STAT 518 --- Section 2.1: Basic Inference

Basic Definitions

<u>Population</u>: The collection of all the individuals of interest.

• This collection may be _____ or even _____.

Sample: A collection of elements of the population.

• Suppose our population consists of a finite number (say, *N*) of elements.

<u>Random Sample</u>: A sample of size *n* from a finite population such that each of the possible samples of size *n* was

Another definition:

<u>Random Sample</u>: A sample of size *n* forming a sequence of

• Note these definitions are equivalent only if the elements are drawn ______ from the population.

• If the population size is very large, whether the sampling was done <u>with</u> or <u>without</u> replacement makes little practical difference.

Multivariate Data

• Sometimes each individual may have <u>more than one</u> variable measured on it.

• Each observation is then a <u>multivariate</u> random variable (or ______)

Example: If the weight and height of a sample of 8 people are measured, our <u>multivariate</u> data are:

• If the sample is random, then the components Y_{i1} and Y_{i2} might not be independent, but the vectors $X_1, X_2, ..., X_8$ will still be independent and identically distributed.

• That is, knowledge of the value of \underline{X}_1 , say, does not alter the probability distribution of \underline{X}_2 .

Measurement Scales

• If a variable simply places an individual into one of several (unordered) categories, the variable is measured on a ______ scale.

Examples:

• If the variable is categorical but the categories have a meaningful ordering, the variable is on the _____ scale.

Examples:

• If the variable is numerical and the value of zero is arbitrary rather than meaningful, then the variable is on the ______ scale.

Examples:

• For <u>interval</u> data, the interval (difference) between two values is meaningful, but <u>ratios</u> between two values are not meaningful.

• If the variable is numerical and there is a meaningful zero, the variable is on the _____ scale.

Examples:

• With <u>ratio</u> measurements, the ratio between two values has meaning.

Weaker ←-----→ Stronger

• Most classical parametric methods require the scale of measurement of the data to be interval (or stronger).

• Some nonparametric methods require ordinal (or stronger) data; others can work for data on any scale.

• A <u>parameter</u> is a characteristic of a population.

Examples:

• Typically a parameter cannot be calculated from sample data.

• A <u>statistic</u> is a function of random variables.

• Given the data, we can calculate the value of a statistic.

Examples of statistics:

Order Statistics

• The *k*-th order statistic for a sample $X_1, X_2, ..., X_n$ is denoted $X^{(k)}$ and is the *k*-th smallest value in the sample.

• The values $X^{(1)} \le X^{(2)} \le ... \le X^{(n)}$ are called the <u>ordered</u> <u>random sample</u>.

Example: If our sample is: 14, 7, 9, 2, 16, 18 then $X^{(3)} =$

Section 2.2: Estimation

• Often we use a statistic to <u>estimate</u> some aspect of a population of interest.

• A statistic used to estimate is called an estimator.

Familiar Examples:

• The sample mean:

• The sample variance:

• The sample standard deviation:

• These are point estimates (single numbers).

• An interval estimate (confidence interval) is an interval of numbers that is designed to contain the parameter value.

• A 95% confidence interval is constructed via a formula that has 0.95 probability (over repeated samples) of containing the true parameter value.

Familiar large-sample formula for CI for µ:

Some Less Familiar Estimators

• The cumulative distribution function (c.d.f.) of a random variable is denoted by **F**(*x*):

$$\mathbf{F}(x) = \mathbf{P}(X \le x)$$

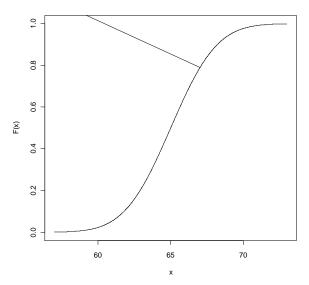
• This is $\int_{-\infty}^{x} f(t)dt$ when X is a continuous r.v.

Example: If X is a normal variable with mean 100, its c.d.f. F(x) should look like:

• Sometimes we do not know the distribution of our variable of interest.

• The empirical distribution function (e.d.f.) is an estimator of the true c.d.f. – it can be calculated from the sample data.

Example: Suppose heights of adult females have normal distribution with mean 65 inches and standard deviation 2.5 inches. The c.d.f. of this distribution is:



• Now suppose we do NOT know the true height distribution. We randomly sample 5 females and measure their heights as: 69.3, 66.3, 62.6, 62.9, 67.4

e.d.f.:

• The <u>survival function</u> is defined as 1 - F(x), which is the probability that the random variable takes a value greater than *x*.

• This is useful in reliability/survival analysis, when it is the probability of the item surviving past time *x*.

• The Kaplan-Meier estimator (p. 89-91) is a way to estimate the survival function when the survival time is observed for only some of the data values.

The Bootstrap

• The nonparametric bootstrap is a method of estimating characteristics (like expected values and standard errors) of summary statistics.

• This is especially useful when the true population distribution is unknown.

• The nonparametric bootstrap is based on the e.d.f. rather than the true (and perhaps unknown) c.d.f.

<u>Method</u>: Resample data (randomly select *n* values from the original sample, with replacement) *m* times.

• These "bootstrap samples" together mimic the population.

• For each of the *m* bootstrap samples, calculate the statistic of interest.

• These *m* values will approximate the sampling distribution.

• From these bootstrap samples, we can estimate the:

- (1) expected value of the statistic
- (2) standard error of the statistic
- (3) confidence interval of a corresponding parameter

Example: We wish to estimate the 85th percentile of the population of BMI measurements of SC high schoolers.

• We take a random sample of 20 SC high school students and measure their BMI.

• See code on course web page for bootstrap computations: