6/4/19

Tuesday, June 4, 2019 1:29 PM

This time: Large random Samples Next time: Markov chains

IID random Sample Z, ..., Xn

$$\mathcal{M} = \mathcal{E}(\mathcal{X}_i)$$

sample Wean: $\overline{\mathcal{X}}_n = \frac{1}{n} \sum_{i=1}^{n-1} \mathcal{X}_i$

It would be nice if \$n approached the right answer M as a increases; how to quantify that idea? Markov inequality

$$P(X = t) \stackrel{c}{=} \frac{E(X)}{t}$$

$$e_{X} = E(X) = 1, X \quad non - regnt = -> \quad P(X = 100) \leq \frac{1}{100}$$

$$(hebysheV \quad Inequality)$$

$$P([X - E(X)] \geq +] \leq \frac{V(X)}{t^{2}}$$

$$\implies BACE \quad H \quad Xn$$

$$E(X;) = M \quad V(X;) = \sigma^{2} < Vo$$

$$E(\overline{X}n) = N \quad V(\overline{X}n) = \frac{\sigma^{2}}{n}$$

$$P(|\overline{X}n - M| \geq +) \leq \frac{\sigma^{2}}{n} \quad for all + >0$$

rewritten as:

$$P(|\overline{X}_{n} - M| \langle t \rangle) \geq 1 - \frac{\sigma^{2}}{nt^{2}}$$

$$Def: A sequence [\Xi_{1,1}, \Xi_{10}, ..., of v.u. is said to converge in probabilityto constant b of for all $\varepsilon > 0$, $\lim_{n \to \infty} P(|\Xi_{1n} - \varepsilon| \langle \varepsilon 1 \rangle) = 1$;
this si cleared $\Xi_{1n} = b$.
(Weak)
Law of
Larg Numbers
 $\overline{X}_{i} \sim IID$ a dist with mean
(orollarg: IF $\Xi_{1n} = b$ and $g(t)$ is construct at $t \ge b$ then $g(t \ge n) = g(t)$)
$$\frac{(entreal Limit)}{I_{in}} = \frac{T_{in} = b}{T_{in}} = b$$
 and $finile variance od $\sigma^{2} \langle \infty \rangle$,
 $\overline{X}_{i} = \frac{1}{T} = \frac{1$$$$

Statement) Def: \mathbb{Z}_1 , \mathbb{Z}_2 , ... a sequence of r.v., let \neq_n be the CDF of \mathbb{Z}_n \rightarrow if here exists a CDF \neq^* such that $\lim_{n \to \infty} \mathbb{F}_n(x) = \mathbb{F}_n^*(x)$ for all x at $\lim_{n \to \infty} \mathbb{F}_n(x) = \mathbb{F}_n^*(x)$ is (antinuous, then people say

$$\overline{\mathbf{X}} \quad \text{hus men } \mathcal{M}_{\mathbf{X}}$$
evpnd $g(\overline{\mathbf{X}}n) \text{ aroud } \mathcal{M}_{\mathbf{X}}$:

$$g(\overline{\mathbf{X}}n) \stackrel{!}{=} 9(\mathcal{M}_{\mathbf{X}}) + g'(\mathcal{M}_{\mathbf{X}})(\overline{\mathbf{X}}n - \mathcal{M}_{\mathbf{X}})$$

$$E(g(\overline{\mathbf{X}}n)]_{=} = E\left[g(\mathcal{M}_{\mathbf{X}}) + g'(\mathcal{M}_{\mathbf{X}})(\overline{\mathbf{X}}n - \mathcal{M}_{\mathbf{X}})\right]$$

$$= g(\mathcal{M}_{\mathbf{X}} + g'(\mathcal{M}_{\mathbf{X}})[E(\overline{\mathbf{X}}n) - \mathcal{M}_{\mathbf{X}}]$$

/ /)

E(g(In)]= g(MI)

 $V[g(\bar{x}_n)] = [g'(\mu_{\bar{x}})]^2 \frac{\sigma_{\bar{x}}^2}{\rho_{\bar{x}}}$

△ ME THOI)

 $E(TVI) \doteq g(M_{TV})$ and $V(\nabla \nabla) \doteq \left(g'(\mu_{\nabla})\right)^2 \sigma^2 \nabla$

