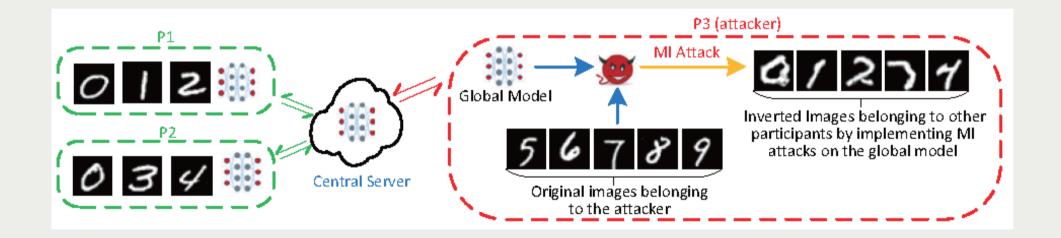


FedInverse: Evaluating Privacy Leakage in Federated Learning

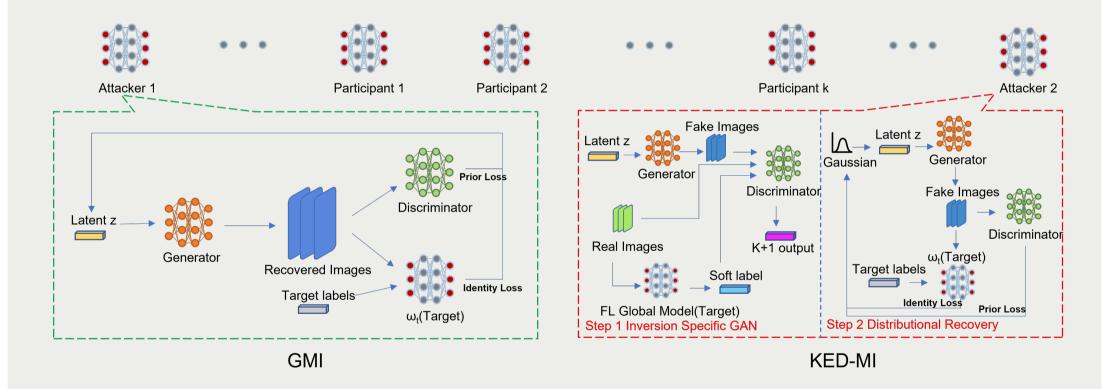
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University of Southern Queensland
Deakin University
The University of Adelaide
Peking University
Swinburne University of Technology

Model Inversion Attacks





FedInverse





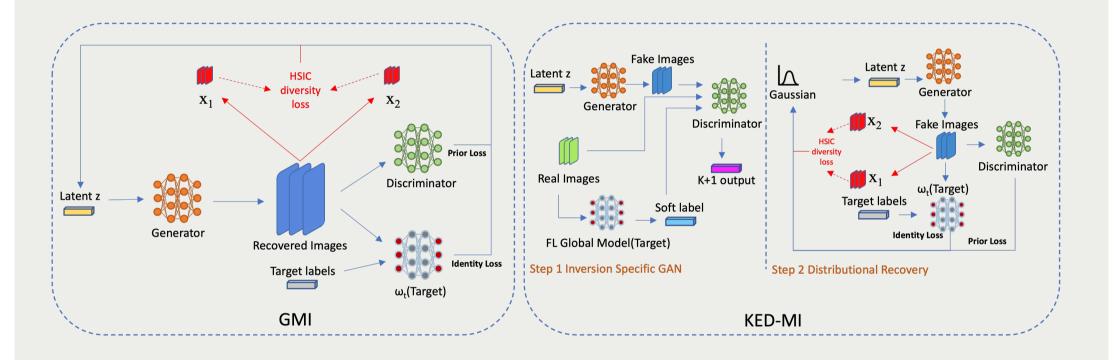
Algorithm

Algorithm 1 FedInverse Algorithm. K indicates the number of participants and k represents the participant number; B represents the local batch size, E indicates the local training epochs, C is the participation rate of participants, while η is learning rate; G and D denote Generator and Discriminator respectively, \mathcal{P}_{aux} represents the auxiliary dataset used to pre-train GAN, \mathcal{N} denotes the Gaussian distribution, while \mathcal{Q}_t indicates the set of generated images by FedInverse.

```
1: Server Initialization: \omega_0
                                                                                             x \leftarrow G(z)
2: for each training round t = 1, 2 \dots do
                                                                         21:
                                                                                             split x into x_1 and x_2
                                                                         22:
                                                                                             compute HSIC(x_1, x_2)
          m \leftarrow \max(C \cdot K, 1)
          S_t \leftarrow (random set of m participants including
                                                                                             update z' for diversity optimization
                                                                         23:
     a single Attacker)
                                                                         24:
                                                                                        end for
          for each participant k \in S_t in parallel do
                                                                         25:
                                                                                        x' \leftarrow G(z')
 5:
              \omega_{t+1}^k \leftarrow \text{ParticipantUpdate}(k, \omega_t)
                                                                                        Q_t \leftarrow Q_t \cup \{x'\}
 6:
                                                                         26:
              evaluate on \mathcal{Q}_t \leftarrow \text{Attacker}(\omega_t)
                                                                         27:
                                                                                   end for
 8:
          end for
                                                                                   return O+
         \omega_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} \omega_{t+1}^k
                                                                         29: end function
10: end for
                                                                         30:
11:
                                                                         31: function ParticipantUpdate(k, \omega_t):
                                                                                   \mathcal{B} \leftarrow (\text{split } \mathcal{P}_k \text{ into batches of Size } B)
12: function ATTACKER(\omega_t):
                                                                         32:
                                                                                   for each local epoch i from 1 to E do
          if needed then
                                                                         33:
13:
               pretrain G and D with \omega_t on \mathcal{P}_{aux}
14:
                                                                         34:
                                                                                        for batch b \in \mathcal{B} do
15:
          else
                                                                         35:
                                                                                             \omega_t \leftarrow \omega_t - \eta \nabla l(\omega_t; b)
16:
               load pretrained G and D
                                                                         36:
                                                                                        end for
                                                                         37:
17:
          end if
                                                                                   end for
          for each attack epoch do
18:
                                                                         38:
                                                                                   return \omega_t to server
19:
               for batch z \in \mathcal{N} do
                                                                         39: end function
```



FedInverse and HSIC





Results

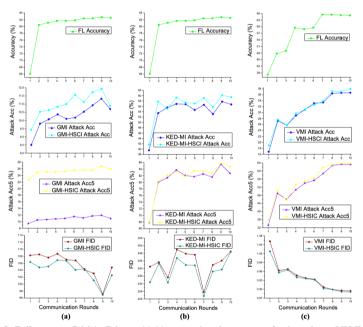


Figure 5: FedInverse on CelebA. Columns (a)-(c) present the relevant curves for three chosen MI/MI-HSIC attacks on CelebA under specific FL conditions. The first row of subplots illustrates global model accuracy changes over communication rounds. Rows two to four display comparative results using Attack Acc, Attack Acc5, and FID metrics for these attacks across ten federated rounds.

Table 1: FL privacy leakage indicated by Attack Acc/Acc5 \pm standard deviation(%) and FID on MNIST via FedInverse using GMI and GMI-HSIC with prior training dataset MNIST. Bold values denote the best metric results obtained by GMI or GMI-HSIC throughout the FL training epoch. The symbol \downarrow (\uparrow) denotes that smaller (larger) values are favored.

Metrics	Methods	FL#R01	FL#R02	FL#R03	FL#R04	FL#R05
Accuracy ↑		83.34	97.59	98.27	98.4	98.52
Attack Acc ↑	GMI	34.00±9.66	38.00±22.01	34.00±16.47	50.00±10.54	56.00±20.66
	GMI-HSIC	44.00±15.78	44.00±12.65	42.00±14.76	56.00±8.43	60.00±9.43
Attack Acc5 ↑	GMI	94.00±9.66	98.00±6.32	98.00±6.32	96.00±8.43	98.00±6.32
	GMI-HSIC	96.00±8.43	98.00±6.32	98.00±6.32	100.00±0.00	98.00±6.32
FID ↓	GMI	20.1373	23.3598	22.3839	17.1018	16.7486
	GMI-HSIC	19.0845	21.1116	21.5377	15.6066	14.469

Table 2: FL privacy leakage indicated by Attack Acc/Acc5 \pm standard deviation(%) and FID on MNIST via FedInverse using KED-MI and KED-MI-HSIC with prior training dataset MNIST. Bold values denote the best metric results obtained by KED-MI or KED-MI-HSIC throughout the FL training epoch. The symbol $\downarrow(\uparrow)$ denotes that smaller (larger) values are favored.

Metrics	Methods	FL#R01	FL#R02	FL#R03	FL#R04	FL#R05
Accuracy ↑		83.34	97.59	98.27	98.4	98.52
Attack Acc↑	KED-MI	64.60±8.46	60.60±4.45	80.00±0.00	80.00±0.00	79.80±2.00
	KED-MI-HSIC	80.00±0.00	64.40±8.33	80.00±0.00	80.20±2.00	80.20±2.00
Attack Acc5 ↑	KED-MI	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
	KED-MI-HSIC	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00	100.00±0.00
FID ↓	KED-MI	209.1448	206.0789	195.1807	184.995	175.9532
	KED-MI-HSIC	204.5017	198.6938	175.9532	161.0252	160.9891





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