Cleaning data

It is mandatory for the overall quality of an assessment to ensure that its primary and secondary data be of sufficient quality. “Messy data” refers to data that is riddled with inconsistencies, because of human error, poorly designed recording systems, or simply because there is incomplete control over the format and type of data imported from external data sources, such as a database, text file, or a Web page. So, a column that contains country names may contain “Burma”, “Myanmar” or “Myanma”.

Such inconsistencies will impede the data processing. Care should be taken to ensure data is as accurate and consistent (i.e. spellings, to allow aggregation) as possible. Inconsistencies can wreak havoc when trying to perform analysis with the data, so they have to be addressed before starting the analysis.

Used mainly when dealing with large volumes of data stored in a database, the terms *data cleansing, data cleaning or data scrubbing* refer to the process of detecting, correcting, replacing, modifying or removing incomplete, incorrect, irrelevant, corrupt or inaccurate records from a record set, table, or database.

This document provides guidance for data analysts to find the right data cleaning strategy when dealing with needs assessment data, either primary or secondary. It covers situations where:

- Raw data is being produced by assessment teams using a questionnaire and is entered into a centralized database.
- Data is obtained from secondary sources (displacement monitoring system, food security data, census data, etc.) and is integrated, compared or merged with the data obtained from field assessment to complement the final analysis.

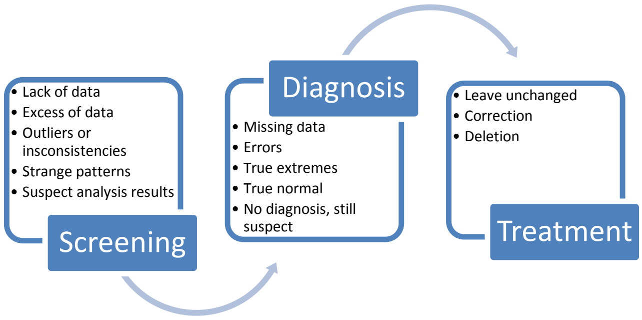
This document complements the ACAPS technical note on How to approach a dataset which specifically details data cleaning operations for primary data entered into an Excel spreadsheet during rapid assessments.

A. The data cleaning process

Data cleaning deals mainly with data problems once they have occurred. Error-prevention strategies (see data quality control procedures later in the document) can reduce many problems but cannot eliminate them. Many data errors are detected incidentally during activities other than data cleaning, i.e.:

- When collecting or entering data
- When transforming/extracting/transferring data
- When exploring or analysing data
- When submitting the draft report to peer review

It is more efficient to detect errors by actively searching for them in a planned way. Data cleaning involves repeated cycles of screening, diagnosing, and treatment.



Adapted from Van den Broeck J, Argeseanu Cunningham S, Eeckels R, Herbst K (2005)

Screening involves systematically looking for suspect features in assessment questionnaires, databases, or analysis datasets (in small assessments, with the analysts closely involved at all stages, there may be little or no distinction between a database and an analysis dataset).

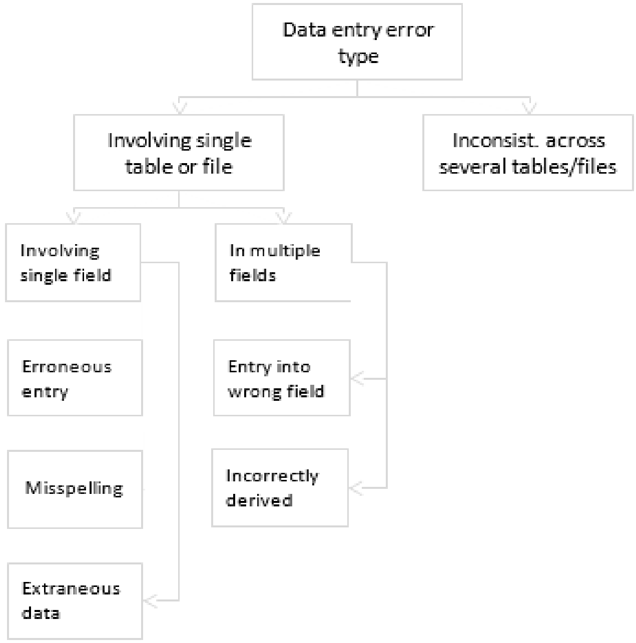
The diagnostic (identifying the nature of the defective data) and treatment (deleting, editing or leaving the data as it is) phases of data cleaning require insight into the sources and types of errors at all stages of the assessment. After measurement, data are the object of a sequence of typical activities: they are entered into databases, extracted, transferred to other tables, edited, selected, transformed, summarized, and presented. It is important to realize that errors can occur at any stage of the data flow, including during data cleaning itself.

B. Sources of errors

Many of the sources of error in databases fall into one or more of the following categories:

Measurement errors: Data is generally intended to measure some physical process, subjects or objects, i.e. the waiting time at the water point, the size of a population, the incidence of diseases, etc. In some cases these measurements are undertaken by human processes that can have systematic or random errors in their design (i.e., improper sampling strategies) and execution (i.e., misuse of instruments, bias, etc.). Identifying and solving such inconsistencies goes beyond the scope of this document. It is recommended to refer to the ACAPS Technical Brief *How sure are you?* To get an empirical understanding of how to deal with measurement errors in general.

Data entry error: "Data entry" is the process of transferring information from the medium that records the response (traditionally answers written on printed questionnaires) to a computer application. Data entry is generally done by humans, who typically extract information from speech (i.e., key informant interviews) or by using secondary data from written or printed sources (i.e. health statistics from health centres). Under time pressure, or for lack of proper supervision, data is often corrupted at entry time. Main errors type include:



Adapted from Kim et Al, 2003; Aldo Benini 2013

- An erroneous entry happens if, e.g., age is mistyped as 26 instead of 25.
- Extraneous entries add correct, but unwanted information, e.g. name and title in a name-only field.
- Incorrectly derived value occurs when a function was incorrectly calculated for a derived field (i.e. error in the age derived from the date of birth).
- Inconsistencies across tables or files occur e.g. when the number of visited sites in the province table and the number of visited sites in the total sample table do not match.

Processing errors: In many settings, raw data are pre-processed before they are entered into a database. This data processing is done for a variety of reasons: to reduce the complexity or noise in the raw data, to emphasize aggregate properties of the raw data (often with some editorial bias), and in some cases simply to reduce the volume of data being stored. All these processes have the potential to produce errors.

Data integration errors: It is actually quite rare for a database of significant size and age to contain data from a single source, collected and entered in the same way over time. Very often, a database contains information collected from multiple sources via multiple methods over time (i.e. tracking of affected population numbers over the crisis, where the definition of “affected” is being refined or changed over time). Moreover, in practice, many databases evolve by merging in other pre-existing databases; this merging task almost always requires some attempt to resolve inconsistencies across the databases involving different data units, measurement periods, formats, and so on. Any procedure that integrates data from multiple sources can lead to errors. The merging of two or more databases will both identify errors (where there are differences between the two databases) and create new errors (i.e. duplicate records).

Table 1 below illustrates some of the possible sources and types of errors in a large assessment, at three basic levels: When filling the questionnaire, when entering data into the database and when performing the analysis.

Table 1: Sources of data error

	Sources of problems	
Stage	Lack or excess of data	Outliers and inconsistencies
Questionnaire	• Form missing • Form double, collected repeatedly • Answering box or options left blank • More than one option selected when not allowed	• Correct value filled out in the wrong box • Not readable • Writing error • Answer given is out of expected (conditional) range
Database	• Lack or excess of data transferred from the questionnaire • Form of field not entered • Value entered in wrong field • Inadvertent deletion and duplication during database handling	• Outliers and inconsistencies carried over from questionnaire • Value incorrectly entered, misspelling • Value incorrectly changed during previous data cleaning • Transformation (programming) error
Analysis	• Lack or excess of data extracted from the database • Data extraction, coding or transfer error • Deletions or duplications by analyst	• Outliers and inconsistencies carried over from the database • Data extraction, coding or transfer error • Sorting errors (spreadsheets) • Data-cleaning errors

Adapted from Van den Broeck J, Argeseanu Cunningham S, Eeckels R, Herbst K (2005)

Inaccuracy of a single measurement and data point may be acceptable, and related to the inherent technical error of the measurement instrument. Hence, data cleaning should focus on those errors that are beyond small technical variations and that produce a major shift within or beyond the analysis. Similarly and under time pressure, consider the diminishing marginal utility of cleaning more and more compared to other demanding tasks such as analysis, visual display and interpretation.

- Understand when and how errors are produced during the data flow.
- Prioritization is essential if the assessment is under time pressures. Resources for data cleaning are limited. Errors related to population number, geo location, affected groups and date are particularly important because they contaminate derived variables and the final analysis. Know when to stop.

The following sections of this document offer a step by step approach to data cleaning.

C. First things first

The first thing to do is to make a copy of the original data in a separate workbook and name the sheets appropriately, or save in a new file. ALWAYS keep the source files in a separate folder and change its attribute to READ-ONLY, to avoid modifying any of those files, even if it is opened for reference.

D. Screening data

No matter how data are collected (in face-to-face interviews, telephone interviews, self-administered questionnaires, etc.), there will be some level of error, including a number of inconsistencies. While some of these will be legitimate, reflecting variation in the context, others will likely reflect a data collection error.

Examine data for the following possible errors:

- Spelling and formatting irregularities: are they categorical variables written incorrectly? Are date format consistent? Etc.
- Lack of data: Do some questions have far fewer answers than surrounding questions?
- Excess of data: Are there duplicate entries? Are there more answers than originally allowed?
- Outliers/inconsistencies: Are there values that are so far beyond the typical distribution that they seem potentially erroneous?
- Strange patterns: Are there patterns that suggest cheating rather than honest answers (i.e. several questionnaires with the exact same answers)?
- Suspect analysis results: Do the answers to some questions seem counterintuitive or extremely unlikely?

Screening methods are not only statistical:

- Many outliers are detected by perceived non-conformity with prior expectations, based on the analyst's experience, results from secondary data review, numerical constraints or common sense (weight can’t be negative, people can’t have more than 2 parents, women can’t bear 35 children, male can’t be pregnant, etc.).

- Descriptive tools can be used to predefine expectations, assumptions or criteria about normal ranges, distribution shapes, and strength of relationships. Comparison of the data with the generated assumptions or criteria can be partly automated (i.e. conditional formatting) and lead to flagging of dubious data, patterns, or results.

A particular problem is that of erroneous inliers, i.e., data points generated by error but falling within the expected range. Erroneous inliers will often escape detection. Detection approaches include:

- Viewing data in relation to other variables, using multivariate views, such as scatter plots or heatmap. More advanced and resource intensive techniques involves regression analysis or consistency checks.
- Examining the history of each data point or by re-measurement, however such examination is rarely feasible. Instead, one can examine and/or re-measure a sample of inliers to estimate an error rate (i.e. contacting enumerators or key informants to ask additional questions).

Useful screening methods are listed hereafter, from simpler to more complex:

- Browsing of data tables after sorting.
- Summary statistics.
- When time allows, validated data entry and double data entry.
- Printouts of variables not passing range checks and of records not passing consistency checks.
- Frequency distributions and cross-tabulations.
- Graphical exploration of distributions: box plots, histograms, and scatter plots using visual analysis software such as Tableau desktop.
- Plots of repeated measurements on the same individual, i.e., growth curves.
- Checking of questionnaires using fixed algorithms.
- Statistical outlier detection.

- In many if not most instances, data can only be cleaned effectively with some human involvement. Know (and/or train data cleaners) common mistakes and what errors to look for.
- Understanding properties of a dataset, including the identification and possible rectification of errors, is closely linked to exploratory data analysis and data visualization.
- Choose the right error detection strategies based on the type of data screened: quantitative, categorical data, P-Codes, or identifiers are subject to different errors type (i.e. misspelling for categorical variable) that calls for different detection approaches (spell check for misspelled categorical variable).

E. Diagnosing data

From the screening phase, you have highlighted data that needs investigation. To clarify suspect data, you often must review all of a respondent's answers to determine if the data makes sense taken in context. Sometimes you must review a cross-section of different respondents' answers, to identify issues such as a skip pattern that was specified incorrectly.

With this research complete, what is the true nature of the data that has been highlighted? Possible diagnoses for each data point are as follows:

- Missing data: Answers omitted by the respondent (nonresponse), questions skipped over by the enumerator / the data entry operator or dropout (when research is undertaken overtime such as school attendance).
- Errors: Typos or answers that indicate the question was misunderstood.
- True extreme: An answer that seems high but can be justified by other answers (i.e., the respondent working 60 hours a week because they work a full-time job and a part-time job)
- True normal: A valid record.
- No diagnosis, still suspect: You may need to make a judgment call on how to treat this data during the treatment phase.

Some data values are clearly logically or biologically impossible (you cannot be 200 years old or -176cm). Hence, one may pre-define cut-offs for immediate diagnosis of error. Sometimes values fall in between acceptable ranges and the diagnosis will be less straightforward. In these cases, it is necessary to apply a combination of diagnostic procedures:

- Go back to previous stages of the data flow to see whether a value is consistently the same. This requires access to well-archived and documented data with justifications for any changes made at any stage.
- Look for information that could confirm the true extreme status of an outlying data point. For example, a very low score for weight-for-age (i.e., −6 Z-scores) might be due to errors in the measurement of age or weight, or the subject may be extremely malnourished, in which case other nutritional variables should also have extremely low values. This type of procedure requires insight into the coherence of variables in a biological or statistical sense. Again, such insight is usually available from experience or lessons learnt and can be used to plan and program data cleaning.
- Collect additional information, i.e., question the enumerator about what may have happened and, if possible or necessary, repeat the measurement. Such procedures can only happen if data cleaning starts soon after data collection, and sometimes re-measuring is only valuable very shortly after the initial measurement.

The diagnostic phase is labour intensive and the budgetary, logistical, time and personnel requirements are typically underestimated or even neglected at the design stage. Costs may be lower if the data-cleaning process is planned and starts early in data collection.

- Use common sense, experience, triangulation and lessons learnt to diagnose the type of error.
- Design your questionnaire form carefully to allow cross checks between questions.

F. Treatment of data

After identification of errors, missing values, and true (extreme or normal) values, analysts must decide what to do with problematic observations:

- Leave it unchanged: The most conservative course of action is to accept this data as a valid response and make no change to it. The larger your sample size, the less one suspect response will affect the analysis; the smaller your sample size, the more difficult the decision.
- Correct the data: If the respondent's original intent can be determined, then fix their answer (i.e. after discussing with the enumerator, it is clear that the ratings were reversed by mistake; you can invert each of the answers to correct the issue).
- Delete the data: The data seems illogical and the value is so far from the norm that it will affect descriptive or inferential statistics. What to do? Delete just this response or delete the entire record? Remember that whenever you begin to toss out data, it raises the possibility that you are "cherry picking" the data to get the answer you want. Alternatively, you can create a binary variable, 1=suspicious record, 0=not so and use this new variable as a record filter in Pivot tables or in-table filtering to understand the impact of potentially erroneous data in your final results.
- Re-measure the suspect or erroneous values, if time and resources allows.

There are some general rules to support the decision:

- If the person doing the data entry has entered values different from the ones in the questionnaire, the value should be changed to what was recorded in the questionnaire form. (I.e. the value in the questionnaire was 40,000 and the data entry operator keyed in 4,000 – a zero was left out).
- When variable values do not make sense, if there is no data entry error, and there are no notes to help you determine where the error comes from, you must leave the data AS IT IS. The case should be listed as an outlier (i.e. by using conditional formatting for instance), and there is no justification for changing it. Extreme values falling into this category must be

handled by the person who is analysing the data. If you change the value because you think you know what is “reasonable”, you are biasing the data.

- When blank cases were inserted or the record type was required even though key informants may not have that type of data or duplicate records were entered, then cases must be deleted from the data file.
- Impossible values are never left unchanged, but should be corrected if a correct value can be found, otherwise they should be deleted. For biological continuous variables, some within-subject variation or small measurement variation will always be present. If a re-measurement is done very rapidly after the initial one and the two values are close enough to be explained by variation alone, take the average of both as the final value.

With true extreme values and with values that are still suspect after the diagnostic phase, the analyst should examine the influence of such data points, individually and as a group, on analysis results before deciding whether or not to leave the data unchanged.

Some authors have recommended that true extreme values should always stay in the analysis. In practice, many exceptions are made to that rule. The investigator may not want to consider the effect of true extreme values if they result from an unanticipated extraneous process. This becomes an “a posteriori” exclusion criterion. The data points should be reported as “excluded from analysis” in the methodology chapter of the final report.

Missing values require particular attention. This is not a data issue like skewness or outliers that you can just ignore (whether you are right or not). The first thing is to decide which blank cells need to be filled with zeros (because they represent genuine negative observations, such as ("no", "not present", "option not taken", etc.) and which to leave blank (if the convention is to use blanks for missing or not applicable). Some analysts replace blank cells with some explicit missing value code (if we want all missing to be explicitly coded).

What to do with those cells remaining blank? Missing values can be classified as either random or non-random:

- Random missing values may occur because the subject inadvertently did not answer some questions. The assessment may be overly complex and/or long, or the enumerator may be tired and/or not paying attention, and miss the question. Random missing values may also occur through data entry mistakes. If there are only a small number of missing values in your dataset (typically, less than 5%), then it is extremely likely to be random.
- Non-random missing values may occur because the key informant purposefully did not answer some questions (confusing or sensitive question, no appropriate choices such as “no opinion” or “not applicable”).

The default option for dealing with missing values is filtering and excluding from analysis:

- Listwise / casewise deletion: cases that have missing values on the variable(s) under analysis are excluded. If you are only analysing one variable, then listwise deletion is simply analysing the existing data. If you are analysing multiple variables, then listwise deletion removes cases if there is a missing value on any of the variables. The disadvantage is a loss of data because you are removing all data from cases who may have answered some of the questions, but not others (e.g., the missing data).
- Pairwise deletion: All available data is included. Unlike listwise deletion which removes cases (subjects) that have missing values on any of the variables under analysis, pairwise deletion only removes the specific missing values from the analysis (not the entire case). In other words, all available data is included. If you are conducting a correlation on multiple variables, this technique allow to conduct the bivariate correlation between all available data points, and ignore only those missing values if they exist on some variables. In this case, pairwise deletion will result in different sample sizes for each correlation. Pairwise deletion is useful when sample size is small or missing values are large because there are not many values to begin with, so why omit even more with listwise deletion.

Try conducting the same test using both deletion methods to see how the outcome change. Note that in these techniques, "deletion" means exclusion within a statistical procedure, not deletion (of variables or cases) from the dataset.

A second option is to delete all cases with missing values. Thus, you are left with complete data for all cases. The disadvantage to this approach is you reduce the sample size of your data, resulting in a loss of power and increased error in estimation (wider confidence intervals). If you have a large dataset, then it may not be a big disadvantage because you have enough cases even after the complete deletion. However, with a small dataset, the sample can be decimated, and results may be biased if missingness is non-random. Another disadvantage to this approach is that the subjects with missing values may be different than the subjects without missing values (e.g., missing values that are non-random), so you have a non-representative sample after removing the cases with missing values.

Another option is to replace the missing values, called imputation (single or multiple). This technique preserves all cases by replacing missing data with a probable value based on other available information (i.e. the mean or median of other similar observed values). Once all missing values have been imputed, the data set can then be analysed using standard techniques for complete data. However this method can also bias results and p-values.

Recently and under certain conditions, maximum likelihood approaches have also proven efficient to dealing with missing data.

Detailing technicalities, appropriateness and validity of each techniques goes beyond the scope of this document. Ultimately, choosing the right technique depends on how much data are missing (and why), patterns, randomness and distribution of missing values, the effects of the missing data and how you will use the data in your analysis. It is strongly recommended to refer to a statistician if you face a small dataset with large quantities of missing values.

Pragmatically, for needs assessment with few statistical resources, creating a copy of the variable and replacing missing values with the mean or median may often be enough and preferable to losing cases in multivariate analysis from small samples.

Also, answering somehow plausibly why data are missing ("women could not be interviewed", “the last questionnaire section could not be filled due to lack of time”) may be much more informative to end user’s than a plethora of statistical fixes. Look for meaning in non-random missingness. Maybe the respondents are telling you something important by not answering one of the questions. Set up a dummy variable with value 0 for those who answered the question and value 1 for those who did not. Use this dummy variable as one of the predictors of the outcome variable.

G. Recoding variables

You may need to recode variables to create new ones that fit your analytic needs. Recoding variables is useful in multiple scenarios, such as:

- Formatting: date (day, month, and year), pre-fixes to create better sorting in tables, rounding (in continuous variables).
- Syntax: Translation, language style and simplification.
- Recoding a categorical variable (e.g. ethnicity, occupation, an “other” category, spelling corrections, etc.).
- Recoding a continuous variable (e.g. age) into a categorical variable (e.g. age group).
- Combining the values of a variables into fewer categories (e.g. grouping all problems caused by access issues).
- Combining several variables to create a new variable (e.g., building an index based on a set of variables).
- Defining a condition based on certain cut-off values (e.g., population “at risk” vs. “at acute risk”).
- Changing a level of measurement (e.g. from interval to ordinal scale).

Conceptually, a distinction is needed between:

- Activities related to recoding “messy data” (i.e. an open question about interventions preferred by the population) so they become structured or formatted in a way that is useful for primary analysis.
- Activities that include deriving new values out of others, such as creating calculation (i.e. percentage), parsing, merging, etc. Here, the analyst is re-expressing what the data have to say in other terms (i.e. re-expressing deviation as a % change, weighted or moving average, etc.). However, the data has (normally) already gone through a cleaning stage before to be transformed.

Recoding variables or values can serve both the purpose of cleaning dirty data and/or transforming clean data. This section focuses primarily on the cleaning objectives rather than the re-expression of values which will be tackled more extensively in another chapter of this document.

Recoding categorical variables starts with a full listing of all variants used in a variable, together with their frequencies. The variant list can be copied into a fresh sheet, to create a table of variants and their desired replacements. ALWAYS keep a copy of the original values, and try out different recoding schemes before settling on a final one.

There are three ways to recode categorical data: collapse a categorical variable into fewer categories, break a categorical variable up into several variables with fewer categories or combine several categorical variables into fewer variables with more categories.

Collapsing is done to combine categories that logically go together or to eliminate categories that have small numbers of observations.

Guidelines for collapsing data are as follows:

- Ordinal variables need to be collapsed in a method that preserves the ordering of categories.
- Combine only categories that go together. Don't combine two logically distinct categories just to eliminate categories with small numbers (e.g. lack of access due to lack of income and lack of access due to insecurity) as interpretation of data becomes difficult or meaningless.
- The way in which categories are collapsed can easily affect the significance level of statistical tests. Categories should be collapsed a priori to avoid the criticism that the data were manipulated just to get a certain result. This does not mean you have to decide this before you collect the data (if you did, you wouldn't bother to collect separate categories).
- Do not oversimplify the data. Unnecessary reduction in the number of categories may reduce statistical power and obscure relationships in the data. As a general guideline, you should keep intact any categories that include 10% or more of your data (or 5 cases, for very small samples).

Breaking: There are several reasons for breaking a categorical variable into several smaller variables:

- Data was collected in a manner easy to collect to ease the burden of data collection on the subject. For example, it is easier for the key informant to provide a list of issues than to review a long list of problems.
- A variable may contain more than one "concept." For example, consider the ordinal variable “severity” below:

    1. There are no shortages
    2. A few people are facing shortages
    3. Many people are facing shortages
    4. Shortages are affecting everyone

This variable contains two concepts, “shortages” and “number of people affected”. It is straightforward to code two new variables, shortages (0 = no shortages, 1 = shortage) and number of people (0 = no people, I= Few people, 2=Many people, 4= All of them).

Combining is the reverse process of breaking up, such as combining “shortages” and “number of people” back into the variable “severity”.

Main techniques for transforming quantitative data into another quantitative variable include:

- Linear transformation (i.e. converting temperature from degrees Fahrenheit to degrees Celsius, Z-score).
- Non-linear transformations (logarithmic transformation, square root).
- Ranking: in a variable having N distinct values, the lowest value is given a rank of 1, the next lowest a rank of 2, continuing until the highest value is given a rank of N (i.e. tests score).

Recoding variables can be tedious. The conceptual effort needed in order to produce a meaningfully recoded category set is often underestimated. Care must be taken to evaluate the combined category sets, to absorb excessive, incoherent or rarely used categories into broader ones, and to be clear about the rationale for the final number and content of distinct categories. Also, be aware that any recoding that reduces the number of categories entails some information loss. As in all stages of data analysis, analysts must be alert for errors.

Basic tips for effective recoding include:

- *Use distinct and easy to remember variable names.* Never use the same variable name to denote both the transformed and untransformed variable. For large data sets, a systematic way to name variables is desirable.
- *Pay attention to missing values.* When recoding is done, the number of cases with missing data should be the same as before recoding. A check that this is so will often be the first clue that recoding was in error. A safe procedure is to start the recoding process by setting the new variable to missing for all cases, and then changing missing values only for those with data on the initial variables to be recoded. For complicated recoding, check a few individual values by hand to make sure they were recoded properly, and check the distribution of values.
- *Use graphs to check the accuracy of recoding.* Recoding is a systematic translation of data values, so scatterplots of raw data *v* recoded data should show highly organized patterns reflecting the recoding system. Histograms can show whether your data is now more normally distributed.
- *Use variable codes consistently.* For example, with dichotomous "yes/no" variables, always use 0 = no and 1 = yes. For polychotomous variables, always make 0 the reference category.
- *Keep a permanent record of your recoding.* For data entry errors, we recommend you make your changes in your raw data file, because you *never* want to see the data entry errors again. With recoding, you may at some point want to go back to your initial data, so don't change your raw data file. Most statistical programs save their data in a specially formatted file, and this file is the one to change. Your recoding commands should all be put in one program (a *do* file) that you can execute again, because inevitably you will discover a data entry error you missed, change your raw data and have to recode again. The *do* file serves as a permanent record as well.

H. Feedback

Once errors have been identified, diagnosed and treated and if data collection/entry is still ongoing, the person in charge of data cleaning should give instructions to enumerators or data entry operators to prevent further mistakes, especially if they are identified as non-random.

Feedback will ensure frequent errors are not repeated and will improve the assessment validity and the precision of outcomes. Main recommendations or corrections can include:

- Programming of data capture, data transformations, and data extractions may need revision.
- Corrections of questions in the questionnaire form.
- Amendment of the assessment protocol, design, timing, enumerators training, data collection, and quality control procedures.
- In extreme cases, it may be necessary to re-conduct some field assessment (few sites) or contact again key informants or enumerators to ask additional information or more details or confirm some records.

- Data cleaning often leads to insight into the nature and severity of error-generating processes.
- Identify basic causes of errors detected and use that information to improve data collection and the data entry process to prevent those errors to re-occurring.
- Reconsider prior expectations and/or review or update quality control procedures.

I. Quality control procedures

Error prevention is far superior to error detection and cleaning, as it is cheaper and more efficient to prevent errors than to try and find them and correct them later.

When deciding upon an approach to data cleaning, it is useful to consider the different types of errors which can be made, and to plan at what point in your data flow (Table 1) you will try to prevent and/or identify them. Best practices include:

Make sure the staff with responsibilities regarding data quality are aware of the cleaning protocols (see annex 1 for a complete checklist for needs assessments). Roles and responsibilities related to error detection and correction should be clearly defined and communicated as part of the job descriptions (see Annex 2), at each stage of the data collection, entry and processing.

Ensure that a second pair of eyes review and compare source data to data entered. Data cleaning should starts in the field (field editing) alongside data collection, as questionnaires are reviewed by supervisors or field editors on a daily basis. Similarly during data entry, double checks should be mandatory, especially when:

- There is a process of translation at data entry, to ensure consistency/accuracy of translation.
- Data entry is distributed across various field locations and consolidation occurs in a different location.

At the data entry stage, computer-assisted quality control procedures should be used. Additional functionality can be added in the data entry software (i.e. Excel, SPHINX, Ethnos, SPSS, STATA, etc.) to highlight rule violations (null codes, conditional formatting, etc.) and prevent mistakes (i.e. drop down menus). The decision to include those rules in the database must be pragmatic, weighing up the merits of having errors detected and rectified by data entry staff, versus the time required to set this up and to quickly make necessary adjustments if the initial setup does not work as expected. Five kind of checks can be automated:

Range checks ensure that every variable in the survey contains only data within a limited domain of valid values. Categorical variables can have only one of the values predefined for them on the questionnaire (for example, gender can be coded only as “1” for males or “2” for females); chronological variables should contain valid dates, and numerical variables should lie within prescribed minimum and maximum values (such as 0 to 120 years for age and should always be expressed as integer of years, with rules for rounding up or down for infants).
Reference data check are used when the data from two or more closely related fields can be checked against external reference tables, i.e. when the recorded values for height, weight and age are checked against the World Health Organization’s standard reference tables.

Skip checks verify whether the skip patterns have been followed appropriately. For example, a simple check verifies that questions to be asked only of schoolchildren are not recorded for a child who answered "no" to an initial question on school enrolment.

Consistency checks verify that values from one question are consistent with values from another question, for example, the date of birth and age of a given individual.

Typographical checks limit, for instance, the transposition of digits like entering “14” rather than “41” in a numerical input. Such a mistake for age might be caught by consistency checks with marital status or family relation. Control totals, for instance, can significantly reduce typographical errors.

- Document the rules to follow, where focus should be given, and how to solve errors/issues. Plan double checks.
- Communicate clear instructions to enumerators, team leaders, data entry clerk, at all relevant stages of the data flow.
- Ensure that data entry staff are familiar with the questionnaire filling procedures, so that mistakes can be identified early on and verified/rectified (i.e. rules such as ‘pick only three’ or ‘must add to 100 %’).
- Design a data-cleaning plan, including:

a) Budget, timeframe and staff requirements.
b) Screening tools.
c) Diagnostic procedures used to discern errors (on going periodic basis and towards the end of the assessment).
d) Instructions or training to enumerators and data entry staff in case of protocol violation and consistency check.
e) Decision rules that will be applied in the editing phase.

J. Data integration

Data sometimes is fine on its own, but becomes problematic when you want to integrate or merge it with other data.

Analysts don't always have control over the format and type of data that they import from an external data source, such as a database, text file, or a Web page. Most common problems are as follow:

- Formats: Not everyone uses the same format. Dates are especially problematic (26/02/1977, 26 February 1977, 26-02-1977, etc.). Analysts also need to be aware that different applications store dates internally in different ways. Thus simple copy-paste from one application to another will cause errors across the board.
- Units: litre, gallons, gourdes, etc.
- Ranges: Age intervals might differ from one survey to another. Sometimes it is possible to bin it (i.e. if you have the birth date, you can virtually create any age interval needed), sometimes not (the age intervals available are different from those you need).
- Inconsistency: When merging different data source, conflicting information can emerge. Analysts must choose between using both, using the most recently updated information, the most trusted source, investigate further or use neither. However, duplicate records should be flagged on merging so that they can be identified and excluded from analysis in cases where duplicate records may bias an analysis, etc., but should generally not be deleted. While appearing to be duplicates, in many cases the records in the two databases may include some information that is unique to each, so just deleting one of the duplicates (“merge and purge”) is not always a good option as it can lead to valuable data loss.
- Spelling: Categorical variable, and specifically place names, may have different spelling.
- Loss of bits of data: Some pieces of data, columns or rows are lost when extracted, i.e. when web scrapping or extracting from a pdf (good luck!).

- Data is dirty. Live with it. Analysts assuming that raw data comes clean and bypassing basic checks live dangerously.
- Check the dataset documentation available. If not available (even after request), DO NOT TRUST THE DATA, even if the source is generally reliable. Start checking for quality.
- Even under time pressure, take the time to screen the data for 15-30mn, focusing first on spelling and formatting, then on outliers (use conditional formatting for quick visual detection). If no mistakes are spotted during this time interval, it is probably of good quality and usable as it is. If mistakes are detected, then proceed rigorously and methodically to screening, diagnosing and treatment.

K. Documenting changes

Good practice for data management require transparency and proper documentation of all procedures. Data cleaning documentation should not be an exception.

Documentation of error, alterations, additions and error checking is essential to:

- Maintain data quality
- Avoid duplication of error checking by different data cleaners.
- Recover data cleaning errors
- Determine the fitness of the data for use.
- Inform users who may have used the data knowing what changes have been made since they last accessed the data

Create a change log within your workbook, where you will store all information related to modified fields. This will serve as an audit trail showing any modifications, and will allow a roll back to the original value if required. Within the change log, store the following fields:

- Table (if multiple tables are implemented)
- Column, Row
- Date changed
- Changed by
- Old value
- New value
- Comments

- Make sure to document in your database what data cleaning steps and procedures were implemented or followed, by whom, how many responses were affected and for which questions.
- ALWAYS make this information available when sharing the dataset internally or externally (i.e. by enclosing the change log in a separate worksheet)

L. Key principles for data cleaning

Key principles for cleaning data are as follows:

1. Create a backup copy of the original data in a separate workbook.
2. Create a routine for back up, at successive points of collating, cleaning and analysing save documents with file names that combine date and time (yymmdd-time prefixed allow for files to be sorted by order of creation).
3. When integrating or merging data, ensure that the data is in a tabular format of rows and columns with: similar data in each column, all columns and rows visible, and no blank rows within the range. Check that there is no subtotals, totals or other calculated records down the columns. Calculated variables to the right are no problem.
4. Format the database for readability and easy navigation: Text left align, number right aligned, variable title horizontal, text variables fully visible, column separated by bold lines, header with background colours, numbers comma separated every 3 digits, etc.
5. Do tasks that don't require column manipulation first, such as spell-checking or using the Find and Replace function.
6. Next, do tasks that do require column manipulation. The general steps for manipulating a column are:

    - Insert a new column (B) next to the original column (A) that needs cleaning.
    - Transform the data in the column (B).
    - Remove the original column (A), which converts the new column from B to A.

Keep the questionnaire close. As each check is done, a list of issues will be produced. The questionnaires should be consulted to double check or identify the problems.

- When you are checking for one type of problem for one site or key informant, verify that the data for the other variables for that case have been entered correctly.
- Look at the values in all the variables and all the cases for that site, key informant or enumerator. Occasionally the data entry person will skip a variable or a key in the values from the previous variable or the subsequent variable, and all the data that have been entered after will not be correct. If you can identify such a problem and fix all the variables, that questionnaire will not show up on subsequent checking.

- Planning and budgeting for data cleaning is essential.
- Organizing data improves efficiency, i.e. by sorting data on location or records by enumerator.
- Prevention is better than cure. It is far more efficient to prevent an error than to have to find it and correct it later.

- Responsibility belongs to everyone, enumerators, custodian and users.
- Prioritisation reduces duplication. Concentrate on those records where extensive data can be cleaned at the lowest cost or that are of most value to end users.
- Feedback is a two way street: data users or analyst will inevitably carry out error detection and must feedback data custodians. Develop feedback mechanisms and encourage users to report back.
- Education and training improve techniques: Poor training of enumerators and data entry operators is the cause of a large proportion of the errors. Train them on quality requirements (readability, etc.) and documentation,
- Data cleaning processes need to be transparent and well documented with a good audit trail to reduce duplication and to ensure that once corrected, errors never re-occur.
- Documentation is the key to good data quality. Without good documentation, it is difficult for users to determine the fitness for use of the data and difficult for custodians to know what and by whom data quality checks have been carried out.

M. Tools and tutorials for data cleaning

Spreadsheets like Excel offer the capability to easily sort data, calculate new columns, move and delete columns, and aggregate data. For data cleaning of humanitarian assessment data, ACAPS developed a specific technical note providing a step by step approach in Excel and detailing cleansing operations, supported by a demo workbook.

For generic instructions about how to use excel formulas, functionalities or options to clean data, the following Microsoft office guidance are available:

- Spell checking
- Removing duplicate rows
- Finding and replacing text
- Changing the case of text
- Removing spaces and nonprinting characters from text
- Fixing numbers and number signs
- Fixing dates and times
- Merging and splitting columns
- Transforming and rearranging columns and rows
- Reconciling table data by joining or matching
- Third-party providers

Those tips have also been commented for their usefulness for data mining Here.
Openrefine (ex-Google Refine) and LODRefine are powerful tools for working with messy data, cleaning it, or transforming it from one format into another. Videos and tutorials are available to learn about the different functionalities offered by this software. Especially the facets function can very efficiently and quickly gives a feel for the range of variation contained within the dataset.

Detailed data cleansing tutorials and courses are also available at the school of data:

- http://schoolofdata.org/handbook/recipes/cleaning-data-with-spreadsheets/
- http://schoolofdata.org/handbook/courses/data-cleaning/

Another tool to accomplish many of these tasks is Data Wrangler by the Stanford Visualization Group. Data Wrangler provides an interface that can automatically find patterns in your data based on things you select, and automatically makes suggestions of what to do with those patterns.

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Annex 1 – Checklist for data cleaning

Prepare for data cleaning

Make sure you have the tools, material and contacts for cleaning your data:

- The questionnaire forms
- The contacts of team leaders or enumerators, in case you need to contact them for questions
- The original database
- A translator, if necessary
- Visual analysis software (i.e. tableau public)
- Spreadsheet (excel) or database (Access, Stata, etc.) software.
- Some would add coffee and music, and a place without noise and disturbance.

Identify the data custodian. He/she will generally be responsible for managing and storing the data, as well as for the supervision of the data cleaning, the consolidation of the changes and the update and maintenance of the change log.

Establish, document and communicate

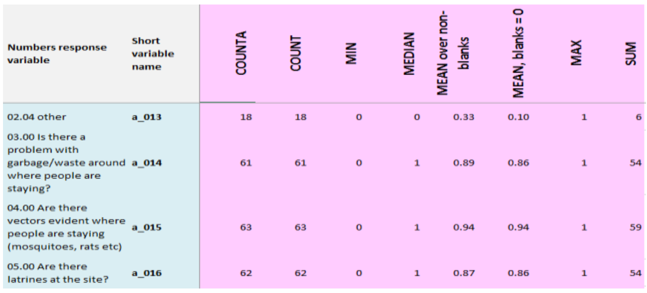
- Train the data entry operators on the questionnaire filling. Explain the instructions given to enumerators. If possible include data entry in the data collectors training so they get to know each other's.
- Establish *decision rules* for when to change a value and when NOT to change it.
- Establish procedures to document data that was modified or not collected, i.e. "missing", or "not collected". Explain how to use the change log file.
- Communicate to data entry operators or others colleague's analysts the procedures to be followed and who to inform of any error identified.
- Establish communication channels for communicating detected errors. Written communication are recommended.
- For rapid assessments where data analysis, mapping and visualization generally coincide with data entry and cleaning, communicate regularly to analysts, GIS officers and graphic designers which parts of the datasets are clean and usable. In case they identify errors, let them know who to inform. Plan with them on which variables are a priority for cleaning.

Review records

- If a sampling strategy was used, the records must be verified first. Verify all the sites have been entered, including those where the assessment was not completed (this is not relevant if a purposive sampling has been used). Compare to the assessment teams field trip records or the spreadsheet where you tracked the visited locations.
- Check the uniqueness of each row in the database (i.e. unique ID for each site or household).
- Check for duplicate cases as a regular routine for each of the data rows. Remove any blank cases where the key variables have been entered but there are no data in any of the variables. Verify first that the blank cases should be removed and how this could affect other data in the row.

Screen, diagnose and treat data

- Clean first the filter questions, i.e. when the population is asked if they did or had a particular activity based on a response (yes/no). In that case there should be data in the following table in the questionnaire (or column in the database) if the response is "yes" or there should be no data if the response is "no".
- Review the skip rules within the questionnaire and run the checks in the database to look for invalid or missing values in variables based on the skip rules.
- Clean questions with min or max response values ("tick three options only", what are the top three priorities among the 5 following choice", etc.).
- Inspect the remaining variables sequentially and as they are recorded in the data file. Create a general summary table of descriptive statistics, where for each variable the min, max, mean, median, sum and count are available.



Numbers response variable	Short variable name	COUNTA	COUNT	MIN	MEDIAN	MEAN over non-blanks	MEAN, blanks = 0	MAX	SUM
02.04 other	a_013	18	18	0	0	0.33	0.10	1	6
03.00 Is there a problem with garbage/waste around where people are staying?	a_014	61	61	0	1	0.89	0.86	1	54
04.00 Are there vectors evident where people are staying (mosquitoes, rats etc)	a_015	63	63	0	1	0.94	0.94	1	59
05.00 Are there latrines at the site?	a_016	62	62	0	1	0.87	0.86	1	54

Screenshot of summary statistics table from Aldo Benini, ACAPS Technical note on how to approach a dataset, preparation

- If the variable is a categorical/qualitative variable, check spelling is consistent and run a frequency count:
  - Look at the counts to see if those are reasonable for the sample – do you have a complete set of data?
  - All values should have labels if the variable is categorical. Check for out of range values.
- If the variable is a continuous/quantitative variable, run descriptive statistics such as min, max, mode, mean and median.
  - Look at minimum and maximum values. Are they reasonable values? Look especially if "0" are really "0" and not missing values.
  - Is the mean and median reasonable?
- Inspect data for missing values (blanks, explicit missing-value codes). Decide:
  - Which blank cells need to be filled with zeros (because they represent genuine negative observations, such as ("no", "not present", "option not taken", etc.)
  - Which to leave blank (if the convention is to use blanks for missing or not applicable)
  - Which to replace with some explicit missing value code (if we want all missing to be explicitly coded).
- Verify that in binary variables (yes/no), the positive value is coded as "1", the negative as "0".
- Check for the distribution of the values (use box plots if available). Look at the extremes and check them against the questionnaire even if the value is possible and may seem reasonable. If it is an extreme, other variables may be incorrect as well. Look for the 5 smallest/largest values.
- Compare the data between two or more variables within the same case to check for logical issues. I.e., can the head of the household be less than 17 years old? Compare age with marital status. Is the person too young to have been married? Are the % of destruction level summing up to 100%?
- Where there are questions asking about a "unit", the data must standardized to a specific unit, i.e. when a response is collected using the unit specified by the respondent. For instance, units for area can be acre, hectare and square meters. To standardize the area unit, a lookup table can be used to merge in the conversion value to convert all areas to hectares.
- Check for consistencies within a set of cases: If there is a spouse, it is expected the spouse will be a different gender. The child of the head of household is not expected to be older than the head. The parent of the head cannot be younger than the head.
- Recode variables. Replace unhelpful entries (e.g. mis-spellings, verbose descriptions, category "others", etc.) with more suitable variants, in consistent manner. Reasons for recoding are: spelling corrections, date (day, month, year) formatting, translation, language style and simplification, clustering, pre-fixes to create better sorting in tables, combination (in categorical variables), rounding (in continuous variables), and possibly others.
- Sort the file in various ways (by individual variables or groups of variables) to see if you can identify data errors that were not found previously.

Final considerations

- If the data are being cleaned by more than one person, then the final step is to merge all the spreadsheets together so that there is only one database. The comments or change logs that are made as the cleaning progresses should be compiled into one document. Problem data should be discussed in the documentation file.
- Update cleaning procedures, change log and data documentation file as the cleaning progress. Provide feedbacks to enumerators, team leaders or data entry operators if the data collection and entry process is still ongoing. If one team or enumerator make consistently the same mistake, make sure to inform him/them.
- Be prepared. Data cleaning is a continued process. Some problems cannot be identified until analysis has begun. Errors are discovered as the data is being manipulated by analysts, and several stages of cleaning are generally required as inconsistencies are discovered. In rapid assessments, it is very common that errors are detected even during the peer review process.

Annex 2 – Sample Job description

The following proposes three job description related to data entry and data cleaning: data cleaner, data entry controller and data entry operator. The word formats are available at http://www.acaps.org/resourcescats/downloader/assessment_team_job_descriptions/97

Title of post: Data Cleaner

Reporting Line
Information Analyst

Requirements

- Assessment and survey experience
- Large scale data entry experience required

Education

Degree in statistics or demographics and/or a degree in IT

Experience

- 2-3 years of experience with statistics institute and/or relevant work experience
- Proven experience with data cleansing and management of large volumes of quantitative and qualitative data.
- Proven experience with management and operation of databases.

Language

Fluent in written and spoken English (or international language use).

Skills

- Professionalism;
- Excellent written and oral communication skills;
- Good knowledge of word processing software (Word, Excel, PowerPoint, email);
- Understanding of the principles of statistical and demographic analysis;
- Understanding of survey techniques;
- Excellent report drafting skills.
- Strong typing skills
- Strong proofreading skills
- Excellent command of IT tools; High level of computer literacy.
- Rigour and accuracy.
- Proven ability to meet deadlines. Ability to work well under pressure;
- Good interpersonal skills and ability work in a multi-cultural environment. Strong ability to work in teams;
- Experience working with the international humanitarian community is an advantage.

Role description and responsibilities:

Under the supervision of the Information analyst, the Data Cleaner is responsible for:

- Ensuring that procedures for checking, coding and entering data are followed;
- Checking the quality of the work conducted by data entry staff during the data checking, coding and entry and providing all assistance and feedback necessary to improve data entry and reduce or prevent mistakes;
- Keeping a documented overview of the daily work; producing a daily report on data cleansing;
- Making sure that raw data were accurately entered into a computer readable file;
- Checking the character variables contain only valid values;
- Checking that numeric values are within the predetermined ranges;
- Checking for and eliminating duplicate data entries;
- Checking if there are missing values for variables where complete data are necessary;
- Checking for uniqueness of certain values, such as subject IDs;
- Checking for invalid data values and invalid date sequences;
- Follows procedures for data cleaning and editing. Document data problems. Update regularly the master database with last changes;

Assessment Coordinator:
Name: ________________________
Position: ________________________
Signature: ________________________
Date: ________________________

Data cleaner:
Name: __________________________
Position: ___________________________
Signature: ___________________________
Date: ___________________________

Title of post: Data Entry Operator

Reporting Line

- Data Entry Controller
- Information Analyst

Requirements

- Assessment and survey experience
- Large scale data entry experience required

Education

Secondary education, diploma in information/data management an asset

Experience

- 1-2 years of experience with statistics institute and/or relevant work experience
- Proven experience with data entry and management of large volumes of quantitative and qualitative data.
- Proven experience with management and operation of databases.

Language

Fluent in written and spoken English (or international language use).

Skills

- Strong typing skills
- Data entry skills
- Strong proofreading skills
- Analytical skills.
- Excellent command of IT tools;
- High level of computer literacy.
- Rigour and accuracy.
- Proven ability to meet deadlines.
- Good interpersonal skills and ability work in a multi-cultural environment.
- Experience working with the international humanitarian community is an advantage.

Role description and responsibilities:

Under the supervision of the Data Entry Controller or the information analyst, the Data Entry operator is responsible for:

- Checking completed questionnaires before data entry;
- Codifying open and semi-closed questions;
- Identifying questionnaires with mistakes or error, where the identifier is incorrectly completed and ensuring they are corrected; Identify and organize forms that needs re assessment
- Conducting data entry of questionnaires according to the procedures set out during the training;
- Support site staff to record and manage accurately the collected data
- Data quality checks and data editing according to specified procedures
- Feedback to Information analyst and assessment teams leaders about recurrent mistakes to avoid
- Maintenance of a change log in case of data cleaning or editing
- Archive and back up data, using the specified drive path
- Maintain and operate database
- Maintain office machines

Assessment Coordinator:

Name: ________________________

Position: ________________________

Signature: ________________________

Date: ________________________

Data entry operator:

Name: __________________________

Position: ___________________________

Signature: ___________________________

Date: ___________________________

Title of post: Data Entry Controller

Reporting Line
Information Analyst

Requirements

- Assessment and survey experience
- Large scale data entry experience required

Education

Degree in statistics or demographics and/or a degree in IT

Experience

- 3-5 years of experience with statistics institute and/or relevant work experience
- Proven experience with data entry and management of large volumes of quantitative and qualitative data.
- Proven experience with management and operation of databases.

Language

Fluent in written and spoken English (or international language use).

Skills for data entry clerk

- Professionalism;
- Strong ability to work in teams;
- Excellent written and oral communication skills;
- Ability to work well under pressure;
- Good knowledge of word processing software (Word, Excel, PowerPoint, email);
- Good command of data processing and analysis software, i.e. CsPro and SPSS;
- Understanding of the principles of statistical and demographic analysis;
- Understanding of survey techniques;
- Excellent report drafting skills. Strong typing skills. Strong proofreading skills
- Excellent command of IT tools; High level of computer literacy.
- Rigour and accuracy.
- Proven ability to meet deadlines.
- Good interpersonal skills and ability work in a multi-cultural environment.
- Experience working with the international humanitarian community is an advantage.

Role description and responsibilities:

Under the supervision of the Information analyst, the Data Entry Controller is responsible for:

- Ensuring that procedures for checking, coding and entering data are followed;
- Monitoring data entry staff;
- Checking the quality of the work conducted by data entry staff during the data checking, coding and entry and providing all assistance necessary;
- Keeping a documented overview of the daily work; producing a daily report on data checking, coding, and entry.
- Write procedures for data cleaning and editing. Supervise data cleaning. Consolidate the data change logs from data entry operators. Document data problems. Update regularly the master database with last changes.
- Ordering questionnaires and returning them to the archives after the data has been entered;
- Ensuring technical documents are kept in a good condition;
- Ensuring working hours are respected, as well as order and discipline in the workplace;

Assessment Coordinator:
Name: ________________________
Position: ________________________
Signature: ________________________
Date: ________________________

Data entry controller:
Name: ___________________________
Position: ___________________________
Signature: ___________________________
Date: ___________________________