# CS 330 Autumn 2023 Homework 2
# Prototypical Networks and Model-Agnostic Meta-Learning

Due Wednesday October 25, 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, since the maml training could take a while on CPU. **To change the training to happen on GPU, use our provided command line argument** `--device gpu` **when you run** `maml.py` **and** `protonet.py`**.**
- **Submit to Gradescope**
  1. the two python files in the submission folder, namely `protonet.py` and `maml.py`
  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.

## Autograding

As in previous homework, we provide autograder for this assignment to facilitate your development. You can simply run:

```
python grader.py
```

to unit-test your implemented code. The maximum points you can see is 13 points, we also leave 19 points to the hidden cases, which you will see when you submit to Gradescope. This makes a total of 32 points for the coding section.

# 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 $n$
- $f_\theta$: neural network parameterized by $\theta$
- $\mathcal{T}_i$: 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 $\theta$

## Part 1: Prototypical Networks (Protonets) [1]

### Algorithm Overview

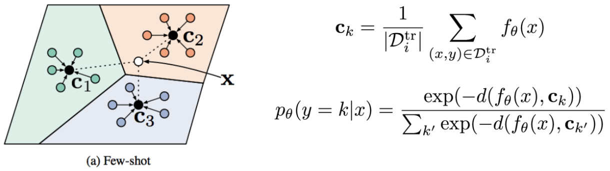

$\mathbf{c}_2$
$\mathbf{c}_1$
$\mathbf{x}$
$\mathbf{c}_3$
(a) Few-shot
$\mathbf{c}_k = \frac{1}{|\mathcal{D}_i^{\text{tr}}|} \sum_{(x,y)\in\mathcal{D}_i^{\text{tr}}} f_\theta(x)$
$p_\theta(y=k|x) = \frac{\exp(-d(f_\theta(x), \mathbf{c}_k))}{\sum_{k'} \exp(-d(f_\theta(x), \mathbf{c}_{k'}))}$

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 $\theta$ 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. **Analysis of No Required Shuffling**

   (a) **[3 points (Written)]** We have provided you with `omniglot.py`, which contains code for task construction and data loading. 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
   it stems from the fact that in black-box methods we use architectures like LSTM's (or transformers) that are designed to learn the contextual relationships between the input data, which means they may just memorize the ordering instead of actually learning, which makes shuffling crucial in such settings.
   in contrast, non-parametric methods-like Protonet-work by embedding the input data in a high dimensional space, and the core goal is to keep the distance of similar data points smaller compared to the ones of different classes, which means that it has nothing to do with the contextual relationship of the data points.
   to put it simple, methods like Protonet are order-invariant, which makes shuffling unnecessary as opposed to black-box models.

2. **Implementation**

   (a) **[8 points (Coding)]** 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.

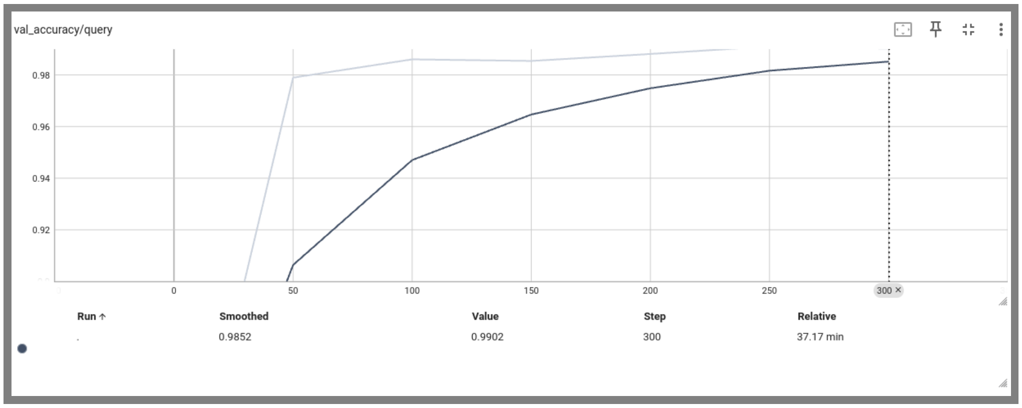
   To resume training a model starting from a checkpoint at {some_dir}/state{some_step}.pt, run

```
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.

   (b) **[3 points (Plots)]** 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 $99\%$.

   **Note**: the accuracies might be slightly lower than expected since the models were not trained for complete 5000 epochs since I had no GPU access.



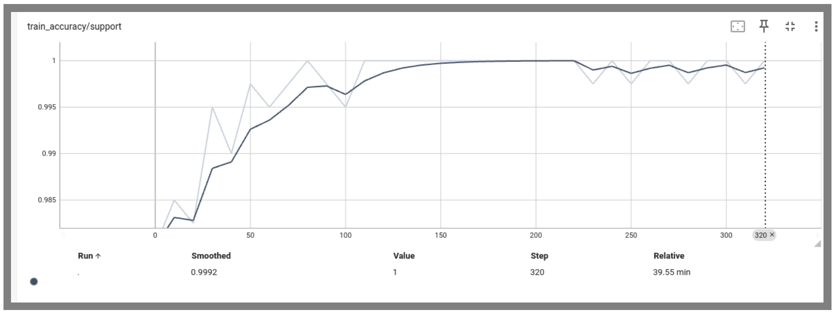
| Run ↑ | Smoothed | Value | Step | Relative |
|---|---|---|---|---|
| . | 0.9852 | 0.9902 | 300 | 37.17 min |

Figure 2: Protonet 5-way 5-shot

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

   (a) **[3 points (Written)]** 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



train_accuracy/support

| Run ↑ | Smoothed | Value | Step | Relative |
|---|---|---|---|---|
| . | 0.9992 | 1 | 320 | 39.55 min |

Figure 3: Protonet 5-way 5-shot training support accuracy

Protonet first embeds the support examples; it then calculates the centroid of the embeddings for each class and classifies each example based on the distribution over the classes given by the distance between each point and the centroids of each class.
More distance between the points of a class would increase their distance from the centroid of the class and increase the chance for the points to be closer to the centroids of other classes, which would lead the algorithm to misclassify those points and decrease the training accuracy for the support set.
As shown in 3, we can see an increase in the accuracy for support examples over the course of training, which means there is enough inter-cluster distance between the classes for the model to classify the points correctly.
So in short, the answer is YES.

   (b) **[3 points (Written)]** Is the model generalizing to new tasks? If not, is it overfitting or underfitting? Support your answer by referring to specific accuracy metrics.

reaching an accuracy of $99\%$ on the validation set as shown in 2, suggests that the model is capable of generalizing to new tasks.

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

   (a) **[2 points (Written)]** 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.

   | **Model** | **Mean** | **95% Conf** |
   |---|---|---|
   | **5-Way 1-shot** | 0.983 | 0.002 |
   | **5-Way 5-Shot** | 0.976 | 0.003 |

   (b) **[2 points (Written)]** How did you choose which checkpoint to use for testing for each model?

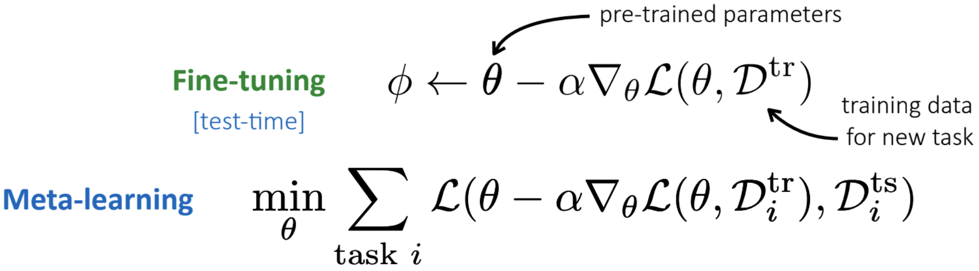
   Answer
   The steps with the highest validation query accuracy were chosen for each model.

   (c) **[2 points (Written)]** Is there a significant difference in the test performance on 5-way 1-shot tasks? Explain this by referring to the protonets algorithm.

   Answer
   The 5-way 1-shot model has a better performance compared to the 5-way 5-shot model. The reason for this lies in the logic behind Protonet. When training 5-way 1-shot, We are forcing the model to put each query example closer to every single support example of the same class compared to other classes. The 5-way 5-shot model on the other hand, puts the query example closer to the proxy (i.e the centroid) of the given support examples compared to the ones of other classes. Such a model may not perform as well when given just one support example. This is because a single support example of a wrong class may be closer to the query example compared to the support example of the same class as the given query. For this reason, the 5-way 1-shot model is more robust in such settings, and performs better.

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

### Algorithm Overview



pre-trained parameters

**Fine-tuning**

[test-time]

$$\phi \leftarrow \boldsymbol{\theta} - \alpha \nabla_{\theta} \mathcal{L}(\theta, \mathcal{D}^{\text{tr}})$$

training data
for new task

**Meta-learning**

$$\min_{\boldsymbol{\theta}} \sum_{\text{task } i} \mathcal{L}(\boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \mathcal{D}_i^{\text{tr}}), \mathcal{D}_i^{\text{ts}})$$

Figure 4: MAML in a nutshell. MAML tries to find an initial parameter vector $\theta$ 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 $\theta$ 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 $\phi$ 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 $\phi^L$. (In lecture, you saw $\phi^L$ denoted as $\phi_i$.) To optimize $\theta$ 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 $\alpha$. 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. **Implementation**

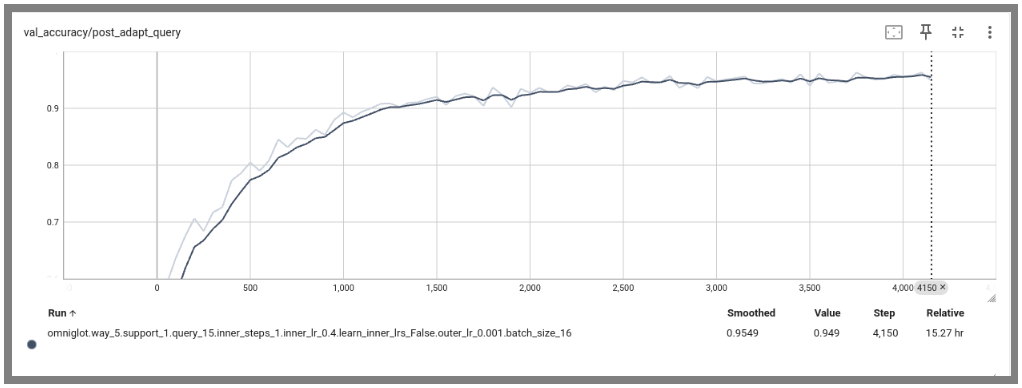
   (a) **[24 points (Coding)]** In the `maml.py` file, complete the implementation of the `MAML._inner_loop` and
   `MAML._outer_step` methods. The former computes the task-adapted network parameters (and accuracy metrics), and the latter computes the MAML objective (and more metrics). Pay attention to the inline comments and docstrings.

   **Hint**: the simplest way to implement `_inner_loop` involves using `autograd.grad`. Check the documentation here on how to use and call the function. In essence, the function computes and returns the sum of gradients of outputs with respect to the inputs. Compared with the PyTorch `backward` function which we typically deal with, `autograd.grad` is a non-mutable function and will not accumulate the gradients on the model parameters.
   **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. Run the command:

   ```
   python maml.py
   ```

(b) **[3 points (Plots)]** 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 $97\%$.



| Run ↑ | Smoothed | Value | Step | 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 | 0.9549 | 0.949 | 4,150 | 15.27 hr |

Figure 5: MAML 5-way 1-shot, inner_lr=0.4,outer_lr=0.001,inner_steps=1

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

   (a) **[10 points (Written)]** State and explain the behavior of the `train_pre_adapt_support` and `val_pre_adapt_support` accuracies. Your answer should explicitly refer to the **task sampling process**.
   **Hint**: consult the `omniglot.py` file. Your explanation should explicitly refer to i) the task format, ii) the model's pre-adaptation parameters, and iii) how images in each task are labeled.

   Answer

   In my experiments, the plots for `train_pre_adapt` and `val_pre_adapt` show oscillating behaviors.
   Checking the `omniglot.py` which provides the dataset, we see that it has a random sampler which gives a random set of classes for a task each time. The dataset then takes `num_way` support samples from each class and labels them in order of appearance.
   Since the sampler returns random classes, we may get the same label for two completely different classes for two tasks.
   On the other hand, it may also be the case that classes close to each other be given similar labels due to randomness. If such thing happens, the model may memorize the pattern appeared in the labels, and if a task appears that has different classes for the same labels, out model's accuracy will decrease, since it just uses the pre-adapted parameters that may have memorized the pattern and not care about the structure of the support examples.

   (b) **[5 points (Written)]** 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

   The post-adapt accuracy is always greater than that of the pre-adapt for both `train` and `val`. The reason for this, as mentioned above, is that the pre-adapt parameters may memorize some patterns that do not apply to the given task. adapting the model's parameters forces the model to learn from the given task and not rely on pre-adapted parameters or memorized patterns.

   (c) **[5 points (Written)]** 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

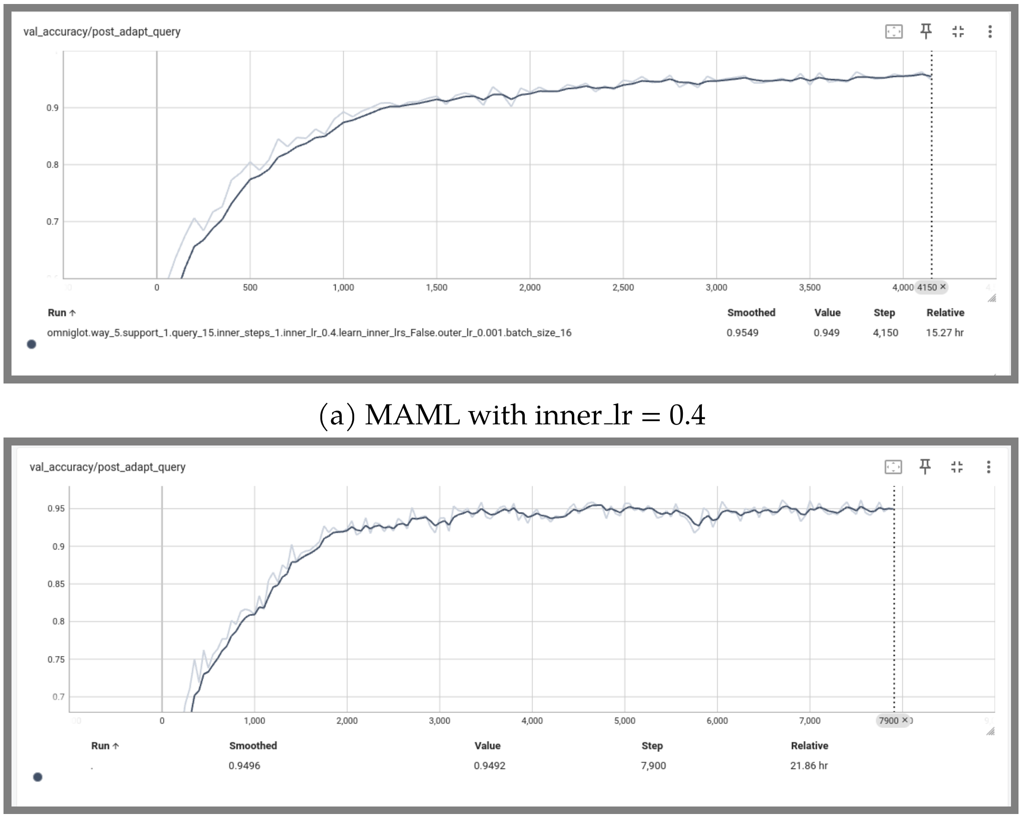
   The two increase in parallel.
   During adaptation, the model is trying to learn the structures specific to the

given task. A higher support accuracy after adaptation means the model has successfully captured the underlying structure of the support examples, which means it would now perform better if we give it a task of the same structure, which is the case about query examples.
The same applies for `val` accuracies.
Although, the rate of growth for support examples is somewhat higher, which may be due to the fact that we have more query examples than support ones.

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

   (a) **[3 points (Plots)]** Submit a plot of the validation post-adaptation query accuracy over the course of training with the two inner learning rates $(0.04, 0.4)$. Run the command:

   ```
   python maml.py --inner_lr 0.04
   ```



| Run ↑ | Smoothed | Value | Step | 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 | 0.9549 | 0.949 | 4,150 | 15.27 hr |

(a) MAML with inner_lr = 0.4

| Run ↑ | Smoothed | Value | Step | Relative |
|---|---|---|---|---|
| . | 0.9496 | 0.9492 | 7,900 | 21.86 hr |

(b) MAML with inner_lr=0.04

Figure 6: MAML Learning Rate Comparison

   (b) **[2 points (Written)]** What is the effect of lowering the inner learning rate on (outer-loop) optimization and generalization?

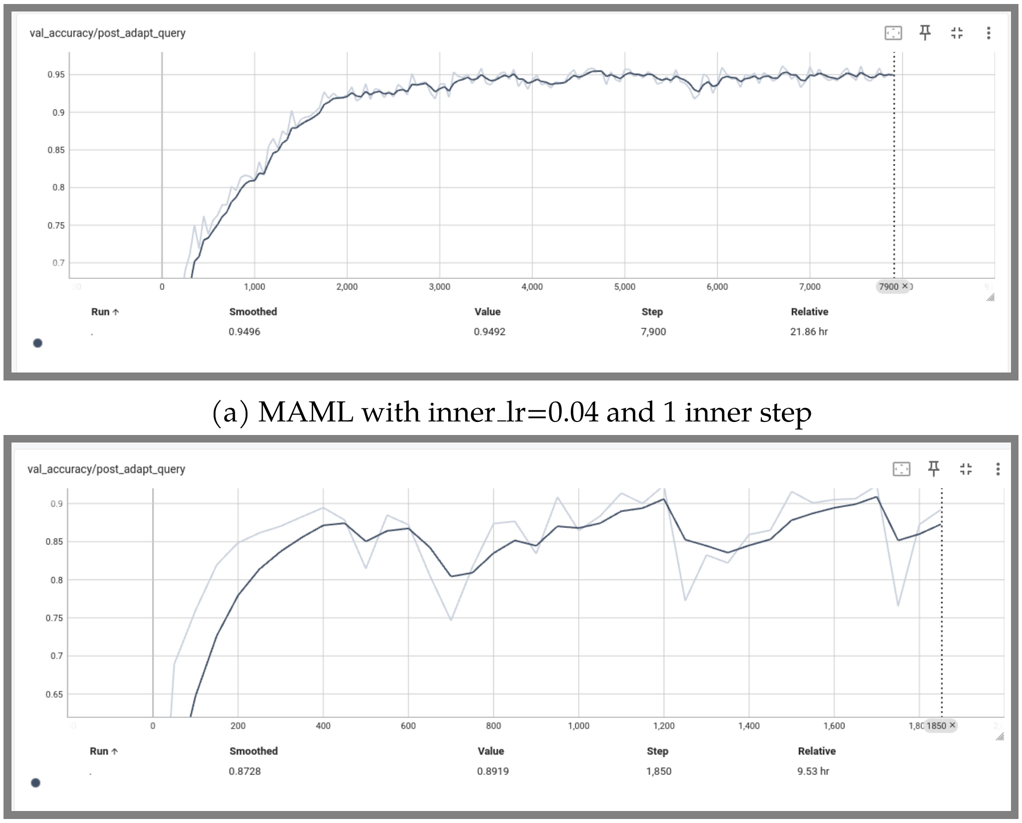
   Answer

   Lowering the inner learning rate would hinder the model's adaptation to new tasks since the updates made in the inner loop at each step are less significant. This could lead to slower convergence rate and lower generalization capability.

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

   (a) **[3 points (Plots)]** 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 $0.04$. Run the command:

   ```
   python maml.py --inner_lr 0.04 --num_inner_steps 5
   ```



| Run ↑ | Smoothed | Value | Step | Relative |
|---|---|---|---|---|
| . | 0.9496 | 0.9492 | 7,900 | 21.86 hr |

(a) MAML with inner_lr=0.04 and 1 inner step

| Run ↑ | Smoothed | Value | Step | Relative |
|---|---|---|---|---|
| . | 0.8728 | 0.8919 | 1,850 | 9.53 hr |

(b) MAML with inner_lr=0.04 and 5 inner steps

Figure 7: Comparison of number of inner steps

   (b) **[2 points (Written)]**What is the effect of increasing the number of inner loop steps on (outer-loop) optimization and generalization?

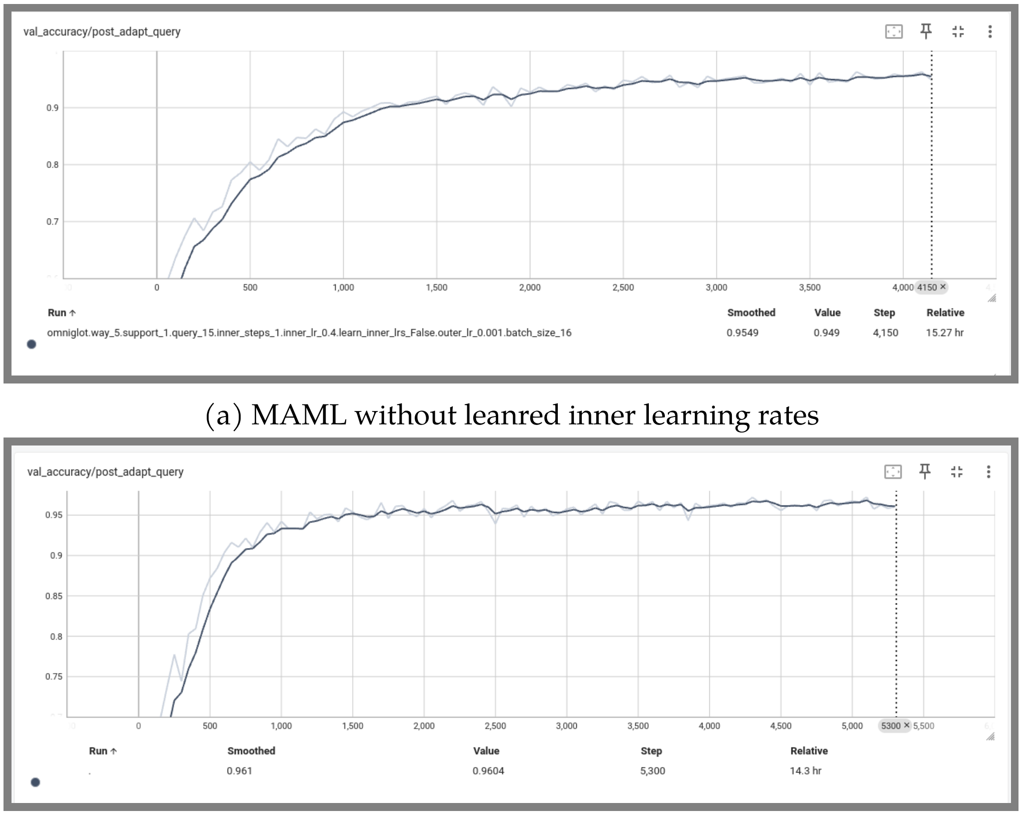
   Answer

   We can see faster convergence and better generalization for 5 inner steps compared at the same number of iterations.

5. **Experiments** Try MAML with learning the inner learning rates. Initialize the inner learning rates with $0.4$.

   (a) **[3 points (Plots)]** 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 $0.4$. Run the command:

```
python maml.py --learn_inner_lrs
```



| Run ↑ | Smoothed | Value | Step | 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 | 0.9549 | 0.949 | 4,150 | 15.27 hr |

(a) MAML without leanred inner learning rates

| Run ↑ | Smoothed | Value | Step | Relative |
|---|---|---|---|---|
| . | 0.961 | 0.9604 | 5,300 | 14.3 hr |

(b) MAML with learned inner learning rates

Figure 8: MAML Learning Inner Rate Comparison

   (b) **[2 points (Written)]** What is the effect of learning the inner learning rates on (outer-loop) optimization and generalization?

   Answer

   Learning the inner learning rated leads to faster convergence and overall better generalization as shown in 8

## 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. **Experiment** 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 $K$. **Please closely check** `protonet.py` **and** `maml.py` **and the commands we provided in above questions on how to set these hyperparameters with command line arguments**.

   (a) **[10 points (Plots)]** 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.

   Answer

   **Note**: As I mentioned above, this plot does not show the actual potential of the models since I did not train them for the default number of epochs due to lack of GPU access.

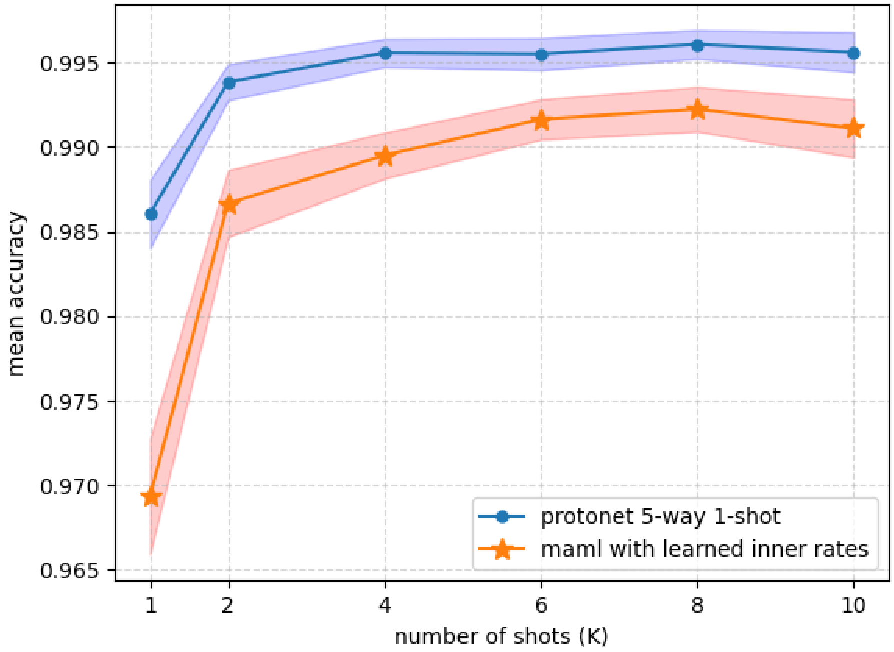


Figure 9: MAML and Protonet Comparison with the parameters set as mentioned in the question

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

Answer

As shown in 9, Protonet shows more capability in using additional data since it achieves higher mean accuracy over the test set.

## Part 4: Meta-learning for Real Dataset

In the previous homework and this homework, you have been experimenting with the Omniglot dataset. In this section, you are going to run your implemented Prototype network on the TDC Metabolism dataset [6], a real bio-related dataset used to predict compound properties. In TDC Metabolism, the authors select 8 sub-datasets related to drug metabolism from the whole TDC dataset [7], including CYP P450 2C19/2D6/3A4/1A2/2C9 Inhibition, CYP2C9/CYP2D6/CYP3A4 Substrate. The aim of each dataset is to predict whether each drug compound has the corresponding property. Correspondingly, the input to your Protonet is going to be a vector of molecule features. Take a look at the referenced paper if you are interested.

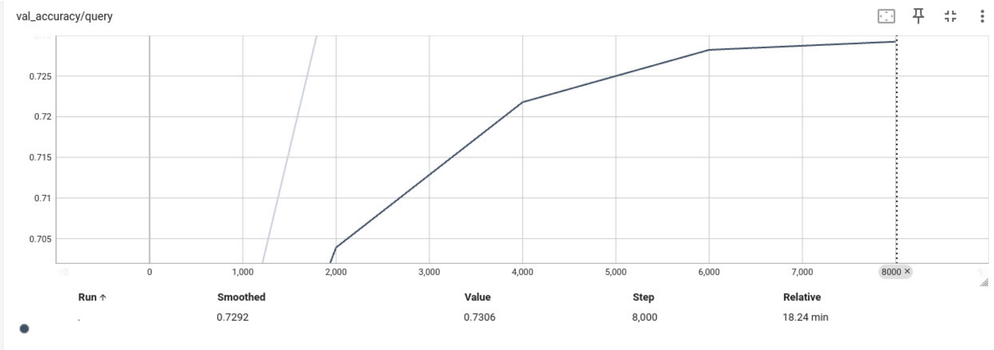
As the first step, please download the dataset here. Next, run the following command (can be found in `run_bio.sh`):

```
python3 run_metabolism.py --num_way 2 --num_support 5 --num_query 10 --batch_size 4 --num_train_iterations 8000 --learning_rate 0.0005 --datadir [DIR] --device gpu
```

Replace [DIR] with the folder path containing your downloaded dataset.

1. **[3 points (Written and Plots)]**Attach a screenshot of Tensorboard logs and report your final printed validation query accuracy with ci95(confidence interval 95%) here:

   Answer



| Run ↑ | Smoothed | Value | Step | Relative |
|---|---|---|---|---|
| . | 0.7292 | 0.7306 | 8,000 | 18.24 min |

Figure 10: Metabolism Validation Accuracy

**Final Validation Query Accuracy**: 0.731
**ci95**: 0.004

## 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 $90^\circ$ 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.

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