MAML is a Noisy Contrastive Learner

NewInML Workshop@NeurIPS'21

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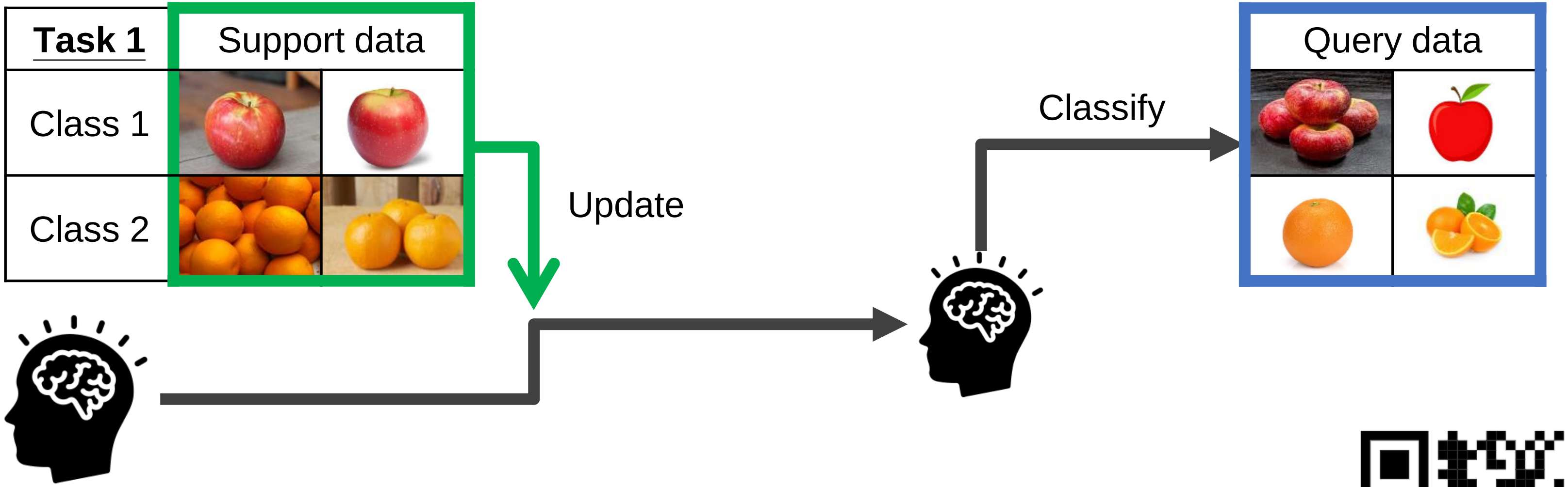
Introduction

Humans learn to classify even with limited experience.



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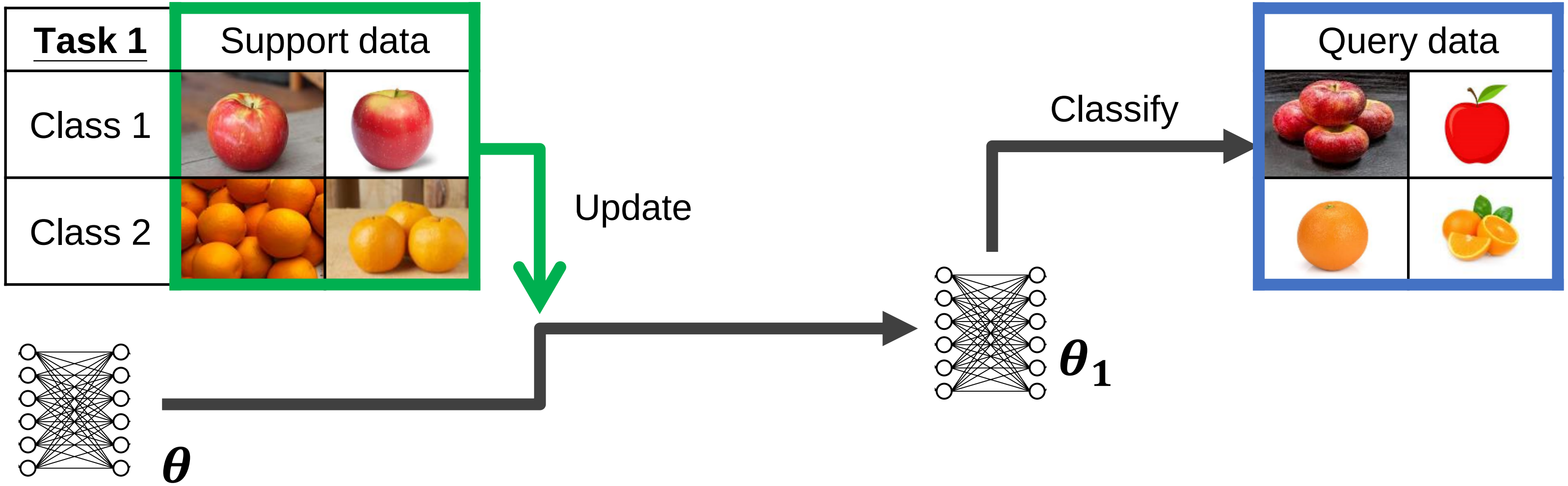

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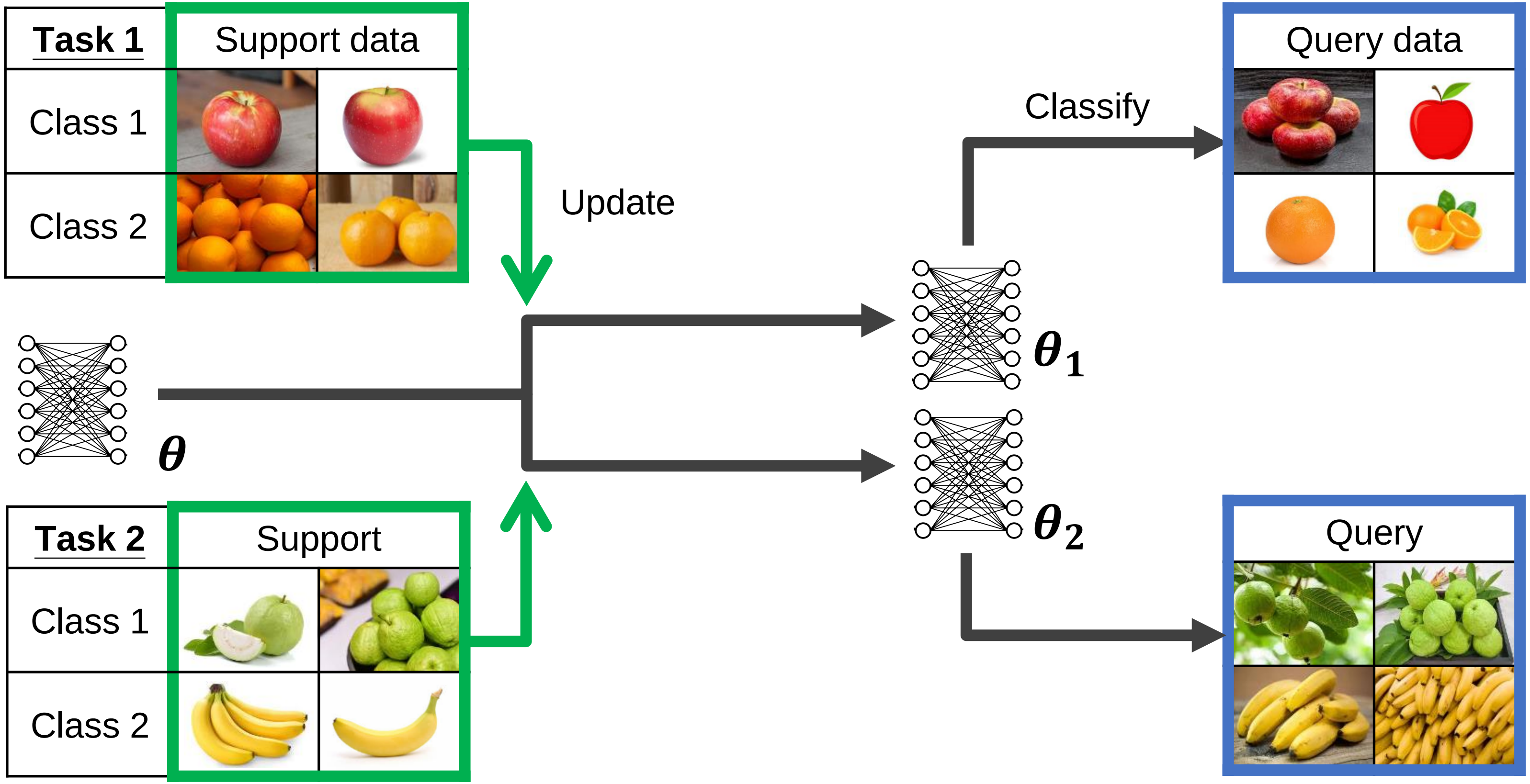

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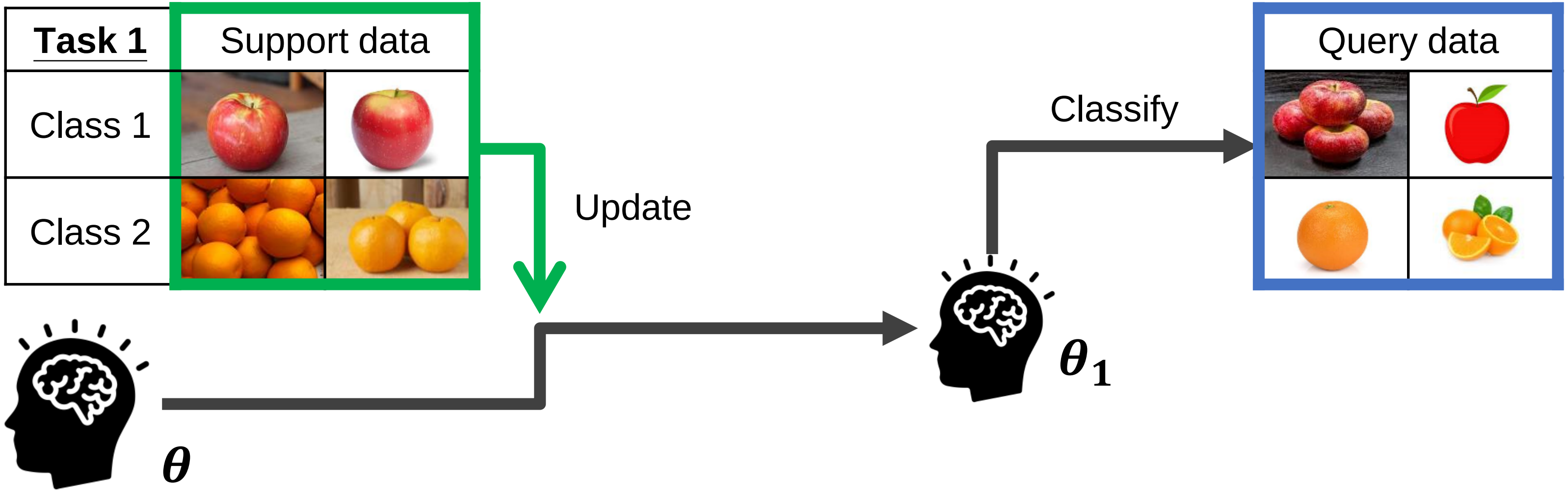

- MAML is a gradient-based meta-learning algorithm that finds a good θ.

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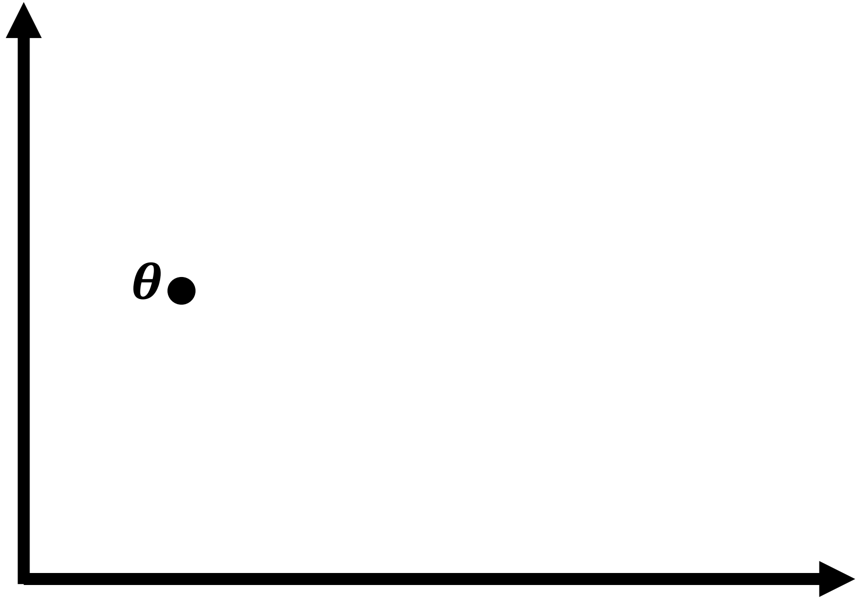

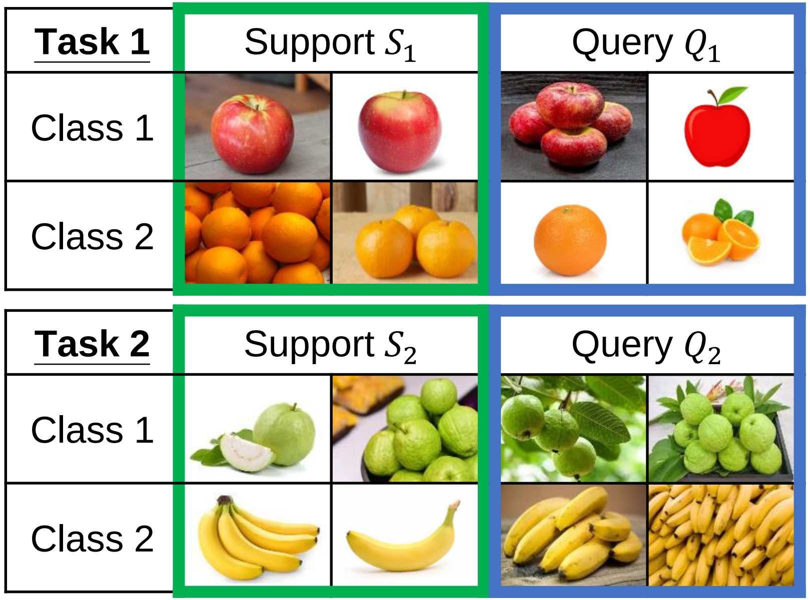

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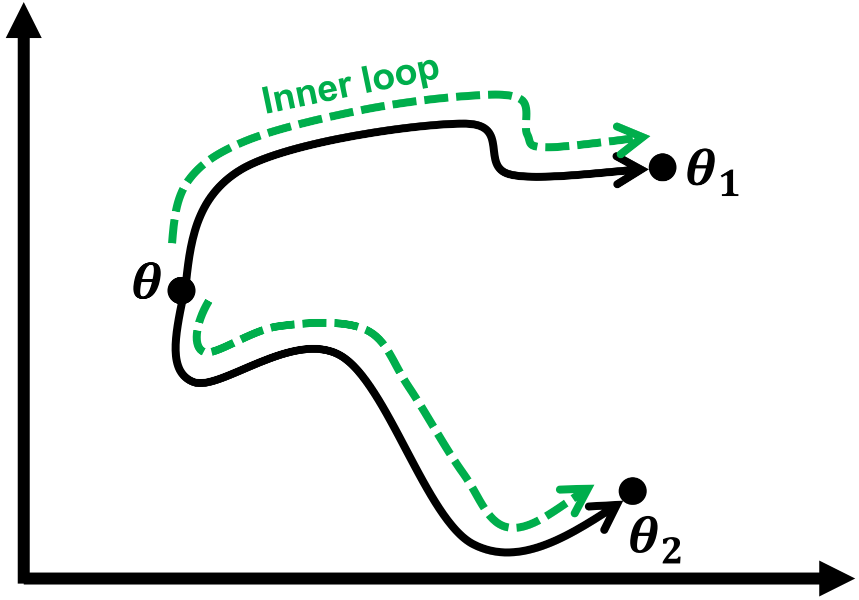

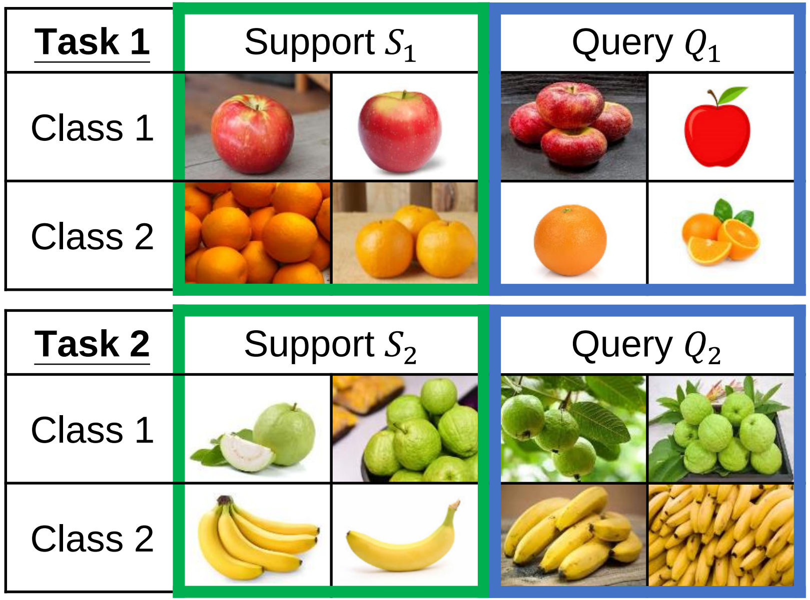

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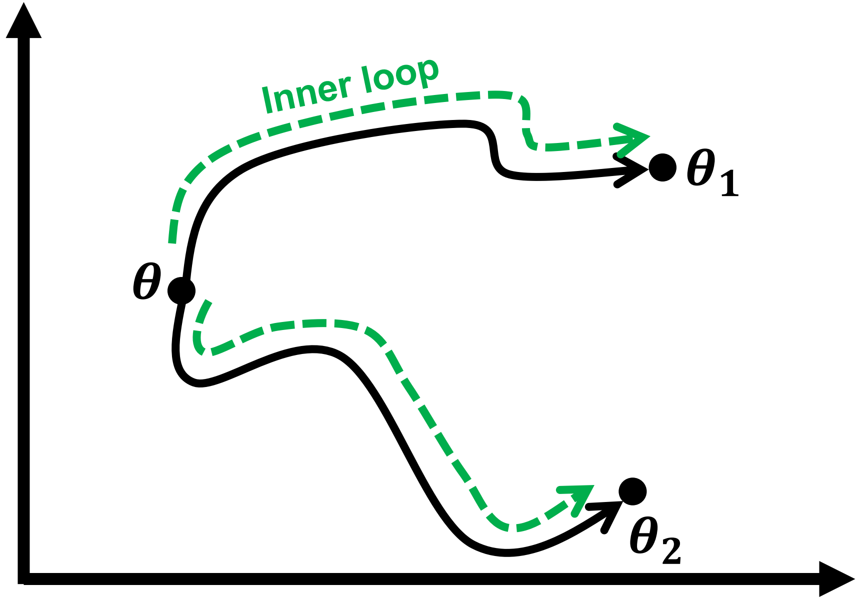

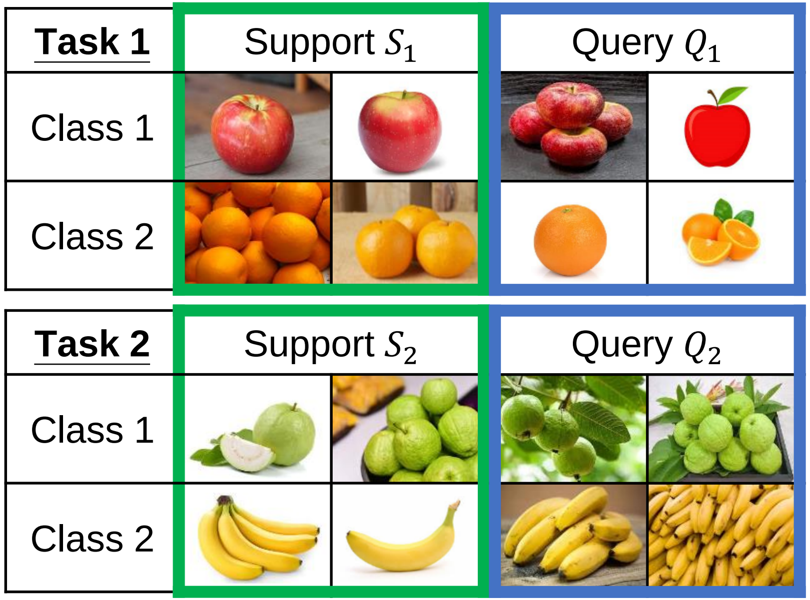

- Goal: Minimize $\mathrm{L}(\theta_1, Q_1)$ and $\mathrm{L}(\theta_2, Q_2)$ by finding best θ.

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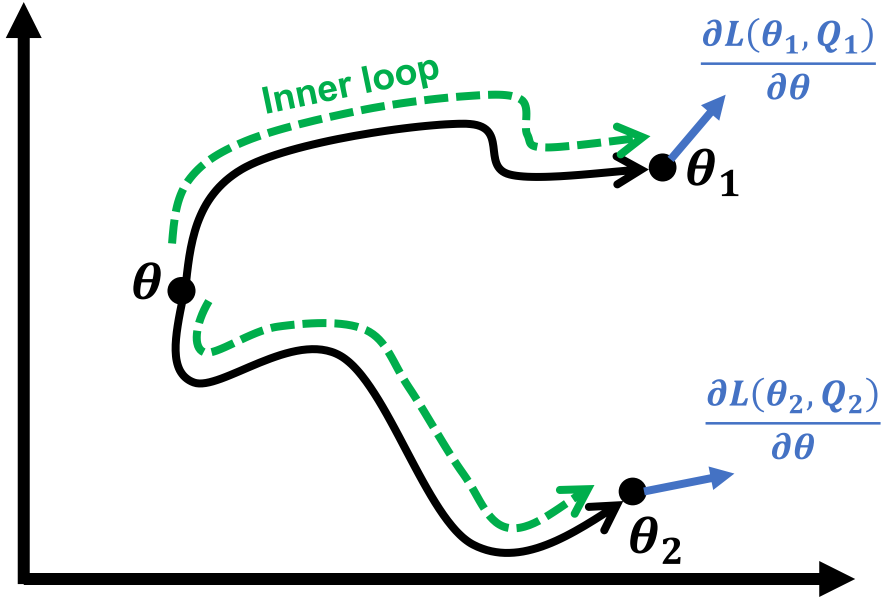

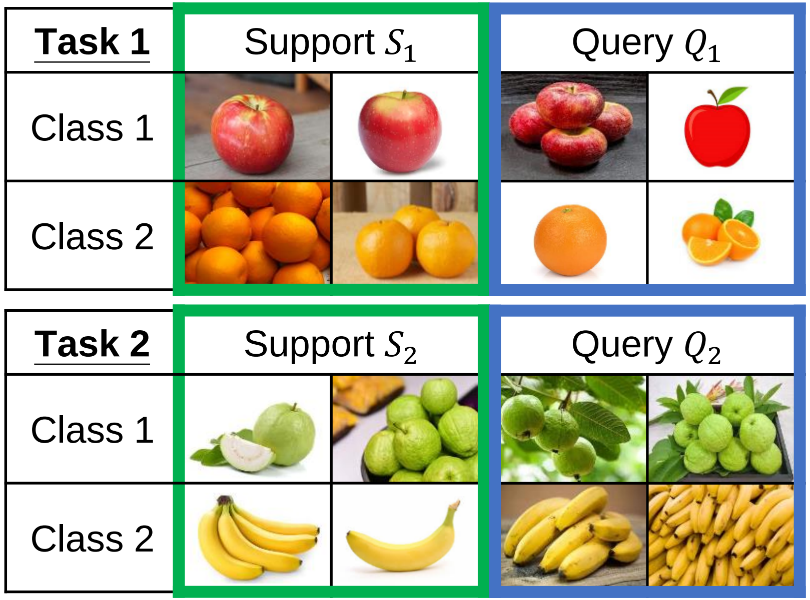

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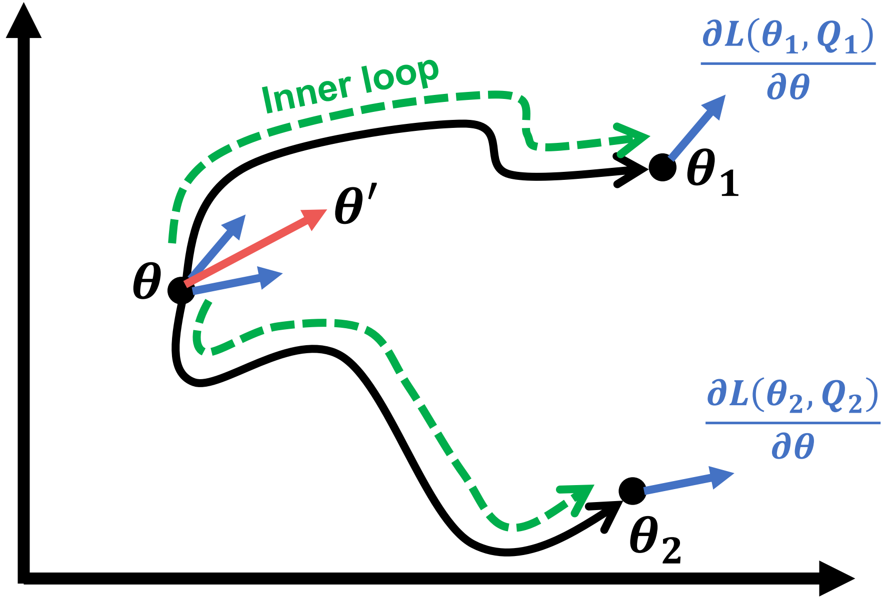

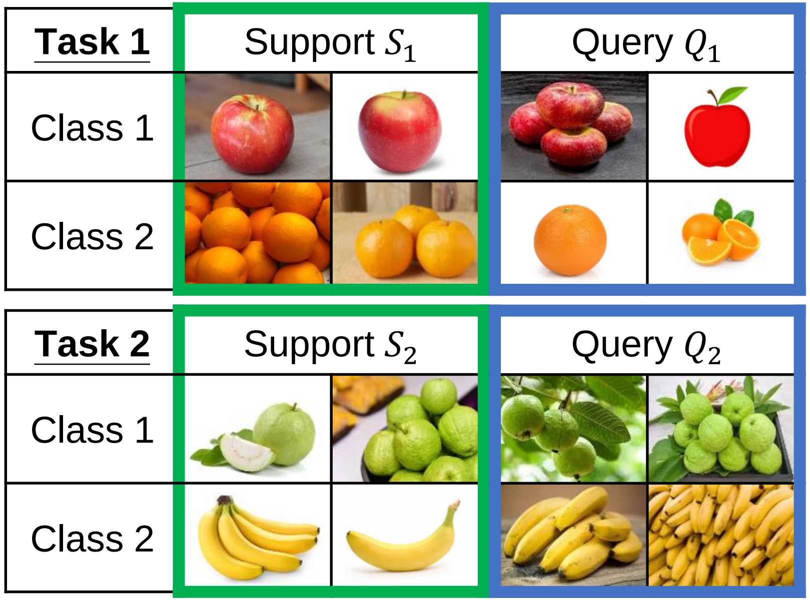

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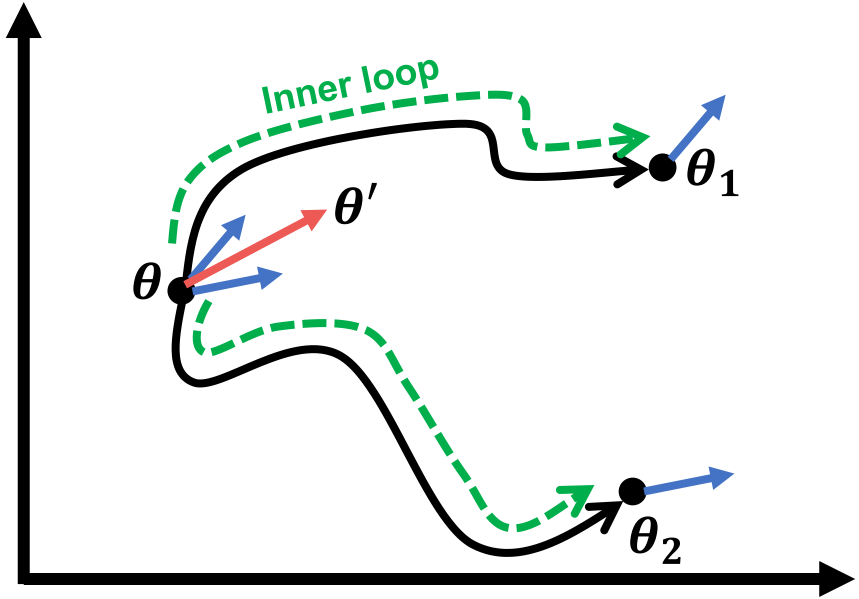

Algorithm 1 Second-order MAML

while not done **do**
  Sample tasks $\{T_1, T_2\}$
  for $n = 1, 2$ **do**
    $\{S_n, Q_n\} \leftarrow$ sample from T_n
    $\theta_n = \theta$
    for $i = 1, 2, \ldots, N_{step}$ **do**
      $\theta_n \leftarrow \theta_n - \eta \nabla_{\theta_n} L(\theta_n, S_n)$
    end for
  end for
  Update $\theta \leftarrow \theta - \rho \sum_{n=1}^{N_{batch}} \nabla_\theta L(\theta_n, Q_n)$
end while

- Goal: Minimize $\mathrm{L}(\theta_1, Q_1)$ and $\mathrm{L}(\theta_2, Q_2)$ by finding best θ.
- Method: update θ by $\theta' = \theta - \sum \frac{\partial L(\theta_n, Q_n)}{\partial \theta}$

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Why is MAML successful?

- It is widely believed that MAML **encourages** models to learn a general-purpose representations which are applicable to novel tasks.

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In this paper, we step further and ask:

- **How** does MAML **encourage** any model to learn general-purpose representations?
- What is the role of the support and query data and how do they interact with each other?

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- **How** does MAML **encourage** any model to learn general-purpose representations?
- What is the role of the support and query data and how do they interact with each other?

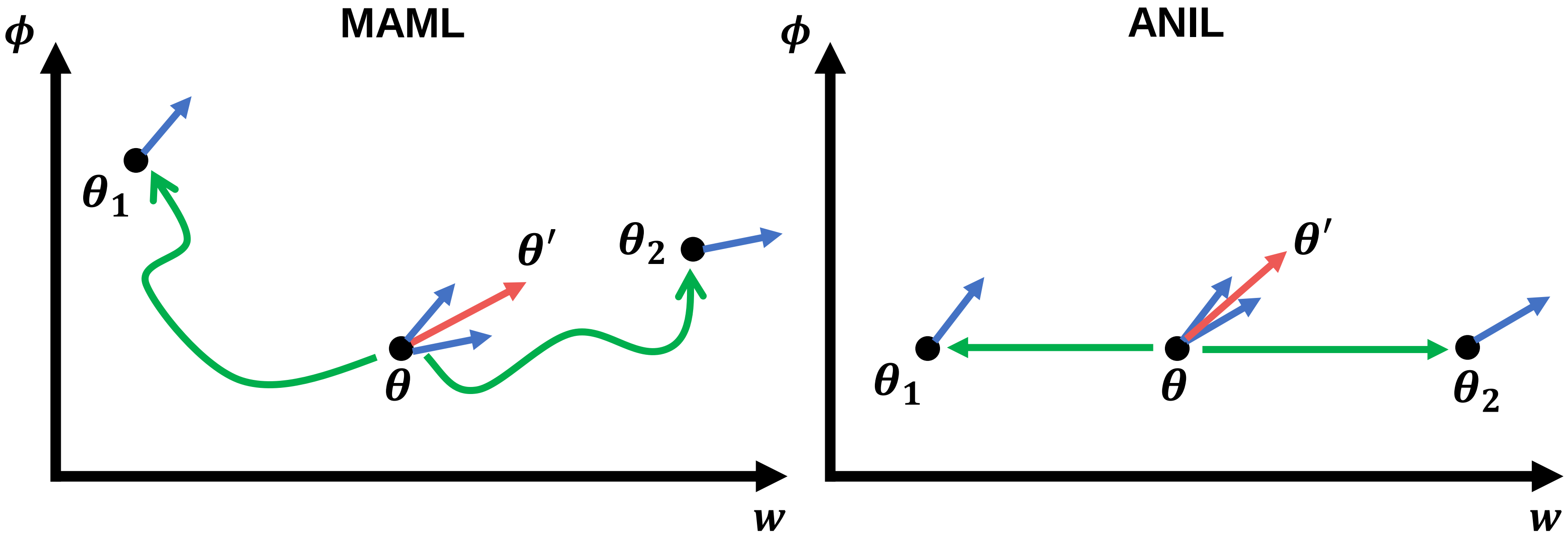
Our contribution:

- We show that MAML is a noisy supervised contrastive learning algorithm.

Assumption
ANIL (Almost no inner loop)

Consider a model $\boldsymbol{\theta} = \{\boldsymbol{\phi}, \boldsymbol{w}\}$, where $\boldsymbol{\phi}$ is an encoder and $\boldsymbol{w}$ is a linear classifier.

ANIL states that **the encoder $\boldsymbol{\phi}$ is not updated during the inner loop**.



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The ANIL Assumption empirically sounds.

	Mini-ImageNet 5way-1shot	**Mini-ImageNet** 5way-5shot	**Omniglot** 20way-1shot	**Omniglot** 20way-5shot
MAML	**46.9±0.2**	**63.1±0.4**	93.7±0.7	96.4±0.1
ANIL	46.7±0.4	61.5±0.5	**96.2±0.5**	**98.0±0.3**

Rapid Learning or Feature Reuse? Towards Understanding the Effectiveness of MAML (ICLR 2020)

Main Derivation
Motivating example

Assumptions:

- ANIL.
- Linear classifier w is zeroed at the beginning.

Loss: Mean square error.

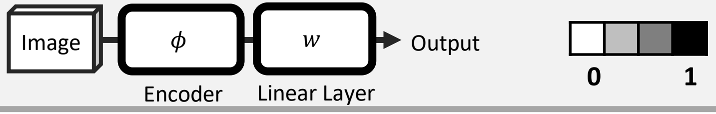
Condition: One inner loop update.

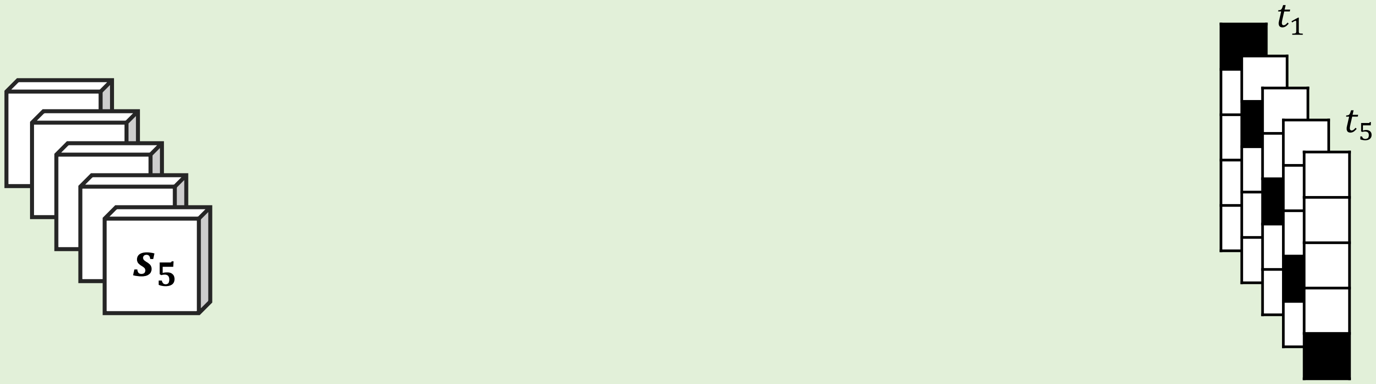
Setting

- 5-way: Each task contains 5 classes of images.
- 1-shot: Only one image per class in the support data.

Setting:
5-way 1-shot using MAML with **one** inner-loop update under **MSE loss**.

Model:





Inner Loop (1 step)

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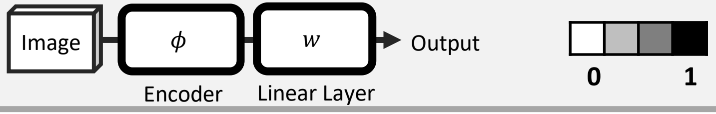
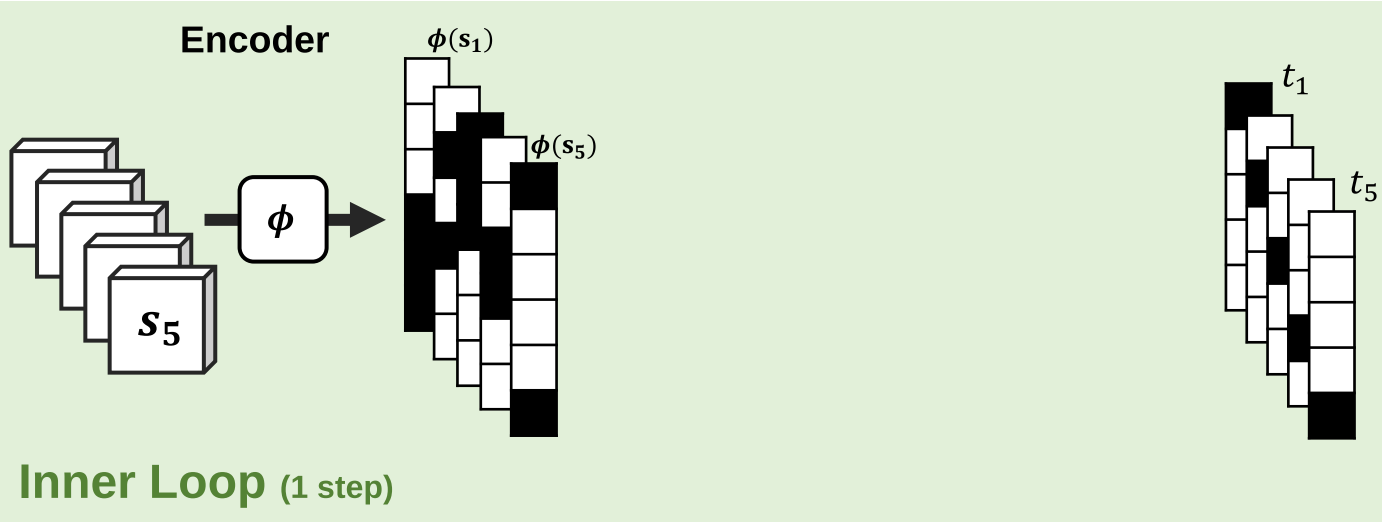
Setting:
5-way 1-shot using MAML with **one** inner-loop update under **MSE loss**.

Model:





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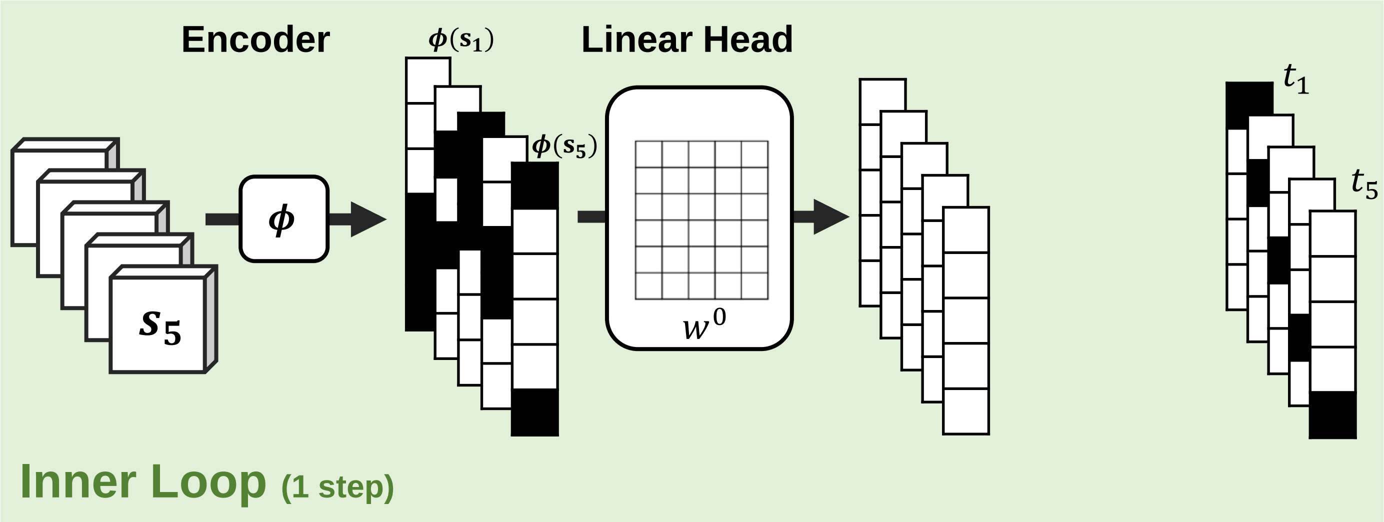
Setting:
5-way 1-shot using MAML with **one** inner-loop update under **MSE loss**.

Model: Image → ϕ (Encoder) → w (Linear Layer) → Output

0 1



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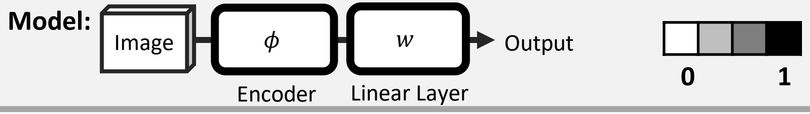

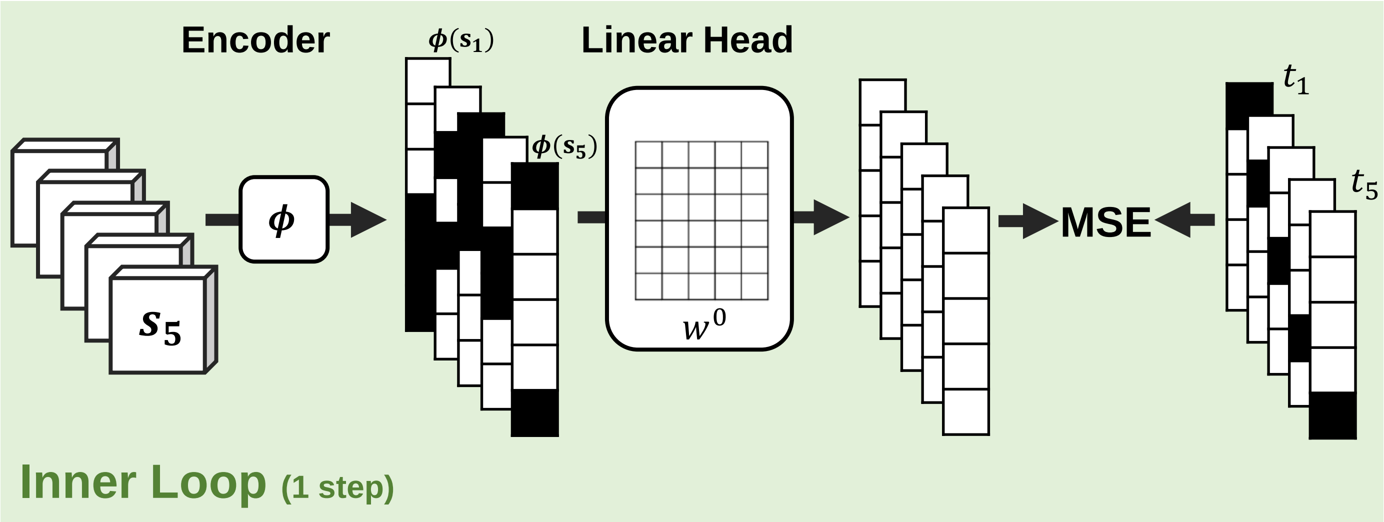

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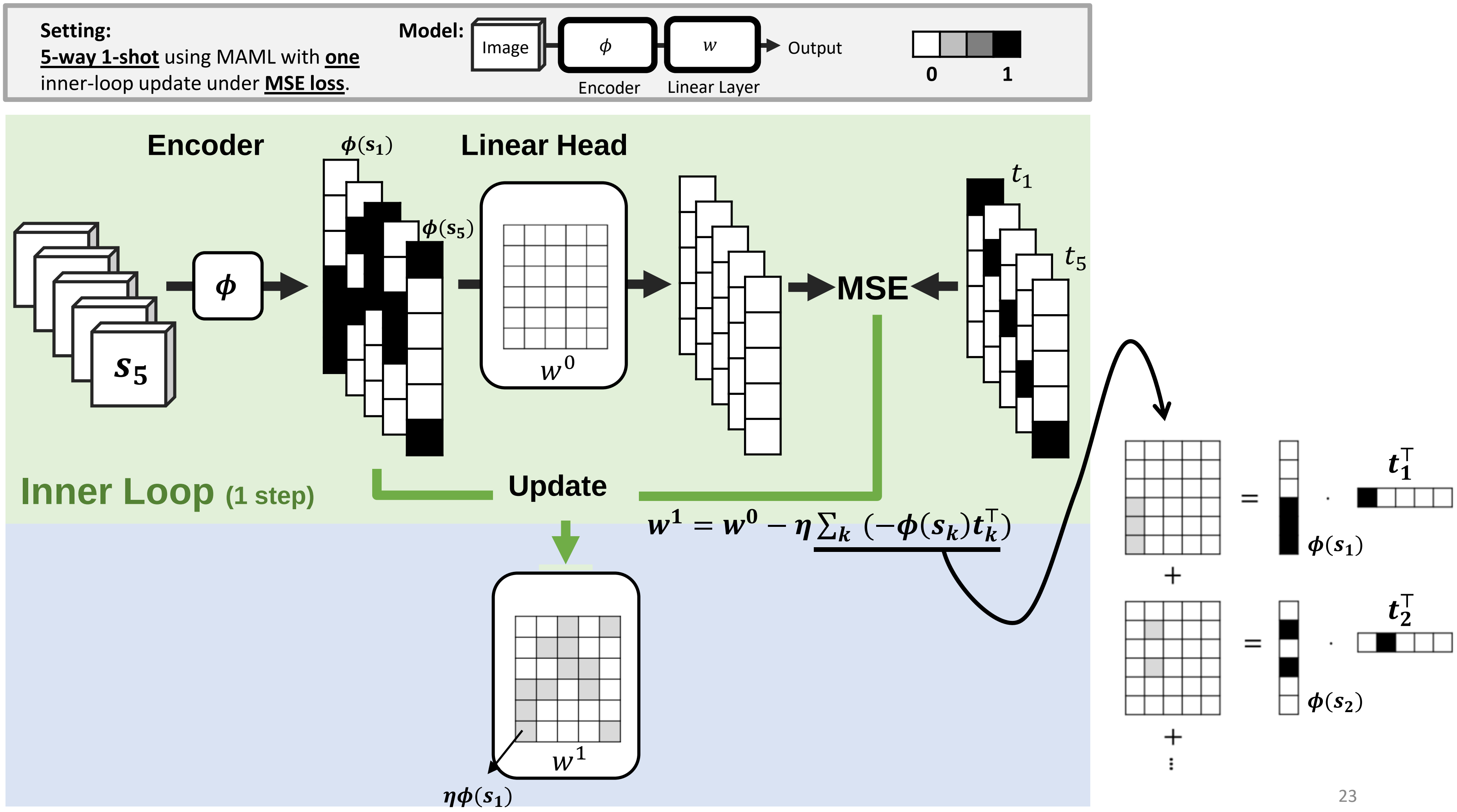
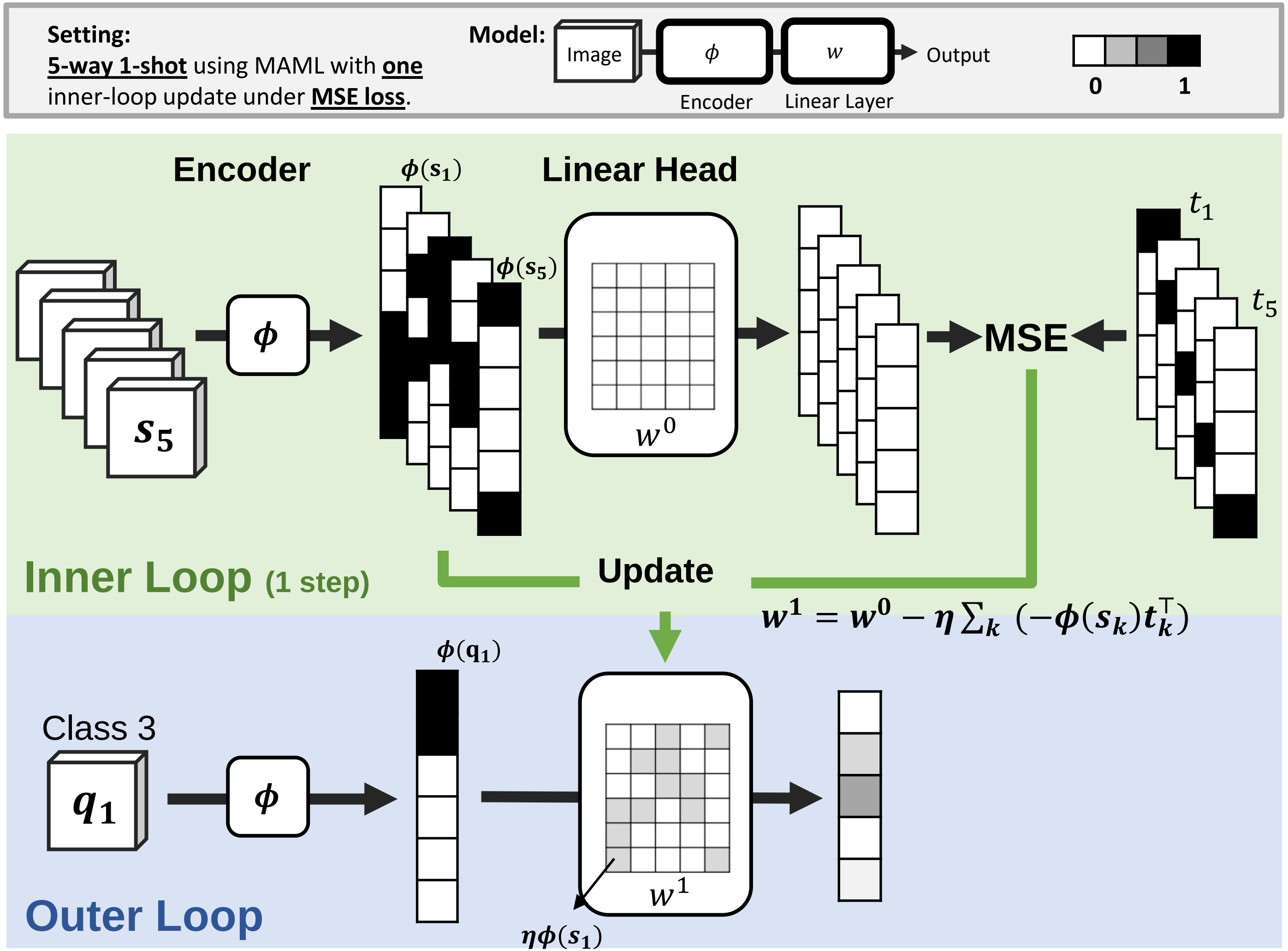


Setting:
5-way 1-shot using MAML with one inner-loop update under MSE loss.
Model:
Image
ϕ
w
Output
Encoder
Linear Layer
0
1
Encoder
$\phi(s_1)$
Linear Head
$\phi(s_5)$
s_5
ϕ
w^0
t_1
t_5
MSE
Inner Loop (1 step)
Update
$w^1 = w^0 - \eta \sum_k (-\phi(s_k) t_k^\top)$
w^1
$\eta\phi(s_1)$
$=$
$\phi(s_1)$
$t_1^\top$
$+$
$=$
$\phi(s_2)$
$t_2^\top$
$+$
⋮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Encoder
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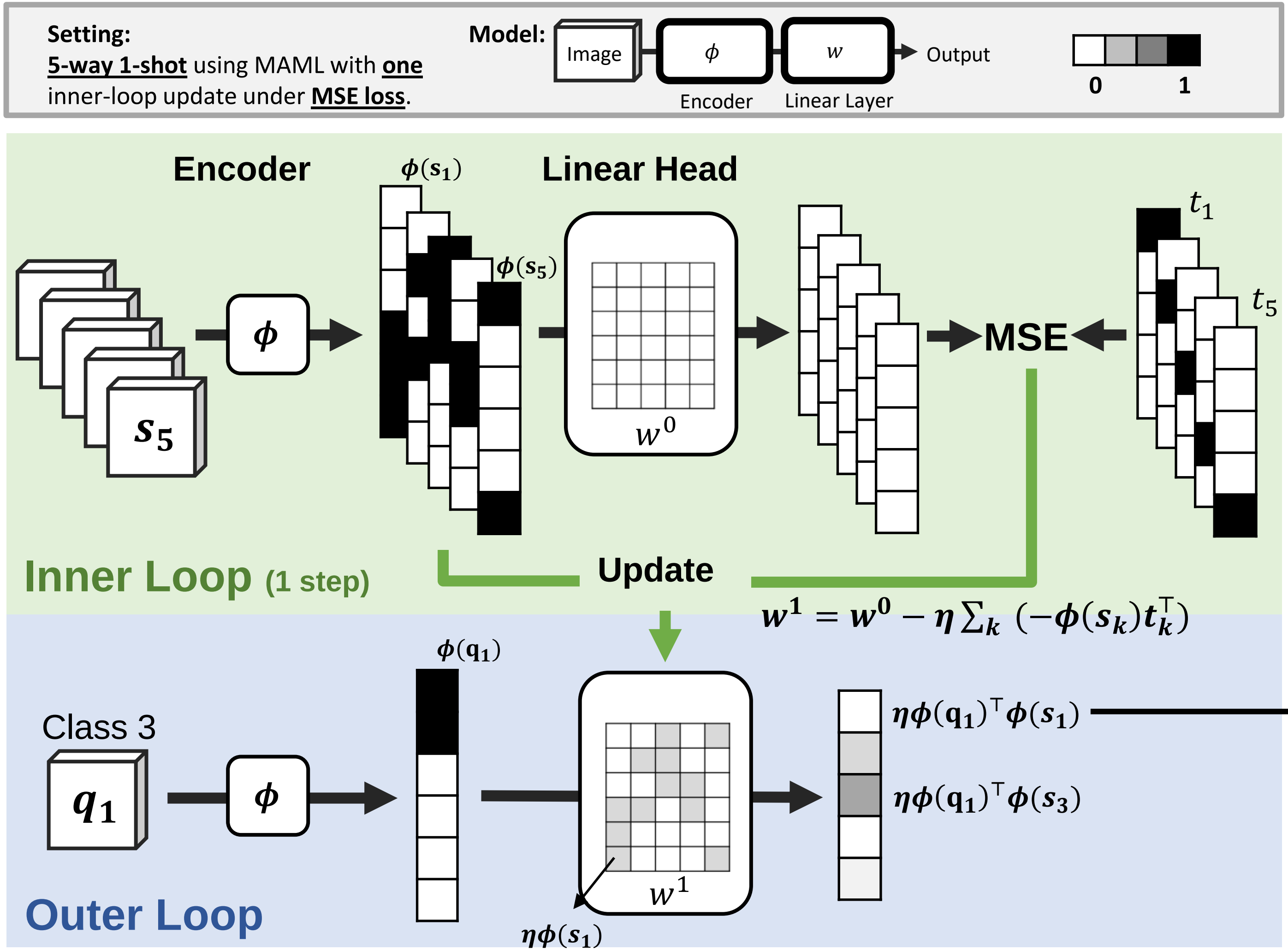
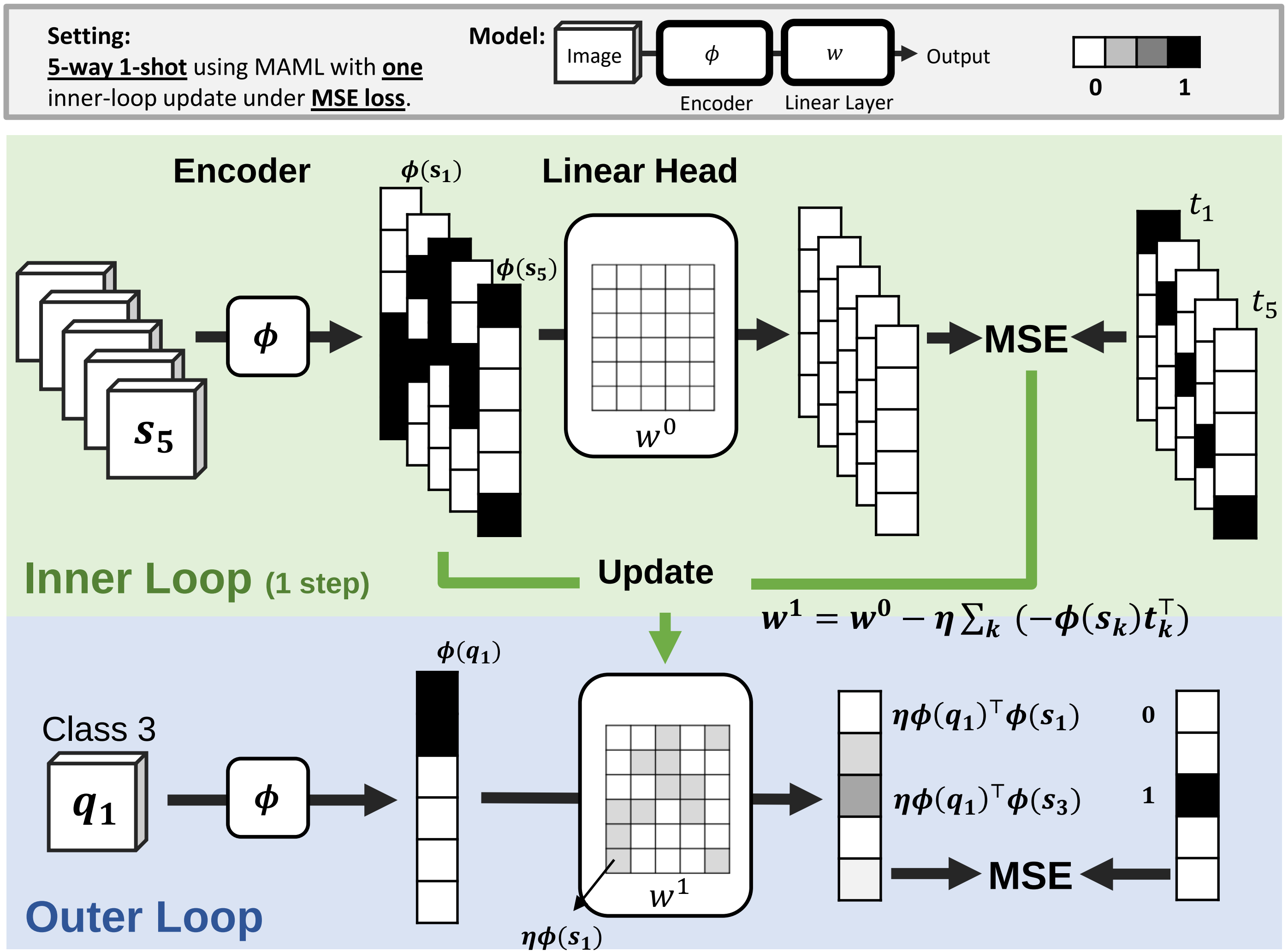
s_5
ϕ
w^0
t_1
t_5
MSE
Inner Loop (1 step)
Update
$w^1 = w^0 - \eta \sum_k (-\phi(s_k) t_k^\top)$
$\phi(q_1)$
Class 3
q_1
ϕ
w^1
$\eta\phi(s_1)$
Outer Loop



The inner product between support feature s_1 and query feature q_1.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ϕ
w
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Encoder
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0
1
Encoder
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t_1
t_5
s_5
ϕ
w^0
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$\phi(q_1)$
Class 3
q_1
ϕ
$\eta\phi(q_1)^\top\phi(s_1)$
0
$\eta\phi(q_1)^\top\phi(s_3)$
1
w^1
MSE
Outer Loop
$\eta\phi(s_1)$

Setting:
5-way 1-shot using MAML with **one** inner-loop update under **MSE loss**.

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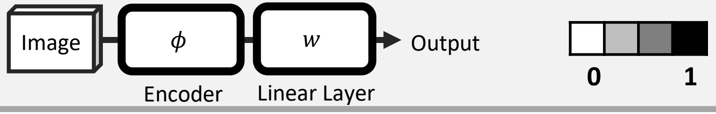
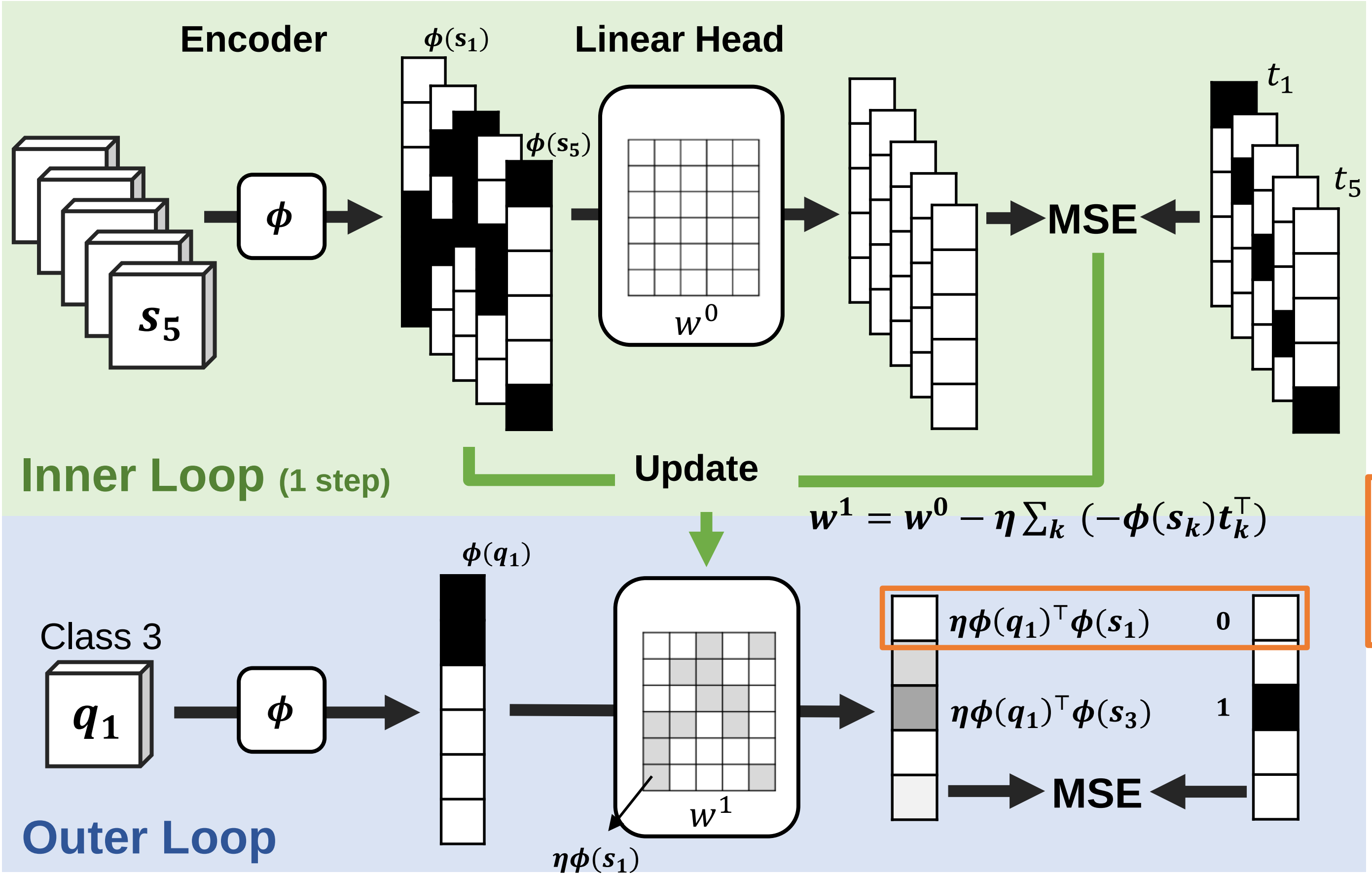
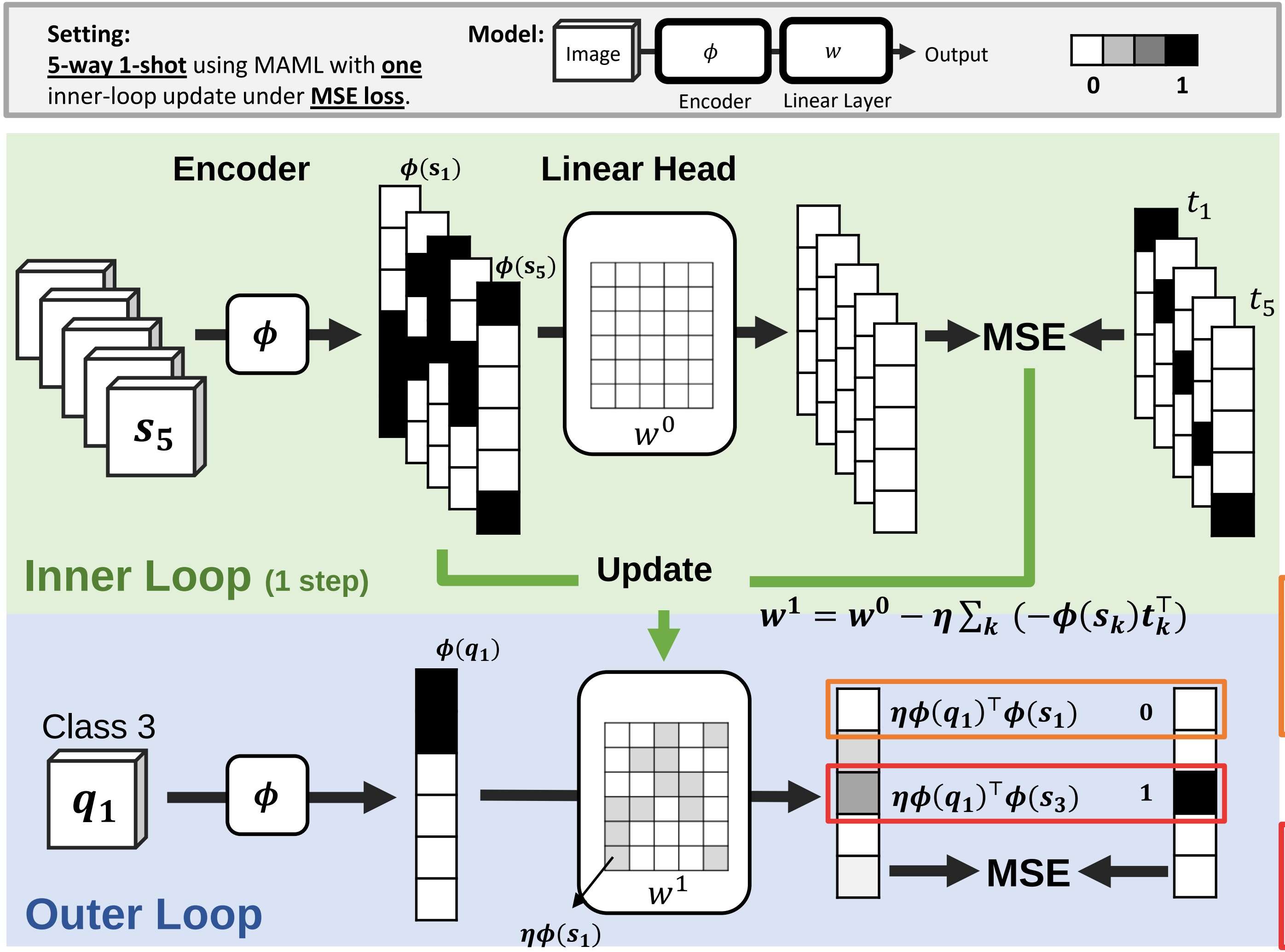




Negative sample

- q_1 and s_1 have **different labels**
- Their **inner product** of their features should **be zero**.



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Positive sample

- q_1 and s_3 have **same labels**,
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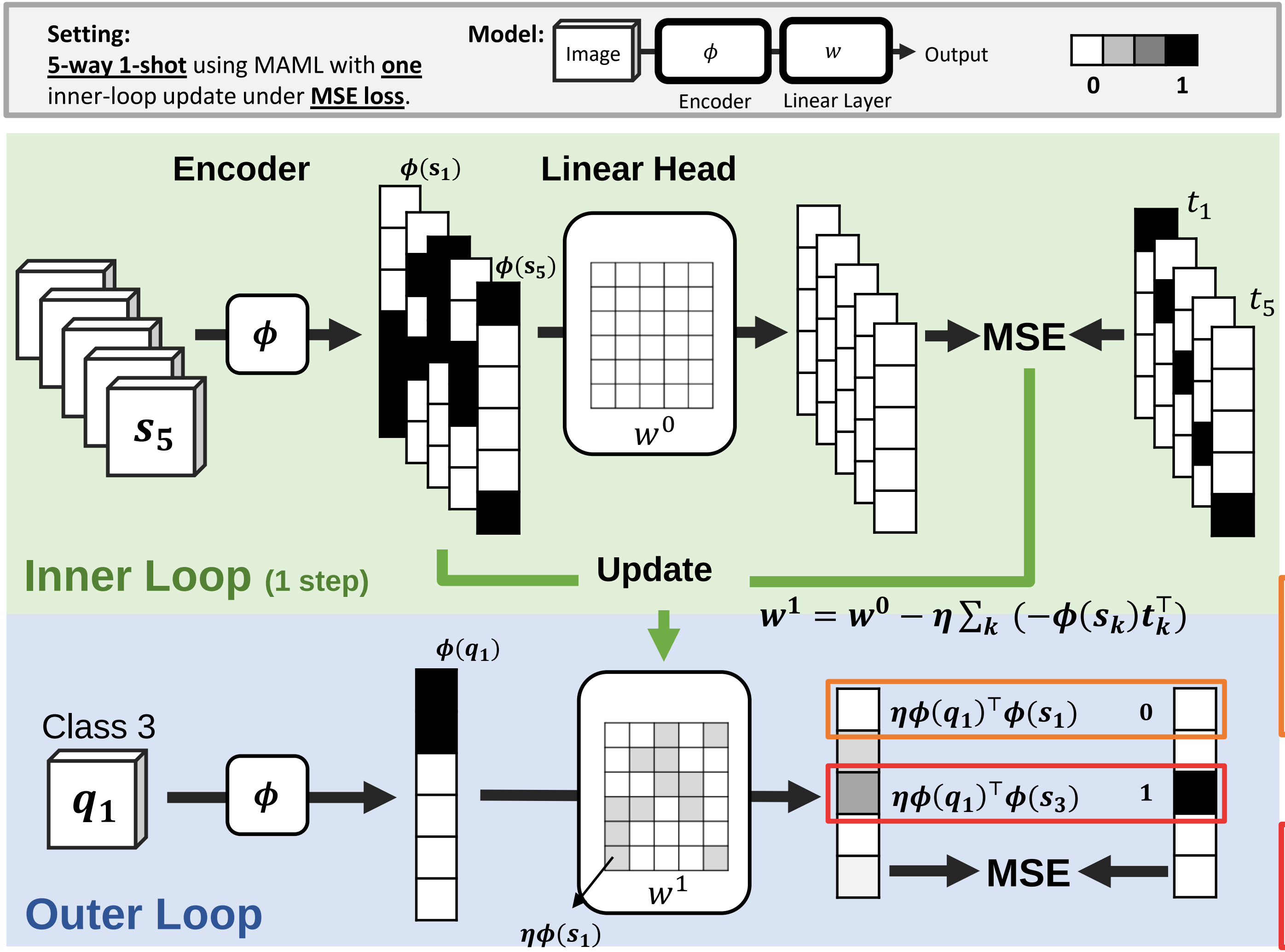

Supervised contrastive learning

Negative sample

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- Their **inner product** of their features should **be zero**.

Positive sample

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Main Derivation
Main result

Consider support data $S = \{(s, t)\}$ and one query data (q, u).

Under **ANIL assumption**, the **loss for the encoder** is :

- First-order MAML:

$$L = \sum_{i=1}^{N_{class}} \underbrace{(\mathrm{q}_i - 1_{i=u})\mathbf{w_i}}_{\text{stop gradient}}^\top \phi(q) + \eta \mathop{\mathbf{E}}_{(s,t)\sim S} \underbrace{\underbrace{[-\sum_{i=1}^{N_{class}} \mathrm{q}_i \mathrm{s}_i + \mathrm{s}_u + \mathrm{q}_t - 1_{t=u}]}_{\text{Contrastive coefficient}} \phi(s)}_{\text{stop gradient}}^\top \phi(q)$$

Contrastive coefficient Inner product

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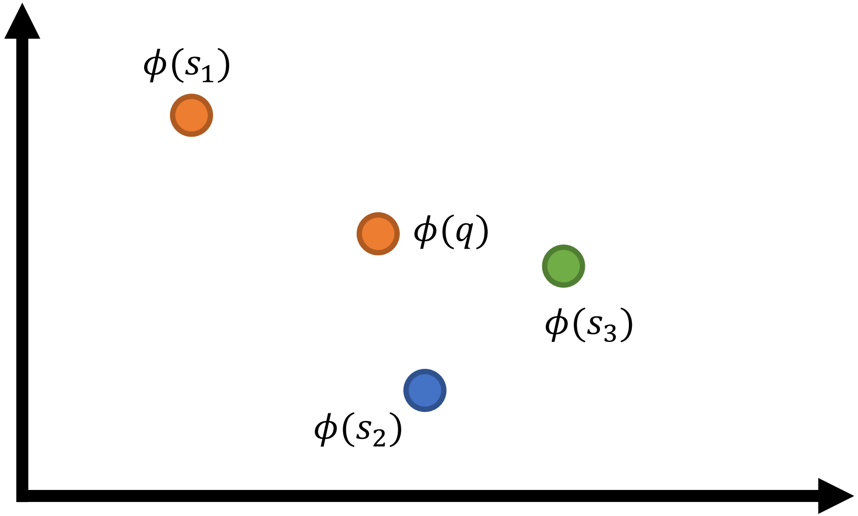
- Expected effect of the second term:
  - If q and s have sample label, then the coefficients is negative, meaning that we are to update ϕ s.t. $\phi(q)$ is closer to $\phi(s)$.
  - If q and s have different labels, then the coefficients should be positive, meaning that we are to update ϕ s.t. $\phi(q)$ is further to $\phi(s)$.

Main Derivation

Main result. Feature space illustration.

Gradient from positive sample
Gradient from negative sample

First-order MAML



update ϕ such that $\phi(q)$ is closer/further to $\phi(s)$

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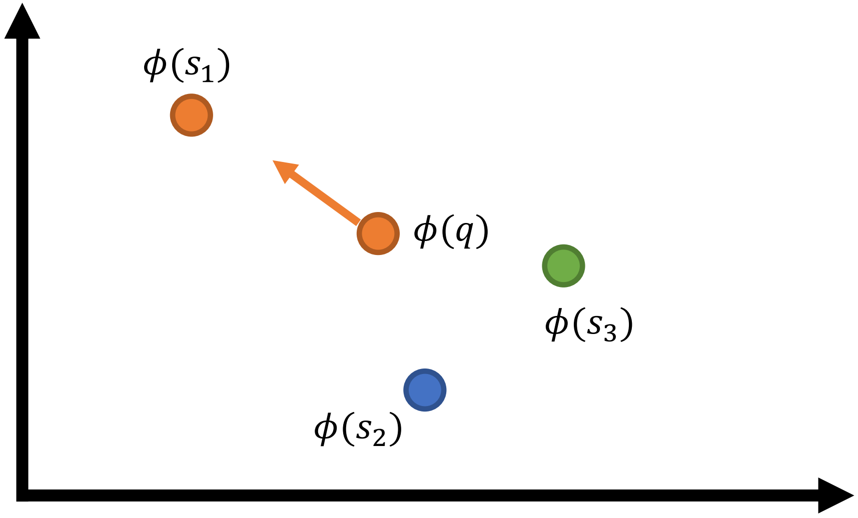

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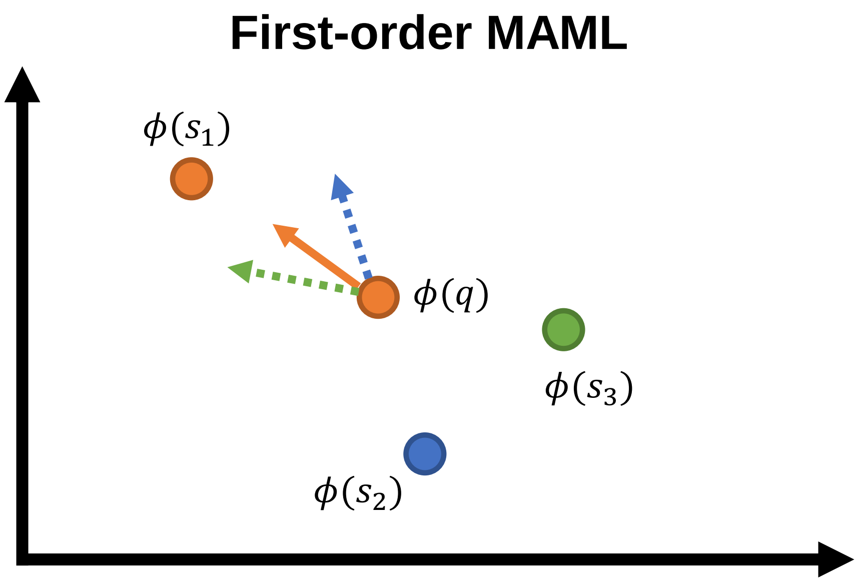

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Contrastive coefficient (CC)

Inner product

- Second-order MAML:

$$L = \sum_{i=1}^{N_{class}} \underbrace{(\mathrm{q}_i - 1_{i=u})\mathbf{w_i}}_{\text{stop gradient}}{}^{\top} \phi(q) + \eta \mathop{\mathbf{E}}_{(s,t)\sim S} \underbrace{[-\sum_{i=1}^{N_{class}} \mathrm{q}_i \mathrm{s}_i + \mathrm{s}_u + \mathrm{q}_t - 1_{t=u}]}_{\text{stop gradient}} \phi(s)^{\top}\phi(q)$$

Contrastive coefficient

Inner product

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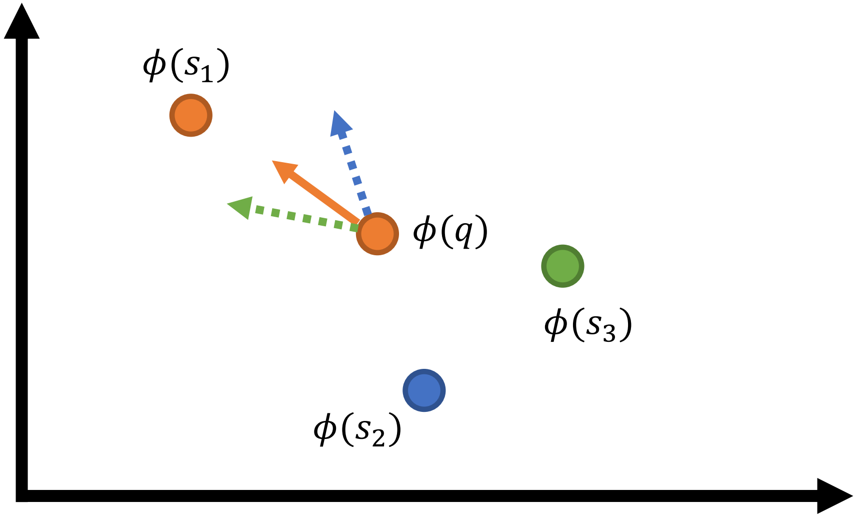

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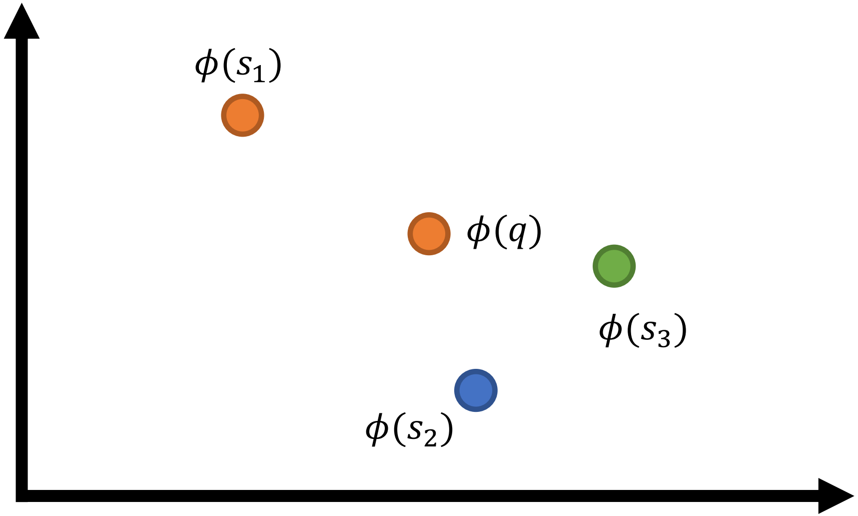
Second-order MAML



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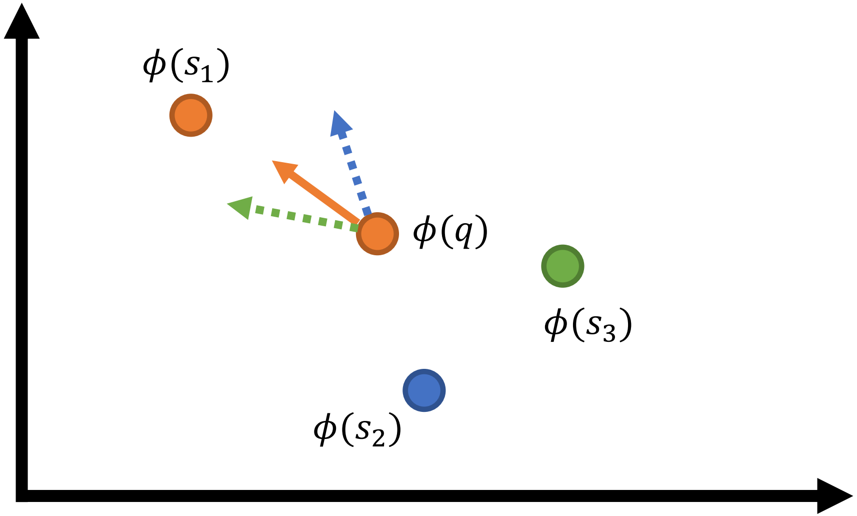
Gradient from negative sample

First-order MAML



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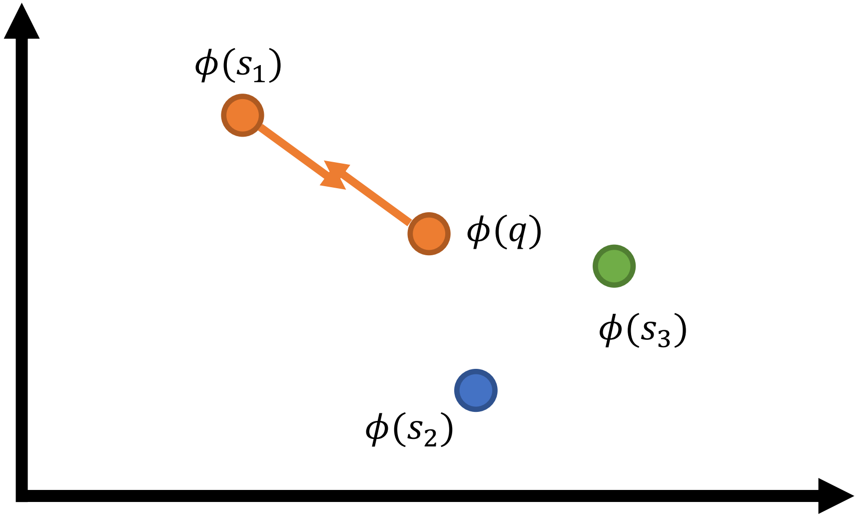

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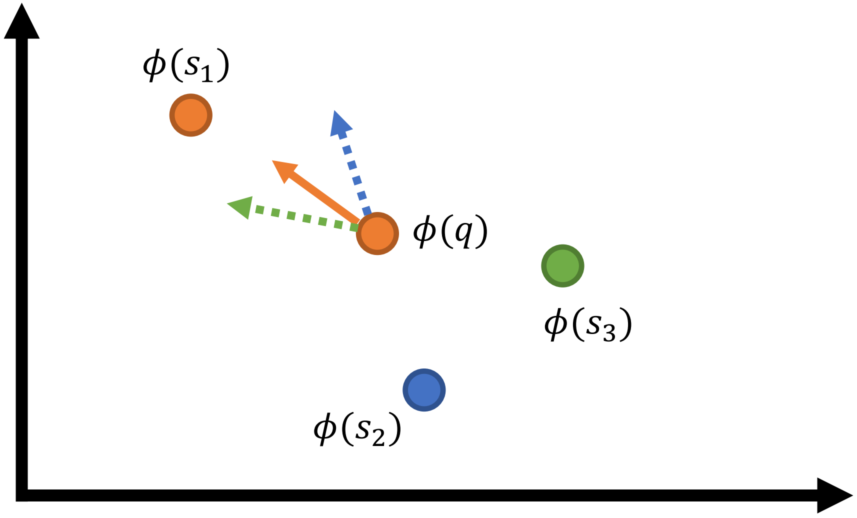

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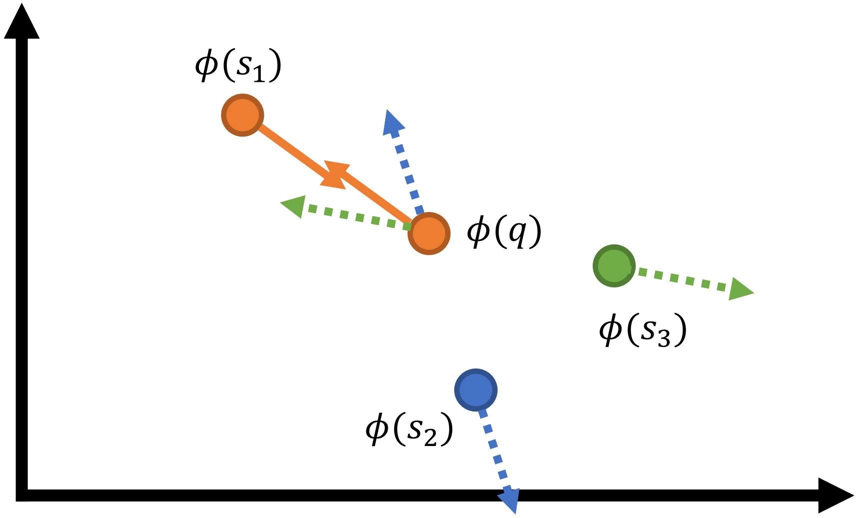

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- Random initialization
- Cross task interference

- The coefficient is not always positive when s and q come from different classes

Theorem 1 *With the assumption of (a) no inner loop update of the encoder, FOMAML is a noisy SCL algorithm. With assumptions of (a) no inner loop update of the encoder and (b) a single inner-loop update, SOMAML is a noisy SCL algorithm.*

Main Derivation

Main result. Introducing the zeroing trick.

Consider support data $S = \{(s, t)\}$ and one query data (q, u).

Under **ANIL assumption** and **the zeroing trick**, the **loss for the encoder** is :

- First-order MAML:

$$L = \eta \mathop{\mathbf{E}}_{(s,t)\sim S} \underbrace{(\mathrm{q}_t - {}_{\mathrm{t=u}})\phi(s)^\top}_{\text{stop gradient}} \phi(q)$$

- Second-order MAML:

$$L = \eta \mathop{\mathbf{E}}_{(s,t)\sim S} \underbrace{(\mathrm{q}_t - 1_{t=u})}_{\text{stop gradient}} \phi(s)^\top \phi(q)$$

Corollary 1 *With mild assumptions of (a) no inner loop update of the encoder, (b) a single inner-loop update and (c) training with the zeroing trick (i.e., the linear layer is zeroed at the end of each outer loop), both FOMAML and SOMAML are SCL algorithms.*

Main Derivation

Main result. Introducing the zeroing trick.

Algorithm 1 Second-order MAML

while not done **do**
  Sample tasks $\{T_1, T_2\}$

  for $n = 1, 2$ **do**
    $\{S_n, Q_n\} \leftarrow$ sample from T_n
    $\theta_n = \theta$
    for $i = 1, 2, \ldots, N_{step}$ **do**
      $\theta_n \leftarrow \theta_n - \eta \nabla_{\theta_n} L(\theta_n, S_n)$
    end for
  end for
  Update $\theta \leftarrow \theta - \rho \sum_{n=1}^{N_{batch}} \nabla_\theta L(\theta_n, Q_n)$

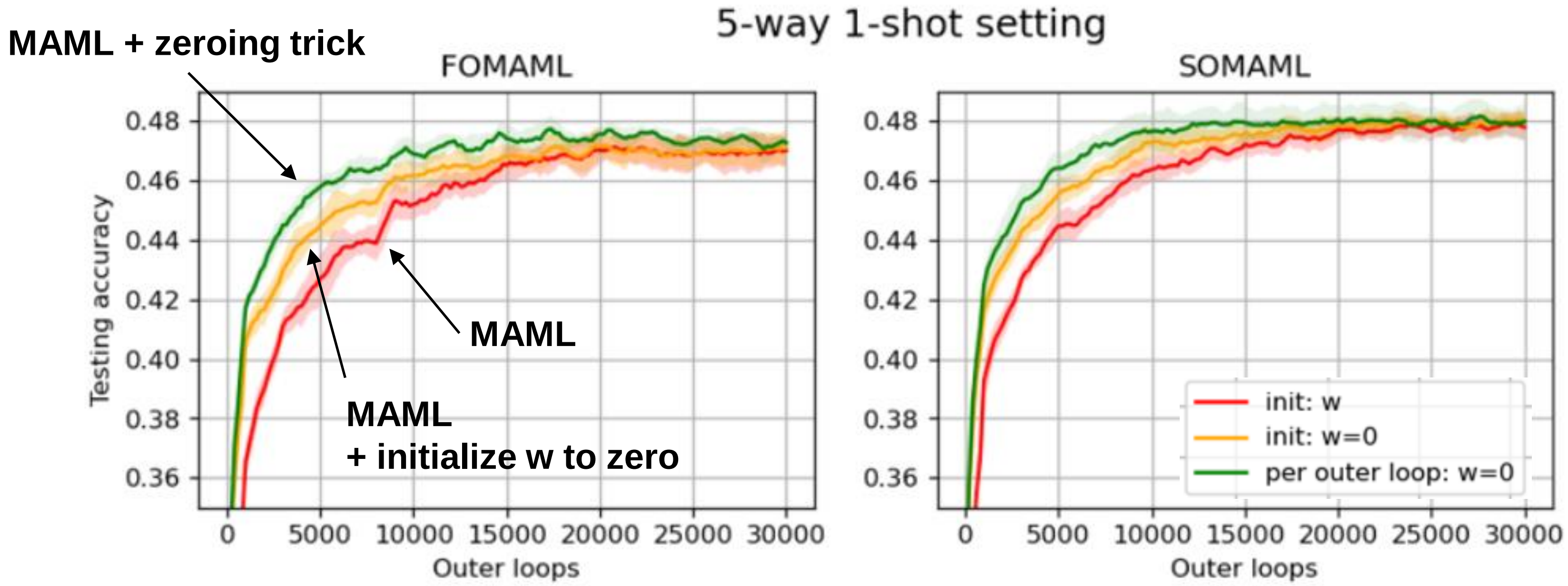
end while

Algorithm 2 Second-order MAML with zeroing trick

while not done **do**
  Sample tasks $\{T_1, T_2\}$
  $w = 0$
  for $n = 1, 2$ **do**
    $\{S_n, Q_n\} \leftarrow$ sample from T_n
    $\theta_n = \theta$
    for $i = 1, 2, \ldots, N_{step}$ **do**
      $\theta_n \leftarrow \theta_n - \eta \nabla_{\theta_n} L(\theta_n, S_n)$
    end for
  end for
  Update $\theta \leftarrow \theta - \rho \sum_{n=1}^{N_{batch}} \nabla_\theta L(\theta_n, Q_n)$
  $w = 0$
end while

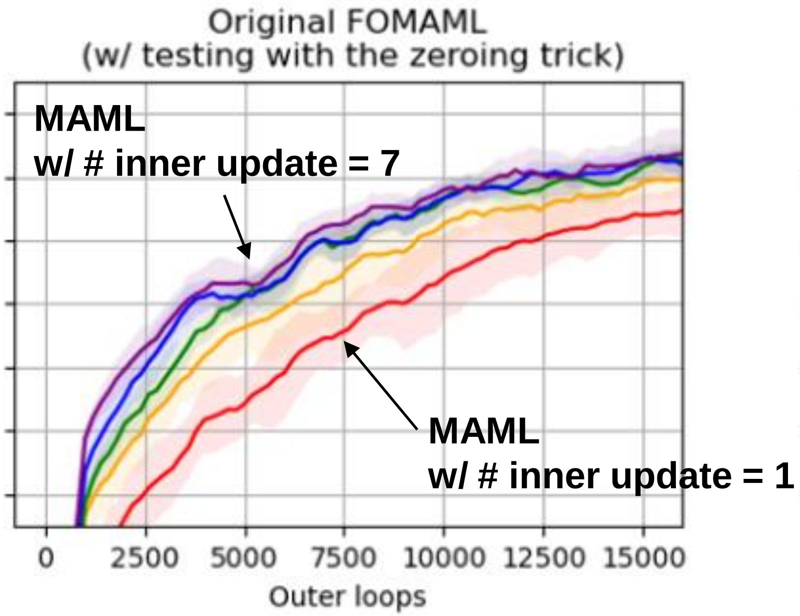
Results
Using the zeroing trick improves performance.

Setting: MiniImageNet.



Results
With zeroing trick, # of inner loop steps no longer matters

Setting: MiniImageNet 5-way 1-shot.

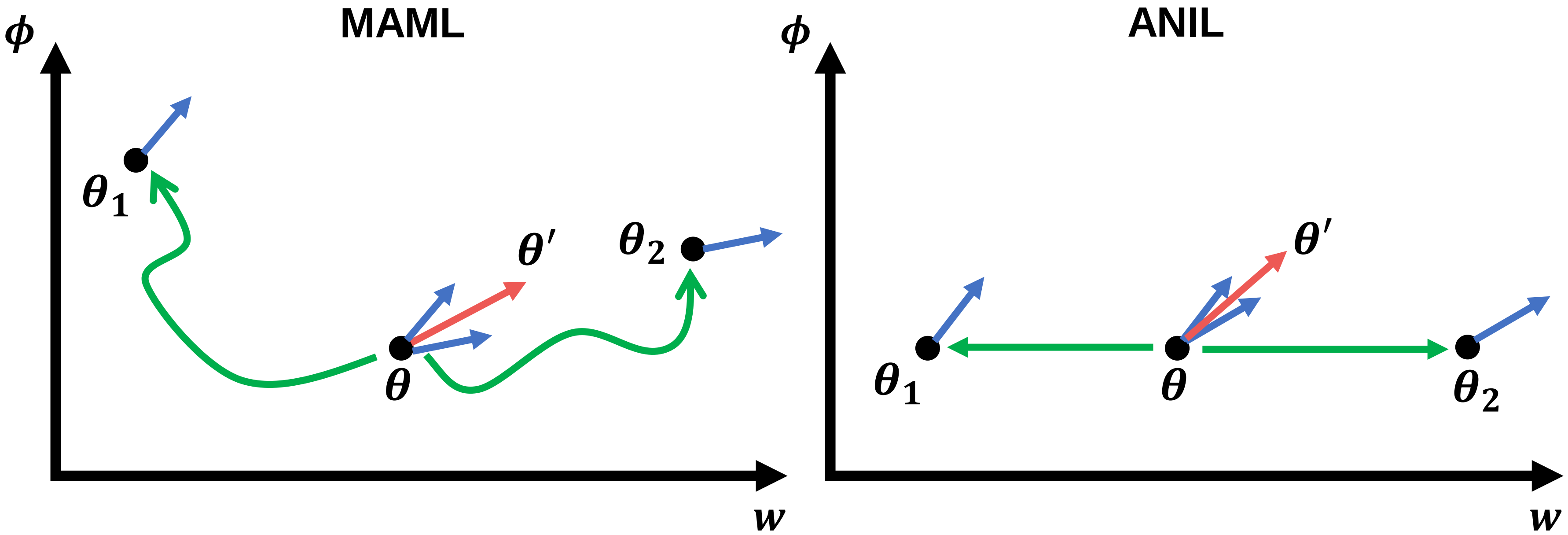


Wrap up

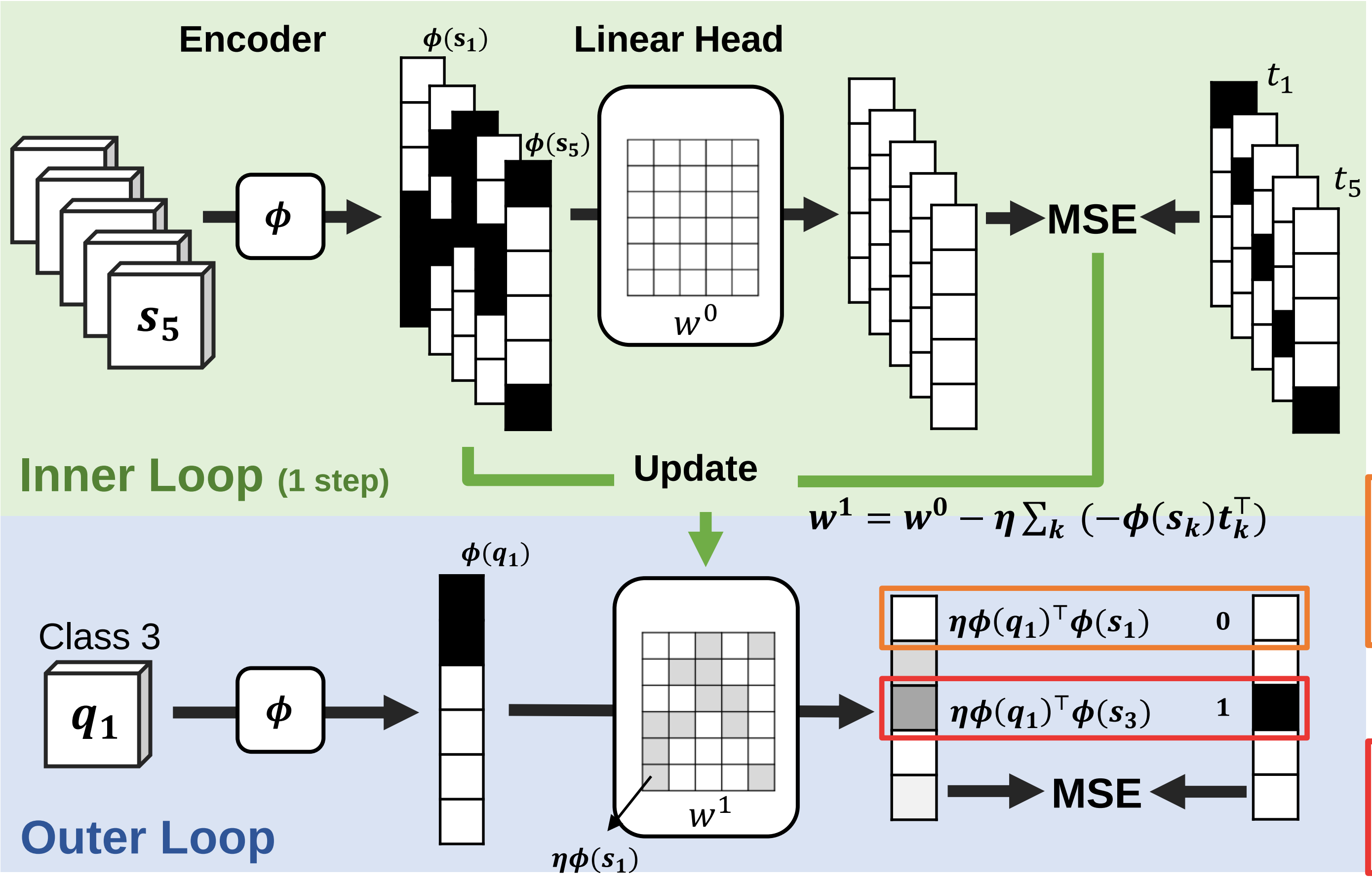
Wrap up
We use the ANIL assumption for derivation.

Consider a model $\boldsymbol{\theta} = \{\boldsymbol{\phi}, \boldsymbol{w}\}$, where $\boldsymbol{\phi}$ is an encoder and $\boldsymbol{w}$ is a linear classifier.

ANIL states that **<u>the encoder $\boldsymbol{\phi}$ is not updated during the inner loop</u>**.



Wrap up



Supervised contrastive learning

Negative sample

- q_1 and s_1 have <u>different labels</u>
- Their <u>inner product</u> of their features should <u>be zero</u>.

Positive sample

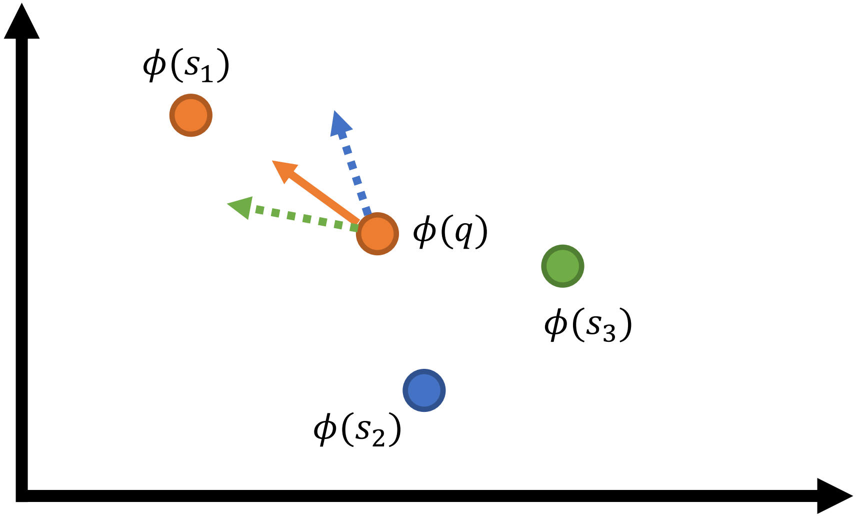
- q_1 and s_3 have <u>same labels</u>,
- Their <u>inner product</u> of their features should <u>be one</u>.

Wrap up

We show how FOMAML different from SOMAML.

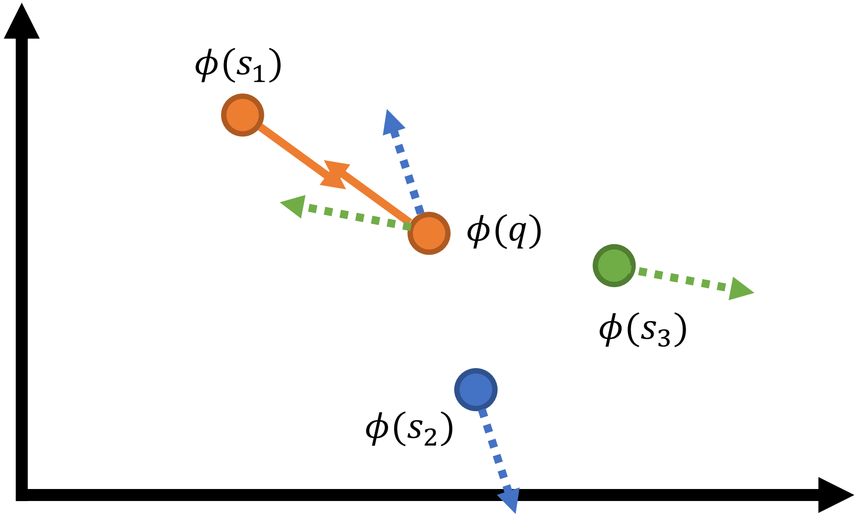
Gradient from positive sample
Gradient from negative sample

First-order MAML



update ϕ such that $\phi(q)$ is closer/further to $\phi(s)$

Second-order MAML



update ϕ such that $\phi(q)$ <u>and</u> $\phi(s)$ move closer/further to <u>each other</u>.

Wrap up

We show that the zeroing trick improves MAML.

Setting: MiniImageNet.