Certifiably robust malware detectors by design

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IFIP SEC, May 23rd, 2025

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Context

Malware

A malware is a malicious software: botnet, encryption, backdoor, cryptocurrency mining...

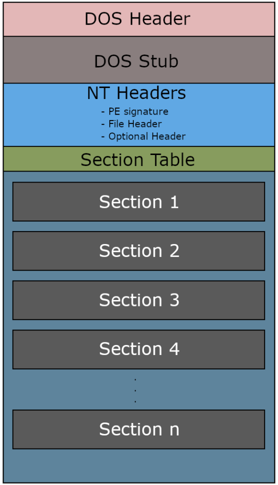
Malware analysis

Two main categories of malware analysis:

- static analysis, where the software is not run
  - extracted features: control flow graph, file metadata, library imports, presence of encryption, etc.
- dynamic analysis, where the software is monitored during its execution
  - extracted features: network activity, modified files, system calls list, etc.

These features can be used by machine learning to help detect, classify and cluster malware

Windows executable file



Our work

- We focus on **Windows malware**, the most common desktop target
- We study **static analysis** for its ease of experiment and scaling capability

PE format

- Legacy content for backward compatibility (DOS header and DOS stub, etc.)
- Flexible format: the order of the sections is free, some parts are optional, etc.

Adversarial attacks

Attacks on machine learning

- Machine learning is increasingly used to analyze malware
- Many attacks against machine learning, at different stages (data collection, learning, inference) and targeting different properties (integrity, privacy, etc.)

Evasion attacks

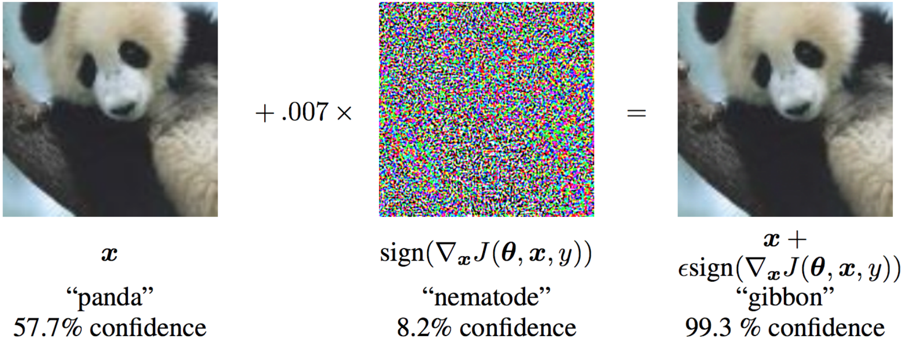
- The goal of the attacker is to modify slightly the features to change the predicted class
- Formally, for an input $x \in \mathbb{R}^n$, the attacker looks for a “small” $\epsilon \in \mathbb{R}^n$ such as $argmax_c f_c(x) \neq argmax_c f_c(x + \epsilon)$ (i.e., the predicted class changed)

Question: how to make malware classifiers more robust?

Adversarial examples against malware detectors

The issue

Even very accurate classifiers can be fooled by slightly modifying the input



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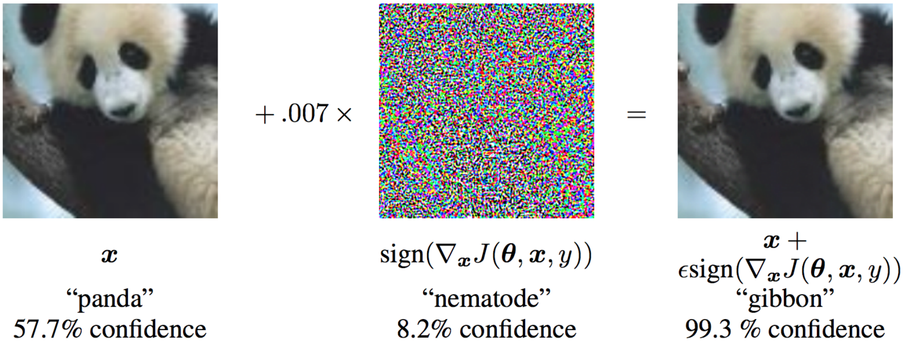


What about malware?

Adversarial examples

Image $\neq$ malware

- We cannot randomly modify a malware and expect it to work correctly
- Images are continuous: small variations do not change their meaning
- Programs are discrete: opcode "0x60" is very different from opcode "0x61"
- Perturbations on images must stay small to be invisible to human eyes
- Perturbations on programs do not have this constraint

$\Rightarrow$ the threat model is very different

Adversarial attacks on malware detection

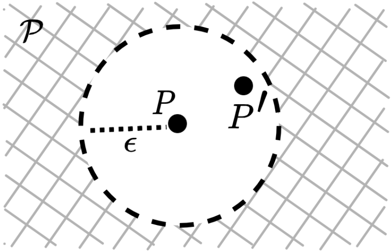
How to attack malware detectors

Most common approach: modify the malware with semantics-preserving operations:

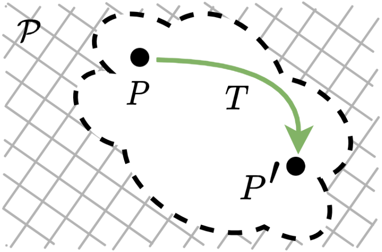
- file padding
- header perturbation
- API import addition
- ... and many more

Adversarial examples are build by chaining such operations in a black-box way

Detection evasion

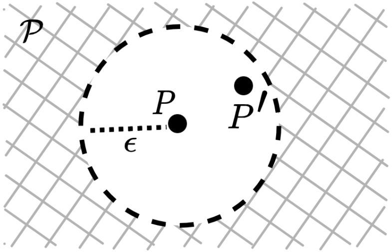


Attack on **images**. The attacker looks for an image within a ϵ-ball



Attack on **malware**. P' must have the same behavior as P

Detection evasion



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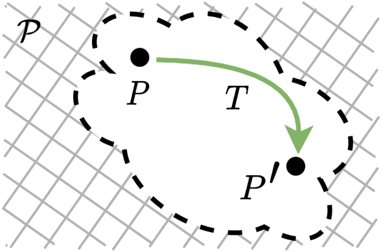

Attack on **malware**. P' must have the same behavior as P

Current techniques against adversarial attacks assume the perturbation is small

This assumption is not reasonable for malware!

Certifiable robustness by design

Certifiably robust detector by design

Related work

- Prior work: one should only use features that cannot be decreased by transformations, along with a monotonic classifier
- Intuition: whatever the attacker does, the output of the classifier can only increase, i.e., the detector can only be more confident it is a malware
- If the assumption holds, then the classifier is robust: no attack is possible, no matter how large the perturbation is
- Accuracy results are underwhelming because many features are discarded

Intuition of our contribution

What about a more complex feature mapping?

- Earlier, the feature mapping is just a projection (keep or drop features)
- We could use adversarial examples to automatically learn the feature mapping ϕ
- That way, we could have much more expressive robust classifiers

Intuition of our contribution

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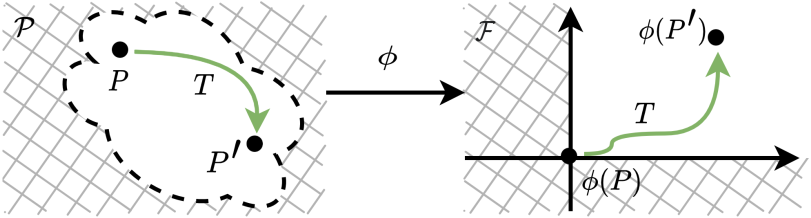


The feature mapping ϕ ensures that perturbations can only increases features

Expressivity

How expressive is it?

- Is this just a "hack"? Or a more profound insight into robust classifiers?
- We prove that **all robust classifiers can be expressed as a features mapping followed by a monotonic classifier**

Proposition

Let ϕ be a feature mapping and f be a classifier such that f is robust against adversarial attacks. There exist g and h such that $f \circ \phi = (f \circ h) \circ (g \circ \phi)$ and $f \circ h$ is monotonically increasing.

Example

Our proposition: learn the feature mapping

- Consider the attack that replaces one API call with a similar one (replacing `CreateFileA` with `CreateFileW`)
- This transformation modifies features f_1 (number of `CreateFileW`) and f_2 (number of `CreateFileA`) such as $f_1 \leftarrow f_1 + 1$ and $f_2 \leftarrow f_2 - 1$
- The previous work would drop f_2 (it can be decreased)
- If the other transformation (`CreateFileW` into `CreateFileA`) is possible, then f_1 would also be dropped!
- Our model could create the feature $f_3 = f_1 + f_2$ (number of `CreateFileA` and `CreateFileW`) and not lose as much information while still ensuring monotonicity

How to do that?

ERDALT

- We showed that every robust classifier can be structured as a monotonic classifier on top of some specially crafted feature mapping
- We propose to learn a neural network with two parts:
  - a first layer for the role of feature mapping
  - monotonic layers for the role of the detection
- We can prove, under some assumption, that this model is robust (by design)

We name our approach ERDALT: *Empirically Robust by Design with Adversarial Linear Transformation*

Properties

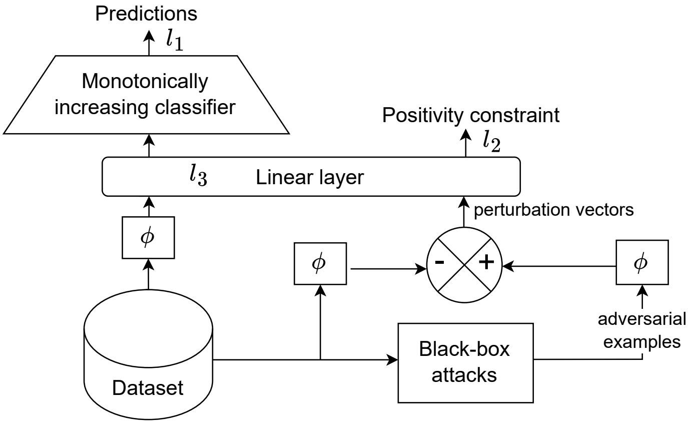
Assumption

- Without any assumption, we cannot hope to learn robust classifiers
- To obtain theoretical guarantees, we assume the effect of the transformations on the features is independent from the initial malware
  - Replacing an API call with a similar one decreases a feature and increments another
  - A padding transformation adds n bytes to a section

Linear feature mapping

- A linear feature mapping ensures that the effect of two transformations on the features is simply the sum of their effects
- If the model is robust against all elementary transformations, then it is robust against any combination of transformations!

ERDALT: empirically robust by design malware detector



ERDALT

- We want to minimise the classification error (loss l_1)
- The first linear layer maps perturbations vectors to positive values (loss l_2)
- A third loss encourages a sparse linear layer (loss l_3)

Experimental assessment

Experimental protocol

Dataset and features

- Dataset: created by EURECOM and Avast, contains 60,000 malware
- Features:
  - EMBER (state-of-the-art): 1871 features
  - Manually selected features: 40 features selected to be difficult to decrease

Adversarial attacks

- `secml-malware`
- Applies semantics-preserving transformations with a genetic algorithm

Metrics

- Performances are evaluated with ROC AUC
- Robustness: proportion of malware not successfully attacked

Performance with no protections

Model	**Manual features** (40)		**EMBER** (1871)	
	ROC AUC	**Robustness**	**ROC AUC**	**Robustness**
Baseline network	89.9%	**100%**	91.6%	**82.0%**
Monotonic network	69.0%	**100%**	87.4%	71.5%
Random Forest	**94.6%**	98.5%	96.2%	81.0%
AdaBoost	85.0%	98.0%	94.2%	75.5%
k-nn	83.7%	93.5%	88.6%	0%
Decision tree	84.1%	99.5%	96.2%	67.0%
Monotonic GBT	76.2%	**100%**	92.7%	73.5%
GBT	92.3%	99.0%	**97.5%**	75.0%

- Feature sets impact a lot the AUROC and robustness
- Manually selected features lead to much higher robustness and limited ROC AUC loss
- **More features means larger attack surface**

Performances with protections

Protection	Model	EMBER	
		ROC AUC	**Robustness**
Increasing-only features	Random Forest	95.2%	**100%**
	Monotonic GBT	86.7%	**100%**
	Gradient-boosted trees	93.8%	**100%**
Adversarial training	Random Forest	**97.6%**	94.5%
	Monotonic GBT	92.7%	95.5%
	Gradient-boosted trees	**97.6%**	96.5%
ERDALT	Neural network	93.0%	96.0%
ERDALT + adv. training	Neural network	85.5%	**100%**

Adversarial training yields the best ROC AUC, but the lowest robustness

Features selections

	Increasing-only features	ERDALT selection	Intersection
Byte	0%	84.9%	0%
Strings	1.9%	94.2%	1.9%
General	30.0%	60.0%	30.0%
Header	77.4%	83.9%	64.5%
Section	55.2%	76.5%	40.8%
Imports	44.5%	66.5%	22.2%
Exports	100%	49.2%	49.2%
Data directories	46.7%	90.0%	43.3%

ERDALT can exploit more features than the previous method due to the linear combinations it allows

Ablation study

Ablation study

- A typical ML experiment to analyze the effect of each component
- We can conclude that both the linear layer and the monotonicity are necessary for high robustness

Linear layer	**Monotonicity**	**ROC AUC**	**Robustness**
×	×	91.6%	82.0%
✓	×	**94.3%**	91.0%
×	✓	87.4%	71.5%
✓	✓	93.0%	**96.0%**

Conclusion

Adversarial attacks against malware detectors

- Attacks on images $\neq$ attacks on malware
- Provably robust methods assume the perturbation is small
- Our provably robust method does not rely on this unrealistic assumption

How to make a robust detector?

- Use a monotonic model with increasing features but expect a large performance drop
- Use ERDALT, which learns a feature mapping, and expect a smaller performance drop
- ERDALT can be combined with adversarial training as well

Perspectives

- Deep learning is not adapted to malware analysis
- We plan to apply this method to other security-related domains