

# Topic 3 – Discrete Distributions

ENVX1002 Introduction to Statistical Methods

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Feb 2024



# Outline – Discrete distributions

- Example
- What is a distribution
- Binomial distribution
- Poisson distribution

# Learning outcomes

At the end of this topic students should be able to:

- Have a good understanding of what a distribution is
  - Definitions
  - Functions
  - Binomial and Poisson distributions
- Apply the correct model to describe data
- Demonstrate proficiency in the use of R and Excel for calculating probabilities

# Types of data

Remember the types of data

## Numerical

- Continuous: yield, weight
- Discrete: weeds per  $m^2$

## Categorical

- Binary: 2 mutually exclusive categories
- Ordinal: categories ranked in order
- Nominal: qualitative data

# Example

- We have 5 insects which we spray with an insecticide, each insect has a 60% chance of being killed;
- $P(K) = 0.6$
- Possible questions:
  - What is the probability that all 5 insects will be killed?
  - What is the probability that at least 3 insects will be killed?
- The data is 'binary' and the events are mutually exclusive (either dead or alive unless it is zombie fly);
  - we can say the data is categorical or numeric discrete
  - we can use a binomial (discrete) distribution to "model" the data.



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# What is a distribution?

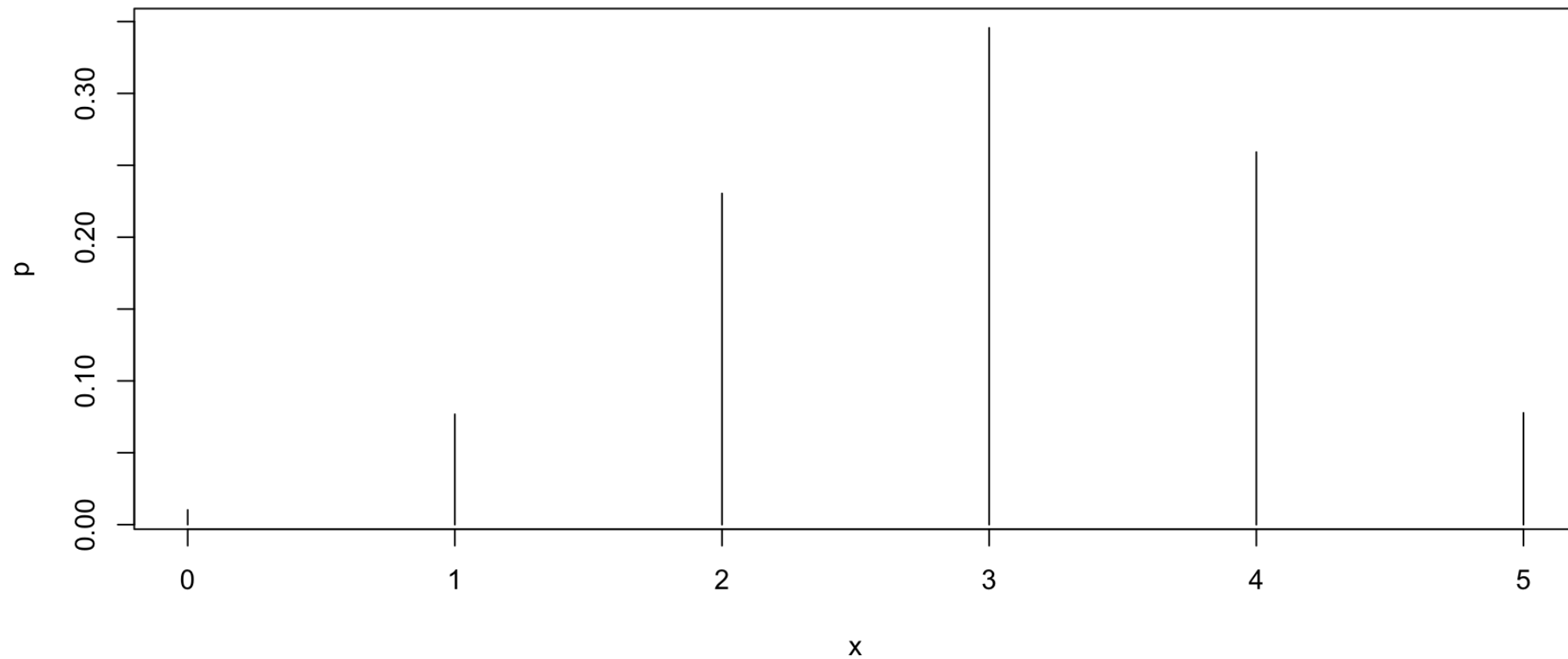
- In our case we are generally referring to a distribution function
  - This is a function (or model) that describes the probability that a system will take on value or set of values  $\{x\}$
- For any variable  $X$ , we describe probabilities by
  - Discrete variables: probability distribution function  $P(X = x)$
  - Continuous variables: probability density function  $f(x)$
  - Discrete and Continuous variables: cumulative density function  $F(x) = P(X \leq x)$

# Back to our example

- We spray 5 flies with insecticide which has 60% chance of killing each insect. If  $X$  is the number of flies that die, what is the distribution of  $X$ ?
- The set of possible values is  $x = 0, 1, 2, 3, 4, 5$
- The likelihood of each value is
- $P(X = 0) = P(\text{no insects die}) = 0.4 \times 0.4 \times 0.4 \times 0.4 \times 0.4 = 0.4^5 = 0.01024$
- $P(X = 1) = P(\text{one insects die}) = 0.6 \times 0.4 \times 0.4 \times 0.4 \times 0.4 + 0.4 \times 0.6 \times 0.4 \times 0.4 \times 0.4 + 0.4 \times 0.4 \times 0.6 \times 0.4 \times 0.4 + 0.4 \times 0.4 \times 0.4 \times 0.6 \times 0.4 + 0.4 \times 0.4 \times 0.4 \times 0.4 \times 0.6 = 0.0768$
- $P(X = 2) = P(\text{two insects die}) = \dots 10 \text{ different combinations} = 0.2304$
- $P(X = 3) = P(\text{three insects die}) = \dots 10 \text{ different combinations} = 0.3456$
- $P(X = 4) = P(\text{four insects die}) = \dots 5 \text{ combinations} = 0.2592$
- $P(X = 5) = P(\text{all insects die}) = 0.6 \times 0.6 \times 0.6 \times 0.6 \times 0.6 = 0.6^5 = 0.07776$

# Example plot

```
1 x <- c(0, 1, 2, 3, 4, 5)
2 p <- c(0.01024, 0.0768, 0.2304, 0.3456, 0.2592, 0.07776)
3 plot(x, p, type = "h")
```





# Example – properties of the distribution

- Remember we have a binomial (dead or alive) distribution here
- A key property of all (discrete) distributions is that all probabilities add to

$$\sum_{i=0}^5 P(X = i) = 0.01024 + 0.0768 + 0.2304 + 0.3456 + 0.2592 + 0.07776 = 1$$

- Note that all probabilities lie between 0 and 1

# Binomial Distribution

- Why does a binomial distribution fit our insect data??
  - Basic element is a Bernoulli trial – each insect;
  - The outcome of each trial can be classified in precisely one of two mutually exclusive ways termed “success” (dead) and “failure” (alive);
    - We usually assign  $p$  to success and  $q$  to failure.
  - Binomial experiments consists of  $n$  Bernoulli (independent binary) trials (i.e. 5 insects);
  - The probability of a success, denoted by  $p$ , remains constant from trial to trial. The probability of a failure,  $q = 1-p$ ;
    - $p = 0.6$  and  $q = 0.4$
  - The trials are independent; that is, the outcome of any particular trial is not affected by the outcome of any other trial;
  - The number of successes,  $x$ , is a binomial variable.

# Example

- How many combinations are there for exactly 2 flies to die out of 5 flies?

$$\binom{5}{2} = \frac{5!}{2!(5-2)!} = \frac{(5 \times 4 \times 3 \times 2 \times 1)}{(2 \times 1 \times 3 \times 2 \times 1)} = 10$$

- What is the probability that exactly 2 flies will die?

$$P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x} = \binom{5}{2} 0.6^2 (1 - 0.6)^{5-2}$$

$$= 10 \times 0.36 \times 0.064 = 0.2304$$



- `dbinom(2, 5, 0.6)`

```
1 dbinom(2, 5, 0.6)
```

[1] 0.2304



- `=BINOM.DIST(2, 5, 0.6, FALSE)`

# Point, cumulative or interval probabilities

- We have already calculated a point probability i.e. the probability of exactly 2 flies dying.
- But what about if we wanted to know the probability of 2 or more flies dying  $P(X \geq 2)$  or between 2 and 4 flies  $P(2 \leq X \leq 4)$  dying??
- So how can we calculate these?
  - One way is to calculate all the point probabilities from 0-5 and add the probabilities cumulatively or in the interval

x	P
0	0.01024
1	0.0768
2	0.2304
3	0.3456
4	0.2592
5	0.07776
SUM	1

# Point, cumulative or interval probabilities

$$P(X \geq 2) = (X = 2) + (X = 3) + (X = 4) + (X = 5) = 0.2304 + 0.3456 + 0.2592 + 0.07776 = 0.91296$$

- You guys try to calculate the following

$$P(2 \leq X \leq 4) = ??$$

x	P
0	0.01024
1	0.0768
2	0.2304
3	0.3456
4	0.2592
5	0.07776
SUM	1

# Cumulative

$$P(X \geq 2)$$



```
1 1 - pbinom(1,5,0.6)
```

```
[1] 0.91296
```

```
1 ## OR  
2  
3 pbinom(1,5,0.6, lower.tail = FALSE)
```

```
[1] 0.91296
```



```
- =1-BINOM.DIST(1,5,0.6,TRUE)
```

# Interval

$$P(2 \leq X \leq 4)$$



```
1 pbinom(4,5,0.6)-pbinom(1,5,0.6)
```

```
[1] 0.8352
```



```
- =BINOM.DIST(4,5,0.6,TRUE)-BINOM.DIST(1,5,0.6,TRUE)
```

# Mean and variance of the binomial distribution

- Mean binomial distribution

$$\mu_x = np$$

$$= 5 \times 0.6 = 3 \text{ On average 3 flies die in 5 trials}$$

- Variance binomial distribution

$$\sigma_x^2 = np(1 - p)$$

$$= 5 \times 0.6(1 - 0.6) = 1.2 \text{ with a variance of 1.2 flies}$$



# Count Data

# Horse kick deaths in the Prussian Army

```
1 library(knitr)
2 kick <- read.csv("data/Kick_deaths.csv")
3 kable(kick[1:12,])
```

Year	GC	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C14	C15
1875	0	0	0	0	0	0	0	1	1	0	0	0	1	0
1876	2	0	0	0	1	0	0	0	0	0	0	0	1	1
1877	2	0	0	0	0	0	1	1	0	0	1	0	2	0
1878	1	2	2	1	1	0	0	0	0	0	1	0	1	0
1879	0	0	0	1	1	2	2	0	1	0	0	2	1	0
1880	0	3	2	1	1	1	0	0	0	2	1	4	3	0
1881	1	0	0	2	1	0	0	1	0	1	0	0	0	0
1882	1	2	0	0	0	0	1	0	1	1	2	1	4	1
1883	0	0	1	2	0	1	2	1	0	1	0	3	0	0
1884	3	0	1	0	0	0	0	1	0	0	2	0	1	1
1885	0	0	0	0	0	0	1	0	0	2	0	1	0	1
1886	2	1	0	0	1	1	1	0	0	1	0	1	3	0

# Horse kick deaths in the Prussian Army

[https://en.wikipedia.org/wiki/Ladislaus\\_Bortkiewicz](https://en.wikipedia.org/wiki/Ladislaus_Bortkiewicz)

```
1 library(tidyverse)
2
3 frequency_kick <- kick %>%
4   select(-Year) %>%
5   pivot_longer(cols = everything(), names_to = "Column",
6   count(Deaths) %>%
7   arrange(Deaths) %>%
8   mutate(Total_Deaths = Deaths*n) %>%
9   mutate(Probability = "?")
10
11 kable(frequency_kick)
```

Deaths	n	Total_Deaths	Probability
0	144	0	?
1	91	91	?
2	32	64	?
3	11	33	?
4	2	8	?

- What is the Probability in any month of
  - 0 injuries by horse kick
  - 1 injuries by horse kick
  - 2 injuries by horse kick
  - 3 injuries by horse kick
  - 4 injuries by horse kick
- $\lambda$  “Lambda” is the mean

# Horse kick deaths in the Prussian Army

```
1 total_kick <- frequency_kick %>%  
2   summarize(n = sum(n), sum_Total_Deaths = sum(Total_Deaths))  
3  
4 kable(total_kick)
```

n	sum_Total_Deaths
280	196

# Poisson Distribution

$$X \sim Po(\lambda)$$

$$P(X = x) = \frac{\lambda^x e^{-\lambda}}{x!} \quad x = 0, 1, 2, \dots \quad \lambda > 0$$

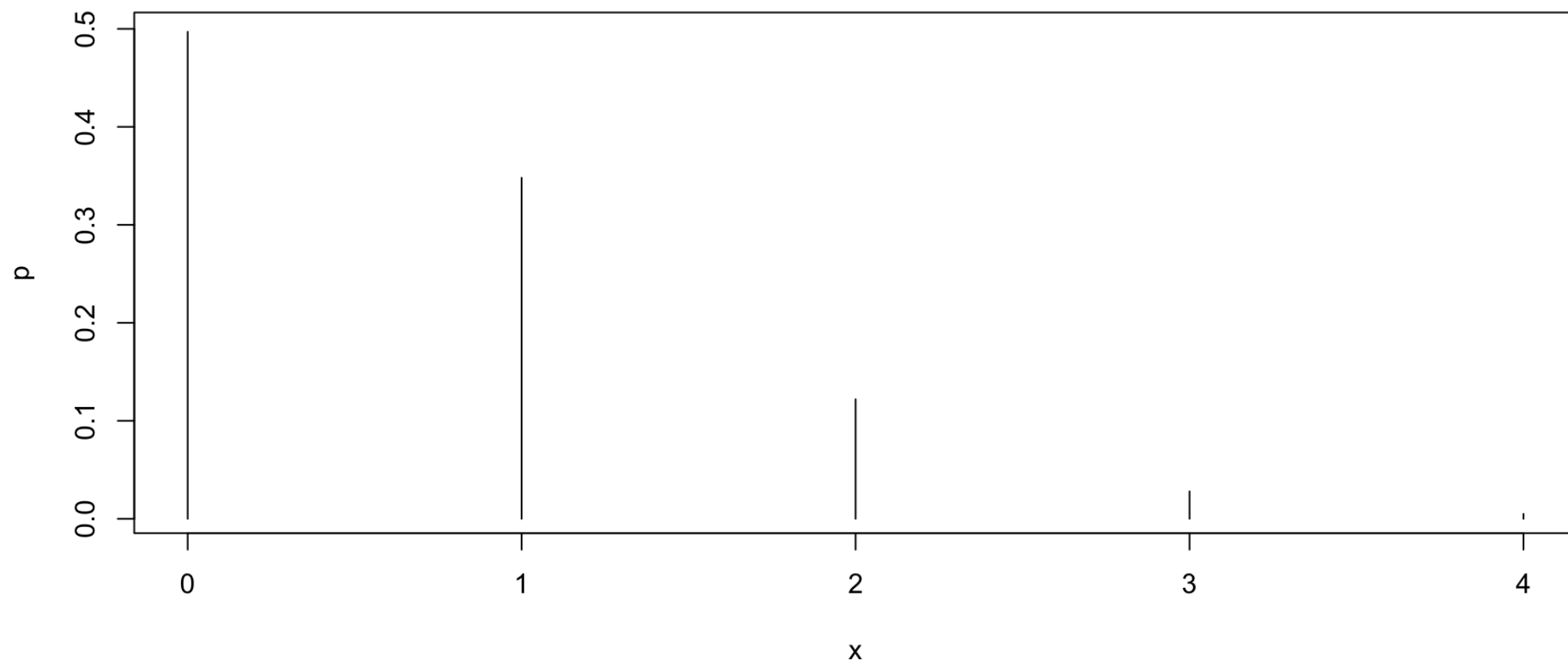
- Note that  $e$  denotes the exponential function such that
  - $e^0 = 1$
  - $e^{-2} = 0.135(3 \text{ d.p.})$
  - $e^{-10} = 4.540 \times 10^{-5}(3 \text{ d.p.})$

# Example with kick deaths

- We first identify the model
  - $X$  = the number of soldiers injured by horse kick  $\sim Po(\lambda)$  where  $\lambda$  = the average number of deaths =  $196/280 = 0.7$ . We can now calculate the probability of having exactly 0, 1, 2, 3, 4, 5 deaths
- $P(X = 0) = \frac{0.7^0 e^{-0.7}}{0!} = \frac{1e^{-0.7}}{1} = 0.497(3 \text{ d.p.})$
- $P(X = 1) = \frac{0.7^1 e^{-0.7}}{1!} = \frac{0.7e^{-0.7}}{1} = 0.348(3 \text{ d.p.})$
- $P(X = 2) = \frac{0.7^2 e^{-0.7}}{2!} = \frac{0.49e^{-0.7}}{2 \times 1} = 0.122(3 \text{ d.p.})$
- $P(X = 3) = \frac{0.7^3 e^{-0.7}}{3!} = \frac{0.343e^{-0.7}}{3 \times 2 \times 1} = 0.028(3 \text{ d.p.})$
- $P(X = 4) = \frac{0.7^4 e^{-0.7}}{4!} = \frac{0.2401e^{-0.7}}{4 \times 3 \times 2 \times 1} = 0.005(3 \text{ d.p.})$

# Example with kick deaths

```
1 x <- c(0, 1, 2, 3, 4)
2 p <- c(0.497, 0.348, 0.122, 0.028, 0.005)
3 plot(x, p, type = "h")
```



# Example with kick deaths

```

1 frequency_kick1 <- kick %>%
2   select(-Year) %>%
3   pivot_longer(cols = everything(), names_to = "Column", values_to = "Deaths") %>%
4   count(Deaths) %>%
5   arrange(Deaths) %>%
6   mutate(Total_Deaths = Deaths*n) %>%
7   mutate(Probability = c(0.497, 0.348, 0.122, 0.028, 0.005)) %>%
8   mutate(Observed_Probability = n/280)
9
10 kable(frequency_kick1)

```

Deaths	n	Total_Deaths	Probability	Observed_Probability
0	144	0	0.497	0.5142857
1	91	91	0.348	0.3250000
2	32	64	0.122	0.1142857
3	11	33	0.028	0.0392857
4	2	8	0.005	0.0071429

- note that observed probability is n divided by the total number of observations (280). For example, for 0 deaths there were 144 observed out of a total of 280 observations i.e. the observed probability of 0 deaths in a cavalry corps over 20 years of observations was 0.51 or 51%



# Example with kick deaths

- So now you all can calculate what the probability is, as an example, the of having less than 2 deaths across all cavalry corps for the period of 1875-1894  $P(X < 2)$ .



```
1 ppois(1,0.7)
```

```
[1] 0.844195
```



```
=POISSON(1,0.7,TRUE)
```

# Example with kick deaths

- Another example, is having exactly 2 deaths across all cavalry corps for the period of 1875-1894  $P(X = 2)$ .



```
1 dpois(1,0.7)
```

```
[1] 0.3476097
```



```
=POISSON(2,0.7,FALSE)
```

# Interesting results with the binomial and Poisson distributions

- For large  $n$  and small  $p$  the Binomial distribution  $X \sim \text{Bin}(n, p)$  can be approximated by the Poisson distribution  $Y \sim \text{Po}(\lambda = np)$ 
  - The general rule is if  $n > 20$  and  $np < 5$
- We often say that the Poisson Distribution models rare events

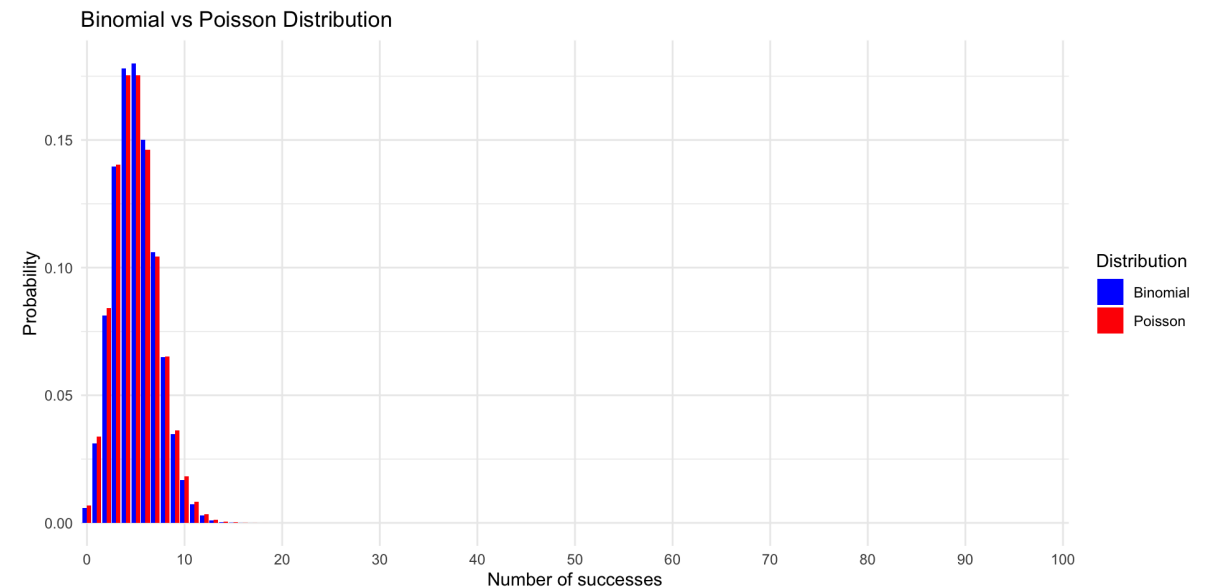
# Interesting results with the binomial and Poisson distributions

```

1 # Parameters for the binomial distribution
2 n <- 100
3 p <- 0.05
4
5 # Calculating lambda for the Poisson approximation
6 lambda <- n * p
7
8 # Generate the range of values
9 x <- 0:n
10
11 # Data frames for plotting
12 data_binom <- data.frame(x = x, probability = dbinom(x, n
13 data_pois <- data.frame(x = x, probability = dpois(x, lam
14
15 # Combine data
16 data_combined <- rbind(data_binom, data_pois)
17
18 # Create the plot
19 p <- ggplot(data_combined, aes(x = factor(x), y = probabi
20   geom_bar(stat = "identity", position = position_dodge
21   ggtitle("Binomial vs Poisson Distribution") +
22   xlab("Number of successes") +
23   ylab("Probability") +
24   scale_fill_manual(values = c("blue", "red")) +

```

```
1 print(p)
```



# Further reading

- Quinn & Keough (2002)
  - Chapter 1. Sections 1.5, p. 9-13
- Mead et al. (2002)
  - Chapter 14. Sections 14.4-14.5, p. 339-377

# Thanks!

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