

# Mean-Squared-Error Estimation Dec 6, 2022

Let  $X, Y$  be two random variables.

Suppose we want to estimate  $Y$  given that  $X = x$ . What is the "best" estimate of  $Y$  given  $X = x$ ?

One criterion commonly used is the minimum-mean-squared-error (MMSE) criterion: Find a function  $c(x)$  such that  $\varepsilon = E[(Y - c(X))^2]$

is minimized.

The result is  $c(x) = E[Y | X = x]$

$$\text{Proof. } \varepsilon = \iint_{\mathbb{R}^2} (y - c(x))^2 f_{X,Y}(x, y) dx dy$$

$$= \int_{\mathbb{R}} f_X(x) \underbrace{\left[ \int_{\mathbb{R}} (y - c(x))^2 f_{Y|X}(y|x) dy \right]}_{h(x)} dx$$

Since  $f_x(x)$ ,  ~~$f_x(x)$~~   $h(x)$  are  $\textcircled{2}$

$\geq 0 \quad \forall x$ , can minimize  $E$  by minimizing  $h(x)$   
 $\forall x \in \mathbb{R}$ , To minimize  $h(x)$ :

$$\frac{\partial}{\partial c(x)} h(x) = -2 \int_{-\infty}^{\infty} (y - c(x)) f_{Y|X}(y|x) dy = 0$$

$$\text{So } \int_{-\infty}^{\infty} (y - c(x)) f_{Y|X}(y|x) dy = 0, \text{ or}$$

$$E[Y|X=x] - c(x) = 0$$

$$\text{So } c(x) = E[Y|X=x]$$

Sometimes  $c(x)$  is constrained to be a linear function.

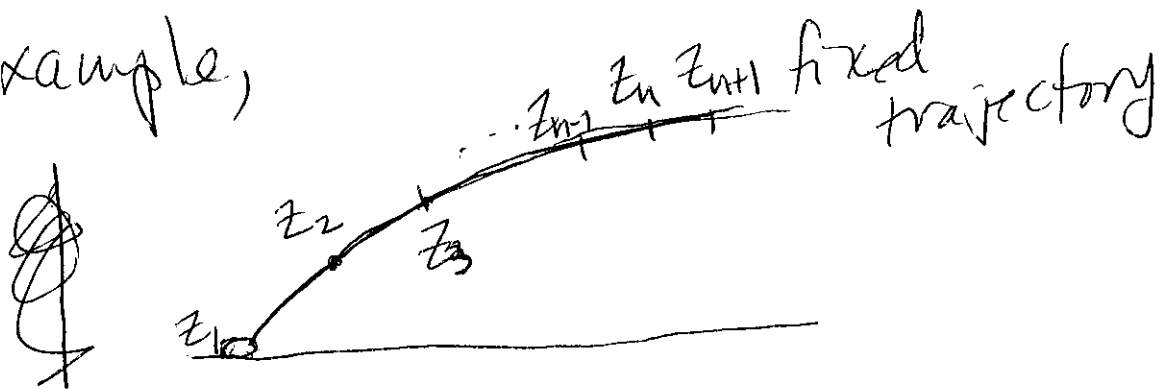
This is the case for the Kalman filter.

# The Kalman Filter

(3)

Estimates the state of a dynamic system from a sequence of noisy measurements of the state.

For example,



Want to estimate the distance  $z_n$  along the trajectory that object has traveled by time  $n$  (actually time  $t_n$ ). Two-stage model:

The state model is

$$z_n = a_{n-1} z_{n-1} + w_{n-1}, \quad n=1, 2, \dots$$

for some initial state  $z_0$

$Z_n \sim$  state variable (4)

(In practice  $Z_n$  is a vector with, e.g., 3 position rvs, 3 velocity rvs, etc.)

$a_n \sim$  constant <sup>sequence</sup> (not random) that quantifies the state transitions

$W_{n-1} \sim$  state model error, modeled as a zero-mean uncorrelated sequence of rvs, so

$$E[W_n] = 0 \quad \forall n$$

$$E[W_j W_k] = 0 \quad \forall j \neq k$$

So  $E[W_n^2] \sim$  model error variance

Want to estimate (or 5)  
predict  $z_n$  from  $z_1, \dots, z_{n-1}$ .

the observation model is

$$X_n = z_n + N_n, \quad \text{where}$$

$X_n$  is our measurement  
of  $z_n$

$N_n$  is measurement  
error (noise), modeled  
as zero-mean, uncorrelated

$$E[N_n] = 0 \quad \forall n$$

$$E[N_j N_k] = 0 \quad \forall j \neq k$$

$E[N_n^2]$  noise  
variance or  
power.

Also assume

$$E[N_j W_k] = 0 \quad \forall j, k$$

We actually estimate  $z_n$  from  $X_1, \dots, X_{n-1}$

The Kalman filter finds  $\textcircled{6}$   
 the linear MMSE estimate of  
 $Z_n$  from measured values of  
 $X_1, \dots, X_{n-1}$ . Let

$$Y_n = \sum_{j=1}^n h_j^{(n-1)} X_{n-j} = h_1^{(n-1)} X_{n-1} + \dots + h_n^{(n-1)} X_0$$

where  $X_0 = Z_0$

Then we want to find  $h_j^{(n-1)}$  for  
 $j=1, \dots, n$  to minimize

$$E[(Y_n - Z_n)^2]$$

↑  
 estimate  
 of  $Z_n$

↑ state at time  $t_n$

Can show that the optimal  
 filter  $h_j^{(n-1)}$  satisfies

$$R_{zx}(n, l) = \sum_{j=1}^n h_j^{(n-1)} R_{xx}(n-j, l)$$