Capacity Management in a Cardiac Surgery Line

by

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Problem Statement

- The Cardiac Surgery service line at the UMMC has 12 beds devoted to the intensive care unit (ICU).
- The Cardiac Surgery service line ICU is operating near capacity and serves as a bottleneck for the flow of patients.
- Cardiac Surgery is a high dollar service line. Disruptions in the flow result in a significant reduction in revenue.
The staffing patterns are made more than a week in advance.

The staffing is then adjusted based on perceived need.

These decisions are made on a same day basis as information becomes available.

Key Question: Can information on the number of discharges be predicted a few days in advance?
Solution Approach

- The lengths of stay (LoS) for individual patients were predicted.
- Using these predictions, a posterior distribution was constructed for each patient (given the patient has stayed in the hospital a certain length of time, how much longer do we expect the patient to stay).
- The individual LoS predictions were aggregated for the ICU.
- These predictions were tested using simulation and in a hospital setting.
Data Set

- The data set contained detailed information about the length of stay for every cardiac surgery patient from FY05 and FY06.
- There were 1,675 cardiac patients in this time frame.
- The data set included current protocol (CPT) codes, LoS, age, sex, and race.
- Because there were a few hundred different CPT codes present they were initially narrowed into 20 different groups.
LoS Prediction

- We tested four methods for predicting patient LoS: Neural Networks, Model Tree, CHAID tree, and Median Regression.
- WEKA was used for the Neural Net, Model Tree and Median Regression.
- AnswerTree was used for the CHAID tree.
- Each of these methods was trained on 66% of the data and tested on the remaining 34%.
- The tests were repeated 10 times with different test sets.
## Prediction Results

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Neural Networks</th>
<th>Least Median Squared</th>
<th>Group Mean</th>
<th>Model Tree</th>
<th>CHAID</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAD</td>
<td>4.3107</td>
<td>3.8660</td>
<td>4.2638</td>
<td>4.4185</td>
<td>4.5982</td>
</tr>
<tr>
<td>Test MAD</td>
<td>4.0925</td>
<td>3.7431</td>
<td>4.1232</td>
<td>4.1779</td>
<td>4.2576</td>
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<tr>
<td>Test RMSE</td>
<td>8.3763</td>
<td>9.8771</td>
<td>8.4512</td>
<td>8.5400</td>
<td>8.8847</td>
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<tr>
<td>Parameters</td>
<td>406</td>
<td>25</td>
<td>21</td>
<td>10</td>
<td>5</td>
</tr>
</tbody>
</table>
CHAID Divisions

Total
N = 1,675
Mean = 4.6901
St. Dev. = 9.5452

No Surgery
N = 127
Mean = 0.3858
St. Dev. = 0.9681

Bypass
N = 679
Mean = 4.2515
St. Dev. = 7.1125

Major
N = 117
Mean = 16.9145
St. Dev. = 21.9775

Minor
N = 530
Mean = 3.3792
St. Dev. = 7.2840

Valve Replacement
N = 222
Mean = 5.2117
St. Dev. = 7.6876
No parametric distribution provided a good fit for any of the LoS groups.

Kaplan-Meier estimators were used to construct the posterior distribution.

These estimators were smoothed.
Aggregating Predictions

- The individual LoS predictions were aggregated using a multinomomial distribution.

- The expected census was determined by summing the probabilities each patient would stay at least one more day.

- The variance of the census was calculated by summing the probability each patient would stay times the probability the patient would be discharged.
Testing

- We tested the census predictions using simulation and then on a daily basis at the hospital for four weeks in June and July of 2007.

- 1, 2, and 3 day predictions were made.

- The population for the simulation was length biased because a patient with a long LoS was more likely to be observed.

- The simulation was run 10,000 times.
Simulation Results

<table>
<thead>
<tr>
<th></th>
<th>1 Day</th>
<th>2 Days</th>
<th>3 Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Absolute Error</td>
<td>1.3173</td>
<td>1.3735</td>
<td>1.3213</td>
</tr>
<tr>
<td>Bias</td>
<td>0.0962</td>
<td>0.1374</td>
<td>0.2579</td>
</tr>
<tr>
<td>% Overestimated</td>
<td>25.25%</td>
<td>30.20%</td>
<td>36.93%</td>
</tr>
<tr>
<td>% Accurate</td>
<td>48.12%</td>
<td>47.33%</td>
<td>42.38%</td>
</tr>
<tr>
<td>% Underestimated</td>
<td>26.63%</td>
<td>22.48%</td>
<td>20.69%</td>
</tr>
</tbody>
</table>
## Actual Results

<table>
<thead>
<tr>
<th></th>
<th>1 Day</th>
<th>2 Days</th>
<th>3 Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Absolute Error</td>
<td>1.15</td>
<td>1.80</td>
<td>2.50</td>
</tr>
<tr>
<td>Bias</td>
<td>-0.17</td>
<td>-0.49</td>
<td>-0.87</td>
</tr>
<tr>
<td>% Overestimated</td>
<td>17%</td>
<td>20%</td>
<td>0%</td>
</tr>
<tr>
<td>% Accurate</td>
<td>33%</td>
<td>30%</td>
<td>25%</td>
</tr>
<tr>
<td>% Underestimated</td>
<td>50%</td>
<td>50%</td>
<td>75%</td>
</tr>
</tbody>
</table>
Implications of the Errors

- The discharge predictions tended to be too low.
- More patients than predicted were discharged on days with a high scheduled volume.
- Robotic surgery is much more common now and those patients generally have a shorter LoS. This means that the posterior distributions for groups 3 and 4 have too much positive skew.
Conclusions

- The model was able to accurately determine when cases would be cancelled because there were more cases scheduled than available capacity.

- The initial results imply that the current model is not accurate enough to determine the required staffing levels.
Further Work

- The expected case volume should be included to improve the predictions.
- The effects of technological improvements on LoS should be determined.
- More advanced distribution fittings such as a gamma mixture model should be tested.
- Work is being done to predict capacity in other service lines.