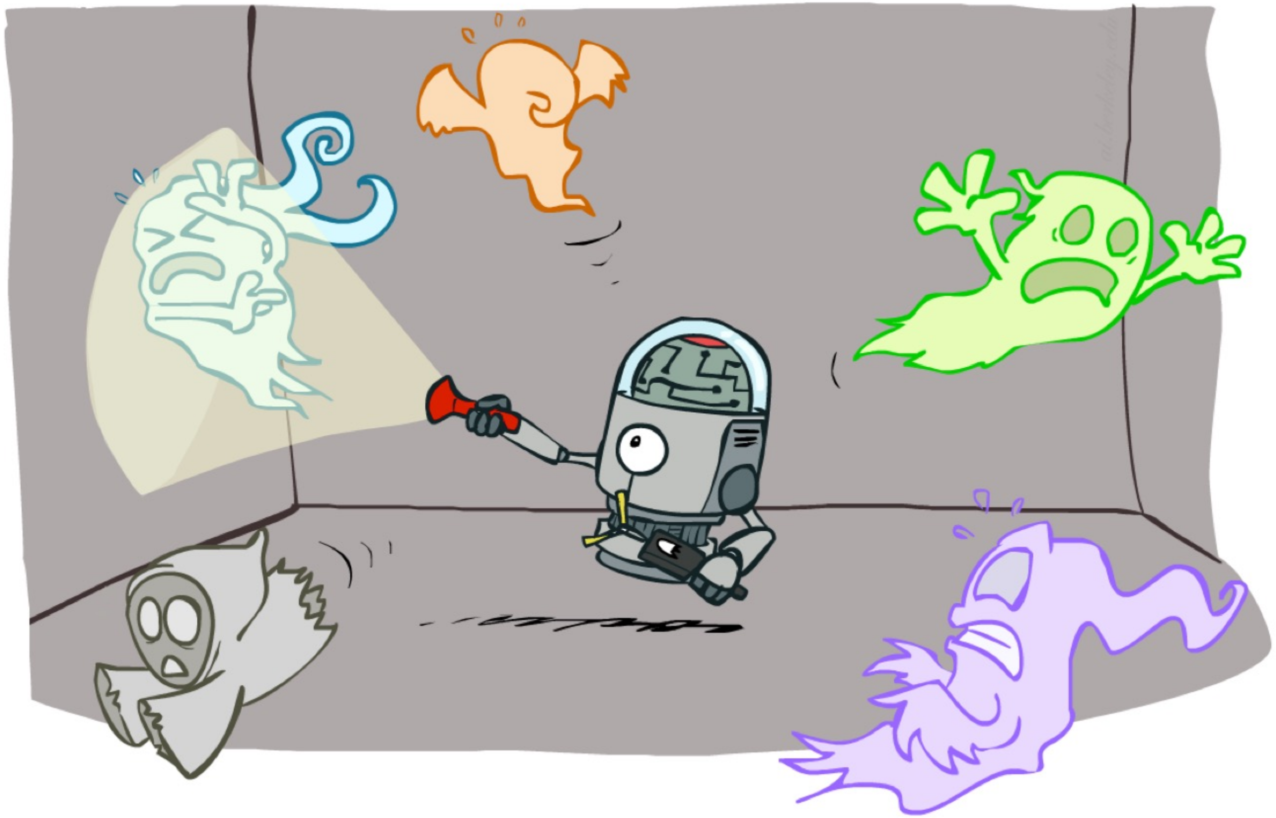
CS 188: Artificial Intelligence

Dynamic Bayes Nets and Particle Filters



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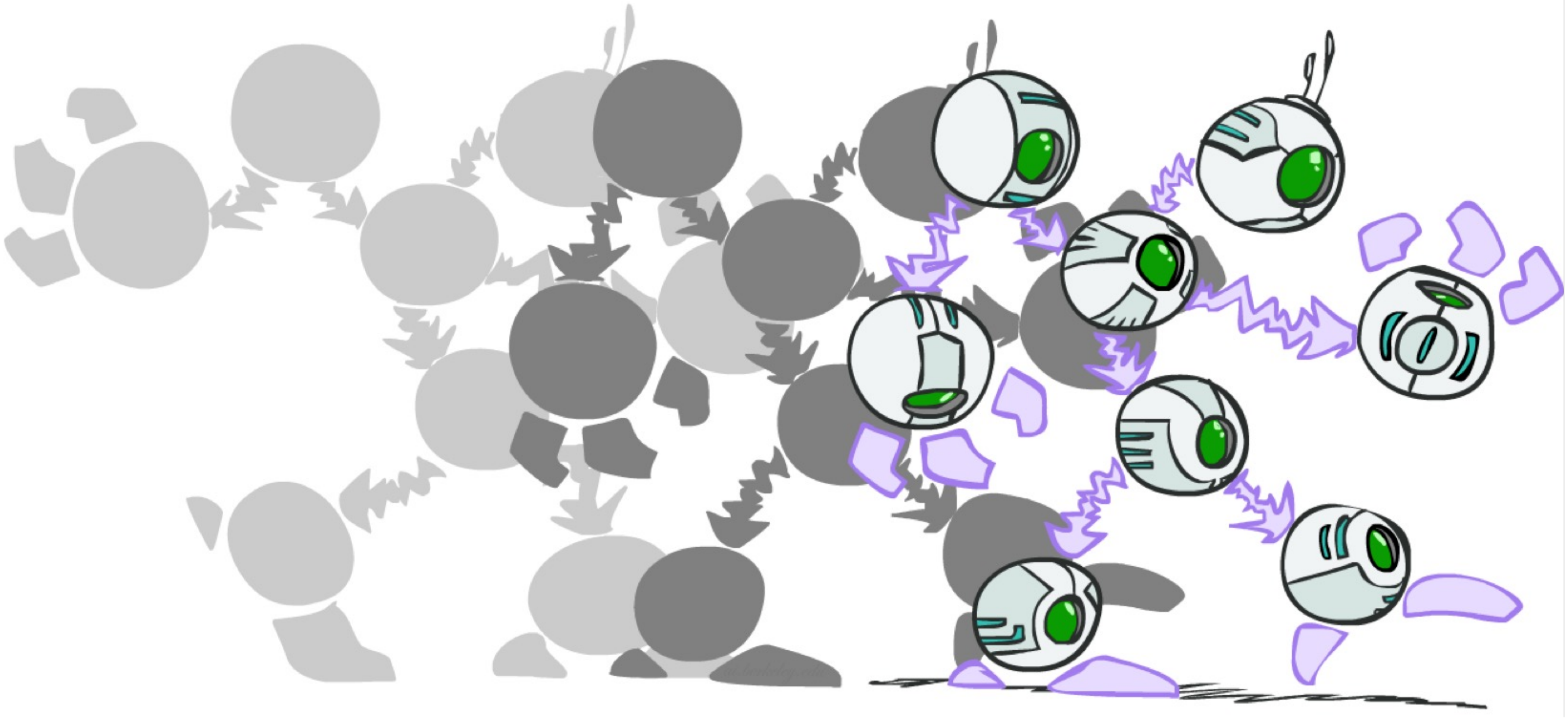
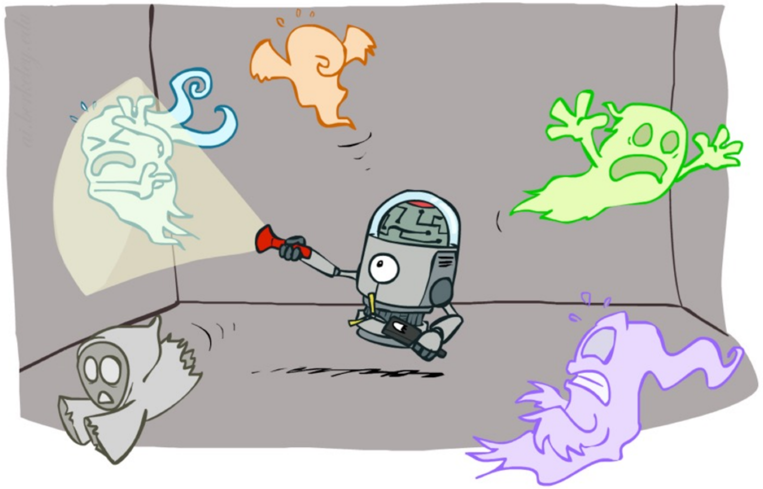
University of California, Berkeley

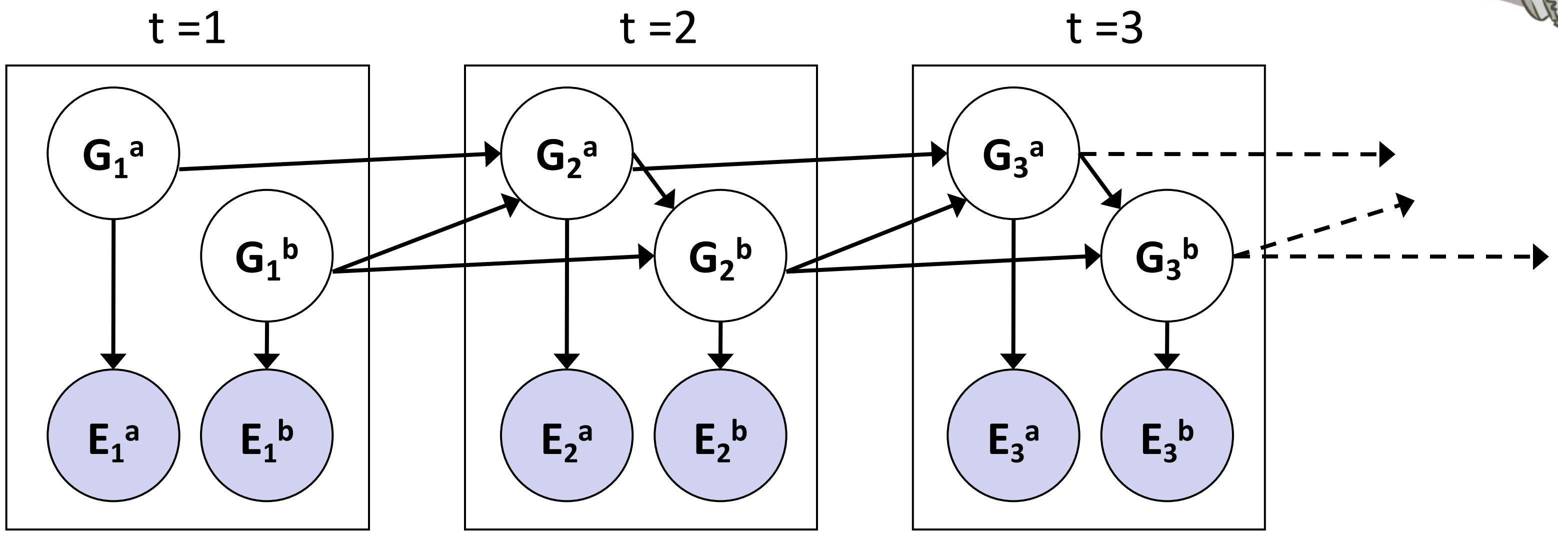
Dynamic Bayes Nets

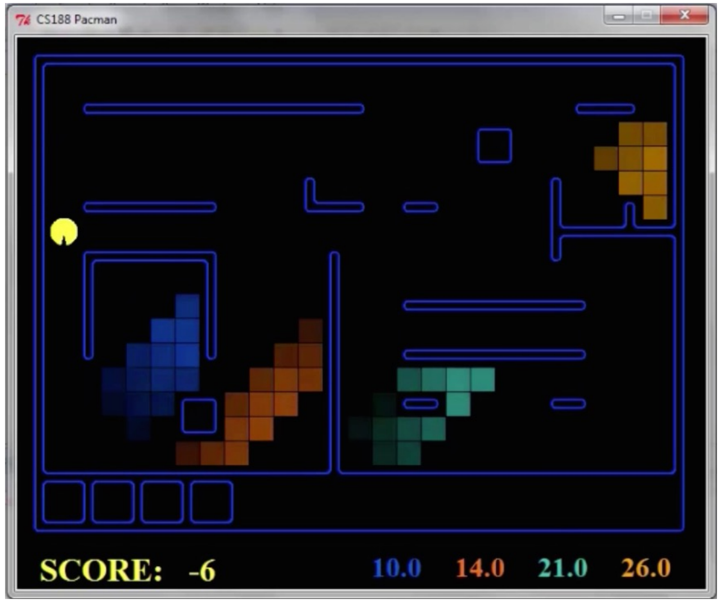


Dynamic Bayes Nets (DBNs)

- We want to track multiple variables over time, using multiple sources of evidence
- Idea: Repeat a fixed Bayes net structure at each time
- Variables at time *t* can have parents at time *t-1*

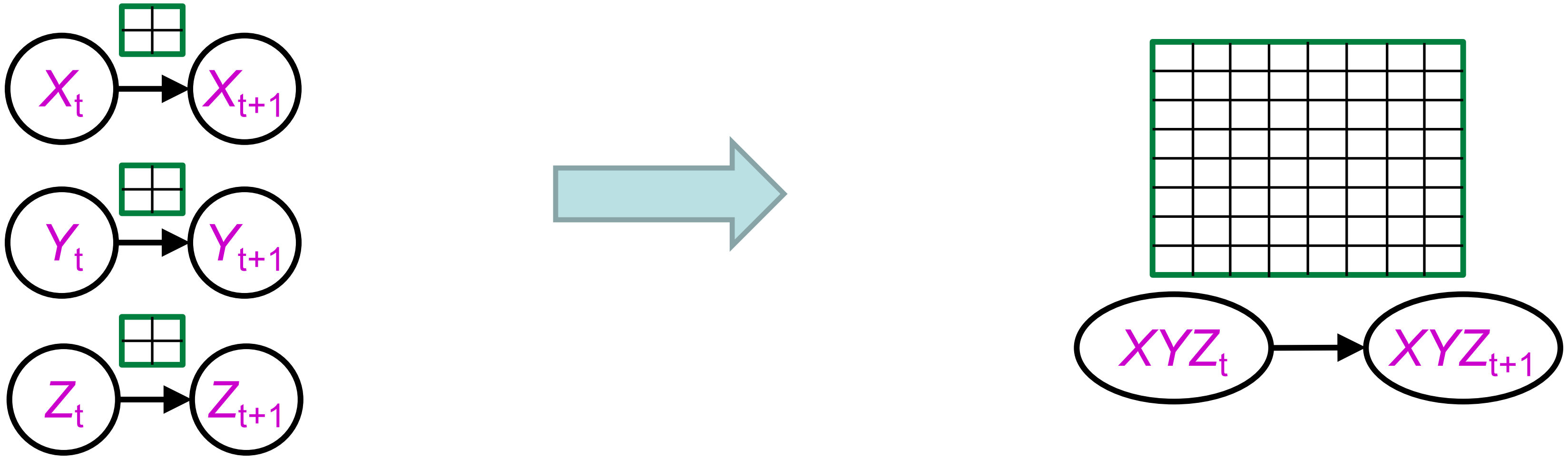






DBNs and HMMs

- Every HMM is a single-variable DBN
- Every discrete DBN is an HMM
  - HMM state is Cartesian product of DBN state variables

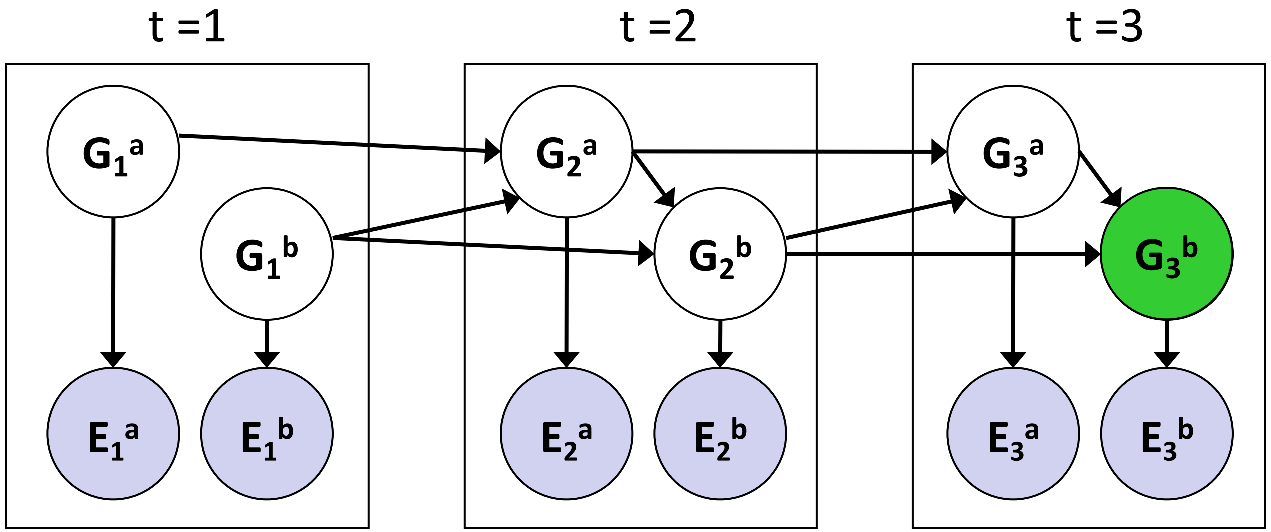


- Sparse dependencies => exponentially fewer parameters in DBN
  - E.g., 20 Boolean state variables, 3 parents each;

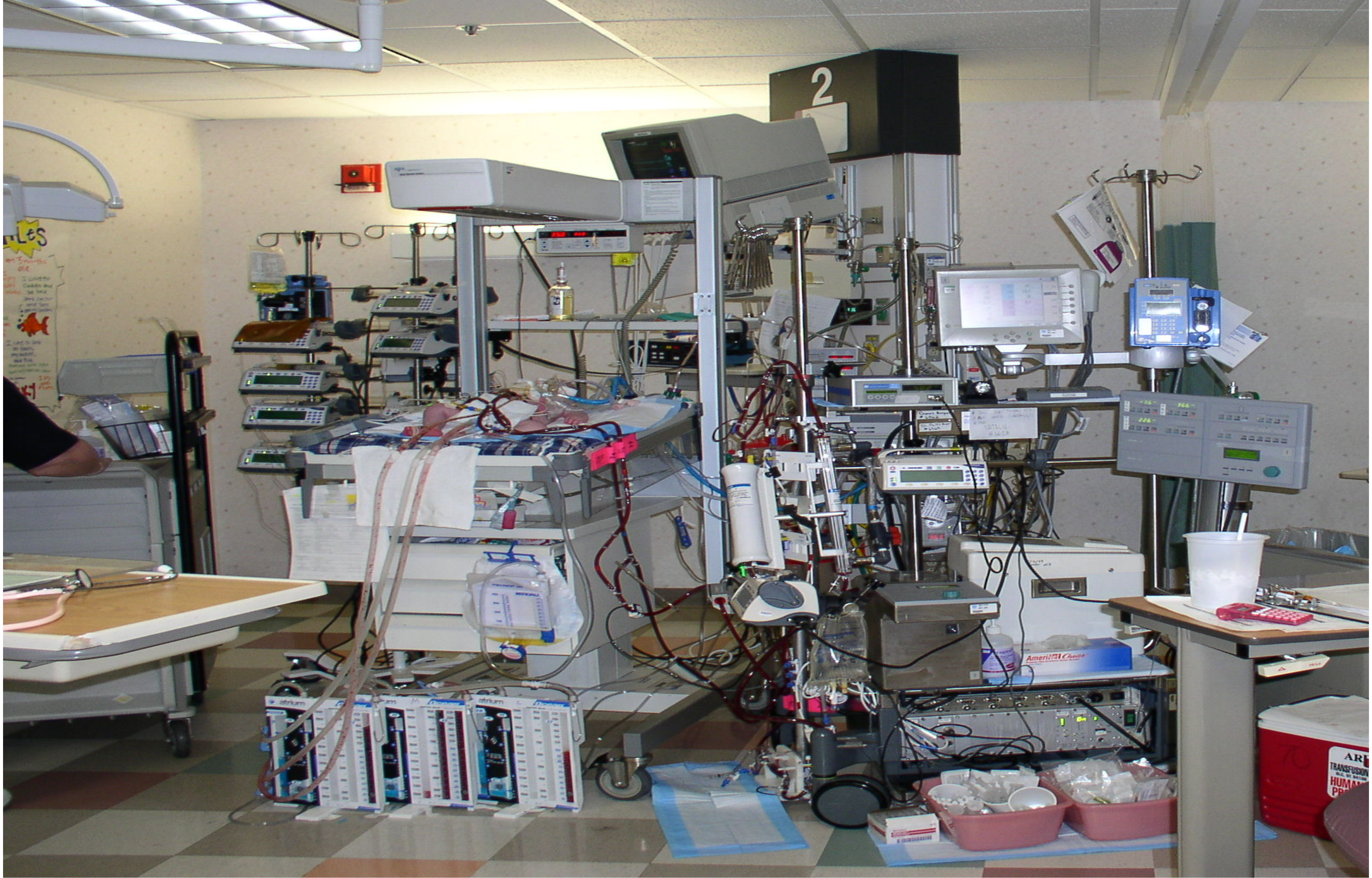
    DBN has $20 \times 2^3 = 160$ parameters, HMM has $2^{20} \times 2^{20} =\sim 10^{12}$ parameters

Exact Inference in DBNs

- Variable elimination applies to dynamic Bayes nets
- Offline: "unroll" the network for T time steps, then eliminate variables to find $P(X_T|e_{1:T})$



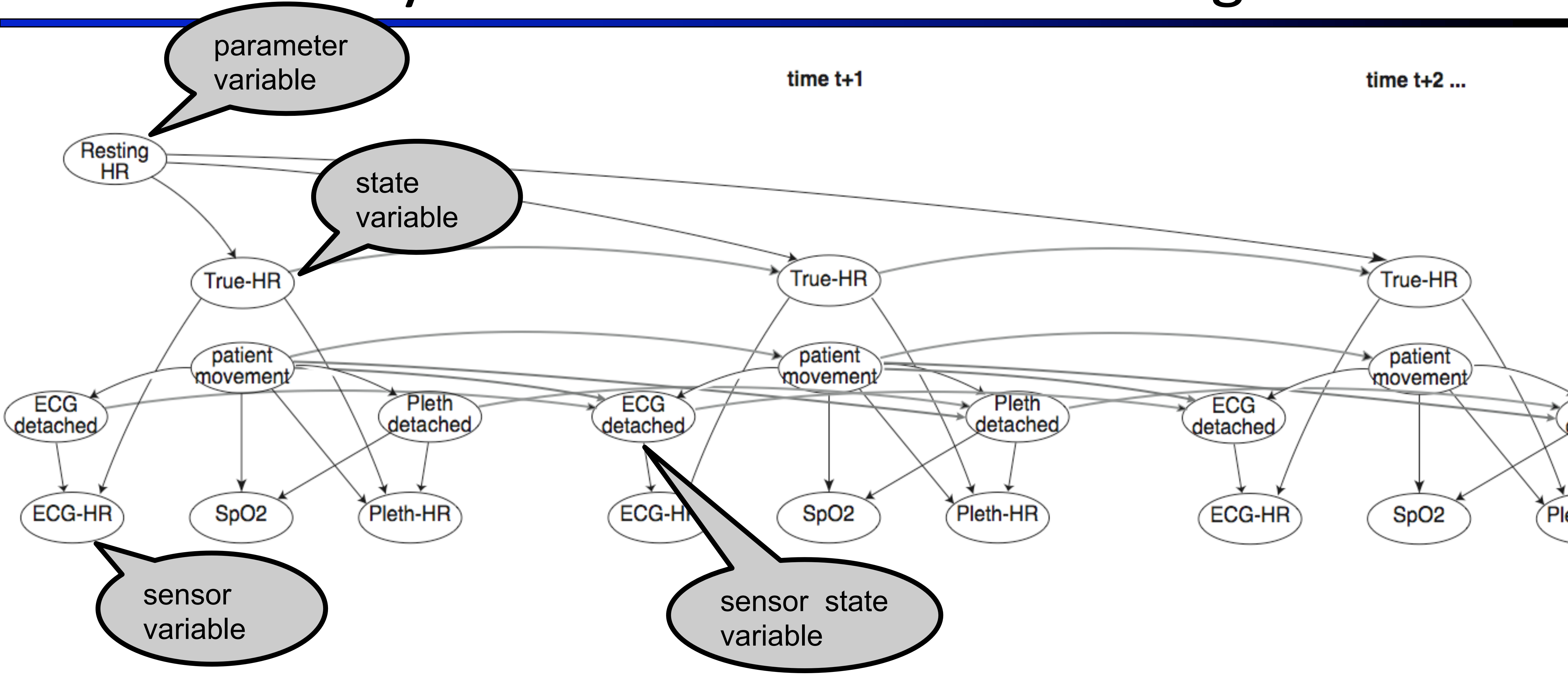
- Online: eliminate all variables from the previous time step; store factors for current time only
- Problem: largest factor contains all variables for current time (plus a few more)


2
atrium

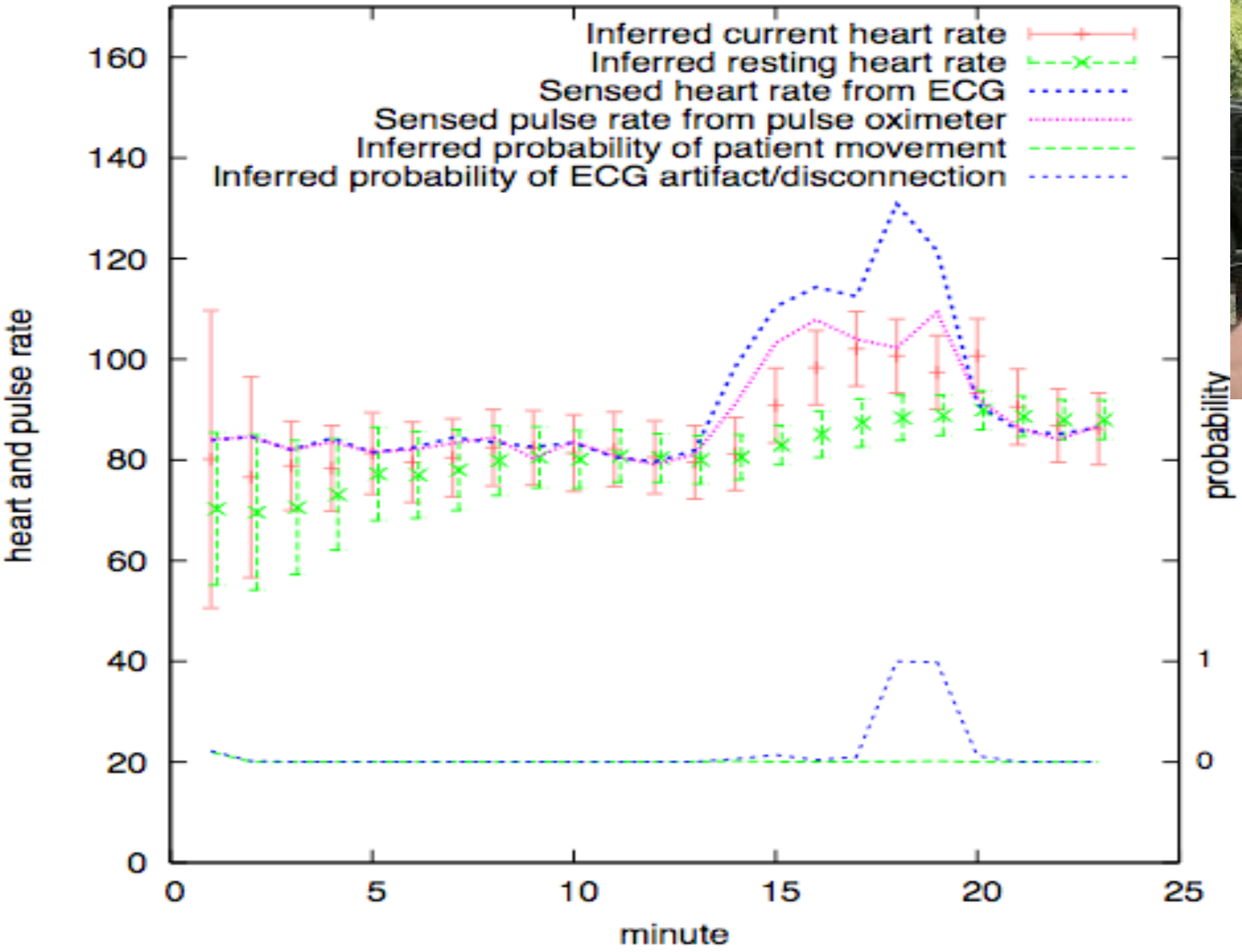
Application: ICU monitoring

- ***State***: variables describing physiological state of patient
- ***Evidence***: values obtained from monitoring devices
- ***Transition model***: physiological dynamics, sensor dynamics
- ***Query variables***: pathophysiological conditions (a.k.a. bad things)

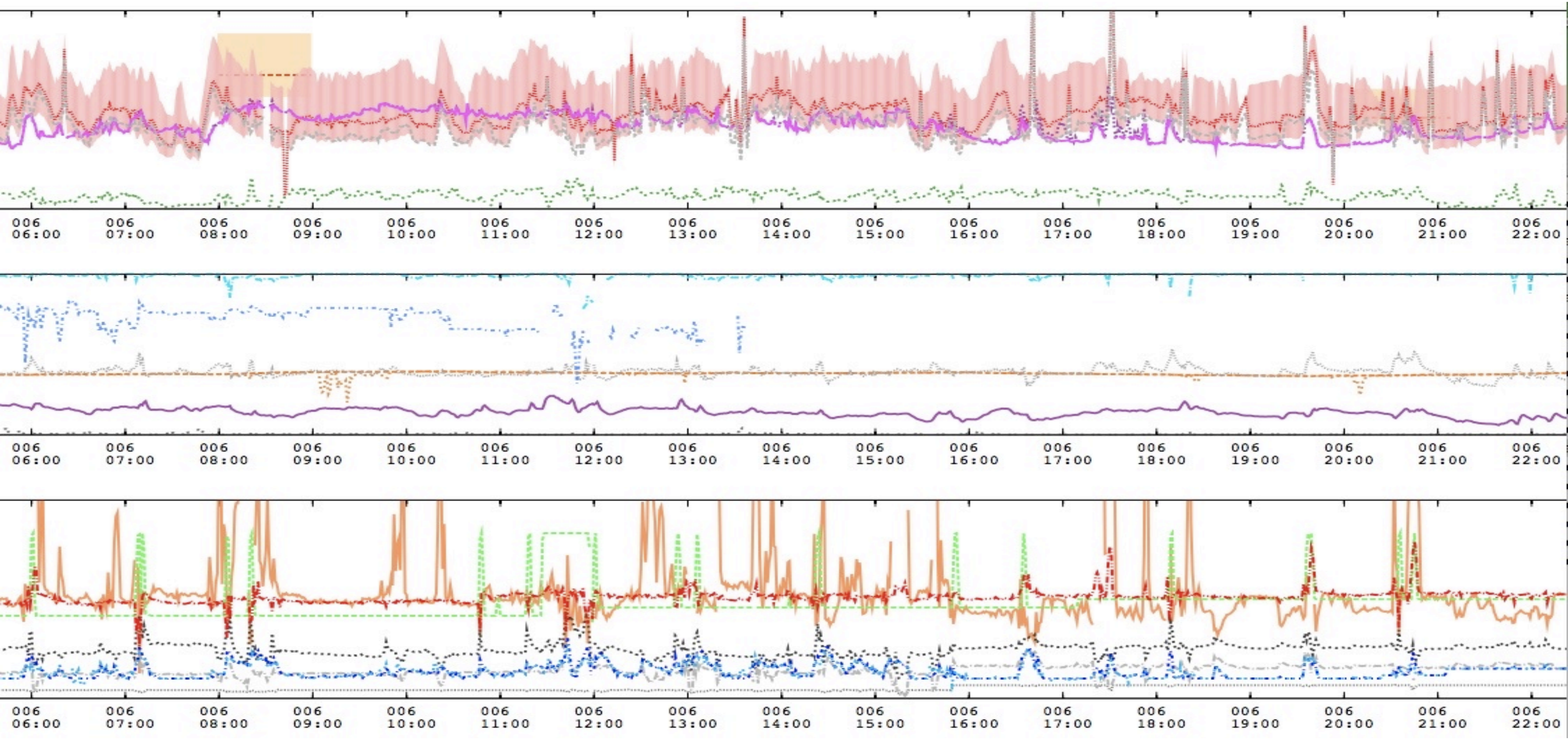
Toy DBN: heart rate monitoring

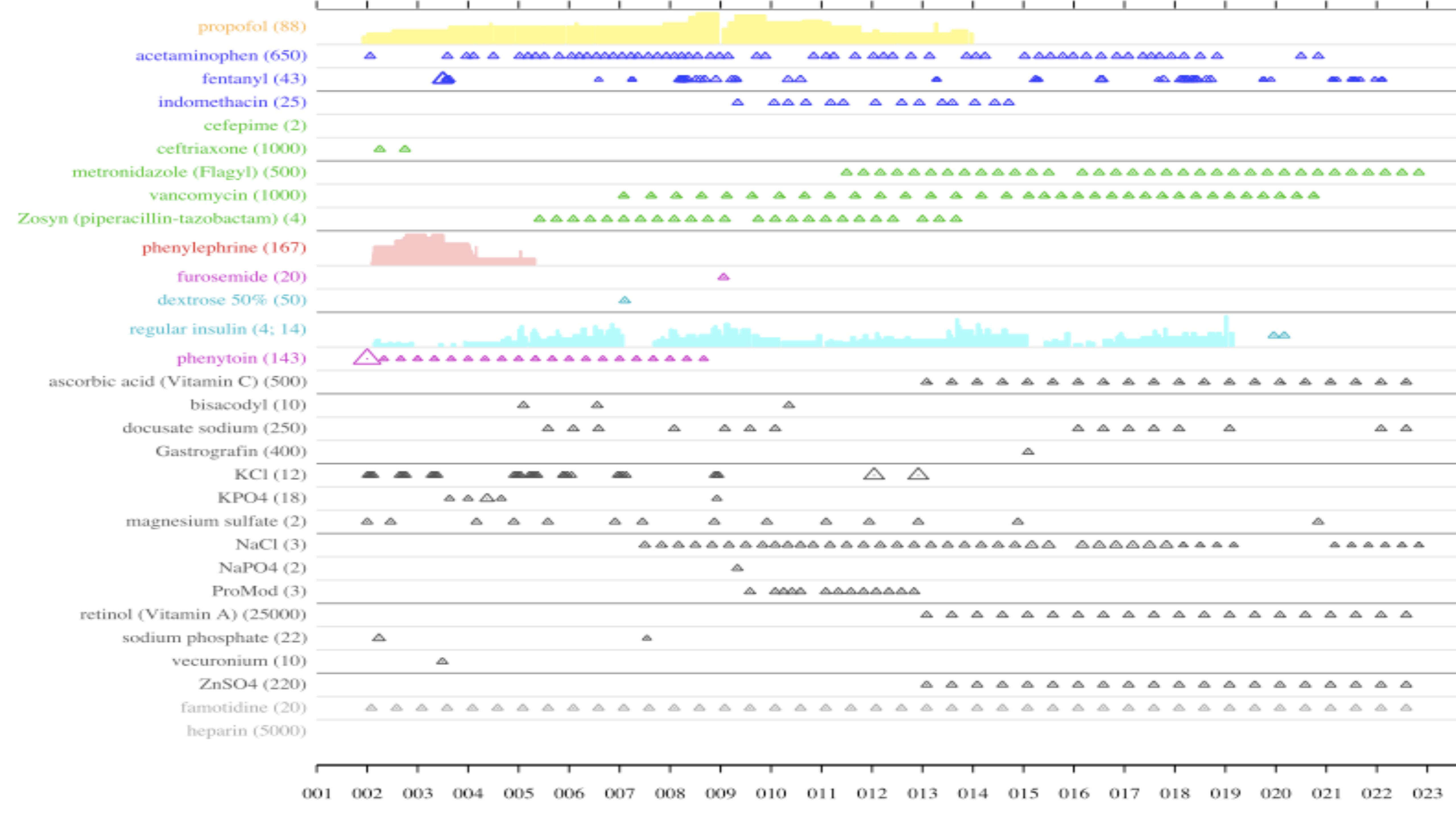


The enhanced heart-rate DBN's inferences on data from a healthy 40-year-



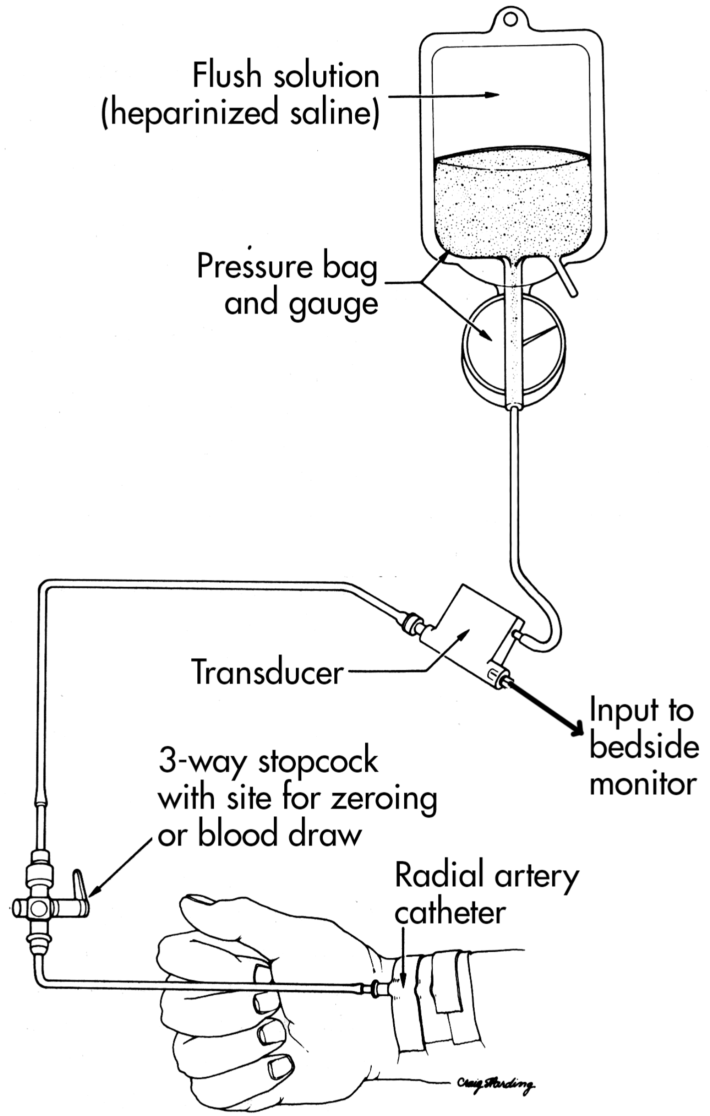
ICU data: 22 variables, 1min ave



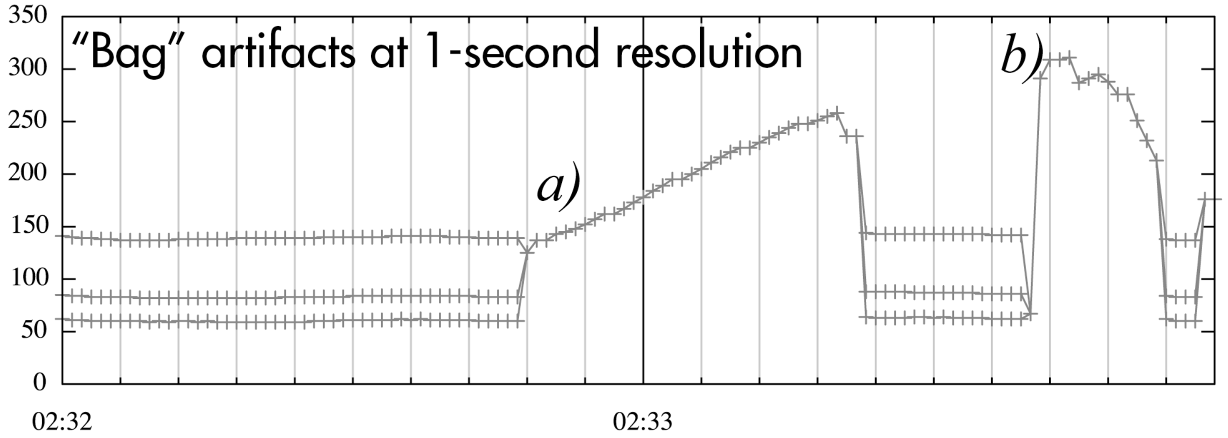


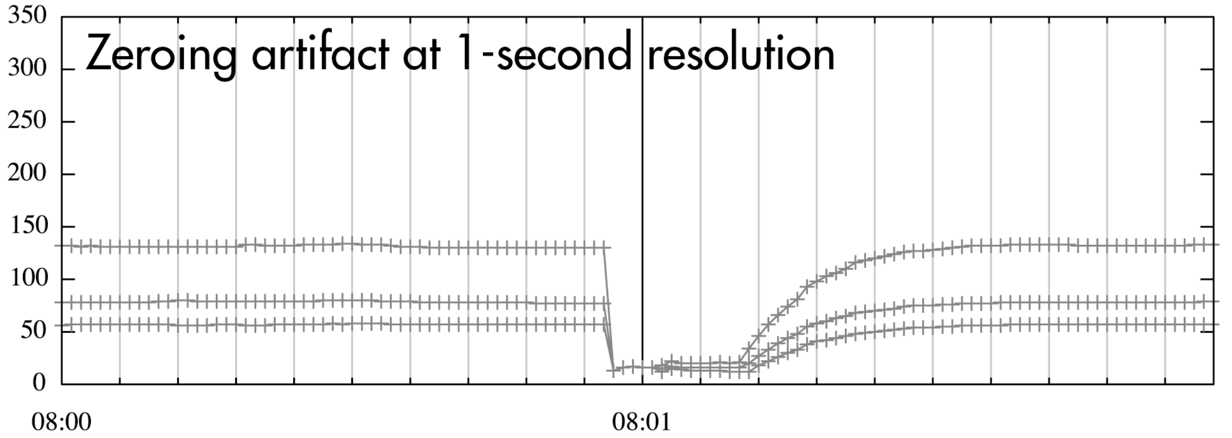
propofol (88)
acetaminophen (650)
fentanyl (43)
indomethacin (25)
cefepime (2)
ceftriaxone (1000)
metronidazole (Flagyl) (500)
vancomycin (1000)
Zosyn (piperacillin-tazobactam) (4)
phenylephrine (167)
furosemide (20)
dextrose 50% (50)
regular insulin (4; 14)
phenytoin (143)
ascorbic acid (Vitamin C) (500)
bisacodyl (10)
docusate sodium (250)
Gastrografin (400)
KCl (12)
KPO4 (18)
magnesium sulfate (2)
NaCl (3)
NaPO4 (2)
ProMod (3)
retinol (Vitamin A) (25000)
sodium phosphate (22)
vecuronium (10)
ZnSO4 (220)
famotidine (20)
heparin (5000)
001 002 003 004 005 006 007 008 009 010 011 012 013 014 015 016 017 018 019 020 021 022 023

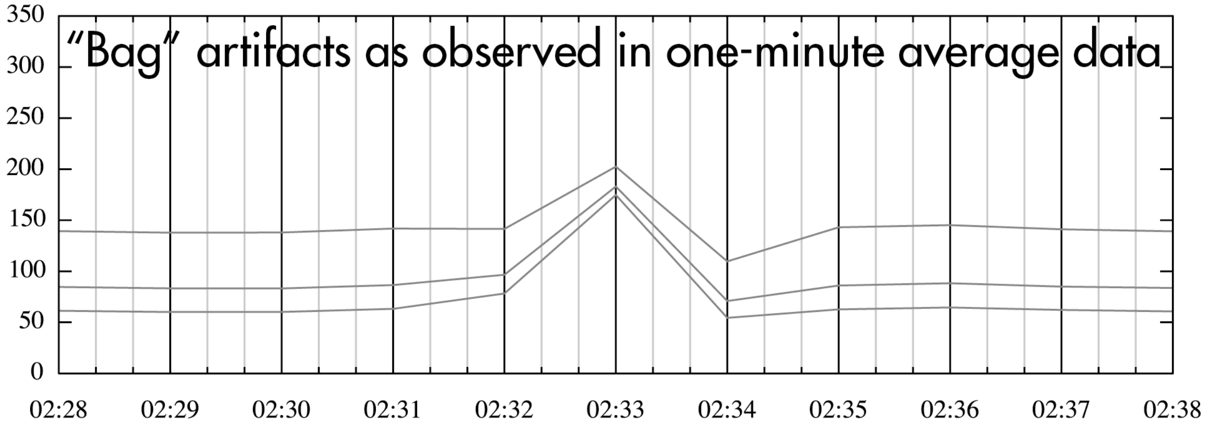
Blood pressure measurement

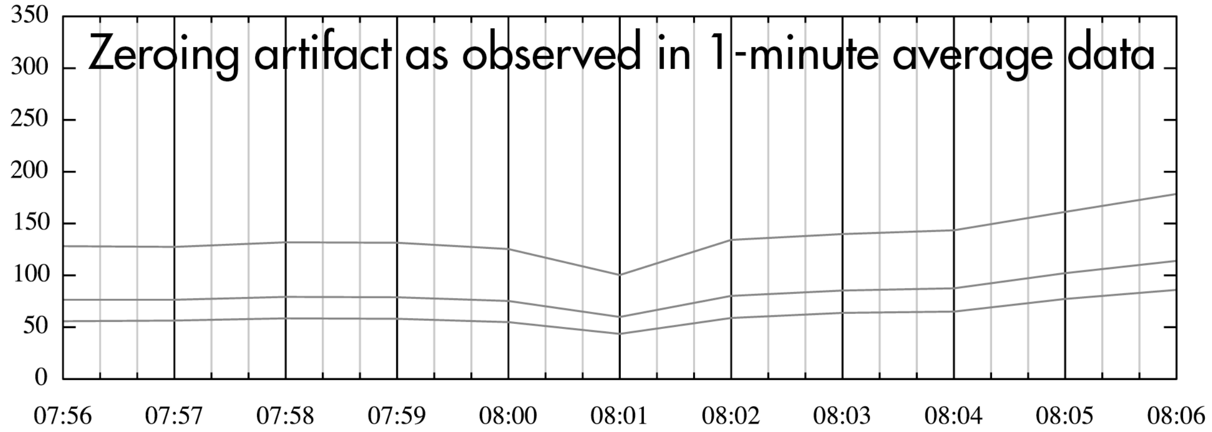


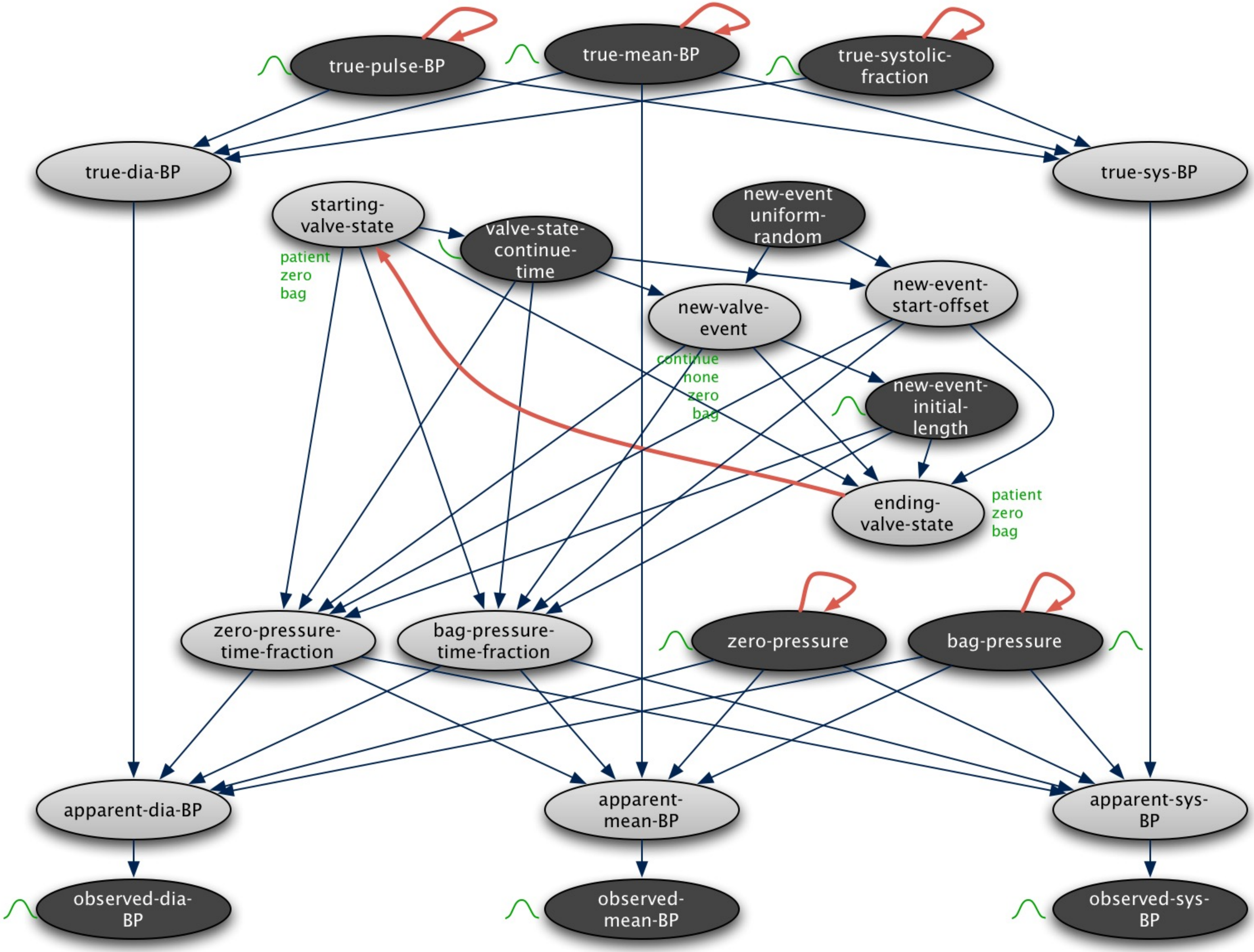
One-second vs one-minute data





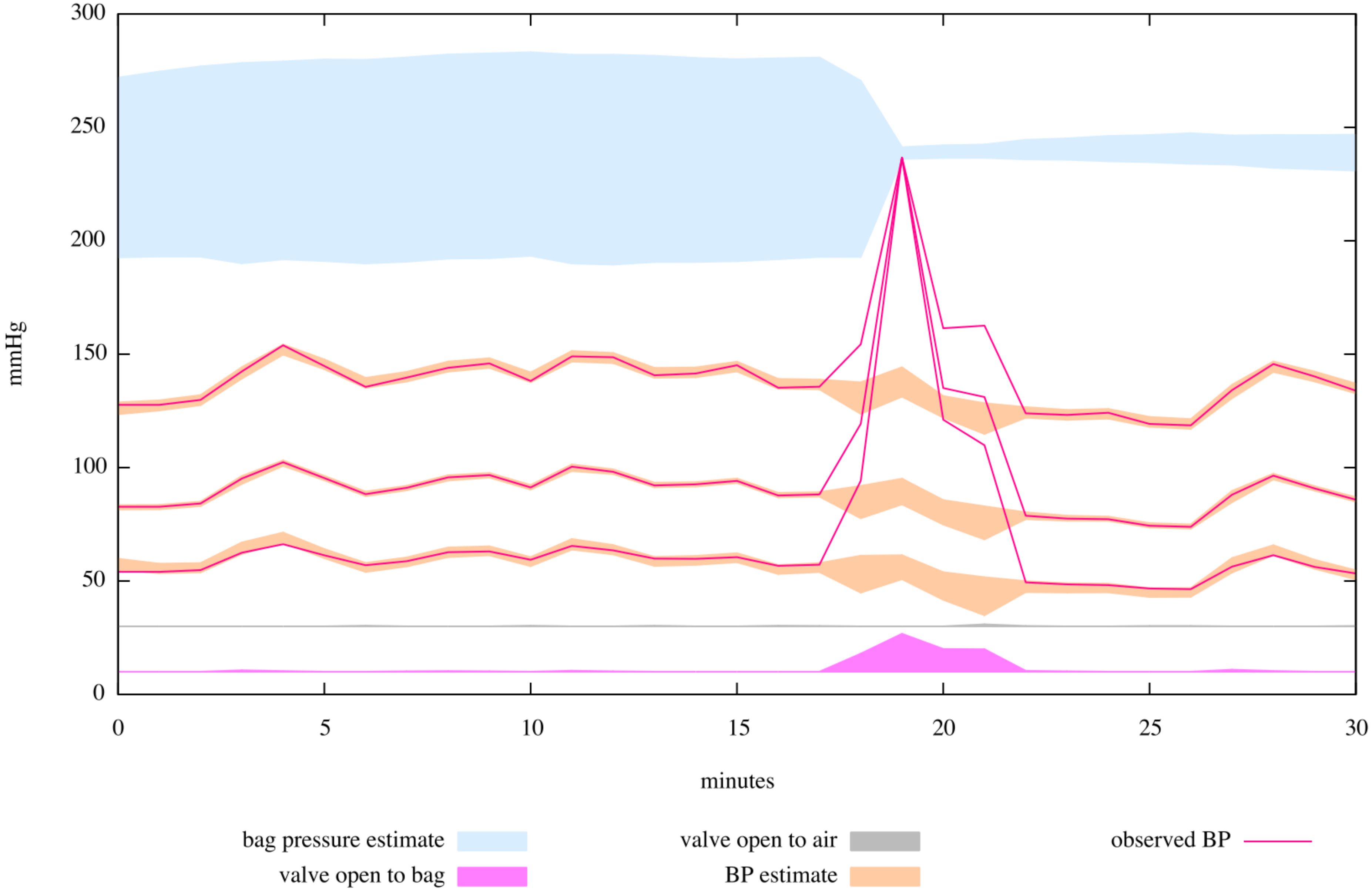


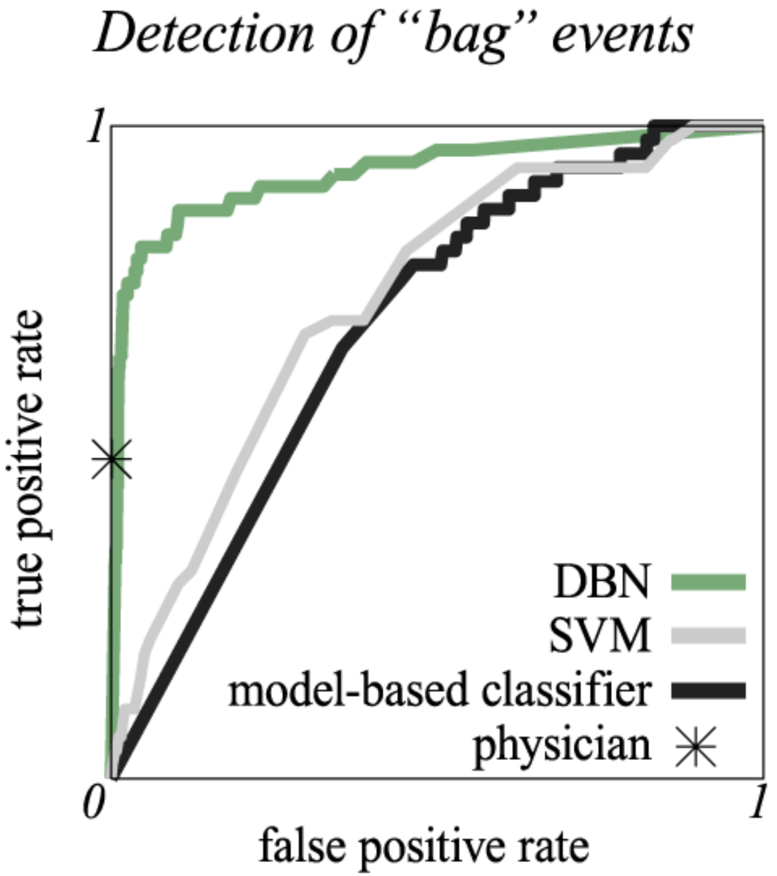




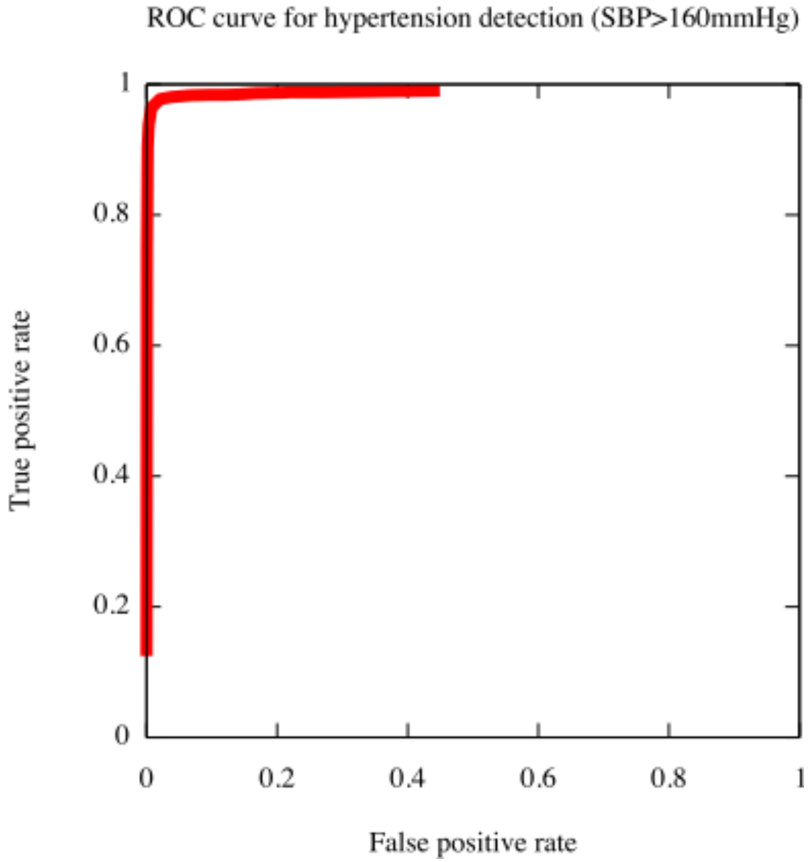
true-pulse-BP
true-mean-BP
true-systolic-fraction
true-dia-BP
true-sys-BP
starting-valve-state
patient
zero
bag
valve-state-continue-time
new-event uniform-random
new-event-start-offset
new-valve-event
continue
none
zero
bag
new-event-initial-length
ending-valve-state
patient
zero
bag
zero-pressure-time-fraction
bag-pressure-time-fraction
zero-pressure
bag-pressure
apparent-dia-BP
apparent-mean-BP
apparent-sys-BP
observed-dia-BP
observed-mean-BP
observed-sys-BP

Sample blood-draw dataset no. 11



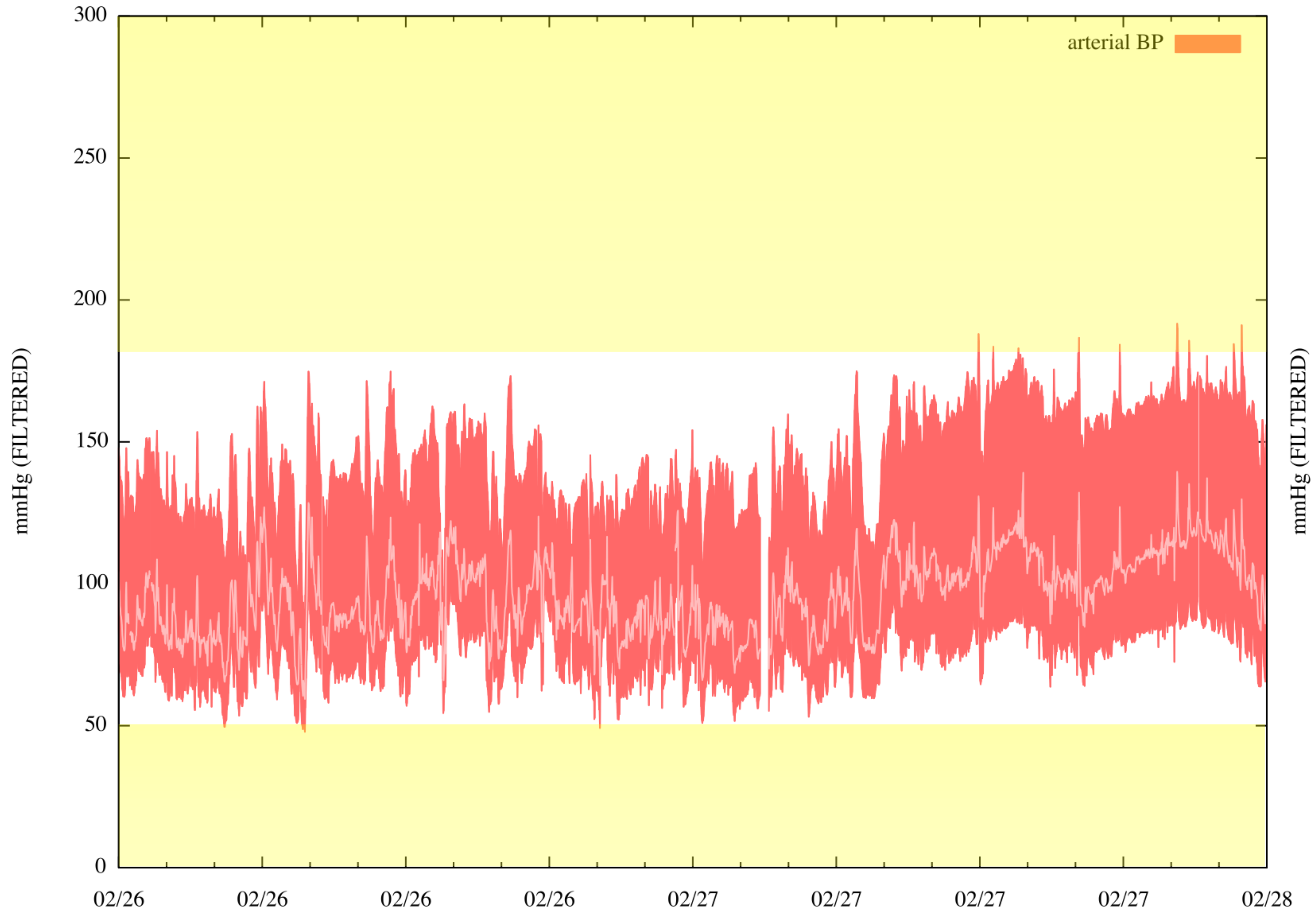


Detection of "bag" events
1
0
1
true positive rate
false positive rate
DBN
SVM
model-based classifier
physician



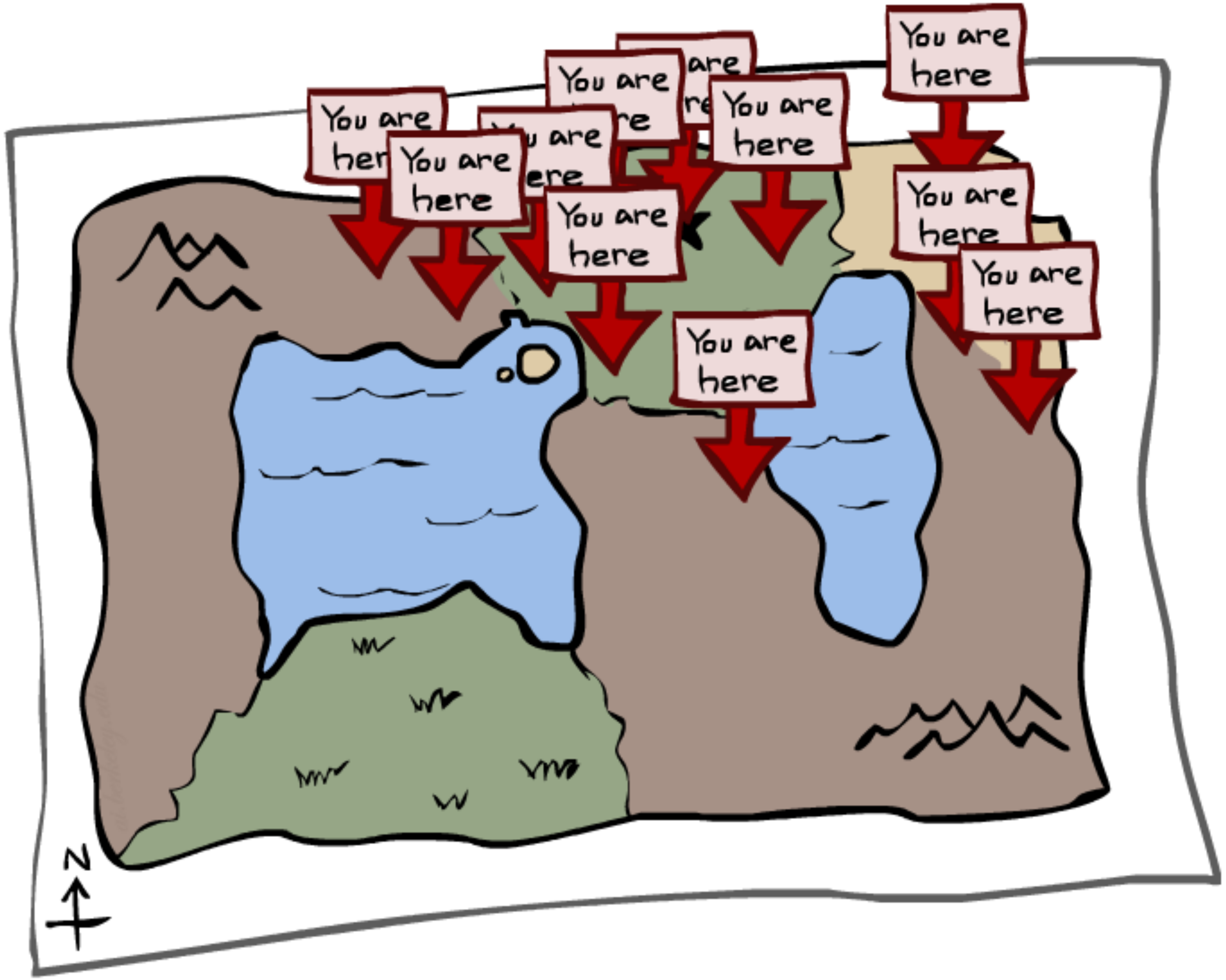
ROC curve for hypertension detection (SBP>160mmHg)
True positive rate
False positive rate
0
0.2
0.4
0.6
0.8
1

ALARM
arterial BP
mmHg
mmHg
300
250
200
150
100
50
0
02/26
02/26
02/26
02/26
02/27
02/27
02/27
02/27
02/28



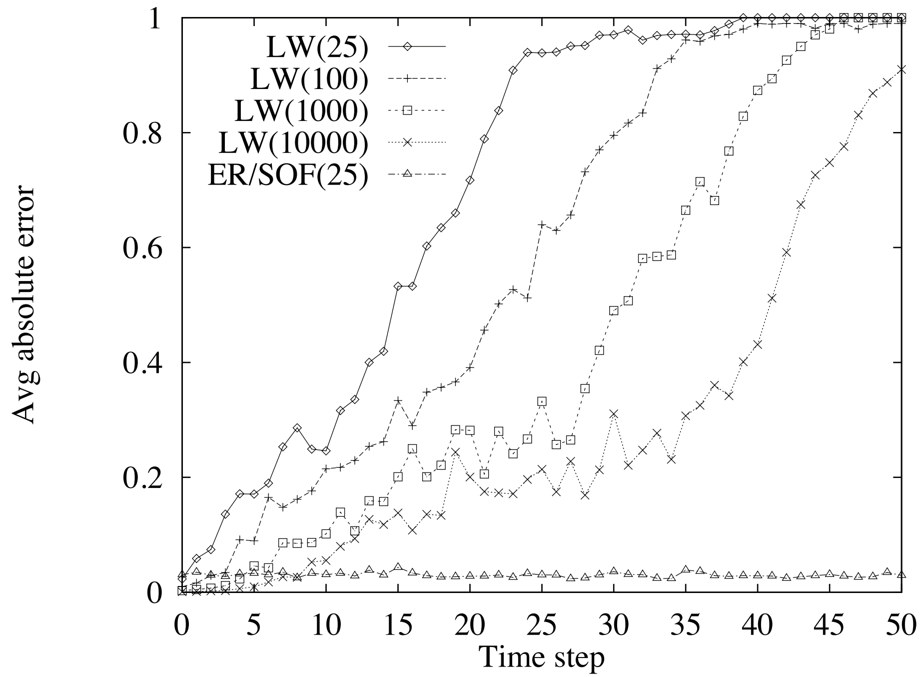
arterial BP
300
250
200
150
100
50
0
mmHg (FILTERED)
mmHg (FILTERED)
02/26
02/26
02/26
02/26
02/27
02/27
02/27
02/27
02/28

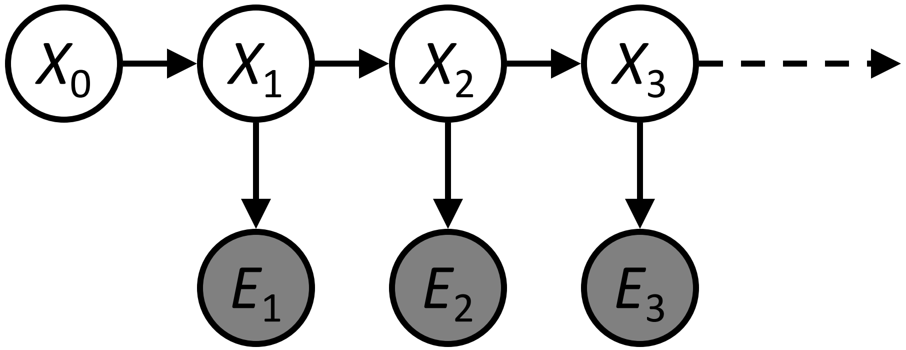
Particle Filtering



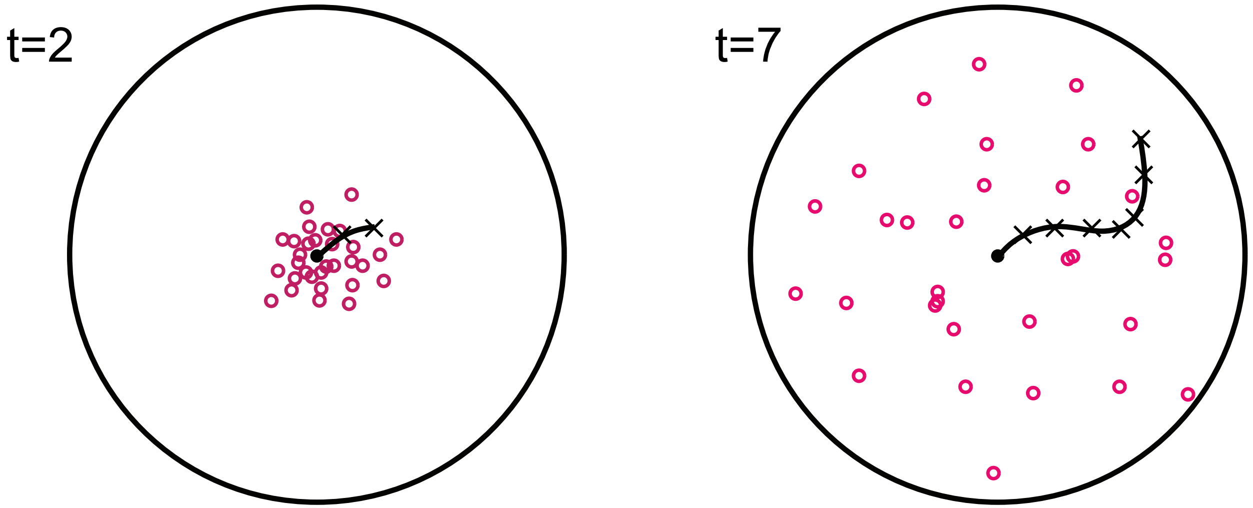
We need a new algorithm!

- When $|X|$ is more than 10^6 or so (e.g., 3 ghosts in a 10x20 world), exact inference becomes infeasible
- Likelihood weighting fails completely – number of samples needed grows ***exponentially*** with T





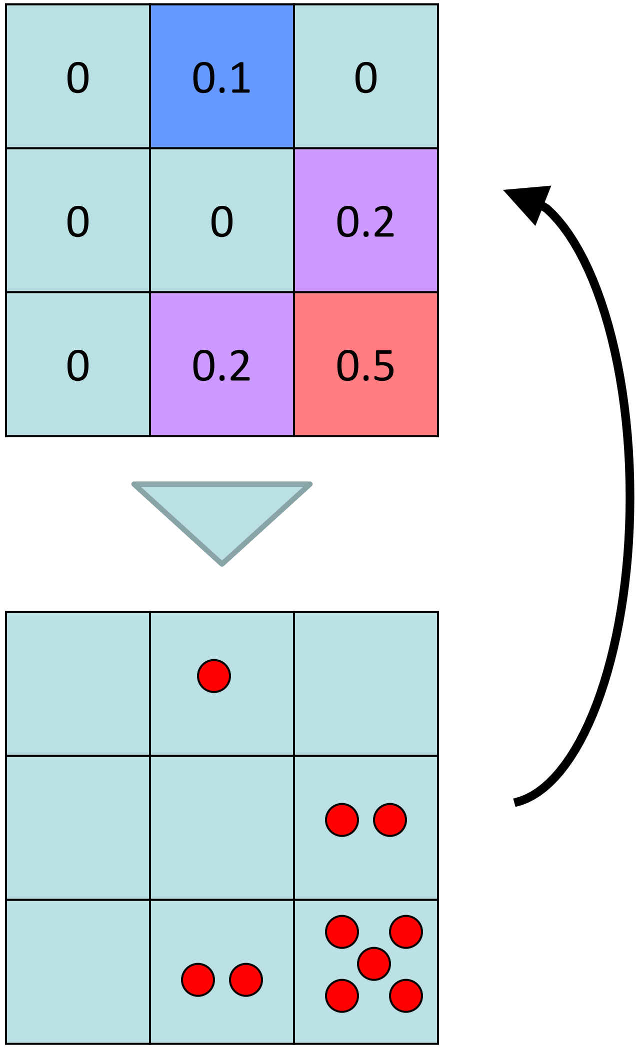
We need a new idea!



- The problem: sample state trajectories go off into low-probability regions, ignoring the evidence; too few "reasonable" samples
- Solution: kill the bad ones, make more of the good ones
- This way the population of samples stays in the high-probability region
- This is called ***resampling*** or survival of the fittest

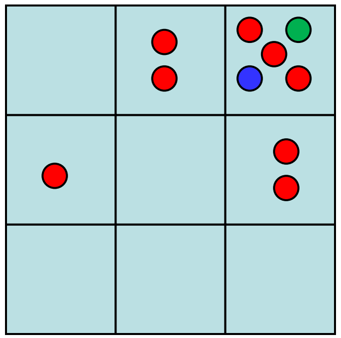
Particle Filtering

- Represent belief state by a set of samples
  - Samples are called ***particles***
  - Time per step is linear in the number of samples
  - But: number needed may be large
- This is how robot localization works in practice



Representation: Particles

- Our representation of $P(X)$ is now a list of $N \ll |X|$ particles
- $P(x)$ approximated by number of particles with value x
  - So, many x may have $P(x) = 0$!
  - More particles => more accuracy (cf. frequency histograms)
  - Usually we want a ***low-dimensional*** marginal
    - E.g., “Where is ghost 1?” rather than “Are ghosts 1,2,3 in [2,6], [5,6], and [8,11]?”

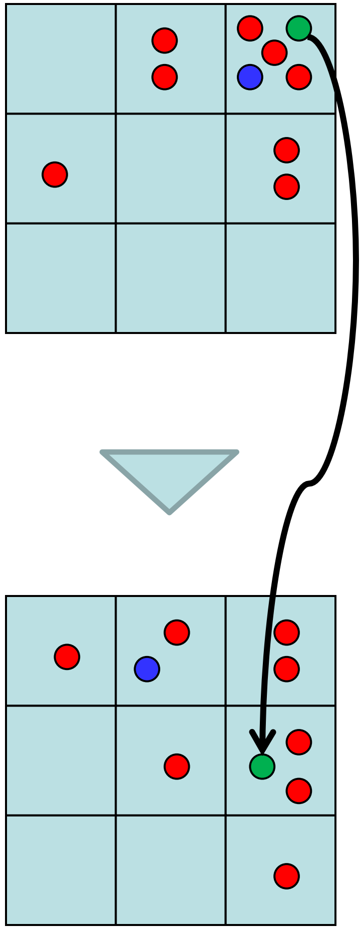


Particles:
(3,3)
(2,3)
(3,3)
(3,2)
(3,3)
(3,2)
(1,2)
(3,3)
(3,3)
(2,3)

Particle Filtering: Prediction step

- Particle j in state $x_t^{(j)}$ samples a new state directly from the transition model:
  - $x_{t+1}^{(j)} \sim P(X_{t+1} \mid x_t^{(j)})$
  - Here, most samples move clockwise, but some move in another direction or stay in place

Particles:
(3,3)
(2,3)
(3,3)
(3,2)
(3,3)
(3,2)
(1,2)
(3,3)
(3,3)
(2,3)

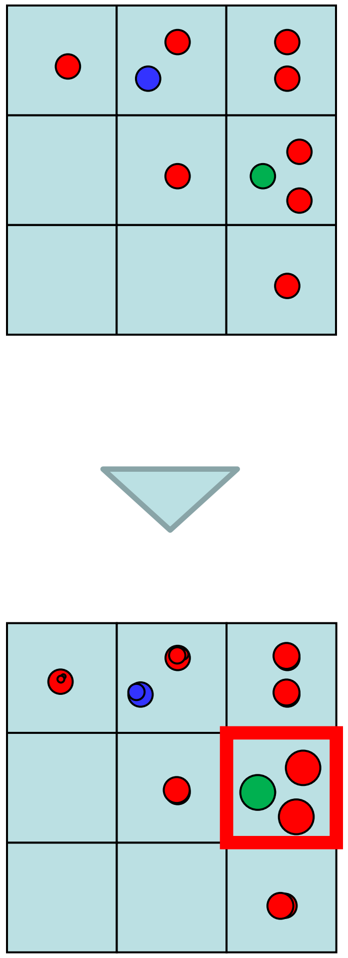


Particles:
(3,2)
(2,3)
(3,2)
(3,1)
(3,3)
(3,2)
(1,3)
(2,3)
(3,2)
(2,2)

Particle Filtering: Update step

- After observing e_{t+1} :
  - As in likelihood weighting, weight each sample based on the evidence
    - $w^{(j)} = P(e_{t+1} \mid x_{t+1}^{(j)})$
  - Particles that fit the data better get higher weights, others get lower weights
  - Normalize the weights across all particles

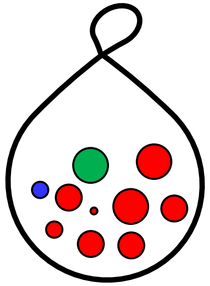
Particles:
(3,2)
(2,3)
(3,2)
(3,1)
(3,3)
(3,2)
(1,3)
(2,3)
(3,2)
(2,2)



Particles:
(3,2) w=~~.9~~ .17
(2,3) w=~~.2~~ .04
(3,2) w=~~.9~~ .17
(3,1) w=~~.4~~ .08
(3,3) w=~~.4~~ .08
(3,2) w=~~.9~~ .17
(1,3) w=~~.1~~ .02
(2,3) w=~~.2~~ .04
(3,2) w=~~.9~~ .17
(2,2) w=~~.4~~ .08

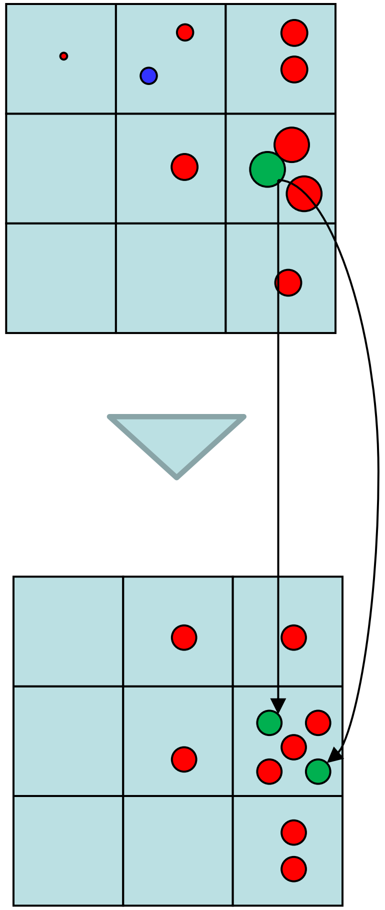
Particle Filtering: Resample

- Rather than tracking weighted samples, we ***resample***
- *N* times, we choose from our weighted sample distribution (i.e., draw with replacement)
- Now the update is complete for this time step, continue with the next one (with weights reset to 1/N)



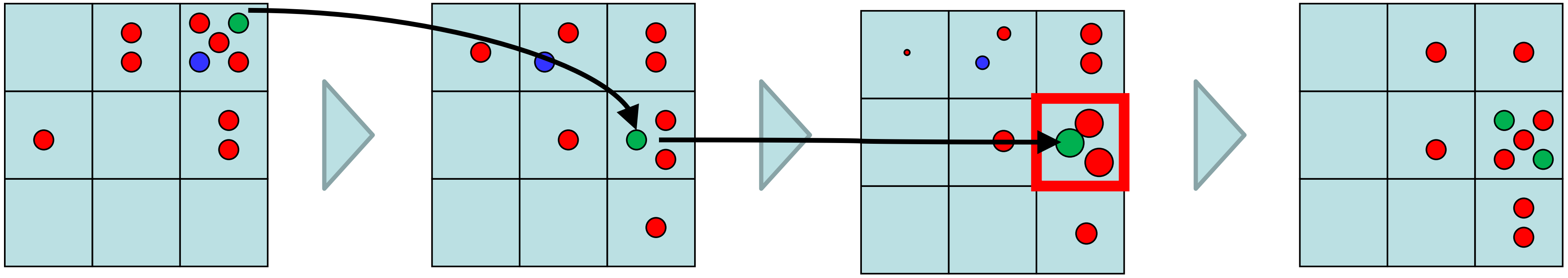
Particles:
(3,2) w=.17
(2,3) w=.04
(3,2) w=.17
(3,1) w=.08
(3,3) w=.08
(3,2) w=.17
(1,3) w=.02
(2,3) w=.04
(3,2) w=.17
(2,2) w=.08

(New) Particles:
(3,2)
(2,2)
(3,2)
(2,3)
(3,3)
(3,2)
(1,3)
(2,3)
(3,2)
(3,2)



Summary: Particle Filtering

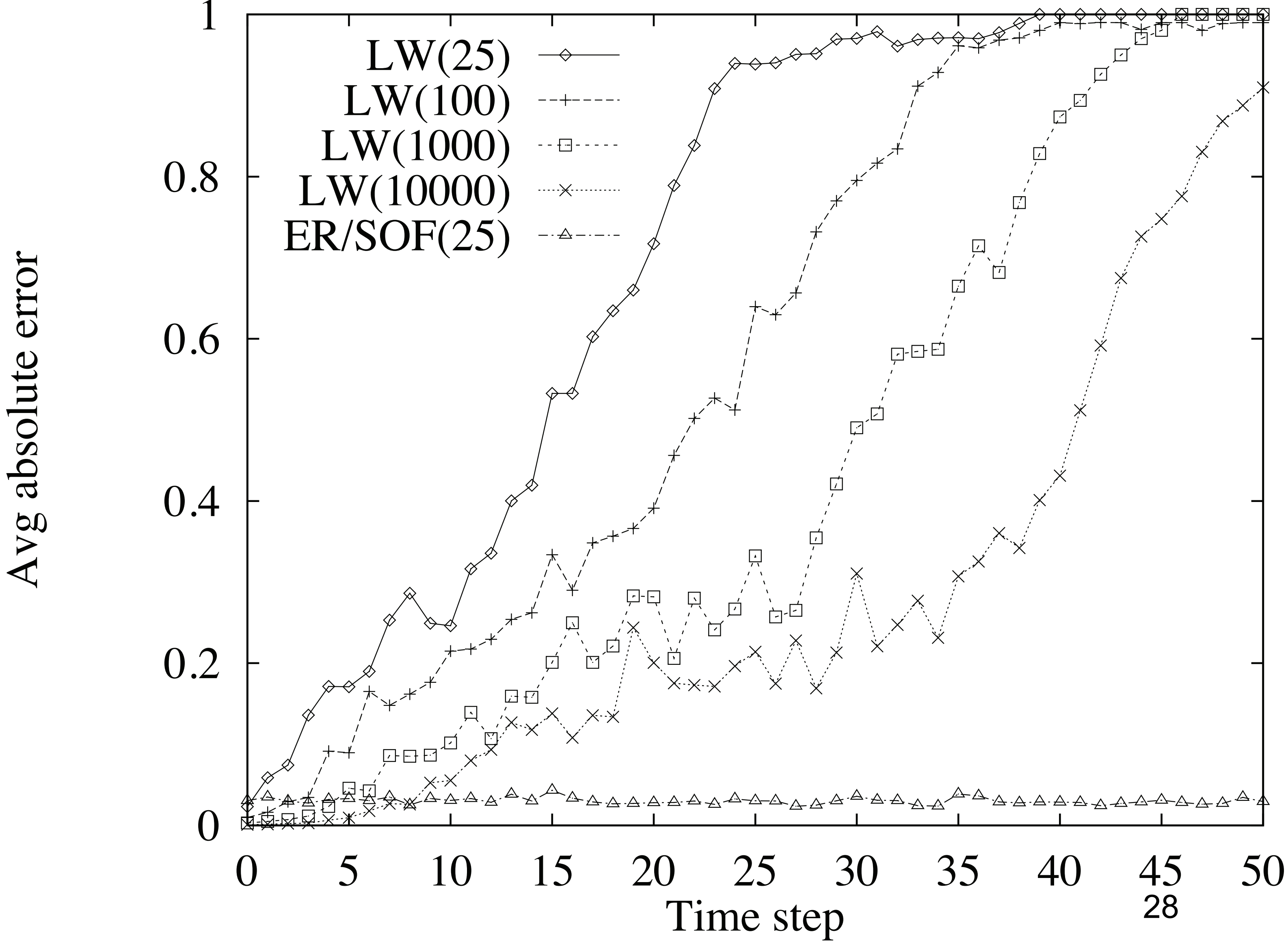
- Particles: track samples of states rather than an explicit distribution



Particles:	Particles:	Particles:	(New) Particles:
(3,3)	(3,2)	(3,2) w=.9	(3,2)
(2,3)	(2,3)	(2,3) w=.2	(2,2)
(3,3)	(3,2)	(3,2) w=.9	(3,2)
(3,2)	(3,1)	(3,1) w=.4	(2,3)
(3,3)	(3,3)	(3,3) w=.4	(3,3)
(3,2)	(3,2)	(3,2) w=.9	(3,2)
(1,2)	(1,3)	(1,3) w=.1	(1,3)
(3,3)	(2,3)	(2,3) w=.2	(2,3)
(3,3)	(3,2)	(3,2) w=.9	(3,2)
(2,3)	(2,2)	(2,2) w=.4	(3,2)

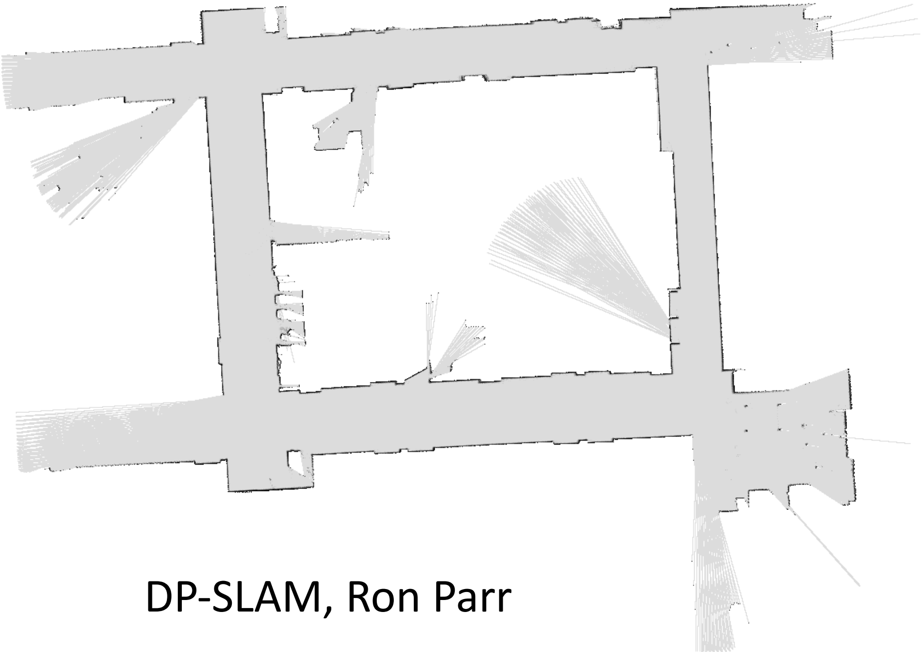
Consistency: see proof in AIMA Ch. 14

Particle filtering on umbrella model

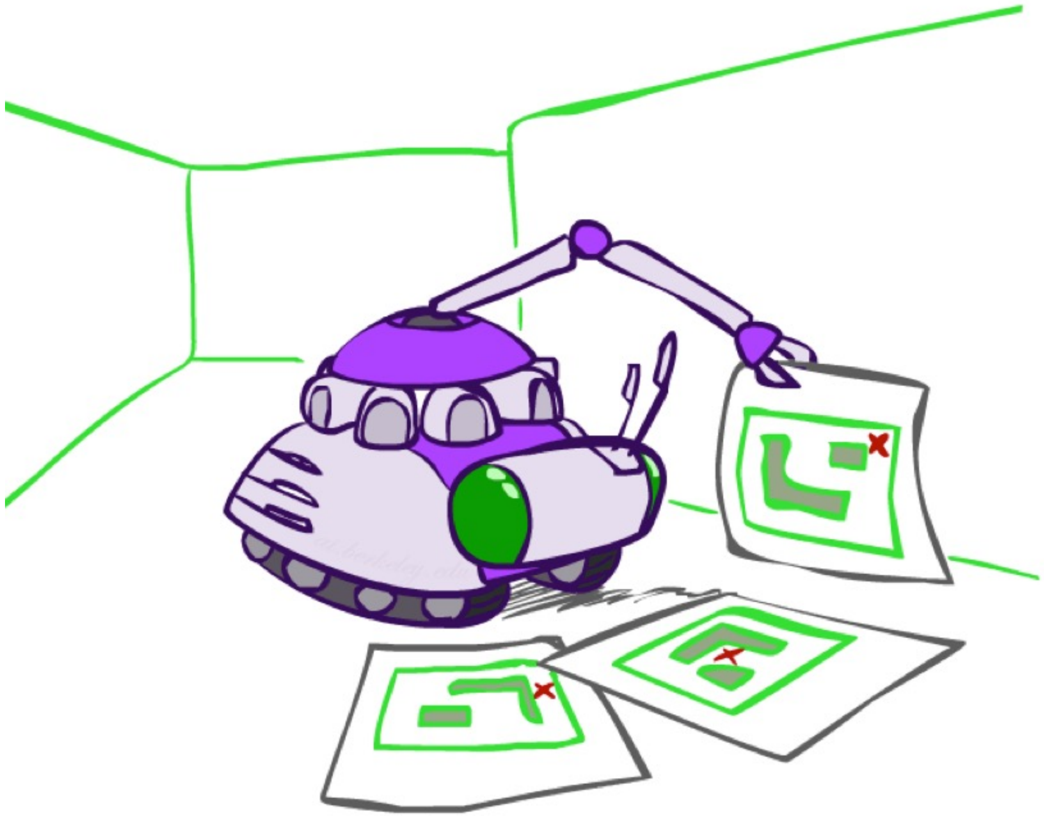


Robot Mapping

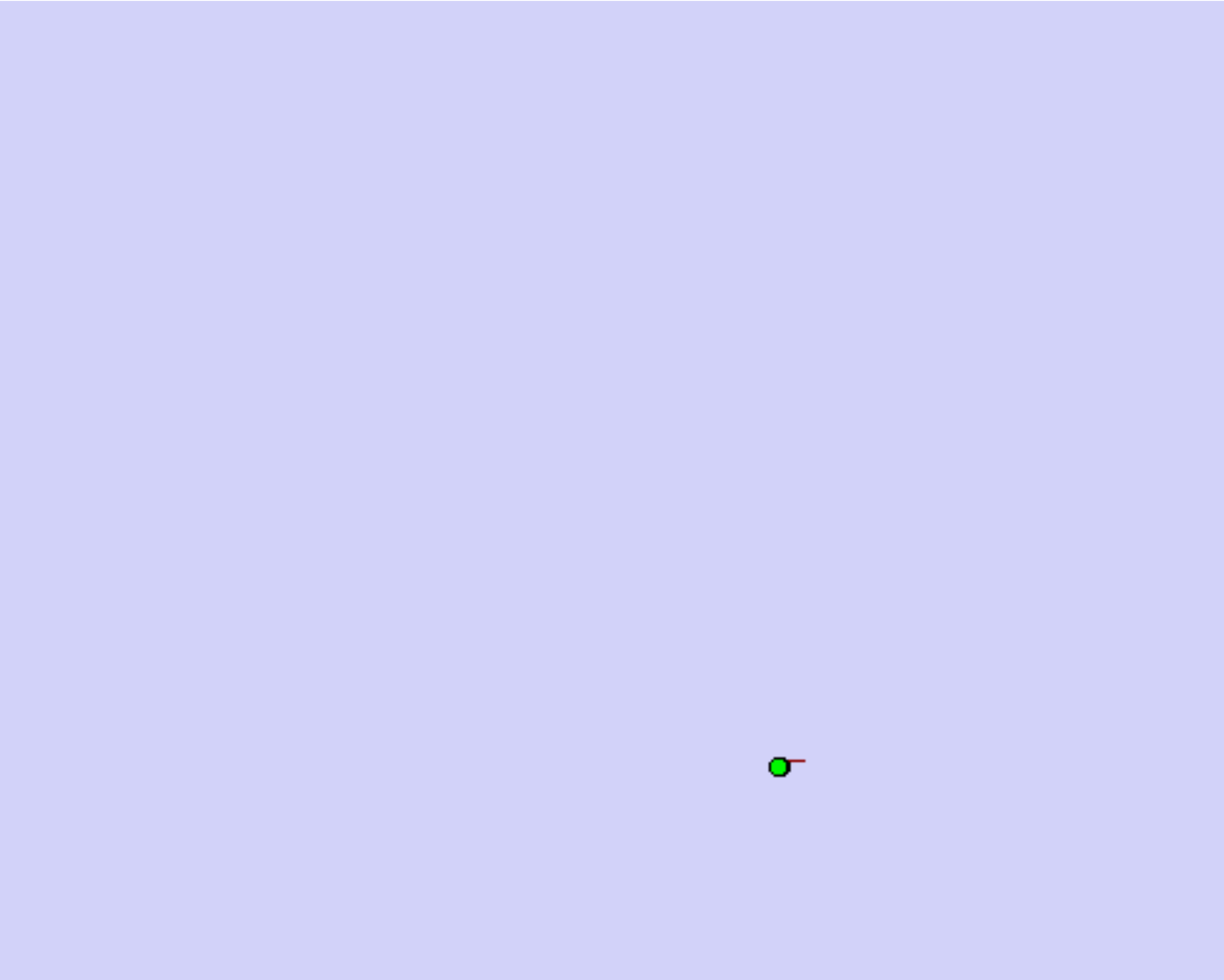
- SLAM: Simultaneous Localization And Mapping
  - Robot does not know map or location
  - State $x_t^{(j)}$ consists of position+orientation, map!
  - (Each map usually inferred exactly given sampled position+orientation sequence: RBPF)



DP-SLAM, Ron Parr



Particle Filter SLAM – Video 2



[Demo: PARTICLES-SLAM-fastslam.avi]