

A Dynamic Method for the Evaluation and Comparison of Imputation Techniques

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Abstract— Imputation of missing data is important in many areas, such as reducing non-response bias in surveys and maintaining medical documentation. Estimating the uncertainty inherent in the imputed values is one way of evaluating the results of the imputation process. This paper presents a new method for the estimation of imputation uncertainty, which can be implemented as part of any imputation method, and which can be used to estimate the accuracy of the imputed values generated by both parametric and non-parametric imputation techniques. The proposed approach can be used to assess the feasibility of the imputation process for large complex datasets, and to compare the effectiveness of candidate imputation methods when they are applied to the same dataset. Current uncertainty estimation methods are described and their limitations are discussed. The ideas underpinning the proposed approach are explained in detail, and a case study is presented which shows how the new method has been applied in practice.

Index Terms— Imputation evaluation, Missing data, Missingness patterns, Uncertainty estimation.

I. INTRODUCTION

Imputation methods attempt to solve the problem of missing data by replacing missing values with plausible estimates. Rubin [1] points out that the primary (usually achievable) objective of imputation is to ensure that data analysis tools “*can be applied to any dataset with missing values using the same command structure and output standards as if there were no missing data*”, and that a further, desirable (but not always achievable) objective is to allow statistically valid inferences to be drawn when analysing imputed datasets. However, [2] also points out that “*a popular misunderstanding is that the goal of imputation is to predict individual missing values*”, and it is important to emphasise that imputed values should *never* be treated as if they are real values, since it is impossible to prove that they are accurate.

This complex definition of imputation objectives presents the owners of missing value datasets with complex evaluation problems, such as; How can the feasibility of the imputation project be assessed? How can the results of the imputation process be evaluated? How can the effectiveness of candidate

imputation methods be compared? We argue that these problems have not been sufficiently addressed, and we present a new method for the estimation and reduction of imputation uncertainty, which helps to solve them. The proposed approach can be implemented as part of any imputation method, and can be used to estimate the accuracy of the imputed values generated by both parametric and non-parametric imputation techniques.

Section II summarises current uncertainty estimation methods, and discusses their limitations. Section III explains the ideas underpinning the proposed method in detail. Section IV presents a case study which shows how the new method has been applied in practice. Section V summarises the paper and discusses the issues it raises.

II. CURRENT METHODS FOR ESTIMATING IMPUTATION UNCERTAINTY

Estimating the uncertainty inherent in the imputed values is one way of evaluating the results of the imputation process. Several methods for the estimation of imputation uncertainty have been proposed, and a good general overview of these can be found in [3]. The following sections summarise the most important methods, and discuss the limitations of these approaches.

A. Bootstrap and Jackknife Variance Estimation

Consider a variable $Y = (y_1, \dots, y_n)$ where some of the values are missing. The bootstrap and jackknife variance estimation methods [4]–[7] can be used to estimate the uncertainty created by imputing the missing values in Y . Where uncertainty is estimated by computing the variance of a set of parameter point estimates (such as the mean or standard deviation etc.), which describe a set of samples that are taken from Y , as follows;

for $b = 1$ to B

1. Create a new bootstrap sample Y_b by randomly selecting a set of values (with replacement) from Y
2. Impute the missing values in Y_b using a suitable imputation method
3. Compute a parameter point estimate $\hat{\theta}_b$ which describes the values in Y_b

next b

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The procedure produces a set of estimates $\{\hat{\theta}_1 \dots \hat{\theta}_B\}$ which describe the bootstrap samples $\{Y_1 \dots Y_B\}$. The bootstrap estimate of the variance \hat{V}_{boot} can then be used to estimate imputation uncertainty, as follows;

$$\hat{V}_{boot} = \frac{1}{B-1} \sum_{b=1}^B (\hat{\theta}_b - \hat{\theta}_{boot})^2 \quad \text{where} \quad \hat{\theta}_{boot} = \frac{1}{B} \sum_{b=1}^B \hat{\theta}_b$$

The method simply imputes the missing Y_b values B times, then computes the variance of the resulting set of $\hat{\theta}_b$ estimates. The jackknife variance estimation method is similar. The difference lies in the method used to create the set of samples, which in turn requires a more complex method of computing the variance, as follows;

Impute the missing values in Y using a suitable imputation method
 Compute a parameter point estimate $\hat{\theta}$ which describes the values in Y

for $j = 1$ to n

1. Delete value j from Y to create a new jackknife sample $Y_{(\setminus j)}$
2. Impute the missing values in $Y_{(\setminus j)}$ using the same imputation method as above
3. Compute the same parameter estimate as above $\hat{\theta}_{(\setminus j)}$ which describes the values in $Y_{(\setminus j)}$

next j

Where n is the number of values in $Y = (y_1, \dots, y_n)$

The procedure produces a set of estimates $\{\hat{\theta}_{(\setminus 1)} \dots \hat{\theta}_{(\setminus n)}\}$ which describe the jackknife samples $\{Y_{(\setminus 1)} \dots Y_{(\setminus n)}\}$. The jackknife estimate of the variance \hat{V}_{jack} can then be used to estimate imputation uncertainty, as follows;

$$\hat{V}_{jack} = \frac{1}{n(n-1)} \sum_{j=1}^n (\tilde{\theta}_j - \hat{\theta}_{jack})^2$$

$$\text{where} \quad \tilde{\theta}_j = n\hat{\theta} - (n-1)\hat{\theta}_{(\setminus j)} \quad \text{and} \quad \hat{\theta}_{jack} = \frac{1}{n} \sum_{j=1}^n \tilde{\theta}_j$$

The jackknife method can be much more computationally intensive than the bootstrap when n is large, since the imputation process must be repeated n times. However, in these cases jackknife performance can be improved by deleting a *set of values* (not just one) at each iteration of the loop.

B. Multiple Imputation

Consider a variable $Y = (y_1, \dots, y_n)$ where some of the values are missing. Multiple imputation (MI), [1] and [8]–[10] can be used to estimate the uncertainty created by imputing the missing values in Y , as follows.

for $d = 1$ to D

1. Impute the missing values in Y using a stochastic method to create a unique imputed dataset Y_d
2. Compute a parameter point estimate $\hat{\theta}_d$ which describes the values in Y_d
3. Compute the variance V_d associated with $\hat{\theta}_d$

next d

The procedure produces a set of estimates $\{\hat{\theta}_1 \dots \hat{\theta}_D\}$ and a set of associated variances $\{V_1 \dots V_D\}$ which describe the imputed datasets $\{Y_1 \dots Y_D\}$. The combined MI complete-data parameter point estimate for $\{Y_1 \dots Y_D\}$ is then given by

$$\bar{\theta}_D = \frac{1}{D} \sum_{d=1}^D \hat{\theta}_d$$

The total variability T_D , associated with $\bar{\theta}_D$, can then be used to estimate imputation uncertainty, as follows;

$$T_D = \frac{1}{D} \sum_{d=1}^D V_d + \frac{D+1}{D} \left(\frac{1}{D-1} \sum_{d=1}^D (\hat{\theta}_d - \bar{\theta}_D)^2 \right)$$

It is important to emphasise that MI is primarily an imputation method, rather than a technique designed for the estimation of imputation uncertainty. However, “*When the D sets of imputations are repeated random draws from the predictive distribution of the missing values under a particular model for nonresponse, the D complete-data inferences can be combined to form one inference that properly reflects uncertainty due to nonresponse under that model*”, as succinctly explained in [3].

C. Limitations of Current Methods

The uncertainty estimation methods described above have their limitations, and they make certain assumptions about the nature of the missing value dataset. These issues have been the subject of some debate among statisticians [1] and [5]–[6]. The main points for discussion are summarised below.

- All of the methods described above assume that the imputation process has removed the bias within the dataset that was caused by the missing values [3].
- The resampling methods described in section IIA are based on large-sample theory - i.e. they will return more reliable variance estimates for larger samples [3].
- The MI method assumes that the model describing the missing value dataset has been correctly specified. i.e. the reliability of the variance estimates returned by the MI method is sensitive to model misspecification. However, resampling methods return consistent variance estimates with minimal modelling assumptions, so they are more robust to model misspecification [5]–[6] and [11].

- Resampling methods usually require several hundred executions of the imputation process, performed against an equal number of samples drawn from the missing value dataset. This can be impractical in some situations. However, MI is less computationally intensive, since it allows good inferences to be drawn for a wide range of estimands, using perhaps 10 (or less) imputed datasets [12].
- The methods described above make no provision for the reduction of imputation uncertainty. However, there seems to be no reason why they could not be adapted for this purpose.

The following section presents a new method for the estimation and reduction of imputation uncertainty, which suffers from none of the above limitations. However, the proposed approach has its own limitations, and makes its own assumptions, which are also described below.

III. A DYNAMIC METHOD FOR ESTIMATING AND REDUCING IMPUTATION UNCERTAINTY

Consider a data matrix Y which has one or more missing values in one or more of its columns, such as the matrix shown below.

$$Y = \begin{bmatrix} - & ? & - & ? & - \\ - & ? & ? & - & - \\ ? & ? & - & - & ? \\ - & ? & - & ? & - \\ - & - & - & - & - \\ - & ? & ? & - & - \end{bmatrix}$$

The missing values are represented by ? symbols.
The known values are represented by - symbols.
The rows are indexed as $i = 1$ to n
The columns are indexed as $j = 1$ to p
Rows 1 and 4 have missingness pattern 10101
Rows 2 and 6 have missingness pattern 10011

Fig. 1 – Missingness patterns in a data matrix

A small proportion (perhaps up to 10%) of the known values are deleted at random from within the variable (column in Y) to be imputed. These values are recorded just before they are deleted, and a measure of how accurately they have been “put back” is taken when the imputation process is complete. This basic technique (with appropriate modifications) has been frequently employed to evaluate the success of various new, and existing, imputation methods [13]–[16], but it has not been utilised as a technique for the estimation and reduction of imputation uncertainty. However, the following equations can be used to estimate imputation uncertainty when this evaluation technique is employed.

$$RD_{ij} = \frac{|Y_{ij.trueVal} - Y_{ij.imputedVal}|}{|Y_{ij.trueVal}|} \quad (1)$$

Where $Y_{ij.trueVal}$ is the known (true) value that was deleted. And $Y_{ij.imputedVal}$ is the value generated by the imputation process.

$$MRD = \frac{1}{m} \sum_{i \in M} RD_{ij} \quad (2)$$

$$SRD = \sqrt{\frac{1}{m} \sum_{i \in M} (RD_{ij} - MRD)^2} \quad (3)$$

$$RZ_{ij} = \frac{RD_{ij} - MRD}{SRD} \quad (4)$$

$$MRZ = \frac{1}{z} \sum_{i \in Z} RZ_{ij} \quad (5)$$

Where j is the column in the Y matrix from which the values were randomly deleted and “put back”. And $M = \{r_1, \dots, r_m\}$ is the set of rows in Y with a deleted value. And i indexes the set of rows in M (which will differ for every execution of the method). And $Z = \{r_1, \dots, r_z\}$ is the set of rows in Y that have an RD outlier value.

The RD gives the relative differences between the known (true) and imputed values in column j of Y . The MRD gives the mean RD value - where larger MRD values indicate greater imputation uncertainty within the set of imputed values. The SRD gives the standard deviation of the RD - where larger SRD values indicate greater variability of the uncertainty.

Values of RZ within any required range, such as ± 3 SRD 's above and below the MRD , define RD outliers. Essentially, the RZ is a measure of the number of SRD 's by which any particular value of RD deviates from the MRD - where the set of RD values are assumed to be approximately normally distributed for this purpose. The MRZ gives the mean RZ value - where $PZ = z/m$ gives the proportion of RD outliers found within the set M .

Randomly deleting values from the variable to be imputed will produce a different set of uncertainty statistics each time the method is executed, which is an essential part of the proposed approach. The idea is to execute the method repeatedly, so that the variability of the statistics produced can be considered. For example, if large, but very similar, values of the MRD and SRD appear under repeated executions of the method, then the imputation process has high uncertainty, but this uncertainty does not depend on the particular set of values that are missing. This repetitive, stochastic approach is a key part of most modern imputation methods. For example, it is adopted (via repeated random sampling) as part of the bootstrap uncertainty estimation method described in IIA

It is important to note that deleting values at random from the

variable to be imputed increases the proportion of missing data in that variable. This affects the results of the imputation process, since more values need to be imputed. Further, since the method deletes values completely at random, it is assumed that the *truly missing values* (unknown values, rather than known values which have been deleted) are also missing completely at random (MCAR), in the rigorous sense defined in [17]. However, the MCAR assumption can never be proved or disproved, regardless of the uncertainty estimation method used, because it is impossible to find any sort of pattern within a set of unknown values, as pointed out in [18].

A. Estimating Uncertainty by Segmenting the Dataset

Generally, larger *MRD* values indicate greater uncertainty within the set of imputed values. However, larger *SRD* values show that this uncertainty is highly variable, and therefore it may be localised within one or more clearly defined data segments within the variable to be imputed - such as a particular set of missingness patterns (see Fig. 1), or a set of categories with clearly defined boundaries. In these cases it can be useful to discover the distribution of the *RD* values across these data segments, or to discover whether some segments contain higher proportions of *RD* outlier values than others (using equations (4) and (5)). To achieve this it is essential to delete the *same* proportion of values from each segment before measuring the uncertainties, so that each segment can be assessed equally.

Segmentation by category can be used to estimate the uncertainty created by imputation methods which do not utilise the missingness patterns within the data matrix - e.g. those methods which do not rely on regression based techniques to generate imputed values. When the dataset is segmented by category the process of deleting the same proportion of values from each category can be easily achieved by detecting the first and last rows of each category within the data matrix, as shown

in the left hand part of Fig. 2, below. However, it should be ensured that the proportion of known values in each category is sufficient to support the imputation process (where this is required - depending on the imputation method used, and on the proportion of *truly missing values* in each category). In cases where this is not possible the offending categories should be excluded from the uncertainty estimation process.

The method can also be used to compare and analyse the uncertainties within the missingness patterns found in the data matrix, as shown in the right hand part of Fig. 2. This can be implemented as part of any regression based imputation method which derives a different set of regression coefficients for each missingness pattern.

For example, the expectation-maximisation (EM) imputation algorithm, as described in [19] and [20], estimates missing values by deriving a unique regression equation for each row within each missingness pattern. Where each term in this equation is formed using the product of one of the derived regression coefficients for the missingness pattern in question, and one of the known values in the row being imputed. However, if the known values within a particular pattern do not form any sort of order within themselves (if they cannot be used to predict one another), then the uncertainty within the imputed values in this pattern will be large.

To properly compare and analyse the uncertainty within the imputed values in each missingness pattern it is essential to delete the same proportion of known values from all of the patterns to be evaluated. The algorithm used to perform these deletions must ensure that deleting values from the variable to be imputed does not create any *new* (and hence artificial) missingness patterns within the data matrix. A description of this algorithm, which is the most procedurally complex part of the proposed approach, is given below.

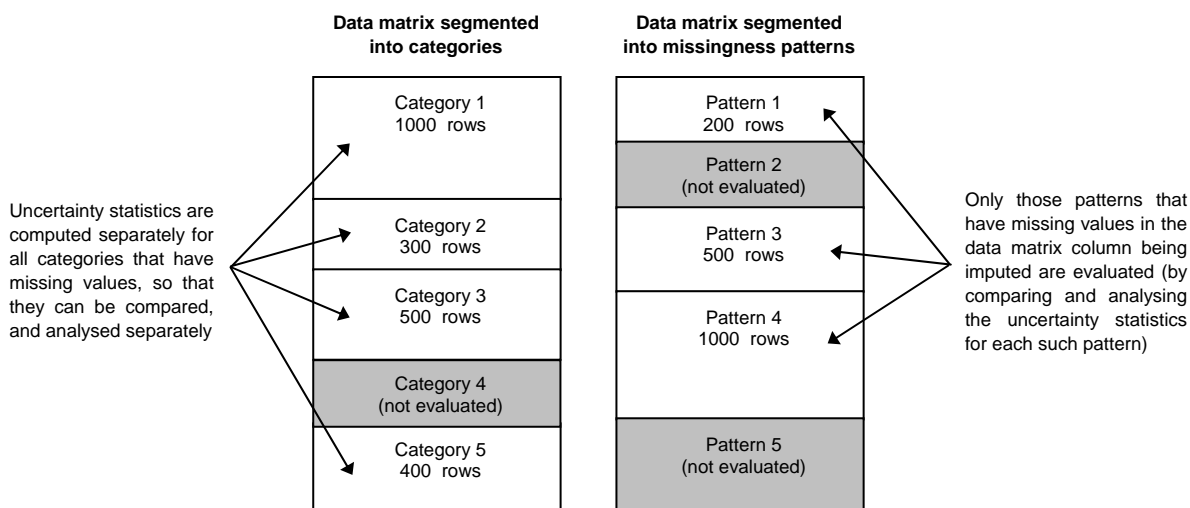


Fig. 2 – Comparing and analysing the uncertainty in different data segments

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function matrix_balanced_random_deletion_across_all_missingness_patterns_in_the_data_matrix
    (matrix data, vector patterns, int c, int d)

    dataMatrixRow data_row
    vector match_rows
    missPatternRow patt
    integer rows_to_add, random_row
    boolean match

    for i = 1 to num_rows_in ( patterns )
        patt = patterns ( i )
        if ( patt ( c ) == missing && some_values_are_present_in ( patt ) == true )
            match_rows = new vector ( )
            for k = 1 to num_rows_in ( data )
                data_row = data ( k )
                if ( data_row ( c ) == present )
                    match = true
                    for j = 1 to num_columns_in ( data )
                        if ( patt ( j ) == present && data_row ( j ) == missing )
                            match = false
                        end if
                    next j
                    if ( match == true )
                        match_rows . Add_To_End ( k )
                    end if
                end if
            next k

            rows_to_add = ( d / 100 ) * num_rows_in ( patt )
            if ( num_rows_in ( match_rows ) > rows_to_add * 2 )
                for k = 1 to rows_to_add
                    random_row = Random ( 1, num_rows_in ( match_rows ) )
                    data_row = data ( match_rows ( random_row ) )
                    match_rows . Remove_Row ( random_row )
                    for j = 1 to num_columns_in ( data )
                        if ( patt ( j ) == missing )
                            data_row ( j ) = missing
                        end if
                    next j
                next k
            end if
        end if
    next i
    return data
end function

```

Algorithm 1 – A procedure to perform balanced random deletions across a set of missingness patterns

The procedure increases the number of rows in each of the missingness patterns to be evaluated by the same proportion, i.e. the number of rows in each pattern that has missing values in column *c* is increased by *d*%. This is achieved by transferring *data* matrix rows from one pattern to another. For example, when deleting from *data* column one the procedure might transfer a *data* row by changing its pattern from “1111” to “0111”. However, the *data* rows transferred must have known values in the same columns as the *data* rows in the pattern to be evaluated (the pattern with rows added to it). For example, if the pattern to be evaluated was “0011”, then *data* rows with the pattern “1100” could not be transferred to that pattern, but *data* rows with the pattern “1111”, could be transferred to it.

The final pair of nested *for* loops perform the random row transfers. However, this can only be achieved for a particular

pattern if the number of *data* rows available for transfer (as stored in the *match_rows* vector) is more than double the number of rows to be added to the pattern to be evaluated. This ensures the stochastic nature of the row transfer process under repeated executions, which is an essential part of the method. If the number of *data* rows available for transfer is too small, then the uncertainty in the pattern to be evaluated cannot be estimated separately. However, this should only occur very rarely - i.e. when the proportion of missing values in column *c* is large (perhaps above 80%), or when the number of missingness patterns is a small proportion of the number of possible patterns. In these cases the method of comparing the uncertainty across a set of categories should be preferred.

B. Reducing Imputation Uncertainty

The method described in the preceding section allows the uncertainty in each data segment (see Fig. 2) to be estimated separately - i.e. the method allows the statistics returned by equations (1) to (5) to be computed separately for each segment. Further, since the same proportion of values were deleted from each segment, an additional uncertainty statistic can be computed for each segment, as follows;

Let j = the column in the Y matrix from which the values were randomly deleted and “put back”.

Let D = the data segment being evaluated for uncertainty (see Fig. 2).

Let $S = \{r_1, \dots, r_s\}$ be the set of rows in D with a deleted value, where i indexes these rows.

Let $M = \{r_1, \dots, r_m\}$ be the set of *all rows in Y* with a deleted value, where i indexes these rows

The expected uncertainty for the data segment D is then given by

$$EU = \frac{s}{m} \sum_{i \in M} RD_{ij}$$

Where each RD_{ij} value is computed using equation (1)

The expected uncertainty is simply a device which enables the calculation of a useful uncertainty statistic. In fact, one would expect the uncertainty within the imputed values in each segment to be very different, rather than conforming to some expected value. For example, one would expect the regression equations derived for each missingness pattern to have different predictive powers. Therefore, one would expect the imputed values generated using these equations to have varying degrees of uncertainty. However, the idea is to use the notion of the expected uncertainty to compute the statistic described below. This is achieved by comparing the expected and actual uncertainties for the data segment D , where the actual uncertainty is given by

$$AU = \sum_{i \in S} RD_{ij}$$

Where each RD_{ij} value is computed using equation (1)

It follows that the equation $SU = AU / EU$ can be used to discover whether the data segment D has contributed more or less than it's expected proportion of the overall uncertainty within the imputed values in column j of the Y data matrix. For example,

If $SU = 0.5$ then D has contributed half of it's expected proportion of the overall uncertainty.

If $SU = 10$ then D has contributed ten times it's expected proportion of the overall uncertainty.

Consequently, all of the data segments which contribute

more than their expected share of the overall uncertainty can be discovered. The MRD and SU for each segment can then be used to estimate the uncertainty in those segments. And in cases where the uncertainty for a particular segment is disproportionately large, the overall uncertainty can be reduced by discarding *all of the imputed values* in that segment. This approach can be beneficial in cases where the proportion of imputed values in the offending segments is relatively small - i.e. in these cases the overall uncertainty will be reduced by discarding a small proportion of the imputed values. However, in cases where the proportion of imputed values in the offending segments is relatively large, a much larger proportion of the imputed values would be discarded - and in the most extreme cases the best decision could be not to proceed with the imputation process at all.

The fundamental argument underpinning this method of uncertainty reduction is as follows. If the *deleted values* in a particular segment were “put back” very inaccurately, then it is probable that the *truly missing values* in this segment will contain imputation errors of a similar magnitude. However, it is impossible to prove, or disprove, this assertion, because the imputation of *truly missing values* can never be proven to be accurate using any approach - since the true values are unavailable for comparison.

It is important to emphasise that the decision to discard the imputed values in a particular data segment must be taken by the user of the imputation software. This decision is complex and difficult to automate, because *all of the uncertainty statistics for all of the segments* need to be considered and compared. For example, an examination of the uncertainty statistics could reveal that the uncertainty in a particular segment has been caused by one or two extreme outlier RD values (see equations (4) and (5)). In such cases the user of the software might decide to examine the data rows in the offending segment in detail, to discover why this has occurred. This could reveal some hidden characteristics of the missing value dataset, which could not be discovered using any other approach.

IV. APPLYING THE METHOD IN PRACTICE: A CASE STUDY

This section describes how the method was used to estimate uncertainty when imputing missing data in a survey dataset which describes 61,389 small to medium-sized business enterprises (SME's), within the United Kingdom (UK). The imputation process was expected to produce high levels of uncertainty within the imputed values because of the poor quality of the dataset, as described below.

Table I – Variables in the case study dataset

| Dataset variable | % missing |
|---------------------|-----------|
| UKSIC Category | 0 % |
| OS Easting | 0 % |
| OS Northing | 0 % |
| Number of Employees | 0 % |
| Payroll | 63.08 % |
| Sales | 67.50 % |
| Net Worth | 40.69 % |
| Profit Before Tax | 58.16 % |
| Directors Pay | 59.40 % |
| Depreciation | 63.90 % |

- The financial variables all have large proportions of missing data.
- 39% of the SME's have no known financial figures whatsoever.
- The known values within the financial variables contain small proportions of extreme outlier values.
- There are 24 missingness patterns within the dataset, but these are unbalanced, with some patterns containing very few SME's.
- There are 479 different UKSIC categories within the dataset, but approximately 11% of these have more than 80% missing values.
- The quality of the UKSIC categorization is poor, with some categories containing SME's that could not be properly classified.

Where the SME's in each UKSIC (United Kingdom Standard Industrial Classification) category carry out the same commercial activities, such as "Publishing of software" etc. And where the OS Easting and OS Northing variables specify the geographical location of each SME, using UK Ordnance Survey mapping co-ordinates.

The imputation experiments described below were designed to discover whether imputation of the missing financial figures was feasible, and to discover whether a parametric imputation method (the EM algorithm) or a non-parametric imputation method (K nearest neighbors (KNN), [15], [16] and [21]) would produce the least uncertainty within the imputed values. For EM imputation a matrix was formed (see Fig. 1) with 61,389 rows and 7 columns - i.e. the 6 SME financial variables and the number of employees. The EM algorithm was then used to impute *all of the missing values* in the matrix using a *single execution* of that algorithm. The following distance function was employed for nearest neighbor imputation

$$S_m.imputedVal = \frac{\sum_{i=1}^k \frac{S_i.donorVal}{d(S_m, S_i)}}{\sum_{i=1}^k \frac{1}{d(S_m, S_i)}}$$

Where S_m is the SME with the missing financial value, and S_i are the set of k nearest neighbor SME's (donors), which are taken from the same UKSIC category as S_m , and which have the same (or the closest available) number of employees as S_m . And where $d(S_m, S_i)$ gives the geographical (Euclidean) distance between S_m and S_i , so that financial values in geographically closer SME donors are given more weight.

The results of the Payroll imputation evaluation experiments are tabulated below - i.e. Tables II and III show the uncertainty statistics that were produced (using equations (1) to (5)) when imputing the missing Payroll figures for 61,389 SME's, using the EM and KNN imputation methods described above.

Table II – Evaluation of the EM imputation process.

| MRD | SRD | MRZ | % Outliers |
|-------------|--------------|--------------|-------------|
| 6.75 | 97.03 | 14.22 | 0.27 |
| 5.65 | 67.13 | 14.01 | 0.32 |
| 6.50 | 55.34 | 8.63 | 0.80 |
| 7.13 | 65.20 | 8.92 | 0.75 |
| 6.22 | 67.29 | 10.78 | 0.48 |
| 5.29 | 57.01 | 11.38 | 0.43 |
| 3.85 | 30.68 | 7.68 | 0.91 |
| 8.92 | 111.07 | 10.76 | 0.54 |
| 7.38 | 76.39 | 9.23 | 0.70 |
| 7.35 | 93.14 | 11.02 | 0.37 |
| 6.50 | 72.03 | 10.66 | 0.56 |

Table III – Evaluation of the KNN imputation process.

| MRD | SRD | MRZ | % Outliers |
|-------------|---------------|--------------|-------------|
| 7.23 | 64.72 | 10.64 | 0.58 |
| 9.65 | 116.04 | 9.96 | 0.47 |
| 11.19 | 245.05 | 11.15 | 0.25 |
| 5.14 | 43.99 | 8.93 | 0.68 |
| 22.01 | 484.75 | 14.01 | 0.22 |
| 5.35 | 54.95 | 9.29 | 0.54 |
| 6.66 | 78.53 | 11.29 | 0.40 |
| 6.76 | 65.32 | 10.66 | 0.58 |
| 8.78 | 174.69 | 12.83 | 0.22 |
| 12.95 | 249.70 | 18.25 | 0.18 |
| 9.58 | 157.78 | 11.70 | 0.41 |

A. Interpreting the Experimental Results

5% of the known Payroll values were randomly deleted for all experiments, so that a measure of how accurately they were "put back" could be taken. The experiments were repeated 10 times for each of the imputation methods, so that the variability

of the uncertainty statistics produced could be considered. The bottom rows of Tables II and III give the mean values of the statistics produced for all 20 experiments. A reasonable uncertainty benchmark for any imputation process would be an MRD value of less than one - i.e. the deleted values should be “put back” (on average) to within 100% of their true values. However, Tables II and III show that the MRD values returned for the SME dataset were 6.50 (for the EM imputation process) and 9.58 (for KNN) - i.e. the expected high uncertainty levels appeared, because of the overall poor quality of the data.

The MRD values in Table II show that the EM imputation process created less uncertainty than the KNN process, and the SRD values show that EM also produced less variable uncertainty than KNN - i.e. the uncertainty for the KNN process was much more dependant on the particular set of values that were deleted. The MRZ and % Outliers show that a small proportion of the deleted values were “put back” very inaccurately for every experiment. Further investigation revealed that these inaccurately replaced values were causing the major portion of the uncertainty - i.e. equation (1) returned RD values of between zero and one for at least 83% of the deleted values for every experiment, but the MRD values were always much larger, as Tables II and III show.

For EM, the *same two* missingness patterns were found to be causing the major portion of the overall uncertainty for every experiment. However, these patterns contained most of the SME’s, and discarding the imputed values in them would have removed over 80% of the imputed values, so this was not attempted. For KNN the UKSIC categories causing the most uncertainty differed for every experiment - i.e. they depended on the particular set of values that were deleted - so there was no point in discarding the imputed values in any of these categories.

It was therefore concluded that the high proportion of missing Payroll values, combined with the overall poor quality of the dataset, made the feasibility of Payroll imputation questionable, and that in this case discarding the imputed values in selected data segments could *not be* effectively used to decrease imputation uncertainty. It was further concluded that if imputation was to be attempted, a parametric method should be used, but the simple EM method described above should be improved. For example, the missing values within each UKSIC category could be imputed separately, and some way of utilising the geographical information could be built into the process.

V. SUMMARY AND DISCUSSION

How can the feasibility of the imputation project be assessed? How can the results of the imputation process be evaluated? How can the effectiveness of candidate imputation methods be compared? We argue that these problems have not been sufficiently addressed, and we have presented a new method for the estimation and reduction of imputation uncertainty, which helps to solve them. All imputation methods

have the same basic objective - i.e. they try to make the best possible use of the information content (the patterns etc.) within the *known* values, to generate the best possible estimates for the *missing* values. We argue that uncertainty evaluation methods should also make the best possible use of the *known* values, and the method described in this paper does just this.

Current uncertainty estimation methods have their limitations. In particular, they take no account of the accuracy of the imputed values, and they make no provision for the reduction of imputation uncertainty. The proposed approach addresses these problems, and we argue that the new method is fully consistent with imputation objectives, since it would be very hard to deny the success of *any* imputation method which can be shown to have repeatedly “put back” a set deleted values with a high degree of accuracy.

The proposed approach allows the uncertainty within different data segments (such as missingness patterns) to be estimated separately. And in cases where the uncertainty for a particular segment is disproportionately large, the overall uncertainty can be reduced by discarding *all of the imputed values* in that segment. Current uncertainty estimation methods do not adopt this approach, but there seems to be no reason why they could not be adapted for this purpose. However, it is important to emphasise that the decision to discard the imputed values in a particular segment must be taken by the user of the imputation software. We argue that there is no substitute for human judgment when considering these matters, and that the proposed method simply facilitates the decision making process, by automating the calculation and display of various uncertainty statistics.

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