## RaNDOMNESS

- what it is and what it isn't
- Las Vegas and Monte Carlo
- approximate counting
- context
https://algs4.cs.princeton.edu


## A brief recap: where we've already encountered randomness

Percolation. Monte Carlo simulation: open random blocked sites.


Randomized queues. Remove item chosen uniformly at random.


## A brief recap: where we've already encountered randomness



```
Test 2: open random sites until the system percolates
Test 7: open random sites with large n
Test 12: call open(), isOpen(), and numberOfOpenSites()
    in random order until just before system percolates
Test 13: call open() and percolates() in random order until just before system
percolates
Test 14: call open() and isFul1() in random order until just before system percolates
Test 15: call all methods in random order until just before system percolates
Test 16: call all methods in random order until almost all sites are open
        (with inputs not prone to backwash)
Test 20: call all methods in random order until all sites are open
        (these inputs are prone to backwash)
```


## A brief recap: where we've already encountered randomness

## DEQUES <br> RANUUMIIZED <br> QUEUES

Tests 1-8 make random intermixed calls to addFirst(), addLast(),
removeFirst(), removeLast(), isEmpty(), and size(), and iterator().
Test 12: check iterator() after random calls to addFirst(), addLast(), removeFirst(), and removeLast() with probabilities (p1, p2, p3, p4)

Tests 1-6 make random intermixed calls to enqueue(), dequeue(), sample(),
isEmpty(), size(), and iterator().
Test 16: check randomness of sample() by enqueueing $n$ items, repeatedly calling sample(), and counting the frequency of each item
Test 17: check randomness of dequeue() by enqueueing $n$ items, dequeueing $n$ items, and seeing whether each of the $n$ ! permutations is equally likely

Test 18: check randomness of iterator() by enqueueing $n$ items, iterating over those n items, and seeing whether each of the $n!$ permutations is equally likely

## A brief recap: where we've already encountered randomness

Quicksort is a (Las Vegas) randomized algorithm.
Shuffling is needed for performance guarantee.
Equivalent alternative: pick a random pivot in each subarray.


Hash tables.


## RaNDOMNESS

- what it is and what it isn't
$\rightarrow$ Las Végas and Monte Carlo
- approximate counting
- context

Which of these outcomes is most likely to occur in a sequence of 6 coin flips?
A.

B.

C.

D. All of the above.
E. Both B and C.

## The uniform distribution

## Coin flip.


$\mathbb{P}[C$ lands heads $]=\mathbb{P}[C$ lands tails $]=\frac{1}{2}$.

Roll of a die.


Notation.
$C$ and $D$ are random variables.
" $C$ lands heads," " $D=4$ " or " $D$ is even" are events with probabilities $\mathbb{P}[C$ lands heads], etc.

A distribution consists of all outcome-probability pairs.
[uniform distribution: all probabilities equal]

$\mathbb{P}[D=1]=\cdots=\mathbb{P}[D=20]=\frac{1}{20}$.

## The uniform distribution

## Generating uniform distributions.

- Over (small) domain of size $n$ : place outcomes in array, return random element.


| 1 | 2 | 3 | 4 | 5 | 6 |
| :--- | :--- | :--- | :--- | :--- | :--- |


| $H$ | $T$ |
| :--- | :--- |

- Over large domains:
- Bit strings of length $n$ : [ size $2^{n}$ ]
flip $n$ coins, output sequence of outcomes ( $H=0, T=1$ ).
- Permutations of $n$ items: [ size $n$ ! ]
sample $n$ elements from $\{1,2, \ldots, n\}$ without replacement.
- Spanning trees of $n$-vertex graph? [ size $\leq n^{n-2}$ ]

Flip a coin 6 times and count how often it lands heads. Which count is most likely?
A. 2
B. 3
C. 4
D. All of the above.
E. None of the above.

## Concentration and the Central Limit Theorem

Normal distribution (a.k.a. Gaussian)


## Concentration and the Central Limit Theorem

Normal distribution (a.k.a. Gaussian)


Mean $\mu$ : peak
Standard deviation $\sigma$ : spread [ $68 \%$ within $\pm \sigma, 95 \%$ within $\pm 2 \sigma$ ]

## Randomness: quiz 3

## What is your height?

A. Less than $5^{\prime} 4^{\prime \prime}$
B. At least 5'4'' and less than 5'6''
C. At least 5'6'' and less than 5'8'
D. At least 5'8'' and less than 5'10'
E. At least 5'10'"

## Fast on average vs. fast with high probability

Quicksort: $C_{n}=\mathbb{E}\left[c_{n}\right] \sim 2 n \ln n$. [fast on average]


Stronger guarantee: $\mathbb{P}\left[c_{n} \leq 3 n \ln n\right] \geq 99 \%$. [fast with high probability]

Tail bounds toolkit. Markov, Chebyshev, Chernoff, ...

## Pseudorandomness

Computers can't generate randomness (without specialized hardware).


Pseudorandom functions.

## random - Generate pseudo-random numbers



Source code: Lib/random.py

This module implements pseudo-random number generators for various distributions.
For integers, there is uniform selection from a range. For sequences, there is uniform selection of a random element, a function to generate a random permutation of a list in-place, and a function for random sampling without replacement.

Goal. Rearrange array so that result is a uniformly random permutation.
all $n$ ! permutations
equally likely


Goal. Rearrange array so that result is a uniformly random permutation.
all $n$ ! permutations
equally likely


Goal. Rearrange array so that result is a uniformly random permutation.
all $n$ ! permutations
equally likely


Challenge. Design a linear-time algorithm.

- In iteration i, pick integer $r$ between 0 and $i$ uniformly at random.
- Swap a[i] and a[r].


## Knuth shuffle

- In iteration i, pick integer $r$ between 0 and $i$ uniformly at random.
- Swap a[i] and a[r].


Proposition. [Fisher-Yates 1938] Knuth shuffling algorithm produces a uniformly random permutation of the input array in linear time.

## Knuth shuffle

- In iteration i, pick integer $r$ between 0 and $i$ uniformly at random.
- Swap a[i] and a[r].
common bug: between 0 and $n-1$ correct variant: between $i$ and $n-1$

```
public class Knuth {
    public static void shuffle(Object[] a) {
        int n = a.length;
            for (int i = 0; i < n; i++) {
            int r = StdRandom.uniform(i + 1);
            exch(a, i, r);
        }
    }
}
```

http://algs4.cs.princeton.edu/11model/Knuth.java.html

## Broken Knuth shuffle

Q. What happens if integer is chosen between 0 and $n-1$ ?
A. Not uniformly random!

| permutation | Knuth shuffle | broken shuffle |
| :---: | :---: | :---: |
| A B C | $1 / 6$ | $4 / 27$ |
| A C B | $1 / 6$ | $5 / 27$ |
| B A C | $1 / 6$ | $5 / 27)$ |
| B C A | $1 / 6$ | $5 / 27$ |
| C A B | $1 / 6$ | $4 / 27$ |
| (but 27 is not a multiple of 6) |  |  |

probability of each permutation when shuffling $\{A, B, C\}$

## Industry story (online poker)

Texas hold'em poker. Software must shuffle electronic cards.


How We Learned to Cheat at Online Poker: A Study in Software Security

[^0]
## Industry story (online poker)

```
for i := 1 to 52 do begin
    r := random(51) + 1; « between 1 and 51
    swap := card[r];
    card[r] := card[i];
    card[i] := swap;
end;
Shuffling algorithm in FAQ at www.planetpoker.com
```

Bug 1. Random number $r$ is never $52 \Rightarrow 52^{n d}$ card can't end up in $52^{n d}$ place.
Bug 2. Shuffle not uniform (should be between 1 and $i$ ).
Bug 3. random() uses 32 -bit seed $\Rightarrow 2^{32}$ possible shuffles.
Bug 4. Seed $=$ milliseconds since midnight $\Rightarrow 86.4$ million shuffles.

[^1]
## Industry story (online poker)

Best practices for shuffling (if your business depends on it).

- Use a hardware random-number generator that has passed both the FIPS 140-2 and the NIST statistical test suites.
- Continuously monitor statistical properties: hardware random-number generators are fragile and fail silently.
- Use an unbiased shuffling algorithm.



## RANDOM.ORG

Bottom line. Shuffling a deck of cards is hard!

## RaNDOMNESS

- what it is and what it isn't
- Las Vegas and Monte Carlo
- approximate counting
- context

Robert Sedgewick $\mid$ Kevin Wayne
https://algs4.cs.princeton.edu

## Las Vegas algorithms

- Guaranteed to be correct.
- Running time depends on outcomes of random coin flips.

Ex. Quicksort, quickselect.

|  | $p$ | $\geq p$ |  |
| :---: | :---: | :---: | :---: |
| $\uparrow$ |  |  |  |
| $\uparrow$ |  | $\uparrow$ |  |
| $l o$ | $j$ | $h i$ |  |



## Monte Carlo algorithms

Monte Carlo algorithm.

- Not guaranteed to be correct.
- Running time is deterministic.
[doesn't depend on coin flips]


Amplification. If $\mathbb{P}[A$ is correct $]=1 \%$, repeat 500 times.
Then, $\mathbb{P}\left[A_{1}, A_{2}, \ldots, A_{500}\right.$ are all incorrect $] \leq\left(\frac{99}{100}\right)^{500}<1 \%$

## Karger's global mincut algorithm

Goal. Find cut in undirected graph with fewest edges (for any source and sink).


Idea. Pick a random cut.
Uniformly? Since there are $2^{V}-1$ cuts, may succeed with only $\sim \frac{1}{2^{V}}$ probability.

## Karger's global mincut algorithm

Algorithm.

- Assign a random weight (uniform between 0 and 1 ) to each edge $e$.
- Run Kruskal's MST algorithm until 2 connected components left.
- 2 connected components defines the cut.

Probability of finding a mincut: $\geq \frac{1}{V^{2}}$. [ no mincut edges in each connected component ]
Run algorithm many times and return best cut.


Remark 1. Finds global mincut in $\Theta\left(E V^{2} \log E\right)$ time - better than $\Theta(V)$ runs of Ford-Fulkerson!
Remark 2. With clever idea, improved to $\Theta\left(V^{2} \log ^{3} V\right)$ time (still randomized).

Randomness: quiz 4

Smallest \# of repetitions of Karger's algorithm to get correct answer with $99 \%$ probability?
A. $\Theta(1)$
B. $\Theta(V)$
C. $\Theta\left(V^{2}\right)$
D. $\Theta\left(V^{3}\right)$
E. None of the above.

## RaNDOMNESS

- what it is and what it isn't
$\rightarrow$ Las Végas and Monte Carlo

Algorithms

Robert Sedgewick I Kevin Wayne
https://algs4.cs.princeton.edu

## Packet counting



Fix $n \in \mathbb{N}$. How many bits must a counter have to count from 0 to $n-1$ ?
A. $\log _{2} n$
B. $\left\lfloor\log _{2} n\right\rfloor \longleftarrow$ round down
C. $\left\lceil\log _{2} n\right\rceil \longleftarrow$ round up
D. $\left\lfloor\log _{2} n\right\rfloor+1$
E. $n$

## Approximate counting

Goal. Count with less memory: from $\sim \log _{2} n$ to $\Theta(\log \log n)$.

Why bother?
Database with 1 billion entries: $\log _{2} 10^{9} \approx 30$ bits, but $\log _{2} \log _{2} 10^{9} \approx 5$ bits.
Factor-6 improvement matters a lot.


## Approximate counting



## Approximate counting

```
public class ApproximateCounter() {
    private byte c;
    public void increment() {
        if (StdRandom.uniformInt(1 << c) == 0)
            C++;
    }
```



```
    public int count() {
        return (1<< c) - 1;
    }
}
```



Value of counter around $k$ after $n=2^{0}+2^{1}+\cdots+2^{k-1}=2^{k}-1$ packets.
Memory requirement: $\sim \log _{2} k \sim \log _{2} \log _{2} n$.

Randomness: quiz 6

Which of the following distributions makes $b=1$ with probability $1 / 8$ ?
A. Flip 3 coins, set $b=1$ if two flips land heads.
B. Flip 3 coins, set $b=1$ if all land heads.
C. Flip 3 coins, set $b=1$ if all land tails.
D. Both A and B.
E. Both B and C.

## Approximate counting: probabilistic analysis

Proposition. The value $c_{n}$ of the counter after $n$ packets satisfies $\mathbb{E}\left[2^{c_{n}}\right]=n+1$.

## Pf. [by induction on $n$ ]

Base case: initially, $\mathbb{E}\left[2^{c_{0}}\right]=2^{0}=0+1$.

Define $P_{n, k}=\mathbb{P}\left[c_{n}=k\right]$. They satisfy the recurrence $P_{0,0}=P_{0,1}=1$ and


## Approximate counting: probabilistic analysis

Proposition. The value $c_{n}$ of the counter after $n$ packets satisfies $\mathbb{E}\left[2^{c_{n}}\right]=n+1$.

## Pf. [by induction on $n$ ]

Decompose $\mathbb{E}\left[2^{c_{n+1}}\right]$ and rearrange:
$\mathbb{E}\left[2^{c_{n+1}}\right]=\sum_{k=0}^{n+1} 2^{k} \times P_{n+1, k}$

## Approximate counting: probabilistic analysis

Proposition. The value $c_{n}$ of the counter after $n$ packets satisfies $\mathbb{E}\left[2^{c_{n}}\right]=n+1$.

## Pf. [by induction on $n$ ]

Decompose $\mathbb{E}\left[2^{c_{n+1}}\right]$ and rearrange:
$\mathbb{E}\left[2^{c_{n+1}}\right]=\sum_{k=0}^{n+1} 2^{k} \times\left(\frac{1}{2^{k-1}} \times P_{n, k-1}+\left(1-\frac{1}{2^{k}}\right) \times P_{n, k}\right)$


## Approximate counting: probabilistic analysis

Proposition. The value $c_{n}$ of the counter after $n$ packets satisfies $\mathbb{E}\left[2^{c_{n}}\right]=n+1$.

## Pf. [by induction on $n$ ]

Decompose $\mathbb{E}\left[2^{c_{n+1}}\right]$ and rearrange:
$\mathbb{E}\left[2^{c_{n+1}}\right]=\sum_{k=0}^{n+1} 2^{k} \times\left(\frac{1}{2^{k-1}} \times P_{n, k-1}+\left(1-\frac{1}{2^{k}}\right) \times P_{n, k}\right)$


## Approximate counting: probabilistic analysis

Proposition. The value $c_{n}$ of the counter after $n$ packets satisfies $\mathbb{E}\left[2^{c_{n}}\right]=n+1$.

## Pf. [by induction on $n$ ]

Decompose $\mathbb{E}\left[2^{c_{n+1}}\right]$ and rearrange:

$$
\begin{aligned}
\mathbb{E}\left[2^{c_{n+1}}\right] & =\sum_{k=0}^{n+1} 2^{k} \times\left(\frac{1}{2^{k-1}} \times P_{n, k-1}+\left(1-\frac{1}{2^{k}}\right) \times P_{n, k}\right) \\
& =2 \sum_{k=0}^{n+1} P_{n, k-1}
\end{aligned}
$$



## Approximate counting: probabilistic analysis

Proposition. The value $c_{n}$ of the counter after $n$ packets satisfies $\mathbb{E}\left[2^{c_{n}}\right]=n+1$.

## Pf. [by induction on $n$ ]

Decompose $\mathbb{E}\left[2^{c_{n+1}}\right]$ and rearrange:

$$
\begin{aligned}
\mathbb{E}\left[2^{c_{n+1}}\right] & =\sum_{k=0}^{n+1} 2^{k} \times\left(\frac{1}{2^{k-1}} \times P_{n, k-1}+\left(1-\frac{1}{2^{k}}\right) \times P_{n, k}\right) \\
& =2 \sum_{k=0}^{n+1} P_{n, k-1}+\sum_{k=0}^{n+1} 2^{k} \times P_{n, k}
\end{aligned}
$$



## Approximate counting: probabilistic analysis

Proposition. The value $c_{n}$ of the counter after $n$ packets satisfies $\mathbb{E}\left[2^{c_{n}}\right]=n+1$.

## Pf. [by induction on $n$ ]

Decompose $\mathbb{E}\left[2^{c_{n+1}}\right]$ and rearrange:

$$
\begin{aligned}
\mathbb{E}\left[2^{c_{n+1}}\right] & =\sum_{k=0}^{n+1} 2^{k} \times\left(\frac{1}{2^{k-1}} \times P_{n, k-1}+\left(1-\frac{1}{2^{k}}\right) \times P_{n, k}\right) \\
& =2 \sum_{k=0}^{n+1} P_{n, k-1}+\sum_{k=0}^{n+1} 2^{k} \times P_{n, k}-\sum_{k=0}^{n+1} P_{n, k}
\end{aligned}
$$

## Approximate counting: probabilistic analysis

Proposition. The value $c_{n}$ of the counter after $n$ packets satisfies $\mathbb{E}\left[2^{c_{n}}\right]=n+1$.

## Pf. [by induction on $n$ ]

Decompose $\mathbb{E}\left[2^{c_{n+1}}\right]$ and rearrange:

$$
\begin{aligned}
\mathbb{E}\left[2^{c_{n+1}}\right] & =\sum_{k=0}^{n+1} 2^{k} \times\left(\frac{1}{2^{k-1}} \times P_{n, k-1}+\left(1-\frac{1}{2^{k}}\right) \times P_{n, k}\right) \\
& =2 \sum_{k=0}^{n+1} P_{n, k-1}+\sum_{k=0}^{n+1} 2^{k} \times P_{n, k}-\sum_{k=0}^{n+1} P_{n, k} \\
& =2+\mathbb{E}\left[2^{c_{n}}\right]-1
\end{aligned}
$$



## Approximate counting: probabilistic analysis

Proposition. The value $c_{n}$ of the counter after $n$ packets satisfies $\mathbb{E}\left[2^{c_{n}}\right]=n+1$.

## Pf. [by induction on $n$ ]

Decompose $\mathbb{E}\left[2^{c_{n+1}}\right]$ and rearrange:

$$
\begin{aligned}
& \mathbb{E}\left[2^{c_{n+1}}\right]=\sum_{k=0}^{n+1} 2^{k} \times\left(\frac{1}{2^{k-1}} \times P_{n, k-1}+\left(1-\frac{1}{2^{k}}\right) \times P_{n, k}\right) \\
&=2 \sum_{k=0}^{n+1} P_{n, k-1}+\sum_{k=0}^{n+1} 2^{k} \times P_{n, k}-\sum_{k=0}^{n+1} P_{n, k} \\
&=2+\mathbb{E}\left[2^{c_{n}}\right]-1 \\
& \text { inductive } \\
& \text { hypothesis } \quad=(n+1)+1
\end{aligned}
$$



## RaNDOMNESS

- what it is and what it isn't
- Las Végas and Monte Carlo

Algorithms

- approximate counting
- context

Robert Sedgewick I Kevin Wayne
https://algs4.cs.princeton.edu

## Beyond this course

- Approximation algorithms [intractability: stay tuned!]
- Cryptography [average-case hardness]
- Complexity theory: $\mathrm{P} \stackrel{?}{=}$ BPP [derandomization]
- Mathematics: the Probabilistic Method E.g., graph with $E$ edges has a cut with $E / 2$ edges. [approximate maxcut] To prove that there exists an object with property $T$ :
- sample a random object;
- show that $\mathbb{P}[T$ is satisfied $]>0$.
- Quantum computation


IBM Quantum System One

COS 495. Probability in Computer Science.
ORF 309. Probability and Stochastic Systems.

## Credits

| image | source | license |
| :---: | :---: | :---: |
| Quarter | $\underline{\text { Adobe Stock }}$ | Education License |
| 6-sided dice | Adobe Stock | $\underline{\text { Education License }}$ |
| 20 -sided die | Adobe Stock | $\underline{\text { Education License }}$ |
| Lava lamps | $\underline{\text { Fast Company }}$ |  |
| Coin Toss | $\underline{\text { clipground.com }}$ | CC BY 4.0 |
| IDQ Quantum Key Factory | $\underline{\text { idquantique.com }}$ |  |
| SG100 | $\underline{\text { protego.bytehost16.com }}$ |  |
| Las Vegas | $\underline{\text { Adobe Stock }}$ | $\underline{\text { Education License }}$ |
| Monte Carlo | $\underline{\text { Adobe Stock }}$ | $\underline{\text { Education License }}$ |
| Router | $\underline{\text { XKCD }}$ | $\underline{\text { Education License }}$ |
| Random number generator |  | $\underline{\text { CC BY-NC 2.5 }}$ |

```
int getRandomNumber()
{
    return 4; // chosen by fair dice roll.
        // guaranteed to be random.
}
```


[^0]:    https://www.developer.com/tech/article.php/616221/How-We-Learned-to-Cheat-at-Online-Poker-A-Study-in-Software-Security.htm

[^1]:    " The generation of random numbers is too important to be left to chance."

    - Robert R. Coveyou

