Lifelong Learning

CS 330

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**

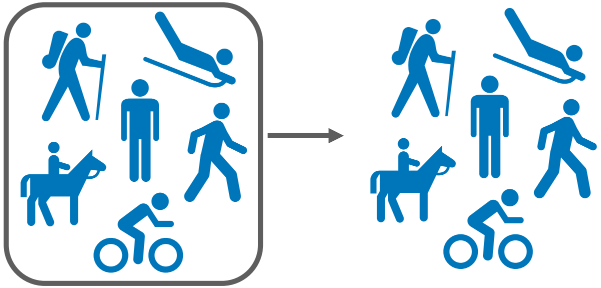
A brief review of problem statements.

Multi-Task Learning

Learn to solve a set of tasks.

learn tasks

perform tasks

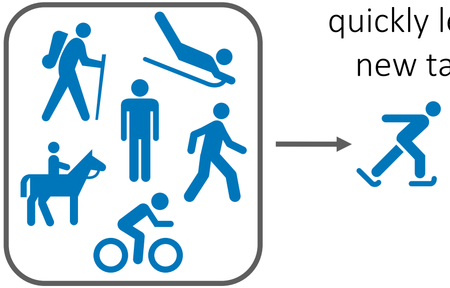


Meta-Learning

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

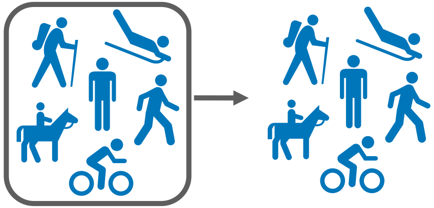
learn to learn tasks

quickly learn
new task



Multi-Task Learning

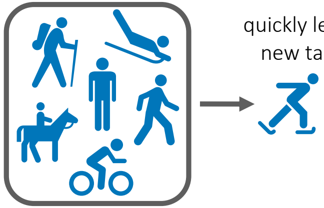
learn tasks perform tasks



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 your break-out room**:

(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

Desirable properties/considerations	Evaluation setup

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

$$Regret_T := \sum_1^T \mathcal{L}_t(\theta_t) - \min_\theta \sum_1^T \mathcal{L}_t(\theta)$$

(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?

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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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

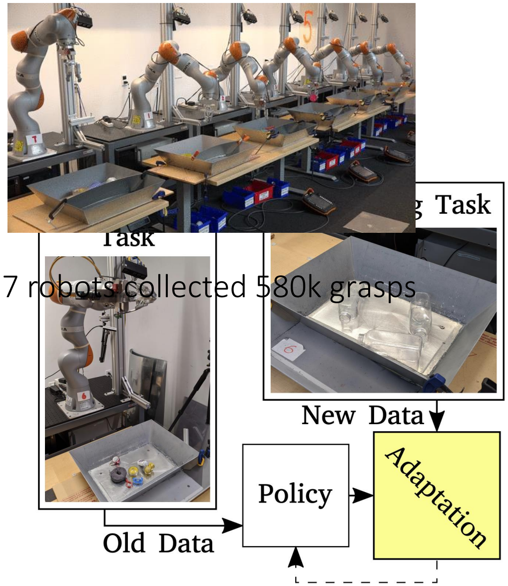
- subject to **negative backward transfer**

  "forgetting"

- slow learning

sometimes referred to as catastrophic forgetting

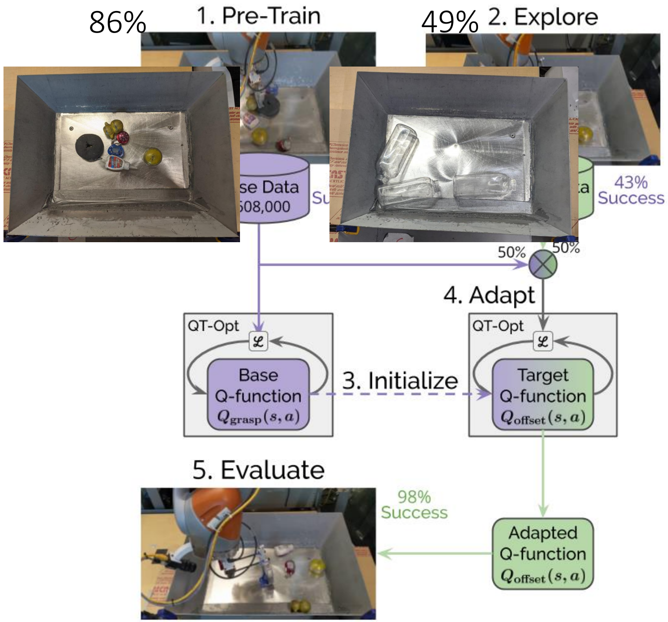
Very simple continual RL algorithm



7 robots collected 580k grasps

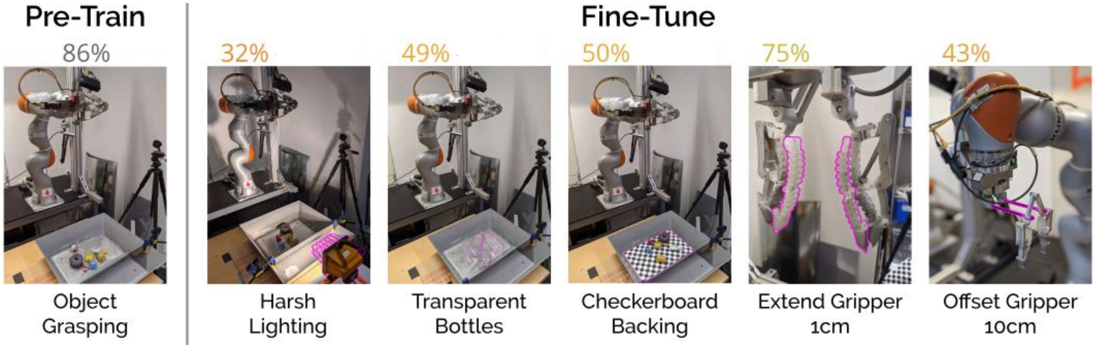
86%

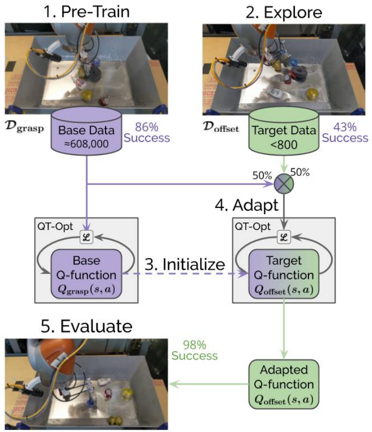
49%



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

Very simple continual RL algorithm





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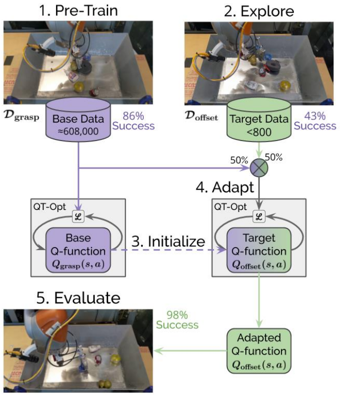

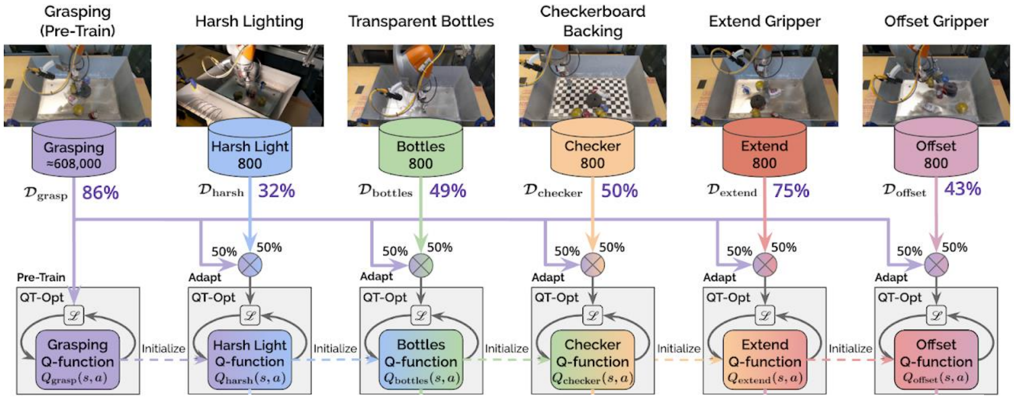

Can we do better?

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 $z_k < z_t$

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

Assume local linearity:

$$\langle g_t, g_k \rangle := \langle \frac{\partial \mathcal{L}(f_\theta, (x_t, y_t))}{\partial \theta}, \frac{\mathcal{L}(f_\theta, \mathcal{M}_k)}{\partial \theta} \rangle \geq 0$$

for all $z_k < z_t$

Can formulate & solve as a QP.

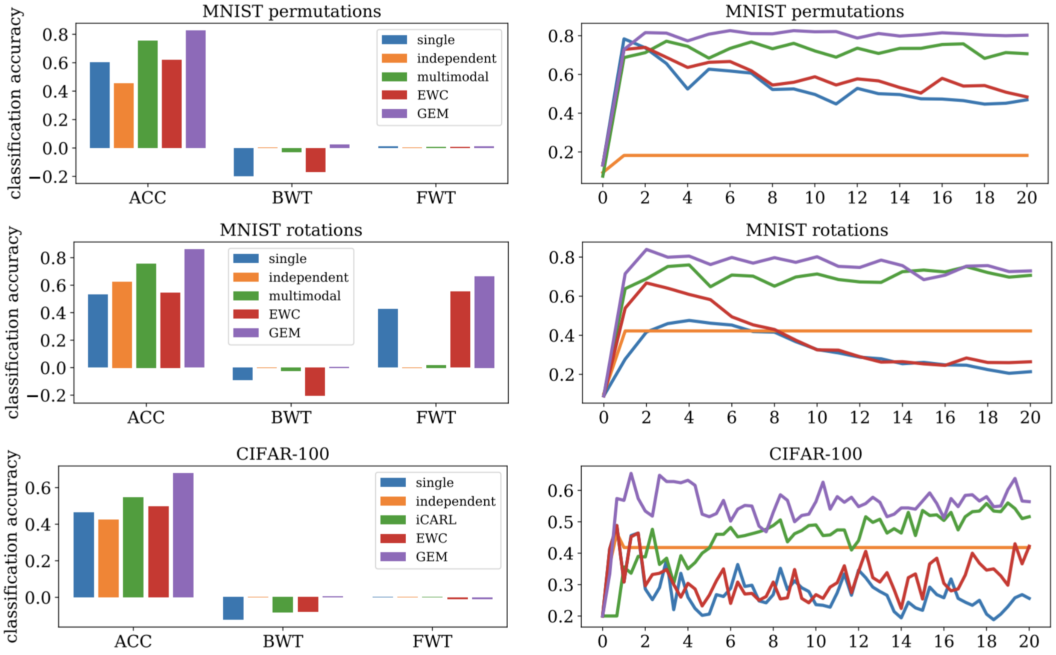
Lopez-Paz & Ranzato. Gradient Episodic Memory for Continual Learning. NeurIPS '17

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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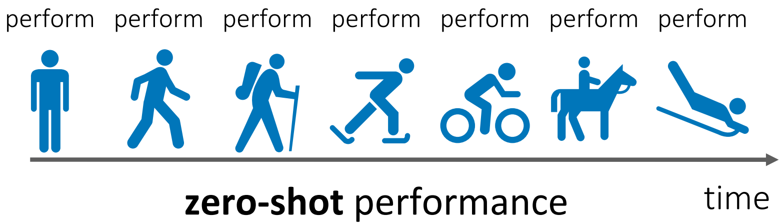
What might be wrong with the online learning formulation?

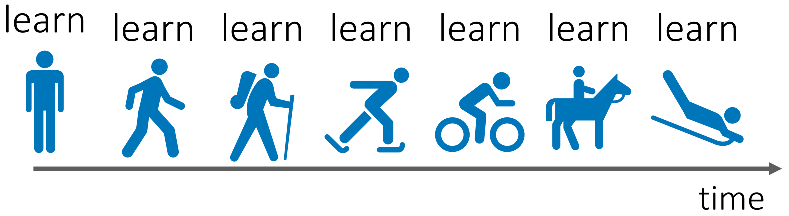
Online Learning
(Hannan '57, Zinkevich '03)

Perform sequence of tasks
while minimizing static regret.



zero-shot performance

More realistically:



slow learning → rapid learning

What might be wrong with the online learning formulation?

Online Learning
(Hannan ’57, Zinkevich ’03)

Perform sequence of tasks
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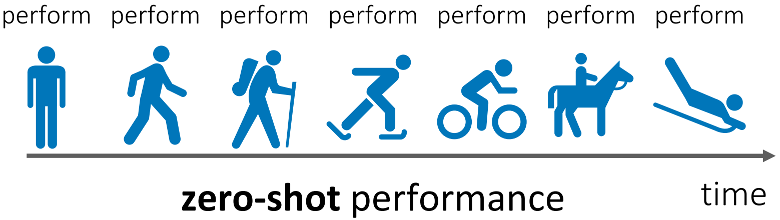
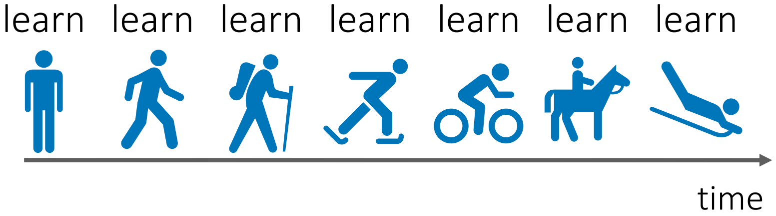


zero-shot performance

Online Meta-Learning

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



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 $\mathcal{D}_t^{tr}$

use update procedure $\Phi(\theta_t, \mathcal{D}_t^{tr})$ 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.

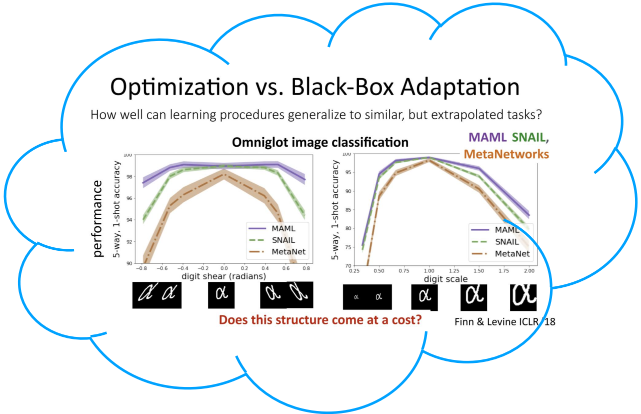
Follow the *meta*-leader (FTML) algorithm:

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

Run update procedure on the current task.

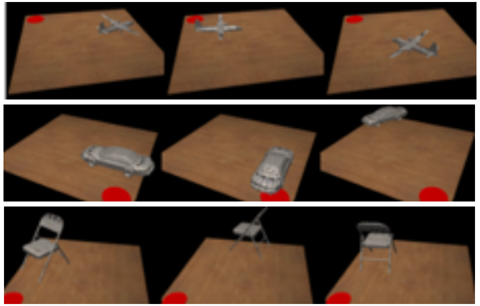
What meta-learning algorithms are well-suited for FTML?

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



Experiments

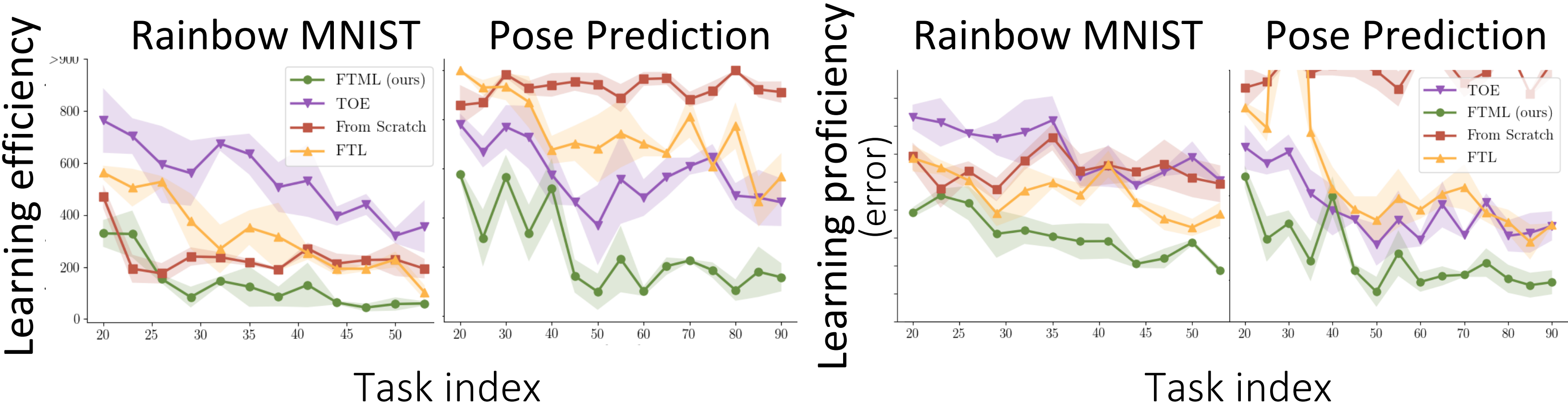
Example pose prediction tasks



Experiment with **sequences of tasks**:
- Colored, rotated, scaled **MNIST**
- **3D object pose prediction**
- **CIFAR-100** classification

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.