Auditing Privacy Defenses in Federated Learning via Generative Gradient Leakage
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Overview

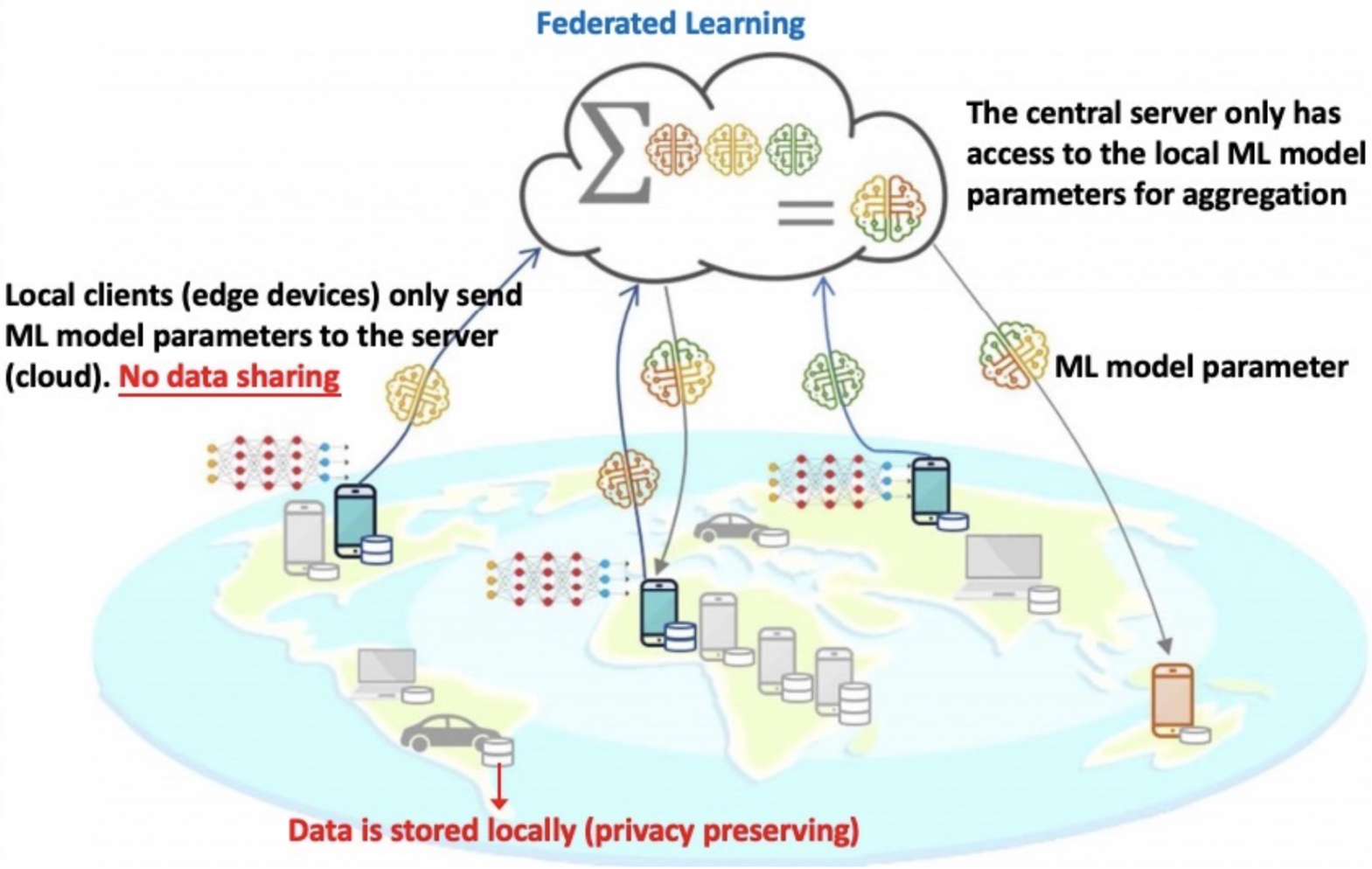
Federated Learning

- Multiple clients collaboratively learn a shared model under coordination of central server

- Clients **do not share private data** instead, they just share the gradient information to central server to update the model

Federated Learning Contd.

- Collaborative learning without centralized training data



Federated Learning Applications.

- Mobile computing
  - e.g. text prediction in Google Gboard
- Telemedicine
  - e.g. multi institutional collaborations for learning medical diagnosis model without sharing patient's private data

Privacy Risks in FL

- Even though only model parameters/gradient information is shared from client, it is found that private information can still be extracted from **exchanged gradients**

Privacy Risks in FL contd..

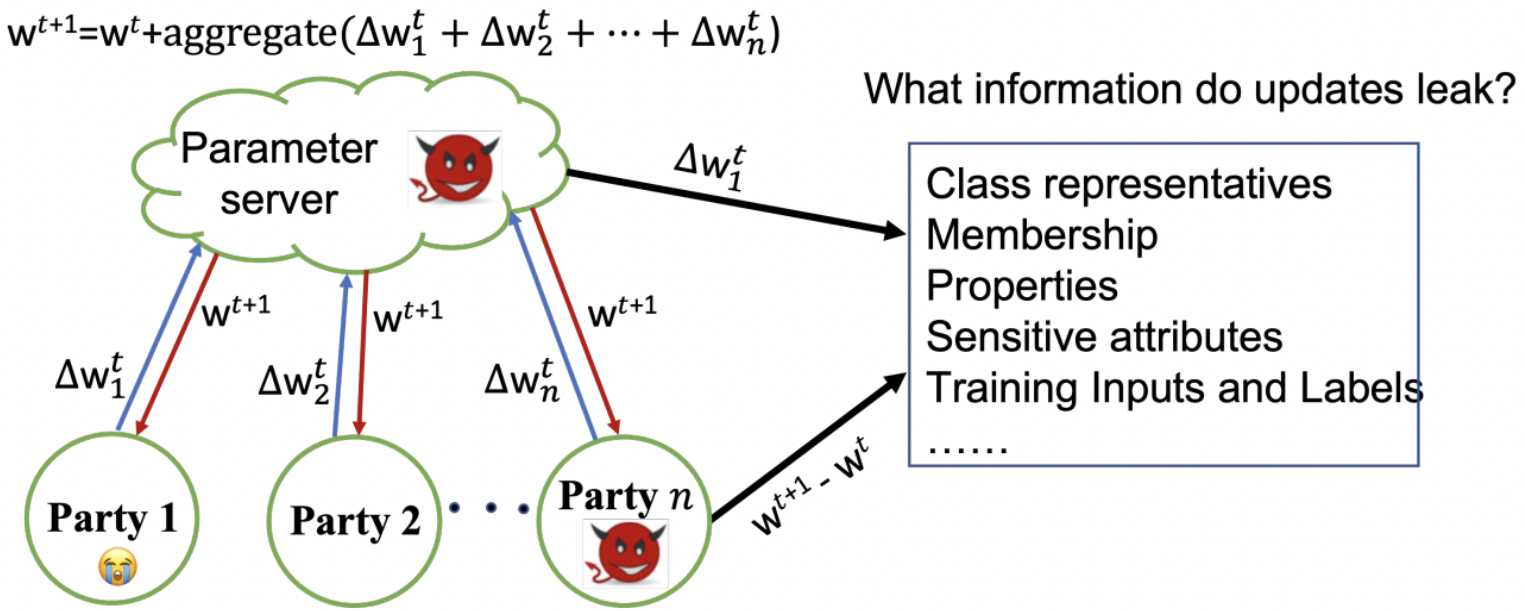


Figure: A demo of privacy leakage in FL. Attacker can infer various private information about the victim participant from the received gradients or the snapshot of the FL model parameters. [2]

[2] Image Credits : **Privacy and Robustness in Federated Learning: Attacks and Defenses**

How to prevent privacy leakage? - Currently Available Privacy Defenses

- Crypto-based solutions
  - e.g. Secure Multi-party computation, Homomorphic encryption. Remains vulnerable to the inference over the output
- Gradient Degradation based solutions
  - Differential Privacy:
    - Use a randomised technique to distort the gradients before sharing it to central server.
    - But there is trade-off in differential privacy is between privacy and utility.
- Gradient Sparsification
  - Compress the gradients by pruning small values

Are these defenses sufficient?

- In this work, author studies the challenging scenario, where clients applies local defenses before sharing the gradients
- And author tries to reconstruct a high fidelity images from the shared degraded gradients.

Are these defenses sufficient? Contd..

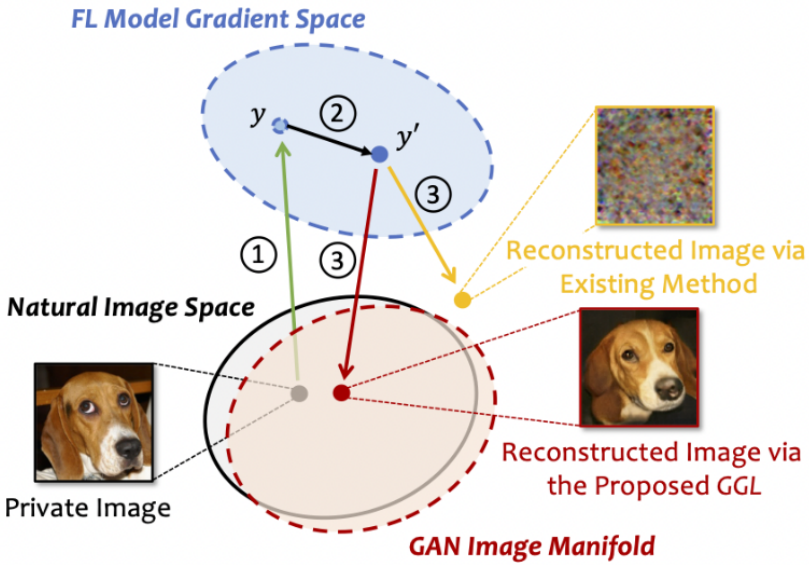


Figure: Illustration of data leakage via gradient.[4]
(1) Client computes gradients on its private data
(2) Client applies defense to degrade the computed gradients y
(3) Adversary attempts to reconstruct the private image from the shared gradients y'

[4] Image Credits : **Auditing Privacy Defenses in Federated Learning via Generative Gradient Leakage**

Problem formulation

The task of reconstructing a training image $x \in R^d$ from its gradients $y \in R^m$ can be formulated as a non-linear inverse problem

$$\mathbf{y} = F(\mathbf{x}),$$

where $F(\mathbf{x}) = \nabla_{\boldsymbol{\theta}} \mathcal{L}\left(f_{\boldsymbol{\theta}}(\mathbf{x}), c\right)$ is forward operator that calculates the gradients of the loss, provided with label c and FL model f_θ
When defense is applied at the client's side, the problem becomes:

$$\mathbf{y} = \mathcal{T}(F(\mathbf{x})) + \boldsymbol{\varepsilon},$$

where $\mathcal{T}(\cdot)$ is referred to as the lossy transformation (e.g., sparsification) and ε is the additive noise (e.g., DP)

Current Approach and Its limitation

- Existing methods aim to solve this inverse problem by using image priors in a penalty form

$$\mathbf{x}^* = \underset{\mathbf{x}\in\mathbb{R}^d}{\operatorname{argmin}} \mathcal{D}(\mathbf{y}, F(\mathbf{x})) + \lambda\omega(\mathbf{x}),$$

where $\mathcal{D}(\cdot)$ is a distance metric, $\omega(\mathbf{x}) : \mathbb{R}^d \to \mathbb{R}$ is the standard image prior (e.g., total variation)

Current Approach and Its limitation

- Only effective for reconstructing images from the actual gradients
- When reconstructing from a set of low-fidelity and noisy gradients, it would suffer from the limited identification ability of hand-crafted priors
- Result: return false solutions that are not valid natural images

Generative Gradient Leakage

- Insight
  - Leverage a generative model trained on public image datasets as a learned natural image prior to ensure that reconstructed image is of good image quality
- Given a well-trained generator $G(\cdot)$, we solve:

$$\mathbf{z}^* = \underset{\mathbf{z}\in\mathbb{R}^k}{\operatorname{argmin}} \underbrace{\mathcal{D}(\mathbf{y}, \mathcal{T}(F(G(\mathbf{z}))))}_{\text{gradient matching loss}} + \lambda \underbrace{\mathcal{R}(G;\mathbf{z})}_{\text{regularization}} ,$$

where $z \in R^k$ is the latent space of the generative model, and $\mathcal{R}(G;\mathbf{z})$ is a regularization term that penalizes latent vectors which deviate from the prior distribution

Generative Gradient Leakage

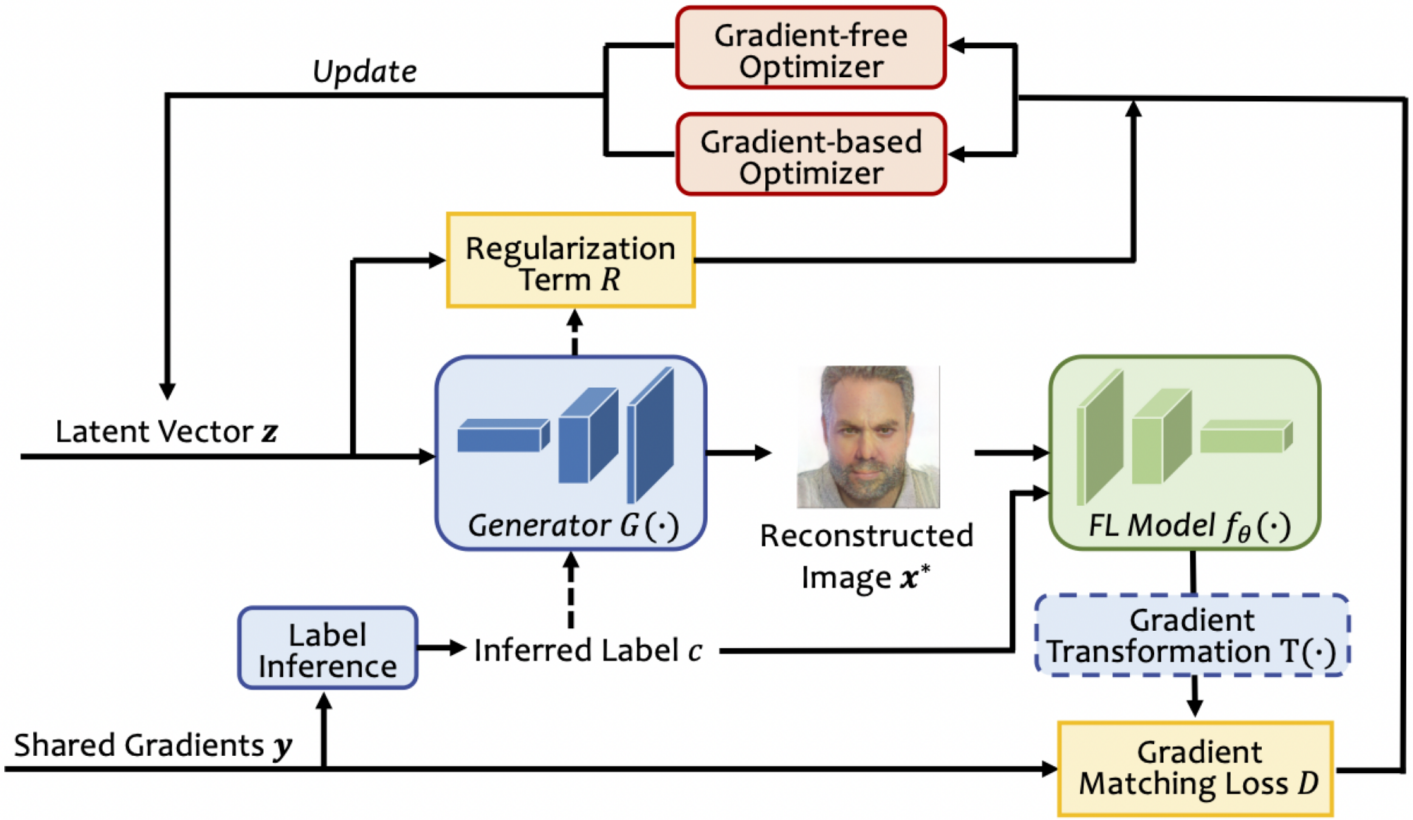


Figure: Overview of author's approach [5]

[5] Image Credits : **Auditing Privacy Defenses in Federated Learning via Generative Gradient Leakage**

Optimization strategies

- Challenges
  - The target inverse problem is highly *non convex and non linear*.
  - The existing data reconstruction attacks are based on the **gradient based optimiser** like $L - BFGS$ [6] and *Adam*.

- Issues with gradient based optimiser
  - Outcome is highly based on choice of initialization
  - For complex models, often high chance that cost function will converge to sub optimal minima

[6] Limited-memory BFGS (L-BFGS or LM-BFGS) is an optimization algorithm in the family of quasi-Newton methods that approximates the Broyden–Fletcher–Goldfarb–Shanno algorithm (BFGS)

Proposed optimisation strategy

- Author explores two gradient-free optimisation strategies
  - Bayesian optimisation(BO)
  - Covariance Matrix Adaptation Evolution Strategy (CMA-ES)

Datasets

- CelebA
  - The dataset was collected from the Internet and contains images of celebrities with a diverse range of ethnicities, ages, and facial features.
- ImageNet
  - ImageNet is a large image database with over 14 million images in 20,000 categories for computer vision tasks.

ImageNet and CelebA has become a popular benchmark dataset for a variety of computer vision tasks, including face recognition, attribute prediction, and generative models.

Experiment Results

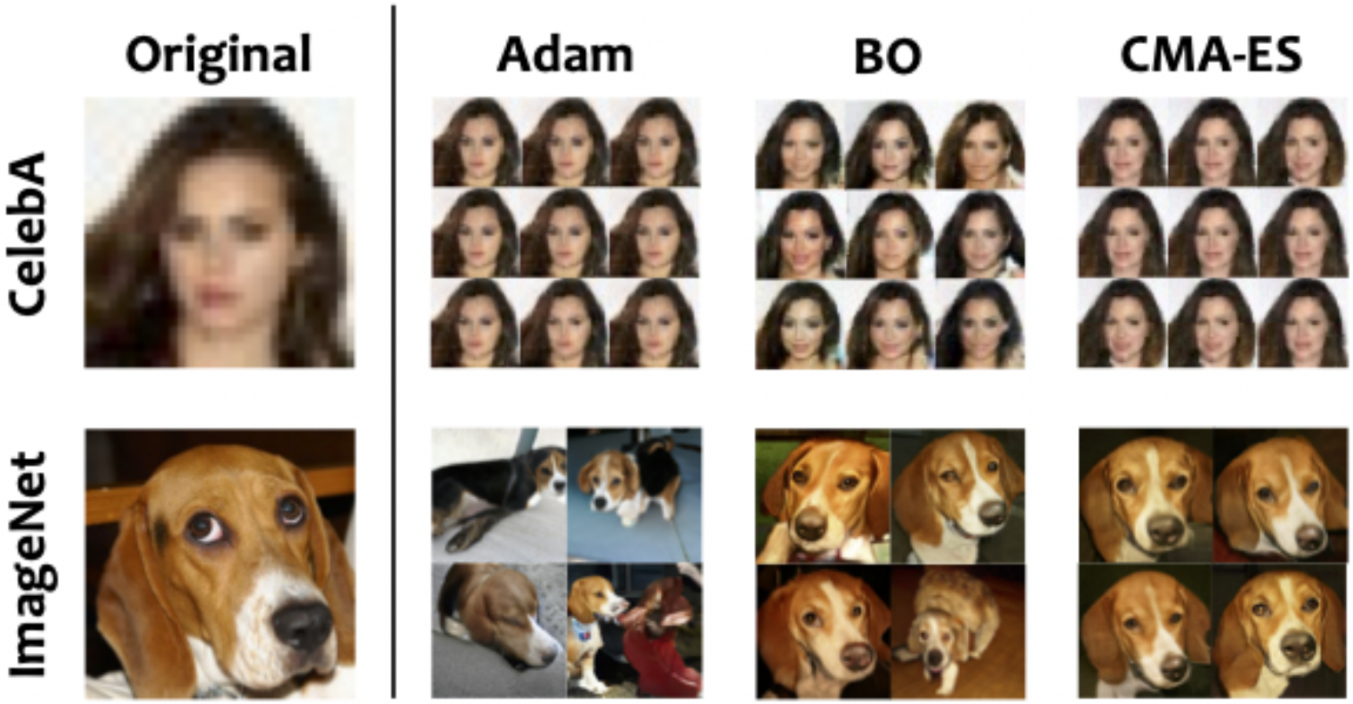


Figure: Visual comparison of different optimizers. The images on the right are the reconstruction samples produced by three types of optimizers with different random seeds[8]

[8]Image Credits : **Auditing Privacy Defenses in Federated Learning via Generative Gradient Leakage**

My observation

- On CelebA, gradient-based and gradient-free optimizers show similar performance
- On ImageNet, the gradient-based Adam fails to recover any useful information
- Gradient-free optimizers **(BO and CMA-ES)** are still able to find samples that resemble the original private image and are more resilient to different initialization conditions

Experiment Results Contd.

Dataset	Metric	Adam		BO		CMA-ES	
		Mean	Std.	Mean	Std.	Mean	Std.
CelebA	MSE-I ↓	**0.0427**	0.0025	0.0813	0.0131	0.0708	**0.0008**
	PSNR ↑	**13.6965**	0.2593	10.9455	0.6816	11.4989	**0.0533**
	LPIPS ↓	**0.1435**	**0.0083**	0.2162	0.0328	0.2136	0.0133
	MSE-R ↓	**0.0003**	**0.0001**	0.0012	0.0003	0.0015	0.0022
ImageNet	MSE-I ↓	0.5918	0.1955	**0.2648**	0.0181	0.2667	**0.0119**
	PSNR ↑	2.4433	1.3565	**5.7783**	0.2992	5.7420	**0.1988**
	LPIPS ↓	0.7983	0.0280	0.6166	0.0590	**0.5736**	**0.0209**
	MSE-R ↓	0.1051	0.0703	0.0035	0.0005	**0.0018**	**0.0002**

Figure: Quantitative comparison of different optimizers.[9]

- MSE-I: the mean squared error (MSE) between the generated and true gradients of the model at iteration i.
- PSNR: the peak signal-to-noise ratio (PSNR) between the generated and true gradients of the model at iteration i.
- LPIPS: the learned perceptual image patch similarity (LPIPS) between the generated and true gradients of the model at iteration i
- MSE-R: the MSE between the generated and true gradients of the model over all iterations

[9] Image Credits : **Auditing Privacy Defenses in Federated Learning via Generative Gradient Leakage**

Experiment Results Contd.

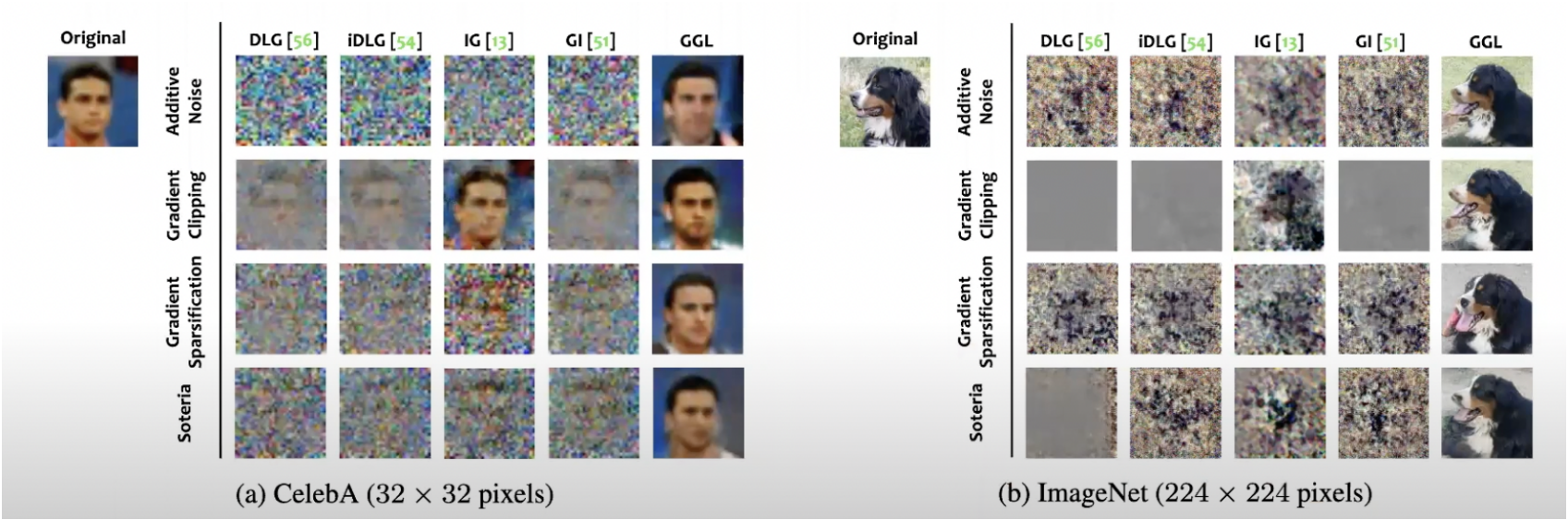


Figure: Comparison with other existing attacks .[10]

[10] Image Credits : **Auditing Privacy Defenses in Federated Learning via Generative Gradient Leakage**

Experiment Results Contd.

Dataset	Attack	Additive Noise [44, 56]				Gradient Clipping [14, 48]				Gradient Sparsification [56]				Soteria [44]			
		MSE-I ↓	PSNR ↑	LPIPS ↓	MSE-R ↓	MSE-I ↓	PSNR ↑	LPIPS ↓	MSE-R ↓	MSE-I ↓	PSNR ↑	LPIPS ↓	MSE-R ↓	MSE-I ↓	PSNR ↑	LPIPS ↓	MSE-R ↓
CelebA	DLG [56]	0.6479	1.8843	0.8197	0.0021	0.2097	6.7831	0.7375	0.0326	0.3335	4.7679	0.7986	0.0155	0.3624	4.4069	0.8007	0.0285
	iDLG [54]	0.6261	2.0329	0.8209	0.0025	0.1960	7.0762	0.7280	0.0326	0.3301	4.8124	0.8035	0.0162	0.3269	4.8553	0.8036	0.0396
	IG [13]	0.4880	3.1151	0.8260	0.0097	**0.0543**	**12.6517**	0.2998	**0.0003**	0.4103	3.8687	0.7975	0.0113	0.3441	4.6326	0.8008	0.0316
	GI [51]	0.5738	2.4116	0.8302	0.0023	0.1790	7.4701	0.7142	0.0322	0.2958	5.2888	0.7775	0.0163	0.3179	4.9768	0.7991	0.0409
	GGL	**0.0780**	**11.0766**	**0.1906**	**0.0010**	0.0760	11.1902	**0.1670**	0.0015	**0.0768**	**11.1466**	**0.1620**	**0.0007**	**0.0968**	**10.1434**	**0.2561**	**0.0007**
ImageNet	DLG [56]	0.7438	1.2852	0.9353	0.0049	0.3809	4.1912	0.9798	2.1610	0.4432	3.5336	0.8907	0.0075	0.5990	2.2253	0.9195	0.5415
	iDLG [54]	0.7352	1.3359	0.9392	0.0041	0.3699	4.3190	0.9473	1.8810	0.4357	3.6077	0.8935	0.0077	0.6089	2.1542	0.9198	0.5425
	IG [13]	0.3081	5.1120	0.8677	0.4490	**0.1432**	**8.4386**	0.7476	0.0214	0.2993	5.2376	0.8805	0.0501	0.3683	4.3373	0.8700	0.5057
	GI [51]	0.6593	1.8090	0.9448	0.0031	0.3702	4.3154	0.9451	1.8807	0.4404	3.5611	0.8889	0.0072	0.6235	2.0511	0.9169	0.5792
	GGL	**0.2686**	**5.7089**	**0.5915**	**0.0018**	0.2230	6.5163	**0.5592**	**0.0015**	**0.2141**	**6.6920**	**0.5170**	**0.0017**	**0.2484**	**6.0477**	**0.5685**	**0.0022**

Figure: Observation : Existing attacks [12] struggle to reconstruct a realistic image with the present of any privacy defense mechanism. The proposed GGL is still able to synthesize high quality images that are similar to the original ones

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1. Deep Leakage from Gradients (DLG) : gradient leakage attack with l2 gradient matching loss and L-BFGS optimizer;
2. Improved Deep Leakage from Gradients (iDLG): improved DLG attack with label inference;
3. Inverting Gradients (IG) : gradient leakage attack with cosine distance as loss and total variation as prior, optimized using Adam;
4. GradInversion (GI): gradient leakage attack with l2 gradient matching loss and Adam optimizer.

Future Work / Novelty idea

- Applying the gradient leakage attack to other types of federated learning, such as horizontal federated learning or federated transfer learning.
- Developing novel privacy defenses specifically designed to defend against the gradient leakage attack.

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THANK YOU


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