Selected Topics for IT Security

Applied Machine Learning for Cyber Security
An Overview

Lecturer

Huang Xiao

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Chair for IT Security (I20), Prof. Dr. Claudia Eckert

Technische Universität München

Course Information

- Vorlesung: 2 SWS / 4,0 ECTS-Credits
- Veranstalter: Claudia Eckert
- Zeit und Ort: Mi, 17:00 – 19:00 Uhr, 00.013.009
- Beginn: Mittwoch, 13.04.2016
- Ende: Mittwoch, 13.07.2016
- Prüfung: Mündliche Prüfung
- Website: https://www.sec.in.tum.de

Questions to the course, please contact:

Thomas Kittel (kittel@sec.in.tum.de)

Topics

13.04.2016: Huang Xiao – Applied Machine Learning on Cyber Security: An Overview
20.04.2016: Huang Xiao – Adversarial Learning: AI as a New Security Target
27.04.2016: Thomas Kittel, Sergej Proskurin – Virtual Machine Introspection
04.05.2016: Alexander Malkis – Proving security properties of multithreaded programs
11.05.2016: Steffen Wagner – Trusted Computing: TPM2.0
18.05.2016: Julian Kirsch – Semi-automated Reverse Engineering Techniques Targeting Contemporary Malware
25.05.2016: Julian Schütte – Android Application Security
01.06.2016: George Webster – Large Scale Malware Analysis
08.06.2016: Apostolis Zarras – Internet of Things: A Playground for Hacking
15.06.2016: Johann Heyszl – Embedded System Security: Common Pitfalls and Solutions
22.06.2016: Andreas Ibing – Symbolic Execution for Automated Bug Detection
29.06.2016: Sascha Wessel, Michael Weiß – Container-Technologie, OS Architectures, trust-me solution
06.07.2016: Paul Muntean – Control Flow based Security Techniques
13.07.2016: TbA

Outline

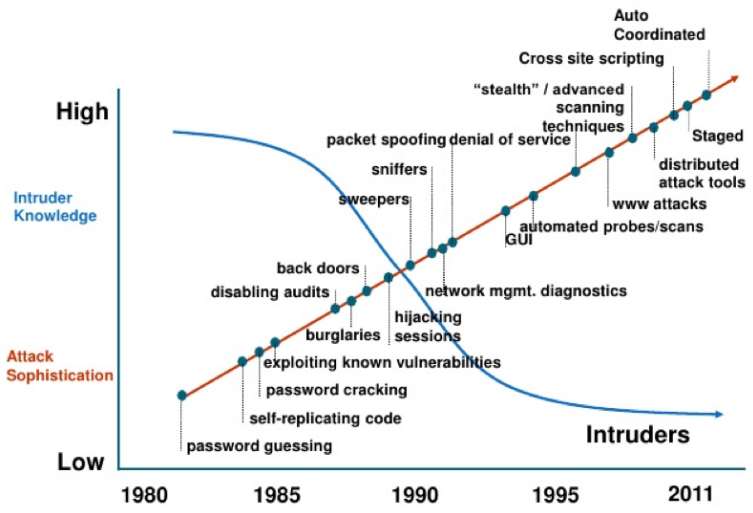
- **Introduction & Motivation**
- Machine Learning for Security
- Research Subfields
- Challenges & Discussion
- References

Introduction

- Information Technology as central role
- Process, interpretation, transmission of information
- Built on technological stacks, e.g., networks, sensors, computers
- No perfect system exists
- Information security is “good enough” solution
- Goals: C-I-A triad
- Data-driven Security

Motivation

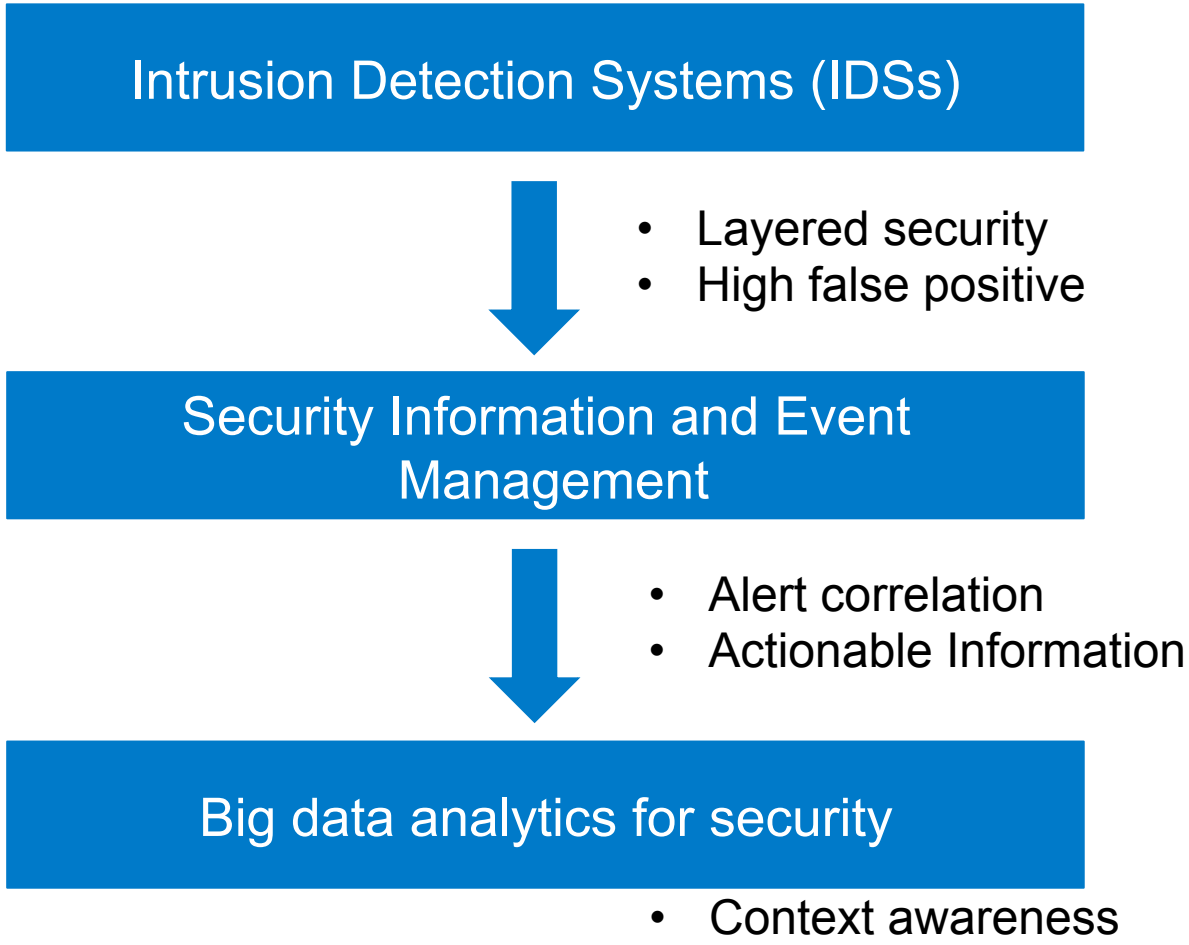
- Attack sophistication is increasing
- Required expertise is decreasing
- Quality of tools is improved constantly
- Technological trends:
  - Big data, Cloud, IoT, Industry 4.0



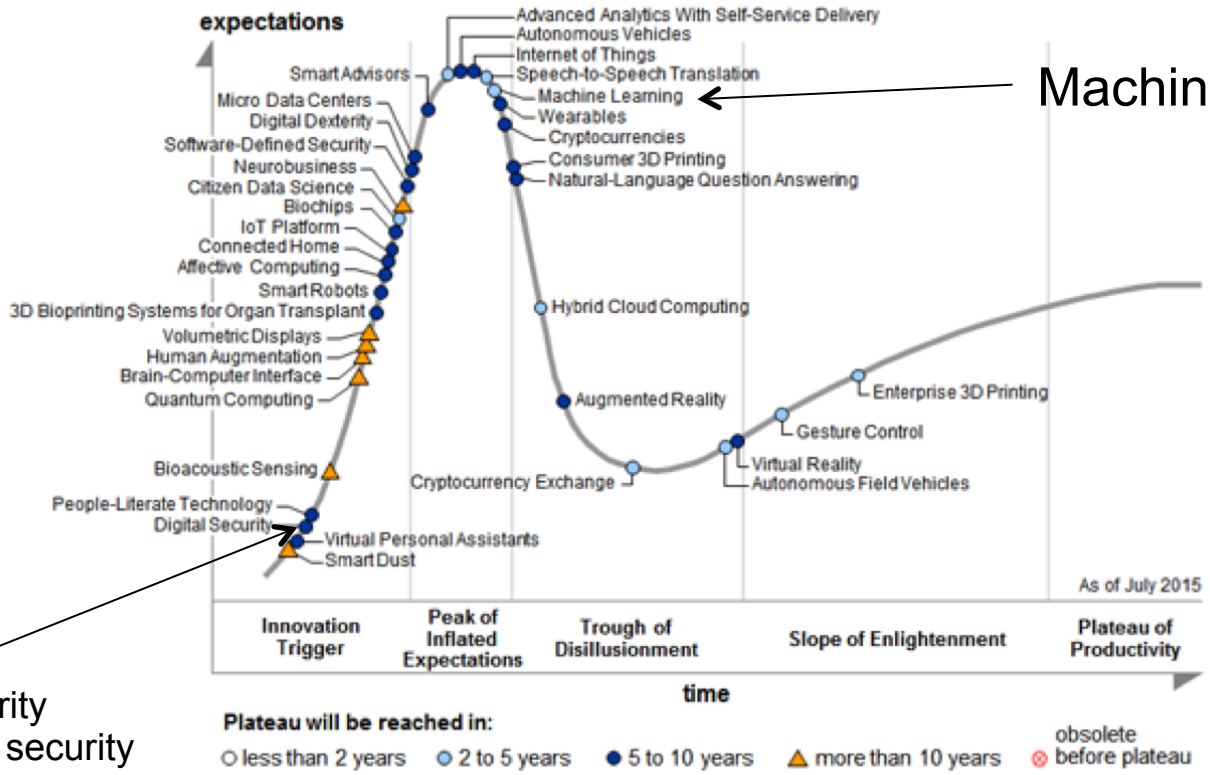
Why now

- Security Analysts are often overwhelmed
- Data collection & Storage & Retrieving is well underway
- Current detection techniques might fail on
  - Polymorphic malwares
  - Zero-day attacks
  - APTs
- Dissolving network perimeter:
  - BYOD/Cloud

Generations of Security



Technology hype ~5 years



Machine learning

- ✓ Digital security
- ✓ Data driven security

Source: Gartner (August 2015) Hype cycle

Digital Security

- Rising research direction in IT security
- Driven by Machine learning / data mining techniques
- Huge amount of data generated
- 2010 Verizon: **86%** cases of breach, evidence was in logs
- How do we make sense of data?
- What machine learning can not do for now? **Cyber Security**

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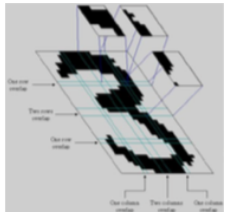
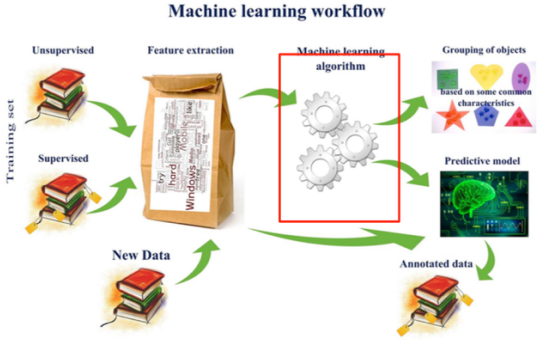
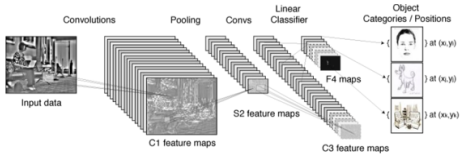
Introduction of Machine Learning

Fast pacing AI development







~70s-80s: Pattern Recognition

- ✓ Based on rules, logic, expert knowledge
- ✓ Automate tasks by program

~90s − now: Machine learning

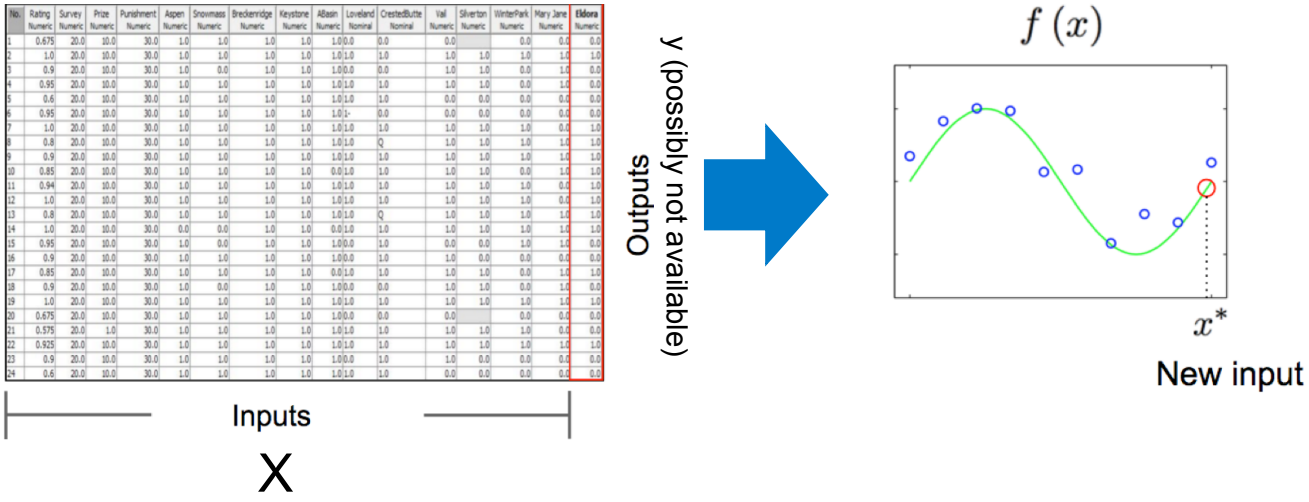
- ✓ Uncertainty introduced by Pearl et al.
- ✓ Learning models from seen data samples (historical view)
- ✓ Focus on prediction
- ✓ E.g., SVM, decision tree, Naïve Bayes, etc…

2006 - now: Deep learning

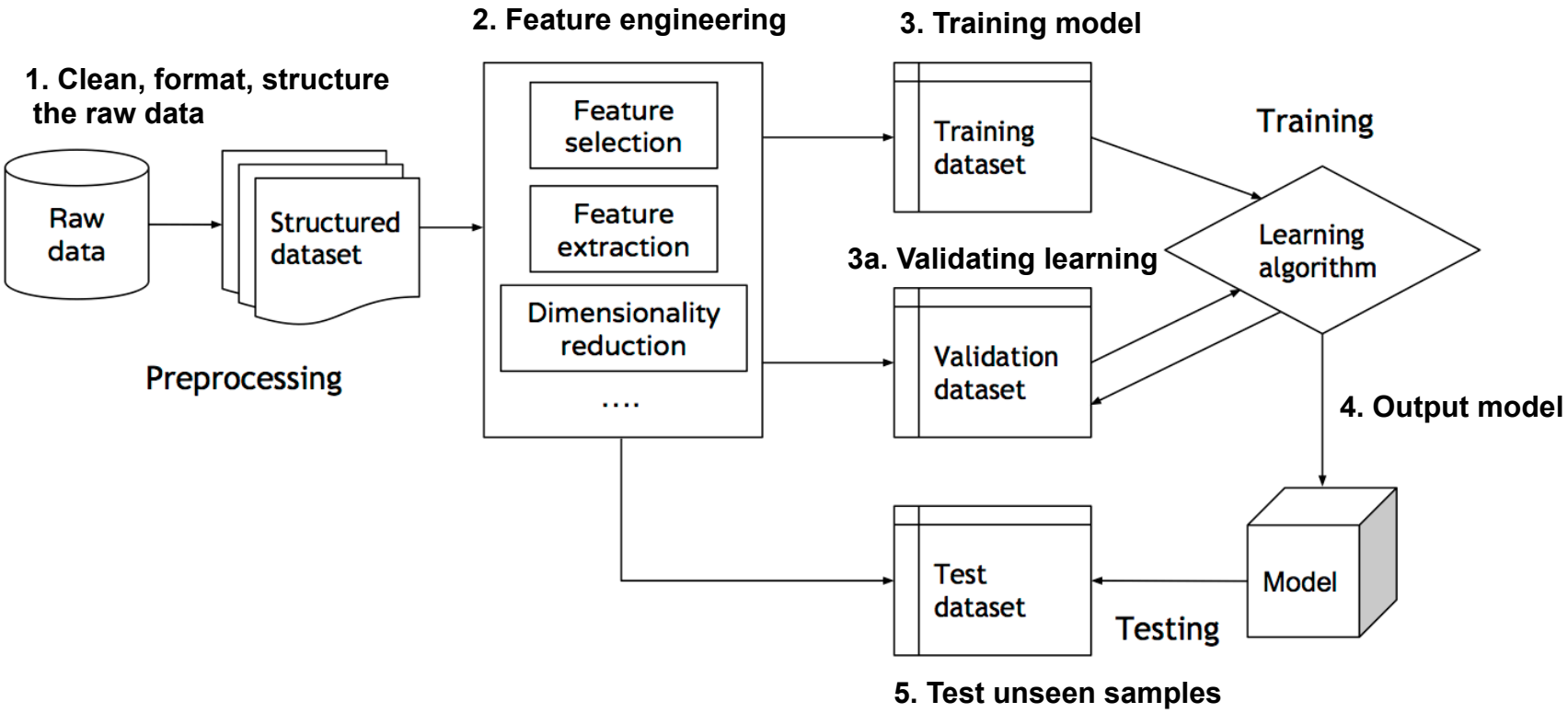
- ✓ Renaissance of NNs
- ✓ Unsupervised feature learning
- ✓ Learning non-local patterns
- ✓ Mimic how cortex works
- ✓ No theoretical ground so far
- ✓ Works like a charm

Make sense of the data

Given a dataset (X, y) consists of N rows(samples), we learn a function f(x) that can predict unseen samples with minimal errors.



Learning Process

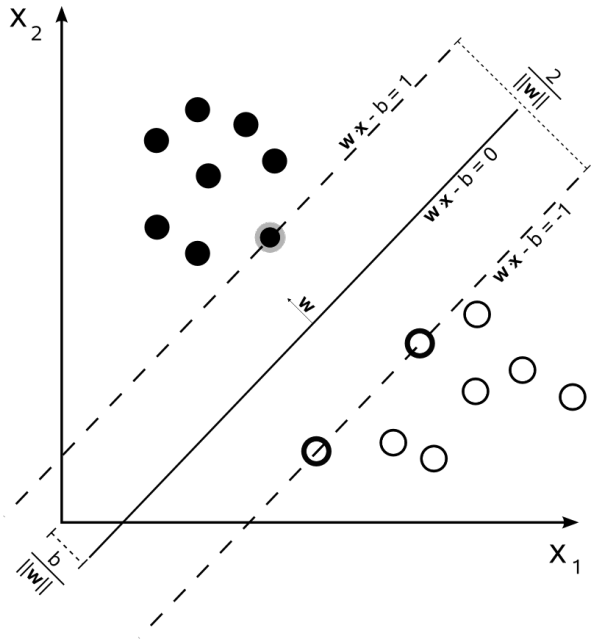


Learning Schema

Representation	Evaluation	Optimization
Instance based • Support vectors • K-nearest neighbor Tree based • Decision trees • Random forest Graphical models • Bayesian networks • HMM	• Accuracy or error rate • Precision and recall • Squared error • F1 score • KL divergence • Likelihood • Cross entropy	• Greedy search • Gradient descent • Conjugate gradient • Newton method • Stoc. gradient descent • Linear programing • Quadratic programing

Example: SVM binary classification

Given N samples X and labels $y \in \{+1, -1\}$, find the maximal margin that separate both classes of samples.



Minimize the objective functions

$$\left[\frac{1}{n}\sum_{i=1}^{n}\max\left(0, 1 - y_i(w \cdot x_i + b)\right)\right] + \lambda\|w\|^2.$$

Hinge-loss

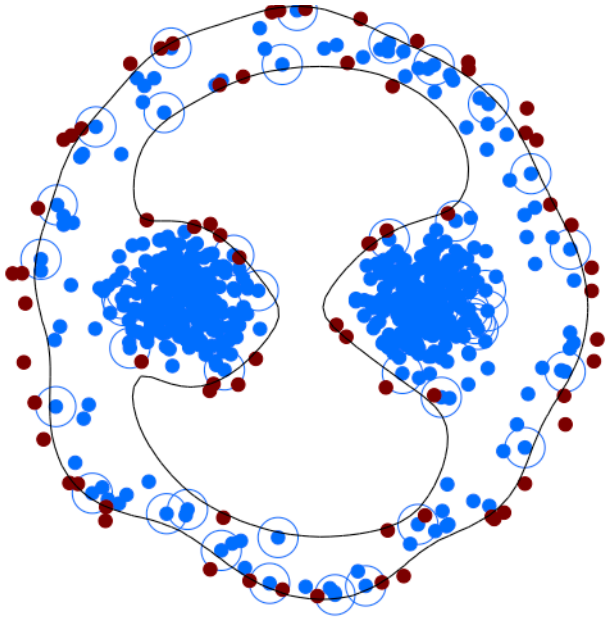
Regularization

Effect of optimization

- Misclassified error is minimal
- Separating hyperplane is not too complex

Example: One-class classification

Given N samples X and without labels, find an optimal data description of the majority class of the data samples. The rest is regarded as anomalies (outliers)



Learn a hypersphere of the data support

$$\min_{R\in\mathbb{R},\boldsymbol{\xi}\in\mathbb{R}^\ell,c\in F} \quad R^2 + \frac{1}{\nu\ell}\sum_i \xi_i$$

$$\text{subject to} \quad \|\Phi(\mathbf{x}_i) - c\|^2 \leq R^2 + \xi_i, \quad \xi_i \geq 0 \quad \text{for } i \in [\ell].$$

R: the radius of the hypersphere

Make Sense of the Security

Data sources

- ✓ Host based
  - ✓ system calls, sys logs
- ✓ Network-based
  - ✓ Inbound/outbound traffic
- ✓ Application logs
  - ✓ DB logs, web logs
- ✓ IDS sensor alerts
  - ✓ low level alarms
- ✓ Behaviour based
  - ✓ mouse, keystrokes
  - ✓ command lines
- ✓ Signatures databases

- ✓ online vs offline
- ✓ misuse vs. anomaly based
- ✓ continuous vs. periodic
- ✓ passive vs proactive

Make sense of it

- ✓ Detection
- ✓ Correlations
- ✓ Clusterings/Similarities
- ✓ Attack vectors
- ✓ Threat models
- ✓ Temporal/Spatial
- ✓ Prevention

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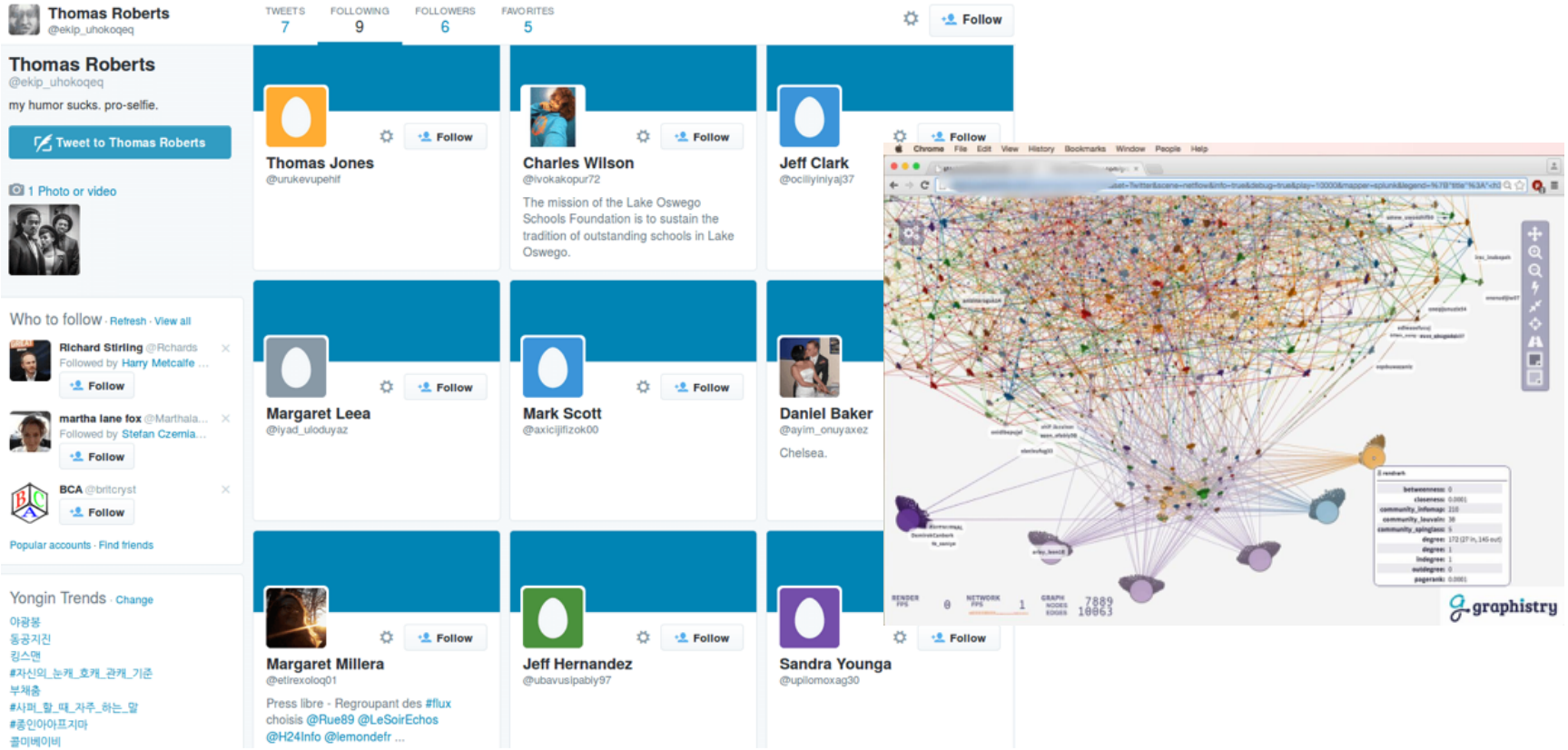
Botnets detection

- Networks of machines compromised by malware
- Threats:
  - Information/identity theft, DDoS, Software piracy, Spamming /Phishing…
- Very prevalent threats
  - It's easy, fun, and low risk …
- Protocols: IRC, HTTP, IM, …
- C&C: centralized, stared, hierarchical, random
- Fast fluxing, evolving, traffic encryption

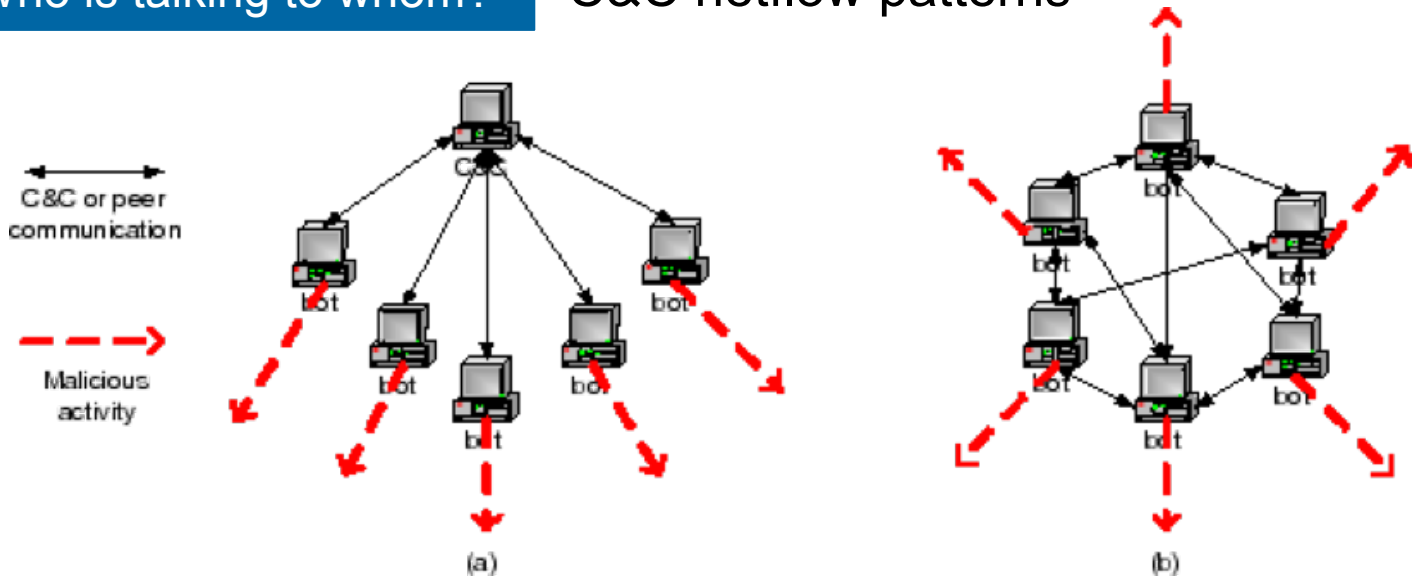
Botnets detection



BotMiner

Who is talking to whom?

C&C netflow patterns



Activity patterns

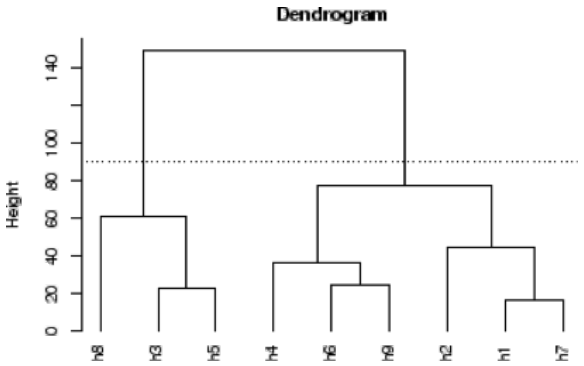
Who is doing what?

Guofei Gu, Roberto Perdisci, Junjie Zhang, and Wenke Lee. 2008. BotMiner: clustering analysis of network traffic for protocol- and structure-independent botnet detection. In Proceedings of the 17th conference on Security symposium (SS'08). USENIX Association, Berkeley, CA, USA, 139-154.

BotMiner

C-Plane features	e.g., ✓ #flows per hour (fph) ✓ #packets per flow (ppf) ✓ avg. #bytes per packets (bpp) ✓ avg. #bytes per second (bps)
A-Plane features	e.g., scanning, spam, binary downloading, exploit

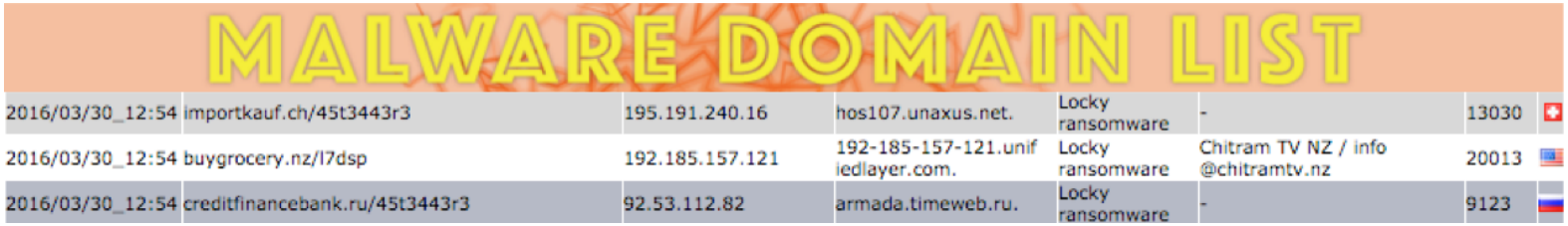
hierarchical clustering



Output: clusters of machines

Bot or not?

Malicious Domains/URLs

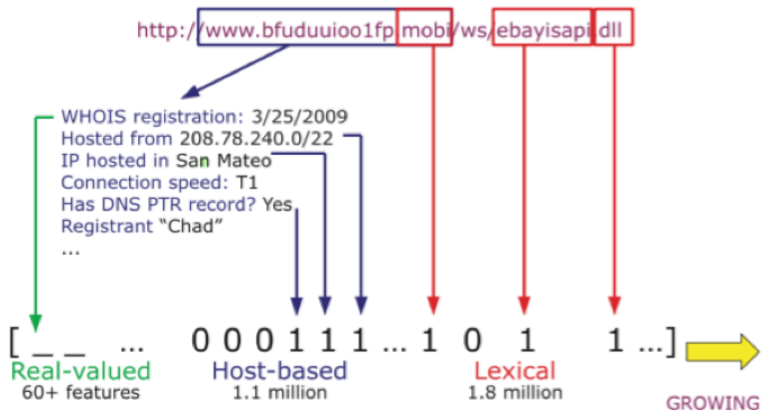


Malware samples from www.malwaredomainlist.com

- Bots to locate C&C
- Links to phishing/spam/scam server
- Drive-by downloads

Learning malicious URLs

Data sources: 100 days, 20,000 URLs/day



Host-based

lexical-based

Features

- ✓ IP address properties
- ✓ WHOIS records
- ✓ Domain TTL
- ✓ Blacklist membership
- ✓ Geographic prop.
- ✓ Connections speed

- ✓ bag of words
- ✓ record every token
- ✓ Separate domain levels, host, path
- ✓ Sparse representation

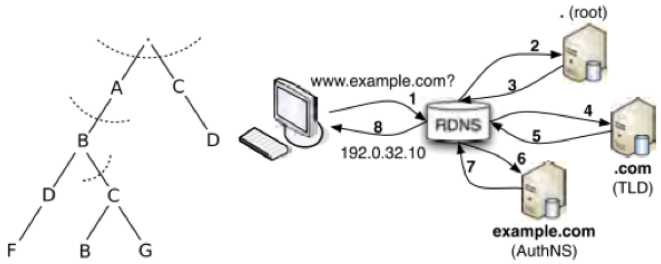
Online Classifiers

- ✓ Perceptron
- ✓ Stochastic gradient descent
- ✓ Confident weighted
- ✓ Passive aggressive

Ma, J., Saul, L.K., Savage, S. and Voelker, G.M., 2011. Learning to detect malicious URLs. ACM Transactions on Intelligent Systems and Technology, 2(3)., pp.1–24.

Leveraging DNS traffic

Time-based	DNS answer based
✓ short life ✓ daily similarity of requests ✓ repeating patterns ✓ access ratio	✓ #distinct IP addresses ✓ #distinct countries ✓ #domains IP shared ✓ Reverse DNS query results
TTL value-based	**Domain name based**
✓ Avg. TTL ✓ Std. TTL ✓ #distinct TTL ✓ # TTL Change ✓ %usg. of TTL range	✓ %numerical characters ✓ %length of the longest meaningful substring



(a) DNS Tree (b) Domain Resolution

Features can be built from DNS traffic

Using C4.5 decision tree as classifier

✧ Bilge, L. et al., 2011. EXPOSURE : Finding Malicious Domains Using Passive DNS Analysis. Ndss., pp.1–17
✧ Antonakakis, M. et al., 2011. Detecting Malware Domains at the Upper DNS Hierarchy. USENIX Security Symposium., 11., pp.1–16.

Insider Attacks

- Traitor or Masquerader
  - Attacks from inside
- Threat: Inside > Outside
- Types of threats are diverse:
  - exfiltration of data, unauthorised downloads, eavesdropping…
- Basic idea: user behaviour modelling
  - Unix command lines
  - Mouse movements, keystrokes
- Re-authentication, continuous authentication

Unix shell commands modeling

```
445  jekyll server --help
446  jekyll server -B
447  atom .
448  ps aux | grep 'jek'
449  kill 9 3530
450  kill -9 3530
451  kill 3530
452  ps aux | grep 'jek'
453  pwd
454  jekyll server -B
455  atom .
456  atom .
457  kill -9 3530
458  kill -9 11035
459  jekyll server
460  pwd
461  cd ~/repos/h3lib
462  git status
463  git add talks/ML4Sec/*
464  git commit -m 'add talk'
465  git push origin master
```

Schonlau dataset

- ✓ 70 users
- ✓ 20 masquerade users
- ✓ 15,000 commands per user
- ✓ Block size: 100
- ✓ clean or dirty block

Bag of words for One-class SVM works well

Wang, K. and Stolfo, S.J., 2003. One-class training for masquerade detection. Workshop on Data Mining for Computer Security, Melbourne, Florida., pp.10–19.

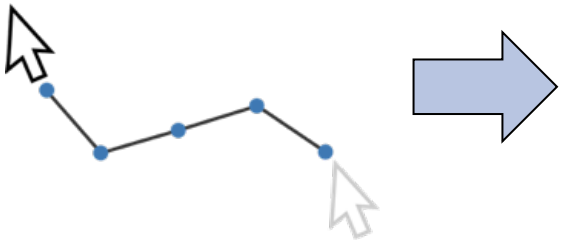
Behavior Biometrics

(physical) What you are	(behavior) What you do	To detect an insider…

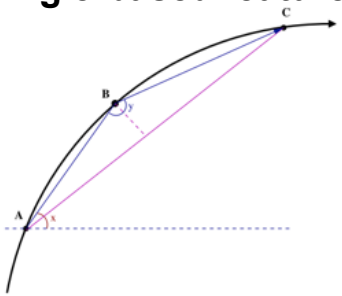
✓ Fingerprint
✓ Retina pattern
✓ Voice
	✓ Handwritten signature
	✓ Gait
	✓ Keystrokes
	✓ Mouse dynamics
		✓ Input interaction:
		  ✓ mouse, keystrokes
		✓ Application level:
		  ✓ GUI events
		  ✓ Habits, strategy
		✓ Low-level:
		  ✓ System traces
		  ✓ Audit logs
		  ✓ Registry access
		  ✓ In/Outbound traffic

Mouse dynamics (cont. auth.)

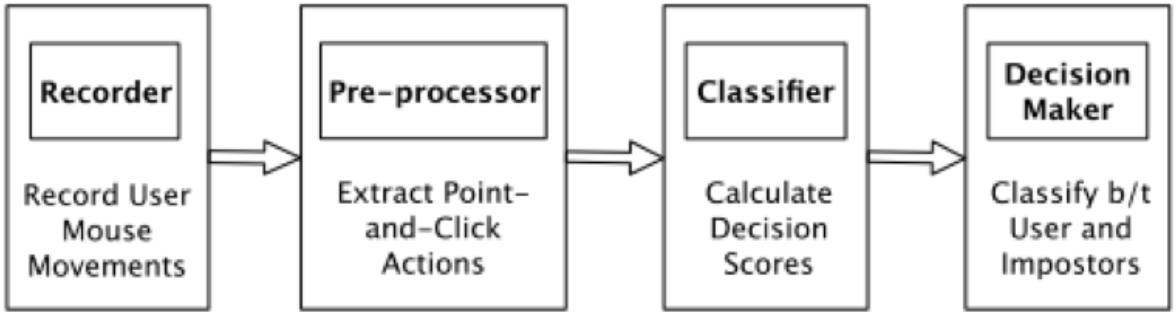
Point-and-click patterns



Angle-based features



Using binary SVM classifier

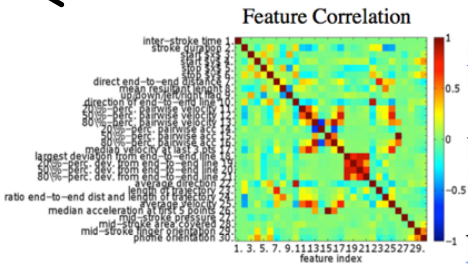


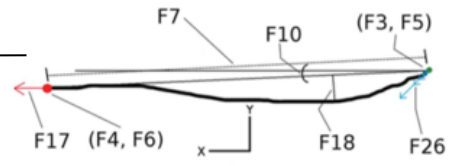
Zheng, N., Paloski, A. and Wang, H., 2011. An efficient user verification system via mouse movements. Proceedings of the 18th ACM conference on Computer and communications security - CCS '11., p.139

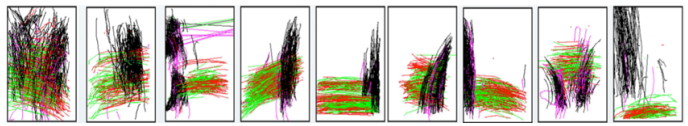
Touchalytics (cont. auth.)

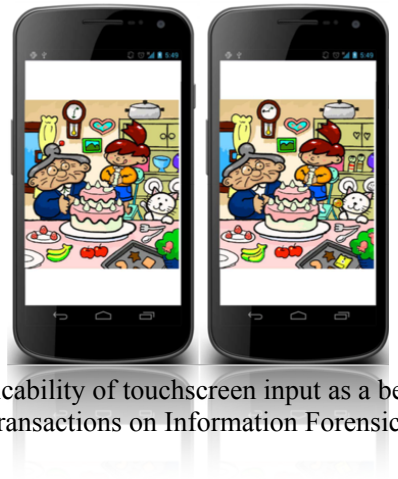
Feature selection

Rel. mutual information	Feature description
20.58%	mid-stroke area covered
19.63%	20%-perc. pairwise velocity
17.28%	mid-stroke pressure
11.06%	direction of end-to-end line
10.32%	stop x
10.15%	start x
9.45%	average direction
9.43%	start y
8.84%	average velocity
8.61%	stop y
8.5%	stroke duration
8.27%	direct end-to-end distance
8.16%	length of trajectory
7.85%	80%-perc. pairwise velocity
7.24%	median velocity at last 3 pts
7.22%	50%-perc. pairwise velocity
7.07%	20%-perc. pairwise acc
6.29%	ratio end-to-end dist and length of trajectory
6.08%	largest deviation from end-to-end line
5.96%	80%-perc. pairwise acc
5.82%	mean resultant lenght
5.42%	median acceleration at first 5 points
5.39%	50%-perc. dev. from end-to-end line
5.3%	inter-stroke time
5.14%	80%-perc. dev. from end-to-end line
5.04%	20%-perc. dev. from end-to-end line
5.04%	50%-perc. pairwise acc
3.44%	phone orientation
3.08%	mid-stroke finger orientation
0.97%	up/down/left/right flag
0%	change of finger orientation









Frank, M. et al., 2013. Touchalytics: On the applicability of touchscreen input as a behavioral biometric for continuous authentication. IEEE Transactions on Information Forensics and Security, 8(1)., pp.136–148.

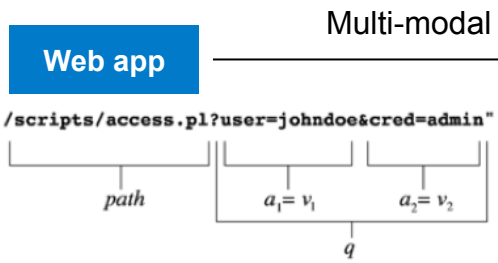
Web Attacks

- Attacks on web applications
- Types: SQLi, RFI, LFI, XSS, DT, CS, etc…
- Web Server Logs: conform to CLF (Common Log Format)
  - *remotehost rfc931 authuser [date] "request" status bytes*
- Misuse-based vs. Anomaly-based
  - Misuse: match signature databases
  - Anomaly: able to detect unknown patterns
- Application oriented multi-modal IDS

Web Attacks

Example (log entry):

```
169.229.60.105 - johndoe [6/Nov/2002:23:59:59 -0800]"GET /scripts/access.pl?user=johndoe&cred=admin" 200 2122
```



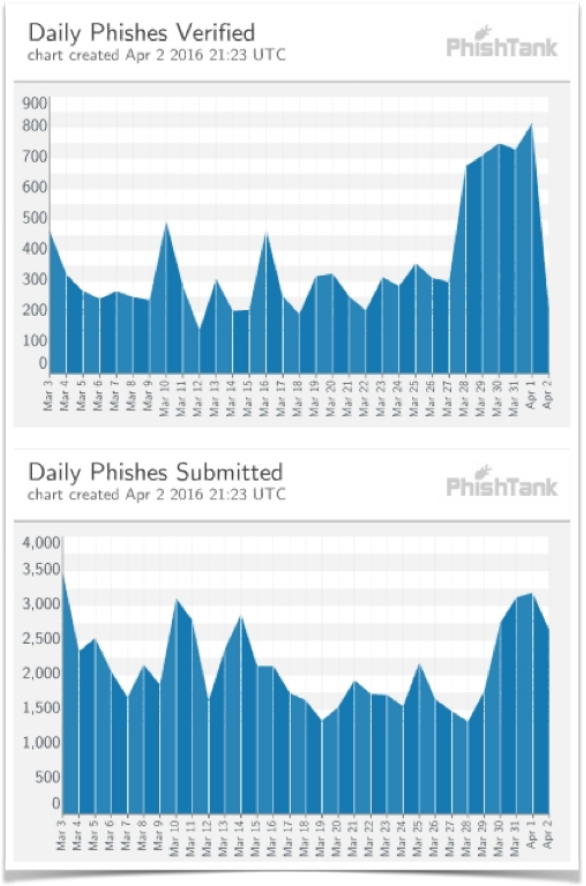
Features

- ✓ attribute length
- ✓ attribute grammer
- ✓ attribute presence
- ✓ attribute order
- ✓ character distribution
- ✓ requests time delay
- ✓ token finder
- ✓ invocation order

Kruegel, C., Vigna, G. and Robertson, W., 2005. A multi-model approach to the detection of web-based attacks. Computer Networks, 48(5)., pp.717–738.

Phishing/Spam

- Normally legitimate-like website/Email
- Detection tools:
  - Spoofguard, Netcraft, SpamAssasin …
- Domain/Content based features



source: PhishTank

Phishing/Spam

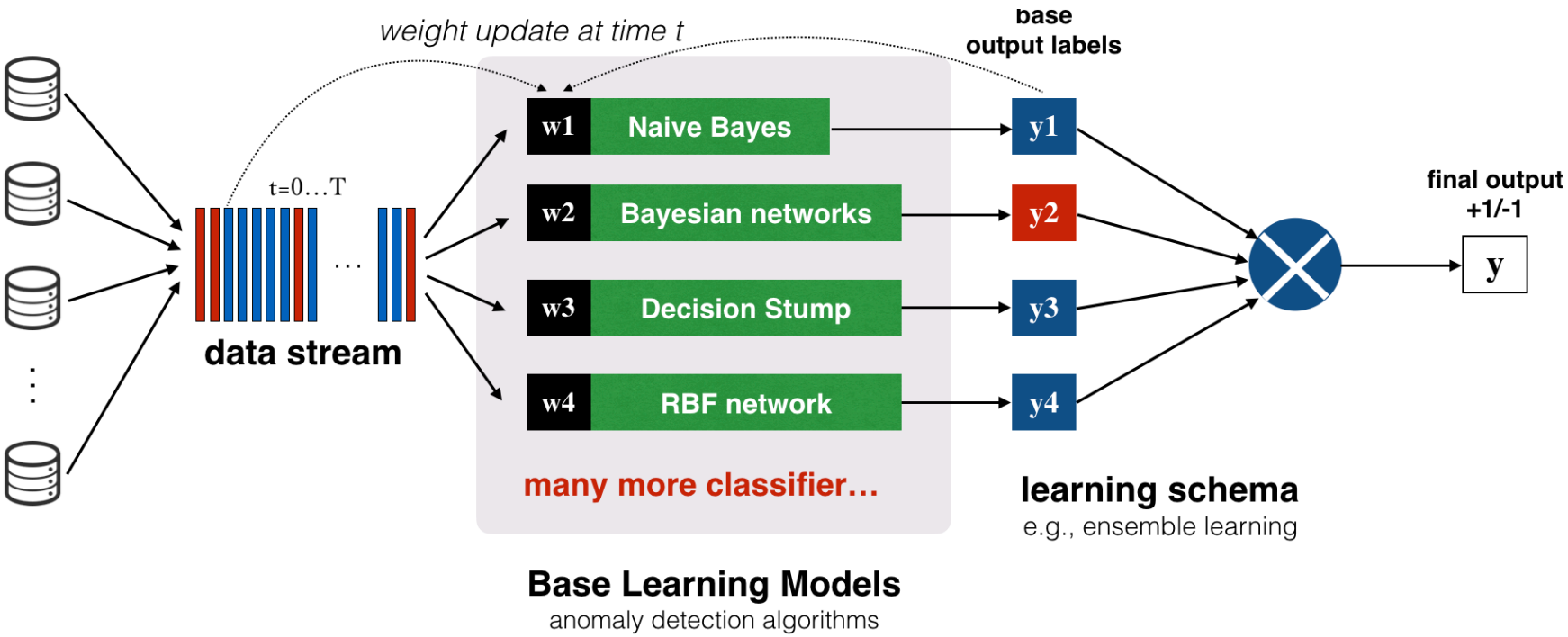
Features	
✓ IP-based URL	✓ http://192.168.0.1/paypal.cgi?fix account
✓ linked-to domain age	✓ less than 60 days?
✓ href/text of link matched	✓ paypal.com
✓ “here” link	✓ links to other domain
✓ Number of links	✓ links by <a> tags with href attribute
✓ Number of domains	✓ main part of domain name counts
✓ Number of dots	✓ more dots is suspicious
✓ If contains javascript	✓ find text ‘javascript’
✓ Spam filter output	✓ result by spam detector

Fette, I., Sadeh, N. and Tomasic, A., 2007. Learning to detect phishing emails. Proceedings of the 16th international conference on World Wide Web - WWW ’07., p.649

Adaptive IDS

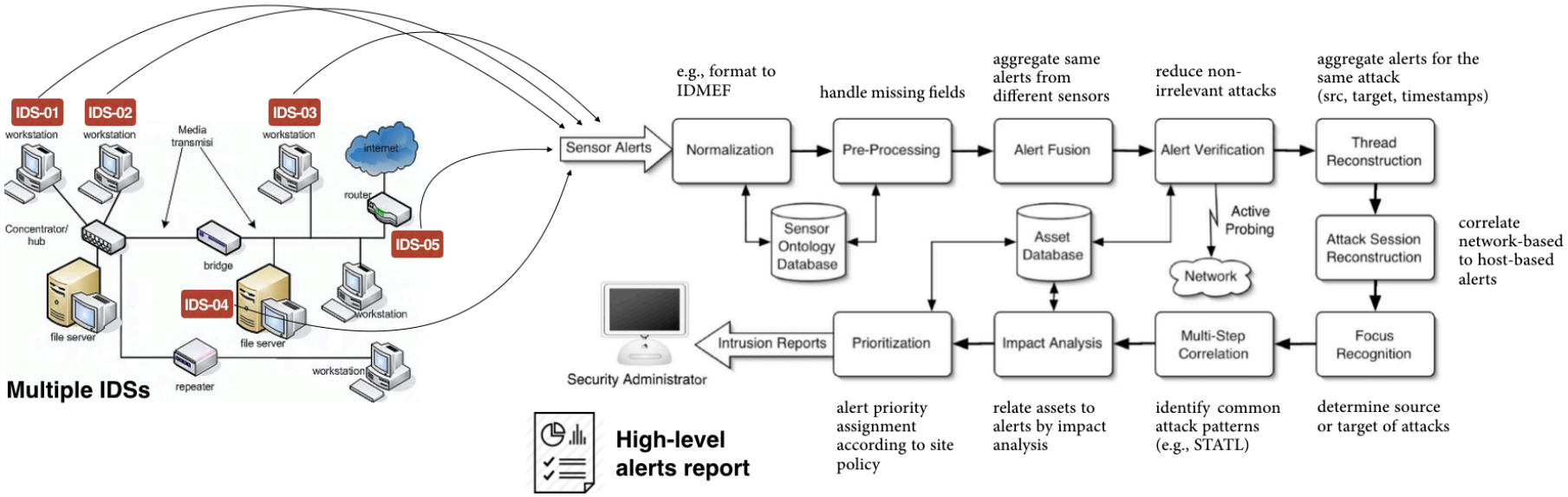
- Diverse network environments
- Possibly adversarial environment
- Single modal IDS not robust
- Dynamic attack landscape
- Heterogeneous data sources (no free lunch)
- Multiple Classifier System (MCS)
- **Goal**: adaptive to changes

Adaptive IDS



Nguyen, H.T. and Franke, K., 2012. Adaptive Intrusion Detection System via online machine learning. Proceedings of the 2012 12th International Conference on Hybrid Intelligent Systems, HIS 2012., pp.271–277.

Alert Correlation

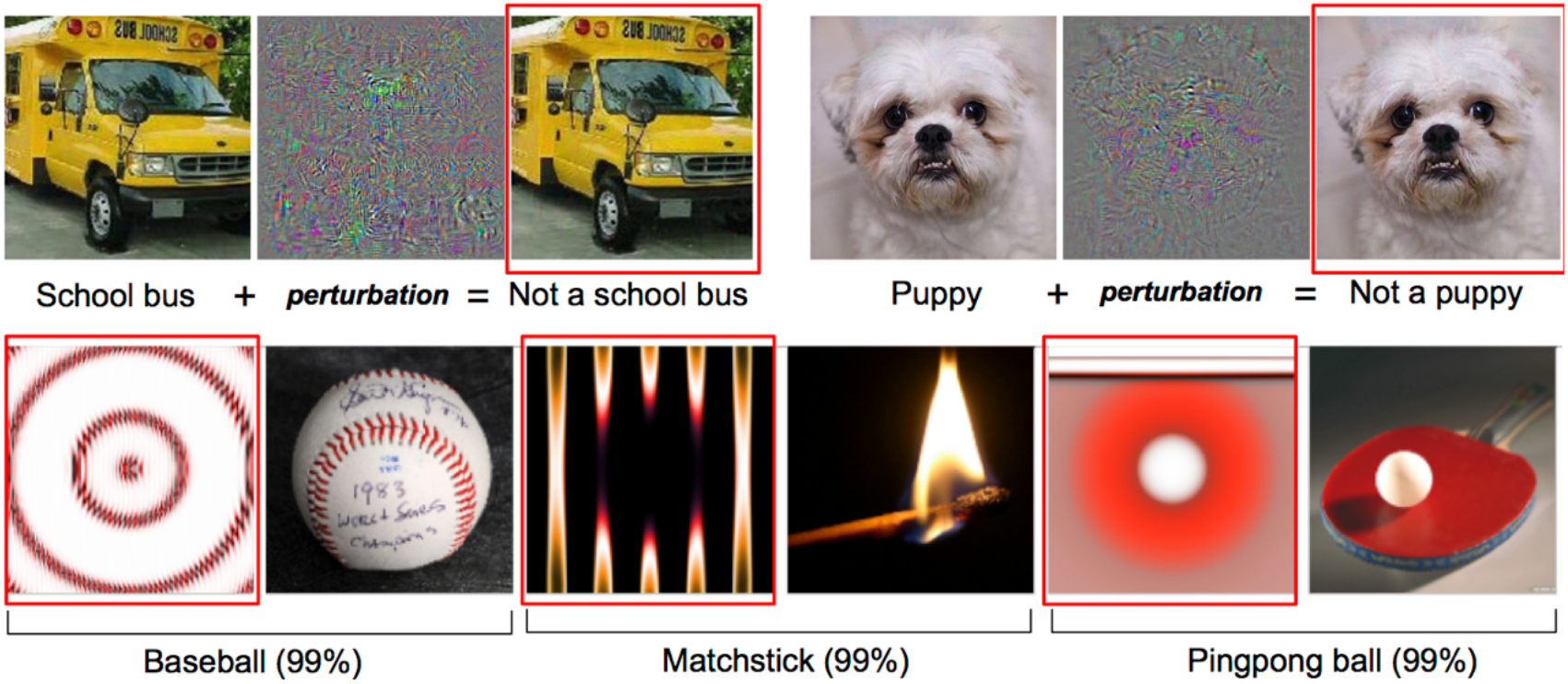


F. Valeur, G. Vigna, C. Kruegel and R. A. Kemmerer, "Comprehensive approach to intrusion detection alert correlation," in IEEE Transactions on Dependable and Secure Computing, vol. 1, no. 3, pp. 146-169, July-Sept. 2004.

Adversarial Learning

- What if a bot learns to behave like a legitimate user?
- Learning algorithm itself can also be a security target
- Data stationary assumption is broken
- Attacks: Causative or Evasive
- Passive or proactive arm-races
- Aim to design learning algorithms robust to adversaries

Adversarial Learning



Deep net is easily fooled

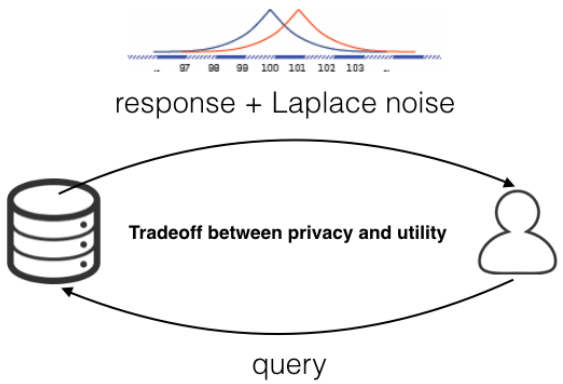
Nguyen, A., Yosinski, J. and Clune, J., 2014. Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images. In Computer Vision and Pattern Recognition 2015. Boston, Massachusetts, US.

Differential Privacy

- Big data is booming up, but privacy is less considered
- Sensitive information can be inferred from statistics
- **Differential privacy***:* even only aggregated statistics is published from samples, we can never tell/infer anything about a particular user.
- Examples:
  - AOL search results scandal
  - Facebook ads -> unclose private information
  - Netflix competition

Differential Privacy

Name	Age	Smoke	Lung cancer
Ian Jonathan	57	Yes	Positive
Kelly Nyn	60	Yes	Positive
Christ Lee	48	No	Negative
Tim Kingston	68	No	Negative
Mark Spring	35	Yes	Negative
Liu Han	78	No	Positive
Yoshua Hiro	40	Yes	Negative



E.g., query age(Jerry), response could be 55, 56, 58, 53 …

Statistics: Prob(lung cancer)=1 where age>50 & smoke=Yes

What if Jerry, age=55, smoke=Yes, … privacy leak

Dwork, C., 2008. Differential Privacy: A Survey of Results. In Theory and Applications of Models of Computation. pp. 1–19., pp.1–19

Outline

- Introduction & Motivation
- Machine Learning for Security
- Research Subfields
- **Challenges & Discussion**
- References

Challenges

- Outlier detection is hard
- High cost of errors (false alarm)
- Lack of appropriate training data
  - Anomalous class is rare
- Interpretation of results
  - How to explain the attacks?
- Variability in network traffic
  - Attack patterns evolve
- Adaptive adversaries
- Evaluation difficulties

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