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Data Visualization of Item-Total Correlation by Median Smoothing

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This paper aims to illustrate how data visualization could be utilized to identify errors prior to modeling, using an example with multi-dimensional item response theory (MIRT). MIRT combines item response theory and factor analysis to identify a psychometric model that investigates two or more latent traits. While it may seem convenient to accomplish two tasks by employing one procedure, users should be cautious of problematic items that affect both factor analysis and IRT. When sample sizes are extremely large, reliability analyses can misidentify even random numbers as meaningful patterns. Data visualization, such as median smoothing, can be used to identify problematic items in preliminary data cleaning.

Data visualization is an indispensable tool for pattern recognition in data analysis (Cleveland, 1993; Few, 2009; Tufte, 1990, 1997, 2001 2006; Yu & Stockford, 2003; Yu, 2014). While some data visualization techniques display both raw data and smoothed structure (e.g. regression line) simultaneously, some aim to reduce data noise by smoothing only (summarizing data). Smoothing is prevalent in many data visualization techniques though users may not be aware of it. Take the histogram as an example. While requesting a histogram from any statistical software package seems to be straightforward, the appearance of the histogram is tied to the interval width, also known as the binwidth. Usually a statistical package does not show all data values with numerous bars. Rather, it groups values into several intervals (bins). When a wider binwidth is used, the histogram appears to be smoother. One of the problems of histogram binning is that the choice of binwidth is arbitrary. As a result, the same data set might appear differently in different histograms. For example, in Figure 1 the distribution of the histogram appears to be normal when the binwidth is set to one, but it turns to a skew distribution when the binwidth is

changed to two. Nonetheless, the boxplots above both histograms show that the distribution is indeed symmetrical. This simple illustration shows that data interpretation can be misconstrued when an analyst is not aware of the arbitrariness of smoothing preference.

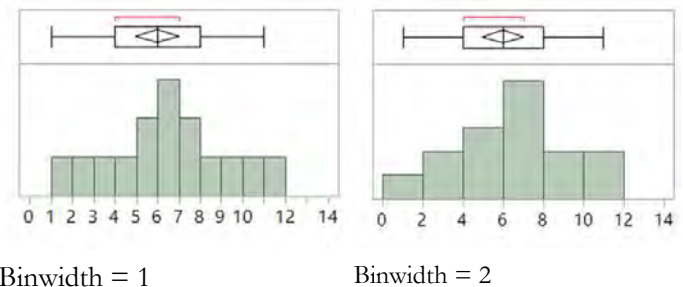


Figure 1. Two histograms depicting the same data set with different binwidths.

Bubble Plot

Histograms depict only one-dimensional data; however, when the data set is bivariate or multi-dimensional, smoothing becomes more complicated and difficult. When the sample size is very large, the dots in a bivariate scatterplot forms a big “cloud.” One way to simplify this over-plotted graph is the binning

approach (Carr, 1991), which follows and extends the same logic of grouping bars in a histogram. The difference is that in a bivariate plot data points are grouped in bivariate intervals and larger symbols indicating more data points. This approach, which is known as the bubble plot, is available in several software packages, such as Mathematica (Wolfram, 2013) and JMP (SAS Institute, 2015) (See Figure 2). Specifically, when data are dense in a particular location of the scatterplot, the bubble becomes bigger. Conversely, when the data are sparse, the bubble is smaller. One shortcoming of the bubble plot approach is that the scale of the bubble is arbitrary. For example, in one plot a circle with an area of 1cm^2 might represent 10 observations but in another it might symbolize 100.

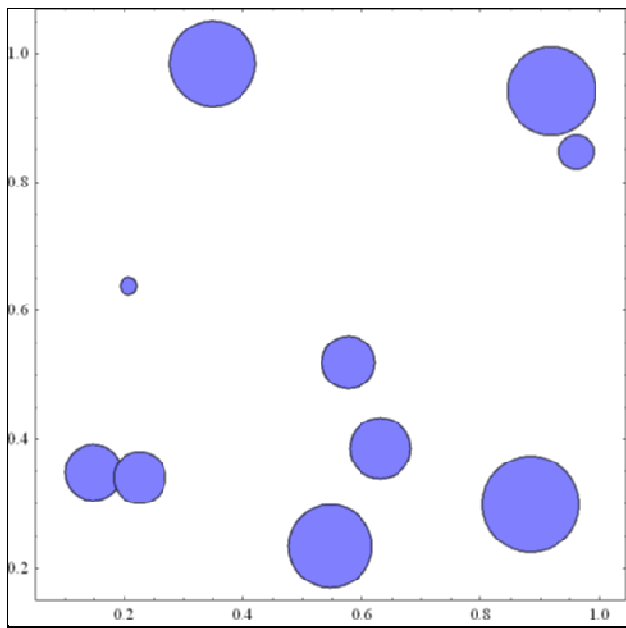


Figure 2. Bubble plot.

Density Contour Plot

Another way to overcome over-plotting is the density contour plot. In this approach the density of data points is represented by both colors and contour lines. As shown in Figure 3, the large amount of data that concentrate on the centroid are depicted by colored contours. One advantage of this method is that noisy data are not hidden. Rather, the contours are superimposed on top of the raw data. However, this type of depiction is not intuitive and even a well-trained data analyst may not be able to discover the pattern or the trend in the data set. The obstacle is that if the

contour lines are not portrayed with additional labels, it is not informative at all (Boyd, 2015).

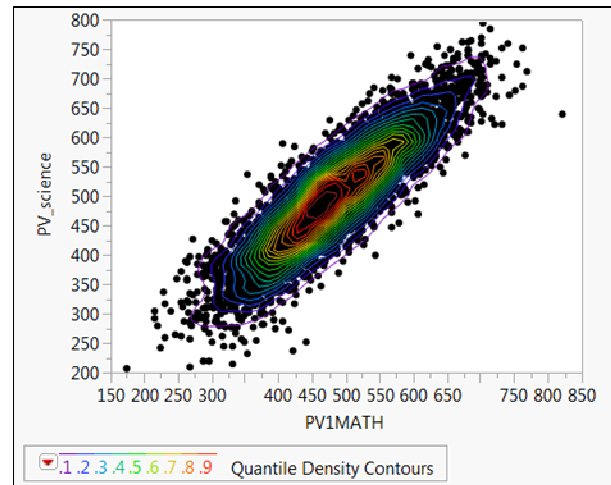


Figure 3. Density contour plot.

Sunflower Plot

The sunflower plot is another proposed solution to over-plotting (Cleveland & McGill, 1984). In a sunflower plot, the density of the data points is symbolized by a glyph. The more observations the spot contains, the more rays it emanates from the center. If there are more observations in a particular location, the glyph would look like a “sunflower” (see Figure 4). However, Schilling, and Watkins (1994) explained that when there is only one observation in a spot, the symbol is just a dot rather than a sunflower. As a result, it is difficult to synthesize both dots and sunflowers into a coherent image. In addition, mentally translating the rays into frequency increases the cognitive load. Further, when there are two observations only, a single line extends from that point. It may mislead the analyst to perceive that only one observation is there.

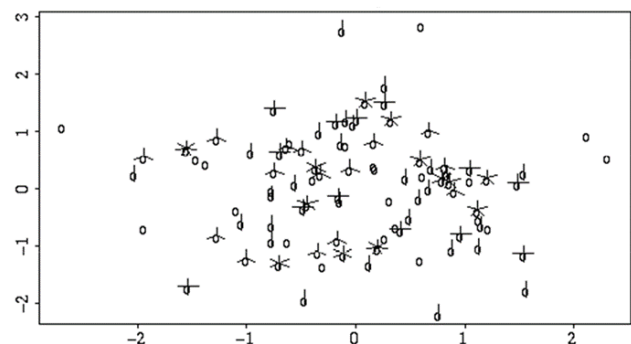


Figure 4. Sunflower plot.

Another way to simplify an over-plotted scattergram is median or mean smoothing. In this approach when the software algorithm encounters too many data, it can divide the data into several partitions along the x-axis and then calculate the median of y in each segment (Tukey, 1977). Hence, the analyst can look at the trend by visually connecting the medians. Mihalisin, Timlin, and Schwegler (1991) extended the preceding idea by using the mean rather than the median. However, using the median is recommended because the median is more resistant against extreme scores, especially when the distribution of a certain slice of the data set is highly skewed. It is the conviction of the authors that the median smoothing approach is more effective than all of the preceding methods. The meaning of median (middle point) is universally accepted while the scale of the bubble or the interval of contour lines is subject to the analyst's preference. Hence, the pattern or the trend unveiled by median smoothing has a more objective ground. This will be demonstrated next.

Methodology

In this paper data visualization by median smoothing is illustrated by an example in item response theory (IRT), which is a powerful psychometric tool that is capable of estimating item attributes and person traits without the restriction of sample-dependence (Embretson & Reise, 2000). IRT assumes unidimensionality, meaning that a test or a survey used with these approaches should examine only a single latent trait of participants. In reality, many tests or surveys are multi-dimensional. If unidimensionality assumption is not satisfied, researchers can choose to remove unfit items, or to identify internal structure by conducting some exploratory factor analysis and confirmatory factor analysis. Then items belonging to different constructs can be scaled separately. However, critics charge that psychometric properties such as factor loadings are sample-dependent (Embretson & Reise, 2000; Wright & Mok, 2000), and thus structure produced from one study may be so unstable that it varies from sample to sample (Yan & Mok, 2012). To address these issues, multi-dimensional IRT (MIRT) was introduced as a synthesis of factor analysis and IRT (Adams, Wilson, & Wang, 1997; Kamata & Bauer, 2008). It performs well when sub-scales within an instrument are strongly correlated with each other (Wang, Yao, Tsai, Wang, & Hsieh, 2006).

MIRT aims to model latent covariance structures between multiple dimensions, and also to model these interactions (Hartig & Hohler, 2009). A classic example involves latent traits required for solving a math problem. When a math problem is presented in a formula or an equation (e.g. Solve $y = 2x + 5$; $2y = x + 10$), the required problem-solving ability is mathematical skill alone. However, if a math problem is explained in text (e.g. A car is running 65 miles per hour and the distance between the starting point and the destination is 485 miles. How long does it take for the car to reach the destination?), both math and reading skills are required.

Several software packages are capable of running MIRT; these include Mplus, ITPRO, flexMIRT, EQSIRT, and SAS (SAS Institute, 2014). At first glance it is efficient to accomplish two tasks (identification of the factor structure and the item characteristics) concurrently. However, it is important to recognize that if problematic items are present in the data set, neither factor modeling nor IRT modeling can be successfully performed. This problem is especially severe when sample sizes are extremely large. Both factor analysis and IRT are very demanding in sample size. The recommended minimum sample sizes for factor analysis range from 150 to 500 (Comrey & Lee, 1992; Hutcheson & Sofroniou, 1999; MacCallum, Widaman, Preacher, & Hong, 1999; Mundfrom, Shaw, & Ke, 2005). For IRT, suggested minimum sample sizes could be as large as 1,000 or 2,000 (Baker, 1992; Hulin, Lissak, & Drasgow, 1982). With such large sample sizes, calibrations and estimations may not be very accurate. At the same time, problematic items may be hidden in the large data set.

There are many ways to detect and remove problematic items. In classical test theory, a typical approach is to examine the point-biserial correlation (item-total correlation) of each item. In IRT or Rasch modeling, it is common to examine discrimination parameters (Nikolausa et al., 2013) and infit or outfit Chi-square, in order to detect bad items (Lai, Cella, Chang, Bode, & Heinemann, 2003; Yu, 2013). This paper illustrates another way of identifying poor items - namely, data visualization of item-total correlation by median smoothing.

Data Source

As mentioned before, problematic items might be buried by an extremely large sample. To make the

illustration as realistic as possible, a large archival data set was downloaded from the website, “Personality Tests” (<http://personality-testing.info/>). Specifically, data collected using the *Consideration of Future Consequences Scale* (CFCS) was chosen. The objective of CFCS is to measure to what extent individuals take potential future outcomes into account while doing things at the present time and to what extent their current behaviors are influenced by imagined outcomes. There were five possible answers on the CFCS: extremely uncharacteristic (1), somewhat uncharacteristic (2), uncertain (3), somewhat characteristic (4), and extremely characteristic (5). Higher scores indicated a greater level of consideration of future consequences. Originally the CFCS was developed as a one-dimensional scale (Strathman, Gleicher, Boninger, & Edwards, 1994). However, recent factor analyses suggested that this scale carries two dimensions: consideration of the immediate and consideration of the future (Heveya et al., 2010; Joireman, Balliet, Sprott, Spangenberg, & Schultz, 2008; Joireman, Shaffer, Balliet, & Strathman, 2012; Joireman, Strathman, & Balliet, 2006). The original sample size of the full data set was 15,035. Two hundred and sixteen observations were removed, due to erroneous data or missing values. As a result, the remaining number of observations was 14,819.

The original CFCS has 12 items and the revised version has 14. This data set is based on the original scale but in order to illustrate the importance of preliminary item selection the authors added two problematic items into the data set. As mentioned before, when sample sizes are too large, even random numbers may appear to form a pattern. Hence, if there are problematic items in the data set, they may not be detected. To demonstrate this problem, random number generating functions were used to insert two items (Q13 and Q14) into the scale. In Q13 the same probability (.2) was assigned to the five answer categories (1= extremely uncharacteristic, 2= somewhat uncharacteristic, 3= uncertain, 4= somewhat characteristic, 5= extremely characteristic). Therefore, this item had a uniform distribution. In Q14 a higher probability (.4) was assigned to the middle category (3), whereas lower probabilities were assigned to the other categories. Specifically, Category 2 and 4 have a probability of .2 to appear whereas Category 1 and 4 have a probability of .1. As a result, a normal distribution was created.

The uniform distribution of item Q13 was generated to mimic how the factors of ‘fatigue’ and ‘boredom’ affect data accuracy. If a survey is too long or participants perceive its items as irrelevant, participants might randomly select one of the five categories, rather than reading the questions carefully. These respondents might not choose the same answers (e.g. all ‘A’s or all ‘B’s) throughout the survey, in order to avoid detection of their feigned or mindless responses. As a result, each category would have an equal chance of being selected.

The normal distribution of item Q14 was generated in order to simulate problems with poorly worded and/or misfit items. Even if an item is intended to fit into a construct under study, a poorly worded item may confuse and mislead participants. For example, in a survey pertaining to the attitude towards science learning the following question could be asked: “Do you think that fundamental physics is difficult?” Fundamental physics is a study of the basic structure and universal properties of nature, such as particles and quantum fields. While some respondents may interpret this question correctly, some might think that it refers to elementary physics. Consequently, its response pattern might still be a normal curve, but it would be disconnected from all other items. In the case of a misfit item there would be no vagueness in the wording, but the item would not be strongly related to the construct under investigation. For example, in a survey about mental wellbeing the following question could be asked: “Do you consider yourself physically healthy?” Responses to this question would not indicate a significant association between happiness and physical health. In this case the responses would still be normally distributed but the item would be misfit to the focal construct.

Results

Exploratory Factor Analysis The original data set yielded a high Cronbach’s Alpha (.8717); no item(s) needed to be excluded in order to substantively improve the scale’s reliability. In other words, the response pattern to all of the questions was internally consistent (see Figure 5).

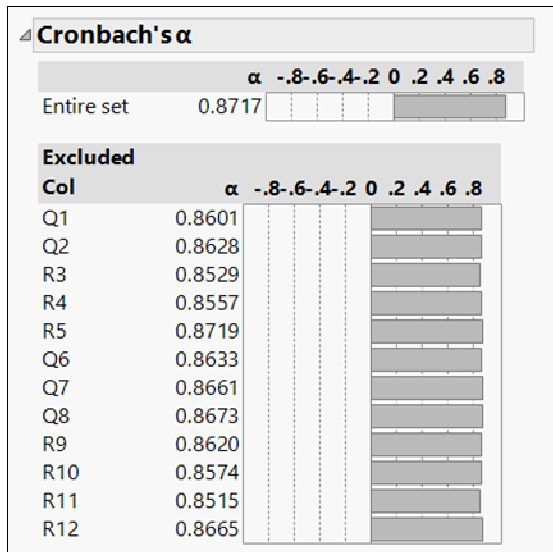


Figure 5. Cronbach's alpha of the original 12 items.

Concurring with the literature, exploratory factor analysis (EFA) suggested a 2-factor solution based on the scree plot (see Figure 6) and the factor structure depicted in the loading plot (see Figure 7).

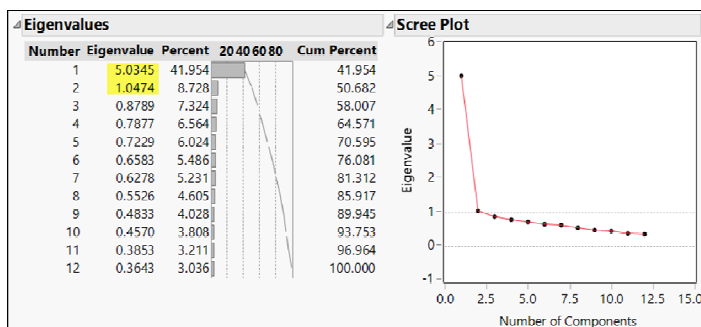


Figure 6. Eigenvalue and scree plot of the original 12 items.

As shown in Figure 7, questions 1, 2, 6, 7, and 8 were loaded in Factor 2, while all others were loaded in Factor 1. The loading plot also shows that the two clusters of vectors are apart from each other, implying their construct distinctness.

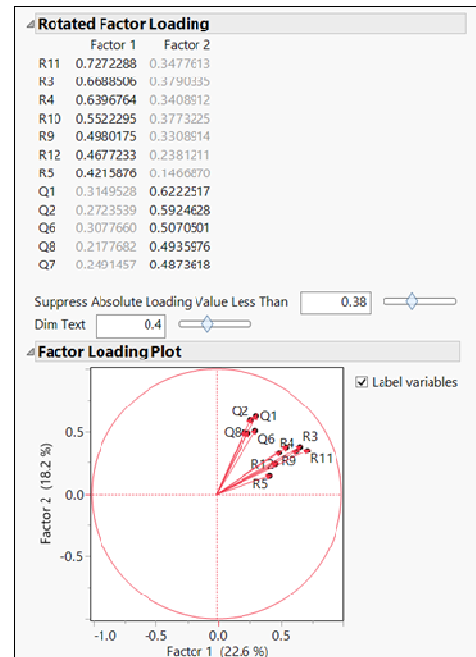


Figure 7. Factor loadings and loading plot of 12 items.

However, the clear factor structure was disrupted by the introduction of the two problematic items (Q13 and Q14). Even though the so-called 'data' in these two items were nothing more than random numbers, a reliability analysis based on Cronbach's Alpha did not detect a problem. If Q13 were removed, the Alpha would increase from .8303 to .8539 (see Figure 8). If Q14 were dropped, the Alpha would increase from .8303 to .8467. Most people would not be alerted by a trivial difference as small as .0236 or .0164.

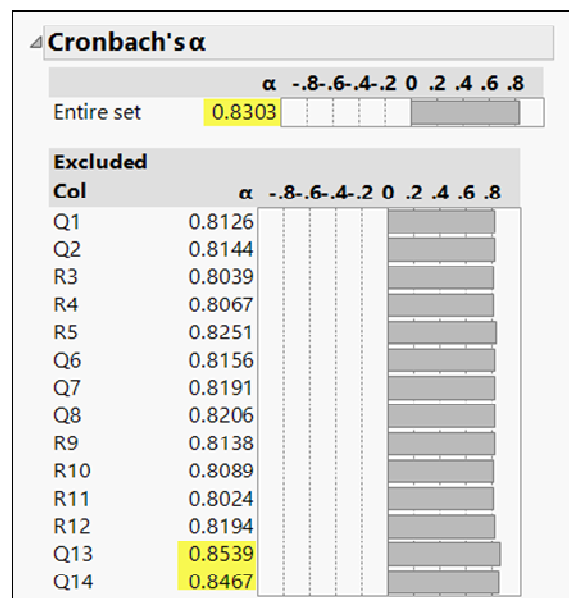


Figure 8. Cronbach's Alpha of 14 items with random data.

With the presence of two problematic items, EFA suggested a three-factor solution (see Figure 9); this resulted in confusion regarding the factor structure.

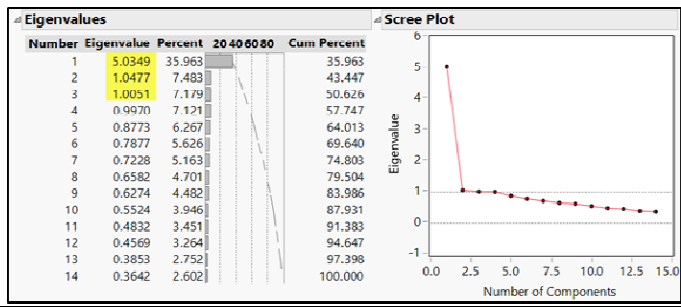


Figure 9. Eigenvalue and Scree plot of 14 items.

One may suspect that Q13 and Q14 do not belong to the original two factors, and thus they form a third factor. However, this is not the case. Figure 6 shows that Q13 and Q14 were not loaded onto any factor. Even if the loading value was increased to .38 as before, Q9 became a one-item factor (Figure 10). In short, the two undetected and misfit items damaged the factor structure.

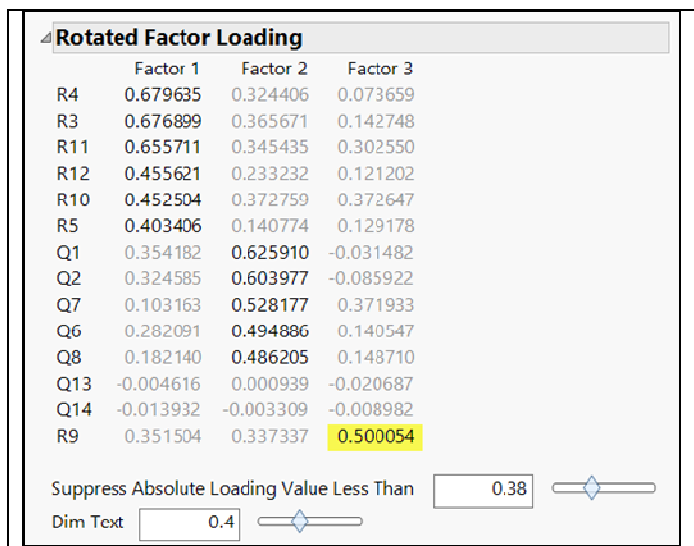


Figure 10. Factor loadings and loading plot of 14 items for a three-factor solution

When a two-factor solution was imposed on the data, it is obvious that Q13 and Q14 do not belong to any construct (see Figure 11).

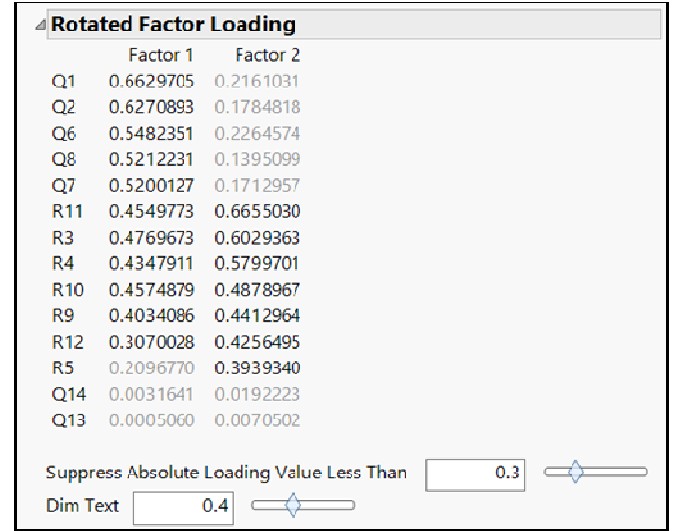


Figure 11. Factor loadings and loading plot of 14 items for a two-factor solution.

Confirmatory Factor Analysis

Interestingly, with such a large sample size the fitness indices of confirmatory factor analysis (CFA) also fail to alert the analyst about the existence of problematic items. CFA was run with SAS 9.4 (SAS Institute, 2014) on the original 12 items of the CFCS and results supported the proposed two-factor structure (see Table 1). The Adjusted Goodness of Fit Index (AGFI) results (.94) support the proposed two factor structure, since AGFI values are considered satisfactory when greater than .90 (Hooper, Coughlan, & Mullen, 2008). Steiger (2007) suggested that the Root Mean Square Error of Approximation (RMSEA) is acceptable when less than .07, and Hu and Bentler (1999) stated that the Standardized Root Mean Square Residual (SMSR) is sufficient when less than .08. Both the RMSEA (.06) and SMSR (.03) results were within these suggested thresholds. Together, these fit indices suggest that the two-factor solution is a better fit than the original 12 item CFCS.

Table 1. CFA results for original 12 items

AGFI	0.9448
Parsimonious GFI	0.7448
RMSEA Estimate	0.0632
SRMR	0.0330
Akaike Information Criterion	3126.5051

In order to assess the impact of the two problematic items (Q13 and Q14) on the factor structure of the CFCS, a separate CFA was run on the scale, which included questions 13 and 14 (see Table 2).

All results from the AGFI (.96), RMSEA (.05), and SMSR (.03) indices meet the cut-off criteria. Therefore, the proposed two-factor structure for the 14-item scale would be considered acceptable. The Akaike Information Criterion (AIC) result for the original 12-item scale (3126.51) did not greatly differ from the AIC of the 14-item scale (3152.86). Together, these results show that CFA failed to detect the problematic items (Q13 and Q14).

Table 2. CFA results on 14-item scale including Q13 and Q14

AGFI	0.9557
Parsimonious GFI	0.7878
RMSEA Estimate	0.0525
SRMR	0.0286
Akaike Information Criterion	3152.8633

As mentioned previously, MIRT is a synthesis of factor analysis and IRT. Nonetheless, when problematic items exist in the data set Cronbach's Alpha, EFA, or CFA may fail to detect them initially. This problem would carry over to MIRT even though the polychoric correlation matrix was utilized in SAS. The polychoric correlation matrix is especially useful for analyzing items on self-report surveys, such as personality inventories that often use rating scales with a small number of response categories (e.g. 5-point Likert scale). Pearson's r works best with a high degree of variability. When the distribution of the item responses is narrow due to limited options, the between-item relationships tend to be attenuated in the Pearson's correlation matrix. Factor analysis based on the polychoric matrix is supposed to reduce these types of statistical artifacts (Lee, Poom & Bentler, 1995; Tello, Moscoso, García, & Chaves, 2006). However, MIRT still suggests a 3-factor solution as EFA did before (see Figure 12 and Table 3).

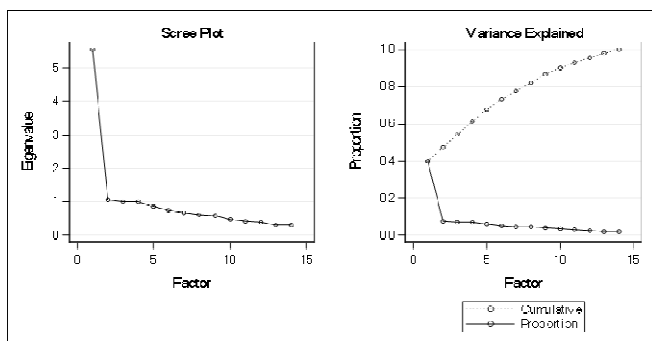


Figure 12. Scree plot from PROC IRT for CSCF items.

Table 3 is the output of the interpret parameter estimates of all 14 items yielded by PROC IRT. All p -values are less than .0001, and the patterns of the slopes and standard errors of all items look alike. By viewing the table alone, even experienced researchers may not be able to tell that Q13 and Q14 contain messy data.

Table 3. Interpret parameter estimates of all 14 items yielded by PROC IRT

Item	Parameter	Estimate	Std. Error	p
Q1	Intercept1	5.16127	0.10362	<.0001
	Intercept2	2.88533	0.06246	<.0001
	Intercept3	2.02889	0.04878	<.0001
	Intercept4	-1.88742	0.04569	<.0001
Q2	Intercept1	2.63126	0.0393	<.0001
	Intercept2	1.09539	0.02646	<.0001
	Intercept3	0.20938	0.02314	<.0001
	Intercept4	-2.20241	0.0345	<.0001
R3	Intercept1	3.95101	0.05552	<.0001
	Intercept2	0.91459	0.02793	<.0001
	Intercept3	0.16281	0.02581	<.0001
	Intercept4	-2.58373	0.04005	<.0001
R4	Intercept1	3.62955	0.0549	<.0001
	Intercept2	0.86535	0.02733	<.0001
	Intercept3	0.10111	0.0249	<.0001
	Intercept4	-2.36039	0.03969	<.0001
R5	Intercept1	1.43904	0.02273	<.0001
	Intercept2	-0.68285	0.01947	<.0001
	Intercept3	-1.32029	0.02192	<.0001
	Intercept4	-2.89727	0.035	<.0001
Q6	Intercept1	3.41807	0.04184	<.0001
	Intercept2	1.55048	0.02507	<.0001
	Intercept3	0.86638	0.02194	<.0001
	Intercept4	-1.3699	0.02412	<.0001
Q7	Intercept1	4.2757	0.07396	<.0001
	Intercept2	2.42502	0.04563	<.0001
	Intercept3	1.69437	0.03612	<.0001
	Intercept4	-0.96843	0.02771	<.0001
Q8	Intercept1	3.66918	0.04637	<.0001
	Intercept2	1.80879	0.02653	<.0001
	Intercept3	0.3596	0.02015	<.0001
	Intercept4	-1.75766	0.02598	<.0001
R9	Intercept1	3.49884	0.05493	<.0001
	Intercept2	1.13264	0.02821	<.0001
	Intercept3	0.45408	0.0242	<.0001
	Intercept4	-1.7882	0.03381	<.0001
R10	Intercept1	3.84987	0.05021	<.0001
	Intercept2	1.28205	0.02656	<.0001
	Intercept3	0.53106	0.02349	<.0001
	Intercept4	-2.05369	0.03148	<.0001
R11	Intercept1	4.67062	0.06848	<.0001
	Intercept2	1.29876	0.03184	<.0001
	Intercept3	0.4193	0.02788	<.0001
	Intercept4	-2.79894	0.04531	<.0001
R12	Intercept1	2.85794	0.03429	<.0001
	Intercept2	0.63506	0.01991	<.0001
	Intercept3	-0.58329	0.01981	<.0001
	Intercept4	-2.63574	0.03177	<.0001
Q13	Intercept1	1.3547	0.02035	<.0001

	Intercept2	0.40542	0.01677	<.0001
	Intercept3	-0.41711	0.01679	<.0001
	Intercept4	-1.36453	0.02041	<.0001
Q14	Intercept1	2.19625	0.02737	<.0001
	Intercept2	0.85683	0.01796	<.0001
	Intercept3	-0.82922	0.01786	<.0001
	Intercept4	-2.19915	0.02741	<.0001

Detection by Data Visualization

When a sample size is small, one may be able to detect problematic items by viewing a scatterplot of total scores (the average of all items except the item under investigation), along with the scores for each item. When a sample size is large, however, data points jam together. This makes pattern recognition difficult and sometimes even impossible (see Figure 13). This issue is known as over-plotting.

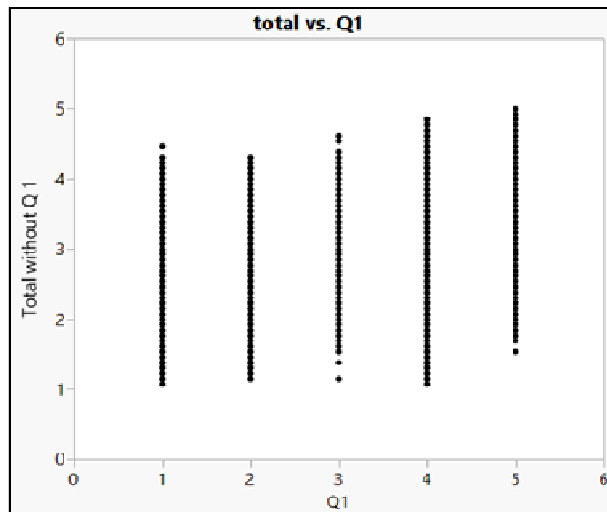


Figure 13. Over-plotting: Patterns are hidden in the scatterplot when data points are displayed.

Method

The remedy to this problem is ‘median smoothing’ – that is, changing the display of individual data points to summarized box plots (Tukey, 1977; Yu & Behrens, 1995; Yu, 2014). Figure 14 displays usage of this technique, indicating the relationship between Q1 and the total without Q1. The boxplots in this figure summarize totals at different levels of Q1 scores. This figure clearly indicates that the medians and boxes for Q1 indicate an upward trend; this trend is consistent with the total response pattern in Q1-Q12. Figure 15 indicates another example of this response pattern.

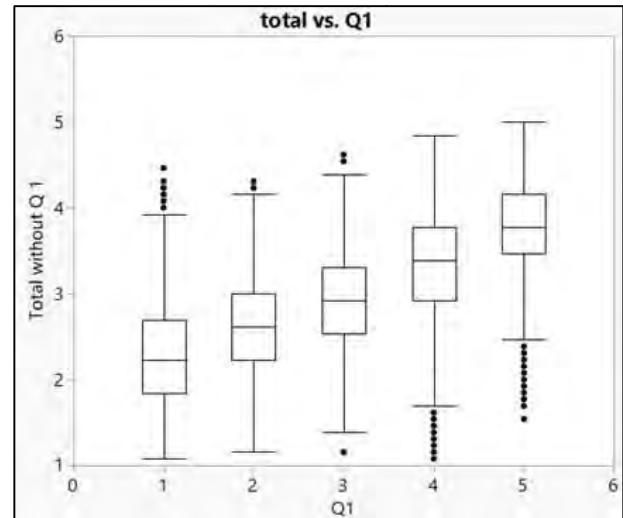


Figure 14. Median smoothing of total without Q1 by Q1

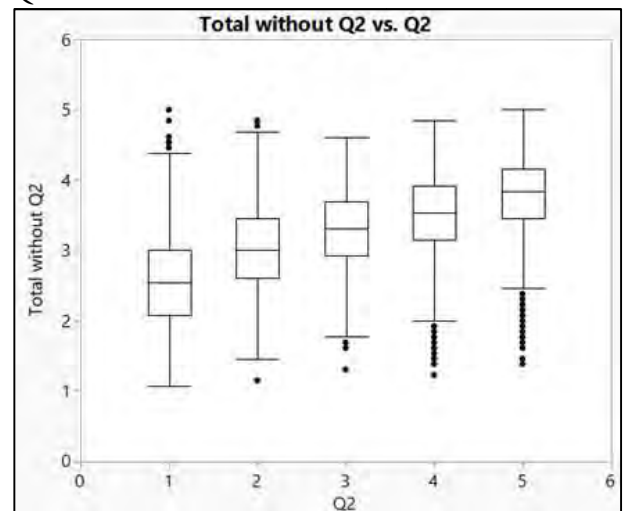


Figure 15. Median smoothing of total without Q2 by Q2

Figures 16 and 17 indicate that the preceding trend is absent in both Q13 and Q14. In short, this graphical inspection enables researchers to spot problematic items that Cronbach’s Alpha and factor analysis failed to detect.

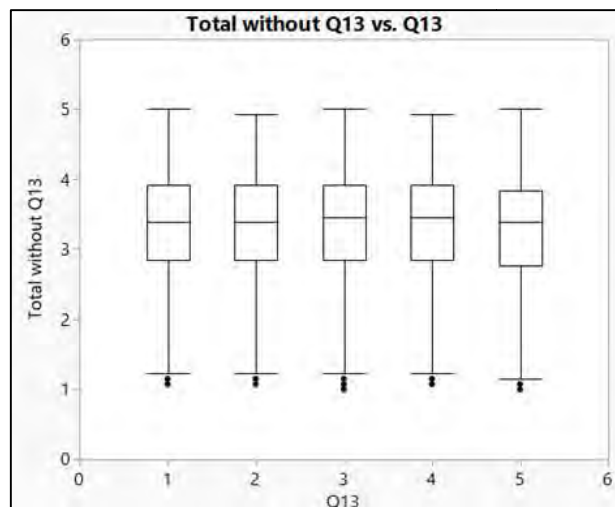


Figure 16. Median smoothing of total without Q13 by Q13

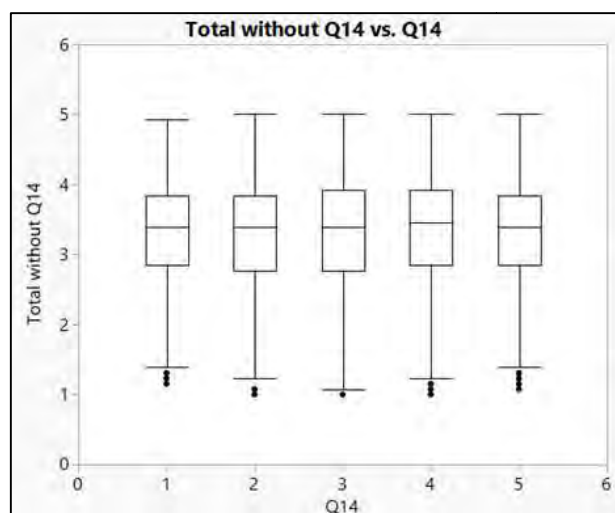


Figure 17. Median smoothing of total without Q13 by Q14

Conclusion

In this paper, we illustrated how data visualization can be utilized to identify errors prior to modeling. We used MIRT as an example, due to the fact that IRT is inherently a visual procedure, meaning that interpretation of it necessitates various graphs (i.e. item-person map, item characteristic curve, item information function curve, test information function curve, and many others). However, very often data visualization of IRT is performed by psychometricians after modeling instead of being used as a diagnosis tool prior to parameter estimation. It is important to mention that the principle of data visualization is in

alignment with the philosophy of exploratory data analysis, which emphasizes examining the data structure, checking assumptions, spotting outliers, and fixing errors before committing the data to confirmatory data analysis (Behrens & Yu, 2003; Turkey, 1977; Yu, 2010). The preceding example illustrates that sometimes even random noise could be mis-identified as structure. Despite the versatility of MIRT, users who work with large data sets are advised against jumping into usage of MIRT without having first conducted a preliminary item removal. While reliability analysis may fail to identify problematic items, data visualization (such as median rendering) is effective for unveiling hidden problems.

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