



CAVIA

Fast Context Adaptation via Meta-Learning

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Problem Setting: Few-Shot Learning

Given distributions over tasks: $p_{\text{train}}(\mathcal{T}), p_{\text{test}}(\mathcal{T})$
- Meta-learn how to adapt fast to any tasks from p_{train}
- Evaluate generalisation ability on tasks from p_{test}

Background: MAML (Finn et al., 2017)

Idea: Learn network initialisation s.t. at test time, only few gradient steps are necessary to perform well.

Inner loop:
- Sample batch of tasks, $\mathcal{T}_i \sim p_{\text{train}}$
- For each task: - Get train/test data: $\mathcal{D}_i^{\text{train}}, \mathcal{D}_i^{\text{test}}$
- Adapt model:
$$\theta_i = \theta - \alpha \nabla_{\theta} \sum_{(x,y) \in \mathcal{D}_i^{\text{train}}} \mathcal{L}_{\mathcal{T}_i}(f_{\theta}(x), y)$$

Outer loop: - Update initial parameters for good test performance by backpropagating through inner loop update

$$\theta \leftarrow \theta - \beta \nabla_{\theta} \sum_i \sum_{(x,y) \in \mathcal{D}_i^{\text{test}}} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i}(x), y)$$

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Many tasks & benchmarks don't require generalisation beyond *task identification*. In this case, we shouldn't update all parameters!

Hence we separate the network into task-specific parameters ϕ , and shared parameters θ , trained similarly to MAML as follows.

Inner loop update:

For each task i , update context parameters:

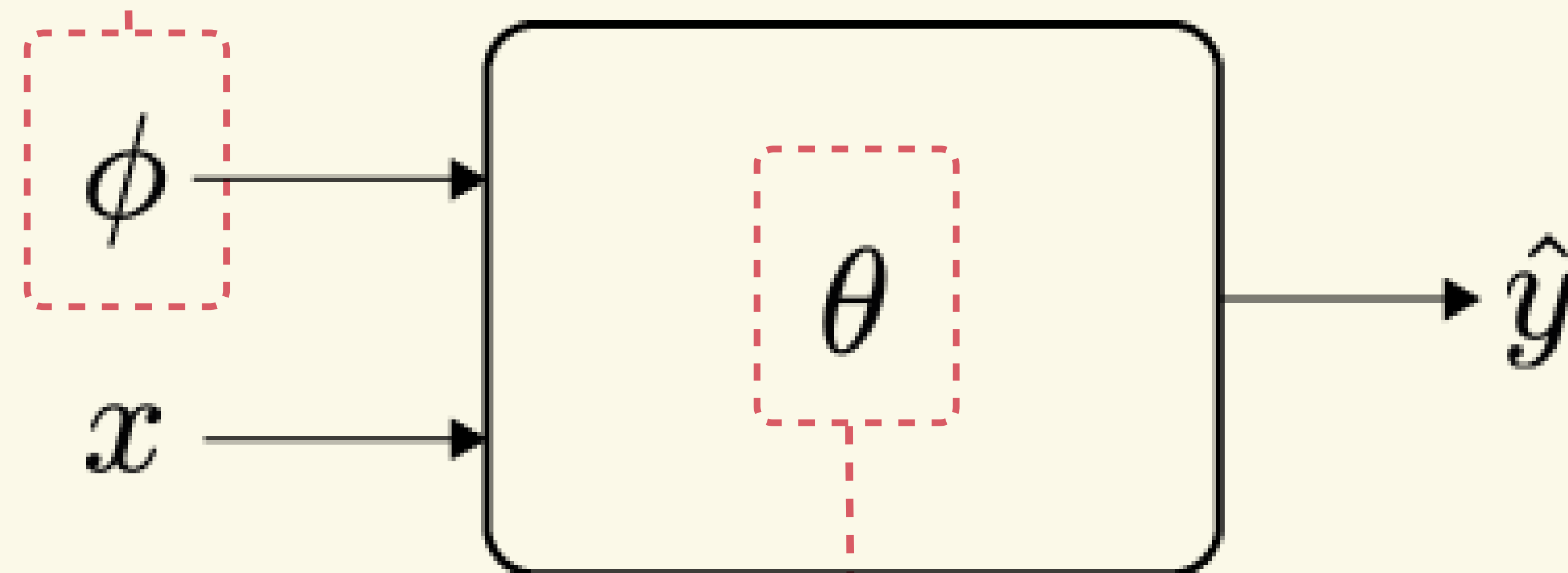
$$\phi_i = \phi_0 - \alpha \nabla_{\phi_0} \sum_{(x,y) \in \mathcal{D}_i^{\text{train}}} \mathcal{L}_{\mathcal{T}_i}(f_{\{\phi_0, \theta\}}(x), y)$$

Outer loop update:

Update shared parameters θ using test loss from individual tasks

$$\theta \leftarrow \theta - \beta \nabla_{\theta} \sum_i \sum_{(x,y) \in \mathcal{D}_i^{\text{test}}} \mathcal{L}_{\mathcal{T}_i}(f_{\{\phi_i, \theta\}}(x), y)$$

Context parameters:
Task-specific, the only thing that's updated test time.
Represent task embedding.



Network parameters:
Shared across tasks, fixed at test time.
Trained in outer loop only.

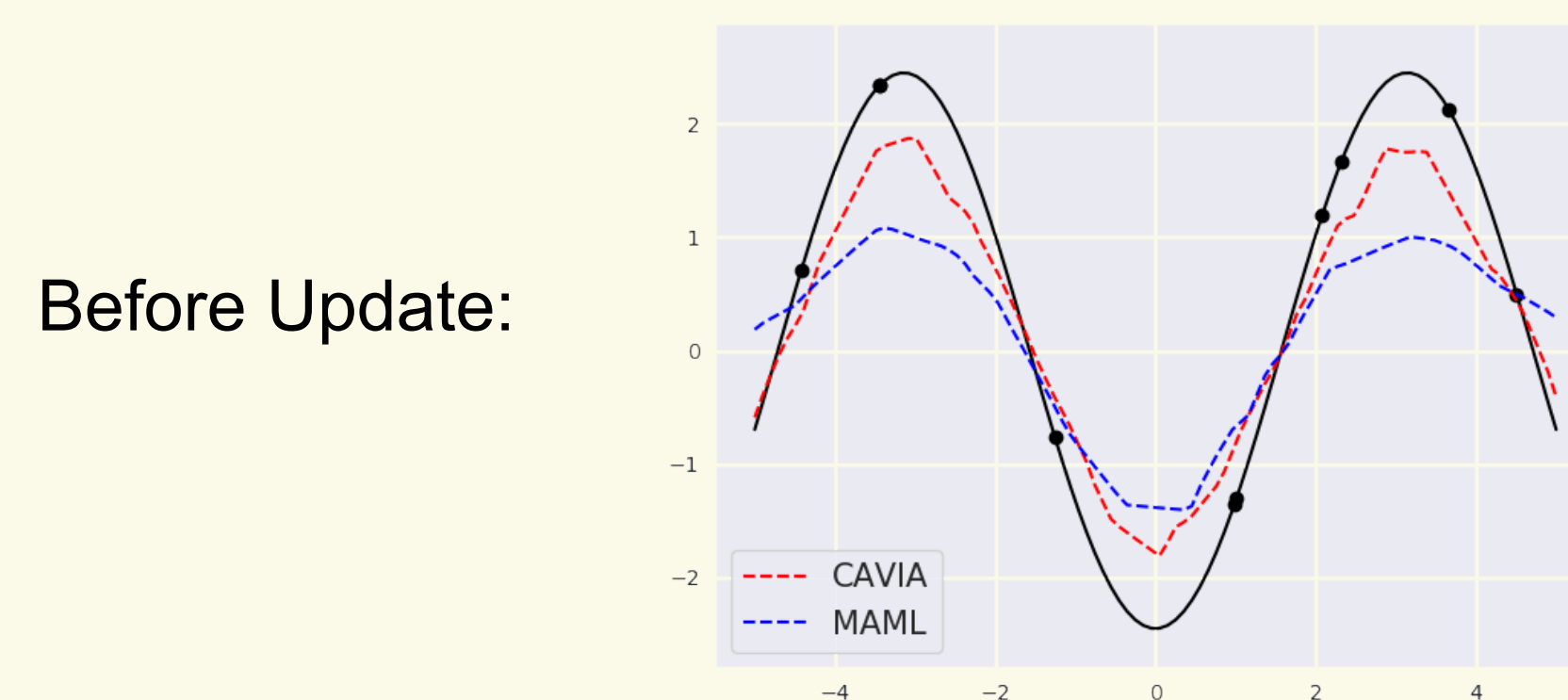
Less prone to overfitting compared to MAML

Context parameters are interpretable / reusable

Easy to parallelise

Sine Curve Regression

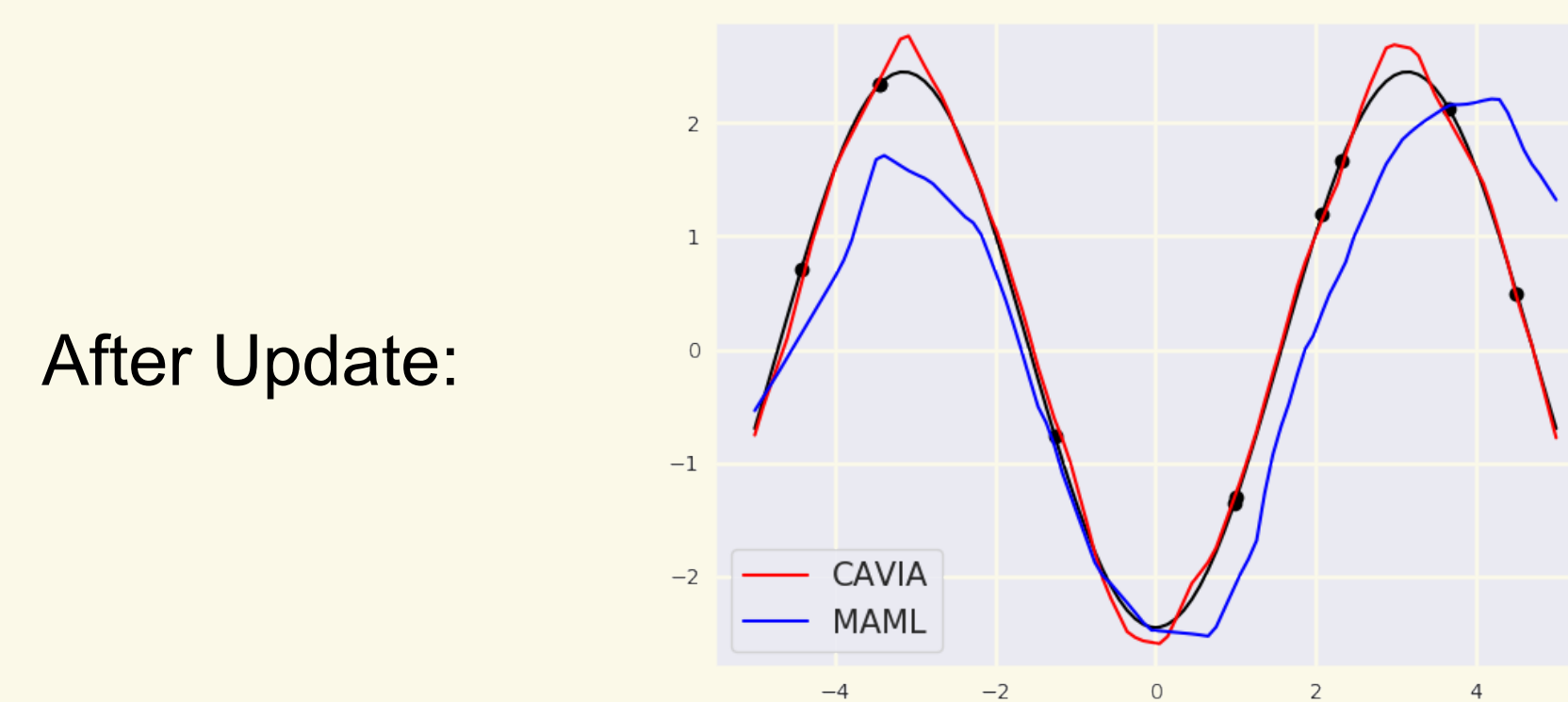
Task = sine curve with randomly chosen amplitude and phase.



Before Update:

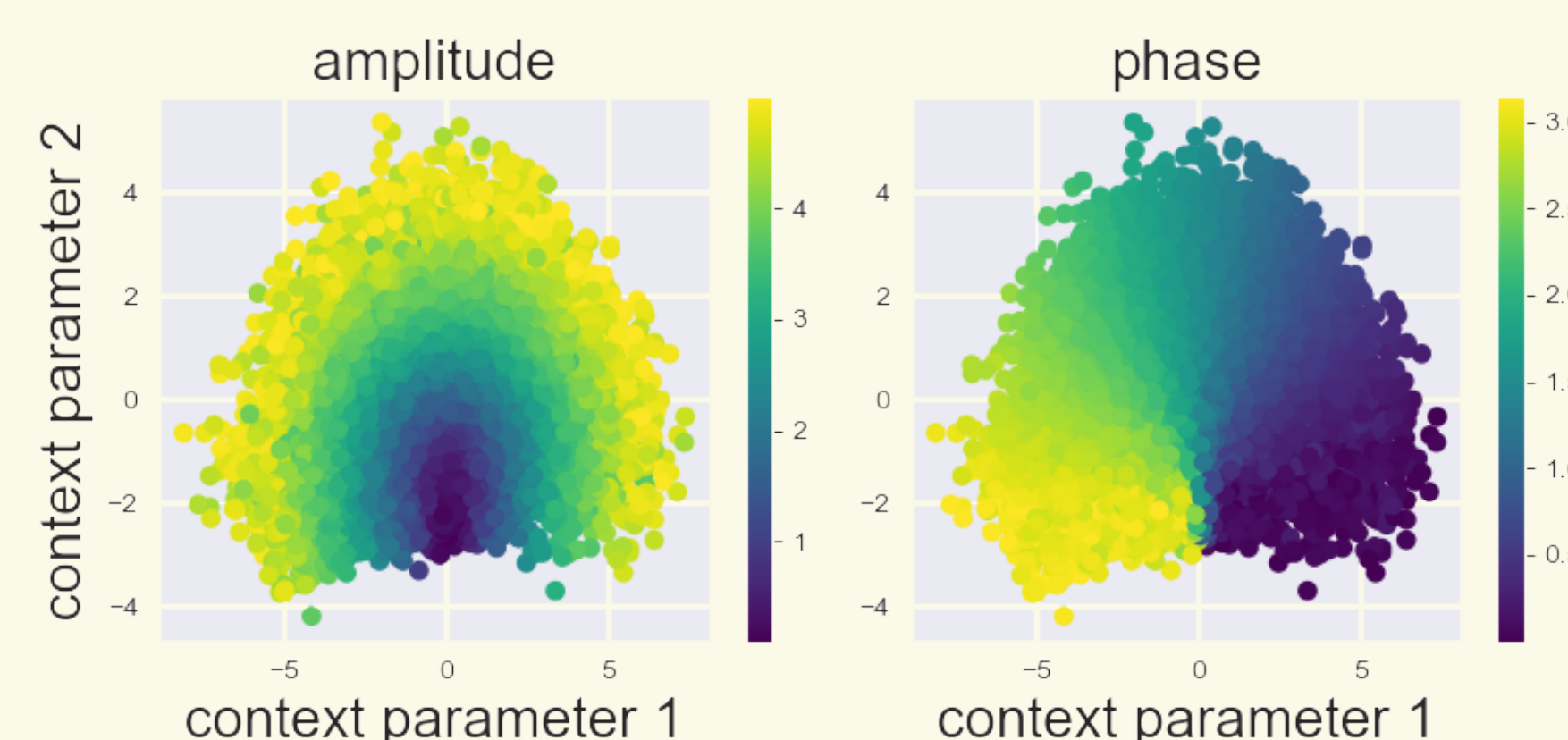
Gradient Update:

MAML: ~1500 params
CAVIA: 2 params



After Update:

Visualisation of the learned context parameters:



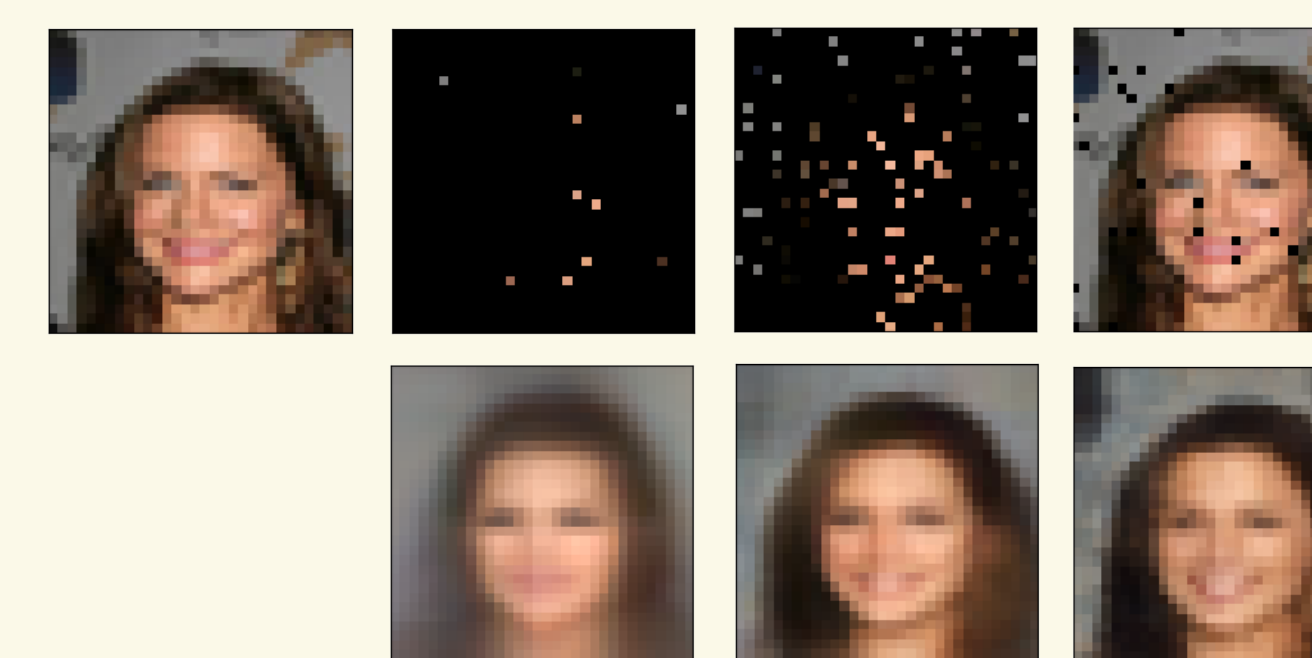
Few-Shot Classification

- Mini-ImageNet benchmark
- Number of context parameters: 100
- Increased network size leads to:
- overfitting for MAML
- better performance for CAVIA

Method	5-way accuracy	
	1-shot	5-shot
Matching Nets (Vinyals et al., 2016)	46.6%	60.0%
Meta LSTM (Ravi & Larochelle, 2017)	43.44 ± 0.77%	60.60 ± 0.71%
Prototypical Networks (Snell et al., 2017)	46.61 ± 0.78%	65.77 ± 0.70%
Meta-SGD (Li et al., 2017)	50.47 ± 1.87%	64.03 ± 0.94%
REPTILE (Nichol & Schulman, 2018)	49.97 ± 0.32%	65.99 ± 0.58%
MT-NET (Lee & Choi, 2018)	51.70 ± 1.84%	-
VERSA (Gordon et al., 2018)	53.40 ± 1.82%	67.37 ± 0.86%
MAML (32) (Finn et al., 2017a)	48.07 ± 1.75%	63.15 ± 0.91%
MAML (64)	44.70 ± 1.69%	61.87 ± 0.93%
CAVIA (32)	47.24 ± 0.65%	59.05 ± 0.54%
CAVIA (128)	49.84 ± 0.68%	64.63 ± 0.54%
CAVIA (512)	51.82 ± 0.65%	65.85 ± 0.55%
CAVIA (512, first order)	49.92 ± 0.68%	63.59 ± 0.57%

Image Completion: CelebA

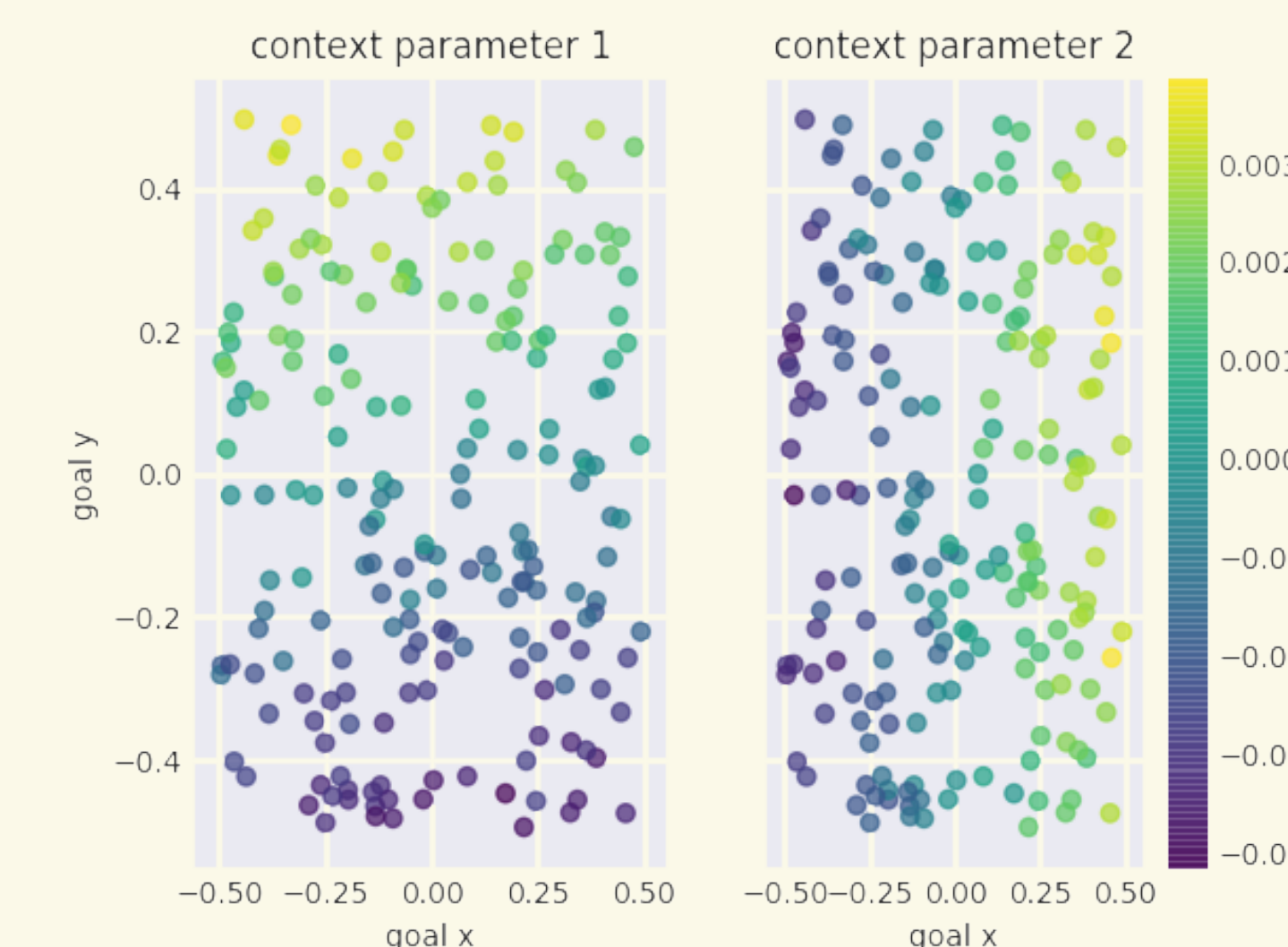
- Challenging regression task (Garnelo et al. 2018)
- Number of context parameters: 128
- CAVIA learns low-level image embeddings solely via backward pass



	Random Pixels			Ordered Pixels		
	10	100	1000	10	100	1000
CNP*	0.039	0.016	0.009	0.057	0.047	0.021
MAML	0.040	0.017	0.006	0.055	0.047	0.007
CAVIA	0.037	0.014	0.006	0.053	0.047	0.006

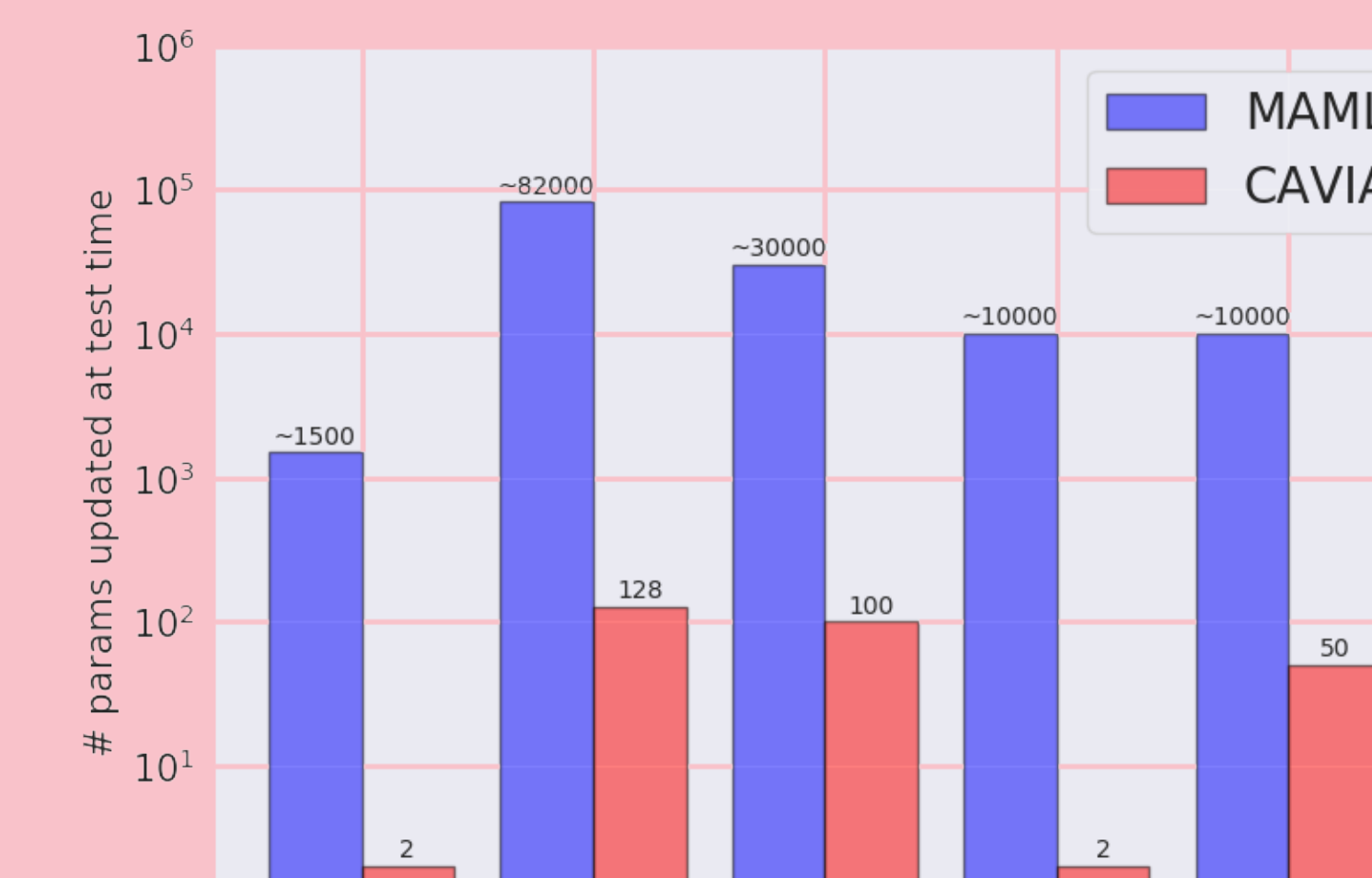
Reinforcement Learning

2D Navigation: Task = goal position.
- Visualisation of learned context parameters:



MuJoCo Cheetah (Vel & Dir):
- Performs similar to MAML, with only 50 context parameters

Number of adapted paramers



Conclusion

- When only task identification is required, don't update entire net!
- Possible weakness of current benchmarks: adaptation required is sometimes small

References: Finn, Chelsea, Pieter Abbeel, and Sergey Levine. "Model-agnostic meta-learning for fast adaptation of deep networks." ICML 2017. Garnelo, M., Rosenbaum, D., Maddison, C. J., Ramalho, T., Saxton, D., Shanhua, M., ... & Eslami, S. M. (2018). Conditional neural processes. ICML 2018.