# 18.175: Lecture 14 Infinite divisibility and so forth

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Infinite divisibility

Higher dimensional CFs and CLTs

Random walks

Stopping times

#### Infinite divisibility

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- More general constructions are possible via Lévy Khintchine representation.

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- ► The inversion theorems and continuity theorems that apply here are essentially the same as in the one-dimensional case.

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- ▶ Let  $\mathcal{E}$  be the  $\sigma$ -field of permutable events.
- ▶ This is related to the tail  $\sigma$ -algebra we introduced earlier in the course. Bigger or smaller?

## Hewitt-Savage 0-1 law

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#### Hewitt-Savage 0-1 law

- ▶ If  $X_1, X_2, \ldots$  are i.i.d. and  $A \in \mathcal{A}$  then  $P(A) \in \{0, 1\}$ .
- ▶ Idea of proof: Try to show A is independent of itself, i.e., that  $P(A) = P(A \cap A) = P(A)P(A)$ . Start with measure theoretic fact that we can approximate A by a set  $A_n$  in  $\sigma$ -algebra generated by  $X_1, \ldots X_n$ , so that symmetric difference of A and  $A_n$  has very small probability. Note that  $A_n$  is independent of event  $A'_n$  that  $A_n$  holds when  $X_1, \ldots, X_n$  and  $X_{n_1}, \ldots, X_{2n}$  are swapped. Symmetric difference between A and  $A'_n$  is also small, so A is independent of itself up to this small error. Then make error arbitrarily small.

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- ▶ Idea of proof: Hewitt-Savage implies the lim sup  $S_n$  and lim inf  $S_n$  are almost sure constants in  $[-\infty, \infty]$ . Note that if  $X_1$  is not a.s. constant, then both values would depend on  $X_1$  if they were not in  $\pm \infty$

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- ▶ In finance applications, *T* might be the time one sells a stock. Then this states that the decision to sell at time *n* depends only on prices up to time *n*, not on (as yet unknown) future prices.

## Stopping time examples

▶ Let  $A_1,...$  be i.i.d. random variables equal to -1 with probability .5 and 1 with probability .5 and let  $X_0 = 0$  and  $X_n = \sum_{i=1}^n A_i$  for  $n \ge 0$ .

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- Which of the following is a stopping time?
  - 1. The smallest T for which  $|X_T| = 50$
  - 2. The smallest T for which  $X_T \in \{-10, 100\}$
  - 3. The smallest T for which  $X_T = 0$ .
  - 4. The T at which the  $X_n$  sequence achieves the value 17 for the 9th time.
  - 5. The value of  $T \in \{0, 1, 2, ..., 100\}$  for which  $X_T$  is largest.
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- Answer: first four, not last two.

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- ▶ Wald's equation: Let  $X_i$  be i.i.d. with  $E|X_i| < \infty$ . If N is a stopping time with  $EN < \infty$  then  $ES_N = EX_1EN$ .

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- ▶ Wald's second equation: Let  $X_i$  be i.i.d. with  $E|X_i|=0$  and  $EX_i^2=\sigma^2<\infty$ . If N is a stopping time with  $EN<\infty$  then  $ES_N=\sigma^2EN$ .

## Wald applications to SRW

▶  $S_0 = a \in \mathbb{Z}$  and at each time step  $S_j$  independently changes by  $\pm 1$  according to a fair coin toss. Fix  $A \in \mathbb{Z}$  and let  $N = \inf\{k : S_k \in \{0, A\}.$  What is  $\mathbb{E}S_N$ ?

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- ▶ What is EN?

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### Reflection principle

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- ▶ How many walks from (0, x) to (n, y) that don't cross the horizontal axis?
- ▶ Try counting walks that *do* cross by giving bijection to walks from (0, -x) to (n, y).

### Ballot Theorem

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- ▶ Answer:  $(\alpha \beta)/(\alpha + \beta)$ . Can be proved using reflection principle.

### Arcsin theorem

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- ▶ Theorem for amount of positive positive time.