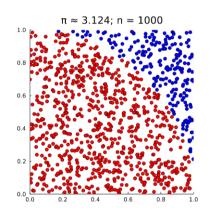
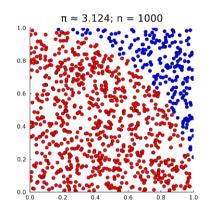
Anatomy of a Random Variable

• A Motivating Example: Monte Carlo Integration

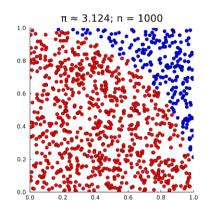


- A Motivating Example: Monte Carlo Integration
- Rigorous Definitions of a Random Variable



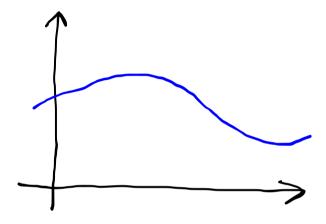
 $X:\Omega o E$

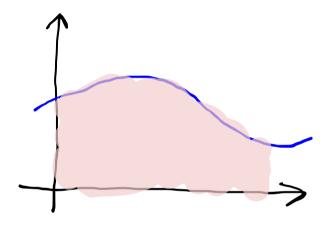
- A Motivating Example: Monte Carlo Integration
- Rigorous Definitions of a Random Variable
- Law of large numbers and the Central Limit Theorem

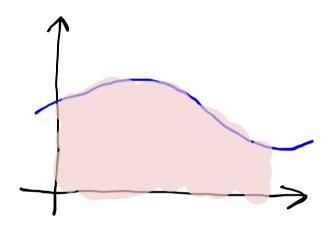


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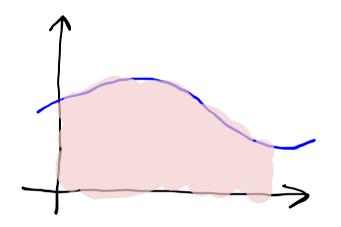
$$\sqrt{n}\left(ar{X}_n-\mu
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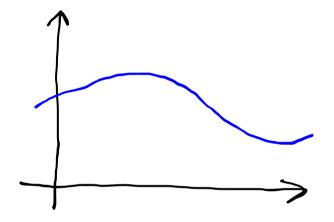




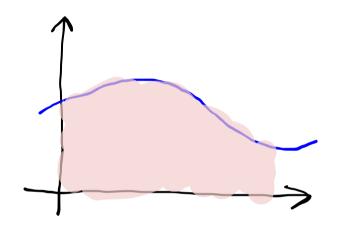


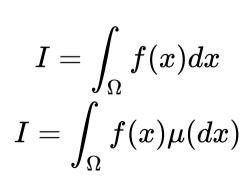
$$I = \int_{\Omega} f(x) dx \ I = \int_{\Omega} f(x) \mu(dx)$$

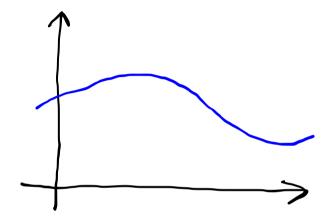




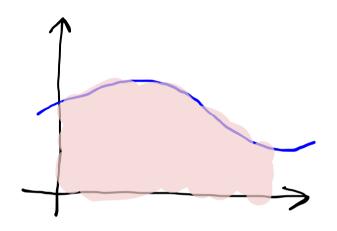
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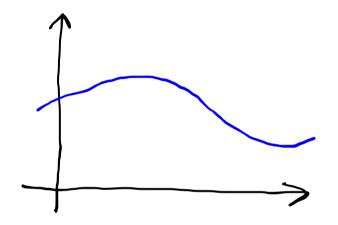




$$X_i \sim U(\Omega)$$

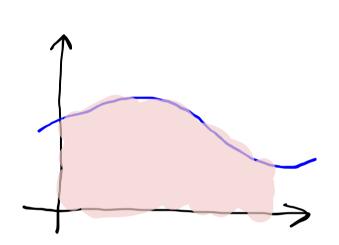


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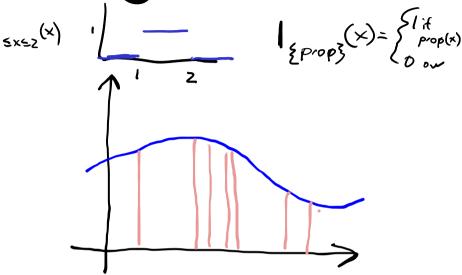


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How accurate is this?

Why are probability distributions not enough?

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Consider this definition: Two random variables are equal if their probability distributions are the same.

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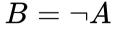
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$$B = \neg A$$

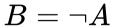
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What is this function?

Example: Coin World

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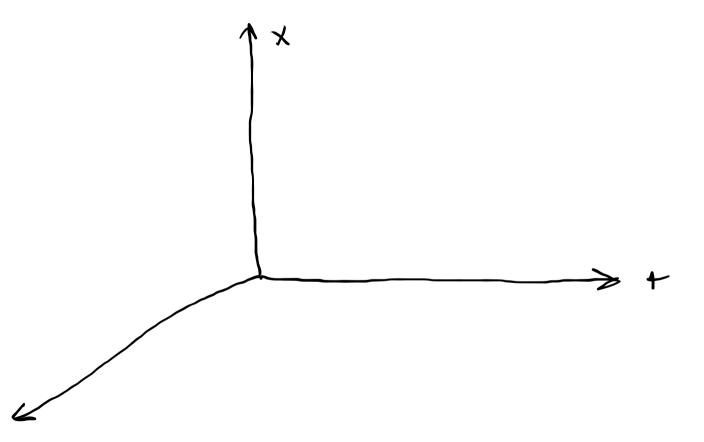


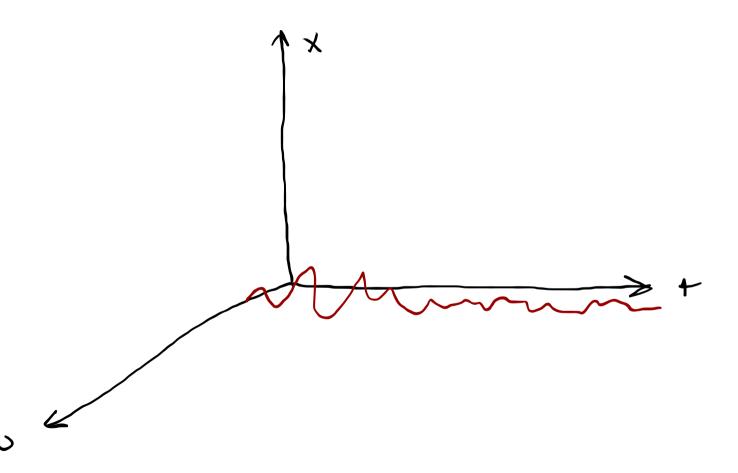
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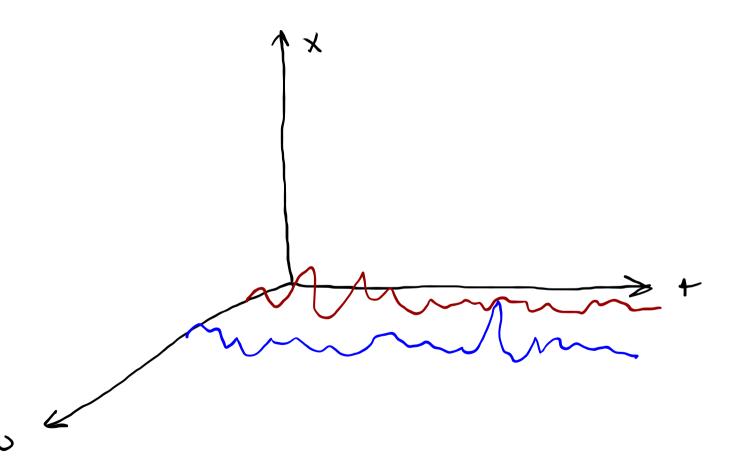
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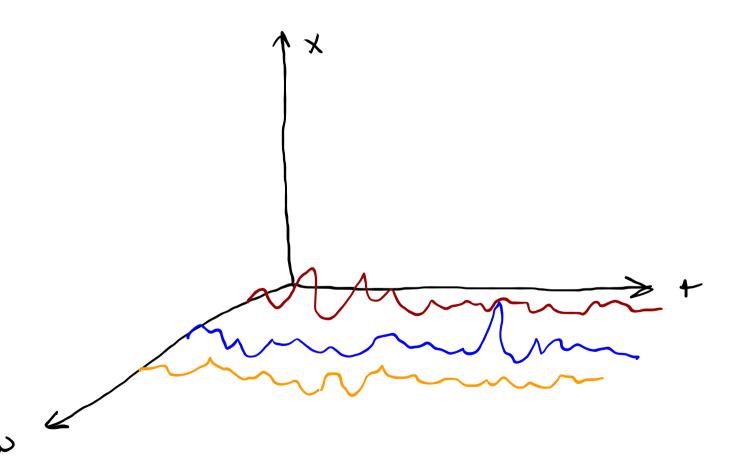


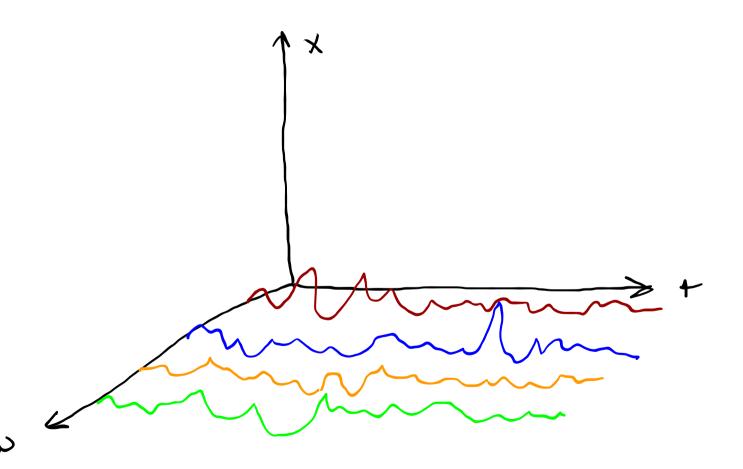
stochastic process {x+3} X(+)

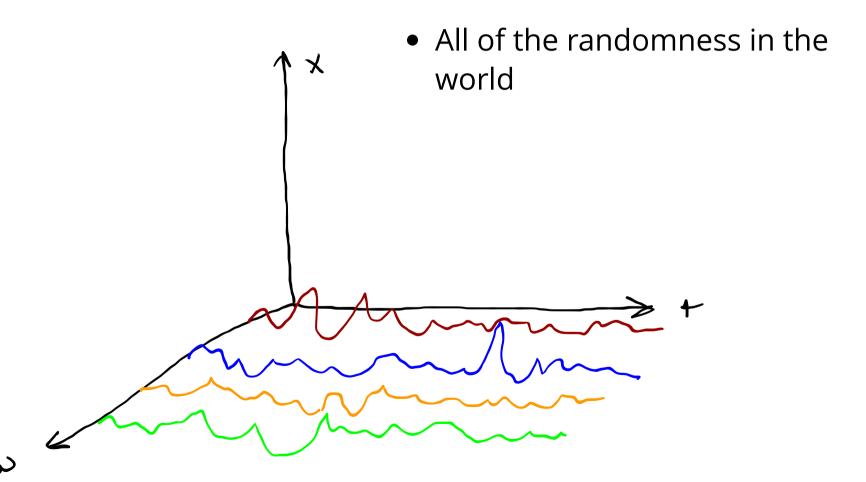


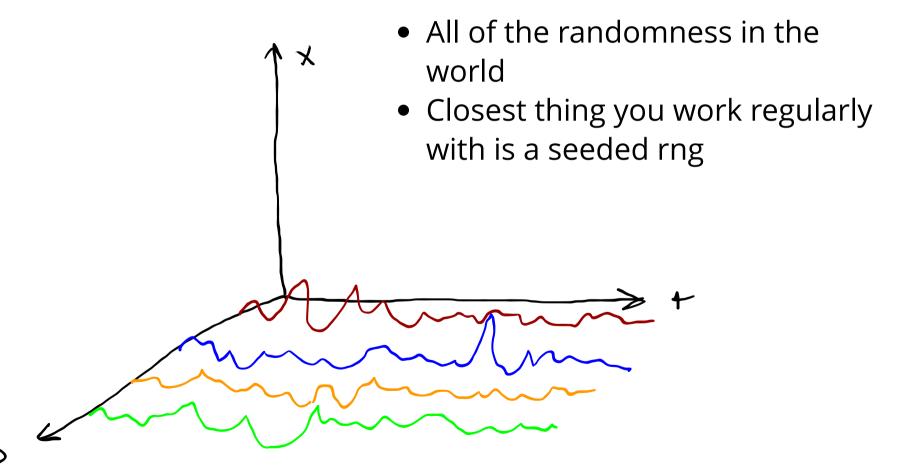


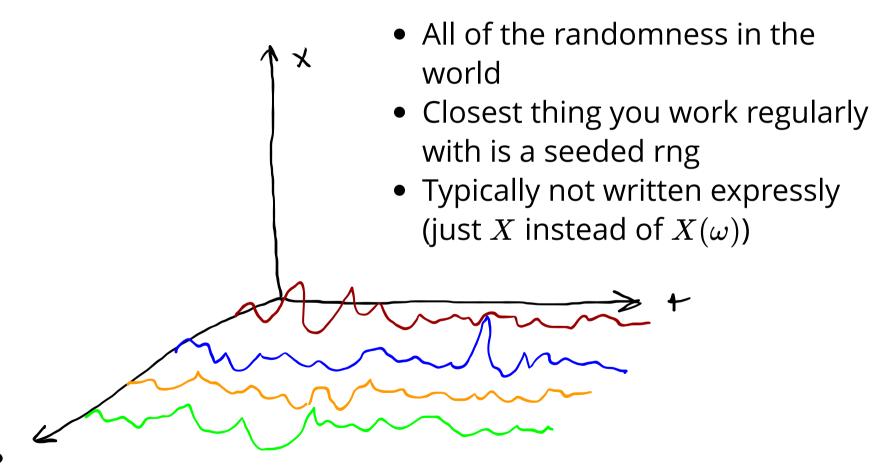












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D: {1,2,3}

Za= 8813,927.837,00,

[1,2], {1,5}, {2,3}

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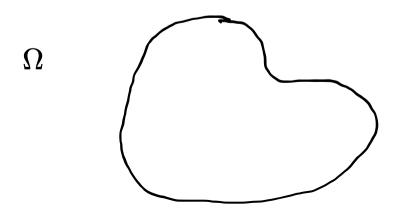
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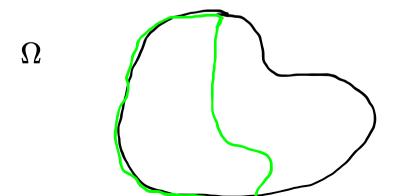
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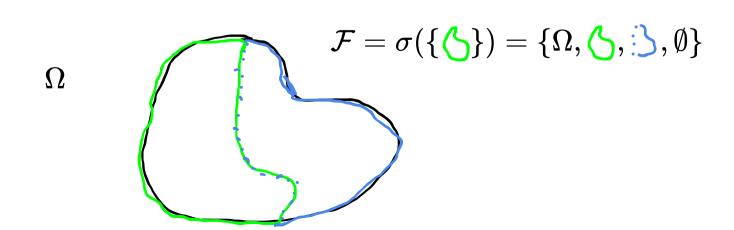
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- 3. (Countable additivity) $P(A)=\sum_{n=1}^{\infty}P(A_n)$ whenever $A=\cup_{n=1}^{\infty}A_n$ is a countable union of disjoint sets $A_n\in\mathcal{F}$

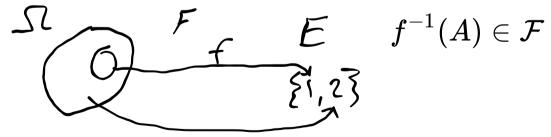
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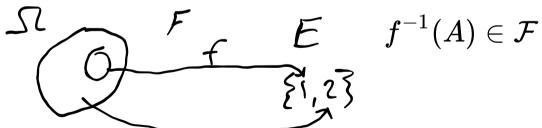
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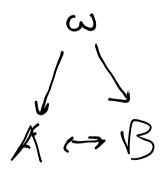
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Are there functions that are not Borel-measurable?

Advantages over pdf definition

- Rigorous treatment of deterministic outcomes
- More sophisticated convergence concepts
- Better way of thinking about related random variables (personally, I think)



Break

Exercise 1.2.5. Let $\Omega = \{1, 2, 3\}$. Find a σ -field \mathcal{F} such that (Ω, \mathcal{F}) is a measurable space, and a mapping X from Ω to \mathbb{R} , such that X is not a random variable on (Ω, \mathcal{F}) .

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$$\underbrace{f^{-1}(A)\in\mathcal{F}}$$

$$\sigma(\{13\}) = \{\{1,2,3\}, \phi, \{13\}, \{2,3\}\}\}$$

$$\times = \mathbf{1}_{\{1,2\}}$$

$$A = \{0\} \quad \times^{-1}(A) = \{3\}$$

X(3)=0 X(1)=(X(2)=1

https://timer.onlineclock.net/

$$\int Z = \{1, 2, 3\}$$

$$F = \sigma(\{13\}) = \{\{1, 2, 3\}, \emptyset, \{13, \{2, 3\}\}\}$$

$$X(\omega) = \mathbf{1}_{\{1, 2\}}(\omega) = \{0 \text{ o.w.} \quad X(z) = 1 \\ X(z) = 1 \\ X(z) = 0$$

$$A \in E \qquad E = \mathbb{R} \quad X(z) = 0$$

$$A = 0 \quad X^{-1}(A) = \{3\}$$

$$X^{-1}(A) \notin F \qquad No \quad X \text{ is not measurable}$$

: X is not a R.V.

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$$\mathcal{F} = \{\Omega,\emptyset,\{1\},\{2,3\}\}$$
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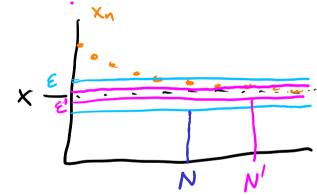
Review: For a (deterministic) sequence

$$\{x_n\}$$
, we say

$$\lim_{n\to\infty}x_n=x$$

or

$$x_n o x$$



if, for every $\epsilon>0$, there exists an N such that $|x_n-x|<\epsilon$ for all n>N.

In what senses can we talk about random variables converging?

- Sure ("pointwise")
- Almost Sure
- In Probability
- Weak ("in distribution"/"in law")

$$X$$
 = Y if $X(\omega) = Y(\omega) \quad orall \omega \in \Omega$

$$\begin{array}{ll}
\mathcal{P} & \text{0.5,0.5,0} \\
& \mathcal{N} = \{1,2,3\} \\
& X = Y \text{ if } X(\omega) = Y(\omega) \quad \forall \omega \in \Omega \\
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In practice, there are often unimportant ω where this is not true.

We say that X is *almost surely* the same as Y if $P(\{\omega: X(\omega) \neq Y(\omega)\}) = 0$.

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This is denoted $X \stackrel{a.s.}{=} Y$ and the terms almost everywhere (a.e.) and with probability 1 (w.p.1) mean the same thing.

Sure Convergence

$$X_n(\omega) o X(\omega) \quad orall\,\omega\in\Omega$$

Almost Sure Convergence

Almost Sure Convergence

 $X_n \overset{a.s.}{\to} X$ if there exists $A \in \mathcal{F}$ with P(A) = 1 such that $X_n(\omega) \to X(\omega)$ for each fixed $\omega \in A$.

Almost Sure Convergence

 $X_n \overset{a.s.}{ o} X$ if there exists $A \in \mathcal{F}$ with P(A) = 1 such that $X_n(\omega) o X(\omega)$ for each fixed $\omega \in A$.

Does sure convergence imply almost sure convergence?

$$X_n \to_p X ext{ if } P(\{\omega: |X_n(\omega) - X(\omega)| > \epsilon\}) o 0 ext{ for any fixed } \epsilon > 0.$$

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Does
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 imply $X_n \to_p X$?

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Does
$$X_n \overset{a.s}{ o} X$$
 imply $X_n o_p X$? Yes.

Does $X_n \to_p X$ imply $X_n \stackrel{a.s}{\to} X$?

Does
$$X_n o_p X$$
 imply $X_n \overset{a.s}{ o} X$?

Does $X_n \to_p X$ imply $X_n \stackrel{a.s}{\to} X$?

No.

PROOF. Consider the probability space $\Omega = (0,1)$, with Borel σ -field and the Uniform probability measure U of Example 1.1.11 Suffices to construct an example of $X_n \to_p 0$ such that fixing each $\omega \in (0,1)$, we have that $X_n(\omega) = 1$ for infinitely many values of n. For example, this is the case when $X_n(\omega) = \mathbf{1}_{[t_n,t_n+s_n]}(\omega)$ with $s_n \downarrow 0$ as $n \to \infty$ slowly enough and $t_n \in [0,1-s_n]$ are such that any $\omega \in [0,1]$ is in infinitely many intervals $[t_n,t_n+s_n]$. The latter property applies if $t_n = (i-1)/k$ and $s_n = 1/k$ when n = k(k-1)/2 + i, $i = 1,2,\ldots,k$ and $k = 1,2,\ldots$ (plot the intervals $[t_n,t_n+s_n]$ to convince yourself).

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But there exists a subsequence n_k such that $X_{n_k} \stackrel{a.s.}{\to} X$.

Let $F_X : \mathbb{R} \to [0,1]$ be the cumulative distribution function of real-valued random variable X.

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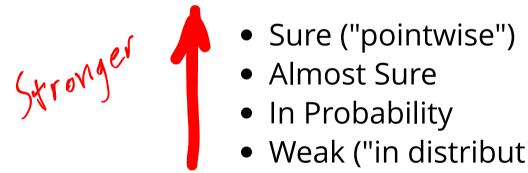
 $X_n \stackrel{D}{ o} X$ if $F_{X_n}(\alpha) o F_X(\alpha)$ for each fixed α that is a continuity point of F_X .

"Weak convergence", "convergence in distribution", and "convergence in law" all mean the same thing.

In what senses can we talk about random variables converging?

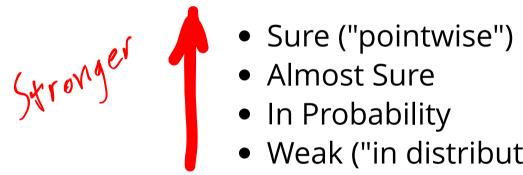
- Sure ("pointwise")
- Almost Sure
- In Probability
- Weak ("in distribution"/"in law")

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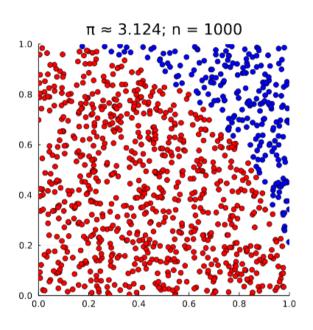
- Weak ("in distribution"/"in law")

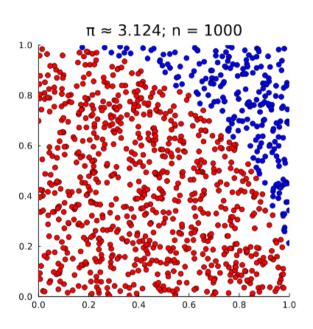
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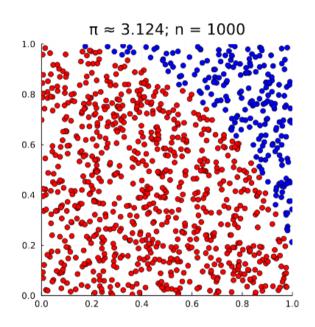
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Let X_i be independent, identically distributed random variables with mean μ , and $Q_N \equiv \frac{1}{N} \sum_{i=1}^N X_i$.



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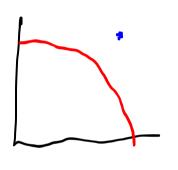
$$Q_N\stackrel{?}{ o} \mu?$$

$$Q_N o \mu ext{ (sure)}?$$

$$Q_N\stackrel{a.s.}{ o} \mu?$$

$$Q_N o_p \mu$$
?

$$Q_N \stackrel{D}{
ightarrow} \mu?$$



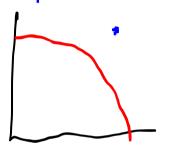
$$Q_N o \mu ext{ (sure)}$$
?

$$Q_N\stackrel{a.s.}{
ightarrow}\mu?$$

$$Q_N o_p \mu ?$$

$$Q_N \stackrel{D}{
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 $\exists \omega \in \Omega$ where you always sample the same point.



$$Q_N \to \mu \text{ (sure)}?$$

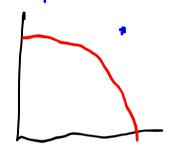


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 $Q_N o \mu ext{ (sure)}?$



$$Q_N\stackrel{a.s.}{ o} \mu?$$

Probability that there are enough measurements off in one direction to keep $|Q_N-\mu|>\epsilon$ decays with more samples.

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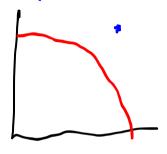
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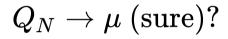
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Weak law of large numbers

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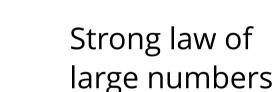
 $Q_N o \mu ext{ (sure)}$?



 $Q_N \stackrel{a.s.}{\rightarrow} \mu$?



 $Q_N \to_p \mu$?





Weak law of large numbers

measurements off in one direction to keep $|Q_N - \mu| > \epsilon$ decays with more samples.

Probability that there are enough

$$Q_N \stackrel{D}{
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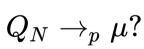
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Strong law of large numbers





Weak law of large numbers

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Probability that there are enough

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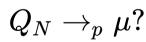
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Strong law of large numbers





Weak law of large numbers

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samples.

Convergence *Rate* of M.C. Integration

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How do you quantify $|Q_N - \mu|$?

Convergence *Rate* of M.C. Integration

How do you quantify $|Q_N - \mu|$?

Run M sets of N simulations and plot a histogram of Q_N^j for $j \in \{1, \dots, M\}$.

Lindeberg-Levy CLT: If
$${
m Var}[X_i]=\sigma^2<\infty$$
, then $\sqrt{N}(Q_N-\mu)\stackrel{D}{
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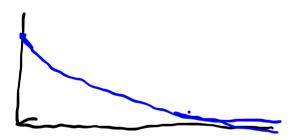
After many samples Q_N starts to look distributed like $\mathcal{N}(\mu, \frac{\sigma}{\sqrt{N}})$

Two somewhat astounding takeaways:

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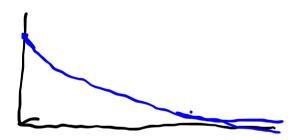
Two somewhat astounding takeaways:

1. Error decays at $\frac{1}{\sqrt{N}}$ regardless of dimension.



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1. Error decays at $\frac{1}{\sqrt{N}}$ regardless of dimension.



2. You can estimate the "standard error" with

$$SE=rac{s}{\sqrt{N}}$$

where s is the sample standard deviation.