# Tutorial 3 Brief Review of Probability Theory

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## Outline

- Discrete random variable
  - probability density function, cumulative distribution function
  - expectation, variance, s.d.
  - conditional expectation, conditional distribution
- Continuous random variable
- Distribution
  - the normal distribution
  - the Chi-Squared distribution
  - the student t distribution

• Discrete: Within a range of numbers, discrete variables can take on only certain sample(1:6, 1) values.

Example: dice roll

Outcome	1	2	3	4	5	6
Probability	1/6	1/6	1/6	1/6	1/6	1/6
Cumulative Probability	1/6	2/6	3/6	4/6	5/6	1

- Discrete: Within a range of numbers, discrete variables can take on only certain values.
- sample(1:6, 1)

- Example: dice roll
- Probability density function
  - the list of all possible values of the variable and their probabilities which sum to 1.
- # generate the vector of probabilities
  probability <- rep(1/6, 6)</pre>
- Cumulative probability distribution function:
- # generate the vector of cumulative probabilities
  cum\_probability <- cumsum(probability)</pre>
- gives the probability that the random variable is less than or equal to a particular value.

• Expected value: the long-run average value of its outcomes when the number of repeated trials is large.

Suppose the random variable Y takes on k possible values,  $y_1,\ldots,y_k$ , where  $y_1$  denotes the first value,  $y_2$  denotes the second value, and so forth, and that the probability that Y takes on  $y_1$  is  $p_1$ , the probability that Y takes on  $y_2$  is  $p_2$  and so forth. The expected value of Y, E(Y) is defined as

$$E(Y)=y_1p_1+y_2p_2+\cdots+y_kp_k=\sum_{i=1}^ky_ip_i$$

where the notation  $\sum_{i=1}^k y_i p_i$  means "the sum of  $y_i$   $p_i$  for i running from 1 to k". The expected value of Y is also called the mean of Y or the expectation of Y and is denoted by  $\mu_Y$ .

Variance and standard deviation

The variance of the discrete random variable Y, denoted  $\sigma_V^2$ , is

$$\sigma_Y^2 = \mathrm{Var}(Y) = E\left[(Y-\mu_y)^2
ight] = \sum_{i=1}^k (y_i - \mu_y)^2 p_i$$

The standard deviation of Y is  $\sigma_Y$ , the square root of the variance. The units of the standard deviation are the same as the units of Y.

Sample variance: an estimator of the population variance

$$s_Y^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2.$$

Conditional expectation

$$E(Y|X = x_i) = \sum_{y_i} y_i P(Y = y_j | X = x_i) = \sum_{y_i} y_i \frac{P(X = x_i, Y = y_j)}{P(X = x_i)} = \sum_{y_i} y_i \frac{p_{ij}}{p_i}, j = 1, 2, \dots$$

Conditional distribution

$$F(y \mid x_i) = \sum_{y_j \le y} P(Y = y_j \mid X = x_i) = \sum_{y_j \le y} p_{j \mid i}.$$

example

	Dance	Sports	TV	Total
Men	0.04	0.20	0.16	0.40
Women	0.32	0.12	0.16	0.60
Total	0.36	0.32	0.32	1.00

Probability density function and cumulative distribution function

Let  $f_Y(y)$  denote the probability density function of Y. The probability that Y falls between a and b where a < b is

$$P(a \leq Y \leq b) = \int_a^b f_Y(y) \mathrm{d}y.$$

We further have that  $P(-\infty \le Y \le \infty) = 1$  and therefore  $\int_{-\infty}^{\infty} f_Y(y) dy = 1$ .

Expected value and variance

As for the discrete case, the expected value of Y is the probability weighted average of its values. Due to continuity, we use integrals instead of sums. The expected value of Y is defined as

$$E(Y)=\mu_Y=\int y f_Y(y)\mathrm{d}y.$$

The variance is the expected value of  $(Y - \mu_Y)^2$ . We thus have

$$\mathrm{Var}(Y) = \sigma_Y^2 = \int (y - \mu_Y)^2 f_Y(y) \mathrm{d}y.$$

 Expected value and variance – implementation in R

Consider the continuous random variable X with probability density function:

$$f_X(x) = \frac{3}{x^4}, x > 1.$$

```
# define functions
f \leftarrow function(x) 3 / x^4
g \leftarrow function(x) x * f(x)
h \leftarrow function(x) x^2 * f(x)
# compute area under the density curve
area <- integrate(f,
                   lower = 1.
                   upper = Inf)$value
area
# compute E(X)
EX <- integrate(a,
                 lower = 1.
                 upper = Inf)$value
EX
# compute Var(X)
VarX <- integrate(h,
                   lower = 1.
                   upper = Inf)$value - EX^2
VarX
```

Conditional expectation

$$E[X|Y=y] = \sum_{x} x f_{X|Y}(x|y)$$

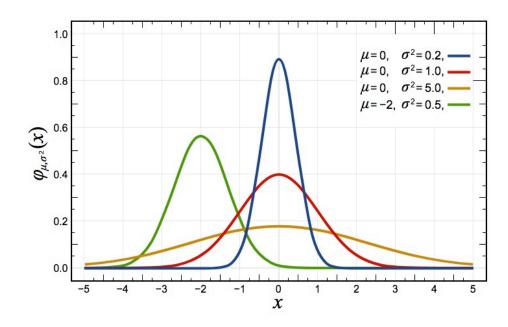
Conditional distribution

$$F(x | y) = \int_{-\infty}^{x} \frac{f(u, y)}{f_Y(y)} du, f(x | y) = \frac{f(x, y)}{f_Y(y)}.$$

#### Normal distribution

- symmetric and bell-shaped.
- characterized by its mean  $\mu$  and standard deviation  $\sigma$ , concisely expressed by  $N(\mu, \sigma^2)$ .
- The normal distribution has the PDF:

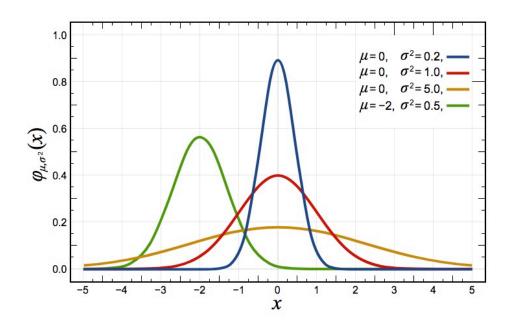
$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp{-(x-\mu)^2/(2\sigma^2)}.$$



Skewness and kurtosis

Skewness = 
$$\int (y - \mu_Y)^3 f_Y(y) dy$$

$$Kurtosis = \int (y - \mu_Y)^4 f_Y(y) dy$$



Distribution FIN 3380

#### Standardized normal distribution

- Standard normal distribution  $\mu$ =0 and  $\sigma$ =1.
- Standard normal variable is denoted by Z.
- the standard normal PDF is denoted by φ
- the standard normal CDF is denoted by Φ

```
\phi(c) = \Phi'(c) \ , \ \Phi(c) = P(Z \le c) \ , \ Z \sim \mathcal{N}(0, 1).
```

```
# draw a plot of the N(0,1) PDF
curve(dnorm(x),
      xlim = c(-3.5, 3.5),
     ylab = "Density",
     main = "Standard Normal Density Function")
# compute denstiy at x=-1.96, x=0 and x=1.96
dnorm(x = c(-1.96, 0, 1.96))
# plot the standard normal CDF
curve(pnorm(x),
     xlim = c(-3.5, 3.5),
     ylab = "Density",
      main = "Standard Normal Cumulative Distribution Function")
# compute the probability using pnorm()
pnorm(1.337)
```

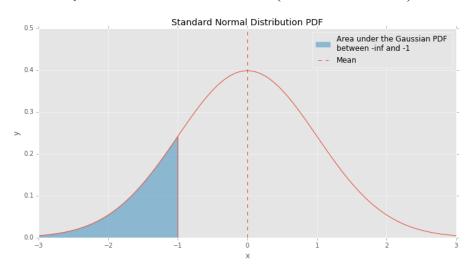
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## Distribution

#### Standardized normal distribution

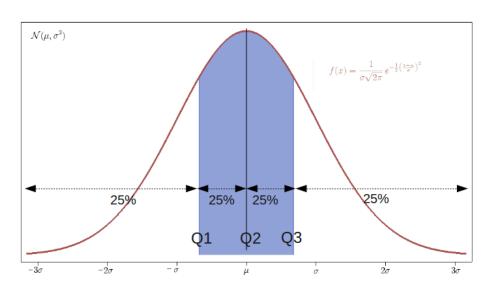
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#### Quantile

$$P(X \le Z_{\alpha}) = \alpha$$

$$P(X \le Z_{0.025}) = 0.025$$

#### Q: How to calculate $P(-1.96 \le Z \le 1.96)$



#### Standardize normal distribution

Suppose Y is normally distributed with mean  $\mu$  and variance  $\sigma^2$ :

$$Y \sim \mathcal{N}(\mu, \sigma^2)$$

Then Y is standardized by subtracting its mean and dividing by its standard deviation:

$$Z = \frac{Y - \mu}{\sigma}$$

Q: If we have a random variable Y with  $Y \sim N(5, 25)$ , what is  $P(3 \le Y \le 4)$ ?

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Q: If we have a random variable Y with  $Y \sim N(5, 25)$ , what is  $P(3 \le Y \le 4)$ ?

```
pnorm(4, mean = 5, sd = 5) - pnorm(3, mean = 5, sd = 5)
```

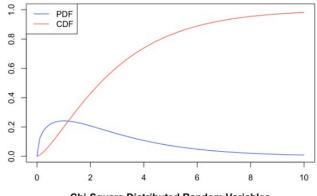
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#### The Chi-squared distribution

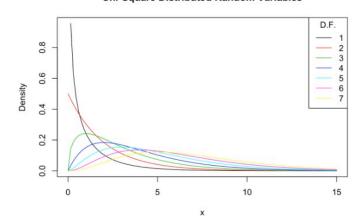
- The sum of M squared independent standard normal distributed random variables
- Freedom degrees M

$$Z_1^2+\cdots+Z_M^2=\sum_{m=1}^M Z_m^2\sim \chi_M^2 ~~ ext{with}~~ Z_m\stackrel{i.i.d.}{\sim} \mathcal{N}(0,1)$$

p.d.f. and c.d.f of Chi-Squared Distribution, M = 3



**Chi-Square Distributed Random Variables** 



#### The t-student distribution

- Z: a standard normal variate
- W:  $\chi^2_M$  random variable
- Z and W are independent
- Then X follow

$$\frac{Z}{\sqrt{W/M}} =: X \sim t_M$$

#### Characteristic

- symmetric, bell-shaped
- look similar to a normal distribution, especially when M is large (M is larger than 30).

