Estimating quantiles

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The *p*th quantile is defined as the value where the estimated cumulative distribution function is equal to *p*. As with quantiles in unweighted data, this definition only pins down the quantile to an interval between two observations, and a rule is needed to interpolate. As the help for the base R function **quantile** explains, even before considering sampling weights there are many possible rules.

Rules in the svyquantile() function can be divided into three classes

- Discrete rules, following types 1 to 3 in quantile
- Continuous rules, following types 4 to 9 in quantile
- A rule proposed by Shah & Vaish (2006) and used in some versions of SUDAAN

Discrete rules

These are based on the discrete empirical CDF that puts weight proportional to the weight w_k on values x_k .

$$\hat{F}(x) = \frac{\sum_{i} \{x_i \le x\} w_i}{\sum_{i} w_i}$$

The mathematical inverse The mathematical inverse $\hat{F}^{-1}(p)$ of the CDF is the smallest x such that $F(x) \ge p$. This is rule hf1 and math and in equally-weighted data gives the same answer as type=1 in quantile

The primary-school median The school definition of the median for an even number of observations is the average of the middle two observations. We extend this to say that the *p*th quantile is $q_{\text{low}} = \hat{F}^{-1}(p)$ if $\hat{F}(q_{\text{low}}) = p$ and otherwise is the the average of $\hat{F}^{-1}(p)$ and the next higher observation. This is school and hf2 and is the same as type=2 in quantile.

Nearest even order statistic The *p*th quantile is whichever of $\hat{F}^{-1}(p)$ and the next higher observation is at an even-numbered position when the distinct data values are sorted. This is hf3 and is the same as type=3 in quantile.

Continuous rules

These construct the empirical CDF as a piecewise-linear function and read off the quantile. They differ in the choice of points to interpolate. Hyndman & Fan describe these as interpolating the points (p_k, x_k) where p_k is defined in terms of k and n. For weighted use they have been redefined in terms of the cumulative weights $C_k = \sum_{i \leq k} w_i$, the total weight $C_n = \sum w_i$, and the weight w_k on the kth observation.

qrule	Hyndman & Fan	Weighted
hf4	$p_k = k/n$	$p_k = C_k / C_n$
hf5	$p_k = (k - 0.5)/n$	$p_k = (C_k - w_k)/C_n$
hf6	$p_k = k/(n+1)$	$p_k = C_k / (C_n + w_n)$
hf7	$p_k = (k-1)/(n-1)$	$p_k = C_{k-1}/C_{n-1}$
hf8	$p_k = (k - 1/3)/(n + 2/3)$	$p_k = (C_k - w_k/3)/(C_n + w_n/3)$
hf9	$p_k = (k - 3/8)/(n + 1/4)$	$p_k = (C_k - 3w_k./8)/(C_n + w_n/4)$

Shah & Vaish

This rule is related to hf6, but it is discrete and more complicated. First, define $w_i^* = w_i n/C_n$, so that w_i^* sum to the sample size rather than the population size, and C^*k as partial sums of w_k^* . Now define the estimated CDF by

$$\hat{F}(x_k) = \frac{1}{n+1} \left(C_k^* + 1/2 - w_k/2 \right)$$

and take $\hat{F}^{-1}(p)$ as the *p*th quantile.

Other options

It would be possible to redefine all the continuous estimators in terms of w^* , so that type 8, for example, would use

$$p_k = (C_k^* - 1/3)/(C_n^* + 2/3)$$

Or a compromise, eg using w_k^* in the numerator and numbers in the denominator, such as

$$p_k = (C_k^* - w_k^*/3)/(C_n^* + 2/3).$$

Comparing these would be a worthwhile \ldots an interesting \ldots a research question for simulation.