Meta-FDMixup: Cross-Domain Few-Shot Learning Guided by Labeled Target Data

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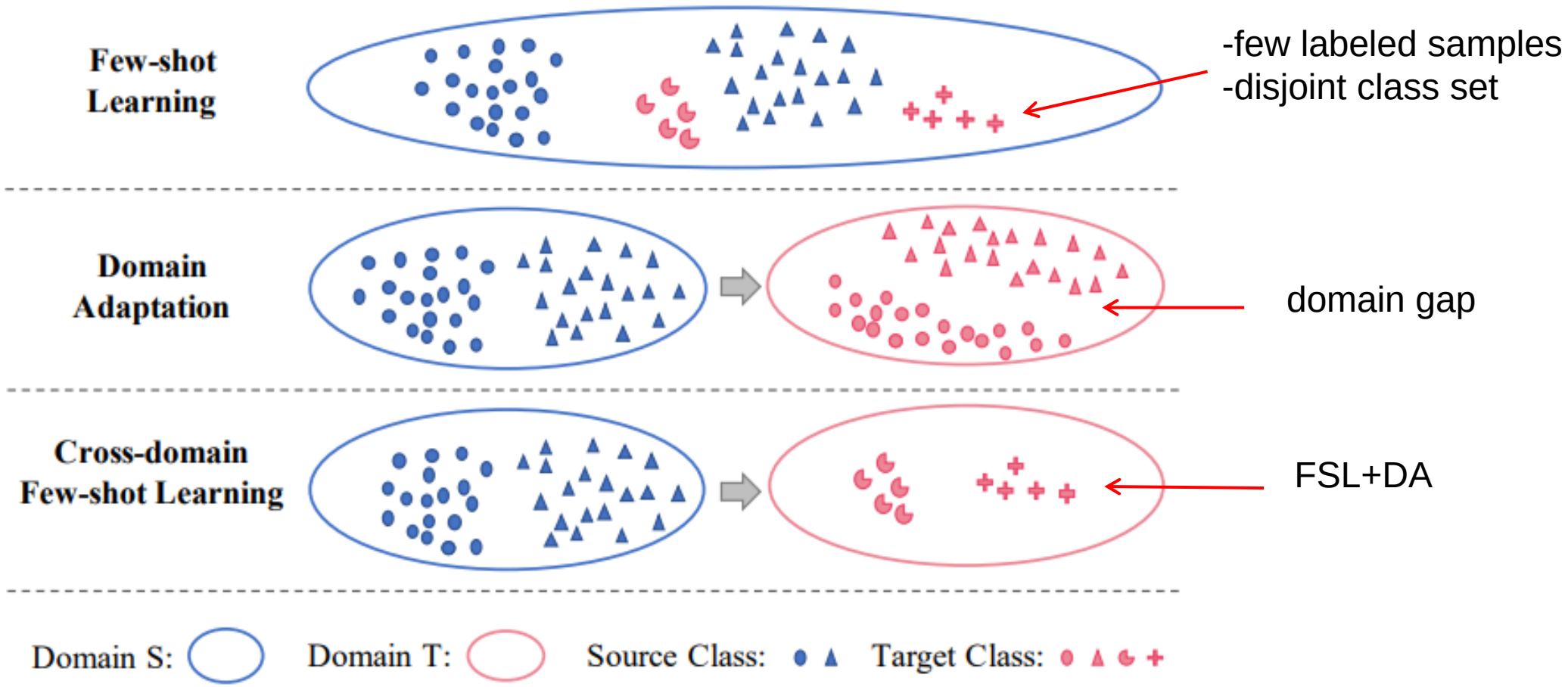
https://github.com/lovelyqian/Meta-FDMixup

Cross-Domain Few Shot Learning(CD-FSL)

A comparison of few-shot learning(FSL),domain adaptation(DA),and CD-FSL



Related Works

Existing FSL methods fail to generalize to garget dataset when a damain gap

Chen et al.ICLR2019

>>Pretrain with only source data

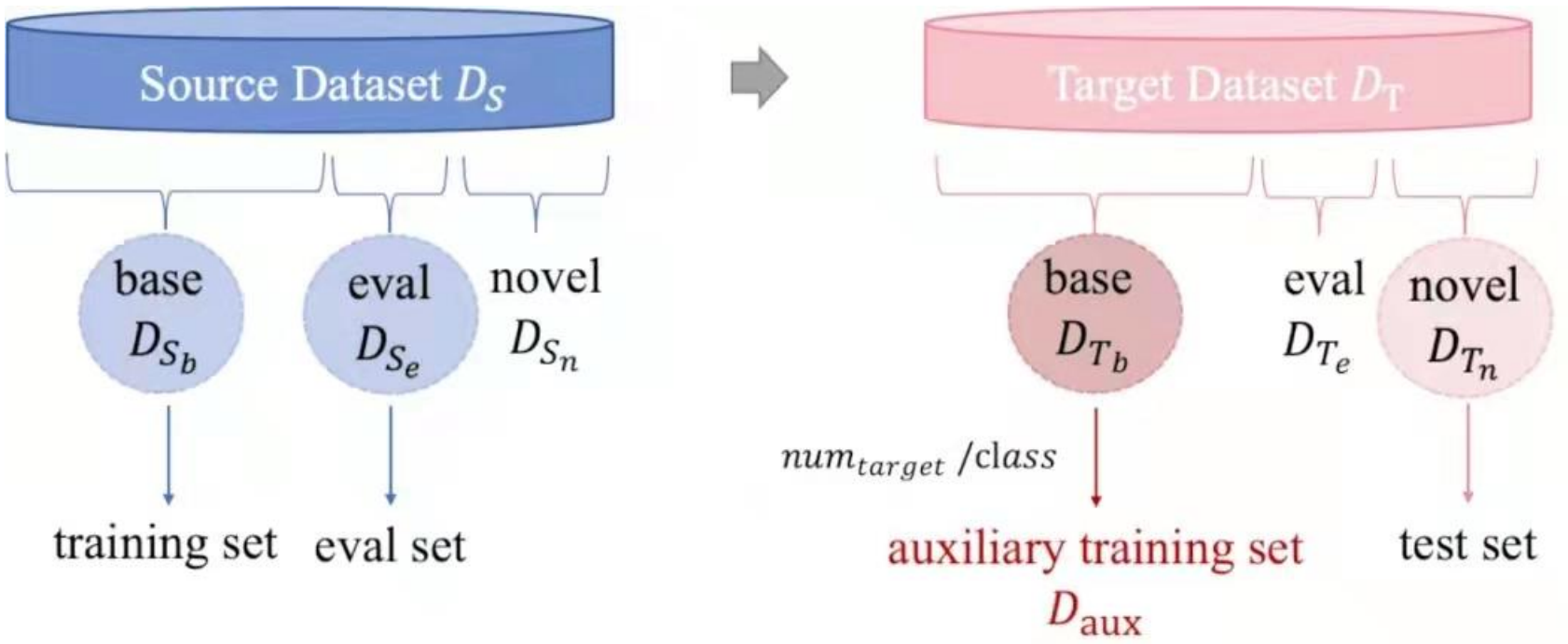
- CD-FSL via learned feature transformation;Tseng et al. ICLR2020
- A broader study of CD-FSL;Guo et al.ECCV2020
- Explanation-guided training for CD-FSL;Sun et al. arxiv2020
- CD-FSL by representation fusion; Adler et al.arxiv2020

>>Pretrain with source data and unlabeled target data

- Self-training for few-shot transfer across extreme task differences; Cheng et al. arxiv 2020

Learn CD-FSL with Labeled Target Data

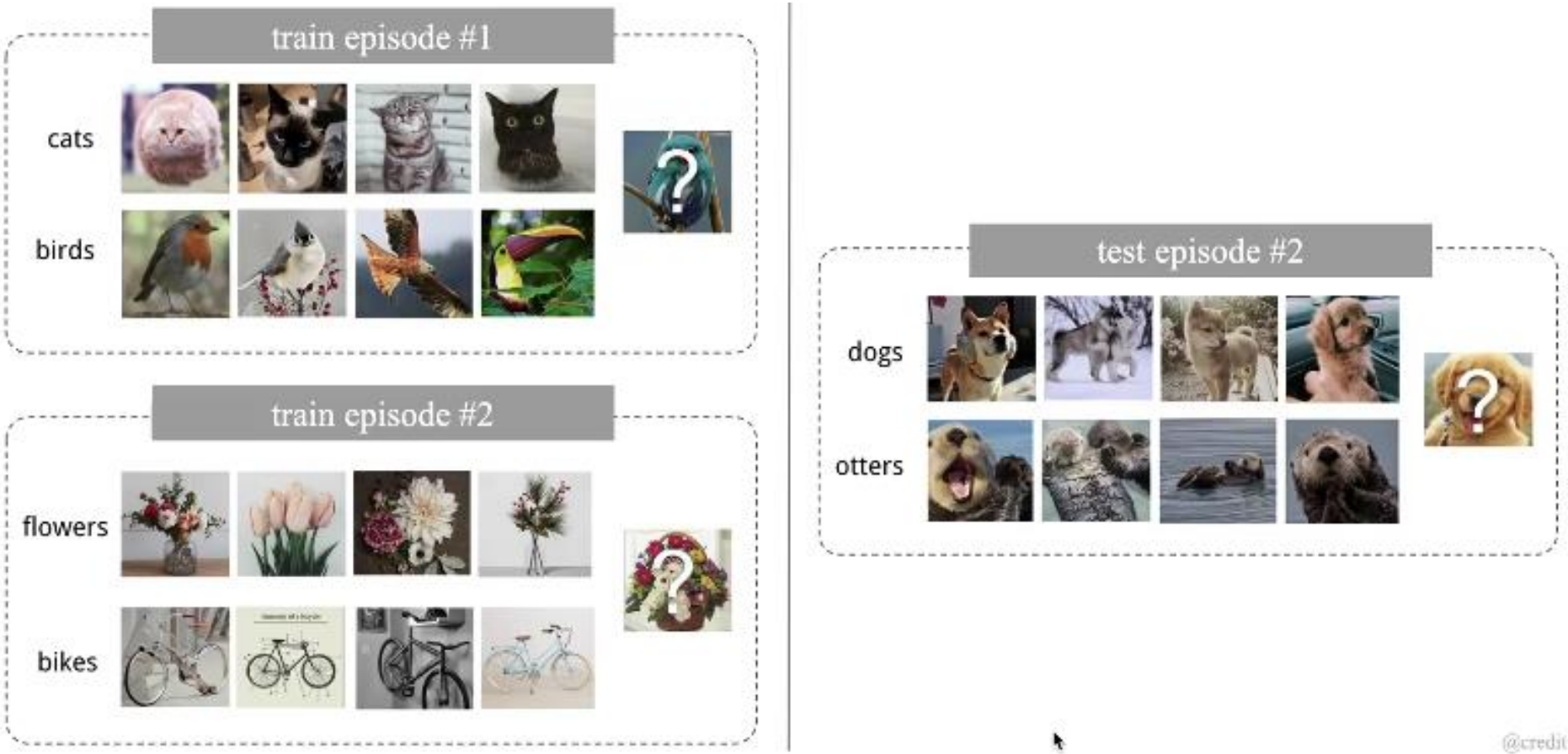
The paper advocate using the extremely few labeled target data to guide the CD-FSL



- more realistic
- good performance
- do not violate the CD-FSL setting

Meta-Learning Mechanism

N-way-K-shot Problem (2-way-4shot)



@credit Lilian

Motivation

source base dataset D_{S_b}
(many examples)

target auxiliary dataset D_{aux}
(few examples)

target novel dataset D_{T_n}
(few examples)

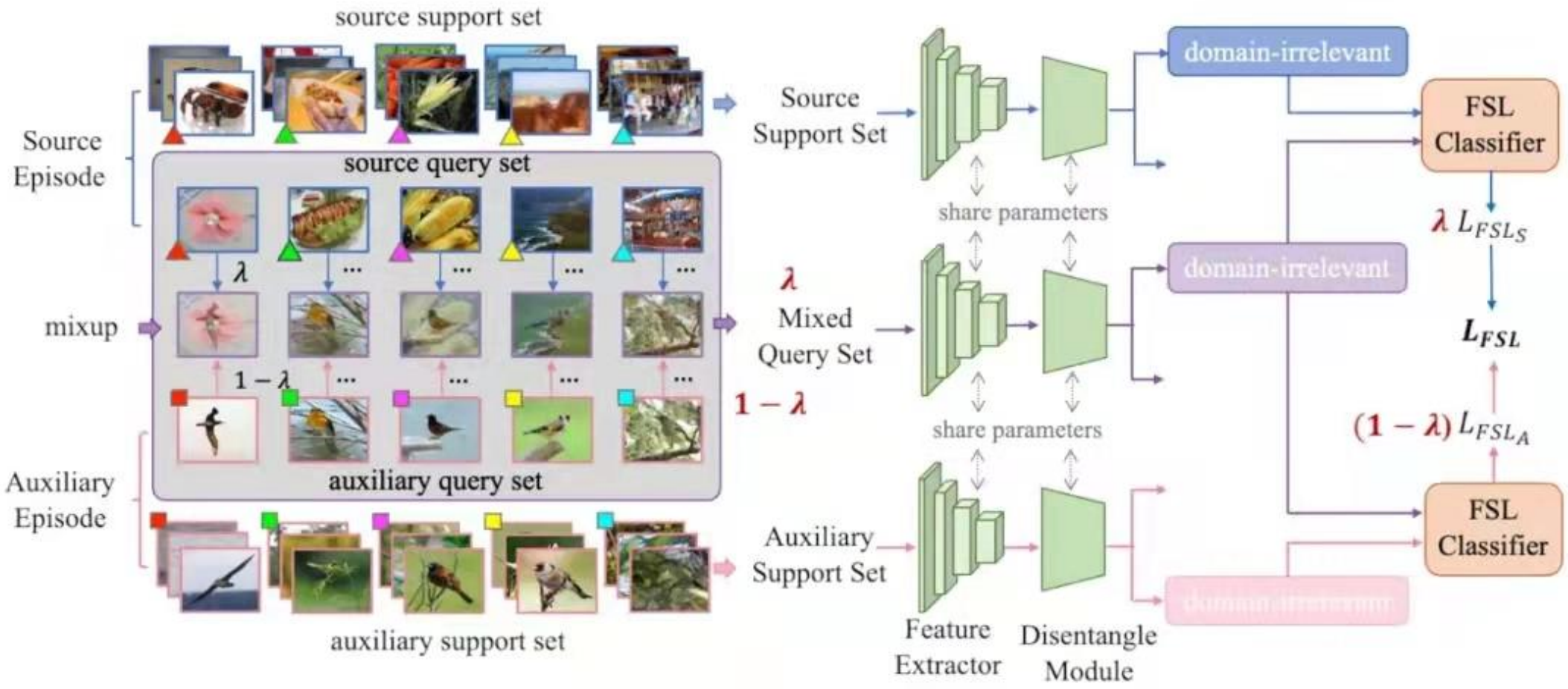
Main Challenges:

- challenge #1:make use of the unbalanced and disjoint source and auxiliary dataset.
- challenge #2: narrow the domain gap between the source and the target datasets.

Mixup Module

- challenges #1:make use of the unbalanced and disjoint source and auxilial data

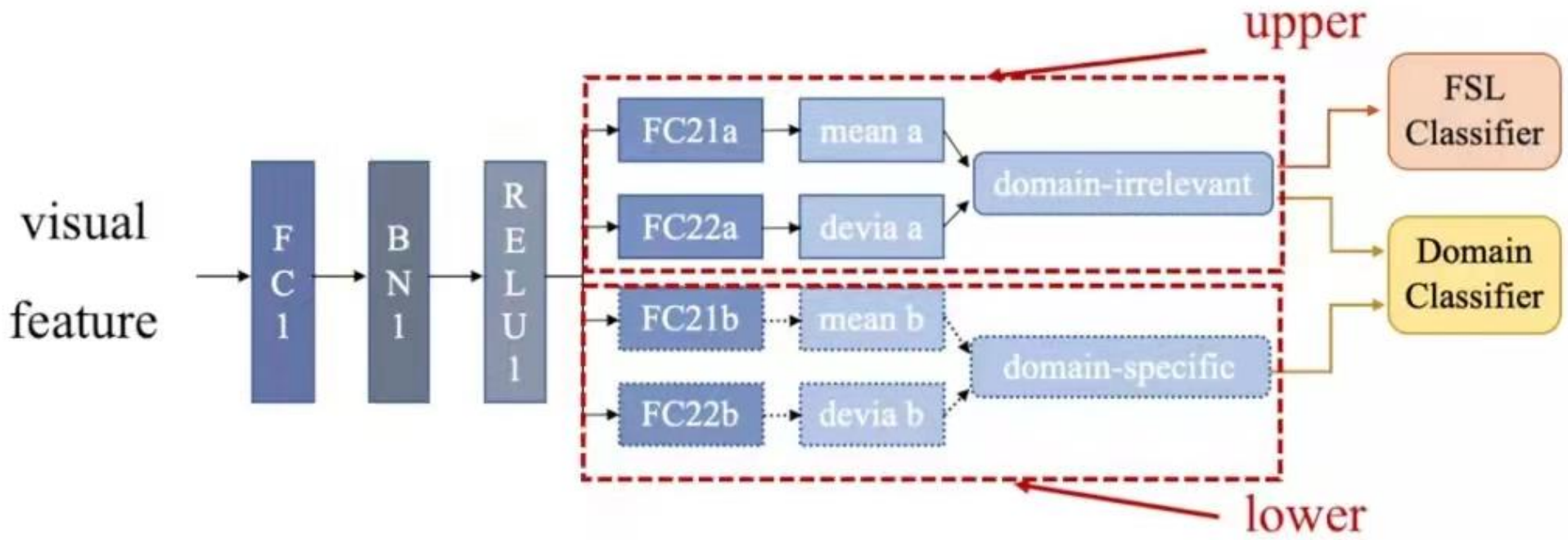
>> the mixup module which collaborates with the meta-learning mechanism



Disentangle Module

- challenge #2:narrow the domain gap between the source and the target dataset

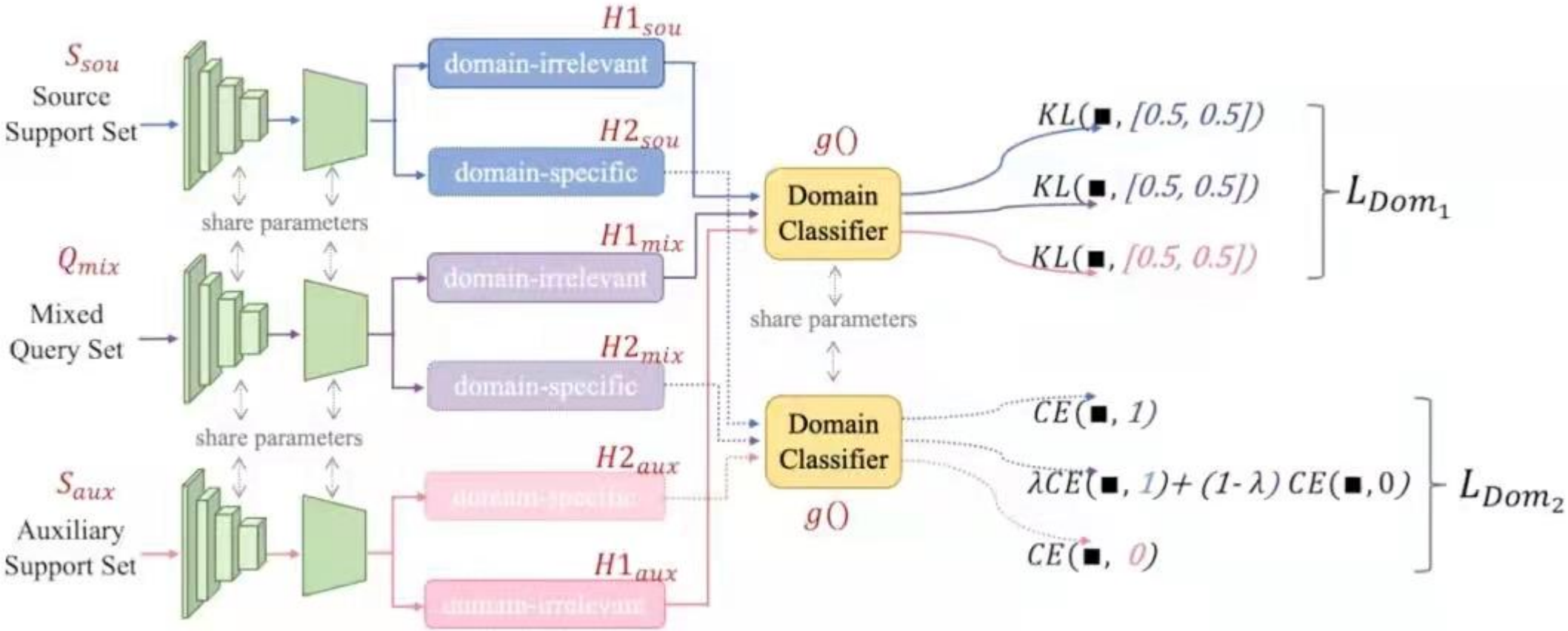
>> the disentangle module decouples the domain-irrelevant and domain-specific features.



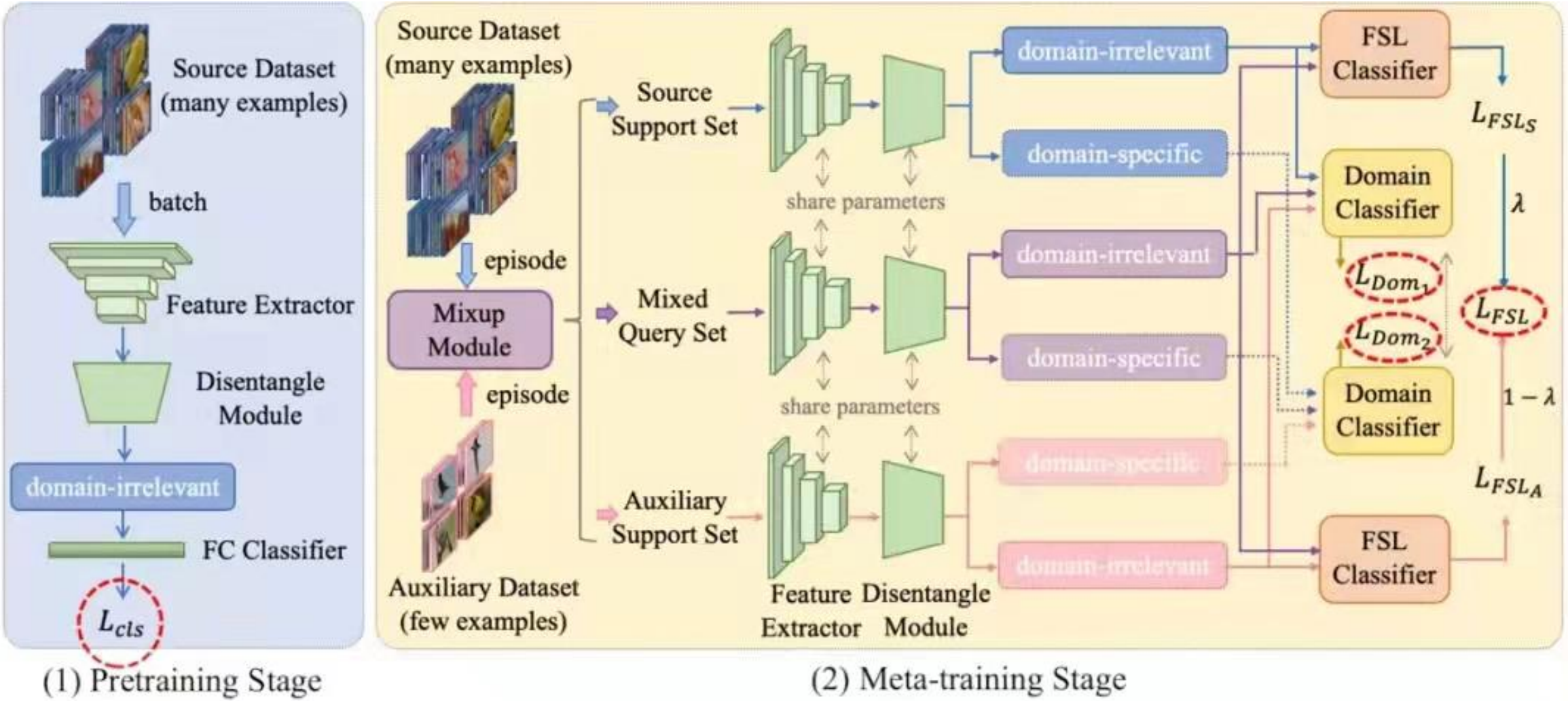
- domain-irrelevant: confuse the domain classifer
- domain-specific： recognize the source/target domian by the domain claaifier

Disentangle Module

Formally,let 1 and 0 denote the category of source and target,respectively.



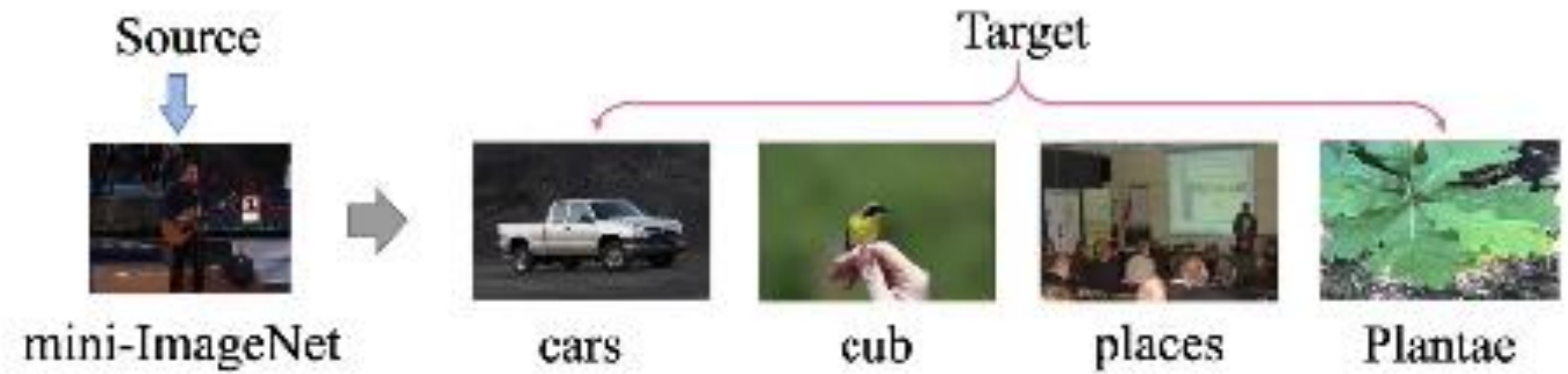
Meta-FDMixup Framework



Network Components

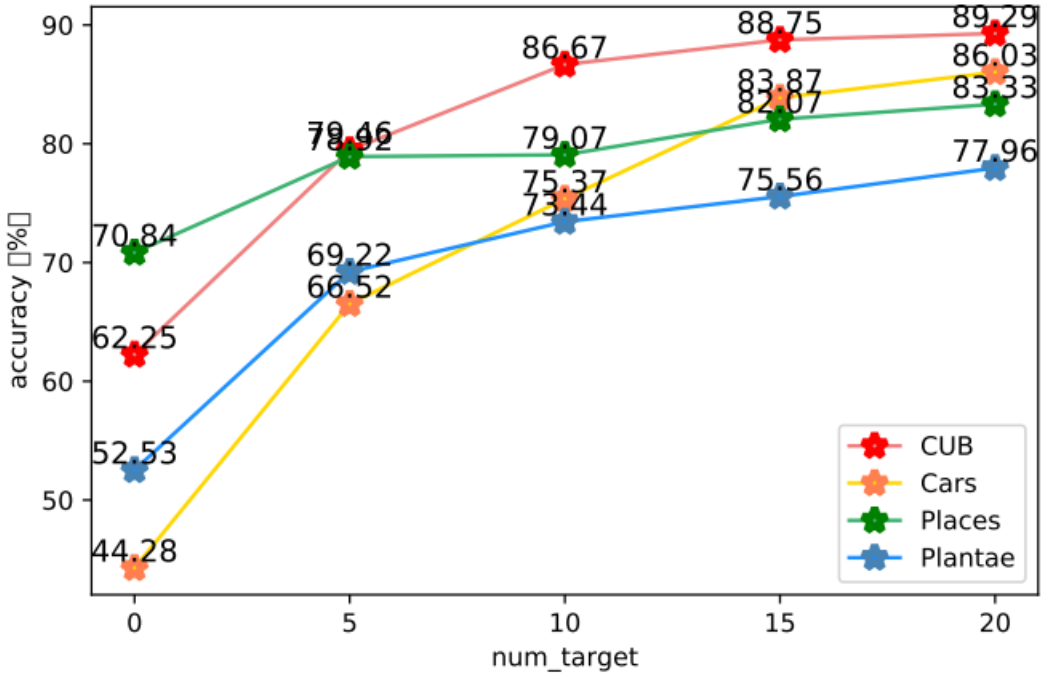
- feature extractor: ResNet-10
- few-shot classifier： GNN
- domain classifier:64-D-->2-D
- disentangle module:FC1: 512-D -->256-D;FC21a(b),FC22a(b);256-D->64-D

Datasets



Results

number target is set as 5,10,15,20,respectively.



- obvious performance improvement
- more images, better performance
- number target =5

Main Results

5-way	1-shot	D_{aux}	CUB	Cars	Places	Plantae
FSL	MatchingNet [33]	-	35.89 ± 0.51	30.77 ± 0.47	49.86 ± 0.79	32.70 ± 0.60
	RelationNet [27]	-	42.44 ± 0.77	29.11 ± 0.60	48.64 ± 0.85	33.17 ± 0.64
	GNN [9]	-	45.69 ± 0.68	31.79 ± 0.51	53.10 ± 0.80	35.60 ± 0.56
Baselines	s-base	-	45.69 ± 0.68	31.79 ± 0.51	53.10 ± 0.80	35.60 ± 0.56
	a-base	✓	50.28 ± 0.77	37.86 ± 0.63	51.09 ± 0.79	44.25 ± 0.74
	m-base	✓	57.65 ± 0.80	46.03 ± 0.72	55.70 ± 0.79	48.25 ± 0.74
CD-FSL	m-base-FT [28]	✓	61.16 ± 0.81	49.01 ± 0.76	57.89 ± 0.82	50.49 ± 0.81
	meta-FDMixup (ours)	✓	**63.24 ± 0.82**	**51.31 ± 0.83**	**58.22 ± 0.82**	**51.03 ± 0.81**
5-way	5-shot	D_{aux}	CUB	Cars	Places	Plantae
FSL	MatchingNet [33]	-	51.37 ± 0.77	38.99 ± 0.64	63.16 ± 0.77	46.53 ± 0.68
	RelationNet [27]	-	57.77 ± 0.69	37.33 ± 0.68	63.32 ± 0.76	44.00 ± 0.60
	GNN [9]	-	62.25 ± 0.65	44.28 ± 0.63	70.84 ± 0.65	52.53 ± 0.59
Baselines	s-base	-	62.25 ± 0.65	44.28 ± 0.63	70.84 ± 0.65	52.53 ± 0.59
	a-base	✓	64.98 ± 0.67	48.53 ± 0.64	67.96 ± 0.68	60.21 ± 0.69
	m-base	✓	78.08 ± 0.60	63.27 ± 0.70	75.90 ± 0.67	66.69 ± 0.68
CD-FSL	m-base-FT [28]	✓	79.14 ± 0.62	65.42 ± 0.70	78.59 ± 0.60	68.26 ± 0.68
	meta-FDMixup (ours)	✓	**79.46 ± 0.63**	**66.52 ± 0.70**	**78.92 ± 0.63**	**69.22 ± 0.65**

Meta-FDMixup outperforms all the baselines and competiitors

Visualization

>> Class activation map(CAM) visualization of the models.