USING PREDICTION TO IMPROVE PATIENT FLOW IN A HEALTH CARE DELIVERY CHAIN

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Outline

- Statement of the problem
  - Context
  - Motivation
- Expert opinion prediction experiment
- Statistical prediction development
- Moving forward
The Emergency Department Problem

- **Emergency Department are the “Safety Net” of our Health Care System [Fields 1999]**
  - Open 24/7, accessible, conspicuous in the community
  - “The Emergency Medical Treatment and Active Labor Act (EMTALA) mandates ...who presents to a hospital ED must receive a medical screening examination ...be offered treatment to stabilize that condition...” [Asplin 2006]

- **Emergency Department Bed/Visit Ratio decreasing [Nawar 2007, GAO 2009]**.
Solutions?

- **Technology**
  - New treatment technologies
  - Electronic medical records
  - Nurses with PDAs
  - More accurate tests

- **Management**
  - Lean/Six Sigma
  - Reimbursement schemes
  - Consolidation of resources

- **Policy**
  - Insurance policy ("Obama" Care)
  - Hospital regulation (Collective Bargaining)
  - Equality vs. equity issues (Taxing "Cadillac" Care)
Quality is connected to flow

The Problem:
- Admitted patients occupy emergency resources, delaying access to new patients

Quality is based on speed to and through treatment:

- Ambulance Diversion [Asplin 2003]
- Exposure to Safety Risks [Trzeciak 2003]
- Diagnosis and Admission of Critically Ill [Cowan 2005, Clark 2007]
- Time to Antibiotics for Patients with Pneumonia [Fee 2007, Pines 2007]
- Time to Pain Assessment and Analgesic [Hwang 2008, Pines 2008]
Faucet Model
Quality is connected to flow

Inpatient Unit Bed Availability is a Severe Bottleneck

- “The inability to transfer emergency patients to inpatient beds was the condition reported most often as contributing to going on diversion…” [US GAO 2003]
- “Inability to transfer emergency patients to inpatient beds as the single most important factor contributing to crowding.” [Olshaker 2006]
Relevant output focused solutions

- Direct admission based on emergency physician decision rather than consult [Howell 2004]
- Cancelling elective surgeries during busy days [ACEP 2008]
- Regular updates of emergency department performance on inpatient side [Howell 2008]
- Hallway admissions [ACEP 2008, Viccellio 2009]
- Bed management programs with Hospital Bed Coordinators [Moskop 2009]
- Discharge by noon [Rubino 2007, ACEP 2008]

Typical Hospital Admission Demand

Typical Hospital Discharge Rate

[Williams 2006]
What is missing?

- “If one can predict earlier in the course of an evaluation whether the patient will likely be admitted, then one may improve timeliness of inpatient placement or discharge planning.” [Yen 2007]

- Echoes sentiments of “Crossing the Quality Chasm” [IOM 2001] and emphasized by GAO report [US GAO 2009]

- Concept has been used in other fields (production management, inventory management, etc.)
Prediction based approach

Current Process
- Deterministic
- Bottlenecked

Process with prediction
- Add Uncertainty
- Reduce Bottleneck
- Add new problems?

Time in ED Bed
Real Demand
Bed Coordination
IU Treatment

Waiting | Triage | ED Treatment | Waiting

Waiting | Triage | ED Treatment | Bed Coordination | IU Treatment

Predicted Demand
Bed Coordination
IU Treatment

Time
Other studies claim that if we can make predictions we can drive actions.

The goal of this study is to explore whether those predictions are even possible and what they would look like.
 Experiment Description

- Nurses given form with triage materials for each patient.

- Attach patient label

- Format designed for understandability and ease of selection.

Patient Flow Prediction Quality Improvement Project Form

Prediction 1. Please predict total time between when the patient is triaged and the decision to admit or discharge is made: (Please circle or check one time block)

- 0-29min
- 30-59 min
- 60-89min
- 90-119min
- 120-239min
- > 240min

Prediction 2. How likely is it that the patient will need admission to the hospital?

- Definitely Yes (95-100%)
- Highly Likely (75-94%)
- Likely (50-74%)
- Unlikely (25-49%)
- Highly Unlikely (5-24%)
- Definitely No (0-4%)
Results of Admit Prediction

Predicted Probability of Admission

<table>
<thead>
<tr>
<th>Percentage of Patient Admitted From Each Category</th>
<th>Predicted Probability of Admission</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definitely Not (0-4%)</td>
<td>98.91%</td>
</tr>
<tr>
<td>Highly Unlikely (5-24%)</td>
<td>97.50%</td>
</tr>
<tr>
<td>Unlikely (25-49%)</td>
<td>92.16%</td>
</tr>
<tr>
<td>Likely (50-74%)</td>
<td>34.00%</td>
</tr>
<tr>
<td>Highly Likely (75-94%)</td>
<td>50.00%</td>
</tr>
<tr>
<td>Definitely Yes (95-100%)</td>
<td>57.21%</td>
</tr>
<tr>
<td>Skip Triage</td>
<td>42.79%</td>
</tr>
</tbody>
</table>
Naïve Bayesian Approach – VHA
Boston West Roxbury
Naïve Bayes Approach

- Total 32% chance of admit, but can Bayes Theorem do better?

- Try 3 Patient factors: F1-Urgent/Non, F2-Male/Female, F3-Over/Under 65

- \[ P(\text{Admit}|\text{Factors}) = P(F_1|\text{Admit}) \times P(F_2|\text{Admit}) \times P(F_3|\text{Admit}) \times P(\text{Admit}) \times P(\text{Factors}) \]

- Urgent over 65 year old male has a 61% chance of admit

- Non-Urgent under 65 year old female has a 1.3% chance of admit
Best Fit Prediction Scheme – VA Bayes

- Complaint + Arrival Mode + Age

Predicted Probability of Admission

<table>
<thead>
<tr>
<th>Percentage of Patient Admitted From Each Category</th>
<th>% Not Admitted</th>
<th>% Admitted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definitely Not</td>
<td>2.56</td>
<td>97.44</td>
</tr>
<tr>
<td>Highly Unlikely</td>
<td>13.40</td>
<td>86.60</td>
</tr>
<tr>
<td>Unlikely</td>
<td>62.50</td>
<td>36.84</td>
</tr>
<tr>
<td>Likely</td>
<td>59.38</td>
<td>40.63</td>
</tr>
<tr>
<td>Highly Likely</td>
<td>66.67</td>
<td>33.33</td>
</tr>
<tr>
<td>Definitely Yes</td>
<td>77.53</td>
<td>20.22</td>
</tr>
</tbody>
</table>
Moving Forward
Uncertainty and Decision Models

- **Models to optimize magnitude and mix of stakeholder actions given uncertain information**
  - Resources reallocation algorithm
  - Protocols may be needed to increase consistency of individual decisions
  - Algorithms or heuristics to suggest the highest impact elective cancelations
  - Model for defining “need to work faster”

- **Can develop multiple Predictive model/Control method combinations**
Context for methodological contribution

- **Broad Problem:** Improving flow (rate, variability, wait times) between two steps in a Health Delivery Chain.

- **Occurs in multiple scenarios:**

<table>
<thead>
<tr>
<th>In Department Level</th>
<th>Cross Department Level</th>
<th>Cross Organizational Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doctor Exam</td>
<td>Emergency Department</td>
<td>Generalist</td>
</tr>
<tr>
<td>Testing (Ex. CT Scan, XRay, Blood Test, etc.)</td>
<td>Inpatient Unit</td>
<td>Specialist</td>
</tr>
<tr>
<td></td>
<td>Cross Department Level</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Long Term Stay</td>
</tr>
<tr>
<td></td>
<td>Inpatient Unit</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Results Time Prediction

![Box plots of actual versus predicted treatment times]

- Predicted Treatment Time (min):
  - 0-29
  - 30-59
  - 60-89
  - 90-119
  - 120-240
  - >240

- Actual Treatment Time (min):
  - 20
  - 35
  - 40
  - 65
  - 73
  - 90
  - 95
  - 105
  - 110
  - 140
  - 160
  - 171
  - 180
  - 245
  - 247
  - 248
  - 302

- % Points Below line:
  - 25%
  - 50%
  - 75%
## Comparison of Predictors

<table>
<thead>
<tr>
<th>Method</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Positive Predictive Value</th>
<th>Negative Predictive Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>VA Test</td>
<td>Expert - Triage</td>
<td>55.66</td>
<td>86.98</td>
<td>48.11</td>
</tr>
<tr>
<td>VA Bayes 1</td>
<td>Naïve Bayes</td>
<td>53.48</td>
<td>91.41</td>
<td>71.94</td>
</tr>
<tr>
<td>VA Bayes 2</td>
<td>Naïve Bayes</td>
<td>94.09</td>
<td>70.11</td>
<td>56.27</td>
</tr>
<tr>
<td>Leegon 2005</td>
<td>Bayesian Network</td>
<td>90</td>
<td>71</td>
<td>56</td>
</tr>
<tr>
<td>Arslanian-Engoren 2004</td>
<td>Expert - Triage</td>
<td>57</td>
<td>59</td>
<td>68</td>
</tr>
<tr>
<td>Clesham 2008</td>
<td>Expert - EMS</td>
<td>71.7</td>
<td>77</td>
<td></td>
</tr>
<tr>
<td>Levine 2006</td>
<td>Expert - EMS</td>
<td>62</td>
<td></td>
<td>59</td>
</tr>
<tr>
<td>Walsh 2004</td>
<td>Neural Network</td>
<td>78</td>
<td>82</td>
<td>68</td>
</tr>
<tr>
<td>Sadeghi 2006</td>
<td>Expert - Triage</td>
<td>64</td>
<td>48</td>
<td>52</td>
</tr>
<tr>
<td></td>
<td>Bayesian Network</td>
<td>90</td>
<td>25</td>
<td>51</td>
</tr>
</tbody>
</table>
Conclusion

- **Motivation** – Emergency department flow/quality

- **Method** – Prediction with expert opinion and statistical methods

- **Expected Merit** – Show that predictions can be made and the data is in a useable format

- **Expected Impact** – Method for approaching flow improvement in a health care delivery chain

- **Academic Contribution** – Addition to methodologies for controlling service systems
“In addition, data now exist to suggest that low-acuity patients with nonurgent conditions contribute little, if at all, to the problems of crowding and ambulance diversion [13]. Nor does lack of insurance seem to be a powerful driver of ED usage: a 2003 report noted that two thirds of the increase in ED visits between 1996 and 1997 and 2000 and 2001 was accounted for by patients with private insurance or Medicare [14].” Bernstein 2006

“Low-complexity ED patients are associated with a negligible increase in ED length of stay and time to first physician contact for other ED patients. Reducing the number of low-complexity ED patients is unlikely to reduce waiting times for other patients or lessen crowding.” [Schull 2007]
## Prediction in Health Care

<table>
<thead>
<tr>
<th>Paper</th>
<th>Prediction and Use</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Robinson 1966</td>
<td>LOS of Surgery Patients for Improved Scheduling</td>
<td>Statistical Classification, Expert Prediction</td>
</tr>
<tr>
<td>Gustafson 1968</td>
<td>LOS of Hospital Patients using direct point estimates and probability distribution estimates. Bayesian Model Performed Best. Suggest use for staffing decisions.</td>
<td>Subjective Expert Point Estimate, Multiple Linear Regression, Historical Mean, Expert Personal Probability Estimate, Bayes’ Theorem</td>
</tr>
<tr>
<td>Gustafson 1971</td>
<td>Diagnosis of Thyroid Disease</td>
<td>Bayesian Predictor</td>
</tr>
<tr>
<td>Vandankumar 1980</td>
<td>Discharges and LOS for Occupancy goals</td>
<td>Conditional Probability based on age, source of admission, physician, historical distributions and current LOS.</td>
</tr>
<tr>
<td>Long 1989</td>
<td>Looking at symptoms to diagnose heart disease</td>
<td>Probabilistic Causal Network</td>
</tr>
<tr>
<td>Glaski 1993</td>
<td>Predicting LOS and Future Treatment requirements of Stroke Patients for resource planning.</td>
<td>Multiple Linear Regression</td>
</tr>
<tr>
<td>Hamilton 1994</td>
<td>Diagnosing biopsy specimens given uncertainty</td>
<td>Bayesian Belief Network</td>
</tr>
<tr>
<td>Szolovits 1995</td>
<td>General discussion of dealing with uncertainty in heath care decisions</td>
<td>“Idiot Bayes” formulation</td>
</tr>
<tr>
<td>Fine 1997</td>
<td>Identify Low Risk Pneumonia Patients</td>
<td>Heuristic Chart (age, history, physical exam, tests)</td>
</tr>
</tbody>
</table>
Roxbury Specifics

- **Inpatient Unit**
  - Approx 35-50 medicine residents,
  - Evenly distributed 5 floor teams, 2 Cardiology teams, 1 MICU team.
  - 1 Senior resident per floor
  - ~5 nurses per floor

- **Emergency Department**
  - 12 Beds
  - 7 Emergency Department Physicians + Residents
  - ~10-15 Nurses
  - 2 Physician Assistants

- **Administrative**
  - Unknown Cleaning Crew Count
  - 1 Bed Coordinator, 2 substitutes
### Best Fit Prediction Scheme

#### Complaint + Arrival Mode + Age

<table>
<thead>
<tr>
<th>Predication</th>
<th>% Not Admitted</th>
<th>% Admitted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definitely Not (0-4%)</td>
<td>152</td>
<td>4</td>
</tr>
<tr>
<td>Highly Unlikely (5-24%)</td>
<td>168</td>
<td>26</td>
</tr>
<tr>
<td>Unlikely (25-49%)</td>
<td>95</td>
<td>56</td>
</tr>
<tr>
<td>Likely (50-74%)</td>
<td>13</td>
<td>19</td>
</tr>
<tr>
<td>Highly Likely (75-94%)</td>
<td>6</td>
<td>12</td>
</tr>
<tr>
<td>Definitely Yes (95-100%)</td>
<td>18</td>
<td>69</td>
</tr>
</tbody>
</table>

- **Number of Patient Admitted From Each Category**
## Best Fit Prediction Scheme

### Urgency + Location + Arrival Mode + Age

<table>
<thead>
<tr>
<th>Predicted Probability of Admission</th>
<th>Number of Patient Admitted</th>
<th># Not Admitted</th>
<th># Admitted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definitely Not Admitted (0-4%)</td>
<td>5</td>
<td>306</td>
<td>5</td>
</tr>
<tr>
<td>Highly Unlikely (5-24%)</td>
<td>8</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Unlikely (25-49%)</td>
<td>3</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Likely (50-74%)</td>
<td>94</td>
<td>94</td>
<td>71</td>
</tr>
<tr>
<td>Highly Likely (75-94%)</td>
<td>3</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>Definitely Yes (95-100%)</td>
<td>99</td>
<td>36</td>
<td>99</td>
</tr>
</tbody>
</table>

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# Excel Tool in Triage

<table>
<thead>
<tr>
<th>What is the primary compliant</th>
<th>P Factor given admit</th>
<th>P Factor</th>
<th>P Admit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abdominal Pain</td>
<td>0.064698</td>
<td>0.045574</td>
<td>0.482705</td>
</tr>
<tr>
<td>Non-Emergent</td>
<td>0.017815</td>
<td>0.401622</td>
<td>0.015082</td>
</tr>
<tr>
<td>Ambulatory</td>
<td>0.404076</td>
<td>0.679466</td>
<td>0.202211</td>
</tr>
<tr>
<td>FT</td>
<td>0.011244</td>
<td>0.376342</td>
<td>0.010159</td>
</tr>
<tr>
<td>Age</td>
<td>0.013352</td>
<td>0.046745</td>
<td>0.097124</td>
</tr>
</tbody>
</table>

## Joint Probability

| Complaint + Urgency + Mode | 0.012733 |
How will the outputs be used?

- Assume Prediction Results are a distribution and a running bed need score is kept
  - **Emergency Department Crowding Index** - knowledge of problem simply causes people to work harder [Bernstein 2003, Epstein 2006, Hoot 2009]

<table>
<thead>
<tr>
<th>Time of Day</th>
<th>Running Bed Need</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>.91</td>
</tr>
<tr>
<td></td>
<td>.67</td>
</tr>
<tr>
<td></td>
<td>.21</td>
</tr>
<tr>
<td>12</td>
<td>.73</td>
</tr>
<tr>
<td></td>
<td>.31</td>
</tr>
<tr>
<td>24</td>
<td>.98</td>
</tr>
<tr>
<td></td>
<td>.87</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time of Day</th>
<th>Running Bed Need</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>.91</td>
</tr>
<tr>
<td>12</td>
<td>1.58</td>
</tr>
<tr>
<td></td>
<td>.88</td>
</tr>
<tr>
<td>24</td>
<td>1.92</td>
</tr>
<tr>
<td></td>
<td>1.04</td>
</tr>
<tr>
<td>1.61</td>
<td>2.98</td>
</tr>
<tr>
<td>2.02</td>
<td>1.85</td>
</tr>
<tr>
<td>2.98</td>
<td>.87</td>
</tr>
</tbody>
</table>
Newsvendor Model

- $F(Q) = \text{Probability that demand is less than or equal to } Q$
- $Co = \text{Cost of over reacting}$
- $Cu = \text{Cost of under reacting}$
- $Co \times F(Q) = Cu \times (1-F(Q))$

- $F(Q) = \frac{Cu}{Co + Cu}$
Uncertainty and Decision Models

- System Study: Yes/No admit from triage to bed coordinator.
- Method Selection: Neural Network [Walsh 2004]
- Tool showed 17% Type 1 error and 9% Type 2 error, VA West Roxbury Admits 32% of Emergency Department Patients

Call for bed?

- Yes
  - 72% Correct
  - 28% Wrong

- No
  - 28% Correct
  - 72% Wrong

59% Predict No Admit

- Yes
  - 5% Correct
  - 95% Wrong

- No
  - 95% Correct
  - 5% Wrong

41% Predict Admit

- Yes
  - 28% Wrong

- No
  - 28% Correct

Cost of Testing – C1

Benefit of preparation – B1
Cost of extra work, lost trust – C2
Benefit of saving opportunity cost – B2
Ill prepared, lost trust – C3

5% Wrong

95% Correct

B2
C2
Threats to validity

- **Internal Validity**
  - Multiple treatment inference - VA Culture of Improvement
  - Maturation – people must adapt to new methods
  - Experimental mortality - Resident Rotations
  - Diffusion of treatments – Other VA hospitals may hear of effort and try to copy, which could influence the control groups
  - Staff cooperation

- **External Validity**
  Reactive effects of Experimental Arrangements – VA:
  - Payment/incentive structure
  - Emergency physician admission decision
  - Use of a bed coordinator
  - Distinct patient population
  - Extensive information technology system
## R² Top 10 Results Compared to Expert

<table>
<thead>
<tr>
<th>Run</th>
<th>1</th>
<th>2</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACM</td>
<td>0.926488</td>
<td>0.850683</td>
<td>0.913728</td>
</tr>
<tr>
<td>CDU</td>
<td>0.851244</td>
<td>0.831173</td>
<td>0.844403</td>
</tr>
<tr>
<td>ACD</td>
<td>0.836273</td>
<td>0.806958</td>
<td>0.838433</td>
</tr>
<tr>
<td>ADL</td>
<td>0.862539</td>
<td>0.792481</td>
<td>0.836905</td>
</tr>
<tr>
<td>CD</td>
<td>0.709309</td>
<td>0.951622</td>
<td>0.834079</td>
</tr>
<tr>
<td>CLU</td>
<td>0.814925</td>
<td>0.826705</td>
<td>0.825613</td>
</tr>
<tr>
<td>D</td>
<td>0.80964</td>
<td>0.794007</td>
<td>0.823712</td>
</tr>
<tr>
<td>ADLU</td>
<td>0.804364</td>
<td>0.719036</td>
<td>0.81761</td>
</tr>
<tr>
<td>LM</td>
<td>0.799189</td>
<td>0.412601</td>
<td>0.815498</td>
</tr>
<tr>
<td>ACDL</td>
<td>0.828979</td>
<td>0.758435</td>
<td>0.814307</td>
</tr>
</tbody>
</table>

A – Age  
C – Complaint  
D – Doctor  
L – Location  
M – Mode  
U – Urgency
Predictive Methods In Health Care

Statistical
- [Gustafson 1971]
- [Long 1989]
- [Hamilton 1994]
- [Szolovits 1995]
- [Fine 1997]
- [Walsh 2004]
- [Galski 1993]
- [Trivedi 1980]
- [Gustafson 1968]
- [Galski 1993]
- [Epstein 2006]
- [Omachonu 2004]
- [Marshall 2001]
- [Hoot 2009]
- [Meehl 1954]

Expert Opinion
- [Gilboy 2005]
- [Arslanian 2004]
- [Gilboy 2005]
- [Cuervo 1966]
- [Levine 2006]
- [Clesham 2008]

Bayesian
- Multiple Linear Regression

Neural Network

Heuristic Chart

Other Options: Fuzzy Logic? Advanced Bayesian Methods?
### Input
- Simulation - adding registration staffing [McGuire 1994]
- Triage protocols for specific tests [Kirtland 1995]
- Doctors at triage discharge patients to a separate acute care unit [Kelen 2001, ACEP 2008]
- Insurance policies to increase use of primary care [Richardson 2002]
- Physician directed ambulance destination control program [Shah 2006]
- Reducing “frequent flyer” visits through education [Michelen 2006]
- Direct to room when emergency department is not full [Bertoty 2007]

### Throughput
- Queuing theory for optimal staffing [Vassilacopoulos 1985, Green 2006]
- Fast Track for low acuity patients [Meislin 1988, Rubino 2007, ACEP 2008]
- Assign takt times to parts of the emergency department [McGuire 1994]
- Simulation for optimal staffing [Rossetti 1999, Samaha 2003]
- Mini-laboratory in the emergency department [Lee-Lewandrowski 2003]
- Electronic tracking board [Boger 2003]
- Emergency department crowding indexes [Bernstein 2003]
- Online analytical processing to improve real time manager decisions [Gordon 2004]
- In room registration [Gorelick 2005, ACEP 2008]
- Lean process mapping [King 2006, Graban 2008, Dickson 2009]
- Layout improvements [Miro 2007]

### Output
- Post treatment buffers [McGuire 1994, ACEP 2008]
- Queuing models for optimal hospital bed levels [Green 2001, de Bruin 2007]
- Prepare patient for non-hospital alternative care [Moss 2002]
- Transition team of nurses to watch boarding patients and free up emergency department doctors for new patients [Ganapathy 2003]
- Direct admission based on emergency physician decision rather than consult [Howell 2004]
- Increase post emergency department care capacity (ICU cardiac units etc.) [ McConnell 2005, Levin 2008]
- Discharge by noon [Rubino 2007, ACEP 2008]
- Scheduling of elective and surgical patients [ACEP 2008]
- Cancelling elective surgeries during busy days [ACEP 2008]
- Regular updates of emergency department performance on inpatient side [Howell 2008]
- Hallway admissions [ACEP 2008, Viscellio 2009]
- Bed management programs with Hospital Bed Coordinators [Moskop 2009]