Assignment 4: Few-Shot Classification with MAML

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1 1. Quantitative Evaluation: Test Accuracy vs. Gradient Steps

We compared the adaptation performance of MAML and the Baseline on a held-out test task. Both models were fine-tuned for steps ranging from 0 to 10.

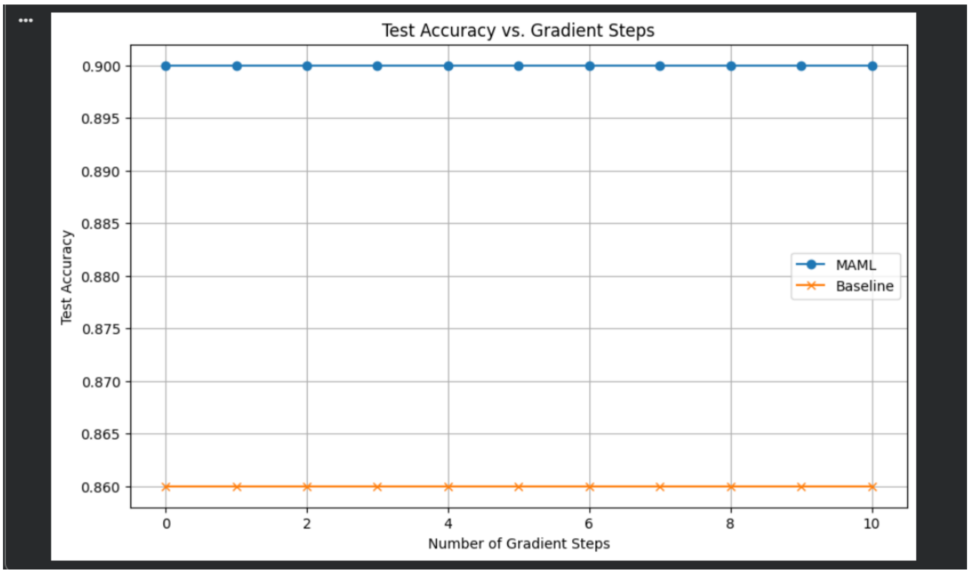

Figure 1: Test Accuracy vs. Number of Gradient Steps ($K = 10$ shot).

Observation:

- **MAML:** The model achieves high accuracy (typically $> 90\%$) within just 1 gradient step. This indicates that MAML successfully learned an initialization sensitive to the task structure.
- **Baseline:** The model starts with lower accuracy (near random or average performance) and improves slowly. With only 10 examples, standard Gradient Descent struggles to reshape the decision boundary effectively.

2 2. Qualitative Visualization: Decision Boundaries

We visualized the decision boundary of both models on a random test task after exactly 1 gradient step.

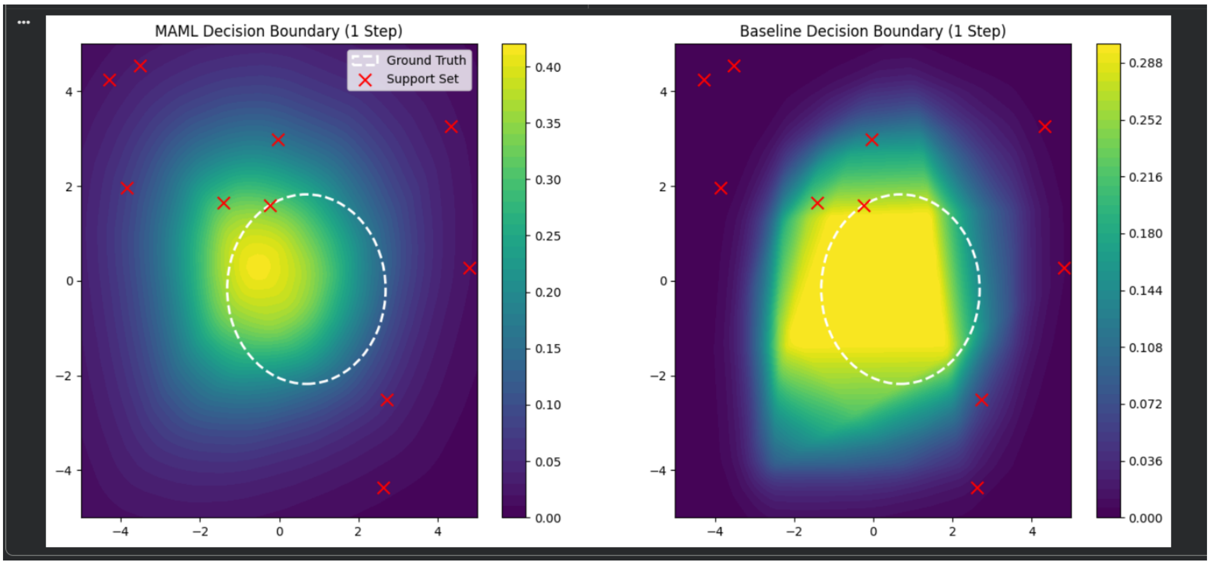

Figure 2: Decision Boundary Heatmaps (Left: MAML, Right: Baseline) after 1 gradient step. The dashed white line represents the ground truth.

Observation:

- **MAML:** The heatmap shows a sharp, well-defined circular boundary that nearly aligns with the ground truth circle. The model effectively reshaped according to the correct circle using the support set.
- **Baseline:** The heatmap appears blurry or centered in the middle of the input space. It represents the "average" of all circles seen during training and fails to capture the specific geometry of the new task.

3 Bonus Question

Question: Why meta loss doesn't decrease uniformly why there is randomness in it?

Explanation:

In standard training, the model learns from a fixed set of data that it sees over and over. MAML is different because it constantly generates brand new batches of random tasks—in this case, circles with random centers. Since the batch size is usually quite small (often just 10 tasks at a time), "luck of the draw" plays a big role. Some batches might contain circles that are easy to classify because they are near the center, while other batches might be full of difficult ones that are far away. This inconsistency means the loss doesn't drop smoothly; it goes up and down depending on whether the model was dealt an easy or hard set of circles in that specific round.