

Interpreting Regression Effects Custom Dialog: An SPSS Plug-in to the R Yhat Package

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This paper presents an SPSS custom dialog (*Interpreting Regression Effects*) that was developed to access R software that helps researchers more fully understand how sets of predictor variables contribute to a regression model. The *Interpreting Regression Effects* custom dialog allows researchers to consider a wide variety of predictor and all-possible subset related metrics when interpreting regression effects including regression weights, validity coefficients, structure coefficients, product measures, relative important weights, all-possible-subsets regression, commonality coefficients, and dominance weights.

Multiple regression is a widely used statistical technique in the behavioral sciences (Hankins, French, & Horne, 2000). Researchers can use this statistical procedure in practical prediction problems where the goal is to forecast an outcome based on data that were collected earlier or to identify a minimum set of variables that yield the best prediction of the criterion for the data. In this procedure, the linear relationships between two or more predictor variables (also called independent variables) and a single criterion (also called a dependent) variable are quantified (Gall, Borg, & Gall, 1996). The result helps identify how well predictor variables explain or predict values of a criterion variable. When there are high correlations among predictor variables, researchers may find it difficult to interpret the results and may make mistakes in their interpretations. In the presence of multicollinearity, even the most seasoned researcher may encounter difficulty determining how predictors work together in forming the regression effect.

For example, consider a model that helps predict employee job satisfaction. While job autonomy is considered a key explanatory variable of job satisfaction, researchers may include additional predictor variables (e.g., peer support, supervisor support, workload, pay, promotional opportunity, working condition, and job involvement) to increase the explanatory ability of the model. Researchers may then get a more powerful model but at the expense of complications in analyses and interpretation, if previous literature indicates there are moderate to high correlations among these additional predictor variables. The explained variance of employee job satisfaction may be attributable to multiple variables because of the interrelationships among these predictor variables and researchers may find that these variables are redundant in the explained variance of job satisfaction. In interpreting such a model, researchers may misinterpret the results if they (a) base their interpretation solely on standardized regression coefficients, which is justifiable only in the case that all predictors are orthogonal or uncorrelated (Courville & Thompson, 2001) or (b) rely on stepwise methods in selecting the best set of predictors (Nathans, Oswald & Nimon, 2012; Zientek & Thompson, 2006). To avoid such misinterpretation of regression models with correlated predictors, Kraha, Turner, Nimon, Zientek, and Henson (2012) recommended the use of multiple indices to interpret multiple regression effects. These indices include, but are not limited to, standardized regression coefficients, validity coefficients, structure coefficients, relative important weights, all possible subsets (APS) regression, commonality coefficients, and dominance weights.

The current paper presents an SPSS custom dialog (*Interpreting Regression Effects*) that was developed to access R software that helps researchers more fully understand how sets of predictor variables contribute to a regression model. R is a powerful programming language that works as an environment for statistical analysis and graphics. R procedures can be carried out using packages, developed by experts and statisticians, and syntax that are similar to C programming. Some researchers may find that R is difficult to learn if they do not have a computer programming background. With the *Interpreting Regression Effects* custom dialog, researchers and practitioners who are unfamiliar with R can conveniently use SPSS to perform multiple procedures for interpreting regression effects as those available in the *yhat* package (cf. Nimon & Oswald, 2013; Nimon et al, 2013).

The *Interpreting Regression Effects* custom dialog allows researchers to consider a wide variety of predictor and all-possible subset related metrics when interpreting regression effects. The following sections provide a brief overview of the indices supported by the custom dialog. For a more in-

depth treatment of each analysis, we refer readers to Kraha et al. (2012), Nathans et al. (2012), and Nimon and Oswald (2013).

Predictor Metrics

Regression Weights

Regression weights indicate how much each predictor contributes to the regression equation with all other predictors held constant. There are two kinds of regression weights: B weights (for variables in their unstandardized/original scale) and beta (β) weights (for variables that have been standardized). The B weight indicates the increase or decrease in the criterion variable for each unit of change in a given predictor with other predictors held constant, while a beta weight uses a standard unit (z-scores) for all variables. Beta weights are heavily used by researchers to assess “predictor importance,” which may be an ambiguous term in the presence of multicollinearity. When predictors are correlated, a variable may have an insignificant beta weight yet be strongly correlated to the criterion variable and predicted criterion variable through its relationship with other predictors. In such cases, additional measures are required to fully understand the effect (Nathans et al., 2012).

Validity Coefficients

Validity coefficients are bivariate correlations between predictors and the criterion variable. When squared they indicate how much variance a predictor has in common with the criterion variable. Validity coefficients (r) are considered measures of direct effect (cf. LeBreton, Ployhart, & Ladd, 2004) as they assess predictor importance without considering the contribution of other predictor variables in the regression equation.

Structure Coefficients

Structure coefficients (r_s) are the bivariate correlation between a predictor variable and a predicted Y or \hat{Y} (Courville & Thompson, 2001). As with validity coefficients, structure coefficients are not affected by the interrelationships among the predictor variables. When used in conjunction with beta weights, structure coefficients, like validity coefficients, may help identify the presence of suppression (Courville & Thompson; Thompson, 2006).

Product Measures (Pratt’s Measures)

Product measures partition the regression effect into k segments, where k equals the number of predictor variables. The beta weight of each predictor is multiplied with its zero-order correlation with the criterion variable. The values that are zero or negative may be viewed as problematic to interpret. Nimon and Oswald (2013) recommended that researchers use this measure in addition to other coefficients (e.g., general dominance weights and relative weights) to more fully interpret regression effects.

Relative Weights

Relative weights also partition the regression effect into k segments through a process that involves principal components analysis (Johnson, 2000). Despite differences in computational methods, relative weights and general dominance weights are almost always identical (LeBreton et al., 2004). Note that researchers may find it difficult to detect any suppression cases through these weights (Kraha et al., 2012).

All-Possible-Subsets Regression

This method tests all possible subsets of the set of potential predictors by conducting linear regressions on all $2^k - 1$ distinct subsets. For selection, researchers evaluate the subsets based on model parsimony and model fit.

Commonality Coefficients

Commonality analysis allows researchers to identify the unique and common effects of respective predictor variables in explaining variance accounted for in the interested criterion variable (Rowell, 1991; Si, 2001). This analysis is appropriate to use when variables are highly related (Pedhazur, 1997). Thompson (2006) explained that commonality analysis partitions regression effects into constituent, non-overlapping segments. Unique effects indicate how much variance is unique to a predictor variable; while common effects indicate how much variance is uniquely common to two or more predictors (Nimon,

2010). While commonality coefficients provide a powerful interpretation of the regression effect including identifying the loci and magnitude of suppression and multicollinearity, they may be difficult to interpret in the presence of a large number of predictors as the number of coefficients produced is $2^k - 1$.

Dominance Weights

Dominance analysis is a method typically used to determine the importance of each variable based on pairwise comparisons of the unique variance contributions to the regression effect across all possible subsets of predictor variables (Nathans et al., 2012). There are three hierarchical levels of dominance weights: complete, conditional, and general dominance. A complete dominance analysis may help detect the presence of suppression (Azen & Budescu, 2003). However, as demonstrated by Nimon and Oswald (2013), commonality analysis may be a more reliable technique to assess the presence of suppression.

Illustrative Example

To demonstrate the use of the SPSS custom dialog, we analyzed data from Holzinger and Swineford (1939). This dataset contains a total of 26 tests aimed to assess the spatial, verbal, mental speed, memory, and mathematical ability of 301 students from Paster High School and Grant-White High School. Four verbal predictors, including general information (*general*), sentence completion (*sentence*), word classification (*wordc*), and word meaning (*wordm*), are used to predict a criterion variable, paragraph comprehension (*paragrap*).

To replicate the results reported in this paper, readers can download the data set from the MBESS R package (Kelly & Lai, 2012) or use the SPSS syntax reported in Kraha et al. (2012) to simulate a dataset that corresponds to the correlation matrix reported in Table 1.

A standard regression analysis can then be conducted on the resulting data using the linear regression analysis in SPSS. The Multiple R^2 from the regression model was .611, indicating that 61% of the variance in paragraph was explained by *general*, *sentence*, *wordc*, and *wordm*. The correlation matrix in Table 1 indicates that the data have collinear predictors. Therefore, some of the explained variance of paragraph comprehension may be attributable to more than one predictor variable. The regression equation was:

$$\text{Predicted Paragraph} = 0.071 + 0.030\text{general} + 0.263\text{sentence} + 0.047\text{wordc} + 0.137\text{wordm}$$

To further investigate and clarify the regression effects, the authors can interpret multiple indices, including structure coefficients, all-possible-subsets regression, commonality coefficients, dominance weights, and relative weights. These metrics will help researchers fully understand the contributions that these predictors make to a regression model and to each other. To facilitate ease of use and maximal understanding, further results are discussed separately for each of the

seven options within the Interpreting Regression Effects custom dialog. Step by step instructions for both preparation and analysis are included in Appendices A and B.

Calc.yhat

The `calc.yhat` function produces four sets of regression metrics: Predictor Metrics (Figure 1), Ordered Predictor Metrics (Figure 1), Paired Dominance Metrics (Figure 1), and APS Related Metrics (Figure 2). The predictor metrics table provides results from several analyses, including the standard B and beta (β) weights and extending to validity, structure, and commonality coefficients. In the same table, researchers can see output from dominance analyses, Pratt's measure, and relative weights. The ordered predictor metrics table provides a ranking of each predictor for each analysis. The paired dominance metrics table provides complete, conditional, and general dominance results for all pairwise comparisons. Finally, the APS related metrics table provides results from all possible subsets regression, including commonality, R^2 , and incremental contribution to R^2 .

By examining the predictor metrics in Figure 1, one sees that across all standardized predictor metrics (e.g., b , β , r , r_s , r_s^2), the most important predictor was *sentence*, followed by *wordm*, *general*, and *wordc*.

Table 1. Correlation Matrix for Heuristic Example

	general	sentence	wordc	wordm
sentence	0.717			
wordc	0.640	0.674		
wordm	0.745	0.720	0.582	
paragrap	0.658	0.733	0.582	0.704

Predictor Metrics														
	b	Beta	r	rs	rs2	Unique	Common	CD:0	CD:1	CD:2	CD:3	GenDom	Pratt	RLW
general	.030	.106	.658	.841	.708	.004	.429	.433	.071	.016	.004	.131	.069	.130
sentence	.263	.389	.733	.938	.879	.054	.484	.538	.153	.080	.054	.206	.285	.201
wordc	.047	.077	.582	.744	.554	.003	.336	.339	.034	.010	.003	.097	.045	.101
wordm	.137	.301	.704	.901	.812	.034	.462	.496	.124	.057	.034	.178	.212	.179
Total	NA	NA	NA	NA	2.953	.095	1.711	1.806	.382	.163	.095	.612	.611	.611

Ordered Predictor Metrics														
	b	Beta	r	rs	rs2	Unique	Common	CD:0	CD:1	CD:2	CD:3	GenDom	Pratt	RLW
general	4	3	3	3	3	3	3	3	3	3	3	3	3	3
sentence	1	1	1	1	1	1	1	1	1	1	1	1	1	1
wordc	3	4	4	4	4	4	4	4	4	4	4	4	4	4
wordm	2	2	2	2	2	2	2	2	2	2	2	2	2	2

Paired Dominance Metrics			
	Comp	Cond	Gen
general>sentence	.000	.000	.000
general>wordc	.500	1.000	1.000
general>wordm	.000	.000	.000
sentence>wordc	1.000	1.000	1.000
sentence>wordm	1.000	1.000	1.000
wordc>wordm	.000	.000	.000

Figure 1. Partial output from the `calc.yhat` option: Predictor, Ordered Predictor, and Paired Dominance Metrics. Unique = uniqueness coefficients; Common = $r^2 - \text{Uniqueness}$; CD = Conditional Dominance Weights; GenDom = General Dominance Weights; Pratt = Pratt’s Measure; RLW = Relative Weights

These findings are consistent with the results of conditional and general dominance. Results from conditional dominance analysis reveal that *sentence* conditionally dominates across all subset sizes with weights of .538 (CD: 0), .153 (CD: 1), .080 (CD: 2), and .054 (CD: 3). The same results can be seen in the general dominance metrics, as *sentence* generally dominates all other variables in the model. Further, while *sentence* completely dominates *wordm* which completely dominates *general*, *general* does not completely dominate *wordc*. This is because *general* adds less incremental validity than *wordc* when added to a model with *wordm* (.040 versus .045, see Figure 2). Also note that although the decomposition of the regression effect as computed by general dominance and relative weights are very similar, the results from Pratt’s measures are unique with more emphasis being placed on *sentence* and *wordm* and less emphases being placed on *general* and *wordc*.

By examining the commonality coefficients in Figure 2, one sees that the largest commonality coefficient relates to variance that is common to *general*, *sentence*, *wordc*, and *wordm*. With over 40% of the regression effect being attributed to variance that is common to all four predictors, one might theorize that the measures are tapping into a form of general intelligence or be subject to common method bias. From the all possible subsets regression depicted in Figure 2, researchers can see that the model with all four predictors yields the highest R^2 effect size ($R^2 = .611$), but the increased prediction by adding a fourth predictor is negligible. Two models with three (*general*, *sentence*, *wordm* and *sentence*, *wordc*, *wordm*) predictors have almost as much explanatory power ($R^2 = .609$ and $.607$, respectively). In light of this information, researchers may opt to choose the more parsimonious or theory-driven model.

All Possible Subsets

The *all possible subsets* option analyzes all possible $2^k - 1$ combinations of the predictor variables, where k represents the number of predictors. Output from this option can be seen in Figure 3. The first three output tables provide information about all possible combinations that is used by the commonality and dominance functions. The APS matrix table provides R^2 information for all of these subsets of size k , as previously discussed in the section on `Calc.yhat`.

Dominance

Figure 4 depicts all output from the dominance analysis. The `dominance` option yields three output tables: Complete Dominance, Conditional Dominance, and General Dominance.

APS Related Metrics

	Commonality	% Total	R2	general.Inc	sentence.Inc	wordc.Inc	wordm.Inc
general	.004	.006	.433	NA	.141	.044	.103
sentence	.054	.088	.538	.036	NA	.014	.065
wordc	.003	.005	.339	.138	.213	NA	.202
wordm	.034	.055	.496	.040	.106	.045	NA
general,sentence	.013	.021	.573	NA	NA	.004	.035
general,wordc	.002	.004	.477	NA	.101	NA	.081
sentence,wordc	.019	.030	.552	.026	NA	NA	.056
general,wordm	.022	.036	.536	NA	.072	.022	NA
sentence,wordm	.047	.077	.602	.006	NA	.005	NA
wordc,wordm	.001	.002	.541	.017	.066	NA	NA
general,sentence,wordc	.021	.034	.578	NA	NA	NA	.034
general,sentence,wordm	.100	.163	.609	NA	NA	.003	NA
general,wordc,wordm	.008	.013	.558	NA	.054	NA	NA
sentence,wordc,wordm	.021	.035	.607	.004	NA	NA	NA
general,sentence,wordc, wordm	.264	.431	.611	NA	NA	NA	NA
Total	.611	1.000	NA	NA	NA	NA	NA

Figure 2. Partial output from `calc.yhat` – All possible subsets metrics. Includes commonality analysis, R^2 , and incremental R^2 contributions

Relative Weight

The `relative weight` option produces one output table displaying the relative weight for each predictor. As noted previously, relative weight results suggest again that sentence (RLW = .201) contributes the most to the model, followed by *wordm* (RLW = .179).

Effect Size

The `effect size` option produces one table that includes six measures of effect size. Further, the table includes recommendations for use (yes/no) based on Yin and Fan's (2001) exploration of multiple indices.

Commonality

The `commonality` option produces two commonality tables: the first provides unique and common coefficients for all possible combinations, while the second provides unique and common coefficients for each individual variable. As noted previously, interpretation of these metrics reveals large amounts of shared variance, thus suggesting that that the measures are tapping into a form of general intelligence or be subject to common method bias.

Bootstrap

The `bootstrap` option produces bootstrapped results for all previous analyses to help estimate the estimators' properties. Confidence intervals for all predictors and all possible subset metrics are reported, as well as the descriptive statistics for Kendall's tau. Users can specify the number of desired bootstrapped samples in the dialog box.

Discussion

In this paper, we demonstrated the use of a custom dialog that allows SPSS users to access a set of functions within the `yhat` (Nimon et al., 2013) package in R. With the use of the `Interpreting Regression Effects` custom dialog, SPSS users can take advantage of software that has been developed to provide a more full interpretation of regression effects including regression weights, validity coefficients, structure coefficients, product measures, relative weights, all-possible-subsets regression,

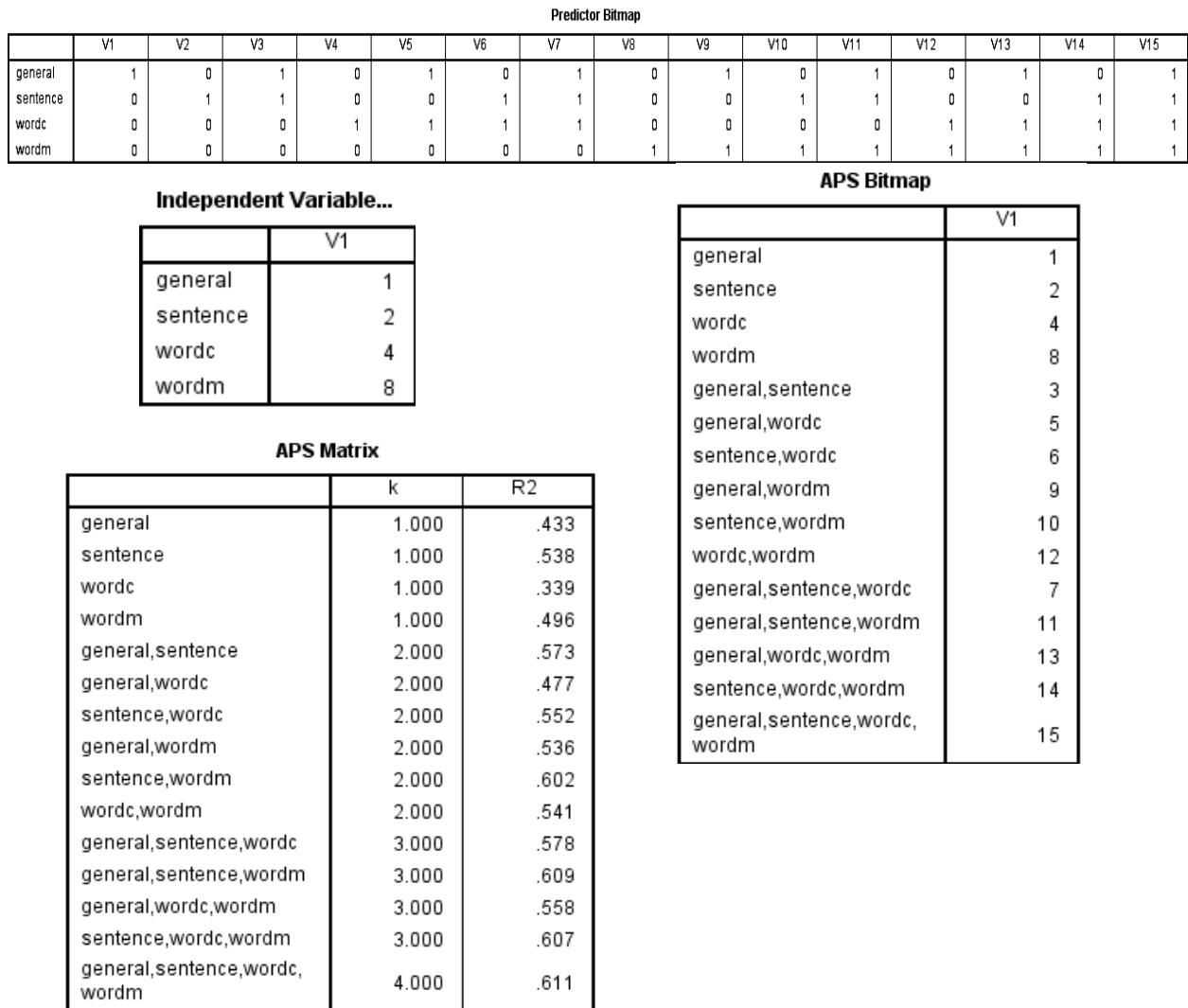


Figure 3. Output from the All Possible Subsets dialog option. Tables marked “APS Bitmap” and “Predictor Bitmap” displays the various models with associated predictors, while the “APS Matrix” table displays the associated R^2 for each model.

commonality coefficients, and dominance weights. While SPSS syntax has been developed and published for each of these coefficients separately (see Kraha et al., 2012), the *Interpreting Regression Effects* custom dialog allows SPSS users to produce all of these coefficients simultaneously. In addition to the ease of not having to execute different sets of syntax, the solution presented in this paper may be useful when SPSS users desire to bootstrap their results.

Although we incorporated multiple functions available from the *yhat* package (cf. Nimon & Oswald, 2013; Nimon et al., 2013) into the *Interpreting Regression Effects* custom dialog, the custom dialog could be developed further in order to include additional functions available in the *yhat* package, such as commonality coefficients for canonical correlation and plotting confident intervals from bootstrap results.

As has been noted elsewhere (cf. Kraha et al., 2012; Nimon et al., 2010), interpreting the relative contribution of predictors within a multiple regression can be a complicated and difficult process, particularly in the presence of multicollinearity (Stevens, 2009). We advise that researchers utilizing SPSS for multiple linear regression analyses consider using the *Interpreting Regression Effects* custom dialog so that they may have a more full interpretation of the regression effect than is offered in the standard SPSS output.

dominance analysis

	k	R2	general.Inc	sentence.Inc	wordc.Inc	wordm.Inc
general	1.000	.433	NA	.141	.044	.103
sentence	1.000	.538	.036	NA	.014	.065
wordc	1.000	.339	.138	.213	NA	.202
wordm	1.000	.496	.040	.106	.045	NA
general,sentence	2.000	.573	NA	NA	.004	.035
general,wordc	2.000	.477	NA	.101	NA	.081
sentence,wordc	2.000	.552	.026	NA	NA	.056
general,wordm	2.000	.536	NA	.072	.022	NA
sentence,wordm	2.000	.602	.006	NA	.005	NA
wordc,wordm	2.000	.541	.017	.066	NA	NA
general,sentence,wordc	3.000	.578	NA	NA	NA	.034
general,sentence,wordm	3.000	.609	NA	NA	.003	NA
general,wordc,wordm	3.000	.558	NA	.054	NA	NA
sentence,wordc,wordm	3.000	.607	.004	NA	NA	NA
general,sentence,wordc, wordm	4.000	.611	NA	NA	NA	NA

conditional dominance					general dominance	
	general	sentence	wordc	wordm		x
CD:0	.433	.538	.339	.496	general	.131
CD:1	.071	.153	.034	.124	sentence	.206
CD:2	.016	.080	.010	.057	wordc	.097
CD:3	.004	.054	.003	.034	wordm	.178

Figure 4. Output from the Dominance option, where .inc represents the incremental contribution to R^2 and CD: 0 represents average additional contribution when the subset size is i

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APPENDIX A

Software Preparation Steps

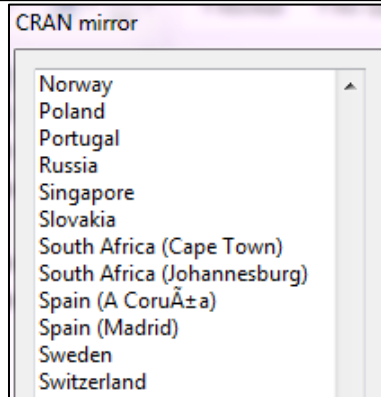
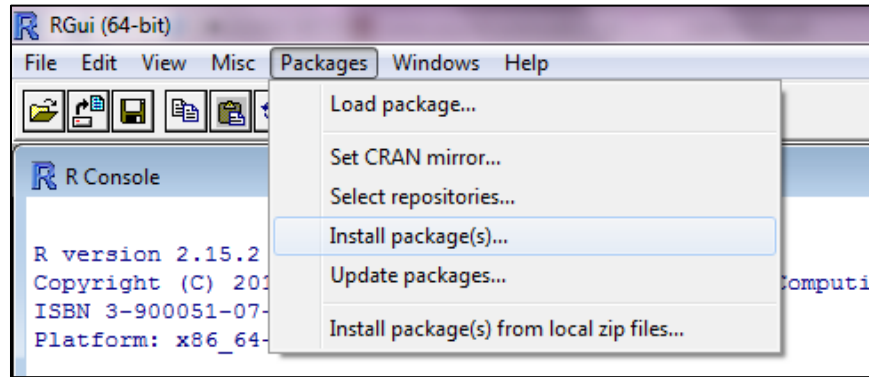
Steps to prepare R for analyses:

Step One: Install R version 2.15.2 from <http://cran.r-project.org/bin/windows/base/old/2.15.2/>

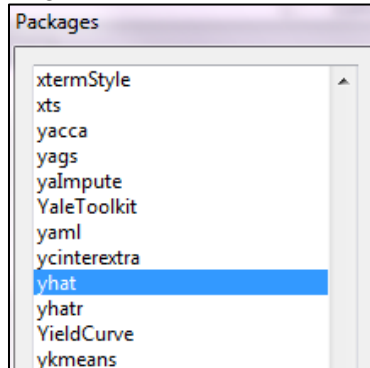
Step Two: Run R-2.15.2-win.exe and follow command prompts

Step Three: Download R packages. This process is required only during the setup. **You are not required** to open the R program in order to use the SPSS custom dialog box in the future.

1. Open R
2. On the menu bar, select Packages, select Install package(s)...



Step Four: The packages window appears. Select boot, foreign, and yhat. Holding CTRL will allow you to select more than one package at a time. Click OK.



Step Five: Once packages have been successfully installed, close R.

Steps to prepare SPSS with R Essentials add-on:

Step One: If you are unsure of your SPSS version, you can check by selecting from the SPSS menu bar, Help -> About. You will need this information in Step 3d below.



Step Two: To determine if you system is 32- or 64-bit (Windows), go to start and right click My Computer. Choose properties, and look for “System type” under System. You will need this information in Step 3f below.

Step Three: Download R Essentials from IBM.

1. Go to <http://www.ibm.com/developerworks/spssdevcentral>
2. [Follow the link to “Download materials for IBM SPSS Statistics”](#)
3. Scroll down to subheading “R Essentials” and click the link to download “The Essentials for R for Statistics versions 19 and later”
 - a. You will be prompted to log in or create a free account.
4. Select the version of Essentials for R that matches your SPSS version and click continue (if you don’t know your SPSS version, see **Step One** above).
5. Select notification preferences, agree to license agreements, and click “I confirm”
6. Select the “Download using http” tab, then scroll down and choose the correct install for your system (keeping in mind operating system and 32- or 64-bit systems; if you don’t know your operating system type, see **Step Two** above)

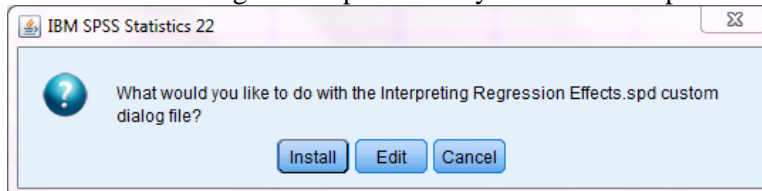
Step Four: Run SPSS_Statistics_REssentials[...].exe. Double click the file and follow command prompts. For certain system set ups, you may need to run this file as an administrator. To do so, right-click the downloaded file and select “Run as administrator.”

Steps to prepare SPSS with Custom Dialog:

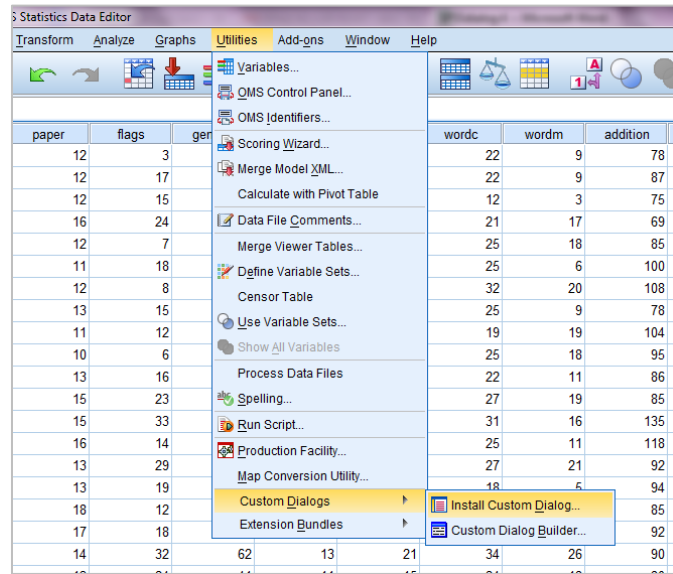
Step One: Download the custom dialog file (Interpreting Regression Effects.spd) from <https://goo.gl/jDJZ9y>

Step Two: Install Interpreting Regression Effects.spd

1. **Option One:** Double click the downloaded file. A new window from SPSS will appear. Select install. The custom dialog will be permanently installed in a specified SPSS menu



2. **Option Two:** Alternatively, you can install the .spd file through the installation menu in SPSS. This procedure requires administrative access to your computer and you will have to run SPSS as an administrator. If your computer is owned by the university or your work place, you may have to contact a technical support person to give you an administrative access.
 - a. On the SPSS menu bar, select Utilities -> Custom Dialogs -> Install Custom Dialog.
 - b. When the window opens, select the downloaded .spd file, click Open.
 - c. Upon successful installation, you will receive a notification stating where the file was installed.

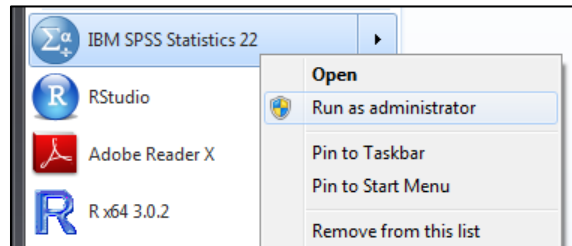


Note: Once you have completed the preparatory steps above, you will be ready to analyze data. Please note that you will only have to complete the steps above *once*—after the files are installed, you will be ready to start with data analysis each time.

APPENDIX B

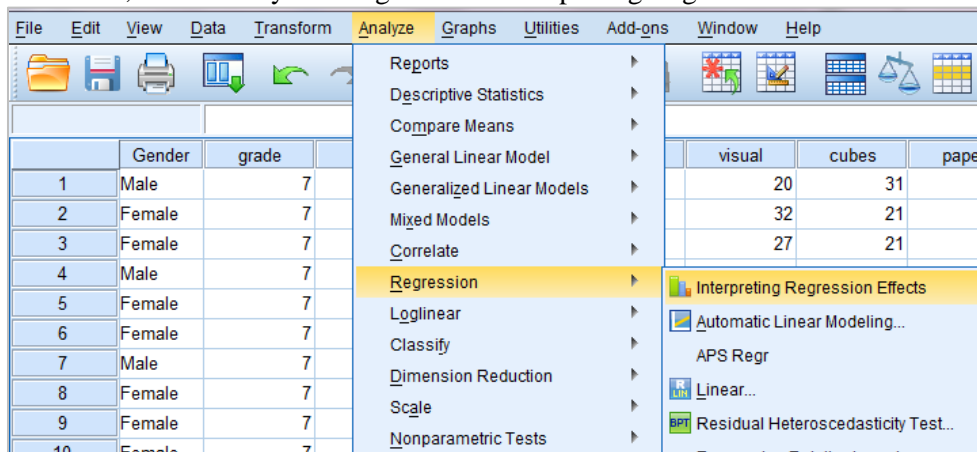
Steps to Replicate Illustrative Sample

Step One: Open SPSS in administrator mode. To run the programs as an administrator, right-click on the program icons, select “Run as administrator.”

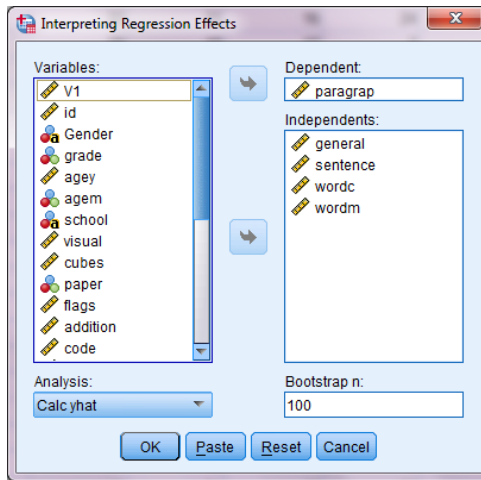


Step Two: Open Holzinger and Swineford (1939) data file in SPSS, select File > Open > Data. The data can be found in the MBESS R Package (Kelly & Lai, 2012) or by using syntax from Kraha et al. (2012).

Step Three: In SPSS, select Analyze > Regression > Interpreting Regression Effects



Step Four: The dialog box opens. Click on the criterion variable (i.e., *paragraph*), then the top right arrow to put the variable into the Dependent box. Click the predictor variables (i.e., *general*, *sentence*, *wordc*, *wordm*), then the bottom right arrow to put the variables into the Independents box.



Step Five: Select one of the analysis options from a drop-down menu (i.e., `calc.yhat`). Click OK to run. The SPSS dataset and output viewer will be processed by R and the output will appear in the SPSS viewer.

