TapNet: Neural Network Augmented with Task-Adaptive Projection for Few-Shot Learning

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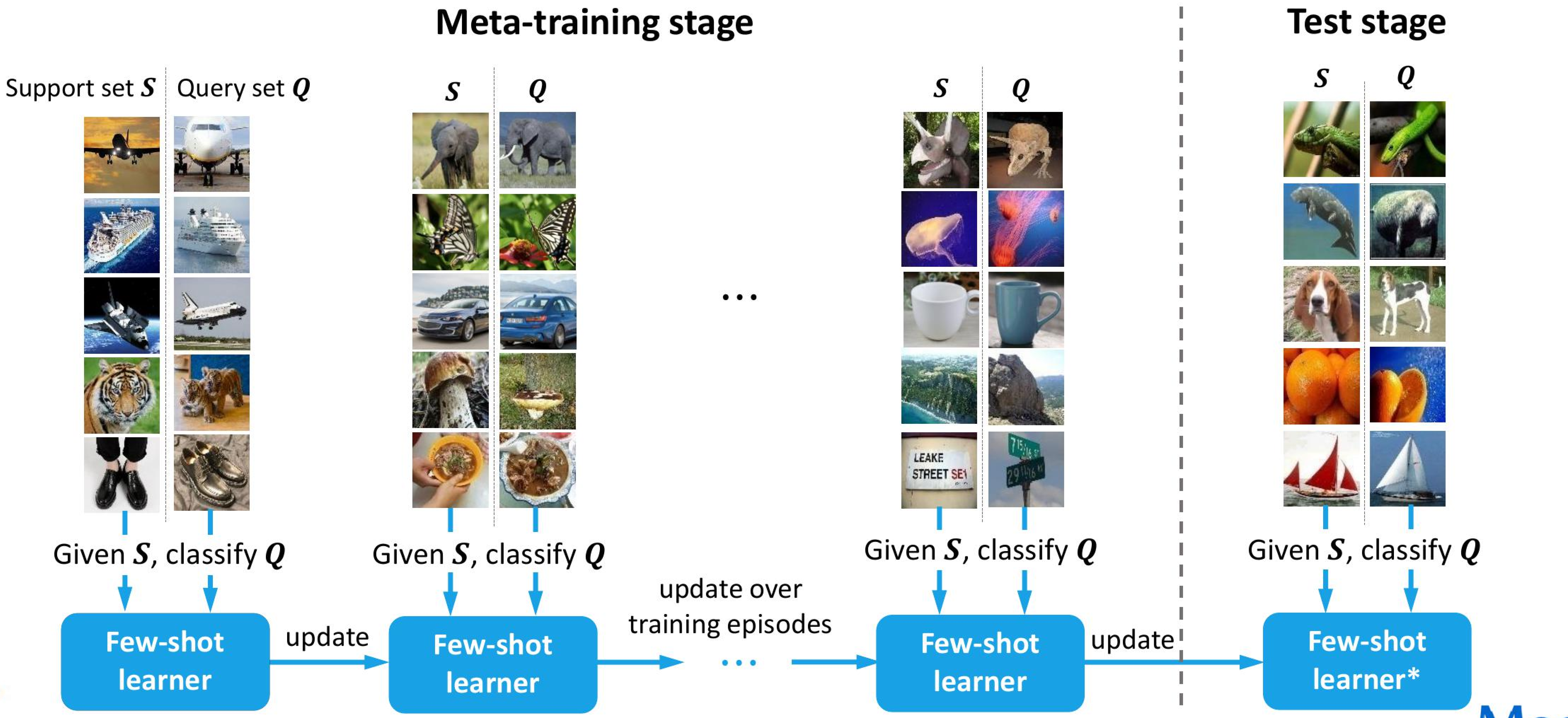
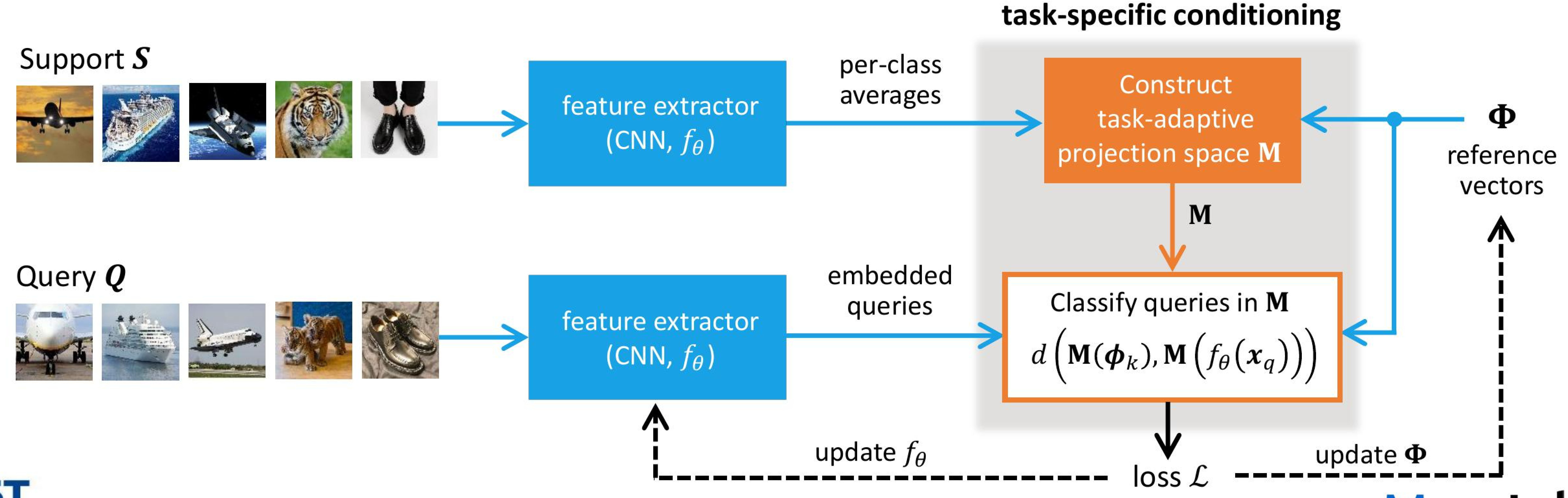
Few-Shot Learning

- Handling previously unseen classification tasks (episodes)
  - Training model with widely varying episodes (episodic training) [Vinyals et al., 2016]



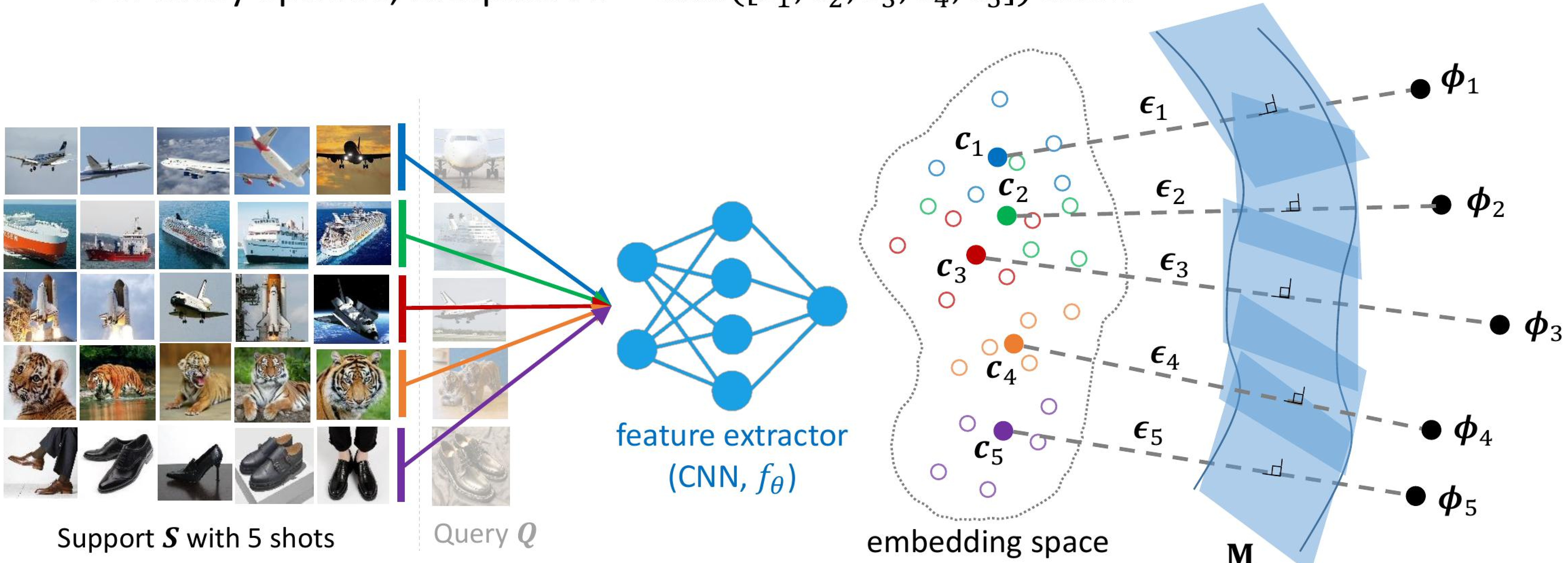
TapNet: Task-Adaptive Projection Network

- Model description (three key elements)
  - Feature extractor f_θ
  - Learnable reference vectors $\mathbf{\Phi} = [\boldsymbol{\phi}_1; \cdots; \boldsymbol{\phi}_N]$
  - Task-adaptive projection space $\mathbf{M}$
    - » Project references $\mathbf{\Phi}$ and embedded queries to $\mathbf{M}$, and apply metric-based classification



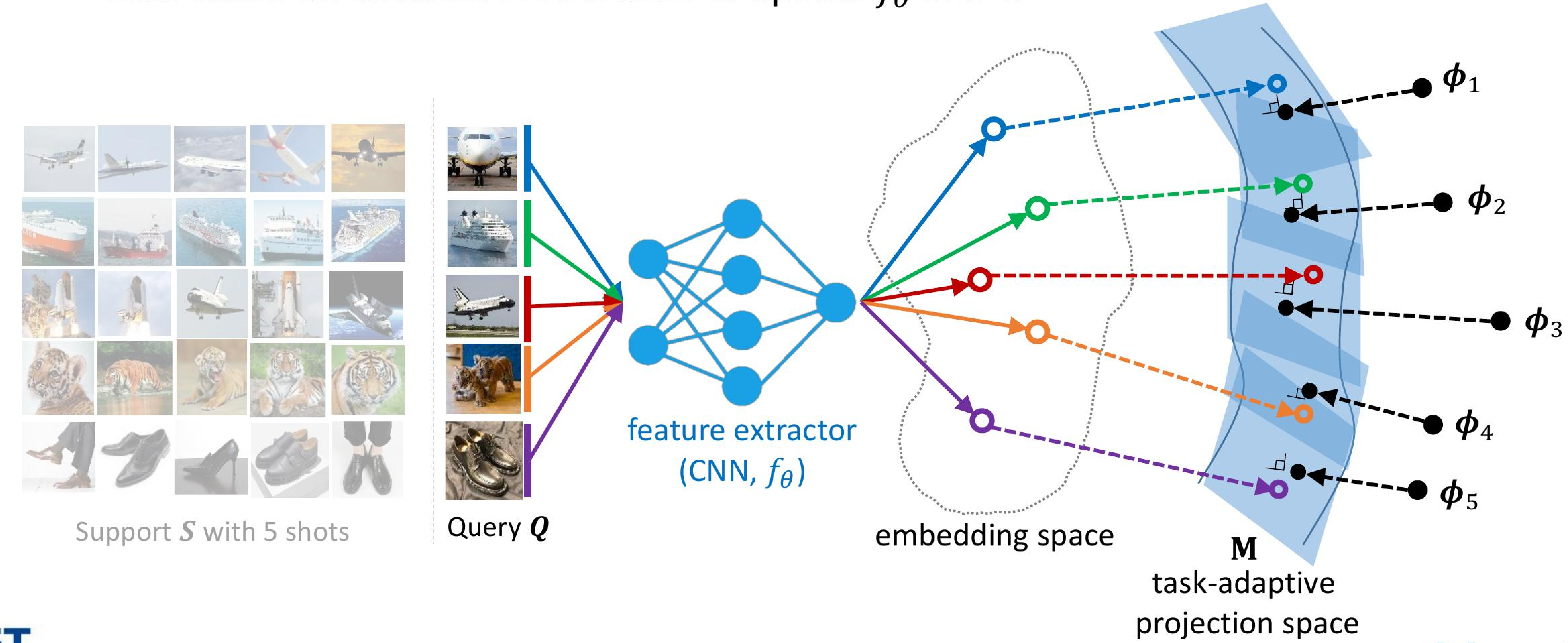
How to Construct Projection Space $\mathbf{M}$

- Construction of projection space via linear nulling
  - Error vector between per-class average $\boldsymbol{c}_k$ and reference $\boldsymbol{\phi}_k$ should be zero-forced in $\mathbf{M}$.
  - For every episode, compute $\mathbf{M} = \mathrm{null}([\boldsymbol{\epsilon}_1; \boldsymbol{\epsilon}_2; \boldsymbol{\epsilon}_3; \boldsymbol{\epsilon}_4; \boldsymbol{\epsilon}_5])$ anew



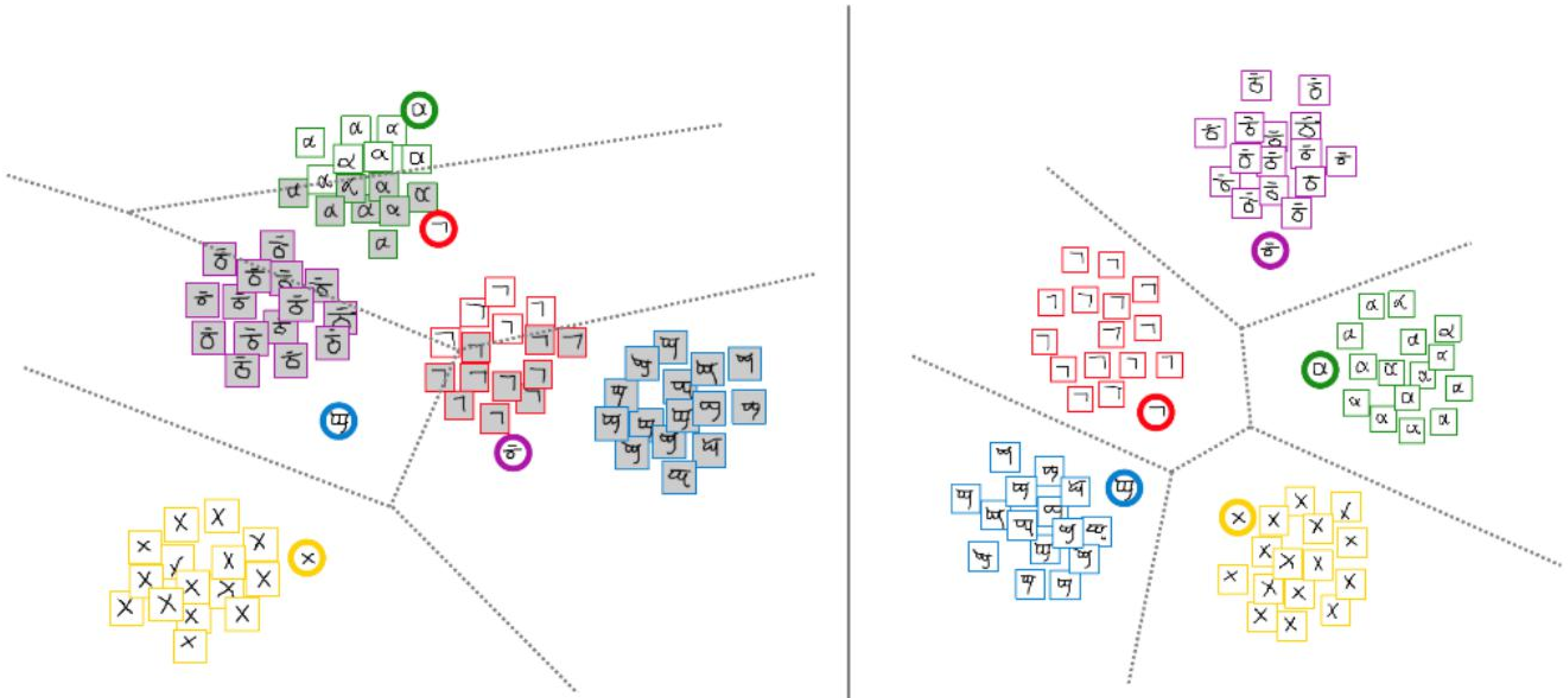
Classification and Learning

- Classifying in the task-adaptive space
  - Project $\mathbf{\Phi}$ and embedded queries to $\mathbf{M}$ → Classify the projected queries with projected $\mathbf{\Phi}$.
  - Loss based on distance in $\mathbf{M}$ is used to update f_θ and $\mathbf{\Phi}$



Observations

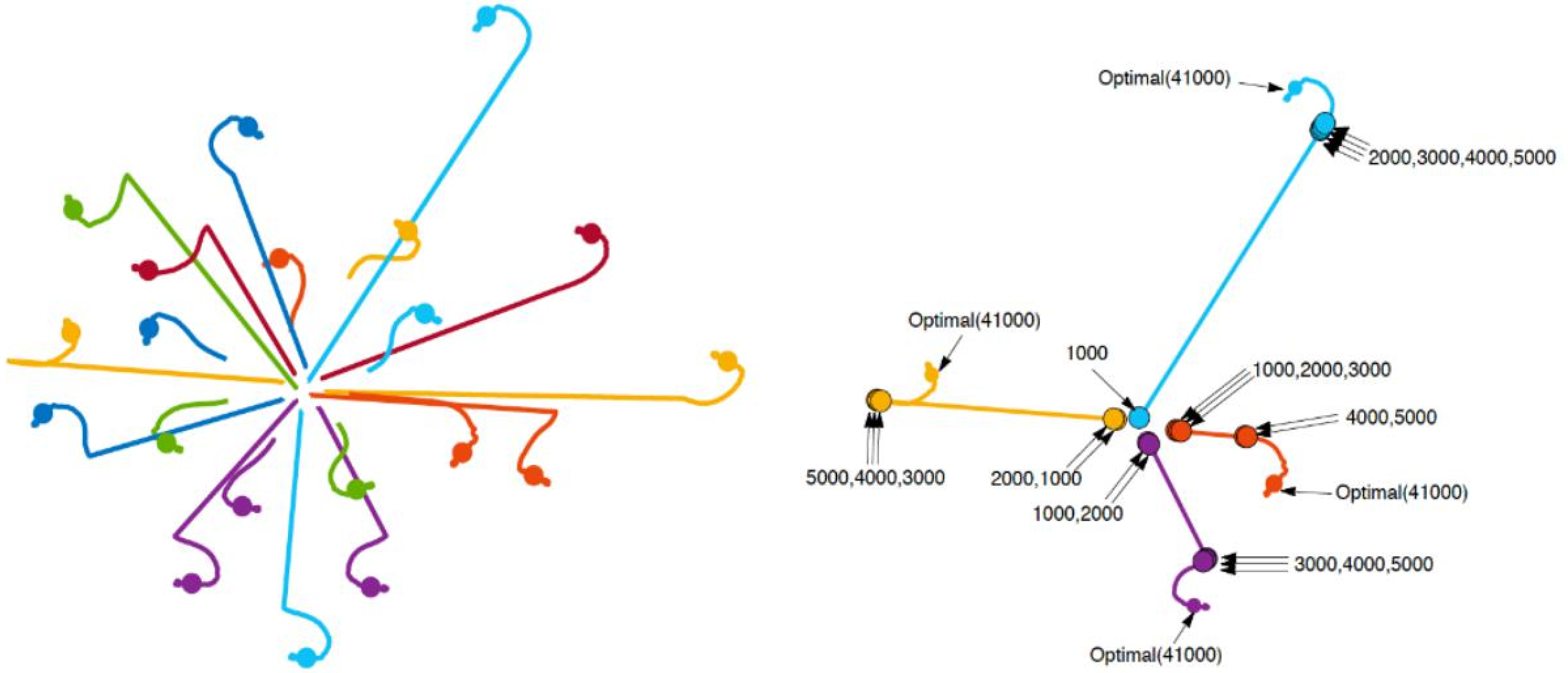
- Projection space gives better separation of classes
- Reference vector tips actually grow apart with training



embedding space

projection space

t-SNE plot



Learning trend of Φ

Results and Conclusions

Visit Poster #4 in Pacific Ballroom for further results!

- Non-learning-based and explicit task-adaptation method
- Excellent generalization performance

Methods	5-way *mini*ImageNet 1-shot	5-way *mini*ImageNet 5-shot
Matching Nets (Vinyals et al., 2016)	$43.56 \pm 0.84\%$	$55.31 \pm 0.73\%$
MAML (Finn et al., 2017)	$48.70 \pm 1.84\%$	$63.15 \pm 0.91\%$
Prototypical Nets (Snell et al., 2017)	$49.42 \pm 0.78\%$	$68.20 \pm 0.66\%$
SNAIL (Mishra et al., 2017)	$55.71 \pm 0.99\%$	$68.88 \pm 0.92\%$
adaResNet (Munkhdalai et al., 2018)	$56.88 \pm 0.62\%$	$71.94 \pm 0.57\%$
Transductive Propagation Nets (Liu et al., 2018)	$55.51 \pm 0.86\%$	$69.86 \pm 0.65\%$
TADAM-α (Oreshkin et al., 2018)	$56.8 \pm 0.3\%$	$75.7 \pm 0.2\%$
TADAM-TC (Oreshkin et al., 2018)	$58.5 \pm 0.3\%$	$\mathbf{76.7 \pm 0.3\%}$
TapNet (Ours)	$\mathbf{61.65 \pm 0.15\%}$	$\mathbf{76.36 \pm 0.10\%}$

Methods	5-way *tiered*ImageNet 1-shot	5-way *tiered*ImageNet 5-shot
MAML (as evaluated in (Liu et al., 2018))	$51.67 \pm 1.81\%$	$70.30 \pm 1.75\%$
Prototypical Nets (as evaluated in (Liu et al., 2018))	$53.31 \pm 0.89\%$	$72.69 \pm 0.74\%$
Relation Nets (as evaluated in (Liu et al., 2018))	$54.48 \pm 0.93\%$	$71.31 \pm 0.78\%$
Transductive Propagation Nets (Liu et al., 2018)	$59.91 \pm 0.94\%$	$73.30 \pm 0.75\%$
TapNet (Ours)	$\mathbf{63.08 \pm 0.15\%}$	$\mathbf{80.26 \pm 0.12\%}$

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