Data and Network Security

(Master Degree in Computer Science and Cybersecurity)

Lecture 5

Outline for today

- Recap last lecture
- Information leakage from ML models
- Privacy preserving learning issues

Sensitive property

DATASET

- **Demographic Information:**
  - Age, gender, ethnicity, income level.
- **Behavioral Patterns:**
  - Shopping habits, browsing history, social interactions.
- **Personal Preferences:**
  - Political affiliations, health conditions, lifestyle choices.

Sensitive property

DATASET

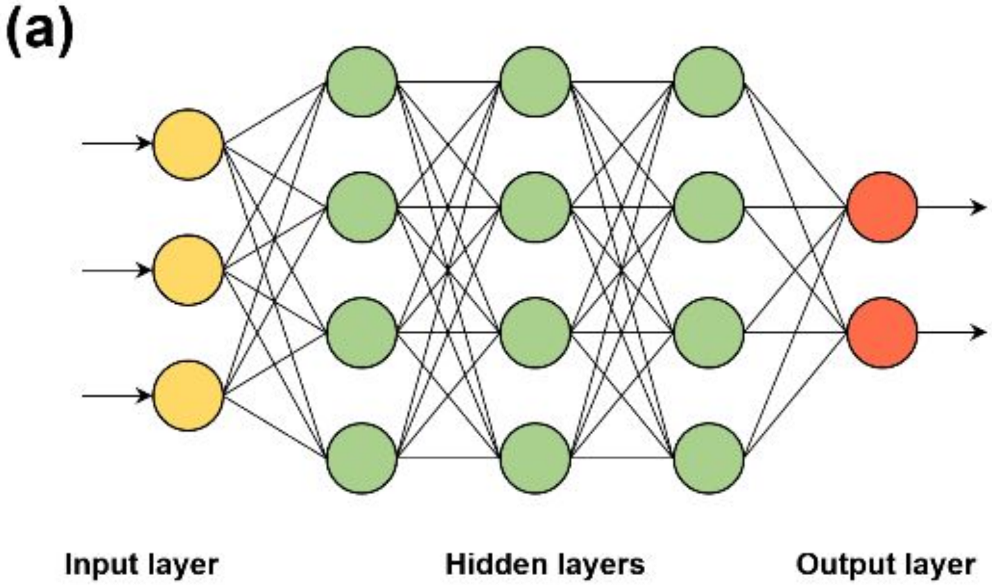
- **Demographic Information:**
  - Age, gender, ethnicity, income level.
- **Behavioral Patterns:**
  - Shopping habits, browsing history, social interactions.
- **Personal Preferences:**
  - Political affiliations, health conditions, lifestyle choices.

Disclosure of such properties can lead to privacy breaches, discrimination, or manipulation of individuals.

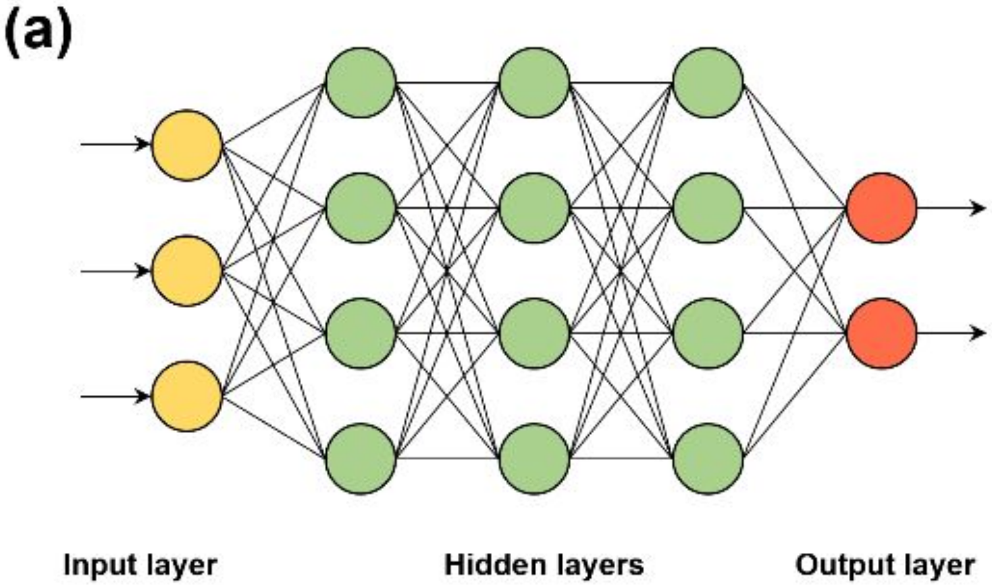
Information leakage from ML models

Can I infer some (sensitive) property of the dataset used to train an ML model?

What can ML models tell?

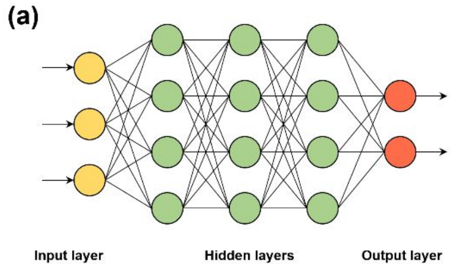


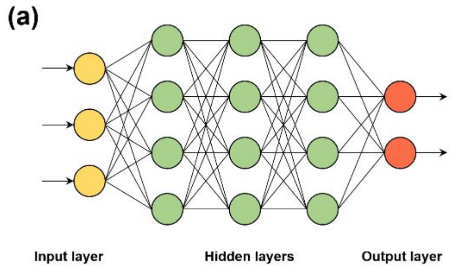
Does this dataset have this property?



But you have only the model…

Does this dataset have this property P?

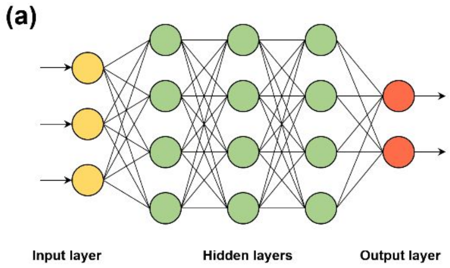




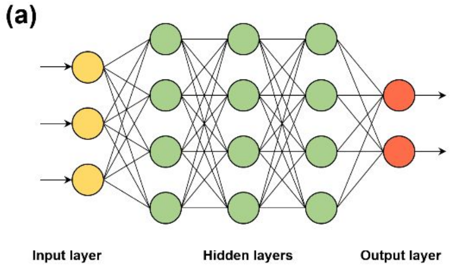
Construct N different ML models, similar to the target model.

- The dataset of some has property P, and the others dont.

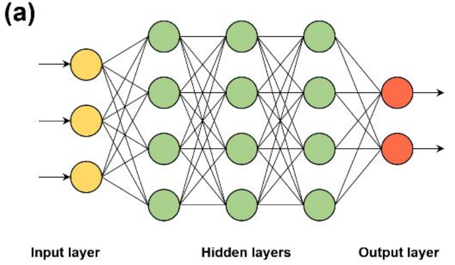
Does this dataset have this property?



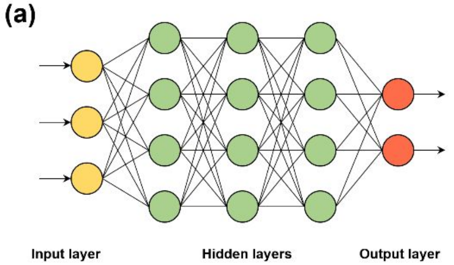
Represent all these ML models as a “feature vector”



Does this dataset have this property?

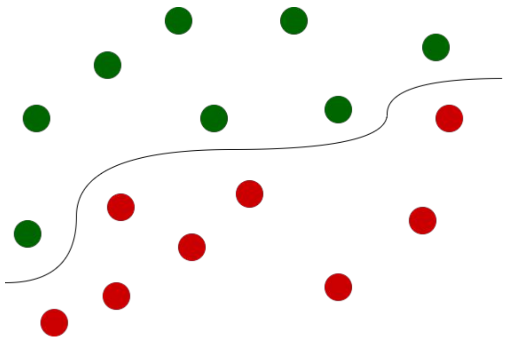


[f1,f2,f3,...fx]

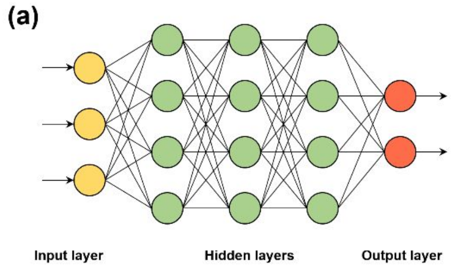


[f1,f2,f3,...fx]

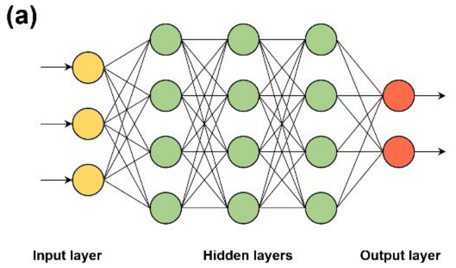
Train a binary classifier on these features



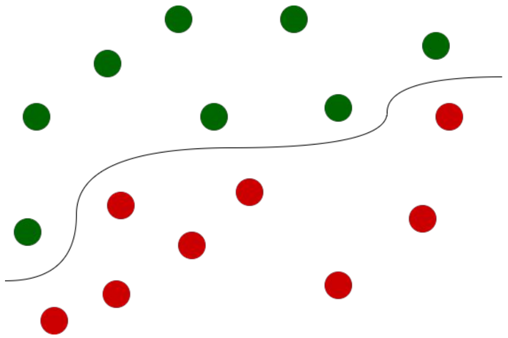
Does this dataset have this property?



[f1,f2,f3,...fx]



[f1,f2,f3,...fx]



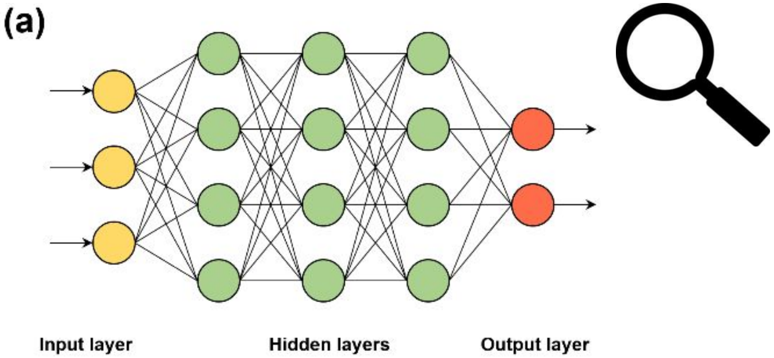
Represent and test the target classifier.

Information leakage from ML models

`Was this datapoint part of this dataset?`

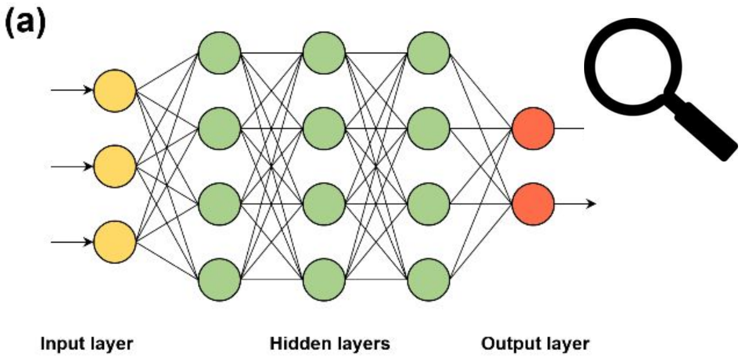
Information leakage from ML models

The model's responses provide valuable information that adversaries can leverage to infer whether a particular data point was part of the training dataset.



Information leakage from ML models

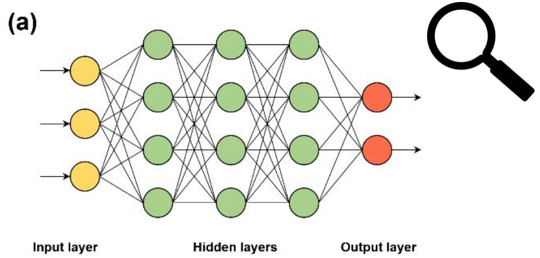
During the training phase, a machine learning model learns to generalize patterns and relationships from the training dataset to make predictions on unseen data. As a result, the model's behavior may vary depending on whether it has seen a particular data point during training.



Information leakage from ML models

When we query the model with input data, we observe the model's responses:

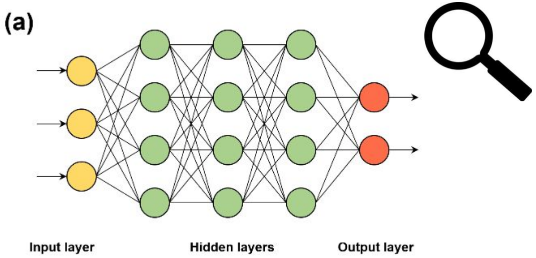
- predicted labels,
- probabilities, or scores assigned to different classes.



Information leakage from ML models

When we query the model with input data, we observe the model's responses:

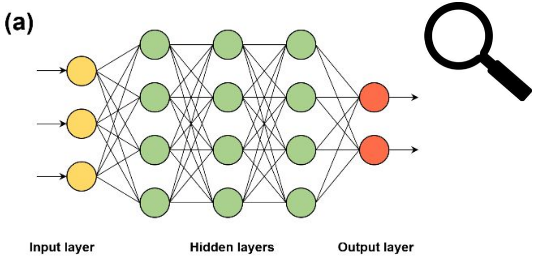
- **predicted labels,**
- **probabilities, or scores assigned to different classes.**



*distinguishing features in these responses that can indicate whether the input data was likely part of the training dataset

Distinguishing features?

One key indicator that a data point was part of the training dataset is overfitting.

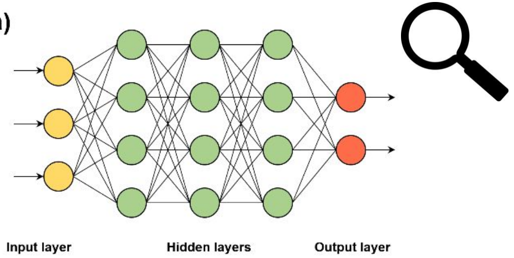


Distinguishing features?

One key indicator that a data point was part of the training dataset is overfitting.

Overfitting occurs when a model learns to memorize specific examples from the training data rather than capturing general patterns.

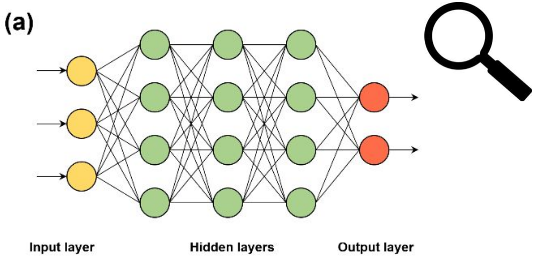
(a)



Distinguishing features?

One key indicator that a data point was part of the training dataset is overfitting.

Overfitting occurs when a model learns to memorize specific examples from the training data rather than capturing general patterns.

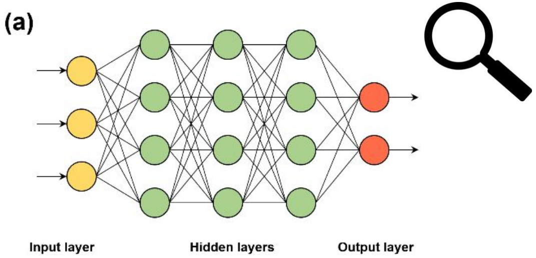


If a model exhibits overfitting, it may produce responses that are overly confident or precise for data points seen during training but less accurate for unseen data.

Distinguishing features?

Another indicator - confidence discrepancy.

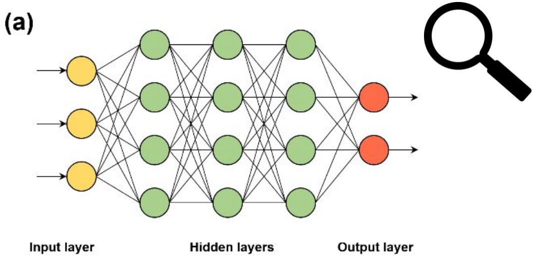
If the model's confidence is significantly higher for certain inputs compared to others, it may suggest that those inputs were present in the training dataset.



Distinguishing features?

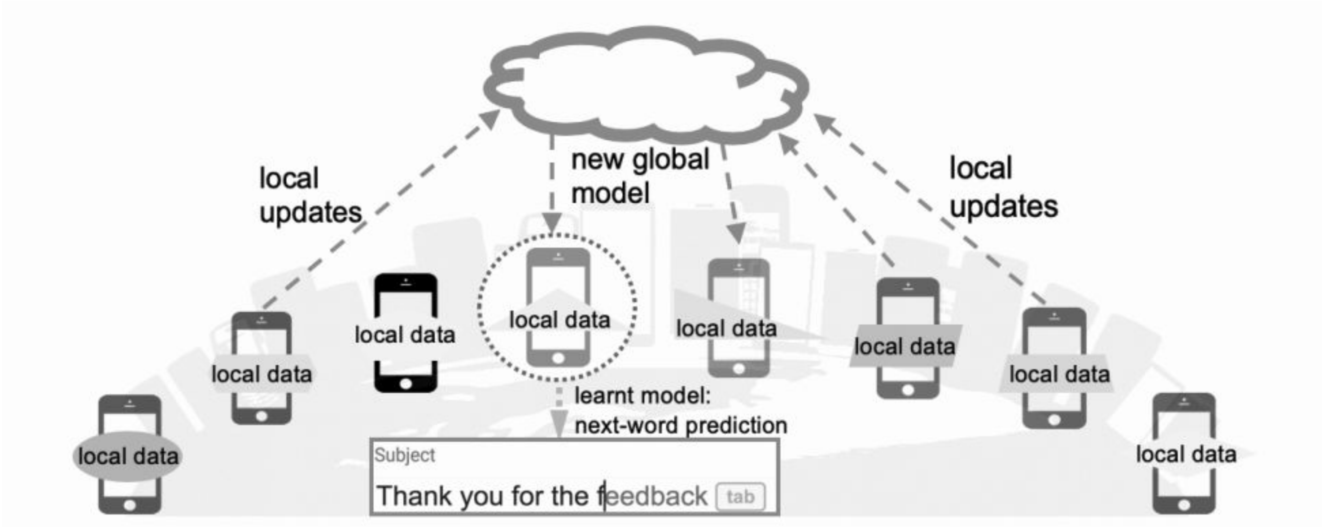
Another indicator - bias in model responses.

If the model consistently predicts certain classes or outputs for specific inputs, it may indicate that those inputs were overrepresented in the training dataset.



Is there any leakage in privacy-preserving learning?

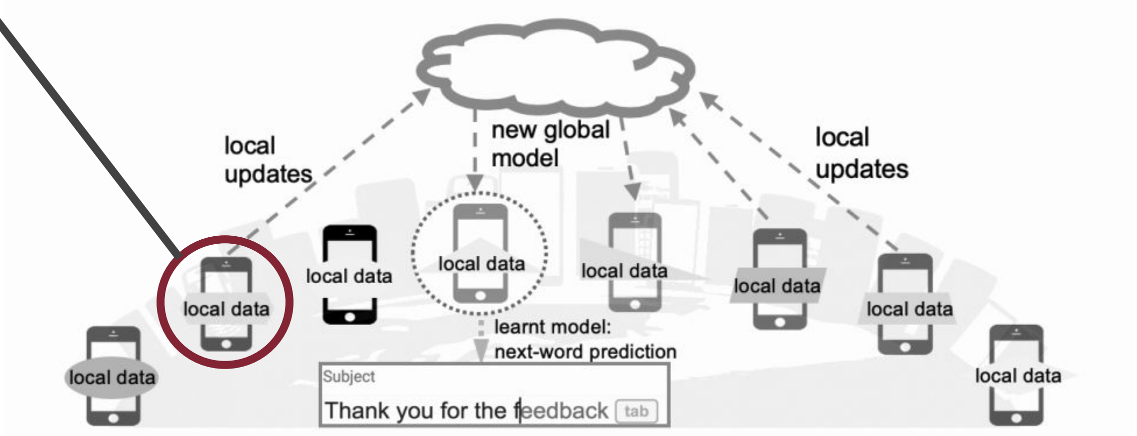
Collaborative learning



Federated learning (FL) (also known as **collaborative learning**) is a machine learning technique that trains an algorithm across multiple decentralized edge devices or servers holding local data samples, without exchanging them.

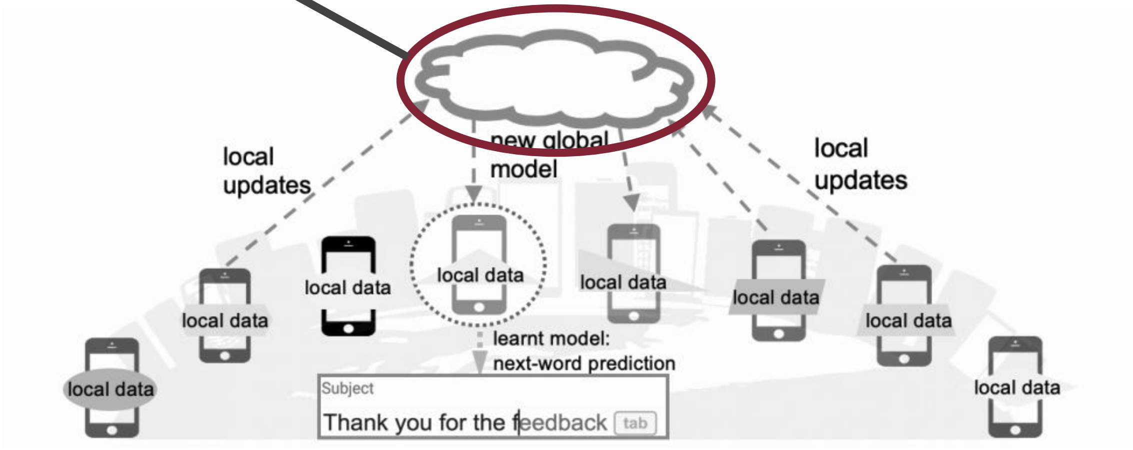
How does FL work? (local update)

$$\mathbf{W}_{t+1}^{k} = \mathbf{W}_t + \alpha \nabla \mathbf{W}_t^{k}$$

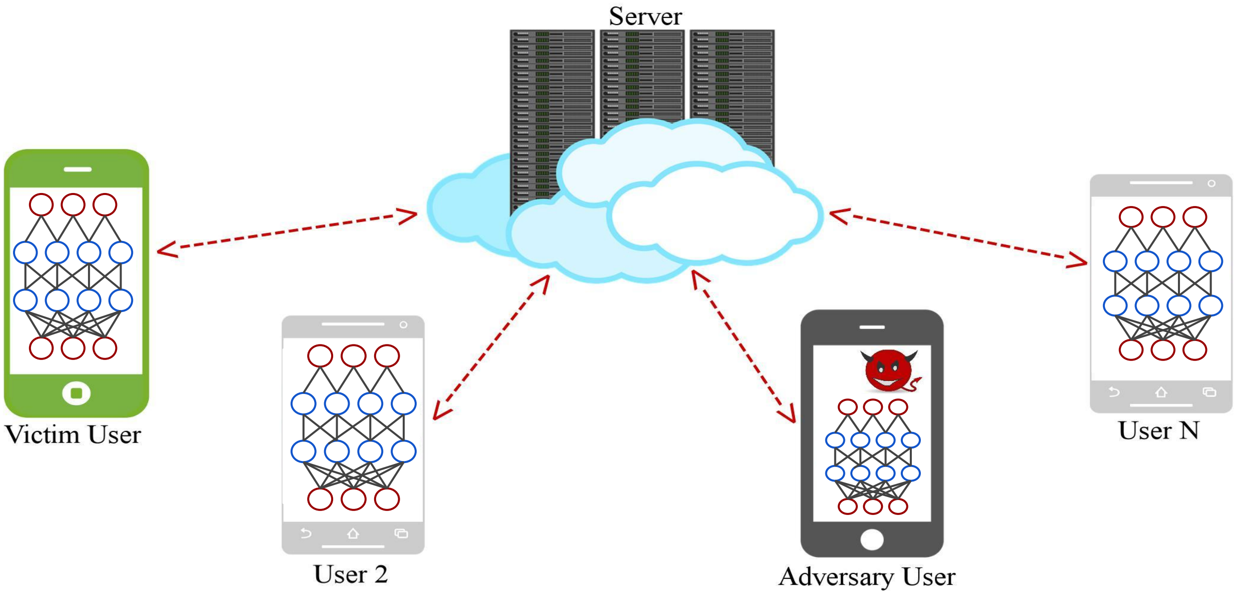


How does FL work? (global update)

$$\mathbf{W}_{t+1} = \mathbf{W}_t + \frac{\alpha}{n'} \sum_{k=1}^{n'} \nabla \mathbf{W}_t^k$$



Collaborative Learning Scheme



Adversary's goal?
Reconstruct private samples from the dataset of the victim indirectly influencing the learning of other participants

How can we reconstruct samples of other participants training data by looking at some gradients?

How should the adversary behave?

- The adversary should operate as an participant within the privacy-preserving collaborative deep learning protocol.

- The objective of the adversary is to infer meaningful information about a label that he does not own.

- The adversary does not compromise the global parameter server that collects and distributes parameters to the participants.

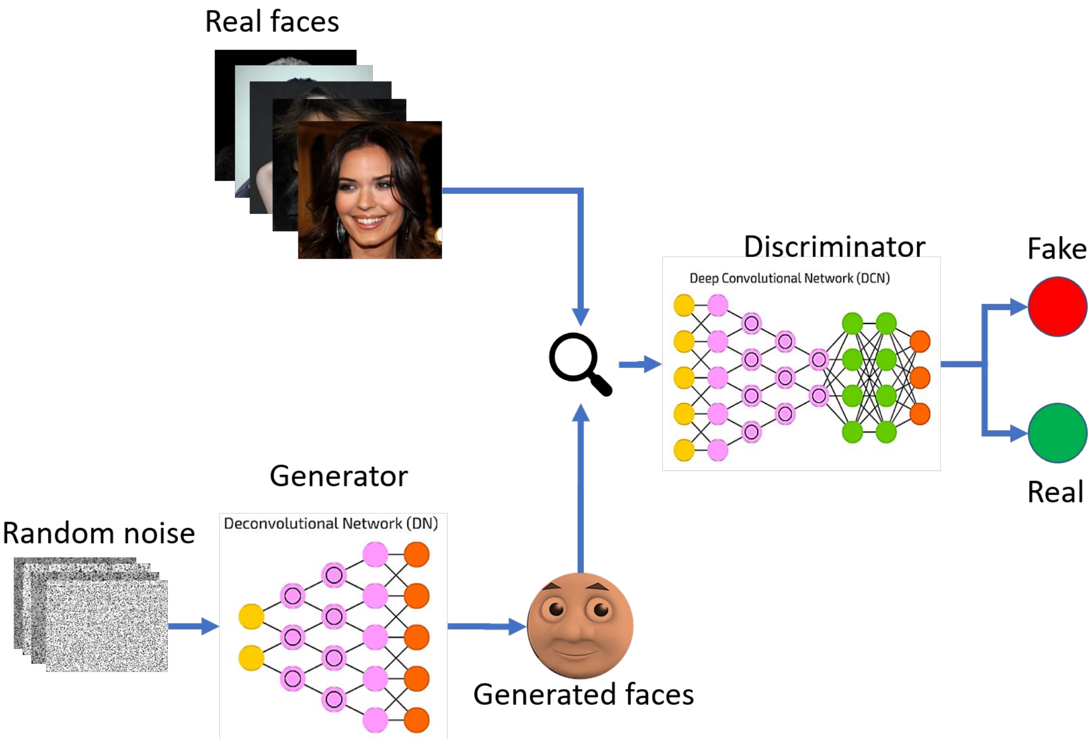
What can the adversary use?

What can the adversary use?

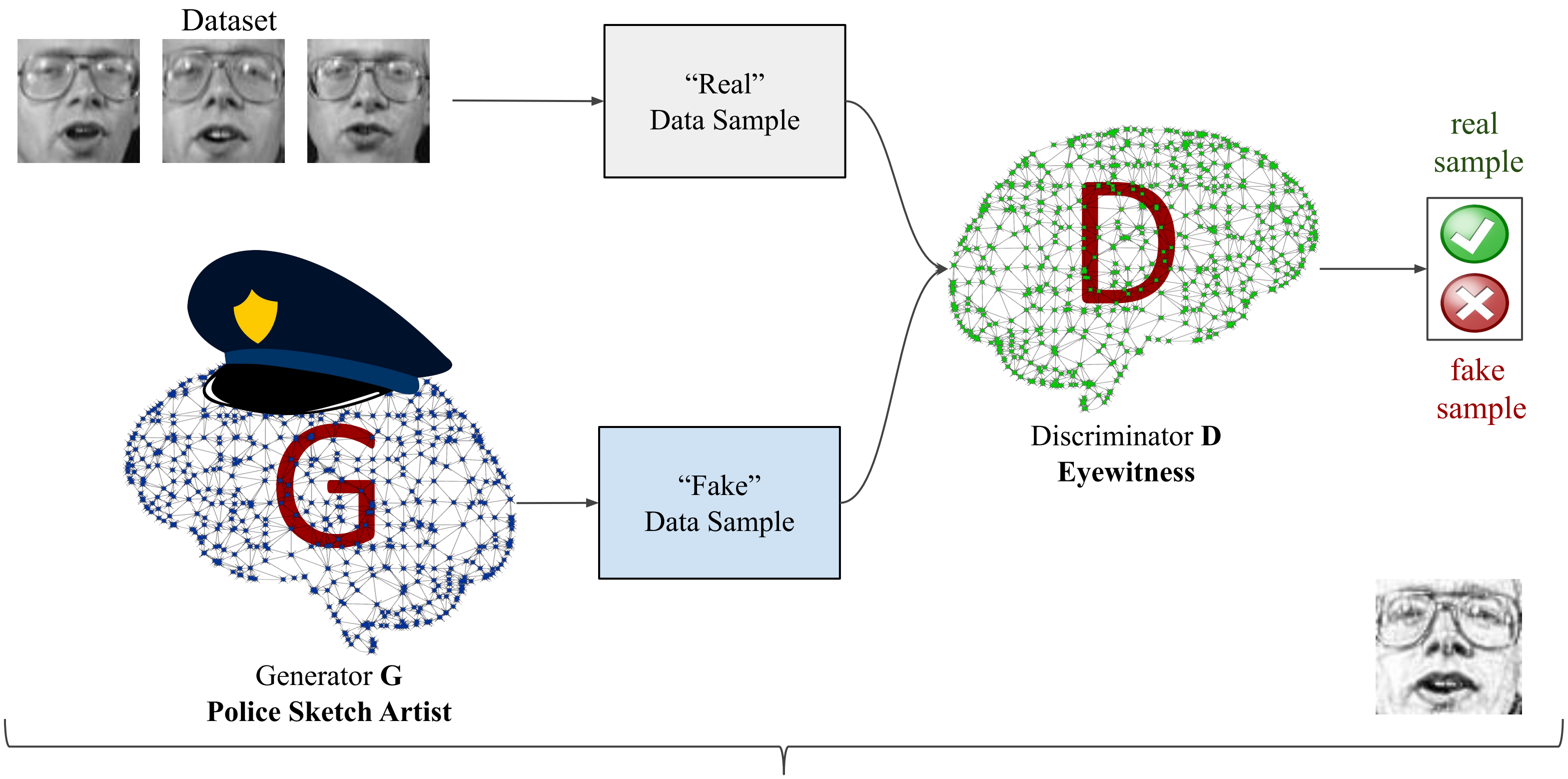
Give me DATA…

Not this..

This...


Real faces
Discriminator
Deep Convolutional Network (DCN)
Fake
Real
Generator
Random noise
Deconvolutional Network (DN)
Generated faces

Generative Adversarial Network



GAN Architecture

Generative Adversarial Networks

Generative

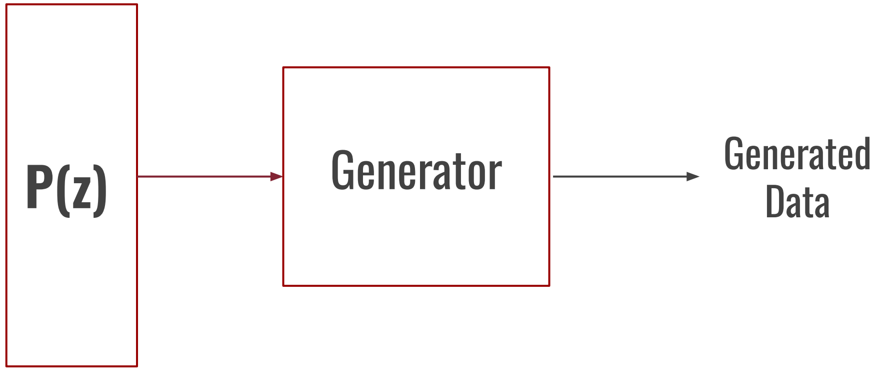
- We try to learn the underlying the distribution from which our dataset comes from.

Generative Adversarial Networks

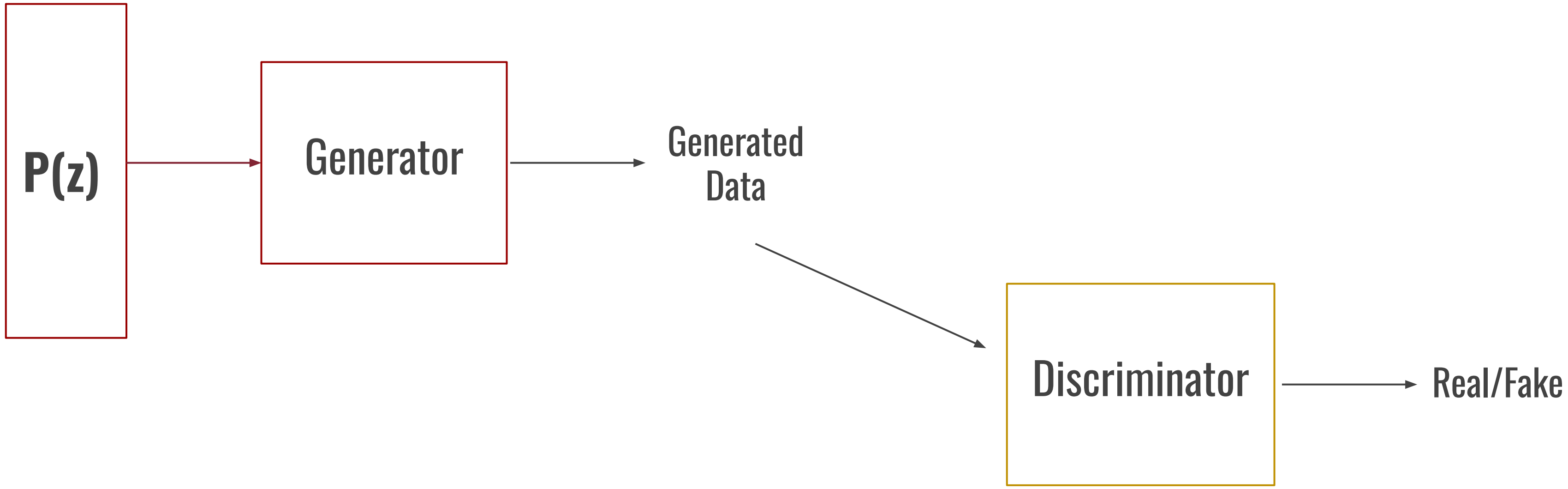
Adversarial

- **GANS are made up of two competing networks (adversaries) that are trying beat each other.**

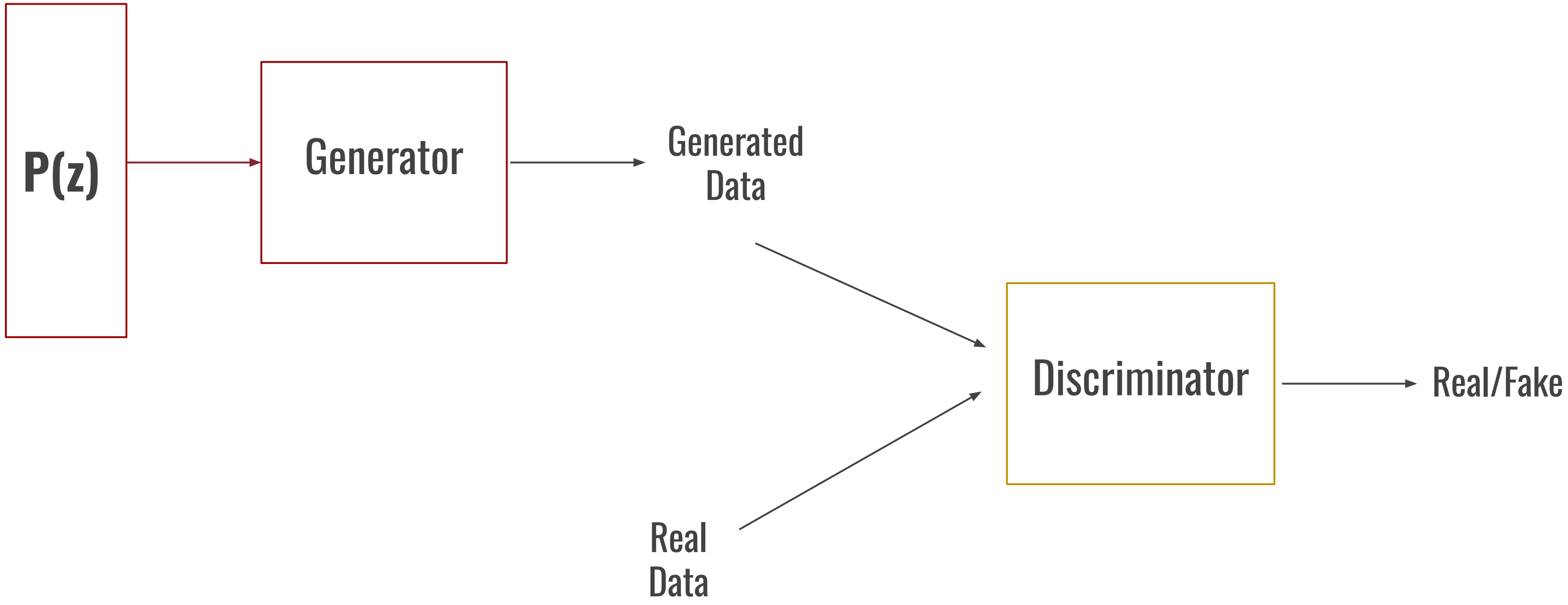
Generative Adversarial Networks



Generative Adversarial Networks

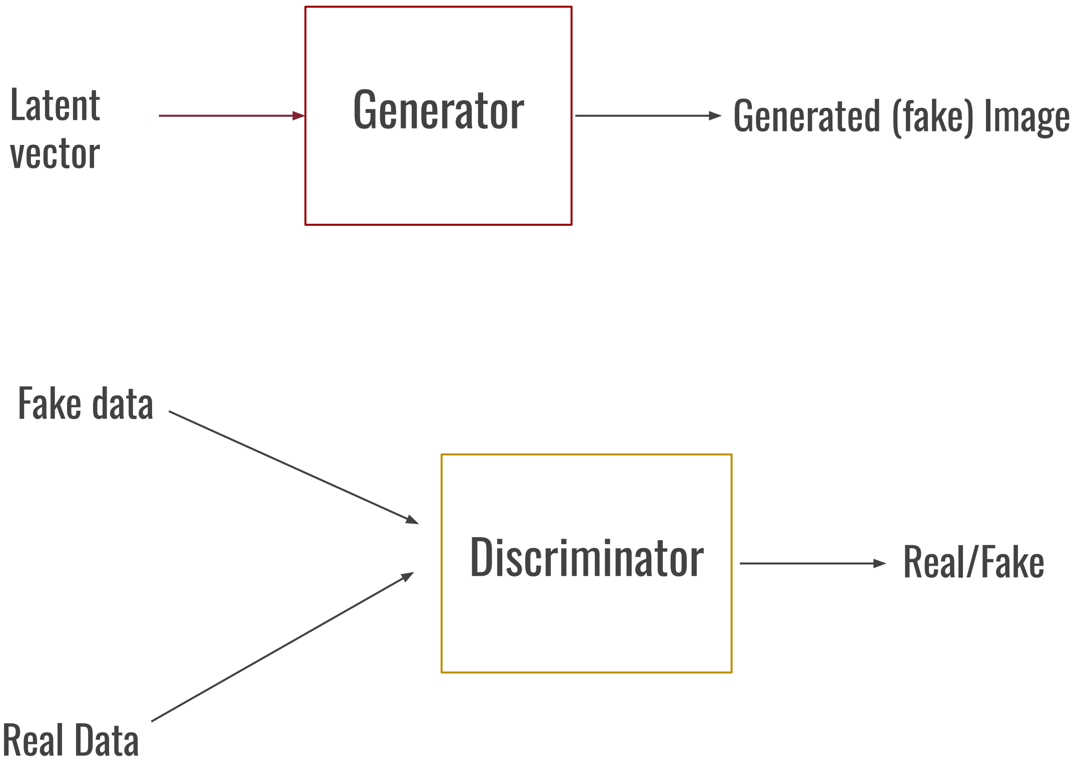


Generative Adversarial Networks



GANs - How are they trained?

At t=0,



GANs - How are they trained?

Which one should I train first?

GANs - How are they trained?

Which one should I train first?

Discriminator

GANs - How are they trained?

With what training data though?

Discriminator

GANs - How are they trained?

With what training data though?

Discriminator

- The Discriminator is a Binary classifier.
- Needs to discriminate between real/fake

GANs - How are they trained?

With what training data though?

Discriminator

- The Discriminator is a Binary classifier.
- Needs to discriminate between real/fake
- The data for Real class if already given:
  - **THE TRAINING DATA**
- The data for Fake class?
  - Generate from the **Generator**

GANs - How are they trained?

What about the Generator?

GANs - How are they trained?

What about the Generator?

Learning objective: Generate images from the Generator such that they are classified incorrectly by the Discriminator.

GANs - How are they trained?

Discriminator

Train the Discriminator
using the current
ability of the Generator

GANs - How are they trained?

Discriminator

Generator

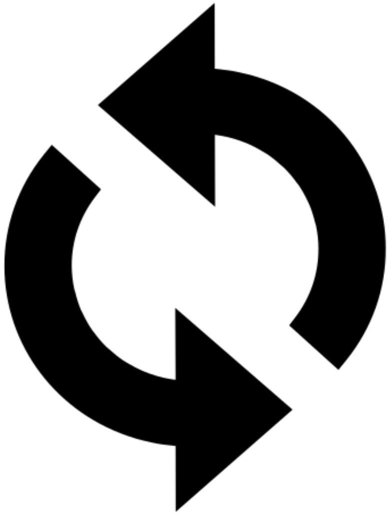
Train the Discriminator
using the current
ability of the Generator

Train the Generator
to beat
the Discriminator

GANs - How are they trained?

Discriminator

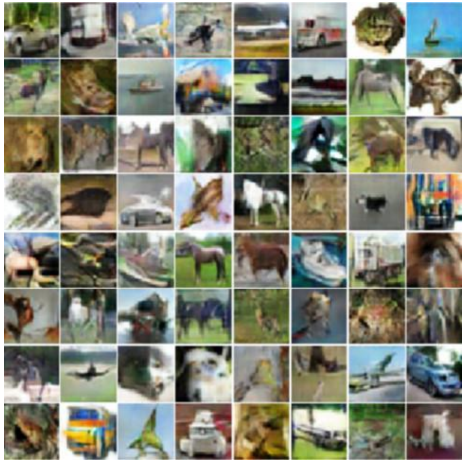
Train the Discriminator
using the current
ability of the Generator



Generator

Train the Generator
to beat
the Discriminator

MNIST images



CIFAR-10 images

faces

album covers

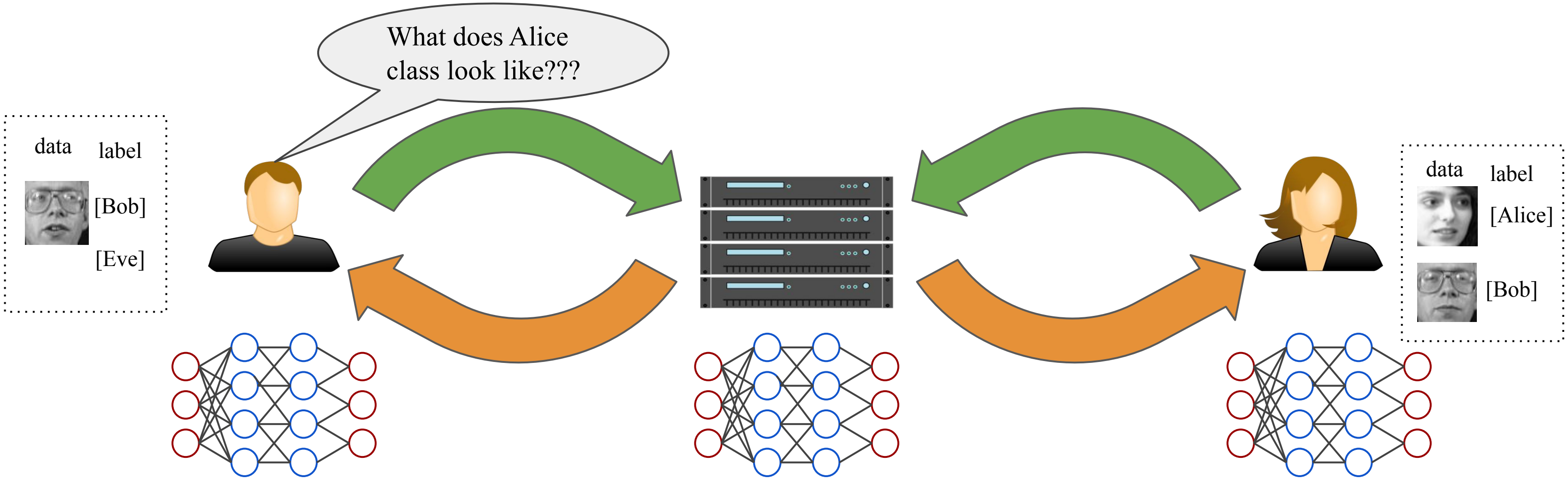
bedrooms

GAN results in the literature

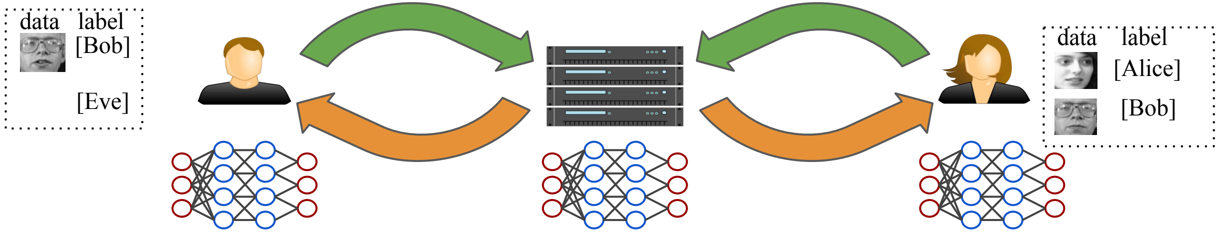
images from:

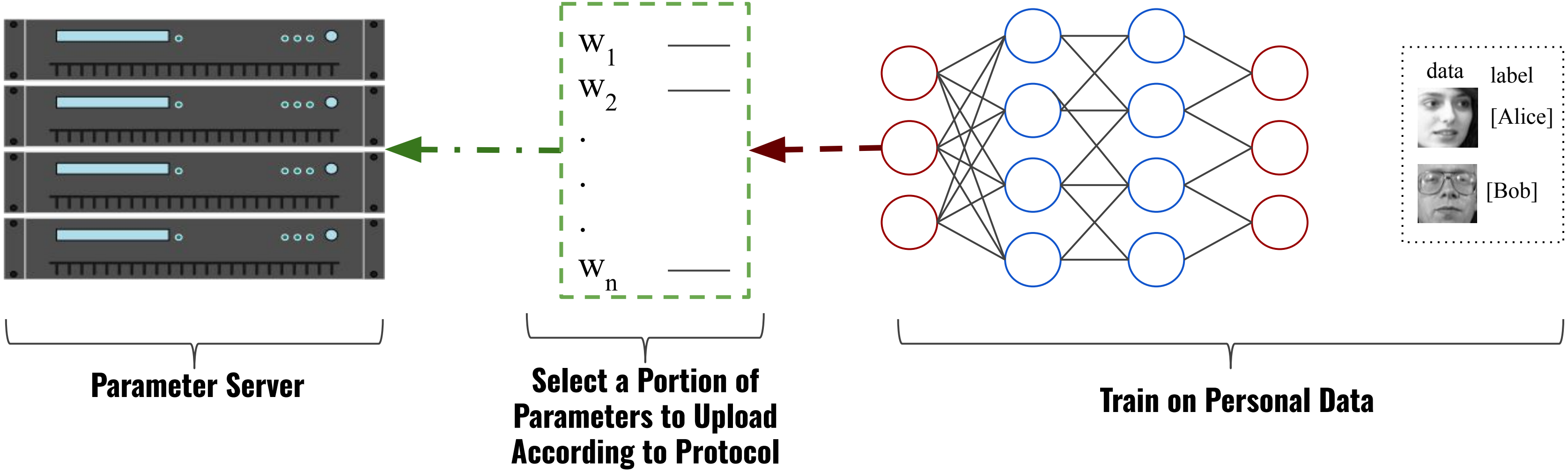
- https://blog.openai.com/generative-models/
- Goodfellow et al. Generative Adversarial Networks
- Radford et al. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks

Violating the privacy...

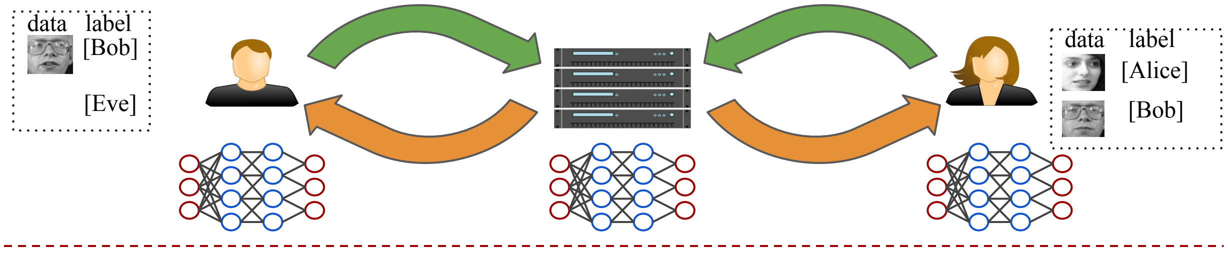


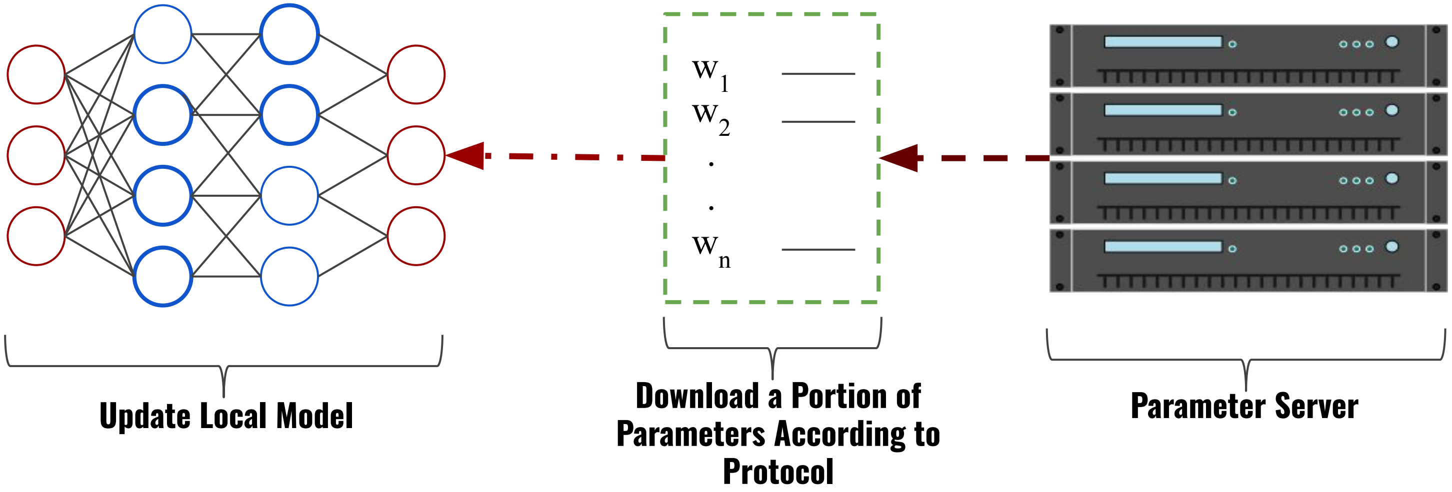
Victim's Turn



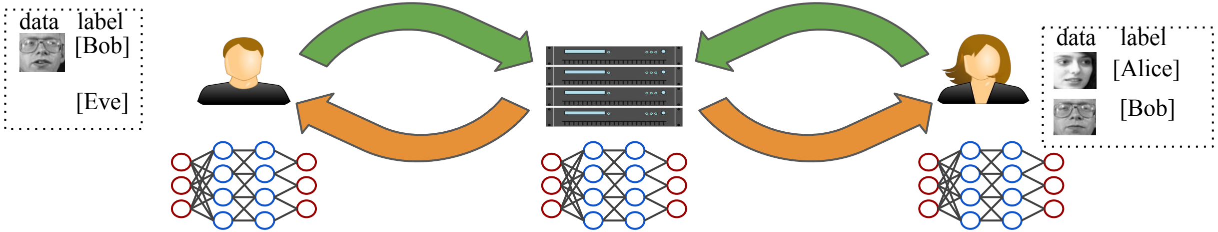


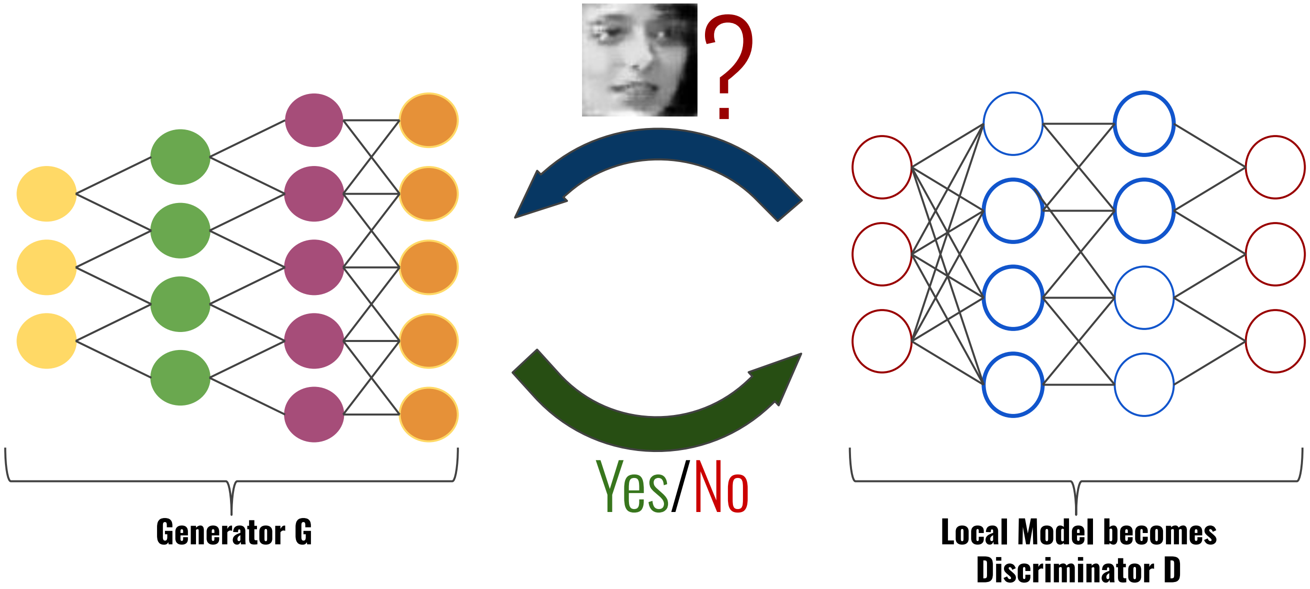
Adversary’s Turn



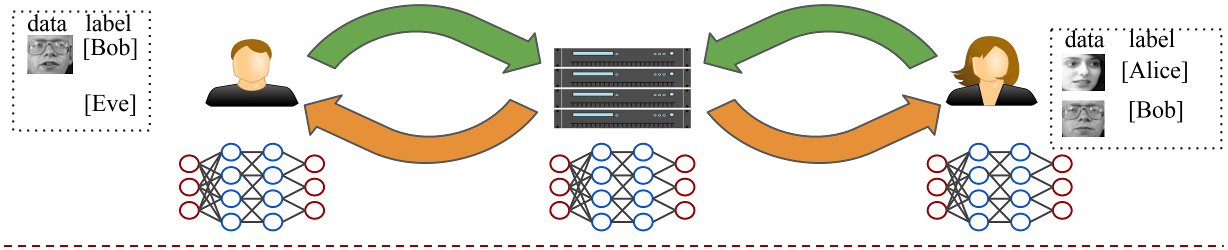


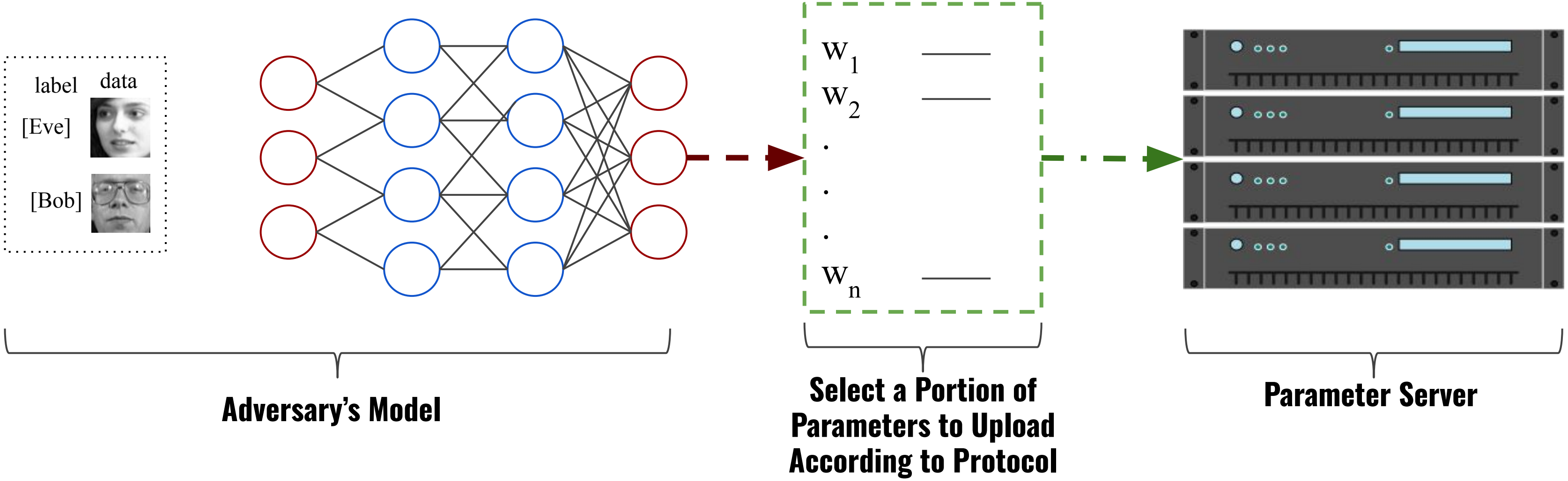
Adversary’s Turn





Adversary's Turn





Experiments without Differential Privacy

Actual Images

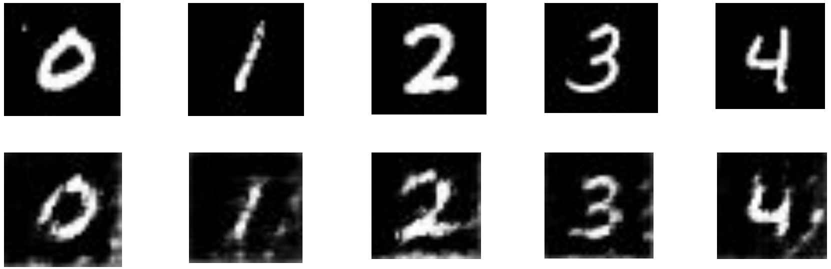
Generated Data

Original vs Generated

Experiments with Differential Privacy

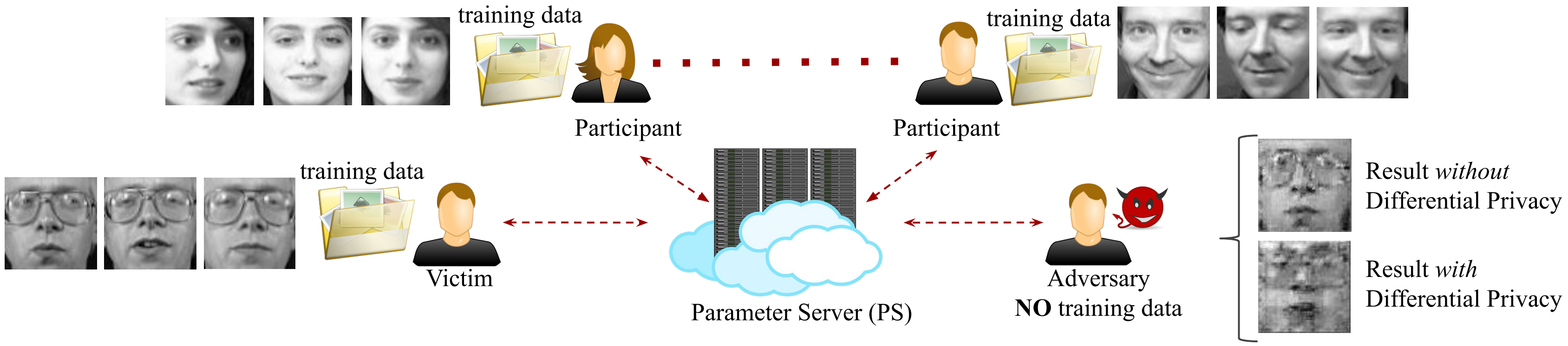
Actual Images

Generated Data



Original vs Generated

Experiments (Adversary has NO data at all)



Reading Material

1. Privacy preserving learning: Link-1, Link-2
2. Generative Adversarial Networks: Link-1
3. Information Leakage from collaborative learning: Link-1