Mid-Term Project Report: MODEL AGNOSTIC META LEARNING

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***Abstract*—This report presents the progress made in a machine learning project during the mid-term evaluation phase. The project began with learning Python and scientific computing tools, followed by classical machine learning theory, deep learning using PyTorch, and finally the study of a modern research paper on Model-Agnostic Meta-Learning (MAML). The goal of the project is to understand how machine learning systems can be trained to generalize and adapt quickly to new tasks using limited data.**

I. Introduction

Machine learning systems are traditionally trained on large datasets to perform a specific task. However, in real-world settings, models must often adapt quickly to new problems using very few examples. This project was designed to build a complete understanding of machine learning, starting from programming foundations and classical algorithms, and progressing toward deep learning and modern meta-learning research.

The work completed so far includes learning Python libraries, understanding classical machine learning, training neural networks using PyTorch, and studying a research paper on Model-Agnostic Meta-Learning (MAML).

II. Python and Scientific Computing

The first stage of the project focused on Python programming and scientific libraries required for machine learning. NumPy was used for numerical computation and matrix operations, Pandas for data manipulation and preprocessing, and Matplotlib for data visualization. These tools are essential for loading datasets, exploring statistical properties, and visualizing model behavior.

III. Classical Machine Learning

Classical machine learning methods were studied to understand the theoretical foundation of learning algorithms.

A. Learning Paradigms

Three major types of learning were covered: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning uses labeled data, unsupervised learning identifies patterns in unlabeled data, and reinforcement learning trains agents by interacting with an environment.

B. Regression and Classification

Regression models predict continuous values, while classification models assign inputs to discrete categories. Models such as linear regression, logistic regression, k-nearest neighbors, and decision trees were studied.

C. Bias–Variance Trade-off

The bias–variance trade-off describes the balance between model simplicity and complexity. High bias leads to underfitting, while high variance causes overfitting. A good model balances both to generalize well.

D. Machine Learning Workflow

The standard machine learning pipeline consists of data collection, preprocessing, train-test splitting, model training, evaluation, and hyperparameter tuning.

IV. Deep Learning with PyTorch

Deep learning models use neural networks trained with gradient descent. Using PyTorch, neural network architectures were implemented, loss functions were defined, and models were trained using backpropagation. These experiments demonstrated how deep networks automatically learn feature representations from data.

V. Motivation for Meta-Learning

Traditional machine learning assumes large datasets and fixed tasks. However, many real-world problems require rapid learning from small datasets. Meta-learning, or learning to learn, addresses this problem by training models that can adapt quickly to new tasks.

VI. Model-Agnostic Meta-Learning (MAML)

The research paper studied in this project was "Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks" by Finn et al. MAML aims to find model parameters that can be quickly adapted to new tasks using a small number of gradient updates.

Let $p(T)$ denote a distribution of tasks. For each task T_i, the model parameters θ are updated using:

$$\theta_i' = \theta - \alpha \nabla_\theta L_{T_i}(f_\theta)$$

The meta-objective is then:

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_i L_{T_i}(f_{\theta_i'})$$

This trains the model so that it performs well after only a few gradient steps on a new task.

VII. Experimental Results

The paper evaluated MAML on regression, classification, and reinforcement learning tasks.

A. Few-Shot Regression

MAML was tested on sinusoidal regression tasks where amplitude and phase vary. The results showed that MAML could fit new sine waves using only a few data points, while conventional pretraining failed to generalize.

B. Few-Shot Classification

On Omniglot and MiniImagenet datasets, MAML achieved state-of-the-art accuracy in 1-shot and 5-shot classification, outperforming many specialized few-shot learning models.

C. Reinforcement Learning

MAML was also applied to navigation and robot locomotion tasks. The results showed that agents trained with MAML could adapt to new goals and velocities much faster than pretrained or randomly initialized models.

VIII. Conclusion

This mid-term phase of the project established a strong foundation in machine learning, deep learning, and meta-learning. The study of MAML demonstrated how modern research aims to create models that learn efficiently and adapt quickly. This provides a strong base for further exploration in advanced machine learning research.

References

[1] C. Finn, P. Abbeel, and S. Levine, "Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks," in *Proceedings of the 34th International Conference on Machine Learning*, 2017.