# Dynamic Distillation Network for Cross-Domain Few-Shot Recognition with Unlabeled Data

A Islam, R Chen, R Panda, L Karlinksky, RS Feris, RJ Radke

# Motivation: Few-shot Learning

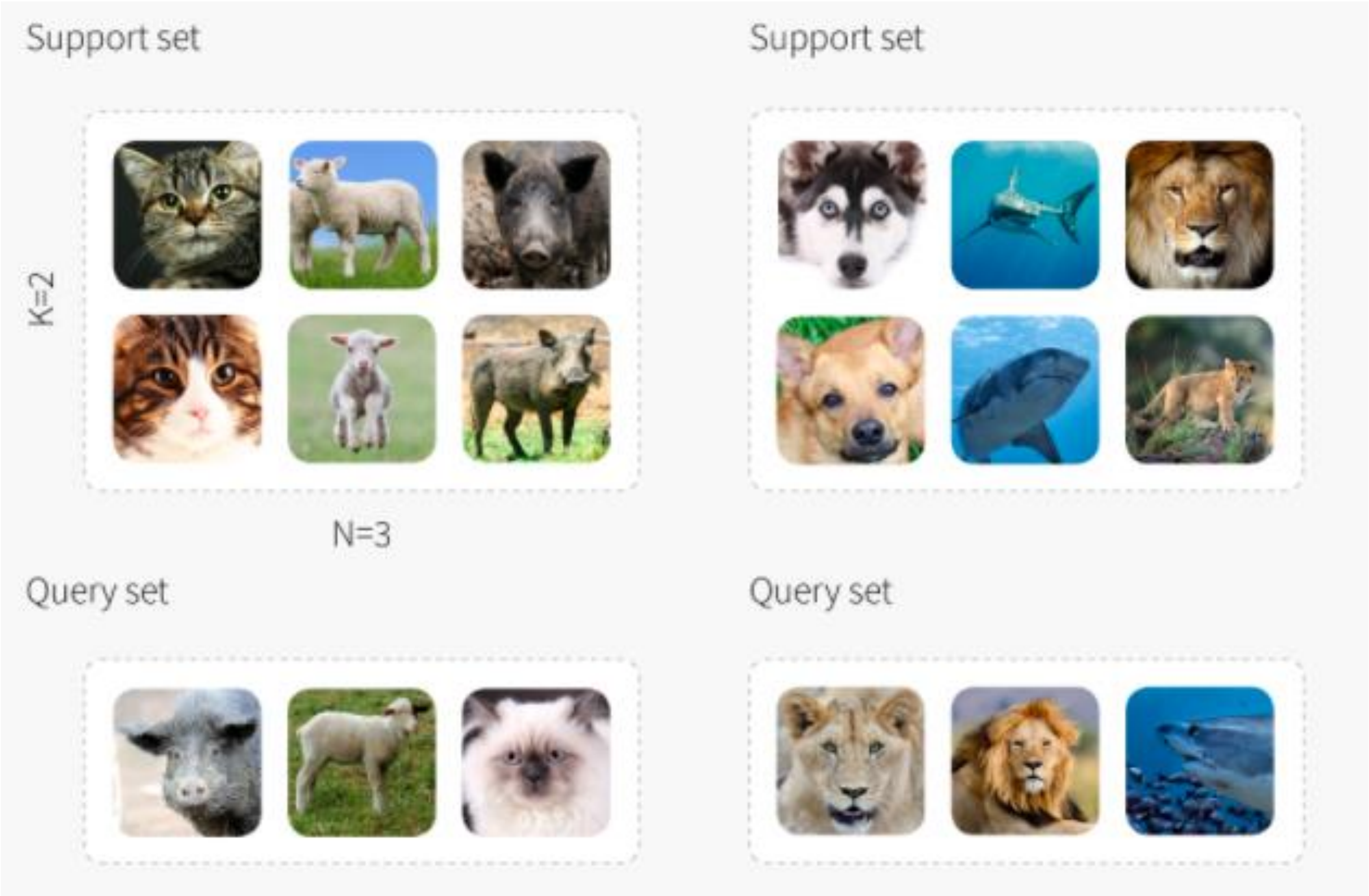
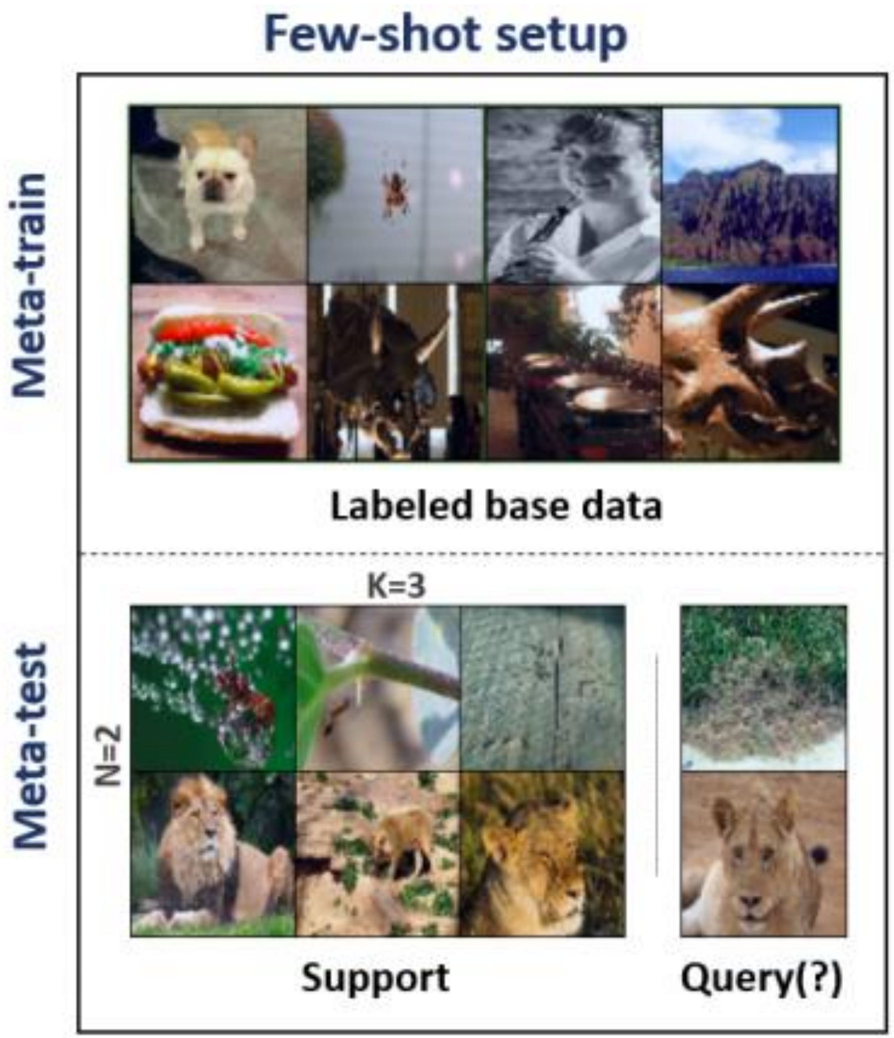
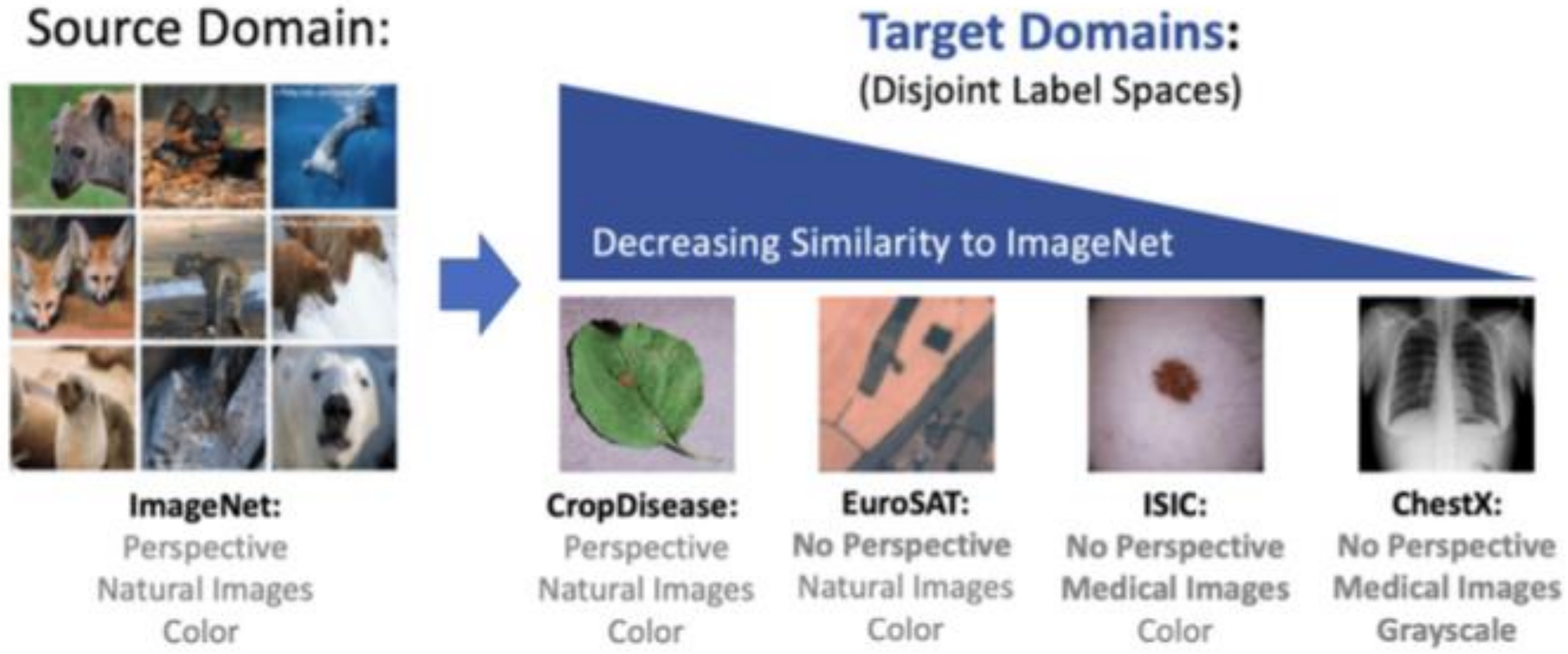



Image source: https://www.borealisai.com/en/blog/tutorial-2-few-shot-learning-and-meta-learning-i/

# Few-shot Setup

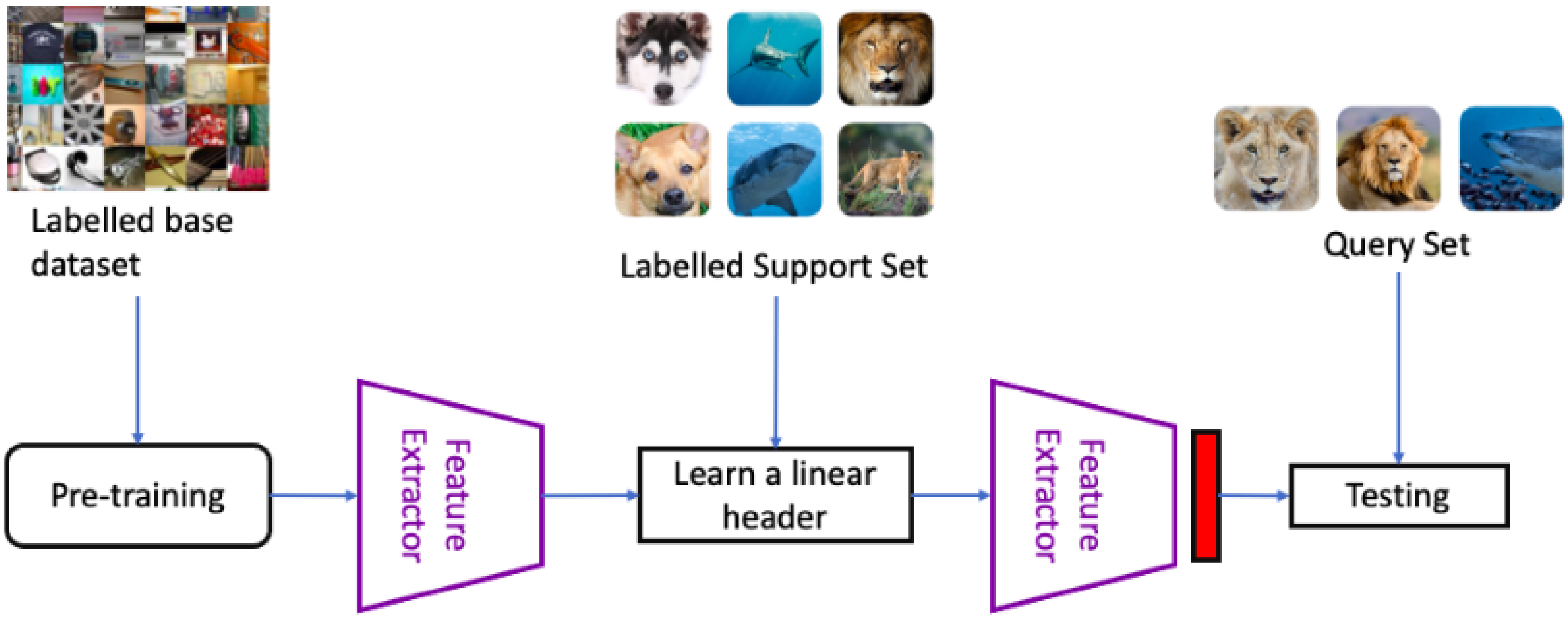


# Cross-domain Few-shot Learning

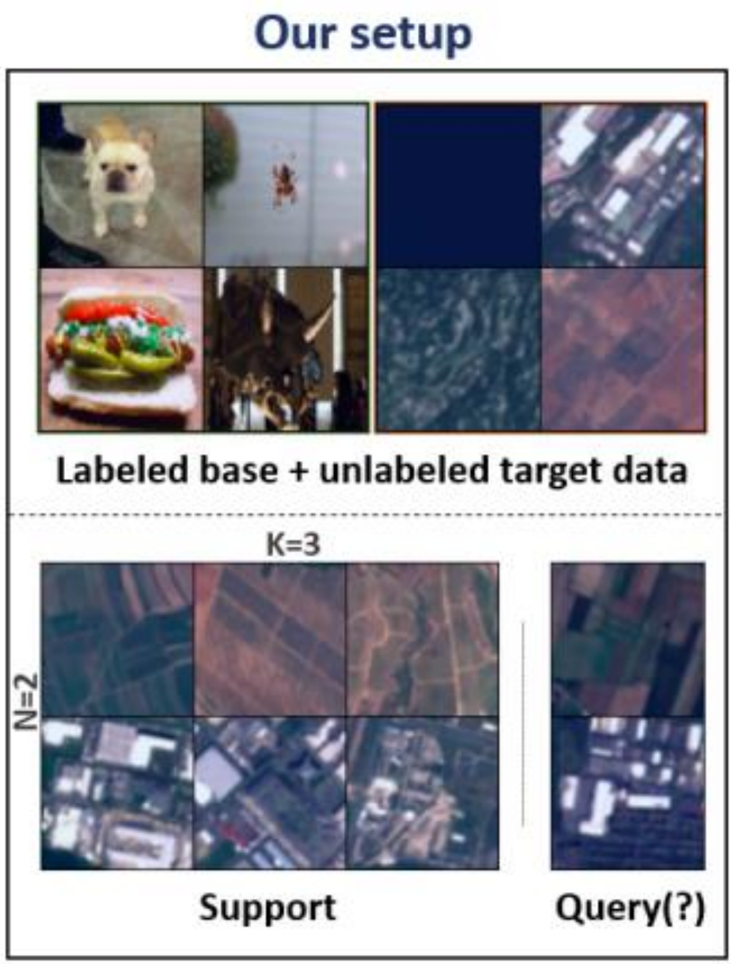


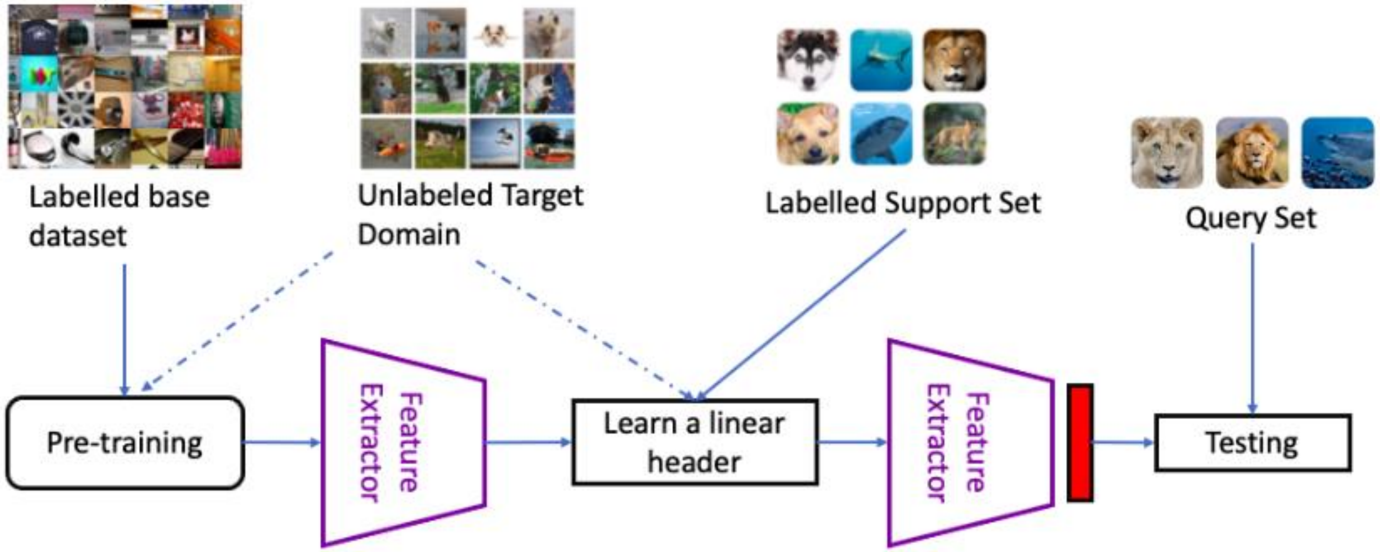

Yunhui Guo and Noel C. Codella and Leonid Karlinsky and James V. Codella and John R. Smith and Kate Saenko and Tajana Rosing and Rogerio Feris, “A Broader Study of Cross-Domain Few-Shot Learning”.

# Existing Approaches

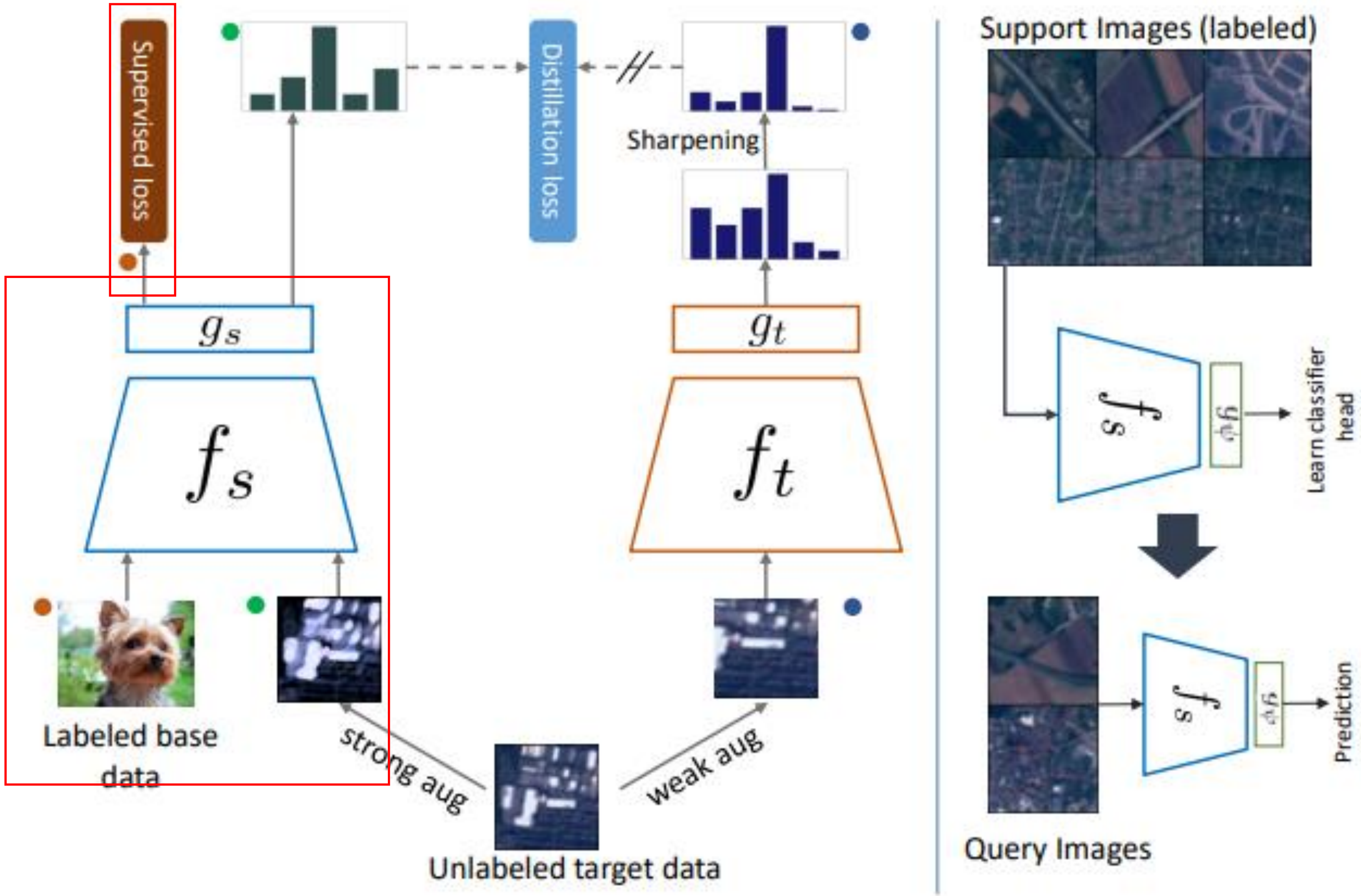


# Our Approach

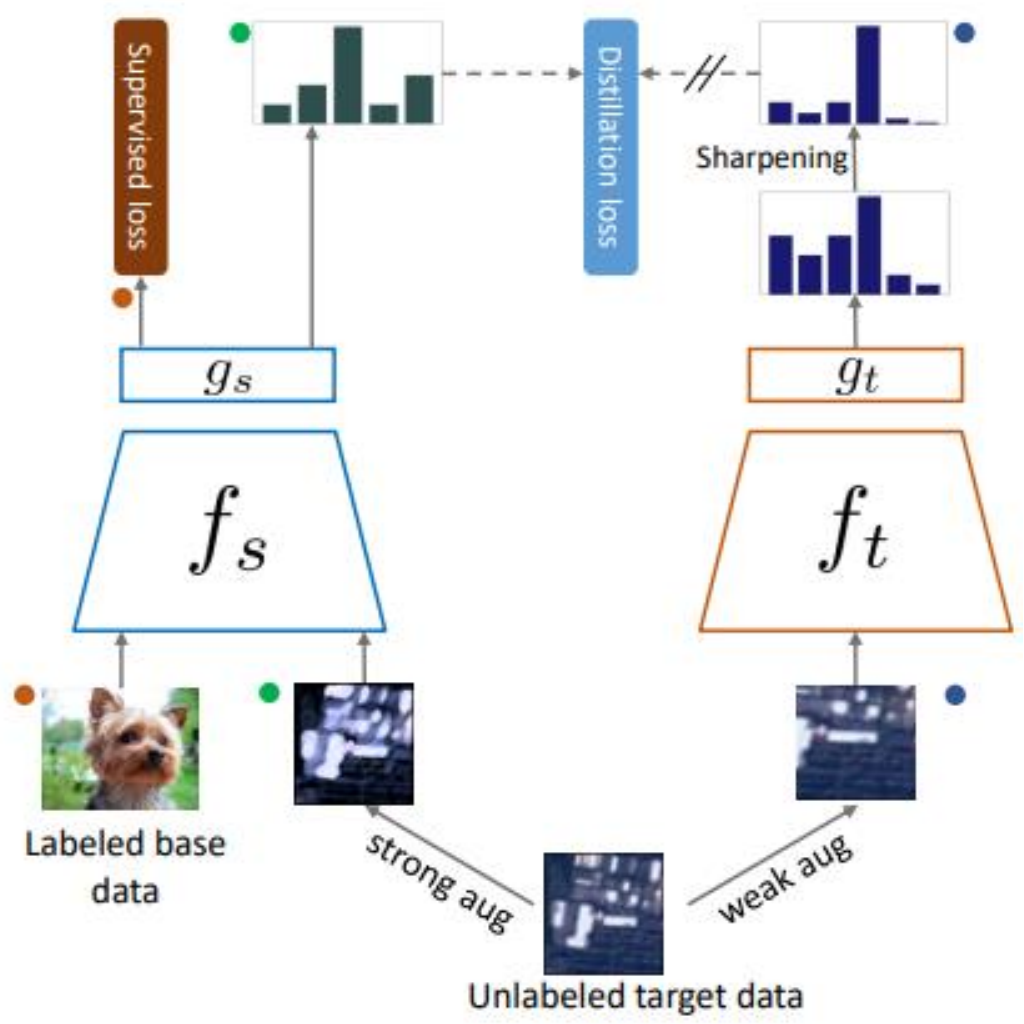


# Our Framework



# Consistency Loss




$$p_i^s = \texttt{Softmax}(g_s(f_s(x_i^s)))$$

$$p_i^w = \texttt{Softmax}(g_t(f_t(x_i^w))/\tau)$$

$$\mathcal{L} = \frac{1}{N_S} \sum_{(x_i, y_i) \in \mathcal{D}_S} l_{\text{CE}}(y, p) + \lambda \frac{1}{N_U} \sum_{x_i \in \mathcal{D}_U} l_U(p_i^w, p_i^s)$$

# Dataset: BSCD-FSL

| Dataset | Train | Test | Classes |
|---|---|---|---|
| Mini-ImageNet | 38400 | 20000 | 100 |
| CropDisease | 43456 | 10849 | 38 |
| EuroSAT | 18900 | 8100 | 10 |
| ISIC | 7007 | 3008 | 7 |
| ChestX | 18090 | 7758 | 7 |

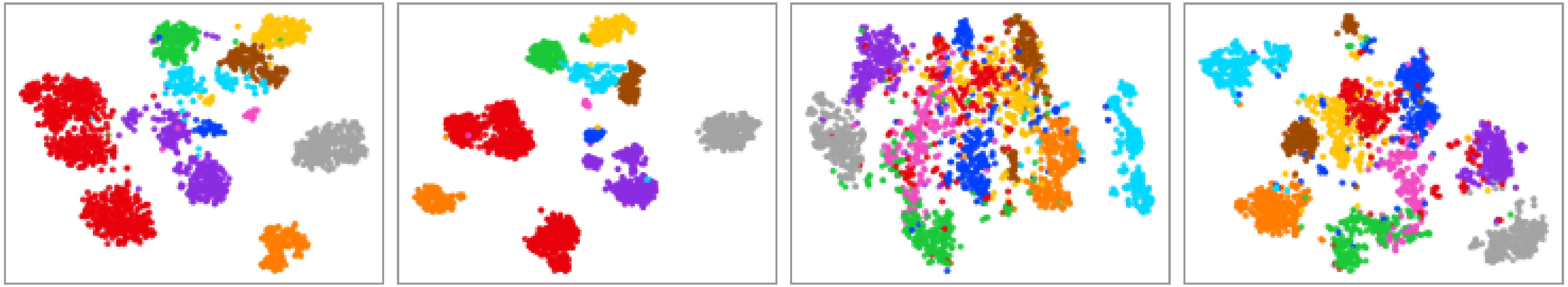
# Results: Cross-domain

| | 1-shot | | | | 5-shot | | | |
|---|---|---|---|---|---|---|---|---|
| Model | EuroSAT | CropDisease | ISIC | ChestX | EuroSAT | CropDisease | ISIC | ChestX |
| MAML* | - | - | - | - | 71.70±.72 | 78.05±.70 | 40.13±.58 | 23.48±.48 |
| ProtoNet* | - | - | - | - | 73.29±.71 | 79.72±.79 | 39.57±.57 | 24.05±1.01 |
| MetaOpt* | - | - | - | - | 64.44±.73 | 68.41±.73 | 36.28±.50 | 22.53±.91 |
| STARTUP† | 63.88±.84 | 75.93±.80 | 32.66±.60 | 23.09±.43 | 82.29±.60 | 93.02±.45 | 47.22±.61 | 26.94±.45 |
| ProtoNet | 55.32±.88 | 52.94±.81 | 29.58±.57 | 21.32±.37 | 76.92±.67 | 81.84±.68 | 42.49±.58 | 24.72±.43 |
| MatchingNet | 54.88±.90 | 46.86±.88 | 27.37±.51 | 20.65±.29 | 68.00±.68 | 63.94±.84 | 33.96±.54 | 22.62±.36 |
| Transfer | 58.14±.83 | 68.78±.84 | 32.12±.59 | 22.60±.39 | 80.09±.61 | 89.79±.52 | 43.88±.57 | 26.51±.43 |
| SimCLR(Base) | 58.28±.90 | 61.58±.88 | 32.43±.56 | 22.37±.42 | 80.83±.64 | 83.44±.61 | 44.04±.55 | 26.63±.46 |
| SimCLR | 62.63±.87 | 69.22±.93 | 31.45±.59 | 23.59±.44 | 82.76±.59 | 89.31±.53 | 42.18±.54 | **29.56±.49** |
| STARTUP | 64.32±.88 | 74.45±.86 | 31.73±.57 | 22.27±.41 | 83.58±.60 | 92.41±.47 | 45.73±.62 | 26.21±.46 |
| Transfer+SimCLR | 63.91±.83 | 70.35±.85 | 31.67±.55 | **23.72±.44** | 85.78±.51 | 91.10±.49 | 45.97±.54 | 29.45±.10 |
| Ours | **73.14±.84** | **82.14±.78** | **34.66±.58** | 23.38±.43 | **89.07±.47** | **95.54±.38** | **49.36±.59** | 28.31±.46 |

# Results: In-domain

| | miniImageNet 1-shot | miniImageNet 5-shot | tieredImageNet 1-shot | tieredImageNet 5-shot |
|---|---|---|---|---|
| ProtoNet | 51.06±.83 | 73.49±.63 | - | - |
| MatchingNet | 52.34±.81 | 67.28±.67 | - | - |
| Transfer | 53.40±.80 | 74.26±.64 | 58.61±.97 | 81.42±.65 |
| Transfer+SimCLR | 51.63±.82 | 74.65±.60 | 61.33±.96 | 82.89±.65 |
| STARTUP | 51.68±.84 | 74.05±.66 | 60.92±.96 | 82.11±.64 |
| Ours | **53.71±.83** | **76.02±.61** | **69.00±.96** | **85.93±.60** |

# Analysis: Effect of Dynamic Distillation



(a) Transfer (b) Ours (c) Transfer (d) Ours

| | EuroSAT | CropDisease | ISIC | ChestX |
|---|---|---|---|---|
| Transfer | 57.01 | 62.58 | **14.67** | 2.45 |
| SimCLR | 60.06 | 62.02 | 12.12 | **3.84** |
| STARTUP | 62.02 | 69.50 | 14.05 | 2.71 |
| Ours | **69.58** | **73.27** | 14.32 | 3.32 |

# Analysis: Comparison with SS Learning

- our model has similarity with self-supervised non-contrastive loss similar to BYOL or DINO
- Using a **supervised classifier linear layer as the projection head** can solve the issue of *trivial solution* for the self-supervised learning.

| | EuroSAT | CropDisease | ISIC | ChestX |
|---|---|---|---|---|
| Ours | 89.07 | 95.54 | 49.36 | 28.31 |
| Ours (distillation head) | 80.06 | 89.31 | 46.63 | 25.29 |
| Ours (DINO head) | 85.74 | 90.55 | 46.24 | 25.42 |
| Ours + SimCLR | 88.48 | 93.80 | 49.10 | 29.45 |

# Experiment on Fine-grained dataset CUB

- For CUB, we found that vanilla Transfer performs surprisingly well
- Adding SimCLR with Transfer decreases the accuracy
- Our method performs best among different approaches for fine-grained few-shot classification

| Model | CUB |
|---|---|
| MatchingNet | 58.23 |
| ProtoNet | 63.19 |
| Transfer | 68.72 |
| SimCLR | 62.84 |
| Transfer+SimCLR | 67.82 |
| STARTUP | 66.10 |
| Ours | **69.50** |

# Limitations

- Improvement is not significant for extreme task difference mini-ImageNet -> ChesX
- More unlabeled dataset does not necessary produce much better feature

# Summary

- We introduced a novel approach to utilize unlabeled data from the target domain for cross-domain few-shot learning
- Experiments show that our method achieves state-of-the-art results in the BSCD-FSL benchmark for both 1-shot and 5-shot classification.
- Our model also outperforms other approaches in the same-domain few-shot learning.
- Future work can be focused on applying our approach in each episode during meta-testing so that the model can learn more category-specific representations.