Privacy-Preserving Publication of Sensitive Data using Differentially Private Generative Adversarial Networks

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MOTIVATION

Share sensitive data to support critical research or help solve problems:
→ **Preserving privacy** of entries of the data
→ **Maintaining usefulness** of data

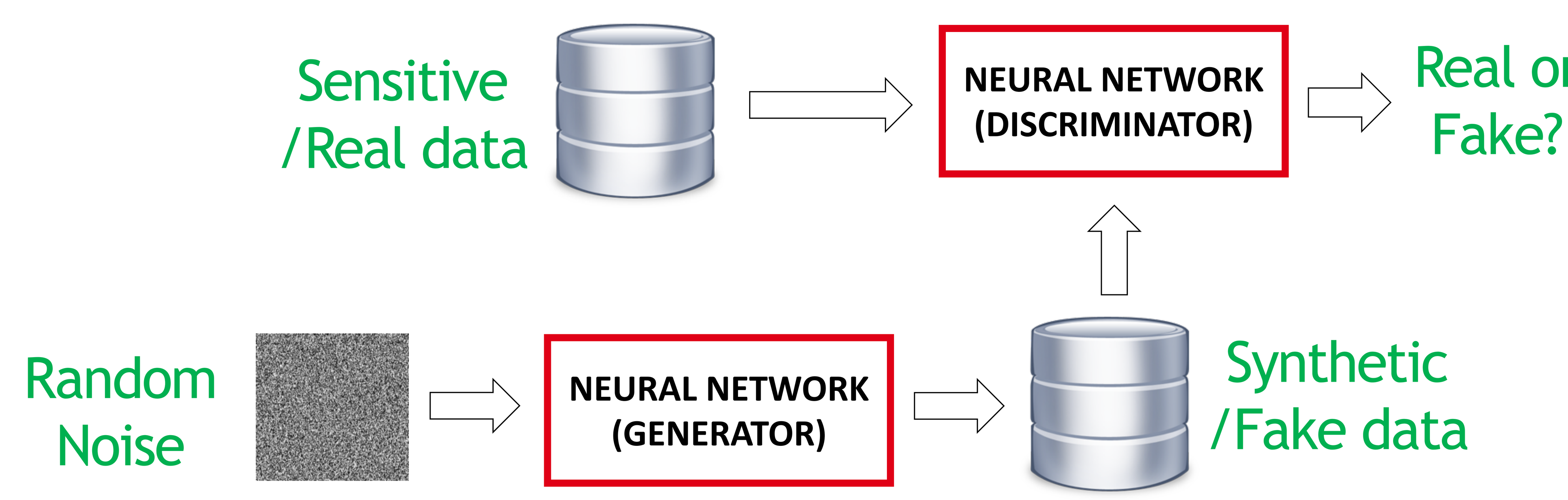
FOCUS

We illustrate the problem for the case of:
→ Data with one **individual/user/patient** per entry
→ Goal of using data is to train a **classification** model
→ Existing a **trusted-curator** of the data

ONE SOLUTION

Generative Adversarial Networks (GANs):
→ **Learn distribution** of sensitive data
→ Generate **synthetic** data

BAD NEWS: GANs can still be vulnerable.
For example: Membership attack [CCS'17]



IMPROVED SOLUTION

GANs + Differential Privacy (DP):
→ Bound **maximum change** (sensitivity: Δf)
→ Add random **noise** proportional to $O(\Delta f/\varepsilon)$
→ **Discriminator** needs to satisfy DP

Deep Learning [CCS'16]:

Clip gradient
$\bar{\mathbf{g}}_t(x_i) \leftarrow \mathbf{g}_t(x_i)/\max\left(1, \frac{\|\mathbf{g}_t(x_i)\|_2}{C}\right)$
Add noise
$\tilde{\mathbf{g}}_t \leftarrow \frac{1}{L}\left(\sum_i \bar{\mathbf{g}}_t(x_i) + \mathcal{N}(0, \sigma^2 C^2 \mathbf{I})\right)$
Descent
$\theta_{t+1} \leftarrow \theta_t - \eta_t \tilde{\mathbf{g}}_t$

A randomized algorithm $\mathcal{M}$ is (ε, δ)-differentially private if for all neighboring datasets D and D' and all sets of outputs $\mathcal{O} \subseteq \text{Range}(\mathcal{M})$:

$$\Pr[\mathcal{M}(D) \in \mathcal{O}] \leq \exp(\varepsilon) \Pr[\mathcal{M}(D') \in \mathcal{O}] + \delta$$

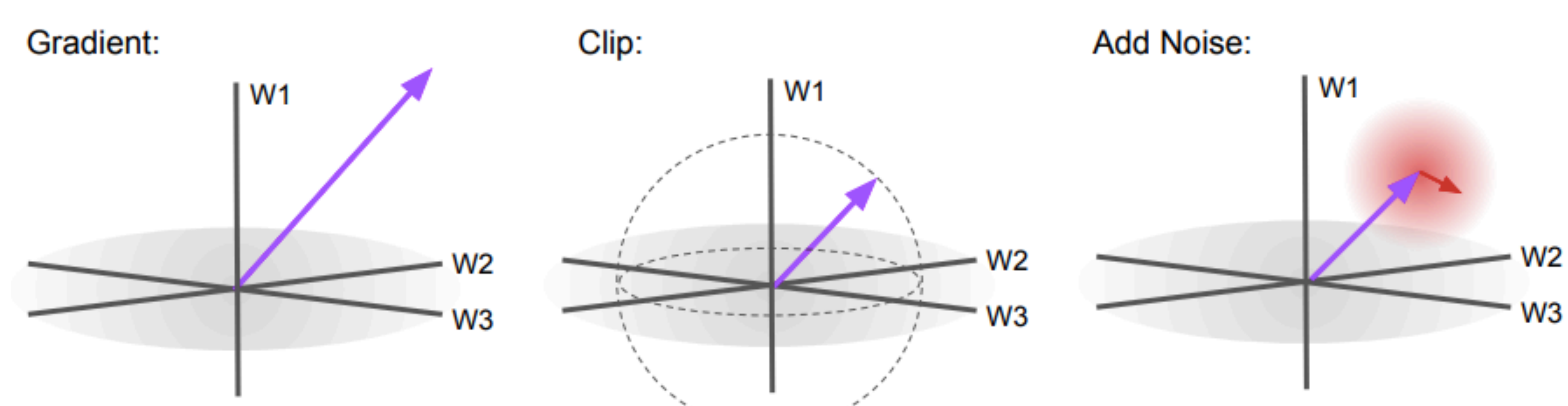


Image from: https://chriswaites.com/posts/differentially-private-deep-learning/

BENCHMARKING

Implementation on TensorFlow 2.0:
→ To the best of our knowledge, the first open implementation of a DP GAN with TensorFlow **2.0**
→ **New custom Optimizer, carefully applying non-trivial DP constraints**
→ Comparing to DP-CGAN [CVPR'2019]

AuROC	Real	CGAN	DP-CGAN TF 1.15 (M=1)	DP-CGAN TF 2.0 (M=B)	+ Separate batches	+ LeakyRelU (alpha=0.2)
LR	0.9217	0.9110	0.8121	0.8642	0.6308	0.8088
MLP	0.9760	0.9106	0.8396	0.8858	0.6586	0.8263

Table 1: AuROC on test data of MNIST using standard sklearn lib of models trained on fake data. Results are average of 3 trials, using differential privacy with parameters $\varepsilon = 9.6$ and $\delta = 10^{-5}$.

Zdim: *100* ***GEN:*** *FC(128) + RelU + FC(784)* ***DISC:*** *FC(128) + RelU + FC(1)*

EXPERIMENTS

Dataset of patients for Thyroid Disease:
→ 7200 patients split into 52.4% (train) + 47.6% (test)
→ 21 attr. (15 binary, 6 continuous) and 3 classes

DP-CGAN: ***GEN:*** *FC(128) + RelU + FC(21)* ***with Zdim:*** *100*
DISC: *FC(128) + RelU + FC(1)*

Table 2: AuROC on test data for model trained with real or fake data

$\varepsilon = 3.7$, $\delta = 10^{-5}$	Real	DP-CGAN TF 2.0 (M=B)
MLP: AuROC	0.9858	0.9746

MLP trained with same GridSearchCV for both

REFERENCES

[CCS'17]: Hitaj et al., Deep Models Under the GAN: Information Leakage from Collaborative Deep Learning.
[CCS'16]: Abadi et al., Deep Learning with Differential Privacy.
[CVPR'19]: Torkzadehmahani et al., DP-CGAN : Differentially Private Synthetic Data and Label Generation.
[Generative Adversarial Networks]: Ian Goodfellow, 2014.
[Differential Privacy]: Cynthia Dwork, 2016.
[Conditional GANs]: Mirza, 2014.