## STAT 703/J703 April 7<sup>th</sup>, 2005 *-Lecture 24-*

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The empirical distribution function (or empirical cumulative distribution function) is defined as:

 $F_n(x) = \frac{1}{n} \{ \# x_i \leq x \}$ 

Notes:

- $\sup_{x} |F_{n}(x) \to F(x)| \to 0$  as  $n \to \infty$
- For each x, F<sub>n</sub>(x) is binomial with mean F(x) and variance (F(x)(1- F(x))/n

Nonparametric Bootstrap

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We previously examined the parametric bootstrap for the case when we assumed the data came from some distribution  $F(\theta)$  with unknown parameter  $\theta$ .

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Estimating  $\theta$ , we then generated "bootstrap samples" from the distribution  $F(\hat{\theta})$ . The statistic  $\hat{\theta}^*$ is then calculated for each sample.

We then use the analogy that the sampling distribution of  $\hat{\theta}$  is to  $\theta$  sampling distribution of  $\hat{\theta}^*$  is to  $\hat{\theta}$ .

The nonparametric bootstrap uses the same basic analogy... except that we don't have a specific distribution in mind for *F*.

Because of this we the parameter  $\theta$  that we are focusing on is usually something like the mean, variance, or median that is "universally defined."

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Example: Estimate the variance and<br/>bias of the sample standard<br/>deviation s for the sample:3.953.793.752.715.526.121.746.053.925.69Generated using x<-10\*rbeta(10,3,4)<br/>so the population has mean<br/>30/7≈4.29 and variance<br/>150/49 ≈3.06 (sd ≈ 1.75).







When can it have trouble?
Small sample sizes (but doesn't everything?)
Statistic is not smooth

Section 10.2,2: Survival Functions Let T=the survival time S(t)=P(T>t)=1-F(t)

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For next time... Recall the Law of Total Probability: Let  $B_1, B_2, ..., B_n$  be disjoint and exhaustive so that  $\cup_{i=1 \text{ to } n} B_i = \Omega$ ,  $B_i \cap B_j = \phi$  for  $i \neq j$ . Then for any A,  $P(A) = P(A|B_1) P(B_1) + P(A|B_2) P(B_2) + \dots + P(A|B_n) P(B_n)$ . STAT 703/703 Billabing Univ. of SC

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Bayes' Rule: Let  $B_1, ..., B_n$  be disjoint and exhaustive  $(\cup B_i = \Omega)$ . Let A be any event. For any j=1, ..., n  $P(B_j|A) = \underbrace{P(A|B_i) P(B_j)}_{P(A|B_1) P(B_1) + ... + P(A|B_n) P(B_n)}$