Data Quality Check: Methods & Procedures

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TECHNICAL REPORT

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CONTENT

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This methodological review has a clear focus on spatial analysis with respect to outlier-detection; and is complemented by worked examples on an ESPON-type data set, where chosen techniques are demonstrated. Worked examples are coded using open-source software so that the applied techniques are easily transferable.

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MULTI DIMENSIONAL DATABASE DESIGN & DEVELOPMENT

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1 INTRODUCTION

The ESPON Database should be as free from errors as possible. It follows from this that detecting errors is an important activity in both data entry and data checking. This technical report is to examine how mathematical, statistical and spatial analysis tools can be applied to the ESPON Database in order to find 'logical input errors' and 'statistical outliers'. In both cases, 'exceptional values' can arise but it is not always clear if such values relate to input errors or true values that are statistically-outlying. In this respect, reliably determining the nature of an exceptional value is important, especially as input errors should be treated differently to statistical outliers. For example, input errors are usually corrected or removed, whilst suspected outliers are usually flagged for further scrutiny.

The outcome of this report is a targeted review of existing outlier-detection tools in the field of statistics, data mining and spatial analysis, and an examination how they can assist in the detection of errors/outliers in the ESPON Database for improved quality control. This methodological review has a clear focus on spatial analysis with respect to outlier-detection; and is complemented by worked examples on an ESPON-type data set, where chosen techniques are demonstrated. Worked examples are coded using open-source software so that the applied techniques are easily transferable. The list of techniques that are applied should not be considered as exhaustive, but form a cross-section of useful techniques which are appropriate for ESPON Database.

A related aim of this report is to examine the effects of the Modifiable Areal Unit Problem (MAUP) with respect to error/outlier identification. This follows previous research by NCG for the ESPON 2006 project on this topic (ESPON 2006).

We describe the software that has been developed in the R[1] language, its operation, and how it was used in practice. Appendices contain the R code in its entirety.

[1] Other researchers have proposed R as well: http://www.ilr.uni-bonn.de/agpo/rsrch/capri-rd/docs/d2.3.5.pdf

2 EXCEPTIONAL VALUES: TYPES AND IDENTIFICATION

2.1 Logical input errors

Logical input errors can arise for a number of reasons. For example, the wrong NUTS[2] code could be specified; incorrect data values could be input; data could be repeated exactly but assigned to different variables; data could be displaced within or between columns; data could be swapped within or between columns. In general, the identification of an input error will follow some logical, mathematical approach. For example, if a land use class could only take a positive integer value from 1 to 9 say, then an input error of say, -2, 4.5 or 10 would be easily identified.

An input error may also be identified statistically. For example, if the number 27 is inadvertently entered as 72 for a region's unemployment rate, the value 72 may lie in the extreme tail of this variable's distribution and as such, is statistically-outlying. A difficulty here would be to distinguish between an input error of 72 and a true value of 72.

In this respect, when dealing with errors/outliers, most input errors can be either be corrected or removed, whilst most outliers should be flagged as: (i) suspected outliers *and* (ii) potential (undetected) input errors. Flagged observations would then require further scrutiny, which should ascertain whether the observation should be: (a) replaced; (b) removed; or if specifically an outlier, (c) retained or possibly down-weighted in some way (so as to provide some robust model fit or statistic of the data).

2.2 Aspatial statistical outliers: identification in univariate to multivariate data sets

A simple, graphical tool for the detection of outliers in univariate data sets is the boxplot (e.g. Frigge et al. 1989). Central to the creation of the boxplot is the inter-quartile range (Q3-Q1) around the median value Q2. Commonly, at the upper end of the distribution, the *inner fence* is defined as the value given by Q2+1.5(Q3-Q1) and the *outer fence* as the value given by Q2+3(Q3-Q1); and there are corresponding values for the lower end of the distribution. Observations whose values lie between the inner and outer fences are usually referred to as *outside* and those whose values lie beyond the outer fence are usually referred to as *far out*. In either case, such observations can be flagged as outlying, however most attention should be placed on observations that lie beyond the outer fence. In this report, we not only demonstrate the use of the standard boxplot but also an adjusted boxplot for skewed distributions (Hubert and Vandervieren 2008). For bivariate data sets, a simple extension of the boxplot, the bagplot (Rousseeuw et al. 1999) can be constructed.

To detect outliers in multivariate data sets, we first demonstrate a technique where outliers are observations that have a *large* squared Mahalanobis Distance

[2] NUTS stands for "nomenclature of territorial units for statistics".

(MD^2), where the MD itself is estimated in a robust manner (Filzmoser et al. 2005). MDs are used as they take into account the covariance matrix from which the shape and size of the multivariate data set can be quantified. In this outlier detection technique, robust MD^2 values are related to some pre-determined (upper) quantile of a chi-square distribution (e.g. the 97.5^{th} percentile), where *large* robust MD^2 values lie above this pre-determined threshold. Furthermore, to address subjectivity in choosing the threshold, the technique automatically adjusts the pre-determined threshold (downwards or upwards) via simulation reflecting specific properties of the sample data. The technique (called here RMD2-AQ-outlier) is applied incorporating useful graphical displays of suspected outliers.

We also demonstrate two further multivariate techniques that each use principal component analysis (PCA) to reduce the dimensions of the multivariate data set, where in the resultant transformed space, outliers may be more readily observable. Of the many PCA-based techniques for outlier detection that have been proposed (e.g. see Rousseeuw et al. 2006; Daszykowski et al. 2007; Filzmoser et al. 2008), we demonstrate: (a) the 'sign' approach of Locantore et al. (1999) (call this technique, PCA-outlier-1) and (b) the 'PCOut' approach of Filzmoser et al. (2008) (call this technique, PCA-outlier-2). Both techniques are computationally fast and thus suited to large, high dimensional data sets (see the comparisons given in Filzmoser et al. 2008).

2.3 Spatial statistical outliers: identification in univariate data sets

Commonly outlier detection techniques ignore any spatial element to the data. Data not observed as an outlier when an *aspatial* technique is used, may nevertheless be a *spatial* outlier. Therefore it is important to consider spatial aspects if false negatives (i.e. outliers undetected by an aspatial technique) are to be avoided. In this respect, we demonstrate a technique of Hawkins (1980) to detect spatial outliers in univariate data sets[3]. This technique has much in common with the more recent techniques of Lui et al (2001); Kou et al. (2005). For this technique, all observations $z(\mathbf{x}_i)$ are suspected a priori as spatial outliers, where $z(\mathbf{x}_i)$ is a spatial outlier if

$$\left(N(z(\mathbf{x}_i)-m_l)^2\right)/\left((N+1)\bar{s}_l^{\,2}\right) \geq \chi^2_{crit-1} \qquad (1)$$

[3] We only present a technique to identify spatial outliers in a univariate sense. Extensions to bivariate and multivariate spatial data sets are not considered here. However our current research in this area concerns the development of geographically weighted PCA techniques with respect to outlier identification (see Charlton et al. 2010), which should allow the identification of *multivariate spatial* outliers in the ESPON database.

Here, $i = 1,\ldots,n$; $\mathbf{x}$ is spatial location; N is the number of neighbouring values of $z(\mathbf{x}_i)$; m_l is the local mean; $\bar{s}_l^{\,2}$ is the average variance for equivalently sized neighbourhoods across the sample area (i.e. the average local variance) and χ^2_{crit-1} is a critical value of the chi-squared distribution for 1 degree of freedom. As there is no objective function for cross-validation, then neighbourhood definitions (for the local mean and variances) are chosen subjectively for this test statistic. In this report, the local mean and variances are found using a geographically weighted approach (see sections 2.4 and 2.5), with 95%, 99% and 99.9% critical levels chosen as appropriate cut-offs.

2.4 The use of statistical models and residual data in outlier identification

In a statistical analysis, it is common to identify outliers via large (positive or negative) prediction errors (or residuals) from some predictive model fit. Observations that are poorly predicted produce large residuals when compared with the actual data, and are therefore deemed as outlying. The key drawback to this approach is the need to specify a model in the first place, where different models may produce different outlying observations. However if several prediction models are applied, then it is reasonable to expect that the most influential outlying observations should be repeatedly identified.

In this respect, we first identify outliers (in a univariate sense) simply using the key component of expression 1, where a spatial outlier relates to a large (absolute) value of the error $z(\mathbf{x}_i) - m_l$. Here our prediction model is simply the one chosen to find the local mean m_l, which in this case is some simple spatial predictor using geographical weights (which we shall call the local mean predictor, LM). The widely-used inverse distance weighting model would be one example of such an LM model.

Furthermore, we also identify outliers (via residual data) using univariate and multivariate regressions in both aspatial and spatial forms. In particular we apply: (a) standard multiple linear regression (MLR) models, (b) attribute-space local regression (LR) models (see Loader 2004) and (c) geographic-space local regression models (Fotheringham et al. 2002) (i.e. geographically weighted regression, GWR). Here LR accounts for nonstationarity and nonlinearity in attribute-space, whilst GWR accounts for nonstationary and nonlinearity in geographic-space. Both LR and GWR are nonparametric in design. The conventional MLR model assumes stationarity and linearity in both attribute- and geographic-space; and is parametric in design. Consequently, each of the three regression forms will identify outliers (or possibly groups of outliers, see section 2.5) according to their particular specification (or set of modelling assumptions).

The investigation of residual data plays a central role in the formulation of a robust regression model, where the influence of outlying data on the regression fit is reduced (e.g. see Faraway 2004, p98-106; Cruz Ortiz et al. 2006). MLR, LR (see Loader 2004) and GWR (Fotheringham et al. 2002, p73-82; Harris et al. 2010) all have robust forms. Commonly, a robust regression will identify outliers as observations with large *standardised* (or *studentised*) residuals via a *leave-one-out* approach. However, in this report we only identify outliers simply, via the *raw* residuals and without the benefit of a *leave-one-out* fit.

2.5 The identification of spatial clusters

A group of observations identified as outliers may actually be spatially clustered with a substantive reason for their 'unusualness' (i.e. false positives are to be avoided as well). In this respect, it is worthwhile applying techniques that identify local (or regional) changes in the spatial process according to some key moment or relationship[4].

Furthermore, seemingly significant clusters can be sometimes be attributable to only a few (influential and outlying) observations; so although the local techniques described below are not specifically designed to identify spatial outliers, they sometimes do so. Indeed, a corresponding robust form of the given local technique would out of necessity identify spatial outliers in order to reduce their influence.

Thus in the first instance, local summary univariate and bivariate statistics are calculated and investigated. In particular, we assess changes in the mean, standard deviation and correlation across space, where these (spatial) moments are all found in a geographically weighted form (Fotheringham et al. 2002)[5]. For the multivariate case, GWR can be applied, which complements a local correlation analysis when investigating relationship-change across space.

From a spatial autocorrelation viewpoint, a local version of Moran's I (Anselin 1995) is used. Positive spatial autocorrelation exists when neighbouring spatial units tend to have similar values of a variable; whilst negative spatial autocorrelation exists when they do not. Local Moran's I is only used to investigate univariate data, but the statistic could be adapted to investigate cross-autocorrelation in bivariate and multivariate data sets.

2.6 Summary: MAUP, temporal outliers and data imputation

We have presented a typology of techniques where variables are analysed singly or in combination; and aspatially or spatially. Underlying all of these techniques is the spatial structure of the reporting units, where results can be influenced not only by the level of spatial aggregation used but also by the spatial configuration of the reporting units (i.e. a MAUP; e.g. see Wong 1996). In this report we demonstrate the consequences of the MAUP for outlier identification via a worked example, where outlier-detection techniques are applied at different NUTS levels (NUTS level 3 through to NUTS level 0).

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[4] Brunsdon and Charlton (2010) assess the effectiveness of multiple hypothesis testing for detecting clusters of geographical anomalies. These tests would complement the techniques demonstrated from this section of the report.

[5] Robust forms of geographically weighted summary statistics (GWSS) can be found in Brunsdon et al. (2002) and in Harris and Brunsdon (2010).

We have not addressed the identification of temporal (or by extension, spatio-temporal) outliers. This is not an oversight, as ESPON time series data is not expected to be of a sufficient length for an outlier detection technique to be reliably applied. Instead it should suffice that the aspatial/spatial detection methods demonstrated here can be repeated at different time intervals. The consequences of the reporting units changing over time (i.e. another MAUP) are addressed elsewhere in ESPON database project.

As already discussed, once an input error has been identified the observation can either be corrected or removed (i.e. replaced with the missing value notation, NA[6]). On the other hand, suspected outliers (which may be an input error) can (after some additional scrutiny) be: (a) replaced; (b) removed (i.e. replaced by NA); or if indeed an outlier, (c) retained or possibly down-weighted in some way. This entails that some form of imputation or prediction of missing valued data will be required, and here the chosen regression models of section 2.4 may be of value.

2.7 Further reading

This report provides a brief overview to subject of error or outlier identification with respect to the task of identifying outliers in the ESPON Database. There is an extensive literature on outlier detection, where the following reading list may be useful.

- An evaluation of aspatial techniques to detect input errors and true outliers (here known as data editing), together with imputation techniques, for large scale survey data can be found in Charlton (2004). This and related articles arose from the EUREDIT project[7]. Related articles include: an outlier identification technique for multivariate data by Béguin and Hulliger (2004); a robust regression technique for data edits by Chambers et al. (2004); and a classification and regression tree technique for data edits by Petrakos et al. (2004).
- An aspatial Bayesian technique that both edits and imputes data in a multivariate context can be found in Ghosh-Dastidar and Schafer (2003).
- Reviews of aspatial outlier identification techniques from univariate to multivariate data sets can be found in Reimann et al. (2005); Rousseeuw et al. (2006); Daszykowski et al. (2007); Morgenthaler (2007).
- Further aspatial outlier identification techniques for multivariate data sets can found in Hoo et al. (2002); Jackson and Chen (2004), where the former article also imputes data.
- Imputation (aspatial) techniques can be found in Plaia and Bondi (2006); Vanden Branden and Verboven (2009), where the former article focuses on time series data.

[6] NA is the missing data indicator used in the R statistical computing package (see section 4).
[7] See http://www.cs.york.ac.uk/euredit/. The project website was still active as of 1/12/09.

- Alternative spatial outlier identification techniques can be found in D'Alimonte and Cornford (2007); Ainsworth and Dean (2008); Meiklit et al. (2009).

3 DATA CHECK CONTROL FILE

3.1 Introduction

The process is initiated by completing the data check control file. The function of the control file is to supply appropriate values to a set of *control variables* which are used to guide the data check process. This is described below, and several example control files are presented in Appendices 1 to 6.

The information in the control file should be entered using a text editor, and then copied/pasted into the R Console window. The file is divided into 6 sections, and all sections must be completed.

```
##############################################################################
##############################################################################
#####                                                                    #####
#####              M4D Data Quality Check                                #####
#####                                                                    #####
##############################################################################
##############################################################################

##############################################################################
##### Information for the dataset under test: USER supplied              #####
##############################################################################

### Section 1
DataFolder    <- "~Dropbox\\2013_03_21_EsaTDOR_Data_check\\"
DatasetName         <-   "2013-01-16-15-22-57_EsaTDOR_ESATDOR_Economic_Use_Composite
v2_syntaxCheckedMC.xls"

### Section 2
NUTSLevel     <- 2                          # NUTS Region level
NUTSDate      <- 2006                       # NUTS Region date

### Section 3
DataColumns   <- seq(4, 38, 2)              # Starts col 4, in pairs 2 + 2*8 vars
DataTypes     <- c("N", "N", rep("R",16))   # T=text N=nominal R=ratio
MV_Columns    <- c(F, F, rep(T, 16))        # All multivariate testable

### Section 4
C1            <- c(1, 2, 3, 4, 5)           # Indicator 1
C2            <- c(1, 2, 3, 4, 5)           # Indicator 2
TestCodes     <- list(C1, C2, rep(0,16))    # Codes for nominal data

### Section 5
DataColRange  <- seq(4,length(DataColumns)+4) # Data columns in DataFrame
MissingValues <- rep(-999, length(DataColumns))  # Missing value codes

### Section 6
DrawPlots     <- TRUE                       # Draw boxplots and maps
DrawMaps      <- TRUE                       # Draw the maps

### section 7
source("C:\\M4D\\Data_Check_Main_Template.R",echo=TRUE)     # Invoke data check
```

3.2 Control file organisation

The control file is organised into seven logical sections which supply initial values to a minimum of 12 variables and data structures (lists, vectors). The names and content of these are described in detail below.

3.2.1: Section 1: Dataset Identification

DataSetFolder: a string which contains the full pathname of the folder in which the Excel spreadsheet is located. This string must be terminated with the folder separator. This can either be '/' or '\\'.

DatasetName: a string which contains the name of the dataset, including its filetype. In the current version of the software, only **.xls** spreadsheets can be handled.

3.2.2: Section 2: Spatial binding information

NUTSLevel: a single value to denote the NUTS level for the data. This may be 0, 1, 2, 3, or 'X'. The 'X' is used when combined NUTS2/3 data are present.

NUTSDate: the year for which the NUTS units are required, The current implementation supports 2003, 2006 or 2010.

In some datasets data was available for several NUTS levels, with complete coverage at each level. If this is the case, the dataset should be split into separate files, one level only.

3.2.3: Section 3: Data Location and Type

DataColumns: indexing for the columns that contain data for the data check in the worksheet *Data*. Columns occur in pairs, the first contains the data for each indicator, the second contains an index to the source of the data in the *Source* worksheet. The R function seq() can be used. In the example above seq(4, 38, 2) generates the vector of indices: 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38

DataTypes: a vector of data type indicators. This must be the same length as the vector of DataColumns. The allowable types are 'R': ratios/counts, 'N': categorical numeric values, 'T': text. This information is used to guide the type of missing values analysis that takes place.

MV_Columns: a vector of logical values indicating which columns can be subjected to testing for multivariate outliers. It should be the same length as the DataColumns and DataTypes vectors. Allowable values are T and F.

3.2.4: Section 4: Coding for nominal data types

Cn: a vector of allowable code values for variables of DataType 'N'. These values are specified in the *Indicator* worksheet.

TestCodes: a list of vectors of allowable code values or 0 if the corresponding variable is ratio or text. The list should have as many members as there are elements in DataColumns.

3.2.5: Section 5: Dataset size and Missing Values

DataColRange: index vector for the data columns in the data frame to be used for the data check. The column ranges normally starts a 4 (the first three columns contain the NUTS code, the NUTS name, and the NUTS level. In the example given, the index vector contains the values: 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22, and is the same length as DataColumns. The R function seq(start.col, length(DataColumns)+start.col) can be used.

MissingValues: Some data suppliers include missing value codes. These are recoded internally to NA. In the example given -999 was used as a missing value code for each variable. The R function rep(value,N) can be used to create a vector of N missing values – N should be the length of the DataColumns vector.

3.2.6: Section 6: Graphics

DrawPlots: some of the data check functions produce graphic output. These graphics can be omitted by specifying FALSE or F for this control variable.

DrawMaps: some of the data check functions produce map output. These graphics can be omitted by specifying FALSE or F for this control variable

3.2.7: Section 7: Invocation

The final line in the control file invokes the data check process for the specified file. Output is in graphical Windows and to the R Console.

```
source("C:\\M4D\\Data_Check_Main_Template.R",echo=TRUE)
```

For debugging purposes the argument **echo=TRUE** can be used.

3.3 In practice

In spite of the existence of documentation with detailed instructions from the Lead Partner on the ways to organise data for the upload, there were many variations which we encountered in practice. This prevented the use of some of the more advanced checks, and auxiliary software was used to compute Moran's I for some of the data check reports[8].

[8] http://geodacenter.asu.edu/ - GeoDa has some useful and robust functions for dealing with the computation of Moran's I, both global and local versions

4 DATA CHECK SYSTEM

4.1: General Order of Operation: Data_Check_Main_Template.R

Once the control file has been completed and its contents executed in the R Console (this can either be done by cut/paste from the Text Editor window to the R Console, or by the menu option of *File/Source R Code…,* then the code in the file C:\M4D\Data_Check_Main_Template.R will be executed. This accomplished a number of high level tasks:

1. Initialisation: create global folder and dataset names
2. Read the appropriate NUTS boundaries (by level and date) into a Spatial Polygons Data Frame
3. Read the worksheets in the Excel spreadsheet into separate data frames
4. Check for unique variable names
5. ** Undertake an analysis of missing data
6. Check for invalid NUTS codes
7. Check for regions in the NUTS data which are omitted from the *Data* worksheet
8. Create a Spatial Polygons Data Frame with complete cases only (for spatial checking)
9. Univariate variable summaries
    a. Frequency tabulation for nominal data
    b. Five number summaries for ratio data
10. Bivariate variable summaries
    a. Crosstabulation for nominal data
11. Plot variables
    a. Univariate histograms for ratio data
    b. Univariate boxplots for ratio data
    c. Univariate barplots for nominal data
    d. Univariate maps
    e. Bivariate bagplots
12. ** Univariate Outlier check
13. ** Spatial Outlier check
14. ** Multivariate Outlier check
15. Outlier report

Function	**Action**
LoadLibraries	Load the require R packages for the operation of the data check
PrintBanner	Printer a header on the output
M4D_Folders	Return a single object containing the various folder pathnames
loadPolyShapefile	Read the NUTS geometries into a Spatial Polygons Data Frame (SPDF)
GetNUTSCodes	Read the current NUTS codes from index file
GetData	Return an object containing the four worksheets (*Dataset, Indicator, Source, Data*) from the Excel spreadsheet
Dataset.Info	Print summary details of the dataset
Indicator.Info	Printer summary metadata on each

	indicator
Data.Unique.Name.Check	Check for duplicate indicator names
UnpackDataWorksheet	Extract and reshape the data for the quality check
Reshaped.Data.Unique.Name.Check	Check for duplicate names in the reshaped data
Update.Missing.Value.Codes	Convert missing data codes from values in *Indicator* worksheet to NA
Missing.Value.Analysis	Summary information on missing data in the indicator data
MergeNUTSNames	Add in region names from the NUTS code index
Print.Invalid.NUTS.Codes	Print any invalid NUTS codes found in the data
Omitted	Create a list of omitted NUTS regions
Print.Omitted	Print regions in the shapefile not in the Data
SubsetSPDF	Remove omitted regions from the SPDF
MissingRecords	Find the NAs in the Data
CleanSPDF	Remove records with incomplete data
summary.Check.variables	Summaries for SPDF variables
summary.Check.univariate	Summaries for Data variables
Summary.Check.bivariate	Summary bivariate checks
UniveriateExplore	Univariate outlier analysis
SpatialExplore	Spatial outlier analysis
MultivariateExplore	Multivariate outlier analysis

4.2 Reading ESPON Database Excel spreadsheets into R data frames

There are several different ways of reading a Microsoft Excel spreadsheet into an R data frame. Tow commonly used libraries are RODBC and gdata. There are other libraries, but our experience using ESPON data is that these two are preferable[9].

RODBC is very flexible. It will read Access databases as well as Exel spreadsheets, but there are some known problems[10] . Because the driver uses the first few lines of each column to determine the data type for the output data frame, it will often select 'Numeric'', even if there are non-numeric entries. If a column is declared as Text, any numeric entries will be set to NA. At the time of writing there is no convenient workaround for this.

An alternative is provided by the **gdata** library. This requires that Perl has been installed, and that the path to the Perl executable is in the PATH environment variable on Windows systems[11].

[9] http://www.r-bloggers.com/read-excel-files-from-r/
[10] See http://cran.r-project.org/web/packages/RODBC/vignettes/RODBC.pdf section 7
[11] ActiveState Perl is easily installed from http://www.perl.org/get.html. See also http://www.activestate.com/activeperl/downloads

An example using the **gdata** library, running on a Windows XP system, follows.

First, load the library routines. This can be done with either the library() or require() functions. The require() function is a little more flexible in that, if the library has already been loaded, it will not be *re*loaded.

```
require(gdata)
```

It will be convenient to assign the name of the file to a variable, in this case, ExcelFile. Note that the name of the file should contain its full pathname unless the working directory has been set {using setwd()} to the folder that contains the file.

```
ExcelFile <- "SEMIGRA_LabourMarket_meta_syntaxChecked.xls"
```

Two useful functions sheetCount() and sheetNames() can be used in an initial check that the XLS file has the required structure. There should be 4 named worksheets in the spreadsheet:

- Dataset
- Indicator
- Source
- Data

… in the order of the above list. sheetCount() can be used to check whether there are four worksheets, and sheetNames() that they are correctly named.

```
sheetCount(ExcelFile)
sheetNames(ExcelFile)
```

Assuming that the four sheets are present, and correctly named, their order can be checked with the match() function as below. If the vector ExcelOrder does not contain {1 2 3 4} but some other such as {4 3 NA 2} then the sheet is incomplete, or one of the names are mis-spelled.

```
ExcelOrder <- match(c("Dataset", "Indicator", "Source", "Data"),
sheetNames(ExcelFile))
```

Finally the sheets can be read in using read.xls(). The sheet= argument supplies the sheet number for the corresponding worksheet, so ExcelOrder from the match() example above is useful.

A second issue concerns the naming of the columns. As with CSV files, the R functions tend to assume that 'legal' variable names are present in the first line of the file. We use the term 'legal' to indicate that they are according to the R variable naming conventions. The variable in the ESPON Database files are a composite of the string in the first row, and the start/end dates in rows 2 and 3. If the start and end dates are the same date, then the cells in rows two and three of the column are merged.

The existence of the merged cells can make the output from these input functions unpredictable, and all cells should be unmerged prior to analysis.

Example input calls are below.

```
Excel.Dataset   <- read.xls(ExcelFile, sheet=ExcelOrder[1], header=FALSE)
Excel.Indicator <- read.xls(ExcelFile, sheet=ExcelOrder[2], header=FALSE)
Excel.Source    <- read.xls(ExcelFile, sheet=ExcelOrder[3], header=FALSE)
Excel.Data      <- read.xls(ExcelFile, sheet=ExcelOrder[4], header=FALSE)
```

The first few lines of each worksheet as read into R are below:

```
> head(Excel.Dataset,5)
                    V1                      V2 V3 V4
1 Dataset information                          NA
2                 Name Population Structure    NA
3              Project               SEMIGRA    NA
4          Upload date            2012-01-22    NA
5       Metadata date            2011-07-04    NA
```

Notice that there is an extra column in the spreadsheet, named V4 by read.xls(). It should be checked for content, since a data entry error might have moved one row across by one column.

```
> head(Excel.Indicator)
                       V1                                                          V2
1 Indicator Identification
2                    Code                                                        Name
3      Typology_Gendergap Typology of gender differences on the labour market
4                    Core                                                       False
5                NAT Type                                                          TS
6                   Theme                                  economyFinanceAndTrade
                                                                                  V3 V4 V5 V6
1                                                                                 NA NA NA
2                                                                           Abstract NA NA NA
3 Typology of gender differences in economic activity in regional perspective NA NA NA
4                                                                                 NA NA NA
5                                                                                 NA NA NA
6                                                                                 NA NA NA
```

There are an extra three columns present in this worksheet – again, they should be checked for content.

```
> head(Excel.Source)
              V1                                    V2                                V3 V4
1 Source Reference                                                                     NA
2           Label                                     1                                NA
3            Date                            2012-07-04                                NA
4       Copyright © Leibniz-Institut für Länderkunde                                   NA
5        Provider                                  Name Leibniz-Institut für Länderkunde NA
6                                                  URI                www.ifl-leipzig.de NA
```

The head() and summary() functions are useful to obtaining a quick first look at the data. It will be noted that the NUTS codes for the data are in lowercase. The column names appear in row three of the data, with the exception of the data columns, where the name is qualified by start and end data as described above. The source columns identify the lineage of the data, the labels in row three are not unique.

```
> head(Excel.Data)
                                      V1                V2          V3      V4
1 see ch.3.Cluster 5 of the Specifications
2
3                                Unit code              Name Object type Version
4                                     at11  Burgenland (AT)        NUTS2    2006
5                                     at12 Niederösterreich        NUTS2    2006
6                                     at13              Wien        NUTS2    2006

                  V5     V6                           V7     V8              V9    V10
1 Typology_Gendergap        Typology_IndustryStructure        GenderGap_15-24
2               2009                              2009                    2008
3                     source                            source                  source
4          Cluster 1      1                 Cluster 1      1         --19.15      1
5          Cluster 1      1                 Cluster 1      1         --15.89      1
6          Cluster 2      1                 Cluster 2      1          --3.92      1

              V11    V12             V13    V14             V15    V16
1 GenderGap_25-34        GenderGap_35-44        WF_Agriculture
2              2009                    2009                  2009
3                  source                  source                source
4           --8.12      1          --11.95      1           6.74      1
5          --13.72      1           --9.43      1           7.26      1
6          --14.07      1           --9.50      1           0.38      1

                       V17    V18    V19    V20               V21    V22               V23
1 WF_IndustryConstruction        WF_TTA        WF_PublicServices        WF_OtherServices
2                      2009           2009                    2009                    2009
3                          source         source                  source
4                    25.09      1  27.83      1             23.46      1             16.88
5                    24.02      1  26.57      1             23.54      1             18.60
6                    16.01      1  26.48      1             24.76      1             32.39

     V24
1
2
3 source
4      1
5      1
6      1
```

4.3 Pre-processing the data for checking

The data frame can be rationalised to remove the columns which are not to be checked, and then to add suitable row and column names.

```
# [1]
Data.Check <- Excel.Data[4:nrow(Excel_Data),c(1,2,seq(3,23,2)]

# [2]
varBase <- Excel.Data[1, seq(3,23,2)])
varStDt <- Excel.Data[2, seq(3,23,2)])
varEnDt <- Excel.Data[3, seq(3,23,2)])
varName <- paste(varBase,varStDt,varEnDt,sep="")
varName <- gsub("-","_",varName)
varName <- gsub(" ","_",varName)

# [3]
rownames(Data.Check) <- toupper(Data.Check[,1])
colnames(Data.Check) <- c("Unit_code","Name",varName)
```

The actions in the preceding box result in the data frame which is suitable for further processing.

Action [1] extracts the subset of the data frame for processing – rows 4 to the end, and columns 1, 2, 3 and every second column thereafter.

Action [2] extracts the indicator names from the first row of the spreadsheet, the start dates from the second row, and the end dates from the third row, and concatenates them into a single string. Any characters which are not allowable in a R variable name are replaced by underscores.

Action [3] assigns row and column names. The row names can be used to index the data frame, and the column names index the individual; columns. The row names that we used in the data check are the NUTS codes, which are converted to uppercase. The column names are created from the variable names from |Action [2].

4.4 Reading geometry data from shapefiles

The spatial extensions to R allow for the input, processing, and output of shapefiles. The ESRI shapefile[12] has emerged as a de facto standard for the exchange of spatial data. The shapefile, in spite of its name consists of at least three separate files, with the extensions .shp, .shx, and .dbf, and a common prefix name.. ESRI refer to the .shp file as the "Main File" – this contains the geometry data. The .shx file is known as the Index File, and is used to index the individual object records in the Main File. The .dbf file is a table of attribute data and has the following characteristics:

- There is one record per shape feature (object)
- The record is order the same as the record order in the Main File

There can be other files, notable a file of projection information (.prj). For the NUTS geometry data used in the Database project, the following projection definition is used:

```
PROJCS["ETRS_1989_LAEA",
   GEOGCS["GCS_ETRS_1989",
      DATUM["D_ETRS_1989",
         SPHEROID["GRS_1980",6378137.0,298.257222101]],
      PRIMEM["Greenwich",0.0],
      UNIT["Degree",0.0174532925199433]],
   PROJECTION["Lambert_Azimuthal_Equal_Area"],
   PARAMETER["False_Easting",4321000.0],
   PARAMETER["False_Northing",3210000.0],
   PARAMETER["Central_Meridian",10.0],
   PARAMETER["Latitude_Of_Origin",52.0],
   UNIT["Meter",1.0]]
```

The underlying projection is a Lambert Azimuthal Equal Area projection, with an origin at 52N, 10W (near the town of Sehlem in Germany). The projection units are meters, and the false eastin and northing parameters ensure that all coordinate measurements are positive. The datum for the projection is based on

[12] http://www.esri.com/library/whitepapers/pdfs/shapefile.pdf

the GRS 80 (Geodetic Reference System) spheroid[13] used in the European Terrestrial Reference System 1980[14].

Several functions exists to read ESRI shapefiles, among them are readShapePoly() from the maptools library, and readOGR() from the rgdal library. There are advantages and drawbacks to using either function. The readShapePoly() function will return an error if it is used to read a non-polygon shapefile; it will not read the projection file, so the Coordinate Reference System string as to be attached by the user in the R code. By contract readOGR() will read any shapefile without checking to see what the type is, it will read and store the projection information if this is present in the shapefile.

4.5 Implementation in the data check

The geometry information is located in a folder whose name is assigned to a global variable in the R code. In a typical Windows application this is **c:\M4D\NUTS_ETRS_1989_LAEA**. There is no reason why this location may not be a networked drive, or the URL to cloud storage. The individual shapefiles are named using a common convention

NUTSn_yyyy.shp

… where n is the NUTS level (0, 1, 2, 3, X) and yyyy refers to the year (2003, 2006, 2010). Other shapefiles can be added to the repository. In this implementation NUTS level X is used to refer to the combined NUTS 2/3 geometries, in order to keep the NUTS level code to a single character.

To read NUTS3_2006.shp using either the maptools or rgdal functions, the following is appropriate:

```
require(maptools)
SPDF.1 <- readShapePoly("C:\\M4D\\NUTS_ETRS_1989_LAEA\\NUTS3_2006.shp")
proj4string(SPDF.1)   <-   "+proj=laea   +lat_0=52   +lon_0=10   +x_0=4321000
+y_0=3210000 +ellps=GRS80 +units=m +no_defs"

require(rgdal)
SPDF.2 <- readOGR("C:\\M4D\\NUTS_ETRS_1989_LAEA","NUTS3_2006")
```

A Spatial Polygons Data Frame (SPDF) is a single object which contains, inter alia, the geometry and attribute information. The objects inside the SPDF object are known as *slots*.

```
> slotNames(SPDF.2)
[1] "data"        "polygons"    "plotOrder"   "bbox"        "proj4string"
```

The attribute data is located in the *data* object, the geometry in the *polygons* object. The *bbox* object contains the coordinates of the bounding box:

[13] Geodetic Reference System 1980, *Bulletin Géodésique*, (54)3, 1980. Republished (with corrections) in Moritz, H., 2000, Geodetic Reference System 1980, *J. Geod*., 74(1), 128–162

[14] http://etrs89.ensg.ign.fr/

```
> bbox(SPDF.2)
       min      max
x -2823914 10026125
y -3076145  5415982
```

The attribute data is fairly minimal, but does contain the NUTS codes and NUTS levels:

```
> head(SPDF.2@data)
  OBJECTID_1 OBJECTID NUTS_ID STAT_LEVL_ AREA LEN Shape_Leng Shape_Le_1  Shape_Area
0        463      463   IS001          3    0   0   4.814391   299120.0  1047327456
1        464      464   FI133          3    0   0  11.247582   783542.7 21584072176
2        465      465   FI1A1          3    0   0   9.442749   638978.5  5456649618
3        466      466   NO062          3    0   0  49.584899  3074302.0 22296592101
4        467      467   NO073          3    0   0 113.311666  6023597.7 48565287828
5        468      468   NO072          3    0   0  86.592704  4839567.6 25820053059
```

The variable NUTS_ID contains the NUTS code, and the variable STAT_LEVL_ contains the NUTS level.

To merge the data from the imported Database spreadsheet, the following can be used:

```
SPDF.Order <- match(SPDF.2$NUTS_ID,rownames(Data.Check))

SPDF.2a <- SPDF.2
SPDF.2a@data <- data.frame(cbind(SPDF.2a@data, Data.Check[SPDF.Order,]))
```

Several of the spatial functions require the removal of the regions which have missing data (coded as NA). If the variable of interest is Test, then creating a subset of the SPDF with only the non-missing data can be achieved with:

```
SPDF.3a <- SPDF.2a[!is.na(SPDF.2a$Test),]
```

5 AVAILABLE DATA CHECKS

The actuality of the data checks proved to be more complex than was ever envisaged in Phase I of the Database project. The control file drives the check process, and the **DataTypes** vector, together with the **TestCodes** list provide the information as to which method will be used at each stage of the analysis.

5.1 Univariate summaries

The initial assessment of the data begins with a series of univariate summaries. These provide an initial 'quick-look', to answer questions such as (i) do the percentages fall between 0 and 100 (ii) are the counts positive (iii) are there any missing values (iv) are there any obviously anomalous values (v) do the categories in the frequency tables for the nominal data match the values in the metadata (vi) are the distributions noticeably skew [long right tail, so the mean differs from the median] (vii) are the original values positive?

Ratio
    Compute 6-number summary (extremes, quartiles, median, mean)
Nominal
    Frequency table of values, and list of values found
Ordinal
    Compute 6-number summary (extremes, quartiles, median, mean)
Count
    Compute 6-number summary (extremes, quartiles, median, mean)

This initial assessment can be augmented with visualisations of the data – in practice boxplots and histograms have proved to be most useful. The great variation in physical size of the NUTS regions means that identifying anomalous values is not always possible visually.

5.2 Univariate Checks

The checking begins by taking each variable in turn. The values in the **DataTypes** variable (assigned in the Control File) direct the nature of the check. For ratio data, the system checks for the existence of boxplot outliers – these are anomalous in terms of the definition of the boxplot. An outlier in boxplot terms is one whose value is more than 1.5 times the interquartile range. The NUTS codes and names are listed in the output together with the anomalous values.

Ordinal and count data are checked to see whether their values belong to the set of positive integers. The values are also checked to see whether they have any inadvertent fractional parts where they are not stored exactly as an integer in the Excel spreadsheet. The upper value of an ordinal variable should not be greater than the number of observations. Any regions which are anomalous are listed.

Nominal data require reference to the **TestCodes** lists in the Control File. TestCodes is a list of either 0 for non-categorical variables or a vector of allowable values (extracted from the metadata in the *Indicator* worksheet[15])

Ratio
    Check for boxplot outliers
Nominal
    Check codes in the Data against codes supplied in the control file
Ordinal
    Check that data values are positive integers and in range
Count
    Check that data values are positive integers

Count data gives rise to some challenges. The variation in the underlying support for the data means that count data are not standardised – each value has not arisen on an equal footing, so we cannot treat the values as comparable.

5.3 Bivariate Checks

For the ratio variables we can compute a correlation matrix. This might seem unnecessary – it's a useful diagnostic tool to determine whether any variables have been entered twice (the correlation will be 1) or whether, in choosing variables, two have been selected which are essentially measurements of the same underlying characteristic.

The bagplot is a two-dimensional extension of the boxplot. The output is a plot showing both the non-outlying and outlying values. The IDs of the outlying values are also listed in the output object, and can be identified for printing. What we observe as an outlier here is a combination of values that is unusual, not necessary from values which are themselves unusual when taken one at a time.

Ratio
    Compute correlation coefficients and p-values
    Bagplot Outliers

The correlation matrix can be augmented by a scatterplot matrix – although once the number of variables exceeds about 15, the individual plots themselves become almost too small to see on the computer screen.

5.4 Multivariate Checks

If there are sufficient variables of ratio type in the dataset, then a trawl for multivariate outliers becomes possible. In the work carried out prior to 2011 the dataset used was a time series of GDP values at NUTS2/3. An ad hoc method was developed in the form of a circulating regression: the values for time period

[15] In future versions of the software, consideration should be given to extracting these data from the metadata directly

t would be regressing on the values for the other n-1 time periods in a multiple regression, and the residuals checked for unusual high or low values. With n time periods, there would be n regressions, and n sets of residuals. A region which was anomalous on a majority of these might be flagged for checking. There are a number of issues of multi-collinearity and multiple testing which would indicate that it would identify too many false positives.

In practice none of the data from the suppliers allowed the possibility of using the circulating regression technique.

Given sufficient data, we can transform the original variables, say n of them, into n principal components. The component scores can then be examined for univariate, and bivariate outliers using the methods outlined above. We restrict the search to components whose eigenvalues are greater than 1 to minimise the possibility of identifying false positives.

A second technique is the computation of Mahalanobis distances to some multivariate centroid. The Mahalanobis distance is a generalisation of the Euclidean distance which takes into account the correlation structure in the data. The mean vector can be used as the position of the multivariate centroid. The output is a vector of distances, which can then be treated as a single variable, and examined for outliers as above.

Circulating regression
Circulating Robust regression
Principal Component outliers
Mahalanobis outliers

These checks are useful, not that they identify anomalous individual values, but that they identify potentially anomalous *combinations* of values on the candidate variables. This does pre-suppose that the candidate set has some thematic coherence.

5.5 Spatial Checks

The original version of the software, developed on GDP time series for NUTS2/3 regions included a version of a test named after Hawkins, which would identify spatial outliers. A spatial outlier is one that is unusual when compared with the values in its neighbours. It was surprising to discover that the test is not mentioned in Professor Hawkins monograph on outlier detection[16]. An alternative is provided by the Local Moran statistic, which will identify values which are either locally high or low in comparison with their neighbours.

Local Moran Outliers
Hawkins' test

The Hawkins test requires further development.

[16] Hawkins, DM, 1980, *Identification of Outliers*, London: Chapman and Hall

5.6 Missing values

Any regions with missing values on one or more variables are listed for further checking. We also check to whether data is missing on all variables. A heatmap can be a useful tool in giving an overall 'quick-look' as to the global pattern ob missing data. The missing data pattern can sometimes give some clues as to the process that generated the missing data[17]. Large quantities of missing data would give rise to a request for confirmation that the data are in fact missing and not omitted by oversight.

5.7 Plots

Two modes of visualisation are useful additional tools. For the univariate ratio data columns boxplots provide a helpful visual summary of the presence or otherwise of anomalous values in the data. The barplot when used with the table function again provides a useful visual summary of the categories in a nominal variable (with the table function to provide the frequency information).

Univariate
- Ratio
  - Boxplot
- Nominal
  - Barplot

Bivariate
- Scatterplot matrix
- Bagplots for selected pairs of variables

Treemaps might be useful ways of summarising the pattern of values, visually, in a crosstabulation of two or more categorical variables – they either help to identify an unusual combination of categories or allow a check on the presence or otherwise of the valid values which represent each category.

5.8 Maps

The data values for many of the datasets refer to individual NUTS regions. Mapping the values, either as choropleth maps for ratio data, and area class maps for categorical data, provides a quick visual summary of the patterns.

Ratio
- Choropleth maps (10 categories)

Nominal
- Plot of data categories

One of the issues with mapping the data is the variation in the physical size of the NUTS regions. If the more distant overseas regions are included, this problem is magnified. In future assessment, consideration might be given to the use of a population cartogram as the basis – areas with larger populations are more prominent than areas with smaller populations. An alternative would be to create a cartogram where the areas are also approximately the same size.

[17] Enders, CK, 2010, *Applied Missing Data Analysis*, New York: Guilford Press

Software for creating cartograms exists both as an extension to ArcGIS[18] and through the ScapeToad website[19]. The reshaped set of zones then allows each data value to visualised on an equal footing.

Both the visual display described in 5.7 and 5.8 are essentially ephemeral displays, they are of less use in presenting the results of the analysis in the output report for the data supplier. However, as diagnostic tools they are useful is helping to identify some of the initial characteristics of the data set.

[18] http://arcscripts.esri.com/details.asp?dbid=15638 and https://uknow.drew.edu/confluence/display/DREWGIS/ArcMap+-+Cartograms+Tutorial
[19] http://scapetoad.choros.ch/

6 DATA CHECKS IN PRACTICE

6.1 Reflections on the data check process

In practice we found that the data supplied by the projects was very different from that which we had envisaged. A "one-size-fits-all" system that we had developed for the ESPON 2013 Database project required radical overhaul and re-organisation. The "exceptions to the exceptions" that we encountered as enumerated below.

6.1.1 Missing data

There was inconsistency in the presentation of missing data. Sometimes a numeric code was used, such as -999, other times we encountered alphameric codes which as "n/r".

For some studies, data was not present for all NUTS regions. Some studies omitted these regions entirely, others coded every variable as missing.

6.2.2 Non-integer counts

In a number of cases projects supply count data – these should be positive integers, yet we occasionally encountered fractional values where rounding had either been omitted or forgotten. Excel will display a rounded value to a number stored with a fractional part.

6.2.3 Duplicated data

We checked to see whether any rows appeared to be duplicated. In one case every NUTS2 region in Denmark was included twice in the data. Again, with the user of Excel, this is easy to overlook.

6.2.4 Internal inconsistencies

In one case a series of indicators were supplied, together with an additional indicator which was their sum. The summations were checked – for one example, the difference was 7.2 percentage points for a value of 24.2%. Either the summation column was correct, in which case individual indicator values were incorrect, or the summation was faulty.

6.2.5 Phantom worksheets

The spreadsheets are supposed to contain four separate worksheets: Dataset, Indicator, Source and Data. In one case we discovered an extra hidden worksheet, named SPSS, which could not be seen in when the spreadsheet was opened in Excel, but was clearly visible to the R software.

6.2.6 Multivariate checks

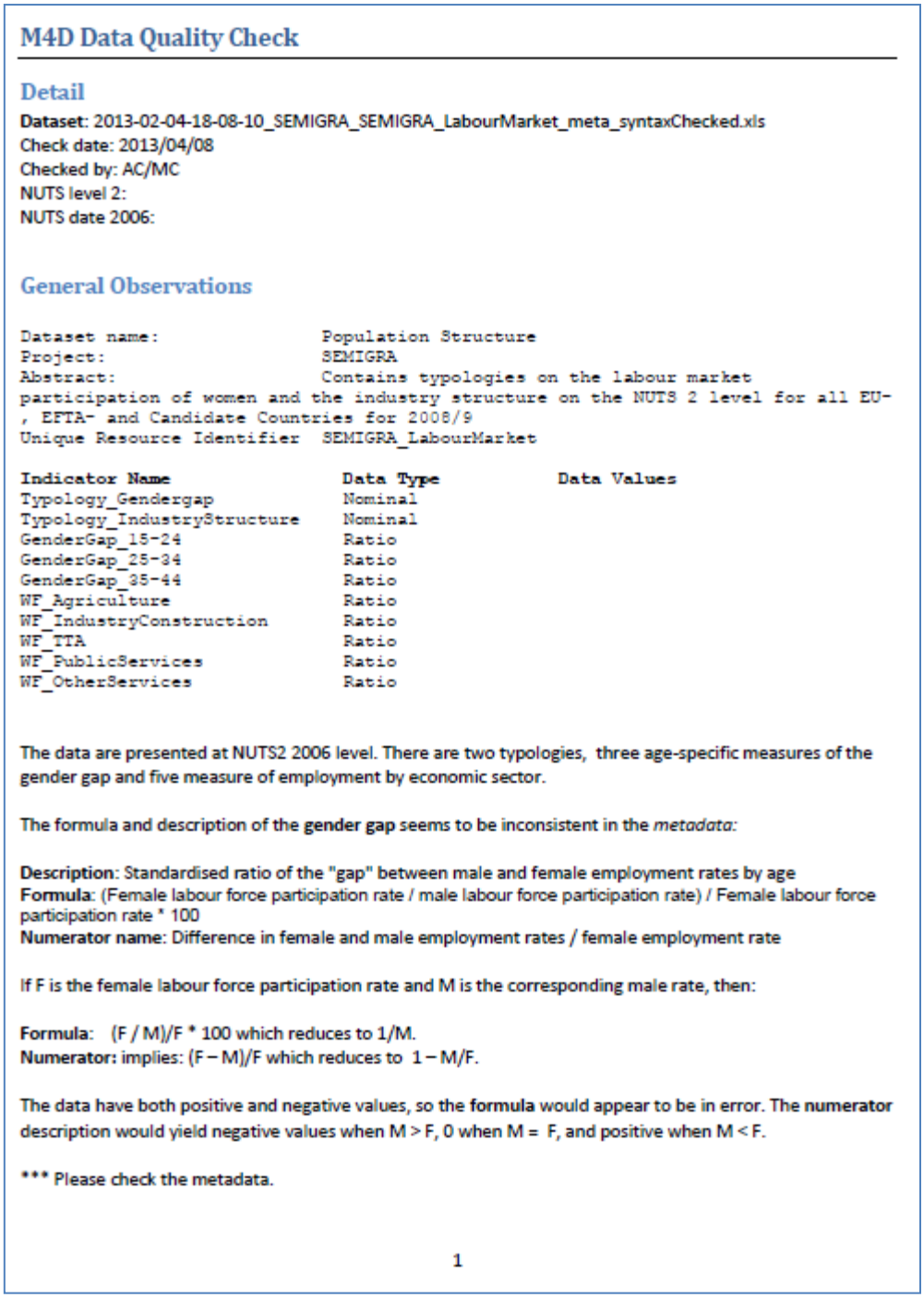
In several cases there was insufficient data to allow a multivariate check, of the data was so disparate as to make this meaningless. Additionally the existing of missing data meant that addinfg additional variables into the multivariate set would have result in a series depletion of the number of regions with sufficiently complete data.

6.2.7 Faulty computation
Notwithstanding the prior semantic and syntaxic checks carried out on the metadata we identified one example were the computation of the indicator was faulty. In another case a commonly used demographic indicator was inverted.

6.2.8 Errors in the metadata
We are very aware that many working under the ESPON programme do not have English as a first language. There were occasional errors in the metadata to which we drew attention. Occasional uncommon English uses appeared in the metadata, and we requested clarification.

6.2.9 Mixed NUTS2/3 data
One project included regions at NUTS 2 for some countries, and NUTS3 for others. We created a new geometry file, and a new geometry code, "X" for these data.

6.2 Helping the suppliers: the report
Rather than a bland printout/listing from the data check software, we decided to arrange our reports in logical sections, with some initial identification from the metadata, a logical organisation of the anomalies that we had found, and a final section with some recommendations for checking and, if necessary, altering the data that was submitted.



M4D Data Quality Check

Detail

Dataset: 2013-02-04-18-08-10_SEMIGRA_SEMIGRA_LabourMarket_meta_syntaxChecked.xls
Check date: 2013/04/08
Checked by: AC/MC
NUTS level 2:
NUTS date 2006:

General Observations

```
Dataset name:              Population Structure
Project:                   SEMIGRA
Abstract:                  Contains typologies on the labour market
participation of women and the industry structure on the NUTS 2 level for all EU-
, EFTA- and Candidate Countries for 2008/9
Unique Resource Identifier  SEMIGRA_LabourMarket
```

Indicator Name	Data Type	Data Values
Typology_Gendergap	Nominal	
Typology_IndustryStructure	Nominal	
GenderGap_15-24	Ratio	
GenderGap_25-34	Ratio	
GenderGap_35-44	Ratio	
WF_Agriculture	Ratio	
WF_IndustryConstruction	Ratio	
WF_TTA	Ratio	
WF_PublicServices	Ratio	
WF_OtherServices	Ratio	

The data are presented at NUTS2 2006 level. There are two typologies, three age-specific measures of the gender gap and five measure of employment by economic sector.

The formula and description of the **gender gap** seems to be inconsistent in the *metadata:*

Description: Standardised ratio of the "gap" between male and female employment rates by age
Formula: (Female labour force participation rate / male labour force participation rate) / Female labour force participation rate * 100
Numerator name: Difference in female and male employment rates / female employment rate

If F is the female labour force participation rate and M is the corresponding male rate, then:

Formula: (F / M)/F * 100 which reduces to 1/M.
Numerator: implies: (F – M)/F which reduces to 1 – M/F.

The data have both positive and negative values, so the **formula** would appear to be in error. The **numerator** description would yield negative values when M > F, 0 when M = F, and positive when M < F.

*** Please check the metadata.

1

Example report section

We noted in one case that many of the indicators had presented apparently anomalous values in the right tail of the distribution. This is not unknown in socio-economic data. We requested, nevertheless, that the supplier checked the values.

7 INSTALLATION

The implementation of the data check assumes that the code and any associated shapefiles and lookup tables will be stored in the folder **C:\M4D**. A batch file (LoadDataCheckCodes.bat) is used to copy the code and data files from the software development folder to C:\M4D. Within the software development folder are the following files and folders:

Data_Check_Main_template.R	high level data check functions
DataCheckFunctions.R	low level data check functions
TERCO_Data_Check.R	example control file
SpatialData\NUTS_Info	folder of NUTS lookup tables
SpatialData\NUTS_ETRS_1989_LAEA	folder of shapefiles

The batch file creates the M4D folder if it is not present, and copies the files.

```
@ECHO OFF
CLS
Echo ****************************************
Echo ****************************************
Echo *** Copying M4D Data Check Functions ***
Echo *** == Destination folder  c:\M4D == ***
Echo ****************************************
echo ****************************************

IF EXIST C:\M4D GOTO M4DPRESENT
@ECHO *** C:\M4D folder does not exist. Creating new version...
MKDIR C:\M4D
@ECHO *** C:\M4D created

:M4DPRESENT
@ECHO *** C:\M4D folder already exists
@ECHO *** Copying R files...
COPY Data_Check_Main_template.R C:\M4D
COPY DataCheckFunctions.R C:\M4D
COPY TERCO_Data_Check.R C:\M4D\Example_Control_file.R
@ECHO *** Copying NUTS lookup tables...
XCOPY Spatial_Data\NUTS_Info C:\M4D\NUTS_Info /E /I /Q /R /Y
@ECHO *** Copying NUTS shapefiles
XCOPY Spatial_Data\NUTS_ETRS_1989_LAEA C:\M4D\NUTS_ETRS_1989_LAEA /E /I /Q /R /Y

ECHO ********************************************
ECHO ********************************************
ECHO *** M4D Data Check Function Copy Completed ***
ECHO ********************************************
ECHO ********************************************
PAUSE
ECHO ON
```

8 FURTHER DEVELOPMENTS

This technical report provides an introduction to the detection of logical input errors and statistical outliers (i.e. exceptional values) for ESPON Database datasets. Some important aspatial and spatial techniques have been introduced and demonstrated within the R statistical computing environment.

The field of robust statistics and outlier detection is extremely large and diverse, and as such can not be comprehensively reviewed within the terms of reference of this report. However, outlier detection techniques applicable (or designed for) *spatial* data sets are not as developed as those for *aspatial* applications.

Robust versions of geographically weighted summary statistics (GWSS), geographically weighted regression (GWR) and geographically weighted principal component analysis (GWPCA) are of interest, as they allow the detection of outliers in both univariate and multivariate spatial data sets, without being influenced by the non-normal nature of the data.

Further developments in the detection methodology might include a selection of the robust geographically weighted techniques that we are currently working on. An improved version of Hawkins' spatial outlier test is also under development, as is a robust version of the local Moran's I statistic (with respect to outlier identification).

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APPENDIX 1

ESaTDOR Data Check Control File (21/3/2013)

```
##############################################################################
##############################################################################
#####                                                                    #####
#####              M4D Data Quality Check                                #####
#####                                                                    #####
##############################################################################
##############################################################################

##############################################################################
##### Information for the dataset under test: USER supplied              #####
##############################################################################

DataFolder    <- "~Dropbox\\2013_03_21_EsaTDOR_Data_check\\"
DatasetName         <-   "2013-01-16-15-22-57_EsaTDOR_ESATDOR_Economic_Use_Composite
v2_syntaxCheckedMC.xls"
NUTSLevel     <- 2                          # NUTS Region level
NUTSDate      <- 2006                       # NUTS Region date
DataColumns   <- seq(4, 38, 2)              # Starts col 4, in pairs 2 + 2*8 vars
DataTypes     <- c("N", "N", rep("R",16))   # T=text N=nominal R=ratio
MV_Columns    <- c(F, F, rep(T, 16))        # All multivariate testable
C1            <- c(1, 2, 3, 4, 5)           # Indicator 1
C2            <- c(1, 2, 3, 4, 5)           # Indicator 2
TestCodes     <- list(C1, C2, rep(0,16))    # Codes for nominal data
DataColRange  <- seq(4,length(DataColumns)+4) # Data columns in DataFrame
MissingValues <- rep(-999, length(DataColumns))  # Missing value codes
DrawPlots     <- TRUE                       # Draw boxplots and maps
DrawMaps      <- TRUE                       # Draw the maps

##############################################################################
#                                                                            #
# Data check begins here                                                     #
# Latest data check functions: to copy these double click on                 #
#     ~Dropbox\00ESPON_M4D\Database_Quality_Check\Live\LoadDataCheckCodes.bat  #
#                                                                            #
##############################################################################

source("C:\\M4D\\Data_Check_Main_Template.R",echo=TRUE)     # Invoke data check




##############################################################################
#                                                                            #
# Bespoke tests                                                              #
#                                                                            #
##############################################################################

TestData <- DQCmData[!is.na(DQCmData$E09SHIPBUI20012009),]          # get the rows
with data
dim(TestData)
colnames(TestData)
# [1] "UnitCode"                    "Level"                        "Year"
# [4] "marine_compo_eco_120012009" "marine_compo_eco_220012009" "E09TOT20092009"
# [7] "E09SHIPBUI20012009"          "E09TRADSEC20012009"          "E09TRANSP20012009"
#[10] "E09TOURISM20012009"          "E09FISHERI20012009"          "E09OTHER20012009"
#[13]    "E09OILGAS20012009"                                        "P_09TOT20092009"
"P_09SHIPBUI20012009"
#[16]    "P_09TRADSEC20012009"                                     "P_09TRANSP20012009"
"P_09TOURISM20012009"
#[19]    "P_09FISHERI20012009"                                      "P_09OTHER20012009"
"P_09OILGAS20012009"
```

```
not.integer <- which(TestData$E09TOT20092009 %% 1 > 0)       # non integer counts
TestData[not.integer,c(1,6)]                                 # list them
not.integer <- which(TestData$E09TOT20092009 %% 1 > 0)
TestData[not.integer,1]

#
# TestData[,14] is the sum of the cols 15:21 - check the summation
#

px <- TestData[,15] +TestData[,16] + TestData[,17] +TestData[,18] +TestData[,19]
+TestData[,20] +TestData[,21]
pt <- rowSums(TestData[,15:21])
x <- TestData$P_09TOT20092009 - pt                          # compare wtih actual sum
big <- which(abs(x) > .1)                                   # which are the big ones
cbind(TestData[big,c(1,14)], pt[big], x[big])               # list the table


mvdata <- TestData[,15:21]
pcs <- princomp(mvdata,cor=T,scores=T)


# > pcs$sdev^2 / sum(pcs$sdev^2)
#     Comp.1     Comp.2     Comp.3     Comp.4     Comp.5     Comp.6     Comp.7
# 0.24929559 0.19683055 0.15896476 0.12046032 0.10538623 0.08982176 0.07924078
#  .25        .45        .61        .73        .83        .91        .99

pcs$loadings
> pcs$loadings

## Loadings:
##                     Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7
## P_09SHIPBUI20012009         -0.663        -0.134  0.494  0.528
## P_09TRADSEC20012009  0.577                       -0.429  0.378  0.576
## P_09TRANSP20012009   0.390 -0.182 -0.569 -0.201  0.338 -0.564  0.136
## P_09TOURISM20012009 -0.288  0.172 -0.663 -0.447 -0.199  0.402 -0.218
## P_09FISHERI20012009 -0.203 -0.370 -0.437  0.765 -0.205
## P_09OTHER20012009    0.603                       -0.180        -0.767
## P_09OILGAS20012009  -0.136 -0.597  0.175 -0.383 -0.587 -0.312

pcs.scores <- pcs$scores
boxplot(pcs.scores)                          # hmmm - some outliers

#
# Bagplot to look at the first couple of components - accounts for about
# 45% of the variance
#
bagplot(pcs$scores[,1],pcs$scores[,2])       # compare the first two

#
# print the results of the mutlivariate analysis
#

# Names can be got from http://http://nuts.geovocab.org/id/NO04.html

k <- which(pcs$scores[,1] > 3 | pcs$scores[,2] < -2.5) # outliers
as.data.frame(cbind(as.character(TestData[k,1]),pcs$scores[k,1:2]))

#     NUTS            Comp.1            Comp.2                  Name
# 165 IS00 -2.62080242231774  -2.7997695388609                sland
# 172 ITD3  4.08584331110513   0.3810196487946                Veneto
# 173 ITD4  4.40887180192335  -0.2562404548776 Friuli-Venezia Giulia
# 174 ITD5  4.38184283329398   0.1497851513156        Emilia-Romagna
# 208 NO04  0.45951451096980  -6.8260406244667     Agder og Rogaland
# 209 NO05  0.92418754519894  -5.0458479442180             Vestlandet
# 238 RO22  0.76849593144108  -3.2802554172067                Sud-Est
# 245 SE21  3.41048199666645   0.4252567502375     Smland med arna
# 318 UKM6 -3.37228171738626  -5.7277554506111 Highlands and Islands
```

```
MVNutsCode <- TestData[k,1]
MVNutsCode
which(NUTSCodes[,1] %in% MVNutsCode)
NUTSCodes[which(NUTSCodes[,1] %in% MVNutsCode),]

#     Code                  Name Level
#1123 ITD3                Veneto     2
#1131 ITD4 Friuli-Venezia Giulia     2
#1136 ITD5        Emilia-Romagna     2
#1488 RO22               Sud-Est     2
#1533 SE21     Smland med arna     2
#1763 UKM6 Highlands and Islands     2




################################################################################
#                                                                              #
# End of data check template                                                   #
#                                                                              #
################################################################################
```

APPENDIX 2

SeGI Data Check Control File (22/3/2013)

```
##############################################################################
##############################################################################
#####                                                                    #####
#####              M4D Data Quality Check                                #####
#####                                                                    #####
##############################################################################
##############################################################################

##############################################################################
##### Information for the dataset under test: USER supplied              #####
##############################################################################

DataFolder    <- "~Dropbox\\00ESPON_M4D (1)\\2013_03_22_SEGI_Data_Check\\"
DatasetName                              <-          "2012-11-05-14-03-19_SeGi_I-
6ESPONindicatorsSeGI_syntaxCheckedMC.xls"
NUTSLevel     <- 2                                  # NUTS Region level
NUTSDate      <- 2006                               # NUTS Region date
DataColumns   <- seq(4, 104, 2)                     # Starts col 4, in pairs
DataTypes     <- rep("R",length(DataColumns))       # All ratios
MV_Columns    <- rep(T, length(DataColumns))        # All multivariate testable
#C1            <- c(1, 2, 3, 4, 5)                  # Indicator 1
#C2            <- c(1, 2, 3, 4, 5)                  # Indicator 1
TestCodes     <- list(rep(0, length(DataColumns)))  # Codes for nominal data
DataColRange  <- seq(4,length(DataColumns)+4)       # Data columns in DataFrame
MissingValues <- rep("n/a", length(DataColumns))    # Missing value codes
DrawMaps      <- FALSE
DrawPlots     <- FALSE

##############################################################################
#                                                                            #
# Data check begins here                                                     #
# Latest data check functions: to copy these double click on                 #
#     ~Dropbox\00ESPON_M4D\Database_QWuality_Check\Live\LoadDataCheckCodes.bat #
#                                                                            #
##############################################################################

source("C:\\M4D\\Data_Check_Main_Template.R",echo=TRUE)     # Invoke data check

##############################################################################
#                                                                            #
# End of data check template                                                 #
#                                                                            #
##############################################################################




library(VIM)
matrixplot(as.data.frame(DQCmData[,4:54]),main="Missing Values Analysis")

x                     <-                      function(i){junk                      <-
is.na(DQCmData[,i]);as.data.frame(cbind(as.character(DQCmData[junk,1]),DQCmData[jun
k,i]))}
v <- colnames(DQCmData)
kk <- 55; x(kk);v[kk]

alldata <- c(15, 27, 28, 32, 33, 34, 41, 42, 43, 44)
somedata <- c(6, 7, 9, 10, 11, 12, 13, 14, 16, 20, 21, 23, 24, 25, 29, 30, 31, 50,
51, 52)
mostdata <- sort(c(alldata,somedata))

pc.data <- DQCmData[,alldata]
```

```
pcs <- princomp(pc.data,cor=T,scores=T)
pcs$sdev^2/sum(pcs$sdev^2)
#     Comp.1      Comp.2      Comp.3      Comp.4      Comp.5      Comp.6      Comp.7
Comp.8     Comp.9    Comp.10
#0.24647463  0.16778182  0.13843203  0.11163209  0.09727827  0.06804657  0.06035619
0.04353280 0.03872245 0.02774315

bagplot(pcs$scores[,1],pcs$scores[,2])
```

APPENDIX 3

SEMIGRA Sex Ratio Data Check (26/3/2013)

```
################################################################################
################################################################################
#####                                                                      #####
#####              M4D Data Quality Check                                  #####
#####                                                                      #####
################################################################################
################################################################################

################################################################################
##### Information for the dataset under test: USER supplied                #####
################################################################################

DataFolder    <- "~Dropbox\\2013_03_26_SEMIGRA_Data_Check\\
DatasetName                                    <-             "2013-02-04-16-13-
19_SEMIGRA_SEMIGRA_SexRatio_meta_syntaxChecked.xls"
NUTSLevel     <- 3                                  # NUTS Region level
NUTSDate      <- 2006                               # NUTS Region date
DataColumns   <- seq(5, 12, 2)                      # Starts col 4, in pairs
DataTypes     <- c("R", "R", "R", "C")              # All ratios
MV_Columns    <- c(T, T, T, F)                     # All multivariate testable
C1                  <- c("Cluster 1","Cluster 2","Cluster 3","Cluster 4","Cluster
5","Cluster 6")   # Indicator 4
TestCodes    <- list( 0, 0, 0, C1) # Codes for nominal data
DataColRange  <- seq(5,length(DataColumns)+4)       # Data columns in DataFrame
MissingValues <- rep(NA, length(DataColumns))       # Missing value codes

################################################################################
#                                                                              #
# Data check begins here                                                       #
# Latest data check functions: to copy these double click on                   #
#     ~Dropbox\00ESPON_M4D\Database_QWuality_Check\Live\LoadDataCheckCodes.bat #
#                                                                              #
################################################################################

source("C:\\M4D\\Data_Check_Main_Template.R",echo=TRUE)     # Invoke data check

X <- DQCmData[1:1487,]
#> colnames(X)
#[1] "UnitCode"    "Level"       "Year"        "SR_20-24"    "SR_25-29"    "SR_30-
34"    "SR_Type2008"


X$SR_Type <- factor(X$SR_Type2008)

summary(X)
boxplot(X[,4]~X$SR_Type)
boxplot(X[,5]~X$SR_Type)
boxplot(X[,6]~X$SR_Type)




################################################################################
#                                                                              #
# End of data check template                                                   #
#                                                                              #
################################################################################
```

APPENDIX 4

SEMIGRA Labour Market Data Check (26/3/2013)

```
##############################################################################
##############################################################################
#####                                                                    #####
#####              M4D Data Quality Check                                #####
#####                                                                    #####
##############################################################################
##############################################################################

##############################################################################
##### Information for the dataset under test: USER supplied              #####
##############################################################################

DataFolder    <- "~Dropbox\\2013_03_26_SEMIGRA_Data_Check\\"
DatasetName                                    <-            "2013-02-04-18-08-
10_SEMIGRA_SEMIGRA_LabourMarket_meta_syntaxChecked.xls"
NUTSLevel     <- 2                                  # NUTS Region level
NUTSDate      <- 2006                               # NUTS Region date
DataColumns   <- seq(5, 24, 2)                      # Starts col 4, in pairs
DataTypes     <- c("T", "T", rep("R",8))            # All ratios
MV_Columns     <- rep(F, F, T, T, T, T,  T, T, T, T)          # All multivariate
testable
C1                  <- c("Cluster 1","Cluster 2","Cluster 3","Cluster 4","Cluster
5","Cluster 6","Underemployment","Extreme values","Not analysed")   # Indicator 1
C2               <- c("Cluster 1","Cluster 2","Cluster 3","Cluster 4","Agriculture
dominant","Industry    dominant","Service    sector    dominant","Public    sector
dominant","Financial sector dominant","Not analysed")  # Indicator 1
TestCodes    <- list(C1, C2, 0, 0, 0, 0,  0, 0, 0, 0) # Codes for nominal data
DataColRange  <- seq(4,length(DataColumns)+4)       # Data columns in DataFrame
MissingValues <- rep(NA, length(DataColumns))       # Missing value codes
DrawPlots <- TRUE
DrawMaps <- TRUE

##############################################################################
#                                                                            #
# Data check begins here                                                     #
# Latest data check functions: to copy these double click on                 #
#     ~Dropbox\00ESPON_M4D\Database_Quality_Check\Live\LoadDataCheckCodes.bat  #
#                                                                            #
##############################################################################

source("C:\\M4D\\Data_Check_Main_Template.R",echo=TRUE)     # Invoke data check

##############################################################################
#                                                                            #
# End of data check template                                                 #
#                                                                            #
##############################################################################



Typology_Gendergap
Typology_IndustryStructure
GenderGap_15-24
GenderGap_25-34
GenderGap_35-44
WF_Agriculture
WF_IndustryConstruction
WF_TTA
WF_PublicServices
WF_OtherServices
```

APPENDIX 5

EU LUPA Data Check

```
################################################################################
################################################################################
#####                                                                      #####
#####              M4D Data Quality Check                                  #####
#####                                                                      #####
################################################################################
################################################################################

################################################################################
##### Information for the dataset under test: USER supplied                #####
################################################################################

DataFolder    <- "~ Dropbox\\2014_01_08_EU_LUPA_LandUse_DataCheck\\"
DatasetName                        <-        "2014-01-08-19-55-38_EU        LUPA_eu-
lupa_land_change_syntaxChecked_v2_syntaxChecked.xls"
NUTSLevel     <- "X"                                      # NUTS Region level (X =
NUTS2/3
NUTSDate      <- 2006                                  # NUTS Region date
DataColumns   <- c(4,6,8)                              # Starts col 4, in pairs
DataTypes     <- c(rep("R",3))                         # All ratios
MV_Columns    <- c(T, T, F)                            # All multivariate testable
TestCodes    <- list(0, 0, 0) # Codes for nominal data
DataColRange  <- seq(4,length(DataColumns)+4)          # Data columns in DataFrame
MissingValues <- rep(NA, length(DataColumns))          # Missing value codes

################################################################################
#                                                                              #
# Data check begins here                                                       #
# Latest data check functions: to copy these double click on                   #
#     ~Dropbox\00ESPON_M4D\Database_Quality_Check\Live\LoadDataCheckCodes.bat  #
#                                                                              #
################################################################################

source("C:\\M4D\\Data_Check_Main_Template.R",echo=TRUE)     # Invoke data check

################################################################################
#                                                                              #
# End of data check template                                                   #
#                                                                              #
################################################################################
```

APPENDIX 6

Data Check Main Template [called from Control File]

```
################################################################################
################################################################################
#####                                                                      #####
#####              M4D Data Quality Check Template                         #####
#####                                                                      #####
################################################################################
################################################################################

################################################################################
##### Load the data check functions package, and the R library
################################################################################

DataCheckFunctions <- "C:\\M4D\\DataCheckFunctions.R"
source(DataCheckFunctions)                          # source the Library code
                                                    # can add ,echo=TRUE
LoadLibraries()                                     # Load the R packages
PrintBanner()                                       # fancy title banner

################################################################################
##### set up the data and file paths
################################################################################

folders            <- M4D_Folders("C:\\M4D")             # Object with filepaths

M4DFolder          <- folders$M4DFolder             # Path to M4D folder
ShapefileFolder    <- folders$ShapefileFolder       # Path to NUTS shapefiles
LookupTableFolder  <- folders$LookupTableFolder     # Path to NUTS lookups
FullDatasetName    <- paste(DataFolder,DatasetName,sep="") # Path to data file

################################################################################
##### Load the NUTS boundaries for this level and year
##### Load the NUTS Lookup tables for this level and year
################################################################################

if (NUTSLevel >= 0)
    {
    cat("################################################################################\n")
    cat("# Loading geometry and lookups                                               #\n")
    cat("################################################################################\n")
    SPDFObject <- loadPolyShapefile(ShapefileFolder,NUTSLevel,NUTSDate)
    SPDF       <- SPDFObject$SPDF                    # SpatialPolygonsDataFrame
    NUTSlist   <- SPDFObject$NUTSlist                # NUTS region codes in SPDF
    Nregions   <- SPDFObject$Nregions                # Number of regions in SPDF
    NUTSCodes  <- GetNUTSCodes(LookupTableFolder,2006,2) # From  change datasets
    Countries  <- read.csv(paste(LookupTableFolder,"Countries.csv",sep="\\"))
    } else {
    cat("################################################################################\n")
    cat("# Data are not for NUTS units                                                #\n")
    cat("################################################################################\n")
    }

################################################################################
##### Load the Dataset for checking                                            #
##### Extract the constituent Worksheets                                       #
##### Reformat the Data worksheet                                              #
##### Add in the region names for the NUTS lookup tables                       #
################################################################################

DatasetObject <- GetData(FullDatasetName)           # Load the dataset

Dataset   <- DatasetObject$Dataset                  # Extract Dataset worksheet
Indicator <- DatasetObject$Indicator                # Extract Indicator w/sheet
```

```
Source    <- DatasetObject$Source                        # Extract Source worksheet
Data      <- DatasetObject$Data                          # Extract Data worksheet

Dataset.Info(Dataset)                                    # print data details
Indicator.Info(Indicator)                                # print summary metadata
Data.Unique.Name.Check(Data)                             # Check Duplicate Names

DQC.out <- UnpackDataWorksheet(Data,DataColumns)      # Reshape for analysis
DQCrData   <- DQC.out$DQC                                # Reshaped data
DQCVnames  <- DQC.out$Vnames                             # Variables
DQCMVnames <- DQCVnames[MV_Columns]                      # Multivariate columns

Reshaped.Data.Unique.Name.Check(DQCVnames)               # check duplicate names
DQCmData <- Update.Missing.Value.Codes(DQCrData,MissingValues) # conv to NA
Missing.Value.Analysis(DQCmData)                         # check incomplete cases


##############################################################################
##### Data are not for any NUTS units                                      #
##############################################################################

DQCData <- MergeNUTSNames(DQCmData,NUTSCodes)             # Add in names from MUTS
lookup
nv <- length(DQCVnames)                                  # number of variables
invalidNUTScodes <- which(is.na(DQCData[,3+nv+1]))    # NUTS codes not in lookup
#Check.Invalid.NUTS.Codes(DQCData,invalidNUTScodes,Countries)
Print.Invalid.NUTS.Codes(DQCData,invalidNUTScodes,Countries) # list the crap

##############################################################################
##### Determine NTS regions in the SPDF are *not* in the data              #
##### Print a list of the omitted regions                                  #
##### Subset the SPDF appropriately                                        #
##############################################################################

   OmittedRegions <- Omitted(NUTSlist,DQCData[,1])      # Which regions are missing
   PrintOmitted(NUTSCodes,OmittedRegions)               # Print the regions in the
                                                        #  shapefile which are not
   SPDF.DQC <- SubsetSPDF(SPDF,OmittedRegions)          #  in the test dataset

##############################################################################
##### Determine NUTS regions in the DQC data that have missing data        #
##### Print the records                                                    #
##### Create a 'clean' subset for the spatial and multivariate tests       #
##############################################################################

   cat("\n\nMissing Data (records with NA check\n")
   MissingDataRecords <- MissingRecords(DQCData,DataColRange)  # Find NAs in data
   if (length(MissingDataRecords) > 0) {
      cat("\n*** Records with missing data\n")
      DQCData[MissingDataRecords,c(1,DataColRange,12)]         # Print names
   } else {
      cat("\n*** There are NO records with missing data\n")
      }

   if (length(MissingDataRecords) > 0){
      DQCData.nomissing <- DQCData[-MissingDataRecords,]       # Remove missing
   } else
      DQCData.nomissing <- DQCData
   SPDF.nomissing    <- CleanSPDF(SPDF,DQCData.nomissing)      # Clean SPDF

##############################################################################
##### Exploratory analysis first                                           #
##### Nominal: frequency tabulation and histogram                          #
#####          valid category check                                        #
##### Ordinal: summary statistics                                          #
##### Ratio:   summary statistics                                          #
#####                                                                      #
##### Then... check plots next - barplots for nominal, boxplots for ratio  #
```

```
####  Finally... map everything that is mappable.                              #
################################################################################

   summary.Check.variables(SPDF.nomissing,DQCVnames,DataTypes,TestCodes)
   #summary.Check.univariate(DQCData,DQCVnames,DataTypes,TestCodes)
   summary.Check.bivariate(SPDF.nomissing,DQCMVnames)
   if (DrawPlots) plot.Check.variables(SPDF.nomissing,DQCVnames,DataTypes)

################################################################################
##### Outlier check                                                            #
#####    (i)    Univeriate tests                                               #
#####    (ii)   Spatial Univeriate tests                                       #
#####    (iii)  Multivariate tests                                             #
#####    (iv)   Outlier summary                                                #
################################################################################

   UV.Outliers             <-             UnivariateExplore(SPDF.nomissing,DQCData,
DQCVnames,DataTypes,TestCodes)
   #Sp.Outliers <- SpatialExplore(SPDF.nomissing,DQCMVnames)
   MV.Outliers <- MultivariateExplore(SPDF.nomissing,DQCMVnames)

   # Outlier.Report(UV.Outliers,Sp.Outliers,MV.Outliers)


################################################################################
#### Completion - print suitable statistics                                    #
################################################################################

print.Completion.Banner()

################################################################################
#### Completion - end of run                                                   #
################################################################################
```

APPENDIX 7

Data_Check_Functions.R

```
##########################################################################
##########################################################################
####                                                                  ####
#### M4D Data Check Functions                                         ####
####                                                                  ####
#### Authors: Paul Harris                                             ####
####          Martin Charlton                                         ####
####          Alberto Caimo                                           ####
####                                                                  ####
#### Version NCG.2012.11.28a                                          ####
####                                                                  ####
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####                                                                  ####
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####                                                                  ####
##########################################################################
##########################################################################

##########################################################################
# Housekeeping                                                          #
##########################################################################
#
# Return folder paths for various users
#
M4D_Folders <- function(folder){
    #Dropbox <- switch(user,
    #       martin.office       =  "C:\\Documents  and  Settings\\mcharlton.NUIM\\My
Documents\\My Dropbox",
    #         martin.fujitsu      =   "C:\\Documents   and   Settings\\mcharlton\\My
Documents\\Dropbox",
    #   martin.laptop   = "C:\\Users\\mcharlton\\Dropbox",
    #   alberto.laptop  = "C:\\Users\\acaimo\\Dropbox"
    #   )
    # M4DFolder <- paste(Dropbox,"\\00ESPON_M4D",sep="")
    #                                ShapefileFolder                                <-
paste(M4DFolder,"\\Spatial_Data\\NUTS_ETRS_1989_LAEA",sep="")
    # LookupTableFolder   <- paste(M4DFolder,"\\Spatial_Data\\NUTS_Info",sep="")

    M4DFolder         <- folder
    ShapefileFolder   <- paste(M4DFolder,"\\NUTS_ETRS_1989_LAEA",sep="")
    LookupTableFolder <- paste(M4DFolder,"\\NUTS_Info",sep="")

    return(list(M4DFolder=M4DFolder,
                ShapefileFolder=ShapefileFolder,
                LookupTableFolder=LookupTableFolder))
}

#
# Banner for the output
#
PrintBanner <- function(){
   cat("+=====================================================================+\n")
   cat("+=====================================================================+\n")
   cat("###                                                                 ###\n")
   cat("### M4D: Data Quality Check                                         ###\n")
   cat("###                                                                 ###\n")
   cat("### National Centre for Geocomputation                             ###\n")
   cat("### National University of Ireland Maynooth                        ###\n")
   cat("### Maynooth, Co Kildare, Ireland                                  ###\n")
```

```
   cat("###                                                                ###\n")
   cat("+=================================================================+\n")
   cat("+=================================================================+\n")
   cat("Run on: ",date(),"\n\n")
   }
#
# Banner for end of run
#
print.Completion.Banner <- function(){
   cat("+=================================================================+\n")
   cat("### M4D: Data Quality Check                                       ###\n")
   cat("###      Completed at: ", date()," ###\n")
   cat("+=================================================================+\n")
   }

#############################################################################
# General purpose and setup routines                                        #
#############################################################################
#
# LoadLibraries()
#
# Load the required libraries
#
LoadLibraries <- function(){
   library(RODBC)        # to import data from excel
   library(MASS)         # this has parallel coordinates plots, rlm
   library(maptools)     # spatial data handling libraries
   library(spdep)        # localmoran in here
   library(forecast)     # auto.arima stuff in here
   library(spgwr)        # gw.cov in here
   library(DMwR)         # Talgo's outlier.ranking routines
   library(RColorBrewer) # Cindy Brewer's palettes
   library(aplpack)      # this has bagplots
}
#
# Country level color palette
#
LoadEUColorPalette <- function(){
#
# Color palette
#
       c( 24,214,236,558, 32,
         553, 59,504, 54, 41,
         620,151,412,146,143,
         385,611,654,494, 51,
         258,614,124,434,615,
          29,594, 31,462,450,
         120,122,609, 88)

}
#
# Reminder of the Brewer Color Palettes which are available
#
PlotBrewerPalettes <- function(){
    display.brewer.all(n=NULL, type="all", select=NULL, exact.n=TRUE)
}
#
# Re-insert the omitted items back in the right order
#     weeded.list is the logical vector without the omits
#     omits is the vector of omitted indices
#
rebuild.list <- function(weeded.list, omits){
   n <- length(weeded.list) + length(omits)
   final.list <- rep(NA,1,n)
   k <- 0
   final.list[omits] <- FALSE
     for (i in 1:n){
         if (is.na(final.list[i])){
```

```
            k <- k + 1
            final.list[i] <- weeded.list[k]
          }
     }
     final.list
}
#
# pause():
# Pause an interactive script
#
pause <- function () {
    if (interactive())
       readline("Hit <enter> to continue...")
    invisible()
}
#########################################################################
# Dataset manipulation and setup routines                               #
#########################################################################
#
# GetData()
# Function to read an M4D Excel Spreadsheet
# Arguments:
# Excel.Spreadsheet:     path to an Excel (.xls) spreadsheet
#
# Requires: library(RODBC)
#
GetData <- function(Excel.Spreadsheet){
   id <- odbcConnectExcel(Excel.Spreadsheet) # file handle
   Dataset   <- sqlFetch(id,"Dataset")       # Read the Dataset description
   Indicator <- sqlFetch(id,"Indicator")     # Read the metadata
   Source    <- sqlFetch(id,"Source")        # Read sources
   Data      <- sqlFetch(id,"Data")          # Read the Data worksheet
   close(id)
   return(list(Dataset=Dataset,Indicator=Indicator,Source=Source,Data=Data))
}
#
# GetNUTSCodes(year)
# Function to read the NUTS codes for a given
# Arguments:
#    Year: year required
#
# Requires: library(RODBC)
#
GetNUTSCodes <- function(filepath,year,NUTSLevel){
      filename <- paste(filepath,"\\NUTS_",year,"_Codes.xls",sep="")
      id     <- odbcConnectExcel(filename)  # file handle
      Lookup <- sqlFetch(id,"Lookup")       # Read the NUTS codes and names
      close(id)
      #
      # Now copy NUTS codes code NUTSLevel (Level in Col 7, Name in Col 10,
      #                                     Code in Col 1)
      # Lookup[which(Lookup[,7] == NUTSLevel),c(1,2,7)]
        colnames(Lookup)[10] <- "Name"
        Lookup[which(Lookup[,7] == NUTSLevel),c(1,10,7)]
}
#
# MergeNUTSNames - add in the names to the data frame - names come from the
#    GetNUTSCodes lookup tables (Excel spreadsheets)
#
MergeNUTSNames <- function(DQCData,NUTSCodes){
   data.frame(DQCData, NUTSCodes[match(DQCData[,"UnitCode"], NUTSCodes[,"Code"]),])
}
#
# Create a variable name from the indicator name
# and date information in the spreadsheet
# NA and null are omitted to keep the variable
# name short
#
```

```
# is.crap : auxiliary function to test for NA, NULL
#           or blank fields
#           Probably should have a more polite name
#
is.crap <- function(x) {is.na(x) | is.null(x) | x == "" | x == " "}
#
create.variable.name  <-  function(a,b,c){
    if (is.crap(b) & is.crap(c)) a            # both missing
    else if (is.crap(b)) paste(a,c,sep="")    # first date missing
    else if (is.crap(c)) paste(a,b,sep="")    # second date missing
    else paste(a,b,c,sep="")                  # neither missing
}
#
# UnpackDataWorksheet
#
UnpackDataWorksheet <- function(DataWorksheet,DataColumns){
   N.Data <- dim(DataWorksheet)[1]               # Worksheet length
   NV <- length(DataColumns)                     # Number of variables to extract
   cnames <- rep("",NV)                          # Array for column names
   dnames <- colnames(DataWorksheet)
   Data.for.checking <- as.data.frame(Data[3:N.Data,c(1:3,DataColumns)])
   for (i in 1:NV){
      VarCol <- DataColumns[i]
      #                                  cnames[i]                                  <-
paste(dnames[VarCol],DataWorksheet[1,VarCol],DataWorksheet[2,VarCol],sep=".")
      cnames[i]                                                                     <-
create.variable.name(dnames[VarCol],DataWorksheet[1,VarCol],DataWorksheet[2,VarCol]
)
   }
   colnames(Data.for.checking) <- c("UnitCode","Level","Year",cnames)
   return(list(DQC=Data.for.checking,Vnames=cnames))
}
#
# Omitted Regions
#
Omitted <- function(NUTSRegions,CheckDataRegions){
   setdiff(NUTSRegions,CheckDataRegions)
}
PrintOmitted <- function(NUTSCodes,OmittedRegions){
   cat("\n\nMISSING REGIONS in the Data for Checking\n")
   if (length(OmittedRegions) > 0) {
      cat("Regions in the NUTS list not in the data for checking\n")
      print(NUTSCodes[which(NUTSCodes[,1] %in% OmittedRegions),])
      cat("\nRegions in the Shapefile not in the data for checking\n")
      print(OmittedRegions)
   } else {
      cat("\n*** There are no omitted regions\n\n")
      }
}
#########################################################################
# Missing Data handlers                                                 #
#########################################################################
#
# MissingRecords
#
MissingRecords <- function(DQCData,DataColRange){
   N <- dim(DQCData)[1]
   MissingData <- which(is.na(DQCData[,DataColRange]))
   MissingData[MissingData <= N]
}
#
# Function ValidCodes()
#
# Arguments:
#   x:              vector of nominal data to be checked
#   ValidCodeList: list of allowable codes for x
#
ValidCodes <- function(x,ValidCodeList){
```

```
    x %in% ValidCodeList
}
#
# Function Data.Unique.Name.Check(Data)
# Check for unique column names in spreadsheet as it comes in
#
# Arguments:
#   Data:    worksheet Data from spreasheet
#
Data.Unique.Name.Check <- function(Data) {

   cat("\n\n")
   cat("+================================================================+\n")
   cat("### Check for duplicated column names in original spreadsheet ###\n")
   cat("+================================================================+\n")
   Column.Names <- colnames(Data)
   Duplicate.List <- which(duplicated(Column.Names))
   if (length(Duplicate.List) > 0) {
       cat("***The following names are duplicated in the column header\n")
       Column.Names[Duplicate.List]
       cat("\n\n")
   } else {
       cat("***There are no duplicated column names\n\n")
   }
}
#
# Function Data.Unique.Name.Check(Data)
# Check for unique column names in spreadsheet as it comes in
#
# Arguments:
#   Data:    worksheet Data from spreasheet
#
Reshaped.Data.Unique.Name.Check <- function(NameList) {
   cat("\n\n")
   cat("+================================================================+\n")
   cat("## Check for duplicated column names in worksheet for checking ##\n")
   cat("+================================================================+\n")
   Duplicate.List <- which(duplicated(NameList))
   if (length(Duplicate.List) > 0) {
       cat("***The following column names are duplicated...\n")
       NameList[Duplicate.List]
       cat("\n\n")
   } else {
       cat("***There are no duplicated column names\n\n")
   }
}
#########################################################################
# Missing Value Handlers                                                #
#########################################################################
#
# Update.Missing.Value.Codes
#
#    Update the supplied missing value codes for each column as NA
#
# Arguments:
#    DQCData: data frame for update
#    MissingValues: vector missing value codes
#
Update.Missing.Value.Codes <- function (DQCData,MissingValues) {
   nv <- length(MissingValues)
   DQCTest <- DQCData
   if (nv > 0) {
      for (i in 1:nv) {
         DQCTest[which(DQCTest[,i+3] == MissingValues[i]),i+3] <- NA
         }
      }
   DQCTest
}
```

```
#
# Missing.Value.Analysis
#
Missing.Value.Analysis <- function(DQCTest) {
   nr <- dim(DQCTest)[1]                          # number of rows
   nv <- dim(DQCTest)[2]                          # number of columns
   vn <- colnames(DQCTest)                        # column headers
   cat("\n\n")
   cat("+=================================================================+\n")
   cat("### Missing Value analysis                                      ###\n")
   cat("+=================================================================+\n")
   cat("\n***Missing value counts and percentages\n")
   for (i in 4:nv) {
      nm <- which(is.na(DQCTest[,i]))             # find Missing
      km <- length(nm)                            # number missing
      kpct <- round(100 * (km / nr),2)            # percent missing
      cat(paste("Indicator ",vn[i],": ",km," (",kpct,"%)\n",sep=""))
   }
   complete <- which(complete.cases(DQCTest[,4:nv]))    # complete cases
   nc <- length(complete)                              # number of complete cases
   cat("\nTotal observations: ",nr,", of which ",nc," have ALL data present\n")
   incomplete <- which(!complete.cases(DQCTest[,4:nv]))
   nt <- nv - 3
   all.missing <- rep(nr,FALSE)
   if (length(incomplete) > 0) {
      cat("\n*** Zones with missing observations\n")
      cat(" ==================================\n")
      for (i in 1:nr) {
         s <- rowSums(is.na(DQCTest[i,4:nv]))
         if (s > 0){
            cntry <- which(Countries[,1]==substr(DQCTest[i,1],1,2))
            if (length(cntry) > 0) {
               cdata <- Countries[as.integer(cntry),2:3]
            } else {
               cdata <- c("Unknown code","Unknown")
            }
            country.name <- unlist(cdata[1])
            country.status <- unlist(cdata[2])
            # print(cdata)
            cat(paste(DQCTest[i,1],", (",s,") ",
               country.name,": ",
               country.status," \n",sep=""))
            }
         }
   }

}

Print.Completely.Missing.Cases <- function(D,incomplete){
   cat("\n\n*** Completely Missing Cases ***\n")
   if(length(incomplete) > 0) {
       cat("\n*** All indicators missing for:\n")
       D[incomplete,"UnitCode"]
   } else {
       cat("\n*** No cases with all indicators missing ***\n")
   }
}


#########################################################################
# Shapefile handling service routines                                   #
#########################################################################
#
# Load shapefile
#
loadPolyShapefile <- function(filepath,NUTSlevel,year){
   filename <- paste(filepath,"\\NUTS",NUTSlevel,"_",year,".shp",sep="")
   # print(filename)
```

```
   SPDF <- readShapePoly(filename,
   proj4string=CRS("+proj=laea   +lat_0=52   +lon_0=10   +x_0=4321000   +y_0=3210000
+ellps=GRS80 +units=m +no_defs "))
   NUTSlist <- sort(SPDF@data$NUTS_ID)
   Nregions <- length(NUTSlist)
   return(list(SPDF=SPDF,NUTSlist=NUTSlist,Nregions=Nregions))
}
#
# Update.SPDF.COlumns
#    Adjust DQCData column positions to allow for SPDF
#    items after merge of DQCData and SPDF@data
#
#Update.SPDF.Columns <- function(DQCCols,year){
#   switch (year,
#      1996 = Offset <- 0,
#      2003 = Offset <- 8,
#      2006 = Offset <- 9,
#      2010 = Offset <- 6)
#      DQCCols + Offset
#}
#
# Subset the Shapefile on the region name
#
SubsetSPDF <- function(SPDF,OmittedRegions){
      valid.regions <- ! SPDF@data$NUTS_ID %in% OmittedRegions
      SPDF[valid.regions,]
}
#
# Clean SPDF for spatial and multivariate tests
#
CleanSPDF <- function(SPDF,DQCData.nomissing){
   Records.nomissing <- dim(DQCData.nomissing)[1]
   SPDF2 <- SPDF
   if (Records.nomissing > 0) {
      CleanRegions <- SPDF@data$NUTS_ID %in% DQCData.nomissing[,1]
      SPDF2 <- SPDF[CleanRegions,]
      SPDF2@data <- MergeDataWithSPDF(SPDF2,DQCData.nomissing,"UnitCode")
   }
   return(SPDF2)
}
#
# Create neighbour list from the subsetted data
#
SPDF.listw <- function(SPDF){
   nb2listw(poly2nb(SPDF))       # Create neighbour list from nb-ed polygons
}
#
# Match the data frame from UnpackDataWorksheet with the SPDF from
# loadPolyShapefile
# See
#   http://stackoverflow.com/questions/3650636/how-to-attach-a-simple-data-frame-to-
a-spatialpolygondataframe-in-r
# x must be a data frame
#
MergeDataWithSPDF <- function(SPDF,x,Code){
      SPDF@data <- data.frame(SPDF@data, x[match(SPDF@data[,"NUTS_ID"], x[,Code]),
])
}
#
#########################################################################
# Metadata service routines                                             #
#########################################################################

Dataset.Info <- function(Dataset){
   Dataset.name <- as.character(Dataset[1,2])
   Project      <- as.character(Dataset[2,2])
   Abstract     <- as.character(Dataset[5,2])
   URI          <- as.character(Dataset[7,2])
```

```
   cat("+================================================================+\n")
   cat("### Dataset identification                                    ###\n")
   cat("+================================================================+\n")
   cat("Dataset name:              ",Dataset.name,"\n")
   cat("Project:                   ",Project,"\n")
   cat("Abstract:                  ",Abstract,"\n")
   cat("Unique Resource Identifier ",URI,"\n")
   cat("\n")

}

Indicator.Info <- function(Indicator){
   vnames       <- Indicator[which(Indicator[,1]=="Code")+1,1]
   datatypes    <- Indicator[which(Indicator[,1]=="Data type"),3]
   values                <-  as.character(Indicator[which(Indicator[,1]=="Unit  of
measure"),3])
   start.dates           <-     as.numeric(Indicator[which(Indicator[,1]=="Temporal
Extent")+1,2])
   finish.dates       <-       as.numeric(Indicator[which(Indicator[,1]=="Temporal
Extent")+1,3])
   z <- cbind(as.character(vnames),as.character(datatypes),as.character(values))

   z <- rbind(c("Indicator Name","Data Type","Data Values"),z)
   cat("+================================================================+\n")
   cat("### Summary information from the metadata                     ###\n")
   cat("+================================================================+\n")
   write.table(format(z,justify="left"),row.names=F,col.names=F,quote=F)
   cat("\n")
}

#########################################################################
# Outlier check service routines                                        #
#########################################################################
#
# Function PositiveInteger
#
PositiveInteger <- function(x){
   x == floor(x) & x >= 0
}
#
# Function BoxplotTest
#
BoxplotTest <- function(x){
   bp <- boxplot.stats(x,coef=1.5)
   x >= bp$stats[1] & x <= bp$stats[5]
}
#
# HawkinsTest
#
# Requires:    library(spgwr)
#
HawkinsTest <- function(x,coords){
    x.spdf <- x
    coordinates(x.spdf) <- coords              # create data frame
    bw <- 0.1                                  # local bandwidth (10% of data)
    chi5pct <- 3.84146                            # test distributed as chi square
with 1df
    gwss  <-  gw.cov(x.spdf,  data=x,  adapt=bw)      #  locally  weighted  summary
statistics
    local.mean <- gwss$SDF$mean.V1             # locally weighted mean
    local.variance <- gwss$SDF$sd.V1^2         # locally weighted variance
    local.N <- bw * length(x)                  # local sample size
    local.alv <- mean(local.variance)          # average local variance
    Hawkins   <-   (local.N*(x   -   local.mean)^2)/((local.N+1)*local.alv)   #   test
statistic
    Hawkins > chi5pct                          # significant test result
}
#
```

```
# Local Moran test
# Anselin, L. 1995. Local indicators of spatial association, Geographical Analysis,
27, 93-115
# Getis, A. and Ord, J. K. 1996 Local spatial statistics: an overview. In P.
Longley and M. Batty (eds)
#    Spatial analysis: modelling in a GIS environment (Cambridge: Geoinformation
International), 261-277.
#
# SPDF must 'clean' - no missing data
#
Local.Moran.Outliers <- function(SPDF,MVCols,p.threshold=0.05){
    # First generate the neighbour lists, and the weights matrix
    # Allow for zero neighboured objects
    print(MVCols)
    neighbour.list <- poly2nb(SPDF)           # build neighbour list
    spatial.weights.matrix <- nb2listw(neighbour.list,zero.policy=TRUE)
    #
    N <- dim(SPDF@data)[1]                    # number of observations
    M <- length(MVCols)                       # number of variables
    evidence <- array(FALSE,c(N,M+1))
    deviates <- array(0,c(N,5))                # weight of evidence
    rownames(evidence) <- seq(1,N)
    colnames(evidence) <- seq(1,M+1)
    k <- 0
    for (i in MVCols) {                       # test each variable in turn
       deviates <- as.matrix(localmoran(SPDF@data[,i],spatial.weights.matrix))
       k <- k + 1
       rownames(deviates) <- seq(1,N)
       # str(deviates)
       # str(evidence)
       evidence[,k] <- deviates[,"Pr(z > 0)"] > p.threshold  # Pr(Z > 0)
    }
    evidence[,M+1] <- rowSums(evidence[,1:M]) / M # weight of evidence
    return(evidence)
}
#############################################################################
###                                                                       ###
### Multivariate Methods                                                  ###
###                                                                       ###
#############################################################################
#
# RunningRegression(x)
# Regress each column of x on the others and compute the
# proportion of standardised residuals greater
# than a user supplied threshold
#
CirculatingRegression <- function(x,thresh=3){
   N <- dim(x)[1]
   M <- dim(x)[2]
   resid.tests <- matrix(0,N,M)
   for (i in 1:M) {
       response <- x[,i]
       predictors <- as.matrix(x[,-i])
       m1 <- lm(response~predictors)
       resid.tests[,i] <- abs(rstandard(m1)) > thresh
       }
   rowSums(resid.tests) / M
}
#
# Robust version: use Boxplot Test
#
CirculatingRobustRegression <- function(x,thresh=3){
   N <- dim(x)[1]
   M <- dim(x)[2]
   resid.tests <- matrix(0,N,M)
   for (i in 1:M) {
       response <- x[,i]
       predictors <- as.matrix(x[,-i])
```

```
        rlm.res <- rlm(response~predictors)$resid
        resid.tests[,i] <- BoxplotTest(rlm.res)
        }
    rowSums(resid.tests) / M
}
#
# Component scores - summarise a large body of variables
# Areas with score > thresh on component 1 are potential
# outliers
#
test_PCA <- function(x,thresh=3){
    princomp(x,cor=T,scores=T)$scores[,1] <= thresh
}

#
# Mahalonobis distances
#
Mahalanobis.Distances <- function(x){
    mahalanobis(x,colMeans(x),cov(x))
}
#
# Mahalanobis plot
#
Mahalanobis.Plot <- function(MD2,bw=0.5,title){
    plot(density(MD2,bw=bw),main=title); rug(MD2)
}
#
# Mahalanobis.Outliers
#
Mahalanobis.Outliers <- function(x,threshold){
    Mahalanobis.Distances(x) < threshold
}
#
# Torgo's routines
# http://www.liaad.up.pt/~ltorgo/DataMiningWithR/
#
Torgo.Probabilities <- function(x){
    inter.object.distances <- daisy(x)
    outliers.ranking(inter.object.distances)$prob.outliers
}
#
# Torgo Outliers
#
Torgo.Outliers <- function(x,threshold=0.8){
    Torgo.Probabilities(x) <= threshold
}
#
# Bagplot Test for two variables
#
bagplot.test <- function(v1,v2){
    N <- length(v1)                          # length of data vectors
    bagplot.test.result <- rep(TRUE,N)       # Initialise output
    z <- compute.bagplot(v1,v2)              # compute bagplot
    out <- z$pxy.outlier                     # extract the outliers
    Nout <- dim(out)[1]                      # Any outliers?
    if (Nout >= 1) {                         # Yes: which are they?
       outliers <- which((v1 %in% out[,1]) & (v2 %in% out[,2]))
       bagplot.test.result[outliers] <- FALSE  # Update the output
    }
    bagplot.test.result                      # return the result vector
}
#
# Bagplot.Analysis
#
# Computes the bagplot statistics for every pairing of the variables
# in a matrix and returns a outlier score (1=OK, <1 possibly an outlier)
#
Bagplot.Analysis <- function(x){
```

```
     N <- dim(x)[1]                          # Observations
     M <- dim(x)[2]                          # variables
     K <- (M^2 -M)/2                         # pairings
     out <- matrix(0,N,K)                    # result matrix
     k <- 0                                  # counter for 'out'
     for (i in 1:M) {
        for (j in 1:i) {
           if (i != j) {
               k <- k + 1
               bpt <- bagplot.test(x[,i],x[,j]) # test variable pair
               out[,k] <- bpt                   # update result
           }
        }
     }
     rowSums(out) / K                         # compute the score
}

##########################################################################
##########################################################################
###                                                                    ###
### Main checking routines [high level routines                        ###
###                                                                    ###
##########################################################################
##########################################################################

##########################################################################
#  UnivariateExplore(SPDF.DQC,DQCData,DataColRange,DataTypes,TestCodes)
##########################################################################
UnivariateExplore <- function(SPDF,DQCData,DQCVnames,DataTypes,TestCodes){
   cat("+=================================================================+\n")
   cat("### Univariate Exception tests                                  ###\n")
   cat("+=================================================================+\n")
   for(ColIndex in 1:length(DQCVnames)){
     switch(DataTypes[ColIndex],
          R = rdc <- RatioCheck  (DQCData,DQCVnames[ColIndex]),
          N                      =                      ndc                      <-
NominalCheck(DQCData,DQCVnames[ColIndex],unlist(TestCodes[ColIndex])),
          O = odc <- OrdinalCheck(DQCData,DQCVnames[ColIndex]),
          C = cdc <- CountCheck  (DQCData,DQCVnames[ColIndex])
          )
   }
}
##########################################################################
#  SpatialExplore(SPDF.nomissing,DQCData.nomissing,DataColRange,Datatypes)
##########################################################################
SpatialExplore <- function(SPDF,DataColRange,threshold=0.05){
   cat("+=================================================================+\n")
   cat("| Spatial exception tests                                        |\n")
   cat("+=================================================================+\n")
#
# Local Moran tests in here; we'll think about Hawkins' test
#
    LMoevidence <- Local.Moran.Outliers(SPDF,DataColRange,threshold)
    N <- dim(LMoevidence)[1]                          # number of observations
    LastCol <- dim(LMoevidence)[2]                    # weight column...
    M <- LastCol -1                                   # max will be M
    lmo <- LMoevidence[,LastCol]                      # get weight of evidence
    Evidence <- cbind(LMoevidence)                    # store for later use

    out <- as.character(SPDF@data[,"UnitCode"])
    testcol <- lmo                                    # weights
    badlist <- testcol > 0.5
    #badlist <- badlist[-which(is.na(badlist))]        # remnove islands
    if (sum(badlist,na.rm=T) < N) {
       cat("### Potential spatial exceptions  ###\n")
       print.Bad.Spatial.Scores(SPDF,badlist,testcol)      # print them
    }
    as.data.frame(cbind(out,Evidence))
```

```
    # to return to NUTS code sort order
    xx <- as.data.frame(Sp.Outliers[order(Sp.Outliers[,1]),])

}

#######################################################################
#  MultivariateExplore(SPDF.nomissing,DQCData.nomissing,MV_Cols)
#######################################################################
MultivariateExplore <- function(SPDF,MVCols){
   cat("+=================================================================+\n")
   cat("### Multivariate Exception tests                                ###\n")
   cat("+=================================================================+\n")
#
#   Circulating regression residuals
#   PCA with boxplots on first component
#   Mahalanobis distances - try with thresh 20 at first
#
    N <- length(SPDF@data[,1])
    ntests <- 5
    CiR.evidence <- 1 - CirculatingRegression(SPDF@data[,MVCols])
    RbR.evidence <- CirculatingRobustRegression(SPDF@data[,MVCols])
    PCA.evidence <- test_PCA(SPDF@data[,MVCols])
    Mah.evidence <- Mahalanobis.Outliers(SPDF@data[,MVCols],20)
    Biv.evidence <- Bagplot.Analysis(SPDF@data[,MVCols])
    Evidence                                                              <-
cbind(CiR.evidence,RbR.evidence,PCA.evidence,Mah.evidence,Biv.evidence)

    out <- as.character(SPDF@data[,"UnitCode"])
    testcol <- rowSums(Evidence)                        # total the scores
    badlist <- testcol >=  ntests / 1.5                 # any less than 5
    if (sum(badlist) < N) {
       cat("### Potential multivariate exceptions  ###\n")
       print.Bad.Spatial.Scores(SPDF,badlist,testcol)      # print them
    }
    as.data.frame(cbind(out,Evidence))


}

#######################################################################
### Main checking routines [high level routines                     ###
#######################################################################
#
# Function NominalCheck(x)
#
# [tests]
# (a) Consistency check - does the codelist agree
#
NominalCheck <- function(x,ColIndex,CodeList){
   cat("Nominal data check for Indicator: ",ColIndex,"\n")
   cat("Valid codes: ",CodeList,"\n")
   cat("\nFrequency Tabulation\n")
   print(table(x[,ColIndex]))                          # Frequency tabulation
   vc <- ValidCodes(x[,ColIndex],CodeList)             # Valid code check
   n.invalid <- length(which(vc==0))                   # List any invalid codes
   if (n.invalid > 0){
      #NUTSCode   <- as.character(DQCData[which(vc==F),1])
      #BadCode    <- DQCData[which(vc==F),ColIndex]
      #cat("Regions with invalid codes\n")
      #print(cbind(NUTSCode,BadCode) )
      cat("\nAnomalous data values found...\n")
      print.Bad.Data.Values(DQCData,vc,ColIndex)
   }
   cat("-------------------------------------------------------------------\n")
   return(vc)                                          # Return vector of T/F
}
```

```
#
# Function OrdinalCheck(x)
#
OrdinalCheck <- function(x,ColIndex){
   cat("Ordinal Data Check for Indicator: ",ColIndex,"\n")
   IsPositiveInteger <- PositiveInteger(x[,ColIndex])
   n.invalid <- length(which(IsPositiveInteger==0))   # List any invalid codes
   if (n.invalid > 0){
      #NUTSCode   <- as.character(DQCData[which(IsPositiveInteger==F),1])
      #BadCode    <- DQCData[which(IsPositiveInteger==F),ColIndex]
      #cat("Regions with invalid ranks\n")
      #print(cbind(NUTSCode,BadCode) )
      cat("\nNon postive-integer data values found...\n")
      print.Bad.Data.Values(DQCData,IsPositiveInteger,ColIndex)
   }
   cat("-----------------------------------------------------------------\n")
   return(IsPositiveInteger)
}

#
# Function CountCheck(x)
#
CountCheck <- function(x,ColIndex){
   cat("Count Data Check for Indicator: ",ColIndex,"\n")
   IsPositiveInteger <- PositiveInteger(x[,ColIndex])
   n.invalid <- length(which(IsPositiveInteger==0))   # List any invalid codes
   if (n.invalid > 0){
      #NUTSCode   <- as.character(DQCData[which(IsPositiveInteger==F),1])
      #BadCode    <- DQCData[which(IsPositiveInteger==F),ColIndex]
      #cat("Regions with non-positive integer data\n")
      #print(cbind(NUTSCode,BadCode) )
      cat("\nNon postive-integer data values found...\n")
      print.Bad.Data.Values(DQCData,IsPositiveInteger,ColIndex)
   }
   cat("-----------------------------------------------------------------\n")
   return(IsPositiveInteger)
}

#
# Function RatioCheck(x)
#
RatioCheck <- function(x,ColIndex){
   cat("Ratio Data Check for Indicator: ",ColIndex,"\n")
   StatOutlier <- BoxplotTest(x[,ColIndex])
   n.invalid <- length(which(StatOutlier==0))    # List potential outliers
   if (n.invalid > 0){
      #NUTSCode   <- as.character(DQCData[which(StatOutlier==F),1])
      #BadCode    <- DQCData[which(StatOutlier==F),ColIndex]
      cat("\nRegions with unusual boxplot data\n")
      #print(cbind(NUTSCode,BadCode) )
      print.Bad.Data.Values(DQCData,StatOutlier,ColIndex)
   }
   cat("-----------------------------------------------------------------\n")
}

##############################################################################
##############################################################################
#####                                                                    #####
##### Summary functions for the ESPON Data Quality Check                 #####
#####                                                                    #####
##############################################################################
##############################################################################
summary.Check.variables <- function(SPDF,DQCVnames,DataTypes,TestCodes){
   cat("+=============================================================+\n")
   cat("### Exporatory data summaries                               ###\n")
   cat("+=============================================================+\n")

   for (i in 1:length(DQCVnames)){
```

```
      cat("Variable:       ",DQCVnames[i],"\n")
      cat("Data Type:      ",DataTypes[i],"\n")
      switch(DataTypes[i],
         R = {ss <- summary(SPDF@data[,DQCVnames[i]])          #  summary for ratio
data
              print(ss)
              },
         N = {tt <- table(as.factor(SPDF@data[,DQCVnames[i]]))
              print(tt)
              cat("Categories found are: ",
                  levels(as.factor(SPDF@data[,DQCVnames[i]])),"\n")
              },
         O = summary(SPDF@data[,DQCVnames[i]]),
         C = summary(SPDF@data[,DQCVnames[i]])
         )
      cat("-----------------------------------------------------------------\n")
   }

   cat("\nCompleted\n\n")
}
#
#   cor.prob(X)
#     correlation matrix of X with correlations in the lower triangle
#     and signficance probabilities in the upper triangle
#
# Due to Bill Venables, r-help@stat.math.ethz.ch,
#        04 Jan 2000 15:05:39
#
cor.prob <- function(X, dfr = nrow(X) - 2) {
        R <- cor(X)
        above <- row(R) < col(R)
        r2 <- R[above]^2
        Fstat <- r2 * dfr / (1 - r2)
        R[above] <- 1 - pf(Fstat, 1, dfr)
        R
}
###############################################################################
### Bivariate summaries for ratio variables                                ####
###############################################################################
summary.Check.bivariate <- function(SPDF,MVnames){
   cat("+=================================================================+\n")
   cat("### Bivariate data summaries                                    ###\n")
   cat("+=================================================================+\n")
   cat("\nBivariate correlations and p-values\n")
   cat("Correlations in the lower triangle and p-values in the upper\n")
   print(cor.prob(SPDF@data[,MVnames]))
   cat("-------------------------------------------------------------------\n")

}

###############################################################################
###############################################################################
#####                                                                     #####
##### Plotting functions for the ESPON Data Quality Check                 #####
#####                                                                     #####
###############################################################################
###############################################################################
#
# Check plots for nominal and ratio data using spplot
# needs the RColorBrewer library
#
# For boxplots, barcharts and maps, plot 4 per display window
# Pairwise plot uses single window only
#
plot.Check.variables <- function(SPDF,varlist,vartypes){
   #
   # Start with boxplots for the ratio variables: requires RColorBrewer
   #
```

```
   X11()
   par(mfrow=c(2,2))
   for (plotvar in varlist[which(vartypes == "R")]){    # ratio variables only
      boxplot(SPDF@data[,plotvar],main=plotvar)         # boxplots
      pause()
   }
   par(mfrow=c(1,1))
   #
   # Next, barcharts for the nominal variables
   #
   X11()
   par(mfrow=c(2,2))
   for (plotvar in varlist[which(vartypes == "N")]){    # nominal variables only
      barplot(table(SPDF@data[,plotvar]),main=plotvar,xlab="Code")                #
barcharts
      pause()
   }
   par(mfrow=c(1,1))
   #
   # Pairwise plot of the ratio variables
   X11()
   pairs(SPDF@data[,varlist[which(vartypes == "R")]], main="Pairwise Plots")
   pause()
   #
   # Plot check plots of the ratio variables
   #
   X11()
   for (i in 1:length(varlist)){
      if (vartypes[i] %in% c("N","R")){                  # ratio/nominal variables
         plotvar <- varlist[i]                           # get the name
         datatype <- vartypes[i]                         # get the type
         p.obj <- plot.SPDF.data(SPDF,plotvar,datatype)  # create the object
         switch.val <- i %% 4
         if (i == length(varlist) || switch.val == 0) {AddToPlot <- FALSE} else
{AddToPlot <- TRUE}
         switch (switch.val+1,
           print(p.obj,position=c(0.5, 0.0, 1.0, 0.5),more=AddToPlot),
           print(p.obj,position=c(0.0, 0.5, 0.5, 1.0),more=AddToPlot),
           print(p.obj,position=c(0.5, 0.5, 1.0, 1.0),more=AddToPlot),
           print(p.obj,position=c(0.0, 0.0, 0.5, 0.5),more=AddToPlot)
           )
         if (!AddToPlot) {pause()}
         } # end if
   } # end for
   par(mfrow=c(1,1))
   #
}

#
# Plot a variable from the SPDF data frame into a trellis plot object
#   Nominal data - coerce the data to a factor
#   Ratio data plot against 10 classes with a general purpose colour ramp
#   from RColorBrewer
#
plot.SPDF.data <- function(SPDF,plotvar,type){
   print(paste(plotvar,type))
   switch(type,
       R                                                                          =
spplot(SPDF,plotvar,main=as.character(plotvar),col.regions=brewer.pal(11,"Spectral"
),cuts=10),
       N = {SPDF2 <- SPDF
            SPDF2@data[,plotvar] <- as.factor(SPDF2@data[,plotvar])
            labeltext <- as.numeric(levels(SPDF2@data[,plotvar]))
            nlabels <- length(labeltext)
            labelat <- seq(1,nlabels)

spplot(SPDF2,plotvar,main=plotvar,col.regions=brewer.pal(nlabels,"Set1"),cuts=nlabe
ls-1)
```

```
           }
          )

}
################################################################################
####                                                                        ####
#### Reporting routines                                                     ####
####                                                                        ####
################################################################################
#
# print.Bad.Spatial.Values()
#      SPDF - spatial polygons data frame
#      badlist: anomalous entries are FALSE
#      testcol: column which has been tested
#
print.Bad.Spatial.Values <- function(SPDF,badlist,testcol){
    Values   <- SPDF@data[!badlist,testcol]
    NUTSCode <- as.character(SPDF@data[!badlist,"UnitCode"])
    NUTSName <- as.character(SPDF@data[!badlist,"Name"])
    outtable <- cbind(NUTSCode,Values,NUTSName)
    outtable <- rbind(c("NUTSCode","Value","NUTS Region Name"),outtable)
    write.table(format(outtable,justify="left"),row.names=F,col.names=F,quote=F)
}
#
# print.Bad.Spatial.Scores()
#      SPDF - spatial polygons data frame
#      badlist: anomalous entries are FALSE
#      testcol: column which has been tested
#
print.Bad.Spatial.Scores <- function(SPDF,badlist,testcol){
    Values   <- testcol[!badlist]
    NUTSCode <- as.character(SPDF@data[!badlist,"UnitCode"])
    NUTSName <- as.character(SPDF@data[!badlist,"Name"])
    outtable <- cbind(NUTSCode,Values,NUTSName)
    outtable <- rbind(c("NUTSCode","Value","NUTS Region Name"),outtable)
    write.table(format(outtable,justify="left"),row.names=F,col.names=F,quote=F)
}
#
# print.Bad.Data.Values()
#      X: data.frame
#      badlist: anomalous entries are FALSE
#      testcol: column which has been tested
#
print.Bad.Data.Values <- function(X,badlist,testcol){
    Values   <- X[!badlist,testcol]
    NUTSCode <- as.character(X[!badlist,"UnitCode"])
    NUTSName <- as.character(X[!badlist,"Name"])
    outtable <- cbind(NUTSCode,Values,NUTSName)
    outtable <- rbind(c("NUTSCode","Value","NUTS Region Name"),outtable)
    write.table(format(outtable,justify="left"),row.names=F,col.names=F,quote=F)
}

#
#
#
Print.Invalid.NUTS.Codes <- function(DQCData,invalidNUTScodes,Countries){
n.inv <- length(invalidNUTScodes)
if (n.inv > 0) {
   InvalidStuff <- DQCData[invalidNUTScodes,c(1,2,3,nv+4,nv+5,nv+6)]
   InvalidStuff[,4] <- "No NUTS lookup code"
   InvalidStuff[,5] <- "Unknown NUTS country"
   InvalidStuff[,6] <- "Unknown"
   }
cat("\n\nRegions with Unknown NUTS codes for this level and date\n")
cat(    "=====================================================\n")
if (n.inv == 0) {
   cat("\n*** All NUTS codes in these data appear to be valid\n\n")
   } else {
```

```
     xc <- substr(InvalidStuff[,1],1,2)
     for (i in 1:n.inv) {
        xp <- which(Countries[,1] == xc[i])
        if        (length(xp)        >        0)        InvalidStuff[i,5]        <-
paste(Countries[xp,2],Countries[xp,3],sep=", ")
     }
   }
 print(InvalidStuff[,c(1,2,3,5)])
}
```