CS334 Machine Learning

Emerging Topics: Privacy-Enhanced and Robust Machine Learning

Li Xiong
Emory University

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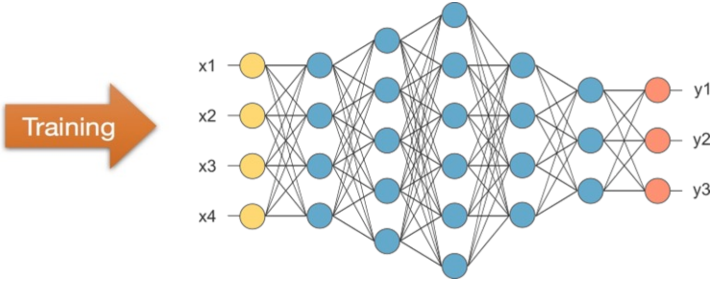
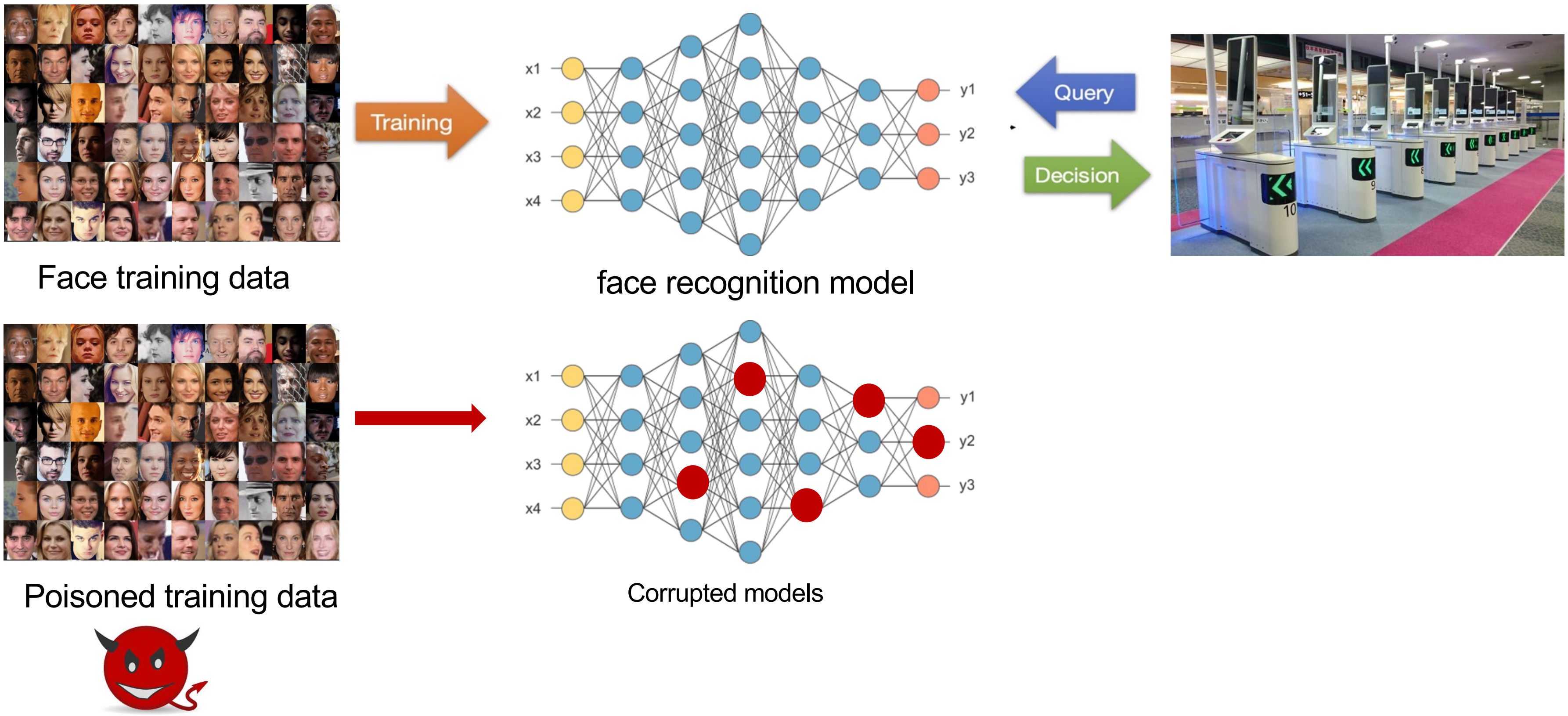
Machine Learning Pipeline

Face training data

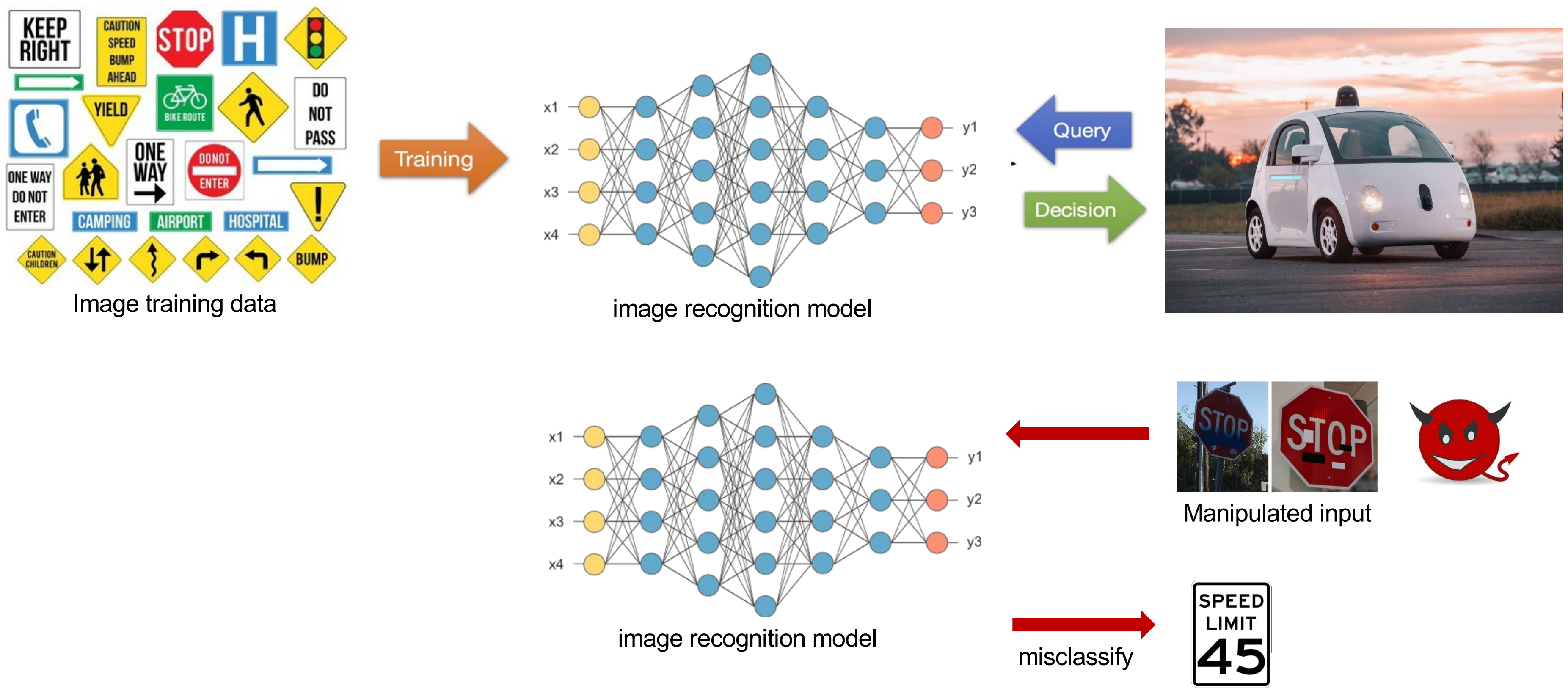


face recognition model

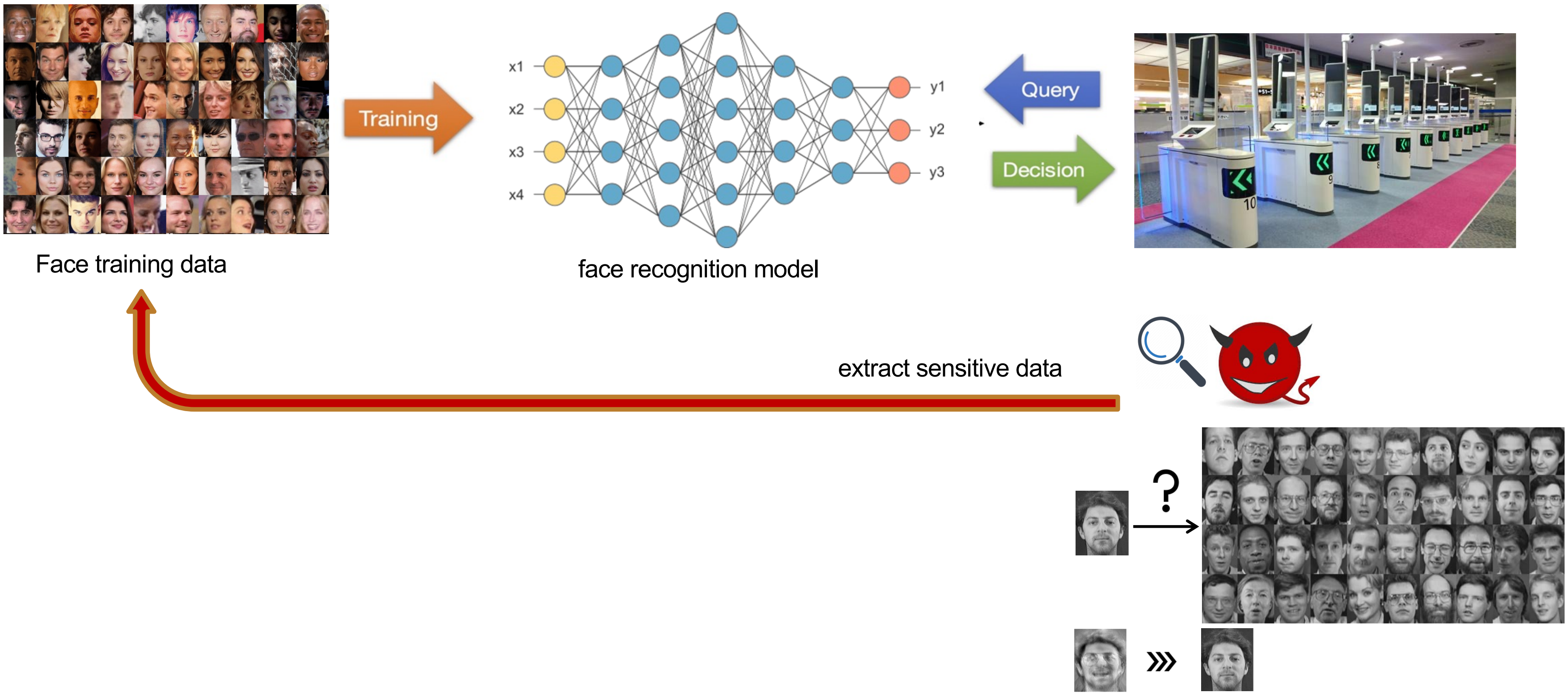
Data Poisoning Attacks (Training Stage)



Adversarial Example Attacks (Inference Stage)



Privacy Attacks (Inference Stage)



Outline

- Privacy attacks
  - Membership inference attacks, model inversion attacks, secret sharer
- Privacy-preserving deep learning
  - Differential privacy, gradient perturbation, noisy ensemble, federated learning
- Security attacks
  - Adversarial example attacks, poisoning attacks, backdoor attacks
- Robust deep learning
  - Detection and reform, adversarial training, certified robustness

Membership Inference Attacks against Machine Learning Models

Reza Shokri, Marco Stronati, Congzheng Song, Vitaly Shmatikov

CORNELL UNIVERSITY FOUNDED A.D. 1865
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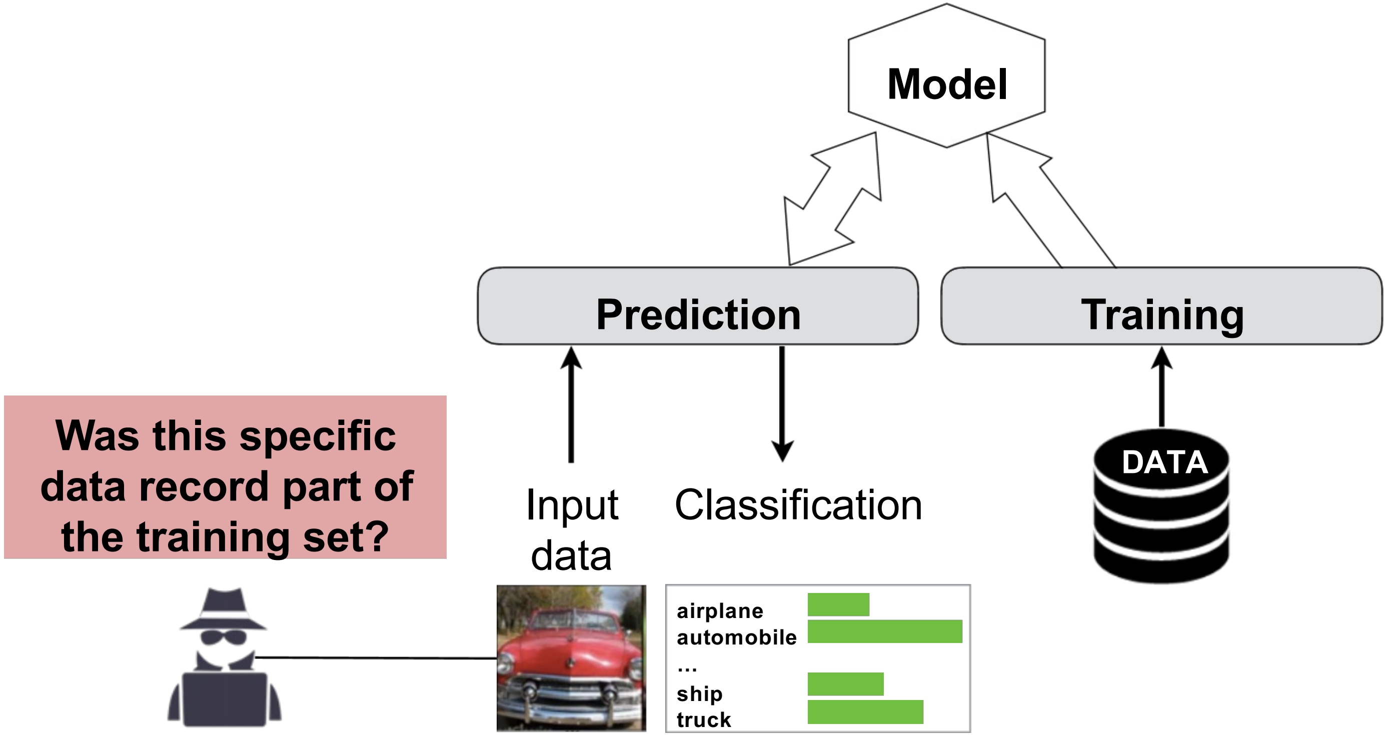
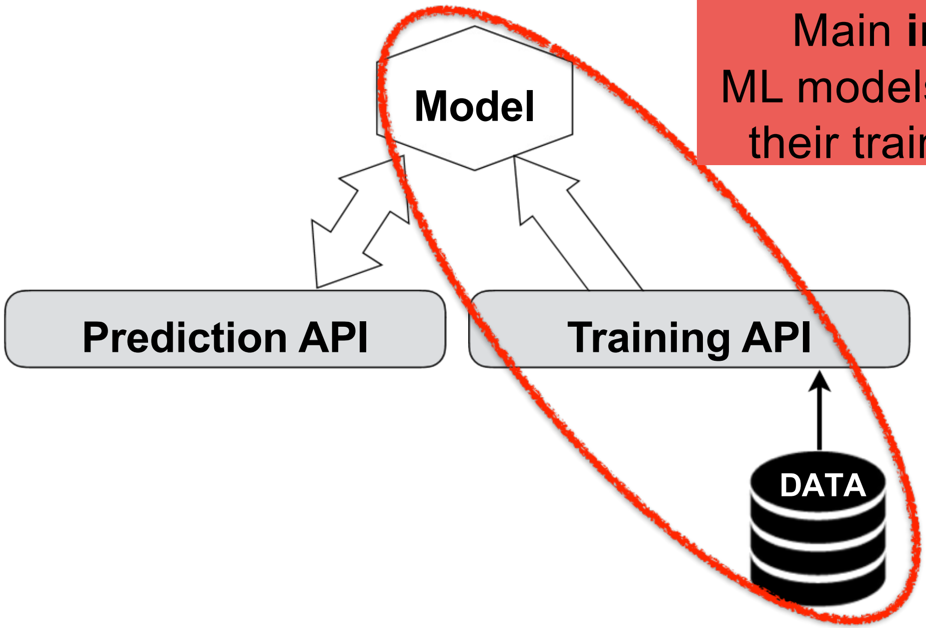
Membership Inference Attacks Against Machine Learning Models, S&P, 2017

Membership Inference Attack

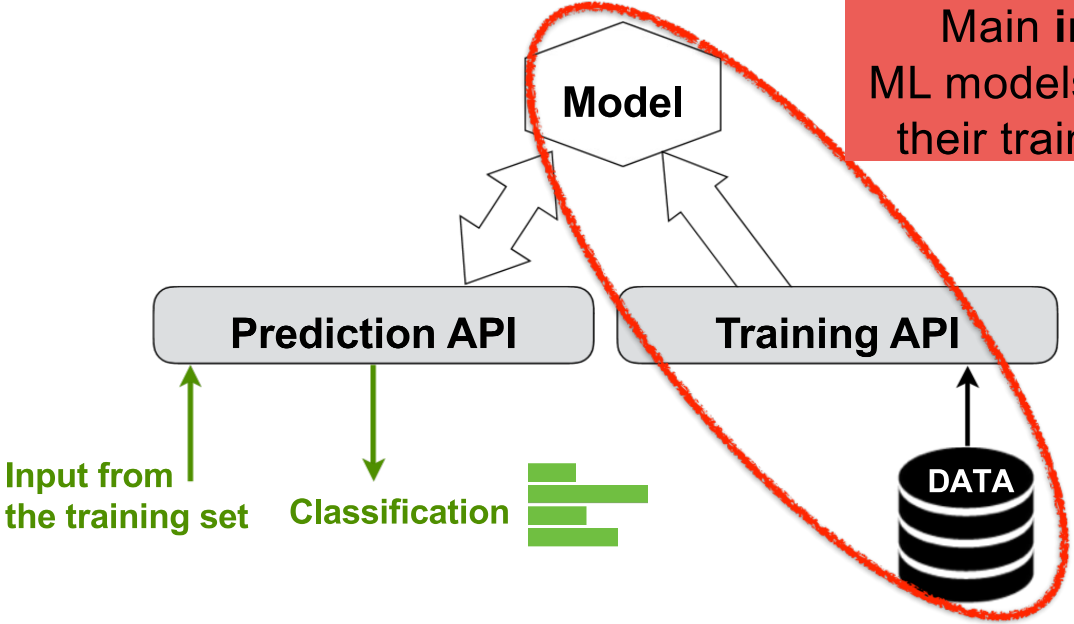


Exploit Model's Predictions



Main **insight**:
ML models overfit to their training data

Exploit Model's Predictions



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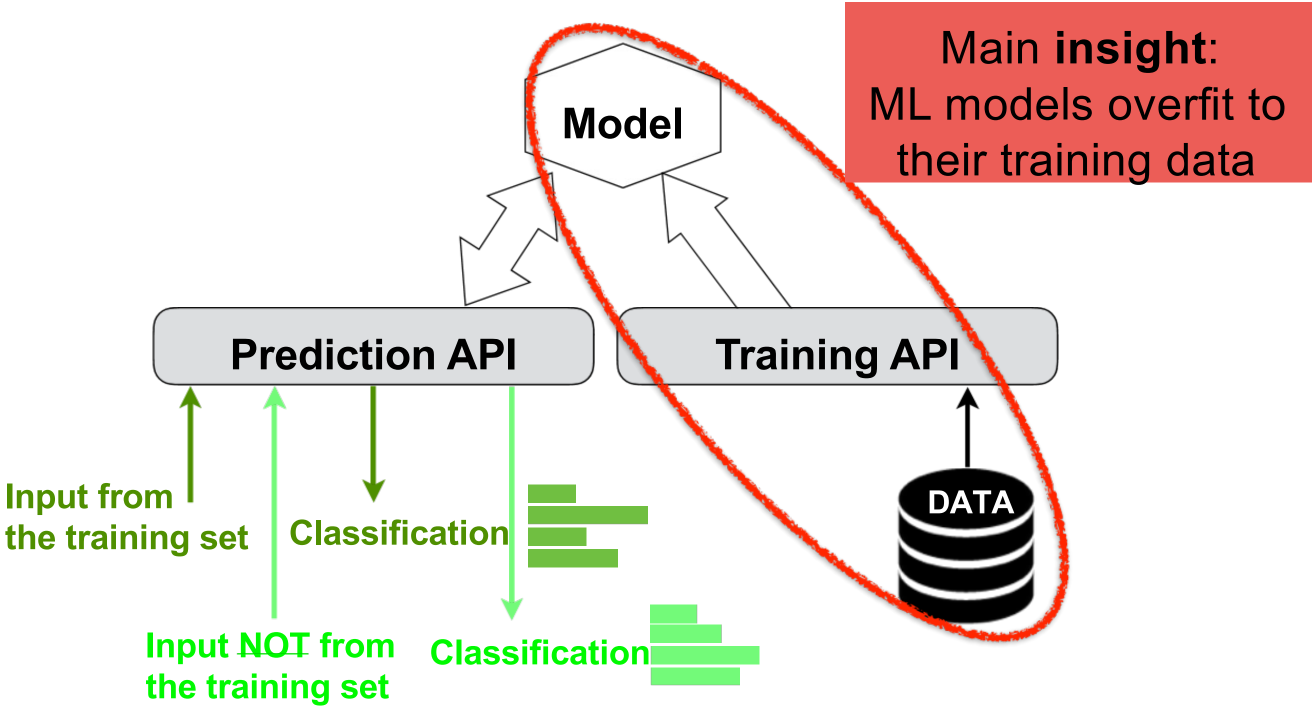

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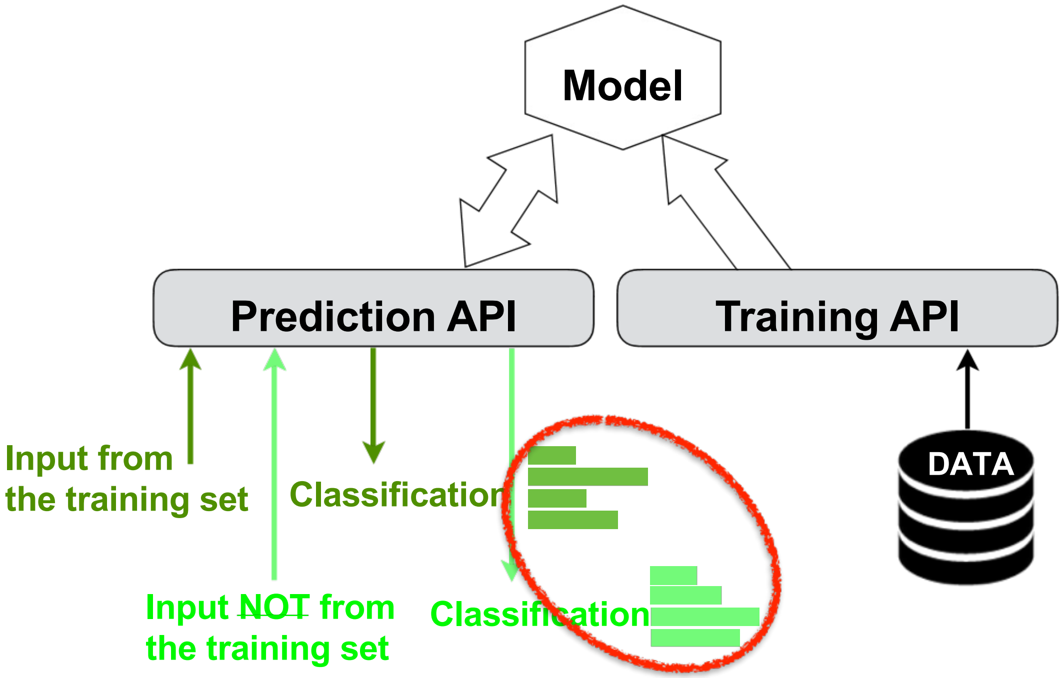
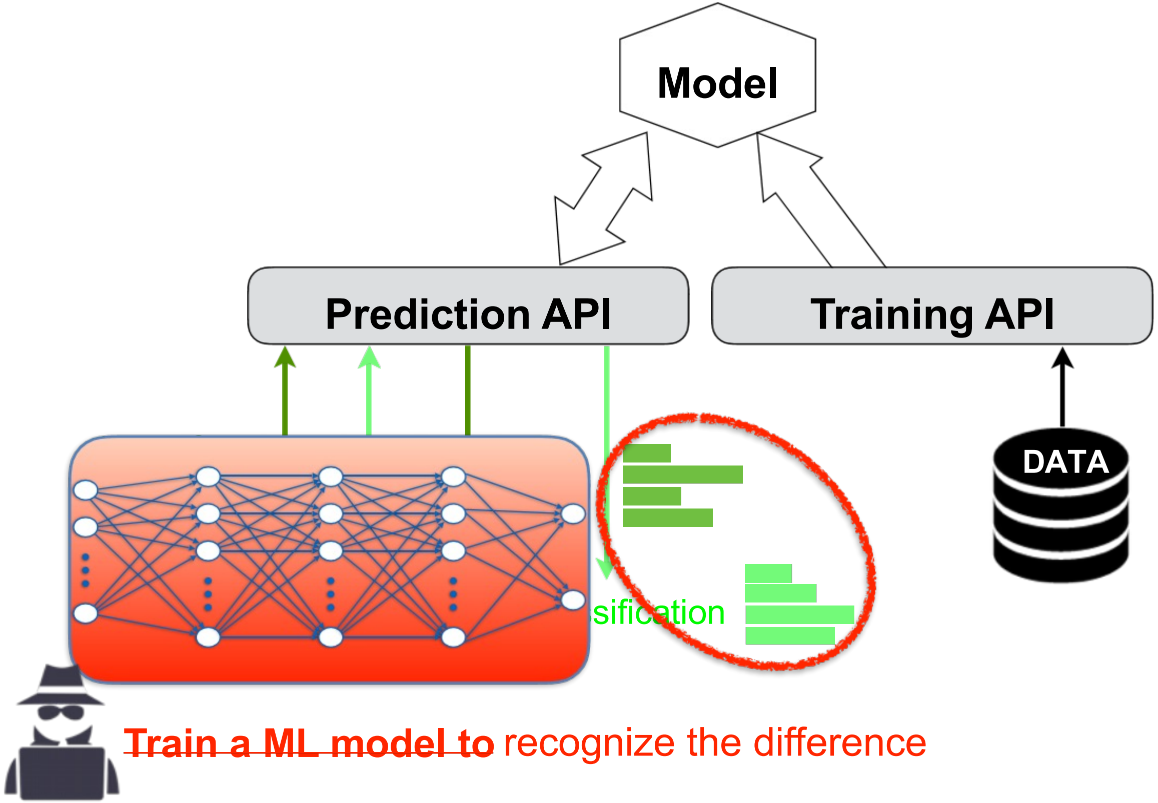


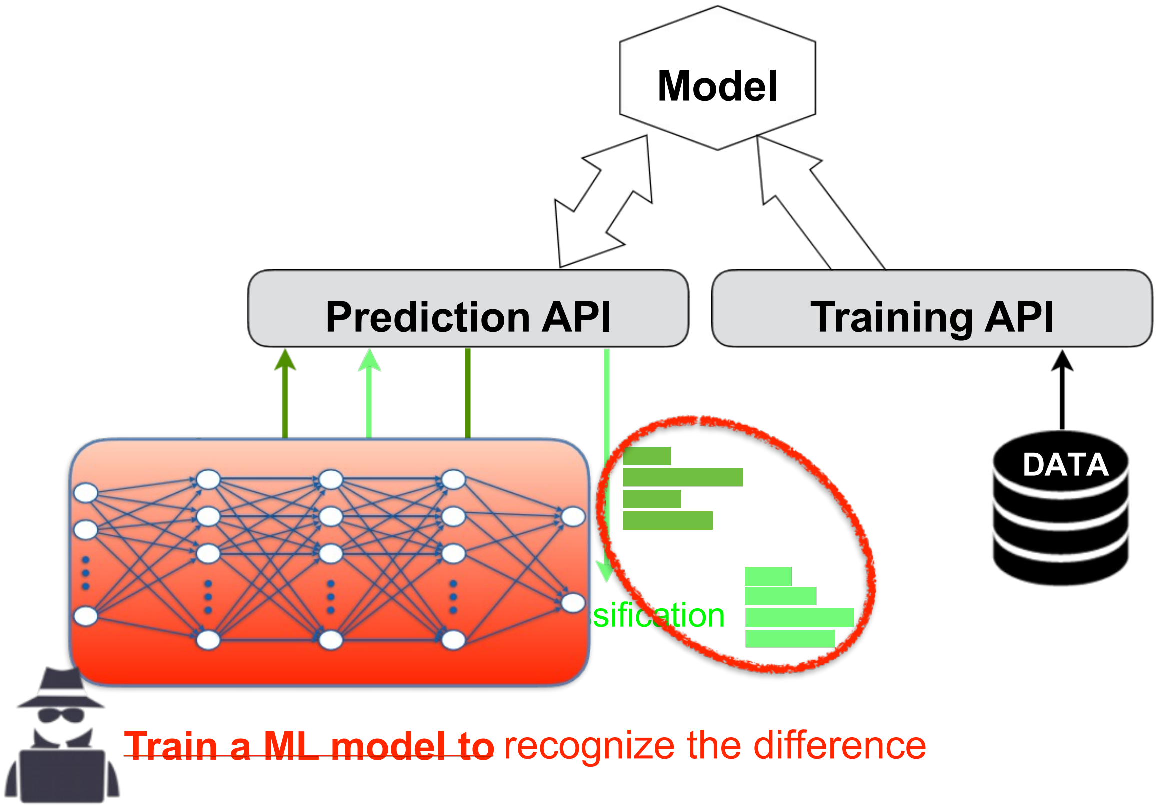
Recognize the difference

ML against ML



~~Train a ML model to~~ recognize the difference

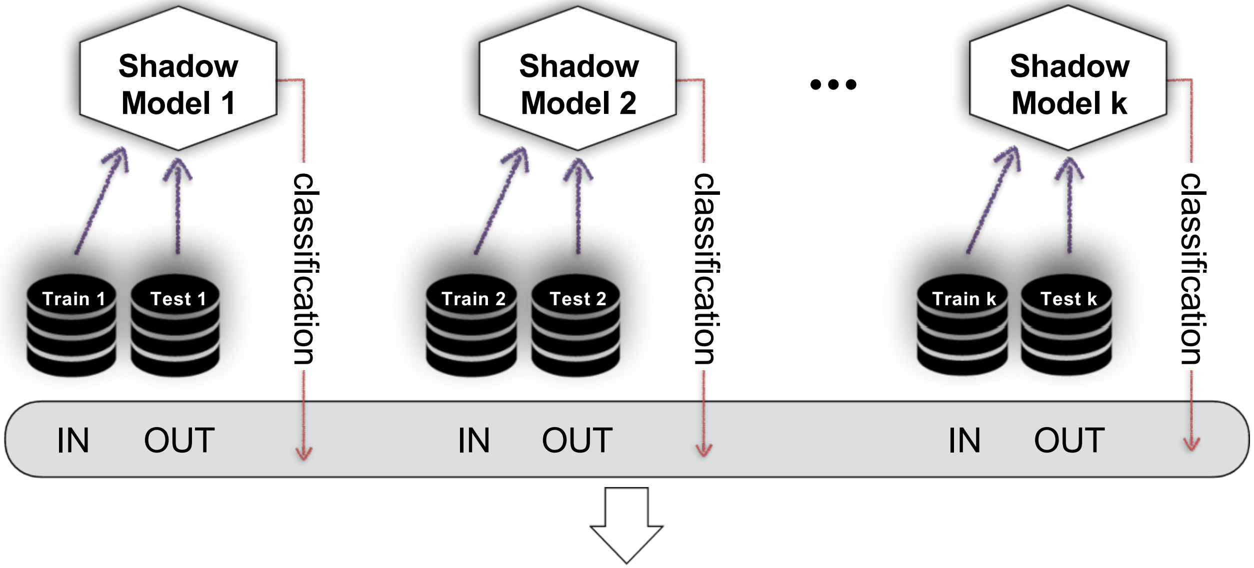
ML against ML



~~Train a ML model to~~ recognize the difference

What kind of training data is needed for training the attack model?

Train Attack Model using **Shadow Models**

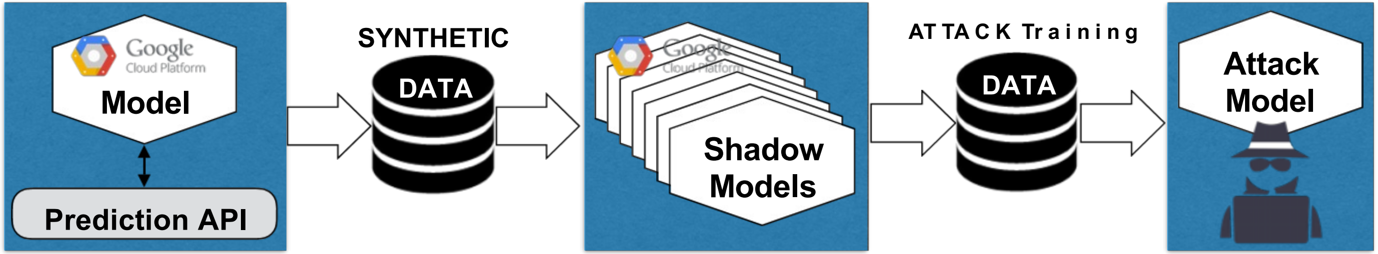


Train the attack model

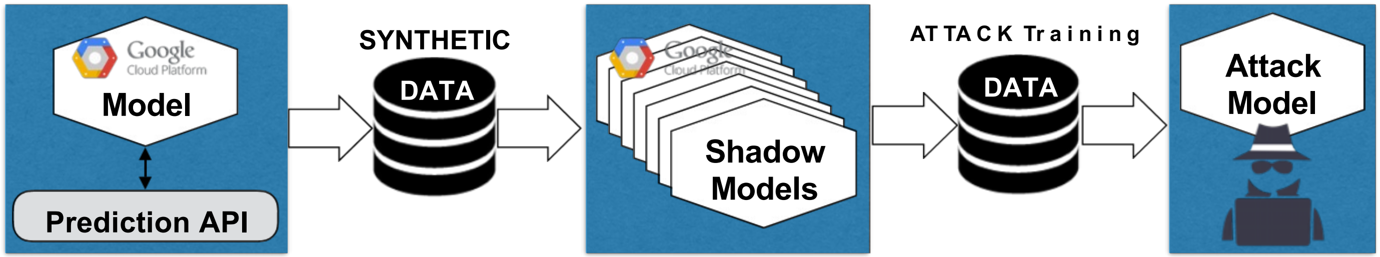
to predict if an input was a member of the training set (in) or a non-member (out)

How to get the training data?

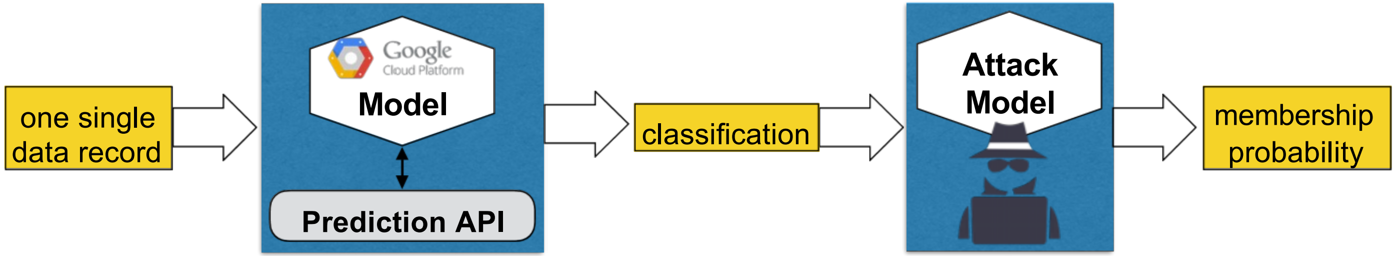
Constructing the Attack Model

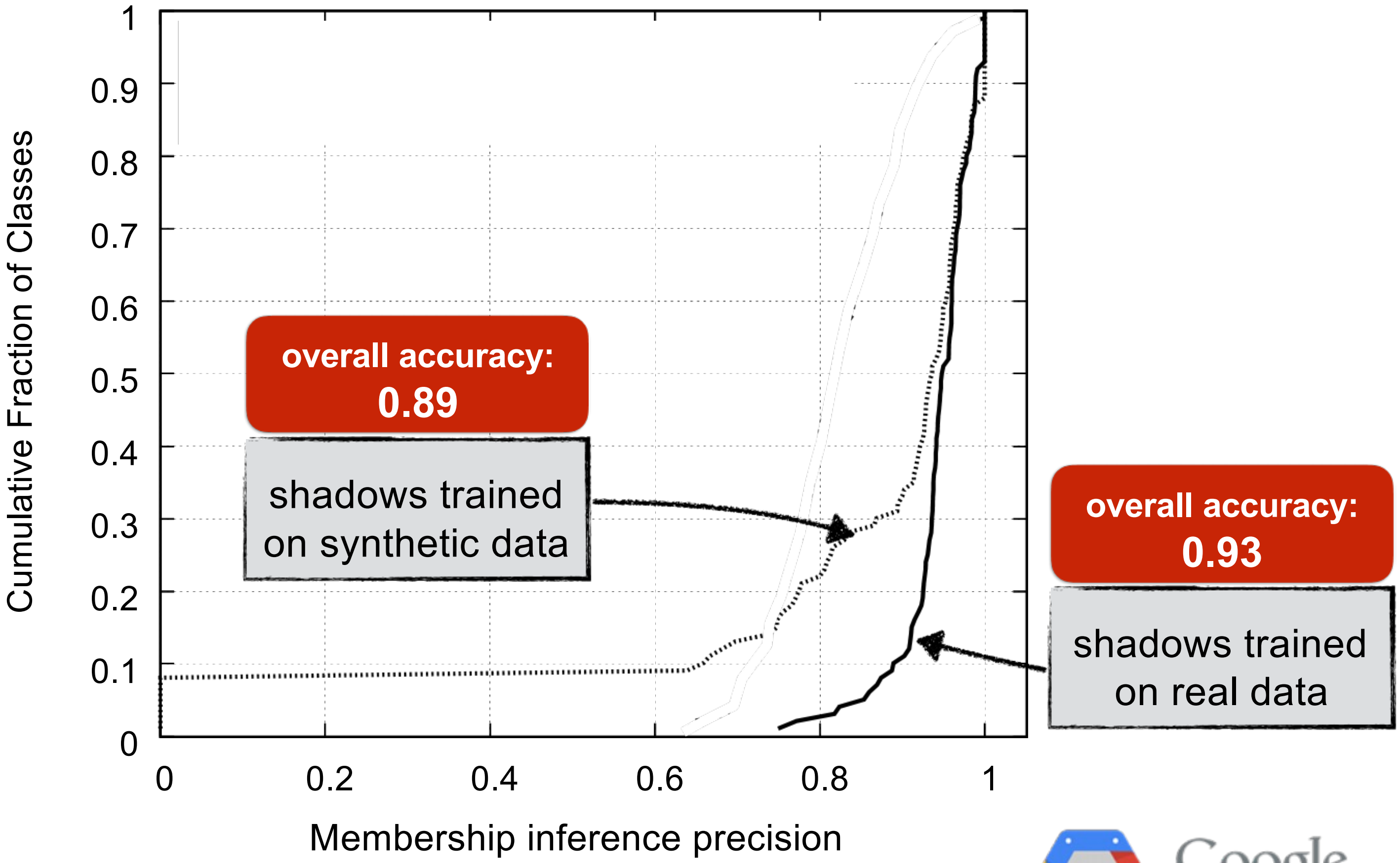


Constructing the Attack Model



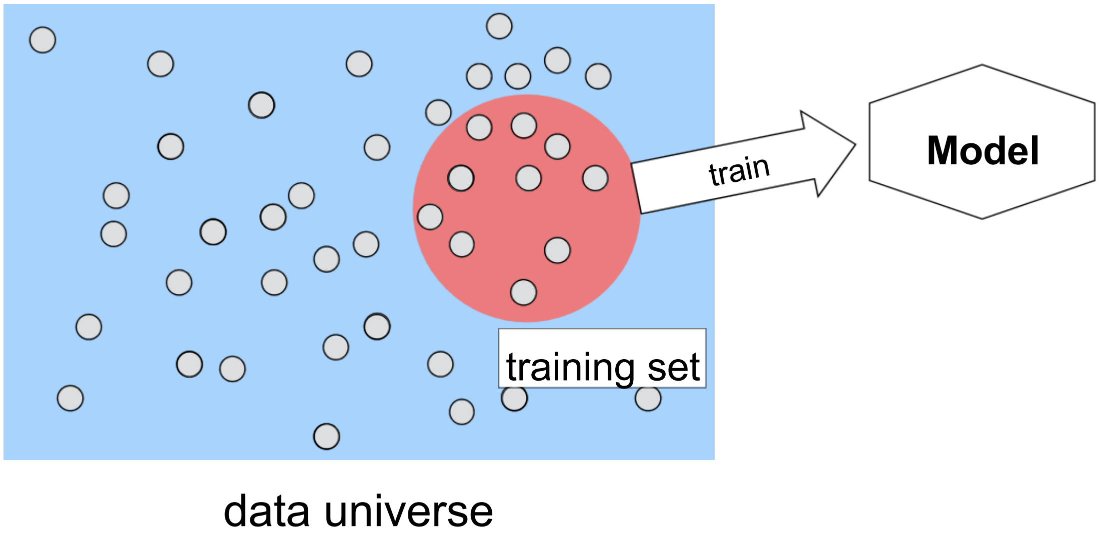
Using the Attack Model





Purchase Dataset — Classify Customers (100 classes)

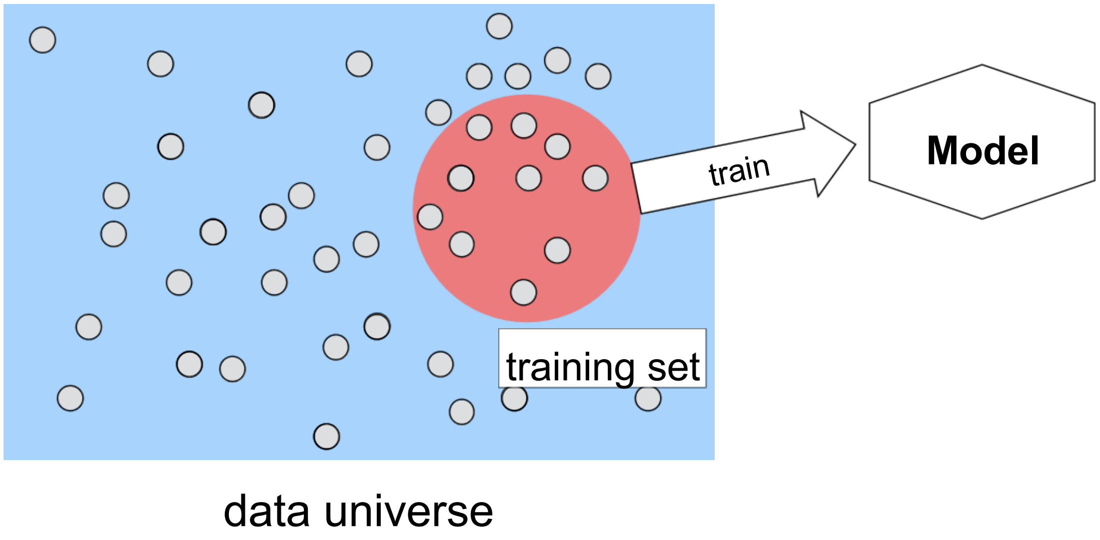
Privacy Learning



Privacy

Learning

Does the model leak information about data in the training set?

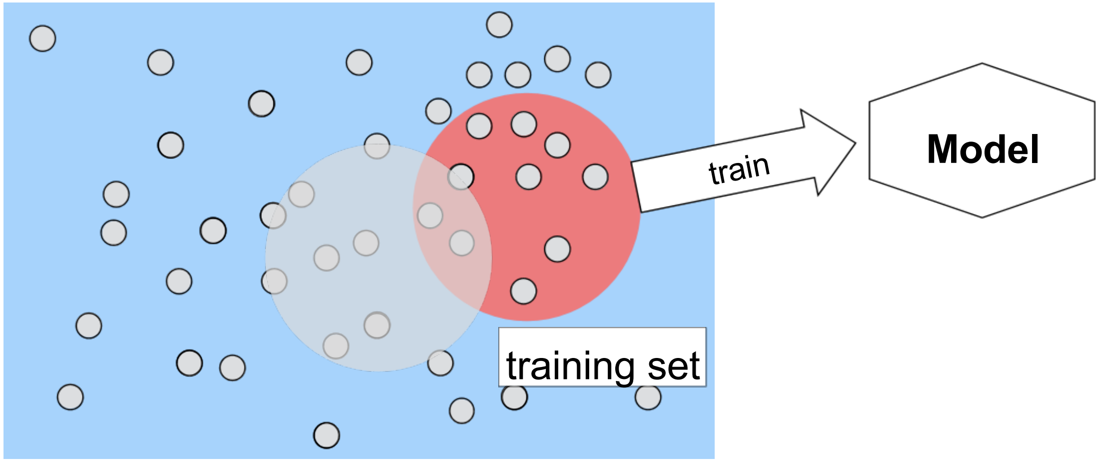


Privacy

Does the model leak information about data in the training set?

Learning

Does the model generalize to data outside the training set?



data universe

Privacy

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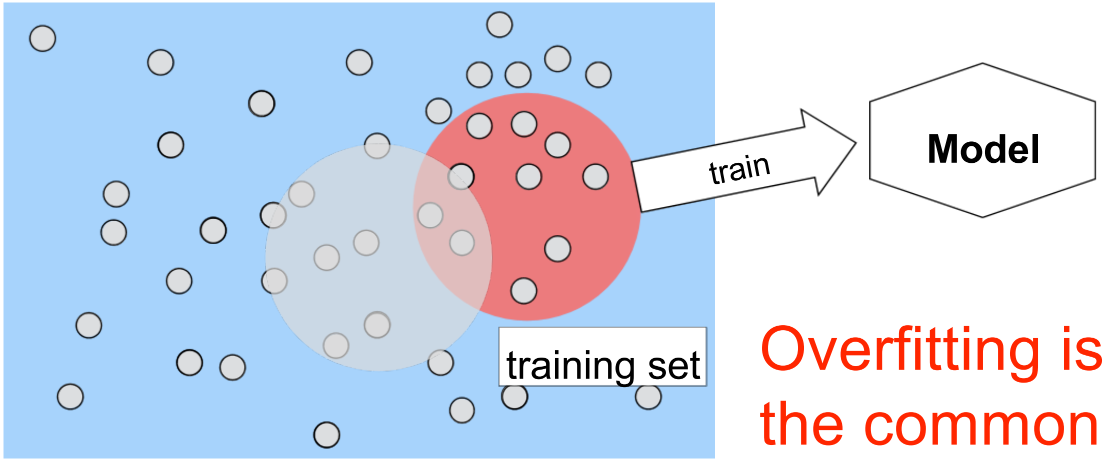
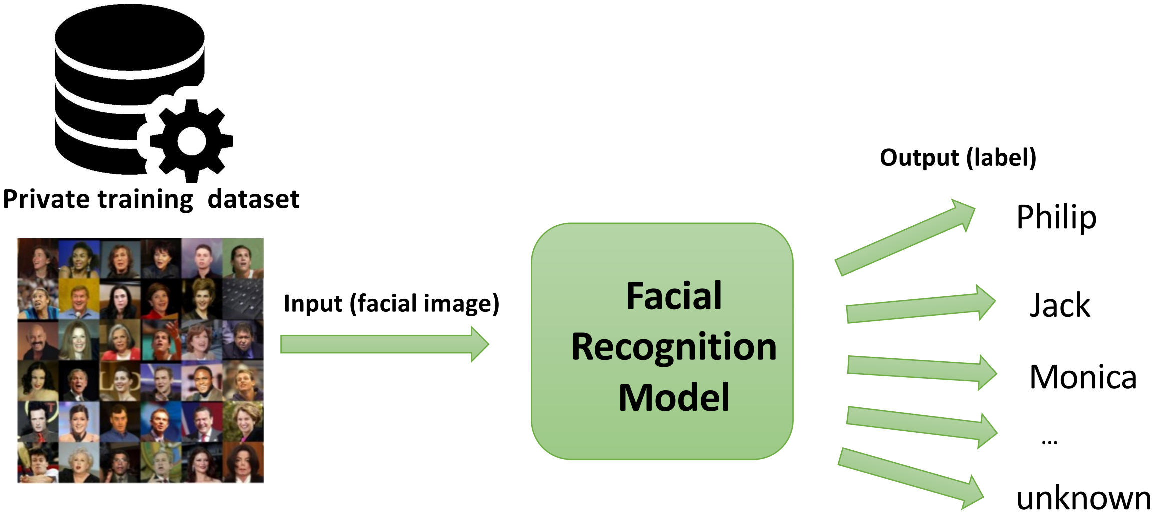


data universe

Overfitting is the common enemy!

Feature Inference Attacks

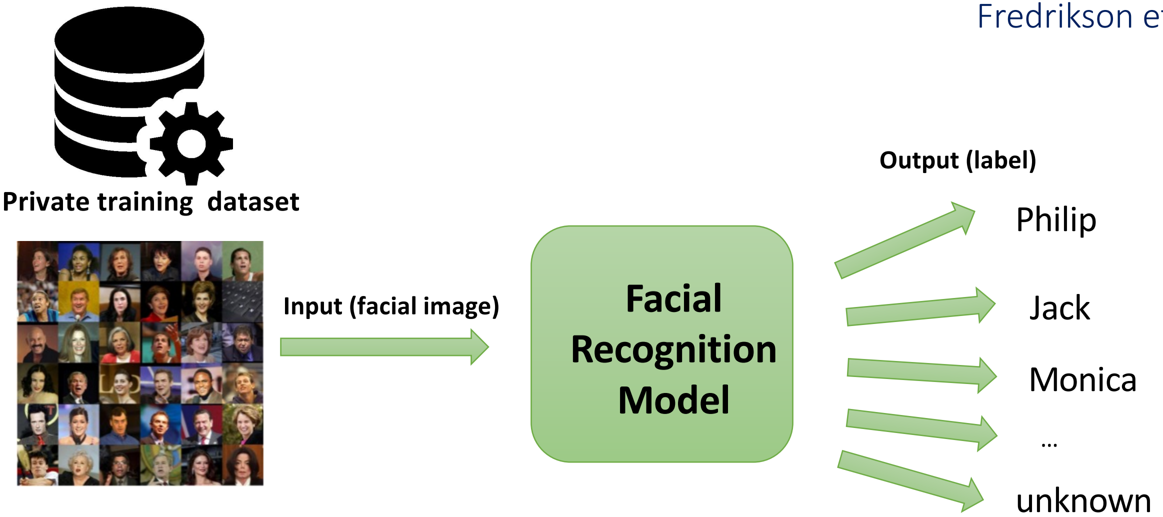
Fredrikson et al. 2015



Can I reconstruct the image of someone?

Feature Inference Attacks

Fredrikson et al. 2015



Can I reconstruct the image of someone?

Find **x** to minimize $c(\mathbf{x}) = 1 - f_{label}(\mathbf{x})$

Feature Inference Attacks

Fredrikson et al. 2015

Private training dataset

Input (facial image)

Facial Recognition Model

Output (label)

- Philip
- Jack
- Monica
- …
- unknown

Can I reconstruct the image of someone?

Find **x** to minimize $c(\mathbf{x}) = 1 - f_{label}(\mathbf{x})$

Use Gradient Descent (require white box access of the model)

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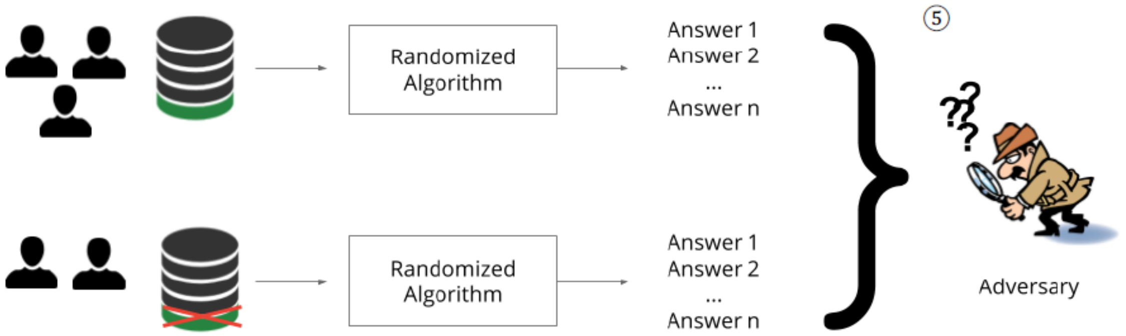
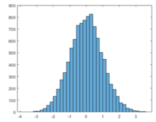
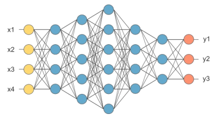
Differential Privacy (DP) [Dwork 06]







Differential Privacy (DP) in practice

Differential Privacy

Definition 2.4 (Differential Privacy)**.** A randomized algorithm $\mathcal{M}$ with domain $\mathbb{N}^{|\mathcal{X}|}$ is (ε, δ)-differentially private if for all $\mathcal{S} \subseteq \text{Range}(\mathcal{M})$ and for all $x, y \in \mathbb{N}^{|\mathcal{X}|}$ such that $\|x - y\|_1 \leq 1$:

$$\Pr[\mathcal{M}(x) \in \mathcal{S}] \leq \exp(\varepsilon) \Pr[\mathcal{M}(y) \in \mathcal{S}] + \delta,$$

where the probability space is over the coin flips of the mechanism $\mathcal{M}$. If $\delta = 0$, we say that $\mathcal{M}$ is ε-differentially private.

quantifies information leakage

allows for a small probability of failure

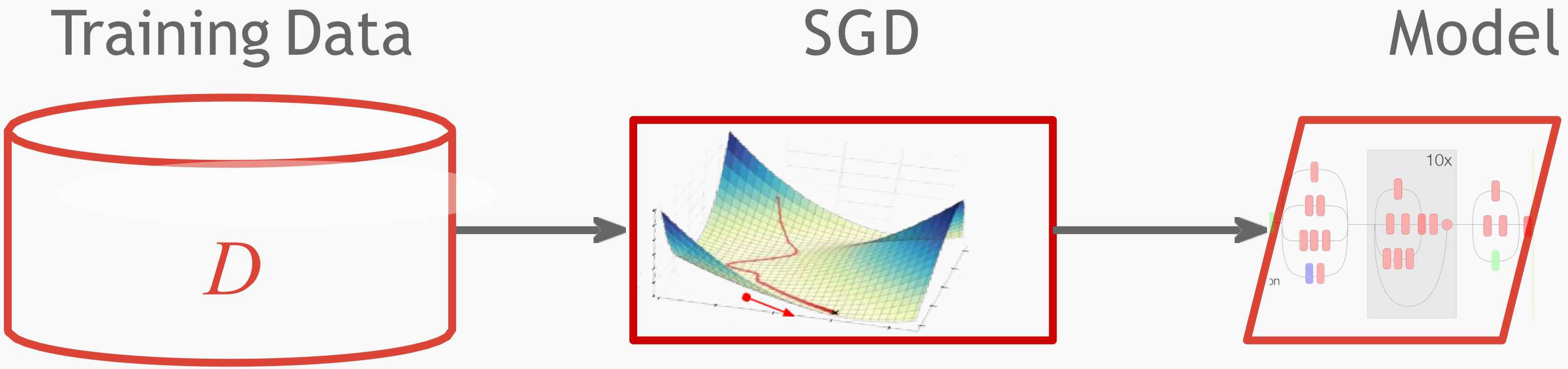
DEEP LEARNING WITH DIFFERENTIAL PRIVACY

Martin Abadi, Andy Chu, Ian Goodfellow*,
Brendan McMahan, Ilya Mironov, Kunal Talwar, Li Zhang
Google

* OpenAI

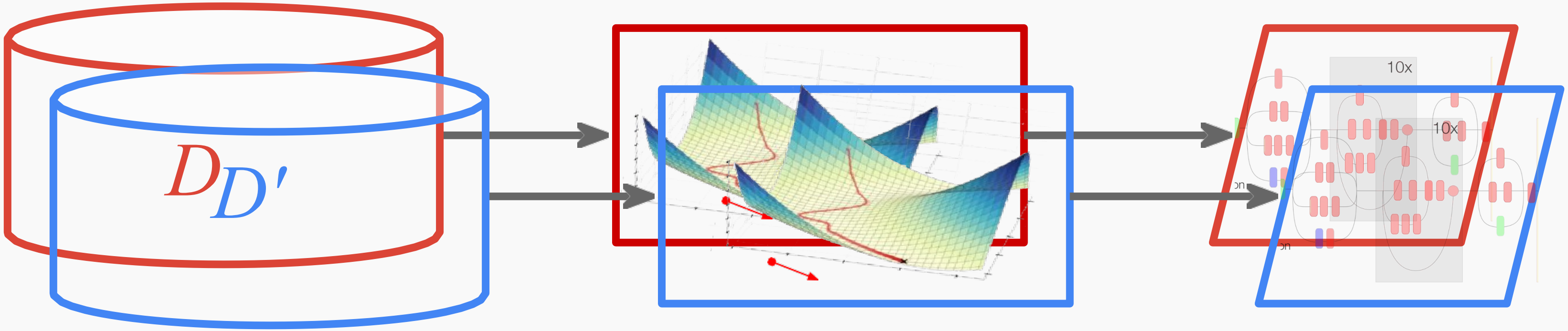
Deep Learning with Differential Privacy, CCS, 2016

Training a deep learning network

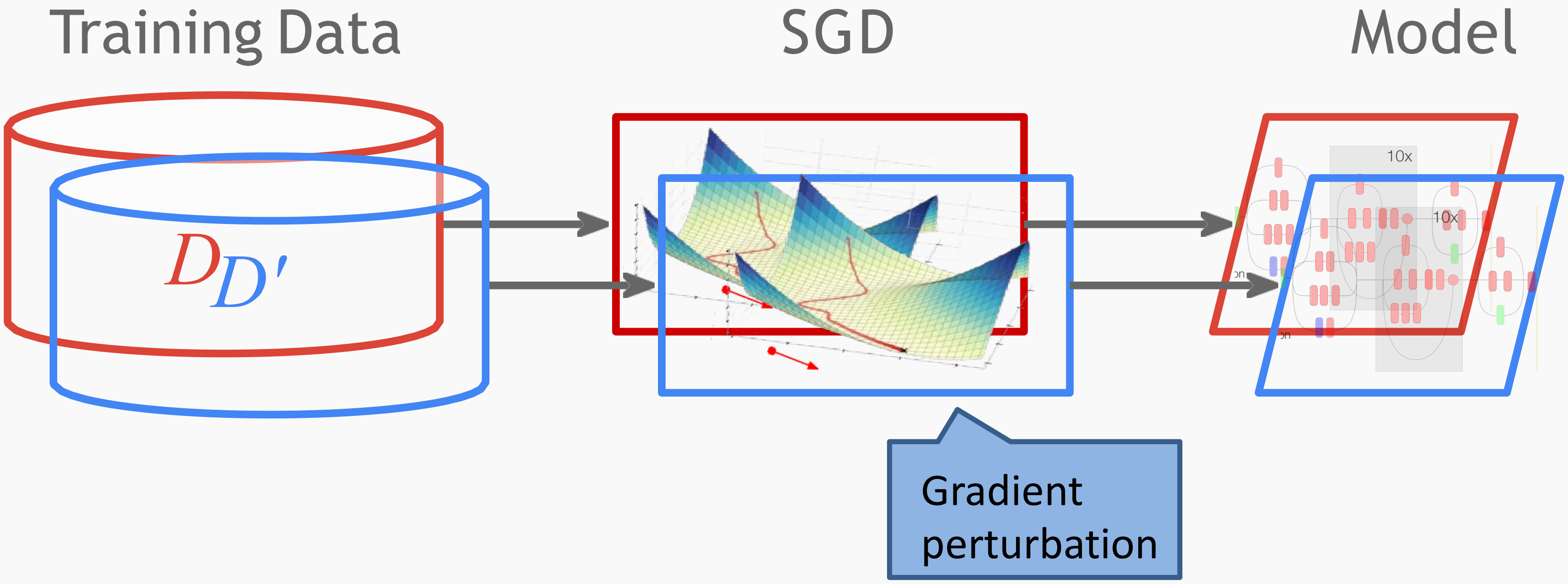


Interpreting Differential Privacy

Training Data SGD Model



Achieving Differential Privacy - DPSGD



Algorithm 1 Differentially private SGD (Outline)

Input: Examples $\{x_1, \ldots, x_N\}$, loss function $\mathcal{L}(\theta) = \frac{1}{N}\sum_i \mathcal{L}(\theta, x_i)$. Parameters: learning rate η_t, noise scale σ, group size L, gradient norm bound C.

Initialize θ_0 randomly

for $t \in [T]$ **do**

Take a random sample L_t with sampling probability L/N

Compute gradient

For each $i \in L_t$, compute $\mathbf{g}_t(x_i) \leftarrow \nabla_{\theta_t} \mathcal{L}(\theta_t, x_i)$

Clip gradient

$\bar{\mathbf{g}}_t(x_i) \leftarrow \mathbf{g}_t(x_i) / \max\left(1, \frac{\|\mathbf{g}_t(x_i)\|_2}{C}\right)$ Clipping with bound C

Add noise

$\tilde{\mathbf{g}}_t \leftarrow \frac{1}{L}\left(\sum_i \bar{\mathbf{g}}_t(x_i) + \mathcal{N}(0, \sigma^2 C^2 \mathbf{I})\right)$ Add noise

Descent

$\theta_{t+1} \leftarrow \theta_t - \eta_t \tilde{\mathbf{g}}_t$

Output θ_T and compute the overall privacy cost (ε, δ) using a privacy accounting method. Privacy composition

Our Datasets: "Fruit Flies of Machine Learning"

MNIST dataset:

70,000 images

28×28 pixels each

CIFAR-10 dataset:

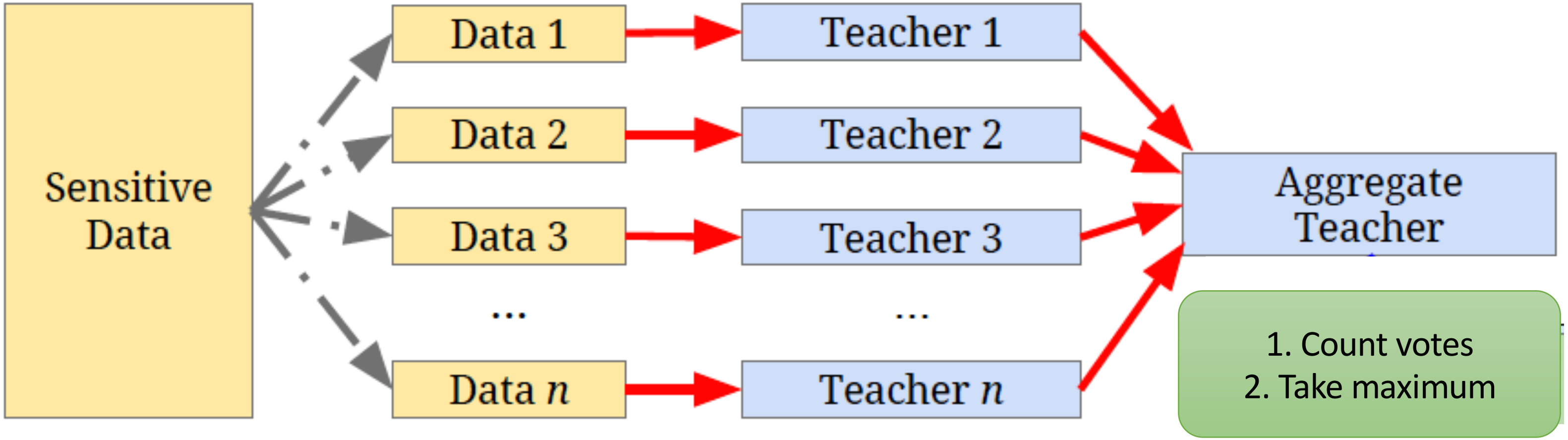
60,000 color images

32×32 pixels each

Summary of Results

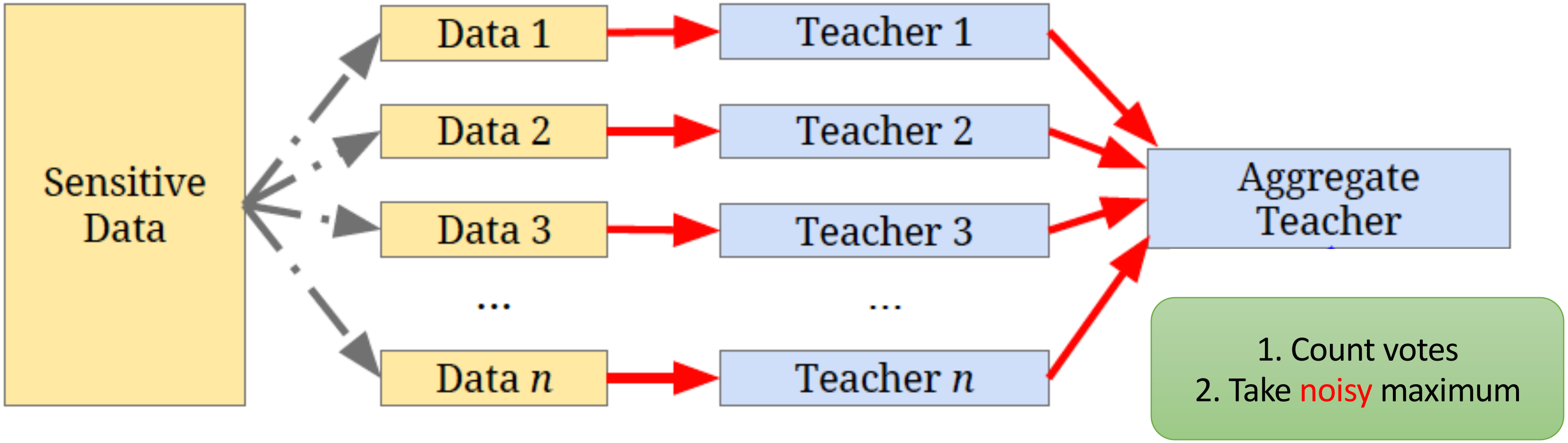
	Baseline	[SS15]	[WKC+16]	this work		
	no privacy	reports ε per parameter	$\varepsilon = 2$	$\varepsilon = 8$ $\delta = 10^{-5}$	$\varepsilon = 2$ $\delta = 10^{-5}$	$\varepsilon = 0.5$ $\delta = 10^{-5}$
MNIST	98.3%	98%	80%	97%	95%	90%
CIFAR-10	80%			73%	67%	

Private Aggregation of Teacher Ensembles (PATE)



How can we ensure DP for the teacher ensemble?

Private Aggregation of Teacher Ensembles (PATE)



The noisy aggregated teacher:

- **Each prediction increases total privacy loss.**

  privacy budgets create a tension between the accuracy and number of predictions

Evaluation

Dataset	ε	δ	Queries	Non-Private Baseline	Student Accuracy
MNIST	2.04	10^{-5}	100	99.18%	98.00%
MNIST	8.03	10^{-5}	1000	99.18%	98.10%
SVHN	5.04	10^{-6}	500	92.80%	82.72%
SVHN	8.19	10^{-6}	1000	92.80%	90.66%

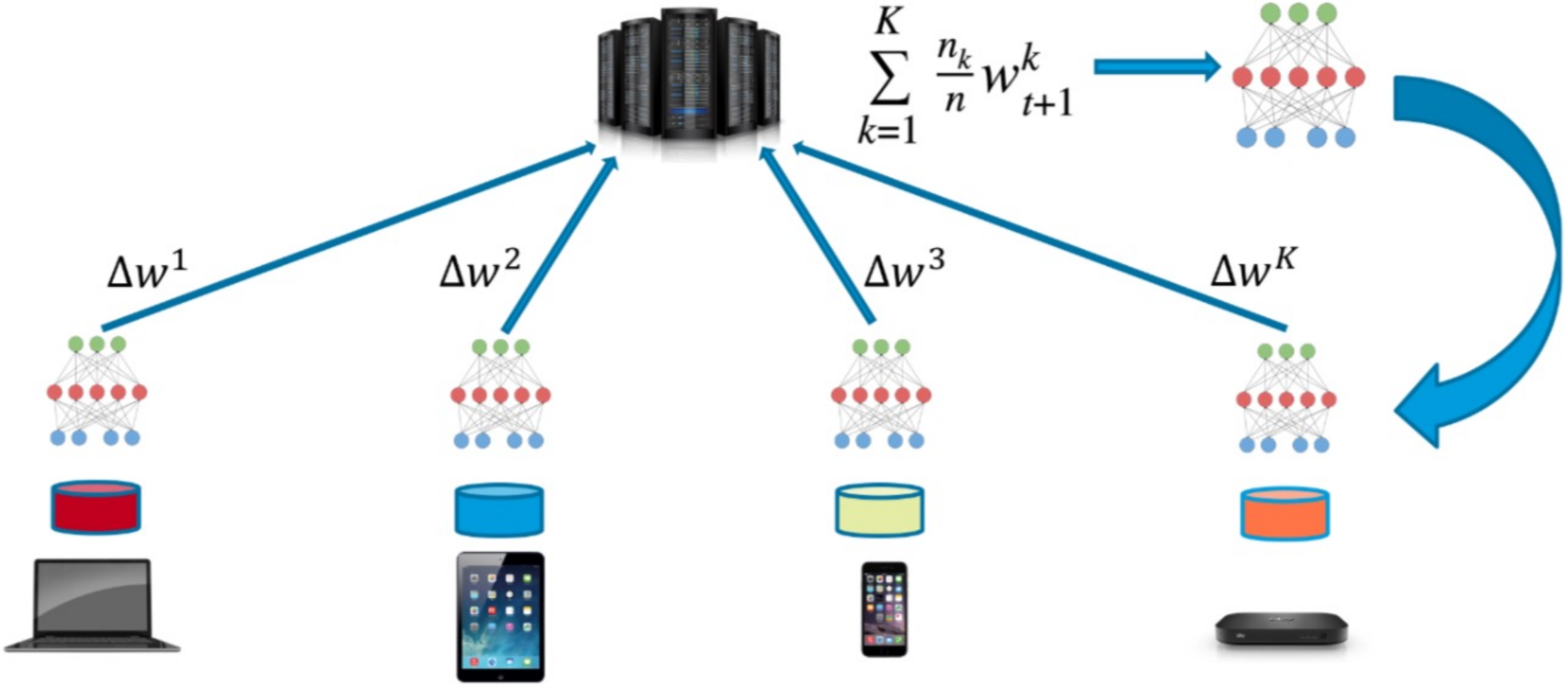
M Abadi et al. (2016) *Deep Learning with Differential Privacy*

$(0.5, 10^{-5})$ 90%

$(2, 10^{-5})$ 95%

$(8, 10^{-5})$ 97%

Federated Learning



Federated Averaging Algorithm

Server executes:

initialize x_0

for each round $t = 1, 2, \ldots,$ T **do**

$S_t \leftarrow$ (random set of M clients)

for each client $i \in S_t$ **in parallel do**

$x^i_{t+1} \leftarrow \text{ClientUpdate}(i, x_t)$

$x_{t+1} \leftarrow \sum_{k=1}^{M} \frac{1}{M} x^i_{t+1}$

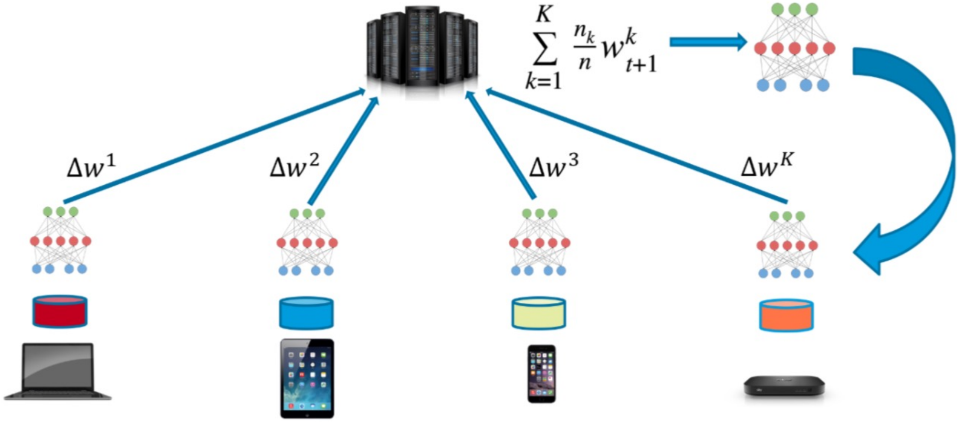
ClientUpdate(i, x)**:**

for local step $j = 1, \ldots, K$ **do**

$x \leftarrow x - \eta \nabla f(x; z)$ for $z \sim \mathcal{P}_i$

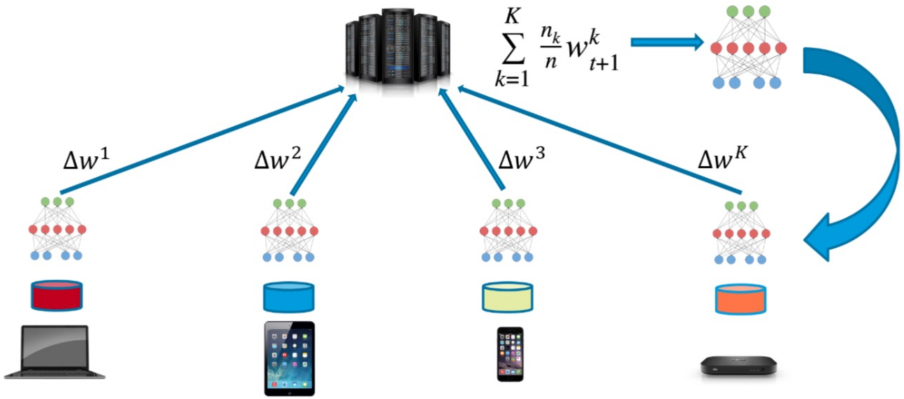
return x to server

Algorithm 1: Federated Averaging (local SGD), when all clients have the same amount of data.



Federated Learning with Differential Privacy

- Server is trusted – ensure DP for global model
  - DP at server
- Server is not trusted – ensure DP for gradients and resulting model
  - DP at client



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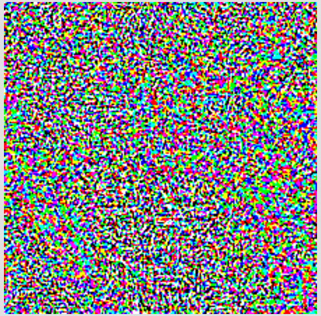
ADVERSARIAL EXAMPLES

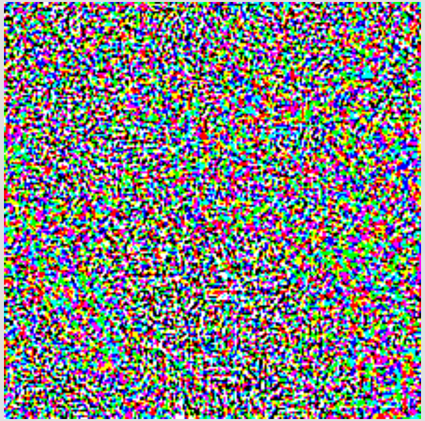
Classified as panda



Small adversarial noise

Classified as gibbon

ADVERSARIAL EXAMPLES



Small adversarial noise

ADVERSARIAL EXAMPLES

Constraint:
$\| x^{*} - x \|_{p} \leq \epsilon$
$p = 0, 1, 2, \infty$

1. Non-targeted attack:
   $y_{true} \neq y^{*}$

2. Targeted attack:
   y^{*} is the target label specified by the adversary

Figure by Qiuchen Zhang

Carlini and Wagner (C&W) (2017)

- Followed L-BFGS work
- Dealt with box constraints by change of variables: X^{adv} = 0.5(tanh(w) + 1)
- K: determine confidence level
- Used Adam optimizer

$$\|x^{adv} - x\|_p + c \underbrace{\max\left(\max_{i \neq Y} f(x^{adv})_i - f(x^{adv})_Y, -\kappa\right)}_{\text{Loss function}} \rightarrow \text{minimum}$$

0.5(tanh(w) + 1)

confidence

Adversarial Example Defenses

- Adversarial training (training stage)
- Detection and reformation (inference stage)
- Preprocessing (inference stage)
- Randomized smoothing for certified robustness (inference stage)

References
Privacy attacks and privacy-preserving deep learning

- Membership Inference Attacks Against Machine Learning Models, S&P, 2017
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- The secret sharer: Evaluating and testing unintended memorization in neural networks, USENIX Security, 2019
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- Semi-supervised Knowledge Transfer for Deep Learning from Private Training Data, ICLR, 2017
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