

# Experiment Planning and Design

## Lecture 4: Statistical Concepts

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# Notes

- Sorry about the sickness last class; Let's try Class 3 again!
- No class on May 19th and May 26th;

# Class Outline

- Random Variables
- Point Estimators
- Interval Estimators
- Hypothesis Testing

The goal of this class is to allow you to do a simple analysis of the data going into, and coming out of an experiment.

# Introduction: Probability vs Statistics

## Probability

Given the pool, what are the odds of drawing a combination of certain colors?



## Statistics

Given the colors of a few balls drawn, what can I know about the pool?



**Statistical Inference:** Using *samples* to draw conclusions about *populations*

# Population, Sample and Observation

“A **population** is a large set of objects of a similar nature which is of interest as a whole”. It can be an actual set (all balls in the pool), or an hypothetical one (all possible outcomes for an experiment).



A **sample** is a subset of a population. “A sample is chosen to make inferences about the population by examining or measuring the elements in the sample”

An **observation** is a single element of a given sample, an individual data point. An observation can also be considered as a sample of size one.



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Glossary of statistical terms: <http://www.statistics.com/glossary>

# Population, Sample and Observation

## Let's remember Alice and Bob's experiments

Alice and Bob build spam filter programs. They test their programs by counting how many spam the system catches in a day.

Observation

Sample

Population

# Population, Sample and Observation

## Let's remember Alice and Bob's experiments

Alice and Bob build spam filter programs. They test their programs by counting how many spam the system catches in a day.

## Observation

If we count the number of spam caught by a system in one day, that is **one observation**.

If we count the number of spam caught by a system another day, that is **a second observation**

## Sample

## Population

# Population, Sample and Observation

## Let's remember Alice and Bob's experiments

Alice and Bob build spam filter programs. They test their programs by counting how many spam the system catches in a day.

### Observation

### Sample

If we count the number of spam caught every day for a week, we will have seven observations. That is a **Sample**

### Population



# Population, Sample and Observation

## Let's remember Alice and Bob's experiments

Alice and Bob build spam filter programs. They test their programs by counting how many spam the system catches in a day.

## Observation

## Sample

## Population

If we know ALL possible results for ALL possible days, that is the **Population**

In practice, it is **usually impossible to KNOW** the population, but we want to learn **as much as possible** from it, by observing samples.

# Point and Interval Estimates

Two central concepts of **Statistical Inference** are **point estimators** and **statistical intervals**

Both terms refer to the idea of using information obtained from a **sample** to infer values about parameters of the **population**.

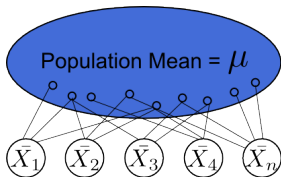
- **Point Estimate**: Estimate a value for a given population parameter
- **Statistical Interval**: Estimate a interval of possible/probable values for a given population parameter;

# Point Estimates, Statistics, and Sampling distributions

Suppose one wants to obtain a point estimate for the mean of a given population. We take a sample of the population, and calculate the mean of that sample.

However, a random sample from a population results in a random variable! Any function of the sample - any *statistic* - is also a random variable.

This means that statistics calculated from samples will also have their own probability distributions, called **sampling distributions**.



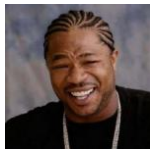
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See D.W. Stockburger: <http://www.psychstat.missouristate.edu/introbook/sbk19.htm>

# I heard you like statistics!

So in order to specify parameters of the population (such as means, deviation, etc), we draw a random sample and calculate the parameters from it.

But because the sample is random, the parameter calculated from the sample will also have its own statistics!



## Everything is easier with an R example

```
> population <- rnorm(100) # Pretend you don't know this!
> x1 <- sample(population,5)
> x2 <- sample(population,5)
> x3 <- sample(population,5)
> x1
[1] 0.6028260 0.1333065 1.1145946 -0.8675467 -0.4329469
> c(pop=mean(population),x1=mean(x1),x2=mean(x2),x3=mean(x3))
      pop           x1           x2           x3
0.05722922 0.11004669 -0.10459150 0.12630965
> c(mean(c(mean(x1),mean(x2),mean(x3))),sd(c(mean(x1),mean(x2),mean(x3))))
[1] 0.04392161 0.12887292
```

# Point Estimators

A **Point Estimator** is a statistic which provides the value of maximum plausibility for a given (unknown) population parameter  $\theta$ .

Consider a random variable  $X$  distributed according to a given  $f(X|\theta)$  (a population whose distribution is controlled by this parameter)

Now consider also a random sample from this variable:

$$X = \{X_1, X_2, \dots, X_N\};$$

A given function  $\hat{\theta} = h(x)$  is called a *point estimator* of the parameter  $\theta$ , and a value returned by this function for a given sample is referred to as a *point estimate*  $\hat{\theta}$  of the parameter.

## What does this mean?

A **Point Estimator** is a function that, given a sample, generates an estimated parameter for the distribution from which the sample was obtained.

# Point Estimators

Point estimation problems arise frequently in all areas of science and engineering, whenever there is a need for estimating a parameter of a population:

- The population mean,  $\mu$ ;
- The population variance,  $\sigma^2$ ;
- a population proportion,  $p$ ;
- the difference in the means of two populations,  $\mu_1 - \mu_2$ ;
- etc...

For each cases (and many others) there are multiple ways of performing the estimation task. We choose the estimators based on its statistics.

## Multiple estimators?

We always consider only one definition for estimators (e.g., the mean). But we can be creative and invent others!

$$\mu = \sum_{i=0}^N \frac{x_i}{N}$$
$$\mu' = \frac{\max(x) - \min(x)}{2}$$

# Evaluating Estimators

A good estimator should consistently generate estimates that are close to the real value of the parameter  $\theta$ .

We say that an estimator  $\hat{\theta}$  is **unbiased** for a parameter  $\theta$  if:

$$E[\hat{\theta}] = \theta$$

or, equivalently:

$$E[\hat{\theta}] - \theta = 0.$$

The difference  $E[\hat{\theta}] - \theta$  is referred as the **bias** of an estimator.

# Evaluating Estimators

The usual estimators for mean and variance are unbiased estimators; Let  $x_1, \dots, x_N$  be a random sample from a given population  $X$ , which is characterized by its mean  $\mu$  and variance  $\sigma^2$ . In this situation, it is possible to show that:

$$E[\bar{X}] = E\left[\frac{1}{N} \sum_{i=1}^N x_i\right] = \mu$$

and:

$$E[s^2] = E\left[\frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{X})^2\right] = \sigma^2$$

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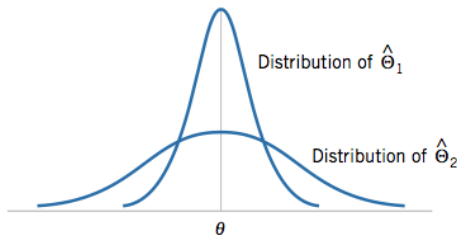
See this link for an example proof:

<http://isites.harvard.edu/fs/docs/icb.topic515975.files/Proof%20that%20Sample%20Variance%20is%20Unbiased.pdf>



## Evaluating Estimators (2)

There usually exists more than one unbiased estimator for a parameter  $\theta$ . One way to choose which to use is to select the one with the smallest variance. This is generally called the *minimal-variance unbiased estimator* (MVUE).



MVUE have the ability of generating estimates  $\hat{\theta}$  that are relatively close to the real value.

# Distribution of samples

Even for an arbitrary population, the sampling distribution of means tends to be approximately normal (with  $E[\bar{x}] = \mu$  and  $s_{\bar{x}} = \sigma^2/N$ )

## Warning! Maths!

More generally, let  $x_1, \dots, x_n$  be a sequence of independent and identically distributed (iid) random variables, with mean  $\mu$  and finite variance  $\sigma^2$ . Then:

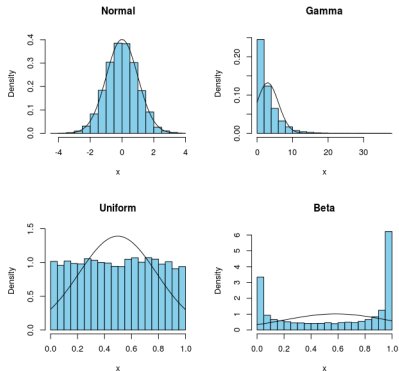
$$z_n = \frac{\sum_{i=1}^n (x_i) - n\mu}{\sqrt{n\sigma^2}}$$

is distributed approximately as a standard normal variable. That is,  $z_n \sim N(0, 1)$

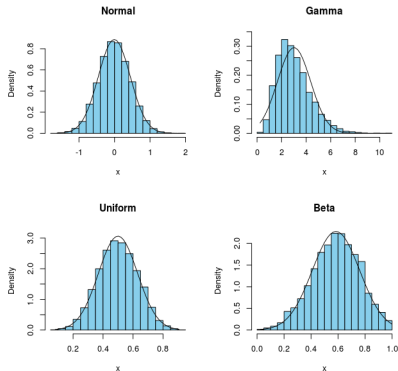
This is the **Central Limit Theorem**.

# Example of the Central Limit Theorem

sample size = 1



sample size = 5



```
# Load the Teaching Demos library if you don't have it.
```

```
> install.packages("TeachingDemos")
```

```
> library(TeachingDemos)
```

```
> clt.examp()
```

```
> clt.examp(5)
```

# Homework 2

- Pool of balls image: <http://goo.gl/y8doaN>
- Green ball: <http://goo.gl/Fb8z68>
- MVUE image: D.C.Montgomery, G.C. Runger, "Applied Statistics and Probability for Engineers", Wiley 2003

This lecture notes is a derived work of

Felipe Campelo (2015), "Lecture Notes on Design and Analysis of Experiments"

Online: [https:](https://github.com/fcampelo/Design-and-Analysis-of-Experiments)

[//github.com/fcampelo/Design-and-Analysis-of-Experiments](https://github.com/fcampelo/Design-and-Analysis-of-Experiments)

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