SECOMP

UTFPR
UNIVERSIDADE TECNOLÓGICA FEDERAL DO PARANÁ

Como enganar modelos de aprendizado de máquina?

Erikson Júlio de Aguiar
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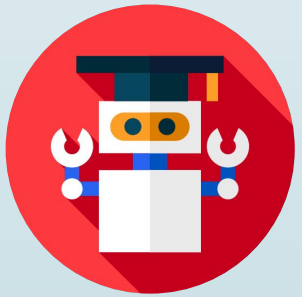

Quem sou eu?

- Doutorando em Ciência de Computação **ICMC - USP** (GBDI)
- Mestre em Ciência de Computação **ICMC - USP**
- Bacharel em Ciência da Computação - **UENP**
- **Áreas de interesse:**
  - Segurança & Privacidade
  - Blockchain
  - Aprendizado de máquina
  - Processamento de imagens

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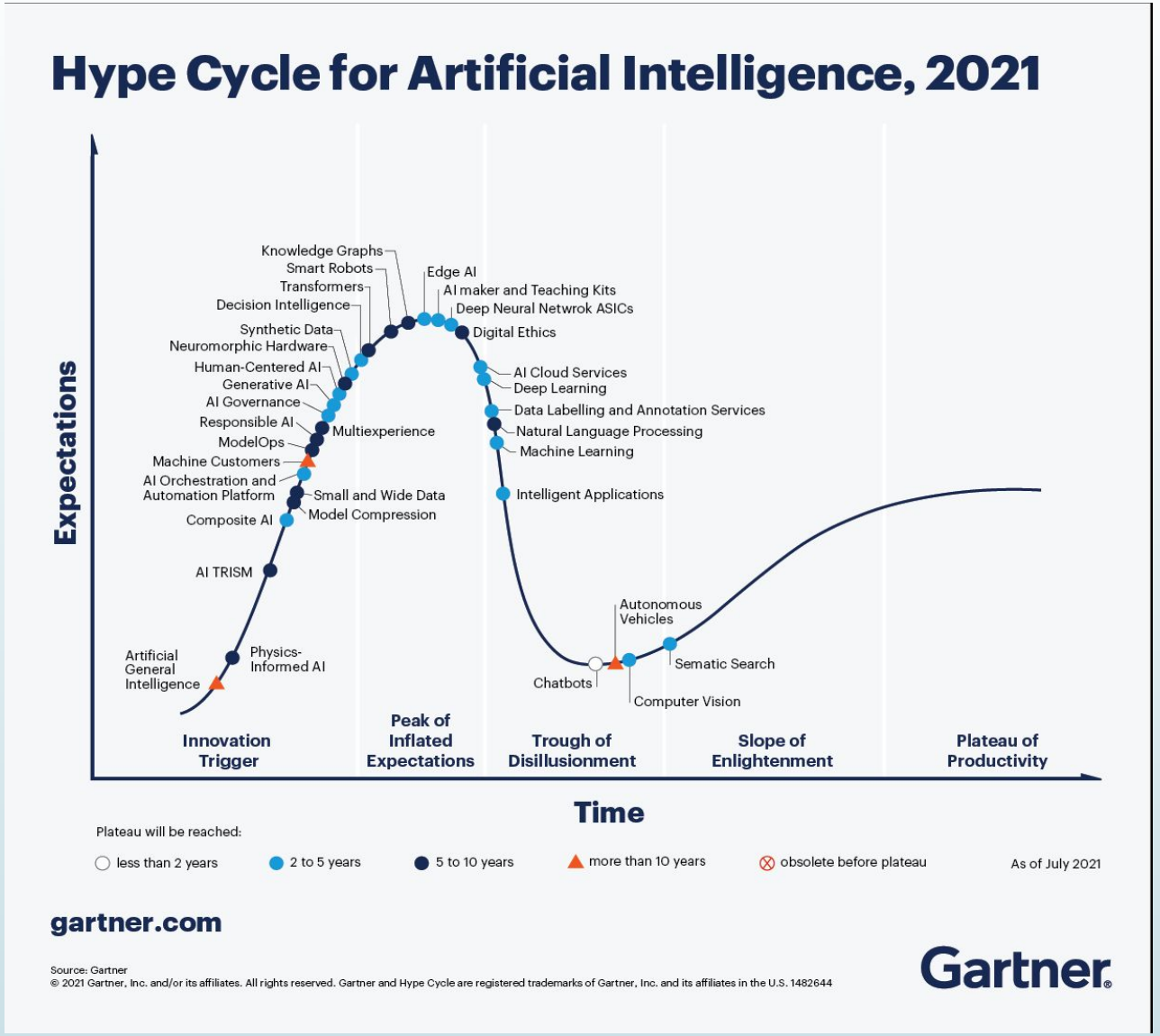
Sumário

1. Motivação
2. Definições
3. Ataques contra modelos de aprendizado de máquina
4. Técnicas de defesa em aprendizado de máquina
5. Privacidade em aprendizado de máquina
6. Projetos
7. Dicas

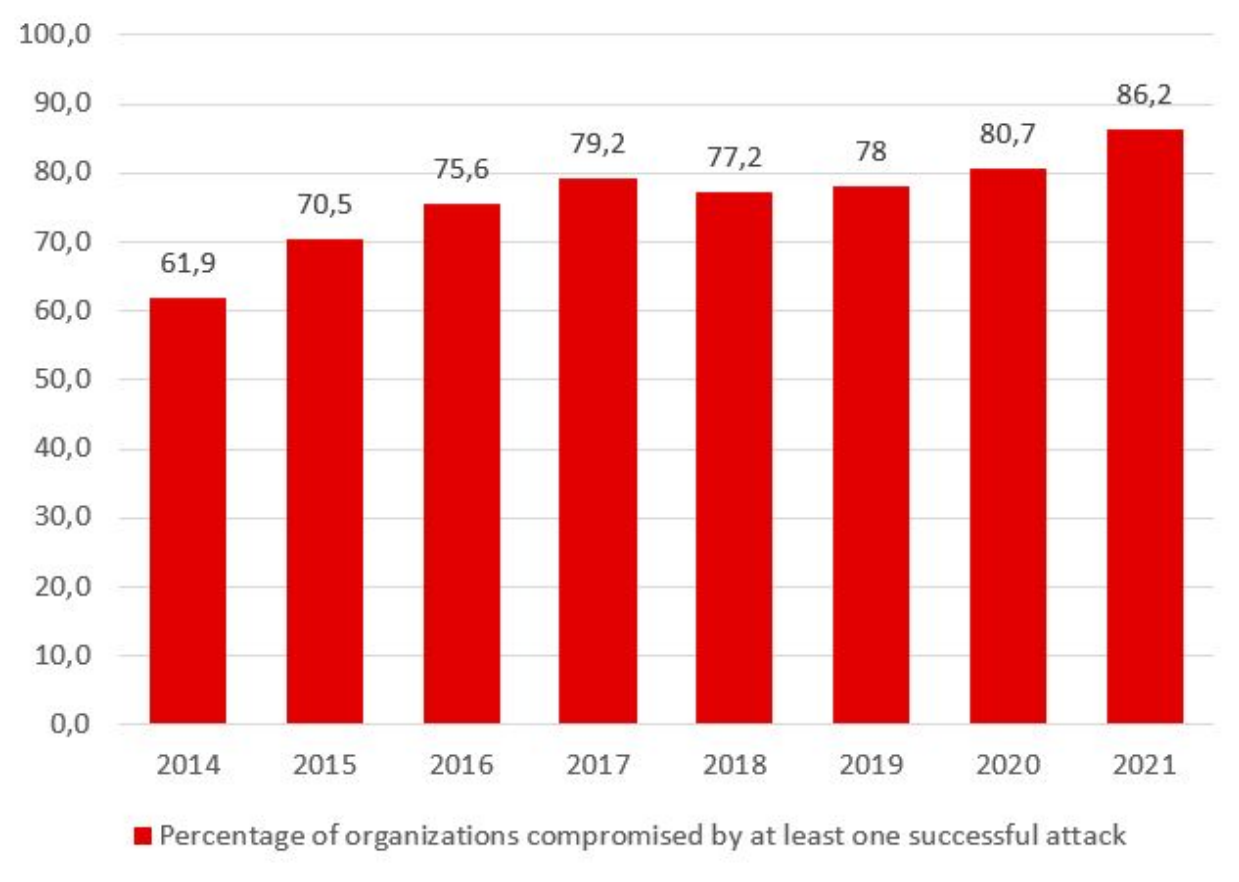
O potencial do aprendizado de máquina no cotidiano



Fonte: (Gartner, 2021)

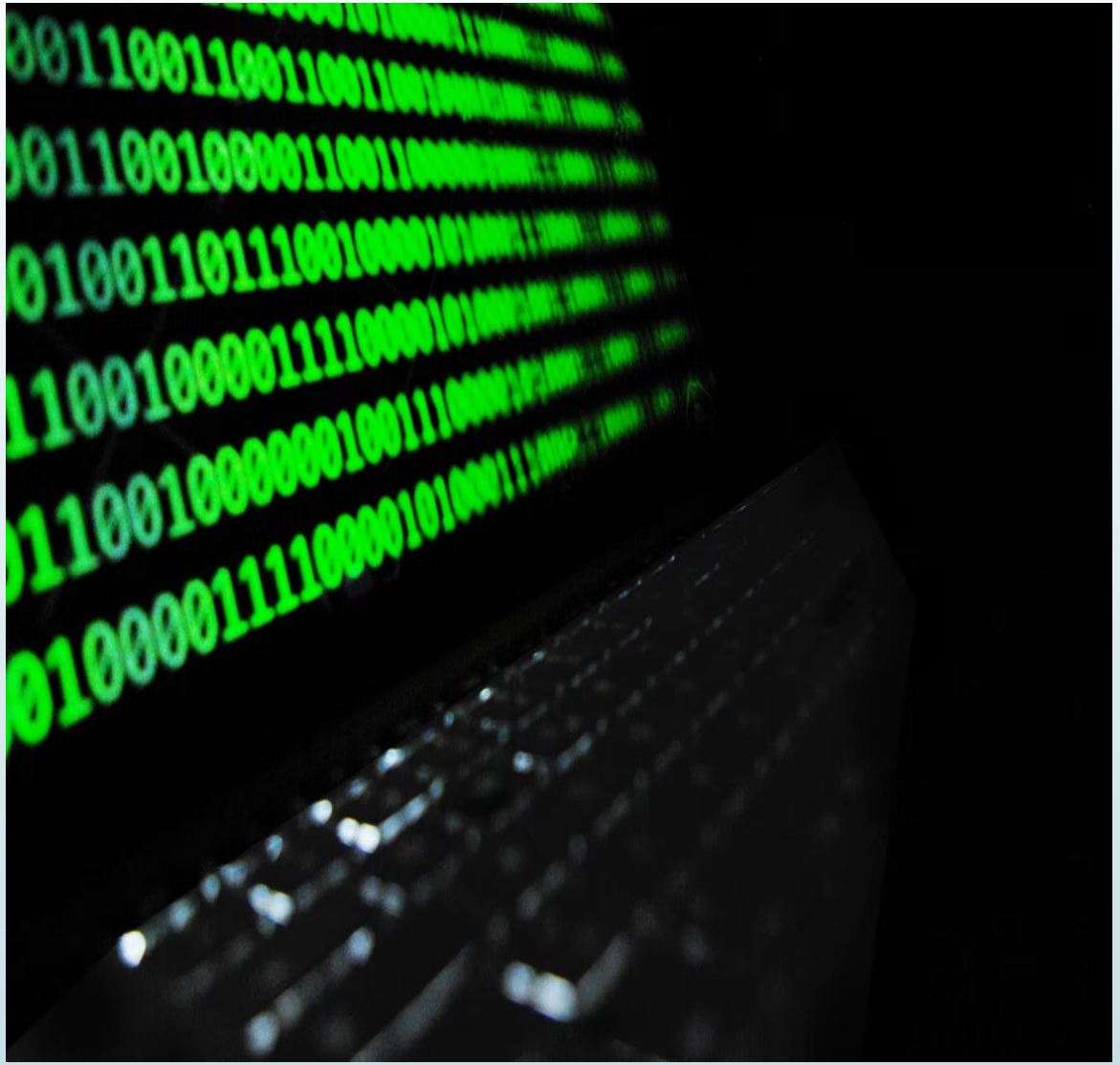
Áreas de aplicação do aprendizado de máquina

O crescimento das ameaças na internet



Fonte: (Stainer, 2021)

Modelos de Aprendizado de máquina são vulneráveis?



Quais seriam os impactos das vulnerabilidades?

#CVE-2019-20634

#CVE-2021-37678

Machine learning classifiers trained via gradient descent are vulnerable to arbitrary misclassification attack

Vulnerability Note VU#425163

Original Release Date: 2020-03-19 | Last Revised: 2020-06-04

CVE-2019-20634 Detail

MODIFIED

This vulnerability has been modified since it was last analyzed by the NVD. It is awaiting reanalysis which may result in further changes to the information provided.

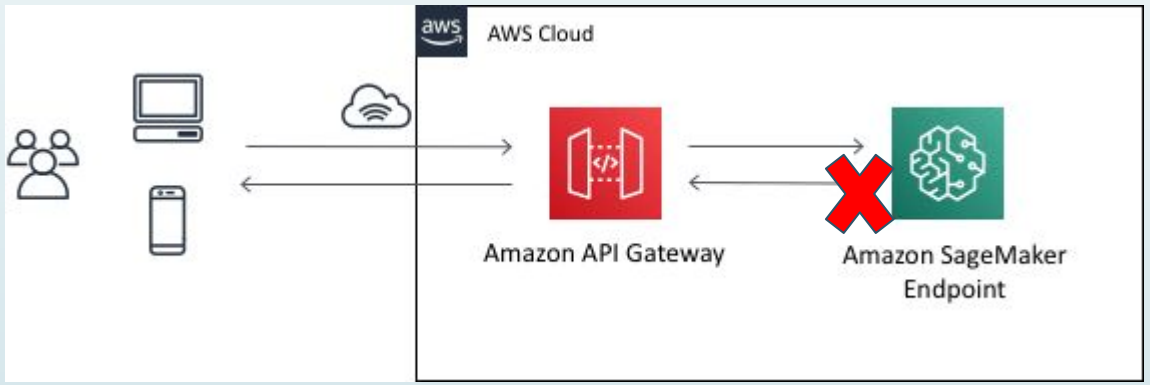
Current Description

An issue was discovered in Proofpoint Email Protection through 2019-09-08. By collecting scores from Proofpoint email headers, it is possible to build a copy-cat Machine Learning Classification model and extract insights from this model. The insights gathered allow an attacker to craft emails that receive preferable scores, with a goal of delivering malicious emails.

Machine Learning Security (MLSec)

Definições

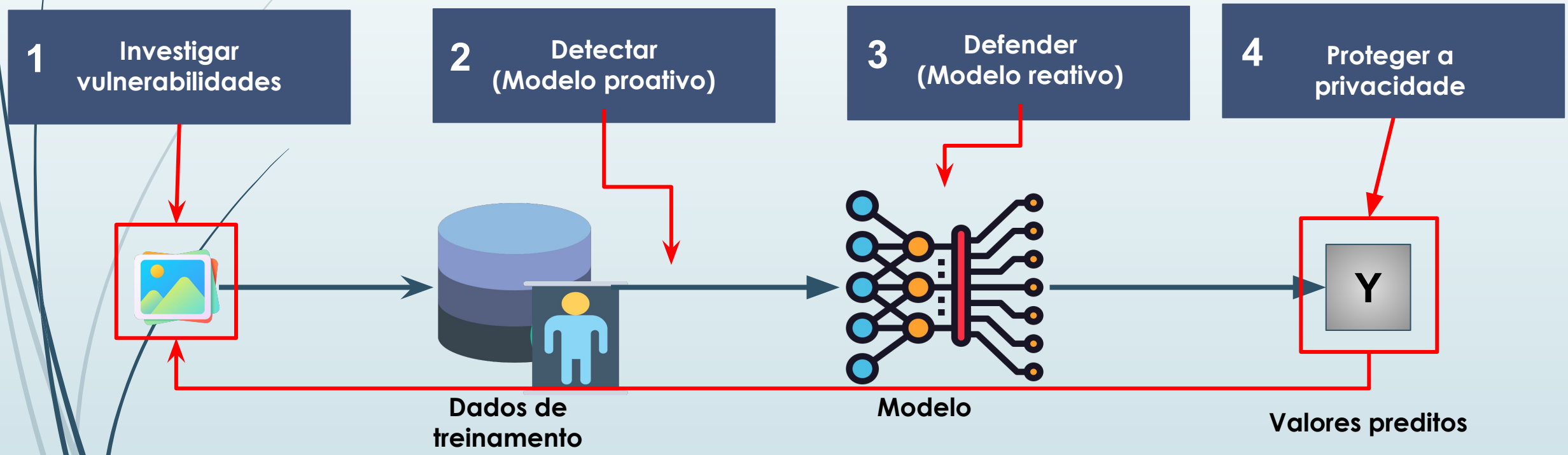
Integridade



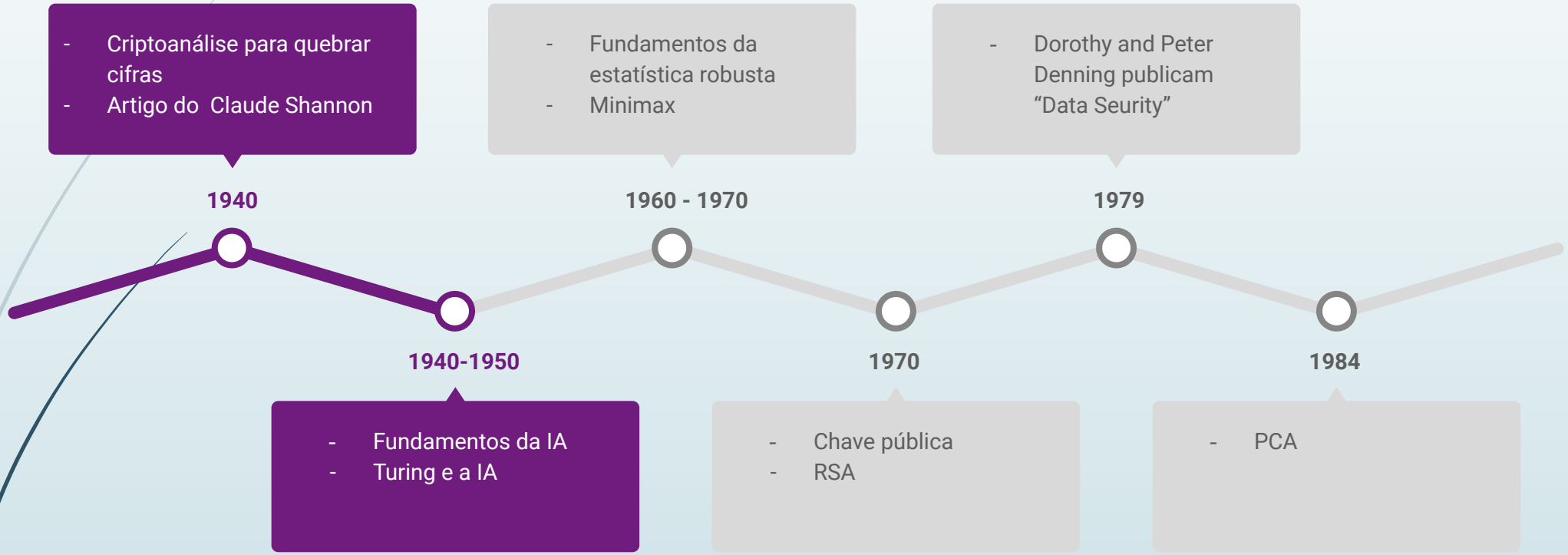
Disponibilidade

Confidencialidade

Níveis das vulnerabilidades - MLSec

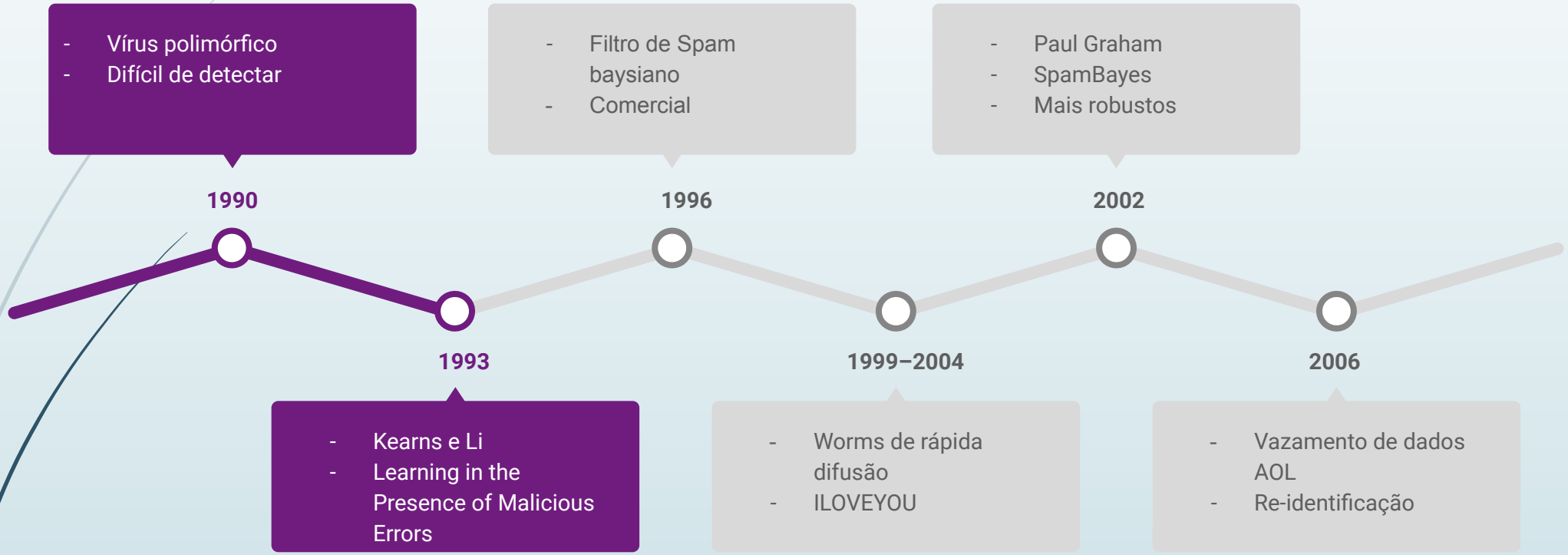


Histórico - MLSec



Adversarial Machine Learning (2019)
Joseph, Anthony D.; Nelson, Blaine; Rubinstein, Benjamin I. P.; Tygar, J. D.

Histórico - MLSec



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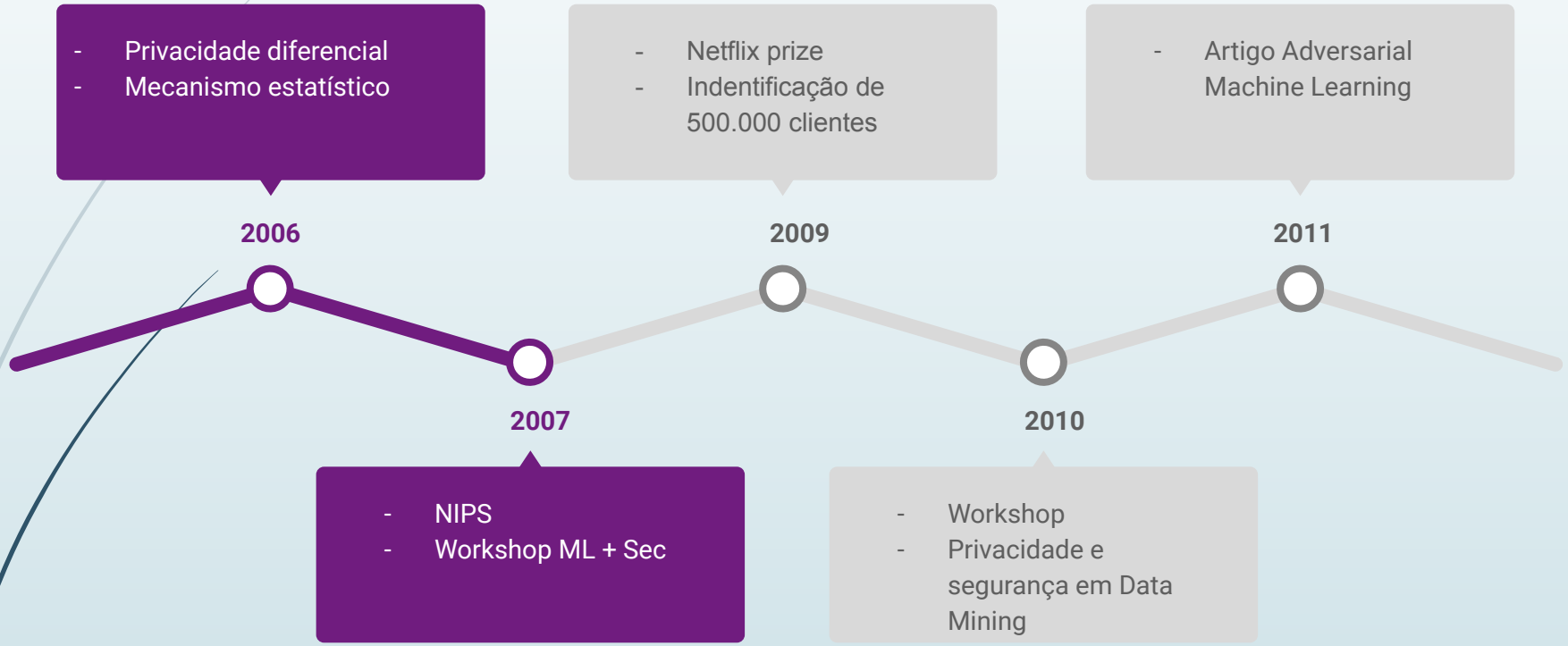
Histórico - MLSec



Adversarial Machine Learning (2019)
Joseph, Anthony D.; Nelson, Blaine; Rubinstein, Benjamin I. P.; Tygar, J. D.

Adversarial examples

Adversarial Examples Are Not Bugs, They Are Features

Andrew Ilyas*
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Aleksander Mądry
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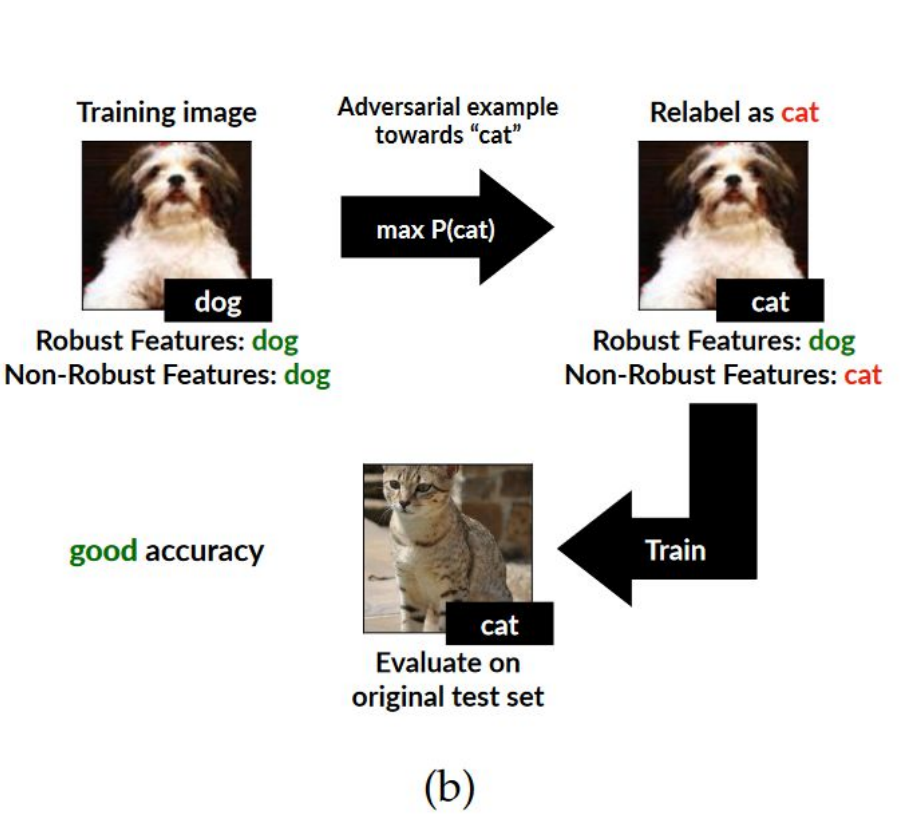
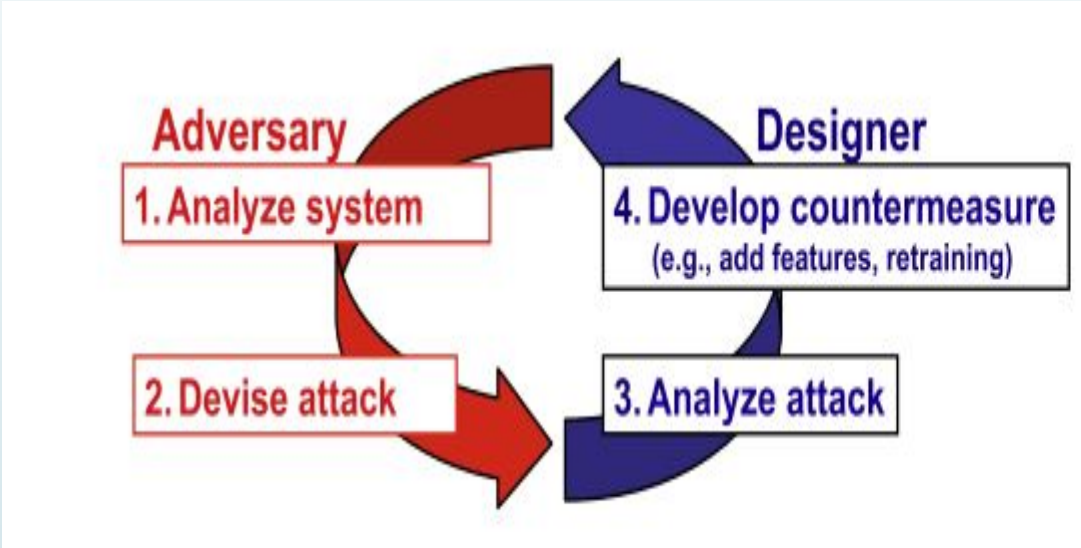
Adversarial examples



Adversarial Examples are not Bugs, they are Features (2019)
Andrew Ilyas; Shibani Santurkar; Dimitris Tsipras; Logan Engstrom; Brandon Tran; Aleksander Madry

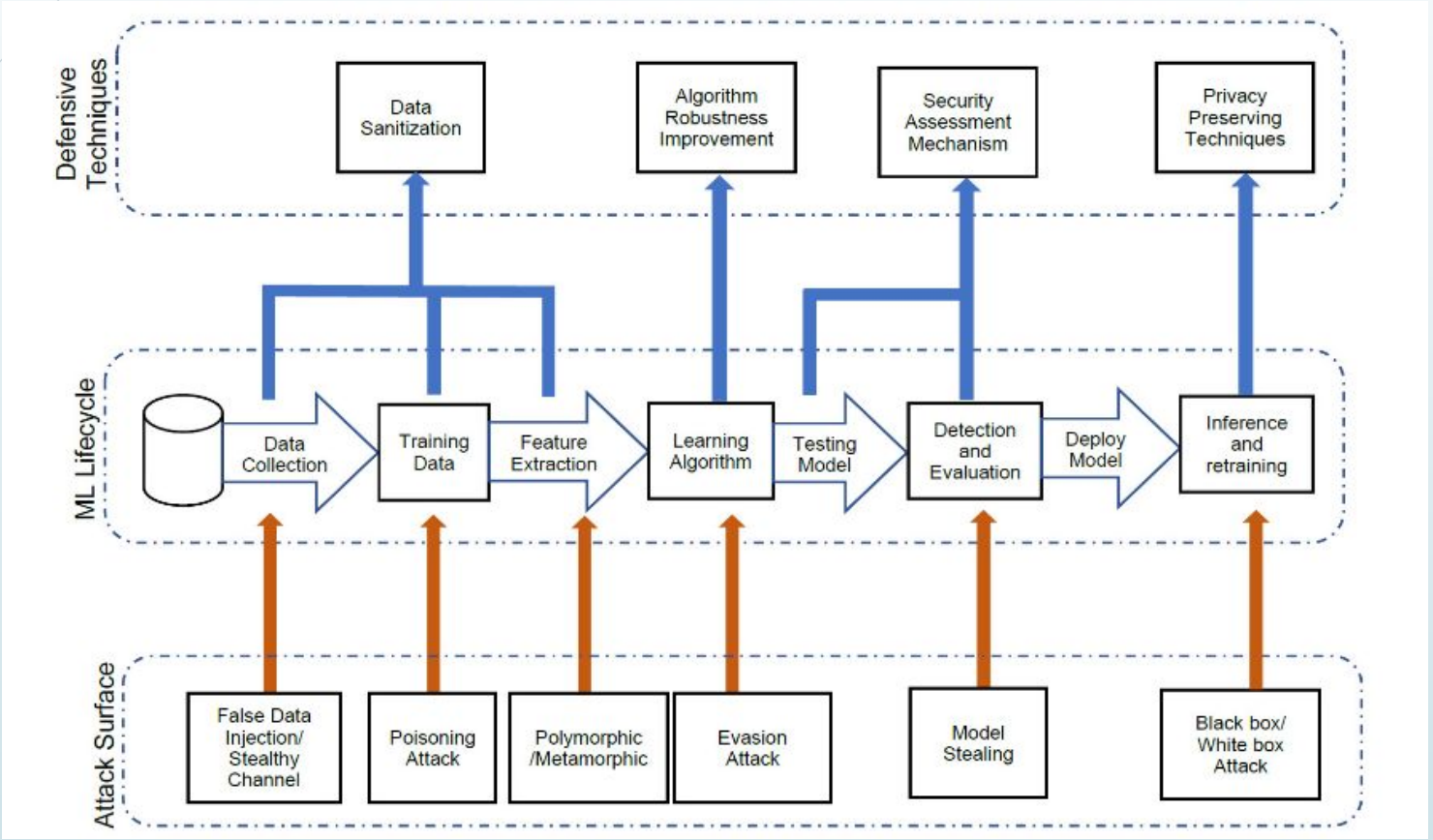
Ataques — MLSec (Adversarial Attacks)

Como um ataque inicia?



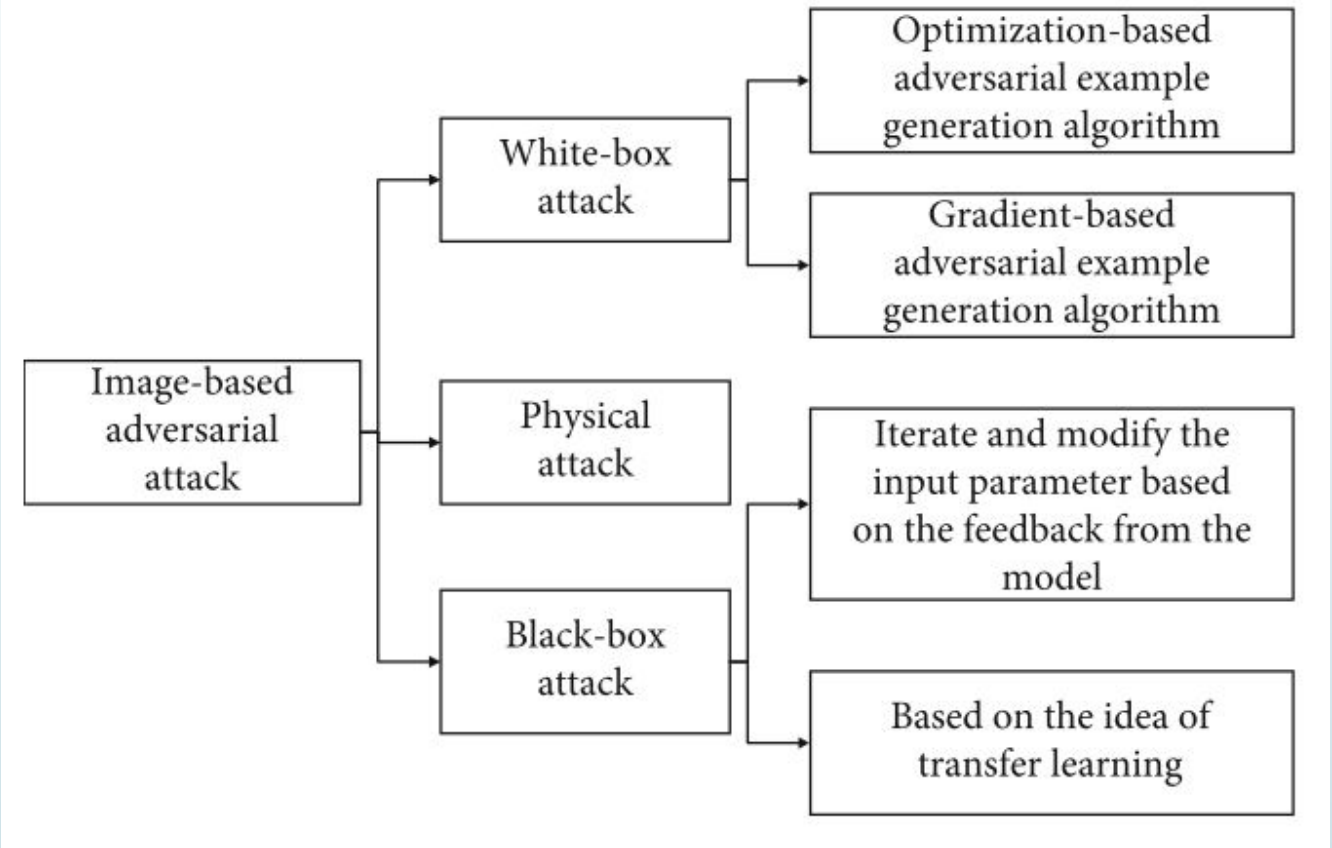
Wild patterns: Ten years after the rise of adversarial machine learning (2018)
Biggio, Battista; Roli, Fabio

Como um ataque inicia?



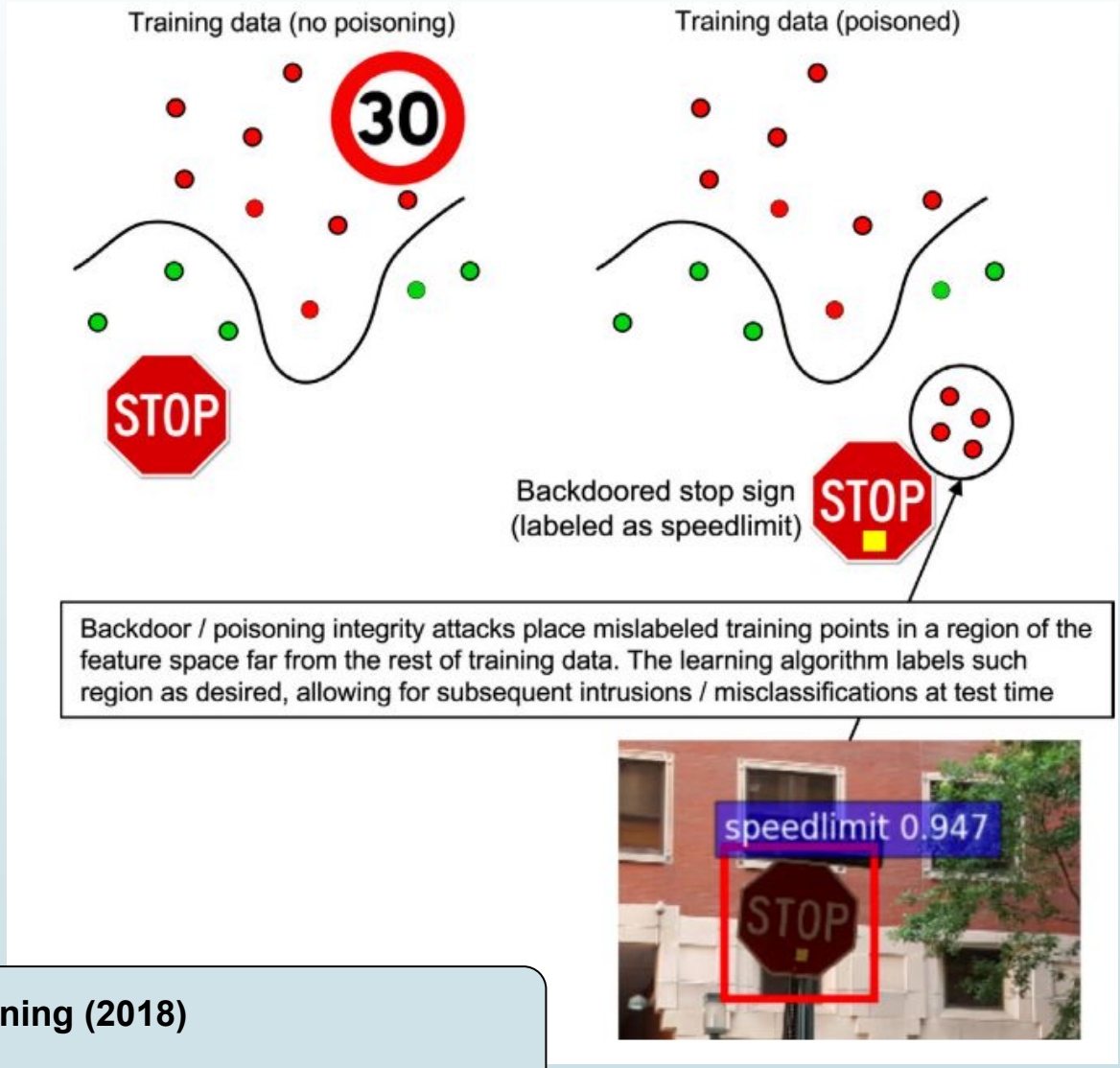
Applications in Security and Evasions in Machine Learning: A Survey (2020)
Sagar, Ramani; Jhaveri, Rutvij; Borrego, Carlos

Conhecimento do alvo



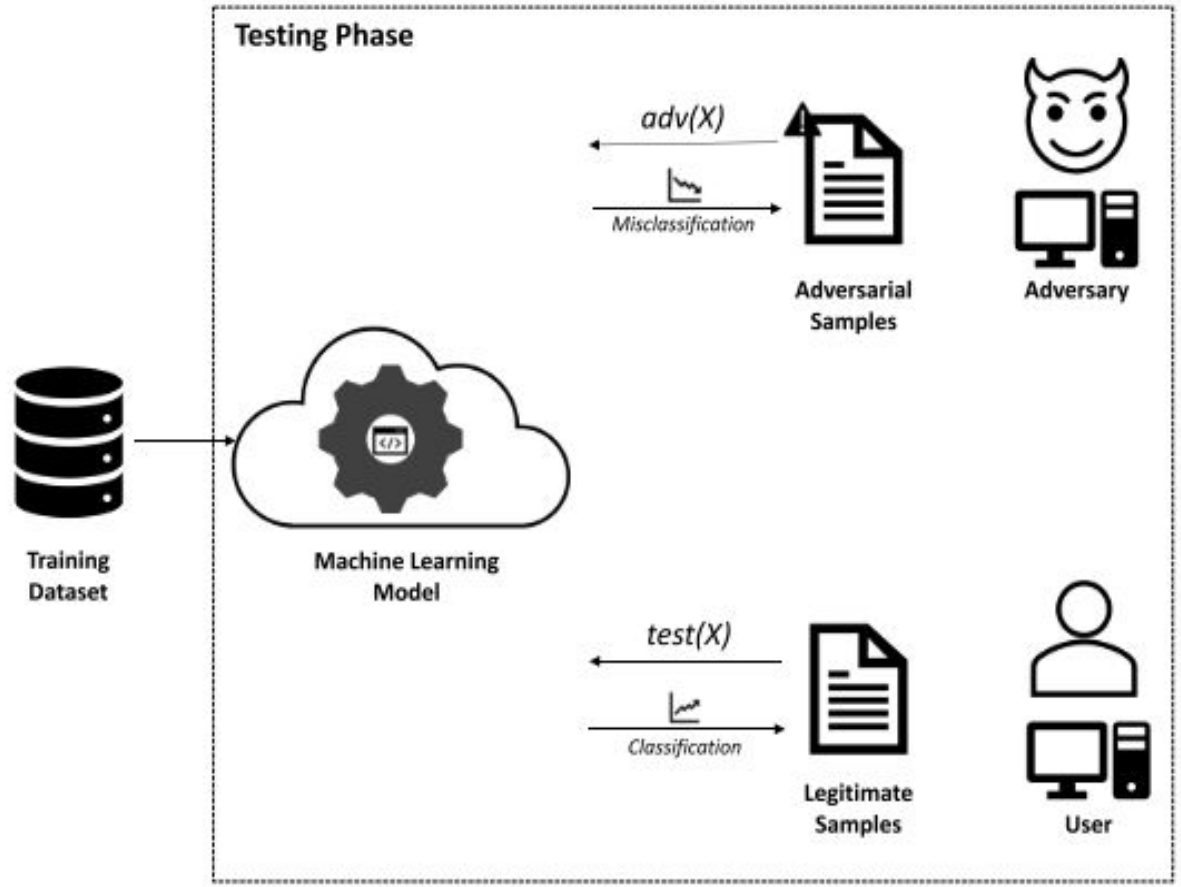
A Survey on Adversarial Attack in the Age of Artificial Intelligence (2021)
Kong, Zixiao; Xue, Jingfeng; Wang, Yong; Huang, Lu; Niu, Zequn; Li, Feng

Poisoning attacks



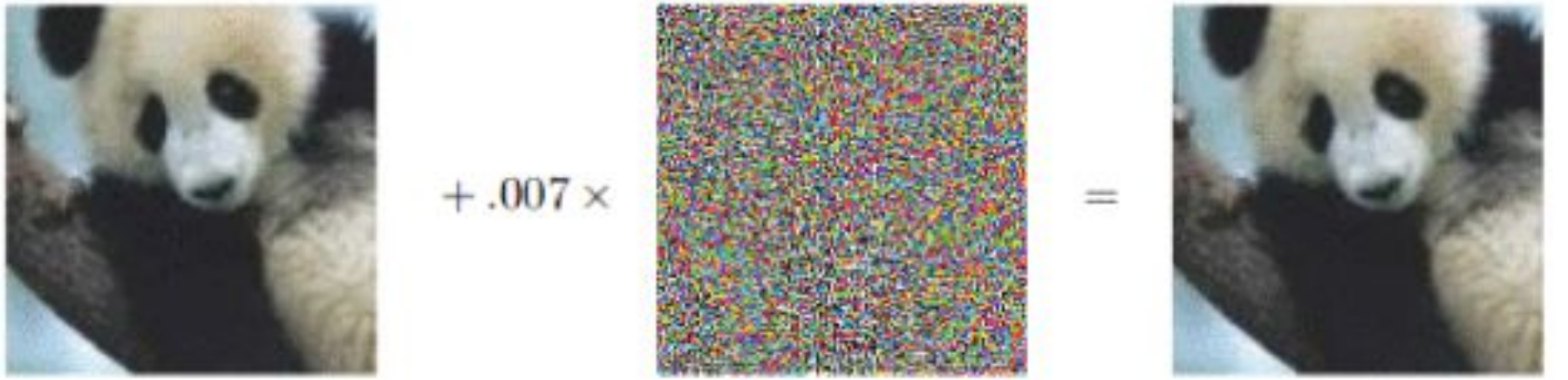
Wild patterns: Ten years after the rise of adversarial machine learning (2018)
Biggio, Battista; Roli, Fabio

Evasion attacks



Model Evasion Attack on Intrusion Detection Systems using Adversarial Machine Learning (2020)
Ayub, Md Ahsan; Johnson, William A.; Talbert, Douglas A.; Siraj, Ambareen

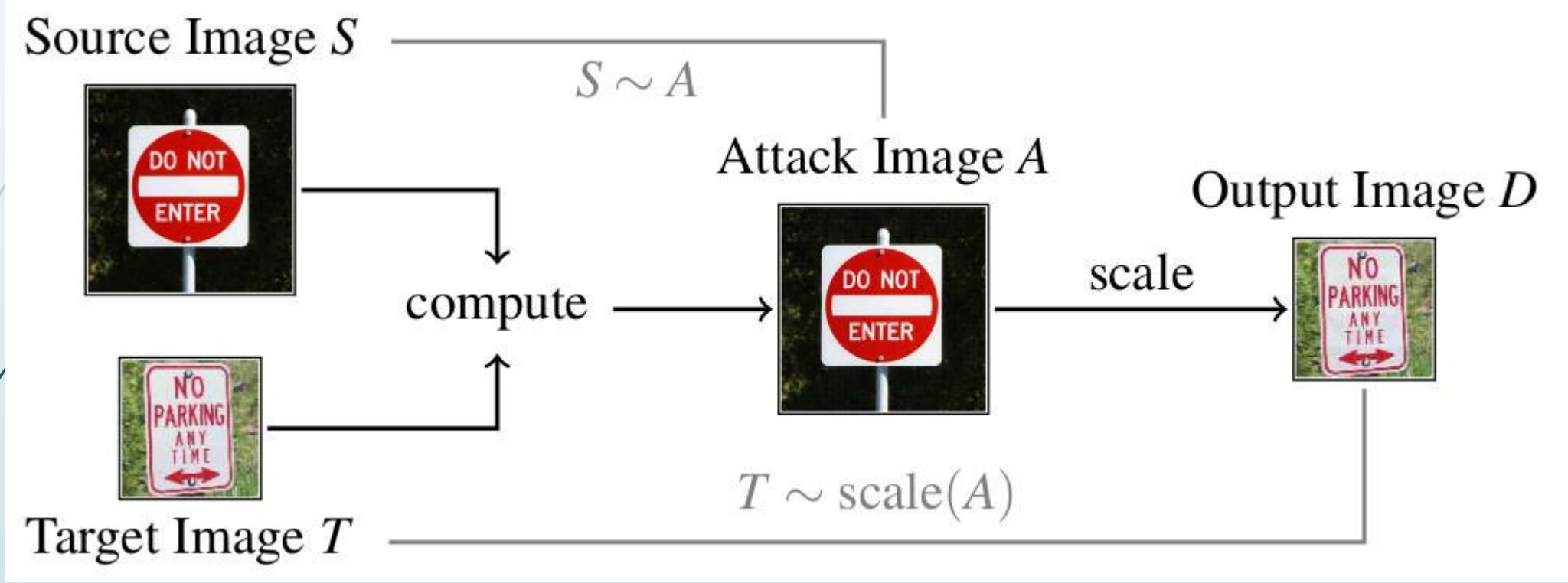
Fast gradient Sign Method



$$\tilde{x} = x + \epsilon sgn(\nabla_x J(w, x, y)).$$

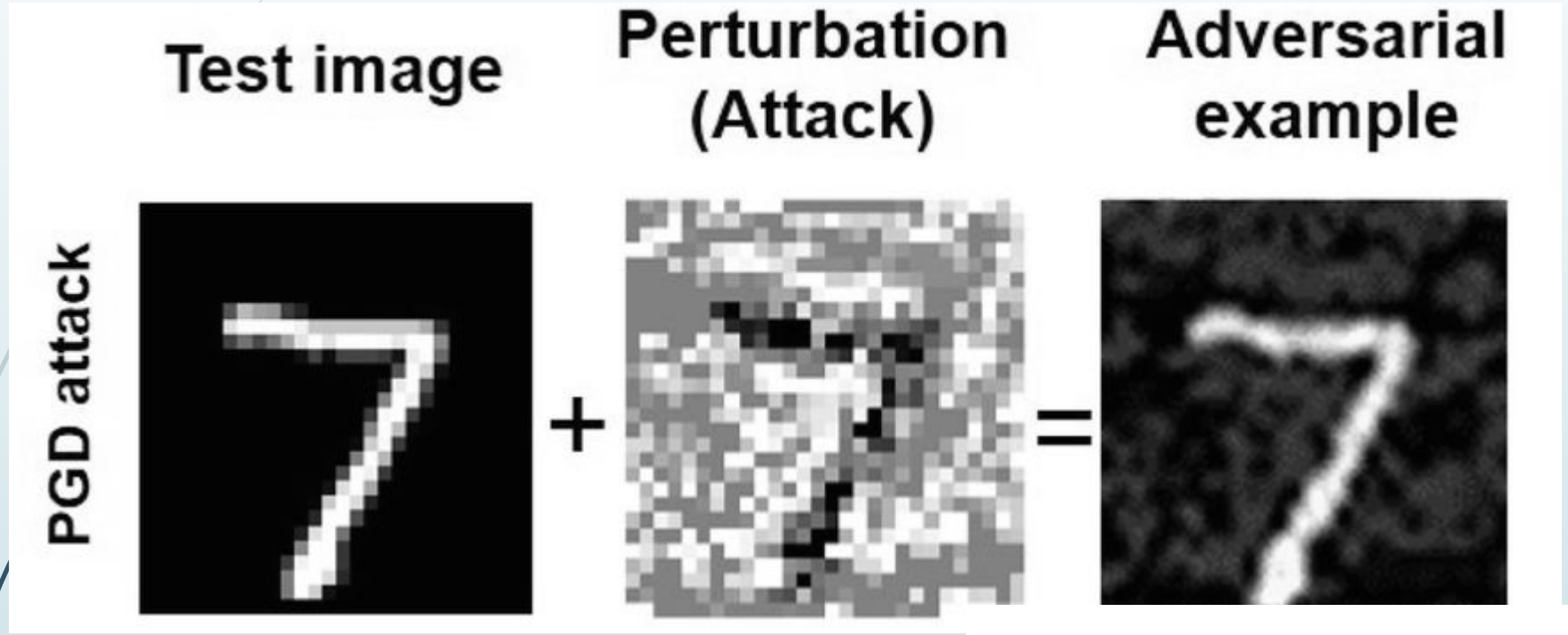
Adversarial Machine Learning Applied to Intrusion and Malware Scenarios: A Systematic Review (2021)
Biggio, Battista; Roli, Fabio

Ataques no pré-processamento



Adversarial Preprocessing: Understanding and Preventing Image-Scaling Attacks in Machine Learning (2020)
Quiring, Erwin; Klein, David; Arp, Daniel; Johns, Martin; Rieck, Konrad

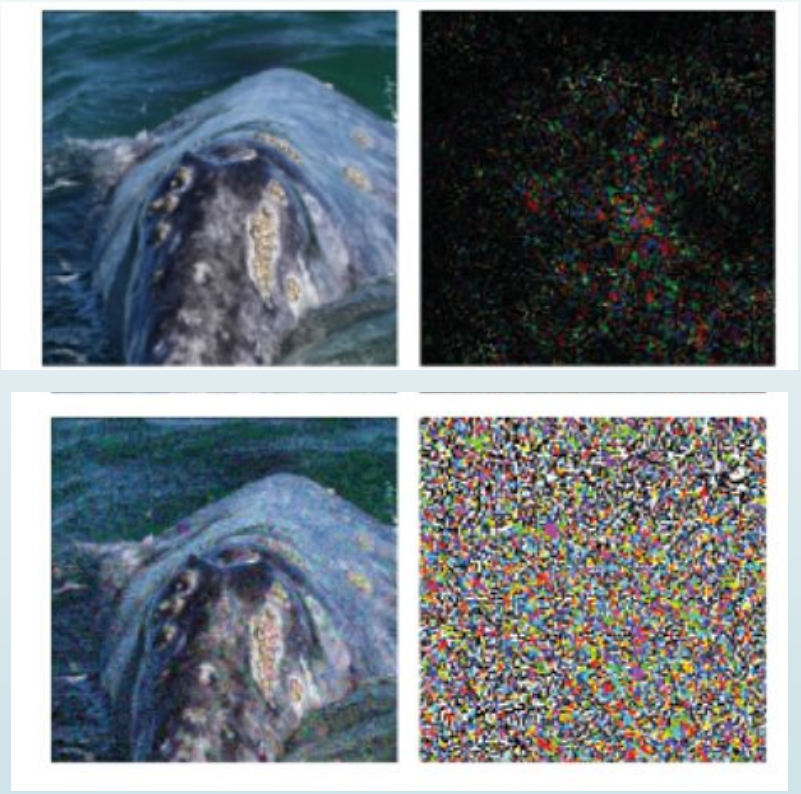
Projected Gradient Descent



$$x^{t+1} = \Pi_{x+s}(x^t + \alpha sgn(\nabla_x J(w, x, y))).$$

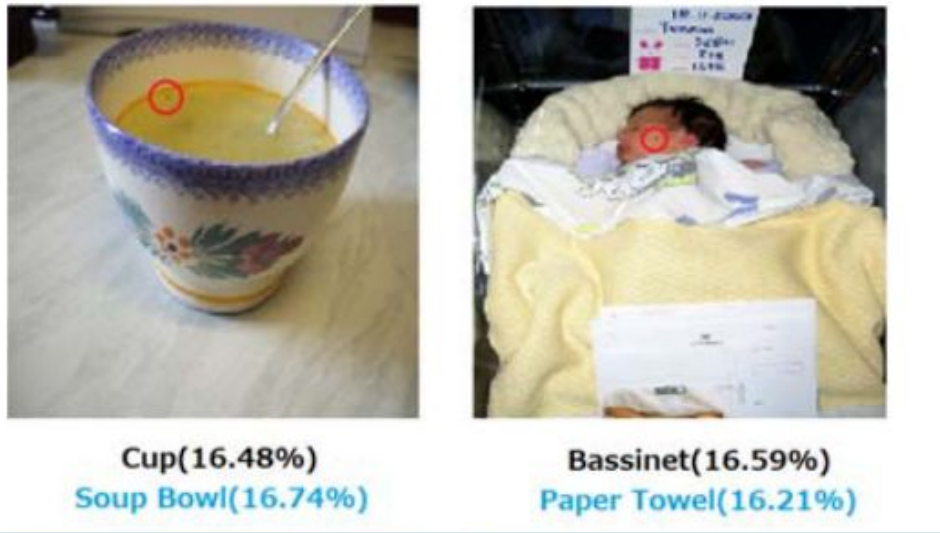
Towards Deep Learning Models Resistant to Adversarial Attacks (2018)
Madry, Aleksander; Makelov, Aleksandar; Schmidt, Ludwig; Tsipras, Dimitris; Vladu, Adrian

DeepFool



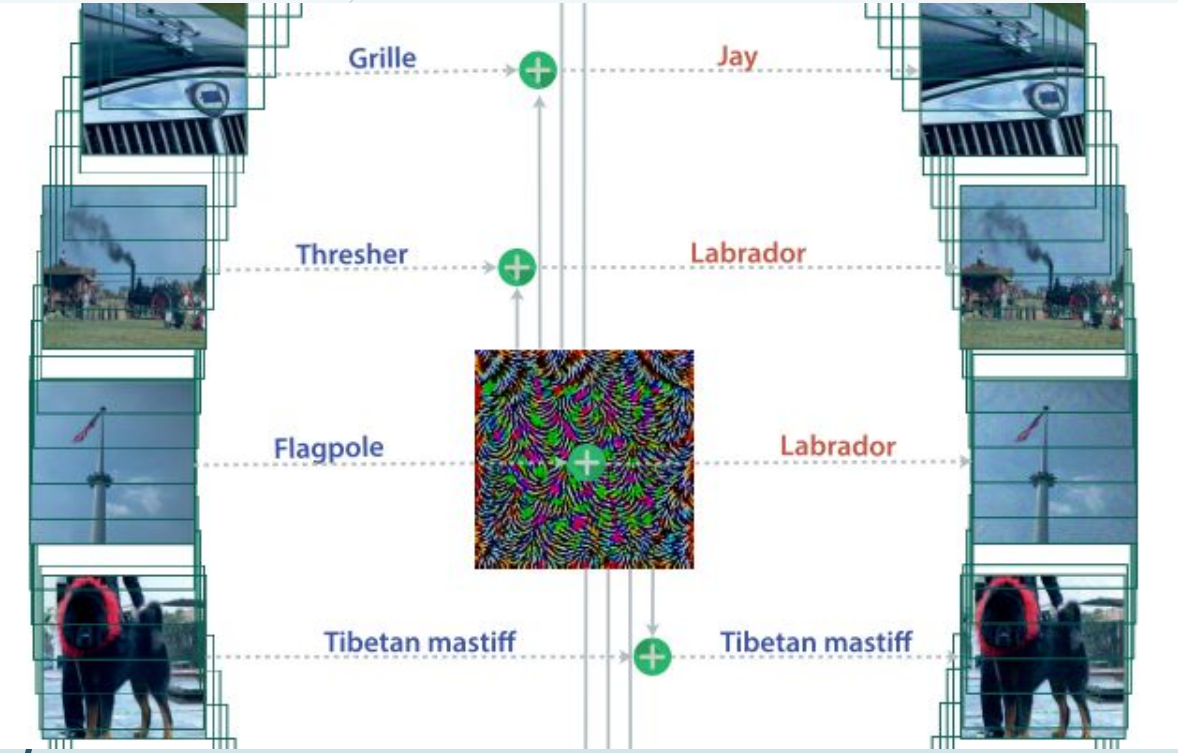
DeepFool: A Simple and Accurate Method to Fool Deep Neural Networks (2016)
Moosavi-Dezfooli; Mohsen, Seyed; Fawzi, Alhussein; Frossard, Pascal

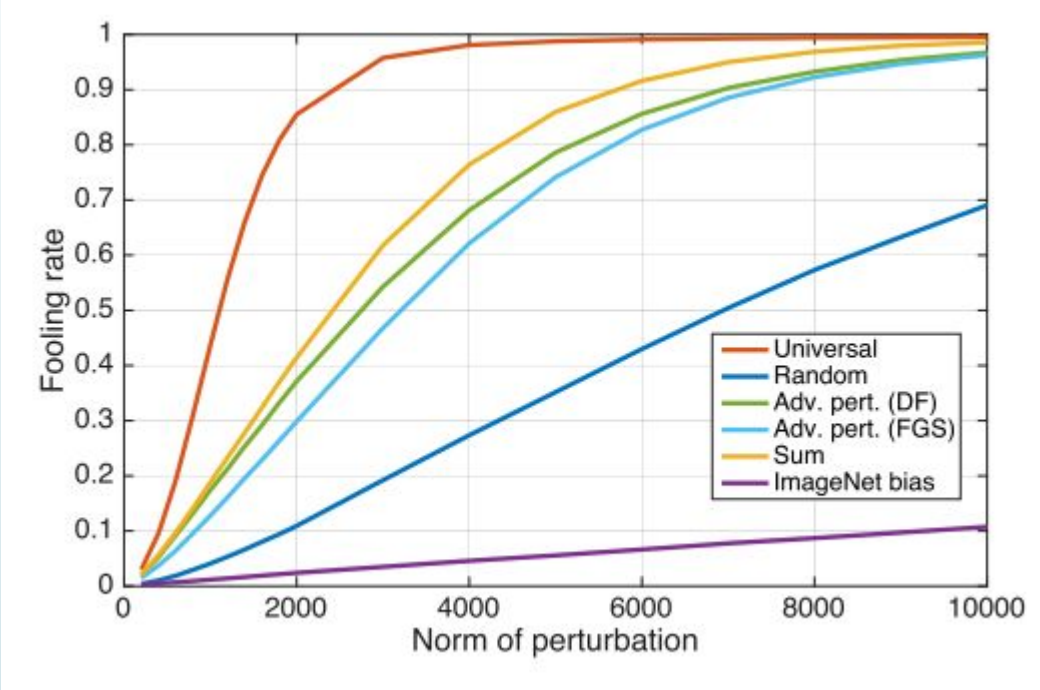
One Pixel Attack



One Pixel Attack for Fooling Deep Neural Networks (2019)
Su, Jiawei; Vargas, Danilo Vasconcellos; Sakurai, Kouichi

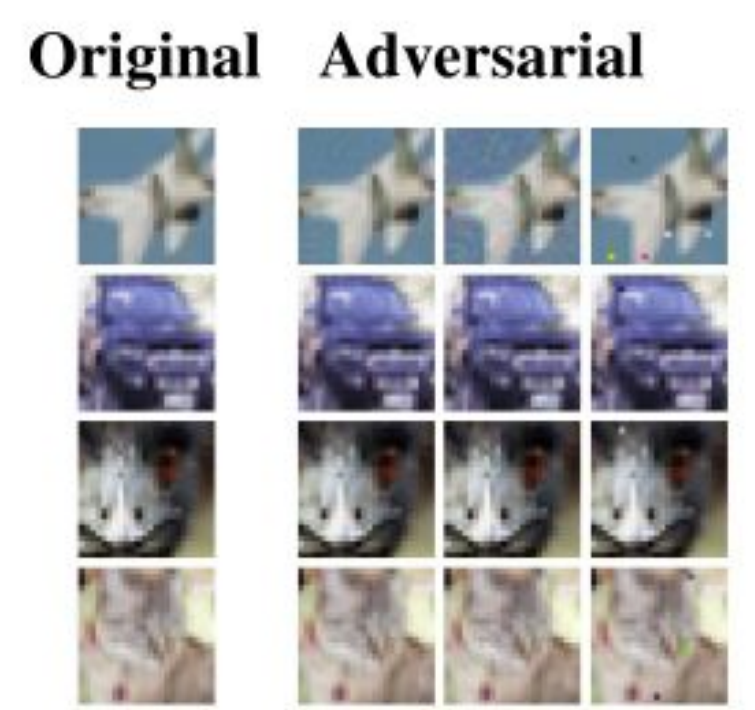
Universal perturbations





Universal adversarial perturbations (2017)
Moosavi-Dezfooli; Seyed Mohsen; Fawzi, Alhussein; Fawzi, Omar; Frossard, Pascal

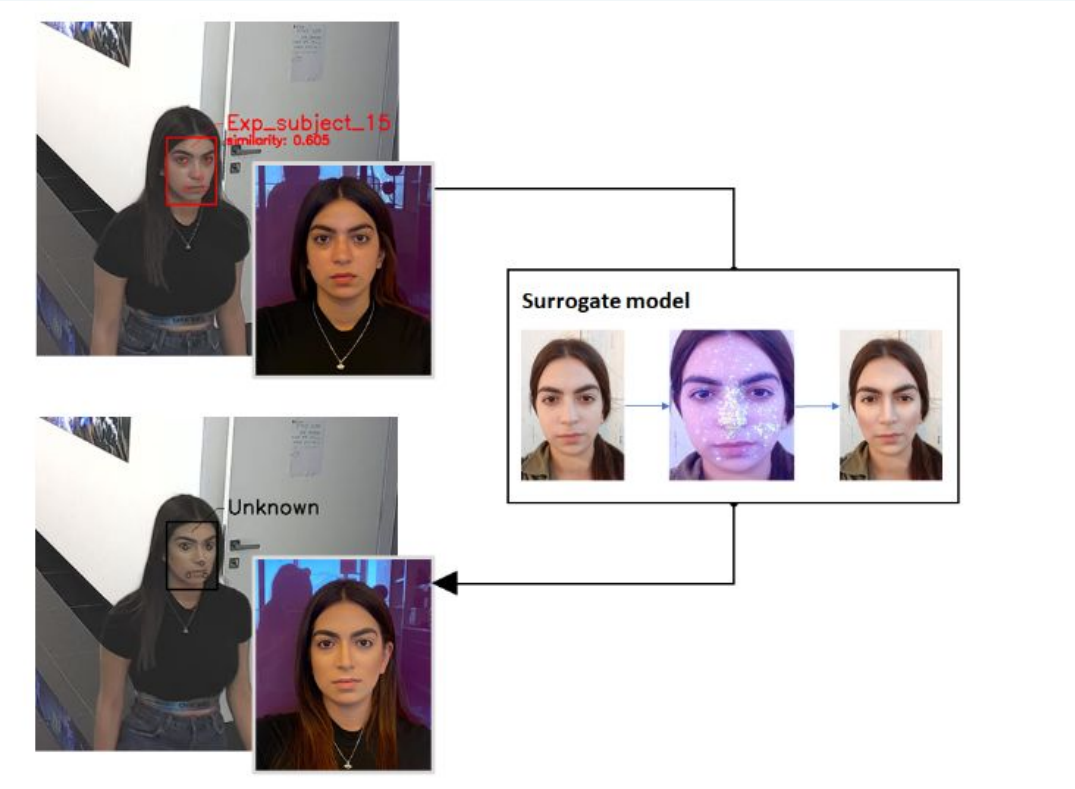
Carlini & Wagner Attack



$$\begin{aligned} \text{minimize} \quad & D(x, x+\delta) \\ \text{such that} \quad & C(x+\delta) = t \\ & x+\delta \in [0,1]^n \end{aligned}$$

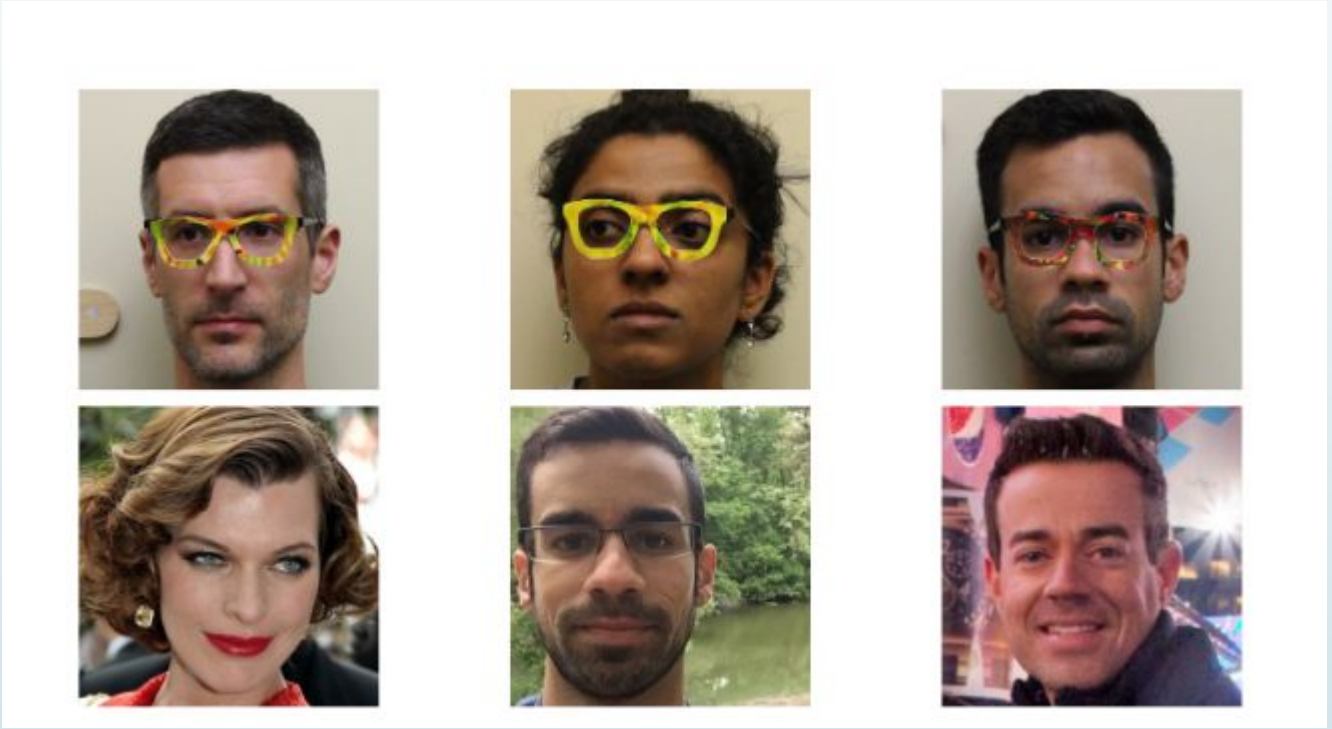
Towards Evaluating the Robustness of Neural Networks (2017)
Carlini, Nicholas; Wagner, David

Aplicações dos ataques no mundo real



Dodging Attack Using Carefully Crafted Natural Makeup (2021)
Nitzan Guett; Asaf Shabtai; Inderjeet Singh; Satoru Momiyama; Yuval Elovici

Aplicações dos ataques no mundo real



Accessorize to a Crime: Real and Stealthy Attacks on State-of-the-Art Face Recognition (2016)
Mahmood Sharif; Sruti Bhagavatula; Lujo Bauer Michael K. Reiter

Os impactos dos ataques adversários

Table 2. Test accuracy of LeNet5 measured between 20 and 50 epochs. The network is trained with data augmentation including random rotation, random translation and random erasing.

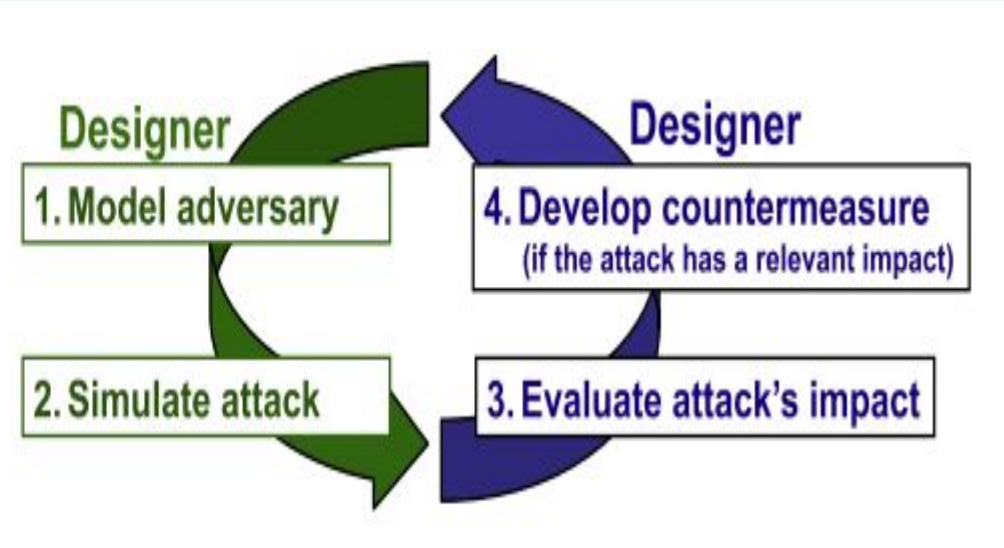
		Maximum				Median			
		Clean	FGSM	JSMA	C&W	Clean	FGSM	JSMA	C&W
Trained model	Clean	99.42	50.23	64.07	55.28	99.23	42.01	61.06	46.07
	FGSM	99.40	99.31	63.90	75.67	99.24	99.27	60.34	65.08
	JSMA	99.42	50.35	96.75	81.20	99.30	48.46	96.35	75.02
	C&W	99.37	74.12	69.00	99.57	99.22	61.17	63.30	99.31
	FGSM + JSMA	99.40	99.32	96.29	90.05	99.28	99.26	95.15	84.94
	FGSM + C&W	99.43	99.32	65.27	99.65	99.24	99.26	62.96	99.42
	JSMA + C&W	99.43	73.98	96.70	98.99	99.35	70.71	95.83	98.58
	FGSM + JSMA + C&W	99.36	99.30	95.82	98.81	99.27	99.21	94.92	98.39

On the Effectiveness of Adversarial Training in Defending against Adversarial Example Attacks for Image Classification (2020)
Ramani Sagar; Rutvij Jhaveri; Carlos Borrego

Código

Defesa — MLSec

Projeto de um modelo defensivo



Wild patterns: Ten years after the rise of adversarial machine learning (2018)
Biggio, Battista; Roli, Fabio

Projeto de um modelo defensivo

***Reactive* Defenses**

1. timely detection of attacks
2. frequent retraining
3. decision verification

***Proactive* Defenses**

Security-by-Design Defenses
against white-box attacks (no probing)

1. secure/robust learning
2. attack detection

Effect on decision boundaries:
noise-specific margin,
enclosure of legitimate training classes

Security-by-Obscurity Defenses
against gray-box and black-box attacks (probing)

1. information hiding, randomization
2. detection of probing attacks

Wild patterns: Ten years after the rise of adversarial machine learning (2018)
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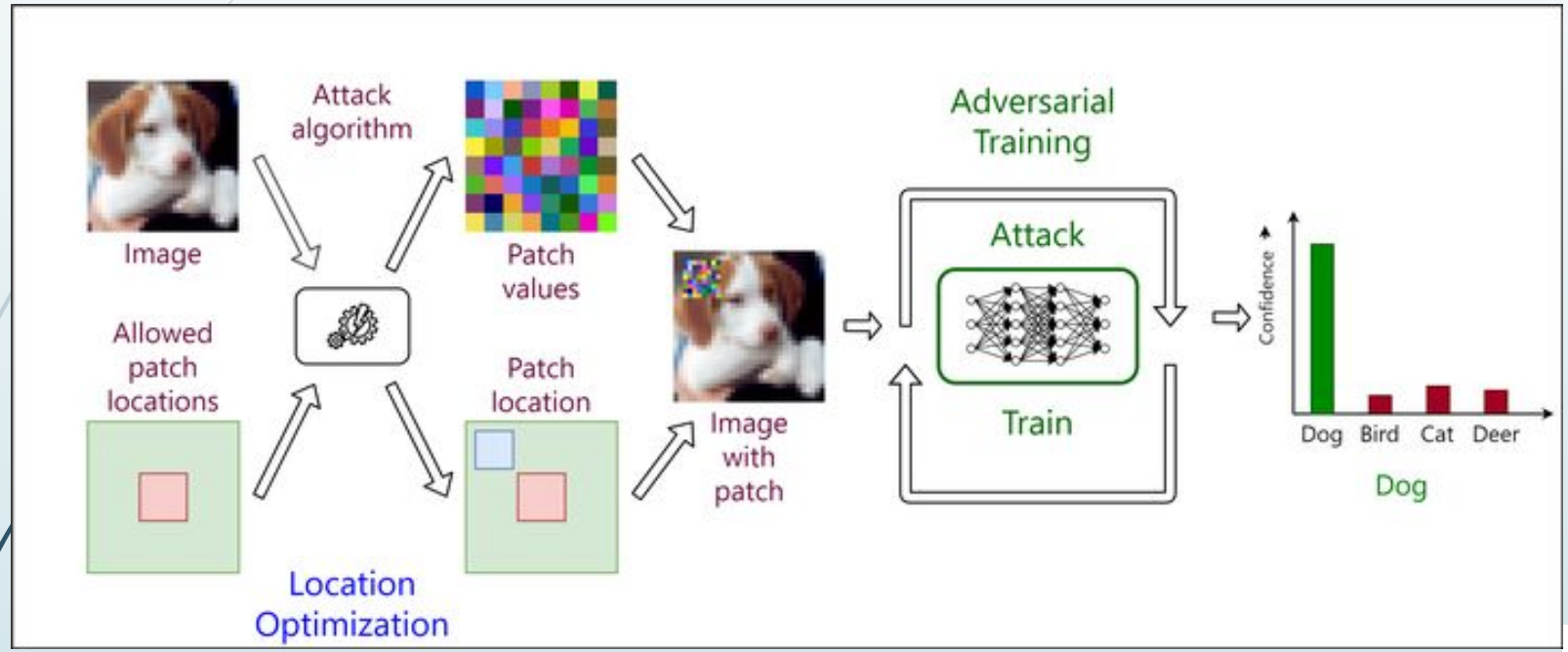
Treino adversário

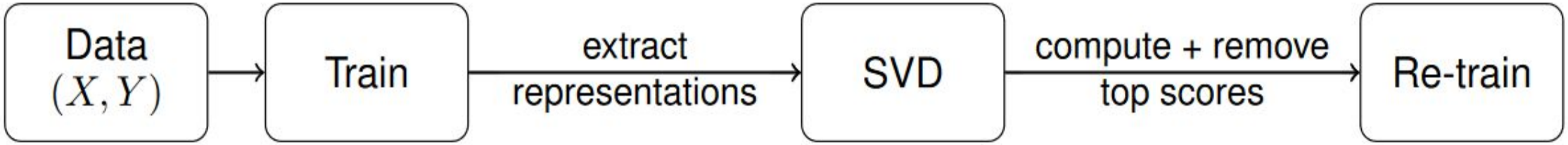


Adversarial Training against Location-Optimized Adversarial Patches (2020)
Sukrut Rao, David Stutz, Bernt Schiele

Towards Deep Learning Models Resistant to Adversarial Attacks (2018)
Madry, Aleksander; Makelov, Aleksandar; Schmidt, Ludwig; Tsipras, Dimitris; Vladu, Adrian

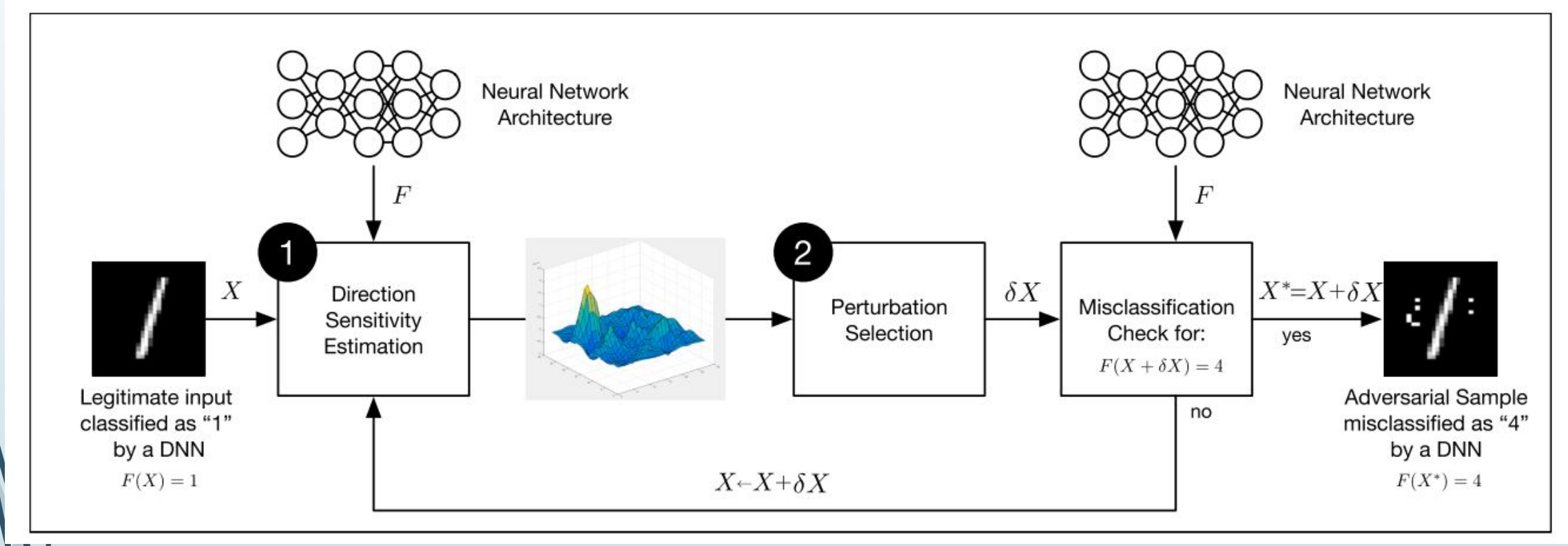
$$\min_{\theta} \max_{\delta \in S} L(\theta, x+\delta, y).$$

Detectção de backdoors - Spectral Signatures



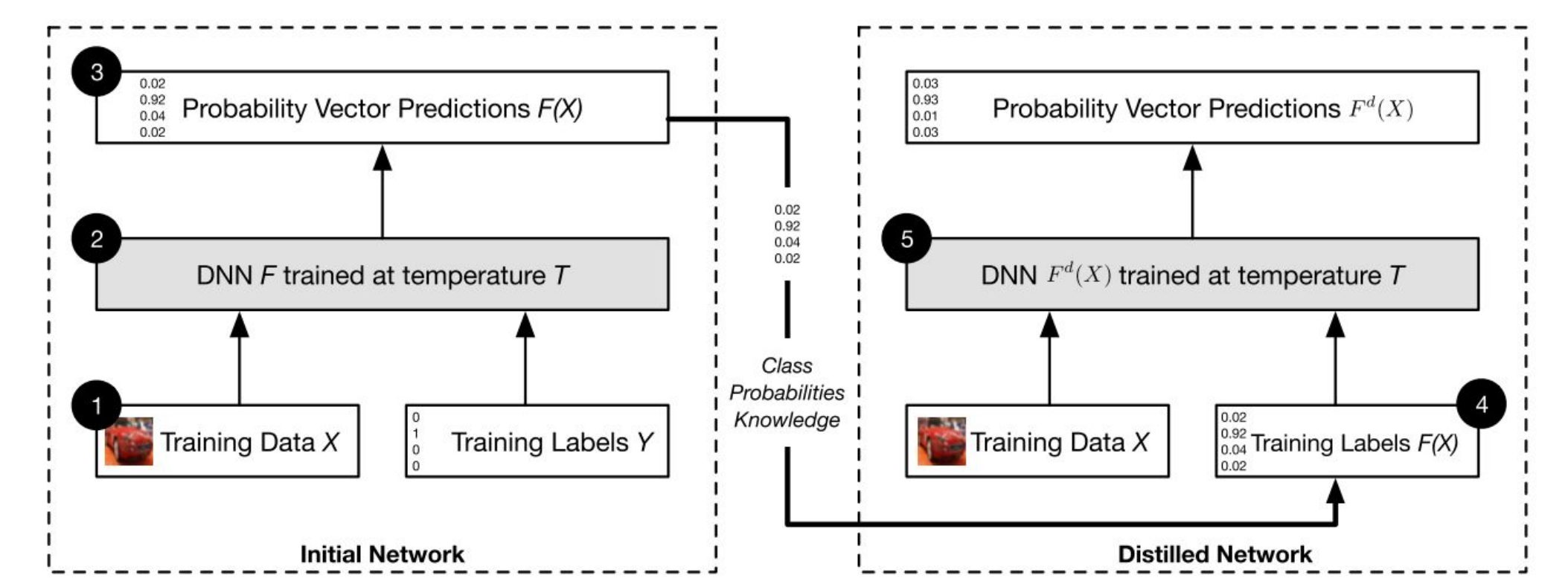
Spectral Signatures in Backdoor Attacks (2018)
Brandon Tran, Jerry Li, Aleksander Madry

Defensive distillation - ataque



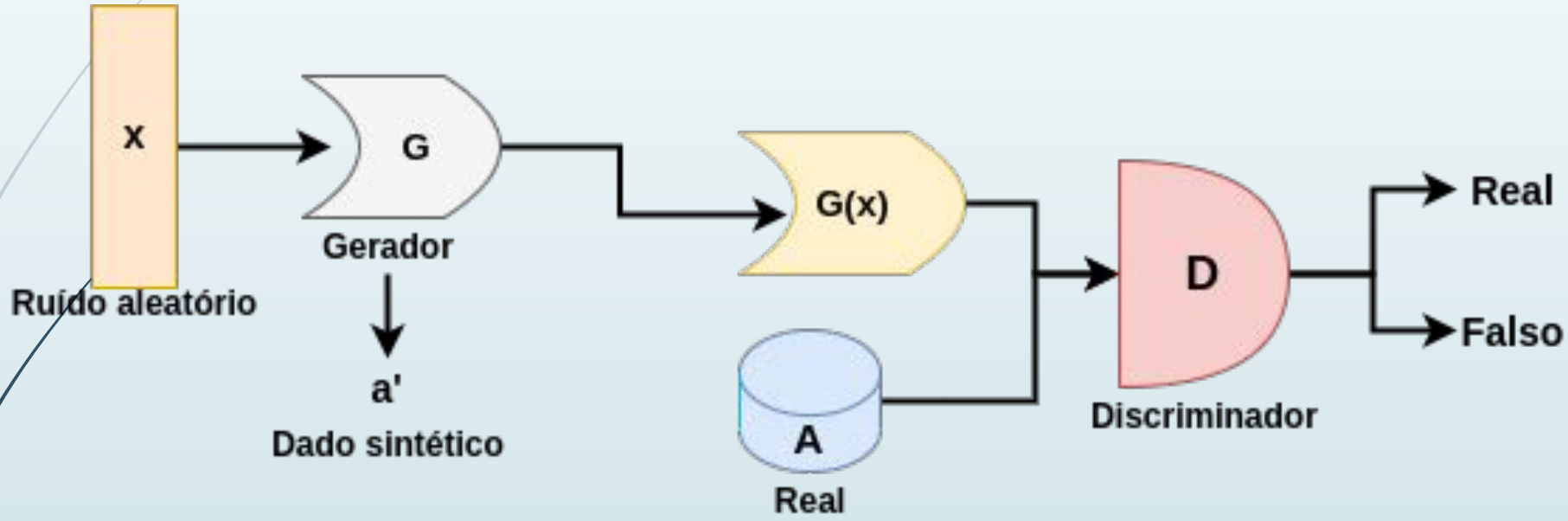
Distillation as a Defense to Adversarial Perturbations against Deep Neural Networks (2016)
Nicolas Papernot; Patrick McDaniel, Xi Wu; Somesh Jha; Ananthram Swami

Defensive distilation - defesa



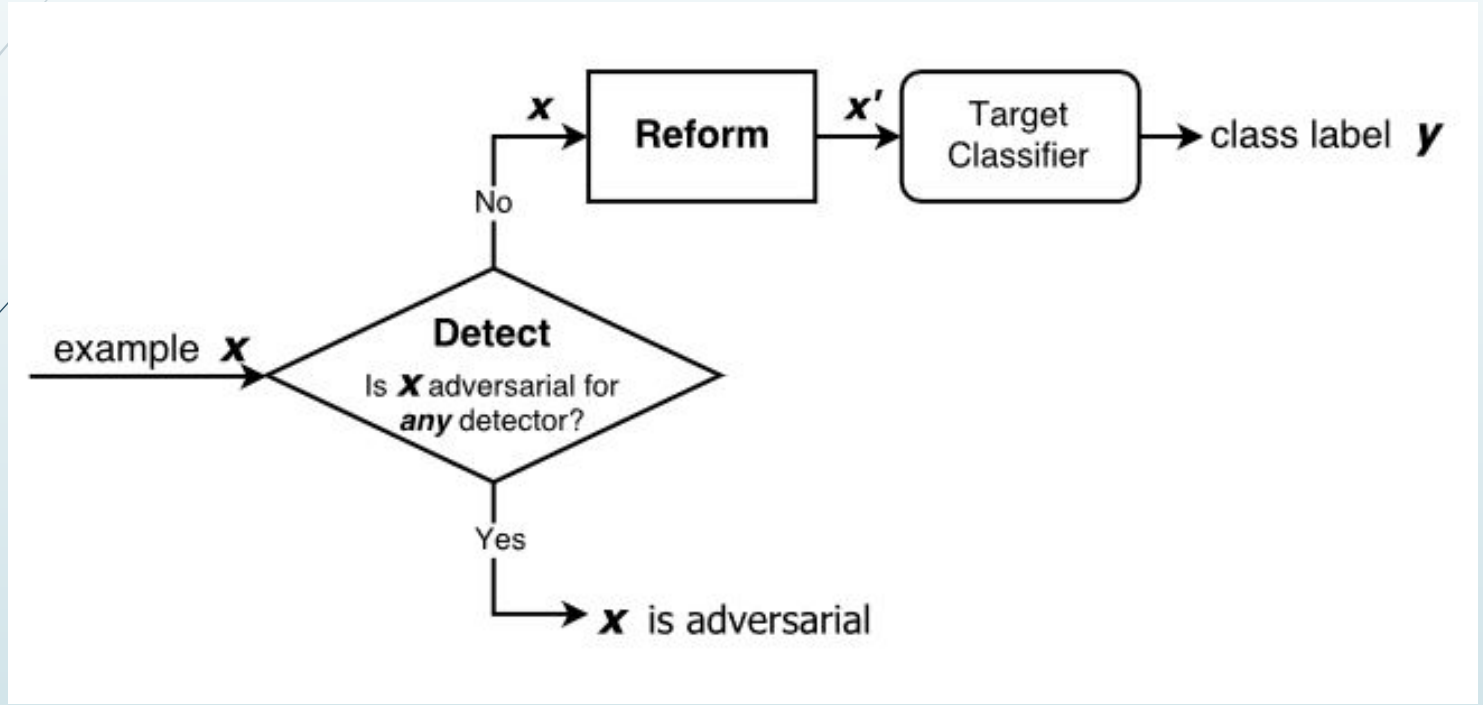
Distillation as a Defense to Adversarial Perturbations against Deep Neural Networks (2016)
Nicolas Papernot; Patrick McDaniel, Xi Wu; Somesh Jha; Ananthram Swami

MagNet - GAN



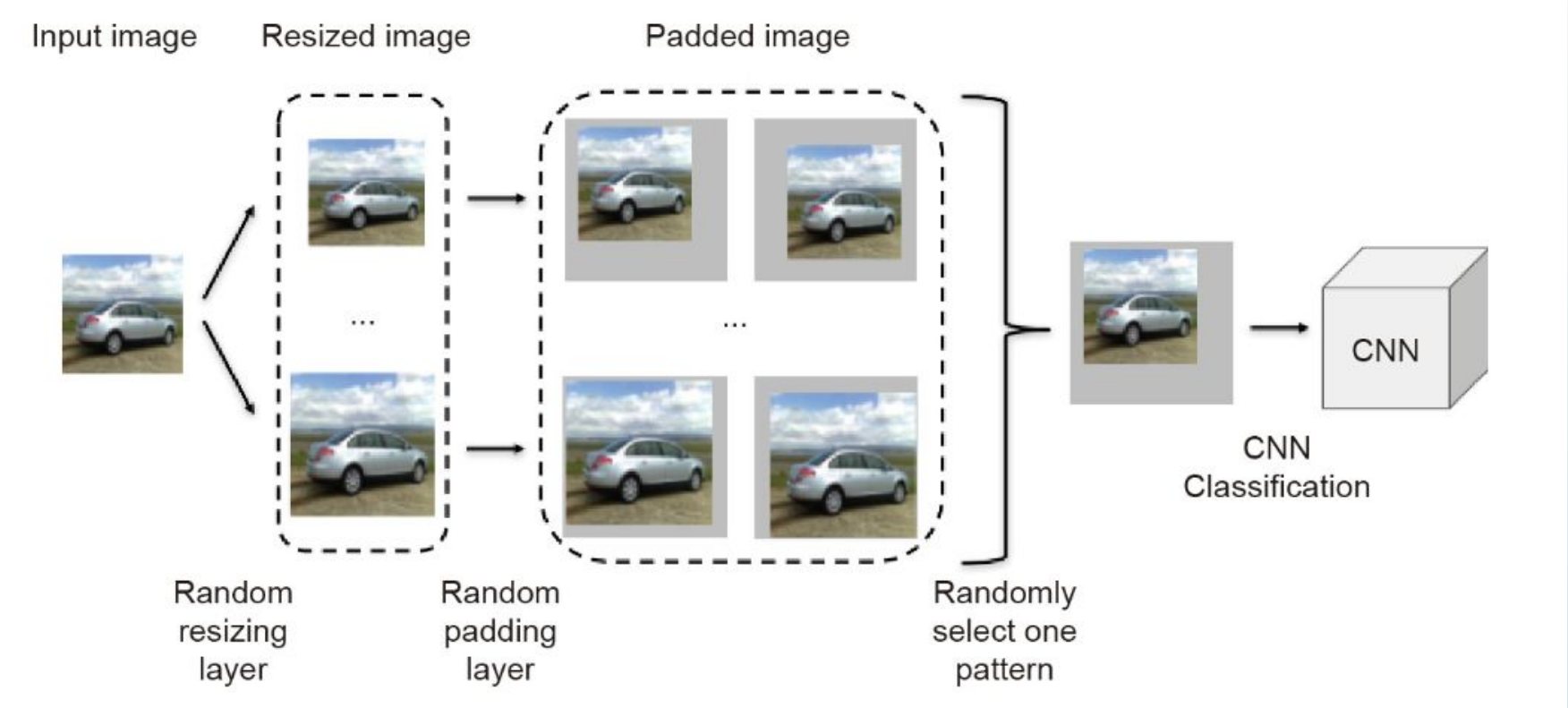
MagNet: a Two-Pronged Defense against Adversarial Examples (2017)
Dongyu Meng; Hao Chen

MagNet



MagNet: a Two-Pronged Defense against Adversarial Examples (2017)
Dongyu Meng; Hao Chen

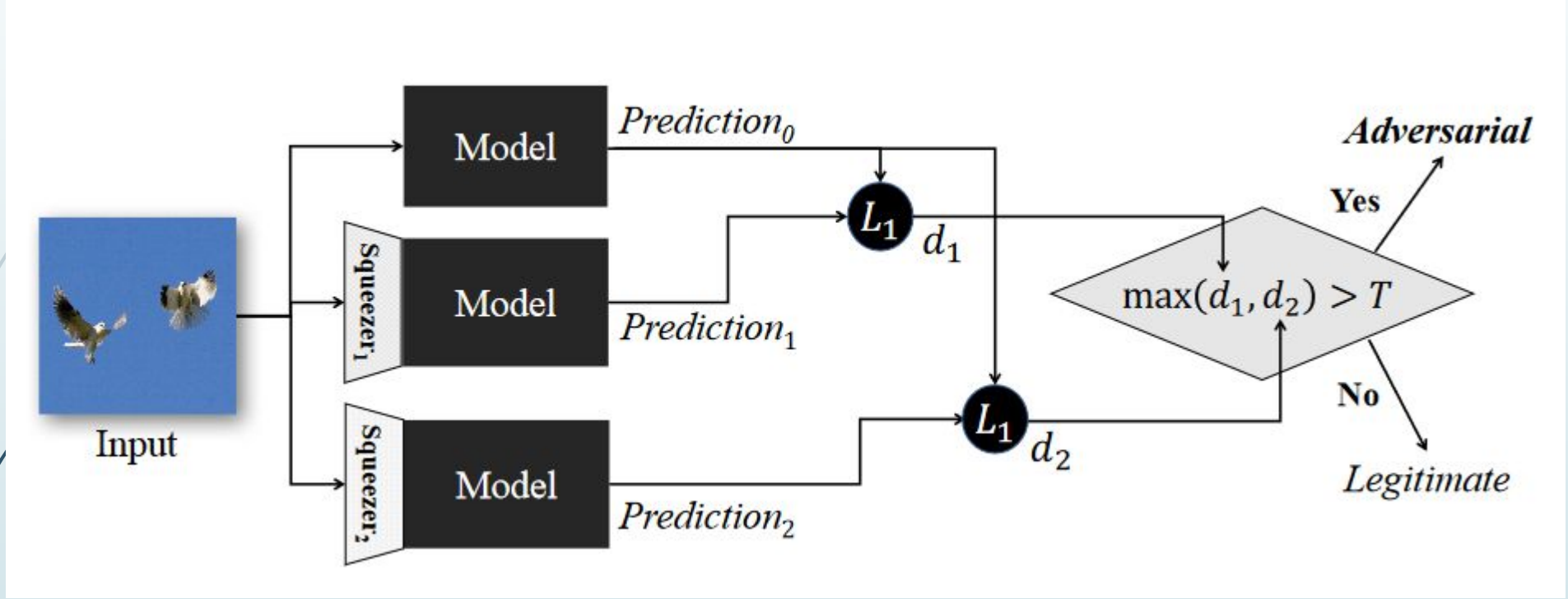
Randomização



Mitigating Adversarial Effects Through Randomization (2017)
Cihang Xie; Jianyu Wang; Zhishuai Zhang; Zhou Ren; Alan Yuille

Adversarial Attacks and Defenses in Deep Learning (2019)
Kui Ren; Tianhang Zheng; Zhan Qin; Xue Liu

feature-squeezing



Adversarial Attacks and Defenses in Deep Learning (2019)
Kui Ren; Tianhang Zheng; Zhan Qin; Xue Liu

Feature Squeezing: Detecting Adversarial Examples in Deep Neural Networks (2017)
Weilin Xu; David Evans; Yanjun Qi

Outros métodos

Research
Artificial Intelligence—Feature Article

Adversarial Attacks and Defenses in Deep Learning

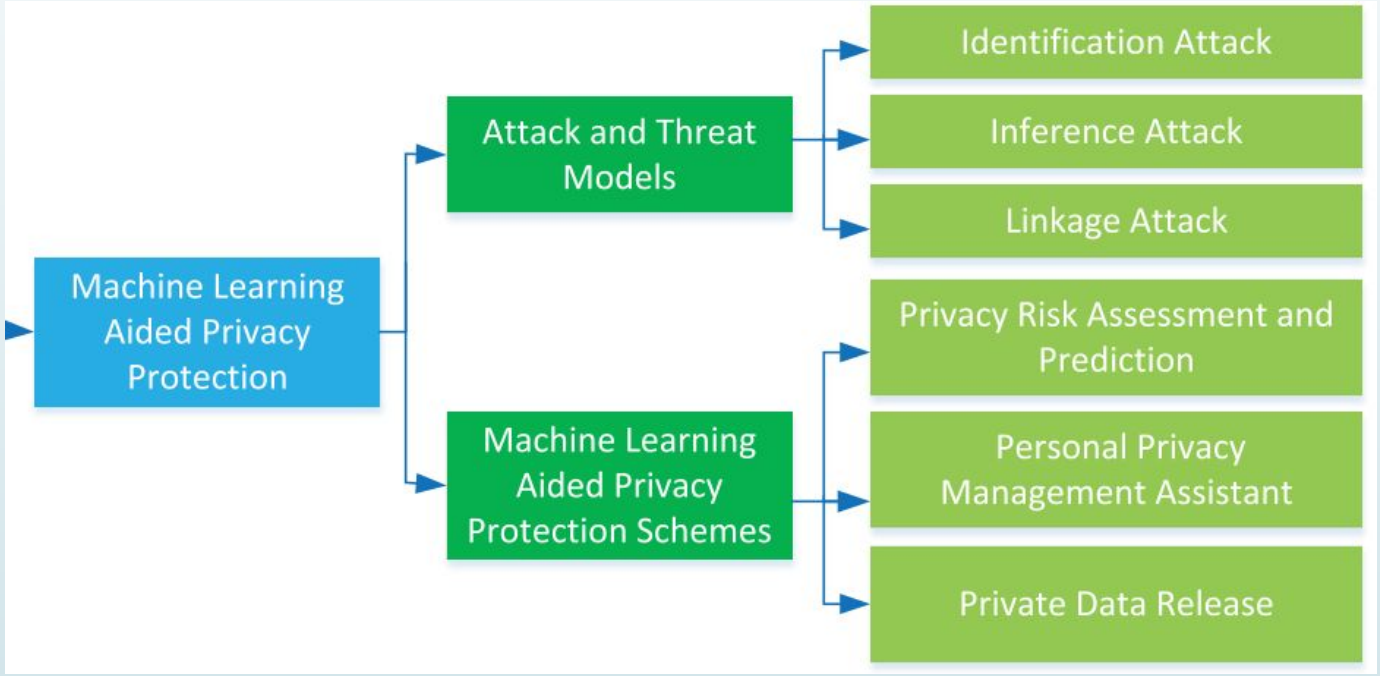
Kui Ren [a,b,*], Tianhang Zheng [c], Zhan Qin [a,b], Xue Liu [d]

[a] *Institute of Cyberspace Research, Zhejiang University, Hangzhou 310027, China*
[b] *College of Computer Science and Technology, Zhejiang University, Hangzhou 310027, China*
[c] *Department of Electrical and Computer Engineering, University of Toronto, Toronto, ON M5S 2E8, Canada*
[d] *School of Computer Science, McGill University, Montreal, QC H3A 0E9, Canada*

Adversarial Attacks and Defenses in Deep Learning (2019)
Kui Ren; Tianhang Zheng; Zhan Qin; Xue Liu

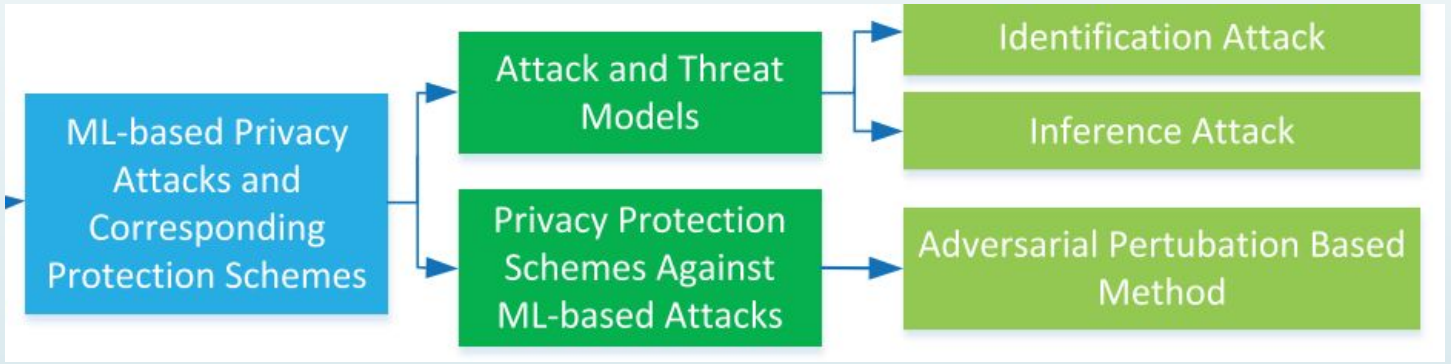
Privacidade — MLSec
Problemas e soluções

Privacidade baseada em ML



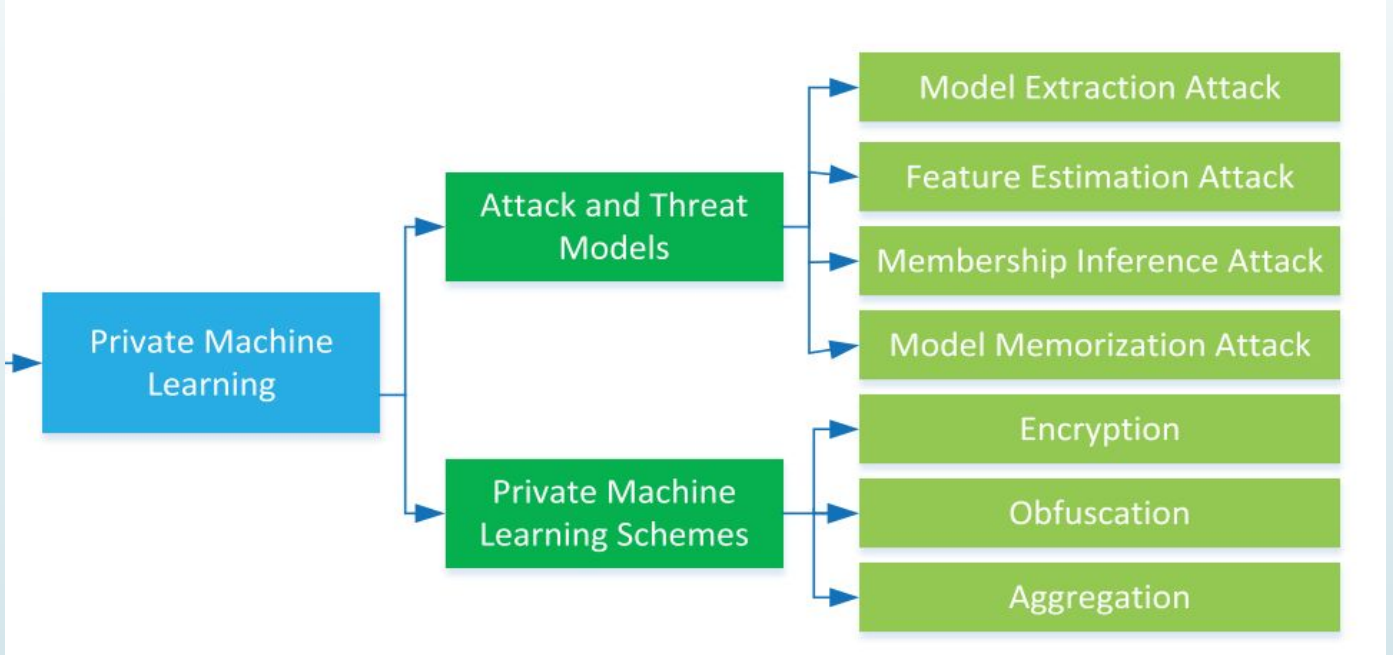
When Machine Learning Meets Privacy: A Survey and Outlook (2021)
Liu, Bo; Ding, Ming; Shaham, Sina; Rahayu, Wenny; Farokhi, Farhad; Lin, Zihuai

Mecanismos de proteção



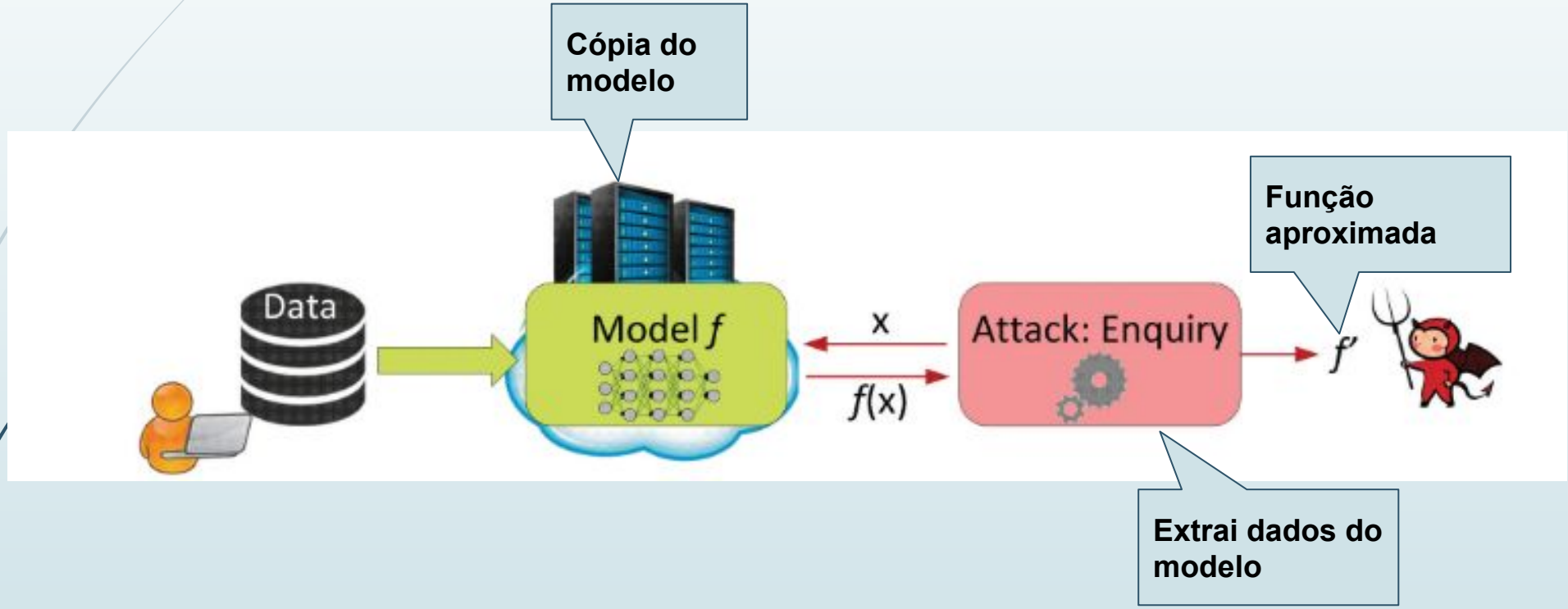
When Machine Learning Meets Privacy: A Survey and Outlook (2021)
Liu, Bo; Ding, Ming; Shaham, Sina; Rahayu, Wenny; Farokhi, Farhad; Lin, Zihuai

Privacidade em ML (Modelos)



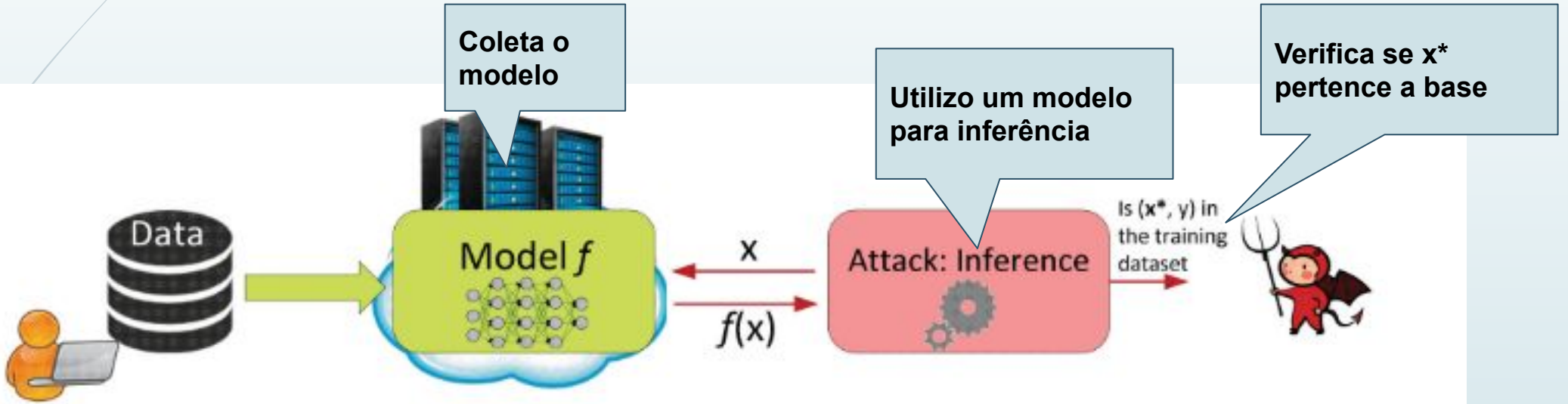
When Machine Learning Meets Privacy: A Survey and Outlook (2021)
Liu, Bo; Ding, Ming; Shaham, Sina; Rahayu, Wenny; Farokhi, Farhad; Lin, Zihuai

Model extraction attack



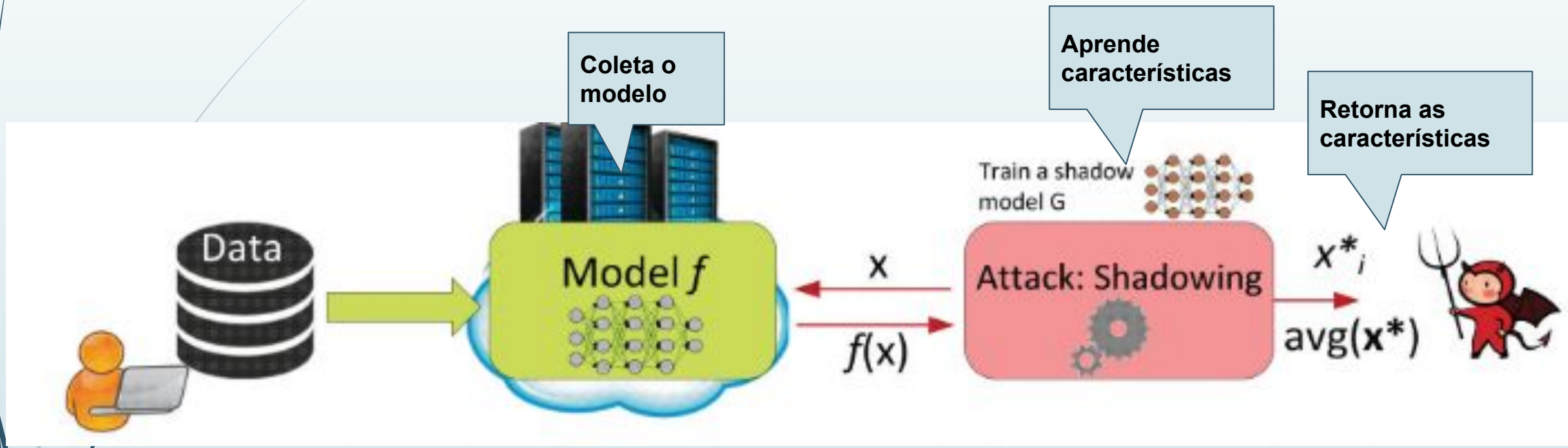
When Machine Learning Meets Privacy: A Survey and Outlook (2021)
Liu, Bo; Ding, Ming; Shaham, Sina; Rahayu, Wenny; Farokhi, Farhad; Lin, Zihuai

Membership inference attack



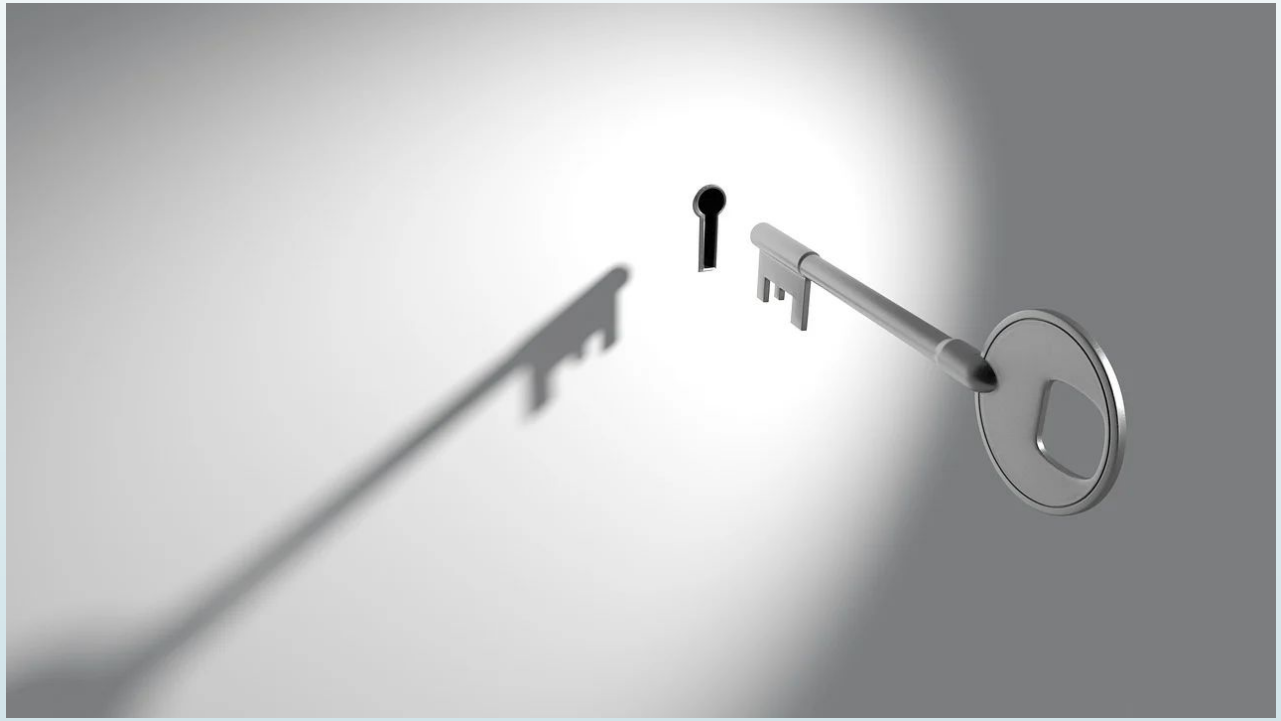
When Machine Learning Meets Privacy: A Survey and Outlook (2021)
Liu, Bo; Ding, Ming; Shaham, Sina; Rahayu, Wenny; Farokhi, Farhad; Lin, Zihuai

Feature Estimation Attack

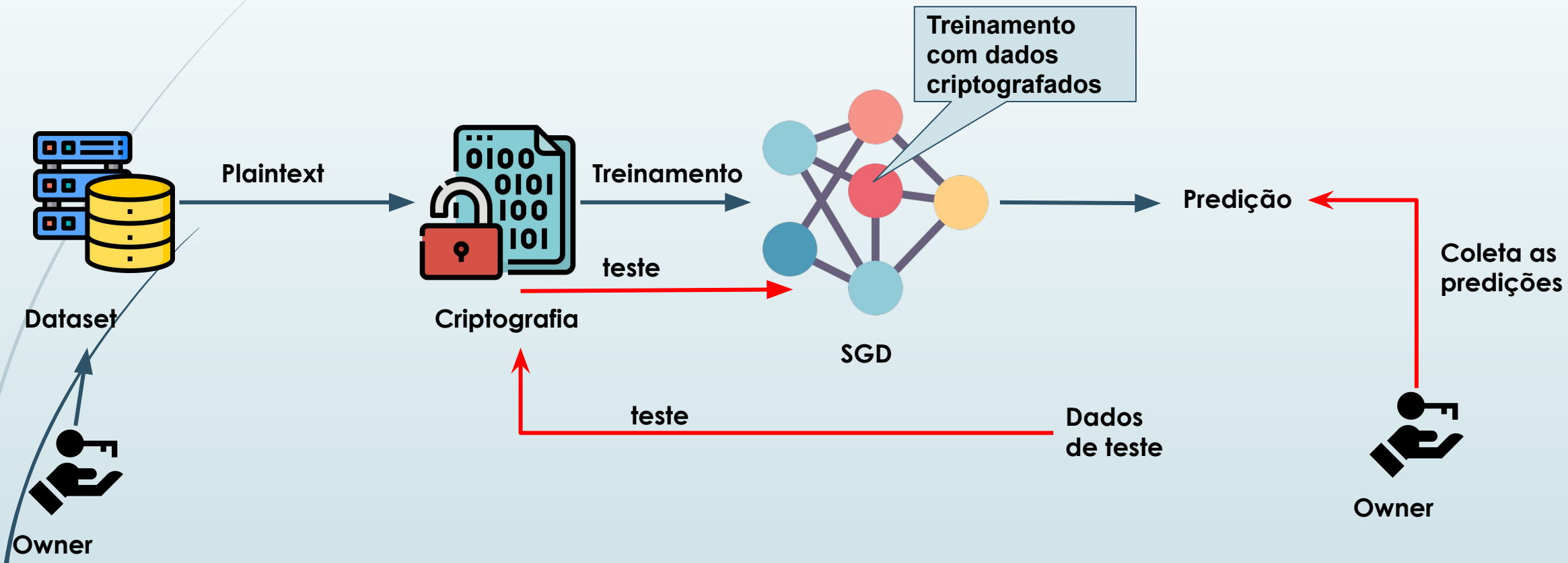


When Machine Learning Meets Privacy: A Survey and Outlook (2021)
Liu, Bo; Ding, Ming; Shaham, Sina; Rahayu, Wenny; Farokhi, Farhad; Lin, Zihuai

Mitigando problemas

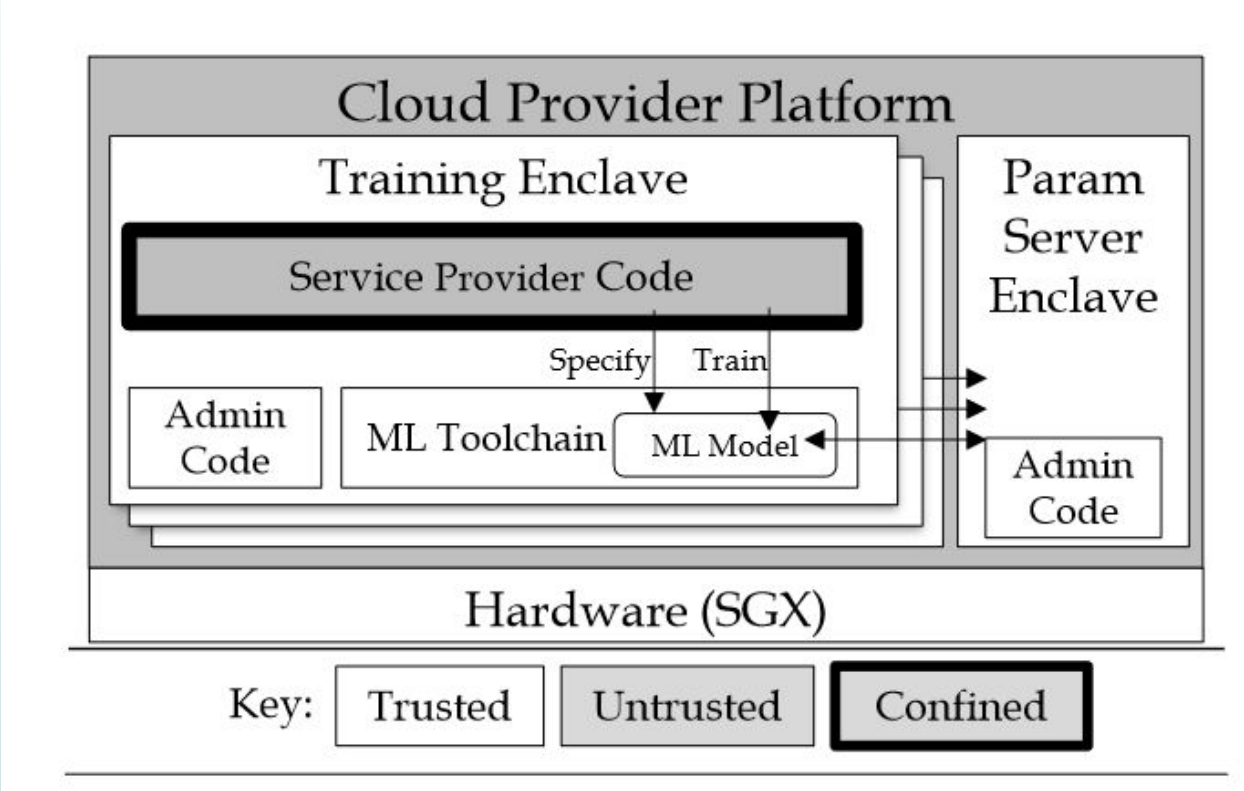


Homomorphic encryption



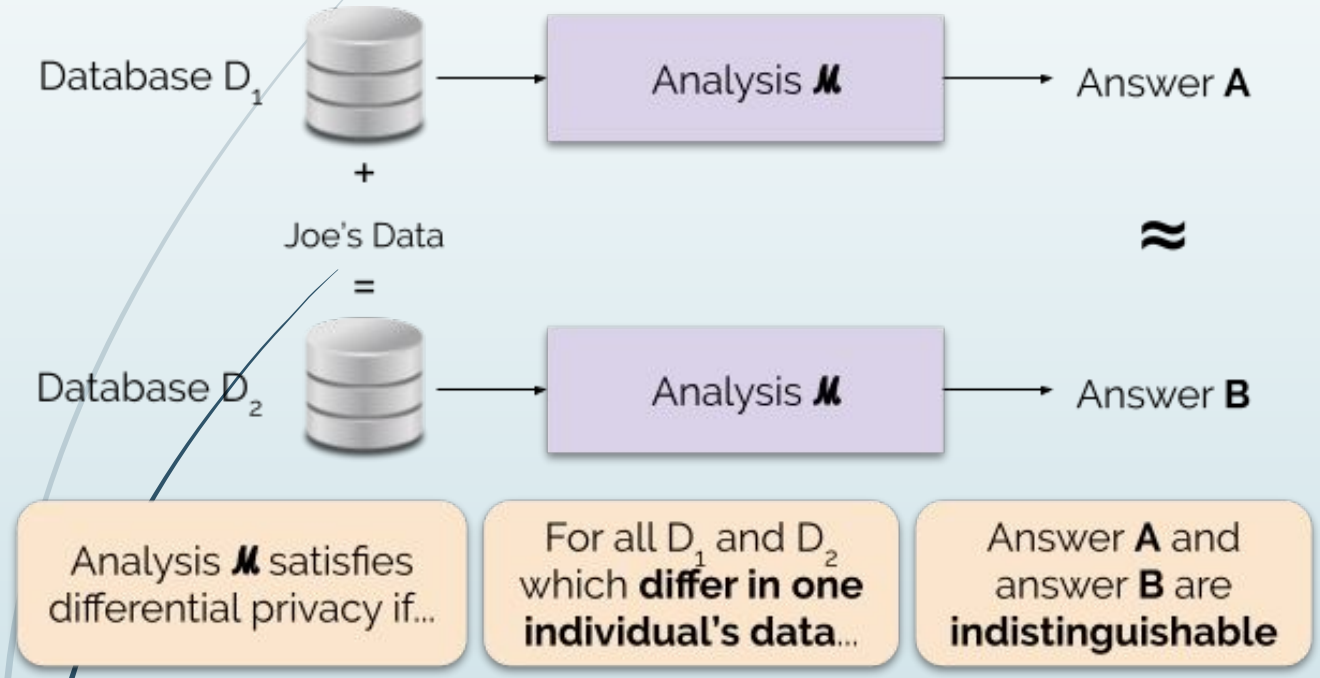
CryptoNets: Applying Neural Networks to Encrypted Data with High Throughput and Accuracy (2016)
Nathan Dowlin; Ran Gilad-Bachrach; Kim Laine; Kristin Lauter; Michael Naehrig; John Wernsing

Homomorphic encryption + SGX



Chiron: Privacy-preserving Machine Learning as a Service (2018)
Tyler Hunt, Congzheng Song, Reza Shokri, Vitaly Shmatikov, Emmett Witchel

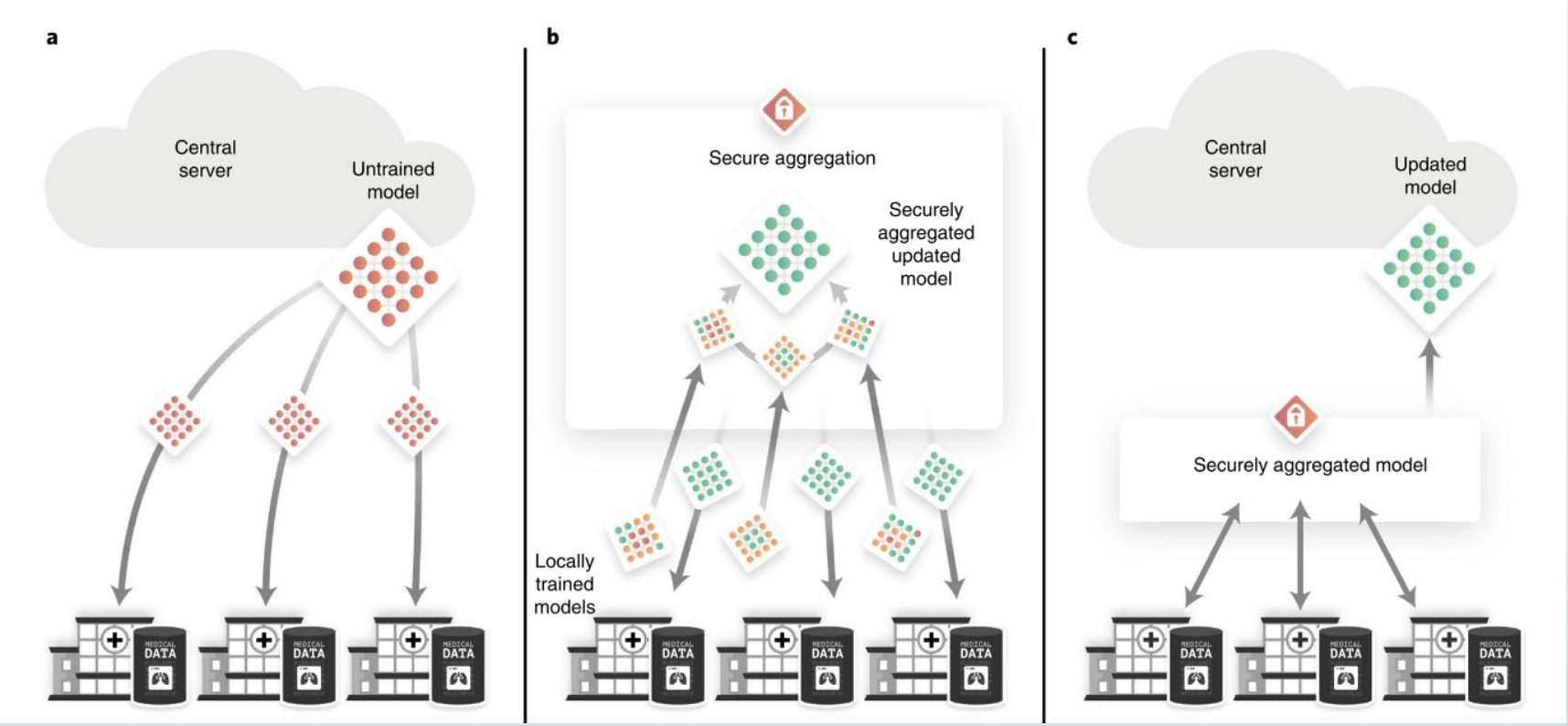
Differential privacy - SGD



Opacus

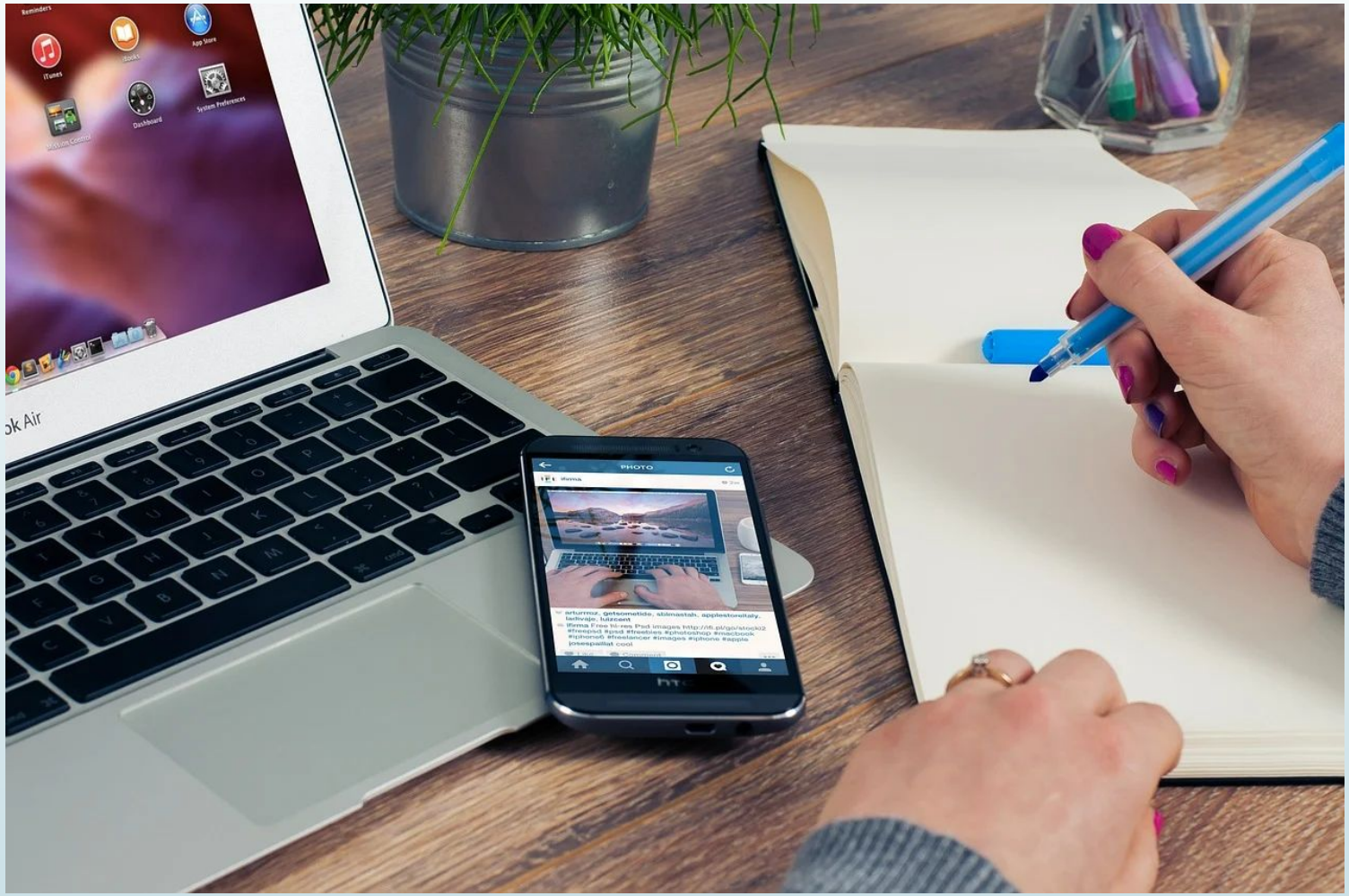
A Differentially Private Stochastic Gradient Descent Algorithm for Multiparty Classification (2012)
Arun Rajkumar; Shivani Agarwal

Treinamento distribuído



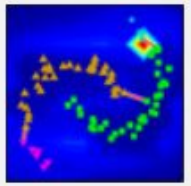
End-to-end privacy preserving deep learning on multi-institutional medical imaging (2021)
Kaissis, G., Ziller, A., Passerat-Palmbach, J. et al.

Projetos


Reminders
iTunes
Books
App Store
Dashboard
System Preferences
PHOTO

University of Cagliari, Italy

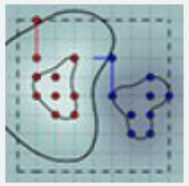
Adversarial Clustering



Clustering algorithms have been increasingly adopted in security applications to spot dangerous or illicit activities. However, they have not been originally devised to deal with deliberate attack attempts that aim to subvert the clustering process itself. Our experimental findings on clustering of malware samples and handwritten digits show that single- and complete-linkage hierarchical clustering can be significantly compromised by carefully targeted attacks.

Read more

Adversarial Feature Selection

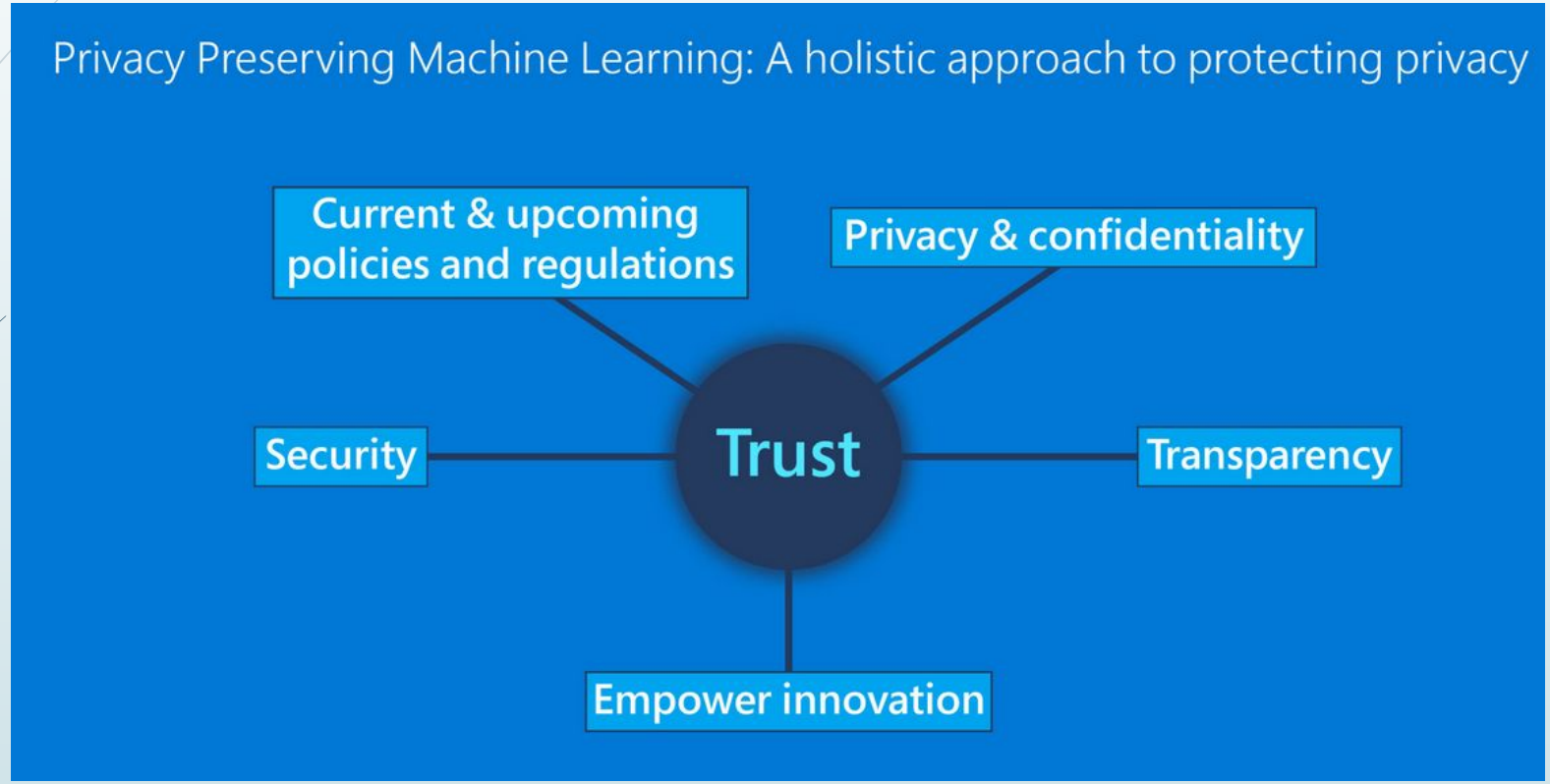


Despite feature selection algorithms are often used in security-sensitive applications, only few authors have considered the impact of using reduced feature sets on classifier security against evasion and poisoning attacks. Within this research area, we first show that feature selection algorithms can significantly worsen classifier security against well-crafted attacks. We then propose novel adversary-aware feature selection procedures to counter these threats.

Read more

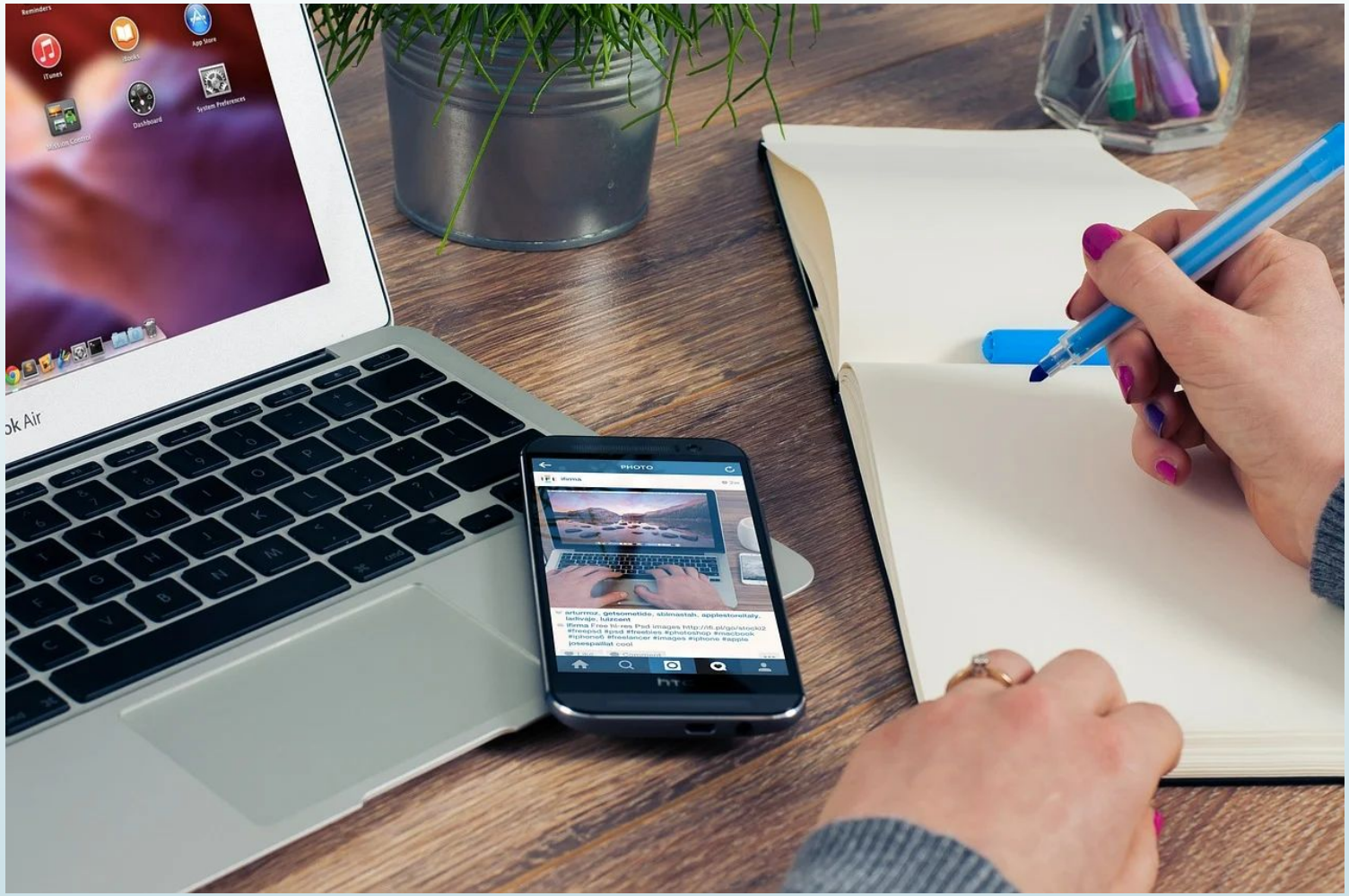
Adversarial Machine Learning
Batista Biggio

Microsoft



Privacy Preserving Machine Learning: Maintaining confidentiality and preserving trust
Microsoft research

Dicas



Dicas

- Algebra linear/ cálculo/ estatística
- Machine Learning: Pattern Recognition and Machine Learning (Bishop,2006)
- Deep Learning - Deep Learning (Goodfellow; Bengio; Courville, 2016)
- Privacidade - When Machine Learning Meets Privacy: A Survey and Outlook (Liu et al.,2020)
- Machine Learning security - Wild patterns: Ten years after the rise of adversarial machine learning (Biggio; Roli, 2018)

Como enganar modelos de aprendizado de máquina?

Obrigado!

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Slides/Codes