## Comparison of Malware Detection Technique of HMM, PCA, and MLP

#### **Abstract**

In this project, we used different machine learning techniques to train on some Malware files to gain models. Then, we used the models to score on the Malware files and benign files to gain some scores. Using these scores, we then did some analysis and comparisons.

Specifically, we used two features of Malware files. One is sequence of the Opcode, another is the frequency of the registers. In the HMM process, we used Opcode to train and score. In then PCA process, we trained and scored on the frequencies of the registers. Then, we calculate the True Positive Rate (TPR), False Positive Rate (FPR) to obtain ROC curve and PR curve. Basing on the curves, we found the thresholds and train the multilayer perceptron to classify the malware and benign files on the HMM scores and PCA scores. At the end, we concluded that PCA technique with frequencies of the registers had a effective way to detect Malware while HMM didn't show an ideal accuracy on the detection. In addition, with an accurate threshold, the MLP can yield a better classification.

### 1. Introduction

Signature detection to malware is simplest and lowest-cost technology. When it detect on some simple malware, it yields a low FPR. However, the viruses we might experience now are no more simple. They already evolved to some metamorphic viruses. At this point, signature detection has no longer advantages. Meanwhile, some machine learning techniques will yield a better result than signature because those techniques can make computer become smarter. Basing on the data we offer, those techniques can train a model to identify the other data belonging to the same or close kind of data that we offered. Informally, the machines can learn the important information from the Malware features and use that information to help us classify the Malware and benign files.

#### 2. Methods

#### 2.1 Cross Validation

We used 5 cross validation to train and score the data sets. First we asked Professor Fabio to get the Malware files. We choose 5 families and 5 files for each Family. We also downloaded 10 benign files as our test set. In each fold, we chose 20 Malware files from those 5 families to train a model, then used the model to score on the rest 5 Malware files and those 10 benign files. That is, in each fold, we obtained 5 Malware scores and 10 benign scores. After 5 folds, we got 25 Malware scores and 50 benign scores. Then, we calculate the average scores with the 50 benign scores since they were repeated.

For every Malware files, we released it in virtual box, and extracted the ASM file. Then using program to read the Opcode sequence and count the register frequency. For convenience, we rename all the Malware files as "family name+ number".

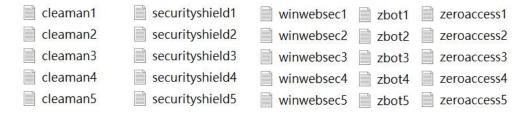


Figure 1: name of Malware files

ChromeSetup.asm
devenv.asm
GrammarlySetup.asm
idealU-2019.2.4.asm
LockDownBrowser-2-0-4-05.asm
ScoringHMM.asm
setup (nxt-g installer v2.0f6 (windows)).asm
VirtualBox-6.0.14-133895-Win.asm
webexapp.asm
WPSOffice\_11.2.0.8942.asm

Figure 2: name of benign files

### 2.2 HMM with Opcode Sequence

In HMM, we used forward and backward algorithm to get the probability at time t while the observation is  $O_t$  and the state is  $q_i$ . We also used Baum-Welch algorithm to

re-estimate the model. In our project, we use 200 iterations for each re-estimate. And we used 2 hidden states, 54 observations and 100 random restart. Then, we use forward algorithm to score on the test set. The normalizing Log probability represented the score.

### 2.3 PCA with Register Frequency

In PCA, we used 16 registers frequency as our measurements/features, used 20 Malware files as our experiments. So, we constructed a 16\*20 matrix called B matrix. Then, we subtract the mean for each row to get A matrix. We used inner product to produce the covariance matrix and calculate the eigenvalue and eigenvector space called U. Then, we discarded the less significant eigenvector with small eigenvalue. We projected the A matrix onto U to gain scored matrix. Finally, we projected the test vector on to U and calculate the Euclidean Distance between the result and each column of the score matrix. The smallest distance was the preferred score.

## 2.4 Analysis with TPR, FPR, ROC and PR

In this process, our main goal was determining the threshold where we can classify

Malware and benign with better accuracy and sensitivity. Therefore, we made the ROC and

PR graph on both HMM and PCA scores.

### 2.5 MLP with HMM and PCA Scores

We then use threshold we just determined from last step to choose samples as the MLP training samples. Then we scored on all the samples to to classify them as 1 or 0. We use these classification to calculate the accuracy.

In this process, we used  $f(s,t) = \frac{1}{1 + e^{-(s+t)}}$  and g(s,t) = s + t to construct the layers.

We also tried single layer with  $f(s,t) = \frac{1}{1 + e^{-(s+t)}}$  to make a single layer perceptron.

#### 3. Result

## 3.1 HMM result and Analysis

After we trained on the 1<sup>st</sup> fold, it yielded a  $\pi$ , A, and B matrix as figures 3. We did see some Opcodes have near 0 probability on the side of B matrix, such as js, jns, jl, rep, and so on. That means these Opcodes barely show up in one of those two states.

```
best model with prolog -93166 is model 18
The pi, A and B matrix of best model:
       0
(0.866655 0.133345
(0.0490685 0.950932
```

0.00870597

test

```
shr
                                                             42834e-105
                                                                             0.0153761
jz
              0.00521027
                               0.0127871
                                             sbb
                                                             0.00373602
                                                                             0.0175713
                               0.0128817
jnz
              0.00745044
                                             sub
                                                              0.0196318
                                                                             0.0454428
              0.00113982
                               0.0026911
jb
                                             xor
                                                               0.020391
                                                                             0.0964526
              0.00062026
jnb
                              0.00472038
                                             pusha
                                                           0.000945583
                                                                           4. 08315e-05
                             0.000282779
                        0
             0.000164301
                             8. 09242e-05
                                             dec
                                                            0.00223115
                                                                            0.00465775
jns
                 0.001456
                              0.00275148
                                                            0.00670232
                                                                             0.0288866
                                             and
ja
                0.0035184
                             0.000613931
                                             fidiv
                                                           9.60485e-05
                                                                          2. 32422e-136
jg
                             0.000197598
              0.00311292
                                             not
                                                           0.000385215
                                                                            0.00611473
jge
jbe
              0.00576881
                             0.000704778
                                                           0.000524908
                                                                            0.00277601
                                             neg
                0.0031696
                             5.62043e-71
                                                           8.46686e-05
                                                                            0.00834618
                                             imul
               0.00363948
jle
                             0.000569372
                                                           0.000480243
                                                                          2.36399e-263
                                             movsb
             9.60485e-05
                            1.61353e-206
jnp
                                                          (7. 23816e-155
                                                                           7.06949e-05
                                             1oop
                0.0215756
                               0.0403798
jmp
                                                           0.000105314
                                                                           3. 19374e-05
                                             std
               0.00758783
                             2.62595e-96
rep
                                                            0.00266837
                                                                             0.0431669
                                             cmp
                 0.146049
                                0.455149
nov
                                                                             0.0176384
                                                              1.044e-08
                                             MOVZX
                 0.068666
                             0.000392012
pop
                                                            0.00557081
                                                                          7.76034e-229
                                             start
                 0.043785
                               0.0466634
add
                                                         (7. 26614e-175
                                                                           0.000106042
                                             popf
                0.0300552
retn
                             0.000497791
                                                           0.000347475
                                                                           0.000649767
                                             retf
                 0.391494
                             3.59671e-23
push
                                                           9.36913e-05
                                                                            0.00173289
                                             sar
             9.60485e-05
                            1.36043e-251
rcl
                                                            0.00144432
                                                                           0.000493542
                                             xchg
call.
                 0.120407
                                0.010618
                                                           0.000192097
                                                                           3.85643e-43
                                             aam
             0.000864437
                             1. 25497e-33
popa
lea
                0.0397963
                               0.0109105
div
             0.000310892
                              0.00681368
             0.000381809
                              0.00010692
cld
              0.00527914
adc
                               0.0194777
sh1
              0.00420063
                               0.0153855
            (1.88982e-209
                              0.00014139
ror
              0.00193407
                              0.00766557
inc
              0.00783356
                               0.0553343
or
                              0.00262839
```

Figure 3: HMM model of 1st fold

After we trained and score for 5 folds, we obtained the scores for 25 Malware and benign Opcodes as figure 4 and figure 5 shown below.

HMM on Opcode
-2.022
-2.020
-2.010
-2.014
-2.174
-2.929
-2.780
-2.684
-2.740
-2.595
-2.695
-2.742
-2.665
-2.677
-2.233
-2.938
-2.072
-2.840
-2.952
-2.744
-2.364
-2.375
-2.376
-2.302
-2.411

	HMM on Opcode
ChromeSetup	-2.924
Devenv	-2.702
GrammarlySetup	-2.837
IdeaIU	-2.724
LockDownBrowser	-2.861
ScoringHMM	-2.446
Setup (nxt-g installer v2.0f6 (windows))	-2.536
VirtualBox-6.0.14-133895-Win	-3.036
Webexapp	-2.279
WPSOffice	-2.718

Figure 5: HMM scores of benign Opcodes

Figure 4: HMM scores of Malware Opcodes

For the Malware from Cleaman and Zeroaccess family, the scores are generally lower than the scores of the benign files, but most of the scores from Securityshield and Zbot are pretty close to the scores of the benign. These two figures show us using HMM on Securityshield, Zbot and even Winwebsec is not so ideal. However, we had an assumption that the benign files we downloaded might show the function as a malware in some ways. That might explain why the scores don't much separation.

Now, we drew the scores on the graph with circles meaning malware scores and triangle meaning benign scores.

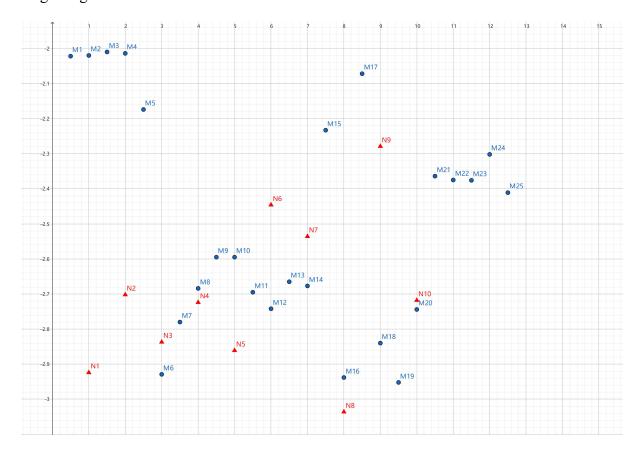


Figure 6: HMM scores of Malware and Benign

From this figure, we can see that , most of the Malware points are mixing with benign points, except Cleaman1~Cleaman5 (M1~M5) and Zeroaccess1~Zeroaccess5 (M21~M25).

Then, we drew the ROC curve and PR curve as figure 7 and 8 to see if there was a threshold that can help us to yield a better accuracy and sensitivity.

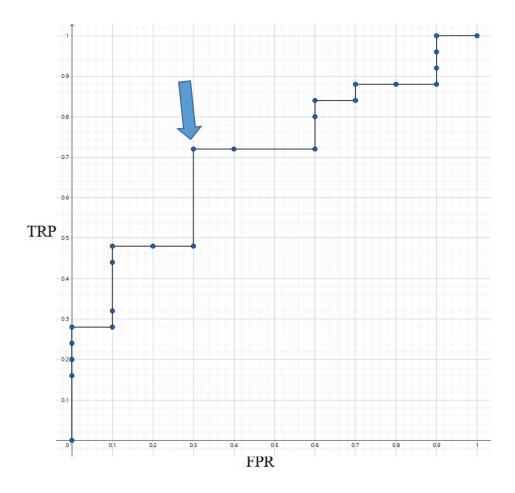


Figure 7: HMM ROC

From this ROC curve, we can see at the point where the arrow is pointing to, the TPR is around 0.7, and the FPR is around 0.3. And the FPR is decreasing from the previous point while the TPR remain the same. However, after this point, the TPR is crashing to lower than 0.5. Then, we find that this point happens at around score -2.7. The accuracy for this threshold is 0.71.

From the PR curve, we also see that while the threshold of score is around -2.7, it yields a Recall = 0.72 and Precision = 0.86. Therefore, we determined to draw the threshold around score = -2.7. That means, if the score is lower than -2.7, the file is more likely to be a benign, and if the score is higher than -2.7, it is more likely to be a Malware.

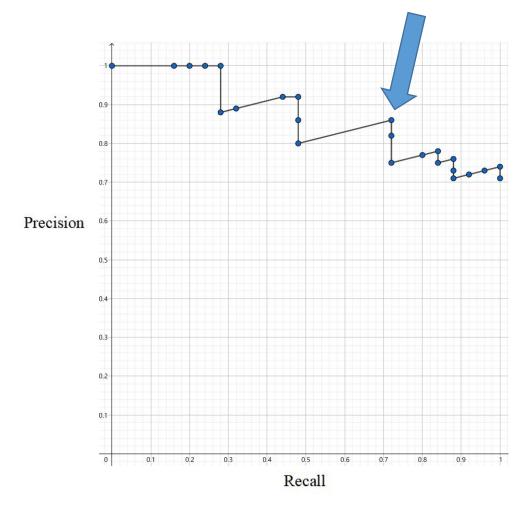
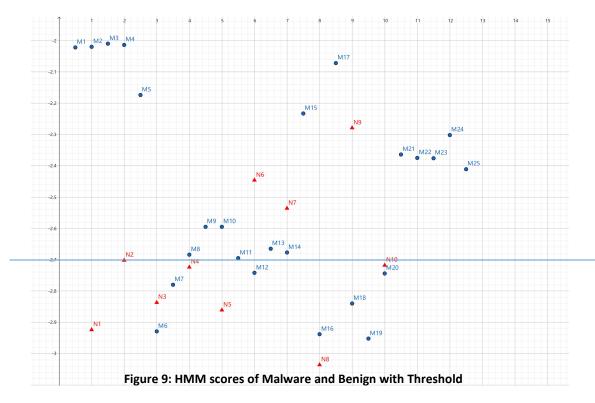


Figure 8: HMM PR



## 3.2 PCA result and Analysis

In the PCA process, we got the eigenvector and eigenvalue. And basing on the eigenvalue, we chose which eigenvector should be saved. We attached the result eigenvector, eigenvalue and significant eignvector of the 1st fold.

eigenvector =											
0. 250056	0.0585006	-0.0366645	0.0052316	-0.0492506	0.0187915	-0. 209483	0.0565226	-0.0278998	0.0244788	-0. 149358	0.384486
-0.081216	0. 210473	-0.808868	0.0783834								
0. 250068	0.0791808	-0.00286666	-0.0611939	0.0804471	-0. 0790307	-0.269187	0. 20525	0. 10921	0. 161287	0.119437	0. 530966
0. 46902	0. 230952	0. 417638	0. 135152								The second
0. 250062	0.0631301	-0. 0460956	-0.0129955	-0.0595266	-0. 111464	-0. 19598	-0. 217961	0. 0310273	-0. 26052	-0. 11525	-0. 34135
0.650192	-0. 396466	-0. 185569	0. 127673	0.0555500	0.0000405	0 0505555	0.100000	0.010001	0.040100	0 450504	0.405000
0. 250066	0. 0623999	-0.0574775	0.00911629	0.0555529	-0.0690425	-0. 0705557	0. 183396	0. 218281	-0. 249123	0. 478564	-0. 467069
-0.116356	0. 484516	-0.0503932	0. 275683	0.00011005	0.0000000	0.00077490	0 055605	0.014500	0.400150	0 000007	0.0100507
0. 250072 -0. 211765	0. 0576647 -0. 636997	-0. 0749969 -0. 0836506	-0. 00641878 0. 120603	0.00611205	0. 0306386	-0.00677438	0. 355635	0. 214583	0.409152	0. 339507	-0. 0103537
0. 250048	0. 0466138	-0. 0192561	-0. 148948	-0.081716	-0.0801006	-0.468626	0.140868	-0.545425	-0. 329399	-0.114668	0.00502365
-0. 385089	-0. 164615	0. 248993	0.0603619	0.001710	0.0001000	0. 100020	0.140000	0.010120	0. 525555	0.111000	0.00002300
0, 250066	0. 0660073	-0. 0393585	-0.0179762	-0.0419421	-0.158927	-0. 252434	-0.43967	0.430994	0.334113	-0.418095	-0.147747
-0.308608	0.0974677	0. 187061	0. 115926	0.0110101	0. 100021	0. 202 10 1	0. 10001	0. 100001	0.001110	0. 110000	01.1111.11
0. 25007	0.0631743	-0.118979	0. 184546	-0.196387	0.373073	0.301699	0.498886	0.129622	-0.134672	-0.542373	-0.107098
0.0426618	0.060954	0.125437	0.075846								
0. 250061	0.0623704	-0.0448595	-0.00980157	-0.0570614	-0.0373285	-0.167497	0.123243	0.0961614	0.0483022	0.0672927	-0.148086
0.0526164	0.0908689	-0.0164364	-0.91337								200 (000)
0. 250073	0.0807983	-0. 0144724	-0. 226825	-0. 154858	-0. 718532	0. 55468	0.0446951	-0.0589644	-0.0819652	-0.0598849	0. 11609
	-0.0030398	0.00225868	-0.0160896								
0. 250122	0.0437166	-0.116433	-0.149012	0.849274	0.0915362	0. 184358	-0.0277047	-0. 25772	0.159827	-0. 149919	-0. 131111
0. 0292907	0. 0413078	-0.0292884	-0.017709	0 105707	0.011400	0.100110	0.000045	0.000500	0 500445	0.107104	0.000000
0. 250056 -0. 194116	0. 0564648 -0. 199512	-0. 0504767 0. 0930288	0. 160289 -0. 0996969	0. 185727	0. 211428	0. 166113	-0. 328847	0. 326506	-0. 560445	0. 167104	0. 382628
0. 250006	0. 0462781	-0.0674606	0.801504	-0.100173	-0.0825665	0. 101107	-0. 201733	-0.379694	0. 220671	0.140377	-0.0161963
0. 0222611	0. 0402781	0. 0548703	0. 0213068	-0.100173	-0.0623003	0. 101107	-0.201733	-0.579094	0. 220011	0.140377	-0.0101903
0. 249231	-0. 9481	0. 186587	0.019874	0.0167709	-0.0316006	0.00111518	0.0301781	0.033477	-0.0074264	-0.0184174	0.000279488
	. 000911588		0.000328587	0.0101103	0.0010000	0.00111010	0.0001101	0.000111	0.0011201	0. 0101111	0.000213100
0. 24984	0. 219805	0.879311	-0. 119559	-0.0826133	0. 224035	0.124506	-0.093149	-0.0882924	0.0826877	0.0488358	-0.0535625
0.00876823	0.0218271	0.00102777	0.012128								
0. 250104	-0.0609571	-0.375018	-0.427584	-0.37053	0.419098	0.206965	-0.329608	-0.231862	0.183016	0.20686	0.00309393
0.0563903	0.101266	0.0425793	0.0234724								

Figure 10: 16\*16 Eigenvector Space

-:1u	after discar	ding the less	significant	eigenvectors
eigenvalue =	eigenvector			
5. 18498e-15	-0.081216	0.210473	-0.808868	0.0783834
3. 30004e-09	0.46902	0. 230952	0.417638	0. 135152
3. 98154e-08	0.650192	-0. 396466	-0. 185569	0.127673
7. 26992e-07	-0. 116356	0. 484516	-0.0503932	0.275683
1. 89145e-06	-0.211765	-0.636997	-0.0836506	0.120603
3.64989e-06	-0.385089	-0. 164615	0. 248993	0.0603619
1. 49184e-05	-0.308608	0.0974677	0.187061	0.115926
3. 06707e-05	0.0426618	0.060954	0. 125437	0.075846
5. 09706e-05	0.0526164	0.0908689	-0.0164364	-0.91337
0.00016577	-0.0425112	-0.0030398	0.00225868	-0.0160896
0. 000209075	0.0292907	0.0413078	-0.0292884	-0.017709
0. 000687356	-0. 194116	-0.199512	0.0930288	-0.0996969
0.00183409	0.0222611	0.0619104	0.0548703	0.0213068
0. 00296781	0.00846106	-0.000911588	0.00131232	0.000328587
0. 00804753	0.00876823	0.0218271	0.00102777	0.012128
0. 0241245	0.0563903	0.101266	0.0425793	0.0234724

Figure 11: Eigenvalue

Figure 12: Significant Eigenvector

Then we projected the matrix A onto those significant eigenvector and gained the score matrix.

score matrix :	=										
0.0178148	0.028984	0.0273814	0.0096428	-0.0790783	-0.0175749	-0.0606527	-0.0241206	-0.080948	-0.0170629	-0.0129195	0.00839778
0.0245069	0.031987	0.031987	0.118793 -	0.000689038	-0.00389634	-0.00111798	-0.00143447				des registratives as
0. 0204776	0.00586627	0.00873914	0.0476367	0.0821644	-0.0568491	-0.0372721	-0.0925581	0.0731963	-0.0183877	-0.0636449	0.0212987
0.0242899	0.0928159	0.0928159	-0.02071	-0.044072	-0.0396987	-0.0440242	-0.0520839				200 2000 2000 2000
-0.059586	-0.080176	-0.0805009	0.0435717	-0.0707933	0.0925013	0.0968496	0.0831629	0.0210861	0.0803706	0.0861485	-0.106703
-0. 169296	0. 12845	0. 12845	0.0808438	-0.0683477	-0.069473	-0.0682267	-0.0683328				
-0.120456	-0. 136272	-0. 120691	-0.480078	0.0902737	-0.0458475	-0.0415405	-0.061339	0. 0332095	-0. 0299859	-0.0430881	-0. 128053
0. 0386957	0. 187225	0. 187225	0.060681	0.152848	0. 147341	0. 152511	0.15734				

Figure 13: 4\*20 Score Matrix

After we did 5 Cross Validations, we got the PCA scores for the Malware and benign as

ChromeSetup

GrammarlySetup

LockDownBrowser

Setup (nxt-g installer v2.0f6

(windows))
VirtualBox-6.0.14-133895-Win

ScoringHMM

Webexapp

WPSOffice

Devenv

IdeaIU

figure 14.

	PCA on Reg Frequence
Cleaman1	0.06181
Cleaman2	0.02227
Cleaman3	0.01600
Cleaman4	0.01603
Cleaman5	0.2989
Securityshield1	0.06035
Securityshield2	0.1114
Securityshield3	0.01329
Securityshield4	0.05168
Securityshield5	0.01770
Winwebsec1	0.01455
Winwebsec2	0.08123
Winwebsec3	0.05356
Winwebsec4	0.01491
Winwebsec5	0.05698
Zbot1	0.04066
Zbot2	0.1539
Zbot3	0.2046
Zbot4	0.04062
Zbot5	0.1411
Zeroaccess1	0.0005145
Zeroaccess2	0.0003901
Zeroaccess3	0.007353
Zeroaccess4	0.0006864
Zeroaccess5	0.008226

Figure 14: PCA Scores

PCA on Reg Frequence

0.1111

0.1022

0.1066

0.0826

0.1032

0.08353

0.1347

0.1077

0.1214

0.1034

From figure 14, we can easily see that PCA with the register frequency has a significant result on the Malware detection since most of the Malware scores are much smaller than the benign scores.

We also drew a graph for these scores:

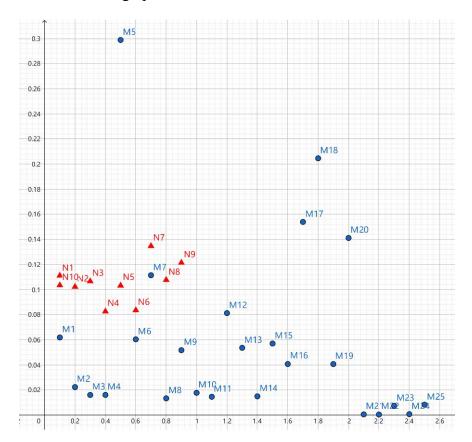


Figure 15: PCA Scores

The blue circles show us the Malware and the red triangles show us the benign. The lower score means the smaller distance between the training sample and scoring sample. That is, if the score is near 0, it means the score sample is much closer to the training sample. From figure 15, we see that most of the scoring Malware samples are close to the training Malware samples. And the benign samples are grouping together and far away from the training samples.

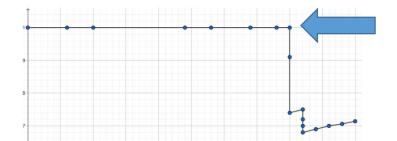


Figure 16: PCA Scores

As our arrow shown, the FPR =0 and TPR = 0.8. And after this point, the TPR is decreasing quickly. When the threshold is around 0.08, we can obtain this FPR and TPR. That means, if we set score =0.08 as a threshold, we can have a 0 FPR, but 0.8 TPR, and

$$Accuracy = \frac{20+10}{25+10} = \frac{30}{35} = 0.86$$

As the arrow point on the figure 17, when score = 0.08, the precision reach 1 and recall keeps at 0.8. Therefore, we can determine that, if the score is lower than 0.08, the scoring sample is most likely to be a Malware while the scoring sample is classified as a benign if the score is higher than 0.08.



# Recall

Figure 17: PCA Scores

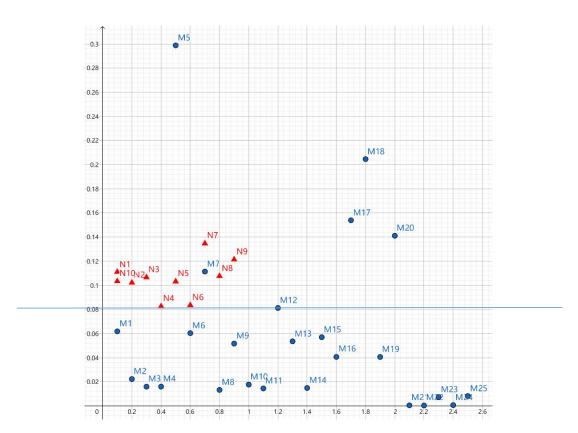


Figure 18: PCA Scores with Threshold

## 3.3 MLP on both HMM and PCA Scores

	HMM on Opcode	PCA on Reg Frequence
Cleaman1	-2.022	0.06181
Cleaman2	-2.020	0.02227
Cleaman3	-2.010	0.01600
Cleaman4	-2.014	0.01603
Cleaman5	-2.174	0.2989
Securityshield1	-2.929	0.06035
Securityshield2	-2.780	0.1114
Securityshield3	-2.684	0.01329
Securityshield4	-2.740	0.05168
Securityshield5	-2.595	0.01770
Winwebsec1	-2.695	0.01455
Winwebsec2	-2.742	0.08123
Winwebsec3	-2.665	0.05356
Winwebsec4	-2.677	0.01491
Winwebsec5	-2.233	0.05698
Zbot1	-2.938	0.04066
Zbot2	-2.072	0.1539
Zbot3	-2.840	0.2046
Zbot4	-2.952	0.04062
Zbot5	-2.744	0.1411
Zeroaccess1	-2.364	0.0005145
Zeroaccess2	-2.375	0.0003901
Zeroaccess3	-2.376	0.007353
Zeroaccess4	-2.302	0.0006864
Zeroaccess5	-2.411	0.008226

	HMM on Opcode	PCA on Reg Frequence
ChromeSetup	-2.924	0.1111
Devenv	-2.702	0.1022
GrammarlySetup	-2.837	0.1066
IdeaIU	-2.724	0.0826
LockDownBrowser	-2.861	0.1032
ScoringHMM	-2.446	0.08353
Setup (nxt-g installer v2.0f6 (windows))	-2.536	0.1347
VirtualBox-6.0.14-133895-Win	-3.036	0.1077
Webexapp	-2.279	0.1214
WPSOffice	-2.718	0.1034

Figure 19: HMM and PCA Scores

Before we chose the data set using the threshold we determine above, we chose the training data from the HMM and PCA scores of the Malware. For example, we chose only 3 Zbot scores:

Zbot2	-2.072	0.1539
Zbot3	-2.840	0.2046
Zbot5	-2.744	0.1411

## And we choose 3 benign scores:

ScoringHMM	-2.446	0.08353
Webexapp	-2.279	0.1214
WPSOffice	-2.718	0.1034

Then we got the training scores and testing scores:

```
error E[w] = 0.00354133

w0 = 0.189236 w1 = 0.375979 w2 = -11.8426 w3 = 13.0362 w4 = -6.4184 w5 = 1.70512

Y[0] = 0.686799

Y[1] = 1.10247

Y[2] = 0.533424

Y[3] = -0.292904

Y[4] = 0.291132

Y[5] = 0.0310502
```

```
test sample Y[0]
test sample Y[1]
test sample Y[2]
test sample Y[3]
                            = -0.713436
                            = -1.55109
                            = -1.69381
                            = -1.69261
                   Y[4]
Y[5]
Y[6]
Y[7]
        sample
                           = 1.50902
                            = -0.688823
        sample
test
                               0.148102
test
        sample
        sample
                               -1.66374
        sample
                    Y[8]
                            = -0.8643
                    Y[9]
        sample
                           = -1.57981
test
                   Y[10] = -1.67981

Y[10] = -1.6349

Y[11] = -0.3248

Y[12] = -0.8328
        sample
        sample
                                 -0.32482
                              = -0.832897
        sample
        sample
                              = -1.62952
        sample Y[14]
                              = -0.794766
test
        sample Y[15]
                             = -1.06511
test sample Y[16]
test sample Y[17]
test sample Y[18]
                             = -1.06469
= -1.99465
                              = -1.99576
        sample
                    Y[19]
                              = -1.83855
test sample Y[19]
test sample Y[20]
test sample Y[21]
test sample Y[22]
test sample Y[23]
test sample Y[24]
test sample Y[25]
test sample Y[26]
test sample Y[27]
test sample Y[28]
                              = -2.00039
                              = -1.8139
                              = 0.141985
                              = 0.0128997
                              = 0.0780503
                             = -0.301957
                             = 0.027519
                             = 0.461487
                             = 0.0917218
v0 = 0.189236 \quad w1 = 0.375979 \quad w2 = -11.8426 \quad w3 = 13.0362 \quad w4 = -6.4184 \quad w5 = 1.70512
```

Figure 20: MLP Scores of Sandom Training Sample

If the score is higher than 0.5, we would round it to 1, and if lower than 0.5, we would round it to 0. And "1" means, it's Malware when "0" means its benign. Then, we calculated the accuracy basing on the classification in the figure 20.

$$Accuracy = \frac{11}{35} = 0.31$$

The accuracy is very low.

But when we chose the training data basing on the threshold we determined before. For example, we choose

Securityshield3	-2.684	0.01329
Winwebsec2	-2.742	0.08123
Winwebsec5	-2.233	0.05698

IdeaIU	-2.724	0.0826
LockDownBrowser	-2.861	0.1032
VirtualBox-6.0.14-133895 -Win	-3.036	0.1077

We had the training scores and testing scores as below:

```
error E[w] = 0.0235859
w0 = 3.21505 w1 = 0.761547 w2 = -1.03171 w3 = -14.2614 w4 = -1.44008 w5 = 9.98143
Y[0] = 0.965749
Y[1] = 0.373596
Y[2] = 0.74699
Y[3] = 0.371492
Y[4] = 0.252588
Y[5] = 0.208309
How many test sets do you have?
29
test sample Y[0] = 0.812054
test sample Y[1] = 1.34715
test sample Y[2] = 1.46436
test sample Y[3] = 1.46004
test sample Y[4] = 0.0258008
test sample Y[6] = 0.23329
test sample Y[7] = 0.559341
test sample Y[8] = 0.969937
test sample Y[10] = 0.575509
test sample Y[10] = 0.575509
test sample Y[10] = 0.575509
test sample Y[11] = 0.50347
test sample Y[12] = 0.562812
test sample Y[13] = 0.522734
test sample Y[14] = 0.0615325
test sample Y[15] = 0.557481
test sample Y[16] = 0.162225
test sample Y[17] = 1.40591
test sample Y[19] = 1.28191
test sample Y[20] = 1.46071
test sample Y[21] = 1.28391
test sample Y[21] = 1.28391
test sample Y[22] = 0.21592
test sample Y[24] = 0.245242
test sample Y[25] = 0.449108
test sample Y[26] = 0.20715
test sample Y[27] = 0.301293
test sample Y[28] = 0.20715
```

Figure 21: MLP Scores of Training Sample Basing on Threshold

The 
$$Accuracy = \frac{28}{35} = 0.8$$

And we also used singler layer perceptron to train and classify on these samples, and we

gained:

```
error E[w]= 0.0790826

w0 = -0.20184    w1 = -10.3599

Y[0] = 0.599662

Y[1] = 0.428472

Y[2] = 0.465157

Y[3] = 0.424112

Y[4] = 0.379498

Y[5] = 0.376842
```

Figure 22: Single Layer Perceptron Scores of Training Sample Basing on Threshold

$$Accuracy = \frac{25}{35} = 0.71$$

```
test sets do you have?
                    0.442203
test sample
                    0.544135
     sample
                    0.559699
                    0.559821
            Y[10]
                   = 0.595286
                   = 0.542838
     sample
     sample
              13
     sample
              14
     sample
     sample
                   = 0.363361
                   = 0.374394
                   = 0.37011
              24
              25
     sample
            Y[26]
Y[27]
     sample
     sample
            Y[28]
 = -0.20184 w1 = -10.3599
```

From these experiments, we knew that when we set up the MLP or single layer perceptron, it's very important to choose the training data that corresponding to the threshold.

And we also want to know which score from HMM or PCA has more impact on the MLP training. Therefore, we decide to make some change to the training samples. We again chose the Malware scores from Zbot family but with low HMM score ( we said lower HMM score is more likely to be classified as benign) and also low PCA score (lower PCA score is more likely to be classified as Malare ). And we also chose the benign that has higher HMM scores and higher PCA score.

Zbot1	-2.938	0.04066
Zbot4	-2.952	0.04062
Securityshield1	-2.929	0.06035
ScoringHMM	-2.446	0.08353
Webexapp	-2.279	0.1214
WPSOffice	-2.718	0.1034

Then we obtained the result as below:

```
error E[w] = 0.0355306
w0 = 0.274388 w1 = -0.508331 w2 = 11.6453 w3 = -5.78965 w4 = -2.76912 w5 = 2.61319
\begin{array}{lll} \text{WO} &= 0.274588 & \text{W}, \\ \text{Y} \left[ 0 \right] &= 0.878507 \\ \text{Y} \left[ 1 \right] &= 0.884709 \\ \text{Y} \left[ 2 \right] &= 0.664947 \\ \text{Y} \left[ 3 \right] &= 0.18861 \\ \text{Y} \left[ 4 \right] &= -0.304529 \\ \text{Y} \left[ 5 \right] &= 0.0970843 \end{array}
         = 0. 18861
= -0. 304529
= 0. 0970843
test sample Y[0] = 0.230113
test sample Y[1]
                                    = 0.674859
test sample Y[2] = 0.73887
test sample Y[3] = 0.740356
test sample Y[4] = -1.7117
test sample Y[5]
                                    = 0.0391414
                                    = 1.05513
test sample Y[6]
test sample Y[7]
                                    = 0.676529
test sample Y[8] = 0.974397
test sample Y[9] = 1.04695
test sample Y[10] = 0.352282
test sample Y[11] = 1.036114
                                                                                                 Figure 22:MLP Score
test sample Y[12]
test sample Y[13]
                                      = 0.622884
                                      = 0.386198
test sample Y[14]
                                      = -0.727373
test sample Y[15]
test sample Y[16]
test sample Y[17]
test sample Y[18]
test sample Y[20]
test sample Y[21]
test sample Y[22]
test sample Y[23]
test sample Y[24]
test sample Y[25]
test sample Y[26]
test sample Y[26]
test sample Y[27]
test sample Y[28]
test sample Y[15]
                                      = -0.830334
                                                                                         Accuracy = \frac{27}{35} = 0.77
                                      = -0.289137
                                      = 1.05334
                                      = 1.05907
                                      = 0.989324
                                       = 1.02616
                                       = 0.994976
                                       = 0.108832
                                       = 0.102722
                                       = 0.117476
                                       = 0.328853
                                      = 0.165488
                                      = -0.320833
 test sample Y[28]
                                      = 0.196527
```

Therefore, now we know that if we choose the Malware samples (that have lower PCA score) and the benign samples (that have higher PCA score) to be the MLP training sample, we will probably get the model with higher accuracy. That is, PCA plays an important role when we train a MLP.

#### 4. Conclusion

From this project, we found that PCA with register frequency played very good in Malware detection, it yielded an accuracy with 0.86. HMM with Opcode sequence also had an accuracy with 0.71, but the malware and benign samples were hardly separated. However, the choices of benign samples in this project maybe not so good. In this situation, PCA can solve this problem effectively. Furthermore, with the correct choice of training samples (especially choosing the samples with significant PCA scores), MLP can perform better than HMM. It yielded an 0.8 accuracy in this project.