# Transfer Learning and Meta Learning

Tao LIN

May 18, 2023

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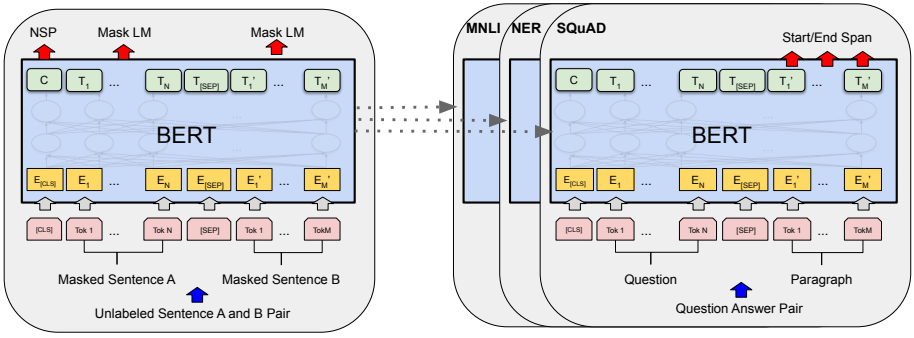
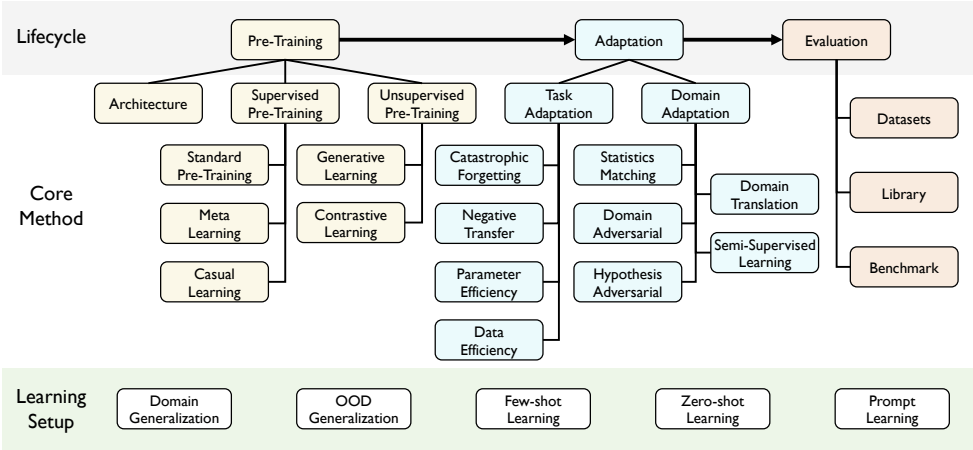



**Transfer Learning**: reuse pre-trained models by fine-tuning it for downstream tasks

[1] *Devlin et al.* Bert: Pre-training of deep bidirectional transformers for language understanding. 2019.

# Roadmap




[8] *Jiang et al.* Transferability in deep learning: A survey. 2022.

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But what if, for example,

- we don't have a large dataset,
- the data has a long tail,
- want to continuously adapt and learn on the job.

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1. Extract prior information $\theta$ from a set of meta-training tasks,
2. Learning a new task uses this prior and small training set

   $\rightarrow$ to infer most likely posterior parameters $\phi$.

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For a new meta-test task $\mathcal{T}_j \sim P(\mathcal{T})$,
we can achieve good generalization performance by using $\boldsymbol{\phi}_j = \mathsf{Alg}(\boldsymbol{\theta}, \mathcal{D}_j^{tr})$.

# Connection to other problems

- **Multi-task learning:**
- **AutoML:**
- **Neural Architecture Search:**

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  learn model with $\boldsymbol{\theta}^\star$ that solves multiple tasks $\boldsymbol{\theta}^\star = \arg\min_{\boldsymbol{\theta}} \frac{1}{M} \sum_{i=1}^{M} \mathcal{L}(\boldsymbol{\theta}, \mathcal{D}_i^{ts})$.

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- **Neural Architecture Search:**

  $\boldsymbol{\theta}$ = architecture, $\phi$ = network weights.

# Some directions for meta learning

Recap the optimization procedure for meta learning

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Some recent research directions

- Black-box Adaptation:
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  Use non-parametric learner, e.g., weighted KNN in latent space.

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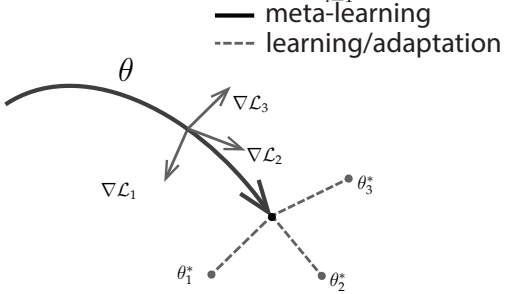


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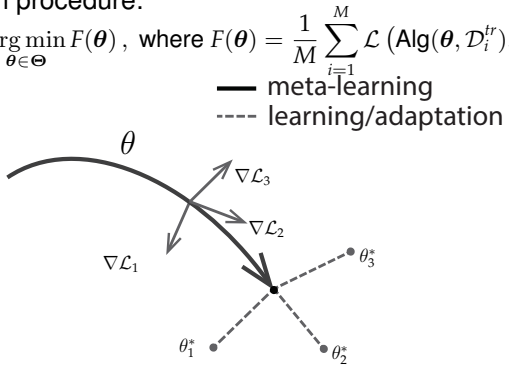


Figure: MAML finds a weight initialization $\boldsymbol{\theta}$ that allows for quick adaptation.

The inner level of MAML is the mini-batch SGD steps initialized at $\boldsymbol{\theta}$

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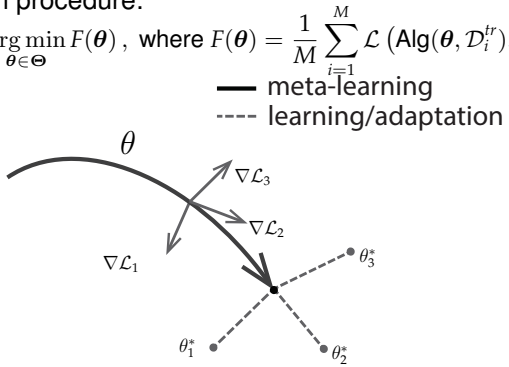


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Note that the update involves a gradient through the gradient.

# Challenge: second-order meta optimization can exhibit instabilities

Simplifying the notations by letting

$$\mathcal{L}_i(\phi) := \mathcal{L}(\phi, \mathcal{D}_i^{ts}), \hat{\mathcal{L}}_i(\phi) := \mathcal{L}(\phi, \mathcal{D}_i^{tr}), \mathsf{Alg}_i(\theta) := \mathsf{Alg}(\theta, \mathcal{D}_i^{tr}).$$

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Considering the bi-level meta learning problem as

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  - It uses a regularized algorithm, instead of $\mathsf{Alg}_i(\boldsymbol{\theta})$,

$$\mathsf{Alg}_i^\star(\boldsymbol{\theta}) = \arg\min_{\boldsymbol{\phi}'} \hat{\mathcal{L}}_i(\boldsymbol{\phi}') + \frac{\lambda}{2} \left\|\boldsymbol{\phi}' - \boldsymbol{\theta}\right\|^2 \,,$$

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    where it works as an early stopping of MAML.
  - It approximates the analytical solution of the Jacobian.

# More for iMAML (optional reading)

For the optimal solution of $\text{Alg}_i^\star(\boldsymbol{\theta})$, one can analytically compute the Jacobian as $\frac{d\text{Alg}_i(\boldsymbol{\theta})}{d\boldsymbol{\theta}} = \left(\mathbf{I} + \frac{1}{\lambda}\nabla^2_{\boldsymbol{\phi}}\hat{\mathcal{L}}_i(\boldsymbol{\phi}_i)\right)^{-1}$.

**Proof.**

The stationary point conditions imply that

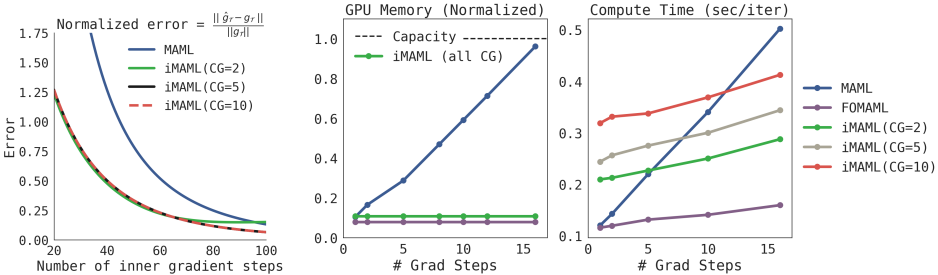
$$\nabla_\phi \hat{\mathcal{L}}_i(\boldsymbol{\phi}_i) + \lambda(\boldsymbol{\phi}_i - \boldsymbol{\theta}) = 0 \rightarrow \boldsymbol{\phi}_i = \boldsymbol{\theta} - \frac{1}{\lambda}\nabla_\phi \hat{\mathcal{L}}_i(\boldsymbol{\phi}_i)\,.$$

When the derivative exists, we have $\frac{d\boldsymbol{\phi}_i}{d\boldsymbol{\theta}} = \mathbf{I} - \frac{1}{\lambda}\nabla^2_{\boldsymbol{\phi}_i}\hat{\mathcal{L}}_i(\boldsymbol{\phi})\frac{d\boldsymbol{\phi}_i}{d\boldsymbol{\theta}}$. □

The meta-gradient $\mathbf{g}_i$ can be approximated:

- approximated solution of $\text{Alg}_i^\star(\boldsymbol{\theta})$, i.e., $\boldsymbol{\phi}_i$.
- conjugate gradient algorithm to solve

$$\left\| \mathbf{g}_i - \left(\mathbf{I} + \frac{1}{\lambda}\nabla^2_{\boldsymbol{\phi}}\hat{\mathcal{L}}_i(\boldsymbol{\phi}_i)\right)^{-1} \nabla_{\boldsymbol{\phi}}\mathcal{L}_i\left(\boldsymbol{\phi}_i\right) \right\| \leq \delta'$$




(a) Synthetic example. (b) 20-way-5-shot Omniglot task.

Figure: Accuracy, computation, and memory trade-off.

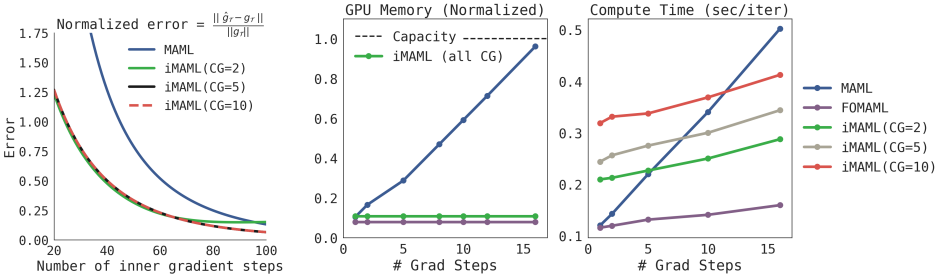



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Figure: Accuracy, computation, and memory trade-off.

| Algorithm | 5-way 1-shot | 5-way 5-shot | 20-way 1-shot | 20-way 5-shot |
|---|---|---|---|---|
| MAML [15] | $98.7 \pm 0.4\%$ | $\mathbf{99.9 \pm 0.1\%}$ | $95.8 \pm 0.3\%$ | $98.9 \pm 0.2\%$ |
| first-order MAML [15] | $98.3 \pm 0.5\%$ | $99.2 \pm 0.2\%$ | $89.4 \pm 0.5\%$ | $97.9 \pm 0.1\%$ |
| Reptile [43] | $97.68 \pm 0.04\%$ | $99.48 \pm 0.06\%$ | $89.43 \pm 0.14\%$ | $97.12 \pm 0.32\%$ |
| iMAML, GD (ours) | $99.16 \pm 0.35\%$ | $99.67 \pm 0.12\%$ | $94.46 \pm 0.42\%$ | $98.69 \pm 0.1\%$ |
| iMAML, Hessian-Free (ours) | $\mathbf{99.50 \pm 0.26\%}$ | $99.74 \pm 0.11\%$ | $\mathbf{96.18 \pm 0.36\%}$ | $\mathbf{99.14 \pm 0.1\%}$ |

Figure: Omniplot results.

# Case study: meta learning for continual learning [6, 7]

MAML-like algorithm solves few-shot learning.

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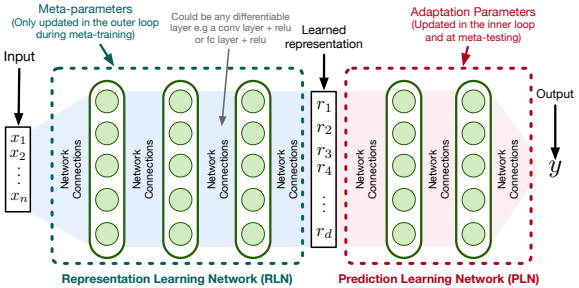

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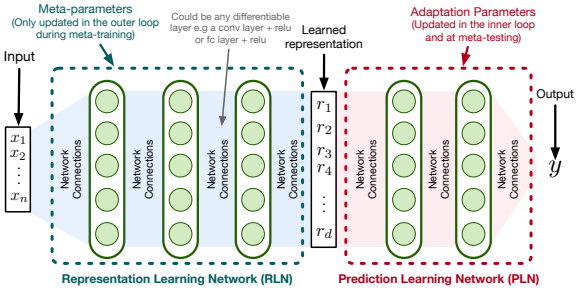


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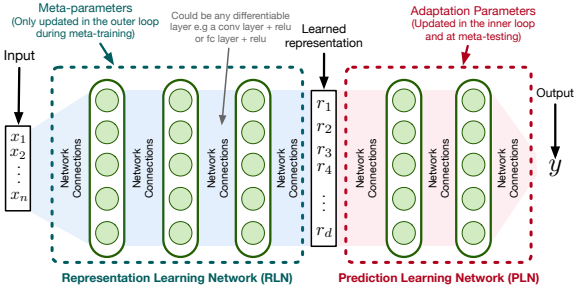


- trains the representation $f_{\boldsymbol{\theta}}$ within the network with a meta-learning objective,
- optimizes through an online update for the later layers $g_{\mathbf{W}}$ used for task learning.

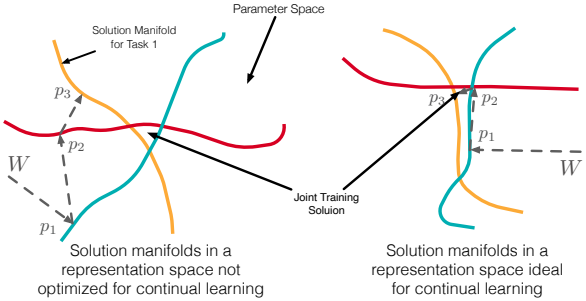


Figure: **Effect of the representation on continual learning** (an intuitive explanation), for a problem where targets are generated from three different distributions $p_1(Y|x), p_2(Y|x)$ and $p_3(Y|x)$.
The representation results in different solution manifolds for the three distributions; we depict two different possibilities here. We show the learning trajectory when training incrementally from data generates first by $p_1$, then $p_2$ and $p_3$. On the left, the online updates interfere, jumping between distant points on the manifolds. On the right, the online updates either generalize appropriately—for parallel manifolds—or avoid interference because manifolds are orthogonal.

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$$\boldsymbol{\theta}_m^b = \boldsymbol{\theta}_{m-1}^b - \eta \nabla_{\boldsymbol{\theta}_{m-1}^b} \mathcal{L}_{\mathcal{S}_{\mathcal{T}_b}}(\boldsymbol{\theta}_{m-1}^b)$$

  - meta loss:

$$\mathcal{L}_{meta}(\boldsymbol{\theta}) = \sum_{b=1}^{B} \mathcal{L}_{\mathcal{Z}_{\mathcal{T}_b}}(\boldsymbol{\theta}_m^b)$$

  - the outer loop optimization:

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta' \nabla_{\boldsymbol{\theta}} \mathcal{L}_{meta}(\boldsymbol{\theta})$$

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- test time deployment:
  - draw unseen tasks $\{\mathcal{T}_1^{test}, \ldots, \mathcal{T}_n^{test}\}$ from $\mathcal{D}$

# Rapid Learning or Feature Reuse?

**Question**: Is MAML's efficacy predominantly due to (1) Rapid Learning or (2) Feature Reuse?

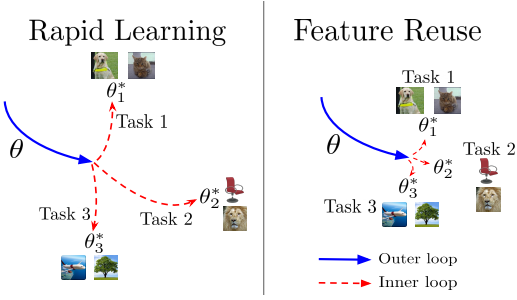


Figure: **Rapid learning and feature reuse paradigms**: the significance of the movement in the parameter space.

# Investigation on the “rapid learning” and “feature reuse”

**Assumption**: There is an important distinction between

1. the *head* (final layer) of the network
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**Experimental design**: two sets of **numerical experiments**

1. evaluate the performance when freezing parameters after MAML training, without test time inner loop adaptation.
2. use representational similarity tools to measure how much the network features and representations change through the inner loop.

# Freezing layer representations (test-time adaptation) experiments

Even when freezing all layers in the *network body*, performance hardly changes.

Table: Test accuracy. Freezing successive layers (preventing inner loop adaptation) does not affect accuracy, supporting feature reuse.

| Freeze layers | MiniImageNet-5way-1shot | MiniImageNet-5way-5shot |
|---|---|---|
| None | $46.9 \pm 0.2$ | $63.1 \pm 0.4$ |
| 1 | $46.5 \pm 0.3$ | $63.0 \pm 0.6$ |
| 1,2 | $46.4 \pm 0.4$ | $62.6 \pm 0.6$ |
| 1,2,3 | $46.3 \pm 0.4$ | $61.2 \pm 0.5$ |
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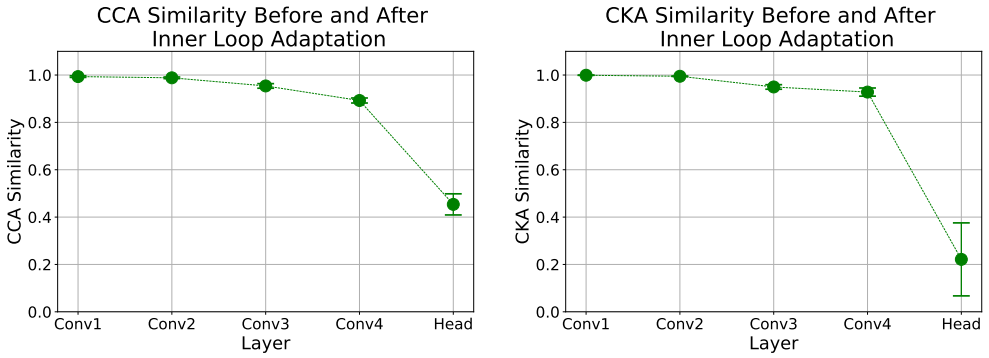
## Representational similarity experiments




(a) (b)

Figure: **High CCA/CKA similarity between representations before and after adaptation for all layers except the head.** This suggests: these layers do not change much during adaptation, but mostly perform feature reuse.

## Feature Reuse happens early in learning

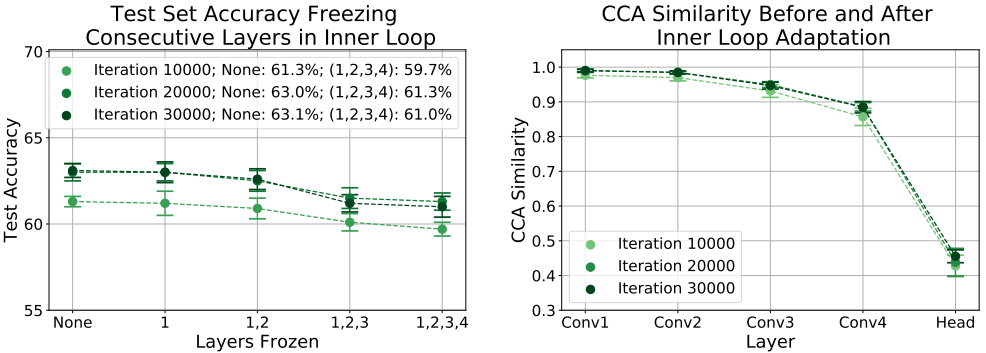



Figure: **Inner loop updates have little effect on learned representations from early on in learning.**

## From insights to efficient method design: ANIL (Almost No Inner Loop) algorithm

**Intuition**: The inner loop updates have little effect on the network body even early in training.

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Table: **ANIL matches the performance of MAML on few-shot image classification and RL.**

| Method | Omniglot-20way-1shot | Omniglot-20way-5shot | MiniImageNet-5way-1shot | MiniImageNet-5way-5shot |
|---|---|---|---|---|
| MAML | $93.7 \pm 0.7$ | $96.4 \pm 0.1$ | $46.9 \pm 0.2$ | $63.1 \pm 0.4$ |
| ANIL | $96.2 \pm 0.5$ | $98.0 \pm 0.3$ | $46.7 \pm 0.4$ | $61.5 \pm 0.5$ |

| Method | HalfCheetah-Direction | HalfCheetah-Velocity | 2D-Navigation |
|---|---|---|---|
| MAML | $170.4 \pm 21.0$ | $-139.0 \pm 18.9$ | $-20.3 \pm 3.2$ |
| ANIL | $363.2 \pm 14.8$ | $-120.9 \pm 6.3$ | $-20.1 \pm 2.3$ |

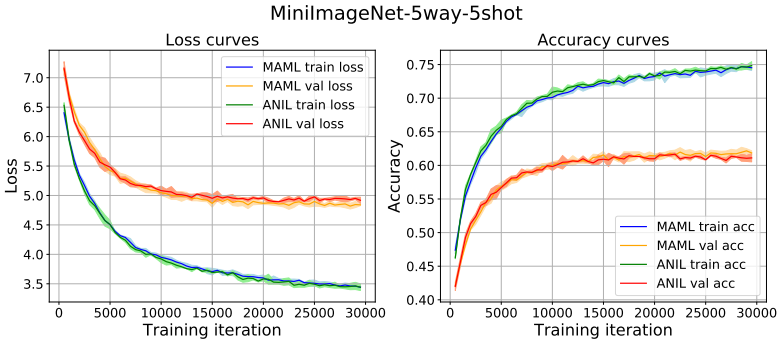


Figure: **MAML and ANIL learn very similarly**.

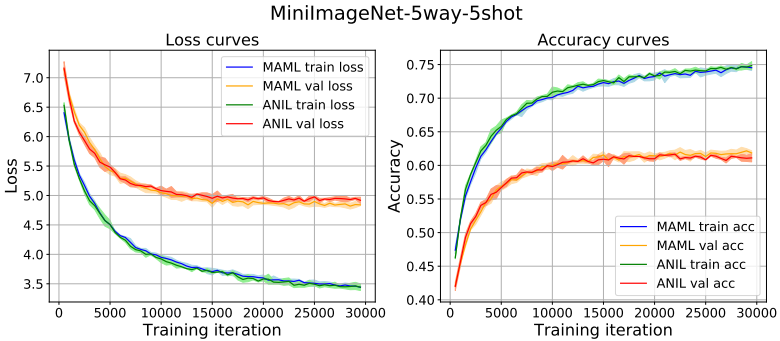


Figure: **MAML and ANIL learn very similarly**.

Table: **MAML and ANIL models learn comparable representations.** (across different random seeds): algorithmic differences between MAML/ANIL does not result in vastly different types of features learned.

| Model Pair | CCA Similarity | CKA Similarity |
|---|---|---|
| MAML-MAML | 0.51 | 0.83 |
| ANIL-ANIL | 0.51 | 0.86 |
| ANIL-MAML | 0.50 | 0.83 |

## From insights to efficient method design: NIL (No Inner Loop) algorithm

**Question**: How important is the head at test time, when good features have already been learned?

[1] Each task first passes the $k$ support set samples through the network body to get their penultimate layer representations. For a test example, compute cosine similarities with support set samples and use them to weight the support set labels.

## From insights to efficient method design: NIL (No Inner Loop) algorithm

**Question**: How important is the head at test time, when good features have already been learned?

The representations can be used directly, with *no* adaptation:

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Table: **NIL algorithm performs as well as MAML and ANIL on few-shot image classification**: the strength of the learned features, and the relative lack of importance of the head at test time.

| Method | Omniglot-20way-1shot | Omniglot-20way-5shot | MiniImageNet-5way-1shot | MiniImageNet-5way-5shot |
|---|---|---|---|---|
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| ANIL | $96.2 \pm 0.5$ | $98.0 \pm 0.3$ | $46.7 \pm 0.4$ | $61.5 \pm 0.5$ |
| NIL | $96.7 \pm 0.3$ | $98.0 \pm 0.0$ | $48.0 \pm 0.7$ | $62.2 \pm 0.5$ |

[1] Each task first passes the $k$ support set samples through the network body to get their penultimate layer representations. For a test example, compute cosine similarities with support set samples and use them to weight the support set labels.

**Question**: How important task alignment and the head are during training to ensure good features.

We answer this question by examining the quality of features arising from different training regimes for the body.

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Table: **MAML/ANIL training leads to superior features learned** over other methods which do not have task-specific heads, supporting the importance of the head at training.

| Method | MiniImageNet-5way-1shot | MiniImageNet-5way-5shot |
|---|---|---|
| MAML training-NIL head | $48.4 \pm 0.3$ | $61.5 \pm 0.8$ |
| ANIL training-NIL head | $48.0 \pm 0.7$ | $62.2 \pm 0.5$ |
| Multiclass training-NIL head | $39.7 \pm 0.3$ | $54.4 \pm 0.5$ |
| Multitask training-NIL head | $26.5 \pm 1.1$ | $34.2 \pm 3.5$ |
| Random features-NIL head | $32.9 \pm 0.6$ | $43.2 \pm 0.5$ |
| NIL training-NIL head | $38.3 \pm 0.6$ | $43.0 \pm 0.2$ |

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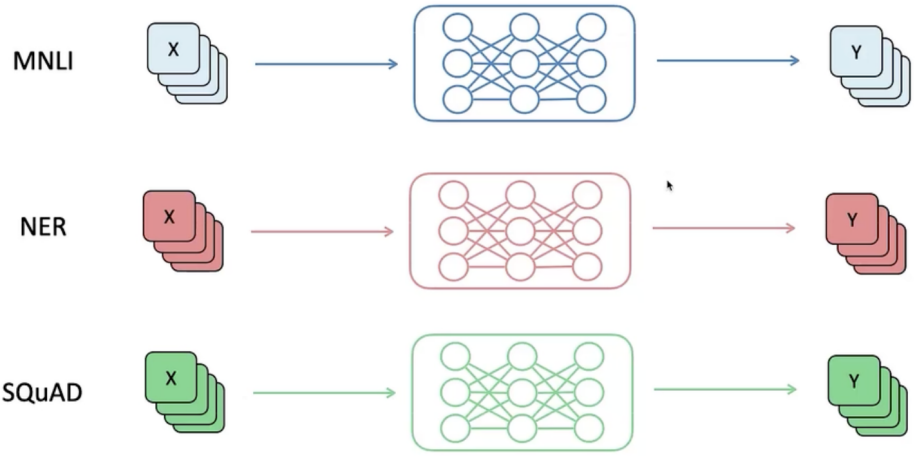
# Full Fine-Tuning




Each task needs a separate model copy

$\rightarrow$ expensive as the number of tasks and model size grow

# Parameter-Efficient Transfer Learning

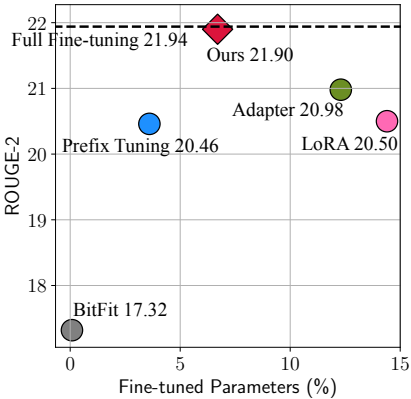
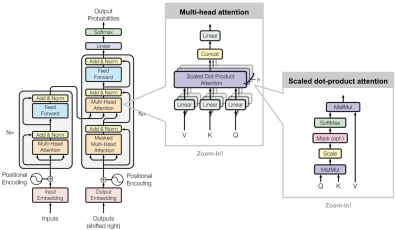



Figure: Performance of different methods on a summarization task. The number of fine-tuned parameters is relative to the tuned parameters in full fine-tuning.

Parameter-efficient tuning matters!

# Recap Transformer



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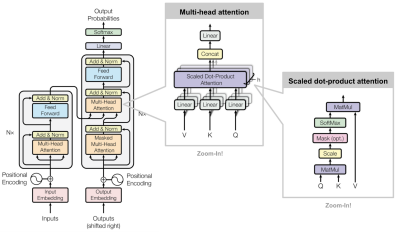


The conventional attention function maps queries $\mathbf{Q} \in \mathbb{R}^{n \times d_k}$ and key-value pairs $\mathbf{K} \in \mathbb{R}^{m \times d_k}, \mathbf{V} \in \mathbb{R}^{m \times d_v}$:

$$\text{Attn}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d_k}}\right)\mathbf{V}\,, \tag{3}$$

and $n$ and $m$ are the # of queries and key-value pairs respectively.

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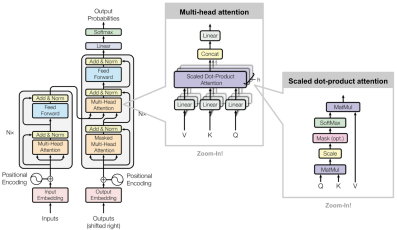


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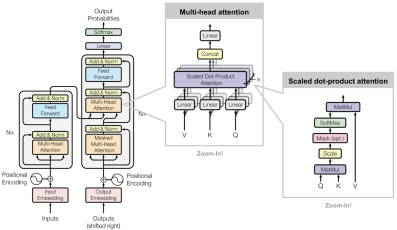
**Multi-Head Attention** (MHA) performs the attention function in parallel over $N_h$ heads:

# Recap Transformer




The conventional attention function maps queries $\mathbf{Q} \in \mathbb{R}^{n \times d_k}$ and key-value pairs $\mathbf{K} \in \mathbb{R}^{m \times d_k}$, $\mathbf{V} \in \mathbb{R}^{m \times d_v}$:

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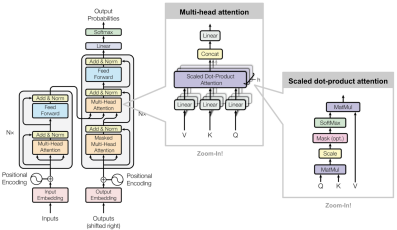


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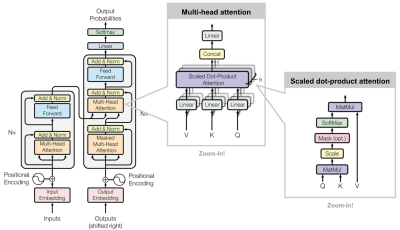


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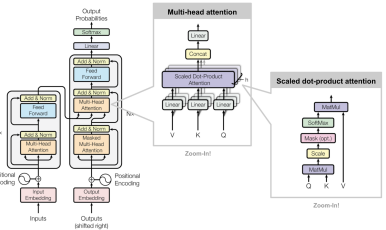
$$\text{MHA}(\mathbf{C}, \mathbf{x}) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)\mathbf{W}_o\,, \qquad \text{head}_i = \text{Attn}(\mathbf{x}\mathbf{Q}_q^{(i)}, \mathbf{C}\mathbf{K}_k^{(i)}, \mathbf{C}\mathbf{V}_v^{(i)})\,, \tag{4}$$

where $d$ is the model dimension, and in MHA, $d_h := \frac{d}{N_h}$.

# Recap Transformer

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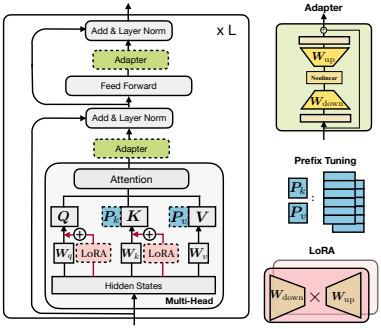
where $d$ is the model dimension, and in MHA, $d_h := \frac{d}{N_h}$.

**Fully connected Feed-Forward Network** (FFN):

$$\text{FFN}(\mathbf{x}) = \text{ReLU}(\mathbf{x}\mathbf{W}_1 + \mathbf{b}_1)\mathbf{W}_2 + \mathbf{b}_2\,, \qquad \mathbf{W}_1 \in \mathbb{R}^{d \times d_m}, \mathbf{W}_2 \in \mathbb{R}^{d_m \times d}, \text{and e.g., } d_m = 4d\,. \tag{5}$$

# Existing methods




- Adapters [4]

$$\mathbf{h} \leftarrow h + f\left(\mathbf{h}\mathbf{W}_{\text{down}}\right)\mathbf{W}_{\text{up}}\,, \qquad \mathbf{W}_{\text{down}} \in \mathbb{R}^{d\times r}, \mathbf{W}_{\text{down}} \in \mathbb{R}^{r\times d} \quad (6)$$

- Prefix tuning [9] (inspired by the success of textual prompting)

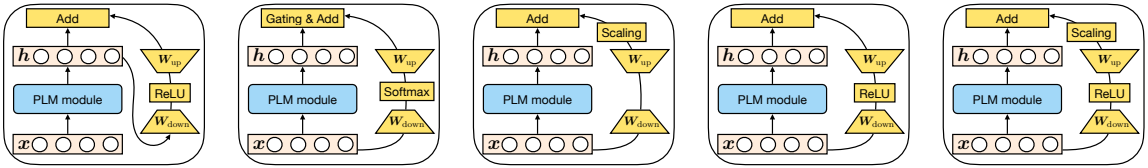
$$\text{head}_i = \text{Attn}\left(\mathbf{x}\mathbf{W}_q^{(i)}, \text{concat}\left(\mathbf{P}_k^{(i)}, \mathbf{C}\mathbf{W}_k^{(i)}\right), \text{concat}\left(\mathbf{P}_v^{(i)}, \mathbf{C}\mathbf{W}_v^{(i)}\right)\right),$$

where two sets of prefix vectors $\mathbf{P}_k, \mathbf{P}_v \in \mathbb{R}^{l\times d}$ are concatenated with the original key $\mathbf{K}$ and value $\mathbf{V}$.

- LoRA [5] (inject trainable low-rank matrices into layers)

$$\mathbf{h} \leftarrow \mathbf{h} + s \cdot \mathbf{x}\mathbf{W}_{\text{down}}\mathbf{W}_{\text{up}}\,, \quad \mathbf{W}_{\text{down}} \in \mathbb{R}^{d\times r}, \mathbf{W}_{\text{up}} \in \mathbb{R}^{r\times k}, r \ll \{d, k\}$$

[4] *Houlsby et al.* Parameter-efficient transfer learning for NLP. 2019.
[9] *Li et al.* Prefix-tuning: Optimizing continuous prompts for generation. 2021.
[5] *Hu et al.* Lora: Low-rank adaptation of large language models. 2021.




(a) Adapter. (b) Prefix Tuning. (c) LoRA. (d) Parallel Adapter. (e) Scaled PA.

Figure: **Graphical illustration of existing methods and some other variants.** "PLM module" represents a certain sublayer of the PLM (e.g. attention or FFN) that is frozen.

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