

Tracking in 1D - the simplest Kalman filter

- Assume:
 - prior is ~~linear~~ Normal
 - state is 1D - x_i
 - dynamics are

$$x_{i+1} = a_i x_i + b_i + \zeta_i$$

$N(0, \sigma_{d_i})$

- Measurement is

$$y_{i+1} = c_{i+1} x_{i+1} + d_{i+1} + \zeta_{i+1}$$

$N(0, \sigma_{m_i})$

Prior :

we have

$$P(x_i | y_0 \dots y_i)$$

after meas!

$$N(\mu_i^+, \sigma_i^+)$$

want

$$P(x_{i+1} | y_0 \dots y_i)$$

prediction
NOTE meas only up to i

$$x_{i+1} = a_i x_i + b_i + \xi_i$$

$$N(0, \sigma_{d_i}^2)$$

i.e.

add const, add normal r.v.,
add normal r.v. mult by const,

\Rightarrow

a)

x_{i+1}

is normal

b)

$$x_{i+1} \sim N(a_i \mu_i^+ + b_i, \sqrt{a_i^2 \sigma_i^2 + \sigma_{d_i}^2})$$

$$\mu_{i+1}^-$$

$$\sigma_{i+1}^-$$

Now we want

$$P(x_{i+1} | y_0 \dots y_{i+1})$$

$$\propto P(y_{i+1} | x_{i+1}) P(x_{i+1} | y_0 \dots y_i)$$

(by Markov assumption)

work w/ logs

$$\log P(x_{i+1} | y_0 \dots y_{i+1})$$

$$= -\frac{1}{2\sigma_{i+1}^2} (y_{i+1} - c_{i+1}x_{i+1} - d_{i+1})^2 - \frac{1}{2\sigma_{i+1}^2} [x_{i+1} - \mu_{i+1}^*]^2 + \text{const } s$$

quadratic in x_{i+1} , so

$$P(x_{i+1} | y_0 \dots y_{i+1})$$

is normal.

$$\left(N(\mu_{i+1}^+, \sigma_{i+1}^+) \right)$$

Now we can use pattern matching

$$\log(\text{Normal}(m, s)) = -\frac{x^2}{2s^2} + \frac{mx}{s^2} + \text{const.}$$

multiply out, etc.

$$\log P(x_{i+1} | y_0 \dots y_{i+1}) =$$

~~$$-\frac{x_{i+1}^2}{2} \left[\frac{c_{i+1}^2}{\sigma_{m,i+1}^2} + \frac{1}{\sigma_{i+1}^{-2}} \right]$$~~

$$+ \left[\frac{(c_{i+1}(y_{i+1} - d))}{\sigma_{m,i+1}^2} + \frac{\mu_{i+1}}{\sigma_{i+1}^{-2}} \right] x_{i+1} + \dots (No x_{i+1})$$

matching yields

$$\sigma_{it+1}^+ = \sqrt{\frac{\sigma_{m,it+1}^2 \sigma_{it+1}^{-2}}{c_{it+1}^2 \sigma_{it+1}^{-2} + \sigma_{m,it+1}^2}}$$

notice

$$\frac{\sigma_{m,it+1}^2}{\sigma_{it+1}^{-2}} \quad v: \text{small} \longrightarrow \frac{\sigma_{m,it+1}}{c_{it+1}}$$

go with meas.

$$v: \text{large} \longrightarrow \sigma_{it+1}^{-2}$$

go with dyn

$$M_{it+1}^+ = \frac{\sigma_{it+1}^{-2} (c_{it+1} (y_{it+1} - d_{it+1})) + \mu_{it+1}^- \sigma_{m,it+1}^2}{c_{it+1}^2 \sigma_{it+1}^{-2} + \sigma_{m,it+1}^2}$$

$$\frac{\sigma_{it+1}}{\sigma_m} \text{ large} \longrightarrow \frac{y_{it+1} - d_{it+1}}{c_{it+1}} \quad (\text{go with meas})$$

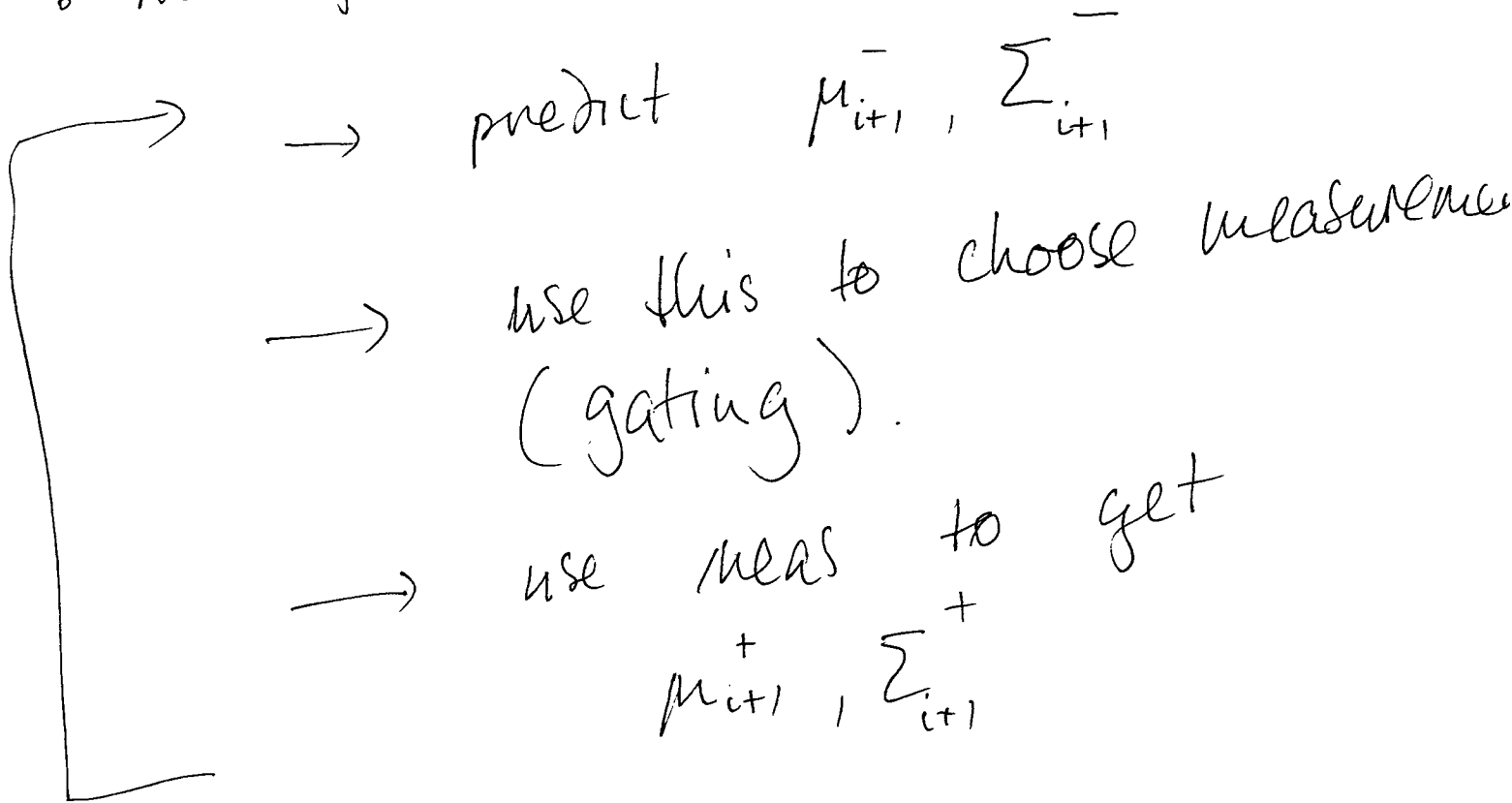
$$\text{small} \longrightarrow \mu_{it+1}^- \quad (\text{go w/ dyn})$$

All this extends to multiple
quite cleanly (Derivation easy, but tedious).

Common, useful recipe:

• Choose Dynamics

• Now from μ_i^+ , Σ_i^+



Duck hunting:

think about the Duck movie
→ how to drop a K.F. on that?

1) Dynam Duck model

• circular blob with center \underline{x} ,

and $\log(\text{radius}) = l$

(Why log? - usual for scales)

• size doesn't change much?

$$l_{i+1} \rightsquigarrow = l_i + \epsilon_i \quad \uparrow \quad N(0, \sigma_{\text{duck}}^2)$$

• seems to have smooth movement?

$$x_{i+1} = x_i + v_i \Delta_t + \xi_i$$

$$v_{i+1} = v_i + a_i \Delta_t + \zeta_i \rightsquigarrow N(0, \dots)$$

$$a_{i+1} = \eta_i \rightsquigarrow N(0, \dots)$$

Measurement:

- make an estimate of center, radius
- possibly weighted from μ_i, Σ_i
- $$c_{est. i} = x_i + \text{noise}$$
$$r_{est. i} = r_i + \text{noise}$$

This will likely deal with parts falling off
Jack

Issues:

- Grating may bias est.
- multiple gates?
- Dynamic model is shaky
 - it's just a smoother
 - (sometimes) mult. dynamic models.

Pr

Issues :

- Birth + Death of tracks.

→ rely on a detector?

→ rely on spatial gates?

~~or~~

- Crossings :

- Sometimes, dynamics will sort this out.

- otherwise, you have a nasty discrete inference problem

Non linear measurement

$$y_i = f(x_i) + \zeta_i$$

options :

1) linearize about μ_i

(Extended) Kalman filter)

but this can lead to misthief

eg: $f(x) = x^2$

around zero

2) Particle Filter