DYNACARE-OP: Dynamic Cardiac Arrest Risk Estimation Incorporating Ordinal Features

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Cardiac arrest occurs when the heart stops beating and blood circulation ceases.

Motivation

- Survival to discharge rate $\sim 20\%$
- $\sim 62\%$ of cardiac arrests can be prevented
- Rapid response teams (RRT) can increase survival rate up to $\sim 40\%$
- Major RRT weakness is inability to identify patients with sufficient intervention time
Model Overview

DYNACARE-OP is a dynamic cardiac arrest risk estimation model that:

- utilizes continuous and ordinal clinical measurements
- continually tracks a patient’s cardiac arrest trajectory
- allows interpretability and predictability of a cardiac arrest event
- provides a dynamic hazard function unobtainable via traditional survival analysis
- generalizes to detecting other medical events
DYNACARE-OP: Components

1. Single latent factor $r_t$ governs clinical observations
2. Two states, healthy and risky state, influence the mean of $r_t$
3. Correlations in fluctuations of $r_t$ captured by a stochastic volatility term
4. Semi-supervised framework to connect cardiac arrest event to $r_t$
5. Data augmentation trick to incorporate ordinal features
Model cardiac arrest trajectory (CAT) as a single latent factor $r_t$

CAT ($r_t$) governs clinical observations

Define cardiac arrest as a temporal signature in CAT
DYNACARE-OP: Simple Dynamic Linear Model

General Linear Model

\[ r_t = r_{t-1} + \epsilon_t \quad \epsilon_t \sim N(0, \lambda_t) \]
\[ y_t = \beta_t r_t + \eta_t \quad \eta_t \sim N(0, \Sigma) \]

Assume \( y_t \) continuous and knowledge of \( \lambda_t, \beta_t, \Sigma \)

Kalman filter is closed form solution to estimate latent variables

Limitations:

- Unable to fully capture the data
- How to encode temporal CAT signature?
Markov switching model (MSM) is a widely adopted financial economics modeling framework to incorporate heterogenous dynamics.

Our model assumes two states, healthy and risky, govern the mean of $r_t$.

Cardiac arrest occurs when patient is in the risky state.

$$ u_t \sim \text{MarkovChain}(u|u_{t-1}) $$

$$ r_t = r_{t-1} + \epsilon_t $$

$$ y_t = \beta_t r_t + \eta_t $$

$$ \epsilon_t \sim N(0, \lambda_t) $$

$$ \eta_t \sim N(0, \Sigma) $$

How to model correlated fluctuations around the mean?
Stochastic volatility models can capture “volatility clustering”, where large residuals are clustered together, using an underlying stochastic process

Stochastic volatility term $\lambda_t$ captures time-to-time correlations as well as patient-to-patient correlations

\[
\begin{align*}
\lambda_t &= \lambda_{t-1} + \delta_t \\
u_t &\sim \text{MarkovChain}(u|u_{t-1}) \\
r_t &= r_{t-1} + \epsilon_t \\
y_t &= \beta_t r_t + \eta_t
\end{align*}
\]

\[
\begin{align*}
\delta_t &\sim N(0, k^2) \\
u_t &\in \{s_h, s_c\} \\
\epsilon_t &\sim N(0, \exp(\lambda_t)) \\
\eta_t &\sim N(0, \Sigma)
\end{align*}
\]

How to estimate $r_t$ with non-linearity term?
Particle filtering and smoothing can be used to perform sophisticated model estimation based on simulation.

Particle filtering characterizes current state given observations up to the current time.

Particle smoothing estimates the distribution of current state given all observations up to some future time.

Excellent tutorial by Arnaud Doucet:
http://www.cs.ubc.ca/~arnaud/doucet_johansen_tutorialPF.pdf

How to connect latent factor to cardiac arrest event?
DYNACARE-OP: Semi-Supervised Learning Framework

Use partial knowledge to connect cardiac arrest risk to latent factor

For each patient:
- Known - cardiac arrest event at specific time point
- Unknown - period in which patient was healthy
- Unknown - unrecorded or unobserved cardiac arrest events

Semi-supervised particle smoother to approximate $E[r_{1:T} | y_{1:T}, T = CA]$
DYNACARE-OP: Semi-supervised particle smoother

Forward filter and backward constrainining framework

- Forward filter to approximate \((r_{1:T}|y_{1:T})\)
- Impose the constraint \(T = CA\): \(p(u_t = s_c|y_t) \approx 1\)
- Backward smooth to get \((r_{1:T}|y_{1:T}, T = CA)\)

Use fixed-lag approach to prevent particle degeneracy

How to utilize ordinal features?
Ordered profit trick introduced by Albert & Chib 1993

Introduce new latent continuous variable $z_t$

For ordinal feature $y_\rho$ with $J$ ordered categories:

$$y_\rho = j, \quad \gamma_{j-1} < z_\rho \leq \gamma_j$$

$$z_\rho \sim N(\beta_\rho r, \sigma_\rho)$$

$$\gamma_0 = -\infty$$

$$\gamma_J = \infty$$

Global bin boundaries $\gamma^o$ defined using empirical distribution of patient measurements
DYNACARE-OP: Graphical Model
DYNACARE-OP: CAT Estimation Algorithm

Combination of expectation maximization and particle smoothing to estimate parameters and latent factors

1. Given a patient’s parameters, $\beta$, estimate latent variables $r$, $u$ with semi-supervised particle smoother
2. Estimate $z$ for ordinal features by drawing from truncated normal centered around $\beta r$ with appropriate bounds
3. Learn $\beta$, $\Sigma$ given $r$, $z$
4. Repeat until convergence occurs
DYNACARE-OP: Estimating a New Patient

1. Draw new patient’s $\beta, \Sigma$, from learned parameter stratum
2. Estimate $r, u$ for each parameter pair using unsupervised particle filter
3. Take average of $r, u$ for new patient’s cardiac arrest risk
Results: Experimental Setup

298 cardiac arrest patients from MIMIC-II database

8 clinical measurements: pulse pressure, pulse pressure index, respiratory rate, heart rate, temperature, Glasgow Coma Score, respiratory pattern, heart rhythm

Data prior to cardiac arrest is discretized into 2-hour bins and normalized.
Results: Single Patient Estimation

Continuously tracking a patient’s CAT based on the clinical measurements

variable

<table>
<thead>
<tr>
<th></th>
<th>pp</th>
<th>hr</th>
<th>heart_rhythm</th>
<th>Own</th>
<th>SB</th>
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</table>

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Results: Estimating CAT

Comparing CAT using individually learned (Own) or stratified bootstrapping (SB) $\beta$ parameters for two types of CA events

<table>
<thead>
<tr>
<th>State</th>
<th>Time</th>
<th>Own</th>
<th>SB</th>
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</thead>
<tbody>
<tr>
<td>Asystole</td>
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<td>Ventachy</td>
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DYNACARE-OP

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Results: Predictive Performance

Evaluation of classification task on 20 time periods before CA 1 for last time period, 0 for others
Conclusions

Our contributions:

- Dynamic cardiac arrest risk estimation model combining financial econometric and semi-supervised learning frameworks
- Incorporation of ordinal features for improved cardiac risk tracking
- Predictive power of temporal signature over static features
- DYNACARE-OP framework can be used for other diagnosis
Survival Analysis

Traditional hazard function:

\[ h(t)dt = p(t < t_{\text{event}} < t + dt|t_{\text{event}} \geq t) \]

Inability to align time across patients is problematic for classical hazard models

DYNACARE-OP survival analysis:
- New patient without observations \( p(\text{CA at time } t) = \pi_c \)
- Sequence of measurements \( h(t) = p(\hat{u}_t = s_c|y_{1:t}) \)
DYNACARE-OP: Kalman Filter

*Notation:* \( D_t = \{ D_{t-1}, y_t \} \) is the information set up to time \( t \)

Forward recursions to estimate current state

**Posterior at \( t-1 \):** \( (r_{t-1}|D_{t-1}) \sim N(m_{t-1}, C_{t-1}) \)

**Prior at \( t \):**

\( (r_t|D_{t-1}) \sim N(m_{t-1}, C_{t-1} + \lambda_t) \)

\( \sim N(a_t, W_t) \)

\( (y_t|D_{t-1}) \sim N(\beta_t m_t, \beta_t W_t \beta_t^T + \Sigma) \)

\( \sim N(f_t, Q_t) \)

**Posterior at \( t \):**

\( (r_t|D_t) \sim N(a_t + G_t e_t, W_t - G_t \beta_t W_t) \)

where \( G_t = W_t \beta_t^T Q_t^{-1} \), \( e_t = (y_t - f_t) \)

\( (r_t|D_t) \sim N(m_t, C_t) \)
DYNACARE-OP: Kalman Filter

Backward smoothing to update state given future observations

Let: \( (r_{t+1}|D_T) \sim N(h_{t+1}, V_{t+1}) \)

Then: \( (r_t|D_T) \sim N(m_t + B_t(h_{t+1} - a_{t+1}), P_t) \)

where \( B_t = C_t W_{t+1}^{-1} \)

\[
P_t = C_t - B_t (W_{t+1} - P_{t+1}) W_{t+1}^{-1} C_t
\]