

General Bayesian Estimation

$$p(\underline{s}[n] | \underline{x}) \quad \underline{x} = [x[0], \dots, x[n-1]]$$

$$= \int p(s[n], \underline{s}[n-1] | \underline{x}) d\underline{s}[n-1]$$

$$\textcircled{1} = \int p(\underline{s}^{[n]} | \underline{s}^{[n-1]}, \underline{x}) \cdot p(\underline{s}^{[n-1]} | \underline{x})^{q_{\underline{s}^{[n-1]}}}$$

↑
↗
↘
Markov condition

Update from $n-1 \rightarrow n$

$$P(\underline{s}^{[n]} | \underline{x}^{[n]}, \underline{x}) = \frac{p(\underline{s}^{[n]}, \underline{x}^{[n]}, \underline{x})}{p(\underline{x}^{[n]}, \underline{x})}$$

$\underline{s}^{[n]} =$
 $P_{\underline{s}^{[n-1]}} + Q_{\underline{x}^{[n]}}$

$$= \frac{p(\underline{x}^{[n]} | \underline{s}^{[n]}, \underline{x}) p(\underline{s}^{[n]}, \underline{x})}{p(\underline{x}^{[n]} | \underline{x}) \cdot p(\underline{x})}$$

$$= \frac{p(\underline{x}^{[n]} | \underline{s}^{[n]}, \underline{x}) p(\underline{s}^{[n]} | \underline{x}) \cdot \cancel{p(\underline{x})}}{p(\underline{x}^{[n]} | \underline{x}) \cdot \cancel{p(\underline{x})}}$$

$$= \frac{\overbrace{p(\underline{x}^{[n]} | \underline{s}^{[n]})}^{\text{likelihood}} \cdot p(\underline{s}^{[n]} | \underline{x})}{p(\underline{x}^{[n]} | \underline{x})}$$

$\textcircled{2}$

all measurements
up to n

all measurements up to n

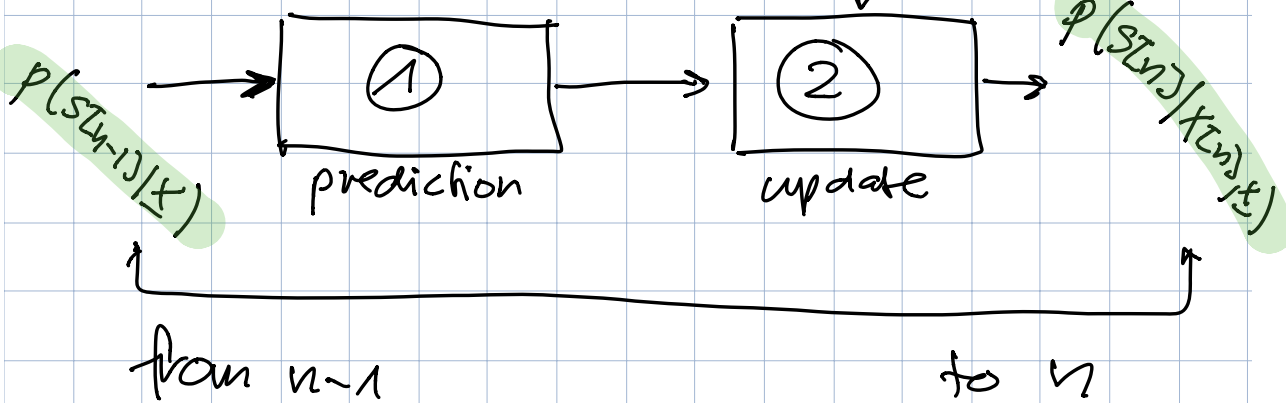
measurements
up to $n-1$

$$P(S[n] | X_{1:n}) = \frac{P(X_{n+1} | S[n])}{P(X_{n+1} | X)} \cdot p(S[n] | X)$$

①

$$P(S[n] | X) = \int p(S[n] | S[n-1]) \cdot p(S[n-1] | X) dS[n-1]$$

prediction
 $S[n] @ n$
 $X \rightarrow n-1$



Prediction Step :

$$\int p(S[n] | S[n-1]) p(S[n-1] | X) \cdot dS[n-1]$$

⇒ Particle is really a modified Monte-Carlo method

$f(S[n-1])$

$$= \int p(s_{[n]} | s_{[n-1]}) \frac{p(s_{[n-1]} | x)}{q(s_{[n-1]} | x)} \cdot q(s_{[n-1]} | x) ds_{[n-1]}$$

System Model

$$s_{[n]} = A s_{[n-1]} + v_{[n]}$$

$$= \lambda(s_{[n-1]}) + w_{[n]}$$

$w_{[n]}$

PDF to use for drawing samples

$w_{[n-1]}$

from the measurement model

system

$$w_{[n]} = w_{[n-1]} \times \frac{p(x_{[n]} | s_{[n]}) p(s_{[n]} | s_{[n-1]})}{q(s_{[n]} | s_{[n-1]}, x)}$$

IS distribution

A factor

$\frac{1}{p(x)}$ was moved out of integral

→ act as normalization

Algorithm steps are:

$$\textcircled{1} \sim \frac{1}{N_p} \sum_{i=1}^{N_p} f(s_i^{[n-1]} w_i^{[n]})$$

use N_p samples
⇒ particles

$$s_{i[t-1]} \sim q(s_{i[t]} | s_{i[t-1]}, \underline{x})$$

$$p(s_{i[t]} | \underline{x}) = \frac{1}{N_p} \sum_{i=1}^{N_p} f(s_{i[t-1]}) w_{i[t]}$$

fix this at desired value

N_p samples enter here

② Update

$$p(s_{i[t]} | x_{i[t]}, \underline{x}) = \frac{p(x_{i[t]} | s_{i[t]})}{p(x_{i[t]} | \underline{x})} \cdot p(s_{i[t]} | \underline{x})$$

measurement model

normalize

Summary

Bootstrap prior

$$q(s_{i[t]} | s_{i[t-1]}, \underline{x})$$

$$= p(s_{i[t]} | s_{i[t-1]})$$

System model

Step 1 sample

$$s_i[n] \sim P(s[n] | s[1:n-1])$$

Step 2 $w_i[n]$ calculate

$$\underline{\text{Step 3}} \quad w_i[n] = \frac{w_i[n]}{\sum_{i=1}^{N_p} w_i[n]}$$

Step 4 $\hat{P}_v(s[n] | \underline{x}, x[n]) =$ prediction & update

Start out sample at $n=0$

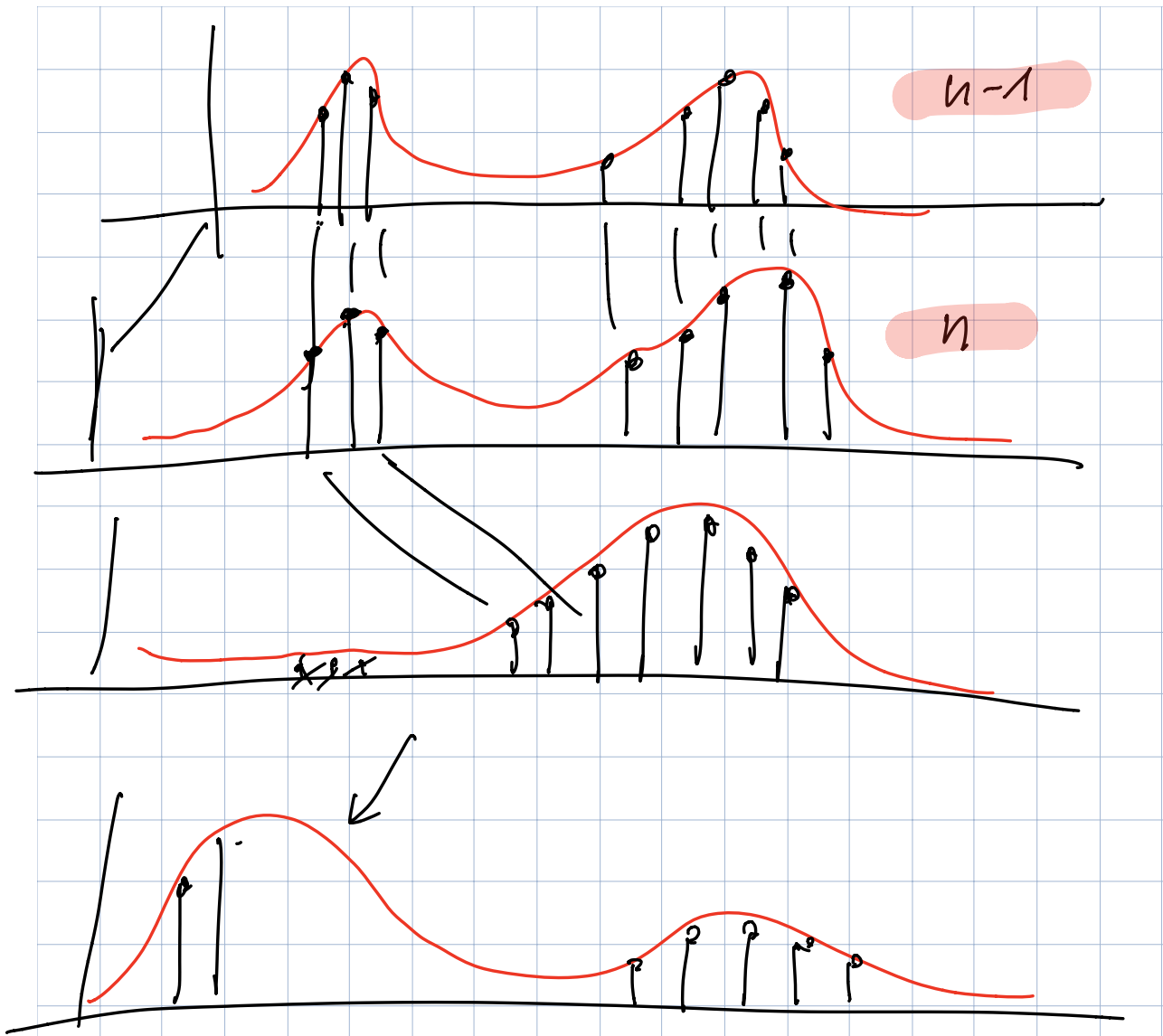
$$s_i[0] \sim P_v(s[0] | x[0])$$

↓

$$s_i[1]$$

↓

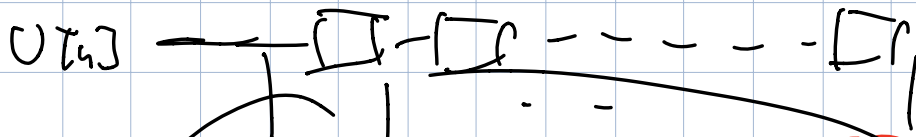
$$\vdots$$
$$s_i[n] \sim P_v(s[n] | x[n], \underline{x})$$

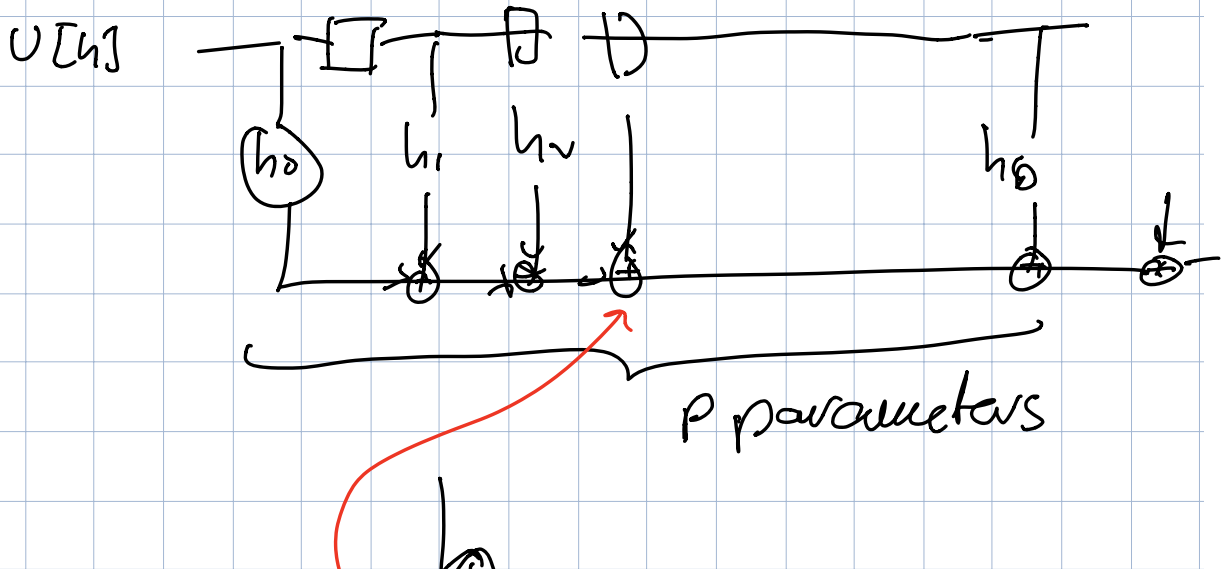
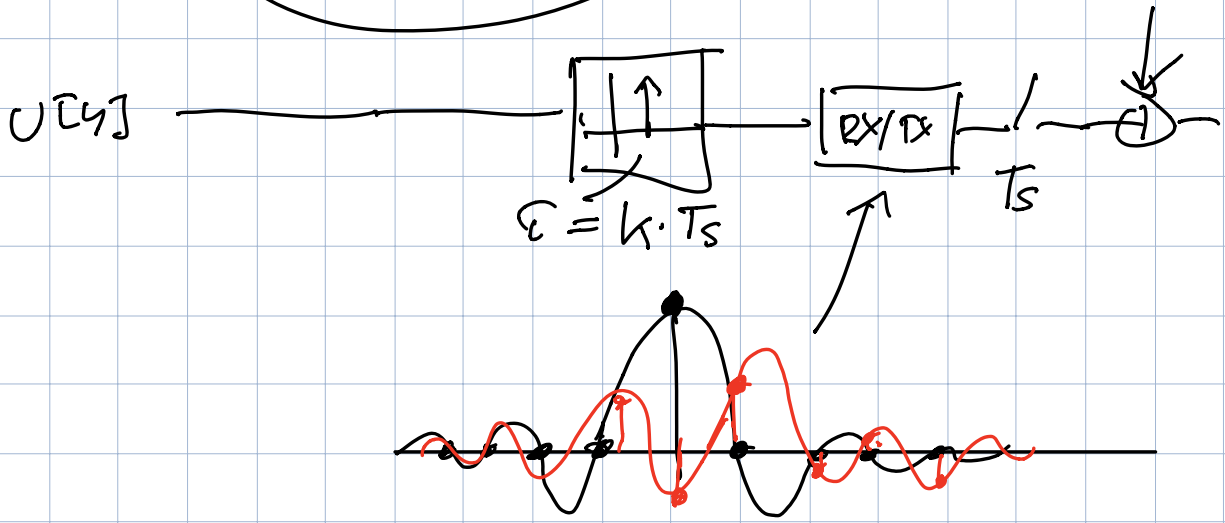
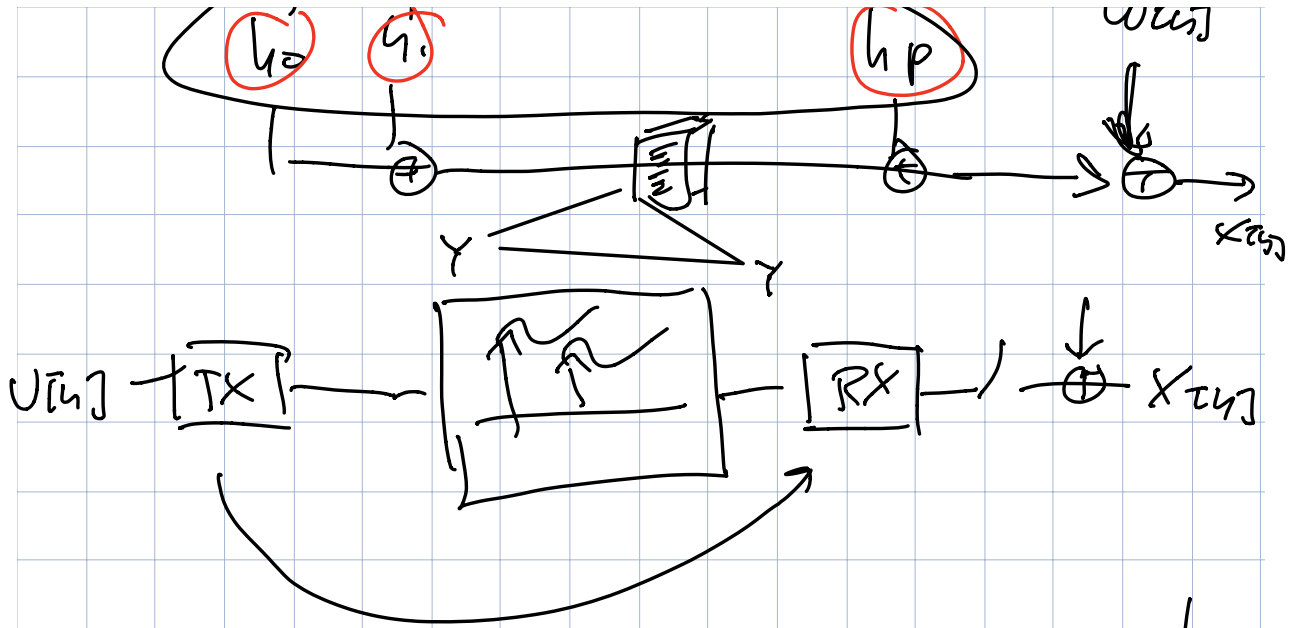


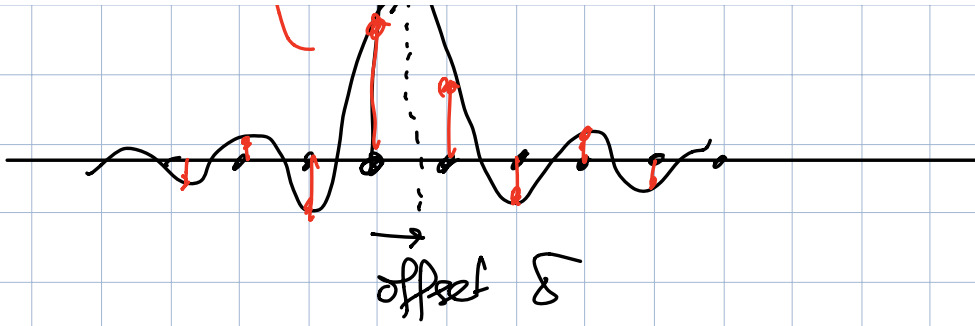
Channel estimator

ext. Kalman
wiener filter

+ include correlation in
the channel taps

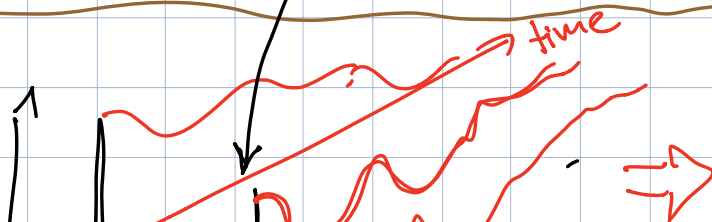
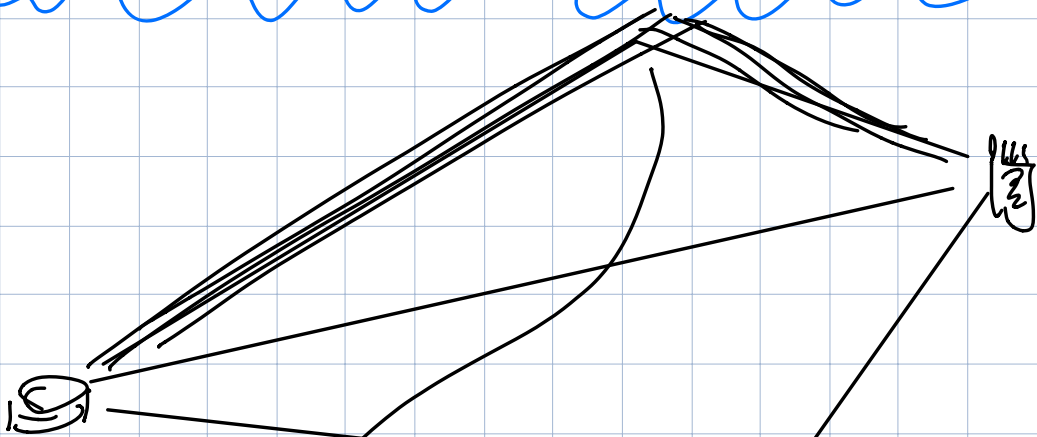
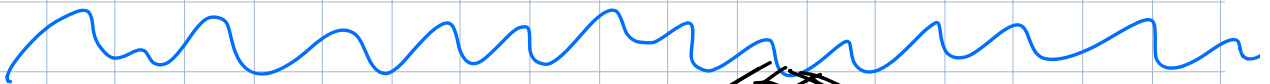
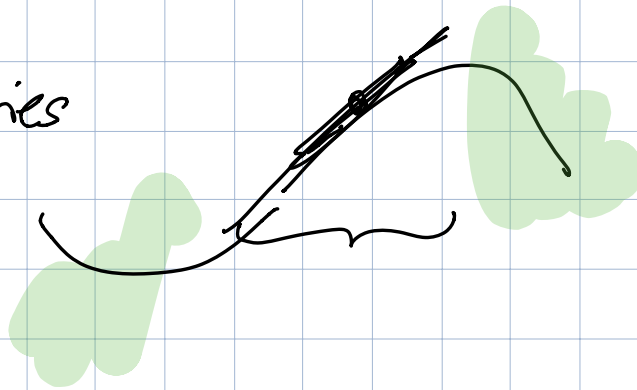




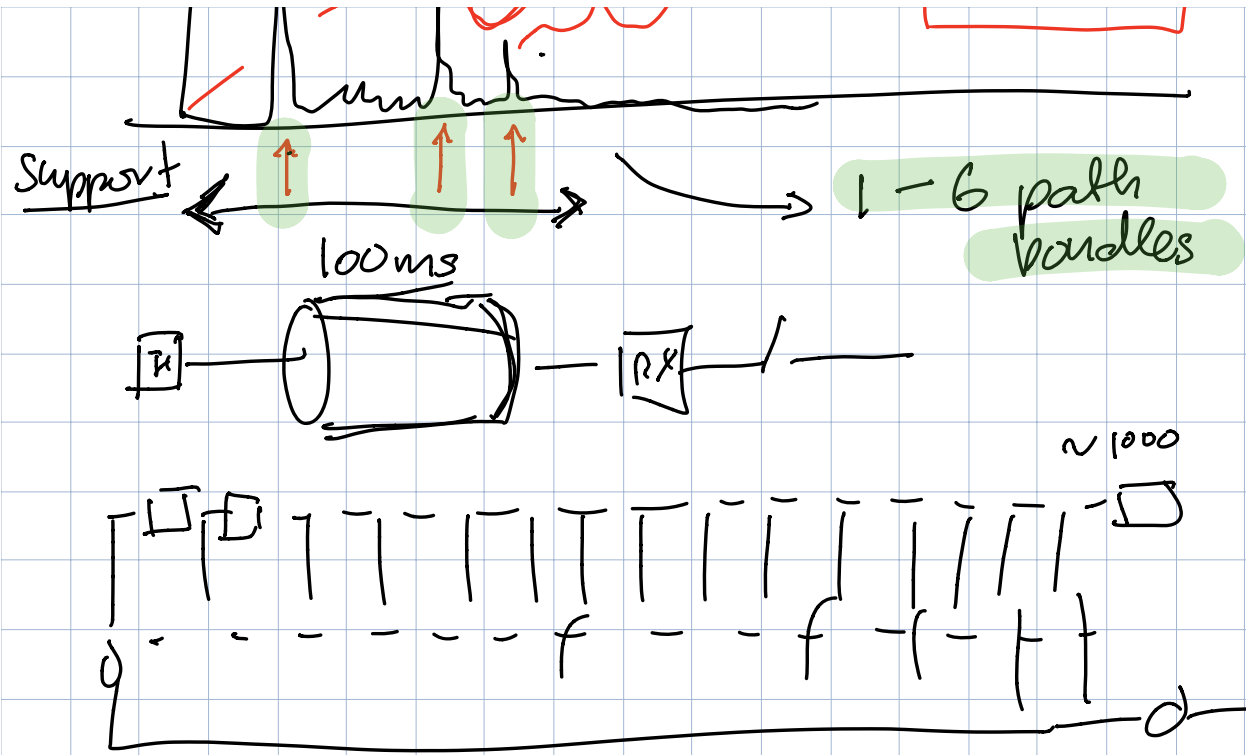


unscented Kalman \gg ext. Kalman

↑
non-linearities



sparse
model
of $h(t; \bar{u})$



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