Poster ID: TUE-AM-376

Re-thinking Federated Active Learning based on Inter-class Diversity


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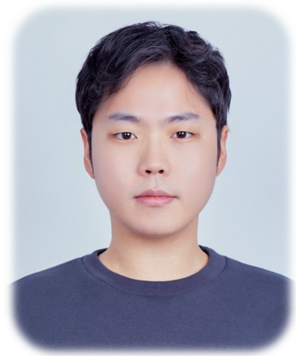
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1 Minute Summary

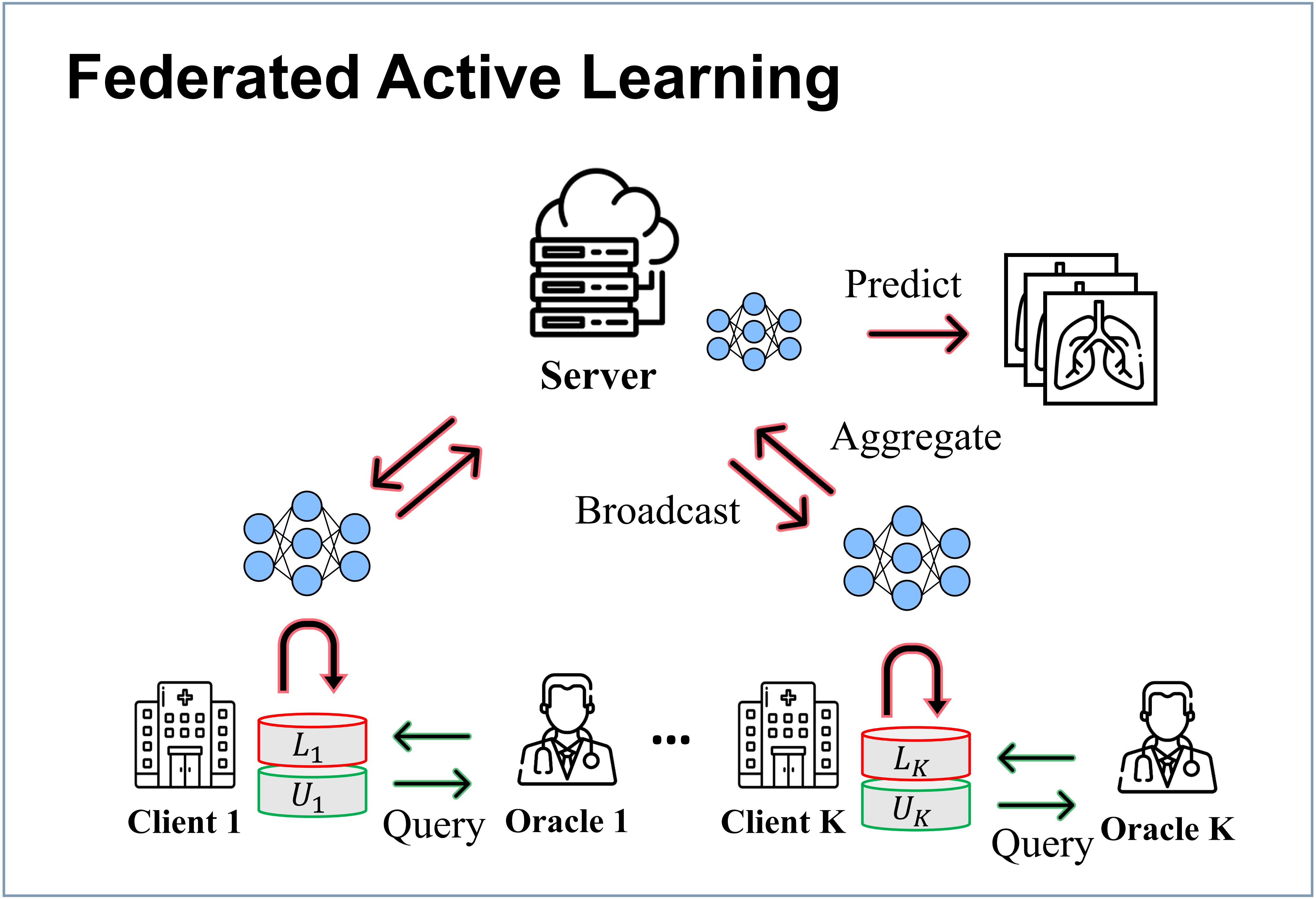
Federated Active Learning(FAL): Select informative samples from client's unlabeled dataset, annotate via Oracle, and use for learning

Federated active learning involves the presence of two query selectors: a global model and a local-only model

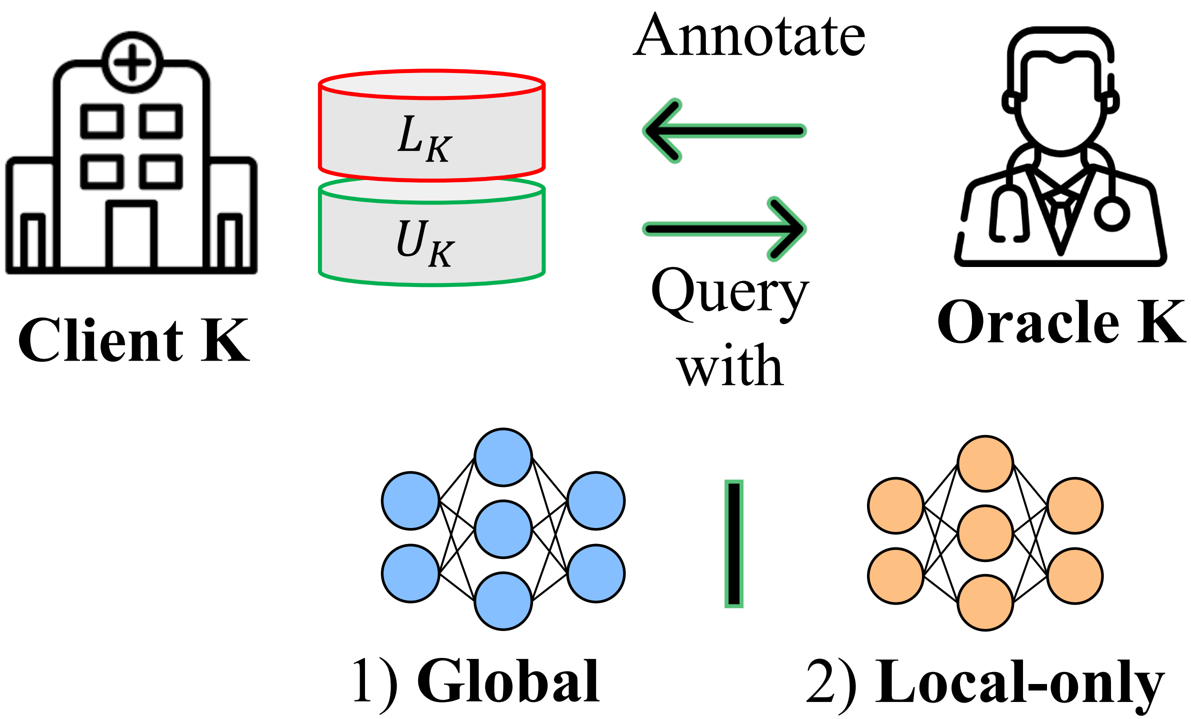
The superiority of global and local models as query selectors in federated active learning stems from inter-class diversity at both global and local levels

We propose LoGo, simultaneously leverages local-only and global models, to be robust to varying heterogeneity levels and global imbalance ratios

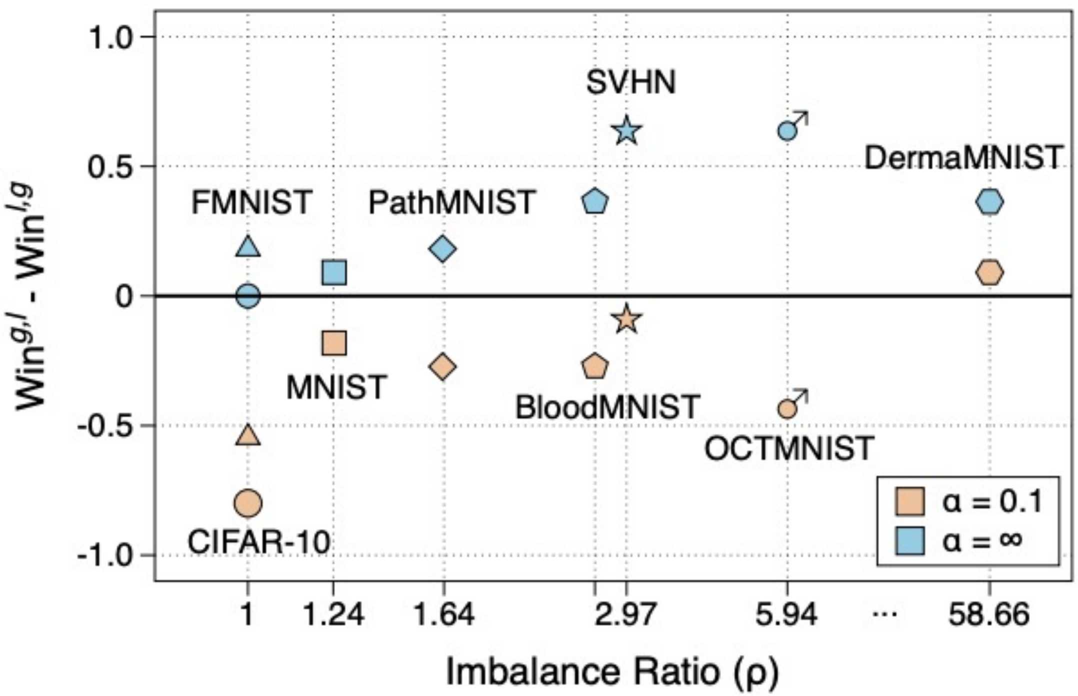
Our experimentation involved 38 total experiment settings conducted on five datasets, encompassing seven active learning strategies including our novel LoGo algorithm


Federated Active Learning
Server
Predict
Aggregate
Broadcast
L_1
U_1
Client 1
Query
Oracle 1
...
L_K
U_K
Client K
Query
Oracle K

Two Query Selector: Global & Local-only



Superiority of Two Query Selectors



$$\rho = \frac{\text{(\# data in major class)}}{\text{(\# of data in minor class)}}$$

We observe superiority changes in varying benchmarks and heterogeneity levels

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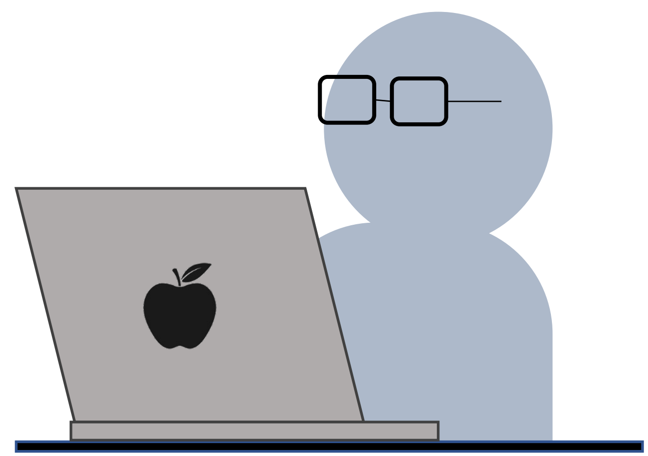
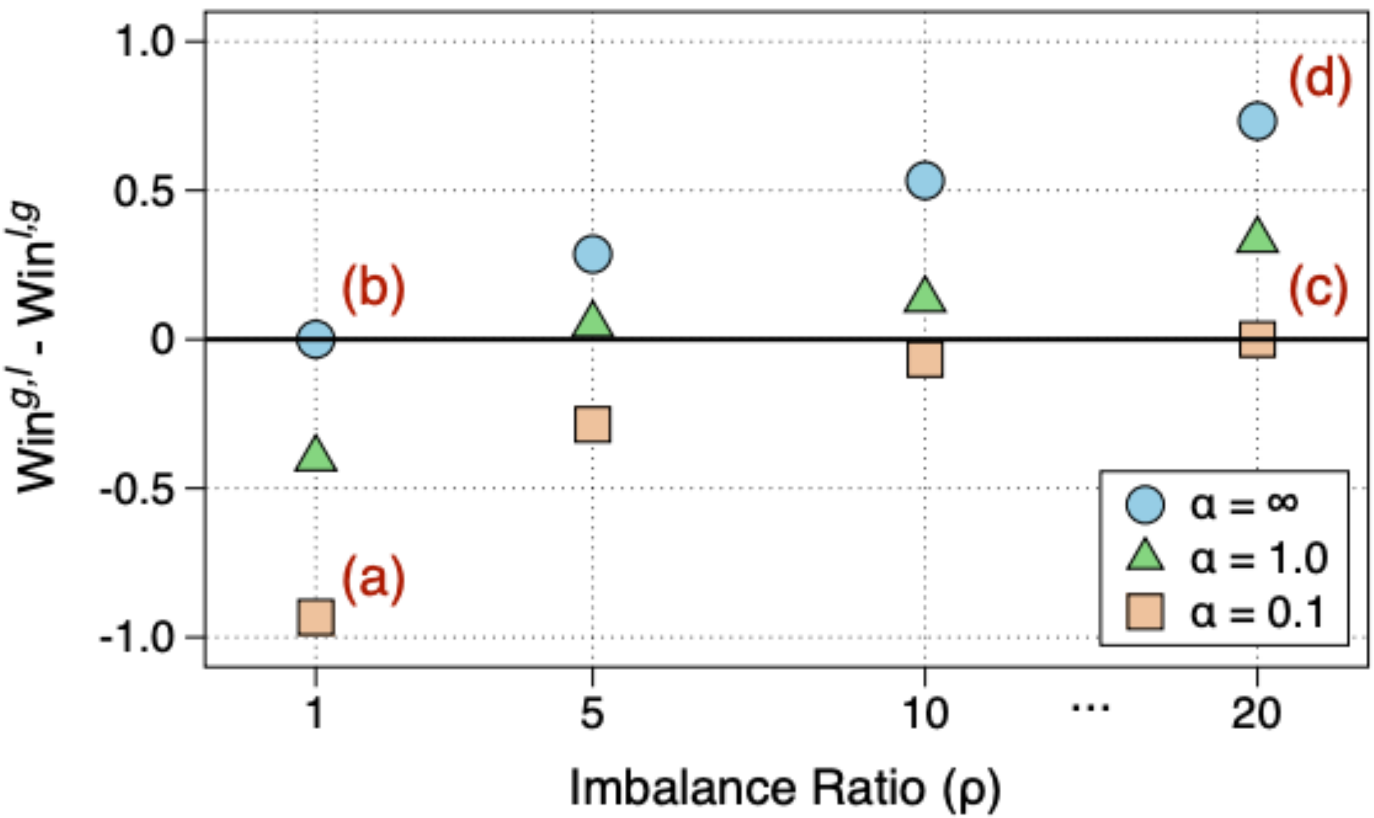
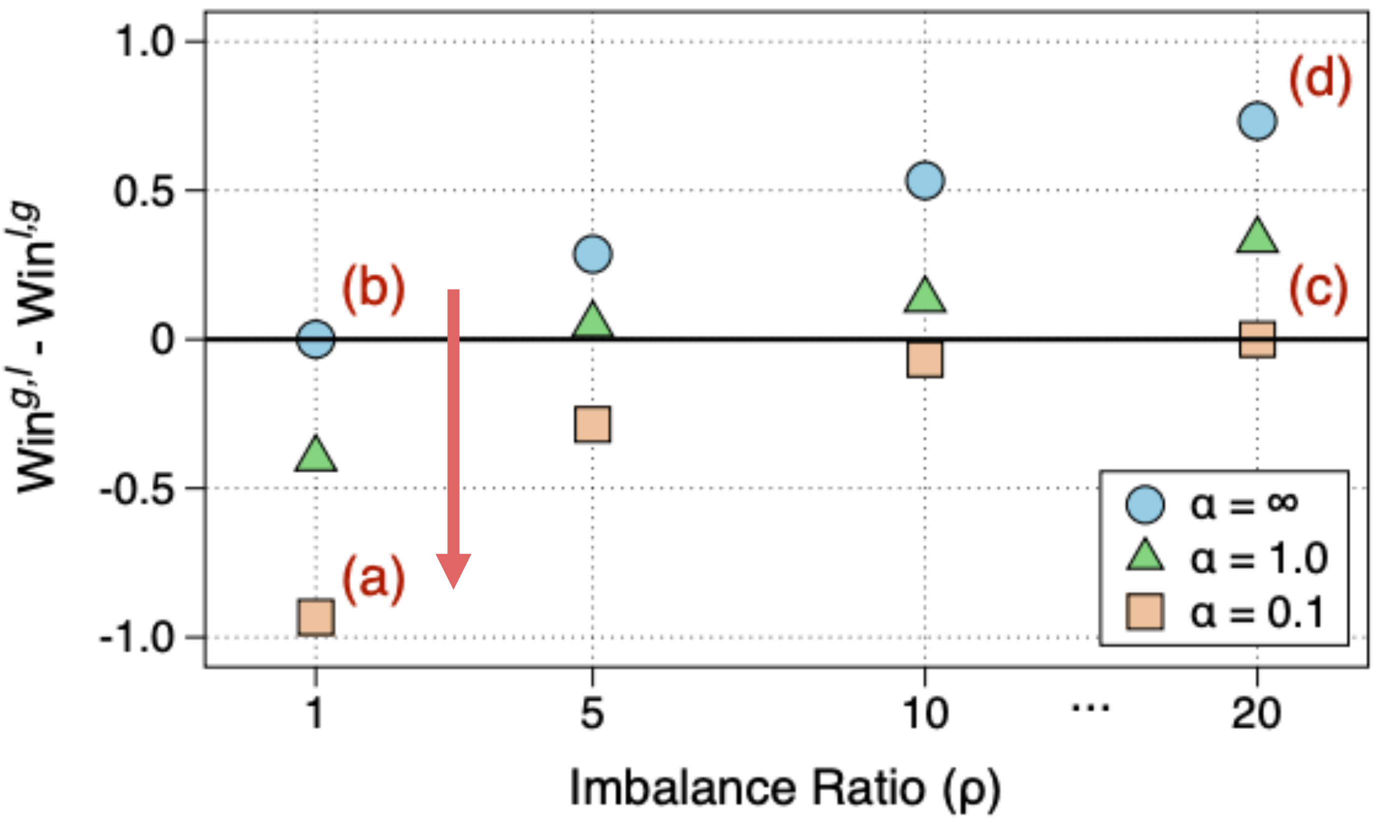


Our Observations



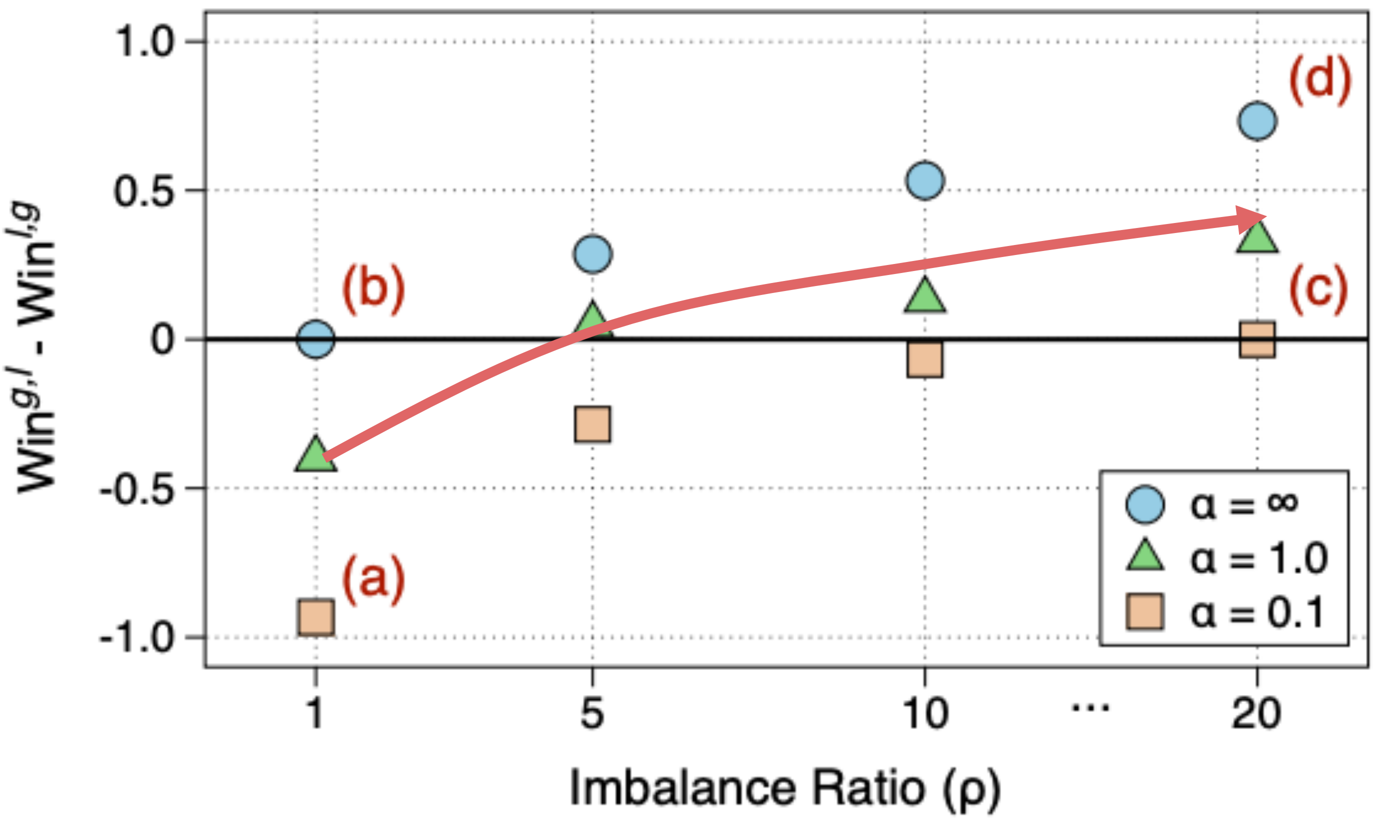
[Observation 1] The superiority of local-only and global query-selecting models varies according to the degree of local heterogeneity and global imbalance ratio

Our Observations



[Observation 2] As local heterogeneity increases, a local-only query selector is preferred due to the increased significance of local inter-class diversity

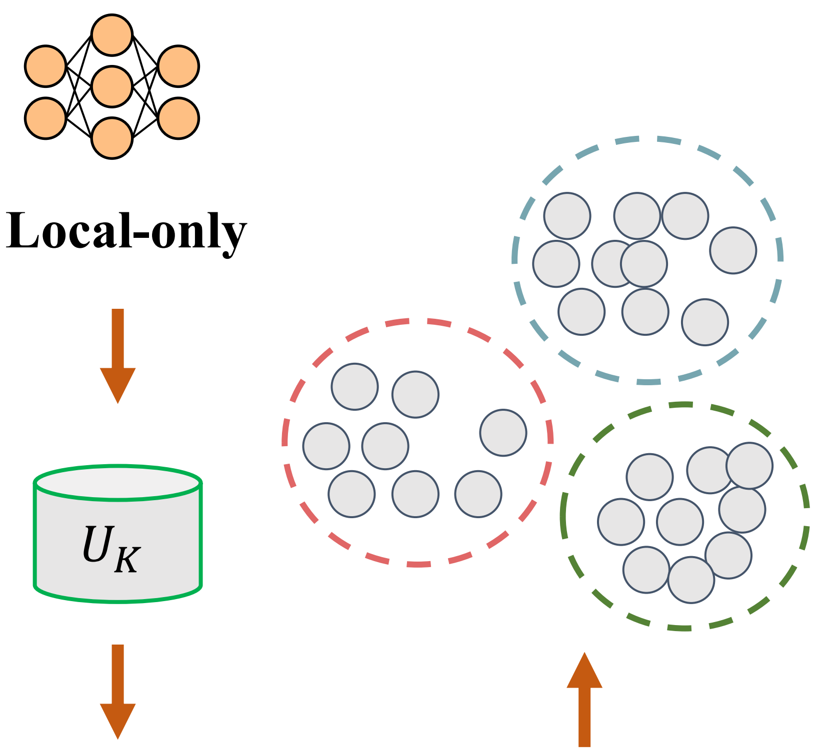
Our Observations



[Observation 3] As the degree of global class imbalance increases, it is more advantageous to exploit a global model that alleviates the global class imbalance

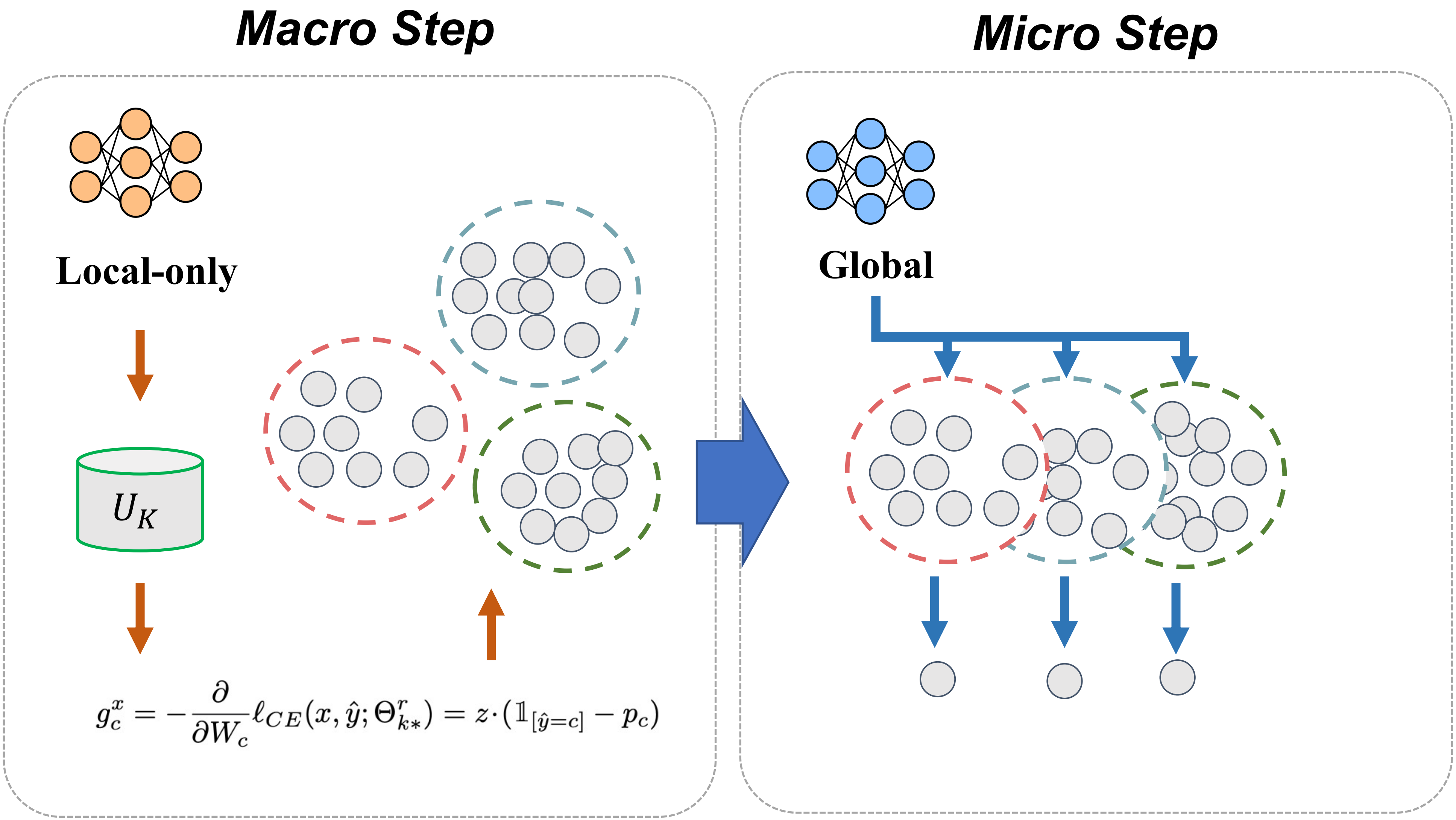
Our Method LoGo

Macro Step



$$g_c^x = -\frac{\partial}{\partial W_c}\ell_{CE}(x,\hat{y};\Theta_{k*}^r) = z\cdot(\mathbb{1}_{[\hat{y}=c]} - p_c)$$

Our Method LoGo



Quantitative Evaluation

Our experimentation involved 38 total experiment settings conducted on five datasets, encompassing seven active learning strategies

Method	Model	CIFAR-10				SVHN				PathMNIST				DermaMNIST			
		20%	40%	60%	80%	20%	30%	40%	50%	20%	30%	40%	50%	20%	30%	40%	50%
Random	-	64.19	69.07	71.63	72.81	80.90	83.07	84.22	84.77	68.41	72.70	73.76	75.49	71.70	72.57	72.66	72.86
Entropy	*G*	64.02	69.12	71.87	73.33	82.08	84.61	85.88	86.31	71.54	74.39	75.91	76.65	72.49	72.63	73.02	73.20
	L	66.29	<u>71.45</u>	<u>73.51</u>	74.02	82.09	84.58	85.69	86.18	**76.52**	<u>78.29</u>	<u>78.71</u>	<u>79.10</u>	71.38	72.04	72.22	72.65
Coreset	*G*	64.66	69.43	71.75	73.1	80.94	82.74	83.81	84.46	74.84	76.24	76.85	76.80	72.02	72.16	72.34	72.74
	L	64.06	68.79	71.49	73.28	80.94	82.92	83.78	84.48	72.53	76.06	76.28	76.86	71.13	71.48	72.15	72.38
BADGE	*G*	65.12	69.57	72.11	73.53	82.81	84.82	85.89	86.2	72.21	74.38	75.53	76.97	<u>72.59</u>	73.09	<u>73.23</u>	<u>73.45</u>
	L	<u>66.32</u>	71.28	73.41	<u>74.28</u>	82.69	84.67	85.61	86.1	76.48	78.51	78.42	78.68	71.35	72.13	72.25	72.99
GCNAL	*G*	65.40	70.05	72.41	73.42	82.05	84.07	85.09	85.61	75.51	77.79	78.13	78.81	72.01	72.60	73.07	73.17
	L	65.62	70.18	72.36	73.42	81.92	83.58	84.55	85.10	74.85	76.46	77.18	77.45	71.95	72.91	72.91	73.29
ALFA-Mix	*G*	65.45	69.87	72.24	73.29	<u>83.02</u>	<u>84.99</u>	**86.05**	<u>86.33</u>	73.34	74.83	76.31	77.43	72.39	<u>73.14</u>	73.27	73.10
	L	64.14	68.79	71.03	72.6	81.08	82.55	83.62	84.33	71.10	75.01	75.81	76.70	71.51	72.18	72.94	73.28
LoGo (ours)	*G, L*	**66.50**	**71.70**	**73.80**	**74.49**	**83.46**	**85.31**	<u>86.02</u>	**86.38**	<u>76.32</u>	**78.72**	**79.51**	**79.58**	**72.61**	**73.18**	**73.33**	**73.77**

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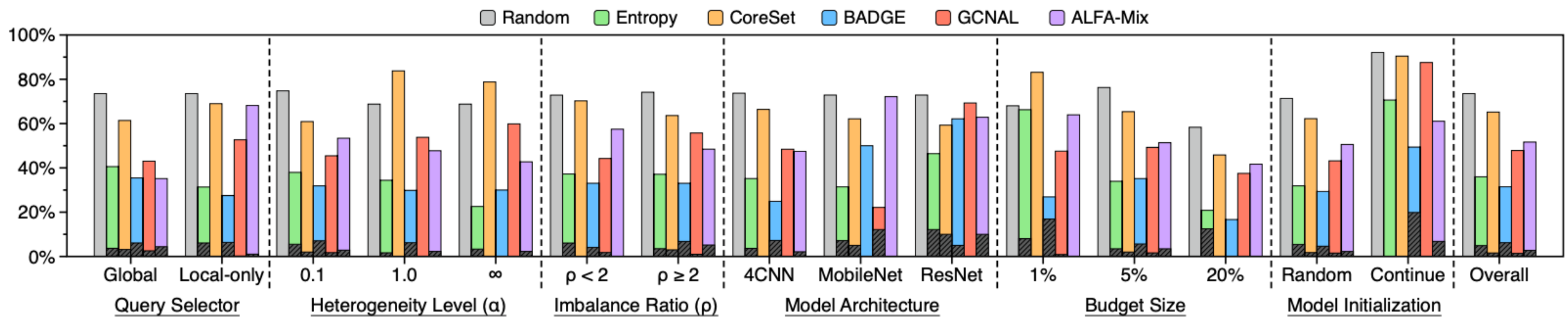

Thank you for listening! 👍

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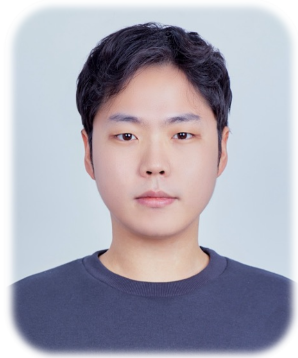

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Codes and more results at

https://github.com/raymin0223/LoGo