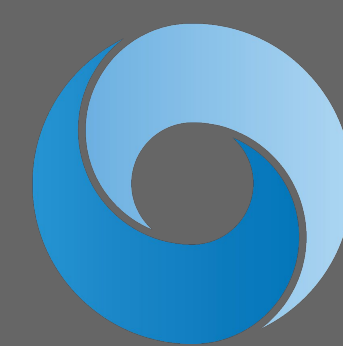


Meta-Learning with Warped Gradient Descent



We introduce a novel family of meta-learned optimisers (WarpGrad)

- WarpGrad optimisers learn to precondition native gradients, ∇f , to form an update rule

$$\theta \leftarrow \theta - \alpha G(\theta; \phi)^{-1} \nabla f(\theta)$$

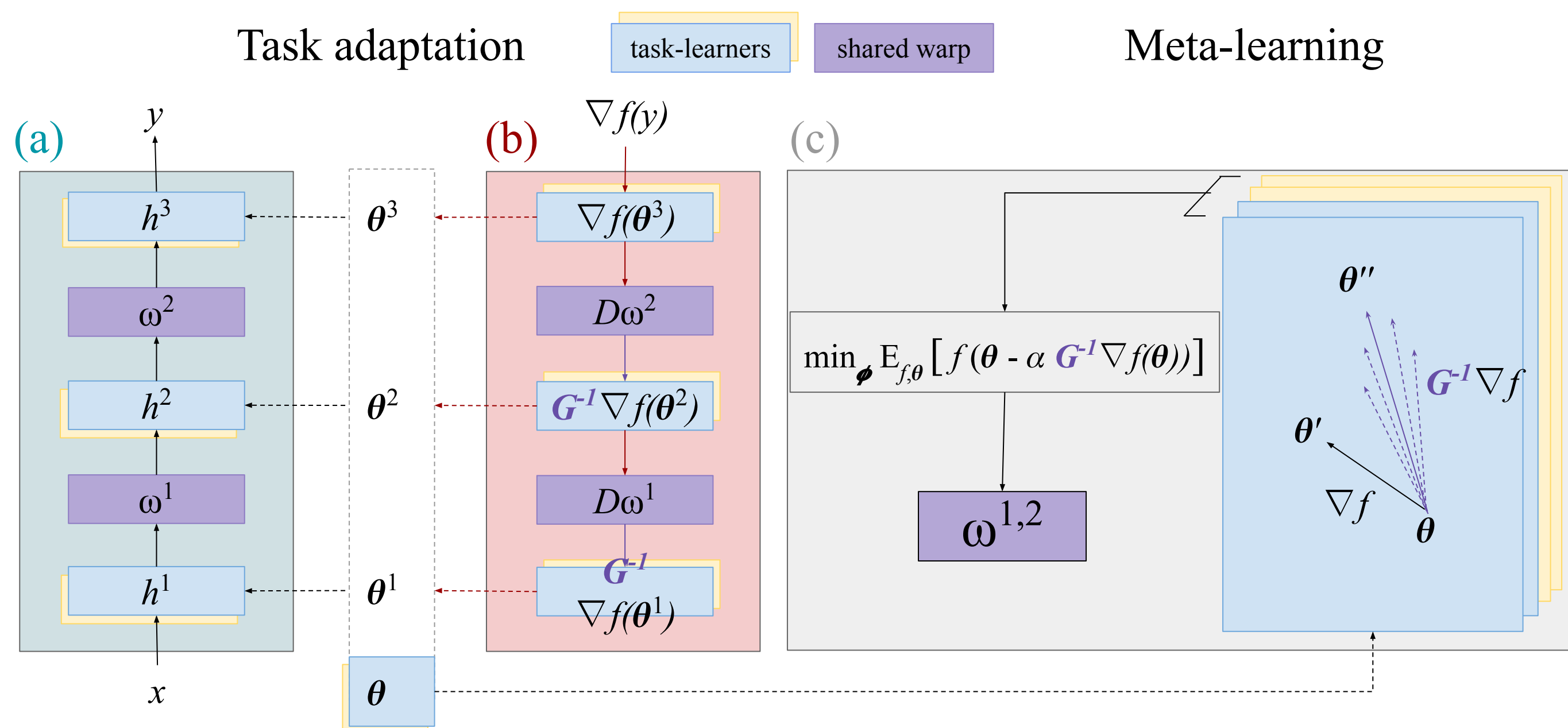
- Preconditioning means we learn a well-behaved optimiser: leverages inductive bias of gradient and inherits its descent properties (e.g. convergence)
- Crucially, WarpGrad methods never explicitly compute G^{-1}

WarpGrad optimisers are *embedded* in the model architecture

(a) Defined by inserting *shared warp layers* $\omega^{1,2}$ in task learners h/h

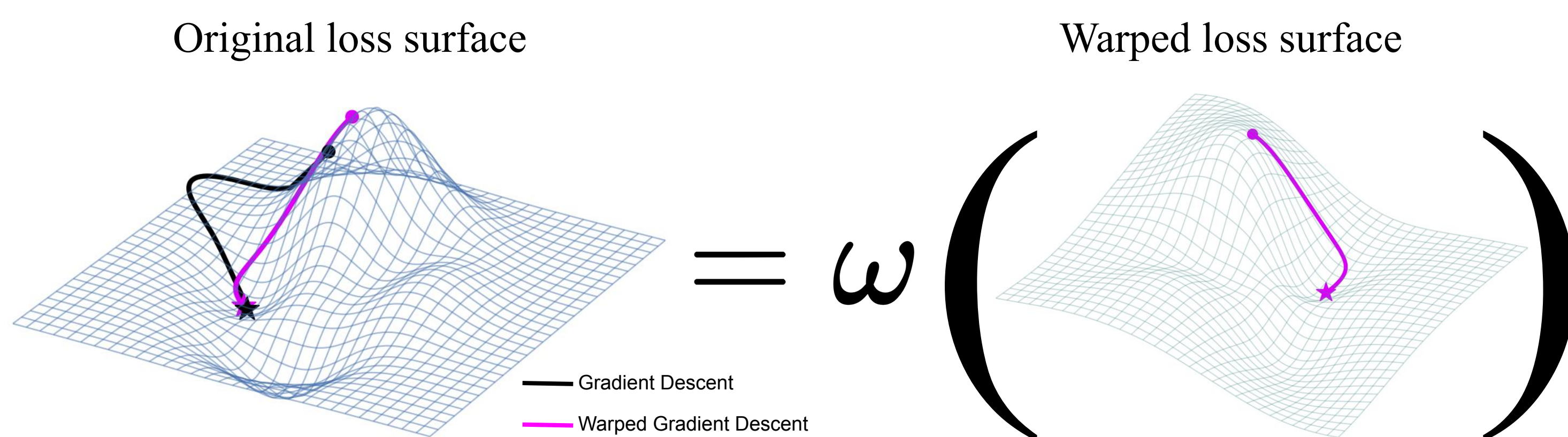
(b) Backprop preconditions task gradients (via Jacobians $D\omega^{1,2}$). We call this *gradient warping*.

(c) We meta-learn *warp parameters* ϕ to facilitate task adaptation

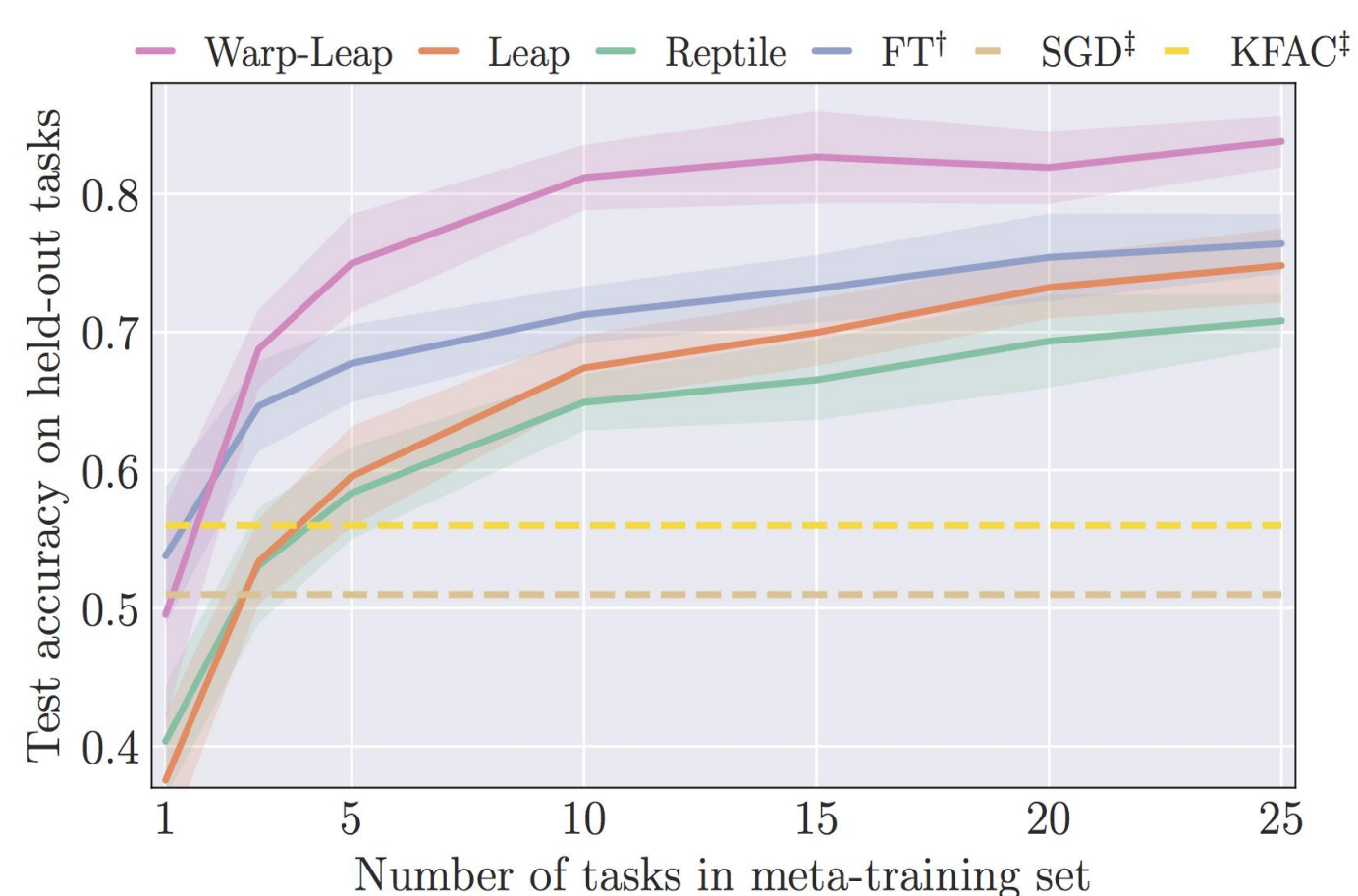


WarpGrad methods embody a meta-learned Riemann Geometry

- Warp layers ω meta-learn a smooth space for task learning
- Equivalent to Riemannian Gradient Descent under a meta-learned metric $G(\cdot; \phi)$

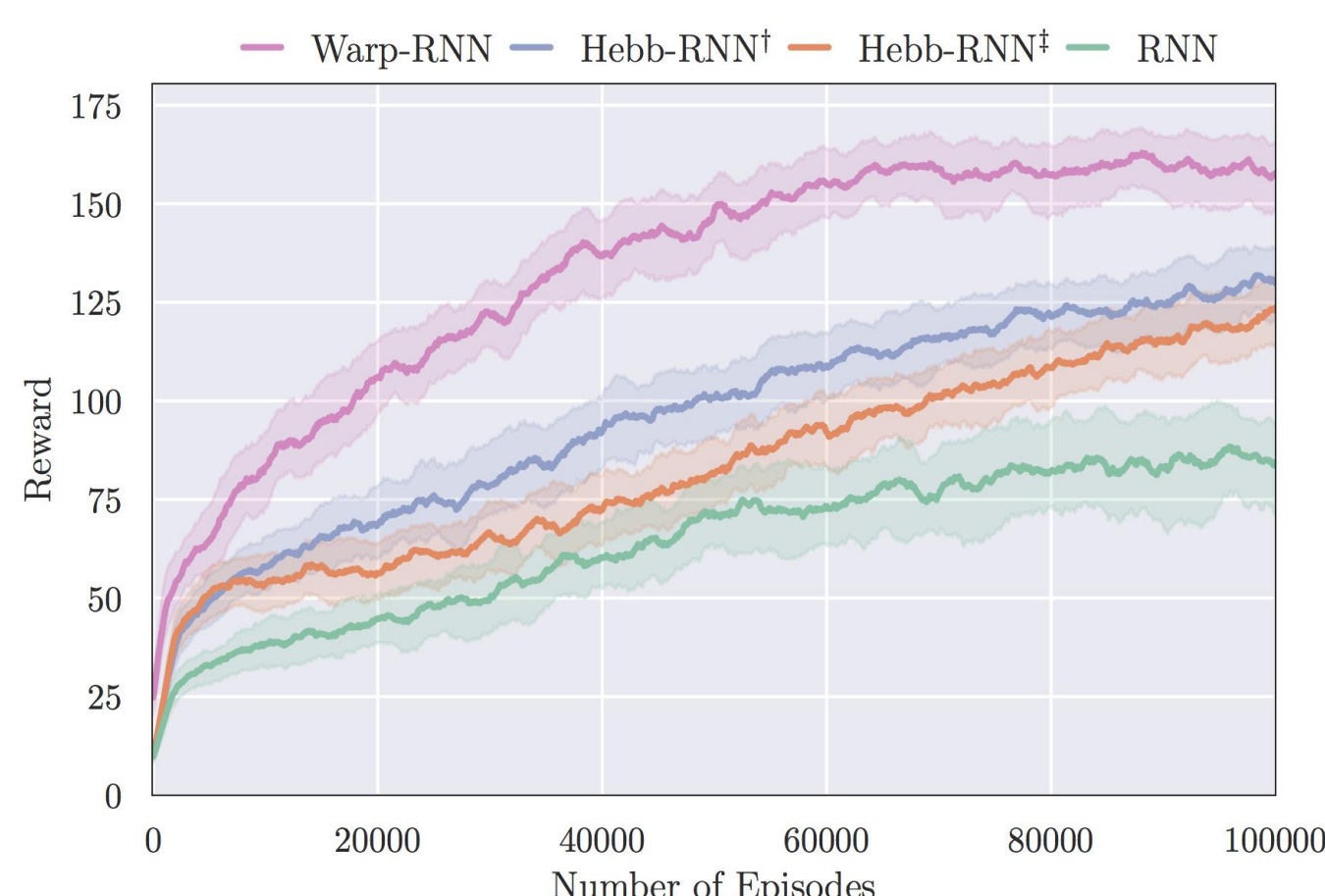


Supervised, Omniglot (alphabet = task)



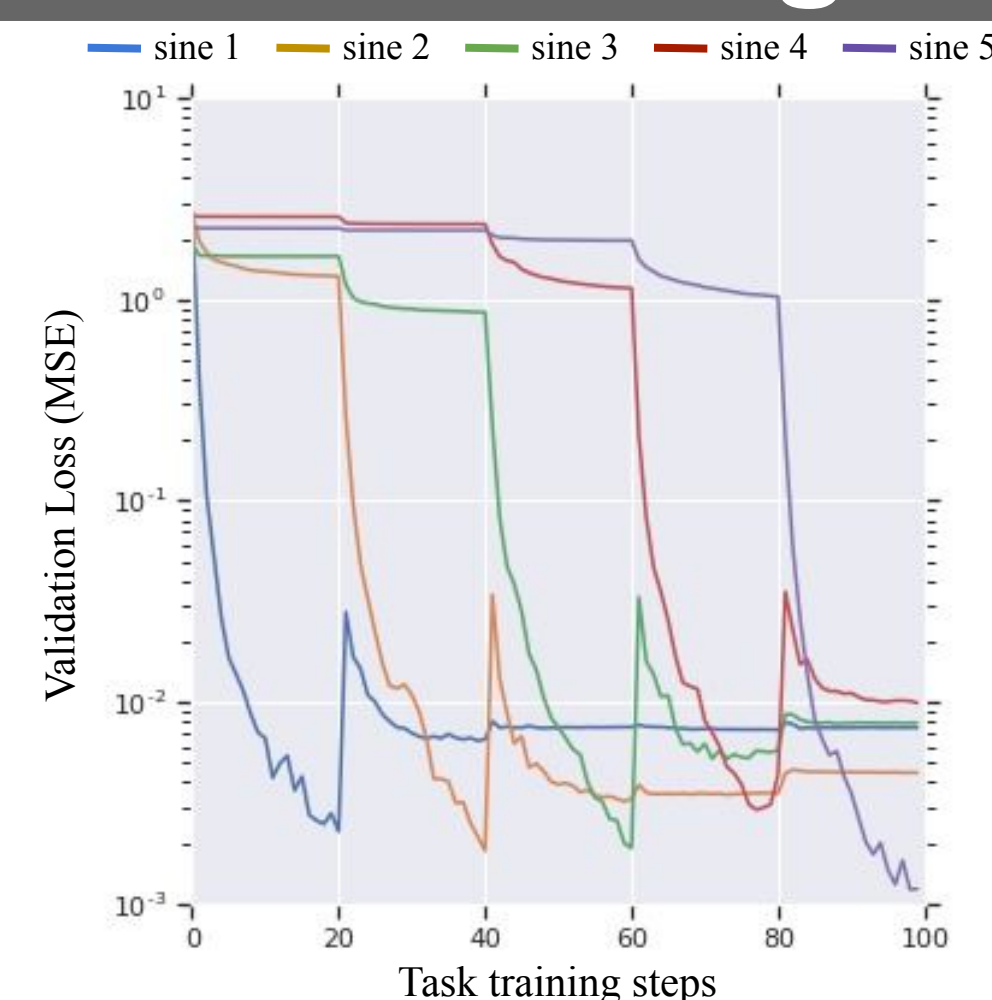
- We train a Warp-Leap meta-learner
- Meta-train on x alphabets, evaluate on held out alphabets
- Task training: 100 steps on randomly sampled task data using SGD (except WarpGrad and KFAC)

RL, Maze Navigation (goal location = task)



- We train a Warp-RNN meta-learner (HyperNetwork)
- Meta-train over 30 randomly sampled goal locations
- Task training: Actor-Critic on randomly sampled goal location. Task: find goal as many times as possible (agent is teleported to random location each time it finds it)

Continual Learning (task = curve segment)



- We train a Warp-MLP to prevent catastrophic forgetting
- Meta-train over random sequences of 5 distinct sine waves
- Task learner sees one curve at a time with no revisits