Malware Detection in the AI Era: Attacks and Defenses on Machine Learning Classifiers

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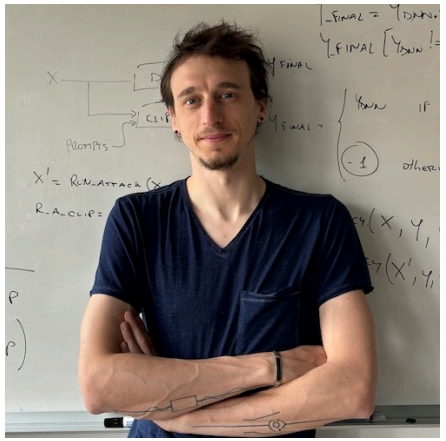
WhoAreWe



Assistant Professor @ UNIGE

Doing research for fun and profit since 2019

Main contribution in offensive security
with Adversarial EXEmples

Reviewer for top-tier journals and conferences

Working in EU projects

elsa
European Lighthouse on Secure and Safe AI

TESTABLE

Security Researcher @ Microsoft
Tech-lead in M365/Azure back-end:
AI/ML for Linux & Kubernetes cyber-threat detection

Doctoral Researcher @ UNIGE
AI/ML based malware detectors

In Past:
- Red Teaming
- NATO events
- OSCP, SANS/GIAC certs
- …

Agenda

Part 3: Attacking ML-based Malware Detection

1. Introduction to Adversarial Machine Learning
2. Adversarial EXEmples: pentesting ML Windows Malware Detectors
3. Defenses against Adversarial EXEmples

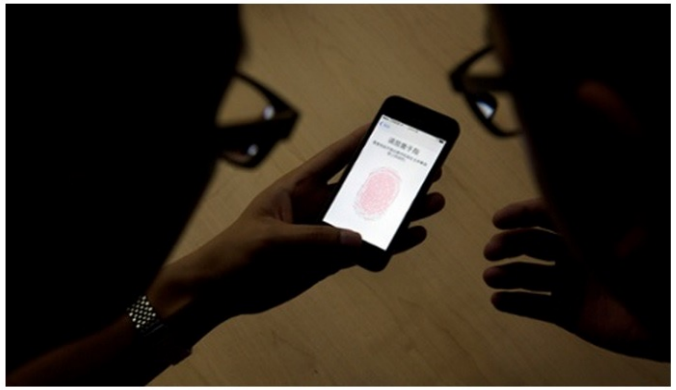
ML is not bulletproof

iPhone 5S fingerprint sensor hacked by Germany's Chaos Computer Club

Biometrics are not safe, says famous hacker team who provide video showing how they could use a fake fingerprint to bypass phone's security lockscreen

Follow Charles Arthur by email BETA

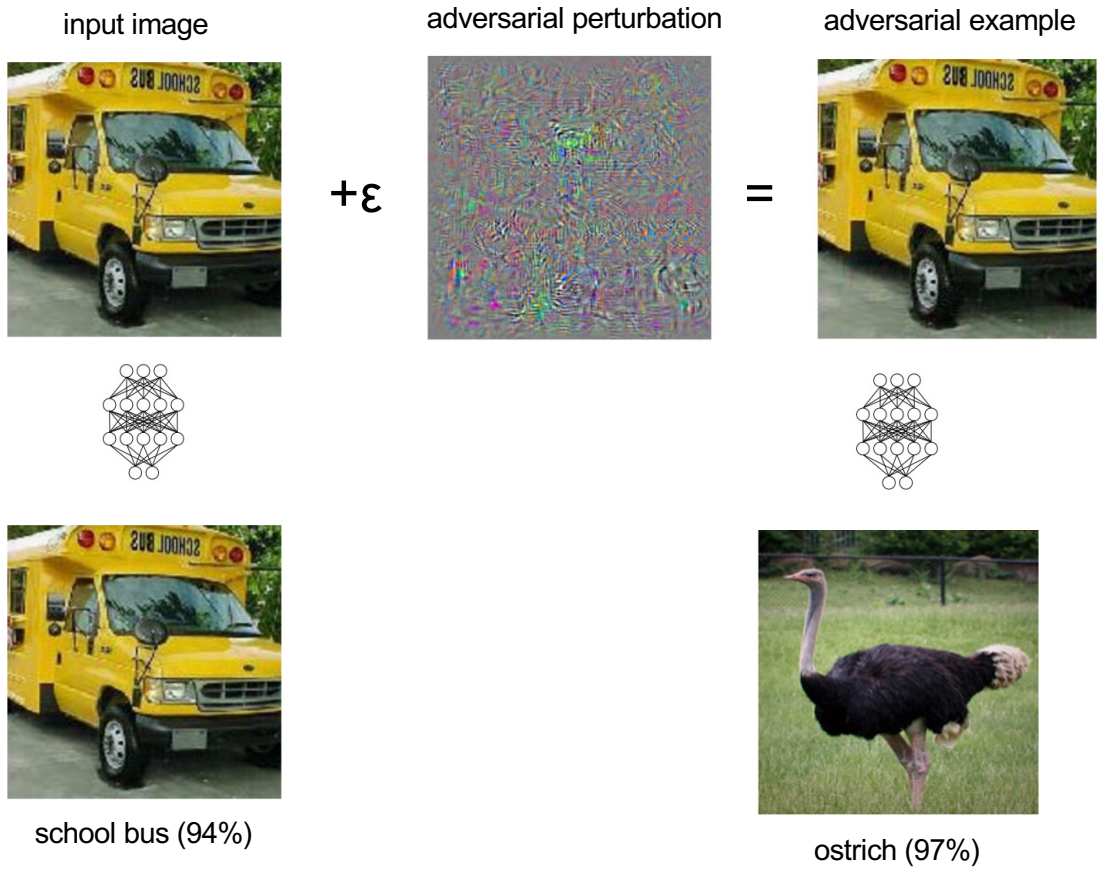
Charles Arthur
theguardian.com, Monday 23 September 2013 08.50 BST
Jump to comments (306)



While ML models possess tremendous performance, they can be target of attacks from anybody with some background in ML and reverse engineering

[Thanks to Prof.Roli, Prof. Biggio for this slide]

Adversarial Examples



Mostly-invisible noise that force the model in predicting

[Thanks to Prof.Roli, Prof. Biggio for this slide]

Szegedy et al., Intriguing properties of neural networks, **ICLR 2014**
Biggio et al., Evasion attacks against machine learning at test time, **ECML-PKDD 2013**

Attacks in the real world

[Thanks to Prof.Roli, Prof. Biggio for this slide]

Eykholt et al., *Robust physical-world attacks on deep learning visual classification*, CVPR 2018

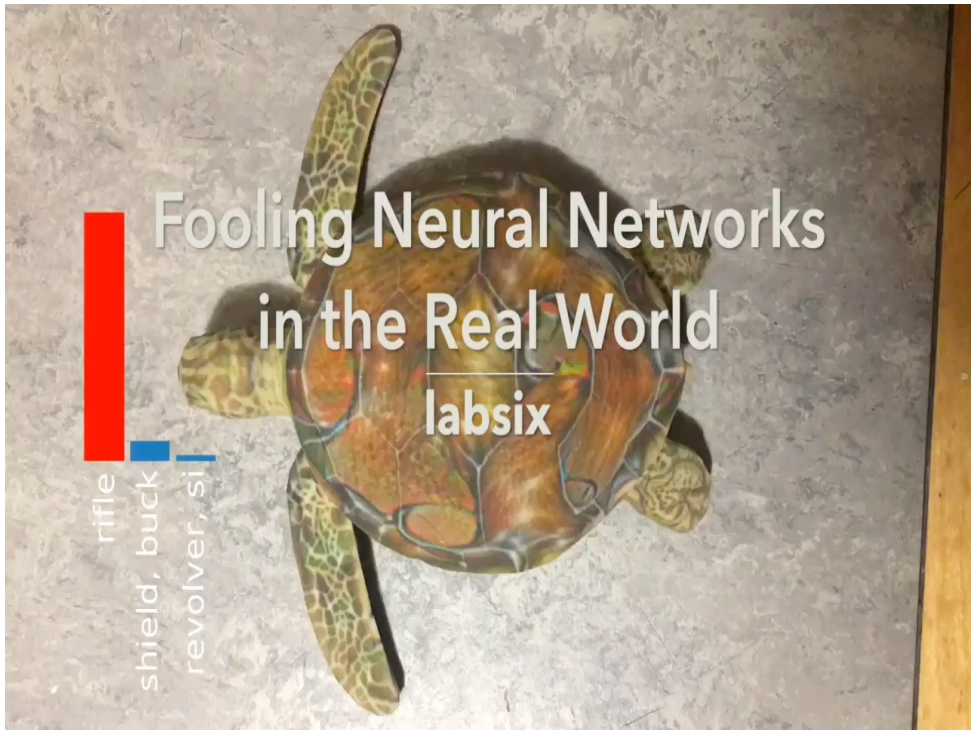
Stealing identities

Attacks against DNNs for face recognition with carefully-fabricated eyeglass frames

When worn by a **41-year-old white male** (left image), the glasses mislead the deep network into believing that the face belongs to the famous actress **Milla Jovovich**

Sharif et al., *Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition*, ACM CCS 2016

Printed objects detected as Rifles



[Thanks to Prof.Roli, Prof. Biggio for this slide]

Athalye et al., *Synthesizing robust adversarial examples*. ICLR, 2018

Adversarial Audios

Audio	Transcription by Mozilla DeepSpeech
	“without the dataset the article is useless”
	“okay google browse to evil dot com”

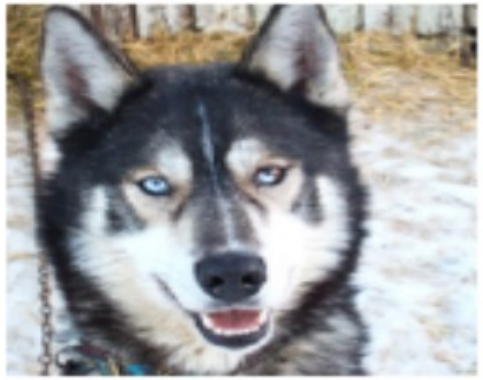
Adding almost-inaudible noise to force speech-to-text models to capture the wrong words

https://nicholas.carlini.com/code/audio_adversarial_examples/

[Thanks to Prof.Roli, Prof. Biggio for this slide]

Why all these insecurities?

Spurious Correlations



(a) Husky classified as wolf

“Why Wolf?”

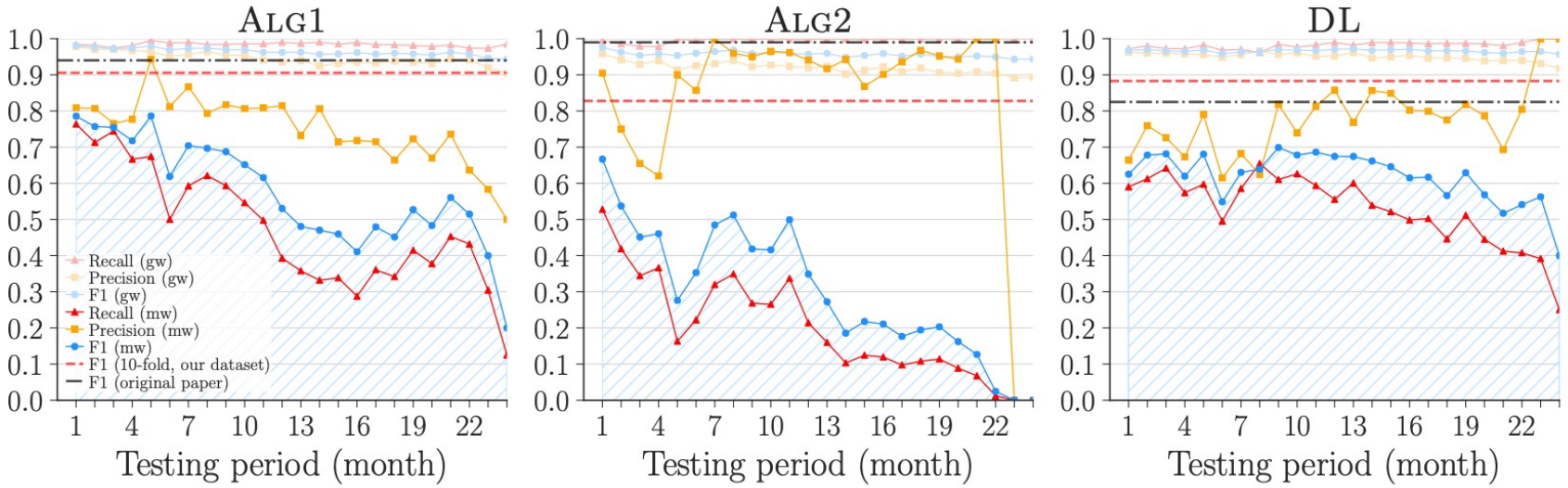
“White background!”

(b) Explanation

Models do not guarantee that they are learning what we believe it’s important, but they just match good correlations in data

[M.T. Ribeiro et al., KDD 2016]

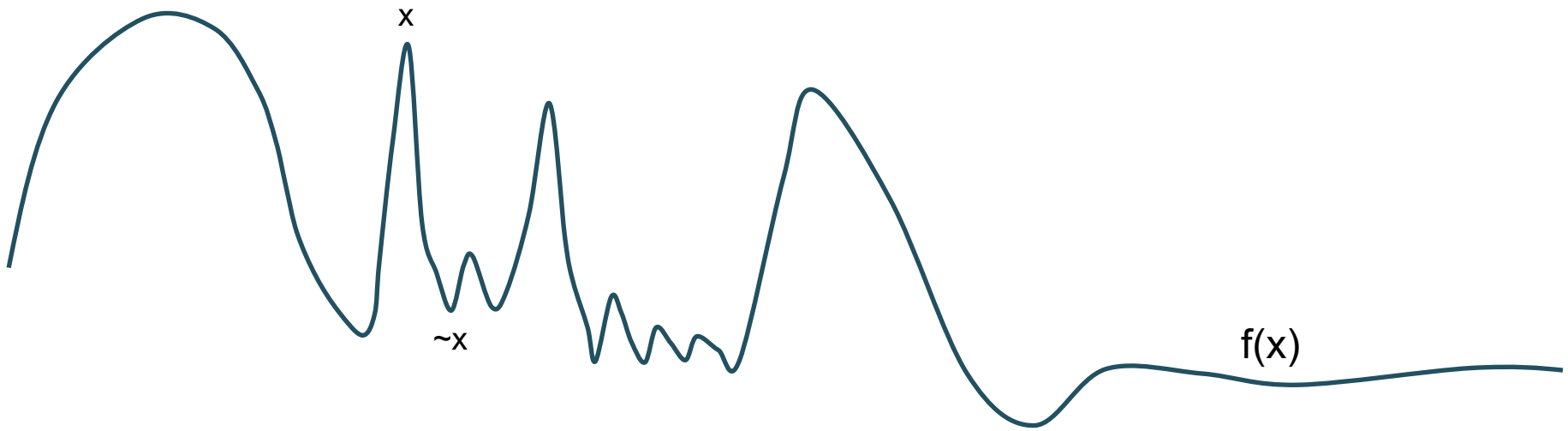
Data is not stationary



Data changes over time, and models are trained with the IID assumption

Pendlebury, Cavallaro et al., TESSERACT, USENIX Sec. 2019

Overfitting



If badly trained, ML models adapt **too much** on training data, becoming mostly useless at test time in presence of minimal noise

Model Adversaries for profit and profit

Anticipate the Arm Race

Instead of waiting for attacks and brace for the impact, system designers should **ALWAYS** simulate attacks and develop countermeasures

System designers should test strong attacks to understand the possible damages that adversaries might do!

Goals, Knowledge and Capabilities

Formalize attackers through
three different dimensions

GOAL	KNOWLEDGE	CAPABILITIES
The security violation that the attacker wants to achieve	What the attackers knows about the system to test	Which action can be performed by the attacker

Biggio and Roli, **Wild Patterns**: *Ten Years After The Rise of Adversarial Machine Learning*, Pattern Recognition, 2018

Attacker's Goal

Integrity Violations

Misclassifications that do not compromise the normal system operation

Availability Violations

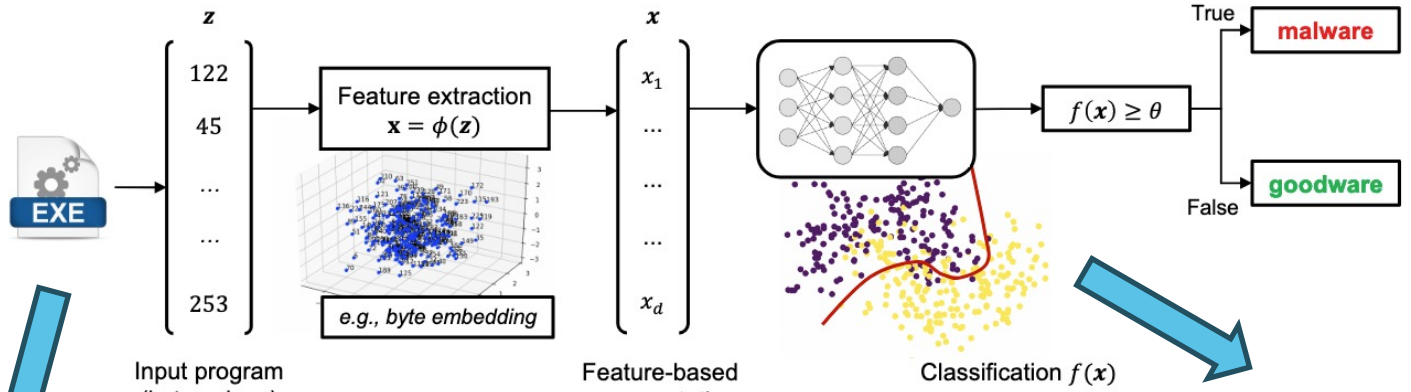
Misclassifications that compromise the normal system operation, causing a **Denial of Service** for all the users of that model

Privacy / Confidentiality Violations

Strategies that leak confidential information about the model, the data used at training time, or stealing industrial and intellectual propertie

Biggio and Roli, **Wild Patterns**: *Ten Years After The Rise of Adversarial Machine Learning*, Pattern Recognition, 2018

Attacker's Knowledge



Training Data
Attacker knows which data have been used to train the model

Representation
Attacker knows how data processed through feature extraction

Learning function
Attacker knows which model has been used along with its variables

Biggio and Roli, **Wild Patterns**: *Ten Years After The Rise of Adversarial Machine Learning*, Pattern Recognition, 2018

Perfect Knowledge

Training Data
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Representation
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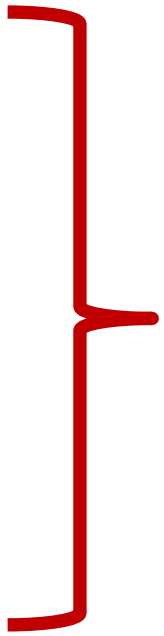


Perfect knowledge
Worst-case nightmarish scenario
The attacker knows EVERYTHING about our system
Also known as **white-box access**

Limited Knowledge

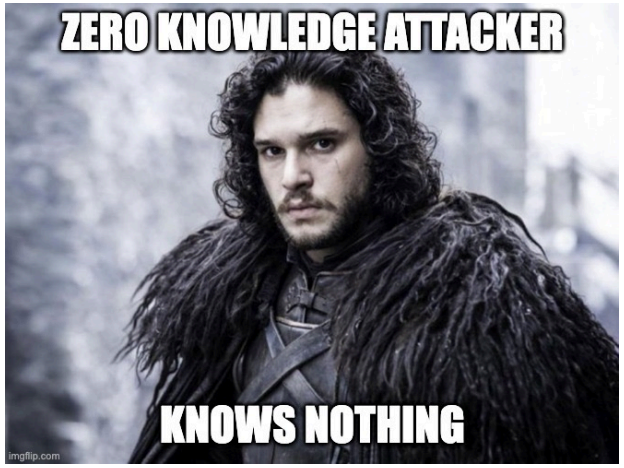
Training Data
Attacker knows which data have been used to train the model

Representation
Attacker knows how data processed through feature extraction

Learning function
Attacker knows which model has been used along with its variables

Limited knowledge
The attacker knows SOMETHING about our system, that could be a combination of the three listed assets,
but not all of them!
Also known as **gray-box access**

Zero Knowledge



Training Data
Attacker knows which data have been used to train the model

Representation
Attacker knows how data processed through feature extraction

Learning function
Attacker knows which model has been used along with its variables

Zero knowledge
The attacker knows NOTHING about our system
Also known as **black-box access**

Attacker's Capabilities

Test Time

The attacker can interact with the model AFTER deployment (at test time)

Training Time

The attacker can tamper, manipulate, and interact with the model BEFORE deployment and while it is training.

Biggio and Roli, **Wild Patterns**: *Ten Years After The Rise of Adversarial Machine Learning*, Pattern Recognition, 2018

Strength of the attack

Test Time

The attacker can perturb data,
but without infinite power

Training Time

The attacker can tamper only
with a fraction of the training data

Biggio and Roli, **Wild Patterns**: *Ten Years After The Rise of Adversarial Machine Learning*, Pattern Recognition, 2018

Recap on modelling attackers

Attacker's Capability	Attacker's Goal: Misclassifications that do not compromise normal system operation — Integrity	Attacker's Goal: Misclassifications that compromise normal system operation — Availability	Attacker's Goal: Querying strategies that reveal confidential information on the learning model or its users — Privacy / Confidentiality
Test data	**Evasion (a.k.a. adversarial examples)**	-	Model extraction / stealing Model inversion (hill-climbing) Membership inference attacks
Training data	Poisoning (to allow subsequent intrusions) – e.g., backdoors or neural network trojans	Poisoning (to maximize classification error)	-

All possible attacks can be recast to this table, making it compact and easy to use in production environments

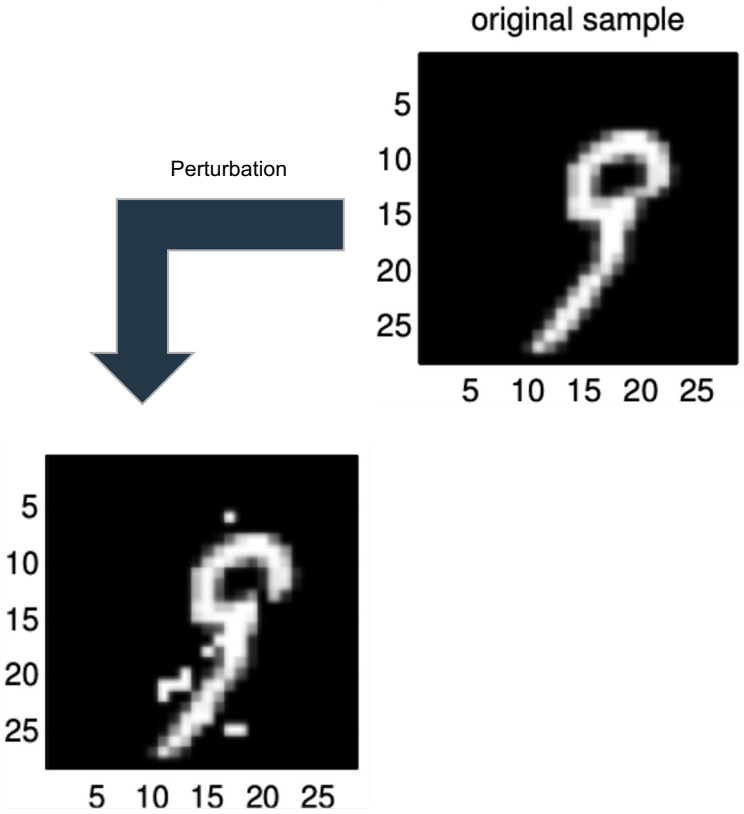
Biggio and Roli, **Wild Patterns**: *Ten Years After The Rise of Adversarial Machine Learning*, Pattern Recognition, 2018

Evasion attacks with Adversarial Examples

Adversarial Examples

Perturbed test samples
Modifying values of pixels that maximise the error at test time

Constraint perturbation
Samples are minimally altered so that they do not look suspicious



Formalization of the attack

Maximisation we want to increase the error of the model

Perturbation what is injected in the test point **x**

Parameters of the model included inside the loss function

$$\max_{\delta} L(x + \delta, y; \theta)$$

Loss function distance function used to quantify the error

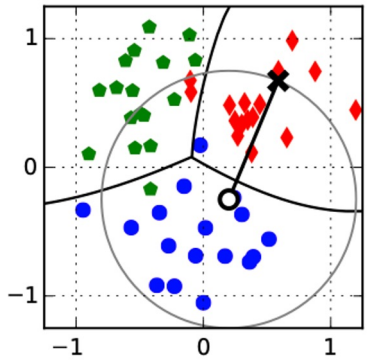
Real label the label from which we want to get away

Error-generic (untargeted) attacks

$$\max_{\delta} \; L(x + \delta, y; \theta)$$

Maximum error at test time

The perturbation is crafted to redirect the decision towards any other class different from the original one

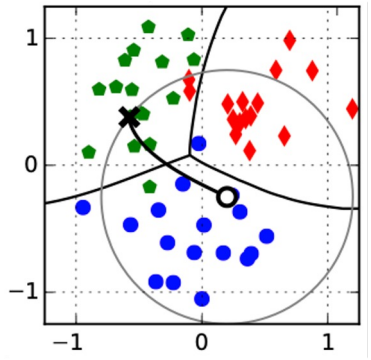


Error-specific (targeted) attacks

$$\min_{\delta} \; L(x + \delta, y_t; \theta)$$

Minimize error of target class

Change from MAX to MIN, force the perturbation to redirect decision towards a specific class



Including the Capabilities

$$\max_{\delta} L(x+\delta, y; \theta)$$
$$\text{s.t. } \|\delta\|_p < \epsilon$$
$$\text{and}$$
$$l_b \preccurlyeq x+\delta \preccurlyeq u_b$$

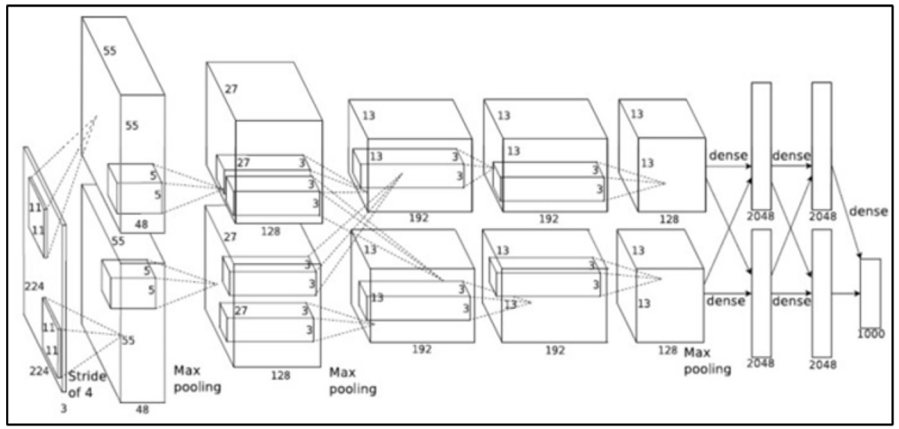
Bounded perturbation
Perturbation is constrained to not exceed a certain budget, that is the *strength of the attack*

Input-domain constraints
Bounds that force the attack to create valid samples inside the input space

Keep this in mind, we will be back on constraints when addressing malware

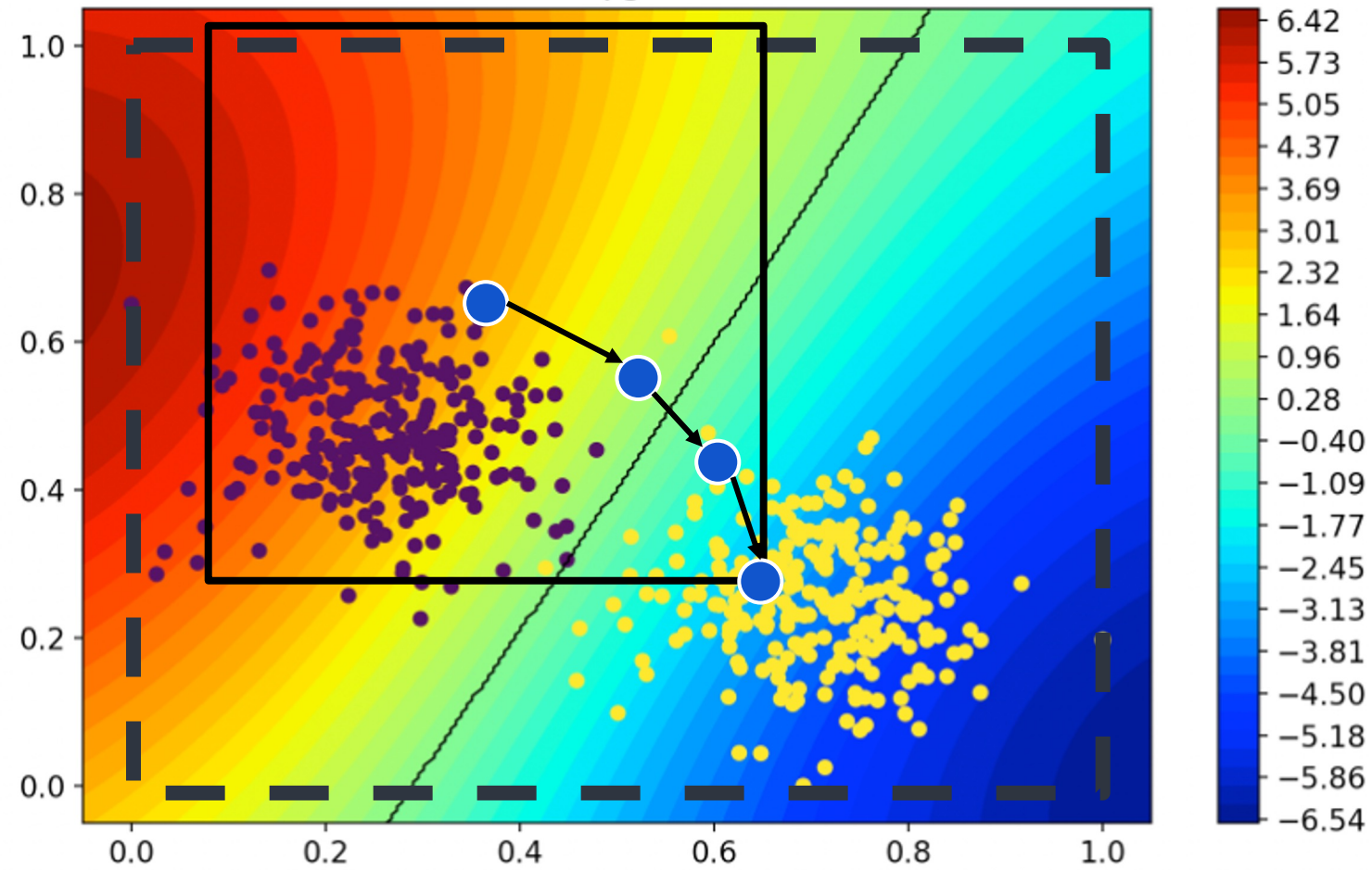
Solutions with Gradients

$x + \delta$



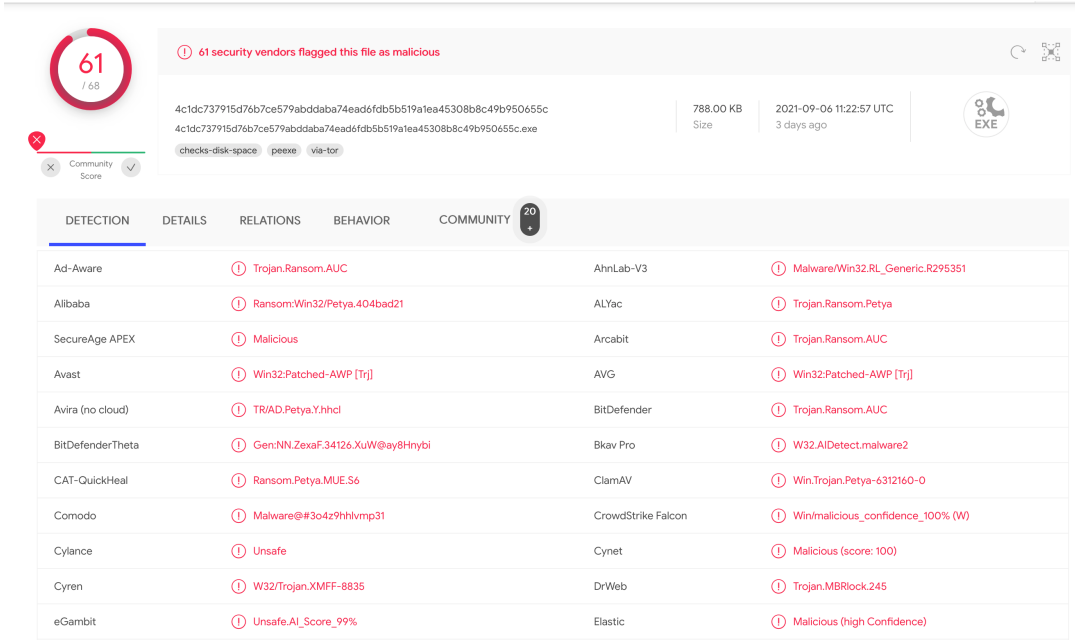
$L(x+\delta, y; \theta)$

$\nabla_\delta L$



[Biggio, Roli, *Wild Patterns*, Pattern Recognition 2018 https://arxiv.org/abs/1712.03141]
[Pintor et al. *Indicators of Attack Failures,* NeurIPS 2022, https://arxiv.org/pdf/2106.09947.pdf]

Reality-check check on Evaluations



Most models are hosted on private servers

Detection performed in cloud

No gradients can be computed!

Solutions without Gradients

Not always possible to compute gradients

Model under test might be non-differentiable, or it might not be available but it can only be queried.

Two ways then:

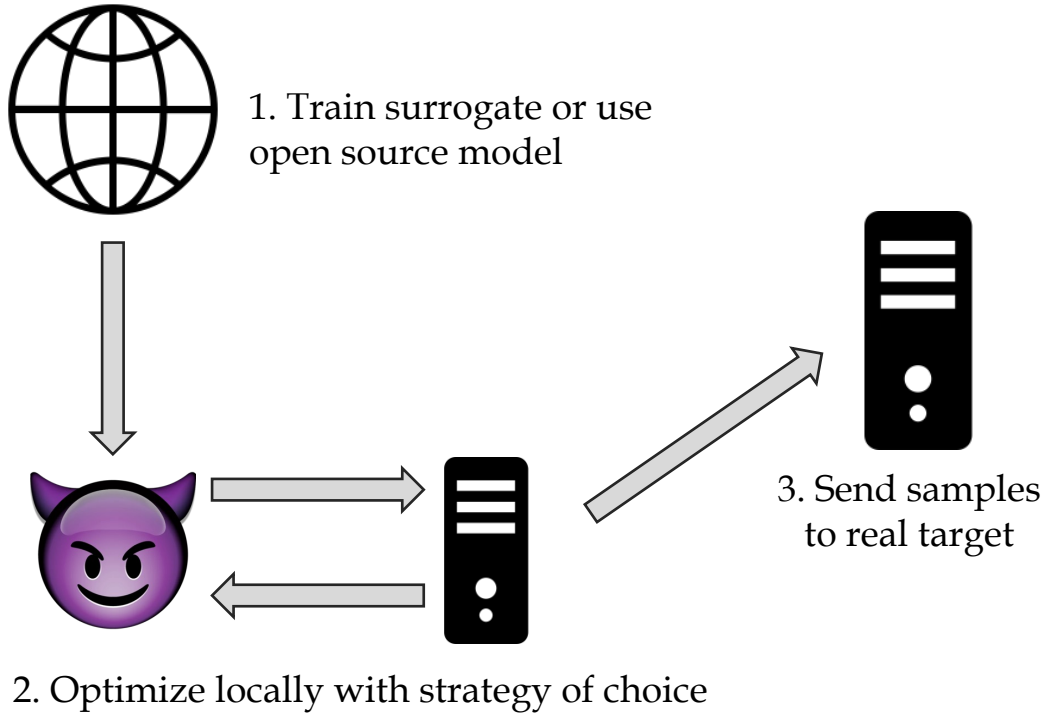
Transfer Evaluations

Compute attacks on owned or similar model and test results on real target

Query-based Optimization

Use the answers of the target to modify the parameters of noise

Transfer Evaluations



Craft surrogate classifier

Deploy or construct locally a model that behave similarly to the one we want to test

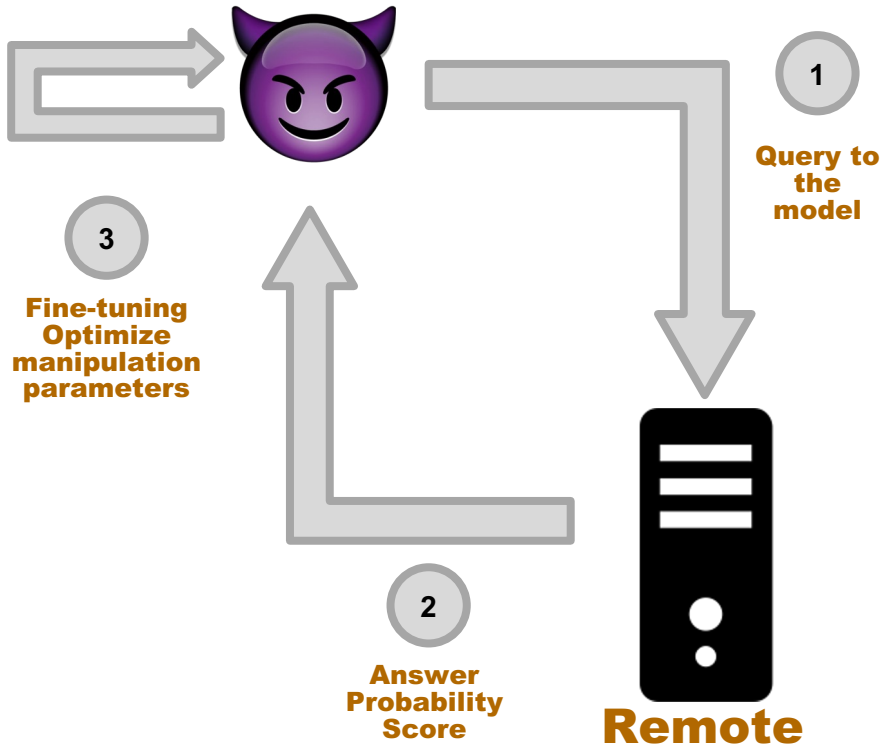
Use strong attack

Attack the surrogate with the best attack in the arsenal

Finger-cross, and test target

Send the computed attacks to the target, and hope they work as intended

Query-based Optimization of Attacks



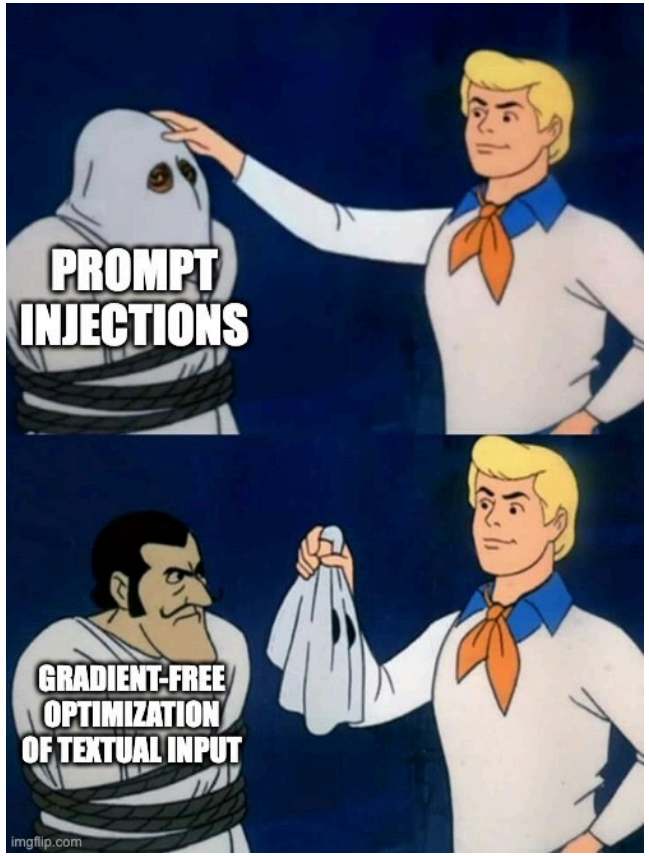
Query the target
Ignoring its internals, send sample and wait for answer

Update parameters of manipulation
Fine-tune manipulations by comparing responses

Byte-per-byte optimization
Optimizer find best patterns, query after query

(more details later in the course)

Digression: LLM Prompt Injections?



Plenty of hype around vulnerabilities of LLMs

BUT

These are EXACTLY optimization techniques applied on machine learning models with textual input

No more, no less

Zou et al. Universal and Transferable Adversarial Attacks on Aligned Language Models

Hands-on exercises time

https://github.com/pralab/secml

Jupyter notebooks to understand how to apply simple adversarial attacks against example classifiers

SecML: Secure and Explainable Machine Learning in Python

status alpha | python 3.6 | 3.7 | 3.8 | platform linux | macos | windows | license Apache-2.0

SecML is an open-source Python library for the **security evaluation** of Machine Learning algorithms. It is equipped with **evasion** and **poisoning** adversarial machine learning attacks, and it can **wrap models and attacks** from other different frameworks.

```
from secml.adv.attacks import CAttackEvasionPGD

distance = 'l2'  # type of perturbation 'l1' or 'l2'
dmax = 2.5  # maximum perturbation
lb, ub = 0., 1.  # bounds of the attack space. None for unbounded
y_target = None  # None if untargeted, specify target label otherwise

# Should be chosen depending on the optimization problem
solver_params = {
    'eta': 0.5, # step size of the attack
    'max_iter': 100, # number of gradient descent steps
}

attack = CAttackEvasionPGD(classifier=secml_model,
                           distance=distance,
                           dmax=dmax,
                           solver_params=solver_params,
                           y_target=y_target)

adv_pred, scores, adv_ds, f_obj = attack.run(x, y)
```

Lab 4:

Hands-on tutorial on SecML Library

aka.ms/malware-lab4

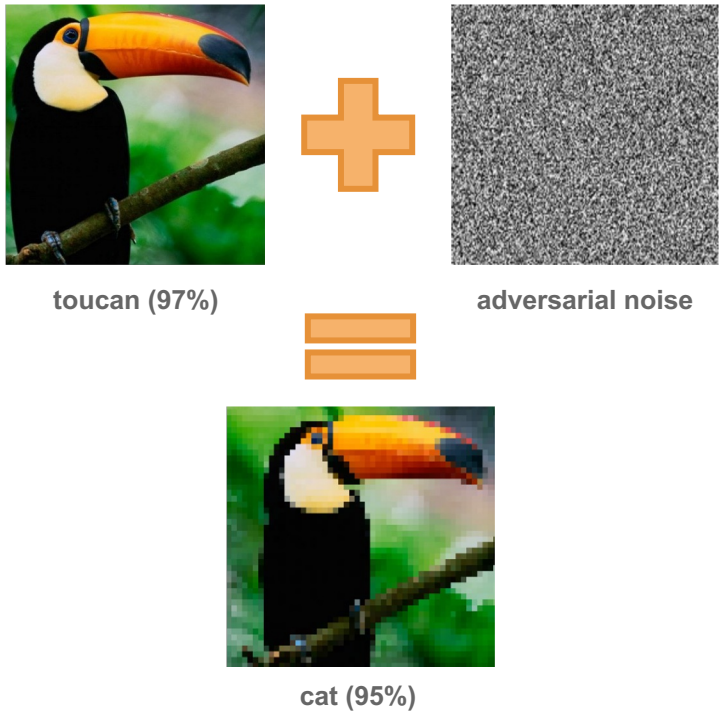
Lab 5:

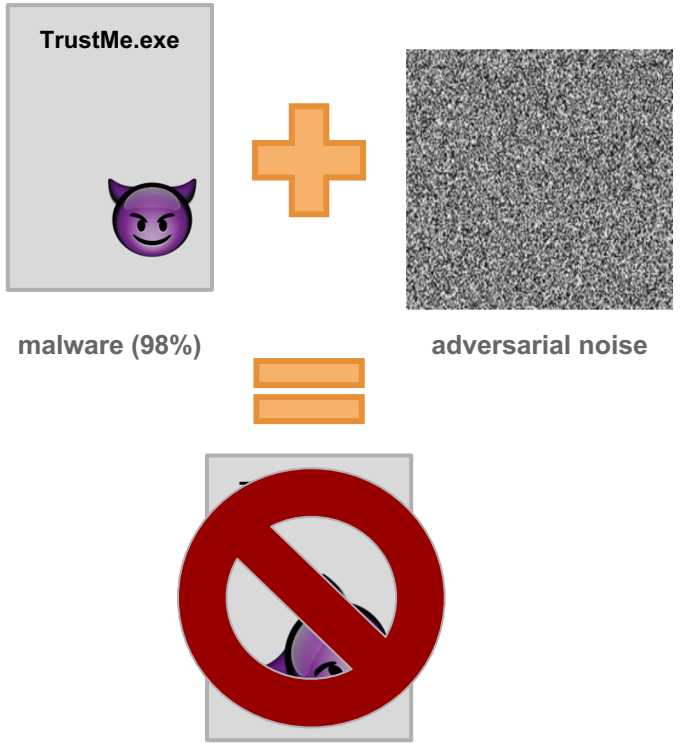
Simple evasion attacks against machine learning models

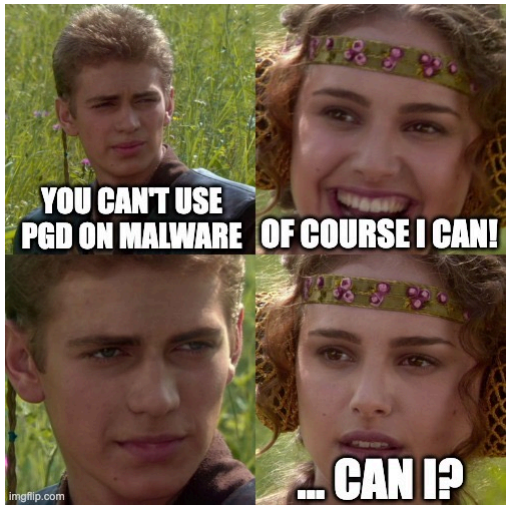
aka.ms/malware-lab5

Adversarial EXEmples
from evil pixels to malicious bytes

We can apply same attacks! Right?







Problem 1: no distance function!

Programs and images are encoded in bytes

RGB is “continuous”, code instructions are not!

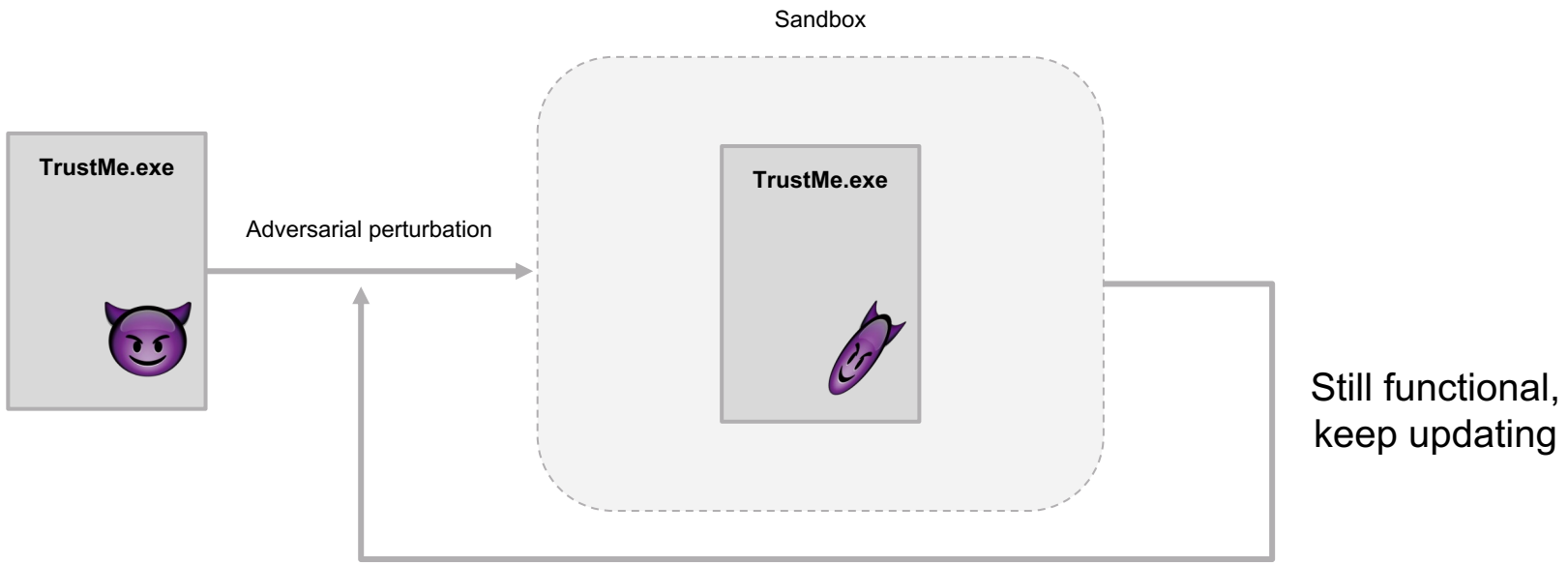
Distance between programs is **undefined**

Example: ASCII table
What does $\sqrt{'a' - 'b'}$ means?

Dec	Hx	Oct	Char	Dec	Hx	Oct	Html	Chr	Dec	Hx	Oct	Html	Chr	Dec	Hx	Oct	Html	Chr
0	0	000	NUL (null)	32	20	040		Space	64	40	100	@	@	96	60	140	`	`
1	1	001	SOH (start of heading)	33	21	041	!	!	65	41	101	A	A	97	61	141	a	a
2	2	002	STX (start of text)	34	22	042	"	"	66	42	102	B	B	98	62	142	b	b
3	3	003	ETX (end of text)	35	23	043	#	#	67	43	103	C	C	99	63	143	c	c
4	4	004	EOT (end of transmission)	36	24	044	$	$	68	44	104	D	D	100	64	144	d	d
5	5	005	ENQ (enquiry)	37	25	045	%	%	69	45	105	E	E	101	65	145	e	e
6	6	006	ACK (acknowledge)	38	26	046	&	&	70	46	106	F	F	102	66	146	f	f
7	7	007	BEL (bell)	39	27	047	'	'	71	47	107	G	G	103	67	147	g	g
8	8	010	BS (backspace)	40	28	050	(	(	72	48	110	H	H	104	68	150	h	h
9	9	011	TAB (horizontal tab)	41	29	051	)	)	73	49	111	I	I	105	69	151	i	i
10	A	012	LF (NL line feed, new line)	42	2A	052	*	*	74	4A	112	J	J	106	6A	152	j	j
11	B	013	VT (vertical tab)	43	2B	053	+	+	75	4B	113	K	K	107	6B	153	k	k
12	C	014	FF (NP form feed, new page)	44	2C	054	,	,	76	4C	114	L	L	108	6C	154	l	l
13	D	015	CR (carriage return)	45	2D	055	-	-	77	4D	115	M	M	109	6D	155	m	m
14	E	016	SO (shift out)	46	2E	056	.	.	78	4E	116	N	N	110	6E	156	n	n
15	F	017	SI (shift in)	47	2F	057	/	/	79	4F	117	O	O	111	6F	157	o	o
16	10	020	DLE (data link escape)	48	30	060	0	0	80	50	120	P	P	112	70	160	p	p
17	11	021	DC1 (device control 1)	49	31	061	1	1	81	51	121	Q	Q	113	71	161	q	q
18	12	022	DC2 (device control 2)	50	32	062	2	2	82	52	122	R	R	114	72	162	r	r
19	13	023	DC3 (device control 3)	51	33	063	3	3	83	53	123	S	S	115	73	163	s	s
20	14	024	DC4 (device control 4)	52	34	064	4	4	84	54	124	T	T	116	74	164	t	t
21	15	025	NAK (negative acknowledge)	53	35	065	5	5	85	55	125	U	U	117	75	165	u	u
22	16	026	SYN (synchronous idle)	54	36	066	6	6	86	56	126	V	V	118	76	166	v	v
23	17	027	ETB (end of trans. block)	55	37	067	7	7	87	57	127	W	W	119	77	167	w	w
24	18	030	CAN (cancel)	56	38	070	8	8	88	58	130	X	X	120	78	170	x	x
25	19	031	EM (end of medium)	57	39	071	9	9	89	59	131	Y	Y	121	79	171	y	y
26	1A	032	SUB (substitute)	58	3A	072	:	:	90	5A	132	Z	Z	122	7A	172	z	z
27	1B	033	ESC (escape)	59	3B	073	;	;	91	5B	133	[	[	123	7B	173	{	{
28	1C	034	FS (file separator)	60	3C	074	<	<	92	5C	134	\	\	124	7C	174			|
29	1D	035	GS (group separator)	61	3D	075	=	=	93	5D	135	]	]	125	7D	175	}	}
30	1E	036	RS (record separator)	62	3E	076	>	>	94	5E	136	^	^	126	7E	176	~	~
31	1F	037	US (unit separator)	63	3F	077	?	?	95	5F	137	_	_	127	7F	177	&#127;	DEL

Source: www.asciitable.com

Problem 2: functionality, is that you?



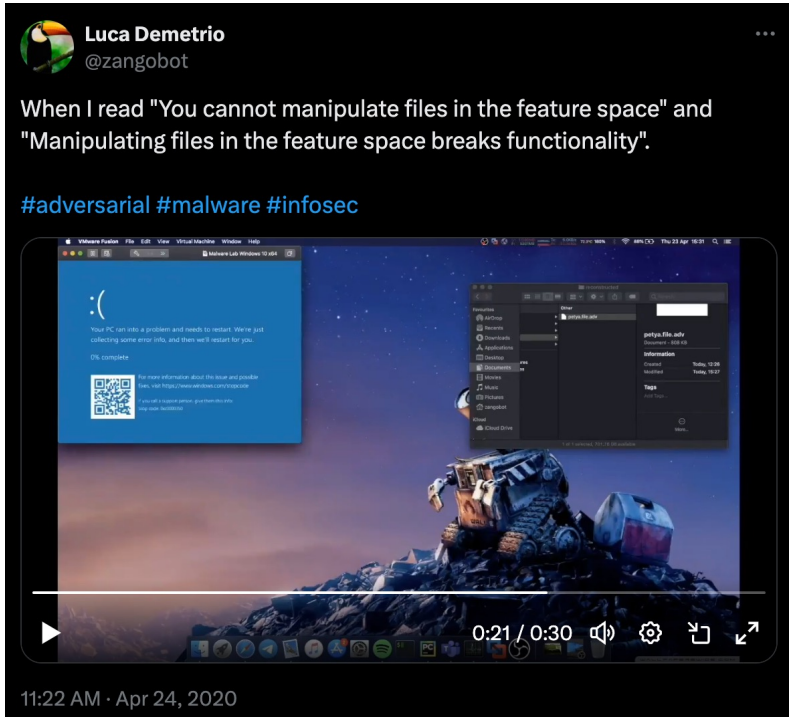
Song et al., *MAB-Malware: A Reinforcement Learning Framework for Attacking Static Malware Classifiers*, AsiaCCS 2022
Castro et al., *AIMED: Evolving Malware with Genetic Programming to Evade Detection*, TrustCom/BigDataSE 2019

Discouraging research?

In 2019 ~ 2020, people were telling us that the problem too hard to solve

ALSO ME IN 2019 ~ 2020

https://x.com/zangobot/status/1253615316569120768



Adversarial EXEmples: change of paradigm

The problem IS possible to solve,
thanks to some twists:

1. **Formulate** the minimization problem differently

2. **Study the format** that represent programs, and understand how to exploit its ambiguites

3. **Create new algorithms** that inject or replace content

Different formulation

$$\min_{\boldsymbol{\delta}} L(\boldsymbol{x} + \boldsymbol{\delta}, y; \boldsymbol{\theta})$$

Network architecture in the loss
All the internals of a neural network / shallow model are hidden inside the loss

Additive Manipulation
Input samples are injected with additive noise, without any concern on the structure of the file

Different formulation

$$\min_{\delta} L(f(\phi(h(x;\delta)), y)$$

Model function and features
Need to explicit the model function and the features, since they might be non differentiable

Practical Manipulations
No additions, but a complex function that handles format specification by design

Demetrio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021

Different formulation

$$\min_{\delta} L(f(\phi(h(x;\delta), y)$$

Define the Optimizer
Depending on the differentiability of the compontens, pick a gradient-based or gradient-free algorithm

Define the Manipulations
Study the format, understand its ambiguities, and write manipulations that do not break the original functionality

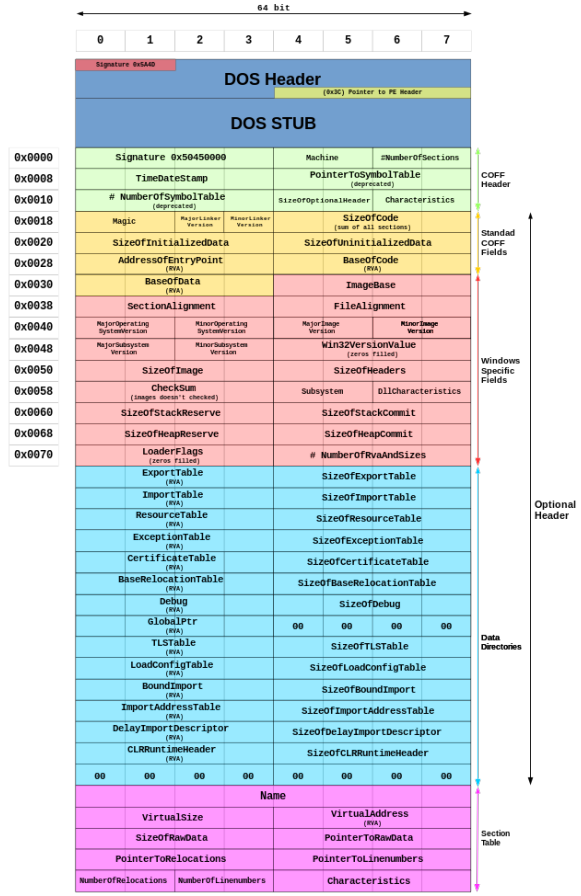
Demetrio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021

Manipulations of Windows PE File Format

Recap: PE format

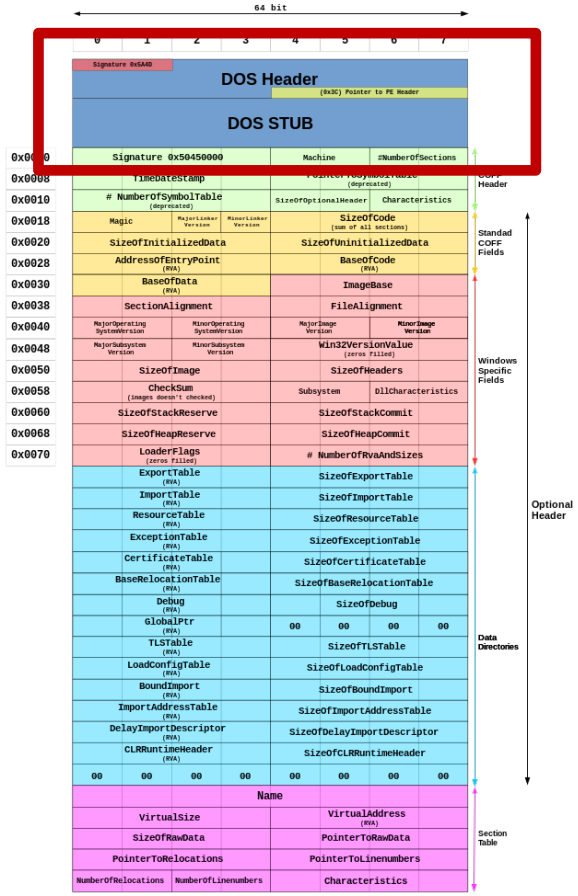
Format adapted for “modern” programs (from Windows NT 3.1 on)

Before there were other formats, one is the DOS (kept for retrocompatibility)



Recap: PE format

DOS Header + Stub
Metadata for DOS program
Executing a modern program in DOS will trigger the “This program cannot be run in DOS mode” output

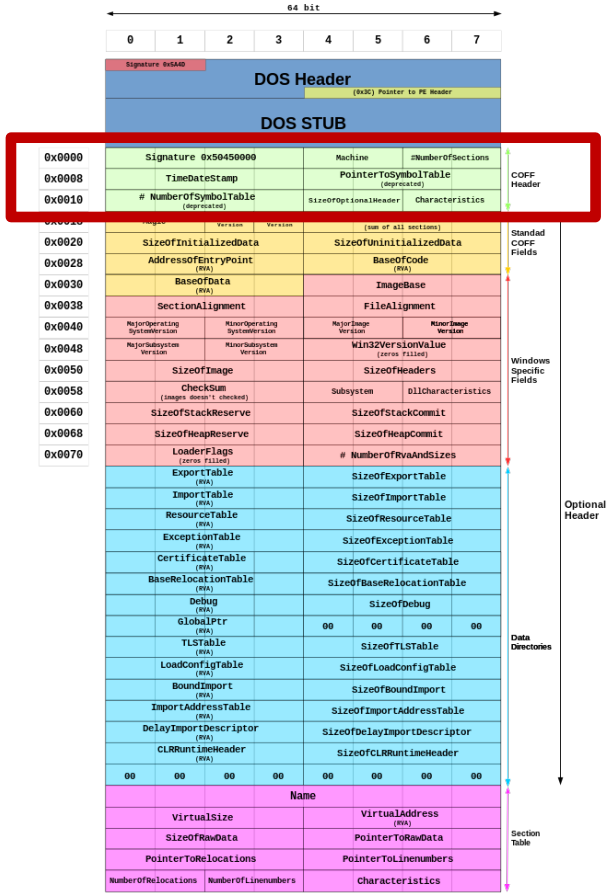


Recap: PE format

PE Header

Real metadata of the program

Dscribes general information of the file

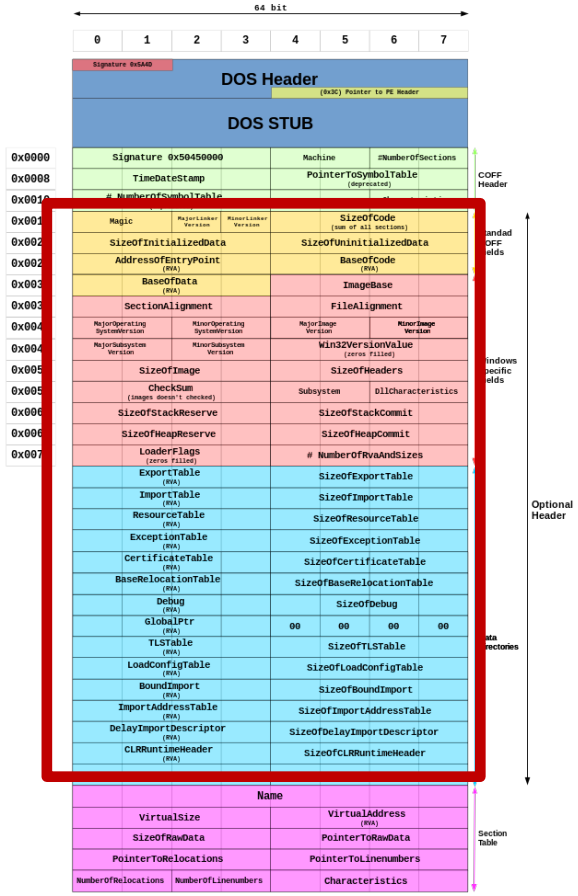


Recap: PE format

Optional Header

Spoiler: not optional at all :)

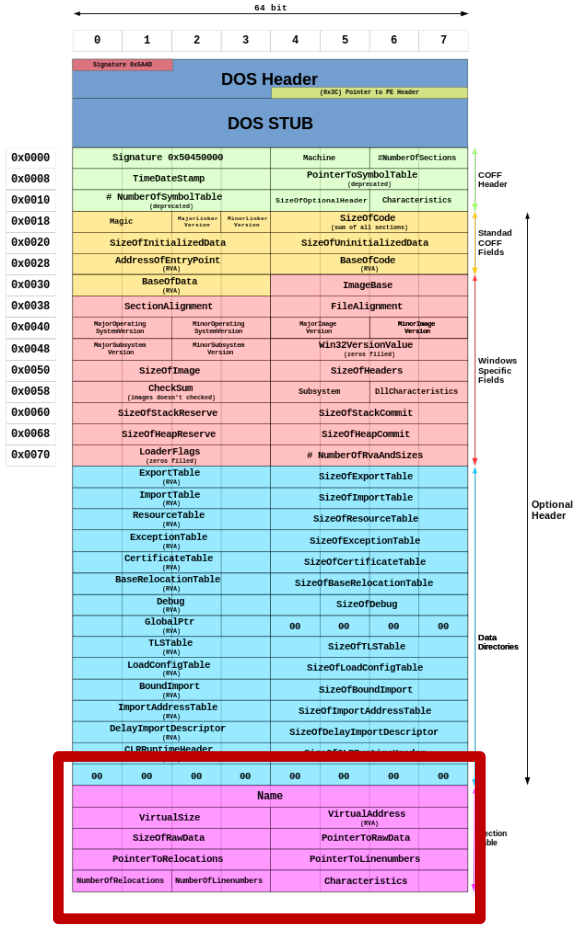
Instructs the loader where to find each object inside the file



Recap: PE format

Section Table and Sections
Describes where to find code, initialized data, resources, etc to the loader
These are “sections”, and each has a “section entry” with its characteristics

Examples: code is “.text”, read-only data is “.rodata”, resources are “.rsc”, and counting



How programs are loaded

❶ Headers

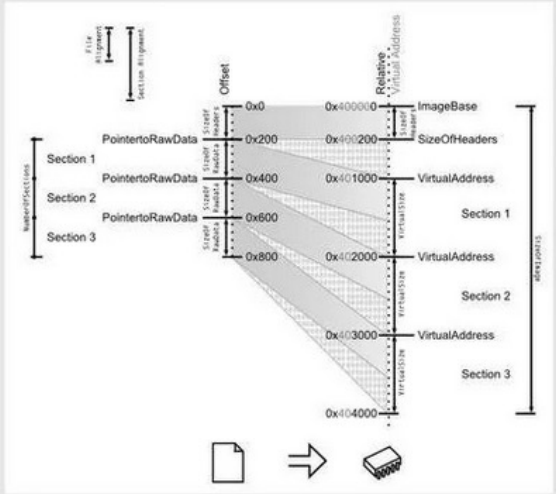
the *DOS Header* is parsed
the *PE Header* is parsed
(its offset is *DOS Header*'s e_lfanew)
the *Optional Header* is parsed
(it follows the *PE Header*)

❷ Sections table

Sections table is parsed
(it is located at: offset (*OptionalHeader*) + *SizeOfOptionalHeader*)
it contains *NumberOfSections* elements
it is checked for validity with alignments:
FileAlignments and *SectionAlignments*

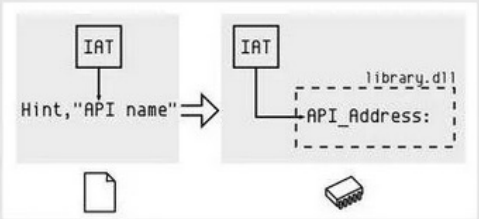
❸ Mapping

the file is mapped in memory according to:
the *ImageBase*
the *SizeOfHeaders*
the Sections table



❹ Imports

DataDirectories are parsed
they follow the *OptionalHeader*
their number is *NumOfRVAAndSizes*
imports are always #2
Imports are parsed
each descriptor specifies a *DLLname*
this DLL is loaded in memory
IAT and *INT* are parsed simultaneously
for each API in *INT*
its address is written in the *IAT* entry



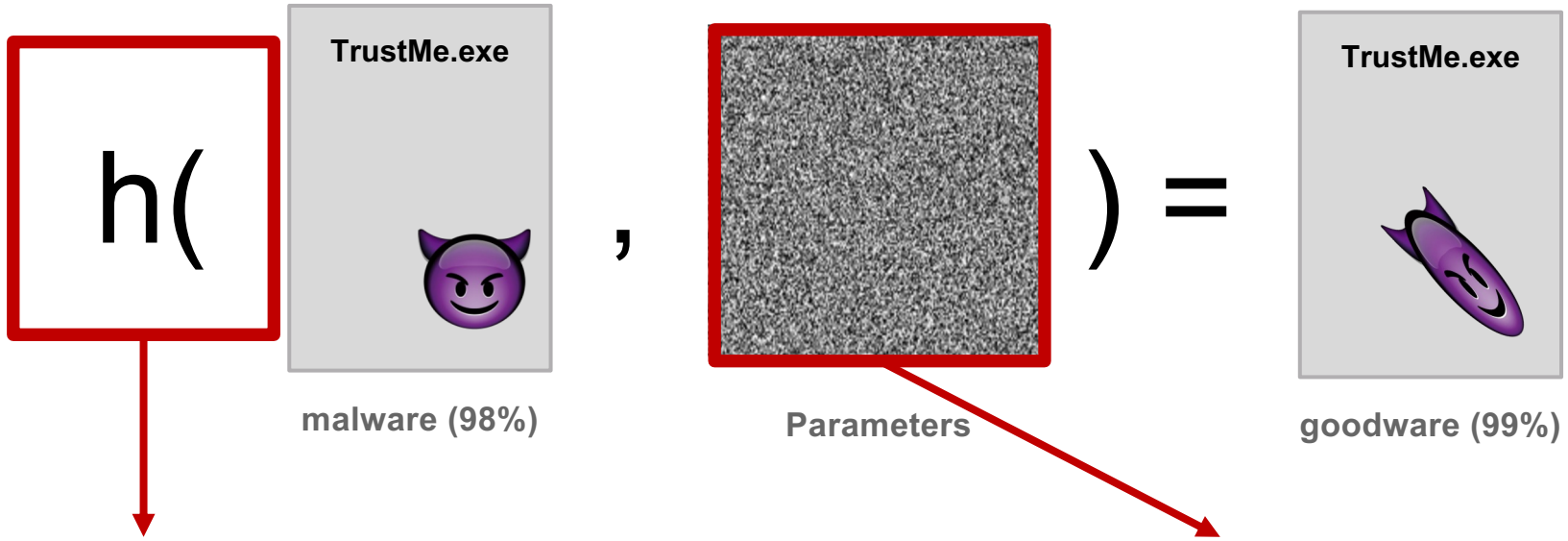
❺ Execution

Code is called at the *EntryPoint*
the calls of the code go via the IAT to the APIs

https://code.google.com/archive/p/corkami/wikis/PE101.wiki

(Thanks Ange Albertini)

Practical Manipulations

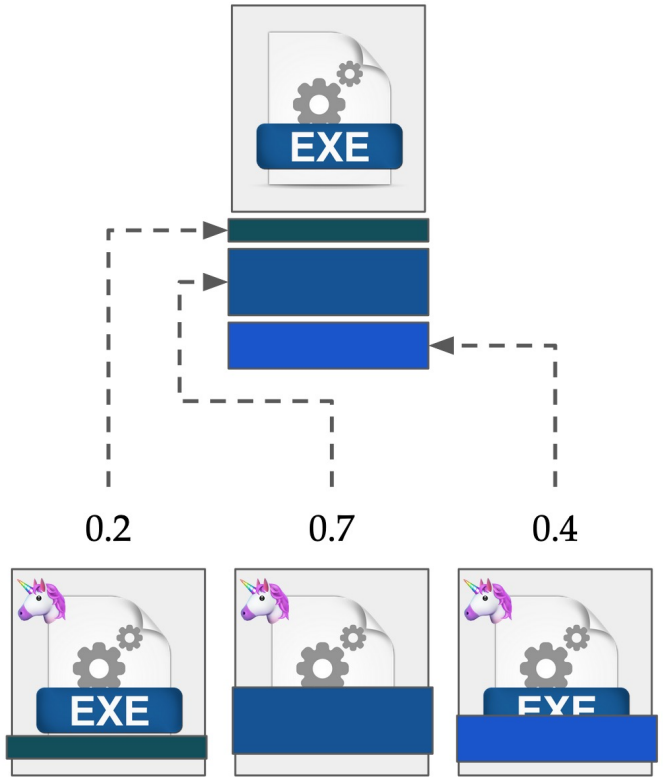


Practical Manipulation function
Alter file representation without destroying the structure and the functionalities and avoid usage of sandboxes

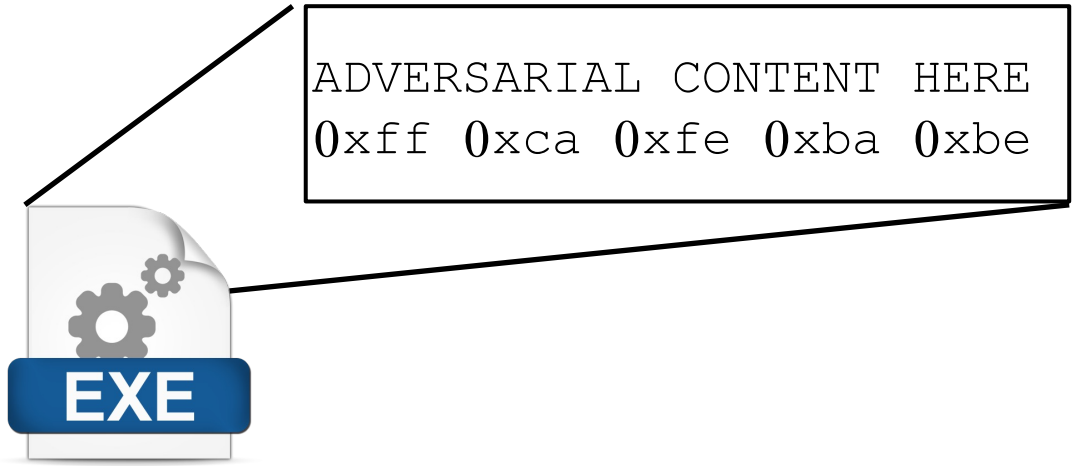
Parameters
Manipulations are parametrized so an optimization algorithm can fine tune them

Demetrio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021

Structural Manipulations



Injecting content
Alter file structure to include more byte sequences

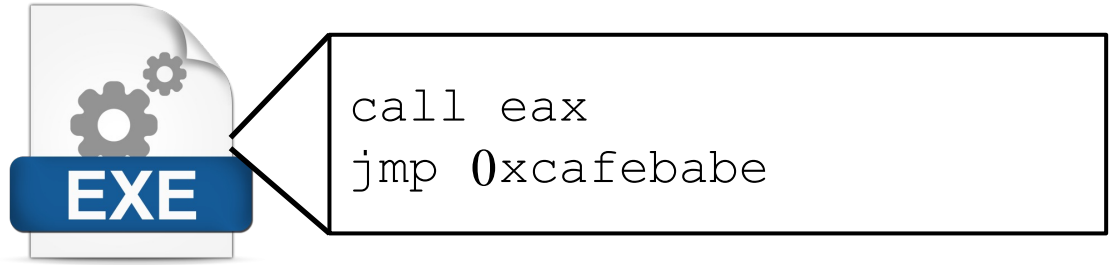


Replacing content
Leverage ambiguous file format specifications to alter bytes that are not considered at runtime

Demetrio et al., *Functionality-preserving Black-box Optimization of Adversarial Windows malware*, IEEE TIFS 2021

WARNING
more difficult to implement!

Behavioral Manipulations



Packing and obfuscation
Encrypt program inside another one, or complicate the sequence of instructions

Inject new execution flows
Call APIs, add loops, jump to new code sections, and more

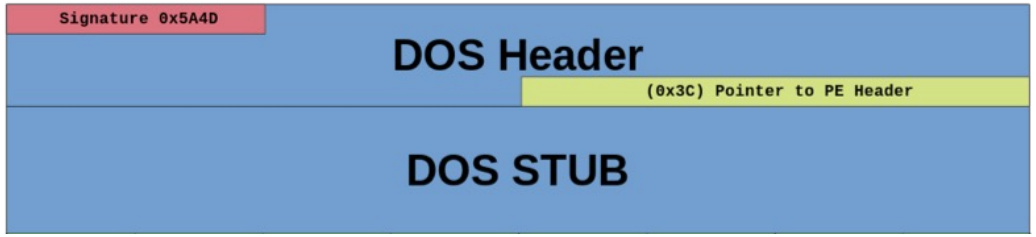
Demetrio et al., *Functionality-preserving Black-box Optimization of Adversarial Windows malware*, IEEE TIFS 2021

DOS Header Manipulation (1/2)

The attacker edit as many bytes as they want

Untouched: magic number MZ and offset to real PE header

Content loaded in memory, not executed



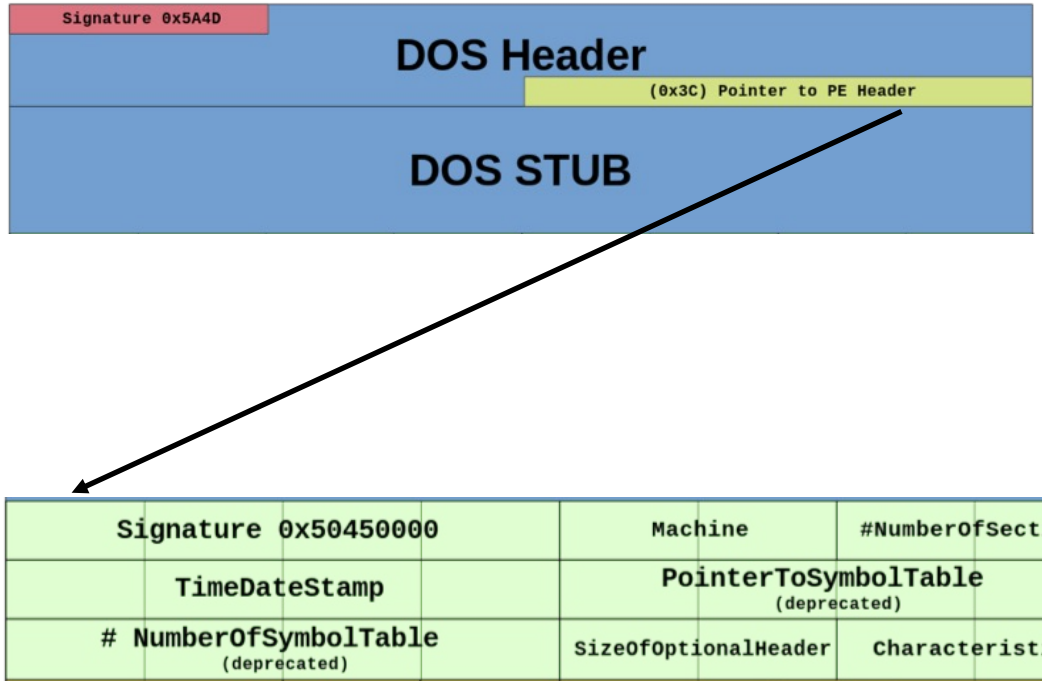
Demetrio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021

DOS Header Manipulation (2/2)

Exploit offset to real header, increment value

Insert arbitrary content between DOS header and PE header

Content loaded into memory, not executed



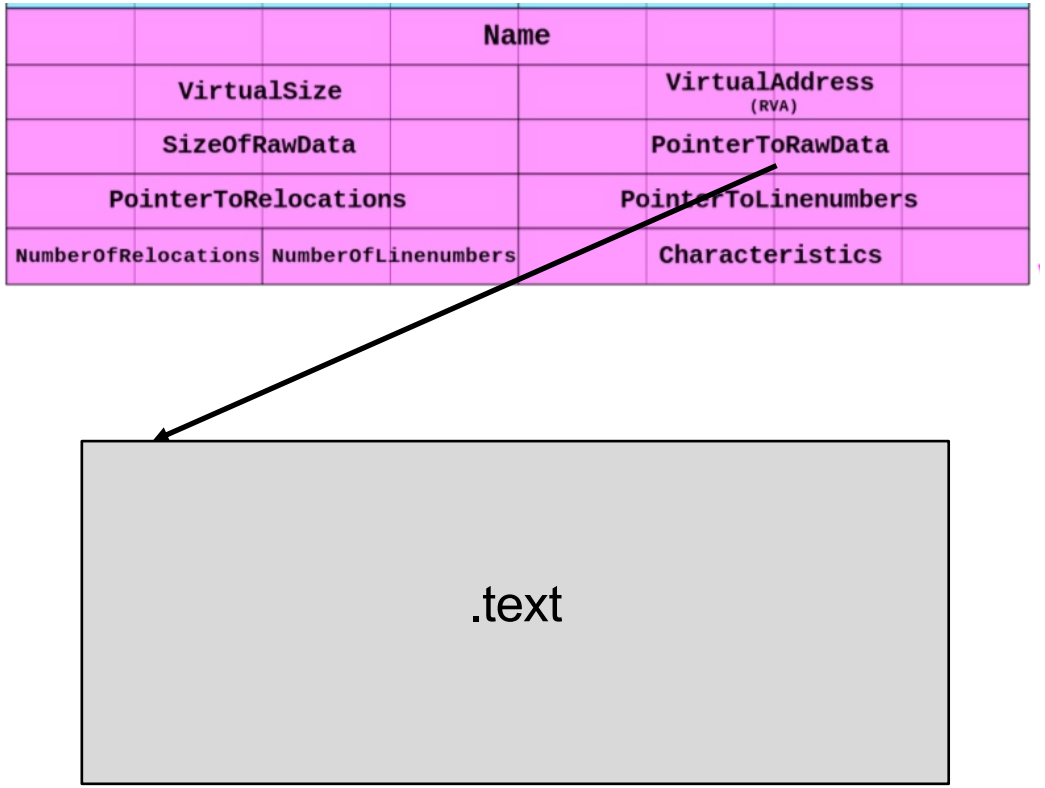
Demetrio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021

Content-shifting Manipulation

Exploit offset in section entry, increment to manipulate the loader in searching for section content

The attacker can inject content after the section table, or between sections

NOT LOADED IN MEMORY, skipped by the loader



Demetrio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021

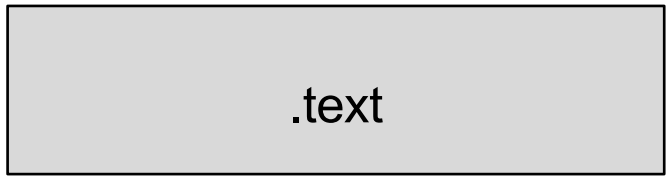
Section-injection Manipulation

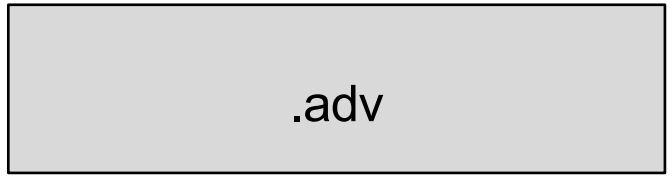
Name	
VirtualSize	VirtualAddress (RVA)
SizeOfRawData	PointerToRawData
PointerToRelocations	PointerToLinenumbers
NumberOfRelocations / NumberOfLinenumbers	Characteristics

Manipulate section table to add new entry

Append chunk of bytes, referenced by newly added entry

Loaded in memory or not, depending by the characteristics set up inside the entry





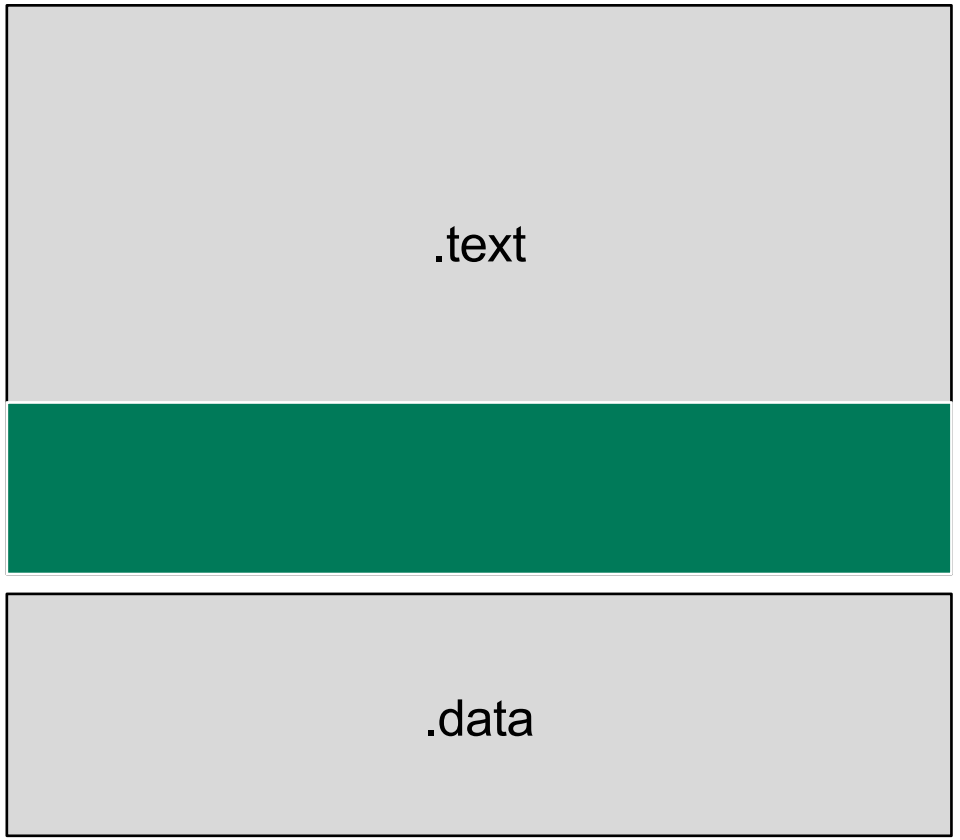
Demetrio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021

Slack Manipulation

Section content is padded with 0 to keep file alignments

The attacker can rewrite such slack space

Loaded in memory, not executed



Demetrio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021

Padding Manipulation

Appending content at the end

Most trivial manipulation

Not loaded in memory

Demetrio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021

Optimization Algorithms

Choose your Fighter

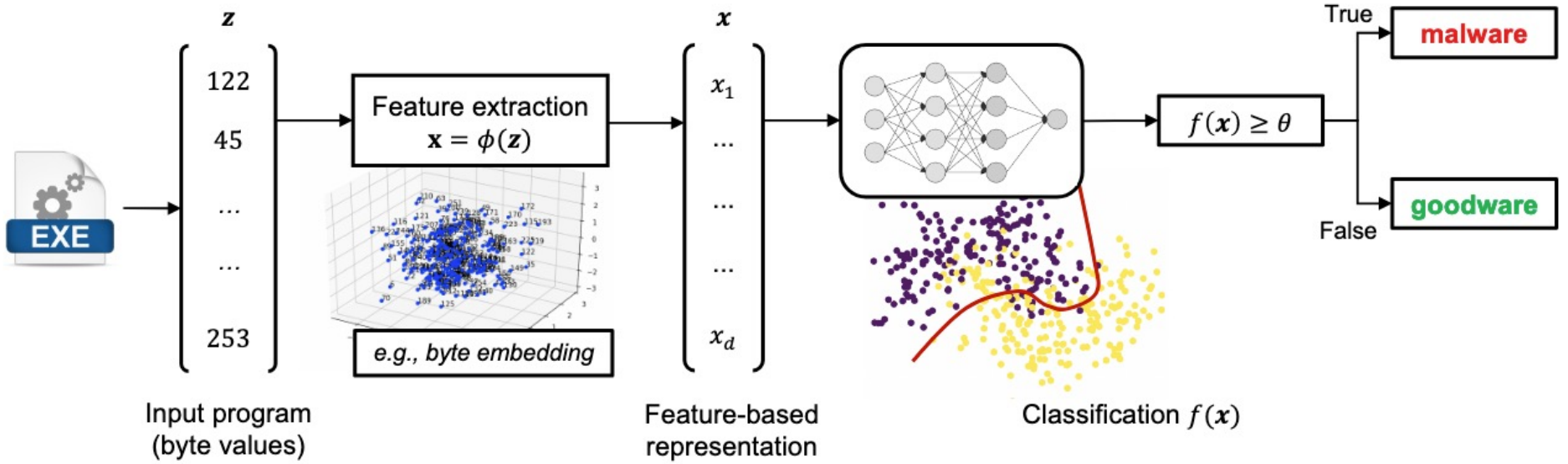
Gradient-based

Own the model
AND
Model is differentiable

Gradient-free

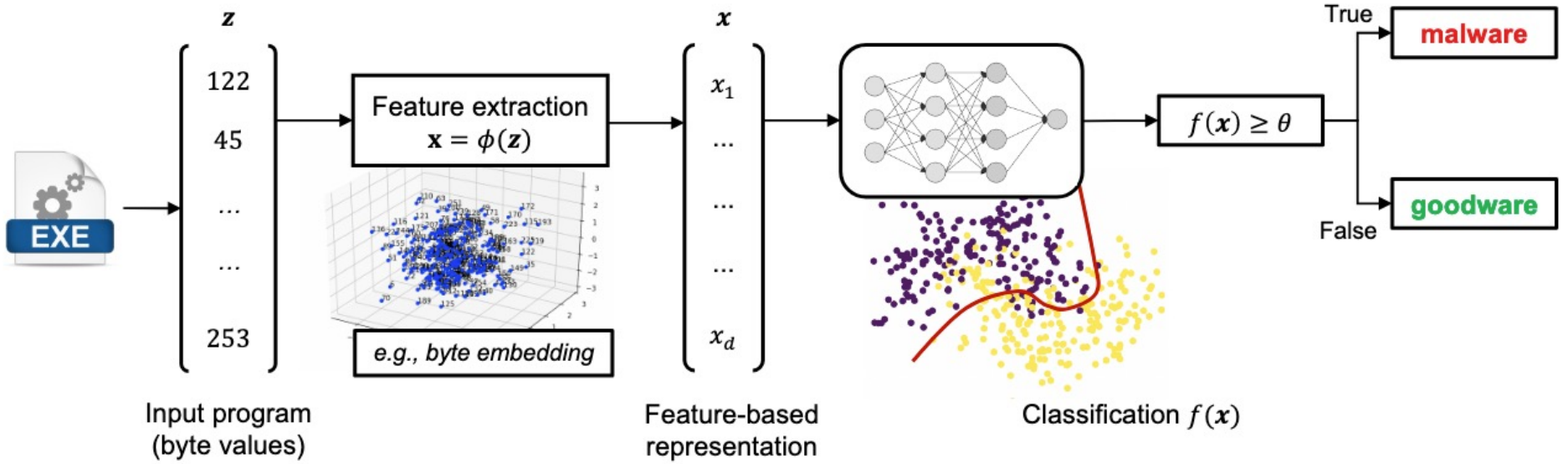
Model not accessible
OR
Model is not differentiable

Gradient-based Attacks



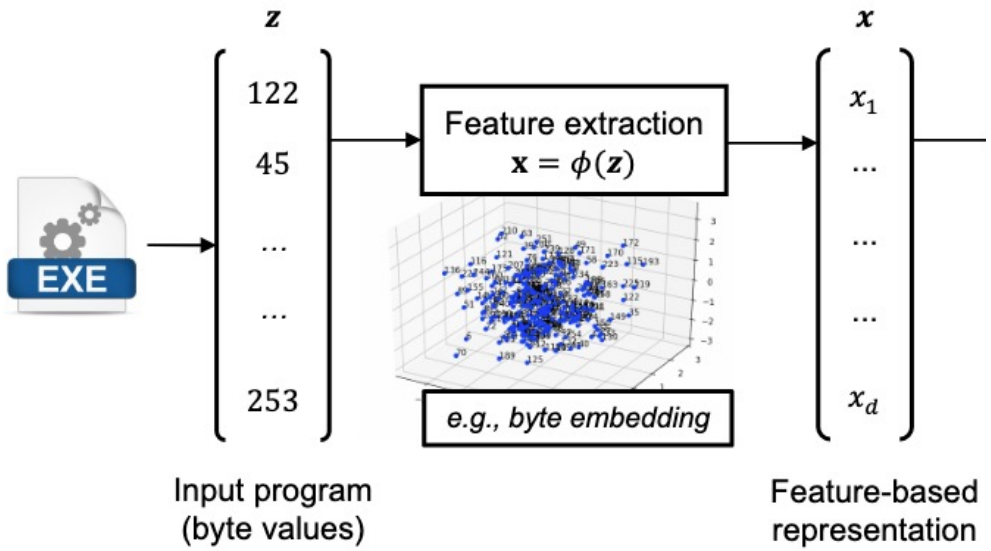
Models might be differentiable, so we can rely on gradient-descent strategies like images

Gradient-based Attacks



~~Models might be differentiable, so we can rely on gradient-descent strategies like images~~
Bytes do not have a distance metric, a feature extractor is **ALWAYS** needed to compute something meaningful

Embedding space again



All bytes are replaced with a vector learned at training time, where a distance metric is imposed…

… but the embedding layer is **not differentiable**

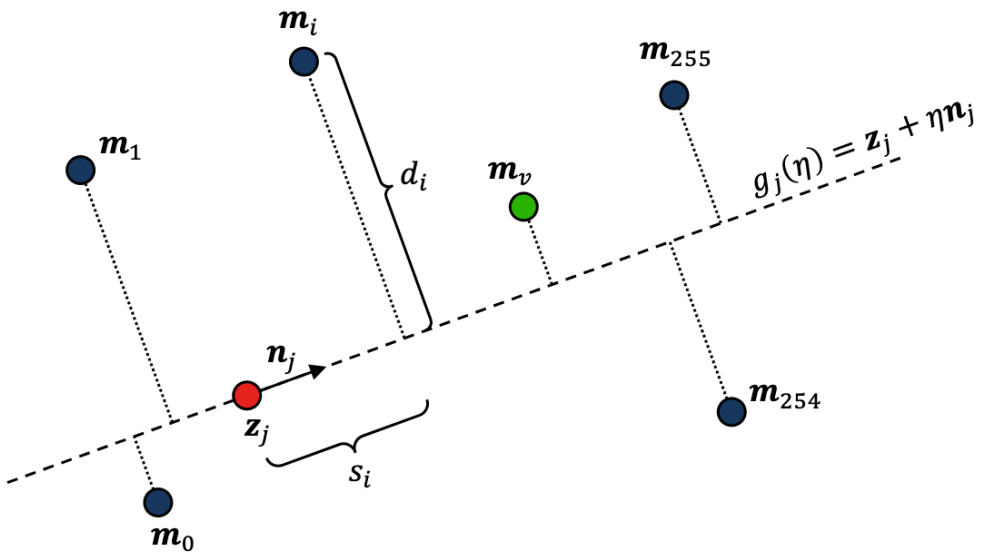
Few differentiable operations!

$$\frac{\partial L}{\partial \delta} = \frac{\partial L}{\partial f}\frac{\partial f}{\partial \phi}\frac{\partial \phi}{\partial h}\frac{\partial h}{\partial \delta}$$

End-to-end gradient you would like to compute

Non-differentiable manipulations and embedding!

Deal with descrete by changing optimization



Still gradient descent, but inside the **embedding space!**

Optimize where gradients are available and reconstruct bytes **after** the search

Demetrio, Biggio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021
Kolosnjaji et al., *Adversarial malware binaries: Evading deep learning for malware detection in executables*, EUSIPICO 2018

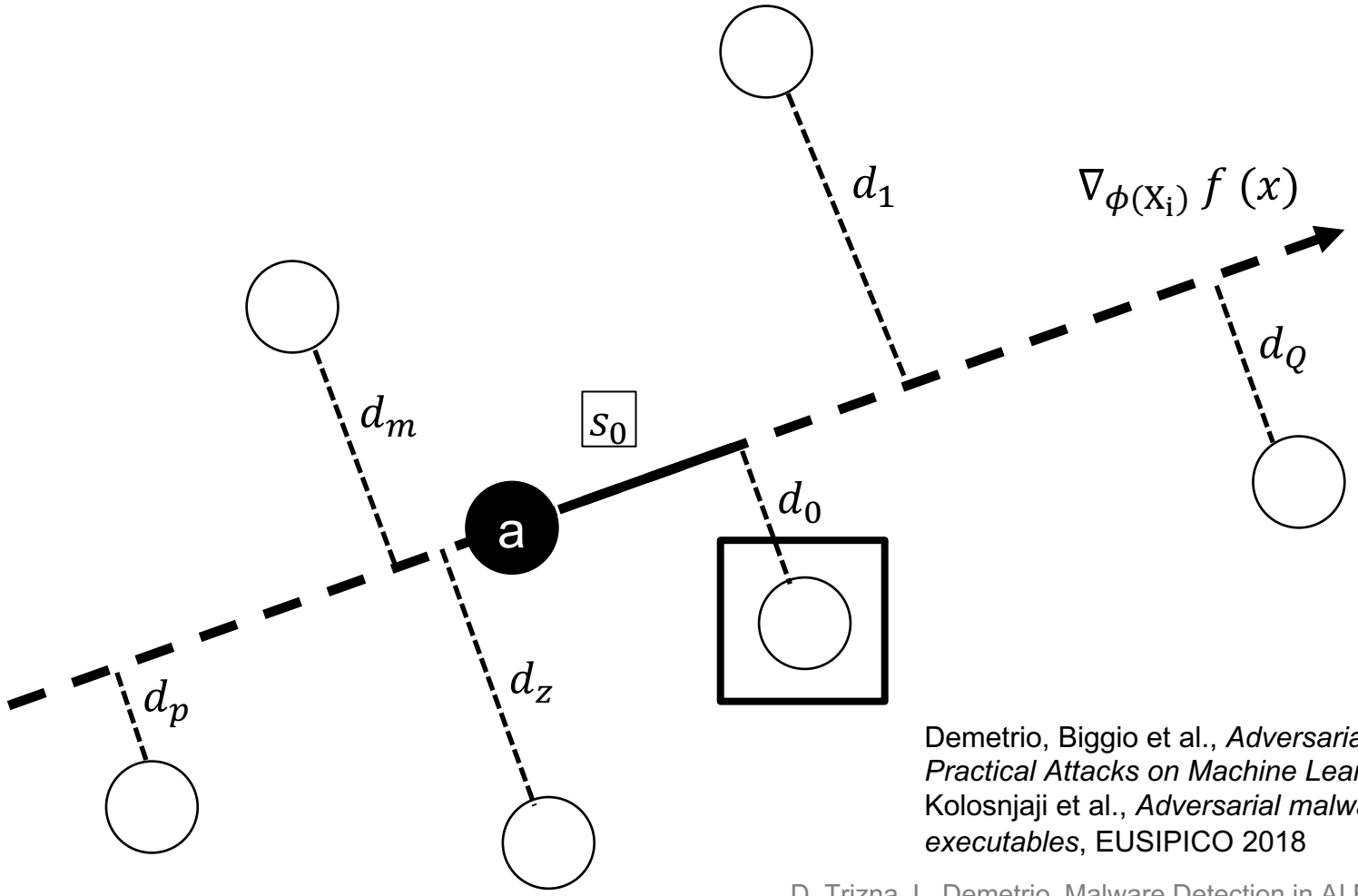
BGD: Byte Gradient Descent

$\mathbf{E}_i = \hat{\phi}(i), \forall i \in [0, 256]$
$t^{(0)} \in \mathcal{T}$
for i **in** $[0, N-1]$
    $\mathbf{X} \leftarrow \phi(h(z, t^{(i)}))$ // feat. space
    $\mathbf{G} \leftarrow -\nabla_{\mathbf{X}} f(\mathbf{X}) \odot \boldsymbol{m}$
    $\boldsymbol{g} \leftarrow (\| \mathbf{G}_0 \|, ..., \| \mathbf{G}_n \|)$
    for k **in** argsort $(\boldsymbol{g})_{0,...,\gamma} \wedge g_k \neq 0$
        for j **in** $[0, ..., 255]$
            $\mathbf{S}_{k,j} \leftarrow \mathbf{G}_k^t \cdot (\mathbf{E}_j - \mathbf{X}_k)$
            $\widetilde{\mathbf{X}}_{k,j} \leftarrow \| \mathbf{E}_j - (\mathbf{X}_k + \mathbf{G}_k \mathbf{S}_{k,j}) \|_2$
        $t_k^{(i+1)} \leftarrow \arg\min_{j:\mathbf{S}_{k,j}>0} \widetilde{\mathbf{X}}_{k,j}$ //input space
$t^\star \leftarrow t^{(N)}$
$z^\star \leftarrow h(z, t^\star)$
return $z^\star$

1. Compute gradient in feature space
2. Define a way for replacing values
   For bytes: inverse look-up of embedding
3. Follow the direction of gradient and replace byte with other byte

Demetrio, Biggio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021
Kolosnjaji et al., *Adversarial malware binaries: Evading deep learning for malware detection in executables*, EUSIPICO 2018

BGD: Byte Gradient Descent



The process is repeated according to the **stepsize of the attack**, that quantifies how many bytes are modified at each iteration

Demetrio, Biggio et al., *Adversarial EXEmples: a Survey and Experimental Evaluation of Practical Attacks on Machine Learning for Windows Malware Detection*, ACM TOPS 2021
Kolosnjaji et al., *Adversarial malware binaries: Evading deep learning for malware detection in executables*, EUSIPICO 2018

BGD: Byte Gradient Descent

At the end of each iteration, I need to replace one byte, **not an embedding value**

But each byte is chosen in the embedding space, reconstruction just invert the look-up function

$$\arg\min_{j:S_{k,j}>0} \tilde{X}_{k,j}$$

Choose your Fighter

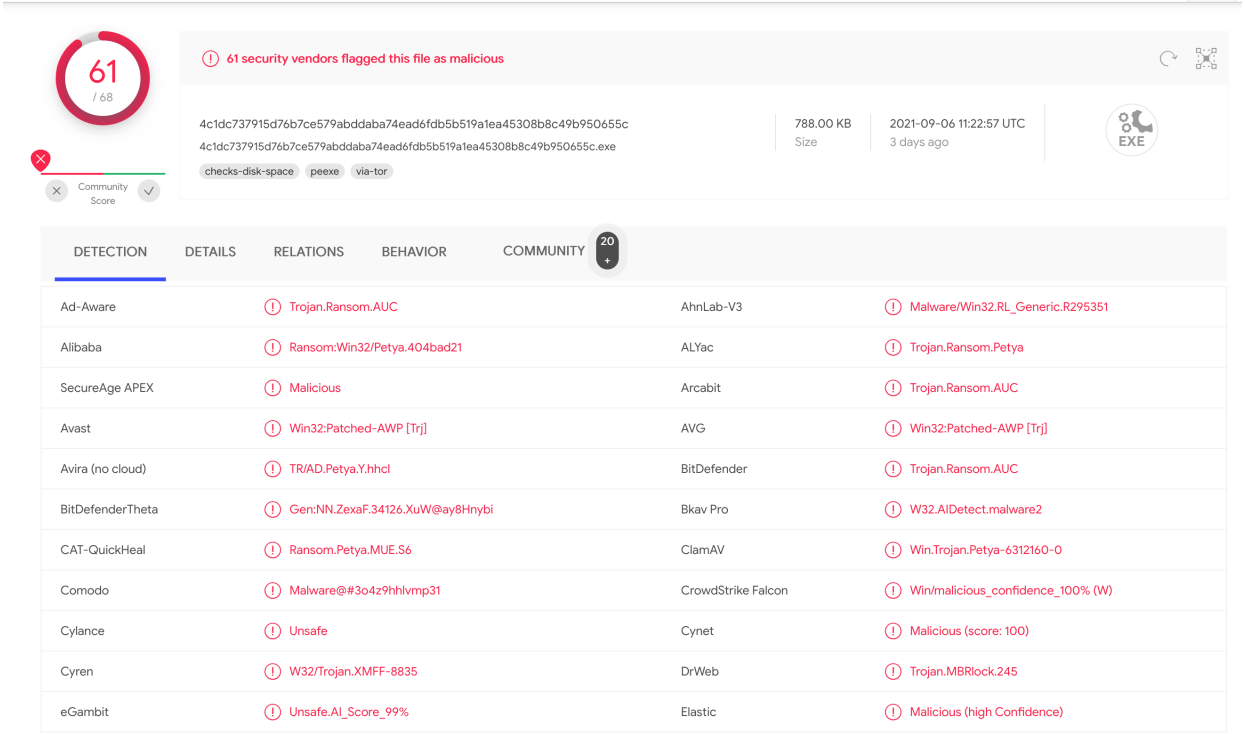
Gradient-based

Own the model
AND
Model is differentiable

Gradient-free

Model not accessible
OR
Model is not differentiable

Reality check: most models are unavailable



61 / 68

Community Score

61 security vendors flagged this file as malicious

4c1dc737915d76b7ce579abddaba74ead6fdb5b519a1ea45308b8c49b950655c
4c1dc737915d76b7ce579abddaba74ead6fdb5b519a1ea45308b8c49b950655c.exe
checks-disk-space peexe via-tor

788.00 KB Size

2021-09-06 11:22:57 UTC
3 days ago

EXE

DETECTION DETAILS RELATIONS BEHAVIOR COMMUNITY 20+

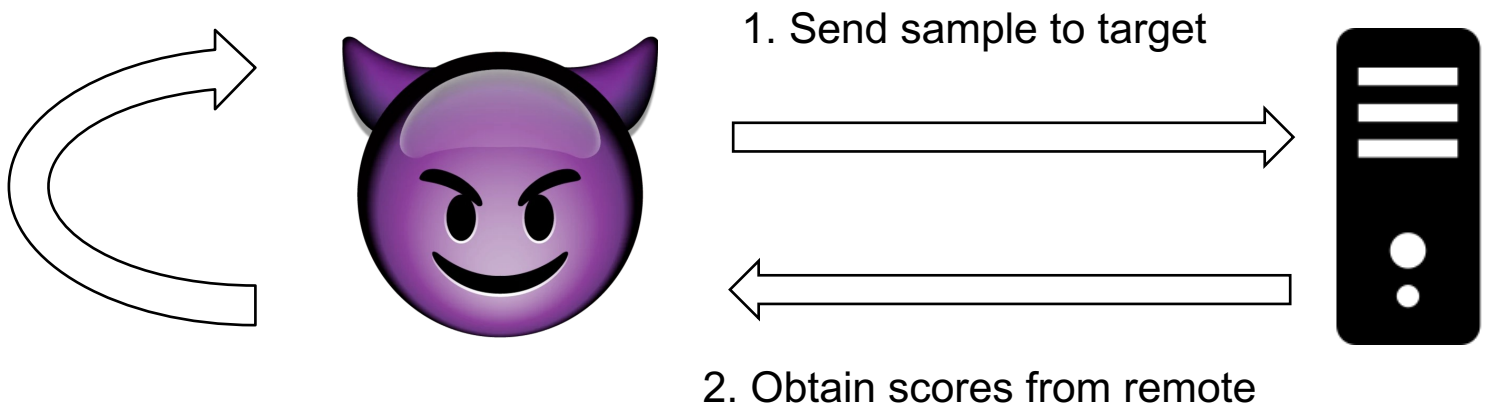
Ad-Aware	Trojan.Ransom.AUC	AhnLab-V3	Malware/Win32.RL_Generic.R295351
Alibaba	Ransom:Win32/Petya.404bad21	ALYac	Trojan.Ransom.Petya
SecureAge APEX	Malicious	Arcabit	Trojan.Ransom.AUC
Avast	Win32:Patched-AWP [Trj]	AVG	Win32:Patched-AWP [Trj]
Avira (no cloud)	TR/AD.Petya.Y.hhcl	BitDefender	Trojan.Ransom.AUC
BitDefenderTheta	Gen:NN.ZexaF.34126.XuW@ay8Hnybi	Bkav Pro	W32.AIDetect.malware2
CAT-QuickHeal	Ransom.Petya.MUE.S6	ClamAV	Win.Trojan.Petya-6312160-0
Comodo	Malware@#3o4z9hhlvmp31	CrowdStrike Falcon	Win/malicious_confidence_100% (W)
Cylance	Unsafe	Cynet	Malicious (score: 100)
Cyren	W32/Trojan.XMFF-8835	DrWeb	Trojan.MBRlock.245
eGambit	Unsafe.AI_Score_99%	Elastic	Malicious (high Confidence)

Most models are hosted on private servers

Detection performed in cloud

No gradients can be computed

Query attacks



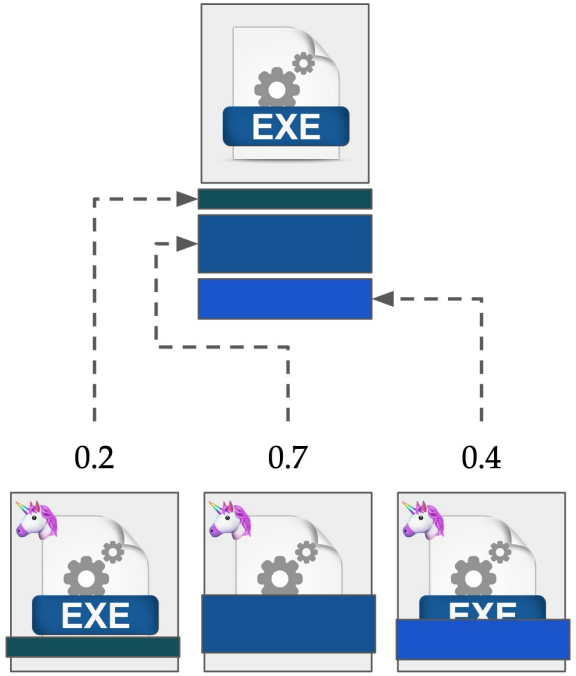
Very slow if optimizer works byte-per-byte

Demetrio et al., *Functionality-preserving Black-box Optimization of Adversarial Windows malware*, IEEE TIFS 2021

GAMMA: Speeding up by injecting benign content

Intuition
classifiers can be fooled by introducing content of the goodware class!

The optimizer explore less space, no modification byte-per-byte, but it relies on portions of goodware programs injected with practical manipulations



Demetrio et al., *Functionality-preserving Black-box Optimization of Adversarial Windows malware*, IEEE TIFS 2021

(In)Famous example: CyLance

Injecting bytes

Reversing the code with some tricks, discovered that the model leverages STRINGS

Inject “benign” values

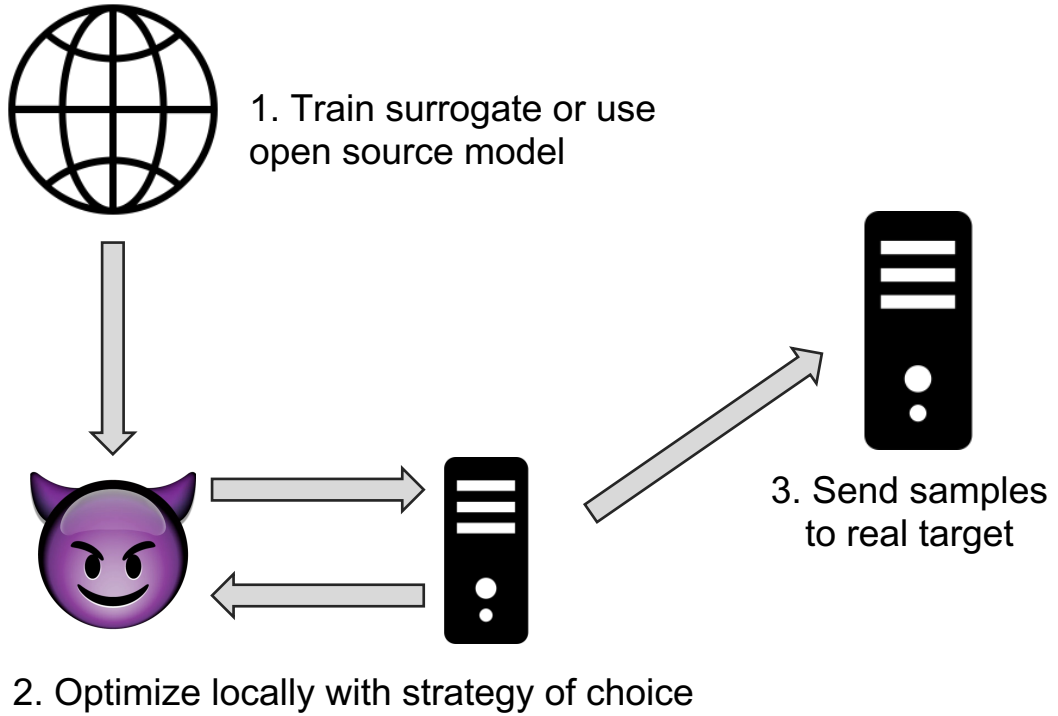
Extract byte sequences from “Rocket League” and include them inside input exacutable

Evasion completed!

The company rolled out an update to try to mitigate the issue

[Skylight Cyber. Cylance, I Kill You! https://skylightcyber.com/2019/07/18/cylance-i-kill-you/]

Transfer Evaluations



Choose a good malware detector as surrogate

As seen in Part 1, GBDT with EMBER is a good choice, since it's predictive capabilities are far better than other models

GAMMA against commercial products

	Malware	Random	Sect. Injection
AV1	93.5%	85.5%	30.5%
AV2	85.0%	78.0%	68.0%
AV3	85.0%	46.0%	43.5%
AV4	84.0%	83.5%	63.0%
AV5	83.5%	79.0%	73.0%
AV6	83.5%	82.5%	69.5%
AV7	83.5%	54.5%	52.5%
AV8	76.5%	71.5%	60.5%
AV9	67.0%	54.5%	16.5%

Breaking signatures and patterns
GAMMA (transfer) reduces the perofrmance of commercial products hosted on VirusTotal (and we'll touch apon this later)

Demetrio et al., *Functionality-preserving Black-box Optimization of Adversarial Windows malware*, IEEE TIFS 2021

Lab 6:

Crafting Adversarial EXEmples against different models

aka.ms/malware-lab6

Lab 7:

Example of evasive C2C sample

aka.ms/malware-lab7

Lab 8:

Effect of Adversarial EXEmples against YARA rules

aka.ms/malware-lab8

Defending against Adversarial EXEmples

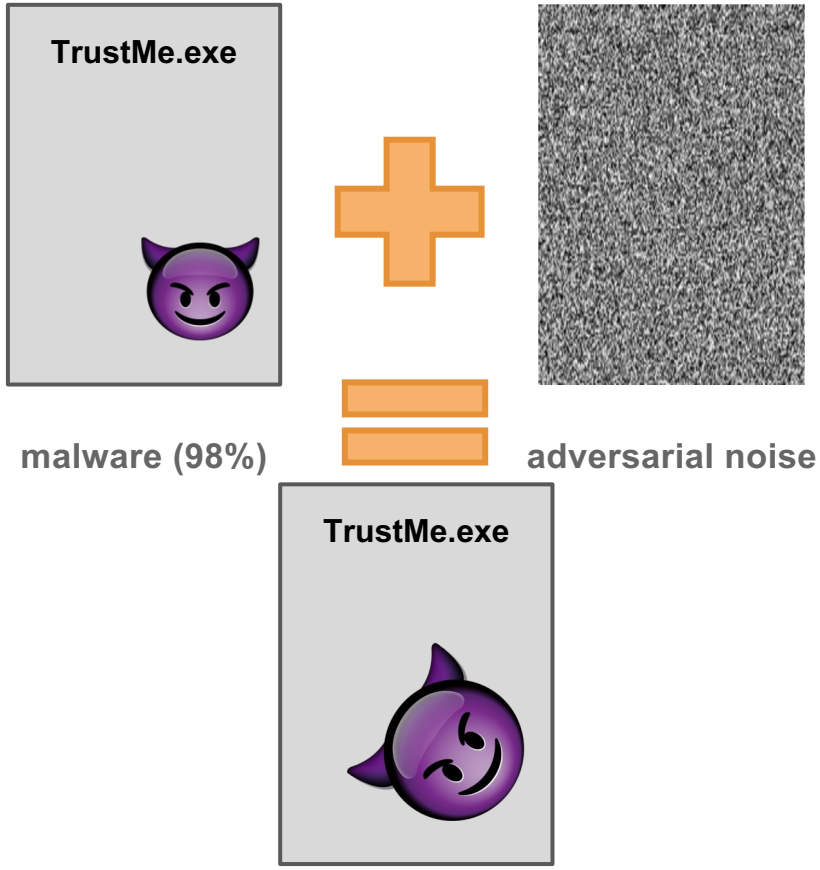
Recap: Adversarial EXEmples

Minimal byte perturbations
Many examples on how machine learning malware detectors can be bypassed with carefully-crafted input

Ambiguities of file format
The Windows PE file format is redundant and many components are not used by the operating system at loading time, giving space to the attacker

Math is unreliable
The domain is discrete, models work mostly with continuous values, and attackers can “fill the blanks” with adversarial manipulations inside this huge mathematical space

How to avoid EXEmples?
Not clear how to patch this problem, but we isolated 4 relevant “claimed-to-be” robust malware detectors



Adversarial EXEmple

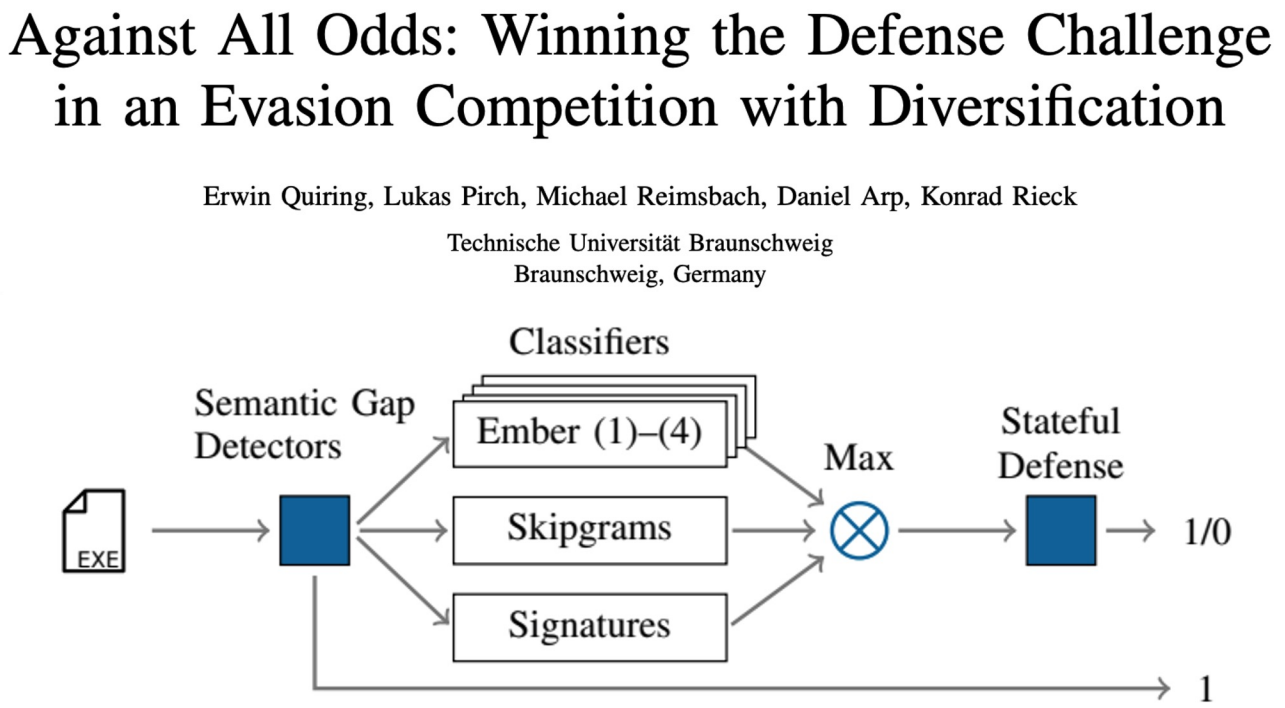
Demetrio, Biggio, et al. *"Adversarial EXEmples: A survey and experimental evaluation of practical attacks on machine learning for windows malware detection."* TOPS 2021

Heuristic defense

Combination of pre-processing
Detect trivial manipulation, and then process input with ensemble of models

Partially reproducible
There are no pre-trained available, but code is available online

https://github.com/EQuiw/2020-evasion-competition



Quiring et al. *Against all the Odds: Winning the Defense Challenge in an Evasion Competition with Diversification,* preprint

Adversarial Training

$$\min_{\theta} \rho(\theta), \quad \text{where} \quad \rho(\theta) = \mathbb{E}_{(x,y)\sim\mathcal{D}} \left[\max_{\delta \in \mathcal{S}} L(\theta, x+\delta, y) \right]$$

Train with EXEmples

Computing state-of-the art attacks and include them inside the training set (process is repeated until the achievement of the desired robustness)

Madry et al. *"Towards Deep Learning Models resistant to Adversarial Attacks"* ICLR 2018

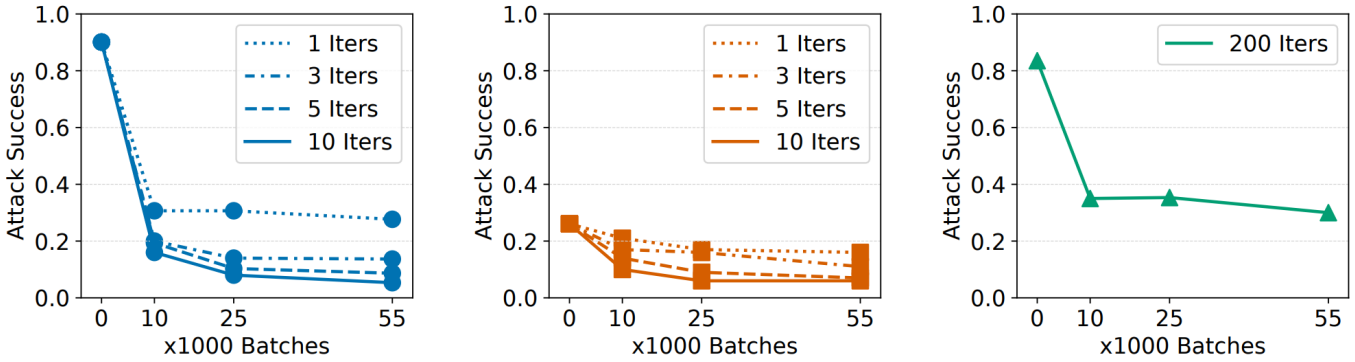
Adversarial Training

Alter code

Leverage behavioral manipulations to rewrite part of assembly code

Published, not reproducible

There are no pre-trained available, nor public source code that can be used to train a model. The technique is known, but the attacks used for this paper as well are closed



Adversarial Training for Raw-Binary Malware Classifiers

Keane Lucas
Carnegie Mellon University

Samruddhi Pai
Carnegie Mellon University

Weiran Lin
Carnegie Mellon University

Lujo Bauer
Carnegie Mellon University

Michael K. Reiter
Duke University

Mahmood Sharif
Tel Aviv University

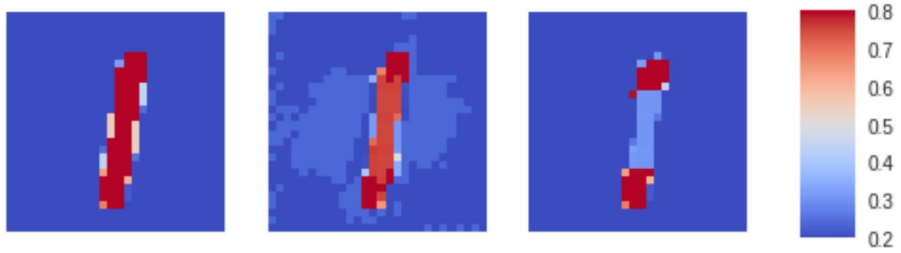
Lucas et al. *Adversarial Training for Raw-Binary Malware Classifiers* USENIX 2023

Non-negative Networks

Malicious contributions
Intuition: classification is based on addition of small malicious triggers, until a threshold is reached

Remove negative weights
Train an end-to-end model, by clipping to positive values all the weights of the network

Attacks constrained
On images, non-negative network force attacks to only tamper with meaningful information



Non-negative Networks

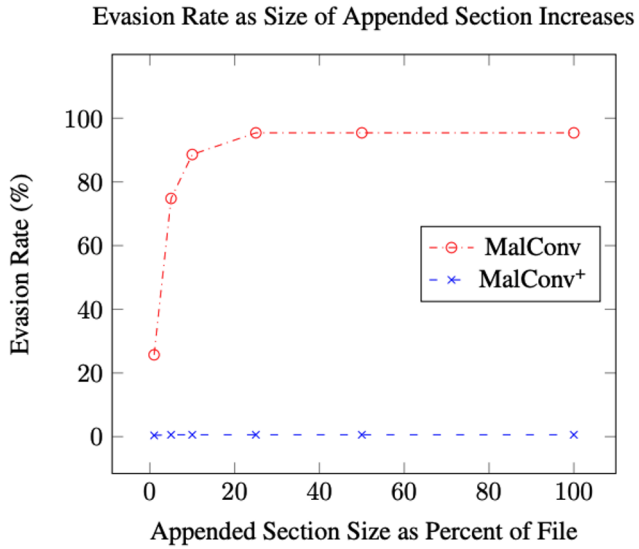
Pre-trained available
Testing through model trained on EMBER, released for a challenge
(performances are debatable)

Unpublished
Still a preprint, never published to either conferences, journals or workshops

Hardly reproducible
Even by trying to re-write code, many papers tried and failed to train NonNeg MalConv

Non-Negative Networks Against Adversarial Attacks

William Fleshman,[1] Edward Raff,[1,2] Jared Sylvester,[1,2] Steven Forsyth,[3] Mark McLean[1]
[1]Laboratory for Physical Sciences, [2]Booz Allen Hamilton, [3]Nvidia
{william.fleshman, edraff, jared, mrmclea}@lps.umd.edu, sforsyth@nvidia.com



Fleshman et al. *Non-negative Networks Against Adversarial Attacks,* preprint

Monotonic Classifiers

Malicious contributions

Intuition: classification is based on addition of small malicious triggers, until a threshold is reached

Gradient boosting decision tree

Use custom training process that trains an additive decision function

Subset of features

Not using EMBER, but the authors propose a reduced features set that is harder to manipulate

Not reproducible

There are no pre-trained available, nor public source code that can be used to train a model

Adversarially Robust Malware Detection Using Monotonic Classification

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David Wagner
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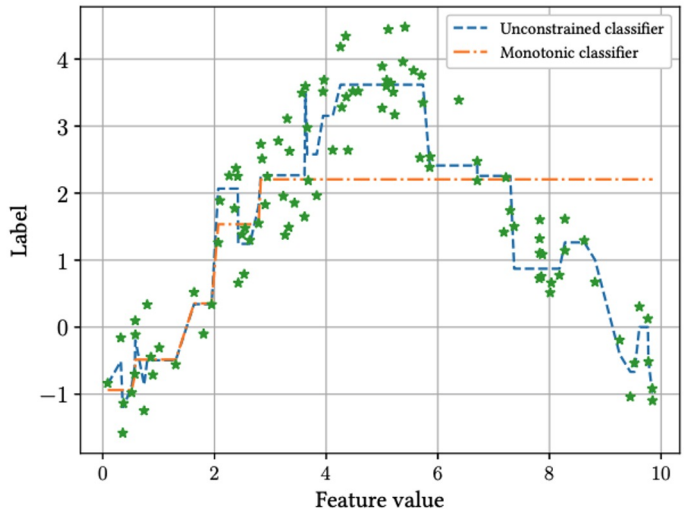

IWSPA'18, March 21, 2018, Tempe, AZ, USA

Incer et al. *Adversarially Robust Malware Detection using Monotonic Classification,* IWSPA 2018

Certified Detector

Formal guarantees
Proofs of non-existence of adversarial examples around input, leveraging edit distance functions. Formalized on static end-to-end detectors

Not reproducible
There are no pre-trained available, nor public source code that can be used to train a model

Certified Robustness of Learning-based Static Malware Detectors

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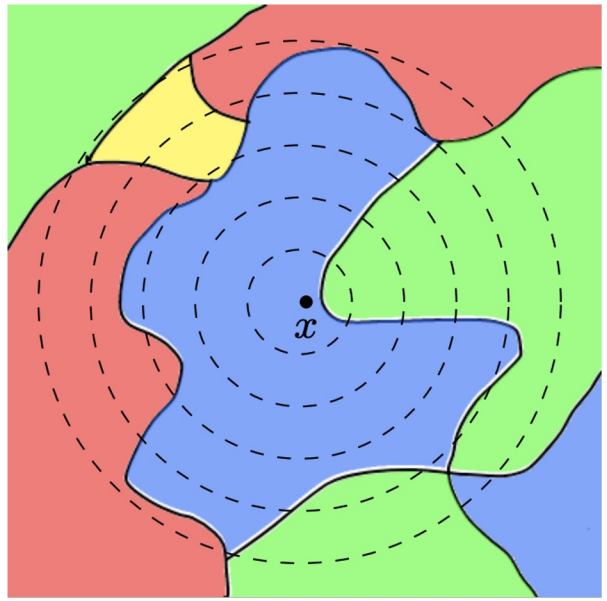

Huang et al. *Certified Robustness of Learning.based Static Malware Detectors,* NeuIPS 2023

Recent innovation in certification

Certification for malware
Recent work certifies against padding and content-editing attacks (easier to formalize)

Specific chunking system
Divide incoming input into chunk according to the format, independently from the size of the file or a fixed number of windows.

Code available
Models can be easily tested, since authors released everything

Certified Robustness of Static Deep Learning-based Malware Detectors against Patch and Append Attacks

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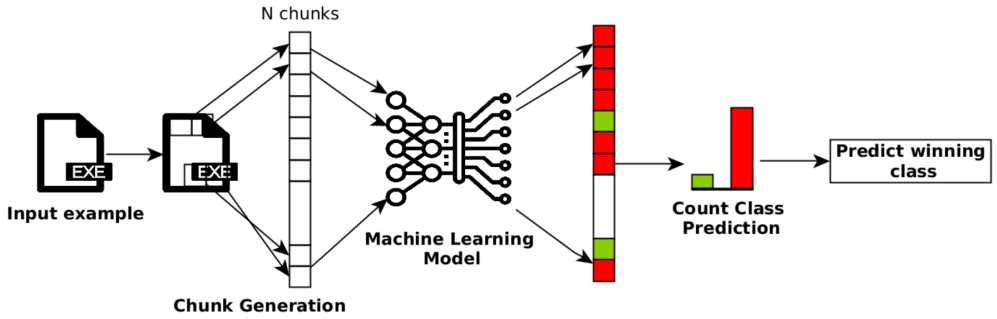


Gibert et al. *Certified Robustness of Static Deep Learning-based Malware Detectors against Patch and Append Attacks* AISec 2023

Lab 9:

Defending against Adversarial EXEmples

aka.ms/malware-lab9

Limitations and Future Directions

Issues with Adversarial EXEmples

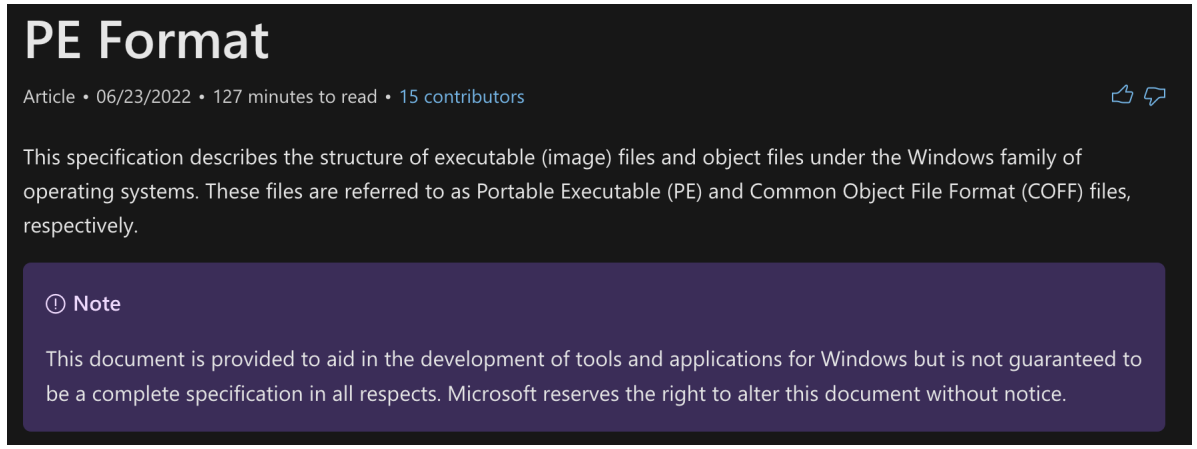
Manipulations are hard to craft
Lack of documentation,
lack of open-source reference code, lack of easily-deployable debugging tools, and tons of hours to work

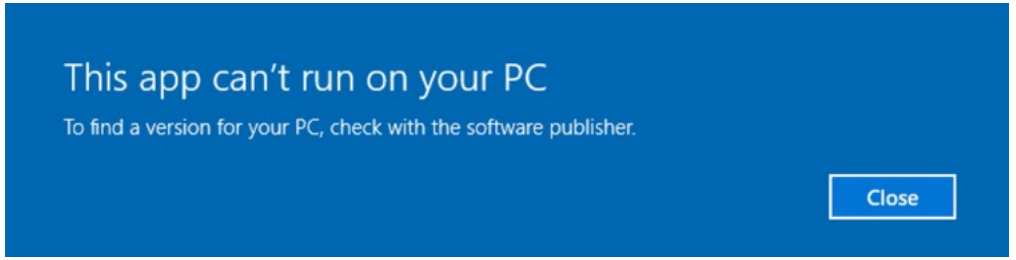
Evasion is not robustness
In system security, evasion should be achieved “no matter what”,
which is not the same as adversarial robustness

Creating practical manipulations is painful

Format is vague
Microsoft released vague documentations for the internal of the Windows OS, and research is done by reverse engineering

Debugging is hard
Manipulations often deal with very specific steps of the loader or runtime execution and it is difficult to get messages from the OS





Format specifications are not specific at all

Many details are omitted

Microsoft released an official format documentation, but it is not complete (as they clearly state)
Example: some header fields *are not used by the loader,* but they are described as meaningful

> **Note**
>
> This document is provided to aid in the development of tools and applications for Windows but is not guaranteed to be a complete specification in all respects. Microsoft reserves the right to alter this document without notice.

Windows loader changes through time

It has been proven that Windows XP, 7, and 10 have different loaders that parse the PE structure in a different way!

Lost in the Loader:
The Many Faces of the Windows PE File Format

Dario Nisi
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Cisco Talos
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Yanick Fratantonio
Cisco Talos
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Davide Balzarotti
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Closed-source code is not helping

No reference and no code: the only way is either test manipulation by hand, or develop complex tools that infer information about constraints

	Discrepancies				
	W1	W2	W3	W4	W5
XP vs 7	✓	✓			✓
XP vs 10		✓	✓	✓	
7 vs XP					
7 vs 10			✓	✓	
10 vs XP					
10 vs 7	✓				✓

[Nisi et al. Lost in the Loader: The Many Faces of the Windows PE File Format. RAID 2021]

Complex pipeline for debugging manipulations

Dealing with kernel components

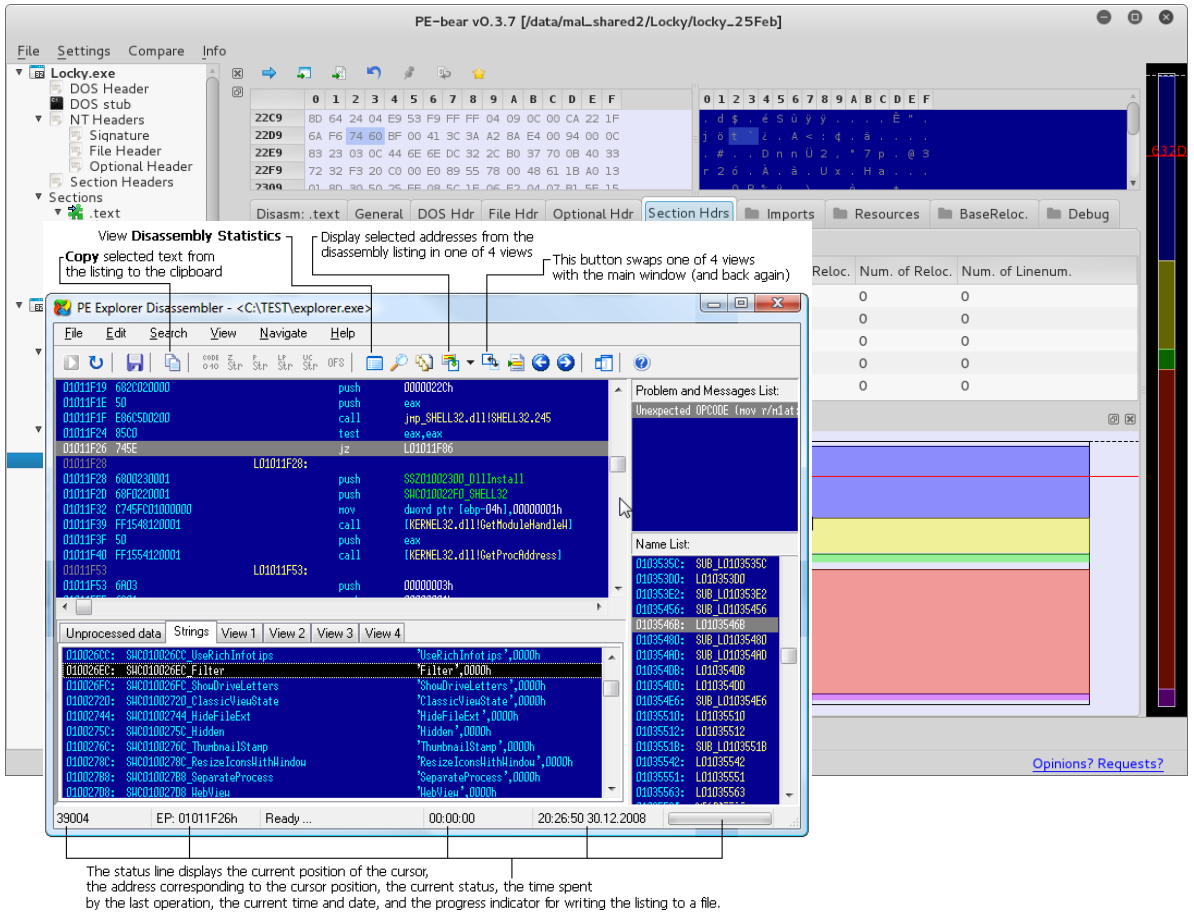
The building blocks of the operating systems are inside the kernel, there is no easy way to connect them to a debugger.
Work-around: manual inspection and tons of wasted hours

The only output is the error

Perturbed sample is not working? Keep digging without any other informative log, or rely on other PE viewer or checker (PE Bear, PE Explorer, LIEF, pefile…)

No constraints check

Utilities are good, but they do not tell you IF there is a format specification problem, or they signal vague alerts
(if you are lucky)



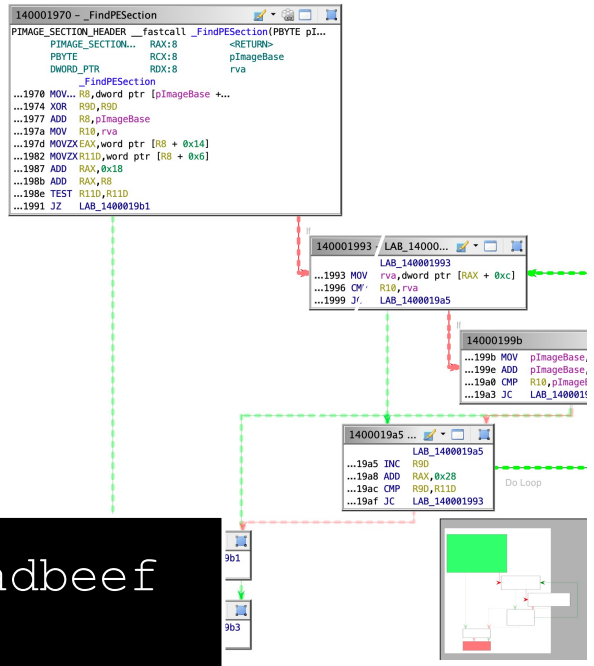
What about attacks against dynamic classifiers?

Not only the structure, the code too!

Code is the only structure that can be manipulated now, so the attacker must act accordingly: code re-writing techniques!

Different instructions, same functionality

Code is re-written to satisfy properties that the attacker wants, like adding new API calls, invert IF statements, add never-to-be executed code to obfuscate…




```
ADD RAX, 0xdeadbeef
        ➔
SUB RAX, -0xdeadbeef
```

In practice: a nightmare scenario!

Problems with addresses
If not correctly handled, content injection will shift all known offsets that the compiler created at compile-time

Problems with executable sections
One could create jumps to other code sections… if they are flagged as executable!

Problems with relocations
Program were usually loaded in the same virtual space, but not secure! The OS randomizes the addresses… and this implies that also adversarial content must take this randomization into account!

Morale: harder than before
It is doable, as there is tons of tools that obfuscate and pack samples, but debugging time levitates from a few to many more hours of human work

```
0x7800: MOV EDI, 1
0x7804: MOV ESI, 2
0x7808 CALL MY_FUNC
. . .
. . .
0x7880 MY_FUNC
```

```
0x7800: MOV EDI, 1
0x7804: MOV ESI, 2
0x7808: XOR EAX, EAX
0x780a CALL MY_FUNC
. . .
. . .
0x7884 MY_FUNC
```

Call for action

Develop attacks against DYNAMIC classifiers

Very little has been done, literally two papers that are not reproducible right now

Working on this topic will be key point in testing all machine learning malware detectors

Hard? ABSOLUTELY

Rewarding? ABSOLUTELY

Evasion is not equal to adversarial robustness

Two different goals

Evasion implies that malware samples bypass detection, while adversarial robustness quantifies the sensitivity of the detector

Interested in evasion? Obfuscate & Pack

Tons of literature, open-source code, and material to evade ANY malware detector (with or without machine learning).
Since tools are automatic, it does not change much to perturb or inject few bytes or kilobytes

Static detection is bypassed by design

Structure of programs can be changed and embedded in other programs, downloaded from the internet after execution, and more

The Enigma Protector
Software Protection

MPRESS
Version: 2.19

UPX
the Ultimate Packer for eXecutables

Themida
ADVANCED WINDOWS SOFTWARE PROTECTION

VMProtect
software

Obsidium

Very well known packer programs that hide malicous content.
Originally created to prevent reverse engineering of legitimate code.

https://resources.infosecinstitute.com/topic/top-13-popular-packers-used-in-malware/

Do companies care about Adversarial robustness?

“We really appreciate this research and would like to collaborate to continue to improve our products and services. At this time this technique does not meet the definition of vulnerability in the product or has demonstrated that it bypassed our products. We will however look into our static ML models to see how we can incorporate this technique to further improve.”

One-of-those-company

Adversarial EXEmples not treated as vulnerability

Companies are interested in evading the overall pipeline, not just portions of the products

Missing the bigger picture

Companies have the feelings that academic settings are unrealistic, as they target “only” the ML component

<u>Naïve solution: test attacks against deployed commercial products</u>

(which are unavailable, as said before)

Call for action

Develop new testing techniques that consider all components

We are starting to create end-to-end pipelines, but we are still missing a complete framework that systematically tell a developer HOW to test these models

Part 2 Survey

aka.ms/malware-survey2