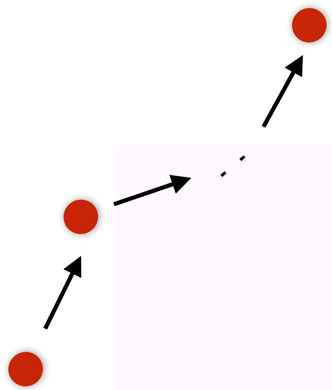
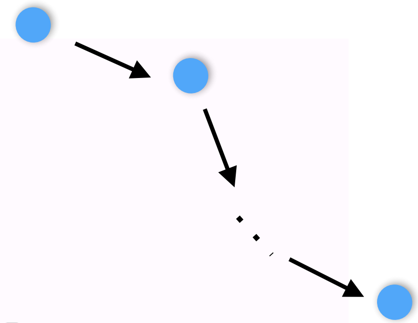
Flexible Learning Reading Group @TU Berlin

3rd Session: 23rd of August 2019





TRANSFERRING KNOWLEDGE ACROSS LEARNING PROCESSES

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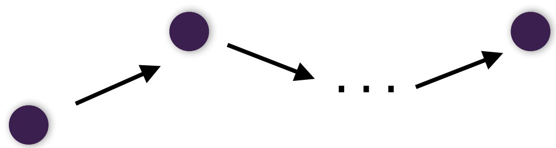
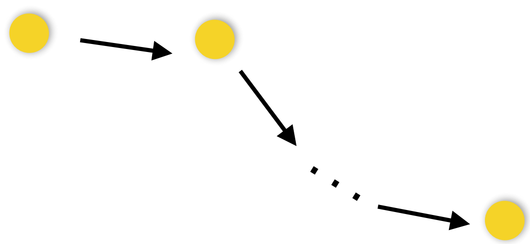
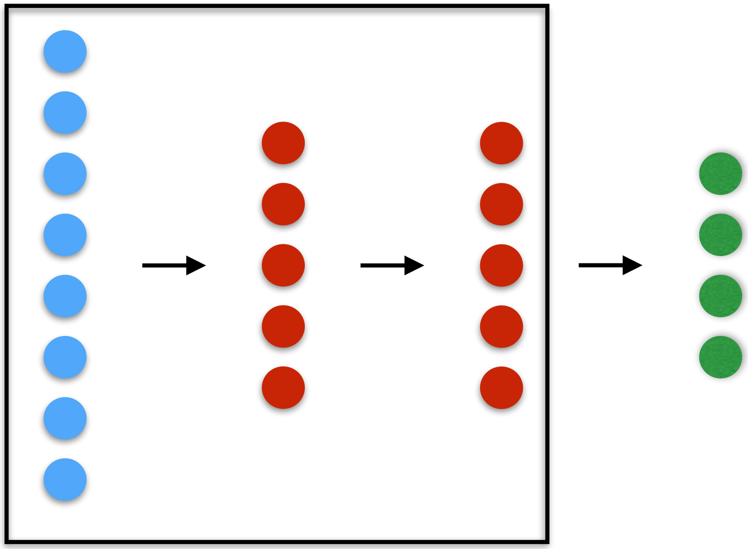




Leap: What Knowledge to Transfer Across Tasks?

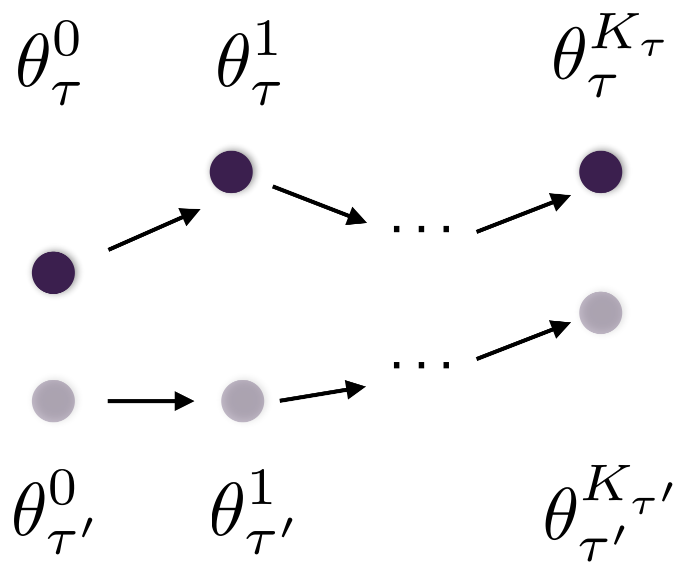
Transfer trained params θ^K



Overly Restrictive:

- Requires structural „affinity“
- Knowledge = representation

Transfer task geometry knowledge



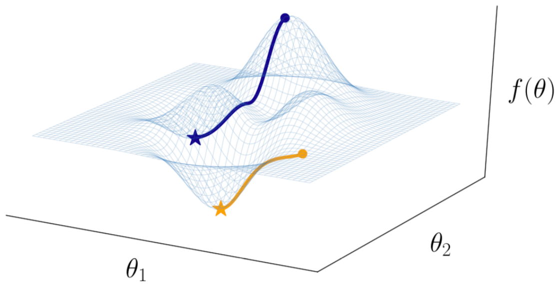
Learning process generalisation:

- Task geometries = Meta-Obj.
- Min exp. length GD trajectories

Problem Formulation & Length of a Learning Process

Weight Initialisation: $$\min_{\theta^0} \mathbb{E}_\tau [L_\tau (\boxed{U_\tau^k}(\theta^0))]$$

$$\theta^{i+1} = \theta^i - \alpha^i S^i \nabla f(\theta^i)$$



- Trajectory = Curve γ on task manifold M
- Task manifold = Loss surface

$$\gamma(t) = (\theta(t), f(\theta(t))) \in M \qquad \dot{\gamma}(t) = \frac{d}{dt}\gamma(t) \in T_{\gamma(t)}M$$

Length = Accumulated infinitesimal changes along trajectory

$$Len(\gamma) = \int_0^1 \sqrt{g_{\gamma(t)}(\dot{\gamma}(t), \dot{\gamma}(t))dt} \qquad < \dot{\gamma}(t), \dot{\gamma}(t) >$$

Induced Metric

Meta-Learning Across Task Manifolds

Gradient Path Len =
Cum. Chordal Distance:

$$d_p(\theta^0, M) = \sum_{i=0}^{K-1} ||\gamma^{i+1} - \gamma^i||_2^p$$

$$\min_{\theta^0} F(\theta^0) = \mathbb{E}_{\tau \sim p(\tau)}[d(\theta^0, M)]$$

$$s.t. \;\; \theta_\tau^{i+1} = U_\tau(\theta_\tau^i), \;\; \theta_\tau^0 = \theta^0$$

Feasibility Constraint: Ensure minimal level of performance

$$\boxed{\theta_0 = \cap_\tau \{\theta_0 | f_\tau(\theta_\tau^{K_\tau}) \leq f_\tau(\psi_\tau^{K_\tau})\}}$$

Iteratively refine
Upper bound!

Leap: Iterative Pulling Forward of the 2nd Best

2nd Best Init | Grad Paths | Set of Baselines

$$\psi^0 \longrightarrow \Psi_\tau = \{\psi_\tau^i\}_{i=0}^{K_\tau} \longrightarrow \Psi = \{\Psi_\tau\}_{\tau\in\mathcal{B}}$$

$$\bar{d}_p(\theta^0; M_\tau, \Psi_\tau) = \sum_{I=0}^{K_\tau - 1} ||\boxed{\bar{\gamma}_\tau^{i+1}} - \gamma_\tau^i||_2^p \qquad \bar{\gamma}_\tau^i = (\psi_\tau^i, f(\psi_\tau^i))$$

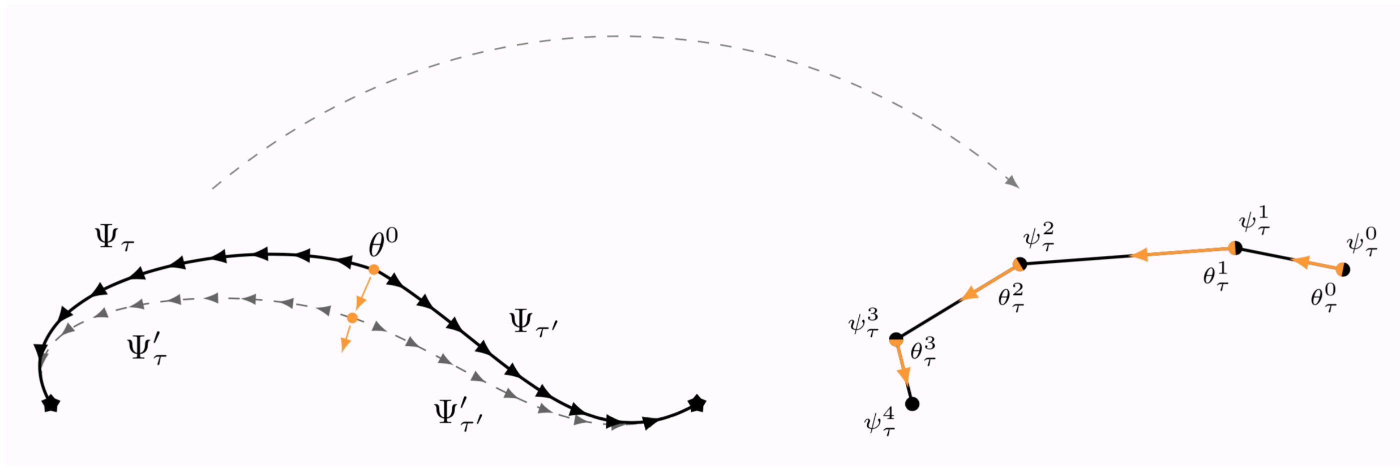
Pull Forward Objective:

$$\min_{\theta^0} \bar{F}(\theta^0; \Psi) = \mathbb{E}_{\tau\sim p(\tau)}[\bar{d}(\theta^0; M_\tau, \Psi_\tau)]$$

Pull Forward Gradient:

$$-p\mathbb{E}\left[\sum_{i=0}^{K_\tau - 1} (\Delta f_\tau^i \nabla f_\tau(\theta_\tau^i) + \Delta\theta_\tau^i)(||\bar{\gamma}_\tau^{i+1} - \gamma_\tau^i||_2^p)^{p-2}\right]$$

$$f_\tau(\psi_\tau^{i+1}) - f_\tau(\theta_\tau^i) \qquad \psi_\tau^{i+1} - \theta_\tau^i$$



Algorithm 1 Leap: Transferring Knowledge over Learning Processes

Require: $p(\tau),\ \tau = (f_\tau, u_\tau, p_\tau)$: distribution over tasks
Require: β: step size
randomly initialize θ^0
while not done **do**
    $\nabla \bar{F} \leftarrow 0$: initialize meta gradient
    sample task batch $\mathcal{B}$ from $p(\tau)$
    for all $\tau \in \mathcal{B}$ **do**
        $\psi_\tau^0 \leftarrow \theta^0$: initialize task baseline
        for all $i \in \{0, \dots, K_\tau - 1\}$ **do**
            $\psi_\tau^{i+1} \leftarrow u_\tau(\psi_\tau^i)$: update baseline
            $\theta_\tau^i \leftarrow \psi_\tau^i$: follow baseline (recall $\psi_\tau^0 = \theta^0$)
            increment $\nabla \bar{F}$ using the pull-forward gradient (eq. 8)
        end for
    end for
    $\theta^0 \leftarrow \theta^0 - \frac{\beta}{|\mathcal{B}|} \nabla \bar{F}$: update initialization
end while

Comparison to MAML & Reptile

- MAML (Finn et al., 2017): $\min_{\theta^0} \mathbb{E}_\tau [L_{\tau,B}(U_{\tau,A}(\theta^0))]$

$\longrightarrow$ Optimization for generalisation (similar to cross-validation)

$$g_{MAML} = \frac{\partial}{\partial \theta_0} L_{\tau,B}(U_{\tau,A}(\theta^0)) = \boxed{U'_{\tau,A}}(\theta^0) L'_{\tau,B}(\boxed{\theta^k})$$

FOMAML: Set to identity $\longleftarrow$ Jacobian Updater

k-step update of params

$\longrightarrow$ Special case of Leap: Only final parametrisation evaluated

- Reptile (Nichols et al., 2018):

$\longrightarrow$ Update: $\theta_0 \leftarrow \theta_0 + \epsilon \left(\mathbb{E}_{\tau \sim p(\tau)}(\theta^k_\tau) - \theta_0 \right)$

$\longrightarrow$ Naive version of Leap: Euclidean space of task geometries

Session 4: 5th of September 2019 (Thursday!)

New neural activity patterns emerge with long-term learning

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Learning has been associated with changes in the brain at every level of organization. However, it remains difficult to establish a causal link between specific changes in the brain and new behavioral abilities. We establish that new neural activity patterns emerge with learning. We demonstrate that these new neural activity patterns cause the new behavior. Thus, the formation of new patterns of neural population activity can underlie the learning of new skills.