

# Behavioral Security: 10 steps forward & 5 steps backward DeepSec 2011

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## Agenda





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# **Threat Landscape**

**Motivation?** 



### Threat Landscape 2010-2011 Trends



Targeted Attacks continued to evolve





Attack Kits get a caffeine boost





Mobile Threats increase





### Social Networking

+ social engineering = compromise





### Hide and Seek

(zero-day vulnerabilities and rootkits)





### Threat Landscape Why is it hard to stop attacks?

Many reasons, one being: Malware authors have switched tactics



### From:

A mass distribution of a relatively few threats e.g.

 Storm made its way onto millions of machines across the globe



- A micro distribution model e.g.
- The average Vundo variant is distributed to 18 Symantec users!
- The average Harakit variant is distributed to 1.6 Symantec users!

What are the odds a security vendor will discover all these threats?





### Analyzing the Problem "Unique" threats are unique at the byte-level



Hacker develops threat

that differ at the byte-level

### Changes at the byte-level evade traditional file-based pattern-matching engines



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Welcome to OnlineCrypter.com ! March 15, 2011

-daemon 10, USA

Protect your programs with our hardware id/licensing system. With your own full

### Examples of Threat Cloning



# Number of Clones:





### Analyzing the Problem Are these "unique" threats really unique ?

• Bytes change. But how about the **behaviors** of these threats ?

### **Password Stealers**

will continue to steal passwords

### **Spam Bots**

will continue to send Spam

### **Rogue AntiVirus**

will continue to popup misleading messages





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...behaviors don't change ...



### Solving the Problem Behavior-based Detection

Engine that ignores what the threat looks like



### But detects threats based on what the threat does





### Clarifying the terminology Detection vs. Prevention vs. Protection



- Detection is "after" the fact
  - After the sample has run on the system, you analyze the impact and conclude if the action taken was malicious and then remediate the threat and reverse its persistent system changes.
- Prevention is "before" the fact
  - You conclude that the action that a sample is about to take is malicious and hence prevent the action from happening in the first place. You remediate the threat and minimal system settings change(restore) is needed.
- Protection
  - Both detection based and prevention based technologies can offer protection.
- Challenges:
  - **Detection based approach**: Can all changes be reversed? File modified on disk?
  - Prevention based approach: Which action do you block and inspect? What is the performance overhead?
- Debatable!
  - Blocked the 5<sup>th</sup> event and hence prevented 6<sup>th</sup> most impactful event!



# Legacy rules based behavioral security



### The Legacy Solution Rules based behavioral security

Rules to identify malicious activity and take action

1. A file runs from the temp folder 2. OpenProcess (...windows service..) 3. WriteProcessMemory + CreateRemoteThread > Then Block It !!

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### The legacy solution Rules based behavioral security

- Simple and intuitive model (Expert System)
  - Domain Experts know how to distinguish between good and bad
  - They analyze the malware, spot the trends/patterns and write rules
  - Product ships with default set of rules & rules are updated regularly
  - The product may also have an ability to let users express new rules in the product
- Applicability
  - Many security products, especially enterprise products use this model
  - Maybe the only answer for some threat scenarios
- Pros
  - Broader coverage for variants, Precise reasoning for detection, Name the threat, Relevant Actions
- Cons
  - Scalability, Domain Expertise

### Low error rate?





# Addressing the challenge **Scalability**

• Fact:



- Behavioral variants are far less than file variants
- New SHA256 = a file variant OR really a new malware?
  - Same malware may be packed differently
  - Same malware may be skinned differently

### • Answer:

- Analyze threat?







# **Machine Learning - Basics**



### Machine Learning Learning by Example

- New approach to AI is to get the computer to program itself by showing it examples (data or past experiences) of behavior we want!
  - This is the *learning* approach to AI



### Face

 Often hand programming is not possible or not a feasible answer like face detectors, handwriting reader, etc.



### Machine Learning What is Machine Learning?



### Central Question

"How can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning process?"

### • What is the learning problem?

A process learns with respect to **<T, P, E>** if it

- Improves its performance P
- At task T
- Through experience E

"The Discipline of Machine Learning" T. Mitchell (2006)

 Machine Learning algorithms discover the relationships between the variables of a system (input, output and hidden) from direct samples of the system



# Machine Learning Building Blocks

- Computer Science
  - How can we build machines that solve problems, and which problems are inherently tractable/intractable?
- Statistics
  - What can be inferred from data plus a set of modeling assumptions, with what reliability?
- Cognitive Science
  - How does the mind process information in faculties such as perception, language, memory, reasoning and emotion?
- Information Theory
  - How can we quantify, process, store and communicate data efficiently?





### Machine Learning Categories of Machine Learning

### Supervised Learning

- Given example of inputs and corresponding desired outputs, predict outputs on future inputs
  - Given input output pairs  $\langle x_i, y_i \rangle$ , learn a function  $f(x_i) = y_i$  for all *i* that makes a good guess at y for unseen x
  - Labeled Data\*
- Example: Classification, Regression

### Unsupervised Learning

- Given only inputs, automatically discover representations, features, structure, etc.
  - Unlabeled Data\*
- Example: Clustering, Outlier detection
- Semi Supervised Learning
  - Learning from a combination of labeled and unlabeled data
  - Example: supervised learning problems like video indexing, bioinformatics
    - Applied where there is less labeled data and abundance of unlabeled data \*
- Reinforcement Learning
  - Given sequence of inputs, actions from a fixed set, and scalar rewards/punishments, learn to select action sequences that maximizes expected reward
  - Example: Robotics





# Machine Learning **Steps**

- 1) Pick a feature representation for your task
  - Inputs and Outputs, Feature identification (power to discriminate)
- 2) Compile data
- 3) Choose a machine learning algorithm
- 4) Train the algorithm
- 5) Evaluate the results

Probably: go to (1)



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# **Machine Learning for behavioral security**







# Machine Learning for behavioral security **Overview**

## • Goal

- Train a model to provide automated meaningful information about unknown samples
  - Identify class/label (Supervised Machine Learning)  $\rightarrow$  Classification
  - Identify association (Unsupervised Machine Learning)  $\rightarrow$  Clustering

### • Application of information extracted

- Classify the sample or provide information to analysts for labeling and writing definitions for detection
- Real time protection



### Machine Learning for behavioral security Overall process

- Steps
  - Collect samples
  - Setup a VM with \*monitoring framework\*
  - Push and run samples in a farm of virtual machines
  - Collect sample behavior data
  - Recycle the VM
  - Extract information into format suitable for data mining
  - Train the models
  - Test and deploy the models





### Supervised Machine Learning For real-time protection

- Monitoring framework
  - Data Collection
  - User mode hooking API: Detours (Microsoft)
    - Hook the APIs
    - Collect the data in the context of the API Hook
      - API Info(Name, Parameters), Called-from API, State of the process, etc.
      - Log the information
    - Extract features: Logs  $\rightarrow$  ARFF files
      - API Called
      - Has UI/Window
      - Does Network Communication
        - IRC
        - HTTP
      - Registered in AutoStart locations
      - Creates Windows Tasks (jobs)
      - Modifies PE Files
      - Creates PE Files
      - Injects into Trusted Processes







<u>File Edit Search View Encoding Language Settings Macro Run Plugins Window ?</u>

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#### 😑 behavioral.arff

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@RELATION behavioral security

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Ln:1 Col:30 Sel:0

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### Example **Data to Models**

**DENIOR** 

...click here if demo GODs act up!..



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## Lab to field Apply Classifiers

## Monitoring and Blocking hook points

- May or may not be the same
  - Some hooks points are merely for state/information collection
- Work done in API Hooks
  - Collect information
  - Transform information into feature vector
  - Evaluate against model
  - Allow or Deny







## Lab to field Apply Classifiers

- Which APIs to hook?
  - Higher level API (CreateProcess @ kernel32.dll)
  - Lower level API (NtCreateProcess? NtCreateThread?, Ldrpxxx?)
  - Higher level APIs (exports by kernel32) provide fine grain control
  - Many high level APIs map to few lower level APIs (functionally)
  - Lower level APIs provide a more comprehensive view

## Block Action:

- Failing an API
  - Out parameter
  - Return code
- Terminate Thread/process





# **Machine Learning for behavioral security**

Reality check...





### Automation Reality check

### Practical Challenges

- Samples fail to run in automation
  - Good Samples fail to run in automation
    - more commonly than Malicious samples
    - Dependency, Configuration, etc.
    - GUI automation

### Malicious Samples deliberately fail to run in automation

- VM Aware
- Automation Aware
  - Check own file name (example: sysdat
  - Check parent process (Threat: Trojan.
  - Check application settings (Threat: Adv je
  - Check commonly used applications (MS Office)
- Samples may be stale: C & C Down
- System state sensitivity
  - Valid Samples: Missing depencies like Java, .NET, etc.
  - Malicious Samples: Missing targeted applications like Ado

#### IMPORTANT

### IMPORTANT: Enabling 3rd Party Extensions in Internet Explorer

In order to run Instant Buzz (or any other toolbar based program like those from Google, Yahoo, or Alexa), we must change a setting in your Internet Exploer called "Enable 3rd Party Extensions." In most cases, this is harmless, but in some rare cases this can activate spyware that is already installed on your system.

Chances are low that this will happen to you, but in the event it does, most spyware can be eliminated using a freeware removal tool such as the great one that can be found at <a href="http://www.safer-networking.org/">http://www.safer-networking.org/</a>.

Yes, please enable 3rd party extensions

No thanks, please abort installation



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cmp ebx, 564d5868h ;'VMXh'

in eax, dx

detected

;'VMXh' ;get VMware version ;'VX'

NNare



### Machine Learning Reality check

## • Machine Learning Challenges

- Imbalanced data sets
- Missing features
- Anomalous feature values
  - outlier or deliberately manufactured?
  - Some tricks observed in malware\*:
    - Non-standard ImageBase
    - Large values in .DATA/SizeofRawdata
    - Bogus values in LoaderFlags

• Section Modification: Or how to kill many tools.

Section Reader Table		
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SigeOfRawData:	0x00001000	
PointerToRayData:	0x00001000	
PointerToRelocations:	0x00000000	
PointerToLinenumbers:	0x00000000	
NumberOfRelocations:	0x0000	
NumberOfLinenumbers:	0x0000	
Characteristics:	0xE0000020	
(CODE, EXECUTE, READ,	WRITE)	
	,	
2. item:		
Name:	DATA	
VirtualSize:	0x00045000	
VirtualAddress:	0x00002000	
SizeOfRawData:	0x00045000	
PointerToRawData:	0x00002000	
PointerToRelocations:	0x0000000	
PointerToLinenumbers:	0x0000000	
NumberOfRelocations:	0x0000	
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(INITIALIZED_DATA, REA	D, WRITE)	
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Name :	NicolasB	
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Characteristics:	0xC0000040	
(INITIALIZED DATA, REA	D, WRITE)	

\*Scan of the Month 33: Anti Reverse Engineering Uncovered By Nicolas Brulez - 0x90(at)Rstack(dot)org



### Stealthy Malware Malicious Payloads

- NPTs (Non Process Threat)
  - Trusted process -> Malicious Behavior
  - File vs. Process
  - Code vs. Data
    - Malicious PDF → Browser or Adobe reader
    - Malicious JAR files → Browser or java.exe
    - Malicious MSI files → msiexec.exe
  - DLLs
    - Regsvr32
    - Rundll32
    - Svchost.exe
    - IE/Explorer Extensions

### How to automate these?

How/where is protection enforced? What is remediated?

.HLP

.LN

.MSI

Μ.

		Infectable Object	Description
		.ASP	Active-X components of Active server pages
		.BAT	DOS Batch files
		.CSH	C Shell Script
		.CHM	MS Compiled HTML Help
		.CLA(SS)	JAVA file
		.CSC	Corel Script
		.CSS	Cascading Style Sheet
		.HT?	HTML variant
		.HTM	HTML variant
		.HTA	HTML variant
		.HTML	HTML variant
		.нтт	Hypertext Template
		.INI	mIRC - SCRIPT.INI
		.INI	pIRCH - EVENTS.INI
ŀ	le	.JS	JavaScript source
		.JSE	JavaScript Encoded Script File
REG		.MHT	HTML code
		.MHTML	HTML code
SCR		.SCT	Windows Script Component
		.sh	Bourne shell or Korn Script
		.SHB	Shell Scrap object
		.SHTML	HTML file
		.VB	VBScript File
		.VBS	Visual Basic script file
		.VBE	Visual Basic encoded script
		.VBX	Visual Basic Extension
		.WBT	Windows Batch file
		.WSC	Windows Script Component
		.WSF	Windows Script File

# **Conclusion & Food for thought!**







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### Recap Scaling to the Malware population

- Volume of malware by unique file fingerprint != New Malware
  - Behaviorally malware is not evolving at every instance
  - Scalability can be handled with Automation
  - Be aware of pitfalls of automation
  - Automation + domain knowledge
  - Use domain experts effectively
- Challenge
  - What if the Malware is a valid application with configuration file?



- Solution: Opportunity for Creative Feature Engineering?





# Thank You!

### Sourabh Satish

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	<ul> <li>Store predictions for visualization</li> <li>Output predictions</li> <li>Output additional attributes</li> <li>Cost-sensitive evaluation Set</li> </ul>	
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	API_ShowWindow	
(Nom) class	API_FINGWINGOW	
Start Stop	API_SHEILEXECULE	
	API_Deleterile	
Result list (right-dick for options)	API CreateFile	
12:32:59 - trees.J48	API HTTPSendReguest	
	API DeviceIoControl	
	HAS_WINDOSW	
	HAS_LISTEN_PORT_OPEN	
	CREATES_TASKS	
	MODIFIES_PE	
	CREATES_PE	
	DOES_INJECT	
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Log

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Classifier		
Chapter 149 - C 0 25 - M 2		
Choose 946 -C 0.25 -M 2		
Test options	Classifier output	
🔘 Use training set	J48 pruned tree	•
Supplied test set Set		
Cross-validation Folds 10	CreatedSinceSecs <= 6587	
Percentage split % 66	CREATES_TASKS = T	
Mara aptions	CreatedSinceSecs <= 9: BAD (18.0/3.0)	
More opuons	CreatedSinceSecs > 9	
	API_ShellExecute = T	
(Nom) class 🔹 👻	API_DeleteFile = T: GOOD (9.0)	
	$      API_DeleteFile = F: BAD (12.0/2.0)$	
Start	API_ShellExecute = r	
Result list (right-click for options)	$\begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 $	
12:32:59 - trees.J48	API MoveFile = F	
	MODIFIES PE = T; BAD (3.0)	=
	MODIFIES PE = F: GOOD (2.0)	
	API_DeleteFile = F: GOOD (13.0)	
	CREATES_TASKS = F	
	API_CreateFile = T	
	API_MoveFile = T: GOOD (8.0/1.0)	
	API_MoveFile = F: BAD (10.0/2.0)	
	API_CreateFile = F	
	CreatedSinceSecs <= 654: BAD (32.0/4.0)	
	CreatedSinceSecs > 654: GOOD (2.0)	
	CreatedSinceSecs > 6587: GOOD (13.0)	
	Number of Leaves : 12	
	Size of the tree : 23	-
Status		

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Log

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🕢 Weka Explorer								
Preprocess Classify Cluster Associate S	Select attributes Visualize							
Classifier								
Choose J48 -C 0.25 -M 2								
Test options	assifier output							
O Use training set								
Supplied test set Set	Time taken to build model: 0 s	econds						
Cross-validation Folds 10								
Percentage split % 66	=== Stratified cross-validatio	n ===						
More options	Junuary							
	Correctly Classified Instances	101	81.4516 %					
(Nom) class	Incorrectly Classified Instanc	es 23	18.5484 %					
	Kappa statistic	0.6249						
Start Stop	Mean absolute error	0.2555						
Result list (right-click for options)	Root mean squared error	0.4142						
12:32:59 - trees 148	Root relative squared error	82.9103 %						
12.02.07 0 003.5 10	Total Number of Instances	124						
	=== Detailed Accuracy By Class	===						
	TP Rate FP Ra	te Precision Recall	F-Measure ROC Area	a Class				
	0.712 0.0	92 0.875 0.712	0.785 0.757	GOOD				
	0.908 0.2		0.837 0.757	BAD				
	Weighted Avg. 0.815 0.1	95 0.625 0.615	0.612 0.757					
	=== Confusion Matrix ===							
				E				
	a b < classified as							
	42 17   a = GOOD							
				*				
Status								
UK								

Weka Explorer				
Preprocess Classify Cluster Associate S	elect attributes Visualize			
Classifier				
Choose RandomForest -I 10 -K 0 -S	1			
	-			
Test options	Classifier output			
🔘 Use training set				*
Supplied test set Set	Time taken to build model: 0.01 s	econds		
Cross-validation Folds 10				
Percentage split % 66	=== Stratified cross-validation =	==		
More options	Summary			
	Correctly Classified Instances	102	82.2581 %	
	Incorrectly Classified Instances	22	17.7419 %	
	Kappa statistic	0.6432		
Start Stop	Mean absolute error	0.2519		
	Root mean squared error	0.3774		
Result list (right-click for options)	Relative absolute error	50.48 %		
12:32:59 - trees.J48	Root relative squared error	75.5492 ₹		
12:39:17 - trees.RandomForest	Total Number of Instances	124		
	=== Detailed Accuracy By Class ==	=		
	TP Rate FP Rate	Precision Recall	F-Measure ROC Area	Class
	0.78 0.138	0.836 0.78	0.807 0.871	GOOD
	0.862 0.22	0.812 0.862	0.836 0.871	BAD
	Weighted Avg. 0.823 0.181	0.823 0.823	0.822 0.871	=
	=== Confusion Matrix ===			-
	a b < classified as			
	46 13   a = GOOD			
	9 56   b = BAD			
				-
Status				

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🤓 Orange Canvas	_ <b>D</b> X
<u>File View Options Widget H</u> elp	
Data Visualize Classify Regression Evaluate Unsupervised Associate Text Mining Bioinformatics Visualize Qt Prototypes	
Image: Select       Data       Select       Rank       Purge       Merge       Concatenate       Data       Select       Image       Image </td <td>ate Feature</td>	ate Feature
Table Attributes Domain Data Sampler Data data	Constructor

Right-click to add widgets



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1111	Data	Visualize	Classify	Regression	Evaluate L	nsupervised	Associate	e Text	t Mining	Bioinformatics	Visualize Qt	Prototypes			
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	•													Þ	•



BehavioralData





BehavioralData





Last event: Classification Tree Viewer: ProcessSignals: Calling < bound method OWClassificationTreeViewer.setClassificationTree of < OWClassificationTreeViewer.OWClassificationTree

Classification Tree Viewer							
Displayed information	Classification Tree	Class	P(Class)	P(Target)	# Inst	Distribution (rel)	Distribution (abs)
Majority class	▲ <root></root>	BAD	0.524	0.476	124	0.476:0.524	59:65
Probability of majority class	CreatedSinceSecs <=7745.500	BAD	0.586	0.414	111	0.414:0.586	46:65
Probability of target class	CreatedSinceSecs <=694.000	BAD	0.641	0.359	92	0.359:0.641	33:59
	API_CreateFile = T	GOOD	0.500	0.500	38	0.500:0.500	19:19
Number of instances	API_ShellExecute = T	BAD	0.714	0.286	21	0.286:0.714	6:15
Relative distribution	API_FindWindow = T	BAD	0.875	0.125	16	0.125:0.875	2:14
Absolute distribution	API_FindWindow = F	GOOD	0.800	0.800	5	0.800:0.200	4:1
	API_ShellExecute = F	GOOD	0.765	0.765	17	0.765:0.235	13:4
Expand/shrink to level	API_DeleteFile = T	BAD	0.800	0.200	5	0.200:0.800	1:4
E	API_DeleteFile = F	GOOD	1.000	1.000	12	1.000:0.000	12:0
3	API_CreateFile = F	BAD	0.741	0.259	54	0.259:0.741	14:40
	CREATES_TASKS = T	BAD	0.545	0.455	22	0.455:0.545	10:12
larget class	CreatedSinceSecs <=	BAD	0.846	0.154	13	0.154:0.846	2:11
GOOD 🔻	CreatedSinceSecs >4	GOOD	0.889	0.889	9	0.889:0.111	8:1
	CREATES_TASKS = F	BAD	0.875	0.125	32	0.125:0.875	4:28
Tree size	API_DeleteFile = T	BAD	0.810	0.190	21	0.190:0.810	4:17
Number of podes: 27	API_DeleteFile = F	BAD	1.000	0.000	11	0.000:1.000	0:11
Number of leaves: 14	CreatedSinceSecs >694.000	GOOD	0.684	0.684	19	0.684:0.316	13:6
Number of leaves. 14	API_MoveFile = T	GOOD	1.000	1.000	9	1.000:0.000	9:0
	API_MoveFile = F	BAD	0.600	0.400	10	0.400:0.600	4:6
	API_FindWindow = T	GOOD	0.750	0.750	4	0.750:0.250	3:1
	API_FindWindow = F	BAD	0.833	0.167	6	0.167:0.833	1:5
	CreatedSinceSecs >7745.500	GOOD	1.000	1.000	13	1.000:0.000	13:0

Report





🤓 Orange Canvas		
<u>File View Option</u>	ns Widget <u>H</u> elp	
Data Vinueliaa	TestLearners	1
Data Visualize	TestLearners   Sampling   © Cross-validation   Number of folds: 5   © Leave-one-out   Random sampling   Repeat train/test: 10   Relative training set size:	
	Specificity Area under ROC curve Information score Target class BAD Report	

Last event: TestLearners: ProcessSignals: Calling < bound method OWTestLearners.setLearner of < OWTestLearners.OWTestLearners object at 0x07A193D8>> with TreeLearner 'Classifica'



### Go <u>back</u>...

![](_page_60_Picture_2.jpeg)