SERICS
SECURITY AND RIGHTS IN THE CYBERSPACE

Pattern Recognition and Applications Lab

University of Cagliari, Italy

Reliable Evaluation and Benchmarking of Machine Learning Models

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GOBIERNO DE ESPAÑA — MINISTERIO PARA LA TRANSFORMACIÓN DIGITAL Y DE LA FUNCIÓN PÚBLICA — SECRETARÍA DE ESTADO DE DIGITALIZACIÓN E INTELIGENCIA ARTIFICIAL

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Attacks against AI are Pervasive!

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

"without the dataset the article is useless"

"okay google browse to evil dot com"

Carlini and Wagner, *Audio adversarial examples: Targeted attacks on speech-to-text*, DLS 2018 https://nicholas.carlini.com/code/audio_adversarial_examples/

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

- Demetrio, Biggio, Roli et al., *Adversarial EXEmples: ...*, ACM TOPS 2021
- Demetrio, Biggio, Roli et al., *Functionality-preserving black-box optimization of adversarial windows malware*, IEEE TIFS 2021
- Demontis, Biggio, Roli et al., *Yes, Machine Learning Can Be More Secure!...*, IEEE TDSC 2019

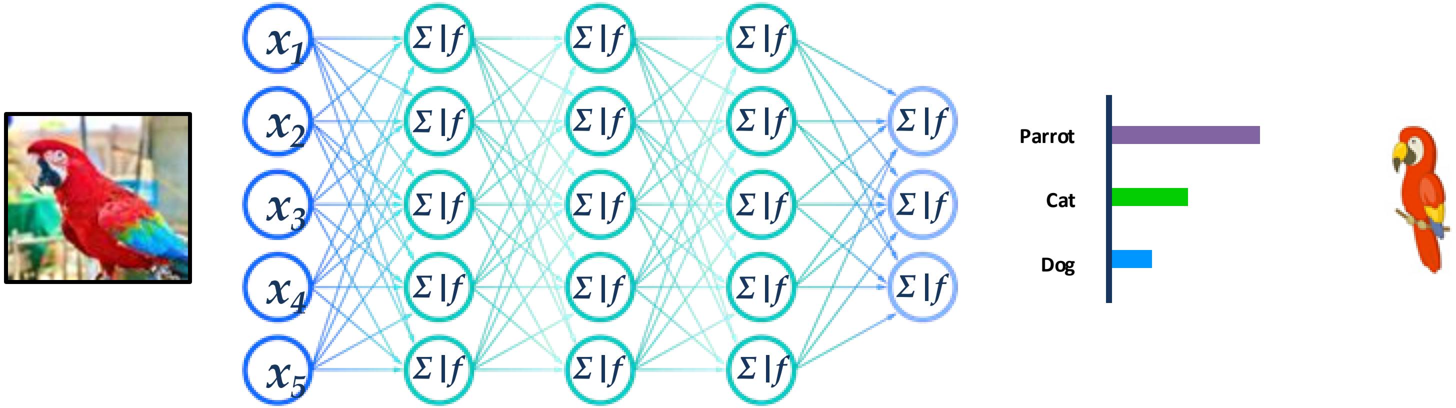
Attacks against Machine Learning

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

Attacker's Knowledge:

- perfect-knowledge (PK) white-box attacks
- limited-knowledge (LK) black-box attacks (*transferability* with surrogate/substitute learning models)

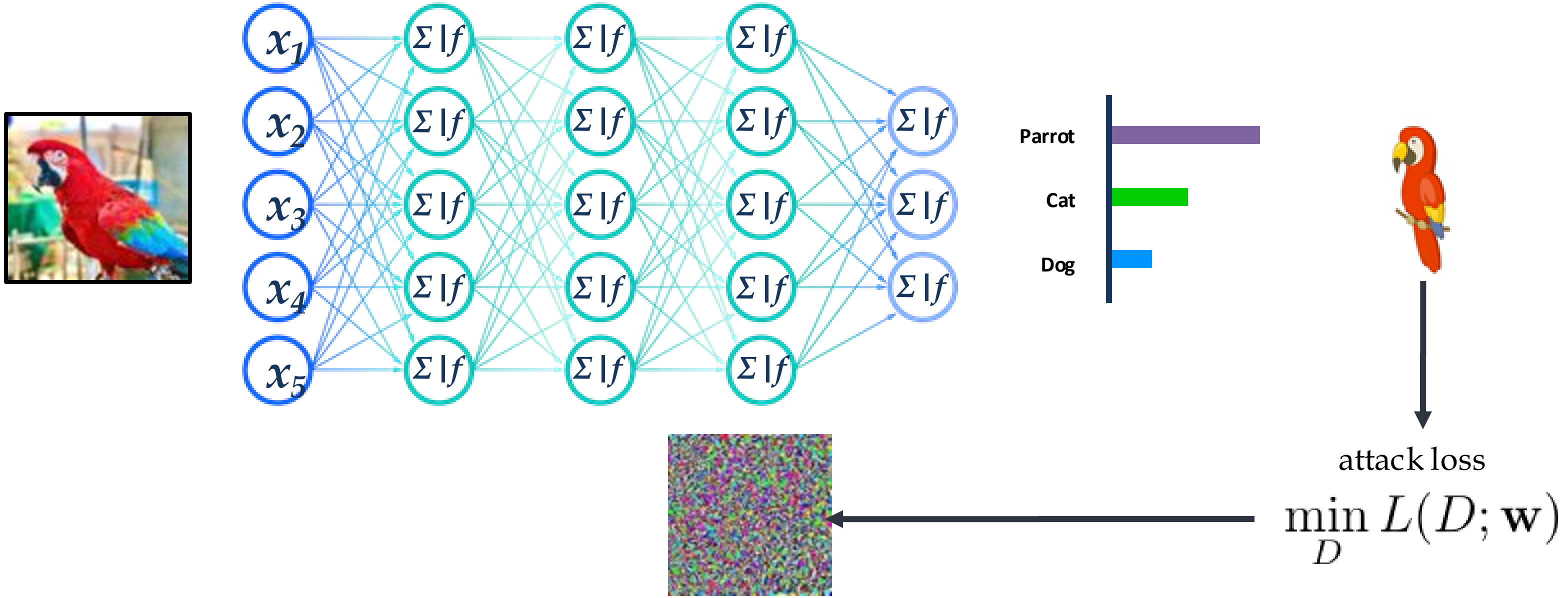
Adversarial Examples (AdvX)



training loss

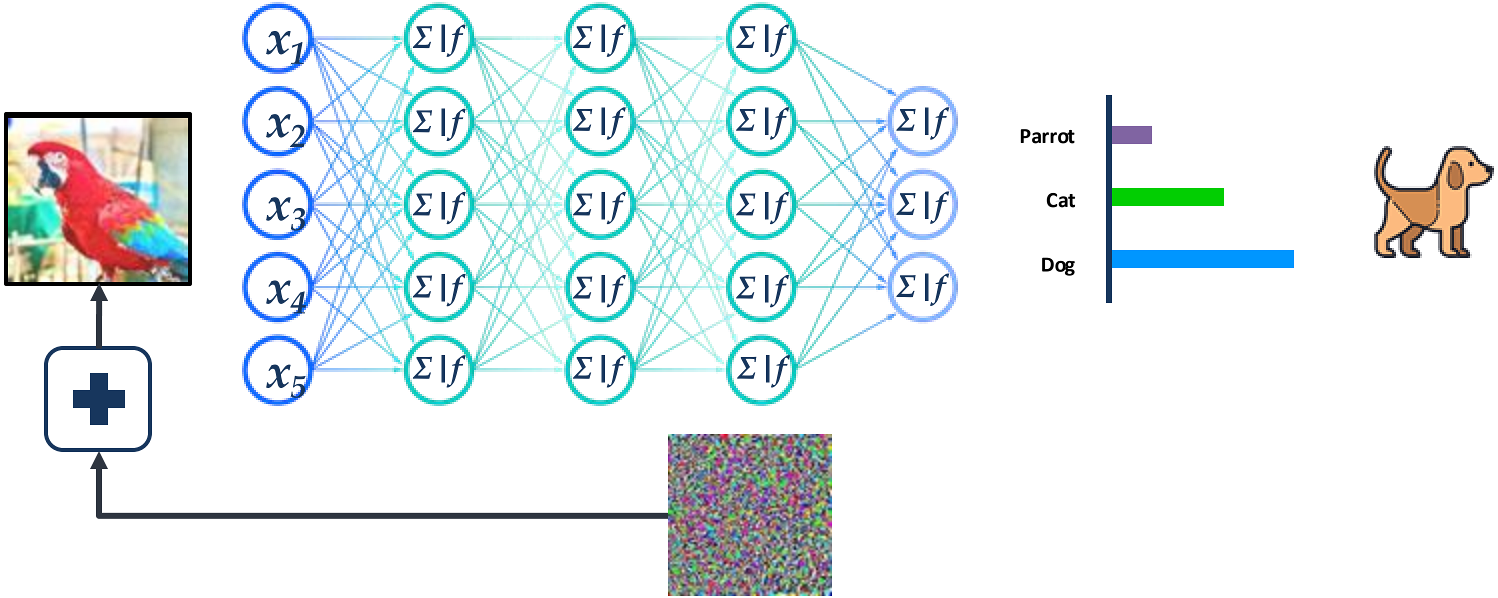
$$\min_{\mathbf{w}} L(D; \mathbf{w})$$

Adversarial Examples (AdvX)



Biggio et al., *Evasion Attacks Against Machine Learning at Test Time*, ECML PKDD 2013
Szegedy et al., *Intriguing Properties of Neural Networks*, ICLR 2014

Adversarial Examples (AdvX)



Biggio et al., *Evasion Attacks Against Machine Learning at Test Time*, ECML PKDD 2013
Szegedy et al., *Intriguing Properties of Neural Networks*, ICLR 2014

How to craft AdvXs

Exhaustive search → not possible for modern deep learning models
Empirical evaluation → attack = optimization problem + solving algorithm

$$\begin{aligned} \boldsymbol{\delta}^\star \in \arg\min_{\boldsymbol{\delta}} \quad & \mathcal{L}(\boldsymbol{x}+\boldsymbol{\delta}, y, \boldsymbol{\theta}) \\ \text{s.t.} \quad & \|\boldsymbol{\delta}\|_p \leq \epsilon \\ & \boldsymbol{x}_{\text{lb}} \preceq \boldsymbol{x}+\boldsymbol{\delta} \preceq \boldsymbol{x}_{\text{ub}} \end{aligned}$$

Optimize model's confidence on bad decision
keeping perturbation small
and respecting feature space constraints

Biggio et al., *Evasion Attacks Against Machine Learning at Test Time*, ECML PKDD 2013
Szegedy et al., *Intriguing Properties of Neural Networks*, ICLR 2014

How to craft AdvXs

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$$
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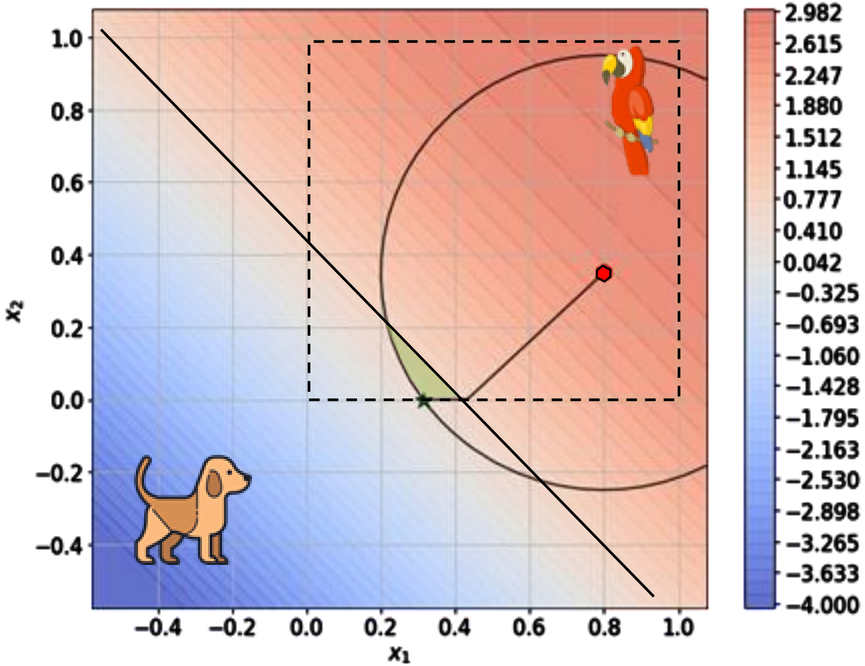
\end{aligned}
$$

Optimize model's confidence on bad decision
keeping perturbation small
and respecting feature space constraints

Robust Accuracy = accuracy under worst-case perturbation (fixed perturbation size)

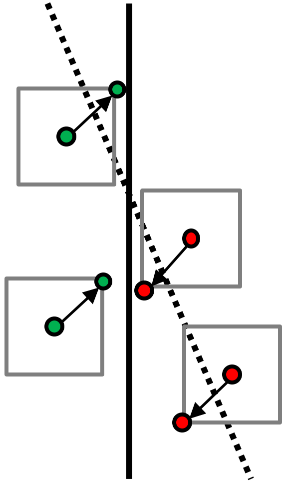


Biggio et al., *Evasion Attacks Against Machine Learning at Test Time*, ECML PKDD 2013
Szegedy et al., *Intriguing Properties of Neural Networks*, ICLR 2014

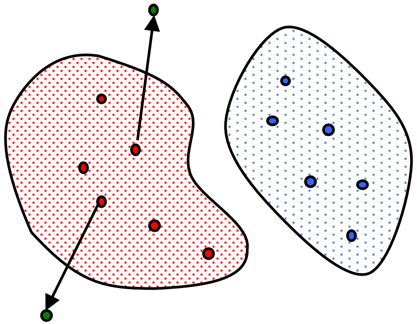
Defending against AdvXs

- Robust training (a.k.a. Adversarial training)

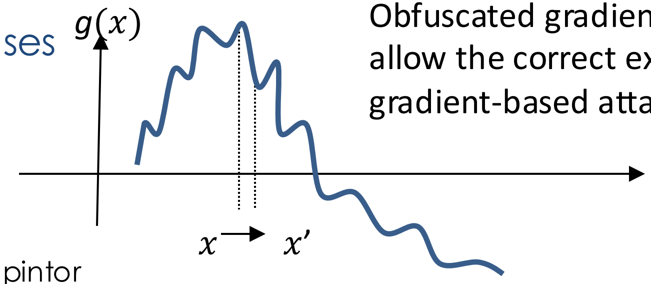
$$\min_{\boldsymbol{w}} \max_{||\boldsymbol{\delta}_i||_\infty \leq \epsilon} \sum_i \ell(y_i, f_{\boldsymbol{w}}(\boldsymbol{x}_i + \boldsymbol{\delta}_i))$$



- Detectors



- Ineffective defenses

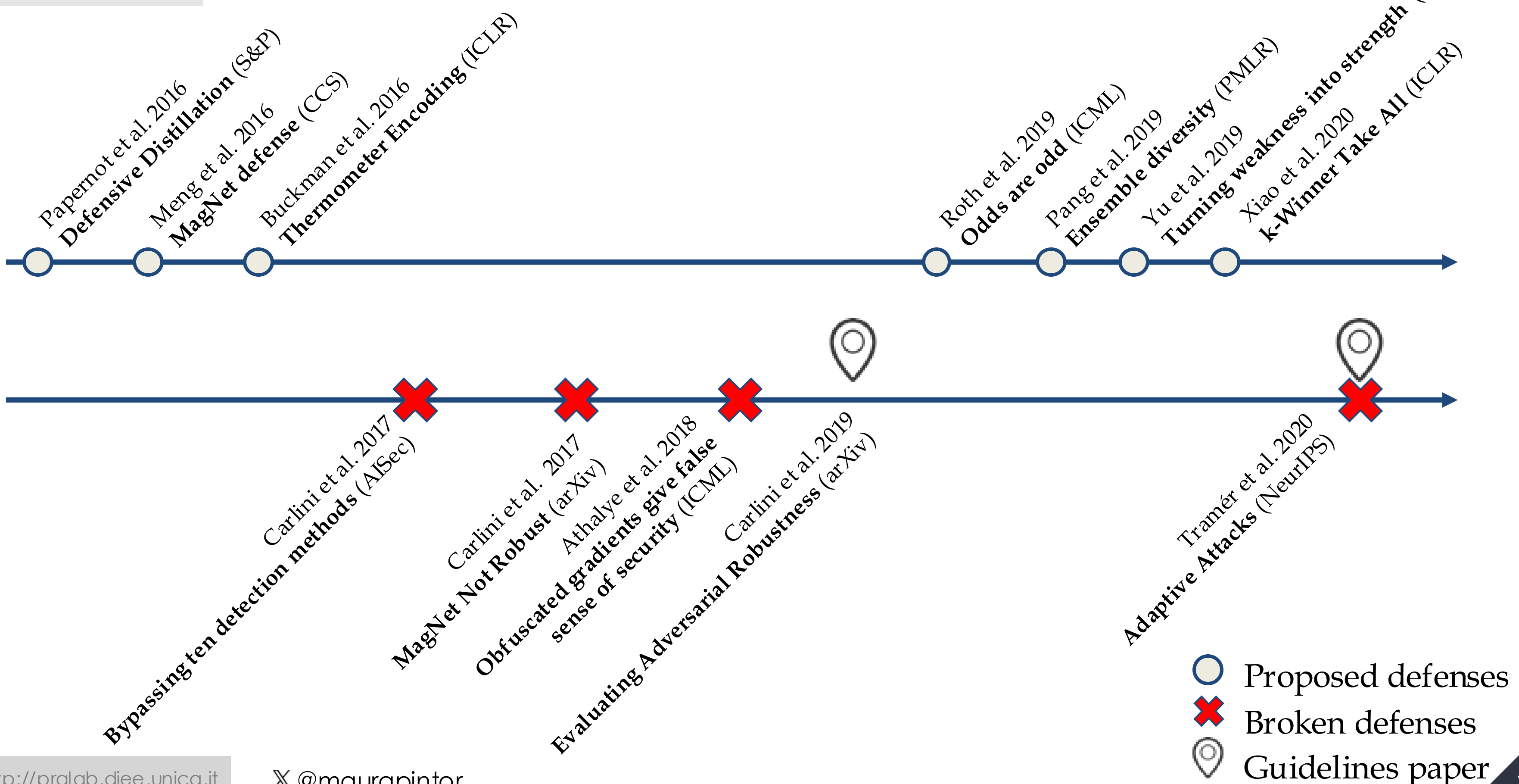


Obfuscated gradients do not allow the correct execution of gradient-based attacks...

The Rise of Adversarial Defenses

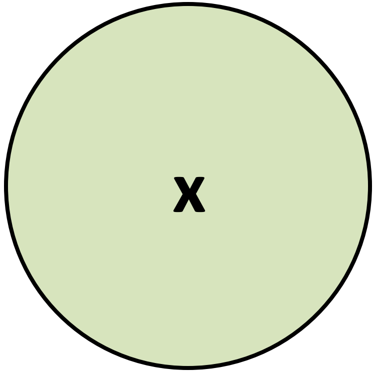
- Papernot et al. 2016 **Defensive Distillation** (S&P)
- Meng et al. 2016 **MagNet defense** (CCS)
- Buckman et al. 2016 **Thermometer Encoding** (ICLR)
- Roth et al. 2019 **Odds are odd** (ICML)
- Pang et al. 2019 **Ensemble diversity** (PMLR)
- Yu et al. 2019 **Turning weakness into strength** (NeurIPS)
- Xiao et al. 2020 **k-Winner Take All** (ICLR)

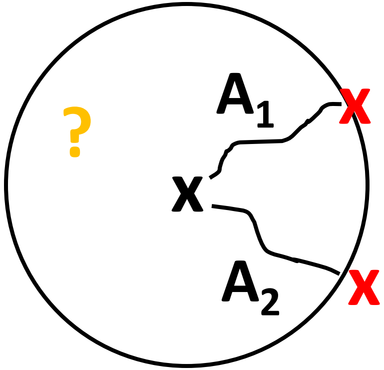
The ~~Rise~~ Fall of Adversarial Defenses



Why is this happening?

Ideal world: formal verification and certified robustness
There is no AdvX in the given perturbation domain





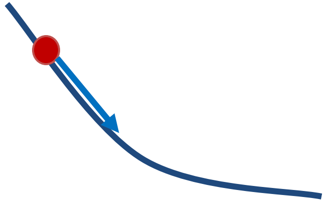
Real world: we can only test with empirical attacks

attack succeeds → the model is not robust
attack fails → <u>we cannot conclude much...</u>

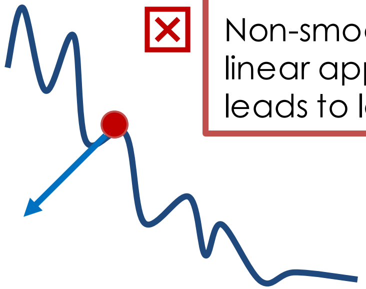
Example: Gradient Obfuscation

When GD works

Smooth function: linear approximation works



When GD does not work



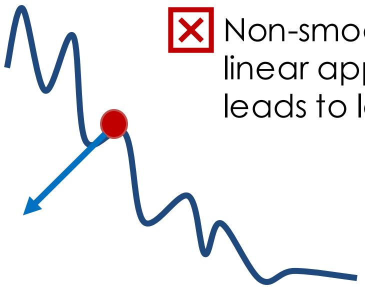
Non-smooth function: linear approximation leads to local minima

Check variability of loss landscape

Attack does not return an adversarial example
... but can we say there is no way of finding one?

Example: Gradient Obfuscation

When GD does not work



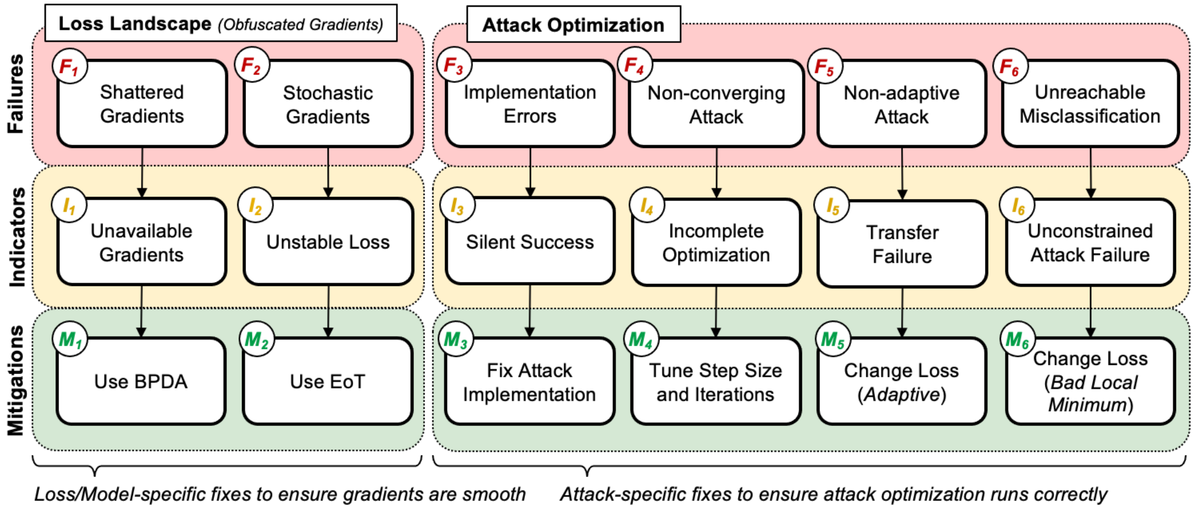
Non-smooth function: linear approximation leads to local minima

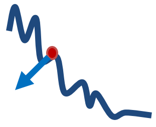
Check variability of loss landscape

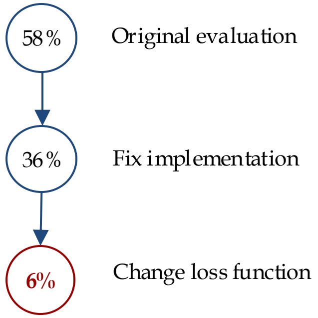
Use smooth approximation

Detect and Avoid Flawed Evaluations

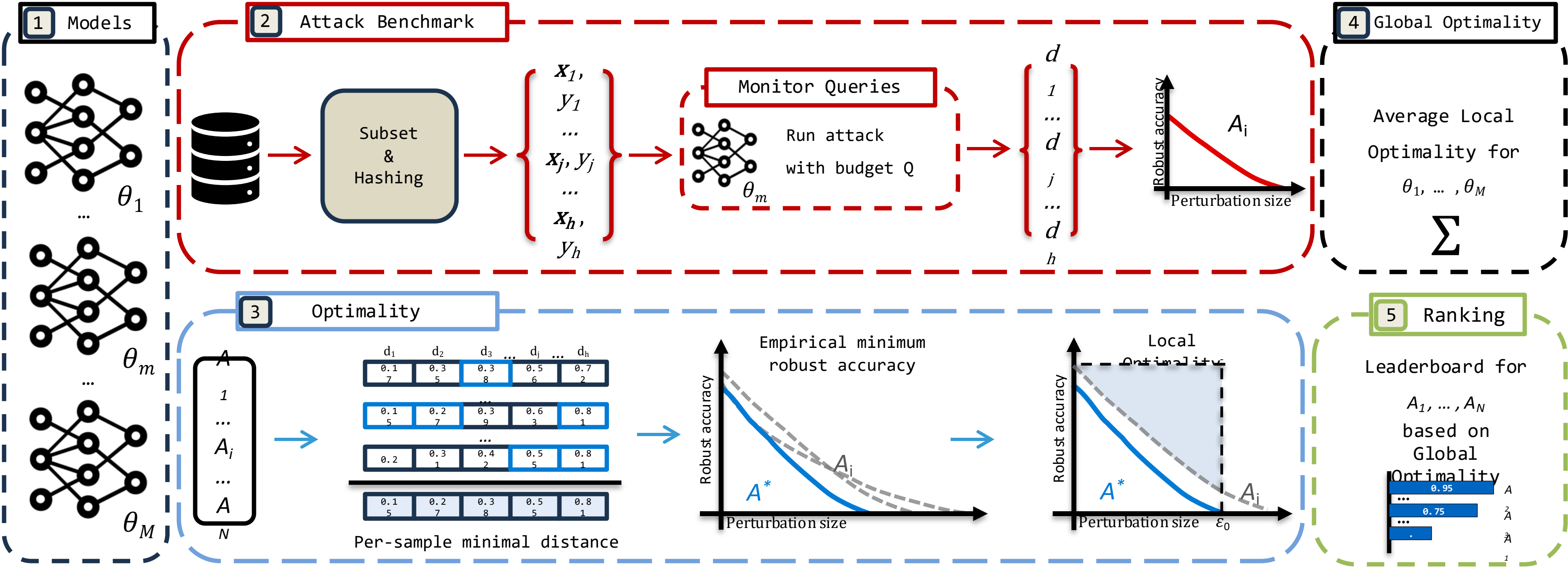
- **Problem**: formal evaluations do not scale, adversarial robustness evaluated mostly empirically, via gradient-based attacks
- **Gradient-based attacks can fail:** many flawed evaluations have been reported, with defenses easily broken by adjusting/fixing the attack algorithms





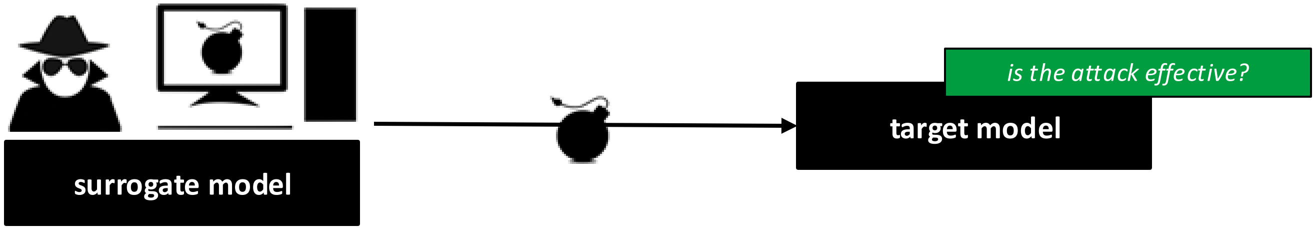


A benchmark of gradient-based attacks

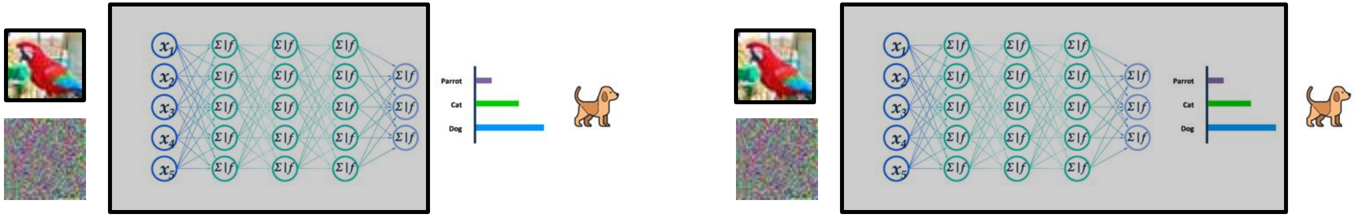


Beyond white-box evaluations

Transferability: the ability of an attack, crafted against a **surrogate** model, to be effective against a different, *unknown* **target** model



Black-box testing: observing input-output pairs (either scores or output labels) and estimating the loss function gradient without accessing to the model internals

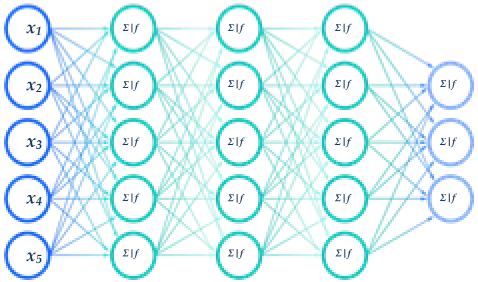


Papernot et al., *Practical Black-Box Attacks against Machine Learning*, ASIACCS 2017
Demontis et al., *Why Do Adversarial Attacks Transfer?* USENIX Security 2019

Realizable attacks: Application-Specific Perturbation Models

- What if there is no clear inverse mapping to the input domain?

feature extraction
$x = \phi(z)$



find AdvX
$x + \delta$

not reversible!
how to go back to the original problem space?

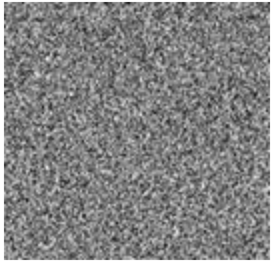
$$\begin{aligned} \boldsymbol{\delta}^\star \in \arg\min_{\boldsymbol{\delta}} \quad & \mathcal{L}(\boldsymbol{x}+\boldsymbol{\delta}, y, \boldsymbol{\theta}) \\ \text{s.t.} \quad & \|\boldsymbol{\delta}\|_p \leq \epsilon \\ & \boldsymbol{x}_{\text{lb}} \preceq \boldsymbol{x}+\boldsymbol{\delta} \preceq \boldsymbol{x}_{\text{ub}} \end{aligned}$$

Pierazzi et al., Intriguing Properties of Adversarial ML Attacks in the Problem Space, IEEE S&P 2020

Even worse…

Thanks Luca Demetrio (@zangobot)!

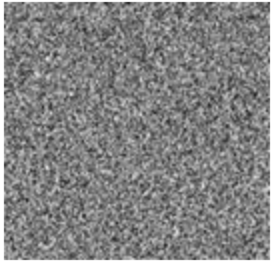
toucan (97%)



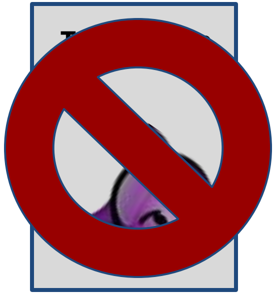
adversarial noise

cat (95%)

malware (98%)



adversarial noise



Not runnable anymore!

For **malware**, we have to manipulate symbols/bytes/strings while **preserving functionality!**

Adversarial attacks for images

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

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

Thanks Luca Demetrio (@zangobot)!

Adversarial attacks for security detectors

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

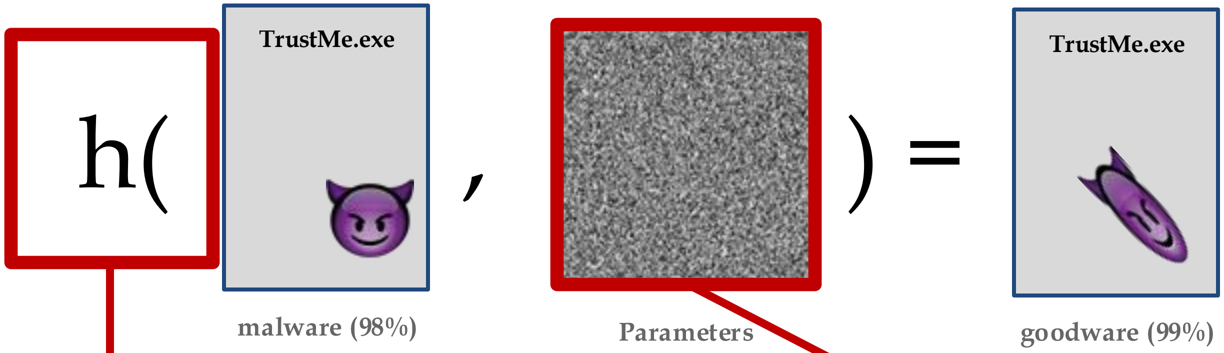
Model function and features
Need to explicit the model function and the features, since they might be non differentiable

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

Thanks Luca Demetrio (@zangobot)!

Practical Manipulations



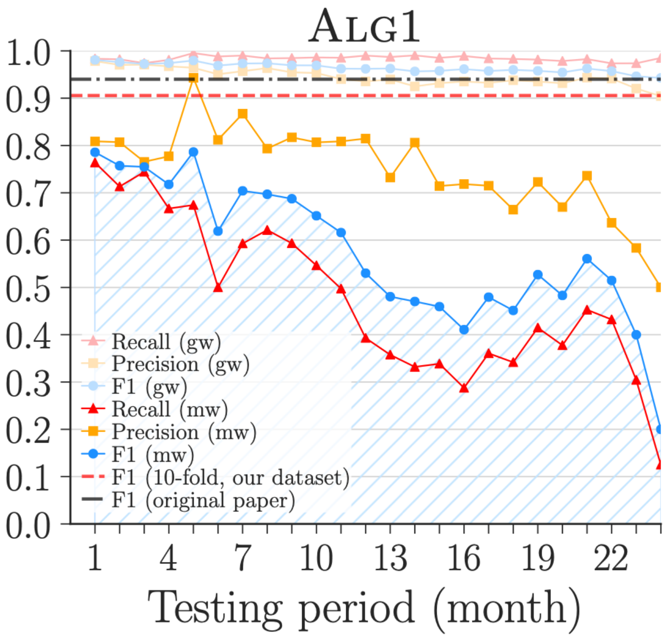
Practical Manipulation function
Alter file representation without destroying the structure and the functionalities and avoid usage of sandboxes

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

Practical Relevance of Perturbation Models

- Are the hypothesized perturbation models realistic enough?
- Let's assume we built a model robust to adversarial examples
  - but it does not seem to be much more robust over time...
  - new types of malware, different distributions unseen in training



Open research problem

To evaluate the soundness of current adversarial robustness methods

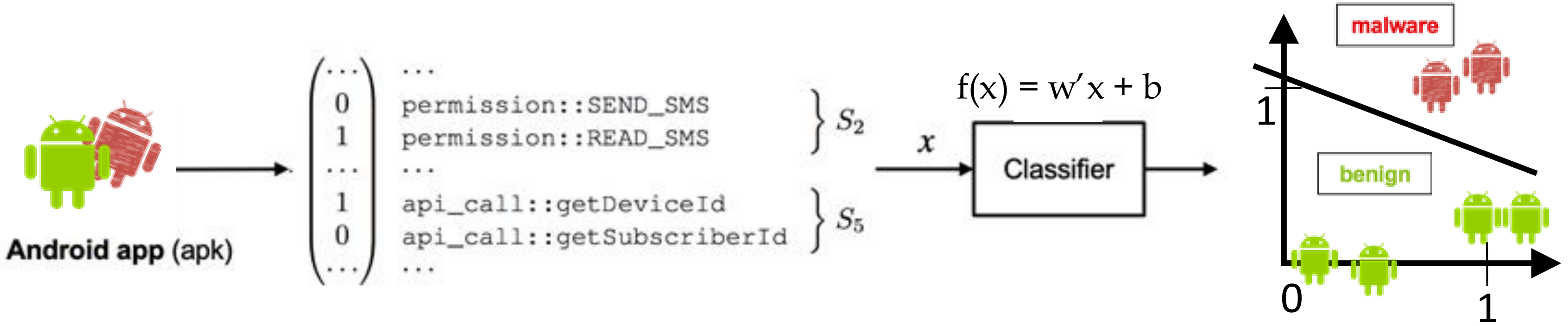
Current solution: frequent model updates

- requires time and (also human) resources

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

Machine Learning for Android Malware

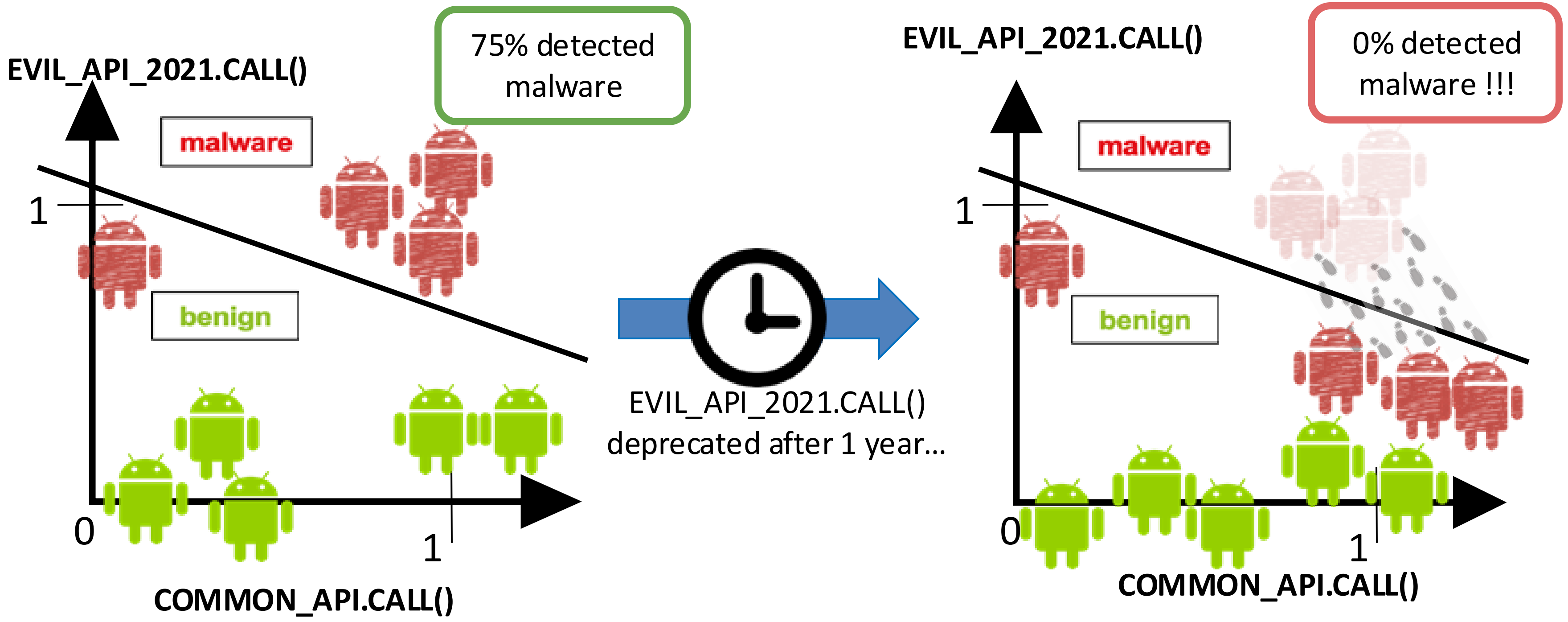
Hand-crafted features extracted from APK
Binary sparse feature vector



Arp et al. Drebin: Effective and explainable detection of android malware in your pocket. NDSS. Vol. 14. 2014.

Concept Drift in Android Malware

Thanks Daniele Angioni (@DAngioni97)!



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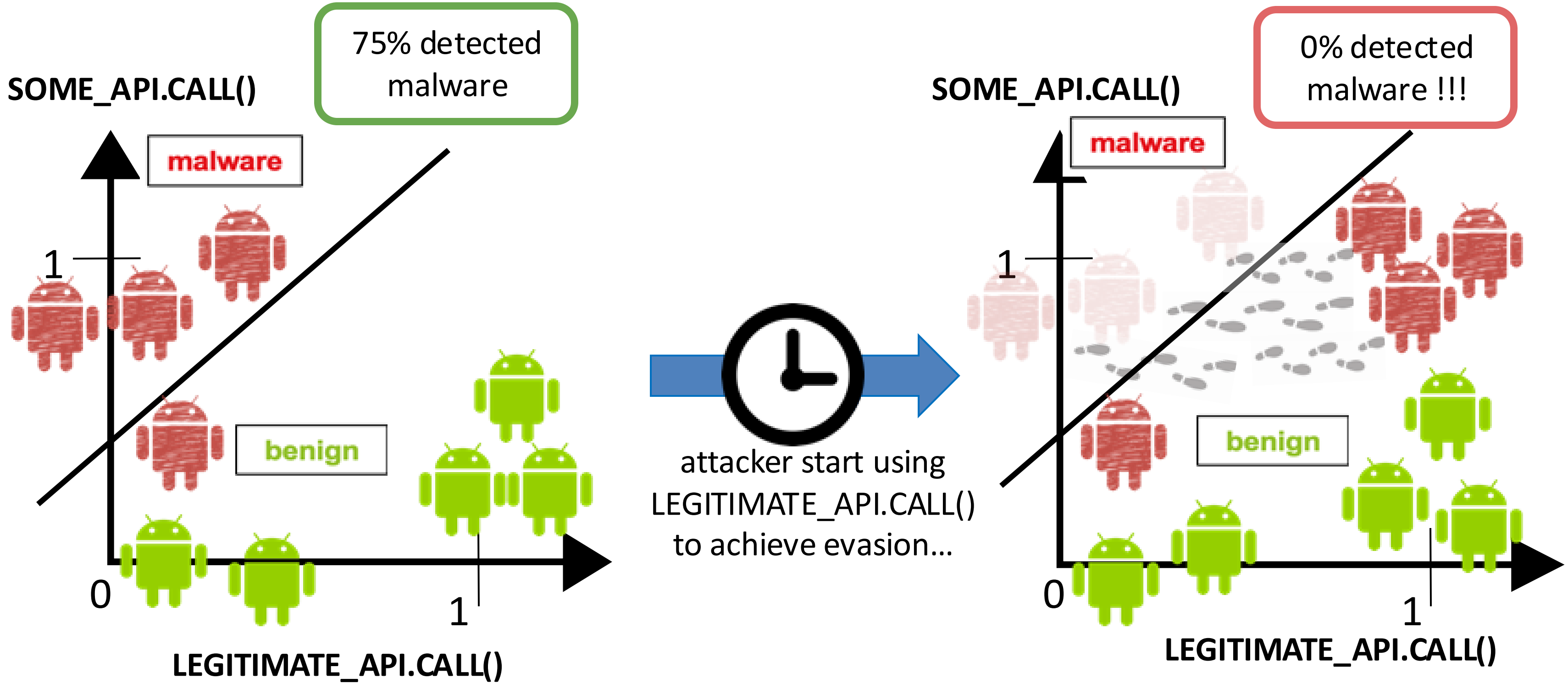
Concept Drift in Android Malware



How to predict a performance drop?
Is this drift similar to the previous?

ELSA Cybersecurity Use Case

Thanks Angelo Sotgiu (@sotgiu_angelo)!

AI-based detectors perform well,
but suffer from:

- performance decay over time
- vulnerability to evasion attacks

Benchmark to assess (and compare) **models' robustness** w.r.t.:

- natural evolution of applications
- adversarial manipulations of malware samples

Goal: build AI-based malware detectors that can be maintained with less effort, and react more promptly to novel threats

Three different competition tracks
Challenge: https://benchmarks.elsa-ai.eu/?ch=6

Thanks Angelo Sotgiu (@sotgiu_angelo)!

ELSA Cybersecurity - Competition Tracks

Track 1: Adversarial Robustness to Feature-space Attacks

- models are trained on the same feature set (DREBIN, extracted features are provided)
- simulated feature injection
- different amounts of adversarial perturbation (i.e., the number of manipulated features)

Date	Method	False Positive Rate	Clean data	25 manipulated features	50 manipulated features	100 manipulated features
2024-05-24	Baseline - DREBIN	0.36%	77.28%	1.20%	0.00%	0.00%

Track 2: Adversarial Robustness to Problem-space Attacks

- practical manipulation of application samples (paper coming soon...)
- the attacker does not know anything about the attacked detector

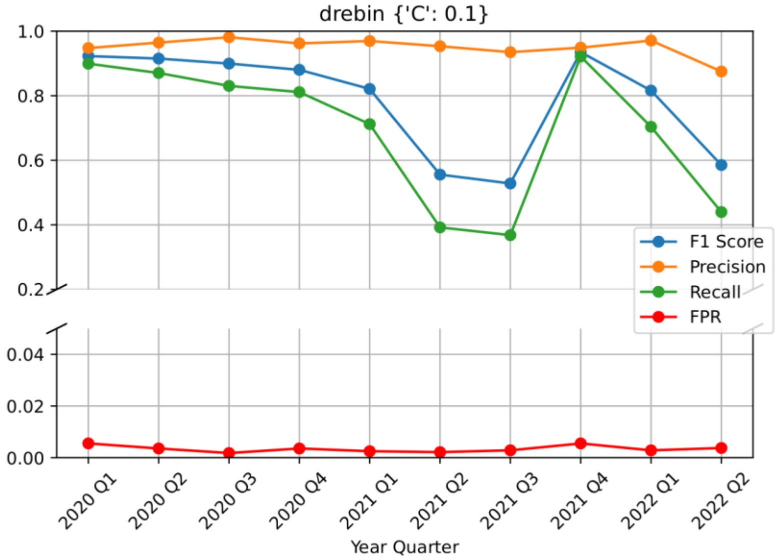
Date	Method	False Positive Rate	Clean data	100 manipulated features
2024-06-24	Baseline - DREBIN	0.36%	77.28%	4.24%

ELSA Cybersecurity - Competition Tracks

Thanks Angelo Sotgiu (@sotgiu_angelo)!

Track 3: Temporal Robustness to Data Drift

- evaluation with new test data collected over time
- Performance metric: Area Under Time on F1-score



Date				Method	Area Under Time - F1 score
2024-06-04				Baseline - DREBIN	0.7927

Pendlebury et al., TESSERACT: Eliminating Experimental Bias in Malware Classification across Space and Time. Usenix, 2018.

ELSA Cybersecurity - Participation Rules

Thanks Angelo Sotgiu (@sotgiu_angelo)!

Participants design their own detector pipeline based on statically-extracted features

- model training is on the users' side
- to participate, they provide a couple of interface methods
- and publish source code and pre-trained models
- we provide the script to automatically evaluate and upload the submission

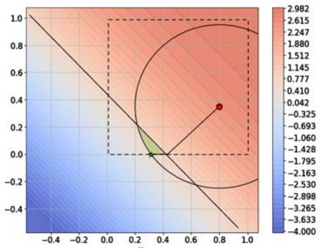
https://github.com/pralab/elsa-cybersecurity

Baselines available (also as examples):

- **DREBIN** from Arp et al. "Drebin: Effective and explainable detection of android malware in your pocket." NDSS. Vol. 14. 2014.
- **SecSVM** from Demontis et al. "Yes, machine learning can be more secure! a case study on android malware detection." IEEE TDSC 2017.

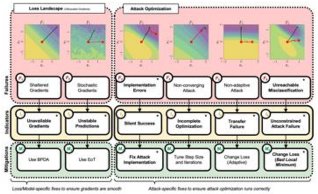
https://github.com/pralab/android-detectors

Let’s fix ML Security



Bug #1: slow, hard-to-configure, limited attacks

Fix #1: improve available attacks



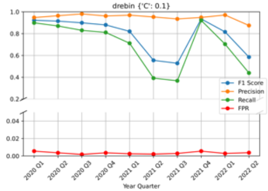
Bug #2: lack of debugging tools for ML Security

Fix #2: develop tests and track metrics on the attacks

Bug #3: Keep in mind the real world

Fix #3: create strong and realizable attacks

Fix #3(bis): benchmark in realistic scenarios



How about tools for ML security?

SecML: An Open-source Python Library for ML Security

ml

- ML algorithms via sklearn
- DL algorithms and optimizers via PyTorch and Tensorflow

adv

- attacks (evasion, poisoning, ...) with custom/faster solvers
- defenses (advx rejection, adversarial training, ...)

expl

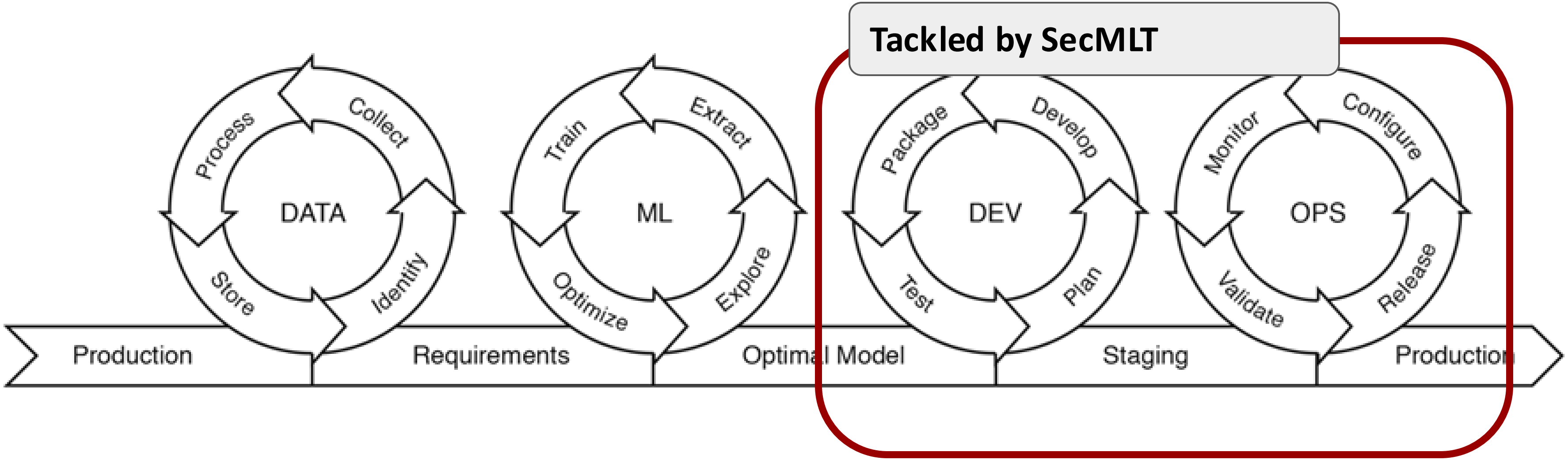
- Explanation methods based on influential features
- Explanation methods based on influential prototypes

others

- Parallel computation
- Support for dense/sparse data
- Advanced plotting functions (via matplotlib)
- Modular and easy to extend

Code: https://github.com/pralab/secml

SecML-Torch! (SecMLT)



MLOPS: Continuous development and deployment cycle

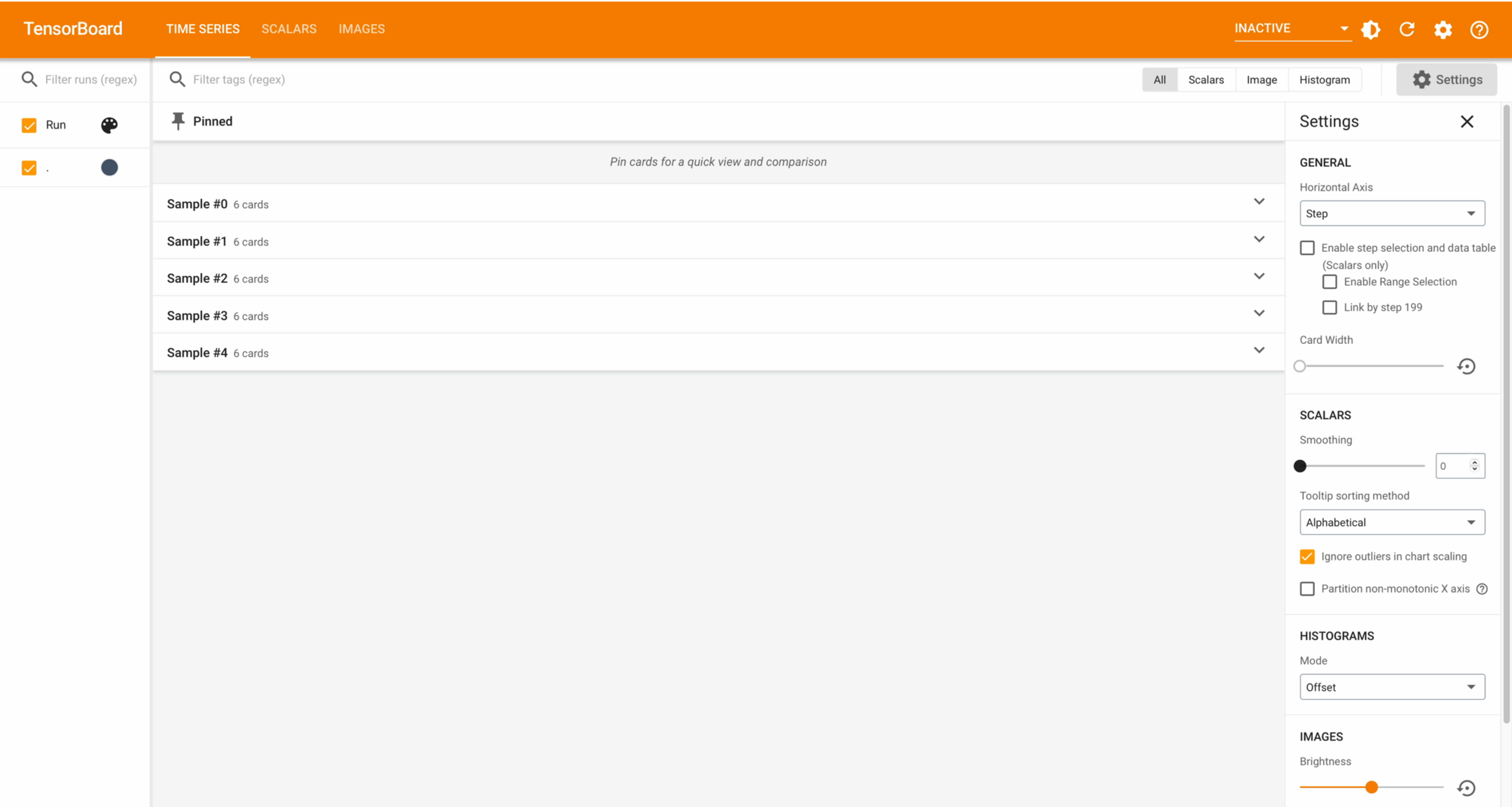
SecMLT will offer the techniques to test and validate the release of novel machine learning models

SecML-Torch example

- Powered by PyTorch
- Model wrapper to expose APIs
- Preprocessing and constraints taken into account
- Attacks (evasion, poisoning, ...) with custom/faster solvers
- Logging / debugging features (e.g., Tensorboard)
- WIP: Defenses (advx rejection, adversarial training, ...)
- WIP: extension to other domains (stay tuned...)

```python
from secmlt.adv.evasion.pgd import PGD
from secmlt.metrics.classification import Accuracy
from secmlt.models.pytorch.base_pytorch_nn import BasePytorchClassifier


model = ...
torch_data_loader = ...

# Wrap model
model = BasePytorchClassifier(model)

# create and run attack
attack = PGD(
    perturbation_model="l2",
    epsilon=0.4,
    num_steps=100,
    step_size=0.01,
)

adversarial_loader = attack(model, torch_data_loader)

# Test accuracy on adversarial examples
robust_accuracy = Accuracy()(model, adversarial_loader)
```

Code: https://github.com/pralab/secml-torch


TensorBoard
TIME SERIES
SCALARS
IMAGES
INACTIVE
Filter runs (regex)
Filter tags (regex)
All
Scalars
Image
Histogram
Settings
Run
.
Pinned
Pin cards for a quick view and comparison
Sample #0 6 cards
Sample #1 6 cards
Sample #2 6 cards
Sample #3 6 cards
Sample #4 6 cards
Settings
GENERAL
Horizontal Axis
Step
Enable step selection and data table (Scalars only)
Enable Range Selection
Link by step 199
Card Width
SCALARS
Smoothing
0
Tooltip sorting method
Alphabetical
Ignore outliers in chart scaling
Partition non-monotonic X axis
HISTOGRAMS
Mode
Offset
IMAGES
Brightness

Red teaming AI Security

- We have to consider the problem as a whole
  - small imperceptible perturbations are only the tip of the iceberg
  - from the security point of view, all models can be exploited, even with attacks that are not targeting the AI component

- Focus on knowing the system's weaknesses
  - we should know when and for what we can trust the system, even if it’s only for small tasks
  - don’t stop at the *ideal* conditions!

Pattern Recognition and Applications Lab

University of Cagliari, Italy

European Lighthouse on Secure and Safe AI

Thanks!

Open Course on MLSec
https://github.com/unica-mlsec/mlsec

Machine Learning Security Seminars
https://www.youtube.com/c/MLSec

Software Tools
https://github.com/pralab

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