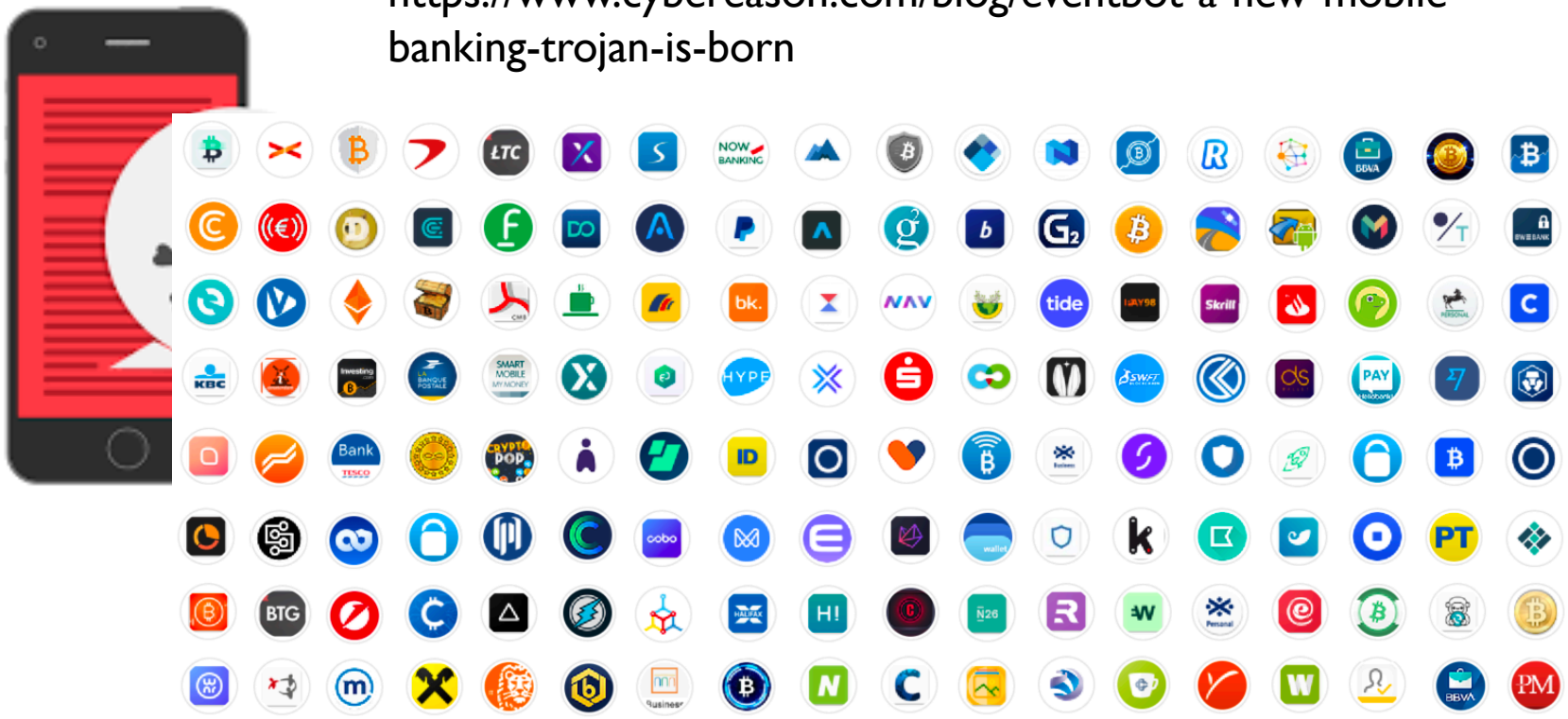
MACHINE LEARNING & SECURITY RESEARCH

Giuseppe Antonio Di Luna

A DAY IN OUR LIFE

A PANOPLY OF THREATS

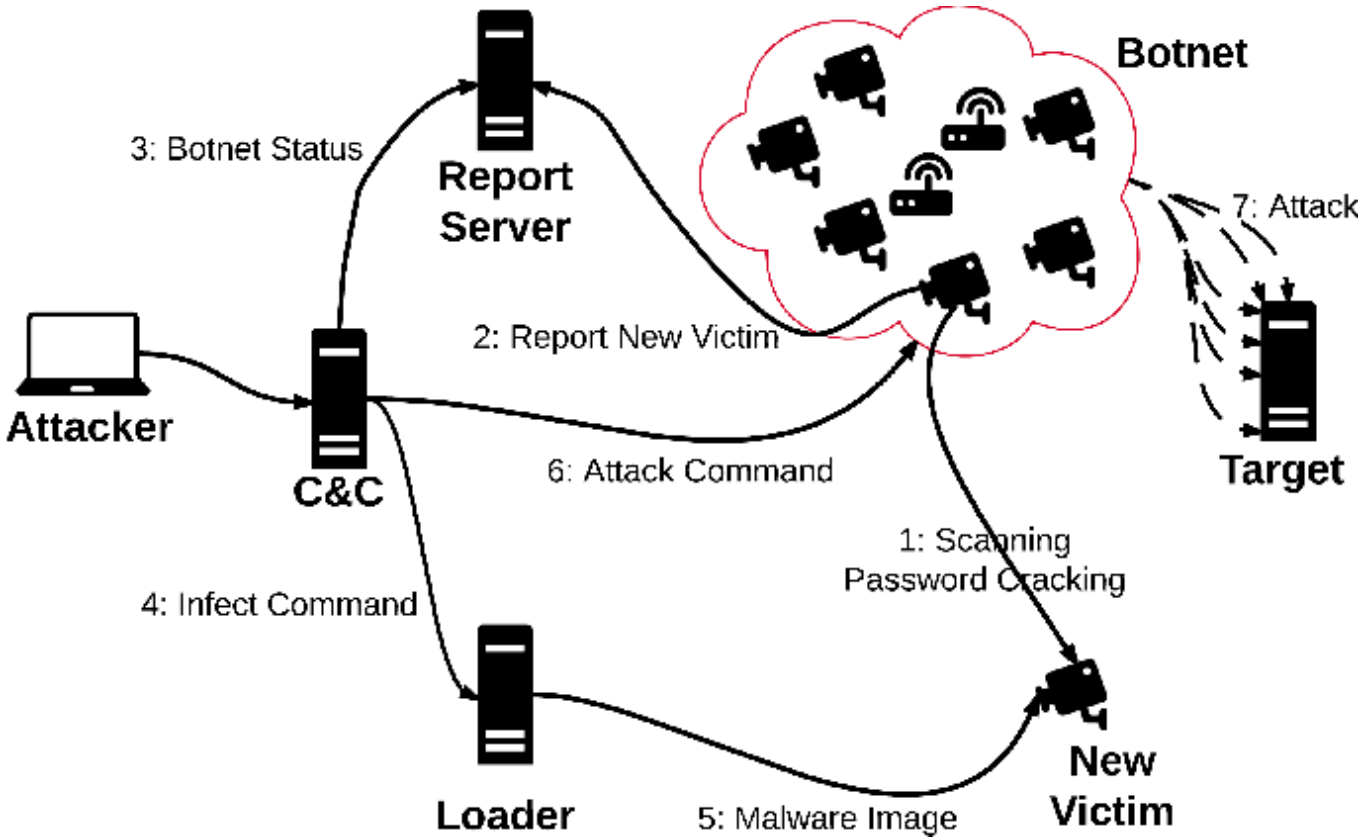
https://www.cybereason.com/blog/eventbot-a-new-mobile-banking-trojan-is-born



A PANOPLY OF THREATS

- Banking data
- Identity theft
- Surveillance

A PANOPLY OF THREATS



Mirai Botnet:
DDoS attack on 20 September 2016 on the Krebs on Security site which reached 620 Gbit/s.
Ars Technica also reported a 1 Tbit/s attack on French web host OVH.

A PANOPLY OF THREATS

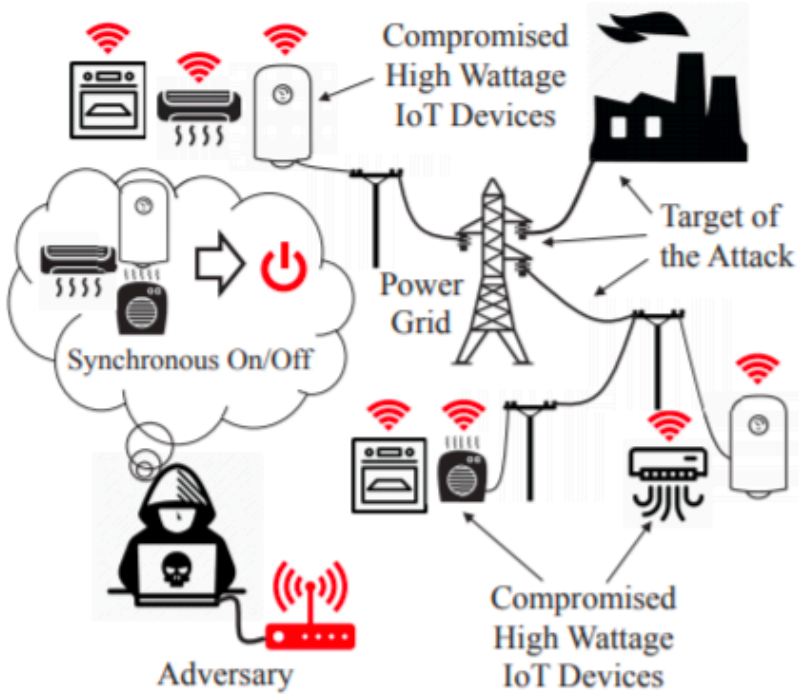
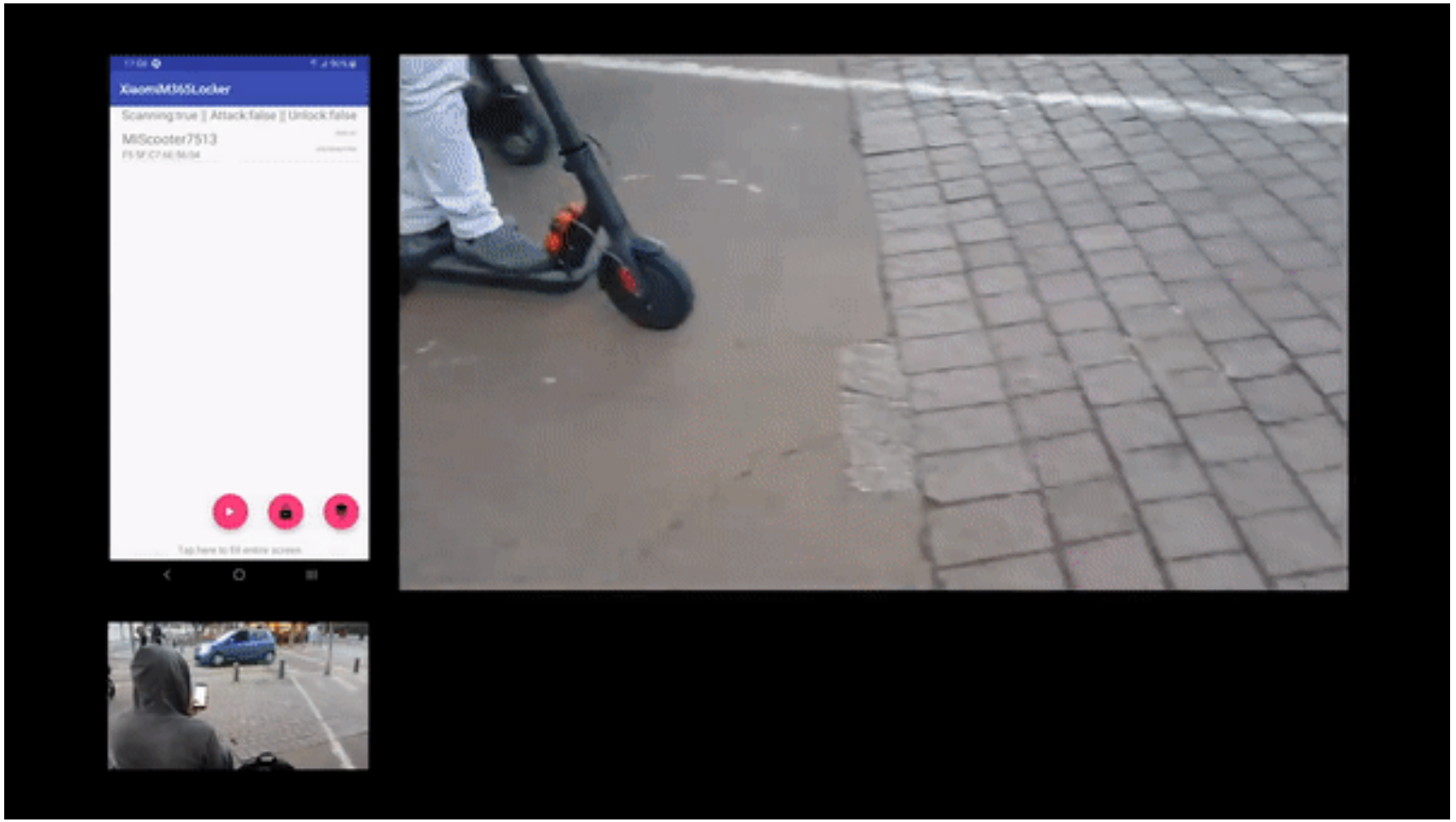


Figure 1: The MadIoT attack. An adversary can disrupt the power grid's normal operation by synchronously switching on/off compromised high wattage IoT devices.

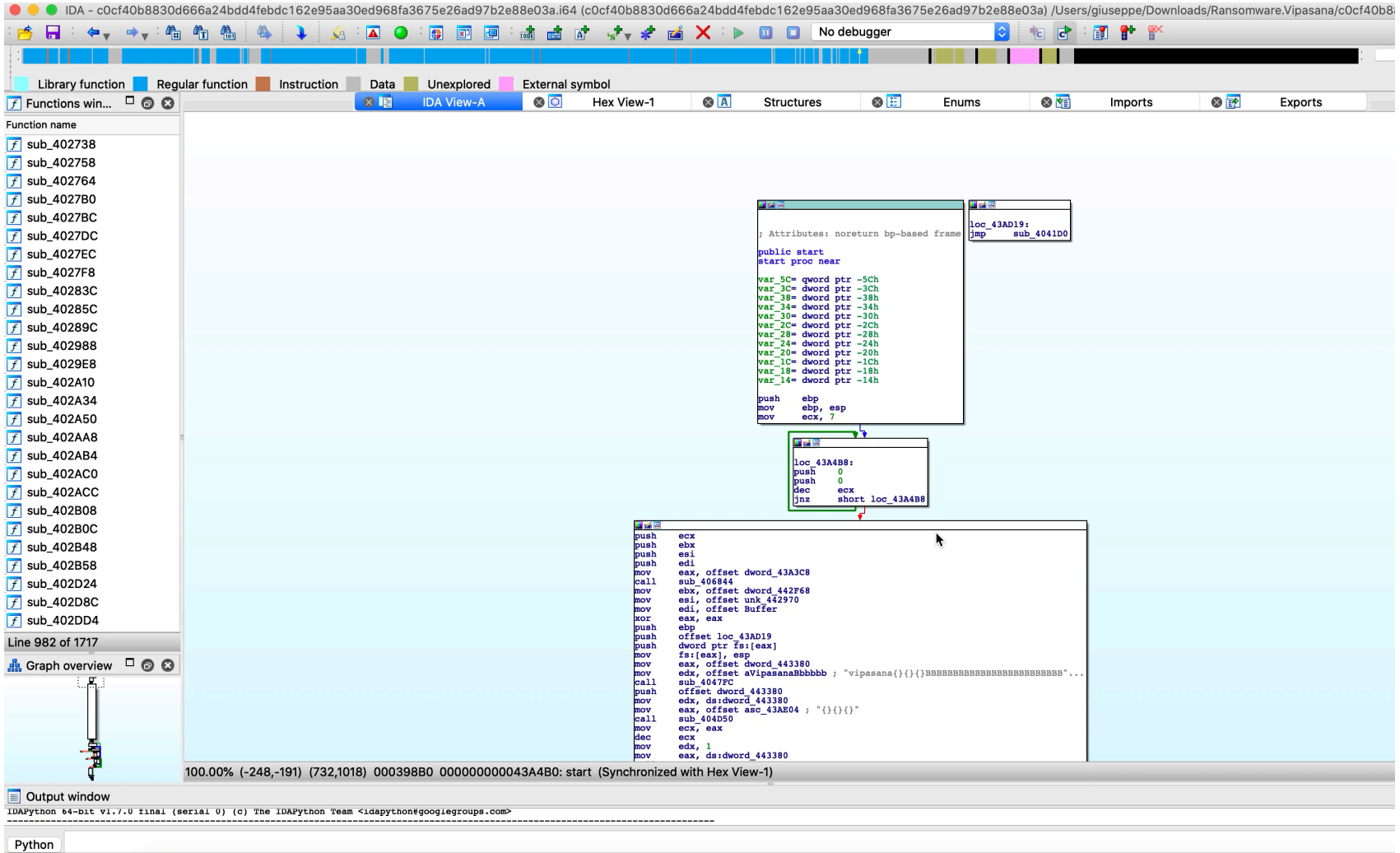
Botnets causing blackouts: how coordinated load attacks can destabilize the power grid. [ACSAC 2017]

A PANOPLY OF THREATS

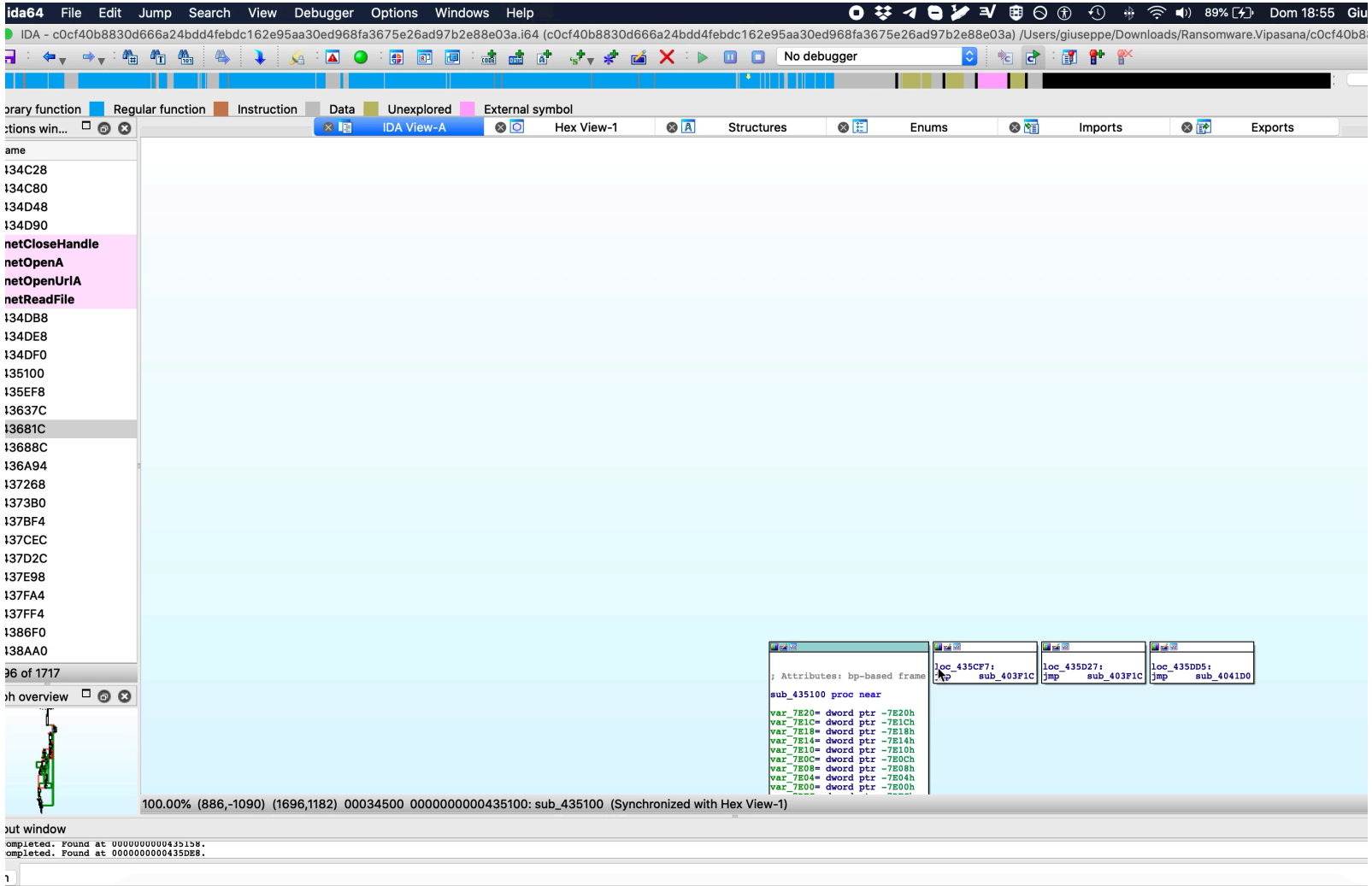


MALWARE, VULNERABILITIES AND FIRMWARES: THE HARD LIFE OF A SECURITY RESEARCHER

REVERSING A MALWARE



REVERSING A MALWARE



AND THAT WAS EASY....

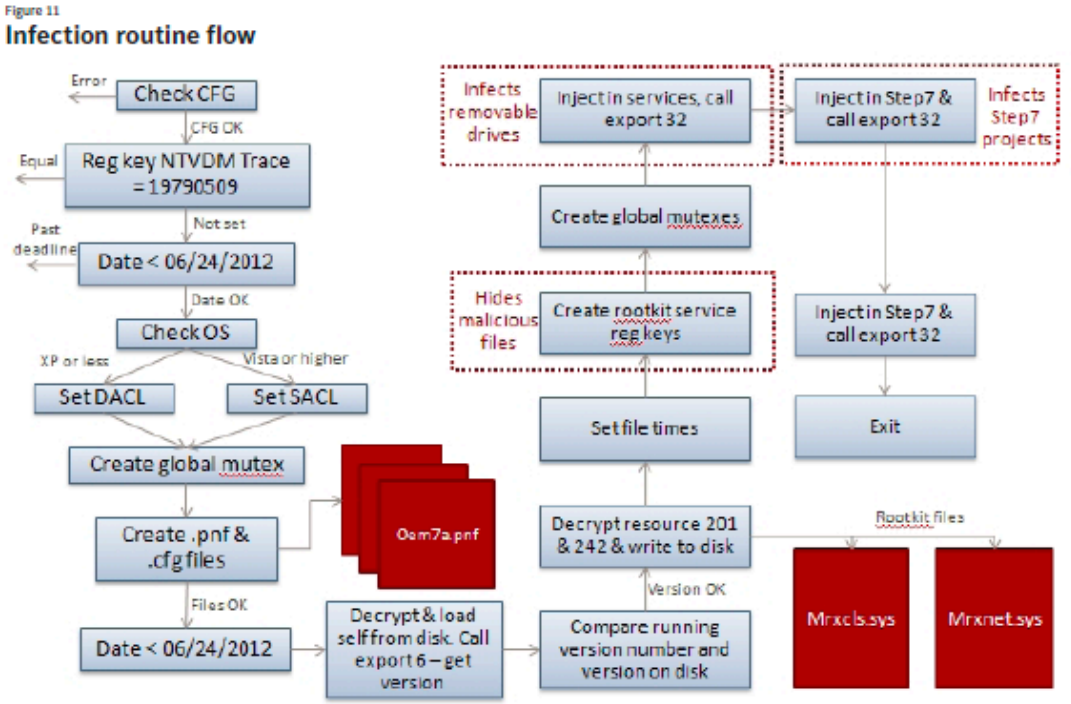
- Malware binaries are often «stripped» removing function and variable name;
- The strings inside a binary can be encrypted with a custom encryption algorithm;
- The libraries can be statically imported and can be indistinguishable from malware code;
- Packing;
- The refined ones have inside a virtual machine that runs the actual malware code.

..IN DOUBT RUN IT?

..IN DOUBT RUN IT? NOT SO SIMPLE!

A lot of malware have anti-vm technques;

Other are tailored against a target and show a normal behaviour;

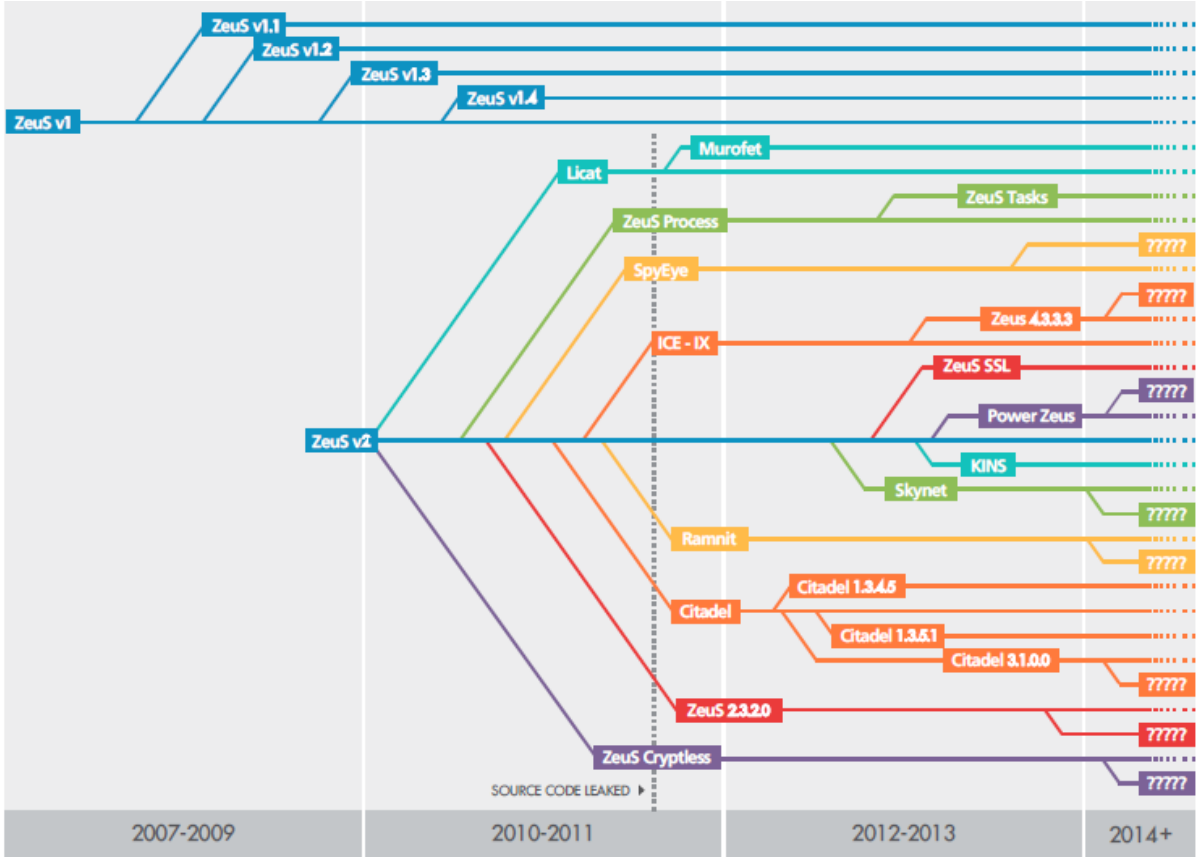


https://media.blackhat.com/bh-us-12/Briefings/Branco/BH_US_12_Branco_Scientific_Academic_WP.pdf

Understanding Linux Malware: https://reyammer.io/publications/2018_oakland_linuxmalware.pdf

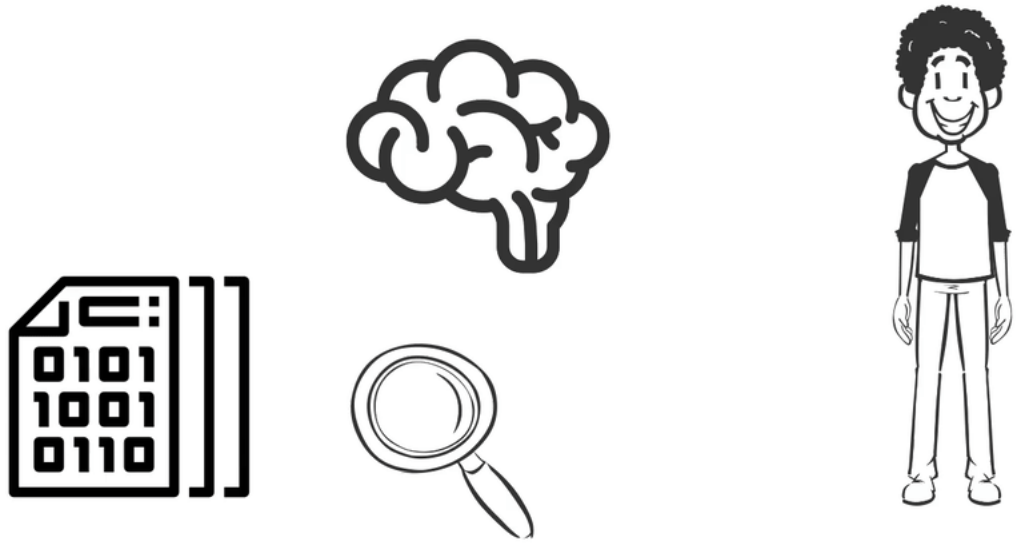
REVERSING REAL-WORLD BINARIES IS A NIGHTMARE

Malware developers produce variants to minimize the effort required to evade updated security defences



REVERSING REAL-WORLD BINARIES IS A NIGHTMARE

It requires skilled people and a lot, a lot, and I mean a lot of time



MACHINE LEARNING: A LIFESAVER?

MACHINE LEARNING FOR DETECTING MALWARES

Binary classification problem: Malware or Not

- Thousands of papers using thousands of techniques (DNN, Random Forest, SVM, ...) (see [0] for a recent suvey);
- Static, Dynamic or Hybrid Approach;
- Extracting features: system call, functions calls [1], strings, file name, dns requests, ...
- Without manual features: MalvConv [2]

ember

an open source malware classifier and dataset

AUC 0.99..

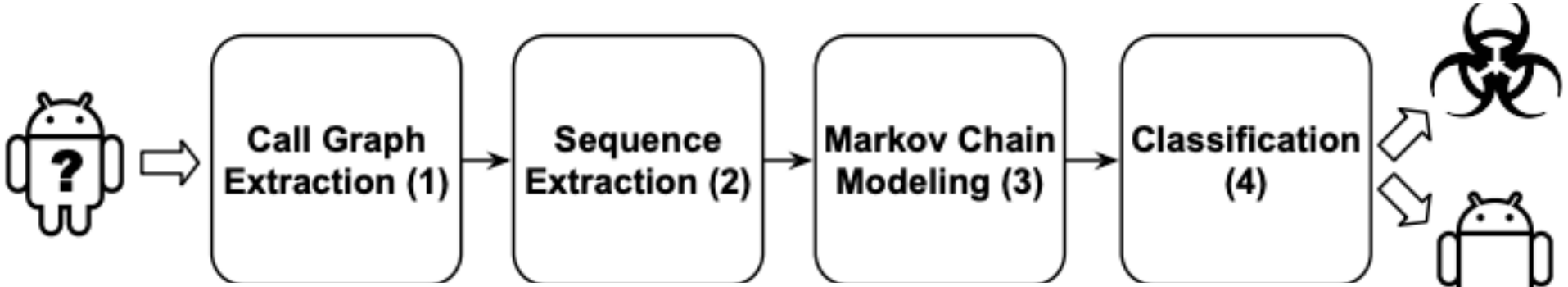
[0] Ucci et al. Survey of Machine Learning Techniques for Malware Analysis. 2018

[1] Enrico Mariconti et al. MaMaDroid: Detecting Android Malware by Building Markov Chains of Behavioral Models. NDSS 2017

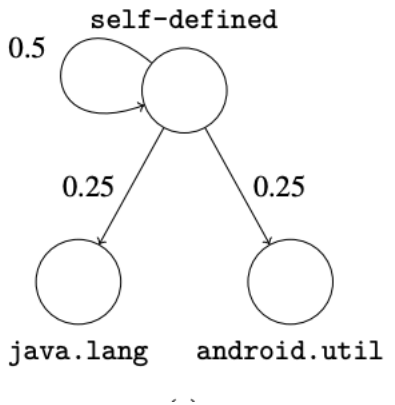
[2] E. Raff et al.. Malware detection by eating a whole exe. arXiv preprint arXiv:1710.09435, 2017

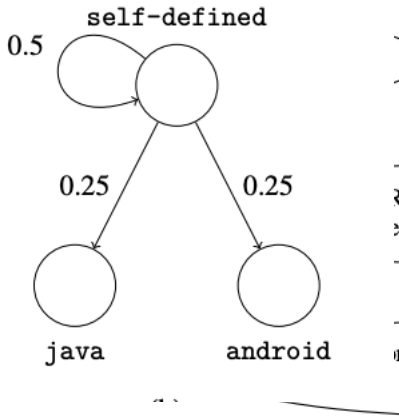
MACHINE LEARNING FOR DETECTING MALWARES

MaMaDroid: Detecting Android Malware by Building Markov Chains of Behavioral Models

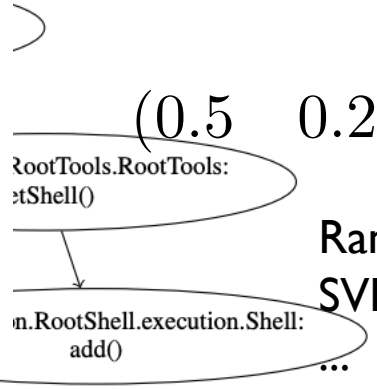


Markov Chain:
Sequence Extraction:





$$(0.5 \quad 0.25 \quad 0.25 \quad 0 \ldots 0)$$



Random Forests
SVM

Images taken from:
[1] Enrico Mariconti et al. MaMaDroid: Detecting Android Malware by Building Markov Chains of Behavioral Models. NDSS 2017

THE BIAS....

			% mw in testing set Ts							
			10% (*realistic*)				90% (*unrealistic*)			
			% mw in training set Tr				% mw in training set Tr			
	Sample dates		10%	90%	10%	90%	10%	90%	10%	90%
Experimental setting	Training	Testing	ALG1 [4]		ALG2 [33]		ALG1 [4]		ALG2 [33]	
10-fold CV	gw: ■■■■■■ mw: ■■■■■■	gw: ■■■■■■ mw: ■■■■■■	**0.91**	0.56	0.83	0.32	0.94	0.98	0.85	**0.97**
Temporally inconsistent	gw: ▒▒▒▒■■ mw: ▒▒▒▒■■	gw: ■■■■▒▒ mw: ■■■■▒▒	0.76	0.42	0.49	0.21	0.86	0.93	0.54	**0.95**
Temporally inconsistent gw/mw windows	gw: ▒▒▒▒■▒ mw: ■■▒▒▒▒	gw: ▒▒▒▒▒■ mw: ▒▒■■▒▒	0.77	0.70	0.65	0.56	0.79	0.94	0.65	**0.93**
Temporally consistent (*realistic*)	gw: ■■▒▒▒▒ mw: ■■▒▒▒▒	gw: ▒▒■■■■ mw: ▒▒■■■■	**0.58**	**0.45**	**0.32**	**0.30**	0.62	0.94	0.33	0.96

Image from: Feargus Pendlebury et al TESSERACT: Eliminating Experimental Bias in Malware Classification across Space and Time. USENIX Security 2019:

[1] Enrico Mariconti et al. MaMaDroid: Detecting Android Malware by Building Markov Chains of Behavioral Models. NDSS 2017

THE BIAS....

Experimen	% mw in testing set Ts	
	10% (*realistic*)	90% (*unrealistic*)
	% mw in training set Tr	% mw in training set Tr
Temporally ir		
Temporally ir gw/mv		
Temporally		

Manual analiysis is still necessary!

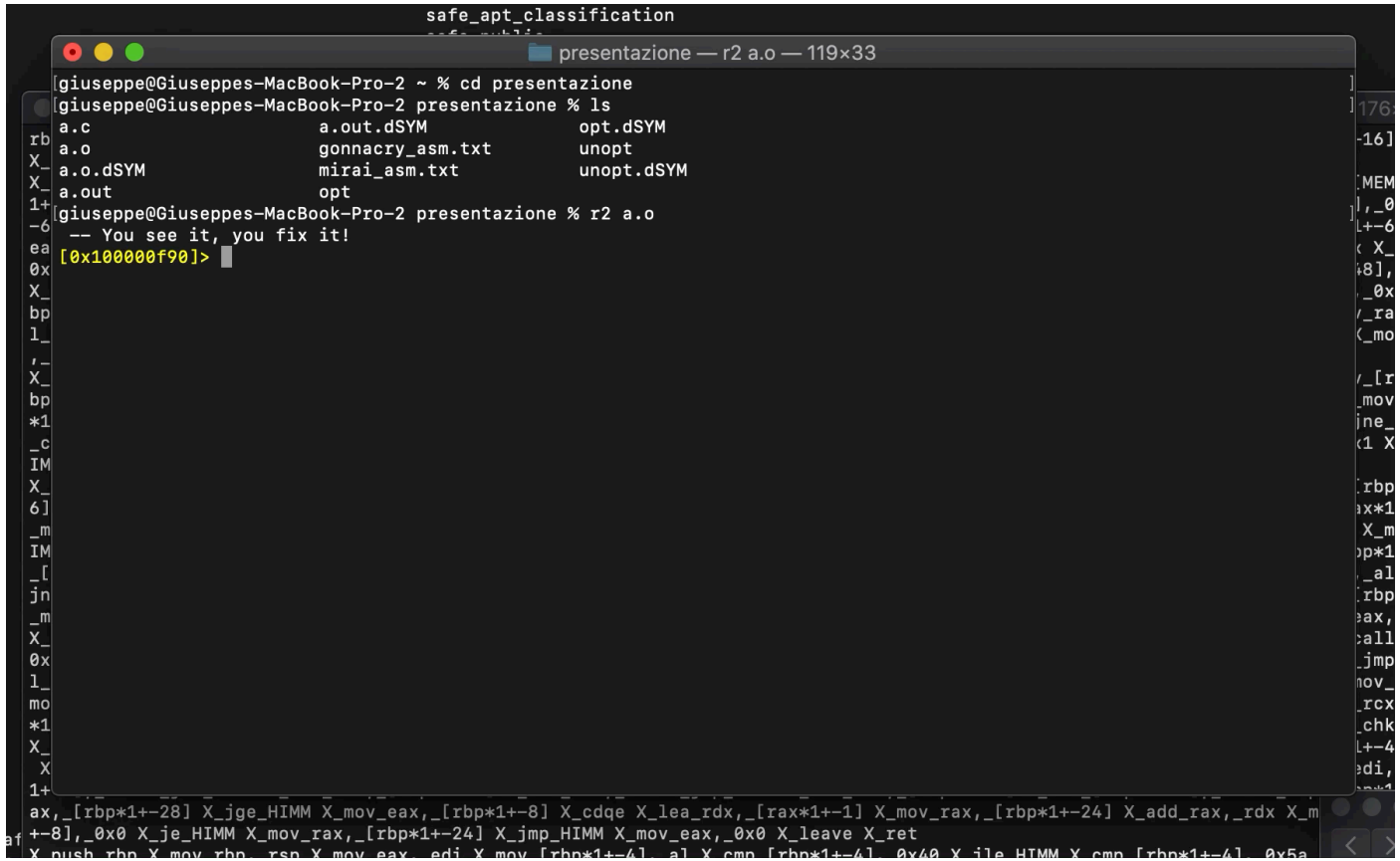
Image from: Feargus Pendlebury et al TESSERACT: Eliminating Experimental Bias in Malware Classification across Space and Time. USENIX Security 2019:

[1] Enrico Mariconti et al. MaMaDroid: Detecting Android Malware by Building Markov Chains of Behavioral Models. NDSS 2017

AN AID TO REVERSE ENGINEERING

Machine learning has been used in a successfull way to help manual analysis:

- **Function boundaries**
- Binary Similarity
- Function Naming
- Decompiling
- …



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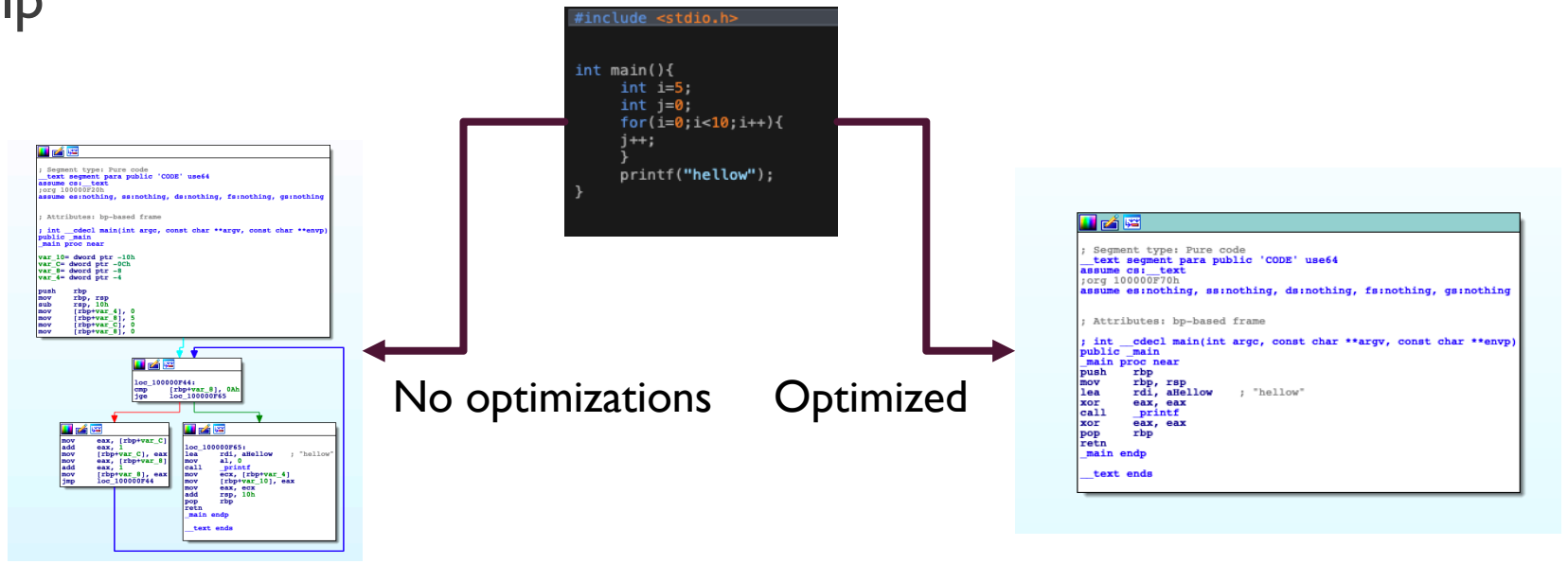


A REVOLUTION IN SOFTWARE ENGINEERING

The BigCode revolution (see **A Survey of Machine Learning for Big Code and Naturalness –** [Allamanis et al. 2018]):

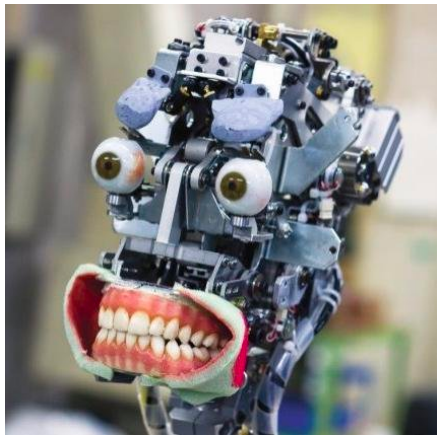
- Use the big codebase given by opensource projects.

The naturalness hypothesis: *«Software is a form of human communication; software corpora have similar statistical properties to natural language corpora; and these properties can be exploited to build better software engineering tools».*

PECULIARITIES OF SOURCE CODE

Code is a mean of communication between humans and machines (*bimodal*)

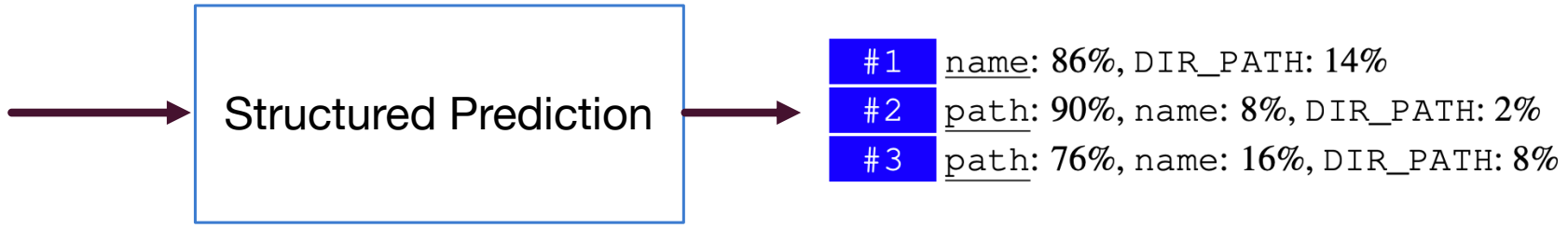
```
author MIKE

This class will use the ghost
to insert a collection of particles
have no net charge. This is used to calcul
chemical potential and activity coefficien

ass widom : public analysis {
private:
  average<double> expsum; //!< Average of
protected:
  int ghostin;
  long long int cnt;          //!< count test
  vector<particle> g;         //!< List of gh
public:
  widom(int n=10);
  string info();
  void add(particle);
  void add(container &);
  void insert(container &, energybase &
  void check(checkValue &);
  void exp(muex());
  log(expsum.a
```



- Code is *executable*
- Code is *formal*

APPS – GENERATIVE MODELS

```
var path = CreateFileName( #1 );
bitmap.Save( #2 , ImageFormat.Png);
return #3 ;
```



LEARNING TO REPRESENT PROGRAMS WITH GRAPHS [Allamanis et al. 2018]

APPS – GENERATIVE MODELS

Structured Prediction

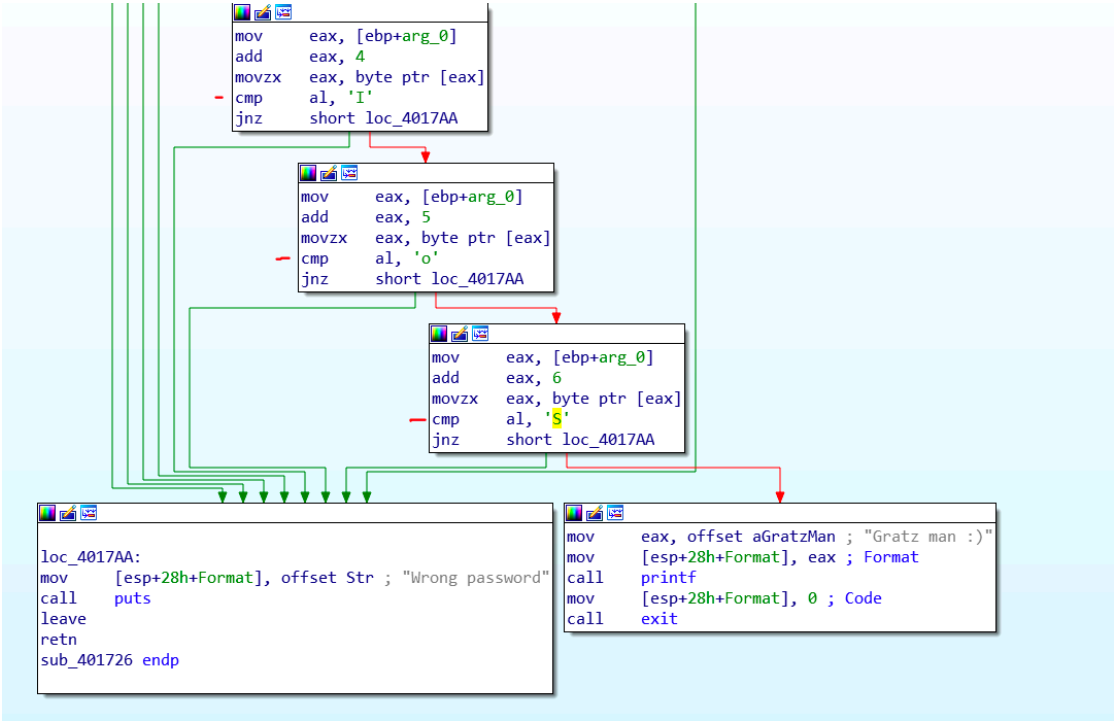
```
public ArraySegment<byte> ReadBytes(int length){
    int size = Math.Min(length, _len - _pos);
    var buffer = EnsureTempBuffer( length );
    var used = Read(buffer, 0, size);
```

LEARNING TO REPRESENT PROGRAMS WITH GRAPHS [Allamanis et al. 2018]

…WHAT ABOUT MACHINE CODE?

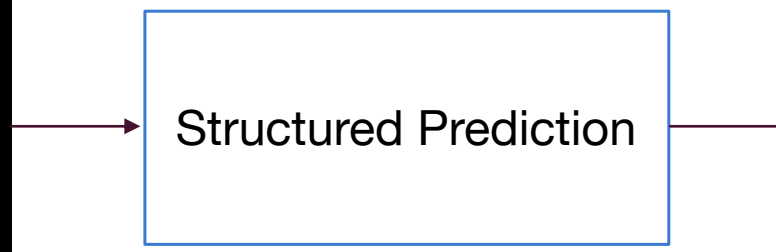
Machine code is harder:

- No variable names
- No types
- Really long sequences of instructions
- No function names (if stripped)

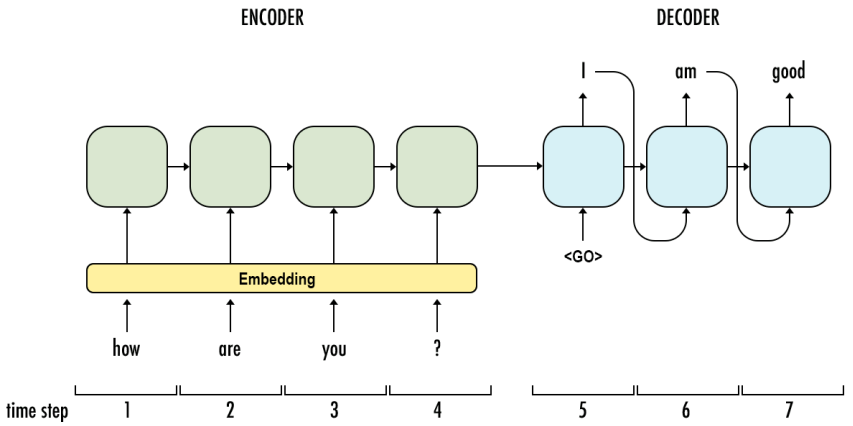


FUNCTION NAMING

```
80483b4:    55                      push   %ebp
80483b5:    89 e5                   mov    %esp,%ebp
80483b7:    83 e4 f0                and    $0xfffffff0,%esp
80483ba:    83 ec 20                sub    $0x20,%esp
80483bd:    c7 44 24 1c 00 00 00    movl   $0x0,0x1c(%esp)
80483c4:    00
80483c5:    eb 11                   jmp    80483d8 <main+0x24>
80483c7:    c7 04 24 b0 84 04 08    movl   $0x80484b0,(%esp)
80483ce:    e8 1d ff ff ff          call   80482f0 <puts@plt>
80483d3:    83 44 24 1c 01          addl   $0x1,0x1c(%esp)
80483d8:    83 7c 24 1c 09          cmpl   $0x9,0x1c(%esp)
80483dd:    7e e8                   jle    80483c7 <main+0x13>
80483df:    b8 00 00 00 00          mov    $0x0,%eax
80483e4:    c9                      leave
80483e5:    c3                      ret
80483e6:    90                      nop
80483e7:    90                      nop
80483e8:    90                      nop
80483e9:    90                      nop
80483ea:    90                      nop
```



Function name



FUNCTION NAMING - PERFORMANCES

Real Name	Predicted Name
client write transition	server write transition
file seek shared	file get size
aes encrypt	shall block enc
section write packet	build array
drop transform by id	remove by id
read array binary	array get slice
generate key ex	digest verify final

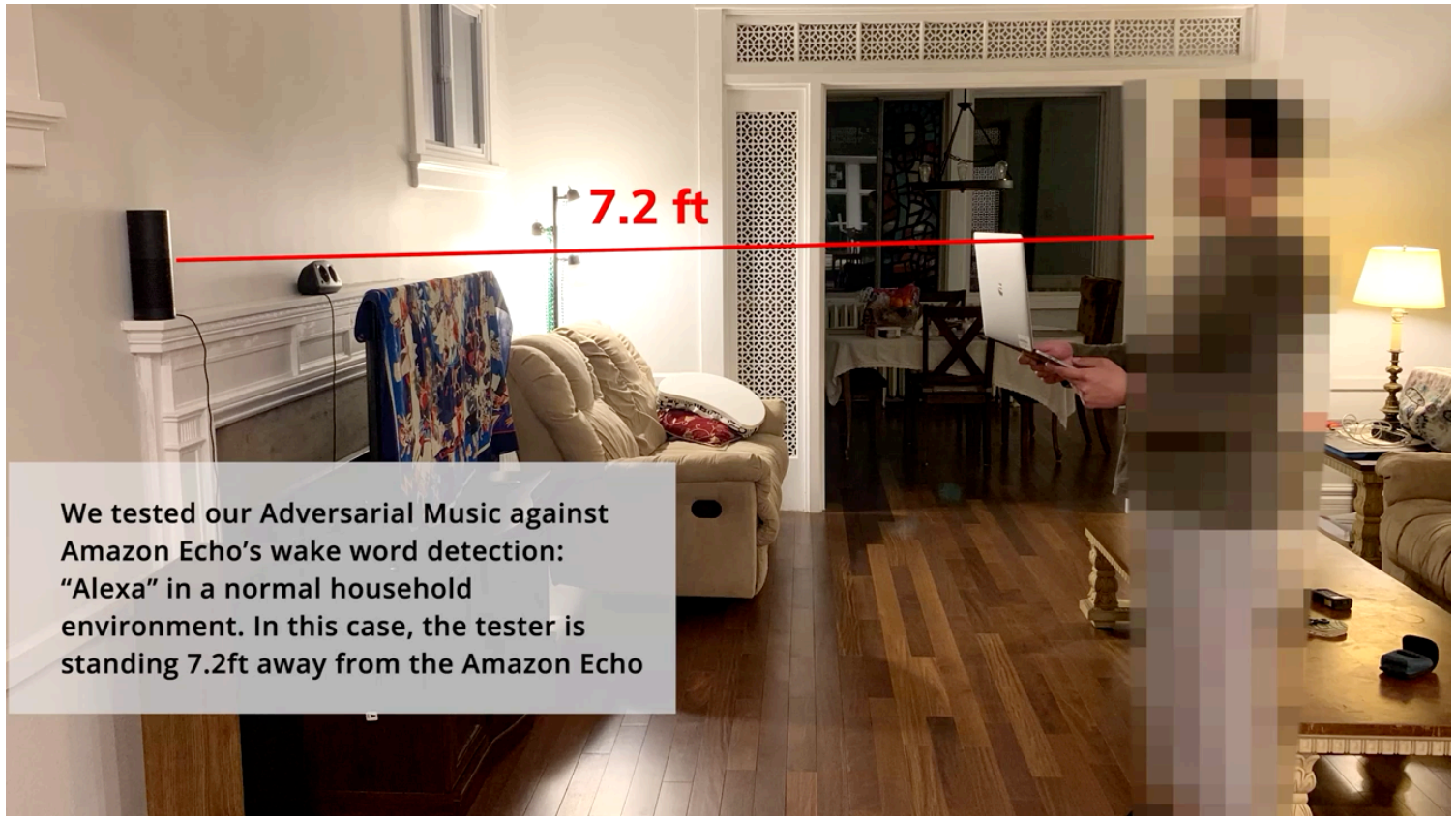
Predicitions on normal file

Real Name	Predicted Name
attack_kill_all	kill all
attack_get_opt_ip	addr
has_exe_access	read pid file
util_memsearch	find
table_retrieve_val	get
util_strncmp	compare
mem_exists	str cmp

Predicitions on mirai

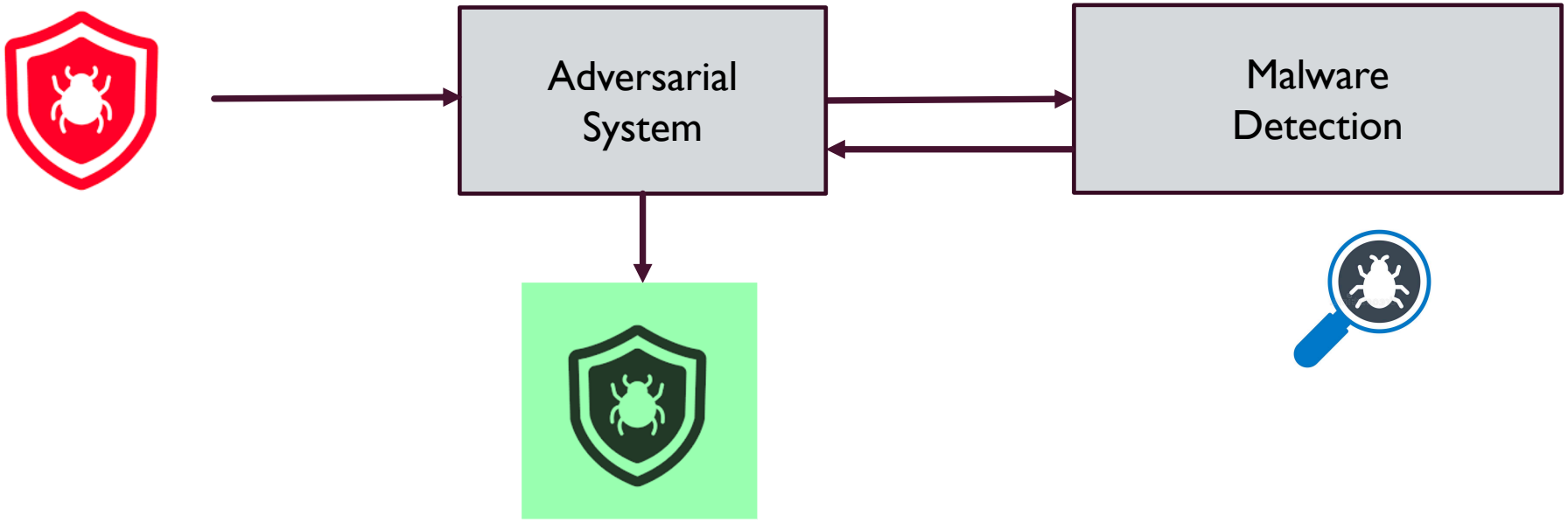
…OR IS THE NEXT THREAT?

ATTACKS ON ML SYSTEMS



Adversarial Music: Real World Audio Adversary Against Wake-word Detection System: https://arxiv.org/pdf/1911.00126.pdf

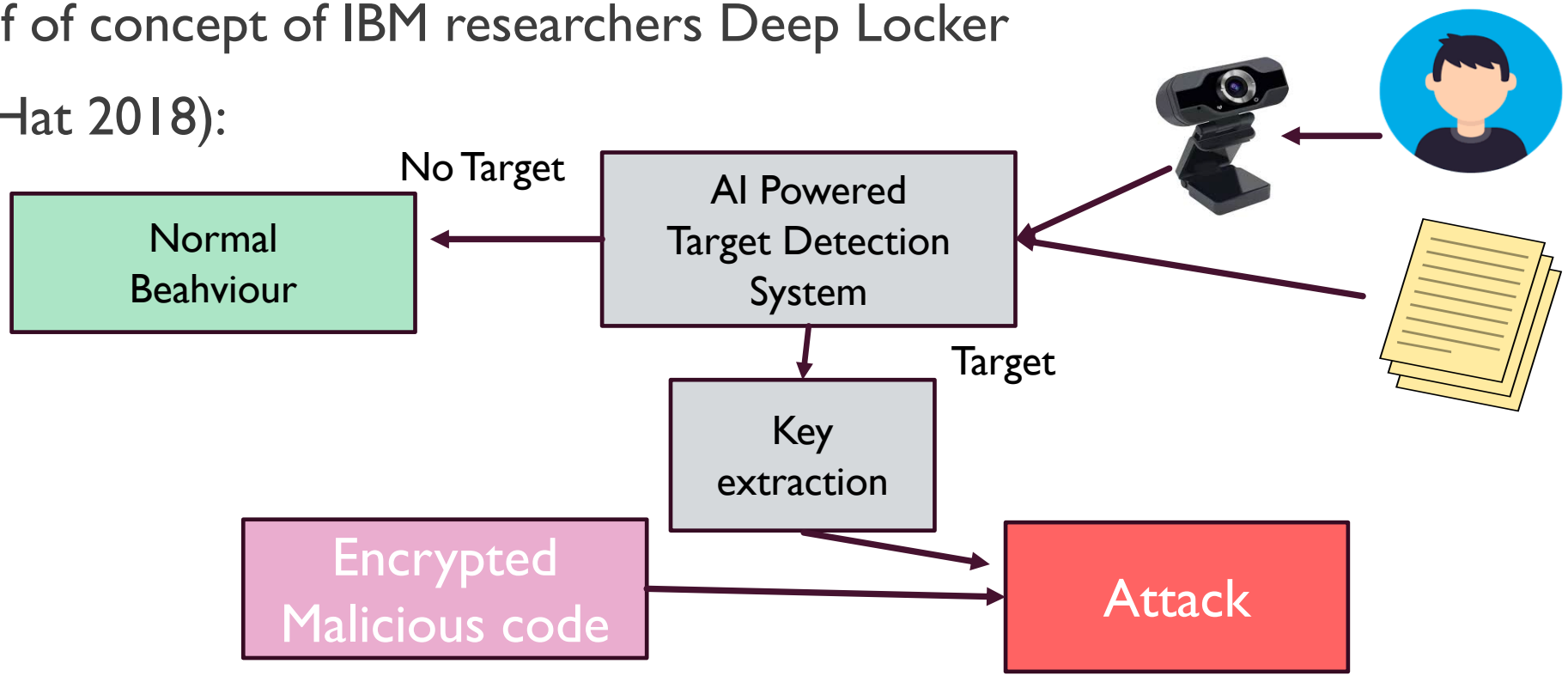
CREATING EVASIVE MALWARE



- Anderson et al. Learning to Evade Static PE Machine Learning Malware Models via Reinforcement Learning - https://arxiv.org/pdf/1801.08917.pdf
- Hu et al. Generating Adversarial Malware Examples for Black-Box Attacks Based on GAN - https://github.com/yanminglai/Malware-GAN

AI POWERED MALWARE

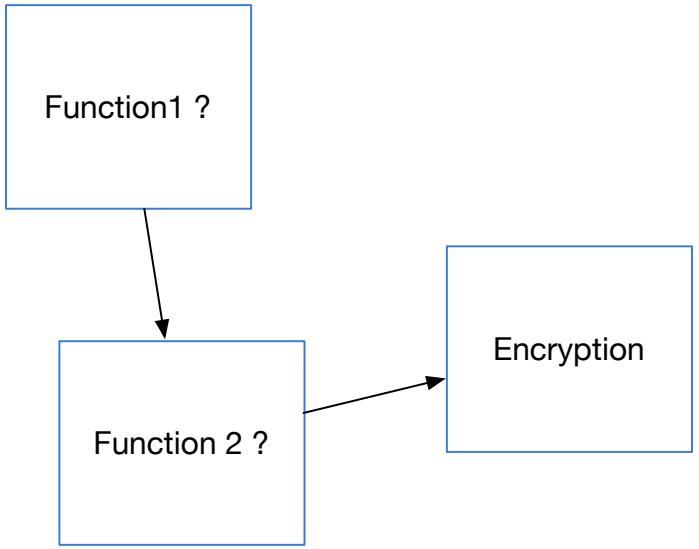
A proof of concept of IBM researchers Deep Locker (Black Hat 2018):



https://i.blackhat.com/us-18/Thu-August-9/us-18-Kirat-DeepLocker-Concealing-Targeted-Attacks-with-AI-Locksmithing.pdf

HOMEWORK – BINARY FUNCTIONS CLASSIFICATION

MOTIVATION



- During reversing of an unkown software it is often useful to find specific functions
- As an example encryption functions in a malware

OBJECTIVE

- You have to classify binary functions belonging to 4 classes:
  - Encryption
  - String Manipulation
  - Math
  - Sorting

DATASET LINK:

https://drive.google.com/file/d/1vKT9OzJwM6gKACyElzECW49X5nFeVxad/view?usp=sharing

DATASET

- You are given a dataset of 14397 functions, each function belongs to one of the aformetioned classes (Encryption, String Manipulation, Math, Sorting)
  - 2724 are Encryption Functions (label: Encryption)
  - 3104 are String Manipulation (label: String)
  - 4064 are Sorting Functions (label: Sort)
  - 4504 are Math Functions (label: Math)
- You are given a blind test file (functions without labels). You have to deliver a simple text file with your predictions for the blind test (keep the original order!).

DATA FORMAT

- Each file is a JSONL file (each line is a json object).
- Each item is a dictionary {key1: value1, key2: value2,...}. The keys are:
  - ID: unique id of each function
  - semantic: the label of each function in {math, sort, encryption, string}
  - lista_asm: the linear list of assembly instruction of each function
  - cfg: the control flow graph encoded as a networkx graph

DATA FORMAT

```
Addr_1: mov eax,10
Addr_2: dec eax
Addr_3: mov [base+eax],0
Addr_4: jnz Addr_2
Addr_5: mov eax,ebx
```

ach line is a json object).

key1: value1, key2: value2,...}. The keys are:

h

nction in {math, sort, encryption, string}

- lista_asm: the linear list of assembly instruction of each function
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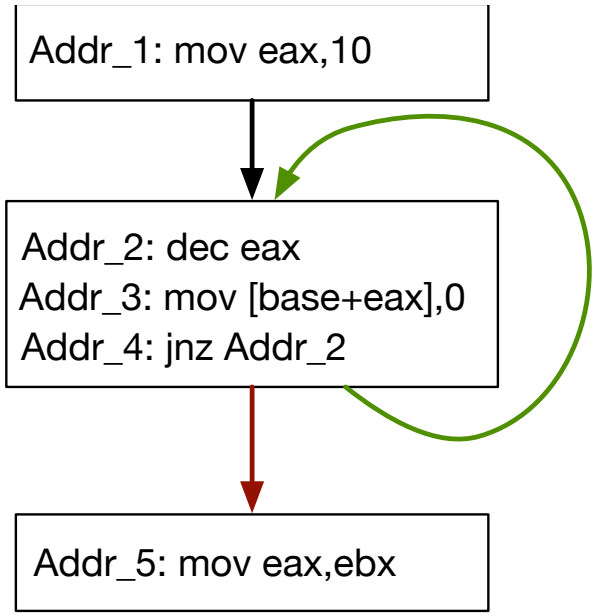

POSSIBLE FEATURES

We have to think about resonable features using the fact that we are experienced developers.

Encryption ?

Fairly Complex Functions (think about AES):

1. A lot of nested For and IF -> Complex CFG
2. They use xor a lot (and I mean a lot..), shifts and bitwise operations
3. Extremely long

Sorting ?

Usually the logic is simple:

1. One or two nested For and some helper functions
2. They use use compare and moves operations

Math ?

Not surprisingly they use a lot of arithmetic operations, and sometimes they do operations on vectors and matrices:

1. They usually use floating point instructions, special registers **xmm***

String Manipulation ?

A lot of comparisons and swap of memory loctions

POSSIBLE FEATURES

We hav enced
develop

Encryptic pulation ?

Good features could be:

1) Features that captures the complexity of the CFG (e.g., number of loops, edges, cyclomatic complexity, ...)
2) Features that take into account the kind of instructions contained in each function:
   1) You can group instructions into broad categories (bitwise operation, floating point, data move, ec...)
3) Global Features:
   1) Number of external call
   2) Number of instructions
   3) Usage of registers (that you can also group in categories)

Fairly Complex F
(think about AES)
1. A lot of nest
   -> Complex
2. They use xo
   mean a lot..)
   bitwise oper
3. Extremely lo

sons and swap
ons

30. LOOP @OUTER_LOOP ; jump

REFERENCES

https://cs.brown.edu/courses/cs033/docs/guides/x64_cheatsheet.pdf

http://web.cecs.pdx.edu/~apt/cs491/x86-64.pdf

https://networkx.org/documentation/stable/reference/readwrite/json_graph.html