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METRICS FOR THE QUALITY OF EDITING, IMPUTATION AND PREDICTION[1]

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Abstract: The quality of statistical information will always be uncertain. To serve the users, quality declarations are desirable. The aim of the editing process is to improve the quality in statistical products. In this paper, metrics for predicting the qualities of statistical products are proposed. The quality measures can be compared with quality requirements and be the basis for quality declarations. The reliability of the proposed metrics are illustrated by empirical tests.

1. Quality of statistics

A statistical product is characterized by a number of properties such as its relevance for a set of applications, details, timeliness, resources used, quality, etc. In this paper, we focus on the quality aspect. Quality has been emphasized as an important goal to aim at for producers of statistics and has also been considered as an overall measure of statistical efficiency. The quality concept is neither unambiguously defined nor easy to measure. The view adopted in this paper is that quality of a statistical estimate is defined as the estimate's deviation from its target value. Since the target value is usually unknown, quality can only be estimated.

Preparation of statistical products can be considered as a chain of processes each of which contributes to the total quality of the final product. The processes may for example be sampling, data collection, preprocessing, editing and imputation, storing data in a statistical data base, retrieval of required data and calculation of the wanted statistics. Each process can be a source of errors and we can name the errors by their source as sampling errors, response errors, prediction errors, etc. One of the production processes, the editing and imputation, has as its purpose to detect and correct errors in the data to promote the quality of the statistical products. Also this process can, however, introduce errors [Nordbotten 1955].

In this paper, we distinguish between three types of data errors, the *response errors* which are the errors in the data when collected, the *imputation errors* which are the errors introduced when original

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values are corrected during editing and *prediction errors* which are errors introduced when values of units not observed are predicted.

A number of indicators for measuring the effect of the editing process have been proposed [Granquist 1997]. The purpose of this paper is to outline metrics predicting the quality of statistical estimates computed from data edited, imputed or predicted. Quality measurements give guidance the producers about the importance of editing and to users about the quality of the statistics after data have been through the editing, imputation and prediction processes. In contrast, monitoring the editing process give the designer of statistical surveys information about to improve the efficiency of the processes [Engstrøm 1996, Jong 1996, Stefanowics 1997, Thomas 1996]. While the monitoring indicators focus on the editing process, the quality metrics discussed in this paper aim at the results of the process.

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2. General problem

Consider a population of N statistical units. Without loss of generality, we assume that each unit is characterized by a single y-variable value and a set of K x-variable values. The y-values are unknown values to be observed.. The x-values are background or auxiliary data available from administrative registers, etc. We denote the individual target values as y_i, $i=1..N$, and the values in the x-set as x_{ik} , $i=1..N$ and $k=1..K$.

The objective of the statistical production is measurement of the target total, $Y = \Sigma_i^N y_i$. To achieve this goal, the producer collects data from the units. Observed values will frequently be infected by different kinds of errors during observation. The producer counteracts the attack of errors with the editing process. Assuming that the editing identifies and correct all errors, the individual data resulting from the editing process can be summarized by the expression $y_i = y_i' - e_i$ where e_i denote errors

We shall in our discussion assume that e_i , $i=1..N$, are independent random variables with a common mean m_e and variance v_e. The estimate $Y' = \Sigma_i^N y_i'$ of unedited data can be different from the target total value Y, and vary if the collection is repeated. The quality of an estimate Y' is defined by the deviation $D=|Y'-Y|$, but cannot usually be observed, and must therefore be predicted.

Since the quality of Y' does not manifest itself before after the statistical information is used, the producer of statistics would want to issue a *quality declaration* or guarantee for the statistical total Y' to the users based on prediction. The declaration must be expressed relative to a preset limit or *quality requirement* C . A low limit C indicates a declaration of high quality estimates, and vice versa. If the predicted quality is $D'=|Y'-Y| <= C$, the estimate Y' will be declared to have required quality, if not, the estimate will not be given a quality declaration. It will be important to predict the quality by means of a metric which provide declarations with a low probability Pr to be incorrectly. By means of Tchebycheff theorem, bounds can be derived for such a probability without any specific assumptions about the distribution of the errors. More specific probabilities can be obtained if conditions permit to rely on the Central Limit Theorem.

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3. Quality metrics

3.1 Case 1: An estimator based on unedited data

Assume that data on the *y*-variable are collected for all units. By means of expert editors, errors in the individual raw observation values y_i ' can be detected and corrected. Complete editing is prohibitive because of few available expert editors, costs and time required, etc. However, editing of observations for a sample of *n* units can be afforded. The editing provides, in addition to the observed y_i'-value, the edited value y_i for each unit which is assumed to be free of errors. The difference, e_i , is the response error which we assume to be a random variable with characteristics as specified in the previous section.

On the basis of the pair of values, y_i' and y_i , for each sample unit, a *composite estimator* can take advantage of the edited values for the *n* units in the sample as well as the knowledge of the *N-n* values for unedited units

$$Y' = \Sigma_1{}^n\, y_i + \Sigma_{n+1}{}^N\, y_j' .$$

By means of Tchebycheff inequality, we can evaluate an approximate upper bound for the probability that the deviation between estimate and the target total is greater than C

$$Pr(|Y'-Y|>C') < S^2/C'^2$$

where S^2 is the squared response error for the estimate Y'. We will use this and similar editing and prediction errors as our quality metrics.

If we want the upper bound for the probability that the deviation of the estimate Y' from Y is greater than, for example, two times the response error of the estimate, the probability will be

$$Pr(|Y'-Y|>C= 2*S) < 1/4$$

If the estimate Y' is including the sum of error variables with a normal distribution, or if the number of the error variables is sufficiently large, the estimates will have an approximate normal distribution according to the Central Limit Theorem,. The uncertainty associated with ther deviation can then be reduced to

$$Pr(|Y'-Y|>C=2*S)=0.05.$$

Let n_0 be the number of observations in the sample of *n* with $e=0$, i.e. with observations accepted by the editors as, and $n_1 = n-n_0$ be the number of values with $e\neq 0$, A response error for Y' can then be expressed as

$$S' = \sqrt{(N-n)*n_1/n} * s_e$$

where s_e is the root mean square of the error in the group of n_1 corrected observations. The response error approaches *0* when *n*, the number of observations sunjected to editing, approaches *N*.

Alternatively, the sample of edited records for *n* units can be used to estimate the total by the traditional *simple unbiased estimator*

$$Y'' = N * \sum_i^n y_i / n$$

from the edited values discarding the *N-n* unedited records. This estimate is not influenced by any *response errors* because it is based on the edited values only. On the other hand, it is influenced by the *sampling error*

$$S'' = N * s_y * \sqrt{(1-f)/n}.$$

where s_y is the ordinary standard deviation for the target variable *y* and *f* the sampling fraction. It is well known that also the sampling error approaches 0 when $n \rightarrow N$. The sampling error has been used for many years as indicated above for assessing the quality of the estimates.

The relative quality of the two estimates is

$$S'/S'' = s_e * \sqrt{n_1} / s_y * \sqrt{N}$$

which indicates that there is a constant ratio between the quality of the two alternative estimates. It should be noted that s_e and s_y are both estimates and that we have disregarded the uncertainty in these estimates.

S' and S'' are both measures indicating the quality lost by incomplete editing. Obviously, if observations are made for all units and only a sample is editede, he quality of estimates depends both on the number of records which are subjected to editing and what is done with the reamininhg observations

3.2 Case 2: An estimate based on simple computer edited data

Assume that all population units are observed with respect to the variable *y* and that data for a single background variable, *x*, are also available. By help from editing experts, a ratio control of the observations has been designed based on knowledge from for example a previous similar survey.

The experts pointed out that the ratio

$$y_i'/x_i = r_i ,$$

where y_i ' and x_i are the observed variable value and the background variable value, respectively, should be within a specified range to be acceptable. Observations with a ratio outside this range were considered suspect and must be examined by human editing experts. The editors were assumed to detect and correct all errors in the observations submitted to them.

The ratio control is implemented in a computer program used for editing the observations. *N1* of the *N* observations are rejected as suspect and passed on for subsequent expert editing. The remaining *(N-N1)* observations are accepted by the computer editing control. Two types of errors can be made in such a situation.

Type I error is rejection of a correct observation. *Type I errors* have in the considered editing process no effects on the quality of the results since all suspected observations are passed on to the expert editors by whom they are identified as correct or corrected. *Type II errors*, acceptance of incorrect observations may, however, be among the (*N-N1)* accepted observations and affect the quality.

Two sets of observations are available for estimating Y':

(1) *N1* observations rejected by computer control and then edited by expert editors, and
(2) (*N-N1)* observations which were accepted by the computer control.

Based on these,

$$Y' = \Sigma_1^{\ N1}\, y_i \ + \Sigma_{N1+1}^{\ \ N}\, y_j\,'$$

is a composite estimator of *Y*. Note that the first term will according to the design of the editing process be free from errors because all items are inspected by the editors.

The estimator can therefore be rewritten as

$$Y' = \Sigma_1^{\ N}\, y_i \ + \ \Sigma_{N1+1}^{\ \ N}\, e_j$$

where $e_j = y_j' - y_j$. If e_j is different from *0*, an error in observation *j* was accepted by the computer control program. The quality of the estimate will obviously be determined by the characteristics of the variable e. By drawing a sample of *n* records from the (*N-N1)* accepted observations and letting expert editors review the sampled observations, estimates of the mean m_e and the standard deviation s_e for the variable *e* as well as an estimate of the number of errors, n_1 , in the *N-N1* accepted observations can be obtained obtained.

A response error of the above estimate would be:

$$S' = s_e * \sqrt{(N-N1)}$$

An improved response error is obtained if the above estimate is multiplied by the factor $\sqrt{n_1/n}$ using the knowledge about the frequency of errors.

A probability expression of the type $Pr(|Y'-Y| <= 2*S') >= 0.75$, or $Pr(|Y'-Y| <= 2*S') = 0.95$ if the distribution of e can be considered normal, can be used to evaluate the quality of the estimate based on the above editing scheme.

3.3 Case 3: An estimate based on editing with several background variables

Let us assume that related to each observation y', a set of K background variables is also available. A relationship or pattern among the variables can be used for classifying the N observations in two groups, *acceptable* and *suspect* observations, based on a computerized classification model:

$$\psi_i = F1(y_i', x_{i1} .. x_{iK}) \text{ where: } \begin{cases} \psi_i = 0 \text{ if } y_i' \text{ is not compatible with the background variables} \\ \psi_i = 1 \text{ if } y_i' \text{ is compatible with the background variables} \end{cases}$$

where $F1$ denotes a mapping function from the set of possible patterns which may occur to the two classes.

The results of the computer classification of the N observations will be a group of $N1$ suspect observations and another group of $(N-N1)$ accepted observations.

Assume that a second computerized model, $F2$, is implemented and used to make imputations of correct values for the set of $N1$ suspect observations . The imputations are based on a function using the observed values and the background values as arguments

$$y_i'' = F2(y'_i, x_{i1} .. x_{iK})$$

The two models $F1$ and $F2$ can be developed from a sample of edited observations, from a previous survey of the same kind, or by means of expert knowledge gained through exensive work in the subject area.

An estimate of Y'' for the target total is obtained by the estimator

$$Y'' = \Sigma_1^{N1} \; y_i'' + \Sigma_{N1+1}^{N} \; y_j'$$

in which the first term is the sum of the values in the group of the N1 suspect observations after computer imputation while the second term are the sum of all observations accepted by the classification porgram.

We denote the deviations of the individual imputed values y'' and accepted observed values y' from their respective target values y as

$$y_i'' = y_i + r_i \,, \qquad i=1...N1,$$

and

$$y_j' = y_j + e_j \,, \qquad j=(N1+1)...N.$$

We assume that the second model may introduce imputation errors r_j which we also assume are random with common mean m_r and standard deviation s_r. The e_j is the response errors which are undetected by the editing control.

Let expert editors examine two small samples, one from the accepted observation class of *N-N1* observations and a second from the class of *N1* imputed observations. By assumption, this examination gives the target values of the *y*-variable for the sample units. The means and standard deviations of the *e*- and *r*-variables can then be estimated.

The estimate Y'' above can be rewritten as

$$Y'' = \Sigma_1^{\,N} \; y_i \; + \Sigma_1^{\,N1} \; r_i \; + \Sigma_{(N1+1)}^{\quad N} \; e_j \,.$$

Subject to the assumptions made, the response error for Y'' is then

$$S'' = \sqrt{N1 * s_r^2 + (N\text{-}N1) * s_e^2} \,.$$

Each of the two terms can be further refined as done in the two previous cases by taking into the account the relative frequencies of $r \neq 0$ and $e \neq 0$ in the two respective samples. Note that in this case the quality evaluation comprises two error typers, response errors not detected and imputation errors introduced.

3.4 Case 4: An estimate based on predicted data

Assume that the producer of statistics can justify to collect and edit observations for only a sample *n* units from the population while background variable values are available for all the *N* units. From a subsample n_1 of *n*, a prediction model

$$y_i'' = f(x_{i1} \,..\, x_{iK})$$

of the same type as the imputation model of the previous case, is developed. The predicted value y_i'' is related to the target value by $y_i'' = y_i + e_i$. The assumptions made in the previous cases for the error variable e are repeated.

Traditionally, the y-values for the sample of n units and the background x-values would be used in some ratio or regression estimator

$$Y' = F(\Sigma_1^n y_i , \Sigma_1^n x_i , \Sigma_{n+1}^N x_i)$$

which takes advantage of the knowledge about the totals of background variables in the sample and the remaining population. The quality measure of this estimate is the sampling error reflecting the fact that uncertainty is introduced because of random sampling of n observations.

Alternatively, the prediction model is used to get individual predictions y_i'' for each of the $(N-n)$ units not observed in the sample. The estimator used is

$$Y'' = \Sigma_1^n y_i + \Sigma_{n+1}^N y_j''$$

which re-written becomes

$$Y'' = \Sigma_1^n y_i + \Sigma_{n+1}^N e_j .$$

The uncertainty is now introduced because the predicted values are assumed to be affected by random errors. The *prediction error* of Y' is

$$S'' = s_{e*}\sqrt{(N-n)}$$

where s_e is the root mean square error for e. An estimate of this parameter is obtained by reserving a small number n_1 of the sample n, only for this purpose. For this subsample, the prediction model is used to compute predicted values in addition to the observed values. The root mean square error s_e is computed as the root of

$$s_e^2 = \Sigma(y_i'' - y_i)^2 /(n_1 -1)$$

As for the previous cases, a quality requirement can be specified for for Y'' and the predictor error be used for quality declarations as discussed for the cases above. It has been proved that the bias of e can be ignored if it is small.

It should be noted that this prediction model deviate from the imputation model of Case 2 by not including any observed value of the variable to be predicted.

4. Empirical examples

4.1 Experimental approach

The reliability of the quality metrics presented in in previous sections of this paper can be tested in a number of ways. One approach will be to use a real statistical survey for which we have edited data as the starting point for the tests. Errors could be imposed on the edited data simulating the processes. Adding the errors to the edited data produces a synthetic raw data set. The editing method to be evaluated would be applied on the synthetic data set to identify and correct errors resulting in a synthetic edited data set. From this set, estimates of totals would be computed, the quality of the estimates be predicted and finally the results from the processing of the synthetic data set be evaluated by comparison with the original edited data set. Because we know the exact target values as well as the imposed errors, we would be able to evaluate both the quality of the results of the method studied as well as the reliability of the quality predictions. Thi approach is illustrated by the UK experiment to evaluate the neural net for editing 'knocked' out components from the edited records to obtain a synthetic, data set with partial non-response [Cruddas 1997].

Another approach would be to find a test material for which both the original observed data including errors and the edited target data, were preserved. Two examples of this approach are presented in the following sections .

In the following section, the scenario from section 3.1 will be demonstrated by means of real data. The basis will be records for enterprises from the Swedish 1990 Annual Statistics on Manufacturing. In the subsequent section 4.3, the the reliability of prediction estimates of totals based on data from the 1990 Population Census of Sweden.

4.2 Example 1: Editing and imputation experiment

Dan Hedlin has carried out an intensive analysis on the editing process of the Swedish 1990 Annual Manufacturing Statistics in which he matched the collected, raw record with the final edited record for each enterprise [Hedlin 1993]. For the present experiment, both these two sets of records were used. Each file included 7289 records for the defined population of enterprises and each record contained 638 bytes and 58 fields or variables.

For the present example, it was assumed that only one third of the records were initially edited. This was simulated by selected as a random sample of both raw and edited records for 2430 enterprises. Both sets of records from the sample were used to compute s_e while the edited values were used for estimating the standard deviation s_y of the edited values for each of the variables.

It was imagined that the statistical producer had to decide satisfactory estimates could be derived from the sample. In this case, should composite estimates be computed for the 58 totals or would simple estimates would be preferable. The answers to these questions required that the effect of the editing on the quality of the final statistics was evaluated. Assume that the publication standard of the producer requires that estimates with a relative deviation from the target totals greater than 0.3 should not be released for publication. The challenge will be to determine the estimates not satisfying this requirement based on predicted quality.

Table 1: Predicted compared with actual quality of composite estimates.

		Actual deviation:		
		<=0.3	**>0.3**	**Sum**
Predicted deviation:	**<=0.3**	*30*	*11*	*41*
	>0.3	10	*7*	*17*
Sum		40	*18*	*58*

Since this was an experiment in which we knew the target values of the totals, it was possible to compare totals of the unedited data with the totals av completely edited data. As a starting point the comparison showed that the relative deviations for 28 of the totals of unedited data from the edited totals exceeded the quality standard 0.3 for publication

Two alternative sets of estimates, composite and simple estimates, with associated quality measures were computed from the 2430 enterprises in the sample. The last column of Table 1 shows that 41 of the 58 estimates were predicted to satisfy the quality standard for publication while the remaining 17 were predicted to deviate with more than 0.3.

Would it be safe for the statistical producer to make his/hers decision on these predictions?

Since this is an experiment, we could complete all cells in the table. The bottom line shows that 40 estimates were in fact satisfying the quality requirement. According to section 3.1 we should expect that less than ¼ or about 15 of the estimates would be incorrectly rejected. The figure for incorrectly rejected estimates is 10 and less than what could be expected when relying on Tcebycheff teorem. On the other hand, the number of estimates incorrectly predicted to satisfy the publication requirement is 11.

Would the producer be better off if he decided to compute simple estimates using edited values only? The above excercise was repeated for the second type of estimates and the results are displayed in Table 2. The number of estimates predicted acceptable is about the same while the actual number of estimates satisfying the requirement is better than for the composite estimates.

Table 2: Predicted compared with actual quality of simple estimates.

		Actual deviation:		
		<=0.3	**>0.3**	**Sum**
Predicted deviation:	**<=0.3**	*33*	*7*	*40*
	>0.3	11	*7*	*18*
Sum		44	*14*	*58*

This example illustrates the possibility to evaluate the quality of estimates which are based on partly edited data, and the effects of editing on the estimates.

4.3 Example 2: Prediction experiment

In this section, data from the 1990 Population Census in Sweden are used to exemplify the discussion in section 3.4. A similar study based on the Norwegian 1990 Population Census has been published elsewhere [Nordbotten 1996]. The Swedish data was compiled partly as responses to population census questionaires and partly from administrative registers. The ideal would be a situation in which all requested population data could be retrieved from administrative registers according to needs. However, new needs will always emerge for which register data are not available. An obvious question would be if such needs can be covered by sample surveys connected to the register data. Can reliable statistics be computed without requiring large sample surveys?

In this second example to be described, a national random sample of size 1.014 records from the Swedish 1990 population files was used. Each individual record contained 126 attribute fields, in total 361 bytes per record. The attributes were considered to be of two types, survey attributes collected by means of a survey and register attributes retrieved from the registers. The survey attributes selected for the example reported here were:

Hours worked in observation week, qualitative attribute, 7 categories
Means of transportation, qualitative attribute, 8 categories

The register attributes used were:

Geographical region, qualitative attribute, 25 categories
Sex, qualitative attribute, 2 categories
Age, quantitative attribute, continuous
Marital status, qualitative attribute , 10 categories
Type of houshold, qualitative attribute, 5 categories
No. of rooms in appartment, quantitative attribute , discrete
People in appartment, quantitative attribute, disctrete
Employment, qualitative attribute, 6 catagories
Type of profession, qualitative attribute, 4 categories
Type of employer, qualitative attribute, 10 categories
Main industry, qualitative attribute, 10 categories
Employment status, qualitative attribute, 6 categories
Gross income, quantitative attribute, continuous
Main education, qualitative attribute, 10 categories.

Each of the qualitative attributes were transformed to a set of binary variables, one for each category. The result were 15 target/survey variables and 88 input/register variables used for this example.

By means of smaple data, two neural network prediction models were trained, one for each of the two target variables, to predict the individual survey variables.

A second national random sample of 209 records and independent of the first sample, was then drawn. The individual survey variable values were predicted for each individual by the two trained neural networks. For each of the15 survey variables of these 209 individuals, both target and predicted values were now available and the individual root mean square prediction errors estimated.

A third independent, random sample of *996* individuals were finally extracted. This sample was assumed to represent a request for statistics for an unknown stratum. Predictions for the survey variables for each of the individuals were also computed for this sample and the prediction estimates of the survey variable totals aggregated. Based on the root mean square errors from the second sample, prediction errors for these estimates were computed for comparison with the actual deviations.

It was assumed that quality publication standards implied that only estimates with an error equal 10 or fewer individuals should be released for this group of *996* individuals. Only estimates with a predicted error satisfying $|Y'-Y|<=10$ were therefore declared for release. Incorrect declaration of estimates with an actual error larger than 10 would only be tolerated for a preset probability.

An analysis of the prediction error distributions of the second sample indicated a distribution which deviated significantly from a normal distribution. Tsebycheff inequlity was therefore used. Using $2*S'>10$ as a prediction for $|Y'-Y|>10$ would then be incorrect in less than *25*% of the estimates.

Table 3: Predicted compared with actual quality. Example 2.

Actual deviation:		**<=10**	**>10**	**Sum**
Predicted deviation:	**<=10**	*5*	*1*	*6*
	> 10	*3*	*6*	*9*
Sum		*8*	*7*	*15*

Table 3 shows that among the 15 estimates, 8 deviated with l0 or less individuals from the target total. The table also indicates that 6 estimates were predicted to have the required quality of which 5 in fact were correct predictions. Three out of the 15 prediction estimates were incorrectly predicted not to satisfy the quality requirement. This is 1/5 of the number of totals, and correspond to what should be expected according to Tchebycheff inequality.

5. Conclusions

The purpose of editing and imputation is to improve statistical quality. In this paper, metrics useful for quality prediction are proposed. Such metrics are closely related the prosesses of editing, imputation and prediction. The quality of a statistical value was defined as the unknown deviation from the its target value. The quality must therefore be predicted.

Quality metrics for predicting quality in 4 different cases were proposed and discussed. These metrics can provide quality measures to be used for quality declarations. The reliability of the quality measures is demonstrated in a couple of empirical experiments and seem promising, but will require further experimentation and analysis.

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5. References

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Table A: Relative estimate errors and quality measures. (Not to be published)

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Variable	(Unedited total-target) /target (1)	(Composite estimate - target) /target (2)	Response error /target (3)	(Simple estimate - target) /target (4)	Sampling error /target (5)
(a) var201	0.17	0.13	0.06	0.00	0.08
(b) var202	0.00	0.01	0.03	-0.56	0.10
(c) var211	-0.21	-0.22	0.03	-0.45	0.07
(d) var212	011	0.06	0.06	-0.05	0.06
(e) var213	-0.08	-0.09	0.05	-0.35	011
(f) var221	4.38	4.40	0.01	-0.03	0.02
(g) var222	0.01	-0.04	0.12	-0.06	0.09
(h) var223	22.31	21.49	1.43	-0.14	0.06
(i) var224	0.03	0.07	0.10	-0.23	0.22
(j) var225	57.79	55.37	4.05	-0.05	0.10
(k) var226	0.07	0.07	0.01	-0.53	0.11
(l) var227	128.50	128.50	0.05	-0.13	0.15
(m) var228	8.83	8.83	0.00	0.32	0.56
(n) var229	301.52	301.49	0.11	-0.33	0.20
(o) var230	4.37	0.21	7.29	0.20	0.70
(p) var301	0.23	0.13	0.08	-0.03	0.07
(q) var302	0.35	0.19	0.12	0.02	0.05
(r) var303	0.74	0.15	1.74	1.03	1.25
(s) var304	0.05	-0.03	0.08	-0.39	0.10
(t) var305	0.28	0.13	0.10	-0.02	0.06
(u) var306	1.02	1.01	0.06	0.02	0.09
(v) var307	-0.08	-0.08	0.04	-0.61	0.08
(w) var308	0.23	0.13	0.15	-0.06	0.10
(x) var309	0.70	0.05	1.06	-0.07	0.10
(y) var310	0.69	0.03	1.21	0.21	0.25
(z) var311	0.27	0.15	0.21	-0.02	0.23
(aa) var312	0.06	0.03	0.04	-0.01	0.07
(ab) var313	0.07	0.03	0.04	0.16	0.15
(ac) var314	0.09	0.04	0.05	-0.03	0.09
(ad) var315	-0.1|7	-0.15	0.06	-0.06	0.10
(ae) var316	0.20	0.14	0.05	-0.15	0.06
(af) var317	0.03	-0.01	0.05	-0.06	0.06
(ag) var401	3.73	3.70	0.03	-0.02	0.08
(ah) var402	3.01	2.96	0.04	0.02	0.07
(ai) var403	0.26	0.19	0.07	-0.03	0.11
(aj) var404	0.20	0.13	0.09	0.06	0.15
(ak) var501	0.04	0.03	0.01	0.17	0.22
(al) var502	0.41	0.32	0.08	0.12	0.34
(am) var503	-0.74	0.00	1.29	1.41	1.82

(an) var601	12.37	6.85	6.80	0.24	0.34
(ao) var602	158.89	150.44	12.55	0.67	0.61
(ap) var604	5.20	5.20	0.01	-0.03	0.07
(aq) var605	0.00	0.00	0.01	-0.04	0.06
(ar) var607	0.11	0.09	0.04	-0.02	0.09
(as) var608	0.10	0.10	0.02	-0.03	0.06
(at) var610	0.00	0.00	0.01	0.01	0.05
(au) var611	0.01	0.01	0.00	-0.01	0.05
(av) var612	10.42	5.72	2.63	0.01	0.04
(aw) var613	-0.01	0.01	0.02	-0.02	0.09
(ax) var614	2.42	2.43	0.01	0.28	0.19
(ay) var615	5.42	2.91	1.90	0.00	0.10
(az) var616	0.17	0.09	0.07	0.26	0.18
(ba) var617	1619.47	16.53	2450.09	-0.64	0.13
(bb) var618	16.02	3.70	15.12	0.18	0.16
(bc) var619	-0.64	-0.03	0.95	1.22	1.35
(bd) var620	-0.47	-0.06	0.68	0.91	0.96
(be) var622	0.81	0.51	0.14	-0.30	0.12
(bf) var623	0.38	0.32	0.05	-0.14	0.19