
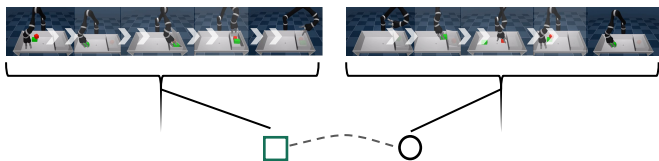


Skill Representation and Supervision in Multi-Task RL

Karol Hausman

Google Brain 



In collaboration with



USC

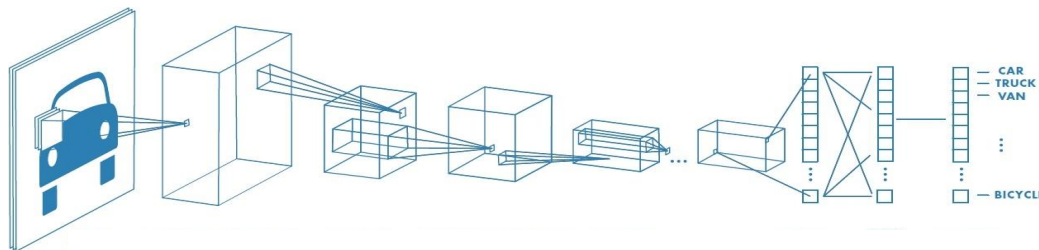
Why multi-task reinforcement learning?

Supervised learning: generalization

training set



training



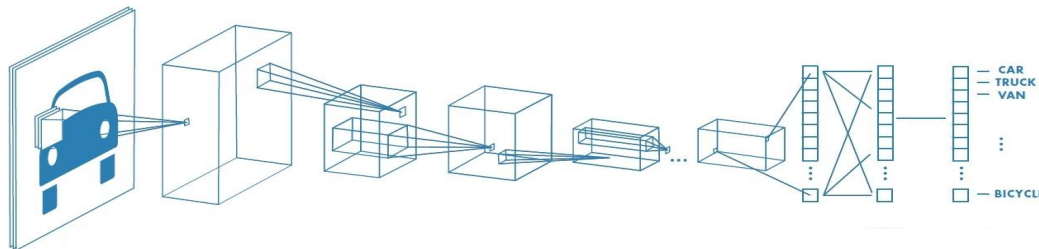
television
cat
car

training labels

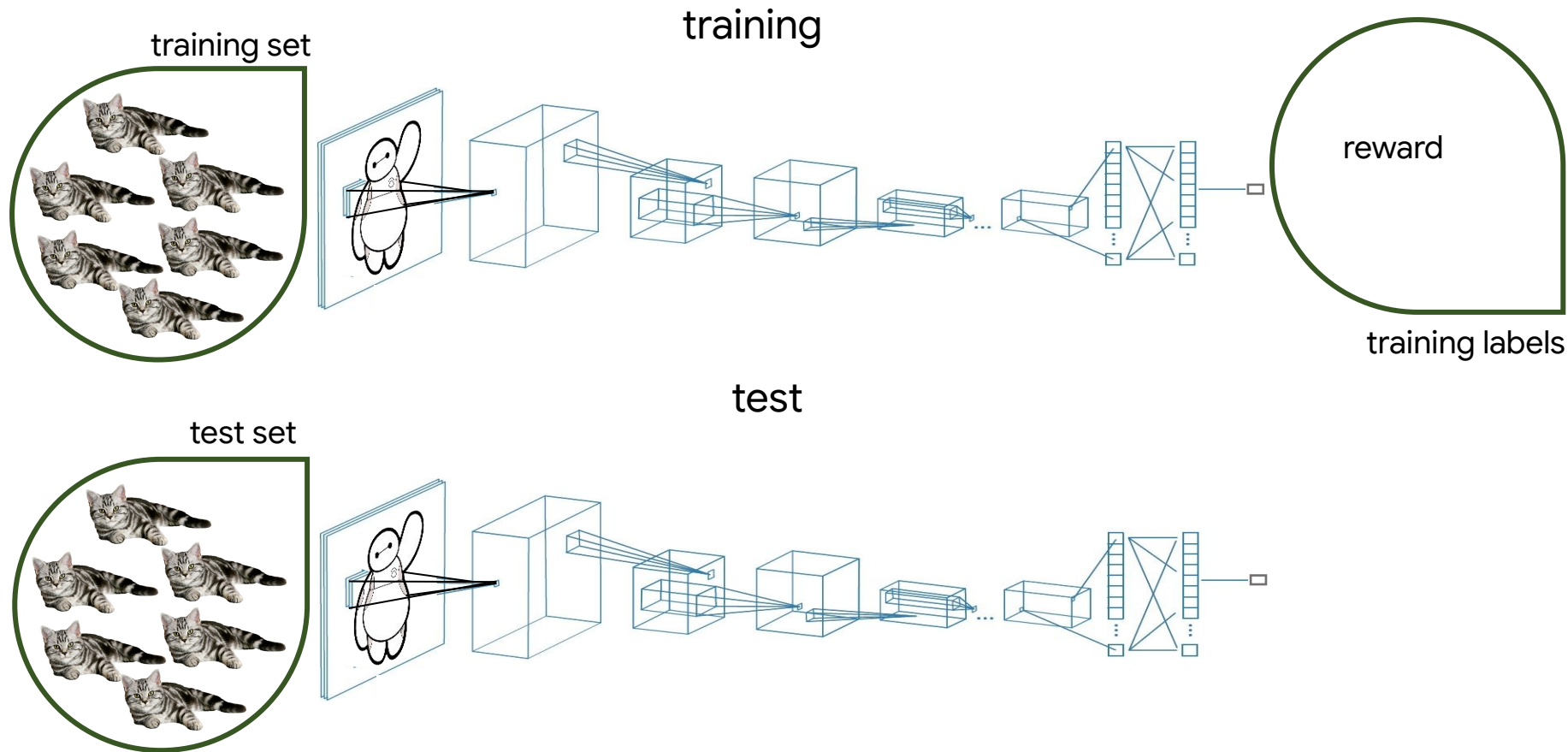
test set



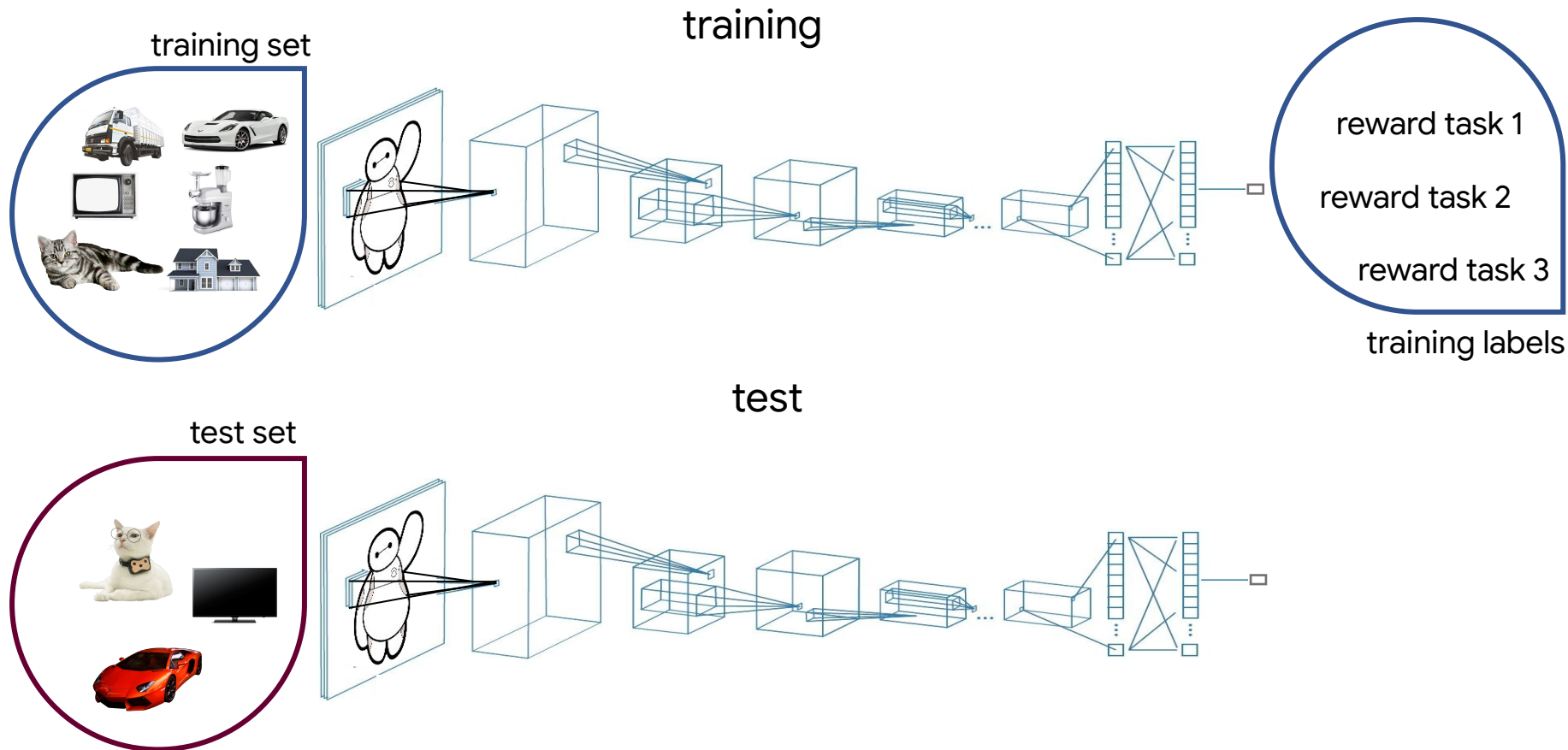
test



Single-task deep RL: generalization



Multi-task deep RL: generalization



Single-task deep RL: resets



[Combining Model-Based and Model-Free Updates for Trajectory-Centric Reinforcement Learning, Chebotar*, Hausman*, Zhang*, et al., 2017]

Multi-task deep RL: resets

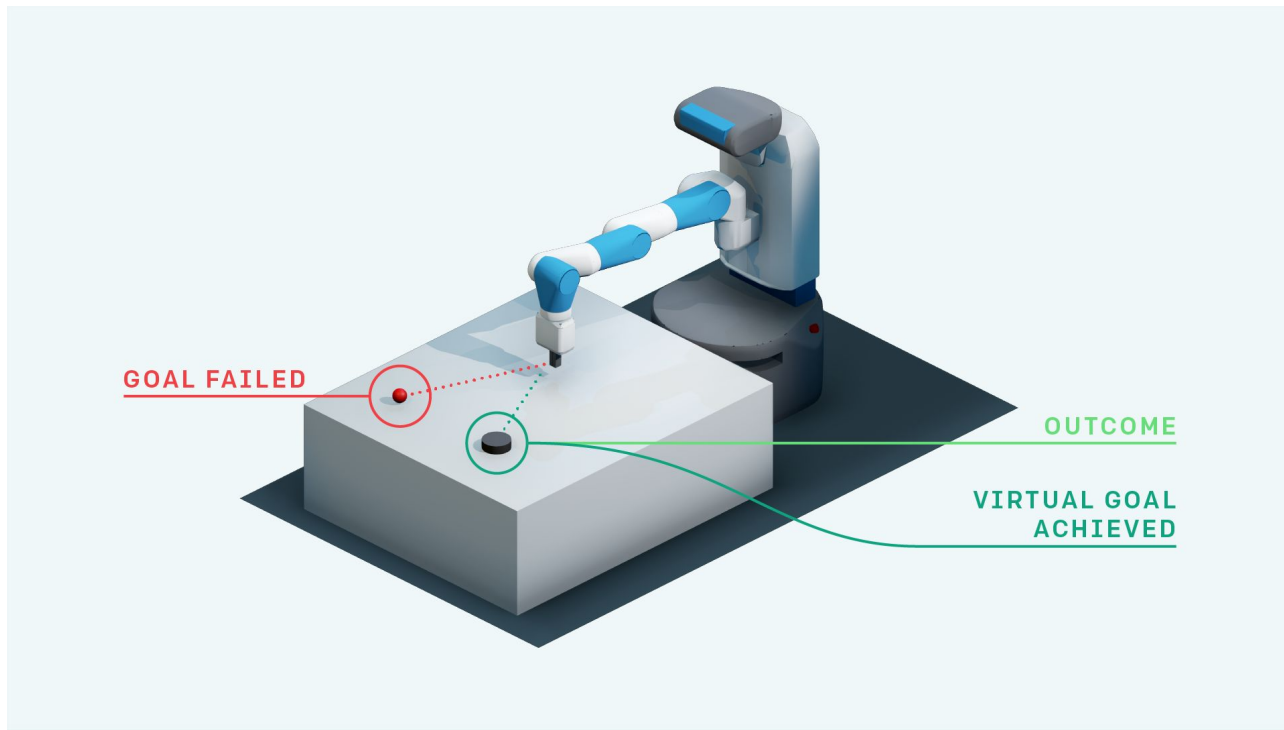


[Supervision via Competition: Robot Adversaries for Learning Tasks,
Pinto, et al., 2017]

Single-task deep RL: rewards



Multi-task deep RL: rewards



Why **not** multi-task reinforcement learning?

Multi-task deep RL

Challenges

- task specifications, what constitutes a task, how to represent a skill?
- reuse of already-learned skills
- optimization of multiple tasks (conflicting gradients, gradient magnitudes)
- data imbalance issues (harder easier tasks, good exploration in all of them)
- multiple skills - multiple pains: rewards, setups, etc.
- efficient sequencing of skills at test time

Multi-task deep RL

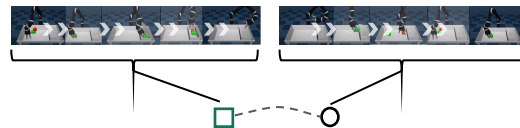
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Multi-task deep RL

Skill Representation and Reusability

- task specifications, what constitutes a task, how to represent a skill?
- reuse of already-learned skills



Supervision and Efficiency

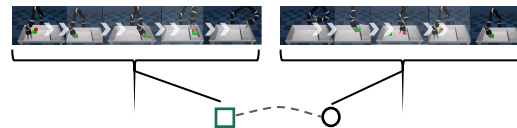
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Multi-task deep RL

Skill Representation and Reusability

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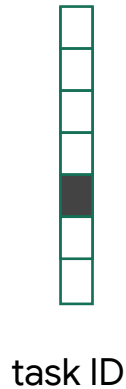


Supervision and Efficiency

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Skill representation



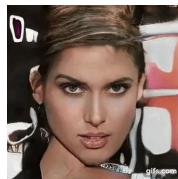
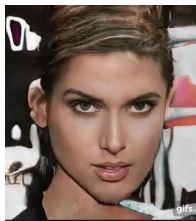
[Visual Reinforcement Learning
with Imagined Goals,
Pong et al. 2018]



[Progressive Growing of GANs for Improved Quality,
Stability, and Variation, Karras et al. 2018]

Latent space in images and policies

Images



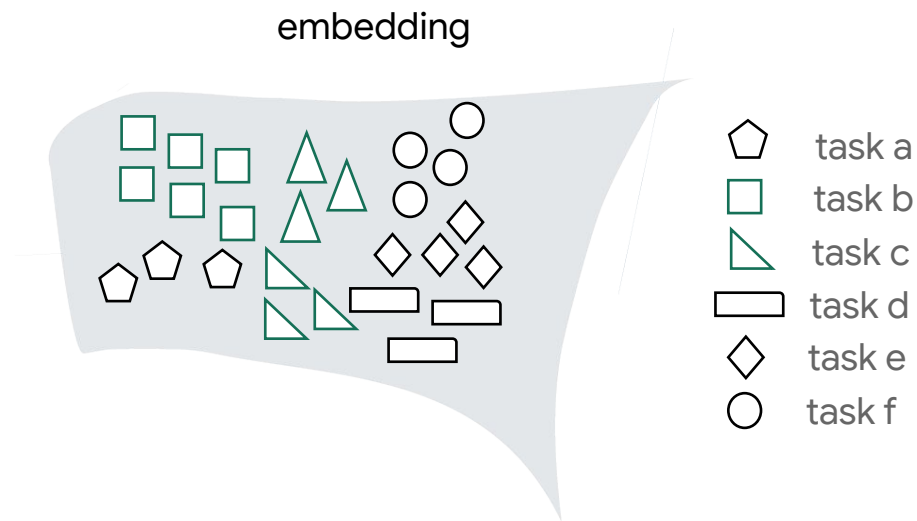
Policies



Robot skill embeddings

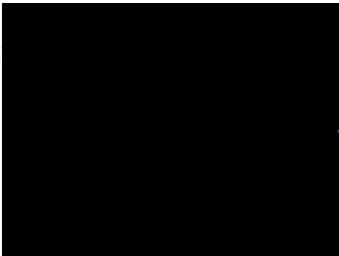
main idea: learn multiple re-usable skills and their skill embedding

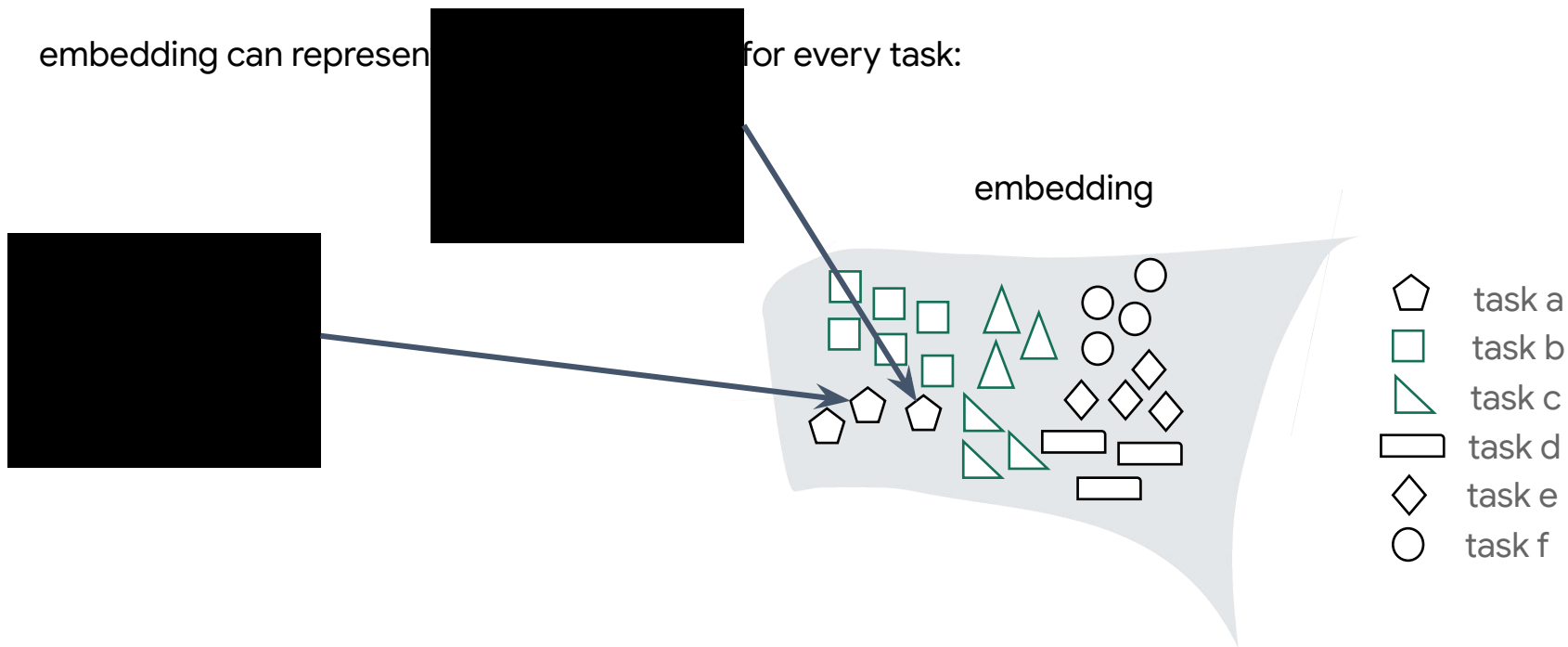
embedding can represent different solutions for every task:



Robot skill embeddings

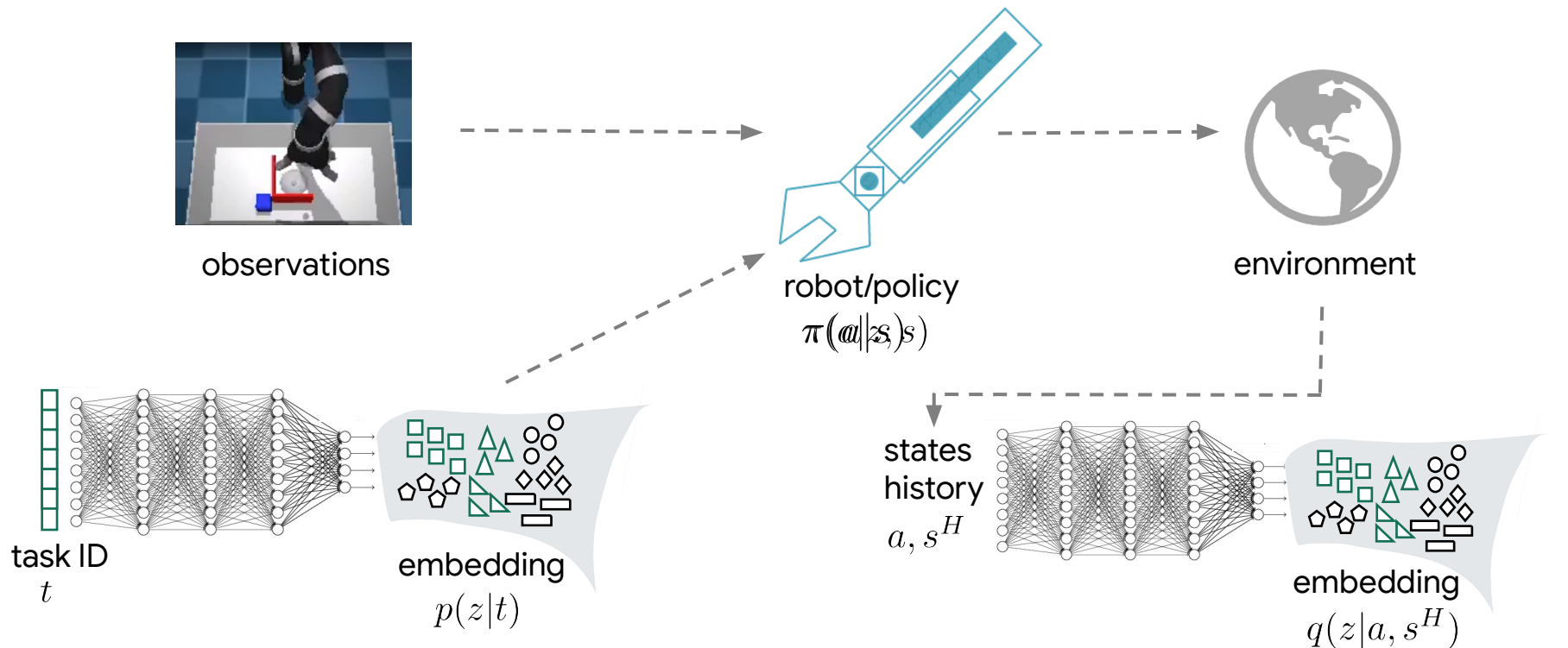
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Robot skill embeddings

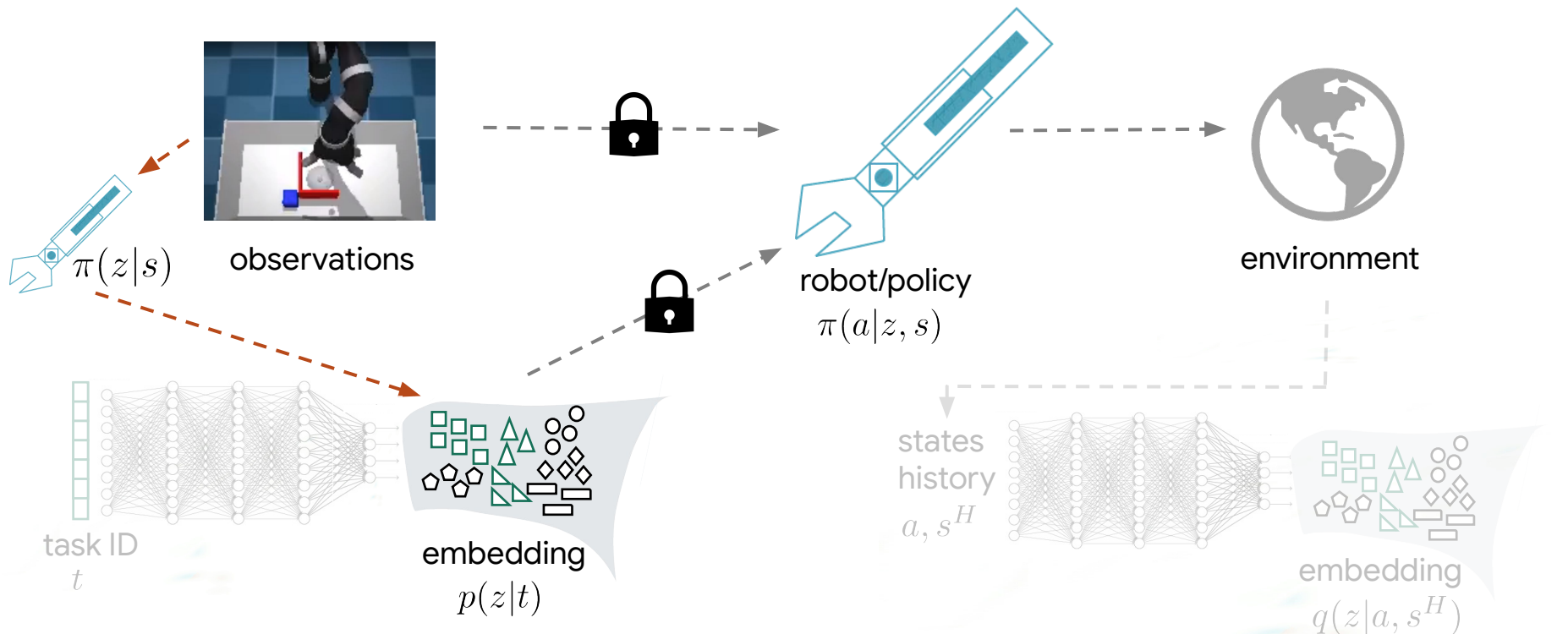
training:



[Learning an embedding space for reusable robotic skills,
Hausman et al.]

Robot skill embeddings

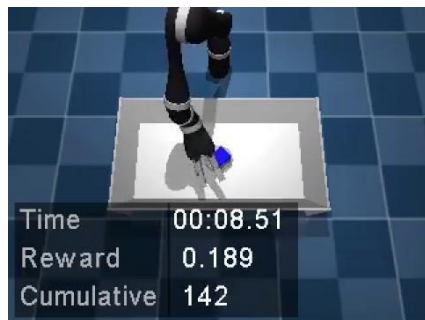
test:



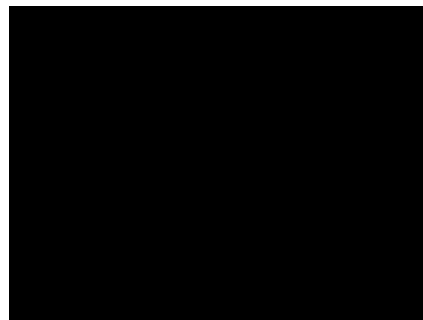
[Learning an embedding space for reusable robotic skills,
Hausman et al.]

Robot skill embeddings - multi-task learning

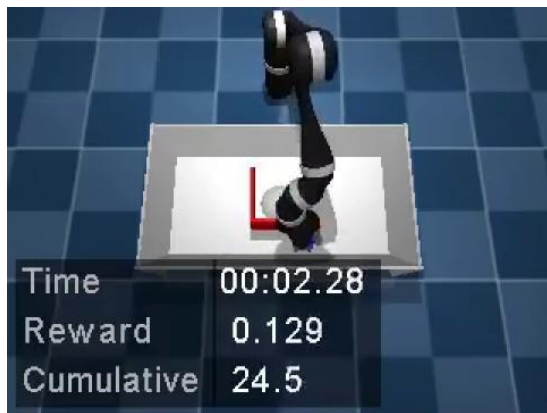
skills: push



lift

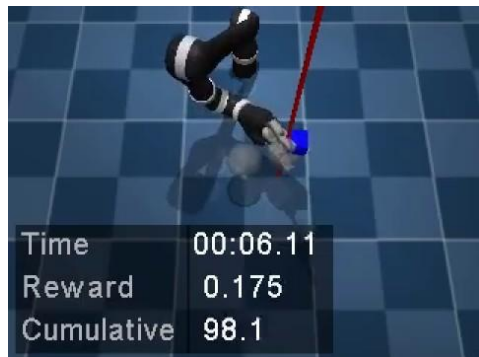


transfer: push around a wall

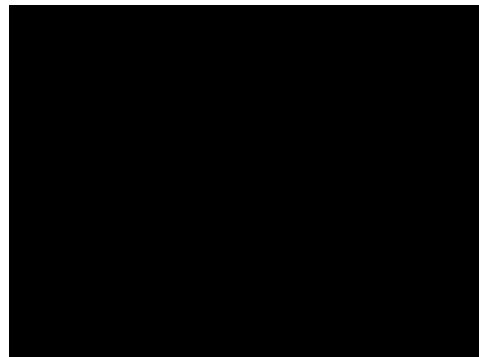


Robot skill embeddings - multi-task learning

skills: lift on a rail



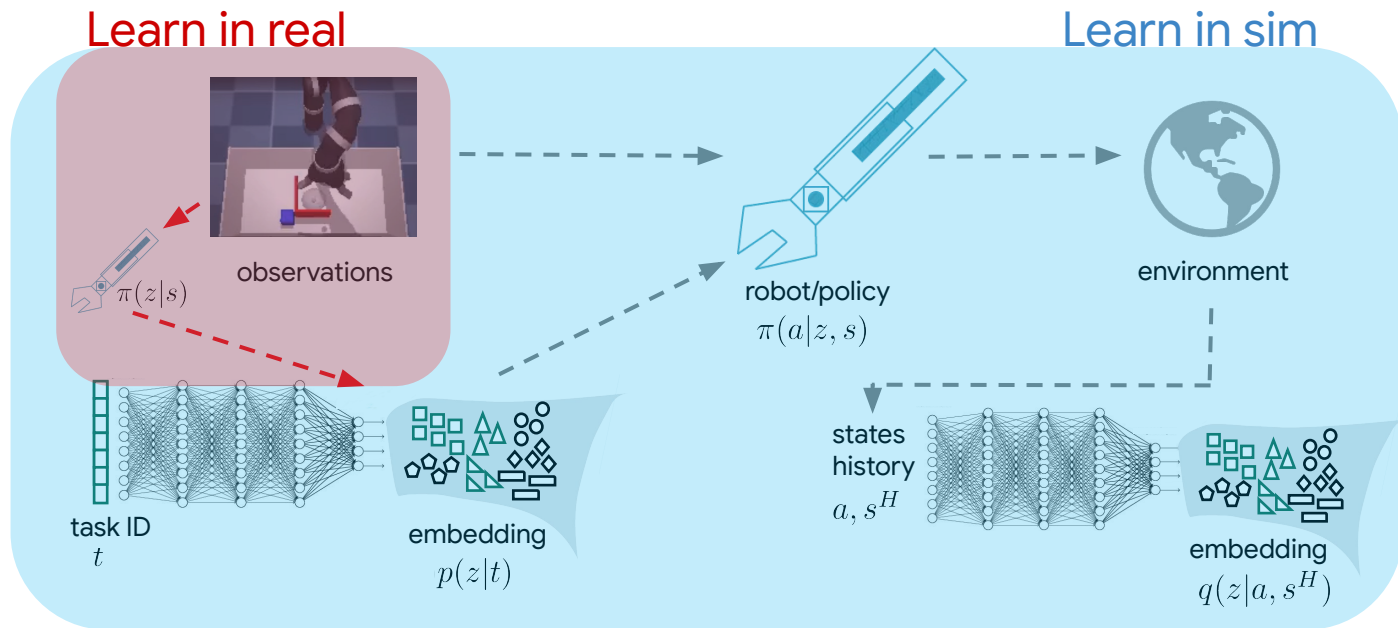
push on a table



transfer: lift and then push



Robot skill embeddings - sim2real transfer



[Scaling simulation-to-real transfer by learning composable robot skills

Julian, et al., 2018]

[Zero-Shot Skill Composition and Simulation-to-Real Transfer by
Learning Task Representations, He, et al., 2018]

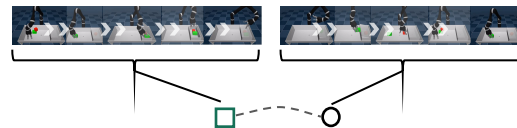
Robot skill embeddings - sim2real transfer



Multi-task deep RL

Skill Representation and Reusability

- task specifications, what constitutes a task, how to represent a skill?
- reuse of already-learned skills



Supervision and Efficiency

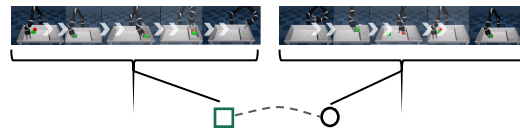
- multiple skills - multiple pains: rewards, setups, etc.
- efficient sequencing of skills at test time



Multi-task deep RL

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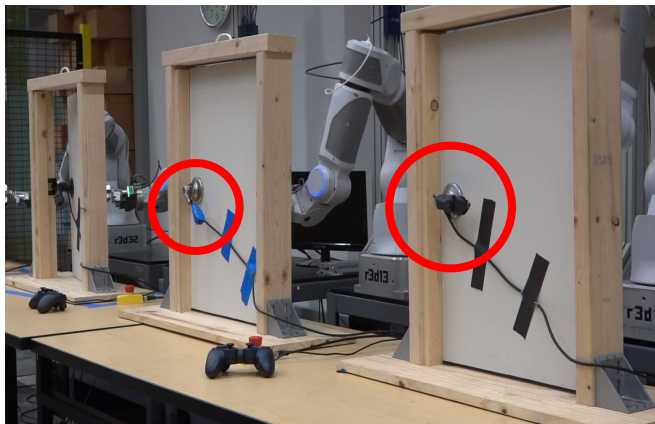


Supervision and Efficiency

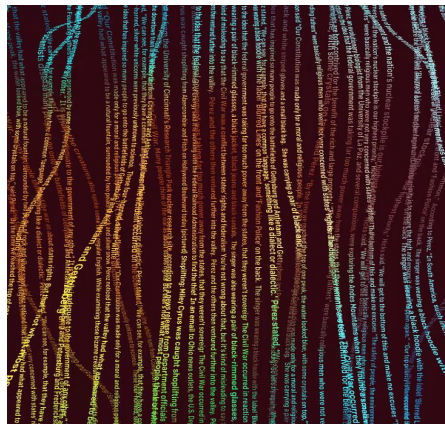
- multiple skills - multiple pains: rewards, setups, etc.
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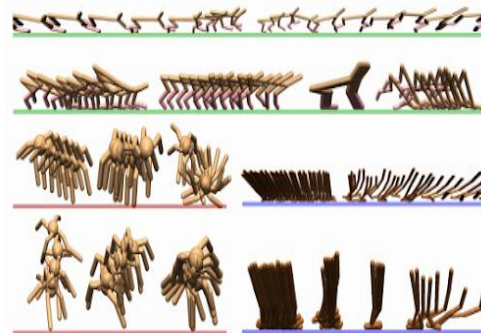
Supervision



[Collective robot reinforcement learning with distributed asynchronous guided policy search, Yahya et al. 2017]

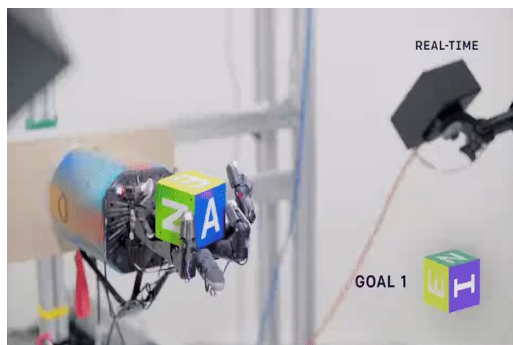


[Better Language Models and Their Implications, OpenAI Blog, 2019]



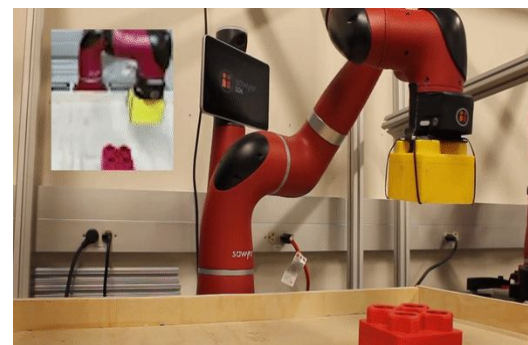
[Diversity is all you need, Learning Diverse Skills without a Reward Function, Eysenbach, 2018]

Efficiency



~100 years of experience

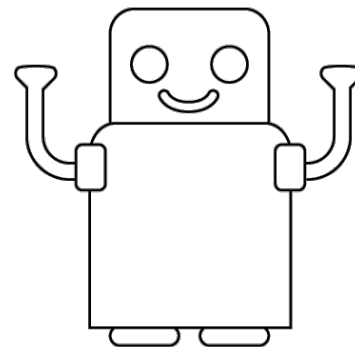
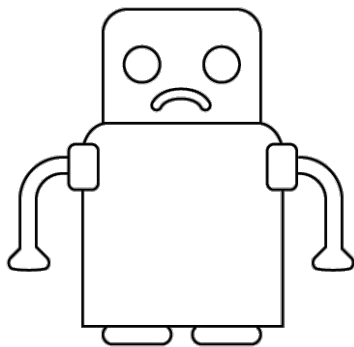
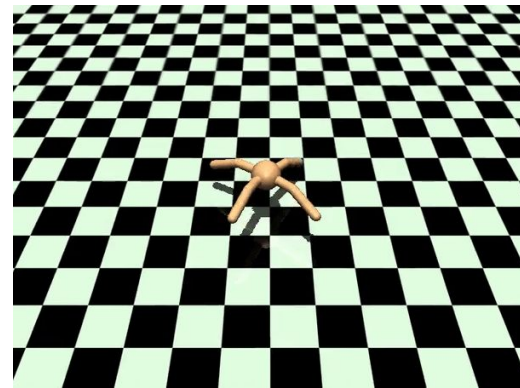
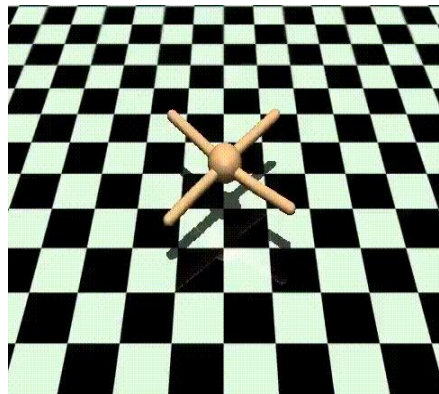
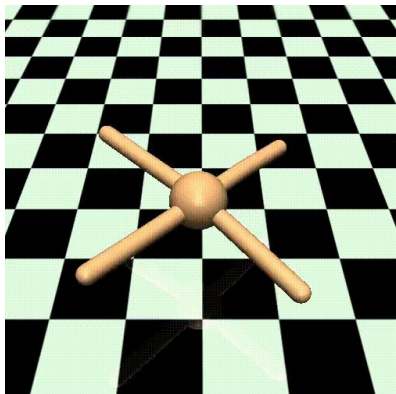
[Learning Dexterous In-Hand Manipulation,
OpenAI et al. 2018]



~1 hour of experience

[SOLAR: Deep Structured Representations
for Model-Based Reinforcement Learning,
Zhang et al. 2019]

Global vs Behavior-Specific Dynamics Models



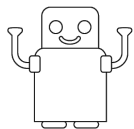
Dynamics-Aware Unsupervised Discovery of Skills (DADS)

main idea: use empowerment to simultaneously optimize for skills and their specific dynamics

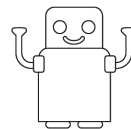
mutual information objective:

$$I(s'; z | s) \geq \mathbb{E}_s \mathbb{E}_z \mathbb{E}_{p(s' | s, z)} \left[\log \frac{q_\phi(s' | s, z)}{p(s' | s)} \right]$$
$$\approx \mathbb{E}_s \mathbb{E}_z \mathbb{E}_{p(s' | s, z)} \left[\log \frac{q_\phi(s' | s, z)}{\sum_{i=1}^L q_\phi(s' | s, z_i)} + \log L \right]$$

Predictability

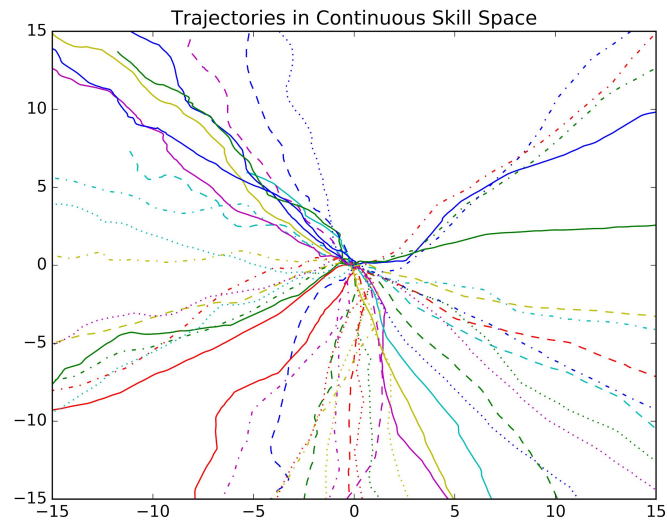
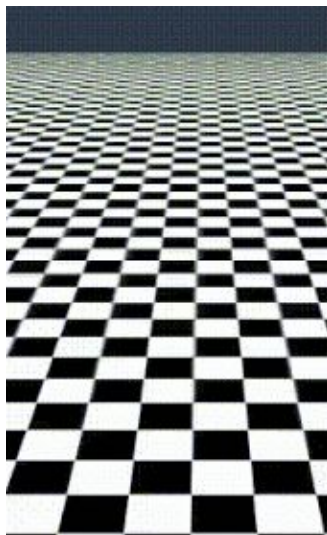
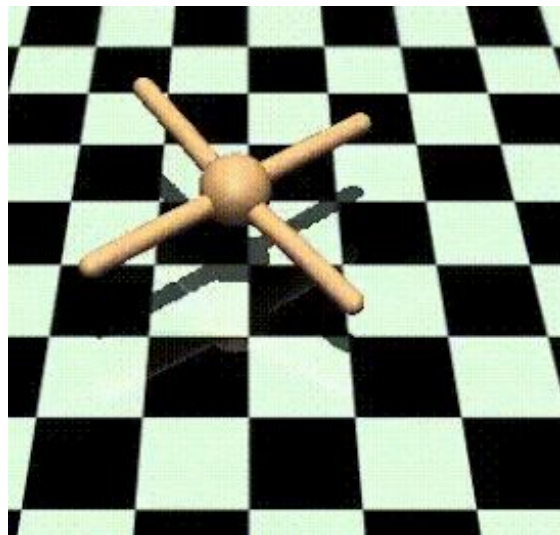


Diversity

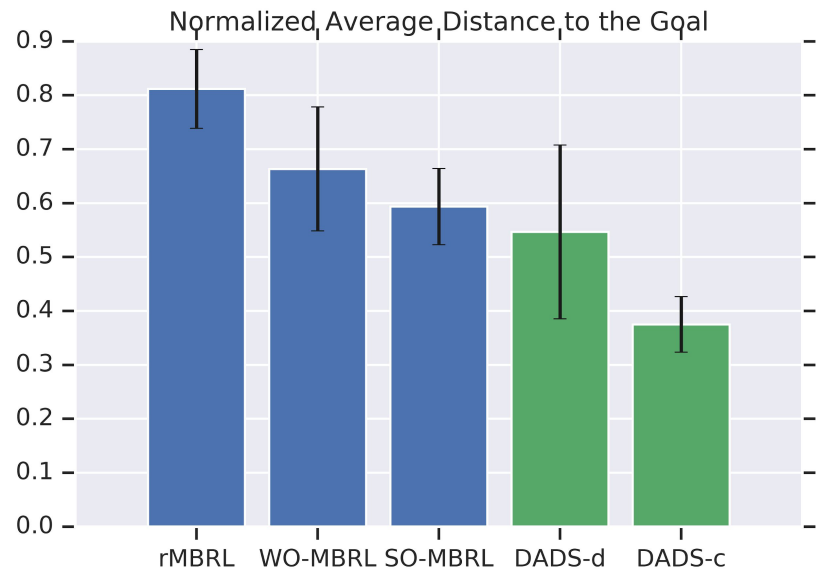


[Dynamics-Aware Unsupervised Discovery of Skills,
Sharma, et al. 2018]

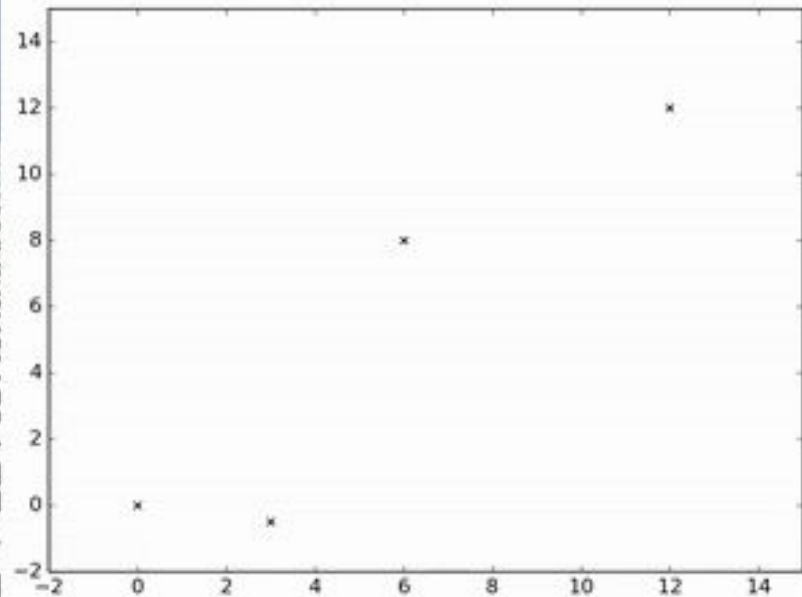
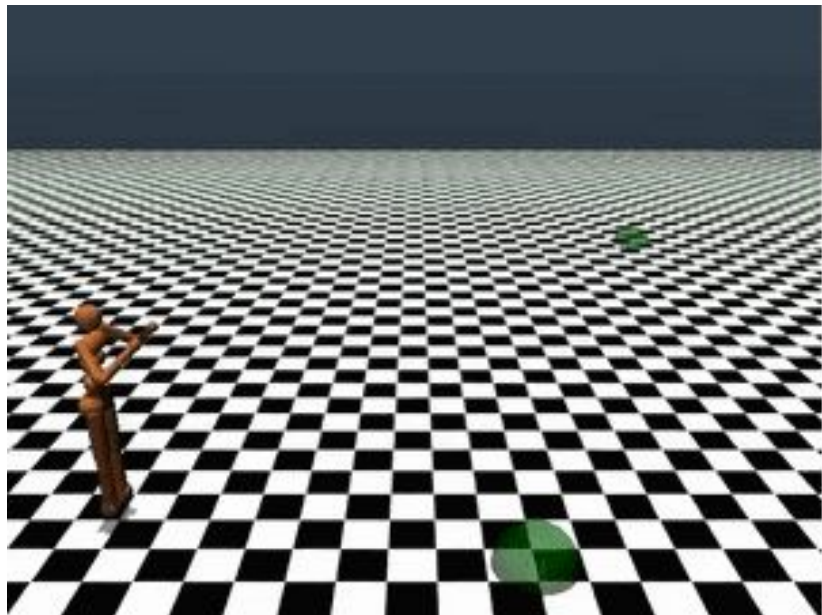
Dynamics-Aware Unsupervised Discovery of Skills (DADS)



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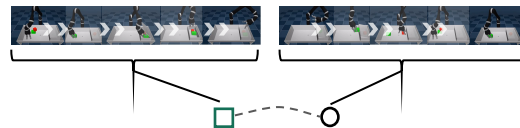
Dynamics-Aware Unsupervised Discovery of Skills (DADS)



Multi-task deep RL

Skill Representation and Reusability

- task specifications, what constitutes a task, how to represent a skill?
- reuse of already-learned skills



Supervision and Efficiency

- multiple skills - multiple pains: rewards, setups, etc.
- efficient sequencing of skills at test time



Multi-task deep RL

Challenges

- task specifications, what constitutes a task, how to represent a skill?
- reuse of already-learned skills
- optimization of multiple tasks (conflicting gradients, gradient magnitudes)
- data imbalance issues (harder easier tasks, good exploration in all of them)
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Future Work



Multi-task deep RL

Challenges

- task specifications, what constitutes a task, how to represent a skill?
- reuse of already-learned skills
- optimization of multiple tasks (conflicting gradients, gradient magnitudes)
- data imbalance issues (harder easier tasks, good exploration in all of them)
- multiple skills - multiple pains: rewards, setups, etc.
- efficient sequencing of skills at test time
- and many more...



Hockey

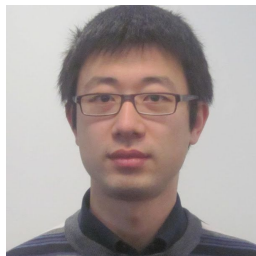
5x

PILQR: 200 samples

freegifmaker.me

Learning an Embedding Space for Transferable Robot Skills, ICLR 2018

K. Hausman, T. Springenberg, Z. Wang, N. Heess, M. Riedmiller



Dynamics-Aware Unsupervised Discovery of Skills, NeurIPS 2019 Submission

A. Sharma, S. Gu, S. Levine, V. Kumar, K. Hausman

