Computational Forensics

Forensic Investigations in Cyberspace: what about big data?

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Computational Forensics

Crime in the Modern World

- Massive amount of data:
  - 247 billion email per day
  - 234 million websites
  - 5 billion mobile-phone users
- ICT Infrastructures:
  - Complex, rapidly growing
  - Dynamically changing
  - Hostile, adversary environment
- Cybercrime:
  - One million victims daily
  - Expected losses 297 billion Euro
  - Crowd sourcing -> Crime sourcing
  - Flash mobs -> Flash robs

- Proactive, Ultra-large scale Forensic Investigations, Computational Forensics:
  - Situation-aware methods
  - Quantified, measurable indicators
  - Adaptive, self-organizing models
  - Distributed, cooperative, autonomous
- Rule-of-Law:
  - Culture, social behaviours
  - Legal & privacy aspects
  - Cross-jurisdiction cooperation
  - European / International cyberlaw
  - Law as framework for ICT
  - Law as contents of ICT, Automation, programming of legal rules

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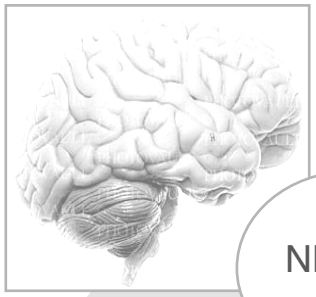
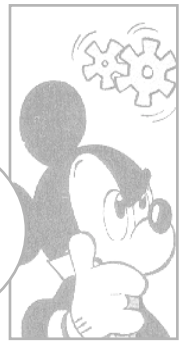
Computational Forensics:

Adding Efficiency and Intelligence to BIG DATA Investigation

Requirement of Adapted Computer Models & Operators



Brain



Reasoning

NN

FL

EC

Natural Evolution

Imprecision, Uncertainty, Partial Truth

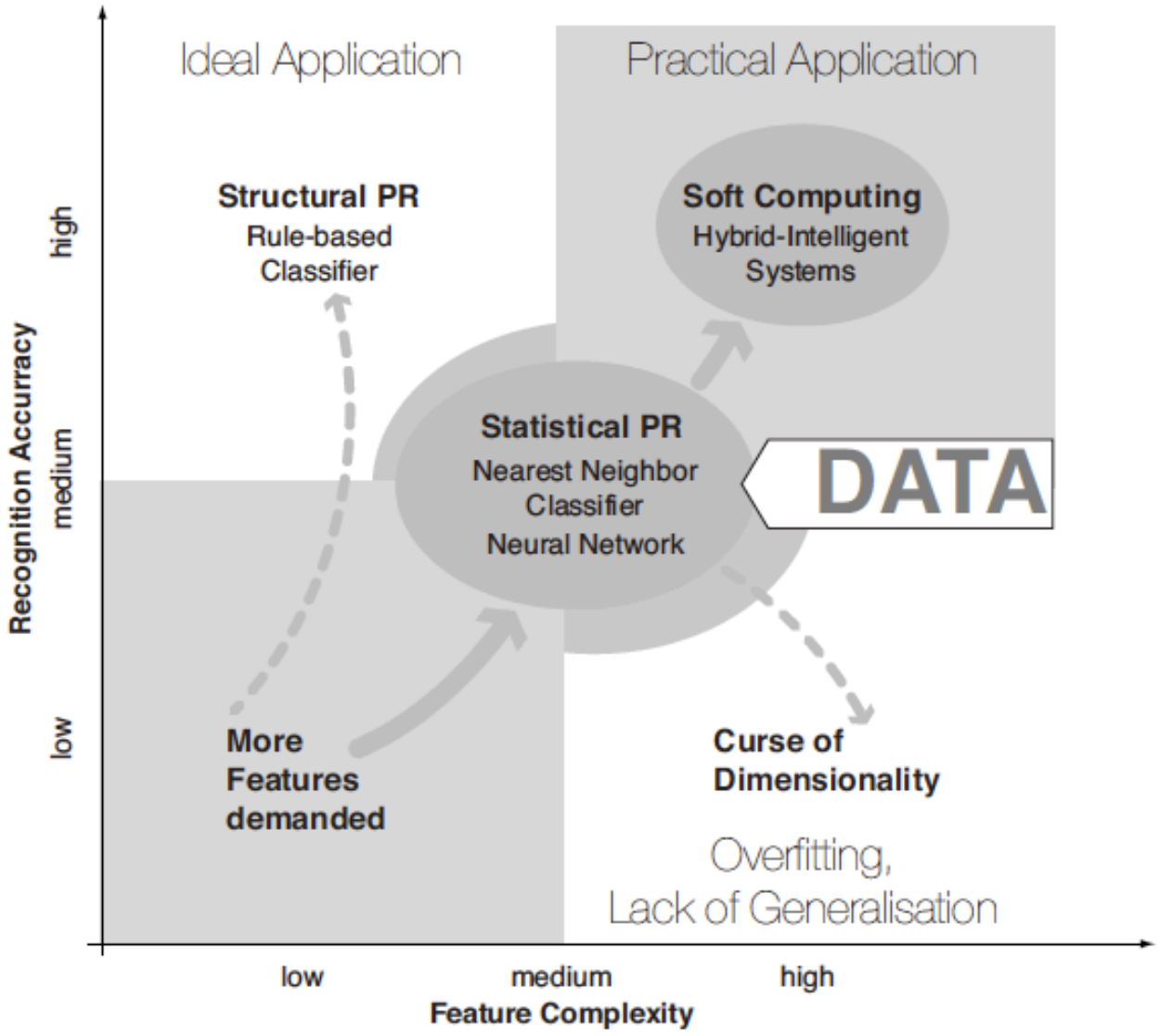
Computational Intelligence

NN: Neuronal Networks
FL: Fuzzy Logic
EC: Evolutionary Computation

Methods of Computational / Machine Intelligence

- **Signal / Image Processing** : one-dimensional signals and two-dimensional images are transformed for the purpose of better human or machine processing,
- **Computer Vision** : images are automatically recognized to identify objects,
- **Computer Graphics / Data Visualization** : two-dimensional images or three-dimensional scenes are synthesized from multi-dimensional data for better human understanding,
- **Statistical Pattern Recognition** : abstract measurements are classified as belonging to one or more classes, e.g., whether a sample belongs to a known class and with what probability,
- **Data Mining** : large volumes of data are processed to discover nuggets of information, e.g., presence of associations, number of clusters, outliers in a cluster,
- **Robotics** : human movements are replicated by a machine, and
- **Machine Learning** : a mathematical model is learnt from examples.

Data-driven Approaches



Big Data Analysis

Inter-relation of feature complexity and expected recognition accuracy.
(Franke 2005)

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Reverse Engineering Malware

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Reverse Engineering Malware

- **Static analysis**
- **System artifacts**
- **Dynamic analysis**
- Debugging
- Analyzing malicious content
  - **PDFs**
  - **JavaScripts**
  - **Office documents**
  - Shellcode
  - **Network traffic**

Static Analysis

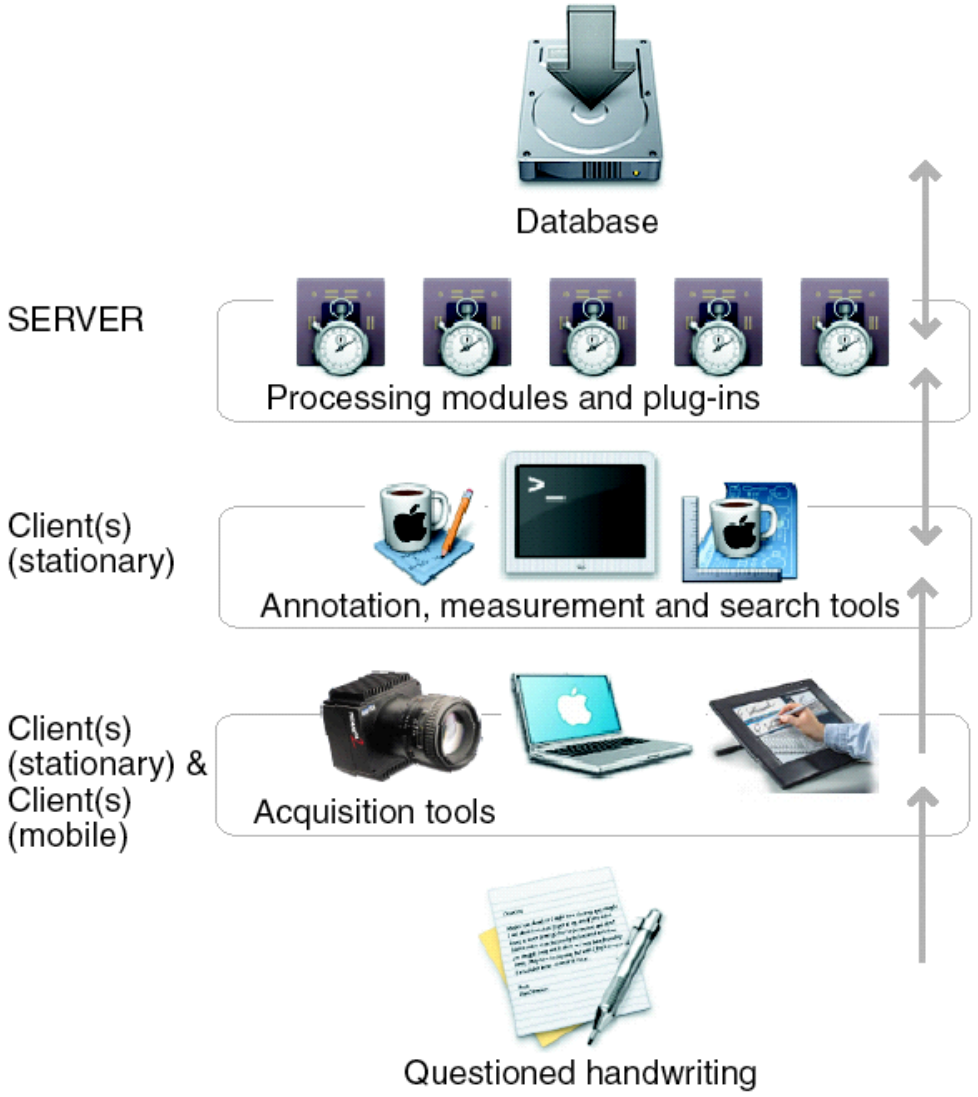
- Static analysis
  - Does not execute malware
  - Analyze:
    - System artifacts
    - Debugging
    - Source code *(not included)*
    - Disassembled code *(not included)*

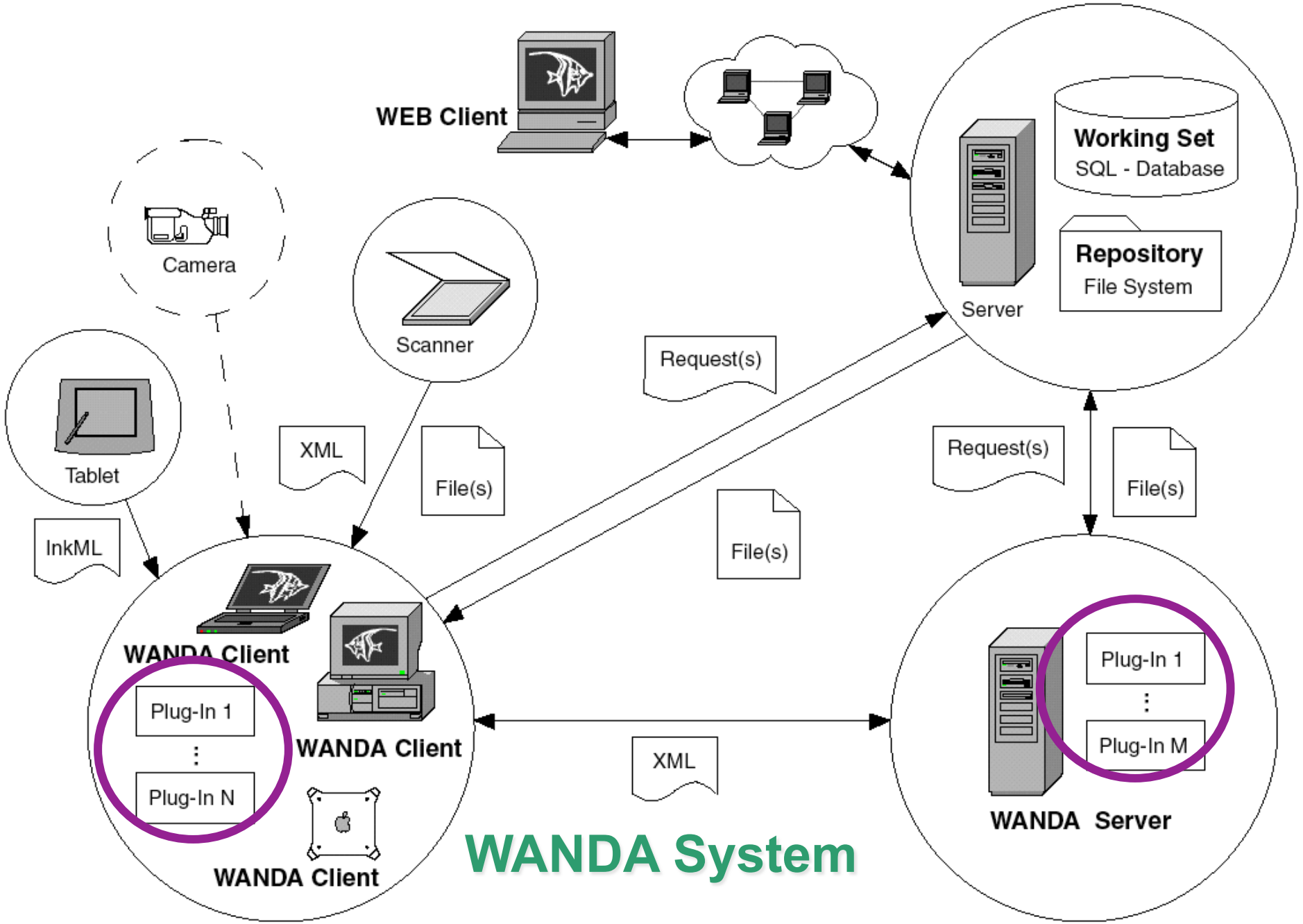
Dynamic Analysis

- Definition
  - *Dynamic analysis is the process of executing malware in a monitored environment to observe its behaviors*
- Deals with finding and understanding the changes made to the system
- Pro:
  - Provide quick information about created and changed files, registry keys, processes, handles, contacted websites, etc.
- Con:
  - Excessive and overwhelming results
  - Need to know the normal behavior of a system

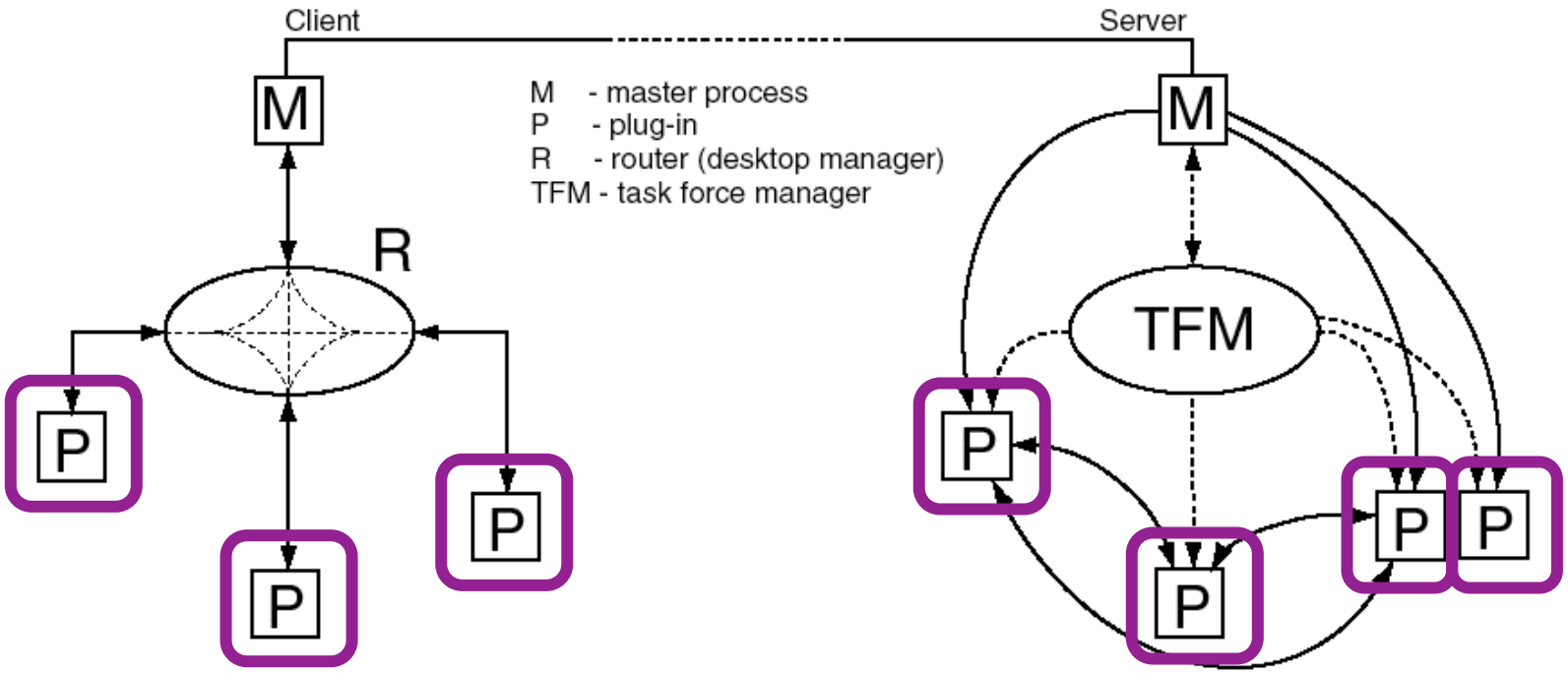
Framework concept

- User interacts via Java client
- Client is the front-end for accessing & processing information
- Information is distributed over and hosted by trusted servers
- Via their clients, users request services provided by the servers




WEB Client
Working Set
SQL - Database
Repository
File System
Server
Camera
Scanner
Tablet
InkML
XML
File(s)
Request(s)
File(s)
Request(s)
File(s)
WANDA Client
Plug-In 1
Plug-In N
WANDA Client
WANDA Client
XML
Plug-In 1
Plug-In M
WANDA Server
WANDA System

Plug-In Concept



a) Client plug-in organization - Master-slave point to point via Router

b) Server plug-in organization - Partial / Full connectivity

Reverse Engineering Malware

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- **Dynamic analysis**
- Debugging
- Analyzing malicious content
  - **PDFs**
  - **JavaScripts**
  - **Office documents**
  - Shellcode
  - **Network traffic**

Behavioral Malware Detection

(static, dynamic, combined)

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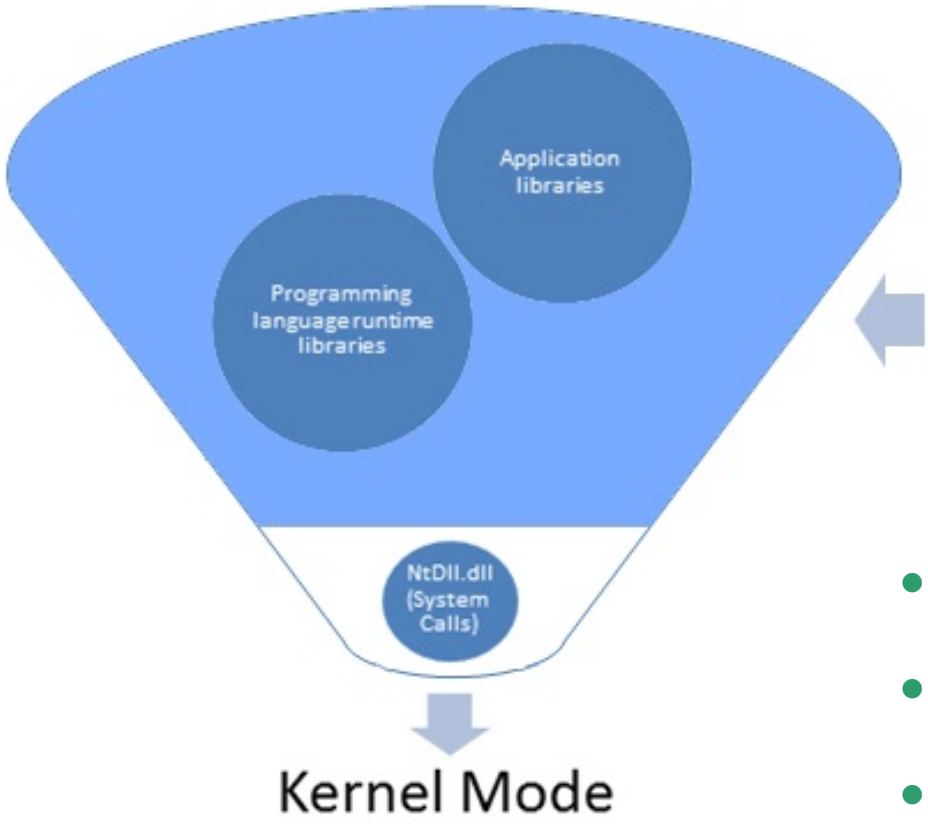
Layers of Detection



- User mode (library calls)
- Kernel mode (system calls)
- Hybrid (function calls)

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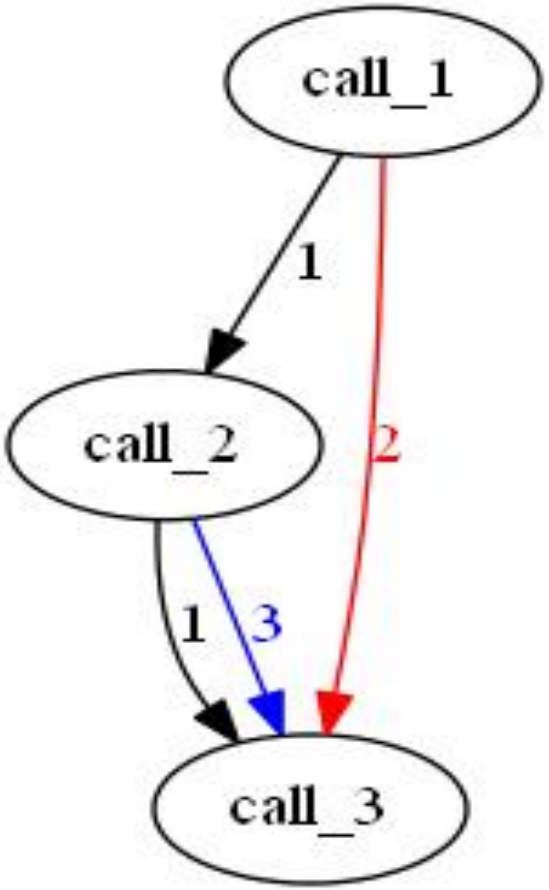
Information-based Dependency Matching

- Ordering dependency (**1**)
  - sequence
- Value dependency (**2**)
  - parameters
- Def-use dependency (**3**)
  - Parameter and return value
- Sample:
  - call_1(parameter1,**ffff0000**)=0
  - call_2(par)=**0x4fff0418**
  - call_3(**0x4fff0418**,**0xffff0000**)=0



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Example #1

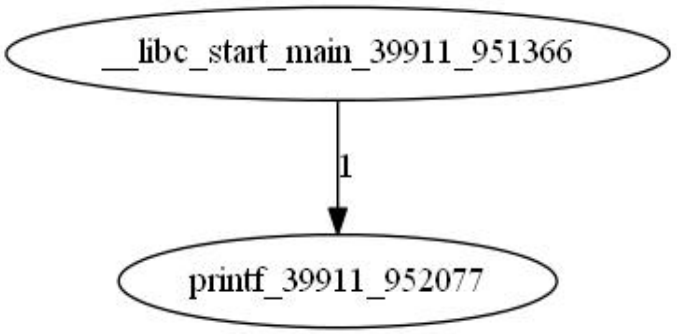
- Library calls (Hello World.c)
  - Code

```c
#include <stdio.h>

int main() {
    printf("Hello world!!!");

    return 0;
}
```

  - Trace

```
11:05:11.951366 __libc_start_main(0x80483c4, 1, 0xbf96afa4,
0x8048400, 0x80483f0 <unfinished ...>
11:05:11.952077 printf("Hello world!!!")          = 14
11:05:11.953227 +++ exited (status 0) +++
```

  - Graph



Example #2

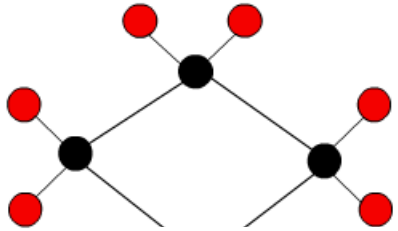
- System calls (Hello world.c)
  - Trace
    - Much more extensive due to memory mapping
    - Example trace
  - Graph
    - Example Graph

Example #3

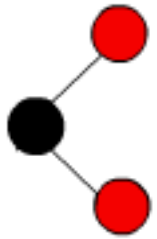
- Actual malware example
  - Malware system call Graph Examples
    - Virus.Linux.Snoopy.a
    - Rootkit.Linux.Matrics.a
    - Exploit.Linux.Small.k

Experimental Design & Data Set #1

- Graph-based Matching
  - http://ailab.wsu.edu/subdue/unsupervised.swf
  - Subdue finds substructures by compressing graphs
  - Supervised Learning is performed by finding substructures that occur frequently in one class but seldom in another



- Dataset
  - Malware
    - Extracted from: vx.netlux.org/index.html (currently down)
    - 190 samples: **7150 vertices, 7790 edges**
  - Benign Software
    - Ubuntu binaries
    - 75 samples: **9025 vertices, 9395 edges**

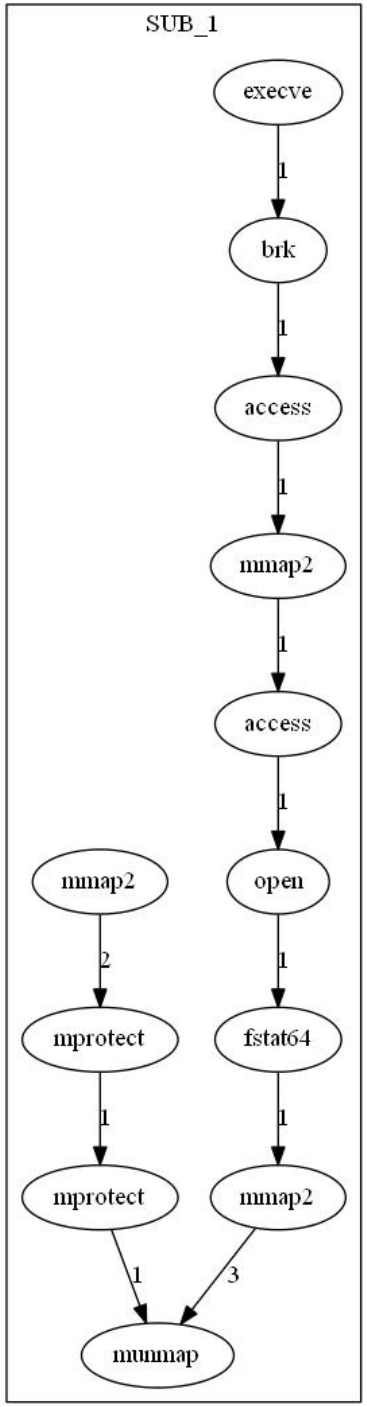


Preliminary Results #1: Graph-based Matching

- Detection rate of 98,9%
- Confusion matrix

System calls		
	Classified as	
Correct class	Malware	Software
Malware	190	0
Software	3	72
	1	0,96

- 190/190 Malware correctly classified
- 72/75 Software correctly classified



Detecting Malicious PDF

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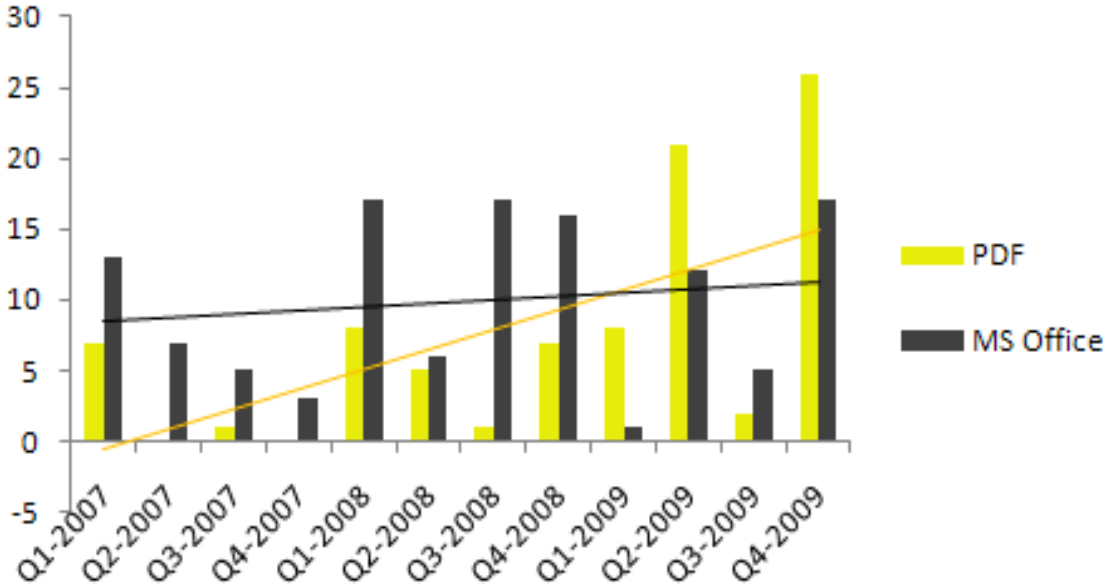
Analyzing Malicious Content #1

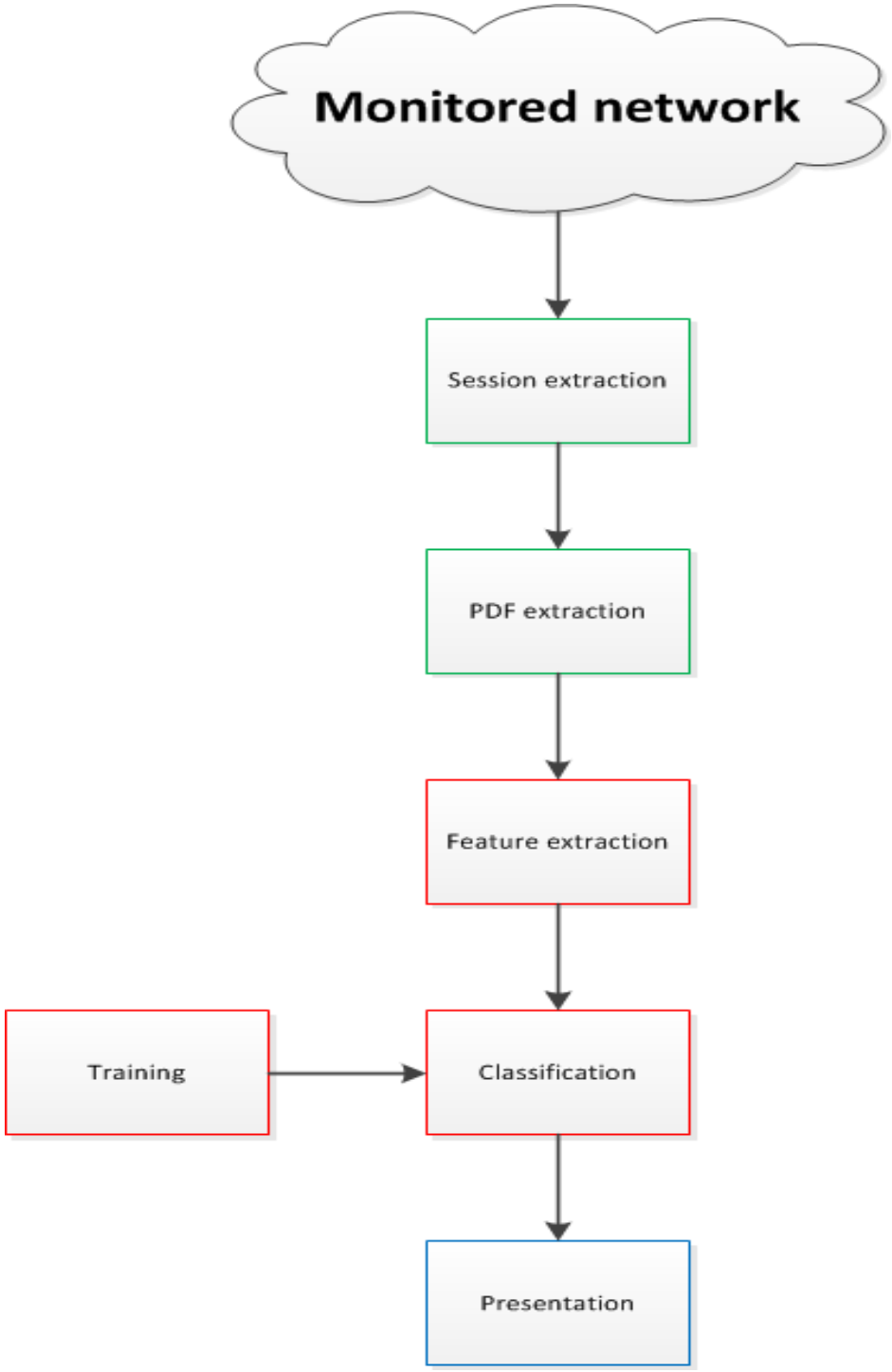
- Frequent analysis:
  - **PDF**
  - **JavaScript**
  - **Office Documents**
  - Flash *(not included)*
  - Shellcode
  - Network Traffic



Research Questions

- Which **features** are significant for detecting malicious PDF documents?
- Which **classifier design** and configuration yields optimal performance in malicious PDF detection?
- How can a real-world IDS, capable of detecting malicious PDFs in network traffic, be implemented?

Method Overview



Data Collection

- PDFs collected within the malware research community and through webcrawling, e.g.,
  - Websense
  - Abuse.ch
  - Sourcefire
- Malicious samples have been submitted globally and detected in various ways, some of the samples are under NDA.
- Data set in total:
  - **7,454 unique benign** PDF samples.
  - **16,296 unique malicious** PDF samples.

Expert-Knowledge Features (KPI)

- Keys from the PDF format (ISO 32000) relevant to malicious PDFs, e.g.,
  - /JavaScript
  - /OpenAction
  - /AcroForm
- Key selection based upon the independed research by (i) Didier Stevens, (ii) Paul Baccas.
- **18 features (keys)** are selected to initialize.
- Additional **feature-set for Javascript**.

Experiments (Exp 1…4)

1. Feature & Classifier Selection
2. Classifier Optimalization and Testing
3. Real-world testing
4. Embedded javascripts

Exp 1: Feature & Classifier Selection

Original feature vector (18):

AA, RichMedia, xref, Encrypt, JBIG2Decode, Launch, JavaScript, OpenAction, Colors,JS, obj_mis, startxref, AsciiHexDecode, ObjStm, AcroForm, stream_mis, Page, trailer

Golub-score feature selection (7):

$$F(x_i) = \left| \frac{\mu_i^+ - \mu_i^-}{\sigma_i^+ + \sigma_i^-} \right|$$

JavaScript, OpenAction, JS, obj_mis, AcroForm, Page, trailer

Generic feature selection GeFS (5)·

JavaScript, JS, startxref, Page, trailer

$$GeFS(x) = \frac{a_o + \sum_{i=1}^{n} A_i(x)\ x_i}{b_o + \sum_{i=1}^{n} B_i(x)\ x_i}$$

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Exp 1: Feature & Classifier Selection

Tested perfomance using 5 different classifiers:

	BayesNet			C45/J48			RBFNet		
	18	**7**	**5**	**18**	**7**	**5**	**18**	**7**	**5**
Bal succ	0.973	0.94	0.976	0.995	0.995	0.975	0.718	0.797	0.874
Auc	0.996	0.995	0.996	0.997	0.998	0.994	0.879	0.922	0.926
	MLP			**SVM**					
	18	**7**	**5**	**18**	**7**	**5**			
Bal succ	0.96	0.966	0.920	0.995	0.995	0.977			
Auc	0.985	0.987	0.978	0.995	0.996	0.974			

Choose **7 features** from Golub-score selection,
SVM* classifier for further experimentation.

*SVM - Support Vector Machine
*Bal succ - Balanced Successrate *AUC - Area Under (ROC) Curve

Computational Forensics

Discussion and Summary

- The dataset
  - Difficulties controlling factors
  - Best solution: MD5, generalization experiment, big dataset from many sources.
- Changes over time
  - Need for re-learning
  - Online learning
- Detecting malicious PDF documents is feasible
  - using reduced expert feature set, javascript features, SVM
- Aquired knowledge & lessons learned:
  - A PDF dataset (**16.296 / 7,454**) for future reseach.
  - Knowledge on significant features for PDF classification.
  - A method for automated detection of malicious PDF in network traffic.
  - A starting point for future research on malicious javascript detection.

Concluding Remarks

- Computational forensics holds the potential to greatly benefit all of the forensic sciences.
- For the computer scientist it poses a new frontier where new problems and challenges are to be faced.
- The potential benefits to society, meaningful inter-disciplinary research, and challenging problems should attract high quality students and researchers to the field.

Further Reading

- NAS Report: *Strengthening Forensic Science in the United States: A Path Forward* http://www.nap.edu/catalog/12589.html
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- Franke, K., Srihari, S.N. (2008). *Computational Forensics: An Overview*, in Computational Forensics - IWCF 2008, LNCS 5158, Srihari, S., Franke, K. (Eds.), Springer Verlag, pp. 1-10.

- Our research center: www.nislab.no
- Our research-lab pages: Testimon Forensics Lab: http://goo.gl/YHMSf
- Our latest publications: http://goo.gl/R58SL

Thank you for your consideration of comments!

Getting in touch

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