EKT-816 Lecture 2

Probability Review (2)

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Desirable Properties of Estimators

- *consistency*: $\widehat{\theta} \longrightarrow_p \theta_0$
- if $E[\widehat{\theta}] = \theta_0$ we say $\widehat{\theta}$ is *unbiased*
- *efficiency* or *precision*: say we have two estimators $\widehat{\theta}$ and $\widetilde{\theta}$
  - for now assume both are unbiased
  - if $V[\widehat{\theta}] \leq V[\widetilde{\theta}]$, say that $\widehat{\theta}$ is *more efficient* than $\widetilde{\theta}$
- the *mean square error* of $\widehat{\theta}$ is $\text{MSE}(\widehat{\theta}) = E[(\widehat{\theta} - \theta_0)^2]$
  - easy to see that $\text{MSE} = V[\widehat{\theta}] + \text{bias}^2$
  - often a trade-off between the two criteria
  - typically people seek unbiased estimators, but not always clear they are better in a MSE sense

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Sufficient Statistics

- suppose there is a statistic $T(X_1, \ldots X_n)$ such that the joint density factors as

$$f(X_1, \ldots X_n, \theta) = g(T(X_1, \ldots X_n), \theta) \cdot h(X_1, \ldots X_n)$$

  - e.g. $T = \sum_{i=1}^{n} X_i$ for normal data with known variance
- then, a maximum likelihood estimator must be a function of T
- in fact, the *Rao-Blackwell Theorem* says (roughly) that any unbiased estimator which is *not* a function of the sufficient statistic has higher variance than "necessary"
  - more precisely, higher variance than the MLE, which hits the (Cramer-Rao) lower bound
  - intuition: if you base estimates on irrelevant information, you are sacrificing precision

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- we will not use an explicit likelihood framework much
    - but, the idea of "sufficiency" is still useful
    - in some situations, all of the relevant information can be reduced to some low-dimensional summaries
    - see Chetty (2009) and Weyl (2019) for examples of how this idea connects theory and econometrics
- this idea also comes up in the guise of "selection (only) on observables"

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Example: Sufficiency and Comparison of Estimators

- say we have an iid sample of size n from a $U(0, \theta_0)$ distribution
  - the sample maximum is, in this case, sufficient for θ_0
  - in fact, can show the MLE is $\widehat{\theta} = \max\{X_1, \dots X_n\}$
- another estimator would be $\widetilde{\theta} = 2\overline{X}_n$
  - this is unbiased (show this!)
- which estimator has lower MSE? Which has lower variance?
- to derive the distribution of the sample maximum:
  - use the fact that $\max\{X_1, \dots X_n\} \leq x$ if and only if each $X_i \leq x$
  - by independence, the CDF of the sample maximum is the product of the individual CDFs

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Sample Design

- some types of data you may encounter:
  - cross-sectional:
    - units from the population are surveyed once, and all at roughly the same time.
    - a "snapshot" of the population
  - stratified or two-stage designs
    - units are sampled randomly within certain pre-specified groups
    - e.g region, race, sex
  - clustered designs
    - often would be expensive to collect a simple random sample
    - save on transport and labor costs by selecting clusters of units
    - attempt to correct for the resulting correlations (why?)
  - panel or longitudinal designs: repeated observations on the same units
    - rotating panels, where some units are "rotated" in and out of the survey
    - retrospective histories
    - synthetic panels: aggregate individuals to form a panel at cohort level

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- some types of data you may encounter:
  - cross-sectional:
    - units from the population are surveyed once, and all at roughly the same time.
    - a "snapshot" of the population
  - stratified or two-stage designs
    - units are sampled randomly within certain pre-specified groups
    - e.g region, race, sex
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  - differential attrition can be a serious problem
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Weighting

- suppose we have a population of N units, and we sample with unequal probabilities
  - let π_i be the probability that unit i is selected
  - in a simple random sample of size $n << N$, $\pi_i \approx n/N$, even if we sample without replacement
  - but we don't always want to sample each unit with equal probability
- let $w_i = (n\pi_i)^{-1}$ be the "design weight"; then the expected sum of the weights is

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\begin{aligned}
E\left[\sum_{i=1}^{n} w_i\right] &= E\left[\sum_{i=1}^{N} t_i w_i\right] \\
&\approx \sum_{i=1}^{N} (\pi_i n) w_i = N \qquad (1)
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Weighting

- intuition: weights are inversely proportional to the probabilities of inclusion
  - in a 1/100 sample, each included unit represents 100 others
- to estimate the population mean, we weight the observations by w_i, forming

$$\overline{x}_w = \sum_{i=1}^{n} w_i x_i \qquad (2)$$

  - exercise: show that $E[\overline{x}_w] = E[X]$
- we may want to deliberately oversample some groups to improve precision of conditional means
  - e.g. white or Indian South Africans
  - this would be true even if response rates were the same across ethnic groups!

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Stratification

- to understand why stratification is useful, think about trying to measure the national average of some X where there are two cities
- variance of a randomly sampled unit is

$$V[X_i] = p\sigma_1^2 + (1-p)\sigma_2^2 + p(\mu_1 - \mu)^2 + (1-p)(\mu_2 - \mu)^2$$

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- consider a stratified design where we take two independent samples from the two strata
  - size n_1 and n_2 respectively, with $n_1 + n_2 = n$
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- say we choose $n_1/n = p$ and $n_2/n = 1 - p$
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$$V[\overline{x}^{STRAT}] = n^{-1}\{p\sigma_1^2 + (1-p)\sigma_2^2\} < n^{-1}V[X]$$

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Clustering

- suppose we have several clusters, indexed by c
- the distribution of the variable of interest, X, obeys the following:

$$x_{ic} = \mu + \alpha_c + \varepsilon_{ic} \tag{4}$$

  - here α and ε are independent of each other, and both have mean zero
  - let σ_α^2 be the variance of the cluster-specific mean
  - σ_ε^2 be the variance of the idiosyncratic error term ε_{ic}
- the mean of sample from k clusters, with m units per cluster, has variance

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  - $\rho = \sigma_\alpha^2/\sigma^2$ is the intercluster correlation coefficient
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- the mean of sample from k clusters, with m units per cluster, has variance

$$V[\overline{x}^{CLUST}] = \frac{\sigma^2}{km}\{(m-1)\rho + 1\} \tag{5}$$

  - here $\sigma^2 = \sigma_\alpha^2 + \sigma_\varepsilon^2$ is the overall variance of X
  - $\rho = \sigma_\alpha^2/\sigma^2$ is the intercluster correlation coefficient
- positive correlations within a cluster reduce the precision of your estimates
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Clustering

- suppose we have several clusters, indexed by c
- the distribution of the variable of interest, X, obeys the following:

$$x_{ic} = \mu + \alpha_c + \varepsilon_{ic} \tag{4}$$

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Hypothesis Testing

- a *hypothesis* is a subset of the parameter space
  - if this is a single point, we say the hypothesis is *simple*
  - e.g. $H_0 : \mu = 1$
  - otherwise, we say the hypothesis is *complex* or *compound*
  - e.g. $H_1 : \mu \neq 1$
- we often designate one particular hypothesis as the "null hypothesis"
  - then, see if the data provides strong enough evidence against it
- the frequentist approach to hypothesis testing takes parameters as fixed and the data as random
  - thus $P(\mu = 1|X)$ makes no sense, but $P(X|\mu = 1)$ does
  - the Bayesian approach is more intuitive here, but econometrics is overwhelmingly frequentist

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- to perform a *test* of the null hypothesis we form a *test statistic*, say $\widehat{S}(X_1, \dots X_n)$
  - not always the estimator itself, e.g. the t-test
  - then, we need to compute (at least approximately) the distribution of $\widehat{S}$ under the null
- suppose we know the distribution of $\widehat{S}$ under H_0
  - now, we can set a *rejection region* R such that $P(\widehat{S} \in R | H_0)$ is "small"
  - given a rejection region R,

$$\alpha = \max_{\theta \in H_0} P(\text{reject } H_0 | \theta)$$

    is called the *size* of the test, or the *significance level*
  - we take the maximum over H_0 (in case H_0 is a compound hypothesis) to be conservative
- the number

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- consider some extreme cases:
  - could ignore the data and never reject: then you never make Type I errors
  - similarly could always reject: never make Type II errors
- in general there is a tradeoff between size and power
- how well you can do, and how severe the tradeoff is, depends on the problem
  - in some "ill-posed" problems, you cannot beat the trivial test
  - i.e. ignore the data, generate a random number $U \sim U(0,1)$ and reject if $U < \alpha$
  - these pathologies often arise when there are "nuisance parameters"
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References

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