MA 6.101 Probability and Statistics

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- ► This helps in checking if data samples you are are from random variable Y or not.

Convergence of Random Variables

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If $N(\epsilon, x) = N(\epsilon)$ (i.e., independent of x) for every $x \in \mathbb{R}$, then such convergence of $F_n(\cdot)$ to $F(\cdot)$ is called as uniform convergence.

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- ▶ But if you were to perform the experiment again, you may not be so 'lucky' and get a different sequence $\{x'_n\}$ which may not converge to x'.
- We will come up with notions of convergence that depend on how often you see the sequence of realizations converging.

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- Here X could even be a deterministic number.
- $\rightarrow X'_n s$ could be dependent on each other.
- Each random variable X_n could have a different law (pmf/pdf).

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- ▶ This is almost sure convergence as $\mathbb{P}\{[0,1)\}=1$.

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Let $\{X_n, n \geq 0\}$ denote a sequence of i.i.d random variables with mean μ and denote $S_n = \sum_{i=1}^n X_i$. Then $\frac{S_n}{n} \to \mu$ a.s.

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- We will soon see CLT that will tell the CDF of $\hat{\mu_n}$ without any information on the law of X_i .

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Such averaging formulas are used extensively in Reinforcement learning.