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Thinking like a hacker

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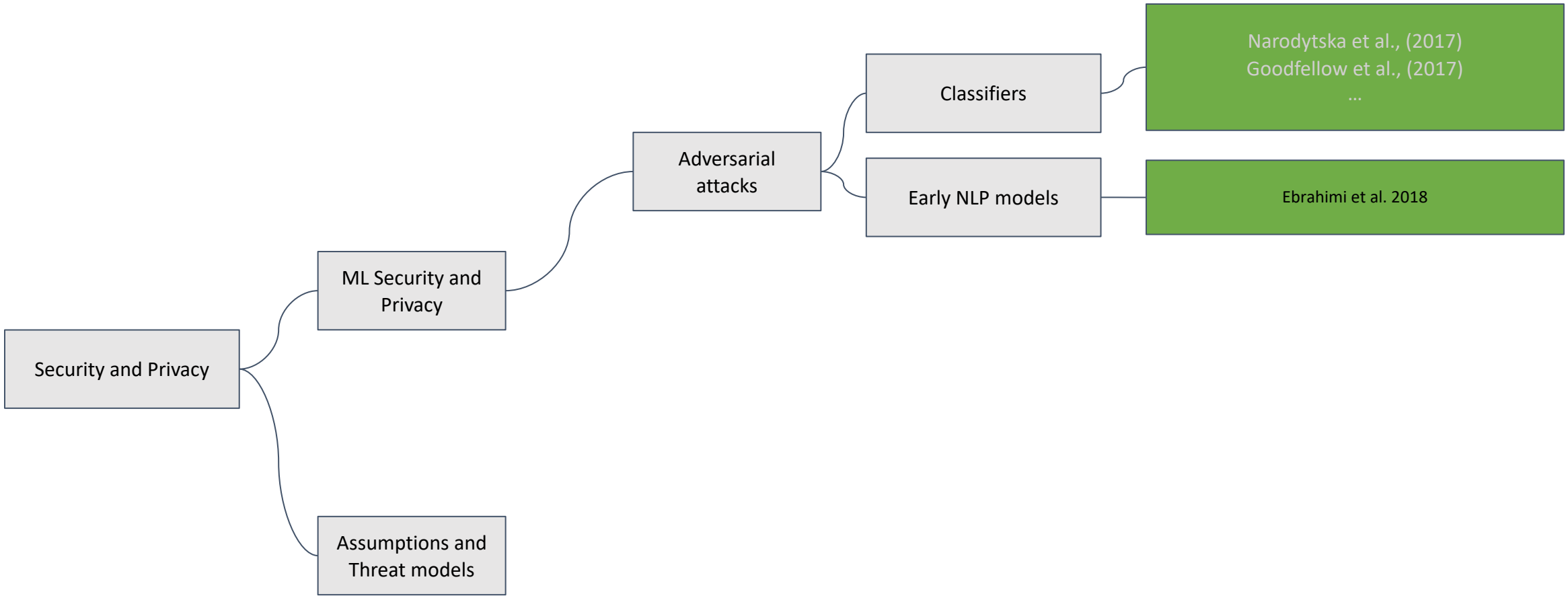
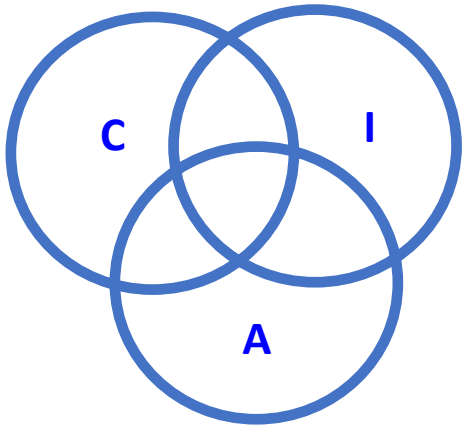
Roadmap


Security and Privacy
ML Security and Privacy
Assumptions and Threat models
Adversarial attacks
Classifiers
Early NLP models
Narodytska et al., (2017)
Goodfellow et al., (2017)
…
Ebrahimi et al. 2018

Early Security: Information Security

- CIA Triad
  - Confidentiality: Who is authorized to use data?
  - Integrity: Has the data been modified?
  - Availability: Can access data whenever need it?



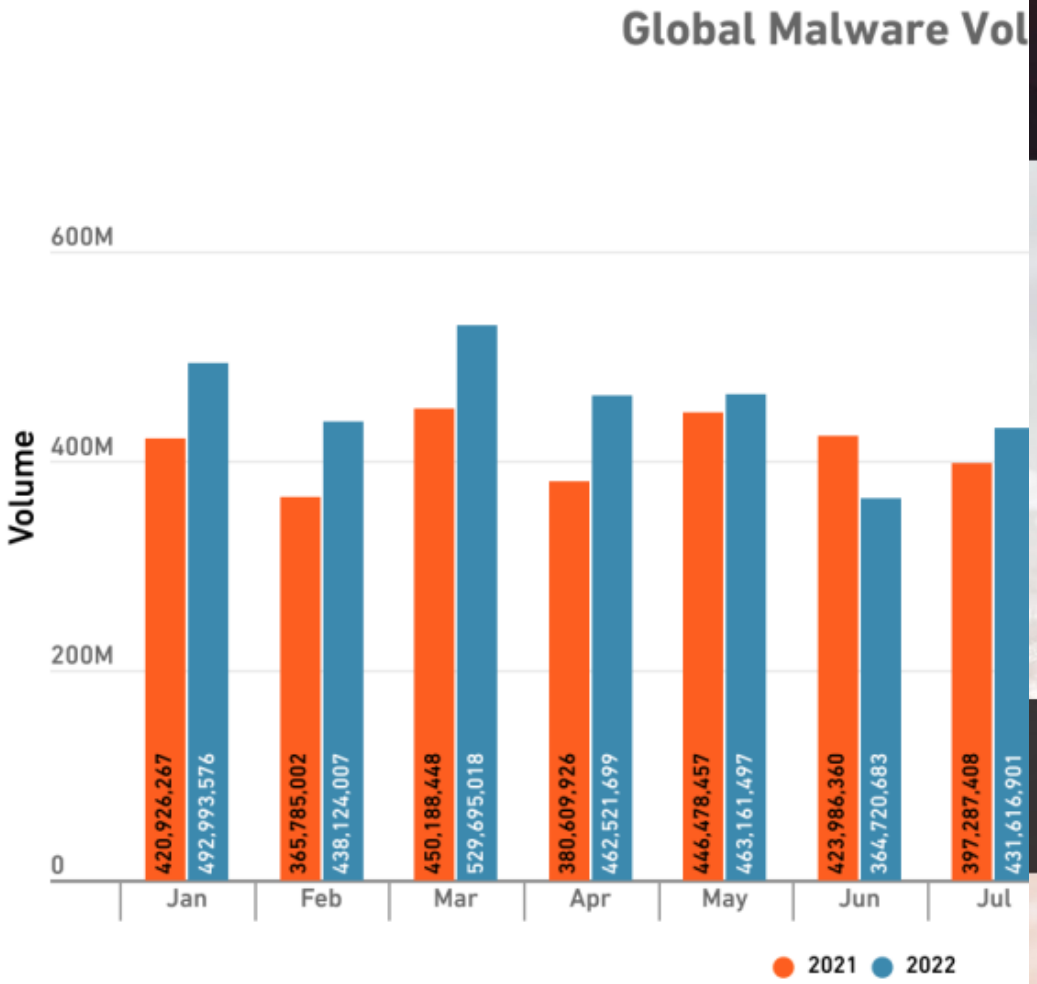
- Other components often added
  - Authentication
  - Authorization
  - Non-repudiation
  - …

An adversarial strategy that compromises any of these is an attack.

New application spaces

- Security no longer just about information
- Cloud is ubiquitous
- Machine learning everywhere
- New threat models
- Increasingly motivated and resourced attackers

What motivates attackers?



Trustworthy ML

- *Trust vs. Security*
- *CIA in the context of ML*
- *New concerns emerge*
  - *Fairness*
  - *Toxicity*
  - *Safety*
  - *…*

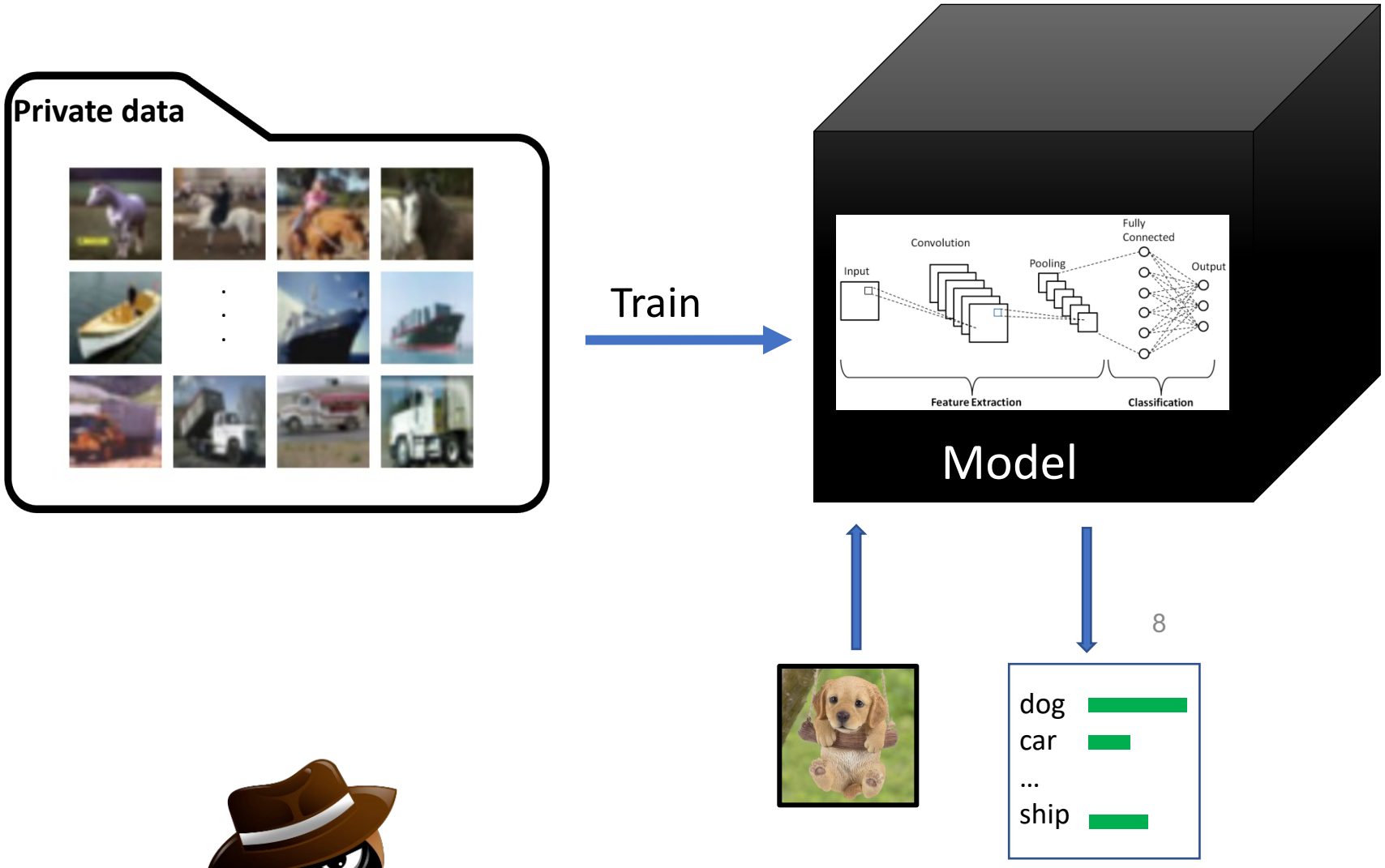
Threat models

- ***What are our assumptions with respect to the attacker?***
  - ***How does the attacker access the system?***
  - ***What are they able to observe?***
  - ***What is their goal?***
  - ***Any other assumptions about the system?***

- ***The less the assumptions, the more dangerous the attack***

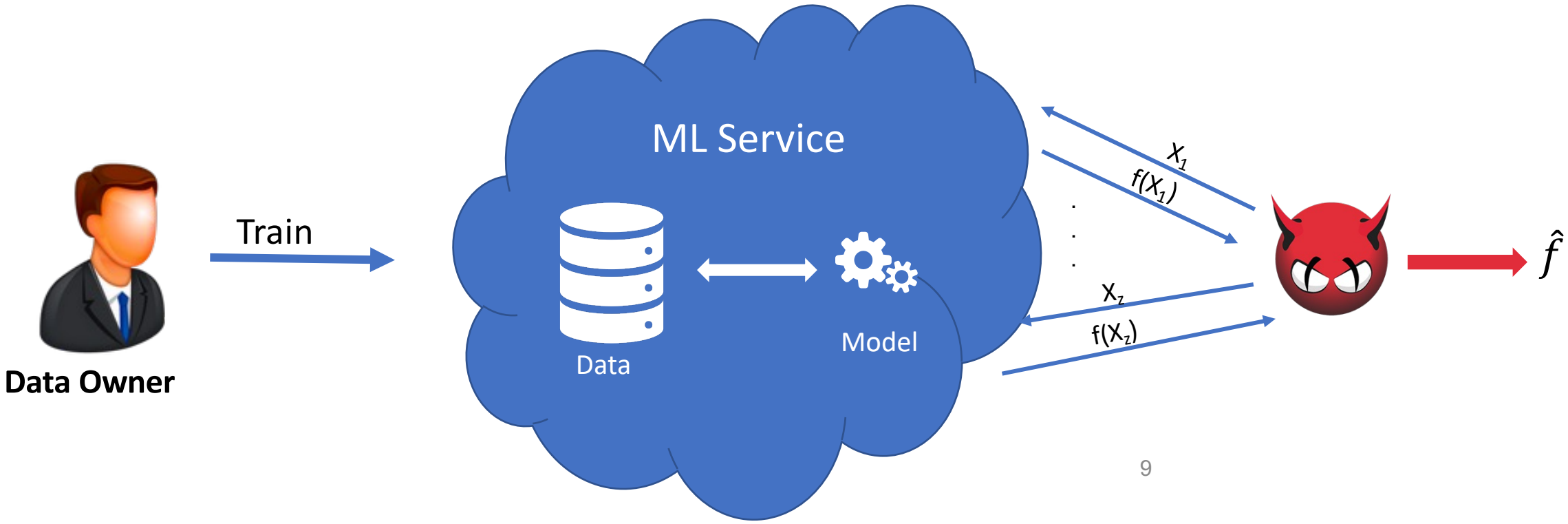
What are some common ML threat models/attacks?

Membership Inference attacks

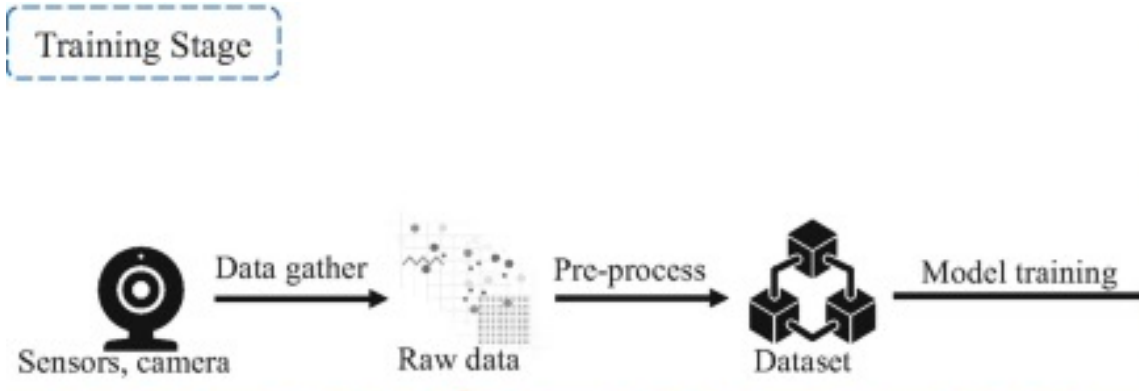


Was this specific picture in the training set?

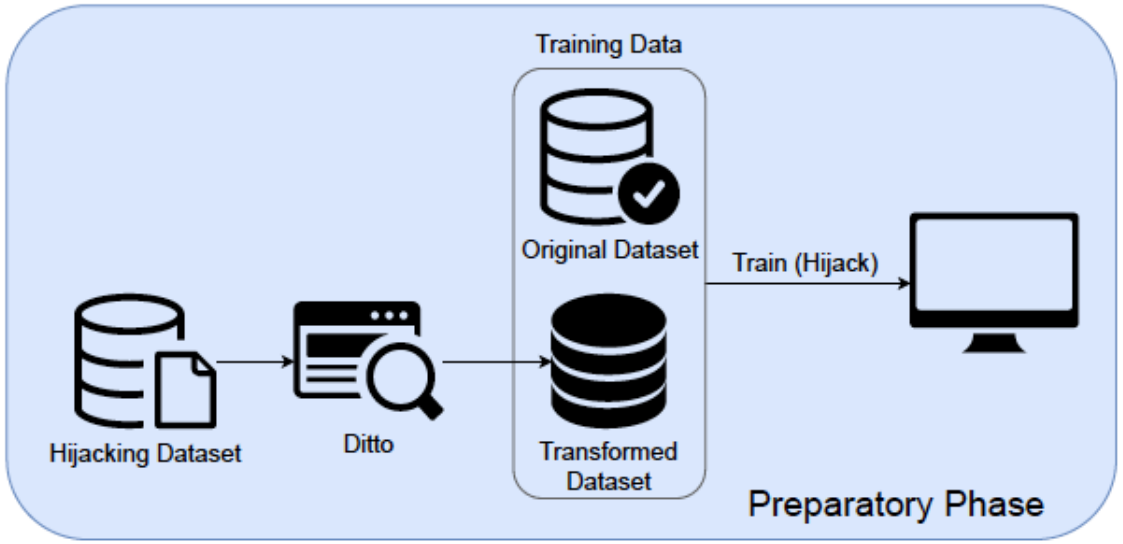
Model Extraction attacks



Poisoning attacks



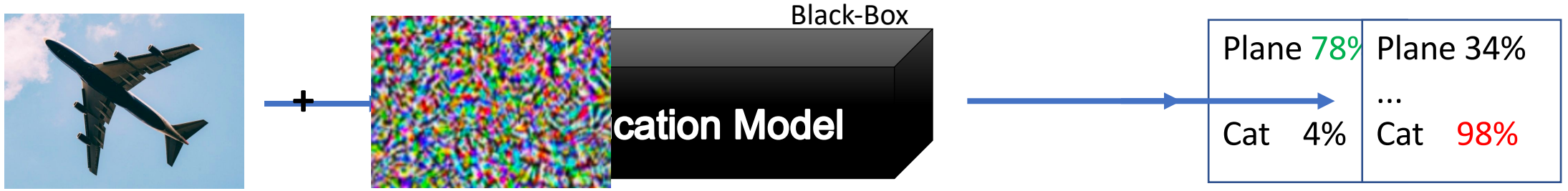
Model Hijacking



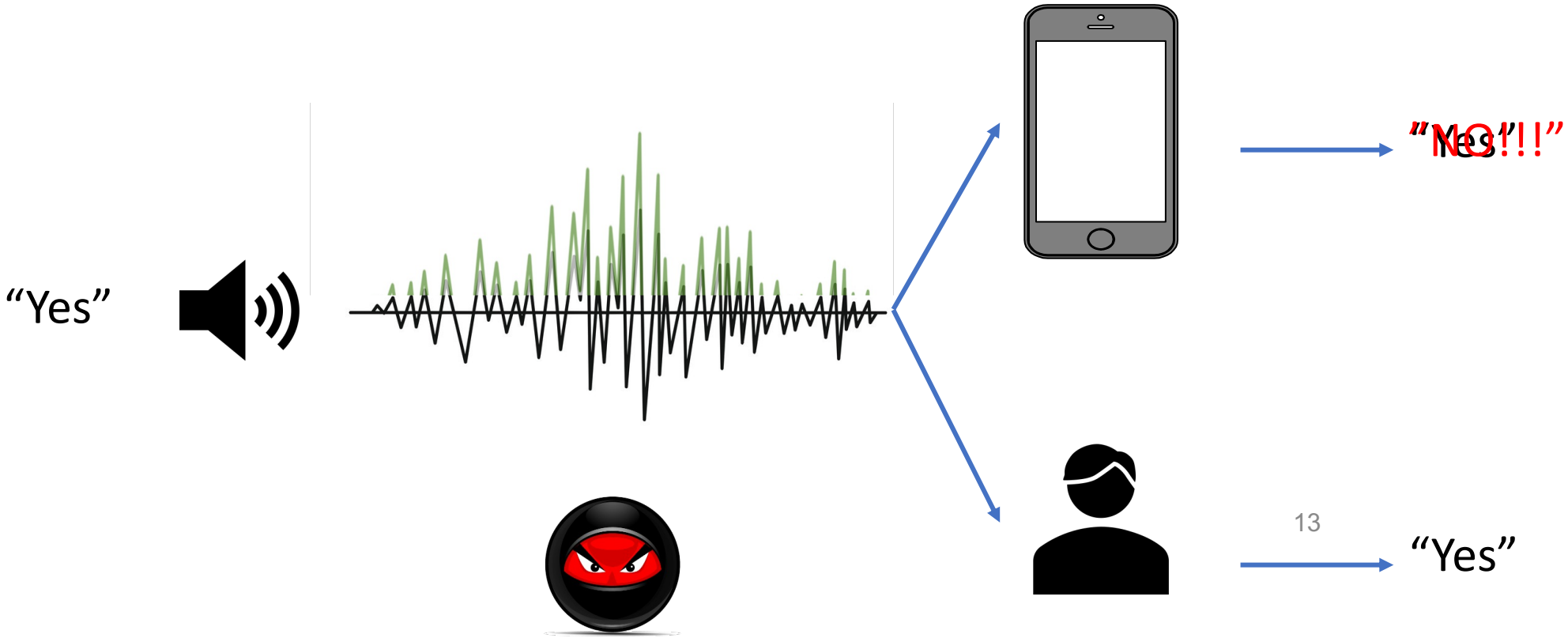
(a) Preparatory phase

Two-in-One: A Model Hijacking Attack Against Text Generation Models, Usenix security 2023

Adversarial attacks



Adversarial attacks



Adversarial Attack

- **Adds noise to the input data which is imperceptible to human but alter the model's prediction**

Original Image + Adversarial noise = Adversarial example

Figure 1: Raw data and example of model's misprediction (an ostrich misclassified as a goose)

Cause was initially a mystery: extreme nonlinearities of the model? Insufficient regularization?

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Narodytska et al., (CVPR 2017): Simple Black-Box Adversarial Attacks on Deep Neural Networks

Interesting properties

- Likely explanation: linear changes in high dimensional models
  - Tension between building models that are easy to train and vulnerability to adversarial attacks

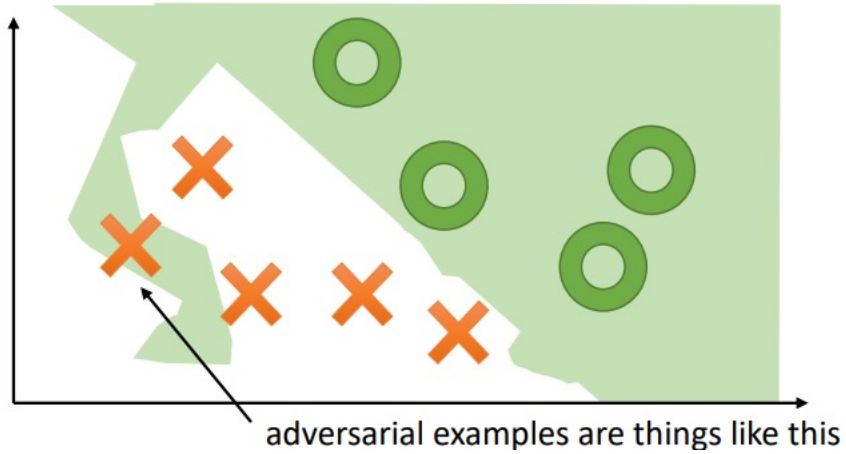
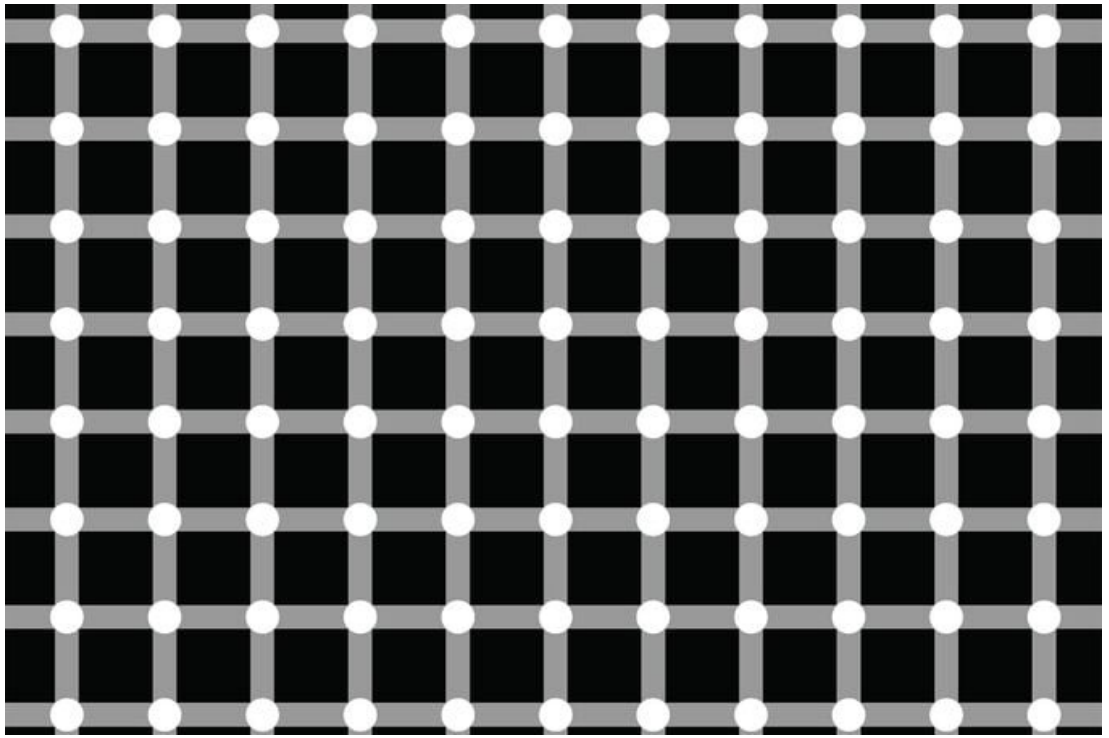


Figure 3: Adversarial examples on the decision boundary

- Attacks can be performed from any class to any class using a constrained noise budget

Interesting properties

- Attacks transfer!
  - They are not a function of the model, but capture something fundamental
- Training on adversarial examples can regularlize models
  - Conventional regularization approaches do not work



Source: Reader's digest (https://www.rd.com/article/optical-illusions/)

White-box Adversarial Attack

- Fast Gradient Sign Method (FGSM)
- Hotflip
- TextFooler

Fast Gradient Sign Method (FGSM)

- ***Each pixel can change by at most a small amount ϵ***

- **Move the dimensions of x in direction of $\nabla_x \mathcal{L}$ by ϵ**

$$x^* = x + \epsilon \text{sign}(\nabla_x \mathcal{L})$$

Hotflip

- Requires access to the internal gradients of the model
- Identifies the most influential characters or tokens in the input text
- Flipping character alters the model's prediction
- *Single character flip* (substitution, insertion, or deletion)

Hotflip

Chancellor Gordon Brown has sought to quell speculation over who should run the Labour Party and turned the attack on the opposition Conservatives.

Original Prediction: 75% World

Chancellor Gordon Brown has sought to quell speculation over who should run the Labour Party and turned the attack on the oBposition Conservatives.

Altered Prediction: 94% Business

Table 1: **Adversarial examples with a single character change cause misclassification by a neural classifier**

TextFooler

- Generates adversarial examples by synonym substitution
- preserves the original meaning but changes the model's prediction
- Identifies and substitute the important words in input text using gradients
- Iteratively substitute the words until the model's prediction changes.

TextFooler

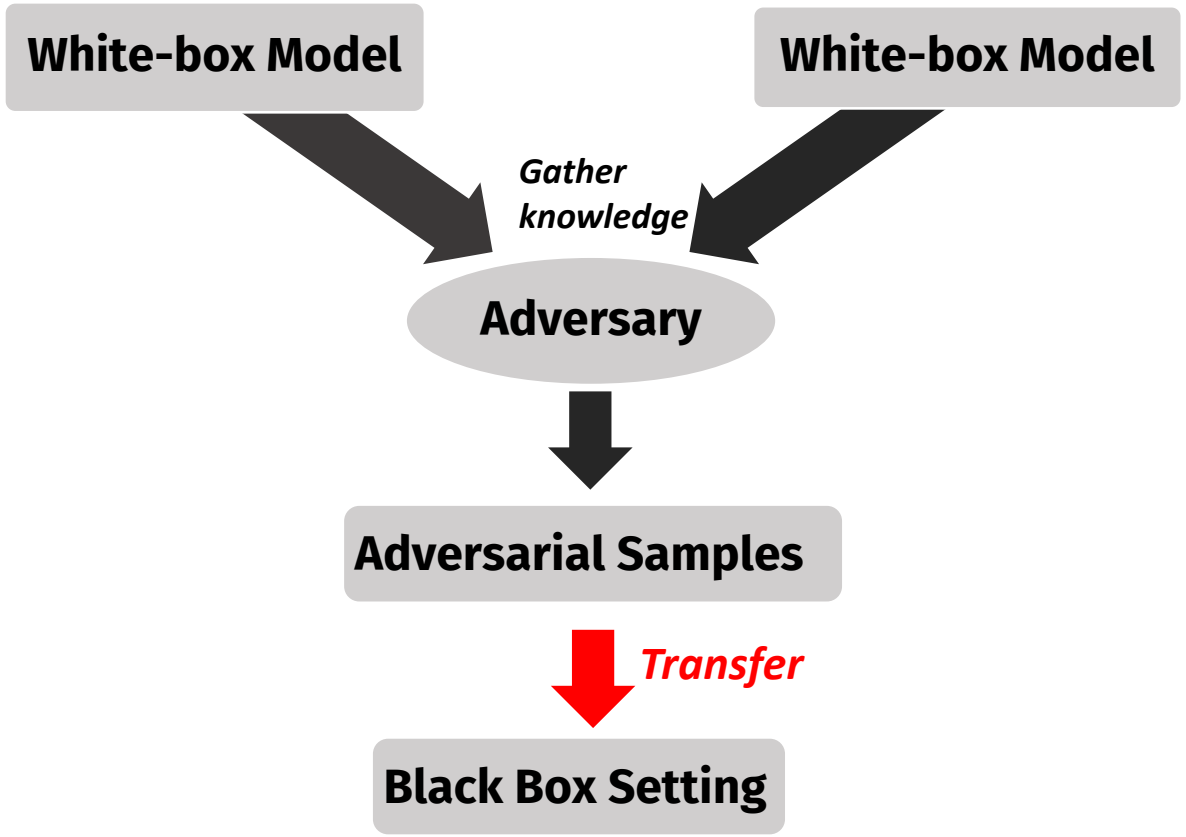
Original Sample: The characters, cast in impossibly **contrived situations**, are **totally** estranged from reality. (Label: NEG)

Adversarial Sample:The characters, cast in impossibly **engineered circumstances**, are **fully** estranged from reality. (Label: POS)

Table 2 : **Examples of original and adversarial examples (Movie Review (Positive (POS) ↔ Negative (NEG)))**

Black Box Adversarial Attack

- *Generate adversarial samples and transfer to the black-box setting*



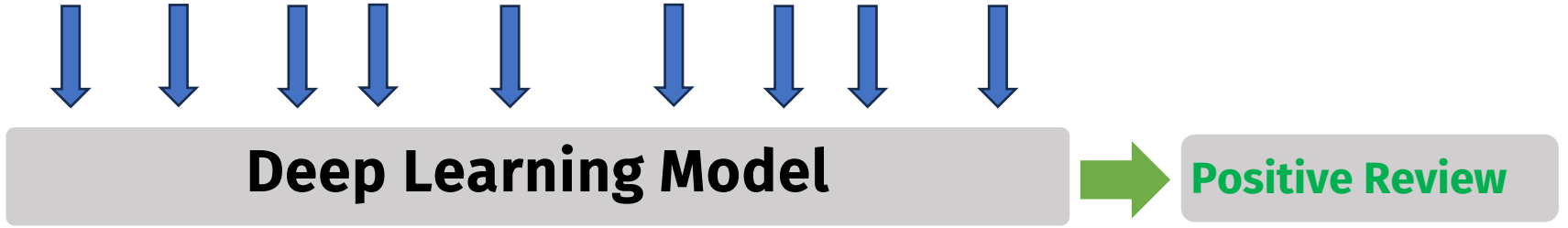
Liu et al., (ICLR 2017): Delving into Transferable Adversarial Examples and Black-box Attacks

DeepWordBug

- By comparing the prediction before and after a word is removed reflects which word influences most to the classification result
- Targets the characters in the most important words
- Perturbations include character swapping, insertion, deletion, or replacement

DeepWordBug

Original Sample: *The film has a special place in my heart*



Adversarial Sample: *The film has a special plcae in my herat*