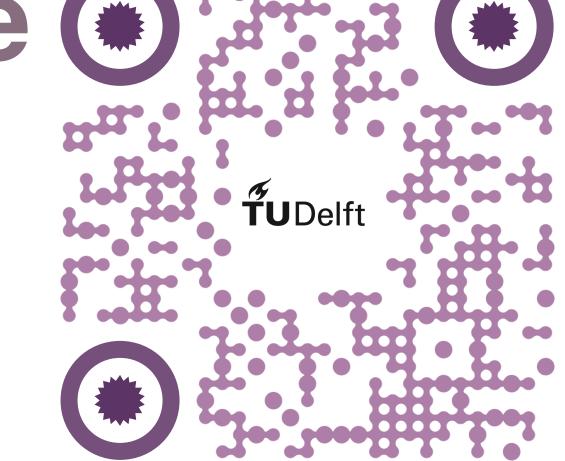
When MAML Learns Quickly Does It Generalize (*)

Well?

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1. Introduction

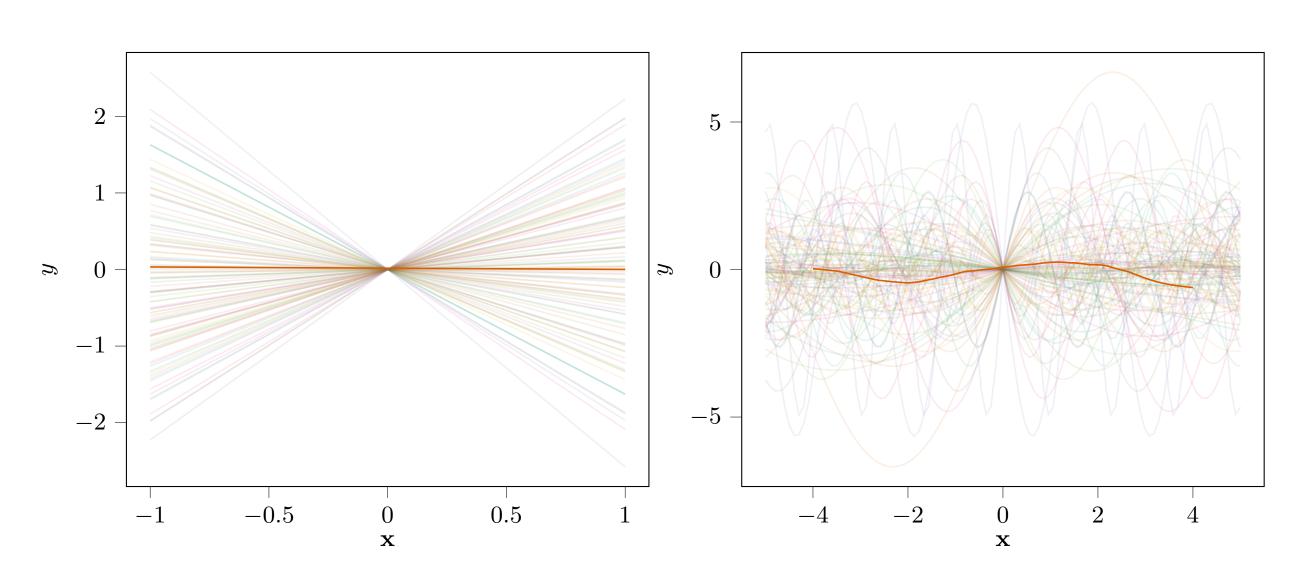
- Learning-to-Learn paradigm: leverages similar learning problems (tasks) for a specific similar data-scarce learning problem (task).
- MAML: tackles meta-learning problem by providing a model initialization for model parameters that facilitates quick adaptation and good generalization.

AIM: Investigating the effect of gradient step limitation.

3. Experimental Setup

Tasks: linear/nonlinear noisy ($\mathcal{N} \sim (0, \sigma^2)$) observations of functions $f(\mathbf{x})$

$$\mathbf{y} = f(\mathbf{x}) + \varepsilon, \tag{1}$$



- Estimator: model \hat{M} trained with a given dataset $\mathcal{Z} := \{\mathbf{x}_i, y_i\}_{i=0}^N$
- Performance: expected error over the task distribution $p_{\mathcal{T}}$ and data distribution $p_{\mathcal{Z}}$

$$\mathcal{E} := \iiint (\hat{\mathcal{M}}(\mathbf{x}) - y)^2 p(\mathbf{x}, y) p_{\mathcal{Z}} p_{\mathcal{T}} d\mathbf{x} dy d\mathcal{Z} d\mathcal{T}$$
 (2)

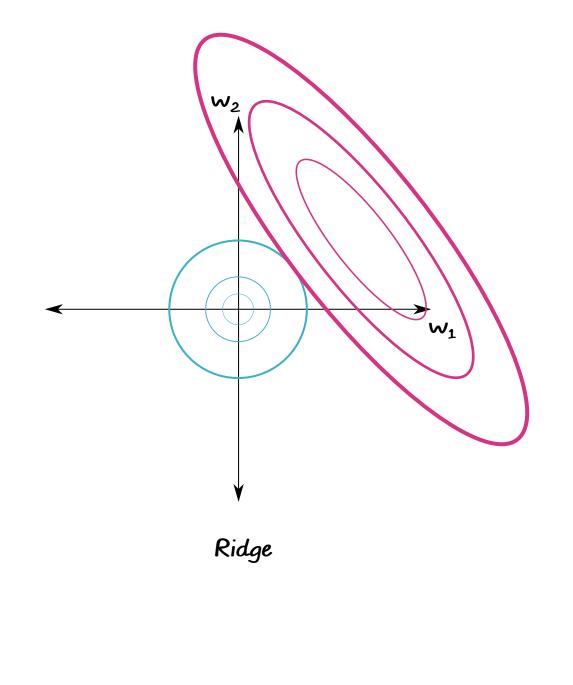
4. Baselines

2. MAML[?]

• Learn a model initialization $\bar{\mathbf{w}}_{meta}$

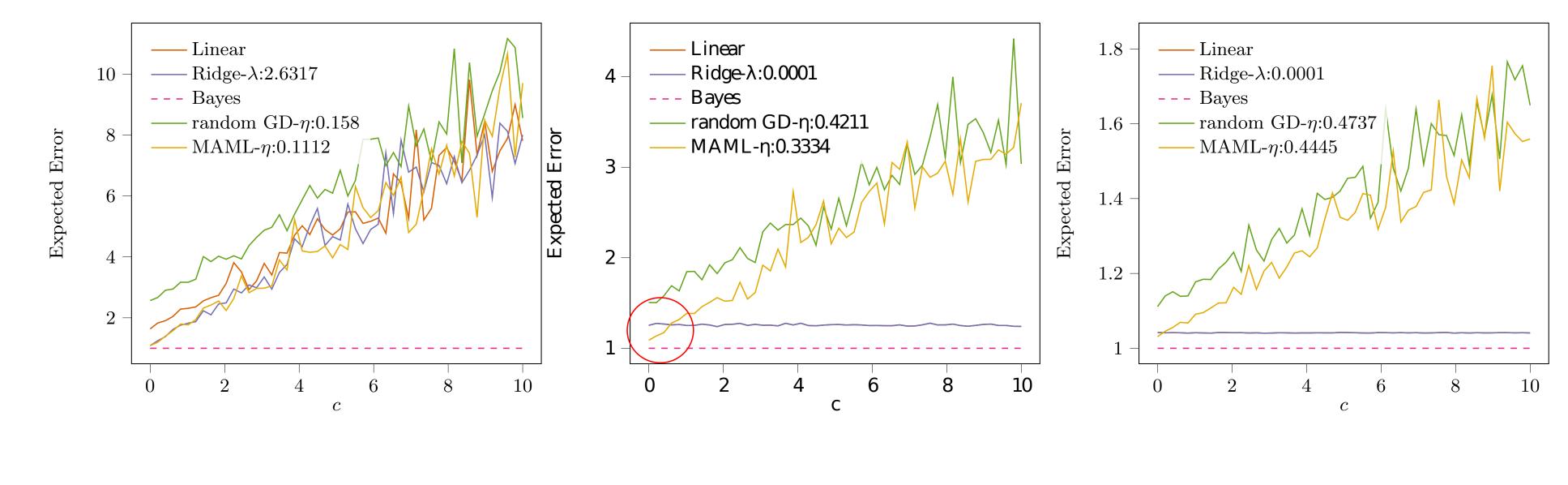
• From a M tasks $\{\mathcal{T}_i\}_{i=0}^M$

- Linear/Kernelized Ridge Regression
- Randomly Initialized Gradient Descent

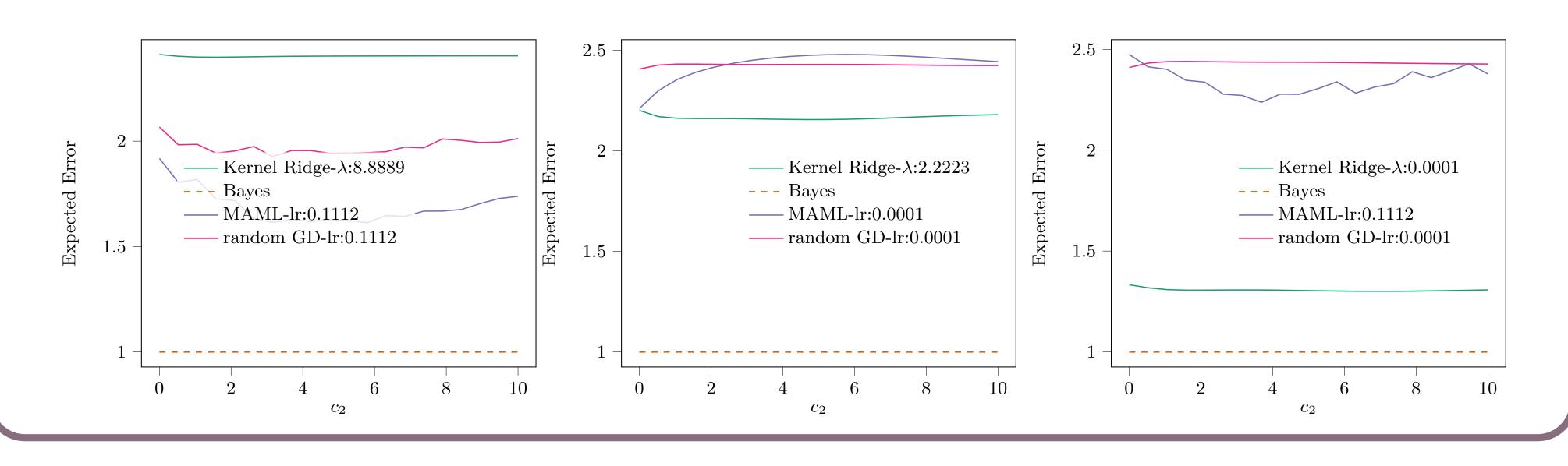


5. Results for Task Variance (N = 1, 10, 50)

• Linear problem: $f(x) := \mathbf{x}^T \mathbf{a}$



• Nonlinear problem: $f(x) := \sin(x + \phi)a$



6. Conclusions

If the adaptation gradient step for MAML is limited;

- Given enough data single-task learners can outperform MAML on expectation in most of the cases
- Task variance highly influences the performance of MAML on expectation.

8. Future Work

 Replicate the same study with the benchmark datasets widely used in metalearning problems.

7. References