A Quality Driven Approach to Managing Collection and Analysis

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Abstract

Statistics Canada is undergoing a redesign of its business surveys. One key component of the new framework is the active collection and analysis management methodology. Using historical and partially collected data, key estimates and quality indicators are produced while collection is still underway. These quality indicators are then compared to previously set quality targets to determine if more effort is required or if active collection can be terminated. If collection needs to continue, item scores are calculated in order to gauge a unit's impact on the quality indicator of each key estimate. These scores are then aggregated within each unit, to create a global unit score. Based on these, decisions regarding follow up activities are made.

This talk will describe the quality driven active collection and analysis management methodology. Some preliminary empirical results and potential savings in the new Canadian Integrated Business Statistics Program will also be discussed.

Key Words: Business Surveys, Adaptive Design, Quality Indicators, Selective Editing

1 Introduction

1.1 Context

In 2009, Statistics Canada launched the Corporate Business Architecture (CBA) review initiative. Growing financial pressures led to this process to review Statistics Canada's business model and survey infrastructure. The CBA main objectives were to achieve further efficiencies, enhance quality and improve responsiveness in the delivery of its statistical programs. As described in [6], [9], [11] and [12], the new Integrated Business Statistics Program (IBSP) was developed to help Statistics Canada achieve the above mentioned CBA objectives for business surveys. The IBSP defines a new survey model and infrastructure that over one hundred business surveys will be using by 2017.

One of the main goals of the IBSP is to achieve greater efficiency in processing its survey data, while producing estimates of similar, if not better, quality. To do this, a new adaptive design has been developed to manage data collection activities as well as data analysis (see [6], [7] and [9]). The Rolling Estimates (RE) model is a processing strategy that combines active collection management, editing, imputation, estimation and analysis. It allows estimates and quality indicators to be produced periodically as soon as an acceptable amount of survey and administrative data are available. Collection and data analysis efforts can then be actively managed by monitoring the progression of these quality indicators and through unit prioritization. Data analysis can start sooner, thus increasing the timeliness of annual estimates and the prioritization of units contributes to reducing the amount of resources dedicated to manual editing.

The original description of the RE model was given in [7]. A more detailed description of the methodology surrounding the process was presented in [9] and [12]. This paper heavily borrows from [9], but also seeks to provide some of the latest updates on the methodology and implementation.

1.2 The IBSP Survey Processing Model

In the IBSP, an optimal use of the resources available will be reached by limiting manual interventions to the more influential units. To achieve this, the estimates and their quality must be taken into account during collection and processing rather than only near the end. To do this, the IBSP will implement an iterative approach (Figure 1) called the Rolling Estimates (RE) model. In this model, once enough data from administrative sources and collection have been received, a series of automated processes will be run, right through to producing estimates and their quality indicators. The current plan is to produce these "rolling estimates" at least once a month during a 4 to 5 month period.

The RE will produce key estimates and related quality indicators. Using these results, decisions will be made whether to stop active collection or not. When the quality indicators have reached pre-specified targets for a given geography-industry domain, active collection can stop in that domain and resources can be redirected towards other domains, as required.

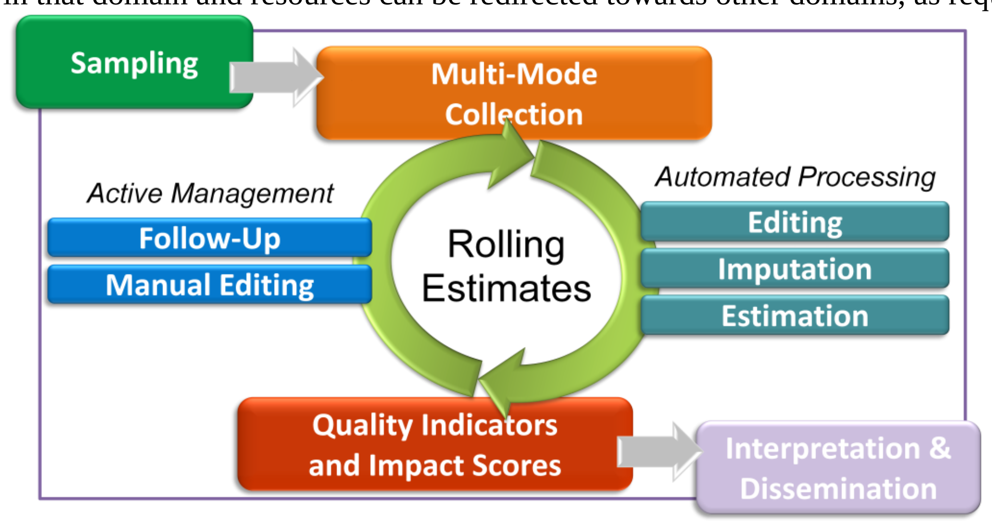

Figure 1: Rolling Estimates Model

The RE will also produce measure of impact scores, for each unit, at each iteration. Active collection will be based on lists of non-responding units or units that failed collection edits, prioritized by their unit scores. Active analysis (also called Selective Editing) will mainly focus on respondents significantly influencing key estimates and their quality or non-respondents that are not eligible for collection follow-up (e.g. hard refusals).

2 Sampling and Estimation Methodology

We are interested in measuring a set of parameters $Y_{vd} = \sum_{k \in U} y_{vdk}$, for the combinations of variables of interest y_v $(v = 1,...,V)$ and domains of interest d $(d = 1,...,D)$, for a population U of size N.

As described in [11] and [12], a sample s of size n is drawn using a 2-phase design with stratified Bernoulli sampling at both phases. Unit or item non-response will be handled by imputation, defining the non-overlapping subset, $s_{vr} \cup s_{vm} = s$, as the set of k units having respectively reported $y_{vk}^{(R)} \equiv y_{vk}$ and imputed $y_{vk}^{(I)}$ values for the variable of interest y_v. The set of respondents is identified as s_{vr} , and non-respondents, s_{vm} .

The estimator for the totals $\hat{Y}_{vd}^{(IMP)}$ under imputation is given by:

$$\begin{aligned} \hat{Y}_{vd}^{(IMP)} &= \sum_{k \in s_{vr}} w_k^{(E)} y_{vdk}^{(R)} + \sum_{k \in s_{vm}} w_k^{(E)} y_{vdk}^{(I)} \\ &= \sum_{k \in s} w_k^{(E)} y_{vdk}^{*} \quad . \end{aligned} \tag{1}$$

The estimation weight $w_k^{(E)} = \pi_k^{-1} g_{ks}$ is the inverse of the sampling probability π_k resulting from the 2-phase design calibrated to known totals. See [10] for more on calibration.

3 Active Management Framework

Some of the collection and analysis activities (referred to as treatments), like fax or email follow-ups, have a relatively low unit cost while other have significant marginal costs, such as telephone follow-up for non-response or failed-edit (see [5]), and manual editing. For simplicity, they are all grouped here into one single treatment *T*.

3.1 Key Estimates, Importance Factors and Quality Targets

The active management parameterization is done through the setting of 3 basic concepts: the list of key estimates, their importance factors and their quality targets. An estimate is identified from 3 attributes: a statistical measure (e.g. total, mean, ratio, etc.), a variable (or many for multivariate statistical measures like ratios) and a domain. In the first years of IBSP, key estimates will consist of totals only.

All key estimates are assigned an importance factor ω_{vd}, used to weigh their relative importance in the active management system, and a quality target QT_{vd} to determine when the quality of an estimate is deemed sufficient for its use. The derivation of ω_{vd} and QT_{vd} is discussed in section 5.

3.2 Quality Indicator and Quality Distance

A quality measure Θ is a type of statistical measure θ used to assess the quality of an estimate or a set of estimates, such as, the coverage rate, the response rate, the coefficient of variation (CV) or the relative root of the mean squared error (RRMSE). A quality indicator (QI) is the estimated value of a quality measure for a given estimate, i.e. $\hat{Q}I_{vd} = \Theta(\hat{Y}_{vd} \left| s, s_{vr} \right.)$.

For a decreasing quality indicator (i.e. being maximal at the beginning of collection and decreasing as the quality improves), the quality distance $\hat{Q}D_{vd}$ for a given key estimate *vd* is defined as $\hat{Q}D_{vd} = \max\{(\hat{Q}I_{vd} - QT_{vd}) \big/ \hat{Q}I_{vd}, 0\}$. Note that, $\hat{Q}D_{vd}$ should be close to 1 when collection starts and 0 when the quality target has been reached. To simplify the management of a set of quality indicators, it is useful to combine them into a global statistic using a distance function (see [8]). The distance function used in IBSP is a weighted quadratic mean derived from the multivariate objective function, also used at sampling (see [12]). Therefore, the active management consists of minimizing the global quality distance ($\hat{Q}D^G$), under constraints on costs, and is defined as:

$$\hat{Q}D^G = \sqrt{\sum_{v=1,\ldots,V} \sum_{d=1,\ldots,D} \left(\omega_{vd} \hat{Q}D_{vd} \hat{Q}I_{vd}\right)^2 \Big/ \sum_{v=1,\ldots,V} \sum_{d=1,\ldots,D} \omega_{vd}^2} . \tag{2}$$

The global quality distance is positive as long as there are key estimates for which the quality targets have not been met and decreases as their quality indicators improve; it will be 0 if and only if all the quality targets are met.

3.3 Unit Scores

The top-down solution used to go from the multivariate objective function from formula (2) to a collection or analysis unit prioritization is the unit measure of impact (MI) score. As described in [12], the definition of the impact $\delta_{kT}(\hat{\theta}_{vd})$ of a treatment T on a unit k on an estimate $\hat{\theta}_{vd}$ of a statistical measure θ, a variable y_v and a domain *d*, conditionally on s and s_{vr}, is given by:

$$\delta_{kT}(\hat{\theta}_{vd}) = \hat{\theta}_{vd} - \tilde{\theta}_{vd|kT} , \tag{3}$$

where $\tilde{\theta}_{vd|kT}$ is the predicted effect on $\hat{\theta}_{vd}$ of treatment T on unit k, assuming treatment will be successful. In the case a quality measure is a function of a vector of statistical measures, i.e. $\Theta = f(\boldsymbol{\theta})$ and $\hat{Q}I_{vd} = f(\hat{\boldsymbol{\theta}}_{vd}) = f(\hat{\boldsymbol{\theta}}(\hat{Y}_{vd} \left| s, s_{vr} \right.))$, the item score of the unit k, variable y_v and domain *d*, under the treatment T is defined as $\hat{M}I_{vdkT} = f(\boldsymbol{\delta}_{kT}(\hat{\boldsymbol{\theta}}_{vd}))$. The unit score $\hat{M}I_{kT}^G$ of a unit k under the treatment T is given by:

$$\hat{M}I_{kT}^{G} = \sqrt{\sum_{v=1,\ldots,V} \sum_{d=1,\ldots,D} (\omega_{vd} \hat{Q}D_{vd} \hat{M}I_{vdkT})^2 \Big/ \sum_{v=1,\ldots,V} \sum_{d=1,\ldots,D} \omega_{vd}^2} . \qquad (4)$$

This unit score measures the impact a unit has on the global distance between the quality indicators and their targets. The score of a unit will be:

- Positive if it has a positive MI score for at least one key estimate for which the quality target has not been met yet;
- Zero if all its MI scores are zero or all its positive MI scores correspond to key estimates which have met their target.

4 Quality Measures

In IBSP, in order to actively manage collection follow up efforts as well as analysis in an integrated way, two quality measures are defined and then combined into one.

4.1 Total Variance

First, as described in [9], in the IBSP the total variance is used to measure the variability of the key estimates, and measure the impact of nonresponse and imputation. The estimate of the total variance can be decomposed into the naïve sampling variance, $\hat{V}_{Ord}$, for which we consider the imputed values as reported, the correction term, $\hat{V}_{Dif}$, proposed in [10] and simplified by [4], to compensate for the effect of the imputation, the non-response variance term, $\hat{V}_{NR}$, and the covariance term, $\hat{V}_{Mix}$. The estimation of the total variance $\hat{V}_{Tot}$ is the sum of these four components:

$$\hat{V}_{Tot}(\hat{Y}_{vd}^{(IMP)}) = \hat{V}_{Ord}(\hat{Y}_{vd}^{(IMP)}) + \hat{V}_{Dif}(\hat{Y}_{vd}^{(IMP)}) + \hat{V}_{NR}(\hat{Y}_{vd}^{(IMP)}) + \hat{V}_{Mix}(\hat{Y}_{vd}^{(IMP)}) . \qquad (5)$$

More information about how those components of variance are derived can be found in [2] and [3]. The resulting unit total impact, obtained by changing the status of the unit from non-respondent to respondent and by considering its imputed values as reported, is therefore given by:

$$\delta_{kT}(\hat{V}_{tot}(\hat{Y}_{vd}^{(IMP)})) = \delta_{kT}(\hat{V}_{Dif}(\hat{Y}_{vd}^{(IMP)})) + \delta_{kT}(\hat{V}_{NR}(\hat{Y}_{vd}^{(IMP)})) + \delta_{kT}(\hat{V}_{Mix}(\hat{Y}_{vd}^{(IMP)})) . \qquad (6)$$

A detailed definition of each component can be found in [9].

4.2 Relative Deviation from Predicted Values

In order to identify potential problems with reported data and measure the potential impact on the estimates, another quality measure is defined, called here the Relative Deviation from Predicted Values (RDPV). Prior to the beginning of collection, predicted values $\tilde{y}_{vdk}^{(P)}$ are generated from tax data and historical data, for each unit k in the sample and for each key estimate vd. Using these predicted values, predicted key estimates can be computed and compared to the current estimates produced using the collected and imputed data. The resulting quality indicator can be formulated as:

$$RDPV(\hat{Y}_{vd}^{(IMP)}) = \frac{\sqrt{\sum_{k \in s}\left(w_k^{(E)} i_{edit,k}(y_{vdk}^{*} - \tilde{y}_{vdk}^{(P)})\right)^2}}{\sum_{k \in s} w_k^{(E)} y_{vdk}^{*}} = \frac{\sqrt{\sum_{k \in s}\left(w_k^{(E)} i_{edit,k}(y_{vdk}^{*} - \tilde{y}_{vdk}^{(P)})\right)^2}}{\hat{Y}_{vd}^{(IMP)}}, \tag{7}$$

where $i_{edit,k}$ is a manual editing status indicator and is set to 1 when unit k has not been reviewed yet and is set to 0 when the value y_{vdk}^{*} has been confirmed or manually edited. It therefore follows that the unit impact score is defined as:

$$\delta_{kT}\left(RDPV(\hat{Y}_{vd}^{(IMP)})\right) = \frac{\sqrt{\left(w_k^{(E)} i_{edit,k}(y_{vdk}^{*} - \tilde{y}_{vdk}^{(P)})\right)^2}}{\hat{Y}_{vd}^{(IMP)}} = \frac{\left|w_k^{(E)} i_{edit,k}(y_{vdk}^{*} - \tilde{y}_{vdk}^{(P)})\right|}{\hat{Y}_{vd}^{(IMP)}}. \tag{8}$$

δ_{kT} will be equal to 0 if unit k has been manually edited or if $y_{vdk}^{*} = \tilde{y}_{vdk}^{(P)}$, otherwise it will be greater than 0.

4.3 Pseudo Relative Root of the Mean Squared Error (PRRMSE)

Finally, the Total Variance and the Relative Deviation from Predicted Values are combined to form the main IBSP quality indicator, called here the Pseudo RRMSE, and is formulated as:

$$PRRMSE(\hat{Y}_{vd}^{(IMP)}) = \left(\hat{Y}_{vd}^{(IMP)}\right)^{-1}\left(\hat{V}_{tot}(\hat{Y}_{vd}^{(IMP)}) + \lambda\left(\hat{Y}_{vd}^{(IMP)}\right)^2\left(RDPV(\hat{Y}_{vd}^{(IMP)})\right)^2\right)^{1/2}, \tag{9}$$

where λ is a constant between 0 and 1 (currently set at 0.1 in IBSP) used to control the impact of the RDPV on the combined quality indicator. Clearly, with the addition of the λ, plus the fact that the RDPV is not estimating the real bias of $\hat{Y}_{vd}^{(IMP)}$, the Pseudo RRMSE defined here is not a good estimator of the real RRMSE of $\hat{Y}_{vd}^{(IMP)}$. This is not a problem though since the goal of this quality indicator is not to estimate the RRMSE but rather to help identify units with the most impact on data quality. The resulting item score of unit k under treatment T based on the Pseudo RRMSE is given by:

$$\hat{MI}_{vdkT}(\hat{Y}_{vd}^{(IMP)}) = \left(\hat{Y}_{vd}^{(IMP)}\right)^{-1}\left(\delta_{kT}(\hat{V}_{tot}(\hat{Y}_{vd}^{(IMP)})) + \lambda\left(\hat{Y}_{vd}^{(IMP)}\right)^2\left(\delta_{kT}\left(RDPV(\hat{Y}_{vd}^{(IMP)})\right)\right)^2\right)^{1/2}. \tag{10}$$

5 Implementation

For the last year or so, the IBSP team has been working on implementing the above framework. As mentioned before, the active management strategy is based on three components: the key estimates, their importance factors and their quality targets. Therefore, for each IBSP survey, key variables and key domains were identified and combined to create the list of key estimates. Then, importance factors were generated and quality targets were set. The strategy used to derive the importance factors and quality targets is discussed in the following sections.

5.1 Importance Factors

For each survey, a list of key variables y_v $(v=1,\ldots,V$ with $V=4$ *or* $5)$ and domains of interest d $(d=1,\ldots,D)$ were identified. In general, the domains of interest d were defined through geography and industry classifications. Let d_1 $(d_1=1,\ldots,D_1)$ and d_2 $(d_2=1,\ldots,D_2)$ represent the geography and industry domains respectively, with $d \equiv d_1 \otimes d_2$ $(d=1,\ldots,D$ with $D=D_1 \times D_2)$. Using historical values, estimates of domain totals $\hat{Y}_{vd_1d_2}=\sum_k y_{vd_1d_2k}^{hist}$ were computed for $v=1,\ldots,V$, $d_1=1,\ldots,D_1$ and $d_2=1,\ldots,D_2$. Using this, the importance factors ω_{vd} were defined as:

$$\omega_{vd} \equiv \omega_{vd_1d_2} = \left(\frac{\hat{Y}_v}{\hat{Y}_T}\right)^{p_0} \left(\frac{\hat{Y}_{vd_1}}{\hat{Y}_v}\right)^{p_1} \left(\frac{\hat{Y}_{vd_1d_2}}{\hat{Y}_{vd_1}}\right)^{p_2}, \tag{11}$$

where $\hat{Y}_{vd_1}=\sum_{d_2}\hat{Y}_{vd_1d_2}$, $\hat{Y}_v=\sum_{d_1}\hat{Y}_{vd_1}$ and $\hat{Y}_T=\sum_v \hat{Y}_v$. The constants p_0, p_1 and p_2 are between 0 and 1 and are used to control the distribution of the importance factors ω_{vd}. Values of p_0, p_1 and/or p_2 close to 0 will result in similar importance put on the different variables and/or domains of interest. Values close to 1 will result in importance factors that are more variable and proportional to the different ratios in formula (11). The concept is the same as the well known *power*-allocation found in [1].

The importance of the different variables y_v is determined first. Since key variables were deemed of similar importance, p_0 was set at 0.1. Then, for each variable y_v, the importance of each domain is derived. In the IBSP, d_1 represents the provincial dimension, the most important dimension. Since it's very important for the IBSP to produce provincial estimates of similar quality, the provincial importance are determined first (i.e., d_1 appears before d_2 in the hierarchical structure used above) and p_1 was set at 0.1. The industrial dimension is represented by d_2 and since the requirement was that their importance be a bit more proportional to their provincial economic contribution, p_2 was set at 0.5. Note that this methodology could easily be generalised to more than 2 dimensions.

5.2 Quality Targets

Next, quality targets QT_{vd} were required for all key estimates. Starting from the second year of the IBSP, historical estimates and quality indicators for all key estimates will be available and usable as a starting point to set up the quality targets for the next cycle. On the other hand, for the first year, since these historical quality targets were not available, expected sampling variances from the sampling stage were used as a starting point to determine an initial set of reasonable and conservative quality targets.

5.3 Collection operations

The unit scores $\hat{MI}_{kT}^{G}$ will be used to create priority groups for collection and analysis operations. For example, units in the top 5% will be put in priority group 1. The following 10% will be put in priority group 2, and so on. Collection efforts will be managed based on those priorities.

Not all units are eligible for collection follow-up. Sometimes appointments have been set up, or units have been identified as hard refusals. The priority units that are eligible for collection will be assigned to collection follow-up and the ineligible ones will be handled by analysts.

Up until now, weighted response rates were used as targets to decide when active collection could be stopped for a specific survey. In the IBSP, the collection operations will be centered on the active management methodology described above. On the other hand, for the first year, since our understanding of how the quality indicators will evolve throughout collection and since our quality targets are not based on historical knowledge, response rates will be used to complement the methodology presented here. To be more specific, the collection activities will stop for a specific survey if both its global quality distance $\hat{Q}D^{G}$ and its weighted response rate have reached pre-specified targets.

6 2012 Empirical Study

In order to evaluate the potential gains on quality and cost that could be achieved through the Rolling Estimates, an empirical study was performed in 2012 using the data from 46 different annual business surveys (40 using paper questionnaires and 6 using electronic questionnaires). Four iterations of Rolling Estimates were run (July, August, September, and October) using the methodology described above, and the results were compared to the ones obtained in production. The study mainly focused on nonresponse follow up activities. A detailed description of this study can be found in [9]. Only a summary of the results will be presented here.

6.1 Summary of results

From Table 1 below, we can observe that at the first iteration in July, with only 47% of the collection units being followed up for non response, 76% of the quality targets were already reached. Between July and October production, which flagged 53% of the collection units for non-response follow-up, only an additional 9% of key estimates reached their targets.

The Rolling Estimates study created four successive prioritization lists, one per iteration, containing the collection units having the largest impact on the global quality distance. The units on the list were assumed resolved by the next iteration. The combination of the prioritized collection units from these four iterations and the collection units followed up before the first iteration contains 34% fewer units than the set of all collection units followed up in production. The results are even stronger for the 6 surveys using electronic questionnaires, with a reduction of 49% of the number of collection units prioritized for non-response follow-up. This can be explained by the new follow-up procedures implemented for the surveys using electronic questionnaires: the early telephone follow-up activities are replaced by email reminders, without significant impact on the response progress (see [5]). Because there was a lower proportion of telephone follow-ups done before the first Rolling Estimates iteration, the potential for relative savings is larger.

Table 1: Results by Survey Group

Survey Groups	**Number of Key Estimates**	**Percentage of quality targets met**			**Percentage of collection units followed up for non-response**		
		Regular production		**RE Empirical Study**	**Regular production**		**RE Empirical Study**
		July	October	October	Before July	July-October	Overall reduction
TOTAL (46 surveys)	**8,600**	**76%**	**85%**	**98%**	**47%**	**53%**	**34%**
Non-EQ* (40 surveys)	7,600	76%	85%	98%	51%	49%	31%
EQ* (6 surveys)	1,000	71%	82%	99%	22%	78%	49%

7 Conclusions

The key features of this innovative active management strategy are the dynamic Rolling Estimates model driven by improved quality indicators.

The quality indicators, combining sampling and imputation variances, plus a measure of deviation to flag potential problematic errors in the data, give an accurate picture of the current quality of all the key estimates. With the importance factors and the quality targets, the framework converts the multivariate objective into a univariate problem, allowing the IBSP to more easily, and efficiently, manage collection and analysis activities. The Rolling Estimates model provides regular, relevant and output-oriented pictures of the quality progress and, in a timely fashion, identifies the estimates that meet the targeted quality so the resources are dynamically redirected to focus on the remaining estimates.

The empirical study has shown that, at a given collection follow-up capacity, the Rolling Estimates model with a unit prioritization based on quality indicators and unit scores can improve the quality of the data while also reducing significantly the number of follow-ups required to meet quality targets. However, due to the limitations of the study, the achieved, theoretical reductions compared with the current survey production cannot be blindly transposed to IBSP. The level of savings that can be expected depends on the collection strategy, the desired level of quality, and the choice of key estimates and their relative importance.

The empirical study demonstrated the feasibility and the power of the model, but also highlighted major requirements on the collection, analysis, processing, and methodology services and on their interactions. The strategy, parameterized through key estimates, importance factors and quality targets, has to be carefully set up. Collection progress needs to be closely monitored so that the joint efforts between collection staff and analysts may maximize non-response and edit resolutions.

The first cycle of the IBSP will go into production in the summer of 2014. The plan is to start with reasonable expectations in terms of data quality and savings, and then use the experience from the first few years to assess the efficiency of the framework under the IBSP model.

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