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**ST1112: Statistics**

70% Exam  
30% Continuous Assessment (3 parts)

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# 1 Descriptive Statistics

## 1.1 Sampling the mean

In **probability** we consider the underlying process which has some randomness or uncertainty, and we try to figure out what happens

In **statistics** we consider the data that we have, and we try to figure out what the underlying process is. The basic aim to infer the population from the sample.

### Example 1.1: Consider a jar of red and green jelly beans

A probabilist starts by knowing the proportion of red and green jelly beans in the jar, and then tries to figure out the probability of drawing a red jelly bean.

A statistician starts by drawing a sample of jelly beans from the jar, and then tries to figure out the proportion of red and green jelly beans in the jar.

### Definition 1.1: Central Limit Theorem

Sample means follow a normal distribution, centered on the population mean, with a standard deviation equal to population standard deviation divided by the square root of the sample size.

$$\bar{X} \sim N\left(\mu, \frac{\sigma}{\sqrt{n}}\right)$$

### Definition 1.2: Standard Error

The standard error is the variability in the sampling distribution.

The standard error describes the typical difference between the sample measurement and the population parameter.

$$SE = \frac{\sigma}{\sqrt{n}}$$

### Definition 1.3: Estimate $\sigma$

Often the value of the population standard deviation is unknown, and hence the standard error of the mean is unknown.

We can estimate the value of the standard error using the sample standard deviation ( $s$ ) as an unbiased estimator of the population standard deviation ( $\sigma$ ).

$$\sigma_{\bar{X}} = \frac{s}{\sqrt{n}}$$

# 2 Inferential Statistics - Interval Estimation

## 2.1 Confidence Intervals

### 2.1.1 Confidence Intervals for a mean

#### Definition 2.1: Confidence Interval for $n > 30$

For a large sample size,  $n > 30$ , a Confidence Interval for the population mean is given by:

$$\bar{X} \pm Z_{\frac{\alpha}{2}} \frac{s}{\sqrt{n}}$$

A 95% Confidence Interval,  $\alpha = 0.05$ , meaning we accept a 5% risk that our interval doesn't contain the true population mean.

This 5% is split into 2.5% in each tail of the distribution :  $Z_{\frac{\alpha}{2}} = Z_{0.025}$ .

When using a normal table that shows "area to the left", we need to find the  $Z$  value that corresponds to

$1 - 0.025 = 0.975$ . Thus:  $Z_{0.025} = 1.96$ .

95% Confidence is most commonly used because increasing the confidence level increases the width of the interval, this may not be useful.

### 2.1.2 Confidence Intervals for a small sample size

When  $\sigma$  is known, a 95% Confidence Interval for the population mean is given by:

$$\bar{X} \pm 1.96 \cdot \frac{\sigma}{\sqrt{n}}$$

When  $\sigma$  is unknown, a 95% Confidence Interval for the population mean is given by:

$$\bar{X} \pm 1.96 \cdot \frac{s}{\sqrt{n}}$$

But, what if  $\sigma$  is unknown and  $n < 30$ ?

#### Definition 2.2: Confidence Interval for $n < 30$

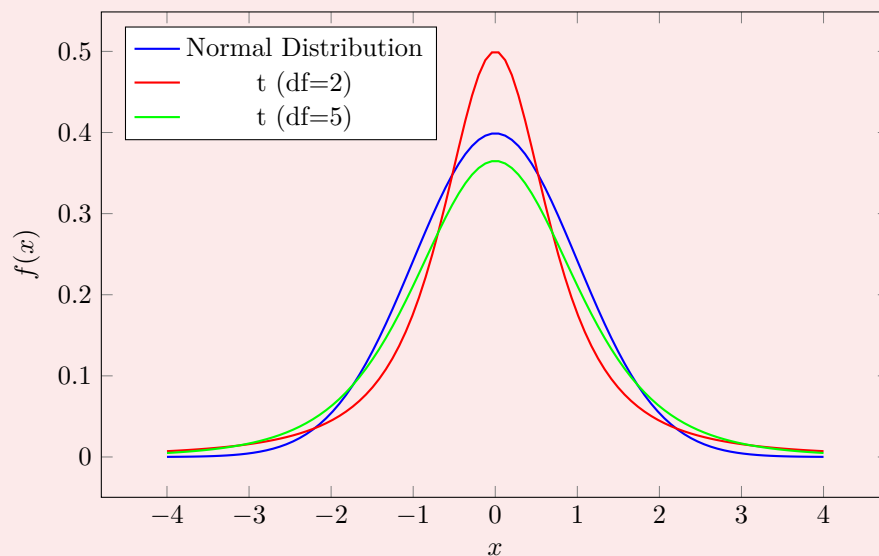
For a small sample size,  $n < 30$ , we use the **t-distribution instead of the normal distribution**. The t-distribution has heavier tails than the normal distribution and accounts for the additional uncertainty when estimating  $\sigma$  with  $s$  in small samples.

The confidence interval is given by:

$$\bar{X} \pm t_{\frac{\alpha}{2}} \frac{s}{\sqrt{n}}$$

Where  $t_{\frac{\alpha}{2}}$  is the critical value from the t-distribution with  $n - 1$  **degrees of freedom**.

The degrees of freedom represent the *number of independent pieces of information used to estimate the standard deviation*. As the degrees of freedom increase, the t-distribution approaches the normal distribution - infinite degrees of freedom is the normal distribution.



#### Example 2.1: Find t-value from tables For a 95% Confidence Interval

We have:

$$a = 1 - 0.95 = 0.05 \Rightarrow \frac{a}{2} = 0.025$$

We also have:

$$n = 13 \Rightarrow df = 13 - 1$$

We want to find the  $t_{12,0.025}$  value from the t-distribution table, which is 2.179.

## 2.2 Bootstrap, proportions and counts

What do we do when our data is not normally distributed? We have two options:

- Transform the data to make it normally distributed (e.g. log transformation, square root transformation)
- Use a non-parametric method (Bootstrap or CI for the population median)

### 2.2.1 Bootstrap

We can quantify the uncertainty in our estimate of the population mean by using the Central Limit Theorem or simulation via the Bootstrap method, as follows:

1. Take a bootstrap sample - random sample taken with replacement from the original sample (same size as original sample)
2. Calculate the bootstrap statistic - such as mean, median, proportion, etc.
3. Repeat steps 1 and 2 many times
4. Calculate the bounds of the 95% Confidence interval as the middle 95% of the bootstrap distribution

## 3 Inferential Statistics - Hypothesis Testing

### 3.1 Hypothesis Testing

#### 3.1.1 Hypothesis Testing Framework