Reenal Boddul

Data Scientist

Agenda

01 About Me

02 Paper Presentation

About Me

- Data Scientist
- ~6 + years of experience in Software Development and Project Implementation
- 3 years' experience as Data Scientist Machine Learning and Deep Learning Developer
- Publish my success story in WINDS Pune, India (https://wimldspune.wordpress.com/2022/04/02/reenal-boddul/) (https://halloffame.ineuron.ai/achiever/Reenal-Zampal-(Boddul)- AtQRPU)
- Open-Source Contributor
- Mentor, and Speaker, GenAI Content Creator
- Playing Cricket, Reading, Traveling, Cooking

Introduction to -MAML

Model-Agnostic Meta-Learning (MAML) enables rapid adaptation to new tasks, mimicking human learning. It focuses on identifying easily adaptable model parameters and minimizing the data needed for task adaptation.

Human Learning vs. Machine Learning

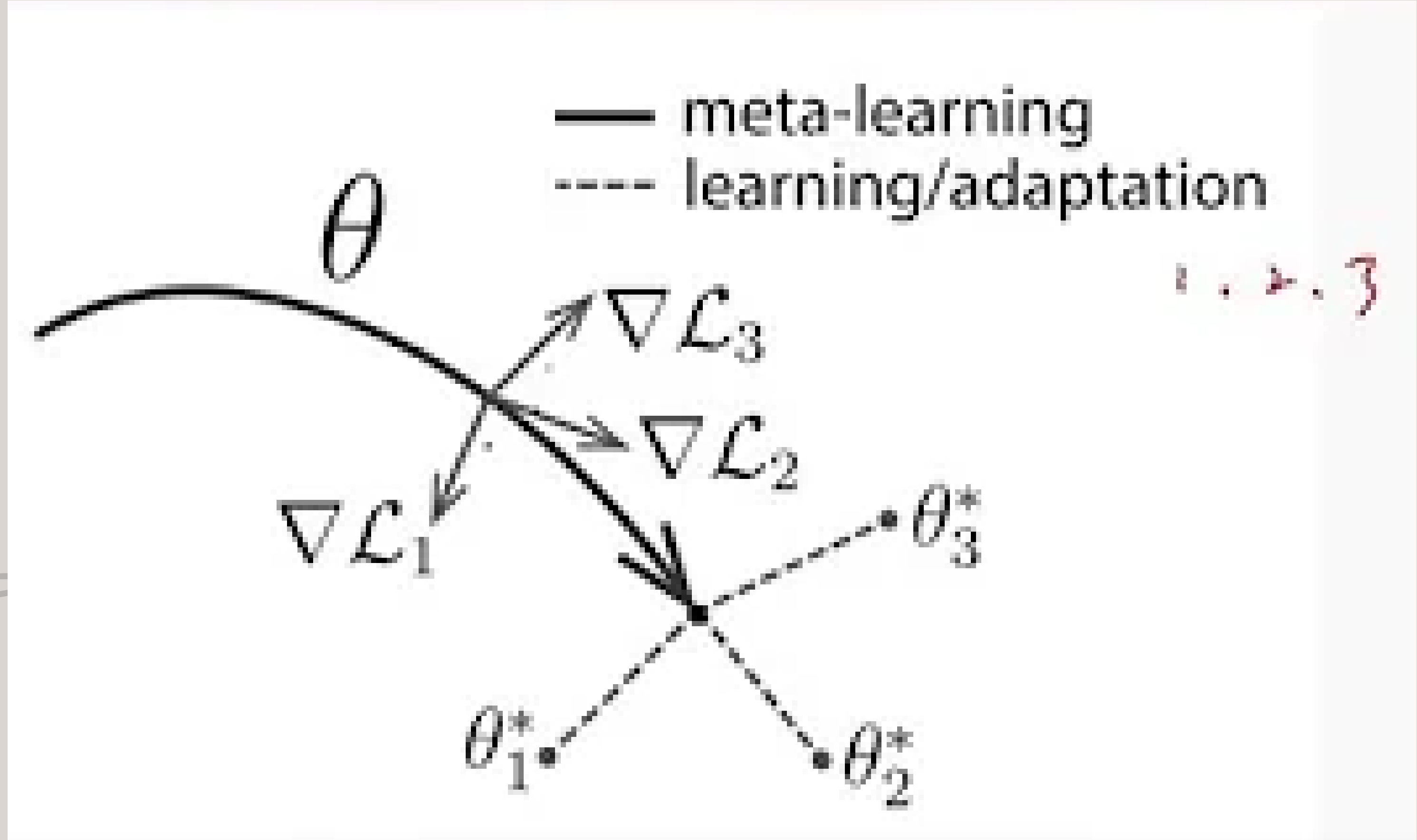
Human Learning

- Humans can recognize objects from just a few examples, demonstrating the efficiency of human learning.
- Learning new skills after a few minutes of experience is a common human ability.
- Human intelligence allows for quick adaptation to new tasks, requiring minimal data.

Machine Learning

- Traditional machine learning models require significantly more data points to learn new tasks.
- Efficiency is lower compared to human learning, especially when tasks require adaptability to new data scenarios.
- Machine learning algorithms typically need extensive data sets for training, making them less efficient in scenarios with limited data.

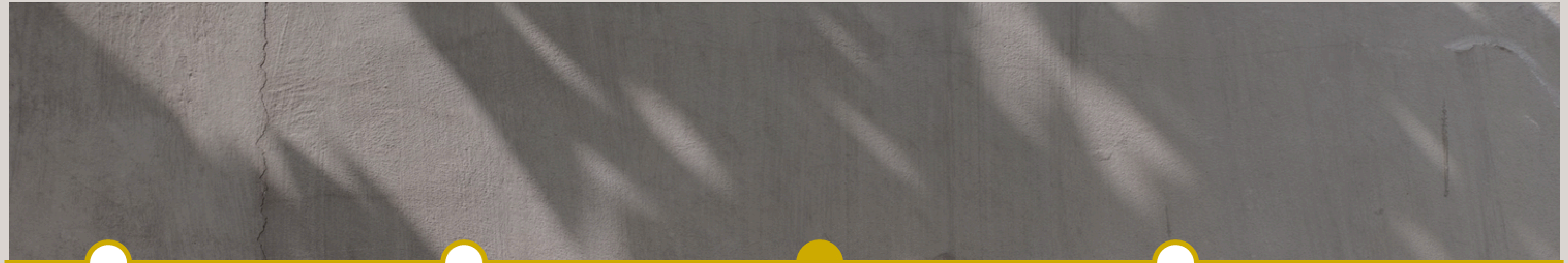
Goal



- The goal of MAML is to train a model on a variety of learning tasks, such that it can solve new learning tasks using only a small number of training samples.
- In MAML, the model's parameters are explicitly trained such that a small number of gradient steps with a small amount of training data from a new task will produce good generalization performance on that task.
- Find parameters that are easy to adapt for new tasks
- Small number of gradient updates
- *fast learning on a new task

The MAML Algorithm Illustrated

The MAML Algorithm Illustrated



Initial Training

Initial learning phase where the model is trained on multiple tasks with limited data for each task.

Trained model on initial tasks
Limited data utilization
Basic task understanding

Meta-Learning

Meta-learning phase to capture the essential features of the tasks and learn how to adapt quickly to new data.

Parameter identification for fast adaptation
Core task feature extraction
Meta-optimization for quick task learning

Gradient Calculation

Gradient calculation for each task to determine the direction of parameter update for task optimization.

Gradient computation for each task
Directional parameter update determination
Optimal update direction for task performance

Parameter Update

Parameter update step guided by the calculated gradients to improve task performance and achieve adaptation.

Parameter update guided by task gradients
Improved task performance
Enhanced adaptation capability

Learning and Meta-Learning Phases

- MAML involves two primary phases: the initial learning phase and the meta-learning phase.
- During the initial learning phase, the model is trained on a specific task with a dataset.
- The meta-learning phase utilizes a support or validation dataset to further adapt the model to new tasks, enhancing its ability for rapid task adaptation.
- This two-phase approach mirrors the way humans learn, enabling machines to quickly grasp new concepts with minimal data.

Novelty of MAML

- Model-Agnostic: MAML can be applied to any model trained with gradient descent, regardless of its architecture or learning problem.

- Fast Adaptation: MAML enables rapid learning on new tasks with only a few examples

- Meta-Learning of Initial Parameters: Instead of learning an update rule or learning rule, MAML focuses on training the initial model parameters for fast adaptation.

- No Additional Parameters or Constraints: Unlike other meta-learning methods, MAML does not introduce additional parameters or require specific model architectures.

Thank You