Anomaly Detection and Forecasting for Malfunctioning Radiation Portal Monitors

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Introduction

- Over 1400 Radiation Portal Monitors (RPMs) used at borders, ports, entrances to weapons facilities, nuclear plants, etc.
- RPM maintenance and calibration is critical to national security and efficient port operations
- Current maintenance strategies unable to forecast when an RPM may malfunction in future
- Currently need to call in a separate organization to test the RPMs: difficult to quantify RPM fleet health from maintenance records

Objectives

Successfully detect and forecast malfunctioning Radiation Portal Monitors

- Develop a method that uses output data from RPMs to detect when one is malfunctioning
- Be able to forecast when an RPM may begin malfunctioning in the future

Data

- Two years of RPM data
- Background gamma counts for 4 Radiation Sensing Panels (RSPs)
- Error counts for 14 possible error codes
- Featurized with moving averages, standard deviations and sums
- 95 possible features

Classification

- All 14 errors classified with 8 different models
- ROC curves used to determine:
  - Which errors were predicted best
  - Which models had best prediction accuracy

ROC Curves show Random Forest is Best Classifier

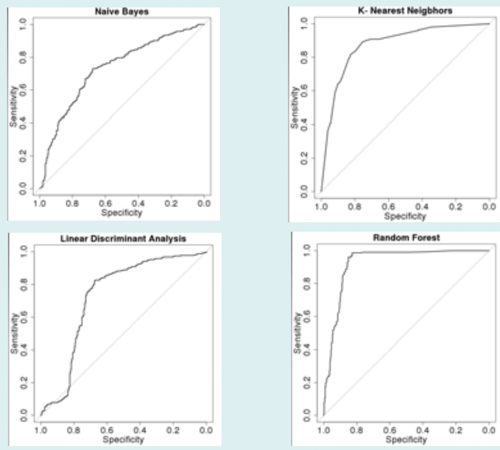

Fig.1: ROC curves for Push Socket Error classifiers

Error	OOB Error	Test Set Error	TPR	FPR
DataCom	4.20%	3.98%	0.98	0.06
Push Socket	10.47%	9.15%	0.96	0.13
VPS	10.09%	15.41%	0.28	0.02
Other	15.60%	19.51%	.028	0.03

Figure. 2: Random Forest Results for Most Common Errors

- Each observation receives a score vector with the probability of each error happening from the classifiers

	DCCC.Test.1	PSE.Test.1	Other.Test.1	VPS.Test.1
1	0.620	0.534	0.606	0.538
2	0.638	0.588	0.630	0.550
3	0.402	0.322	0.332	0.350
4	0.604	0.522	0.588	0.532
5	0.596	0.504	0.598	0.528
6	0.604	0.482	0.560	0.520

Figure 3: A few of the 4-score vectors

Kernel Density Estimation

- Preliminary 2 Dimensional KDE shows definite anomalous observations

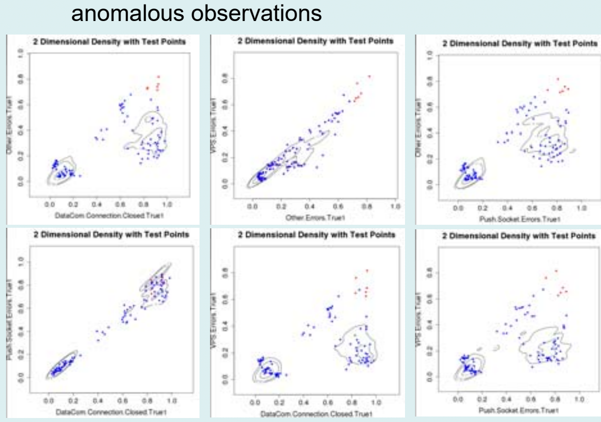

Figure 4: 2D KDE for 1 set of Train/Test observations, red points are observations later flagged as potential anomalies

KDE Continued

- 4 dimensional KDE for all errors
- Output for each observation is probability of score vector under KDE
- Observation probabilities > 2 standard deviations from mean probability were flagged as potential anomalies

Results

- 29/752 observations flagged
- 9 RPMs represented
- Same time frame (May 2015 – August 2015)
- Low gamma counts, high error amounts

Raw Data Shows Flagged Points Highly Different from Median Observations

	RSP 3 (min:2882) (med: 3898)	DataCom (med:2)	Push Socket (med:0)	VPS (Med:0)	All Others (Med:0)
#1	3184	5	1	13	13
#2	3162	5	3	9	13*
#3	3110	5	4	7	8
#4	3113	4	3	7	7
#5	3187	8	2	4	6*
#6	2900	9	3	14	2,365*

Figure 6: The 6 top anomalous points raw data compared to median of all observations (median is in parentheses)
* Some of the errors were highly unusual, rare errors

Future Work

- Test the accuracy/ success of the anomaly detector on known malfunctions
- Incorporate more RPM data
- Use different featurizations
- Add other error scores into one combined score vector

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