#### Deep Models under the GAN: Information Leakage from Collaborative Deep Learning

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We investigate whether decentralized (a.k.a collaborative) deep learning is *more* privacy-preserving than the centralized one.

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### New active inference attack on collaborative deep learning models using GANs

#### Deep Learning 101

Branch of machine learning that makes use of neural networks, to find solutions for a variety of complex tasks either in supervised or unsupervised way

\*\*\* AlphaGo

- Areas used:
  - Computer vision
  - Image processing
  - Face recognition
  - Speech recognition
  - Text-to-speech systems
  - Natural language processing
  - Games...



image source: https://goo.gl/u26HM3



#### **Deep Learning**

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#### Huge computational power



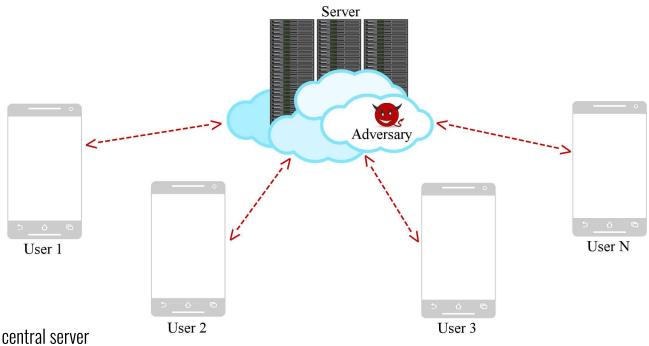
#### Large quantities of data

image source: http://www.nvidia.com/docs/IO/67561/GeForce\_GTX\_280M\_preview.jpg



image source: http://karpathy.github.io/assets/cnntsne.jpeg

#### **Centralized Learning Scheme**

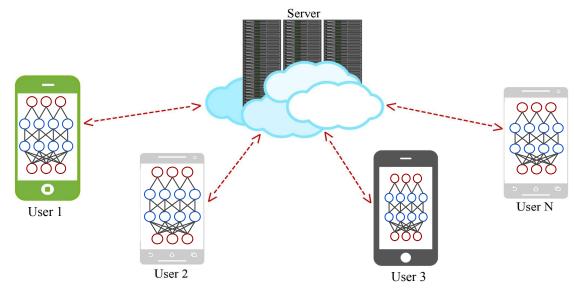


- data pooled on a central server
- no control over the learning process

### is it possible to learn while preserving privacy

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#### Decentralized Learning Scheme (collaborative/federated)



- local training on data

Shokri et al. Privacy-Preserving Deep Learning, CCS'15

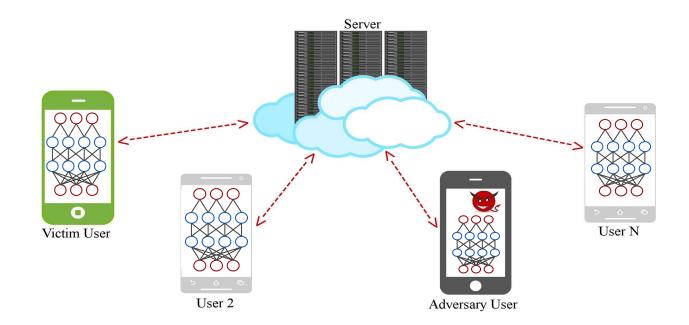
- updates shared via a parameters server (ex. Google's federated learning)
- participants **indirectly** influence each other's learning
- differential privacy can be used to minimize leakages from parameter uploads
- NOTE: Shokri et al. only assume a "passive" adversary model

#### Attacks on ML models (Prior to Ours)

- 1) Hacking Smart Machines with Smarter Ones, 2011 by Ateniese et al.
- 2) Model Inversion Attacks, 2015 by Fredrikson et al.
- 3) Membership Inference Attacks, 2017 by Shokri et al.



#### Decentralized Learning Scheme (collaborative/federated)



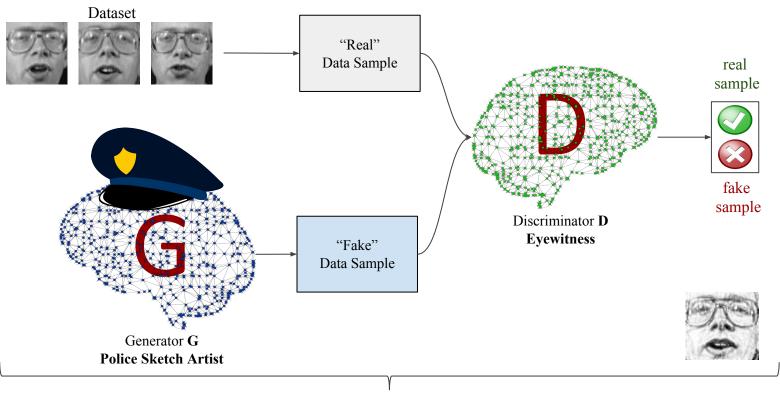
- Indirectly influencing the learning of other participants, allows potentially anyone to be an adversary

# can neural networks attack neural networks networks

### YES!

by using Generative Adversarial Networks (GAN)

#### How does a GAN work?





#### **GAN** results in the literature

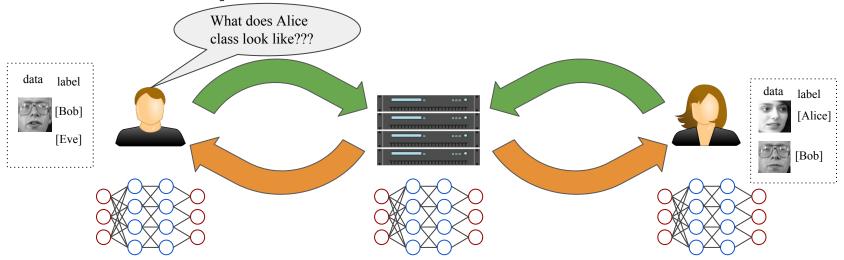
#### images from:

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



bedrooms

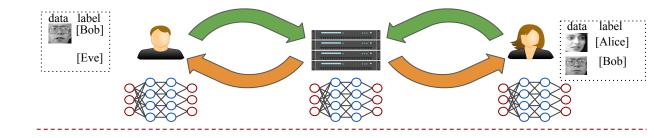
#### Our Attack: Deep Models Under the GAN

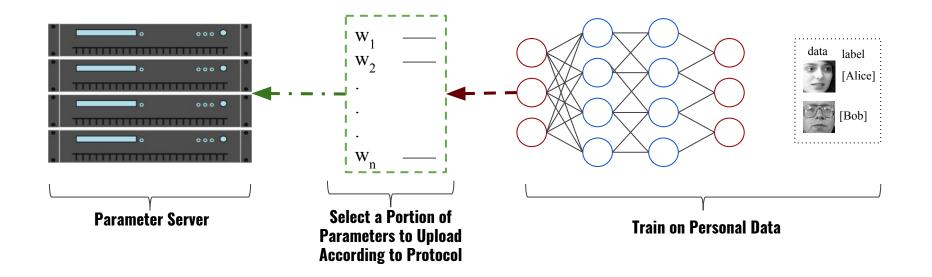


#### Agreement

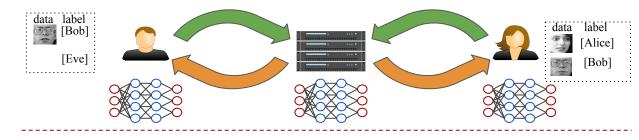
- Common learning objective
- Architecture of the model
- Labels/Classes present

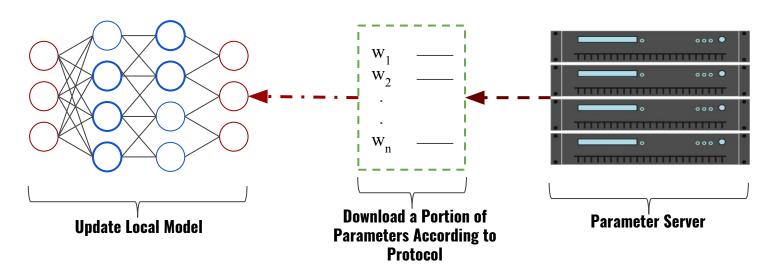
#### Victim's Turn



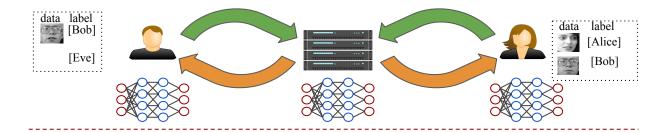


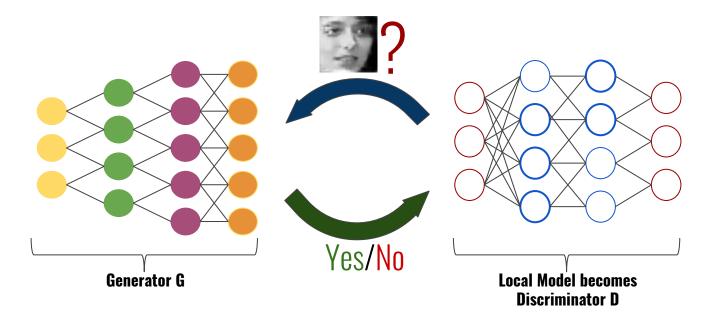
#### Adversary's Turn



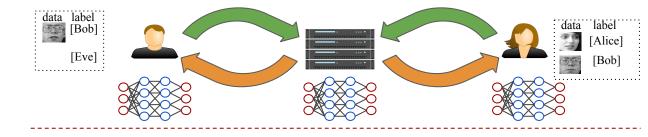


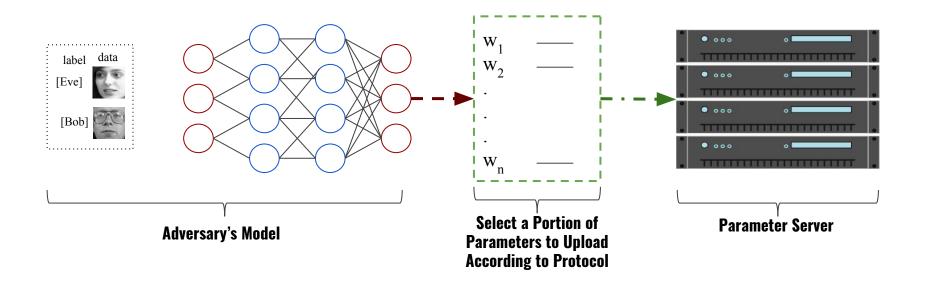
#### Adversary's Turn





#### Adversary's Turn





#### **Experiments without Differential Privacy**

Actual Images O I 2 3 4

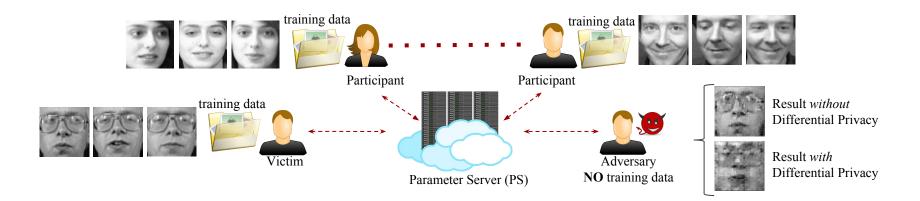
Generated Data O I 3 4





Original vs Generated

#### Experiments (Adversary has NO data at all)

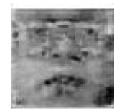


#### **Experiments with Differential Privacy**

Actual Images / 1 2 3 4

Generated Data / 2 3 4





Original vs Generated

### is anything wrong with differential privacy



### NOI

Problem concerns the granularity at which differential privacy is *currently* applied

#### **Further Results**

#### **Actual Images**







Generated Images









Generated images when targeting 'horse' class from CIFAR-10

## Collaborative learning for privacy is less desirable than centralized learning

### What's next?

#### What's next?

- Extending on a broader range of datasets
- Further improving the GAN model (more art than science)
- Devising countermeasures

A version of the paper can be found at: https://arxiv.org/abs/1702.07464

## Thank You!