Using Artificial Neural Networks in the *stop squark* Search

R. Brockman, J. DeVito, and R. LeVan

Department of Electrical Engineering
Rice University

Spring 2013

Outline

Introduction

Overall Plan

From a large data set we try to separate a signal from a specific type of noise.

- Signal := *stop squark* event
- Noise := top quark background event
- Use SOM and Back-prop as filters

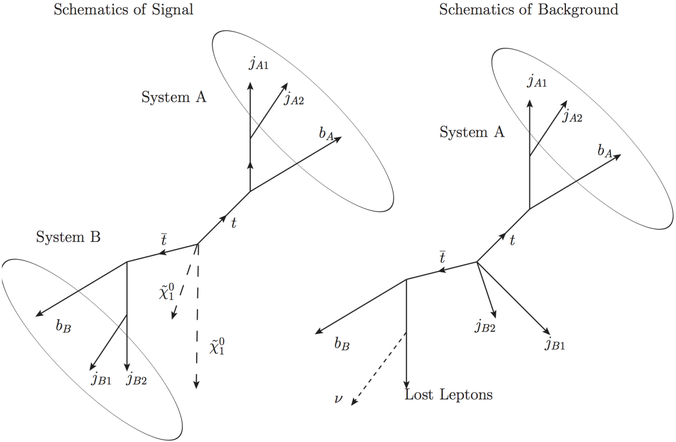
Purpose

- Search for the *stop squark*, predicted by SUSY
- Guided by Dr. Paul Padley of Bonner Lab
- Simulated data generated by PYTHIA

Aim

Improve on the results in the paper by Dutta, et al. [1], working in parallel with Onkur Sen, who is attacking the same problem using boosted decision trees.

What is a *stop squark* Event?



[1]

Classification Basics

From the simulated data, with the help of Onkur's code, we were able to create:

- a length 24 vector of raw data for each signal or background event
- a length 8 vector of derived variables from the raw data [1]

Previously attempted strategy:

- Thresholds on derived variables as outlined in Dutta, et al. [1]

Significance: A Filter Comparison Metric

- A measure of discovery confidence based on a certain number of high energy particle collisions

$$\text{significance} = \frac{N_{\text{Signal}}}{\sqrt{N_{\text{Background}}}}$$

N_{Signal} := number of signal events that come through the filter
$N_{\text{Background}}$:= number of noise events that come through the filter

- Used commonly in physics
- Every significance measure in the Results Section is based on a standard number of collisions

Back-Propagation Filter Settings

ARCHITECTURE	
Topology	$(8 + 1_{Bias})$ - $(30 + 1_{Bias})$ - 2_{output}
Transfer Function	tanh with slope $b = 1$
LEARNING PARAMETERS	
Initial weights	$w \sim U[-0.1, 0.1]$
Learning rate, $\gamma(t)$	$\gamma(t) = 0.01(1 - 0.0001)^t$
Momentum, α	$\alpha = 0.3$
Epoch size	$K = 1$
Stopping criteria	learning step > 100,000
Error measure (Err)	RMSE
Monitoring frequency (m)	1,000 Learning Steps
INPUT/OUTPUT SCALING	
Input Scaling	(-0.9,0.9)
Output Scaling	(-0.9,0.9)
PERFORMANCE EVALUATION	
Accuracy measure (Acc_X)	Significance = $\frac{S}{\sqrt{B}}$

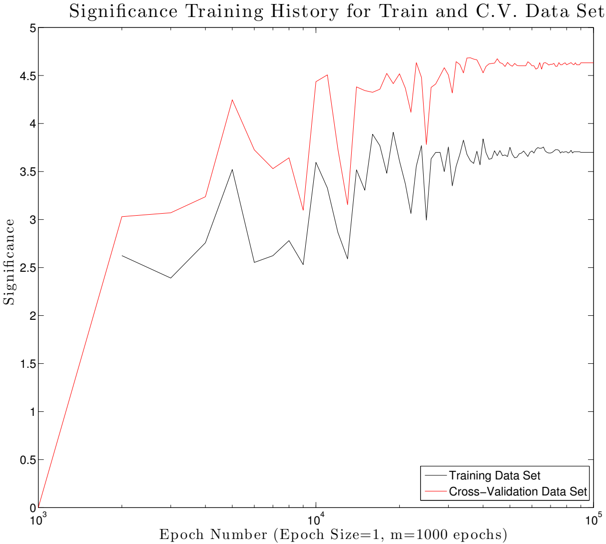
RICE

Self-Organizing Map Filter Settings

ARCHITECTURE	
Topology	10 x 10
LEARNING PARAMETERS	
Initial weights	$w \sim U[-0.1, 0.1]$
Learning rate, $\gamma(t)$	$\gamma(t) = 0.3(1-0.00001)^t$
Neighborhood, $\sigma(t)$	$\sigma(t) = 1.5 + 3.5\,(1-0.00001)^t$
Epoch size	$K = 1$
Stopping criteria	learning step > 750,000
Monitoring frequency (m)	1,000 Learning Steps
INPUT/OUTPUT SCALING	
Input Scaling	Angles in Degrees, Otherwise None
Output Scaling	None
PERFORMANCE EVALUATION	
Accuracy measure (Acc_X)	Significance = $\frac{S}{\sqrt{B}}$

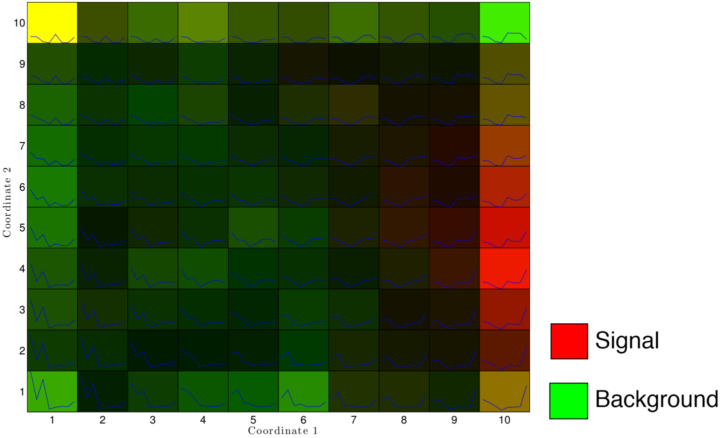
RICE

Back-Propagation Results for Derived Variables

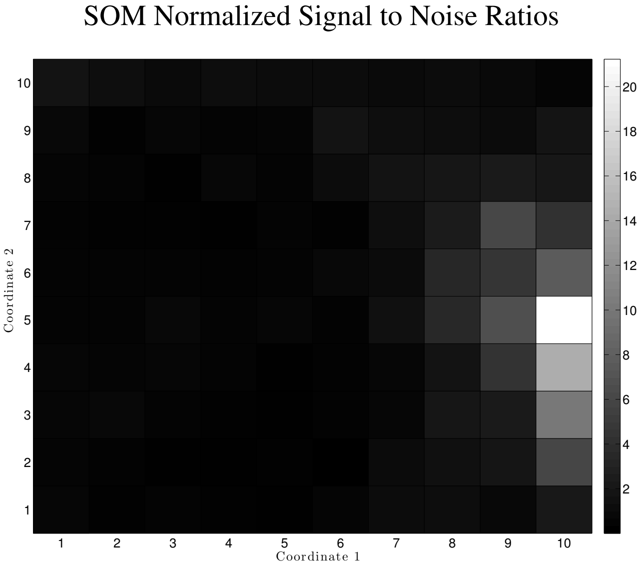


SOM for Derived Variables

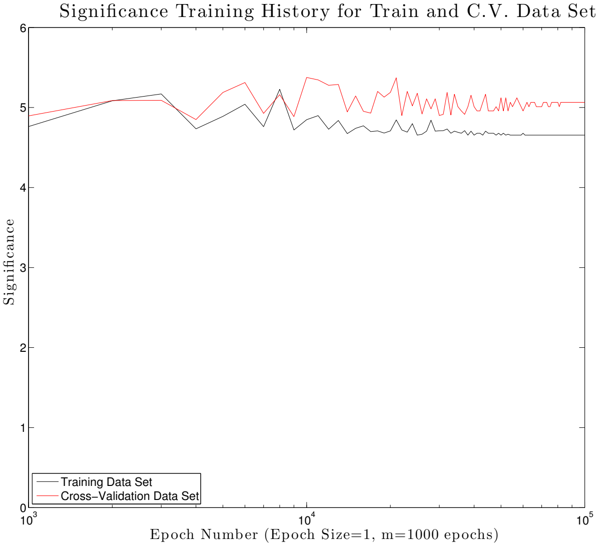
SOM Signal and Noise Density plots with weights



SOM for Derived Variables

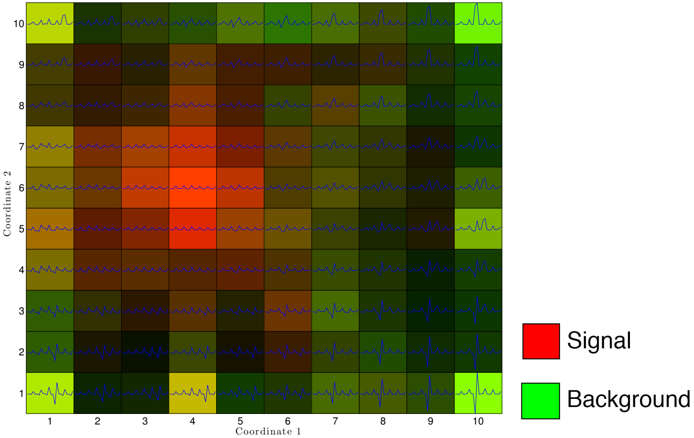


SOM followed by BP for Derived Variables

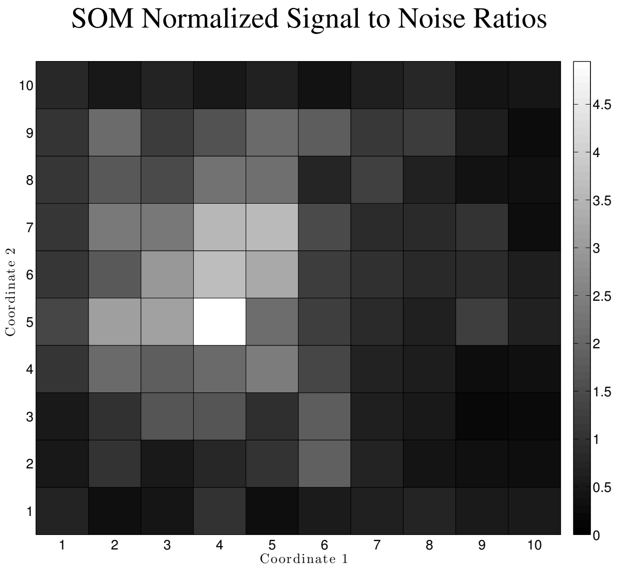


SOM on Raw Data

SOM Signal and Noise Density plots with weights



SOM on Raw Data



Significance Analysis

Method	Test Set Significance
Thresholding [1]	1.93σ
No Filter	2.62σ
Back-Propagation	3.79σ
Self-Organizing Map for Derived Variables	3.69σ
SOM then Back-Propagation	4.36σ
Self-Organizing Map for Raw Data	2.62σ

Analysis

- Back-Propagation and the SOM using the 8 derived variables produced interesting results
- The SOM using 24 raw variables did not
- The two-stage SOM and BP process was slightly superior to either method alone
- We suspect the success of the 8 derived variables is due to the jet angle invariance of these parameters

Next Steps

- Determine a method of aligning the 24 non-derived variables
- Further Experimentation with Training Parameters
- Run a second SOM on the SOM cells with high signal to noise ratios

References

[1] B. Dutta, T. Kamon, N. Kolev, K. Sinha, and K. Wang, "Searching for top squarks at the lhc in fully hadronic final state," *High Energy Physics - Phenomenology*, 2012.