**SAS gets talents to use.**

One of the many talents is knowing the details of every algorithm and understand the interconnections of various statistical model. No methodologies are built out of nowhere, but instead, they are continuous intellectual development built upon existing knowledge. For example, GLM is a natural extension of LM and employs an iterative algorithm that is based on OLS to find the solutions.

SAS provides a wide array of classic statistical models for SAS analysts, but still can’t keep up with the ever-increasing speed of progress in Statistics. In many cases, however, smart SAS analysts can leverage the relationship between methodologies implemented in SAS and those outside the scope of SAS/STAT for their own good.

We can use several examples to demonstrate this point.

Example 1. SVD is at the core of modern regression analysis and predictive modeling. Unless SAS/IML is licensed, there thought to be no way to conduct SVD within SAS. However, for analysts without access to IML, there is a way to work around by understanding the connection between SVD and PCA which can be solved using PROC PRINCOMP. By Eckart-Young theorem [7], any matrix of n-by-m X can be factorized as:

X=USV’

Where U, and V are unitary matrix of size n-by-n and m-by-m, respectively, and S is a diagonal matrix of size n-by-m. This is the Singular Value Decomposition and it serves as the computing vehicle for Principal Component Analysis, where we apply SVD on symmetric X’X instead of X. In such case, the factorization becomes:

X’X=VSV’

On the other hand, given X, S, V’, it is straightforward to obtain matrix U as:

U=XVS-1

This is exactly the idea implemented in the SVD macro shown at [1].

Example 2. To obtain the inverse matrix of a given matrix, how can SAS analyst do it in SAS/STAT? They can use PROC REG on an expanded matrix or use ODS InvXPX= if using SAS 9.2 or above. On the other hand, if the analyst understands the connection between Eigen value decomposition and matrix inversion, SVD can be utilized to obtain very high precision pseudo inverse of a given matrix. See [2] for details.

Example 3. If a L2-regularized logistic regression is desired, a good SAS programmer is able to work it out by understand that the computation details behind a Logistic regression is IRLS and he should be able to program such algorithm in SAS. What the SAS analyst can do is implement IRLS using PROC REG with RIDGE= option. Of course, when a penalized regression is used, one of the major objectives is to obtain a more parsimonious model based on some good-of-fitness measures, and one commonly used is Generalized Cross Validation (GCV), which can also be readily implemented in SAS [3].

Example 4. ElsaticNet is a very flexible regularized regression that is able to handle large number of predictors and stand in between of ridge regression and LASSO. It is proven to be powerful in data mining competitions [4] when used appropriately. While this algorithm is not readily available, it is not difficult to program in SAS. Of course, a SAS programmer should not directly follow the conjugate gradient algorithm outlined in the paper [5], [6], but instead, should use their so called naïve algorithm which turns out to be useful when the ElasticNet algorithm is extended to GLM. In fact, only a little bit data manipulation is needed to replicate the result from the original ElasticNet paper using naïve algorithm, as shown in the Appendix.

All being said, SAS still has a lot to give. For many statistical analyses that need customization, linear algebra computation that are built in SAS/BASE and callable from within PROC are highly desired. While this is not readily available yet, highly talent SAS analysts can program these computational routines using PROC FCMP, which deserves a separate article for further discussion.

**Reference:**

[1] <http://www.sas-programming.com/2010/03/macro-for-svd.html>

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[3] <http://www.sas-programming.com/2011/10/obtain-trace-of-projection-matrix-in.html>

[4] <http://www.kaggle.com/c/overfitting/forums/t/542/variable-selection-routine>

[5] H Zou and T Hastie (2005), "*Regularization and Variable Selection via the Elastic Net*", JRSS, Series B, vol.67, Part 2, pp301-320

[6] J Friedman, T Hastie and R Tibshirani (2010); “*Regularization Paths for Generalized Linear Models via Coordinate Descent*”, Journal of Statistical Software, vol.33 (1)

[7] C Eckart, G Young (1936); "*The approximation of one matrix by another of lower rank*". Psychometrika (3): 211–8

**Appendix:**



