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Model-assisted Variance Estimator for the GREG Estimator

Praful A. Patel

Department of Statistics, Sardar Patel University Vallabh Vidhyanagar-388120, Gujarat, India.

E-mail: patelpraful_a@yahoo.co.in

Abstract

This paper describes a model-based estimation procedure for the variance of the generalized regression (GREG) estimator for the finite population totals. Two model-based estimators for the design variance of the GREG estimator are proposed. A simulation study is conducted to study the bias and efficiency of both estimators.

Keywords: GREG estimator, Model-based inference, Variance estimation.

1. Introduction

Let U be a finite population of size N. Let $s \subset U$ be a sample of size n drawn according to a known probability sampling design $p(s)$ (non-informative) with positive first and second order inclusion probabilities π_i and π_{ij}. Let (y_i, x_i) be pair of values associated with each unit $i \in U$. Suppose that the values $y_i,\ i \in s$, and $x_i,\ i \in U$, are known. The problem is how to use this information to make inference about the finite population total $Y = \sum_U y_i$. If $A \subseteq U$, we write $\sum_A$ for $\sum_{i \in A}$ and $\sum\sum_A$ for $\sum\sum_{i \neq j \in A}$. The customary design-based unbiased estimator of Y which makes no use of auxiliary information at the estimation stage is the Horvitz-Thompson [8] (HT) estimator

$$\hat{Y}_{HT} = \sum_s y_i/\pi_i \tag{1}$$

with variance

$$V_{HT} = V_{HT}(\hat{Y}_{HT}) = \sum_U \Delta_{ii} y_i^2 + \sum\sum_U \Delta_{ij} y_i y_j, \tag{2}$$

for which an unbiased estimator is given by

$$\hat{V}_{HT}(\hat{Y}_{HT}) = \sum_s \frac{\Delta_{ii}}{\pi_i} y_i^2 + \sum\sum_s \frac{\Delta_{ij}}{\pi_{ij}} y_i y_j \tag{3}$$

where $\Delta_{ij} = \pi_i^{-1} - 1$ if $i = j$ and $= \pi_{ij}\pi_i^{-1}\pi_j^{-1} - 1$ if $i \neq j$.

If n is fixed, (2) may be expressed in the form

$$V_{YG}(\hat{Y}_{HT}) = \sum\sum_{i<j \in U} \Lambda_{ij} \left(\frac{y_i}{\pi_i} - \frac{y_j}{\pi_j}\right)^2 \tag{4}$$

(see [20], [24]) for which an unbiased estimator is given by

$$\hat{V}_{YG}(\hat{Y}_{HT}) = \sum\sum_{i<j\in s} \frac{\Lambda_{ij}}{\pi_{ij}}\left(\frac{y_i}{\pi_i} - \frac{y_j}{\pi_j}\right)^2 \quad (5)$$

where $\Lambda_{ij} = \pi_i\pi_j - \pi_{ij}$, $i \neq j \in U$. This restriction eliminated this variance estimator from consideration for many applications (See, [22]).

In survey sampling, auxiliary information about the finite population is often available at the estimation stage. Utilizing this information more efficient estimators may be obtained. There exist several approaches, such as model-based, calibration, etc., each of which provides a practical approach to incorporate auxiliary information at the estimation stage (e.g. ratio and regression estimators).

Recently, more attention has been given to the design-consistent generalized regression (GREG) estimator [2] of a finite population total. One of the reasons is that most of estimators of the total belong to the class of the GREG estimators. Some other reasons are discussed in [17]. Latter on, it was obtained as a model-assisted estimator (see, [19]). Deville and Särndal [4] proposed a general method of deriving calibration estimators $\hat{Y} = \sum_s w_i y_i$ by minimizing a distance measure $\sum_s c_i(w_i - a_i)^2/a_i$ subject to the calibration constraint $\sum_s w_i x_i = X$, where $a_i = \pi_i^{-1}$ are the basic weights and $c_i{}'s$ are constants. They have also shown that a chi-square distance leads to the GREG estimator. There are a number of ways to construct a regression estimator of the population total (see, e.g., [6]). See [19] for more thorough coverage of the GREG estimator.

A GREG estimator of Y, using a single auxiliary variable x, is given by

$$\hat{Y}_{GREG} = \hat{Y}_{HT} + \hat{\beta}(X - \hat{X}_{HT}) \quad (6)$$

where $\hat{X}_{HT}$ is the HT estimator of an auxiliary variable x and $\hat{\beta} = \left(\sum_s x_i^2/\eta_i\pi_i\right)^{-1}\left(\sum_s x_i y_i/\eta_i\pi_i\right)$ is a consistent regression estimator of $\beta_U = \left(\sum_U x_i^2/\eta_i\right)^{-1}\left(\sum_U x_i y_i/\eta_i\right)$, the weighted least squares population regression estimator of β for the superpopulation model

$$E_\xi(Y_i) = \beta x_i, \quad V_\xi(Y_i) = \sigma^2\eta_i \quad and \quad C_\xi(Y_i, Y_j) = 0 \text{ for } i \neq j \in U \quad (7)$$

where β and $\sigma^2 > 0$ are the parameters and η_i are known constants. Here E_ξ, V_ξ and C_ξ denote expected value, variance and covariance under the model, respectively.

The GREG- estimator, given in (6), can also be written as

$$\hat{Y}_{GREG} = \sum_s \frac{g_{is}y_i}{\pi_i} = \beta X + \sum_s \frac{g_{is}e_i}{\pi_i} \quad (8)$$

where $g_{is} = 1 + \left(\sum_s x_i^2/\eta_i\pi_i\right)^{-1}(X - \hat{X}_{HT})(x_i/\eta_i)$ and $e_i = y_i - \hat{\beta}x_i$, $i \in s$ are the sample fit residuals.

g_{is} converges in design probability to unity, under certain regularity conditions [15], [16] and [18]. As a consequence the GREG estimator can be approximated by βX plus the HT estimator of the sample residuals $e_i^{'}s$. Using (4) and (5), Särndal et al. [18] had suggested approximate variance and simple (ordinary) variance estimator as

$$V_{YG}\left(\hat{Y}_{GREG}\right) \approx \sum\sum_{i<j\in U} \Lambda_{ij} \left(\frac{E_i}{\pi_i} - \frac{E_j}{\pi_j}\right)^2 \tag{9}$$

$$v_s = \sum\sum_{i<j\in s} \frac{\Lambda_{ij}}{\pi_{ij}} \left(\frac{e_i}{\pi_i} - \frac{e_j}{\pi_j}\right)^2 \tag{10}$$

where $E_i = y_i - \beta_U x_i$, the population fit residuals.

Duchesne discussed a design-based jackknife variance estimation [5]. [9], [18] proposed different model-based variance estimators for the GREG estimator. Both are design consistent estimators under reasonable conditions. Särndal et al. [18] proposed the following g-weighted variance estimators for (9) and investigated their properties:

$$v_g = \sum\sum_{i<j\in s} \frac{\Lambda_{ij}}{\pi_{ij}} \left(\frac{g_{is} e_i}{\pi_i} - \frac{g_{js} e_j}{\pi_j}\right)^2 \tag{11}$$

This estimator is not exactly model-unbiased of model variance in most cases.

An alternative model variance estimator was proposed by Kott [9]. His point of departure is to create a variance estimator that is unbiased with respect to the model but is still design consistent. The objective is achieved by attaching a ratio adjustment to the estimator [10]. However, his variance estimator is some what more complicated than [10]. [3], following Kott suggested various model-assisted variance estimators. [21] proposed a high-level calibration approach for estimation of variance of the GREG estimator. But their estimators require additional auxiliary variable over and above the one used to define the inclusion probabilities.

The Yates-Grundy type variance estimators [10] and [11] are useful only for fixed-size designs and $\pi_i\pi_j - \pi_{ij} \neq 0$. Random-size designs sometimes have advantages from a survey operations viewpoint. The use of Bernoulli sampling reduces delays in data capture and provides relatively uniform workload to operations staff, as explained by [1]. Motivated by this we propose two variance estimators for the GREG estimator, which are general in that they apply for any sampling design. This article is organized as follows. In Section 2, we derive an optimal model-unbiased estimator of the HT variance, given in (2), based on a working model (7) with $V_\xi(Y_i) = \sigma^2 x_i^2$. Following the optimal estimator, derived in the previous section, we suggest two variance estimators for the GREG estimator. In Section 4 we present the results of a Monte Carlo comparison of the various estimators of the variance of the GREG estimator. Our conclusions will be presented in Section 5.

2. The Optimal Variance Estimator for the HT Estimator

To construct alternative design-based variance estimators of (2) that make efficient use of auxiliary information, we combine design-based and model-based approaches. For this we consider (7) as our working model where we assume that $Y_1, \ldots Y_N$ are exchangeable random variables with $V_\xi(Y_i) = \sigma^2 x_i^2$ $i.e., \eta_i = x_i^2$. We shall first focus on deriving the optimal (in the sense minimum $E_\xi E_p(v - V_{HT})^2$, $E_p(\cdot)$ denotes p (design)-expectation) predictor for the HT variance, given in (2), among a class of all quadratic p-unbiased predictors of V_{HT} under Model (7).

We must find v to minimize

$$E_\xi E_p(v - V_{HY})^2 = E_p\{V_\xi(v)\} + E_p\{B_\xi(v)\}^2$$

subject to $E_\xi E_p(v) = E_\xi(V_{HT})$, where $B_\xi(v) = E_\xi(v - V_{HT})$.

Under the working model, ξ-expectation of V_{HT} is readily found to be

$$E_\xi(V_{HT}) = (\sigma^2 + \beta^2)\sum_U \Delta_{ii} x_i^2 + \beta^2 \sum\sum_U \Delta_{ij} x_i x_j \quad (12)$$

where $\sigma^2 + \beta^2$ and β^2 are the parameters to be estimated. To obtain the best estimators of these parameters and consequently the optimal predictor of V_{HT} we shall use theory on one-sample U-statistics (see, e.g., [14]).

Note that $\sigma^2 + \beta^2$ and β^2 both are ξ-estimable of degree 2 with the kernels y_i^2/x_i^2 and $y_i y_j / x_i x_j$, respectively. Moreover y_i^2/x_i^2 and $[y_i y_j / x_i x_j + y_j y_i / x_j x_i]/2$ are symmetric kernels and so the U-statistic estimators of $\sigma^2 + \beta^2$ and β^2 are, respectively, given by $\sum_s y_i^2 / n x_i^2$ and $\sum\sum_s y_i y_j / n(n-1) x_i x_j$ which are ξ-unbiased and consequently $p\xi$-unbiased. Since $Y_i's$ are exchangeable variables, it follows that such U-statistics are the unique minimum ξ-variance ξ-unbiased predictors of $\sigma^2 + \beta^2$ and β^2. As ξ-unbiasedness implies $p\xi$-unbiasedness, the optimal $p\xi$-unbiased predictor of V_{HT}, after inserting $p\xi$-unbiased predictors of $\sigma^2 + \beta^2$ and β^2 in [12], is found to be

$$\hat{V}_{OPT}(\hat{Y}_{HT}) = \sum_s \frac{\Delta_{ii}}{\pi_{i0}} y_i^2 + \sum\sum_s \frac{\Delta_{ij}}{\pi_{ij\,0}} y_i y_j \quad (13)$$

where

$$\pi_{i0} = \frac{n\Delta_{ii} x_i^2}{\sum_U \Delta_{ii} x_i^2} \text{ and } \pi_{ij\,0} = \frac{n(n-1)\Delta_{ij} x_i x_j}{\sum\sum_U \Delta_{ij} x_i x_j}$$

These inclusion probabilities are not consistent since $\sum_{j(\neq i)\in U} \pi_{ij\,0} \neq (n-1)\pi_{i0}$. See, also, [13].

Remark 1. It is unlikely that a design is chosen solely for the purpose of optimum estimation of a variance function.

3. The Proposed Variance Estimators for the GREG Estimator

In this section we now extend the above result to the GREG estimator. Recall that the GREG estimator $\hat{Y}_{GREG} = \sum_s g_{is} y_i / \pi_i$ can be approximated, under mild restrictions, as βX plus the HT estimator of the sample residuals. Its variance is then approximated by the HT variance expression given at (2) just by replacing population values y_i by the population residuals E_i, i.e.

$$V_{HT}(\hat{Y}_{GREG}) \approx \sum_U \Delta_{ii} E_i^2 + \sum\sum_U \Delta_{ij} E_i E_j \quad (14)$$

The ordinary design-based estimator of (14) is given by

$$v_{HT}(\hat{Y}_{GREG}) = \sum_s \frac{\Delta_{ii}}{\pi_i} e_i^2 + \sum\sum_s \frac{\Delta_{ij}}{\pi_{ij}} e_i e_j \quad (15)$$

This estimator does not make any use of auxiliary information at the estimation stage.

3.1 The Optimal-type Variance Estimator

Imitating (13), we suggest the following optimal-type variance estimator for the GREG estimator:

$$v_{OPT} = \hat{V}_{OPT}\left(\hat{Y}_{GREG}\right) = \sum_s \frac{\Delta_{ii}}{\pi_{i0}} e_i^2 + \sum\sum_s \frac{\Delta_{ij}}{\pi_{ij\,0}} e_i e_j \tag{16}$$

where π_{i0} and $\pi_{ij\,0}$ are defined as above and the $e_i{}'s$ are sample residuals.

3.2 The Internally Adjusted Ratio-type Variance Estimator

There are two methods to make ratio adjustment to improve an estimator. The first method is an external ratio adjustment and second method is an internal ratio adjustment to the estimator. The idea is to multiply the estimator or each term of the estimator by a suitable ratio, constructed using an appropriate model, so that the resultant estimator becomes model unbiased and design-consistent.

Applying the second method to [15] we suggest the internally adjusted ratio-type (IAR) variance estimator

$$v_{IAR} = \frac{\sum_s \Delta_{ii} e_i^2/\pi_i}{\sum_s \Delta_{ii} x_i^2/\pi_i} \sum_U \Delta_{ii} x_i^2 + \frac{\sum\sum_s \Delta_{ij}\, e_i e_j/\pi_{ij}}{\sum\sum_s \Delta_{ij}\, x_i x_j/\pi_{ij}} \sum\sum_U \Delta_{ij}\, x_i x_j \tag{17}$$

Remark 2. Following [12], it is easy to verify that v_{IAR} is asymptotically design unbiased and asymptotically design-consistence.

Remark 3. The construction of v_{OPT} and v_{IAR} would suggest that these estimators perform well if the variance structure is strongly heteroscedastic so that the variance of the population scatter increases with x at least as strongly as $V_\xi(y_i) \propto x_i^2$.

Remark 4. The estimators v_{OPT} and v_{IAR} are general in the sense that these can be used for fixed-size or non-fixed-size design; πps or non- πps sampling design; designs having $\pi_{ij} = \pi_i \pi_j$ for all $i \neq j$ (e.g., Poisson sampling, Bernoulli sampling, Promix sampling), the case for which (10) and (11) can not be used as $\Delta_{ij} = \pi_i \pi_j - \pi_{ij} = 0$.

4. Simulation Study

A small scale simulation study was carried out in order to compare the finite sample performance of the estimators v_g, v_{OPT}, v_{IAR} and the conventional estimator v_s. For this study, we used the populations listed in Table 2 of Appendix A. We drew 5000 samples each of size *n* = 6 using Sunter sampling design [23] from each of the study populations. From each sample, we then calculated the estimates of $V_{HT}(\hat{Y}_{GREG})$.

Table 1 reports the relative biases (RBs) in percentage and relative efficiencies (REs) of the estimators, where for any estimator v we define the relative bias as

$$RB(v) = \frac{1}{V_{HT}\left(\hat{Y}_{GREG}\right)} \left[\frac{1}{5000} \sum_{r=1}^{5000} \left\{v^{(r)} - V_{HT}\left(\hat{Y}_{GREG}\right)\right\}\right] \times 100$$

and the relative efficiency of v as compared to the simple estimator v_s as

$$RE(v) = \sum_{r=1}^{5000} \left\{v_s^{(r)} - V_{HT}\left(\hat{Y}_{GREG}\right)\right\}^2 \Bigg/ \sum_{r=1}^{5000} \left\{v^{(r)} - V_{HT}\left(\hat{Y}_{GREG}\right)\right\}^2$$

where $v^{(r)}$ is the value of v for the rth simulated sample.

Table 1. RBs and REs of estimators under the Sunter's sampling scheme.

Population No	Relative biases in percentage				Relative efficiency			
	v_s	v_g	v_{OPT}	v_{IAR}	v_s	v_g	v_{OPT}	v_{IAR}
1	-85.4189	7.073	-7.904	-21.556	1	1.259	2.767	2.502
2	-89.7759	-8.456	-30.035	-30.824	1	1.368	3.044	2.598
3	-92.1025	-12.932	-1.448	-46.782	1	1.207	6.871	2.581
4	-94.2926	12.808	-20.075	-16.921	1	1.598	5.558	5.352
5	-86.5436	-5.210	-29.328	-15.557	1	3.491	3.993	4.312
6	-94.7124	21.405	-19.394	-24.089	1	0.607	5.100	3.468
7	-84.5782	3.027	11.306	-17.802	1	1.739	4.225	3.554
8	-90.3122	-10.853	-42.058	-23.227	1	4.916	3.362	4.489
9	-91.3650	-32.345	-63.978	-50.554	1	2.051	1.912	2.266
10	-91.0820	-15.527	-49.590	-25.275	1	2.537	2.627	3.196
11	-94.9503	46.596	-27.928	0.309	1	0.313	4.298	3.015
12	-95.0675	33.963	-34.883	-11.057	1	0.410	3.853	3.434
13	-87.878	-22.454	-26.904	-34.660	1	2.185	4.239	3.129
14	-95.6632	-42.283	-66.996	-66.249	1	1.930	1.854	1.730
15	-87.7766	-4.300	-26.269	-7.556	1	1.600	4.604	2.601

Table 1 leads to the following comments.

(1) In v_g the value of η_i in (7) should be chosen such that the value of g_{is} lies near the unity for a majority of the units $i \in s$. The larger the sample size, the stronger is the tendency for the g_{is} to hover near unity. Here, in our small scale simulation, we have drawn a sample of size n = 6. This may be one of the reasons for very poor performance of v_g as compared to v_{OPT} and v_{IAR} with respect to the relative efficiencies.

(2) In terms of REs, the optimal-type estimator v_{OPT} is considerably more efficient than v_g. The price paid for this efficiency is marginal increase in overall relative bias as compared to v_g for some populations.

(3) All the variance estimators included in the study have taken non-negative values with probabilities 1 and therefore these probabilities have not reported.

Remark 5. The above simulations are rather artificial since the population size and the sample size are extremely small and the sampling fraction is extremely large. To facilitate the computation of the real population variance we had chosen small population and sample sizes.

Appendix A

Table 2. List of Study Populations

Popl. No.	N	CV(x)	CV(y)	ρ(x,y)	Source	x	y
1	15	0.137	0.301	0.451	D. Gujarati (1995), p.307 [7]	Mean Family Size	% in labor Force
2	16	0.254	0.161	0.497	D. Gujarati (1995), p.277	Housing Starts thousands of units	Total Plastic Purchases
3	24	0.136	0.173	0.531	Montgomery et al. (2003),Appendix B, Table B.4, p.571 [10]	Number of rooms	Sale price of the house/1000
4	14	0.298	0.217	0.759	D. Gujarati (1995), p.352	Farm income	Consumption
5	15	0.052	0.197	0.826	D. Gujarati (1995), p.216	Labor input (per thousand persons)	Real gross product millions of NT ($)
6	23	0.232	0.186	0.840	D. Gujarati (1995), p.228	Real retail price of chicken per lb (¢)	Per capita consumption of chickens (lbs)
7	17	0.607	0.712	0.853	Murthy(1967), p.399 (18-34) [11]	cultivated area (1961)	area under wheat (1964)
8	17	0.089	0.287	0.861	D. Gujarati (1995), p.230	Implicit Price deflator	Nominal money crores of rupees
9	15	0.289	0.197	0.871	D. Gujarati (1995), p.216	Real Capital input (millions of NT,$)	Real gross product millions of NT ($)
10	17	0.136	0.287	0.887	D. Gujarati (1995), p.230	Long-term interest rate (%)	Nominal money crores of rupees
11	23	0.390	0.186	0.912	D. Gujarati (1995), p.228	Real retail price of pork per lb	Per capita consumption of chickens (lbs)
12	23	0.369	0.186	0.937	D. Gujarati (1995), p.228	Composite real price of chicken substitutes per lb weighted avg.of x2 to x5	Per capita consumption of chickens (lbs)
13	14	0.260	0.217	0.944	D. Gujarati (1995), p.352	Non wage, Nonfarm income	Consumption
14	20	0.480	0.346	0.980	D. Gujarati (1995), p.227	Aerospace industry sales	Defense budget outlays
15	15	0.240	0.571	0.995	D. Gujarati (1995), p.224	Real Capital input (millions of NT,$)	Real gross product millions of NT ($)

References

[1]. Armstrong J., Block, C., and Srinath, K. P. (1993). Two-phase sampling of tax records for business surveys, J. of Businee and Economics Statist. 11, 407-416.

[2]. Cassel, C. M., Särndal, C. E. and Wretman, J. H. (1977). Foundation of Inference in Survey Sampling, John Wiley, New York.

[3]. Chaudhari, A. and Maiti, T. (1994). Variance estimation in model assisted survey sampling. Communication is Statistical Theory and Methods, 23 (4), 1203-1214.

[4]. Deville, J.C., Särndal, C.E. (1992). Calibration using auxiliary information. Journal of the American Statistical Association, 78, 117-123.

[5]. Duchesne, P. (2000). A note on jackknife variance estimation for the general regression estimator. Journal of Official Statistics, 16 (2), 133-138.

[6]. Fuller, W. A. (2002) Regression estimation for survey samples, Survey Methodology, 28, 5-23.

[7]. Gujarati, D. N. (1995). Basic Econometrics, McGraw-Hill, Inc.

[8]. Horvitz, D. G., and Thompson, M. E. (1952). A generalization of sampling without replacement from a finite universe. J. Amer. Statist. Assoc. 47, 663- 685.

[9]. Kott, P. S. (1990). Estimating the conditional variance of a design consistent regression estimator. Journal of Statistical Planning and Inference, 24, 287-296.

[10]. Montgomery, D. C.; Peck, E. A. and Vining, G. G. (2003). Introduction to linear regression analysis. Third Edition, John Wiley & Sons, Inc.

[11]. Murthy, M. N. (1967). Sampling Theory and Methods. Calcutta: Statistical Publishing Society.

[12]. Patel, P. A. and Chaudhari, R. D. (2008). Model-based variance estimation under unequal probability sampling. Metrika, 67, 171-189.

[13]. Patel, P. A. and Patel, J. S. (2010). A Monte Carlo comparison of some variance estimators of the Horvitz-Thompson estimator. Journal of Statistical Computation and Simulation, 80(5), 489-502.

[14]. Randles, R. H. and Wolfe, D. A. (1979). Introduction to the Theory of Nonparametric Statistics. Wiley, NY.

[15]. Robinson, P. M. and Särndal, C. E. (1983). Asymptotic properties of the generalized regression estimator in probability sampling. Sankhya, Series B, 45, 240-248.

[16]. Särndal, C.E. (1980). On π-inverse weighting versus best linear unbiased weighting in probability sampling. Biometrika, 67, 639-650.

[17]. Särndal, C.E. (1996). Efficient estimators with simple variance in unequal probability sampling. Journal of the American Statistical Association, 91,1289-1300.

[18]. Särndal, C.E., Swensson, B. and Wretman, J. H. (1989). The weighted residual technique for estimating the variance of the general regression estimator of the finite population total. Biometrika, 76, 527-537.

[19]. Särndal, C.E., Swensson, B. and Wretman, J. H. (1992). Model Assisted Survey Sampling. Springer Verlag, New York.

[20]. Sen, A. R. (1953). On the estimate of the variance in sampling with varying probabilities. J. indian Soc. Agrlc. Statist. 7, 119-127.

[21]. Singh, S., Horn, S., Chowdhury, S. and Yu. S. (1999). Calibration of the estimators of variance. Australian and New Zealand Journal of Statistics., 41, 199-212.

[22]. Stehman, S. V. and Overton, W. S. (1987). Results of simulation studies of the estimation methodology prescribed for the National Stream Survey. Technical Report 118, Department of Statistics, Oregon State University, Corvallis, Oregon, 97331.

[23]. Sunter, A. B. (1986). Solution to the problem unequal probability sampling without replacement. International Statistical Review, 54, 33-50.

[24]. Yates, F., and Grundy, P. M. (1953). Selection without replacement from within strata with probability proportional to size. J. Roy. Statist. Soc. Ser. B 15, 235-261.

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