
MAML is a Noisy Contrastive Learner

NewInML Workshop@NeuroIPS'21

Chia-Hsiang Kao¹, Wei-Chen Chiu¹, Pin-Yu Chen²

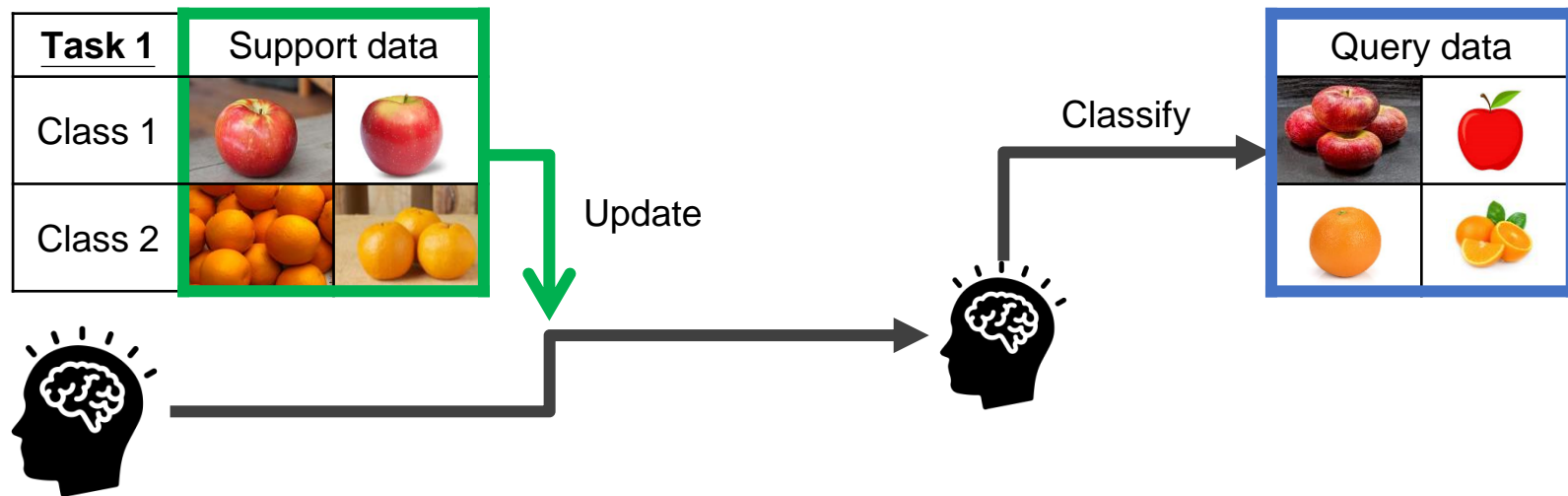
¹National Yang Ming Chiao Tung University

²MIT-IBM Watson AI Lab



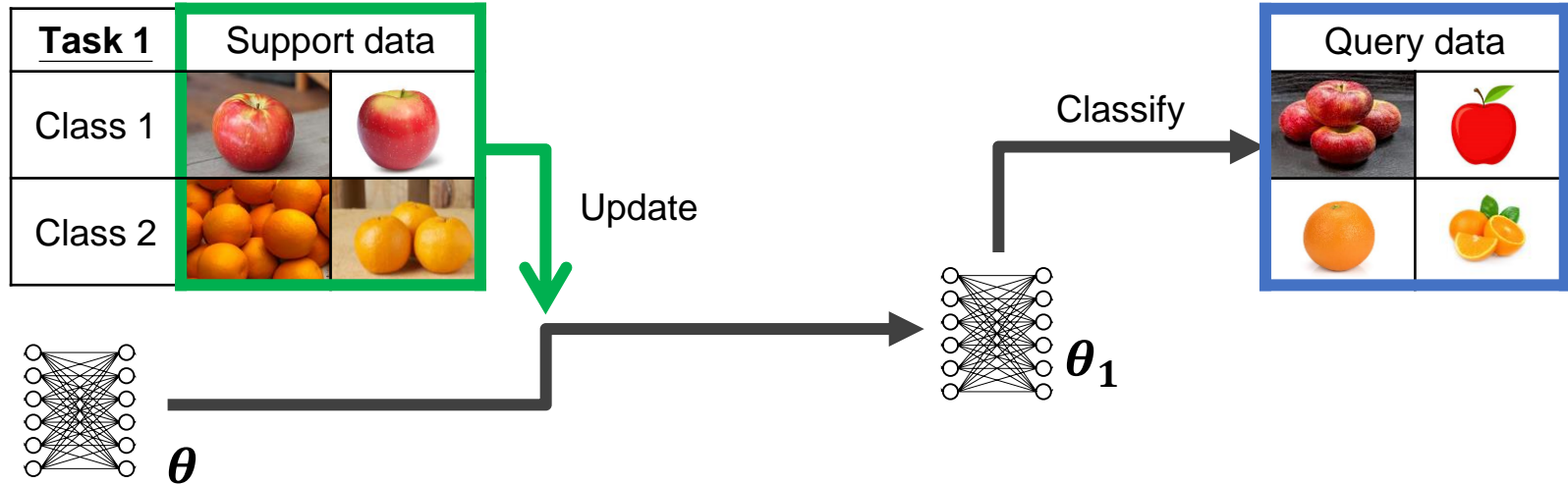
Introduction

Humans learn to classify even with limited experience.



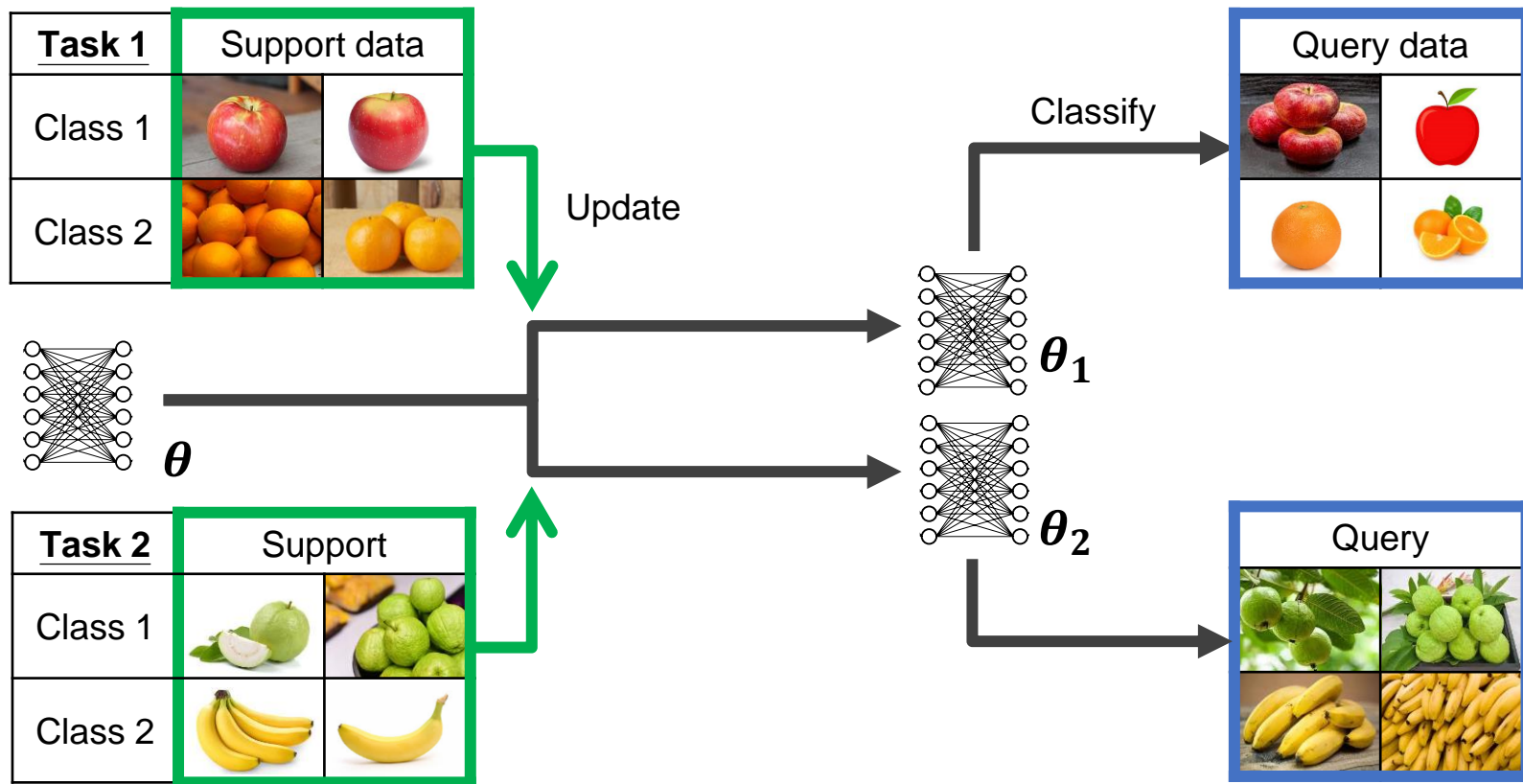
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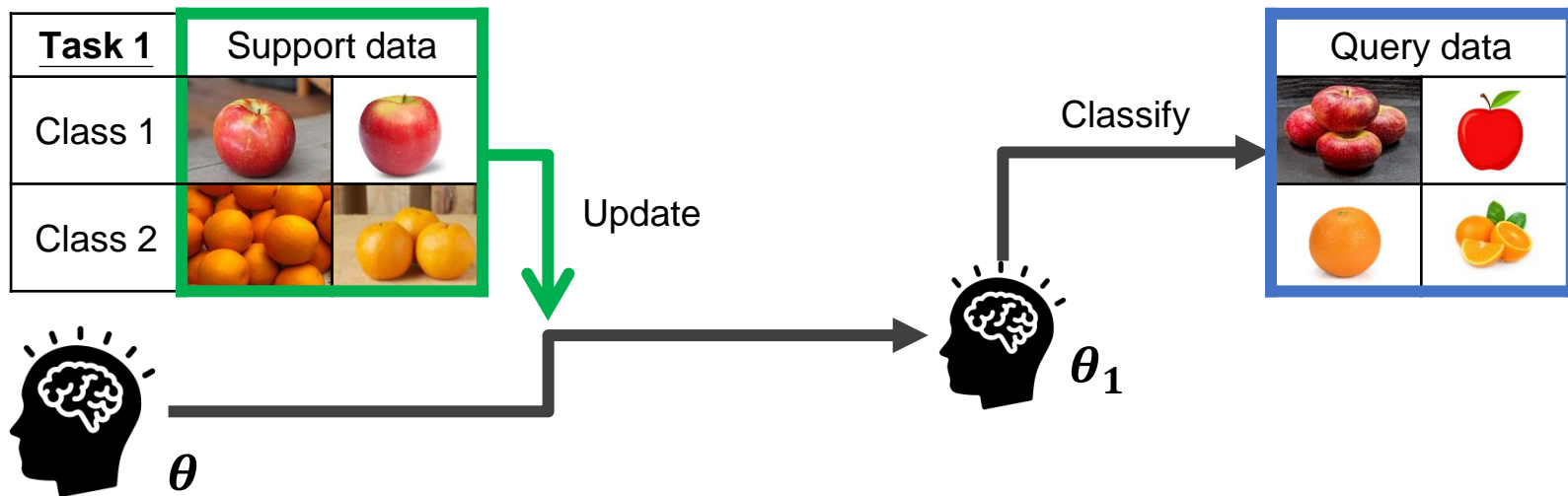
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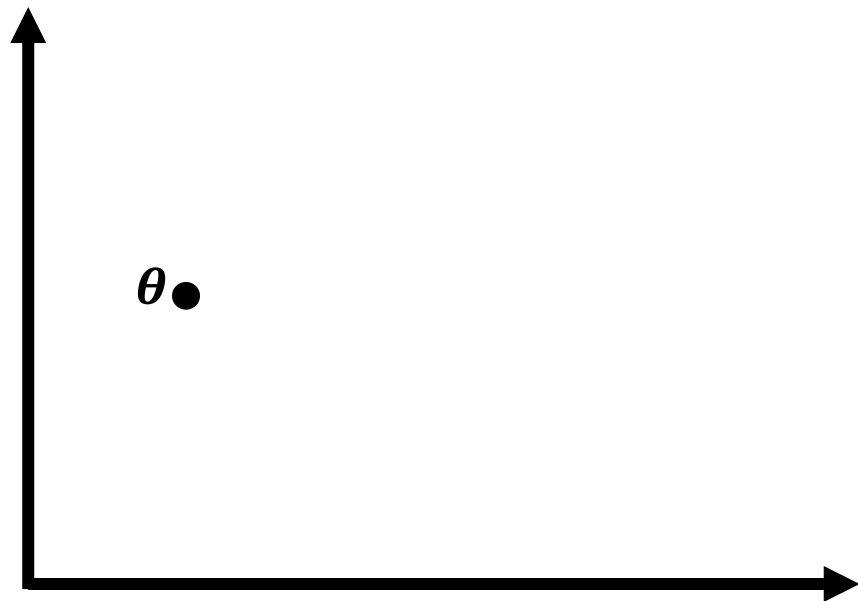
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- MAML is a gradient-based meta-learning algorithm that finds a good θ .

Introduction

MAML makes model learn to classify after seeing little data.

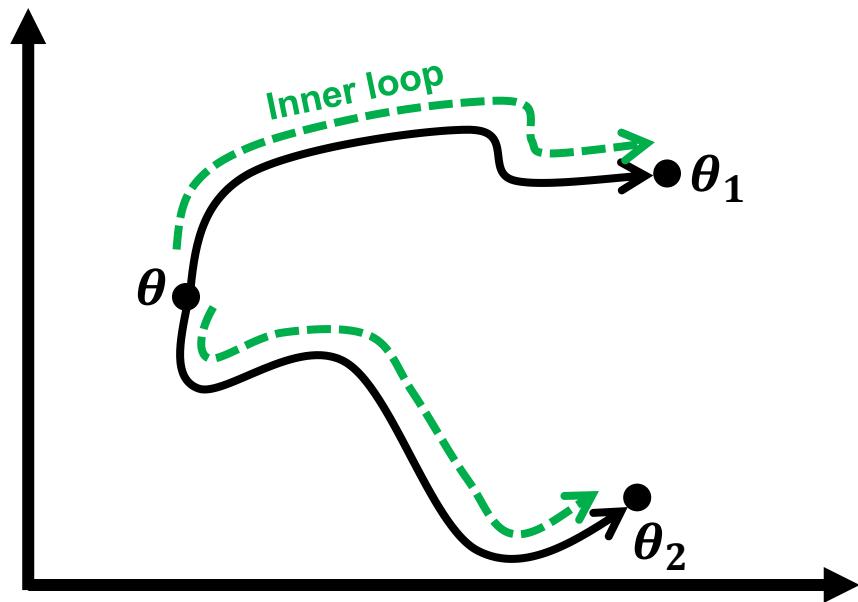





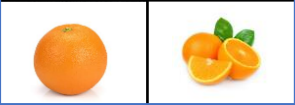












| <u>Task 1</u> | Support S_1 | | Query Q_1 | |
|---------------|---|---|---|---|
| Class 1 |  |  |  |  |
| Class 2 |  |  |  |  |

| <u>Task 2</u> | Support S_2 | | Query Q_2 | |
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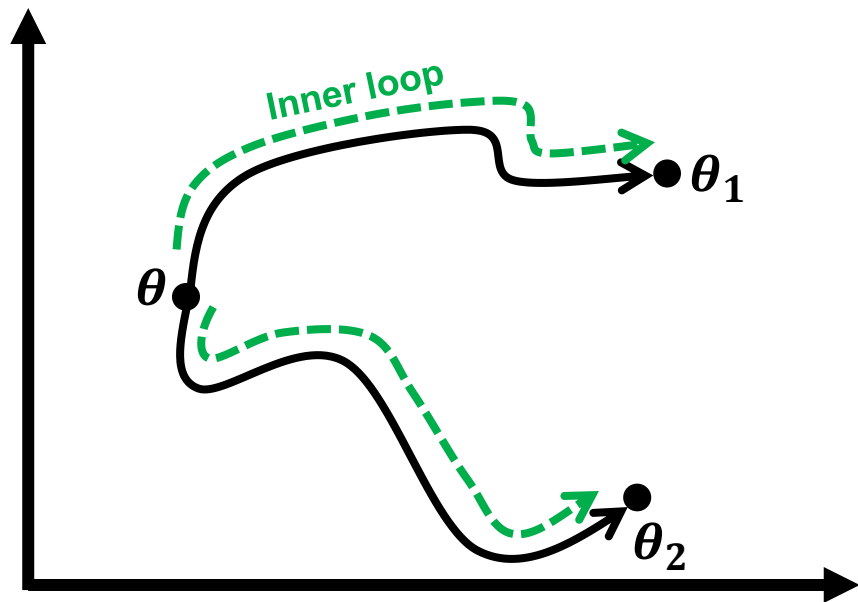
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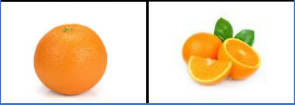



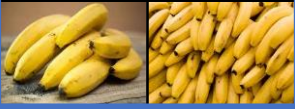










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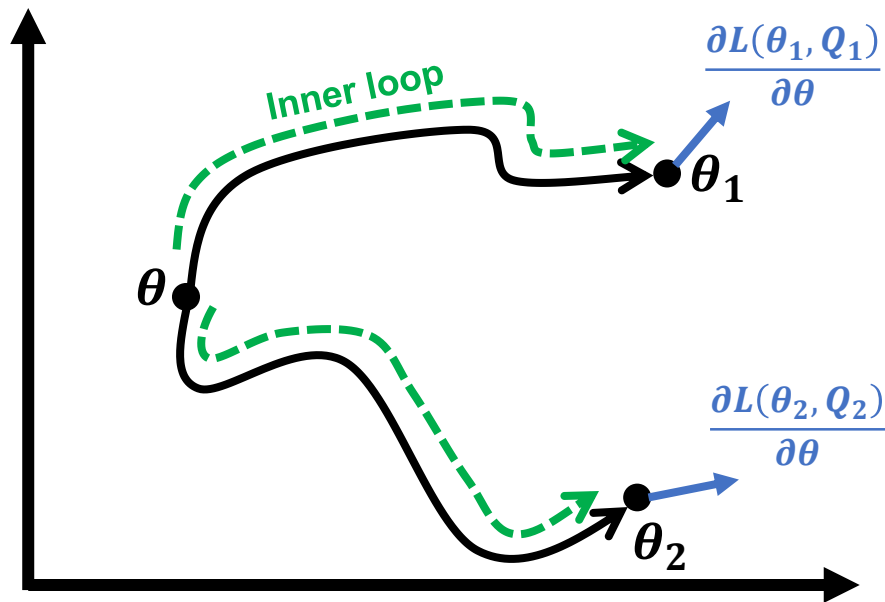
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- Goal: Minimize $L(\theta_1, Q_1)$ and $L(\theta_2, Q_2)$ by finding best θ .

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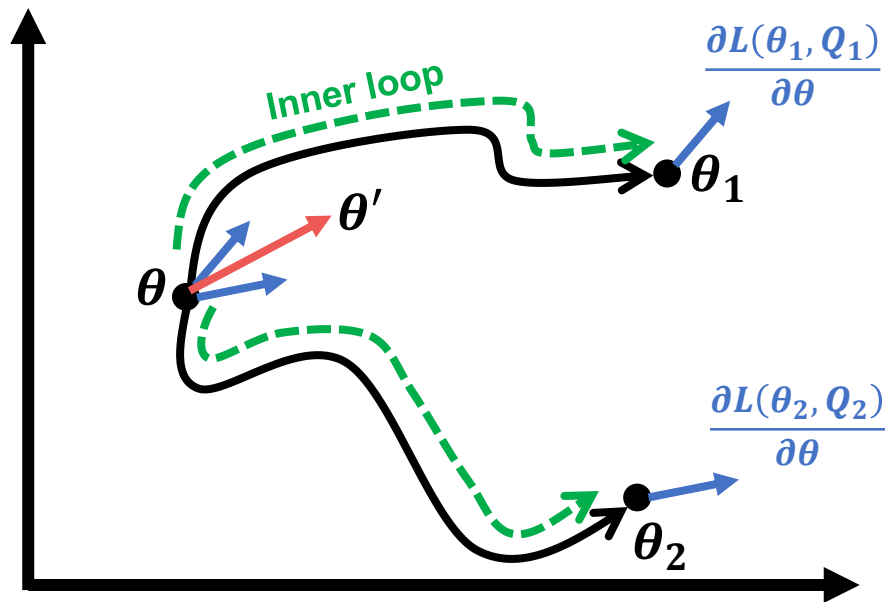
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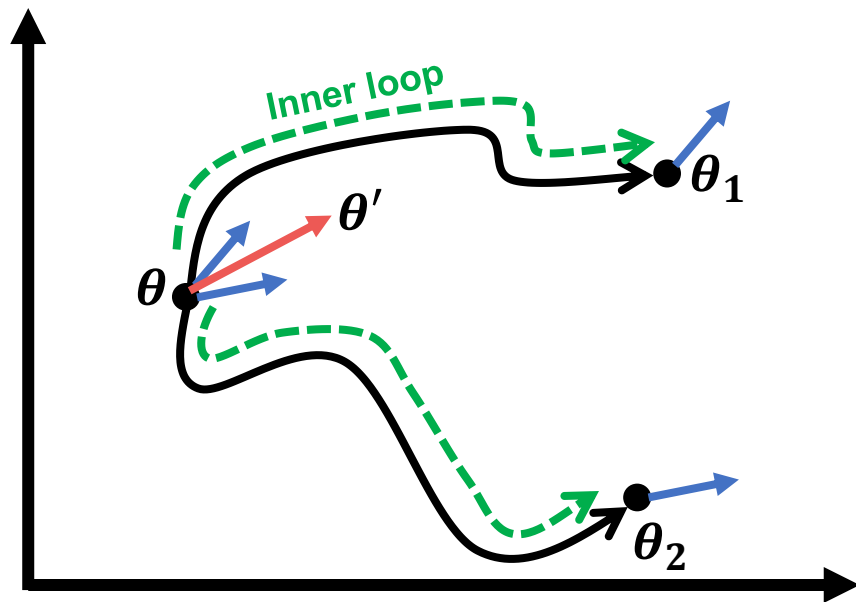
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Algorithm 1 Second-order MAML

```
1: while not done do
2:   Sample tasks  $\{T_1, T_2\}$ 
3:   for  $n = 1, 2$  do
4:      $\{S_n, Q_n\} \leftarrow$  sample from  $T_n$ 
5:      $\theta_n = \theta$ 
6:     for  $i = 1, 2, \dots, N_{step}$  do
7:        $\theta_n \leftarrow \theta_n - \eta \nabla_{\theta_n} L(\theta_n, S_n)$ 
8:     end for
9:   end for
10:  Update  $\theta \leftarrow \theta - \rho \sum_{n=1}^{N_{batch}} \nabla_{\theta} L(\theta_n, Q_n)$ 
11: end while
```

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

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- 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:

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- What is the role of the support and query data and how do they interact with each other?

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Our contribution:

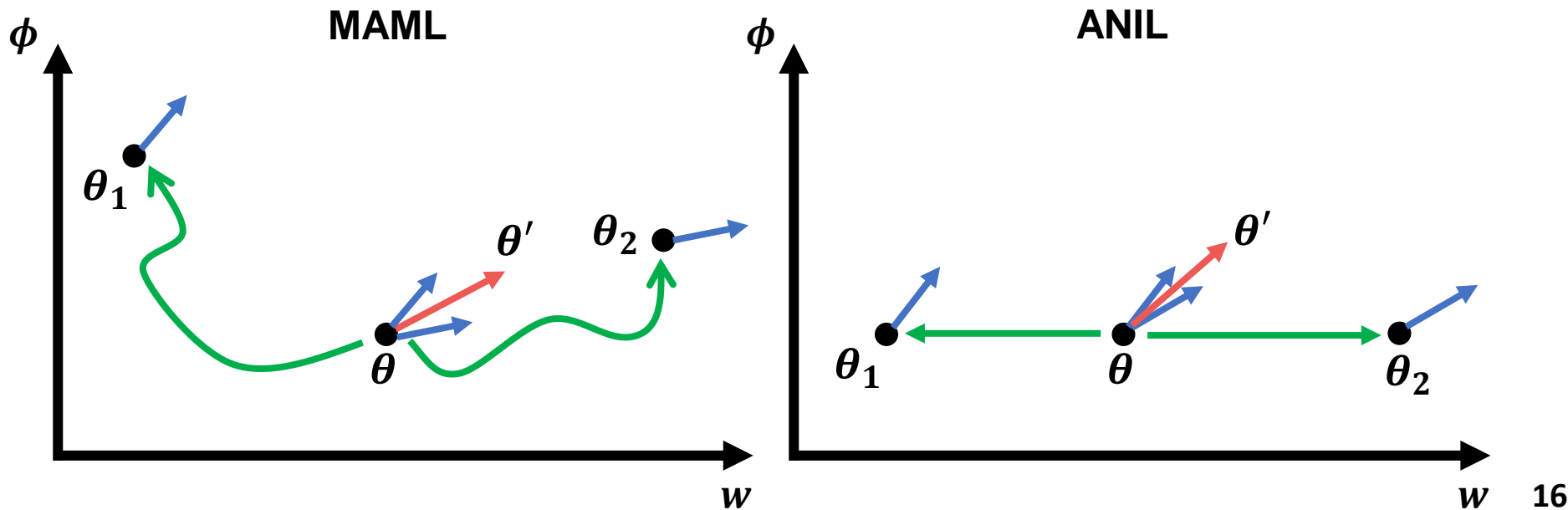
- We show that MAML is a noisy supervised contrastive learning algorithm.

Assumption

ANIL (Almost no inner loop)

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

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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\pm0.2 | 63.1\pm0.4 | 93.7 \pm 0.7 | 96.4 \pm 0.1 |
| ANIL | 46.7 \pm 0.4 | 61.5 \pm 0.5 | 96.2\pm0.5 | 98.0\pm0.3 |

Main Derivation

Motivating example

Assumptions:

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

Loss: Mean square error.

Condition: One inner loop update.

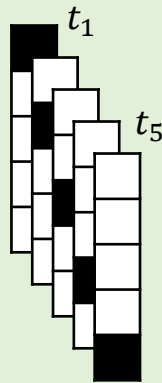
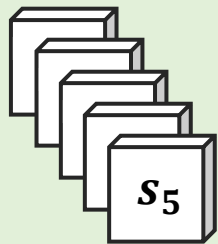
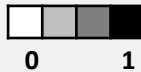
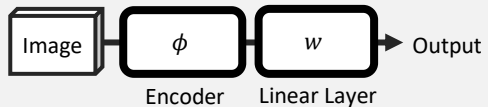
Setting

- 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:

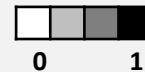
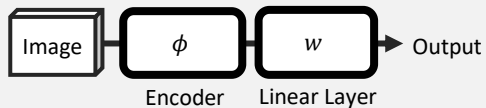


Inner Loop (1 step)

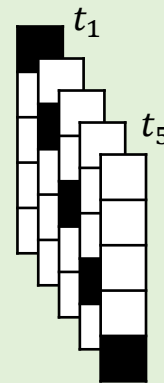
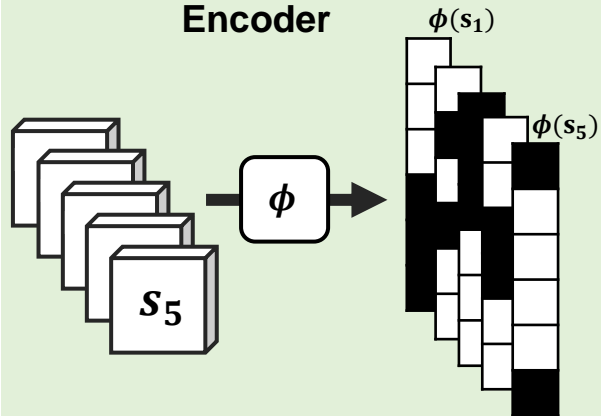
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Encoder

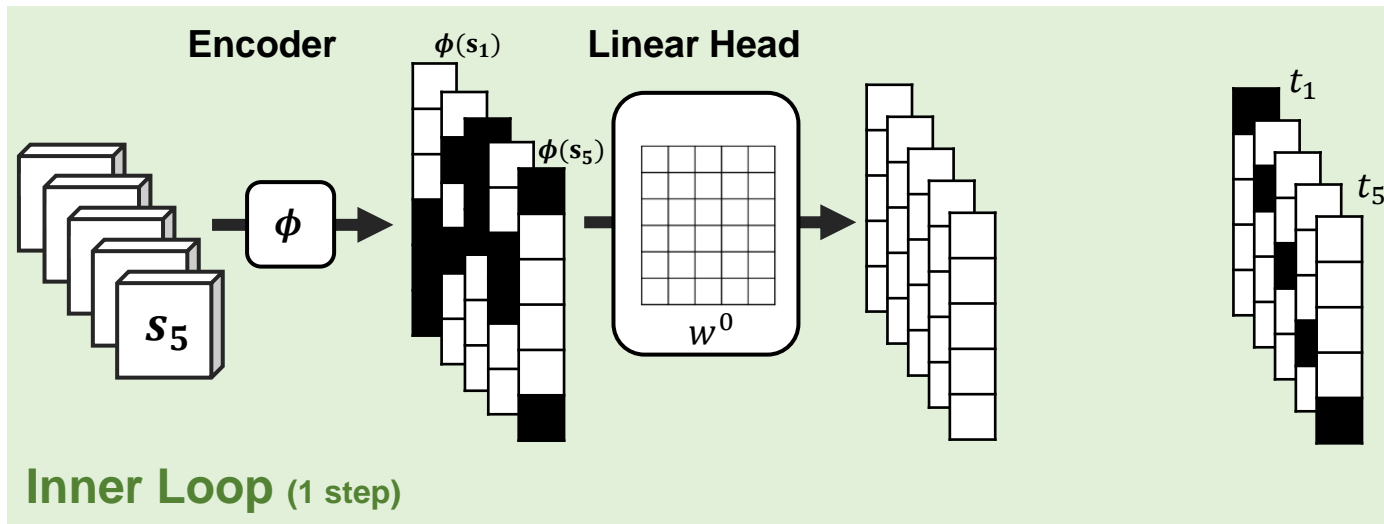
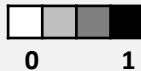
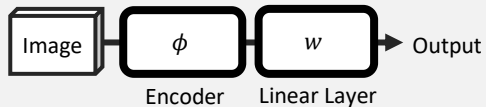


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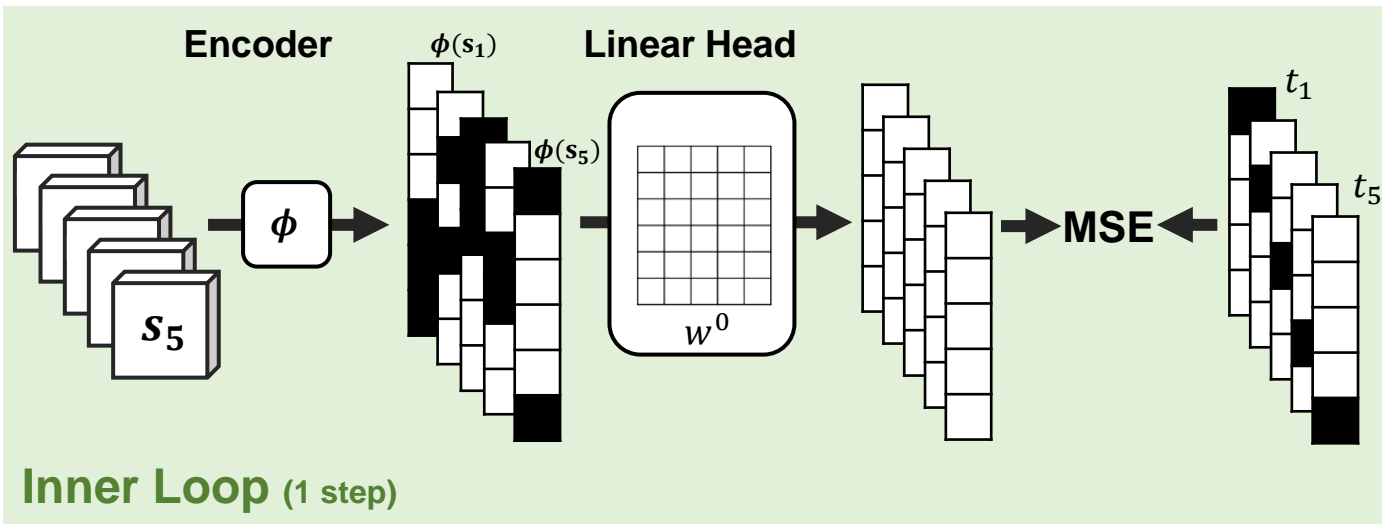
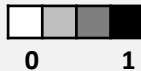
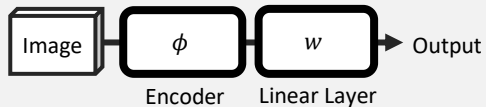
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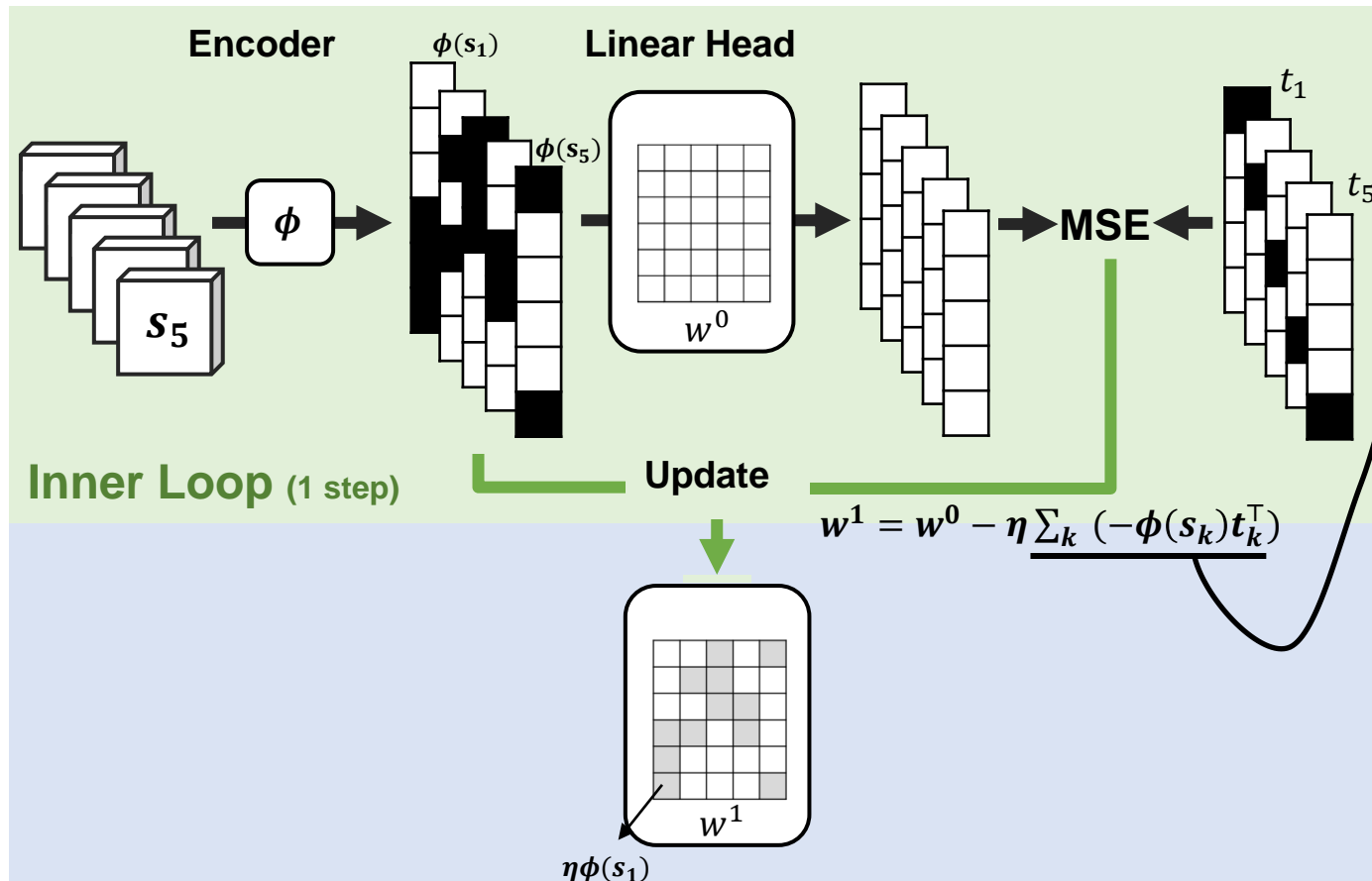
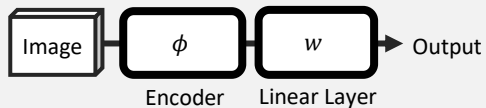
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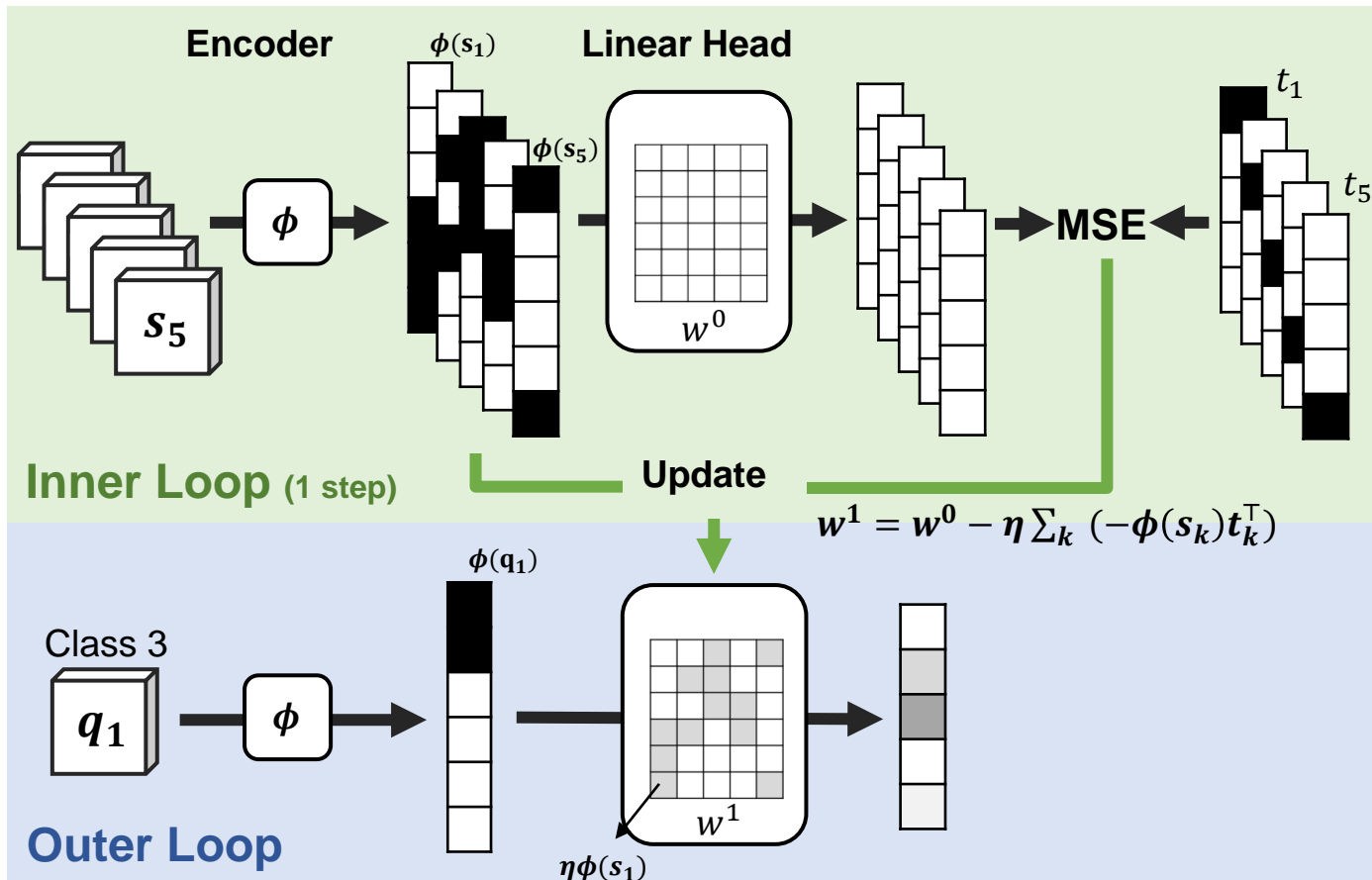
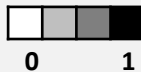
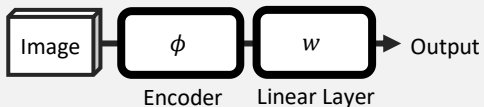
$$w^1 = w^0 + \phi(s_1) t_1^T$$

$$w^1 = w^0 + \phi(s_2) t_2^T + \dots$$

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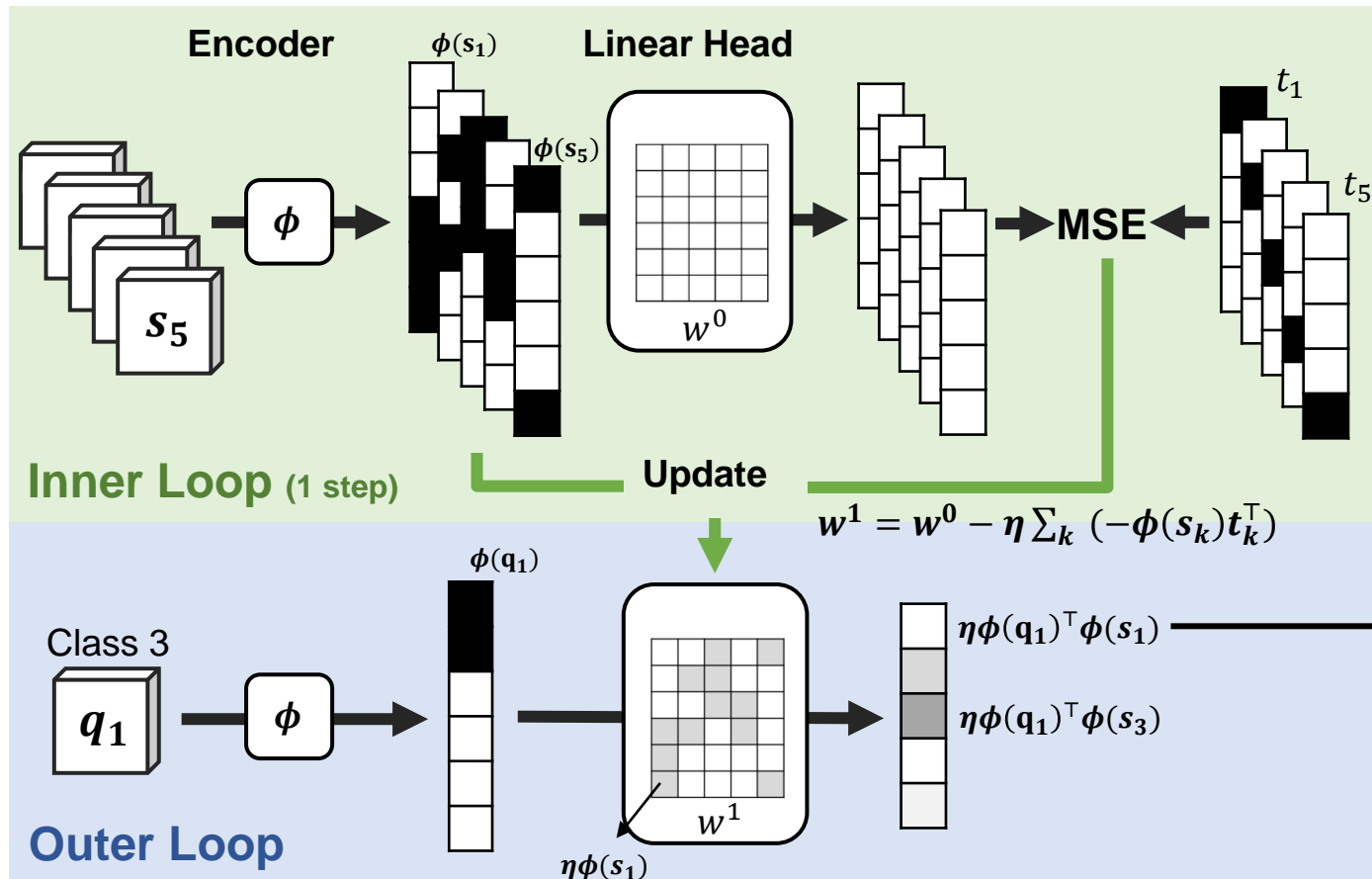
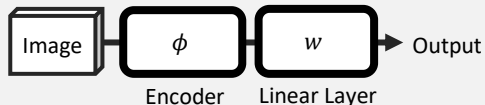
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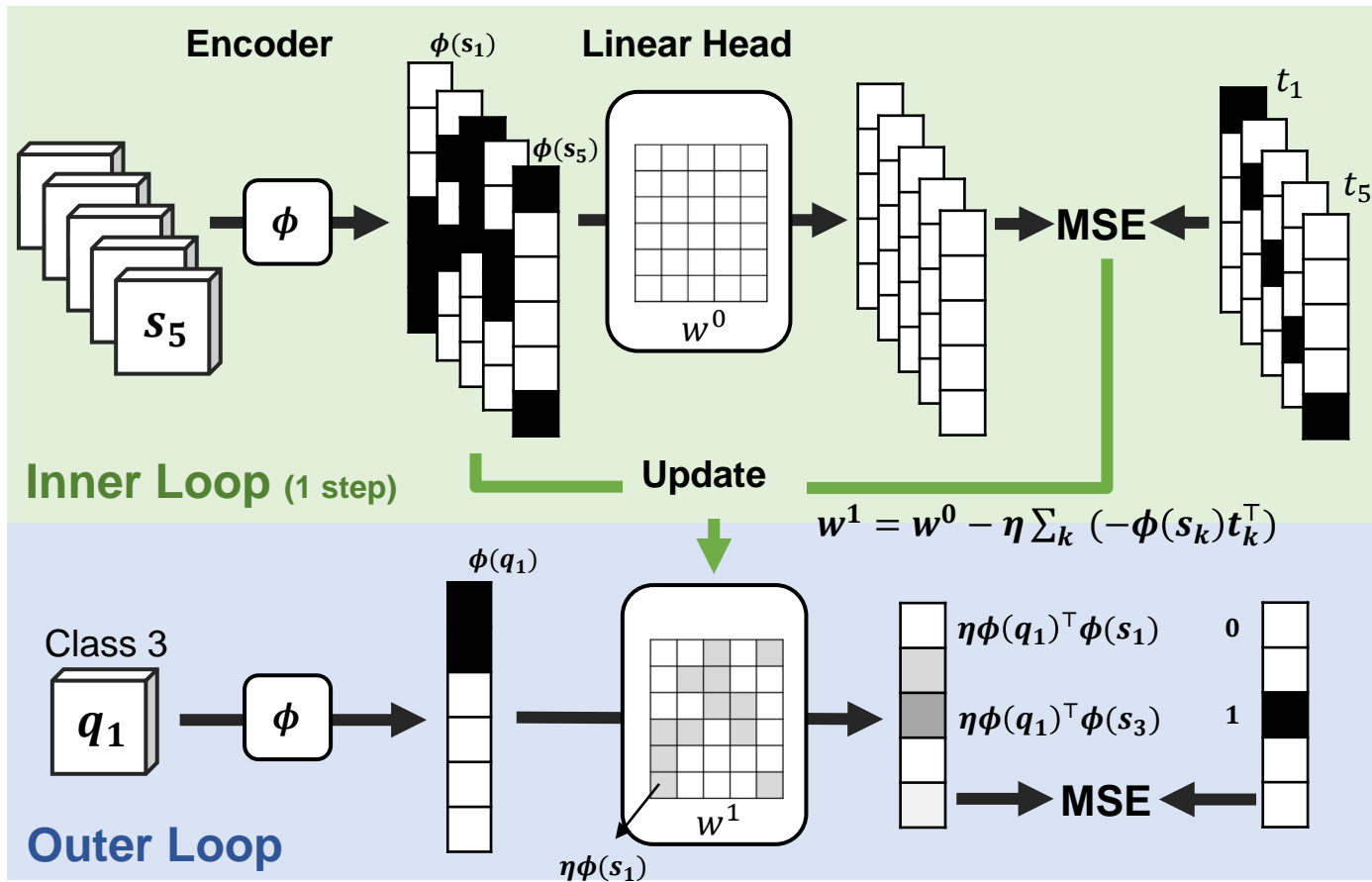
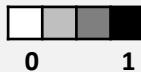
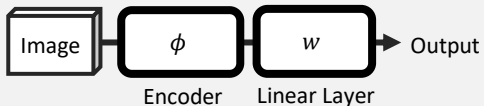


The inner product
between support feature
 s_1 and query feature q_1 .

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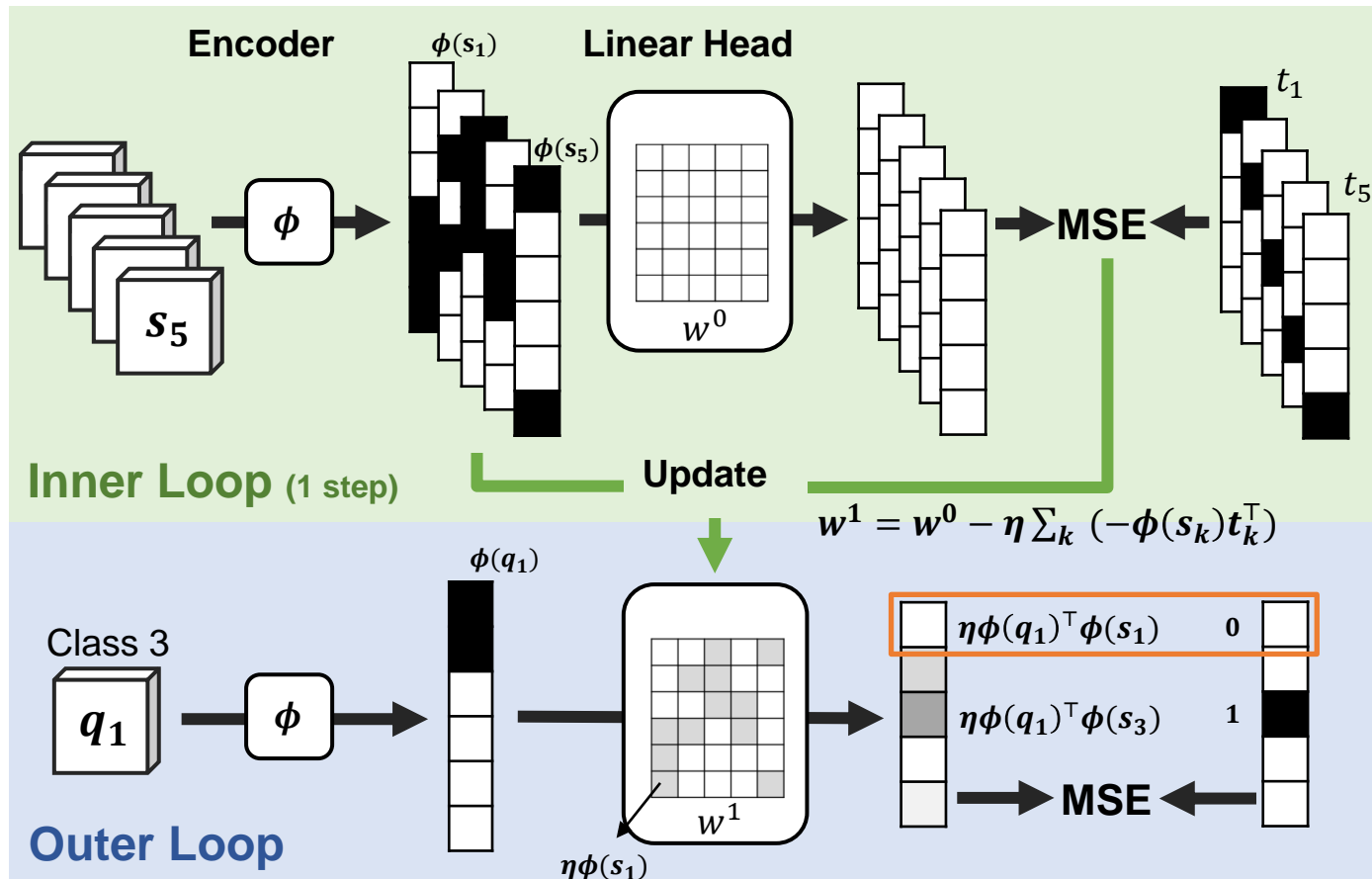
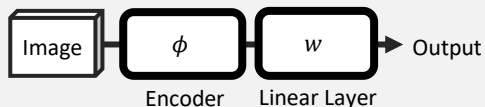
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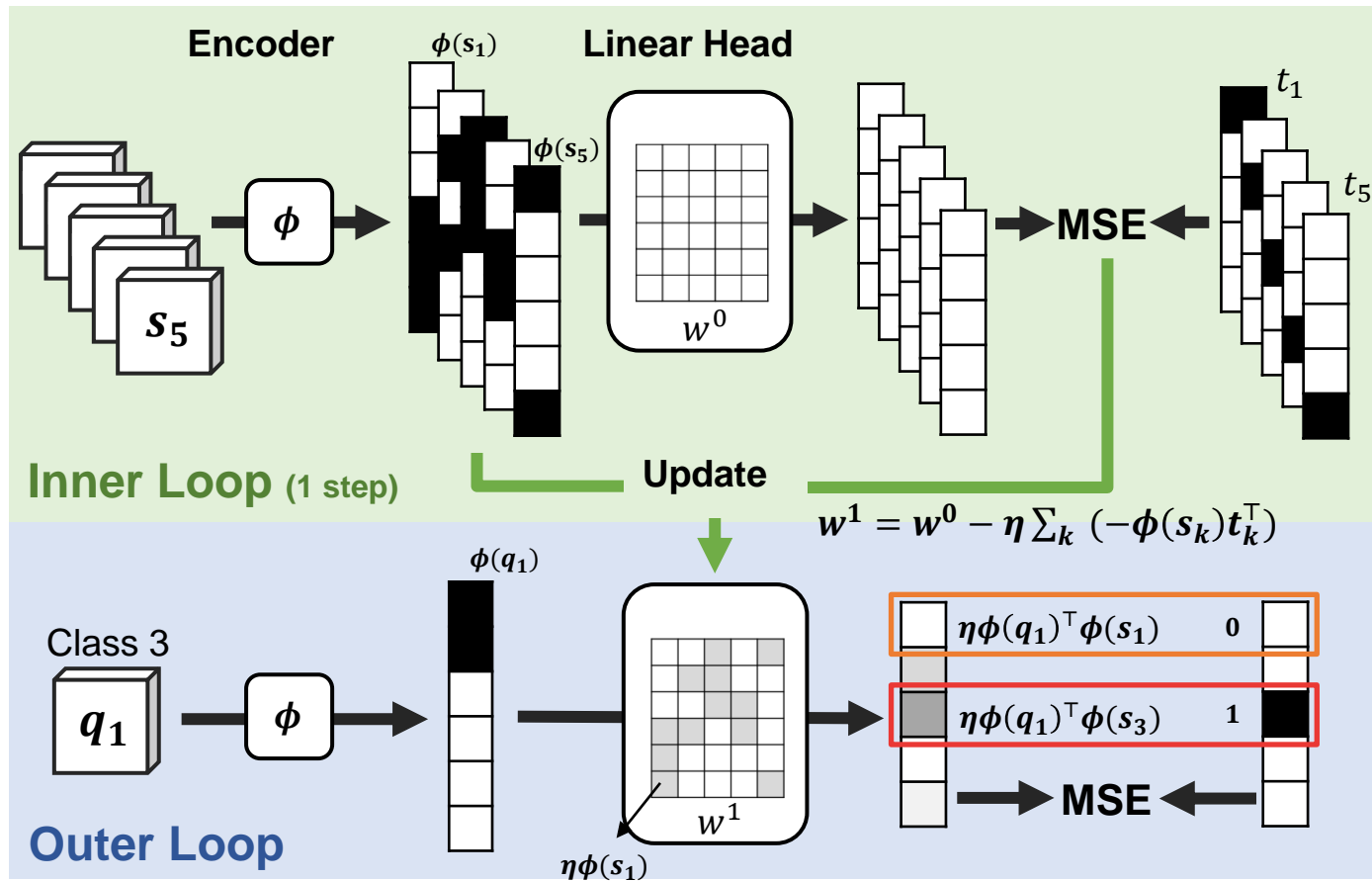
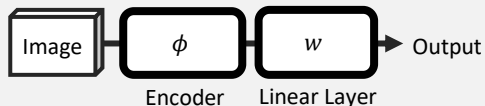
Negative sample

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

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Model:



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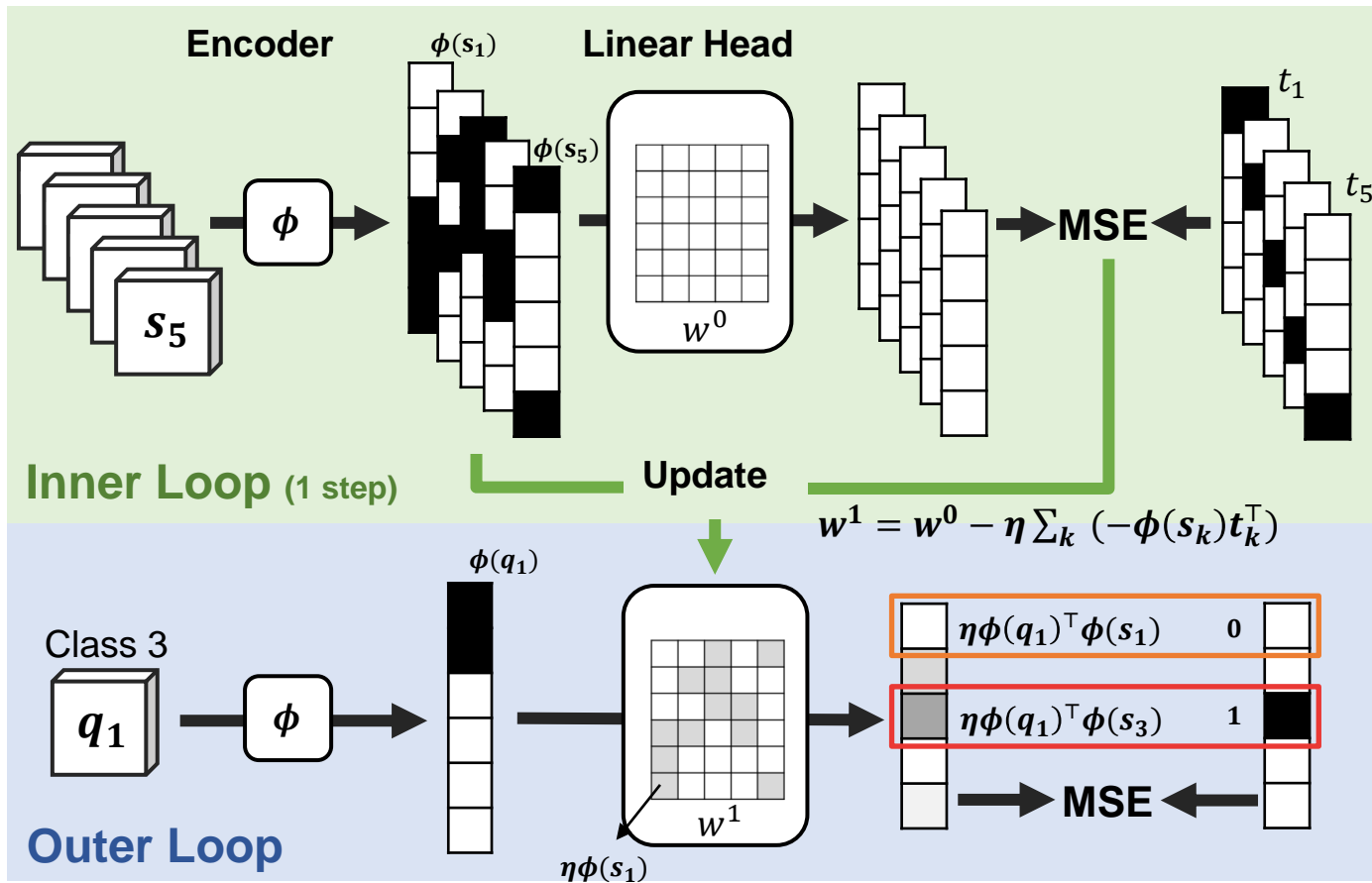
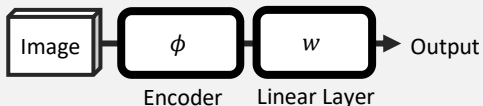
Positive sample

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

Setting:

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

Model:



**Supervised
contrastive
learning**



Negative sample

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

Positive sample

- q_1 and s_3 have same labels,
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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:

$$L = \sum_{i=1}^{N_{class}} \underbrace{(q_i - 1_{i=u}) \mathbf{w}_i^\top}_{\text{stop gradient}} \phi(q) + \eta \mathbf{E}_{(s,t) \sim S} \underbrace{\left[- \sum_{i=1}^{N_{class}} q_i s_i + s_u + q_t - 1_{t=u} \right] \phi(s)^\top \phi(q)}_{\text{stop gradient}}$$

- Meaning:
 - If q and s have sample label, then update ϕ s.t. $\phi(q)$ is closer to $\phi(s)$.
 - Otherwise, update ϕ s.t. $\phi(q)$ is closer to $\phi(s)$.

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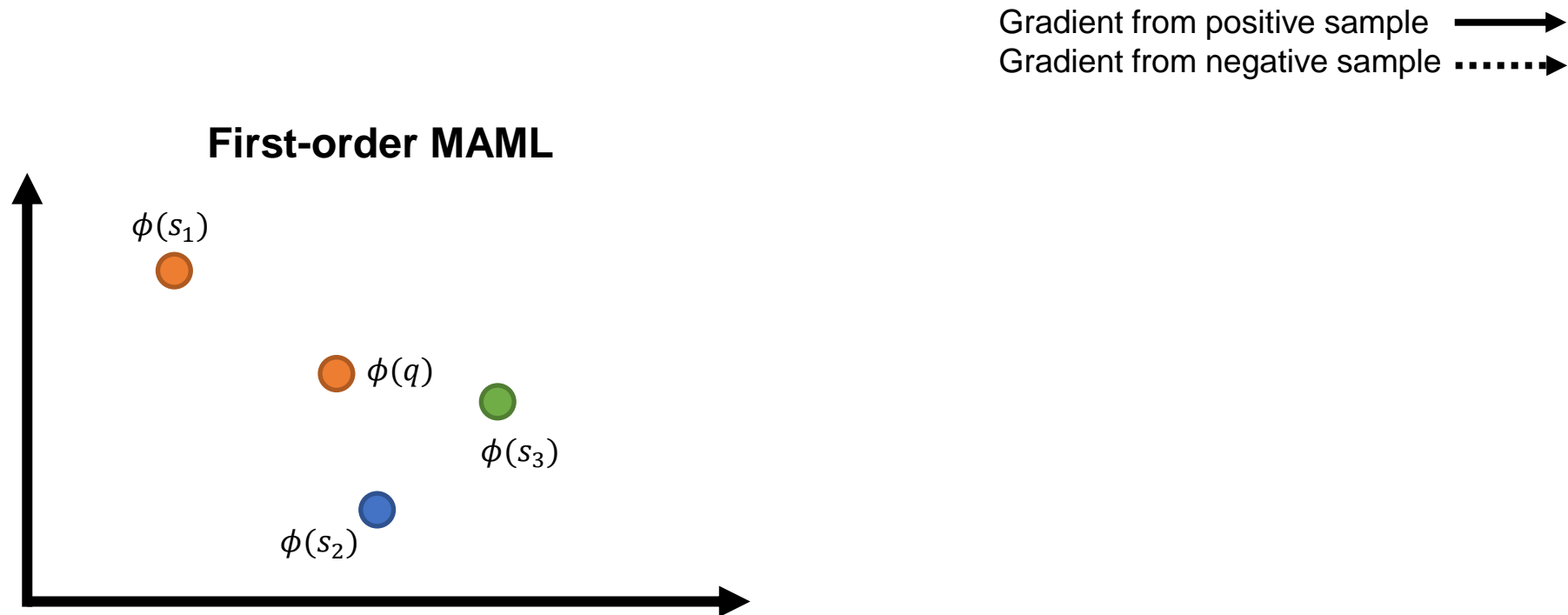
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- Expected effect of the second term:
 - If q and s have sample label, then update ϕ s.t. $\phi(q)$ is closer to $\phi(s)$.
 - Otherwise, update ϕ s.t. $\phi(q)$ is closer to $\phi(s)$.

Main Derivation

Main result. Feature space illustration.



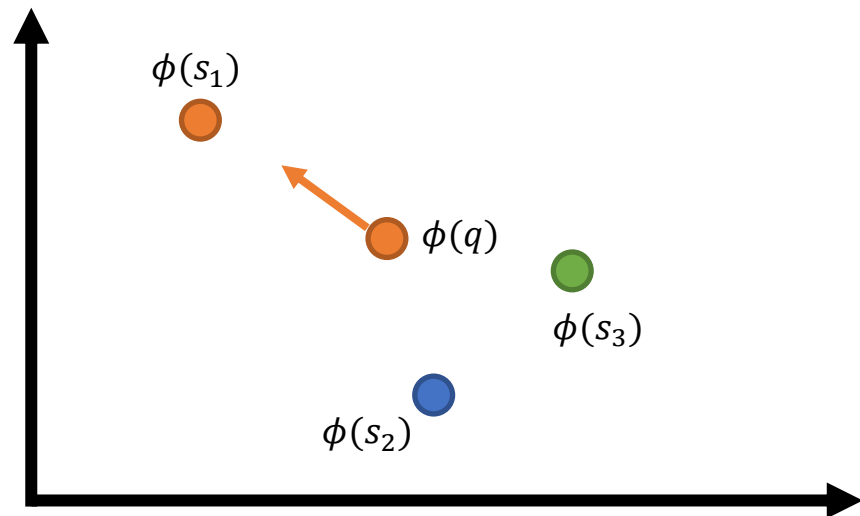
update ϕ such that $\phi(q)$ is closer/further to $\phi(s)$

Main Derivation

Main result. Feature space illustration.

Gradient from positive sample \longrightarrow
Gradient from negative sample $\cdots\cdots\longrightarrow$

First-order MAML



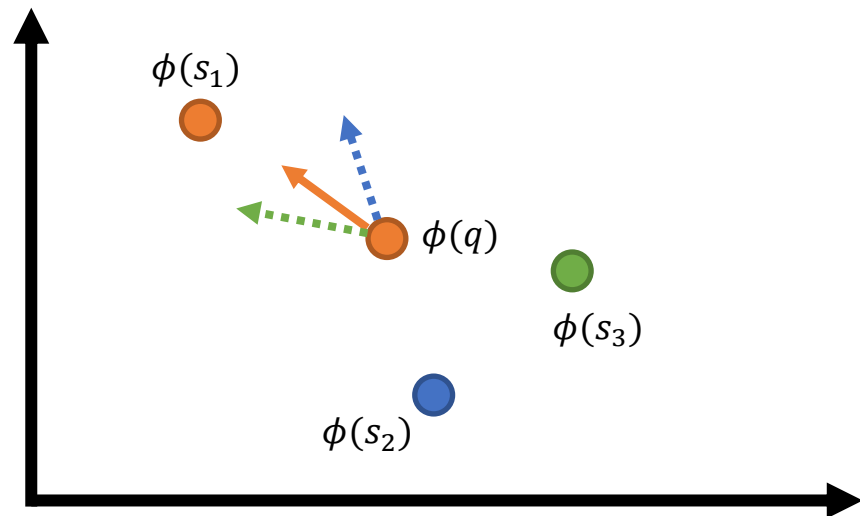
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First-order MAML



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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 :

- Second-order MAML:

$$L = \sum_{i=1}^{N_{class}} \underbrace{(q_i - 1_{i=u}) \mathbf{w}_i^\top}_{\text{stop gradient}} \phi(q) + \eta \mathbf{E}_{(s,t) \sim S} \left[\underbrace{- \sum_{i=1}^{N_{class}} q_i s_i + s_u + q_t - 1_{t=u}}_{\text{Contrastive coefficient}} \underbrace{\phi(s)^\top \phi(q)}_{\text{Inner product}} \right]$$

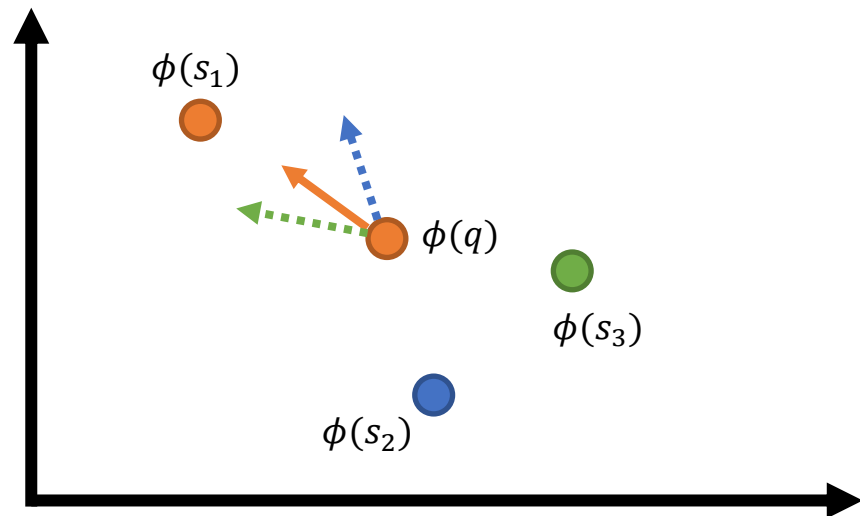
- Expected effect of the second term:
 - If q and s have sample label, then update ϕ such that $\phi(q)$ and $\phi(s)$ move closer to each other.
 - Otherwise, update ϕ such that $\phi(q)$ and $\phi(s)$ move further to each other.

Main Derivation

Main result. Feature space illustration.

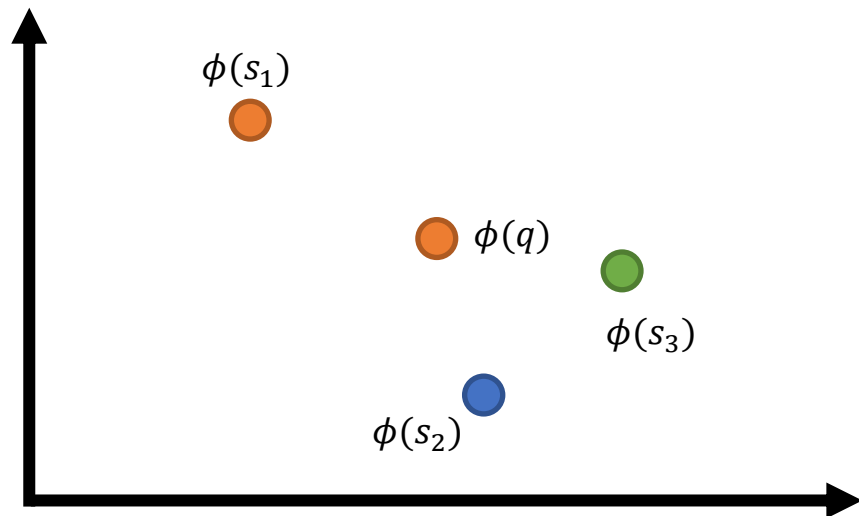
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First-order MAML



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

Second-order MAML



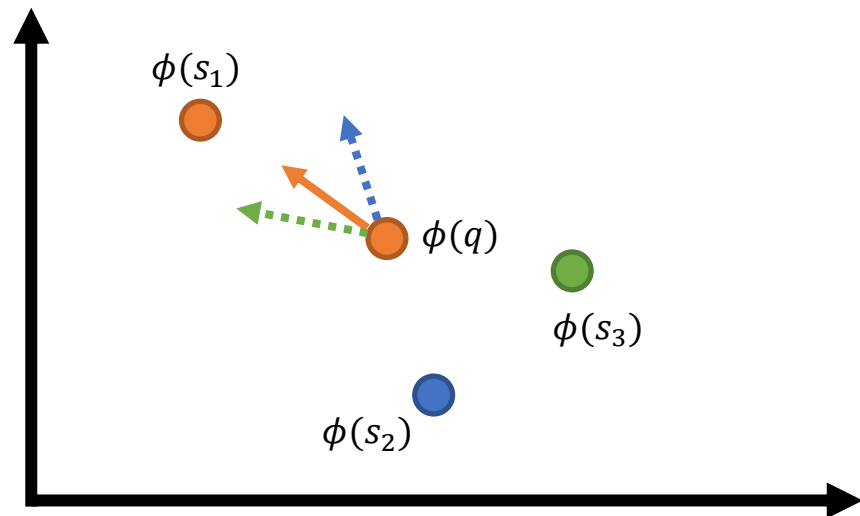
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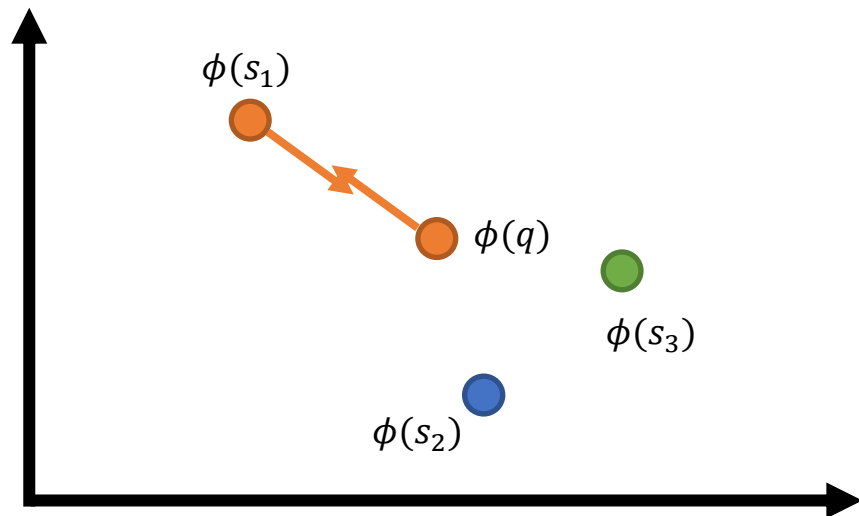
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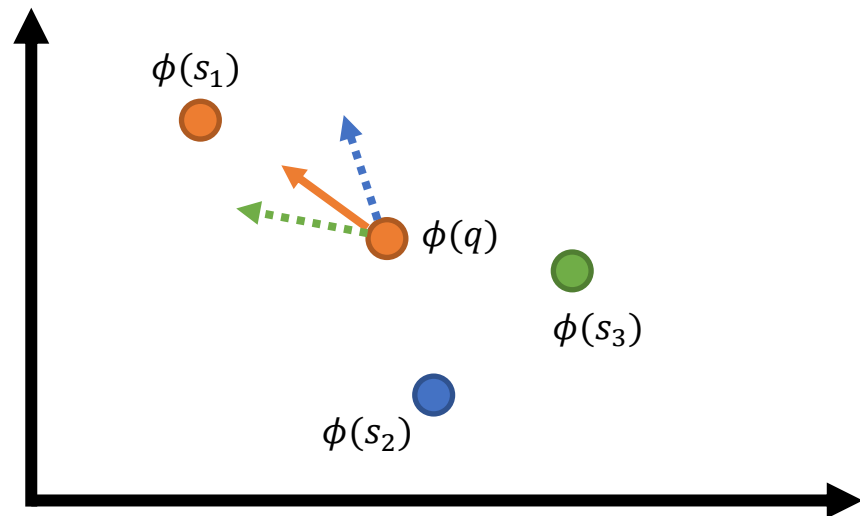
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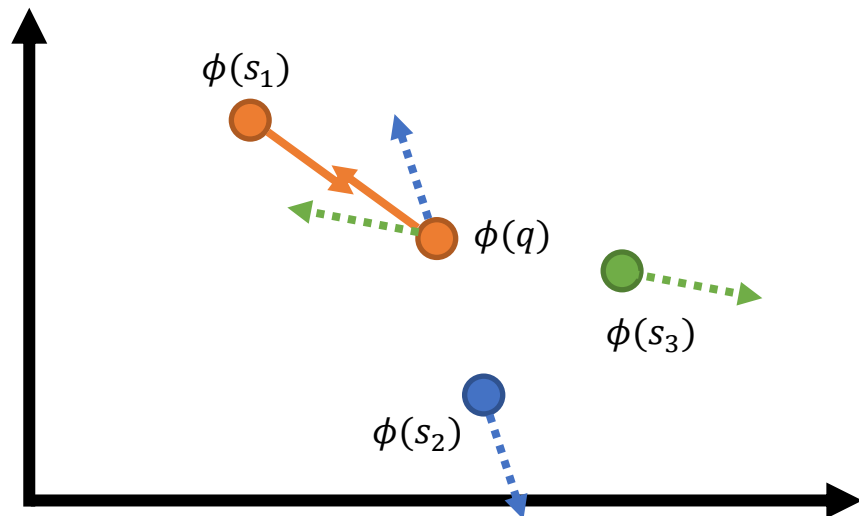
Gradient from positive sample \longrightarrow
Gradient from negative sample $\cdots\cdots\longrightarrow$

First-order MAML



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Second-order MAML



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

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

- First-order MAML:

$$L = \underbrace{\sum_{i=1}^{N_{class}} (\underbrace{q_i - 1_{i=u}}_{\text{stop gradient}}) \mathbf{w}_i^\top \phi(q)}_{\text{Random initialization / Cross task interference}} + \eta \underbrace{\mathbf{E}_{(s,t) \sim S} \left[- \sum_{i=1}^{N_{class}} q_i s_i + s_u + q_t - 1_{t=u} \right] \phi(s)^\top \phi(q)}_{\text{The coefficient is not always positive when } s \text{ and } q \text{ come from different classes}}$$

- 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:

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

- Second-order MAML:

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

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

```
1: while not done do
2:   Sample tasks  $\{T_1, T_2\}$ 
3:
4:   for  $n = 1, 2$  do
5:      $\{S_n, Q_n\} \leftarrow$  sample from  $T_n$ 
6:      $\theta_n = \theta$ 
7:     for  $i = 1, 2, \dots, N_{step}$  do
8:        $\theta_n \leftarrow \theta_n - \eta \nabla_{\theta_n} L(\theta_n, S_n)$ 
9:     end for
10:   end for
11:   Update  $\theta \leftarrow \theta - \rho \sum_{n=1}^{N_{batch}} \nabla_{\theta} L(\theta_n, Q_n)$ 
12:
13: end while
```

Algorithm 2 Second-order MAML with zeroing trick

```
1: while not done do
2:   Sample tasks  $\{T_1, T_2\}$ 
3:    $w = 0$ 
4:   for  $n = 1, 2$  do
5:      $\{S_n, Q_n\} \leftarrow$  sample from  $T_n$ 
6:      $\theta_n = \theta$ 
7:     for  $i = 1, 2, \dots, N_{step}$  do
8:        $\theta_n \leftarrow \theta_n - \eta \nabla_{\theta_n} L(\theta_n, S_n)$ 
9:     end for
10:   end for
11:   Update  $\theta \leftarrow \theta - \rho \sum_{n=1}^{N_{batch}} \nabla_{\theta} L(\theta_n, Q_n)$ 
12:    $w = 0$ 
13: end while
```

Results

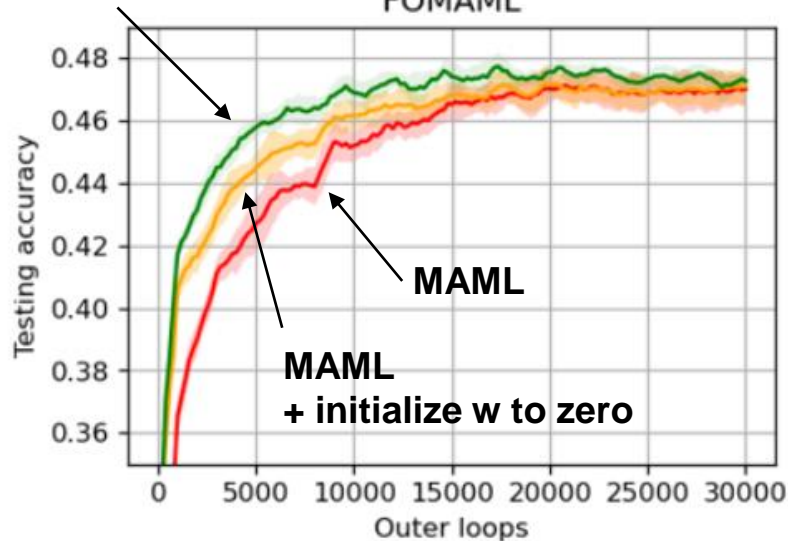
Using the zeroing trick improves performance.

Setting: MinImageNet.

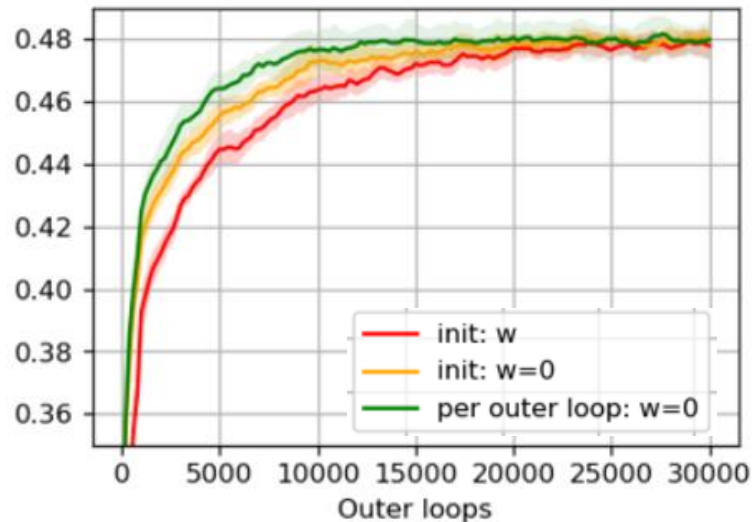
5-way 1-shot setting

MAML + zeroing trick

FOMAML



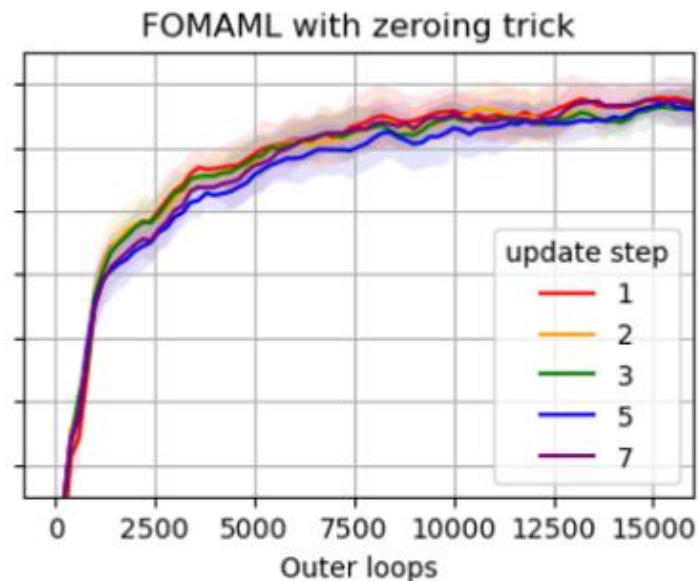
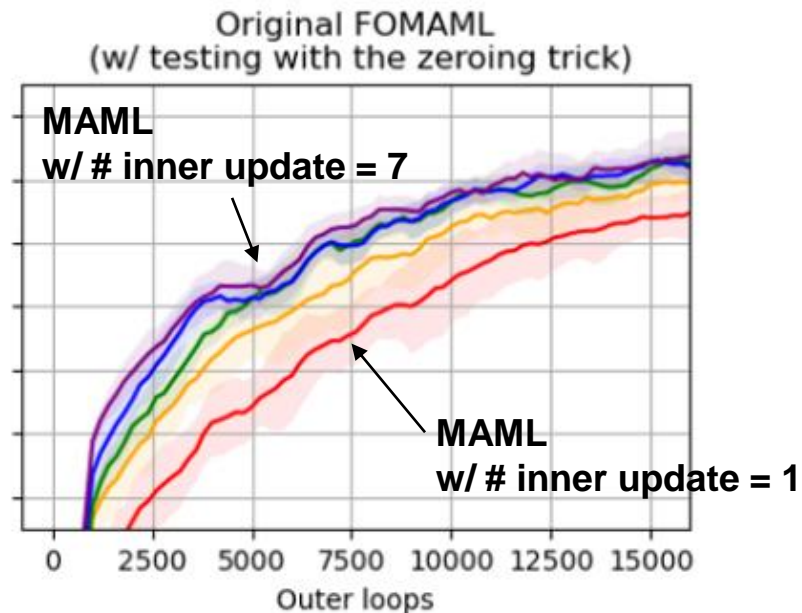
SOMAML



Results

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

Setting: MinImageNet 5-way 1-shot.

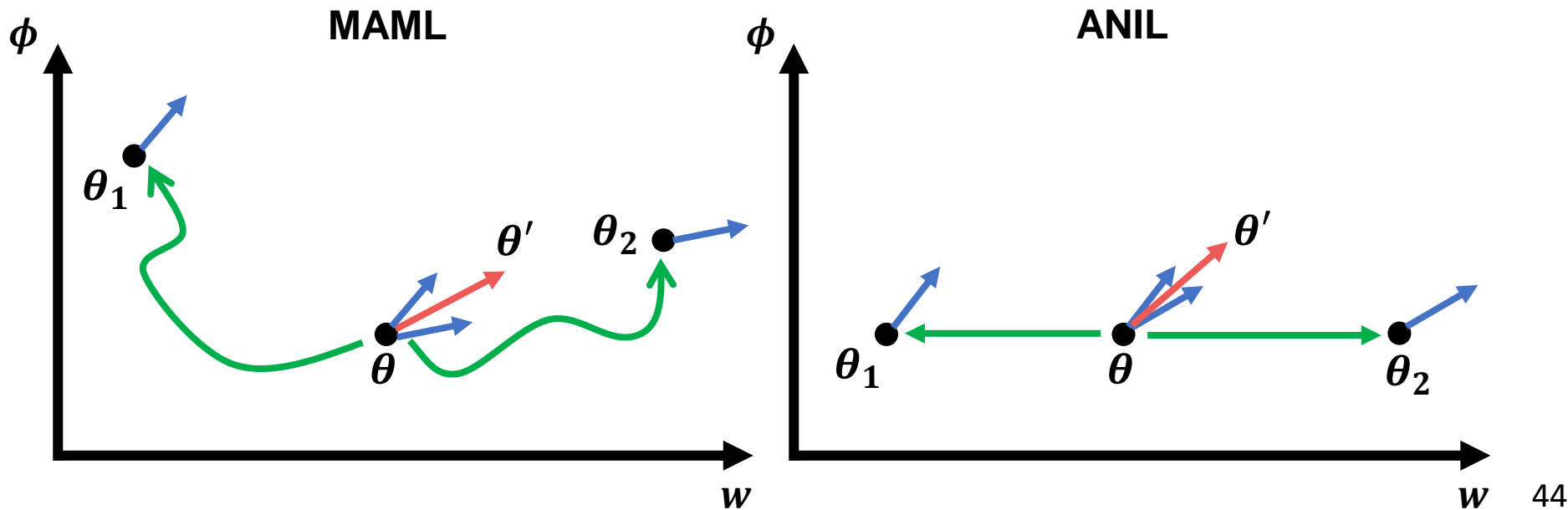


Wrap up

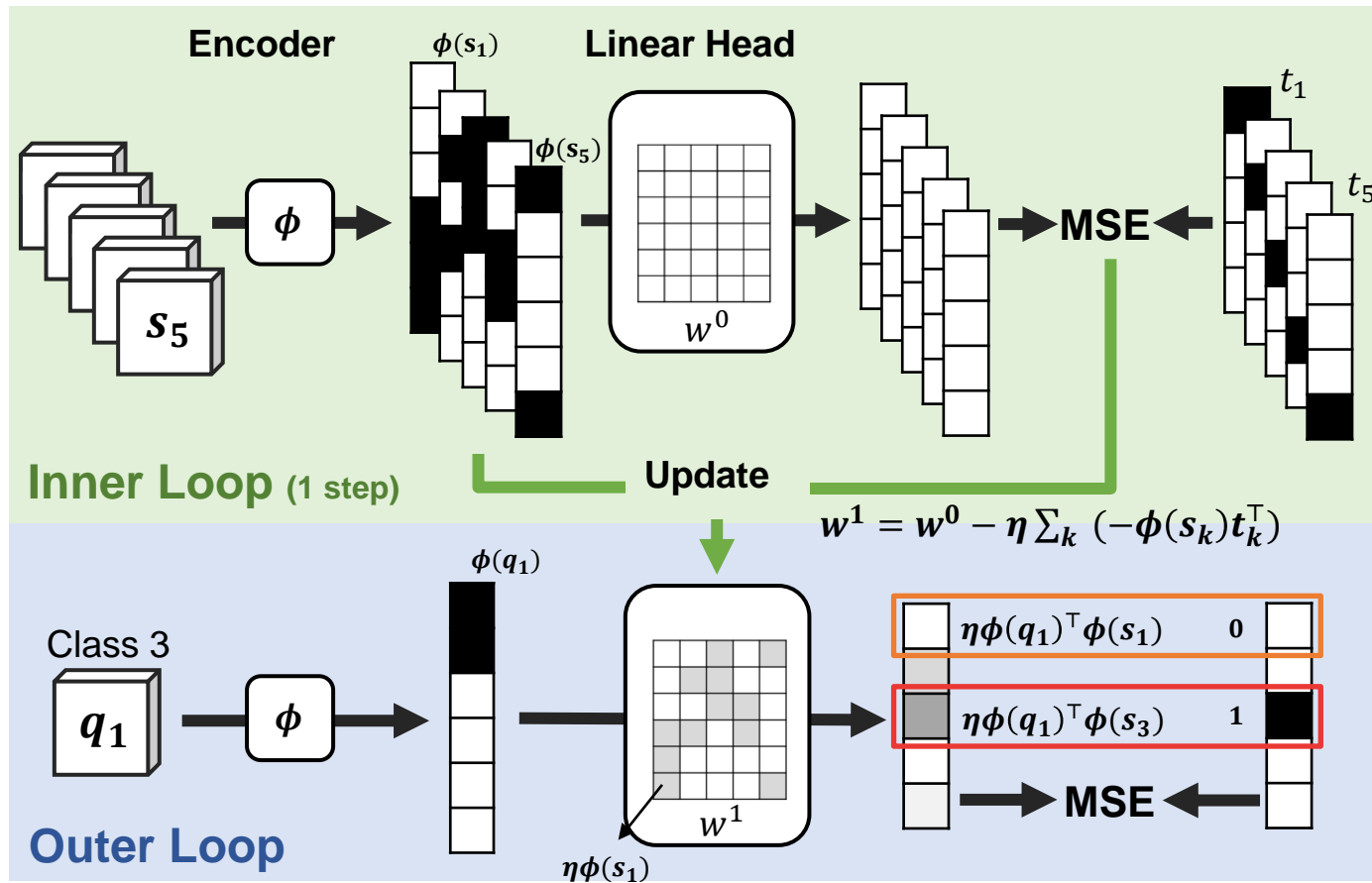
We use the ANIL assumption for derivation.

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

ANIL states that the encoder ϕ is not updated during the inner loop.



Wrap up



**Supervised
contrastive
learning**



Negative sample

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

Positive sample

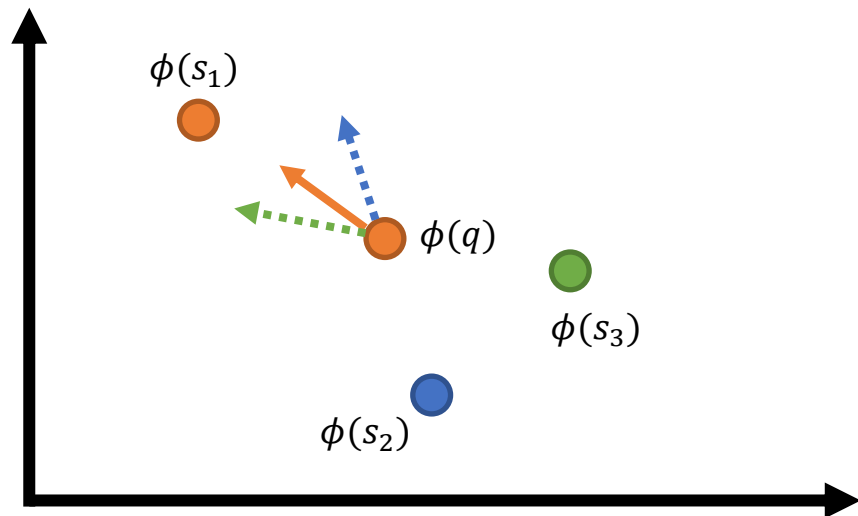
- q_1 and s_3 have same labels,
- Their inner product of their features should be one.

Wrap up

We show how FOMAML different from SOMAML.

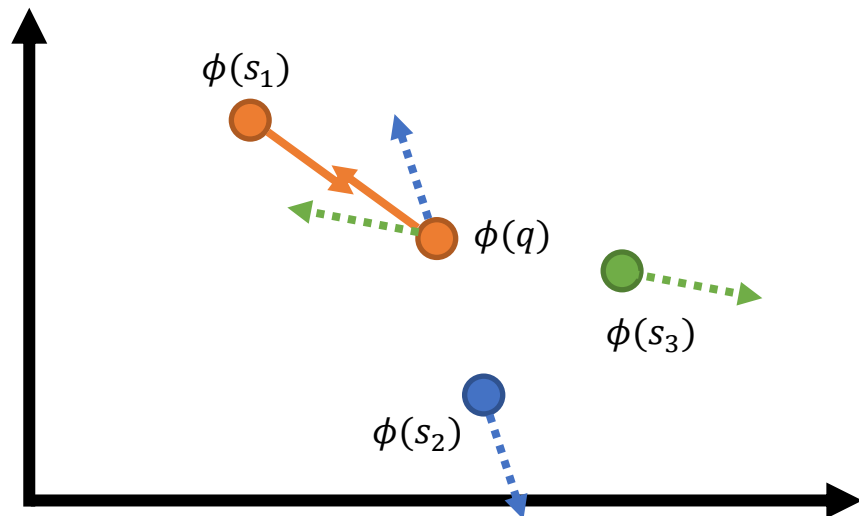
Gradient from positive sample \longrightarrow
Gradient from negative sample $\cdots\cdots\longrightarrow$

First-order MAML



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

Second-order MAML



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

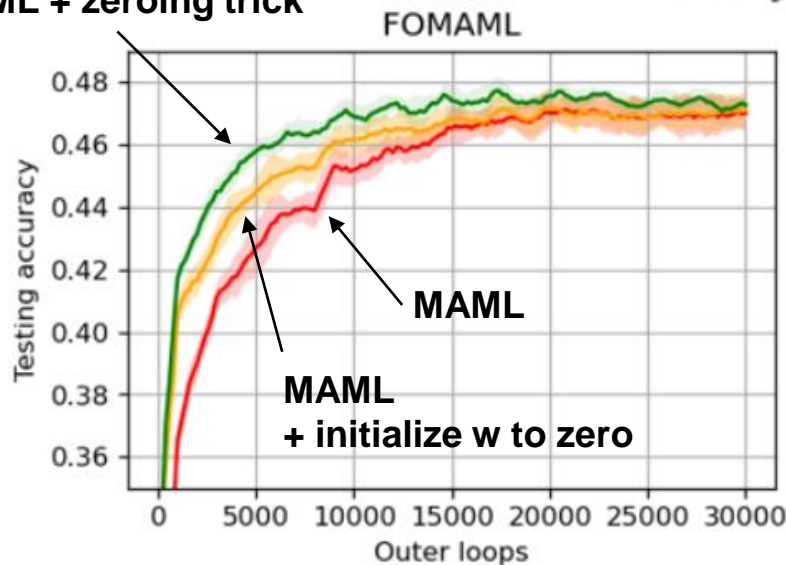
Wrap up

We show that the zeroing trick improves MAML.

Setting: MinImageNet.

5-way 1-shot setting

MAML + zeroing trick



SOMAML

