1703.03400 - Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks

- **Yunqiu Xu**
- 2nd for this paper, try to understand both paper and code
- Other reference:
    - https://www.jiqizhixin.com/articles/2017-07-20-4
    - http://bair.berkeley.edu/blog/2017/07/18/learning-to-learn/
- Implementation:
    - Original: https://github.com/cbfinn/maml
    - PyTorch: https://github.com/katerakelly/pytorch-maml

1. Introduction

- The goal of meta-learning: train a model with some learning tasks, then it can solve new tasks with only a few samples
- Our work:
    - MAML: pretrain the model with a series of tasks
    - Then this model can be generated to new task with a small number of training samples / gradient steps on that task
- Comparison with another recent related work: **Ravi & Larochelle, 2017. Optimization as a Model for Few-Shot Learning**
    - Their work :
        - Learns both the weight initialization and the optimizer $\rightarrow$ they learn an update function or learning rule
        - Meta-based LSTM
    - Our advantage :
        - The MAML learner’ s weights are updated using the gradient, not a trained update method
        - So we do not need additional parameters
        - And we are not limited to LSTM, our model can be generalized to both SL

and RL
- **Other advantages: see 6.Discussion and Future Work**

2. MAML

2.1 Problem Setup

- Goal: train a "meta learning" model on a set of tasks, then this model can adapt to a new task with only a few data / iterations $\rightarrow$ learn **as much as** possible with limited data
- Model $f: x \rightarrow a$
  - x : observations
  - a : outputs
  - This model is like a "base model" which will be able to adapt to a lot of new tasks
- General notion of task $T = \{L(x_1, a_1, \ldots, x_H, a_H), q(x_1), q(x_{t+1}|x_t, a_t), H\}$:
  - $L \rightarrow R$: loss function
  - $q(x_1)$: distribution over initial observations
  - $q(x_{t+1}|x_t, a_t)$: transiion distribution
    - 对于监督学习, 不存在这个分布 : $H = 1$
    - 对于强化学习, $q(x_{t+1}|x_t, a_t)$ 代表某时间点观察值的分布, e.g. 初始观察值后观察值取自$q(x_2|x_1, a_1)$
  - H :
    - Episode length, model may generate samples of length H by choosing an output a_t at each time t
    - For supervised learning, $H = 1$ and loss function $L(x_1, a_1)$ could be MSE or cross entropy

2.2 K-shot meta-learning:

- Train model f:
  - Sample a new task T_i from $p(T)$ (training taskset)

- Learn T_i :
  - Train model with K samples drawn from q_i
  - Get feedback L_{T_i} from T_i
- Test on new samples from T_i and get test error
- Improve model f : treat the test error on sampled tasks T_i as the training error of meta-learning process

- Test meta-learning:
  - Sample new task from $p(T)$ (testing taskset), try to adapt f to this new task
  - Learn the model with K samples
  - Treat the performance as "meta-performance"

2.3 A MAML Algorithm

- What our model does?
  - Be able to learn parameters of any standard model via meta-learning
  - Why: some internal representations are more transferrable
  - E.G. 我们可以通过一系列任务学到一个神经网络模型, 而非仅仅通过一个任务, 这样这个模型就比较容易迁移到类似的新任务上
- How we learn
  - Learn a model that gradient-based learning rule can make rapid progress on new tasks drawn from $p(T)$ without overfitting
  - Find model parameters that are **sensitive** to changes of the task $\rightarrow$ small changes lead to large improvement (direction of gradient)
  - 为什么这样做: 之前的目标就是在样本/更新次数有限的情况下学到的东西尽可能多, 因此我们要尽量让每一点点小改变都能获得较大的提升
  - **此处存疑: 代码里该怎么体现"sensitive", 看了代码好像没有具体提及**

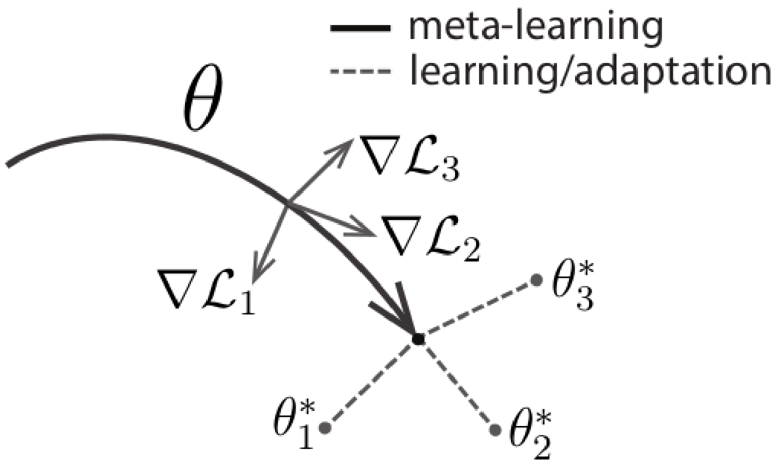


Figure 1. Diagram of our model-agnostic meta-learning algorithm (MAML), which optimizes for a representation θ that can quickly adapt to new tasks.

- Algorithm 1:
  - f_θ, when adapting to a new training task T_i, the model's parameter θ becomes θ_i'
  - Then we learn θ_i' by gradient update:
    $$\theta_i' = \theta - \alpha \nabla_\theta L_{T_i}(f_\theta)$$
    - 这里我理解为调整梯度的方向, 比如为了适应 T_2 我们需要将梯度方向稍微上移
    - 经过多次梯度更新(内循环)后, 我们就可以学到比较适合 T_2 的参数向量 θ_2'
    - Step size α : fixed as a hyperparameter or meta-learned
  - After learning the parameter vectors for all tasks in training task set ($\theta_1', \theta_2', \ldots \theta_n'$), compute their test error to update θ:
    - Meta objective
    $$min_\theta \sum_{T_i \sim p(T)} L_{T_i}(f_{\theta_i'}) = \sum_{T_i \sim p(T)} L_{T_i}(f_{\theta - \alpha \nabla_\theta L_{T_i}(f_\theta)})$$
    - SGD:
    $$\theta \leftarrow \theta - \beta \nabla_\theta \sum_{T_i \sim p(T)} L_{T_i}(f_{\theta_i'})$$

Algorithm 1 Model-Agnostic Meta-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 $\mathcal{T}_i \sim p(\mathcal{T})$
  for all $\mathcal{T}_i$ **do**
    Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ with respect to K examples
    Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
  end for
  Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$
end while

- This process involves a gradient through a gradient $\rightarrow$ an additional backward pass through f to compute Hessian-vector products

3. Species of MAML

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 $\mathcal{T}_i \sim p(\mathcal{T})$
  for all $\mathcal{T}_i$ **do**
    Sample K datapoints $\mathcal{D} = \{\mathbf{x}^{(j)}, \mathbf{y}^{(j)}\}$ from $\mathcal{T}_i$
    Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ using $\mathcal{D}$ and $\mathcal{L}_{\mathcal{T}_i}$ in Equation (2) or (3)
    Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
    Sample datapoints $\mathcal{D}_i' = \{\mathbf{x}^{(j)}, \mathbf{y}^{(j)}\}$ from $\mathcal{T}_i$ for the meta-update
  end for
  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
end while

Algorithm 3 MAML for Reinforcement 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 $\mathcal{T}_i \sim p(\mathcal{T})$
  for all $\mathcal{T}_i$ **do**
    Sample K trajectories $\mathcal{D} = \{(\mathbf{x}_1, \mathbf{a}_1, ...\mathbf{x}_H)\}$ using f_θ in $\mathcal{T}_i$
    Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ using $\mathcal{D}$ and $\mathcal{L}_{\mathcal{T}_i}$ in Equation 4
    Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
    Sample trajectories $\mathcal{D}_i' = \{(\mathbf{x}_1, \mathbf{a}_1, ...\mathbf{x}_H)\}$ using $f_{\theta_i'}$ in $\mathcal{T}_i$
  end for
  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 4
end while

3.1 Supervised learning

- Model is to predict output value given input value
- For each training task T_i
  - $H = 1$: single input and single output
  - $L =$ MSE or corss entropy
  - $q_i(x_1)$: 因为不存在时序观察值, 这个分布就是监督学习训练集样本的分布
  - I think there is no $q_i(x_{t+1}|x_t, a_t)$
  - Then generate K samples x from $q_i(x_1)$, compute the error between predicted value a and ground truth y

3.2 RL

- Model is to predict action a_t given state x_t
- For each training task T_i:
  - timestep $t \in \{1, \ldots, H\}$
  - The initial state distribution $q_i(x_1)$: 为了训练这个子任务, 我们会从这个初始值分布选取K个起始点
  - Transition distribution $q_i(x_{t+1}|x_t, a_t)$:
    - 对每个当前观察值及选取的动作, 未来观察值同样构成一个分布
    - 比如我选择吃一口饭, 接下来可能观察到 $\{$饱了, 还饿$\}$等状态
    - 当然我们训练好T_i, 获得的未来状态可能就是选取最优动作后的结果了
  - For T_i and its model parameter ϕ, the loss function is

$$L_{T_i}(f_\psi) = -E_{x_t, a_t \sim f_{\psi, q_{T_i}}}\left[\sum_{t=1}^{H} R_i(x_t, a_t)\right] \quad (4)$$

    - As reward function is to maximize reward, in loss function we multiply "-1" to minimize the value
    - Here ϕ is θ_i' , which we mentioned before
  - Why in step 8 we sample trajectories using $f_{\theta_i'}$ instead of f_{θ_i} : PG is on-policy, thus each additional gradient updateing during the adaption of f_θ need to sample from current policy

4. Related work

Omniglot (Lake et al., 2011)	5-way Accuracy 1-shot	5-way Accuracy 5-shot	20-way Accuracy 1-shot	20-way Accuracy 5-shot
MANN, no conv (Santoro et al., 2016)	82.8%	94.9%	–	–
MAML, no conv (ours)	$\mathbf{89.7 \pm 1.1\%}$	$\mathbf{97.5 \pm 0.6\%}$	–	–
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)	$\mathbf{98.7 \pm 0.4\%}$	$\mathbf{99.9 \pm 0.1\%}$	$\mathbf{95.8 \pm 0.3\%}$	$\mathbf{98.9 \pm 0.2\%}$

MiniImagenet (Ravi & Larochelle, 2017)	5-way Accuracy 1-shot	5-way Accuracy 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)	$\mathbf{48.70 \pm 1.84\%}$	$\mathbf{63.11 \pm 0.92\%}$

- RNNs as learners: MANN
    - Search space includes all conceivable ML algorithms
    - Moves the burden of innovation to RNNs
    - Ignors advances achieved in ML by humans
    - The results are not good
- Metric learning: Siamese nets, matching nets
    - Learn a metric in input space
    - Specialized to one/few-shot classification
    - Can't use in other problems
- Optimizer learning: meta-learner LSTM
    - Learn parameter update given gradients (search space includes SGD, RMSProp, Adam etc)
    - Applicable to any architecture / task
    - But we can achieve better performance with MAML

5. Experimental evaluation

- Questions need to be answered:

- Can MAML enable fast learning of new tasks
    - Can MAML be used for meta-learning in multiple different domains: SL / RL ...
    - Can a model learned with MAML continue to improve with additional gradient updates and/or examples
- An oracle work:
    - Receives the identity of the task (which is a problem-dependent representation) as an additional input,
    - Thus oracle will be an upper bound on the performance of the model
    - 我们主要对比用或不用MAML的情形, 越接近oracle代表效果越好

5.1 Regression

- 模拟sin曲线
- Each task:
    - The shape of curve varies by amplitude and phase
    - Input and output of a sine wave
    - Data points sampled from [-5.0, 5.0]
    - Loss: MSE
- Model architecture: NN with 2 hidden layers, 40 hidden nodes, ReLU
- Training:
    - K = 10
    - \alpha = 0.01
    - Adam
    - After all training tasks, we get a pretrained model
- Testing:
    - Fine-tune the pretrained model with K test samples and a number of GDs
- Result
    - Left is pretrained with MAML, right is without MAML

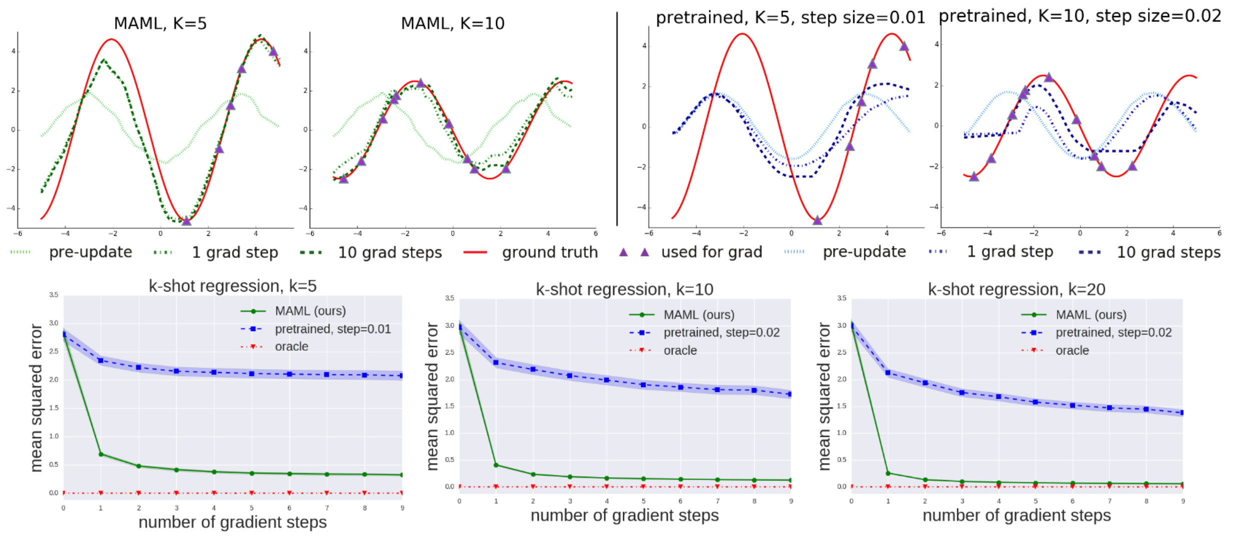


Figure 6. Quantitative sinusoid regression results showing test-time learning curves with varying numbers of K test-time samples. Each gradient step is computed using the same K examples. Note that MAML continues to improve with additional gradient steps without overfitting to the extremely small dataset during meta-testing, and achieves a loss that is substantially lower than the baseline fine-tuning approach.

- Even with only 5 datapoints the fitting curve is nice
- When all the points are in one half, the model can still infer the shape of the other half → model the periodic nature
- Quantitative results: improve with addition gradient steps
    - 但素, sin曲线这种简单任务好像也就是再多迭代一个循环的事情 :)
- 总之对Regression可以用很少的样本/循环finetune, 不会overfitting

5.2 Classification

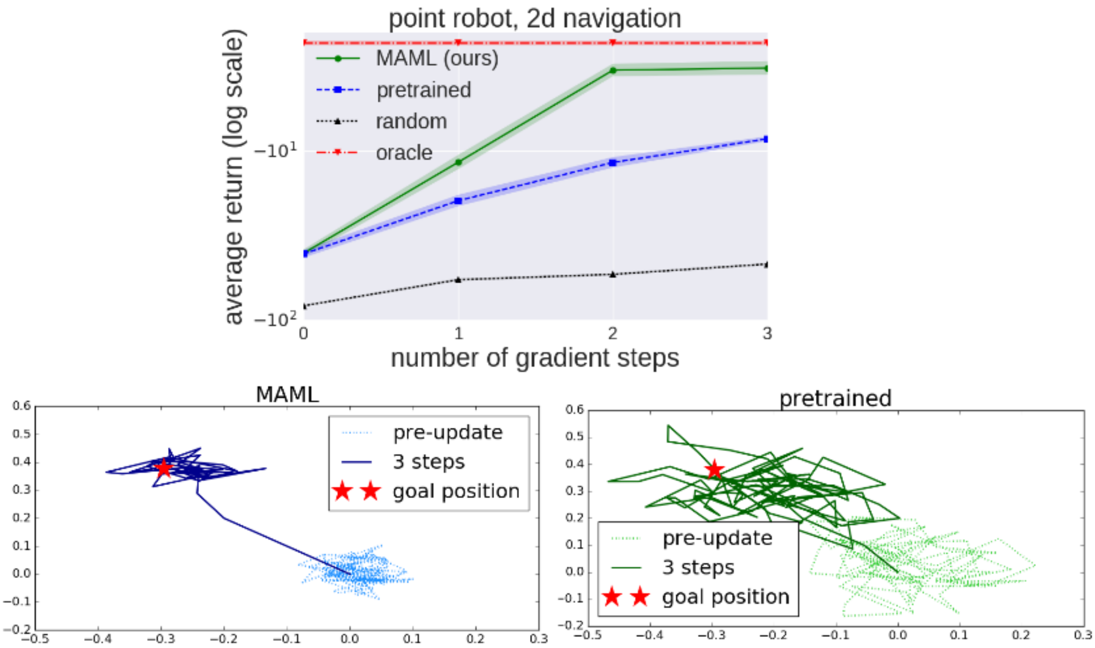
- Vinyals et al. 2016 Matching networks for one shot learning
- Tasks : Few-shot image recognition
- Datasets
    - Omniglot:
        - 20 instances of 1623 characters from 50 different alphabets
        - Downsampled to 28 * 28
        - 1200 characters for training, remain for testing
        - Augmentation: degree retations
    - MiniImagenet: 64 training classes, 12 validation classes, and 24 test classes
- Evaluation : N-way classification
    - Select N unseen classes

- Provide the model with K different instances of each of the N classes
- Evaluate the model' s ability to classify new instances within the N classes
- Model architecture
  - 4 modules, each module:
    - 3*3 conv, 64 filters (32 filters for MiniImagenet)
    - Batch normalization
    - ReLU nonlinearity
    - Strided convolutions (2*2 max-pooling for MiniImagenet)
  - A non-conv network for comparison: 256-128-64-64, BN, ReLU
  - Loss: cross entropy
- **Comparision result : see 4. related work**
- We also compare the performance between first order and second order derivatives
  - From $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{T_i \sim p(T)} L_{T_i}(f_{\theta_i'})$ we can find that there is second order derivatives, which maybe computational expensive
  - Thus we compare it with first-order approximation
    - Compute the meta-gradient at the post-update parameter values θ_i'
  - Result:
    - **1st order is similar to 2nd order, less need to use 2nd derivatives**
    - Improvement of MAML comes from gradients of the objective at the post-update parameter values
    - Not 2nd derivative for differentiating through the gradient update
    - The use of ReLU make most of 2nd derivatives close to 0

5.3 Reinforcement Learning

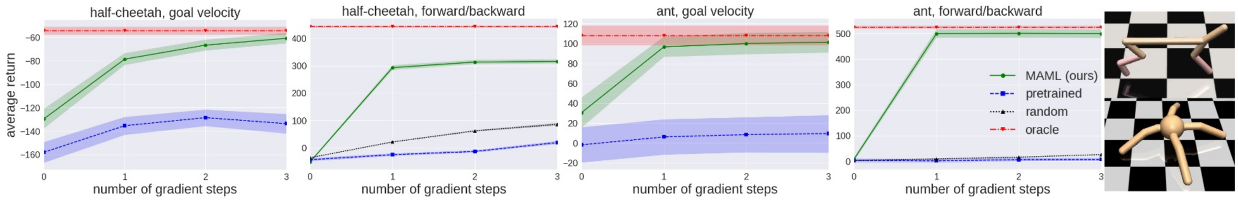
- Dual et al. 2016 Benchmarking deep reinforcement learning for continuous control
- Model architecture
  - 2 hidden layers, 100 hidden nodes, ReLU
  - Vanilla PG + TRPO
  - Use finite differences to compute Hessian-vector products for TRPO: avoid computing third derivatives

- Comparison:
  - policy inited with MAML
  - policy inited with randomly weights
  - oracle policy
- 2D Navigation
  - Goal: move to goal positions in 2D
  - Observation: current 2D position
  - Action: velocity commands
  - Reward: negative squared distance
  - When to terminate: too close to the goal, or H = 100
  - Comparison: adaptation to a new task with up to 4 gradient updates, each with 40 samples



- MuJoCo Simulation:
  - Goal velocity experiment: the reward is the negative absolute value between the current velocity of the agent and a goal
  - Goal direction experiments: the reward is the magnitude of the velocity in either the forward or backward direction
  - Result : MAML learns a model that can quickly adapt its velocity and direction with even just a single gradient update, and continues to improve with more gradient steps

- 本文中经过MAML预训练的模型强于随机初始化, 不过在Parisotto et al 2016.的工作中, 也有预训练不如随机初始化的情况
- Note that random baseline curves for game velocity are removed (worse return)



6. Discussion and Future Work

- MAML can be treated as an initialization method to get pretrained model that is easy to fine-tune
- Benefits:
  - Simple, does not introduce any learned parameters for meta-learning
  - Can be applied to regression / classification / RL
  - Adaptation on new tasks with few shot / updates
- Future work:
  - Generalize meta-learning technique to apply to any problem and any model → 1709.04905 - One-Shot Visual Imitation Learning via Meta-Learning
  - Apply to multi-task

7. Code

- Here I try to understand `maml.py` in https://github.com/cbfinn/maml
- Note that this is only the code for SL, RL version is more complex
- How will it be used:
  - Suffix 'a': training data for inner loop
  - Suffix 'b': testing data for inner loop

```
model = MAML(dim_input, dim_output, test_num_updates = test_num_updates)
input_tensors = {'inputa': inputa, 'inputb': inputb, 'labela': labela, 'labelb': labelb}
```

```
model.construct_model(input_tensors=..., prefix='...')
```

7.1 Initialize the model

- `update_lr` : learning rate α
- `meta_lr` : learning rate β
- `lossesa` : the training loss of inner loop $\rightarrow$ for updating α
- `lossesb` : the testing loss of inner loop (the training loss of meta) $\rightarrow$ for updating β

```
lossesa, outputas, accuraciesa = [], [], []
num_updates = max(self.test_num_updates, FLAGS.num_updates)
lossesb, outputbs, accuraciesb = [[]]*num_updates, [[]]*num_updates,
[[]]*num_updates
```

7.2 Inner loop

- Helper function `task_metalearn(inp, reuse=True)`
    - Input : `inp = (self.inputa, self.inputb, self.labela, self.labelb)`
    - Output : `task_output = [task_outputa, task_outputbs, task_lossa, task_lossesb]`
        - For classification, add another 2 elements `task_accuracya, task_accuraciesb`
        - **Question: I can't find how `outputas, outputbs` will be used later**
    - Here we use another 2 hellper functions:
        - `forward` : forward pass, get task outputs
        - `loss_func` : compute loss
- The first iteration and remaining are splitted:
    - `task_outputa` and `task_lossa` will only be computed in first iteration, in remaining iterations this will be computed as `loss` directly
    - Thus the final output of `task_outputa` and `task_lossa` will be computed in **first iteration**

```python
# For first iteration:
task_outputa = self.forward(inputa, weights, reuse=reuse)
task_lossa = self.loss_func(task_outputa, labela)
# For remaining iterations:
loss = self.loss_func(self.forward(inputa, fast_weights, reuse=True),
labela)
```

- Then we compute gradients for inner loop
  - Recall that we will make comparison between 2nd order derivation and 1st order

```python
# For first iteration:
grads = tf.gradients(task_lossa, list(weights.values()))
# For remaining iterations:
grads = tf.gradients(loss, list(fast_weights.values()))
# if True --> only use 1st order
if FLAGS.stop_grad:
    grads = [tf.stop_gradient(grad) for grad in grads]
# Transfer to dict
gradients = dict(zip(weights.keys(), grads))
```

- Update the weights for sub-task: $\theta' \leftarrow \theta' - \alpha * grad$

```python
fast_weights = dict(zip(weights.keys(), [weights[key] - self.update_lr*
gradients[key] for key in weights.keys()]))
```

- Compute the test error for inner loop $\rightarrow$ the train error of meta process

```python
output = self.forward(inputb, fast_weights, reuse=True)
task_outputbs.append(output)
task_lossesb.append(self.loss_func(output, labelb))
```

7.3 Meta update

- Note that meta update is only for **meta-training**
- Map `meta_tasklearn` to all data

```python
result = tf.map_fn(task_metalearn, elems=(self.inputa, self.inputb, sel
f.labela, self.labelb), dtype=out_dtype,
parallel_iterations=FLAGS.meta_batch_size)
```

```python

if self.classification:
    outputas, outputbs, lossesa, lossesb, accuraciesa, accuraciesb = result
else:
    outputas, outputbs, lossesa, lossesb  = result
```

- Compute **average loss** to update meta params
  - `total_loss1` : the training loss of inner loop
  - `total_losses2` : the testing loss of inner loop
  - For classification we also need to compute accuracy

```python
self.total_loss1 = total_loss1 = tf.reduce_sum(lossesa) / tf.to_float(FLAGS.meta_batch_size)
self.total_losses2 = total_losses2 = [tf.reduce_sum(lossesb[j]) / tf.to_float(FLAGS.meta_batch_size) for j in range(num_updates)]
```

- Meta update
  - There are 2 kinds of update operations: `pretrain_op` and `metatrain_op`
  - In `main.py`: `iter = pretrain_iter + metatrain_iter`, metatrain will only happen when it reaches metatrain_iter
  - However in default settings these 2 iterations will not be together : one is 0 that there is only 1 kind of iteration

```python
# meta update for pretrain_op will be in all iterations
self.pretrain_op = tf.train.AdamOptimizer(self.meta_lr).minimize(total_loss1)

# meta update for metatrain_op
if FLAGS.metatrain_iterations > 0:
    optimizer = tf.train.AdamOptimizer(self.meta_lr)
    self.gvs = gvs = optimizer.compute_gradients(self.total_losses2[FLAGS.num_updates-1])
    if FLAGS.datasource == 'miniimagenet':
        gvs = [(tf.clip_by_value(grad, -10, 10), var) for grad, var in gvs]
    self.metatrain_op = optimizer.apply_gradients(gvs)
```

7.4 Meta testing

- `metaval_total_loss1` : training error of test task
- `metaval_total_losses2` : testing error of test task

```
self.metaval_total_loss1 = total_loss1 = tf.reduce_sum(lossesa) / tf.to_float(FLAGS.meta_batch_size)
self.metaval_total_losses2 = total_losses2 = [tf.reduce_sum(lossesb[j]) / tf.to_float(FLAGS.meta_batch_size) for j in range(num_updates)]
if self.classification:
    self.metaval_total_accuracy1 = total_accuracy1 = tf.reduce_sum(accuraciesa) / tf.to_float(FLAGS.meta_batch_size)
    self.metaval_total_accuracies2 = total_accuracies2 =[tf.reduce_sum(accuraciesb[j]) / tf.to_float(FLAGS.meta_batch_size) for j in range(num_updates)]
```