

Continuous Random Variables

General Information

- A function $f: \mathbb{R} \rightarrow \mathbb{R}$ is a *probability mass function* (pdf) of a continuous random variable X iff f is nonnegative and $\int_{-\infty}^{\infty} f(x) dx = 1$.
- For any probability mass function f , we have $P(a \leq X \leq b) = \int_a^b f(x) dx$. Whether the inequality is strict or nonstrict does not affect the above identity.
- A *mode* of X is any value m such that $f(m)$ is maximum.
- A *cumulative distribution function* (cdf) $F: \mathbb{R} \rightarrow [0, 1]$ of a random variable X is defined by

$$F(x) := P(X \leq x) = \int_{-\infty}^x f(x) dx.$$

- When writing out the cdf as a piecewise function, we explicitly write out the range of values for each case. We reserve the use of “otherwise” for pdf’s.
- Any cdf is continuous and nondecreasing.
- Let X be a continuous random variable with cdf F . To find the pdf g of any $y(X)$, we first find its cdf, then differentiate. We achieve this by reverse engineering $y(X) \leq y$ to find an inequality that relates X with y . E.g. $e^X \leq y$ iff $X \leq \ln(y)$.
- A *median* of X is any value m such that $P(X \leq m) = F(m) = 1/2$.
- Mean/Expectation:

$$\mu = E(X) := \int_{-\infty}^{\infty} x f(x) dx \quad \text{and} \quad E(g(X)) = \int_{-\infty}^{\infty} g(x) f(x) dx.$$

- Important property:

$$E(ag(X) \pm bh(x)) = a E(g(X)) \pm E(h(X)).$$

- Variance:

$$\text{Var}(X) := E(X^2) - [E(X)]^2.$$

- Important property:

$$\text{Var}(aX \pm b) = a^2 \text{Var}(X).$$

Special Continuous Random Variables

Definition 2.1

A continuous random variable X has a *normal distribution* with mean μ and standard deviation σ , denoted by $X \sim N(\mu, \sigma^2)$, iff its pdf f is such that

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

General Information

- A normal distribution is symmetrical about the line $x = \mu$. That is

$$P(X \leq \mu - \delta) = P(X \geq \mu + \delta)$$

for each $\delta > 0$. Note that the mean, median, and mode coincide with μ .

- Properties of the normal distribution. Let X and Y be independent, such that $X \sim N(\mu, \sigma^2)$ and $Y \sim N(m, s^2)$. Then, for any $n \in \mathbb{N}$ and $x, y \in \mathbb{R}$,
 - $nX \sim N(n\mu, n^2\sigma^2)$,
 - $X_1 + X_2 + \dots + X_n \sim N(n\mu, n\sigma^2)$,
 - $aX \pm bY \sim N(a\mu \pm bm, a^2\sigma^2 + b^2s^2)$.
- Question phrasing may be misleading at times. Try to use some inference as to what exactly does the setter mean.

Example 2.1

“The mass of the padding is 30% of the mass of a randomly selected light bulb of mass L . Find the probability that a light bulb with padding has mass c .”

Then for any light bulb of mass L_1 , the mass of the padding is $0.3L_1$ (and *not* $0.3L_2$). i.e. we are to find $P(L_1 + 0.3L_2)$.

- A variable $Z \sim N(0, 1)$ is said to follow the *standard* normal distribution.
Note: Z is reserved for this purpose.
- Let $X \in N(\mu, \sigma^2)$. Then, $\frac{X-\mu}{\sigma}$ follows the standard normal distribution.
- A continuous random variable X has a *uniform distribution* over the interval (a, b) , which is denoted by $X \sim U(a, b)$, iff its pdf f is such that

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{if } a < x < b, \\ 0 & \text{otherwise.} \end{cases}$$

- What Tail do we select for `invNorm`?

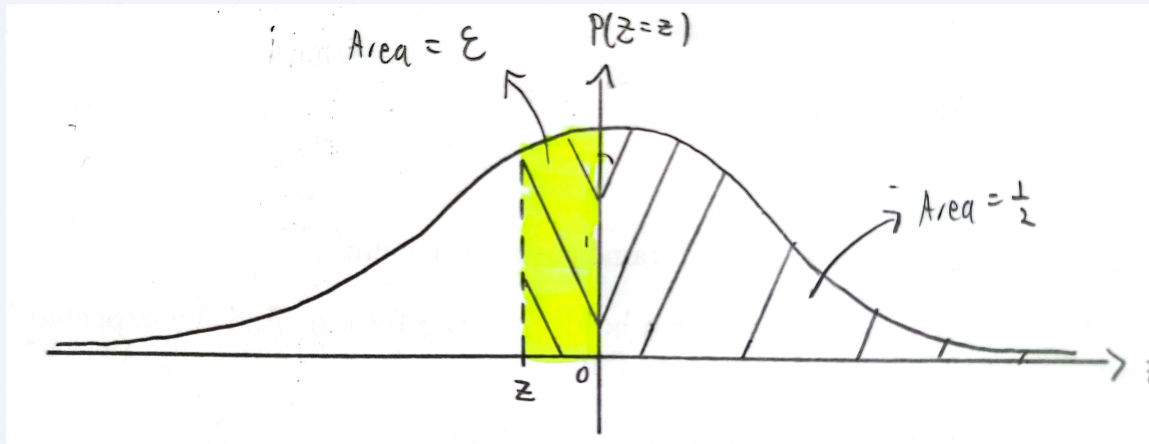
$P(X < x) = p$	LEFT
$P(-x < X < x) = p$	CENTER
$P(X > x) = p$	RIGHT

- When using `invNorm` on an inequality, what should the sign be? For simplicity, we write $\mathcal{L}(p) = \text{invNorm}(p, 0, 1, \text{RIGHT})$, and $\mathcal{R}(p) = \text{invNorm}(p, 0, 1, \text{LEFT})$. Then,

$P(Z > z) \geq p$	$z \leq \mathcal{L}(p)$
$P(Z > z) \leq p$	$z \geq \mathcal{L}(p)$
$P(Z < z) \geq p$	$z \geq \mathcal{R}(p)$
$P(Z < z) \leq p$	$z \leq \mathcal{R}(p)$

Example 2.2

Suppose we want to find the least integer value of m for which $P(Z > 1 - m) \geq 1/2$. Then, using `invNorm (RIGHT)`, we infer that $z \leq 0$, *not* $z \geq 0$. An illustration:



- A continuous random variable Y has an (negative) exponential distribution, which we denote with $Y \sim \text{Exp}(\lambda)$, iff its pdf g is such that

$$g(Y) = \begin{cases} \lambda e^{-\lambda x} & \text{if } x \geq 0 \\ 0 & \text{otherwise.} \end{cases}$$

- Expectation and variance:

Distribution	Expectation	Variance
$X \sim U(a, b)$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$
$Y \sim \text{Exp}(\lambda)$	$\frac{1}{\lambda}$	$\frac{1}{\lambda^2}$

Note: We need to remember the expectation and variance for the uniform distribution, as it is not provided in the MF26 formula sheet (unlike all other distributions).

- *Warning:* The G.C. tends to incorrectly process an integral if its upper and lower bounds contain $\pm E99$.

Sampling and Estimation

Definition 3.1

A sample is a finite subset of the population.

Definition 3.2

A random sample is a sample selected such that each member of the population has an equal probability of being selected.

Definition 3.3

Any statistic T derived from a random sample and used to estimate an unknown population parameter θ is known as an *estimator*. It is an *unbiased* estimator iff $E(T) = \theta$. If T is unbiased we commonly write $\hat{\theta}$ for T .

General Information

- Either write $\hat{\mu}$ or write out “Unbiased estimate of the population mean μ , $\bar{x} = \dots$ ” Same holds for other population parameters θ .
- Estimators you should know:

Parameter	Estimator	Unbiased?	Formula
Population Mean μ	Sample Mean \bar{X}	✓	$\frac{X_1 + X_2 + \dots + X_n}{n}$
Population Variance σ^2	Sample Variance σ_n^2	×	$\frac{\sum (X_i - \bar{X})^2}{n}$ $\frac{\sum X_i^2}{n} - \bar{X}^2$
	S^2	✓	$\frac{n}{n-1} \sigma_n^2$ $\frac{\sum (X_i - \bar{X})^2}{n-1}$ $\frac{1}{n-1} \left[\sum X_i^2 - \frac{(\sum X_i)^2}{n} \right]$
Population Proportion p	Sample Proportion P_s	✓	$\frac{X}{n}$

- Let X be a random variable following *any distribution*, and suppose we have a random sample X_1, X_2, \dots, X_n of size $n \geq 50$.

Then by CLT (Central Limit Theorem), since $n \geq 50$ is large,

$$\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right) \quad \text{and} \quad X_1 + X_2 + \dots + X_n \sim N(n\mu, n\sigma^2)$$

approximately.

- Assumptions when using CLT:
 - The sample is random.
 - Each X_i is independent and identically distributed.
- Suppose $X \sim N(\mu, \sigma^2)$ is known and we pick a *particular* sample. Let the unbiased estimates for the population mean and variance of this sample be \bar{x} and s^2 , respectively. Then,

Distribution	Is An Approximation?
$\bar{X} \sim N(\mu, \sigma^2)$	No
$\bar{X} \sim N(\bar{x}, \sigma^2)$	Yes
$\bar{X} \sim N(\mu, s^2)$	Yes
$\bar{X} \sim N(\bar{x}, s^2)$	Yes

So, if we obtain any of the latter three in solving a question, we must write “ $X \sim N(_, _) \text{approximately}$ ” (even though we knew X *exactly* follows a normal distribution!)

- Pooled estimators you should know. First assume we have two populations, from which we select a random sample of size n_1 and n_2 . We let \bar{X}_1 and S_1^2 denote the sample mean and unbiased estimator for variance, respectively. Similarly define \bar{X}_2 and S_2^2 .

Parameter	Unbiased Pooled Estimator
Mean	$\hat{\mu} = \frac{n_1 \bar{X}_1 + n_2 \bar{X}_2}{n_1 + n_2}$
Variance	$S_p^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}$

- Let $0 < \alpha < 1$

The following definition is found in [Hogg-McKean-Craig](#). Similar definitions are also found in [Wackerly-Mendenhall-Schaefer](#) and [Nitis Mukhopadhyay](#).

Definition 3.4

Let X_1, X_2, \dots, X_n be a sample on a random variable X , where X has pdf $f(x; \theta)$, $\theta \in \Omega$. Let $0 < \alpha < 1$ be specified. Let $L = L(X_1, X_2, \dots, X_n)$ and $U = U((X_1, X_2, \dots, X_n))$ be two statistics. We say that the interval (L, U) is a $(1 - \alpha)100\%$ *confidence interval* for θ iff

$$1 - \alpha = P_\theta[\theta \in (L, U)].$$

That is, the probability that the interval contains θ is $1 - \alpha$, which is called the *confidence coefficient* or *confidence level* of the interval.

- We cannot write “a $\frac{1-\alpha}{100}$ confidence interval”. The $\frac{1-\alpha}{100}$ must always be expressed as a *percentage*.
- Let $0 < \alpha < 1$ and X_1, X_2, \dots, X_n be a sample on a random variable X . Suppose n is large ($n \geq 50$). Then, CLT allows us to obtain the approximation

$$\frac{\bar{X} - \mu}{\frac{s}{\sqrt{n}}} = Z \sim N(0, 1).$$

Hence, by solving $P(-z_{1-\alpha/2} < Z < z_{1-\alpha/2}) = 1 - \alpha$, we obtain a $(1 - \alpha)100\%$ confidence interval

$$\left(\bar{x} - z_{1-\alpha/2} \frac{s}{\sqrt{n}}, \bar{x} + z_{1-\alpha/2} \frac{s}{\sqrt{n}} \right).$$

When the variance σ^2 is known, we can replace s with σ .

Correlation and Linear Regression

Note

A good scatter diagram should follow the guidelines below.

- The relative position of each point on the scatter diagram should be clearly shown.
- The range of values for the set of data should be clearly shown by marking out the extreme x and y values on the corresponding axis.
- The axes should be labeled clearly with the variables.

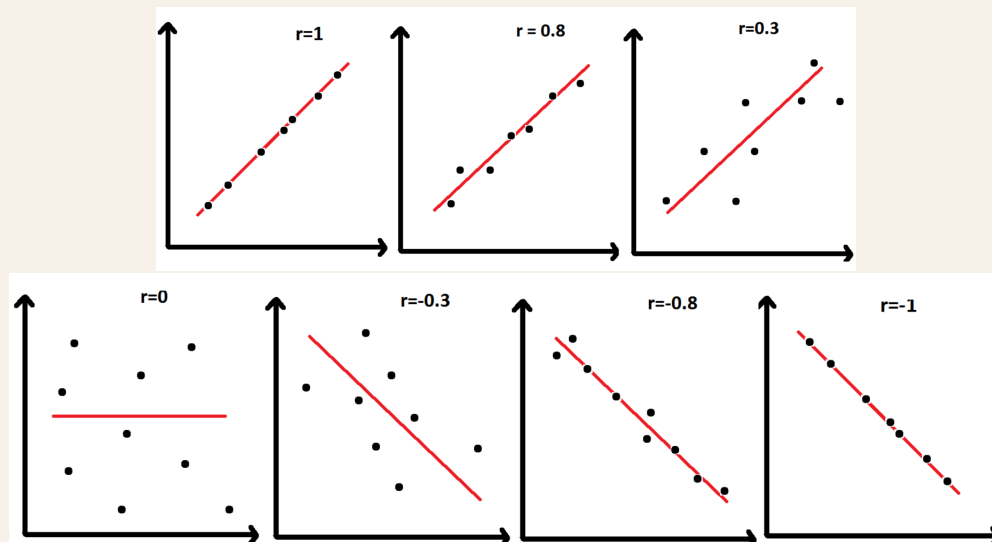
General Information

- The Product Moment Correlation Coefficient is a measure of the linear correlation between two variables. It is defined by

$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}} = \frac{\sum xy - \frac{\sum x \sum y}{n}}{\sqrt{\left[\sum x^2 - \frac{(\sum x)^2}{n} \right] \left[\sum y^2 - \frac{(\sum y)^2}{n} \right]}}$$

which takes on a value from 0 to 1.

- When $r = 0$, there is no linear relationship. But, a nonlinear relationship may be present. Additionally, the regression lines are perpendicular.
- The closer the value of r is to 1 (or -1), the stronger the positive (or negative) linear correlation. Furthermore, the regression lines coincide.



- The regression line of y on x minimises the sum of squares deviation (error) in the y -direction. (i.e. we are assuming x is the independent variable whose values are known exactly.) It is given by

$$y = \bar{y} + b(x - \bar{x}), \quad \text{where} \quad b = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sum (x - \bar{x})^2} = \frac{\sum xy - \frac{\sum x \sum y}{n}}{\sum x^2 - \frac{(\sum x)^2}{n}}.$$

- The point (\bar{x}, \bar{y}) always lies on both the regression lines of y on x , and x on y .
- Say we are given the value of one variable, and asked to approximate the value of the other variable. Then, we should always use the line of the *dependent* variable on the *independent*.
- Estimations should not be taken for data outside the range of the sample provided, even if the value of r is close to 1.