Pattern Recognition

Meta Learning

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Slide credit

- Some slides are collected/modified from Chelsea Finn, Hung-yi Lee, Sergey Levine, HyeongJoo Hwang et al., Yifang Sun, Yee Whye Teh

Outline

- Problem statement of meta learning

- Representative meta learning algorithms
  - MAML [Finn et al., ICML 2017]
  - LSTM-based meta learner [Ravi and Larochelle, ICLR 2017]
  - Relation network [Sung et al. CVPR 2018]

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Deep learning for AI research

- Deep learning at the core of the current AI revolution
  - Affordable GPU hardware
  - Large annotated datasets

- Deep models with hundreds of layers and millions of parameters are able to
  - Extract knowledge from a huge set of data
  - Map an input to the desire outputs
  - Greatly improve existing applications
  - Even initiate new applications

Deep learning for AI research

- Large deep models from huge training data result in broad generalization

Russakovsky,et al. arXiv'14

https://jalammar.github.io/illustrated-gpt2/

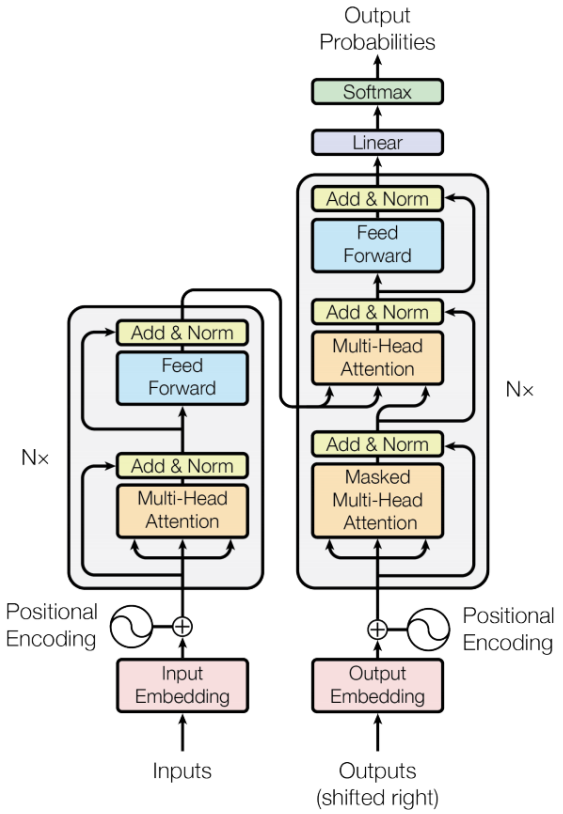


Figure 1: The Transformer - model architecture.

Vaswani et al. NIPS'17

Difficulties

- Supervised deep models need/have
  - Large amounts of labeled training data
  - Many optimization iterations to train a large set of parameters
  - Severe demands on the computing resources
- Applications with small data
  - Medical imaging, robotics, personalized data, recommendations, rare object categories…
- These issues limit the scalability of deep models to rare events, newly emerging domains, and new data categories

An example

training data

Braque

Cezanne

test datapoint

By Braque or Cezanne?

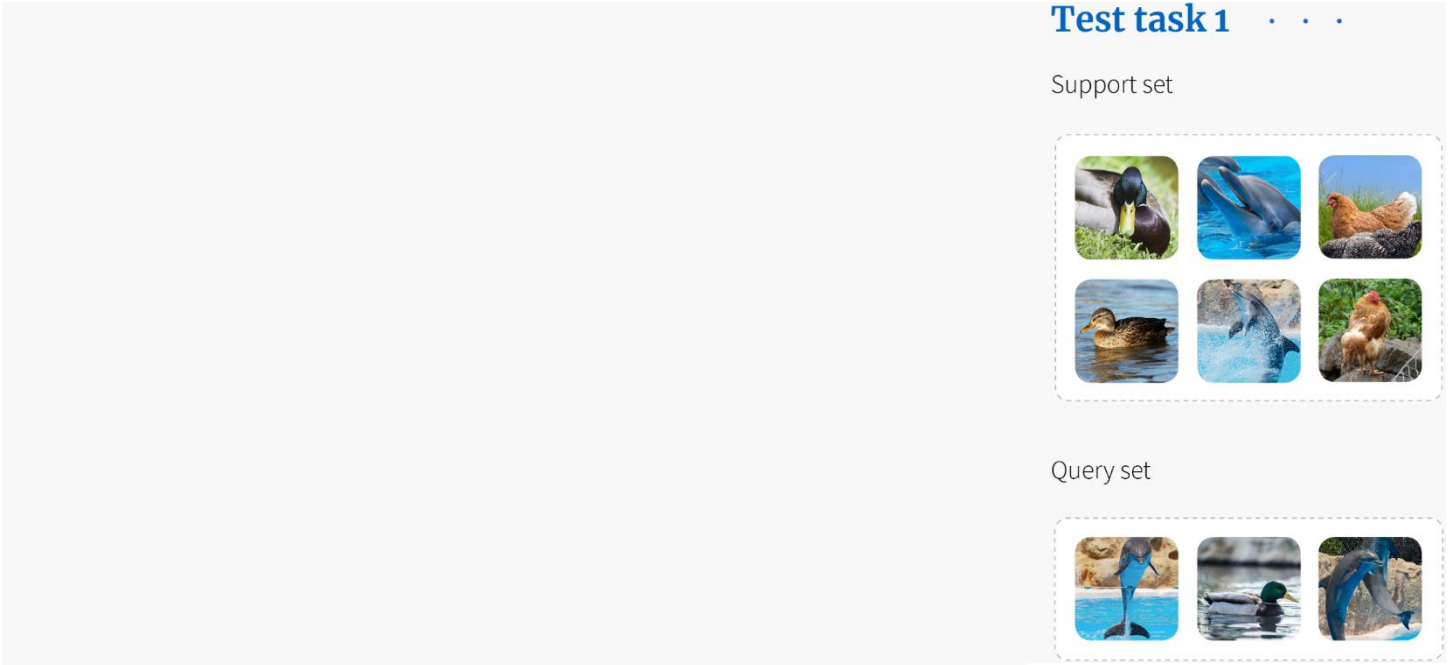
Few shot learning

- N-way K-shot task: A machine learning task deals with N classes, each of which has K data examples
- An example of 3-way 2-shot classification:

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

Idea of meta learning

- Can we explicitly learn priors from previous experience that lead to efficient downstream learning?
  - Can we learn to learn?



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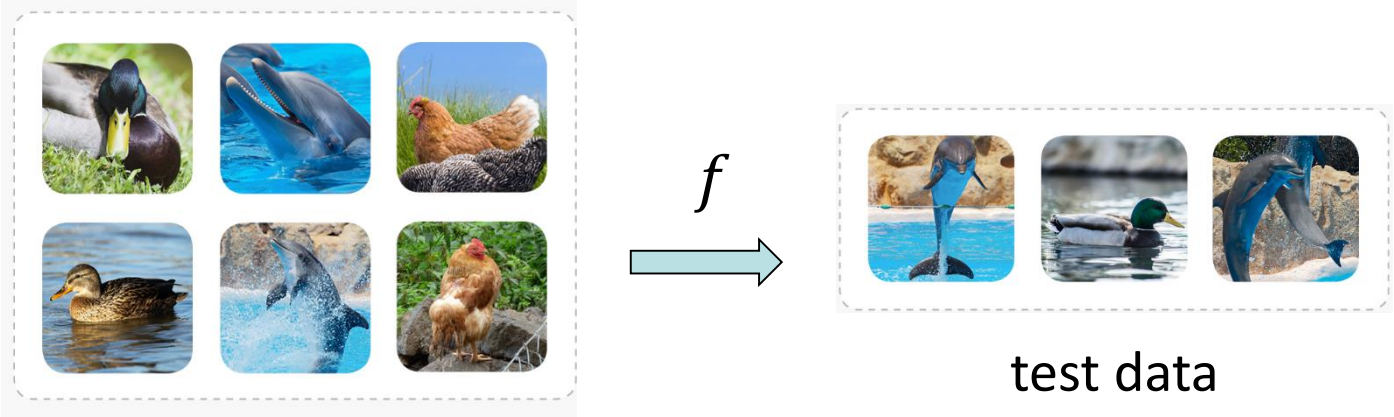
Meta learning

- Meta learning implements the learning-to-learn strategy
  - It learns some transferrable knowledge from a set of auxiliary tasks, which helps learn a target task with a few training data quickly and without suffering from overfitting

Meta learning vs. Supervised learning

- Supervised learning
  - Given a set of training data $\{(\mathbf{x}_i \in X, \mathbf{y}_i \in Y)\}_{i=1}^{N}$
  - We learn a model $f: X \rightarrow Y$
  - So that this model generalizes well to another set of test data
  - Limited performance if no sufficient training data are available

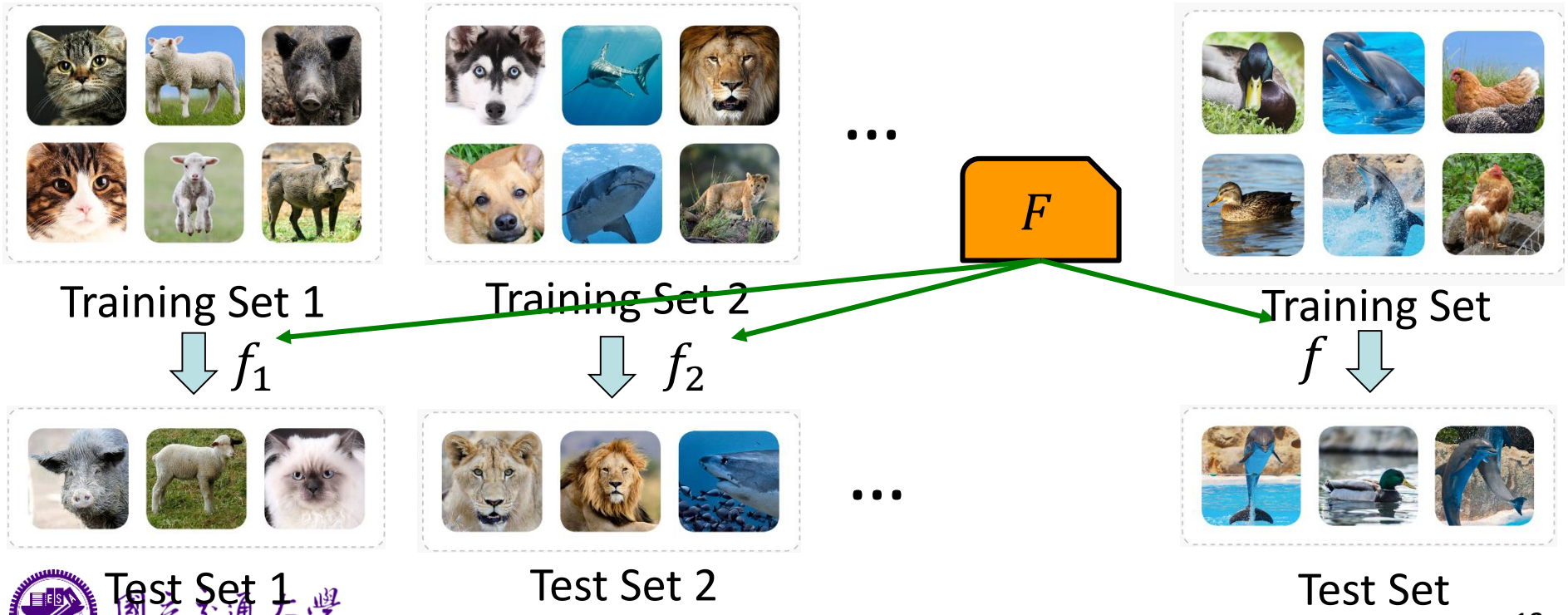


training data

test data

Meta learning vs. Supervised learning

- Given a set of learning tasks
- Derive a meta learner F that outputs a model f_i for each training task *i*
- So that each f_i works well on the respective test set
- The meta learner F can then be applied to a new test task



Support set and Query set in a task

Training Task 1

Training Set 1

Training Task 2

Training Set 2

...

Testing Task

Training Set

Test Set 1

Test Set 2

...

Test Set

Support set and Query set in a task

Training Task 1

Support Set 1

Query Set 1

Training Task 2

Support Set 2

Query Set 2

...

Testing Task

Support Set

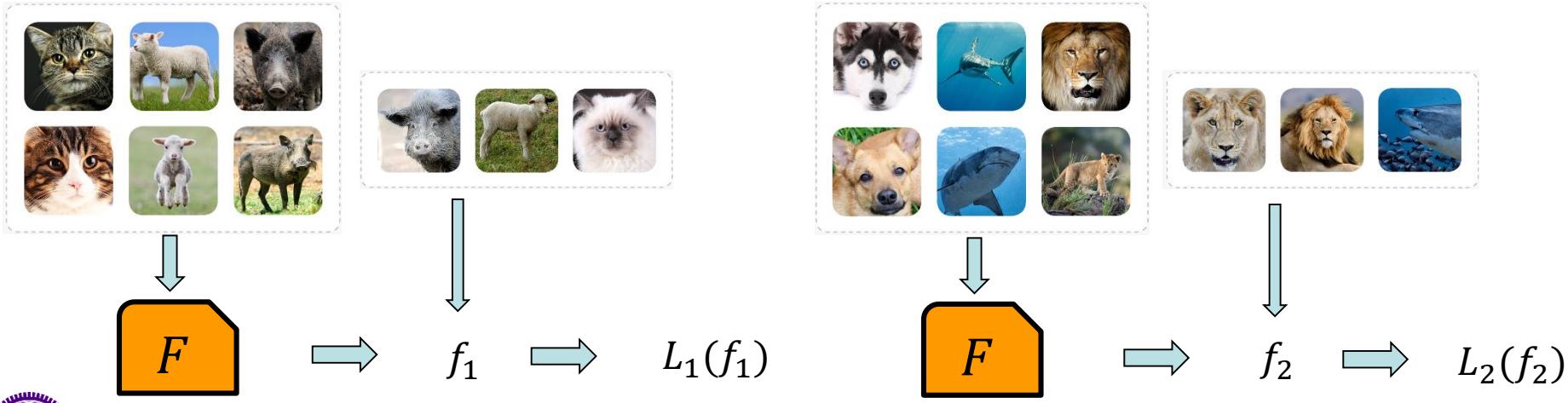
Query Set

Meta training/Meta-Train/Meta-training

- Goal of meta training is to derive a meta learner F
- Training objective function

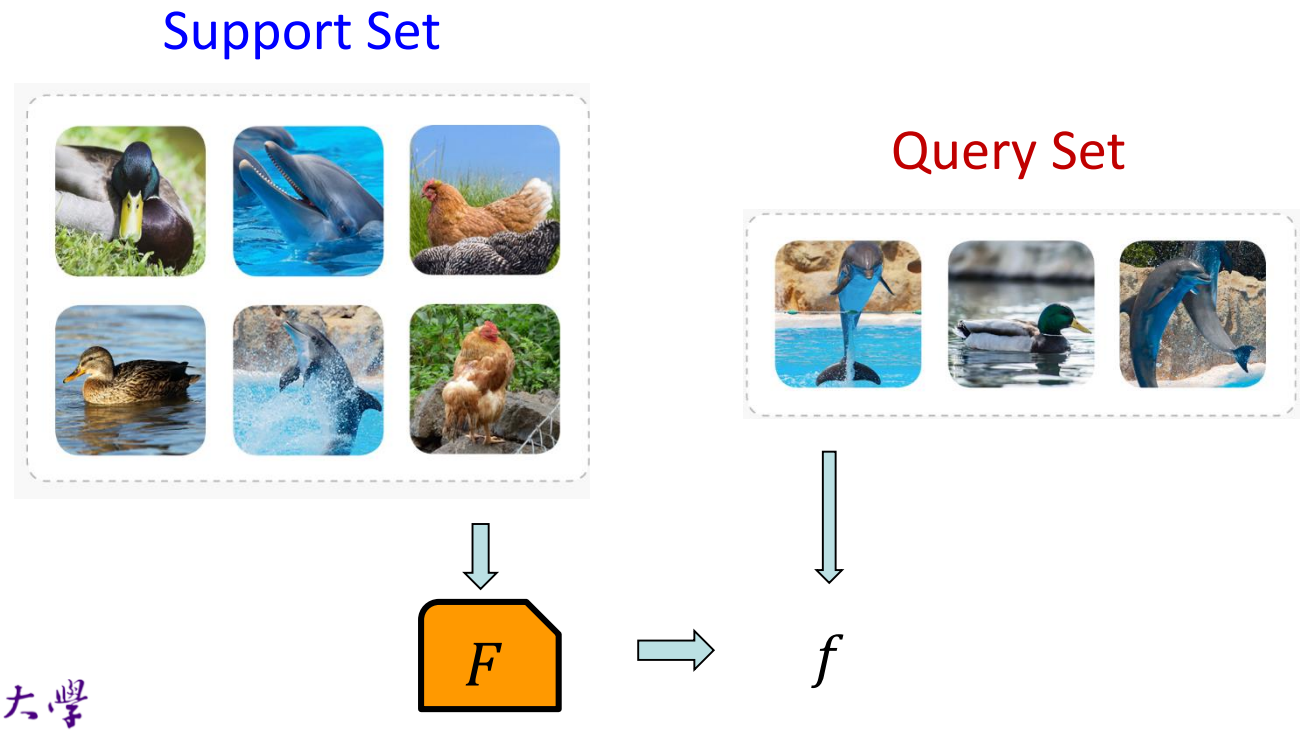
$$L(F) = \sum_{t=1}^{T} L_t(f_t)$$

  - $L(F)$: Loss of F
  - $L_t(f_t)$: Loss of f_t on training task t



Meta testing/Meta-Test/Meta testing

- During meta testing, the meta learner F is applied to the support set of a new testing task and outputs a model f
- The meta learner F is evaluated based on the performance of f on the query set of this task



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MAML (Model-Agnostic Meta-Learning)

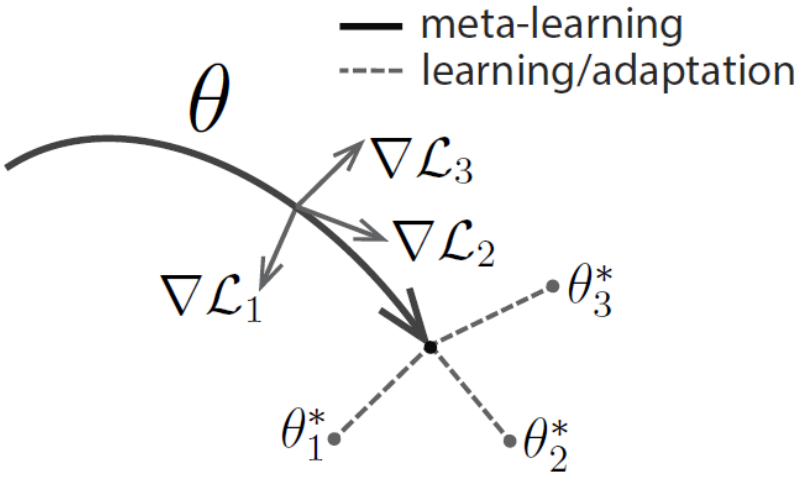
[Finn et al. ICML 2017]

- MAML is a meta-learning algorithm for fast deep network adaptation
- Goal: Quickly adapt to new tasks with only a small amount of data and with only a few gradient steps, even one gradient step
- Meta learner: It learns a generalized parameter initialization of a model
- Learner: It learns a new task by using a single gradient step

Characteristics of MAML

- The MAML learner's weights are updated using the gradient
  - Not need additional parameters nor require a particular learner architecture
- Fast adaptability through good parameter initialization
  - It explicitly optimizes to learn an internal representation for all training tasks, i.e., representation suitable for these tasks
- Model-agnostic
  - The model should be parameterized. No other assumpitons.
- Task-agnostic
  - Classification, regression, reinforcement learning, …

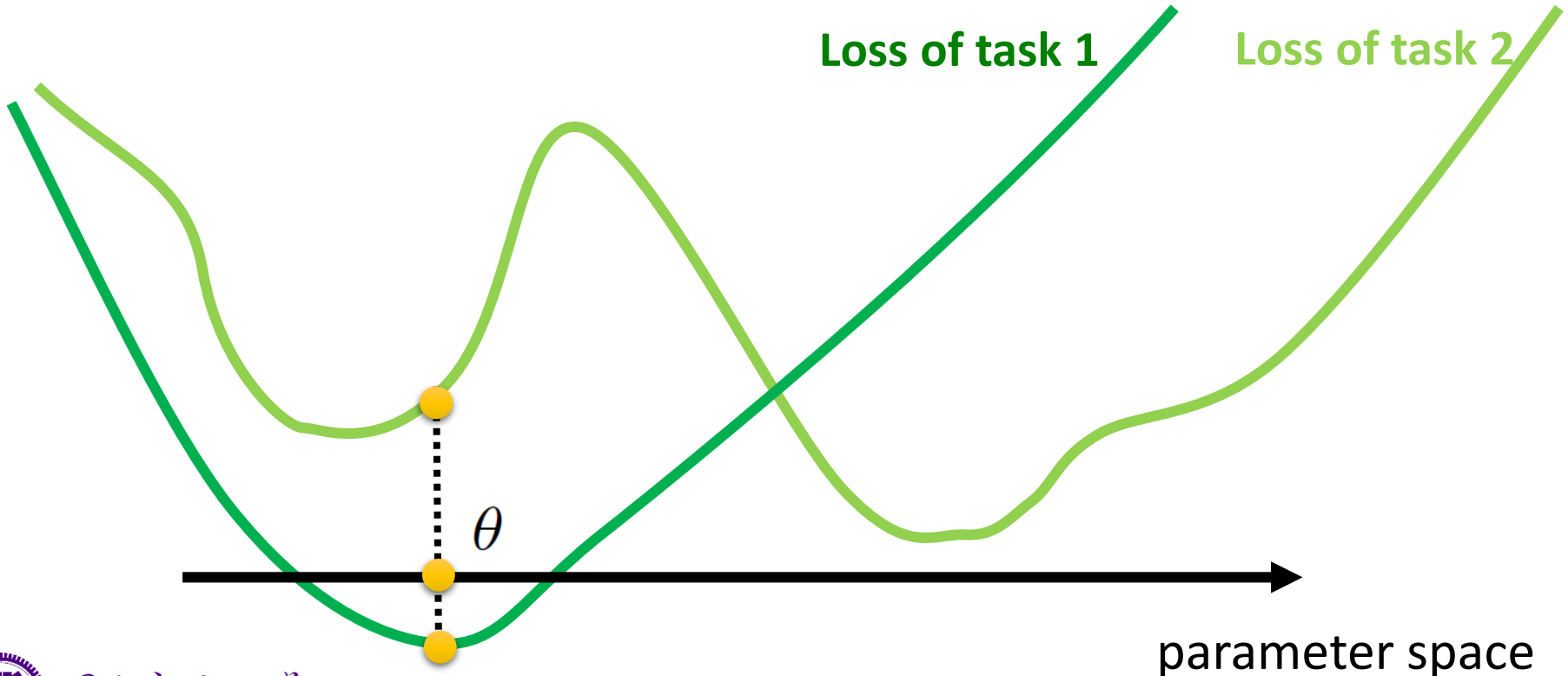
Idea of MAML



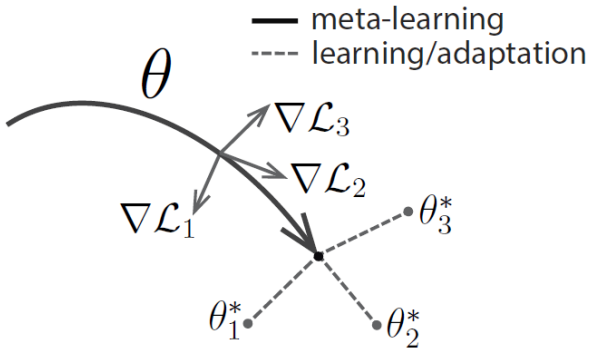
- Some internal representations are more transferrable than others
- f_θ : deep network model parametrized by θ
- Desire a model parameter set θ that:
  - Applying one (or a few) gradient step to θ on a new task produces maximally effective behavior
- Namely, θ commonly decreases loss of each task after adaptation

Good initialization of θ

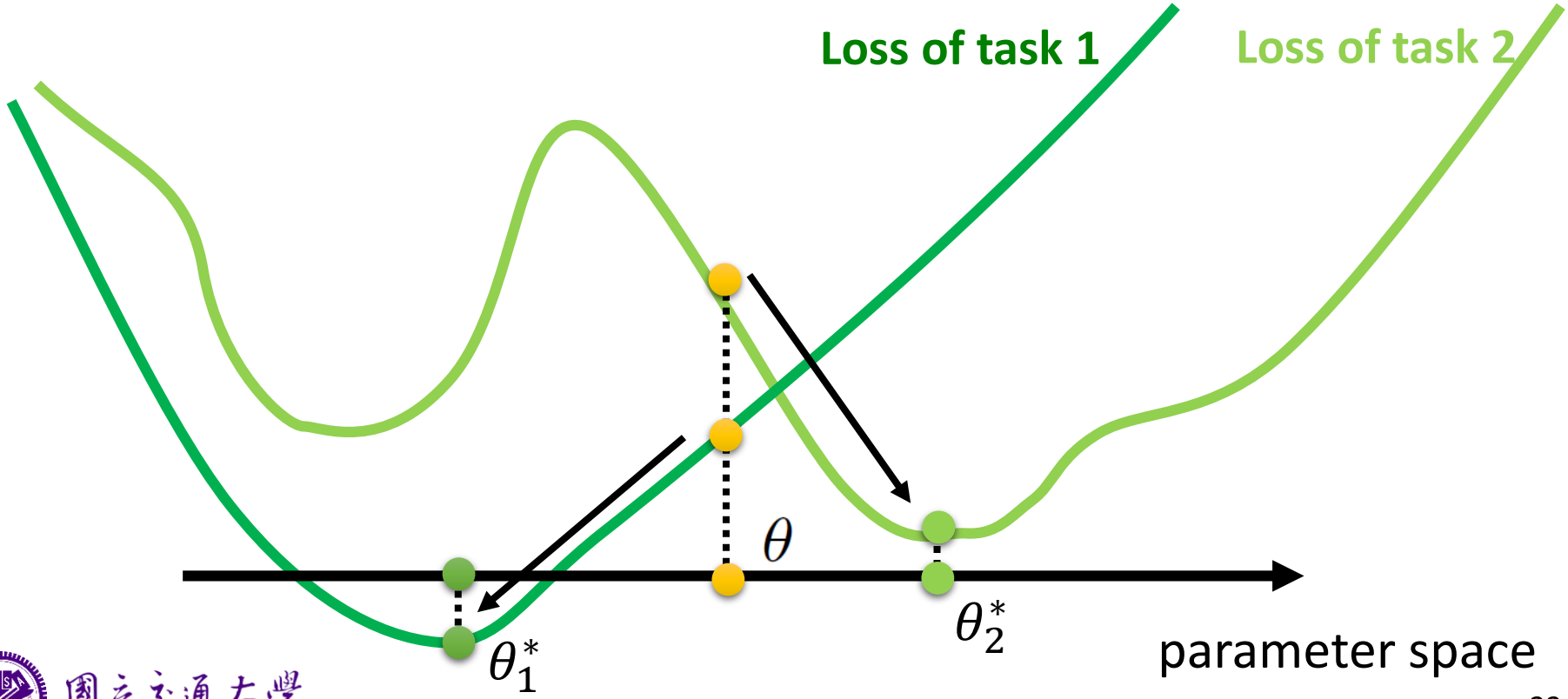
- Option 1: θ that minimizes the losses of all tasks
  - Model pre-training



Good initialization of θ



- Option 1: θ that minimizes the losses of
  - Model pre-training
- Option 2: θ that minimizes the losses of all tasks after adaptation
  - MAML adopts



Supervised meta learning

- Notations
  - Model: f_θ
  - Task distribution: $p(\mathcal{T})$

- For each task: $T = \{L(x_1, y_1, \ldots, x_K, y_K), (x, y) \sim q\}$
  - Data distribution: q (K samples are drawn from q)
  - Loss function: L
    - MSE (mean squared error) for regression
    - Cross entropy for classification
    - Any other differentiable loss functions can be used

MAML Algorithm

- Sampling training tasks
- Compute the gradient based on the support set and update parameters for each sampled task
- Update the initial parameters based on the query set

Algorithm 2 MAML for Few-Shot Supervised Learning

Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters
1: randomly initialize θ
2: **while** not done **do**
3: Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$
4: **for all** $\mathcal{T}_i$ **do**
5: Sample K datapoints $\mathcal{D} = \{\mathbf{x}^{(j)}, \mathbf{y}^{(j)}\}$ from $\mathcal{T}_i$
6: Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ using $\mathcal{D}$ and $\mathcal{L}_{\mathcal{T}_i}$
7: Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
8: Sample datapoints $\mathcal{D}_i' = \{\mathbf{x}^{(j)}, \mathbf{y}^{(j)}\}$ from $\mathcal{T}_i$ for the meta-update
9: **end for**
10: Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$ using each $\mathcal{D}_i'$ and $\mathcal{L}_{\mathcal{T}_i}$
11: **end while**

1st order approximation

- The update rule

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$$

$$= \theta - \beta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$$

$$= \theta - \beta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} (\nabla_\theta \theta_i') \nabla_{\theta_i'} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$$

Hessian matrix is required.
MAML suggests 1st order approximation:
Consider it as an identity matrix

Experiments on classification: Omniglot dataset

- The Omniglot dataset
  - 1623 characters (tasks)
  - 20 instances for each character were drawn by 20 people
  - 1200 for training, 423 for test.

Experiments on classification: Omniglot dataset

- MAML outperforms the state-of-the-arts

Omniglot (Lake et al., 2011)	5-way Accuracy		20-way Accuracy	
	1-shot	5-shot	1-shot	5-shot
MANN, no conv (Santoro et al., 2016)	82.8%	94.9%	–	–
MAML, no conv (ours)	**89.7 ± 1.1%**	**97.5 ± 0.6%**	–	–
Siamese nets (Koch, 2015)	97.3%	98.4%	88.2%	97.0%
matching nets (Vinyals et al., 2016)	98.1%	98.9%	93.8%	98.5%
neural statistician (Edwards & Storkey, 2017)	98.1%	99.5%	93.2%	98.1%
memory mod. (Kaiser et al., 2017)	98.4%	99.6%	95.0%	98.6%
MAML (ours)	**98.7 ± 0.4%**	**99.9 ± 0.1%**	**95.8 ± 0.3%**	**98.9 ± 0.2%**

Experiments on classification: Mini-ImageNet dataset

- Mini-Imagenet (Ravi & Larochelle, 2017)
  - 100 classes sampled from the ImageNet dataset
  - 64 classes for training, 12 classes for validation, and 24 classes fro testing

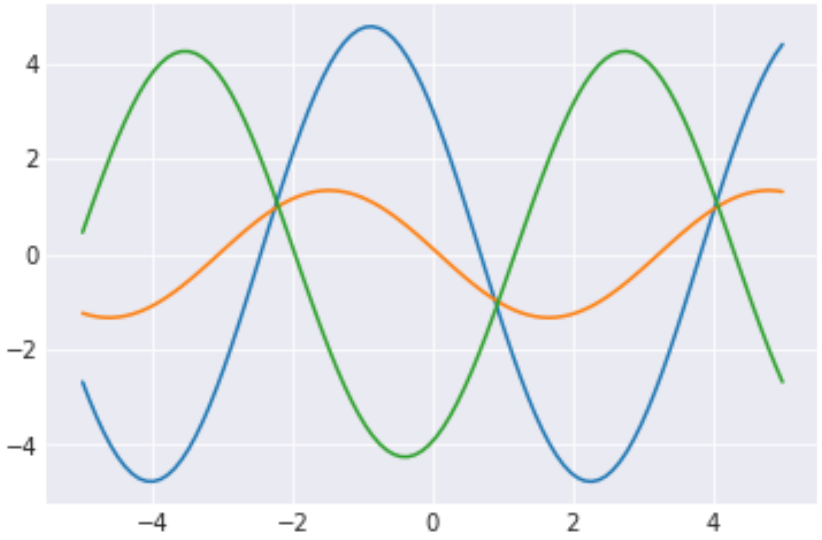
Experiments on classification: Mini-ImageNet dataset

- MAML outperforms the state-of-the-arts
- 1st order approximation does not hurt the performance, but saves the computation cost

MiniImagenet (Ravi & Larochelle, 2017)	5-way Accuracy	
	1-shot	5-shot
fine-tuning baseline	$28.86 \pm 0.54\%$	$49.79 \pm 0.79\%$
nearest neighbor baseline	$41.08 \pm 0.70\%$	$51.04 \pm 0.65\%$
matching nets (Vinyals et al., 2016)	$43.56 \pm 0.84\%$	$55.31 \pm 0.73\%$
meta-learner LSTM (Ravi & Larochelle, 2017)	$43.44 \pm 0.77\%$	$60.60 \pm 0.71\%$
MAML, first order approx. (ours)	$\mathbf{48.07 \pm 1.75\%}$	$\mathbf{63.15 \pm 0.91\%}$
MAML (ours)	$\mathbf{48.70 \pm 1.84\%}$	$\mathbf{63.11 \pm 0.92\%}$

Experiments on regression

- A regression task
  - Given a target sine function $y = a\ sin(x + b)$
    - Amplitude a and phase b are varied between tasks
    - a in [0.1,0.5] and b in [0, π]
  - Sample K points from the target function
  - Use the samples to estimate the target function

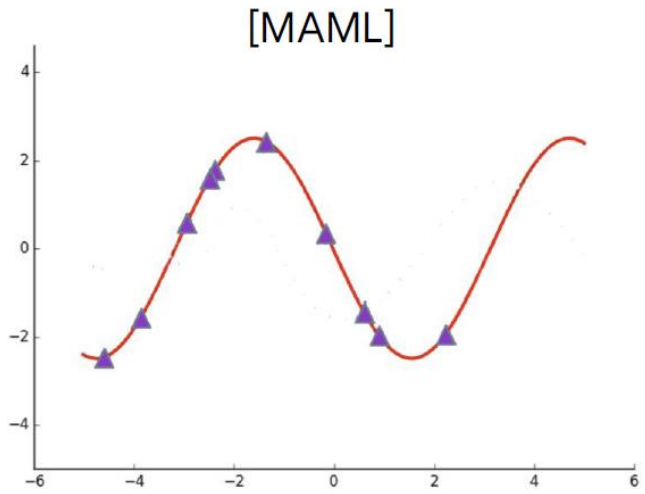


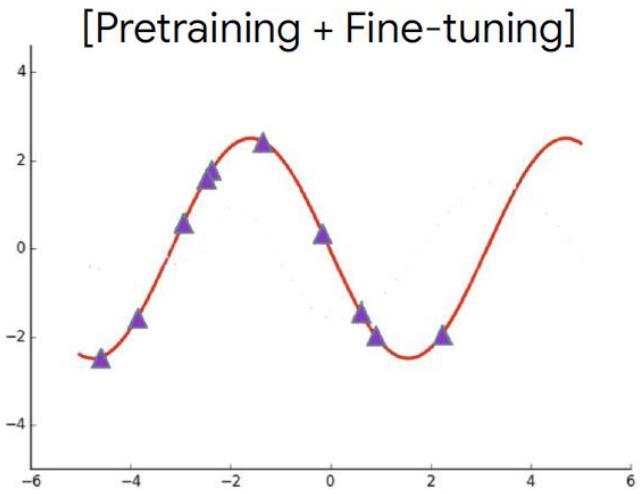
Experiments on regression

- Loss function: Mean Squared Error (MSE)
- Regressor: 2 hidden layers with 40 units and ReLU
- Training
  - Use only 1 gradient step for learner
  - K = 5 or 10 example (5-shot learning or 10-shot learning)

Experiments on regression

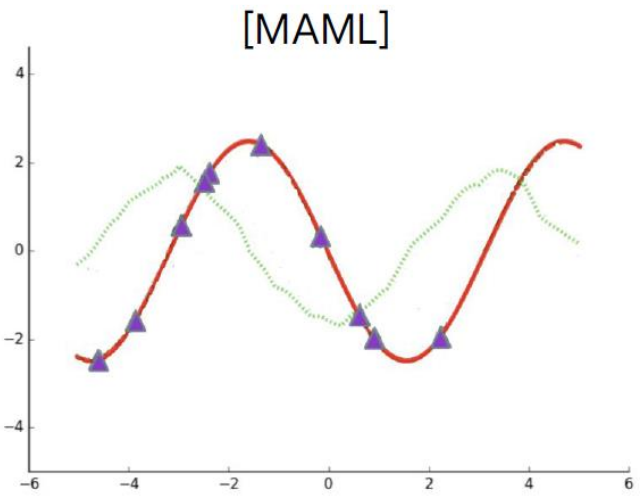
- 10 points and ground truth

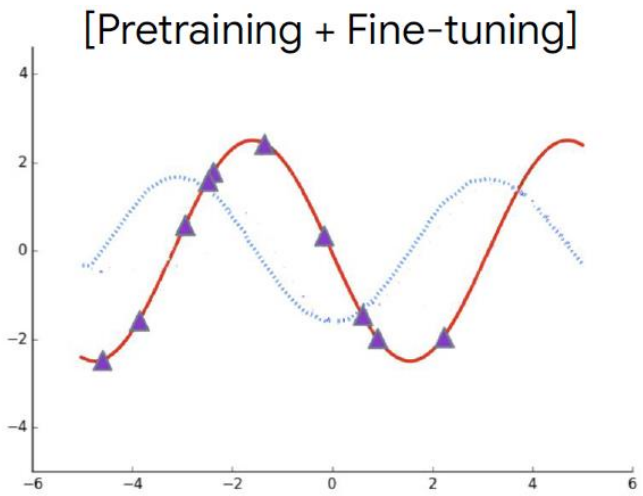




Experiments on regression

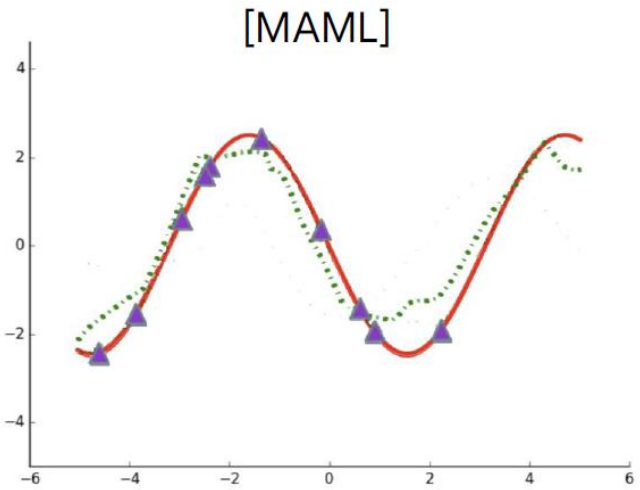
- Initialization by using MAML vs. Pre-training

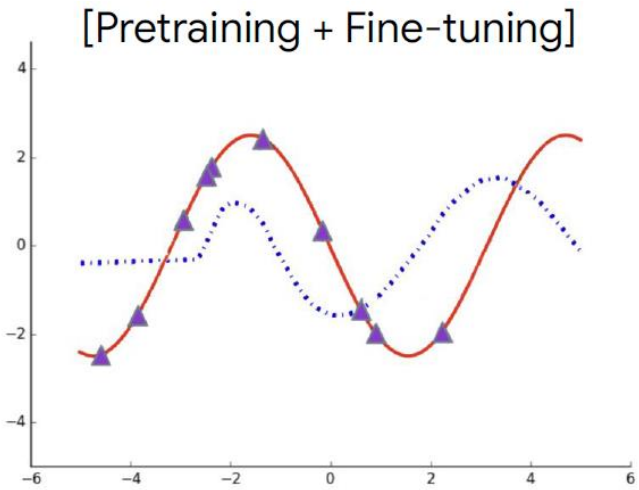




Experiments on regression

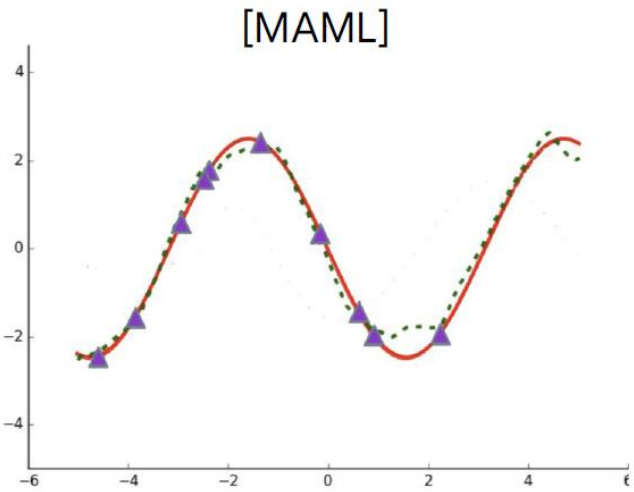
- After one gradient step update

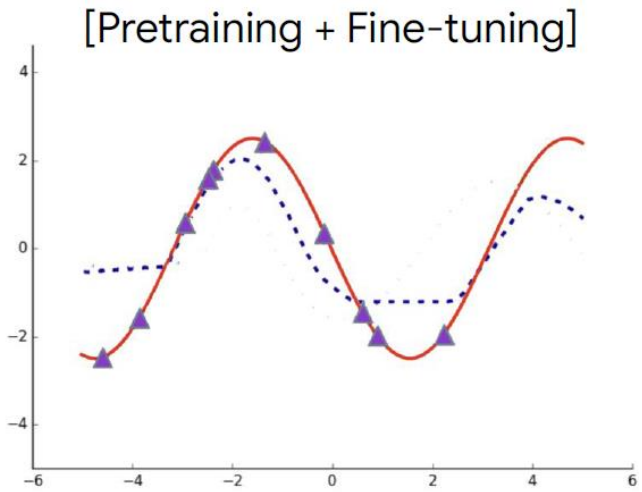




Experiments on regression

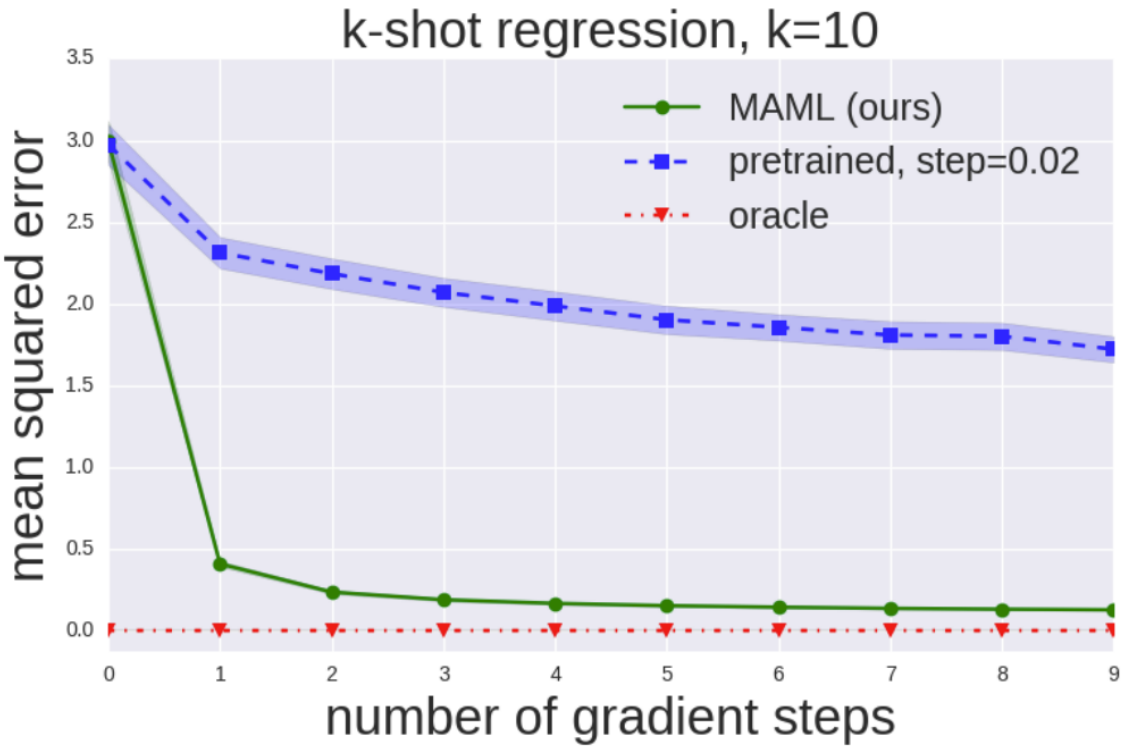
- After 10 gradient step update





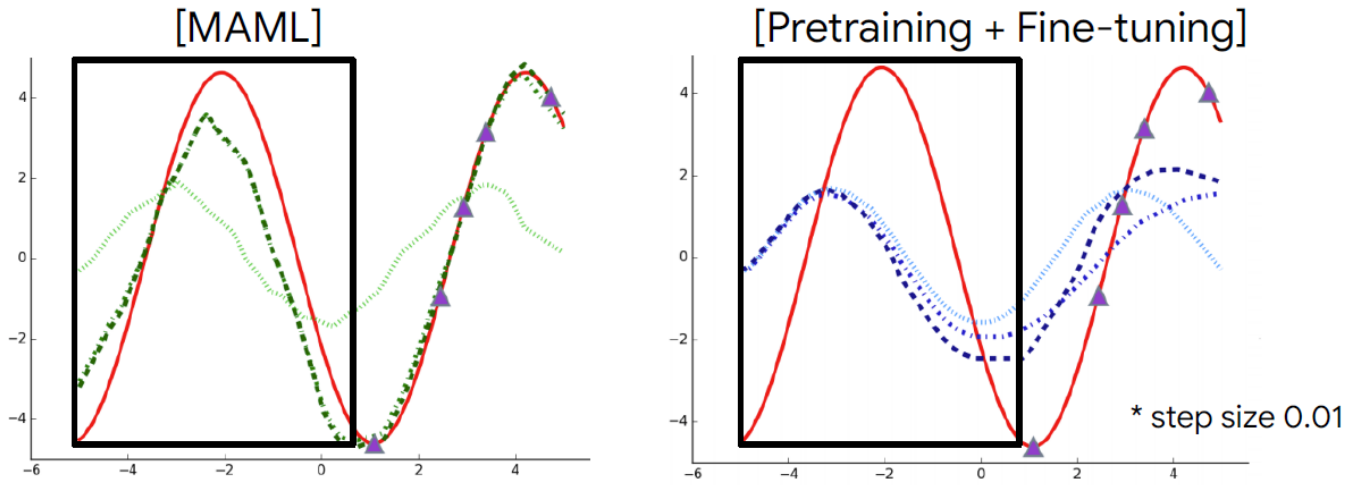
Experiments on regression

- Quantitative results



Experiments on regression

- 5-shot case
- Good predictions are also made for ranges not particularly seen



Conclusions

- Simple: MAML learns easily adaptable model parameters via gradient descent
- Compact: MAML does not introduce any learned parameters for meta learning
- General: MAML is amenable to gradient-based models, any differentiable objective functions, and various tasks

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LSTM-based meta-learner

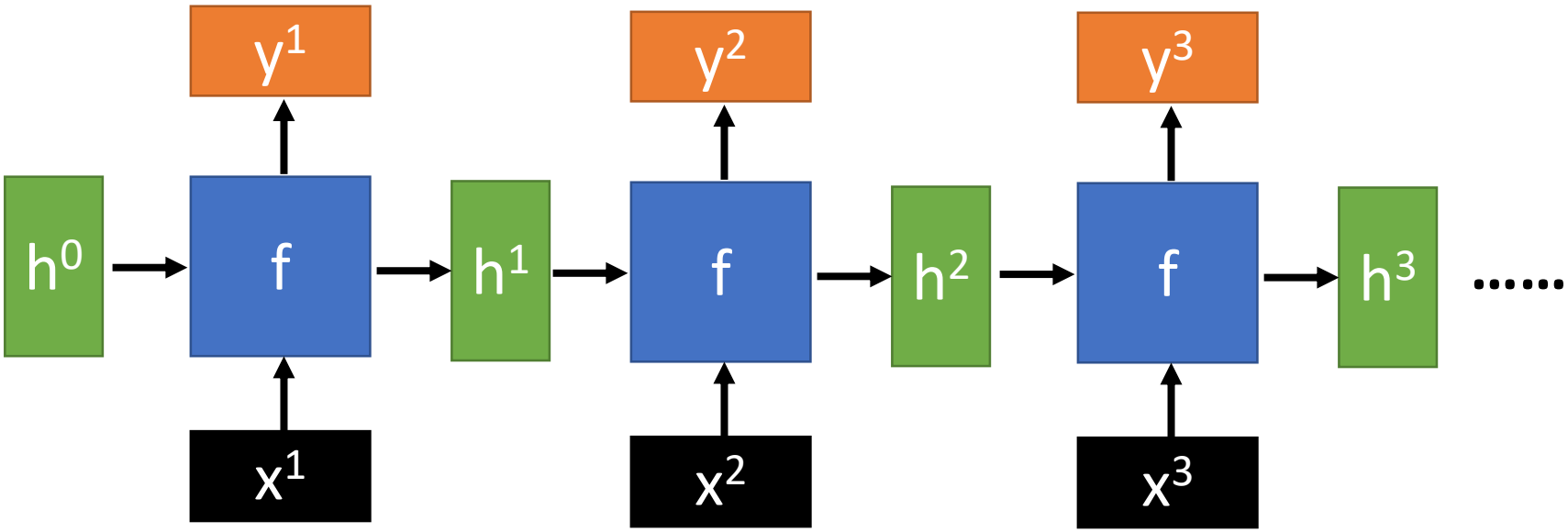
[Ravi and Larochelle, ICLR 2017]

- Deep neural networks show great success in large data domains, and generally perform poorly on few-shot tasks
- This paper presents an LSTM-based meta-learner, which is optimized to train another learner neural network classifier in the few-shot regime
- The LSTM-based meta learner captures
  - Short-term knowledge within a task
  - Long-term knowledge common among all tasks
- The meta-learner model learns a task-common initialization for the learner classifier

Recurrent neural networks

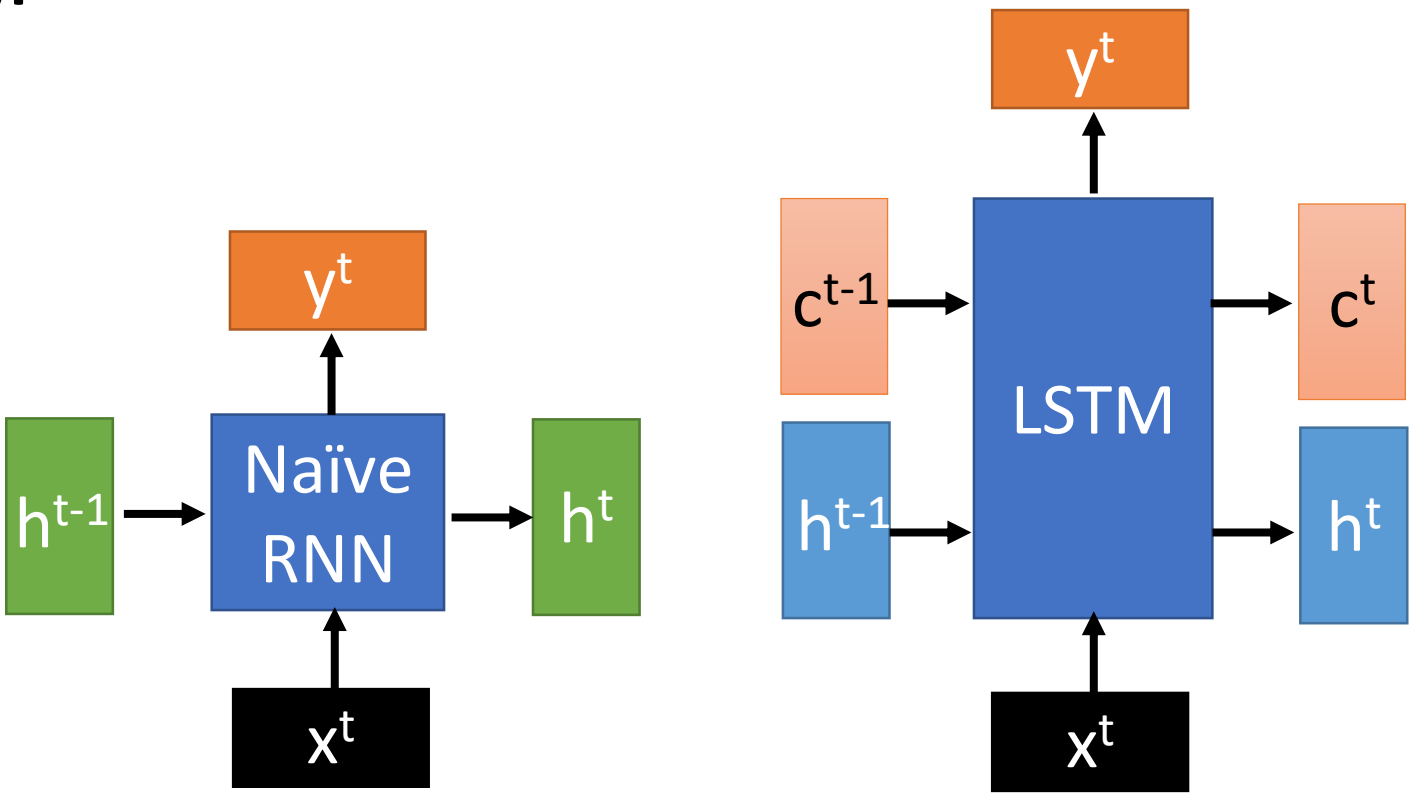
- Given function f: $(h', y) = f(h, x)$

h and h' are vectors with the same dimension



No matter how long the input/output sequence is, we only need one function f

LSTM

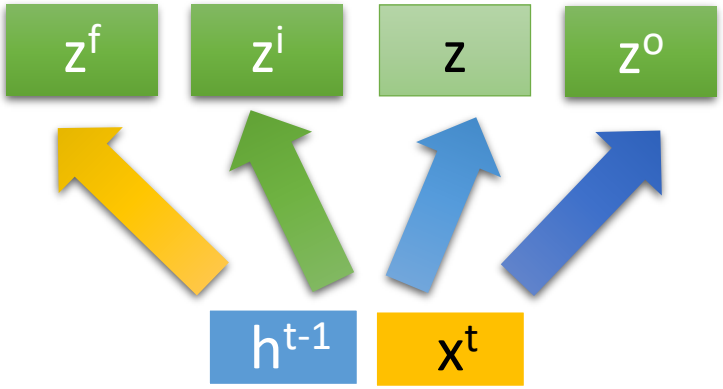


c changes slowly ➡ c^t is c^{t-1} added by something

h changes faster ➡ h^t and h^{t-1} can be very different

LSTM

c^{t-1}



$$z = tanh\left(W \begin{matrix} x^t \\ h^{t-1} \end{matrix}\right)$$

$$z^i = \sigma\left(W^i \begin{matrix} x^t \\ h^{t-1} \end{matrix}\right)$$

input

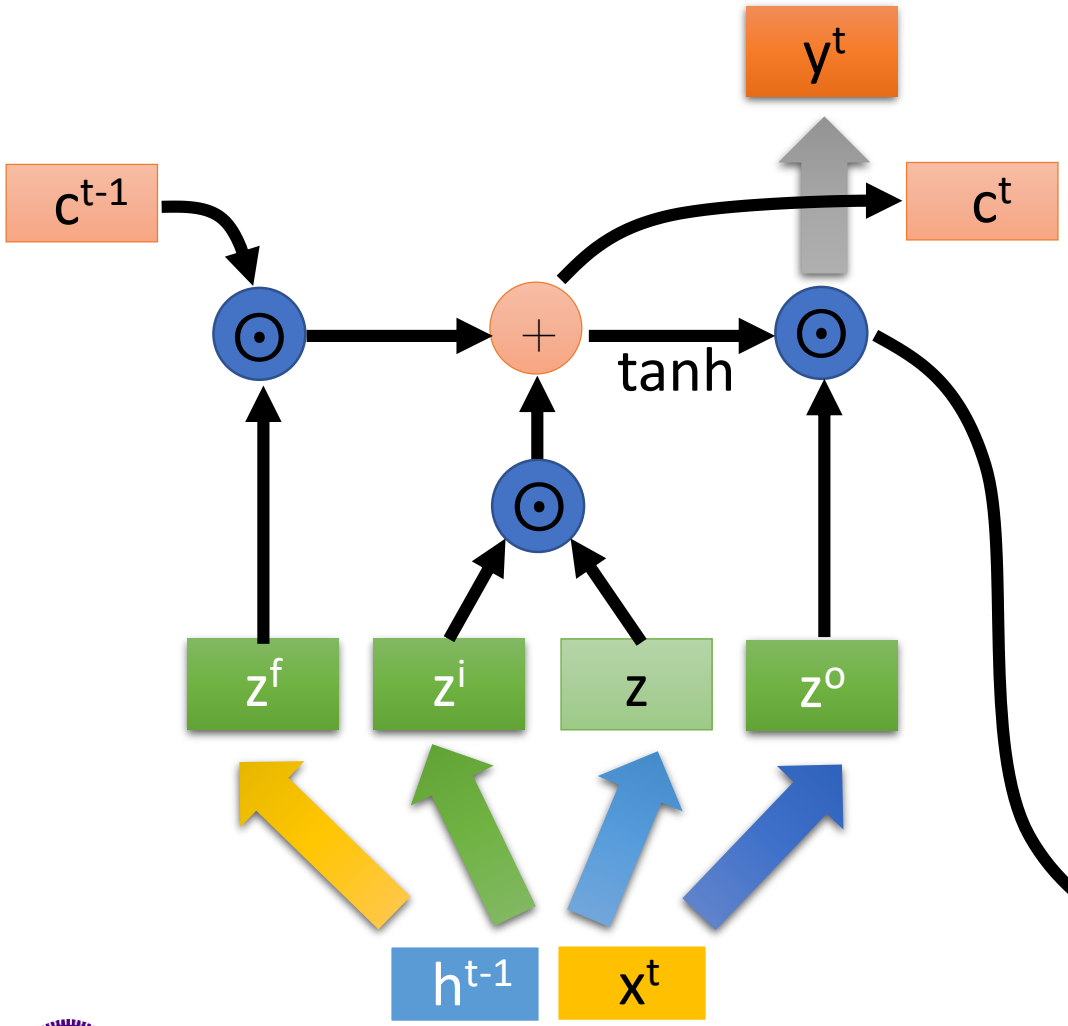
$$z^f = \sigma\left(W^f \begin{matrix} x^t \\ h^{t-1} \end{matrix}\right)$$

forget

$$z^o = \sigma\left(W^o \begin{matrix} x^t \\ h^{t-1} \end{matrix}\right)$$

output

LSTM

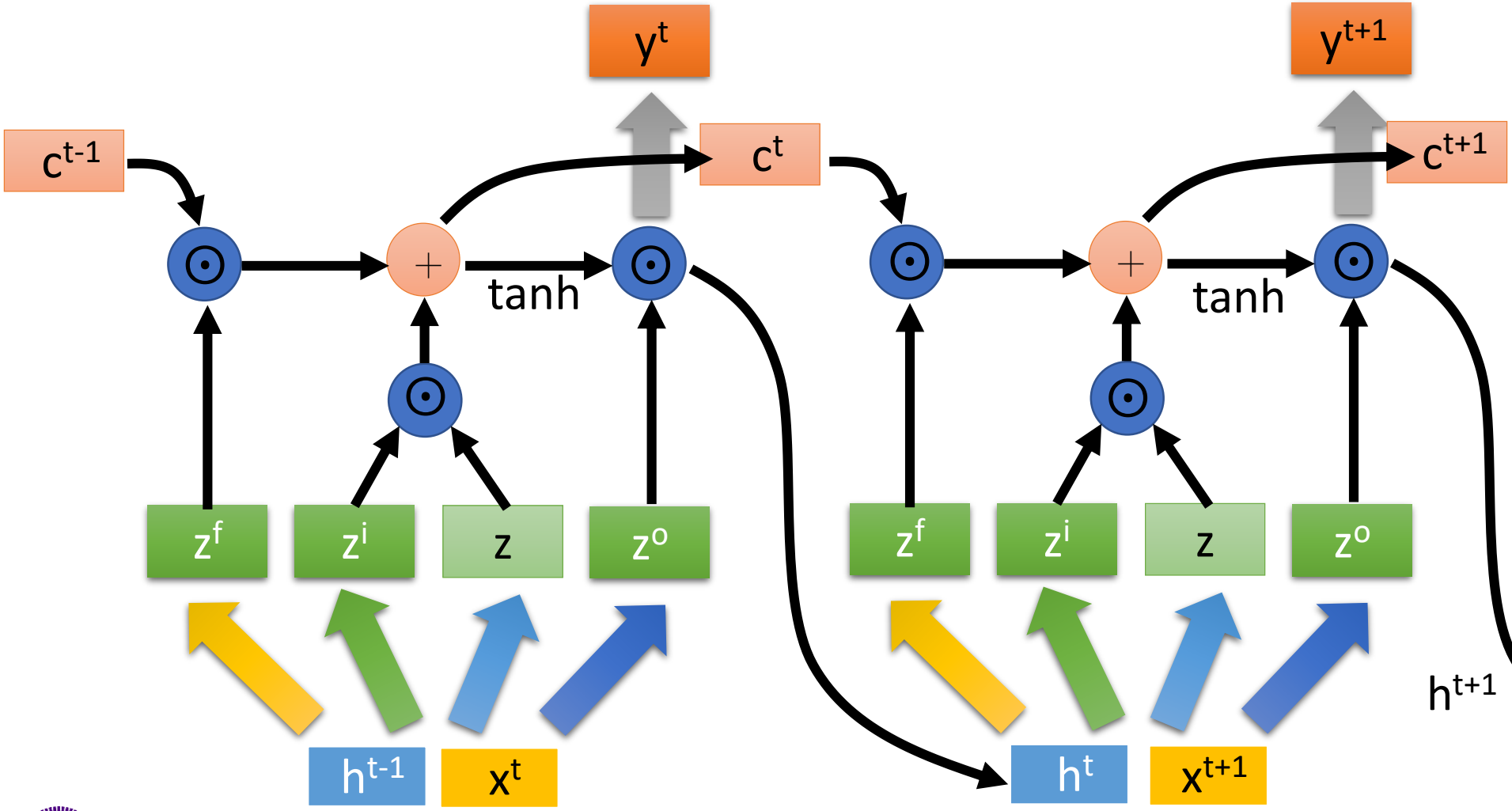


$$c^t = z^f \odot c^{t-1} + z^i \odot z$$

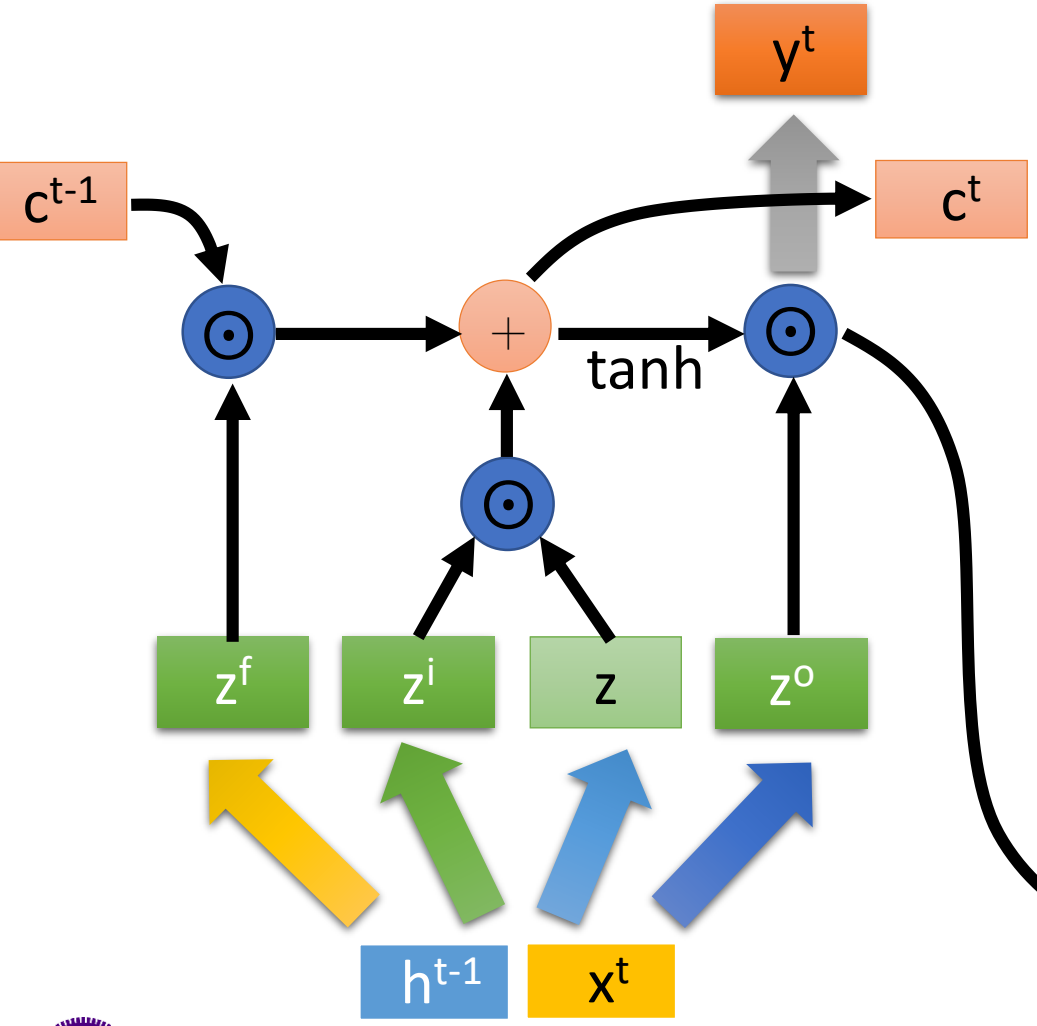
$$h^t = z^o \odot tanh(c^t)$$

$$y^t = \sigma(W' h^t)$$

LSTM



LSTM



$$c^t = z^f \odot c^{t-1} + z^i \odot z$$

$$h^t = z^o \odot tanh(c^t)$$

$$y^t = \sigma(W' h^t)$$

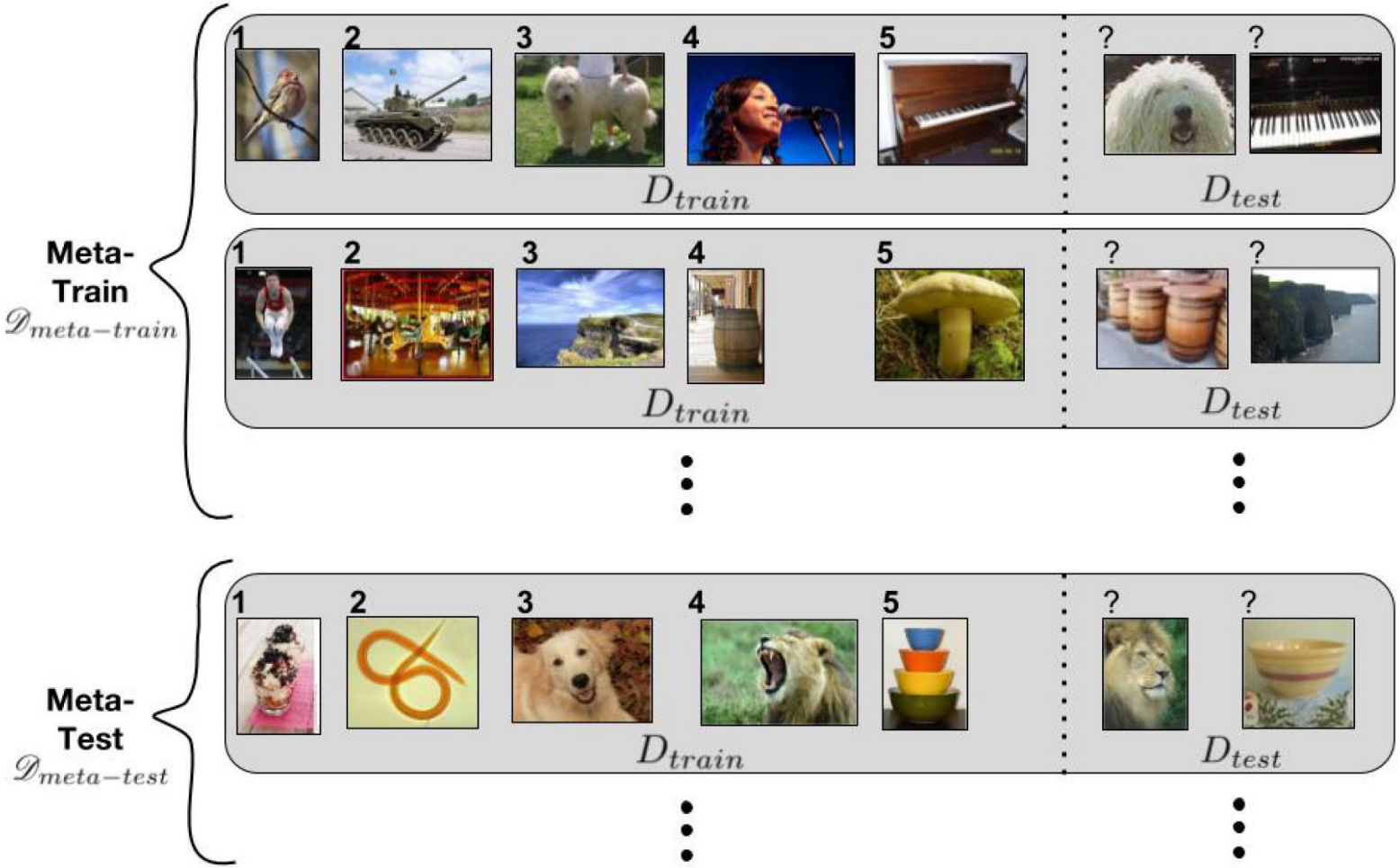
Problem statement

- Regular machine learning task
  - Given a dataset D, we split it into two disjoint sets D_{train} and D_{test}
  - We optimize a model with parameters θ on the training set D_{train}
  - And evaluate its generalization on the test set D_{test}
- In meta learning, we are dealing with a meta-set $\mathscr{D}$ containing multiple regular datasets
  - For each dataset $D \in \mathscr{D}$, it has a split of D_{train} and D_{test}
  - Consider a *k*-shot, *C*-way classification task for each D. D_{train} has *kC* training examples while D_{test} has a number of examples for evaluation

Problem statement

- We have different meta-sets $\mathscr{D}_{meta-train}$, $\mathscr{D}_{meta-validation}$, and $\mathscr{D}_{meta-test}$ for meta-training, meta-validation, and meta-testing respectively
  - Meta-training: Produce a learning procedure (meta-learner), which takes D_{train} as input while outputs a classifier (learner) that has a good generalization on D_{test}
  - Meta-validation: Perform hyper-parameter selection of the meta-learner
  - Meta-testing: Evaluate the performance of the meta-learner on $\mathscr{D}_{meta-test}$

Problem statement



Observation and idea

- For $D \in \mathscr{D}$, the learner, a neural net classifier, with parameters θ is optimized by gradient descent, i.e.,

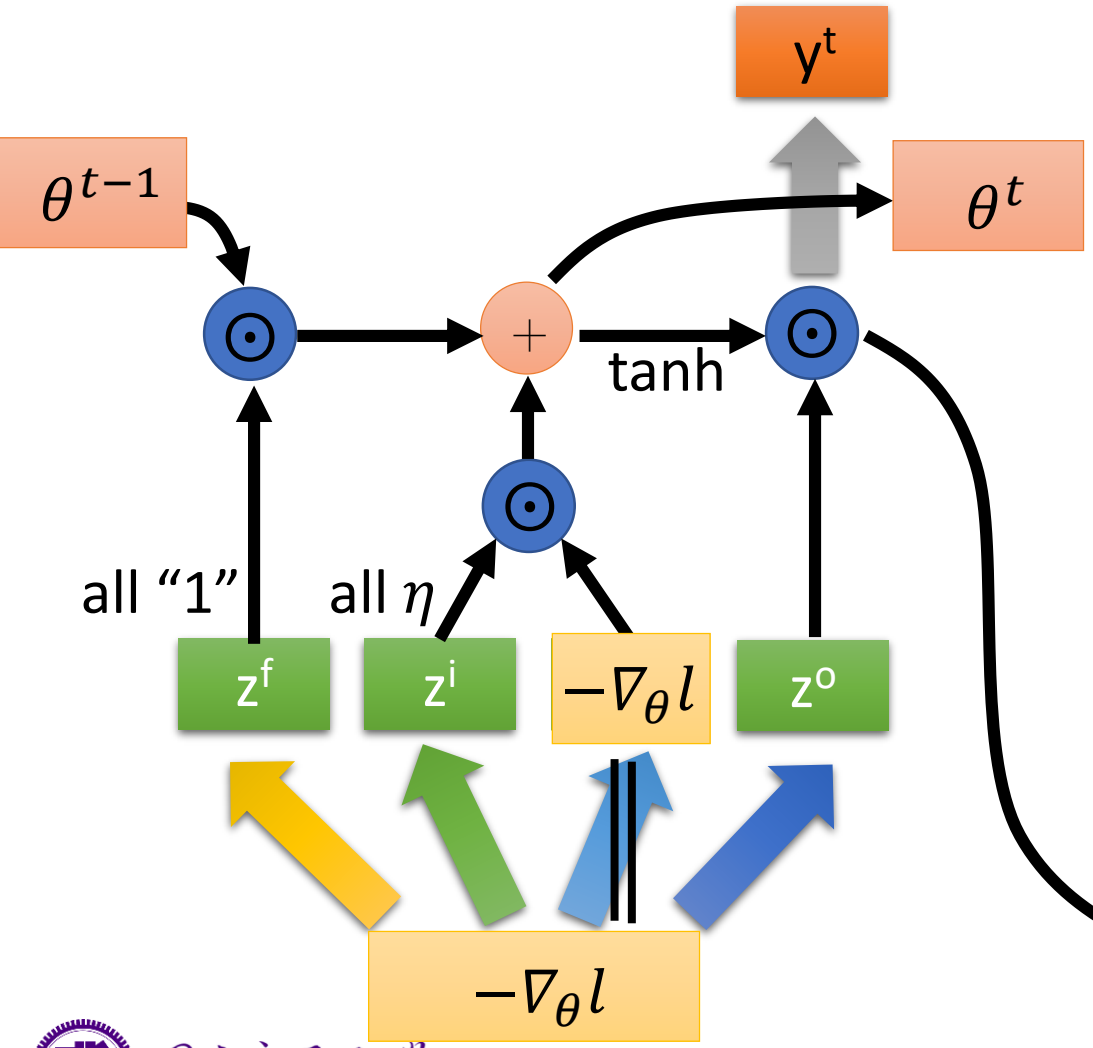
$$\theta^t = \theta^{t-1} - \eta \nabla_\theta l$$

- The update above is similar the cell state in an LSTM

$$c^t = z^f \odot c^{t-1} + z^i \odot z$$

  - θ^t --> c^t
  - θ^{t-1} --> c^{t-1}
  - η --> z^i
  - $-\nabla_\theta l$ --> z

LSTM as meta learner



$$\theta^t = \theta^{t-1} - \eta \nabla_\theta l$$

$$\theta^t = z^f \odot \theta^{t-1} + z^i \odot -\nabla_\theta l$$

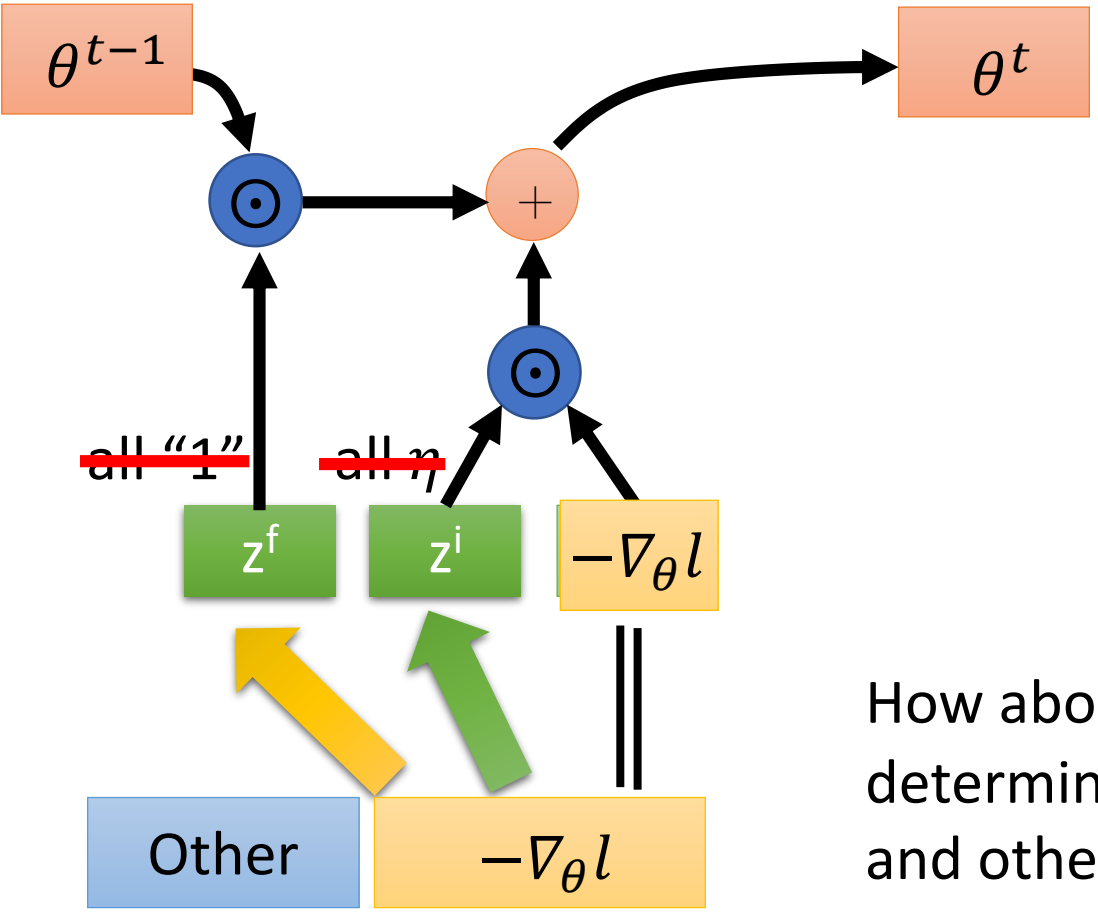
$$\begin{bmatrix} 1 \\ 1 \\ \vdots \end{bmatrix} \qquad \begin{bmatrix} \eta \\ \eta \\ \vdots \end{bmatrix}$$

$$h^t = z^o \odot tanh(c^t)$$

$$y^t = \sigma(W' h^t)$$

LSTM as meta learner

$$\theta^t = \theta^{t-1} - \eta \nabla_\theta l$$



Something like regularization

$$\theta^t = z^f \odot \theta^{t-1} + z^i \odot -\nabla_\theta l$$

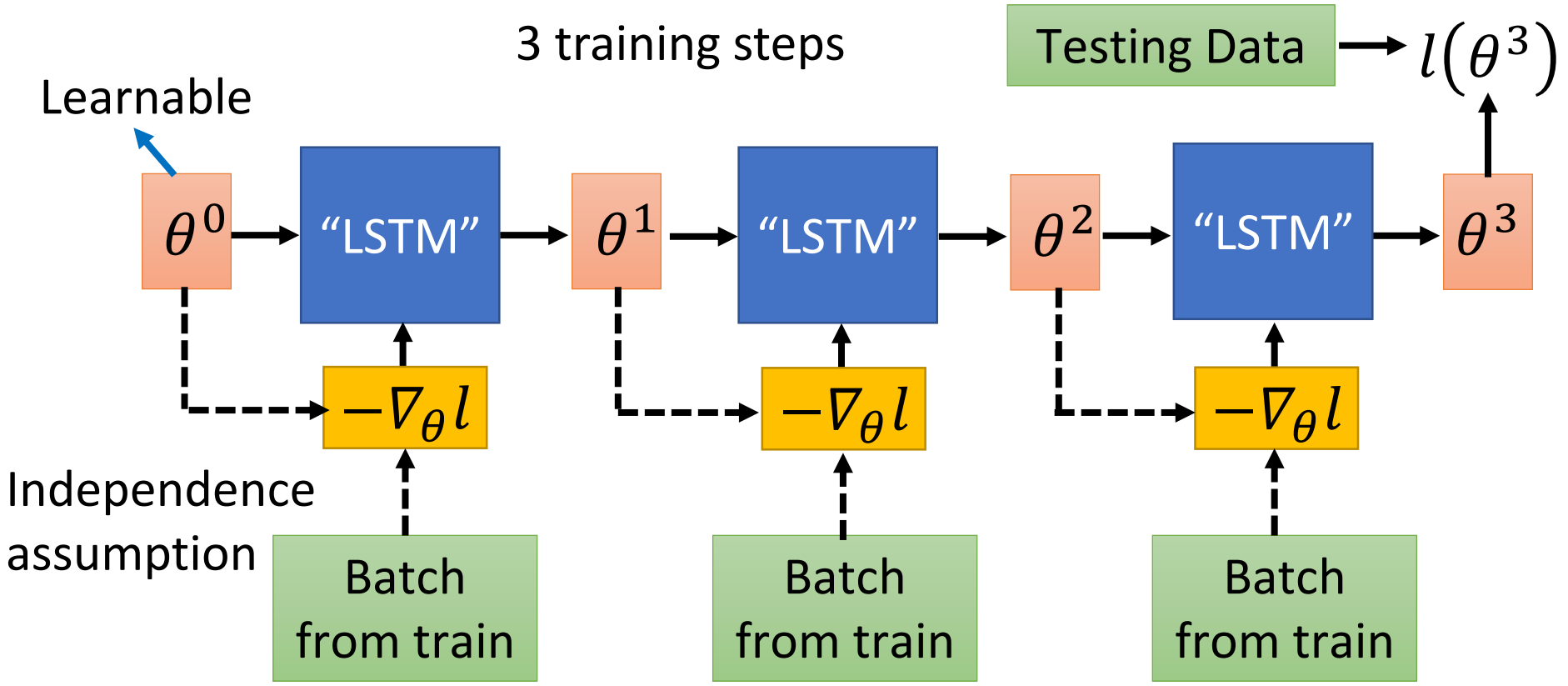
Dynamic learning rate

How about machine learn to determine z^f and z^i from $-\nabla_\theta l$ and other information?

Optimization

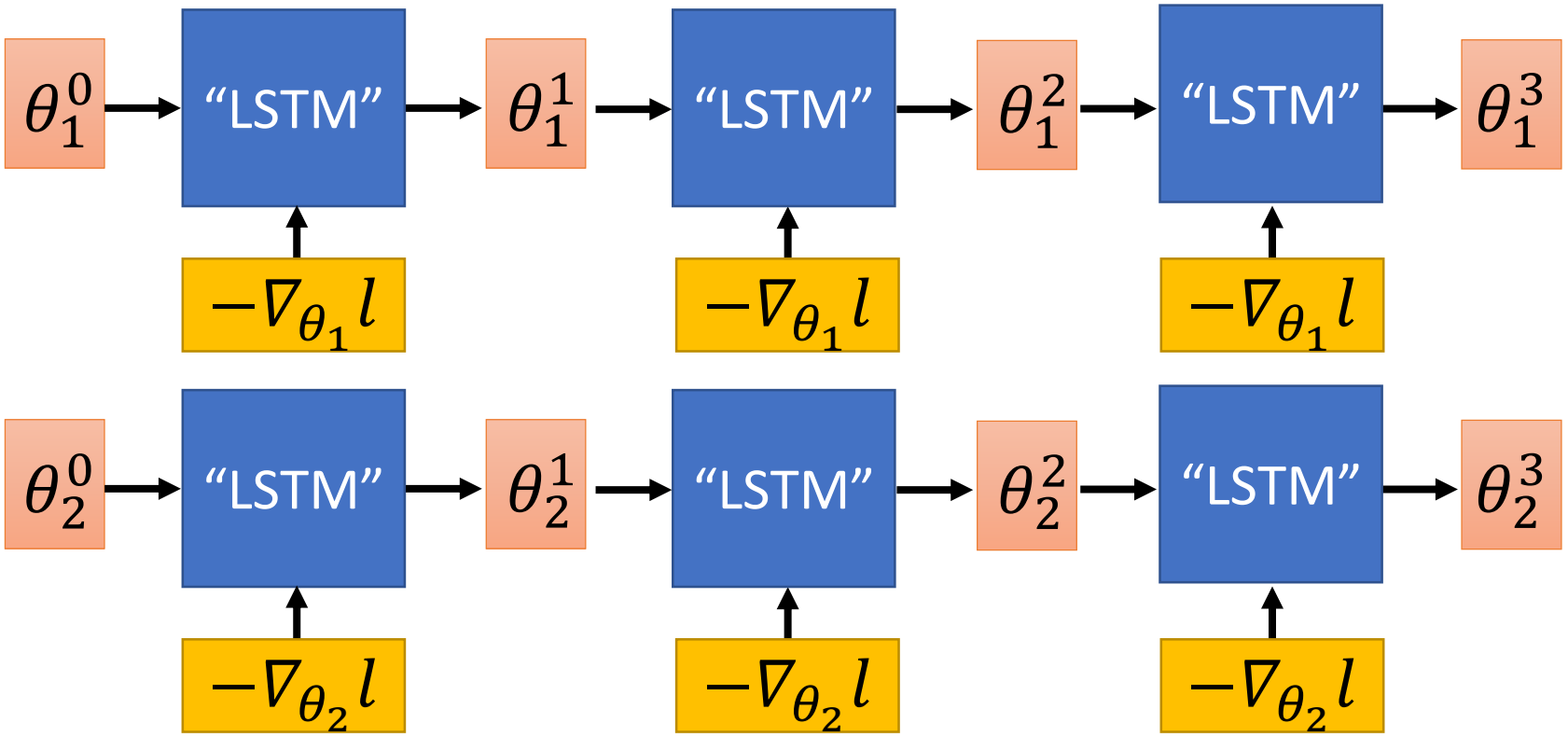
$$\theta^t = z^f \odot \theta^{t-1} + z^i \odot -\nabla_\theta l$$

Learn to minimize



Implementation

- The LSTM used only has one cell. Share across all parameters



Algorithm 1 Train Meta-Learner

Input: Meta-training set $\mathscr{D}_{meta-train}$, Learner M with parameters θ, Meta-Learner R with parameters Θ.

$\Theta_0 \leftarrow$ random initialization

for $d = 1, n$ **do**
  $D_{train}, D_{test} \leftarrow$ random dataset from $\mathscr{D}_{meta-train}$
  $\theta_0 \leftarrow c_0$ ▷ Intialize learner parameters
  for $t = 1, T$ **do**
    $\mathbf{X}_t, \mathbf{Y}_t \leftarrow$ random batch from D_{train}
    $\mathcal{L}_t \leftarrow \mathcal{L}(M(\mathbf{X}_t; \theta_{t-1}), \mathbf{Y}_t)$ ▷ Get loss of learner on train batch
    $c_t \leftarrow R((\nabla_{\theta_{t-1}} \mathcal{L}_t, \mathcal{L}_t); \Theta_{d-1})$ ▷ Get output of meta-learner using Equation 2
    $\theta_t \leftarrow c_t$ ▷ Update learner parameters
  end for
  $\mathbf{X}, \mathbf{Y} \leftarrow D_{test}$
  $\mathcal{L}_{test} \leftarrow \mathcal{L}(M(\mathbf{X}; \theta_T), \mathbf{Y})$ ▷ Get loss of learner on test batch
  Update Θ_d using $\nabla_{\Theta_{d-1}} \mathcal{L}_{test}$ ▷ Update meta-learner parameters
end for

Experiments on miniImageNet

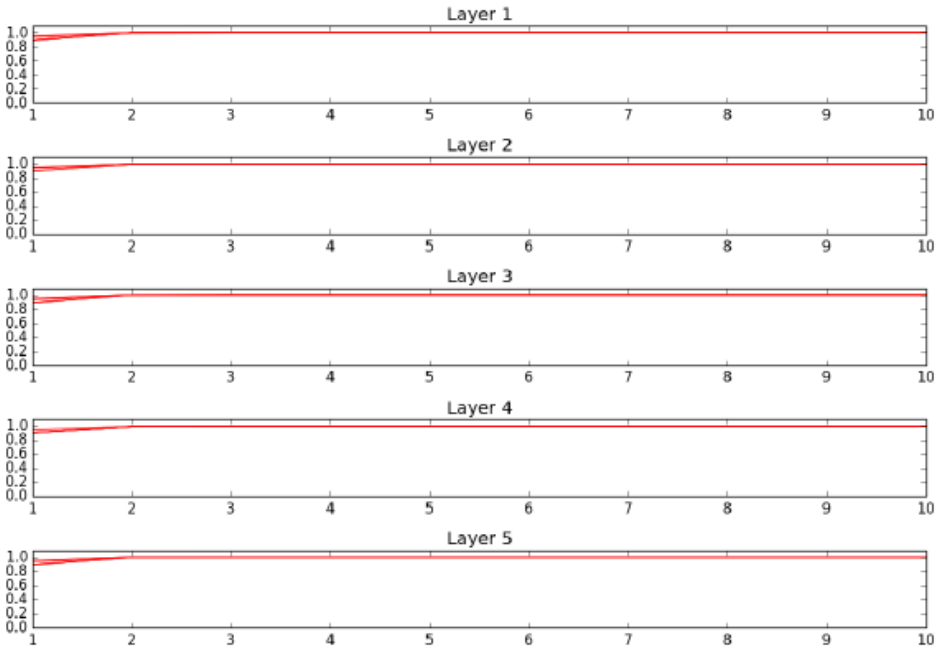
- The results

Model	5-class	
	1-shot	5-shot
Baseline-finetune	$28.86 \pm 0.54\%$	$49.79 \pm 0.79\%$
Baseline-nearest-neighbor	$41.08 \pm 0.70\%$	$51.04 \pm 0.65\%$
Matching Network	$\mathbf{43.40 \pm 0.78\%}$	$51.09 \pm 0.71\%$
Matching Network FCE	$\mathbf{43.56 \pm 0.84\%}$	$55.31 \pm 0.73\%$
Meta-Learner LSTM (OURS)	$\mathbf{43.44 \pm 0.77\%}$	$\mathbf{60.60 \pm 0.71\%}$

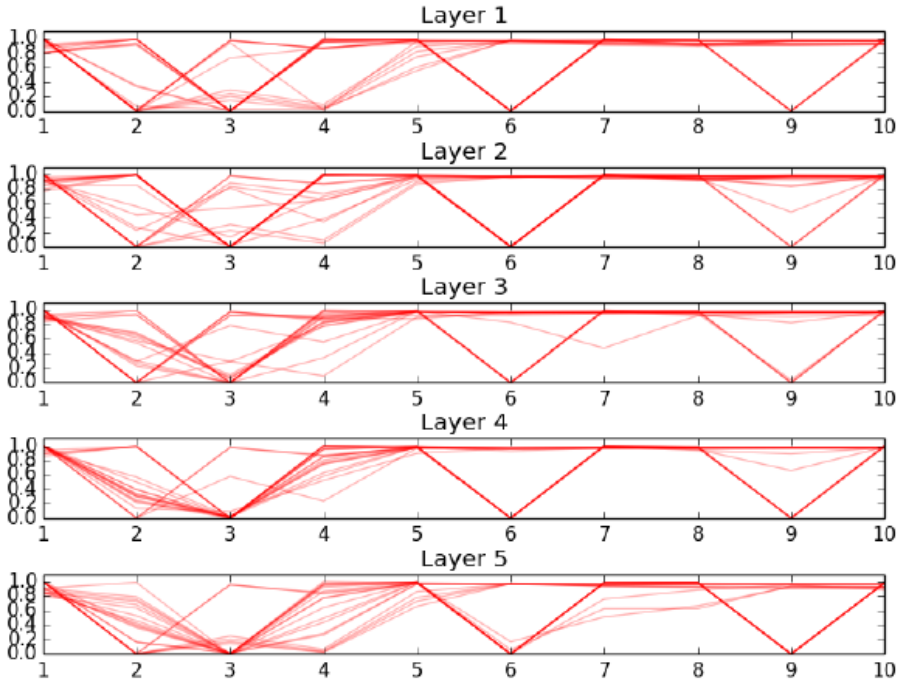
Experiments on miniImageNet

- The values of the forget gate and the input gate

$$\theta^t = z^f \odot \theta^{t-1} + z^i \odot -\nabla_\theta l$$



(a) Forget gate values for 1-shot meta-learner



(b) Input gate values for 1-shot meta-learner

Conclusions

- An LSTM-based model for meta learning
- The LSTM meta-learner uses its state to represent the learning updates of the parameters of a learner
- It discovers both a good initialization for a learner's parameters and an effective mechanism for updating the learner's parameters
  - It works well for new classes with few training data

Outline

- Problem statement of meta learning

- Representative meta learning algorithms
  - MAML [Finn et al., ICML 2017]
  - LSTM-based meta learner [Ravi and Larochelle, ICLR 2017]
  - Relation network [Sung et al. CVPR 2018]

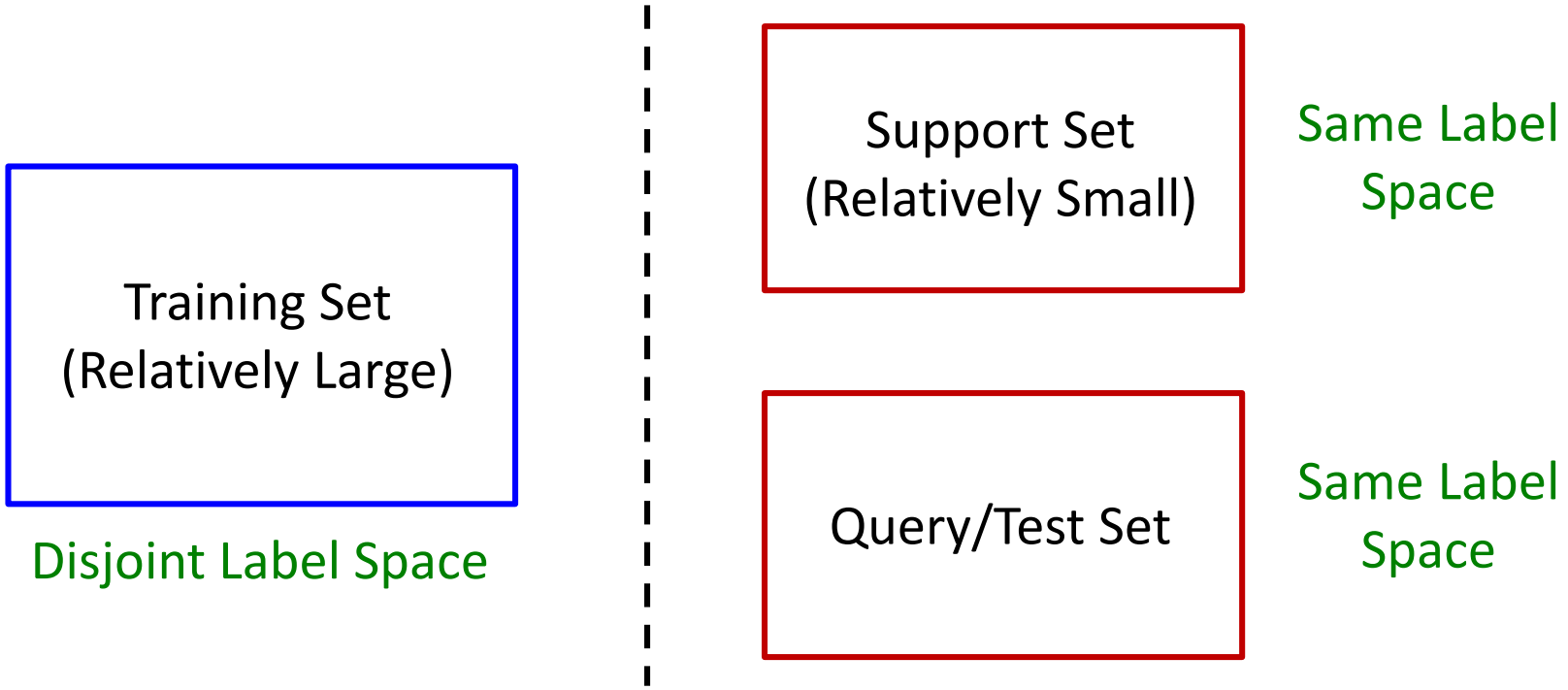
Relation network for meta learning

[Sung et al. CVPR 2018]

- Relation network: A simple, flexible, and general framework for few-shot learning
- It learns to recognize new classes given only few examples from each task
- It is trained end-to-end from scratch
- During meta-training, it learns a deep distance metric to compare a small number of images within episodes
- During meta-testing, it classifies images by computing relation scores between query and support images
- It can be extended to zero-shot learning

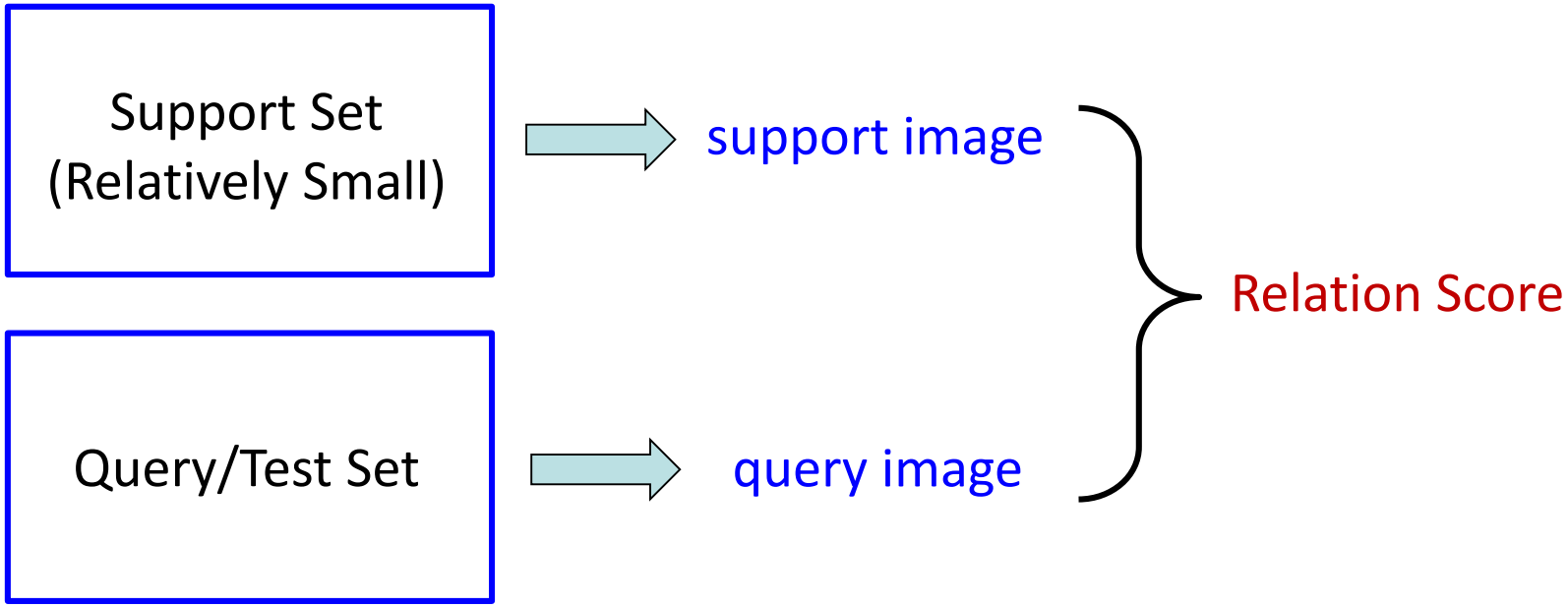
Meta learning for few shot learning

- Goal: Train a classifier to recognize new classes given few examples of each class
- Problem setting



Relation network: Recognition by comparison

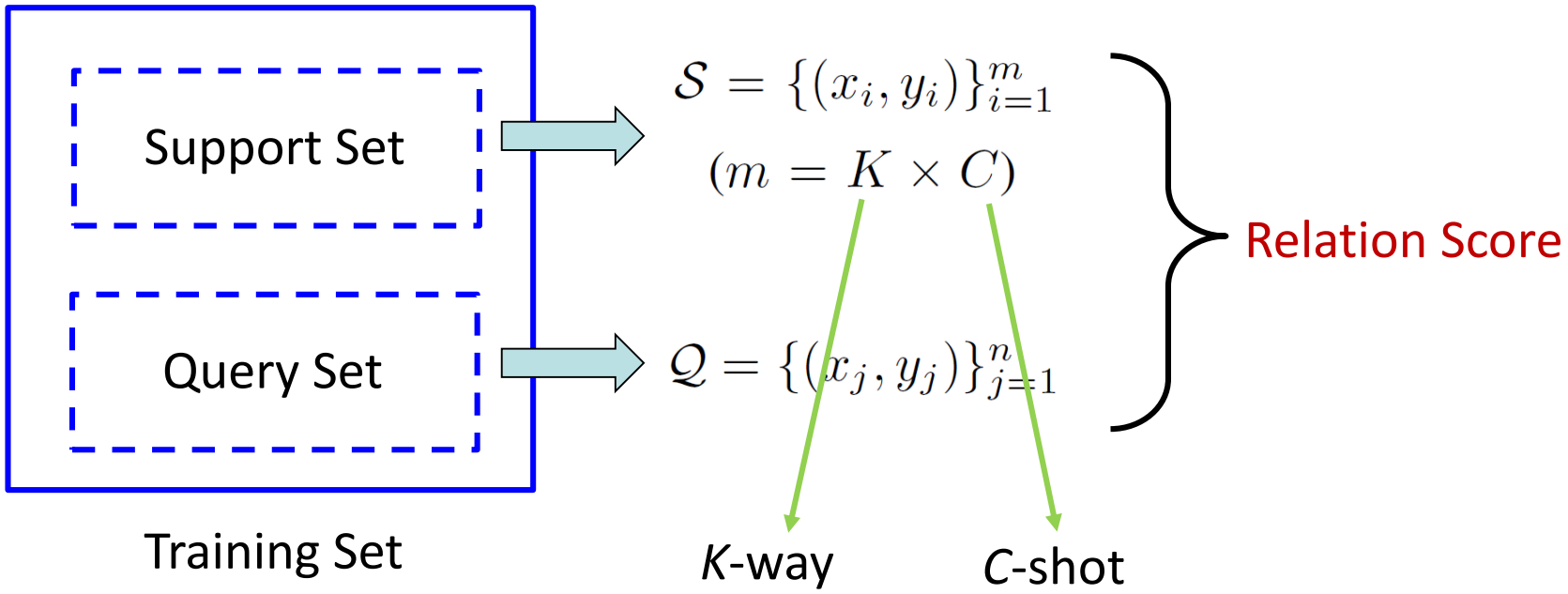
- Relation network compares support images and query images and makes classification according to the returned relation scores



- Formulate a recognition task as several verification comparisons

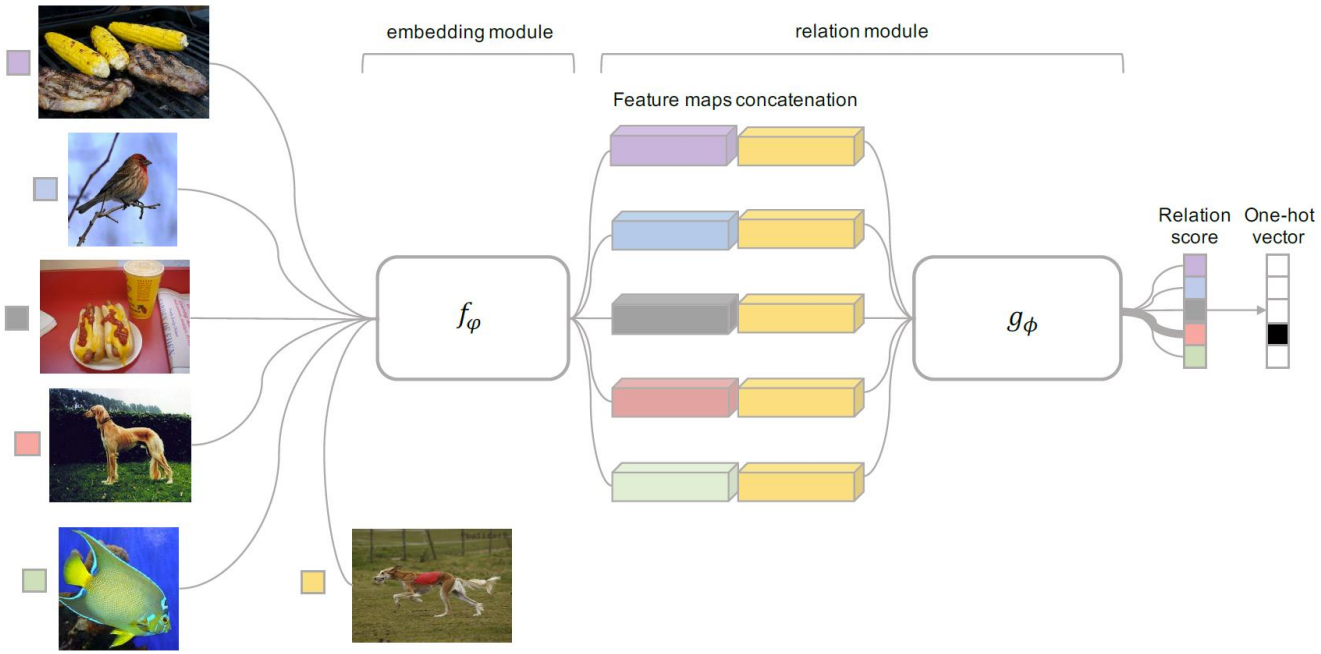
Relation network: Recognition by comparison

- Relation network learns to compare using meta learning: It mimics the comparison procedure on the training set and derives the model for comparison



Network architecture

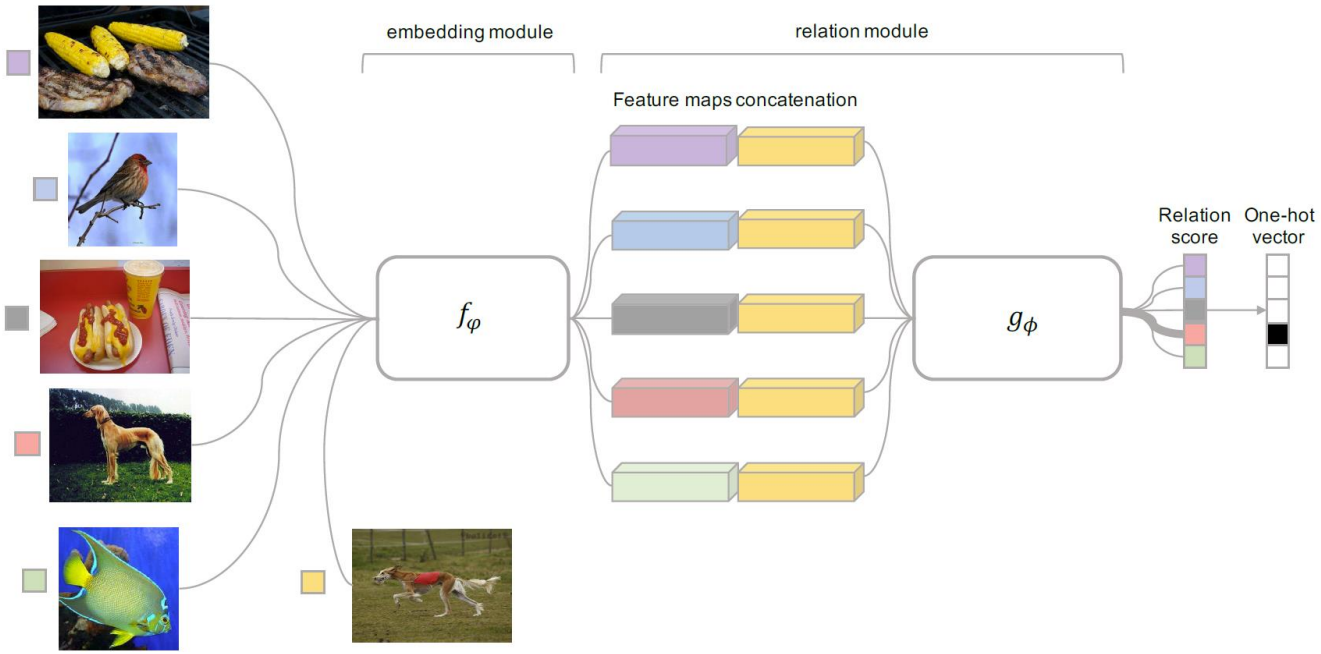
- An example of the 5-way 1-shot setting



- The embedding module computes the feature maps of each input image

Network architecture

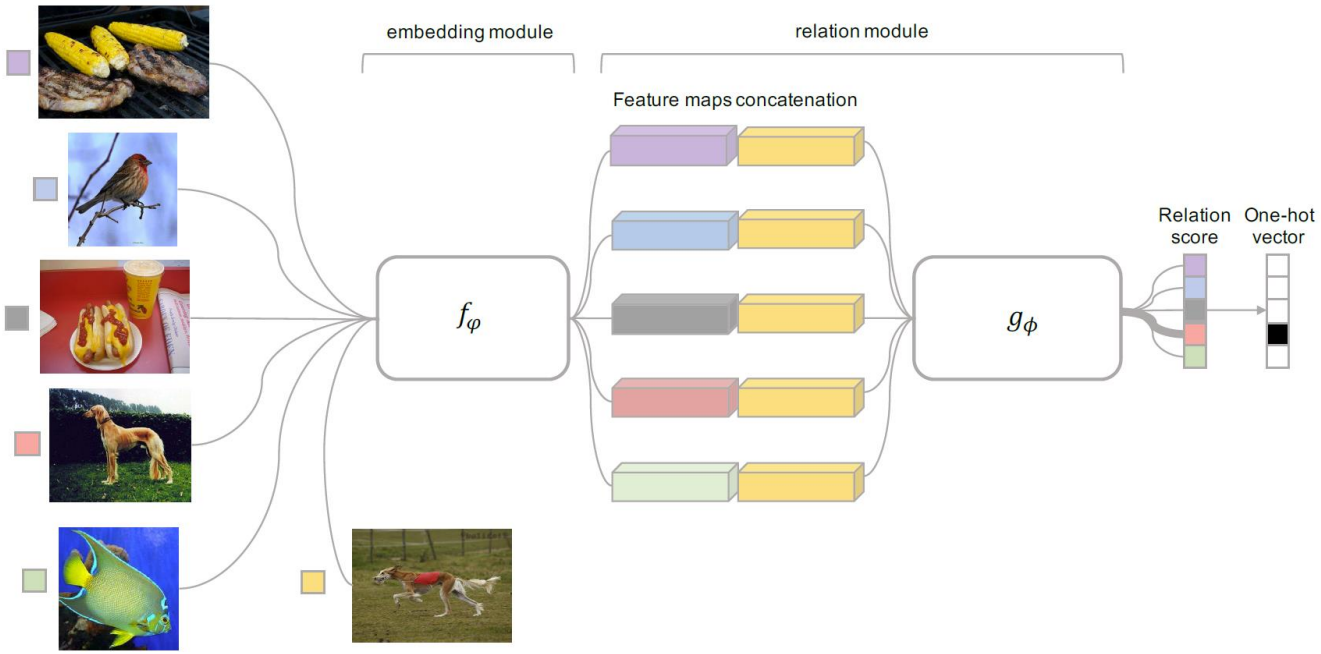
- An example of the 5-way 1-shot setting



- The relation module, working on the concatenation of a support image and a query image, returns a similarity score in range of 0 and 1

Network architecture

- An example of the 5-way 1-shot setting

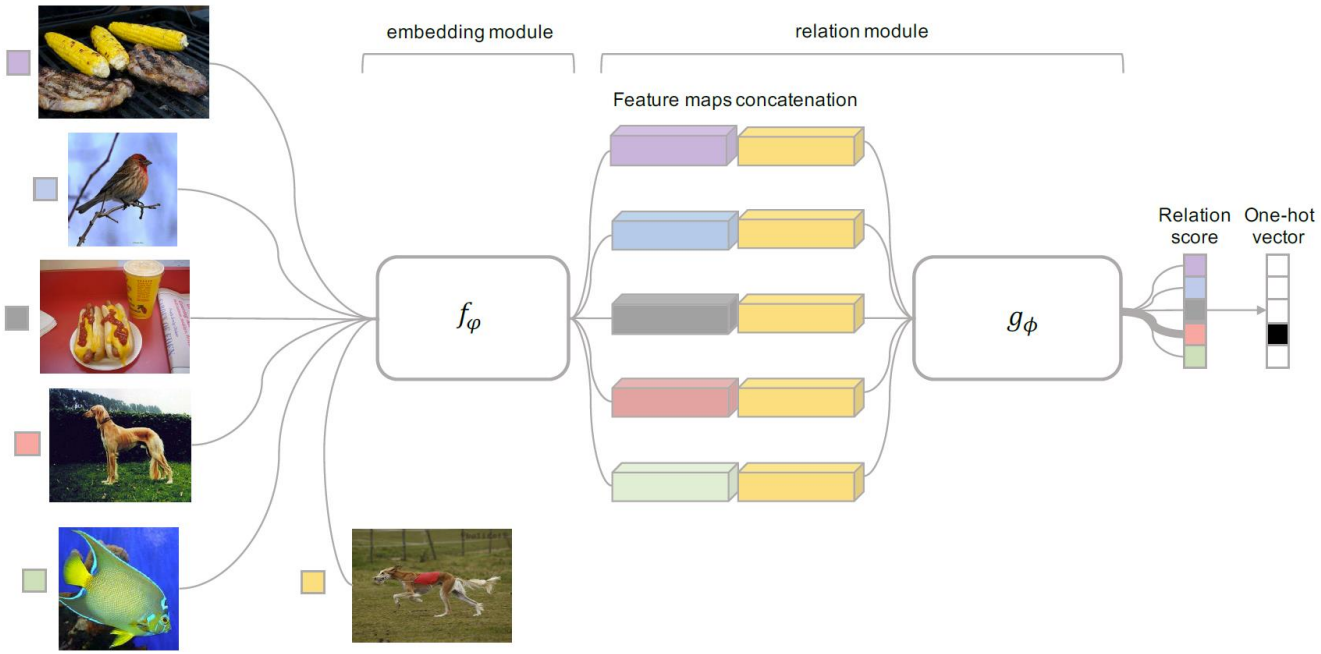


- The formulation

$$r_{i,j} = g_\phi(\mathcal{C}(f_\varphi(x_i), f_\varphi(x_j))), \quad i = 1, 2, \ldots, C$$

Network architecture

- An example of the 5-way 1-shot setting

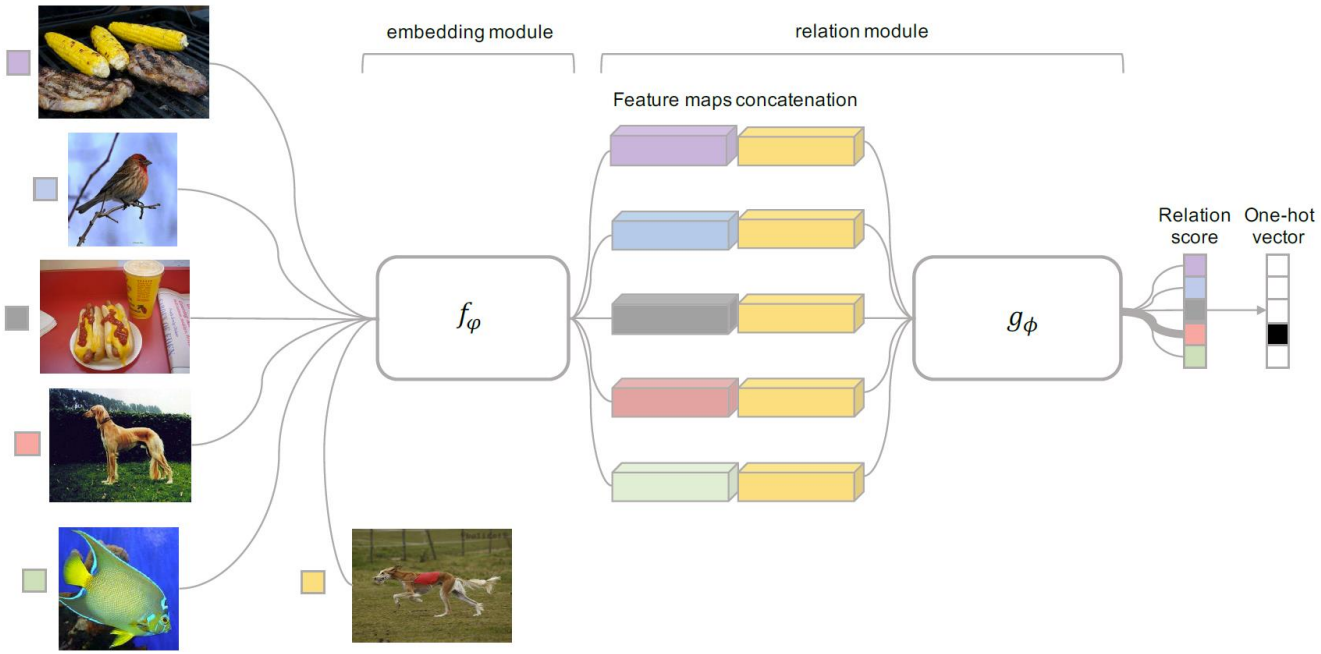


- Training objective

$$\varphi, \phi \leftarrow \underset{\varphi,\phi}{\operatorname{argmin}} \sum_{i=1}^{m}\sum_{j=1}^{n}(r_{i,j} - \mathbf{1}(y_i == y_j))^2$$

Network architecture

- An example of the 5-way 1-shot setting



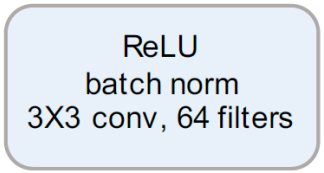
- For *K*-shot extension, we element-wise sum over the embedding module outputs of all samples of each class to form the feature maps of this class

Implementations

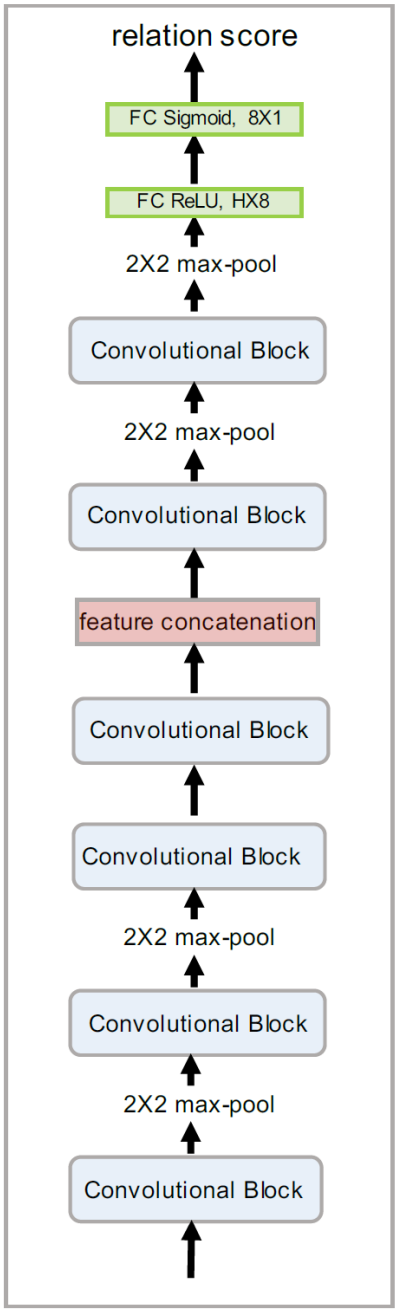
- Embedding module
  - 4 conv. blocks
  - Each block contains a 64 3x3 filters
  - First two blocks have 2x2 max-pooling layers

- Relation module
  - 2 conv. blocks
  - Both blocks are followed by 2x2 max-pooling
  - Two fully connected layers
  - The size of H depends on the dataset

(a) Convolutional Block



(b) RN for few-shot learning



Experiments: Datasets and settings

- Datasets for few shot learning
  - Omniglot
    - 1623 characters, each of which has 20 samples
    - 1200 characters for training and 423 for testing
  - miniImagenet
    - 100 classes, each of which has 600 samples
    - 64, 16, and 20 classes are used for training, validation, and testing respectively
- Settings
  - Way: 5-way and 20-way
  - Shot: 1-shot and 5-shot

Experimental results: Omniglot

- Relation network achieves the state-of-the-art performance on this dataset
- No fine-tuning during the meta-test phase is required

Model	Fine Tune	5-way Acc.		20-way Acc.	
		1-shot	5-shot	1-shot	5-shot
MANN [32]	N	82.8%	94.9%	-	-
CONVOLUTIONAL SIAMESE NETS [20]	N	96.7%	98.4%	88.0%	96.5%
CONVOLUTIONAL SIAMESE NETS [20]	Y	97.3%	98.4%	88.1%	97.0%
MATCHING NETS [39]	N	98.1%	98.9%	93.8%	98.5%
MATCHING NETS [39]	Y	97.9%	98.7%	93.5%	98.7%
SIAMESE NETS WITH MEMORY [18]	N	98.4%	99.6%	95.0%	98.6%
NEURAL STATISTICIAN [8]	N	98.1%	99.5%	93.2%	98.1%
META NETS [27]	N	99.0%	-	97.0%	-
PROTOTYPICAL NETS [36]	N	98.8%	99.7%	96.0%	98.9%
MAML [10]	Y	98.7 ± 0.4%	**99.9 ± 0.1%**	95.8 ± 0.3%	98.9 ± 0.2%
RELATION NET	N	**99.6 ± 0.2%**	**99.8± 0.1%**	**97.6 ± 0.2%**	**99.1± 0.1%**

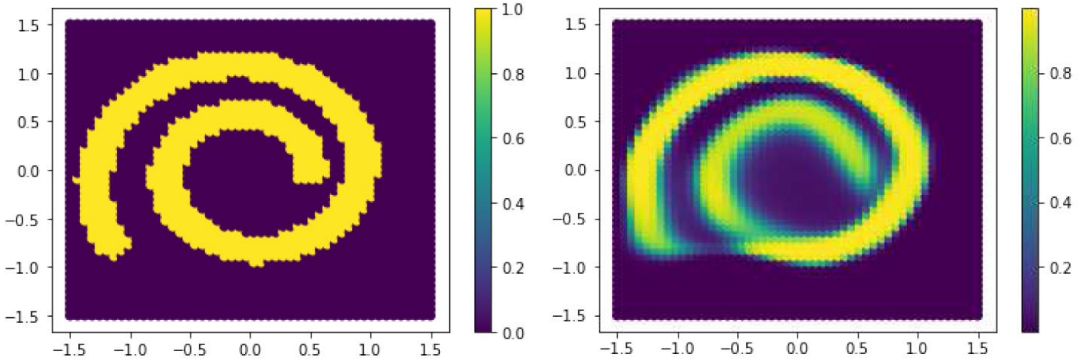
Experimental results: miniImagenet

- The performance on the miniImagenet dataset

Model	FT	5-way Acc.	
		1-shot	5-shot
MATCHING NETS [39]	N	$43.56 \pm 0.84\%$	$55.31 \pm 0.73\%$
META NETS [27]	N	$49.21 \pm 0.96\%$	-
META-LEARN LSTM [29]	N	$43.44 \pm 0.77\%$	$60.60 \pm 0.71\%$
MAML [10]	Y	$48.70 \pm 1.84\%$	$63.11 \pm 0.92\%$
PROTOTYPICAL NETS [36]	N	$49.42 \pm 0.78\%$	$\mathbf{68.20 \pm 0.66\%}$
RELATION NET	N	$\mathbf{50.44 \pm 0.82\%}$	$65.32 \pm 0.70\%$

Experimental results: Visualization

- Relation network learns a deep embedding and learning a deep non-linear metric



(a) Ground Truth (b) Relation Network

(c) Metric Learning (d) Metric + Embedding

Experimental results: Visualization

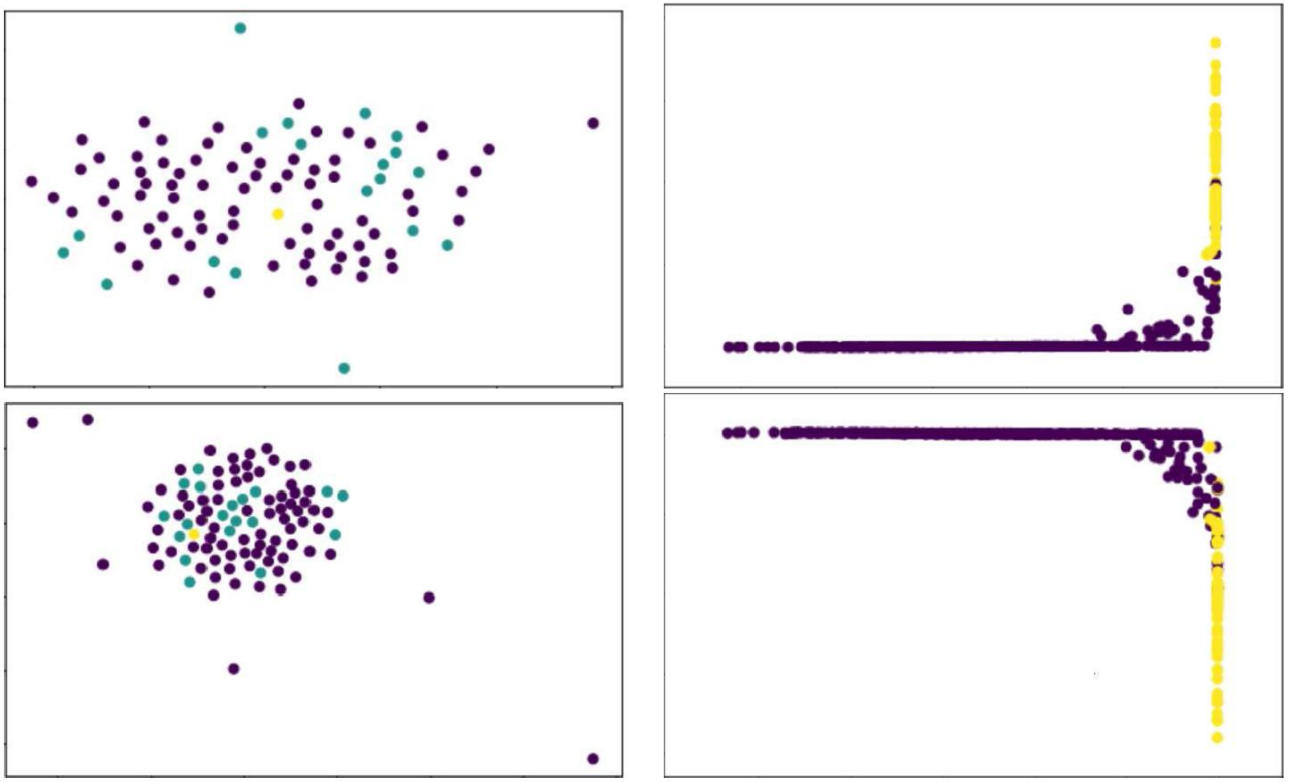


Figure 5: Example Omniglot few-shot problem visualisations. Left: Matched (cyan) and mismatched (magenta) sample embeddings for a given query (yellow) are not straightforward to differentiate. Right: Matched (yellow) and mismatched (magenta) relation module pair representations are linearly separable.

Conclusions

- A simple metric-learning method for few-shot learning and meta learning
- Relation network learns an embedding and a deep non-linear distance metric
- It is end-to-end trainable
- It produces the state-of-the-art performance without fine-tuning

Outline

- Problem statement of meta learning

- Representative meta learning algorithms
  - MAML [Finn et al., ICML 2017]
  - LSTM-based meta learner [Ravi and Larochelle, ICLR 2017]
  - Relation network [Sung et al. CVPR 2018]

References

- MAML
  - Chelsea Finn, Pieter Abbeel, and Sergey Levine, “Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks,” ICML 2017.
- LSTM-based meta-learner
  - Sachin Ravi and Hugo Larochelle, “Optimization as A Model for Few-Shot Learning,’’ ICLR 2017.
- Relation Network
  - Sung et al., “Learning to Compare: Relation Network for Few-Shot Learning,’’ CVPR 2018.

Thank You for Your Attention!

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