Predicting intervention onset in the ICU with switching state space models

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Problem: When will ICU patient need *intervention*?

e.g.
- mechanical ventilation
- vasopressor *(blood pressure drug)*
- or fluid transfusion

Early prediction helps:
- prepare patient
- plan staffing
- try less aggressive options early
Possible Approaches

What to predict?

– lots of work on general risk scores
  • mortality, SAPS, APACHE
– less work on actionable interventions

How to represent patient state?

hand-engineered features
continuous-state temporal models
discrete switching-state temporal models

Lehman et al. 2015
Caballero Barajas et al. 2014
Contribution

We show that an **unsupervised** auto-regressive Markov model trained on a **large cohort** of 36,000 patients can improve predictions for **5 interventions** several hours ahead:

- mechanical ventilation
- red blood cell transfusion
- vasopressor
- plasma transfusion
- platelet transfusion
Cohort from MIMIC-III dataset

36,050 patients
recorded at Beth-Israel Deaconess in Boston
between 2001-2012
kept all adults with record within 6-360 hours

<table>
<thead>
<tr>
<th>Intervention</th>
<th>Training Num Positive</th>
<th>Training Num Control</th>
<th>Heldout Num Positive</th>
<th>Heldout Num Control</th>
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<tbody>
<tr>
<td>Vasopressor</td>
<td>6987</td>
<td>21865</td>
<td>1737</td>
<td>5461</td>
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<tr>
<td>Red blood cell transfusion</td>
<td>19171</td>
<td>9681</td>
<td>4776</td>
<td>2422</td>
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<tr>
<td>Fresh frozen plasma transfusion</td>
<td>2759</td>
<td>26093</td>
<td>620</td>
<td>6578</td>
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<tr>
<td>Platelet transfusion</td>
<td>27818</td>
<td>1034</td>
<td>6944</td>
<td>254</td>
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<tr>
<td>Mechanical Ventilation</td>
<td>13710</td>
<td>15142</td>
<td>3393</td>
<td>3805</td>
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mimic.physionet.org
(Johnson et al. Sci. Data 2016)
Observed data

7 nurse-validated vital signs (hourly)
  heart rate, blood pressure, temp., SpO2, ...

11 lab measurements (much less than hourly)
  hematocrit, lactate, ...

Each channel standardized to mean=0, var=1 with carry-and-hold for missing data.
Switching Autoregressive Model

Latent State

one of $K$ possible values

Observed Vitals

$z_t$  

$\ldots$  

hour $t$  

hour $t+1$  

$\ldots$
Switching Autoregressive Model

Latent State

\[ z_t \]

Observed Vitals

\[ x_t \]

\[ x_t | z_t = k \sim \mathcal{N}(A_k x_{t-1} + \mu_k, \Sigma_k) \]

Autoregressive Gaussian allows modeling trajectories/trends in vitals
Training Phase

Learn model parameters from many patients

variational EM algorithm
Prediction Step 1: Belief features

Infer distribution over hidden states at each timestep

HMM dynamic programming (forward alg.)
Step 2: Classify given features

Binary Intervention (did ventilate at hour $t$)

Logistic regression (with label-balanced cost function)
Task: predict onset in advance

+2 hrs ahead
Vasopressor prediction: 1 hr ahead

Area-under-ROC

<table>
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<tr>
<th></th>
<th>s</th>
<th>x</th>
<th>s+x</th>
<th>b</th>
<th>b+s+x</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.66</td>
<td>0.77</td>
<td>0.79</td>
<td>0.66</td>
<td>0.82</td>
</tr>
</tbody>
</table>

- static demographics
- dynamic patient vitals at time t
- SSAM belief vector at time t using 10 states
Vasopressor prediction: 4 hr ahead

Area-under-ROC chart:

- s: 0.66
- x: 0.70
- s+x: 0.74
- b: 0.64
- b+s+x: 0.78
Ventilator: 4 hr ahead
Fresh Frozen Plasma: 4 hr ahead
Interpreting Latent States

Inspect classifier weights across all 10 states

Inspect data associated with belief state 9

increased lactate,
lowered SpO2 and bicarbonate

Conclusion: state 9 seems to capture general physiological decline
Future Directions

Can we optimize generative models for particular downstream tasks without losing (too much) generalization?

Compare to alternative representation learning

auto-encoders
RNNs, LSTMs, etc

Move towards reinforcement learning approach
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Summary

unsupervised auto-regressive Markov model
large cohort of 36,000 patients
improves prediction on 5 interventions several hours ahead

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