



Figure 1. Comparison of OOD Spearman rank correlation on Superconductor task between UniSO-N from pre-trained embedder (blue) and from scratch (red). The OOD dataset is constructed following [Chen et al. \(2023\)](#). Higher correlation indicates better surrogate model for offline BBO ([Tan et al., 2025](#)).

Table S1. Computational resources comparison between improved UniSO-N and UniSO-T. All measurements are conducted on a machine with 4 RTX 4090 D GPUs and AMD EPYC 9754 128-Core Processor.

	Training	Search (one task)	GPU memory
UniSO-N	22530s	44s	21G
UniSO-T	71225s	203s	89G

Table S2. Ablation studies on different metadata components (name, description, and objective) on various tasks. All experiments are conducted based on improved UniSO-T. The first part includes tasks appearing in training dataset, i.e., unconstrained tasks from Design-Bench and SOO-Bench. The remaining two parts contain unseen tasks during training, where we compare them under both zero-shot and few-shot settings. The best and runner-up results on each task are **Blue** and **Violet**.  $\mathcal{D}(\text{best})$  denotes the best score in the offline dataset.

Task	$\mathcal{D}(\text{best})$	UniSO-T	w/o name	w/o desc.	w/o obj.	w/o metadata
Ant	165.326	<b>374.665 <math>\pm</math> 56.057</b>	345.369 $\pm$ 40.675	362.842 $\pm$ 33.008	<b>363.812 <math>\pm</math> 59.380</b>	358.379 $\pm$ 64.211
D’Kitty	199.363	225.752 $\pm$ 8.521	<b>235.715 <math>\pm</math> 11.617</b>	226.479 $\pm$ 15.311	<b>245.135 <math>\pm</math> 15.571</b>	227.169 $\pm$ 12.278
Superconductor	74.000	92.200 $\pm$ 15.209	85.207 $\pm$ 6.261	<b>99.113 <math>\pm</math> 12.742</b>	<b>97.610 <math>\pm</math> 10.297</b>	90.871 $\pm$ 10.611
TF Bind 8	0.439	0.903 $\pm$ 0.041	<b>0.954 <math>\pm</math> 0.025</b>	0.935 $\pm$ 0.041	0.937 $\pm$ 0.012	<b>0.950 <math>\pm</math> 0.025</b>
TF Bind 10	0.005	<b>0.823 <math>\pm</math> 0.542</b>	<b>0.696 <math>\pm</math> 0.126</b>	0.664 $\pm$ 0.141	0.596 $\pm$ 0.148	0.651 $\pm$ 0.121
GTOPX 2	-195.586	<b>-72.848 <math>\pm</math> 9.576</b>	-97.806 $\pm$ 40.646	<b>-63.670 <math>\pm</math> 20.381</b>	-80.789 $\pm$ 8.908	-79.864 $\pm$ 13.338
GTOPX 3	-151.190	<b>-45.602 <math>\pm</math> 8.433</b>	-50.788 $\pm$ 8.706	<b>-45.981 <math>\pm</math> 4.211</b>	-50.660 $\pm$ 10.713	-48.178 $\pm$ 12.638
GTOPX 4	-215.716	-84.271 $\pm$ 8.307	-84.962 $\pm$ 11.300	-92.163 $\pm$ 9.529	<b>-75.233 <math>\pm</math> 5.734</b>	<b>-79.887 <math>\pm</math> 14.729</b>
GTOPX 6	-112.599	-47.794 $\pm$ 11.943	<b>-42.181 <math>\pm</math> 11.671</b>	<b>-45.591 <math>\pm</math> 12.310</b>	-48.050 $\pm$ 13.901	-45.764 $\pm$ 7.685
RobotPush (zero-shot)	0.102	<b>3.171 <math>\pm</math> 0.984</b>	2.747 $\pm$ 1.455	<b>3.416 <math>\pm</math> 1.455</b>	2.634 $\pm$ 0.953	2.517 $\pm$ 1.640
Rover (zero-shot)	-16.148	<b>-8.888 <math>\pm</math> 2.119</b>	-11.009 $\pm$ 0.598	-10.854 $\pm$ 0.859	<b>-9.099 <math>\pm</math> 2.202</b>	-9.089 $\pm$ 3.070
LunarLander (zero-shot)	7.038	<b>31.186 <math>\pm</math> 27.971</b>	30.105 $\pm$ 57.577	30.892 $\pm$ 54.657	<b>52.108 <math>\pm</math> 47.941</b>	6.251 $\pm$ 53.042
RobotPush (few-shot)	0.102	<b>7.067 <math>\pm</math> 0.169</b>	7.026 $\pm$ 0.219	<b>7.129 <math>\pm</math> 0.486</b>	6.310 $\pm$ 1.677	6.155 $\pm$ 1.495
Rover (few-shot)	-16.148	<b>-8.239 <math>\pm</math> 1.270</b>	-8.850 $\pm$ 0.703	<b>-8.084 <math>\pm</math> 0.569</b>	-8.342 $\pm$ 1.573	-10.511 $\pm$ 2.070
LunarLander (few-shot)	7.038	<b>248.573 <math>\pm</math> 45.386</b>	226.726 $\pm$ 65.244	<b>244.252 <math>\pm</math> 38.329</b>	233.169 $\pm$ 51.037	233.919 $\pm$ 60.467
Avg. Rank	/	<b>2.333 <math>\pm</math> 1.350</b>	3.600 $\pm$ 1.451	<b>2.467 <math>\pm</math> 1.310</b>	3.067 $\pm$ 1.340	3.533 $\pm$ 1.087

Table S3. Ablation studies of loss balancing strategy in improved UniSO-T on unconstrained tasks from Design-Bench and SOO-Bench, where the better one is **Bold**.  $\mathcal{D}(\text{best})$  denotes the best score in the offline dataset.

Task	$\mathcal{D}(\text{best})$	UniSO-T w/ balance	UniSO-T w/o balance
Ant	165.326	<b>374.665 <math>\pm</math> 56.057</b>	185.597 $\pm$ 165.661
D’Kitty	199.363	<b>225.752 <math>\pm</math> 8.521</b>	203.553 $\pm$ 32.507
Superconductor	74.000	<b>92.200 <math>\pm</math> 15.209</b>	79.635 $\pm$ 5.777
TF Bind 8	0.439	0.903 $\pm$ 0.041	<b>0.929 <math>\pm</math> 0.049</b>
TF Bind 10	0.005	<b>0.823 <math>\pm</math> 0.542</b>	0.696 $\pm$ 0.126
GTOPX 2	-195.586	<b>-72.848 <math>\pm</math> 9.576</b>	-175.327 $\pm$ 73.053
GTOPX 3	-151.190	<b>-45.602 <math>\pm</math> 8.433</b>	-56.221 $\pm$ 18.342
GTOPX 4	-215.716	<b>-84.271 <math>\pm</math> 8.307</b>	-122.291 $\pm$ 54.913
GTOPX 6	-112.599	<b>-47.794 <math>\pm</math> 11.943</b>	-70.352 $\pm$ 25.870
Avg. Rank	/	<b>1.111 <math>\pm</math> 0.314</b>	1.889 $\pm$ 0.314

Table S4. Performance comparison between UniSO-N with pre-trained and randomly initialized embedders on Design-Bench and SOO-Bench unconstrained tasks, where the better one is **Bold**.  $\mathcal{D}(\text{best})$  denotes the best score in the offline dataset.

Task	$\mathcal{D}(\text{best})$	UniSO-N from scratch	UniSO-N from pre-trained
Ant	165.326	<b>305.576 <math>\pm</math> 120.465</b>	269.691 $\pm$ 77.425
D’Kitty	199.363	<b>223.104 <math>\pm</math> 23.838</b>	173.911 $\pm$ 46.662
Superconductor	74.000	<b>101.754 <math>\pm</math> 6.972</b>	67.333 $\pm$ 10.838
TF Bind 8	0.439	<b>0.883 <math>\pm</math> 0.048</b>	0.833 $\pm$ 0.005
TF Bind 10	0.005	0.578 $\pm$ 0.108	<b>0.959 <math>\pm</math> 0.115</b>
GTOPX 2	-195.586	<b>-102.632 <math>\pm</math> 22.635</b>	-124.995 $\pm$ 56.170
GTOPX 3	-151.190	<b>-55.743 <math>\pm</math> 7.490</b>	-62.622 $\pm$ 22.261
GTOPX 4	-215.716	<b>-102.684 <math>\pm</math> 19.227</b>	-110.284 $\pm$ 17.559
GTOPX 6	-112.599	<b>-56.469 <math>\pm</math> 10.337</b>	-57.435 $\pm$ 18.832
Avg. Rank	/	<b>1.111 <math>\pm</math> 0.314</b>	1.889 $\pm$ 0.314