CS 330 Autumn 2022 Homework 2
Prototypical Networks and Model-Agnostic Meta-Learning

Due Monday October 24, 11:59 PM PST

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By turning in this assignment, I agree by the Stanford honor code and declare that all of this is my own work.

Overview

In this assignment, you will experiment with two meta-learning algorithms, prototypical networks (protonets) [1] and model-agnostic meta-learning (MAML) [2], for few-shot image classification on the Omniglot dataset [3], which you also used for Homework 1. You will:

1. Implement both algorithms (given starter code).
2. Interpret key metrics of both algorithms.
3. Investigate the effect of task composition during protonet training on evaluation.
4. Investigate the effect of different inner loop adaptation settings in MAML.
5. Investigate the performance of both algorithms on meta-test tasks that have more support data than training tasks do.

Expectations

- We expect you to develop your solutions locally (i.e. make sure your model can run for a few training iterations), but to use GPU-accelerated training (e.g. Azure) for your results.
- Submit to Gradescope
    1. a `.zip` file containing your modified version of `hw2/starter/`
    2. a `.pdf` report containing your responses
- You are welcome to use TensorBoard screenshots for your plots. Ensure that individual lines are labeled, e.g. using a custom legend, or by text in the figure caption.
- Figures and tables should be numbered and captioned.

Preliminaries

Notation

- x: Omniglot image
- y: class label
- N (way): number of classes in a task
- K (shot): number of support examples per class
- Q: number of query examples per class
- c_n: prototype of class n
- f_θ: neural network parameterized by θ
- $\mathcal{T}_i$: task i
- $\mathcal{D}_i^{\text{tr}}$: support data in task i
- $\mathcal{D}_i^{\text{ts}}$: query data in task i
- B: number of tasks in a batch
- $\mathcal{J}(\theta)$: objective function parameterized by θ

Part 1: Prototypical Networks (Protonets) [1]

Algorithm Overview

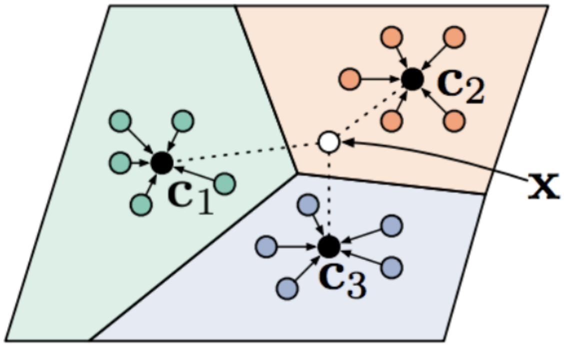


Figure 1: Prototypical networks in a nutshell. In a 3-way 5-shot classification task, the class prototypes c_1, c_2, c_3 are computed from each class's support features (colored circles). The prototypes define decision boundaries based on Euclidean distance. A query example x is determined to be class 2 since its features (white circle) lie within that class's decision region.

As discussed in lecture, the basic idea of protonets is to learn a mapping $f_\theta(\cdot)$ from images to features such that images of the same class are close to each other in feature space. Central to this is the notion of a *prototype*

$$c_n = \frac{1}{K} \sum_{(x,y)\in\mathcal{D}_i^{\text{tr}}:y=n} f_\theta(x), \tag{1}$$

i.e. for task i, the prototype of the n-th class c_n is defined as the mean of the K feature vectors of that class's support images. To classify some image x, we compute a measure of distance d between $f_\theta(x)$ and each of the prototypes. We will use the squared Euclidean distance:

$$d(f_\theta(x), c_n) = \|f_\theta(x) - c_n\|_2^2. \tag{2}$$

We interpret the negative squared distances as logits, or unnormalized log-probabilities, of x belonging to each class. To obtain the proper probabilities, we apply the softmax operation:

$$p_\theta(y = n|x) = \frac{\exp(-d(f_\theta(x), c_n))}{\sum_{n'=1}^{N} \exp(-d(f_\theta(x), c_{n'}))}. \tag{3}$$

Because the softmax operation preserves ordering, the class whose prototype is closest to $f_\theta(x)$ is naturally interpreted as the most likely class for x. To train the model to generalize, we compute prototypes using support data, but minimize the negative log likelihood of the query data

$$\mathcal{J}(\theta) = \mathbb{E}_{\mathcal{T}_i \sim p(\mathcal{T}), (\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{ts}}) \sim \mathcal{T}_i} \left[\frac{1}{NQ} \sum_{(x^{\text{ts}}, y^{\text{ts}}) \in \mathcal{D}_i^{\text{ts}}} - \log p_\theta(y = y^{\text{ts}} | x^{\text{ts}}) \right]. \tag{4}$$

Notice that this is equivalent to using a cross-entropy loss.

We optimize θ using Adam [4], an off-the-shelf gradient-based optimization algorithm. As is standard for stochastic gradient methods, we approximate the objective (4) with Monte Carlo estimation on minibatches of tasks. For one minibatch with B tasks, we have

$$\mathcal{J}(\theta) \approx \frac{1}{B} \sum_{i=1}^{B} \left[\frac{1}{NQ} \sum_{(x^{\text{ts}}, y^{\text{ts}}) \in \mathcal{D}_i^{\text{ts}}} - \log p_\theta(y = y^{\text{ts}} | x^{\text{ts}}) \right]. \tag{5}$$

Problems

1. We have provided you with `omniglot.py`, which contains code for task construction and data loading.

   (a) (5 pt) Recall that for training black-box meta-learners in the previous homework we needed to shuffle the query examples in each task. This is not necessary for training protonets. Explain why.
   answer:Because support data and query data are in the same model in BBML, query_data can learn the order in which support_data appear through hiddent state, but in prototypical network, prototype does not contain any order information of support data appearing

2. In the `protonet.py` file, complete the implementation of the `ProtoNet._step` method, which computes (5) along with accuracy metrics. Pay attention to the inline comments and docstrings.

   Assess your implementation on 5-way 5-shot Omniglot. To do so, run

   ```
   python protonet.py
   ```

   with the appropriate command line arguments. These arguments have defaults specified in the file. To specify a non-default value for an argument, use the following syntax:

   ```
   python protonet.py --argument1 value1 --argument2 value2
   ```

   Use 15 query examples per class per task. Depending on how much memory your GPU has, you may want to adjust the batch size. Do not adjust the learning rate from its default of 0.001.

   As the model trains, model checkpoints and TensorBoard logs are periodically saved to a `log_dir`. The default `log_dir` is formatted from the arguments, but this can be overriden. You can visualize logged metrics by running

   ```
   tensorboard --logdir logs/
   ```

   and navigating to the displayed URL in a browser. If you are running on a remote computer with server capabilities, use the `--bind_all` option to expose the web app to the network. Alternatively, consult the Azure guide for an example of how to tunnel/port-forward via SSH.

   To resume training a model starting from a checkpoint at `{some_dir}/state{some_step}.pt`, run

   ```
   python protonet.py --log_dir some_dir --checkpoint_step some_step
   ```

   If a run ended because it reached `num_train_iterations`, you may need to increase this parameter.

(a) (20 pt) Submit a plot of the validation query accuracy over the course of training.
Hint: you should obtain a query accuracy on the validation split of at least 99

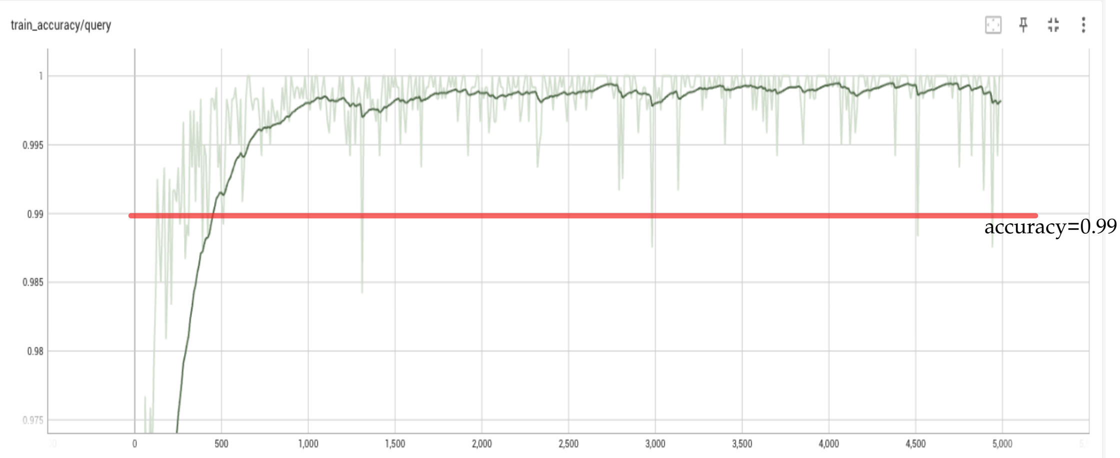


figure1: validation_query_accuracy with n_support=5

3. 4 accuracy metrics are logged. For the above run, examine these in detail to reason about what the algorithm is doing.

   (a) (5 pt) Is the model placing support examples of the same class close together in feature space or not? Support your answer by referring to specific accuracy metrics.
   Answer:It can be seen from the accuracy of the support in the val phase that the value is basically maintained above 0.998, which indicates that the samples of the same class are close together in the feature space, and the samples of different classes are spaced apart .

   (b) (5 pt) Is the model generalizing to new tasks? If not, is it overfitting or underfitting? Support your answer by referring to specific accuracy metrics.
   Answer:By looking at the support_accuracy and quey_accuracy of the val stage, the accuracy can converge to more than 0.99, indicating that the generalization performance of the model task dimension is better.
   In addition, by comparing val_query_support and train_query_ support, the latter is better than the former, and the latter fluctuates greatly, and the model has an overfitting phenomenon

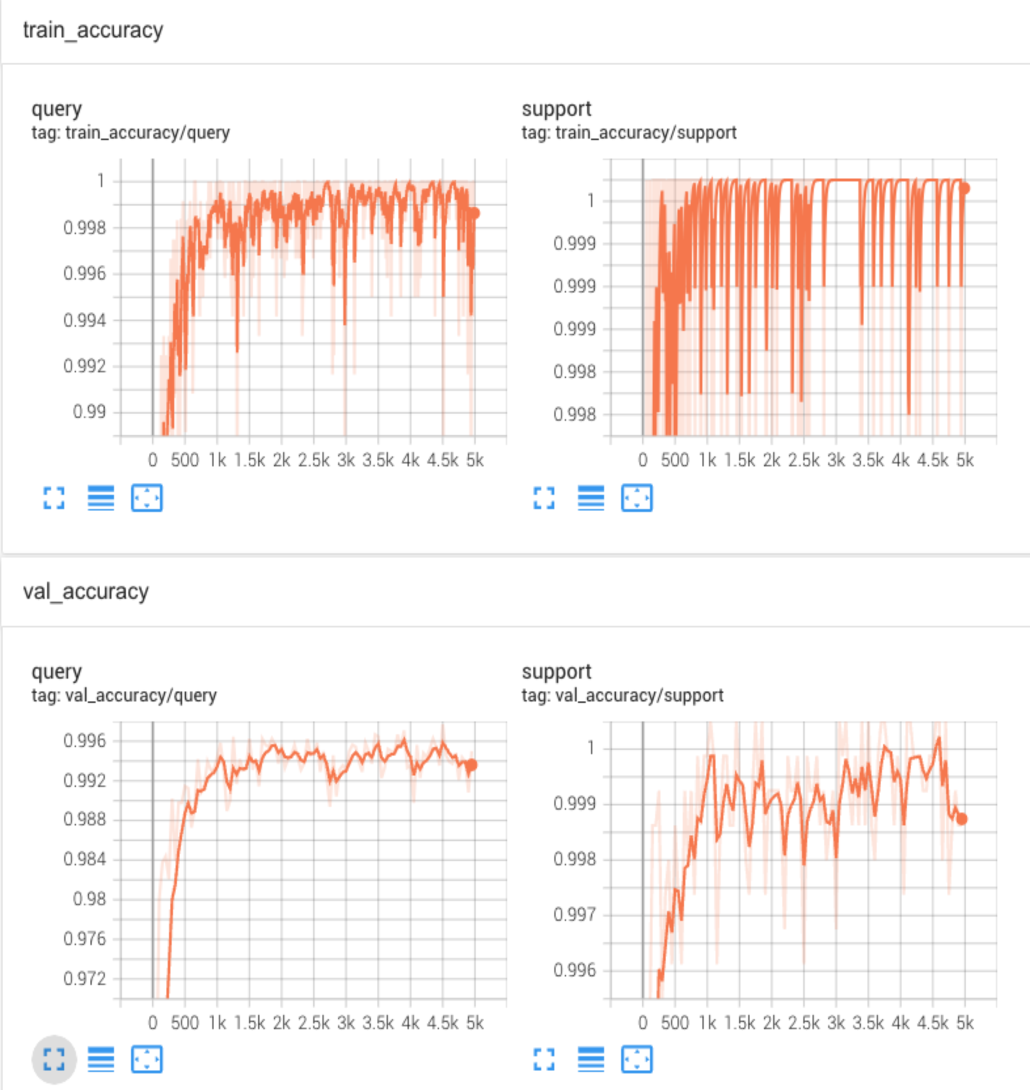


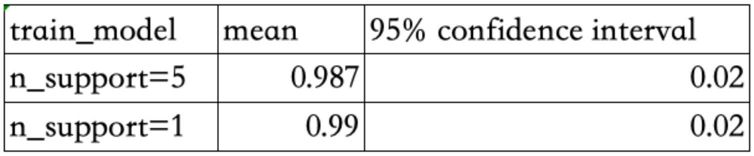
figure2: 4 accuray metrics with n_support=5

4. We will now compare different settings at training time. Train on 5-way 1-shot tasks with 15 query examples per task.

   (a) (3 pt) Compare your two runs (5-way 1-shot training and 5-way 5-shot training) by assessing test performance on 5-way 1-shot tasks. To assess a trained model on test tasks, run

   ```
   python protonet.py --test
   ```

   appropriately specifying `log_dir` and `checkpoint_step`. Submit a table of your results with 95% confidence intervals.



train_model	mean	95% confidence interval
n_support=5	0.987	0.02
n_support=1	0.99	0.02

table1:test performance on 5-way 1-shot task

run code for test performance of 5-way 1-shot training on 5-way 1-shot tasks :

```
python  protonet.py --log_dir  './logs/protonet/omniglot.way:5.support:1.query:15.lr:0.001.batch_size:16'
--checkpoint_step  4200 --test  --num_way 5 --num_support 1
```

   (b) (2 pt) How did you choose which checkpoint to use for testing for each model?

   Answer: According to the val_query_loss minimum, for 5-shot training, the loss is around check_point=3900, and its value reaches the lowest point (0. 0111), for 1-shot training, the loss is around check_point=4200, and its value reaches the lowest point (0.023).

   (c) (5 pt) Is there a significant difference in the test performance on 5-way 1-shot tasks? Explain this by referring to the protonets algorithm.

   Answer：For the Protonets model, the 1-shot training task is more difficult, and the model will test better

Part 2: Model-Agnostic Meta-Learning (MAML) [2]

Algorithm Overview

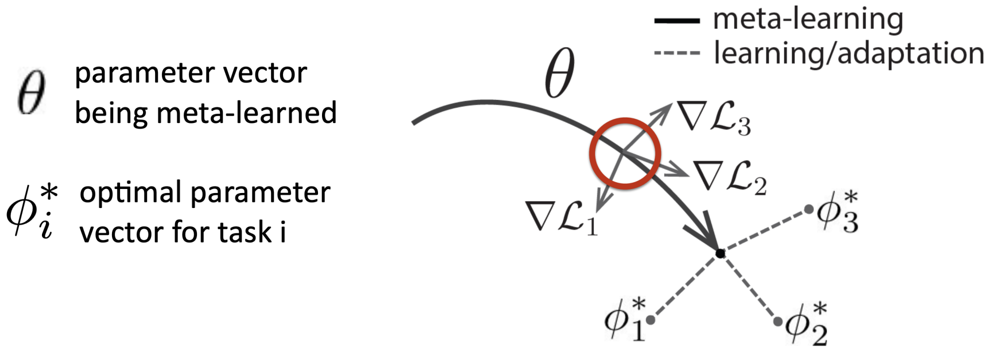


Figure 2: MAML in a nutshell. MAML tries to find an initial parameter vector θ that can be quickly adapted via task gradients to task-specific optimal parameter vectors.

As discussed in lecture, the basic idea of MAML is to meta-learn parameters θ that can be quickly adapted via gradient descent to a given task. To keep notation clean, define the loss $\mathcal{L}$ of a model with parameters ϕ on the data $\mathcal{D}_i$ of a task $\mathcal{T}_i$ as

$$\mathcal{L}(\phi, \mathcal{D}_i) = \frac{1}{|\mathcal{D}_i|} \sum_{(x^j, y^j) \in \mathcal{D}_i} -\log p_\phi(y = y^j | x^j) \tag{6}$$

Adaptation is often called the *inner loop*. For a task $\mathcal{T}_i$ and L inner loop steps, adaptation looks like the following:

$$\begin{aligned}
\phi^1 &= \phi^0 - \alpha \nabla_{\phi^0} \mathcal{L}(\phi^0, \mathcal{D}_i^{\text{tr}}) \\
\phi^2 &= \phi^1 - \alpha \nabla_{\phi^1} \mathcal{L}(\phi^1, \mathcal{D}_i^{\text{tr}}) \\
&\vdots \\
\phi^L &= \phi^{L-1} - \alpha \nabla_{\phi^{L-1}} \mathcal{L}(\phi^{L-1}, \mathcal{D}_i^{\text{tr}})
\end{aligned} \tag{7}$$

where we have defined $\theta = \phi^0$.

Notice that only the support data is used to adapt the parameters to ϕ^L. (In lecture, you saw ϕ^L denoted as ϕ_i.) To optimize θ in the *outer loop*, we use the same loss function (6) applied on the adapted parameters and the query data:

$$\mathcal{J}(\theta) = \mathbb{E}_{\mathcal{T}_i \sim p(\mathcal{T}), (\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{ts}}) \sim \mathcal{T}_i} \left[\mathcal{L}(\phi^L, \mathcal{D}_i^{\text{ts}}) \right] \tag{8}$$

For this homework, we will further consider a variant of MAML [5] that proposes to additionally learn the inner loop learning rates α. Instead of a single scalar inner learning rate for all parameters, there is a separate scalar inner learning rate for each parameter group (e.g. convolutional kernel, weight matrix, or bias vector). Adaptation remains the same as in vanilla MAML except with appropriately broadcasted multiplication between the inner loop learning rates and the gradients with respect to each parameter group.

The full MAML objective is

$$\mathcal{J}(\theta, \alpha) = \mathbb{E}_{\mathcal{T}_i \sim p(\mathcal{T}), (\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{ts}}) \sim \mathcal{T}_i} \left[\mathcal{L}(\phi^L, \mathcal{D}_i^{\text{ts}}) \right] \tag{9}$$

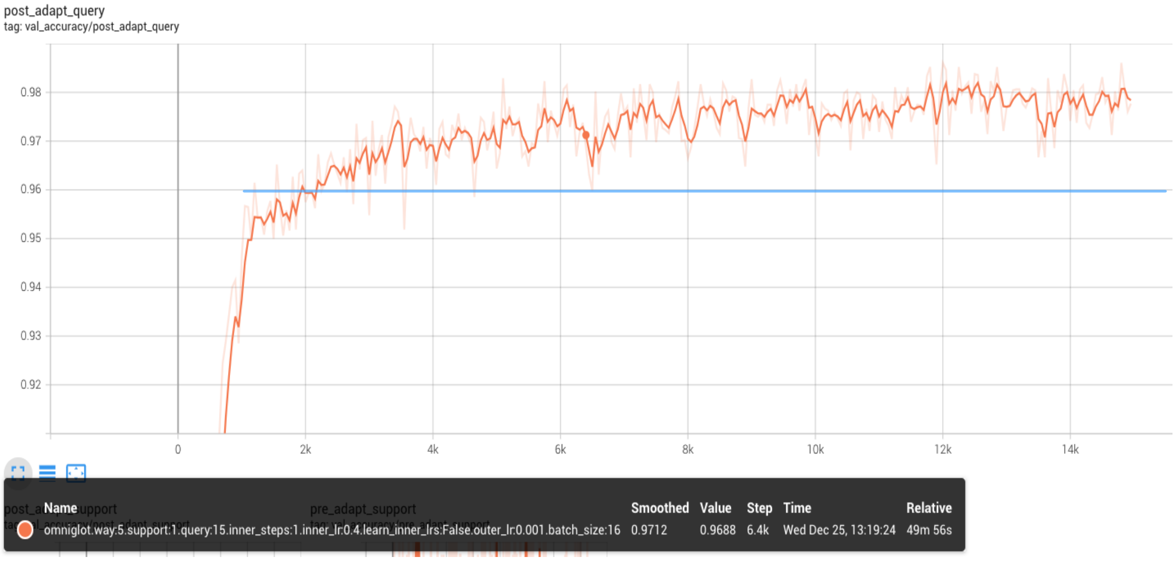
Like before, we will use minibatches to approximate (9) and use the Adam optimizer.

Problems

1. In the `maml.py` file, complete the implementation of the `MAML._inner_loop` and `MAML._outer_step` methods. The former computes the task-adapted network parameters (and accuracy metrics), and the latter computes the MAML objective (and more metrics). Pay attention to the inline comments and docstrings.
   Hint: the simplest way to implement `_inner_loop` involves using `autograd.grad`.
   Hint: to understand how to use the Boolean `train` argument of `MAML._outer_step`, read the documentation for the `create_graph` argument of `autograd.grad`.

   Assess your implementation of vanilla MAML on 5-way 1-shot Omniglot. Comments from the previous part regarding arguments, checkpoints, TensorBoard, resuming training, and testing all apply. Use 1 inner loop step with a **fixed** inner learning rate of 0.4. Use 15 query examples per class per task. Do not adjust the outer learning rate from its default of 0.001. Note that MAML generally needs more time to train than protonets.

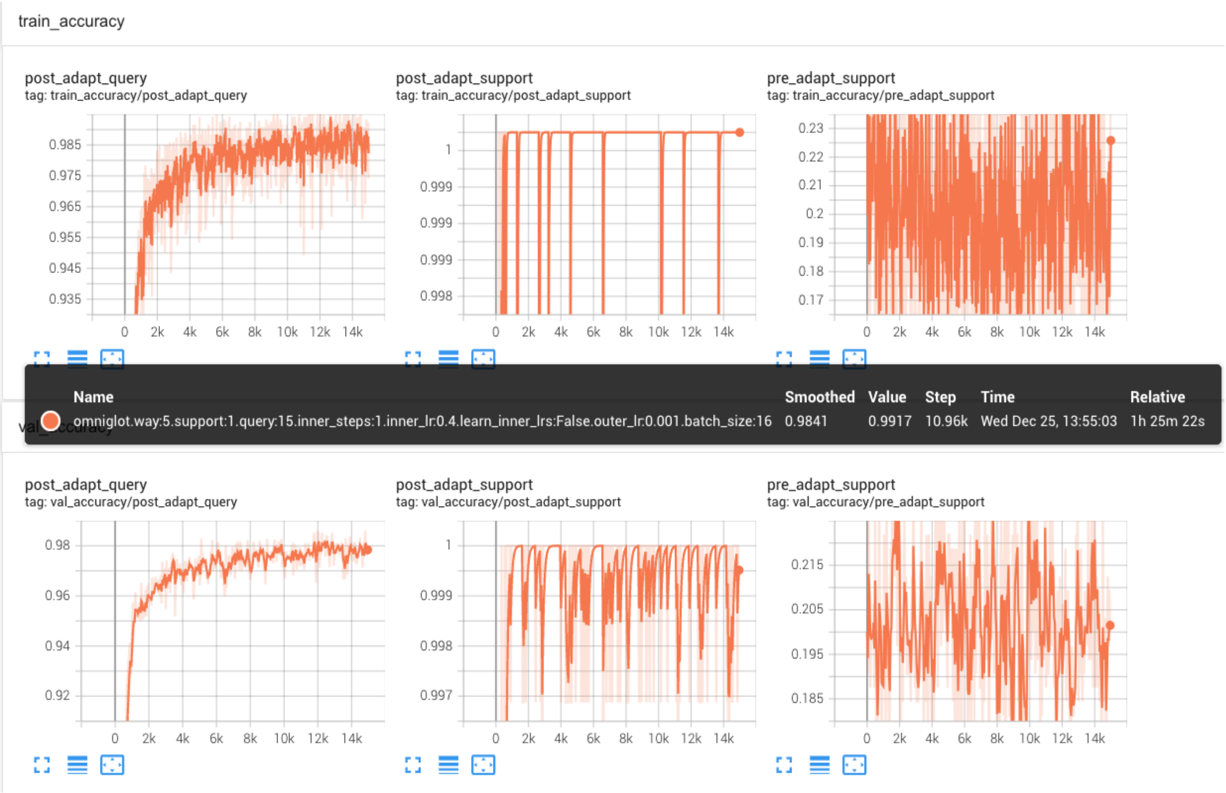
(a) (20 pt) Submit a plot of the validation post-adaptation query accuracy over the course of training.
Hint: you should obtain a query accuracy on the validation split of at least 96%.



	Name	Smoothed	Value	Step	Time	Relative
●	omniglot.way:5.support:1.query:15.inner_steps:1.inner_lr:0.4.learn_inner_lrs:False.outer_lr:0.001.batch_size:16	0.9712	0.9688	6.4k	Wed Dec 25, 13:19:24	49m 56s

figure 2_1_a: plot of validation post-adaption query accuracy

2. 6 accuracy metrics are logged. Examine these in detail to reason about what MAML is doing.



Name	Smoothed	Value	Step	Time	Relative
● omniglot.way:5.support:1.query:15.inner_steps:1.inner_lr:0.4.learn_inner_lrs:False.outer_lr:0.001.batch_size:16	0.9841	0.9917	10.96k	Wed Dec 25, 13:55:03	1h 25m 22s

figure 2_2: 6 accuracy metrics with inner_lr=0.4,inner_steps=1,learn_inner_lrs=False

(a) (10 pt) State and explain the behavior of the `train_pre_adapt_support` and `valpreadaptsupport`accuracies. Your answer should explicitly refer to the task sampling process.
Hint: consult the `omniglot.py`file.
Answer: Training phase NUM_TRAIN_CLASSES = 1100, validation stage only has 100 classes for choice, which results in a training phase where the similarity between tasks is low and the pre_adap_support fluctuates more severely(train_process 0.17-0.23,valid_process:0.185-0.215).

(b) (5 pt) Compare the `train_pre_adapt_support` and `train_post_adapt_support` accuracies. What does this comparison tell you about the model? Repeat for the corresponding `val` accuracies.
Answer: Both train_data and valid_data experienced a dramatic increase in accuracy after inner_loop iterations (from around 0.18 to around 0.99 on average).

(c) (5 pt) Compare the `train post adapt support` and `train post adapt query` accuracies. What does this comparison tell you about the model? Repeat for the corresponding `val` accuracies.
Answer:Whether it's train_data or valid_data, the post_adapt_support is much better than the post_adapt_12query. The reason for this is simple, because post-adapt parameters are optimized using support_data data and then used on support_data raw data, and the results are definitely very good.

3. Try MAML with the same hyperparameters as above except for a fixed inner learning rate of 0.04.

(a) (3 pt) Submit a plot of the validation post-adaptation query accuracy over the course of training with the two inner learning rates $(0.04, 0.4)$.

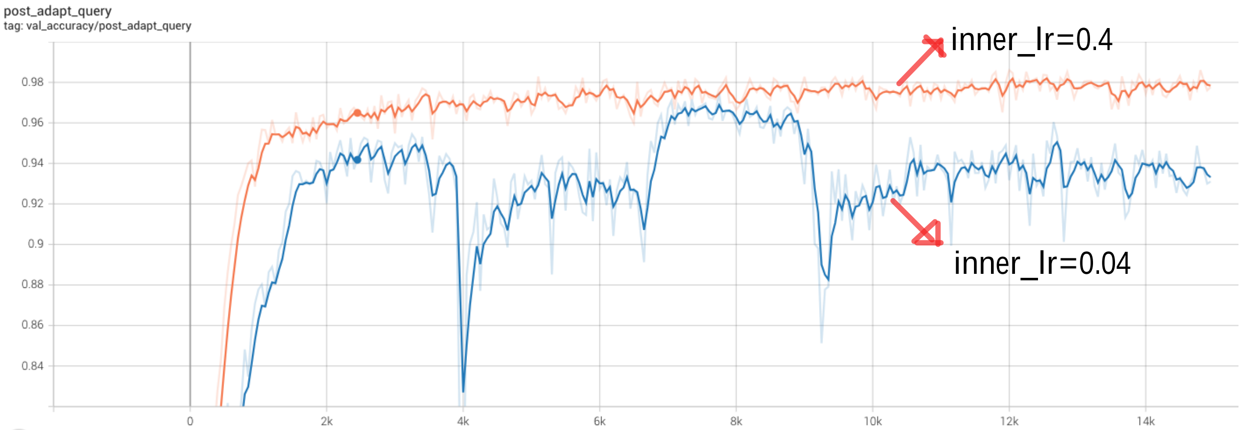


figure 2_3_a: validationpost-adaptationqueryaccuracywiththetwoinnerlearningrates(0.04,0.4).

(b) (2 pt) What is the effect of lowering the inner learning rate on (outer-loop) optimization and generalization?
Answer:Compared to larger learning rates, smaller inner_lr have the following characteristics in valid_post_adap_query
1. The effect of the model cannot be converged and the volatility is large
2. The overall effect of the model is poor
The reason is that the inner_lr is too small, resulting in a small update amplitude of model parameters, and it is easy to fall into the local optimum

4. Try MAML with a fixed inner learning rate of 0.04 for 5 inner loop steps.

   (a) (3 pt) Submit a plot of the validation post-adaptation query accuracy over the course of training with the two number of inner loop steps $(1, 5)$ with inner learning rate 0.04.

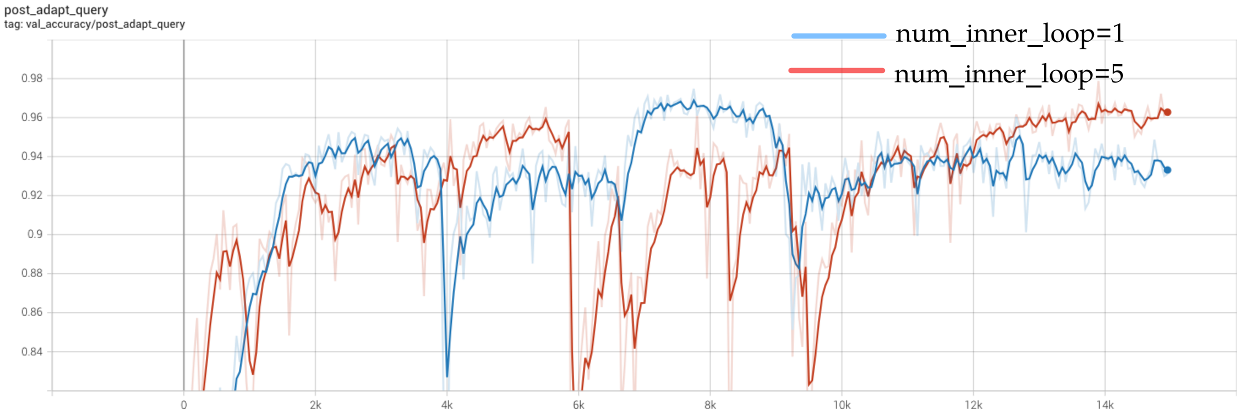


figure 2_4_a: validation post-adaption query accuracy with inner_loop(1,5)

   (b) (2 pt) What is the effect of increasing the number of inner loop steps on (outer-loop) optimization and generalization?

   Answer:The model effect fluctuates more dramatically, but the final model convergence effect is better than the former model accuracy.

5. Try MAML with learning the inner learning rates. Initialize the inner learning rates with 0.4.

   (a) (3 pt) Submit a plot of the validation post-adaptation query accuracy over the course of training for learning and not learning the inner learning rates, initialized at 0.4.

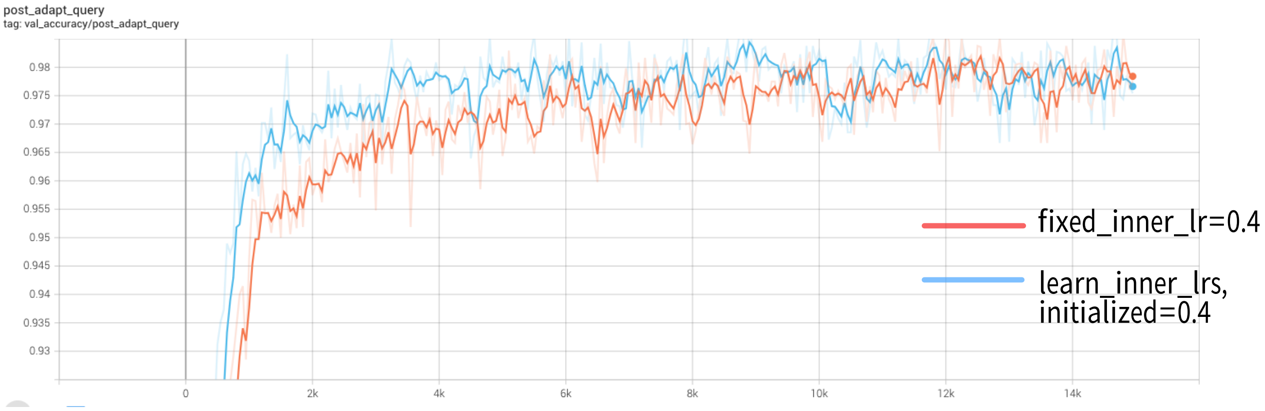


figure 2_5_a: validationpost-adaptationqueryaccuracy

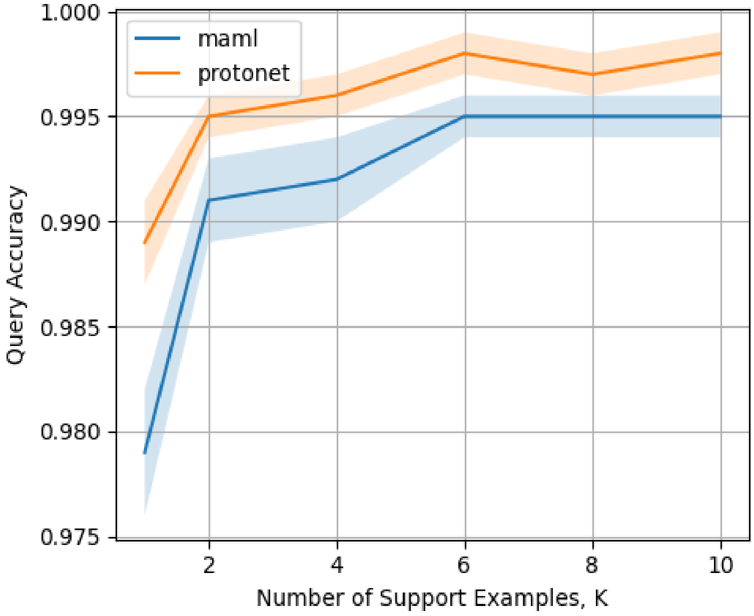
   (b) (2 pt) What is the effect of learning the inner learning rates on (outer-loop) optimization and generalization?
   Answer: 1. Initial stage. The model is improving faster 2. Before step=10k, the overall model effect is better。

Part 3: More Support Data at Test Time

In practice, we usually have more than 1 support example at test time. Hence, one interesting comparison is to train both algorithms with 5-way 1-shot tasks (as you've already done) but assess them using more shots.

1. Use the protonet trained with 5-way 1-shot tasks, and the MAML trained with **learned** inner learning rates initialized at 0.4. Try $K = 1, 2, 4, 6, 8, 10$ at test time. Use $Q = 10$ for all values of K.

   (a) (10 pt) Submit a plot of the test accuracies for the two models over these values of K with the 95% confidence intervals as error bars or shaded regions.



   (b) (5 pt) How well is each model able to use additional data in a task without being explicitly trained to do so?

   Answer: Whether it is the maml model or the protonet model, as the number of num_support increases, the model effect will gradually improve and finally converge; compared with the two, the overall effect of protonet is higher than that of maml, and the maml effect is greatly affected by the number of num_support. When num_support increases from 1 to 2, the maml effect increases more significantly.

A Note

You may wonder why the performance of these implementations don't match the numbers reported in the original papers. One major reason is that the original papers used a different version of Omniglot few-shot classification, in which multiples of 90° rotations are applied to each image to obtain 4 times the total number of images and characters. Another reason is that these implementations are designed to be pedagogical and therefore straightforward to implement from equations and pseudocode as well as trainable with minimal hyperparameter tuning. Finally, with our use of batch statistics for batch normalization during test (see code), we are technically operating in the *transductive* few-shot learning setting.

References

[1] Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In *Advances in Neural Information Processing Systems*, pages 4077–4087, 2017.

[2] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 1126–1135. JMLR. org, 2017.

[3] Brenden M. Lake, Ruslan Salakhutdinov, and Joshua B. Tenenbaum. Human-level concept learning through probabilistic program induction. *Science*, 350(6266):1332–1338, 2015.

[4] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[5] Antreas Antoniou, Harrison Edwards, and Amos Storkey. How to train your maml. *arXiv preprint arXiv:1810.09502*, 2018.