

# STAT 350 Notes

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Summer 2024

# Chapter 1

## An Introduction to Statistics and Statistical Inference

### 1.1 Intro

1. Data Collection: The process of gathering information.
2. Descriptive Statistics: Summarizing and organizing data.
3. Inferential Statistics: Drawing conclusions from data.

### 1.2 What Are Statistics and Probability?

**Definition.** *Claim:* a statement that we assume to be true

**Definition.** *Status quo:* existing state/condition

**Definition.** *Population:* set of all things to be studied

**Definition.** *Sample:* subset of population

**Definition.** *Probability:* know everything about population; want to know about sample

**Definition.** *Inferential Statistics:* know everything about sample; want to know about population

## Chapter 2

# Summarizing Data Using Graphs

### 2.1 Variables

#### 2.1.1 number of observations

single - univariate  
double - bivariate  
3+ - multivariate

#### 2.1.2 type

numerical; categorical (nominal[unordered] or ordinal[ordered]); discrete; continuous;

### 2.2 Basics of graphing

look for overall pattern; deviations; shape; center; variability

#### 2.2.1 Frequency Distribution

**Definition.** categorical variables sorted into *bins* or *classes*

**Definition.** frequency distribution consists of the *frequency* of number of observations in each class

**Definition.** the *relative frequency* is the measured frequency divided by the total data points

$$relative\ freq = \frac{freq}{totalcount} \quad (2.1)$$

### 2.3 Displaying quantitative variables

#### 2.3.1 Histogram - appropriate number of classes

$$\#ofbins \approx \sqrt{\#ofobservations}$$

#### 2.3.2 Identify the shape

peaks: unimodal, bimodal, or multimodal  
positively skewed unimodal (peak goes left)  
negatively skewed unimodal (peak goes right)

## Chapter 3

# Numerical Summary Measures

### 3.1 Center of a distribution

#### 3.1.1 Notation

$x$  = random variable

$x_i$  = specific observation

$n$  = sample size

#### 3.1.2 Sample mean

$$\bar{x} = \frac{\text{sum of observations}}{n} = \frac{1}{n} \sum x_i \quad (3.1)$$

R command: `mean(variable)`

#### 3.1.3 Sample median

$$\tilde{x} = \text{centermost value in ordered dataset} \quad (3.2)$$

R command: `median(variable)`

### 3.2 Spread or variability of the data

three common ways to measure spread:

1. sample range
2. sample variance (or stdev)
3. interquartile range (IQR)

#### 3.2.1 Range

$\text{range} = \max(x) - \min(x)$

completely depends on extreme values, so not very reliable

no R command for this

#### 3.2.2 Sample Variance (sample standard deviation)

**Variance**

$$\text{variance} = s_x^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$$

R command: `var(variable)`

## Standard Deviation

$$\text{standard deviation} = s_x = \sqrt{\frac{1}{n-1} \sum (x_i - \bar{x})^2}$$

R command: `sd(variable)`

if  $\text{var} = \text{sd} = 0$ , there is no spread (all data is the same)

### 3.2.3 Interquartile range (IQR)

#### Quartile

quartile = 1/4 of the data

R command = `quantile(variable)`

R command for % = `quantile(variable, prob=c(p1, p2))`

#### IQR

$$\text{IQR} = Q_3 - Q_1$$

## 3.3 Boxplots

fast way to visualize five-number summary

five number summary: minimum, first quartile, median, third quartile, maximum

### 3.3.1 Outliers

IF = inner fence

OF = outer fence

subscript L = lower bound

subscript H = higher bound

$$IF_L = Q_1 - 1.5(IQR) \quad IF_H = Q_3 + 1.5(IQR) \quad \text{mild} \quad (3.3)$$

$$OF_L = Q_1 - 3(IQR) \quad OF_H = Q_3 + 3(IQR) \quad \text{extreme} \quad (3.4)$$

## 3.4 Choosing Measures of Center and Spread

if data is skewed, use median and IQR.

if symmetric, use mean and standard deviation.

## 3.5 z-score

### 3.5.1 z-score

the z-score of a data point  $x_i$  quantifies distance from the mean value in terms of standard deviations.

$$z_i = \frac{x_i - \bar{x}}{s} \quad (3.5)$$

# Chapter 4

## Probability

### 4.1 Experiments, Sample Spaces, Events

#### 4.1.1 Experiments

**Definition.** A random *experiment* is any activity in which there are at least two possible outcomes and the result of the activity can not be predicted with absolute certainty.

**Note.** By this definition, all experiments are random.

**Definition.** An *outcome* is the result of an experiment.

**Definition.** Each time the experiment is done is called a *trial*.

#### 4.1.2 Tree Diagrams

**Note.** skip

#### 4.1.3 Sample Spaces

**Definition.** The *sample space* of an experiment is the set of all possible outcomes, denoted by  $S$  or  $\Omega$ .

#### 4.1.4 Events

**Definition.** An *event* is any collection of outcomes from an experiment.

**Example.** The sample space is one possible event.

**Definition.** A *simple event* only has one outcome.

We say that an event has occurred if the resulting outcome is contained in the event.

#### 4.1.5 Set Theory

**Definition.** The *complement* of an event  $A$  contains every outcome in the sample space that is not in  $A$ , denoted by  $A'$ .

**Note.** Remainder of section is trivial.

## 4.2 Introduction to Probability

### 4.2.1 What is Probability?

#### Frequentist POV

In the frequentist interpretation of probability, we say the probability of any outcome of any random experiment is the long term proportion of times that the outcome occurs over the total number of trials.

$$P(A) = \lim_{N \rightarrow \infty} \frac{n}{N} \quad (4.1)$$

#### Bayesian POV

In Bayesian probability, the probabilist specifies some *prior probability*, which is then updated upon collection of *relevant data*.

### 4.2.2 Properties

1. Given any event  $A$ , it must be that  $0 \leq P(A) \leq 1$ .
2. Assuming  $\omega$  is an outcome of  $A$ , then  $P(A) = \sum P(\omega)$ . That is, the sum of probabilities of all outcomes in an event is equal to the probability of the event.
3. The probability of the sample space is 1. That is,  $P(\Omega) = 1$ .
4. The probability of the empty set is 0. That is,  $P(\emptyset) = 0$ .

### 4.2.3 Rules

**Definition.** The *complement rule* says that for any event  $A$ ,  $P(A') = 1 - P(A)$

**Definition.** The *general additional rule* says that  $P(A \cup B) = P(A) + P(B) - P(A \cap B)$

**Note.** When adding disjoint probabilities we need not subtract the last term, as the intersection will be empty.

## 4.3 Conditional Probability and Independence

### 4.3.1 What is conditional probability?

A *conditional probability* is written  $P(A|B)$  and is read ‘the probability of A, given that B occurs’.

### 4.3.2 General Multiplication Rule

To calculate a union (or), we can use the general additional rule. To calculate an intersection (and), we can use the general multiplication rule.

$$P(B|A) = \frac{P(B \cap A)}{P(A)} \implies P(A \cap B) = P(A)P(B|A) \quad (4.2)$$

Additionally, this rule can be applied to an arbitrary number of unions.

$$P(A \cap B \cap C) = P(A)P(B|A)P(C|A \cap B) \quad (4.3)$$

### 4.3.3 Tree Diagrams revisited

**Note.** skip

### 4.3.4 Bayes' Rule using Tree Diagrams

#### Bayes' rule

We use Bayes' rule when calculating a conditional probability in one direction, but you only know the conditional probability in the other direction. This method is not needed when the probability of the intersection is known.

To find the probability of A given B,

$$P(A|B) = \frac{P(A \cap B)}{P(B)}. \quad (4.4)$$

If we don't know  $P(A \cap B)$ , we use the general multiplication rule to write

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}. \quad (4.5)$$

If we know what  $P(B)$  is, we are done. Otherwise, we use the fact that

$$P(B) = P(B \cap A) + P(B \cap A') = P(B|A)P(A) + P(B|A')P(A'). \quad (4.6)$$

This is called the *Law of Total Probabilities for Two Variables*.

Subbing eqn 4.6 into eqn 4.5, we get *Bayes' Rule for two variables*:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|A')P(A')} \quad (4.7)$$

For more than two variables, suppose the sample space is partitioned into  $k$  disjoint events,  $A_1, A_2, \dots, A_k$ , none of which have a probability of 0, such that

$$\sum_{i=1}^k P(A_i) = 1 \quad (4.8)$$

Then, the *Law of Total Probability* is

$$\sum_{i=1}^k P(B|A_i)P(A_i) \quad (4.9)$$

and Bayes' rule is

$$P(A_j|B) = \frac{P(B|A_j)P(A_j)}{\sum_{i=1}^k P(B|A_i)P(A_i)} \quad (4.10)$$

#### Bayesian Statistics

To summarize Bayesian Statistics, we first begin with a prior probability  $A$ . Then, given additional context,  $B$ , we can improve our prediction of the probability of  $A$  by calculating  $P(A|B)$ . This is called the *posterior* probability. In the example from the book, after someone tested positive for the disease, the probability that they have the disease increased from 0.01 to 0.165.

### 4.3.5 Independence

**Definition.** Two events are *independent* if knowing the outcome of one does not affect the outcome of the other. Mathematically, we write

$$P(A|B) = P(A) \quad (4.11)$$

$$P(B|A) = P(B) \quad (4.12)$$

$$P(A \cap B) = P(A)P(B|A) \implies P(A \cap B) = P(A) \times P(B) \quad (4.13)$$



## Disjoint vs Independence

**Definition.** Two events are *disjoint* if they can not possibly occur at the same time.

**Definition.** Two events are *independent* if the outcome of one does not impact the other.

1. Draw a card. A: card is a heart, B: card is not a heart  
disjoint; not independent
2. Toss 2 coins. A: first coin is head, B: second coin is head  
not disjoint; independent
3. Roll 2 4-sided die. A: first die is 2, B: sum of die is 3  
not disjoint; not independent

## Chapter 5

# Random Variables and Discrete Probability Distributions

### 5.1 Random Variables

#### 5.1.1 Random Variables

**Definition.** A *random variable* is a numerical characteristic obtained from a random experiment. So, random variables are functions and follow all properties of mathematical functions.

#### 5.1.2 Probability Distributions - pmf

**Definition.** The probability distributions of a random variable is called the *probability mass function (pmf)*. In symbols,  $p(x) = P(X = x)$

#### 5.1.3 Properties

Pmfs are valid probability distributions, so they follow the axioms of probability.

1.  $0 \leq p_i \leq 1$ . Each probability lies between 0 and 1.
2.  $\sum_i p_i(x) = 1$ . The sum of all probabilities is 1.

### 5.2 Expected Value and Variance

#### 5.2.1 Expected Value

**Definition.** The *expected value* of a discrete random variable  $X$  is the weighted average of each value.

$$E(X) = \mu_X = \sum_{i=1}^m x_i p_i \quad (5.1)$$

#### 5.2.2 Rules of Expected Values

1. If  $X$  is a random variable and  $a$  and  $b$  are fixed, then

$$E(a + bX) = a + bE(X)$$

2. If  $X$  and  $Y$  are random variables, then

$$E(X + Y) = E(X) + E(Y)$$

3. If  $X$  is a random variable and  $g$  is a function of  $X$ , then

$$E(g(X)) = \sum_{i=1}^m g(x_i)p_i$$

**Note.**  $g(x)$  does not have to be linear

### 5.2.3 Expectation, Variance, and Standard Deviation for a Discrete Variable

Recall sample variance measures spread by taking the average of the squared differences between observations and their center

$$s^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n - 1} \quad (5.2)$$

**Note.** Define the population variance of  $X$  by  $Var(X)$ ,  $\sigma^2$ , or  $\sigma_X^2$ .

$$Var(X) = \sigma^2 = \sigma_X^2 \quad (5.3)$$

The population variance is the expected squared difference between  $X$  and  $\mu_X$ .

$$Var(X) = E[(X - \mu_X)^2] = \sum (x_i - \mu_X)^2 \cdot p_i \quad (5.4)$$

Simplify.

$$Var(X) = E[(X - \mu_X)^2] = E(X^2) - (E(X))^2 \quad (5.5)$$

Then, the standard deviation is the square root of the variance

$$\sigma_X = \sqrt{Var(X)} \quad (5.6)$$

### 5.2.4 Rules of Variance

1. if  $X$  is a random variable and  $a, b \in \mathbb{R}$  are fixed then

$$Var(a + bX) = b^2 Var(X) \quad (5.7)$$

**Note.** the variance does not rely on where the center of the distribution is so  $a$  is not on RHS

2. if  $X$  and  $Y$  are independent random variables,

$$Var(X + Y) = Var(X) + Var(Y) \quad \text{and} \quad Var(X - Y) = Var(X) + Var(Y) \quad (5.8)$$

addition rule for variances

can be added for both addition and subtraction

## 5.3 Cumulative Distribution Function

skip

## 5.4 Binomial Random Variable

### 5.4.1 Binomial Experiment (BInS)

Binary - are there only 2 options?

Independence - is each trial independent?

Number - is the number of trials a constant?

Success - is the probability of success a constant?

### 5.4.2 Binomial Random Variables

**Definition.** The *binomial random variable*  $X$  must come from a binomial experiment and maps every outcome to some  $k \in \mathbb{R}$ .  $X$  has parameters  $n$  (num trials) and  $p$  (prob success).

### 5.4.3 PMF of Binomial Random

If  $X$  is a binomial random variable with  $n$  trials and probability of a success  $p$ , then

$$P(X = x) = \binom{n}{x} p^x (1-p)^{n-x}, \quad x = 0, 1, \dots, n \quad (5.9)$$

### 5.4.4 Shapes of Binomial Distributions

skewedness of a binom random variable depends on  $p$ .

$p < 0.5$ ; distribution is skewed right

$p = 0.5$ ; distribution is symmetric

$0.5 < p$ ; distribution is skewed left

### 5.4.5 Binomial Distribution: Mean and Standard Deviation

If  $X \sim B(n, p)$ , then

$$\mathbb{E}(X) = \mu_X = np \quad (5.10)$$

$$\text{Var}(X) = np(1-p) \quad (5.11)$$

$$\sigma_X = \sqrt{np(1-p)} \quad (5.12)$$

## 5.5 Poisson Random Variables

**Definition.** the *poisson random variable* is used to count the number of events that happen during some interval or in some area.

**Example.** # of people who enter the PMU per day; # of radioactive particles emitted from some material in 1 minute

### 5.5.1 Poisson Experiment

The poisson distribution also has an experiment, but it is more complex than binomial

1. the probability that an event occurs in some given interval is equal for any unit of equal size; the *rate* is proportional to the size
2. the number of events that occur within an interval is independent of the number that occur in any other non-overlapping interval
3. the probability that more than one event occurs within a unit of measure is negligible for small units

### 5.5.2 Poisson Distribution

only one param:  $\lambda$

Read  $X \text{Poisson}(\lambda)$  as “ $X$  is distributed as a Poisson random variable with parameter  $\lambda$ ”

$$p(x) = P(X = x) = \frac{e^{-\lambda} \lambda^x}{x!}, \quad x \in \mathbb{N}_0 \quad (5.13)$$

### 5.5.3 Mean and Variance

The mean and variance of the Poisson random variable are the same as  $\lambda$ . So,

$$\mu_X = \sigma^2 \quad (5.14)$$

$$\sigma_X = \sqrt{\lambda} \quad (5.15)$$

$\lambda$  used instead of  $\mu$  to maintain consistency with exponential distribution.

If units for  $\lambda$  were different than the units given in the problem, the problem can still be solved due to the independence property (2) of the Poisson experiment.

## Chapter 6

# Continuous Probability Distributions

### 6.1 Probability Distribution for Continuous Random Variables - General

#### Objectives

1. Describe the basis of the probability density function (pdf).
2. Use the probability density function (pdf) and cumulative distribution function (cdf) of a continuous random variable to calculate probabilities and percentiles (median) of events.
3. Be able to use a pdf to find the mean of a continuous random variable.
4. Be able to use a pdf to find the variance of a continuous random variable.

#### 6.1.1 Density curves and probabilities (pdf)

Define the pdf  $f(x)$  such that  $\int_{-\infty}^{\infty} f(x)dx = 1$ .

Then, the probability that  $a < X < b$  is

$$P(a < X < b) = \int_a^b f(x)dx \quad (6.1)$$

**Note.** When  $X = a$ ,  $\int_a^a f(x)dx = 0$ , so  $P(X \leq a) = P(X < a)$

#### 6.1.2 Properties

A valid density curve must have the two following properties:

1.  $f(x) \geq 0$
2.  $\int_{-\infty}^{\infty} f(x)dx = 1$

**Note.** Notice that  $f(x) \leq 1$  need not be true; consider the function  $g(x) = 4$  on the interval  $[0, 0.25]$ .

**Note.** In the case of  $g(x)$ , the bounds on the integral for property 2 must be adjusted

### 6.1.3 Mean and Variance

**Note.** The rules for the means and variances are the same for both discrete and continuous random variables; the only difference is how the values are computed.

$$\text{Discrete:} \quad E(X) = \mu_X = \sum xp(x) \quad E(g(X)) = \sum g(x)p(x) \quad (6.2)$$

$$\text{Continuous:} \quad E(X) = \mu_X = \int_{-\infty}^{\infty} xp(x)dx \quad E(g(X)) = \int_{-\infty}^{\infty} g(x)p(x)dx \quad (6.3)$$

Recall the formula for variance of discrete random variables

$$\begin{aligned} Var(X) &= E[(X - \mu_X)^2] = \sum (x_i - \mu_X)^2 \cdot p_i \\ &= E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x_i - \mu_X)^2 \cdot p_i \end{aligned} \quad (6.4)$$

$$Var(X) = E(X^2) - (E(X))^2 \quad (6.5)$$

$$\sigma_X = \sqrt{Var(X)} \quad (6.6)$$

Equation 6.4 is recommended as it is computationally much easier to evaluate.

### 6.1.4 Cumulative Distribution Function (cdf)

The cumulative distribution function (cdf) is the probability that the random variable will be less than or equal to some value. It is written  $F(X)$  and the formula is

$$F(x) = P(X \leq x) = \int_{-\infty}^x f(s)ds \quad (6.7)$$

**Note.** The variable of integration is changed to be some dummy variable  $s$ , as the bounds of a definite integral can not be a function of the variable of integration.

To recap, we now have

$$p(x) = \text{probability mass function} \quad (6.8)$$

$$f(x) = \text{probability density function} \quad (6.9)$$

$$F(x) = \text{cumulative distribution function} \quad (6.10)$$

### 6.1.5 Percentiles

For continuous distributions, percentiles are much simpler to compute. Given that  $0 < p < 1$ , the 100<sup>th</sup> percentile for a value  $x$  can be computed with the integral

$$p = \int_{-\infty}^x f(s)ds \quad (6.11)$$

Note that this integral is the same as the cdf. Thus if the cdf is already known, we can simply find when  $F(x) = p$ . Again, the 100<sup>th</sup> percentile is when 100 $p$  percent of the data is less than  $p$ , and the rest is above

**Note.** The median occurs when  $p = 0.5$ . Hence,

$$p = 0.5 = \int_{-\infty}^{\mu'} f(x)dx = F(\mu') \text{ where } \mu' = \tilde{\mu} \quad (6.12)$$

## 6.2 Normal Distribution

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \text{ where } -\infty < \mu < \infty \quad (6.13)$$

don't need to know closed form

defined as long as we know the variance  $\sigma^2$  and the mean  $\mu$

thus  $X \sim N(\mu, \sigma^2)$

### 6.2.1 Normal Distribution

shape: symmetric; bell shaped; unimodal

variance  $\sigma^2$  is spread; mean is also median since symmetric

curve is concave down when  $x$  is  $\mu \pm \sigma$  otherwise concave down

### 6.2.2 Standardization

empirical rule - 68% of data within 1 stdev; 95 within 2; 99.7 within 3

standard normal distribution:  $\mu = 0; \sigma = 1$

**Definition.**  $z = f(z)$

probability of certain outcome  $x = \text{cdf of } z$ ; values are in z table

### 6.2.3 Using the z-table

$$P(-2.77 < Z < 1.54) = P(Z < 1.54) - P(Z < -2.77) = 0.9382 - 0.0028 = 0.9354 \quad (6.14)$$

### 6.2.4 Probabilities

normalize any given distribution to be standard normal with

$$z = \frac{x - \mu}{\sigma} \quad (6.15)$$

then  $z$  is z-score; tells how many standard deviations  $x$  is from the mean  $\mu$

### 6.2.5 Percentiles

**Example.** 89th percentile =  $P(Z < b) = 0.89$

must find corresponding value in z-table (don't interpolate; use printed value)

now un-normalize z score by

$$z = \frac{x - \mu}{\sigma} \implies x = \mu + \sigma z \quad (6.16)$$

### Symmetry

How do we find  $P(\mu - b \leq X \leq \mu + b)$  (symmetry around the mean)?

Let  $P(\mu - b \leq X \leq \mu + b) = C$ . Then each little "wedge" on each end is  $\frac{1-C}{2}$

Then upper bound of  $C$  is  $P(X < \mu + b) = 1 - \frac{1-C}{2}$ ; and lower bound is  $\frac{1-C}{2}$



## 6.3 Determining Normality

### 6.3.1 Normal probability plots

Ways to check normality

1. graph and compare
2. backward empirical rule to see if proportions match
3. ratio of IQR:s should be about 1.4
4. normal probability plot (QQ) (best method)
5. inference

### 6.3.2 Conceptual Procedure for Normal Probability Plots

idea: if data fits distribution, the percentiles should correspond with the percentiles of that distribution

1. arrange from smallest to largest
2. record corresponding percentiles (complicated)
3. find z value
4. plot original data point vs new z point

If data is normal, we can use  $x$  and  $z$  to obtain the mean and standard

## 6.4 Uniform Distribution

continuous distribution; all points are distributed evenly between  $a, b$ .

density curve:

$$f(x) = \begin{cases} \frac{1}{b-a} & a < x < b \\ 0 & \text{else} \end{cases} \quad (6.17)$$

Mean is

$$\mathbb{E}(X) = \frac{a+b}{2} \quad (6.18)$$

standard deviation

$$\sigma_X = \frac{b-a}{\sqrt{12}} \quad (6.19)$$

**Example.** 200 boxes an hour; distribution is uniform from 18.2 to 20.4 (nearest tenth)

1. what is the probability that the package weighs less than 20 lbs?

$$P(X < 20) = \int_{18.2}^{20} \frac{1}{20.4 - 18.2} dx = \int_{18.2}^{20} \frac{1}{2.2} dx = 0.818 \quad (6.20)$$

2. what are the mean and standard deviation of the weights?

$$\mathbb{E}(X) = \frac{18.2 + 20.4}{2} = 19.3 \quad (6.21)$$

$$\sigma_X = \frac{20.4 - 18.2}{\sqrt{12}} = 0.635 \quad (6.22)$$

## 6.5 Exponential Distribution

exponential distribution pdf:

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & else \end{cases} \quad (6.23)$$

cdf:

$$F(x) = \begin{cases} 0 & x < 0 \\ 1 - e^{-\lambda x} & x \geq 0 \end{cases} \quad (6.24)$$

$$E(X) = \frac{1}{\lambda} \quad Var(X) = \frac{1}{\lambda^2} \quad \sigma_X = \frac{1}{\lambda} \quad (6.25)$$

# Chapter 7

## Sampling Distributions

### 7.1 Parameters and Statistics

**Definition.** a *parameter* is a number that represents a characteristics of a *population*

**Example.**  $\mu, \sigma$

**Definition.** a *statistic* is any number calculated from a *sample*

**Example.**  $\bar{x}, s$

statistics are random variables because the results of each random experiment is unknown

### 7.2 Sampling Distribution of a Sample Mean and CLT

**Definition.** the probability distribution of a statistic is called a *sampling distribution*

**Note.** now have 2 distributions: sampling (for a statistic) and population (for the population)

#### 7.2.1 What is a sampling distribution?

sampling distr is theoretical; can never take all samples. also called probability distribution of the statistic

#### 7.2.2 The mean and standard deviation of a sampling distribution

we use  $\bar{x}$  (sample mean) to make inferences about the population mean

$\bar{x}$  varies from different samples so we must consider the distribution of  $\bar{X}$

**Note.**  $\bar{X}$  is the sample mean, so we are interested in  $\mathbb{E}(\bar{X})$

#### 7.2.3 The shape of a sampling distribution

If a population distribution is normal, the sampling distribution is also normal

$$\text{If } X \sim N(\mu, \sigma^2), \text{ then the sample distribution of } \bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

If a population is not normal, the sampling distribution is approximately normal (given large sample size)

Let  $\bar{X}$  be the mean of observations in a random sample space of size  $n$  drawn from a population with mean  $\mu$  and finite variance  $\sigma^2$ . If the sample size  $n$  is large enough, then  $\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$