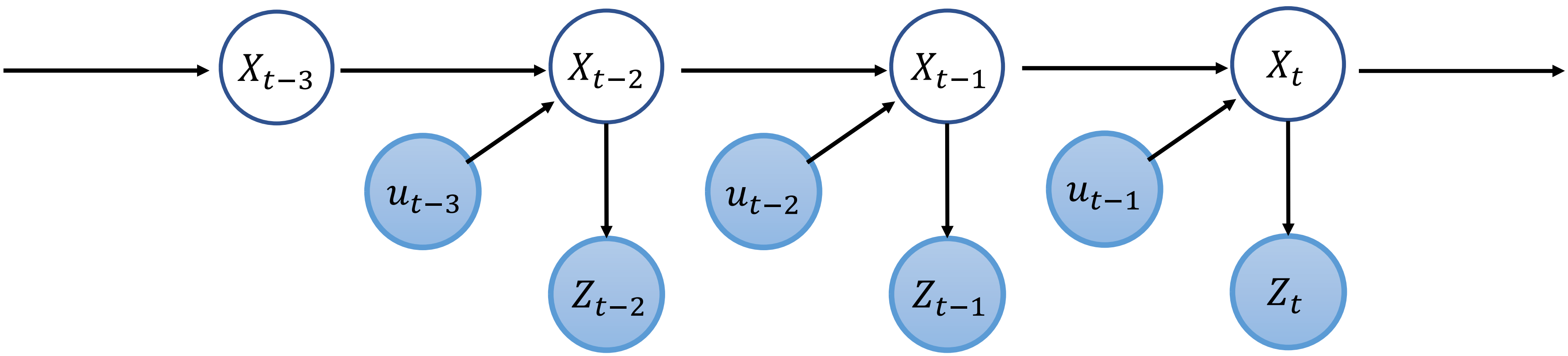
EECE 5550: Mobile Robotics



Lecture 10: All About That Bayes Filter

David M. Rosen

Plan of the day

Last time: Probabilistic robotics and the Bayes Filter

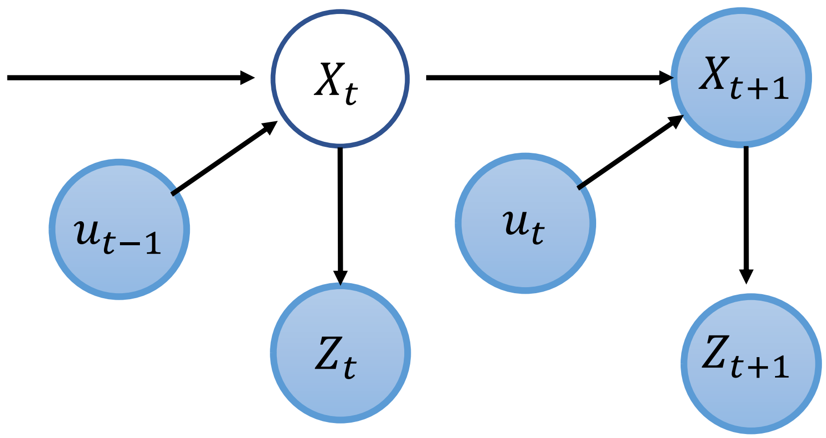
Bayes Filter: For t = 1, 2 … repeat the following operations:

- **Predict** belief for current state X_t given previous control u_{t-1}:

$$p(X_t|u_{0:t-1}, Z_{1:t-1}) = \int p(X_t|X_{t-1}, u_{t-1}) \cdot p(X_{t-1}|u_{0:t-2}, Z_{1:t-1})\ dX_t$$

- **Update** belief after incorporating measurement Z_t at current state X_t:

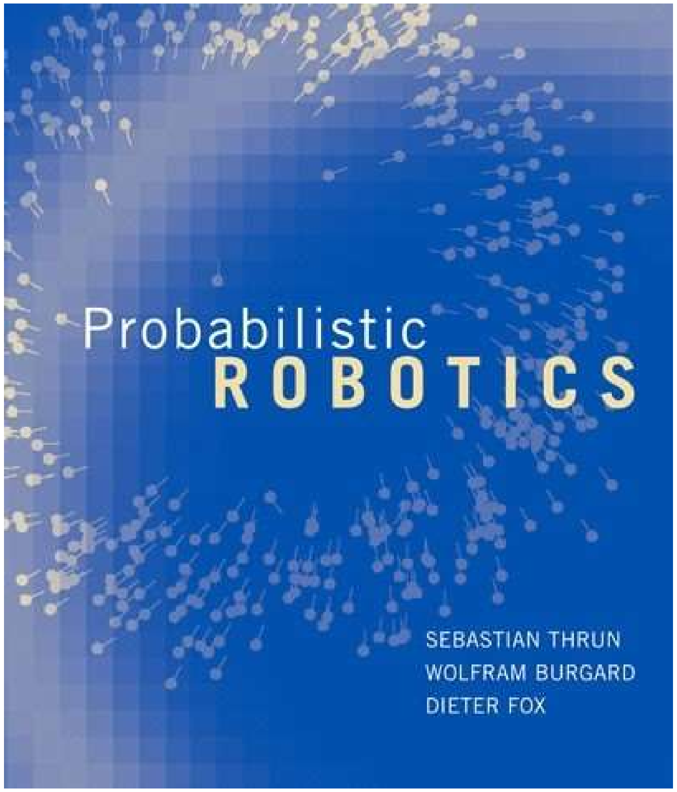
$$p(X_t|u_{0:t-1}, Z_{1:t}) = \frac{p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})}{\int p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})\ dX_t}$$



Today: Three Implementations of the Bayes Filter

1. Linear-Gaussian case: The Kalman Filter (KF)
2. Nonlinear-Gaussian case: The extended Kalman Filter(EKF)
3. Nonlinear, non-Gaussian case: The Particle Filter (PF)

References



Chapters 3 & 4 of “Probabilistic Robotics”

The Kalman Filter (KF)

The *Kalman Filter* is the special case of the Bayes Filter for systems with linear process and measurement models and Gaussian beliefs and uncertainty.

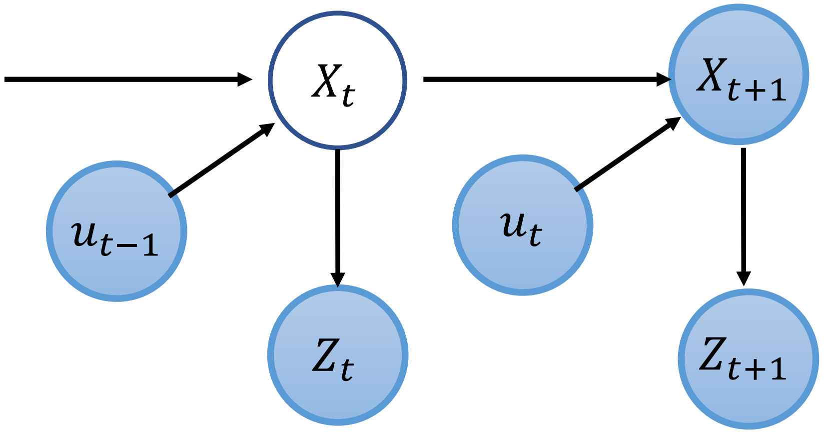
Given: State $x_t \sim N(\mu_t, \Sigma_t)$, control u_t

- **Process model:**

$$x_{t+1} = A_t x_t + B_t u_t + \epsilon_t, \qquad \epsilon_t \sim N(0, R_t)$$

- **Measurement model:**

$$z_t = C_t x_t + \delta_t, \qquad \delta_t \sim N(0, Q_t)$$



Kalman Filter: Propagation step

Given: Current belief $x_t \sim N(\mu_t, \Sigma_t)$ and control u_t

Find: Predicted belief $N(\mu_{t+1}, \Sigma_{t+1})$ for next state x_{t+1}

Process model:

$$x_{t+1} = \underbrace{A_t x_t + B_t u_t}_{\text{Affine transformation of } x_t} + \epsilon_t, \qquad \epsilon_t \sim N(0, R_t)$$

$$\Rightarrow A_t x_t + B_t u_t \sim N(A_t \mu_t + B_t u_t,\ A_t \Sigma_t A_t^T)$$

$$\Rightarrow x_{t+1} \sim N(A_t \mu_t + B_t u_t,\ A_t \Sigma_t A_t^T) + N(0, R_t)$$

$$\Rightarrow x_{t+1} \sim N(\underbrace{A_t \mu_t + B_t u_t}_{\hat{\mu}_{t+1}},\ \underbrace{A_t \Sigma_t A_t^T + R_t}_{\hat{\Sigma}_{t+1}})$$

Kalman Filter: Measurement update step

Given: Prior belief $x_t \sim N\left(\hat{\mu}_t, \hat{\Sigma}_t\right)$ for current state x_t, observation z_t

Find: Posterior belief $x_t | z_t \sim N(\mu_t, \Sigma_t)$

Measurement model:

$$z_t = C_t x_t + \delta_t, \qquad \delta_t \sim N(0, Q_t)$$

Bayes' Rule:

$$p(x_t | z_t) \propto p(z_t | x_t) p(x_t)$$

NB: If we condition on x_t, then the only random variable in the measurement model is δ_t.
Therefore:

$$p(x_t | z_t) \propto p(\delta_t) p(x_t)$$

Substituting for δ_t:

$$p(x_t | z_t) \propto \exp\left(-\frac{1}{2}(z_t - C_t x_t)^T Q_t^{-1} (z_t - C_t x_t)\right) \exp\left(-\frac{1}{2}(x_t - \hat{\mu}_t)^T \hat{\Sigma}_t^{-1} (x_t - \hat{\mu}_t)\right)$$

Kalman Filter: Measurement update step (cont'd)

$$p(x_t|z_t) \propto \exp\left(-\frac{1}{2}(z_t - C_t x_t)^T Q_t^{-1}(z_t - C_t x_t)\right) \exp\left(-\frac{1}{2}(x_t - \hat{\mu}_t)^T \hat{\Sigma}_t^{-1}(x_t - \hat{\mu}_t)\right)$$

Combine exponentials and collect like terms:

$$p(x_t|z_t) \propto \exp\left(-\frac{1}{2}\underbrace{\left[x_t^T\left(C_t^T Q_t^{-1} C_t + \hat{\Sigma}_t^{-1}\right)x_t - 2\left(C_t^T Q_t^{-1} z_t + \hat{\Sigma}_t^{-1}\hat{\mu}_t\right)^T x_t + \left(z_t^T Q_t^{-1} z_t + \hat{\mu}_t^T \hat{\Sigma}_t^{-1}\hat{\mu}_t\right)\right]}_{\triangleq L(x_t)}\right)$$

NB: $L(x)$ is quadratic
$\Rightarrow$ Posterior $p(x_t|z_t)$ is Gaussian!

Pattern matching:

- Quadratic term provides posterior covariance:

$$\Sigma_t = \left(C_t^T Q_t^{-1} C_t + \hat{\Sigma}_t^{-1}\right)^{-1}$$

- Posterior mean μ_t is minimizer of $L(x)$

Kalman Filter: Measurement update step (cont'd)

$$L(x) = x^t\left(C_t^T Q_t^{-1} C_t + \hat{\Sigma}_t^{-1}\right)x - 2\left(C_t^T Q_t^{-1} z_t + \hat{\Sigma}_t^{-1}\hat{\mu}_t\right)^T x + \left(z_t^T Q_t^{-1} z_t + \hat{\mu}_t^T \hat{\Sigma}_t^{-1}\hat{\mu}_t\right)$$

$$\Rightarrow \frac{\partial L}{\partial x}(x) = 2\left(C_t^T Q_t^{-1} C_t + \hat{\Sigma}_t^{-1}\right)x - 2\left(C_t^T Q_t^{-1} z_t + \hat{\Sigma}_t^{-1}\hat{\mu}_t\right)$$

Set $\frac{\partial L}{\partial x} = 0$ to obtain an expression for posterior mean μ_t. After rearranging:

$$C_t^T Q_t^{-1}\underbrace{(z - C_t\mu_t)}_{\text{Measurement residual for posterior mean}} = \hat{\Sigma}_t^{-1}\underbrace{(\mu_t - \hat{\mu}_t)}_{\text{Difference of posterior and prior means}}$$

Let's rewrite the left-hand side above in terms of prior mean:

$$C_t^T Q_t^{-1}(z - C_t\hat{\mu}_t + C_t\hat{\mu}_t - C_t\mu_t) = \hat{\Sigma}_t^{-1}(\mu_t - \hat{\mu}_t)$$

$$\Leftrightarrow C_t^T Q_t^{-1}\underbrace{(z - C_t\hat{\mu}_t)}_{\text{Measurement residual at prior mean}} = \underbrace{\left(C_t^T Q_t^{-1} C_t + \hat{\Sigma}_t^{-1}\right)}_{\Sigma_t^{-1}}\underbrace{(\mu_t - \hat{\mu}_t)}_{\text{Difference of posterior and prior means}}$$

Rearranging the above:

$$\mu_t = \hat{\mu}_t + \underbrace{\Sigma_t C_t^T Q_t^{-1}}_{\text{"Kalman gain"}}\underbrace{(z - C_t\hat{\mu}_t)}_{\text{"innovation"}}$$

Kalman Filter: Measurement update step

Given: Prior belief $x_t \sim N\left(\hat{\mu}_t, \hat{\Sigma}_t\right)$ for current state x_t observation z_t

Find: Posterior belief $x_t | z_t \sim N(\mu_t, \Sigma_t)$

Measurement model:

$$z_t = C_t x_t + \delta_t, \qquad \delta_t \sim N(0, Q_t)$$

1. Compute posterior covariance:

$$\Sigma_t = \left(C_t^T Q_t^{-1} C_t + \hat{\Sigma}_t^{-1}\right)^{-1}$$

2. Compute Kalman gain:

$$K_t = \Sigma_t C_t^T Q_t^{-1}$$

3. Compute posterior mean:

$$\mu_t = \hat{\mu}_t + K_t(z \; - C_t \hat{\mu}_t)$$

An alternative formulation

With a bit of algebra (cf. Sec. 3.2 of *Probabilistic Robotics*), one can an *alternative but equivalent* form of the Kalman filter measurement update

Version 1 (previous slide)

1. Compute posterior covariance:

$$\Sigma_t = \left(C_t^T Q_t^{-1} C_t + \hat{\Sigma}_t^{-1}\right)^{-1}$$

2. Compute Kalman gain:

$$K_t = \Sigma_t C_t^T Q_t^{-1}$$

3. Compute posterior mean:

$$\mu_t = \hat{\mu}_t + K_t(z - C_t \hat{\mu}_t)$$

Three inverses

Version 2 ("standard" form)

1. Compute Kalman gain:

$$K_t = \hat{\Sigma}_t C_t^T \left(C_t \hat{\Sigma}_t C_t^T + Q_t\right)^{-1}$$

2. Compute posterior mean:

$$\mu_t = \hat{\mu}_t + K_t(z - C_t \hat{\mu}_t)$$

3. Compute posterior covariance:

$$\Sigma_t = (I - K_t C_t)\hat{\Sigma}_t$$

One inverse

The Kalman Filter: Complete Algorithm

Predict: Given belief $x_t \sim N(\mu_t, \Sigma_t)$ for the current state x_t, control u_t, and process model:

$$x_{t+1} = A_t x_t + B_t u_t + \epsilon_t, \qquad \epsilon_t \sim N(0, R_t)$$

the belief for the *next* state x_{t+1} is $N(\mu_{t+1}, \Sigma_{t+1})$, where:

$$\mu_{t+1} = A_t \mu_t + B_t u_t, \quad \Sigma_{t+1} = A_t \Sigma_t A_t^T + R_t$$

Update: Given prior belief $x_t \sim N\left(\hat{\mu}_t, \hat{\Sigma}_t\right)$ for the current state x_t, measurement z_t, and measurement model:

$$z_t = C_t x_t + \delta_t, \qquad \delta_t \sim N(0, Q_t)$$

the posterior belief for x_t given z_t is $N(\mu_t, \Sigma_t)$, where:

$$\mu_t = \hat{\mu}_t + K_t(z - C_t \hat{\mu}_t), \qquad \Sigma_t = (I - K_t C_t)\hat{\Sigma}_t$$

and

$$K_t = \hat{\Sigma}_t C_t^T \left(C_t \hat{\Sigma}_t C_t^T + Q_t\right)^{-1}$$

Plan of the day

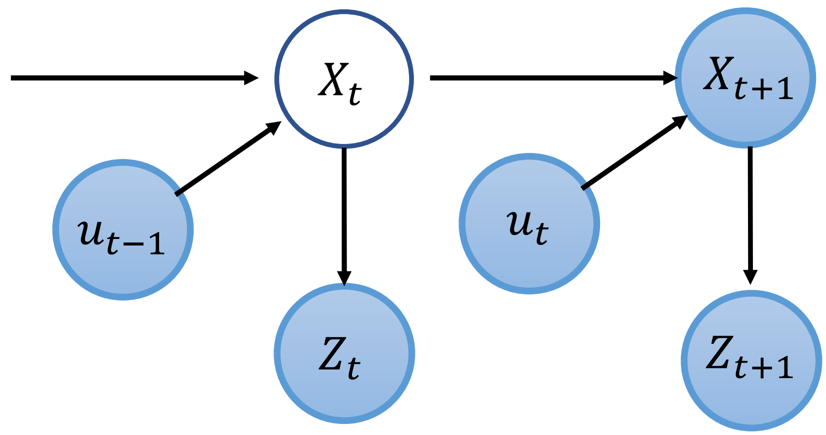
Bayes Filter: For t = 1, 2 … repeat the following operations:

- **Predict** belief for current state X_t given previous control u_{t-1}:

$$p(X_t|u_{0:t-1}, Z_{1:t-1}) = \int p(X_t|X_{t-1}, u_{t-1}) \cdot p(X_{t-1}|u_{0:t-2}, Z_{1:t-1})\ dX_t$$

- **Update** belief after incorporating measurement Z_t at current state X_t:

$$p(X_t|u_{0:t-1}, Z_{1:t}) = \frac{p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})}{\int p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})\ dX_t}$$



Today: Three Implementations of the Bayes Filter

1. Linear-Gaussian case: The Kalman Filter (KF)
2. Nonlinear-Gaussian case: The extended Kalman Filter(EKF)
3. Nonlinear, non-Gaussian case: The Particle Filter (PF)

The Extended Kalman Filter (EKF)

The *extended Kalman Filter* is a linearized approximation of the Bayes Filter for systems with nonlinear process and/or measurement models and Gaussian beliefs and uncertainty.

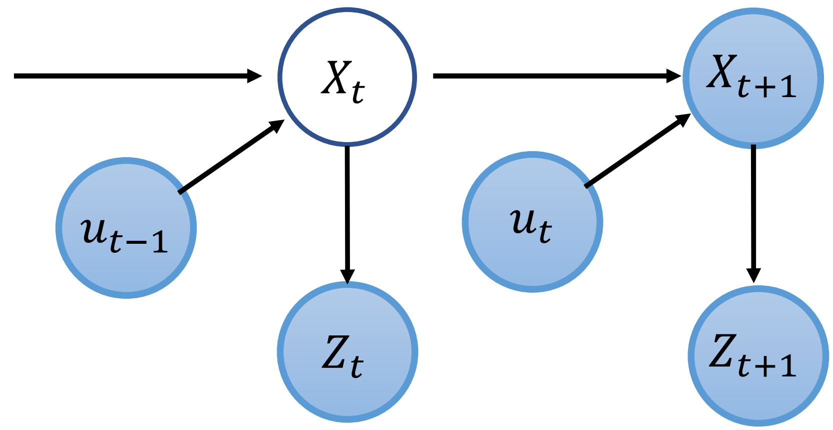
Given: State $x_t \sim N(\mu_t, \Sigma_t)$, control u_t

- **Process model:**

$$x_{t+1} = g_t(x_t, u_t) + \epsilon_t, \qquad \epsilon_t \sim N(0, R_t)$$

- **Measurement model:**

$$z_t = h_t(x_t) + \delta_t, \qquad \delta_t \sim N(0, Q_t)$$



Main idea: *Locally approximate* g_t and h_t as linear functions via *linearization*

Extended Kalman Filter: Propagation step

Given: Current belief $x_t \sim N(\mu_t, \Sigma_t)$ and control u_t

Find: Predicted belief $N(\mu_{t+1}, \Sigma_{t+1})$ for next state x_{t+1}

Approximate mean using *exact* state propagation model:

$$\mu_{t+1} = g_t(x_t, u_t)$$

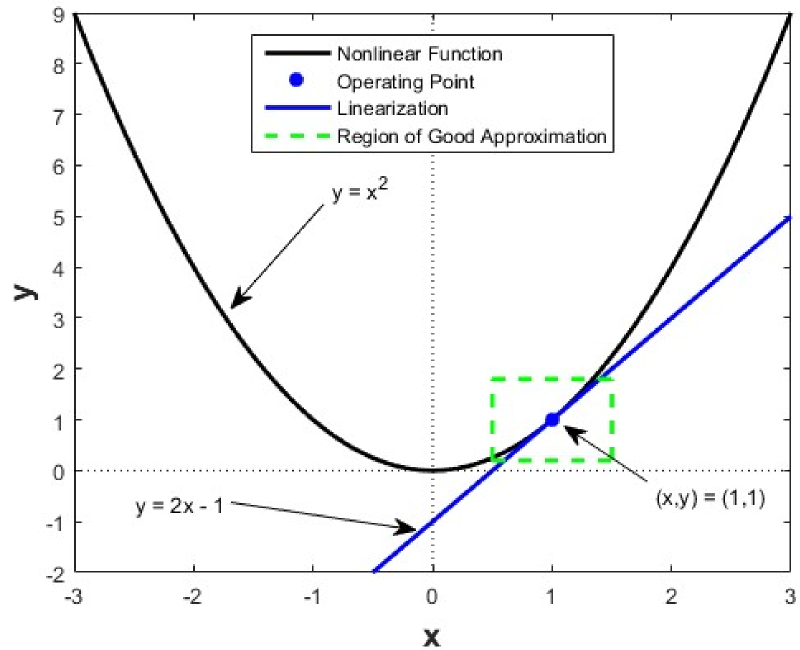
Approximate covariance using *local linearization* of g_t about the current mean μ_t:

$$\Sigma_{t+1} = G_t \Sigma_t G_t^T + R_t$$

where

$$G_t \triangleq \frac{\partial g_t}{\partial x}(x, u),$$

$$g_t(x, u_t) = g_t(\mu_t, u_t) + G_t(x - \mu_t) + O(x - \mu_t)^2$$



Extended Kalman Filter: Measurement update step

Given: Prior belief $x_t \sim N(\hat{\mu}_t, \hat{\Sigma}_t)$ for current state x_t observation z_t

Find: Posterior belief $x_t | z_t \sim N(\mu_t, \Sigma_t)$

Linearize measurement model about current mean estimate μ_t:

$$h_t(x) \approx h_t(\mu_t) + H_t(x - \mu_t) + O(x - \mu_t)^2$$

where

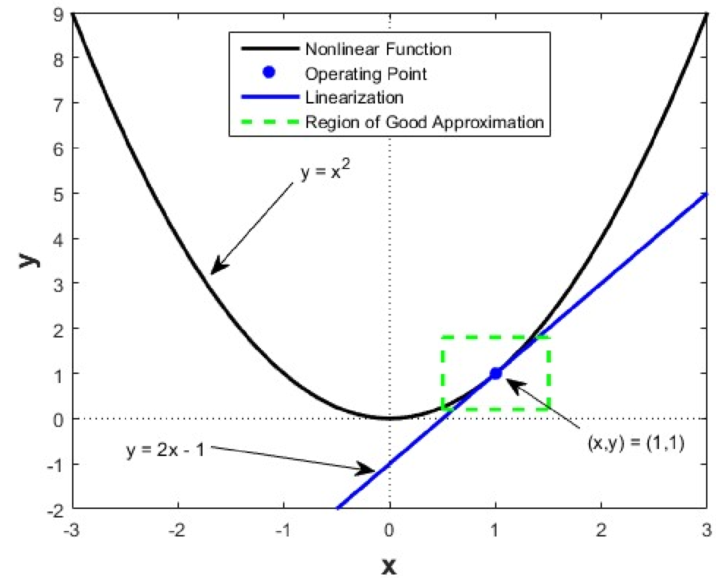
$$H_t \triangleq \frac{\partial h_t}{\partial x}(x).$$

1. Compute Kalman gain:

$$K_t = \hat{\Sigma}_t H_t^T \left(H_t \hat{\Sigma}_t H_t^T + Q_t\right)^{-1}$$

2. Approximate posterior mean and covariance:

$$\mu_t = \hat{\mu}_t + K_t(z - h_t(\hat{\mu}_t)), \qquad \Sigma_t = (I - K_t H_t)\hat{\Sigma}_t$$



The Kalman Filter: Complete Algorithm

Predict: Given belief $x_t \sim N(\mu_t, \Sigma_t)$ for the current state x_t, control u_t, and process model:

$$x_{t+1} = g_t(x_t, u_t) + \epsilon_t, \qquad \epsilon_t \sim N(0, R_t)$$

the belief for the *next* state x_{t+1} is approximated by $N(\mu_{t+1}, \Sigma_{t+1})$, where:

$$\mu_{t+1} = g_t(\mu_t, u_t), \quad \Sigma_{t+1} = G_t \Sigma_t G_t^T + R_t, \quad G_t \triangleq \frac{\partial g_t}{\partial x}(x, u)$$

Update: Given prior belief $x_t \sim N\left(\hat{\mu}_t, \hat{\Sigma}_t\right)$ for the current state x_t, measurement z_t, and measurement model:

$$z_t = h_t(x_t) + \delta_t, \qquad \delta_t \sim N(0, Q_t)$$

the posterior belief for x_t given z_t is approximated by $N(\mu_t, \Sigma_t)$, where:

$$\mu_t = \hat{\mu}_t + K_t(z - h_t(\hat{\mu}_t)), \qquad \Sigma_t = (I - K_t H_t)\hat{\Sigma}_t, \qquad K_t = \hat{\Sigma}_t H_t^T \left(H_t \hat{\Sigma}_t H_t^T + Q_t\right)^{-1}$$

and

$$H_t \triangleq \frac{\partial h_t}{\partial x}(x)$$

The Extended Kalman Filter: Fun Facts

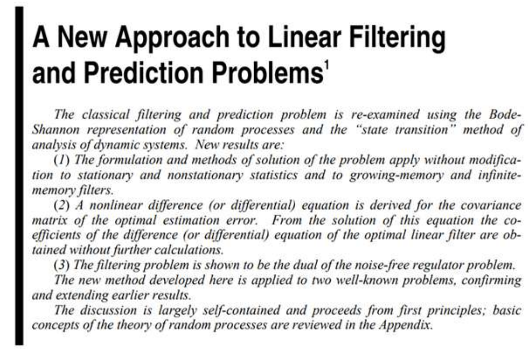
Probably *the* single most important state estimation algorithm of all time

- Kalman supposedly had difficulty publishing: the KF was thought “too good to be true”

- Applications in robotics, computer vision, aviation, astronautics, signal processing, economics, …

- **In particular**: Foundation of the primary guidance, navigation, and control systems (PGNCS) in Apollo Project spacecraft

R.E. Kalman receives the National Medal of Science



A New Approach to Linear Filtering and Prediction Problems[1]

The classical filtering and prediction problem is re-examined using the Bode-Shannon representation of random processes and the “state transition” method of analysis of dynamic systems. New results are:

(1) The formulation and methods of solution of the problem apply without modification to stationary and nonstationary statistics and to growing-memory and infinite-memory filters.

(2) A nonlinear difference (or differential) equation is derived for the covariance matrix of the optimal estimation error. From the solution of this equation the coefficients of the difference (or differential) equation of the optimal linear filter are obtained without further calculations.

(3) The filtering problem is shown to be the dual of the noise-free regulator problem.

The new method developed here is applied to two well-known problems, confirming and extending earlier results.

The discussion is largely self-contained and proceeds from first principles; basic concepts of the theory of random processes are reviewed in the Appendix.

Kalman Filtering, simply explained

Algorithm Extended_Kalman_filter($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t$):

$\bar{\mu}_t = g(u_t, \mu_{t-1})$

$\bar{\Sigma}_t = G_t \, \Sigma_{t-1} \, G_t^T + R_t$

$K_t = \bar{\Sigma}_t \, H_t^T (H_t \, \bar{\Sigma}_t \, H_t^T + Q_t)^{-1}$

$\mu_t = \bar{\mu}_t + K_t(z_t - h(\bar{\mu}_t))$

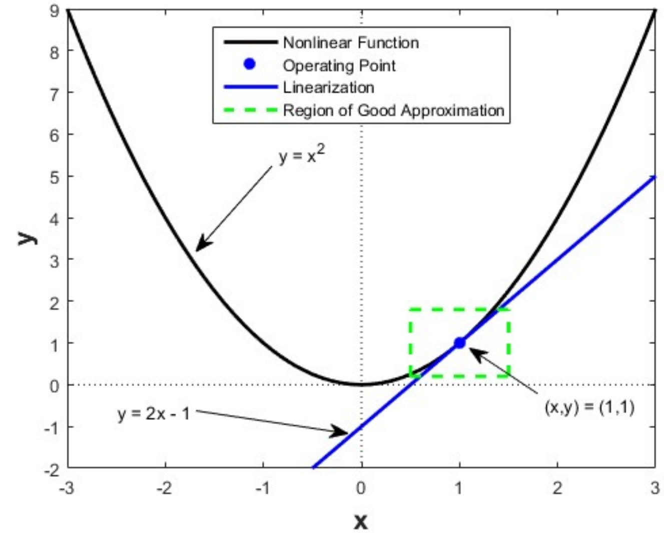
$\Sigma_t = (I - K_t \, H_t) \, \bar{\Sigma}_t$

return μ_t, Σ_t

Kalman filter practicalities

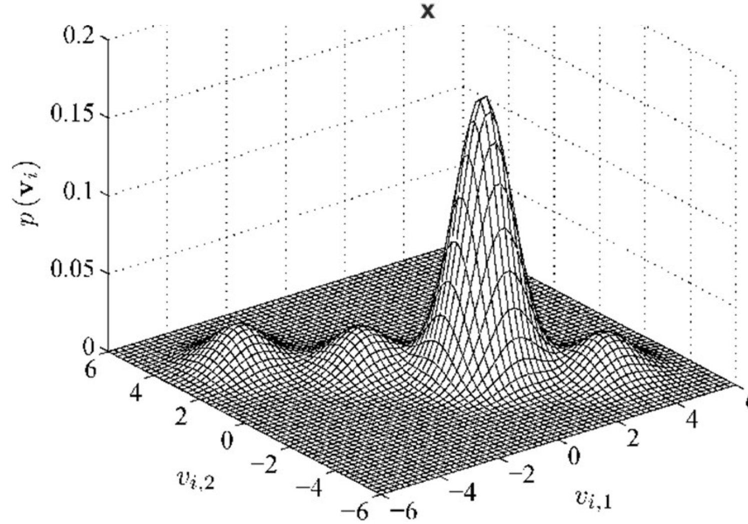
The EKF is a *compact*, *parametric* approximation of the Bayes Filter for nonlinear systems with Gaussian beliefs

- Super handy :-D!
- Requires only a bit of calculus and linear algebra to implement



BUT: Crucially depends upon two key assumptions:

- Local linearization provides a good approximation of the nonlinear state and measurement models g_t and h_t
- A Gaussian distribution is a good model of the true uncertainty



⇒ Kalman filtering works best for systems with:

- Unimodal (true) distributions (priors + posteriors)
- Concentrated distributions (relative to scale of nonlinearities)

Plan of the day

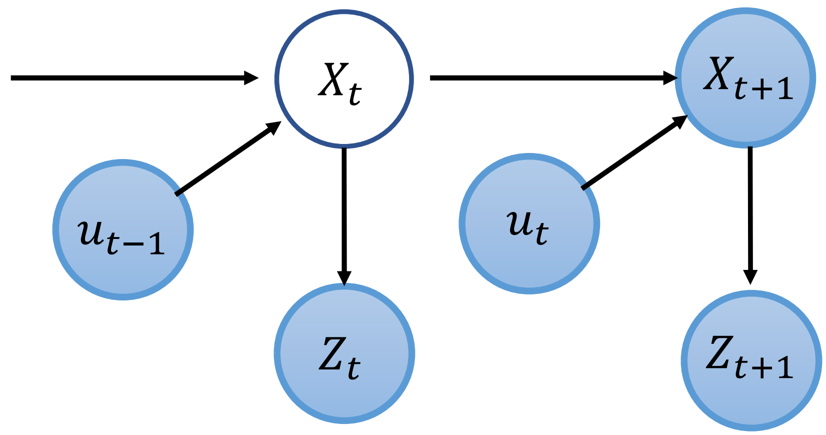
Bayes Filter: For t = 1, 2 … repeat the following operations:

- **Predict** belief for current state X_t given previous control u_{t-1}:

$$p(X_t|u_{0:t-1}, Z_{1:t-1}) = \int p(X_t|X_{t-1}, u_{t-1}) \cdot p(X_{t-1}|u_{0:t-2}, Z_{1:t-1})\ dX_t$$

- **Update** belief after incorporating measurement Z_t at current state X_t:

$$p(X_t|u_{0:t-1}, Z_{1:t}) = \frac{p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})}{\int p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})\ dX_t}$$



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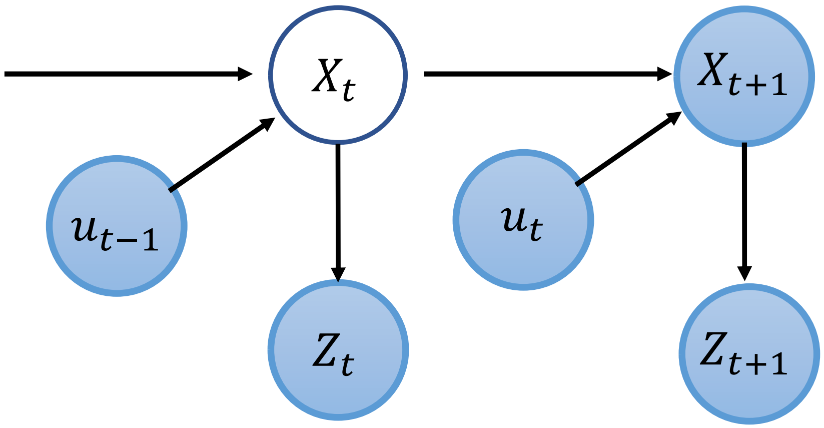
The Particle Filter (PF)

The *particle filter* is an approximate Bayes Filter implementation for systems with nonlinear process and measurement models and general beliefs and uncertainty.

Given: State $x_t \sim p(x_t)$, control u_t



- **Process model:**

$$x_{t+1} \sim p(x_{t+1} | x_t, u_t)$$

- **Measurement model:**

$$z_t \sim p(z_t | x_t)$$

NB: Unlike the KF & EKF, the particle filter *does not* assume that the belief takes a specific form

Key question: How can we represent an *arbitrary* belief $p(x)$ in practice??

Sampling-based simulation and inference

Main idea: We can (*implicitly*) represent a probability distribution $p(x)$ using a *set of samples* $\{x\}_{i=1}^{n}$ drawn from it

In practice, we are often interested in some statistic:

$$T = E_{x \sim p}[f(x)]$$

of the distribution $p(x)$ (e.g. mean, covariance, etc.)

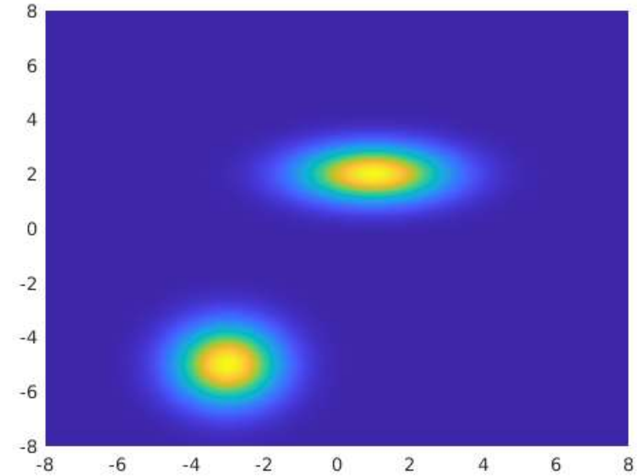
If we can *sample* from $p(x)$, then we can always approximate *T* using a *sample* or (*empirical*) *estimate*:

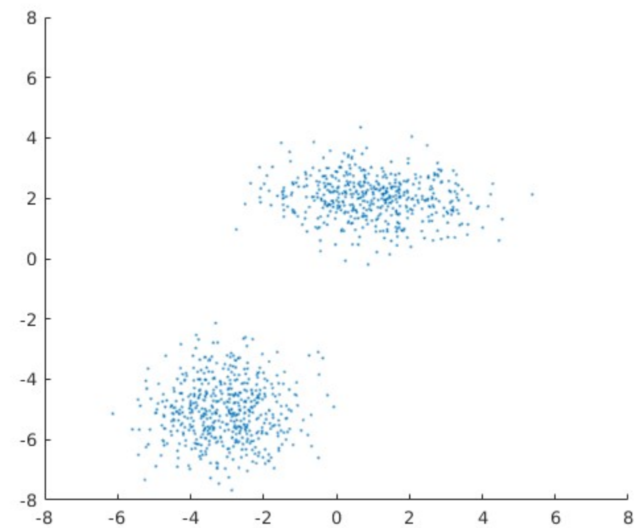
$$S_n \triangleq \frac{1}{n}\sum_{i=1}^{n} f(x_i)$$

Note that:

$$T = \lim_{n \to \infty} S_n$$

by the Law of Large Numbers





Importance sampling

Problem: What if we *don't know how* to sample from our target distribution $p(x)$?

Importance sampling provides a means of simulating draws from $p(x)$ using draws from a tractable *proposal distribution* $q(x)$

Algorithm:

1. Draw *n* samples $x_i \sim q$
2. Assign each sample x_i the *weight* $w_i \triangleq p(x_i)/q(x_i)$
3. Calculate weighted sample statistic:

$$S_n \triangleq \frac{1}{n} \sum_{i=1} w_i f(x_i)$$

One-slide derivation of importance sampling

Consider:

$$
\begin{aligned}
E_{x\sim q(x)}[w(x)f(x)] &= E_{x\sim q(x)}\left[\frac{p(x)}{q(x)}f(x)\right] \\
&= \int \left(\frac{p(x)}{\cancel{q(x)}}f(x)\right)\cancel{q(x)}dx \\
&= \int p(x)f(x)dx \\
&= E_{x\sim p(x)}[f(x)]
\end{aligned}
$$

Particle Filter: Propagation step

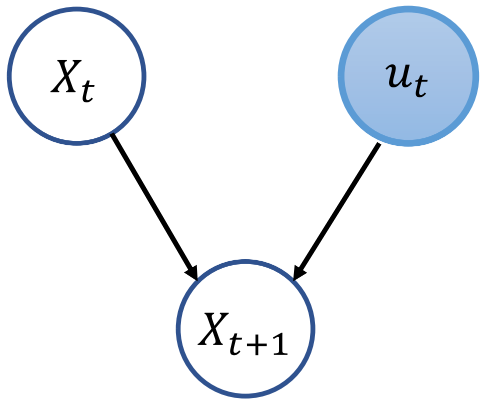
Given: Sample set $\left\{x_t^{[i]}\right\}_{i=1}^{n}$ for *current* state x_t, control u_t, process model $p(x_{t+1}|x_t, u_t)$

Find: Sample set $\left\{x_{t+1}^{[i]}\right\}_{i=1}^{n}$ for *next* state x_{t+1}

Solution: Use ancestral sampling!

For *i* = 1, … *n*, sample $x_{t+1}^{[i]}$ according to:

$$x_{t+1}^{[i]} \sim p(x_{t+1}|x_t^{[i]}, u_t)$$



Particle Filter: Measurement update step

Given: Sample set $\left\{\hat{x}_t^{[i]}\right\}_{i=1}^{n}$ for *prior* belief over x_t, measurement z_t, measurement model $p(z_t|\hat{x}_t)$

Find: Sample set $\left\{x_t^{[i]}\right\}_{i=1}^{n}$ for *posterior* belief over x_t given z_t

Bayes' Rule:

$$p(x_t|z_t) = \frac{p(z_t|x_t)p(x_t)}{p(z_t)}$$

Importance sampling: Calculate importance weights:

$$w_i = \frac{p(x_t|z_t)}{p(x_t)} = \frac{p(z_t|x_t)}{p(z_t)} \propto p(z_t|x_t)$$

For *i* = 1, …, n:

Draw a *posterior* sample $x_t^{[i]}$ from the set of *prior* samples $\left\{\hat{x}_t^{[i]}\right\}_{i=1}^{n}$ by selecting $\hat{x}_t^{[i]}$ with probability proportional to $w_i = p\left(z_t \middle| \hat{x}_t^{[i]}\right)$

Particle Filter: Complete algorithm

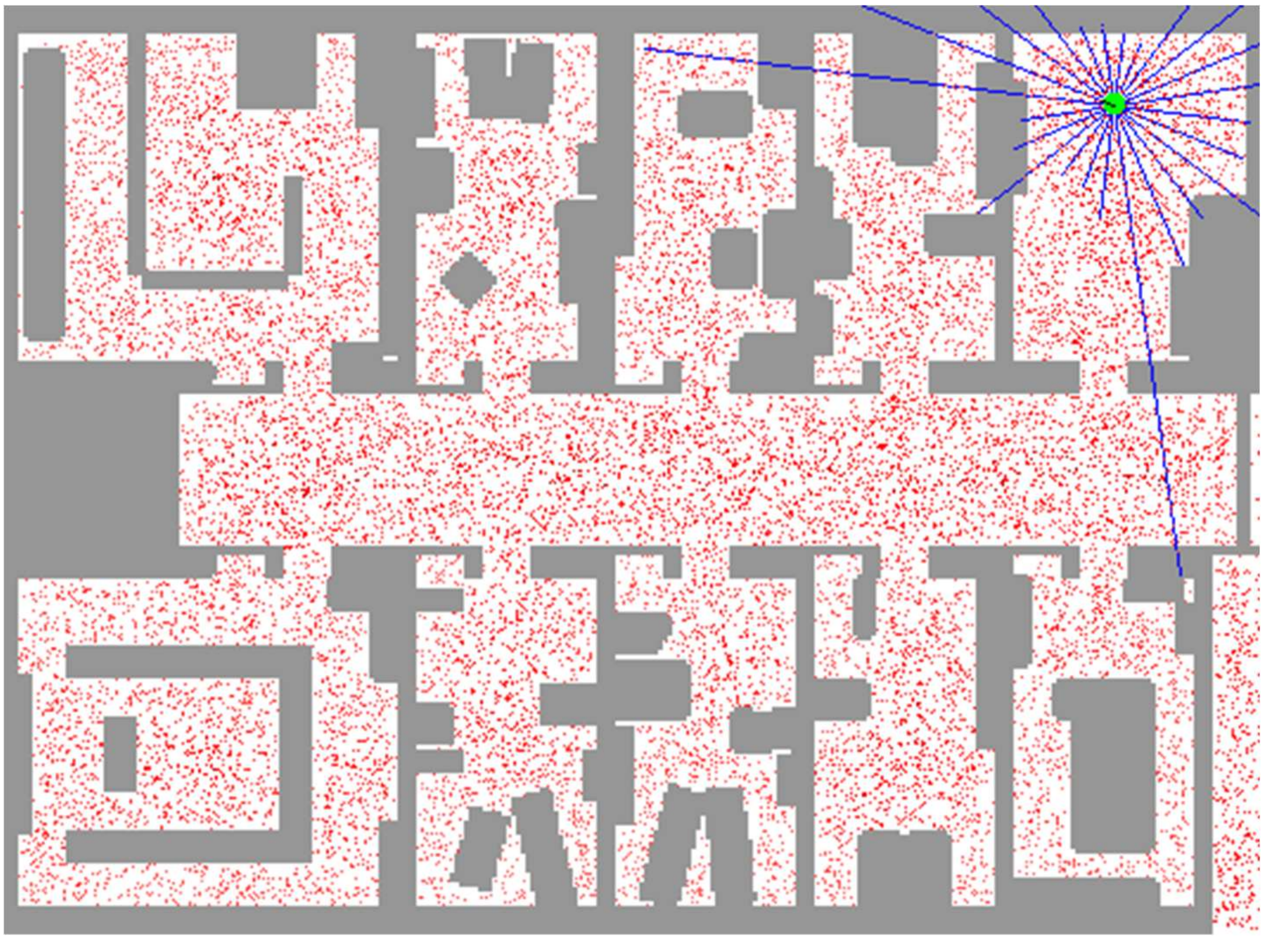
Predict: Given sample set $\left\{x_t^{[i]}\right\}_{i=1}^n$ for belief over *current* state x_t, control u_t, and process model $p(x_{t+1}|x_t, u_t)$, draw sample set $\left\{x_{t+1}^{[i]}\right\}_{i=1}^n$ for belief over *next* state x_{t+1} according to:

$$x_{t+1}^{[i]} \sim p(x_{t+1}|x_t^{[i]}, u_t)$$

Update: Given sample set $\left\{\hat{x}_t^{[i]}\right\}_{i=1}^n$ for *prior* belief over x_t, measurement z_t, and measurement model $p(z_t|x_t)$, draw sample set $\left\{x_t^{[i]}\right\}_{i=1}^n$ for *posterior* of x_t given z_t by:

1. **Calculate weights:** Compute particle importance weights: $w_i \triangleq p(z_t|\, \hat{x}_t^{[i]})$
2. **Resample:** For each *i* = 1, …, n, sample $x_t^{[i]}$ from $\left\{\hat{x}_t^{[i]}\right\}_{i=1}^n$ by drawing $\hat{x}_t^{[i]}$ with probability proportional to its weight w_i

Example: Particle filter localization



Particle filter practicalities

The PF is a *nonparametric* approximation of the Bayes Filter for general (nonlinear + non-Gaussian) state estimation problems

Super simple to implement – requires only:

- A sampler for the motion model. Typically this is very simple (simulation)
- The likelihood function for your sensors – usually this comes straight from the sensor geometry

BUT: Particle filters can be finicky in practice!

- How many samples do we need? Typically *exponential* in the dimension of the state!
  ⇒Can require lots of storage, compute
- **Particle depletion:** If particle set is *insufficiently diverse*, it may not be able to track all relevant modes of the true posterior!

⇒ Particle filtering works best for low-dimensional state estimation problems

Plan of the day

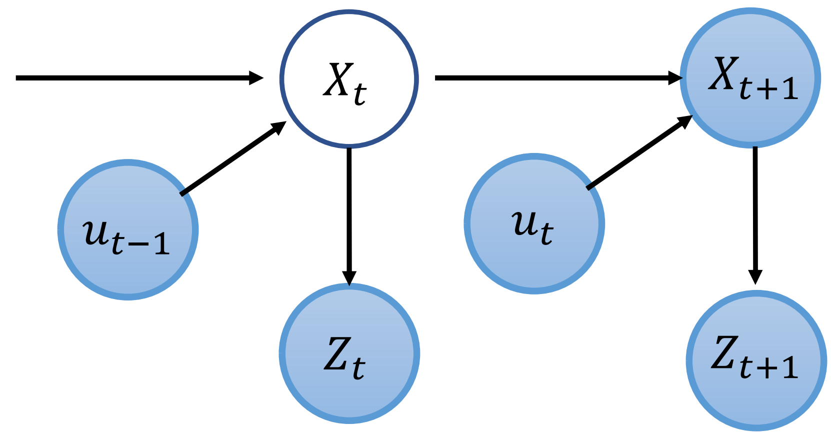
Bayes Filter: For t = 1, 2 … repeat the following operations:

- **Predict** belief for current state X_t given previous control u_{t-1}:

$$p(X_t|u_{0:t-1}, Z_{1:t-1}) = \int p(X_t|X_{t-1}, u_{t-1}) \cdot p(X_{t-1}|u_{0:t-2}, Z_{1:t-1})\ dX_t$$

- **Update** belief after incorporating measurement Z_t at current state X_t:

$$p(X_t|u_{0:t-1}, Z_{1:t}) = \frac{p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})}{\int p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})\ dX_t}$$



Today: Three Implementations of the Bayes Filter

1. Linear-Gaussian case: The Kalman Filter (KF)
2. Nonlinear-Gaussian case: The extended Kalman Filter(EKF)
3. Nonlinear, non-Gaussian case: The Particle Filter (PF)