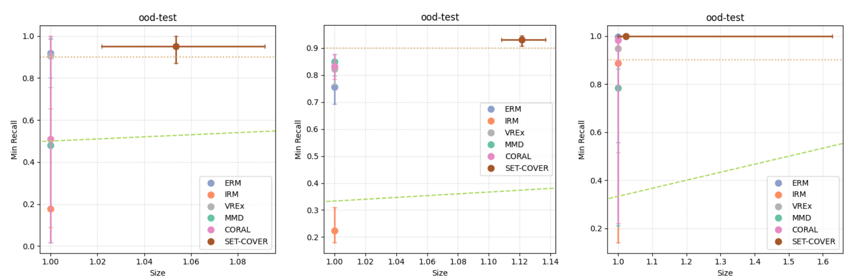
1 Experiments on Other OOD Baselines

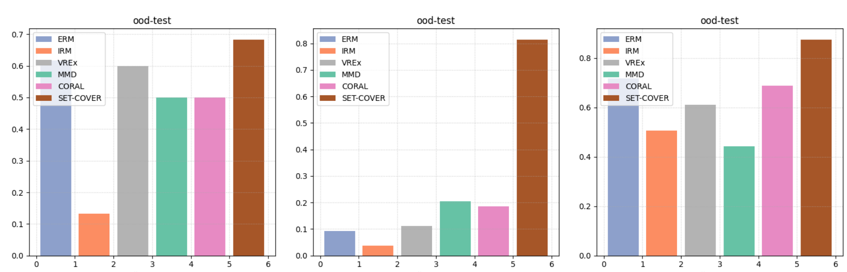
For the main experiments of this work we chose the ERM method as the single-prediction basekine, due to its vast popularity in real-world applications, and its superior, or at least compatible performance in various OOD baselines [Koh et al., 2021, Gulrajani and Lopez-Paz, 2020]. In the next section we compare SET-COVER to additional common OOD baselines. These include IRM [Arjovsky et al., 2019], VREx [Krueger et al., 2021], MMD [Li et al., 2018], and CORAL [Sun and Saenko, 2016]. We use the DomainBed [Gulrajani and Lopez-Paz, 2020] package to train these models.

The results show an advantage for SET-COVER over common single-prediction baselines in maintaining the 90% min-recall target across unseen domains. These results suggest that set-valued predictors may be a step in the right direction for robust OOD generalization.



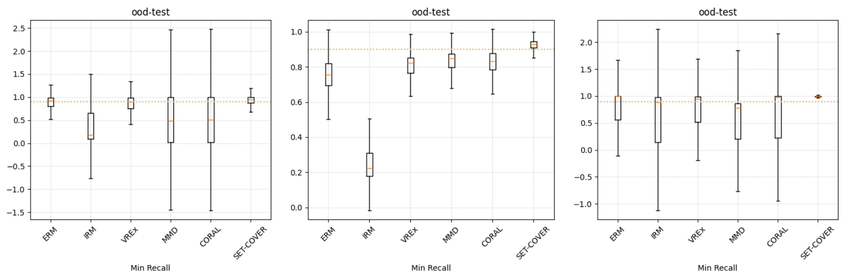
(a) Camelyon (b) FMoW (c) iWildCam

Figure 1: Each figure represents Min-Recall over Avg Set Size cross. y-axis represents min-recall, and x-axis represents average set size. Each cross shows the median and the 25th and 75th percentiles for both metrics across domain. The horizontal solid line represents the 90% recall target value, and dashed yellow diagonal line represents performance of a random predictor.



(a) Camelyon (b) FMoW (c) iWildCam

Figure 2: Percentage of OOD domains where the min-recall is higher than 90%. Each bar represents a different model.



(a) Camelyon (b) FMoW (c) iWildCam

Figure 3: Boxplots represent the distribution of min-recall across OOD domains.

Table 1: Summary of OOD Results for different OOD baselines.

Model	**Camelyon**			**FMoW**		
	Median Min Recall ↑	Median Avg Size ↓	Recall $\geq$ 90% Pctg ↑	Median Min Recall ↑	Median Avg Size ↓	Recall $\geq$ 90% Pctg ↑
ERM	0.91	1.0	0.61	0.75	1.0	0.09
IRM	0.17	1.00	0.13	0.22	1.00	0.03
VREx	0.90	1.00	0.60	0.82	1.00	0.11
MMD	0.48	1.00	0.50	0.84	1.00	0.20
CORAL	0.50	1.00	0.50	0.83	1.00	0.18
SET-COVER	0.95	1.05	0.68	0.93	1.12	0.81

Model	**iWildCam**		
	Median Min Recall ↑	Median Avg Size ↓	Recall $\geq$ 90% Pctg ↑
ERM	0.99	1.0	0.71
IRM	0.88	1.00	0.50
VREx	0.94	1.00	0.60
MMD	0.78	1.00	0.44
CORAL	0.98	1.00	0.68
SET-COVER	1.00	1.02	0.87

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