## Expected value over countably infinite sets

S = a countably infinite subset of R

$$S = \{s_1, s_2, \ldots\}$$

X = a random variable which gets values in S

$$E(X) \doteq \sum_{i=1}^{\infty} s_i \Pr(X(\omega) = s_i)$$

### Consider the distribution

distribution is over the natural numbers = positive integers

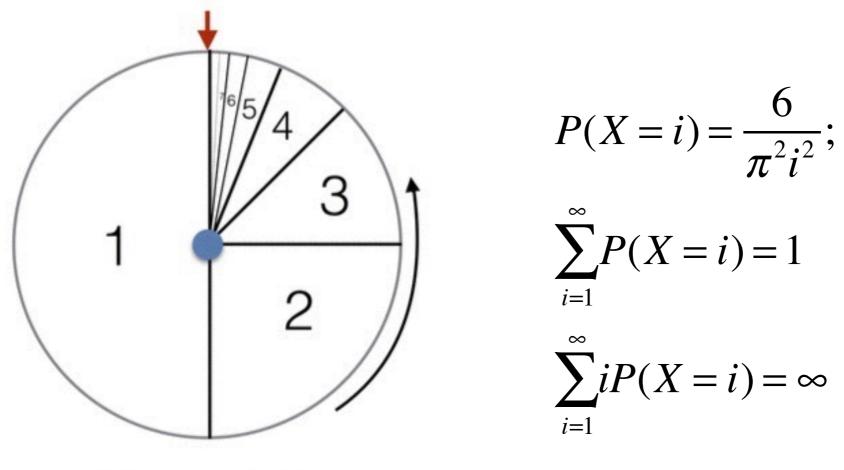
$$P(X=i) = \frac{1}{zi^3}; \quad z = \sum_{i=1}^{\infty} \frac{1}{i^3} < \infty$$

$$E(X) = \sum_{i=1}^{\infty} \frac{i}{zi^3} = \sum_{i=1}^{\infty} \frac{1}{zi^2} < \infty$$
 Expectation is finite

Consider next the distribution

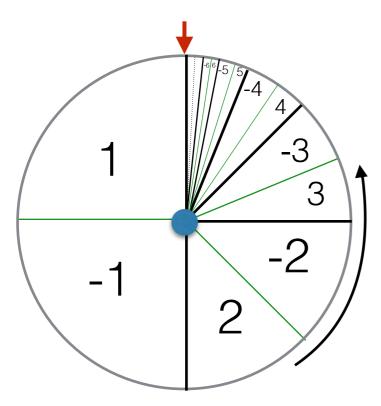
$$P(X = i) = \frac{1}{zi^2}; \quad z = \sum_{i=1}^{\infty} \frac{1}{i^2} < \infty$$

$$E(X) = \sum_{i=1}^{\infty} \frac{i}{zi^2} = \sum_{i=1}^{\infty} \frac{1}{zi} = \infty$$
 Distribution is well defined but Expectation is infinite



(b) A wheel with Infinitely many outcomes

Participation in this game is worth any price (on the long term)



A wheel with Infinitely many outcomes both positive and negative

Consider a game with both wins and losses

$$i \in \{0,-1,+1,-2,+2,\dots\}$$

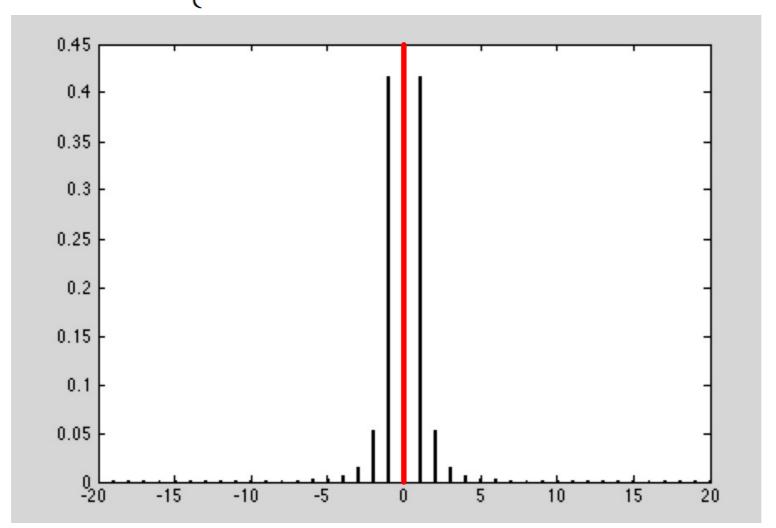
$$P(X=i) = \begin{cases} \frac{1}{Z} \frac{1}{i^{1.5}} & \text{if } i \neq 0 \\ 0 & \text{if } i = 0 \end{cases}, \quad Z = 2 \sum_{i=1}^{\infty} \frac{1}{i^{1.5}}$$

$$\sum_{i=-\infty}^{\infty} P(X=i) = 1$$

$$\sum_{i=\infty}^{\infty} iP(X=i) is undefined$$

### Expectation over pos and neg integers: the good case

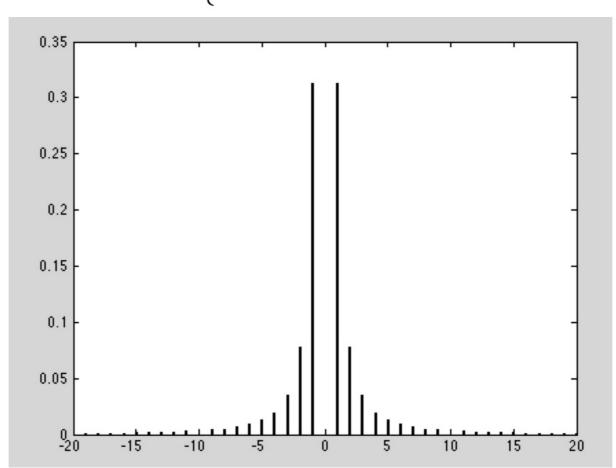
$$P(X = i) = \begin{cases} 0 & \text{if } i = 0\\ \frac{1}{Z|i|^3} & \text{if } i \neq 0 \end{cases}; \quad Z = 2\sum_{i=1}^{\infty} \frac{1}{|i|^3} < \infty$$



$$E(X) = \sum_{i=1}^{\infty} iP(X=i) + \sum_{i=-1}^{-\infty} iP(X=i) = \frac{1}{Z} \left( \sum_{i=1}^{\infty} \frac{1}{i^2} - \sum_{i=1}^{\infty} \frac{1}{i^2} \right) = \frac{c-c}{Z} = 0$$

# A symmetric distribution on pos and neg integers, the bad case

$$P(X = i) = \begin{cases} 0 & \text{if } i = 0\\ \frac{1}{Zi^2} & \text{if } i \neq 0 \end{cases}; \quad Z = 2\sum_{i=1}^{\infty} \frac{1}{i^2} < \infty$$



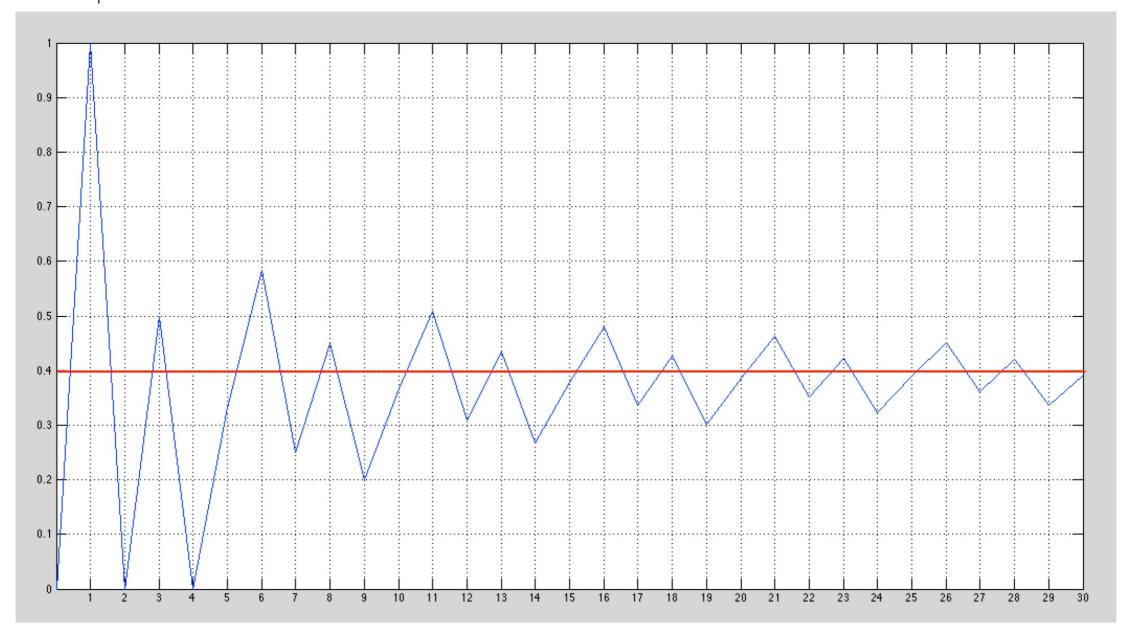
$$E(X) = \sum_{i=1}^{\infty} iP(X=i) + \sum_{i=-1}^{-\infty} iP(X=i) = \frac{1}{Z} \left( \sum_{i=1}^{\infty} \frac{1}{i} - \sum_{i=1}^{\infty} \frac{1}{i} \right) = \frac{\infty - \infty}{Z} = undefined$$

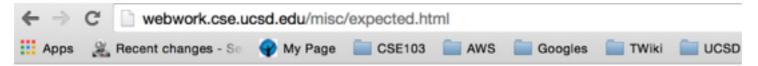
Undefined limit means you can get the limit of your choice by changing the order of summation.

You have at your disposal two infinitely large sums with shrinkingly small pieces: 1/1,1/2,1/3,1/4,.... -1/1,-1/2,-1/3,-1/4,...

Suppose you want the limit to be 0.4, by alternating between positives and negatives you can get arbitrarily close to 0.4 (or to any other number)

1/1-1/1+1/2-1/2+1/3+1/4-1/3+1/5-1/4+1/6+1/7-1/5+1/8-1/6+1/9+1/10-1/7+1/11-1/8+1/12+1/13-1/9+1/14-1/10+1/15+1/16-1/11+1/17-1/12+1/18 = 0.3919





Let X be a random variable whose probability distribution is defined as:

$$P(X=i) = \begin{cases} \frac{1}{|i|^{\alpha}} & \text{if } i \neq 0 \\ 0 & \text{if } i = 0. \end{cases}$$

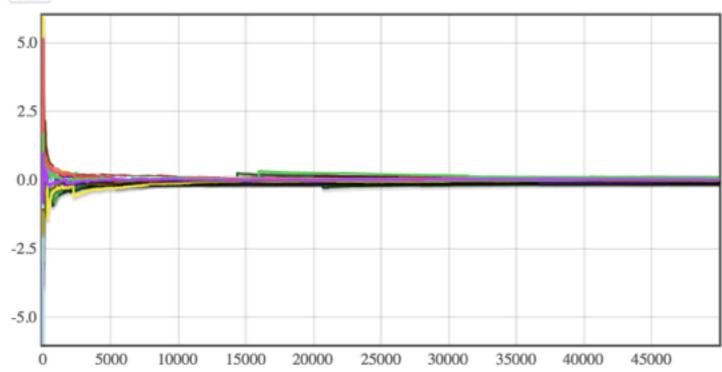
#### Simulation parameters:

α: 2.5

Number of trajectories: 50

Number of data points: 50000

Run



Let X be a random variable whose probability distribution is defined as:

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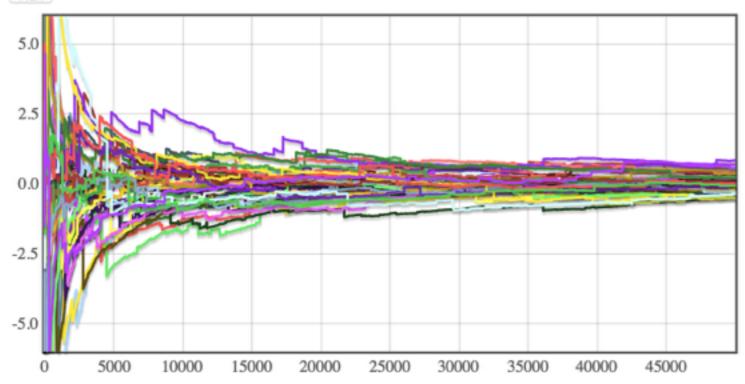
#### Simulation parameters:

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Run





Let X be a random variable whose probability distribution is defined as:

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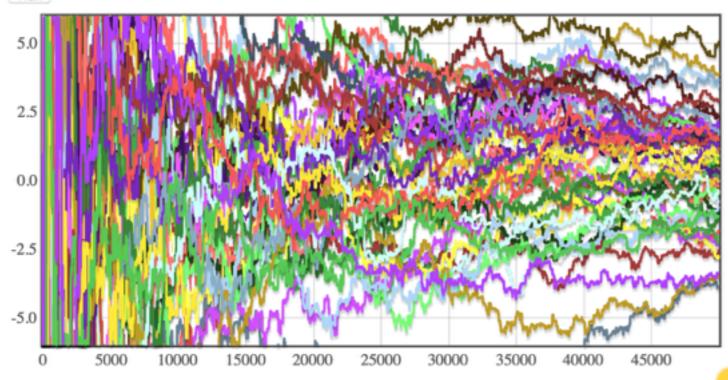
#### Simulation parameters:

α: 1.5

Number of trajectories: 50

Number of data points: 50000

Run



#### KQS cards

I want to know how to improve my teaching Your feedback is important to me.

On the index card provided, please give a one-sentence to each of the following questions

Keep: One thing I should keep doing?

Quit: One thing I should quit doing?

Start: One thing I should start doing?

# A random algorithm for computing percentiles

# A problem with the average

Average 
$$(X_1,...,X_n) \doteq \frac{1}{n} \sum_{i=1}^n X_i$$

The average is the most common estimator of the "center" of a distribution. It takes linear time to compute.

However, the average is "sensitive to outliers" :

Suppose that you have a company in which 1000 employees earn 1\$/day and one employee earns 1000\$/day. The average dayly pay is 2000/1001 ~ 2\$/day, but that is double what most people earn.

## Using the Median instead of the average

To compute the median sort all n elements from smallest to largest and take the value of the element that is the middle of the list (position n/2) (take the average of the two middle elements if the list length is even).

In the earlier example, the median will be 1\$ regardless of how big is the largest salary - outliers are ignored.

## The median is a special case of percentiles

To compute the P-percentile sort all n elements from smallest to largest and take the value of the element that is in the floor(Pn) position.

The Median is the 1/2-percentile

Often used when describing distribution of income: The top

#### US Median Household Income, Inflation Adjusted

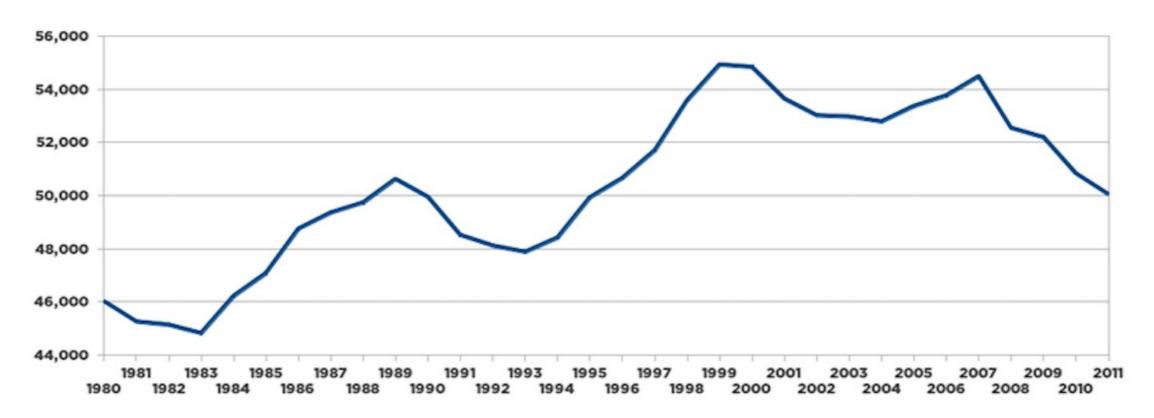


Table 1: Income, net worth, and financial worth in the U.S. by percentile, in 2010 dollars

Wealth or income class	Mean household income	Mean household net worth	Mean household financial (non- home) wealth
Top 1 percent	\$1,318,200	\$16,439,400	\$15,171,600
Top 20 percent	\$226,200	\$2,061,600	\$1,719,800
60th-80th percentile	\$72,000	\$216,900	\$100,700
40th-60th percentile	\$41,700	\$61,000	\$12,200
Bottom 40 percent	\$17,300	-\$10,600	-\$14,800

From Wolff (2012); only mean figures are available, not medians. Note that income and wealth are separate measures; so, for example, the top 1% of income-earners is not exactly the same group of people as the top 1% of wealth-holders, although there is considerable overlap.

A linear time algorithm for computing percentiles

We can calculate P-percentile by sorting and then picking the element in location Pn. But this requires time O(n log n) (unless distribution of data is known).

We will now describe a randomized algorithm whose expected running time is O(n)



Solution 1, sort and locate ---- takes worst case time O(n log n):



Expected time is also Omega(n log n):

7 10 3 20 15 16 70 33 30 7

Solution 2, randomized algorithm ---- takes *expected* time O(n):



Choose a random element as pivot

7         10         3         20         15         16         70         3	33 30 7
--	---------

7	10	3	20	15	16	70	33	30	7
---	----	---	----	----	----	----	----	----	---

Choose a random element as pivot

7	10	3	20	15	16	70	33	30	7
---	----	---	----	----	----	----	----	----	---

Partition list into 3 lists: <7, =7, >7

7	10	3	20	15	16	70	33	30	7
---	----	---	----	----	----	----	----	----	---

Choose a random element as pivot



Partition list into 3 lists: <7, =7, >7

3

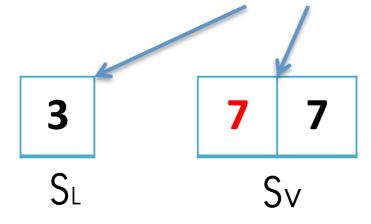
 $\mathsf{S}_\mathsf{L}$ 

7	10	3	20	15	16	70	33	30	7
---	----	---	----	----	----	----	----	----	---

Choose a random element as pivot



Partition list into 3 lists: <7,=7,>7



7	10	3	20	15	16	70	33	30	7
---	----	---	----	----	----	----	----	----	---

Choose a random element as pivot



Choose a random element as pivot



Partition list into 3 lists: <7,=7,>7

3 7 7 10 20 15 16 70 33 30

 $S_R$ 

Find the 2<sup>nd</sup> smallest element in the following table:

Sv

10 20 15 16 70 33 30

7 10 3 20 15 16 70 33 30 7	7	10	10 3	20	15	16	70	33	30	7
----------------------------	---	----	------	----	----	----	----	----	----	---

Choose a random element as pivot



Find the 2<sup>nd</sup> smallest element in the following table:

10	20	15	16	70	33	30
----	----	----	----	----	----	----

# The split operation

 Choosing a split value v we divide the set S into three subsets:

$$-S_L = \{x \in S \mid x < v\}$$

$$-S_v = \{x \in S \mid x = v\}$$

$$-S_R = \{x \in S \mid x > v\}$$

# After we split, we know how to continue

- We know the size of the three sets:  $|S_1|$ ,  $|S_v|$ ,  $|S_R|$ .
- If median is in  $S_v$ , then we are done.
- Otherwise we continue with either S<sub>L</sub> or S<sub>R</sub>

## Randomized algorithm

- Let S be a set of N different numbers. Suppose we pick a random element of S to be the pivot v. What is the probability that the size of S<sub>L</sub> is equal to 10?
  - **1/10**
  - 9/10
  - -1/N

# Randomized algorithm

- Let S be a set of N different numbers. Suppose we pick a random element of S to be the pivot v. What is the probability that the size of  $S_L$  is between  $\lceil N/4 \rceil$  and  $\lceil 3N/4 \rceil$ ?
  - A. About ¼
  - B. About ½
  - C. About <sup>3</sup>/<sub>4</sub>
  - D. About 1/N

# Lucky splits

- We say that the split of a set S of size N is lucky if
- $\frac{1}{4}N \le |S_L| \le (3/4)N$
- Which implies also that ¼N≤ |S<sub>u</sub>|≤(3/4)N
- If the split is lucky then the size of the set we operate on decreases by a factor of (3/4)
- In order to reduce the set to all-equal elements we need at most k lucky splits:

$$\left(\frac{3}{4}\right)^k N \le 1 \implies k \log \frac{3}{4} + \log N \le 0 \implies k \ge \frac{\log N}{\log(3/4)}$$

# Expected time to first lucky split

 What is the expected number of random splits until we get a lucky split?

A. 1

B. 2

C. 1/2

## Expected Running time

n = The number of elements in the input array.

T(n) = The expected running time of the algorithm

$$T(n) \le n + \frac{1}{2}T(n) + \frac{1}{2}T\left(\frac{3}{4}n\right)$$

Multiply both sides by 2 and rearrange:

$$2T(n) \le 2n + T(n) + T\left(\frac{3}{4}n\right); \qquad T(n) \le 2n + T\left(\frac{3}{4}n\right)$$

$$T(n) \le 2n + T\left(\frac{3}{4}n\right)$$

$$T(n) \le 2n + \frac{3}{4}2n + T\left(\left(\frac{3}{4}\right)^2 n\right)$$

$$T(n) \le 2n + \left(\frac{3}{4}\right)2n + \left(\frac{3}{4}\right)^2 2n + T\left(\left(\frac{3}{4}\right)^2 n\right)$$

$$T(n) \le 2n\left(1 + \left(\frac{3}{4}\right) + \left(\frac{3}{4}\right)^2 + \left(\frac{3}{4}\right)^3 + \dots\right) + T(\le 1)$$

$$T(n) \le 2n\frac{1}{1 - (3/4)} = 8n$$

This is an upper bound - the actual constant is smaller.

Before you leave, please bring me your filled-in KQS cards

# Two styles of random algorithms

- Las Vegas: always gives the correct answer, time to terminate varies from run to run, known bound on expected running time.
- Monte Carlo: Takes a pre-defined time to terminate, gives the correct answer with nonzero probability.

Tip for remembering:

Monte Carlo - outcome not always Correct

Las Vegas - run-time Varies

## From Las Vegas to Monte-Carlo

A Las Vegas algorithm always outputs the correct answer but it's run-time varies, the expected run time is bounded.

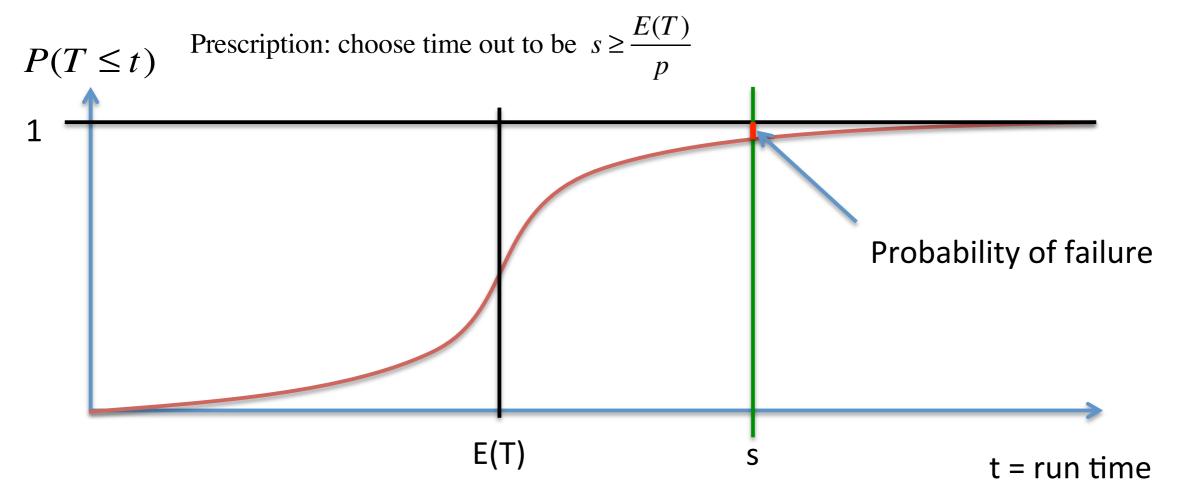
We want to transform the algorithm into a Monte-Carlo algorithm that Always takes the same same time to complete but has a small probability p of generating an incorrect answer.

Method: Time out the LV algorithm at time s and output "fail".

T = the random variable equal to the run-time of the algorithm.

T is non-negative and E(T) is known

Markov inequality: 
$$P(T \ge s) \le \frac{E(T)}{s}$$



## From Monte-Carlo to Las Vegas

A Monte-Carlo algorithm always takes the same same time to complete but has probability p of not generating the correct answer.

We want to transform it into a Las Vegas algorithm, i.e. one that always outputs the correct answer has a varying run time with finite expected value.

Method: run the MC algorithm repeatedly until the answer that it outputs is correct.

Same analysis as the expected number of flips of a biased coin until the first "heads".

p = the probability that MC fails.

I = the number of times MC is run until the first correct answer.

$$Pr(I = i) = p^{i-1}(1-p)$$

$$E(I) = (1-p) + 2p(1-p) + 3p^{2}(1-p) + \cdots =$$

$$= (1-p)\sum_{i=1}^{\infty} ip^{i-1} = \frac{1-p}{p}\sum_{i=1}^{\infty} ip^{i} = \frac{1-p}{p}\frac{p}{(1-p)^{2}} = \frac{1}{1-p}$$

Example: What is the expected number of iteration If the MC algorithm Succeeds with probability ¼?