LEARNING FROM DIFFERENT PERSPECTIVES: ROBUST CARDIAC ARREST PREDICTION VIA TEMPORAL TRANSFER LEARNING

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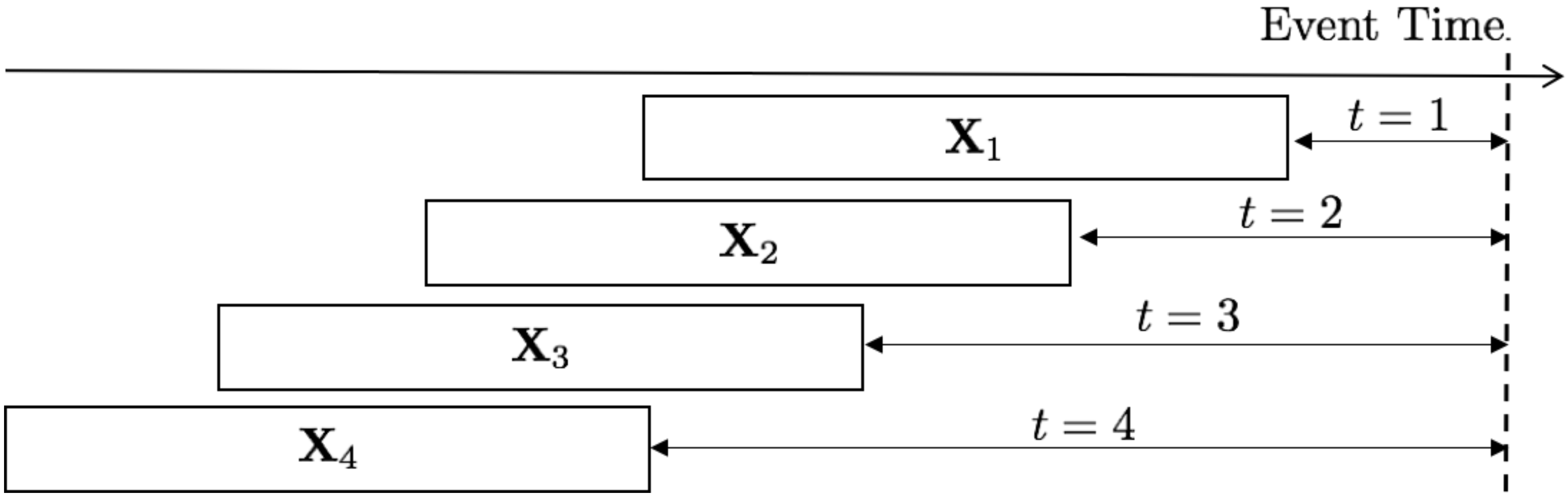
CARDIAC ARREST PREDICTION & PREVENTION

http://images.counselheal.com/data/images/full/9825/getty-images.jpg

- Greatest challenges of contemporary cardiology
  - ~80% in-hospital mortality rate
  - 300,000 deaths in the US annually
- Early warning / risk stratification only look at summary statistics of vital signs
  - Ignore temporal patterns
  - Unable to identify high-risk patients with sufficient intervention time

CARDIAC ARREST PREDICTION: SETUP



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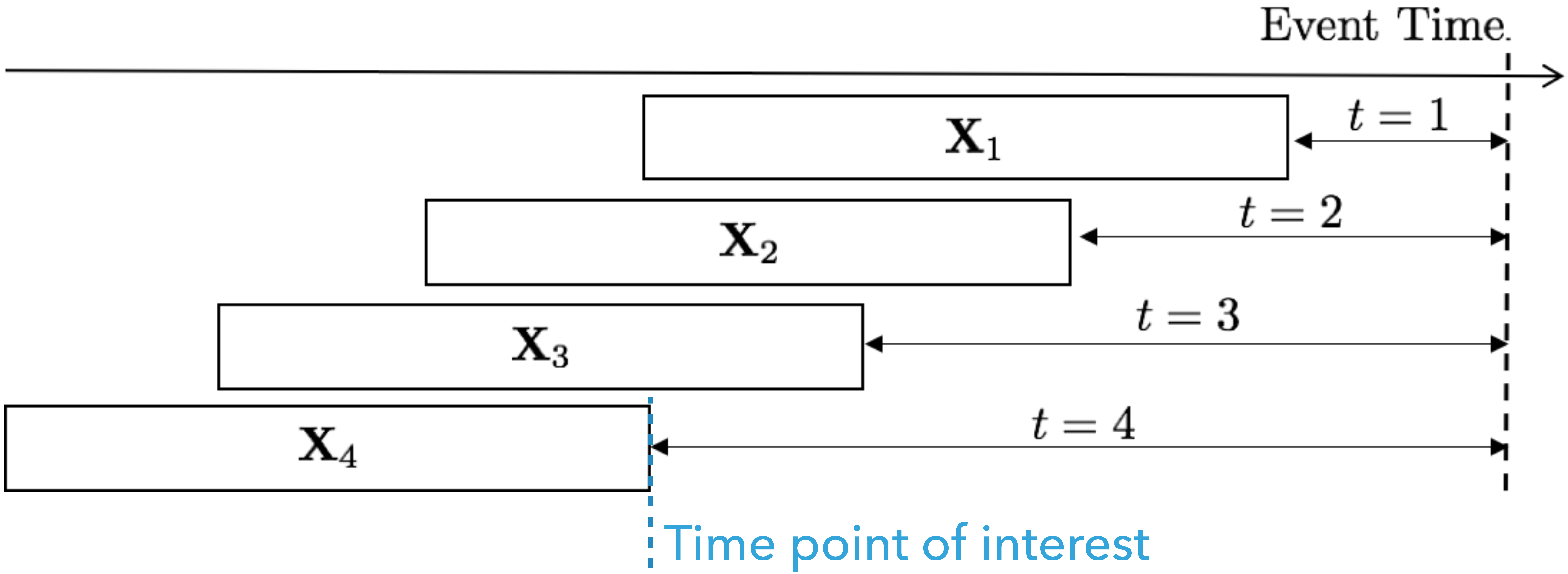

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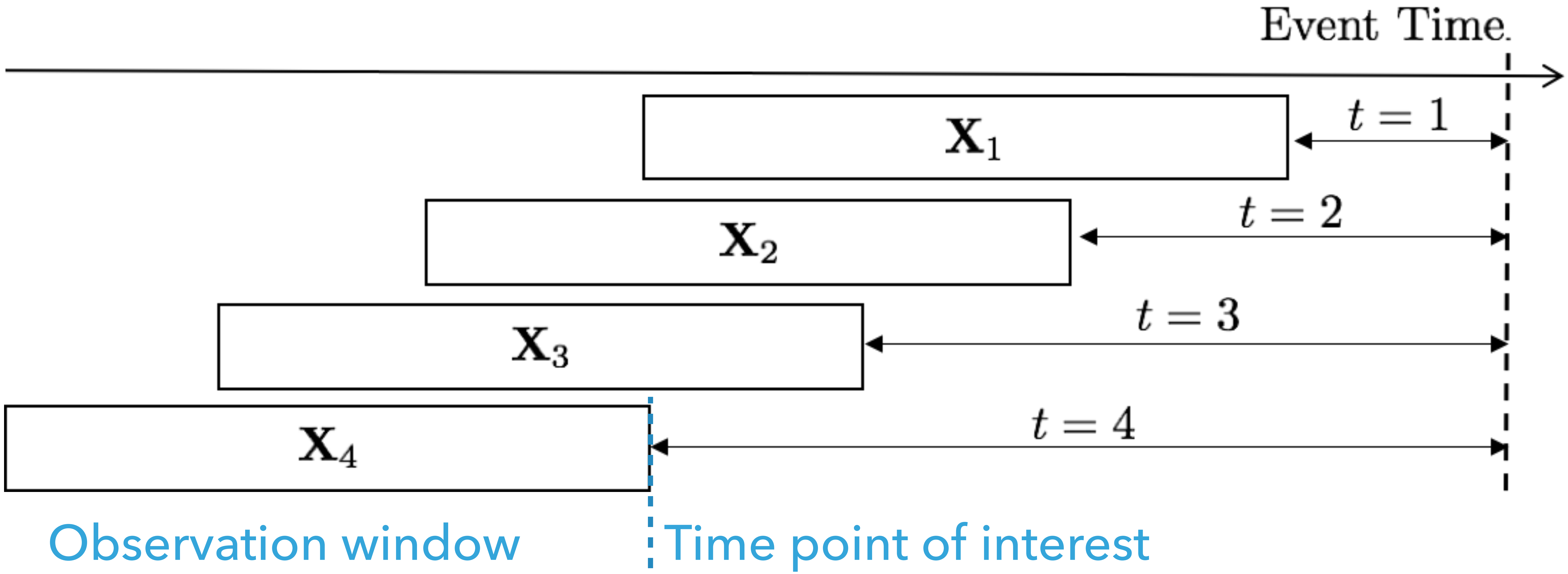

Observation window or training data

Time point of interest

CAPTURING TEMPORAL TRENDS IN MACHINE LEARNING MODELS

- Standard “static” models: logistic regression, support vector machines, decision trees
  - Temporal trends need to be encoded as features
  - Insufficient data to fit time point of interest models
- “Dynamic” models: state-space models, multivariate matrix normals, Gaussian processes, etc.
  - Less interpretable compared to risk-stratification systems due to “black”-box nature

TTL-REG: TEMPORAL TRANSFER LEARNING BASED MODEL

- Pose estimation of coefficients at different time points as related tasks
- Borrow information from adjacent time points by smoothing estimated coefficients between time point before (z - 1) and time point after (z + 1)

$$f(\boldsymbol{\beta}) = \sum_{k=1}^{T} \ell(y_k, \mathbf{X}_k \beta_k) - \sum_{k=1}^{T-1} \frac{\lambda}{2} ||\beta_t - \beta_{t+1}||_2^2 - \sum_{k=2}^{T} \frac{\lambda}{2} ||\beta_t - \beta_{t-1}||_2^2$$

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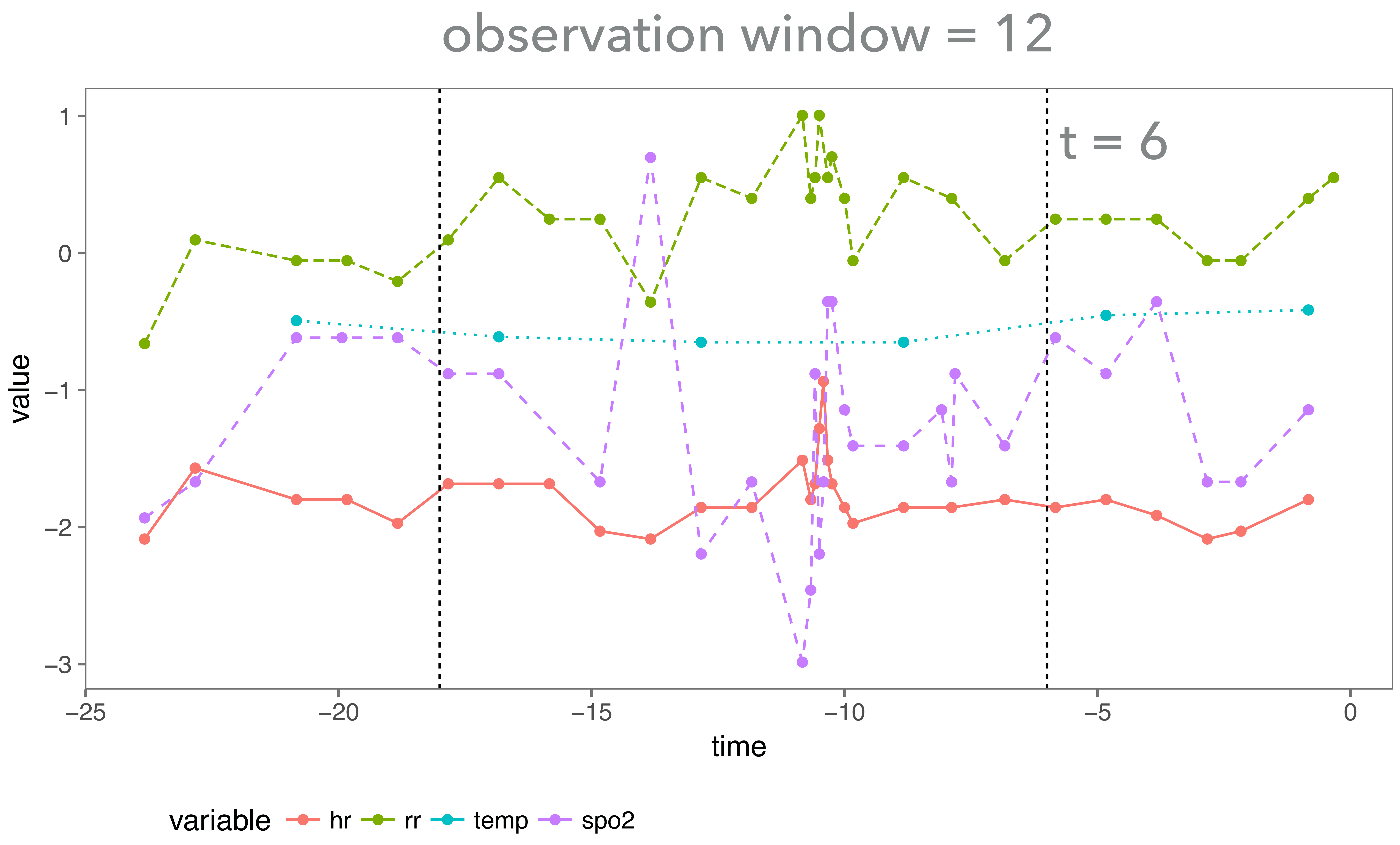
Regularization parameter controls amount of information shared between adjacent points

DATA: MIMIC-II

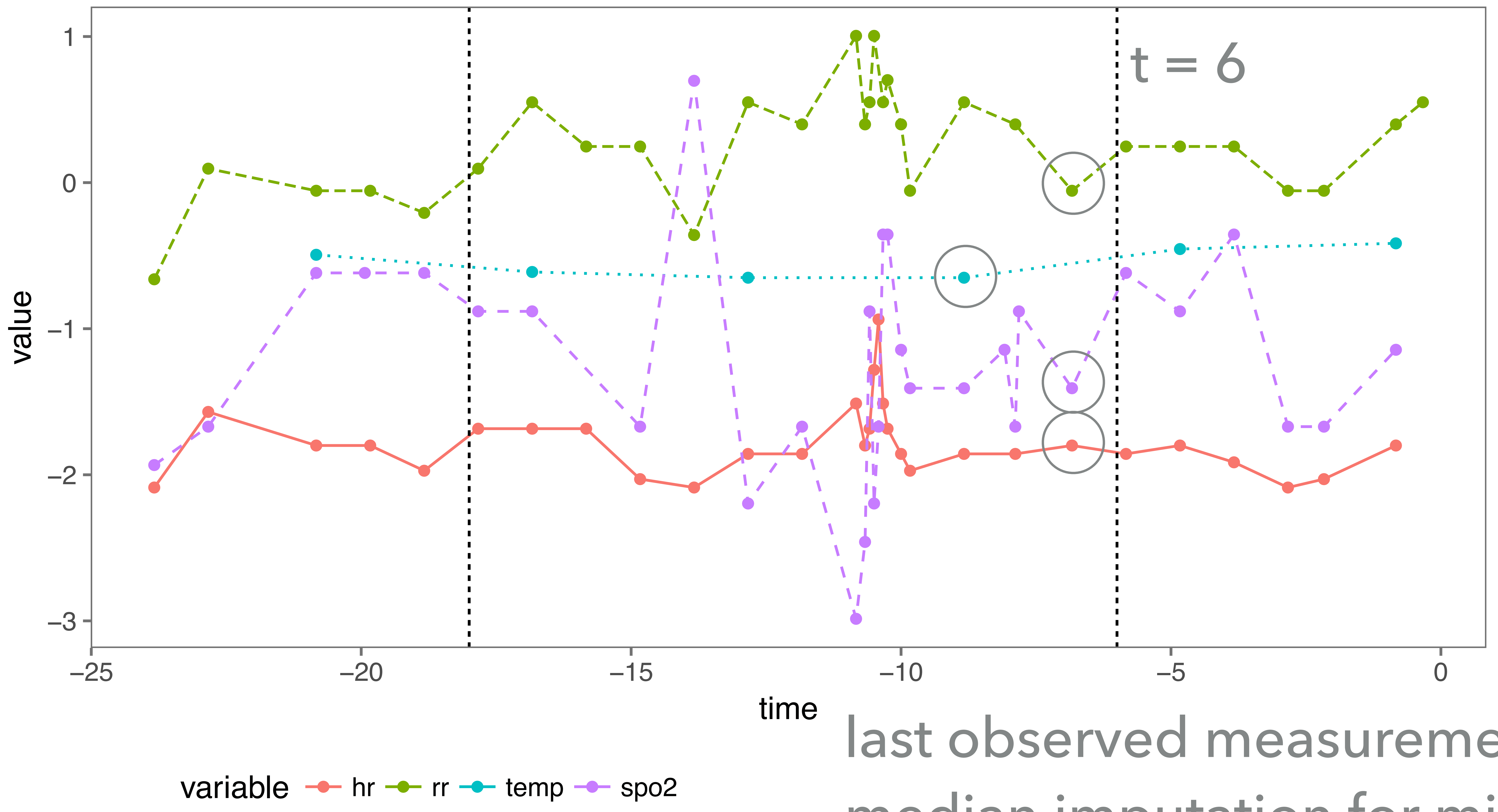
- Publicly available intensive care unit (ICU) database https://mimic.physionet.org/
- 7 features: temperature, peripheral capillary oxygen saturation, heart rate, respiratory rate, diastolic blood pressure, systolic blood pressure, and pulse pressure
- 763 elderly (aged 50+) patients with 197 of them experiencing a cardiac arrest event (~26% prevalence)

DATA: PATIENT EXAMPLE



DATA: PATIENT EXAMPLE

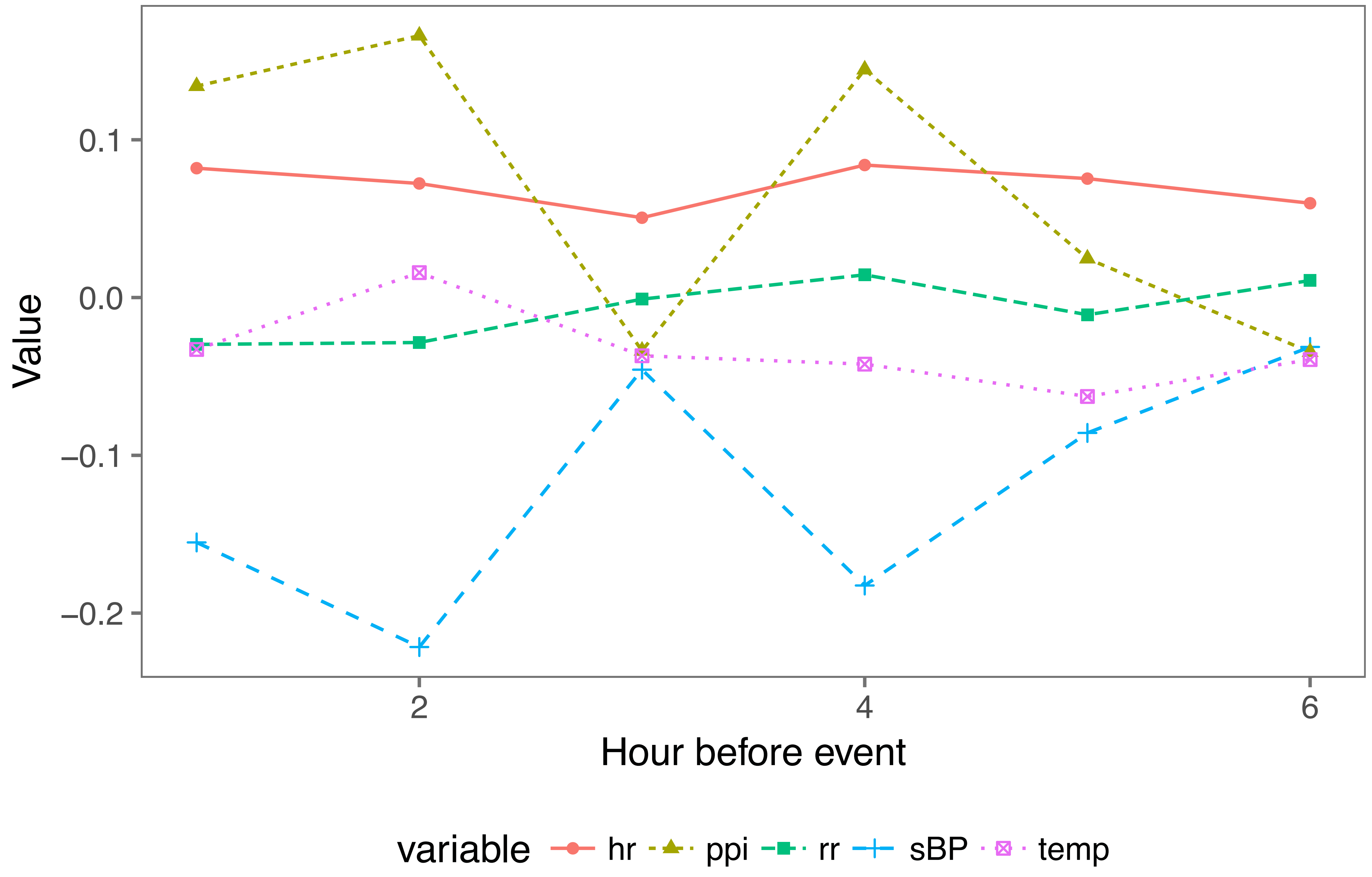
observation window = 12



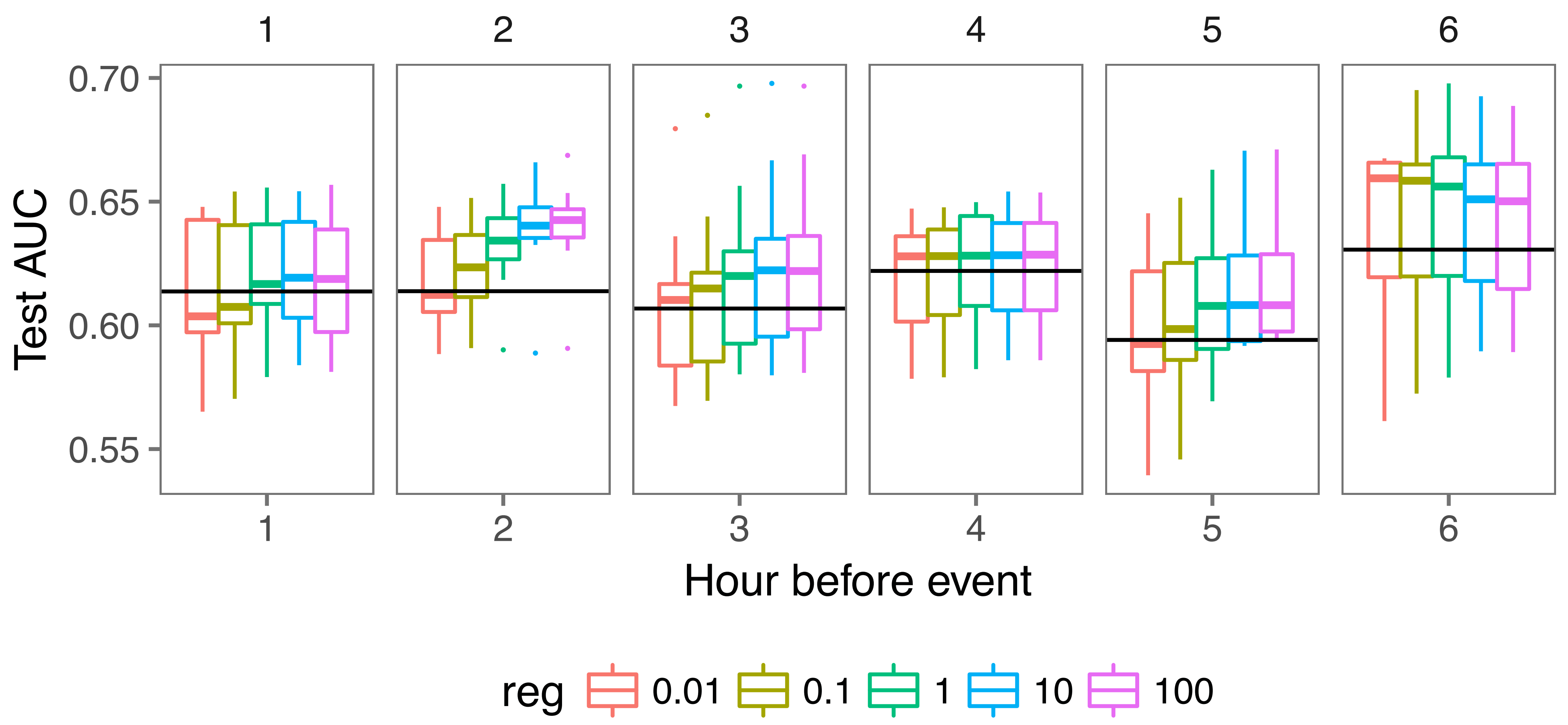
last observed measurement + median imputation for missing data

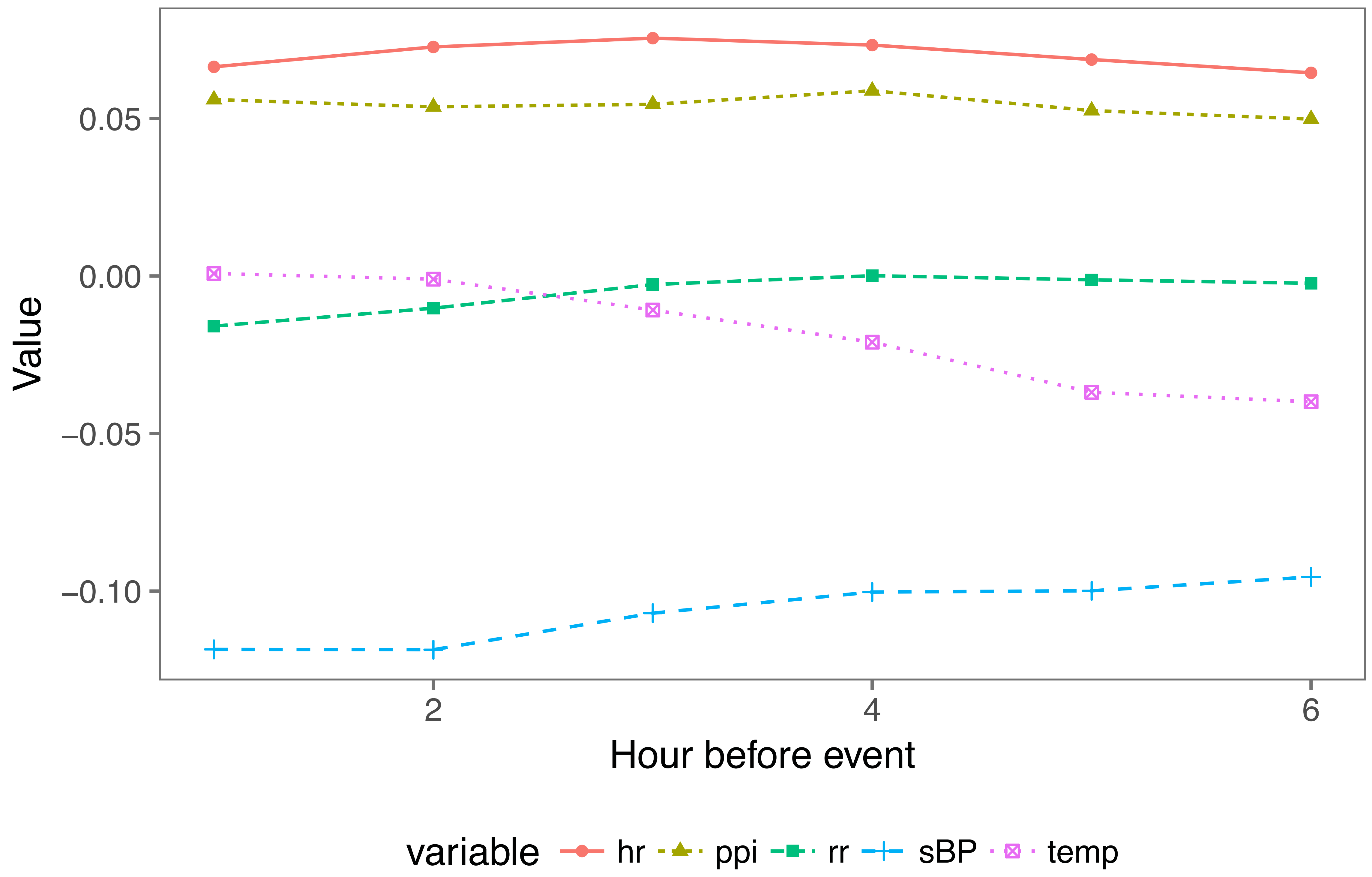
BASELINE MODELS: AUC + ESTIMATED COEFFICIENTS

Hour	Train Mean	Train SD	Test Mean	Test SD
1	0.6588	0.0155	0.6137	0.0289
2	0.6612	0.0116	0.6138	0.0208
3	0.6483	0.0174	0.6068	0.0230
4	0.6777	0.0112	0.6220	0.0230
5	0.6522	0.0125	0.5941	0.0328
6	0.6467	0.0179	0.6306	0.0397



TTL-REG MODEL: AUC + ESTIMATED COEFFICIENTS





DISCUSSION + CONCLUSION

- Temporal transfer learning by smoothing coefficients of adjacent time points
  - Yields coefficient trajectories that are easily interpreted
  - Provides improved early prediction of cardiac arrest
- Future work
  - Explore various prediction problems (readmission, etc.)
  - Explore different classification models (SVM, decision tree, etc.)

Q&A

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