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Dubhe: Towards Data Unbiasedness with Homomorphic Encryption in Federated Learning Client Selection

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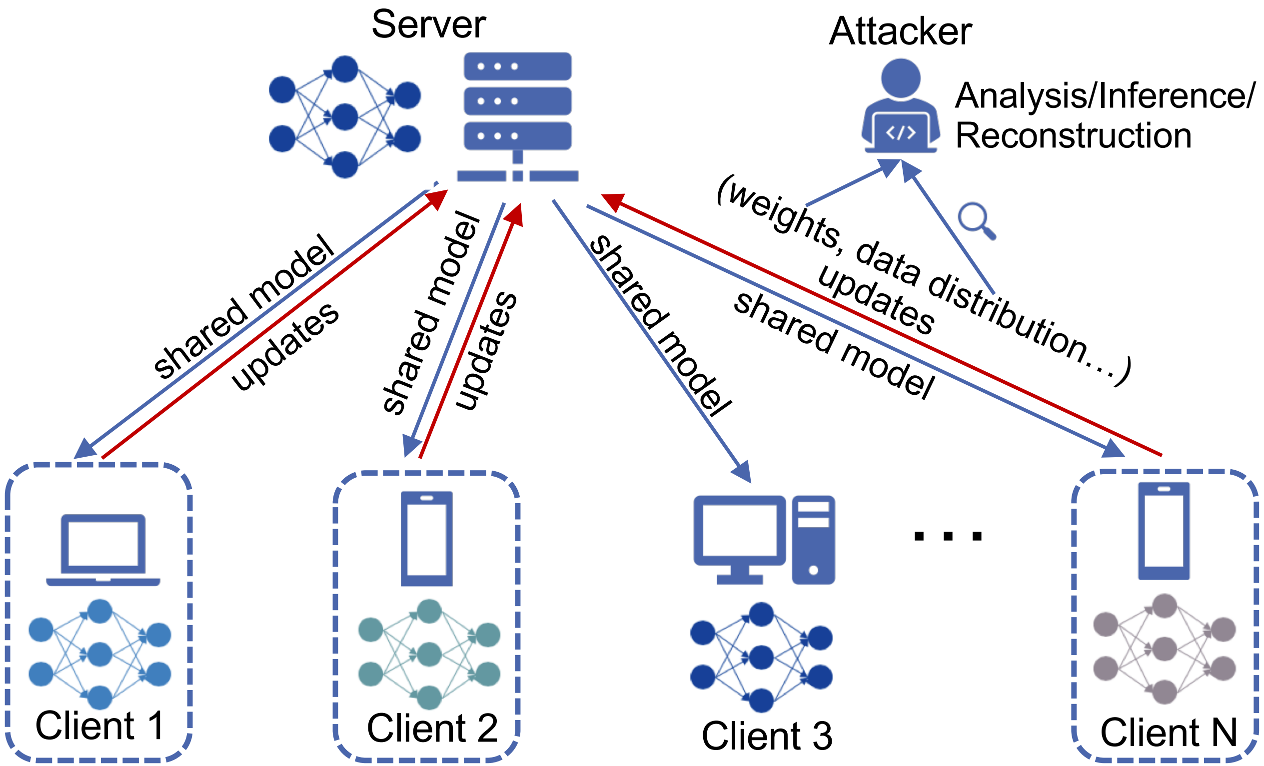
Federated Learning

- ***Demand:** Security promise*
  - Homomorphic Encryption
- ***Problem:** Statistical heterogeneity*
  - Local data skewness
  - Data discrepancy among clients
  - Global data skewness
- ***Method:** Client selection*
  - Random selection
  - Greedy selection



The framework of Federated Learning

Background

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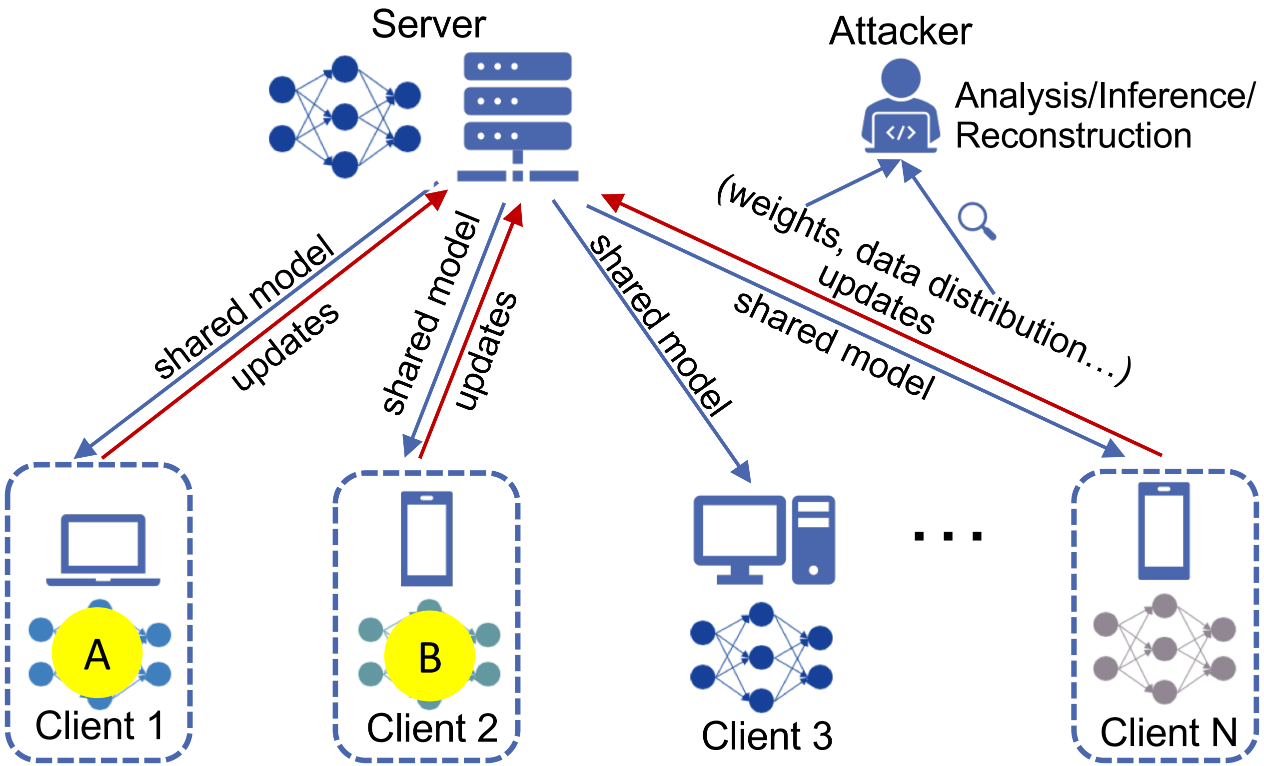

The framework of Federated Learning

Motivation

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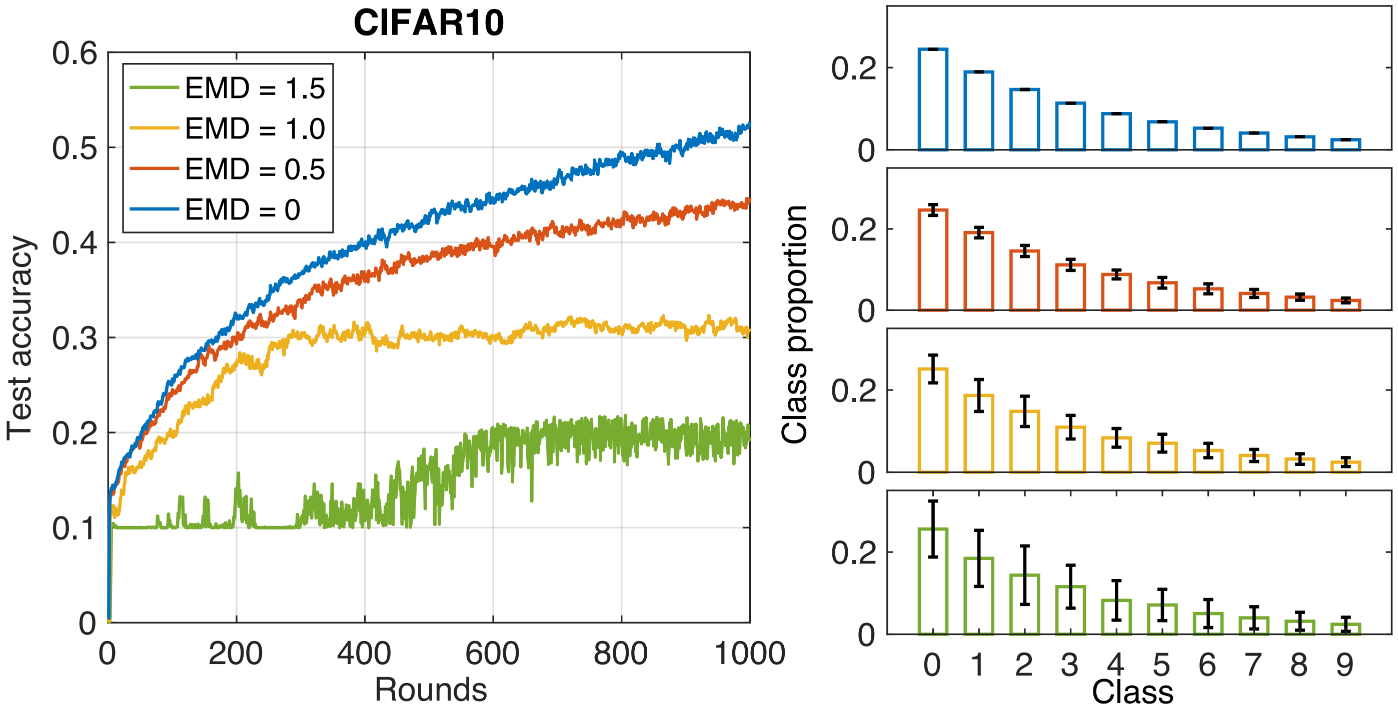

Discrepancy of clients in CIFAR10 classification

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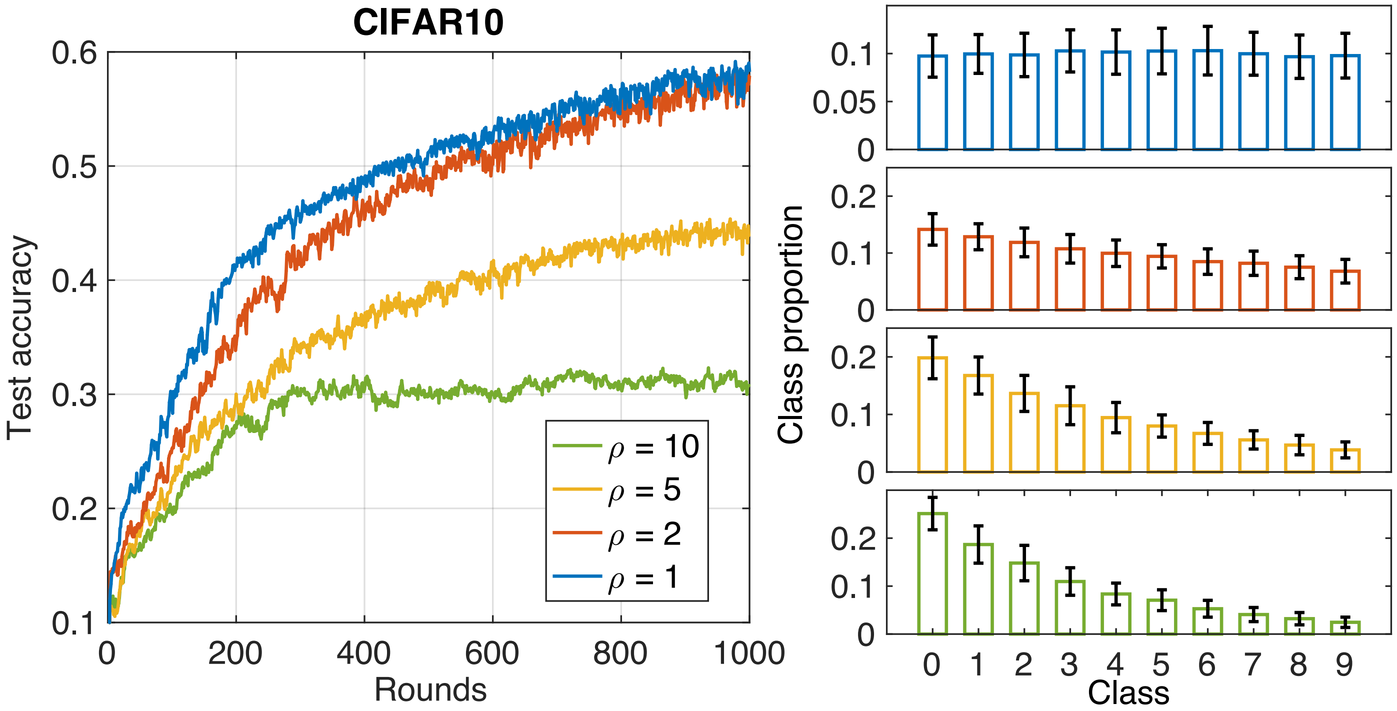

Global data skewness in CIFAR10 classification

Mathematical Demonstration

Federated Learning

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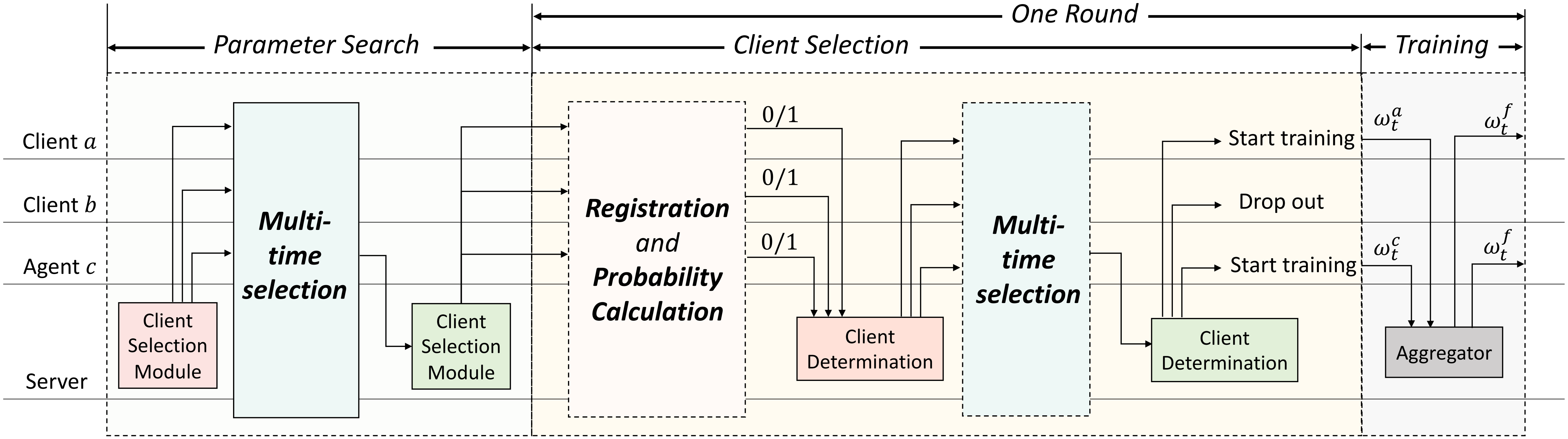
$$
\begin{aligned}
||\omega^f_{mT} - \omega^*_{mT}|| \leq & ||\omega^f_{mT} - \omega^c_{mT} + \omega^c_{mT} - \omega^*_{mT}|| \\
\leq & \frac{1}{K}\sum_{i=1}^{K}[(1+\eta\lambda)^T ||\omega^k_{(m-1)T} - \omega^c_{(m-1)T}|| \\
& + \underbrace{\eta||p^k_l - p_o||_1}_{①}(\sum_{j=2}^{T} \mathrm{g}(\omega^c_{mT-j})(1+\eta\lambda)^{j-1})] \\
& + (1+\eta\lambda)^T ||\omega^c_{(m-1)T} - \omega^*_{(m-1)T}|| \\
& + \underbrace{\eta||p_o - p_u||_1}_{②}(\sum_{j=1}^{T} \mathrm{g}(\omega^*_{mT-j})(1+\eta\lambda)^{j-1}),
\end{aligned}
$$

Target: $\min||p_o - p_u||_1$

The Design of Dubhe



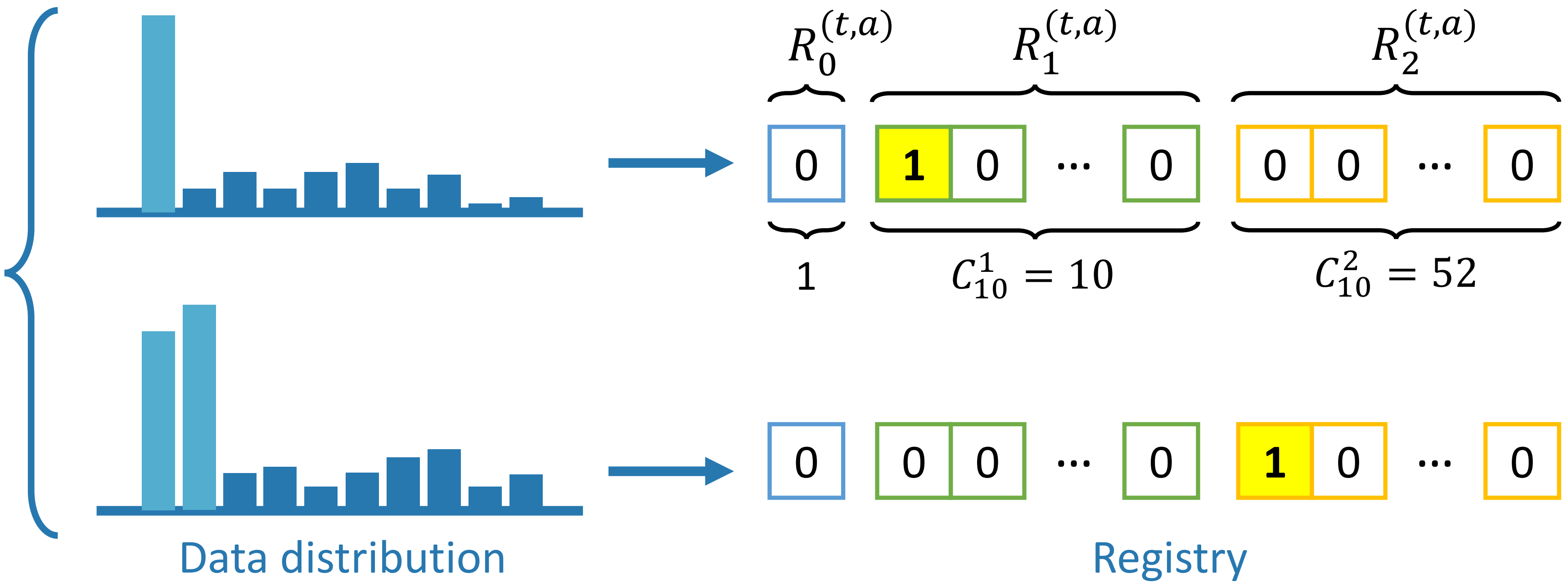
The framework of Dubhe

The Design of Dubhe

Registration *and* ***Probability Calculation***

- The ***registry*** encodes the client's data distribution information in a one-hot manner.
- In classification problems, the registry encodes each client's data distribution by its ***dominating classes***.

Samples of a 10-class classification



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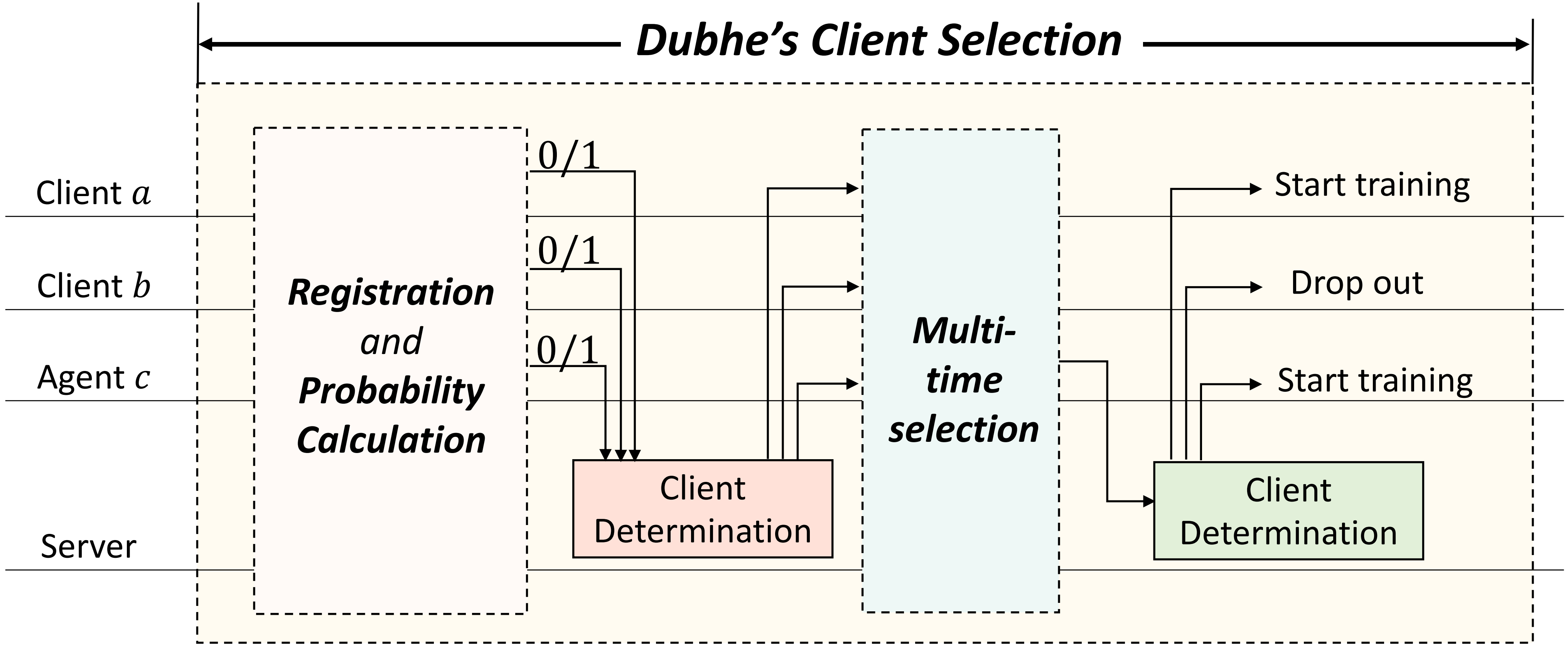
Registration and *Probability Calculation*



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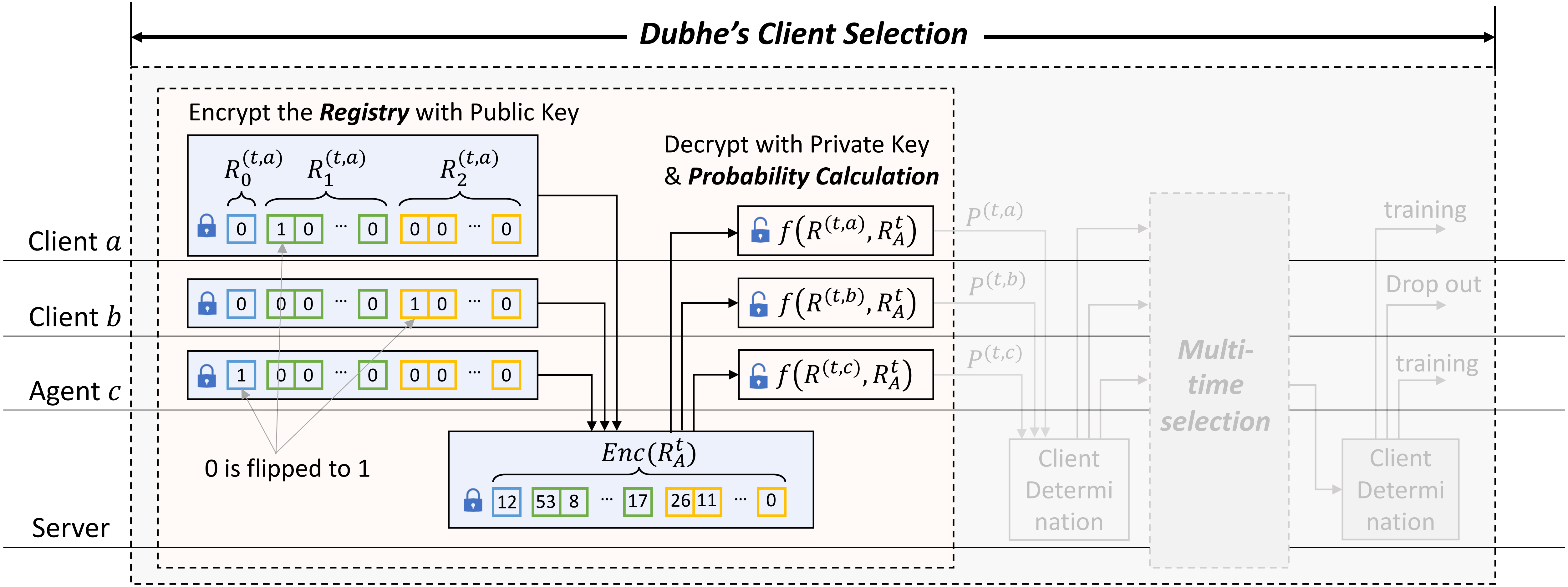
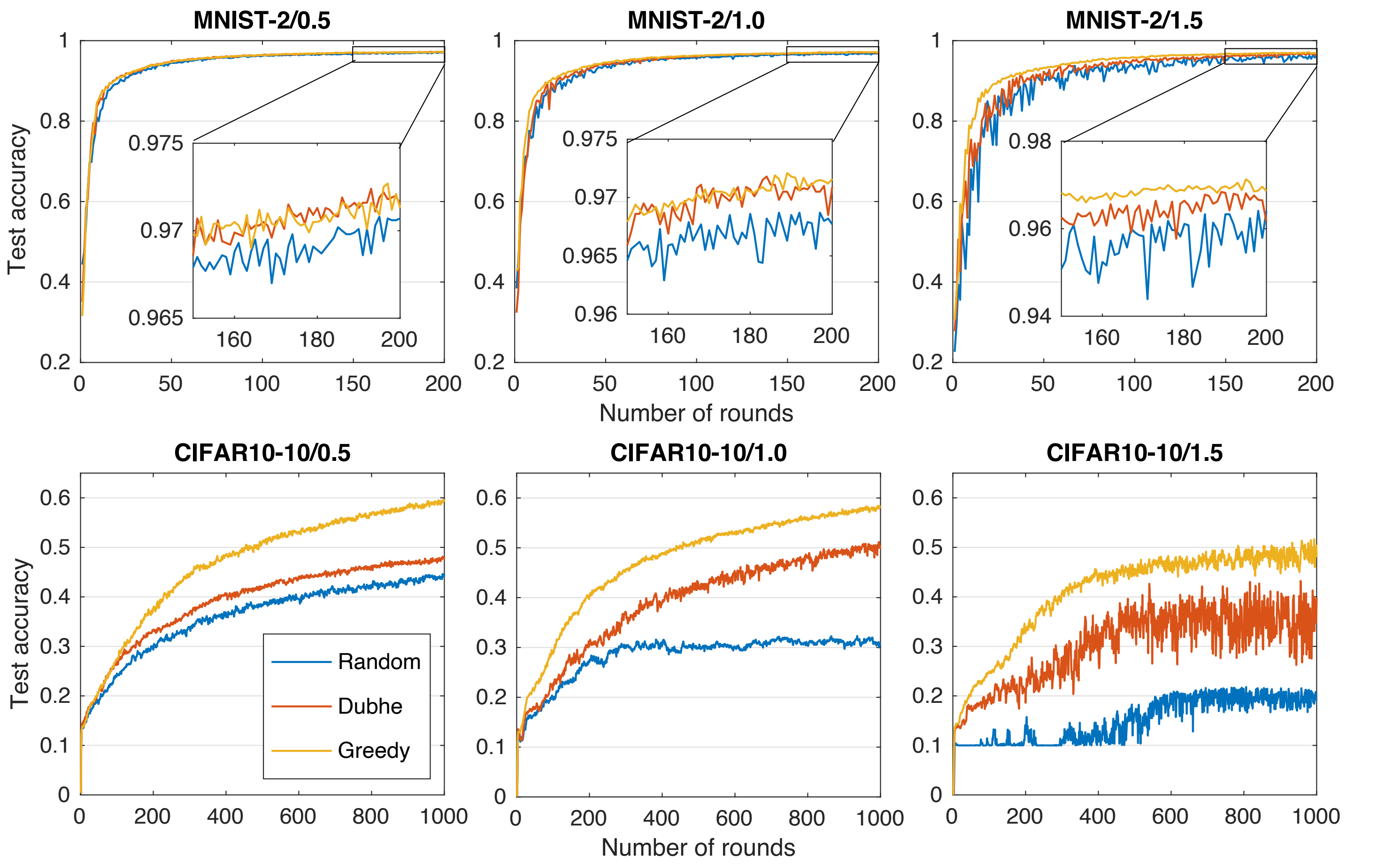
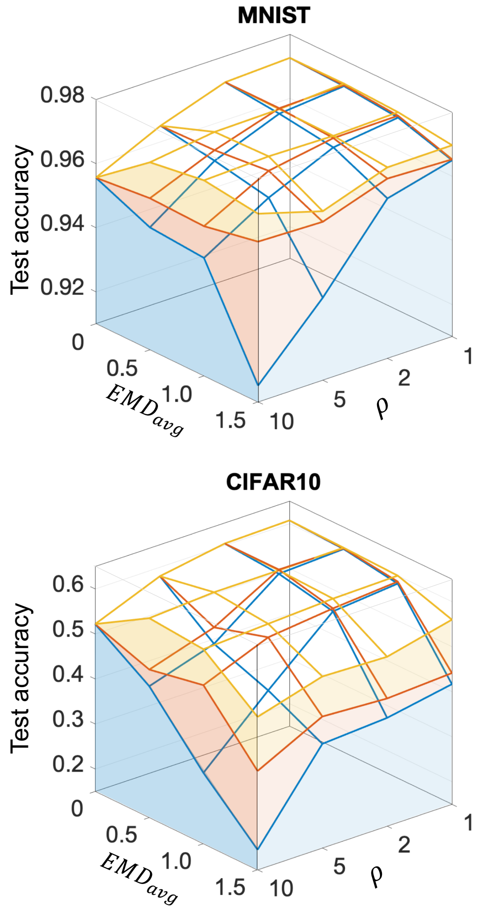
Registration** and **Probability Calculation



Evaluation of Dubhe

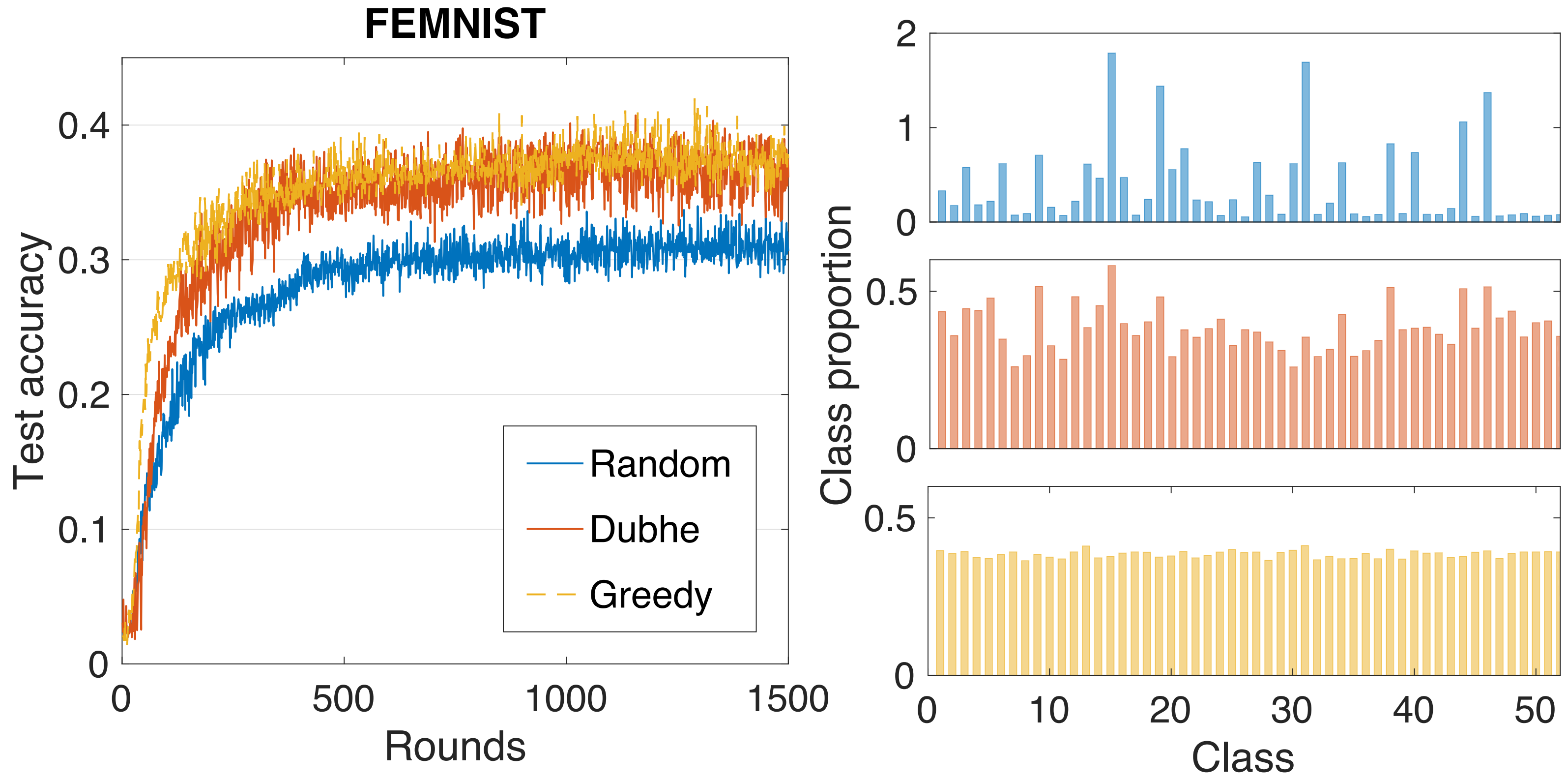


Test accuracy curves on MNIST and CIFAR10



Average accuracy

Evaluation of Dubhe



Results on FEMNIST

- The data balancing performance of Dubhe is approaching the performance of the greedy selection.

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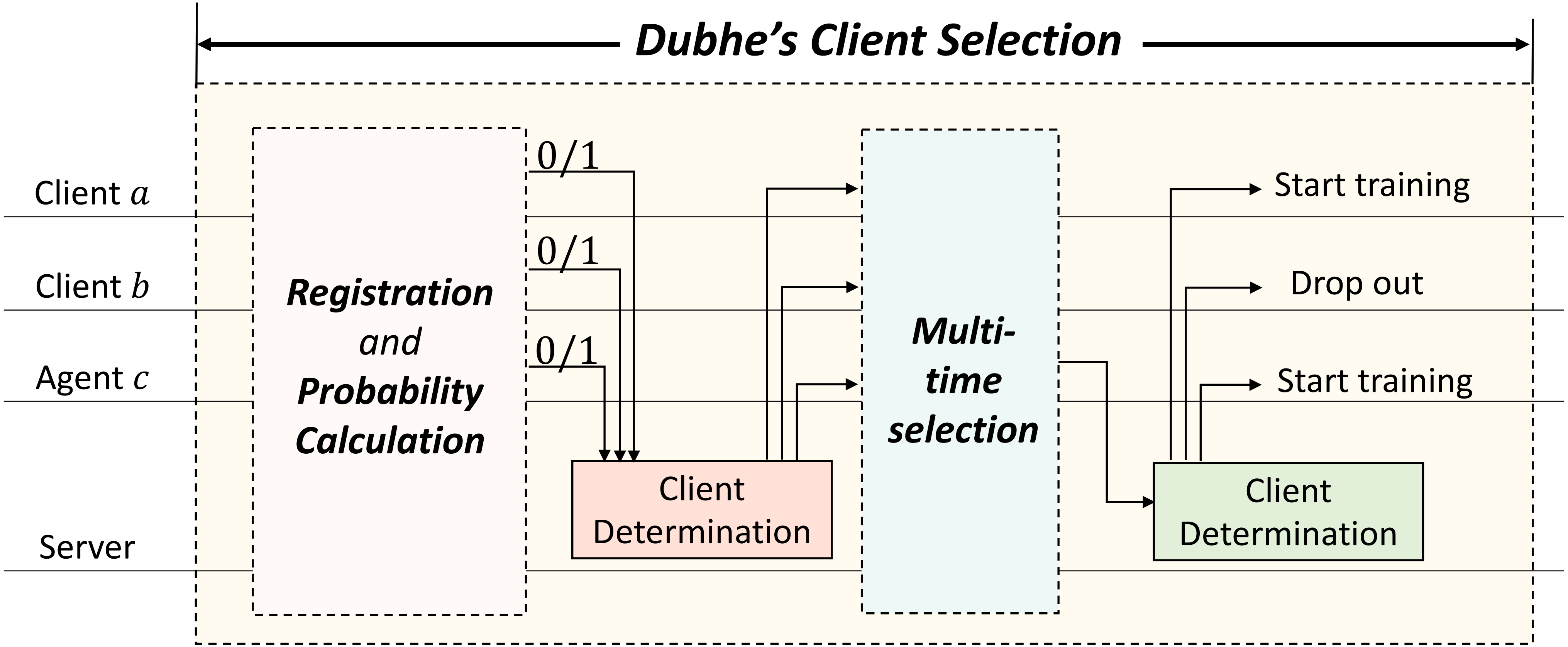
Multi-time selection



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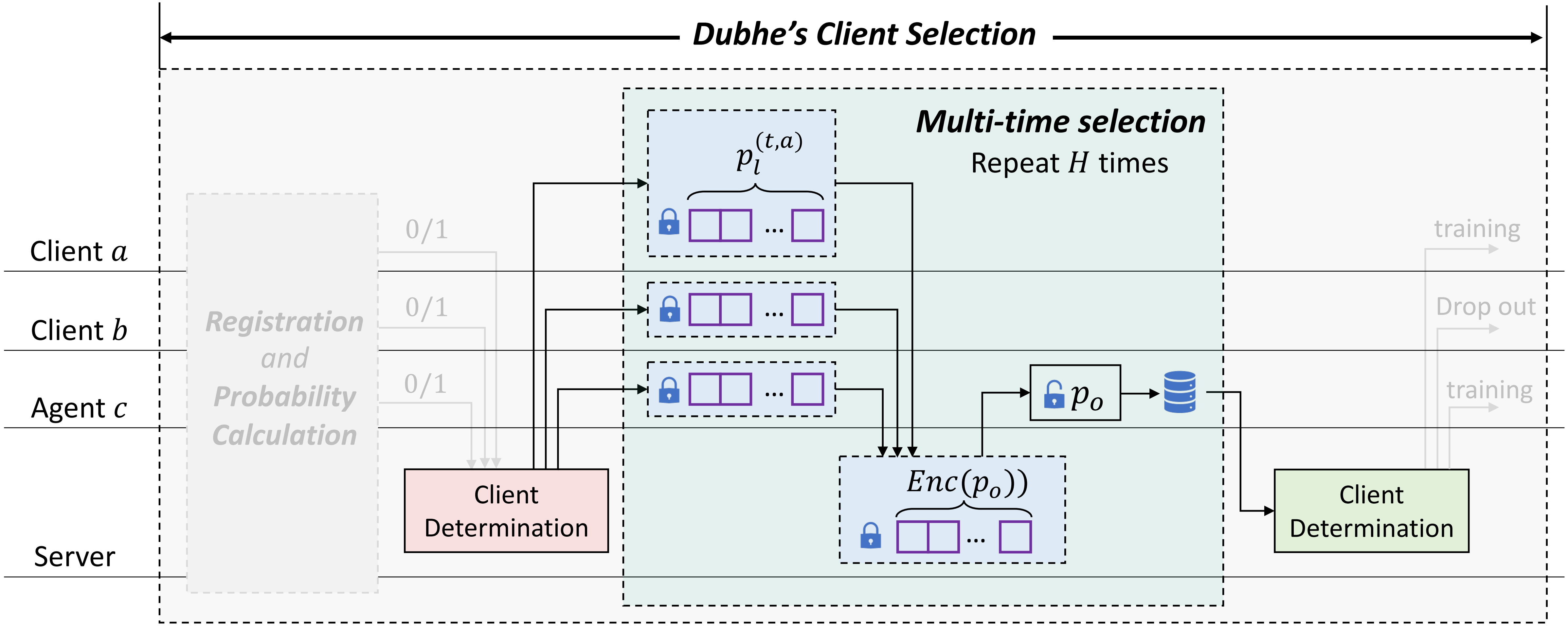
Multi-time selection



Evaluation of Dubhe

Multi-time selection

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Results with multi-time selection. *M* refers to MNIST and *C* refers to CIFAR10.

H	1	2	5	10	20	opt
EMD^*	0.2946	0.2588	0.2176	0.1971	**0.1750**	0.0144
Acc^M	0.9662	0.9668	0.9665	**0.9684**	0.9678	0.9694
β^M	0.0%	17.6%	10.5%	**69.5%**	51.5%	100%
Acc^C	0.4300	0.4518	0.4486	0.4441	**0.4577**	0.5295
β^C	0.00%	14.8%	12.6%	9.5%	**18.8%**	100%

EMD^* decreases with larger H, thereby improving the model accuracy

Evaluation of Dubhe

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Registry sparsity

$R_{A,0}$

(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
179	130	89	60	39	18	8	2	1	0

$R_{A,1}$

(0,1) 22	(0,2) 20	(0,3) 19	(0,4) 19	(0,5) 21	(0,6) 13	(0,7) 13	(0,8) 14	(0,9) 9
(1,2) 13	(1,3) 20	(1,4) 16	(1,5) 14	(1,6) 16	(1,7) 13	(1,8) 10	(1,9) 8	
(2,3) 20	(2,4) 19	(2,5) 16	(2,6) 12	(2,7) 11	(2,8) 8	(2,9) 3		
(3,4) 12	(3,5) 9	(3,6) 12	(3,7) 9	(3,8) 5	(3,9) 8			
(4,5) 7	(4,6) 6	(4,7) 6	(4,8) 7	(4,9) 4				
(5,6) 4	(5,7) 9	(5,8) 6	(5,9) 2					
(6,7) 6	(6,8) 3	(6,9) 7						
(7,8) 2	(7,9) 1							
(8,9) 0								

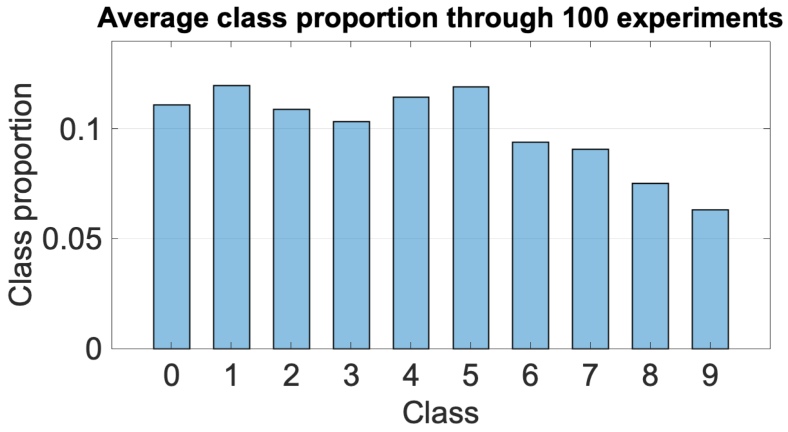
$R_{A,10}$

None
0

There are 3 out of 1000 clients who have class 2 and class 9 dominated.

$$\kappa\big(u = (2,9)\big) = 3$$

- An example of the overall registry and its corresponding participated class proportion.



The sparsity of the overall registry is the primary cause of this deviation from expectation.

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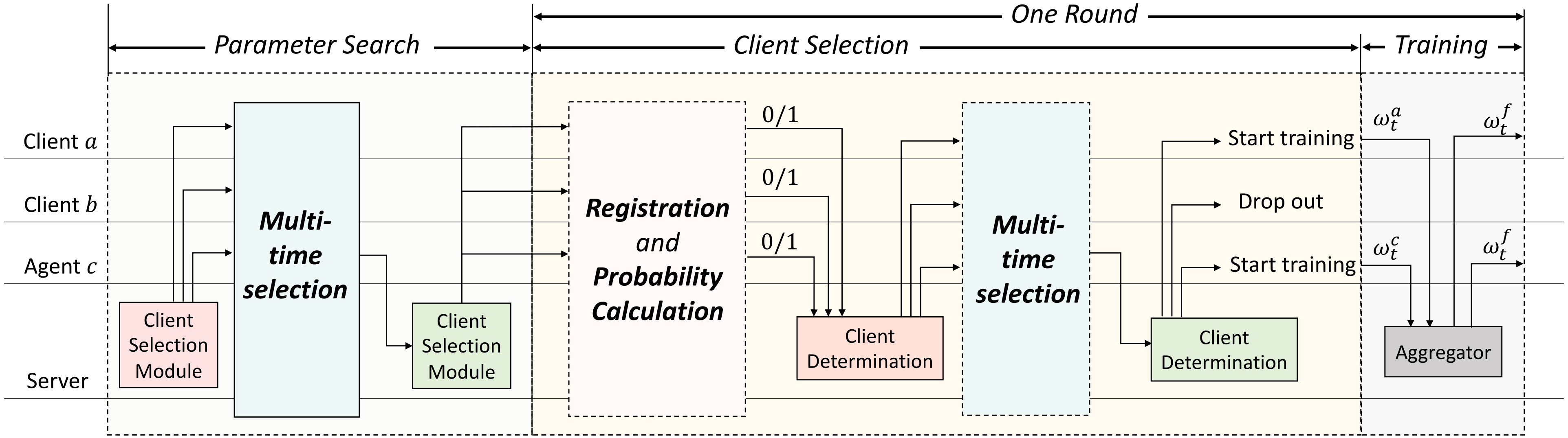
Conclusions

- The impact of data skewness on the performance degradation in FL is mathematically demonstrated.
- We propose ***Dubhe***, a proactive client selection system to balance skewed data
  - pluggable, adaptive and robust to various FL settings
  - with negligible encryption and communication overhead
  - improves the training performance without bringing security threats.



Thanks for listening!

Any questions? Comments? Please contact:

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