Lifelong Learning

CS 330

Course Reminders

Optional homework 4 due **today**.

Project milestone due **Wednesday.**

Guest lecture on Wednesday!

Hanie Sedghi

Please try to show up in person & on-time.

Plan for Today

The lifelong learning **problem statement**

Basic approaches to lifelong learning

Can we do **better** than the basics?

Revisiting the problem statement
from **the meta-learning perspective**

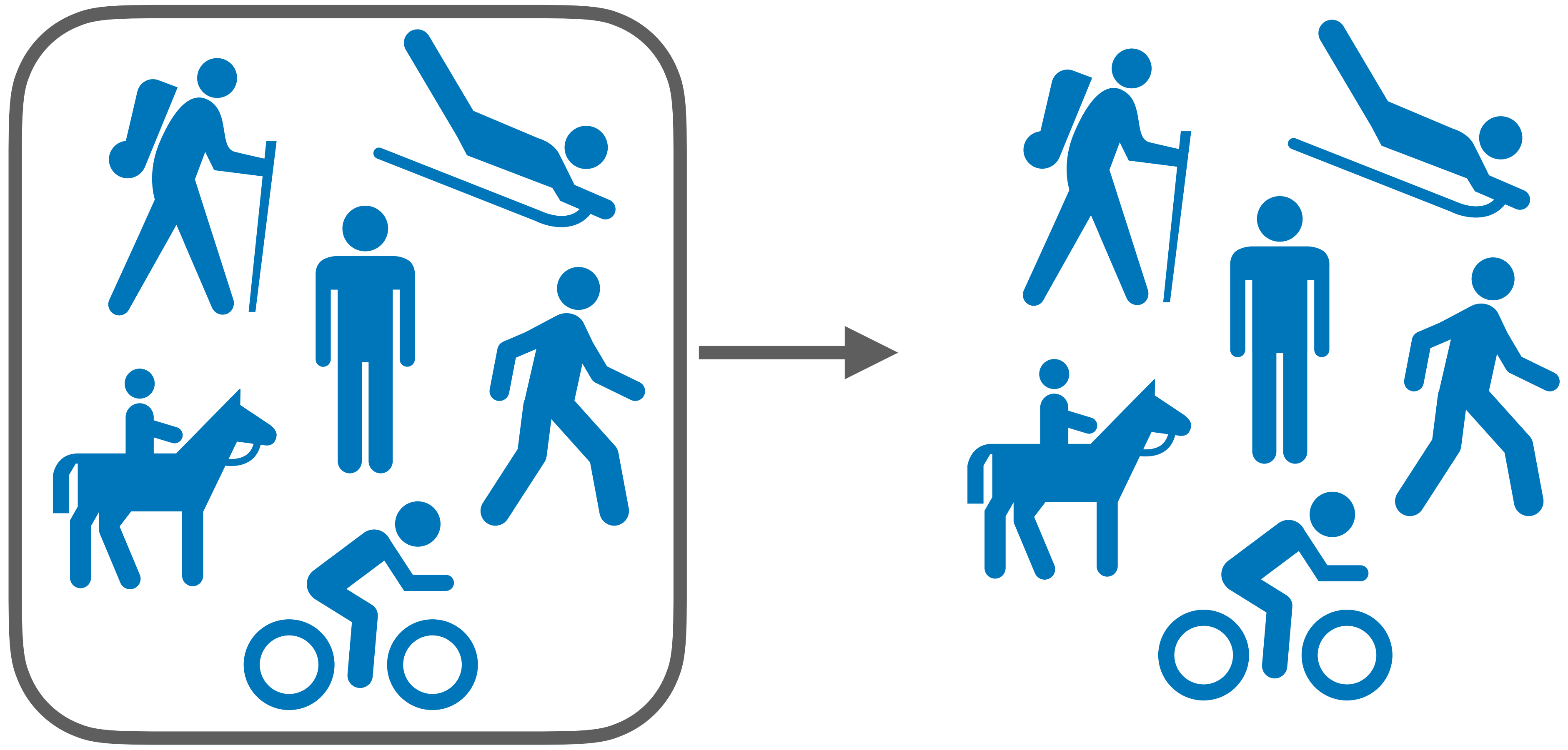
A brief review of problem statements.

Multi-Task Learning

Learn to solve a set of tasks.

learn tasks

perform tasks

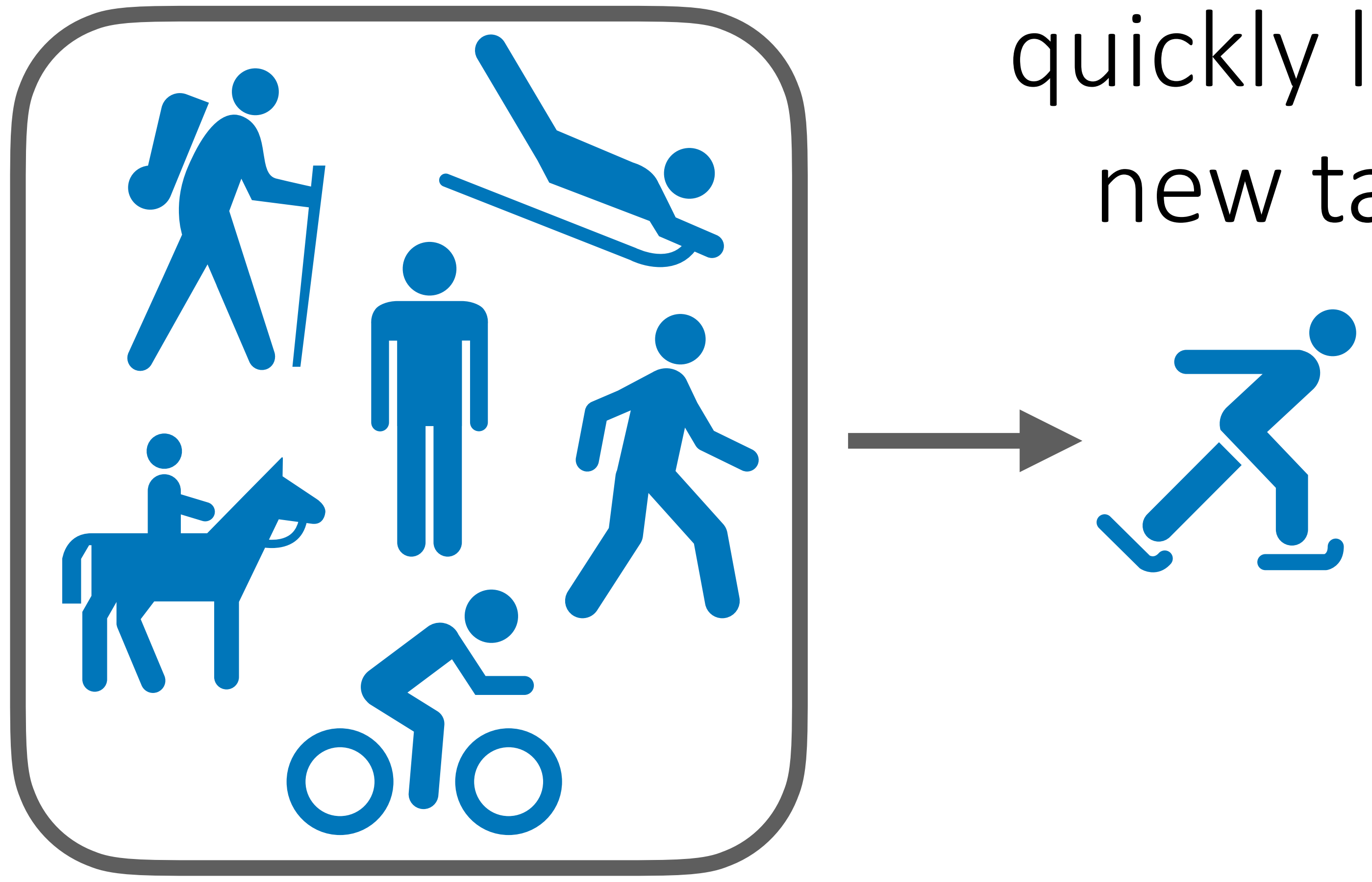


Meta-Learning

Given i.i.d. task distribution,
learn a new task efficiently

learn to learn tasks

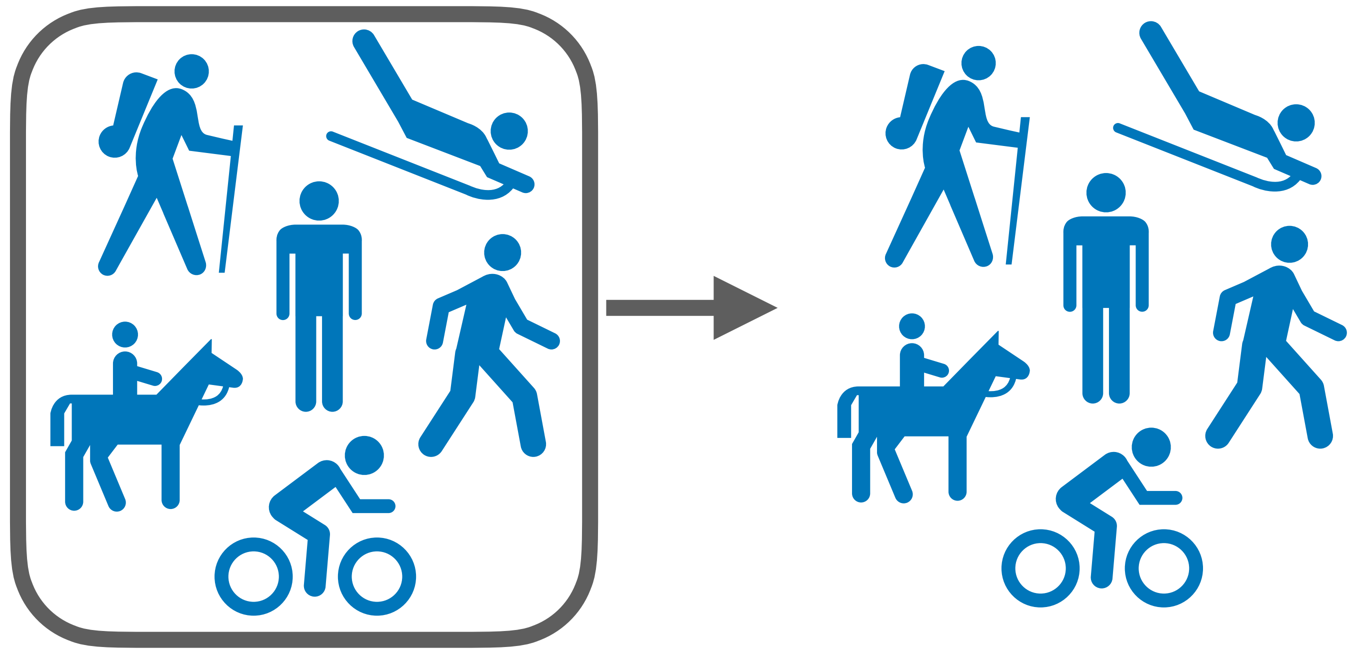
quickly learn
new task



Multi-Task Learning

learn tasks

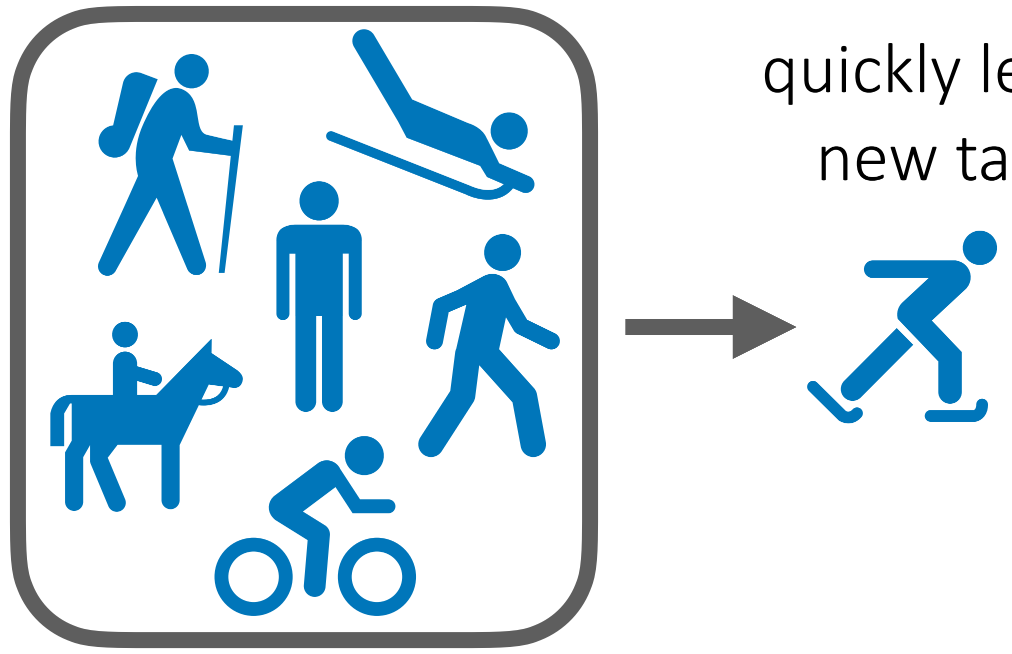
perform tasks



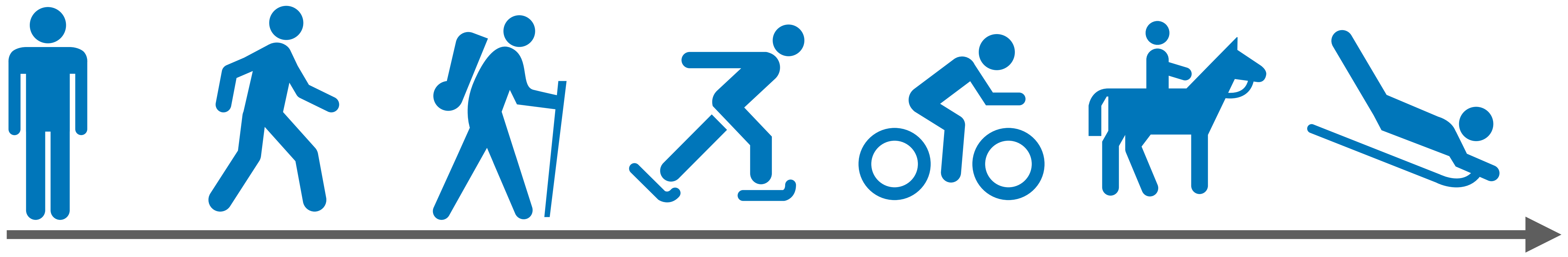
Meta-Learning

learn to learn tasks

quickly learn new task



In contrast, many real world settings look like:



time

Our agents may not be given a large batch of data/tasks right off the bat!

Some examples:

- a **student** learning concepts in school
- a deployed **image classification system** learning from a stream of images from users
- a **robot** acquiring an increasingly large set of skills in different environments
- a **virtual assistant** learning to help different users with different tasks at different points in time
- a **doctor's assistant** aiding in medical decision-making

Some Terminology

Sequential learning settings

online learning, lifelong learning, continual learning, incremental learning, streaming data

distinct from **sequence data** and **sequential decision-making**

What is the lifelong learning *problem statement*?

Exercise:

1. **Pick an example setting.**

2. **Discuss problem statement in small groups**:

(a) how would you set-up an experiment to develop & test your algorithm?

(b) what are desirable/required properties of the algorithm?

(c) how do you evaluate such a system?

Example settings:

A. a **student** learning concepts in school

B. a deployed **image classification system** learning from a stream of images from users

C. a **robot** acquiring an increasingly large set of skills in different environments

D. a **virtual assistant** learning to help different users with different tasks at different points in time

E. a **doctor's assistant** aiding in medical decision-making

What is the lifelong learning *problem statement*?

Problem variations:

- **task/data order**: i.i.d. vs. predictable vs. curriculum vs. adversarial
- **discrete** task boundaries vs. **continuous** shifts (vs. both)
- **known** task boundaries/shifts vs. **unknown**

Some considerations:

- model **performance**
- data **efficiency**
- **computational** resources
- **memory**
- others: privacy, interpretability, fairness,
test time compute & memory

Substantial variety in problem statement!

What is the lifelong learning *problem statement*?

General [supervised] online learning problem:

for t = 1, ..., n

observe x_t <— if **observable task boundaries**: observe x_t, z_t

predict $\hat{y}_t$

observe label y_t

i.i.d. setting: $x_t \sim p(x)$, $y_t \sim p(y|x)$

p not a function of t

otherwise: $x_t \sim p_t(x)$, $y_t \sim p_t(y|x)$

streaming setting: cannot store (x_t, y_t)

- lack of memory
- lack of computational resources
- privacy considerations
- want to study neural memory mechanisms

true in some cases, but not in many cases!

- recall: replay buffers

What do you want from your lifelong learning algorithm?

minimal regret (that grows slowly with t)

regret: cumulative loss of learner — cumulative loss of best learner in hindsight

$$\mathrm{Regret}_T := \sum_1^T \mathscr{L}_t(\theta_t) - \min_\theta \sum_1^T \mathscr{L}_t(\theta)$$

(cannot be evaluated in practice, useful for analysis)

Regret that grows linearly in t is trivial. Why?

What do you want from your lifelong learning algorithm?

minimal regret (that grows slowly with t)

regret: cumulative loss of learner — cumulative loss of best learner in hindsight

$$\text{Regret}_T := \sum_{1}^{T} \mathscr{L}_t(\theta_t) - \min_{\theta} \sum_{1}^{T} \mathscr{L}_t(\theta)$$

t	1	2	3
			
$\hat{y}_t$	10	~~10~~ 30	~~10~~ 29
y_t	30	28	32

What do you want from your lifelong learning algorithm?

positive & negative transfer

positive forward **transfer**: previous tasks cause you to do better on future tasks compared to learning future tasks from scratch

positive backward **transfer**: current tasks cause you to do better on previous tasks compared to learning past tasks from scratch

positive -> negative : better -> worse

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Can we do **better** than the basics?

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Approaches

Store all the data you've seen so far, and train on it. —> **follow the leader** algorithm

+ will achieve very **strong performance**

- **computation intensive** —> **Continuous fine-tuning** can help.

- can be **memory intensive** [depends on the application]

Take a gradient step on the datapoint you observe. —> **stochastic gradient descent**

+ computationally cheap

+ requires 0 memory

- subject to **negative backward transfer**
  "forgetting"

- slow learning

sometimes referred to as catastrophic forgetting

Can we do better?

Applying a simple continual learning algorithm to robotics

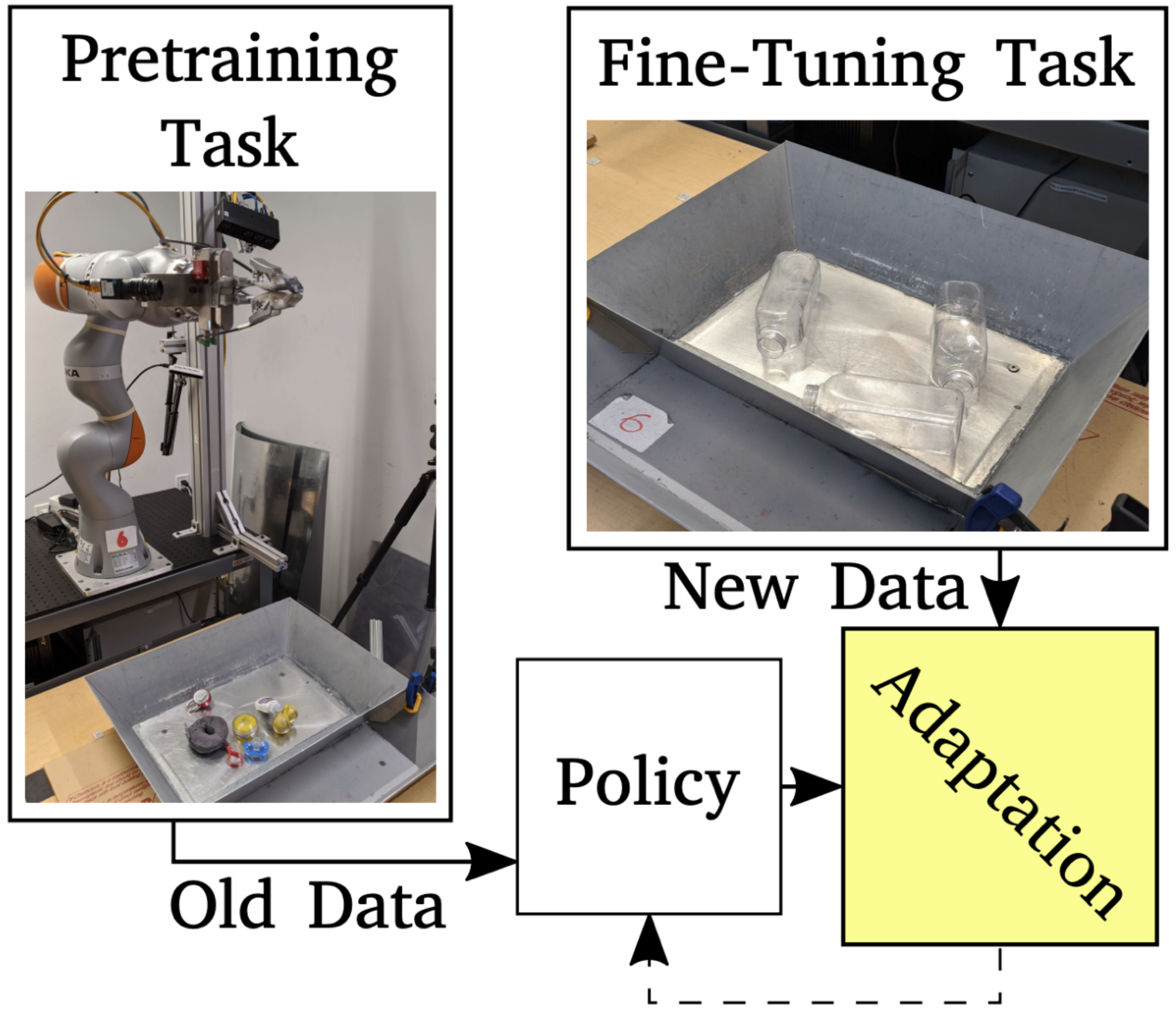
7 robots collected 580k grasps

86%

49%

Julian, Swanson, Sukhatme, Levine, Finn, Hausman, Never Stop Learning, 2020

Applying a simple continual learning algorithm to robotics



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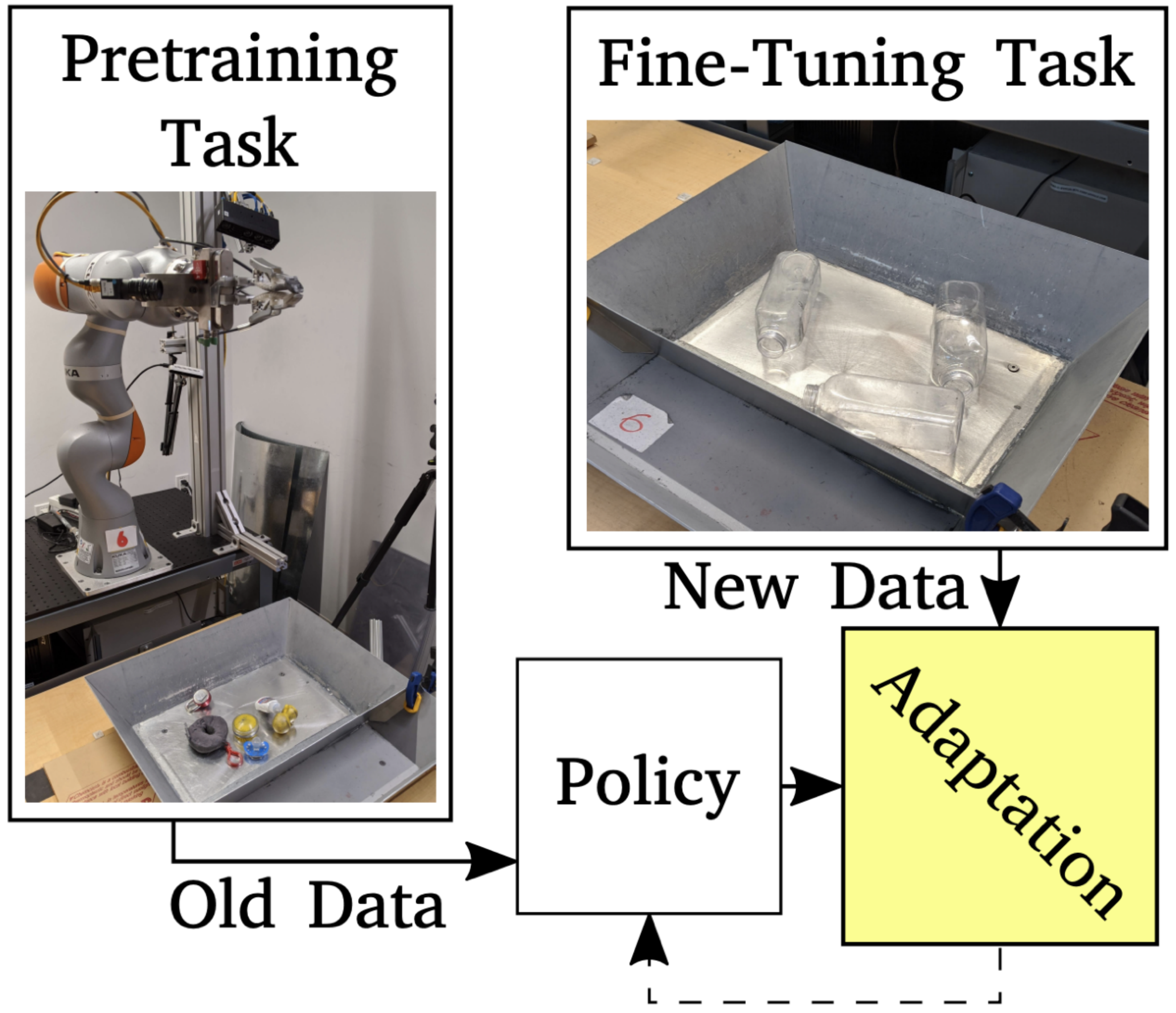

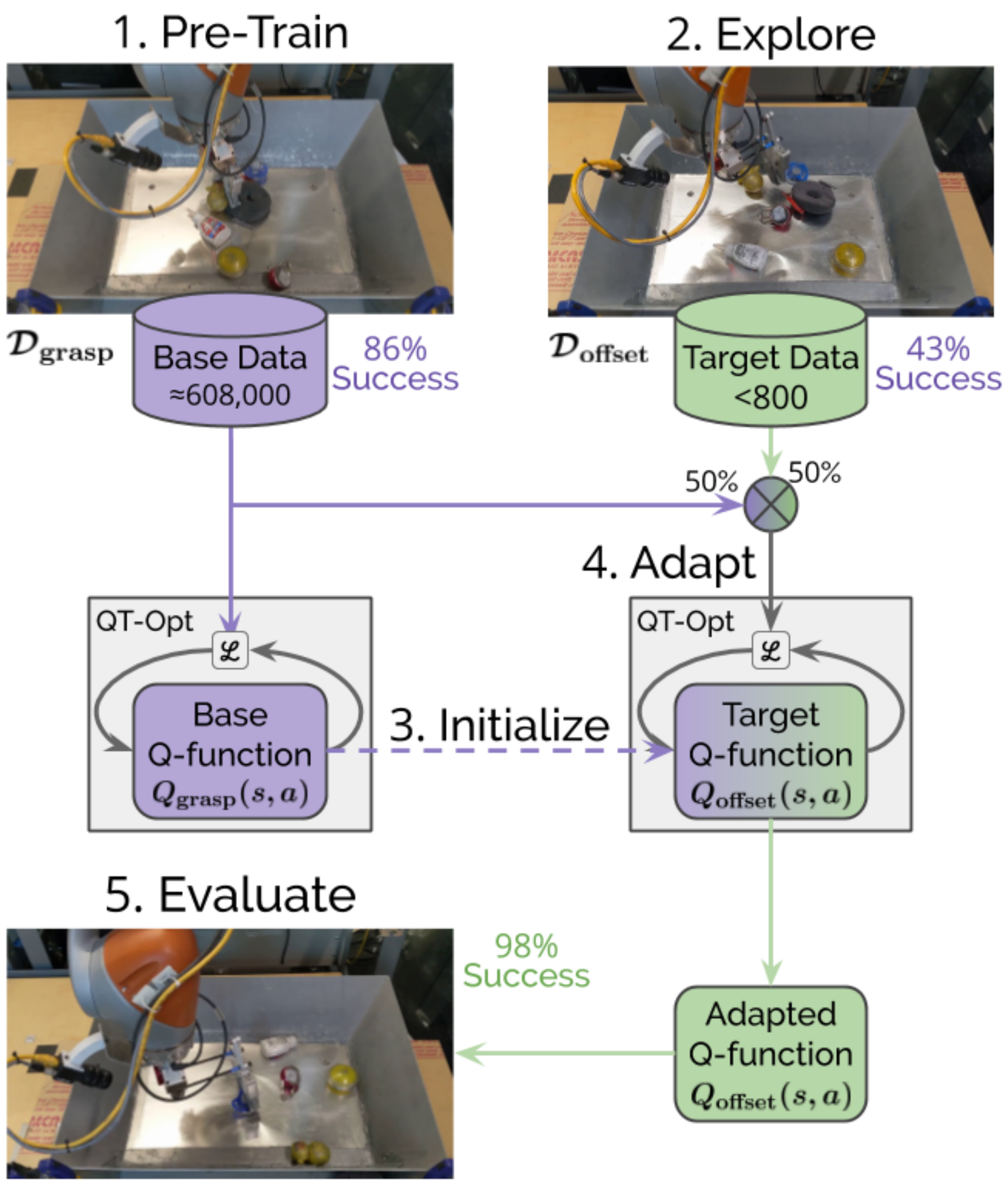

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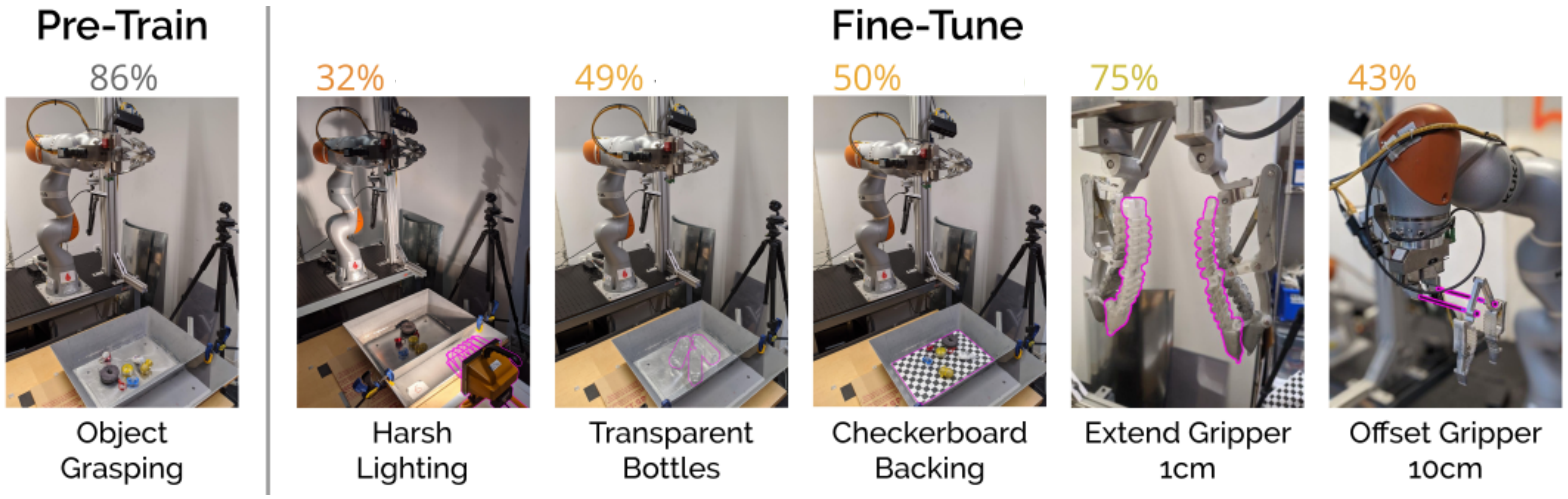

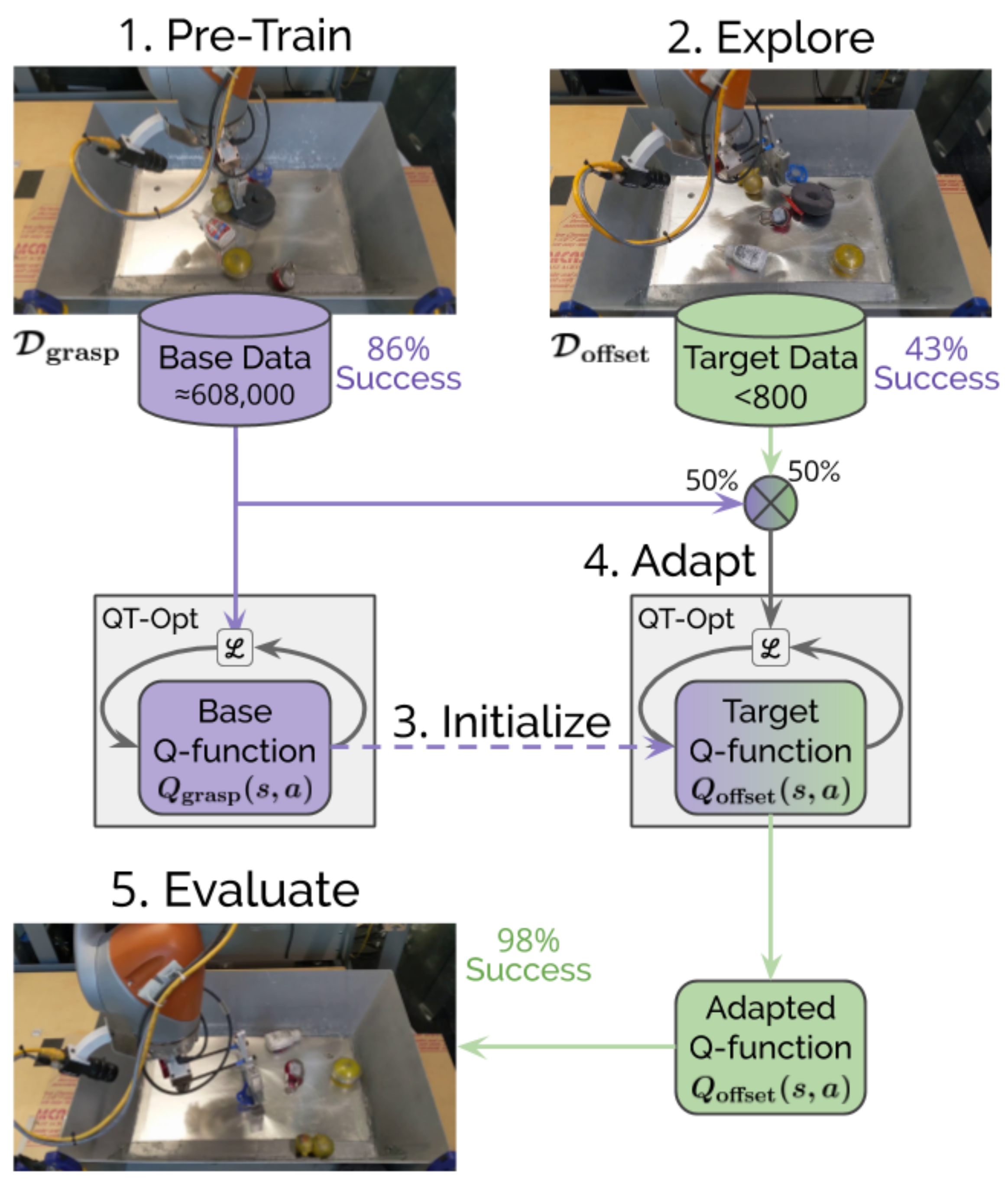

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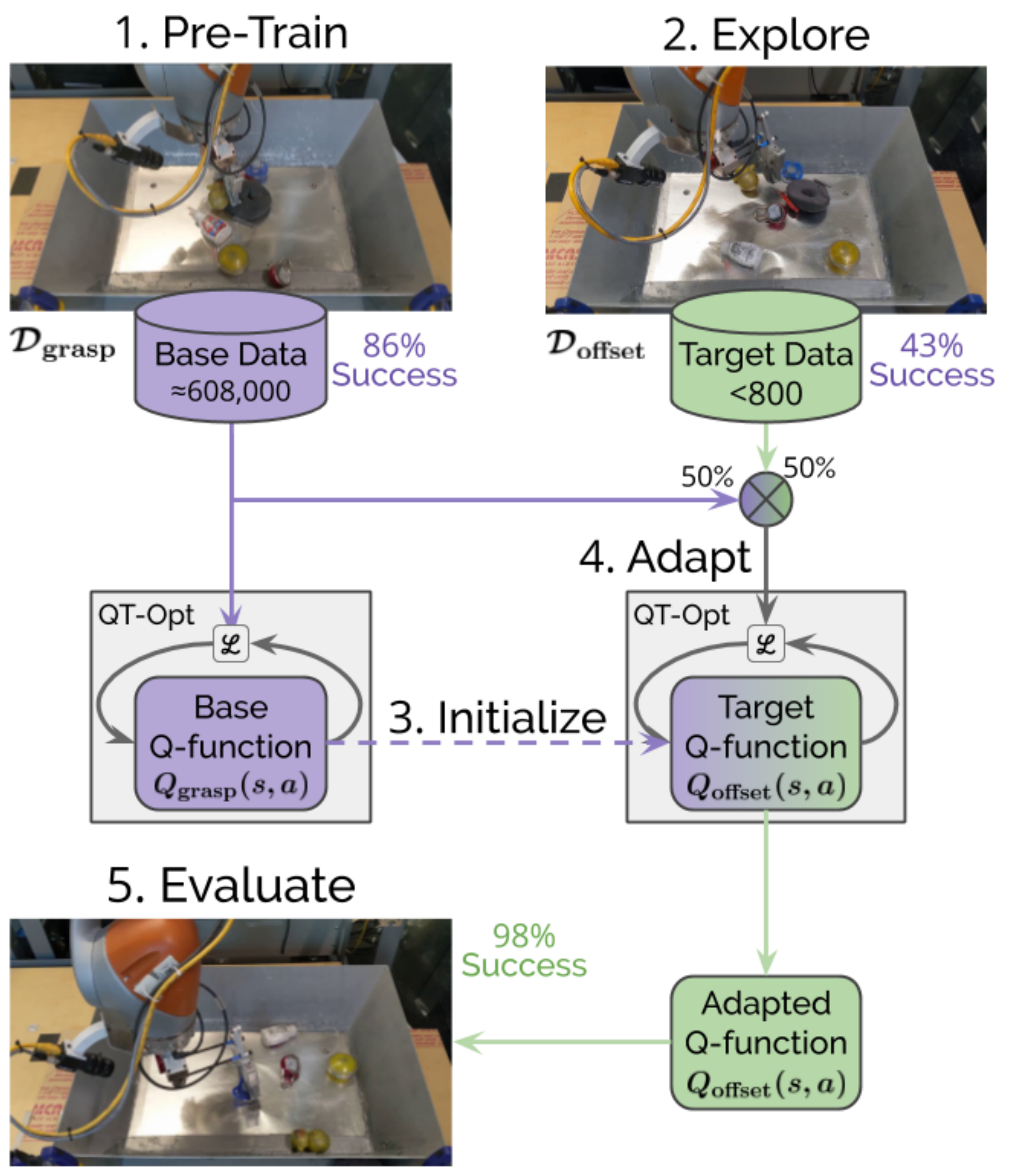

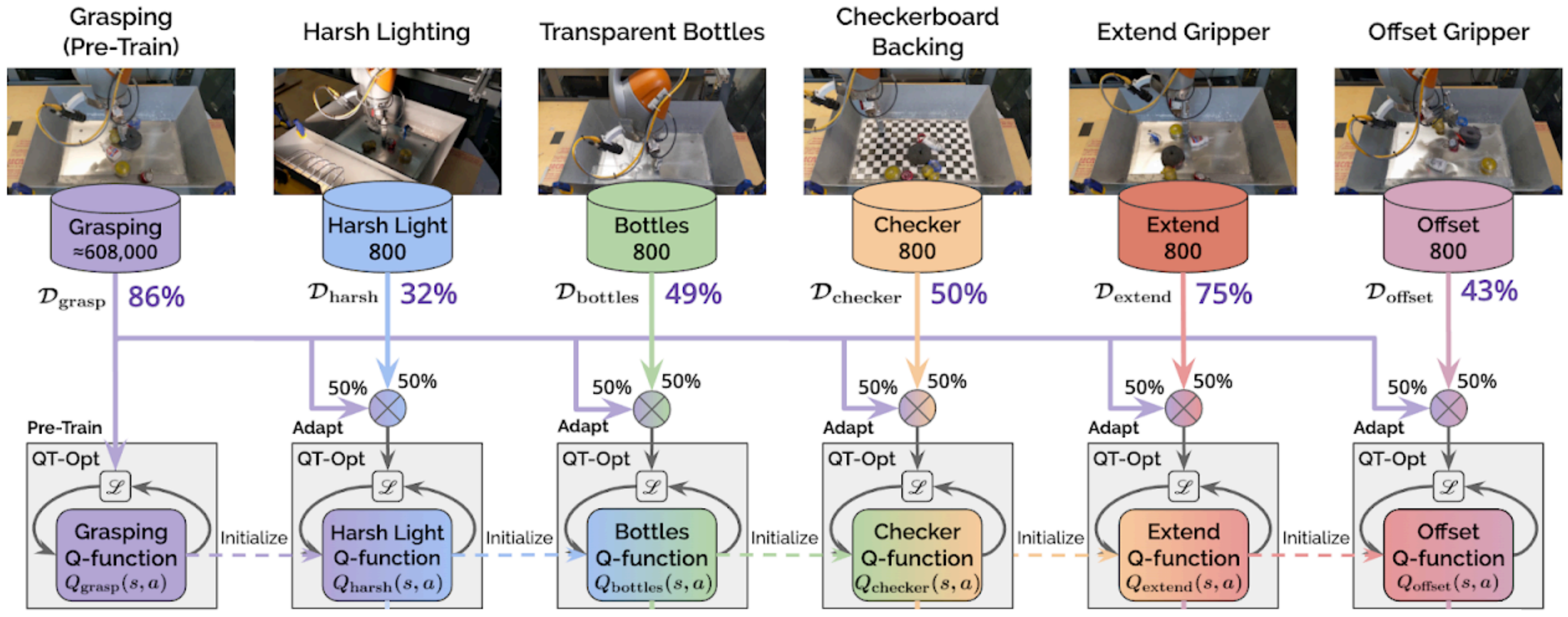

What about backward transfer?

Can we do better?

Julian, Swanson, Sukhatme, Levine, Finn, Hausman, Never Stop Learning, 2020

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Case Study: Can we modify vanilla SGD to avoid negative backward transfer?

(from scratch)

Idea: (1) store small amount of data per task in **memory**

(2) when making updates for new tasks, ensure that they don't **unlearn** previous tasks

How do we accomplish (2)?

learning predictor $y_t = f_\theta(x_t, z_t)$ memory: $\mathcal{M}_k$ for task z_k

For $t = 0, \ldots, T$

minimize $\mathcal{L}(\ f_\theta(\cdot, z_t)\ ,\ (x_t, y_t)\ )$

subject to $\mathcal{L}(\ f_\theta\ ,\ \mathcal{M}_k\ ) \leq \mathcal{L}(\ f_\theta^{t-1}\ ,\ \mathcal{M}_k\ )$ for all $k < t$

(i.e. s.t. loss on previous tasks doesn't get worse)

Assume local linearity:

$$\langle g_t, g_k \rangle := \left\langle \frac{\partial \mathcal{L}(\ f_\theta\ ,\ (x_t, y_t)\ )}{\partial \theta}, \frac{\partial \mathcal{L}(\ f_\theta\ ,\ \mathcal{M}_k\ )}{\partial \theta} \right\rangle \geq 0 \quad \text{for all } z_k < z_t$$

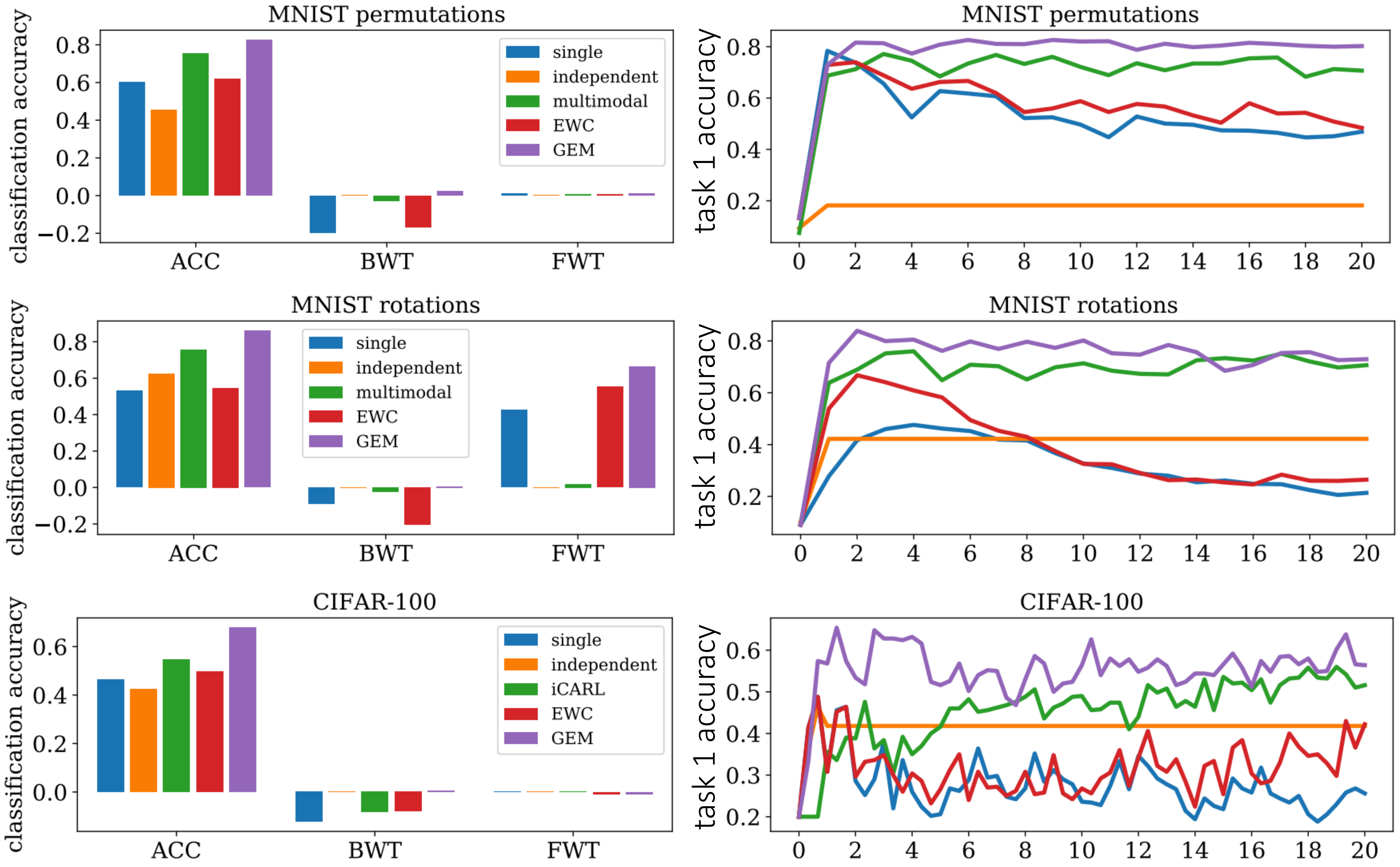
Can formulate & solve as a QP.

Lopez-Paz & Ranzato. Gradient Episodic Memory for Continual Learning. NeurIPS '17

Experiments

Problems:

- MNIST permutations
- MNIST rotations
- CIFAR-100 (5 new classes/task)



BWT: backward transfer,

FWT: forward transfer

Total memory size:

5012 examples

If we take a step back… do these experimental domains make sense?

Lopez-Paz & Ranzato. Gradient Episodic Memory for Continual Learning. NeurIPS '17

Can we meta-learn how to avoid negative backward transfer?

Javed & White. ***Meta-Learning Representations for Continual Learning.*** NeurIPS '19

Beaulieu et al. ***Learning to Continually Learn.*** '20

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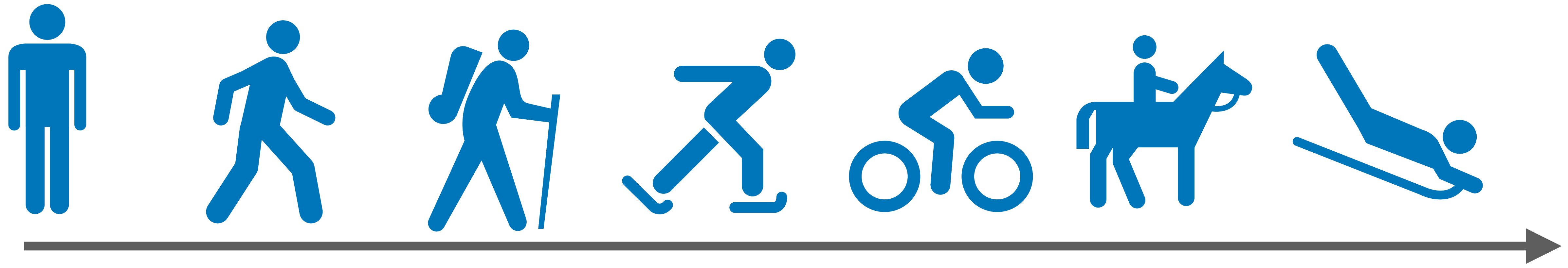
Formulation of online learning when faced with sequence of tasks

Online Learning

(Hannan ’57, Zinkevich ’03)

Perform sequence of tasks
while minimizing static regret.

More realistically:



Formulation of online learning when faced with sequence of tasks

Online Learning

(Hannan '57, Zinkevich '03)

Perform sequence of tasks
while minimizing static regret.

perform perform perform perform perform perform perform

time

zero-shot performance

Online Meta-Learning

Efficiently learn a sequence of tasks
from a non-stationary distribution.

learn learn learn learn learn learn learn

time

evaluate performance after seeing a small amount of data

Primarily a difference in *evaluation*, rather than the *data stream*.

(Finn*, Rajeswaran*, Kakade, Levine ICML '18)

The Online Meta-Learning Setting

for task t = 1, …, n

observe $\mathscr{D}_t^{\mathrm{tr}}$

use update procedure $\Phi(\theta_t, \mathscr{D}_t^{\mathrm{tr}})$ to produce parameters ϕ_t

observe x_t

predict $\hat{y}_t = f_{\phi_t}(x_t)$

observe label y_t

Standard online learning setting

Loss of algorithm

Loss of best algorithm in hindsight

Goal: Learning algorithm with sub-linear $\mathrm{Regret}_T := \sum_{t=1}^{T} \ell_t(\Phi_t(\theta_t)) - \min_{\theta \in \Theta} \sum_{t=1}^{T} \ell_t(\Phi_t(\theta))$

(Finn*, Rajeswaran*, Kakade, Levine ICML '18)

Can we apply meta-learning in lifelong learning settings?

Recall the **follow the leader** (FTL) algorithm:

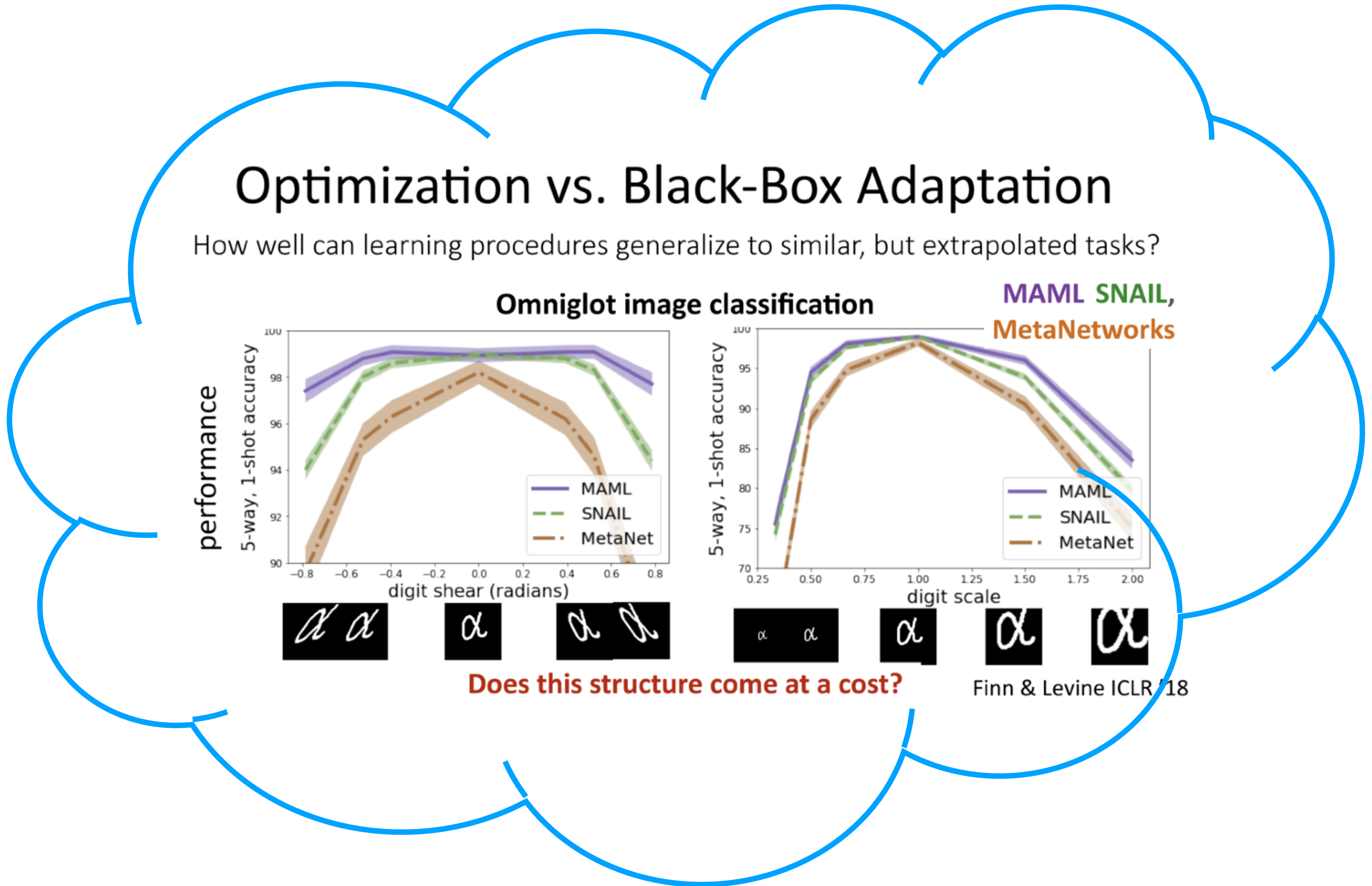
Store all the data you've seen so far, and train on it.

Deploy model on current task.

Follow the *meta*-leader (FTML) algorithm:

Store all the data you've seen so far, and **meta**-train on it.

Run update procedure on the current task.



What meta-learning algorithms are well-suited for FTML?

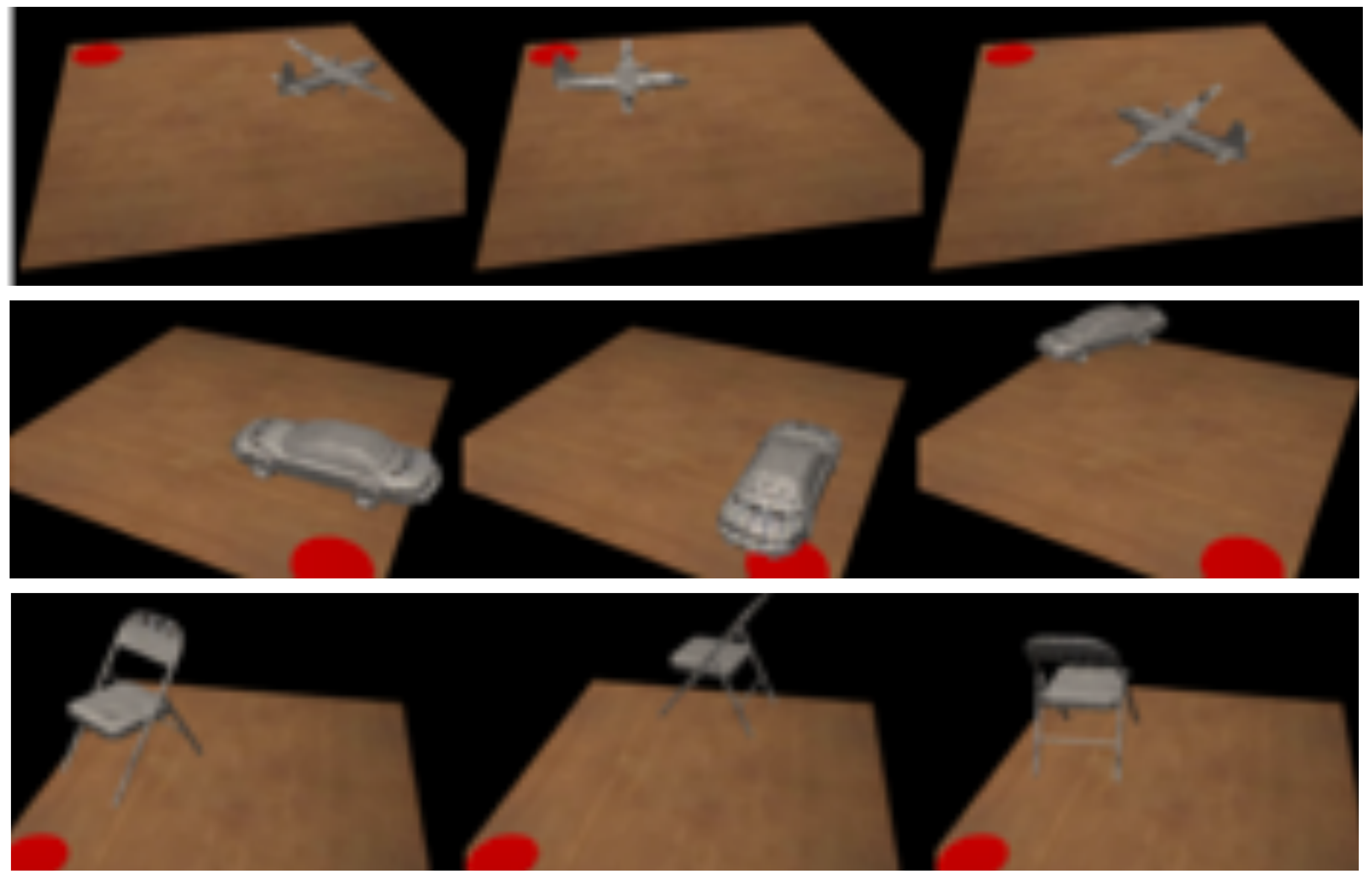
What if $p_t(\mathcal{T})$ is non-stationary?

Online meta-learning experiments

Experiment with **sequences of tasks**:

- Colored, rotated, scaled **MNIST**
- **3D object pose prediction**
- **CIFAR-100** classification

Example pose prediction tasks



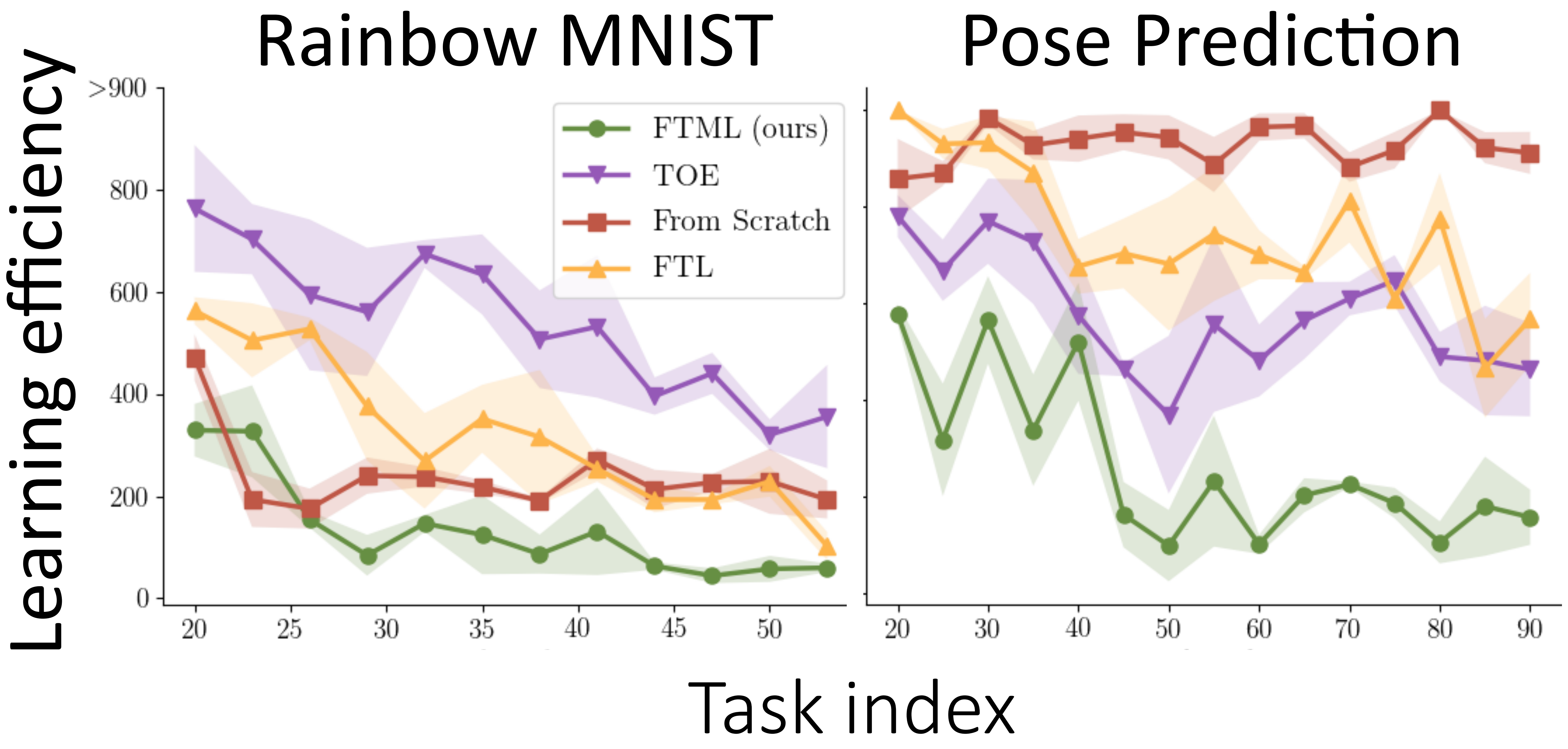
plane

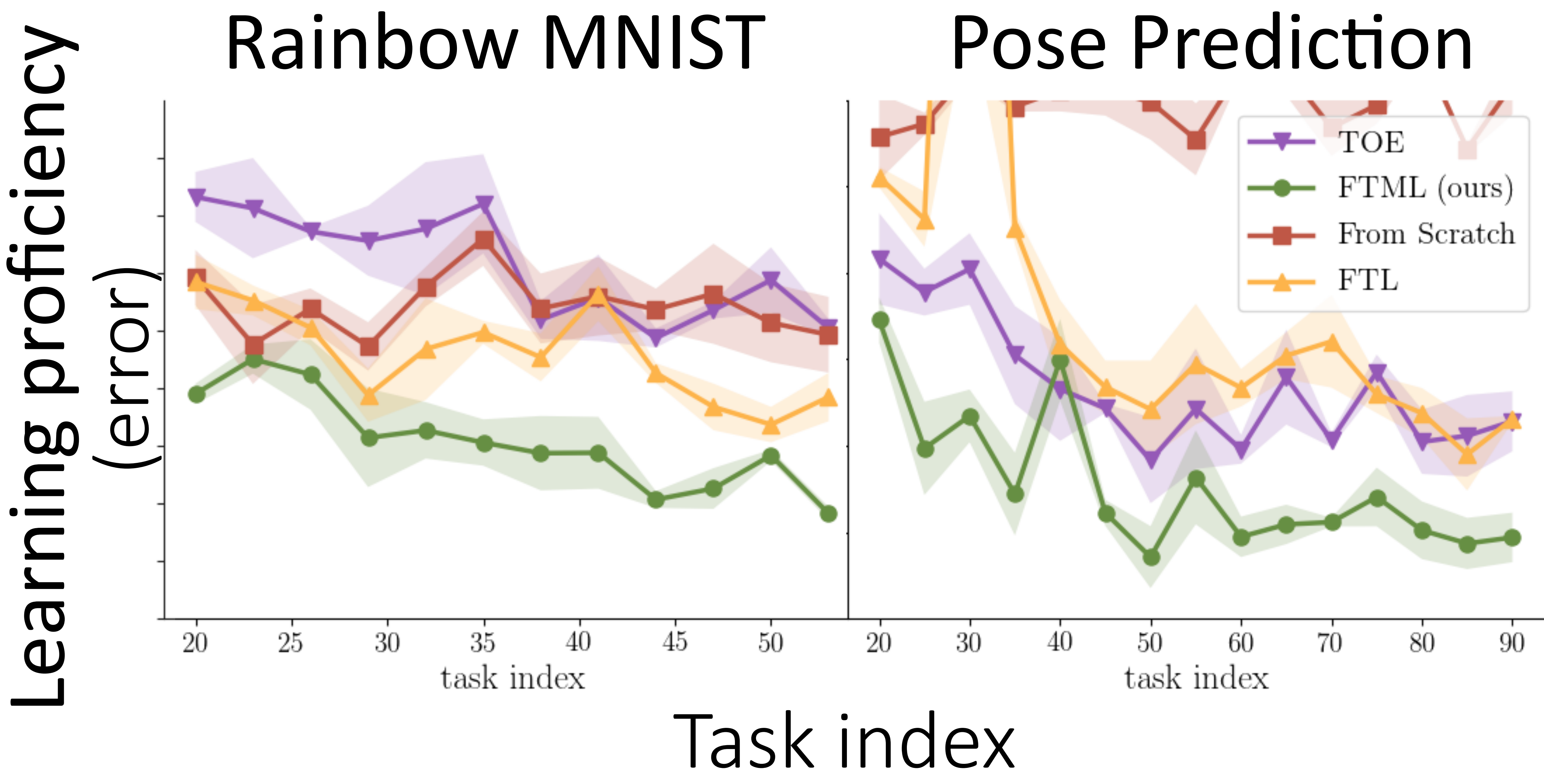
car

chair

Online meta-learning experiments

Comparisons:
- **TOE** (train on everything): train on all data so far
- **FTL** (follow the leader): train on all data so far, fine-tune on current task
- **From Scratch:** train from scratch on each task





Follow The Meta-Leader
learns each new task faster & **with greater proficiency**,
approaches **few-shot learning** regime

Takeaways

Many flavors of lifelong learning, all under the same name.

Defining the problem statement is often the hardest part

Meta-learning can be viewed as a slice of the lifelong learning problem.

A very open area of research.

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