Table 1: Comparison of Algorithms on DTLZ1

	DTLZ1(4)	DTLZ1(5)	DTLZ1(6)
PHN-EPO	11.8155	21.7964	42.6230
PHN-LS	11.9910	23.3634	47.8617
PHN-Tche	9.7352	18.6714	47.2200
COSMOS	11.9769	23.6661	45.4436
PHN-HVI	12.0378	24.4189	49.1362
PHN-HVVS	**12.1652**	**24.5912**	**49.2156**

Table 2: Results of MS Metric under different datasets

Algorithm	MM.	MF.	FM.	Drug	Jura	SAR
PHN-EPO	0.1968	0.2983	0.6766	0.5226	0.2123	0.1420
PHN-LS	0.0752	0.0863	0.1940	0.1570	0.1983	0.1005
PHN-Tche	0.2667	0.4644	0.8286	**0.9722**	0.3632	0.1226
COSMOS	0.2883	0.3010	0.2989	NA	0.1121	0.1500
PHN-HVI	0.4588	0.5350	0.4346	0.3149	0.5760	0.2000
PHN-HVVS	**1**	**1**	**0.9854**	0.6259	**0.8885**	**0.3324**

Table 3: Comparison of Algorithms on Different Problems

Algorithm	Pro.1	Pro.2	Pro.3	Pro.4	Pro.5	Pro.6	Pro.7
PHN-EPO	0.7297	0.9806	0.9982	0.8129	0.9802	0.8316	0.9506
PHN-LS	0.9617	0.9777	0.7071	0.9869	0.9938	0.9854	0.9898
PHN-Tche	0.7859	0.9261	0.9982	0.8204	0.9875	0.8544	0.9887
COSMOS	0.6947	0.9439	0.9948	0.7276	0.9498	0.7136	0.9769
PHN-HVI	0.7344	0.9833	0.9857	0.7159	0.9856	0.7562	0.9894
PHN-HVVS	**1**	**0.9919**	**1**	**0.9988**	**0.9988**	**1**	**0.9937**

Table 4: Comparison of Different Sampling Methods on Jura and SARCOS

	Random	Latin	Polar	Dir	K-means	Voronoi
Jura	0.928	0.922	0.928	0.923	0.925	**0.935**
SARCOS	0.884	0.883	0.881	0.888	0.877	**0.949**

Table 5: Previous FL works

	Peoblem Description
Stable Coalition (KDD'22)	Clients are divided into multiple groups or coalitions. Let $\pi(i)$ denote the unique coalition to which client i belongs. Cui et al. (2022) studied how to form a core-stable coalition structure π such that there is no other coalition $\mathcal{C}$ where every client $i \in \mathcal{C}$ prefers $\mathcal{C}$ over $\pi(i)$. Only clients within the same coalition contribute to each other in the FL network, forming a subgraph of $\mathcal{G}_b$.
Conflict of Interest (AAAI'24)	In cross-silo FL, clients are typically organizations. Clients in the same market area may compete while those in different areas are independent. Tan et al. (2024) extended the principle "the friend of my enemy is my enemy" to prevent clients from benefiting their enemies in collaborative FL, forming a subgraph of $\mathcal{G}_b$.
Free-riders (NeurIPS'24)	Addressing self-interested clients in cross-silo FL, Chen et al. (2024) proposed a framework to simultaneously eliminate free riders (who benefit without contributing) and avoid conflict of interest between clients, forming a subgraph of $\mathcal{G}_b$.

Table 6: Results comparison on different problems.

	PHN-EPO	PHN-LS	PHN-TCHE	COSMOS	PHN-HVI	PHN-HVVS
Pro.1	3.790±0.007230	3.832±0.000526	3.813±0.005223	3.210±0.736292	3.791±0.002538	**3.833±0.000026**
Pro.2	3.304±0.063656	3.362±0.016258	3.321±0.086994	3.344±0.043419	3.374±0.011347	**3.387±0.007168**
Pro.3(DTLZ4)	7.380±0.010358	6.020±1.096984	7.267±0.010933	7.236±0.010072	7.383±0.005471	**7.386±0.003612**
Pro.4(ZDT1)	3.651±0.075391	3.654±0.085641	NA	3.631±0.036321	3.520±0.012252	**3.735±0.001754**
Pro.5(ZDT2)	2.047±1.094539	2.0±0	2.800±0.652913	3.057±0.528525	3.321±0.022386	**3.323±0.004026**
Pro.6(VLMOP1)	3.810±0.003677	3.825±0.010152	3.816±0.006643	3.747±0.012842	3.782±0.000523	**3.829±0.000629**
Pro.7(VLMOP2)	3.308±0.020874	3.313±0.021368	3.329±0.012204	3.299±0.014255	3.335±0.001013	**3.339±0.000001**

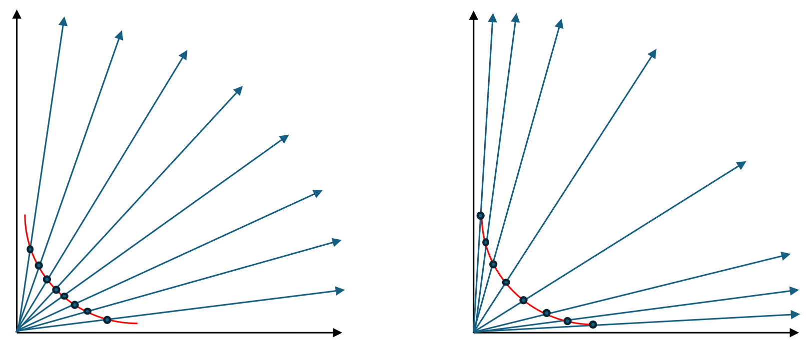

Figure 1: The solutions obtained by uniformly sampling will cluster in certain local areas.

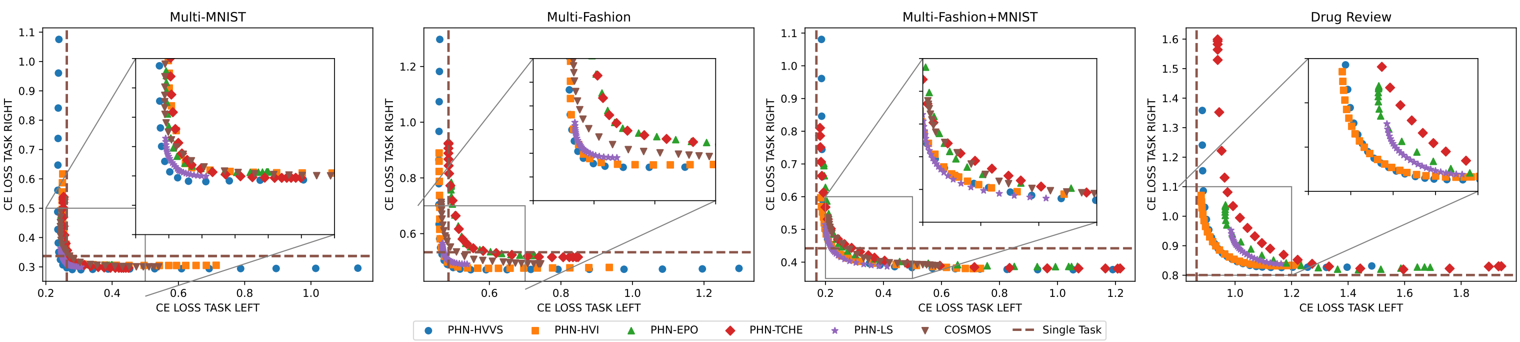

Figure 2: Results comparison on different Multi-Task Dataset.