An SPSS implementation of the nonrecursive outlier deletion procedure with shifting z score criterion (Van Selst & Jolicœur, 1994)

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Sophisticated univariate outlier screening procedures are not yet available in widely used statistical packages such as SPSS. However, SPSS can accept user-supplied programs for executing these procedures. Failing this, researchers tend to rely on simplistic alternatives that can distort data because they do not adjust to cell-specific characteristics. Despite their popularity, these simple procedures may be especially ill suited for some applications (e.g., data from reaction time experiments). A user friendly SPSS Production Facility implementation of the shifting z score criterion procedure (Van Selst & Jolicœur, 1994) is presented in an attempt to make it easier to use. In addition to outlier screening, optional syntax modules can be added that will perform tedious database management tasks (e.g., restructuring or computing means).

Participants generate multiple raw scores within each cell of reaction time (RT) experiment designs. For analysis, the raw scores within each condition are summarized by an estimate of central tendency (e.g., the mean). Unfortunately, these estimates may be biased because raw RT scores contain spurious or erroneous observations (Ulrich & Miller, 1994). The spurious scores reflect various nontarget processes. For instance, the RT recorded by the computer may be due to a guess, an accidental buttonpress, or a momentary lapse in attention. Such scores can cause problems because (1) they introduce bias and reduce the power of significance tests (Ratcliff, 1993) and (2) they are more likely to take on values that are more extreme than those that are generated by the psychological process of interest (Ulrich & Miller, 1994). Values are considered extreme when they fall outside an arbitrarily defined interval that contains most of the scores. These outliers can bias the mean by over 50 msec, even when they constitute 1% of all the scores (Ratcliff, 1993). The importance of this bias is mediated by variables that are cell specific.

In an ideal world, researchers would have access to a procedure that can distinguish theoretically interesting scores from those that are spurious. In reality, it is impossible to achieve this end with absolute certainty. At this level of analysis, the researcher is forced to assume that

the true pattern of results has not been distorted (Ulrich & Miller, 1994). However, if individual scores are classified into groups, the possibility presents itself of *amputating* or *truncating* score ranges where spurious scores are especially dense. The obvious candidates for truncation are the extreme tails of the RT distribution (Ulrich & Miller, 1994).

First, the classification rule is operationally defined using arbitrary lower and upper limits. These limits can be specified in various ways, including absolute values (e.g., $150 \text{ msec} < \text{valid } x < 3,000 \text{ msec}$). A few examples are discussed below, along with their respective advantages and disadvantages. Second, the researcher must decide whether to eliminate scores falling outside the boundary or to recode the scores to a more acceptable value (e.g., the mean, or a value generated by multiple imputation). The issues associated with these choices have been discussed elsewhere (Enders, 2001; Schafer & Graham, 2002; Sinharay, Stern, & Russell, 2001).

Truncation Procedures

Several variables make it difficult to truncate RT distributions without distorting the data (Miller, 1991; Ratcliff, 1993; Van Selst & Jolicœur, 1994). The main problem lies in the fact that the existing ways of defining cutoff values eliminate a proportion of scores under the population curve that differs for each participant $\times$ condition cell. Within each cell, characteristics that are specific to the individual and to the condition cause the observed scores to be distributed in an idiosyncratic way. If the parameters that describe these distributions are ignored, the effect of truncation will differ across cells. Indeed, the truncation solution may exacerbate the original problem by creating an even greater bias (Ratcliff, 1993).

The problem is especially conspicuous in the case of absolute cutoff values (Ratcliff, 1993; Van Selst &

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Jolicœur, 1994). To apply this strategy, the researcher rejects all scores falling outside two absolute values (e.g., $150 \text{ msec} < \text{valid } x < 3,000 \text{ msec}$). It is simple to apply, and the idea that each score is being treated equally is intuitively appealing. However, in this case, each score should not be treated equally. Each score belongs to a distribution with its own mean, standard deviation, and shape. Because of this, the absolute cutoff criterion eliminates a different percentage of scores under the theoretical “true” curve within each cell. These cell-specific effects can distort real between-condition differences in population means. The magnitude of this bias is proportional to the variability of cell parameters such as the mean and skewness and whether or not these variations are associated with experimentally manipulated variables (Ratcliff, 1993).

If the truncation solution is applied, special precautions must be taken. To avoid biasing the data, the cutoff criteria must be adjusted to the parameters of each cell. If the adjustments are perfect, each estimated mean is based on an equivalent proportion of scores under the curve (i.e., they are unbiased). As it happens, this ideal is exceedingly difficult to achieve (Ulrich & Miller, 1994). The best available approximation is obtained by defining the cutoff criteria in terms of z scores (Van Selst & Jolicœur, 1994), in which the distance between a score and a mean can be expressed in terms of a standard deviation unit. For example, a score that is one standard deviation above its mean is said to have a z score of 1. If the z score of an observation exceeds an arbitrary predetermined value (e.g., ± 2.5 or 3.0), it is considered extreme.

The z score is superior to an absolute cutoff because the mean (i.e., $0 = 0$) and the standard deviation (i.e., $1 = 1$) for each cell are equated. The limitation of z scores as cutoff criteria is that they are vulnerable to between-cell variability in distribution shape (e.g., skew). RT distributions tend to be positively skewed. This means that in general, a symmetrically applied z score cutoff value results in an underestimated mean. This general bias is not critical, because researchers are typically interested in relative differences between condition means. Substantive bias is introduced when the extent and form of positive skew differ across cells and, especially, across conditions (Van Selst & Jolicœur, 1994). This assertion is based on the fact that (1) the number of scores classified as outliers varies with skew and (2) the number of scores eliminated by the outlier screening procedure is inversely related to estimated mean latency (Miller, 1991; Van Selst & Jolicœur, 1994). Nevertheless, if there is reason to believe that distribution shape does not vary much across conditions, truncation based on z scores will not greatly bias estimation of the mean (Van Selst & Jolicœur, 1994).

Unfortunately, RT experiments are commonly associated with two characteristics that invalidate the simple z score criterion (Miller, 1991). The first is that RT distributions tend to be positively skewed. The second is that the number of observations can vary across cells of the de-

sign. This second characteristic is the result of discarding the RT values of incorrect responses. Because the number of errors may vary, each participant $\times$ condition cell can contain a different number of observations. Together, these features can cause problems if between-cell differences in accuracy are important and/or systematic. The problem lies in the fact that the estimated value of a standard deviation increases as cell n decreases for positively skewed distributions (Miller, 1991). In terms of the z score cutoff, this means that cells with relatively few observations lose a relatively small percentage of scores from the tail end of their distributions (Miller, 1991; Van Selst & Jolicœur, 1994). Conversely, the distributions of cells that contain many observations are severely truncated, and their means are relatively underestimated.

In response to this issue, Van Selst & Jolicœur (1994) proposed an outlier screening procedure that relies on a corrected z score criterion. The proposed z score criterion varies as a function of the number of observations available within each cell. This *shifting* z score boundary ensures that the percentage of scores classified as outliers remains constant despite differences in the number of observations. The authors describe two versions of this procedure. The first screens each participant $\times$ condition cell once for outliers. The second is a recursive procedure that repeats the screening process until no extreme scores are identified. Both solutions effectively neutralize the bias introduced by differences in the number of observations (Van Selst & Jolicœur, 1994). In situations in which distributional skew does not vary greatly across experimental condition (Ratcliff, 1993) and the number of observations per cell is less than 100, the shifting z score criterion compares favorably with existing alternatives (Van Selst & Jolicœur, 1994).

In fact, at least two alternative solutions are available for addressing this problem. A maximum likelihood procedure can be implemented (Dolan, van der Maas, & Molenaar, 2000; Ulrich & Miller, 1994), or the median can be used instead of the mean. Both solutions to the outlier problem have the advantage of not discarding any information. However, the first requires prohibitive sample sizes in a field in which the number of observations per cell is usually under 20 (Balota, Cortese, Sergent-Marshall, Spieler, & Yap, 2004). Furthermore, the second strategy (i.e., use of the median) suffers from the same drawbacks as the simple recursive procedure described earlier (Miller, 1988; Ratcliff, 1993). Clearly, these alternatives do not supplant the procedure proposed by Van Selst and Jolicœur (1994).

Implementation of the Shifting z Score Procedure

The article that introduced the shifting z score procedure was published over 10 years ago, and yet it is still not being applied consistently in situations where it may be appropriate. Apart from the occasional exception (e.g., Roberts, Rastle, Coltheart, & Besner, 2003), the use of absolute cutoffs (see, e.g., Yates, Locker, & Simpson, 2004)

and uncorrected z scores (see, e.g., Perry, 2003) for defining extreme scores continues unabated. The apparent lack of interest by the research community may be attributed to a number of factors.

Generally, the application of standard cutoff criteria (i.e., absolute values or uncorrected z scores) results in the deletion of between 1% and 5% of all the observations. A fraction of these scores are actually valid. When this is the case, the loss of information and potential for bias may seem trivial. In reality, the overall percentage of the scores that are eliminated reveals nothing about the possibility of bias (Ratcliff, 1993; Ulrich & Miller, 1994). First, even a small number of (valid) outliers can have a major influence on parameter estimation. Second, the loss of valid outlier scores may be concentrated within a single condition, because of the way in which the outliers were defined (e.g., absolute value). In a field in which all statistically significant effects (e.g., 10 msec) are considered interpretable, it is clear that a naive approach to outlier screening can be costly.

A more practical barrier to the widespread application of a shifting z score criterion may also be at work. This procedure is not standard with statistical packages such as SPSS. To obtain a shifting z score criterion, the user must either implement the procedure manually or supply the program with appropriate code (e.g., SPSS syntax). In SPSS, implementing the shifting z score procedure can be time consuming if the number of participant $\times$ condition cells is large. In contrast, an absolute cutoff or uncorrected z score cutoff can be applied in a matter of minutes. A program for executing the shifting z score criterion was developed as a way of correcting this imbalance in their relative ease of use. An SPSS Production Facility implementation of the nonrecursive shifting z score outlier screening procedure (Van Selst & Jolicoeur, 1994) will be presented below.

Production Facility is a program that comes bundled with the full version of SPSS (11.5 or better). It performs a number of useful functions. For instance, Production Facility allows a series of syntax files to be executed in sequence automatically. More important, it provides a user friendly interface for the specification of macro variables. A macro variable is a slot within a syntax file that can represent a file path, a variable name, or a string/numeric value. The main advantage of macro variables is that they allow users to customize syntax files without wasting time and risking errors by directly modifying the syntax. Defining macro variables is especially straightforward in Production Facility. When a program is executed, the user is prompted for input by a series of descriptive questions [e.g., "Name the first independent variable (required, must be numeric):"]. Even novice users of SPSS can successfully execute such a program with minimal instruction.

The program presented here makes applying a shifting z score criterion relatively painless (z score limit = 2.5). If the data file conforms to the requirements specified in the instructions, five steps suffice to execute the

program: (1) read the instructions, (2) download the .spp file (see Appendix A) and the .sps files (see Appendix B), (3) open the .spp file with Production Facility, (4) press Run, and (5) answer a series of questions. The program accepts SPSS data files structured like those generated by programs designed to control computerized experiments (e.g., MEL or E-Prime). The data files should contain a single column of data for each dependent variable and a series of categorical independent variables (e.g., Subject ID, Condition) that are numeric. When the screening process is finished, the program creates two data files. The first data file is free of outliers and contains the information needed to audit the screening process (e.g., cell n , before and after z scores). The second data file is a cleaned-up version that can be used for analysis.

In addition to outlier screening, the program comes with optional syntax files that perform a number of mundane tasks. For example, they compute means for each participant $\times$ condition cell and then restructure the RT data file for analysis. In addition, syntax files are available that can compute mean accuracy data and restructure the database for a repeated measures analysis. These "extra" syntax files must be added to the Production Facility file that is available for download. The complete set of syntax files takes an SPSS datafile as input and automatically performs outlier screening, the computation of means, and tedious database management procedures (e.g., restructuring). For additional details, see the instruction manual that can be downloaded with the programs.

Summary

The presence of outliers can bias the results of RT experiments. A common solution to this problem is to truncate the extreme tails of RT distributions before estimating within-cell means. The strategy can distort the true pattern of results when cell-specific variables such as the mean, standard deviation, skew, and n are ignored. Van Selst and Jolicoeur (1994) proposed a truncation criterion that controls for the mean, for the standard deviation, and for n . If skew does not vary much, the shifting z score criterion that they propose will not distort the results (Van Selst & Jolicoeur, 1994). In fact, when cell sizes are small (e.g., 20), the shifting z score criterion is probably superior to existing alternatives, despite variation in skew. The present article introduces an SPSS implementation of the shifting z score criterion. The purpose of presenting this program here is to remove any practical barriers that may prevent the application of this strategy when it is appropriate. Alternative strategies should be applied when a large number of observations (e.g., >100) occur within each cell (see, e.g., Ulrich & Miller, 1994).

Program Availability

The most recent version of the program and its associated instruction file are available for download (www.geocities.com/glennleothompson/OriginalCode.html). These files may also be obtained directly from the author

via e-mail (glennlthompson@gmail.com). An implementation of the recursive shifting z score procedure is currently under development and will be available for download at the same address.

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(Continued on next page)

APPENDIX A
SPSS Production Facility Script
(ASCII File With an .spp Extension)

```
SET MXCELLS=AUTOMATIC .
INCLUDE FILE='C:\V&J1994_RT1.SPS'.
INCLUDE FILE='C:\V&J1994_RT2.SPS'.
INCLUDE FILE='C:\V&J1994_RT3.SPS'.
INCLUDE FILE='C:\V&J1994_RT4.SPS'.
```

***Comments:**

*Please read the instructions before using this program. Outlier screening program for RT data. Based on the nonrecursive shifting z-score criterion advocated by Van Selst & Jolicoeur (1994). The z-score limit that is applied by the program is approximately 2.5

*Handles up to 3 independent variables: enter the string 'NA' without quotation marks in slots that are not needed. Accept all default values unless you have a reason to change them.

***Output Folder: C:.**

*Exported Chart Format: JPEG File.

*Exported File Format: 1.

*Export Objects: 3.

*Output Type: 0.

*Print output on completion: Off.

***Macro Symbols.**

* @file	Please supply the file path for the SPSS datafile (.sav):				
* @ID	Subject ID variable (required)?			c:\exp1_raw(1).sav	Yes
* @IV1	Name the first independent variable (required, must be numeric):			subjects	No
* @IV2	If applicable, name the second independent variable (must be numeric, if NA enter 0):			block	No
* @IV3	If applicable, name the third independent variable (must be numeric, if NA enter 0):			NA	No
* @ac	Name of the accuracy variable (Errors are discarded, define 'correct' below):			NA	No
* @rt	Name of the Reaction Time variable:			rt	No
* @Lexst	Lexical status variable (1 = words 2 = nonwords, if NA enter 0 instead of name):			NA	No
* @nfile	File path for the temp file containing number of records per cell (N):			c:\temp.sps	Yes
* @nfile2	File for the final cell count computation:			c:\temp2.sps	Yes
* @listn	File for the original cell count:			c:\temp3.sps	Yes
* @list	Name the list variable (1 + = experimental, 0 = practice):			NA	No
* @outfile1	Supply a file path for the datafile summarizes the datacleaning process:			c:\zz_screeningaudit.sav	Yes
* @outfile2	Supply a file path for the cleaned up datafile, before calc. means & restructuring:			c:\zz_cleandata.sav	Yes
* @correct	What value denotes a correct response within the accuracy variable?			1	No
* @lower	Truncate the file at what lower-bound RT value (if NA keep the default)?			1	No
* @upper	Truncate the file at what upper-bound value (optional)?			10000	No
* @practice	What value denotes an item from a practice list (in the '@list' variable):			0	No
* @outfile3	Use only when 'V&J1994_RT5.sps' is in the list:				Yes
* @outfile4	Use only when 'V&J1994_RT6.sps' is in the list:				Yes
* @outfile5	Use only when 'V&J1994_error1.sps' is in the list:				Yes

APPENDIX A (Continued)

* @outfile6		Use only when 'V&J1994_error2.sps' is in the list:				Yes
* @IV4		If 'V&J1994_RT6.sps' is in the list, name blocking variable (pure = 1, mixed = 2):				Yes
*End Macro Symbols.						
*Publish ToWeb Cfg GUID: .						
*Publish ToWeb Objects: 6.						
*Publish ToWeb Table: 1.						
*Publish ToWeb UsrID: .						
*Publish ToWeb Authentication: .						
* @upper		@lower		Truncate the file at what lower-bound RT value (if NA keep the default)?		1
* @practice		Truncate the file at what upper-bound value (optional)?		10000		No
* @outfile3		What value denotes an item from a practice list (in the '@list' variable):		0		No
* @outfile4		Use only when 'V&J1994_RT5.sps' is in the list:				
* @outfile5		Use only when 'V&J1994_RT6.sps' is in the list:				
* @outfile6		Use only when 'V&J1994_error1.sps' is in the list:				
* @IV4		Use only when 'V&J1994_error2.sps' is in the list:				
* @IV4		If 'V&J1994_RT6.sps' is in the list, name blocking variable (pure = 1, mixed = 2):				
*End Macro Symbols.						
*Publish ToWeb Cfg GUID: .						
*Publish ToWeb Objects: 6.						
*Publish ToWeb Table: 1.						
*Publish ToWeb UsrID: .						
*Publish ToWeb Authentication: .						

APPENDIX B
Four SPSS Syntax Files (ASCII Files with an .sps Extension)

1. Filename: 'V&J1994_RT1.sps'

```
GET
  FILE = @file.
compute NA = 1.
Exe.
SELECT IF(@list ~= @practice).
Exe.
COMPUTE t1 = @iv1 * 1000 .
COMPUTE t2 = @iv2 * 10000 .
COMPUTE t3 = @iv3 * 100000 .
COMPUTE t4 = @lexst * 1000000 .
COMPUTE t5 = sum (@id, t1, t2, t3, t4).
Exe.
RANK
  VARIABLES=t5 (A) /RANK /PRINT=NO
  /TIES=CONDENSE .
SORT CASES BY rt5.
COMPUTE nobreak=1.
AGGREGATE OUTFILE=@listn
  /PRESORTED
  /BREAK=nobreak rt5
  /listn=N.
MATCH FILES FILE=*
  /TABLE=@listn
  /BY=nobreak rt5.
Exe.
select if (@ac = @correct).
select if (@rt > @lower & @rt < @upper).
Exe.
```

2. Filename: 'V&J1994_RT2.sps'

```
SORT CASES BY rt5.
COMPUTE nobreak=1.
AGGREGATE OUTFILE=@nfile
  /PRESORTED
  /BREAK=nobreak rt5
  /count=N.
MATCH FILES FILE=*
  /TABLE=@nfile
  /BY=nobreak rt5.
```

Exe.

3. Filename: 'V&J1994_RT3.sps'

```
SORT CASES BY rt5.
SPLIT FILE
  SEPARATE BY rt5.
descriptives @rt (z1).
Exe.
SPLIT FILE
  OFF.
Exe.
Do if (count gt 100).
compute #n7 = count - 100.
compute #i7 = (((2.50/100)*(#n7)) + 2.50).
SELECT IF(ABS(z1) < #i7).
else if (count eq 100).
select if (ABS(z1) < 2.50).
else if (count gt 50).
compute #n6 = count - 50.
```

APPENDIX B (Continued)

```

compute #i6 = (((2.50 - 2.48)/50) * (#n6)) + 2.48).
SELECT IF (ABS(z1) < #i6).
else if (count eq 50).
SELECT IF(ABS(z1) < 2.48).
else if (count gt 35).
compute #n5 = count - 35.
compute #i5 = (((2.48-2.45)/15) * (#n5)) + 2.45).
SELECT IF (ABS(z1) < #i5).
else if (count eq 35).
SELECT IF(ABS(z1) < 2.45).
else if (count gt 30).
compute #n4 = count - 30.
compute #i4 = (((2.45 - 2.431)/5) * (#n4)) + 2.431).
SELECT IF (ABS(z1) < #i4).
else if (count eq 30).
SELECT IF(ABS(z1) < 2.431).
else if (count gt 25).
compute #n3 = count - 25.
compute #i3 = (((2.431-2.41)/5) * (#n3)) + 2.41).
SELECT IF (ABS(z1) < #i3).
else if (count eq 25).
SELECT IF(ABS(z1) < 2.41).
else if (count gt 20).
compute #n2 = count - 20.
compute #i2 = (((2.41-2.391)/5) * (#n2)) + 2.391).
SELECT IF (ABS(z1) < #i2).
else if (count eq 20).
SELECT IF(ABS(z1) < 2.391).
else if (count gt 15).
compute #n1 = count - 15.
compute #i1 = (((2.391 - 2.326)/5) * (#n1)) + 2.326).
SELECT IF (ABS(z1) < #i1).
else if (count eq 15).
SELECT IF(ABS(z1) < 2.326).
else if (count eq 14).
SELECT IF(ABS(z1) < 2.31).
else if (count eq 13).
SELECT IF(ABS(z1) < 2.274).
else if (count eq 12).
SELECT IF(ABS(z1) < 2.246).
else if (count eq 11).
SELECT IF(ABS(z1) < 2.22).
else if (count eq 10).
SELECT IF(ABS(z1) < 2.173).
else if (count eq 9).
SELECT IF(ABS(z1) < 2.12).
else if (count eq 8).
SELECT IF(ABS(z1) < 2.05).
else if (count eq 7).
SELECT IF(ABS(z1) < 1.961).
Else if (count eq 6).
SELECT IF(ABS(z1) < 1.841).
else if (count eq 5).
SELECT IF(ABS(z1) < 1.68).
else if (count eq 4).
SELECT IF(ABS(z1) < 1.458).
end if.

```


APPENDIX B (Continued)

```

Exe.
SORT CASES BY rt5.
COMPUTE nobreak=1.
AGGREGATE OUTFILE=@nfile2
    /PRESORTED
    /BREAK=nobreak rt5
    /Fcount=N.
MATCH FILES FILE=*
    /TABLE=@nfile2
    /BY=nobreak rt5.

Exe.
SORT CASES BY rt5.
SPLIT FILE
    SEPARATE BY rt5.
descriptives @rt (zfinal).
Exe.
SPLIT FILE
    OFF.
4. Filename: 'V&J1994_RT4.sps'
SAVE OUTFILE=@outfile1
    /COMPRESSED.
SAVE OUTFILE=@outfile2
    /DROP=@list @ac t1 t2 t3 t4 t5 Rt5 nobreak listn count z1 Fcount zfinal NA /COMPRESSED.

```

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