Unfolding Physiological State

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Mortality Modeling in Intensive Care Units

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We’ve Got A Really Big Problem

• ICUs are busy, and carestaff are often inundated with information.

• How do I figure out which patient needs my attention?

• Use mortality as acuity surrogate.
Lots of Data Sources

Signals

Numerical

Narrative

Snapshot

00:00 12:00 24:00 36:00 48:00

Age
Gender
SAPS I

Nurse Note
Doc Note
Doc Note
Path Note
Discharge Note

ICD9 EH CoMor

Signals

Numerical

Narrative

Snapshot

00:00 12:00 24:00 36:00 48:00

Age
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Nurse Note
Doc Note
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Path Note
Discharge Note

ICD9 EH CoMor
What Do We Already Know?

- In 2009, 118 validated mortality prediction tools published.**
  - Modest accuracy
  - Large variability
  - Models based on numeric, waveform, or snapshot data
  - Snapshot data (e.g. ICD9) is not “realtime” or actionable

- A good predictive rule must be*:
  - **Accurate** in a wide variety of clinical settings
  - **Easy** to incorporate into routine clinical practice
  - Improves **prognostic** accuracy

* Grady, Deborah, and Seth A. Berkowitz. "Why is a good clinical prediction rule so hard to find?." *Archives of internal medicine* 171.19 (2011): 1701-1702.

Every Cat Needs a Plan

- Create forward-facing models every 12 hours that only use data what would have actually been available, or “realtime” data.

- Incorporate clinical text with snapshot data.

- Measure performance on mortality prediction in-hospital, at 30-days and 1-year post-discharge.

Hypothesis: Text information decomposed into topic features adds value to snapshot data.
Model Setup: Overview

Data

12 Hours 24 Hours 36 Hours

Patient 1

N₁ N₁ N₁

Patient N

N₁ N₁ N₁ N₁

Un-supervised LDA Model

Aggregated Feature Matrix

Structured SVM Model

12 Hours

Age Sex SAPS I max\{SAPS I\} ... EH_Comor₃₀

... ... ... ...

... ... ...

T₁ ... T₅₀ Age Sex SAPS I max\{SAPS I\} ... EH_Comor₃₀

... ...

... ...

SVM Model
Model Setup: Data

- Use 19,308 adult patient records
- Gather per-patient snapshot information
- Collect 473,764 notes
  - Use only first admissions
  - Ignore discharge summaries
Model Setup: Latent Topic Features

<table>
<thead>
<tr>
<th>Topic #</th>
<th>Top Ten Words</th>
<th>Possible Topic</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-Hospital Mortality</td>
<td>27  name family neuro care noted status plan stitle dr remains</td>
<td>Discussion of end-of-life care</td>
</tr>
<tr>
<td></td>
<td>15  intubated vent ett secretions propofol abg respiratory resp care sedated</td>
<td>Respiratory care</td>
</tr>
<tr>
<td></td>
<td>7   thick secretions vent trach resp tf tube coarse cont suctioned</td>
<td>Respiratory failure</td>
</tr>
<tr>
<td></td>
<td>5   liver renal hepatic ascites dialysis failure flow transplant portal ultrasound</td>
<td>Renal failure</td>
</tr>
<tr>
<td>Hospital Survival</td>
<td>1   cabg pain ct artery coronary valve post wires</td>
<td>Cardiovascular Surgery</td>
</tr>
<tr>
<td></td>
<td>40  left fracture ap views reason clip hip distal lat report joint</td>
<td>Fracture</td>
</tr>
<tr>
<td></td>
<td>16  gtt insulin bs lasix endo monitor mg am plan iv</td>
<td>Chronic diabetes</td>
</tr>
<tr>
<td>1 Year Mortality</td>
<td>3   picc line name procedure catheter vein tip placement clip access</td>
<td>PICC line insertion</td>
</tr>
<tr>
<td></td>
<td>4   biliary mass duct metastatic bile cancer left ca tumor clip</td>
<td>Cancer treatment</td>
</tr>
<tr>
<td></td>
<td>45  catheter name procedure contrast wire french placed needle advanced clip</td>
<td>Coronary catheterization</td>
</tr>
</tbody>
</table>
Model Setup: Time-varying Topics

- Time-varying Topic Model:
  - Normalized topic distribution (50 features)
Model Setup: Admission Baseline

- Admission Baseline Model:
  - Age, gender, admitting SAPS I score (3 features)
Model Setup: Combined Time-varying

• Combined Time-varying Model:
  • Admission and topic features (53 features)
Model Setup: Retrospective Topics

• Retrospective Topic Model:
  - Retrospective note features from entire patient stay (50 features).
Model Setup: Retrospective Topics + Admission

- Retrospective Topic + Admission Model:
  - Combined topic and admission feature (53 features).
Model Setup: Retrospective Derived

- Retrospective Derived Features Model:
  - Age, gender, admitting/min/max/final\{SAPS I\} and Elixhauser co-morbidity scores (36 features).
Model Setup: Retrospective Topics + Derived

- Retrospective Topic + Derived Features Model:
  - Combine all retrospective (86 features).
Mortality Prediction Results

In-Hospital Mortality

Time (Hours from First Note)

AUC

0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

0 24 48 72 96 120 144 168 192 216 240 264 288

1-Year Mortality

Time (Hours from First Note)

AUC

0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

0 24 48 72 96 120 144 168 192 216 230

30-Day Mortality

Time (Hours from First Note)

AUC

0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

0 24 48 72 96 120 144 168 192 216 228

SVM Model

Admission Baseline Model

Time-varying Topic Model

Combined Time-Varying Model

Retrospective Derived Feature Model

Retrospective Topic Model

Retrospective Topic + Admission Model

Retrospective Topic + Derived Feature Model
We Solved A Problem, So Everything Is Awesome

- Text Data Is Valuable
  - A combination of latent topic features and snapshot features worked best

- Long-term Predictions Are Harder
  - Combinations of features were best able to perform well initially and over first 24 hours.

- “Realtime” Models Are More Valuable
  - Retrospective models out-performed continuous models, but are not actionable.
Future Work

• A good predictive rule must be:
  • Accurate in a wide variety of clinical setting
  • Easy to incorporate into routine clinical practice
  • Improves prognostic accuracy
  • Indicate effective treatment to improve outcomes

“Prediction of risk is not enough—we need evidence that prediction can lead to actions that reduce risk beyond what would occur without the prediction rule.”

Grady, Deborah, and Seth A. Berkowitz. "Why is a good clinical prediction rule so hard to find?." Archives of internal medicine 171.19 (2011): 1701-1702.
Acknowledgements

Come by our poster tonight!

Thanks to:
Intel Science and Technology Center for Big Data
NIH NLM Biomedical Institute Research Training
Backup
Latent Topic Inference

- Inferred topics provide weighted posterior $q_{n,k}$ for each note $n$ and topic $k$ such that for all $n$, $\sum_{k=1}^{K} q_{n,k} = 1$
- Probability of mortality for each topic as, $\theta_k = \frac{\sum_{n=1}^{N} q_{n,k} \cdot y_k}{\sum_{n=1}^{N} q_{n,k}}$

where $y_n$ is the mortality outcome (0 lives/1 dies).
Number of patients over time goes down
Prediction

• Separate linear support vector machine (SVM) for each of three outcomes: in-hospital, 30-day, and 1-year mortality.

• Loss and class weight parameters selected using five fold cross-validation to determine optimal values.

• Class imbalances were addressed with random sub-sampling from the negative class to establish a 70%/30% ratio from:
  • 10.9% in-hospital mortality rate
  • 3.7% 30-day mortality rate
  • 13.7% 1-year mortality rate
  • Test set distributions were not modified.

• Prediction task becomes increasingly difficult over time since fewer patients have long ICU stays.

• Retrospective outcome predictions were included in order to provide relative upper bounds for each type of model.