Using Neural Networks for remote OS Identification

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PacSec/core05 conference

OUTLINE

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3. OS Detection based on Nmap signatures
4. Dimension reduction and training

1. Introduction

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OS Identification

- OS Identification = OS Detection = OS Fingerprinting
- Crucial step of the penetration testing process
  - actively send test packets and study host response
- First generation: analysis of differences between TCP/IP stack implementations
- Next generation: analysis of application layer data (DCE RPC endpoints)
  - to refine detection of Windows versions / editions / service packs

Limitations of OS Fingerprinting tools

- Some variation of “best fit” algorithm is used to analyze the information
  - will not work in non standard situations
  - inability to extract key elements
- Our proposal:
  - focus on the technique used to analyze the data
  - we have developed tools using neural networks
  - successfully integrated into comercial software

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Windows DCE-RPC service

- By sending an RPC query to a host's port 135
  you can determine which services or programs are registered

- Response includes:
  - UUID = universal unique identifier for each program
  - Annotated name
  - Protocol that each program uses
  - Network address that the program is bound to
  - Program's endpoint

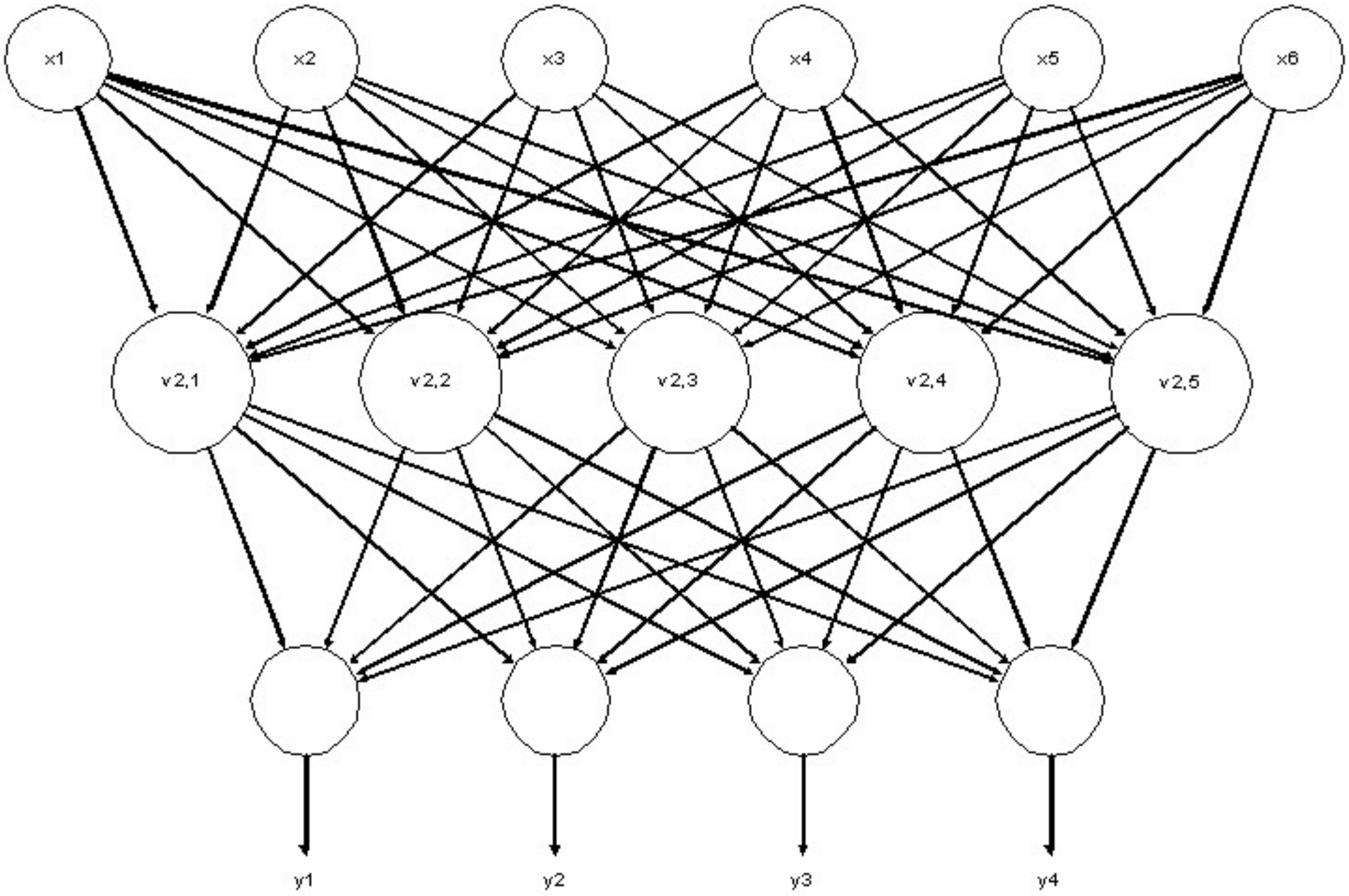
Endpoints for a Windows 2000 Professional edition service pack 0

- uuid="5A7B91F8-FF00-11D0-A9B2-00C04FB6E6FC" annotation="Messenger Service"
  - protocol="ncalrpc" endpoint="ntsvcs" id="msgsvc.1"
  - protocol="ncacn_np" endpoint="\PIPE\ntsvcs" id="msgsvc.2"
  - protocol="ncacn_np" endpoint="\PIPE\scerpc" id="msgsvc.3"
  - protocol="ncadg_ip_udp" id="msgsvc.4"
- uuid="1FF70682-0A51-30E8-076D-740BE8CEE98B"
  - protocol="ncalrpc" endpoint="LRPC" id="mstask.1"
  - protocol="ncacn_ip_tcp" id="mstask.2"
- uuid="378E52B0-C0A9-11CF-822D-00AA0051E40F"
  - protocol="ncalrpc" endpoint="LRPC" id="mstask.3"
  - protocol="ncacn_ip_tcp" id="mstask.4"

Neural networks come into play…

- It's possible to distinguish Windows versions, editions and service packs based on the combination of endpoints provided by DCE-RPC service
- Idea: model the function which maps endpoints combinations to OS versions with a multilayer perceptron neural network
- Several questions arise:
  - what kind of neural network do we use?
  - how are the neurons organized?
  - how do we map endpoints combinations to neural network inputs?
  - how do we train the network?

Multilayer Perceptron Neural Network



413 neurons

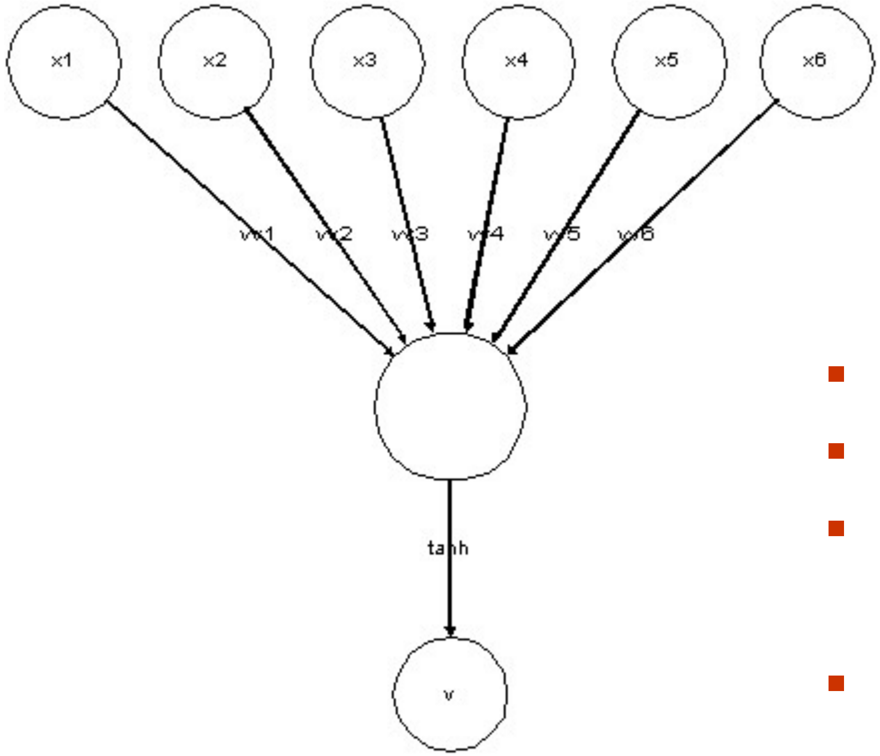
42 neurons

25 neurons

3 layers topology

- Input layer : 413 neurons
  - one neuron for each UUID
  - one neuron for each endpoint corresponding to the UUID
  - handle with flexibility the appearance of an unknown endpoint
- Hidden neuron layer : 42 neurons
  - each neuron represents combinations of inputs
- Output layer : 25 neurons
  - one neuron for each Windows version and edition
    - » Windows 2000 professional edition
  - one neuron for each Windows version and service pack
    - » Windows 2000 service pack 2
  - errors in one dimension do not affect the other

What is a perceptron?



$$v_{i,j} = f(\sum_{k=0}^{n} w_{i,j,k} \cdot x_k)$$

- x_1 … x_n are the inputs of the neuron
- $w_{i,j,0}$ … $w_{i,j,n}$ are the weights
- f is a non linear activation function
  - we use hyperbolic tangent tanh
- $v_{i,j}$ is the output of the neuron

Training of the network = finding the weights for each neuron

Back propagation

- Training by back-propagation:
- for the output layer
  - given an expected output $y_1 \dots y_m$
  - calculate an estimation of the error

$$\delta_{i,j} = f'(v_{i,j})\ (y_j - v_{i,j})$$

- this is propagated to the previous layers as:

$$\delta_{i,j} = f'(v_{i,j})\ \sum_k w_{i,j,k} \cdot \delta_{i+1,j}$$

New weights

- The new weights, at time *t+1*, are:

$$w_{i,j,k}(t+1) = w_{i,j,k}(t) + \Delta w_{i,j,k}(t)$$

- where:

$$\Delta w_{i,j,k}(t) = (\underbrace{\lambda}_{\text{learning rate}} \cdot \delta_{i+1,k} \cdot v_{i,j}) + \underbrace{\mu}_{\text{momentum}} \cdot \Delta w_{i,j,k}(t-1)$$

Supervised training

- We have a dataset with inputs and expected outputs
- One generation: recalculate weights for each input / output pair
- Complete training = 10350 generations
  - it takes 14 hours to train network (python code)
- For each generation of the training process, inputs are reordered randomly (so the order does not affect training)

Sample result

```
Neural Network Output (close to 1 is better):
Windows NT4: 4.87480503763e-005
Editions:
    Enterprise Server: 0.00972694324639
    Server: -0.00963500026763
Service Packs:
    6: 0.00559659167371
    6a: -0.00846224120952
Windows 2000: 0.996048928128
Editions:
    Server: 0.977780526016
    Professional: 0.00868998746624
    Advanced Server: -0.00564873813703
Service Packs:
    4: -0.00505441088081
    2: -0.00285674134367
    3: -0.00936655583402
    0: -0.00320117552666
    1: 0.921351036343
```

Sample result (cont.)

```
Windows 2003: 0.00302898647853
Editions:
    Web Edition: 0.00128127138728
    Enterprise Edition: 0.00771786077082
    Standard Edition: -0.0077145024893
Service Packs:
    0: 0.000853988551952
Windows XP: 0.00605168045887
Editions:
    Professional: 0.00115635710749
    Home: 0.000408057333416
Service Packs:
    2: -0.00160404945542
    0: 0.00216065240615
    1: 0.000759109188052
Setting OS to Windows 2000 Server sp1
Setting architecture: i386
```

Result comparison

- Results of our laboratory:

	Old DCE-RPC module	DCE-RPC with neural networks
Perfect matches	6	7
Partial matches	8	14
Mismatches	7	0
No match	2	2

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Nmap tests

- Nmap is a network exploration tool and security scanner
- includes OS detection based on the response of a host to 9 tests

Test	send packet	to port	with flags enabled
T1	TCP	open TCP	SYN, ECN-Echo
T2	TCP	open TCP	no flags
T3	TCP	open TCP	URG, PSH, SYN, FIN
T4	TCP	open TCP	ACK
T5	TCP	closed TCP	SYN
T6	TCP	closed TCP	ACK
T7	TCP	closed TCP	URG, PSH, FIN
PU	UDP	closed UDP	
TSeq	TCP * 6	open TCP	SYN

Nmap signature database

- Our method is based on the Nmap signature database
- A signature is a set of rules describing how a specific version / edition of an OS responds to the tests. Example:

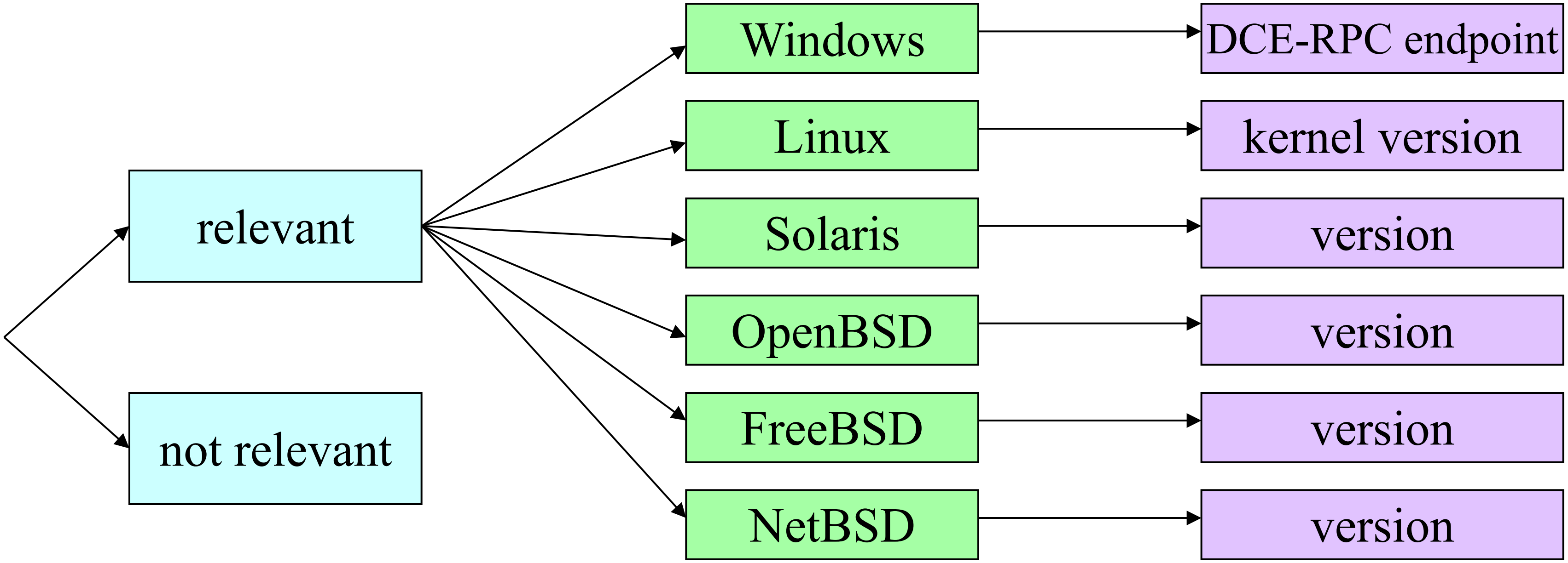
```
# Linux 2.6.0-test5 x86
Fingerprint Linux 2.6.0-test5 x86
Class Linux | Linux | 2.6.X | general purpose
TSeq(Class=RI%gcd=<6%SI=<2D3CFA0&>73C6B%IPID=Z%TS=1000HZ)
T1(DF=Y%W=16A0%ACK=S++%Flags=AS%Ops=MNNTNW)
T2(Resp=Y%DF=Y%W=0%ACK=S%Flags=AR%Ops=)
T3(Resp=Y%DF=Y%W=16A0%ACK=S++%Flags=AS%Ops=MNNTNW)
T4(DF=Y%W=0%ACK=O%Flags=R%Ops=)
T5(DF=Y%W=0%ACK=S++%Flags=AR%Ops=)
T6(DF=Y%W=0%ACK=O%Flags=R%Ops=)
T7(DF=Y%W=0%ACK=S++%Flags=AR%Ops=)
PU(DF=N%TOS=C0%IPLEN=164%RIPTL=148%RID=E%RIPCK=E%UCK=E%UL
  EN=134%DAT=E)
```

Wealth and weakness of Nmap

- Nmap database contains 1464 signatures
- Nmap works by comparing a host response to each signature in the database:
  - a score is assigned to each signature
  - score = number of matching rules / number of considered rules
  - “best fit” based on Hamming distance
- Problem: improbable operating systems
  - generate less responses to the tests
  - and get a better score!
  - e.g. a Windows 2000 version detected as Atari 2600 or HPUX …

Hierarchical Network Structure

- Analyze the responses with a neural network based function
- OS detection is a step of the penetration test process
  - we only want to detect Windows, Linux, Solaris, OpenBSD, FreeBSD, NetBSD



So we have 5 neural networks…

- One neural network to decide if the OS is relevant / not relevant
- One neural network to decide the OS family:
  - Windows, Linux, Solaris, OpenBSD, FreeBSD, NetBSD
- One neural network to decide Linux version
- One neural network to decide Solaris version
- One neural network to decide OpenBSD version
- Each neural network requires special topology design and training!

Neural Network inputs

- Assign a set of inputs neurons for each test
- Details for tests T1 … T7:

- one neuron for ACK flag
  - one neuron for each response: S, S++, O
- one neuron for DF flag
  - one neuron for response: yes/no
- one neuron for Flags field
  - one neuron for each flag: ECE, URG, ACK, PSH, RST, SYN, FIN
- 10 groups of 6 neurons for Options field
  - we activate one neuron in each group according to the option EOL, MAXSEG, NOP, TIMESTAMP, WINDOW, ECHOED
- one neuron for W field (window size)

Example of neural network inputs

- For flags or options: input is 1 or -1 (present or absent)
- Others have numerical input
  - the W field (window size)
  - the GCD (greatest common divisor of initial sequence numbers)

- Example of Linux 2.6.0 response:

```
T3(Resp=Y%DF=Y%W=16A0%ACK=S++%Flags=AS%Ops=MNNTNW)
```

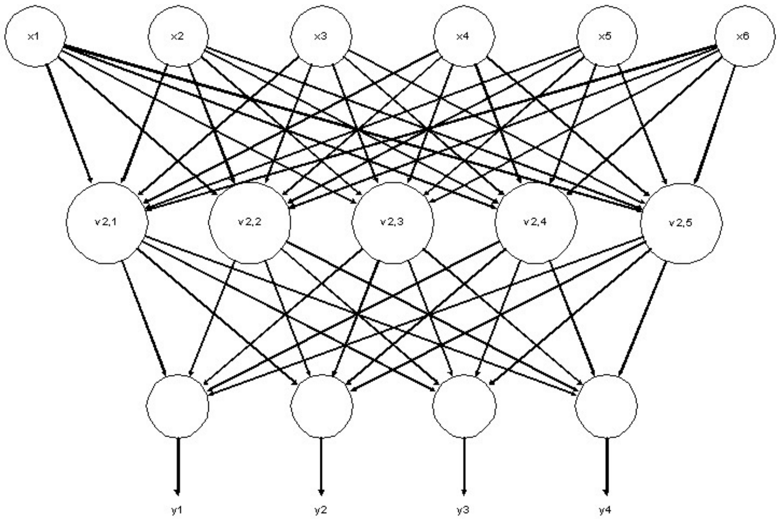
- maps to:

ACK	S	S++	O	DF	Yes	Flags	E	U	A	P	R	S	F	…
1	-1	1	-1	1	1	1	-1	-1	1	-1	-1	1	-1	…

Neural network topogy

- Input layer of 560 dimensions
  - lots of redundancy
  - gives flexibility when faced to unknown responses
  - but raises performance issues!
  - dimension reduction is necessary…

- 4 layers neural network, for example the first neural network (relevant / not relevant filter) has:



input layer : 204 neurons

hidden layer1 : 96 neurons
hidden layer2 : 20 neurons

output layer : 1 neuron

Dataset generation

- To train the neural network we need
  - inputs (host responses)
  - with corresponding outputs (host OS)
- Signature database contains 1464 rules
  - a population of 15000 machines needed to train the network!
  - we don't have access to such population…
  - scanning the Internet is not an option!

- Generate inputs by Monte Carlo simulation
  - for each rule, generate inputs matching that rule
  - number of inputs depends on empirical distribution of OS
    - » based on statiscal surveys
  - when the rule specifies options or range of values
    - » chose a value following uniform distribution

4. Dimension reduction and training

Inputs as random variables

- We have been generous with the input
  - 560 dimensions, with redundancy
  - inputs dataset is very big
  - the training convergence is slow…

- Consider each input dimension as a random variable X_i
  - input dimensions have different orders of magnitude
    - » flags take 1/-1 values
    - » the ISN (initial sequence number) is an integer
  - normalize the random variables:

$$\frac{X_i - \mu_i}{\sigma_i}$$

expected value

standard deviation

Correlation matrix

- We compute the correlation matrix *R*:

$$R_{i,j} = \frac{E[(X_i - \mu_i)(X_j - \mu_j)]}{\sigma_i \, \sigma_j}$$

- After normalization this is simply:

$$R_{i,j} = E[X_i \, X_j]$$

expected value

- The correlation is a dimensionless measure of statistical dependence
  - closer to 1 or -1 indicates higher dependence
  - linear dependent columns of *R* indicate dependent variables
  - we keep one and eliminate the others
  - constants have zero variance and are also eliminated

Principal Component Analysis (PCA)

- Further reduction involves Principal Component Analysis (PCA)

- Idea: compute a new basis (coordinates system) of the input space
  - the greatest variance of any projection of the dataset in a subspace of k dimensions
  - comes by projecting to the first k basis vectors

- PCA algorithm:
  - compute eigenvectors and eigenvalues of R
  - sort by decreasing eigenvalue
  - keep first k vectors to project the data
  - parameter k chosen to keep 98% of total variance

Resulting neural network topology

- After performing PCA we obtain the following neural network topologies (original input size was 560 in all cases)

Analysis	Input layer	Hidden layer 1	Hidden layer 2	Output layer
Relevance	204	96	20	1
Operating System	145	66	20	6
Linux	100	41	18	8
Solaris	55	26	7	5
OpenBSD	34	23	4	3

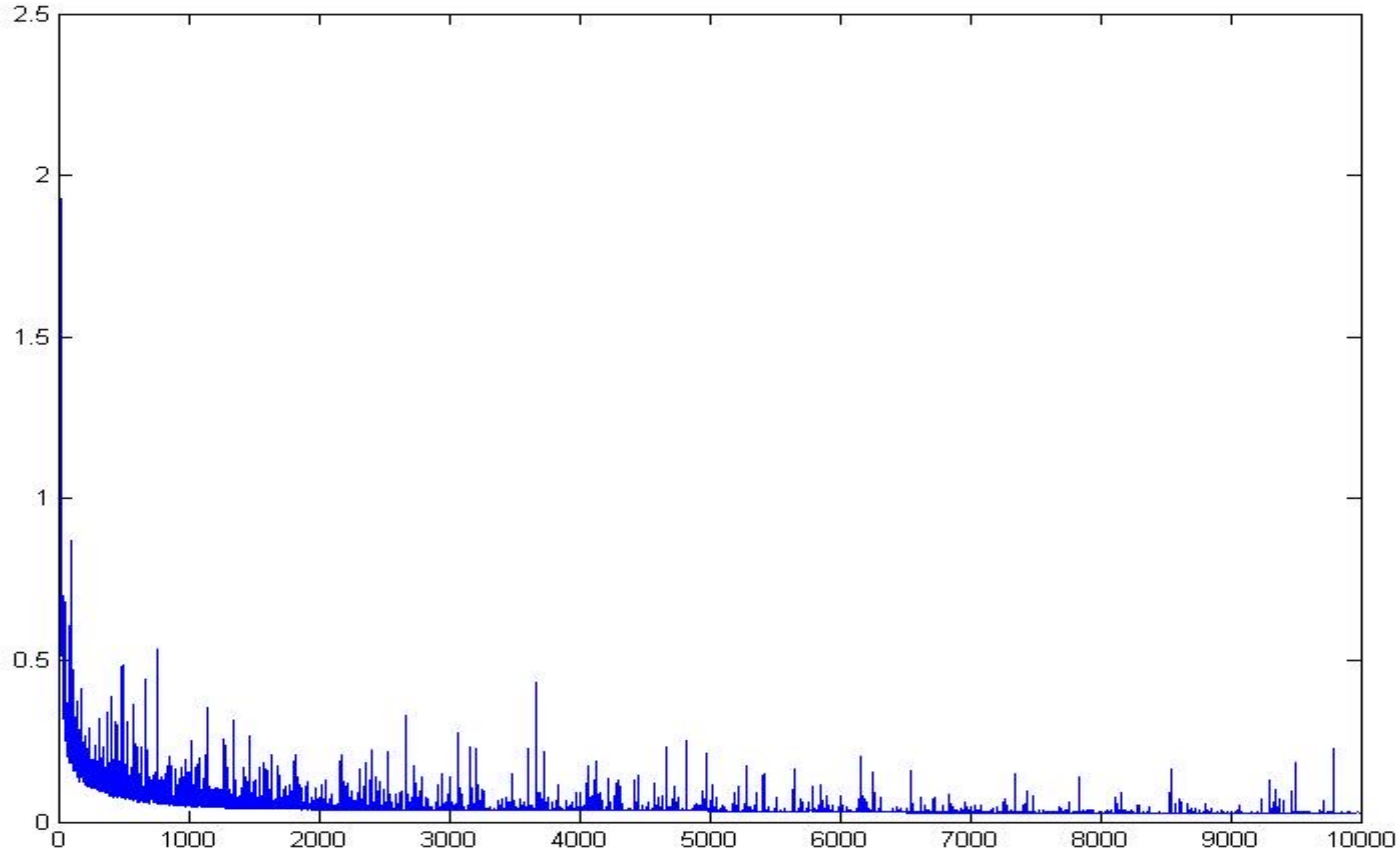
Adaptive learning rate

- Strategy to speed up training convergence
- Calculate the cuadratic error estimation
  (y_i are the expected outputs, v_i are the actual outputs):

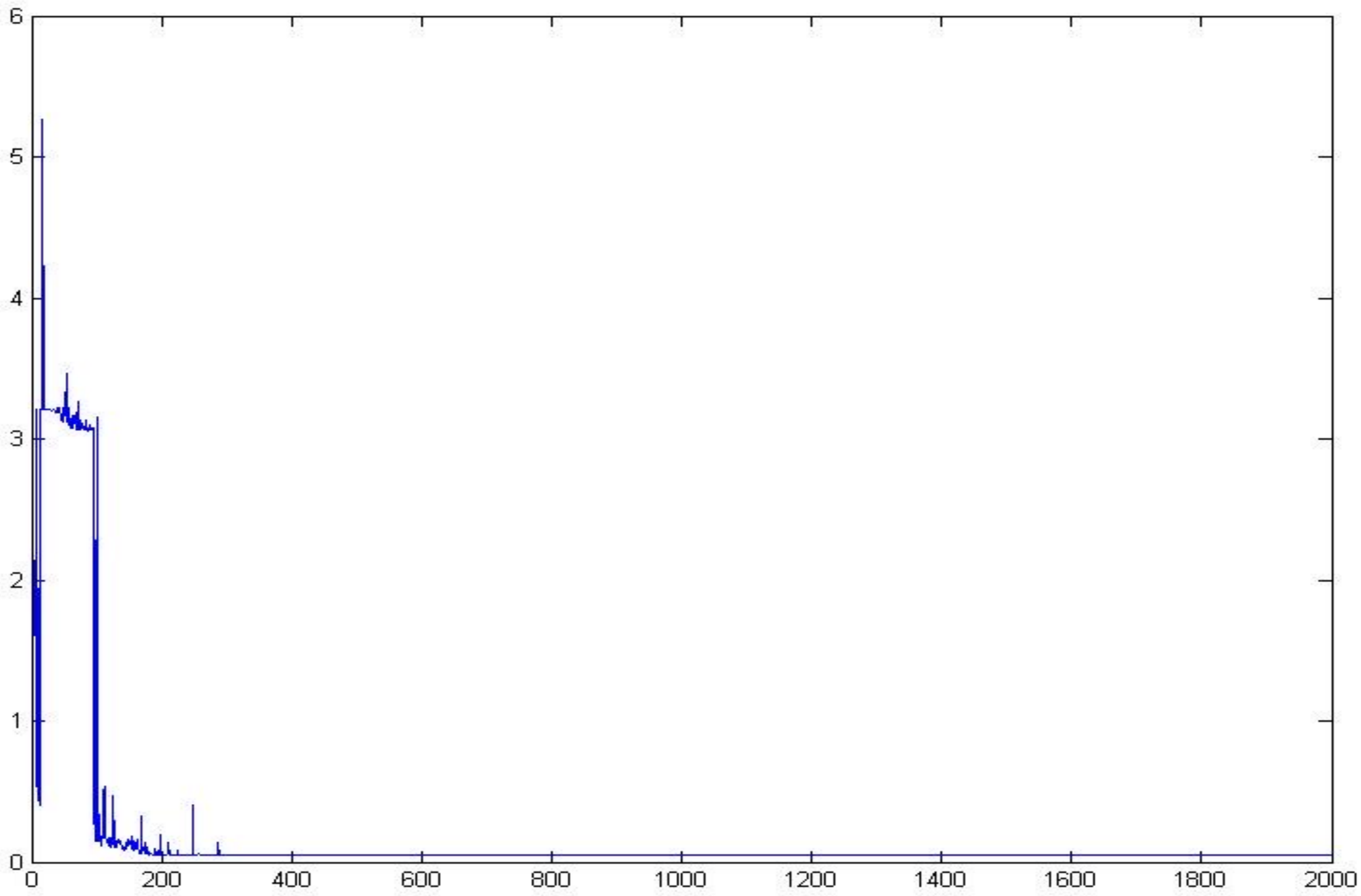
$$\frac{\sum_{i=1}^{n}(y_i - v_i)^2}{n}$$

- Between generations (after processing all dataset input/output pairs)
  - if error is smaller then increase learning rate
  - if error is bigger then decrease learning rate
- Idea: move faster if we are in the correct direction

Error evolution (fixed learning rate)



Error evolution (adaptive learning rate)



Subset training

- Another strategy to speed up training convergence
- Train the network with several smaller datasets (subsets)
- To estimate the error, we calculate a goodness of fit G
  - if the output is 0/1:

    G = 1 – (Pr[false positive] + Pr[false negative])
  - other outputs:

    G = 1 – number of errors / number of outputs
- Adaptive learning rate:
  - if goodness of fit G is higher, then increase the initial learning rate

Sample result (host running Solaris 8)

- Relevant / not relevant analysis

0.99999999999999789	**relevant**

- Operating System analysis

-0.99999999999999434	Linux
0.99999999921394744	**Solaris**
-0.99999999999998057	OpenBSD
-0.99999996651426454	FreeBSD
-1.0000000000000000	NetBSD
-1.0000000000000000	Windows

- Solaris version analysis

0.98172780325074482	**Solaris 8**
-0.99281382458335776	Solaris 9
-0.99357586906143880	Solaris 7
-0.99988378968003799	Solaris 2.X
-0.99999999977837983	Solaris 2.5.X

Ideas for future work 1

- Analyze the key elements of the Nmap tests
  - given by the analysis of the final weights
  - given by Correlation matrix reduction
  - given by Principal Component Analysis
- Optimize Nmap to generate less traffic
- Add noise and firewall filtering
  - detect firewall presence
  - identify different firewalls
  - make more robust tests

Ideas for future work 2

- This analysis could be applied to other detection methods:
- xprobe2 – Ofir Arkin, Fyodor & Meder Kydyraliev
  - detection by ICMP, SMB, SNMP
- p0f (Passive OS Identification) – Michal Zalewski
- OS detect by SUN RPC / Portmapper
  - Sun / Linux / other System V versions
- MUA (Outlook / Thunderbird / etc) detection using Mail Headers

Questions?

Thank you!