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The only unifying theme among the six papers in the session is methodology for inference. The papers deal with different types of inference and different types of data. With such variety, it is not possible to adequately review the content of all the papers. Even so, the authors should be commended for their efforts in trying to tackle problems that face the practitioner.

Two papers deal with regression estimators. The first of these by Lee defines several polynomial regression models and develops criteria for determining where, in the universe of data points, each model be would the best among the models considered. The concept is suggestive of that for spline functions, although spline functions are never mentioned. The paper presents the theory behind each model. However, it is not clear that the results accommodate data for other than simple random samples, which are rare in practice.

Chhikara, McKeon, and Bouillion empirically illustrate the small sample behavior of three regression estimators and their asymptotic variance estimators. They show that for samples of size 10 or less, the "classic" regression estimator is not always best and that better variance estimators are needed for the variances of the regression estimators. The authors could investigate estimators of the variances to determine which would be adequate with their small samples. They could also determine the minimum sample sizes required for the asymptotic variances to be adequate.

The next three papers are about tests for goodness of fit or independence. It is pleasing that all three assume cluster sampling and two assume variation in design effects across population subgroups. These situations exist in practice, since clustering frequently cuts survey costs and subgroups targeted in surveys are frequently clustered differently in the population.

In the first of these three papers, Thomas and Rao compare the power of four alternative tests using Monte Carlo techniques with varying numbers of clusters, numbers of population subgroups, and alternative hypotheses. They, however, assume constant cluster sizes and probabilities of selection. In the future, the authors could confirm whether the their findings will still hold when cluster sizes and probabilities vary.

Wilson and Warde present a technique for testing independence in the presence of clustering that occurs in capture-recapture type samples and discuss its properties relative to those of Pearson and Wald statistics. In particular they alter the estimates entered into the contingency table from which test statistics are constructed. While they apply the technique to samples of animals which move from one sample site to another, it would also be interesting to see it applied to sample data from household surveys where a person may be reported by more than one household, for example cancer victims could be reported by siblings.

Wilson, in his test of independence in cluster samples, applies cell design effects to each cell independently instead of as an overall adjustment, which is done in other test statistics. The author could extend his work by determining when the proposed statistic would be preferable to other statistics.

The Meyer paper deals with the estimation of confidence intervals for quantile (percentile) statistics based on samples from multinomial populations. The results are limited in that simple random or systematic samples are assumed. The author should consider extending his work to quantile statistics based on data from stratified cluster samples.