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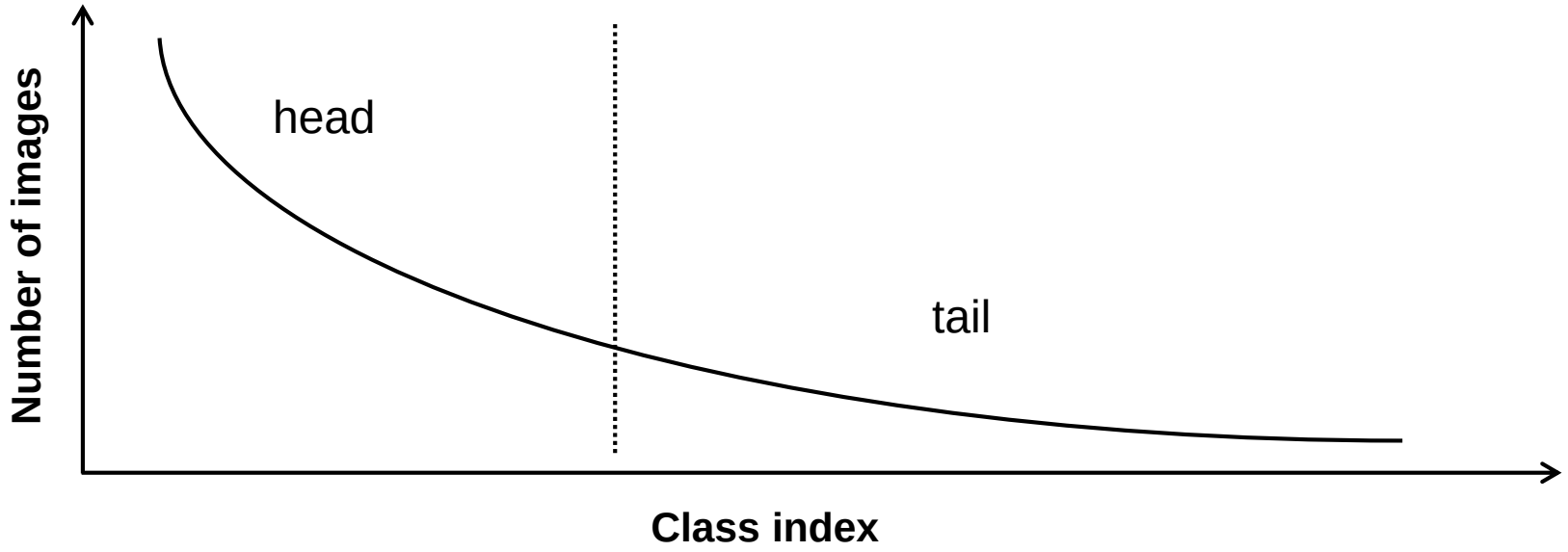
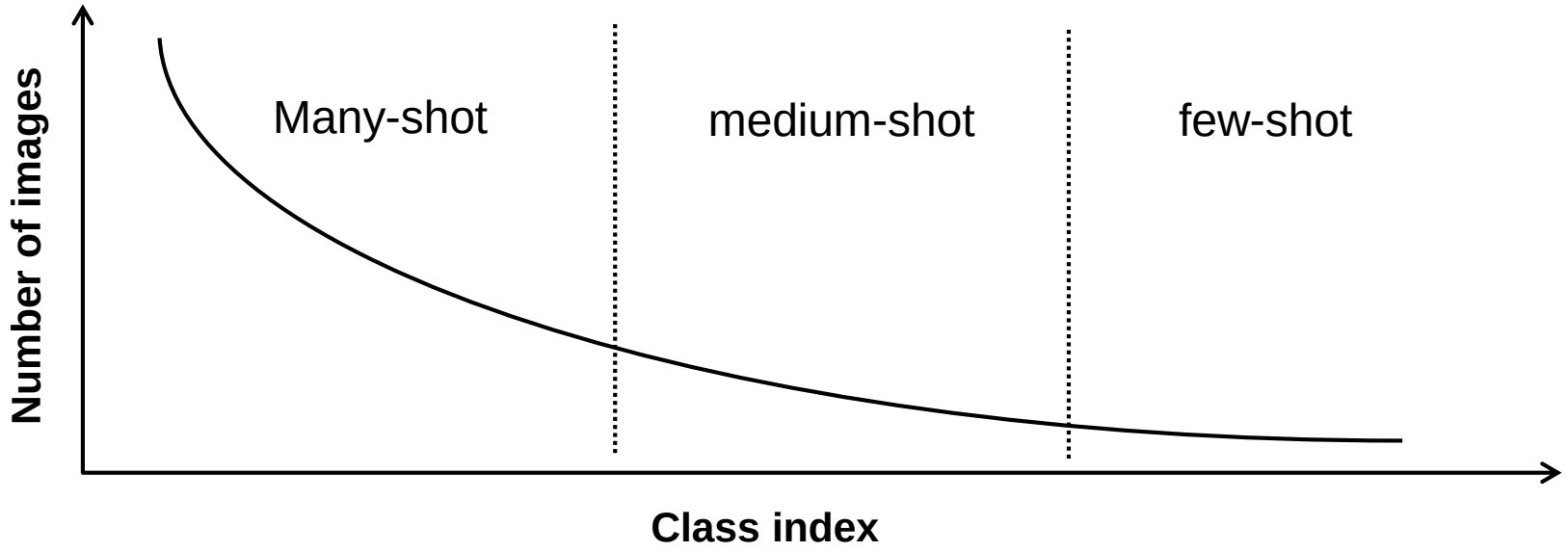
Long-Tailed Visual Recognition

QingHeng Zhang

Long-Tailed Distributions



Long-Tailed Distributions



RELATED WORKS

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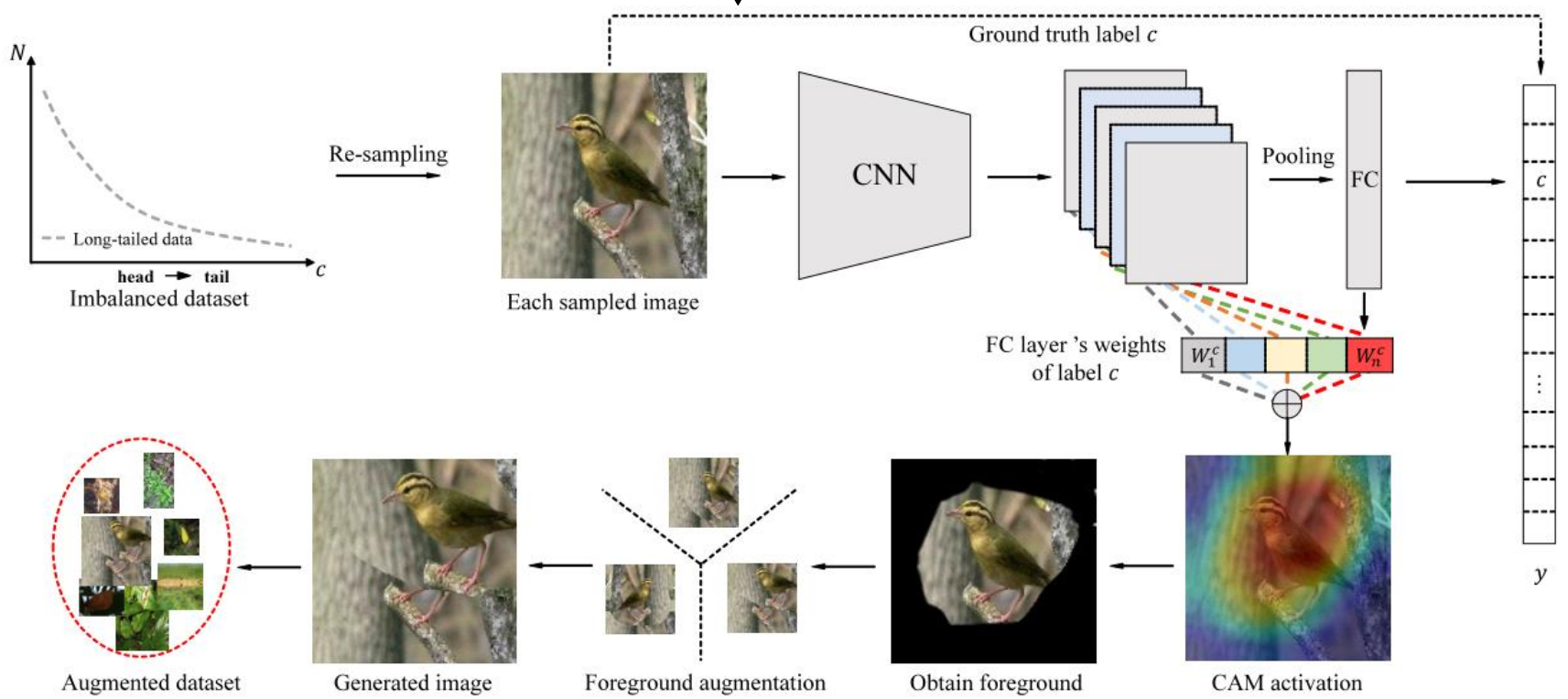
Re-sampling

- Random over/under sampling
- Distribution-aware sampling
  - Decoupling Representation and Classifier (2019) $\longrightarrow$ $p_j = \frac{n_j^q}{\sum_{i=1}^{C} n_i^q}$
- Class Activation Map based sampling
  - Bag of Tricks for Long-Tailed Visual Recognition(2021)

Re-weighting

Multi-Expert



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- Focal loss (2017)
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$$\mathrm{FL}(p_t) = -\alpha_t(1-p_t)^{\gamma}\log(p_t)$$

$$\mathrm{CB}(\mathbf{p}, y) = \frac{1}{E_{n_y}}\mathcal{L}(\mathbf{p}, y) = \frac{1-\beta}{1-\beta^{n_y}}\mathcal{L}(\mathbf{p}, y)$$

$$\mathcal{L}_{\mathrm{LDAM}}((x, y); f) = -\log\frac{e^{z_y-\Delta_y}}{e^{z_y-\Delta_y}+\sum_{j\neq y}e^{z_j}}$$

$$\text{where } \Delta_j = \frac{C}{n_j^{1/4}} \text{ for } j \in \{1, \ldots, k\}$$

Multi-Expert

$$L_{SEQL} = -\sum_{j=1}^{C} y_j \log(\tilde{p}_j) \quad \text{where} \quad \tilde{p}_j = \frac{e^{z_j}}{\sum_{k=1}^{C}\tilde{w}_k e^{z_k}}$$

$$\tilde{w}_k = 1 - \beta T_\lambda(f_k)(1-y_k)$$

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Multi-Expert

- **LFME**: **L**earning **F**rom **M**ultiple **E**xperts (2020)
- **BBN**: **B**ilateral-**B**ranch **N**etwork (2020)
- **RIDE**: **R**out**I**ng **D**iverse **E**xperts (2021)

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LFME:Learning From Multiple Experts

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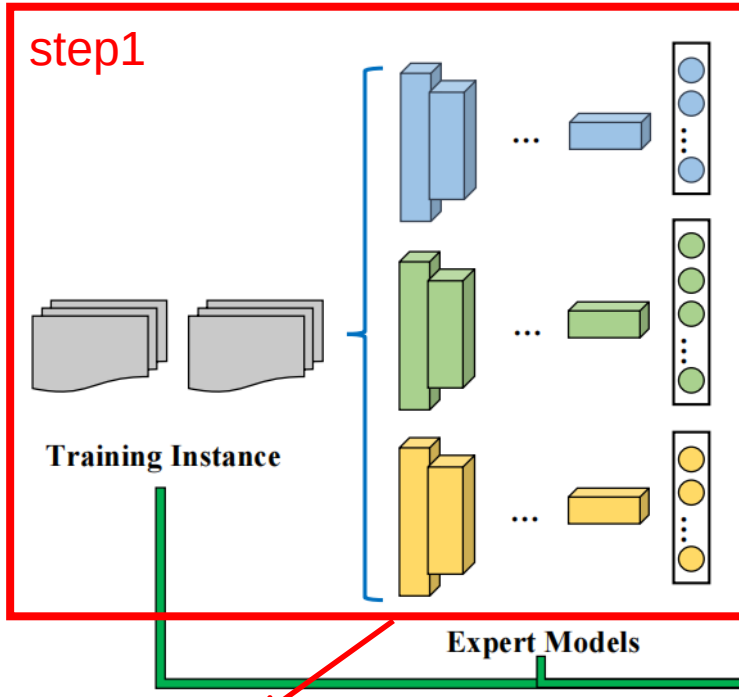
observation1:

Training a CNN on **a balanced dataset** with **fewer samples** sometimes leads to superior performances than on a long-tailed dataset with more samples.

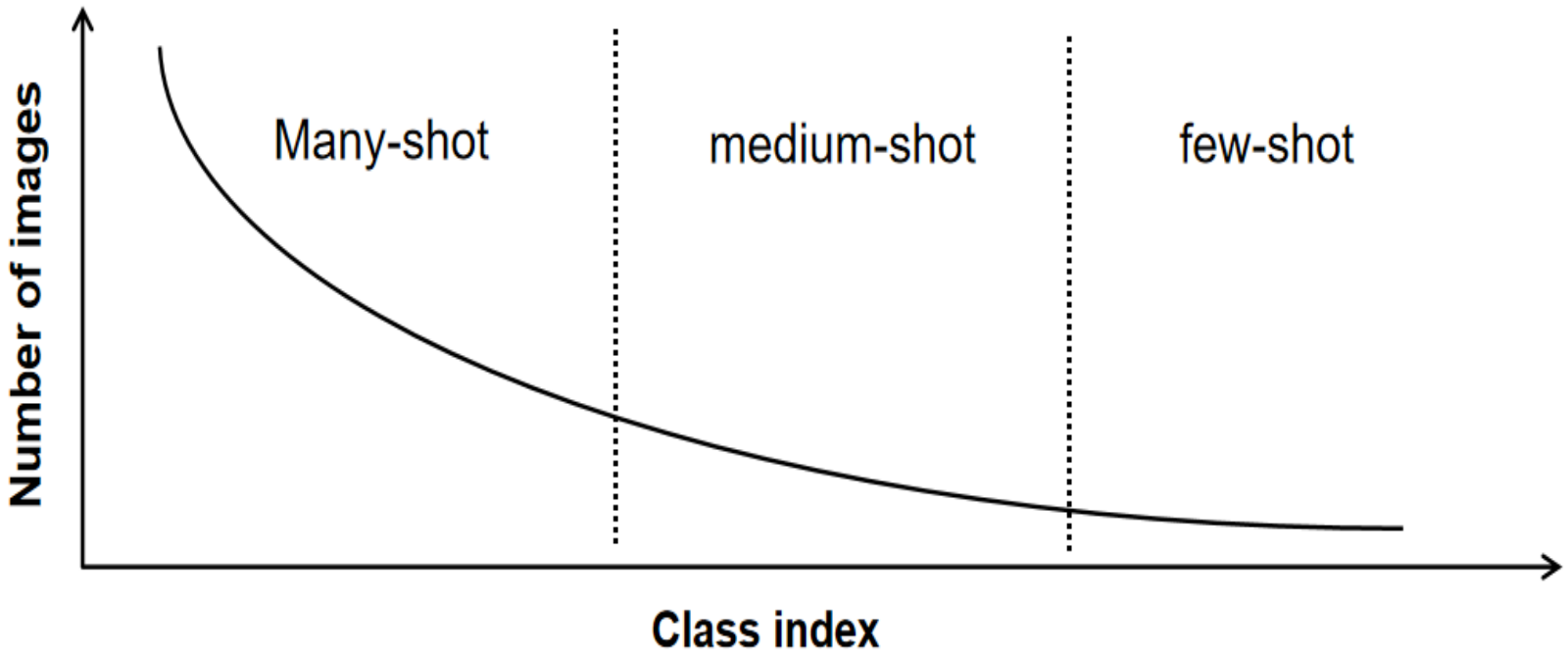
step1. Train “Experts”

1) provide output logits’ distribution for knowledge transfer
2) provide output confidence as instance difficulty cues.

setp2. Train “Student” based on prior knowledge(Experts)



sorted by numbers



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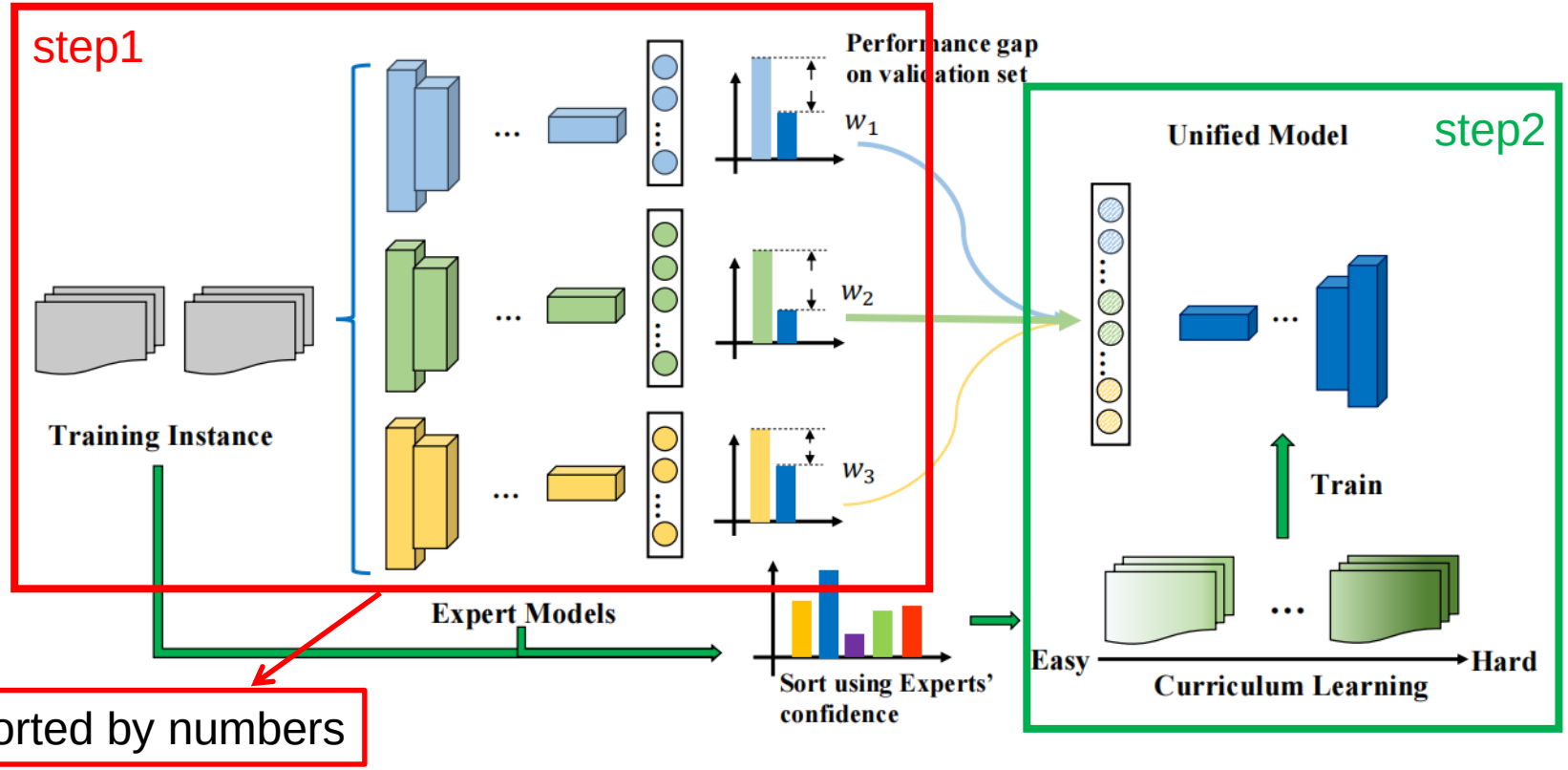

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BBN: Bilateral-Branch Network

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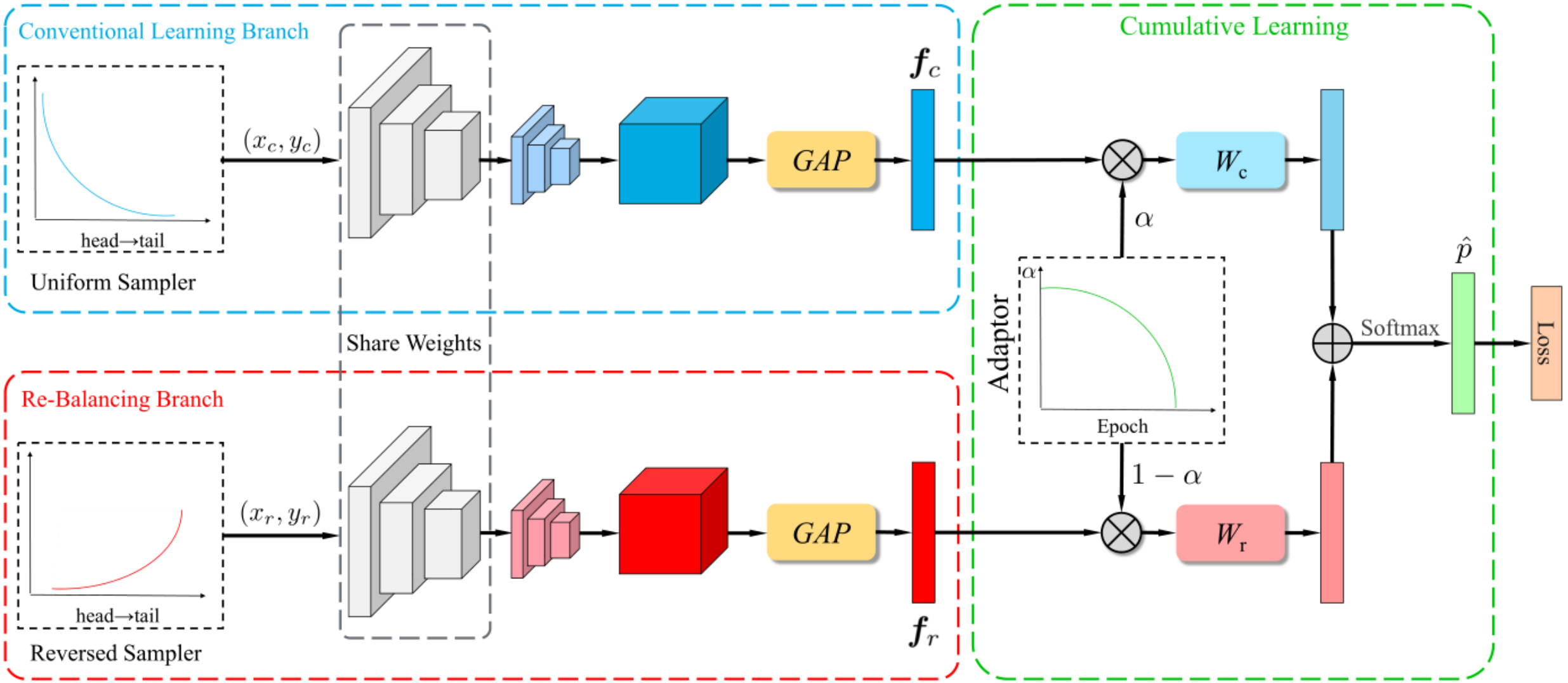

BBN: Bilateral-Branch Network

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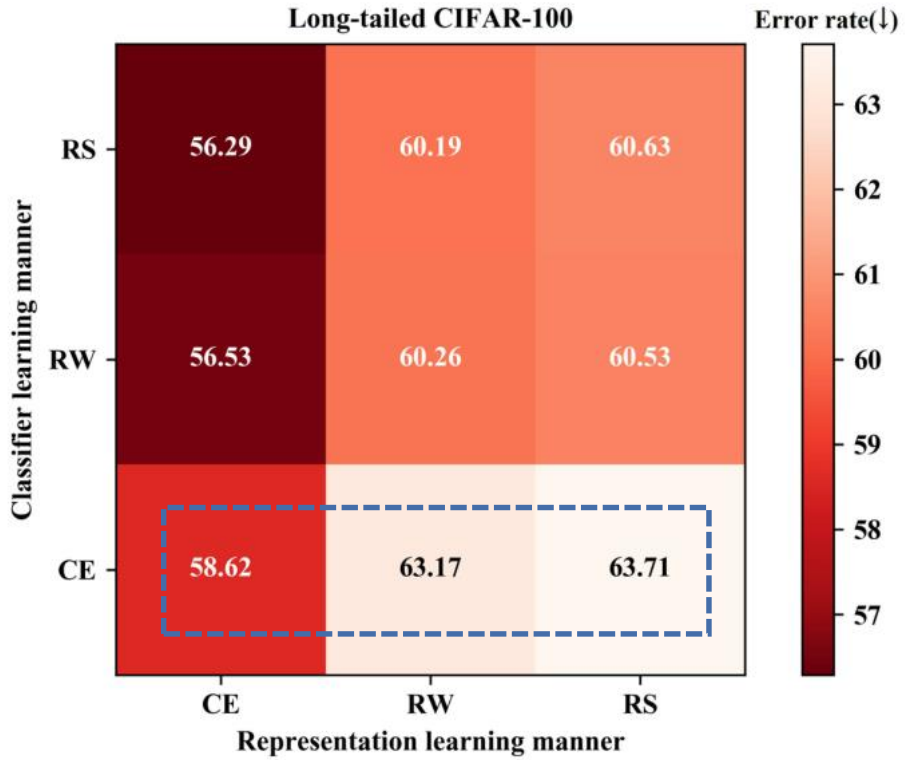
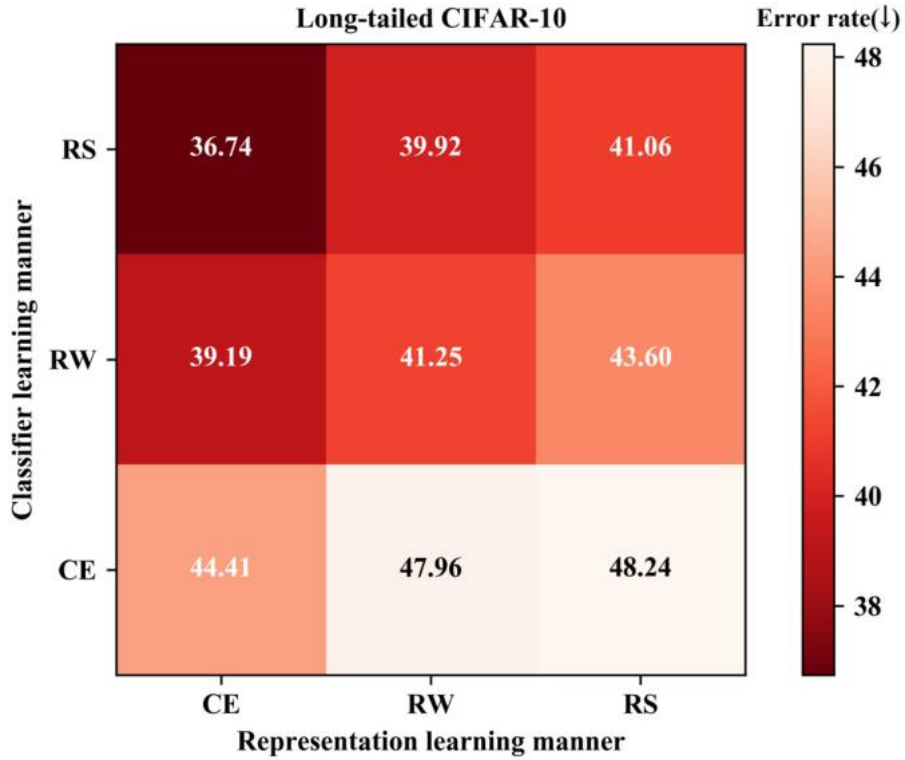
observation:

Long-tailed dataset can learn a very good feature representation.





Summary

LFME:

Each expert focuses on a relatively balanced group such as **many-shot** classes, **medium-shot** classes, and **few-shot** classes.

BBN:

Each expert focuses on the **head** and the **tail** classes respectively.

RIDE: (evaluation)

Each expert in **BBN** and **LFME** has **no** balanced access to the **entire** dataset.

What did RIDE do ?

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RIDE: RoutIng Diverse Experts

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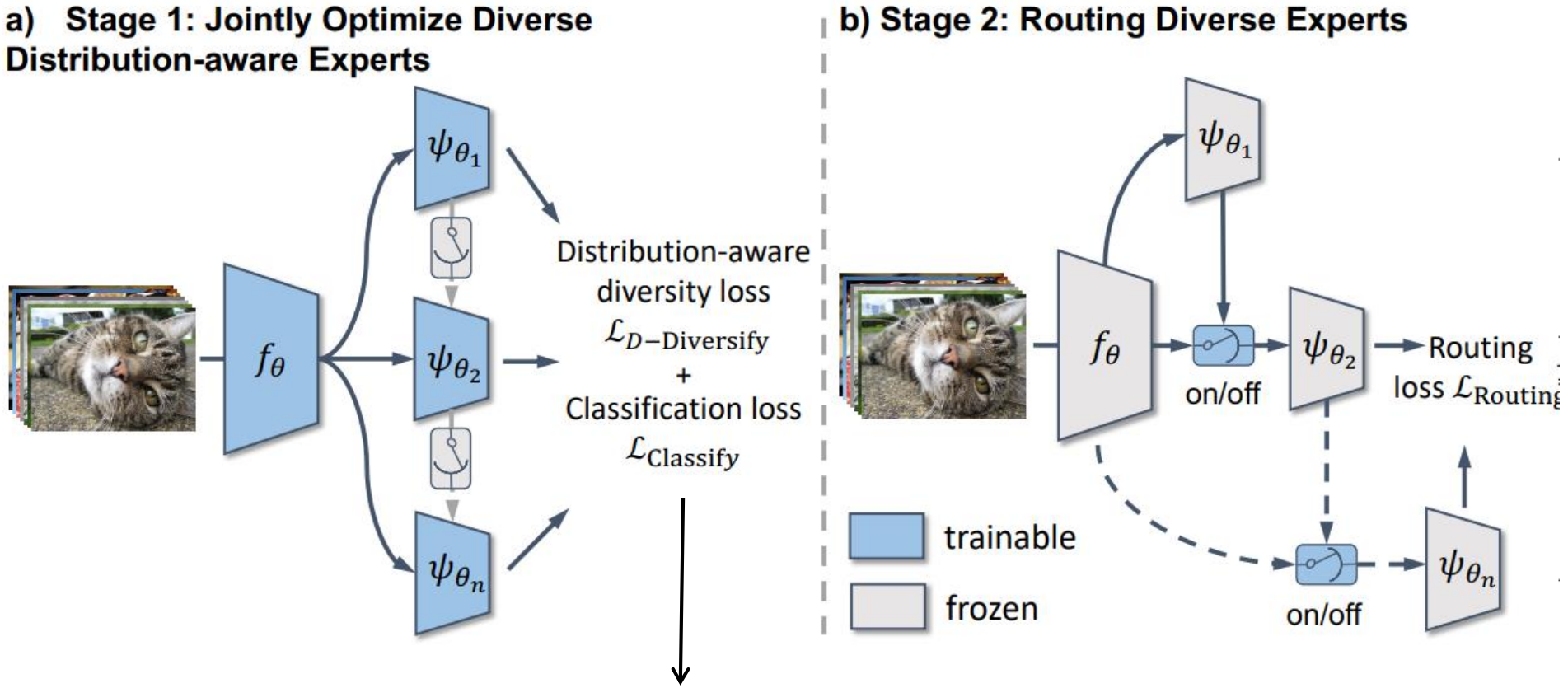

$$\mathcal{L}^{\text{individual}}(x, y) = \sum_{i=1}^{n} \mathcal{L}\left(\psi_{\theta_i}\left(f_\theta(x)\right), y\right)$$

$$\mathcal{L}^{\text{collaborative}}(x, y) = \mathcal{L}\left(\frac{1}{n}\sum_{i=1}^{n} \psi_{\theta_i}\left(f_\theta(x)\right), y\right)$$

RIDE: RoutIng Diverse Experts

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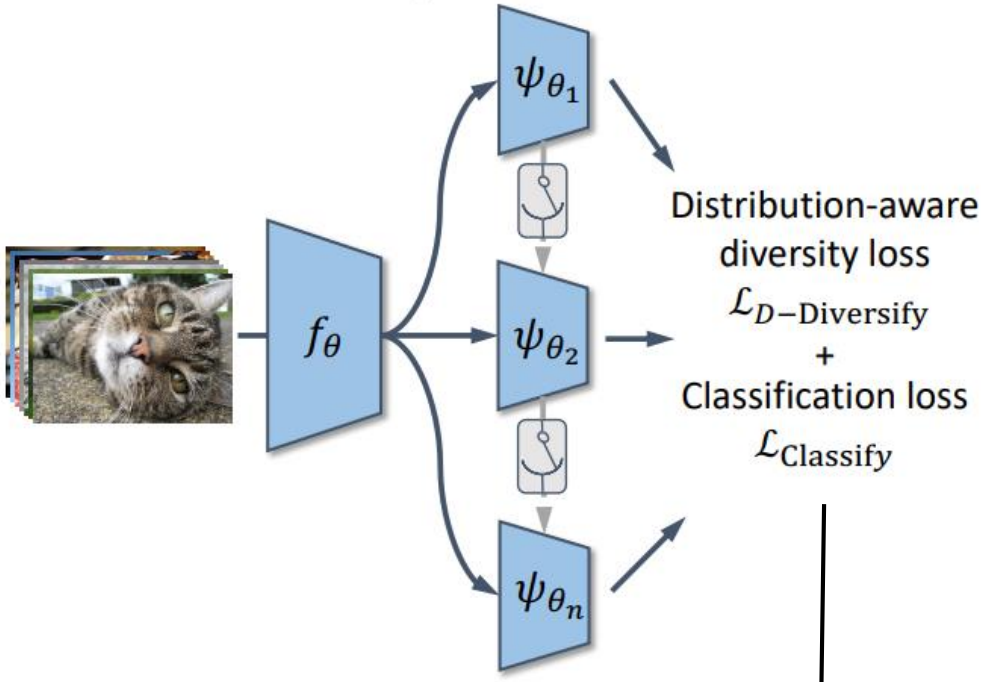
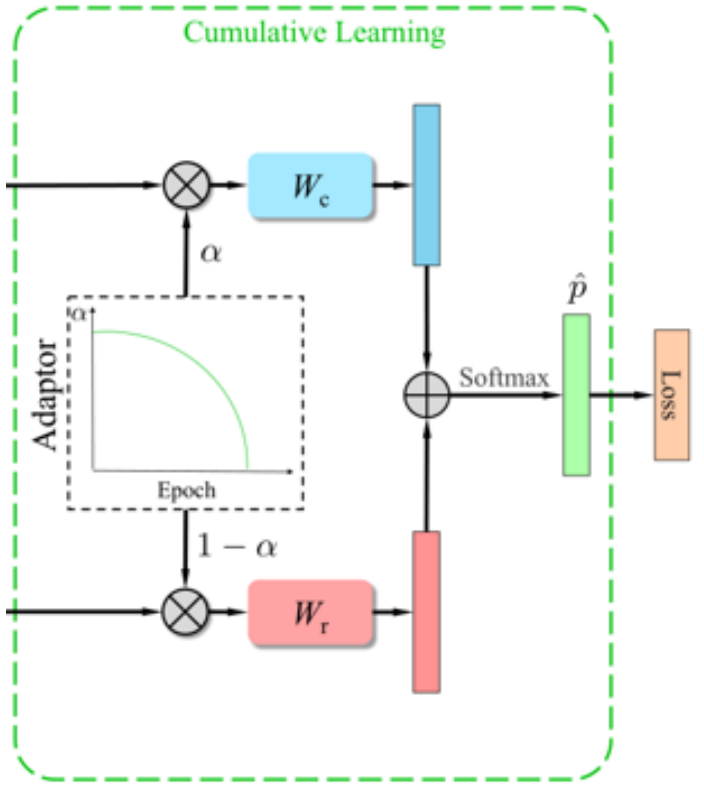
RIDE:

a) Stage 1: Jointly Optimize Diverse Distribution-aware Experts



$$\mathcal{L}^{\text{individual}}(x, y) = \sum_{i=1}^{n} \mathcal{L}\left(\psi_{\theta_i}\left(f_\theta(x)\right), y\right)$$

BBN:



$$\mathcal{L}^{\text{collaborative}}(x, y) = \mathcal{L}\left(\frac{1}{n}\sum_{i=1}^{n} \psi_{\theta_i}\left(f_\theta(x)\right), y\right)$$

RIDE: RoutIng Diverse Experts

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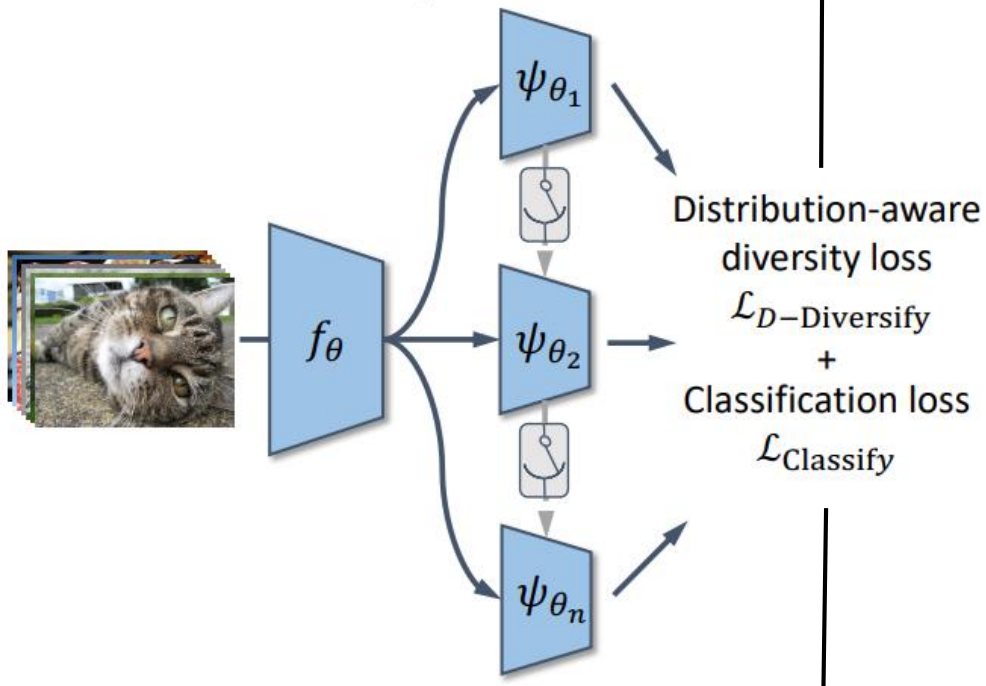
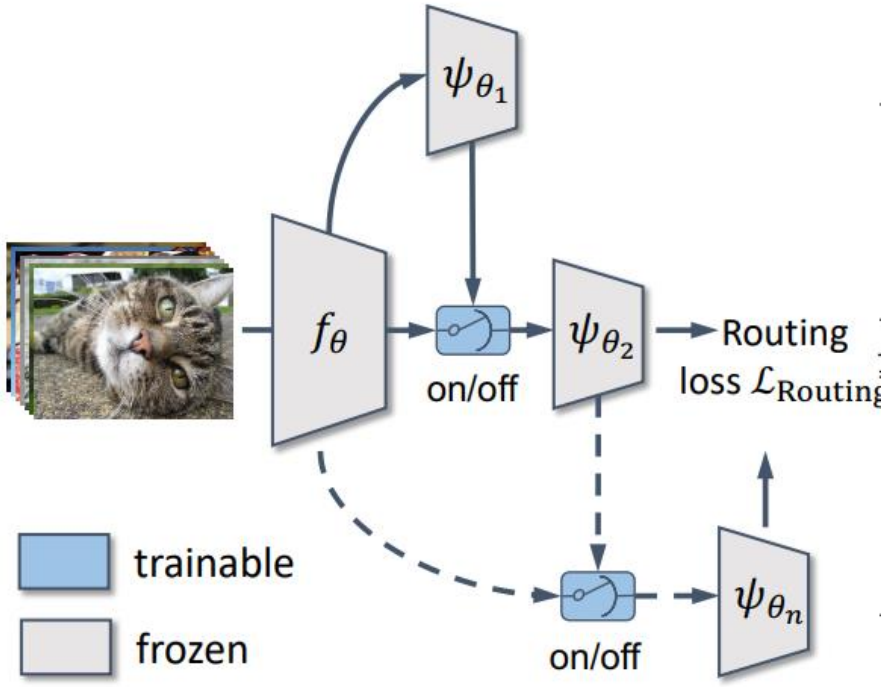
$$\mathcal{L}_{\text{D-Diversify}}(x, y; \theta_i) = \frac{-1}{n-1} \sum_{j=1, j\neq i}^{n} D_{\text{KL}}\left(\mathbf{p}^{(i)}(x, y) \| \mathbf{p}^{(j)}(x, y)\right)$$

Each expert focuses on different classes.

a) Stage 1: Jointly Optimize Diverse Distribution-aware Experts



b) Stage 2: Routing Diverse Experts



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Summary

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LFME:

Each expert focuses on a relatively **balanced** group such as many-shot classes, medium-shot classes, and few-shot classes.

BBN:

Each expert focuses on the **head** and the **tail** classes respectively.

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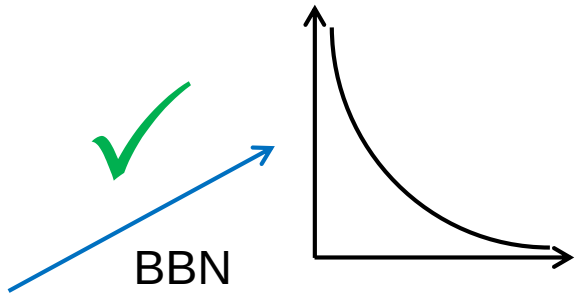
Each expert in **BBN** and **LFME** has **no** balanced access to the **entire** dataset.

What did RIDE do ?

RIDE:

Each expert in **RIDE** has a balanced access to the **entire** dataset, and each expert focuses on **different** classes.



$$\mathcal{L}_{\text{D-Diversify}}(x, y; \theta_i) = \frac{-1}{n-1} \sum_{j=1, j\neq i}^{n} D_{\text{KL}}\left(\mathbf{p}^{(i)}(x, y) \| \mathbf{p}^{(j)}(x, y)\right)$$

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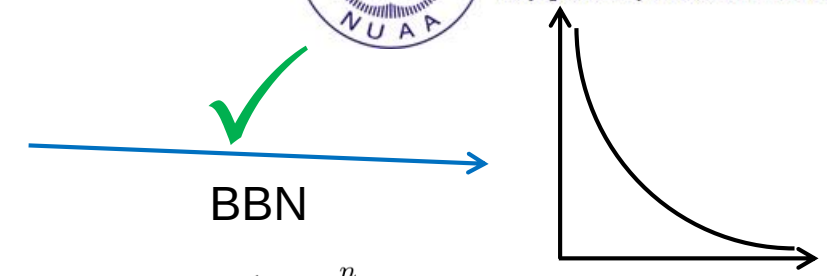
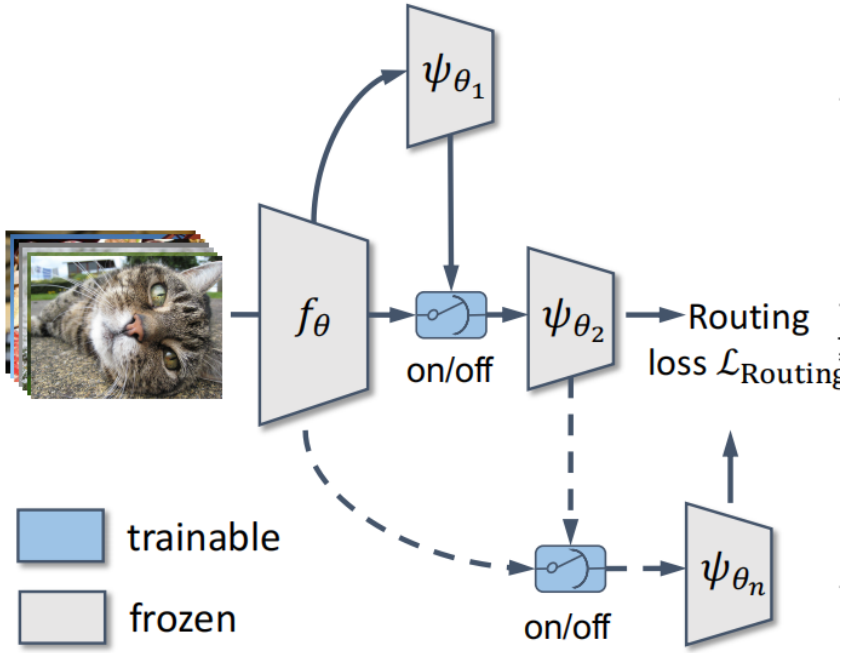
Each expert in **RIDE** has a balanced access to the **entire** dataset, and each expert focuses on different classes.





$$\mathcal{L}_{\text{D-Diversify}}(x, y; \theta_i) = \frac{-1}{n-1} \sum_{j=1, j\neq i}^{n} D_{\text{KL}}\left(\mathbf{p}^{(i)}(x, y) \| \mathbf{p}^{(j)}(x, y)\right)$$

0.4 < threshold(0.5)

(0.8 + 0.4) / 2 = 0.6 > threshold(0.5)

Diversity → KL

Train each expert independently

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→ ours

Our Framwork

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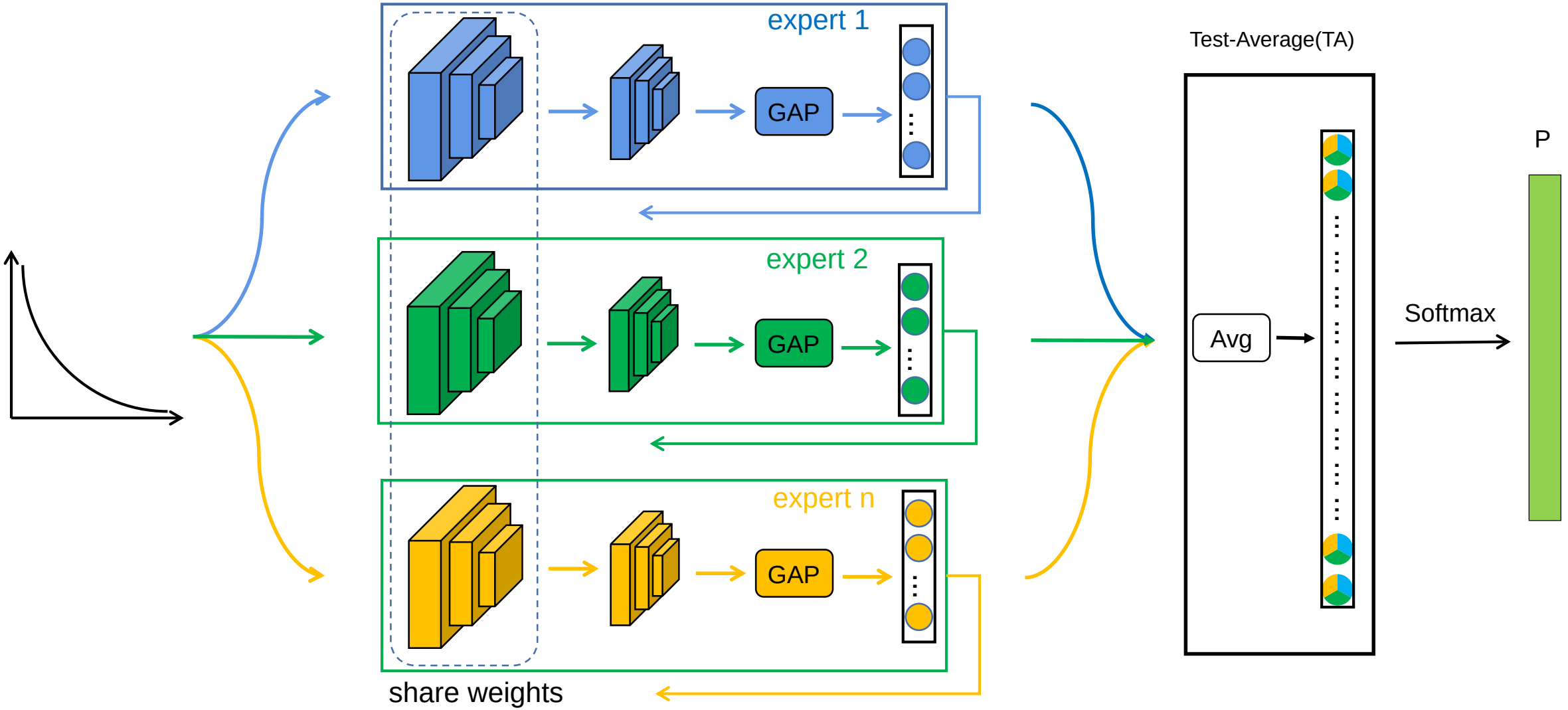
Insight : Training each expert on the **entire** dataset and **independently.**



Comparisons

Method	Data for experts	learning manner of experts
LFME	independent	independent
BBN	reverse	dependent
RIDE	same	dependent
Ours	same	independent

Table 1.Comparisons between Ours and three SOTA multi-expert networks.

Experiments

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Method	Long-tailed CIFAR10				Long-tailed CIFAR100			
Imbalance radio	200	100	50	10	200	100	50	10
Class Balance(19)	68.89	74.57	79.27	87.49	36.23	39.60	45.32	57.99
LDAM(19)	-	77.03	-	88.16	-	42.04	-	58.71
Equalization(20)	-	-	-	-	-	43.38	-	-
LFME(20)	-	-	-	-	-	43.8	-	-
BBN(20)	-	79.82	82.18	88.32	-	42.56	47.02	59.12
RIDE(21)	-	-	-	-	-	49.1	-	-
CAM(21)	-	80.03	83.59	-	-	47.83	51.69	-
SOTA	68.89	80.03	83.59	88.32	36.23	49.1	51.69	59.12
Ours	**77.87**	**82.19**	**85.14**	**90.15**	**46.82**	**51.53**	**56.23**	**65.27**

Table 2.The top-1 accuracy on Cifar10,100-LT with ResNet-32.

All results are copied from papers.

Experiments

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Method	Long-tailed ImageNet
OLTR(19)	35.60
LDAM(19)	36.00
Decoupling(19)	41.80
Feature space augmentation(20)	35.20
Equalization Loss(20)	36.44
LFME(20)	38.80
Class Activation Map(21)	43.13
Ours	**43.60**

Table 3.The top-1 accuracy on ImageNet-LT with ResNet-10.

All results are copied from papers.

Ablation

Method	Long-tailed CIFAR10				Long-tailed CIFAR100			
SOTA	68.89	80.03	83.59	88.32	36.23	49.1	51.69	59.12
Ours(w/o diversity)	69.28	76.21	81.46	87.48	37.53	42.04	48.10	59.00
Ours(w/o TA)	75.00	79.91	83.11	88.64	43.26	47.36	51.76	61.86
Ours(diversity+TA**)**	**77.87**	**82.19**	**85.14**	**90.15**	**46.82**	**51.53**	**56.23**	**65.27**

Table 4.Ablation study on diversity and TA on Cifar10,100-LT with ResNet-32.

Experiments

cifar10
Imbalance radio = 50

```
avg Result: Prec@1 85.140 Prec@5 99.180
avg Class Accuracy: [0.962,0.983,0.846,0.798,0.867,0.795,0.846,0.800,0.819,0.798]
**********************************************************************************
each experts:
expert1 Result: Prec@1 82.730 Prec@5 98.850
expert1 Class Accuracy: [0.941,0.965,0.803,0.763,0.830,0.783,0.820,0.777,0.815,0.776]
expert2 Result: Prec@1 81.820 Prec@5 99.020
expert2 Class Accuracy: [0.950,0.975,0.820,0.749,0.842,0.745,0.821,0.757,0.777,0.746]
expert3 Result: Prec@1 82.660 Prec@5 98.960
expert3 Class Accuracy: [0.948,0.977,0.812,0.775,0.838,0.766,0.823,0.766,0.779,0.782]
**********************************************************************************
```

expert1 VS Avg :
TF :expert True and Avg Flase 237
FT :expert False and Avg True 478

(478-237)/100=2.41
82.73 + 2.41 = 85.14

Experiments

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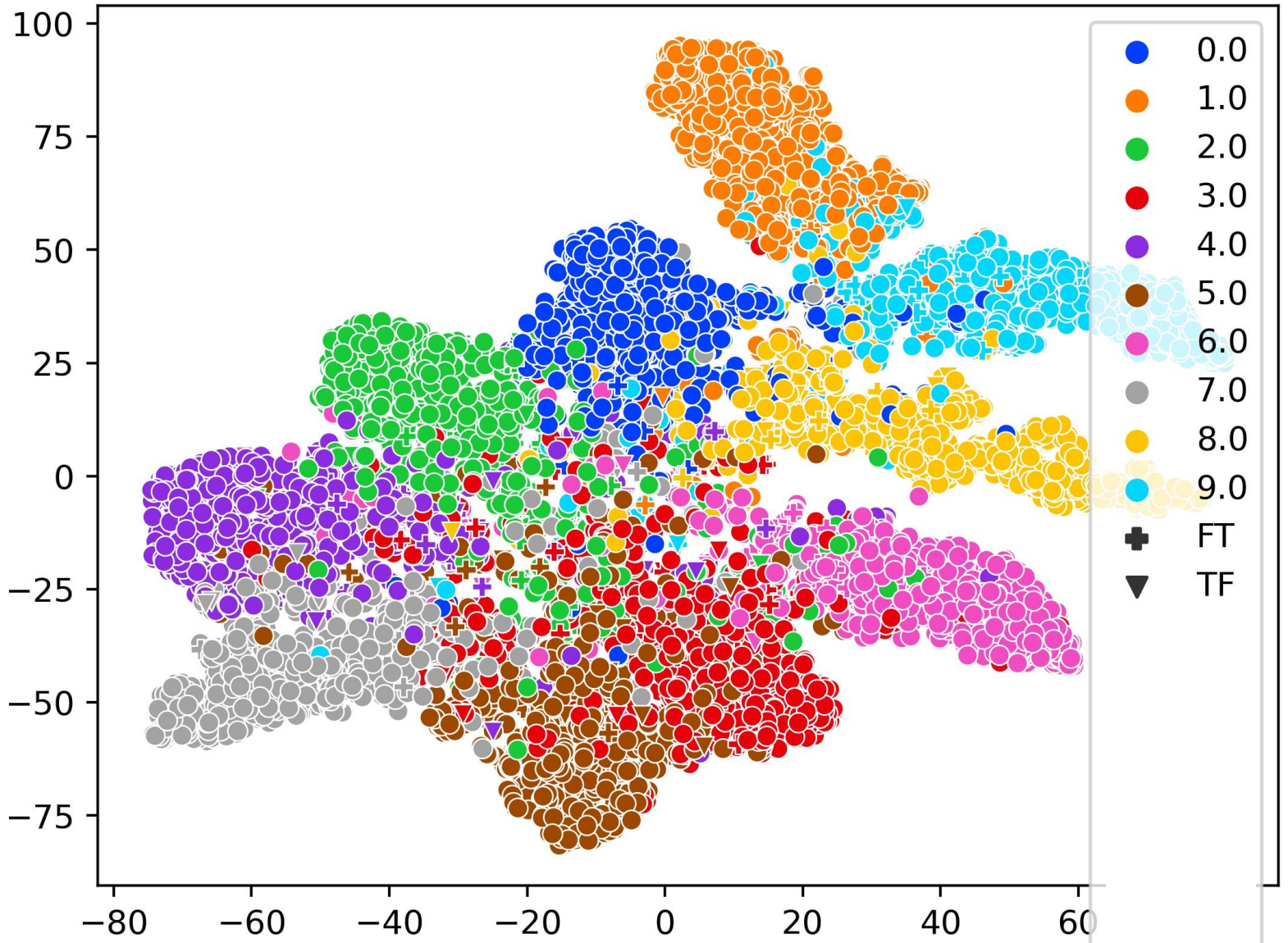

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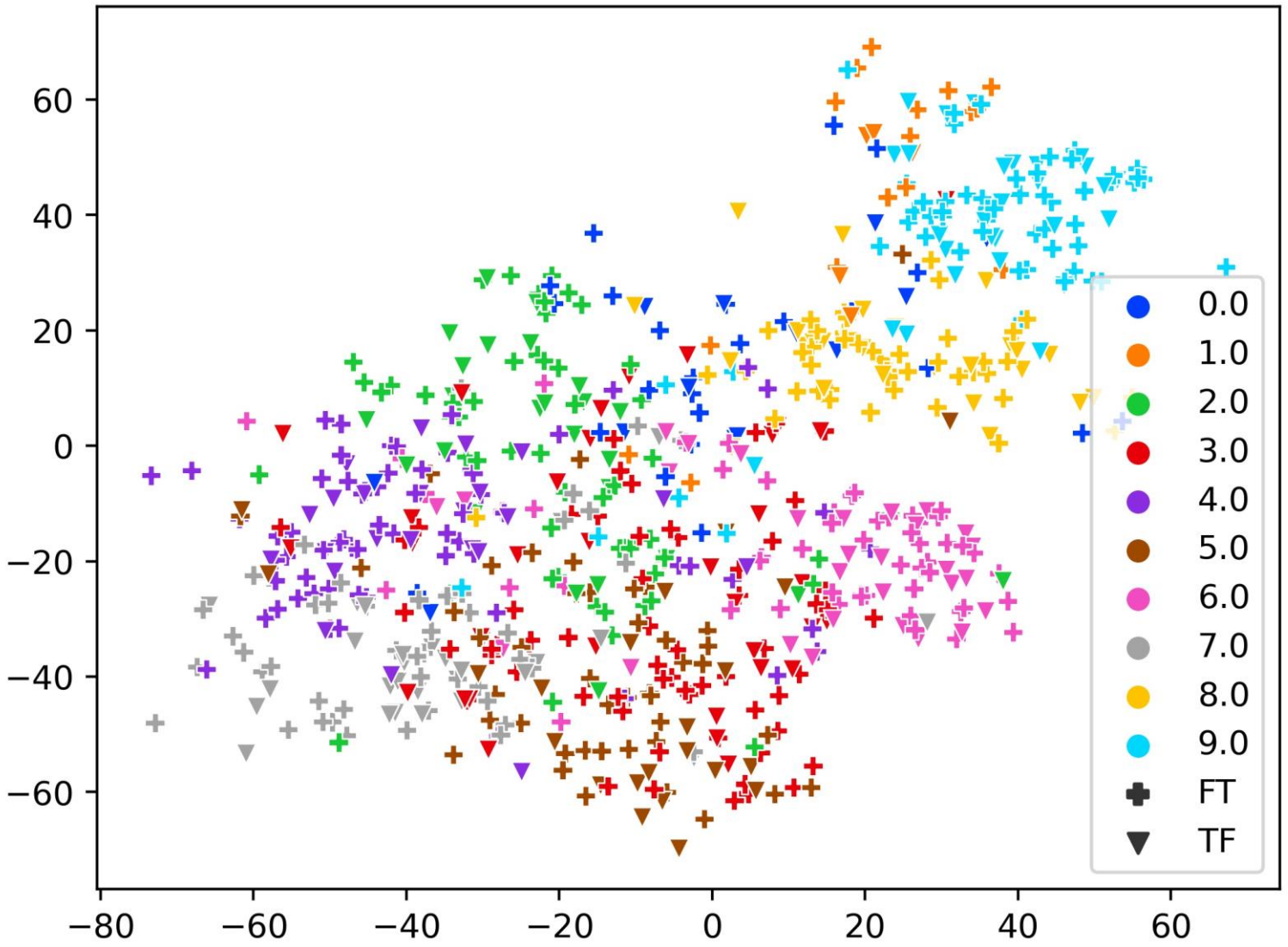

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: 237

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RIDE:

Each expert has a balanced access to the **entire** dataset, and each expert focuses on **different** classes.

Ours:

Each expert has a balanced access to the **entire** dataset, and each expert focuses on **all** classes.

Advantages

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- The independent **training manner** brings **diversity** to experts, and the Test-Average(TA) makes the network more **robust**.
- The **diversity** and the **Test-Average** are working at the same time.
- Our network is **One-stage** model, while LFME and RIDE aren’t.
- Our network outperforms **SOTA** methods.

THANKS