# Probabilistic Analysis and Randomized Algorithms 

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## Today

- Counting.
- Basic probability.
- Introduction to randomized algorithms.

Chapter 5

## Counting

- Rule of sum.
- Number of ways of choosing from one of two sets.

$$
|A \cup B|=|A|+|B|-|A \cap B|
$$

- Rule of product.
- Number of ways of choosing an ordered pairs from two sets.

$$
|A \times B|=|A||B|
$$

## Counting

- Permutations (on ordered sequences):
- $(A, B, C, D) \neq(B, A, C, D) \neq(C, D, A, B)$...
- How many possible permutations?
- Choose $1^{\text {st }}$ element, choose $2^{\text {nd }} \ldots \Rightarrow n$ !
- k-permutations:
- Choose $k$ elements among n: Choose $1^{\text {st }}, 2^{\text {nd }}$, $\ldots \mathrm{k}^{\mathrm{th}}$. How many? $\Rightarrow \frac{n!}{(n-k)!}$


## Counting

- k-combination - k subsets:
- Set $\{A, B, C, D, E\}(n=5)$, choose 3 among it ( $k=3$ ): $\{A, B, C\},\{A, B, D\},\{B, C, D\} \ldots$
- How many combinations?
- We count a k-permutation and we keep only one representant for every set of equivalent combination, e.g., $\{A, B, C\}=\{B, A, C\}=\{C, A, B\} \ldots$



## Counting

- Binomial coefficients ( $n$ choose $k$ )

$$
\binom{n}{k}=\binom{n}{n-k}=\binom{n-1}{k}+\binom{n-1}{k-1}
$$

symmetry recursion
useful for Pascal's triangle

## Pascal's Triangle



## Binomial Expansion

$$
(x+y)^{n}=\sum_{k=0}^{n}\binom{n}{k} x^{k} y^{n-k}
$$

$1 \quad(x+y)^{0}=1$
11

$$
(x+y)^{1}=x+y
$$

121
$(x+y)^{2}=x^{2}+2 x y+y^{2}$
$1331(x+y)^{3}=x^{3}+3 x^{2} y+3 x y^{2}+y^{3}$
$14641(x+y)^{4}=x^{4}+4 x^{3} y+6 x^{2} y^{2}+4 x y^{3}+y^{4}$

## Probability



Sample space S
Elementary events

Probability defined in terms of a sample space. Elementary events = outcomes of an experiment, e.g. head/tail.

An event is a subset of $S$ :
obtaining one tail and one head $=\{\mathrm{HT}, \mathrm{TH}\}$.
$\mathrm{S}=$ certain event.
$\varnothing=$ null event.
Exclusive events=disjoints subsets.
Elementary events are exclusive. 9

## Axioms of Probability

- $\operatorname{Pr}\{A\} \geq 0$ for any $A$.

Probability distribution $\operatorname{Pr}\}$ =mapping from events of $S$ to real numbers s.t.


- $\operatorname{Pr}\{S\}=1$.
- $\operatorname{Pr}\{A \cup B\}=\operatorname{Pr}\{A\}+\operatorname{Pr}\{B\}$ for exclusive events.
- $\operatorname{Pr}\{A\}$ is called the probability of the event $A$.
- $\operatorname{Pr}\{\varnothing\}=0$
- $A \subseteq B \Rightarrow \operatorname{Pr}\{A\} \leq \operatorname{Pr}\{B\}$
- $\operatorname{Pr}\{A\}=1-\operatorname{Pr}\{A\}$
- $\operatorname{Pr}\{A \cup B\}=\operatorname{Pr}\{A\}+\operatorname{Pr}\{B\}-$ $\operatorname{Pr}\{A \cap B\}$


## Example

Experiment: Toss 2 coins.
Elementary events: outcomes.
Each elementary event has probability $1 / 4$.


$$
\begin{aligned}
& \text { Probability of getting at least } \\
& \text { one head? } \\
& \begin{aligned}
& \operatorname{Pr}\{\mathrm{HT}, \mathrm{TH}, \mathrm{HH}\}= \operatorname{Pr}\{\mathrm{HT}\}+\operatorname{Pr}\{\mathrm{TH}\}+\operatorname{Pr}\{\mathrm{HH}\} \\
&=3 / 4 .
\end{aligned} \\
& =\operatorname{Pr}\{\overline{\mathrm{T}}\}=1-\operatorname{Pr}\{\mathrm{TT}\}
\end{aligned}
$$

## Don't panic!

## Discrete Probability Distributions

- A probability distribution is discrete if it is defined over a countable sample space.

$$
\operatorname{Pr}\{A\}=\sum_{s \in A} \operatorname{Pr}\{s\} \quad \text { (s elementary event) }
$$

- Uniform probability distribution if

$$
\operatorname{Pr}\{s\}=1 /|S|
$$

(Pick an element at random, fair coin...)

## Example

Experiment: Flip a fair coin $n$ times.
Sample space $=\{\mathrm{H}, \mathrm{T}\}^{\mathrm{n}}$ of size $2^{\mathrm{n}}$.
Elementary events $=$ sequences of length $n$, of probability $1 / 2^{n}$.

$\operatorname{Pr}\{A\}$ with?
$A=\{$ exactly $k$ heads and exactly $n-k$ tails $\}$
$|A|=\binom{n}{k}$

$$
\operatorname{Pr}\{A\}=\binom{n}{k} / 2^{n}
$$

## Conditional Probability

- We have partial knowledge of the outcome.
- Flip 2 coins.
- Tell your friend one is a head.
- It's not possible that both are tails! $\operatorname{Pr}\{T T\}$ knowing there is one $\mathrm{H}=0$.
- The remaining events are equally equal \{HT,TH,HH\}.
- $\operatorname{Pr}\{\mathrm{HH}\}$ knowing there is one $\mathrm{H}=1 / 3$.
- $\operatorname{Pr}\{\mathrm{HH}\}$ not knowing there is one $\mathrm{H}=1 / 4$.


## Conditional Probability

- "Probability of $A$ given $B$ " (with $\operatorname{Pr}\{B\} \neq 0$ ):

$$
\operatorname{Pr}\{A \mid B\}=\frac{\operatorname{Pr}\{A \cap B\}}{\operatorname{Pr}\{B\}} \longleftarrow \begin{aligned}
& \text { Both } A \text { and } B \text { occur. } \\
& \begin{array}{l}
\text { Outcome is in } B, \\
\text { we normalize. }
\end{array}
\end{aligned}
$$



Previous example:
$\operatorname{Pr}\{H H \mid$ there is a $H\}=(1 / 4) /(3 / 4)$.

## Independent Events

- Events $A_{i}$ are pair-wise independent if $\operatorname{Pr}\left\{A_{i} \cap A_{j}\right\}=\operatorname{Pr}\left\{A_{i}\right\} \operatorname{Pr}\left\{A_{j}\right\}$.
- Events are mutually independent if
$\operatorname{Pr}\left\{\bigcap_{i \in K} A_{i}\right\}=\prod_{i \in K} \operatorname{Pr}\left\{A_{i}\right\} \quad$ for a subset $K$ of indices.
- If $A$ and $B$ are independent, $\operatorname{Pr}\{\mathrm{A} \mid \mathrm{B}\}=\operatorname{Pr}\{\mathrm{A}\}$.


## Bayes' Theorem



- For two events $A$ and $B$ with non-zero probabilities:

$$
\begin{aligned}
\operatorname{Pr}\{A \cap B\} & =\operatorname{Pr}\{B\} \operatorname{Pr}\{A \mid B\} \\
& =\operatorname{Pr}\{A\} \operatorname{Pr}\{B \mid A\} \\
& \downarrow \\
\operatorname{Pr}\{A \mid B\} & =\frac{\operatorname{Pr}\{A\} \operatorname{Pr}\{B \mid A\}}{\operatorname{Pr}\{B\}}
\end{aligned}
$$

## Bayes' Theorem

- Alternative form using

$$
B=(B \cap A) \cup(B \cap \bar{A})
$$



$$
\operatorname{Pr}\{A \mid B\}=\frac{\operatorname{Pr}\{A\} \operatorname{Pr}\{B \mid A\}}{\operatorname{Pr}\{A\} \operatorname{Pr}\{B \mid A\}+\operatorname{Pr}\{\bar{A}\} \operatorname{Pr}\{B \mid \bar{A}\}}
$$

$$
\operatorname{Pr}\{A \mid B\}=\frac{\operatorname{Pr}\{A\} \operatorname{Pr}\{B \mid A\}}{\operatorname{Pr}\{A\} \operatorname{Pr}\{B \mid A\}+\operatorname{Pr}\{\bar{A}\} \operatorname{Pr}\{B \mid \bar{A}\}}
$$

## Example

We have a fair coin and a biased coin (always head).
Experiment: Choose a coin, flip it twice.
Suppose it comes up head twice.
What is the probability that it is biased?
$A=$ Event that the biased coin is chosen.
$B=$ Event that the coin comes up head twice.
$\operatorname{Pr}\{\mathrm{A} \mid \mathrm{B}\}$ ?

$$
\operatorname{Pr}\{A\}=1 / 2, \operatorname{Pr}\{B \mid A\}=1, \operatorname{Pr}\{\bar{A}\}=1 / 2, \operatorname{Pr}\{B \mid \bar{A}\}=1 / 4
$$

$$
\operatorname{Pr}\{A \mid B\}=\frac{(1 / 2) \cdot 1}{(1 / 2) \cdot 1+(1 / 2) \cdot(1 / 4)}=4 / 5
$$

## Discrete Random Variables

Probability distribution $\operatorname{Pr}\}$
=mapping from events of $S$
to real numbers s.t. ... (axioms) to real numbers.


Discrete random variable $\mathrm{X}=$ function from outcomes of $S$


## Discrete Random Variables

- For a random variable X and a real number $x$ (we choose), the event " $X=x$ " is defined as $\{s \in S: X(s)=x\}$.

$$
\operatorname{Pr}\{X=x\}=\sum_{\{s \in S: X(s)=x\}} \operatorname{Pr}\{s\}
$$

(called the probability density function of $X$ )

## Example

Experiment: Roll two 6 sided dices. 36 elementary events in the sample space. Uniform probability distribution: $\operatorname{Pr}\{\mathrm{s}\}=1 / 36$. $X=$ maximum of the two values on the dice. $\operatorname{Pr}\{X=3\}$ ?

Corresponding set of elementary events: $(1,3),(2,3),(3,3),(3,2),(3,1)$. $\operatorname{Pr}\{X=3\}=5 / 36$.

## Expected Value

- Average of the values of a random variable.

$$
\begin{aligned}
& E[X]=\sum_{x} x \operatorname{Pr}\{X=x\} \\
& E[X+Y]=E[X]+E[Y]
\end{aligned}
$$

## Example

Game: You flip two fair coins. You earn $\$ 3$ for heads, but lose $\$ 2$ for tails. $X=y o u r ~ e a r n i n g . ~$ $\mathrm{E}[\mathrm{X}]$ ? ?

$$
\begin{aligned}
\mathrm{E}[\mathrm{X}] & =6 * \operatorname{Pr}\{H H\}+1 * \operatorname{Pr}\{H T\}+1 * \operatorname{Pr}\{T H\}-4 * \operatorname{Pr}\{T T\} \\
& =6(1 / 4)+1 / 4+1 / 4-4(1 / 4)=1
\end{aligned}
$$

## Geometric \& Binomial Distributions

- Appendix C.4.
- Interesting read.


## Probabilistic Analysis and Randomized Algorithms

- What is it about?
- Worst case analysis = worst cost or running time of an algorithm.
- Probabilistic = average in terms of cost or running time.
- Randomized algorithms = algorithms that have a randomized decision but the result is not random!


## Hiring Problem Example

- Hire new office assistant and fire the old (worse) one.
- Cost of interviewing and hiring $O\left(n c_{i}+m c_{h}\right)$.
- Idea: Cheap to interview, expensive to hire.
- Result is independent of the ordering.
best=0
for $i=1$ to $n$ do interview candidate i
if candidate $i$ is better than candidate best then best=i
hire candidate i


## Hiring Problem Example

- Worst case = hire everyone (focus on hiring): $O\left(n c_{h}\right)$.
- More interesting: probabilistic analysis.
- Saying that applicants arrive in a random order is the same as choosing randomly any possible permutation of applicants ( n ! permutations).
- Expected cost of hiring?
- How do we do?


## Indicator Variables

- $I\{A\}=1$ if $A$ occurs, $I\{A\}=0$ if it does not.
- Example: Expected number of heads if we flip one fair coin.
- $S=\{H, T\}$
- $\mathrm{X}=\mathrm{I}\{\mathrm{Y}=\mathrm{H}\}$
- $E[X]=1 * \operatorname{Pr}\{Y=H\}+0 * \operatorname{Pr}\{Y=T\}=1 / 2$.
- Lemma: Given an event $A$ in $S$, let $X_{A}=I\{A\}$. Then $E\left\{X_{A}\right\}=\operatorname{Pr}\{A\}$.


## Hiring Problem cont.

- $\mathrm{X}_{\mathrm{i}}=\mathrm{I}\{$ hire candidate i$\}$.
- $X=$ Number of hired candidates $=X_{1}+X_{2} \ldots X_{n}$.
- $\mathrm{E}[\mathrm{X}]=\mathrm{E}\left[\mathrm{X}_{1}\right]+\mathrm{E}\left[\mathrm{X}_{2}\right]+\ldots \mathrm{E}\left[\mathrm{X}_{n}\right]$
- $\mathrm{E}\left[\mathrm{X}_{\mathrm{i}}\right]=\operatorname{Pr}\{$ hire candidate i$\}=1 / \mathrm{i}$.
- $E[X]=\operatorname{sum}(1 / i)$ harmonic serie, see $A .7$ $\mathrm{E}[\mathrm{X}]=\ln n+O(1)$.
- Expected cost $=O\left(c_{h} \ln n\right)$


## Randomized Algorithms

- What we did: Knowing the distribution (uniform) of an input, we analyzed an algorithm.
- When we don't know, we can impose a distribution beforehand $\Rightarrow$ we can analyze such a randomized algorithm for any input.
- The point: Even your worst enemy cannot produce a bad input since the execution time depends on the (randomized) algorithm.
- Every run is different.
- The end result is the same.


## Permuting Arrays

- A way to randomize inputs
- Permute by sorting
- Assign random priorities and sort $\Theta(n \lg n)$.

```
n=length[A]
for i=1 to n do P[i]=Random(1,n}\mp@subsup{n}{}{3
sort A using P as keys
```

- It is a uniform random permutation, i.e., every output has probability $1 / n!$.


## Permuting Arrays

- Randomize in-place.
- Swap elements randomly.

```
n=length[A]
for i=1 to n do swap(A[i],A[Random(i,n)])
```

- It is also a uniform random permutation.
- Proof technique: Based on a loop invariant.
- Initialization.
- Maintenance.
- Termination.

