



# STAT3914 APPLIED STATISTICS LECTURE NOTES



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# STAT3014 APPLIED STATISTICS Advanced

- This course Much more working with data
- Dr John Ormerod

Lecture 1.

## Introduction

### Lecture times and locations

- STAT3014 Lectures (Carslaw 350): Tue. 1pm , Wed. 1pm and Thu. 1pm.
- STAT3914 Lectures (E. Ave 312): Tue. 4pm.
- STAT3014 Tutorial Fri. 9am (360) and Labs Fri. 10am (705/706).
- STAT3914 Lab/Tutorial Fri. 10am (610/611).
- Tutorials start in Week 2 and computer labs start in Week 2.

### Content:

5 parts:

- Survey sampling (week 1-2)
  - Unsupervised learning (week 3-4)
  - Supervised learning (week 5-6)
  - Multivariate testing (week 7-8)
  - Categorical data analysis (week 9-11)
- 
- Major presentations week 12
  - Review week 13

### Assessment:

- 5 labs on each of the 5 parts (20%)
  - 2 weeks for each lab; due on the Wednesday after the second Friday. Mini report written on each data set.
- Collaborative project with NUTM3001 (nutrition) students (weeks 6-12)
  - Major report (due week 12) (30%)
  - Presentations (to be given during week 12)
- STAT3914 has an additional assignment (5%) and quiz (5%)
- Final exam (40%); (40% in exam needed to pass course)



## Dates

|        |                |                       |  |
|--------|----------------|-----------------------|--|
| Week 1 | 31/07 to 04/08 | Survey Sampling       |  |
| Week 2 | 07/08 to 11/08 | Survey Sampling       | Lab 1 start.   |
| Week 3 | 14/08 to 18/08 | Unsupervised learning | Lab 1 due.   |
| Week 4 | 21/08 to 25/08 | Unsupervised learning | Lab 2 start. Census date 31/08                         |
| Week 5 | 28/08 to 01/09 | Supervised learning   | Lab 2 due.   |
| Week 6 | 04/09 to 08/09 | Supervised learning   | Lab 3 start. 7.09.17 Team building CPC Dry Lab 1.2/1.3 |
| Week 7 | 11/09 to 15/08 | Multivariate testing  | Lab 3 due. Honours meeting on Thursday                 |
| Week 8 | 18/09 to 22/09 | Multivariate testing  | Lab 4 start.   |

Mid-semester break: 25/09 to 29/09

|         |                |                  |   |
|---------|----------------|------------------|---|
| Week 9  | 02/10 to 06/10 | Categorical data | Lab 4 due. 5.10.17 Team work (NLS S022/028)     |
| Week 10 | 09/10 to 13/10 | Categorical data | Lab 5 start. 12.10.17 Team work (CPC LS TC215)  |
| Week 11 | 16/10 to 20/10 | Categorical data | Lab 5 due. 19.10.17 Team work (CPC DRY 1.2/1.3) |
| Week 12 | 23/10 to 27/10 |                  | Major assignment due/Presentations              |
| Week 13 | 30/10 to 03/11 | Revision Week    |   |

## Why applied statistics?

- Data science

Data Science has recently captured the imagination of mainstream media for its impact on a wide range of academic disciplines and business endeavors. Data Science is an emerging interdisciplinary field whose aim is to solve real word problems in areas including (but not limited to) Information Technology, the Biological sciences, Medicine, Psychology, Neuroscience the Social Sciences and the humanities, Business and Finance.

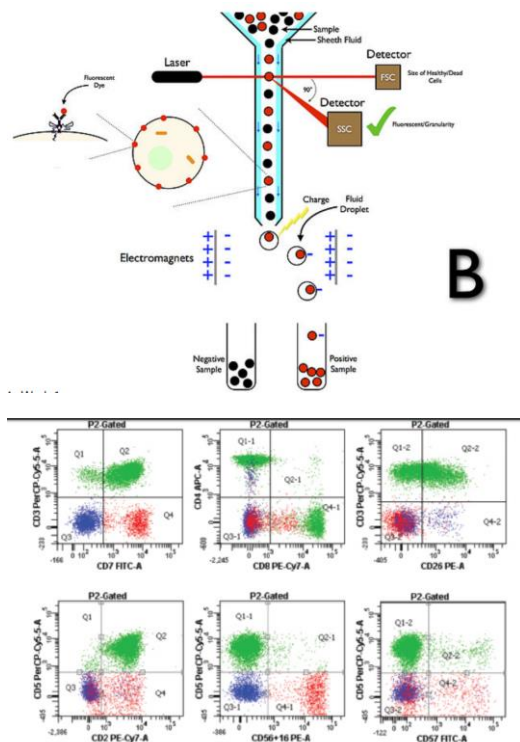
Data science success stories include Internet companies such as Google, eBay and Amazon.

- Eg: politics; historical texts; medicine (IBM Watson)

## Motivating data:

### Flow cytometry:

- In biotechnology, flow cytometry is a laser-based, biotechnology for cell counting, cell sorting, biomarker detection and protein engineering.
- Works by suspending cells in a stream of fluid and passing them by an electronic detection apparatus.
- It allows simultaneous multivariate analysis of the physical and chemical characteristics of up to thousands of particles per second.
- Flow cytometry has been used in the diagnosis of health disorders, especially blood cancers.



★ Lupus (erythematosus) is the name given to a collection of autoimmune diseases in which the human immune system becomes hyperactive and attacks normal healthy tissues. ★ Symptoms of these diseases can affect many different body systems, including joints, skin, kidneys, blood cells, heart, and lungs. ★ Can even result in psychosis in rare cases

The data:

Loretta Lee (a PhD student over a period of 5 year) collected  $n = 236$  samples in total from 154 subjects

total from 154 subjects.

| SLE | HEALTHY | DC | INACTIVE | MILD | MODERATE | SEVERE |
|-----|---------|----|----------|------|----------|--------|
| 150 | 68      | 19 | 81       | 25   | 18       | 15     |

There are 24 symptom types which can be summarised into 4 main types:

|        | SLE | %     |
|--------|-----|-------|
| Neuro  | 6   | 4     |
| Joints | 34  | 22.67 |
| Renal  | 34  | 22.67 |
| Skin   | 18  | 12    |

Predictors:

- Treatment information (4 main types).
- Some results from blood tests taken from the hospitals the patients were taken from (14 variables).

- (Very) basic demographic variables (4 variables).
- Flow cytometry variables (77 variables).

#### Data cleaning:

- Measurement error
- Outliers and high leverage points.
- Missing values.
- Text in numeric fields.
- Covariate censoring.
- Highly non-normal covariates.

My former PhD student Dr. Chong You having found a job in a bioinformatics

research lab recently told me:

“Data in my UG degree was so clean compared to what I deal with now!”

---

## Tidyverse lectures

### Lecture 2. Wednesday, 2 August 2017

- Assume we have data
- It can answer our questions
- It is clean
- We interrogated the right aspects
- We communicate correctly

#### Data cleaning:

- Corrupted column names
- Missing columns/rows
- Rows with missing values
- Rows with random values

#### Reading data

Base R functions are not sufficient for modern uses

- Readr functions superior in data import warning, column type handling, speed, scalability and consistency

#### Cleaning data:

- Cleaning data allows us to do statistical modelling without extra processing
  - o Good documentation
  - o Each column is a variable

- No bad characters
  - Inconsistent capitalisation or separators
- Each row is an observation
  - No bad characters
  - No poorly esiregned row names
  - No repeated row names
- Clean data is well designed data.frame
  - Data cleaning using janitor

### Janitor

- Clean up bad column names (clean\_names)

```
## Clean up column names
better = clean_names(dirtyIris)
glimpse(better)

## Observations: 650
## Variables: 6
## $ sepal_length <dbl> 7.700000000, -0.18425254, 7.200000000, 6.300000000, ...
## $ sepal_width <dbl> 3.80000000, NA, 3.60000000, 2.30000000, 2.90000000, -...
## $ petal length <dbl> 6.70000000, NA, 6.10000000, 4.40000000, 3.60000000, 0...
```

- Remove empty rows/cols

```
## Removing empty rows/columns
evenBetter = remove_empty_rows(better)
evenBetter = remove_empty_cols(evenBetter)

glimpse(evenBetter)
```

- Genuine missing values should be mainted, in which case NA is added. (na.omit)

```
evenBetterBetter = na.omit(evenBetter)
almostIris = evenBetterBetter
```

```
glimpse(almostIris)
```

## Cleaning Code

- 'inside out' code structure doesn't read well

"x%>%f" means "f(x)" (called 'x pipe f')

```
almostIris$sepal_length %>% mean
```

```
## [1] 3.602734
```

```
almostIris$sepal_length %>%  
  density %>%  
  plot(col = "red", lwd = 2)
```

## Subsetting data in R

- If I want to remove observations of sepal\_length < 2

```
cleanIris = almostIris[almostIris[, "sepal_length"] > 2, ]  
glimpse(cleanIris)
```

## Using dplyr

- Rows and columns two separate different procedures
  - o Select columns are operations on variables
  - o Filter rows are operations on observations

```
library(dplyr)  
  
cleanIris %>%  
  filter(sepal_length < 5,  
         sepal_width < 3) %>%  
  select(contains("length"))
```

```

arrangeCleanIris = cleanIris %>%
  arrange(sepal_length, sepal_width, petal_length, petal_width)

## The true iris data
arrangeIris = iris %>%
  clean_names() %>%
  arrange(sepal_length, sepal_width, petal_length, petal_width)

```

- We sorted both the processed dirtyIris data and the arranged iris data

```

## The 'Species' column is character or factor
all.equal(arrangeCleanIris, arrangeIris)

```

```

## [1] "Incompatible type for column `species`: x character, y factor"

```

```

arrangeIris = arrangeIris %>%
  mutate(species = as.character(species))

```

```

## Great!
all.equal(arrangeCleanIris, arrangeIris)

```

```

## [1] TRUE

```

Modelling using dplyr

**mutate** to create new columns

```

iris_mutated = mutate(cleanIris,
  V1 = sepal_length - sepal_width,
  V2 = V1 + sepal_width
)

```

```

iris_mutated

```

- Group\_by and summarise create summary statistics for grouped variables

```
bySpecies = cleanIris %>%
  group_by(species)

bySpecies
```

- select only if a column satisfy a certain condition

```
bySpecies %>%
  summarise_if(is.numeric,
               funs(m = mean))
```

```
## # A tibble: 3 x 5
##   species sepal_length_m sepal_width_m petal_length_m petal_width_m
##   <chr>         <dbl>         <dbl>         <dbl>         <dbl>
## 1 setosa         5.006         3.428         1.462         0.246
## 2 versicolor    5.936         2.770         4.260         1.326
## 3 virginica     6.588         2.974         5.552         2.026
```

```
cleanIris %>%
  select(starts_with("sepal")) %>%
  top_n(3, sepal_width)
```

- Left\_join to merge data

```
flowers = data.frame(species = c("setosa", "versicolor", "virginica"),
                     comments = c("meh", "kinda_okay", "love_it!"))
```

```
## cleanIris has the priority in this join operation
iris_comments = left_join(cleanIris, flowers, by = "species")
```

```
## Warning: Column `species` joining character vector and factor, coercing
## into character vector
```

```
## Randomly sampling 6 rows
sample_n(iris_comments, 6)
```

## Ggplot2

## ggplot2: the philosophy

- Di Cook - the real reason that you should use `ggplot2` is that, its design will force you to use a certain **grammar** when producing a plot.
- $\frac{1}{n} \sum_{i=1}^n X_i$  is a transformation of random variables, i.e., a statistic which provides insights into a data.
- Similarly, ggplot is also a statistic, because we take components of the data and presented it in an informative way.
- Publishing quality, rigourous syntax and design, flexible customisations, facetting.

---

Lecture 3.

---

Lecture 4. Tuesday, 8 August 2017

### Survey Sampling

Topic:

- \* Only 5-6 lectures.
- \* Terminology and examples of uses of sampling.
- \* Advantages of sampling.
- \* Methods of sampling.
- \* Sources of bias.
- \* Census.
- \* Various sampling designs: advantages and designs.

#### Example 1:

An opinion poll on America's health concern was conducted by Gallup Organization between October 3-5, 1997, and the survey reported that 29% adults consider AIDS is the most urgent health problem of the US, with a margin of error of +/- 3%. The result was based on telephone interviews of 872 adults.

Where did the margin of error come from?



From the central limit theorem:

$$\hat{p} = \frac{s}{n} \sim N\left(p_0, \frac{p_0(1-p_0)}{n}\right)$$

The CI is

$$\hat{p} \pm 1.96 \sqrt{\frac{p_0(1-p_0)}{n}}$$

*Some issues part of the sample survey:*

- Target population? (US pop)
- Sample pop? (adults reached by phone)
- How is the survey conducted? (phone)
- How is the sample selected? (randomly from phone list)
- How reliable are the estimates? Precision of the estimates?
- How much confidence do we have on the estimates?
- Were any bias introduced
- Why were  $n$  adults selected?
- Can an estimate on 1000 representatives represent 187 million adults?

From above:

If we have the standard error  $\sqrt{\frac{p_0(1-p_0)}{n}} < \sqrt{\frac{1}{4n}}$

To get an error <1%; we need at least 1000 people

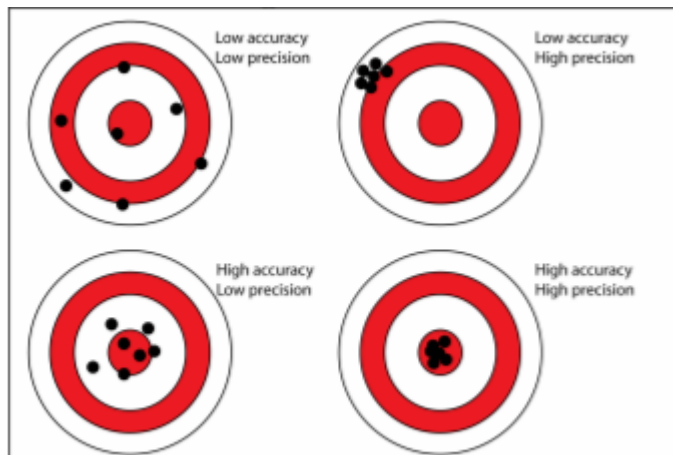
*Revision:*

- A sample is part of a population.
- A parameter is a numerical descriptor of a population.
- Usually a parameter cannot be determined exactly, but can only be estimated.
- A statistic can be computed from a sample, and used to estimate a parameter.
- A statistic is what the researcher know. A parameter is what the researcher wants to know.
- When estimating a parameter, one major issue is accuracy: how close is the estimate close to be?

Population described by a parameter; sample described by a statistic

We will also look at accuracy and precision (bias vs variance)

- Accuracy is bias
- Precision is variance



### Example 2:

★ Census data showed that in 1980, there were 227 million people in the US of whom 11.3% were 65 or older. ★ In 2000, there were 281 million people, of whom 12.3% were 65 or older. ★ Is the difference in the percentages statistically significant?

- Calling this statistically different is meaningless; as the census is the whole population, so there's no 'statistical significance'

### Discussion:

- You can try to do a two sample test, but the result is close to meaningless. Why?
- We have census data, i.e., the whole population. There is no sampling variability to worry about. The collection of census data is subject to many different sources of error. We are no longer dealing with a chance model.
- The aging of the population is real and this may make a difference to the health care system.
- If a test of significance is based on data from a whole population... watch out

We don't usually observe the entire population, due to:

- Time
- Resources
- Hard to observe
  - So we collect a sample instead

### Sampling

The solution is for us to collect samples in the hope or expectation of making a general statement about the entire population

- Reduce the number of measurements

- Save time, money resources
- Can be essential in destructive testing (eg car crash testing)

#### Survey design:

- What survey design is appropriate
- How will it be conducted/implemented

#### Procedure:

- Sample size needed
- How does the design affect sample size

Appropriate survey design provides the best estimation with high reliability at the lowest cost with the available resources

$$\text{Survey design} + \text{Survey Strategy} = \text{Survey sampling}$$

Eg: opinion polls

#### Case study: literary digest

1936, poll for Roosevelt vs Landon



#### Background:

- 1936 Franklin Roosevelt was completing his term of office.

- The US was struggling with high unemployment (9 million), just at the end of the Great Depression (1929–1939).
- Took a list of 10 million subscribers.
- Received 20% response (2.4 million people reply)
- Digest was prestigious as they had called the winning election since 1916.
- They predicted victory for Landon.
- Results: Roosevelt won by 62% to 38%. Roosevelt won 46 of 48 states. What went wrong?

Whereas: a Gallup poll did a survey of 3000 from digest, and another of 500000 using a special method, and predicted Roosevelt's victory

#### *What went wrong?*

\* How did Digest pick their sample ? \* Digest mailed questionnaires to 10 million people (sources like telephone books and club memberships). \* Sample from this list was not representative of the population.

#### Selection bias

- Affluent people
- Went selection procedure is biased, a larger sample compounds the bias; and **does not** help

Whether results from a sample can be extrapolated to the population depends on the design of the sampling process.

#### Bias in question wording: (measurement bias)

- Sensitive topics (eg abortion),
- How do you ask the questions?

\* Should a woman have control over her own body, including her reproductive system? \* Should a doctor be allowed to murder unborn children who can't defend themselves?

- Plenty of literature on this
  - o Order of questions
  - o Emotive language
  - o Who asks the questions
  - o How they are asked

#### *Measurement bias*

Some sources can be:

- Recall bias
  - o Forgetting the truth
- Sensitive questions
  - o May not tell the truth
    - Use of illegal drugs
    - Paying taxes
- Misinterpreting questions
- Ambiguity of word choice
- Wording of questions and order
- Interview process

#### Example: race riots measurement bias

After major racial riots in 1968 in Detroit, a sample of African American were asked: "Do you personally feel that you can trust most white people, some white people, or none at all"

- White interview: 35% "most"
- African American interviewer: 7% "most"

#### Example: Hite's Love Survey (non response bias)

\* Shere Hite send out 100, 000 questionnaires to study how women feel about their relationship with men and reported the findings in a book called "Women and Love". \* Kinsey (1953) 26% with extra-marital affair. \* Hite (1980) found 70%. \* Redbook (1991) survey found 31%

- Why is Hite's different?

Looking at the sampling, it doesn't look biased:

Hite Sample versus US  
Population: (annual  
income)/1000

| Stratum         | Study% | US%  |
|-----------------|--------|------|
| <\$2000         | 19     | 18.3 |
| \$2000-4000     | 12.0   | 13.2 |
| \$4000-6000     | 12.5   | 12.2 |
| \$6000-8000     | 10.0   | 9.7  |
| \$8000-10,000   | 7.0    | 7.4  |
| \$10,000-12,500 | 8.0    | 8.8  |
| \$12,500-15,000 | 5.0    | 6.2  |
| \$15,000-20,000 | 0.0    | 9.8  |
| \$20,000-25,000 | 8.0    | 6.4  |
| >\$25,000       | 8.5    | 8.2  |

Area

| Stratum    | Study% | US% |
|------------|--------|-----|
| City/Urban | 60     | 62  |
| Rural      | 27     | 26  |
| Small Town | 13     | 12  |

| Region        |        |     |
|---------------|--------|-----|
| Stratum       | Study% | US% |
| Northeast     | 21     | 22  |
| North Central | 27     | 26  |
| South         | 31     | 33  |
| West          | 21     | 19  |

| Race            |        |      |
|-----------------|--------|------|
| Stratum         | Study% | US%  |
| White           | 82.5   | 83.0 |
| Black           | 13.0   | 12.0 |
| Asian           | 1.8    | 2.0  |
| Hispanic        | 1.8    | 1.5  |
| Native American | 0.9    | 1.0  |
| Middle Eastern  | 0.3    | 0.5  |

But:

In the 100,000 people asked, had a 95.5% non response rate

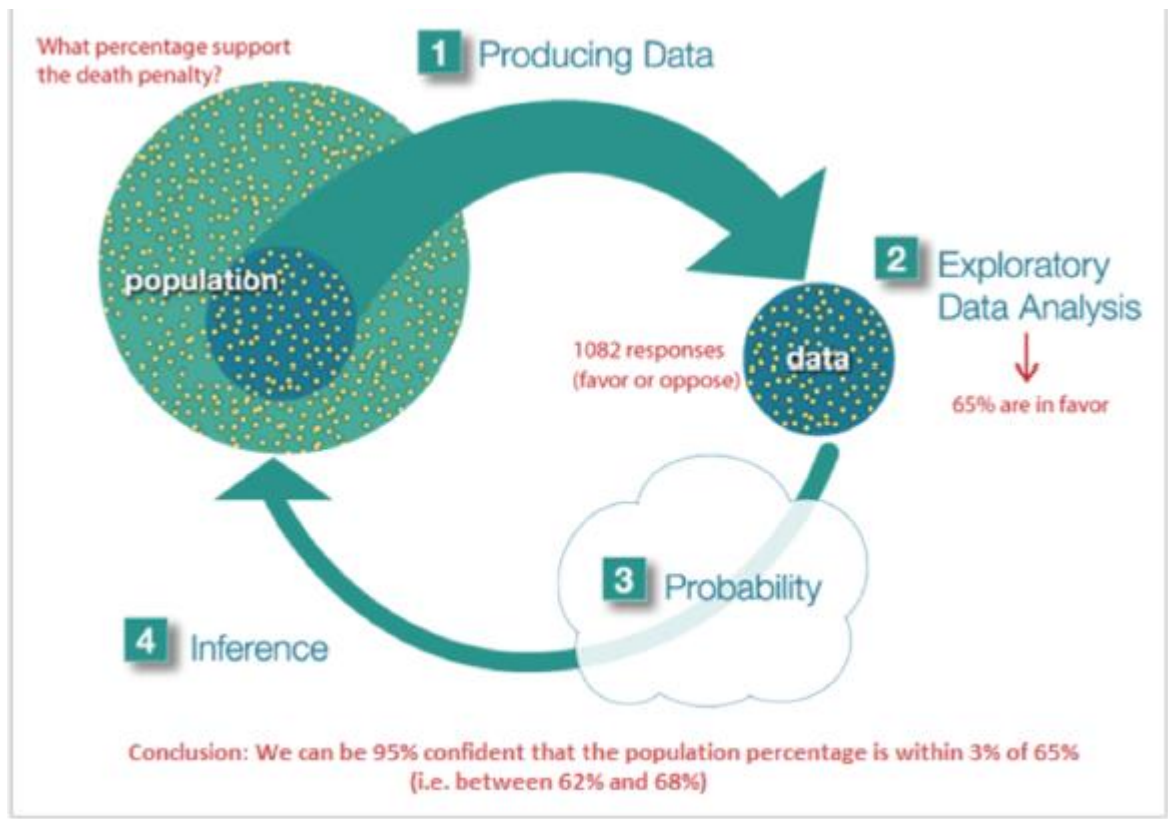
- Unhappy people are often more likely to respond
- Non response bias

Mode of survey administration:

- Mail
- Personal interview
- Telephone
- Combination of methods

Each can introduce its own biases

In an ideal world, we would like to see the characteristics of the samples matches that of the population. Ideally, we would like to have a list of everyone in the population. In practice, we often don't have this list. If the sample is not representative of the population, then the results may be inaccurate. If a survey is ambiguous, subjective, or biased, then the results may be inaccurate



## Sampling terms

**Population:** a population signifies the units that we are interested in studying. These units could be people, cases and pieces of data.

**Unit:** The element of the sample selected from the population. The population that you are interested consists of units, which can be people, cases or pieces of data. Consider that you want to examine the erect of health care facilities in a community on prenatal care. What is the unit of analysis: health facility or the individual woman?

**Sample:** A subset of the population selected for the study.

**Sample size:** number of units

**Sampling frame**

**Sampling bias** (selection bias)

**Sampling techniques**

- Ways to help select units
- Method for creating samples

### Sampling frame

- A sampling frame is a clear and concise description of the population under study, from which the population units can be identified unambiguously and contacted, if desired for the purpose of study

For probability sampling, we should know the selection probability of an individual to be included in the sample. It is important that every individual is included in the selection process.

The sampling frame is very similar to the population you are studying, and may be exactly the same. When selecting units from the population to be included in your sample, it is sometimes desirable to get hold of a list of the population from which you select units. This list can be referred to as the sampling frame.

In addition to physical lists, this could also be used in procedures that can account for all the sampling units without the physical effort of actually listing them.

- Simple random sample refers to randomly selecting sample without replacement
  - o How to select elements
  - o Randomisation?

### Example:

50000 households, 750 sample taken. The average number of TV sets is 1.86 with  $\sigma = 0.8$ . if possible, find 95% CI; if not explain

$$CI = \mu \pm 1.96 \frac{\sigma}{\sqrt{n}} = (1.803, 1.917)$$

### Example 2:

As part of the survey, all person aged 16 or over in the sample households are interviewed. This makes 1528 people. On the average, the sample people watched 5.2 hours of television the Sunday before this survey, and the SD was 4.5 hours. If possible find a 95% confidence interval for the average number of hours spent watching television on the Sunday by all person age 16 and over in the 50,000 households.

- This is a harder question, as not a simple random sample.
  - o You can get everybody in a household or nobody, so the SE cannot be estimated (by previous year's methods)
- Household can be seen as a cluster and other methods could be used to calculate SE
- People in same house have similar watching patterns
- Usual problem with cluster samples is "chance error" and not bias

Lecture 5.

### Sampling techniques



- Probability sampling
- Non probability sampling

Types of samples / methods for creating a samples:

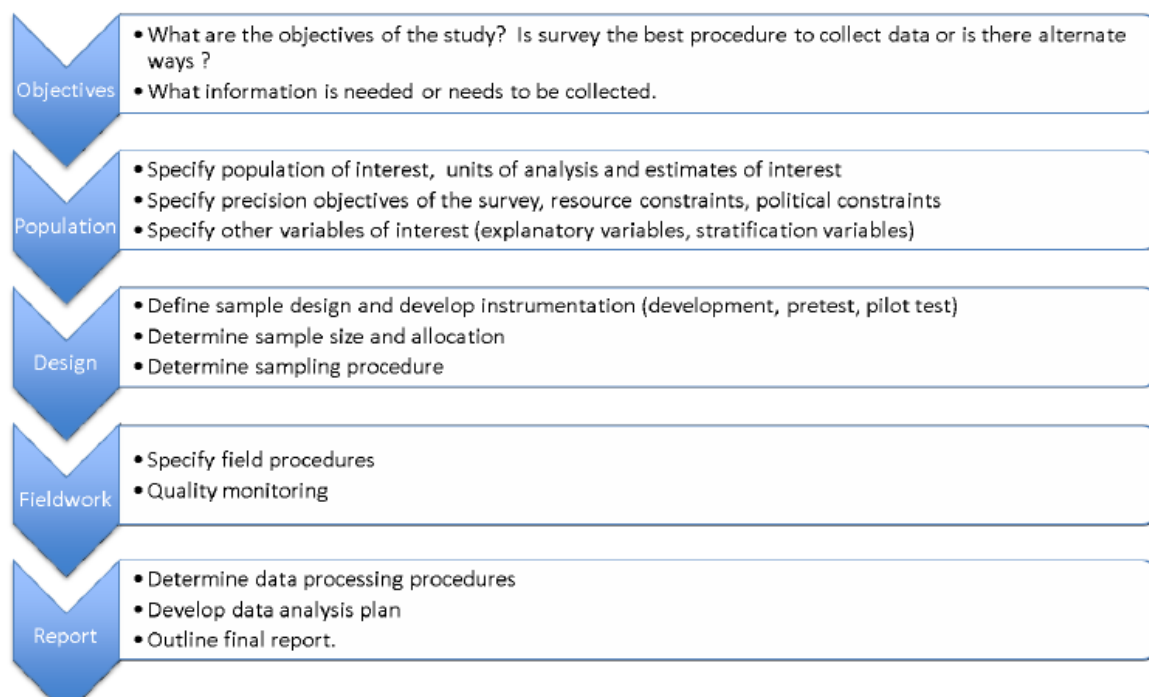
| Probability Sampling  | Non-probability Sampling   |
|---|--|
| Note: Statistical theory can be used to make useful statements (inferences) and statistical theory is applicable only in this case. | <ul style="list-style-type: none"> <li>* Purposive or judgment sample or convenience sample: subjective.</li> <li>* Snow-ball sampling: rare group/disease study.</li> </ul> |

**Quota:** matching certain characteristic of the population. Read Section 3 in the extra reading for more info.

#### *Characteristics of good sampling*

- Address study objectives
- Reliable/robust results
- Procedure understandable
- Realistic timeline
- Economical
- Accurate interpretation and representative results
- Acceptability

#### *Survey design*



1. Specify population of interest.
2. Specify units of analysis and estimates of interest.
3. Specify precision objectives of the survey, resource constraints, and political constraints.
4. Specify other variables of interest (explanatory variables, stratification variables).
5. Review population characteristics (Distributional cost).
6. Develop instrumentation (development, pretest, pilot test).
7. Develop sample design.
8. Determine sample size and allocation.
9. Specify sample selection procedure.
10. Specify \_eld procedures.
11. Determine data processing procedures.
12. Develop data analysis plan.
13. Outline \_nal report.

#### Probability Samples:

##### Types

- Simple random sample (SRS)
  -
- Systematic
- Cluster
- Stratified random sample

(all multistage sampling if combined together)

#### Random sample

Every element of the population has equal probability of being chosen. If selected at random, said to be unbiased. However incorrect sampling may introduce bias.

#### Systematic sampling

Start your sampling by selecting an element from the list at random and then every  $k$ th; where  $k$  is known as the sampling interval or skip

#### Cluster sampling

- Selecting random clusters. You want the cluster to be heterogeneous as possible, so that each cluster is a good small scale representation of the population

#### Stratified sampling:

- Dividing members of the population into homogeneous, non-overlapping subgroups and then sample.
- Non population unit/element can be excluded

## Example: estimate size of UG class

- 100 rand samples from Sydney student and average
- Take a random 50 students, list the courses each student takes and average the list
- Take 50 instructors, list the courses each instructor takes and average the list?
- 5 from each school?
- Take rand sample of 5 schools from science and humanities; from each of these take 5 instructors and average the course sizes
  - o Used by gallup
  - o Multistage sampling
  - o Definite procedure for selecting the sample and it involves the planned use of chance
  - o Offers advantages over quota sampling and eliminates the worst feature of quota sampling which is selection bias on the part of the interviewer

## Sample theory:

Objective: devise sample scheme which is

- Economical
- Easy to implement
- Unbiased estimators
- Minimise sample variations

## Chance error and bias in theory (with SRS)

$$\begin{aligned} \text{Observed Value} &= \text{Expected Value} + \text{Chance Error} \\ \text{statistic} &= \text{parameter} + \text{error} \end{aligned}$$

$$\hat{p} = p + \epsilon$$

In practice:

$$\text{statistic} = \text{parameter} + \text{error} + \text{bias}$$

Eg:

- Selection bias
- Nonresponse bias
- Question bias
- Systematic error in estimate

## Finite population:

- Contains finite number of items
- Compared to
  - o Infinite population
  - o Natural population (birth/death/immigration)

- Homogeneous vs heterogeneous population

### Relationship of sample to population

|              | Population<br>Parameters       |                                      | Sample<br>statistics           |
|--------------|--------------------------------|--------------------------------------|--------------------------------|
|              | N                              |                                      | n                              |
| Variable (Y) | $Y_i$                          |                                      | $y_i$                          |
| Mean         | $\bar{Y} = \frac{\sum Y_i}{N}$ |                                      | $\bar{y} = \frac{\sum y_i}{n}$ |
| Total        | $Y = \sum Y_i = N\bar{Y}$      | ← $N\bar{y} = \frac{N}{n}n\bar{y}$ ← | $y = \sum y_i = n\bar{y}$      |

In summary,  $\bar{y}$  is an unbiased estimator of  $\mu$ , the population mean, and  $N\bar{y}$  is an unbiased estimator of population total.

$N\bar{y}$  is called expansion estimator

### With and without replacement

- Sample with replacement (SRSWR)
- Sample without replacement (SRWOR)

How many ways can we select 2 elements from 4 things?

With replacement = 16

Without = 6

### Element selection probability (inclusion probability)

From  $A, B, C, D$ ; what is the probability of selective A (from 2 selections)

- With replacement?
- Without replacement?

### Unbiased estimator

Unbiased estimator of  $Var(p)$  from a SRS with replacement is

$$Var(p) = \frac{pq}{n-1}$$

Correction for sampling without replacement is

$$Var(p) = \frac{pq}{n-1} \left(1 - \frac{n}{N}\right)$$

## Lecture 6. Thursday, 10 August 2017

## The Census:

## Adjustment:

- 'capture recapture' method

$$Pop = Birth + Death + Immigration + Emigration$$

- Take census
- SRS and find how many were also in the census
- Estimate total number of people by  $\frac{\text{Number in census}}{\text{Fraction in sample found by census}}$
- 

## Population

Finite number of elements,  $N$ ;  $N$  is assumed known. This is a finite population

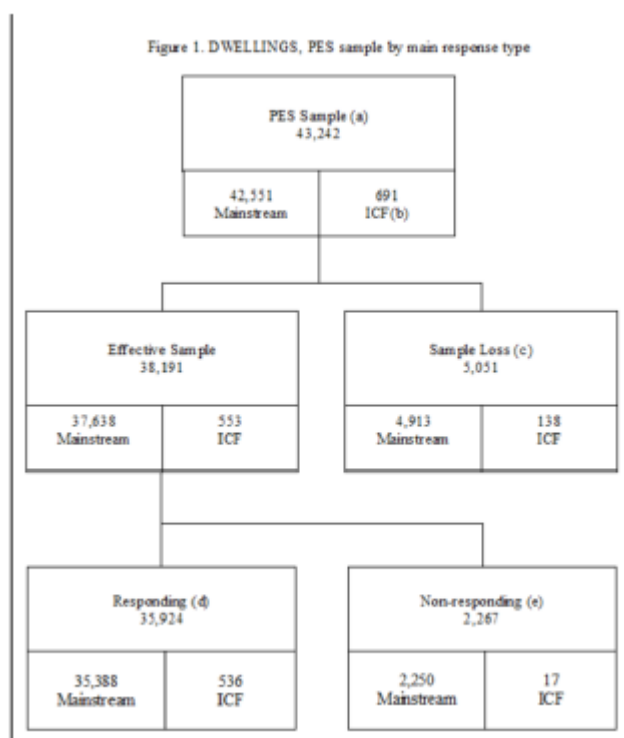
## Post enumeration survey: (PES)

- 40000 households participate in PES, to estimate how many people were not included in the census
- The PES is designed to collect just enough information to determine whether someone was counted in the Census and to enable the ABS to produce a range of net undercount information.
- This included important demographic information (name, sex, age, date of birth, country of birth), the address where each person was on Census night, and any other addresses where each person may have been included on a Census form.
- While the PES asked whether each respondent thought they were included on a Census form, the ABS actually compared Census and PES data to determine whether someone was in fact counted or not.

## Sampling:

- Specially trained PES interviewers collected data through face-to-face interviews which started around three weeks after Census night. Some telephone interviews were conducted by office staff where the respondent made contact with the office and asked to complete the interview on the spot. All mainstream dwellings were enumerated using Computer Assisted Interviewing (CAI).

- Interviews were conducted with any responsible adult of the household who was asked to respond on behalf of all household members.
- This collection methodology differed to the way Census collected its information, where most forms were self-completed.
- A major advantage of interviewer-administered questionnaires is that people can be provided with assistance if they are uncertain about the meaning of questions, and help is also given to ensure no questions are left unanswered.
- To ensure a high response rate was achieved, the number of repeat visits made to non-contact dwellings was twice that of most other ABS household surveys



### The population:

$Y_1, \dots, Y_N$  is the population. We adopt the Cochran notation where capitals are characteristics of the population, small letters are used for corresponding characteristics of sample

Pop total:

$$Y = \sum_{i=1}^N Y_i$$

Mean:

$$\mu = Y \backslash bat = \frac{Y}{N} = \frac{1}{N} \sum_{i=1}^N Y_i$$

Variance:

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (Y_i - \bar{Y})^2; S^2 = \frac{N}{N-1} \sigma^2$$

These are fixed population quantities. If we have to consider 2 numerical values  $Y, X$ , the ratio of totals is

$$R = \frac{\sum Y_i}{\sum X_i} = \frac{\bar{Y}}{\bar{X}}$$

Simple Random Sample:

Focus on numerical value of  $Y_i$

Rand samp of size  $n$  taken without replacement, and  $y_i, \dots, y_n$  are random variables that are stochastically dependent.

Sampling frame is a list of values of  $Y_i; i = 1, \dots, N$

*Estimatos*

**Natural estimator of  $\mu$**

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n y_i = \bar{y}$$

Hence, a natural estimator for  $Y = N\mu$  is

$$\hat{Y} = N\bar{y}$$

Distributional properties of  $\bar{y}$  are complicated by the dependence of the  $y_i$ 's;

Sample variance:

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

*Fundamental results*

Sampling without replacement from a finite population:

$$E(\bar{y}) = \mu$$

$$Var(\bar{y}) = \frac{S^2}{n} \left(1 - \frac{n}{N}\right) = \frac{S^2}{n} (1 - f) = \frac{\sigma^2}{n} \left(\frac{N-n}{N-1}\right)$$

- Where  $f$  is the sampling fraction, and the finite population correction (fpc) is  $1 - f$

$$E(s^2) = S^2$$

So  $s^2$  is an unbiased estimator of  $S^2$

- Remember the SE of an estimator =  $\sqrt{\text{Var}}$

Comparison:

- Derivations on Ed

$$\begin{aligned}\text{Var}(Y) &= \sigma^2 \\ \text{Var}(\bar{y}) &= \frac{S^2}{n} \left(1 - \frac{1}{N}\right) = \frac{\sigma^2}{n} \text{ [for SRSWR]} \\ \text{Var}(\bar{y}) &= \frac{S^2}{n} \left(1 - \frac{n}{N}\right) \text{ [for SRSWOR]}\end{aligned}$$

Note that  $1 - \frac{n}{N} = 1 - f$  is the fpc.

- This is approximately the multiplying factor to convert SRSWR → SRSWOR variance
- As the variance of SRSWOR is smaller, SRSWOR is always more efficient than SRSWR

Lecture 7. Tuesday, 15 August 2017

## Sample Size Determination

“In the planning of a sample survey, a stage is always reached at which a decision must be made about the size of the sample. The decision is important. Too large a sample implies a waste of resources, and too small a sample diminishes the utility of the results.”

Purpose:

- One objective of sample size determination is precision analysis
  - o We like to measure with precision
  - o Goal is to determine size of a sample that is large enough to have errors within desired limits
- We want a sample size to ensure that we can estimate a value, say  $p$  from the sample which corresponds to the population parameter  $P$ .
- \* We want the error in our estimate to be limited to a certain extent, that is, this error should be within a pre-specified **margin-of-error**  $d$ .

$$P = p \pm d$$

- More specifically we want a confidence interval of the form  $P = p \pm d$
- \* Another key element is to describe the confidence we have in our estimate. That is, we want some confidence limits say 95% to our error estimate of  $d$ . You will often see the term



$$1 - \alpha$$

### Confidence interval:

If we have  $S^2$  (population), with  $s^2$  (sample), a 95% CI for  $\mu$  is

$$y \pm 1.96 \frac{s}{\sqrt{n}} \sqrt{1-f}$$

$f = \frac{n}{N}$  for SRSWOR.

Corresponding CI for  $Y$  is  $N$  times greater

- Remember that capitals denotes population

$$N \left( y \pm 1.96 \frac{s}{\sqrt{n}} \sqrt{1-f} \right)$$

To calculate the sample size needed for sampling yet to be carried out, for specified precision, use past information, or information from a pilot survey.

*Eg: pilot survey*

Suppose we want

$$P \left( \frac{|\bar{y} - \mu|}{\mu} \leq \delta \right) \geq 0.95$$

With 1%  $\delta = 0.01$  of actual  $\mu$  (relative error)

Then

$$\mathbb{P} \left( \frac{|\bar{y} - \mu|}{\sqrt{\text{Var}(\bar{y})}} \leq \frac{\delta \cdot \mu}{\sqrt{\text{Var}(\bar{y})}} \right) \geq 0.95$$

Then

$$\frac{\delta \cdot \mu}{\sqrt{\text{Var}(\bar{y})}} \geq 1.96.$$

Ignoring f.p.c., i.e., taking  $f = 0$ , (remember  $\text{SE}^2 = \text{Var}(\bar{y}) = S^2/n$ )

$$n \geq \frac{(1.96)^2 S^2}{\delta^2 \mu^2} \approx \frac{(1.96)^2 s^2}{\delta^2 \bar{y}^2}$$

where  $s^2$  and  $\bar{y}$  are estimates from a pilot survey.

### Sample size calculations for $p$

Suppose we want

$$P(|\bar{p} - p| \leq \delta) \leq 1 - \frac{\alpha}{2}$$

Using CLT:

$$\bar{p} \sim_{\text{approx}} N\left(p, \frac{p(1-p)}{n}\right)$$

Then

Then

$$\mathbb{P}\left(\frac{|\bar{p} - p|}{SE} \leq \frac{\delta}{SE}\right) \geq 1 - \alpha/2$$

and so

$$\frac{\delta}{SE} \geq z_{1-\alpha/2} \quad \text{with} \quad SE \approx \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

Giving sample size

$$n \geq z_{1-\alpha/2}^2 \frac{p(1-p)}{\delta^2}$$

- We want this to be at least the smallest integer greater than the RHS
- Note that, the sample size requirement is highest when  $p = 0.5$ . It is a common practice to take  $p = 0.5$  when no information is available about  $p$  for a conservative estimation of sample size.
- You can justify this to yourself via calculus or in an ad-hoc way via computation.

Sample size calcs for  $p$  under SRSWOR

We know that

You were given the following fundamental results

$$\text{Var}(\bar{y}) = \frac{S^2}{n} \left(1 - \frac{n}{N}\right) = \frac{S^2}{n} (1 - f) = \frac{\sigma^2}{n} \left(\frac{N-n}{N-1}\right)$$

So under SRSWOR

$$SE \approx \frac{p(1-p)}{n} (1 - f)$$

So we get the sample size

$$n \geq z_{1-\alpha/2}^2 \frac{p(1-p)}{\delta^2} (1 - f)$$

Example:

Example if we like to estimate  $p = 0.4$  with 95% confidence with  $\delta = 0.1$  Then under SRSWOR

$$n \geq 1.96^2 \times \frac{0.4 \times 0.6}{\delta^2} = 92.19$$

$$n = 93$$

## Example 2:

Adjusting for SRSWOR:

- The adjustment is done looking at  $n'$  represents the number of sample under simple random sampling with replacement  $n$  represents the number of sample without replacement. What is the relationship between  $n$  and  $n'$ ?
  - o  $n'$  WR (from before)
  - o  $n$  WOR (want to find now)

$$\frac{S^2}{n'} = \frac{S^2}{n} \left(1 - \frac{n}{N}\right)$$

Giving

$$n = \frac{n'}{1 + \frac{n'}{N}}$$

If  $N = 200$ ; from before; we found  $n' = 93$ 

$$\therefore n = \frac{93}{1 + \frac{93}{200}} = 63.48$$

$$n = 64$$

## SRS: Inference over Subpopulations

Population of size  $N$  individuals, SRS sample size  $n$ ; measurements of which  $Y_i, i = 1, \dots, N$  is considered.

Separate estimates wanted for one of a number of subclasses  $\{C_1, C_2, \dots\}$  are subsets of the population (sampling frame)

Eg:

| <u>Population (Sampling Frame)</u> | <u>Subpopulation</u>          |
|------------------------------------|-------------------------------|
| Australian population              | unemployed Queenslanders      |
| retailers                          | supermarkets                  |
| the employed                       | the employed working overtime |

## Notation and Estimators:

Denote number of items in each class  $C_j$  by  $N_j$ . (generally unknown)

Estimated by

$$\hat{N}_j = N \frac{n_j}{n}$$

Where  $\frac{n_j}{n}$  = preportion of total sample size in  $C_j$

We find  $\bar{Y}_{C_j}$  and  $Y_{C_j}$  as:

$$\bar{Y}_{C_j} = \sum_{i \in C_j} \frac{Y_i}{N_j}$$

$$Y_{C_j} = \sum_{i \in C_j} Y_i$$

We use

$$Y'_i = \begin{cases} Y_i; i \in C_j \\ 0; i \notin C_j \end{cases}$$

Correspondingly, in the sample

$$y'_i = \begin{cases} y_i; i \in C_j \\ 0; i \notin C_j \end{cases}$$

Then  $\bar{y}'$  estimates  $\bar{Y}'$ ; where  $\bar{y}' = \sum_{i=1}^n \frac{y'_i}{n}$

So we haave:

$$N\bar{Y}' = Y_{C_j}$$

- So  $N\bar{y}'$  estimates  $Y_{C_j}$
- $\hat{\bar{Y}}_{C_j} = \frac{N\bar{y}'}{N_j}$  estimates  $\bar{Y}_{C_j}$ 
  - o These estiamteros are unbiased

We get that:

$$Var(\hat{\bar{Y}}_{C_j}) = \left(\frac{N}{N_j}\right)^2 Var(\bar{y}') = \left(\frac{N}{N_j}\right)^2 \frac{(S'_{C_j})^2}{n} \left(1 - \frac{n}{N}\right)$$

Where  $S'^2_{C_j}$  is estimated by  $s'^2_{C_j}$

$$(S'_{C_j})^2 = \sum_{i=1}^N \frac{(Y'_i - \bar{Y}')^2}{N-1}, \quad (s'_{C_j})^2 = \frac{\sum_{i=1}^n (y'_i - \bar{y}')^2}{n-1}.$$

*Example:*

There are 200 children in a village. One dentist takes a simple random sample of 20 and finds 12 children with at least one decayed tooth and a total of 42 decayed teeth. Another dentist quickly checks all 200 children and finds 60 with no decayed teeth

Estimate the total number of decayed teeth.

$C_1$  : children with at least one decayed tooth       $C_2$  : children with no decayed teeth

$$N_1 = 140$$

$$N_2 = 60$$

$$n = 20$$

$$n_1 = 12$$

$$(n_2 = 8)$$

Then

$$\bar{y}' = 42/20 = 2.1 \quad \text{and} \quad N\bar{y}' = 200 \times 2.1 = 420$$

 *$N_j$  not known*

If  $N_j$  is *not known*, we can estimate the total  $Y_{C_j}$  by  $N\bar{y}'$  but we cannot estimate  $\bar{Y}_{C_j}$  by  $(N/N_j)\bar{y}'$ . It is natural to consider trying to estimate it by  $(n/n_j)\bar{y}'$ , that is, taking

$$\bar{y}_{C_j} = \sum_{i \in C_j} y_i / n_j = (n/n_j)\bar{y}'.$$

Estimators are then:

$$\mathbb{E}(\bar{y}_{C_j}) = \bar{Y}_{C_j}$$

$$\text{Var}(\bar{y}_{C_j}) \approx \left( \frac{N}{N_j} \right)^2 \frac{S_{C_j}^2}{n} \left( 1 - \frac{n}{N} \right)$$

where  $S_{C_j}^2 = \frac{\sum_{i \in C_j} (Y_i - \bar{Y}_{C_j})^2}{N_j - 1}$ , provided we define  $\mathbb{E}(\bar{y}_{C_j})$  and  $\text{Var}(\bar{y}_{C_j})$  appropriately when  $n_j = 0$ .

Note  $S_{C_j}^2$  can be estimated by

$$s_{C_j}^2 = \frac{\sum_{i \in C_j} (y_i - \bar{y}_{C_j})^2}{n_j - 1}.$$

## Lecture 8.

Proof: (not examinable)

**Proof: (not examinable)** Use conditional expectations.

$$\begin{aligned} \mathbb{E}(\bar{y}_{C_j}) &= \mathbb{E}(\bar{y}_{C_j} | n_j = 0) \cdot \mathbb{P}(n_j = 0) + \sum_{i \geq 1} \mathbb{E}(\bar{y}_{C_j} | n_j = i) \cdot \mathbb{P}(n_j = i) \\ &= \bar{Y}_{C_j} \mathbb{P}(n_j = 0) + \sum_{i \geq 1} \bar{Y}_{C_j} \mathbb{P}(n_j = i) \\ &= \bar{Y}_{C_j}, \end{aligned}$$

where for  $n_j$  fixed, we are looking at a simple random sample of size  $n_j$  from  $C_j$ .

Further

$$\begin{aligned} \text{Var}(\bar{y}_{C_j}) &= \underbrace{\text{Var}(\mathbb{E}(\bar{y}_{C_j} | n_j))}_{\bar{Y}_{C_j}} + \mathbb{E}(\text{Var}(\bar{y}_{C_j} | n_j)) \\ &= 0 + \mathbb{E}(\text{Var}(\bar{y}_{C_j} | n_j)). \end{aligned}$$

Now, if  $n_j > 0$

$$\text{Var}(\bar{y}_{C_j} | n_j) = \left\{ \frac{1}{n_j} \sum_{i \in C_j} \frac{(Y_i - \bar{Y}_{C_j})^2}{N_j - 1} \left( 1 - \frac{n_j}{N_j} \right) \right\}$$

- a simple random sample of size  $n_j$  from  $C_j$ . Now use  $\frac{n_j}{n} \approx \frac{N_j}{N}$  (an unbiased estimator).

$$\begin{aligned} \text{Var}(\bar{y}_{C_j} | n_j) &\approx \left\{ \frac{N}{n N_j} \frac{\sum_{i \in C_j} (Y_i - \bar{Y}_{C_j})^2}{N_j - 1} \left( 1 - \frac{n}{N} \right) \right\} \\ &\approx \left\{ \left( \frac{N}{N_j} \right)^2 \frac{1}{n} S_{C_j}^2 \left( 1 - \frac{n}{N} \right) \right\}. \end{aligned}$$

## Corollary

**Corollary:** The estimator  $\hat{Y}_{C_j} = N_j \bar{y}_{C_j}$  is unbiased for  $Y_{C_j}$  and has

$$\text{Var } \hat{Y}_{C_j} = (N_j)^2 \text{Var}(\bar{y}_{C_j}).$$

When  $N_j$  is known, the estimator  $N_j \bar{y}_{C_j}$  for  $Y_{C_j}$  uses more information (by using  $N_j$  and  $n_j$ ) than  $N \bar{y}'$  and so should be a better unbiased estimator.

## Summary of unbiased estimators

**Summary of the Unbiased Estimators of  $Y_{C_j}$** 

|                    | Estimator           | Variance                                       |
|--------------------|---------------------|--|
| $N_j$ known or not | $N \bar{y}'$        | $N^2 \frac{(S'_{C_j})^2}{n} (1 - \frac{n}{N})$ |
| $N_j$ known        | $N_j \bar{y}_{C_j}$ | $N^2 \frac{S_{C_j}^2}{n} (1 - \frac{n}{N})$    |

$$(S'_{C_j})^2 = \frac{\sum_{i=1}^N (Y'_i - \bar{Y}')^2}{N-1}, \quad S_{C_j}^2 = \frac{\sum_{i \in C_j} (Y_i - \bar{Y}_{C_j})^2}{N-1}$$

$$S_{C_j}^2 \leq (S'_{C_j})^2.$$

## Lecture 9.

## Stratified sampling

In stratified sampling, the population is partitioned into groups, called strata, and sampling is performed separately within each stratum.

1. Stratum variables are mutually exclusive.
2. Aim to have homogenous population within-stratum and heterogenous between strata

### Reasoning for stratification:

- Natural stratification may exist
- We can improve the precision of our estimator if the population can be divided into subpopulations where the variability within each subpopulation or strata is known. We can "redirect" observations from the less variable strata to the more variable ones (relative to a simple overall random sample) to reduce overall variability in our estimator.
- Administrative convenience, for example, if separate administrative units exist, such as states or local government areas, it may be easier to sample in each individually, and then put the information together.
- Cost. If the cost of taking observations varies across subpopulations (eg cost of surveys in remote rural areas vs the cities) then savings may be possible by adjusting the proportions of the subpopulations sampled to minimise overall costs.

### Advantages

- Provides opportunity to study the stratum variations - estimation could be made for each stratum
- Disproportionate sample may be selected from each stratum
- The precision likely to increase as variance may be smaller than SRS with same sample size
- Field works can be organized using the strata (e.g., by geographical areas or regions)
- Reduce survey costs.

**The principal objective of stratification is to reduce sampling errors.**

### Disadvantages:

- Sampling frame is needed for each stratum.
- Analysis method is complex such as correct variance estimation.
- Data analysis should take sampling weight into account for disproportionate sampling of strata.
- Sample size estimation is difficult in practice.

### Stratified random sampling

When sample is selected by SRS technique independently within each stratum, the design is called stratified random sampling.

Pop size  $N$  divided into subpopulations  $N_1, \dots, N_L$ , the strata are mutually exclusive and exhaustive;  $N_h$  is known.

A SRS of size  $n_h$  is drawn from the  $h^{th}$  stratum;  $h = 1, \dots, L$