When MAML Can Adapt Fast And How to Assist When it Cannot

Séb Arnold, Shariq Iqbal, Fei Sha

USC University of Southern California

Google AI

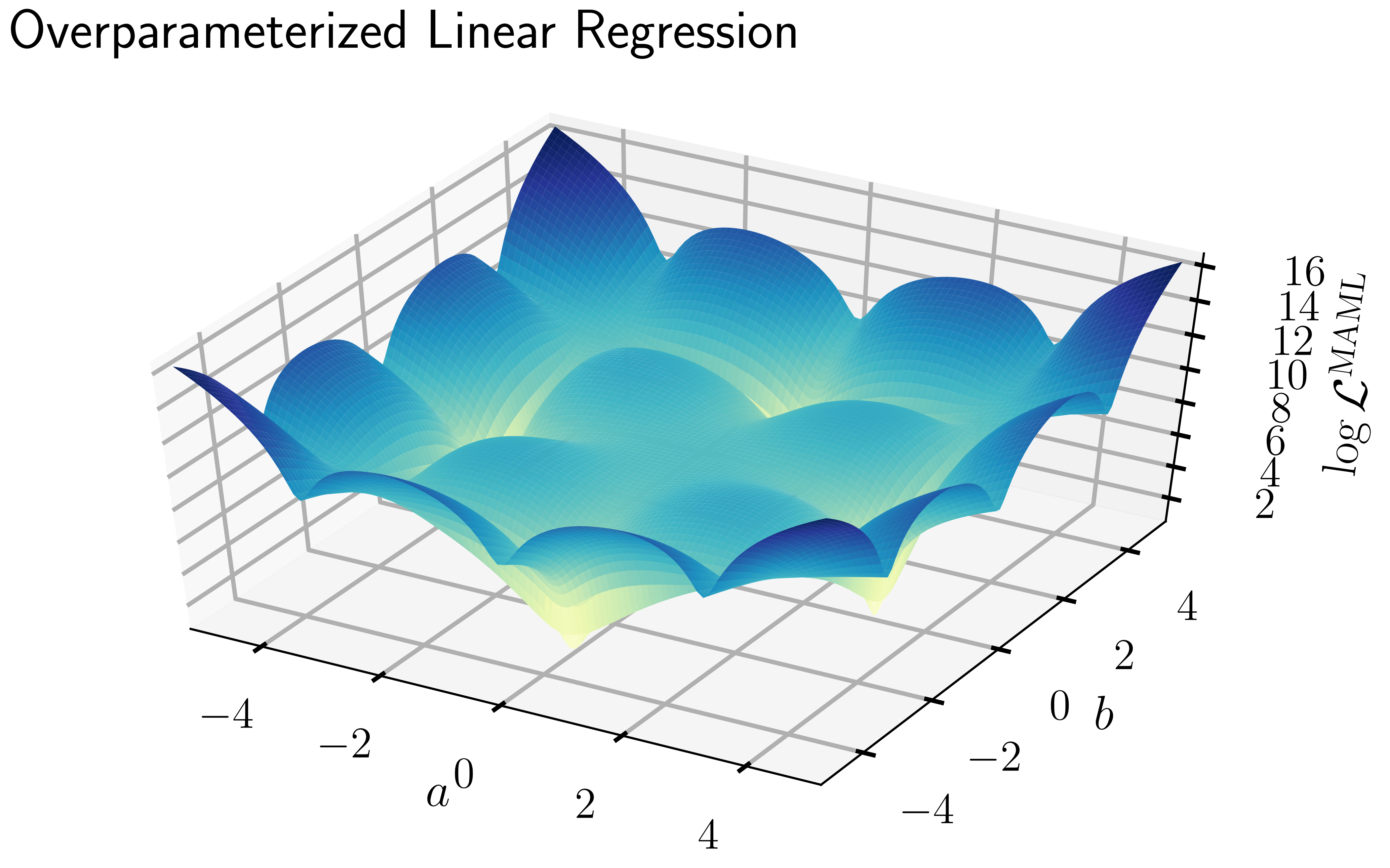
Meta-Learning with MAML

Objective:

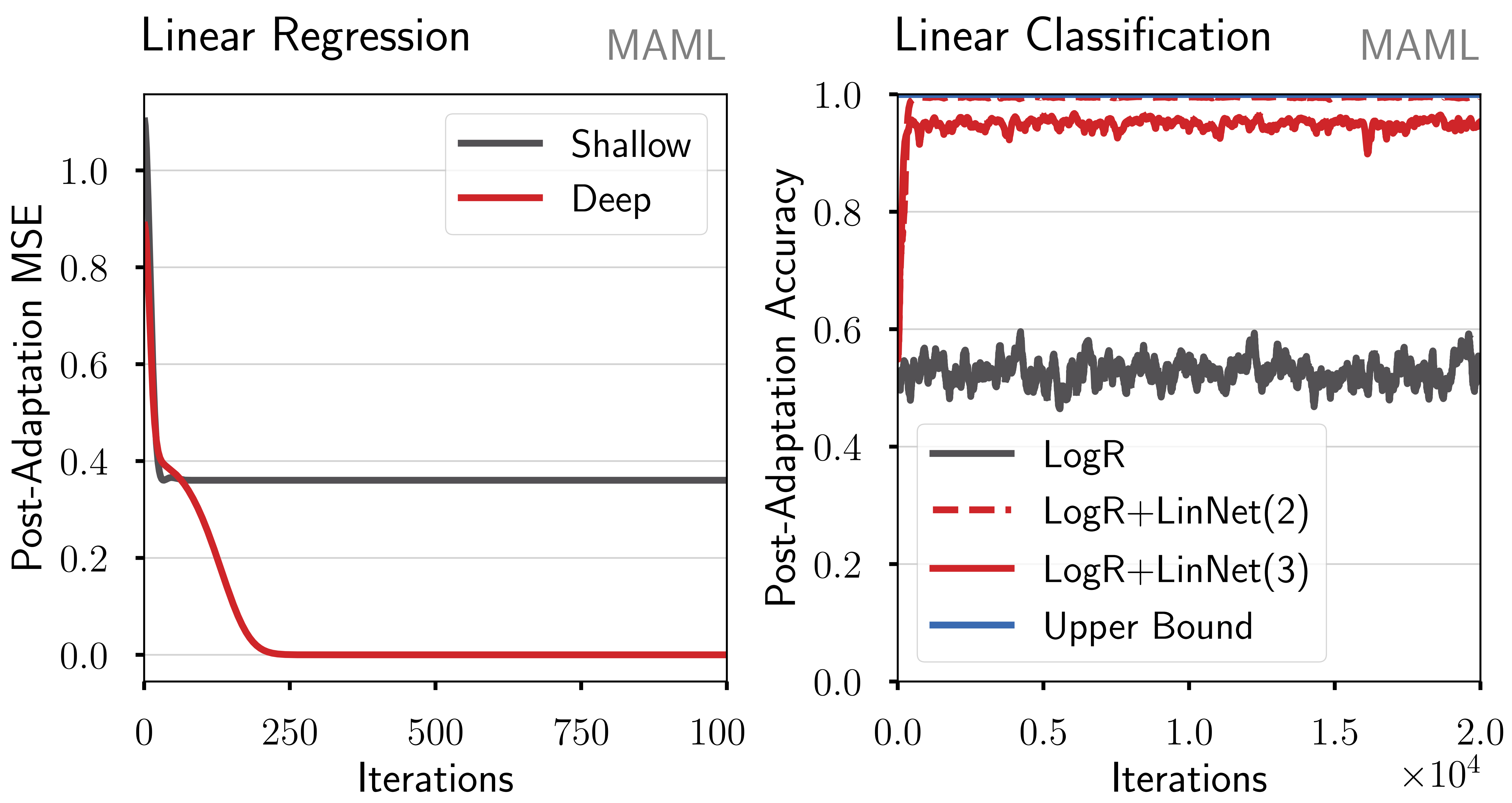
$$\min_{\theta} \mathbb{E}_{\tau} \left[\mathcal{L}_{\tau}(\theta - \alpha \nabla_{\theta} \mathcal{L}_{\tau}(\theta)) \right]$$

where:

- $\theta \triangleq$ parameters to learn,
- $\tau \triangleq$ task index, and
- $\mathcal{L}\tau \triangleq$ the task-specific loss.



Failure Mode



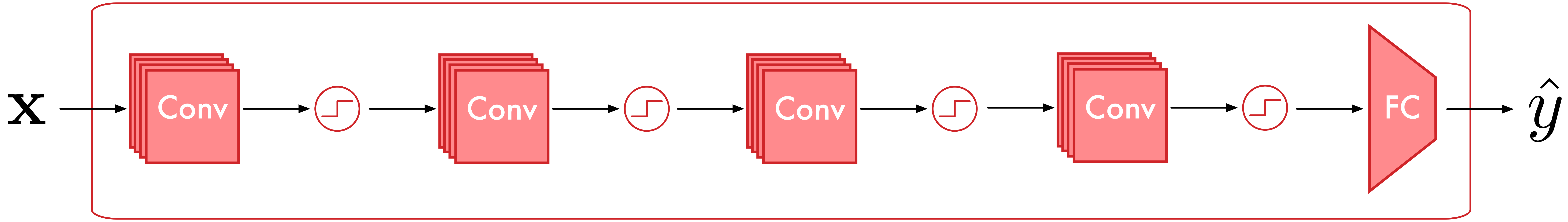
- Tasks: linearly separable
- Models: linear (shallow vs deep)

Insights

- Theoretical analysis:
  - Deep models are required for meta-learning.
  - Some parameters act like implicit meta-optimizers.
- Empirical analysis confirms on linear and deep models.

Solutions

1. Use deeper and larger models.
2. Just add a few linear layers.
3. Move parameters to KFO, our new meta-optimizer.



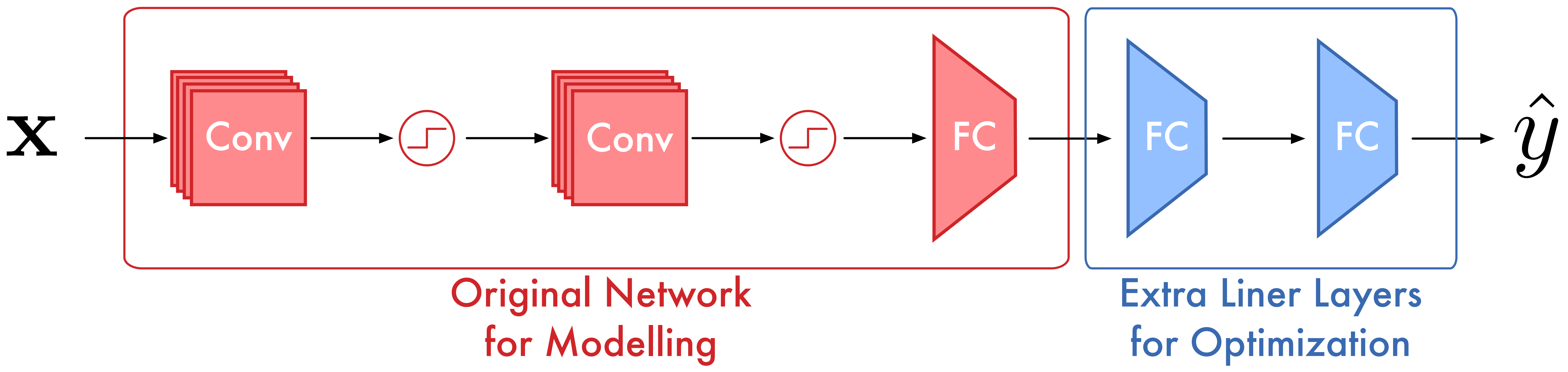
Larger and Deeper Network
for Modelling

Solutions

1. Use deeper and larger models.

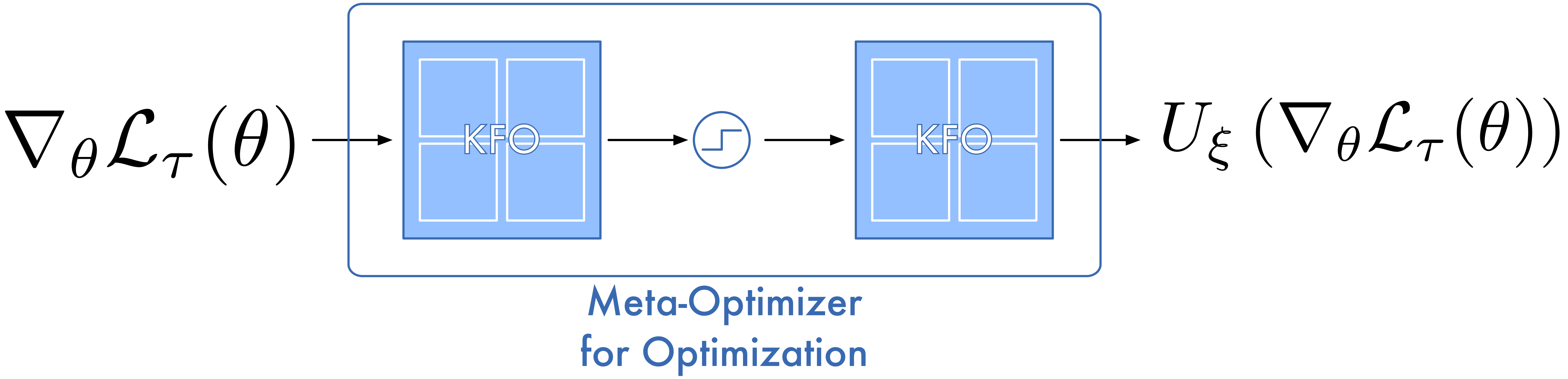
2. Just add a few linear layers.

3. Move parameters to KFO, our new meta-optimizer.



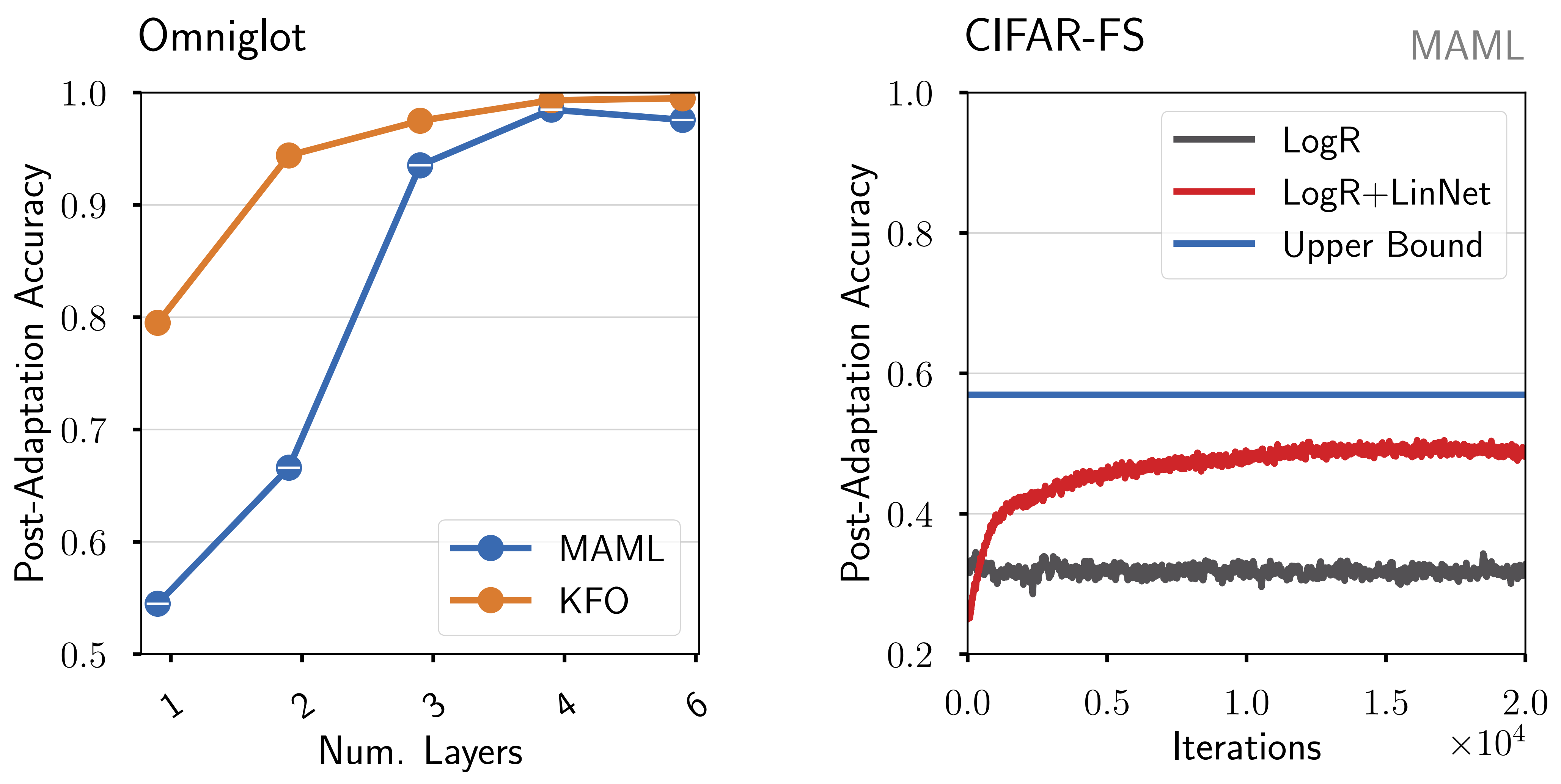
Solutions

1. Use deeper and larger models.
2. Just add a few linear layers.
3. Move parameters to KFO, our new meta-optimizer.



Results

- Extra linear layers improve shallow and deep meta-learning.
- Meta-optimizers (KFO) always perform best.
- Meta-optimizers are most beneficial with shallow models.
- + a few more…



Thank You

- Learn more:
  - Poster: ID 108 — Session 4: April 14 at 12:45-14:45 PDT
  - Web: sebarnold.net/projects/kfo
  - Code: github.com/Sha-Lab/kfo
  - Email: seb.arnold@usc.edu