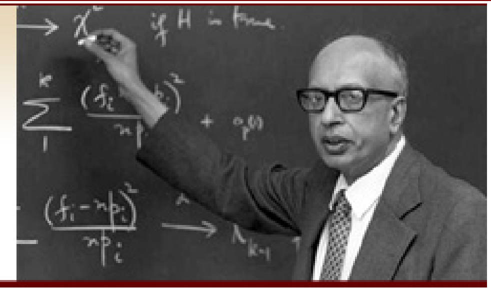
BAHADUR
MEMORIAL LECTURES

In honor of Raj Bahadur's fundamental contributions to statistics and to our department.



The University of Chicago, Department of Statistics, presents the

Eighteenth Annual Bahadur Memorial Lectures

Xiao-Li Meng

Whipple V. N. Jones Professor of Statistics

Department of Statistics, Harvard University

Wednesday, April 19, 2017

3:30 PM, Stevanovich Center, MS 112, 5727 S. University Avenue

Joint lecture with the Department of Public Health Sciences

Reception following lecture in Stevanovich Center, MS 112

"There is Individualized Treatment. Why Not Individualized Inference?"

Doctors, perhaps implicitly, predict a treatment's efficacy for a particular patient from its performance on reasonably matched "control" individuals, e.g., a subpopulation of a clinical trial. Similarly, to identify the best statistical procedure for a given problem, we simulate a set of relevant control problems and then evaluate candidate procedures on these controls. The central issue—for both individualized medicine and individualized inference—is how to make the right relevance-robustness trade-off. If we exercise too much judgment in determining which controls are relevant, the extreme of which being the fully Bayesian approach, our inferences may not be robust (e.g., to prior misspecification). But if we include too many controls to ensure robustness, the extreme of which being the unconditional frequentist approach, then our inferences may not be relevant to the particular problem at hand, just as a treatment that works for 90% of a population may not work at all for particular individuals. We use Basu's classic example where no maximal ancillary is present to illustrate that the controversial Fiducial approach is a reasonable strategy for striking a compromise between the two aforementioned extremes, though the search for an optimal compromise is still the Holy Grail of statistical inference.

Thursday, April 20, 2017

3:30 PM, Stevanovich Center, MS 112, 5727 S. University Avenue

"From Eckhart Hall to (almost) White House: An Unexpected Statistical Journey (Or: How small are my big data?)"

The phrase "Big Data" has greatly raised expectations of what we can learn about ourselves and the world in which we live or will live. It also appears to have boosted general trust in empirical findings, because it seems to be common sense that the more data, the more reliable are our results. Unfortunately, this commonsense conception can be falsified mathematically even for methods such as the time-honored ordinary least squares regressions (Meng and Xie, 2014). Furthermore, whereas the size of data is a common indicator of the amount of information, what matters far more is the quality of data. A largely overlooked statistical "Euler's Identity," which I learned during my first year of teaching in Eckhart Hall, reveals that trading quantity for quality in statistical estimation is a mathematically demonstrably doomed game (Meng, 2017). Without taking into account the data quality, Big Data can do more harm than good because of the drastically inflated precision assessment, and hence the gross overconfidence, which at a minimum can seriously surprise us when reality unfolds, as illustrated by the 2016 US election.