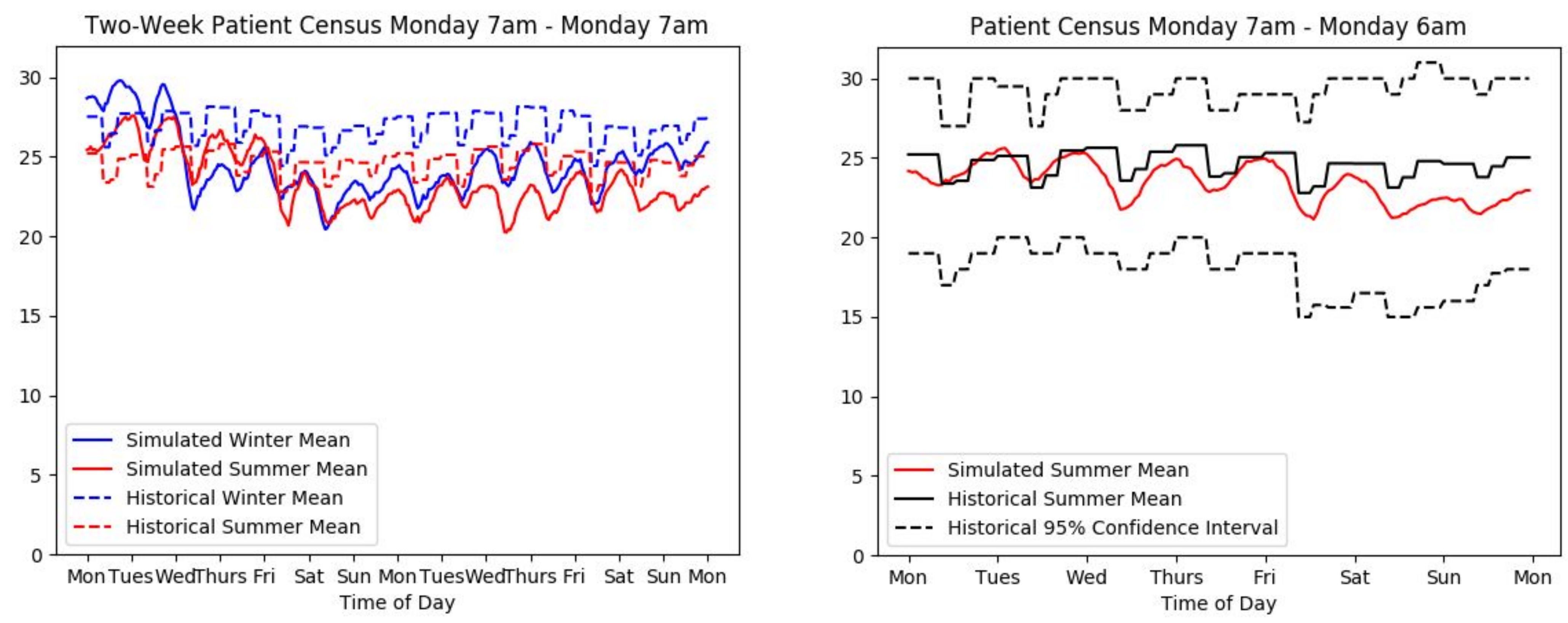
- There is increasing pressure on hospitals to improve their resource management, including staff scheduling, and reduce budgetary waste.
- Predicting patient flow is vital for staff scheduling and is linked heavily to patient safety, satisfaction, and quality of care.
- Currently, clinicians determine staff schedules by manually predicting patient census every morning, which is inefficient and subjective.
- This process should be automated and improved in accuracy by using historical data, which will ultimately reduce budgetary costs and be more effective.

Approach



The temporal organization used throughout the project was determined after consulting a nurse manager on the unit and examining trends evident in the data provided. A lookup table of historical distributions for each temporal parameter set was obtained. This included a census, length of stay, and patient entry rate information. The simulation moved patients through the unit based on these historical distributions, outputting an hourly patient census.

Results



On the left the simulated and historical mean census values over a two week period are shown; 25 simulation iterations were used. On the right the simulated mean for a one week period is shown; the historical mean and 95% confidence interval are plotted as well; 50 simulation iterations were used.

Simulation	t-test p-value	Pearson correlation coefficient
Winter- 25 weeks	0.0169	0.393
Summer- 25 weeks	0.0653	0.438
Winter- 50 weeks	0.051	0.578
Summer- 50 weeks	0.137	0.561

The census distributions from various simulation iterations were compared to the historical census data. The t-test tested the null hypothesis that the means of the distributions were equal. The Pearson's correlation coefficient indicates the degree of linear correlation.

As seen in the figures above, both seasonal and hourly temporal trends seen in historical data are shown in the simulation results. Simulation mean census results that included 50 iterations or more fell within the 95% confidence interval of the corresponding historical mean. The largest discrepancy was seen in the first few days of the simulation. This can be attributed to difficulties accurately assigning lengths of stay to patients added to the simulation at the start time.

Future Work

- Work could be done to make the simulation more accurate by improving the length of stay assignment to patients initially introduced to the simulation; the code is well documented to easily allow for this adjustment.
- Additional patient attributes like age and reason for visit could be included to create a more accurate tool for staff scheduling on the unit.
- A user interface could be implemented to make the simulation more accessible to clinical professionals involved in staffing or hiring on hospital units.

Lessons Learned

- Careful planning at the beginning of a large project is necessary for things to run smoothly and on time.
- It is important to keep the needs of the end-user in mind throughout the design and implementation of the project to ensure that the results will be useful and meaningful.
- Communication among team members is important.

Credits

Evelyn developed the simulation structure that could output an hourly census, implemented a method for user input, and implemented nurse scheduling that is updated according to the census. Sara performed the analyses of the historical data, generated distributions of patient movement attributes, and created and analyzed visualizations of the simulation results.

Acknowledgements

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