

PubSub-VFL: Towards Efficient Two-Party Split Learning in Heterogeneous Environments via Publisher/Subscriber Architecture

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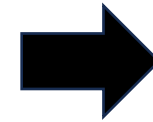
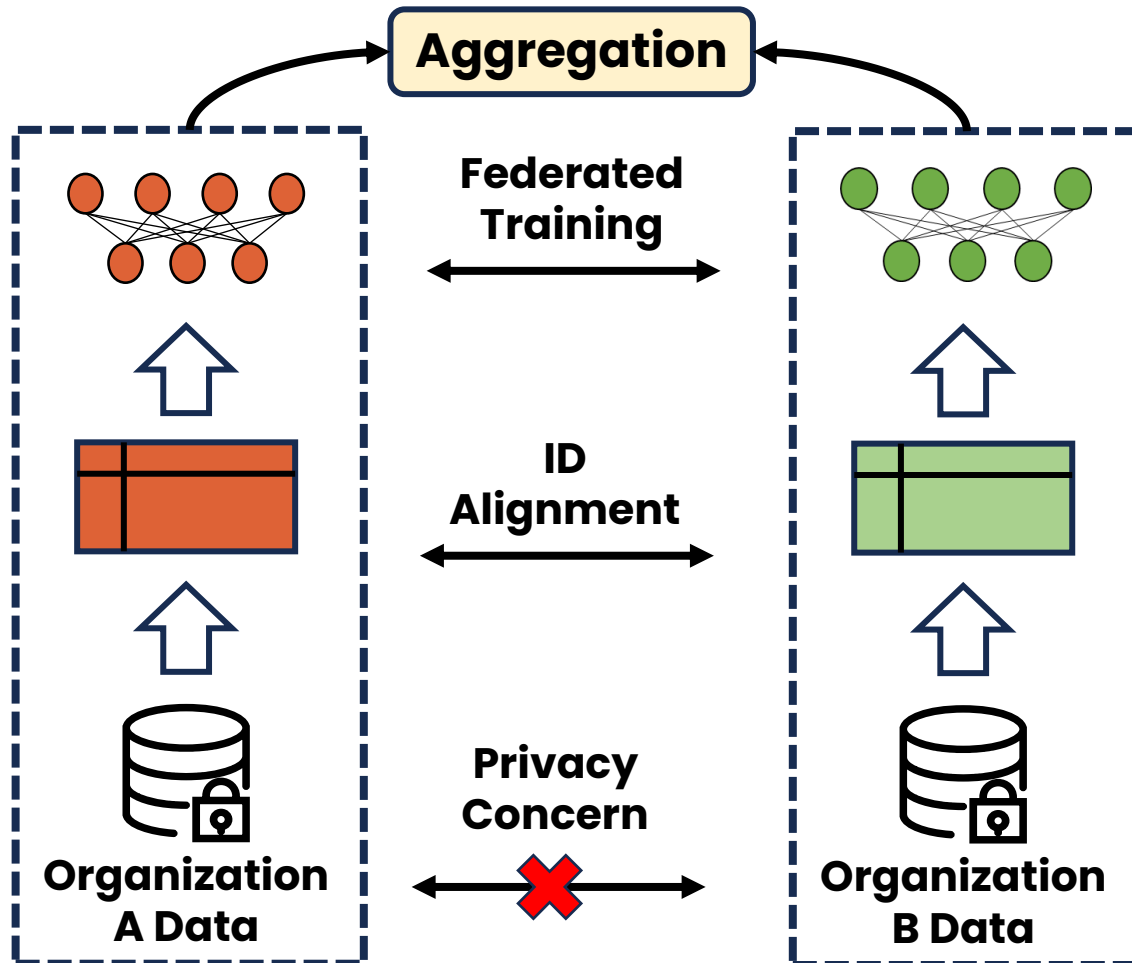


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BACKGROUND

Vertical Federated Learning (VFL) is applicable to the cases that two data sets share the same sample ID space but differ in feature space.



Organization A Data

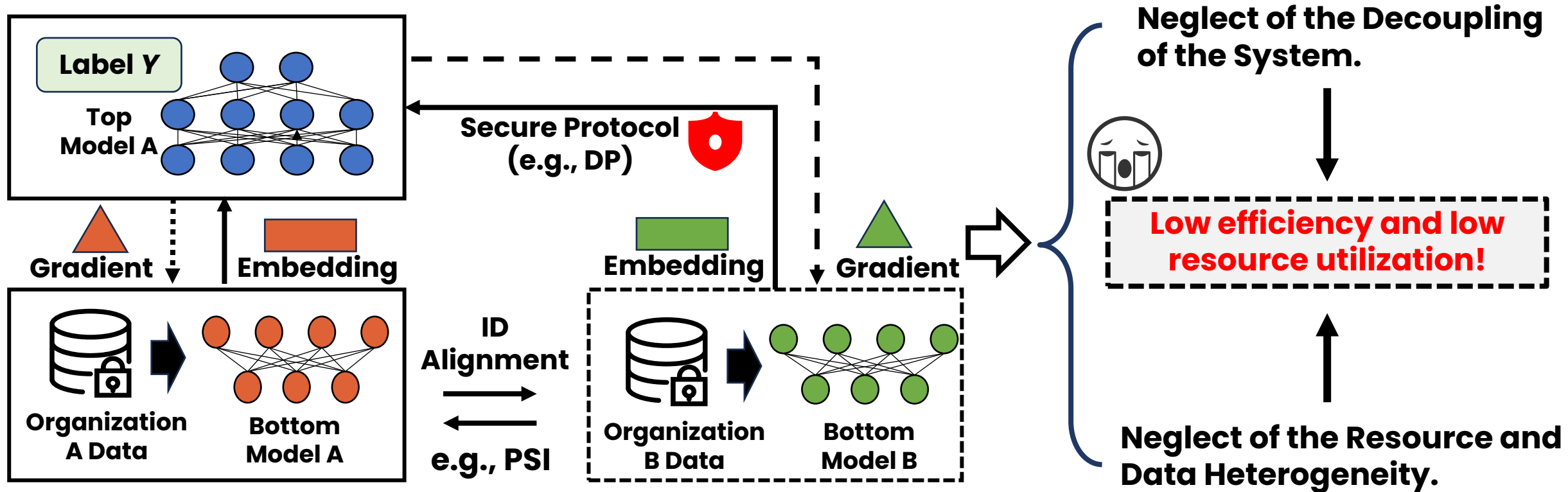
ID	x1	x2	x3	y	
0	value	value	value	0	★
1	value	value	value	1	
2	value	value	value	0	★
3	value	value	value	1	★

Organization B Data

ID	x4	x5	x6	x7	
0	value	value	value	value	★
2	value	value	value	value	★
3	value	value	value	value	★
4	value	value	value	value	

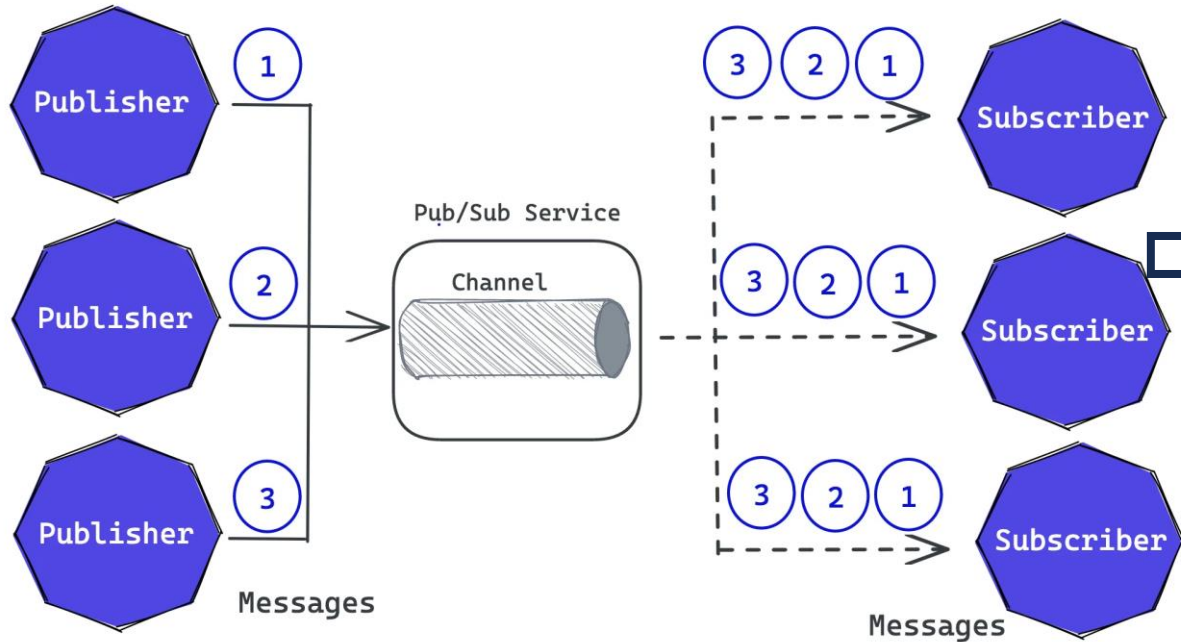
SPLIT LEARNING-BASED VFL

Two-Party Split Learning-based VFL has emerged as a promising solution for secure collaborative learning.

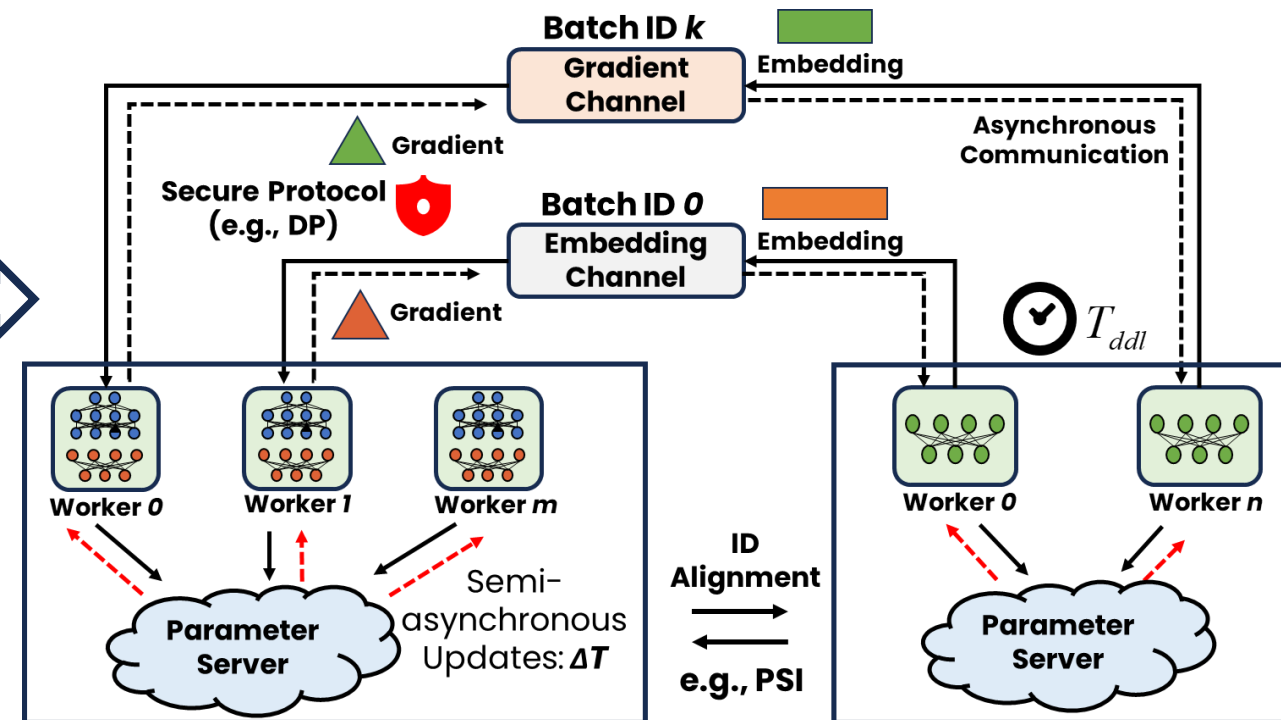


Overview of the split learning-based VFL framework.

Core Design 1: We first leverage the **loose coupling of the PubSub** model to enable asynchronous exchange of gradients and embeddings in VFL, thereby improving efficiency.



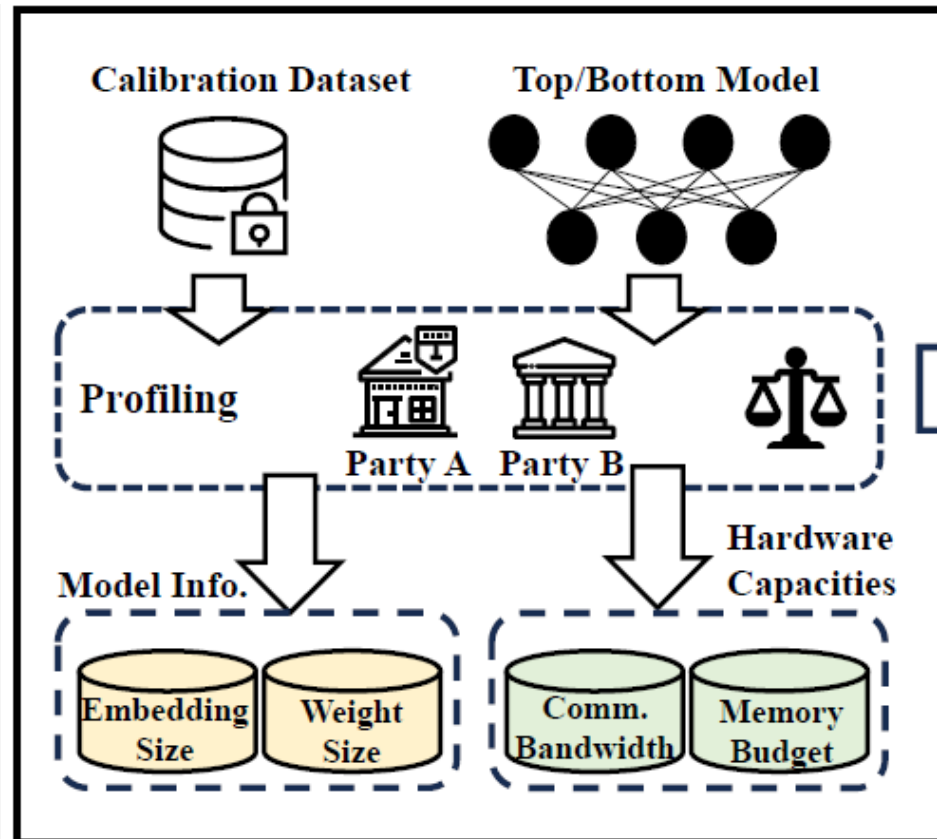
PubSub Model



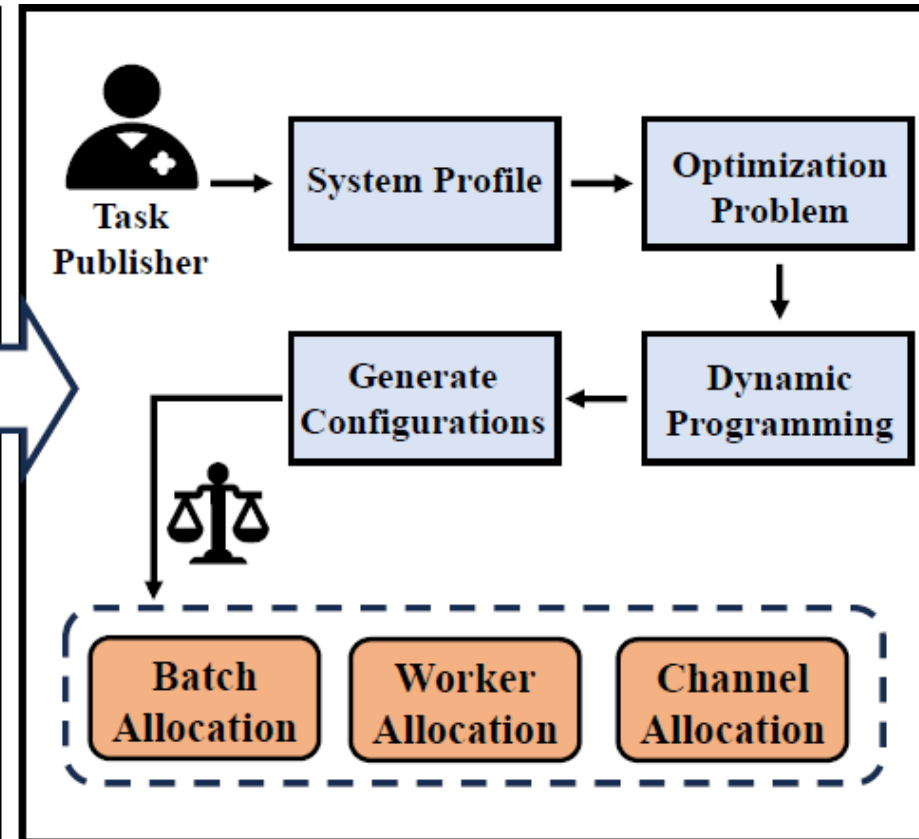
PubSub-VFL Model

Core Design 2: We **formalize an optimization problem** based on participants' system profiles, enabling the selection of optimal hyperparameters while preserving privacy to mitigate the training imbalance caused by resource and data heterogeneity.

System Profiling



Algorithm Design



RESULTS

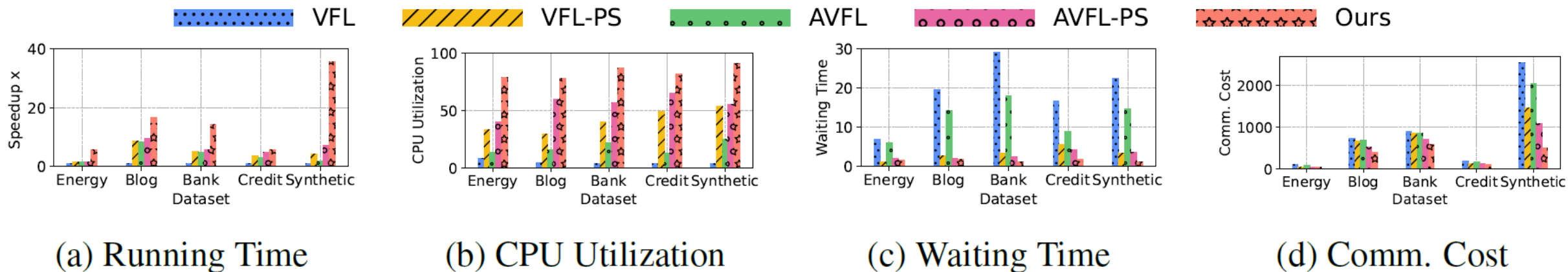


Fig. 1. Comparison with existing baselines in computation and communication efficiency.

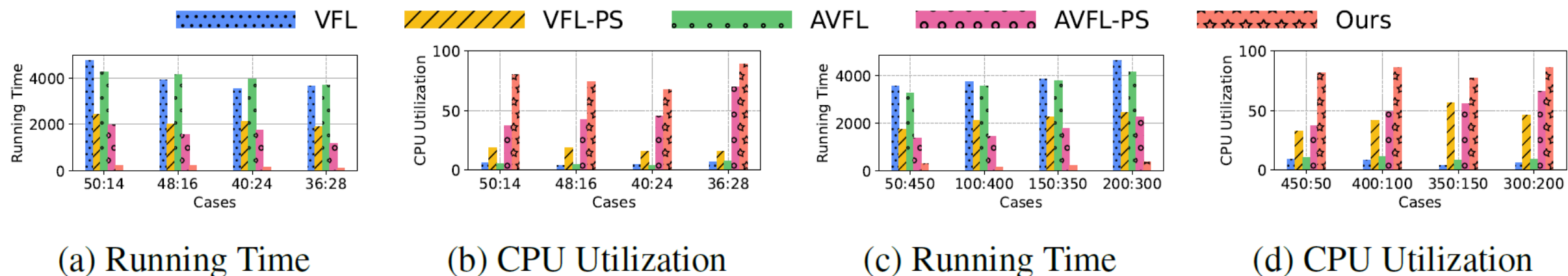


Fig. 2. Comparison with existing baselines on computation efficiency in resource and data heterogeneous scenarios.

RESULTS

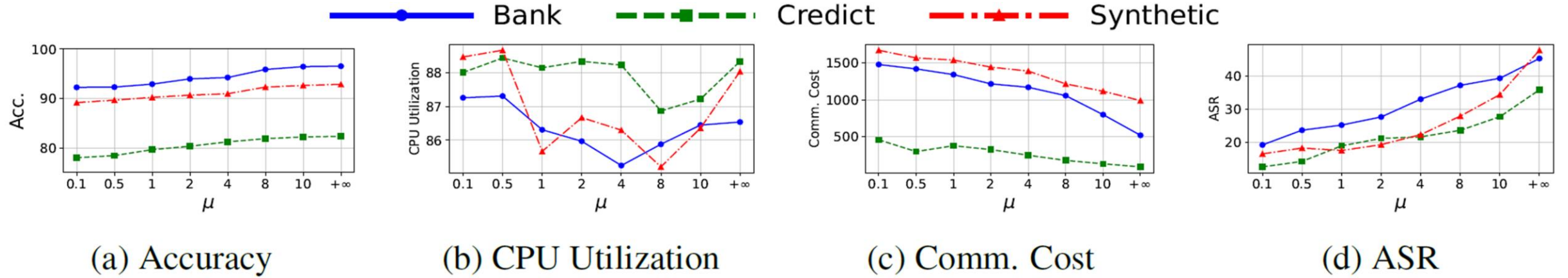


Fig. 3. The impact of privacy budget on the performance, efficiency, and security of PubSub-VFL.

Table 1: Effect of the number of workers.

# of Workers	4	5	8*	10	20	30	50
Acc.(%)	92.13	92.05	92.06	92.28	92.00	92.36	92.21
Time (s)	712.78	805.90	668.11	885.01	1420.32	1067.57	1661.74
CPU (%)	67.52	63.30	88.04	76.18	42.77	40.78	45.12
Waiting (s)	1.4686	1.9273	1.5288	3.461	8.088	9.687	19.843
Comm. (MB)	878.91	1098.63	888.77	1318.36	1867.68	1538.09	2197.27

Table 2: Effect of the different batch size.

Batch Size	16	32	64	128	256	512	1024
Acc.(%)	91.70	92.06	91.75	92.63	92.67	92.36	92.21
Time (s)	987.64	668.11	344.76	124.01	92.54	578.69	865.74
CPU (%)	48.64	88.04	90.12	89.97	91.07	84.47	52.67
Waiting (s)	1.087	1.5288	1.688	1.263	1.1389	1.324	1.789
Comm. (MB)	1298.32	888.77	329.59	439.45	439.45	736.89	1070.36



Thanks for your Listening!