Prediction Rules for Mortality from Decedent Data at NorthShore

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• Bayes’ Theorem: \[ P(A|B) = \frac{P(B|A)}{P(B)} P(A) \]

"Yesterday’s Posterior is Tomorrow’s Prior”

Rev. Thomas Bayes
“Over seven billion people are alive today, and billions more have come before us. Yet the vast majority lived and died, taking their experiences to the grave with them...”

“...only a small fraction have been empowered, through participation as subjects in RCTs and other such research, to contribute their personal experiences with health and healthcare to the body of scientific knowledge”

*Your Life, Your Health, JHK*
Why Interest in Decedents?

• Patients who have run a full course in life / medical circumstances
• Being deceased, they are not “human subjects” hence no IRB protocol
• Likely to have significant portions of medical history captured in EMR
• End of Life Planning

• Decedents remain protected by HIPAA for 50 years after death date
• At NorthShore, we consider as deceased anyone with a non-missing SSA Death Date
Decedents in NS EMR

• 200,000 Deceased Patients
• 40,000 Patients with Medication Information (e.g. Antihypertensives)
• 40,000 Patients with Laboratory Information (e.g. Creatine, WBC)

• NS Age at Death (Histogram)
• mortality.org Age of Death
• Weibull Distribution for Age of Death
Censoring in Time-to-Event Models

<table>
<thead>
<tr>
<th>Component</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exact Lifetime</td>
<td>( f(x) )</td>
</tr>
<tr>
<td>Right-Censored Observations</td>
<td>( S(C_r) )</td>
</tr>
<tr>
<td>Left-Censored Observations</td>
<td>( 1 - S(C_l) )</td>
</tr>
<tr>
<td>Interval-Censored Observations</td>
<td>( S(L) - S(R) )</td>
</tr>
<tr>
<td>Left-Truncated Observations</td>
<td>( \frac{f(x)}{S(Y_L)} )</td>
</tr>
<tr>
<td>Right-Truncated Observations</td>
<td>( \frac{1 - S(Y_R)}{f(x)} )</td>
</tr>
<tr>
<td>Interval-Truncated Observations</td>
<td>( \frac{S(Y_L) - S(Y_R)}{f(x)} )</td>
</tr>
</tbody>
</table>

![Graph showing Censoring in Time-to-Event Models]

Censoring in Time-to-Event Models.
White Blood Counts
(Population Level)
White Blood Counts
(Patient Level)

There is no such thing as an "Average Patient" -- *Personalized Medicine*
Antihypertensive Medication Prescription (Patient Level)

<table>
<thead>
<tr>
<th>Year</th>
<th>Medication Type</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>Antihypertensive</td>
<td>Olmesartan Medoxomil-HCTZ</td>
</tr>
<tr>
<td>2008</td>
<td>Antihypertensive</td>
<td>Olmesartan Medoxomil</td>
</tr>
<tr>
<td>2010</td>
<td>Antihypertensive</td>
<td>Losartan Potassium</td>
</tr>
<tr>
<td>2012</td>
<td>Diuretics</td>
<td>Hydrochlorothiazide</td>
</tr>
<tr>
<td>2014</td>
<td>Pressors</td>
<td>Phenylephrine HCl (Pressors)</td>
</tr>
<tr>
<td>2016</td>
<td>Antihypertensive</td>
<td></td>
</tr>
</tbody>
</table>

*Diuretics, Pressors, Angiotensin II Receptor Antagonists, Thiazides and Thiazide-Like Diuretics, Vasopressors*
What do we need?

• Good Problems
• Good Data
• Good Models
• Adequate Computer Resources
• Adequate Personnel

Bayesian inference
Bayesian graphical models
Markov chain Monte Carlo methods

Chest clinic example with parameters and plate indicating repeated cases.
Joint Models

- Survival

- Lab Values

Assembling Together Different Data Domains
Prediction of Time to Event (Mortality)

- How long do I have to live, given my history?
- Which treatments are associated with better life, for me?

- Which measurements are associated with prediction power?
- Model Comparison and Diagnostics