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Semi-automatic Feature Engineering from Transactional Data

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ABSTRACT

Transactional data are ubiquitous: whether you are looking at point-of-sale data, weblog data, social media data, genomic sequencing data, text, or even a standard relational database, these data generally come in transactional form. But data mining assumes that all the data are neatly packaged into a single record for each individual being observed. With experts noting that 80% of a data scientist's time is spent in data preparation, is there a way to automate this process to make that job easier? We have developed a toolkit that can be deployed through SAS® Studio and SAS® Data Management Studio software to address this conundrum. Given transactional tables, which represent both categorical and numerical data, you can use this toolkit to pipeline a series of steps—including steps to reduce cardinality of categorical data, to roll columns up to a subject level, and to generate "embeddings" of those columns at the subject level—in order to prepare the data for the modeling task. In addition, the process automatically creates a scoring script so that you can replicate that pipeline for any additional data that come in.

INTRODUCTION

In database theory, it is very important to normalize your data:[1,5] that is, to place it in various tables linked by primary and secondary keys in order to minimize data redundancy and dependency. Over the years, most organizations have become quite effective at performing this normalization task.

However, for most forms of modeling, the opposite approach is needed: the data need to be *denormalized*. The goal is to create a table that contains all the information necessary to build an effective predictive model. This resulting table is often referred to as an analytical base table (ABT).[2] The process of creating this table is usually an ad hoc approach of figuring out which features need to be extracted and massaged from any of a multitude of transactional tables to be put into the ABT, with a single row for each subject of interest. The amount of time that this activity takes can be many times that required for the analysis itself.[3]

We have discovered some clever techniques that you can use to effectively perform this feature extraction across a wide variety of sources and types of transactional data. We have encapsulated these techniques in a set of SAS® macros that we call the "transactional data toolbox." You can plug these tools into a pipeline, and the toolbox is extensible so that you can write your own additional tools, tailored specifically to transformations that you want to perform. In addition, for your convenience, we have created a set of SAS Studio tasks to call these macros.

The tools communicate with each other via SAS macro variables, and at any point, these macro variables can be used to do the following:

- Indicate the current ABT name that has all transformations applied from the current pipeline.
- Indicate the current target variable, its level, and all categorical and continuous predictors added by the various tools.
- Create a macro variable that contains score code concatenated for all tools in the pipeline, to assist in deploying the data preparation in a production environment.

The remainder of the paper discusses the structure of the tool macros and macro variables, the types of transactional data that the tools are designed to use, the use of SAS Studio tasks, and, finally, an example that shows how to apply these techniques to a database.

As currently formulated, the tasks assume that you have a SAS® Viya® installation, and many (but not all) tools use analytical techniques that require a license for SAS® Visual Data Mining and Machine Learning software. However, if you do not currently have SAS Viya, you could still use the structure as an example of how to create a similar toolbox for yourself. Planning is underway to provide these tools and to make SAS Studio tasks callable from SAS® Data Management Studio to facilitate the data preparation task. In the meantime, we could provide interested users with the macros and tasks on an experimental basis; you can contact the authors by using the email address at the end of this paper.

TOOL AND TOOLBOX STRUCTURE

The tools are designed to work with an optional "subject" table (which will be massaged into the ABT when feature extraction is complete) and one or more "transactional" tables. If there is a subject table, there must be a single join field between the subject table (unique key required) and any transactional tables processed (secondary keys). Each transactional table contains an optional numeric variable, which can represent either quantities or ratings, and zero or more categorical variables, which are referred to as "item" variables. What these item variables are can vary according to the type of data being processed: for purchase data, the item variable might be a UPC code or department code; for internet data, it might be a domain name or page name; for genomic data gene assemblage, it might be a gene or protein, and so on. The current tools all assume unordered data, but in the future, we plan to include an ordering variable (such as a datetime indicator) to perform order-specific feature extraction. We also plan to provide the ability to have more than one variable that can link to the subject table; this feature could be useful for any kind of social network or other data in which the transactions connect to more than one subject.

The first tool in any pipeline is the Setup tool. This tool establishes all macro variables as global variables and sets their initial values. It sets up the initial transaction table and creates an initial subject table if one is not provided; if a subject table is provided, then the tool adds summary information to that table for the initial transaction table. The Setup tool is currently the only tool that can accept input data that are not stored in a CAS library—in which case the tool moves the data into a CAS library (using the same data set names) for further processing.

All other tools add to the pipeline that is originally created by this Setup tool. Each tool does the following:

1. Ensures that its requirements are met, in terms of the tools that precede it in the pipeline, and that the appropriate input data are present. If the requirements are not met, it returns an error.
2. Performs any processing that is restricted to training the tool that is not also done when new data are scored.
3. Saves any tables (such as an analytic store) that are needed for scoring to a permanent CAS library on disk.

4. Appends score code that the tool needs to the &_trans_scoring macro variable.
5. Calls the scoring macro associated with this tool, which does the following:
    a. If the macro is called at scoring time, loads any tables needed for scoring from the permanent disk-based CAS library to the active CAS library.
    b. For tools that create a new subject table, creates the name of the new subject table by appending a tool-specific letter to the current subject table name. Runs code to create the new subject table, and, if successful, updates the &_subject_table macro variable to correspond.
    c. For tools that create a new transaction table, creates the name of the new transaction table by appending a tool-specific letter to the current transaction table name. Applies code to create the new transaction table, and, if successful, updates the &_trans_data macro variable to correspond.
    d. Updates macro variables for the current target variable, if it has been transformed, and for character or numeric predictors.
6. For tools that create multiple new variables added to the subject table, calls a macro that takes a sample of the data, and projects all new variables down to a two-dimensional space that can then be shown in a plot visualization to users so they can visualize the effects of the new variables.

At any point in the list above, if the operation fails to complete successfully, the tool is aborted and a runtime error is generated. The order ensures that macro variables are not updated until after the operations complete that they reference.

The current list of tools is shown in Table 1, which displays the name of the tool, the name of the training macro for that task, the character corresponding to that tool's naming, which new tables are created, the requirements for that task, and the effects of running that tool.

Table 1. List of Tools

Tool Name	Training Macro	Char-acter	New Tables	Require-ments	Effects
Setup	%setup_trans	S	Subject	None	Sets macro variables, including initial score code; creates user-selected summary statistics for count or rating variables; calculates user-selected summary statistics for each subject ID, which is then joined to subject table if one is selected or used to create subject table if not; calculates frequency counts for each value of each item variable.
Reduce Levels	%reduce_levels_sup	T	Transaction	Setup	Collapses rarely occurring levels of item variables that have a similar effect on the target variable to more common levels, to reduce their cardinality.

MBAnal	%mbanal	M	Subject	Setup	Generates association rules for levels of item variables. If the item variables are in a taxonomy, uses that taxonomy in the rule creation. Each new rule created adds a new variable to the subject table.
Rollup Counts	%rollup_cnts	R	Subject	Setup	Creates new variables in the subject table for each item that is among the *k* most frequently occurring values that occur at least *i* times. The value of each variable is the frequency of that item weighted by any count variable.
Pseudodoc	%pseudodoc	D	Subject	Setup	Creates a pseudo-document text variable that contains space-separated strings for each value of each item variable across all transactions for that subject; also creates a string indicating the number of transactions for each subject ID. Optionally, each string can have the first *k* characters in the item variable's name prefixed to the string to distinguish the item variables from each other.
Parse Document	%parse_docs	P	Subject	Document variable	Parses _document_var. Parameters indicate whether it should be considered user text or pseudo-document text. Optionally creates *k* topic variables for each subject.
Predictive Rule Generation	%doc_boolrule	B	Subject	Parse document	Generates rules to predict target levels based on combinations of presence and absence of different items, or terms in the case of document text, from the documents. One variable is added to the subject table for each rule generated.
New Transaction	%new_trans	N	Subject	Setup	Sets up a new transaction table for the subject. This table must use the same join key as the original transaction table, and it replaces that key for consideration of all tools that use the transaction table.

As mentioned earlier, the tools in the pipeline, both during training and at deployment time, use global macro variables. That way, all the key information is included in the Setup tool and can be used by any other tool. Also, some of this information is modified by the tools so that subsequently used tools have the correct information based on transformations created by tools previously used in the pipeline. Table 2 displays a list of these macro variables, which tools set them and modify them, and what they are used for.

Table 2. List of Global Macro Variables

Macro Variable Name	Set by	Modified by	Description
&_subject_data	Setup	Cf. Table 1	Name of the current subject table
&_trans_data	Setup, New Transaction	Cf. Table 1	Name of the current transaction table
&_subject_id	Setup		Name of the key variable by which the subject and transaction tables are joined
&_trans_target_var	Setup		Name of the target variable to be used for modeling
&_target_type	Setup		Indicator of whether the target is nominal, binary, or interval
&_item_vars	Setup, New Transaction	Reduce Levels	List of item variables from the current transaction table. This is assumed to be ordered so that the top level of the hierarchy is listed first.
&_count_var	Setup, New Transaction		Name of a variable representing a positive or negative quantity of a given item in a given transaction
&_rating_var	Setup, New Transaction		Name of a variable corresponding to the rating of a given item in a given transaction
&_document_var	Setup, Pseudodoc		Name of the current document variable; required and used by Parse Document tool
&_step_cntr	Setup	Any that create stored data	Incremented each time a tool writes a stored table. This ensures that the stored table name does not interfere with another name from this pipeline.
&_parse_cntr	Setup	Parse	Incremented each time parsing is done so that the generated data (terms, etc.) do not interfere with other variables parsed
&_trans_cassess	Setup		Name of the CAS session
&_trans_caslib	Setup		Name of the default CAS library. All data from execution of pipeline during training and scoring are placed here.
&_store_lib	Setup		Name of the permanent disk-based CAS library that data sets needed for scoring are written to during training and loaded from during scoring

EXAMPLE USING VAERS DATA

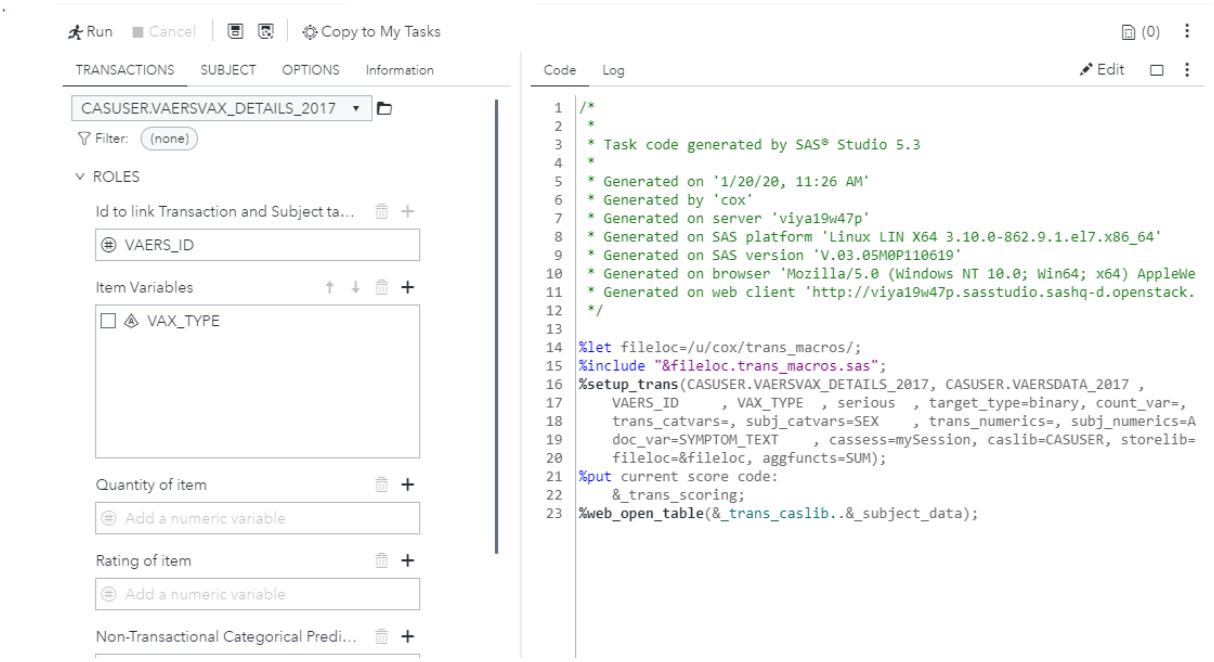
As mentioned, these tools can be used with a wide variety of data. In this section we walk you through an example, using the publicly available Vaccine Adverse Events Response System (VAERS) data for 2017.[4] These data contain some reports by users and other reports by clinics. The data consist of three tables for each year:

- VAERSDATA: contains demographic information for each adverse event reported and text that was used to describe the issue. Also contains a unique identifier, VAERS_ID.
- VAERSVAX: contains a row for each vaccination that each patient received, with a type (VAX_TYPE) and ID (VAERS_ID) to link to the VAERSDATA table.
- VAERSSYMPTOMS: contains a separate line for each symptom reported by the patient, using the MedDRA classification code. Also links to the subject table by using the VAERS_ID.

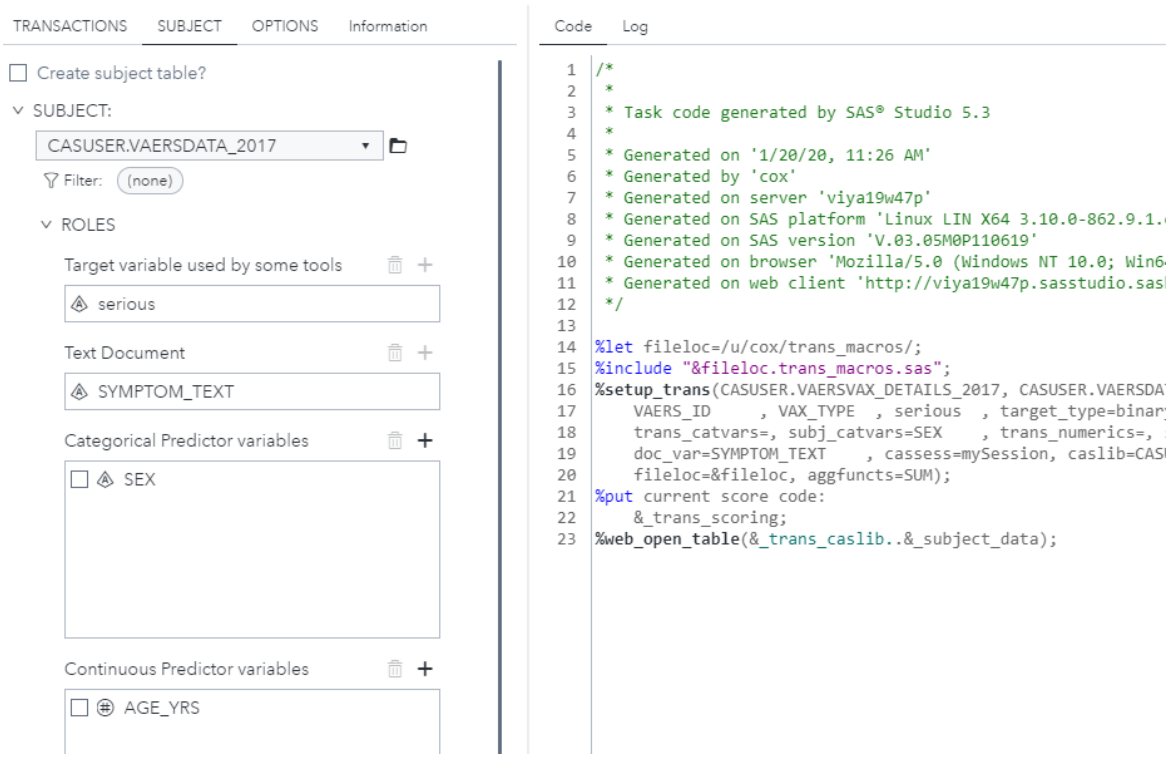
We use SAS Studio tasks to call some of the tools that were introduced earlier.

STEP 1: SET UP THE DATA

First, we use the Setup Data task as shown in Displays 1–2, initially using the vaccination data along with the VAERSDATA data, and then, as the target variable, using the information about whether the reported adverse event was serious.

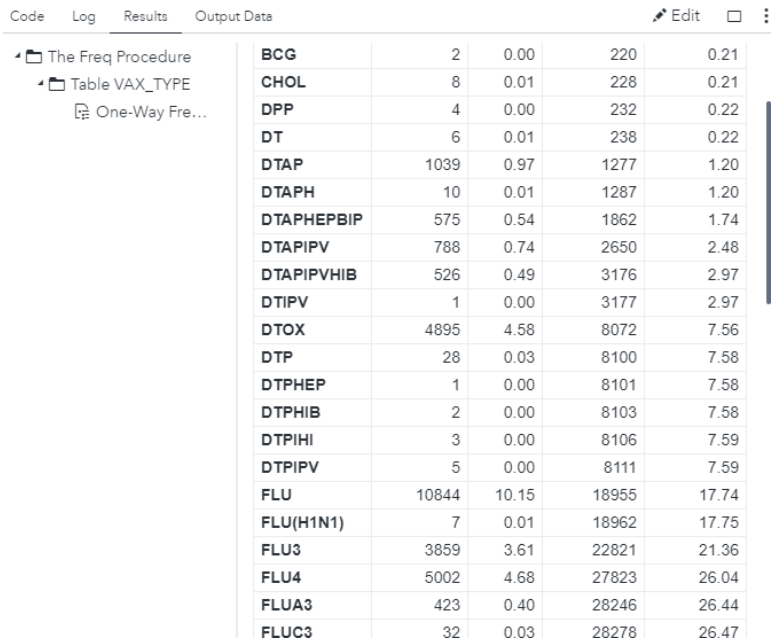


Display 1. Vaccination Details



Display 2. VAERS Data Subject File

The macro creates a frequency table of the vaccination types, as shown in Display 3. The table contains 82 values of varying frequency.



BCG	2	0.00	220	0.21
CHOL	8	0.01	228	0.21
DPP	4	0.00	232	0.22
DT	6	0.01	238	0.22
DTAP	1039	0.97	1277	1.20
DTAPH	10	0.01	1287	1.20
DTAPHEPBIP	575	0.54	1862	1.74
DTAPIPV	788	0.74	2650	2.48
DTAPIPVHIB	526	0.49	3176	2.97
DTIPV	1	0.00	3177	2.97
DTOX	4895	4.58	8072	7.56
DTP	28	0.03	8100	7.58
DTPHEP	1	0.00	8101	7.58
DTPHIB	2	0.00	8103	7.58
DTPIHI	3	0.00	8106	7.59
DTPIPV	5	0.00	8111	7.59
FLU	10844	10.15	18955	17.74
FLU(H1N1)	7	0.01	18962	17.75
FLU3	3859	3.61	22821	21.36
FLU4	5002	4.68	27823	26.04
FLUA3	423	0.40	28246	26.44
FLUC3	32	0.03	28278	26.47

Display 3. Vaccination Frequency Counts

STEP 2: ROLL UP COUNT FREQUENCIES

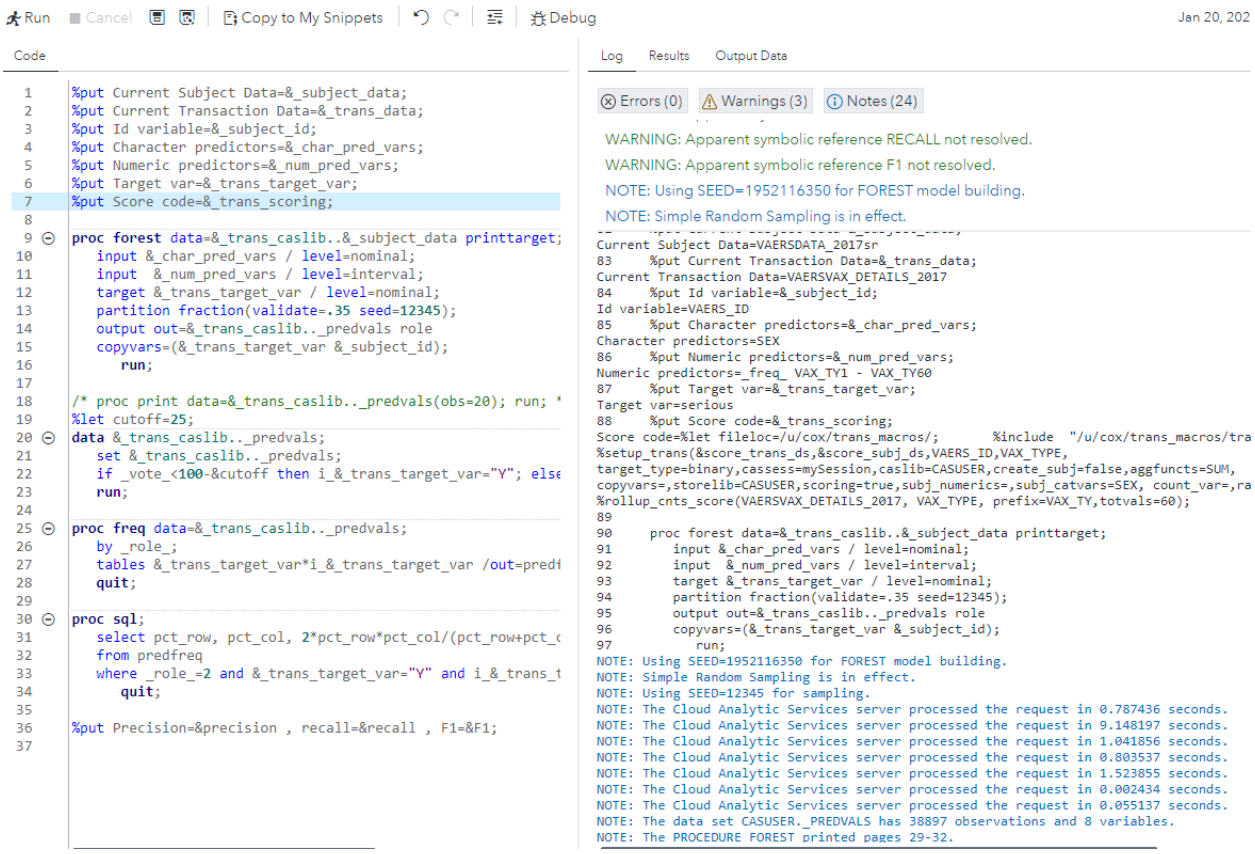
The toolkit gives you a number of different ways to extract features from transactional items. One of the most important questions to consider is the cardinality of the item variables. If there are many hundreds or thousands of values, you might want to perform a dimension reduction or use the Reduce Levels tool to compress the levels. In this case, however, with only 82 different values, there is no need to do that. Instead you can use the Rollup Counts tool. In Display 4, we create one variable in the subject table for each of the vaccinations that occur at least 10 times in the data (in this case, there are 60 variables created) and then generate a *t*-distributed stochastic neighbor embedding (t-SNE)[7] on a sample, plotting the result in a two-dimensional plot, colored by the target variable.

Display 4. Results of Using Rollup Counts Tool

From the plot, it appears that the serious event reports are clustered in the bottom left corner.

Notice how simple the task parameters are on the left. There is no need to enter a table name or any variable names. That is because the toolbox keeps track of all this information in its global macro variables, updating them as it goes along.

Now is a good time to look at how the model is affected by the variables in the main table, as well as by the new variables we have added. We could do this with a task for modeling, but the purpose of this paper is to show how to prepare the data to be modeled. So let's use a code snippet instead, as shown in Display 5.



Display 5. Forest Model from Results

First look at the code on the left side of the display. Here we print to the log the value of some of the macro variables discussed in the earlier section. In the log on the right, notice some of these values:

- The current subject table is named VAERSDATA_2017sr. Recall from Display 2 that this was originally named VAERSDATA_2017. We have run two tools since then, each of which added its respective character (cf. Table 1) to the data set name when creating the new tables.
- There is one character predictor variable at this point: SEX, from the original subject table.
- There are 62 numeric predictor variables: AGE_YRS (the patient's age); _FREQ_, which contains the number of vaccinations each patient received; and 60 variables, VAX_TY1–VAX_TY60, one for each of the vaccinations that occurred at least 10 times.
- The score code calls two macros here: %setup_trans() and %rollup_cnts_score(). You could copy and paste this code into a brand-new SAS session, and it would enable you to score new data without changes, as long as you set up two macro variables first: &score_trans_ds (for transaction data to be scored) and &score_subj_ds (for subject data to be scored).

Notice how easy it is to specify the syntax for PROC FOREST: this same code can and will be used many times in our example without the need for any changes, because it always uses the current target variable as well as the current character and numeric predictors. In this case, we have a rare target that occurs less than 5% of the time. Model performance

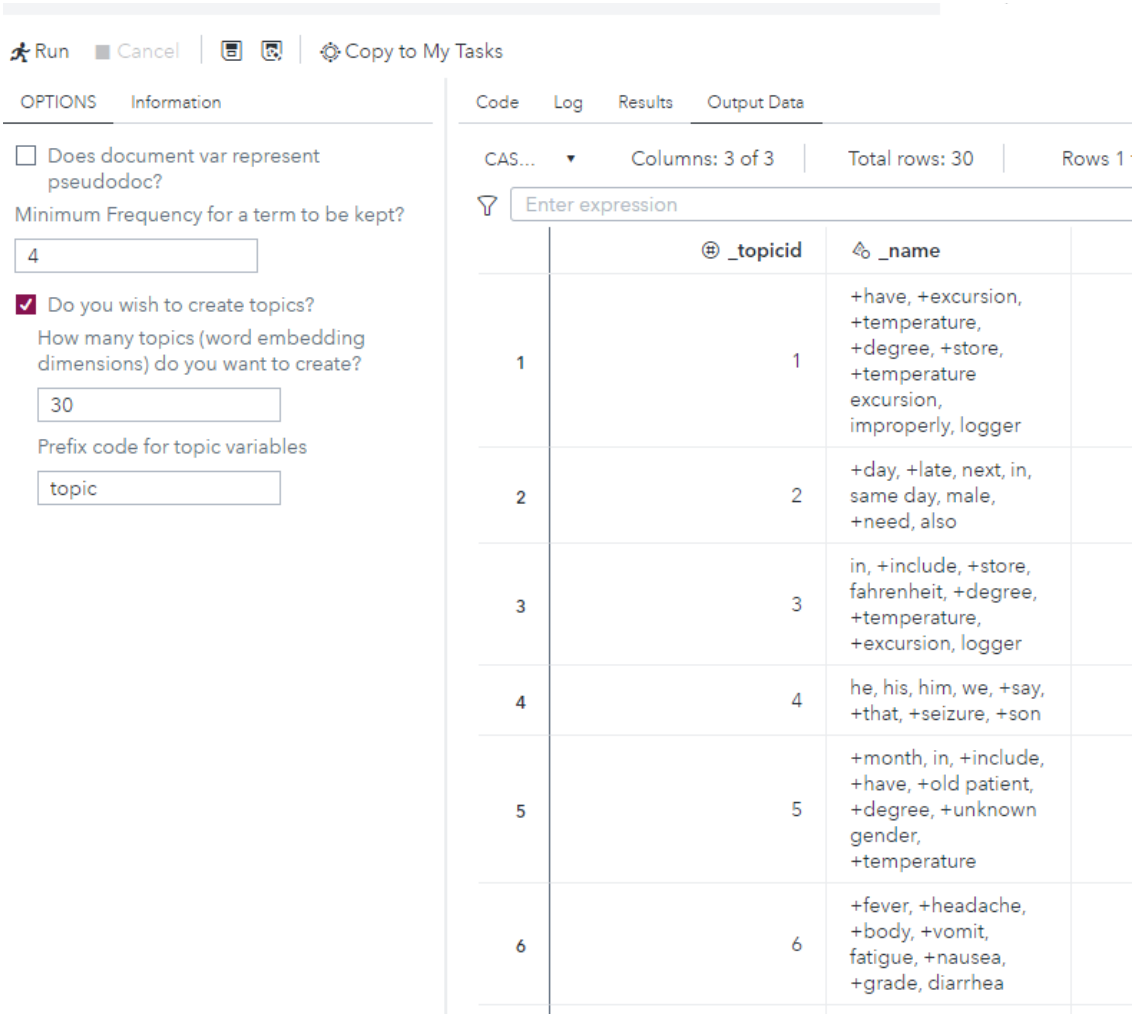
metrics such as the misclassification rate are not effective for problems with high class imbalance (rare targets).[6] Therefore, we have included code to calculate the precision, recall, and F1 statistic (the harmonic mean of the two) for the results of the forest model. We are setting the cutoff in this case to 25%, meaning that if the posterior probability for "serious" is greater than that, we assign the case as serious. We have also set a seed for generating the validation set, so that the same data are held out for validation every time this model is run.

When we run the code, we can see that, with these variables at least, there are no transactions in the validation set that are assigned as serious, so the F1 statistic is 0 (even though the misclassification rate is only 4.5%).

STEP 3: PARSE DOCUMENT AND GENERATE TOPICS

Note that, in Display 2, we chose a document variable, SYMPTOM_TEXT, that contains any text typed by the patient or clinic that reported the adverse event. Perhaps that variable can add some discriminative capability to the model.

To check this, we can use the Parse Document tool, as shown in Display 6.



Display 6. Results of Using Parse Document Tool

On the left side of the display, you see that we have chosen to create 50 topics, named (according to their prefix) topic1 to topic50. These topics will be added to the subject table. You can see, in the middle of the display, the key terms for some of the topics that are generated in this way.

We can then run the PROC FOREST code snippet again, to see how the added topics affect the results:

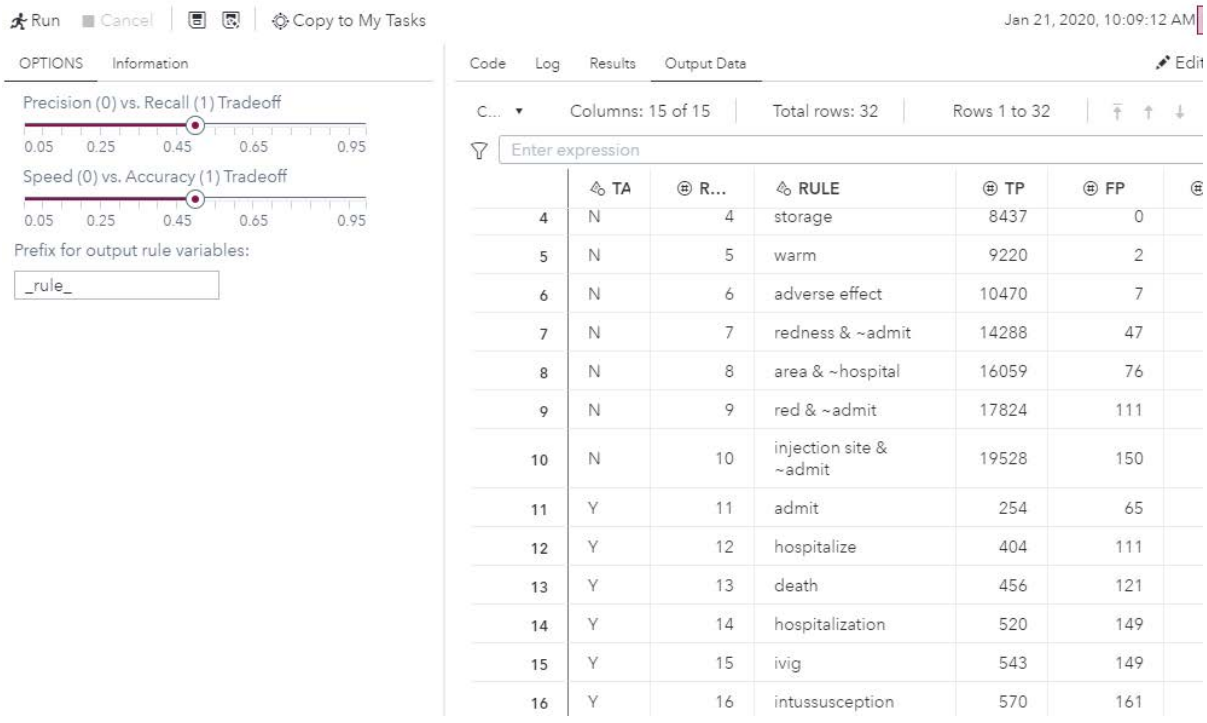
```
117    %put Precision=&precision , recall=&recall , F1=&F1;
Precision= 51.0989 , recall=30.69307 , F1=38.35052
```

Here, Precision is the percentage of adverse events that the model predicted as serious that were actually serious, Recall is the percentage of adverse events that were actually serious and were predicted as serious, and the F1 score is the harmonic mean of the two.[6]

We have now produced a much more useful model, one where topics dominate in importance (particularly topic 19) but one that also uses some information from vaccination type.

STEP 4: ADD RULES FROM TEXT TO PREDICT TARGET

Next, we use the Predictive Rule Generation tool to try to predict serious adverse events based on combinations of the presence and absence of particular terms in the symptom text. Here we set three parameters. Display 7 shows the resulting rules from the tools.

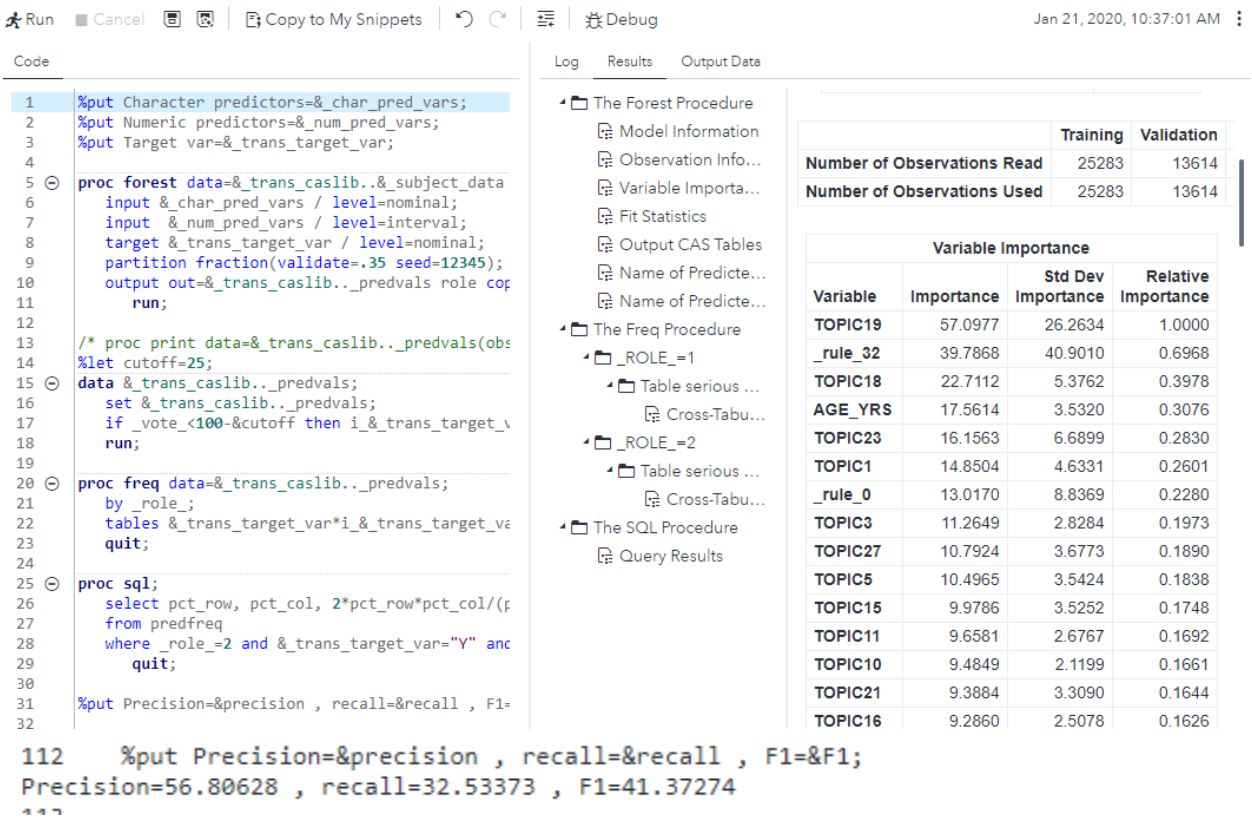


	TA	R...	RULE	TP	FP
4	N	4	storage	8437	0
5	N	5	warm	9220	2
6	N	6	adverse effect	10470	7
7	N	7	redness & ~admit	14288	47
8	N	8	area & ~hospital	16059	76
9	N	9	red & ~admit	17824	111
10	N	10	injection site & ~admit	19528	150
11	Y	11	admit	254	65
12	Y	12	hospitalize	404	111
13	Y	13	death	456	121
14	Y	14	hospitalization	520	149
15	Y	15	ivig	543	149
16	Y	16	intussusception	570	161

Display 7. Results of Using Predictive Rule Generation Tool

Notice that there are rules associated with both serious="Y" and serious="N" and that there are true positives (TP) and false positives (FP) associated with each one. A tilde (~) indicates the absence of that term.

Display 8 shows the results of running PROC FOREST after these steps.

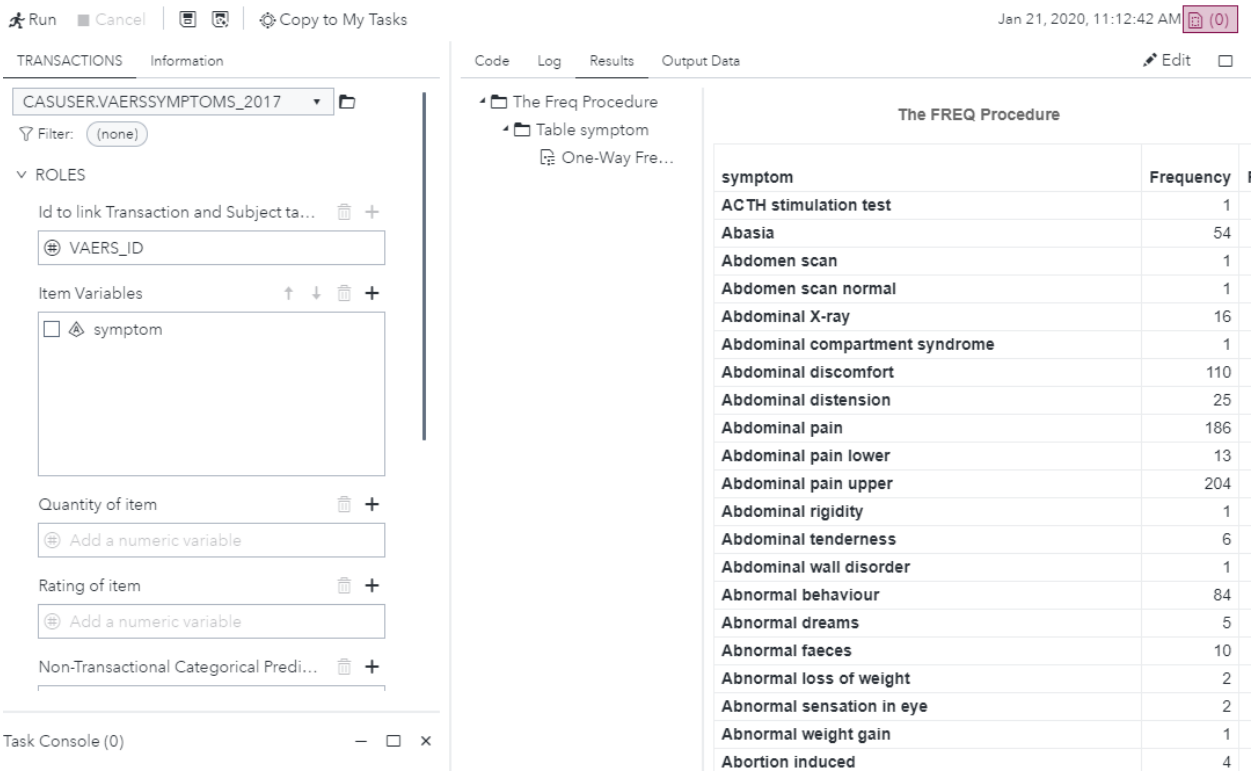


Display 8. PROC FOREST Results after Using Predictive Rule Generation Tool

You can see that adding rules does improve the model to some extent. Some topic variables, some rule variables, and AGE_YRS from the original table all contribute to improving the accuracy of the model.

STEP 4: SET UP TRANSACTION DATA FOR SYMPTOMS

Recall that there was another transaction table—in this case, a table that details the symptoms. It is now time to change focus from the vaccination table to the symptom table. To do this, we use the New Transaction tool as shown in Display 9.

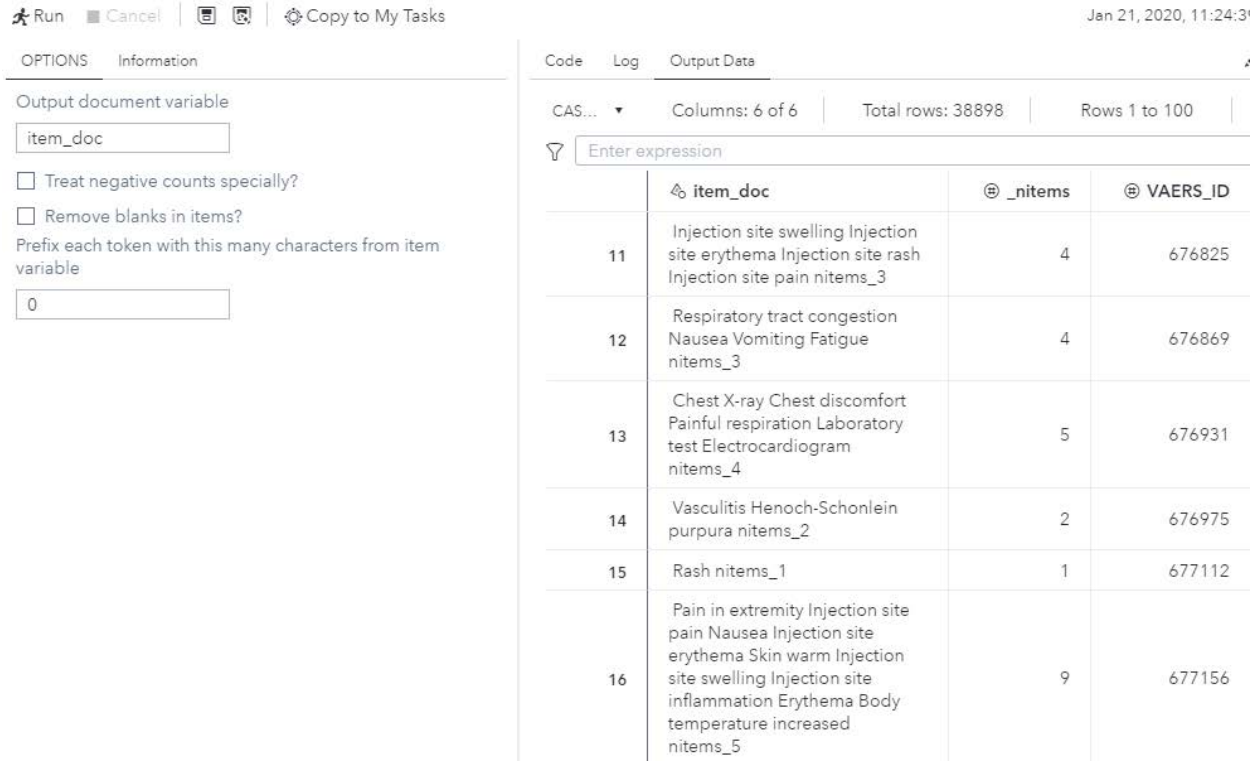


Display 9. Setting Up Symptom Transaction Table

In this case, there are thousands of unique values, many of which occur only once. We don't want to create *that* many new variables, because the high dimensionality can overwhelm whatever model we want to create.

One technique that is often used in this case is to collapse values into a smaller subset based on the relationship with the target variable, by using the Reduce Levels tool.[8] However, in this case, we have textual data that provide more information. See all the values beginning with "abdominal" in the table in Display 9? They all have to do with the abdomen.

In situations like this, creating a pseudo-document appears to be the best option. Then you can analyze all symptoms reported by each patient as text, in the same way that we analyzed the text document earlier. So we use the Pseudodoc tool as shown in Display 10.

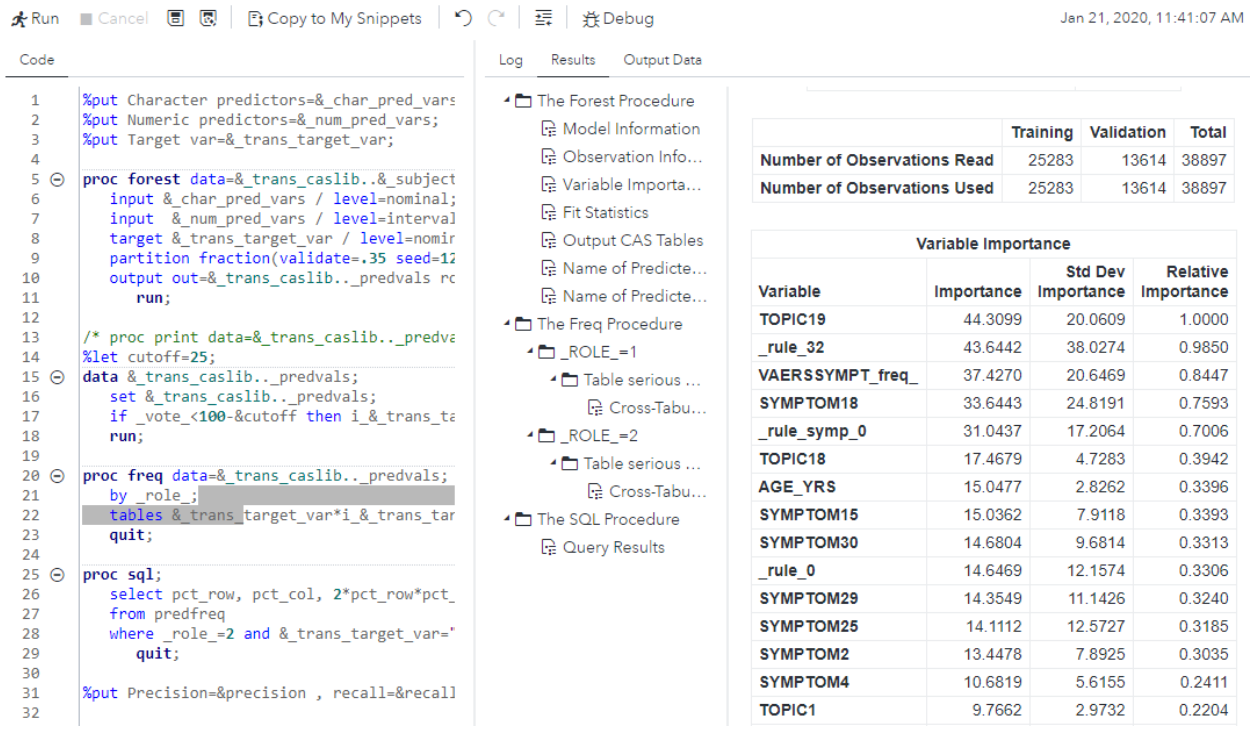


	item_doc	_nitems	VAERS_ID
11	Injection site swelling Injection site erythema Injection site rash Injection site pain nitems_3	4	676825
12	Respiratory tract congestion Nausea Vomiting Fatigue nitems_3	4	676869
13	Chest X-ray Chest discomfort Painful respiration Laboratory test Electrocardiogram nitems_4	5	676931
14	Vasculitis Henoch-Schonlein purpura nitems_2	2	676975
15	Rash nitems_1	1	677112
16	Pain in extremity Injection site pain Nausea Injection site erythema Skin warm Injection site swelling Injection site inflammation Erythema Body temperature increased nitems_5	9	677156

Display 10. Results of Using Pseudodoc Tool

This tool concatenates the strings for each reported symptom and adds a special term to indicate the total number of symptoms reported for that patient.

We can now analyze the pseudo-document that was created in the same way that we created the symptom text earlier, by running the Parse Document and Predictive Rule Generation tools, and then running PROC FOREST on the result. Display 11 shows the results.



Display 11. Results of Running PROC FOREST after Parsing Symptom Document

Notice that the model is improved dramatically with the symptom table, and the important variables come from all of our sources: in this case, symptom<i> is a symptom topic, and _rule_symp_ is a symptom-based rule. Vaersympt_freq_ represents the number of symptoms reported.

Output 1 shows the score code generated for all the tools run in the sequence described.

```
%include  "/u/cox/trans_macros/trans_macros.sas";
%setup_trans(&score_trans_ds,&score_subj_ds,VAERS_ID,VAX_TYPE,
       target_type=binary,cassess=mySession,caslib=CASUSER,create_subj=false,
      aggfuncts=SUM,copyvars=,storelib=CASUSER,scoring=true,
      subj_numerics=AGE_YRS,subj_catvars=SEX,
      count_var=,rating_var=,trans_numerics=,trans_catvars=);

%rollup_cnts_score(VAERSVAX_DETAILS_2017, VAX_TYPE,prefix=VAX_TY,totvals=60);

%score_parse("_textstate_1",1,document=SYMPTOM_TEXT,ntopics=30,prefix=topic);
%score_doc_boolrule(_rules_3,_ruleterms_3,prefix=_rule_) ;

%let score_trans_ds=&score_trans_ds2;
%new_trans(&score_trans_ds,VAERS_ID,symptom,trans_numerics=,trans_catvars=,
       scoring=true,count_var=,rating_var=,aggfuncts=);
%pseudodoc_score(symptom,doc_var=item_doc,prefix_chars=0,doclen=32000,
       neg=0,compress_items=0);
%score_parse("_textstate_3",2,document=item_doc,ntopics=30,prefix=symptom) ;
%score_doc_boolrule(_rules_5,_ruleterms_5,prefix=_rule_symp_) ;
```

Output 1. Score Code for Entire Model

Note the following from the score code in Output 1:

- The %include file contains all the macro definitions (or has %include statements to separate files for each one).
- There is one scoring macro call for each tool in the pipeline.
- The score code references the subject table to be scored as &score_subj_ds and the two transaction tables as &score_trans_ds and &score_trans_ds2.

You could put this code in any production system to reproduce the results on any new data, assuming that you set &score_subj_ds, &score_trans_ds, and &score_trans_ds2 ahead of that code.

CONCLUSION

This paper presents a toolbox that we have been developing for transactional data and shows how to apply it to some real-world sample data. Note that this toolbox is extensible and modular, with an easy API that you can use to create more tools. Each tool consists of a SAS Studio task and two SAS macros: one for training and another one for scoring. The tools communicate with each other, both at training time and at scoring time, via SAS macro variables.

We plan to make this toolbox available in a future version of SAS® Data Management Studio, but in the meantime, we want to expand the list of available tools to handle other kinds of transactional data—sequence data, social network data, and so on. But even with the current toolbox, you can perform many types of feature extraction to prepare your data for modeling. We hope this toolbox helps you analyze your data in a far easier fashion than you have done previously.

REFERENCES

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