Online Meta-Learning

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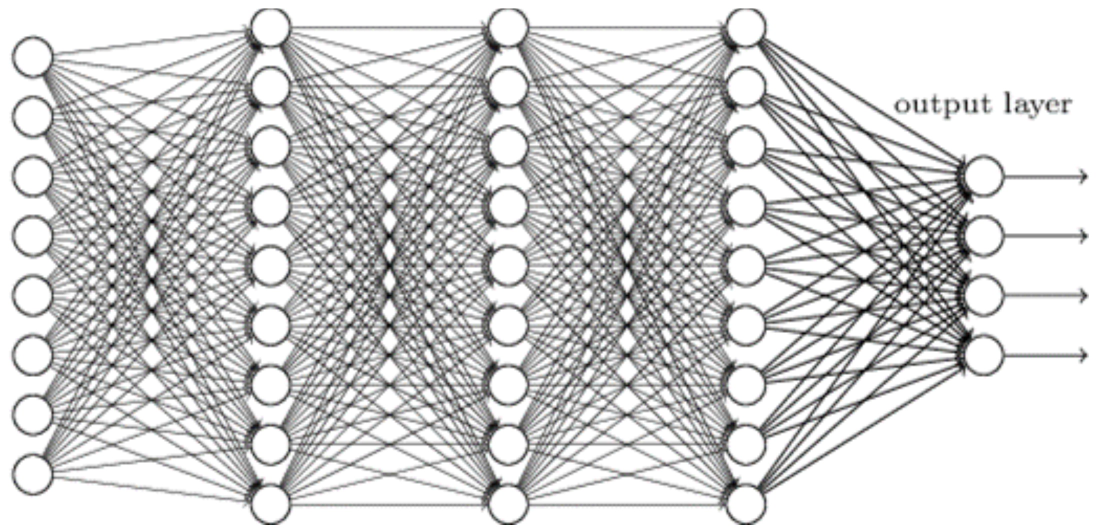
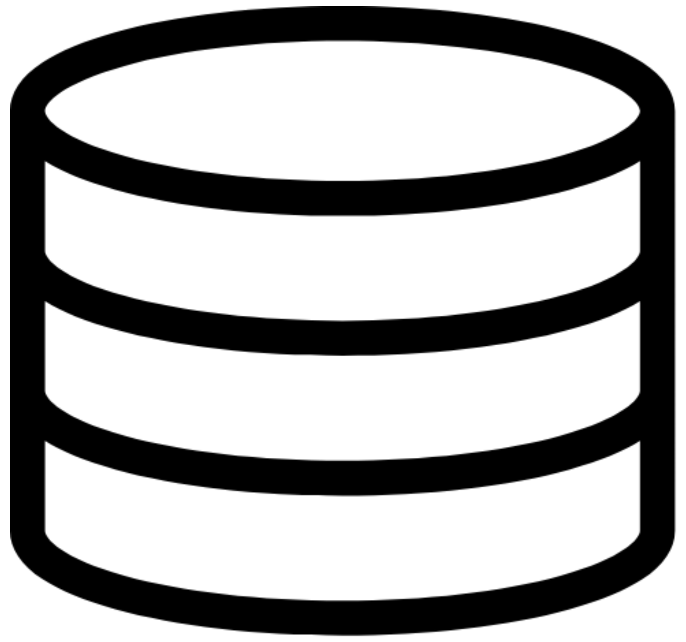
BAIR
BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

W PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

Deep networks + large datasets = 





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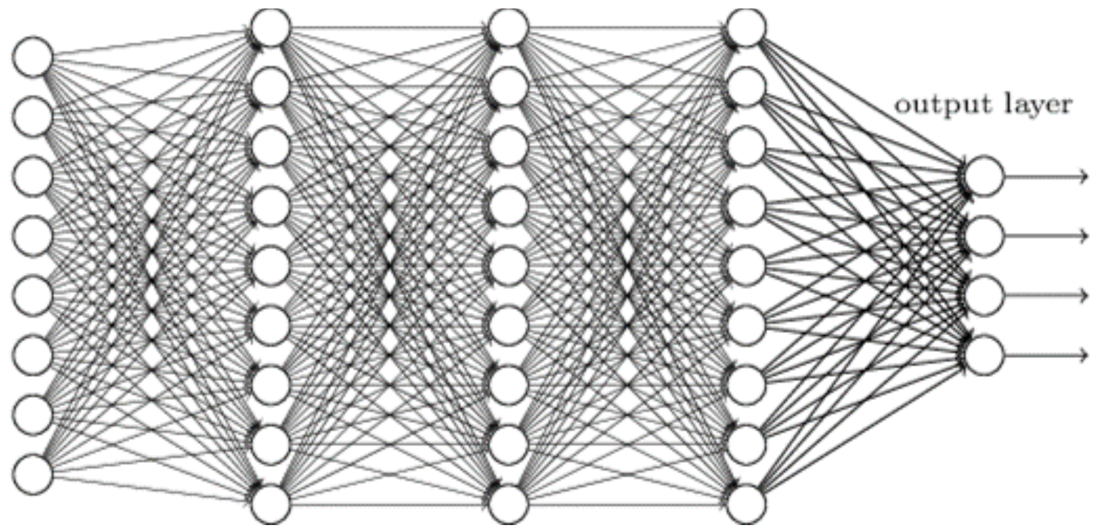

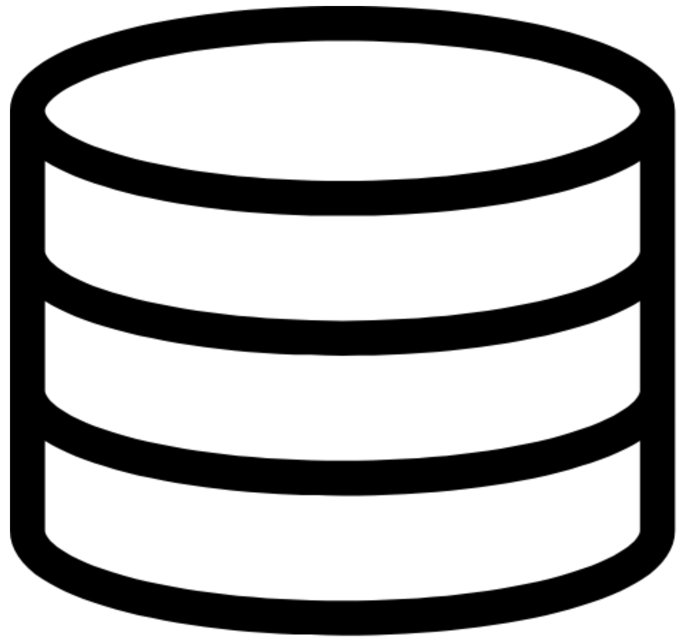

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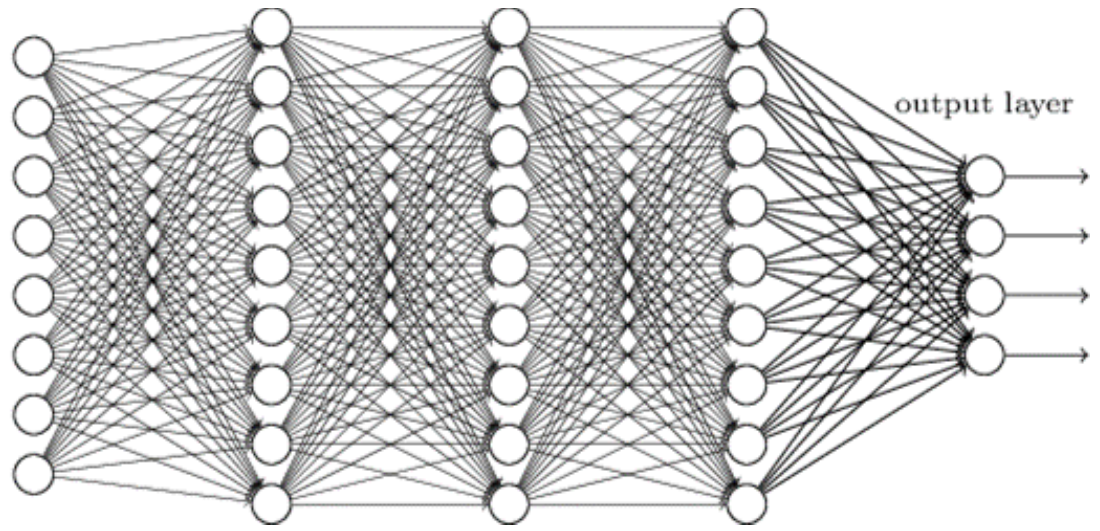
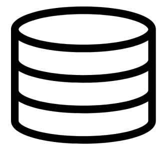
Learn new task with only a **few** datapoints





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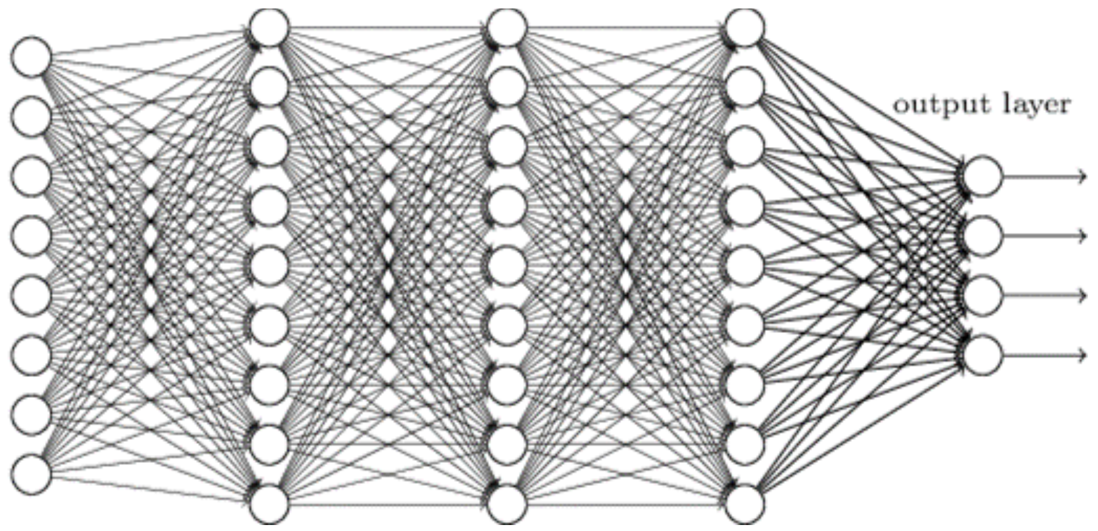

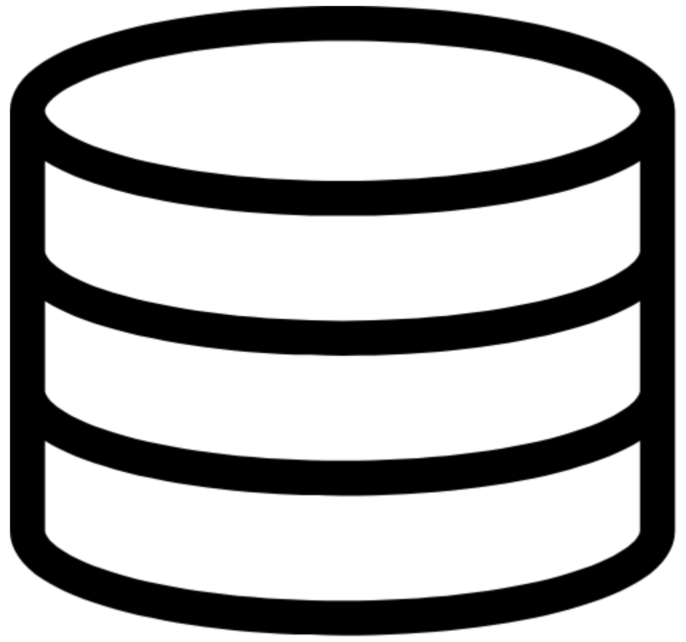

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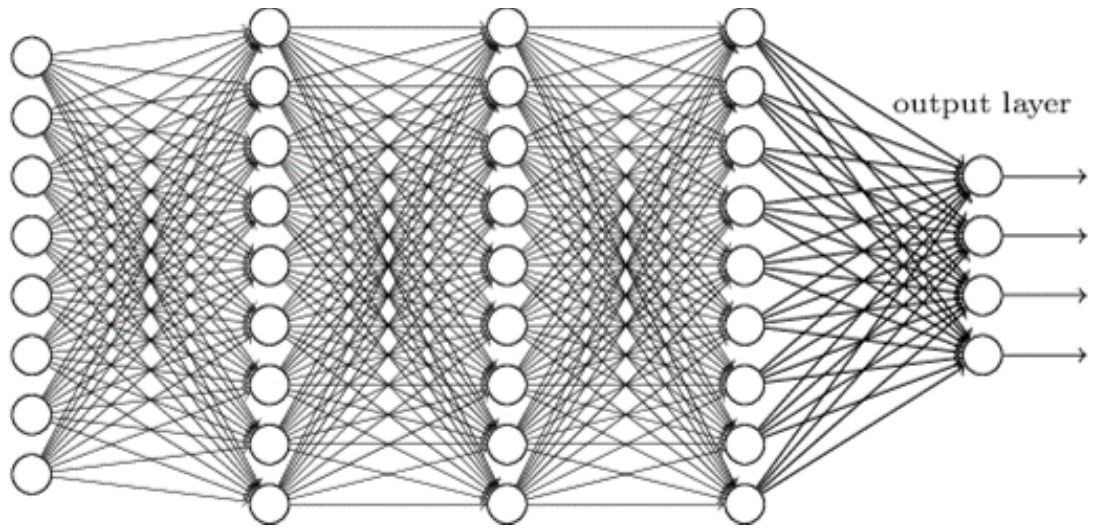

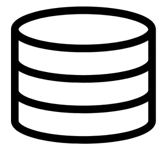

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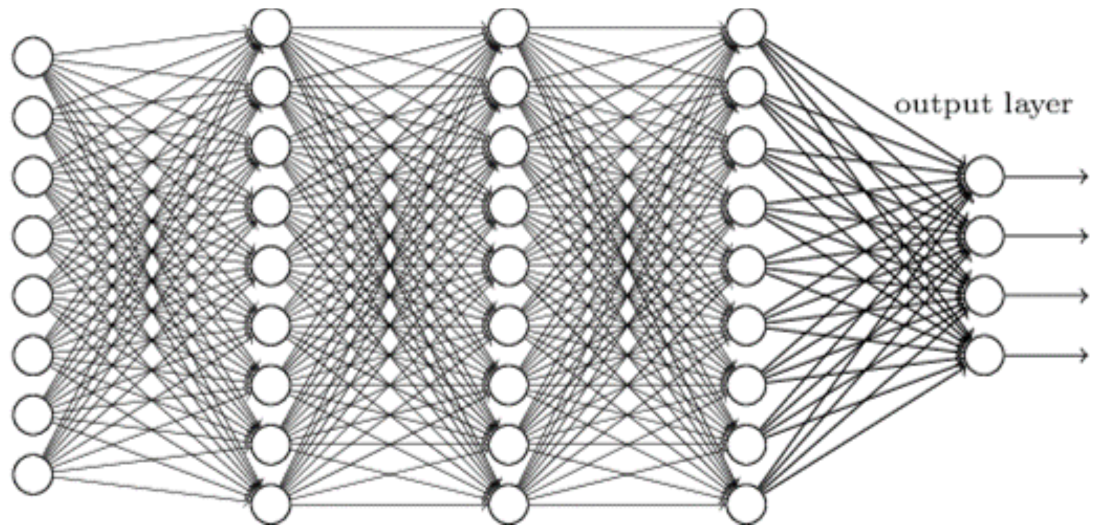

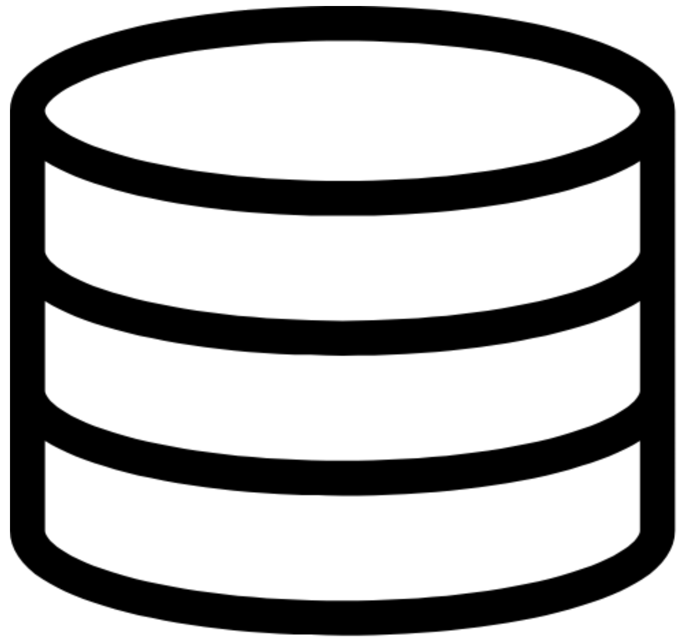

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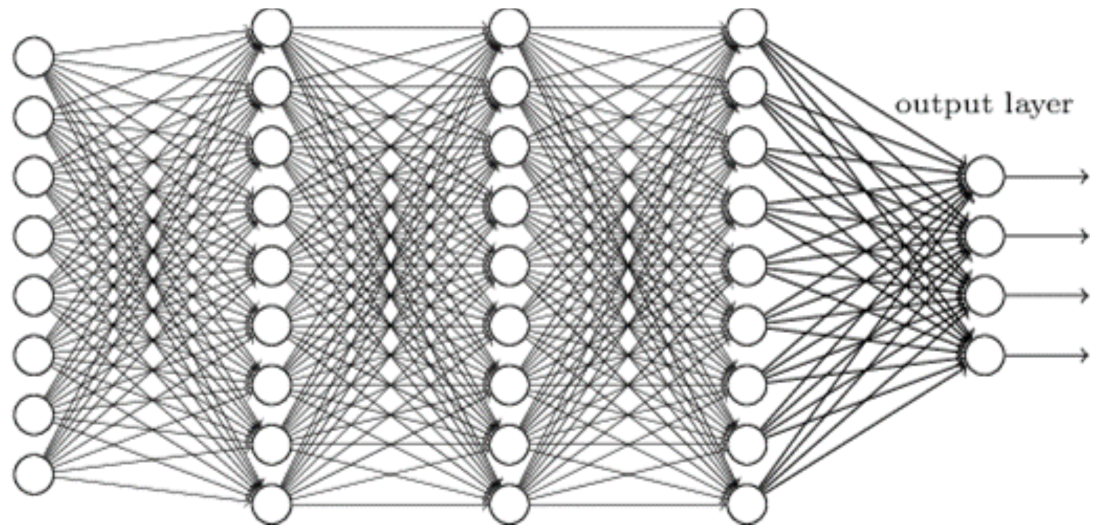

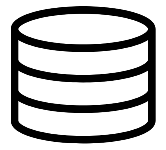

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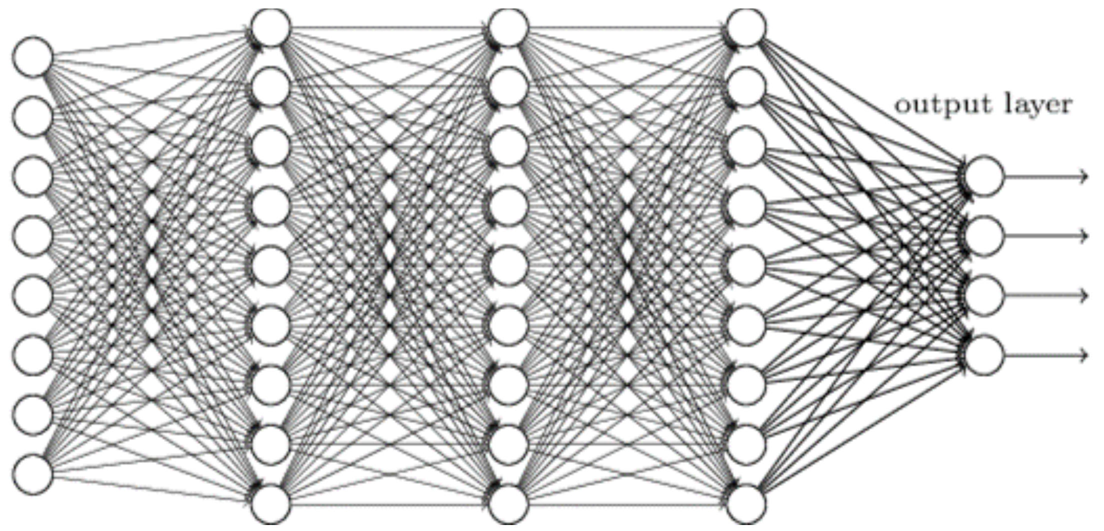

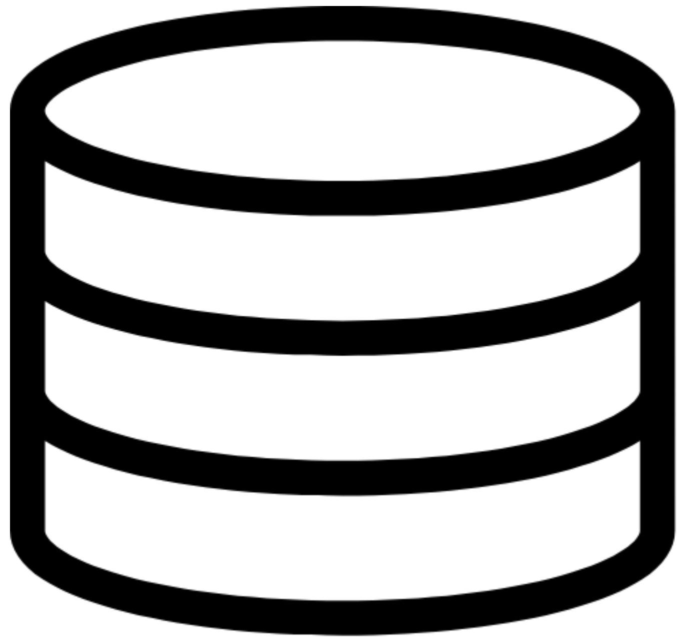

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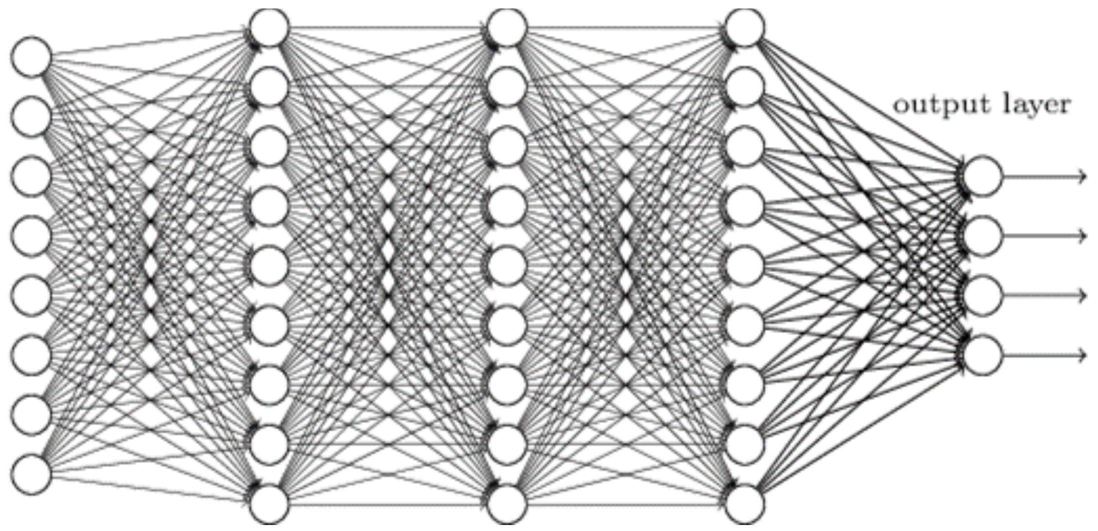

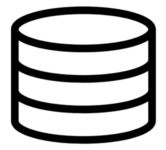

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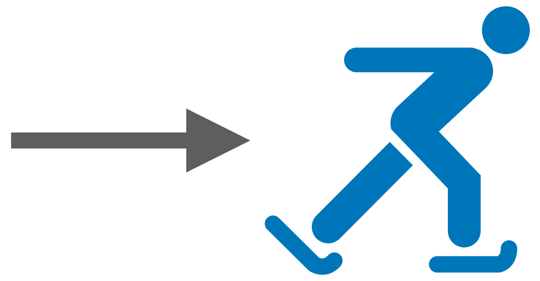

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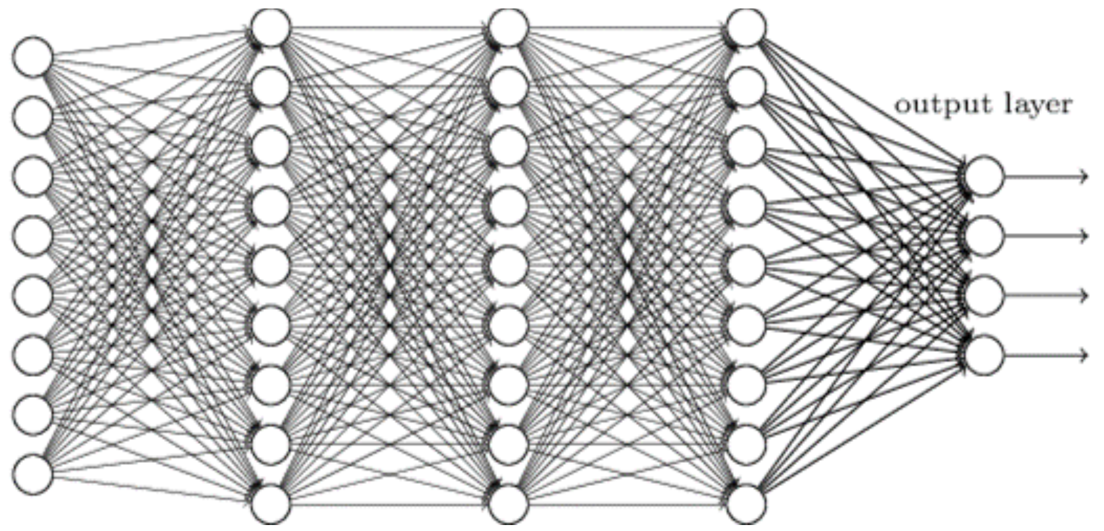

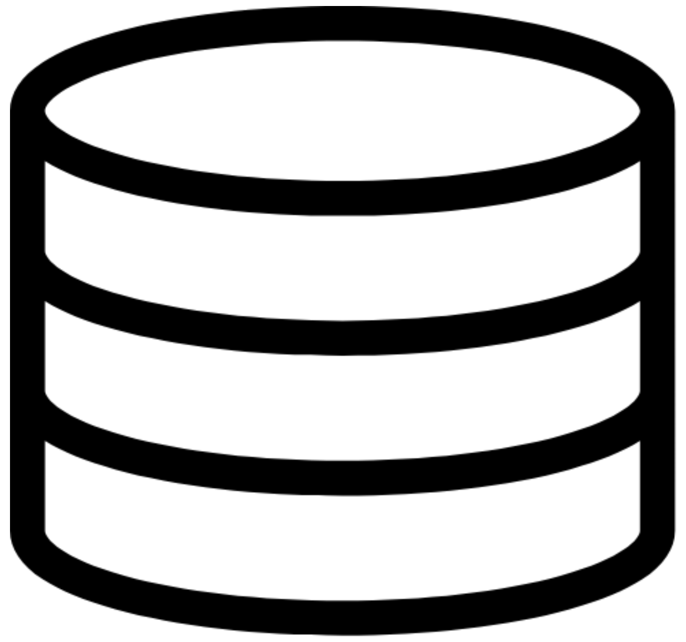

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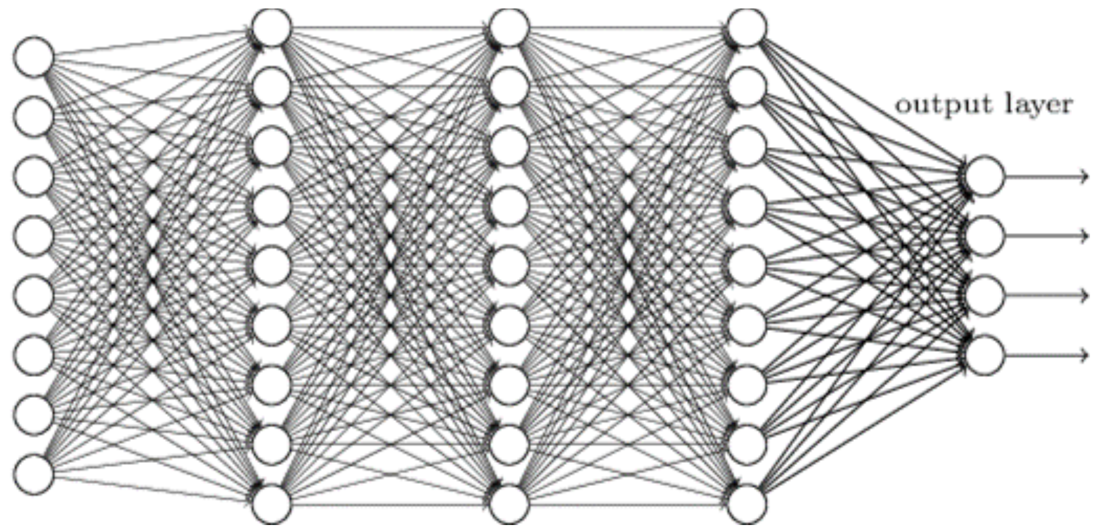

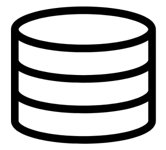

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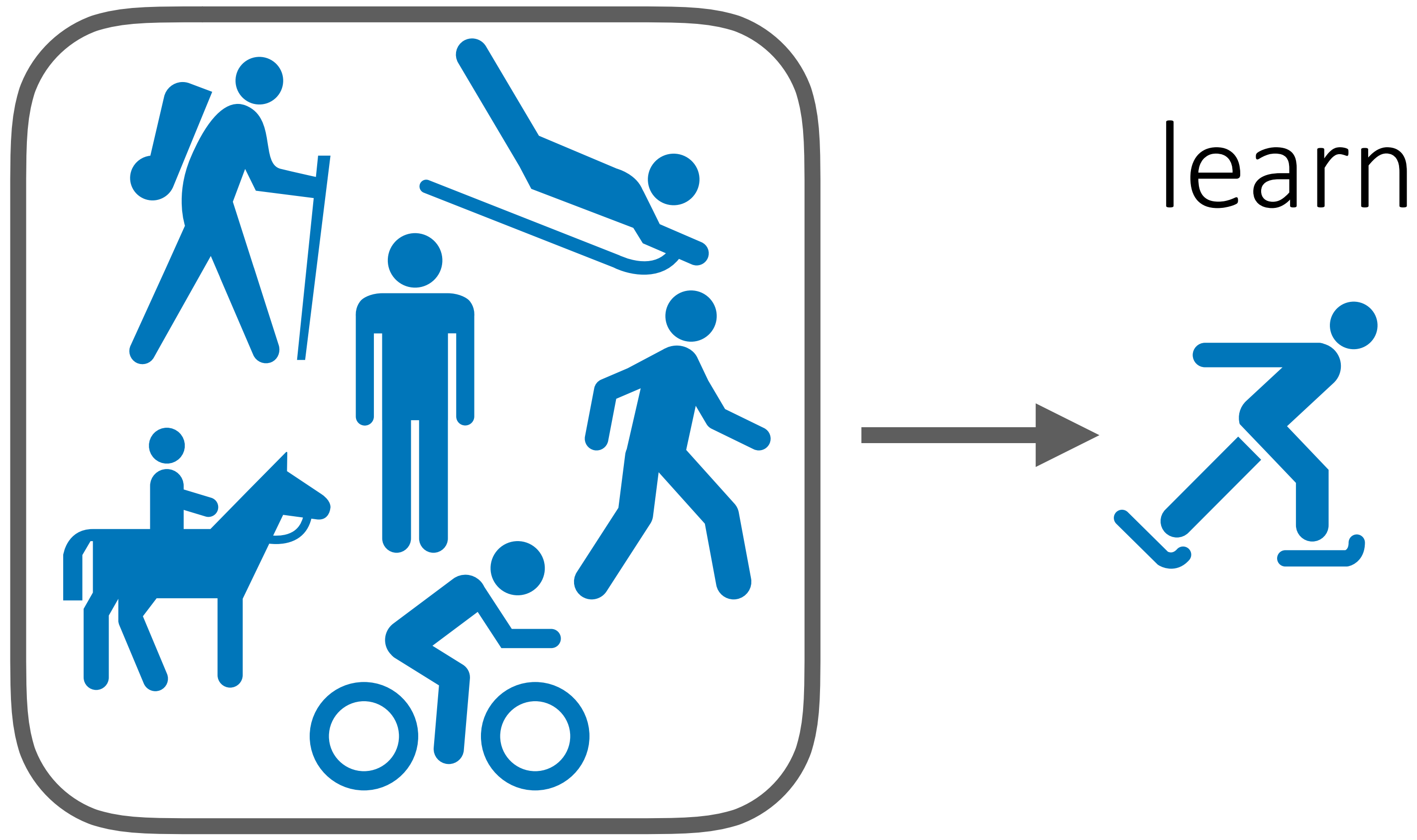

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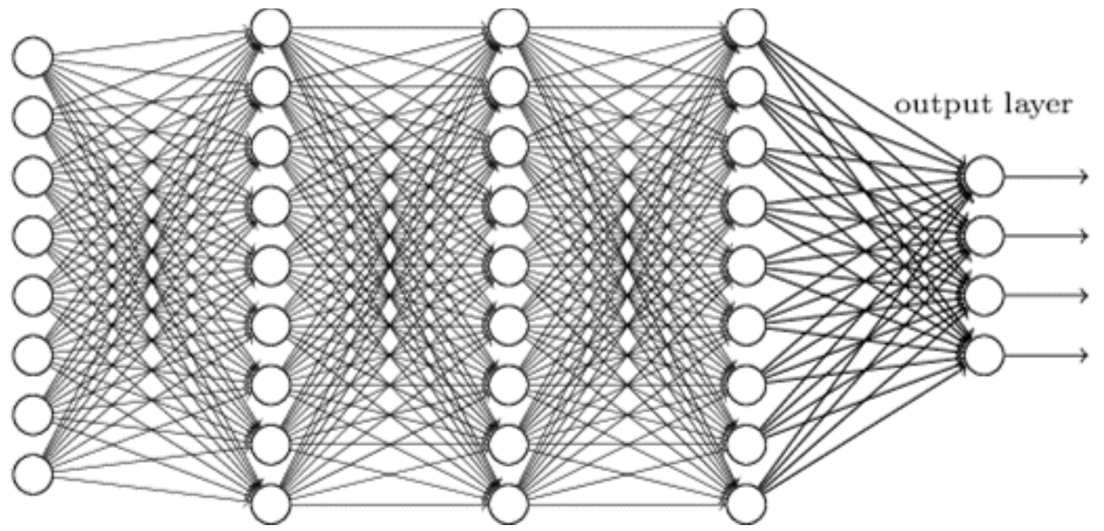

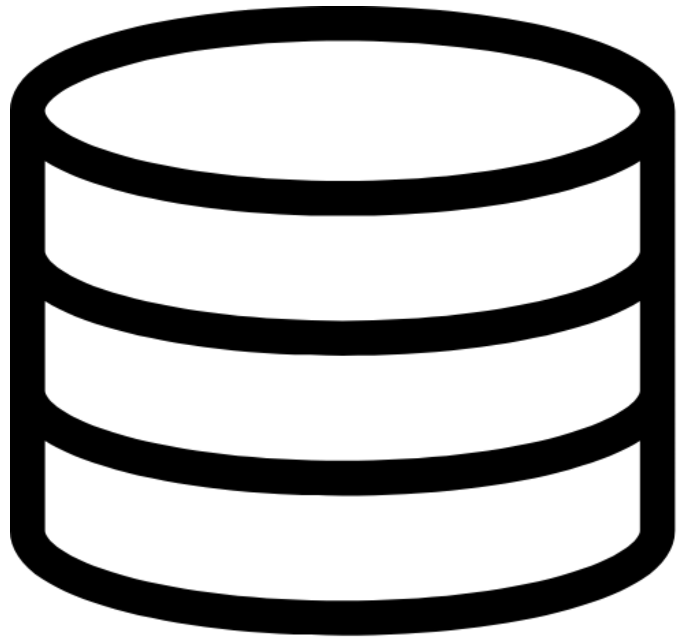

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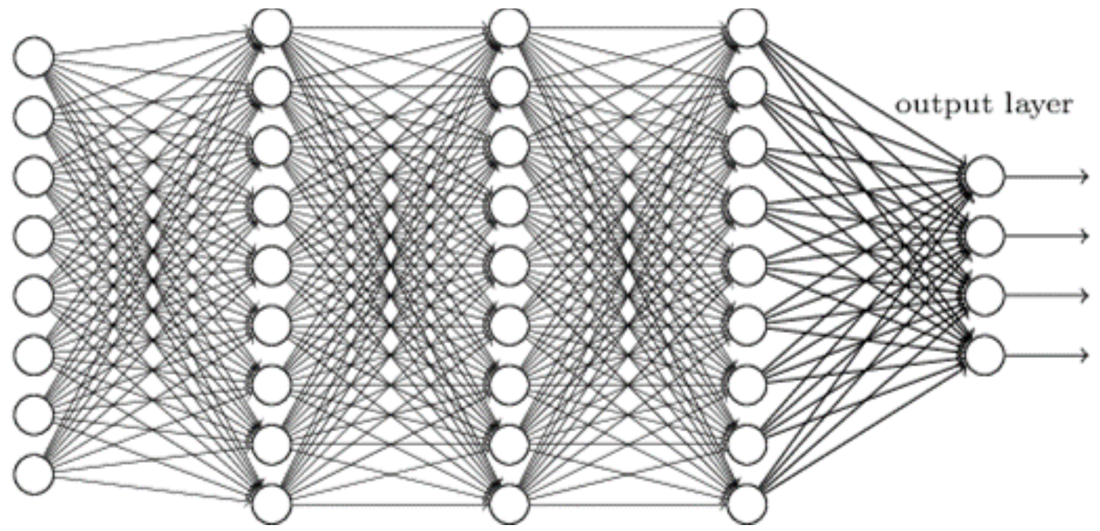

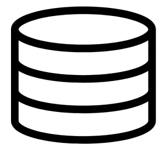

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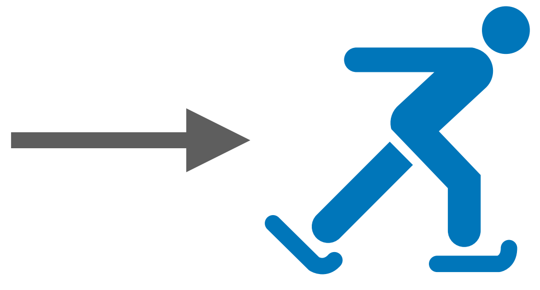

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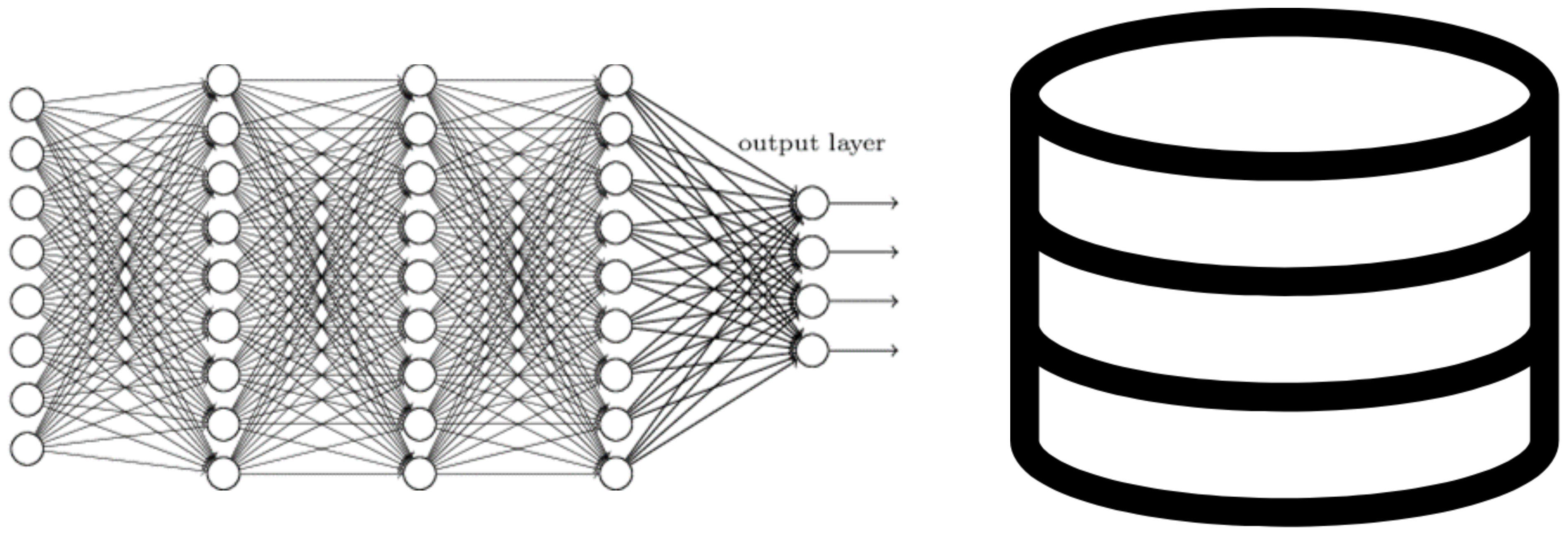

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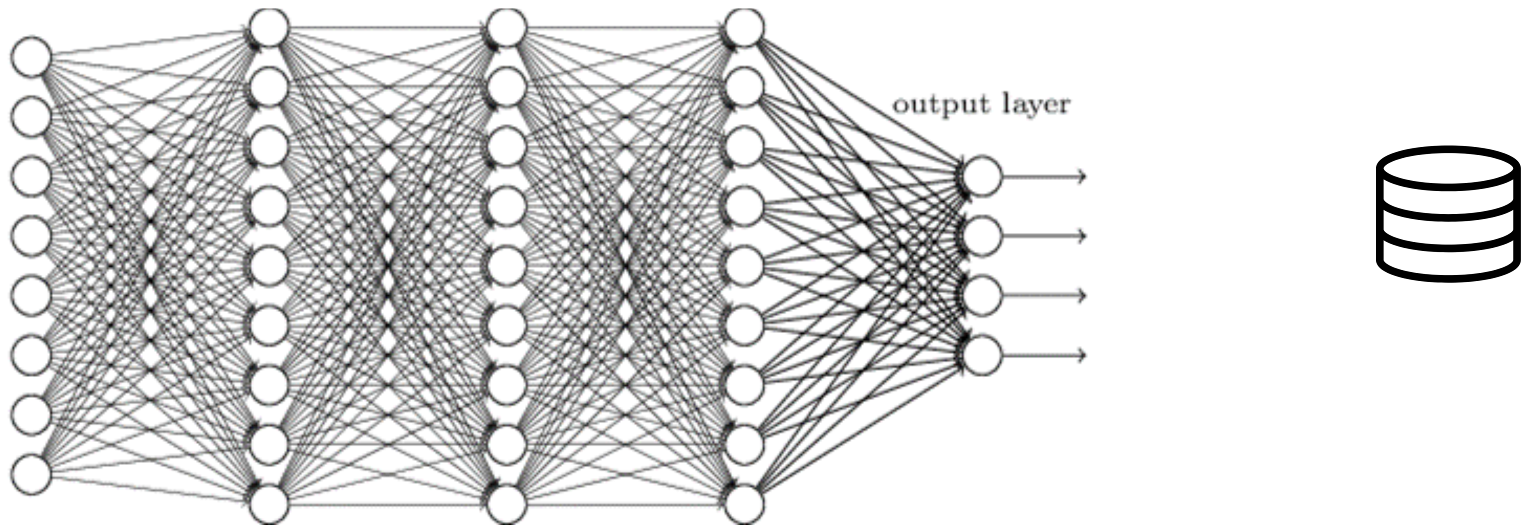

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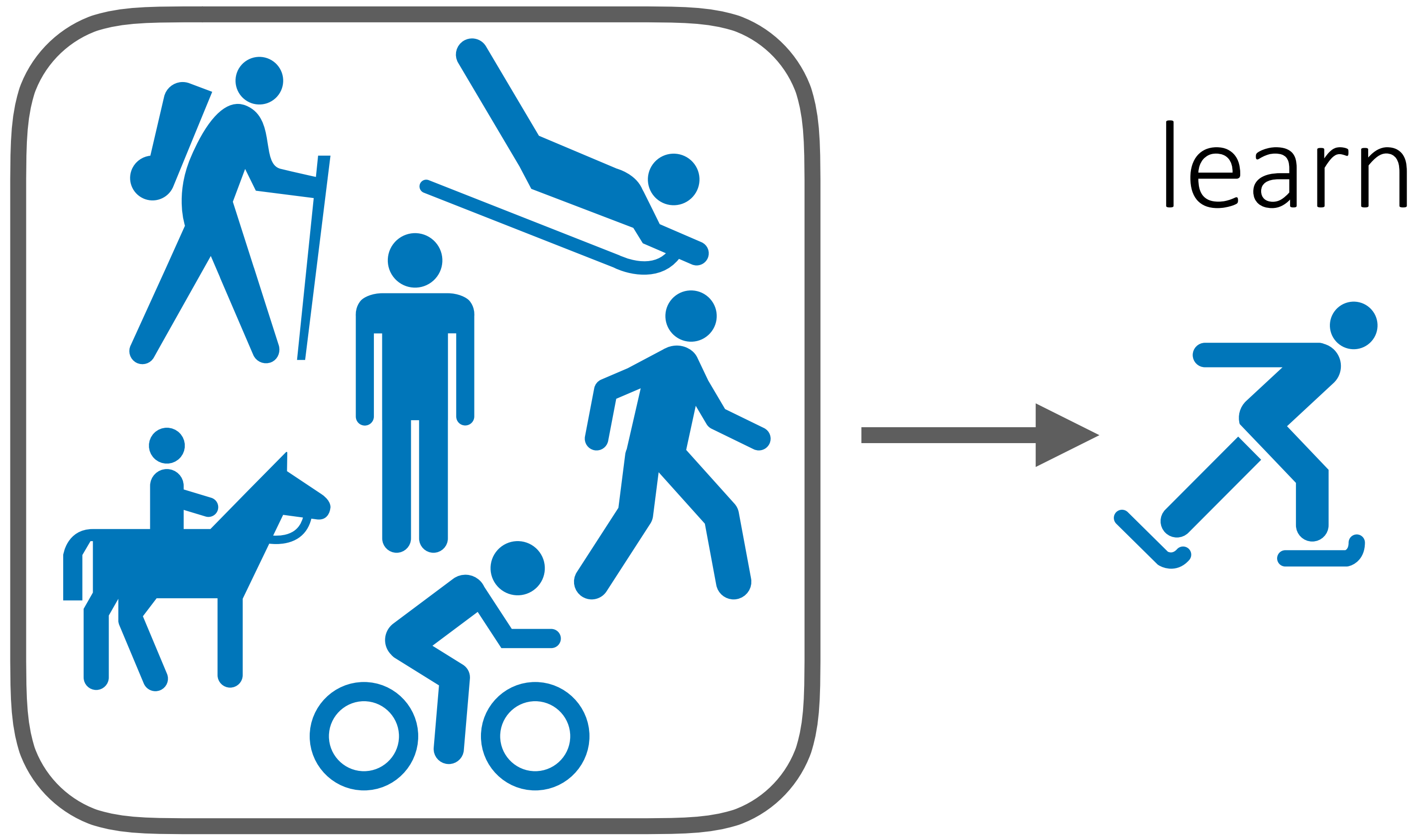

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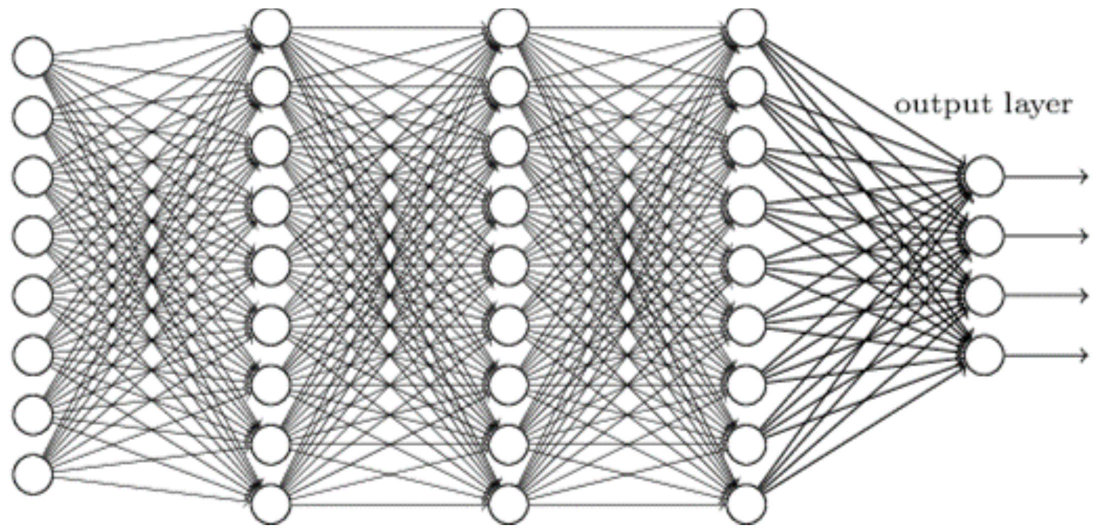

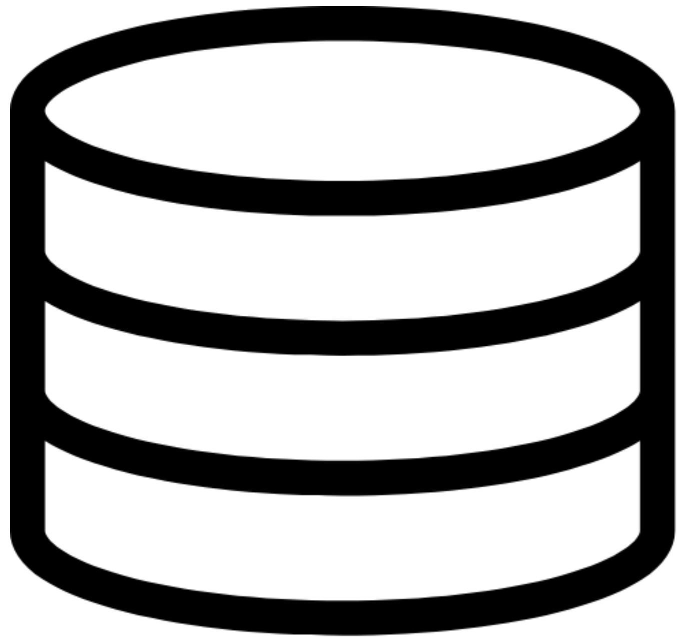

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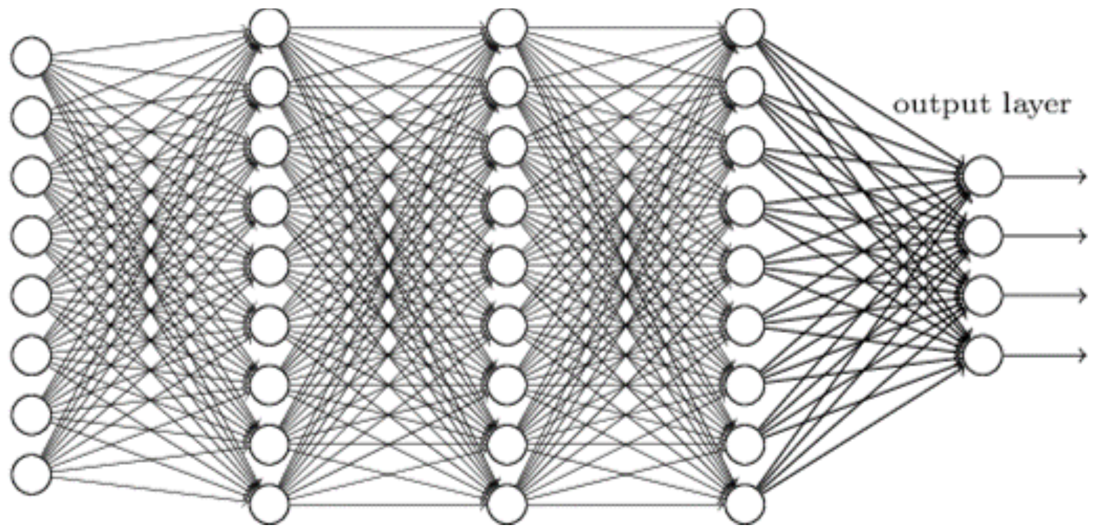

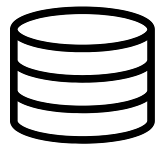

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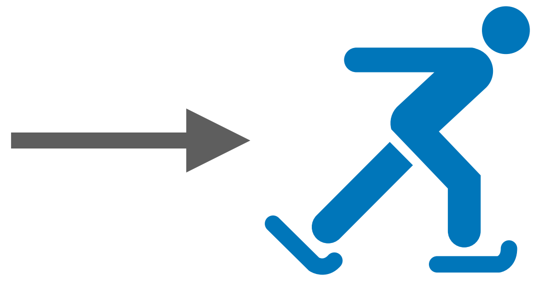

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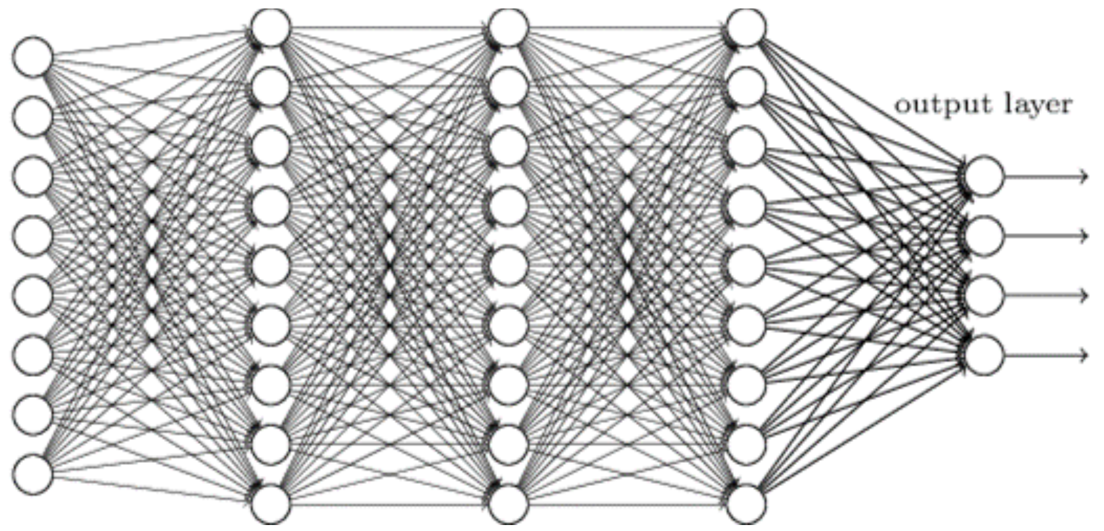

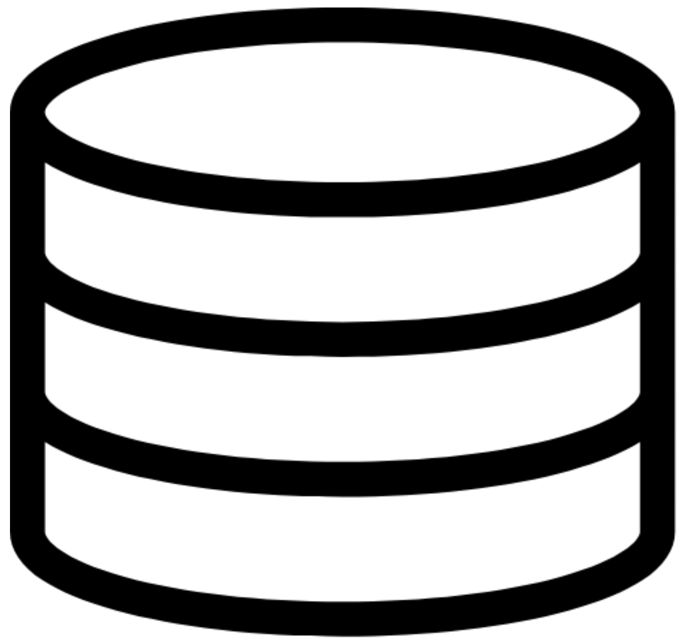

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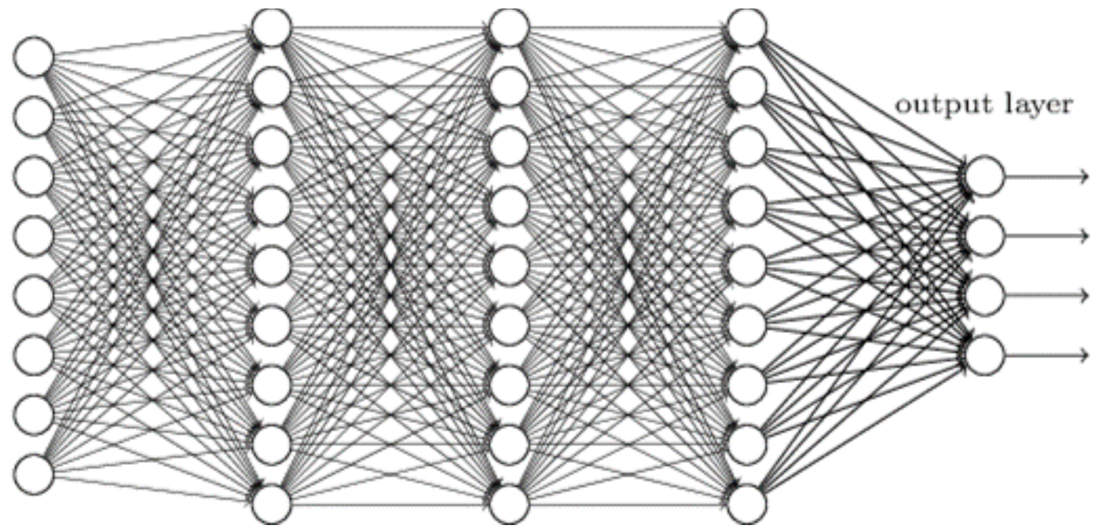

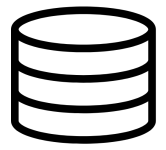

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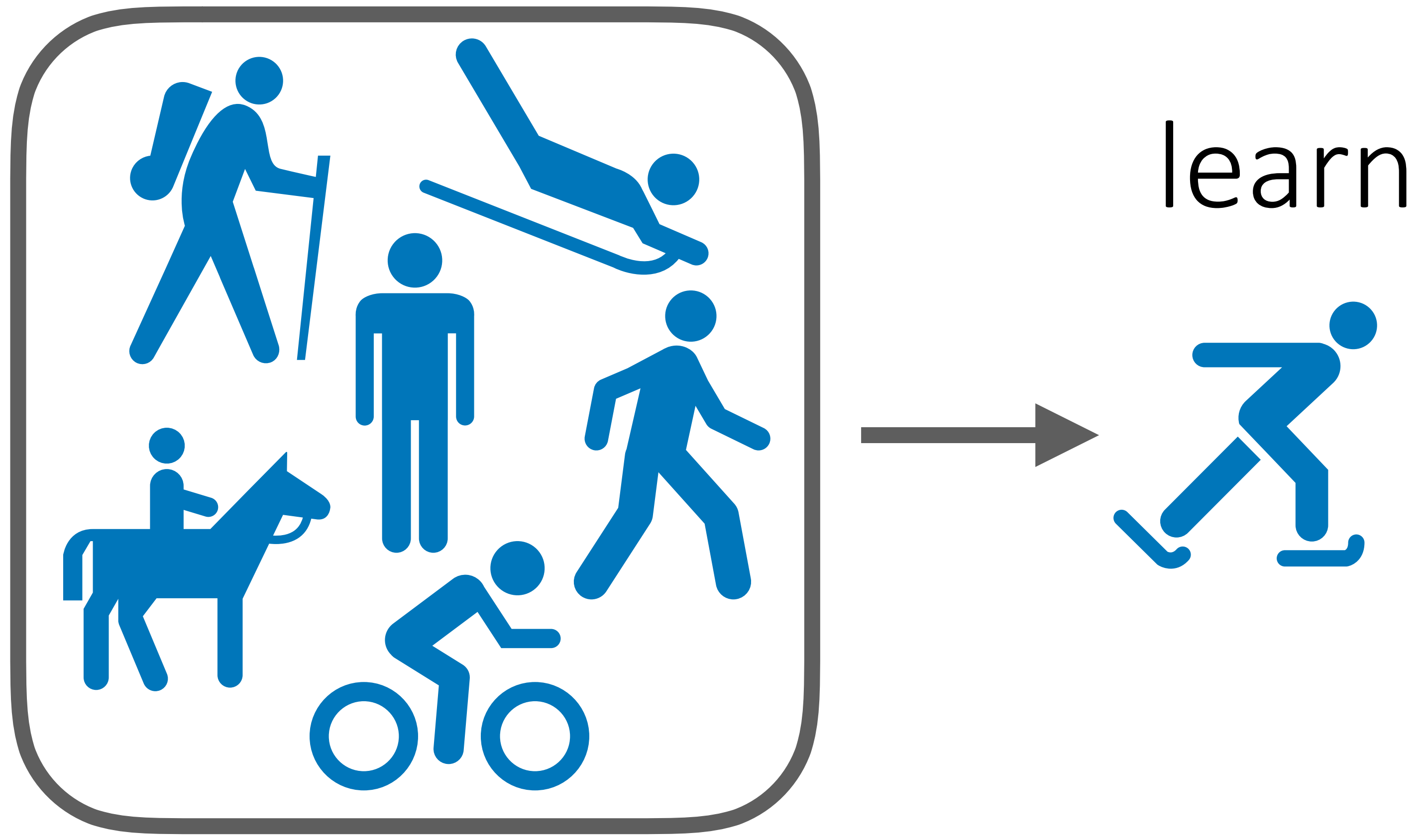

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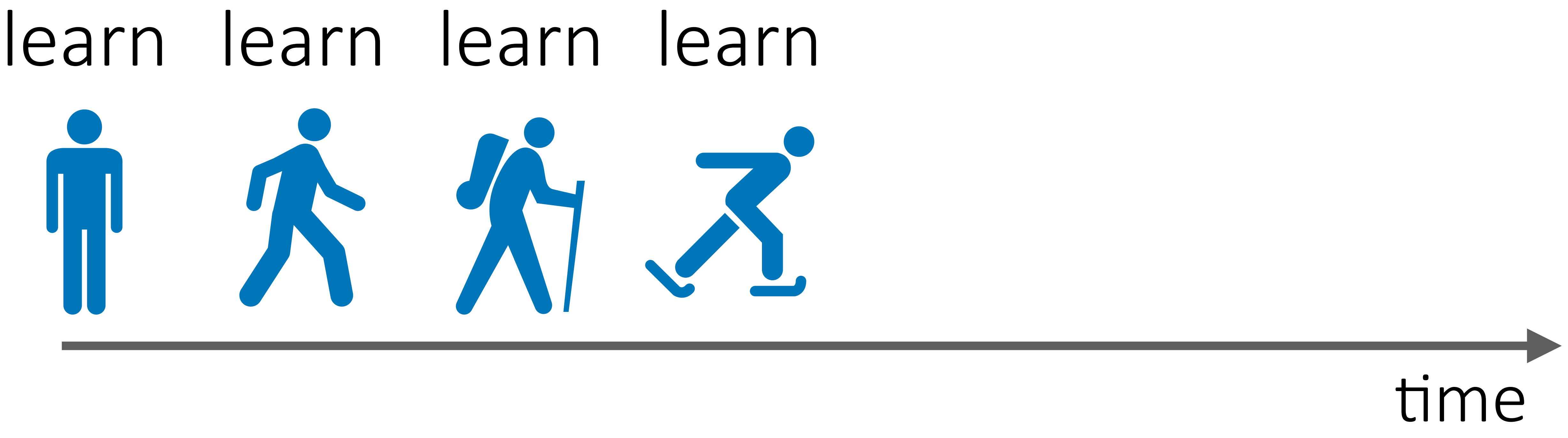

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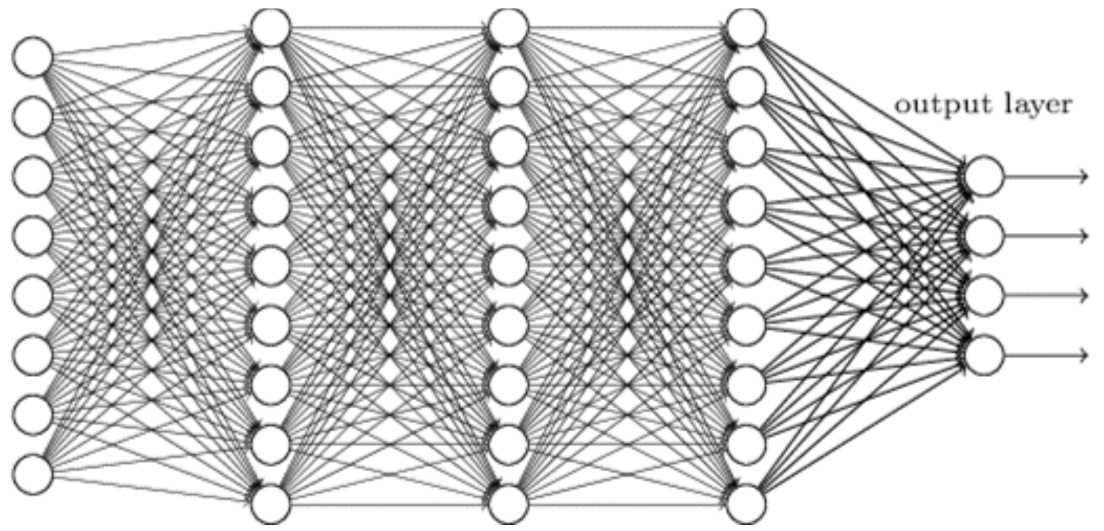

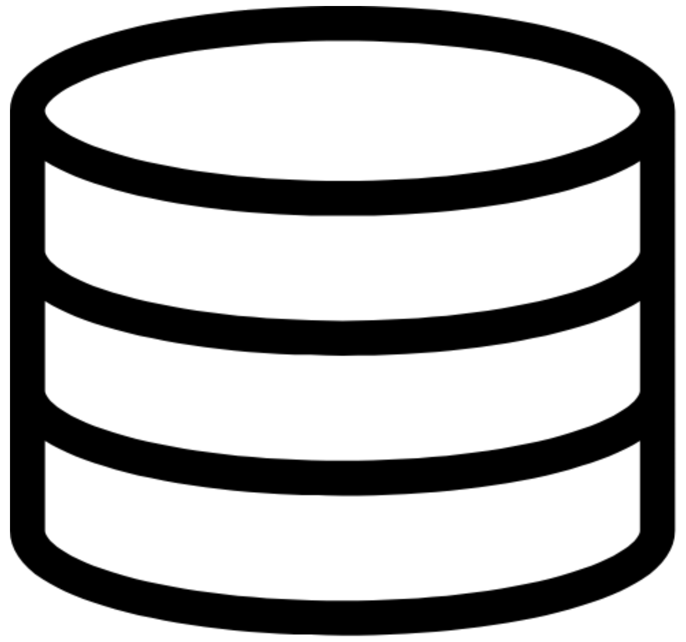

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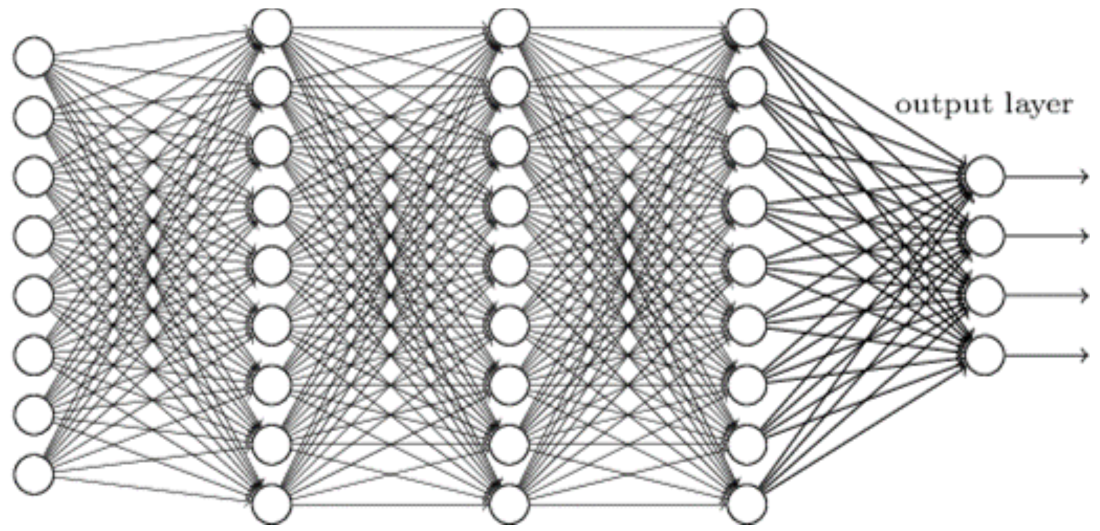

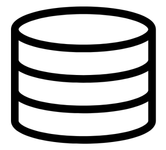

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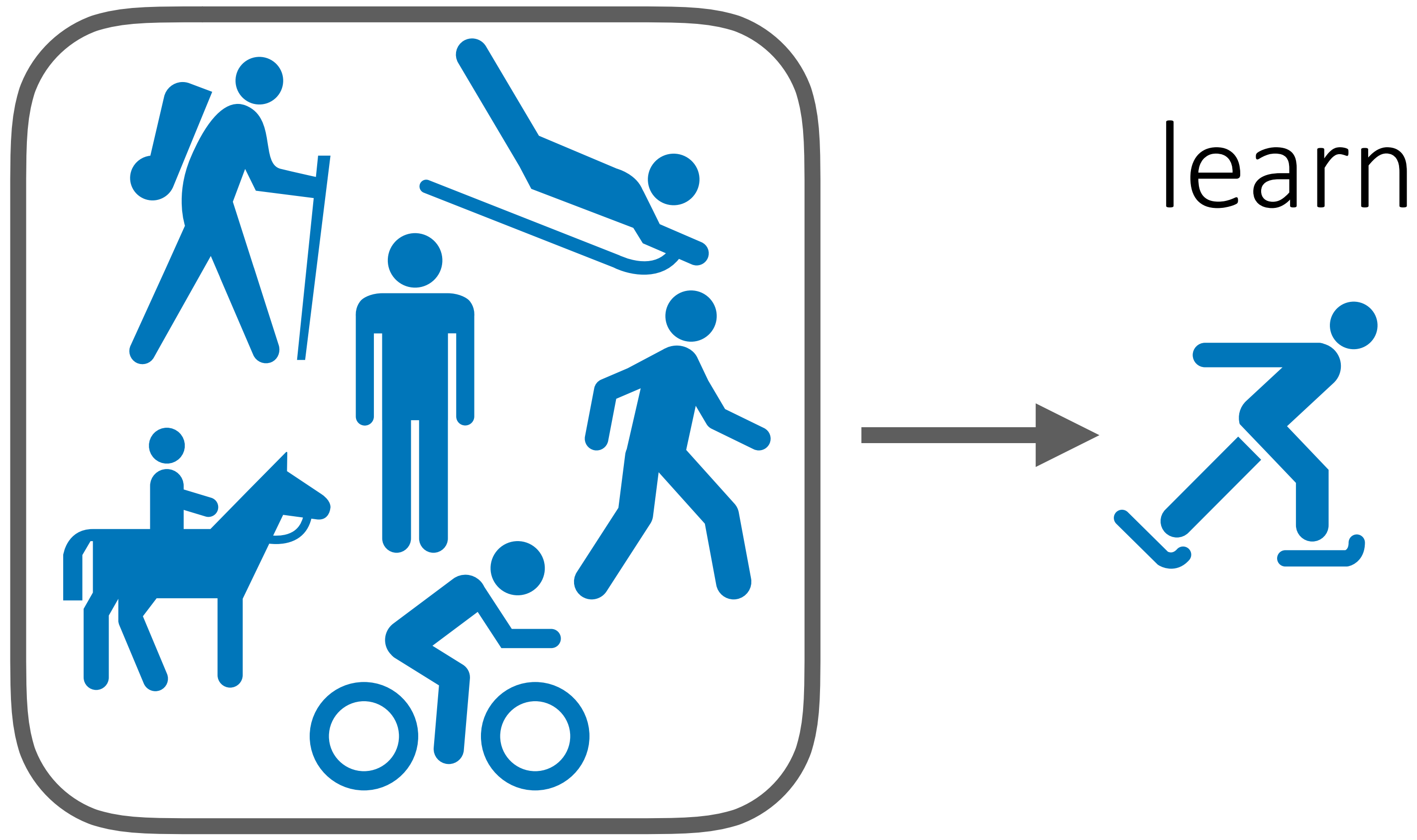

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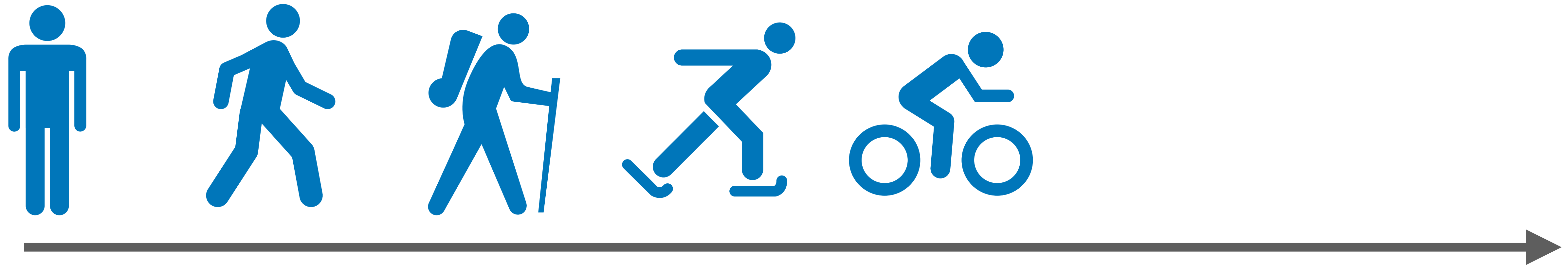

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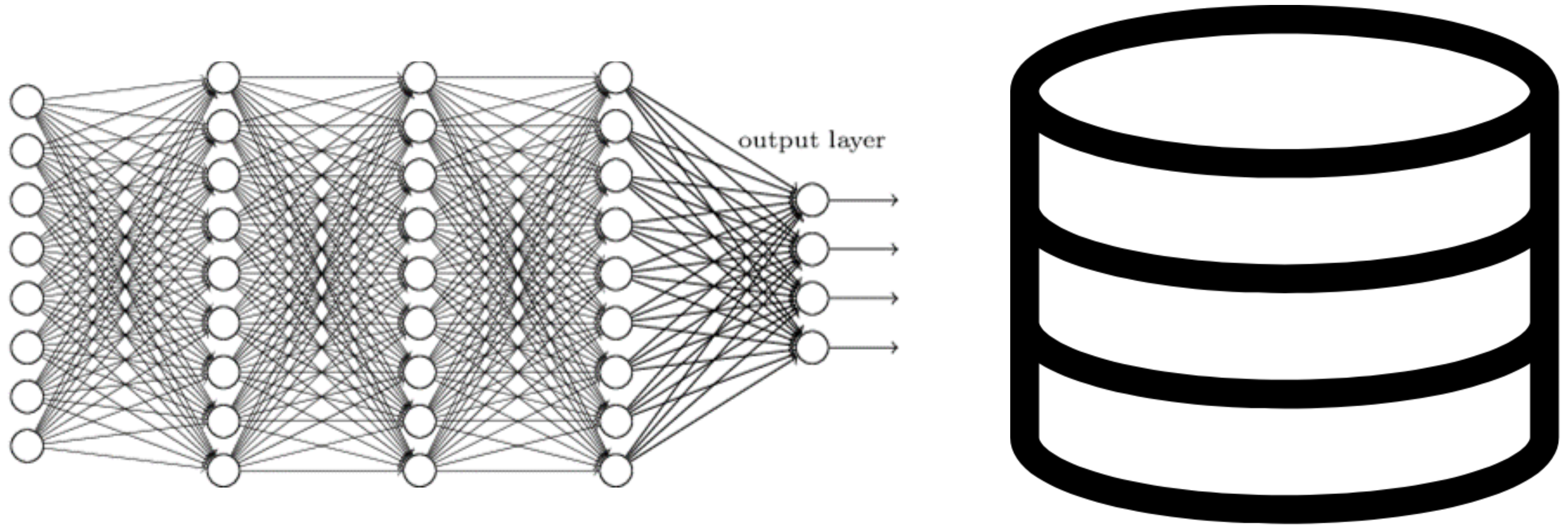

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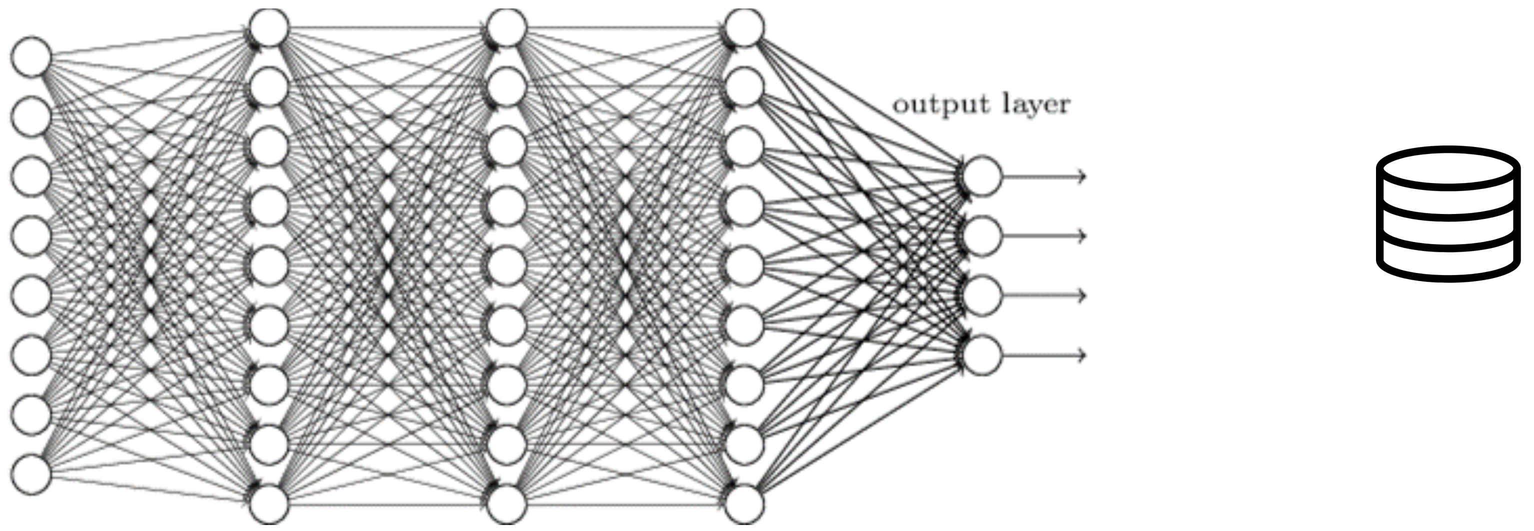

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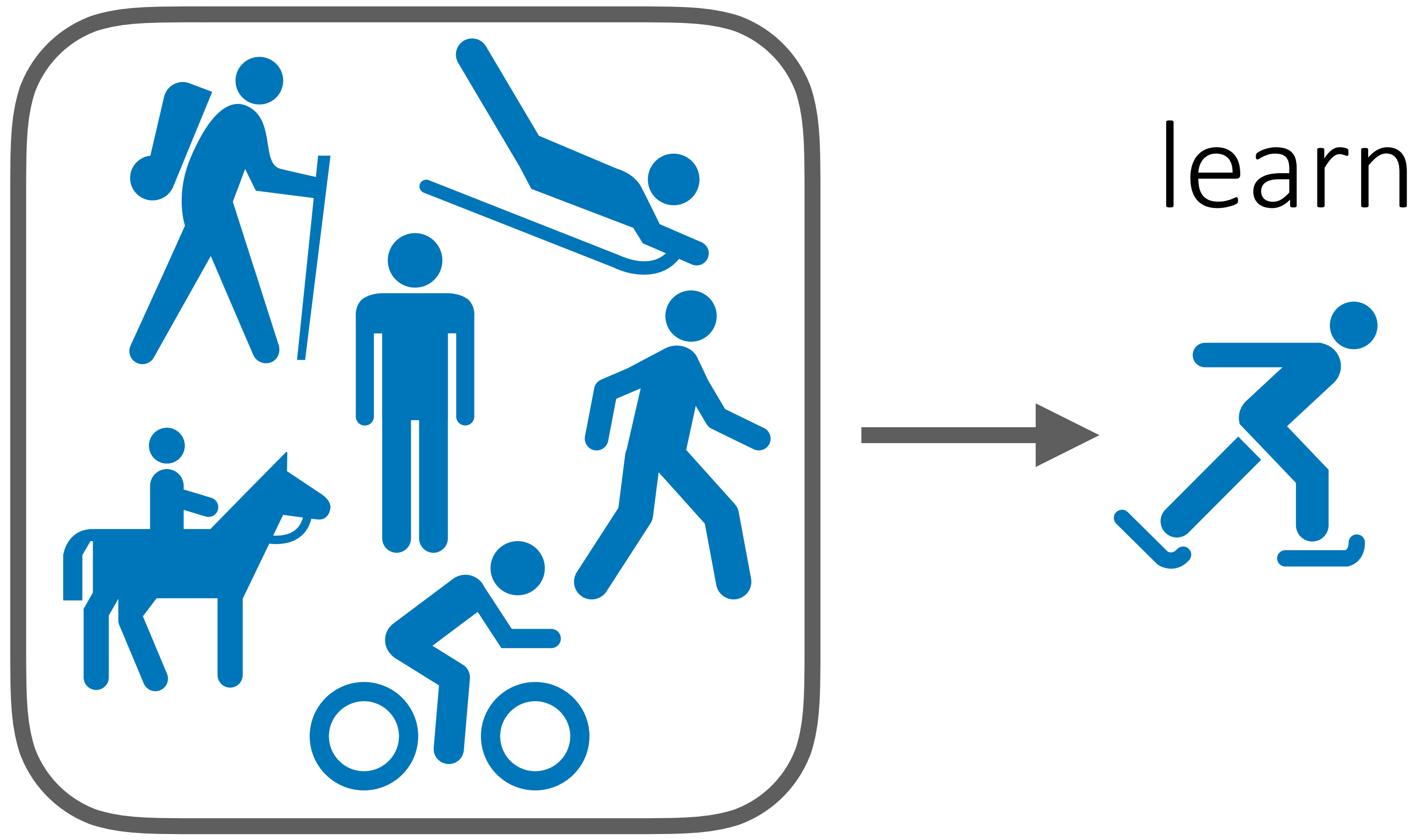

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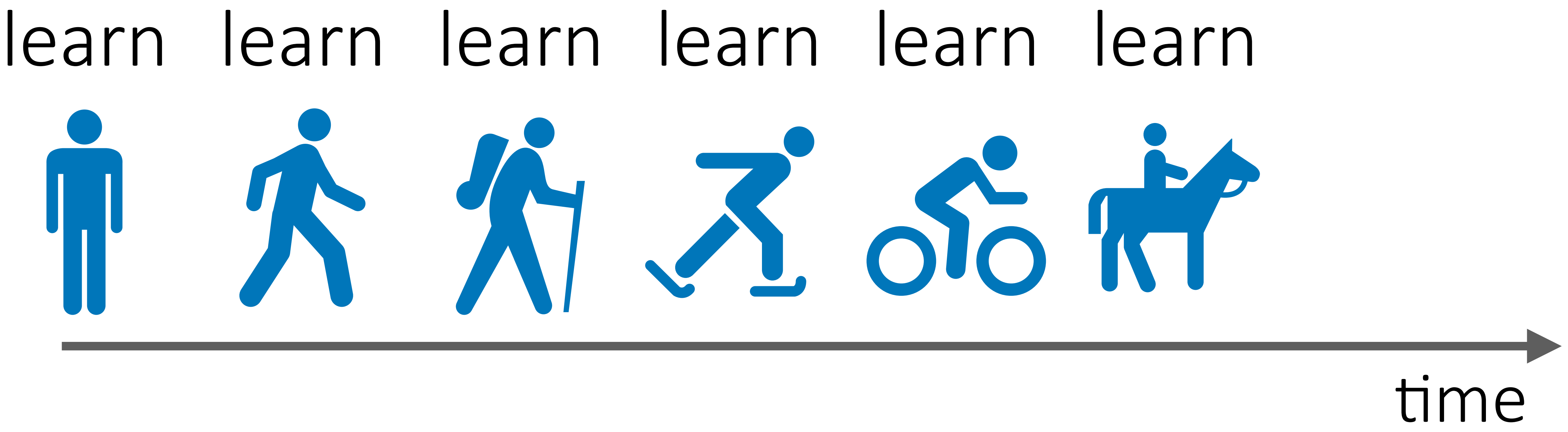

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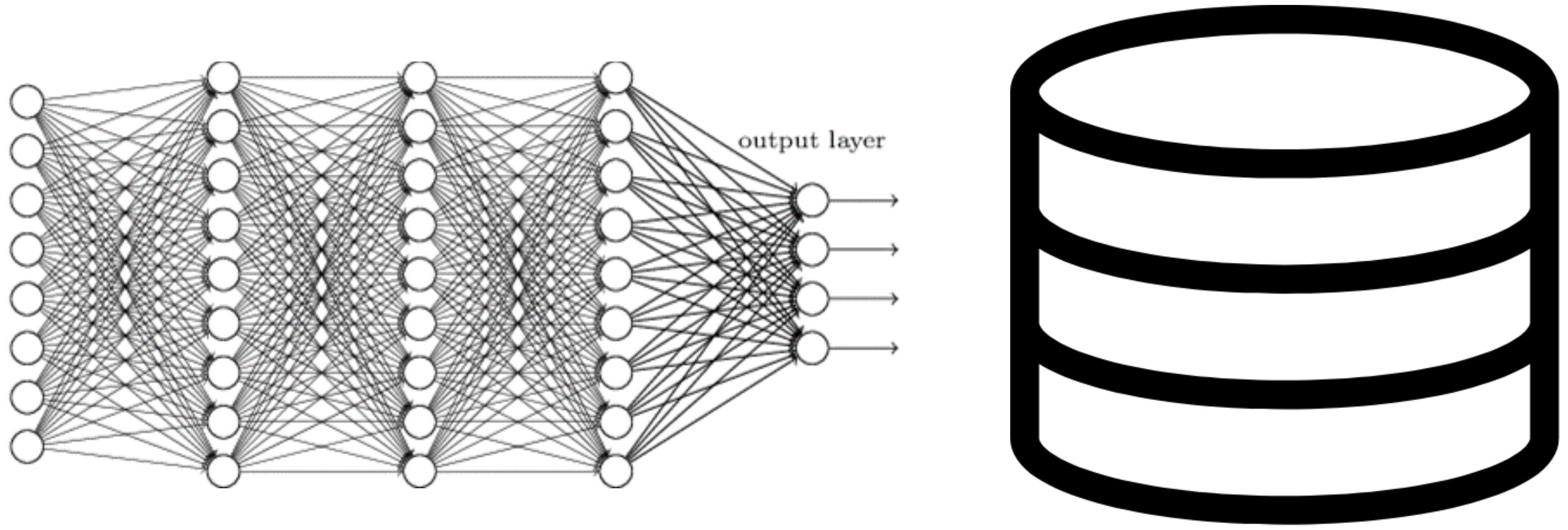

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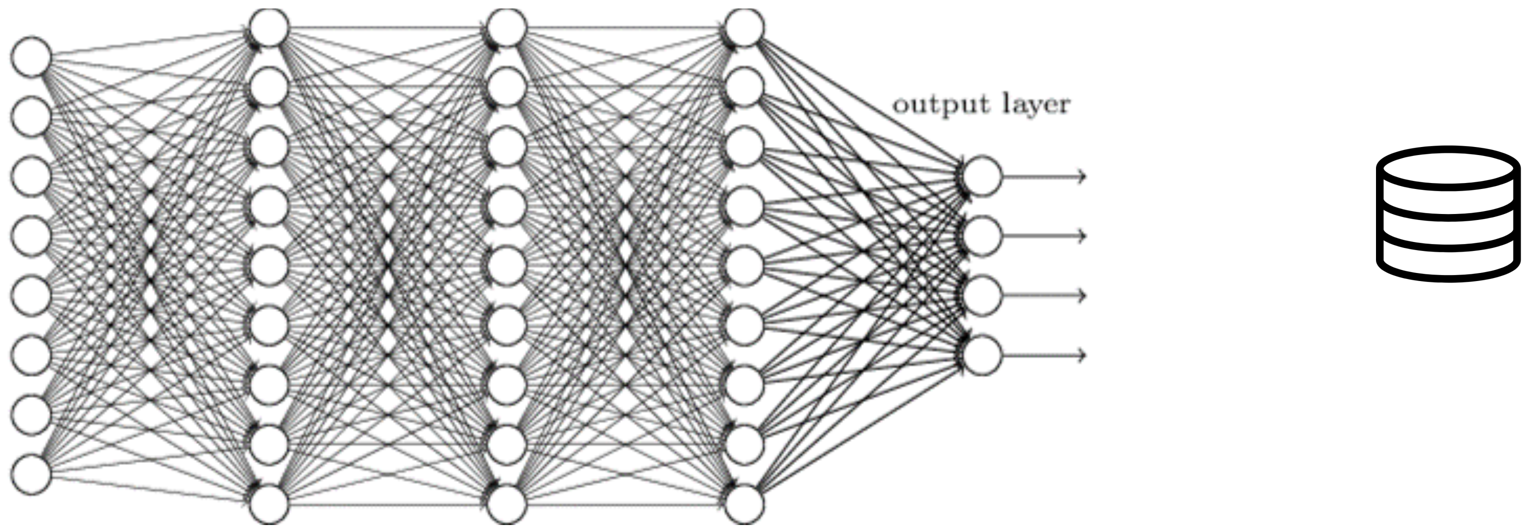

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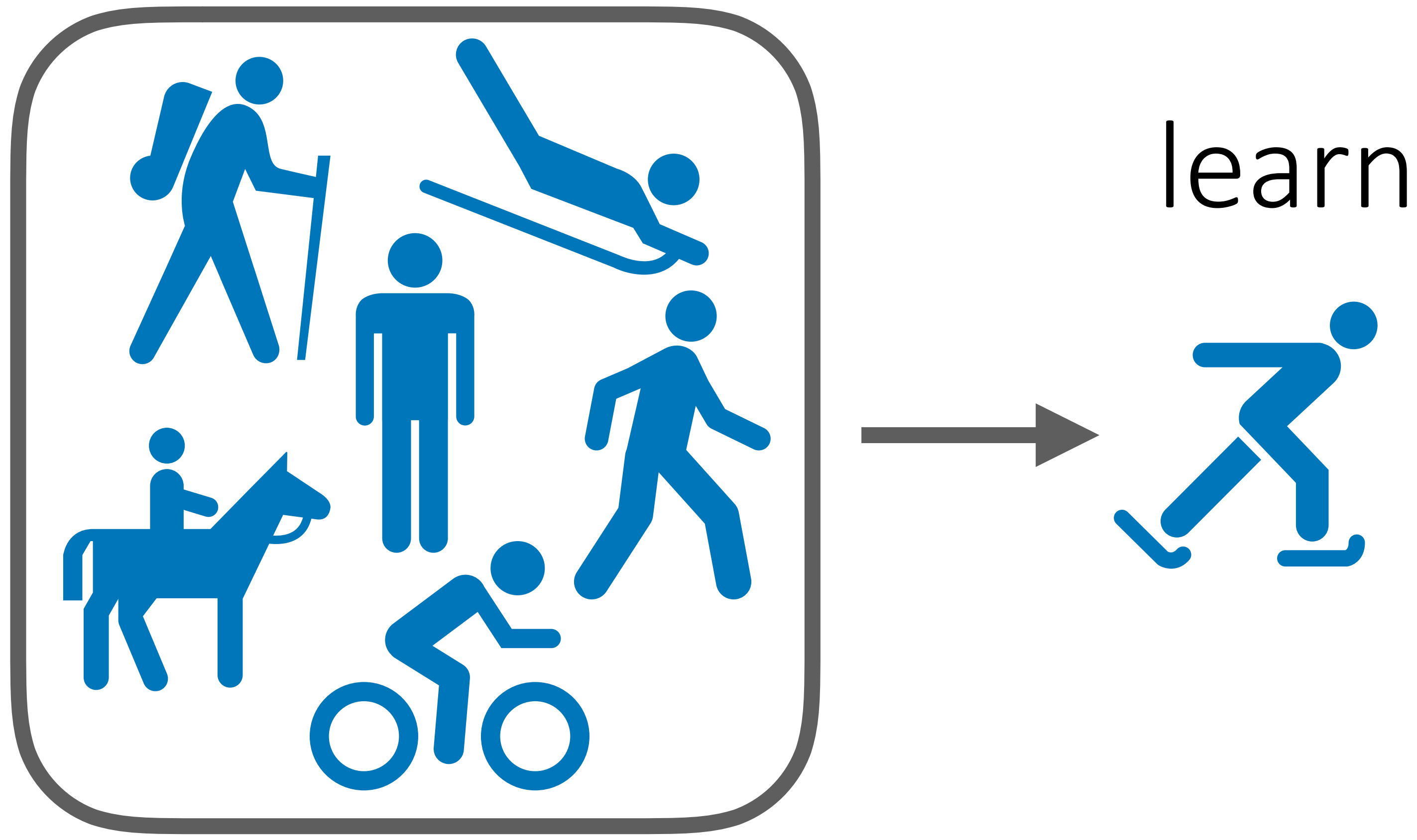

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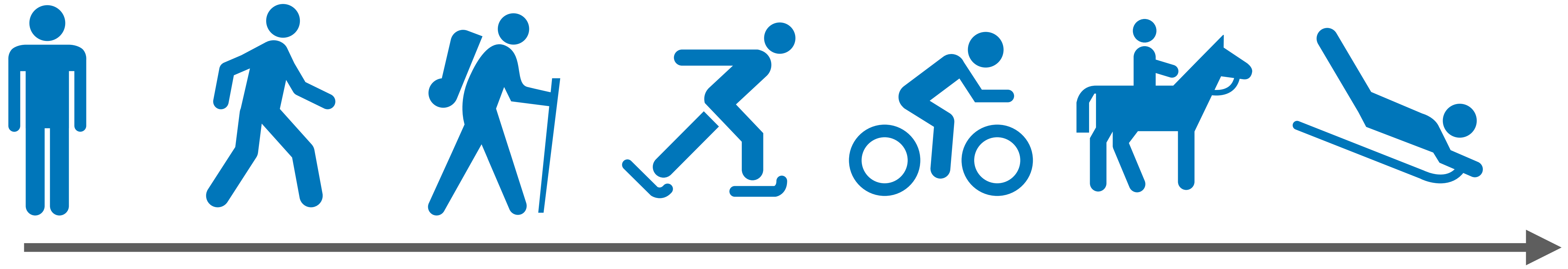

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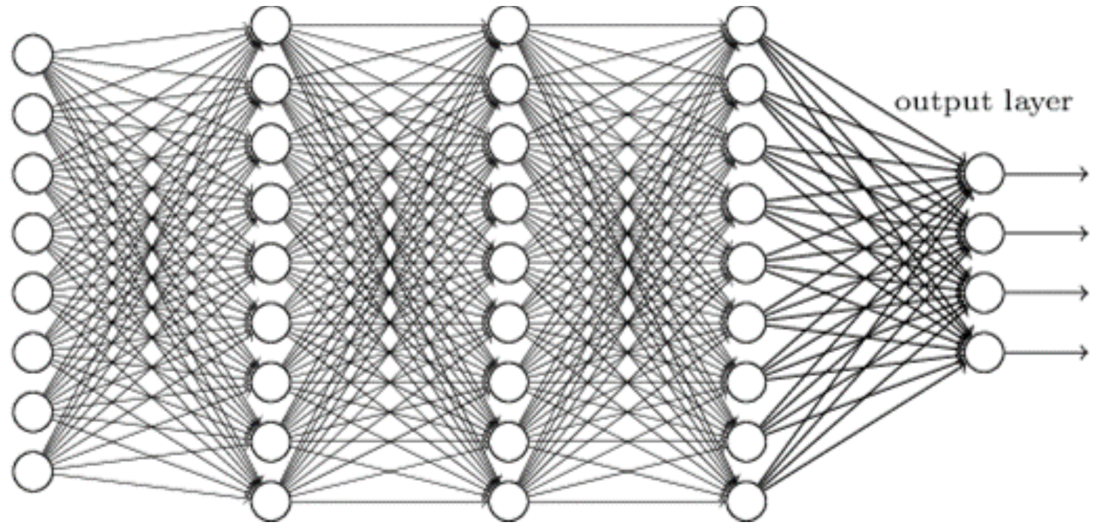

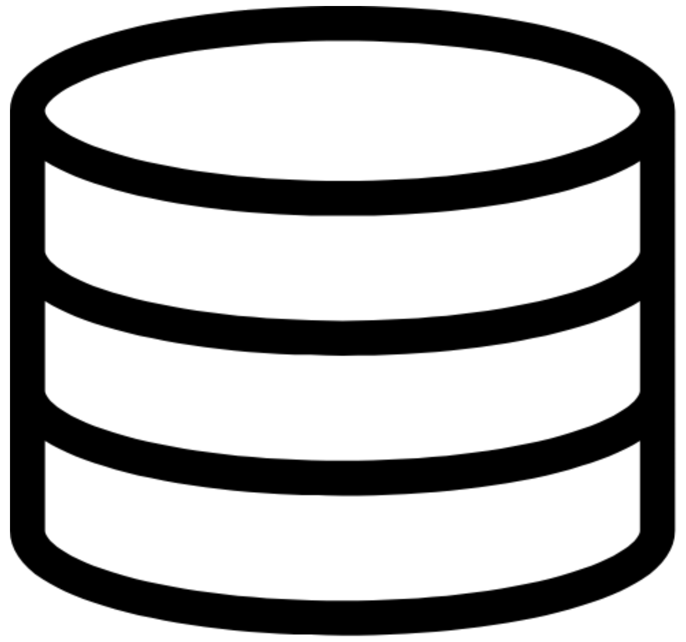

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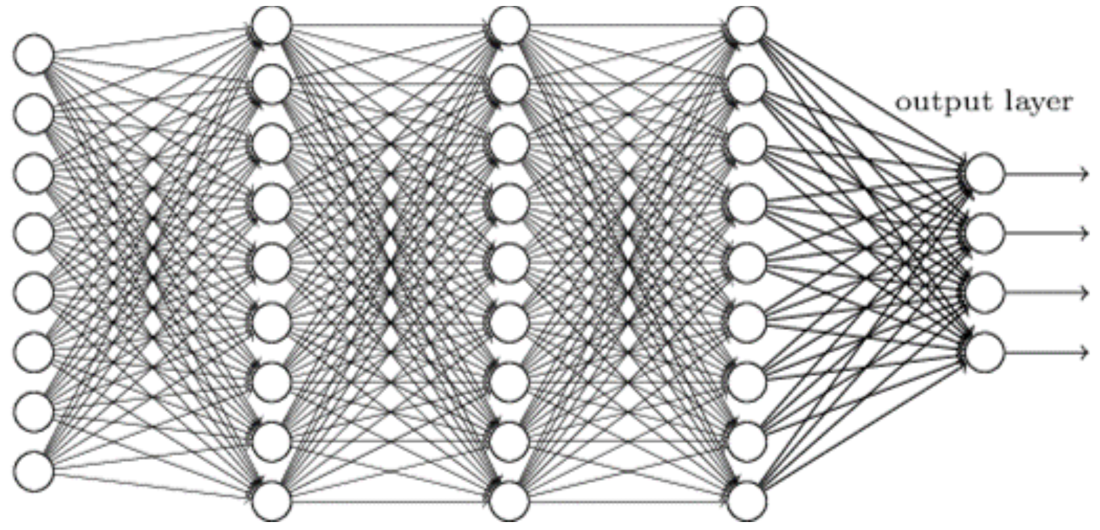

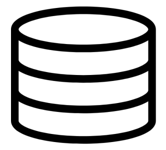

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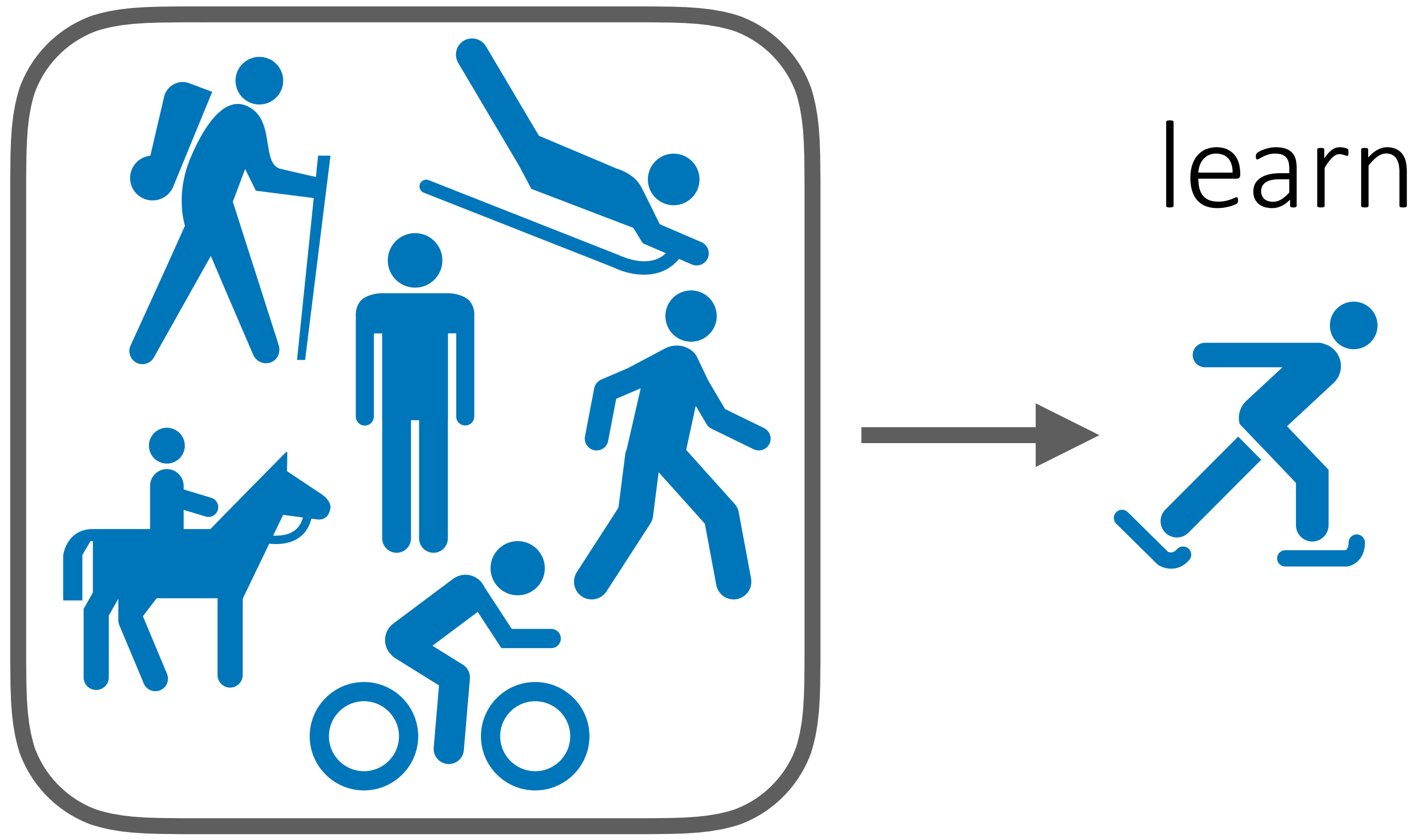

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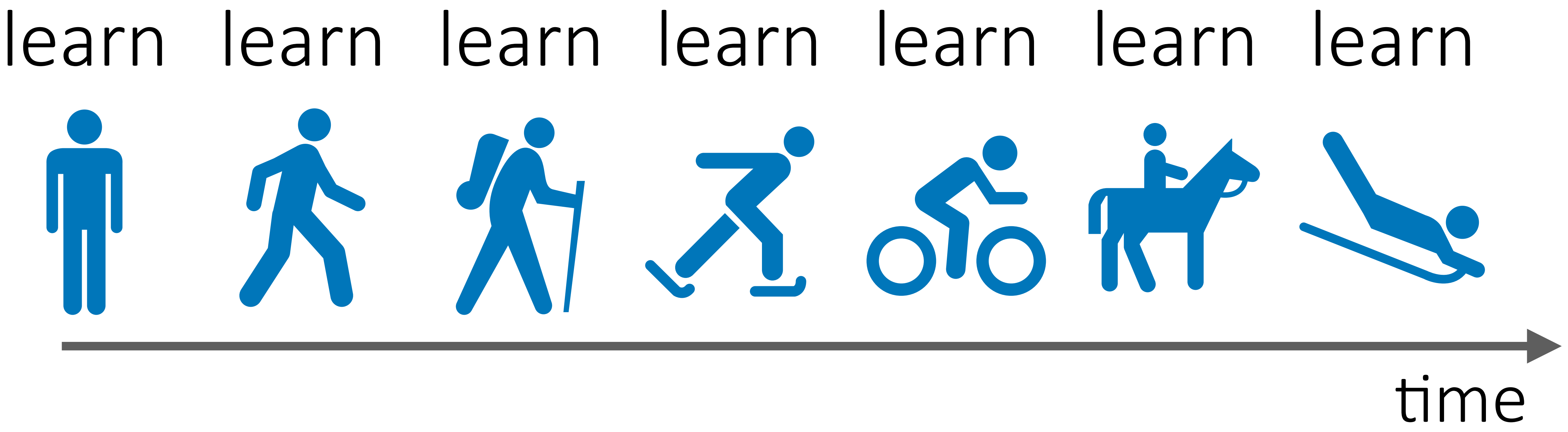

slow learning → rapid learning

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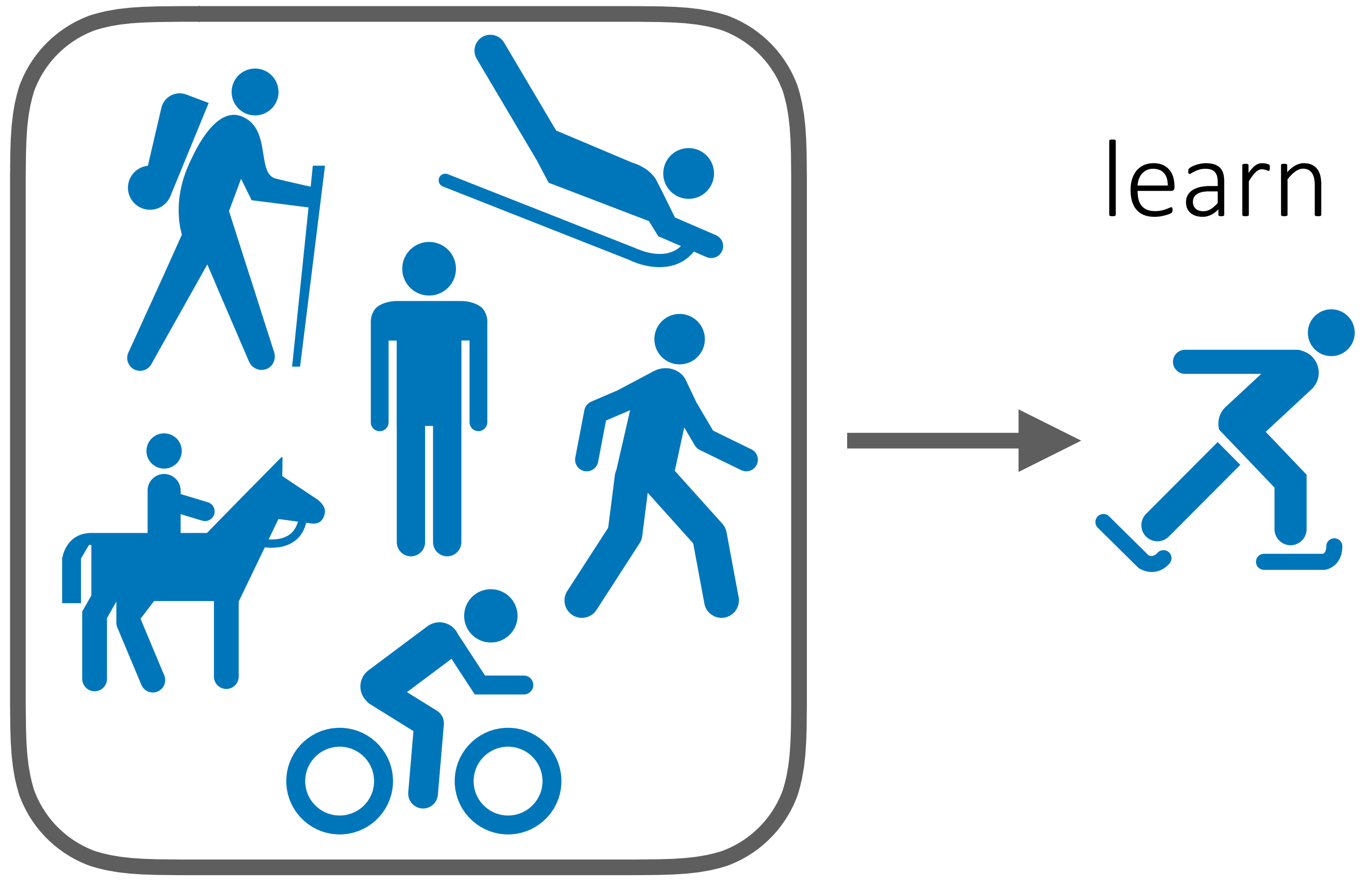

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(Hannan ’57, Zinkevich ’03)

Perform sequence of tasks
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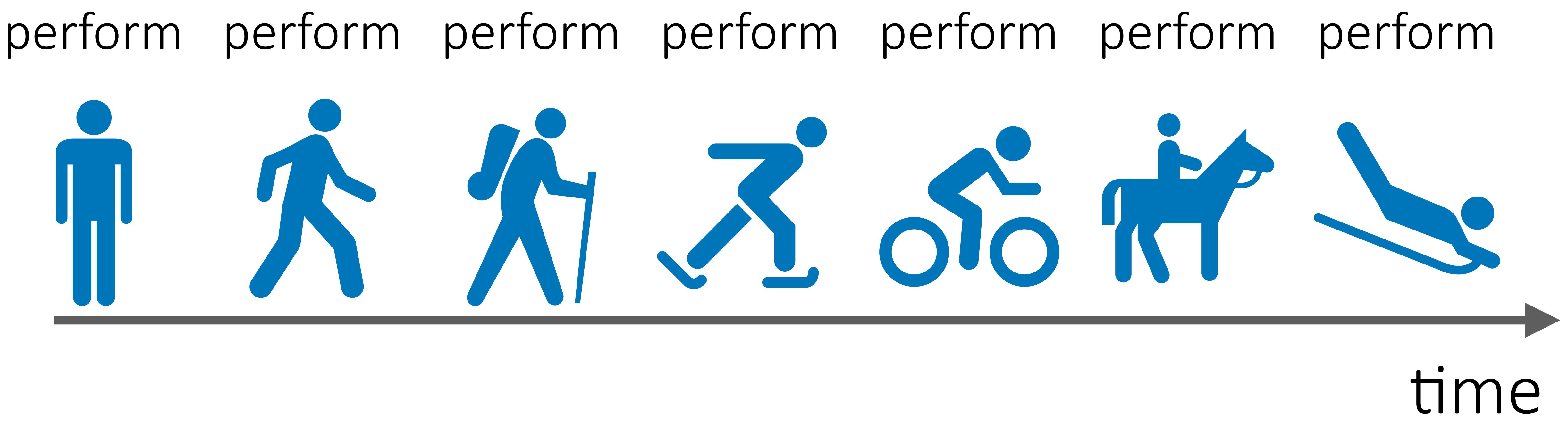

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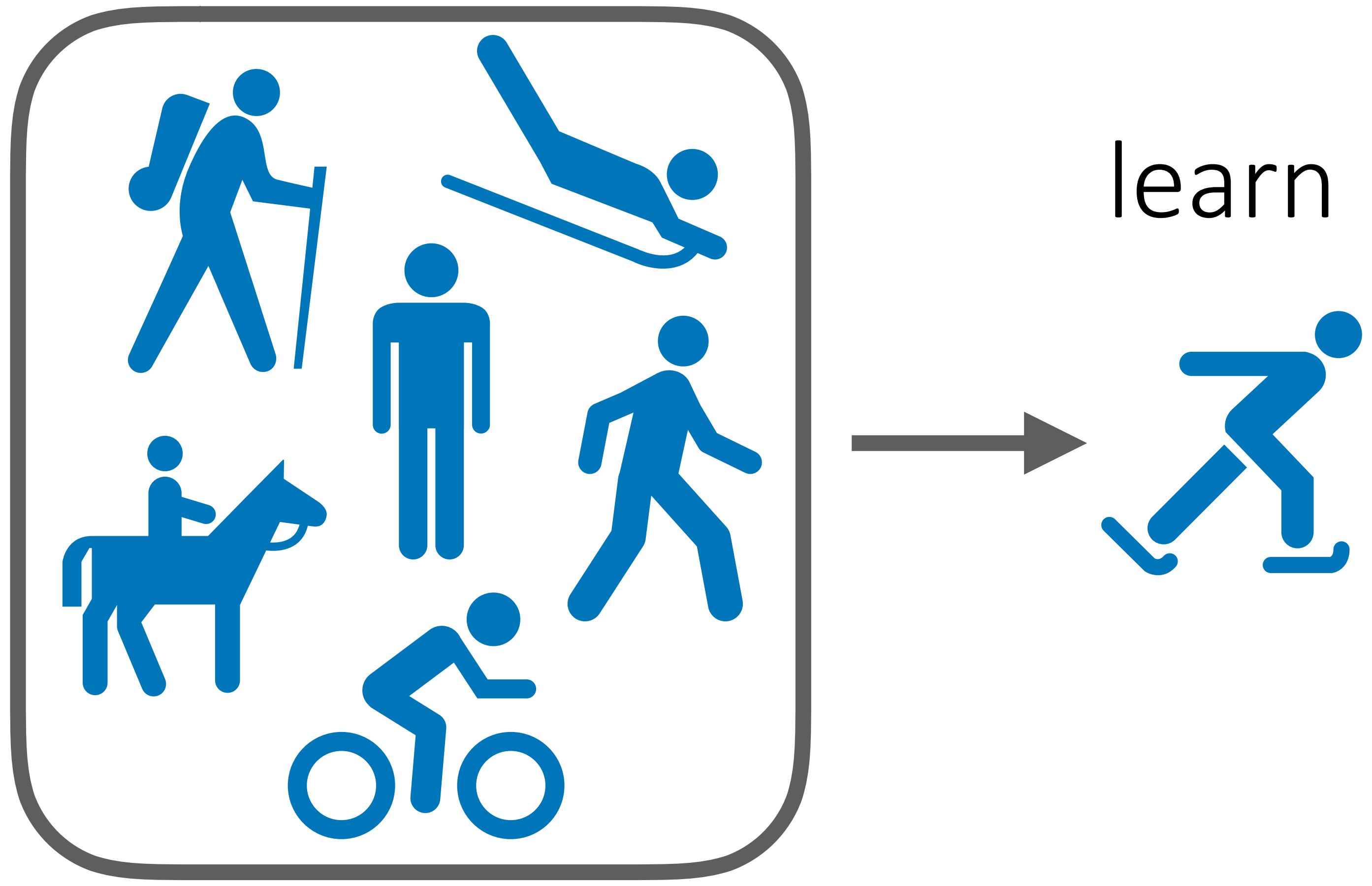

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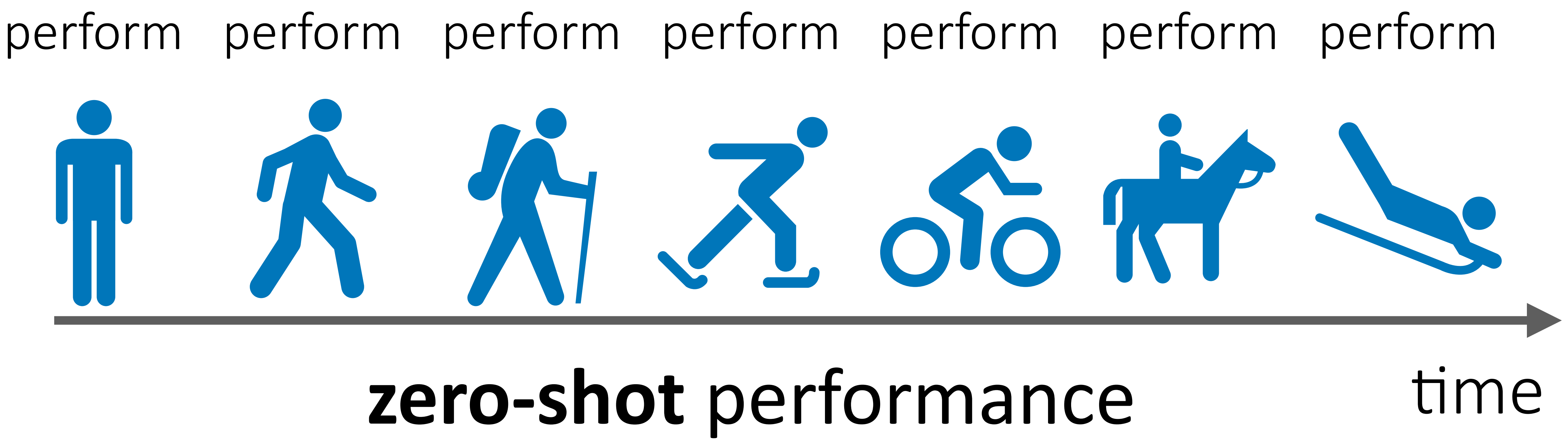
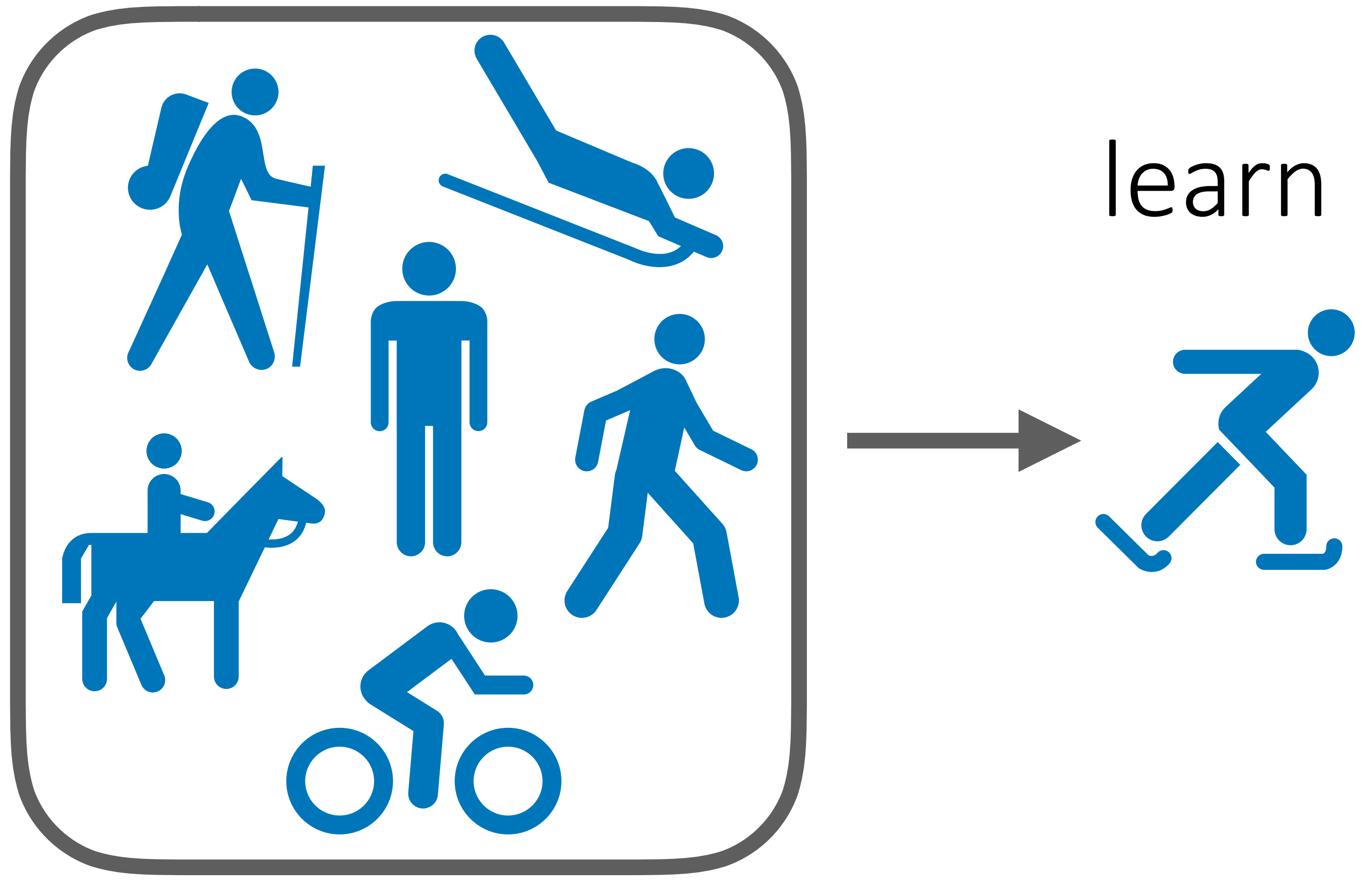


Meta-Learning
(Schmidhuber et al. ’87, Bengio et al. ’92)

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



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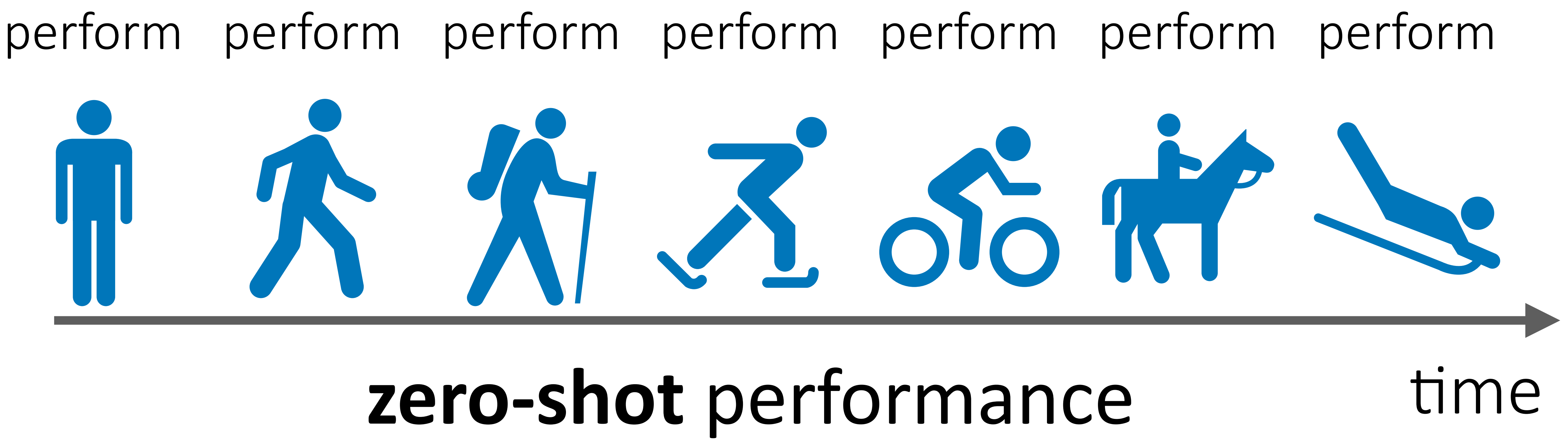

zero-shot performance

Online Meta-Learning
(this work)

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

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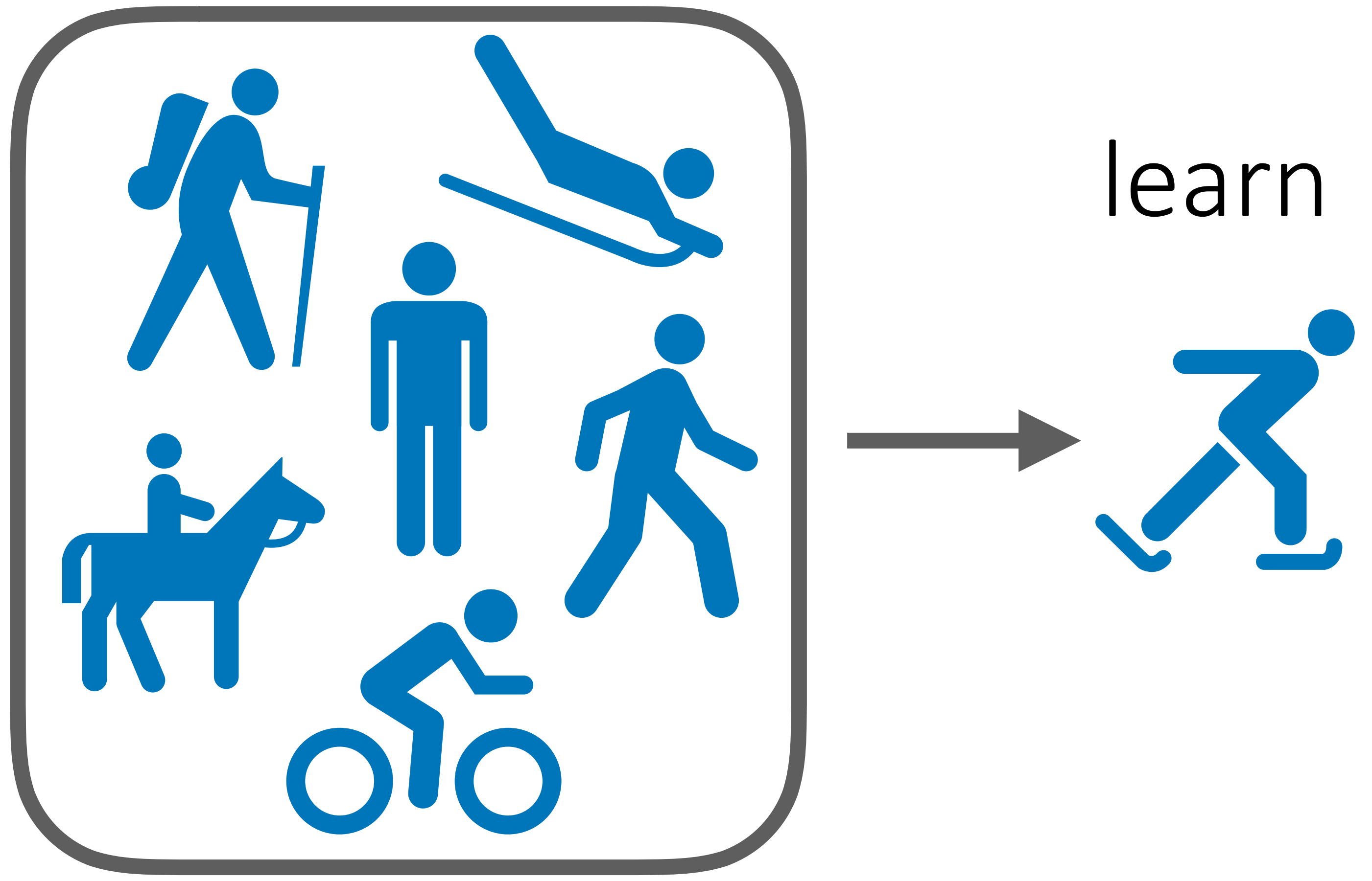

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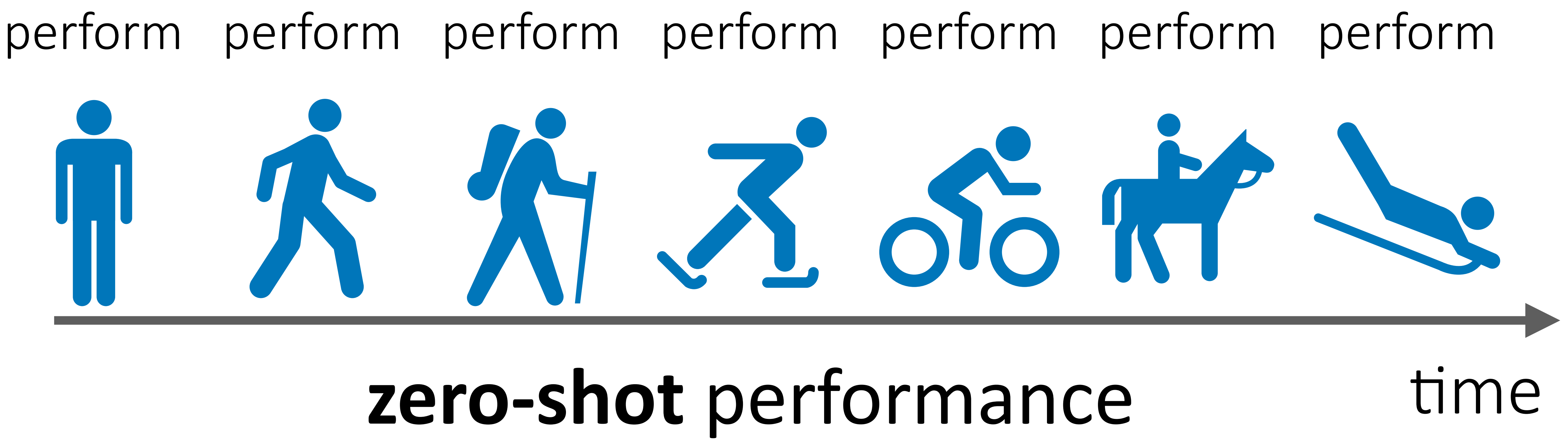

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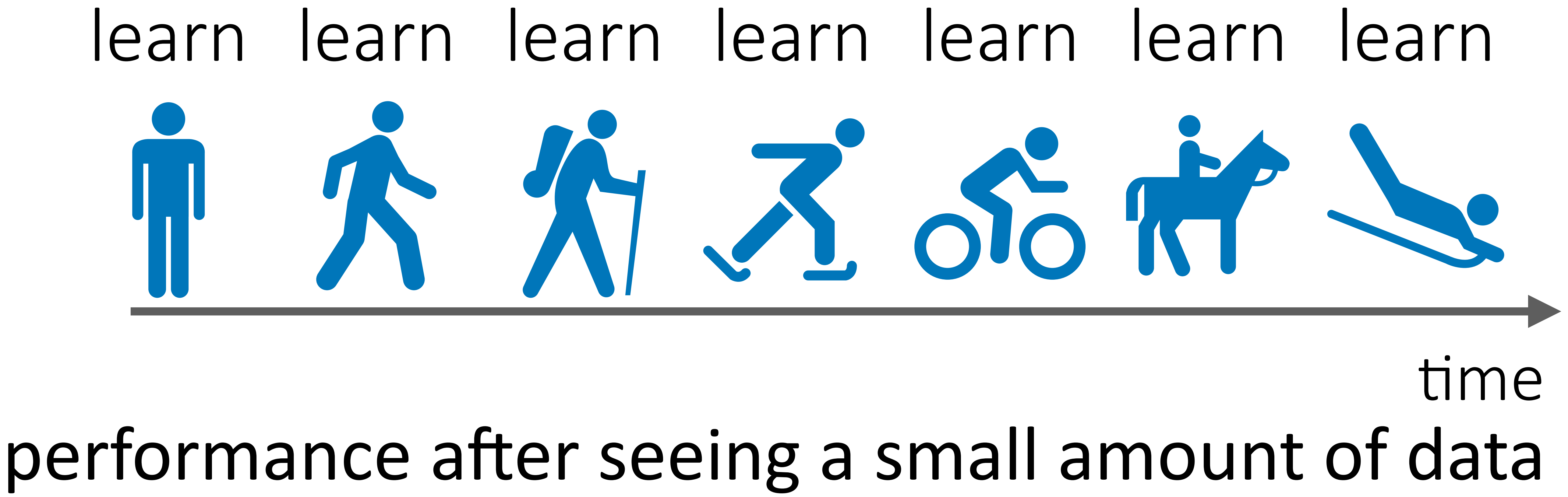
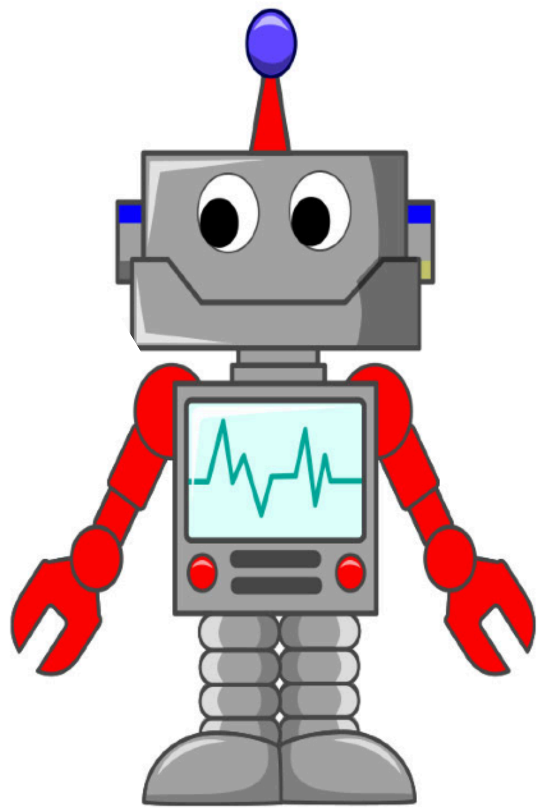


The Online Meta-Learning Setting



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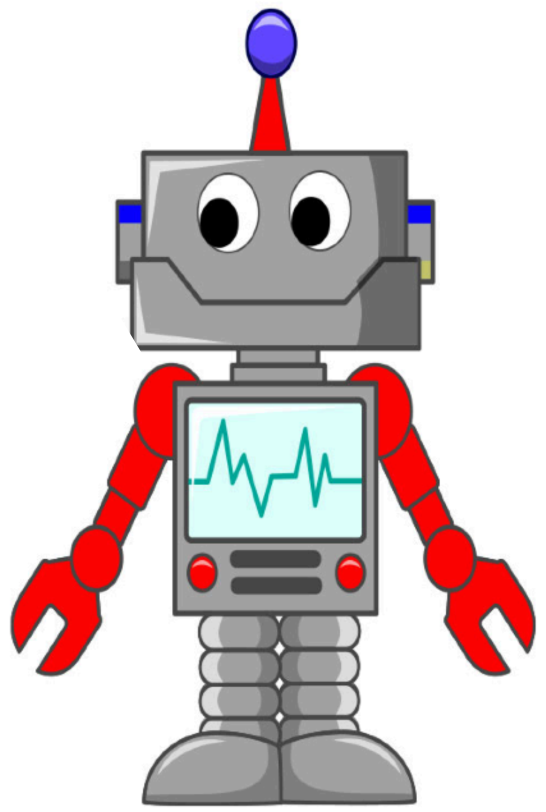

Space of parameters $\theta \in \Theta \subseteq \mathbb{R}^d$ and loss functions $\ell : \Theta \to \mathbb{R}$

For round $t \in \{1, 2, \ldots \infty\}$:

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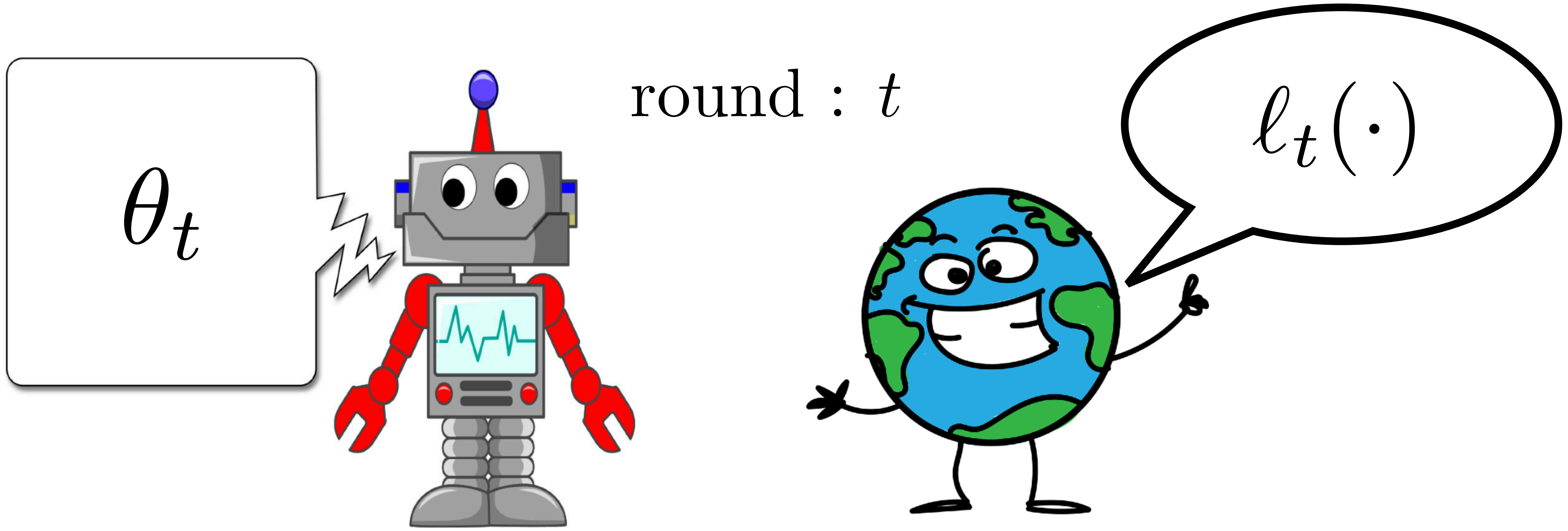

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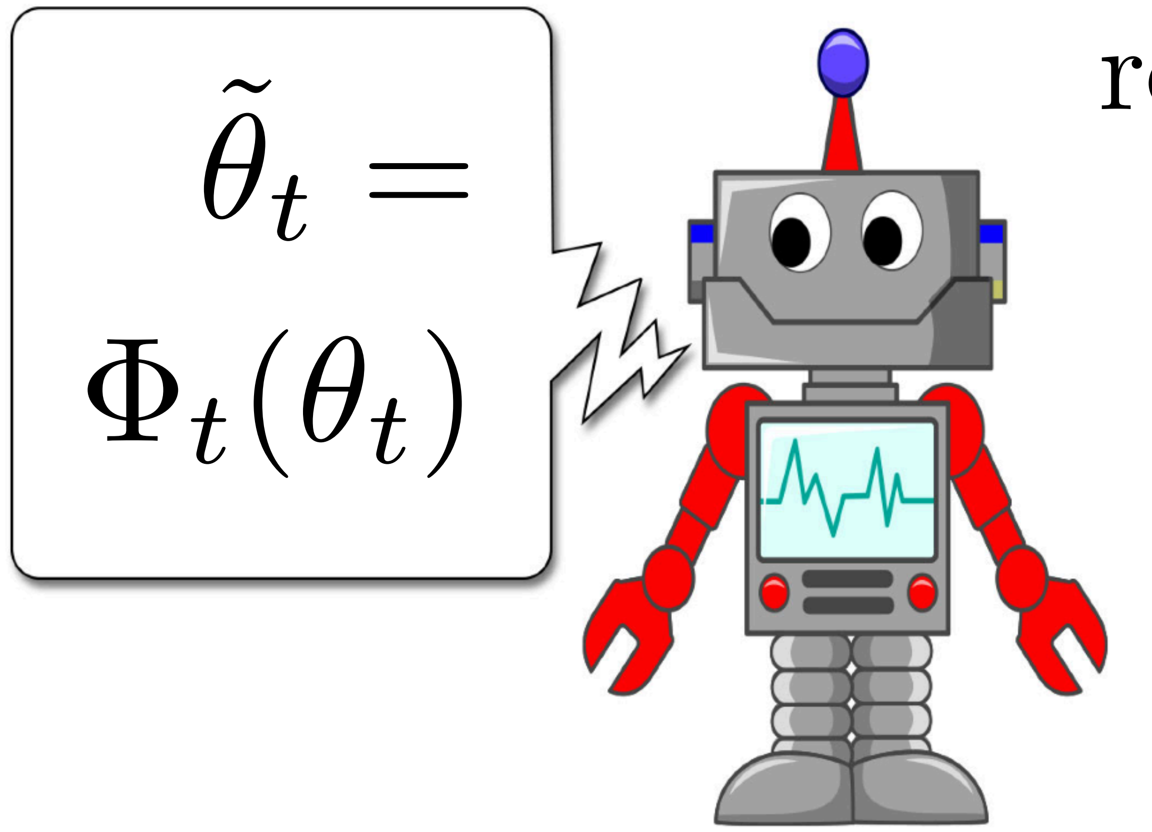
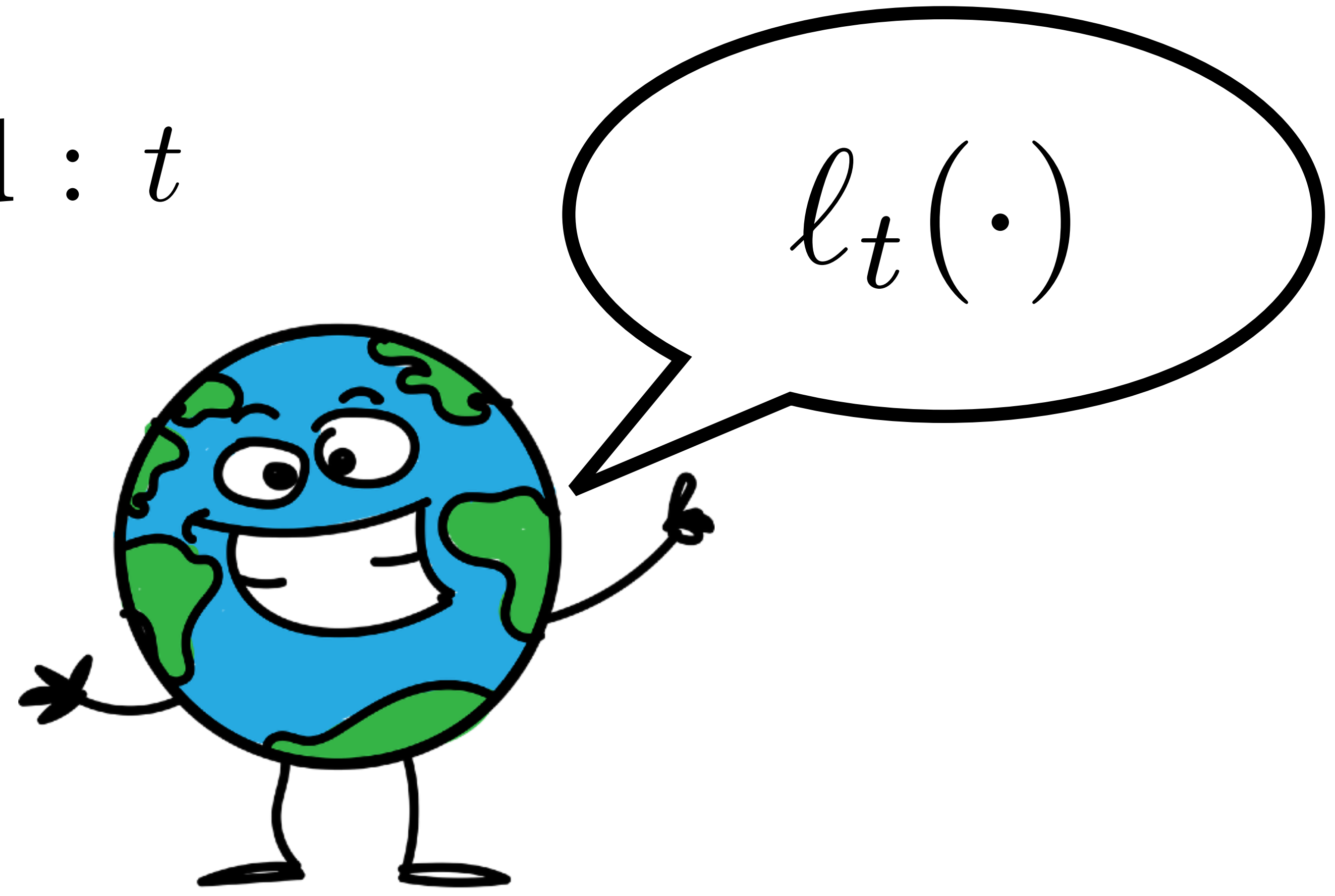


round : t



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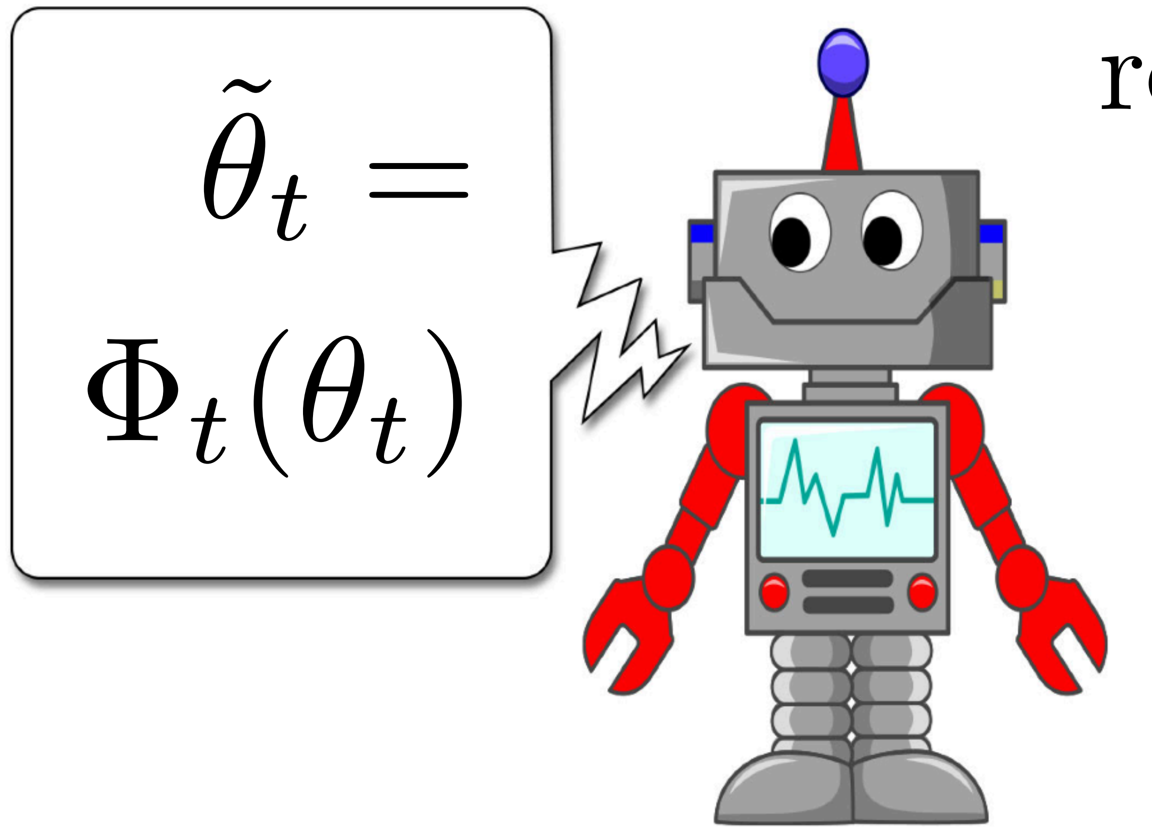

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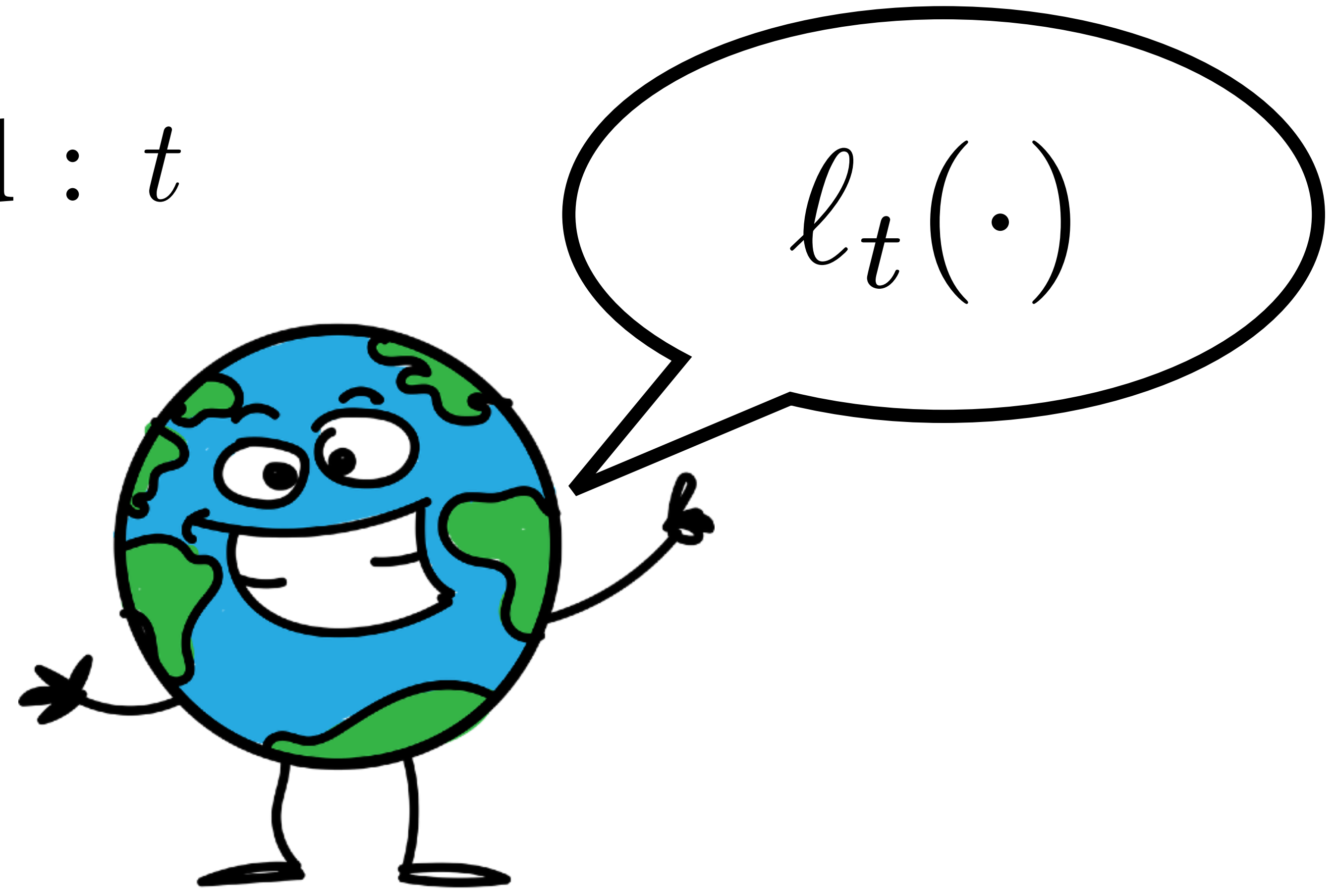

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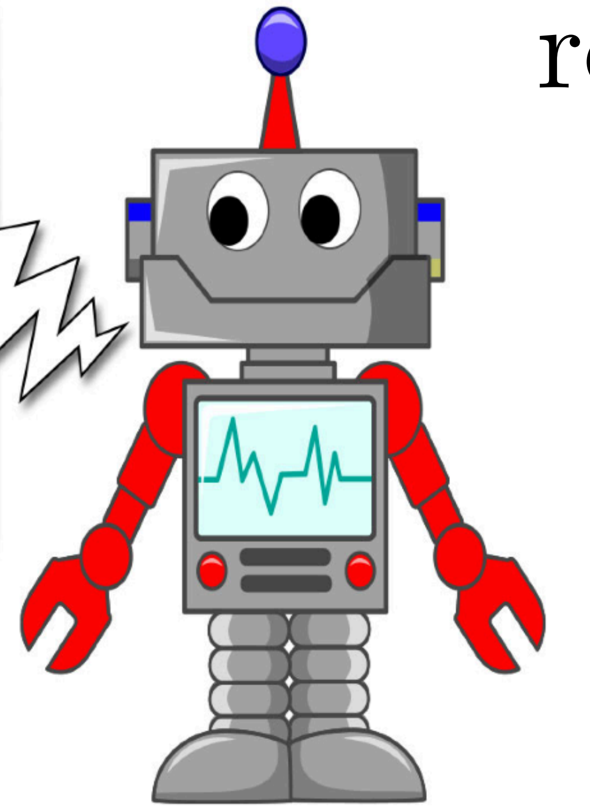

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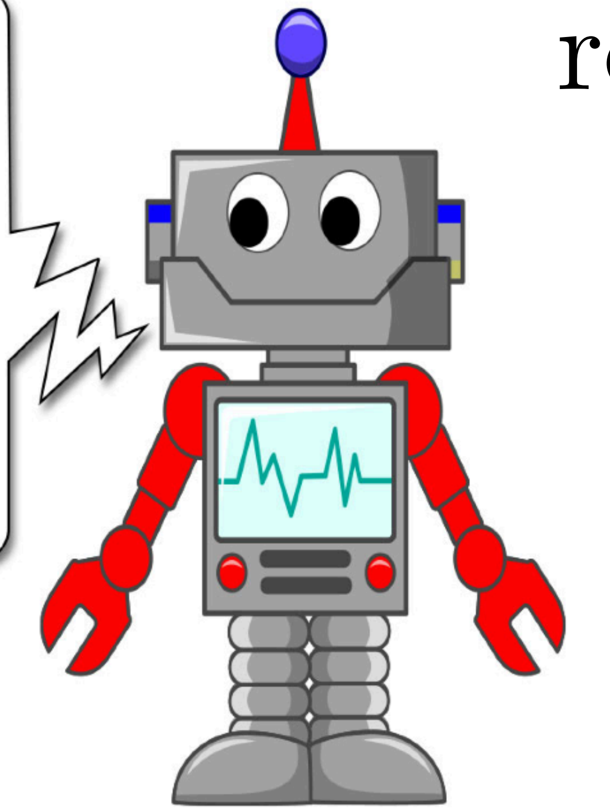

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Goal: Learning algorithm with sub-linear

Loss of algorithm

Loss of best algorithm in hindsight

$$\text{Regret}_T := \sum_{t=1}^{T} \ell_t(\Phi_t(\theta_t)) - \min_{\theta \in \Theta} \sum_{t=1}^{T} \ell_t(\Phi_t(\theta))$$

Follow the Meta-Leader (FTML) :

$$\theta_{t+1} = \arg\min_{\theta} \sum_{t=1}^{T} \ell_t(\Phi_t(\theta))$$

Can be implemented with MAML

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Theorem (Informal): If $\{\ell_t(\cdot), \hat{\ell}_t(\cdot)\}\ \forall t$ are C^2-smooth and strongly convex, the sequence of models $\{\theta_1, \theta_2, \ldots, \theta_T\}$ returned by FTML has the property:

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$$\implies \text{Avg. Regret} = \frac{\text{Regret}_T}{T} \to 0 \text{ as } T \to \infty$$

Learning in a sequential non-stationary setting, but still competitive with best meta-learner in hindsight!

FTML: practical instantiation of our approach, extending MAML[1]
meta-train on all data so far, fine-tune on current task

[1] Finn et al. ICML '17

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Experiment with **sequences of tasks**:

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Experiment with **sequences of tasks**:

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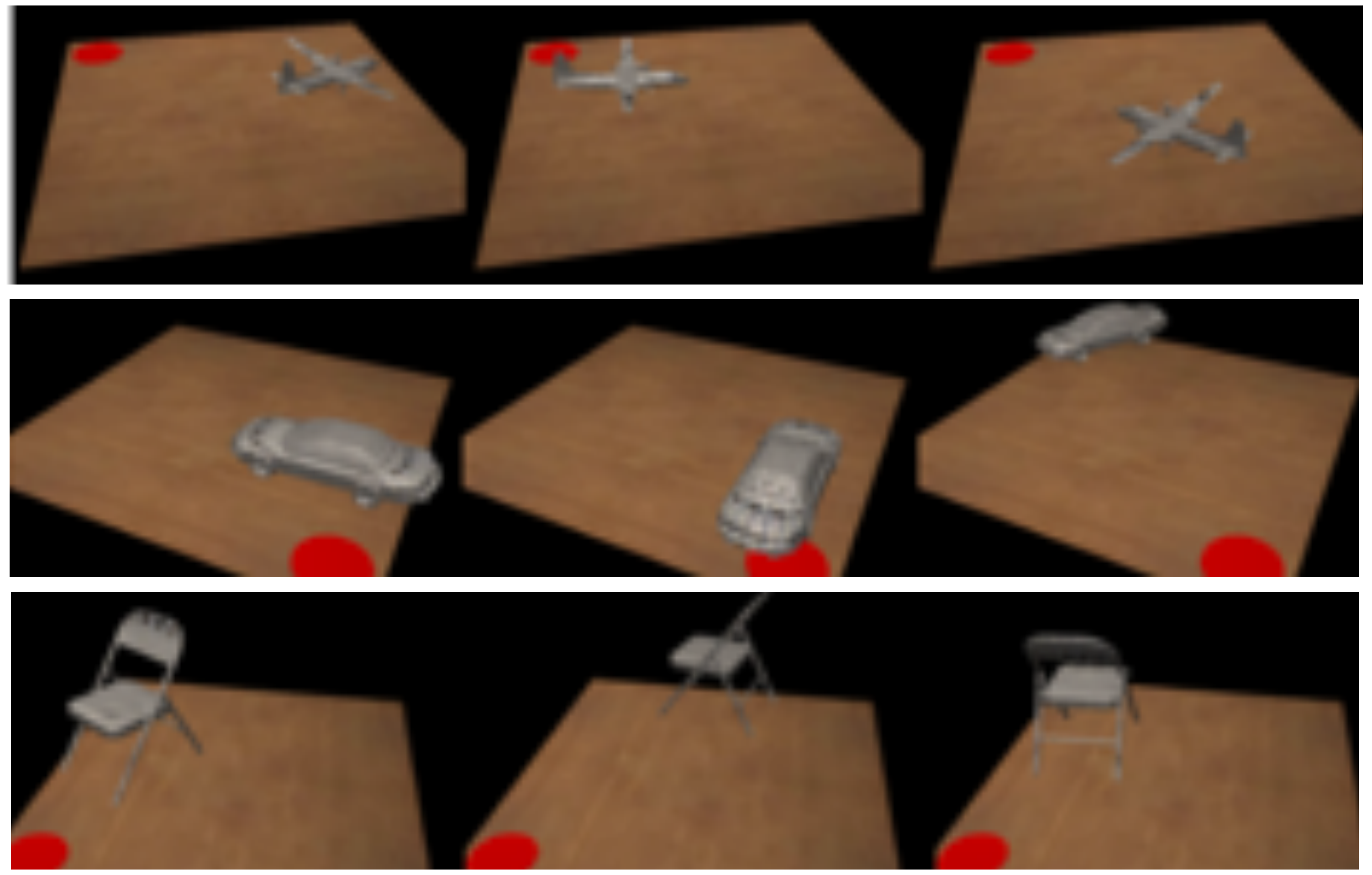
Example pose prediction tasks



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Experiment with **sequences of tasks**:

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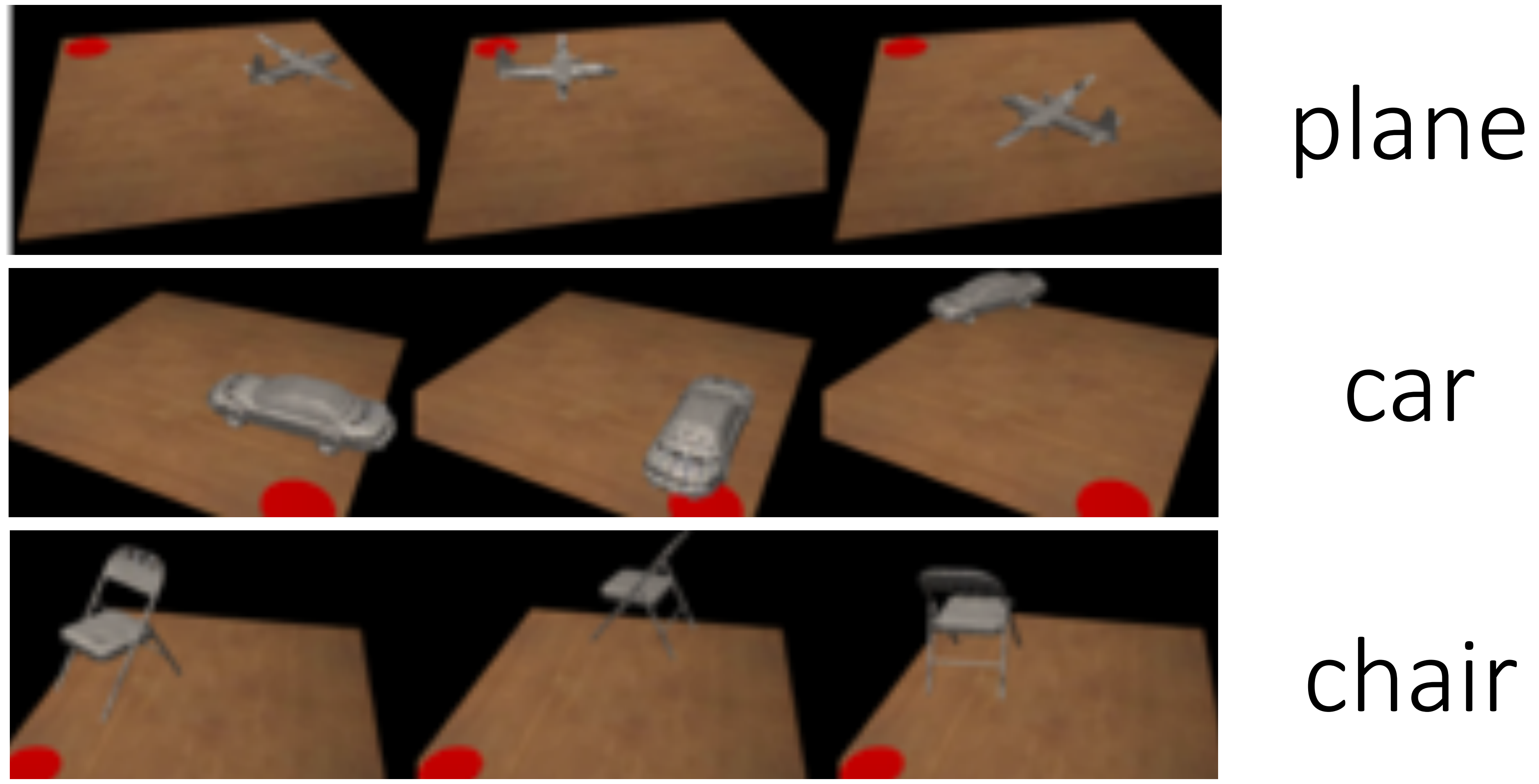
- **3D object pose prediction**
- **CIFAR-100** classification

Example pose prediction tasks



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Experiments

Experiments

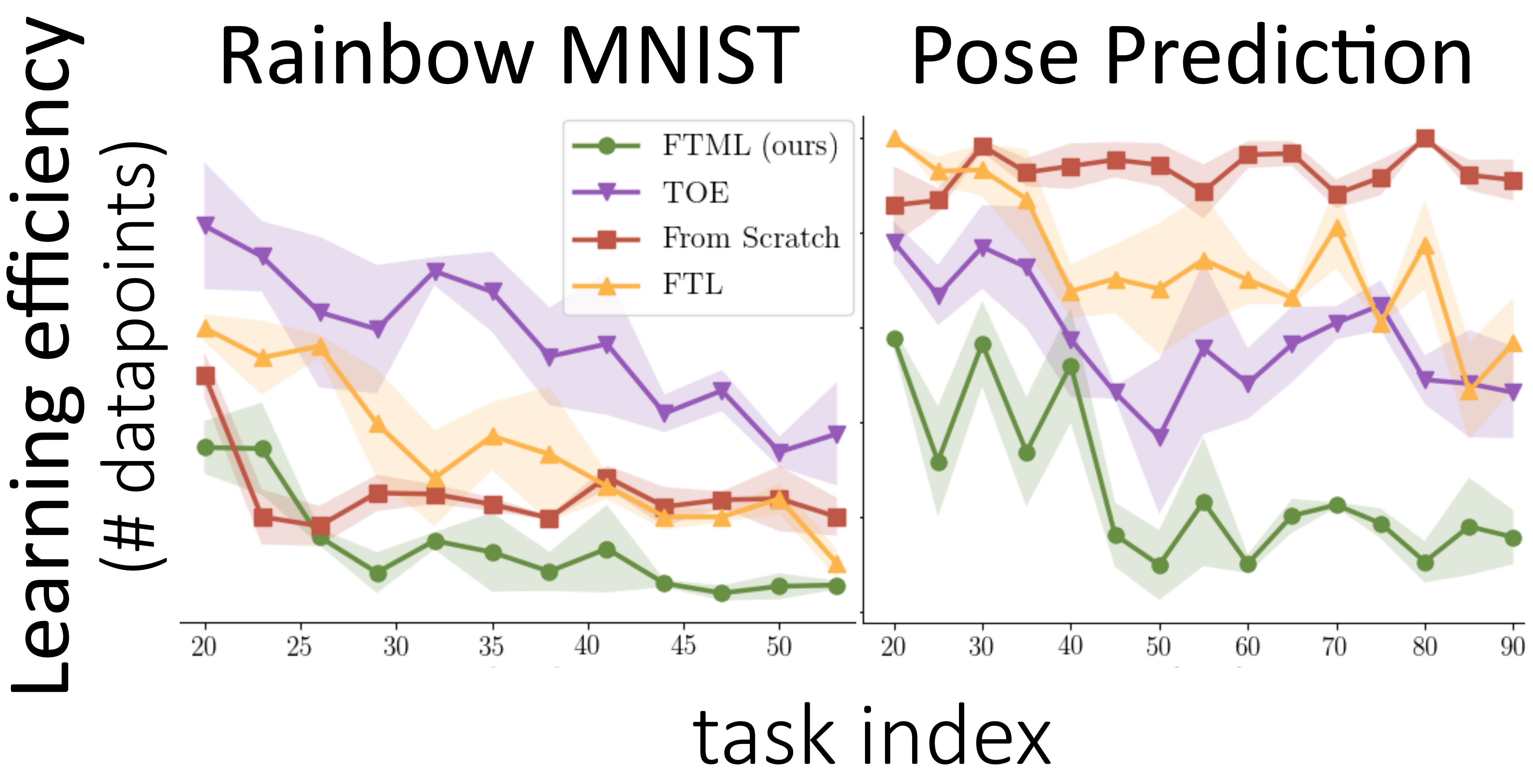
Learning efficiency
(# datapoints)

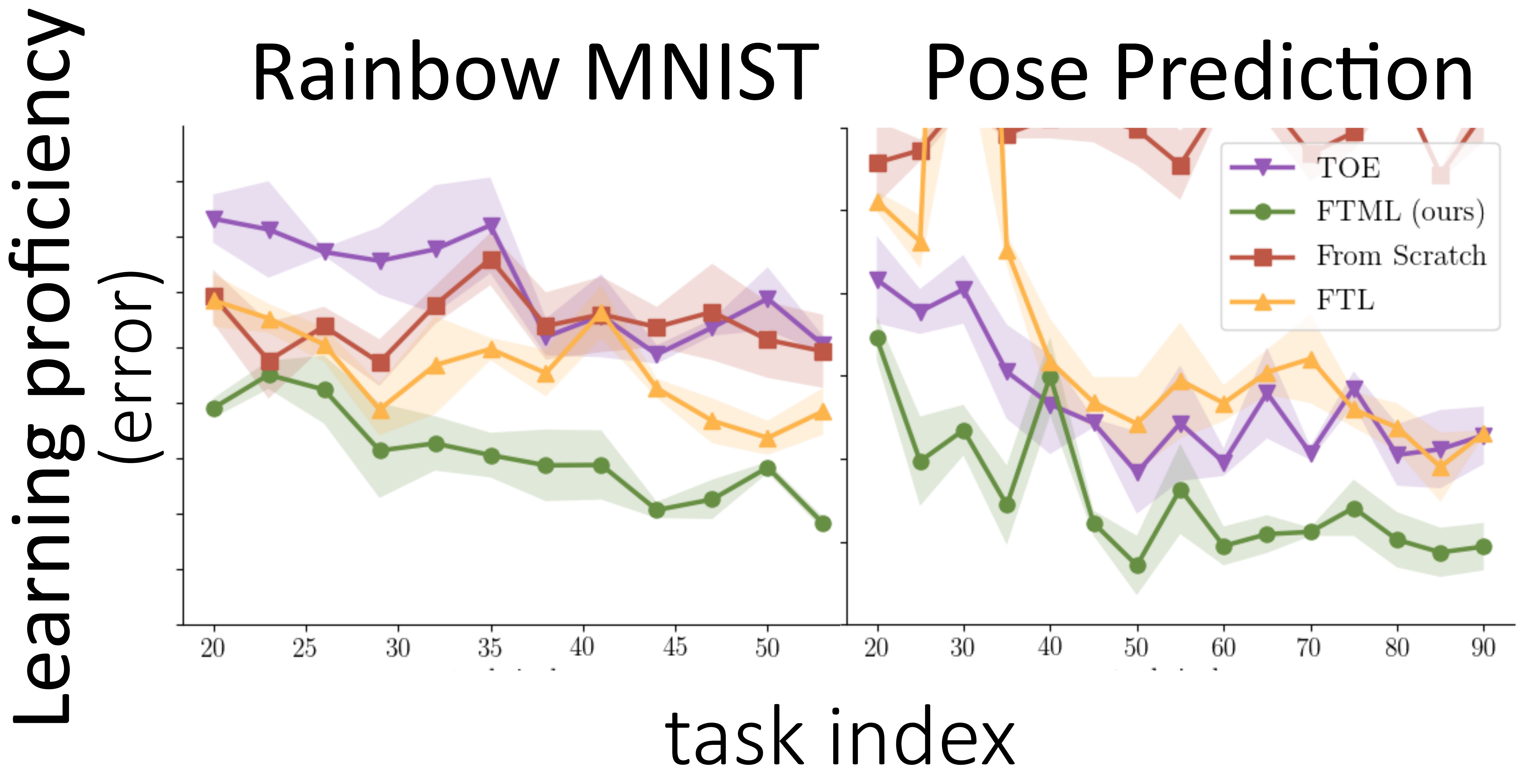
task index

Learning proficiency
(error)

task index

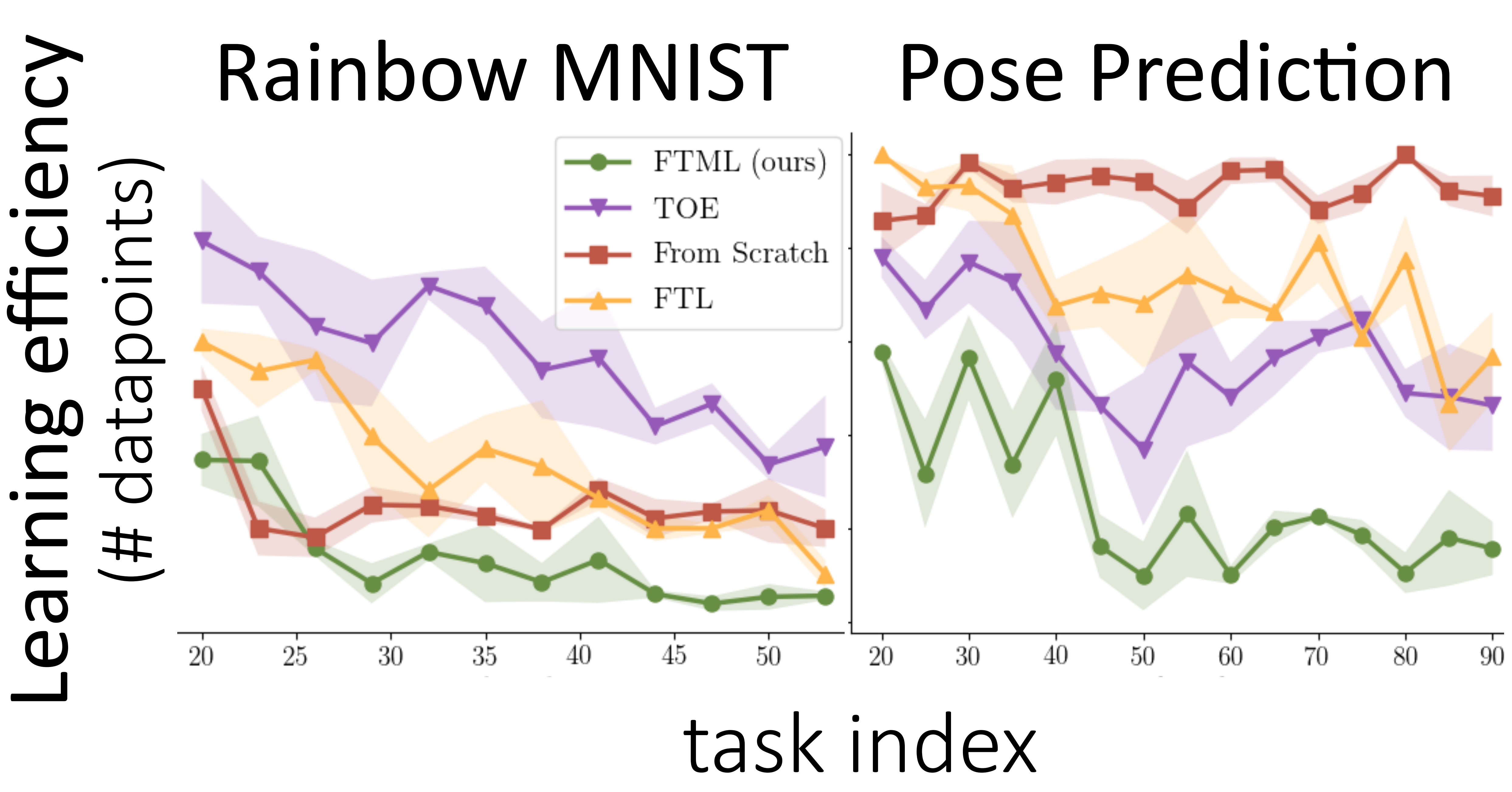
Experiments

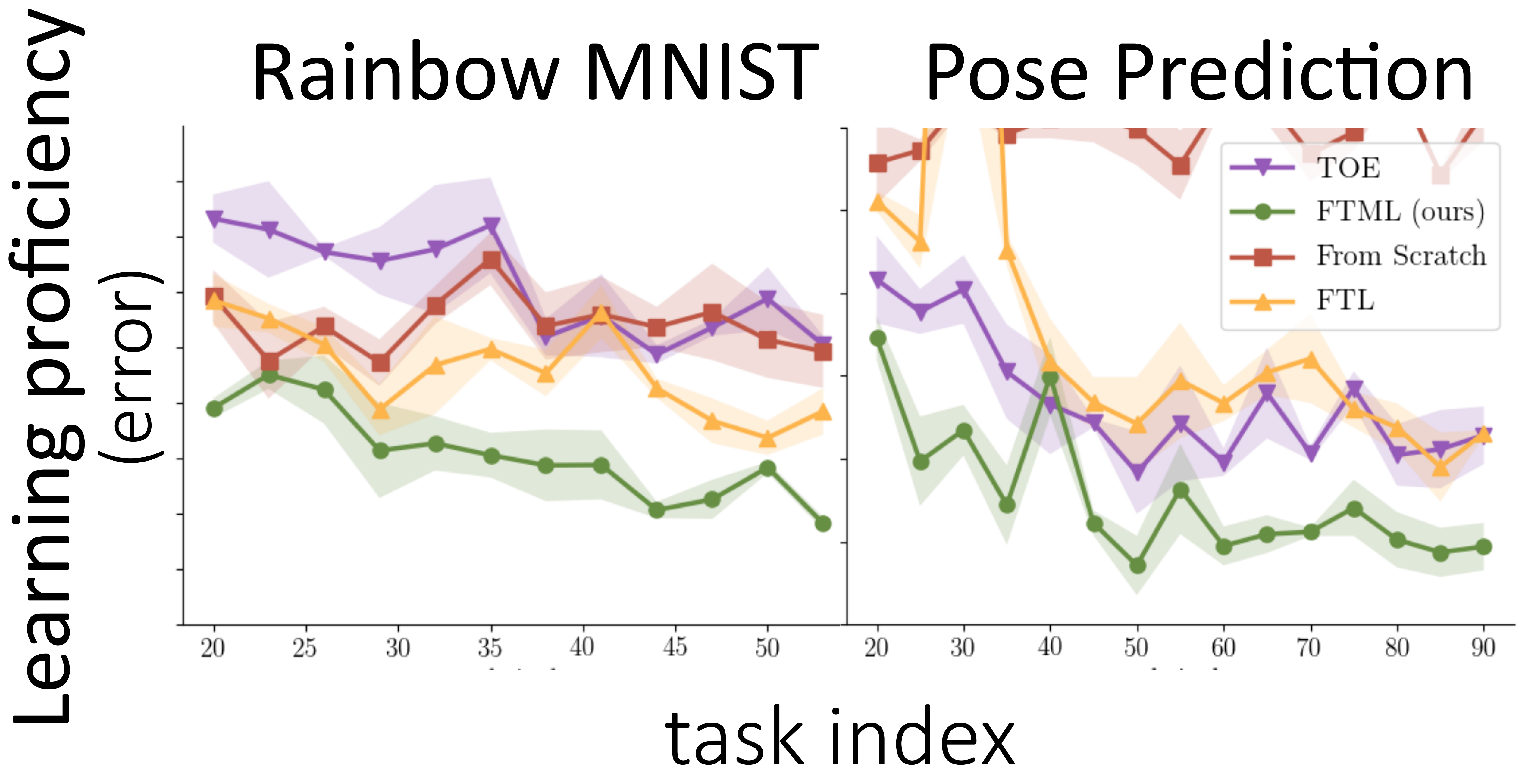




FTML (ours)

Experiments





FTML (ours)

learns each new task faster & **with greater proficiency**,

Experiments

FTML (ours)

learns each new task faster & **with greater proficiency**,

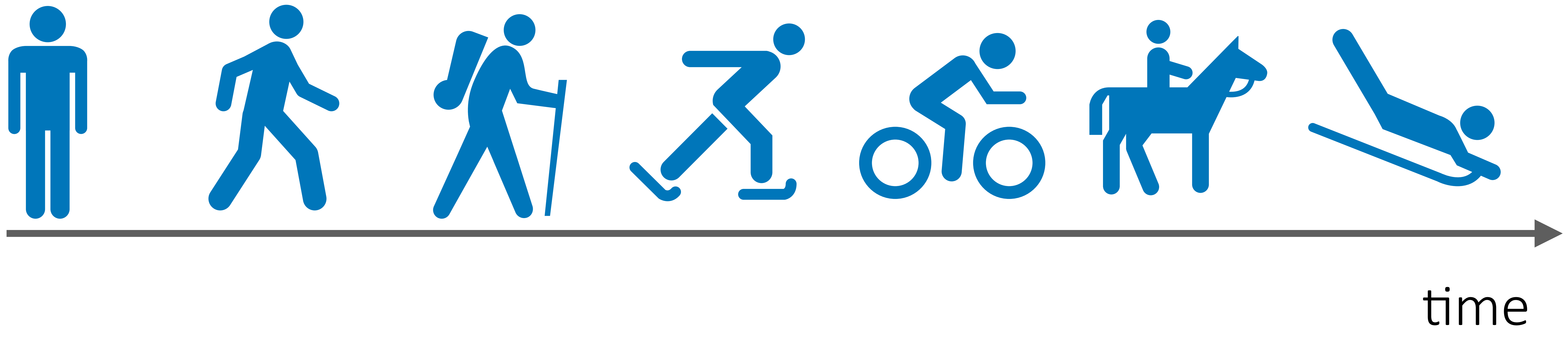
approaches **few-shot learning** regime

Takeaways

Introduced **online meta-learning** problem formulation

Meta-learning is effective in **non-stationary settings**

Similar guarantees to online learning, but **better empirical performance**



For more, come see us at **poster #5**!