Membership and Property Inference Attacks Against Machine Learning

Emiliano De Cristofaro
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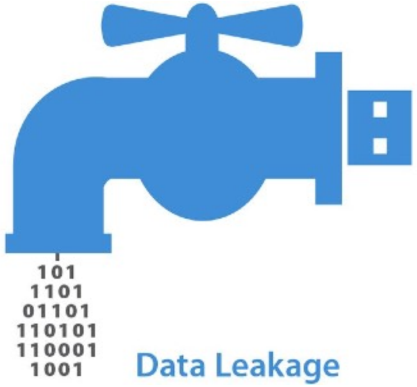
Reasoning about "privacy" in ML



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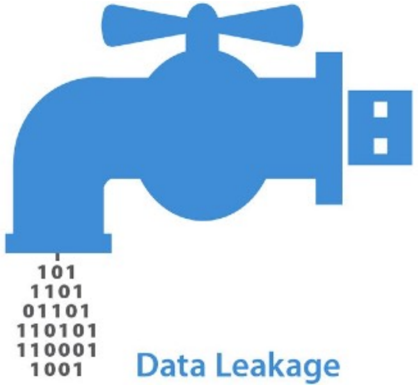

Reasoning about "privacy" in ML

Most papers on privacy attacks in ML focus on inferring:

1. Inclusion of a data point in the training set (aka "membership inference")
2. What class representatives look like

1. Membership Inference

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Well-understood problem, besides the more obvious leakage

- Establish wrongdoing
- Assess protection, e.g., from differentially private defenses

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In a nutshell: given a gender classifier, infer race of people in Bob's photos

Agenda

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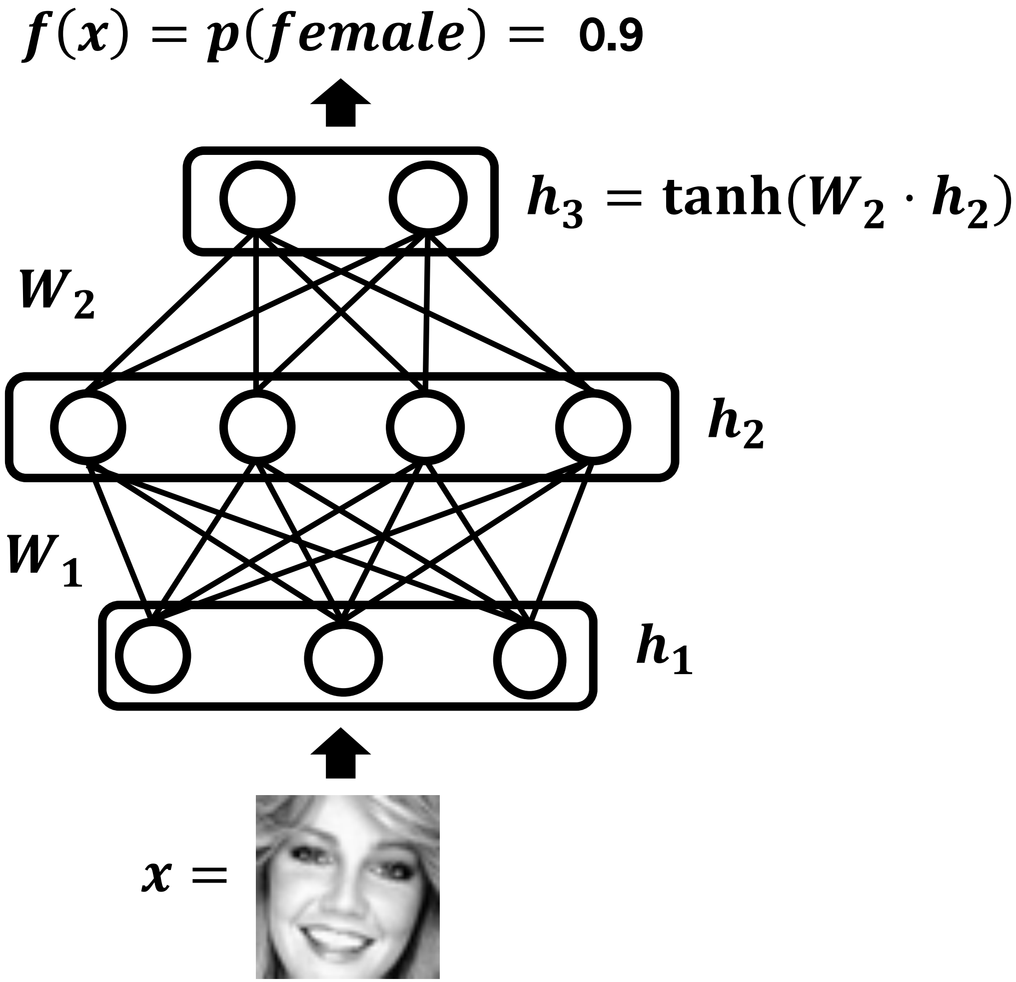
Luca Melis, Congzheng Song, Emiliano De Cristofaro, Vitaly Shmatikov. Exploiting Unintended Feature Leakage in Collaborative Learning. IEEE Symposium on Security & Privacy (S&P'19)

Deep Learning

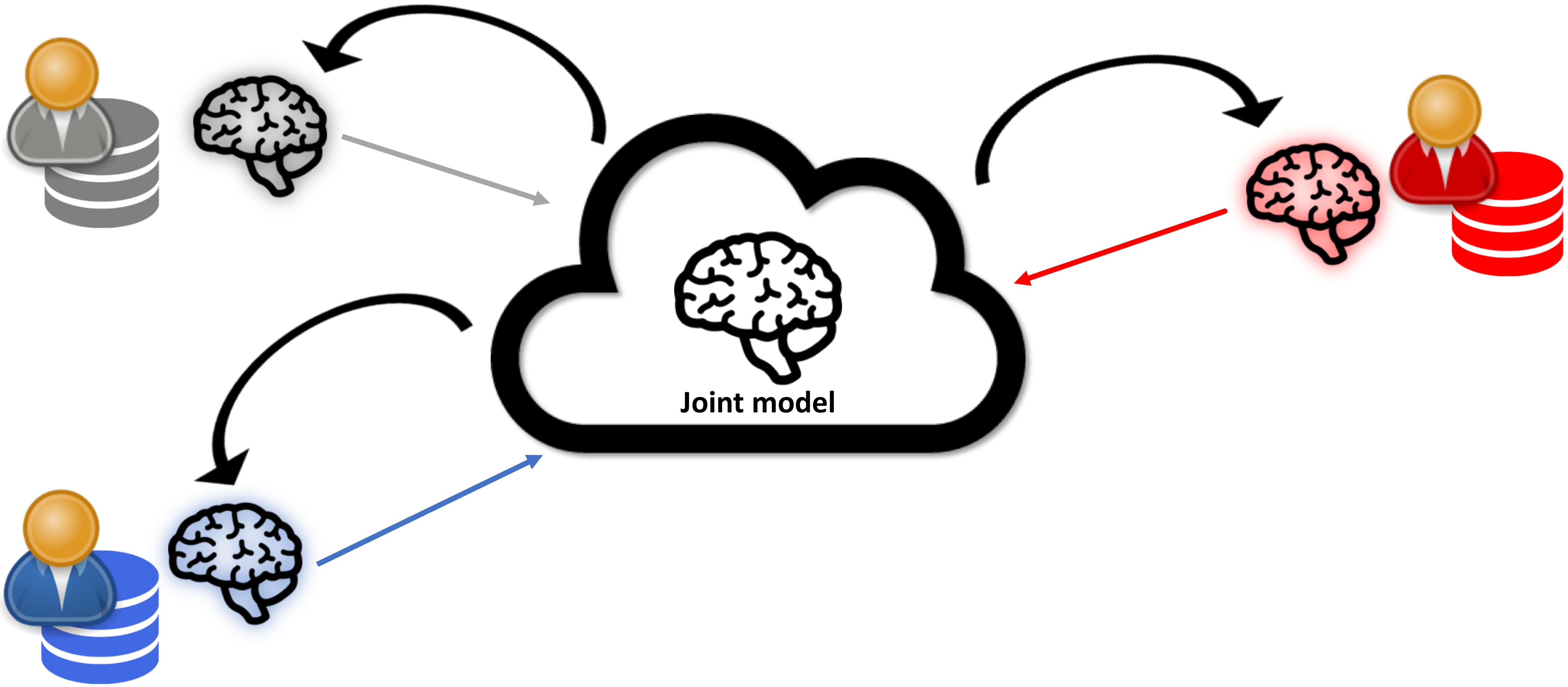


- Map input x to layers of hidden representations h, then to output y
- $h_{l+1} = a(W_l \cdot h_l)$ with parameter W_l
- Train model to minimizes loss:

$$W = \text{argmin}_W L(f(x), y)$$

- Gradient descent on parameters:
  - Each iteration train on a batch
  - Update W based on gradient of L

Collaborative/Federated Learning



Collaborative

Federated

Algorithm 1 Parameter server with synchronized SGD

Server executes:

Initialize θ_0
for $t = 1$ to T **do**
  for each client k **do**
    $g_t^k \leftarrow$**ClientUpdate**(θ_{t-1})
  end for
  $\theta_t \leftarrow \theta_{t-1} - \eta \sum_k g_t^k$
end for

ClientUpdate(θ):

Select batch b from client's data
return local gradients $\nabla L(b;\theta)$

Algorithm 2 Federated learning with model averaging

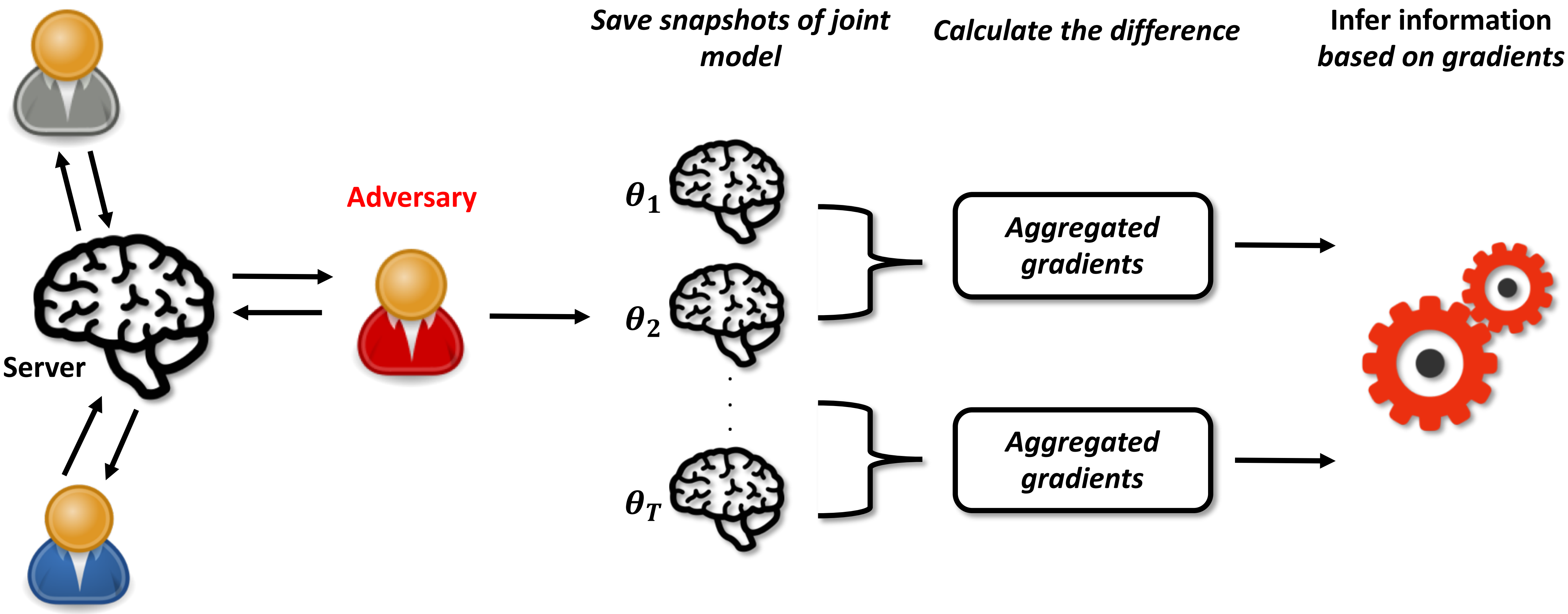
Server executes:

Initialize θ_0
$m \leftarrow max(C \cdot K, 1)$
for $t = 1$ to T **do**
  $S_t \leftarrow$ (random set of m clients)
  for each client $k \in S_t$ **do**
    $\theta_t^k \leftarrow$**ClientUpdate**(θ_{t-1})
  end for
  $\theta_t \leftarrow \sum_k \frac{n^k}{n} \theta_t^k$
end for

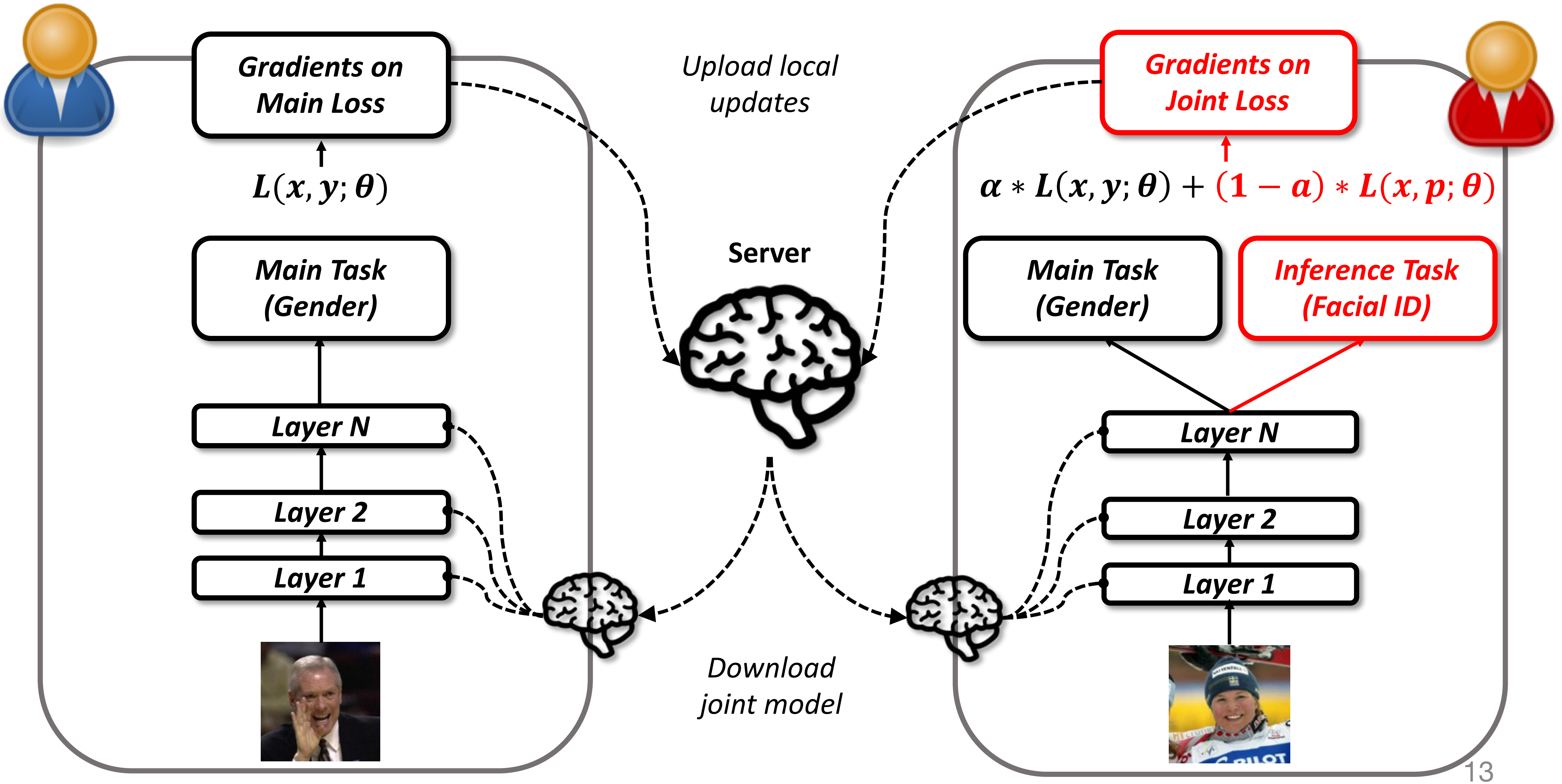
ClientUpdate(θ):

for each local iteration **do**
  for each batch b in client's split **do**
    $\theta \leftarrow \theta - \eta \nabla L(b;\theta)$
  end for
end for
return local model θ

Passive Property Inference Attack



Active Property Inference Attack

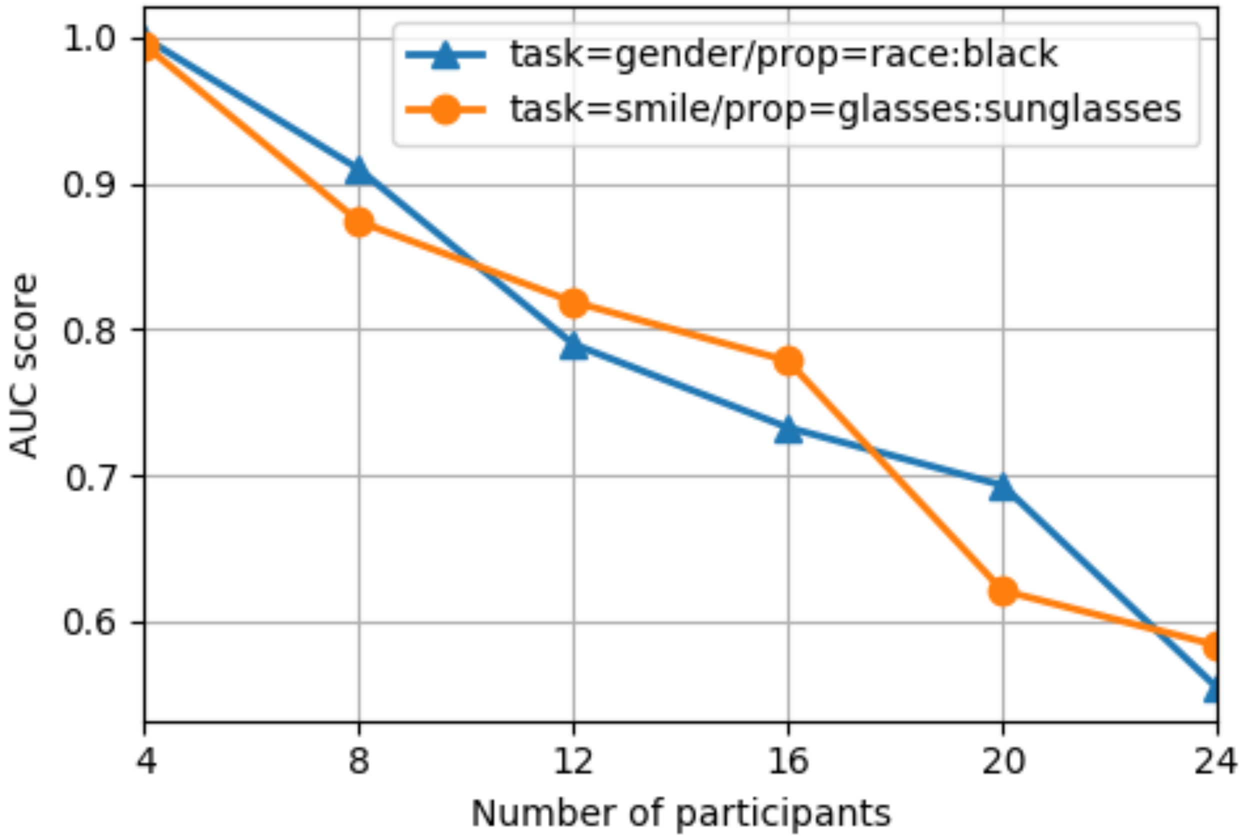


Dataset	Type	Main Task	Inference Task
LFW	Images	Gender/Smile/Age Eyewear/Race/Hair	Race/Eyewear
FaceScrub	Images	Gender	Identity
PIPA	Images	Age	Gender
FourSquare	Locations	Gender	Membership
Yelp-health	Text	Review Score	Membership Doctor specialty
Yelp-author	Text	Review Score	Author
CSI	Text	Sentiment	Membership Region/Gender/Veracity

Property Inference on LFW

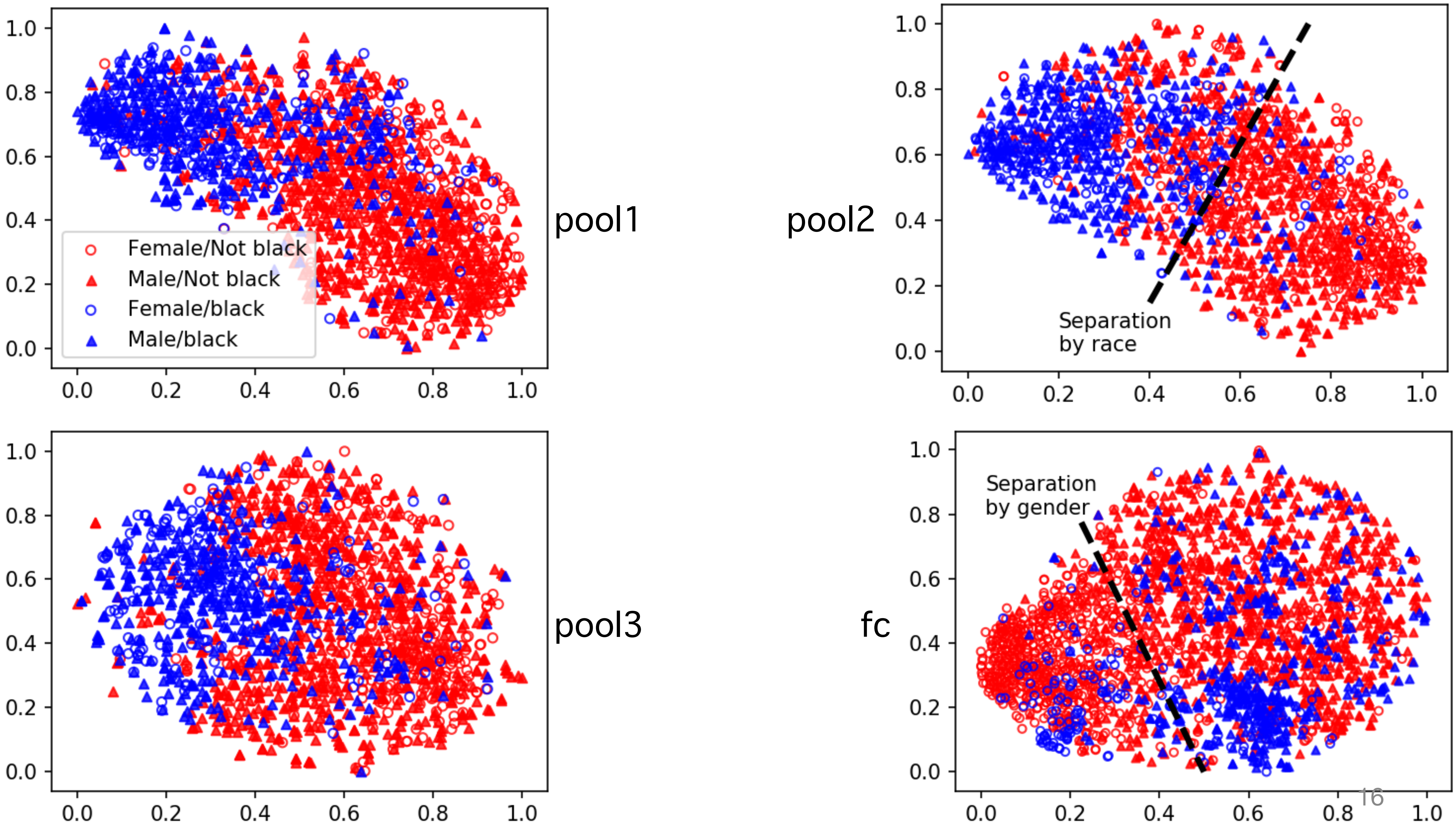
Main Task	Inference Task	Correlation	AUC score
Gender	Sunglasses	-0.025	1.0
Smile	Asian	0.047	0.93
Age	Black	-0.084	1.0
Race	Sunglasses	0.026	1.0
Eyewear	Asian	-0.119	0.91
Hair	Sunglasses	-0.013	1.0

Two-Party



Multi-Party

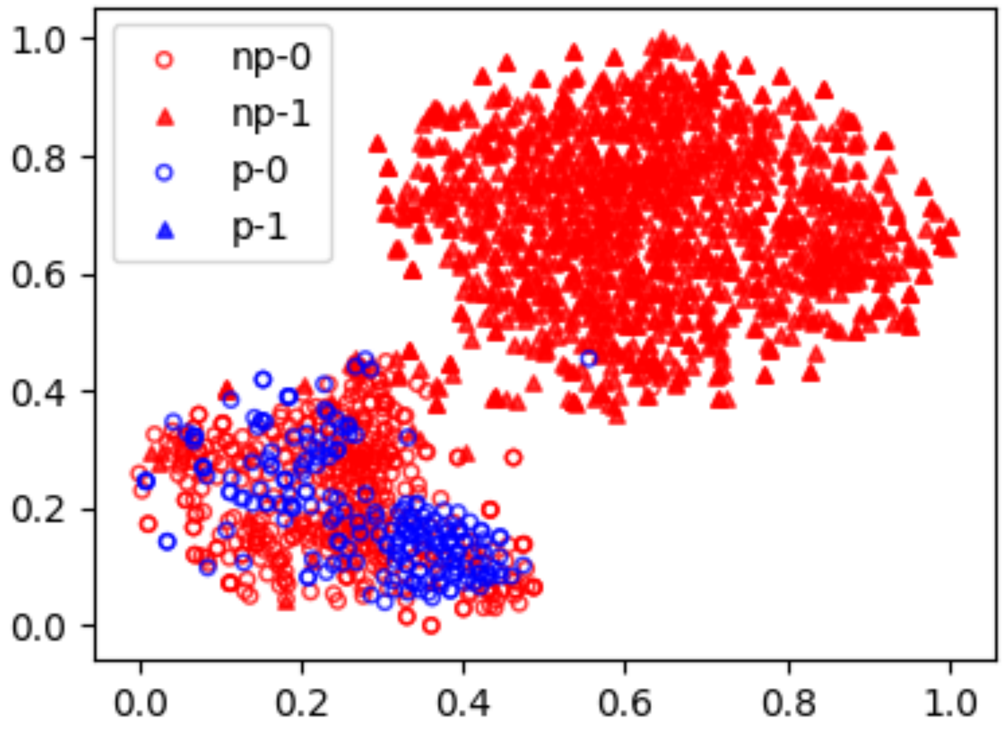
Feature t-SNE projection


pool1
pool2
pool3
fc
Female/Not black
Male/Not black
Female/black
Male/black
Separation
by race
Separation
by gender
0.0
0.2
0.4
0.6
0.8
1.0

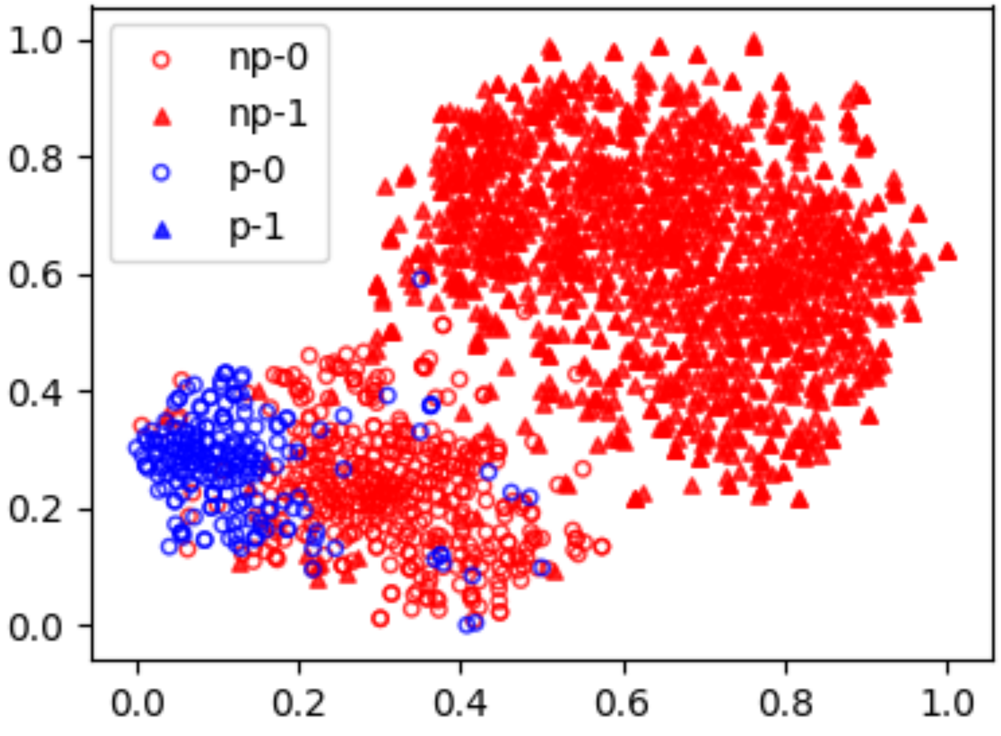
Passive vs Active Attack on FaceScrub

Main Task: ▲/●= female/male

Inference Task: Blue points with the property (identity)



Passive attack



Active attack

Inferring when a property occurs

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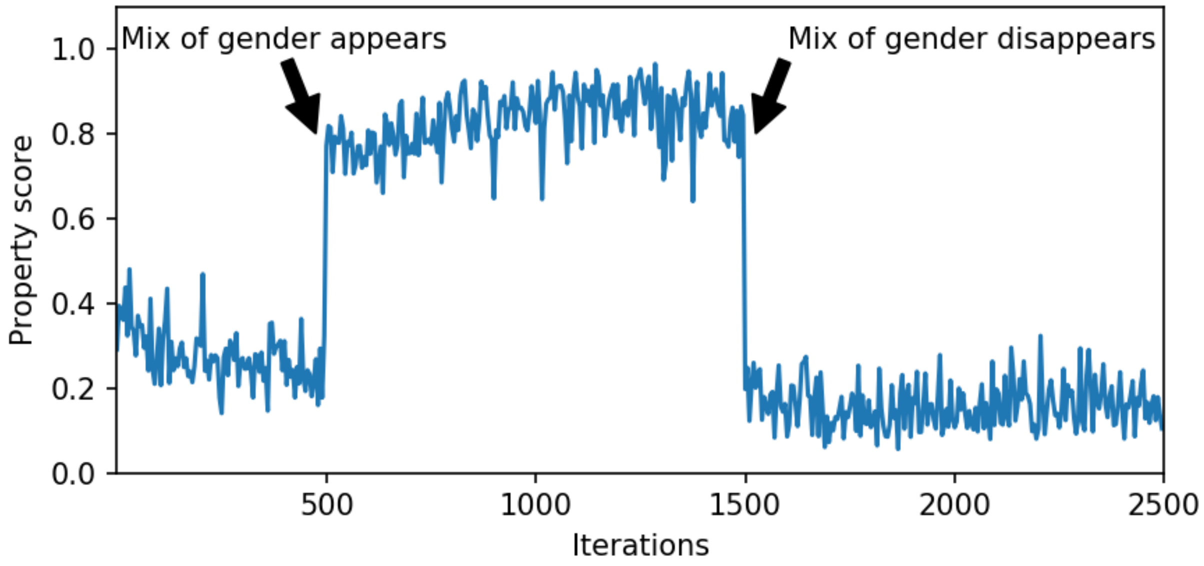
Batches with the property appear



Main task: Age / Two-party

Inference task: people in the image are of the same gender (PIPA)

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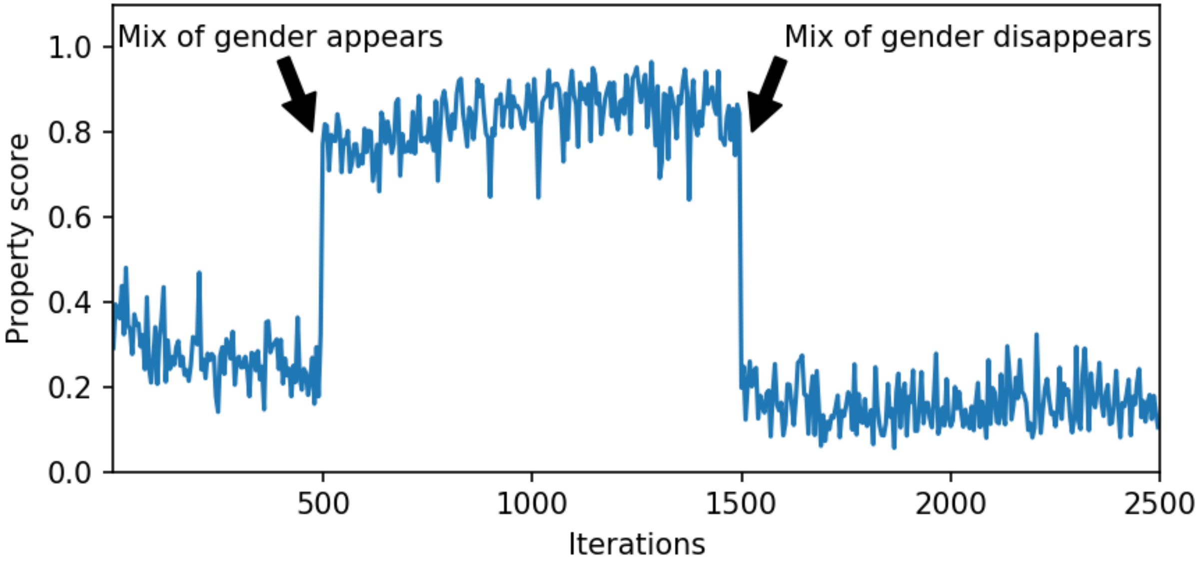

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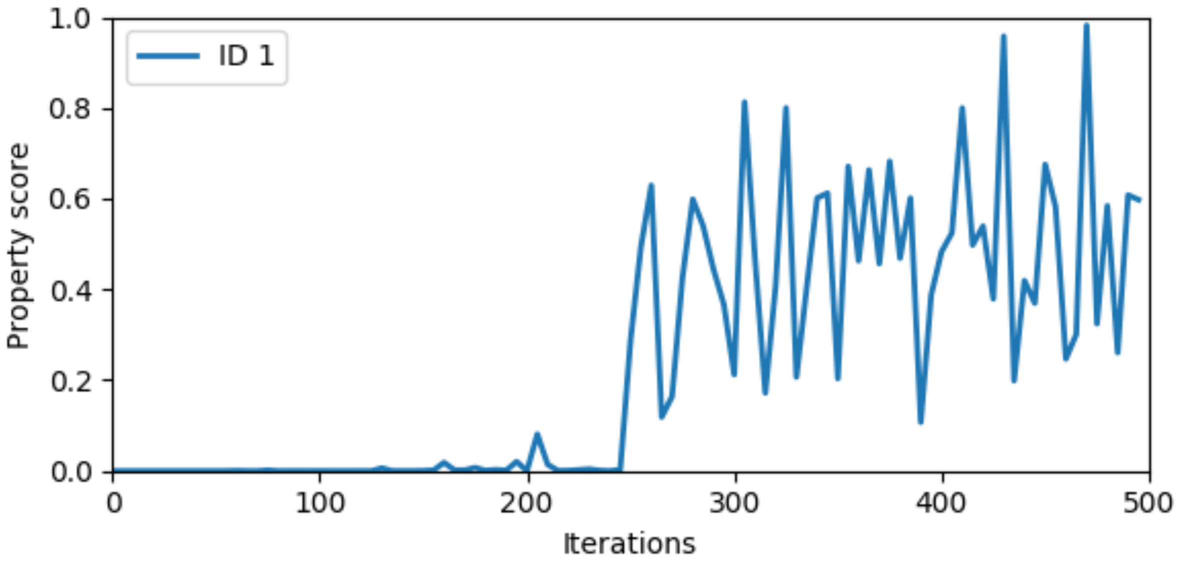
Participant with ID 1 joins training



Main task: Gender / Multi-Party

Inference task: author identification

Defenses?

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Selective gradient sharing

Dataset: Text reviews

Main Task: Sentiment classifier

Doesn’t really work…

Property / % parameters shared	10%	50%	100%
Top region	0.84	0.86	0.93
Gender	0.90	0.91	0.93
Veracity	0.94	0.99	0.99

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Participant-level differential privacy

Hide participant's contributions

Only two mechanisms in the literature

Fail to converge for "few" participants

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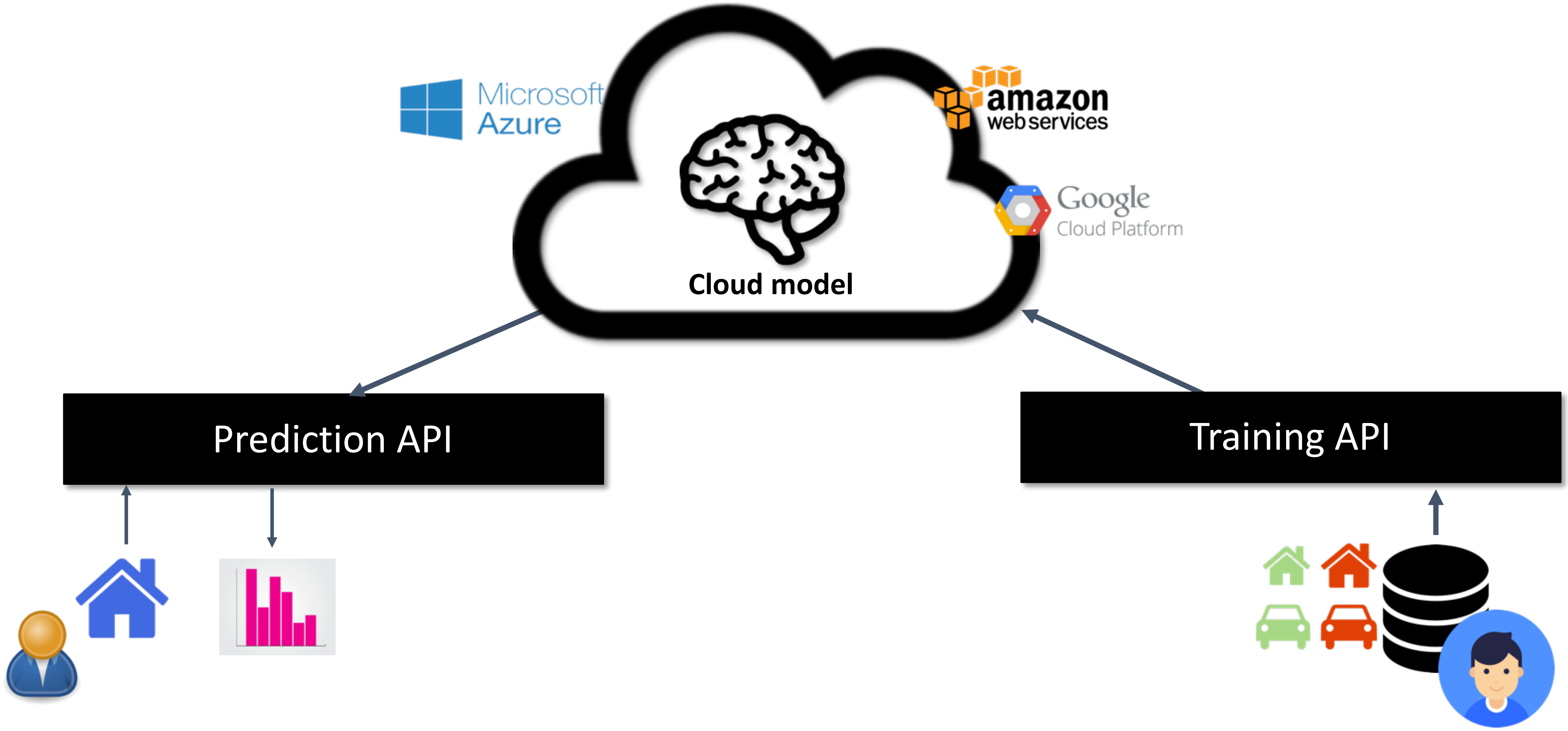

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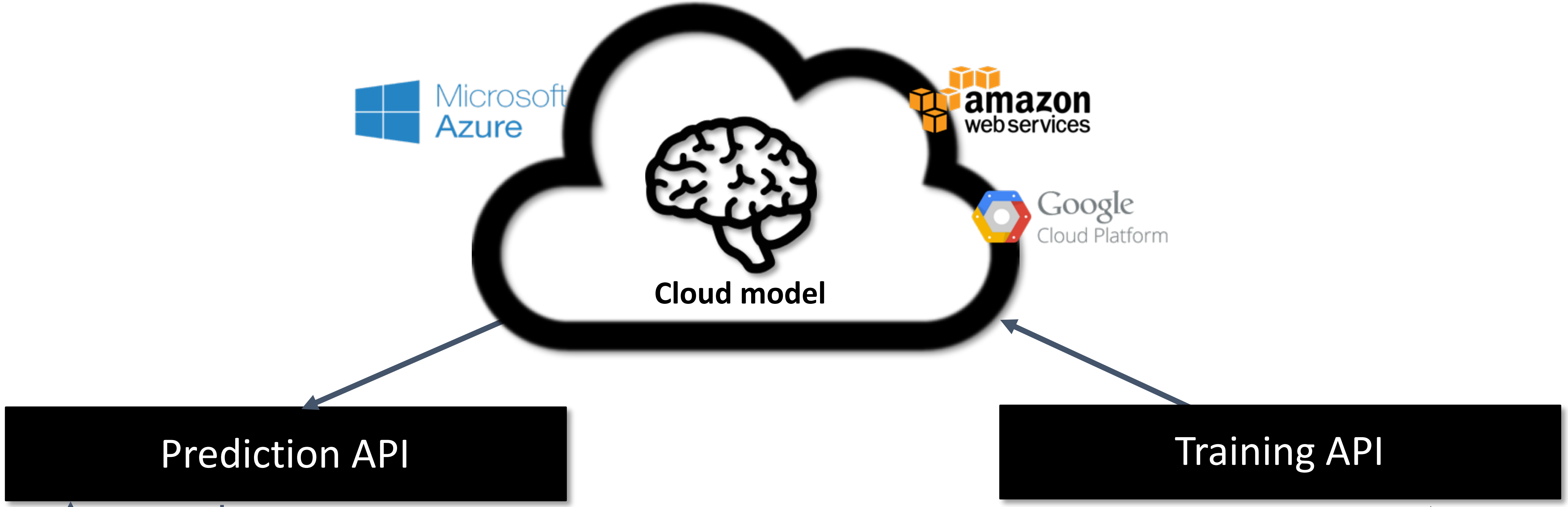

Predictions are leaky!

Shokri et al. Membership inference attacks against machine learning models. S&P'17

Membership Inference in Generative Models

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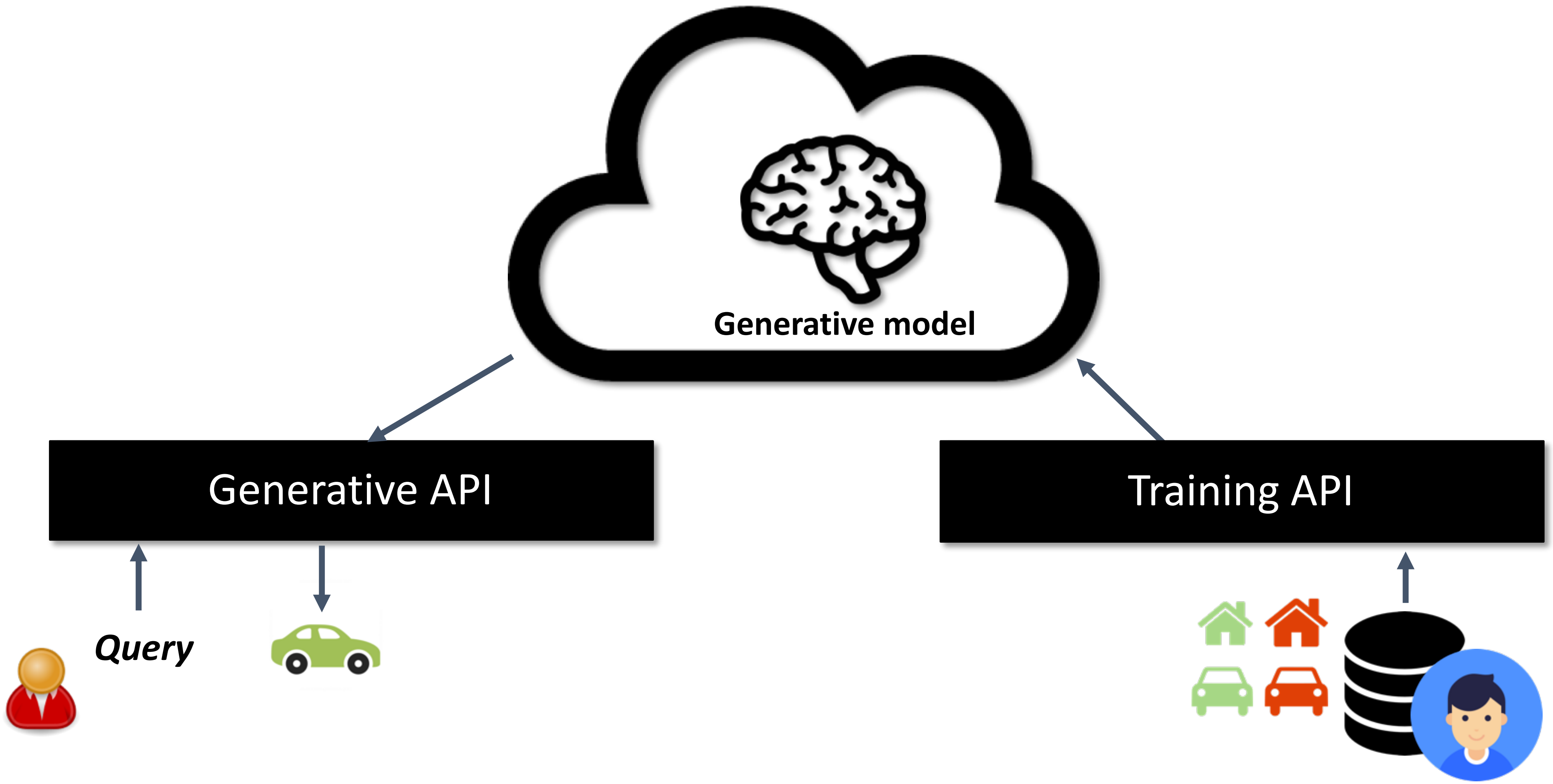
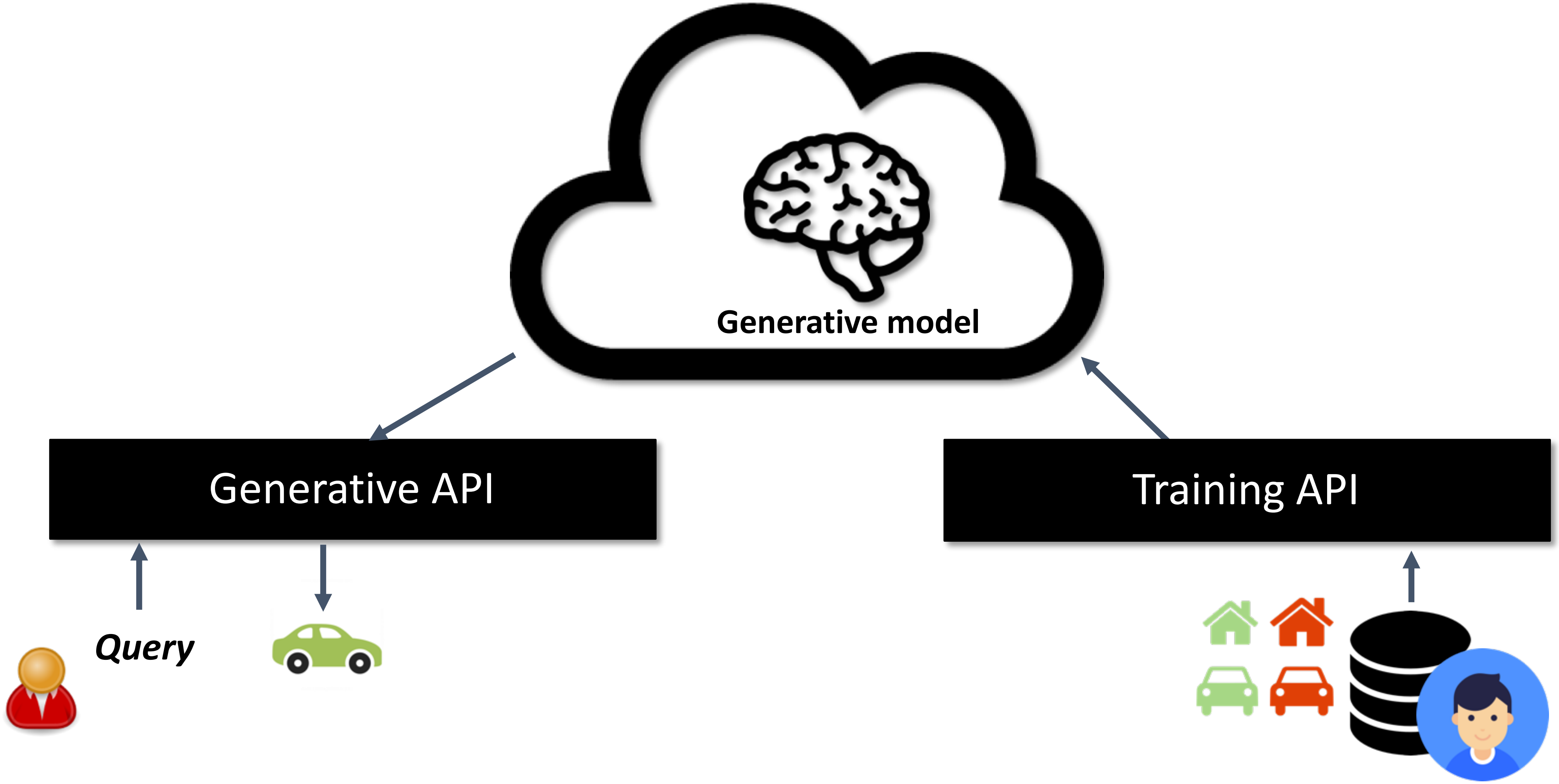


Membership Inference in Generative Models



Jamie Hayes, Luca Melis, George Danezis, Emiliano De Cristofaro. LOGAN: Membership Inference Attacks Against Generative Models. PETS 2019.

Inference without predictions?

Use generative models!

Train GANs to learn the distribution and a prediction model at the same time

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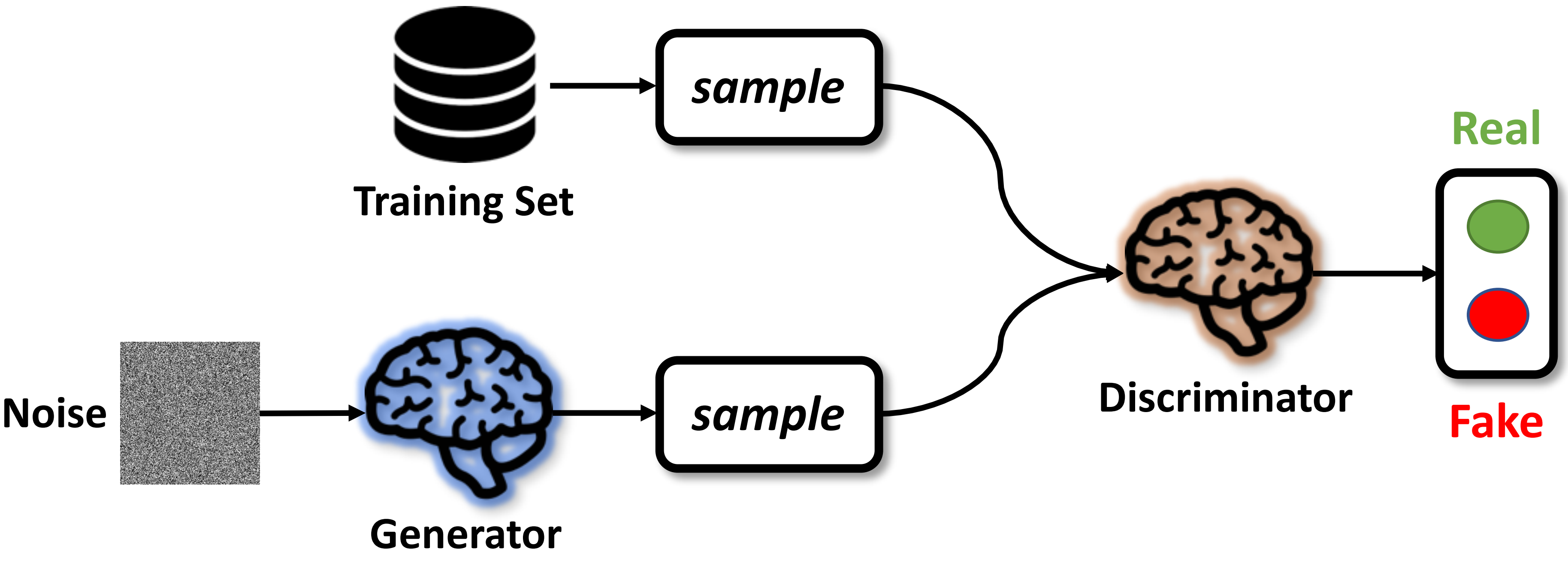
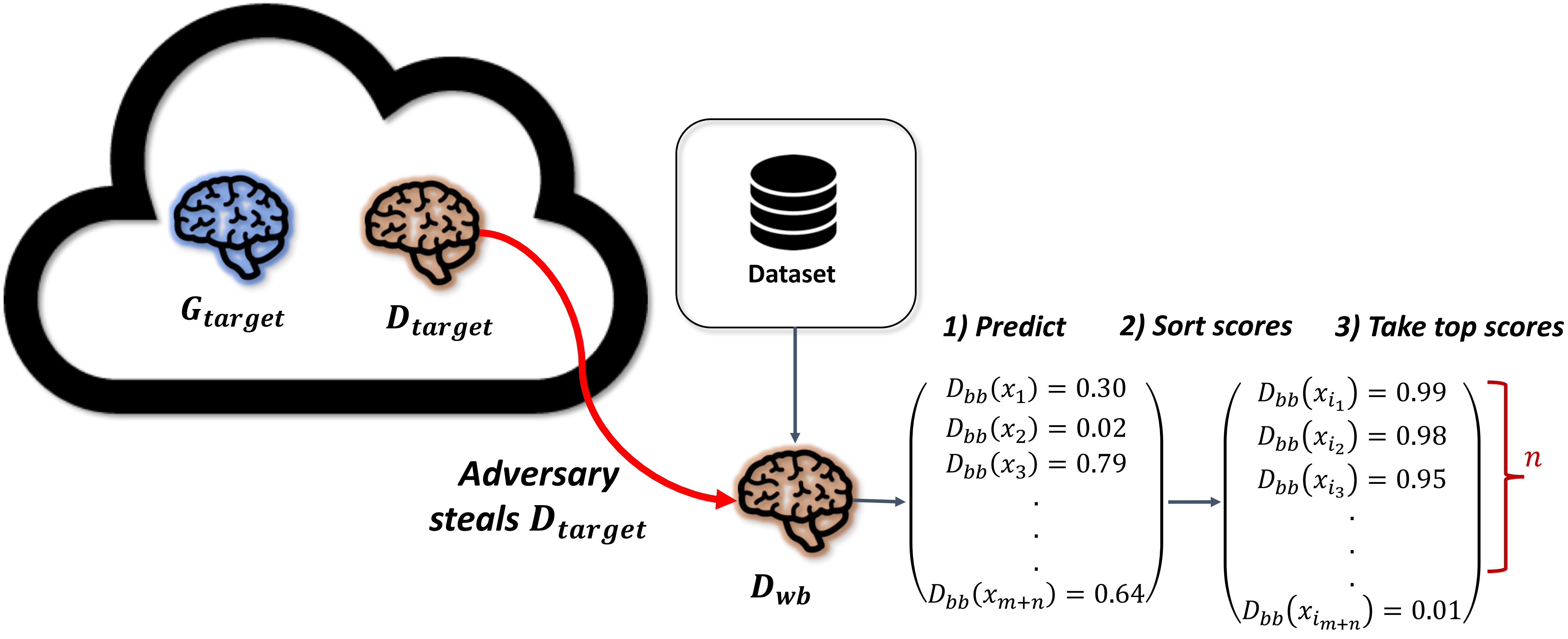
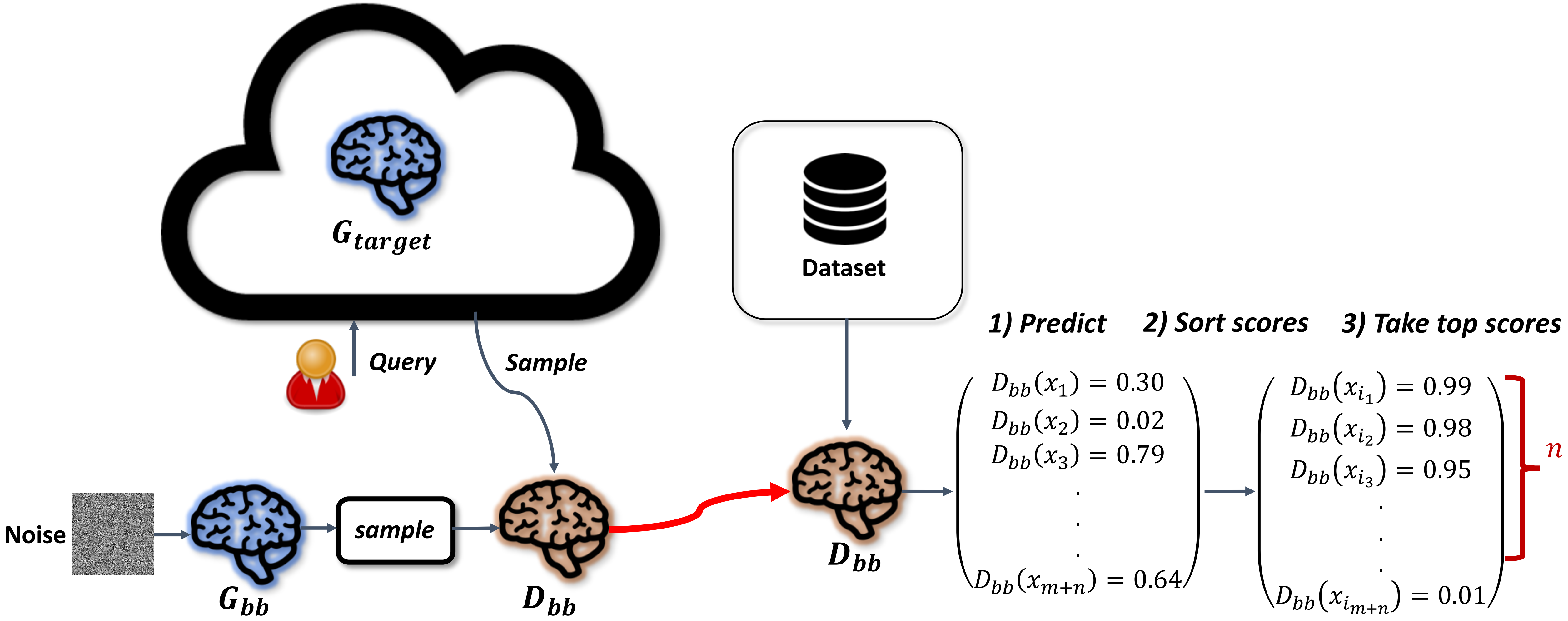


White-Box Attack



Black-Box Attack

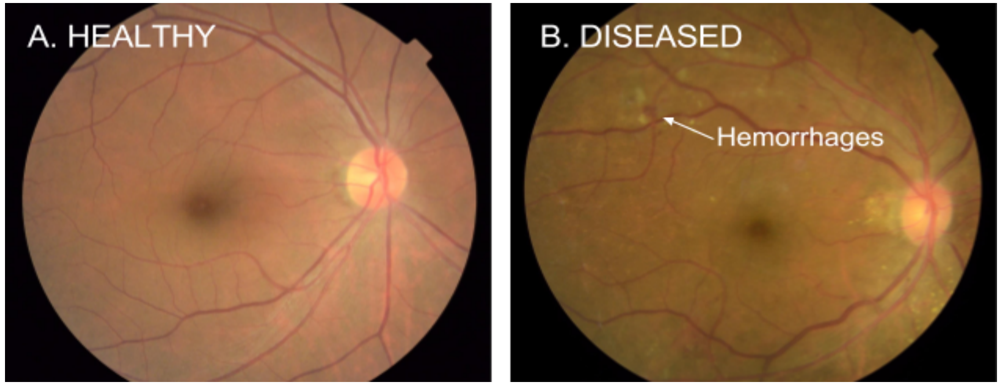


Datasets

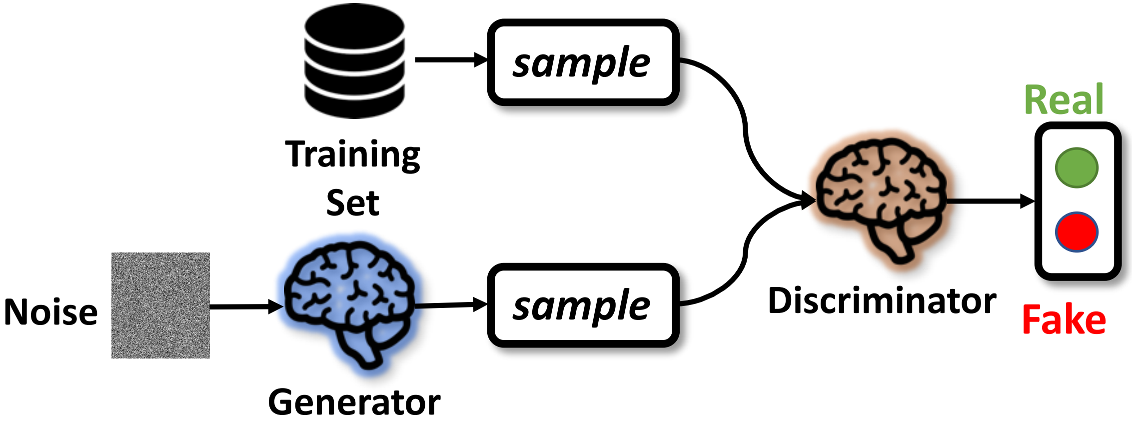
LFW

CIFAR-10

DR



Models



Attacker Model:

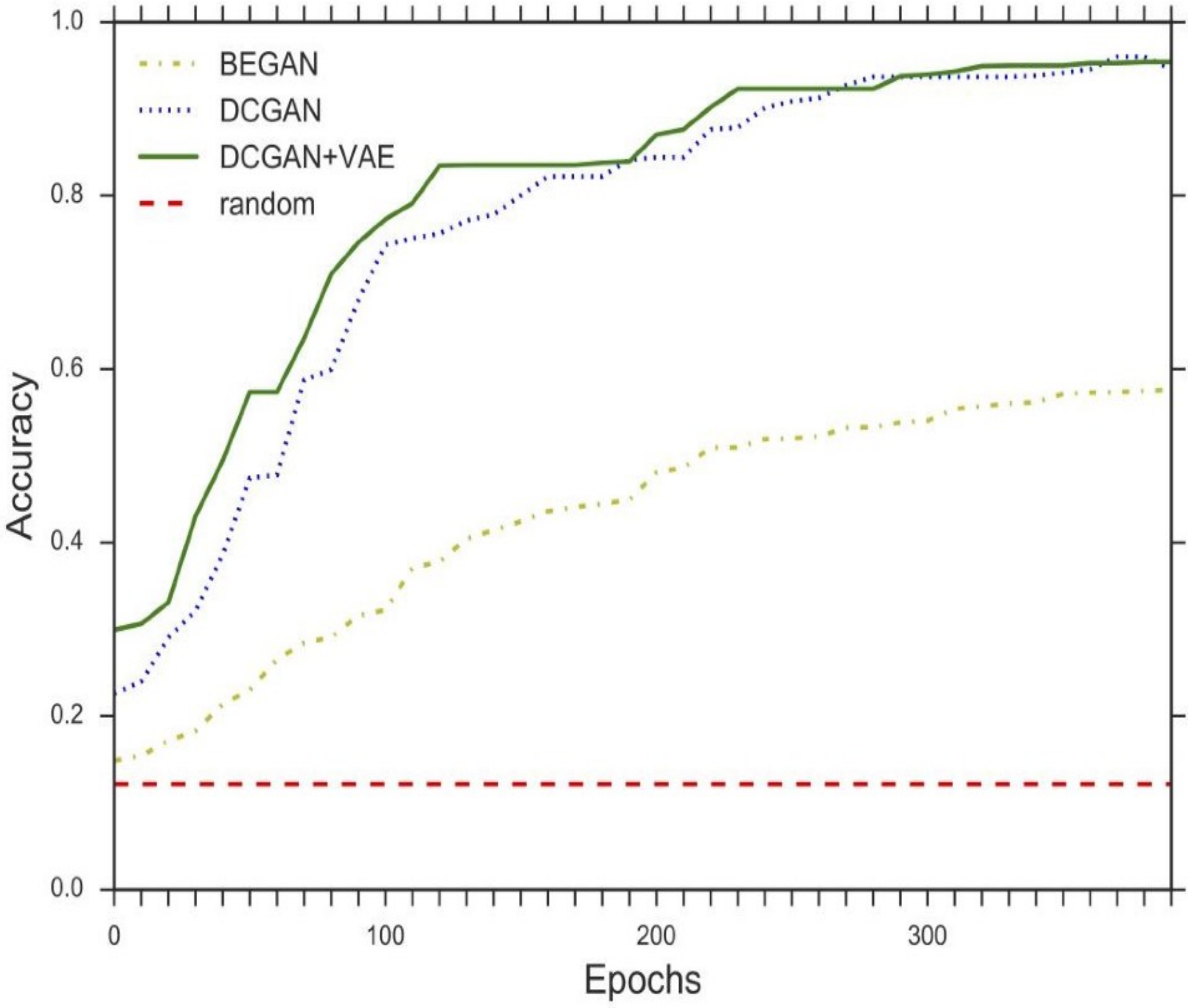
DCGAN

Target Model:

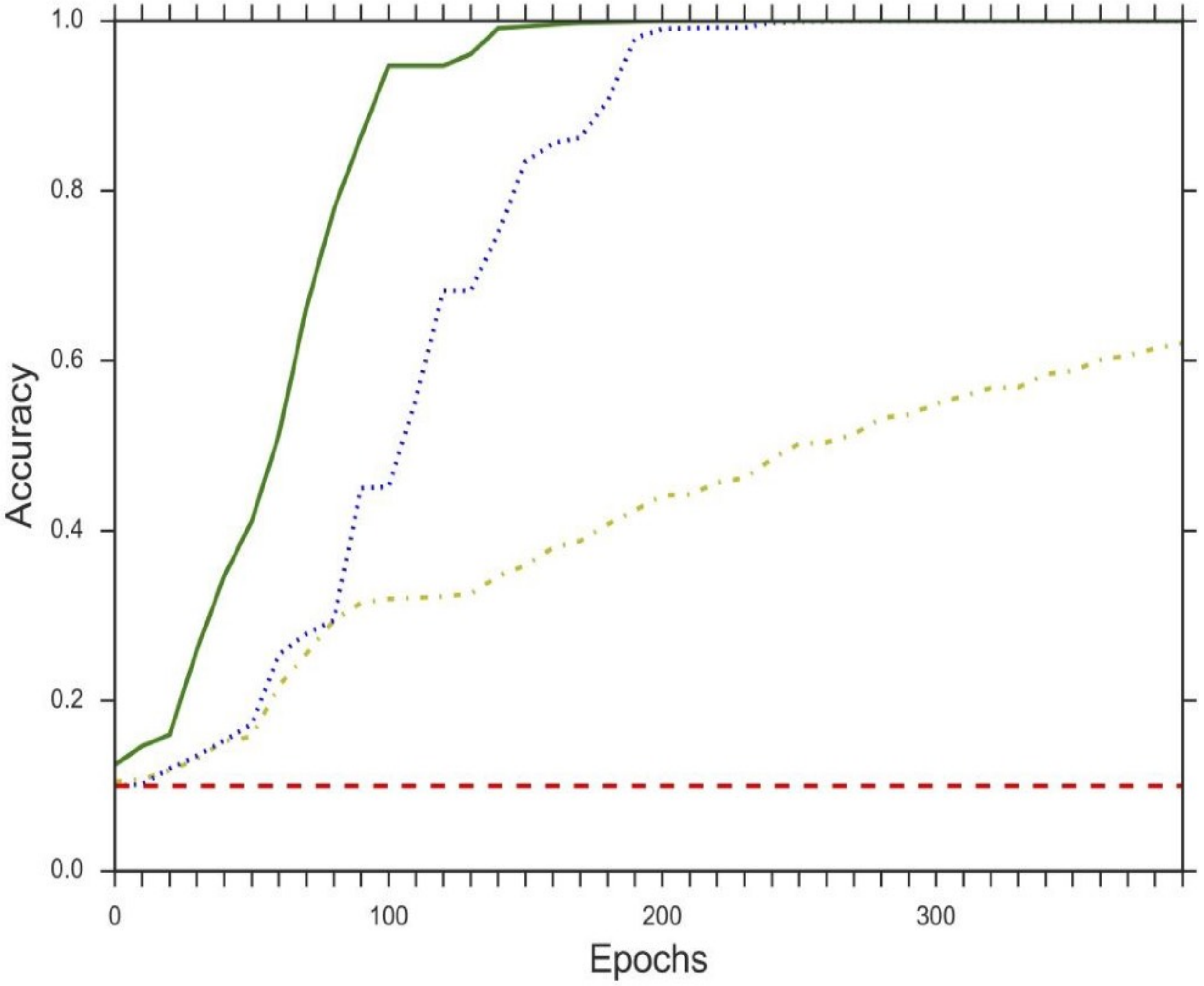
DCGAN, DCGAN+VAE, BEGAN

White-Box Results

LFW, top ten classes



CIFAR-10, random 10% subset



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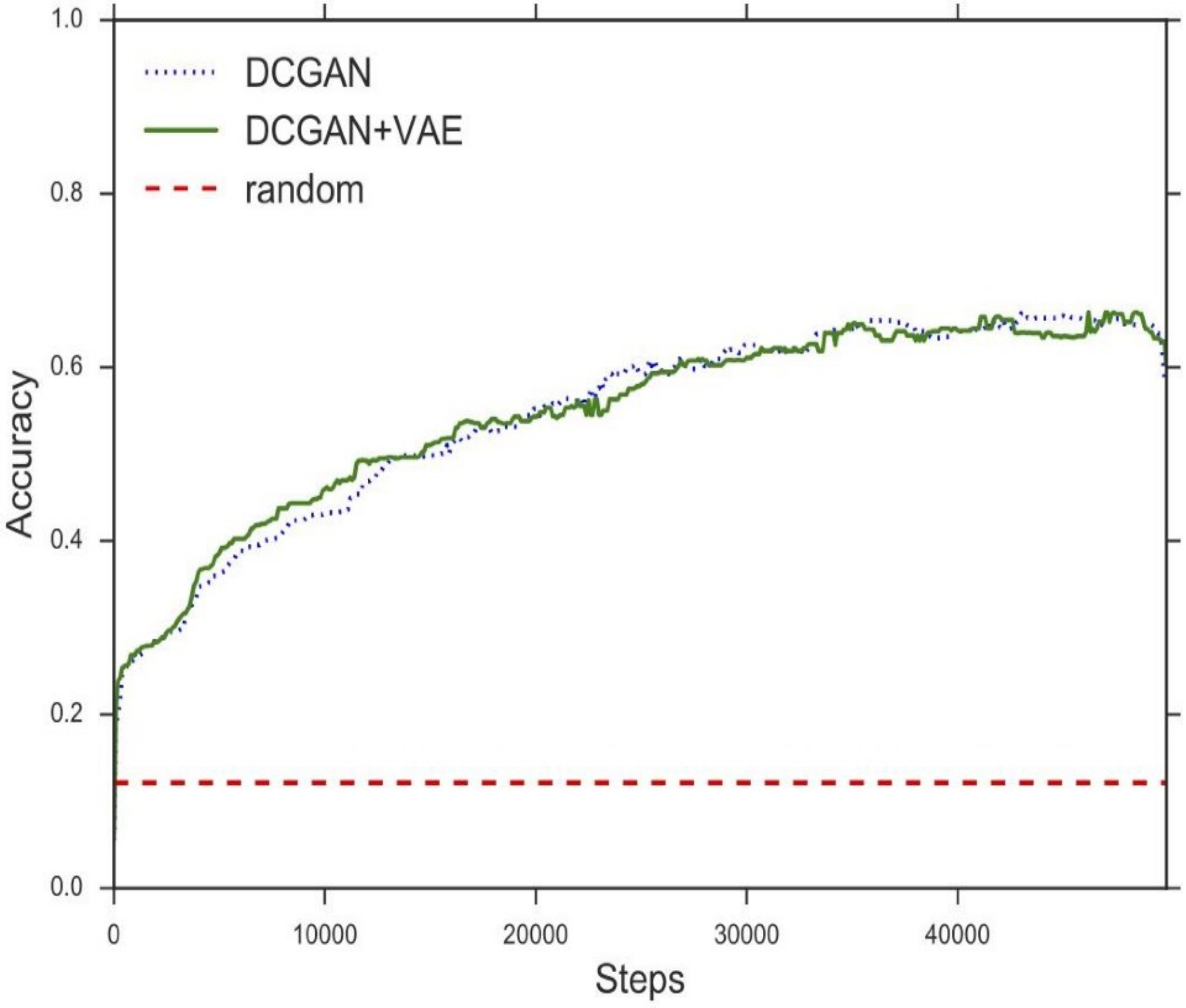

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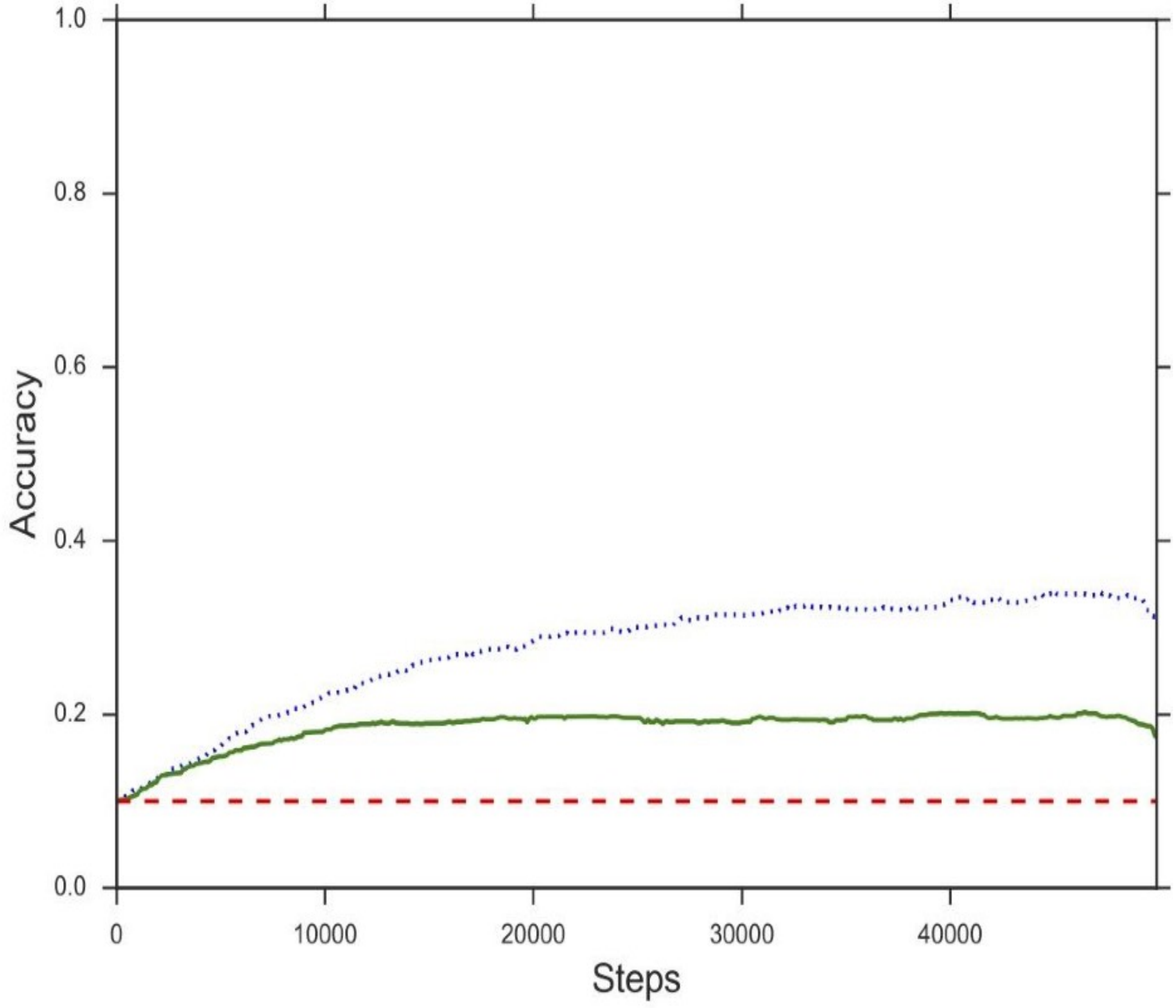
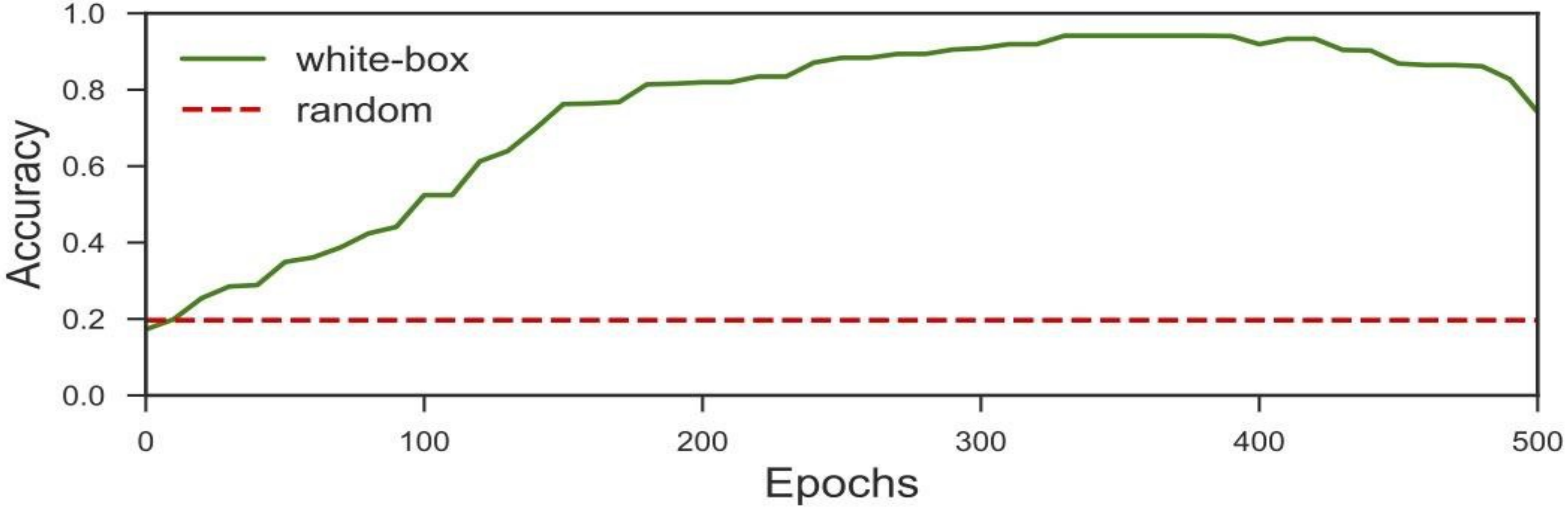
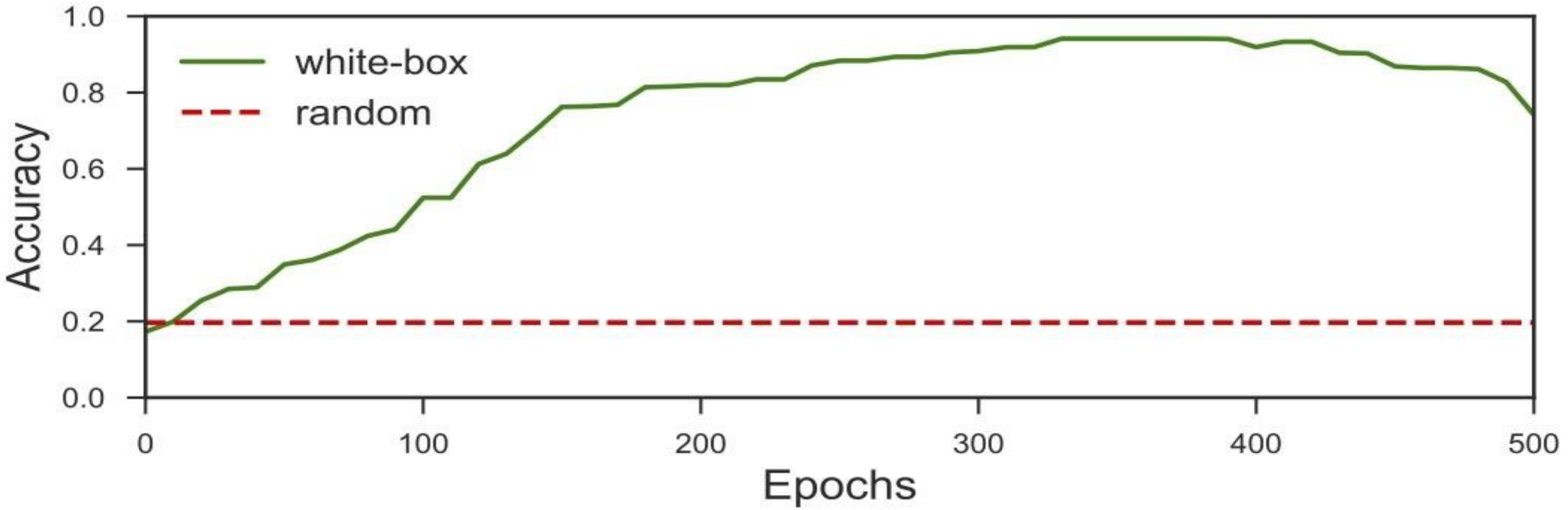


DR Dataset



1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
white-box
random
0
100
200
300
400
500
Epochs

DR Dataset



white-box
random
Accuracy
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0.8
0.6
0.4
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0
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200
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400
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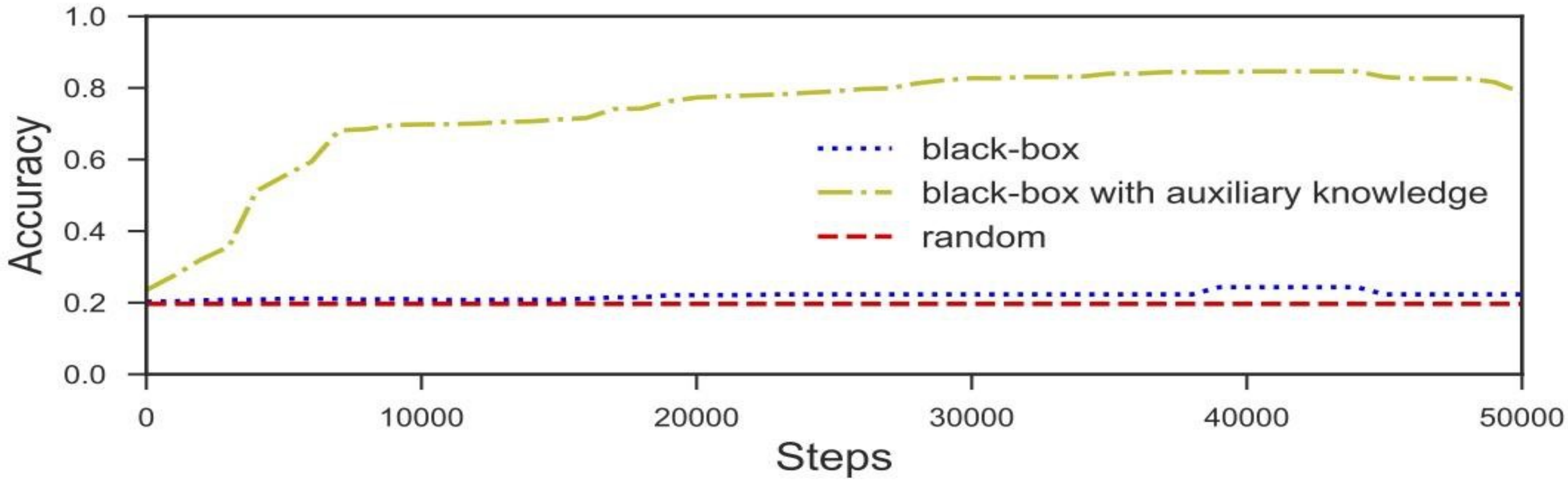
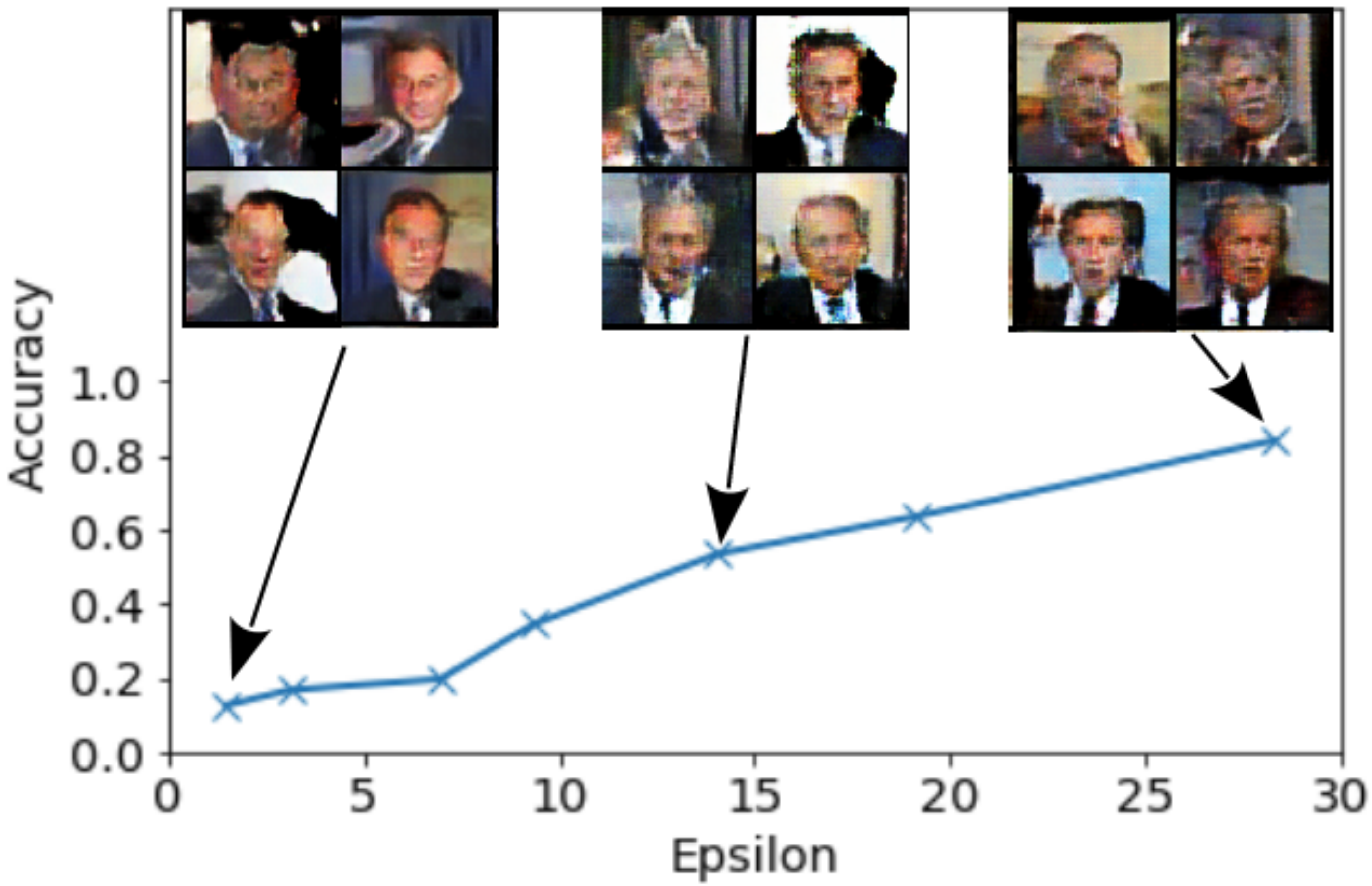
Epochs



black-box
black-box with auxiliary knowledge
random
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
0
10000
20000
30000
40000
50000
Steps

Defense? Differentially Private GAN*



White-box, LFW, top ten classes

*Triastcyn et al. "Generating differentially private datasets using GANs." arXiv 1803.03148

Thank you!

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