the Bayes predictor is also the BLUP. The HB predictor, typically with no closed-form, is obtained by integrating the above Bayes predictor with respect to the posterior distribution of the hyperparameters. Instead of assigning priors to the hyperparameters, if one estimates them from the marginal distribution of the data and replaces the variance components by their estimates in the Bayes predictor of γ_i, the result is the EB predictor. In fact, the EB predictor is identical to the EBLUP of γ_i. The HB predictor and associated measure of uncertainty given by the posterior variance can be computed by numerical integration or *Gibbs sampling*.

While the EBLUP is applicable to mixed linear models, the HB and the EB approaches can be applied even to generalized linear models, thereby making a unified analysis of both discrete and continuous data feasible.

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See also Composite Estimation; Parameter

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Snowball Sampling

Snowball sampling is a technique that can be applied in two survey contexts. The first context involves surveying members of a rare population. The second involves studying mutual relationships among population members. In both cases, respondents are expected to know about the identity of other members of the same population group.

Studying Rare Populations

In this context, snowball sampling is a nonprobability sampling technique. The general objective is to identify members of the rare population. It involves identifying one or more members of a rare population and asking them to name other members of the same population. These additional persons are then contacted and asked to name additional persons in the rare population; and so forth. The process continues until an adequate sample size has been obtained or until no new names are elicited from the process.

If terminated when adequate sample size is obtained, the method yields a sample, but not a probability sample.

If the population can be restricted in some way, say to a limited geographic area such as a county, snowball sampling may be successful as a rare population frame-building technique. To be successful, several rounds of the process must be conducted, and the initial sample should be large and adequately distributed among the rare population members. Within this restricted population, the identified rare population members can then be sampled using probability sampling techniques, or a complete enumeration (census) may be conducted. If the limited geographic areas are first-stage units in a multi-stage probability sample design, the approach can yield an estimate for a larger target population.

If some members of the targeted rare population are isolated from the remainder of the population, they are not likely to be named even after several rounds of enumeration. Serious coverage problems may remain even if the process is carried out diligently.

Studying Relationships

In the early 1960s, sociologist Leo Goodman proposed a probability sample–based method for studying relationships among individuals in a population. An initial zero-stage (Stage 0) probability sample is drawn. Each person in the sample is asked to name k persons with some particular relationship; example relationships are best friends, most frequent business associate, persons with most valued opinions, and so on. At Stage 1 these k persons are contacted and asked to name k persons with the same relationship. The Stage 2 sample consists of new persons named at Stage 1, that is, persons not in the original sample. At each subsequent stage, only newly identified persons are sampled at the next stage. The process may be continued for any number of stages, designated by s.

The simplest relationships involve two persons where each names the other. If the initial sample is a probability sample, an unbiased estimate of the number of pairs in the population that would name each other can be obtained. More complex relationships such as "closed rings" can be studied with more stages of sampling. For example, person A identifies person B; person B identifies person C; and person C identifies person A.

If the initial sample is drawn using binomial sampling so that each person has probability p of being in the sample and $s = k = 1$, an unbiased estimate of the number of mutual relationships in the population designated by M_{11} is

$$\hat{M}_{11} = \frac{y}{2p},$$

where y is the number of persons in the Stage 0 sample who named a person who also names them when questioned either in the initial sample or in Stage 1.

The theory for estimating the population size for various types of interpersonal relationships has been, or can be, developed assuming binomial sampling and may apply, at least approximately, when using other initial sample designs more commonly applied in practice, for example, simple random sampling (without replacement).

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See also Coverage Error; Multi-Stage Sample; Nonprobability Sampling; Probability Sample; Rare Populations; Respondent-Driven Sampling (RDS); Sampling Frame; Sampling Without Replacement

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Social Capital

Building on the work of sociologist James Coleman, political scientist Robert Putnam popularized the term *social capital* to describe how basic features of civic life, such as trust in others and membership in groups, provides the basis for people to engage in collective action. Even though social capital is not explicitly political, it structures various types of activities that are essential to maintaining civil and democratic institutions. Thus, *social capital* is defined as the resources of information, norms, and social relations embedded in communities that enable people to coordinate collective action and to achieve common goals.

It is important to recognize that social capital involves both psychological (e.g., trusting attitudes) and sociological (e.g., group membership) factors and, as such, is a multi-level construct. At the macro level, it is manifested in terms of connections between local organizations, both public and private. At the meso level, it is observed in the sets of interpersonal networks of social affiliation and communication in which individuals are embedded. And at the micro level, it can be seen in the individual characteristics that make citizens more likely to participate in community life, such as norms of reciprocity and feelings of trust in fellow citizens and social institutions.

Research on social capital, despite its multi-level conception, has focused on the micro level with individuals as the unit of analysis, typically using cross-sectional surveys to measure citizens' motivation, attitudes, resources, and knowledge that contribute to the observable manifestation of social capital: civic participation. The meso-network level is represented through individuals' reports of their egocentric networks in terms of size and heterogeneity as well as frequency of communication within these networks. Examinations of individuals' connections to community institutions