

Probabilistic Models and Optimization Algorithms for Personalized Medicine



Mike Hughes

joint work with Assistant Professor of Computer Science

Finale Doshi-Velez (Harvard)

Erik Sudderth & Gabe Hope (UC Irvine)

Tom McCoy, M.D. and Roy Perlis, M.D. (MGH)

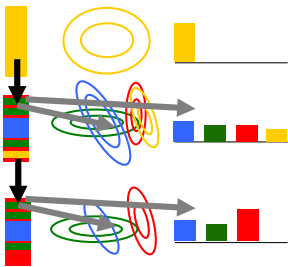
Marzyeh Ghassemi (Toronto), Mike Wu (Stanford)

slides / papers / code

www.michaelchughes.com

My Research Mission:

Reliable Training of Interpretable Models for Complex Data

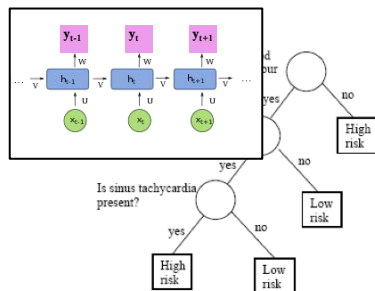


Inference Algorithms for Probabilistic Models:

Adapt Model Size to Data (Bayesian Nonparametrics)

- Dirichlet process mixtures *Hughes & Sudderth NeurIPS 2013*
- Topic models of news articles *Hughes, Kim & Sudderth AISTATS 2015*
- HMMs for epigenomics *Hughes, Stephenson, & Sudderth NeurIPS 2015*

BNPy open-source software | `pip install bnpy` | github.com/bnpy/bnpy



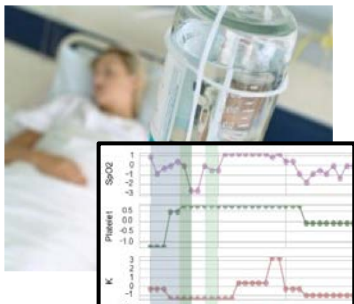
Explainable AI:

Optimize Deep NNs for Interpretability

- Find alternate explanations *Ross, Hughes, Doshi-Velez IJCAI 2017*
- Find tree-like neural nets *Wu, Hughes, Parbhoo, et al. AAAI 2018*

Applications: Personalized Treatments in Medicine

- Predict interventions in ICU *Ghassemi, Wu, Hughes, et al. AMIA CRI 2017*
- Discovering subtypes and treatments for depression *Hughes et al. (AISTATS 2018)*
Hughes et al. (in prep. for JAMA Psychiatry)



Problem: When will ICU patient need intervention?

*Ghassemi, Wu, **Hughes**, et al. AMIA CRI 2017*

Interventions:

- Ventilators to assist breathing
- blood pressure drugs

Early prediction helps:

prepare patient
plan staffing
try less aggressive options early



Cohort from MIMIC-III dataset

mimic.physionet.org

(Johnson et al. Sci. Data 2016)

36,050 patients

- from Beth-Israel Deaconess in Boston 2001-2012
- kept all adults with record within 6-360 hours

| Intervention | Training Num Positive | Training Num Control | Heldout Num Positive | Heldout Num Control |
|---------------------------------|--------------------------|-------------------------|-------------------------|------------------------|
| Vasopressor | 6987 | 21865 | 1737 | 5461 |
| Red blood cell transfusion | 19171 | 9681 | 4776 | 2422 |
| Fresh frozen plasma transfusion | 2759 | 26093 | 620 | 6578 |
| Platelet transfusion | 27818 | 1034 | 6944 | 254 |
| Mechanical Ventilation | 13710 | 15142 | 3393 | 3805 |

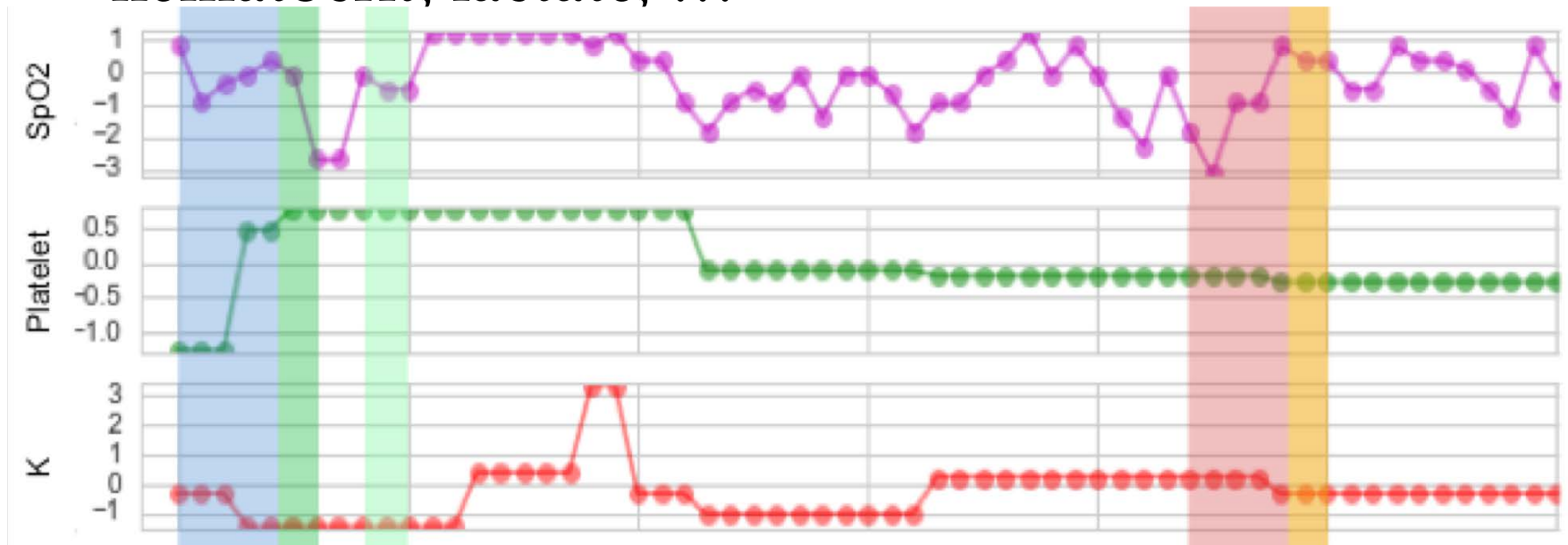
Observed data

7 nurse-validated vital signs (hourly)

heart rate, blood pressure, temp., SpO2, ...

11 lab measurements (much less than hourly)

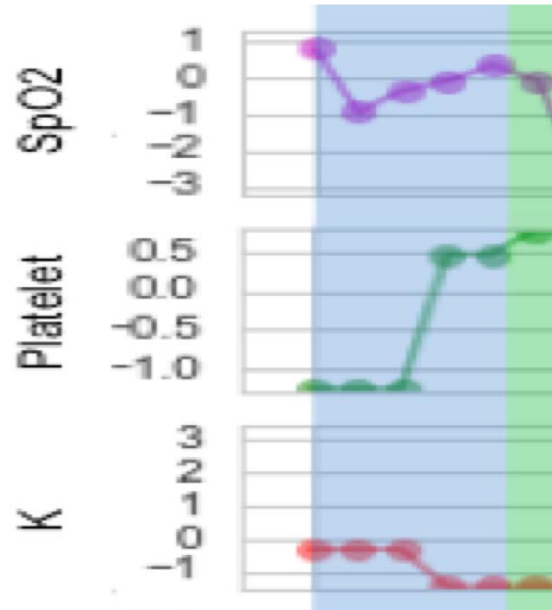
hematocrit, lactate, ...



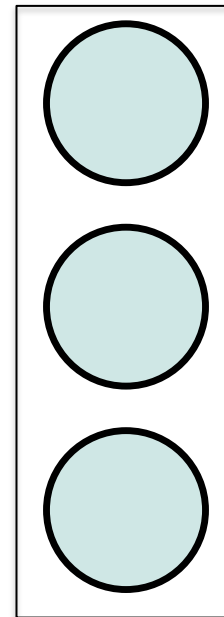
Challenge: how to build models that effectively handle irregular data arrival times

Probabilistic time-series model

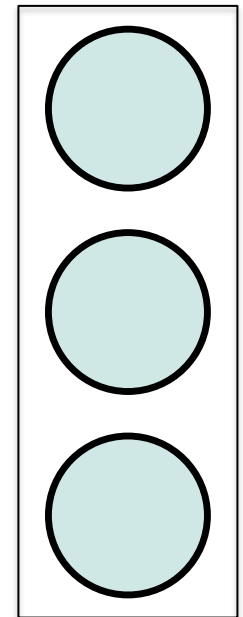
Observed Feature Vector x_t



....



hour t

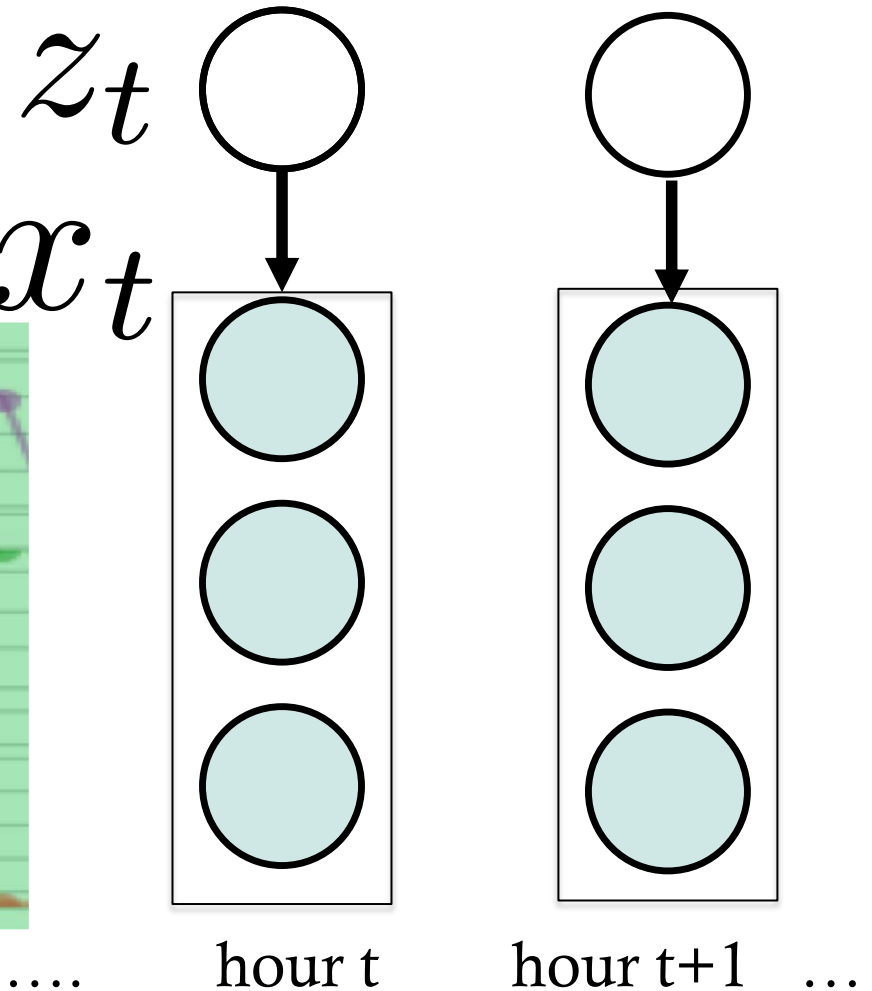
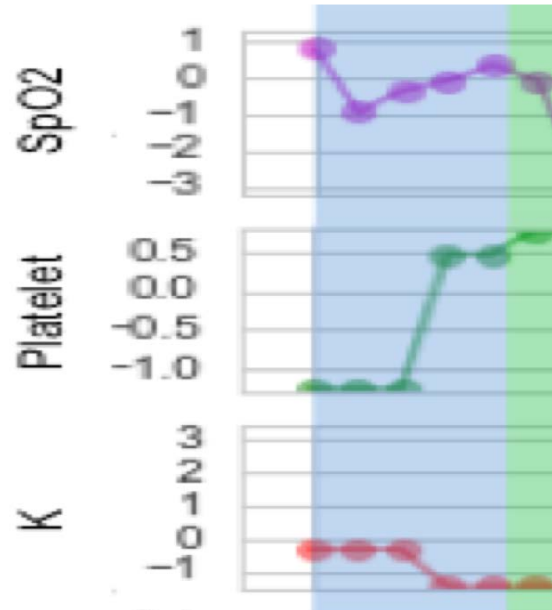


hour t+1 ...

Probabilistic time-series model

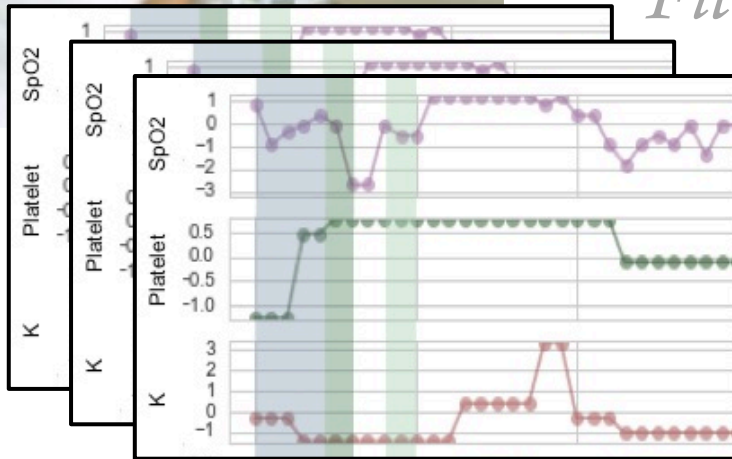
Hidden Patient State
one of K possible values

Observed Feature Vector x_t



Goal: Summaries of Health

ICU signals from many patients



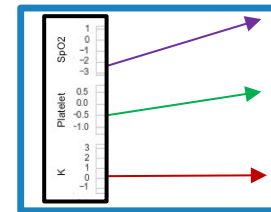
Fit the model



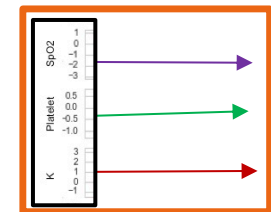
Health state trajectories

$z_1 \dots z_T$

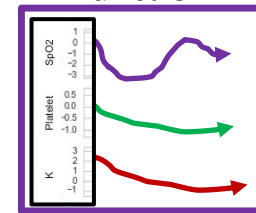
Improving kidney
function



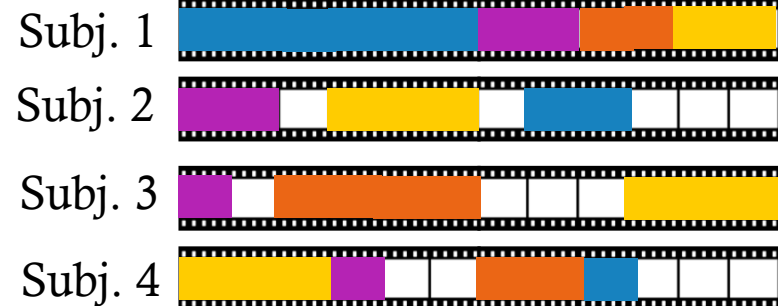
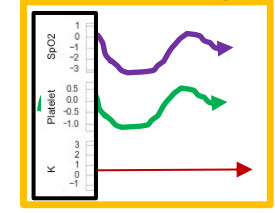
steady state



Dropping lung
function

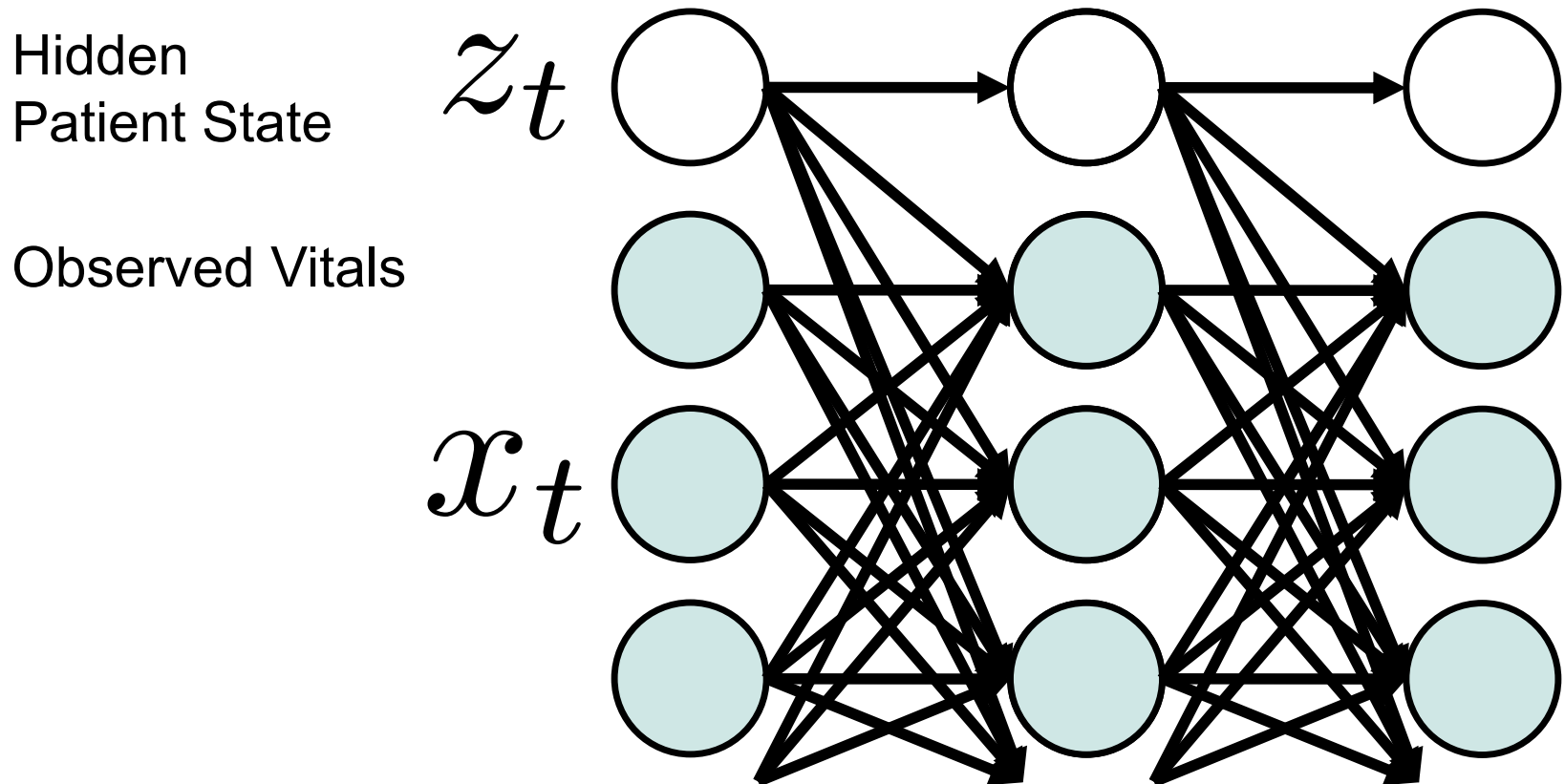


oscillating



(Ghassemi, Wu, Hughes, et al AMIA CRI '17)

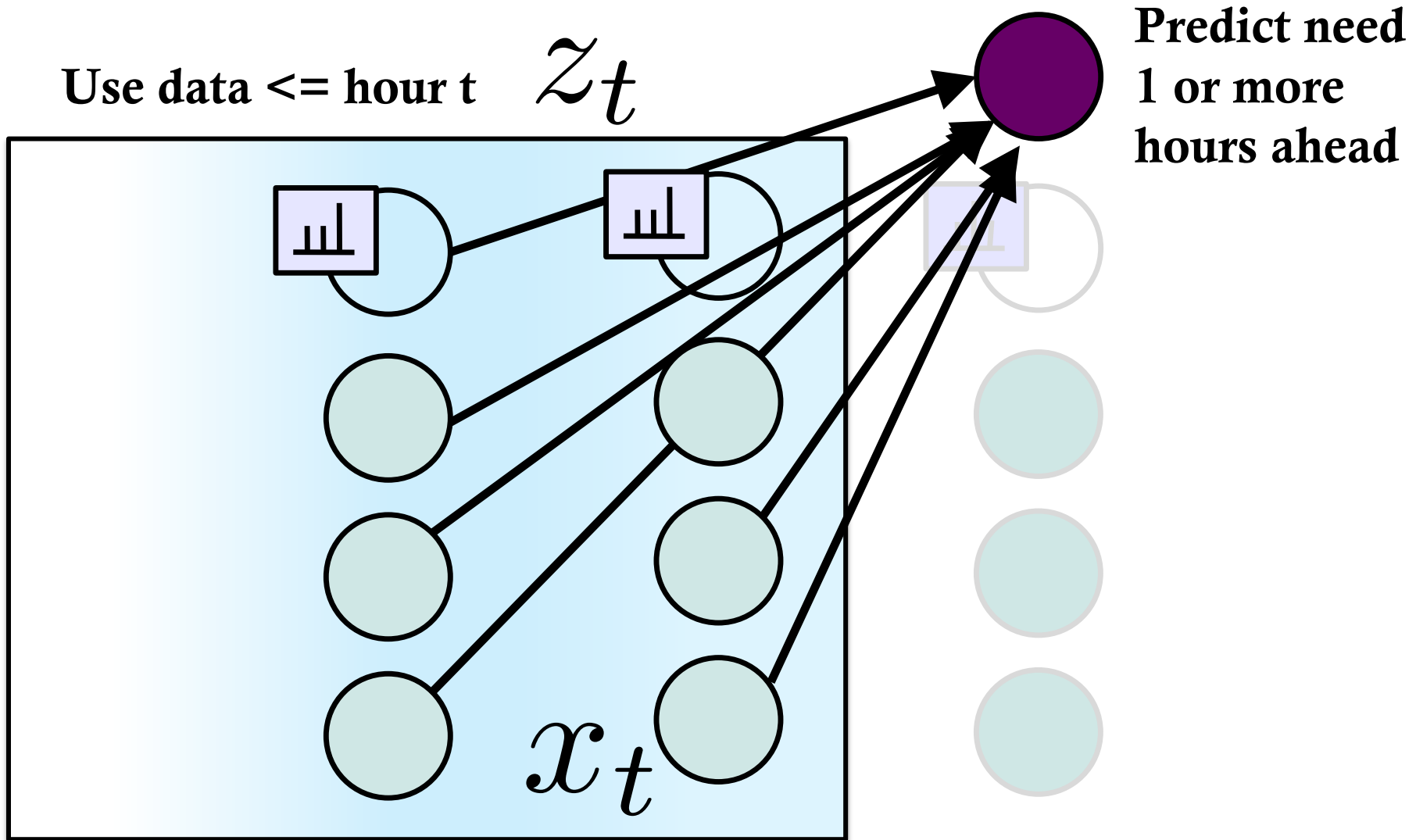
Autoregressive time-series model



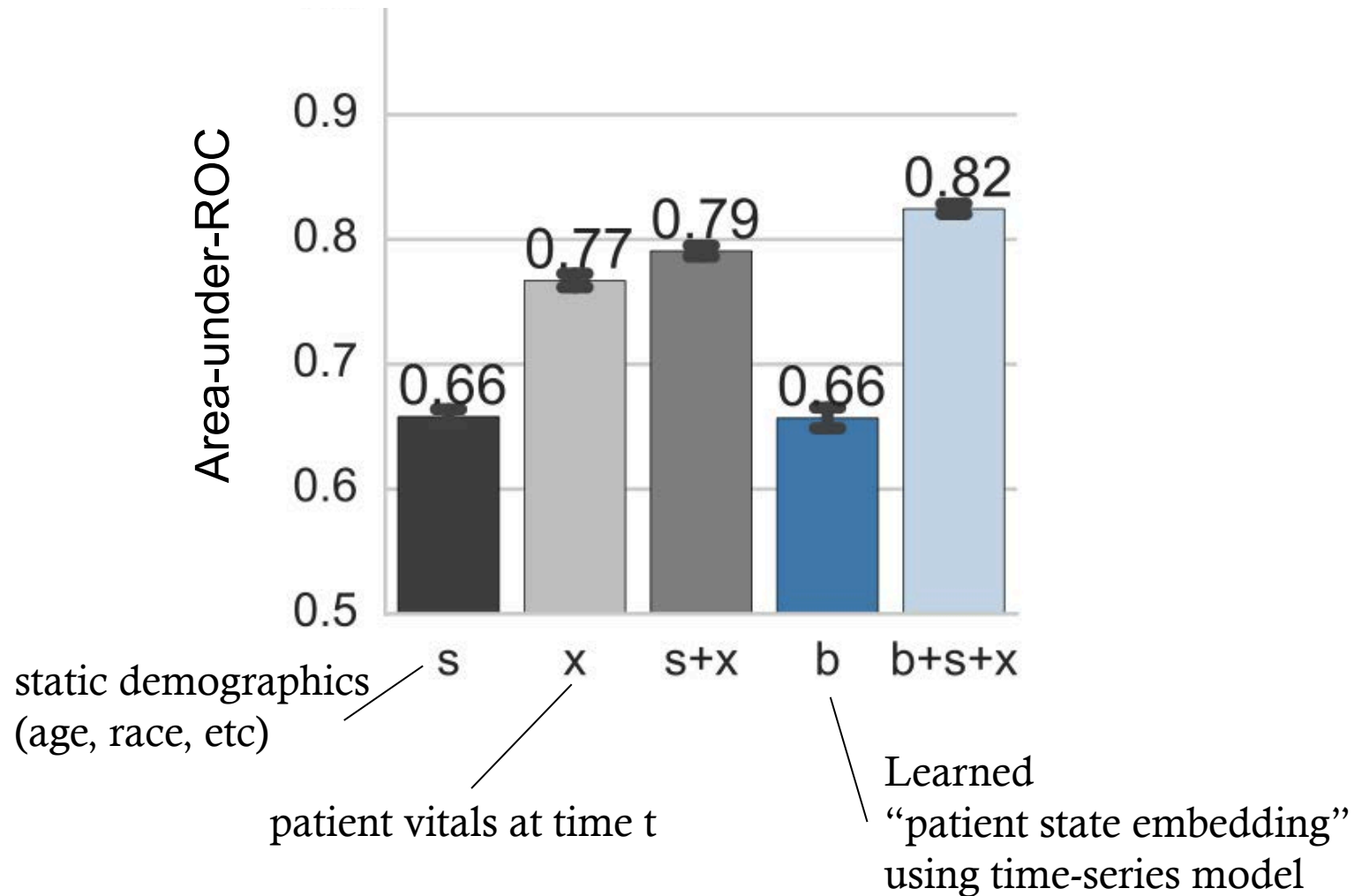
$$x_t | z_t = k \sim \mathcal{N}(A_k x_{t-1} + \mu_k, \Sigma_k)$$

autoregressive Gaussian allows modeling trajectories/trends in vitals

Task: predict need in advance



Vasopressor prediction : 1 hr ahead



Medical Data is **Exciting**

Good models can improve

- **personalized treatments** for patients
- **scientific knowledge** about disease
 - subtypes
 - co-occurring conditions

Medical Data is Challenging

Challenges

- how to interpret and trust model?
- labeled data hard to get, lots of unlabeled data
- causality

How Can ML Help Psychiatrists?



Prof. Finale Doshi-Velez



Prof. Erik Sudderth

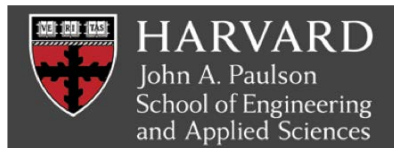
+



Roy Perlis, MD



Tom McCoy, MD



Leah Weiner



Gabe Hope

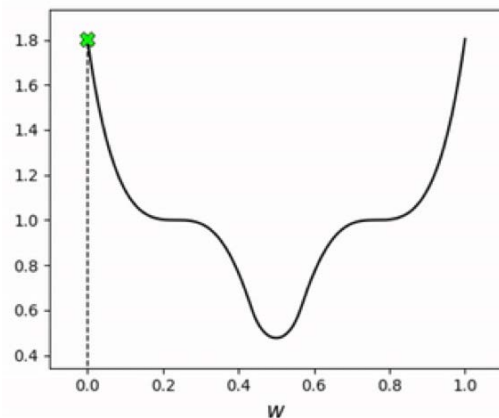


MASSACHUSETTS
GENERAL HOSPITAL
PSYCHIATRY



How to optimize?

$$\max_{\phi, \eta} \quad \lambda \log p(y|x, \phi, \eta) + \log p(x|\phi)$$



Optimize via stochastic gradient descent

- Write objective as Python code
- Automatic gradients from Tensorflow



*Credit:
Jeremy Watt*

Compare to Human Doctors

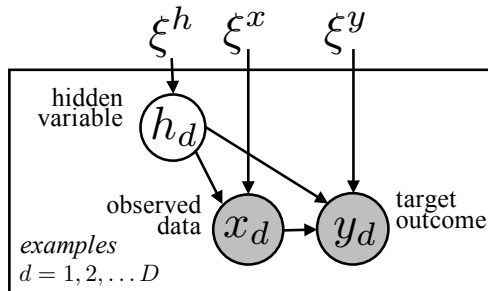
- Evaluation with retrospective data is challenging
- Reasonable attempt:

TOP-3 Accuracy

Given 3 guesses to recommend antidepressants for each patient,
what fraction of patients have guess match at least 1 drug on stable list.

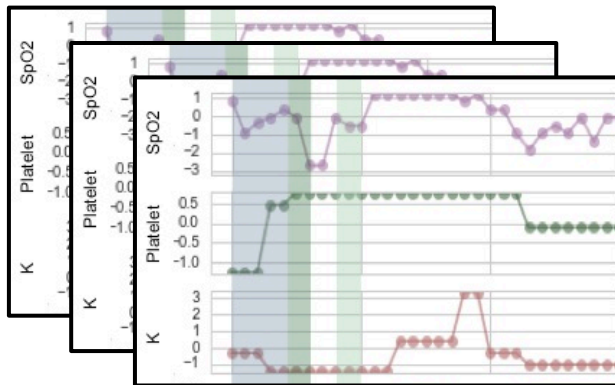
| | 1 st visit | ... | 3 rd visit |
|-----------------------------------|-----------------------|-----|-----------------------|
| human doctors (observed practice) | 87% (+/- 2) | | 40% (+/- 7) |
| always give most common drugs | 54% (+/- 3) | | 35% (+/- 7) |
| our method | 58% (+/-2) | | 46% (+/- 7) |

Future: Time-Series Models to combine data from data



- Mixture models
- Topic models
- Hidden Markov models
- Network models (MMSB)
- PCA or factor analysis
- Non-negative matrix factorization
- Probabilistic encoder/decoder (VAE)

- Disease progression over time



- Models of many data sources



Social Media



Patient Records



Gene Sequencing



Claims



Home Monitoring



Mobile Apps