Table 1: The comparison results with pre-training methods ($\mathrm{F}_{\max}$) on GO term and EC number prediction. The best results are shown in bold.

Category	Method	GO-BP	GO-MF	GO-CC	EC
Sequence	ESM-1b [1]	0.452	0.659	0.477	0.869
	ESM-2 [2]	0.472	0.662	0.472	0.874
Sequence-Function	ProtST-ESM-1b [3]	0.480	0.661	0.488	0.878
	ProtST-ESM-2 [3]	0.482	0.668	0.487	0.878
	DeepGO-SE [4]	0.438	0.564	0.427	0.810
Sequence-Structure	ESM-GearNet [5]	0.516	0.684	0.506	0.890
	GearNet-ESM-INR-MC [6]	0.518	0.683	0.504	**0.896**
	SaProt [7]	0.356	0.678	0.414	0.884
	ProtGO-ESM (Student)	**0.520**	**0.693**	**0.536**	0.887

Table 2: Experimental results comparison on the CATH dataset (inverse folding).

Model	Perplexity ↑			Recovery (%) ↓		
	Short	Single	All	Short	Single	All
ESM-IF [8]	8.18	6.33	6.44	31.30	38.50	38.30
PiFold [9]	6.04	6.31	4.55	39.84	38.53	51.66
VFN-IF [10]	5.70	5.86	4.17	41.34	40.98	54.74
ProtGO (Ours)	**5.65**	**5.70**	**4.08**	**42.88**	**41.03**	**55.21**

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