International Conference on Advanced Data Mining and Applications

#59 Cryptography-Inspired Federated Learning for Generative Adversarial Networks and Meta Learning

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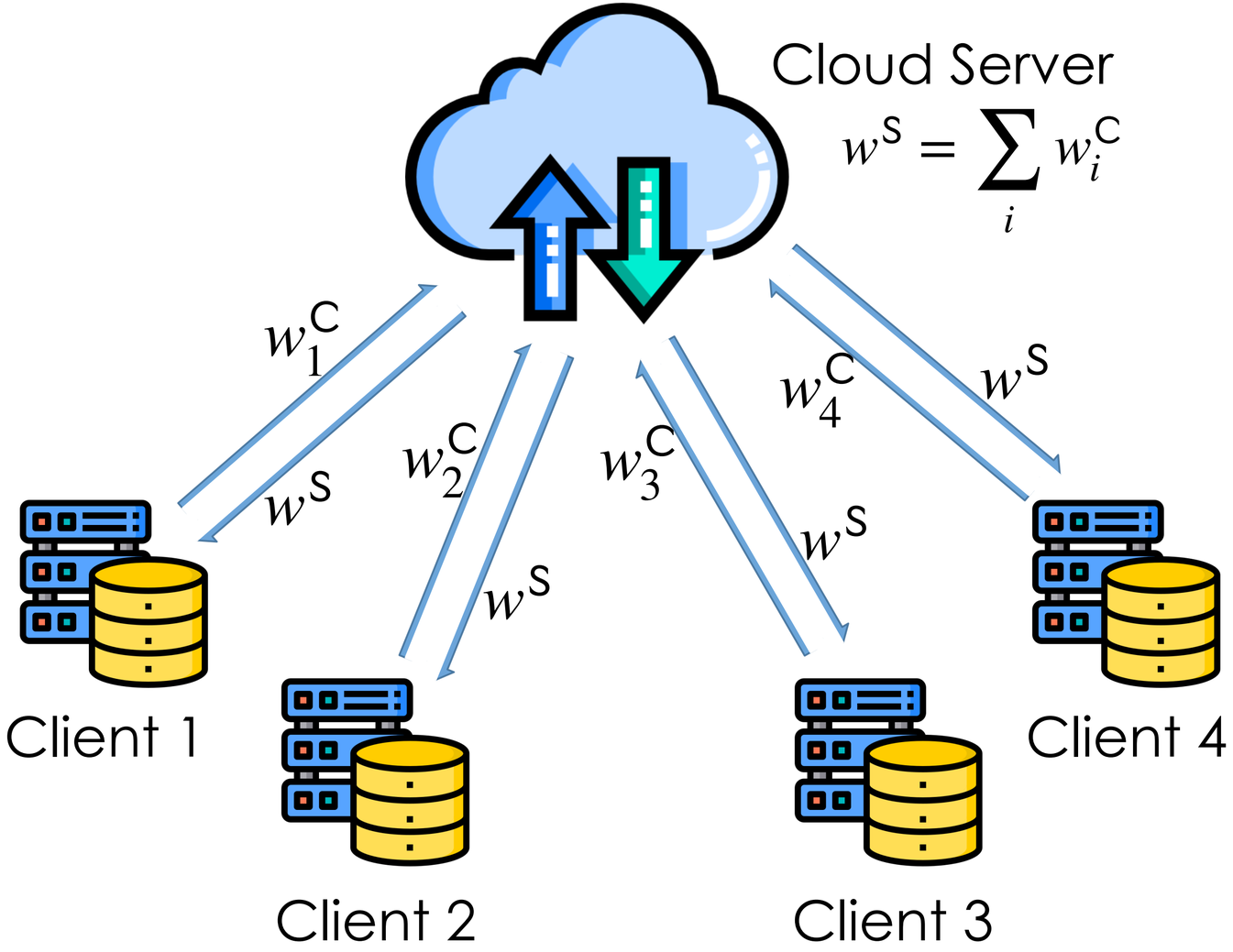
Conventional Federated Learning (FL)



- Client $i \in \{1,2,3,4\}$ owns
  - local model w_i^C
  - local private dataset d_i
- Cloud server S owns
  - aggregated model w^S
  - no/public data

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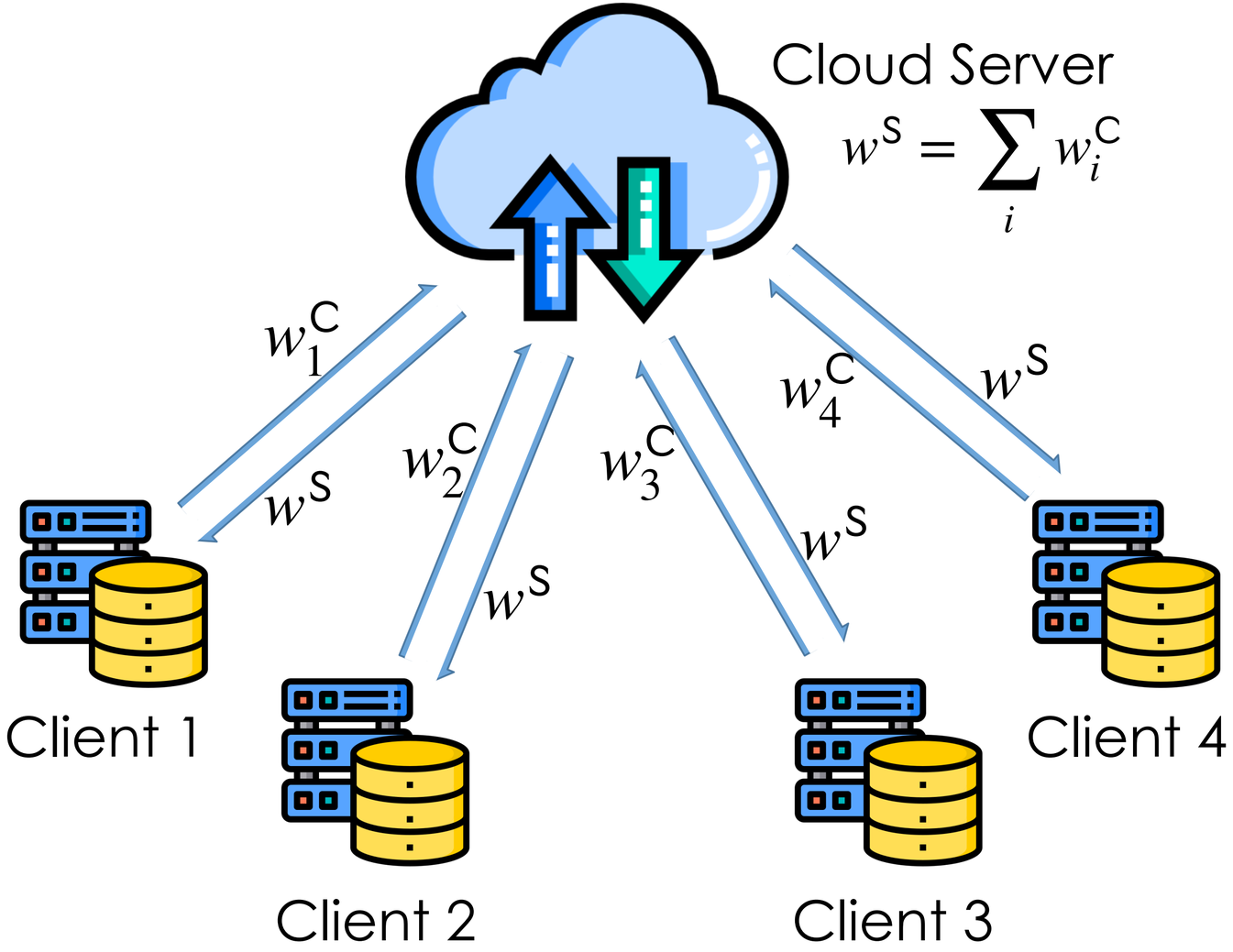

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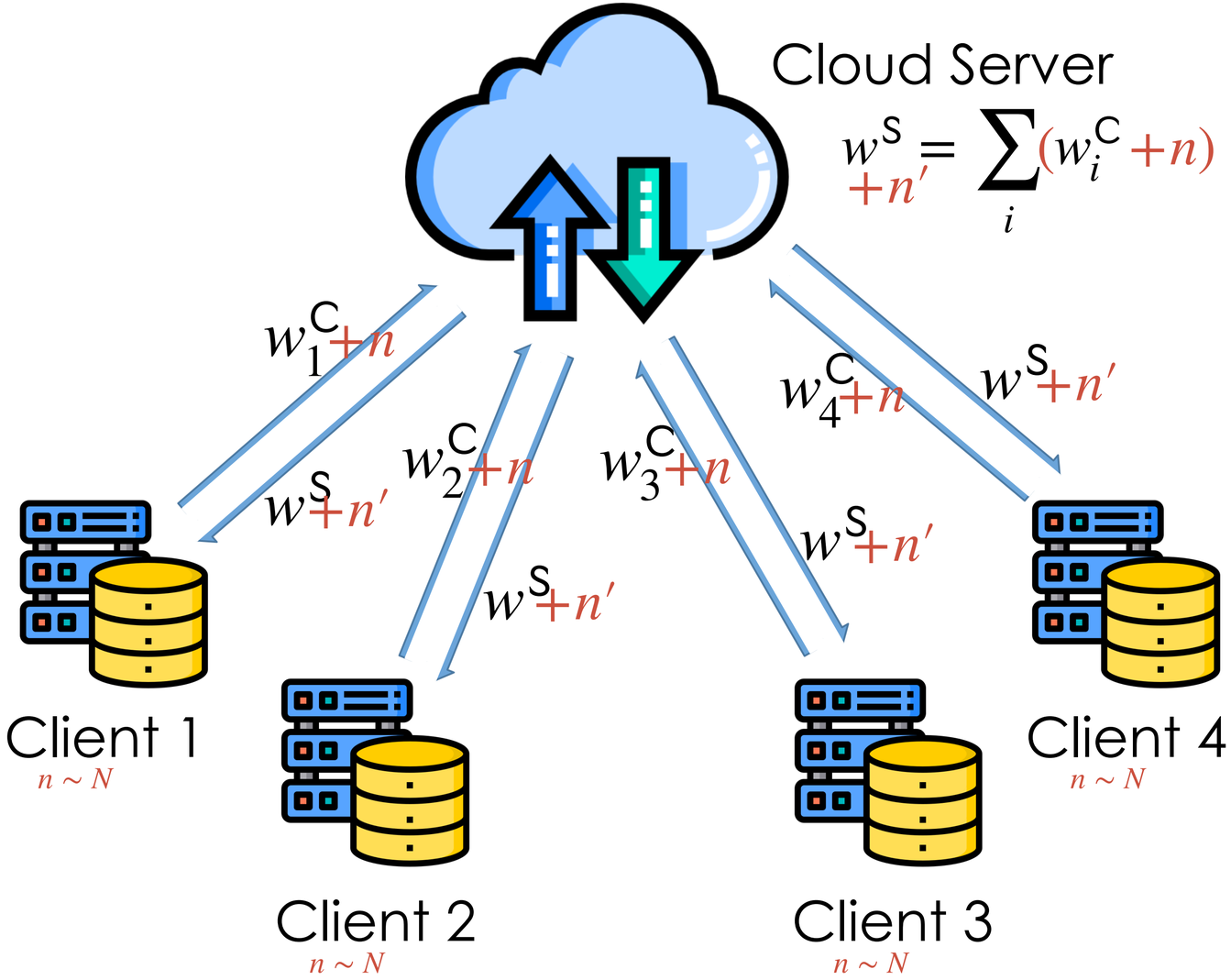
Guarantee: no access to d_i

Issue: expose w_i^C at each update

Imply: private data

Federated Learning with Privacy



- Client i protects her data
  - Keep d_i locally
  - add i.i.d. noise n to w_i^C
- Server S observes
  - no access to d_i
  - Noisy $w_i^C + n$
  - aggregated model $w^S + n'$

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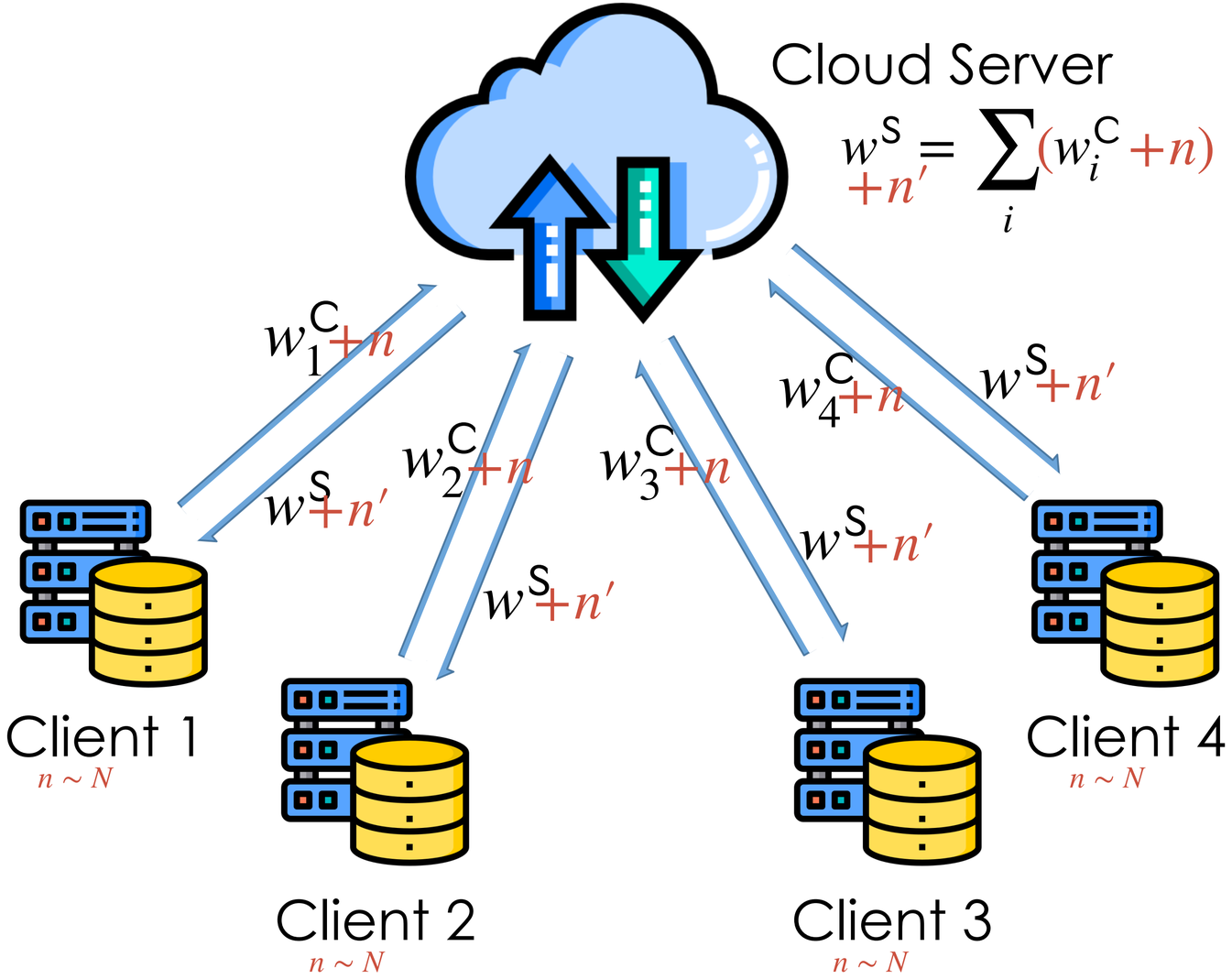

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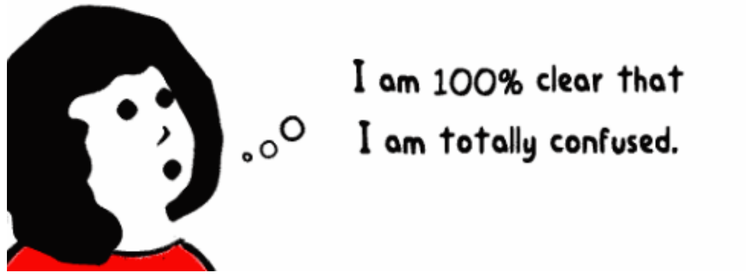
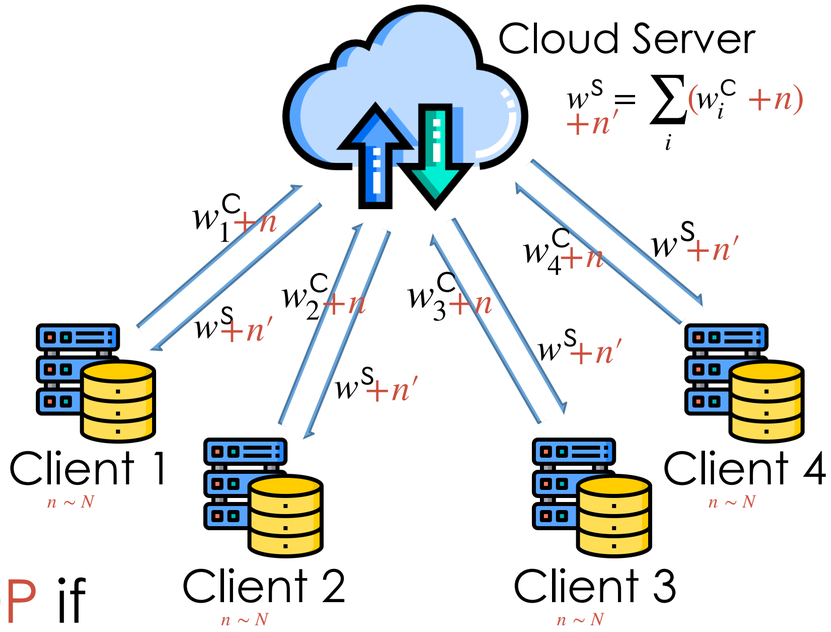
➡ What is so called "noise"?



Differential Privacy (DP)

- "Noisy" protection — add DP noise
  - n sampled from Gaussian distribution $N(0,\sigma^2 \cdot S_2^2(f))$
  - Mean 0 and standard deviation $\sigma \cdot s_2(f)$



Formal Definition

- A randomized mechanism $M : \mathbb{D} \rightarrow \mathbb{R}$ ensures (ϵ, δ)-DP if
  - for any two neighboring datasets D, D' differing in a single example
  - the output space of M satisfying $\Pr(M(D) \in \mathbb{R}) \leq e^{\epsilon} \cdot \Pr(M(D') \in \mathbb{R}) + \delta$
  - where $\epsilon \geq 0$ and $0 \leq \delta \leq 1$

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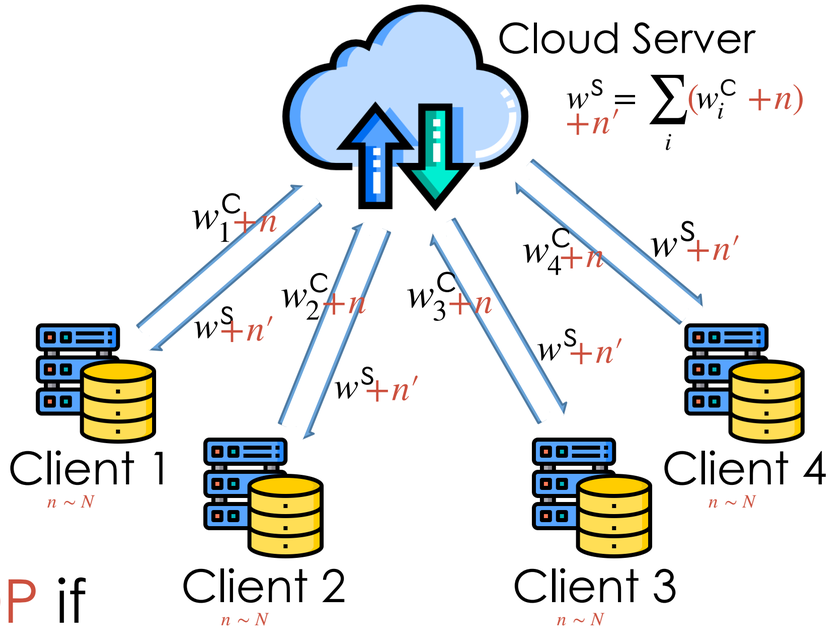

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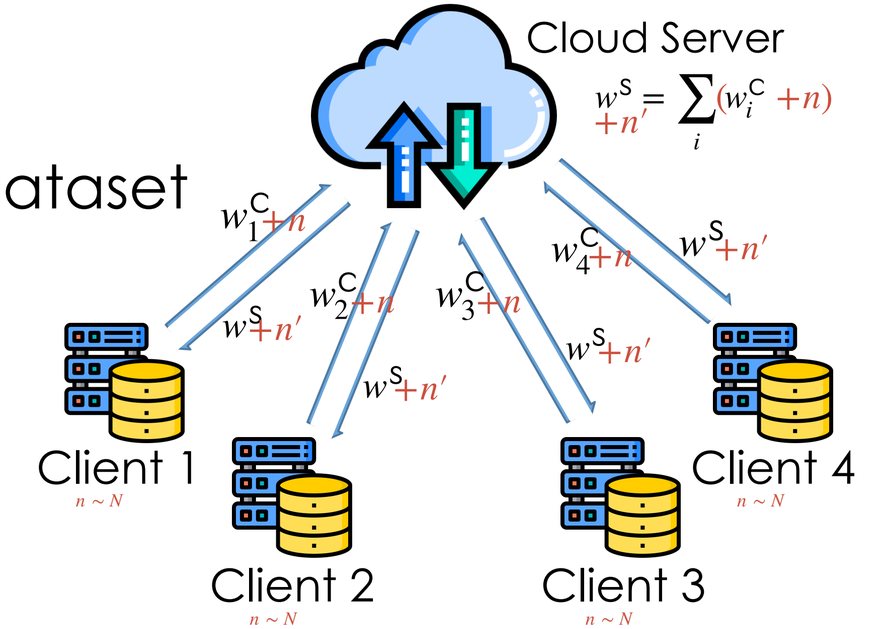
- DP guarantee: de facto standard to protect individual privacy
  - a single data example incurs a very-limited impact on statistical analytics performed on the entire dataset of all individuals

Differential Privacy in Federated Learning

- What can DP do in FL?
  - protect individual data example in local private dataset
  - ensure limited variation on statistics of local data

➡ What if we wanna protect statistics? (**Privacy**)



- Does DP protection come at a price?
  - utility-privacy trade-off
    - intuition: more noise <=> lower accuracy; less noise <=> higher accuracy
  - worse: accumulated effect of noise on the server

➡ Is there any protection with lossless accuracy? (**Functionality**)

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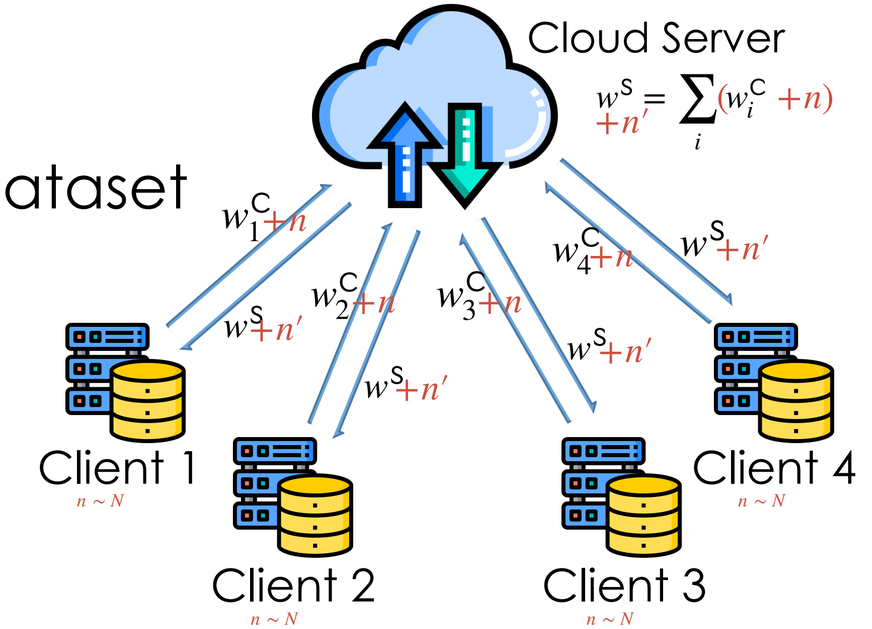

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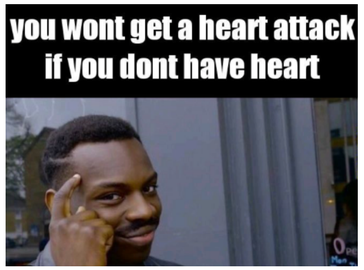
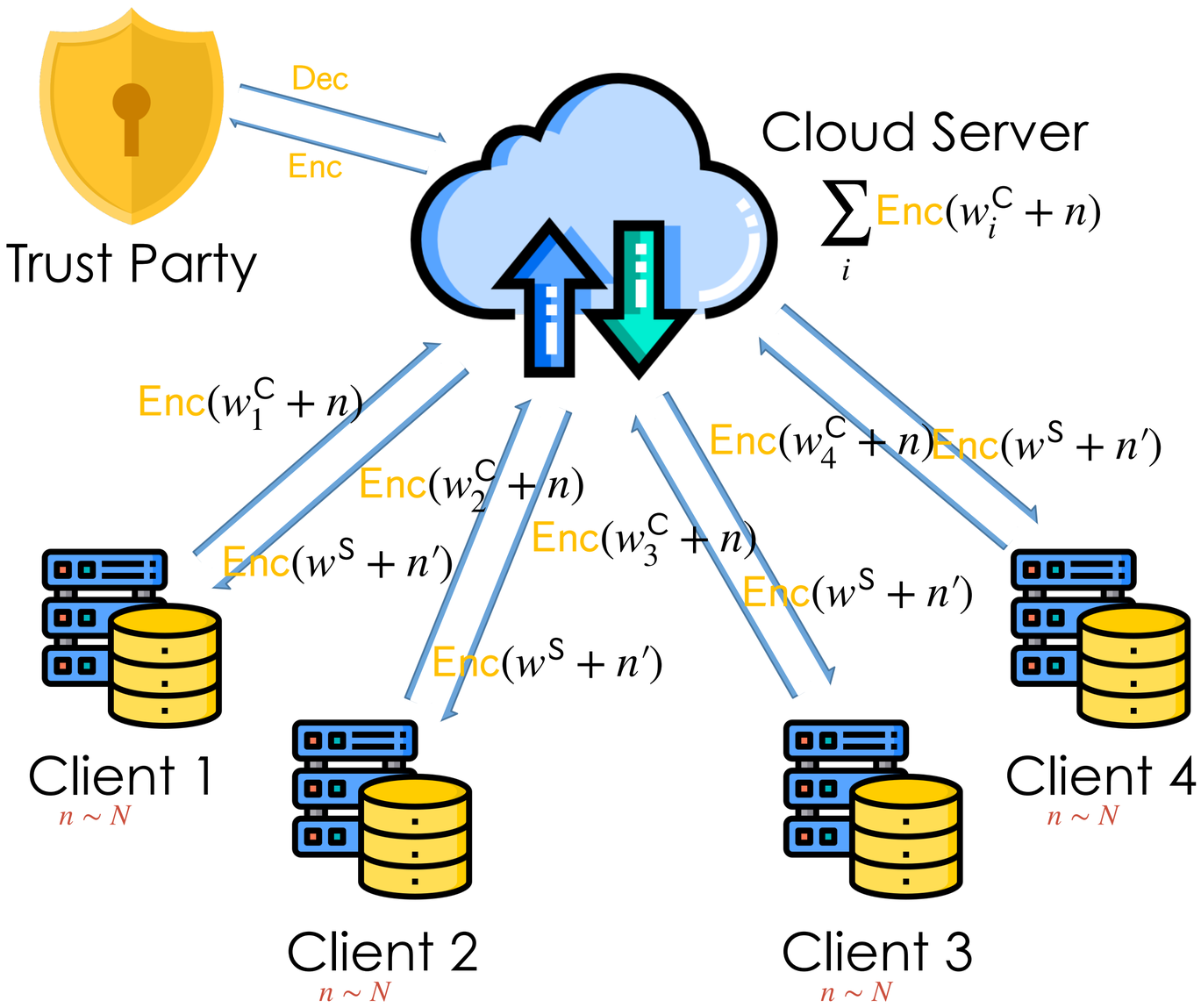
➡ 

So easy! Cryptography helps! Let's encrypt w_i^C.

Let's encrypt "everything" transmitted …



- Client i protects her data
  - individual privacy - DP
  - local statistics - Crypto
- Server **S** operates
  - aggregation over **Enc**($\cdot$)
  - no access to $w_i^{\text{C}}, w_i^{\text{C}} + n$

➡ Obviously, communication/computation **efficiency** would be very low…

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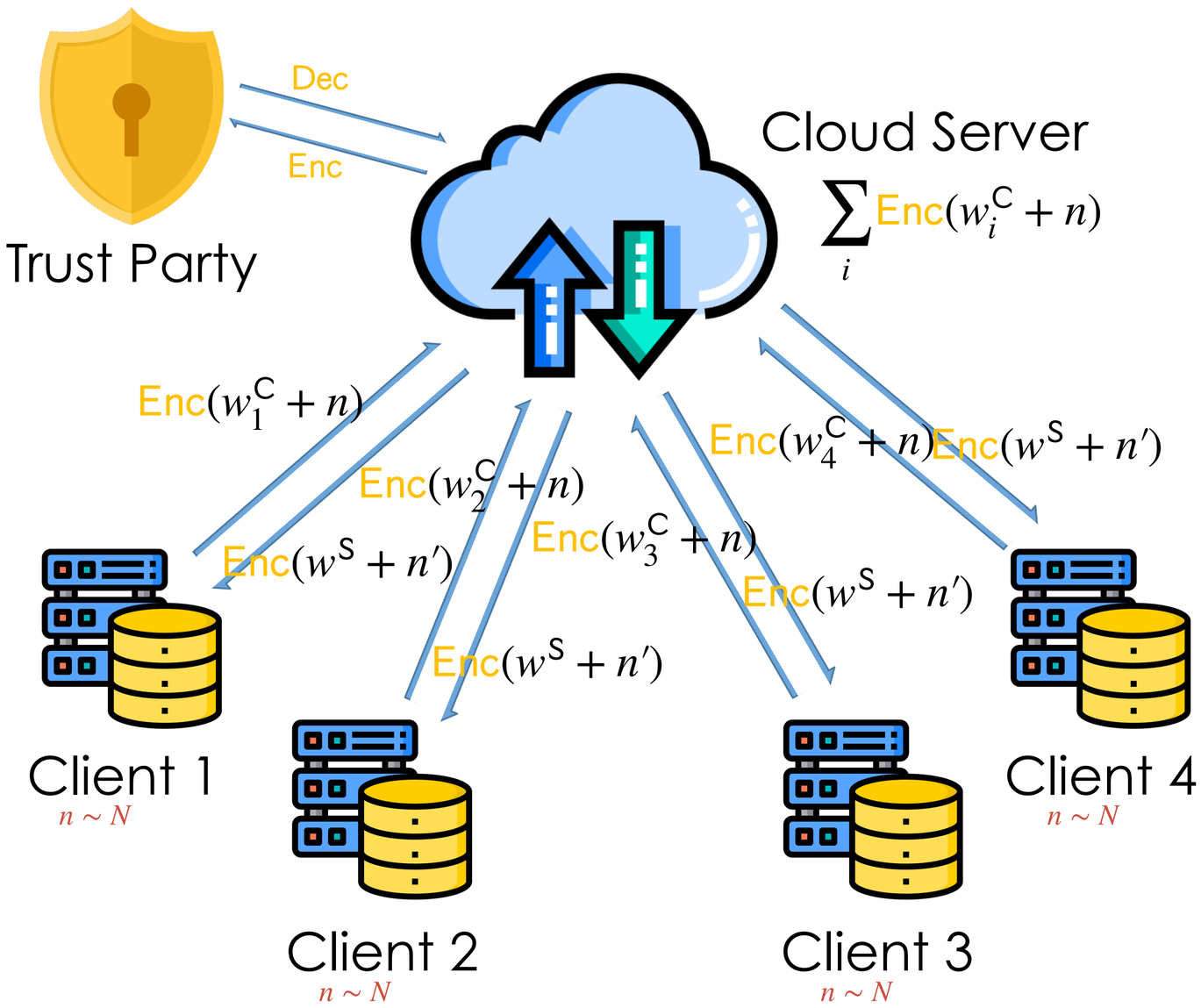

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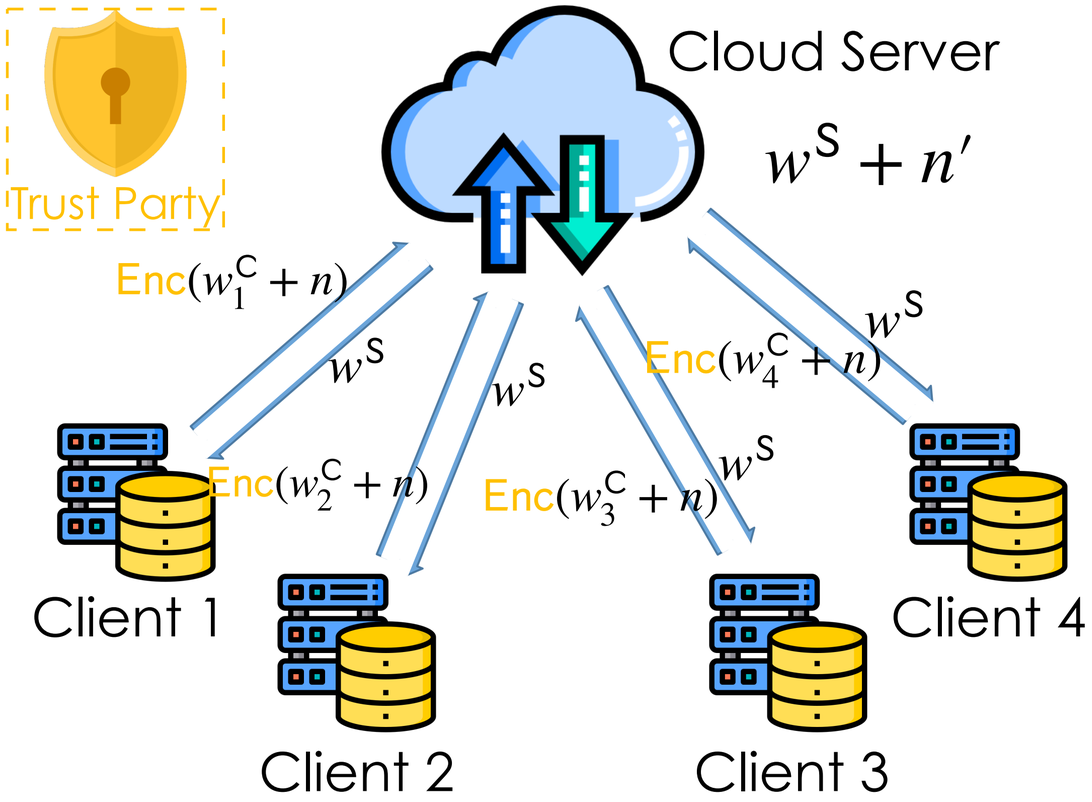
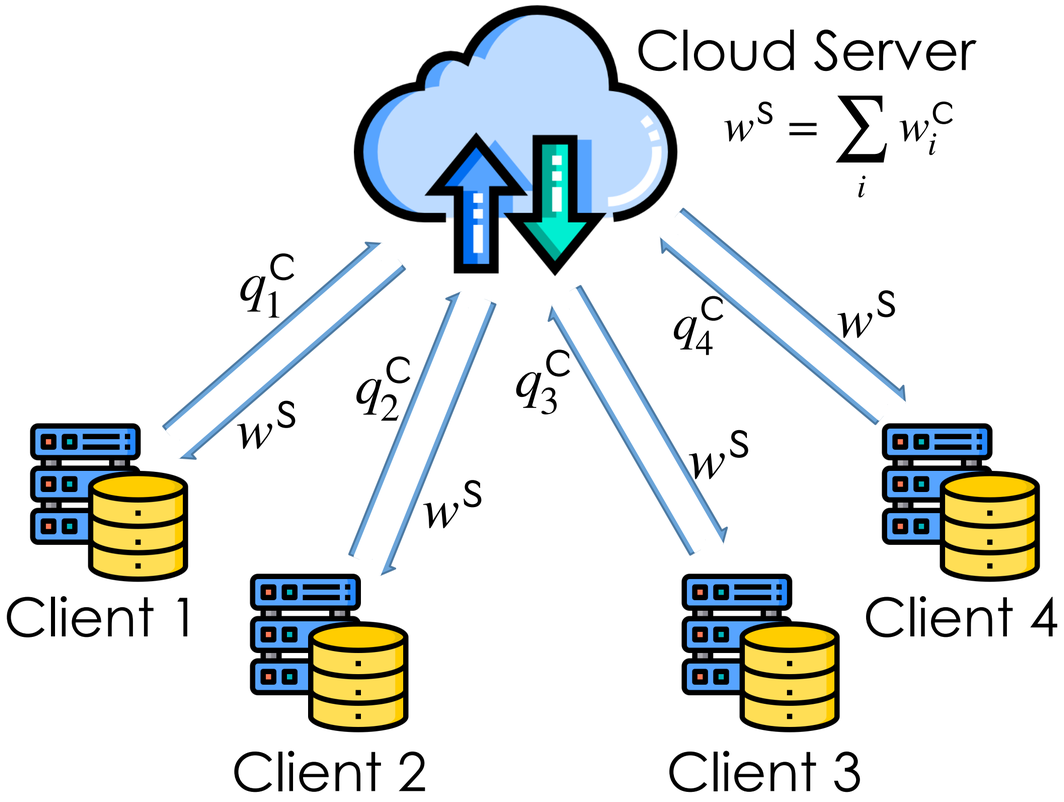
Can we do better regarding **privacy**, **functionality**, and **efficiency**?

Our Hierarchical Protection in General



Phase 1: secure aggregation



Phase 2: global tuning with DP

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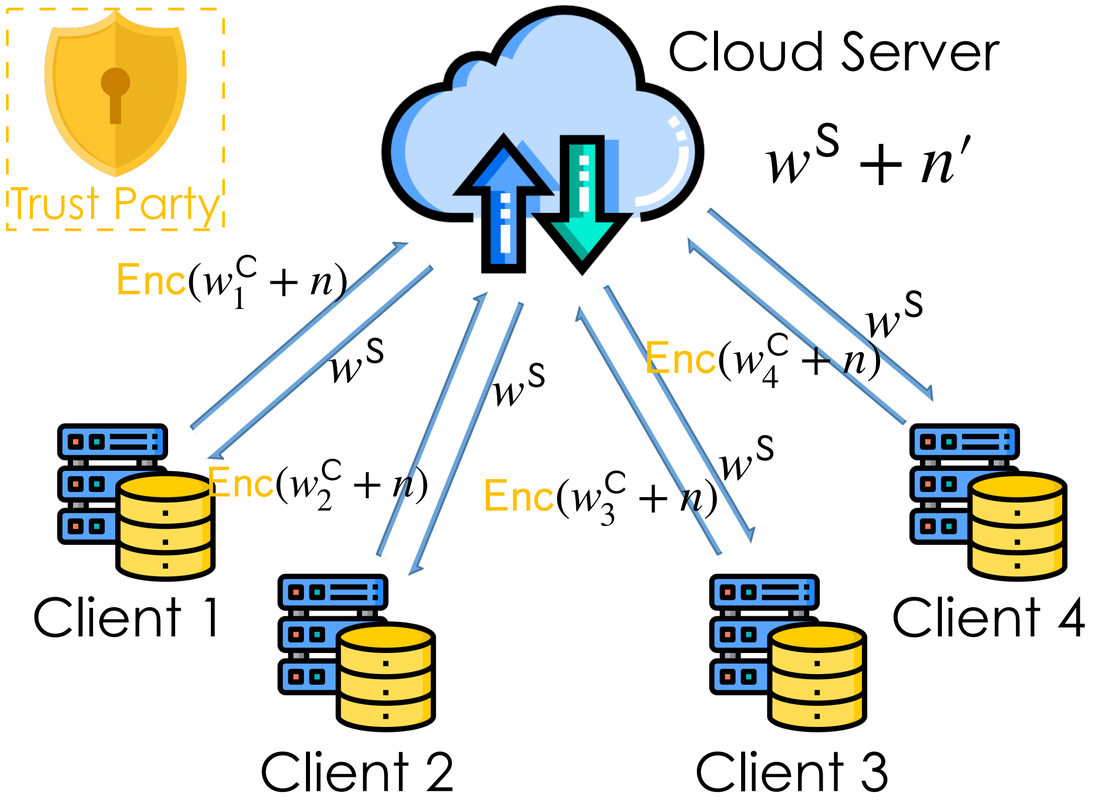
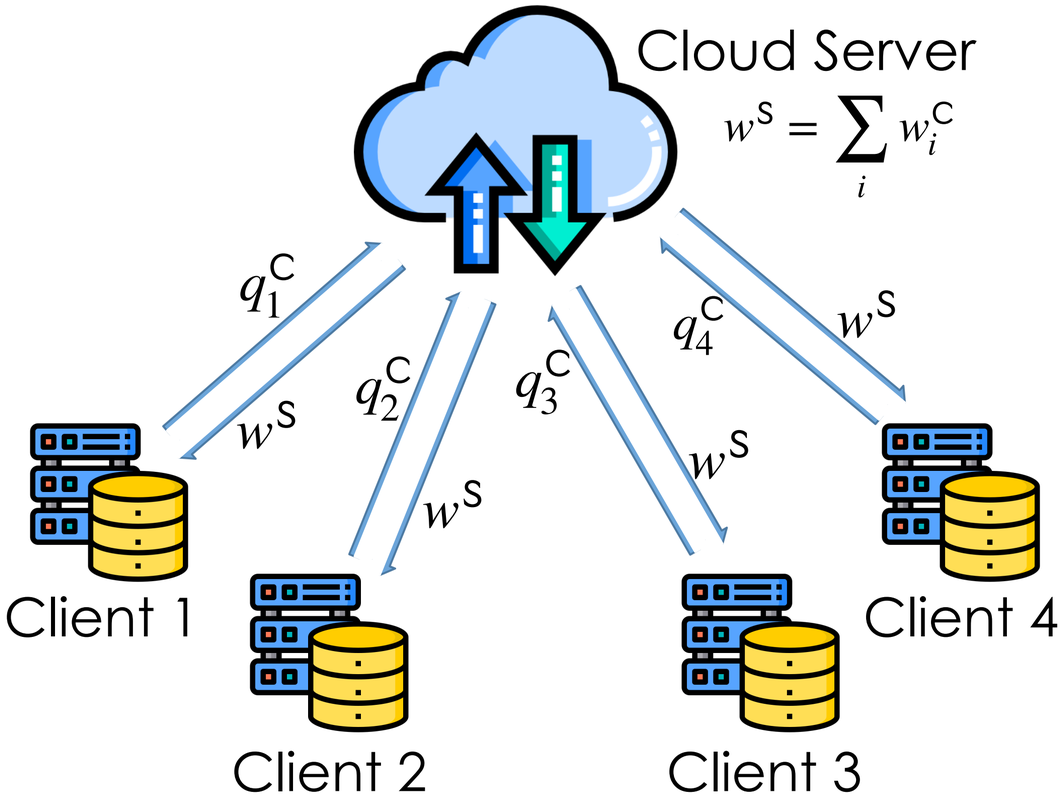


Phase 1: secure aggregation

- Client i sends $\mathrm{Enc}(W_i^C + n)$
- Crypto: guarantees only $W^S + n'$ revealed to the server
  - only once



Phase 2: global tuning with DP

- Client i slightly tunes the global model
- DP: guarantees individual privacy
  - Limited number of data
  - can be repeated

Concrete Instantiation and Outline

- Federated learning
  - server: train a global model over "indirect-use" data (i.e., global data)
  - client: train a local model over local private data
  - intuition: clients train over data for "knowledge", server trains over "knowledge"
- Cryptography: heavy communication/computation, thus only once
  - CKKS (**KeyGen**, **Enc**, **Dec**, **Add**): protect local statistics (phase 1)
  - remove trusted party: additive secret sharing
- Differential privacy
  - DP-Adam: converges better & example-level privacy (phase 2)
  - Following the style of DP-SGD
- Learning scenarios
  - Generative neural networks (GAN)
    - **S**: train a generative model for generating representative samples
  - Meta learning
    - **S**: train a new task by learning knowledge from related tasks

How do we construct Secure Federated GAN? (3 Steps)

- **Step 1.** Non-federated/centralized DP-GAN
  - devise DP-Adam as a plug-in module
  - GAN training
    - contain a generator θ^G and a discriminator θ^D
    - solve the min-max optimization
  - replace DP-Adam with Adam in GAN training
    - essentially add the DP noise to discriminator (input private data)
    - post-processing technique for DP guarantee

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  - server obtains initial global model

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- **Step 3.** Construct Phase 2
  - client i tunes global model using its θ_i^{D}

DP-Adam

- Input: examples $\{x_1, \ldots, x_N\}$, hyper-parameters $\alpha, \beta_1, \beta_2, \gamma, L, C, \sigma$
- Output: model parameters θ_T

1 Initialize Θ_0 randomly;
2 **for** $t \in [T]$ **do**
3 Randomly sample L examples as a batch B_t;
4 Compute gradient $\mathbf{g}_t(x_i)$ for $\forall x_i \in B_t$;
5 Clip gradient $\bar{\mathbf{g}}_t(x_i) = \mathbf{g}_t(x_i)/\max(1, \frac{\|\mathbf{g}_t(x_i)\|_2}{C})$;
6 Add noise $\tilde{\mathbf{g}}_t = \frac{1}{L}(\sum_i \bar{\mathbf{g}}_t(x_i) + \mathcal{N}(0, \sigma^2 C^2 \mathbf{I}))$;
7 $\beta_1' = 1 - \beta_1, \beta_2' = 1 - \beta_2, u_t = \beta_1 \cdot u_{t-1} + \beta_1' \cdot \tilde{\mathbf{g}}_t, v_t = \beta_2 \cdot v_{t-1} + \beta_2' \cdot \tilde{\mathbf{g}}_t^2$;
8 $\bar{u}_t = u_t/\beta_1', \bar{v}_t = v_t/\beta_2'$;
9 $\Theta_{t+1} = \Theta_t - \alpha \cdot \bar{u}_t/(\sqrt{\bar{v}_t} + \gamma)$
10 **end**
11 Return Θ_T

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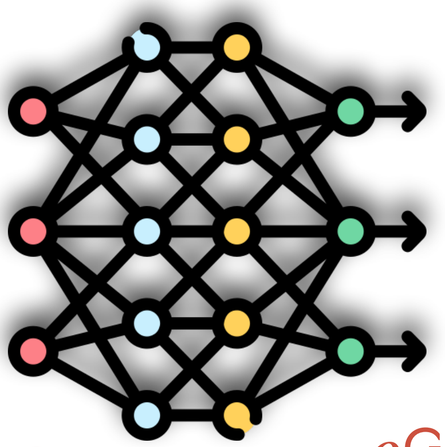
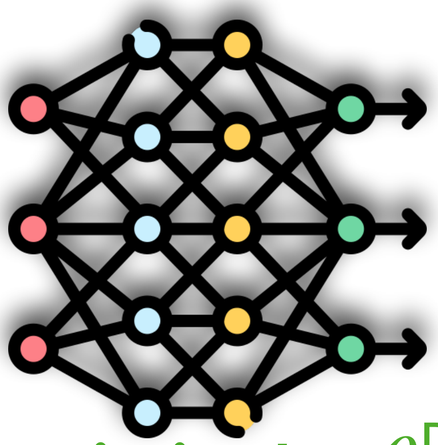


Generator θ_i^G



Discriminator θ_i^D

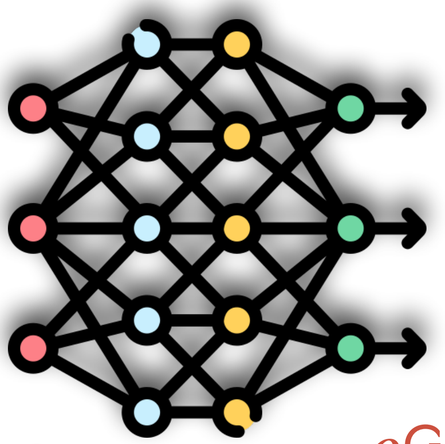
- θ^{G_i} — Adam
- θ^{D_i} — DP-Adam

- Each client holds a pair of $(\theta^{G_i}, \theta^{D_i})$
- Training over private data locally

- Produce initial θ^G
- θ^G's DP guarantee
  - post-processing technique

DP-GAN

private real data



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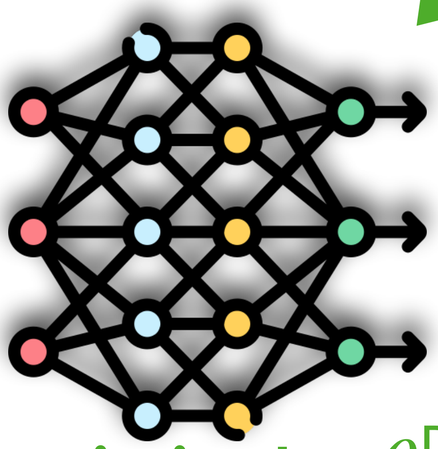
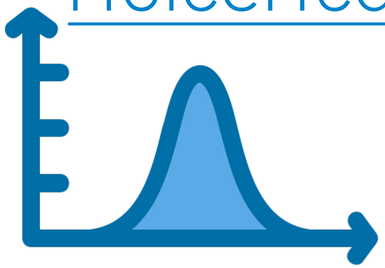


Discriminator θ_i^D

Predict	Target
0.1	0
~	or
0.9	1

Add DP noise sampled from



Protect real data only

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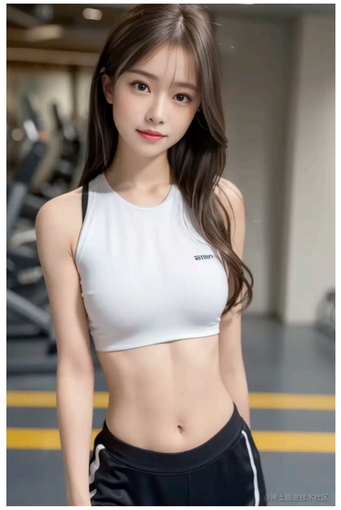
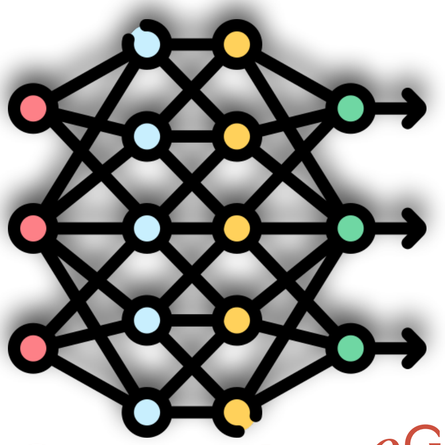


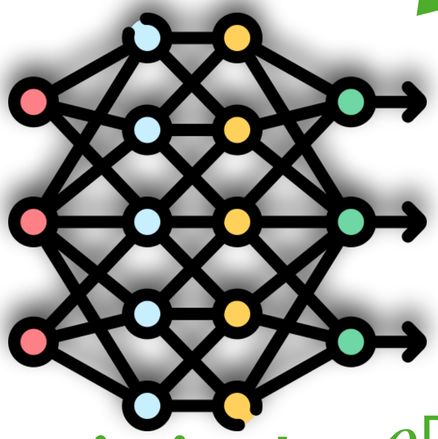
generated sample



Generator θ_i^G

feedback

disturbance vector



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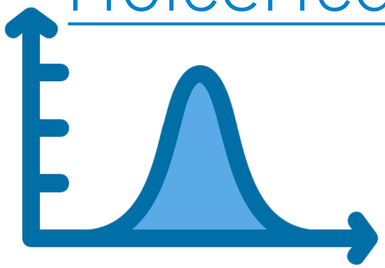

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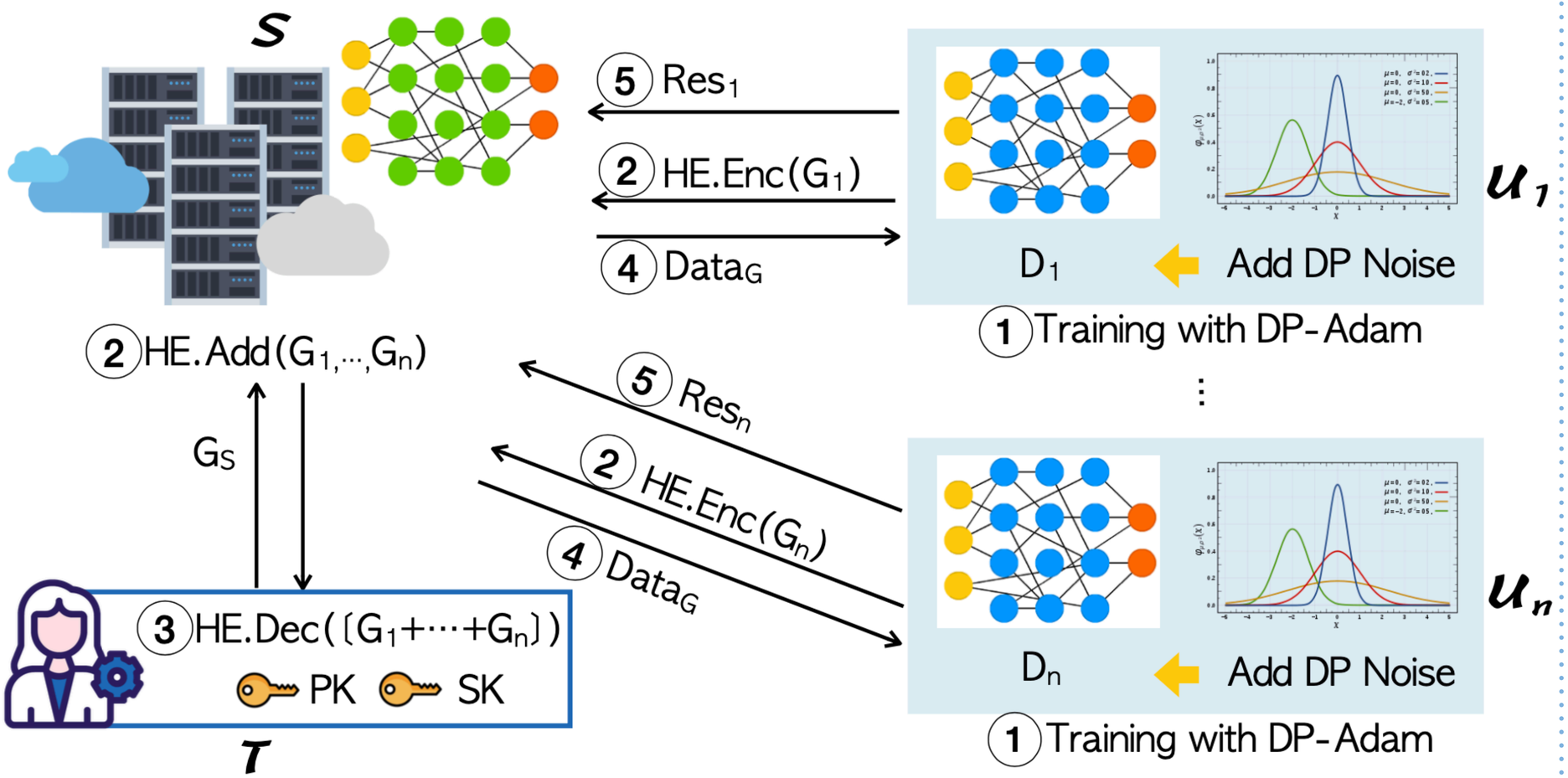
Secure Federated GAN — Our Framework



- User, Server,
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- Integrate CKKS + DP+ federated learning

- 1: pretraining
- 2,3: phase 1
- 4,5: phase 2

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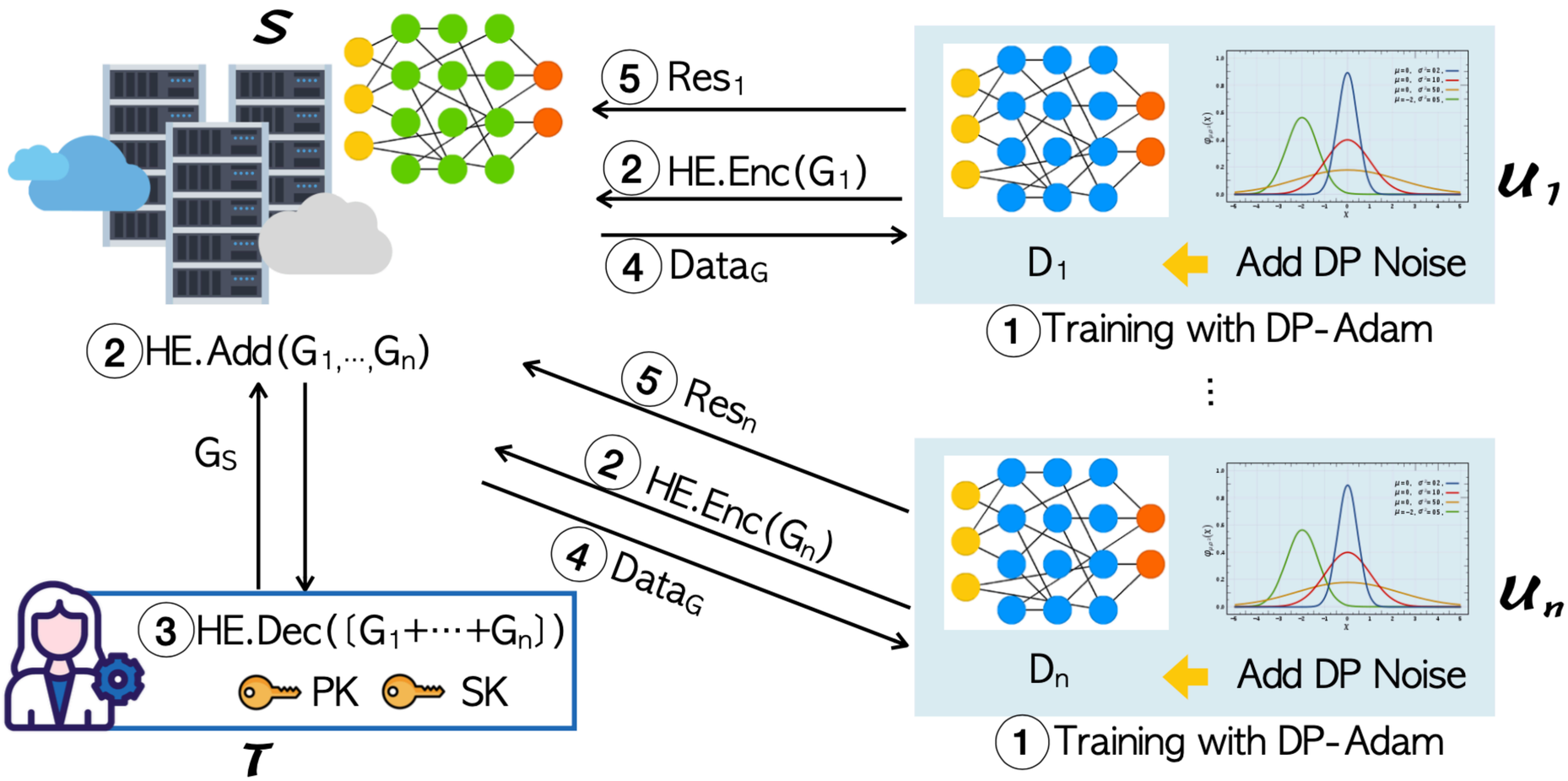

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- 4,5: phase 2

- Generalization with meta-learning
  - S holds a meta-leaner capturing short-term knowledge within a task and long-term knowledge among tasks

Experiments

- Commodity server: CentOS, 24-core CPU, 62.5GiB RAM, GeForce RTX 2080Ti GPU
- Datasets: MNIST, Mini-ImageNet
- Configuration: $\delta = 10^{-5}, \sigma = \{0.005, 0.5, 5, 8\}$
- Findings for DP training
  - Generally, DP-Adam converges more stable than DP-SGD.
  - Adding noise with lager σ increases the training instability, making the convergence slower
  - The noise "tolerance" depends on the parameter configuration.
- Communication costs compared with BatchCrypt
  - 73 vs 211GB (250 epochs)
  - 90 vs 1090 GB (100 epochs)

Conclusion

- Jump out of "folklore FL approach" — **Motivate further research**
  - **new thinking**
    - different types of privacy required in the FL process
  - **new route**
    - non-trivial combination of protective techniques
    - for a stronger protection

- Practical Hierarchical protection
  - (DP and crypto) in privacy-efficiency design space

- Potentiality of privacy-preserving application tailored with various learning **applications**