## INDIAN INSTITUTE OF TECHNOLOGY, KANPUR

## COURSE PROJECT REPORT

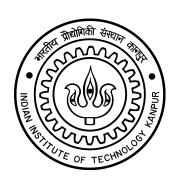
# **Bayesian Meta Learning**

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Department of Computer Science and Engineering



#### **Abstract**

Our project is on..

#### Subsection (if any) Name

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## 1 Literature Review

MAML has been designed to enable fast adaptation to unseen tasks by training on statistically related tasks. The algorithm is Model-Agnostic which means that it can be used on any model trained through gradient-descent.

#### 1.1 Problem Formulation

The paper presents a generic formulation applicable to tasks like regression, classification and reinforcement learning. Let f denote the common model for all tasks with  $\theta$  being the central parameter to be learned. It maps input x to output a. Each Task is denoted by

$$\mathcal{T}: \{L(x_1, a_1, ..., x_H, a_H), q(x_1), q(x_{t+1}|x_t, a_t), H\}$$

here L is the task specific loss function,  $q(x_1)$  is the distribution of inputs,  $q(x_{t+1}|x_t,a_t)$  is the transition probability for all states , and episode length is H.

H is specifically for non-iid data, for example the unfolding of reinforcement learning training sample. For the supervised iid classification and regression experiments, H=1.

#### 1.2 Algorithm

 $p(\mathcal{T})$  is the distribution over tasks over which we would train and test the meta-learning model. We will follow a K-Shot learning setting. First, a batch of tasks is sampled from  $p(\mathcal{T})$  and for each sample task  $\mathcal{T}_i$ , K inputs are sampled from  $q_i$ . These sampled inputs are used to learn task specific  $\theta_i$ s which were initialized to the central parameter  $\theta$ . Then, we sample K more inputs to evaluate that particular task with the  $\theta_i$ s. The sum of the loss incurred in all the tasks is used as the meta-loss function to find the optimal  $\theta$ .

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Input: p(\mathcal{T}): Distribution over tasks, \alpha, \beta: Step size hyper parameters Output: Parameters for this model randomly initialize \theta while not done do

| Sample batch of tasks \mathcal{T}_i \approx p(\mathcal{T}) for all \mathcal{T}_i do

| Sample K data points D = \{x^{(j)}, y^{(j)}\} from \mathcal{T}_i | Compute \nabla_{\theta} \mathcal{L}_{\mathcal{T}_i}(f_{\theta}) using K samples | Compute adapted parameters with gradient descent: \theta_i' = \theta - \alpha \nabla_{\theta} \mathcal{L}_{\mathcal{T}_i}(f_{\theta}) | Sample data points D_i' = \{x^{(j)}, y^{(j)}\} from \mathcal{T}_i for the meta update end

| Update \theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{\mathcal{T}_i \approx p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{(\theta_i')}) using each D_i' and \mathcal{L}_{\mathcal{T}_i}. end return \theta
```

Formally, for each  $\mathcal{T}_i$ , we calculate  $\theta'_i$  using the K samples by the following gradient descent update.

$$\theta_i' = \theta - \alpha \nabla_{\theta} \mathcal{L}_{\mathcal{T}_i}(f_{\theta})$$

Here  $\alpha$  is the step size and is a hyperparameter for the model. The meta objective is minimizing the sum of loss incurred in testing the sampled tasks against  $D_i$ s.

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

Finally, we perform the meta optimization step using gradient descent for the central parameter  $\theta$  on the loss function defined above.

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

## 1.3 Algorithm for supervised learning (Regression and classification)

To formalize in the context of meta learning, the loss function used for regression is the mean squared error loss as shown below

$$\mathcal{L}_{\mathcal{T}_i}(f_{\phi}) = \sum_{x^{(j)}, y^{(j)} \sim \mathcal{T}_i} ||f_{\phi}(x^{(j)}) - y^{(j)}||_2^2$$

where  $\phi$  is the model parameter. For classification, the loss function is given as

$$\mathcal{L}_{\mathcal{T}_i}(f_{\phi}) = \sum_{x^{(j)}, y^{(j)} \sim \mathcal{T}_i} y^{(j)} \log f_{\phi}(x^{(j)}) + (1 - y^{(j)}) \log(1 - f_{\phi}(x^{(j)}))$$

#### **Algorithm Review**

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#### **Bayesian ML**

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#### **Reinforcement Learning**

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## 2 Experiments

Most of the experiments carried out required automated differentiation through gradient update, for which we used TensorFlow. A signification computation was required in finding the second derivative, in the meta gradient update step, which involved backpropogating the meta-gradient through gradient calculation in meta gradient objective  $(\theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{T_i \approx p(T)} L_{T_i}(f_{\theta_i'}))$ .

We have tested the MAML algorithm for Regression and Classfication problem. Now let's discuss each of these experiment in details.

## 2.1 Regression

We tested our model on the task of regressing from the input to output of a sine wave, where each task had a different amplitude and phase, where amplitude varies within [0.1, 5.0] and phase varies within  $[0, \pi]$ . Note that input and output in our problem are just 1 dimensional. Datapoints are sampled uniformly from [-5.0, 5.0] and the loss function is simply the mean sqaured error between prediction and the ground truth.

#### 2.1.1 Architecture

Our regressor is a neural network model which has 2 hidden layers of 40 hidden units, and each each containing activation function as ReLU.

While training hyperparameter  $\alpha = 0.01$ , and our meta optimizer is Adam [4].

Classification
Conclusion
Subsection (if any) Name
Future Work
Subsection (if any) Name
Acknowledgments

## References

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