Random Sample

X₁... X_n are called Random Sample of Size n
from a population of (n)

if * X₁... X_n are mutually independent
* marginal PDF or PMF of each Xi is f(n)

Also, X₁... X_n \rightarrow independent and identically distributed random samples (iid)

$$f(x_1,...,x_n) = f(x_1) f(x_2) f(x_n) = \frac{n}{|I|} f(x_i) - (1)$$

$$f(x_1,...,x_n) = f(x_n) f(x_2) f(x_n) = \frac{n}{|I|} f(x_i) - (1)$$

The Likelihood Function

$$f(x_{10}) \rightarrow j_{0in} + PDF \text{ or } PMF \text{ of } X = (x_{1}...x_{n})$$

Given $X = x$ is observed,

the function of G defined by

 $L(G|x) = f(x_{10})$ is

the likelihood function.

means

O, is more plausible than 02

Estimation

Classic Estimation

0 -> fined, unknown

* Manimum likelihood estimator
(MLE)

* $\hat{\Theta}(x)$ is the parameter at which $L(\Theta|n)$ aftains maximum as a function of Θ , n is help fined

Bayesian Estimation

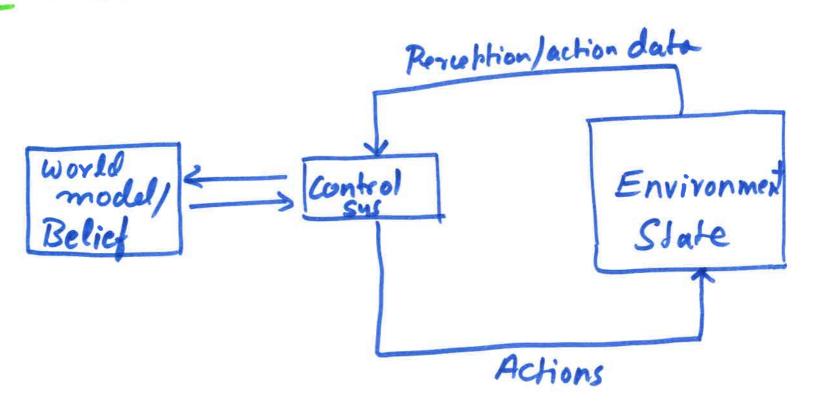
0 -> Variable, unknown

* Normal Bayes estimator

* $\pi(\theta|x) = f(n|\theta) \pi(\theta)$ $\frac{\pi(\theta)}{\pi(n)}$

m(n) = \ \ \f(n 10) T(0) do

Bayesian Estimation Content: mobile robot localization / tracking of targets Thrun et al "Probabilistic Robotics" 2005]



Robot Environment Interaction.

State

State Dynamic

Static

* Pose Velocity

Attitude

 \mathcal{X}_t

* Londmorks - features of the environment.

Environment Interaction

* Measurement (using sensors)

 $- 2t_1: +2 = 2t_1, 2t_1 + \cdots 2t_2$

- Obtain information about the State

* Control (using actuators)

- Ut 1:+2 = Ut1, Ut 1+1 Ut2

- actions that change the state of the world

Probabilistic generative laws

Evolution of State and Measurements

State: N_t is stochastically generaled from N_{t-1} $\frac{1}{p(N_t \mid N_0: t-1, 2_{1:t-1}, V_{1:t})} = \frac{1}{p(N_t \mid N_{t-1}, U_t)}$

Measurement:

model the process by which measurements ar generated.

p(2+ | no:t, 21:+-1, U1:t) = p(Zt|nt)

Belief Distributions

belief with regard to the state

bel(n+)= p(n+ 121:t, U1:t)

Algorithm Bayes Filter.

```
1. Alg Bayes-fiter (bel(n_{t-1}, u_{t}, z_{t}))

2. for all n_{t} do

3. \overline{bel}(n_{t}) = \int p(n_{t}|u_{t}, n_{t-1}) bel(n_{t-1}) dn_{t-1}

4. bel(n_{t}) = \eta(z_{t}|n_{t}) bel(n_{t})
```

5. end for

6. return beel (nx)

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