Pushing the Limits of Simple Pipelines for Few-Shot Learning: External Data and Fine-Tuning Make a Difference

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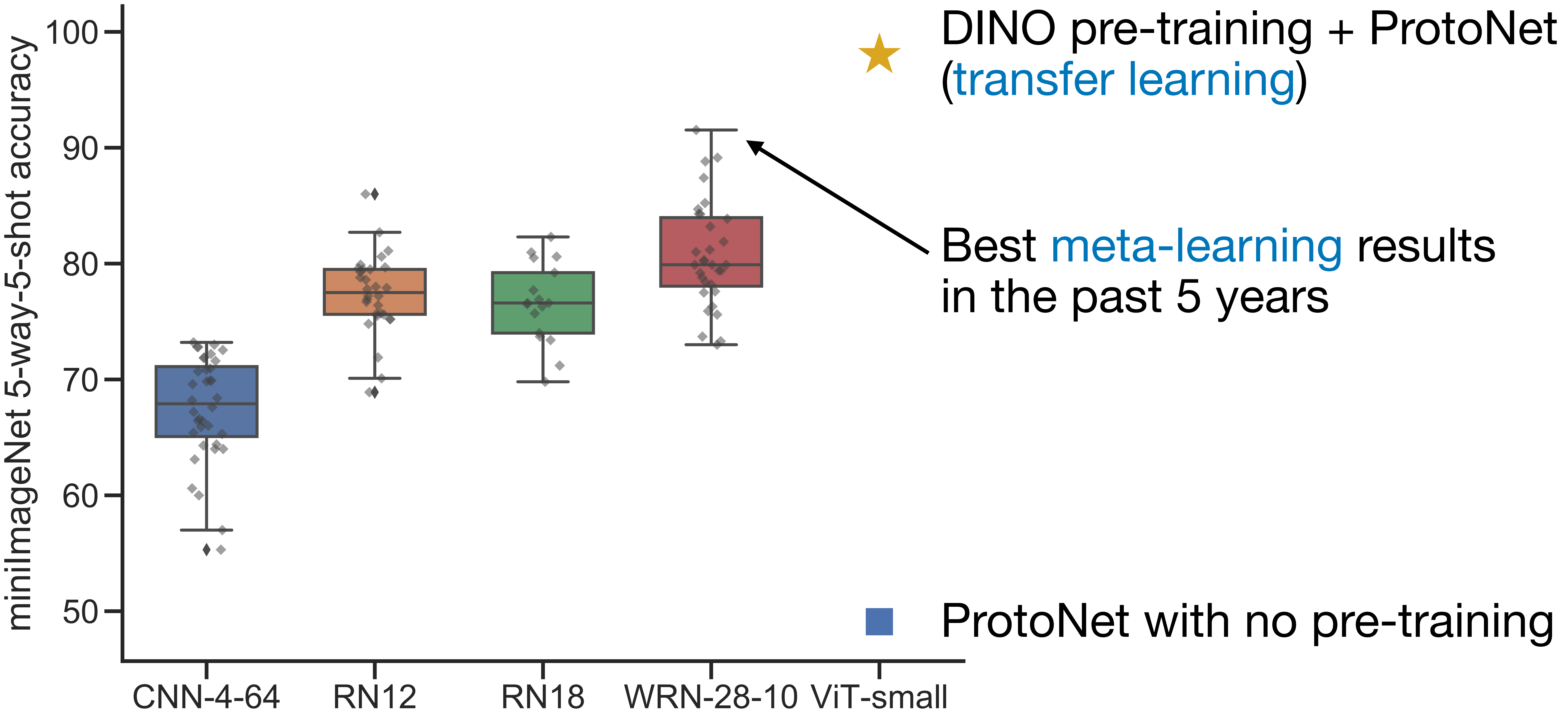
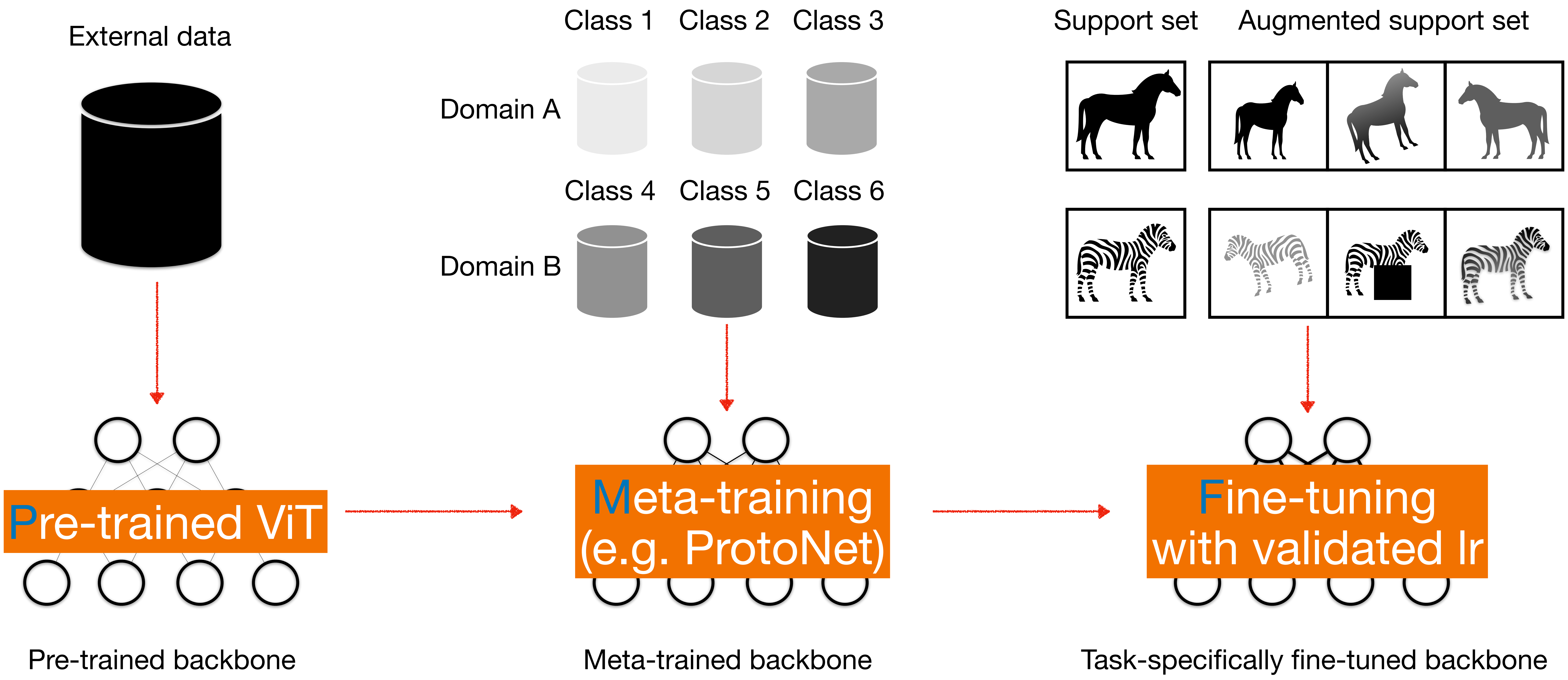
Does few-shot classification need fancy meta-learning?



What is our recipe for a transfer learning pipeline?



Questions behind the recipe

- Q1: How does pre-training regime affect few-shot learning?
- Q2: Is ViT better suited for few-shot learning?
- Q3: How to best exploit fine-tuning for meta-testing?

Q1: How does pre-training regime affect FSL?

Training Configuration				Benchmark Results		
ID	Arch	Pre Train	MetaTr	MD	miniIN	CIFAR
0	ViT-small	DINO (IN1K)	-	67.4	97.0	79.8
1	ViT-small	DeiT (IN1K)	-	67.5	98.8	84.6
2	ResNet50	DINO (IN1K)	-	63.8	91.5	76.1
3	ResNet50	Sup. (IN1K)	-	62.4	96.4	82.3
4	ViT-small	DINO (IN1K)	PN	78.4	98.0	92.5
5	ViT-small	DEIT (IN1K)	PN	79.3	99.4	93.6
6	ViT-small	-	PN	52.8	49.1	59.8
7	ResNet50	DINO (IN1K)	PN	72.4	92.0	84.0
8	ResNet50	Sup. (IN1K)	PN	70.2	97.4	87.6
9	ResNet50	-	PN	62.9	72.2	68.4
10	ResNet18	-	PN	63.3	73.7	70.2
11	ViT-base	DINO (IN1k)	PN	79.2	98.4	92.2
12	ViT-base	CLIP (YFCC)	PN	80.0	98.1	93.2
13	ViT-base	Sup (IN21K)	PN	81.4	99.2	96.7
14	ViT-base	BEIT (IN21K)	PN	82.8	99.0	97.5
15	ResNet50	CLIP (YFCC)	PN	75.0	92.2	82.6

Pre-training alone may be > ProtoNet (PN) baseline

Without pre-training larger networks can be worse: e.g., ResNet50 < ResNet18

Pre-training offers a strong feature to boost PN baseline

Q2: Is ViT better suited for FSL?

Training Configuration				Benchmark Results		
ID	Arch	Pre Train	MetaTr	MD	miniIN	CIFAR
0	ViT-small	DINO (IN1K)	-	67.4	97.0	79.8
1	ViT-small	DeiT (IN1K)	-	67.5	98.8	84.6
2	ResNet50	DINO (IN1K)	-	63.8	91.5	76.1
3	ResNet50	Sup. (IN1K)	-	62.4	96.4	82.3
4	ViT-small	DINO (IN1K)	PN	78.4	98.0	92.5
5	ViT-small	DEIT (IN1K)	PN	79.3	99.4	93.6
6	ViT-small	-	PN	52.8	49.1	59.8
7	ResNet50	DINO (IN1K)	PN	72.4	92.0	84.0
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14	ViT-base	BEIT (IN21K)	PN	82.8	99.0	97.5
15	ResNet50	CLIP (YFCC)	PN	75.0	92.2	82.6

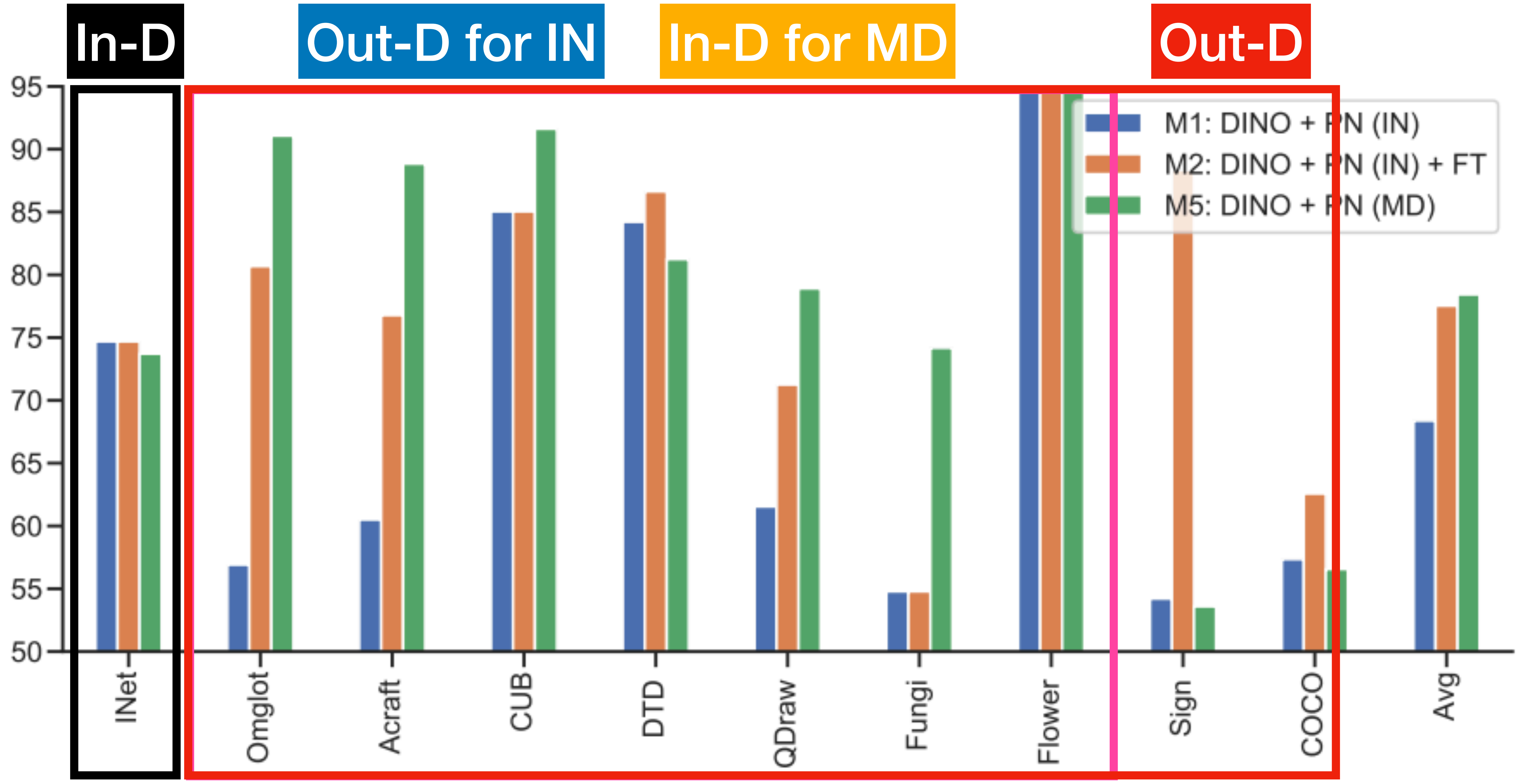
ViT-small > ResNet50

Yes, DINO ViT yields a stronger FSL baseline

Better foundation models make the baseline stronger

Q3: How to best exploit fine-tuning for meta-testing?

M	Arch	PreTr	MetaTr	MetaTe	Avg	Out-D
1	ViT-small	DINO	PN (IN)	PN	68.380	67.679
2	ViT-small	DINO	PN (IN)	PN+FT(lr=0.01)	76.051	76.536
3	ViT-small	DINO	PN (IN)	PN+FT(lr=0.001)	74.469	74.509
4	ViT-small	DINO	PN (IN)	PN+FT(Tuned)	77.532	77.848
5	ViT-small	DINO	PN (MD)	PN	78.428	55.705
6	ViT-small	DINO	PN (MD)	PN+FT(lr=0.01)	76.094	73.26
7	ViT-small	DINO	PN (MD)	PN+FT(lr=0.001)	74.642	69.965
8	ViT-small	DINO	PN (MD)	PN+FT(Tuned)	83.133	75.72



Fine-tuning during meta-testing improves substantially for Out-D

Validating the best learning rate for each domain is important

Fine-tuning of Out-D ≈ meta-training of In-D

Comparison with SOTA: Meta-Dataset

8 in-domain datasets	In-domain								Out-of-domain		
	INet	Omglot	Acraft	CUB	DTD	QDraw	Fungi	Flower	Sign	COCO	Avg
ProtoNet [60]	67.01	44.5	79.56	71.14	67.01	65.18	64.88	40.26	86.85	46.48	63.287
CNAPs [52]	50.8	91.7	83.7	73.6	59.5	74.7	50.2	88.9	56.5	39.4	66.9
SUR [54]	56.1	93.1	84.6	70.6	71	81.3	64.2	82.8	53.4	50.1	70.72
Trans. CNAPS [7]	57.9	94.3	84.7	78.8	66.2	77.9	48.9	92.3	59.7	42.5	70.32
URT [42]	55.7	94.4	85.8	76.3	71.8	82.5	63.5	88.2	51.1	52.2	72.15
FLUTE [59]	51.8	93.2	87.2	79.2	68.8	79.5	58.1	91.6	58.4	50	71.78
URL [40]	57.51	94.51	88.59	80.54	76.17	81.94	68.75	92.11	63.34	54.03	75.749
ITA [39]	57.35	**94.96**	89.33	81.42	76.74	**82.01**	67.4	92.18	83.55	55.75	78.069
DINO > PN > FT (RN50)	67.51	85.91	80.3	81.67	**87.08**	72.84	60.03	94.69	87.17	58.92	77.612
DINO > PN > FT (ViT-small)	74.59	91.79	88.33	91.02	86.61	79.23	74.2	94.12	88.85	62.59	83.133
DINO > PN > FT (ViT-base)	**77.02**	91.76	**89.73**	**92.94**	86.94	80.2	**78.28**	**95.79**	**89.86**	**64.97**	**84.749**

+ 6.7%

In-domain = ImageNet	In-domain	Out-of-domain									
	INet	Omglot	Acraft	CUB	DTD	QDraw	Fungi	Flower	Sign	COCO	Avg
ProtoNet [60]	50.5	59.98	53.1	68.79	66.56	48.96	39.71	85.27	47.12	41	56.099
ALFA+fo-Proto-MAML [5]	52.8	61.87	63.43	69.75	70.78	59.17	41.49	85.96	60.78	48.11	61.414
BOHB [54]	51.92	67.57	54.12	70.69	68.34	50.33	41.38	87.34	51.8	48.03	59.152
CTX [23]	62.76	82.21	79.49	80.63	75.57	72.68	51.58	**95.34**	82.65	59.9	74.281
DINO > PN > FT (RN50)	67.08	75.33	75.39	72.08	86.42	66.79	50.53	94.14	86.54	58.2	73.25
DINO > PN > FT (ViT-small)	74.69	80.68	76.78	85.04	86.63	71.25	54.78	94.57	88.33	62.57	77.532
DINO > PN > FT (ViT-base)	**76.69**	**81.42**	**80.33**	**84.38**	**86.87**	**75.43**	**55.93**	95.14	**89.68**	**65.01**	**79.088**

+ 4.8%

Comparison with SOTA: Cross-domain FSL

	ChestX			ISIC			EuroSAT			CropDisease		
	5w5s	5w20s	5w50s	5w5s	5w20s	5w50s	5w5s	5w20s	5w50s	5w5s	5w20s	5w50s
ProtoNet [55]	24.05	28.21	29.32	39.57	49.5	51.99	73.29	82.27	80.48	79.72	88.15	90.81
RelationNet [57]	22.96	26.63	28.45	39.41	41.77	49.32	61.31	74.43	74.91	68.99	80.45	85.08
MetaOptNet [38]	22.53	25.53	29.35	36.28	49.42	54.8	64.44	79.19	83.62	68.41	82.89	91.76
Finetune [29]	25.97	31.32	35.49	48.11	59.31	66.48	79.08	87.64	90.89	89.25	95.51	97.68
CHEF [1]	24.72	29.71	31.25	41.26	54.3	60.86	74.15	83.31	86.55	86.87	94.78	96.77
STARTUP [47]	26.94	33.19	36.91	47.22	58.63	64.16	82.29	89.26	91.99	93.02	97.51	98.45
DINO > PN > FT (RN50)	27.13	31.57	34.17	43.78	54.06	57.86	**89.18**	**93.08**	**96.06**	**95.06**	97.25	97.77
DINO > PN > FT (ViT-small)	**27.27**	**35.33**	**41.39**	**50.12**	**65.78**	**73.5**	85.98	91.32	95.4	92.96	**98.12**	**99.24**

+ 4.5% + 7.0% + 4.0% + 0.8%

Thank you for your attention!

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