

I. Probability

① y : label ② x : observation (attributes)

$P(y)$: prior

$P(y|x)$: likelihood.

$P(x|y)$: posterior

③ joint probability $P(x, y) = P(x|y)P(y) = P(y|x)P(x)$

$P(x_1, x_2) = P(x_1)P(x_2)$ if x_1, x_2 are independent.

④ marginal probability $P(x) = \sum_i P(x, y_i)$
 $= \sum_i P(x|y_i)P(y_i)$

II. Bayes rule.

① single observation: From I.②, we know $P(x|y)P(y) = P(y|x)P(x)$

$$\text{so, } P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$\text{from I.④, } = \frac{P(x|y_i)P(y_i)}{\sum_i P(x|y_i)P(y_i)}$$

since $P(x)$ is a fixed value.

$$P(y|x) \propto P(x|y_i)P(y_i)$$

② multiple $x_1, x_2, x_3 \dots x_d$. Assume they are independent, then

$$P(x_1, x_2, x_3 \dots x_d | y) = P(x_1|y) \cdot P(x_2|y) \cdot \dots \cdot P(x_d|y)$$
$$= \prod_{i=1}^d P(x_i|y)$$

substitute into

To compute likelihood $P(y|x)$ on $(x_1, x_2, x_3 \dots x_d)$!

III. Tracking with dynamics.

① Find smooth, coherent trajectory of moving targets the distribution of

② current state + A model of expected motion = predicted next state.

③ search around predicted area \rightarrow measurement (noisy)

④ predicted next state + measurement = improved estimate

\rightarrow loop forever!

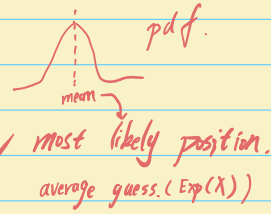
⑤ loop 可被看作 detect + predict = tracking.

Assumption: continuous motion pattern (no sudden moving objects or viewpoint)

IV. Tracking as Inference.

state X : position + velocity
 Measurement Y : noisy observation of underlying state.

- At time t , $X_{t-1} \rightarrow X_t$ (predict)
 Y_t (measurement)
- goal: recover the distribution of state X_t from:
 - All observations so far.
 - Model about dynamics of state transitions.

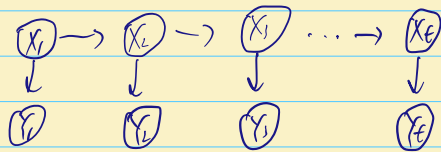


- prediction: $P(X_t | Y_0, Y_1, Y_2, \dots, Y_{t-1})$ prior without Y_t .
 measurement: $P(X_t | Y_0, Y_1, Y_2, \dots, Y_t)$ posterior with Y_t .
 Tracking: propagate $P(X_t | Y_t)$ over time.

- Q why probability? A: You have something uncertain!
 A1: Difference between X & Y . such like include velocity in X but not in Y .
 A2: Y is noisy due to detection algorithm/device.
 A3: Y may be missing nor invalid for time t .

V. Markovian assumption.

- $P(X_t | X_0, \dots, X_{t-1}) = P(X_t | X_{t-1})$ only immediate past matters
 dynamic model.
- $P(Y_t | X_0, Y_0, X_1, Y_1, \dots, X_t) = P(Y_t | X_t)$ measurements dependent on current state.
 observation model



VI. Tracking as induction.

- initial guess $P(X_0)$
- give Y_0 .
- update $P(X_0)$
- repeat.

Prediction

Given: $P(X_{t-1} | y_0, \dots, y_{t-1})$

Guess: $P(X_t | y_0, \dots, y_{t-1})$

$$= \int P(X_t, X_{t-1} | y_0, \dots, y_{t-1}) dX_{t-1}$$

joint dis tribution

$$= \int P(X_t | X_{t-1}, y_0, \dots, y_{t-1}) P(X_{t-1} | y_0, \dots, y_{t-1}) dX_{t-1}$$

$$= \int P(X_t | X_{t-1}) P(X_{t-1} | y_0, \dots, y_{t-1}) dX_{t-1}$$

Independence assumption

Next state probability of getting a specific point is the integral of weighted getting the point
 dynamics model \rightarrow corrected estimate from $t-1$.

Correction

Given predicted value $P(X_t | y_0, \dots, y_{t-1})$ and y_t

Compute $P(X_t | y_0, \dots, y_t)$

$$= \frac{P(y_t | X_t, y_0, \dots, y_{t-1}) P(X_t | y_0, \dots, y_{t-1})}{P(y_t | y_0, \dots, y_{t-1})}$$

$$= \frac{P(y_t | X_t) P(X_t | y_0, \dots, y_{t-1})}{P(y_t | y_0, \dots, y_{t-1})}$$

$$= \frac{P(y_t | X_t) P(X_t | y_0, \dots, y_{t-1})}{\int P(y_t | X_t) P(X_t | y_0, \dots, y_{t-1}) dX_t}$$

observation
made

→ if you really at X_t , what is the likelihood of getting the measurement y_t .

Really a normalization

from all points before

Bayes rule.

predicted.

$$\begin{aligned} P(X_t, y_t | y_0 \dots y_{t-1}) \\ &= P(X_t | y_0 \dots y_{t-1}) P(y_t | y_0 \dots y_{t-1}) \\ &= P(y_t | X_t, y_0 \dots y_{t-1}) P(X_t | y_0 \dots y_{t-1}) \end{aligned}$$

$$\therefore P(X_t | y_0 \dots y_t) = \frac{P(y_t | X_t, y_0 \dots y_{t-1}) P(X_t | y_0 \dots y_{t-1})}{P(y_t | y_0 \dots y_{t-1})}$$

$$\begin{aligned} \therefore y_t \text{ only depends on } X_t, \\ P(y_t | X_t, y_0 \dots y_{t-1}) = P(y_t | X_t) \end{aligned}$$