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Reuse, Don't Reinvent: Extending Model Selection Using Recursive Macro

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ABSTRACT

The existing SAS® macro*: %MODEL_SELECT* - used recursively to select the "best" model based on the R^2 selection method - is performing great for specific data and specific variables. The steps of the macro *%MODEL_SELECT* are as follows: perform a BEST SUBSETS selection based on R^2 to get the list of candidate models, calculate the estimates and associated p-values, eliminate the covariates that are never significant, and repeat. This macro does not allow for multilevel variables to be considered for model selection, it does not allow for hierarchical modeling, and it only considers one model selection method: R^2. This paper aims to enhance existing SAS® methods, specifically, by allowing various model selection methods (e.g., adjusted-R^2, Mallows's C_p, etc.) and the inclusion of categorical variables with multiple levels. The added capabilities will allow the macro to still be user friendly, yet be more robust. Several PROCEDURES, CALL SYMPUT, SCAN, DO-LOOP, IF-THEN-ELSE statements and functions, and various Output Delivery System (ODS) statements are used in expanding the *%MODEL_SELECT* macro. This paper is intended for the intermediate SAS® user, with intermediate statistical skills and SAS® 9.1 or above.

INTRODUCTION

The existing SAS® macro: *%MODEL_SELECT* - used recursively to select the "best" model based on the R^2 selection method - is performing great for specific data and specific variables. For example, if the goal is to find predictors of a continuous outcome (thus using PROC REG), the existing macro performs very well and provides comprehensive information on various candidate models. However, if the outcome is defined as binary categorical – thus requiring PROC LOGISTIC, the existing macro, as is, will not be a good tool. The selection process for PROC LOGISTIC would entail a similar algorithm to the one for PROC REG, and given that the existing macro was designed for eventual reuse and/or extension, we set out to extend the *%MODEL_SELECT* macro and make it more robust. Most of the code was adapted quite easily to meet the specifications of PROC LOGISTIC, and eventually, more procedures.

In the design of the outer wrapper, several factors had to be considered. The first factor was the outcome type: numeric versus character. If the outcome is numeric, PROC REG is called; if the outcome is categorical, PROC LOGISTIC is called. The second factor was the type of the covariates: if the list provided by the user contains categorical covariates, then for each categorical variable with *n* levels this enhanced macro will automatically create *n-1* dummy variables; if the list provided by the user contains only continuous covariates, then the list provided is used as-is in the model.

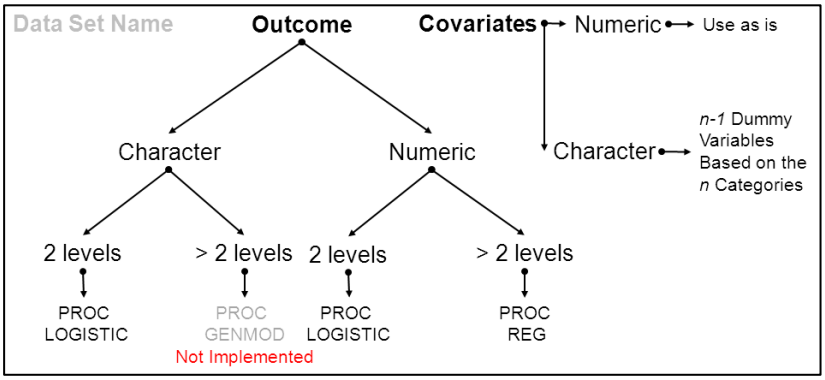


Figure 1**:** Logical flowchart of the proposed macro

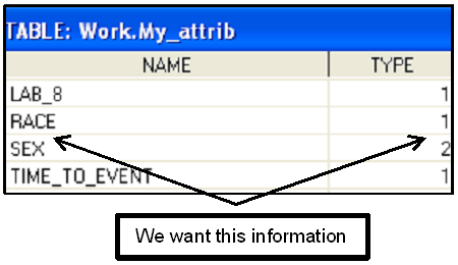
As the aim of this paper is not to provide details of the *%MODEL_SELECT* macro, the focus shall be placed on the outer wrapper logic. Two new, rather elegant macros have been written to aid in satisfying the two aforementioned design factors (i.e., outcome type and covariates type).

SAS® CODE

The additional code logic that extends the *%REGRESSION_MODEL_SELECT* macro is described.

The first step of the macro is to assess the outcome type. The type of a given variable is easily extracted from the SAS® table that PROC CONTENTS could output. However, there is one problem: there exists the possibility that the variable name that the user has entered (the *outcome*) does not syntactically match the name of the variable as it is found (i.e., spelled) in the data set (i.e., typographical difference). For example, below is an excerpt from a PROC CONTENTS data output.

If the user enters *outcome = LAB_8*, everything will work as planned, but if the user enters *outcome = lab_8*, there will be no way to match a value in the NAME column with a value in the TYPE column. Thus, instead of placing a restriction on the user to carefully enter the *outcome* as it really is in the data set, we developed a small macro, *%ISOLATE_OUTCOME* that "matches" (PROC regardless of the letter case) what the user entered with how it is spelled in the data set. Below the details of the *%ISOLATE_MACRO* follow:




```
%MACRO ISOLATE_OUTCOME();
%LET REAL_VAR = ;
PROC SQL;
   SELECT NAME INTO: TABLE_VARS SEPARATED BY " "
   FROM DICTIONARY.COLUMNS
   WHERE LIBNAME = "%UPCASE(%SCAN(&DSNAME.,1, "."))" &
   MEMNAME = "%UPCASE(%SCAN(&DSNAME.,-1, "."))";
QUIT;
%LET NUM_OF_VARS = %EVAL(%SYSFUNC(COUNTW(&TABLE_VARS.)));
DATA TEMP;
   LENGTH ONE_VAR $200;
   %DO I = 1 %TO &NUM_OF_VARS.;
      ONE_VAR = "%SCAN("&TABLE_VARS.", &I., " ")";
                     OUTPUT;
   %END;
RUN;
DATA _NULL_;
   SET TEMP;

   IF PRXMATCH("/^&OUTCOME.[\s]*$/i", ONE_VAR) THEN
   CALL SYMPUT ("REAL_VAR", ONE_VAR);
%MEND ISOLATE_OUTCOME;
```

- save the variable names as they exist in SAS® (from DICTIONARY.COLUMNS) in a macro variable called *table_vars* (a string containing the variable names separated by space)
- save the total number of variables in the data set in a macro variable *num_of_vars* and create a temporary data set, with one column: *one_var* containing the variable names
- *prxmatch* is used to extract the variable name as it is found in the SAS® data set (save the info in macro variable *real_var*)

Another component of the proposed macro is to create DUMMY variables, if categorical variables are included in the list of covariates. This could be accomplished easily via PROC FREQ followed by manipulation of data sets outputted using ODS statements. However, there is one problematic scenario: a formatted categorical variable. For example, there is a variable *Age* with four groups ("1", "2", "3", and "4") and the following format:

```
PROC FORMAT;
VALUE $ AGE_CAT "1" = "Age <= 55"
                "2" = "Age (55, 65]"
                "3" = "Age (65, 75]"
                "4" = "Age > 75"
              ;
```

VIEWTABLE: Work.My_freq_1 (One-W

	AGE_CATEG	Frequency	Percent
1	Age <= 55	602	28.17
2	Age (55, 65]	450	21.06
3	Age (65, 75]	585	27.37
4	Age > 75	500	23.40

Running PROC FREQ on this variable would result in the following output, which will be a problem when trying to create DUMMY variables based on the listed categories. For example, one way to create DUMMY variables is

```
…
DUMMY_AGE_1 = (AGE_CATEG = "Age <= 55");
…
```

However, that would not work as intended! The "real" value of AGE_CATEG is actually 1, thus we need to:

1. create a copy of the data set provided
2. remove the formats from the copy (i.e., the original data is left intact)
3. use PROC FREQ to get the categories/levels for all categorical variables

4. create the DUMMY variables for each categorical variable in the copy data set
5. update the *COVARIATES* list with the DUMMY variables

Below is an explanation of key SAS® code that accomplishes the aforementioned points.

`%MACRO COVARIATE_LEVELS();`
`PROC SQL;`
`CREATE TABLE TEMP_DATA (COMPRESS = YES) AS`
`SELECT * FROM &DSNAME.;`
	• create a copy of the data set

`SELECT NAME, COUNT(NAME) INTO: CHAR_VARS SEPARATED BY " ",`
`:CHAR_CNT`
`FROM DICTIONARY.COLUMNS`
`WHERE LIBNAME = "%UPCASE(%SCAN(&DSNAME.,1, "."))" &`
`MEMNAME = "%UPCASE(%SCAN(&DSNAME.,-1, "."))" &`
`TYPE = "char";`
	• select the character variables and the number (how many there are) into two macro variables *CHAR_VARS* and *CHAR_CNT*

`SELECT NAME INTO: CHAR_FORMAT_VARS SEPARATED BY " "`
`FROM DICTIONARY.COLUMNS`
`WHERE LIBNAME = "%UPCASE(%SCAN(&DSNAME.,1, "."))" &`
`MEMNAME = "%UPCASE(%SCAN(&DSNAME.,-1, "."))" &`
`TYPE = "char"& FORMAT NE " ";`
	• separately select the variables that have a format attached to them in a macro variable called *CHAR_FORMAT_VARS*

`ALTER TABLE TEMP_DATA` `MODIFY &CHAR_FORMAT_VARS FORMAT = $75.;`	• modify the copied data set (from above) and remove the formats

`SELECT NAME INTO: TABLE_VARS SEPARATED BY " "`
`FROM DICTIONARY.COLUMNS`
`WHERE LIBNAME = "%UPCASE(%SCAN(&DSNAME.,1, "."))" &`
`MEMNAME = "%UPCASE(%SCAN(&DSNAME.,-1, "."))"  ;`
`QUIT;`
	• select all variables existing in the data set in a macro variable called *TABLE_VARS* for later use

`%DO I = 1 %TO &CHAR_CNT.;`
`  PROC FREQ DATA = TEMP_DATA NLEVELS;`
`  TABLES %SCAN("&CHAR_VARS.", &I., " ");`
`  ODS OUTPUT NLEVELS = MY_LEVELS_&I.;`
`  ODS OUTPUT ONEWAYFREQS = MY_FREQ_&I.(KEEP = F_:);`
`  RUN;`
	• do-loop through all categorical variables
	• run PROC FREQ
	• save the levels information in a SAS® data set

`  PROC SQL;`
`  SELECT NAME INTO: FREQ_VARS SEPARATED BY ","`
`  FROM DICTIONARY.COLUMNS`
`  WHERE LIBNAME = "WORK" & MEMNAME = "MY_FREQ_&I.";`
 	
`  SELECT &FREQ_VARS. INTO: _LEVELS_&I. SEPARATED BY "**"`
`  FROM MY_FREQ_&I.;`
`  SELECT NLEVELS INTO: NUM_LEVELS_&I`
`  FROM MY_LEVELS_&I.`
`  WHERE TABLEVAR = "%SCAN(&CHAR_VARS., &I., " ")";`
`  QUIT;`
	• select the levels of each categorical variable into a macro variable (*_LEVELS_&I.*) separated by **, and store the corresponding number of levels into a macro variable (*_NUM-LEVELS_&I.*)

…
`  DATA FINAL_DATA;`
`  SET TEMP_DATA;`
`  %LET VAR = %SCAN(&CHAR_VARS., &I., " ");`
`  %DO J = 1 %TO &&NUM_LEVELS_&I.- 1 ;`
`  %LET CURRENT_LEVEL=%SCAN("&&_LEVELS_&I.",&J.," **");`
`  %PUT &CURRENT_LEVEL.;`
`  %LET VALUE = %SCAN( &CURRENT_LEVEL., &J., "**");`
`  DUMMY_&VAR._&J. = (%SCAN(&CHAR_VARS., &I., " ") =`
`  "&CURRENT_LEVEL.");`
`  %END;`
`  RUN;`
`%END;`
…
	• create the DUMMY variables and add to the copy data set
	• using PROC SQL and a couple of data steps, update the *covariates* list by replacing the categorical variables with the newly created DUMMY variables

Once the outcome has been assessed and the covariates list has been scanned for categorical variables, the %*REGRESSION_MODEL_SELECT* macro is ready to be employed. This macro uses several logical IF-THEN-ELSE statements, as it was depicted in the flowchart.

The %*REGRESSION_MODEL_SELECT* macro takes five parameters:

- three are required:
  - DATA SET NAME
  - OUTCOME of interest
  - COVARIATES list
- two are optional:
  - SELECTION METHOD
  - NUM_SUBSETS

If the selection method is not provided, the macro will use the R^2 – for PROC REG, and the SCORE statistic for PROC LOGISTIC. The top 5 models will be included if BEST option is not provided.

```
%MACRO REGRESSION_MODEL_SELECT(DSNAME = , OUTCOME = ,
COVARIATES = , SELECTION_METHOD = , NUM_SUBSETS = );
…
%ISOLATE_OUTCOME();
%COVARIATE_LEVELS();
…
%LET DSNAME = WORK.FINAL_DATA;

%IF &LEVELS. = 2 %THEN %DO;
   %INCLUDE "&PATH.\MODEL_SELECT.SAS";
   %IF &NUM_SUBSETS. NE  %THEN %DO;
      %MODEL_SELECT(MY_DATA = &DSNAME., outcome =
      &OUTCOME.,covariates = &covariates, best =
      &NUM_SUBSETS.);
   %END;
   %ELSE %DO;
      %MODEL_SELECT(MY_DATA = &DSNAME., outcome =
      &OUTCOME.,covariates = &covariates, best = 5);
   %END;
%END;
…
%MEND REGRESSION_MODEL_SELECT;
```

- identify the *OUTCOME* variable correctly
- modify *COVARIATES* list if needed

- a series of IF-THEN-ELSE statements are used to call either PROC LOGISTIC with *SCORE* selection method, or PROC REG with &SELECTION_METHOD (provided by the user)

SAMPLE OUTPUT

Sample results from the %*REGRESSION_MODEL_SELECT* macro are shown in Figure 2 with the following key components:

1. Original Sample Size: the original size of the data set, with missing data included
2. Complete-case N: sample size for the BEST SUBSETS models (complete-case data including all covariates of interest)
3. R-Square: Model-based R^2 for the BEST SUBSETS models
4. Number in Model: total number of covariates in each model
5. Variables in Model: list of the covariates used in each model
6. Variables Significant in the Model: significant covariates from each model
7. Potential N: complete-case sample size for a model using a subset of variables (≥ Complete-case N)
8. Potential R-square: Model-based R^2 for models based on Potential N.

The rest of the columns represent the individual estimates and p-values

Model Index	Original Sample Size	Complete Data Sample Size	R-Square	Model significant overall ? (Yes = 1,No = 0)	Number in Model	Variables in Model	Variables Significant in This Model	Potential N	Potential R	(1)Estimate	(1) P-value
1	2141	1272	0.0834	1	1	LAB_4	LAB_4	1713	0.0727	1.675	<.0001
2	2141	1272	0.0047	1	1	DUMMY_SEX_1	DUMMY_SEX_1	2133	0.0098	2.127	<.0001
3	2141	1272	0.0003	0	1	bmi		1561	0.0003	0.027	0.5043
4	2141	1272	0.0003	0	1	age		2133	0.0001	0.007	0.6497
5	2141	1272	0.0840	0	2	LAB_4 bmi	LAB_4	1272	0.084	1.776	<.0001
6	2141	1272	0.0838	0	2	age LAB_4	LAB_4	1713	0.0728	0.008	0.6206
7	2141	1272	0.0837	0	2	DUMMY_SEX_1 LAB_4	LAB_4	1713	0.0745	0.911	0.0654

Figure 2. Sample output result

LIMITATIONS

In the presence of multilevel categorical outcome, the current macro does not implement PROC GENMOD – mostly due to its lack of model selection method(s). The authors pondered the possibility of creating (and running) ALL possible models for a given set of covariates, but realized the run-time complexity and the logic still needed to be thought through. Furthermore, the current macro does not handle time-varying data (i.e., PROC MIXED) or survival models. A shell has been developed to implement a baseline PROC PHREG, and it is envisioned that it will shortly be integrated in the current macro.

CONCLUSION

The updated macro makes the task of (manual) model selection much easier and time-efficient. The authors provided a tool that will aid the analyst in the rather tedious process of selecting a model. The code in its entirety (and all the macros) is available on the http://www-personal.umich.edu/~atilea website.

REFERENCES

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