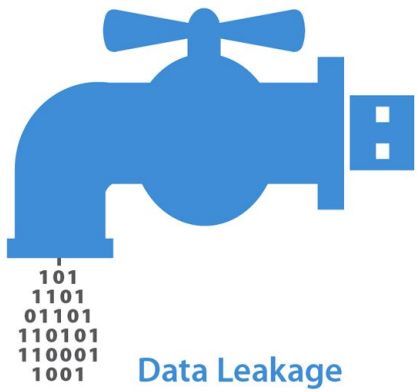
Privacy in ML... It's Complicated

Emiliano De Cristofaro
https://emilianodc.com

Reasoning about "privacy" in ML



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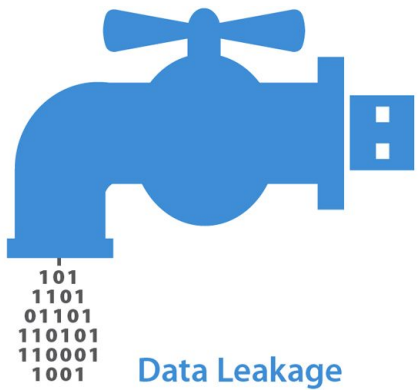

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1. Inclusion of a data point in the training set
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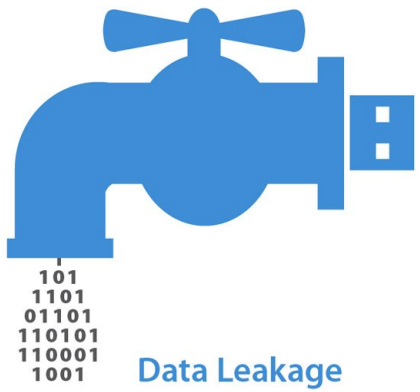

Reasoning about "privacy" in ML

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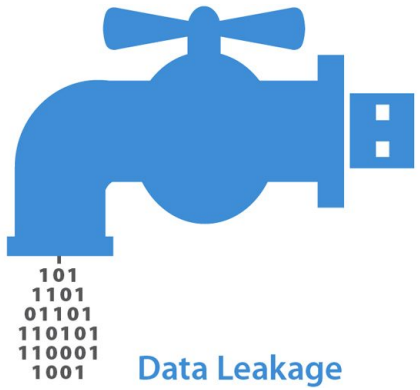
1. Inclusion of a data point in the training set
   (aka "membership inference")
2. What class representatives (in training set) look like
   (aka "model inversion")



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Well-understood problem (besides leakage)

- Use it to establish wrongdoing
- Or to assess protection, e.g., with differentially private noise

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Let's call this a
Property Inference Attack

Attacks

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2. Property Inference in Collaborative/Federated ML

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Machine Learning as a Service

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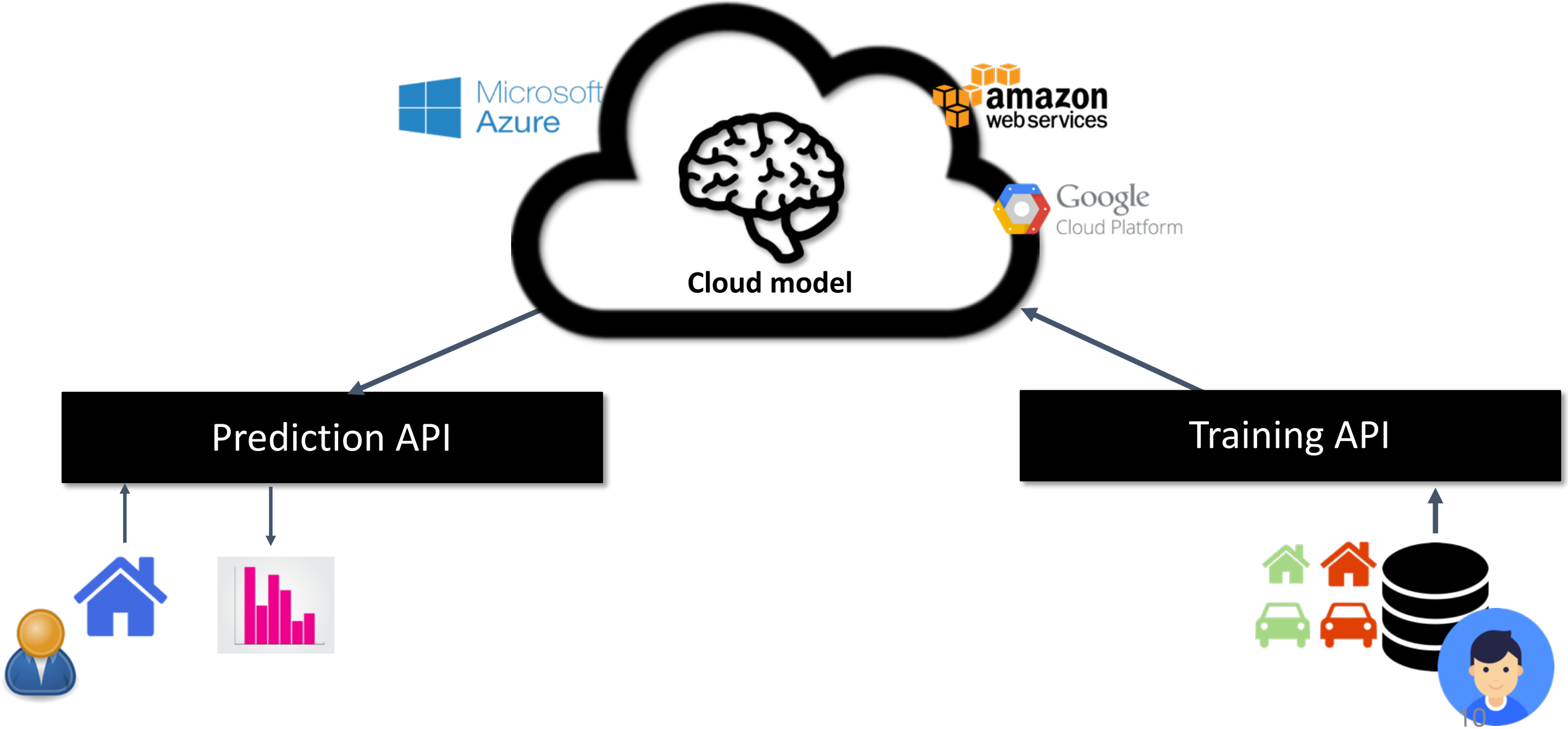
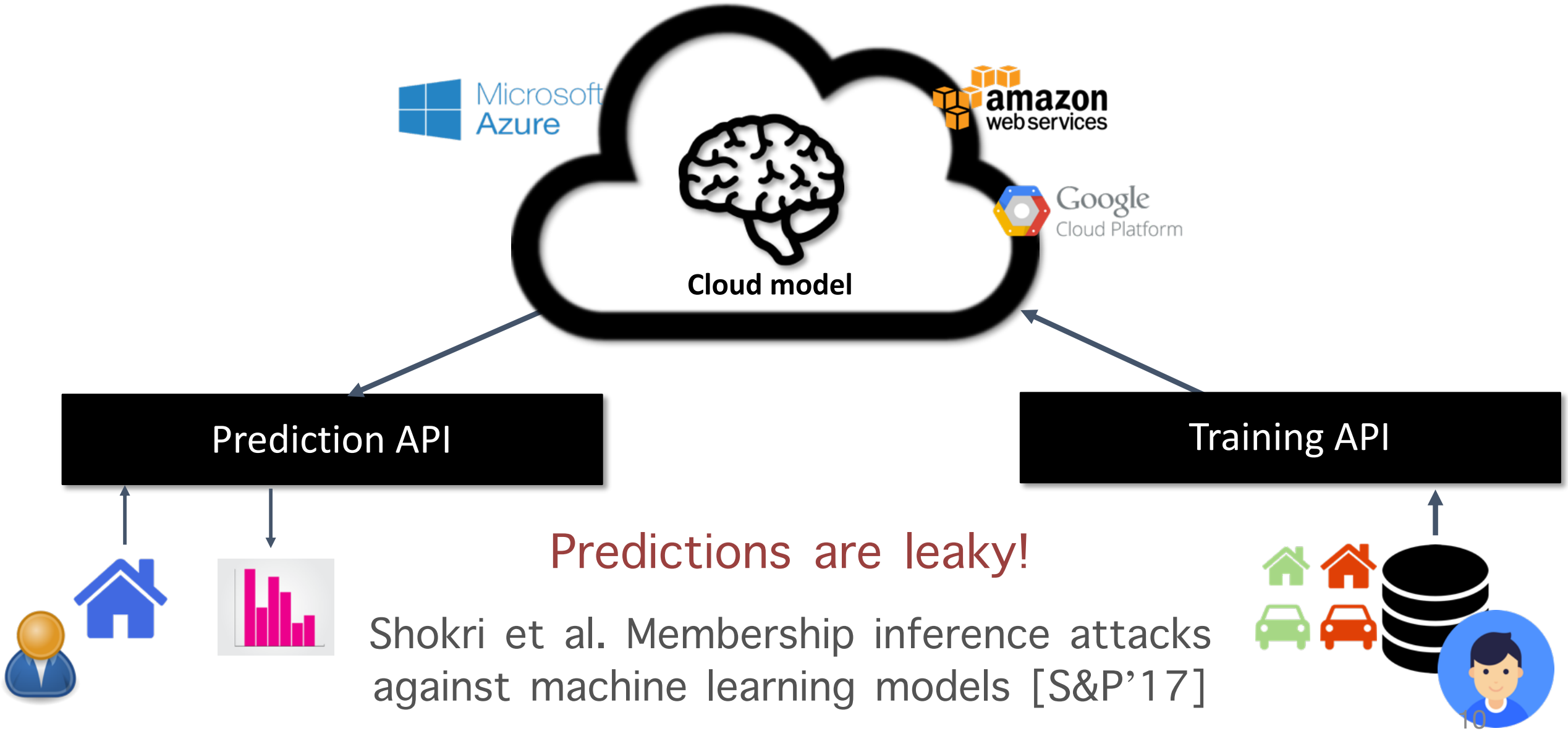


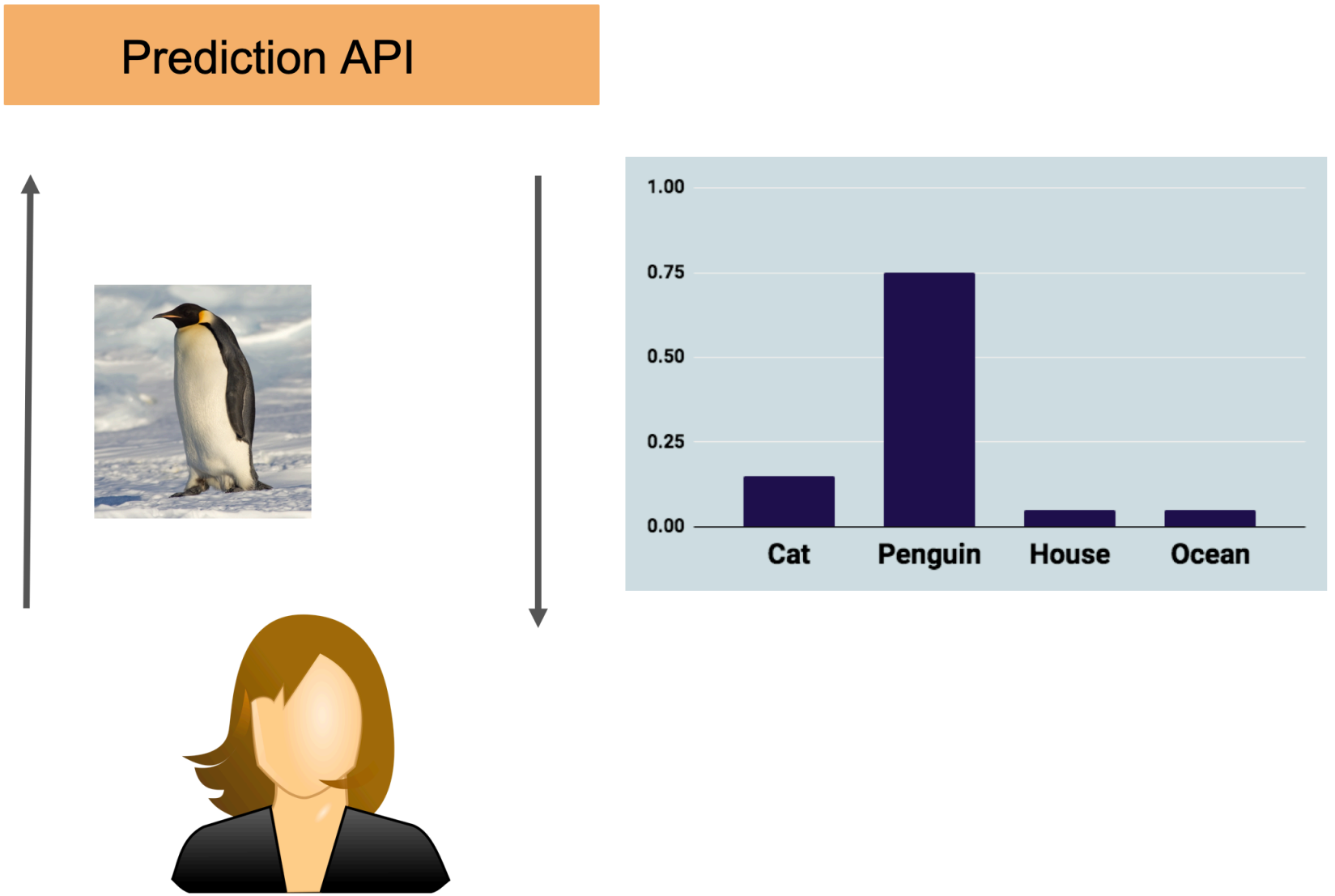
Machine Learning as a Service

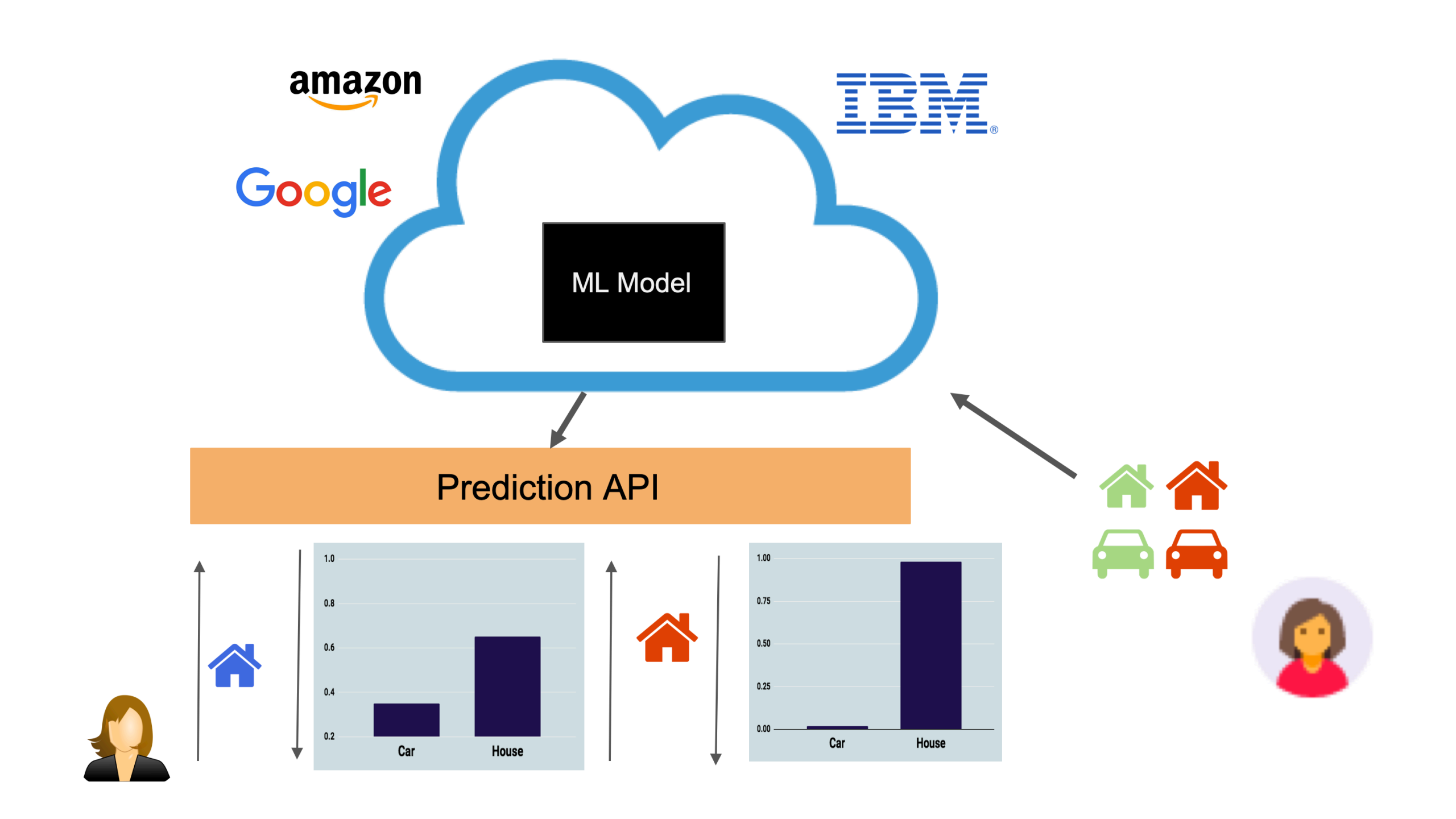


Predictions are leaky!

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

Membership Inference/Discriminative




amazon
IBM
Google
ML Model
Prediction API
1.0
0.8
0.6
0.4
0.2
Car
House
1.00
0.75
0.50
0.25
0.00
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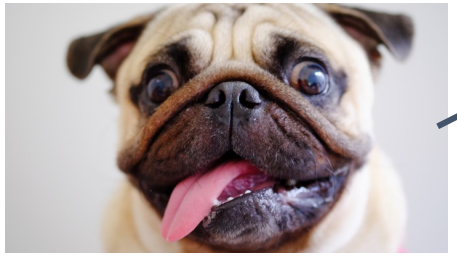
What About Generative Models?



Discriminative Model

cat | dog

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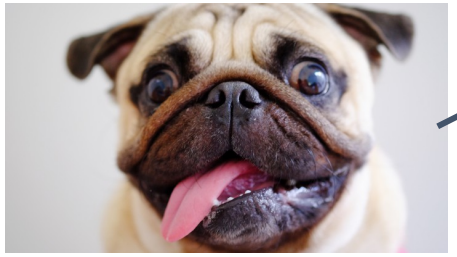

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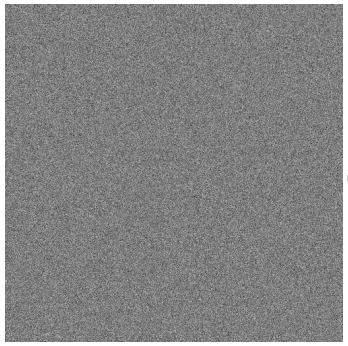

Generative Model

Membership Inference in Generative Models

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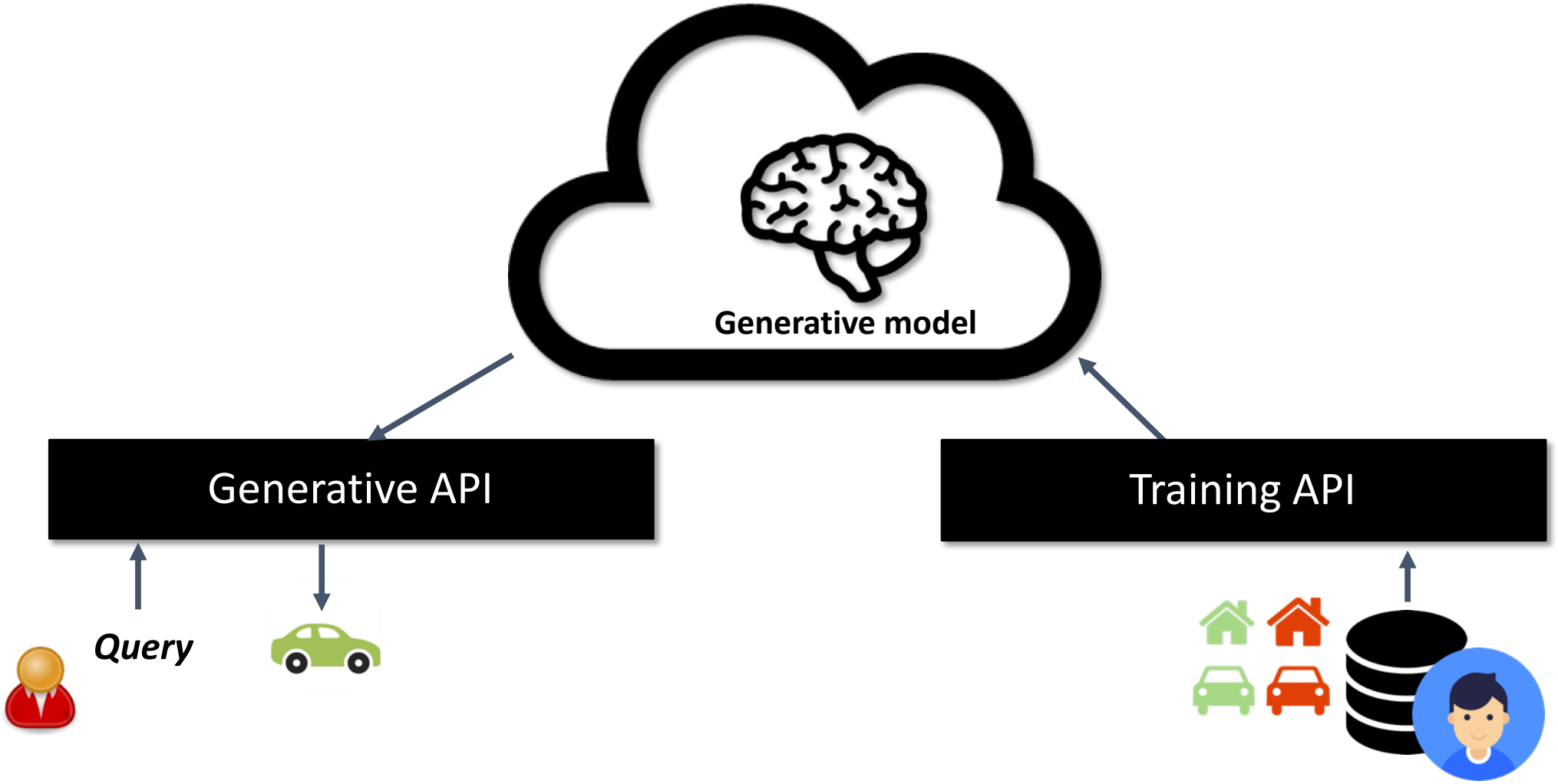
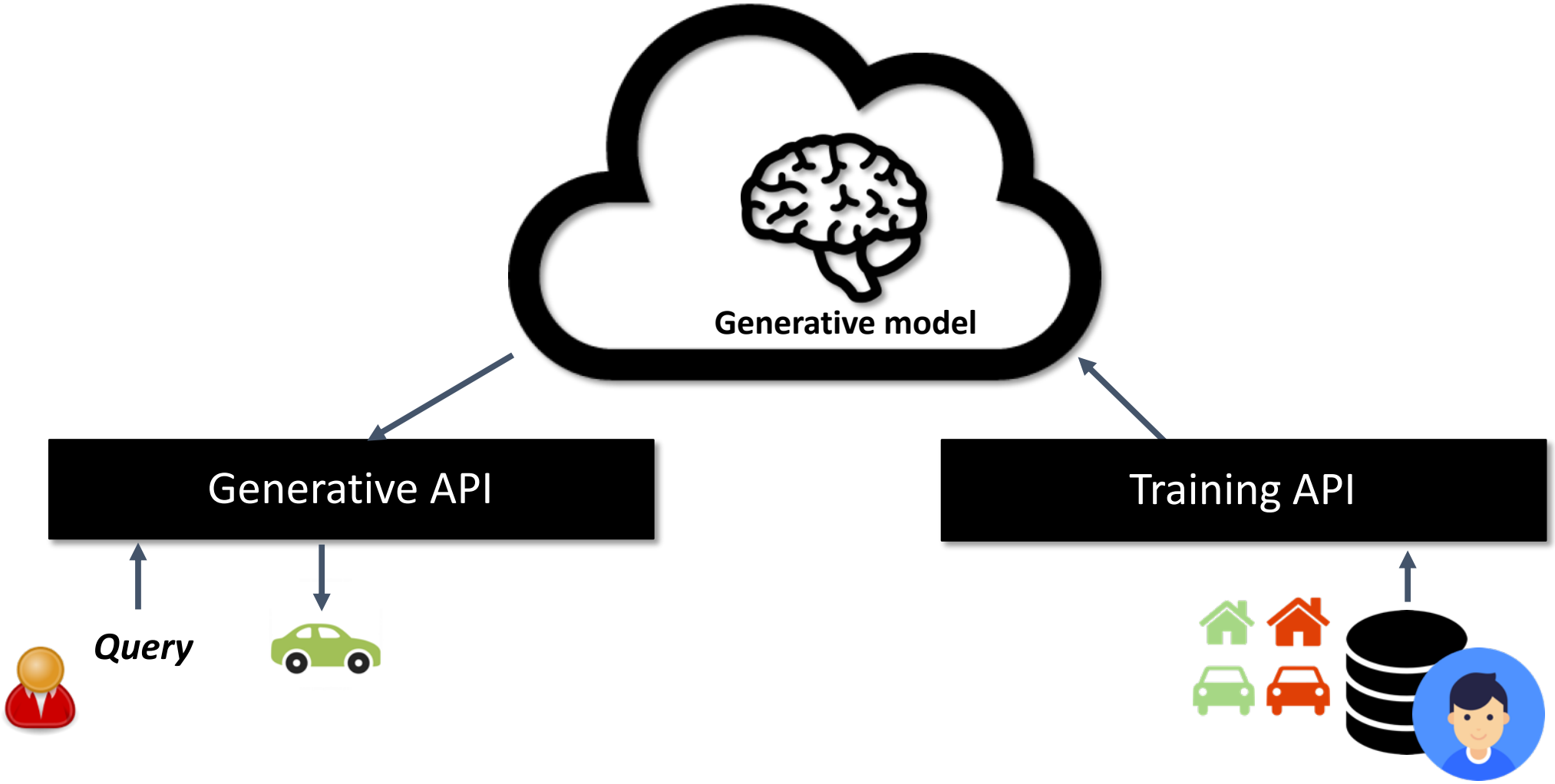


Membership Inference in Generative Models



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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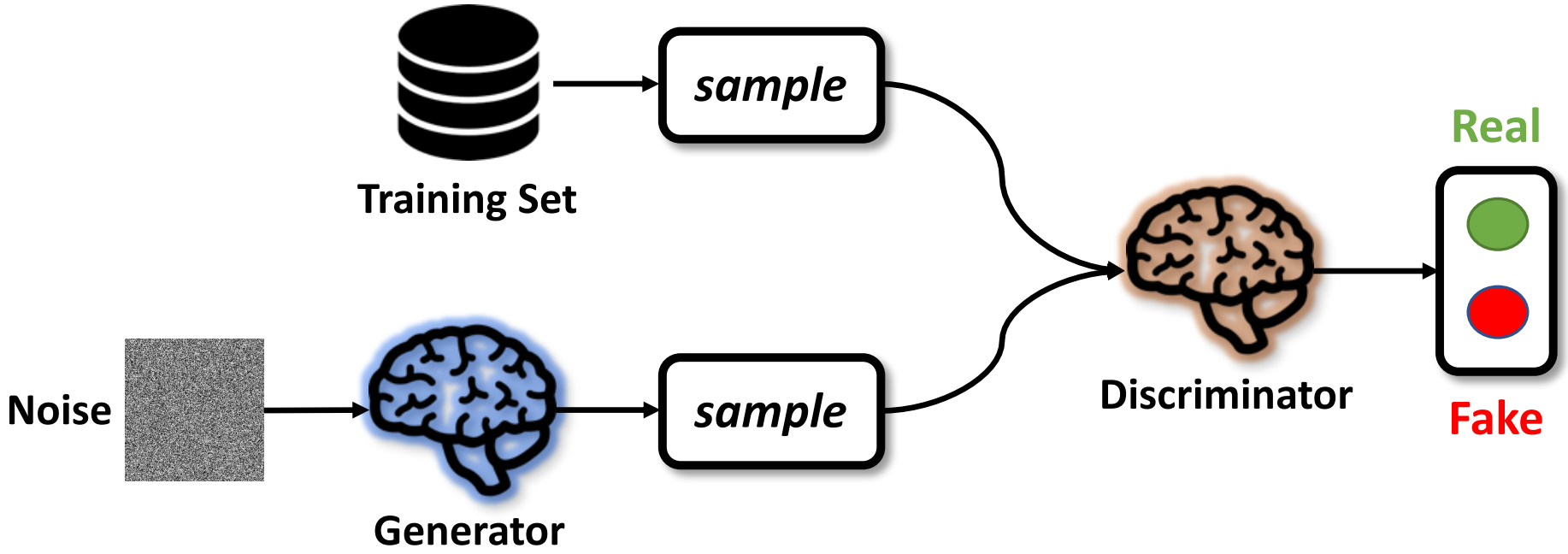
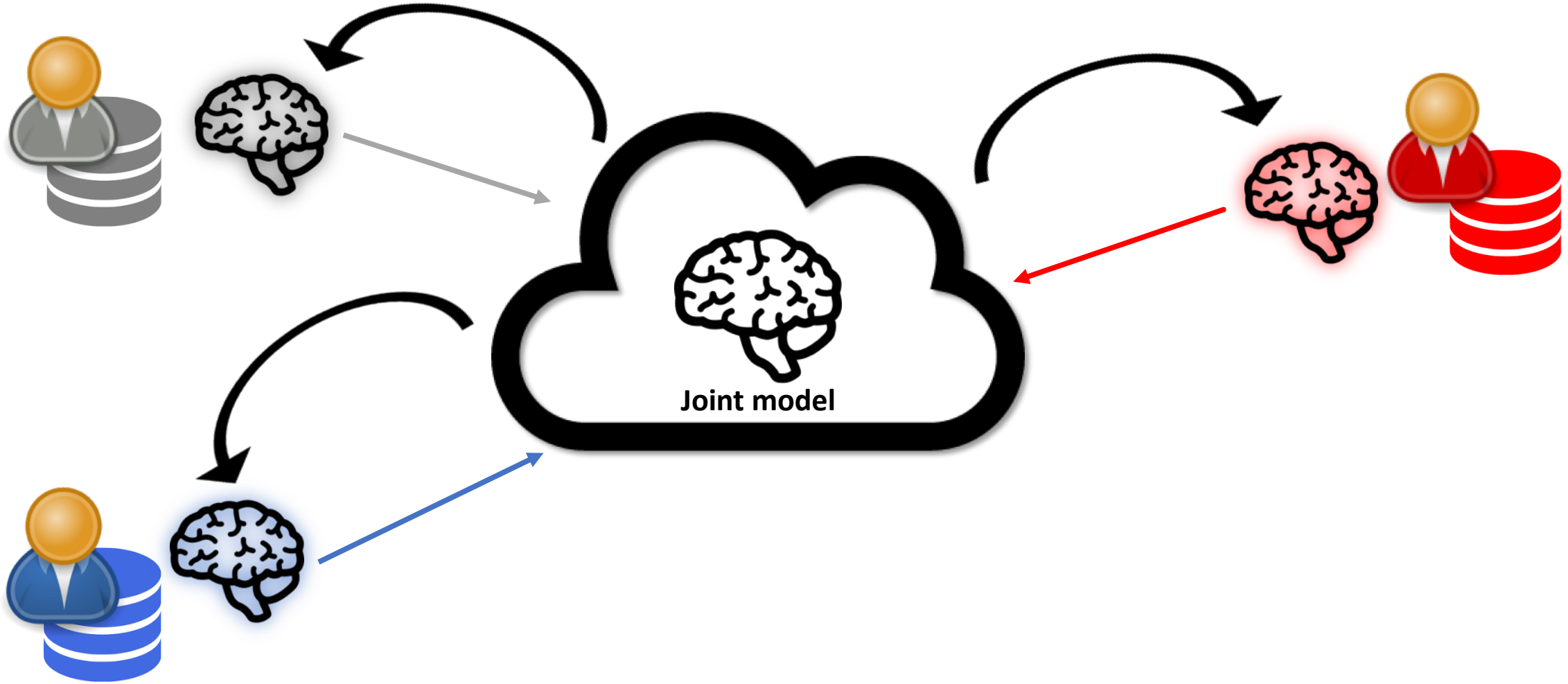


Attacks

1. Membership Inference

2. Property Inference in Collaborative/Federated ML

Collaborative/Federated Learning



Collaborative

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 $\nabla L(b; \theta)$

Federated

Algorithm 2 Federated learning with model averaging

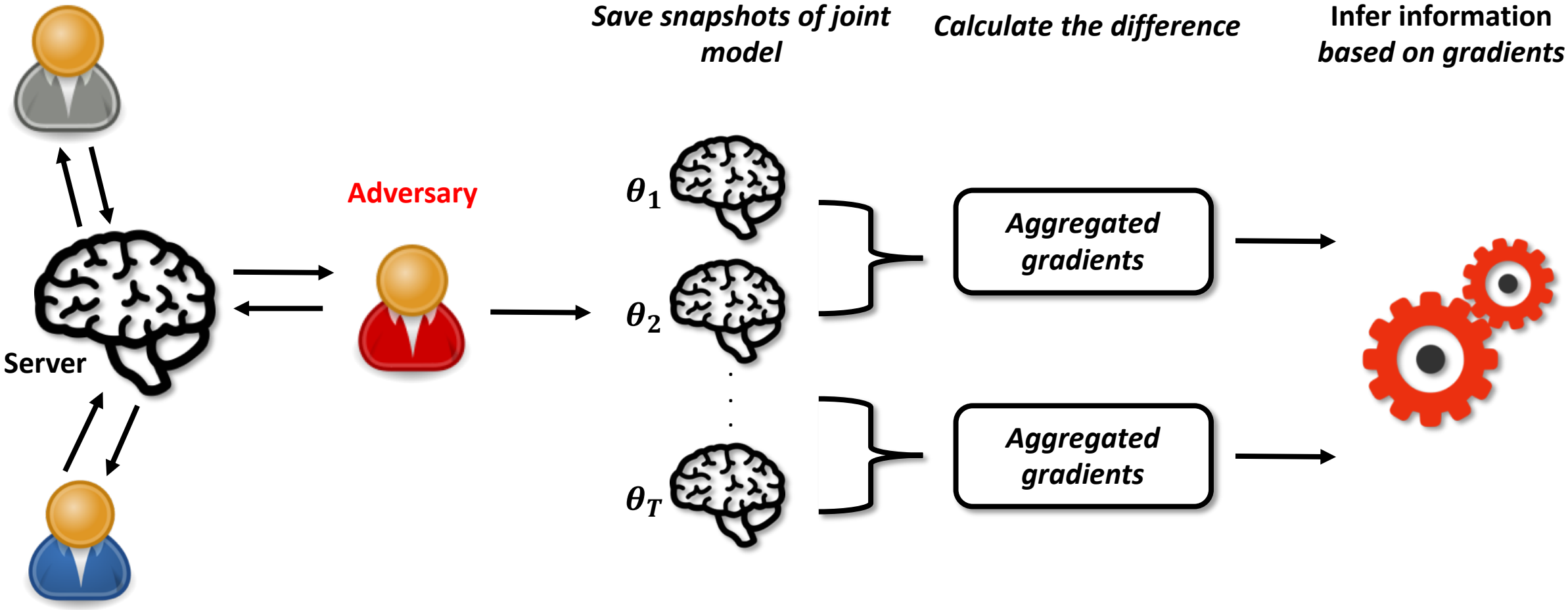
Server executes:

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

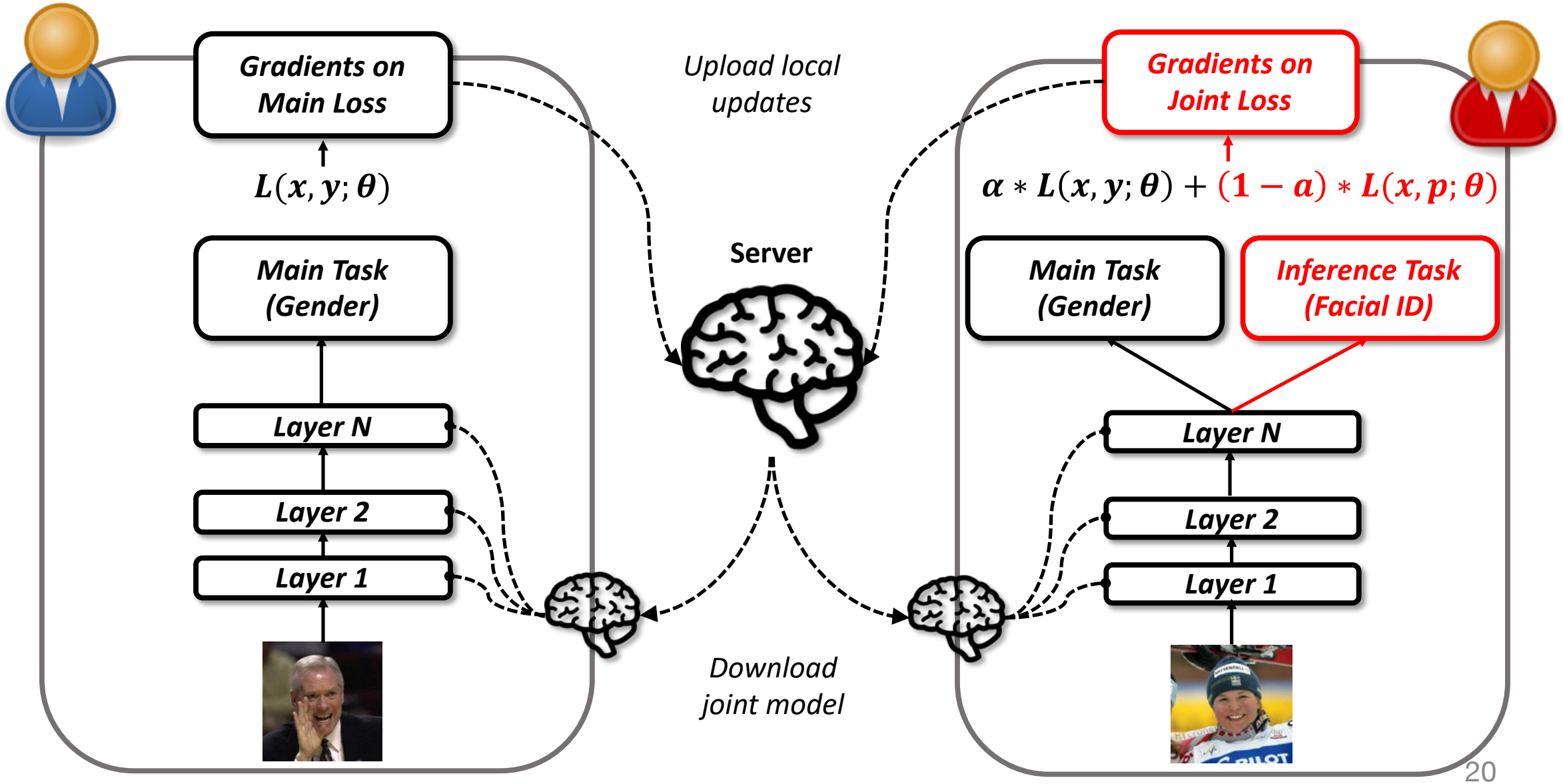
ClientUpdate(θ):

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

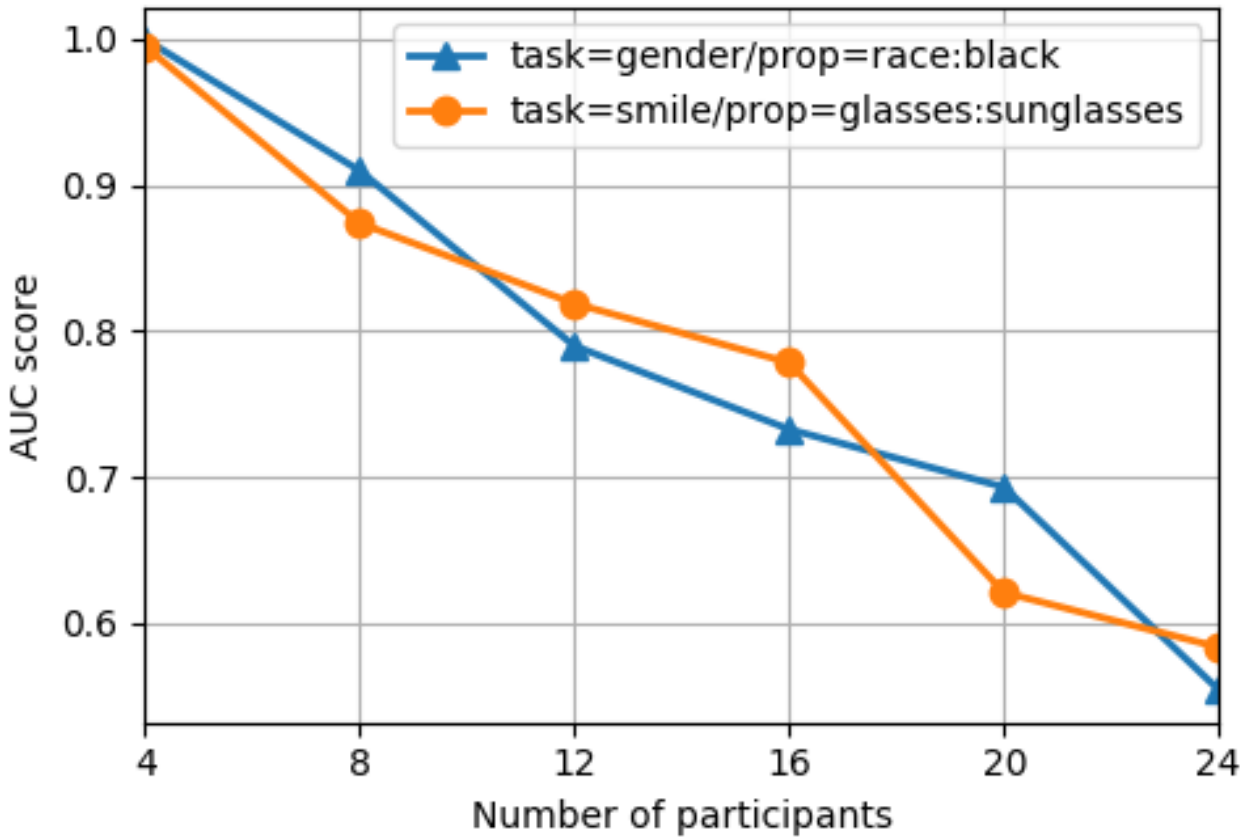


Dataset	Type	Main Task	Inference Task
LFW	Images	Gender/Smile/Age Eyewear/Race/Hair	Race/Eyewear
FaceScrub	Images	Gender	Identity
PIPA	Images	Age	Gender
FourSquare	Locations	Gender	Membership
Yelp-health	Text	Review Score	Membership Doctor specialty
Yelp-author	Text	Review Score	Author
CSI	Text	Sentiment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

Property Inference on LFW

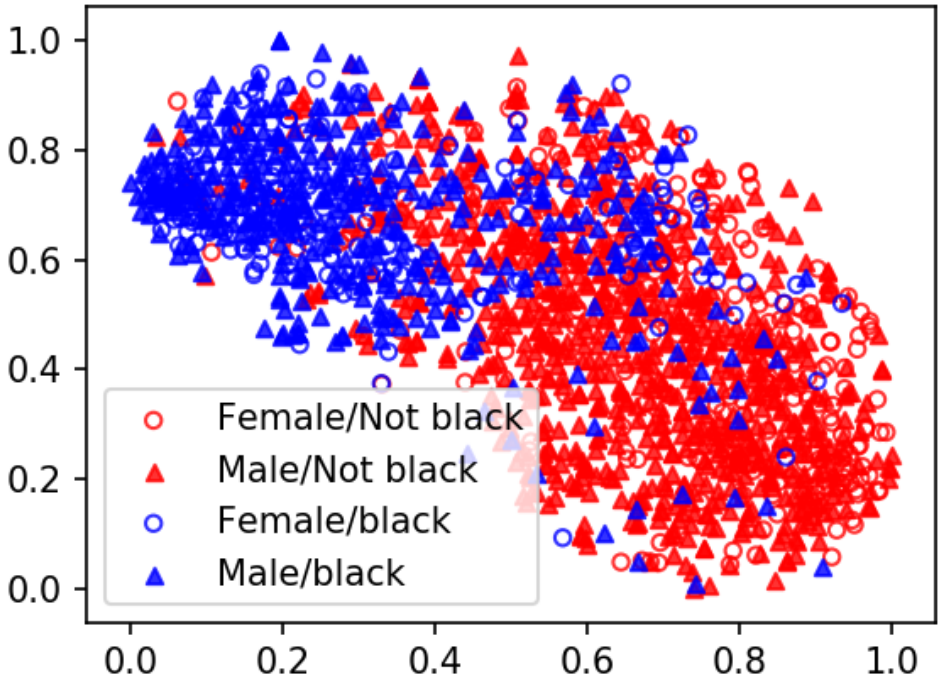
Main Task	Inference Task	Correlation	AUC score
Gender	Sunglasses	-0.025	1.0
Smile	Asian	0.047	0.93
Age	Black	-0.084	1.0
Race	Sunglasses	0.026	1.0
Eyewear	Asian	-0.119	0.91
Hair	Sunglasses	-0.013	1.0

Two-Party



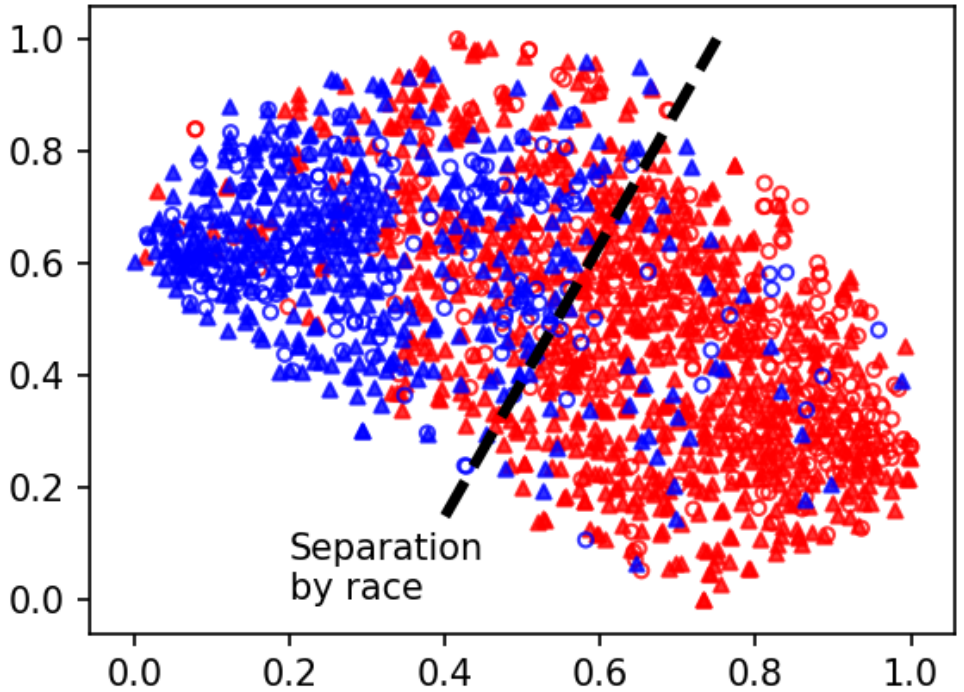
Multi-Party

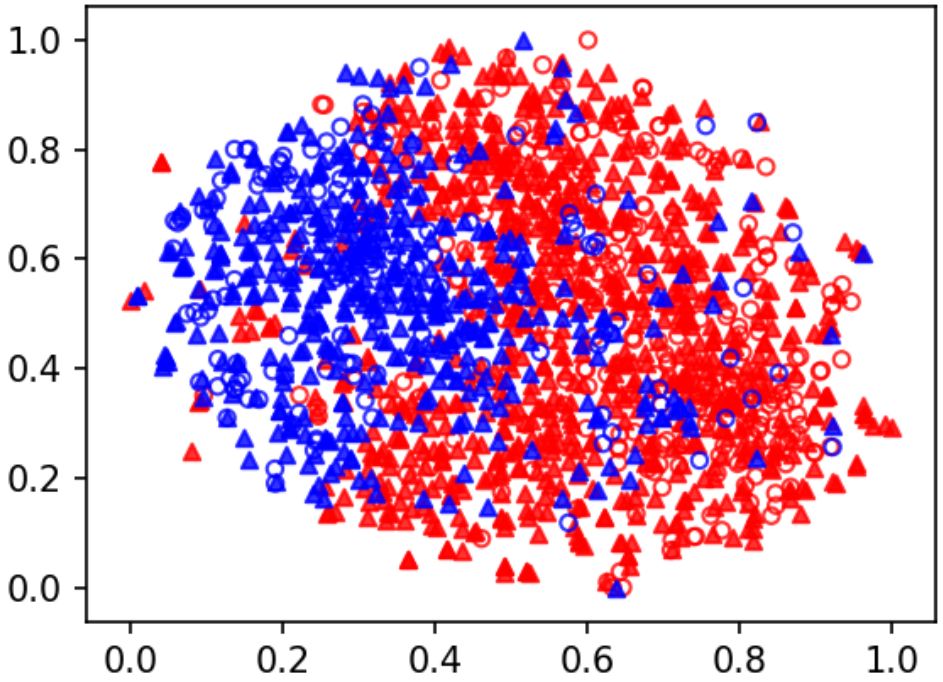
Feature t-SNE projection



pool1

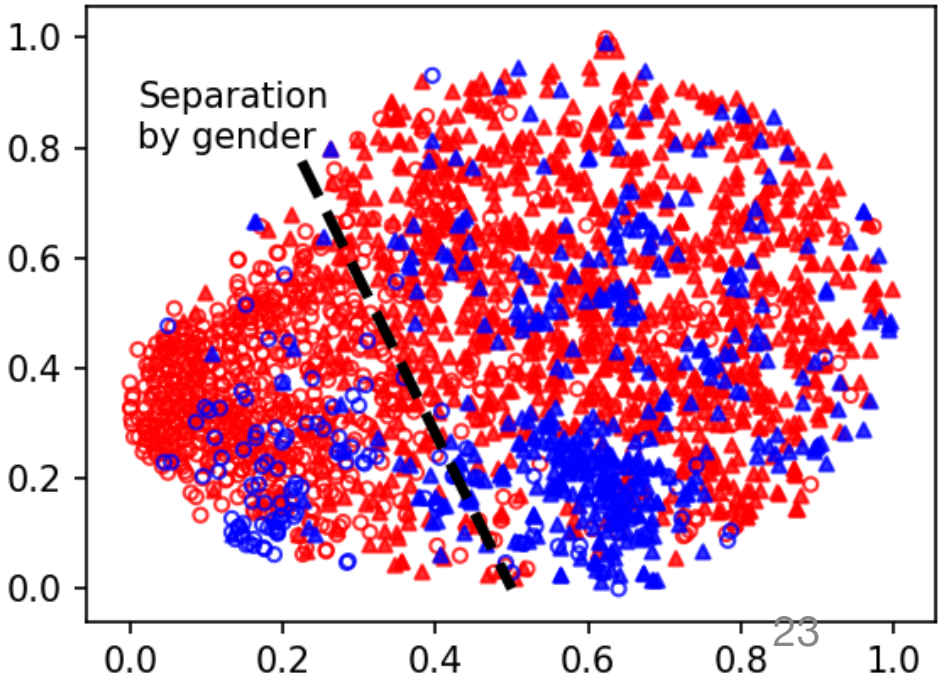
pool2



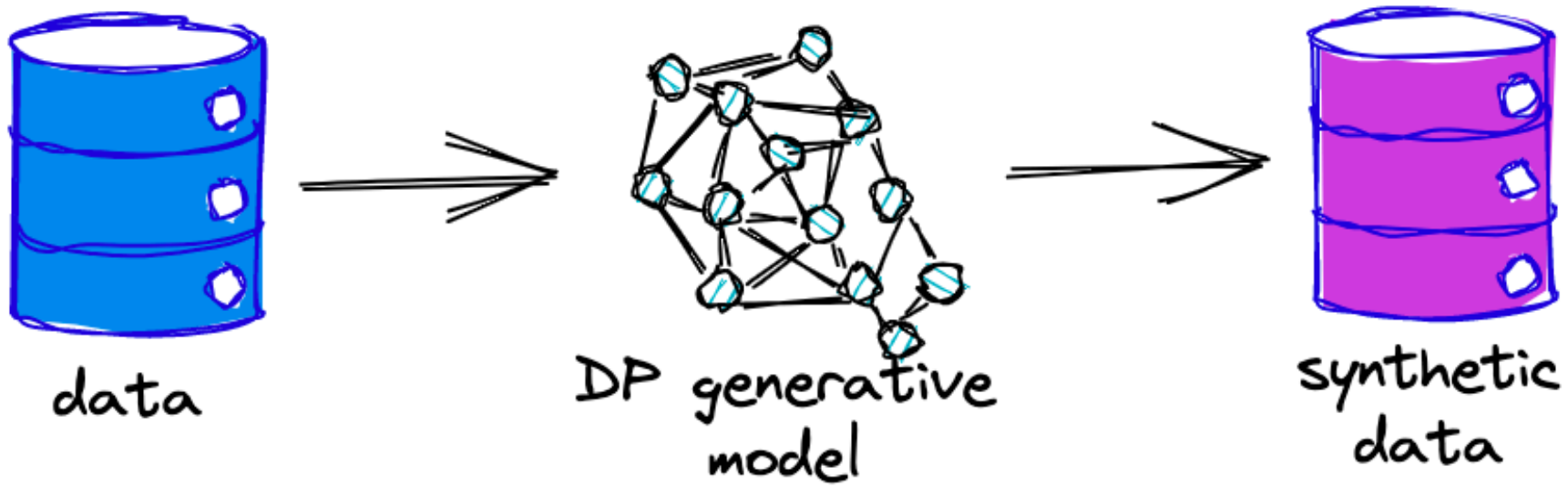


pool3

fc

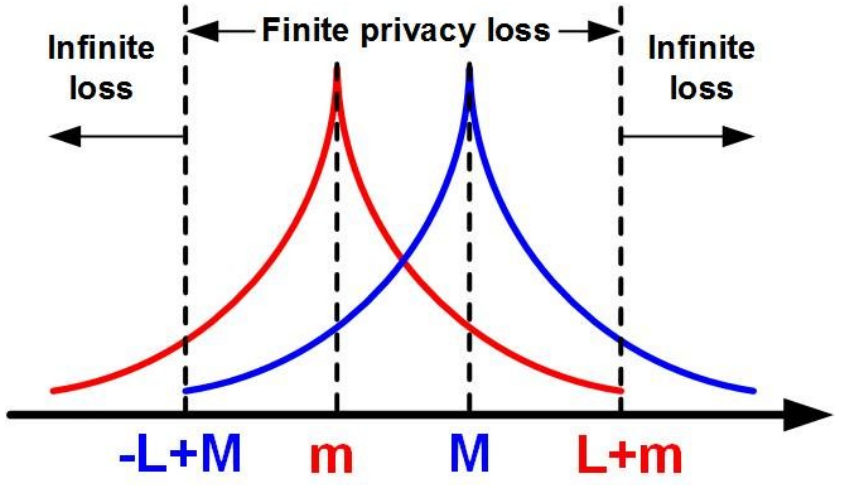


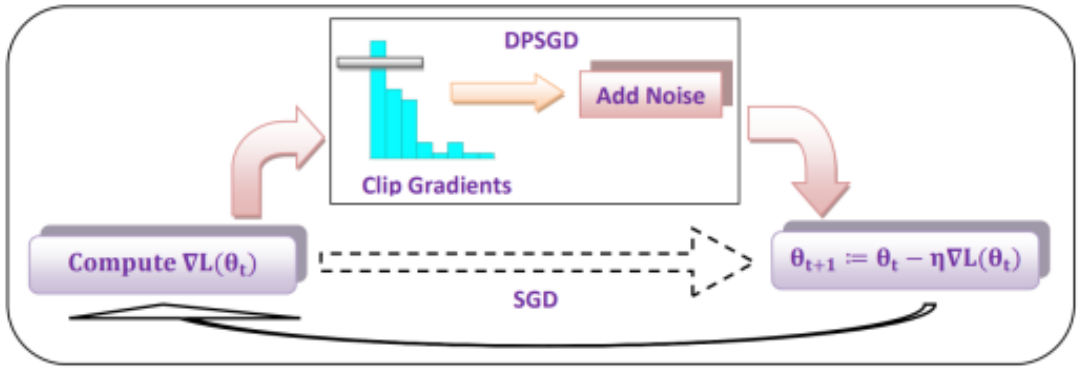
Differentially Private (DP) Synthetic Data

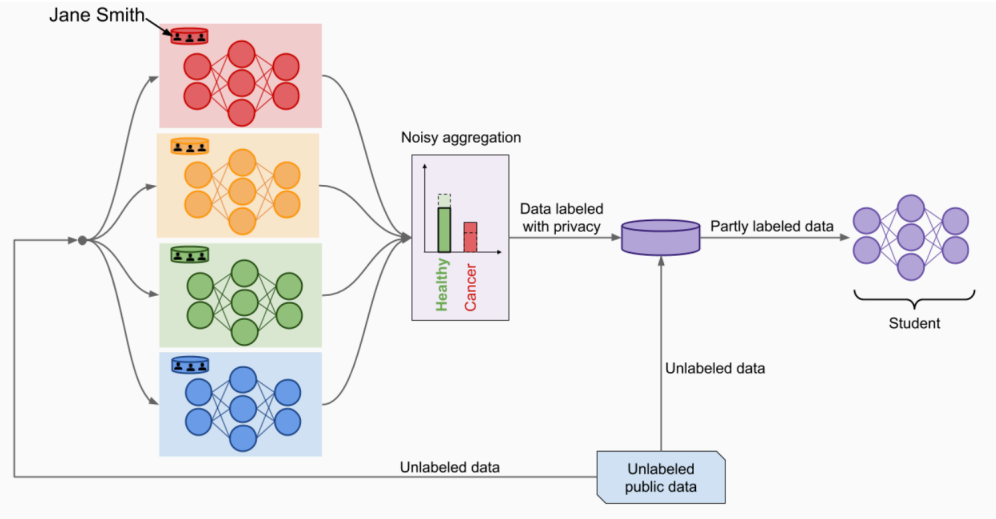


DP mechanisms:

- Laplace
- DP-SGD
- PATE



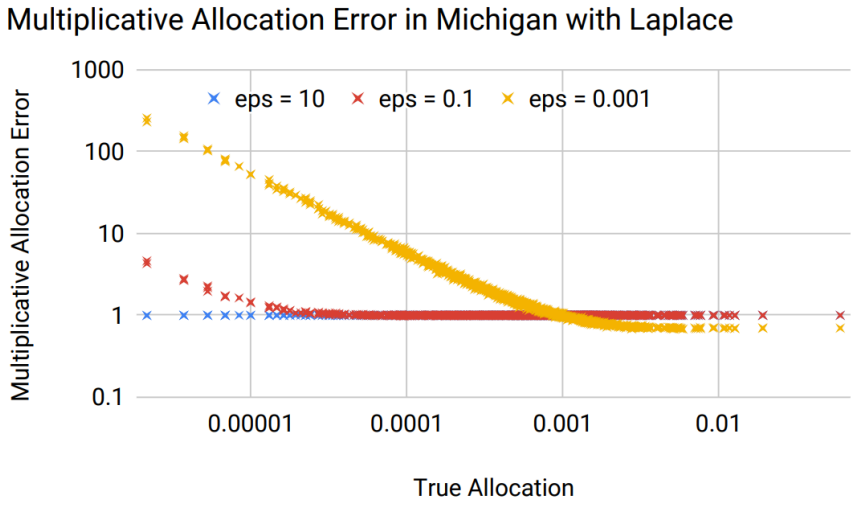


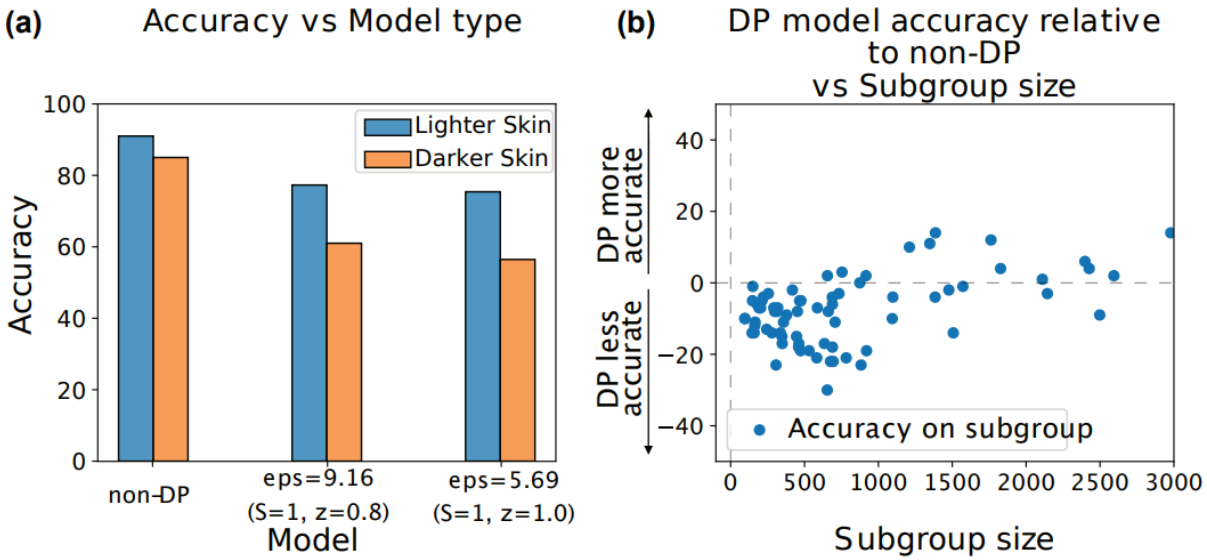


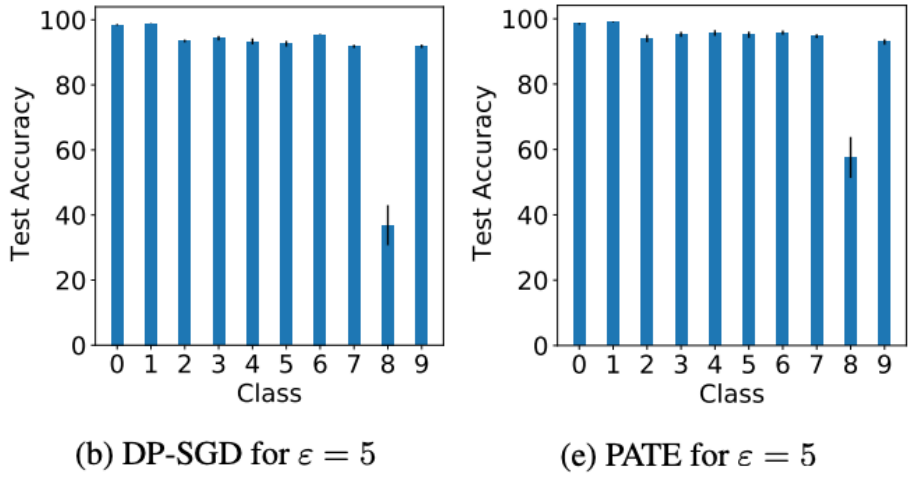
Motivation

DP has a disparate effect[1] on:

- Statistics[2]
- Deep learning classifiers[3,4]







(b) DP-SGD for $\varepsilon = 5$ (e) PATE for $\varepsilon = 5$

[1]Fioretto et al., Differential Privacy and Fairness in Decisions and Learning Tasks: A Survey
[2]Kuppam et al., Fair Decision Making using Privacy-Protected Data
[3]Bagdasaryan et al., Differential privacy has disparate impact on model accuracy
[4]Uniyal et al., DP-SGD vs PATE: Which Has Less Disparate Impact on Model Accuracy?

Goal

Empirically evaluate the disparate effect DP causes on generative models:

- class/subgroup size
- class/subgroup accuracy

Settings

We consider three DP generative models:

1. PrivBayes[1] (Laplace) 2. DP-WGAN[2] (DP-SGD) 3. PATE-GAN[3] (PATE)

Four data settings:

S1: Binary class size, precision, and recall

S2: Multi-class size, precision, and recall

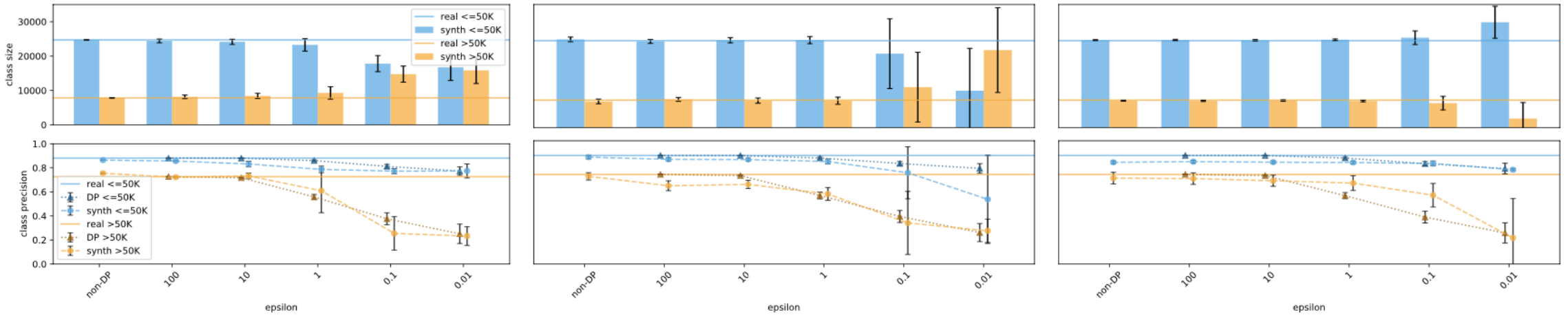
S3: Single-attribute subgroup size and accuracy

S4: Multi-attribute subgroup size and accuracy

Multiple privacy budget and subgroup imbalance levels.

[1]Zhang et al., PrivBayes: Private Data Release via Bayesian Networks
[2]Alzantot et al., Differential Privacy Synthetic Data Generation using WGANs
[3]Jordon et al., PATE-GAN: Generating Synthetic Data with Differential Privacy Guarantees

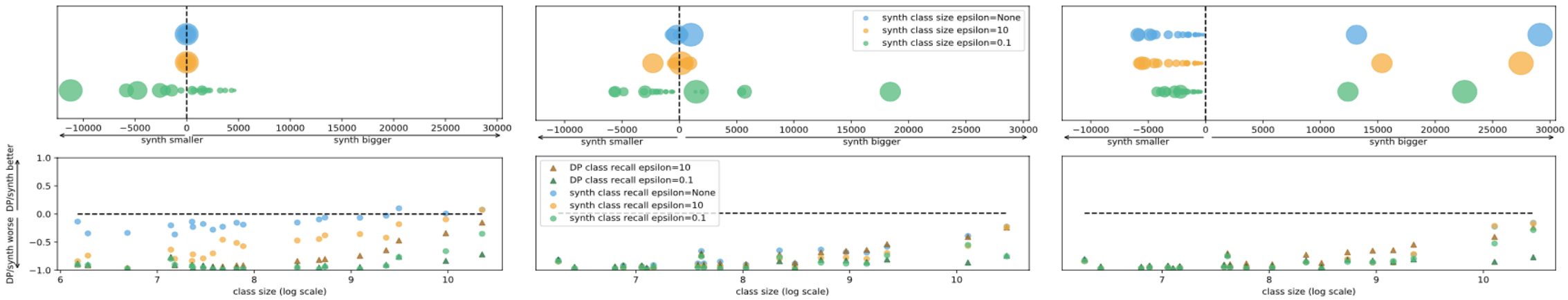
S1: Binary Class Size, Precision, and Recall



(a) PrivBayes (b) DP-WGAN (c) PATE-GAN

Figure 1: Synthetic data class size (top), real, DP, and synthetic classifiers precision (bottom) for different levels of ϵ, ***Adult***.

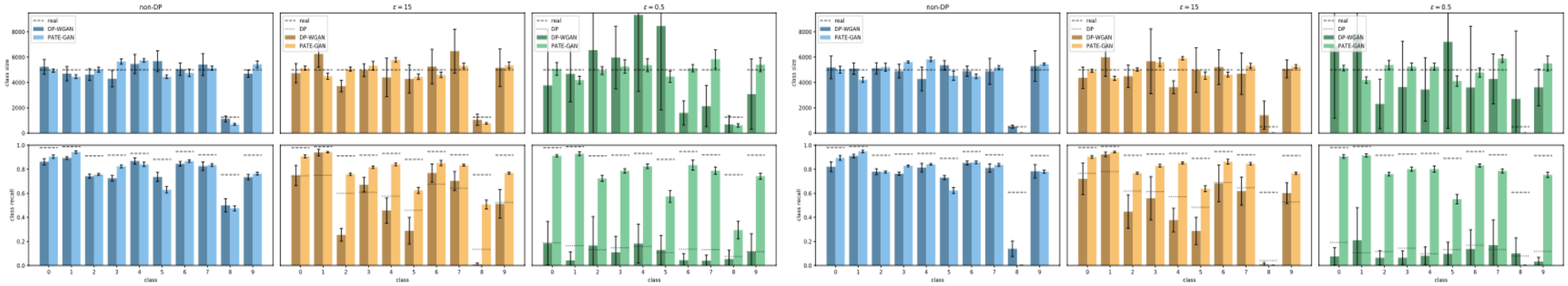
S2: Multi-Class Size, Precision, and Recall 1



(a) PrivBayes (b) DP-WGAN (c) PATE-GAN

Figure 3: Synthetic data class (multi-class) size relative to real (top) (the size of the bubbles denotes the relative size in the real data), DP classifiers and synthetic classifiers recall relative to real (bottom) for different levels of ϵ, ***Purchases***.

S2: Multi-Class Size, Precision, and Recall 2



(a) DP-WGAN and PATE-GAN with imbalance 0.25

(b) DP-WGAN and PATE-GAN with imbalance 0.1

Figure 4: Synthetic data class (multi-class) size (top), real, DP and synthetic classifiers recall (bottom) for different imbalance of class "8" and levels of ϵ, ***MNIST***.

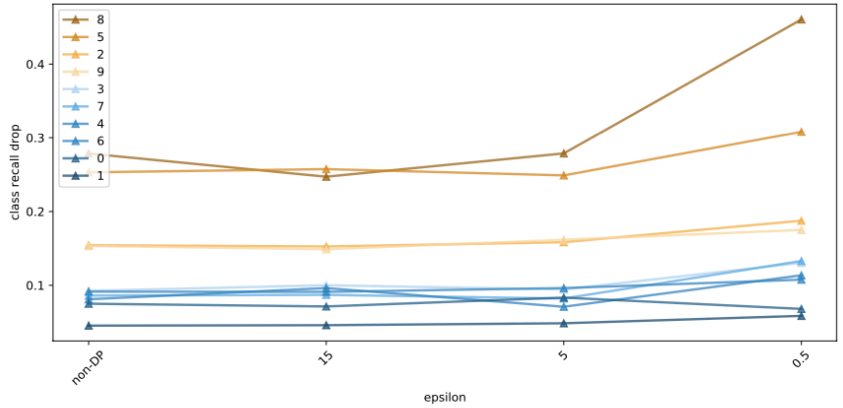


Figure 9: PATE-GAN synthetic classifier class recall drop vs ϵ, ***MNIST*** with 0.25 imbalance of class "8."

S3: Single-Attribute Subgroup Size and Accuracy

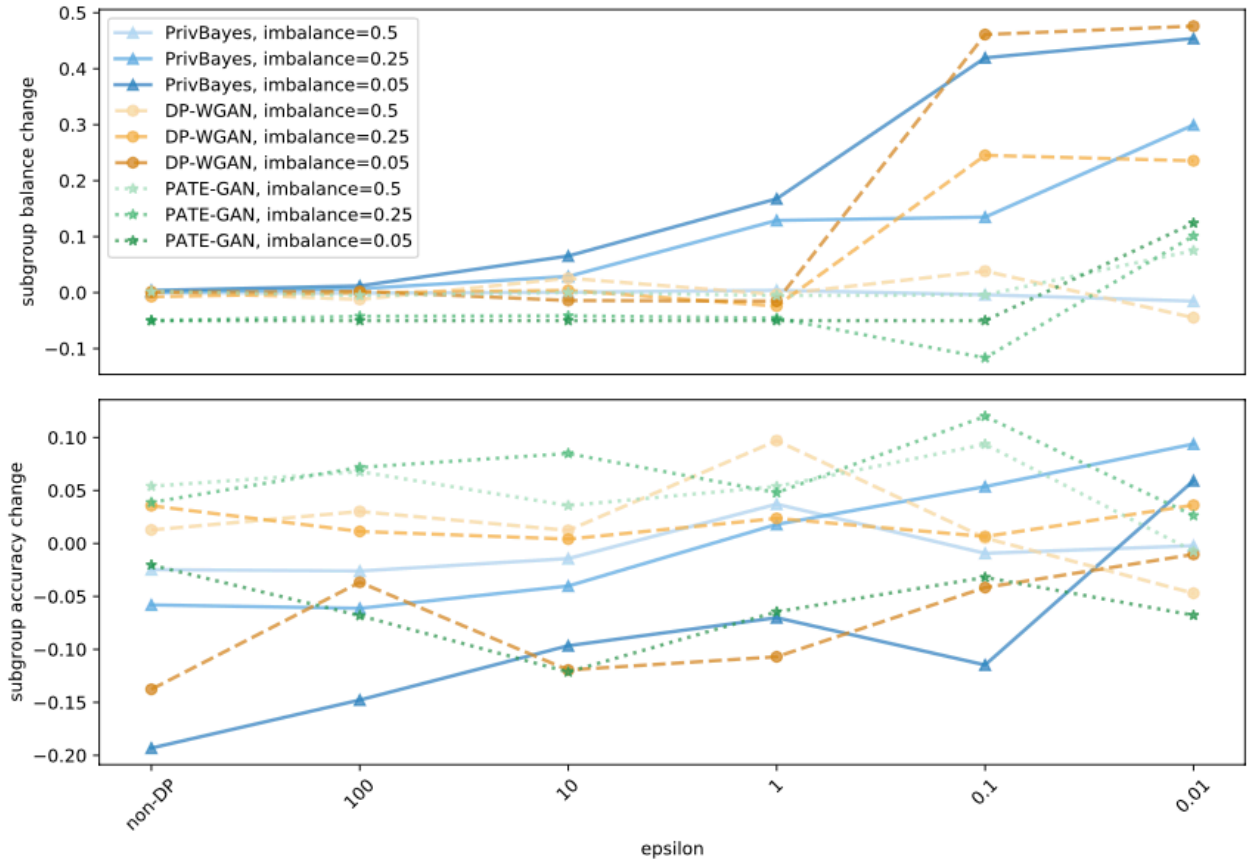
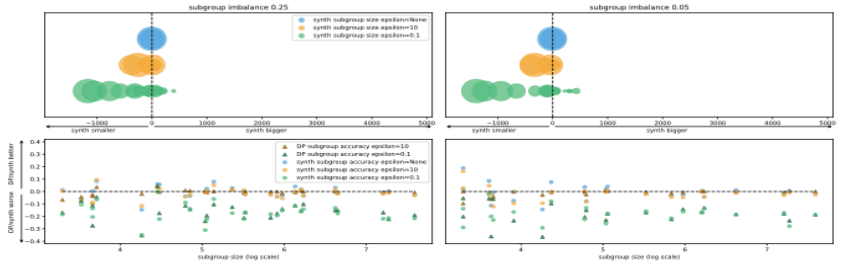
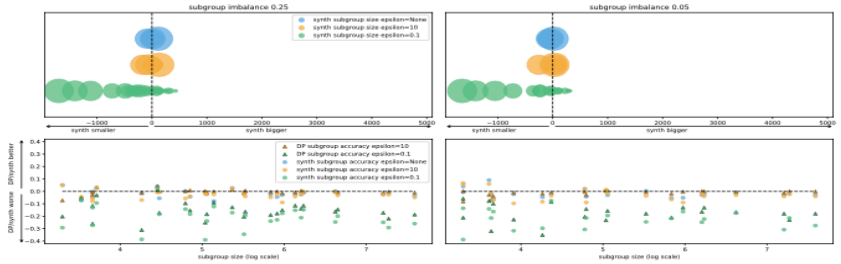


Figure 5: Minority single-attribute (sex) subgroup imbalance level change (top), minority subgroup drop in accuracy vs. majority (bottom) for different subgroup imbalance and ϵ levels, ***Texas***.

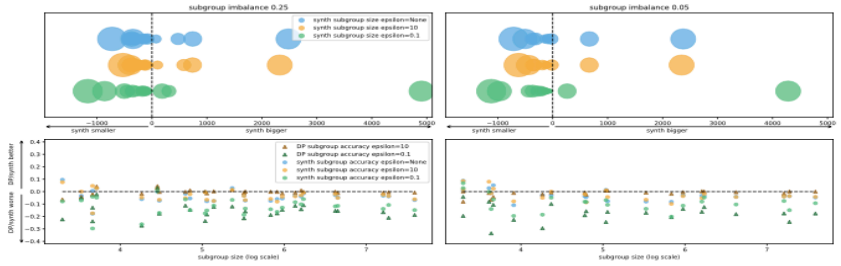
S4: Multi-Attribute Subgroup Size and Accuracy



(a) PrivBayes

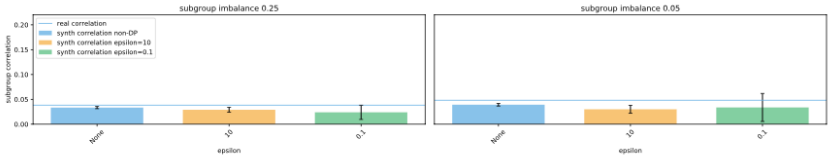


(b) DP-WGAN

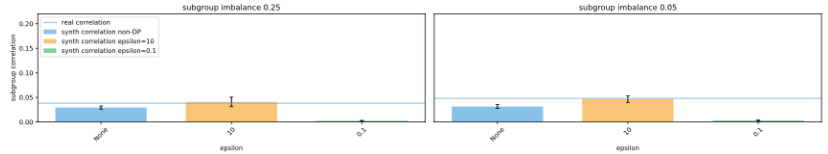


(c) PATE-GAN

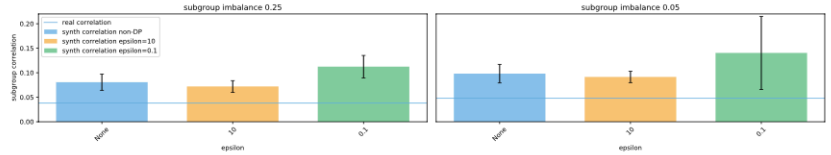
Figure 13: Size of synthetic data multi-attribute subgroup (intersection of age, sex, and race) relative to real (top) and accuracy of DP and synthetic classifiers relative to real classifier accuracy (bottom) for different single-attribute (sex) subgroup imbalance and ϵ levels, ***Texas***.



(b) PrivBayes, Texas



(d) DP-WGAN, Texas



(f) PATE-GAN, Texas

Figure 14: Mutual information between the multi-attribute subgroup and the target (income/length of stay) columns for different single-attribute subgroup imbalance (sex) and ϵ levels, ***Adult*** (left) and ***Texas*** (right).

Take-Aways

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No, different DP generative models behave differently.

Thank you!