

# Almost sure convergence

$X_n$  converges to  $X$  almost surely if

$$P(\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) = X(\omega)) = 1.$$

- ▶ The set of outcomes where the convergence does not happen has measure 0.  $P\{\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) \neq X(\omega)\} = 0.$
- ▶ Consider  $\Omega = [0, 1]$  where you pick a number uniformly in  $[0, 1]$ . Let  $X_n(\omega) = \omega^n$  for all  $\omega \in \Omega$  and  $X(\omega) = 0$  for all  $\omega$ .
- ▶  $X_n(\omega) \rightarrow X(\omega)$  for  $\omega \in [0, 1)$ .
- ▶  $X_n(\omega) \not\rightarrow X(\omega)$  for  $\omega = 1$  and  $\mathbb{P}\{\omega = 1\}.$
- ▶ This is almost sure convergence as  $\mathbb{P}\{[0, 1)\} = 1.$

# Almost sure (a.s.) convergence

$X_n$  converges to  $X$  almost surely if

$$P(\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) = X(\omega)) = 1.$$

- ▶ Example 2: Strong law of large numbers (SLLN).

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

- ▶ Toss a biased coin (probability of head is  $\mu$ ) repeatedly. What is  $\omega$  and  $\Omega$ ?
- ▶ Let  $X_i$  denote the outcome of the  $i^{\text{th}}$  toss and  $S_n$  denotes the number of heads in  $n$  tosses.
- ▶ The empirical mean is given by  $\frac{S_n}{n}$ .

## Detour: Incremental formula for sample mean

- ▶ Now that we know  $\frac{S_n}{n} \rightarrow \mu$  we can use  $\hat{\mu}_n := \frac{S_n}{n}$  as an 'estimator' for the mean especially in cases when the underlying distribution is not known.
- ▶ Note that the estimator  $\hat{\mu}_n$  is a random variable. What is its cdf? what is its mean & Variance?
- ▶  $\hat{\mu}_n = \frac{S_n}{n}$  is an 'unbiased estimator' since  $E[\hat{\mu}_n] = \mu$ .
- ▶  $Var(\hat{\mu}_n) = \frac{\sigma^2}{n}$
- ▶ We will soon see CLT that will tell the CDF of  $\hat{\mu}_n$  without any information on the law of  $X_i$ .

## Detour: Incremental formula for sample mean

- ▶ Now given  $\hat{\mu}_n$ , suppose you see an additional sample  $X_{n+1}$ .
- ▶ How will you compute  $\hat{\mu}_{n+1}$ ?
- ▶ Naive way :  $\hat{\mu}_{n+1} = \frac{\sum_{i=1}^{n+1} X_i}{n+1}$ .
- ▶ There is an incremental formula that uses  $\hat{\mu}_n$ .

$$\hat{\mu}_{n+1} = \hat{\mu}_n + \frac{1}{n+1} [X_{n+1} - \hat{\mu}_n]$$

- ▶ Such averaging formulas are used extensively in Reinforcement learning.

# Recap: Modes of Convergence

$\{X_n, n \geq 0\}$  converges to  $X$  pointwise or surely if for all  $\omega \in \Omega$  we have  $\lim_{n \rightarrow \infty} X_n(\omega) = X(\omega)$

$X_n$  converges to  $X$  almost surely if  $P(\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) = X(\omega)) = 1$ .

$\{X_n, n \geq 0\}$  is a sequence of i.i.d random variables with mean  $\mu$  and  $S_n = \sum_{i=1}^n X_i$ . Then  $\hat{\mu}_n := \frac{S_n}{n} \rightarrow \mu$  a.s. (SLLN)

- ▶ Estimator  $\hat{\mu}_n$  has mean  $\mu$  and Variance  $\frac{\sigma^2}{n}$ .
- ▶  $\hat{\mu}_{n+1} = \hat{\mu}_n + \frac{1}{n+1} [X_{n+1} - \hat{\mu}_n]$

# Borel Cantelli Lemma

Self-Study: Theorem 7.5 ([probabilitycourse.com](http://probabilitycourse.com))

Consider a sequence of random variables  $X_1, X_2, \dots$ . If for all  $\epsilon$  we have

$$\sum_{n=1}^{\infty} P(|X_n - X| > \epsilon) < \infty$$

then  $X_n \rightarrow X$  a.s.

- ▶ This is only a sufficient condition for almost sure convergence!
- ▶ Thm 7.6 (HW) gives necessary and sufficient conditions.
- ▶ Lot of problems in [probabilitycourse](http://probabilitycourse.com), practice them!

## Another example of a.s. convergence

- ▶ Consider a uniform r.v.  $U$  and define  $X_n = n1_{\{U \leq \frac{1}{n}\}}$ .
- ▶  $X_n = n$  when  $U \leq \frac{1}{n}$  and  $X_n = 0$  otherwise.
- ▶ Given a realization of  $U$ , what can you say about the sequence  $\{X_n\}$  ?
- ▶ Once an  $X_n$  is zero, all higher indexed variables are also zero!
- ▶ This happens for all realizations  $U$  other than  $U = 0$ . In this case since  $0 \leq \frac{1}{n}$  for all  $n$ ,  $X'_n$ s run off to infinity and we don't see convergence to 0.
- ▶ But  $P(U = 0) = 0$ .
- ▶ Does  $E[X_n] \rightarrow 0$  ?
- ▶ Almost sure convergence does not imply their means converge!

# Towards convergence in probability

- ▶ Now define  $X_n = n1_{\{U_n \leq \frac{1}{n}\}}$  where  $\{U_n\}$  are i.i.d uniform.
- ▶  $X_n = n$  when  $U_n \leq \frac{1}{n}$  and  $X_n = 0$  otherwise.
- ▶ What can you say about the sequence  $\{X_n\}$  ?
- ▶ Is it true that once an  $X_n$  is zero, all higher indexed variables are also zero!? No!
- ▶ Every time (on every run of the experiment or every sample path), we will have a sequence of zero and non-zero values, where the non-zero values become rarer and rarer but will keep happening once in a while.
- ▶ On no sample path would you see convergence to zero but occurrence of non-zero values become rare.
- ▶ We now characterize this notion of convergence.



# Convergence in probability (w.h.p)

$X_n$  converges to  $X$  in probability if

$$\lim_{n \rightarrow \infty} P(|X_n - X| > \epsilon) = 0 \text{ for all } \epsilon > 0.$$

- ▶ How would you compute  $P(|X_n - X| > \epsilon)$  when  $X_n, X$  are either continuous or discrete random variables ?
- ▶ Ex:  $X_n = n$  with probability  $\frac{1}{n}$  and  $X_n = 0$  otherwise.
- ▶  $P(|X_n - X| > \epsilon) = P(X_n > \epsilon) = \frac{1}{n}$  when  $n > \epsilon$ .
- ▶ When  $n < \epsilon$ , we have  $P(|X_n - X| > \epsilon) = 0$ .
- ▶ Once  $n > \epsilon$  we have  $\lim_{n \rightarrow \infty} P(X_n > \epsilon) = \lim_{n \rightarrow \infty} \frac{1}{n} = 0$ .
- ▶  $X_n$  converges to 0 in probability, but not almost surely.
- ▶ a.s. convergence implies convergence in probability