Meta Learning for Few-shot Generation and Classification Tasks

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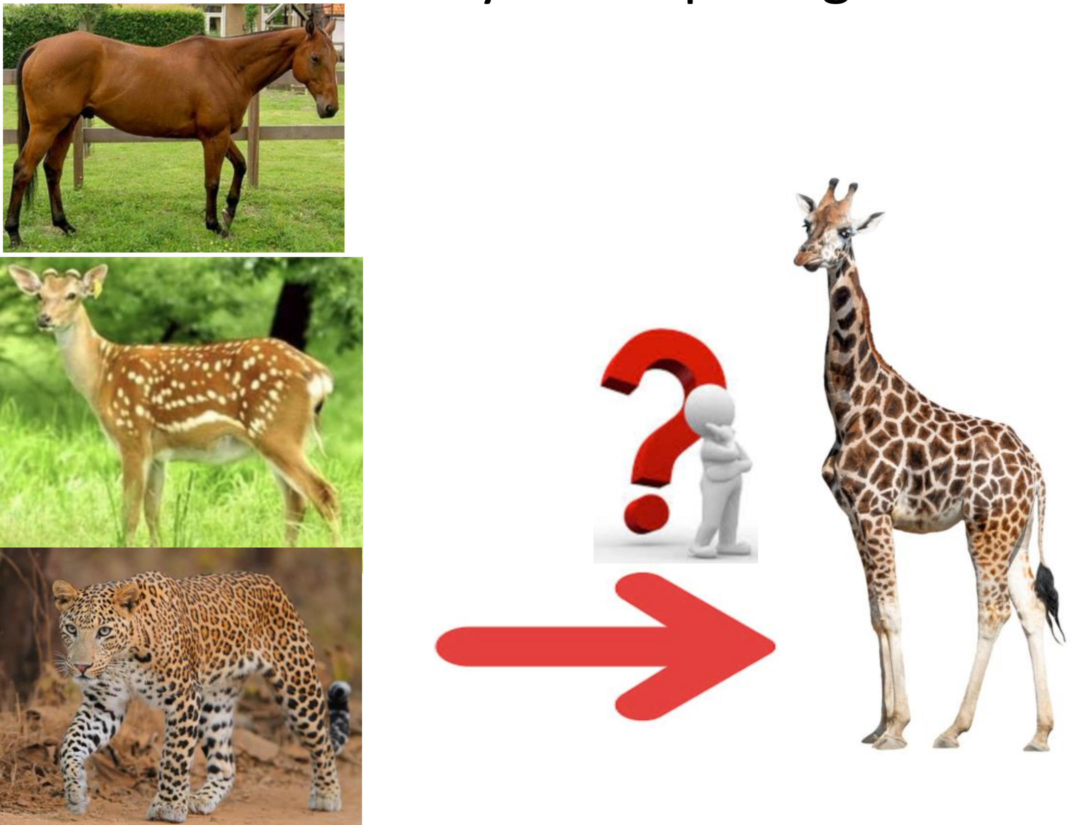
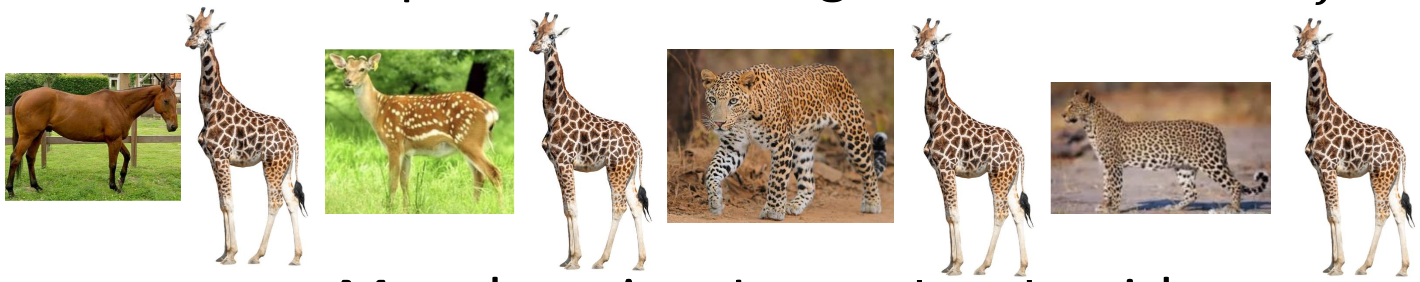
Introduction of Meta Learning

- Humans learn new concepts or skills faster than machines
  - Humans can recognize new species with few photos
  - Humans learn to ride a motorcycle fast if they can ride a bicycle.
- Reason:
  - Ability to adapt or generalize to new tasks



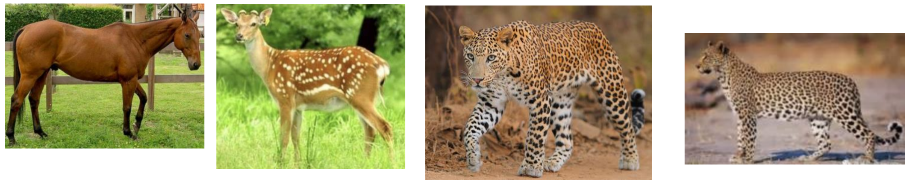
Introduction of Meta Learning

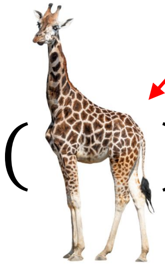
- Meta-learning (learn to learn)
  - Supervised learning: Learn a function f



$\longrightarrow f \longrightarrow f($  $) =$ "giraffe"

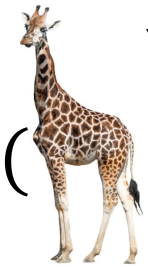
  - Meta learning: Learn the algorithms
    - Learn a function F to find a function f^* for new task



$\longrightarrow F \longrightarrow F($  $) = f^*$

Requires few examples

$\downarrow$

$f^*($  $) =$ "giraffe"

Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks

PMLR 2017

Chelsea Finn, Pieter Abbeel, Sergey Levine

Berkeley, OpenAI

Introduction

- Application
  - Model-agnostic
    - Any supervised (classification/regression) & reinforcement learning models learnt by gradient descent.
  - Few-shot scenarios
    - Many tasks
    - Only few examples for the new task
- Idea
  - Find a good global parameter θ that can be adapted to all tasks with few examples
    - θ is a task independent parameter, serving as the initial parameters for all tasks.

Model

- MAML for supervise learning (classification & regression)

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 $\mathcal{L}_{\mathcal{T}_i}$ in Equation (2) or (3)
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 $\mathcal{L}_{\mathcal{T}_i}$ in Equation 2 or 3
11: **end while**

A batch of tasks $\mathcal{T}_0, \ldots, \mathcal{T}_i, \ldots, \mathcal{T}_N$

K: Shot num

Feed forward of base model f_θ on support set, get gradients

Update θ for one step

Obtain samples for query set

Update θ based on the performance of θ'_i on query set $\mathcal{D}'_i$

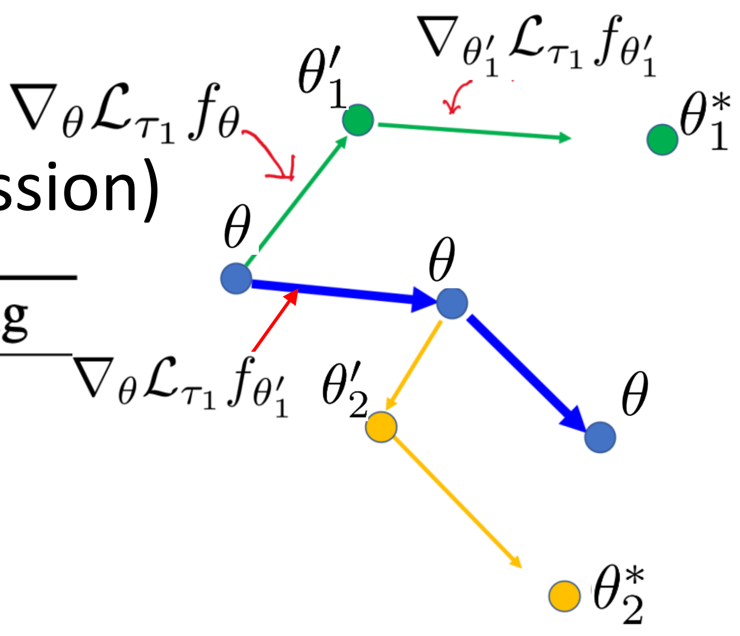
$\mathcal{D}$: Support set

$\mathcal{T}_i$ is a task

Equ2: mean sqaure loss for regression;
Equ3: cross entropy loss for classification

Model

- MAML for supervise learning (classification & regression)



Algorithm 2 MAML for Few-Shot Supervised Learning

Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters

```
randomly initialize θ
while not done do
    Sample batch of tasks T_i ~ p(T)
    for all T_i do
        Sample K datapoints D = {x^(j), y^(j)} from T_i
        Evaluate ∇_θ L_{T_i}(f_θ) using D and L_{T_i} in Equation (2) or (3)
        Compute adapted parameters with gradient descent: θ'_i = θ − α∇_θ L_{T_i}(f_θ)
        Sample datapoints D'_i = {x^(j), y^(j)} from T_i for the meta-update
    end for
    Update θ ← θ − β∇_θ Σ_{T_i~p(T)} L_{T_i}(f_{θ'_i}) using each D'_i and L_{T_i} in Equation 2 or 3
end while
```

A batch of tasks $\mathcal{T}_0, \ldots, \mathcal{T}_i, \ldots, \mathcal{T}_N$

K: Shot num

$\mathcal{D}$: Support set

$\mathcal{T}_i$ is a task

Feed forward of base model f_θ on support set, get gradients

Update θ for one step

Obtain samples for query set

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Equ2: mean sqaure loss for regression;
Equ3: cross entropy loss for classification

Learning to Customize Model Structures for Few-shot Dialogue Generation Tasks

Yiping Song, Zequn Liu, Wei Bi, Rui Yan, Ming Zhang
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Wangxuan Institute of Computer Technology, Peking University

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Few-shot Text Generation

- Cold start in text generation tasks
- Multi-language machine translation
- Personalized dialogue generation
- Emotional dialogue generation

Methods for Few-shot Dialogue Generation

- W/ task description
  - explicit: user profile
  - implicit: user description
- Pre-train
  - from non-target domain to target domain
  - require sufficient data for fine-tuning

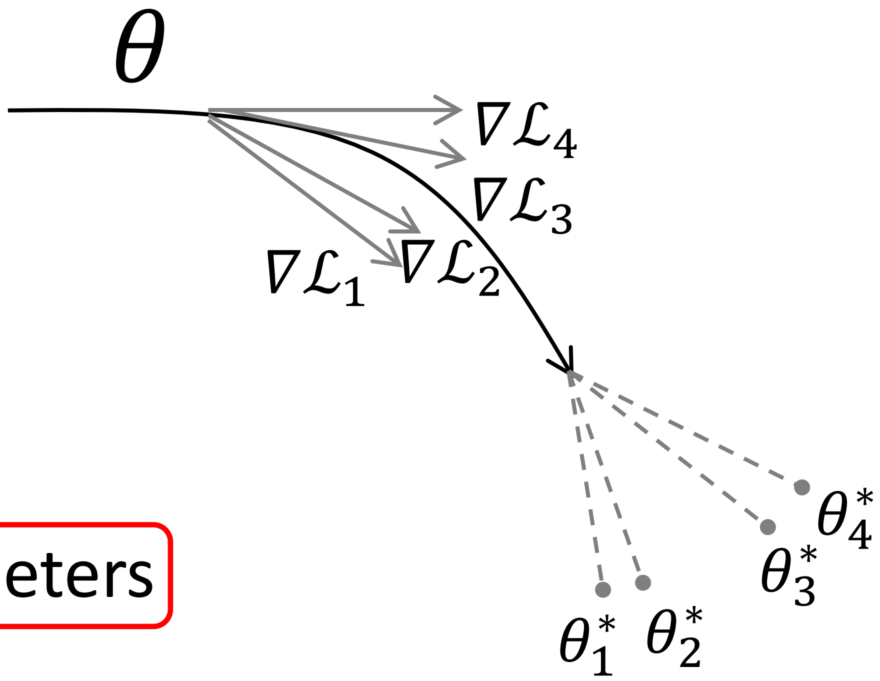
Methods for Few-shot Dialogue Generation

- W/O task description
  - meta-learning

- Meta-learning
  - metric-based methods -> classification
  - model-based methods -> classification
  - optimization-based methods -> model agnostic
  - MAML (model agnostic meta-learning)

MAML

- Training
  - find an initialization of all tasks
- Testing:
  - fine-tuning
- Model = model structure + $\boxed{\text{model parameters}}$



How about the model structure?

Adjust MAML for Larger Model Diversity

- Customize models
  - different network structures + parameters

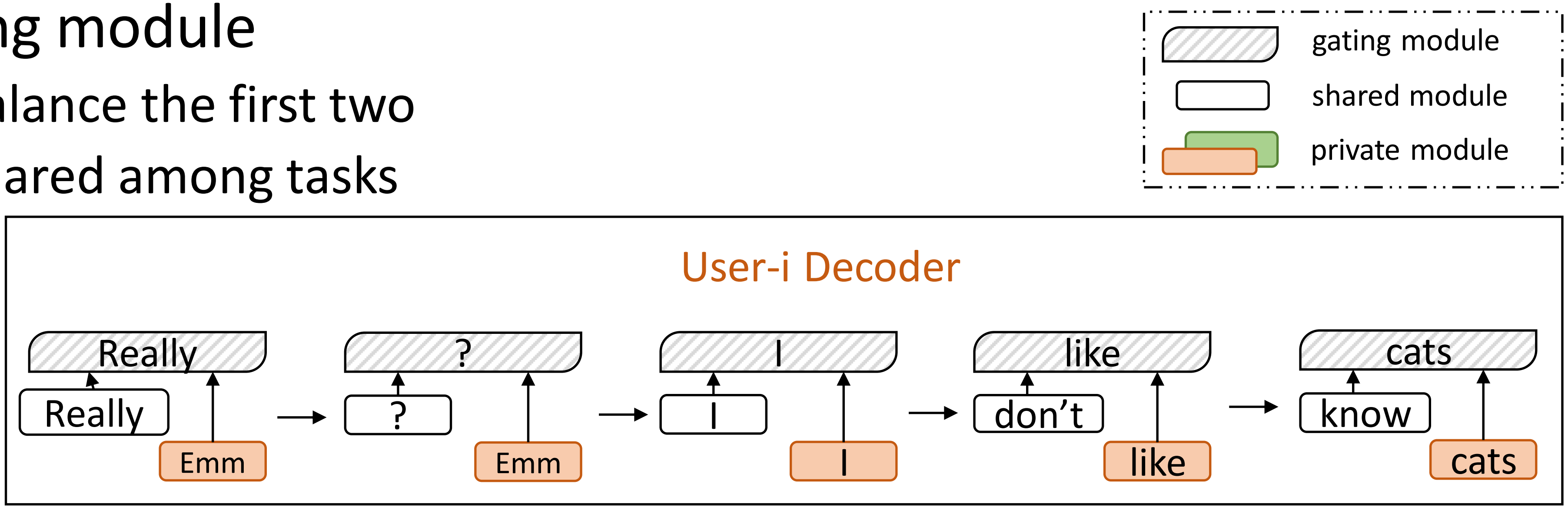
- Unique model structure
  - memorize task characteristics

- Few-shot setting
  - do not require extra data

Customized Model Agnostic Meta-Learning algorithm (CMAML)

The Dialogue Model

- Shared module
  - general generation ability
  - seq2seq
  - shared among tasks
- Gating module
  - balance the first two
  - shared among tasks
- Private module
  - memorize the characteristics of the task
  - multi-layer perception
  - unique for each task



Seq2SPG

Training Overview

- Pre-training
  - MAML: meta-training & meta-testing
  - models are the same

- Customized Model Training
  - private network pruning
    - differentiate the MLP structure
  - joint meta learning
    - re-train 3 modules of each task together

Customized Model Training

- Private network pruning
  - only on private module
- L-1 regularization
  - make parameters sparse
- Up-to-bottom pruning
  - upper layers have been pruned
  - keep edges of current layer whose weight > threshold
  - a node is pruned, nodes connected to it are pruned

Algorithm 1: Private Network Pruning

Input: All parameters θ^p in the private MLP module, the sparsity threshold γ, the total number of layers L in the private MLP module.

Output: The pruned parameters θ_i^p in private module for task T_i.

Finetune θ^p on the training data of T_i with L-1 regularization to otain θ_i^p.

for $j \in \{1, \dots, L\}$ **do**
- $E_j \leftarrow$ All edges (i.e. parameters w.r.t. each edge) in the j-th layer in θ_i^p
- $N_j \leftarrow$ All nodes in the j-th layer in θ_i^p

$E_{keep} \leftarrow E_{|L|} \cup E_1$;

$k \leftarrow |L| - 1; N_{keep} \leftarrow N_{|L|} \cup N_1$.

while $k > 1$ **do**
- **for** *each edge e in E_k* **do**
  - **if** $e > \gamma$ *and the node connected with e in N_{k+1} is in N_{keep}* **then**
    - $E_{keep} \leftarrow E_{keep} \cup \{e\}$.
- **for** *each node n in N_k* **do**
  - **for** *each edge e in E_k connected with n* **do**
    - **if** *e in E_{keep}* **then**
      - $N_{keep} \leftarrow N_{keep} \cup \{n\}$;
      - break.
- $k \leftarrow k - 1$.

return E_{keep} *as* θ_i^p

Customized Model Training

- Joint meta-training
  - joint training for all modules of tasks
  - start from the pre-trained MAML initialization
- Shared & Gating module
  - trained with all training data
- Private module
  - trained with task-specific data
  - no enough data for training

Algorithm 2: Customized Model Training

Input: The distribution over the task set $p(\mathcal{T})$, the step size α and β.

Output: The customized dialogue models $\theta^s \cup \theta_i^p \cup \theta^g$ for every task T_i.

for *each* T_i *in* T **do**

  $\theta_i^p \leftarrow$ Private_Network_Pruning(T_i).

while *not converge* **do**

  Sample a batch of tasks $T_i \sim p(\mathcal{T})$.

  for *each sampled task* T_i **do**

    Adapt θ^s / θ^g to $\theta_i'^s / \theta_i'^g$ with D_i^{train} using Eq. 2;

    Adapt θ_i^p to $\theta_i'^p$ with D_i^{train} using Eq. 4.

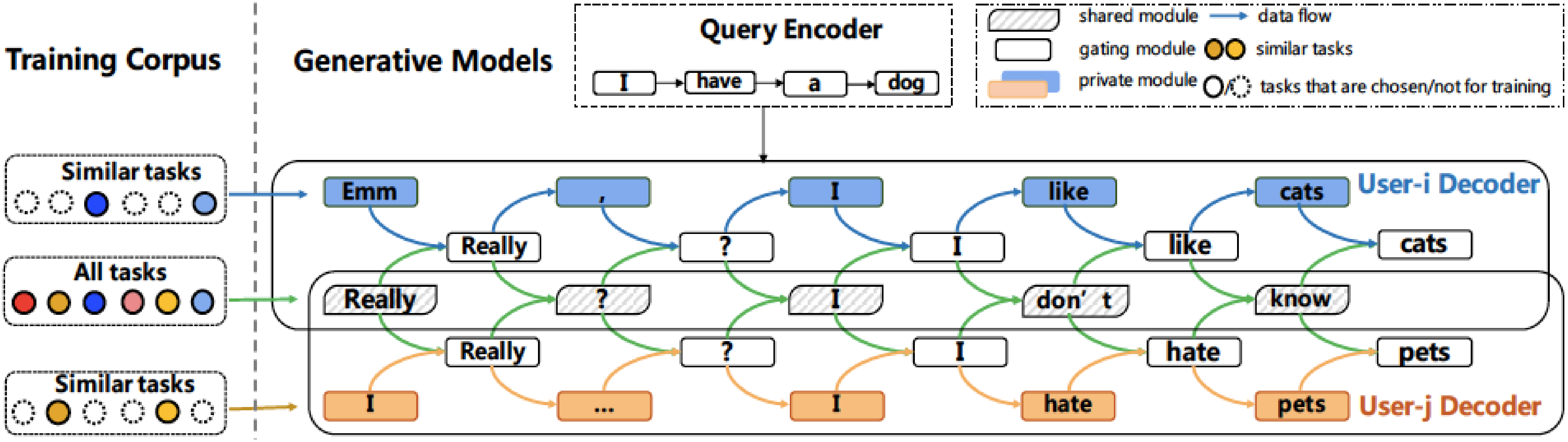
  Update θ^s, θ^g with D_i^{valid} using Eq. 3.

  Update θ_i^p with D_i^{valid} using Eq. 5.

return $\theta^s \cup \theta_i^p \cup \theta^g$

Customized Model Training

- Similar tasks share partial networks
- Dissimilar tasks have no overlaps



CMAML

Experiments

- Persona-chat
  - 1137/99/100 users for training/validation/evaluation
  - each user has 121 utterances

- MojiTalk
  - 50/6/8 emojis for training/validation/evaluation
  - each emoji has 1000 training samples

Competing Methods

- Pretrain-Only
  - Seq2seq
  - Speaker
  - Seq2SPG
- Fine-tune
  - Seq2seq-F
  - Speaker-F
  - Seq2SPG-F
- MAML
  - MAML-Seq2seq
  - MAML-Seq2SPG
- CMAML
  - CMAML-Seq2SP’G
  - CMAML-Seq2SPG

Evaluation Metrics

- Response quality/diversity
  - BLEU
  - PPL
  - Distinct-1
- Task consistency
  - C score
  - E-acc
- Model difference
  - Diff Score
  - Δ Score
  - $D(T_i, T_j) = \frac{||\theta_i - \theta_j||^2}{M}$
- Human Evaluation
  - quality
  - task consistency

Results

Fine-tune > Pre-train

Method	Human Evaluation		Automatic Metrics				Model Difference	
	Quality	Task Consistency	PPL	BLEU	Dist-1	C score/E-acc	Diff Score	Δ Score
Persona-Chat								
Seq2seq	0.67	0.10	37.91	1.27	0.0019	-0.16	0.00	0.00
Speaker	0.85	0.10	40.17	1.25	0.0037	-0.14	0.00	0.00
Seq2SPG	0.67	0.03	36.46	1.41	0.0023	-0.14	0.00	0.00
Seq2seq-F	0.78	0.11	33.65	1.56	0.0046	-0.05	17.97	9.19
Speaker-F	0.87	0.25	35.61	1.52	0.0059	0.03	285.11	143.90
Seq2SPG-F	0.7	0.07	**32.68**	1.54	0.0045	-0.05	292.85	156.30
MAML-Seq2seq	0.97	0.37	37.43	1.54	0.0087	0.14	134.01	67.79
MAML-Seq2SPG	0.85	0.36	35.89	**1.70**	0.0074	0.16	401.28	198.90
CMAML-Seq2SP′G	0.98	0.58	37.32	1.43	0.0089	0.15	479.21	238.64
CMAML-Seq2SPG	**1.15**	**0.69**	36.30	**1.70**	**0.0097**	**0.18**	**514.44**	**263.82**
MojiTalk								
Seq2seq	0.56	0.39	218.95	0.36	0.0342	0.73	0.00	0.00
Speaker	0.38	0.26	418.96	0.19	**0.0530**	0.70	0.00	0.00
Seq2SPG	0.77	0.46	158.74	0.64	0.0239	0.74	0.00	0.00
Seq2seq-F	0.50	0.35	217.60	0.40	0.0326	0.72	15.96	8.88
Speaker-F	0.39	0.25	403.92	0.21	0.0528	0.72	39.08	29.10
Seq2SPG-F	0.76	0.47	**157.92**	0.65	0.0228	0.74	72.43	40.94
MAML-Seq2seq	0.66	0.29	179.02	0.54	0.0109	0.70	183.05	117.09
MAML-Seq2SPG	0.71	0.40	181.56	0.73	0.0246	0.74	306.40	176.31
CMAML-Seq2SP′G	0.64	0.32	172.92	0.76	0.0102	0.75	142.90	81.15
CMAML-Seq2SPG	**0.78**	**0.49**	185.97	**0.85**	0.0210	**0.77**	**345.42**	**190.64**

Overall performance

Results

MAML > Fine-tune

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Overall performance

Results

CMAML > MAML

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Overall performance

Results

Method	100-shot			110-shot		
	PPL	BLEU	C score	PPL	BLEU	C score
Seq2seq	38.13	1.19	-0.11	37.58	1.29	-0.15
Speaker	40.95	1.02	-0.25	42.59	1.27	-0.06
Seq2SPG	39.75	1.27	-0.10	37.71	1.30	-0.15
Seq2seq-F	**34.86**	1.39	-0.03	**34.14**	1.52	-0.10
Speaker-F	37.11	1.30	-0.16	39.10	1.36	-0.06
Seq2SPG-F	37.19	1.31	0.00	37.00	1.33	-0.15
MAML-Seq2seq	36.94	1.47	0.03	37.20	1.53	0.07
MAML-Seq2SPG	36.50	1.52	0.11	35.98	1.47	0.13
CMAML-Seq2SP′G	37.18	1.46	0.11	37.08	1.44	0.09
CMAML-Seq2SPG	36.52	**1.52**	**0.14**	36.44	**1.57**	**0.15**

Different few-shot settings

Pre-train & Fine-tune: data ↑ task consistency =

MAML & CMAML: data ↑ task consistency ↑

Results

Method	Similar Users			Dissimilar Users		
	PPL	BLEU	C score	PPL	BLEU	C score
Seq2seq	76.54	1.49	-0.03	42.87	1.10	-0.10
Speaker	162.44	0.65	-0.09	46.86	1.11	-0.13
Seq2SPG	73.58	1.32	-0.04	42.21	1.14	-0.22
Seq2seq-F	74.53	1.53	-0.07	42.33	1.33	-0.06
Speaker-F	103.81	1.04	**0.04**	40.47	1.40	0.01
Seq2SPG-F	**70.15**	1.44	-0.04	**36.22**	1.35	-0.05
MAML-Seq2seq	83.17	1.52	-0.08	39.67	1.34	0.06
MAML-Seq2SPG	82.37	1.52	-0.06	39.41	1.41	0.12
CMAML-Seq2SP′G	82.56	1.50	0.00	40.50	1.40	0.13
CMAML-Seq2SPG	82.78	**1.56**	-0.07	39.55	**1.43**	**0.16**

Different task consistency settings

Pre-train & Fine-tune: similar tasks

MAML & CMAML: dissimilar tasks

Summary

- Customize models
  - different network structures & parameters
  - hundreds of training samples in each task
- Unique structure
  - memorize characteristics of each task
  - similar tasks are sharing data in the view of model structure
- Generation tasks
  - applicable to all few-shot generation tasks
- Code is available at: https://github.com/zequnl/CMAML

Hierarchically Structured Meta-learning

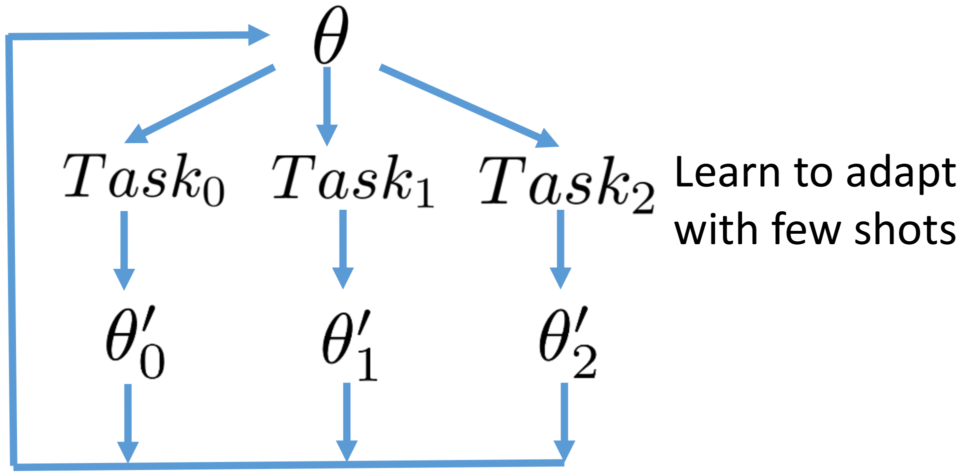
ICML 2019

Huaxiu Yao, Ying Wei, Junzhou Huang, Zhenhui Li

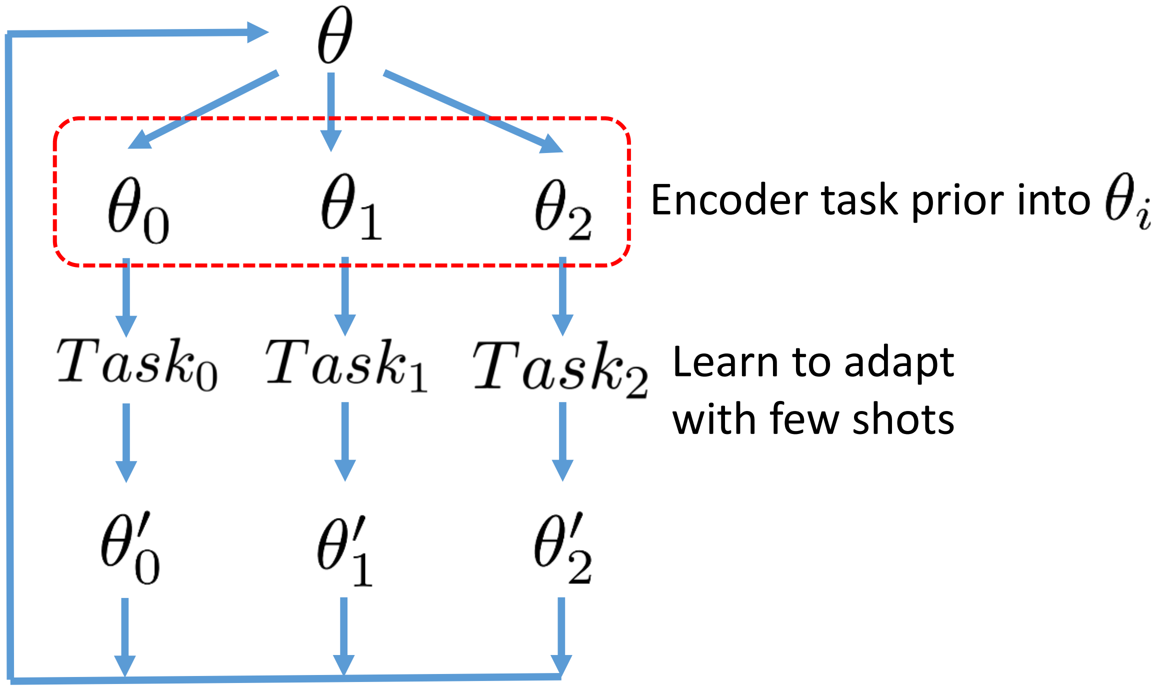
Pennsylvania, Tencent AI lab

Introduction

- Idea
  - Import task priors for MAML
  - Learn to represent tasks
  - Encode the task representation to the initial parameter θ of MAML



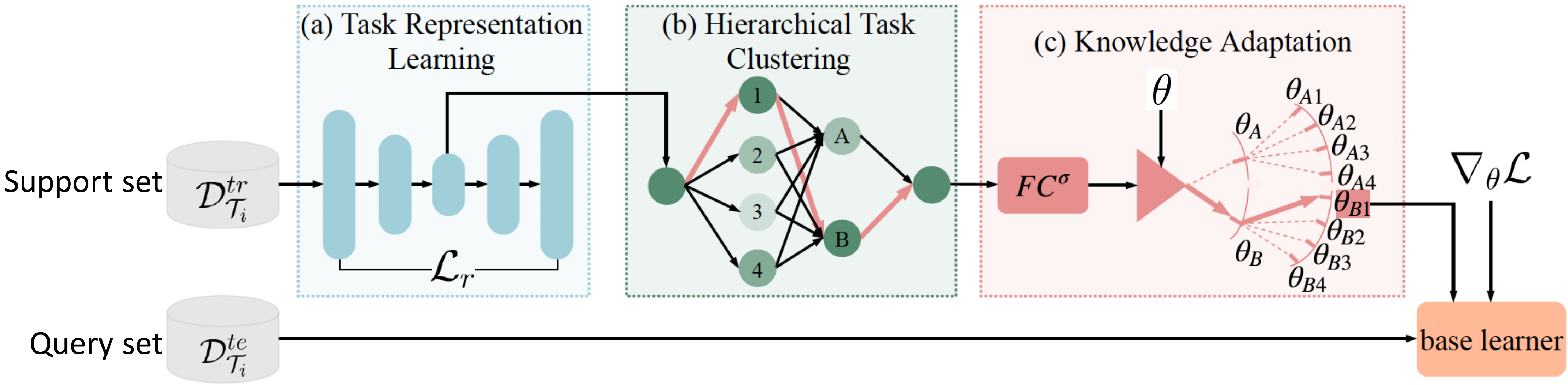
MAML



HSML

Model

- Step1 Task representation learning
- Step2 Hierarchical soft task clustering
- Step3 Adaptation on tasks



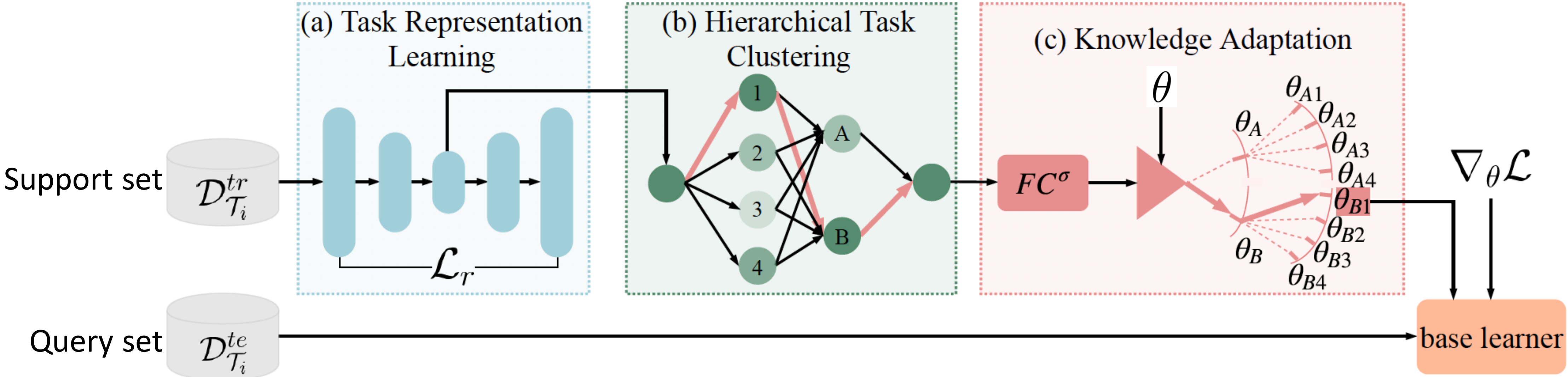
Model

- Step1 Task representation learning
  - Step1.1 train sample-level representation with autoencoder
    - Embed input x and output y (with CNN) $\mathcal{F}(\mathbf{x}_{i,j}^{tr}, \mathbf{y}_{i,j}^{tr})$
    - Reconstruct $\mathcal{F}(\mathbf{x}_{i,j}^{tr}, \mathbf{y}_{i,j}^{tr})$ with autoencoder models
      - FC- based (Fully Connected Layer)
      - RNN-based: treat all samples in a task as a sequence
      - Train by square loss

$$\mathbf{g}_{i,j} = \mathrm{FC}_{enc}(\mathcal{F}(\mathbf{x}_{i,j}^{tr}, \mathbf{y}_{i,j}^{tr}))$$

$$\mathcal{L}_r(\mathcal{D}_{\mathcal{T}_i}^{tr}) = \sum_{j=1}^{n^{tr}} \|\mathrm{FC}_{dec}(\mathbf{g}_{i,j}) - \mathcal{F}(\mathbf{x}_{i,j}^{tr}, \mathbf{y}_{i,j}^{tr})\|_2^2$$

  - Step1.2 aggregate sample-level representation to task representation
    - Merge by max/mean Pooling $\mathbf{g}_i = \mathrm{Pool}_{j=1}^{n^{tr}}(\mathbf{g}_{i,j})$



Model

- Step2 Hierarchical soft clustering on tasks
  - Step2.1 Assignment (Soft)
    - Prob of task i transferring from cluster k^l (at layer l) to cluster k^{l+1} (at layer $l+1$)

$$p_i^{k^l \to k^{l+1}} = \frac{\exp\left(-\|(\mathbf{h}_i^{k^l} - \mathbf{c}_{k^{l+1}})/\sigma^l\|_2^2/2\right)}{\sum_{k^{l+1}=1}^{K^{l+1}} \exp\left(-\|(\mathbf{h}_i^{k^l} - \mathbf{c}_{k^{l+1}})/\sigma^l\|_2^2/2\right)}$$

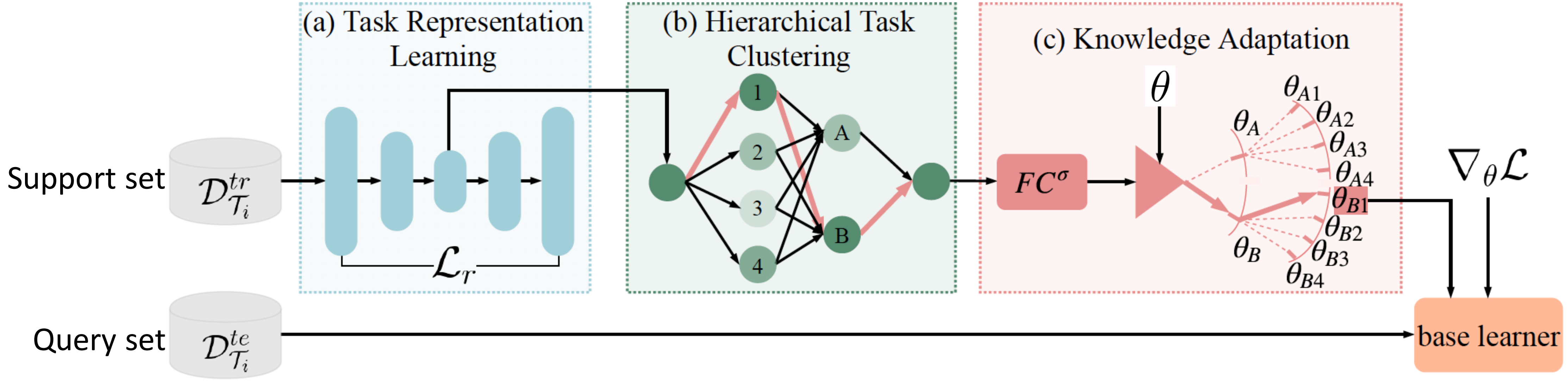
$\mathbf{h}_i^{k^l}$ Task representation of task i in cluster k^l at layer l

$\mathbf{c}_{k^{l+1}}$ Representation of cluster center k^{l+1} at layer $l+1$ (learnable)

  - Step2.2 Update
    - Update task representations
      - Weighted aggregate vectors from lower layers

$$\mathbf{h}_i^{k^{l+1}} = \sum_{k^l=1}^{K^l} p_i^{k^l \to k^{l+1}} \tanh\left(\mathbf{W}^{k^{l+1}} \mathbf{h}_i^{k^l} + \mathbf{b}^{k^{l+1}}\right)$$

$$\mathbf{h}_i^{k^0} = \mathbf{g}_i$$



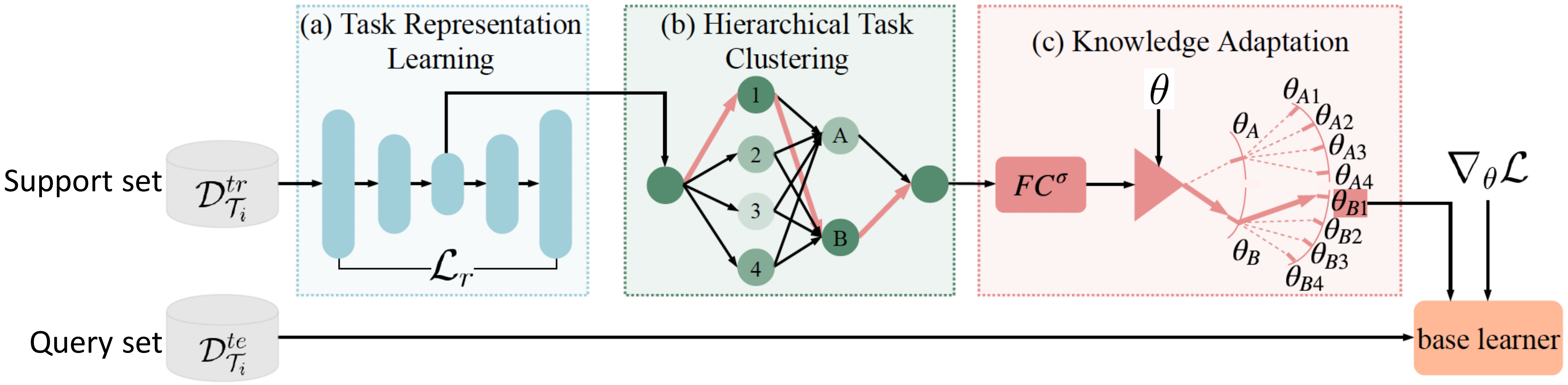
Model

- Step3 Adaptation on tasks
  - FC (Task embedding $\mathbf{g}_i$ + task representation $\mathbf{h}_i^L$ at top clustering layer)

$$\mathbf{o}_i = \mathrm{FC}^{\sigma}_{\mathbf{W}_g}(\mathbf{g}_i \oplus \mathbf{h}_i^L), \qquad \theta_{0i} = \theta \circ \mathbf{o}_i$$

- Loss
  - Meta-learning Loss as MAML + Reconstruction loss at step1

$$\min_{\Theta} \sum_{i=1}^{N_t} \mathcal{L}(f_{\theta_{0i} - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_{\mathcal{T}_i}^{tr})}, \mathcal{D}_{\mathcal{T}_i}^{te}) + \xi \mathcal{L}_r(\mathcal{D}_{\mathcal{T}_i}^{tr})$$



Optimization as a model for few-shot learning

ICLR 2017

Sachin Raviand, Hugo Larochelle

Twitter

Introduction

- Motivation (Similar to MAML based)
  - Obtain task-specific model parameters θ_i for new task with few examples
- Idea
  - Treats samples in a task as a sequence
  - LSTM learns to generate model parameters from a sequence of samples

Introduction

- Motivation
  - Obtain task-specific model parameters θ_i for new task with few examples
- Idea
  - Treats samples in a task as a sequence
  - LSTM learns to generate model parameters from a sequence of samples
  - Gradient descent

    $$\theta_t = \theta_{t-1} - \alpha_t \nabla_{\theta_{t-1}} \mathcal{L}_t$$

    - Few shot: make full use of few samples
  - LSTM (only use input and forget gates)

    $$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

    - LSTM balances previous information and current input
  - LSTM+GD
    - LSTM balances previous parameters and current gradients

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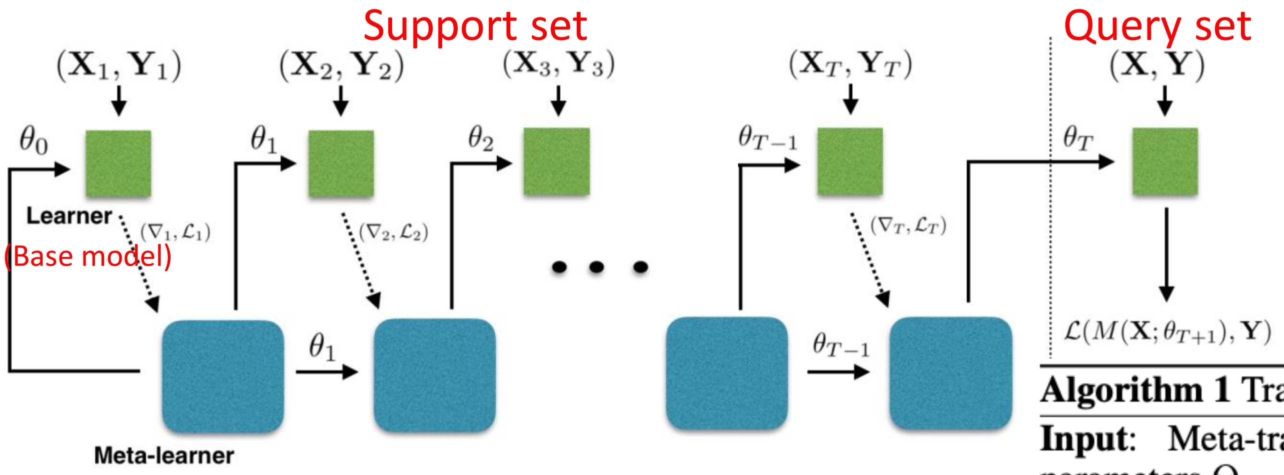
    - LSTM balances previous information and current input
  - LSTM+GD
    - LSTM balances previous parameters and current gradients
    - learn to generate θ_t from gradient $\nabla_{\theta_{t-1}} \mathcal{L}_t$ and previous θ_{t-1}

    $$\theta_t = f_t \theta_{t-1} + i_t \nabla_{\theta_{t-1}} \mathcal{L}_t$$

Model



Meta-learner

$$\theta_t = f_t \theta_{t-1} + i_t \nabla_{\theta_{t-1}} \mathcal{L}_t$$

$$i_t = \sigma\left(\mathbf{W}_I \cdot \left[\nabla_{\theta_{t-1}} \mathcal{L}_t, \mathcal{L}_t, \theta_{t-1}, i_{t-1}\right] + \mathbf{b}_I\right)$$

$$f_t = \sigma\left(\mathbf{W}_F \cdot \left[\nabla_{\theta_{t-1}} \mathcal{L}_t, \mathcal{L}_t, \theta_{t-1}, f_{t-1}\right] + \mathbf{b}_F\right)$$

Algorithm 1 Train Meta-Learner

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

```
Θ_0 ← random initialization

for d = 1, n do
    D_train, D_test ← random dataset from 𝒟_meta−train
    θ_0 ← c_0                                          ▷ Intialize learner parameters

    for t = 1, T do
        X_t, Y_t ← random batch from D_train
        ℒ_t ← ℒ(M(X_t; θ_{t−1}), Y_t)                  ▷ Get loss of learner on train batch
        c_t ← R((∇_{θ_{t−1}} ℒ_t, ℒ_t); Θ_{d−1})       ▷ Get output of meta-learner using Equation 2
        θ_t ← c_t                                      ▷ Update learner parameters
    end for

    X, Y ← D_test
    ℒ_test ← ℒ(M(X; θ_T), Y)                           ▷ Get loss of learner on test batch
    Update Θ_d using ∇_{Θ_{d−1}} ℒ_test                ▷ Update meta-learner parameters

end for
```

Support set
Query set
Task
Training set
Sample a batch from support set of this task
Base model
Meta-learner
All samples in query set compose one batch
Evaluate on query set
Update meta-learner according to the performance on query set

Thanks for listening!