Private Set Generation with Discriminative Information

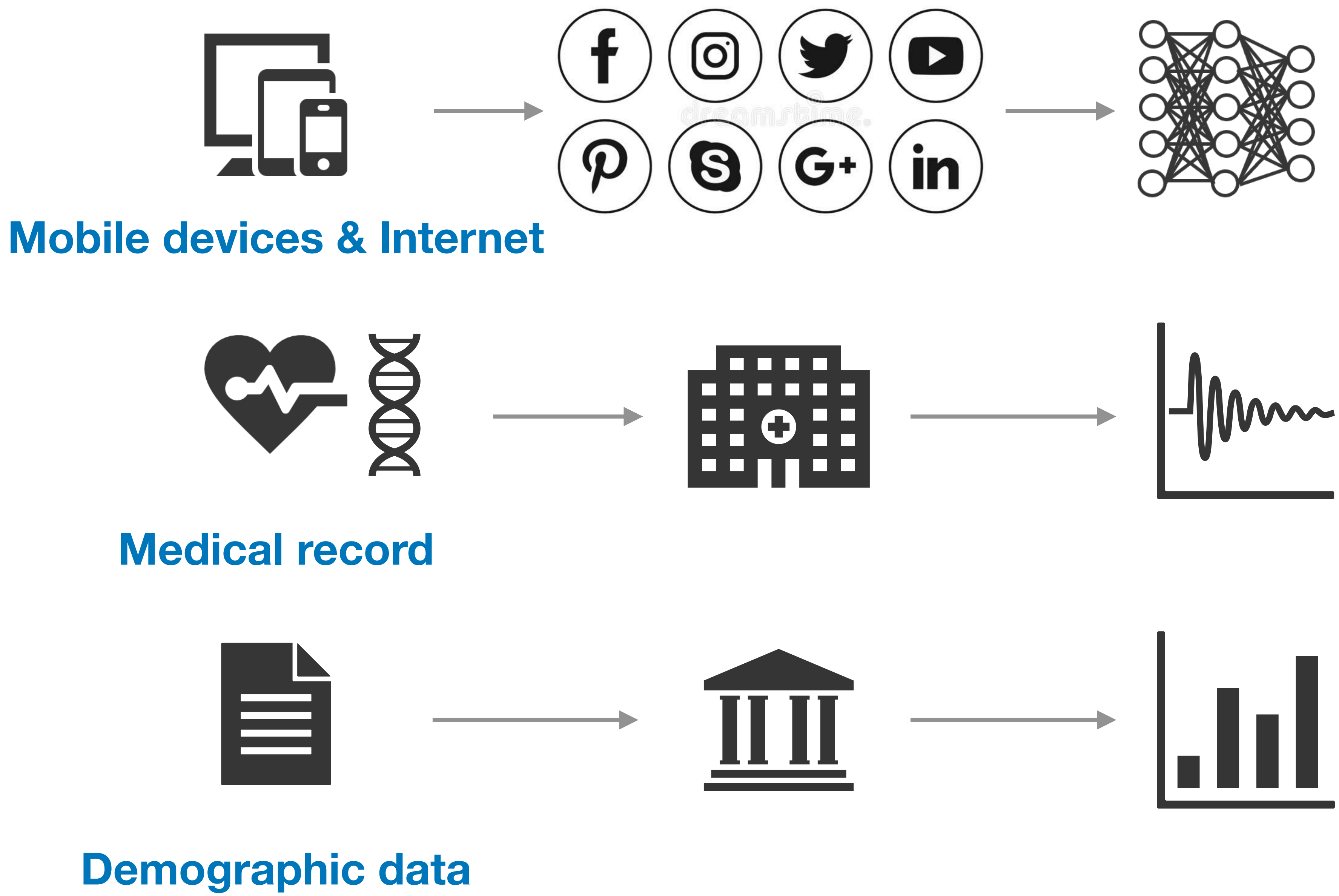
Dingfan Chen   Raouf Kerkouche   Mario Fritz

CISPA Helmholtz Center for Information Security

Data Privacy in ML:

NEURAL INFORMATION PROCESSING SYSTEMS

- Sensitive data is **ubiquitous**



Data Privacy in ML:

NEURAL INFORMATION PROCESSING SYSTEMS

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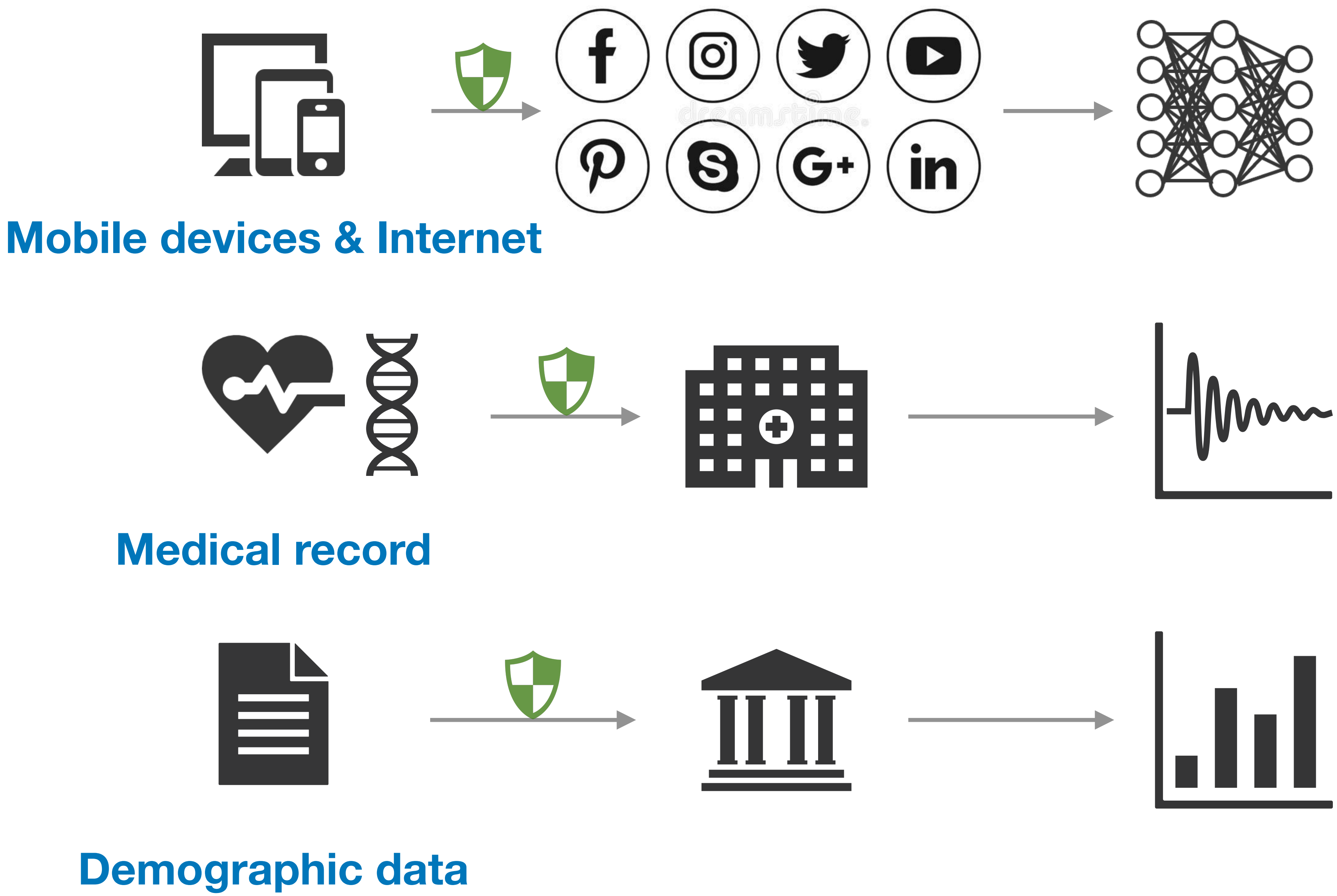
Our task:
Data sanitization



Problem

- **Privacy-preserving data generation**
  - High-dimensional data → Deep Neural Network (NN)
  - Rigorous privacy guarantee → Differential Privacy (DP)

- **Existing approaches**

Problem

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[1] Jordon, James, et al., "PATE-GAN: Generating synthetic data with differential privacy guarantees.", *ICLR,* 2018.
[2] Torkzadehmahani, Reihaneh et al., "Dp-cgan: Differentially private synthetic data and label generation.", *CVPR Workshops,* 2019.
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[10] Liew, Seng Pei, et al., "PEARL: Data Synthesis via Private Embeddings and Adversarial Reconstruction Learning.", *ICLR*, 2022.

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  - Aim at fitting the complete data distribution

- **Our approach**

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  - Target at common downstream tasks (e.g., classification)

Generally easier

Problem

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  - Aim at fitting the complete data distribution
  - Optimize deep generative models

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  - Directly optimize a set of representative samples

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Better convergence

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  - Suboptimal utility: <85% for MNIST with $(\varepsilon, \delta)=(10,10^{-5})$
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- **Our approach**
  - Target at common downstream tasks (e.g., classification)
  - Directly optimize a set of representative samples
  - ~10% downstream test accuracy improvement over SOTA

Generally easier

Better convergence

Useful samples

Approach

NEURAL INFORMATION PROCESSING SYSTEMS

- **Target:**
  - Optimize for training downstream Neural Network classifier
- **Basic idea:**
  - Gradient-based **coreset generation**[1,2]
  - DP stochastic gradient descent (DP-SGD)

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fake $\mathcal{S}$

real $\boldsymbol{x}, y \sim P_{\mathcal{D}}$

inner loop outer loop sensitive (ε,δ)-private

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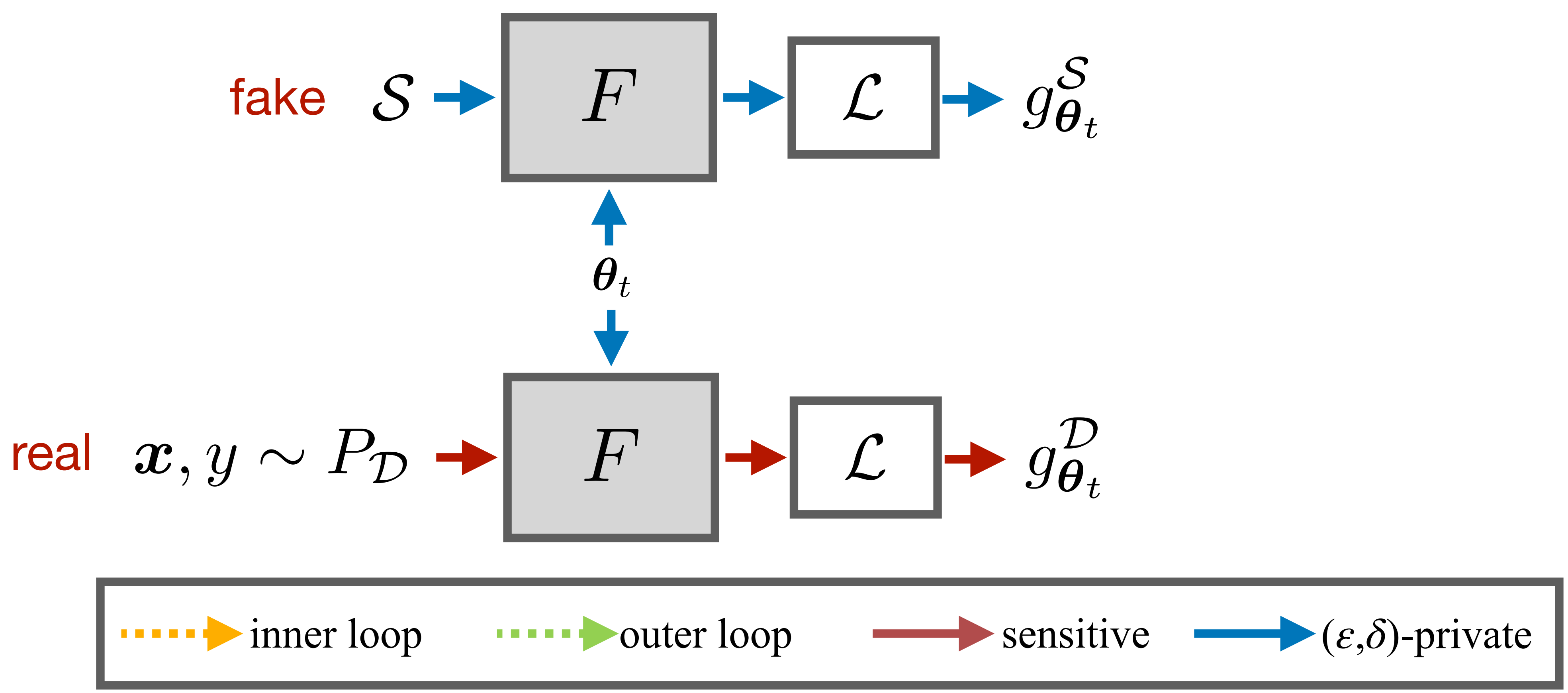

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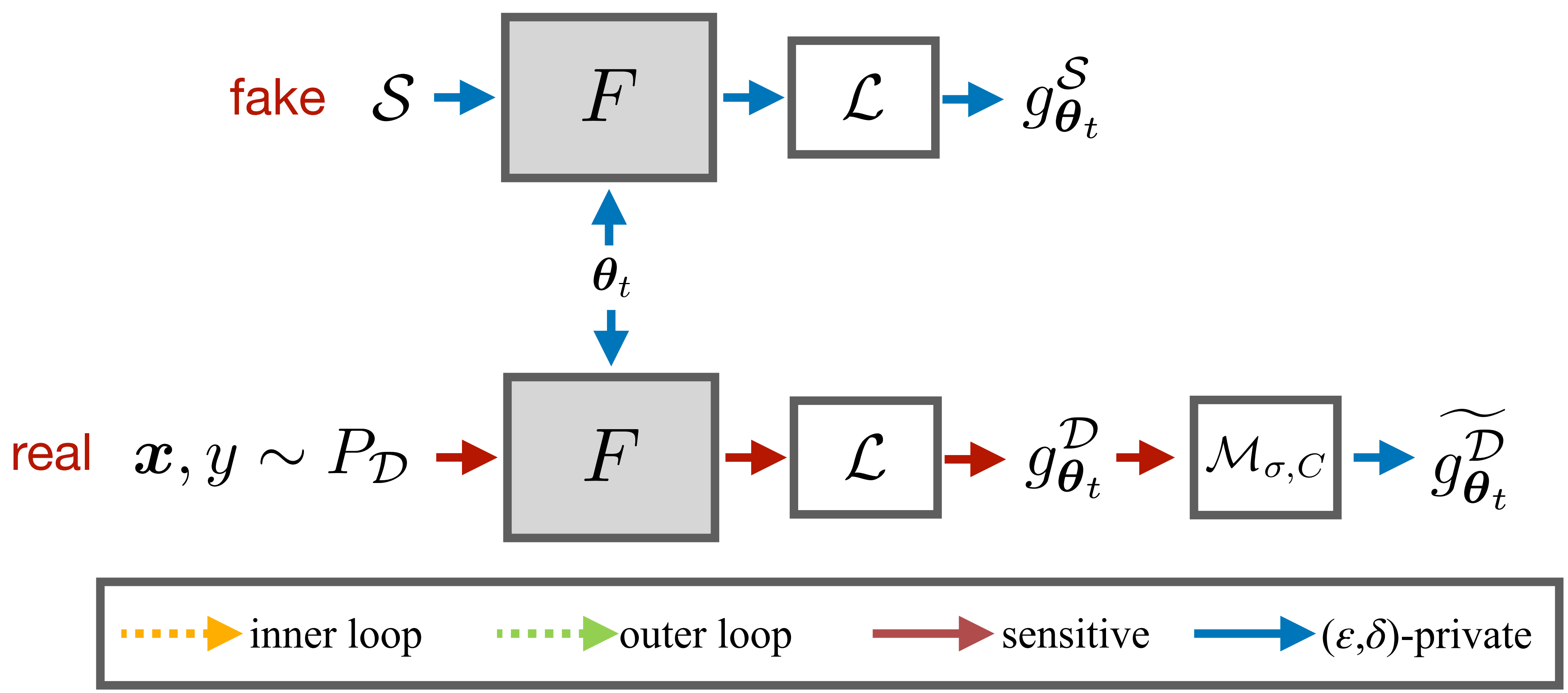

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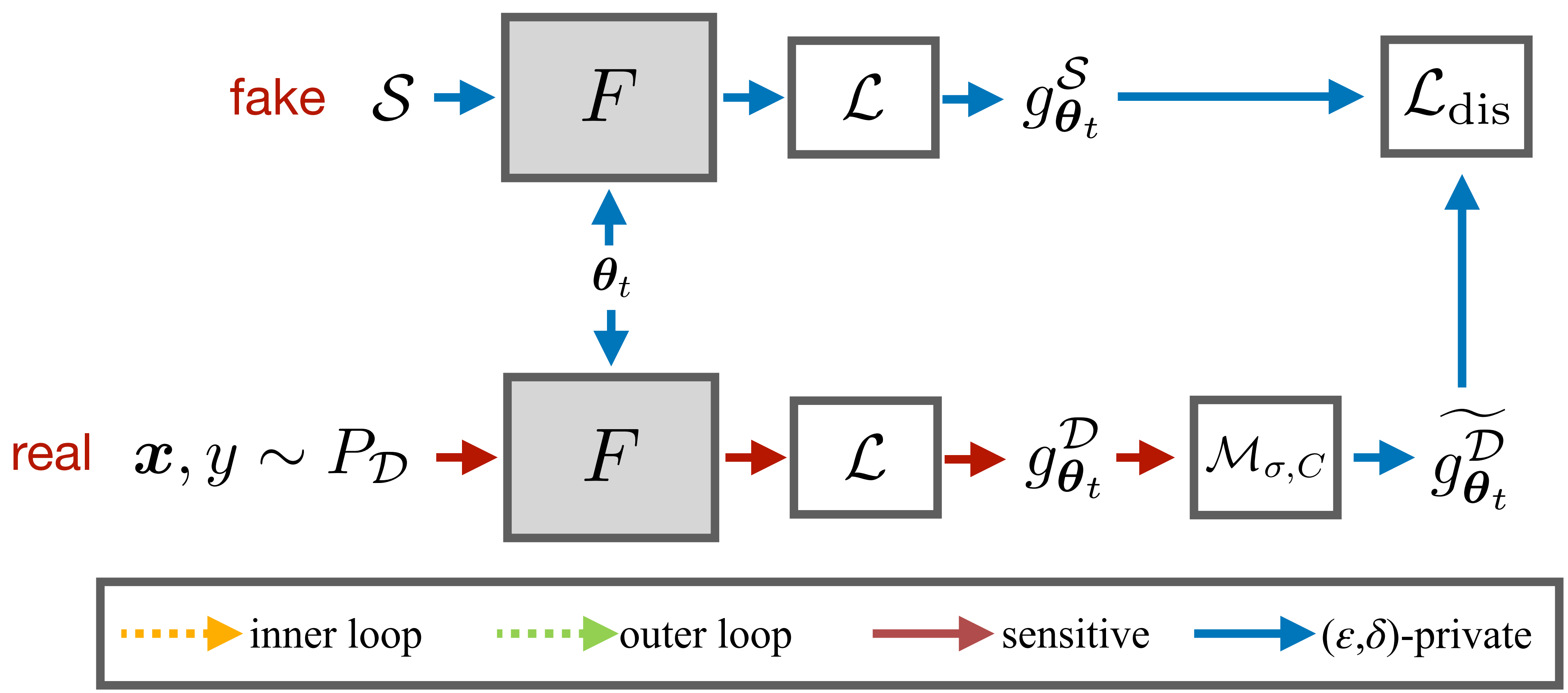

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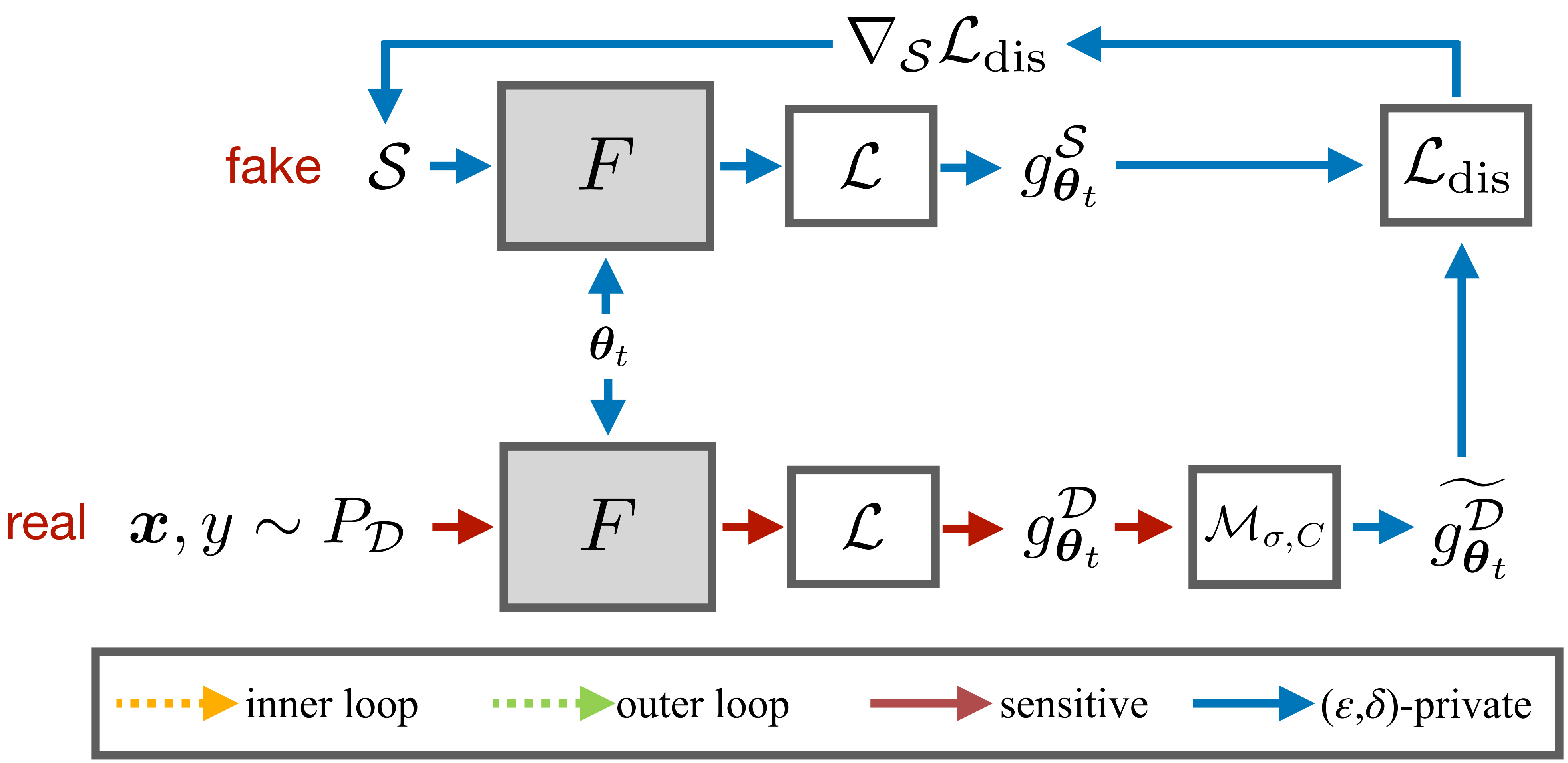

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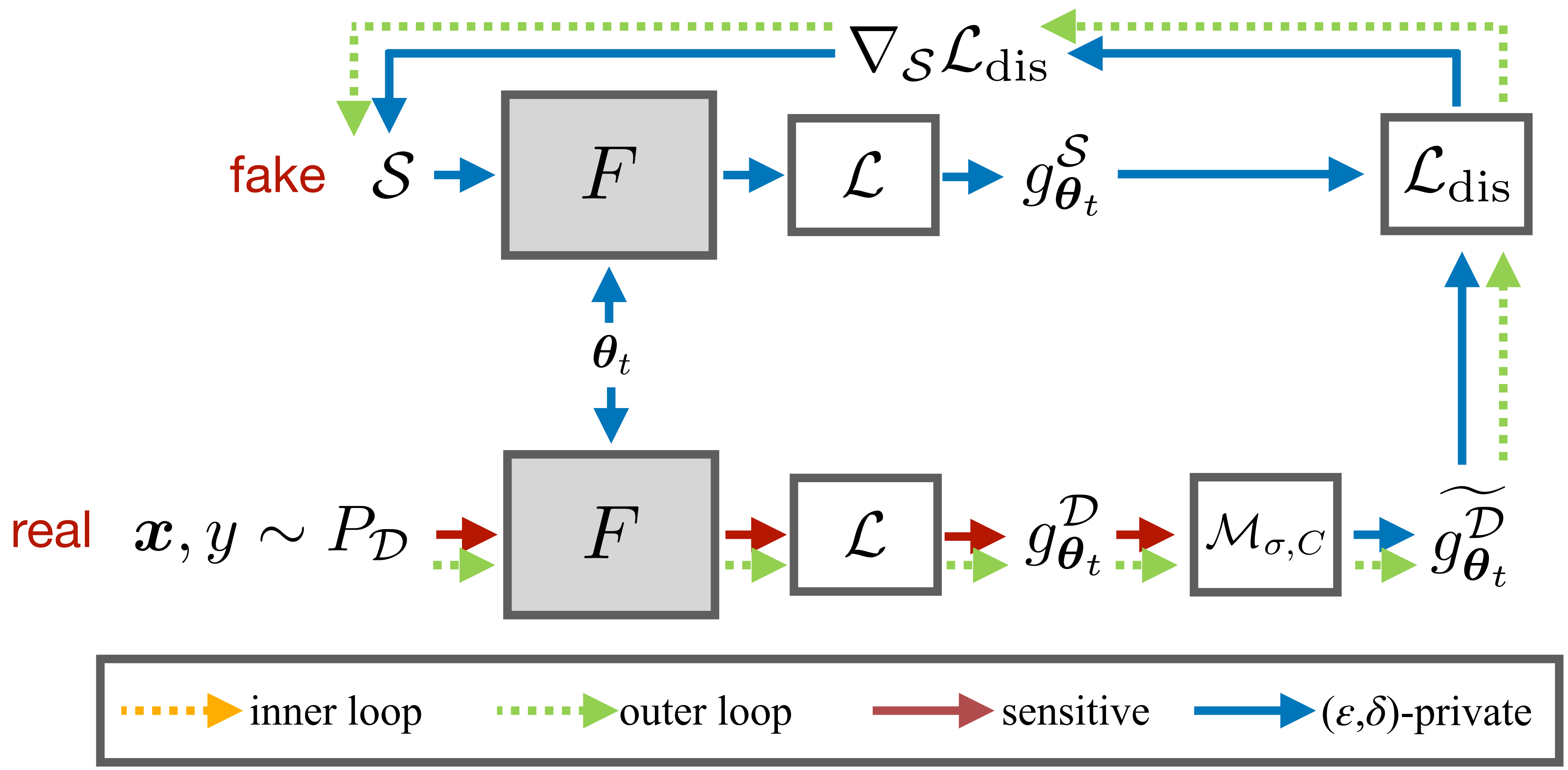

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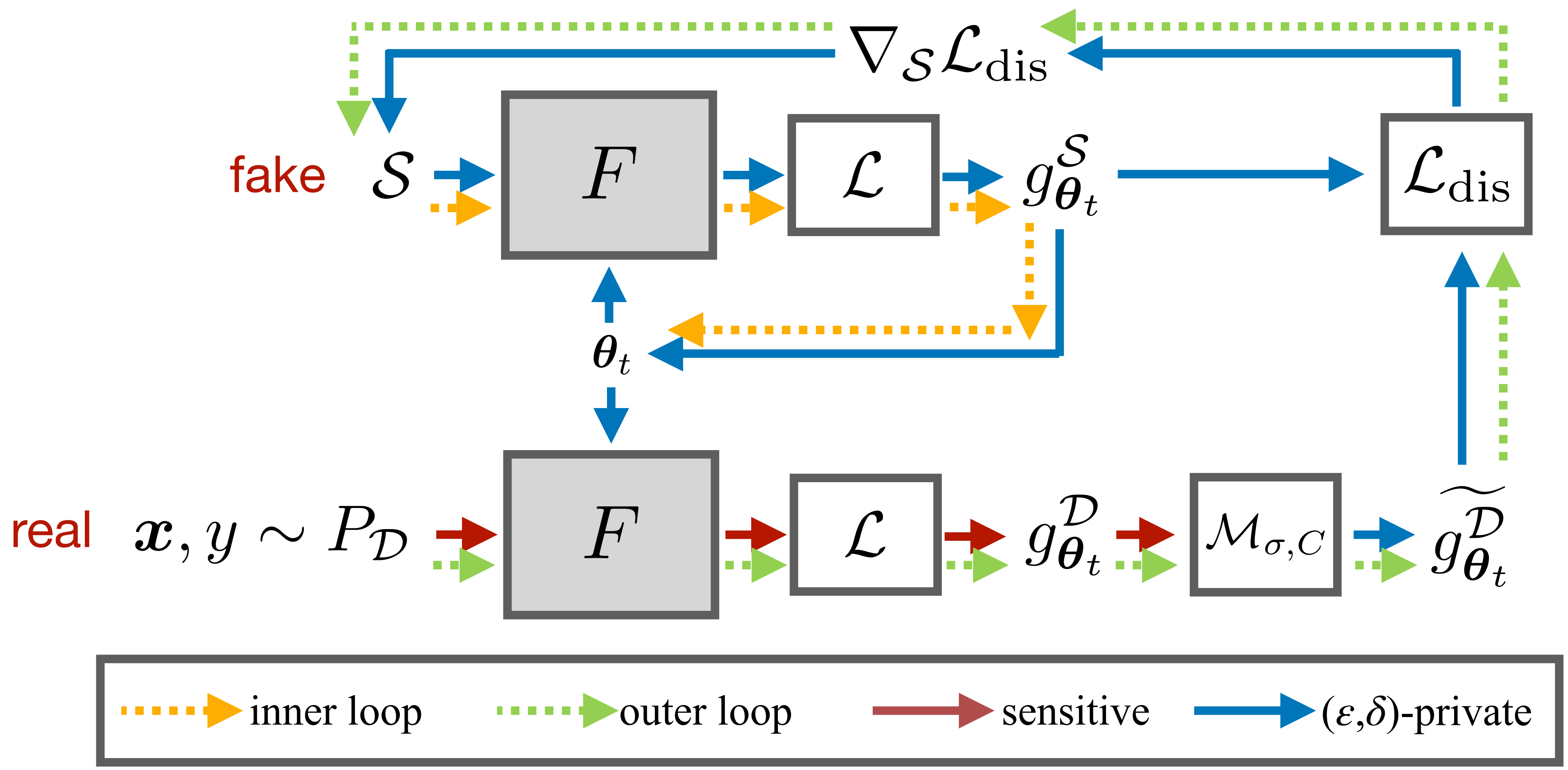

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Evaluation

NEURAL INFORMATION PROCESSING SYSTEMS

- **Comparison to SOTA**
  - Utility for downstream classification task (train on fake; test on real)

Evaluation

NEURAL INFORMATION PROCESSING SYSTEMS

- **Comparison to SOTA**
  - Utility for downstream classification task (train on synthetic; test on real)

	MNIST		FashionMNIST	
	ε=1	ε=10	ε=1	ε=10
DP-CGAN	-	52.5	-	50.2
G-PATE	58.8	80.9	58.1	69.3
DataLens	71.2	80.7	64.8	70.6
GS-WGAN	-	84.9	-	63.1
DP-Merf	72.7	85.7	61.2	72.4
DP-Sinkhorn	-	83.2	-	71.1
Ours (spc=20)	**80.9**	**95.6**	**70.2**	**77.7**

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- **Comparison to SOTA**
  - Generalization across model architecture

	MNIST						FashionMNIST					
	ConvNet	LeNet	AlexNet	VGG11	ResNet18	MLP	ConvNet	LeNet	AlexNet	VGG11	ResNet18	MLP
Real	99.6	99.2	99.5	99.6	99.7	98.3	93.5	88.9	91.5	93.8	94.5	86.9
DP-CGAN	50.2	52.6	52.1	54.7	51.8	54.3	50.2	52.6	52.1	54.7	51.8	54.3
GS-WGAN	84.9	83.2	80.5	87.9	89.3	74.7	54.7	62.7	55.1	57.3	58.9	65.4
DP-Merf	85.7	87.2	84.4	81.7	81.3	85.0	72.4	67.9	64.9	70.1	66.7	**73.1**
Ours (spc=10)	94.9	91.3	90.3	93.6	**94.3**	86.1	75.6	**68.0**	**66.2**	74.7	**72.1**	62.8
Ours (spc=20)	**95.6**	**93.0**	**92.3**	**94.5**	94.1	**87.1**	**77.7**	**68.0**	59.1	**76.8**	70.8	62.2

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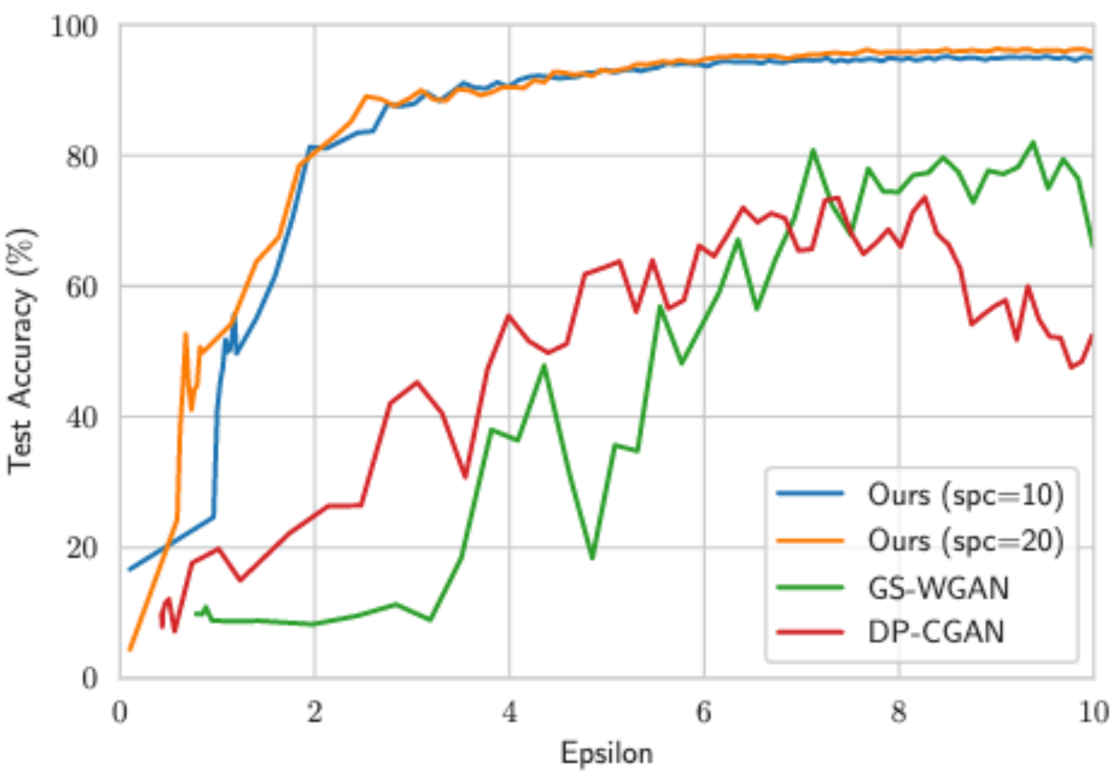
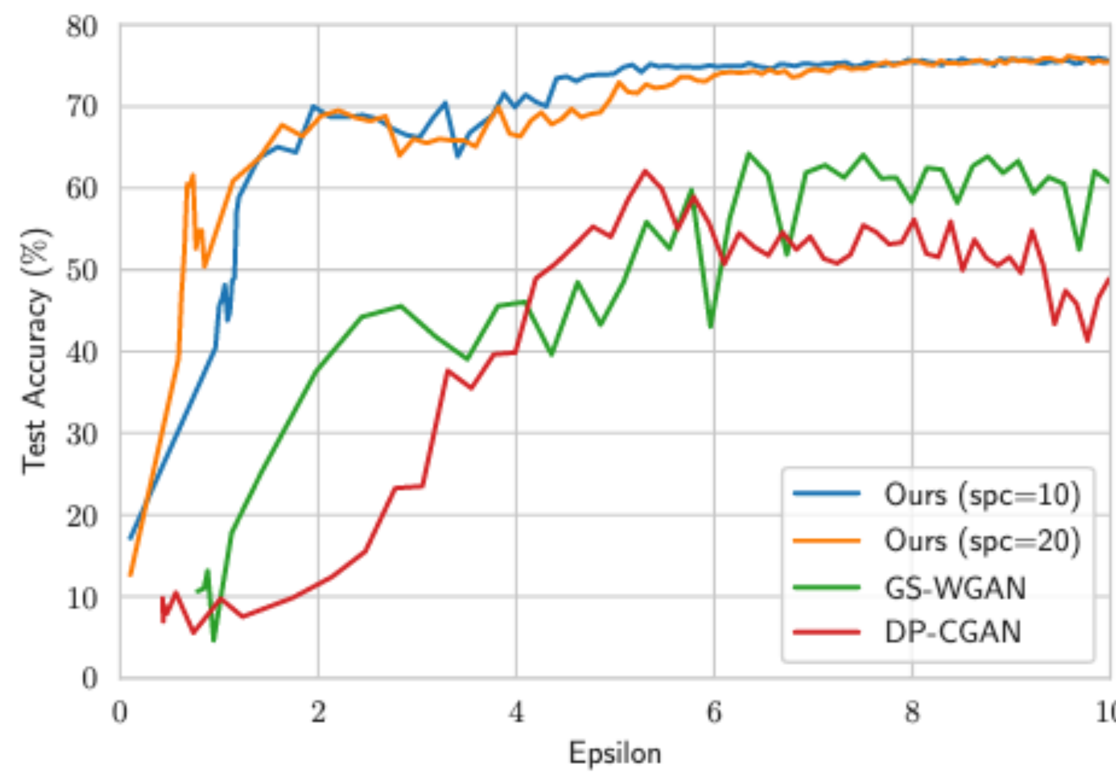
- **Comparison to SOTA**
  - Convergence rate



(a) MNIST



(b) FashionMNIST

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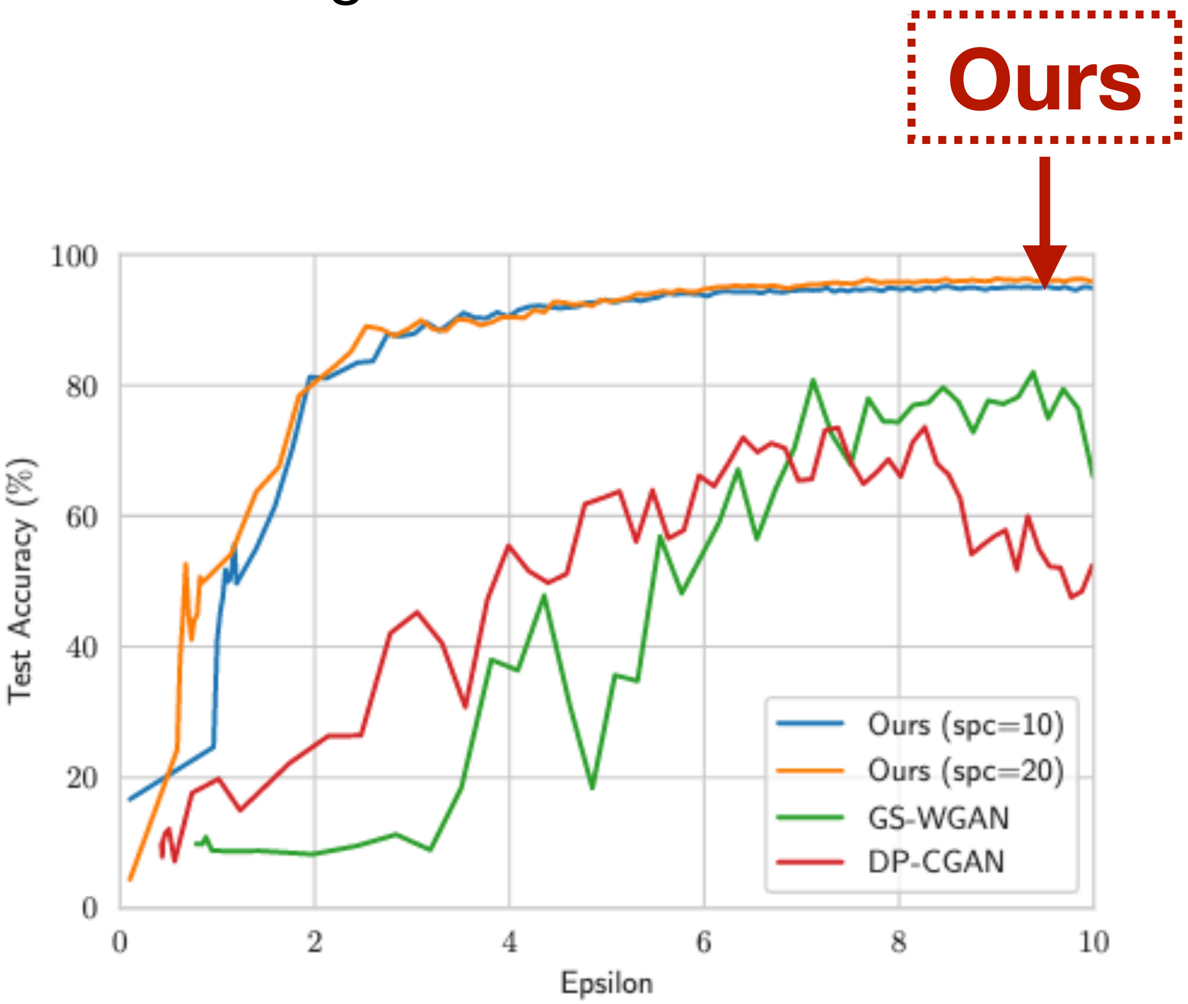

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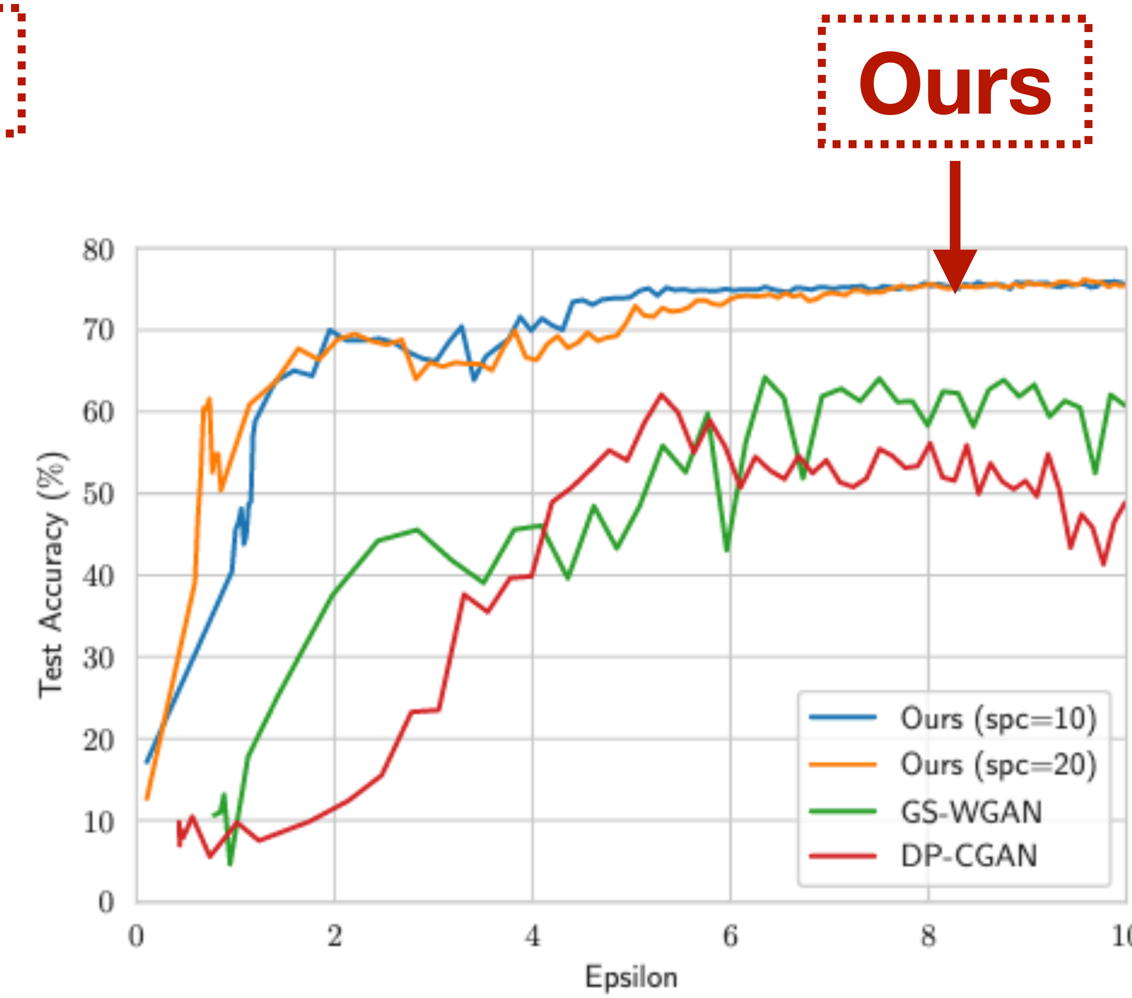

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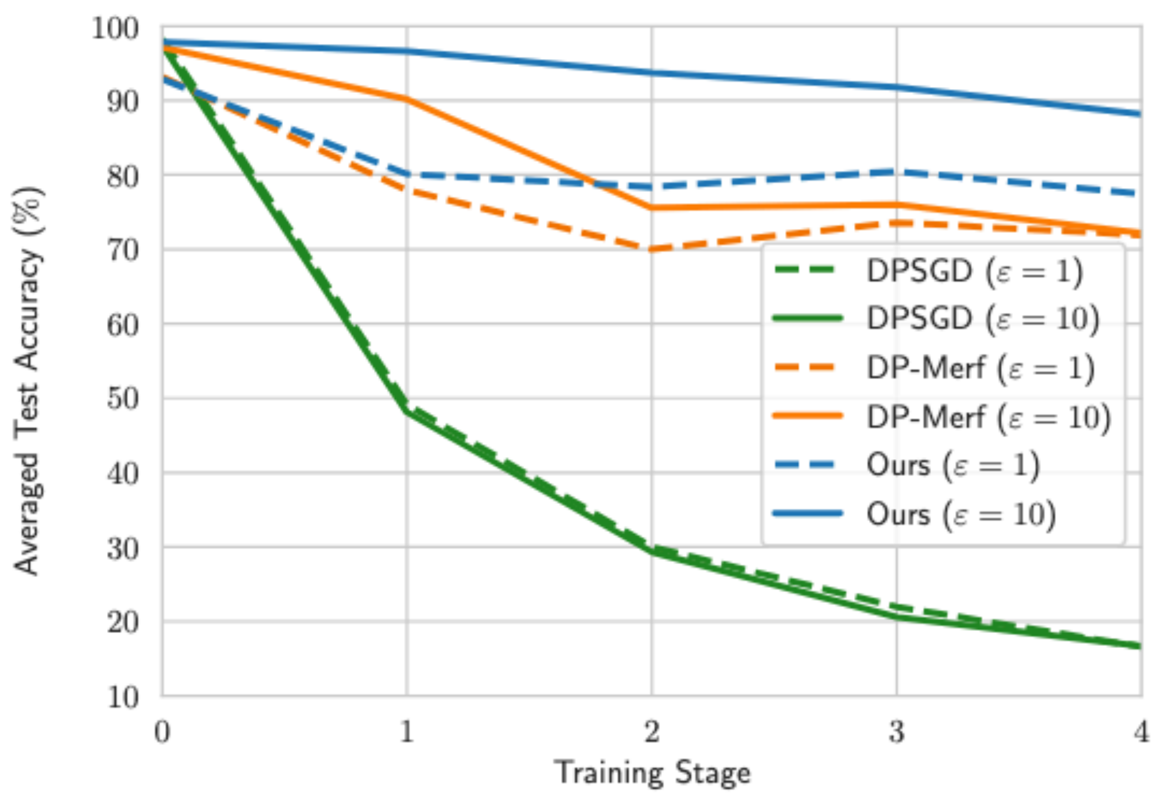
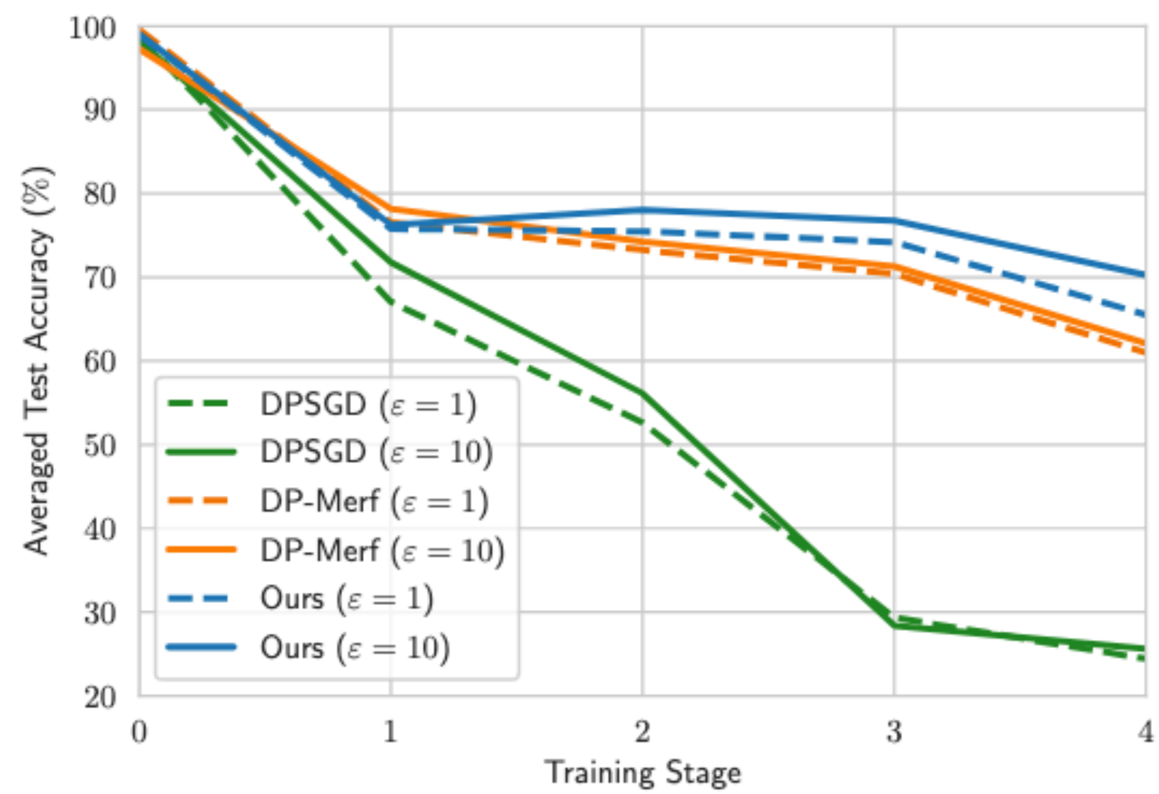
Evaluation

- **Application:** Continual learning with DP



(a) SplitMNIST



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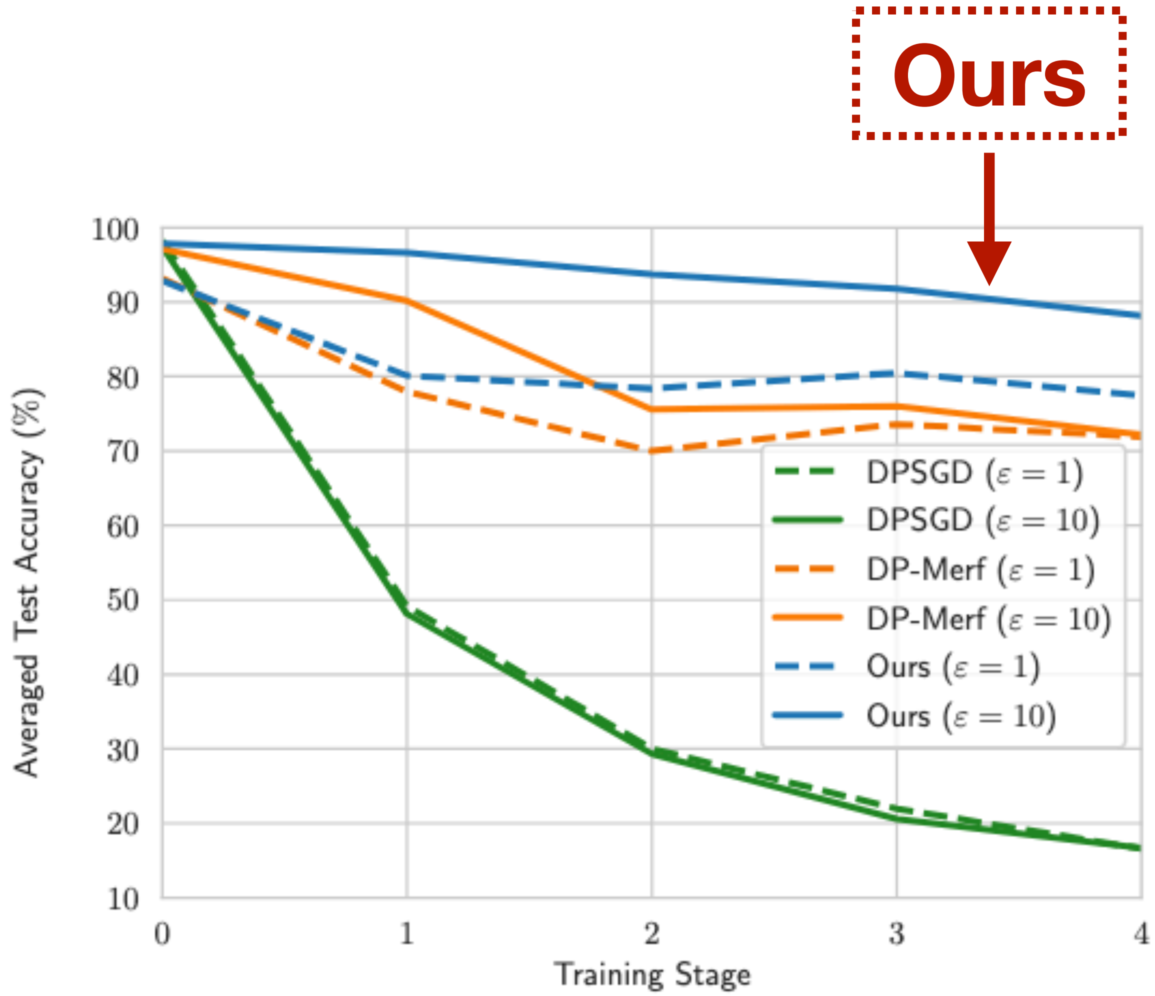

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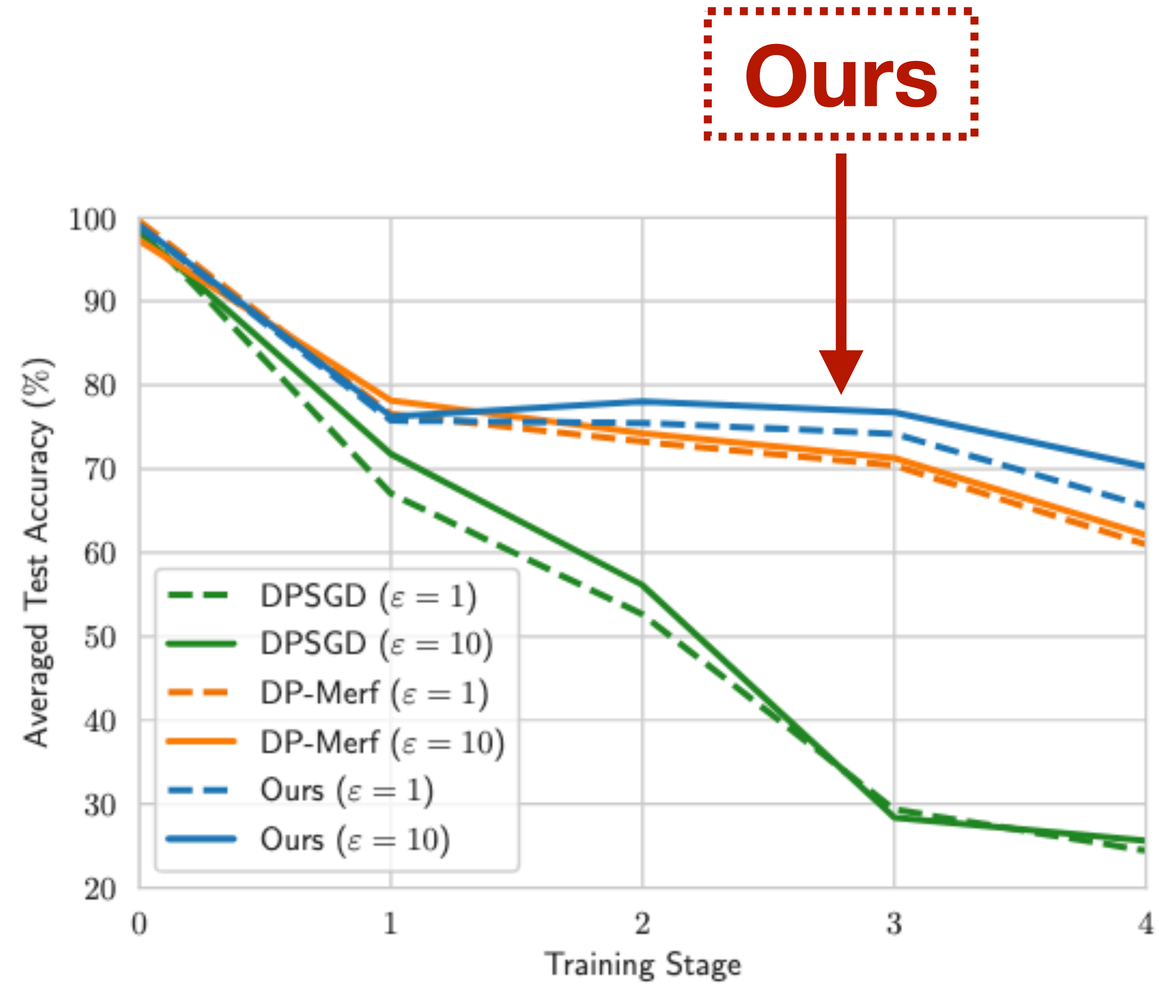

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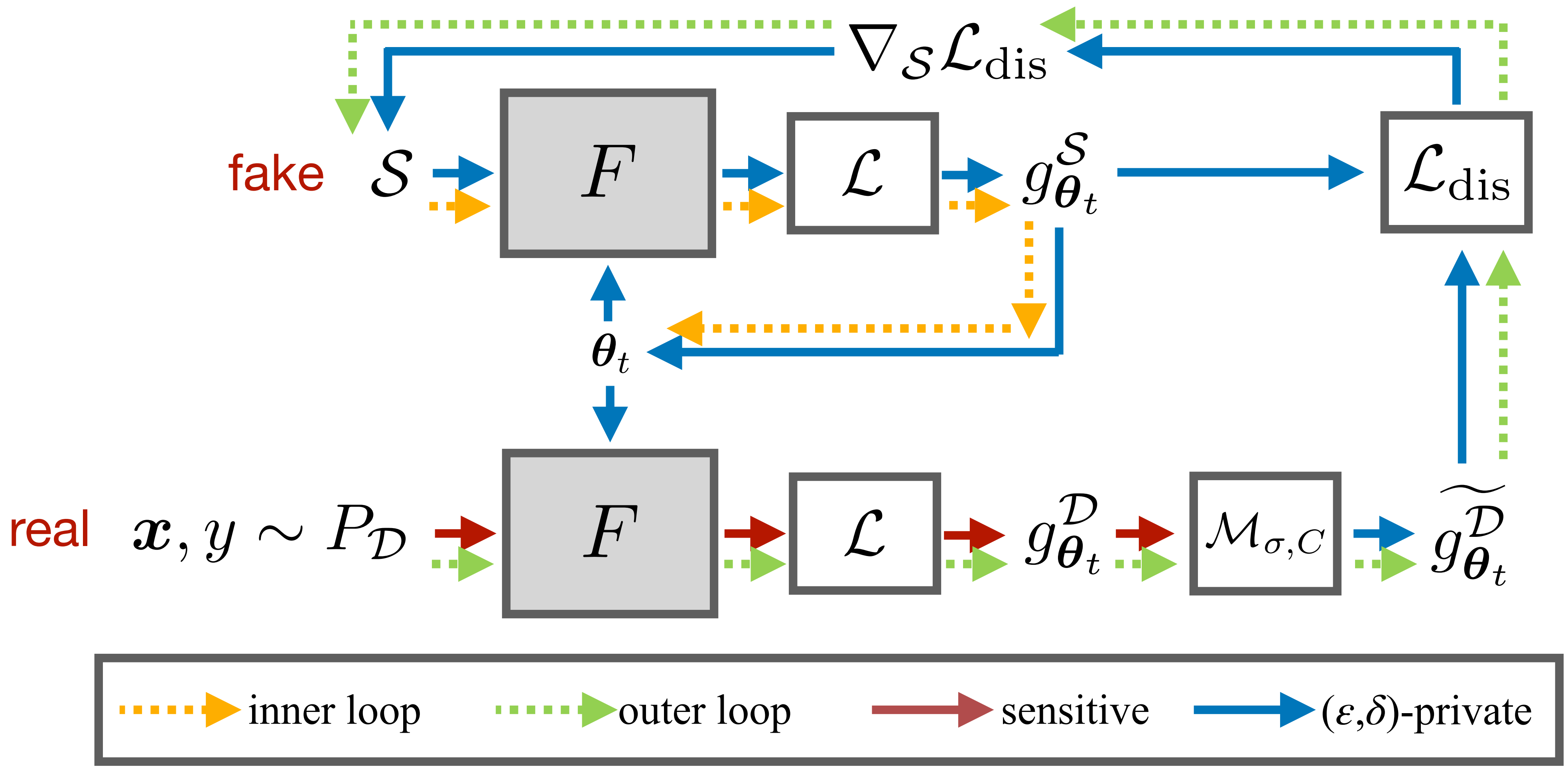

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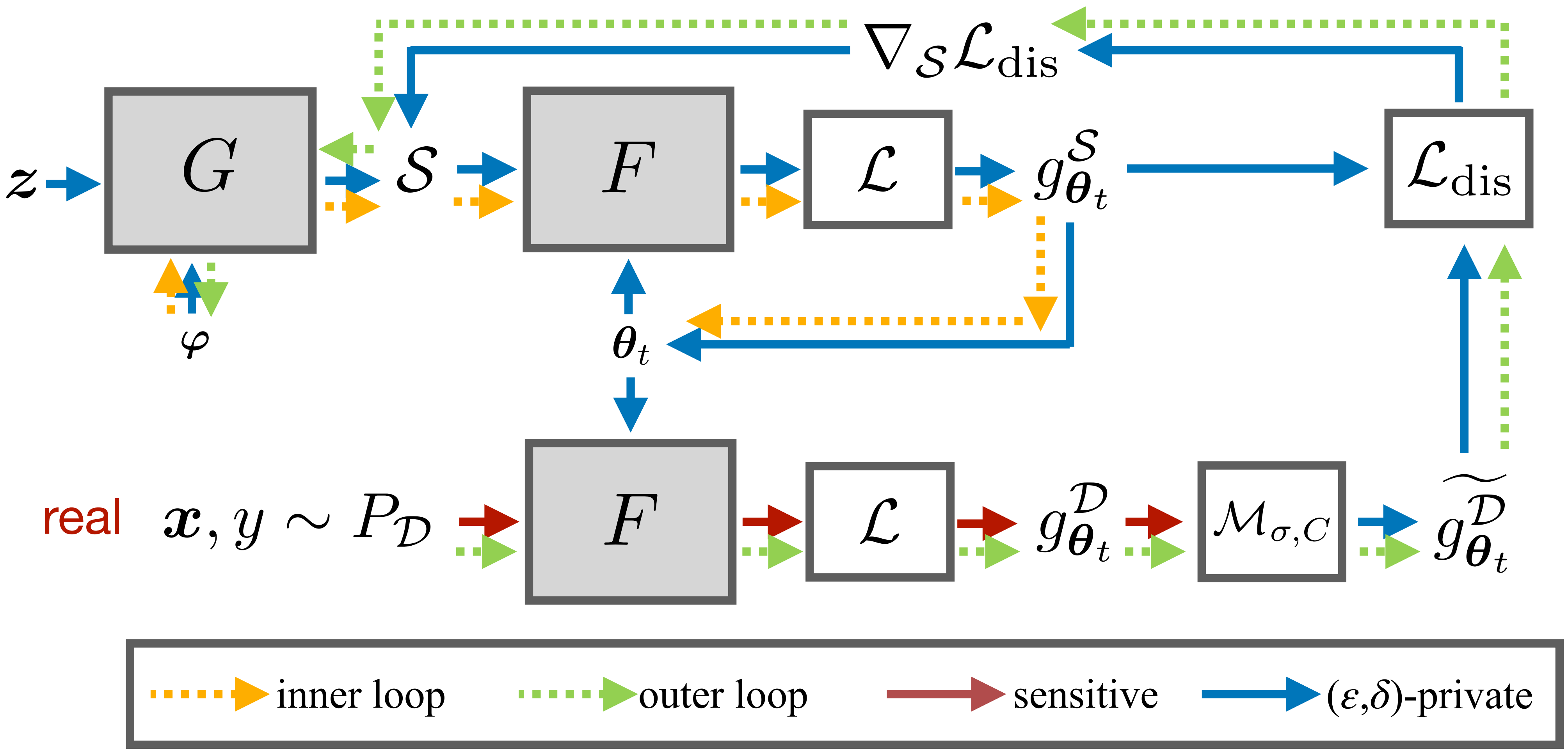

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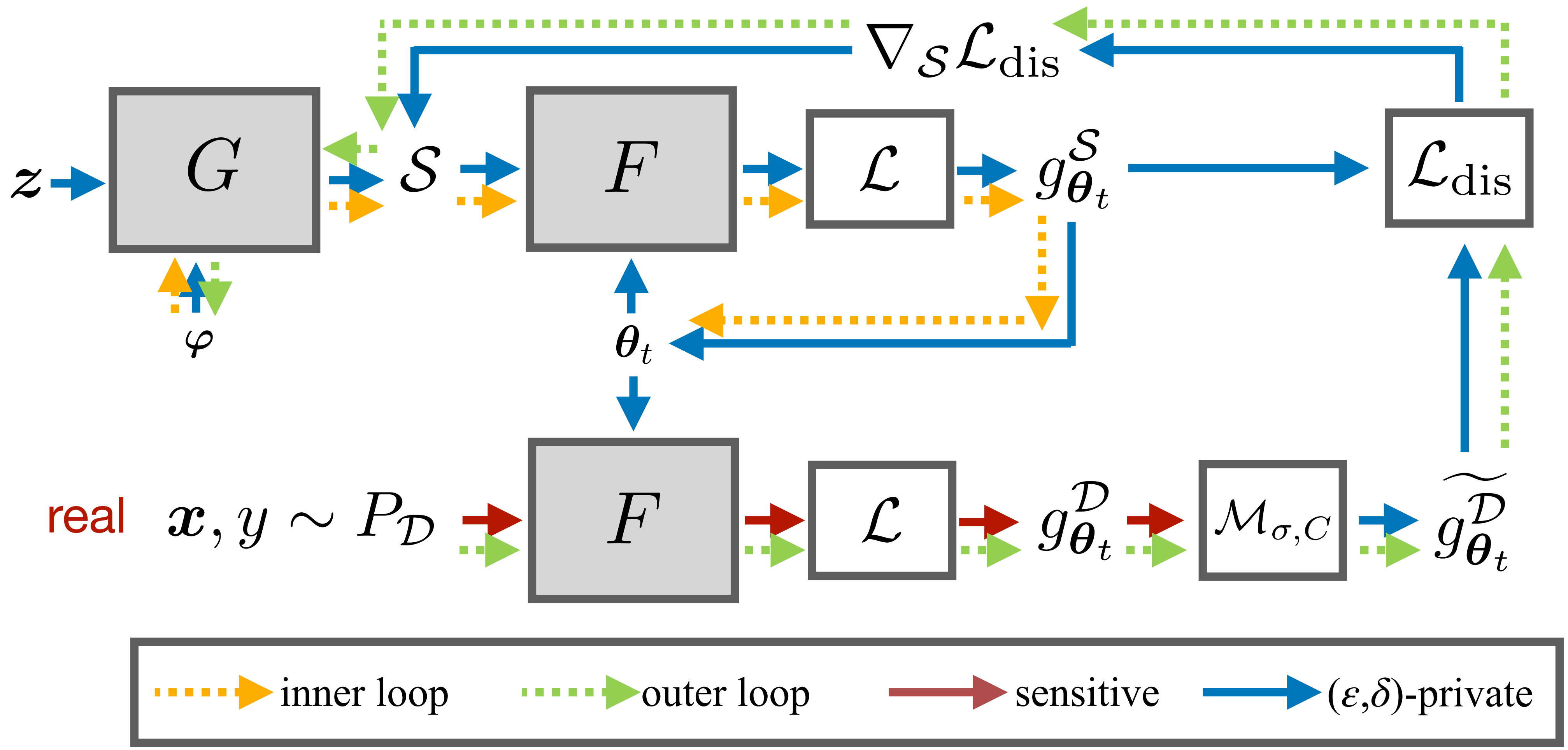

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    - Better visual quality
    - Sub-optimal downstream utility

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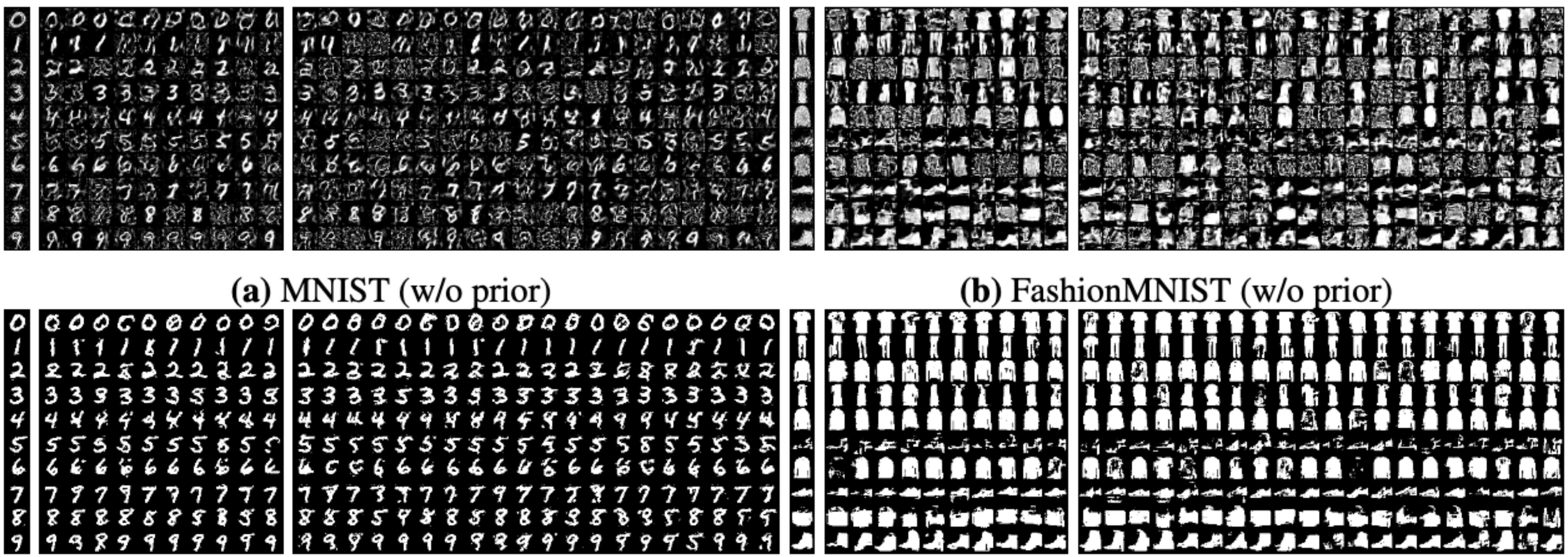

(a) MNIST (w/o prior) (b) FashionMNIST (w/o prior)

(c) MNIST (with prior) (d) FashionMNIST (with prior)

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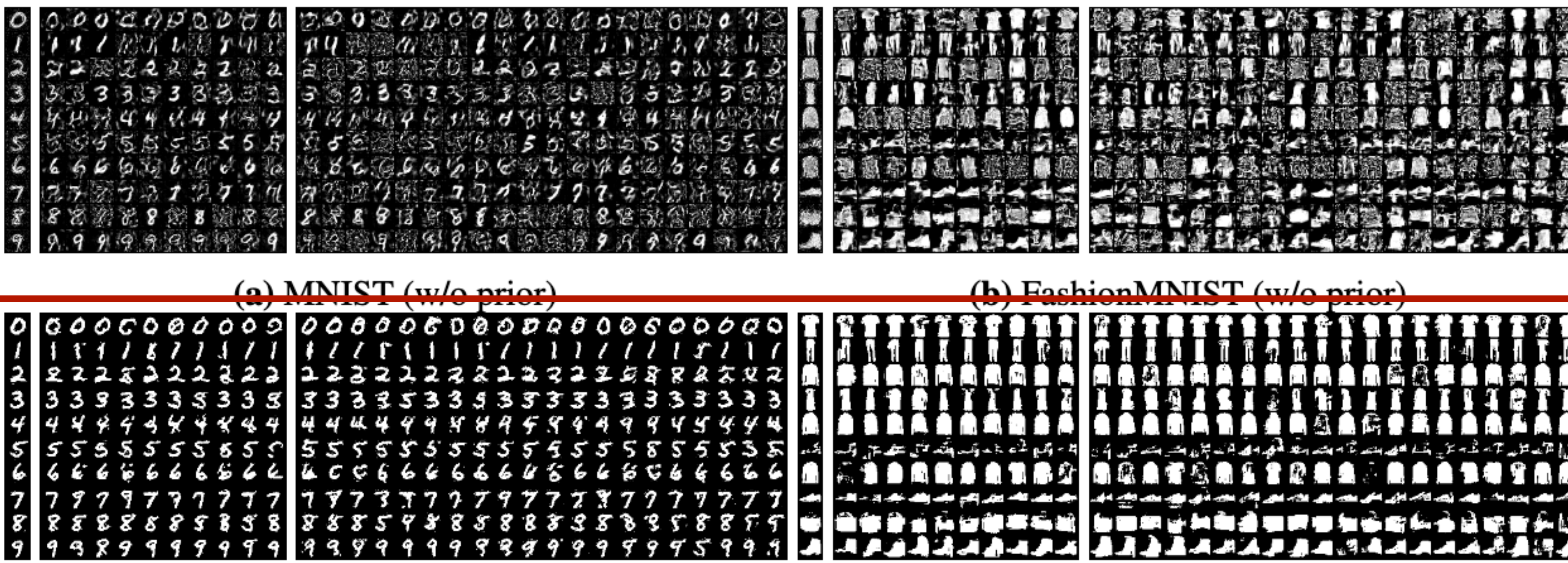

(a) MNIST (w/o prior)

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with generative model

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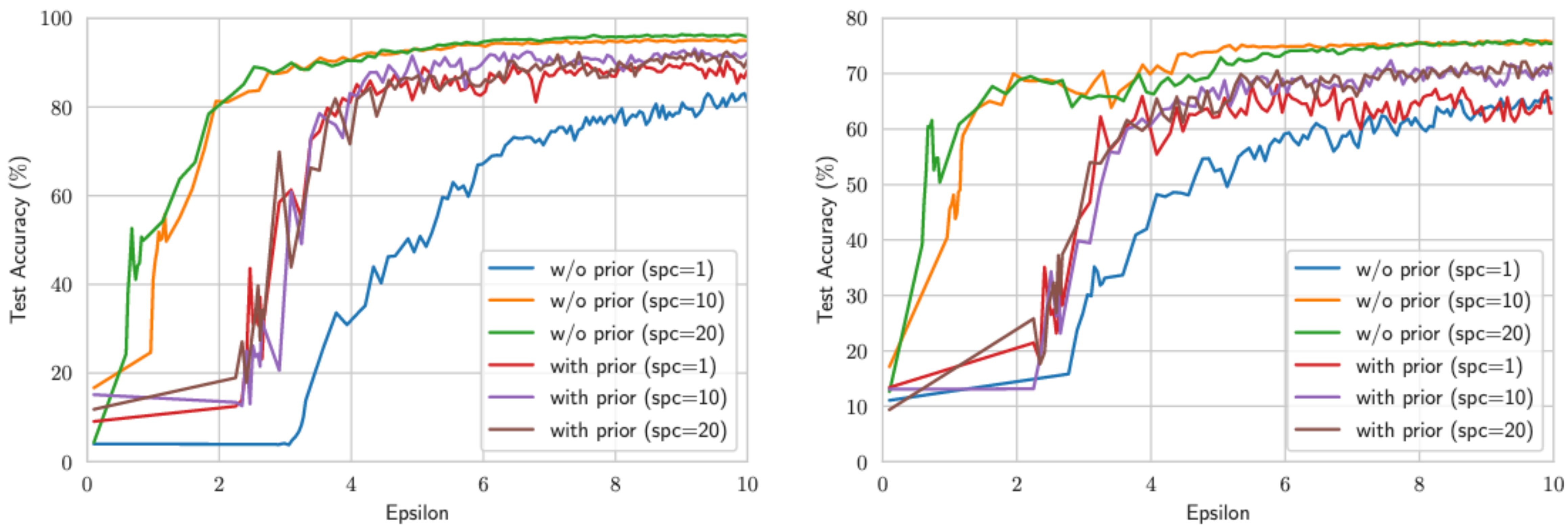

(a) MNIST **(b)** FashionMNIST

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	1	10	20	1	10	20
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with generative model

More details in the paper

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Source code available on Github:

https://github.com/DingfanChen/Private-Set

Contact:
Dingfan Chen, dingfan.chen@cispa.de