

7.2.6 Bernoulli trials & binomial distribution

Experiment with 2 outcomes

- success prob p
- failure prob $1-p$

Repeat experiment n times

Theorem 2 The probability of having exactly k successes in n independent Bernoulli trials with success prob p is $\binom{n}{k} p^k (1-p)^{n-k}$

P: let (x_1, x_2, \dots, x_n) be the ordered set of outcomes. so $x_i \in \{ \underset{S}{\text{success}}, \underset{F}{\text{failure}} \}$
We can choose k experiments among the n in $\binom{n}{k}$ ways. The probability that a fixed choice of k experiments are all successes while the remaining $n-k$ are all failures is $p^k (1-p)^{n-k}$. Hence the desired probability is $\binom{n}{k} p^k (1-p)^{n-k}$ \square

Define $b(k, n, p)$ as probability of exactly k successes in n independent B-trials so $b(k, n, p) = \binom{n}{k} p^k (1-p)^{n-k}$

Let $q = 1-p$ so $b(k, n, p) = \binom{n}{k} p^k q^{n-k}$

NB:
$$\sum_{k=0}^n \binom{n}{k} p^k q^{n-k} = (p+q)^n \quad \text{by binomial formula}$$

$$= (p+(1-p))^n = 1$$

So $b(k, n, p)$ is a probability distribution
called the binomial distribution

7.2.7 Random variable

Def 6 A random variable associated with a sample space S is a function $f: S \rightarrow \mathbb{R}$

So each event $s \in S$ is assigned a value $f(s)$

Example 10+11 Flip fair coin 3 times $X(t) = \# \text{heads}$ $t \in S$

$$P(X=t)$$

$$X(HHH) = 3$$

$$1/8$$

$$X(HHT) = X(HTH) = X(THH) = 2$$

$$3/8$$

$$X(HTT) = X(THT) = X(TTH) = 1$$

$$3/8$$

$$X(TTT) = 0$$

$$1/8$$

Def 7 The distribution of a random variable X on a sample space S is

$$\{ (r, p(X=r)) \mid r \in X(S) \} \text{ when}$$

$X(S)$ is the set of values taken by X on S

Example 13 Birthday problem

Find min # persons in a room such that probability of having 2 with the same birthday is at least $1/2$.

Assumptions

- birthdays independent
- all days equally likely as a birthday

We find P_n = prob. all distinct

when all distinct then are

366	possibilities for person 1	2
365	- - -	
366 - (i-1)	- - - - i	

366^n outcomes in total so

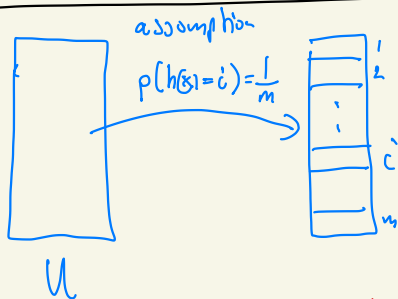
$$P_n = \frac{366}{366} \cdot \frac{365}{366} \cdot \dots \cdot \frac{366-n}{366}$$

when $n = 22$ P_n is still larger than $1/2$

$n = 23$

$P_n \sim 0.494$ so $1 - P_n \sim 0.506$

Example 14 Probability of collisions in hashing



probability that n different keys from U map to n distinct cell in hash table is

$$P_n = \frac{m}{m} \cdot \frac{m-1}{m} \cdot \dots \cdot \frac{m+1-n}{m}$$

probability of a collision is $1 - P_n$

Smallest n such that $1 - P_n \geq \frac{1}{2}$ is $n \sim 1.177 \sqrt{m}$

If $m = 10^6$ it means that n should be larger than 1177

7.2.9 Monte Carlo Algorithms

- probabilistic algorithm that always outputs an answer true/unknown (or false) running time bounded (fixed)

- The answer may be wrong

- true-biased : always correct when true is returned

- false-biased : always correct when false is returned

Suppose $p(\text{test returns 'true'} \mid \text{answer} = \text{true}) = p$

Then $p(\text{test returns unknown} \mid \text{answer} = \text{true}) = 1-p$

} assume true-biased

Assume that the test only returns 'true' if this is the correct answer (can be deduced from the execution)

⇒ If correct answer is 'false' then the test will correctly return false

Amplifying probability of a correct answer:

- run the algorithm n times

- Assume the correct answer is 'true'

Then the n runs of the algorithm will result in at least one true with probability $1 - (1-p)^n \rightarrow 1$ as n increases

Here we need that the n runs of the test are independent.

Example (not in book) Majority element

$$S = \{x_1, x_2, \dots, x_n\} \quad x_i \in \mathbb{Z} \quad n = 2k$$

Question is there a value $x \in \mathbb{Z}$ s.t. $|\{x_i \mid x = x_i\}| > k$?

Test: pick a random x_i
check if x_i occurs more than k times
if yes return 'true'
else return false/unknown

Observation at most one majority element
($\geq k+1$ copies)

So $p(\text{test returns true} \mid \exists \text{ majority}) > \frac{1}{2}$

and test always returns false if no majority element

A: found \leftarrow false, count $\leftarrow 0$
while not found and count $\leq n$
 count \leftarrow count + 1
 pick random $i \in [n]$
 if x_i majority
 found \leftarrow true
end
return found

- If S has no majority the algorithm will return the correct answer 'false'
- if S has a majority the probability that A returns true is $1 - \text{prob that all } n \text{ tests fail}$. Each test fails with $\text{prob} < \frac{1}{2}$ (when there is a majority)
so probability that all n test fail is less than $\left(\frac{1}{2}\right)^n$

with $n=10$ we have $\text{prob}(\text{wrong answer}) < \frac{1}{2}^{10} < \frac{1}{1000}$
 $n=20$ $< \frac{1}{10^6}$

Example 15 Quality control

Testing chips

- assume that if a batch of n chips has not been tested, then is a $\frac{1}{10}$ chance of bad chip in batch and if it has been tested and passed they are all good

Q: how many of the n chips in an unchecked batch should we check to be very sure they are all good?

MC test: pick random chip and test it
repeat k times until all passed or bad chip found

probability that there is a bad chip in batch but we did not find it is $\left(\frac{9}{10}\right)^k$ (independent of n !!)

$$\left(\frac{9}{10}\right)^{132} < \frac{1}{10^6} \quad \left(\frac{9}{10}\right)^{264} < \frac{1}{10^{12}}$$

So by running just a small number of tests we can become very sure that the batch is good!

Example 16 Primality testing

Miller Rabin test $MR(n, b)$ uses $0 < b < n$

to test whether n is a prime.

probability that test says 'prime' for composite n is $< \frac{1}{4}$

MC Algorithm to test if n is composite

Repeat r times

pick random $b \in]0, n[$

run $MR(n, b)$

if 'composite' output this and stop

end

output unknown

probability of answer 'unknown' for composite n
is at most $\left(\frac{1}{4}\right)^r$

The Probabilistic Method (Erdős - Spencer)

Basic idea: If $P(\text{some element in } S \text{ has property } P) < 1$
then $\exists x \in S$ without property P

Very strong tool to prove existence of configuration

Theorem $\forall k \geq 2 \quad R(k, k) \geq 2^{k/2}$

($R(k, k)$ is min n s.t.
 \forall 2-col of K_n \exists either
red K_k or blue K_k)

$p: R(2, 2) = 2, R(3, 3) = 6 \geq 2^{3/2} \quad \checkmark$

assume $k \geq 4$

Consider a random 2-col r/b of the edges of K_n

$$(p(\text{col } r) = p(\text{col } b) = \frac{1}{2})$$

Consider the $\binom{n}{k}$ k -subsets of the vertices of K_n

and denote them $S_1, S_2, \dots, S_{\binom{n}{k}}$

E_i : all edges in S_i have same colour

$$p(\text{monochromatic } K_k) = p(\bigvee E_i) \leq \sum p(E_i) \quad \begin{array}{l} \text{Union} \\ \text{bound} \\ \text{Boole} \end{array}$$

$$p(E_i) = 2 \cdot \left(\frac{1}{2}\right)^{\binom{k}{2}} \quad \text{red or blue}$$

$$\text{so } p(\text{monochromatic } K_k) \leq \binom{n}{k} 2 \cdot \left(\frac{1}{2}\right)^{\binom{k}{2}}$$

$$p(\text{monochromatic } K_n) \leq \binom{n}{k} 2 \cdot \left(\frac{1}{2}\right)^{\binom{k}{2}}$$

$$\leq \frac{n^k}{2^{k-1}} \cdot 2 \cdot \left(\frac{1}{2}\right)^{\binom{k}{2}} \quad \left(\binom{n}{k} \leq \frac{n^k}{2^{k-1}} \right)$$

Suppose $n < 2^{k/2}$ then

$$< \frac{(2^{k/2})^k}{2^{k-1}} \cdot 2 \cdot \left(\frac{1}{2}\right)^{\frac{k(k-1)}{2}}$$

$$= 2^{\frac{k^2/2 + 1 - k + 1 - \frac{k^2}{2} + \frac{k}{2}}{}}$$

$$= 2^{2 - \frac{k}{2}}$$

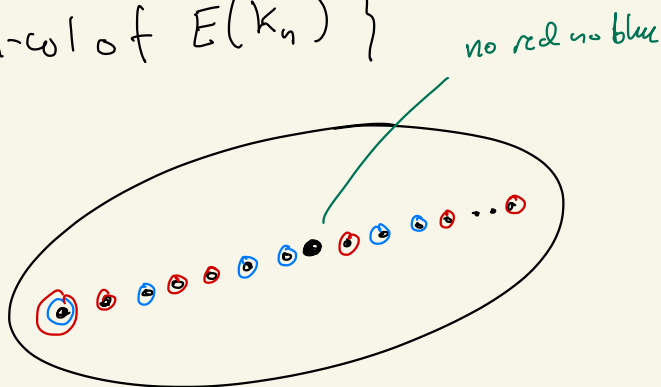
$$\leq 1 \quad \text{as } k \geq 4$$

We have shown that when $n < 2^{k/2}$ the probability that a random 2-col leads to monochromatic K_k is < 1

Hence \exists 2-col of K_n s.t no monochr. K_k !

$$S = \{ \text{all 2-col of } E(K_n) \}$$

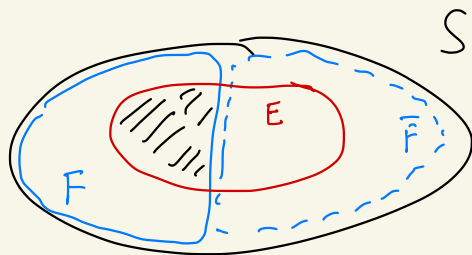
$$|S| = 2^{\binom{n}{2}}$$



7.3 Bayes theorem

Let E and F be events s.t. $p(E), p(F) \neq 0$

$$\text{then } p(F|E) = \frac{p(E|F) \cdot p(F)}{p(E|F) \cdot p(F) + p(E|\bar{F}) \cdot p(\bar{F})}$$



$$F \cap E = \text{shaded area}$$

We know by def of conditional prob $p(F|E) = \frac{p(F \cap E)}{p(E)}$

and $p(E|F) = \frac{p(E \cap F)}{p(F)}$ so $p(F|E) \cdot p(E) = p(E|F) \cdot p(F)$

$$\Rightarrow p(F|E) = \frac{p(E|F) \cdot p(F)}{p(E)}$$

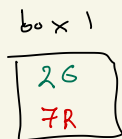
$$\begin{aligned} p(E) &= p(E \cap S) = p(E \cap F) \cup p(E \cap \bar{F}) \\ &= p(E|F) \cdot p(F) + p(E|\bar{F}) \cdot p(\bar{F}) \end{aligned}$$

$$\Rightarrow p(F|E) = \frac{p(E|F) \cdot p(F)}{p(E|F) \cdot p(F) + p(E|\bar{F}) \cdot p(\bar{F})}$$

□

Example 1

2 boxes



box 2



Experiment: 1. pick box with $p = \frac{1}{2}$ each
2. pick random ball from the chosen box

outcome red ball

Question: what is probability that we took from box 1?

E: outcome = red F: chosen box 1
we seek $p(F|E)$ and by Bayes theorem we know this is

$$p(F|E) = \frac{p(E|F) \cdot p(F)}{p(E|F) \cdot p(F) + p(E|\bar{F}) \cdot p(\bar{F})}$$
$$= \frac{\frac{7}{9} \cdot \frac{1}{2}}{\frac{7}{9} \cdot \frac{1}{2} + \frac{3}{7} \cdot \frac{1}{2}} = \frac{\frac{7}{9}}{\frac{7}{9} + \frac{3}{7}} = \frac{49}{49 + 27} = \frac{49}{76}$$

Ex 2 1 in 10^5 have disease D

Test correct is $\frac{99}{100}$ if person has D

$\frac{995}{1000}$ if person does not have D

(a) Find prob (you are sick) if test = positive

F : person has D

E : positive test

We seek $p(F|E)$

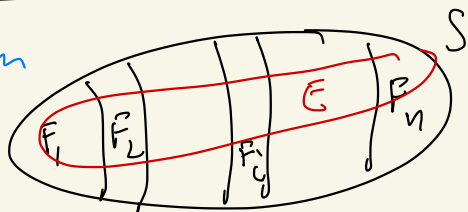
$$p(F|E) = \frac{p(E|F) \cdot p(F)}{p(E|F) \cdot p(F) + p(E|\bar{F}) \cdot p(\bar{F})}$$

$$= \frac{\frac{99}{100} \cdot \frac{1}{10^5}}{\frac{99}{10^7} + \frac{5}{10^3} \left(1 - \frac{1}{10^5}\right)} \sim 0.002$$

Conclusion: prob of having disease is very small even if you test positive

Generalized Bayes then

$$S = F_1 \cup F_2 \cup \dots \cup F_n$$



$$p(F_j|E) = \frac{p(E|F_j)}{\sum_{i=1}^n p(E|F_i) \cdot p(F_i)}$$