



# Using Task Features for Zero-Shot Knowledge Transfer in Lifelong Learning



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#### Motivation



#### "Bookshelf with 5 shelves"

Need to transfer from prior experience

**Key Idea:** Use a high-level task description to identify relevant knowledge for transfer in lifelong learning

- Improve task performance
- Zero-shot transfer
- Task descriptors used for pairwise transfer by Sinapov et al. (2015)

## **Lifelong Machine Learning**

[Bou Ammar, Eaton, et al. ICML14]



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# **Our Contribution**



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#### **Background: Policy Gradient Methods for Control**

Agent interacts with environment, taking consecutive actions

- Continuous state and action spaces
- Demonstrated in robotic control [Kober & Peters '11; Peters & Schaal '08; Sutton '00]



Goal: find policy  $\pi_{\theta}$  that maximizes  $\mathcal{J}(\theta) = \int_{\pi} p_{\theta}(\boldsymbol{\tau}) \mathcal{R}(\boldsymbol{\tau}) d\boldsymbol{\tau}$ 

$$p_{\theta}(\boldsymbol{\tau}) = p_0(\mathbf{x}_0) \prod_{h=1}^{H} p(\mathbf{x}_{h+1} | \mathbf{x}_h, \mathbf{a}_h) \pi_{\boldsymbol{\theta}}(\mathbf{a}_h | \mathbf{x}_h) \qquad \qquad \mathcal{R}(\boldsymbol{\tau}) = \frac{1}{H} \sum_{h=0}^{H} r_{h+1}$$
probability of trajectory reward function

### Sharing Knowledge Between Tasks



#### **Incorporating Task Descriptors**

**Coupled dictionaries** relate policy parameters and task descriptors



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Multi-Task Learning: TaDeMTL

Lifelong Learning: TaDeLL

#### **Zero-Shot Transfer**



**Given:** descriptor for new task

 Use descriptor and descriptor dictionary to recover sparse coefficients via LASSO:

 $\tilde{\boldsymbol{s}}^{(t_{new})} \leftarrow \arg\min_{\boldsymbol{s}} \left\| \phi(\boldsymbol{m}^{(t)}) - \boldsymbol{D} \boldsymbol{s} \right\|_{2}^{2} + \mu \left\| \boldsymbol{s} \right\|_{1}$ 

2. Use recovered coefficients and policy dictionary to predict policy parameters

 $ilde{oldsymbol{ heta}}^{(t_{new})} = L ilde{s}^{(t_{new})}$ 

#### **Lifelong Learning on Dynamical Systems**

- Train on 40 tasks, predict the policy on a new task
- Warm Start: Zero-shot predicted policy used as an initialization



**TaDeLL predicts effective policies for unseen tasks** 

### **Application to Quadroter Control**



Effective zero-shot transfer to controlling new quadrotor systems

### **Runtime Comparison**

- TaDeLL scales effectively to numerous tasks
- Sinapov et al. has quadratic complexity in the number of tasks







# Thank you! Questions?

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