Machine Learning for Signal Processing
Prediction and Estimation, Part II

Bhiksha Raj

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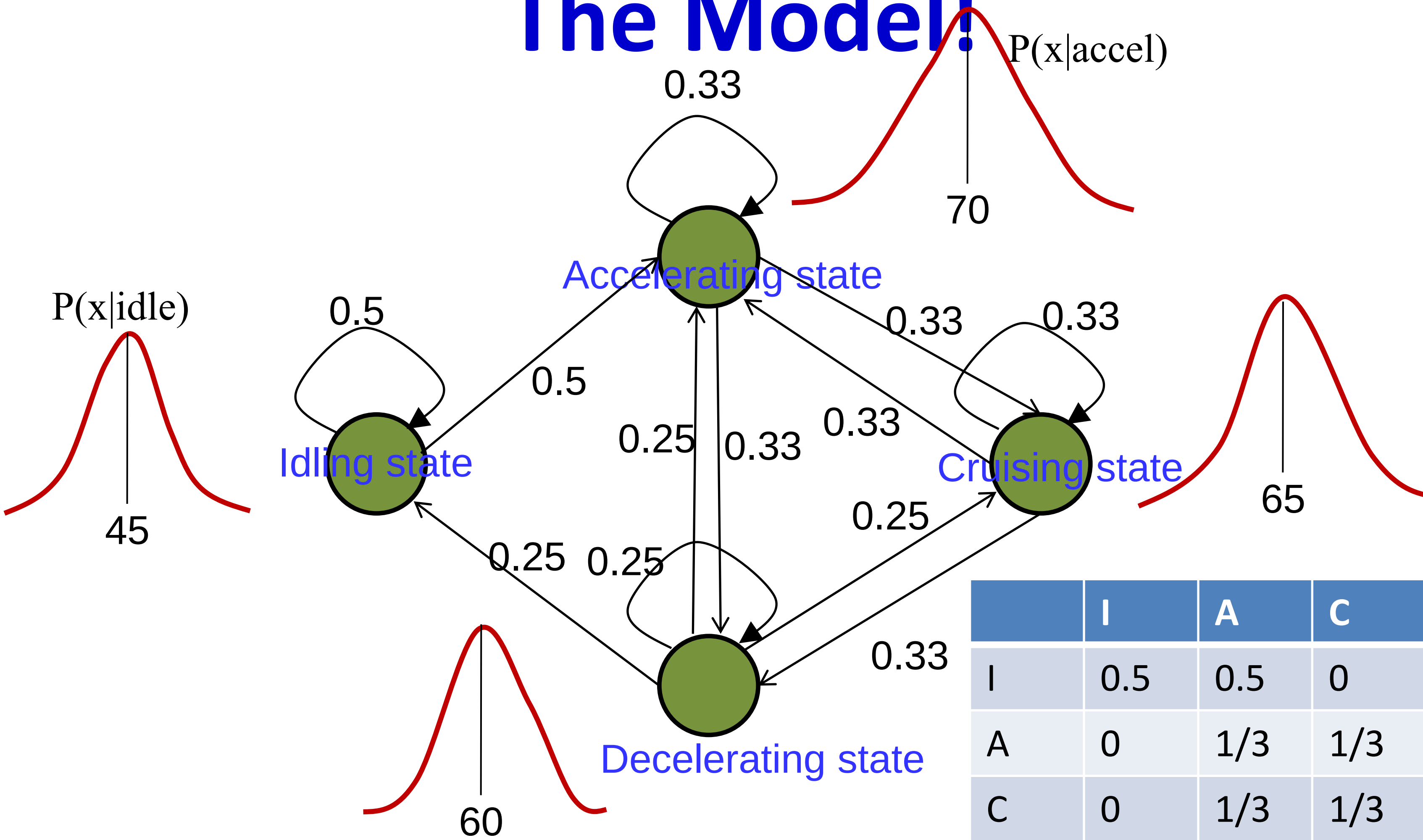
Recap: An automotive example

- Determine automatically, by only *listening* to a running automobile, if it is:
  - Idling; or
  - Travelling at constant velocity; or
  - Accelerating; or
  - Decelerating
- Assume (for illustration) that we only record energy level (SPL) in the sound
  - The SPL is measured once per second

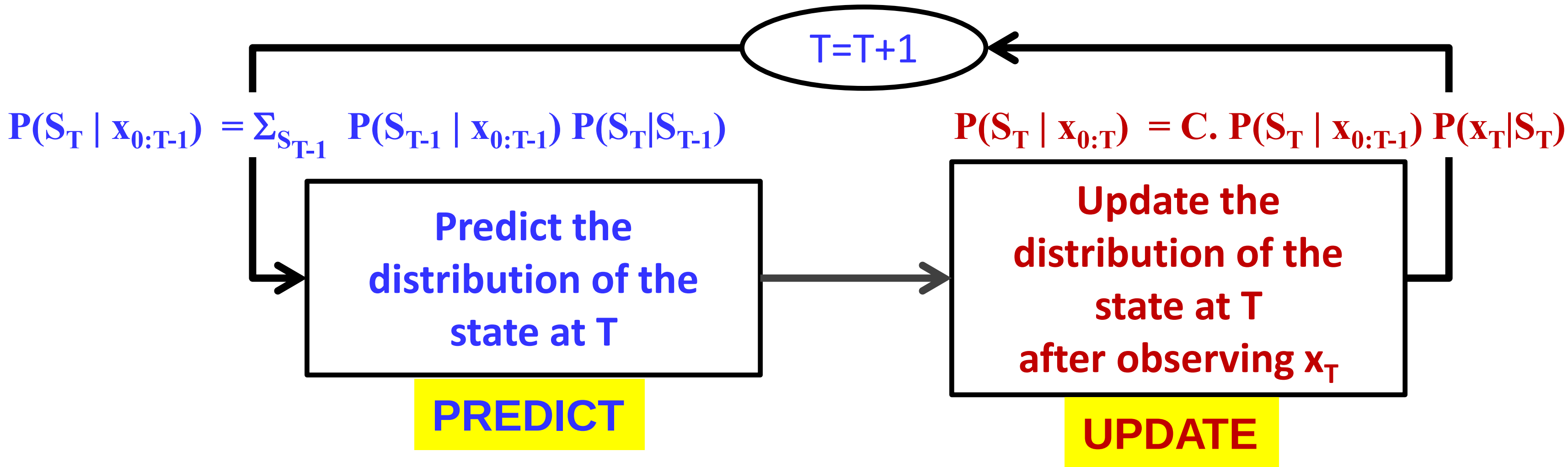
The Model!



	I	A	C	D
I	0.5	0.5	0	0
A	0	1/3	1/3	1/3
C	0	1/3	1/3	1/3
D	0.25	0.25	0.25	0.25

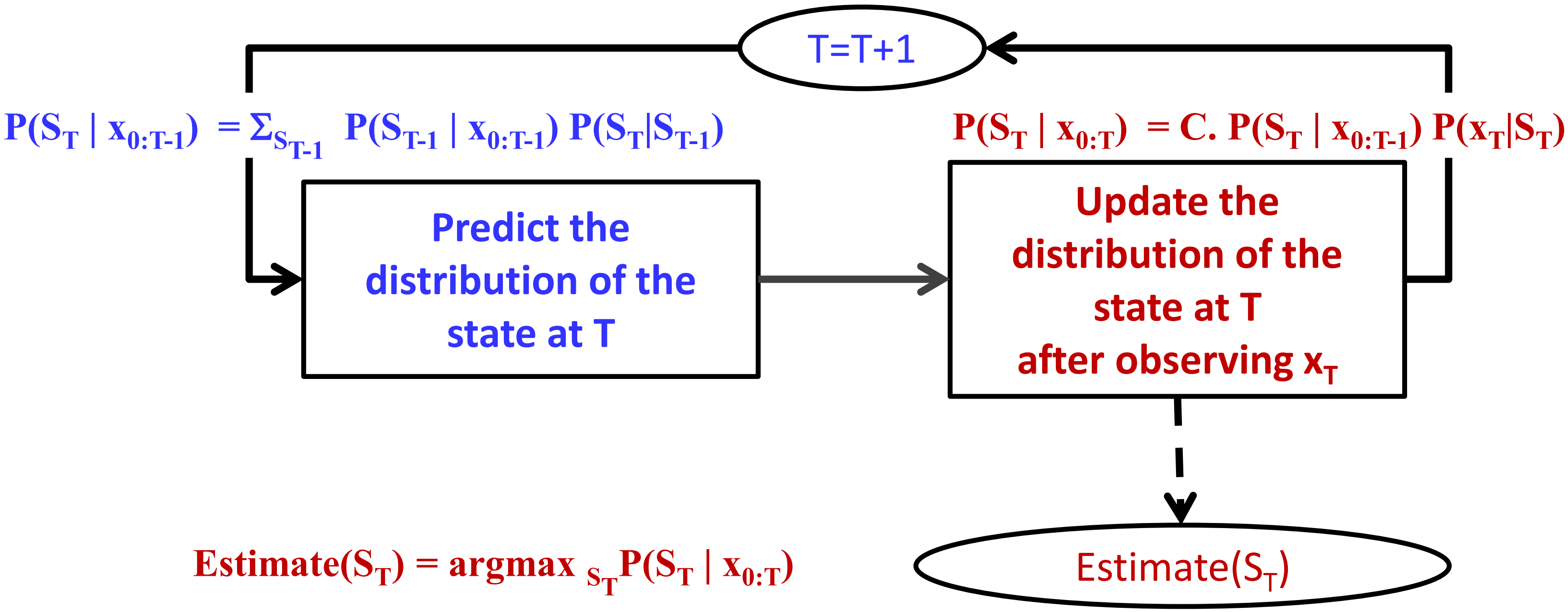
- The state-space model
  - Assuming all transitions from a state are equally probable

Overall procedure



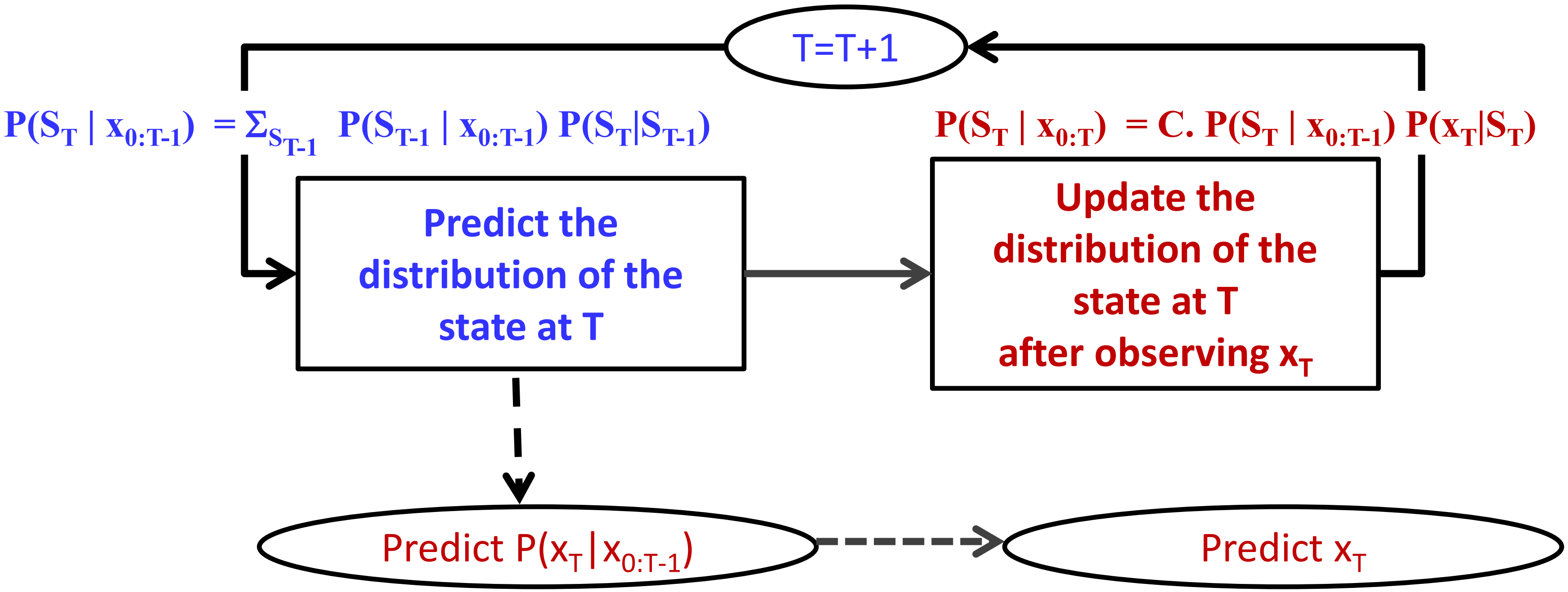
- At T=0 the predicted state distribution is the initial state probability
- At each time T, the current estimate of the distribution over states considers *all* observations $x_0 \ldots x_T$
  - A natural outcome of the Markov nature of the model
- The prediction+update is identical to the forward computation for HMMs to within a normalizing constant

Estimating the *state*



- The state is estimated from the updated distribution
  - The updated distribution is propagated into time, not the state

Predicting the *next observation*



- The probability distribution for the observations at the next time is a mixture:
  - $P(x_T|x_{0:T-1}) = \Sigma_{S_T} P(x_T|S_T)\, P(S_T|x_{0:T-1})$
- The actual observation can be predicted from $P(x_T|x_{0:T-1})$

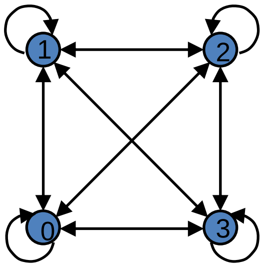
Continuous state system

$$s_t = f(s_{t-1}, \varepsilon_t)$$

$$o_t = g(s_t, \gamma_t)$$

- The state is a continuous valued parameter that is not directly seen
  - The state is the position of navlab or the star
- The observations are dependent on the state and are the only way of knowing about the state
  - Sensor readings (for navlab) or recorded image (for the telescope)

Discrete vs. Continuous State Systems



$$s_t = f(s_{t-1}, \varepsilon_t)$$

$$o_t = g(s_t, \gamma_t)$$

Prediction at time t:

$$P(s_t \mid O_{0:t-1}) = \sum_{s_{t-1}} P(s_{t-1} \mid O_{0:t-1}) P(s_t \mid s_{t-1})$$

$$P(s_t \mid O_{0:t-1}) = \int_{-\infty}^{\infty} P(s_{t-1} \mid O_{0:t-1}) P(s_t \mid s_{t-1}) ds_{t-1}$$

Update after O_t:

$$P(s_t \mid O_{0:t}) = C P(s_t \mid O_{0:t-1}) P(O_t \mid s_t)$$

$$P(s_t \mid O_{0:t}) = C P(s_t \mid O_{0:t-1}) P(O_t \mid s_t)$$

Special case: Linear Gaussian model

$$s_t = A_t s_{t-1} + \varepsilon_t$$

$$P(\varepsilon) = \frac{1}{\sqrt{(2\pi)^d |\Theta_\varepsilon|}} \exp\left(-0.5(\varepsilon - \mu_\varepsilon)^T \Theta_\varepsilon^{-1} (\varepsilon - \mu_\varepsilon)\right)$$

$$o_t = B_t s_t + \gamma_t$$

$$P(\gamma) = \frac{1}{\sqrt{(2\pi)^d |\Theta_\gamma|}} \exp\left(-0.5(\gamma - \mu_\gamma)^T \Theta_\gamma^{-1} (\gamma - \mu_\gamma)\right)$$

- A ***linear*** state dynamics equation
  - Probability of state driving term ε is Gaussian
  - Sometimes viewed as a driving term μ_ε and additive zero-mean noise
- A ***linear*** observation equation
  - Probability of observation noise γ is Gaussian
- A_t, B_t and Gaussian parameters assumed known
  - May vary with time

The Linear Gaussian model (KF)

$$P_0(s) = Gaussian(s; \bar{s}, R)$$
$$P(s_t \mid s_{t-1}) = Gaussian(s_t; \mu_\varepsilon + A_t s_{t-1}, \Theta_\varepsilon)$$
$$P(o_t \mid s_t) = Gaussian(o_t; B_t s_t, \Theta_\gamma)$$

$$s_t = A_t s_{t-1} + \varepsilon_t$$
$$o_t = B_t s_t + \gamma_t$$

$$P(s_t \mid o_{0:t-1}) = Gaussian(s; \bar{s}_t, R_t)$$

$$\bar{s}_t = \mu_\varepsilon + A_t \hat{s}_{t-1}$$
$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

$\Updownarrow$

$$P(s_t \mid o_{0:t}) = Gaussian(s; \hat{s}_t, \hat{R}_t)$$

$$\hat{s}_t = \bar{s}_t + R_t B_t^T (B_t R_t B_t^T + \Theta_\gamma)^{-1} (o - B_t \bar{s}_t)$$
$$\hat{R}_t = (I - R_t B_t^T (B_t R_t B_t^T + \Theta_\gamma)^{-1} B_t) R_t$$

- Iterative prediction and update

The Kalman filter

$$s_t = A_t s_{t-1} + \varepsilon_t$$

$$o_t = B_t s_t + \gamma_t$$

- Prediction

$$\bar{s}_t = A_t \hat{s}_{t-1} + \mu_\varepsilon$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

- Update

$$K_t = R_t B_t^T \left(B_t R_t B_t^T + \Theta_\gamma \right)^{-1}$$

$$\hat{s}_t = \bar{s}_t + K_t \left(o_t - B_t \bar{s}_t \right)$$

$$\hat{R}_t = \left(I - K_t B_t \right) R_t$$

The Kalman filter

- Prediction

$$s_t = A_t s_{t-1} + \varepsilon_t$$

$$o_t = B_t s_t + \gamma_t$$

$$\bar{s}_t = A_t \hat{s}_{t-1} + \mu_\varepsilon$$

The *predicted* state at time t is obtained simply by propagating the estimated state at t-1 through the state dynamics equation

$$K_t = R_t B_t^T \left(B_t R_t B_t^T + \Theta_\gamma\right)^{-1}$$

$$\hat{s}_t = \bar{s}_t + K_t\left(o_t - B_t \bar{s}_t\right)$$

$$\hat{R}_t = \left(I - K_t B_t\right) R_t$$

The Kalman filter

- Prediction

$$s_t = A_t s_{t-1} + \varepsilon_t$$

$$\bar{s}_t = A_t \hat{s}_{t-1} + \mu_\varepsilon$$

$$o_t = B_t s_t + \gamma_t$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

The prediction is imperfect. The variance of the predictor = variance of ε_t + variance of As_{t-1}

The two simply add because ε_t is not correlated with st

The Kalman filter

- Prediction

$$s_t = A_t s_{t-1} + \varepsilon_t$$

$$\bar{s}_t = A_t \hat{s}_{t-1} + \mu_\varepsilon$$

$$o_t = B_t s_t + \gamma_t$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

$$\hat{o}_t = B_t \bar{s}_t$$

We can also predict the *observation* from the predicted state using the observation equation

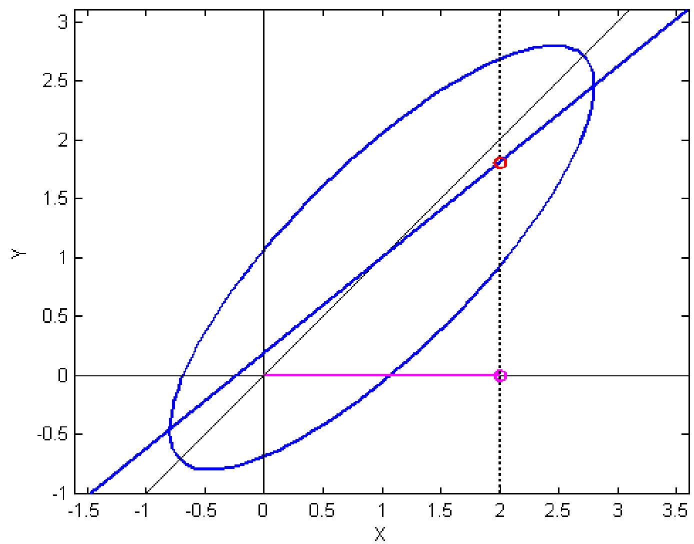
$$\hat{s}_t = \bar{s}_t + K_t(o_t - B_t \bar{s}_t)$$

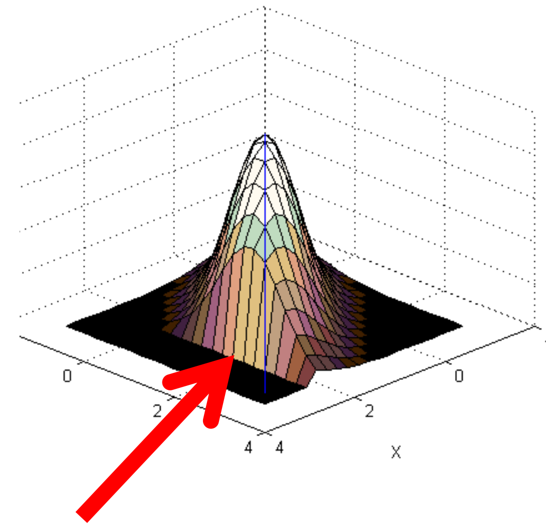
$$\hat{R}_t = (I - K_t B_t) R_t$$

MAP Recap (for Gaussians)

- If P(x,y) is Gaussian:

$$P(\mathbf{x},\mathbf{y}) = N\left(\begin{bmatrix}\mu_{\mathbf{x}} \\ \mu_{\mathbf{y}}\end{bmatrix}, \begin{bmatrix} C_{\mathbf{xx}} & C_{\mathbf{xy}} \\ C_{\mathbf{yx}} & C_{\mathbf{yy}}\end{bmatrix}\right)$$





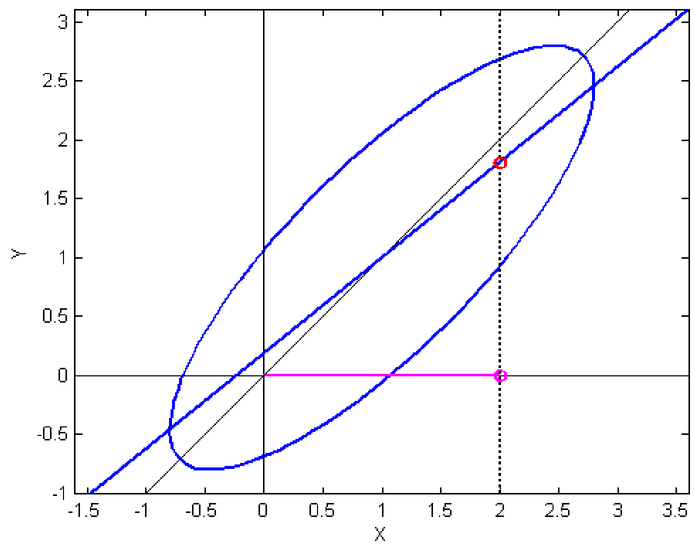
$$P(y \mid x) = N(\mu_y + C_{yx}C_{xx}^{-1}(x-\mu_x), C_{yy} - C_{yx}^{T}C_{xx}^{-1}C_{xy})$$

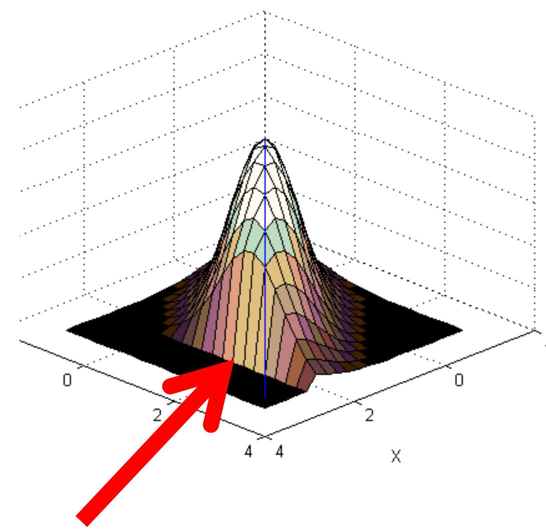
$$\hat{y} = \mu_y + C_{yx}C_{xx}^{-1}(x-\mu_x)$$

MAP Recap: For Gaussians

- If P(x,y) is Gaussian:

$$P(\mathbf{y},\mathbf{x}) = N\left(\begin{bmatrix}\mu_{\mathbf{x}} \\ \mu_{\mathbf{y}}\end{bmatrix}, \begin{bmatrix}C_{\mathbf{xx}} & C_{\mathbf{xy}} \\ C_{\mathbf{yx}} & C_{\mathbf{yy}}\end{bmatrix}\right)$$





$$P(y \mid x) = N(\mu_y + C_{yx}C_{xx}^{-1}(x-\mu_x), C_{yy} - C_{yx}^T C_{xx}^{-1} C_{xy})$$

$$\hat{y} = \mu_y + C_{yx}C_{xx}^{-1}(x-\mu_x)$$

"Slope" of the line

The Kalman filter

$$s_t = A_t s_{t-1} + \varepsilon_t$$

- Prediction

$$\bar{s}_t = A_t \hat{s}_{t-1} + \mu_\varepsilon$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

$$o_t = B_t s_t + \gamma_t$$

- Update

$$K_t = R_t B_t^T \left(B_t R_t B_t^T + \Theta_\gamma \right)^{-1}$$

This is the slope of the MAP estimator that predicts s from o

$RB^T = C_{so}$, $(BRB^T + \Theta) = C_{oo}$

This is also called the **Kalman Gain**

The Kalman filter

$$s_t = A_t s_{t-1} + \varepsilon_t$$

- Prediction

$$\bar{s}_t = A_t \hat{s}_{t-1} + \mu_\varepsilon$$

$$o_t = B_t s_t + \gamma_t$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

We must correct the predicted value of the state after making an observation

$$\hat{s}_t = \bar{s}_t + K_t\left(o_t - B_t \bar{s}_t\right)$$

$$\hat{o}_t = B_t \bar{s}_t$$

The correction is the difference between the *actual* observation and the *predicted* observation, scaled by the Kalman Gain

The Kalman filter

$$s_t = A_t s_{t-1} + \varepsilon_t$$

- Prediction

$$\bar{s}_t = A_t \hat{s}_{t-1} + \mu_\varepsilon$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

$$o_t = B_t s_t + \gamma_t$$

- Update:

The uncertainty in state decreases if we observe the data and make a correction

The reduction is a multiplicative "shrinkage" based on Kalman gain and B

$$\hat{R}_t = (I - K_t B_t) R_t$$

$$\hat{o}_t = B_t \bar{s}_t$$

The Kalman filter

$$s_t = A_t s_{t-1} + \varepsilon_t$$

$$o_t = B_t s_t + \gamma_t$$

- Prediction

$$\bar{s}_t = A_t \hat{s}_{t-1} + \mu_\varepsilon$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

- Update:

$$K_t = R_t B_t^T \left(B_t R_t B_t^T + \Theta_\gamma \right)^{-1}$$

$$\hat{s}_t = \bar{s}_t + K_t \left(o_t - B_t \bar{s}_t \right)$$

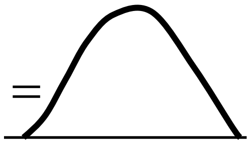
- Update

$$\hat{R}_t = \left(I - K_t B_t \right) R_t$$

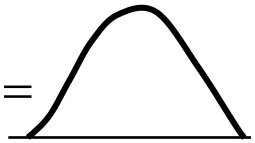
Linear Gaussian Model

$$s_t = A_t s_{t-1} + \varepsilon_t$$

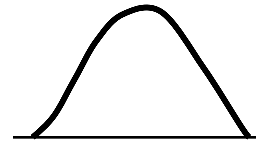
$$o_t = B_t s_t + \gamma_t$$

$P(s) =$ 

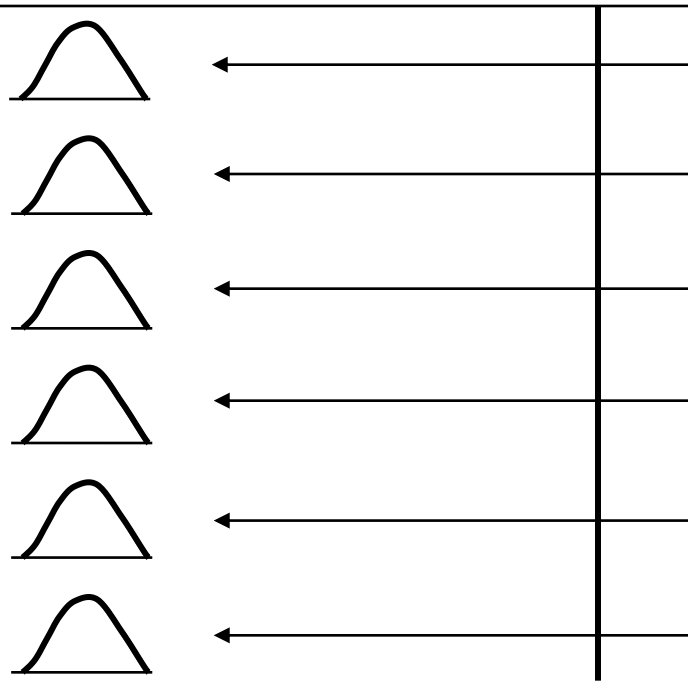
a priori

$P(s_t|s_{t-1}) =$ 

Transition prob.

$P(O_t|s_t) =$ 

State output prob



$P(s_0) = P(s)$

$P(s_0| O_0) = C\, P(s_0)\, P(O_0| s_0)$

$$P(s_1 | O_0) = \int_{-\infty}^{\infty} P(s_0 | O_0) P(s_1 | s_0) ds_0$$

$P(s_1| O_{0:1}) = C\, P(s_1| O_0)\, P(O_1| s_0)$

$$P(s_2 | O_{0:1}) = \int_{-\infty}^{\infty} P(s_1 | O_{0:1}) P(s_2 | s_1) ds_1$$

$P(s_2| O_{0:2}) = C\, P(s_2| O_{0:1})\, P(O_2| s_2)$

All distributions remain Gaussian

Problems

$$s_t = f(s_{t-1}, \varepsilon_t)$$

$$o_t = g(s_t, \gamma_t)$$

- f() and/or g() may not be nice linear functions
  - Conventional Kalman update rules are no longer valid
- ε and/or γ may not be Gaussian
  - Gaussian based update rules no longer valid

Problems

$$s_t = f(s_{t-1}, \varepsilon_t)$$

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The problem with non-linear functions

$$s_t = f(s_{t-1}, \varepsilon_t)$$

$$o_t = g(s_t, \gamma_t)$$

$$P(s_t \mid \mathrm{o}_{0:t\text{-}1}) = \int_{-\infty}^{\infty} P(s_{t-1} \mid \mathrm{o}_{0:t\text{-}1}) P(s_t \mid s_{t-1}) ds_{t-1}$$

$$P(s_t \mid \mathrm{o}_{0:t}) = CP(s_t \mid \mathrm{o}_{0:t\text{-}1}) P(\mathrm{o}_t \mid s_t)$$

- Estimation requires knowledge of $P(o|s)$
  - Difficult to estimate for nonlinear $g()$
  - Even if it can be estimated, may not be tractable with update loop
- Estimation also requires knowledge of $P(s_t|s_{t-1})$
  - Difficult for nonlinear $f()$
  - May not be amenable to closed form integration

The problem with nonlinearity

$$o_t = g(s_t, \gamma_t)$$

- The PDF may not have a closed form

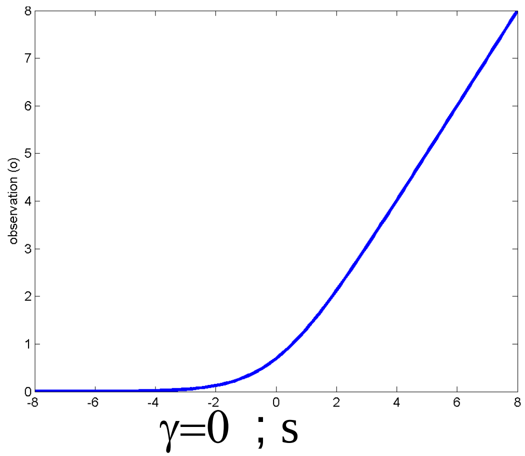
$$P(o_t \mid s_t) = \sum_{\gamma : g(s_t, \gamma) = o_t} \frac{P_\gamma(\gamma)}{\left| J_{g(s_t,\gamma)}(o_t) \right|}$$

$$\left| J_{g(s_t,\gamma)}(o_t) \right| = \begin{vmatrix} \frac{\partial o_t(1)}{\partial \gamma(1)} & \cdots & \frac{\partial o_t(1)}{\partial \gamma(n)} \\ \vdots & \ddots & \vdots \\ \frac{\partial o_t(n)}{\partial \gamma(1)} & \cdots & \frac{\partial o_t(n)}{\partial \gamma(n)} \end{vmatrix}$$

- Even if a closed form exists initially, it will typically become intractable very quickly

Example: a simple nonlinearity

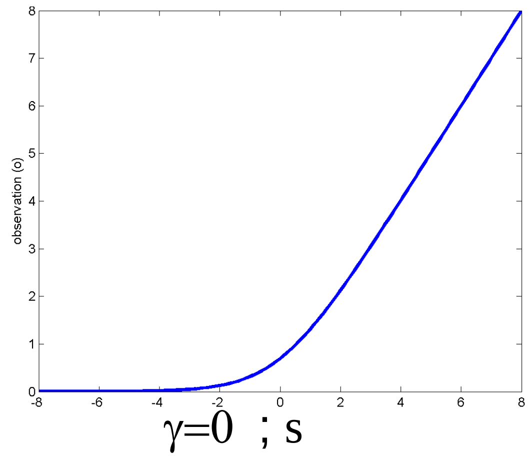
$$o = \gamma + \log(1 + \exp(s))$$



- P(o|s) = ?
  - Assume γ is Gaussian
  - $P(\gamma) = Gaussian(\gamma; \mu_\gamma, \Theta_\gamma)$

Example: a simple nonlinearity

$$o = \gamma + \log(1 + \exp(s))$$



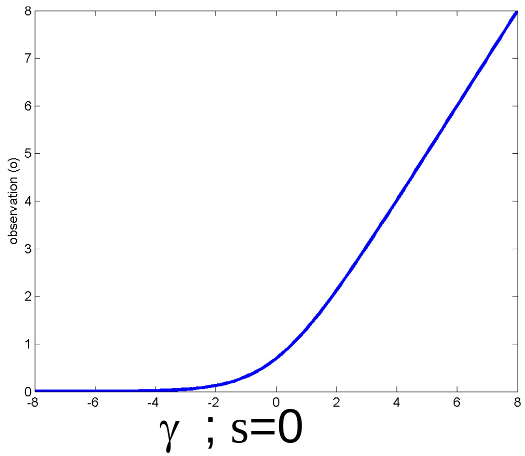
- P(o|s) = ?

$$P(\gamma) = Gaussian(\gamma; \mu_\gamma, \Theta_\gamma)$$

$$P(o \mid s) = Gaussian(o; \mu_\gamma + \log(1 + \exp(s)), \Theta_\gamma)$$

Example: At T=0.

$$o = \gamma + \log(1 + \exp(s))$$



- Assume initial probability P(s) is Gaussian

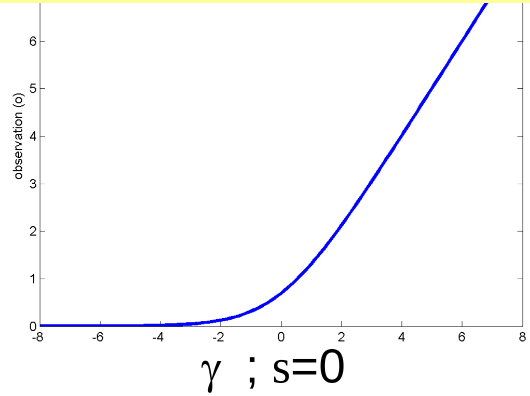
$$P(s_0) = P_0(s) = Gaussian(s; \bar{s}, R)$$

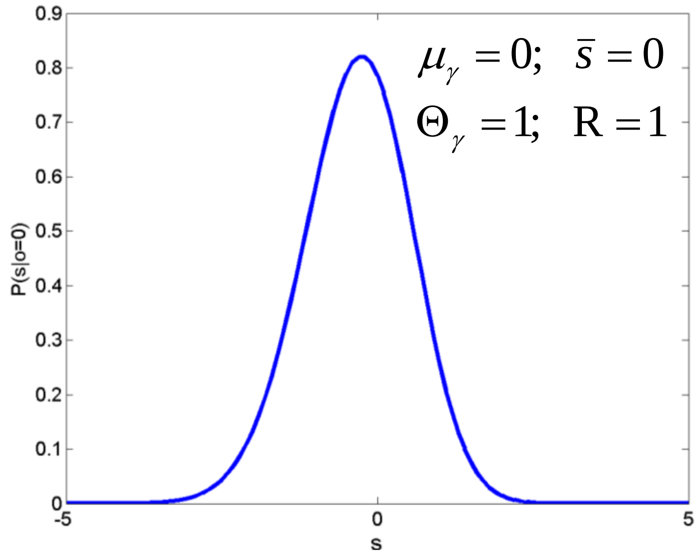
- Update $P(s_0 \mid o_0) = CP(o_0 \mid s_0)P(s_0)$

$$P(s_0 \mid o_0) = CGaussian(o; \mu_\gamma + \log(1 + \exp(s_0)), \Theta_\gamma)Gaussian(s_0; \bar{s}, R)$$

UPDATE: At T=0.

$$o = \gamma + \log(1+\exp(s))$$





$$P(s_0 \mid o_0) = C\,Gaussian(o; \mu_\gamma + \log(1+\exp(s_0)), \Theta_\gamma)\,Gaussian(s_0; \bar{s}, R)$$

$$P(s_0 \mid o_0) = C\exp\begin{pmatrix} -0.5(\mu_\gamma + \log(1+\exp(s_0)) - o)^T \Theta_\gamma^{-1} (\mu_\gamma + \log(1+\exp(s_0)) - o) \\ -0.5(s_0 - \bar{s})^T R^{-1} (s_0 - \bar{s}) \end{pmatrix}$$

- = Not Gaussian

Prediction for T = 1

$$s_t = s_{t-1} + \varepsilon$$

$$P(\varepsilon) = Gaussian(\varepsilon; 0, \Theta_\varepsilon)$$

- Trivial, linear state transition equation

$$P(s_t \mid s_{t-1}) = Gaussian(s_t; s_{t-1}, \Theta_\varepsilon)$$

- Prediction $P(s_1 \mid \mathrm{o}_0) = \int_{-\infty}^{\infty} P(s_0 \mid \mathrm{o}_0) P(s_1 \mid s_0) ds_0$

$$P(s_1 \mid \mathrm{o}_0) = \int_{-\infty}^{\infty} C \exp\begin{pmatrix} -0.5(\mu_\gamma + \log(1+\exp(s_0)) - o)^T \Theta_\gamma^{-1} (\mu_\gamma + \log(1+\exp(s_0)) - o) \\ -0.5(s_0 - \bar{s})^T R^{-1} (s_0 - \bar{s}) \end{pmatrix} \exp\left((s_1 - s_0)^T \Theta_\varepsilon^{-1} (s_1 - s_0)\right) ds_0$$

- = intractable

Update at T=1 and later

- Update at T=1

$$P(s_t \mid \mathrm{o}_{0:t}) = CP(s_t \mid \mathrm{o}_{0:t-1})P(\mathrm{o}_t \mid s_t)$$

  – Intractable

- Prediction for T=2

$$P(s_t \mid \mathrm{o}_{0:t-1}) = \int_{-\infty}^{\infty} P(s_{t-1} \mid \mathrm{o}_{0:t-1})P(s_t \mid s_{t-1})ds_{t-1}$$

  – Intractable

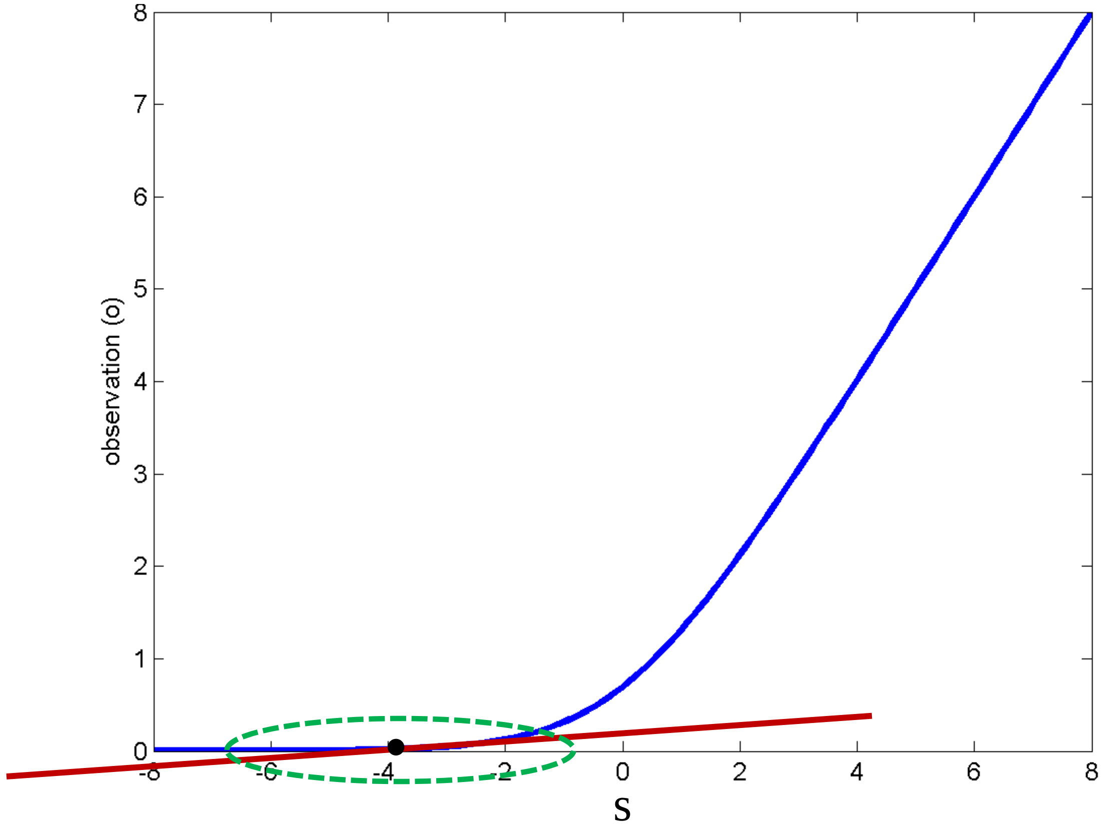
The State prediction Equation

$$s_t = f(s_{t-1}, \varepsilon_t)$$

- Similar problems arise for the state prediction equation

- $P(s_t|s_{t-1})$ may not have a closed form
- Even if it does, it may become intractable within the prediction and update equations
  - Particularly the prediction equation, which includes an integration operation

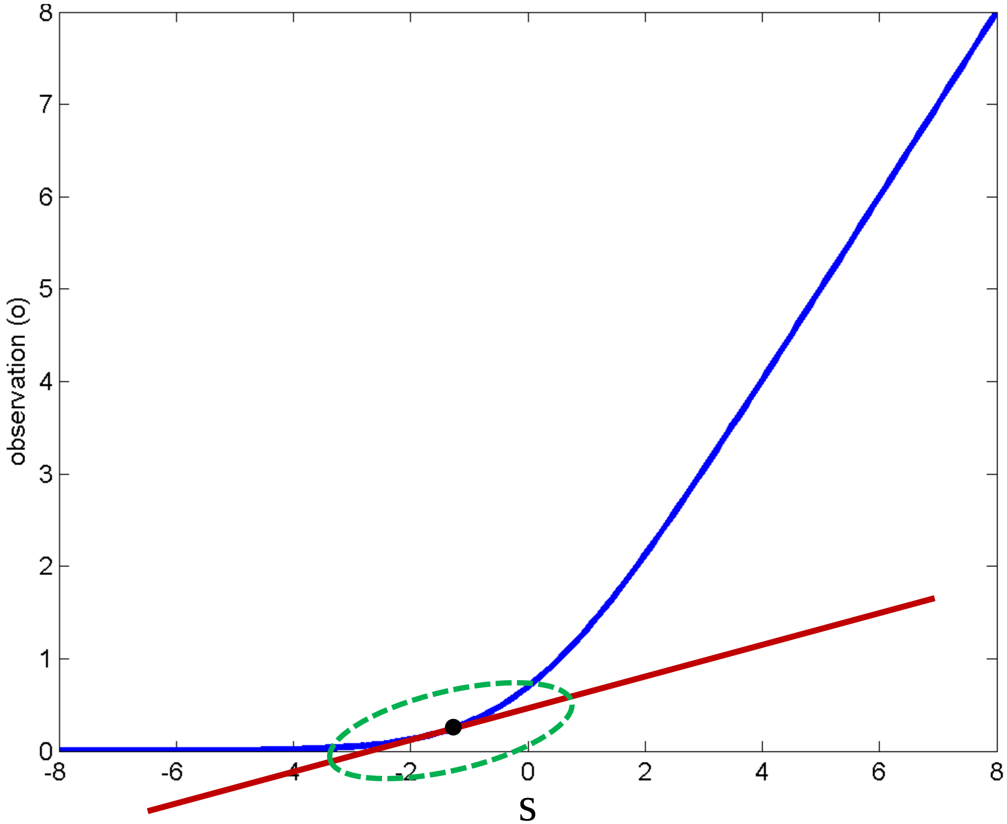
Simplifying the problem: Linearize



$$o = \gamma + \log(1 + \exp(s))$$

- The *tangent* at any point is a good *local* approximation if the function is sufficiently smooth

Simplifying the problem: Linearize



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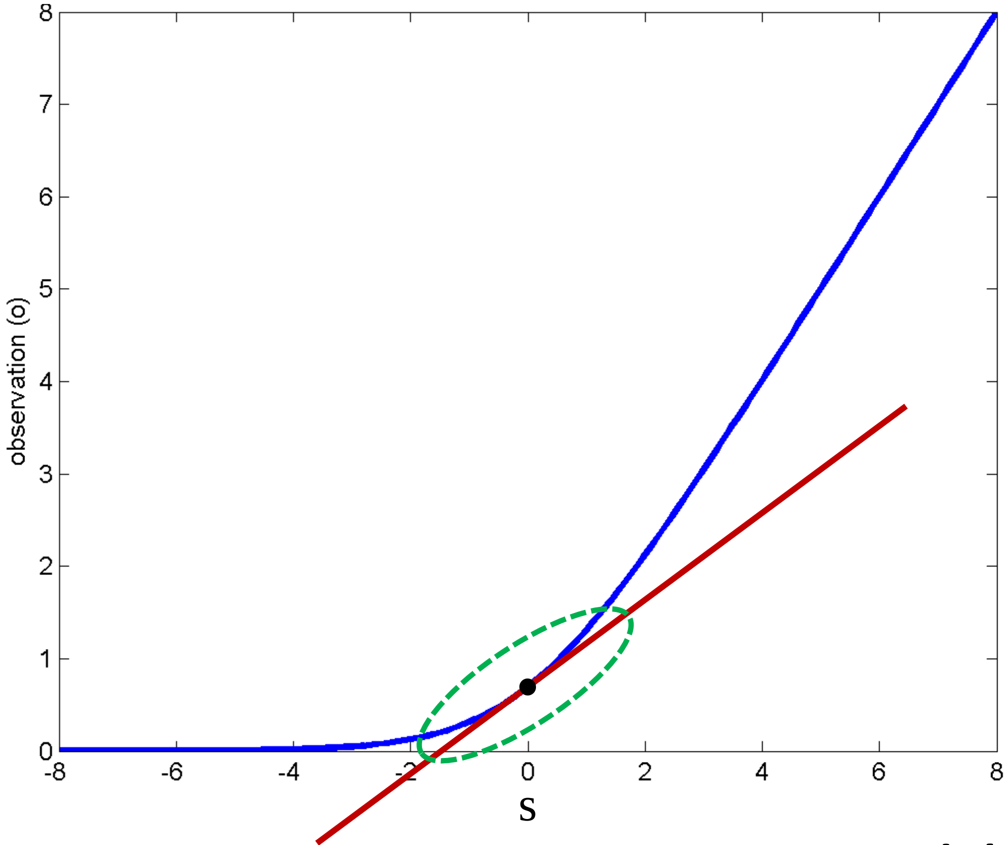

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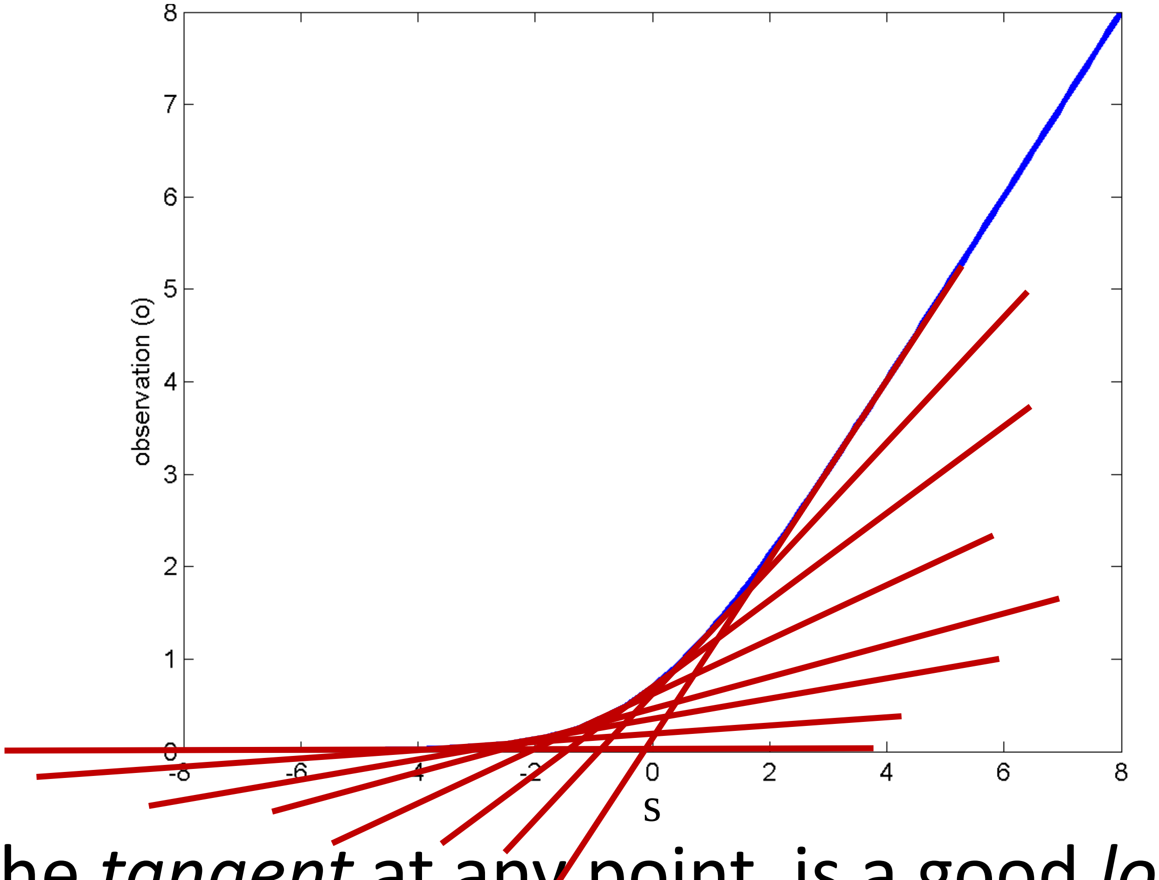
Simplifying the problem: Linearize



- The *tangent* at any point is a good *local* approximation if the function is sufficiently smooth

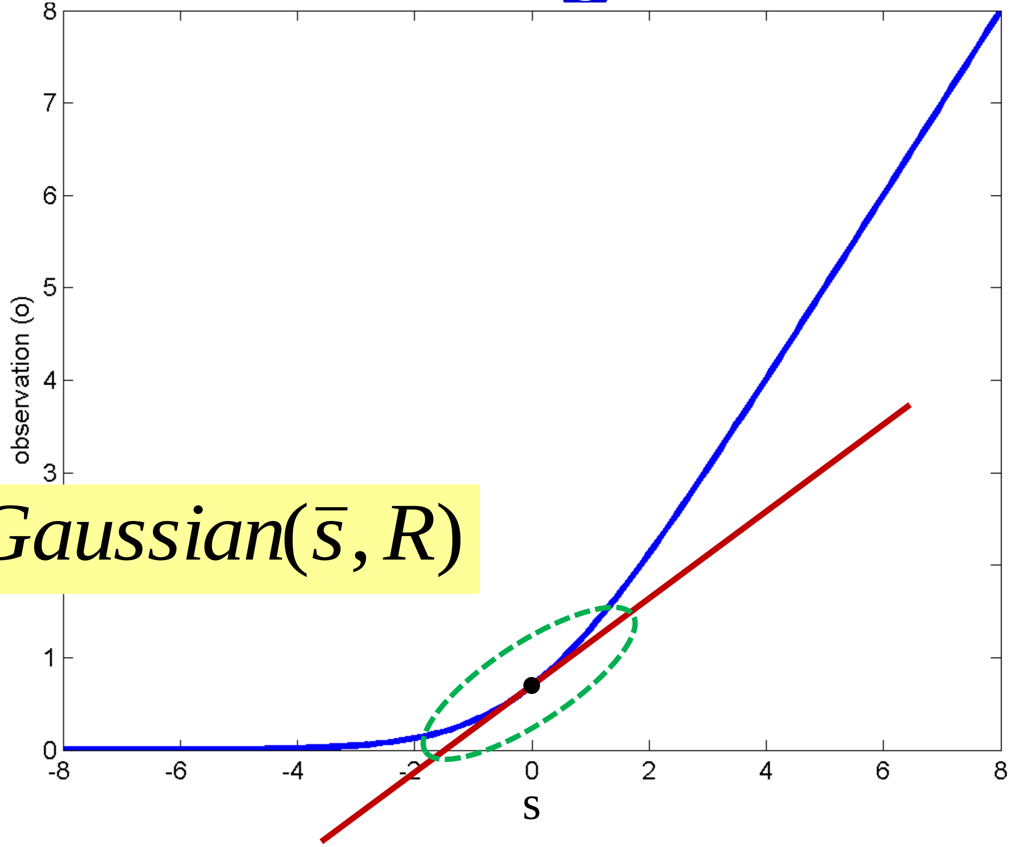
Linearizing the observation function

$$P(s) = Gaussian(\bar{s}, R)$$

$$o = \gamma + g(s) \quad \Rightarrow \quad o \approx \gamma + g(\bar{s}) + J_g(\bar{s})(s - \bar{s})$$

- Simple first-order Taylor series expansion
  - J() is the Jacobian matrix
    - Simply a determinant for scalar state
- Expansion around *a priori* (or predicted) mean of the state

Most probability is in the low-error region



$$P(s) = Gaussian(\bar{s}, R)$$

- P(s) is small approximation error is large
  - Most of the probability mass of *s* is in low-error regions

Linearizing the observation function

$$P(s) = Gaussian(\bar{s}, R)$$

$$o = \gamma + g(s) \quad \Rightarrow \quad o \approx \gamma + g(\bar{s}) + J_g(\bar{s})(s - \bar{s})$$

- Observation PDF is Gaussian

$$P(\gamma) = Gaussian(\gamma; 0, \Theta_\gamma)$$

$$P(o \mid s) = Gaussian(o; g(\bar{s}) + J_g(\bar{s})(s - \bar{s}), \Theta_\gamma)$$

UPDATE.

$$o \approx \gamma + g(\bar{s}) + J_g(\bar{s})(s-\bar{s})$$

$$P(o \mid s) = Gaussian(o; g(\bar{s}) + J_g(\bar{s})(s-\bar{s}), \Theta_\gamma)$$

$$P(s) = Gaussian(s; \bar{s}, R) \quad P(s \mid o) = CP(o \mid s)P(s)$$

$$P(s \mid o) = CGaussian(o; g(\bar{s}) + J_g(\bar{s})(s-\bar{s}), \Theta_\gamma)Gaussian(s; \bar{s}, R)$$

$$P(s \mid o) = Gaussian\left(s; \bar{s} + RJ_g(\bar{s})^T (J_g(\bar{s})RJ_g(\bar{s})^T + \Theta_\gamma)^{-1}(o - g(\bar{s})), \left(I - RJ_g(\bar{s})^T (J_g(\bar{s})RJ_g(\bar{s})^T + \Theta_\gamma)^{-1} J_g(\bar{s})\right)R\right)$$

- **Gaussian!!**
  - **Note: This is actually only an approximation**

Prediction?

$$s_t = f(s_{t-1}) + \varepsilon \qquad P(\varepsilon) = Gaussian(\varepsilon; 0, \Theta_\varepsilon)$$

- Again, direct use of f() can be disastrous

- Solution: Linearize

$$P(s_{t-1} \mid o_{0:t-1}) = Gaussian(s_{t-1}; \hat{s}_{t-1}, \hat{R}_{t-1})$$

$$s_t = f(s_{t-1}) + \varepsilon \Rightarrow s_t \approx \varepsilon + f(\hat{s}_{t-1}) + J_f(\hat{s}_{t-1})(s_{t-1} - \hat{s}_{t-1})$$

- Linearize around the mean of the updated distribution of s at t-1
  - Which should be Gaussian

Prediction

$$s_t = f(s_{t-1}) + \varepsilon \quad \Rightarrow \quad s_t \approx \varepsilon + f(\hat{s}_{t-1}) + J_f(\hat{s}_{t-1})(s_{t-1} - \hat{s}_{t-1})$$

$$P(s_{t-1} \mid o_{0:t-1}) = Gaussian(s_{t-1}; \hat{s}_{t-1}, \hat{R}_{t-1}) \qquad P(\varepsilon) = Gaussian(\varepsilon; 0, \Theta_\varepsilon)$$

- The state transition probability is now:

$$P(s_t \mid s_{t-1}) = Gaussian(s_t; f(\hat{s}_{t-1}) + J_f(\hat{s}_{t-1})(s_{t-1} - \hat{s}_{t-1}), \Theta_\varepsilon)$$

- The predicted state probability is:

$$P(s_t \mid \mathrm{o}_{0:t\text{-}1}) = \int_{-\infty}^{\infty} P(s_{t-1} \mid \mathrm{o}_{0:t\text{-}1}) P(s_t \mid s_{t-1}) ds_{t-1}$$

Prediction

$$P(s_{t-1} \mid o_{0:t-1}) = Gaussian(s_{t-1}; \hat{s}_{t-1}, \hat{R}_{t-1})$$

$$P(s_t \mid s_{t-1}) = Gaussian(s_t; f(\hat{s}_{t-1}) + J_f(\hat{s}_{t-1})(s_{t-1} - \hat{s}_{t-1}), \Theta_\varepsilon)$$

$$P(s_t \mid \mathrm{o}_{0:t\text{-}1}) = \int_{-\infty}^{\infty} P(s_{t-1} \mid \mathrm{o}_{0:t\text{-}1}) P(s_t \mid s_{t-1}) ds_{t-1}$$

$$P(s_t \mid \mathrm{o}_{0:t\text{-}1}) = \int_{-\infty}^{\infty} Gaussian(s_{t-1}; \hat{s}_{t-1}, \hat{R}_{t-1}) Gaussian(s_t; f(\hat{s}_{t-1}) + J_f(\hat{s}_{t-1})(s_{t-1} - \hat{s}_{t-1}), \Theta_\varepsilon) ds_{t-1}$$

- The predicted state probability is:

$$P(s_t \mid \mathrm{o}_{0:t\text{-}1}) = Gaussian\left(s_t; \hat{f}(s_{t-1}), J_f(\hat{s}_{t-1}) \hat{R}_{t-1} J_f(\hat{s}_{t-1})^T + \Theta_\varepsilon\right)$$

- **Gaussian!!**
  - This is actually only an approximation

The linearized prediction/update

$$o_t = g(s_t) + \gamma$$

$$s_t = f(s_{t-1}) + \varepsilon$$

- Given: two non-linear functions for state update and observation generation
- Note: the equations are *deterministic* non-linear functions of the state variable
  - They are *linear* functions of the noise!
  - Non-linear functions of stochastic noise are slightly more complicated to handle

Linearized Prediction and Update

- Prediction for time t

$$P(s_t \mid \mathrm{o}_{0:t-1}) = Gaussian\left(s_t; \bar{s}_t, R_t\right)$$

$$\bar{s}_t = f(\hat{s}_{t-1}) \qquad R_t = J_f(\hat{s}_{t-1})\hat{R}_{t-1}J_f(\hat{s}_{t-1})^T + \Theta_\varepsilon$$

- Update at time t

$$P(s_t \mid o_{0:t}) = Gaussian\left(s_t; \hat{s}_t, \hat{R}_t\right)$$

$$\hat{s}_t = \bar{s}_t + R_t J_g(\bar{s}_t)^T \left(J_g(\bar{s}_t) R_t J_g(\bar{s}_t)^T + \Theta_\gamma\right)^{-1}\left(o_t - g(\bar{s}_t)\right)$$

$$\hat{R}_t = \left(I - R_t J_g(\bar{s}_t)^T \left(J_g(\bar{s}_t) R_t J_g(\bar{s}_t)^T + \Theta_\gamma\right)^{-1} J_g(\bar{s}_t)\right) R_t$$

Linearized Prediction and Update

$$A_t = J_f(\hat{s}_{t-1})$$
$$B_t = J_g(\bar{s}_t)$$

- Prediction for time t

$$P(s_t \mid \mathrm{o}_{0:t-1}) = Gaussian\left(s_t; \bar{s}_t, R_t\right)$$

$$\bar{s}_t = f(\hat{s}_{t-1}) \qquad R_t = A_t \hat{R}_{t-1} A_t^T + \Theta_\varepsilon$$

- Update at time t

$$P(s_t \mid o_{0:t}) = Gaussian\left(s_t; \hat{s}_t, \hat{R}_t\right)$$

$$\hat{s}_t = \bar{s}_t + R_t B_t^T (B_t R_t B_t^T + \Theta_\gamma)^{-1} \left(o_t - g(\bar{s}_t)\right)$$
$$\hat{R}_t = \left(I - R_t B_t^T (B_t R_t B_t^T + \Theta_\gamma)^{-1} B_t\right) R_t$$

The Extended Kalman filter

$$A_t = J_f(\hat{s}_{t-1})$$
$$B_t = J_g(\bar{s}_t)$$

- Prediction

$$\bar{s}_t = f(\hat{s}_{t-1})$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

- Update

$$K_t = R_t B_t^T \left(B_t R_t B_t^T + \Theta_\gamma\right)^{-1}$$

$$\hat{s}_t = \bar{s}_t + K_t\left(o_t - g(\bar{s}_t)\right)$$

$$\hat{R}_t = \left(I - K_t B_t\right) R_t$$

The Kalman filter

- Prediction

$$\bar{s}_t = A_t \hat{s}_{t-1} + \mu_\varepsilon$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

- Update

$$K_t = R_t B_t^T \left(B_t R_t B_t^T + \Theta_\gamma \right)^{-1}$$

$$\hat{s}_t = \bar{s}_t + K_t \left(o_t - B_t \bar{s}_t \right)$$

$$\hat{R}_t = \left(I - K_t B_t \right) R_t$$

The Extended Kalman filter

- Prediction

$$\bar{s}_t = f(\hat{s}_{t-1})$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

- Update

$$K_t = R_t B_t^T \left(B_t R_t B_t^T + \Theta_\gamma \right)^{-1}$$

$$\hat{s}_t = \bar{s}_t + K_t \left(o_t - g(\bar{s}_t) \right)$$

$$\hat{R}_t = \left(I - K_t B_t \right) R_t$$

$$s_t = f(s_{t-1}) + \varepsilon$$

$$o_t = g(s_t) + \varepsilon$$

$$A_t = J_f(\hat{s}_{t-1})$$

$$B_t = J_g(\bar{s}_t)$$

The Extended Kalman filter

- Prediction

$$s_t = f(s_{t-1}) + \varepsilon$$

$$o_t = g(s_t) + \varepsilon$$

$$\bar{s}_t = f(\hat{s}_{t-1})$$

The *predicted* state at time t is obtained simply by propagating the estimated state at t-1 through the state dynamics equation

$$K_t = R_t B_t^T (B_t R_t B_t^T + \Theta_\gamma)^{-1}$$

$$\hat{s}_t = \bar{s}_t + K_t\left(o_t - g(\bar{s}_t)\right)$$

$$\hat{R}_t = (I - K_t B_t) R_t$$

The Extended Kalman filter

$$s_t = f(s_{t-1}) + \varepsilon$$

$$o_t = g(s_t) + \varepsilon$$

$$A_t = J_f(\hat{s}_{t-1})$$

- Prediction

$$\bar{s}_t = f(\hat{s}_{t-1})$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

The prediction is imperfect. The variance of the predictor = variance of ε_t + variance of As_{t-1}

A is obtained by linearizing f()

The Extended Kalman filter

$$s_t = f(s_{t-1}) + \varepsilon$$

$$o_t = g(s_t) + \varepsilon$$

- Prediction

$$\bar{s}_t = f(\hat{s}_{t-1})$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

- Update

$$B_t = J_g(\bar{s}_t)$$

$$K_t = R_t B_t^T \left(B_t R_t B_t^T + \Theta_\gamma \right)^{-1}$$

The Kalman gain is the slope of the MAP estimator that predicts s from o

$RB^T = C_{so}$, $(BRB^T + \Theta) = C_{oo}$

B is obtained by linearizing g()

The Extended Kalman filter

- Prediction

$$s_t = f(s_{t-1}) + \varepsilon$$

$$\bar{s}_t = f(\hat{s}_{t-1})$$

$$o_t = g(s_t) + \varepsilon$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

We can also predict the *observation* from the predicted state using the observation equation

$$\hat{s}_t = \bar{s}_t + K_t \left(o_t - g(\bar{s}_t)\right)$$

$$\hat{R}_t = (I - K_t B_t) R_t$$

$$\bar{o}_t = g(\bar{s}_t)$$

The Extended Kalman filter

$$s_t = f(s_{t-1}) + \varepsilon$$

$$o_t = g(s_t) + \varepsilon$$

- Prediction

$$\bar{s}_t = f(\hat{s}_{t-1})$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

We must correct the predicted value of the state after making an observation

$$\hat{s}_t = \bar{s}_t + K_t\left(o_t - g(\bar{s}_t)\right)$$

$$\bar{o}_t = g(\bar{s}_t)$$

The correction is the difference between the *actual* observation and the *predicted* observation, scaled by the Kalman Gain

The Extended Kalman filter

- Prediction

$$s_t = f(s_{t-1}) + \varepsilon$$

$$o_t = g(s_t) + \varepsilon$$

$$\bar{s}_t = f(\hat{s}_{t-1})$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

$$B_t = J_g(\bar{s}_t)$$

The uncertainty in state decreases if we observe the data and make a correction

The reduction is a multiplicative "shrinkage" based on Kalman gain and B

$$\hat{R}_t = (I - K_t B_t) R_t$$

The Extended Kalman filter

$$s_t = f(s_{t-1}) + \varepsilon$$

$$o_t = g(s_t) + \varepsilon$$

$$A_t = J_f(\hat{s}_{t-1})$$

$$B_t = J_g(\bar{s}_t)$$

- Prediction

$$\bar{s}_t = f(\hat{s}_{t-1})$$

$$R_t = \Theta_\varepsilon + A_t \hat{R}_{t-1} A_t^T$$

- Update

$$K_t = R_t B_t^T \left(B_t R_t B_t^T + \Theta_\gamma\right)^{-1}$$

$$\hat{s}_t = \bar{s}_t + K_t\left(o_t - g(\bar{s}_t)\right)$$

$$\hat{R}_t = \left(I - K_t B_t\right) R_t$$

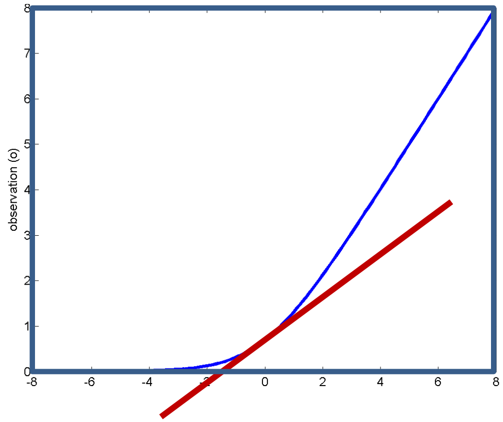
EKFs

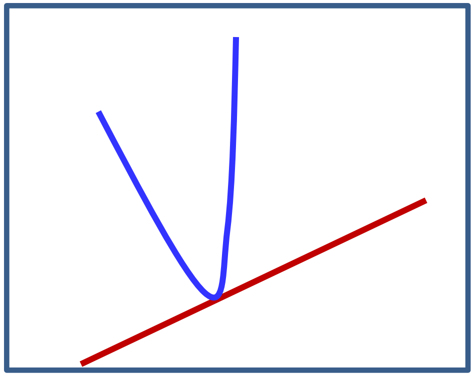
- EKFs are probably the most commonly used algorithm for tracking and prediction
  - Most systems are non-linear
  - Specifically, the relationship between state and observation is usually nonlinear
  - The approach can be extended to include non-linear functions of noise as well

- The term "Kalman filter" often simply refers to an *extended* Kalman filter in most contexts.

- But..

EKFs have limitations





- If the non-linearity changes too quickly with s, the linear approximation is invalid
  - Unstable
- The estimate is often biased
  - The true function lies entirely on one side of the approximation

- Various extensions have been proposed:
  - Invariant extended Kalman filters (IEKF)
  - Unscented Kalman filters (UKF)

A different problem: Non-Gaussian PDFs

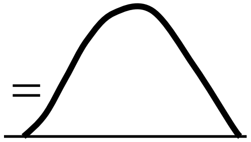
$$o_t = g(s_t) + \gamma \qquad s_t = f(s_{t-1}) + \varepsilon$$

- We have assumed so far that:
  - $P_0(s)$ is Gaussian or can be approximated as Gaussian
  - $P(\varepsilon)$ is Gaussian
  - $P(\gamma)$ is Gaussian
- This has a happy consequence: All distributions remain Gaussian

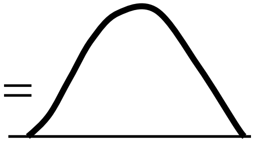
Linear Gaussian Model

$$s_t = A_t s_{t-1} + \varepsilon_t$$

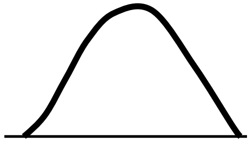
$$o_t = B_t s_t + \gamma_t$$

$P(s) =$ 

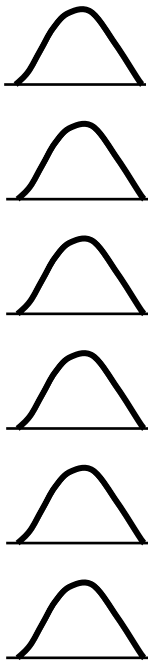
a priori

$P(s_t|s_{t-1}) =$ 

Transition prob.

$P(O_t|s_t) =$ 

State output prob



$P(s_0) = P(s)$

$P(s_0| O_0) = C\, P(s_0)\, P(O_0| s_0)$

$$P(s_1 | O_0) = \int_{-\infty}^{\infty} P(s_0 | O_0) P(s_1 | s_0) ds_0$$

$P(s_1| O_{0:1}) = C\, P(s_1| O_0)\, P(O_1| s_0)$

$$P(s_2 | O_{0:1}) = \int_{-\infty}^{\infty} P(s_1 | O_{0:1}) P(s_2 | s_1) ds_1$$

$P(s_2| O_{0:2}) = C\, P(s_2| O_{0:1})\, P(O_2| s_2)$

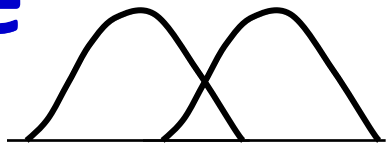
All distributions remain Gaussian

A different problem: Non-Gaussian PDFs

$$o_t = g(s_t) + \gamma \qquad s_t = f(s_{t-1}) + \varepsilon$$

- We have assumed so far that:
  - $P_0(s)$ is Gaussian or can be approximated as Gaussian
  - $P(\varepsilon)$ is Gaussian
  - $P(\gamma)$ is Gaussian
- This has a happy consequence: All distributions remain Gaussian
- But when any of these are not Gaussian, the results are not so happy

A simple case

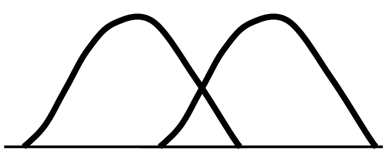


$$o_t = Bs_t + \gamma$$

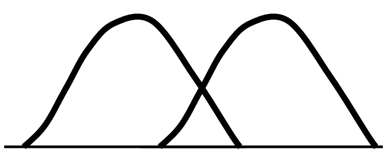
$$P(\gamma) = \sum_{i=0}^{1} w_i Gaussian(\gamma; \mu_i, \Theta_i)$$

- P(γ) is a mixture of only two Gaussians
- *o* is a linear function of *s*
  - Non-linear functions would be linearized anyway
- P(o|s) is also a Gaussian mixture!

$$P(o_t \mid s_t) = P(\gamma = o_t - Bs_t) = \sum_{i=0}^{1} w_i Gaussian(o; \mu_i + Bs_t, \Theta_i)$$

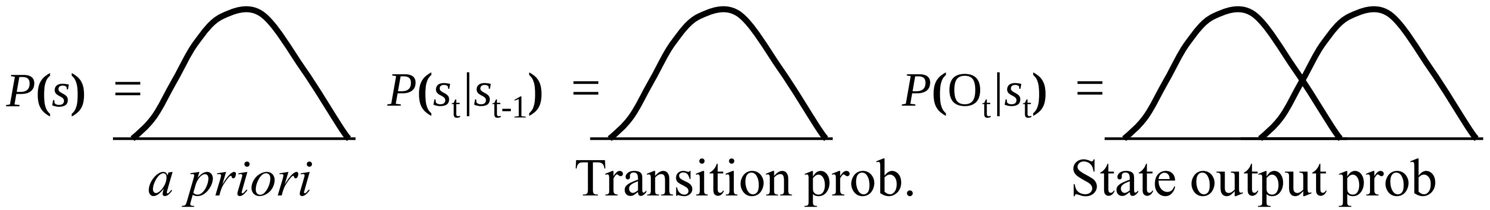


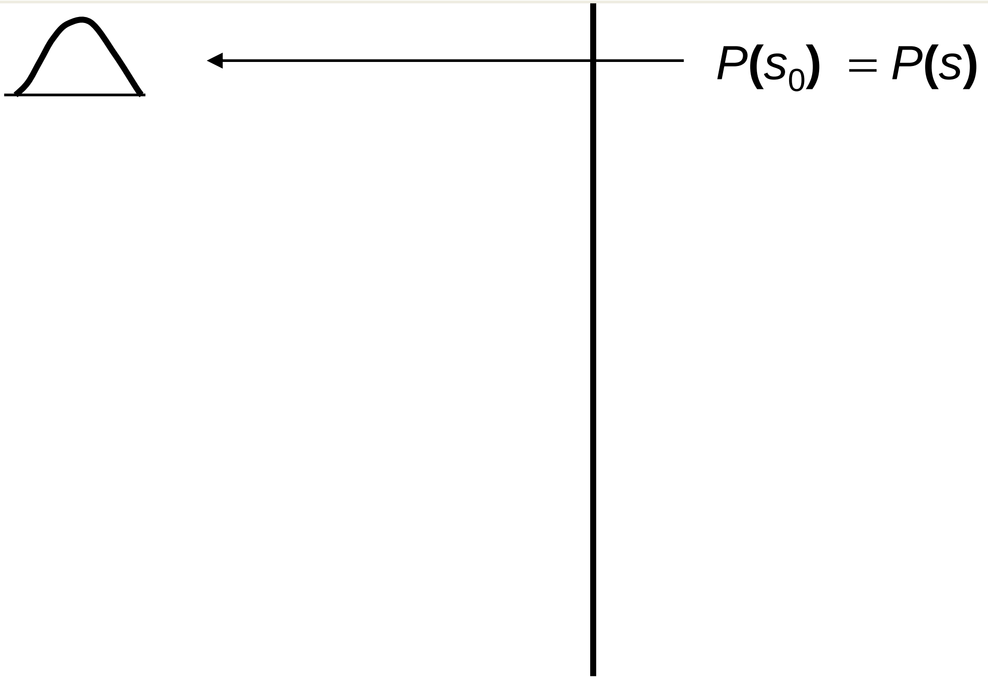
$P(\gamma)$



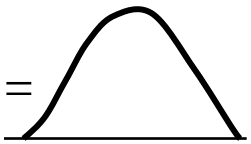
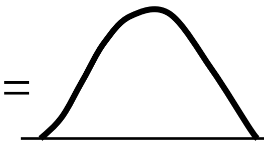
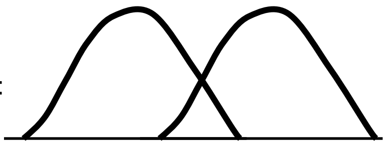
$P(o_t \mid s_t)$

When distributions are not Gaussian

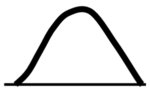




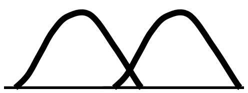
When distributions are not Gaussian

$P(s)$ =  $P(s_t|s_{t-1})$ =  $P(O_t|s_t)$ = 

a priori Transition prob. State output prob

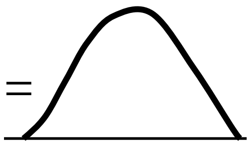
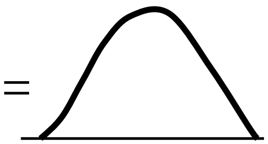
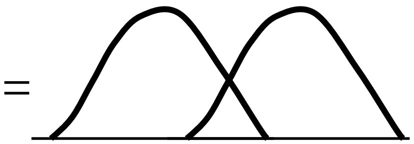


$P(s_0) = P(s)$

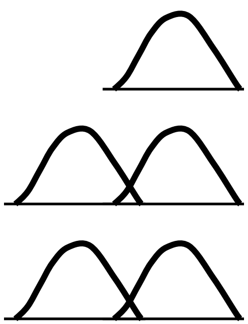


$P(s_0| O_0) = C\, P(s_0)\, P(O_0| s_0)$

When distributions are not Gaussian

$P(s)$ =  $P(s_t|s_{t-1})$ =  $P(O_t|s_t)$ = 

a priori Transition prob. State output prob

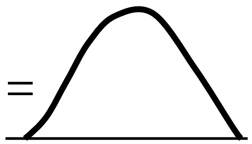


$P(s_0) = P(s)$

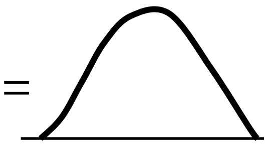
$P(s_0| O_0) = C\, P(s_0)\, P(O_0| s_0)$

$$P(s_1 | O_0) = \int_{-\infty}^{\infty} P(s_0 | O_0) P(s_1 | s_0) ds_0$$

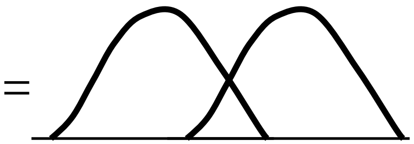
When distributions are not Gaussian

$P(s)$ = 

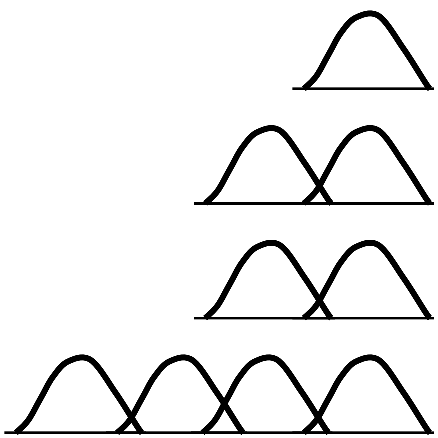
a priori

$P(s_t|s_{t-1})$ = 

Transition prob.

$P(O_t|s_t)$ = 

State output prob



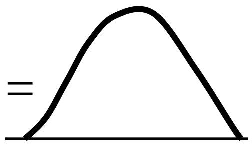
$P(s_0) = P(s)$

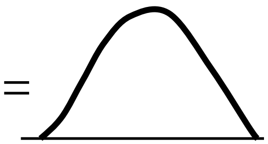
$P(s_0| O_0) = C\, P(s_0)\, P(O_0| s_0)$

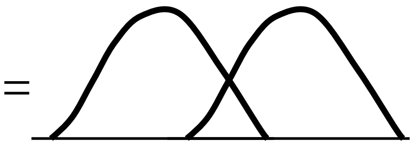
$$P(s_1 | O_0) = \int_{-\infty}^{\infty} P(s_0 | O_0) P(s_1 | s_0) ds_0$$

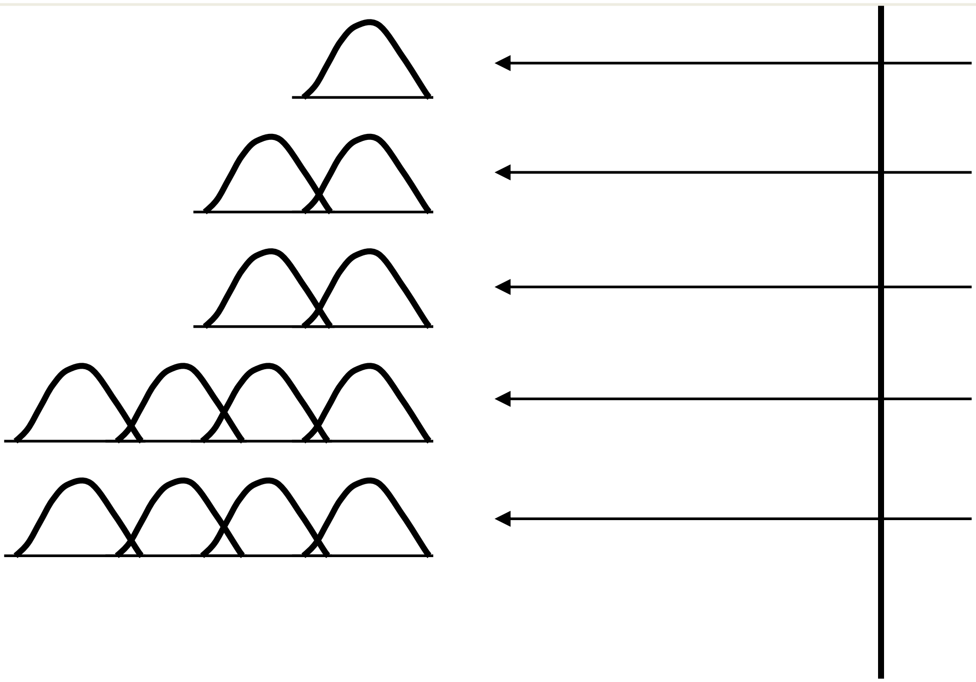
$P(s_1| O_{0:1}) = C\, P(s_1| O_0)\, P(O_1| s_0)$

When distributions are not Gaussian

$P(s)$ =  *a priori*

$P(s_t|s_{t-1})$ =  Transition prob.

$P(O_t|s_t)$ =  State output prob



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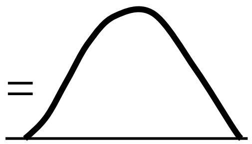
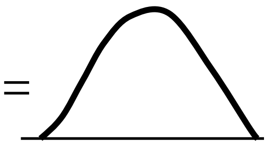
$P(s)$ = 

a priori

$P(s_t|s_{t-1})$ = 

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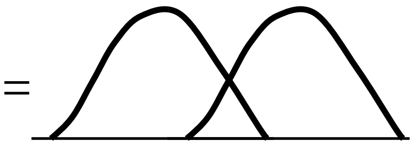
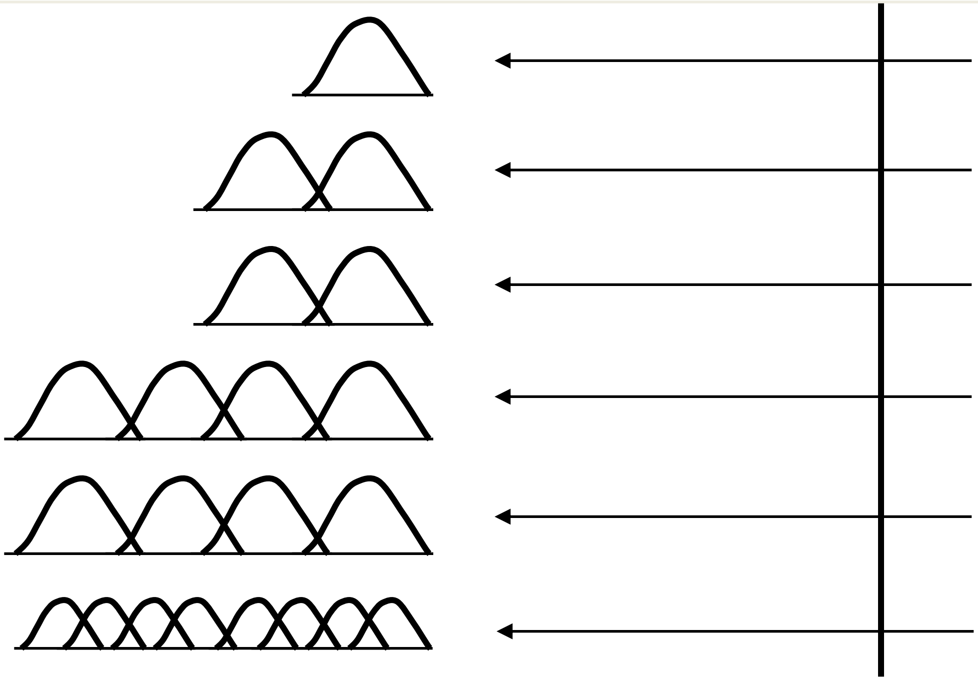
$P(O_t|s_t)$ = 

State output prob



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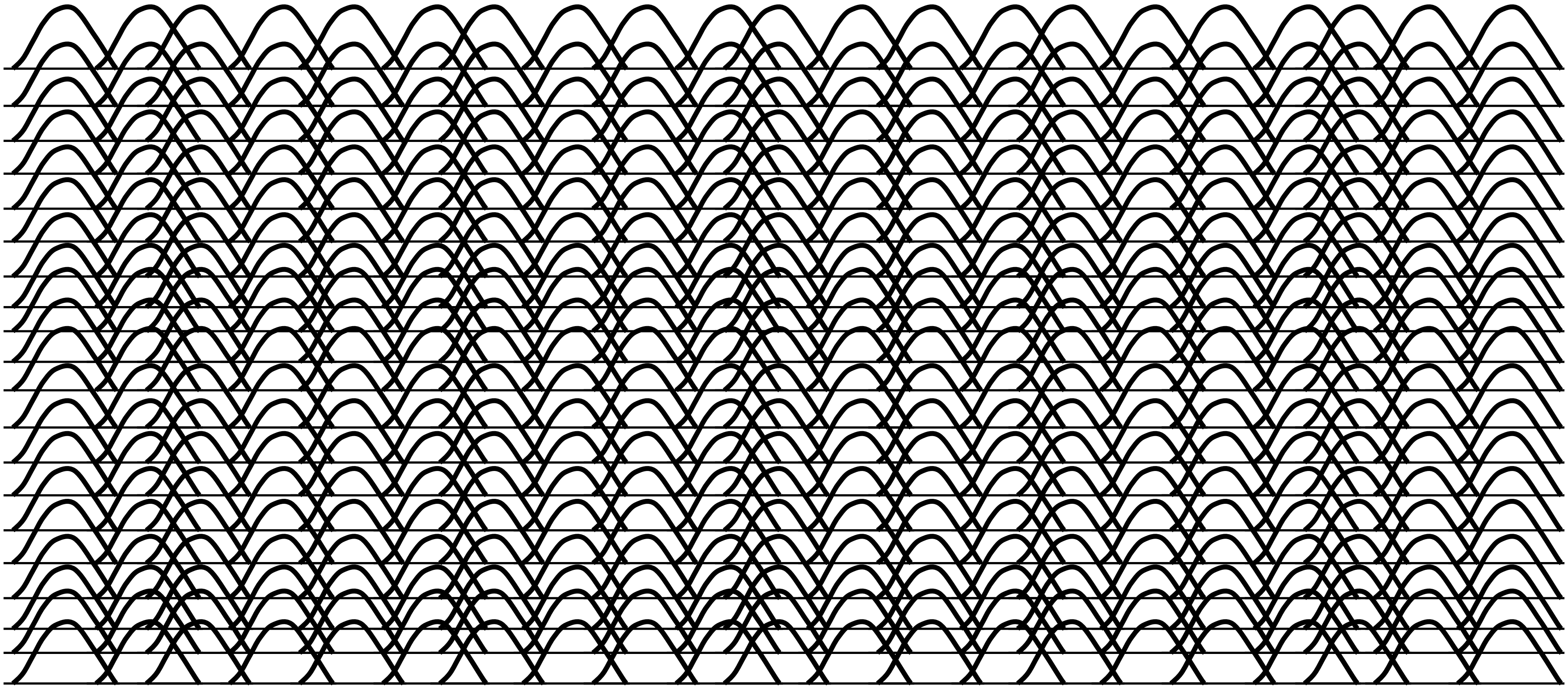
$P(s_2| O_{0:2}) = C\, P(s_2| O_{0:1})\, P(O_2| s_2)$

When $P(O_t|s_t)$ has more than one Gaussian, after only a few time steps…

When distributions are not Gaussian

$$P(s_t \mid \mathrm{O}_{0:\mathrm{t}}) =$$



We have too many Gaussians for comfort..

Related Topic: How to sample from a Distribution?

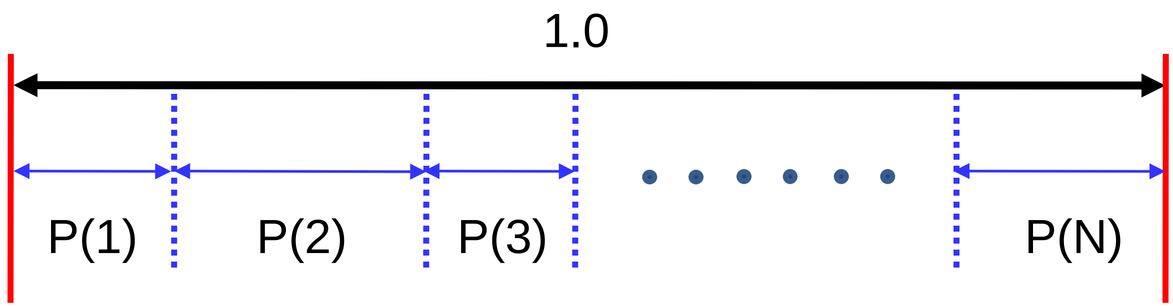
- "Sampling from a Distribution $P(x; \Gamma)$ with parameters Γ"
- Generate random numbers such that
  - The distribution of a large number of generated numbers is $P(x; \Gamma)$
  - The parameters of the distribution are Γ

- Many algorithms to generate RVs from a variety of distributions
  - Generation from a uniform distribution is well studied
  - Uniform RVs used to sample from multinomial distributions
  - Other distributions: Most commonly, transform a uniform RV to the desired distribution

Sampling from a multinomial

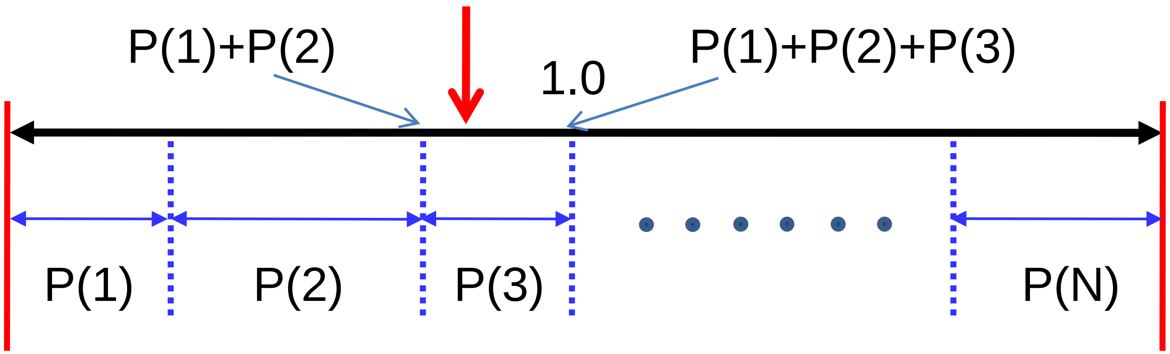
- Given a multinomial over N symbols, with probability of i^{th} symbol = P(i)
- Randomly generate symbols from this distribution
- Can be done by sampling from a uniform distribution

Sampling a multinomial



- Segment a range (0,1) according to the probabilities P(i)
  - The P(i) terms will sum to 1.0

Sampling a multinomial



- Segment a range (0,1) according to the probabilities P(i)
  - The P(i) terms will sum to 1.0
- Randomly generate a number from a uniform distribution
  - Matlab: "rand".
  - Generates a number between 0 and 1 with uniform probability
- If the number falls in the i^{th} segment, select the i^{th} symbol

Related Topic: Sampling from a Gaussian

- Many algorithms
  - Simplest: add many samples from a uniform RV
  - The sum of 12 uniform RVs (uniform in (0,1)) is approximately Gaussian with mean 6 and variance 1
  - For scalar Gaussian, mean μ, std dev σ:

$$x = \sum_{i=1}^{12} r_i - 6$$

- Matlab : $x = \mu + \text{randn} * \sigma$
  - "randn" draws from a Gaussian of mean=0, variance=1

Related Topic: Sampling from a Gaussian

- Multivariate (d-dimensional) Gaussian with mean μ and covariance Θ
  - Compute eigen value matrix Λ and eigenvector matrix E for Θ
    - $\Theta = E \Lambda E^T$
  - Generate d 0-mean unit-variance numbers $x_1..x_d$
  - Arrange them in a vector:

$$X = [x_1 .. x_d]^T$$

  - Multiply X by the square root of Λ and E, add μ

$$Y = \mu + \mathrm{E}\ \mathrm{sqrt}(\Lambda)\ X$$

Sampling from a Gaussian Mixture

$$\sum_i w_i Gaussian(X;\mu_i,\Theta_i)$$

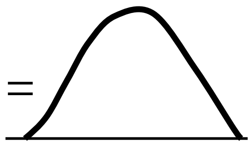
- Select a Gaussian by sampling the multinomial distribution of weights:

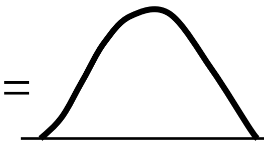
$$j \sim \text{multinomial}(w_1, w_2, \ldots)$$

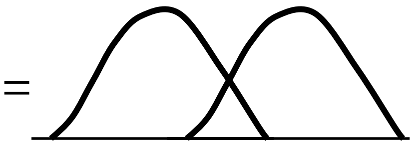
- Sample from the selected Gaussian

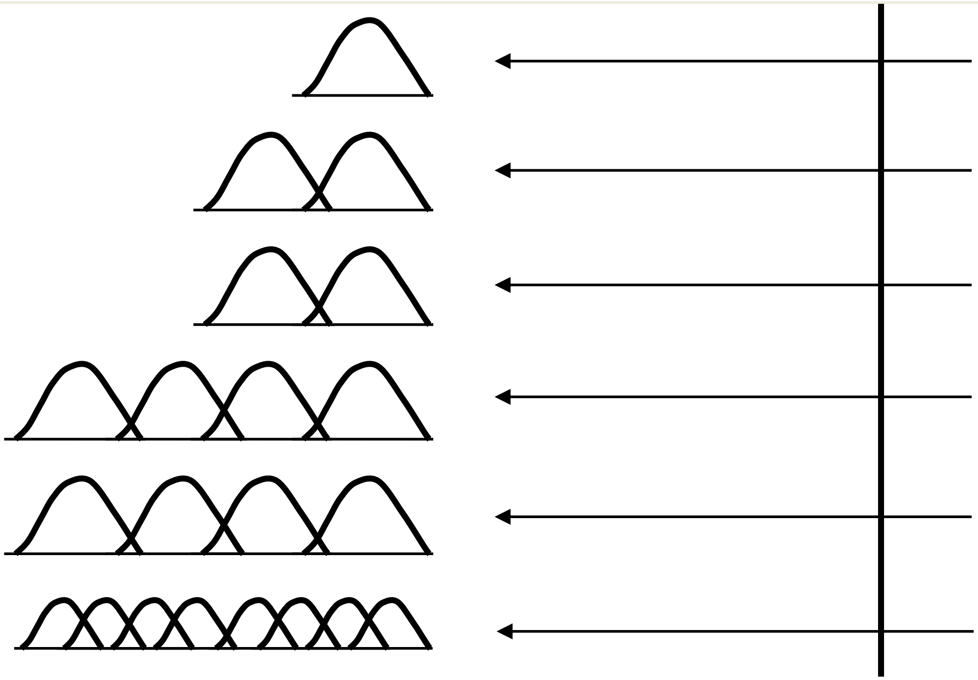
$$Gaussian(X;\mu_j,\Theta_j)$$

When distributions are not Gaussian

$P(s)$ = 
a priori

$P(s_t|s_{t-1})$ = 
Transition prob.

$P(O_t|s_t)$ = 
State output prob



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When $P(O_t|s_t)$ has more than one Gaussian, after only a few time steps…

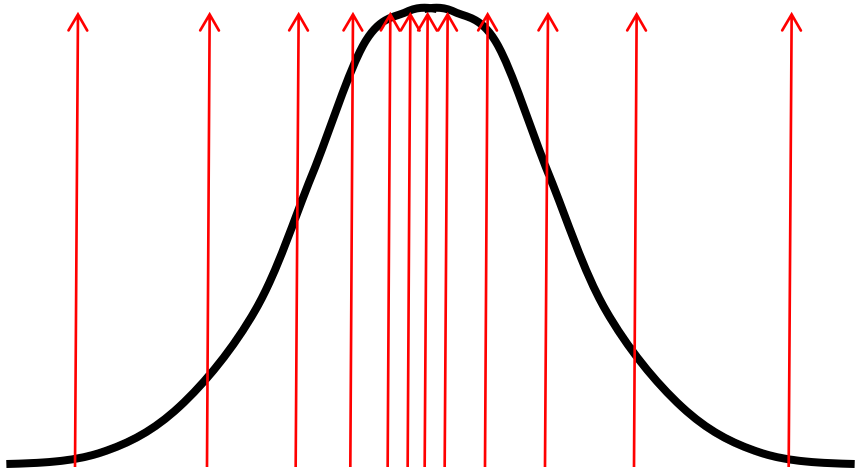
The problem of the exploding distribution

- The complexity of the distribution increases exponentially with time
- This is a consequence of having a *continuous* state space
  - Only Gaussian PDFs propagate without increase of complexity

- *Discrete-state* systems do not have this problem
  - The number of states in an HMM stays fixed
  - However, discrete state spaces are too coarse

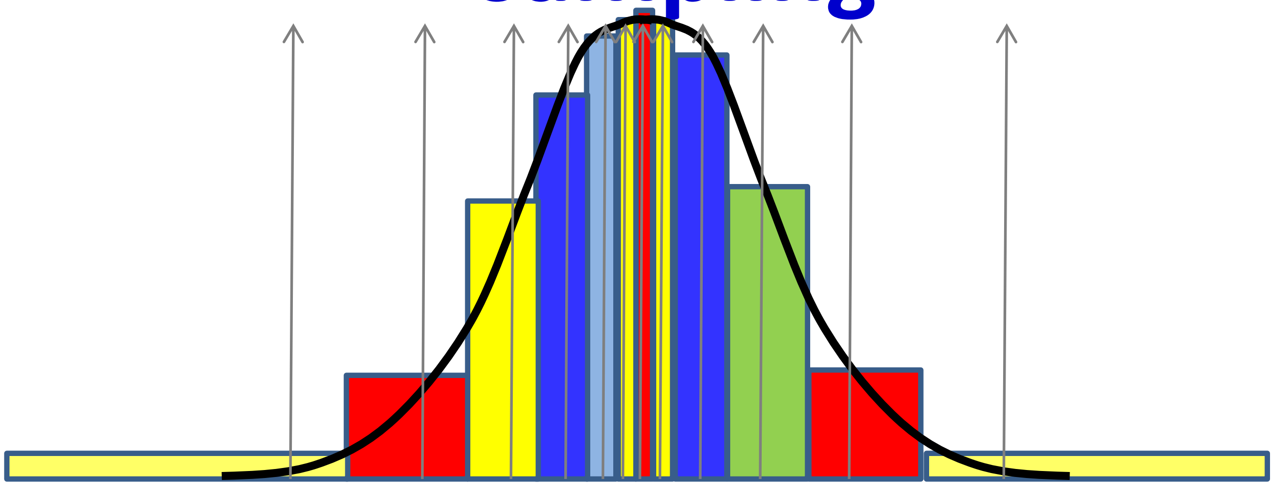
- Solution: Combine the two concepts
  - *Discretize* the state space dynamically

Discrete approximation to a distribution



- A large-enough collection of randomly-drawn samples from a distribution will approximately quantize the space of the random variable into equi-probable regions
  - We have more random samples from high-probability regions and fewer samples from low-probability reigons

Discrete approximation: Random sampling



- A PDF can be approximated as a uniform probability distribution over randomly drawn samples
  - Since each sample represents approximately the same probability mass (1/M if there are M samples)

$$P(x) \approx \frac{1}{M}\sum_{i=0}^{M-1}\delta(x - x_i)$$

Note: Properties of a discrete distribution

$$P(x) \approx \frac{1}{M}\sum_{i=0}^{M-1}\delta(x - x_i)$$

$$P(x)P(y \mid x) \propto \sum_{i=0}^{M-1} P(y \mid x_i)\delta(x - x_i)$$

- The product of a discrete distribution with another distribution is simply a weighted discrete probability

$$P(x) \approx \sum_{i=0}^{M-1} w_i \delta(x - x_i)$$

$$\int_{-\infty}^{\infty} P(x)P(y \mid x)dx = \sum_{i=0}^{M-1} w_i P(y \mid x_i)$$

- The integral of the product is a mixture distribution

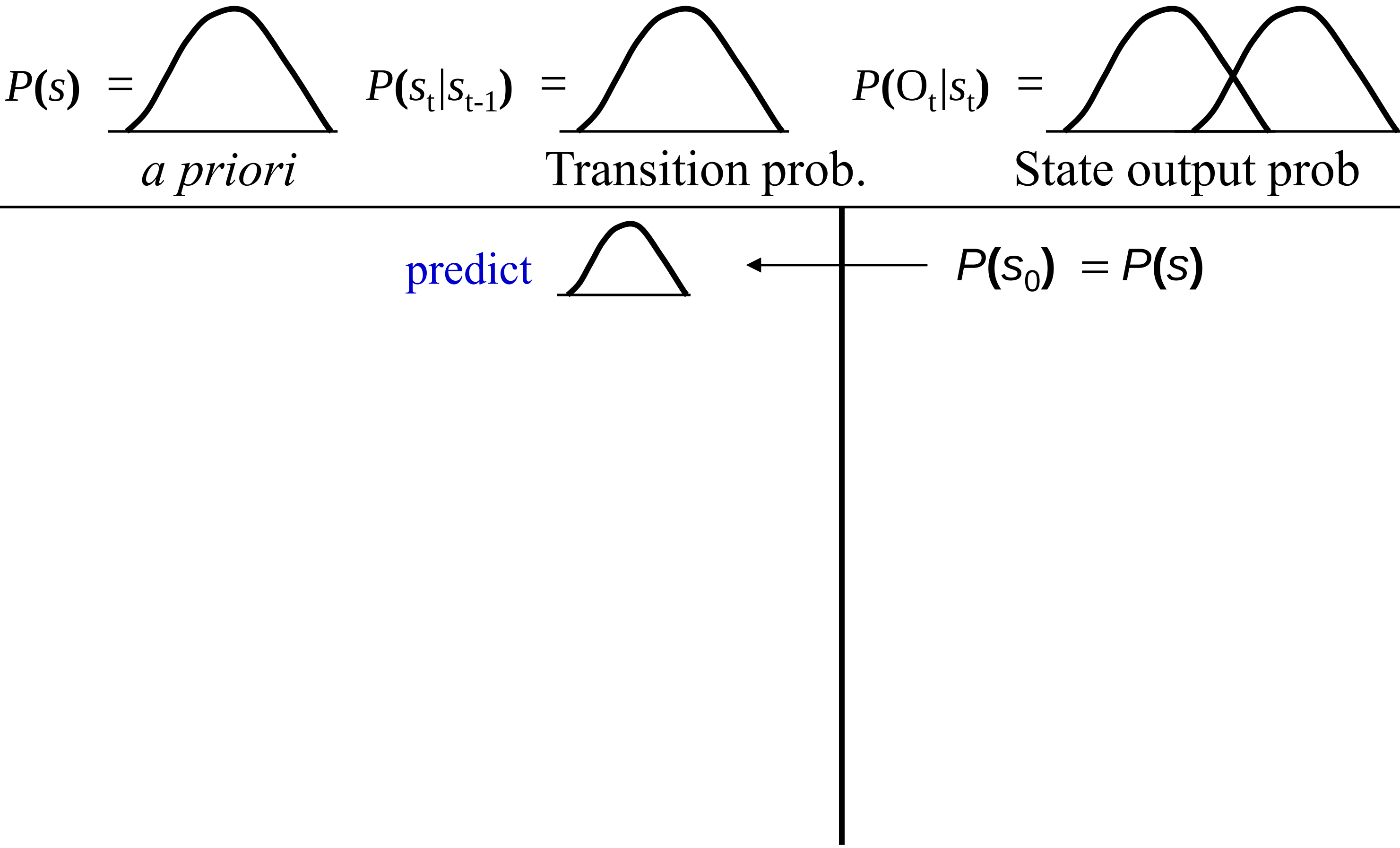
Discretizing the state space

- At each time, discretize the predicted state space

$$P(s_t \mid o_{0:t}) \approx \frac{1}{M} \sum_{i=0}^{M-1} \delta(s_t - s_i)$$

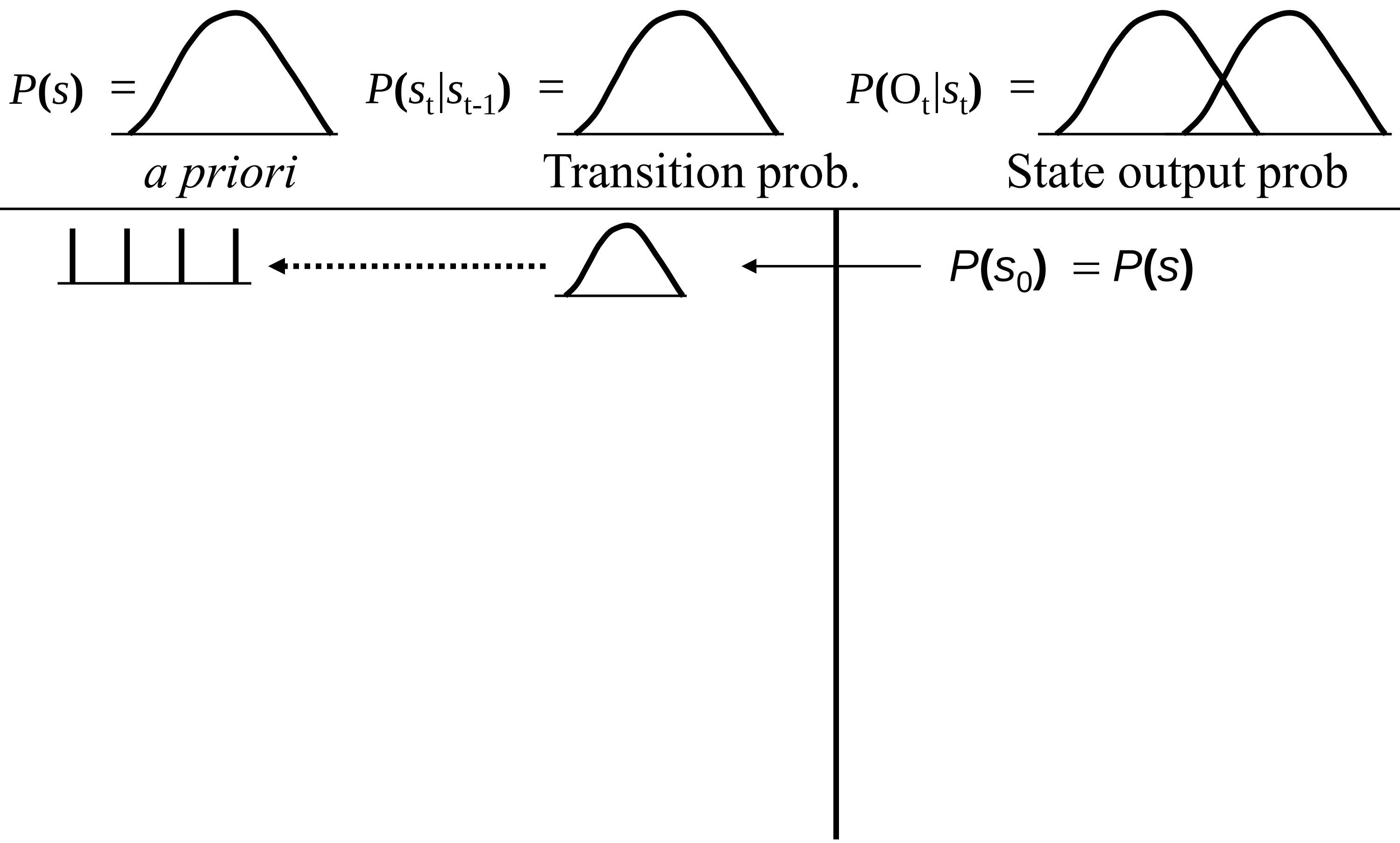
  - s_i are randomly drawn samples from $P(s_t|o_{0:t})$
- Propagate the discretized distribution

Particle Filtering



Assuming that we only generate ***FOUR*** samples from the predicted distributions

Particle Filtering



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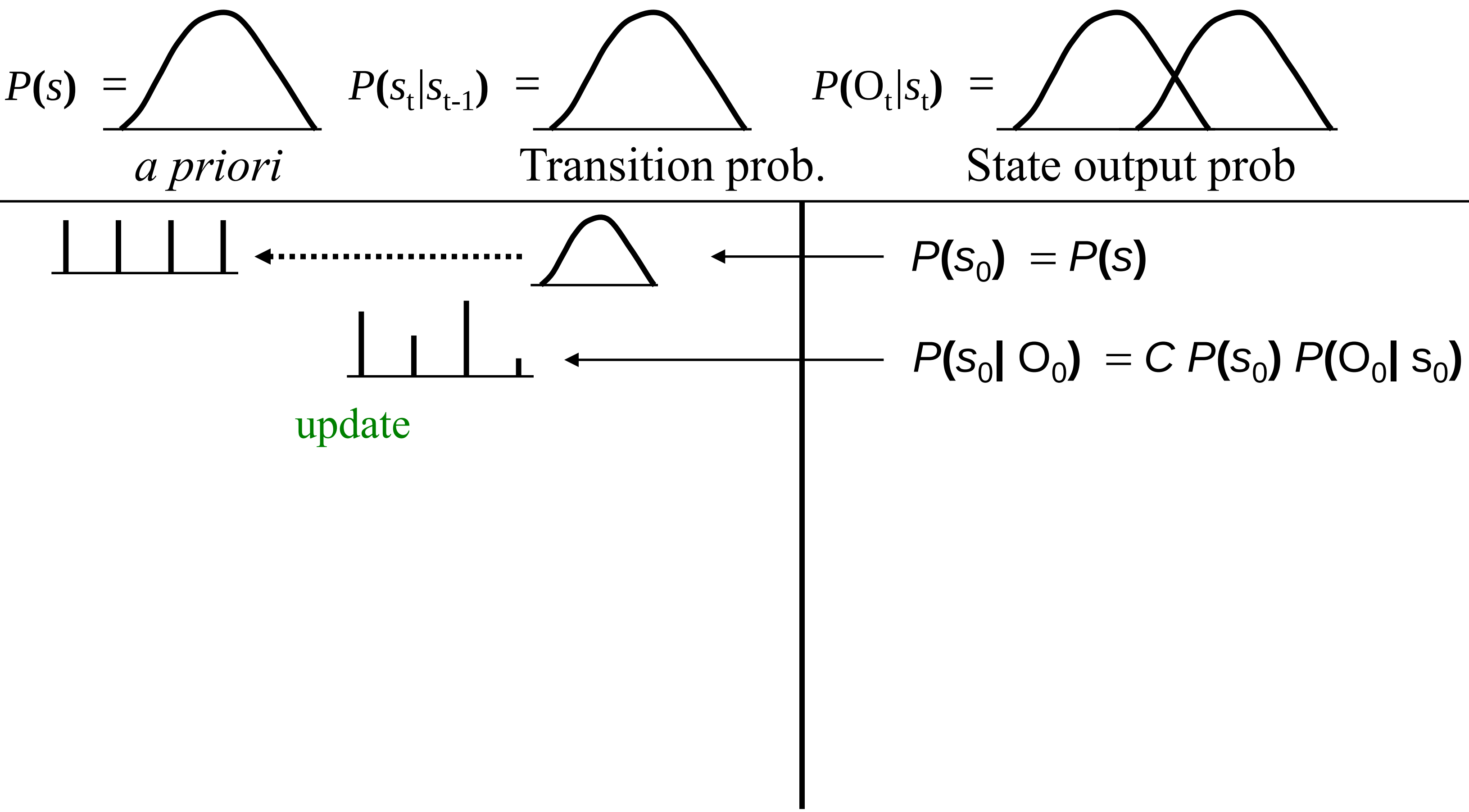

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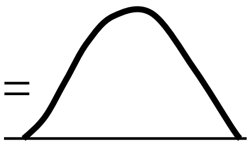
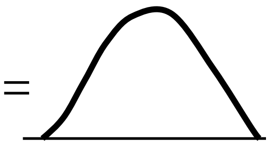
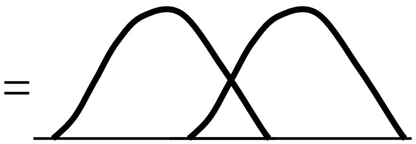
$P(s) =$ 

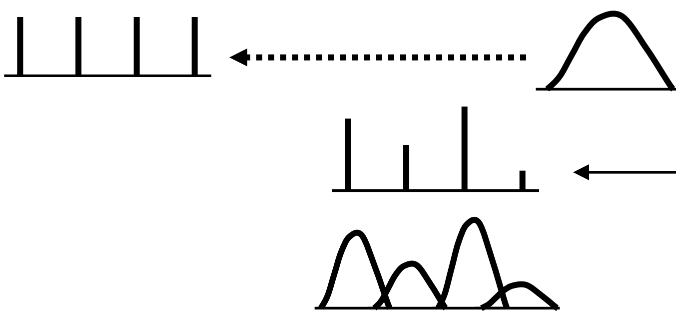
a priori

$P(s_t|s_{t-1}) =$ 

Transition prob.

$P(O_t|s_t) =$ 

State output prob



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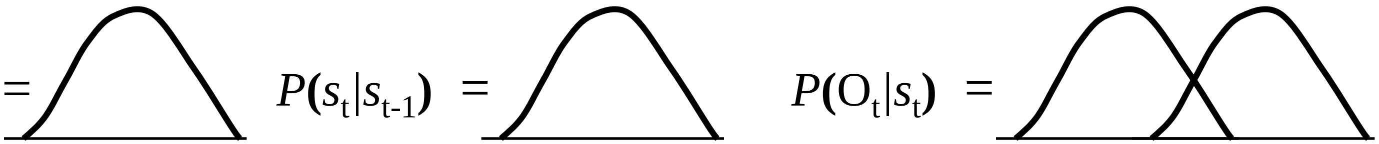
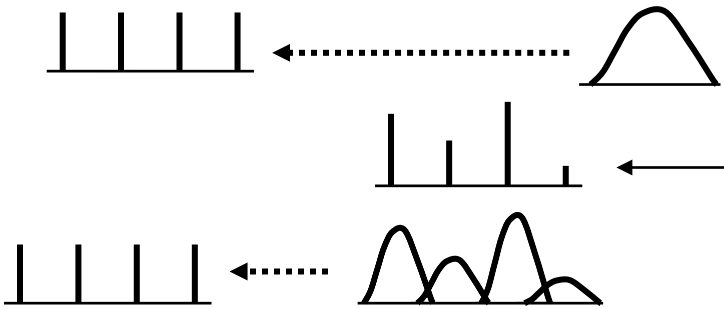
predict

Assuming that we only generate ***FOUR*** samples from the predicted distributions

Particle Filtering

$P(s) =$  $P(s_t|s_{t-1}) =$ $P(O_t|s_t) =$

a priori — Transition prob. — State output prob



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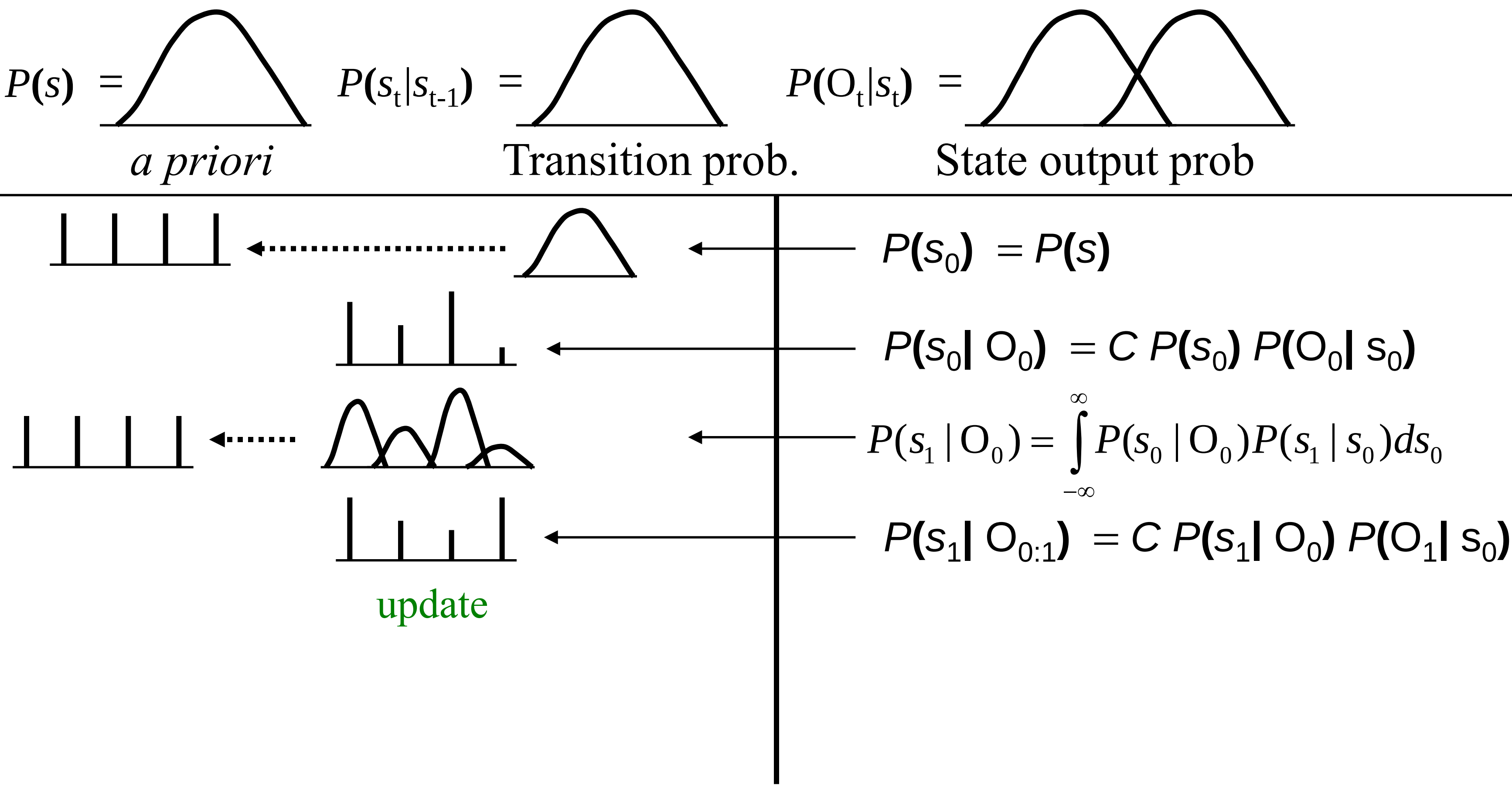

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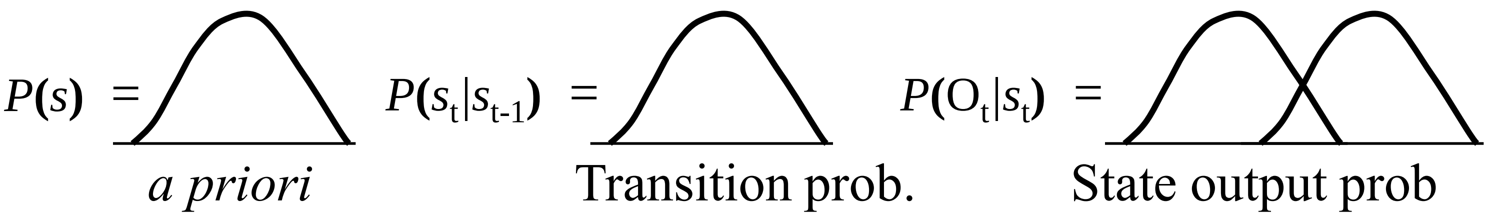

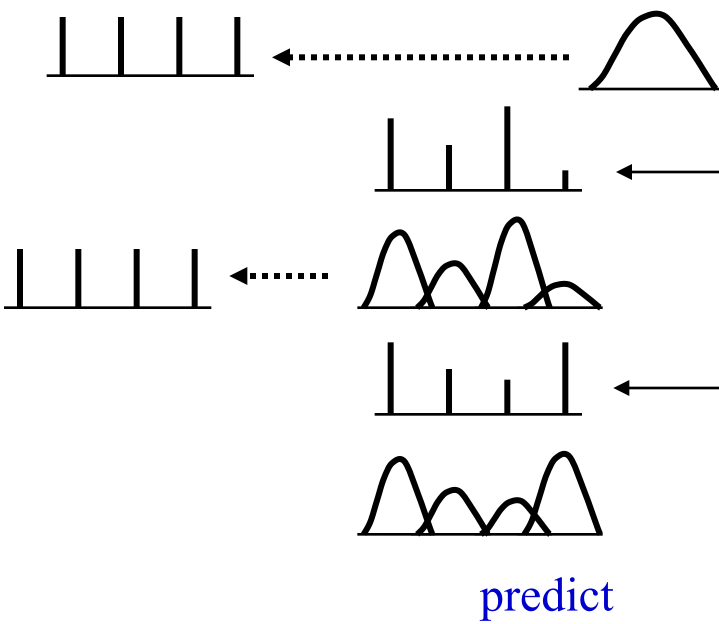

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Assuming that we only generate ***FOUR*** samples from the predicted distributions

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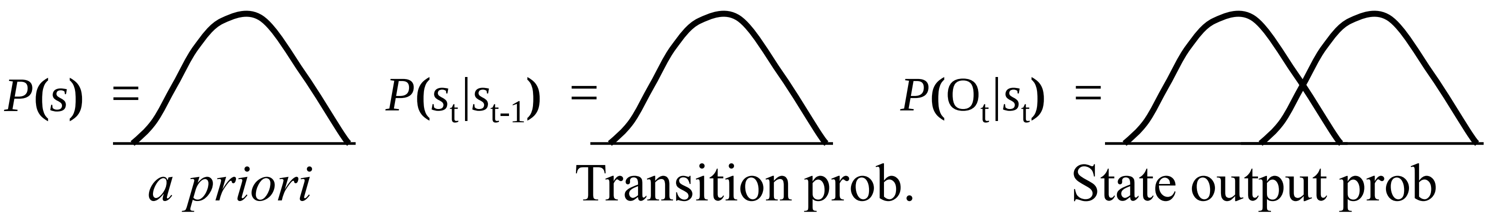

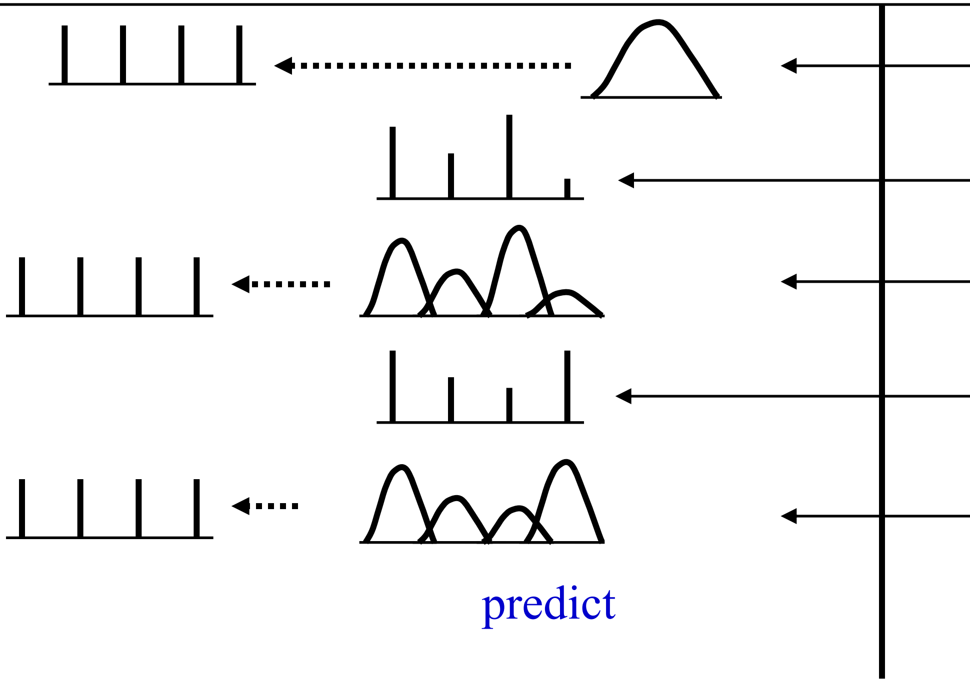

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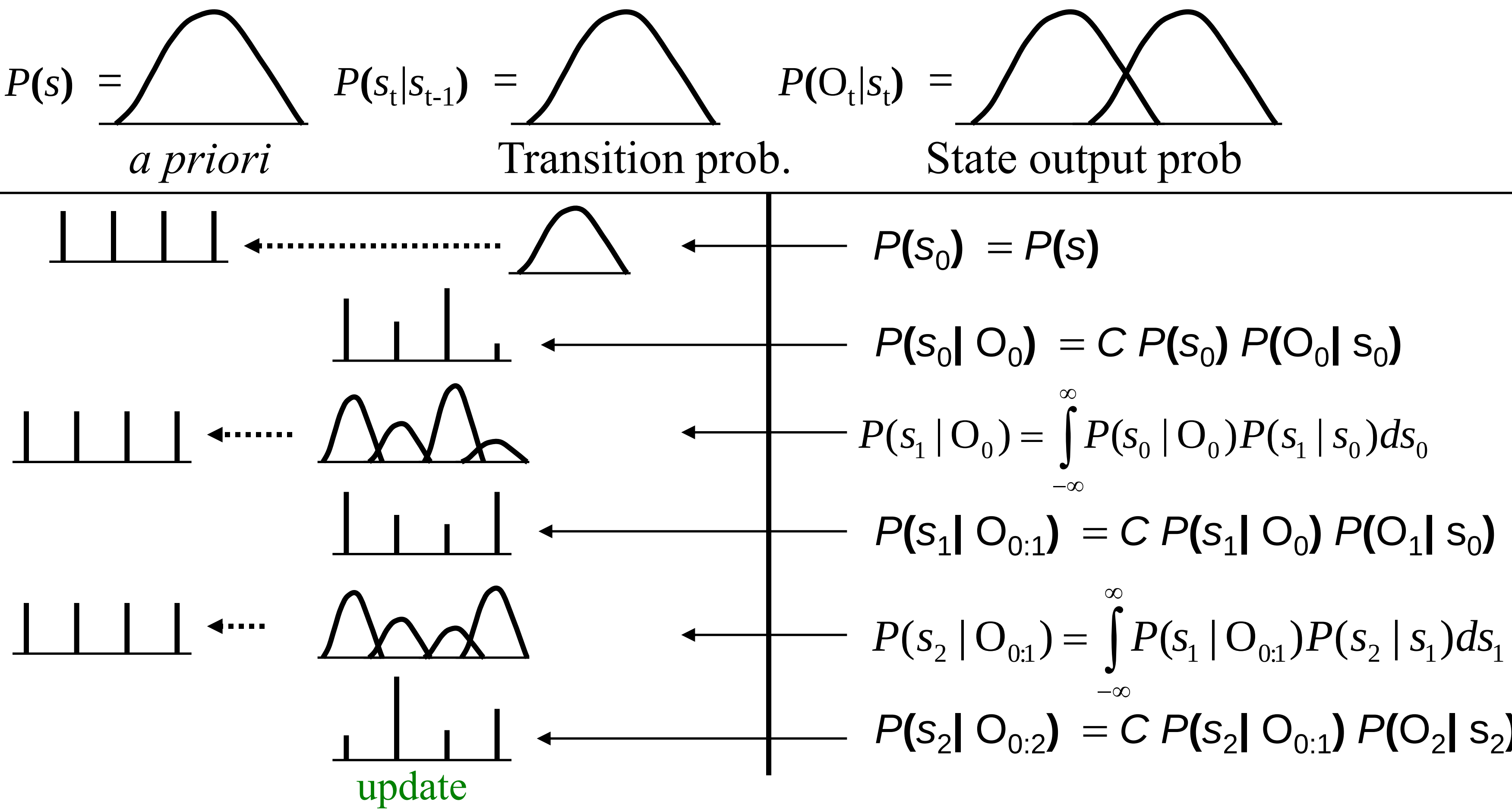
Assuming that we only generate ***FOUR*** samples from the predicted distributions

Particle Filtering



Assuming that we only generate ***FOUR*** samples from the predicted distributions

Particle Filtering

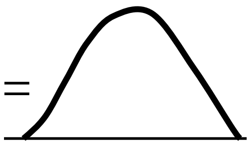
- Discretize state space at the prediction step
  - By sampling the continuous predicted distribution
    - If appropriately sampled, all generated samples may be considered to be equally probable
  - Sampling results in a **discrete** uniform distribution

- Update step updates the distribution of the quantized state space
  - Results in a **discrete** non-uniform distribution

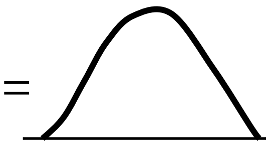
- Predicted state distribution for the next time instant will again be continuous
  - Must be **discretized** again by sampling

- At any step, the current state distribution will not have more components than the number of samples generated at the previous sampling step
  - The complexity of distributions remains constant

Particle Filtering

$P(s)$ = 

a priori

$P(s_t|s_{t-1})$ = 

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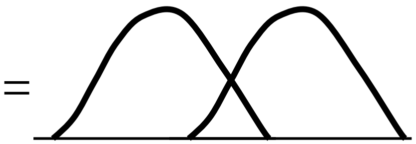
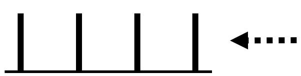
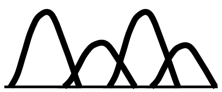
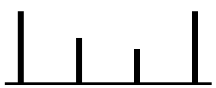
$P(O_t|s_t)$ = 

State output prob





predict



update

Prediction at time t:

$$P(s_t \mid O_{0:t-1}) = \int_{-\infty}^{\infty} P(s_{t-1} \mid O_{0:t-1}) P(s_t \mid s_{t-1}) ds_{t-1}$$

Update at time t:

$$P(s_t \mid O_{0:t}) = CP(s_t \mid O_{0:t-1}) P(O_t \mid s_t)$$

Number of mixture components in predicted distribution governed by number of samples in discrete distribution

By deriving a small (100-1000) number of samples at each time instant, all distributions are kept manageable

Particle Filtering

$$o_t = g(s_t) + \gamma$$

$$s_t = f(s_{t-1}) + \varepsilon$$

$$P_\gamma(\gamma)$$

$$P_\varepsilon(\varepsilon)$$

- At t = 0, sample the initial state distribution

$$P(s_0 \mid o_{-1}) = P(s_0) \approx \frac{1}{M}\sum_{i=0}^{M-1}\delta(s_0 - \bar{s}_i^{\,0}) \quad \text{where} \quad \bar{s}_i^{\,0} \leftarrow P_0(s)$$

- Update the state distribution with the observation

$$P(s_t \mid o_{0:t}) = C\sum_{i=0}^{M-1} P_\gamma(o_t - g(\bar{s}_i^{\,t}))\delta(s_t - \bar{s}_i^{\,t})$$

$$C = \frac{1}{\sum_{i=0}^{M-1} P_\gamma(o_t - g(\bar{s}_i^{\,t}))}$$

Particle Filtering

$$o_t = g(s_t) + \gamma$$

$$s_t = f(s_{t-1}) + \varepsilon$$

$$P_\gamma(\gamma)$$

$$P_\varepsilon(\varepsilon)$$

- Predict the state distribution at the next time

$$P(s_t \mid o_{0:t-1}) = C \sum_{i=0}^{M-1} P_\gamma(o_{t-1} - g(\bar{s}_i^{t-1})) P_\varepsilon(s_t - f(\bar{s}_i^{t-1}))$$

- Sample the predicted state distribution

$$P(s_t \mid o_{0:t-1}) \approx \frac{1}{M} \sum_{i=0}^{M-1} \delta(s_t - \bar{s}_i^t) \text{ where } \bar{s}_i^t \leftarrow P(s_t \mid o_{0:t-1})$$

Particle Filtering

$$o_t = g(s_t) + \gamma \qquad P_\gamma(\gamma)$$

$$s_t = f(s_{t-1}) + \varepsilon \qquad P_\varepsilon(\varepsilon)$$

- Predict the state distribution at t

$$P(s_t \mid o_{0:t-1}) = C \sum_{i=0}^{M-1} P_\gamma(o_{t-1} - g(\bar{s}_i^{t-1})) P_\varepsilon(s_t - f(\bar{s}_i^{t-1}))$$

- Sample the predicted state distribution at t

$$P(s_t \mid o_{0:t-1}) \approx \frac{1}{M} \sum_{i=0}^{M-1} \delta(s_t - \bar{s}_i^t) \quad \text{where} \quad \bar{s}_i^t \leftarrow P(s_t \mid o_{0:t-1})$$

- Update the state distribution at t

$$P(s_t \mid o_{0:t}) = C \sum_{i=0}^{M-1} P_\gamma(o_t - g(\bar{s}_i^t)) \delta(s_t - \bar{s}_i^t)$$

$$C = \frac{1}{\sum_{i=0}^{M-1} P_\gamma(o_t - g(\bar{s}_i^t))}$$

Estimating a state

- The algorithm gives us a discrete updated distribution over states:

$$P(s_t \mid o_{0:t}) = C \sum_{i=0}^{M-1} P_\gamma(o_t - g(\bar{s}_i^t))\delta(s_t - \bar{s}_i^t)$$

- The actual state can be estimated as the mean of this distribution

$$\hat{s}_t = C \sum_{i=0}^{M-1} \bar{s}_i^t P_\gamma(o_t - g(\bar{s}_i^t))$$

- Alternately, it can be the most likely sample

$$\hat{s}_t = \bar{s}_j^t \;:\; j = \arg\max_i P_\gamma(o_t - g(\bar{s}_i^t))$$

Simulations with a Linear Model

$$s_t = s_{t-1} + \varepsilon_t \qquad o_t = s_t + x_t$$

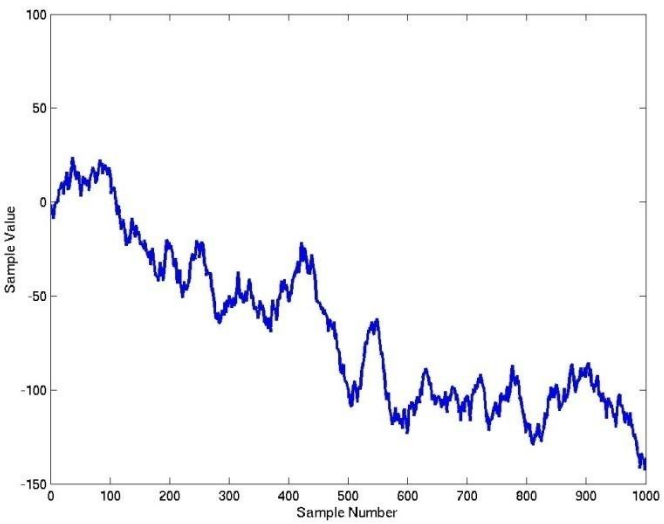
- ε_t has a Gaussian distribution with 0 mean, known variance
- x_t has a mixture Gaussian distribution with known parameters
- Simulation:
  - Generate state sequence s_t from model
  - Generate sequence of x_t from model with one x_t term for every s_t term
  - Generate observation sequence o_t from s_t and x_t
  - Attempt to estimate s_t from o_t

Simulation: Synthesizing data

Generate state sequence according to:

ε_t is Gaussian with mean 0 and variance 10

$$s_t = s_{t-1} + \varepsilon_t$$



Simulation: Synthesizing data

Generate state sequence according to: $s_t = s_{t-1} + \varepsilon_t$

ε_t is Gaussian with mean 0 and variance 10

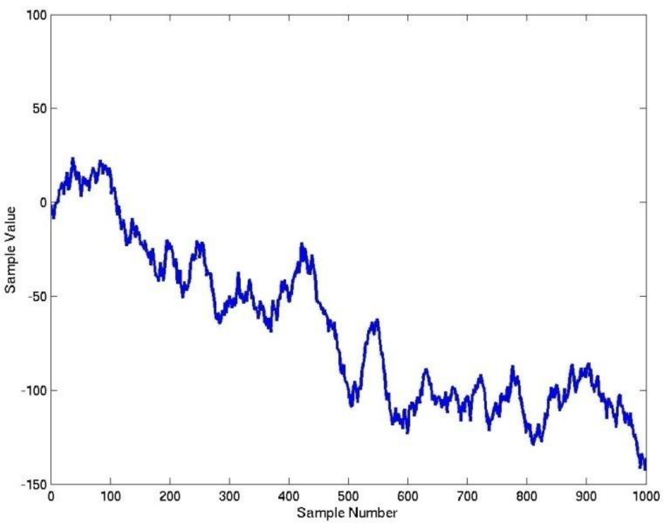
Generate observation sequence from state sequence according to: $o_t = s_t + x_t$

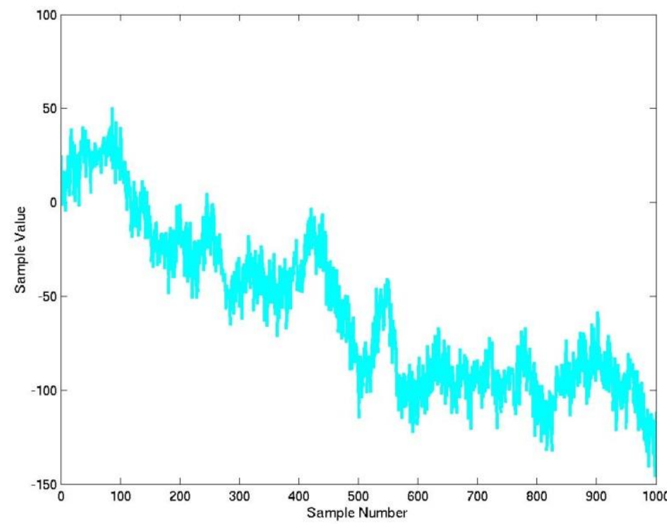
x_t is mixture Gaussian with parameters:

Means = [-4, 0, 4, 8, 12, 16, 18, 20]

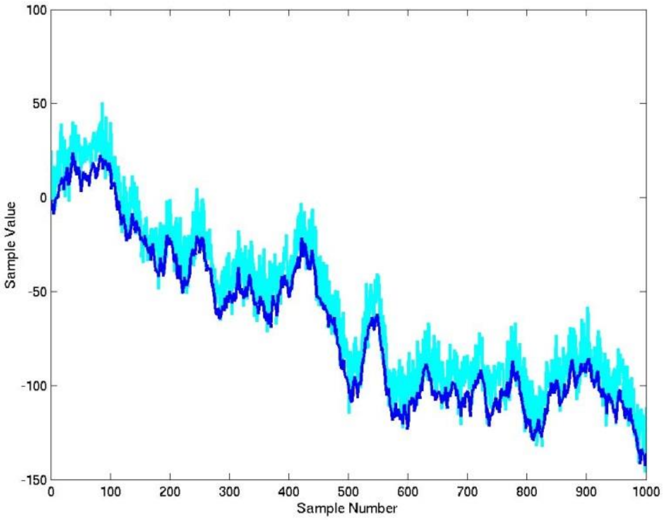
Variances = [10, 10, 10, 10, 10, 10, 10, 10]

Mixture weights = [0.125, 0.125, 0.125, 0.125, 0.125, 0.125, 0.125, 0.125]



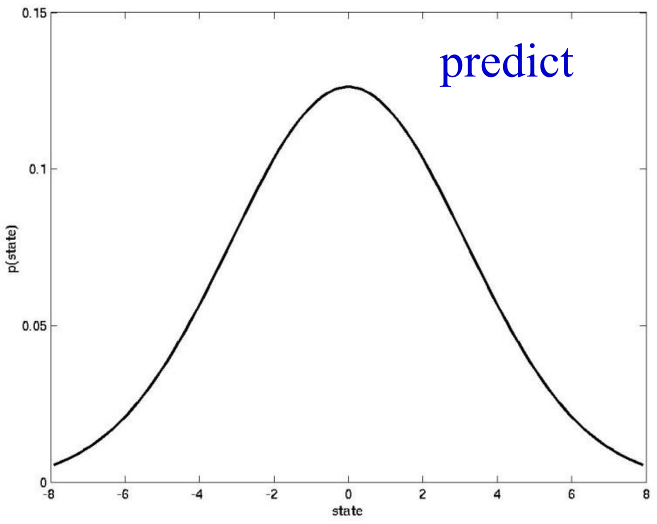


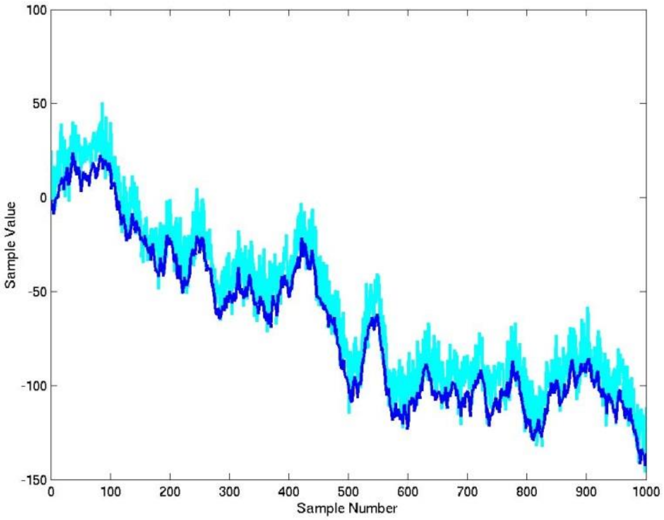
Simulation: Synthesizing data



Combined figure for more compact representation

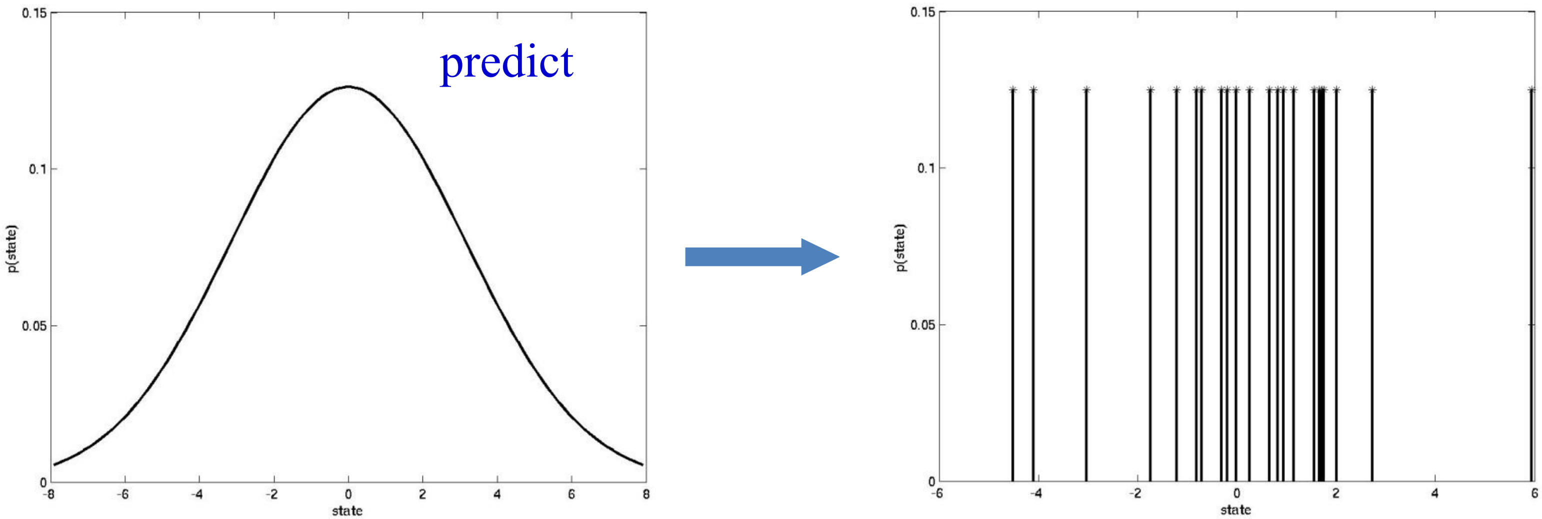
SIMULATION: TIME = 1

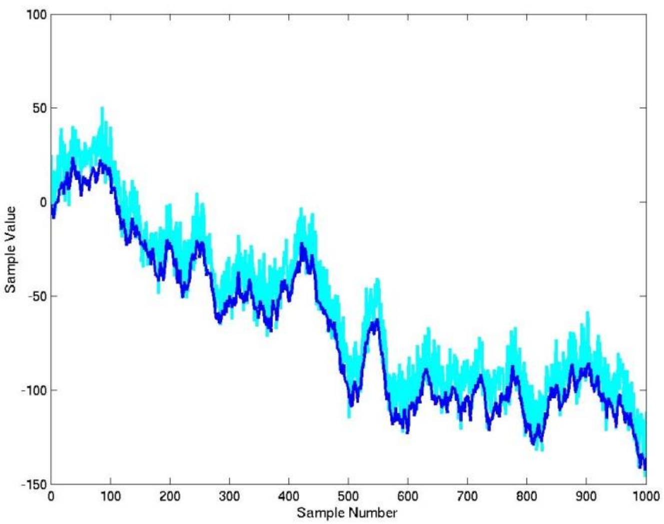




PREDICTED STATE DISTRIBUTION AT TIME = 1

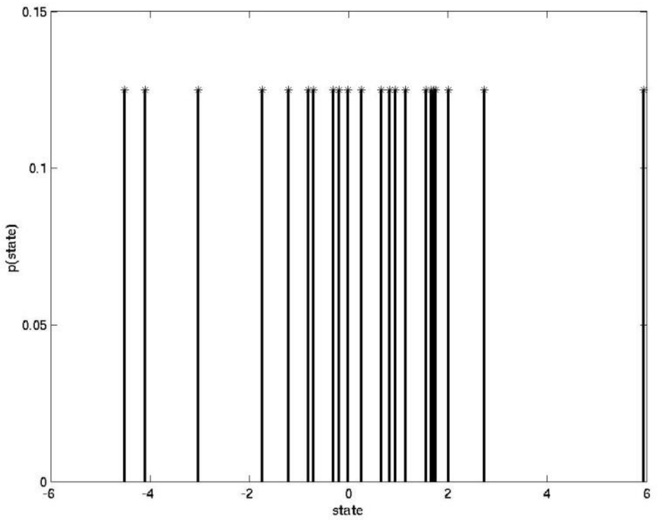
SIMULATION: TIME = 1

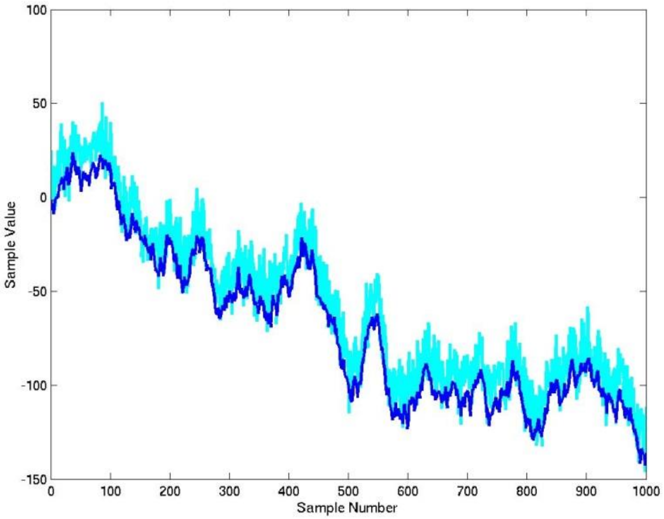




SAMPLED VERSION OF PREDICTED STATE DISTRIBUTION AT TIME = 1

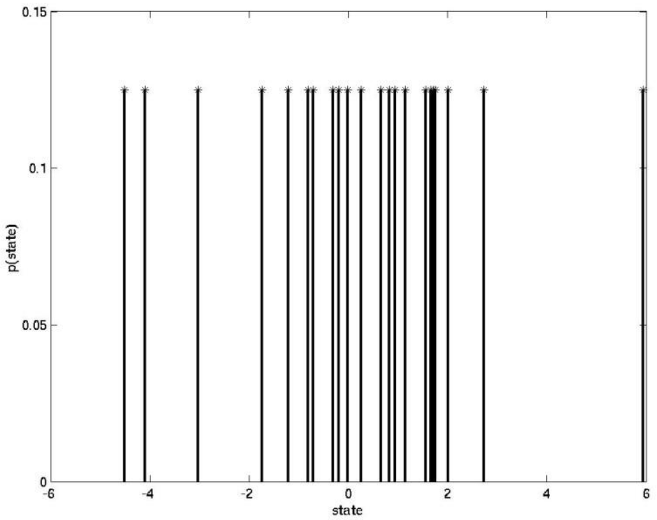
SIMULATION: TIME = 1

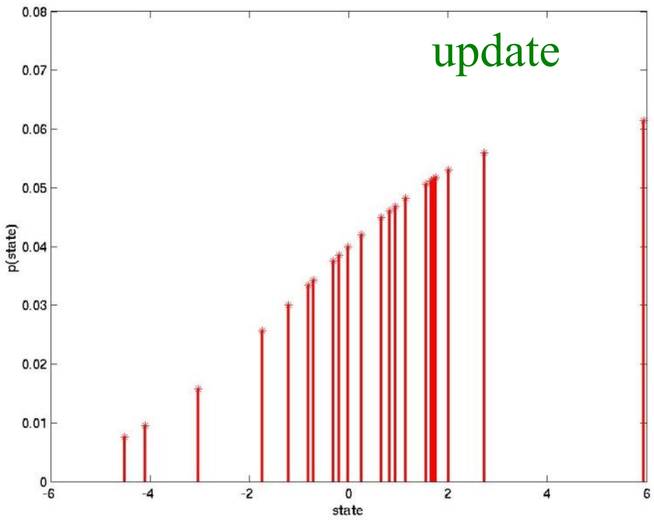


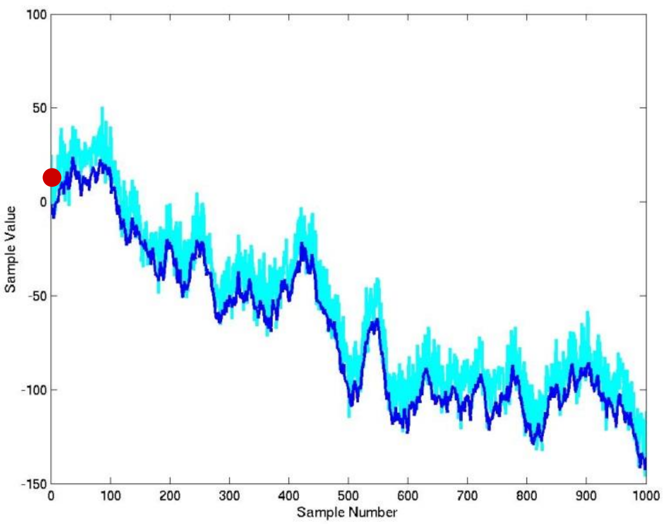


SAMPLED VERSION OF PREDICTED STATE DISTRIBUTION AT TIME = 1

SIMULATION: TIME = 1

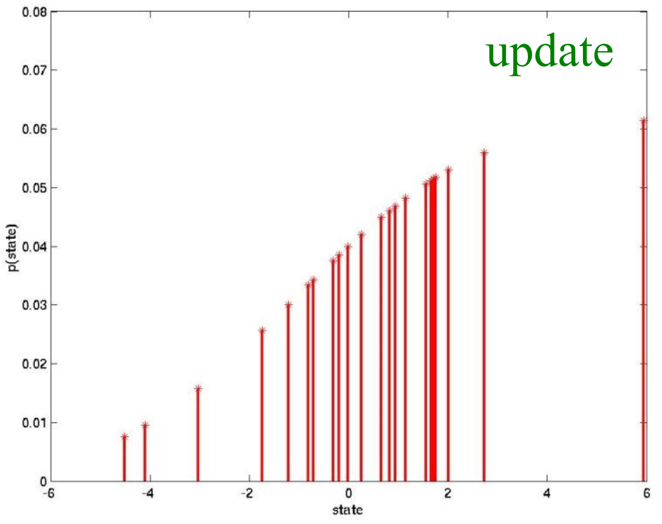


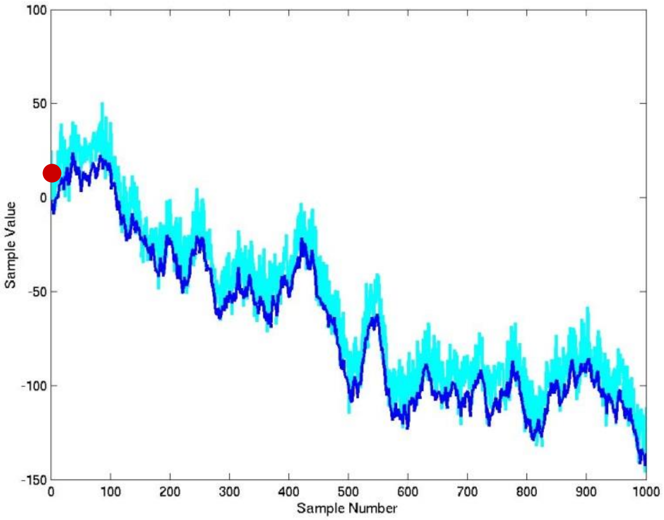


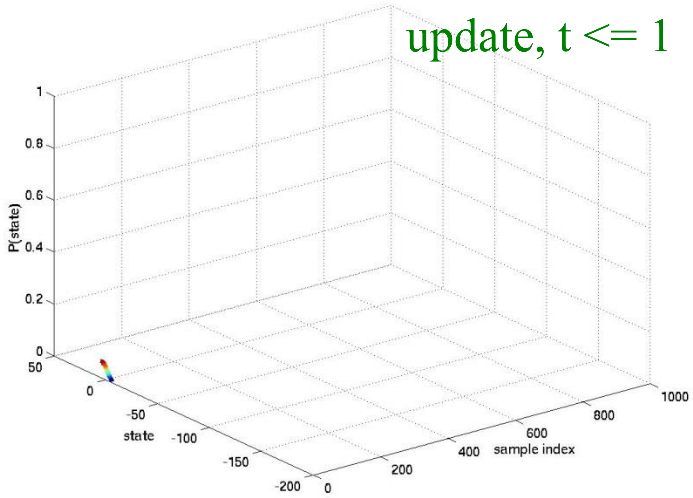


UPDATED VERSION OF
SAMPLED VERSION OF
PREDICTED STATE DISTRIBUTION
AT TIME = 1
AFTER SEEING FIRST OBSERVATION

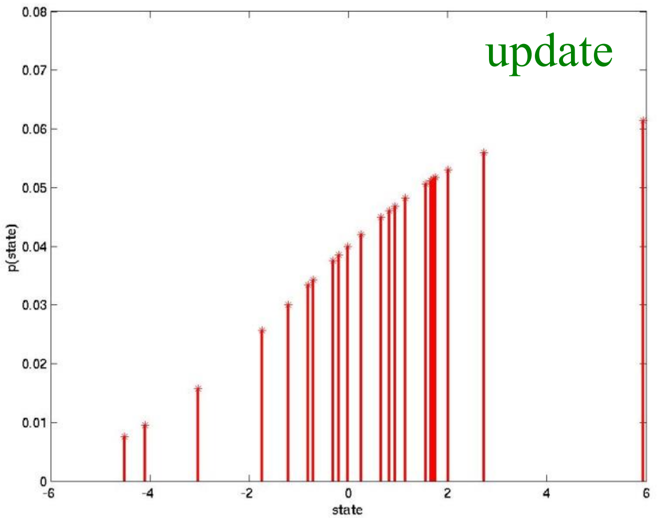
SIMULATION: TIME = 1

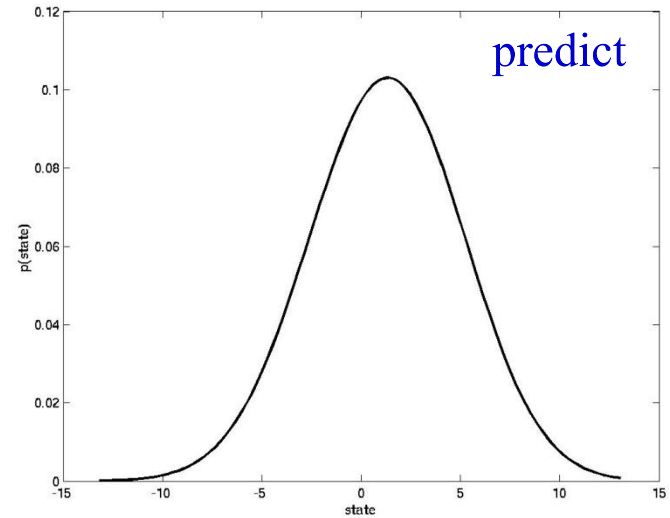


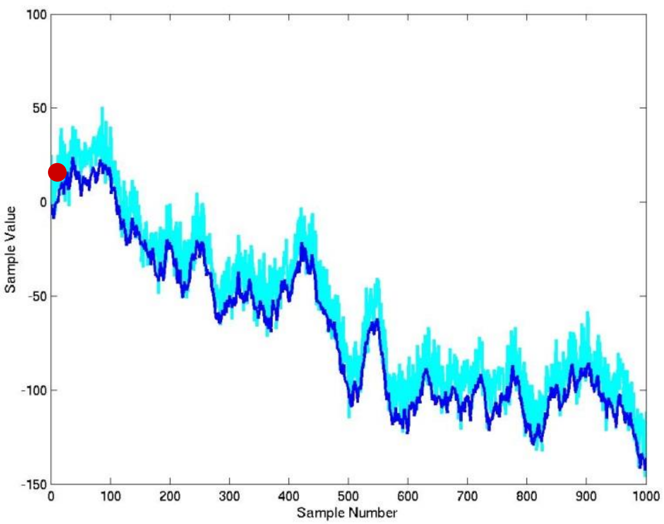


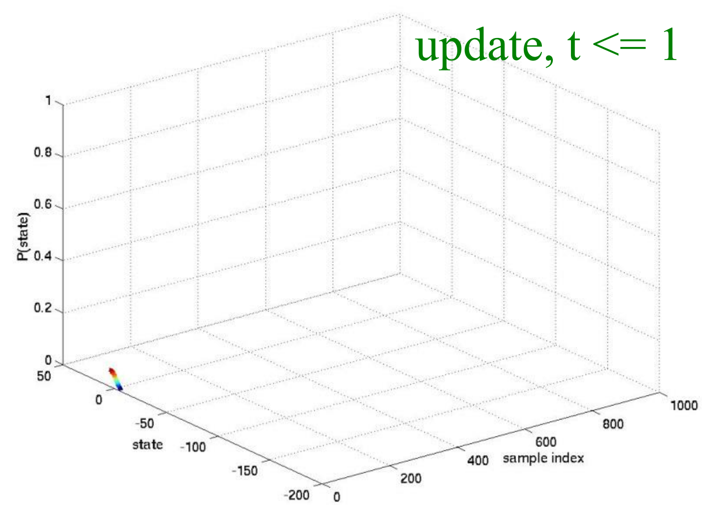


SIMULATION: TIME = 2

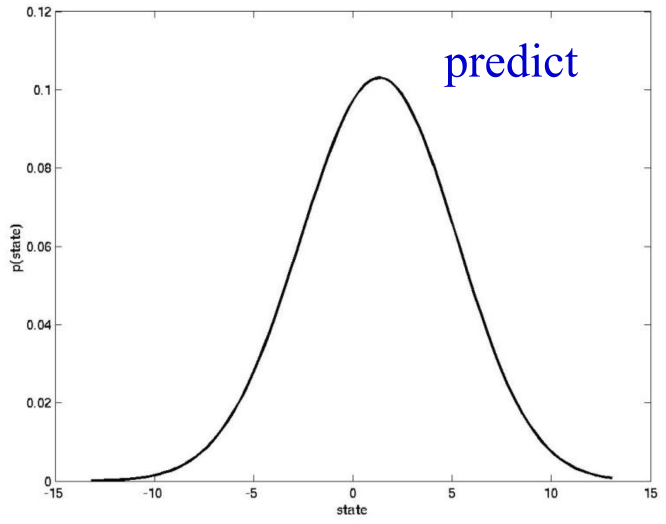


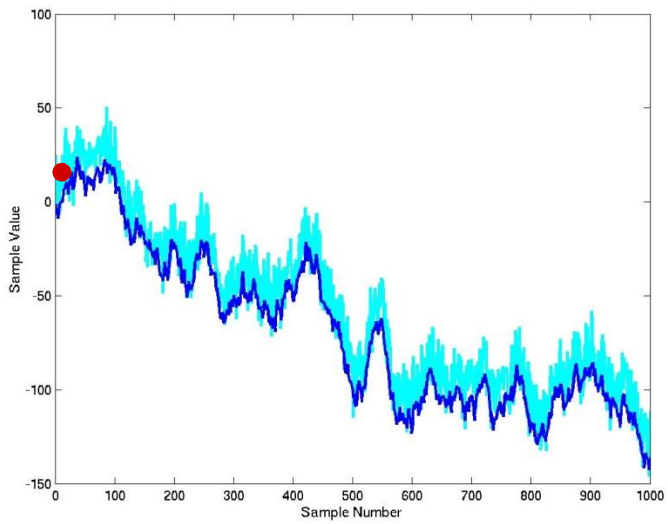


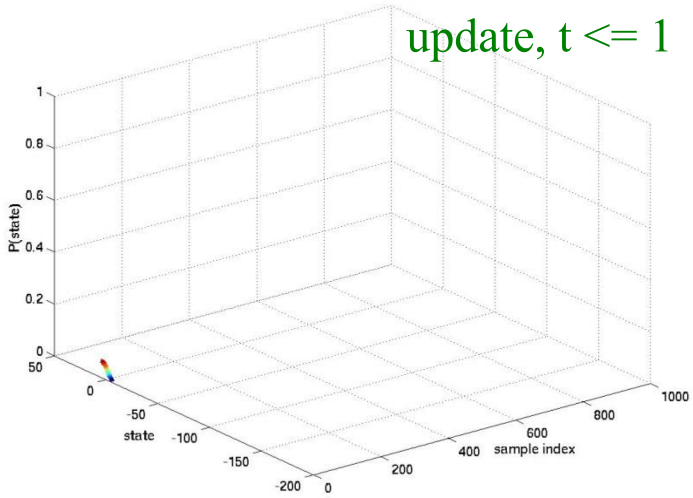




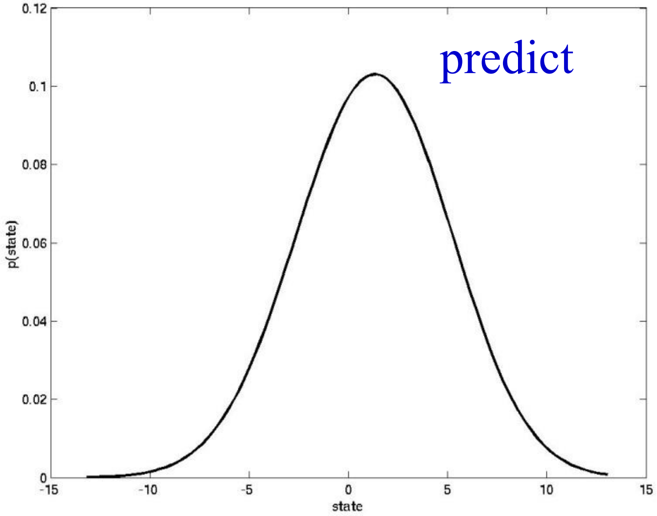
SIMULATION: TIME = 2

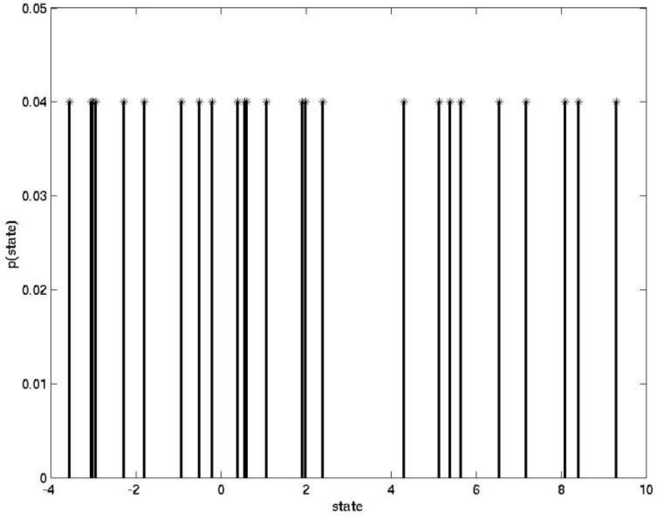


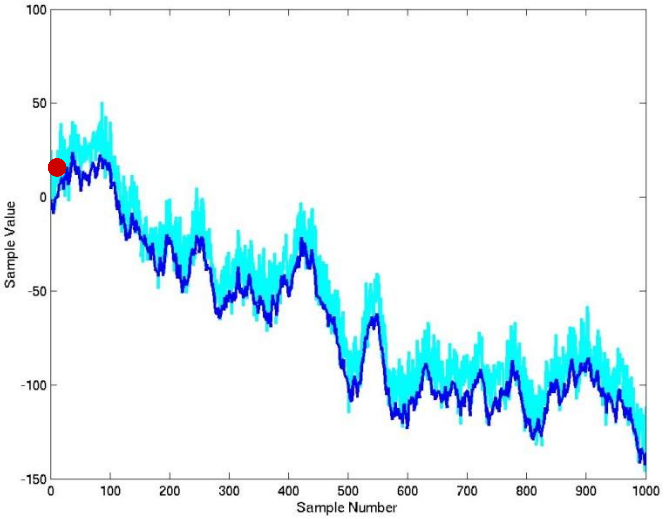


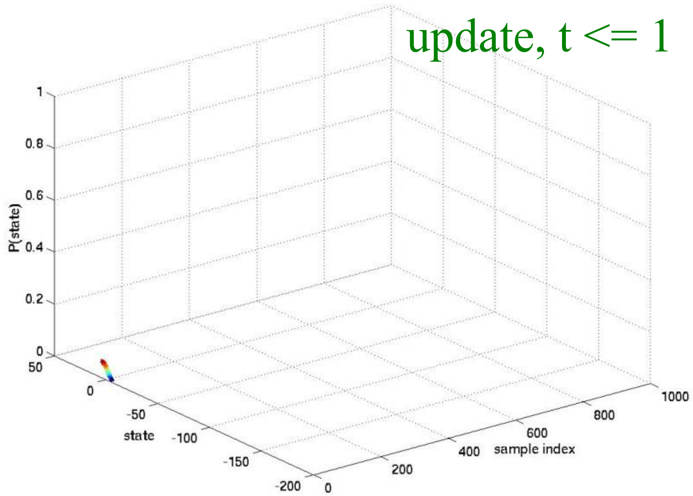


SIMULATION: TIME = 2

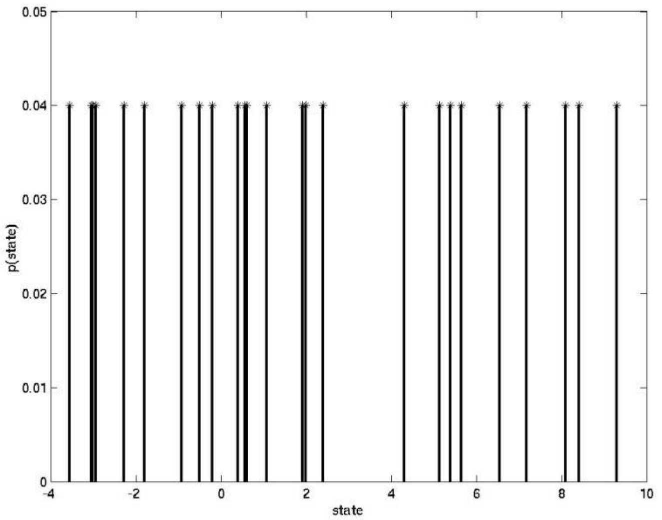


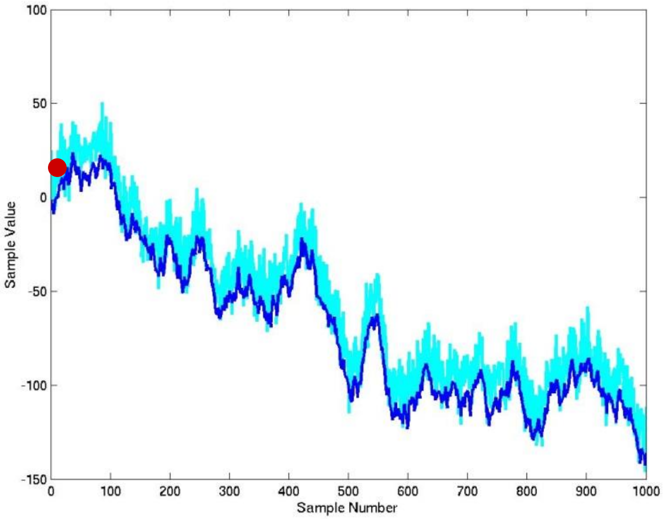


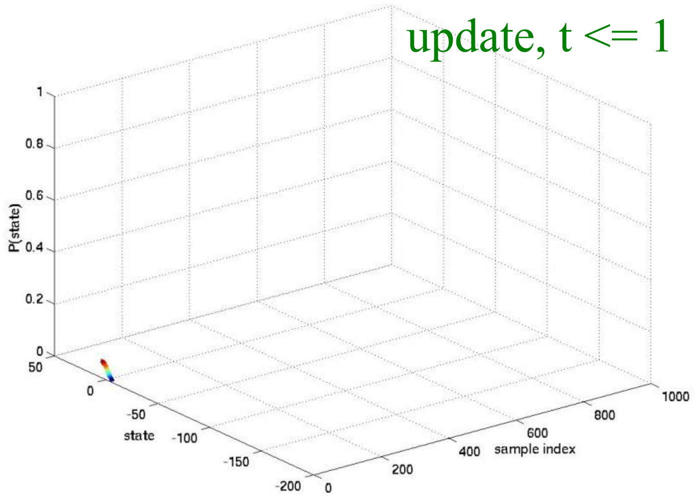




SIMULATION: TIME = 2







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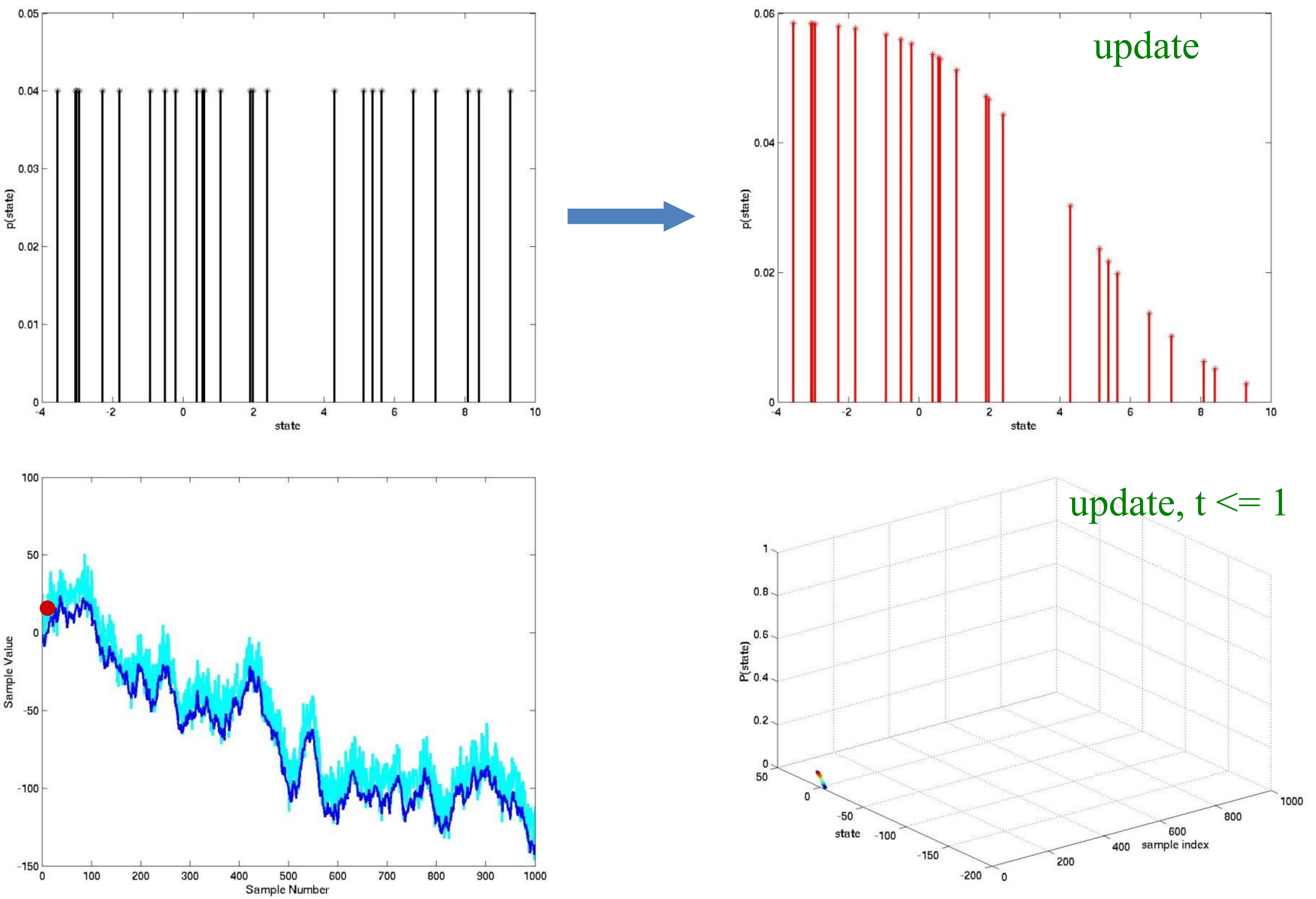

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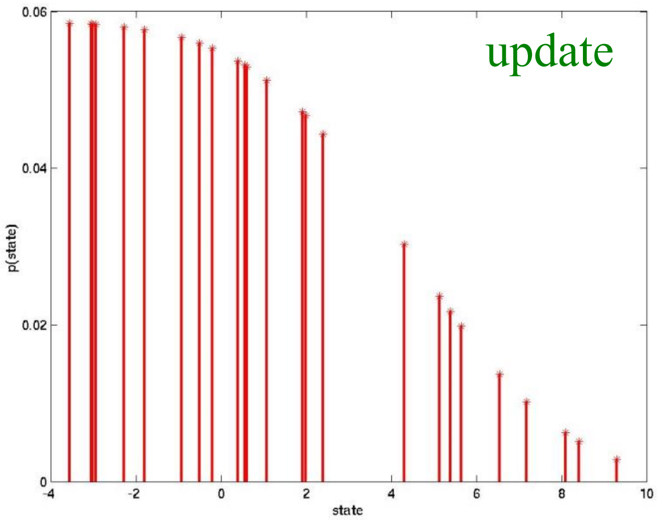
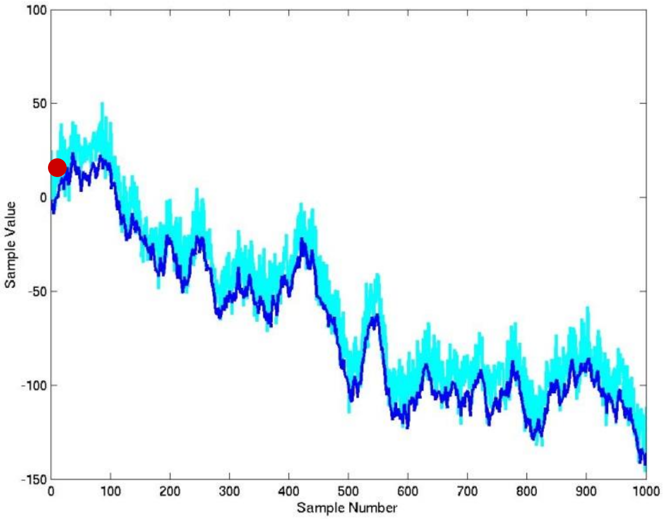
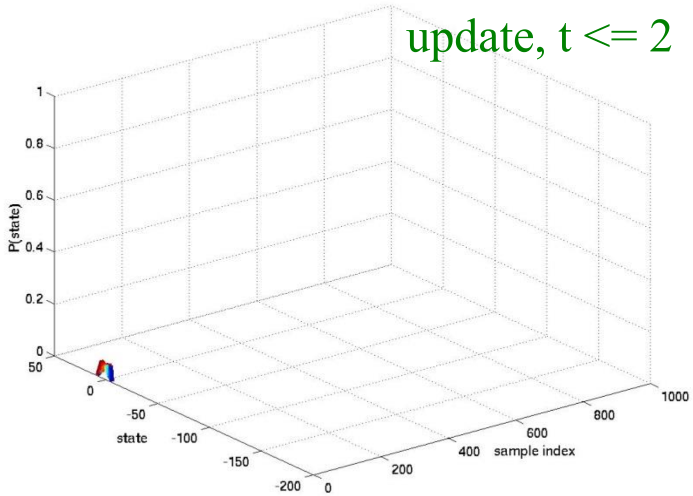
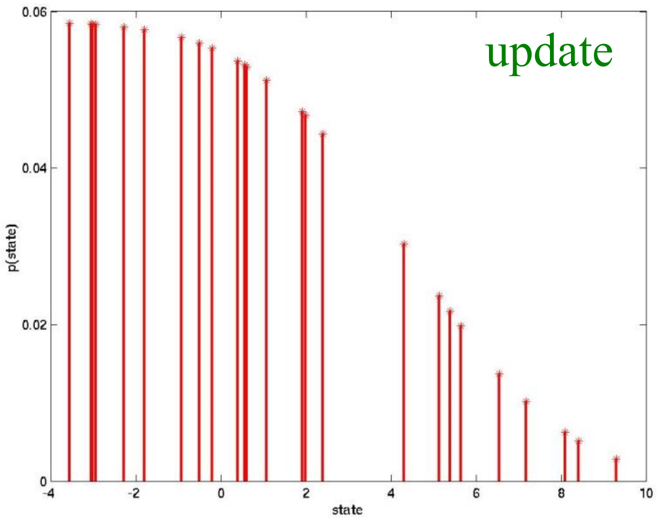
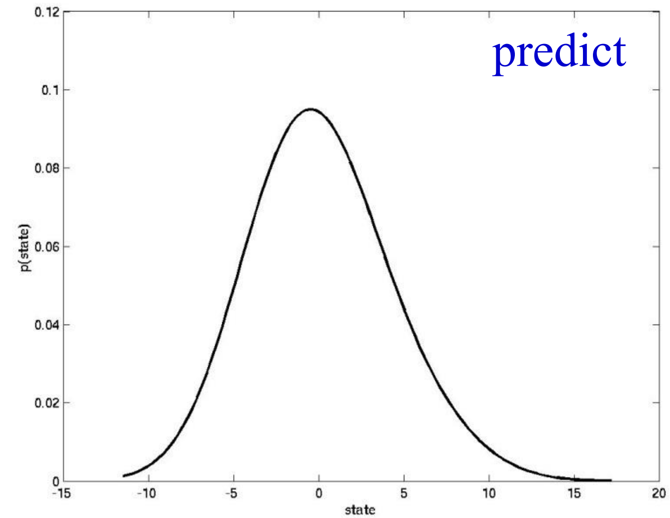


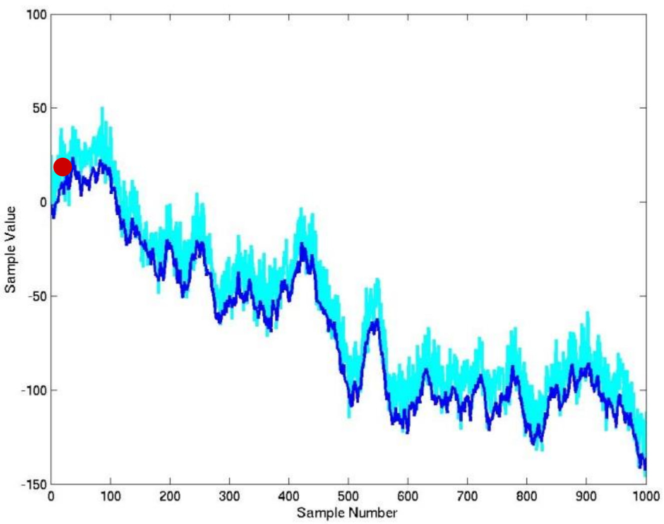


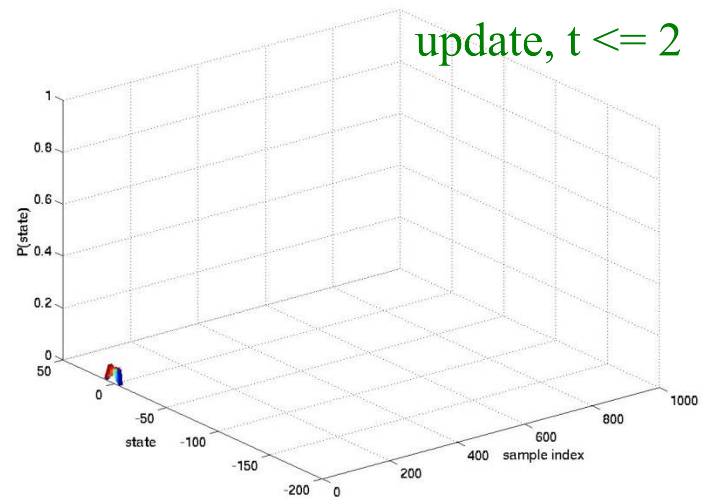


SIMULATION: TIME = 3

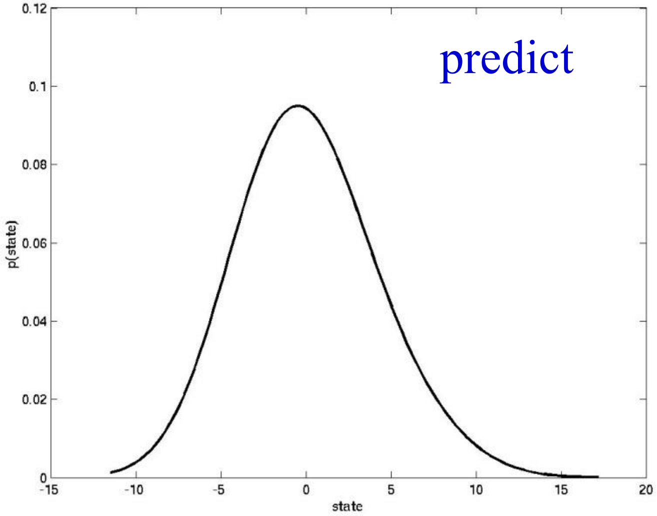


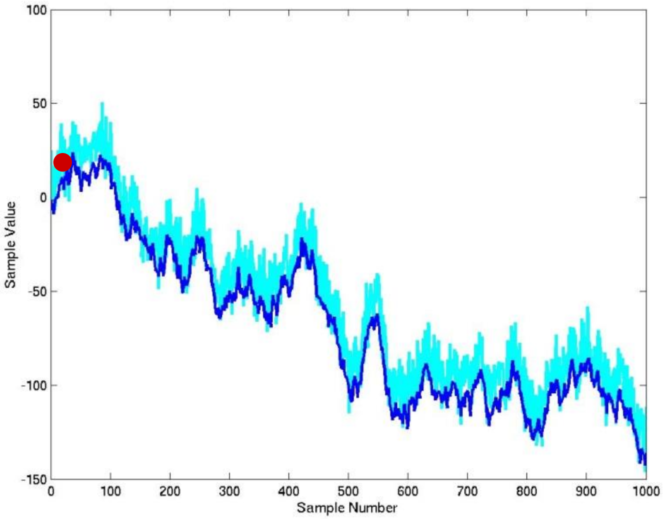


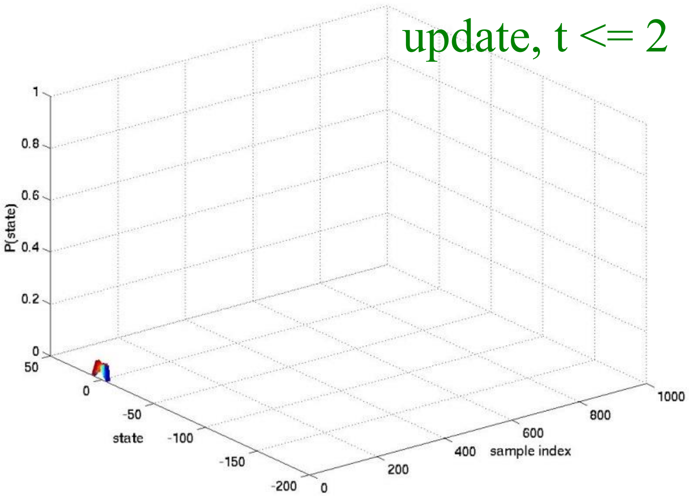




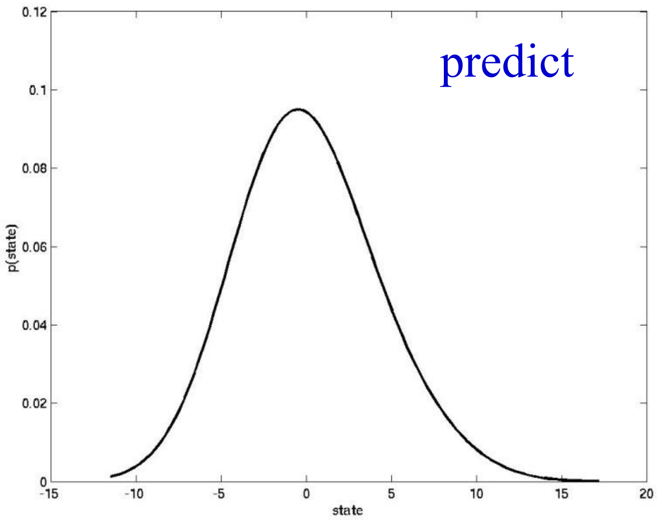
SIMULATION: TIME = 3

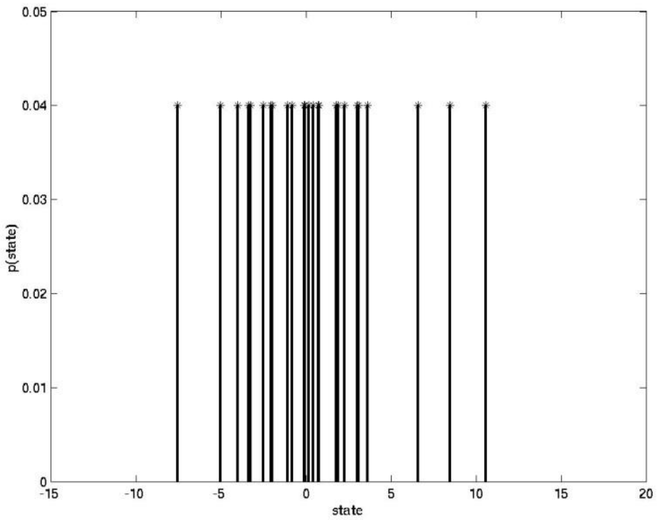


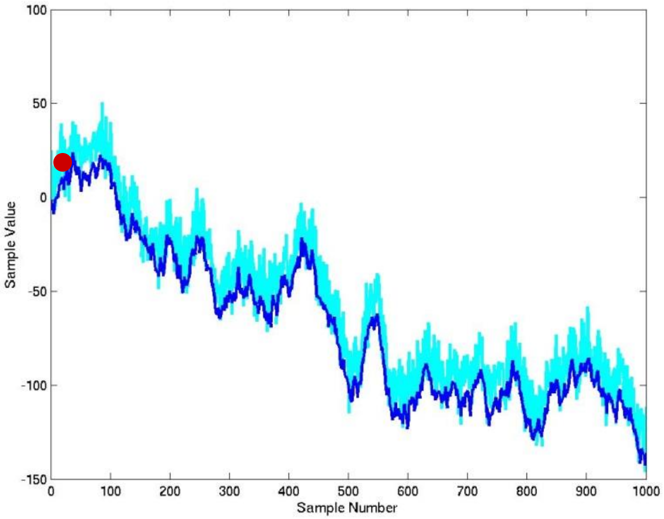


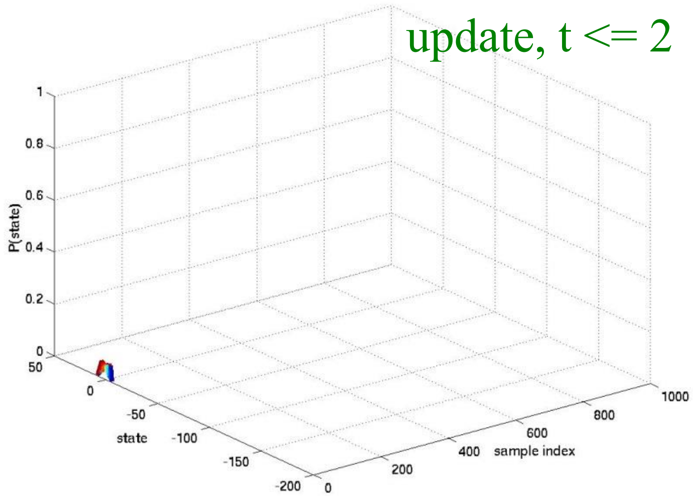


SIMULATION: TIME = 3

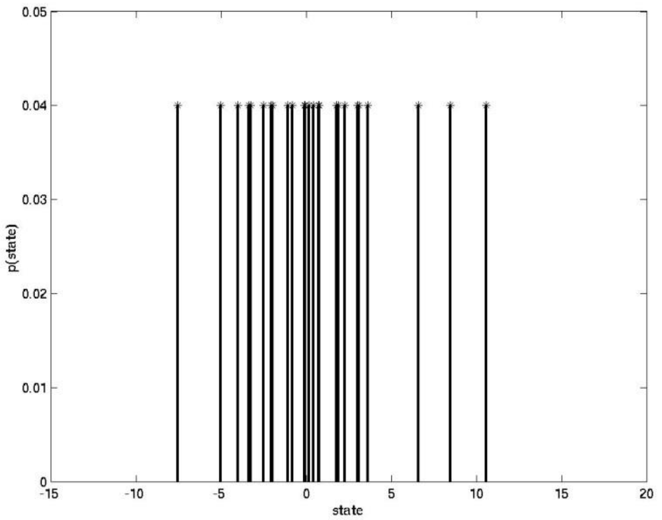


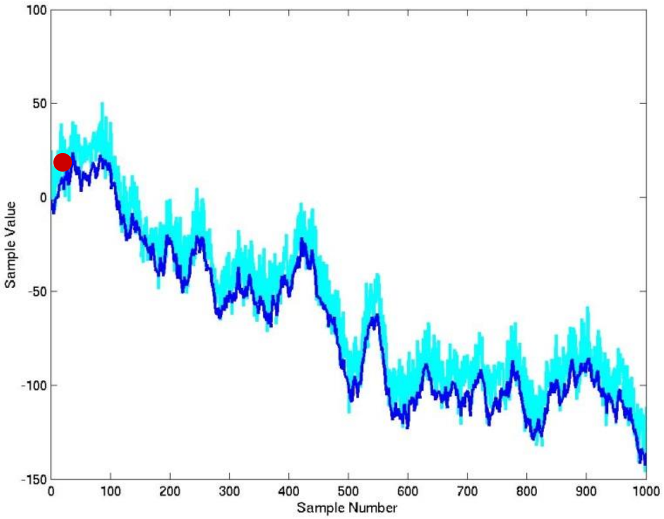


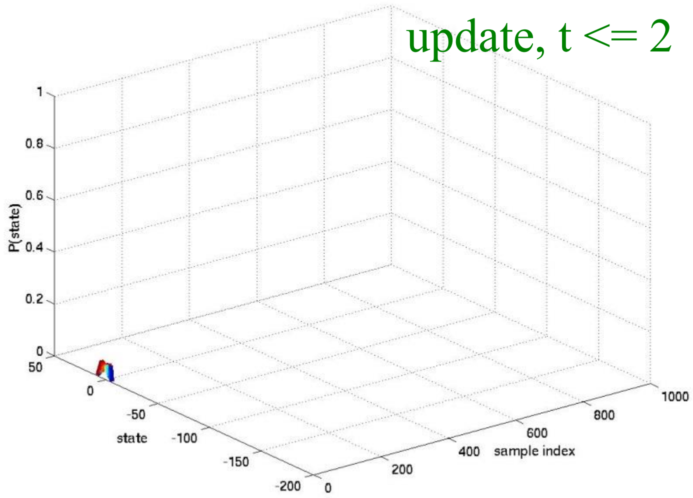




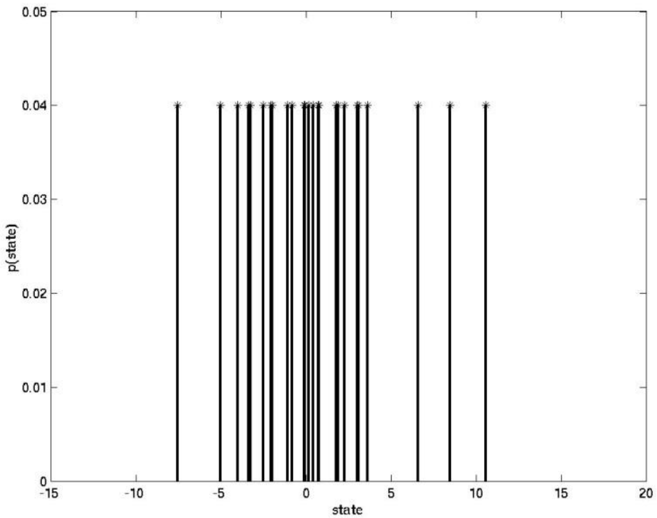
SIMULATION: TIME = 3

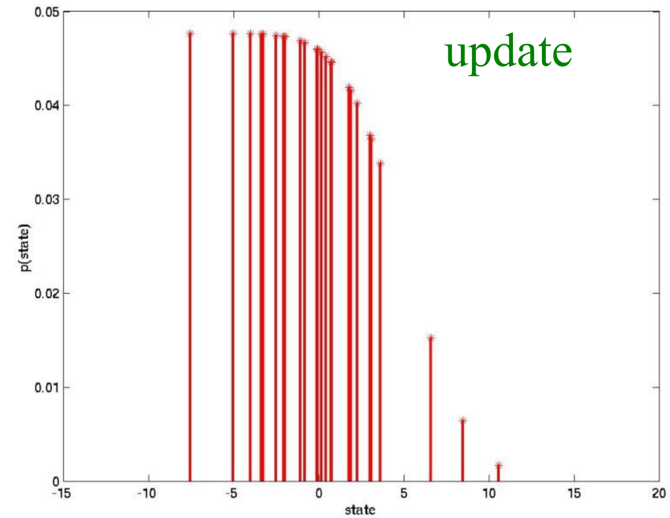


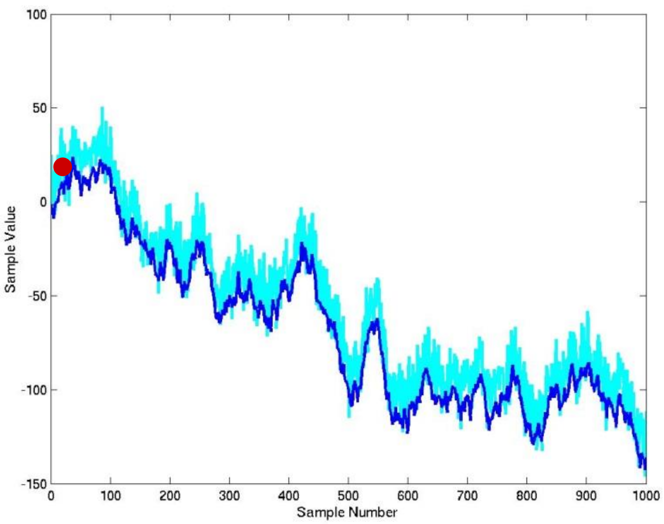


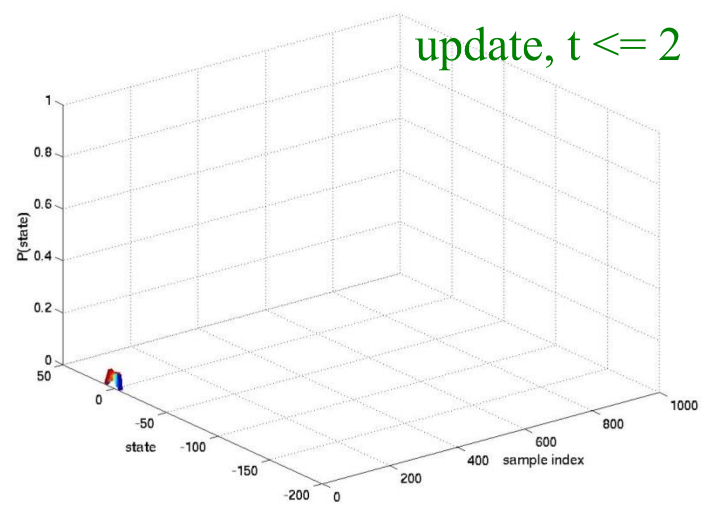


SIMULATION: TIME = 3

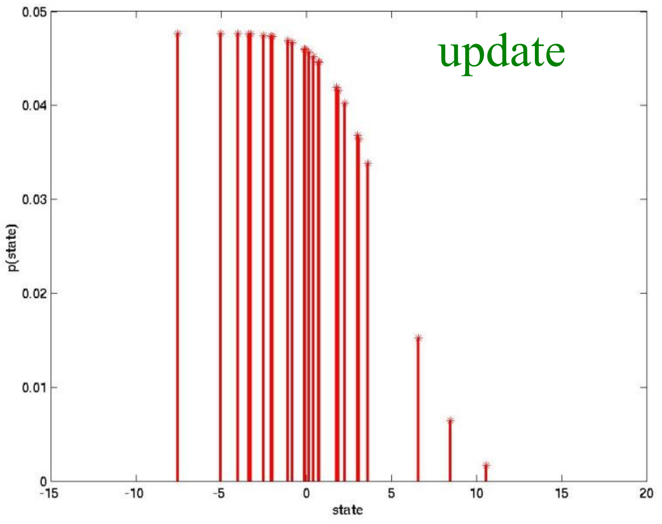




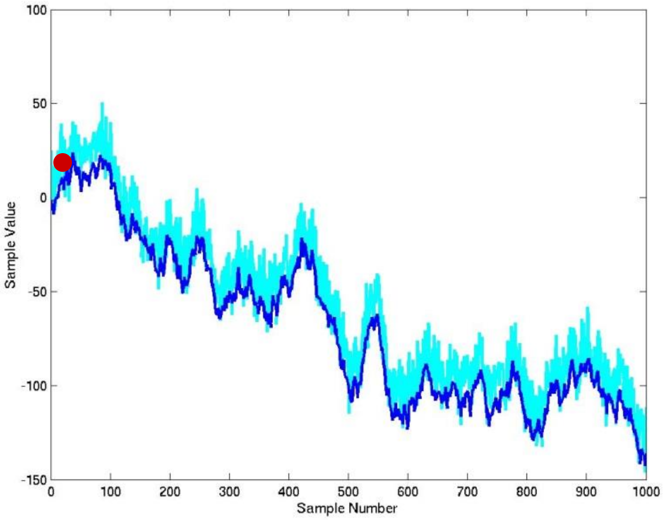


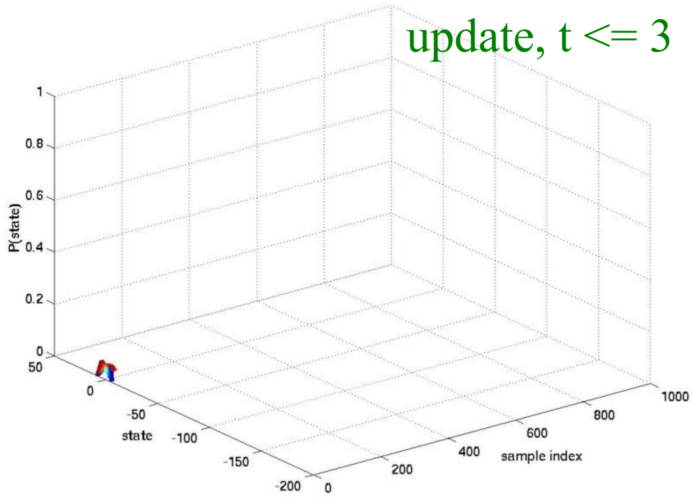


SIMULATION: TIME = 3

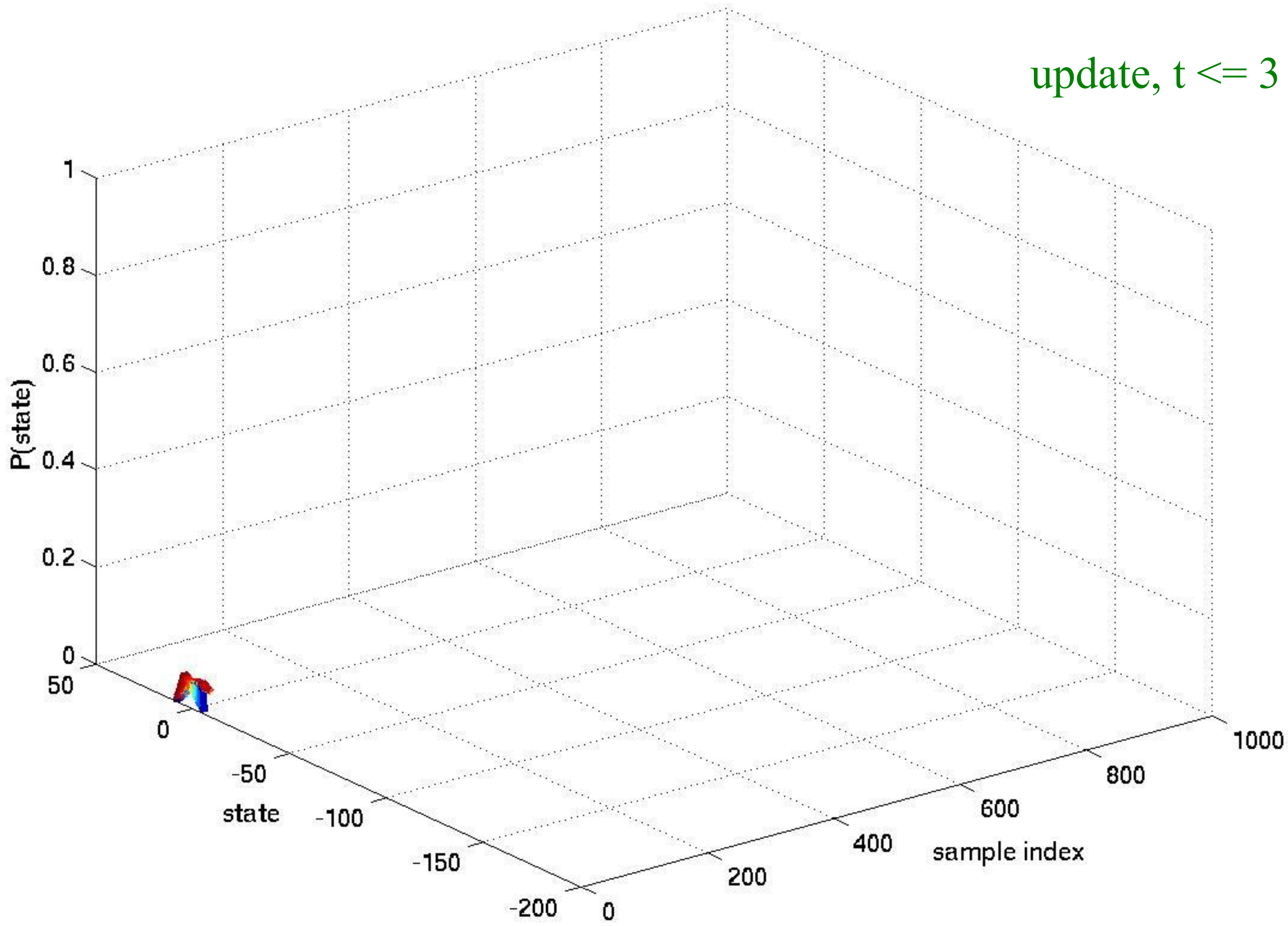


The figure below shows the contour of the updated state probabilities for all time instants until the current instant

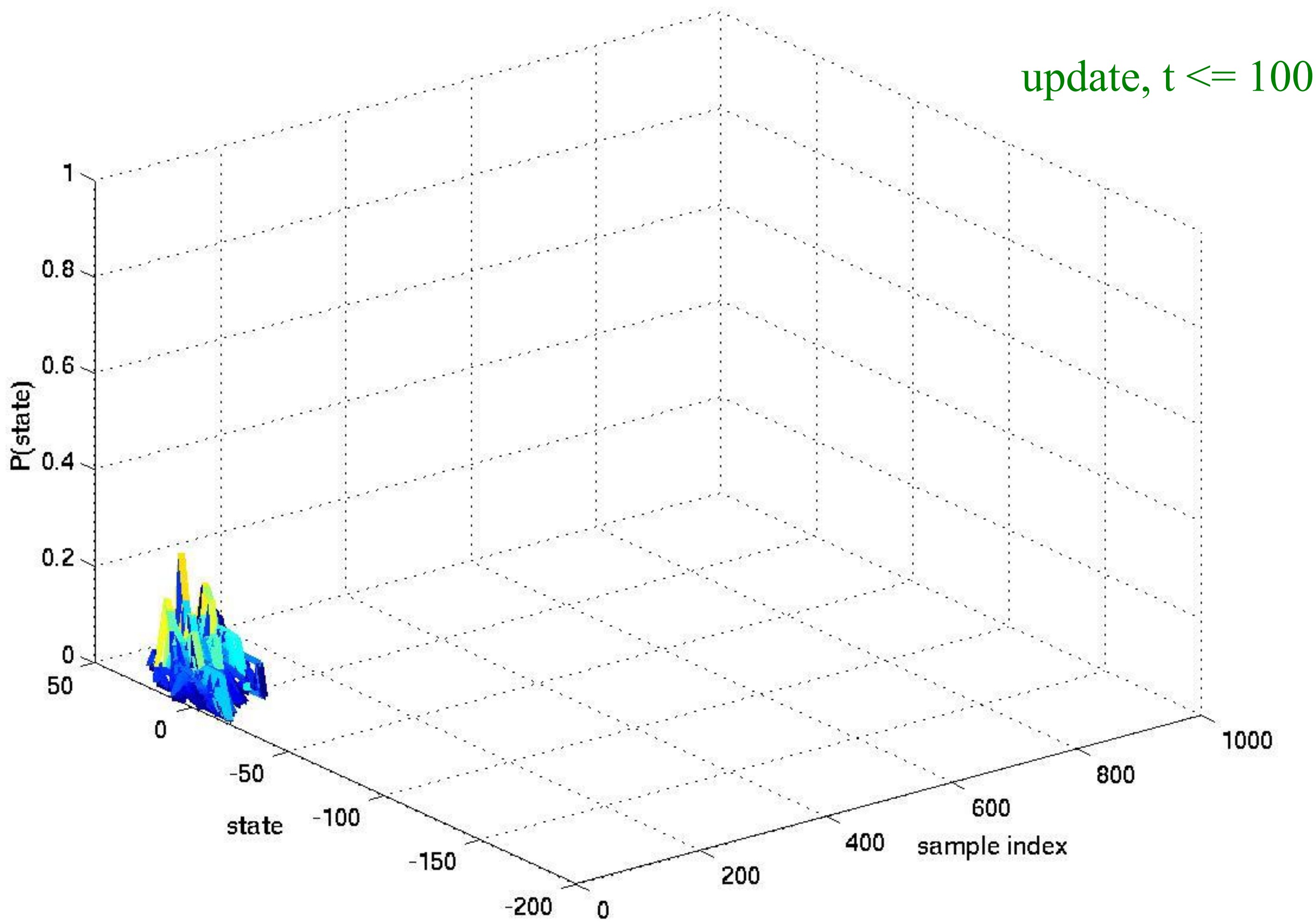




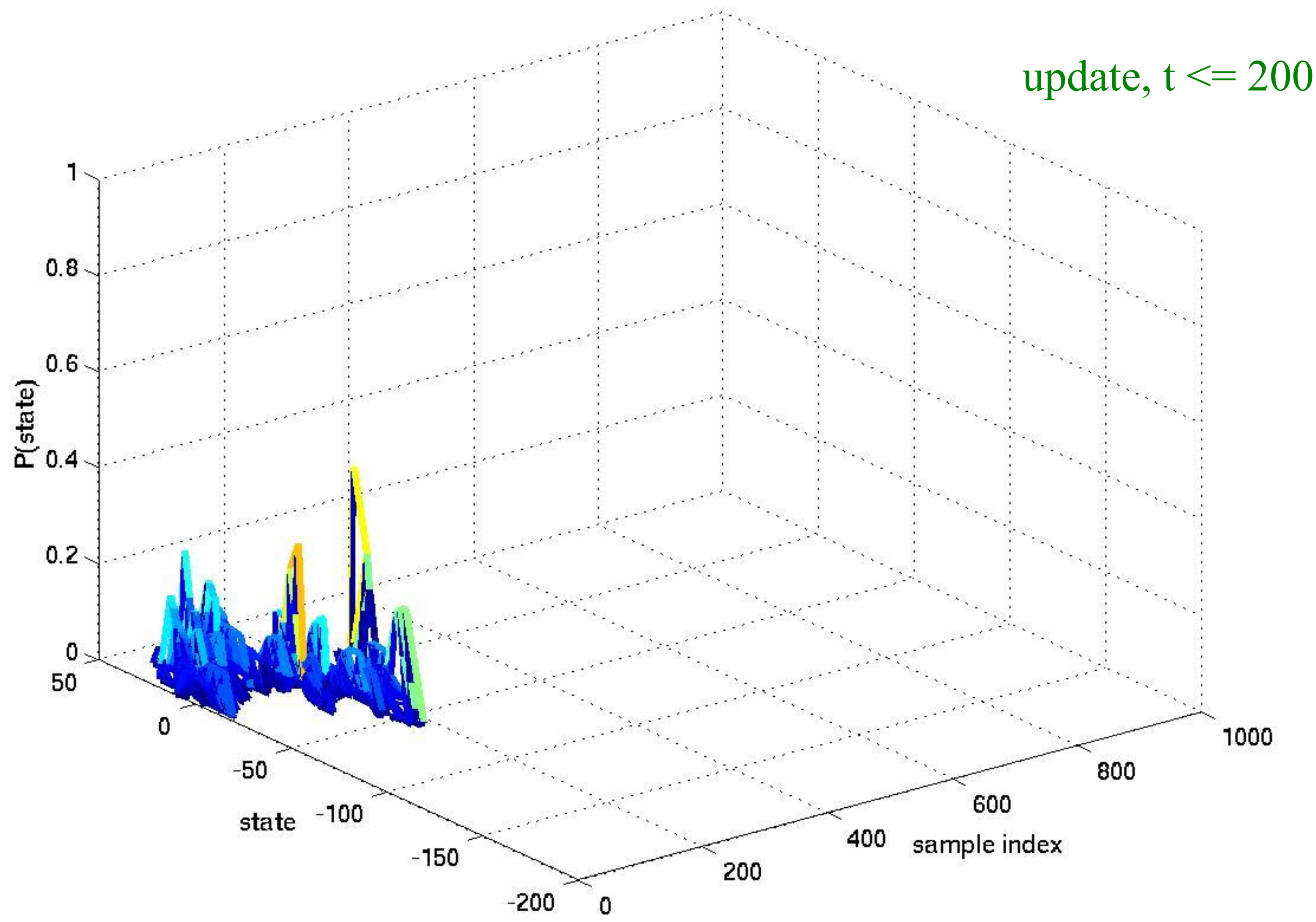
Simulation: Updated Probs Until T=3



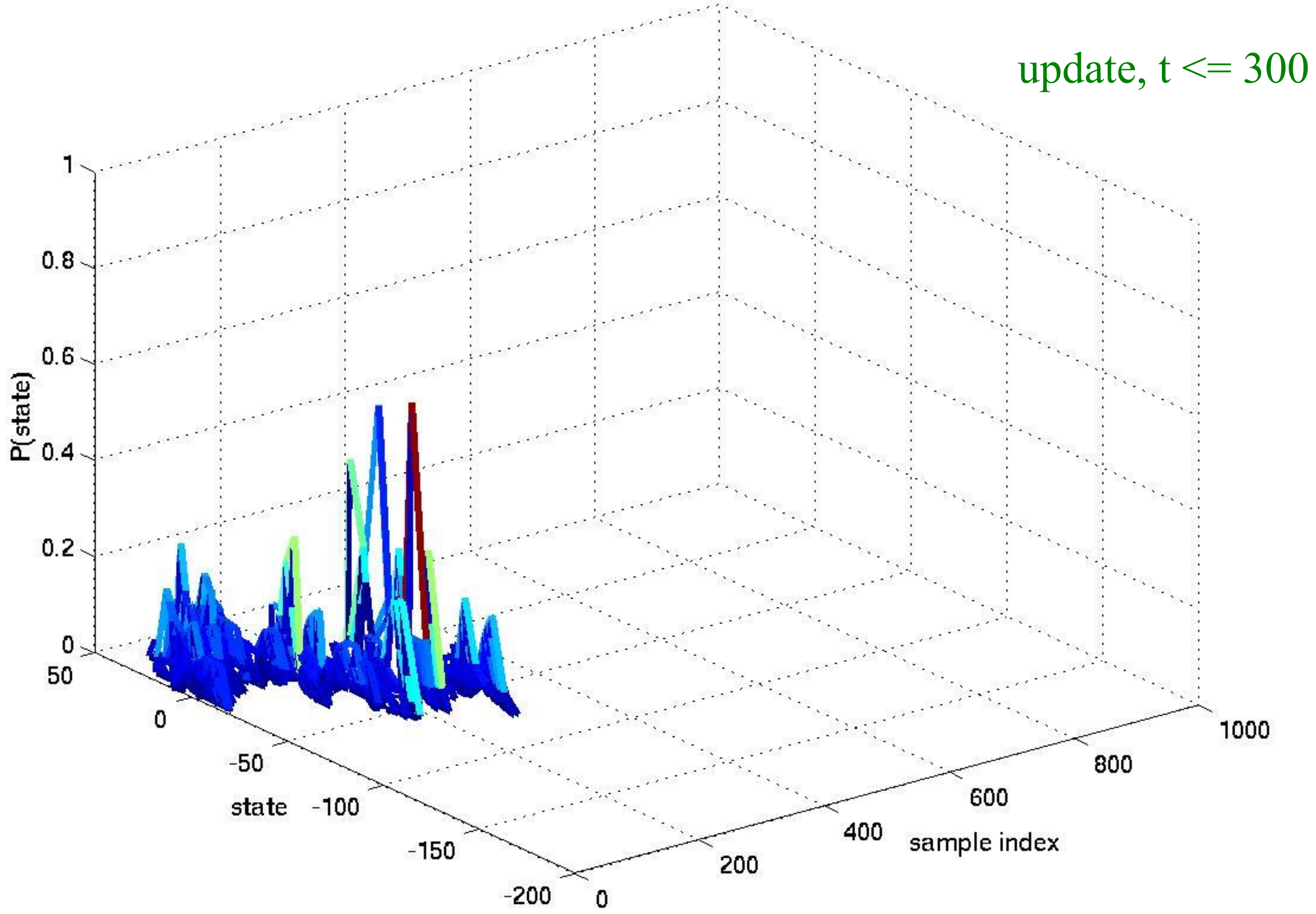
Simulation: Updated Probs Until



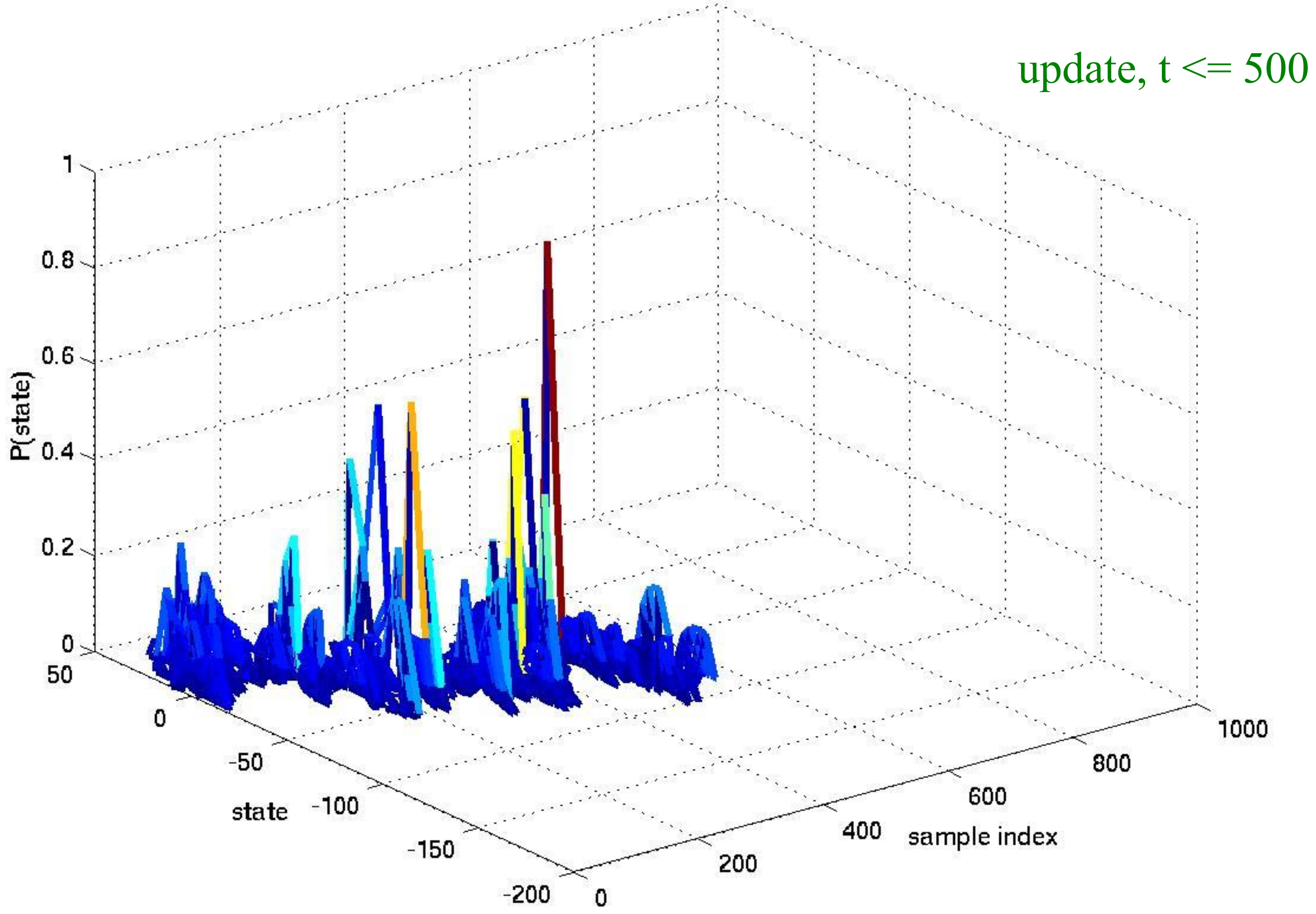
Simulation: Updated Probs Until



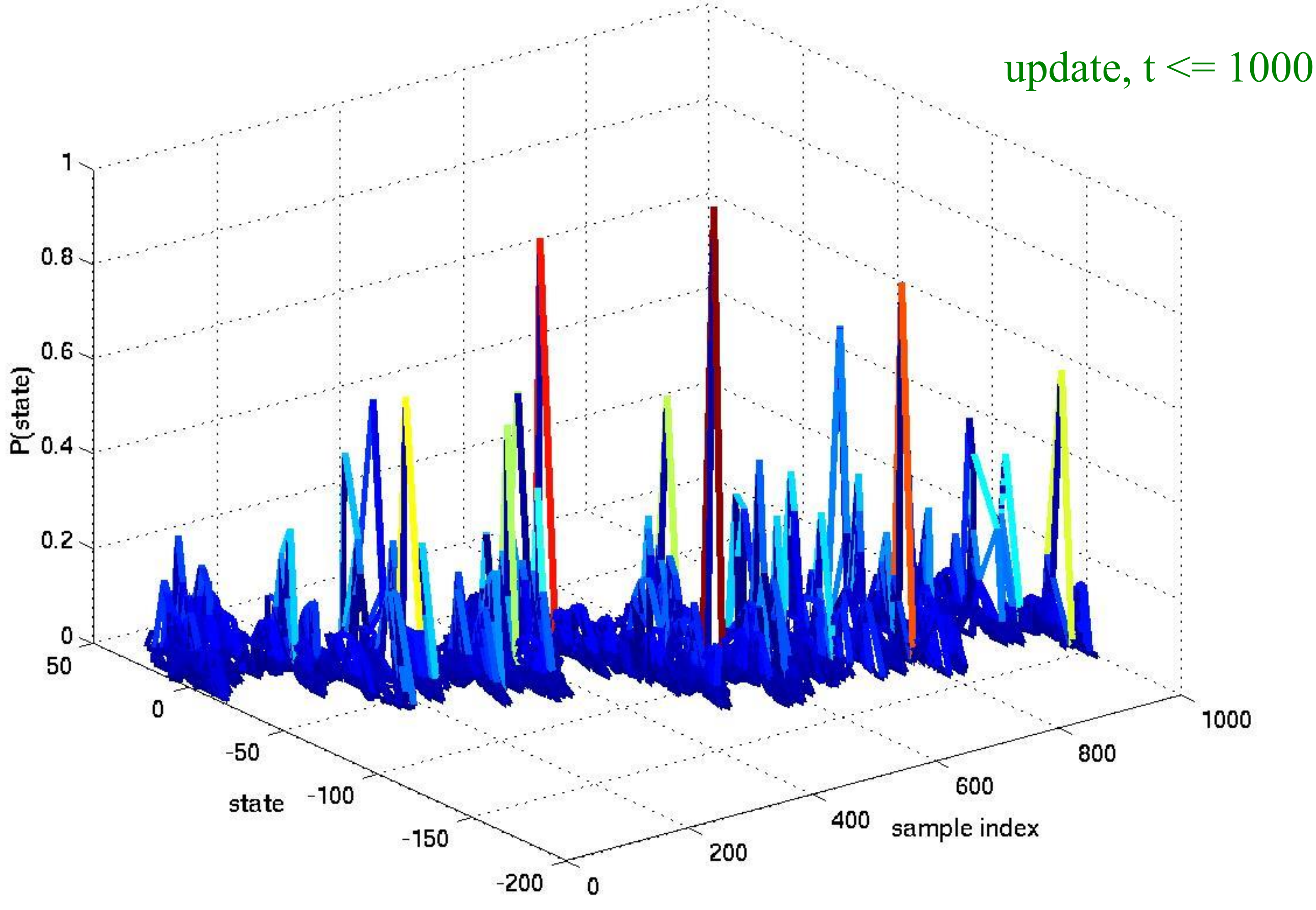
Simulation: Updated Probs Until T=300



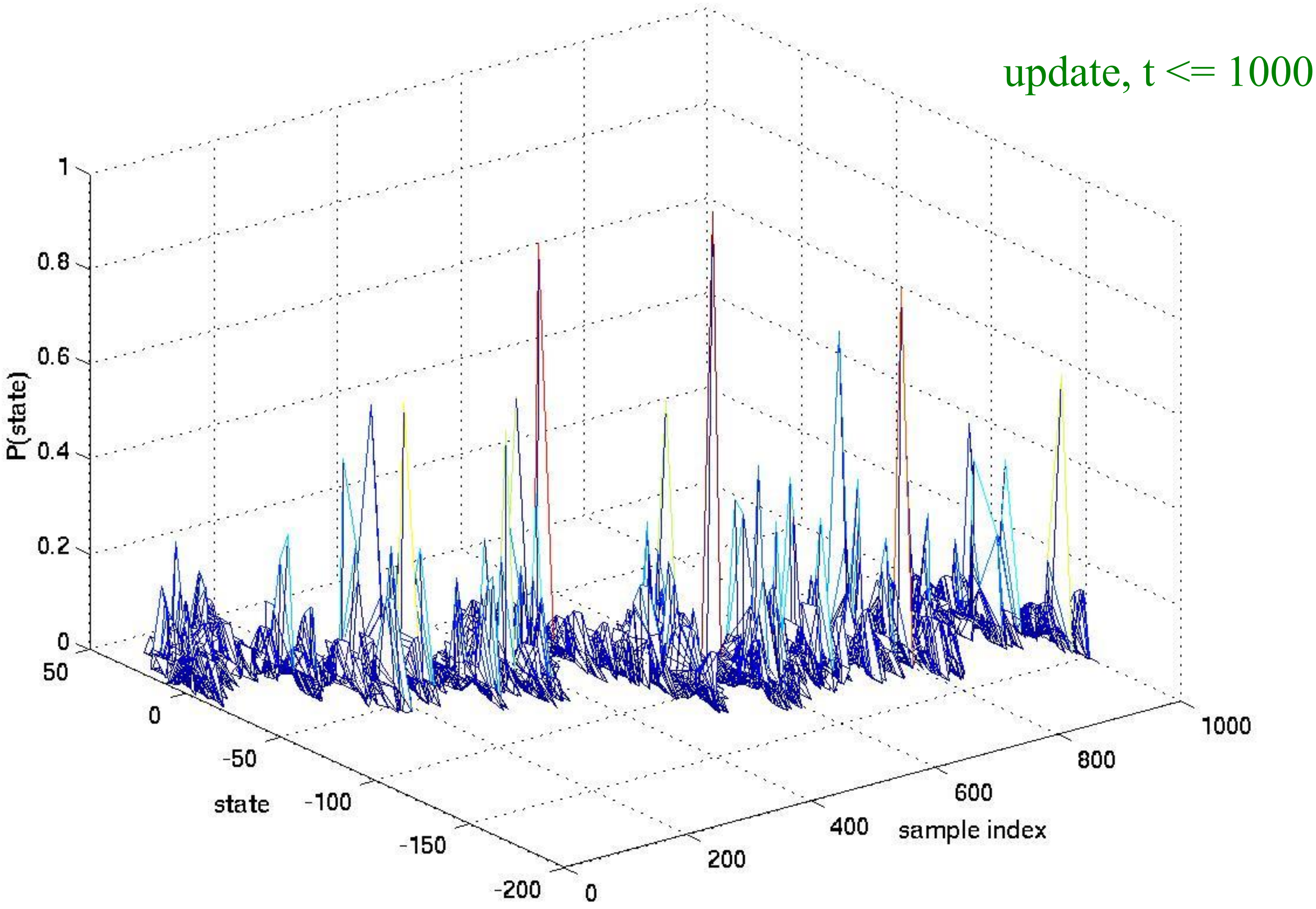
Simulation: Updated Probs Until T=500



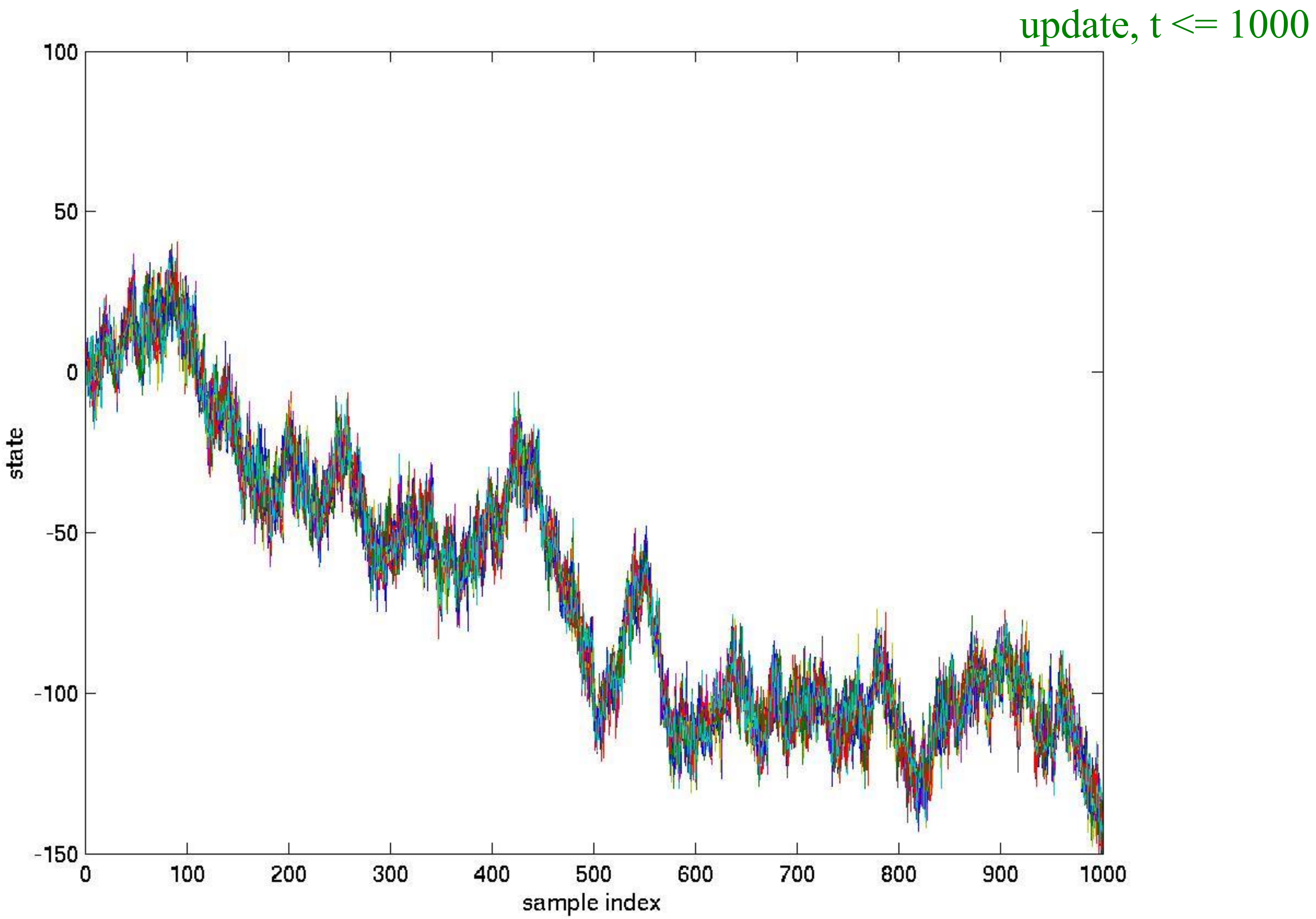
Simulation: Updated Probs Until T=1000



Updated Probs Until T = 1000

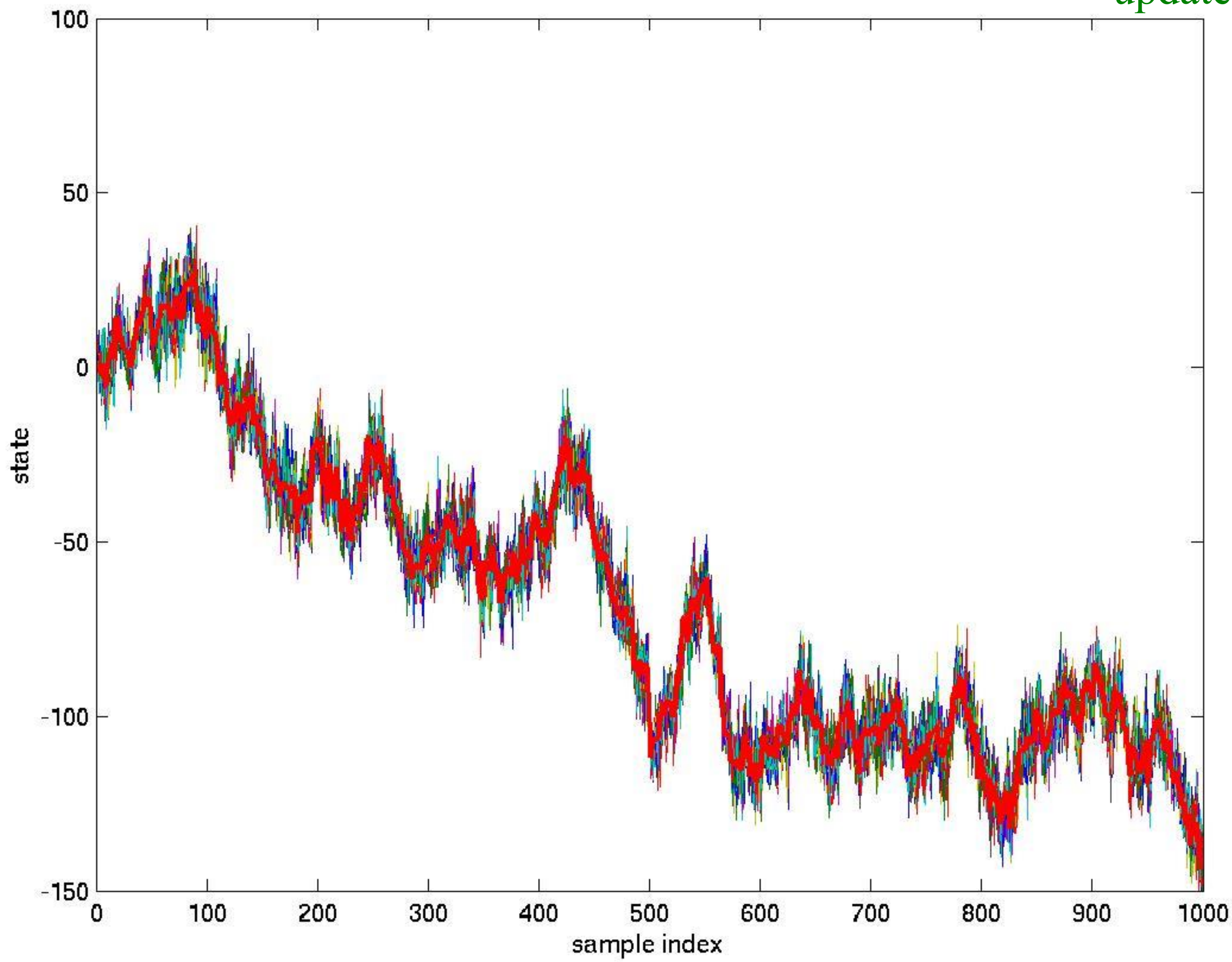


Updated Probs Until T = 1000

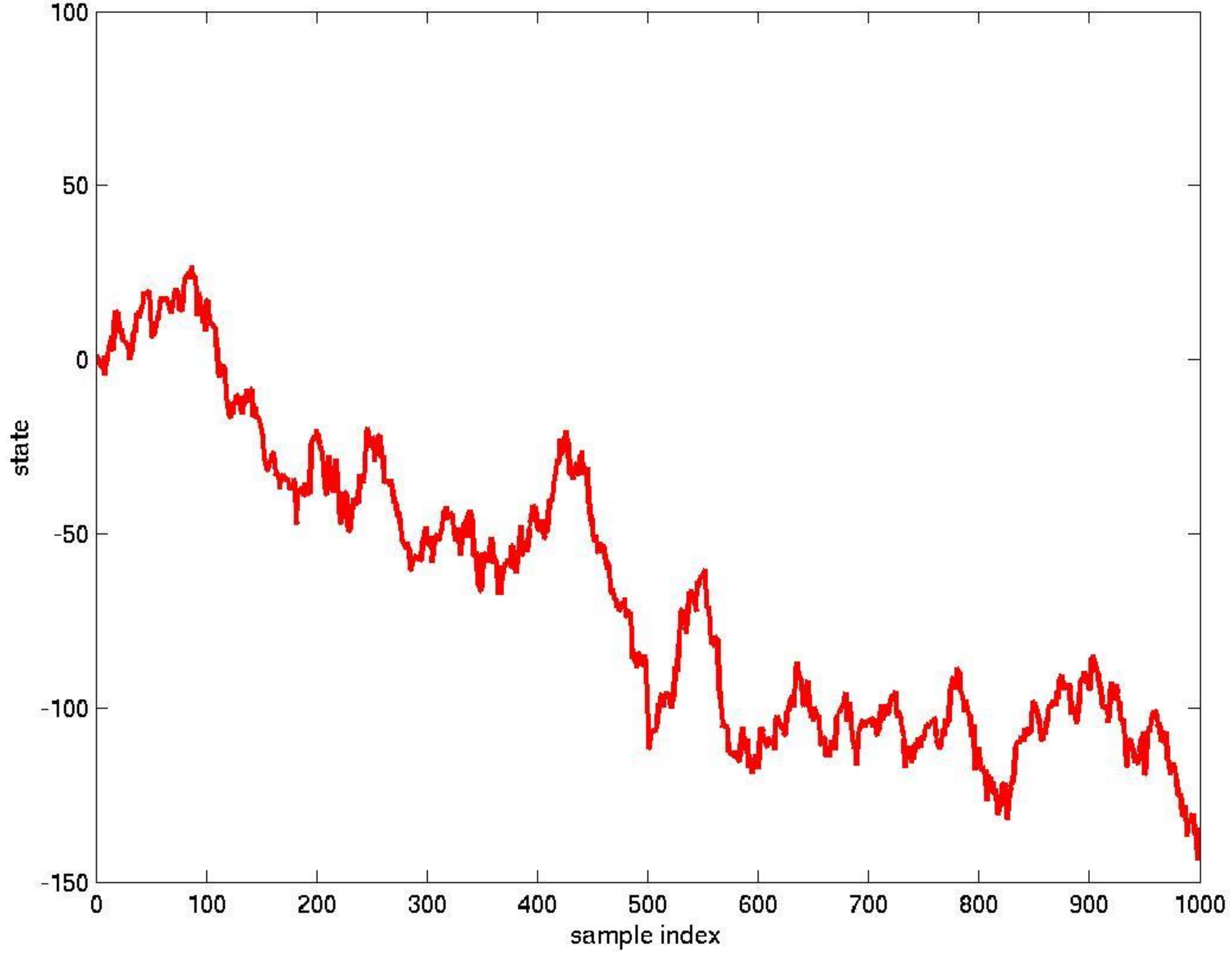


Updated Probs: Top View

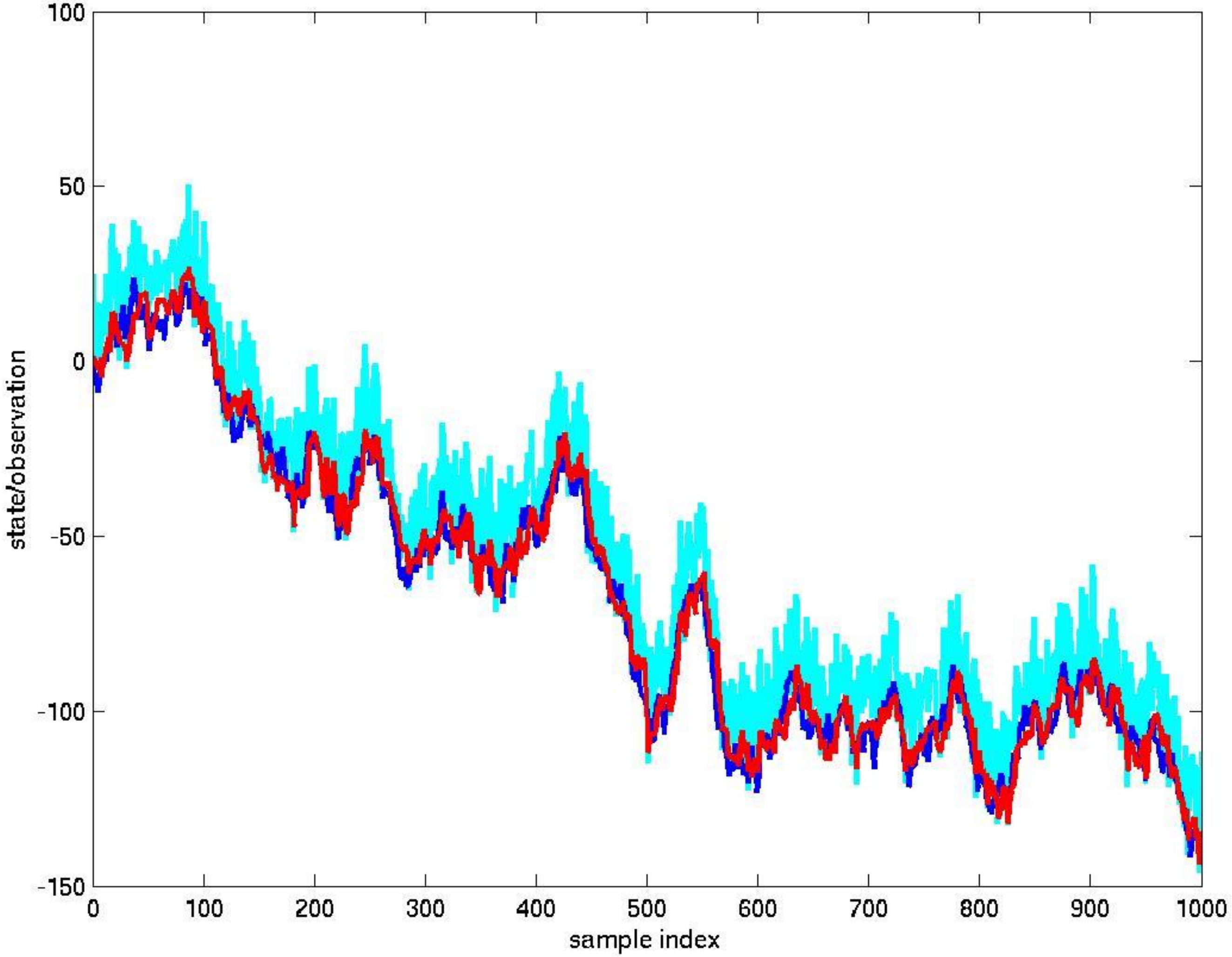
update, t <= 1000



ESTIMATED STATE



Observation, True States, Estimate



Particle Filtering

- Generally quite effective in scenarios where EKF/UKF may not be applicable
  - Potential applications include tracking and edge detection in images!
  - Not very commonly used however
- Highly dependent on sampling
  - A large number of samples required for accurate representation
  - Samples may not represent mode of distribution
  - Some distributions are not amenable to sampling
    - Use importance sampling instead: Sample a Gaussian and assign non-uniform weights to samples

Prediction filters

- HMMs
- Continuous state systems
  - Linear Gaussian: Kalman
  - Nonlinear Gaussian: Extended Kalman
  - Non-Gaussian: Particle filtering

- EKFs are the most commonly used kalman filters..