

## Discrete probability distributions II

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- 1 Poisson distribution
- 2 Negative binomial distribution
- 3 Geometric distribution
- 4 Hypergeometric distribution
- 5 Multinomial distribution
- 6 Power series distribution
- 7 Normal distribution

## Poisson distribution

# Definition

A random variable  $X$  is said to follow Poisson distribution if it assumes only non-negative values and its probability mass function is given by:

$$P(k, \lambda) = P(X = k) = \begin{cases} e^{-\lambda} \frac{\lambda^k}{k!}; & x = 0, 1, 2, \dots, n; \lambda > 0 \\ 0, & \text{otherwise} \end{cases}$$

Here,  $\lambda$  is known as the parameter of the distribution. We shall use the notation  $X \sim p(\lambda)$ , to denote that  $X$  is a poisson variate with parameter  $\lambda$ .

A poisson distribution is a limiting version of the binomial distribution, where  $n$  becomes large and  $np$  approaches some  $\lambda$ , which is the mean value.

The poisson distribution can be used for the number of events in other specified intervals such as distance, area or volume. Examples that may follow a Poisson include the number of phone calls received by a call center per hour and the number of decay events per second from a radioactive source.

## Problem 1

The average number of goals in a World Cup football match is 2.5.

Probability of 4 goals in a match can be calculated as:

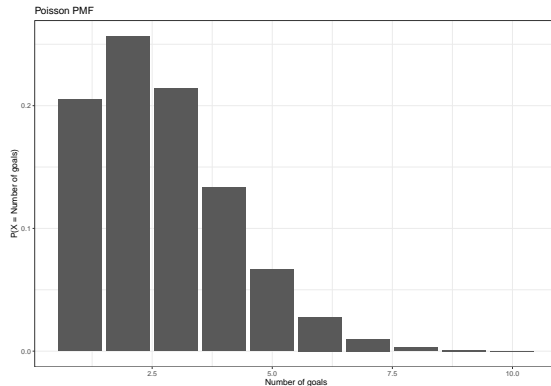
```
## [1] 0.133601885781085
```

This can be accomplished using built-in function

```
## [1] 0.133601885781085
```

# Problem

Find probabilities of occurrence of 1:10 goals and plot the poisson probability distribution



## Negative binomial distribution



## Definition

A random variable  $X$  is said to follow a negative binomial distribution with parameters  $r$  and  $p$  if its probability mass function is given by:

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

## Geometric distribution

## Definition

A random variable  $X$  is said to have a geometric distribution if it assumes only non-negative values and its probability mass function is given by:

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

## Hypergeometric distribution

## Definition

A random variable  $X$  is said follow the hypergeometric distribution with its parameters  $N$ ,  $M$  and  $n$  if it assumes only non-negative values and its pmf is given by:

$$P(X = k) = h(k; N, M, n) \begin{cases} \frac{\binom{M}{k} \binom{N-M}{n-k}}{\binom{N}{n}}; & k = 0, 1, 2, \dots, \min(n, M). \\ 0, & \text{otherwise} \end{cases}$$

## Multinomial distribution

## Meaning

This distribution can be regarded as a generalization of Binomial distribution.

When there are more than two mutually exclusive outcomes of a trial, the observations lead to multinomial distribution. Suppose  $E_1, E_2, \dots, E_k$  are  $k$  mutually exclusive and exhaustive outcomes of a trial with respective probabilities  $p_1, p_2, \dots, p_k$ .

The probability that  $E_1$  occurs  $x_1$  times,  $E_2$  occurs  $x_2$  times  $\dots$  and  $E_k$  occurs  $x_k$  times in  $n$  independent observations, is given by  $p(x_1, x_2, \dots, x_k) = cp_1^{x_1} p_2^{x_2} \dots p_k^{x_k}$ , where  $\sum x_i = n$  and  $c$  is the number of permutation of the events  $E_1, E_2, \dots, E_k$ .

To determine  $c$ , we have to find the number of permutations of  $n$  objects of which  $x_1$  are of one kind,  $x_2$  of another kind,  $\dots$ ,  $x_k$  of the  $k$ th kind, which is given by:

$$c = \frac{n!}{x_1!x_2!\dots x_k!}$$

$$\begin{aligned}\text{Hence } p(x_1, x_2, \dots, x_k) &= \frac{n!}{x_1!x_2!\dots x_k!} p_1^{x_1} p_2^{x_2} \dots p_k^{x_k}, 0 \leq x_i \leq n \\ &= \frac{n!}{\prod_{i=1}^k x_i!} \prod_{i=1}^k p_i^{x_i}; \sum_{i=1}^k x_i = n\end{aligned}$$

Which is the required probability function of the multinomial distribution. It is so called since the above expression is the general term in the multinomial expansion:

$$(p_1 + p_2 + \dots + p_k)^n, \sum_{i=1}^k p_i = 1$$



## Power series distribution

## Definition

A discrete r.v.  $X$  is said to follow a generalized power series distribution (g.p.s.d), if its probability mass function is given by:

$$P(X = x) = \begin{cases} \frac{a_x \theta^x}{f(\theta)}; & x = 0, 1, 2, \dots; a_x \geq 0 \\ 0, & \text{elsewhere} \end{cases}$$

Where  $f(\theta)$  is a generating function i.e.,

$$f(\theta) = \sum_{x \in S} a_x \theta^x, \theta \geq 0$$

So that  $f(\theta)$  is positive, finite and differentiable and  $S$  is a non-empty countable subset of non-negative integers.

## Normal distribution

## Normal density

The `dnorm(x, mean = 0, sd = 1, log = FALSE)` function simply calculates the result for the value plugged into the probability density distribution or probability mass function if it is a discrete distribution.

So for the normal distribution with  $mean = 0$ ,  $sd = 1$ , we have

$$\frac{1}{\sqrt{2\pi}} e^{\frac{-x^2}{2}}$$

If we plug  $x = 2$  inside the pdf, we have

```
## [1] 0.0539909665131881
```

## Normal distribution function

`pnorm(q, mean = 0, sd = 1, lower.tail = TRUE, log.p = FALSE)` returns the probability of  $p(X \leq x)$  by default. If we set `low.tail = FALSE`, then it returns  $p(X > x) = 1 - p(X \leq x)$ .

Let's look at an extreme example which is the one I mentioned above. What is the probability that  $p(X < 10000)$  for  $N(0, 1)$ . It is almost certainly that it should be 1. In another word,  $p(x > 10000)$  is 0. You can imagine the chance of having a human being whose height is 40m (ultraman).

```
## [1] 0.5
```

```
## [1] 1
```

## Normal quantile

One way of defining `qnorm` is that it is the inverse of `pnorm`. So in expression `qnorm(p, mean = 0, sd = 1, lower.tail = TRUE, log.p = FALSE)`, the parameter `p` inside the `qnorm` need to be within  $[0, 1]$  ( $p \in [0, 1]$ ).

So,

```
## [1] 3.09023230616781
```

And,

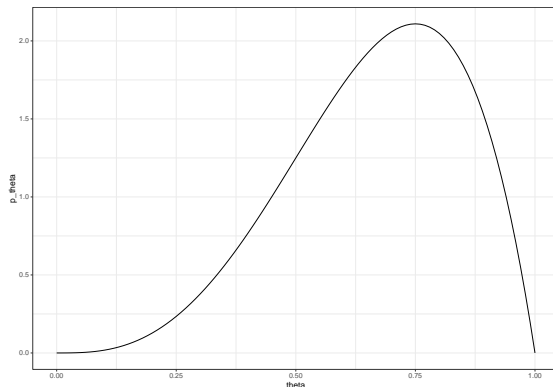
```
## [1] 0.998999992234898
```

## Inferring a binomial distribution



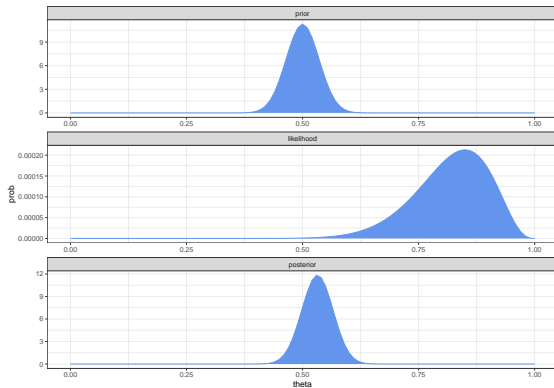
## Beta Distribution

Defined here is a function `bern_beta()` which assumes a beta prior with the prior parameters,  $a$  and  $b$  to be input along with the data parameters  $N$  and  $z$ . The output is a faceted plot of the prior, likelihood, and posterior distributions.



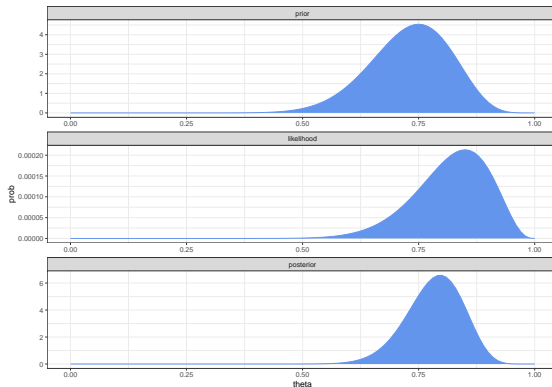
```
bern_beta(100, 100, 20, 17)
```

```
## posterior beta parameters 117 103
```



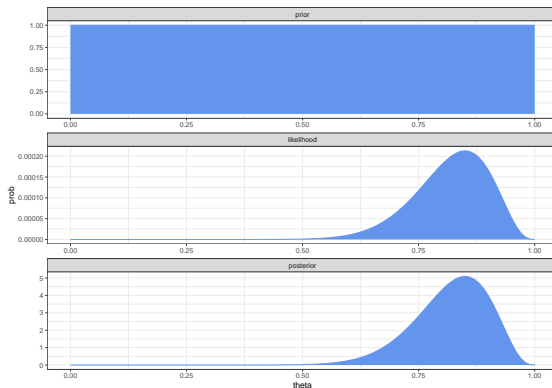
```
bern_beta(18.25, 6.75, 20, 17)
```

```
## posterior beta parameters 35.25 9.75
```



```
bern_beta(1, 1, 20, 17)
```

```
## posterior beta parameters 18 4
```



## Bayesian probabilistic inference

## Which coin

Create three coins, one fair and two biased:

Randomly select one of them but keep its identity secret:

Flip it 5 times and report the number of heads:

```
## [1] 3
```

Use this information to calculate likelihoods:

Update your belief about which coin is being flipped:

```
## # A tibble: 3 x 5
##   model prior likelihood product posterior
##   <fct> <dbl>         <dbl>    <dbl>         <dbl>
## 1 coin1 0.333         0.226    0.0754         0.255
## 2 coin2 0.333         0.315    0.105          0.356
## 3 coin3 0.333         0.345    0.115          0.389
```

Repeat.

## Bibliography



## Further study

Also see: Gupta (2002)

## References

Gupta, VK, SC; Kapoor. 2002. *Fundamentals of Mathematical Statistics: A Modern Approach*. Eleventh. Sultan Chand; Sons.