

Nov 1, 2023

Random Variables $\{Y\}_{i=1}^n$

Numbers

$\{y_i\}_{i=1}^n$

(No randomness)

Realized value
of R.V.

$Z \rightarrow$ to create randomness, generate a new random var.

$$P(Z = y_i) = \frac{1}{n}$$

what is this?

(*) Risk $R(\theta) = E[l(Y, \theta)]$

what is a loss l^n

Empirical Risk $\hat{R}(\theta) = E_n[l(Z, \theta)] = \frac{1}{n} \sum_{i=1}^n l(y_i, \theta)$

$\theta \in \Theta \subset \mathbb{R}^p$ Capital Theta

$$\theta_0 = \arg \min R(\theta)$$

$$\hat{\theta} = \arg \min_{\theta \in \Theta} \hat{R}(\theta)$$

$$\hat{R}(\theta) = \frac{1}{n} \sum_{i=1}^n l(y_i, \theta)$$

Uncertainty in $\hat{R}(\theta)$: How can we evaluate how far $R(\theta)$ is from $\hat{R}(\theta)$. Let's look at the data collection process \rightarrow reverse engineer the r.v. from which the data was collected. This reverse engineering is imagined. You can't actually do it.

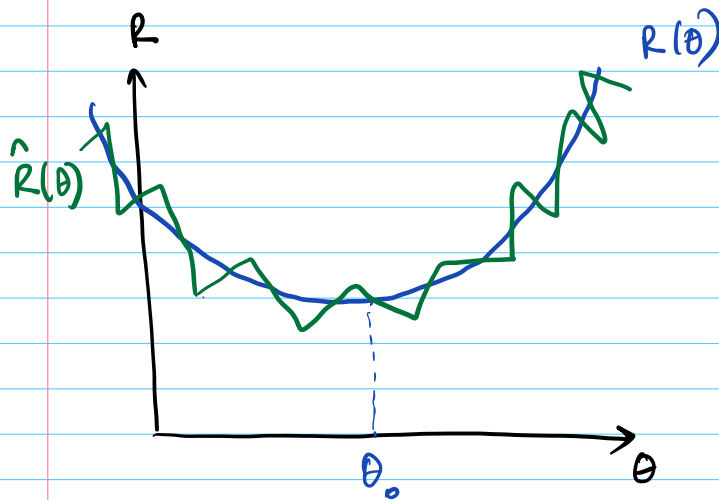
$$\hat{R}(\theta) = \frac{1}{n} \sum_{i=1}^n l(Y_i, \theta) \rightarrow \text{R.V.}$$

By law of large number;

$$\hat{R}(\theta) = \frac{1}{n} \sum_{i=1}^n l(Y_i, \theta) \xrightarrow{P} E[l(Y, \theta)] = R(\theta)$$

⊗ Theory of empirical process

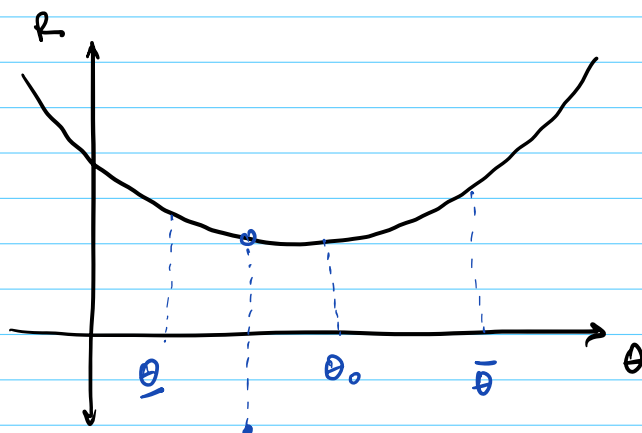
$\theta \rightarrow$ single dimensional parameter



Let $\hat{R}^*(\theta)$ be close to $R(\theta)$

$$\hat{R}(\theta) = R(\theta) - 1000 \cdot \mathbb{1}\{\theta^*\} ; \quad \theta^* \sim U[\mathbb{H}] \quad (\text{spoiled version})$$

$$\underset{\theta \in \mathbb{H}}{\operatorname{Argmin}} \hat{R}(\theta) = \theta^* \sim U[\mathbb{H}]$$



$$P(\hat{R}(\theta) = R(\theta)) = 1$$

Uniform Convergence

Def: $\hat{R}(\cdot)$ converges to $R(\cdot)$ uniformly in probability if

$$X_n = \sup_{\theta \in \Theta} |\hat{R}_n(\theta) - R(\theta)| \xrightarrow{P} 0$$

(How supremum behaves as $n \rightarrow \infty$)

↓ sample size.

for every n .

L_∞ L infinity norm : $\sup_{x \in \mathcal{R}} |f(x)|$

(Converge Uniformly in probability \rightarrow Converge in probability in the worst case)

Def: $\hat{R}(\cdot)$ converges to $R(\cdot)$ uniformly a.s.:- if

$$X_n = \sup_{\theta \in \Theta} |\hat{R}_n(\theta) - R(\theta)| \xrightarrow{\text{a.s.}} 0$$

(*) We are ultimately interested in proximity of $\hat{\theta}$ to θ_0
what are the conds. when $\hat{\theta} \xrightarrow{P} \theta_0$?

Theorem :- Suppose following conditions are satisfied: —

1. Θ is a compact set.
2. $R(\cdot)$ is continuous
3. $\hat{R}(\cdot)$ is converging to R uniformly in probability
4. (Identification) $R(\cdot)$ attains a unique global min at θ_0 .
 \downarrow
 popⁿ risk

Then, $\hat{\theta} \xrightarrow{P} \theta_0$ [convergence of sequence of r.v. to θ_0 as $n \rightarrow \infty$]

LOSS FUNCTION :-

empirical

$$l = \frac{1}{2} (y, -\theta)^2$$

$$\Rightarrow \hat{R}(\theta) = \frac{1}{2n} \sum_{i=1}^n (y_i - \theta)^2$$

Parameter of the distⁿ.
 (say your guess of popⁿ mean)
 using theory

$$\hat{\theta} = \underset{\theta \in \Theta}{\operatorname{argmin}} \hat{R}(\theta) = \frac{1}{n} \sum_{i=1}^n y_i$$

How close your estimated θ is to actual θ .