

# Statistics for Data Science

## Lecture 2

Counting, Bayes Theorem, Mass and Density Functions

Ken Cameron

# Bayes Theorem, Mass and Density Functions

- Counting Approaches
- Bayes Theorem
- Mass/Density Functions

c. If  $A \subset B$ , then  $P(A) \leq P(B)$

- Did you manage to prove it?
- Answer:

If  $A \subset B$  then  $A \cap B = A$ .

From (a)  $P(B \cap A^c) = P(B) - P(A \cap B)$  we therefore have,

$$0 \leq P(B \cap A^c) = P(B) - P(A)$$

# The Frequentist Approach

- Statisticians can turn counting into a very sophisticated and powerful process.
- The challenge is that the counting can be subject to many restrictions.
- The answer is to break a problem into simpler problems that are easier to count and then combine those using our known rules.

# Separate Tasks

- Theorem: If a job consists of  $k$  separate tasks, the  $i^{\text{th}}$  of which can be done in  $n_i$  ways,  $i = 1, \dots, k$ , then the entire job can be done in

$$n_1 \times n_2 \times n_3 \times \dots \times n_k \text{ ways.}$$

- Proof: Sufficient to prove for  $k = 2$ . The proof is just a matter of careful counting. The first task can be done in  $n_1$  ways, and for each of these ways we have  $n_2$  choices for the second choice. So we can perform the job in

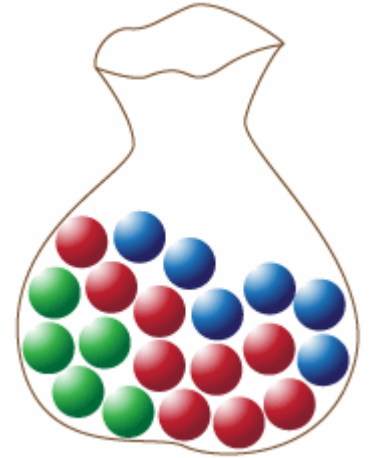
$$(1 \times n_2) + (1 \times n_2) + (1 \times n_2) + \dots + (1 \times n_2) = n_1 \times n_2$$

$$\text{^^^^ } n_1 \text{ ways } \text{^^^^}$$

ways.

# Replacement

- We need to consider if counting is done with or without replacement.
- Consider picking your lottery numbers.
  - Would it make a difference if you could choose the same number twice?
  - Your first choice is from 59. Your second is from 58. So there are  $59 \times 58$  choices available. (3422)
  - With replacement it's  $59 \times 59$  choices. (3481)



# Ordered or not?

- Does the order of the choices matter?
  - If we treat the choice 1, 2 as equal to 2, 1, then there are half as many combinations (assuming without replacement).
- Two useful notations:
  - $n!$  n-factorial. It's the product of all the positive integers between 1 and  $n$ . i.e.  $n \times (n-1) \times (n-2) \times \dots \times 3 \times 2 \times 1$ .
  - And the symbol  $\binom{n}{r} = \frac{n!}{r!(n-r)!}$

# Ordered or not?

- Six ordered without replacement  $59!/53!$
- Six ordered with replacement  $59^6$
- Six unordered without replacement  $59!/(6!53!)$
- Six unordered with replacement ...



# Unordered with Replacement

- The hardest case to count.
- Let's try visualising it:
  - Think of each of our 59 defining a bin and we're going to distribute 6 markers between the bins.
  - The answer is then the number of ways we can put the 6 markers in the 59 bins.

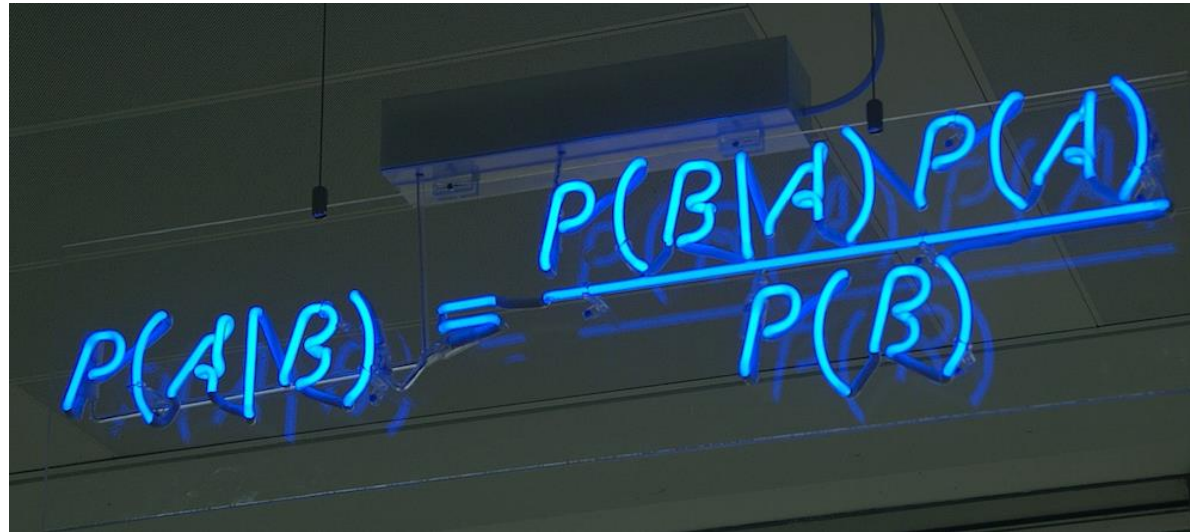


# Unordered with Replacement

- We only need to consider the arrangement of the bin walls and markers.
- We can ignore the outer walls.
- So only need to consider the 58 walls and 6 markers.
- We have  $58 + 6 = 64$  objects that can be arranged in  $64!$  ways.
- However we have to eliminate the redundant orderings so divide by  $6!$  and  $58!$

$$\frac{64!}{6! 58!}$$

# Beyond Counting



A photograph of a chalkboard with the Bayes' Theorem formula written in blue chalk. The formula is  $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$ . The chalkboard is dark, and the blue chalk is clearly visible. The formula is written in a slightly slanted, handwritten style.

- Bayes Theorem/Law.
- This rule simple is one of the most powerful tools when manipulating probabilities.

# Bayes' Law

$$p(y|x) = \frac{p(x|y)p(y)}{p(x)}$$

- This is the Bayesian principle that allows us to incorporate our *prior beliefs* into our mathematical statements
- In particular we call
  - $p(y)$  the prior probability
  - $p(y|x)$  the posterior probability
  - $p(x|y)$  the likelihood
  - $p(x)$  the evidence density

# Example

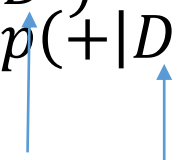
- A realistic hypothetical
  - The police are stopping vehicles at random and testing them for drink driving with a breathalyser
  - 1 in 1000 of the people on the road are drunk
  - The device has been rigorously tested and it has shown that it has 95% accuracy
  - They stop someone, and the test is positive
- What is the probability that they are drunk?

# Example

- Denote drunk as  $D$ , positive test as  $+$
- We want to know  $p(D|+)$ , let's use Bayes:

$$p(D|+) = \frac{p(+|D)p(D)}{p(+)}$$

- From the question
  - $p(+|D) = 0.95$
  - $p(D) = 0.001$
- Can calculate  $p(+)$

$$\begin{aligned} p(+) &= p(+, D) + p(+, D') \\ p(+) &= p(+|D)p(D) + p(+|D')p(D') \end{aligned}$$


# Example

- Continuing...

$$p(+) = p(+|D)p(D) + p(+|D')p(D')$$

- From question:

- $p(+|D') = 0.05$

- $p(D') = 1 - p(D) = 0.999$

- So,  $p(+) = 0.95 \times 0.001 + 0.05 \times 0.999 = 0.0509$

- Hence

$$p(D|+) = \frac{0.95 \times 0.001}{0.0509} \approx 0.019$$

# Example

- Less than 2%!
- The fact is that 95% accuracy is not very good given how rare (0.1%) it is for someone to be drunk in the first place, the false positives hugely outweigh the true positives
- Bayes' Law lets us put that accuracy into context
- Even if the accuracy was better the outcome would still be low.
  - So how do you get to 'beyond a reasonable doubt'?



# Distribution Functions

- For every random variable  $X$ , we have an associated cumulative distribution function of  $X$ . (cdf)

$$F_X(x) = P(X \leq x), \text{ for all } x.$$

- All cdf satisfy certain properties:
  - $\lim_{x \rightarrow -\infty} F(x) = 0$  and  $\lim_{x \rightarrow \infty} F(x) = 1$
  - $F(x)$  is a non-decreasing function
  - $F(x)$  is right continuous. i.e. for every  $x_0$ ,  $\lim_{x \downarrow x_0} F(x) = F(x_0)$

# Distribution Functions Example

- Example: Tossing three coins.  $X$  = number of heads observed.

$$F_X(x) = \begin{array}{ll} 0 & \text{if } -\infty \leq x < 0 \\ 1/8 & \text{if } 0 \leq x < 1 \\ 1/2 & \text{if } 1 \leq x < 2 \\ 7/8 & \text{if } 2 \leq x < 3 \\ 1 & \text{if } 3 \leq x < \infty \end{array}$$

# Density and Mass Functions

- Associated with a random variable  $X$  and its cdf  $F(x)$  is another function:
- Either, the probability density function (pdf)
  - For continuous random variables.
- Or, the probability mass function (pmf)
  - For discrete random variables.

# Probability Mass Functions

- $f_x(x) = P(X = x)$  for all  $x$
- Note that  $P(X = x)$  is the size of the jump in the cdf at  $x$ .
- We can use the pmf to calculate probabilities. For example,

$$f_x(x) = P(X = x) = \begin{cases} (1 - p)^{x-1}p & \text{for } x = 1, 2, \dots \\ 0 & \text{otherwise} \end{cases}$$

$$P(a \leq X \leq b) = \sum_{k=a}^b f_x(k) = \sum_{k=a}^b (1 - p)^{k-1}p.$$

# Probability Density Functions

- A probability density function of a continuous random variable  $X$  satisfies:

$$F_x(x) = \int_{-\infty}^{\infty} f_x(t) dt \text{ for all } x.$$

$$\frac{d}{dx} F_x(x) = f_x(x)$$