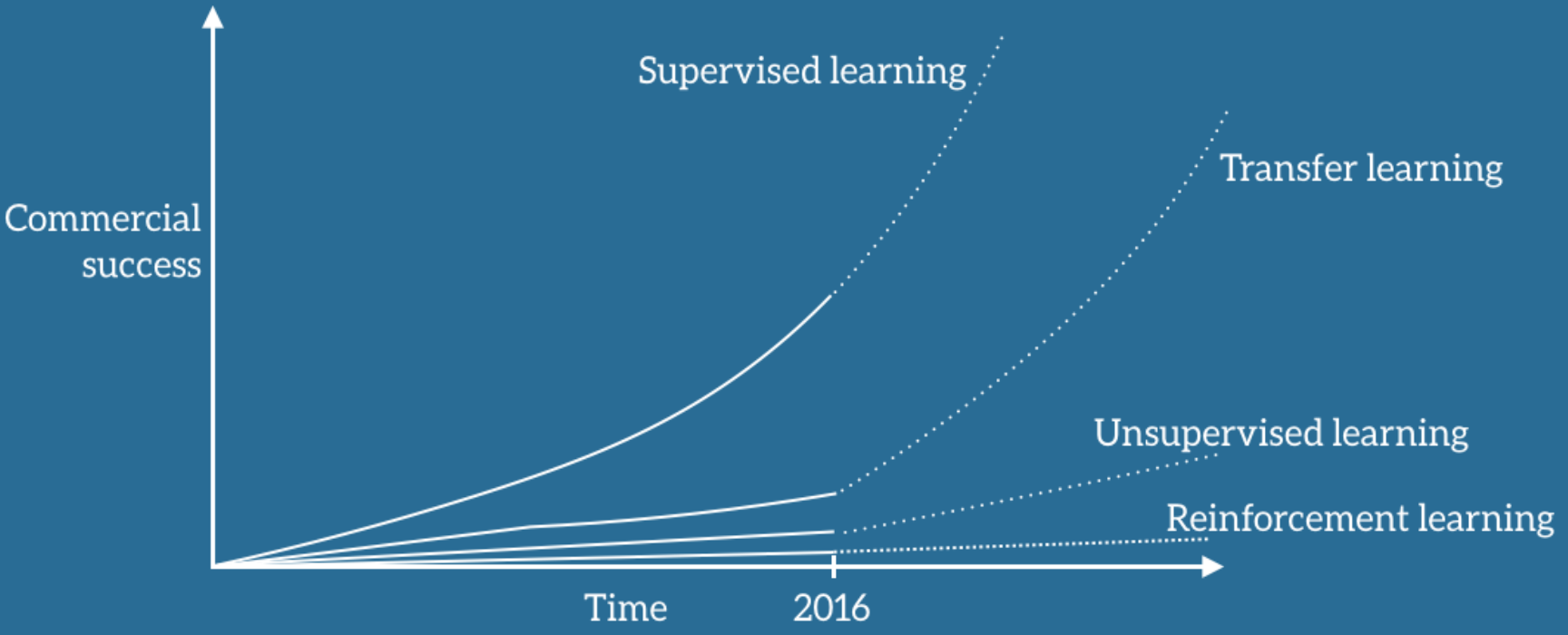
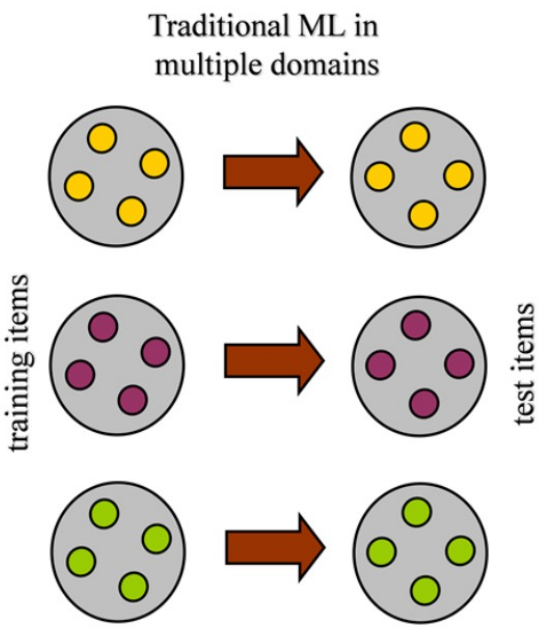
Transfer- and Meta-Learning

Drivers of ML success in industry

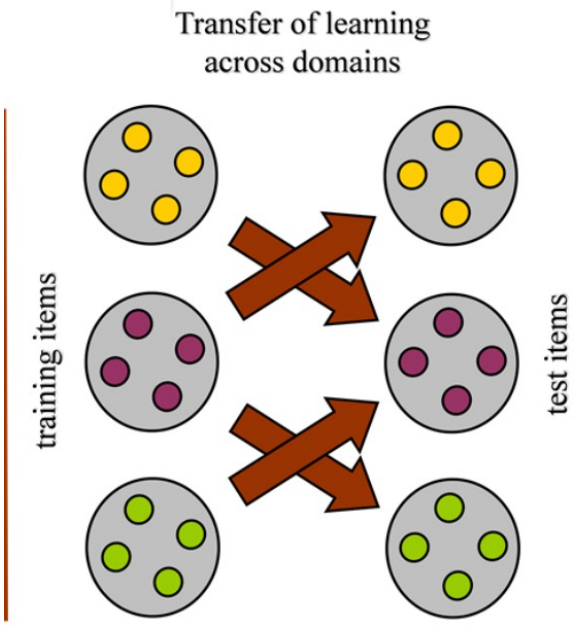


- Andrew Ng, NIPS 2016 tutorial

Transfer Learning

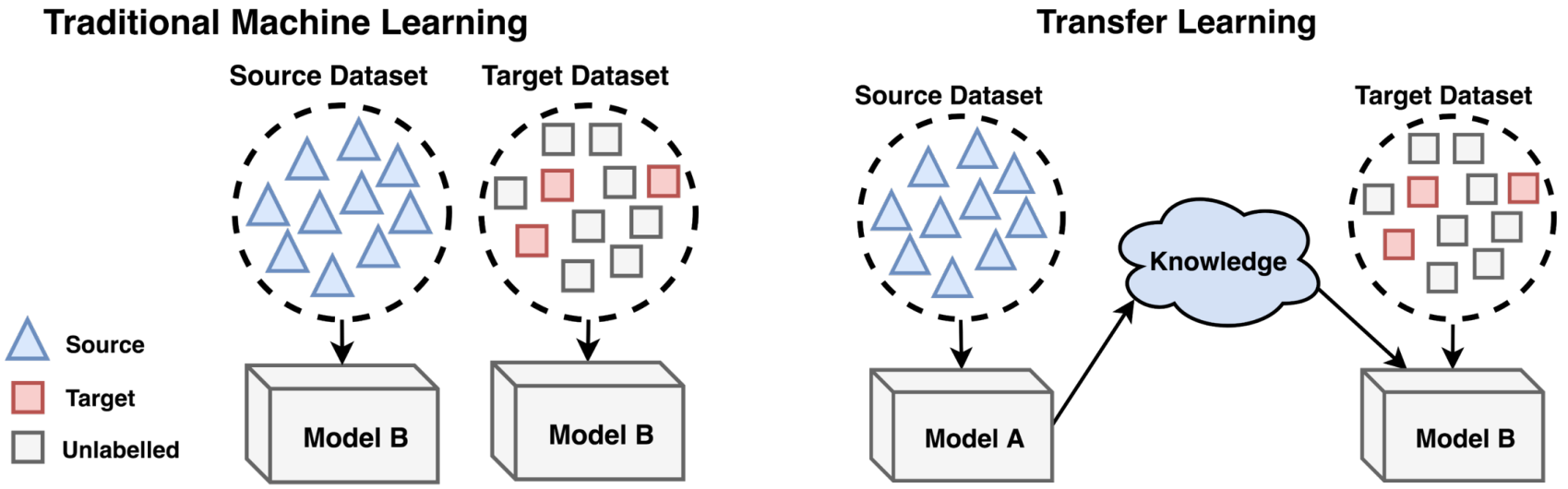


Humans can learn in many domains.



Humans can also transfer from one domain to other domains.

Transfer Learning



Why transfer learning?

- Labeled data might be limited, *data-poor*
- Calibration – training – can be very *expensive*
- The learning process can be (too) *long*

Objectives of transfer learning:

- Extract knowledge learned from related domains to help training in a target domain with a few labeled data
- Extract knowledge learned from related domains to speed up learning in a target domain

For simplicity, we only consider at most two domains and two tasks.

Source domain:

$$\mathcal{P}(X_S), \text{where } X_S = \{x_{S_1}, x_{S_2}, ..., x_{S_{n_S}}\} \in \mathcal{X}_S$$

Task in the source domain:

$$\mathcal{P}(Y_S|X_S), \text{where } Y_S = \{y_{S_1}, y_{S_2}, ..., y_{S_{n_S}}\} \text{ and } y_{S_i} \in \mathcal{Y}_S$$

Target domain:

$$\mathcal{P}(X_T), \text{where } X_T = \{x_{T_1}, x_{T_2}, ..., x_{T_{n_T}}\} \in \mathcal{X}_T$$

Task in the target domain

$$\mathcal{P}(Y_T|X_T), \text{where } Y_T = \{y_{T_1}, y_{T_2}, ..., y_{T_{n_T}}\} \text{ and } y_{T_i} \in \mathcal{Y}_T$$

Approaches to Transfer Learning

Transfer learning approaches	Description
Instance-transfer	To re-weight some labeled data in a source domain for use in the target domain
Feature-representation-transfer	Find a "good" feature representation that reduces difference between a source and a target domain or minimizes error of models
Model-transfer	Discover shared parameters or priors of models between a source domain and a target domain
Relational-knowledge-transfer	Build mapping of relational knowledge between a source domain and a target domain.

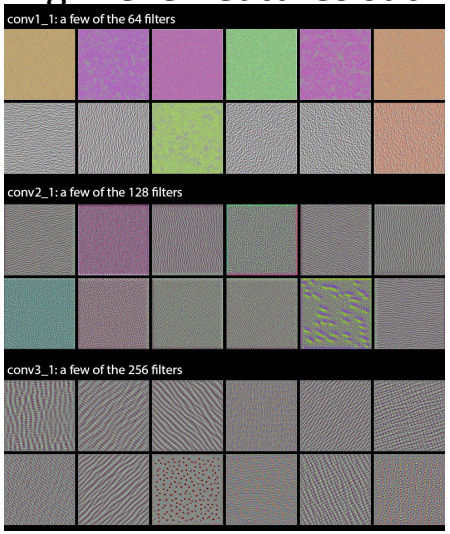
Transfer learning types (inductive model transfer)

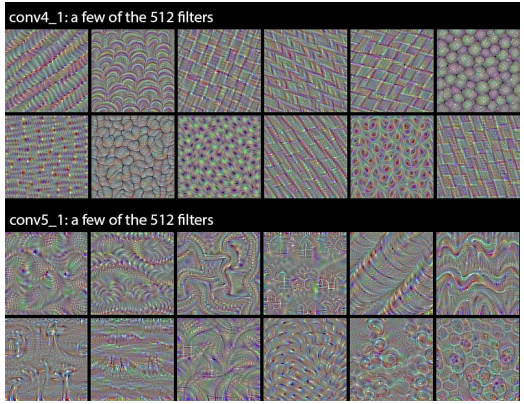
Type	Description	Examples
Inductive	Adapt existing **supervised** training model on new **labeled** dataset	Classification, Regression
Transductive	Adapt existing **supervised** training model on new **unlabeled** dataset	Classification, Regression
Unsupervised	Adapt existing **unsupervised** training model on new **unlabeled** dataset	Clustering, Dimensionality Reduction

From generic to specific

Neural Network Layers: General to Specific

- Bottom/first/earlier layers: general learners
  - Low-level notions of edges, visual shapes
- Top/last/later layers: specific learners
  - High-level features such as eyes, nose

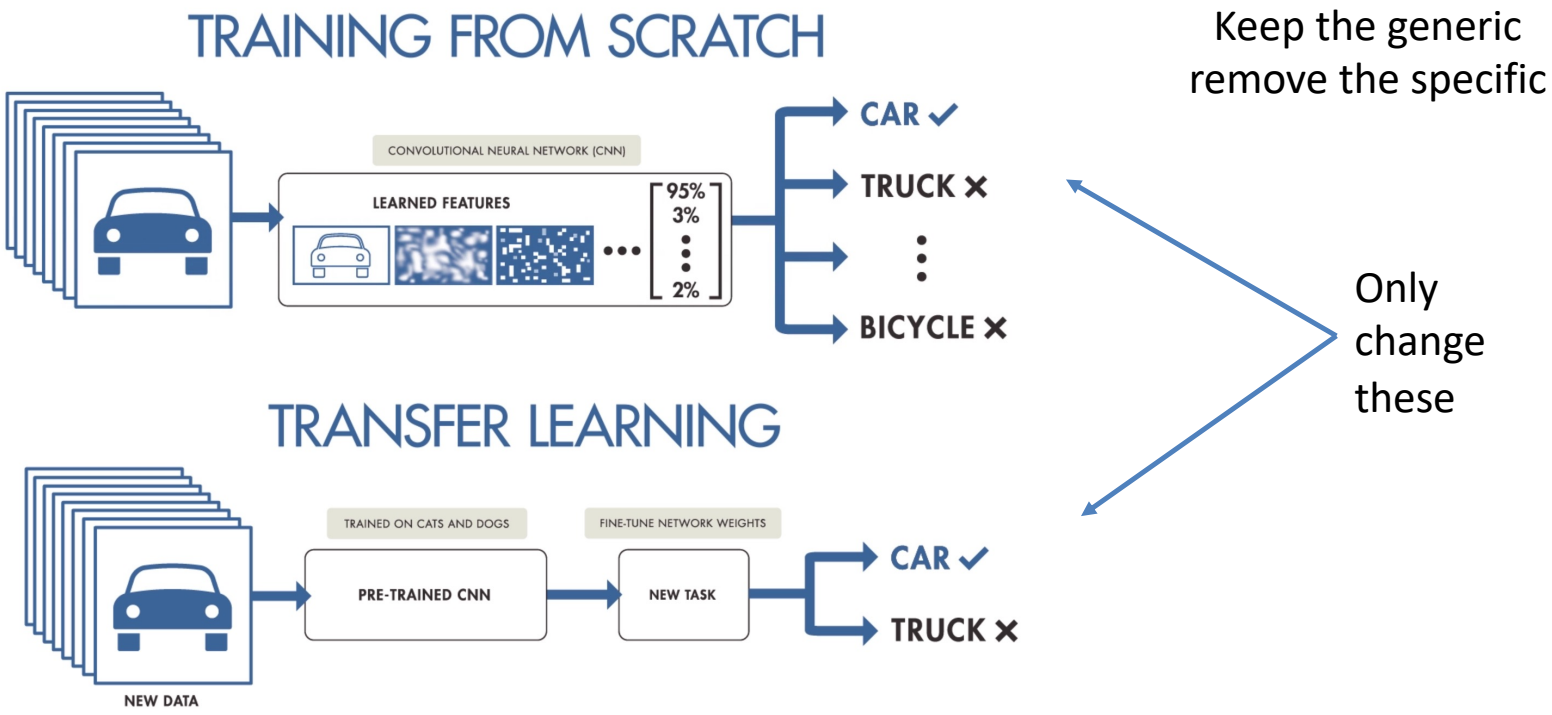




Keep the generic
adjust the specific

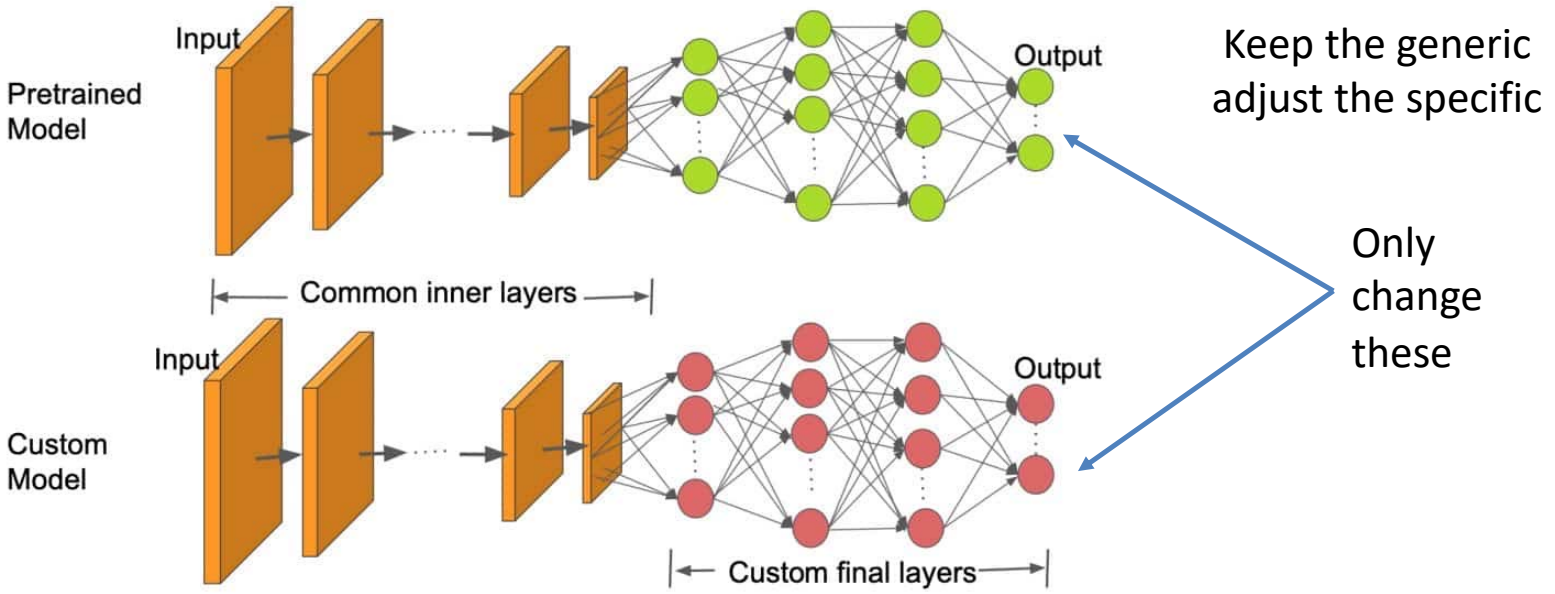
From generic to specific

Neural Network Layers: General to Specific



From generic to specific

Neural Network Layers: General to Specific



Current example

ChatGPT fine tuning
https://platform.openai.com/docs/guides/fine-tuning/when-to-use-fine-tuning

Some common use cases where fine-tuning can improve results:

- Setting the style, tone, format, or other qualitative aspects
- Improving reliability at producing a desired output
- Correcting failures to follow complex prompts
- Handling many new cases in specific ways (e.g., new type of data)
- Performing a new skill or task that's hard to articulate in a prompt

Current example

Fine Tuning for El Niño: climate prediction

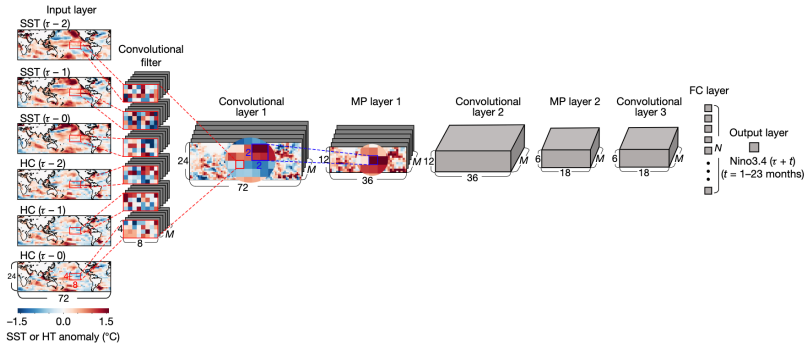
Model trained on large ensemble of climate models, fine-tuned on observations

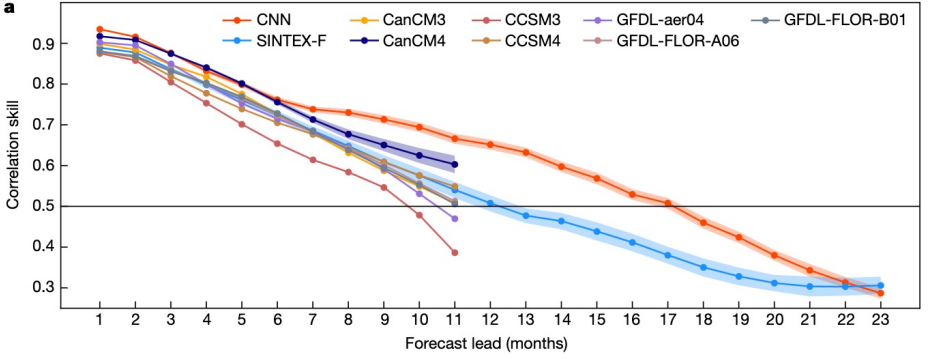
LETTER

https://doi.org/10.1038/s41586-019-1559-7

Deep learning for multi-year ENSO forecasts

Yoo-Geun Ham[1]*, Jeong-Hwan Kim[1] & Jing-Jia Luo[2,3]



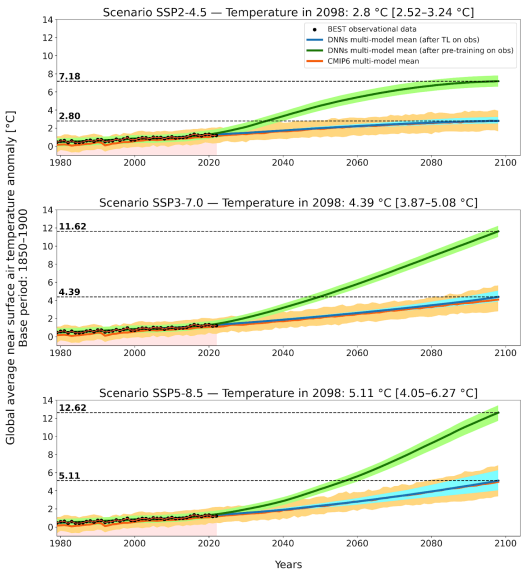


Current example

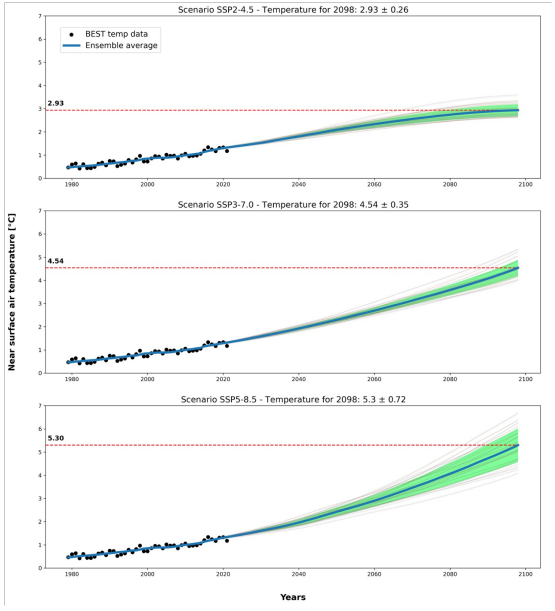
Fine Tuning for climate projections

Model trained on large ensemble of climate models, fine-tuned on observations

Without pretrained network

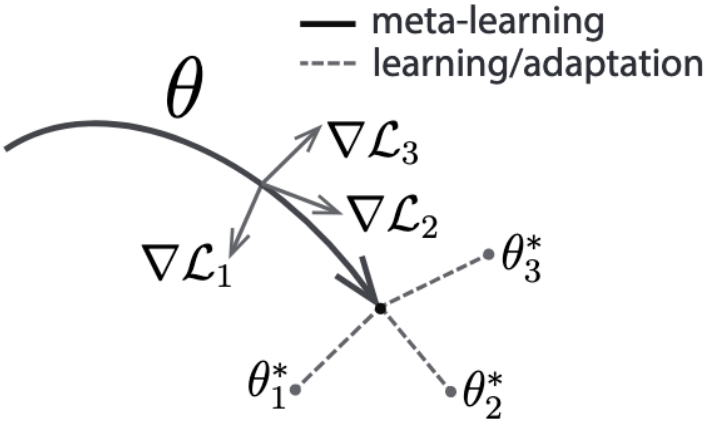


After transfer learning+ pretrained network



MetaLearning: learning to learn

Learning across tasks for rapid adaptation,
a problem setting that is often formalized as few-shot learning



Finn et al. 2017 MAML

MetaLearning: learning to learn

Model-Agnostic Meta-Learning MAML over different **tasks**

Algorithm 1 Model-Agnostic Meta-Learning

Require: $p(\mathcal{T})$: distribution over tasks

Require: α, β: step size hyperparameters

1: randomly initialize θ

2: **while** not done **do**

3: Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$

4: **for all** $\mathcal{T}_i$ **do**

5: Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ with respect to K examples

6: Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$

7: **end for**

8: Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$

9: **end while**

β is the meta step size.

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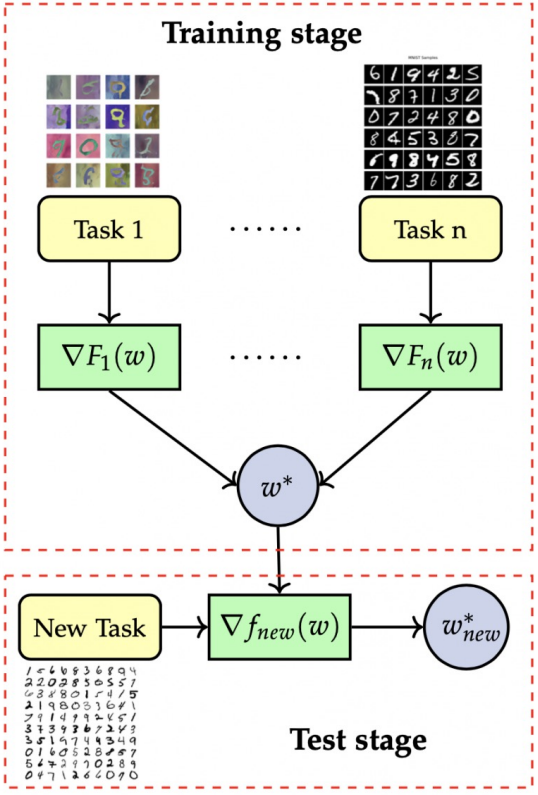
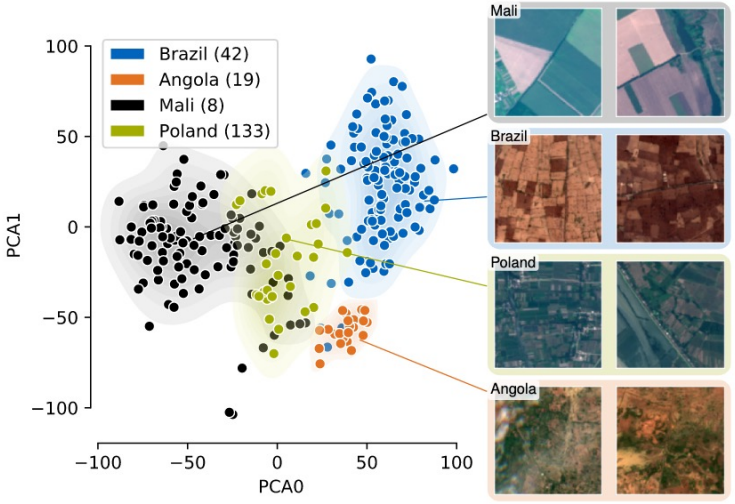
Model-Agnostic Meta-Learning MAML



Example Meta-Learning for Few-Shot Land Cover Classification



Principal component analysis (PCA) on VGG-16 features of cropland images from different countries. Representations of the same class vary geographically; applying models trained on one geography to another would violate the assumption in traditional supervised learning that train and test distributions are the same.

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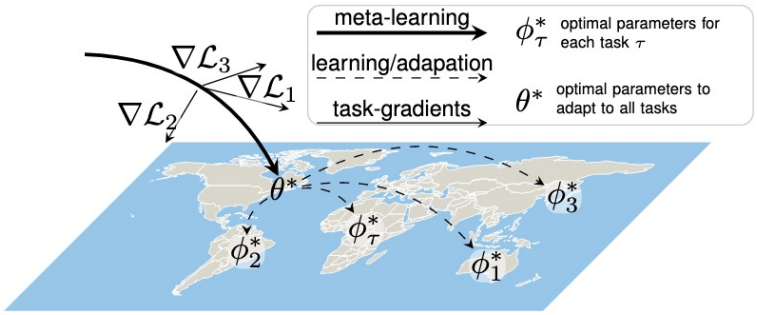
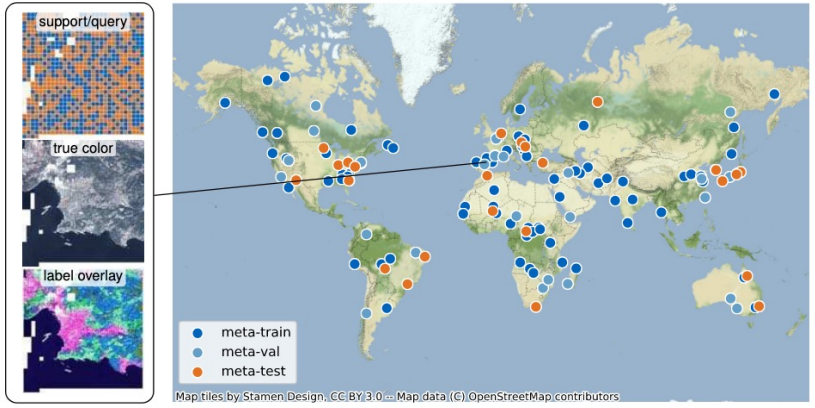
Example Meta-Learning for Few-Shot Land Cover Classification





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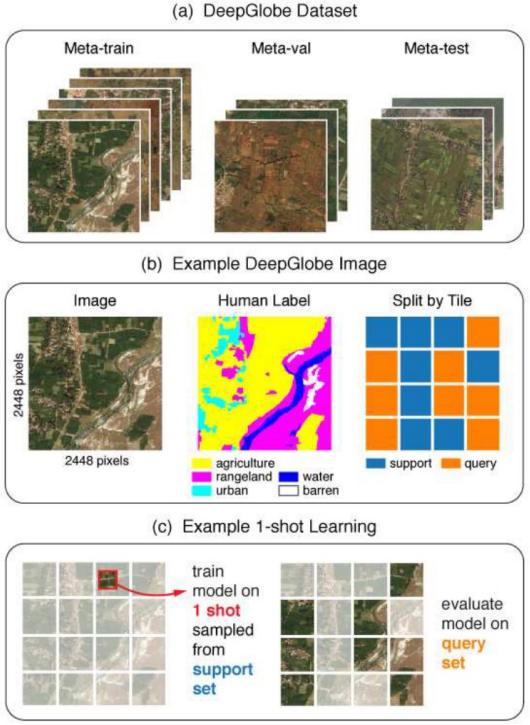
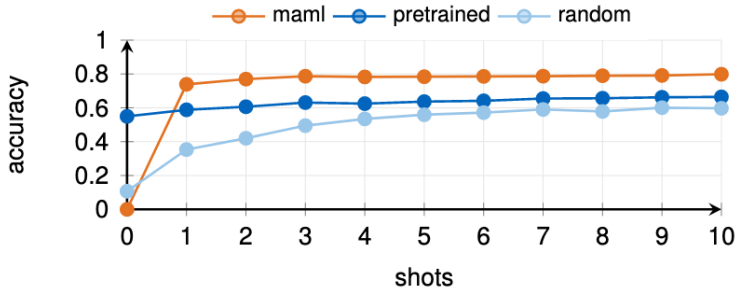
Example Meta-Learning for Few-Shot Land Cover Classification





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Example Meta-Learning for Carbon Fluxes

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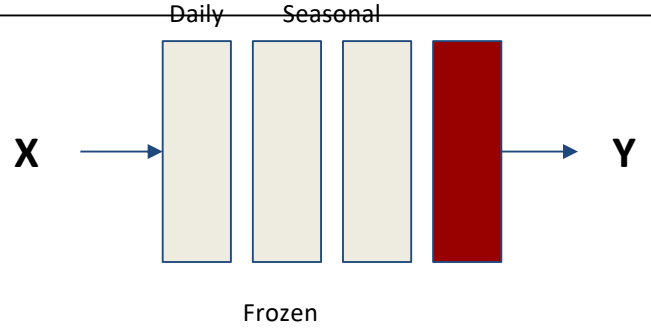
Example Meta-Learning for Carbon Fluxes

Data processing
Balancing the data

Idea: get the same number of data across classes

Problem: reduce sample size significantly



Modeling
Transfer learning

Idea: train a model on classes with a lot of data, and transfer the learned knowledge to new domains (probably with few data)

Problem(s):
(i) freeze/unfreeze which part of the model?
(ii) assumes frozen parts of the model are not changing across tasks → not capturing the right representation

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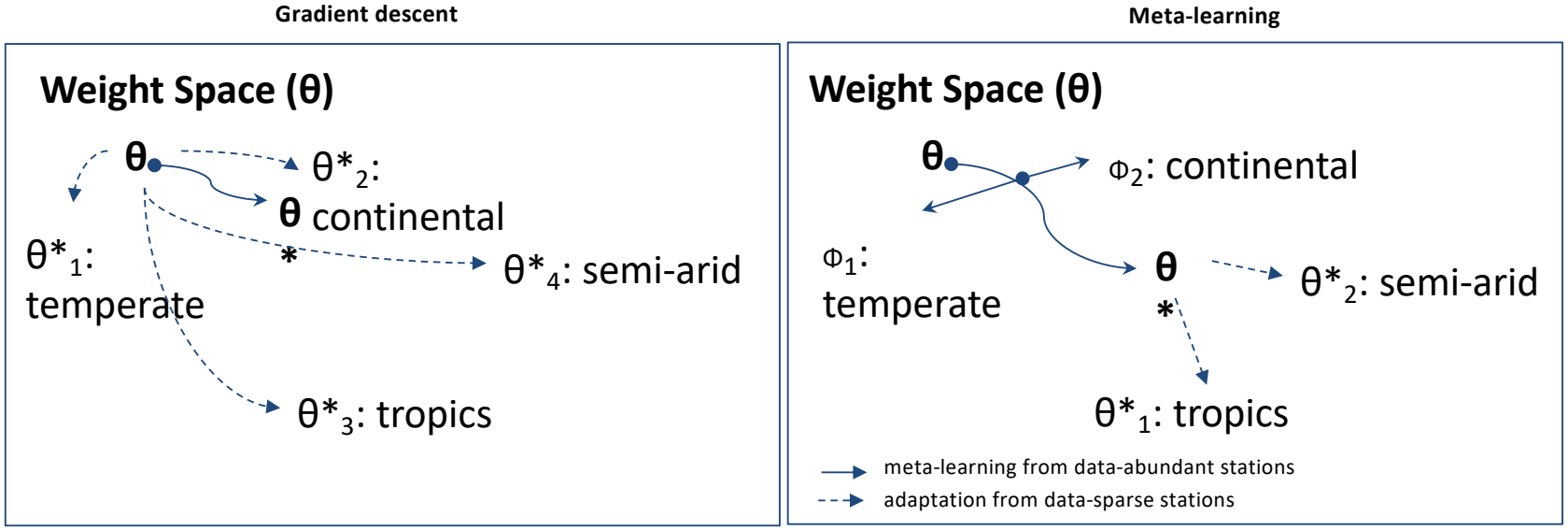
Example Meta-Learning for Carbon Fluxes



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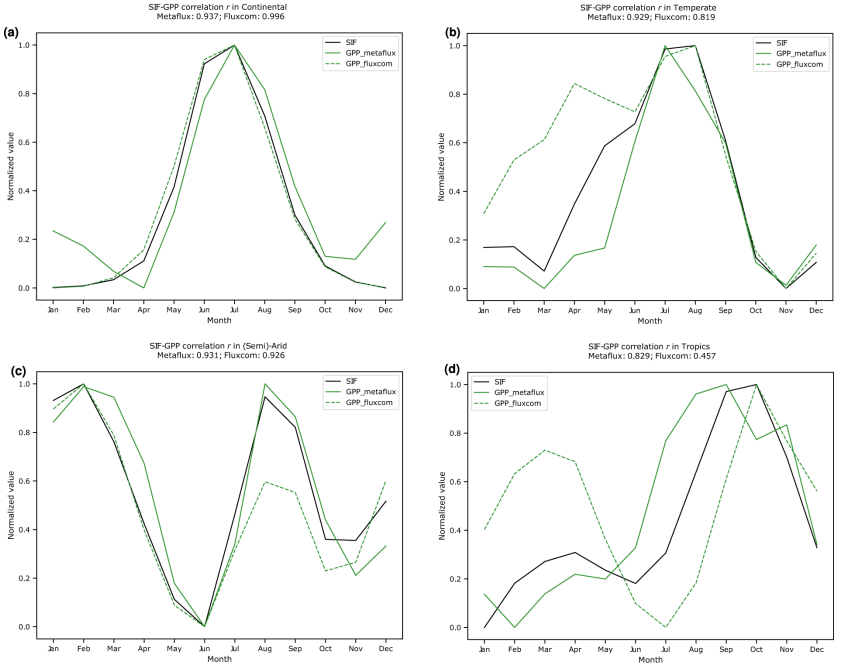
Example Meta-Learning for Carbon Fluxes

Climate zones	r($GPP_{fluxcom}$, SIF)	r($GPP_{metaflux}$, SIF)
Semi-arid	0.726 ± 0.165	$\mathbf{0.856 \pm 0.083}$
Continental	$\mathbf{0.965 \pm 0.002}$	0.937 ± 0.012
Temperate	0.826 ± 0.021	$\mathbf{0.919 \pm 0.002}$
Tropics	0.343 ± 0.164	$\mathbf{0.546 \pm 0.299}$



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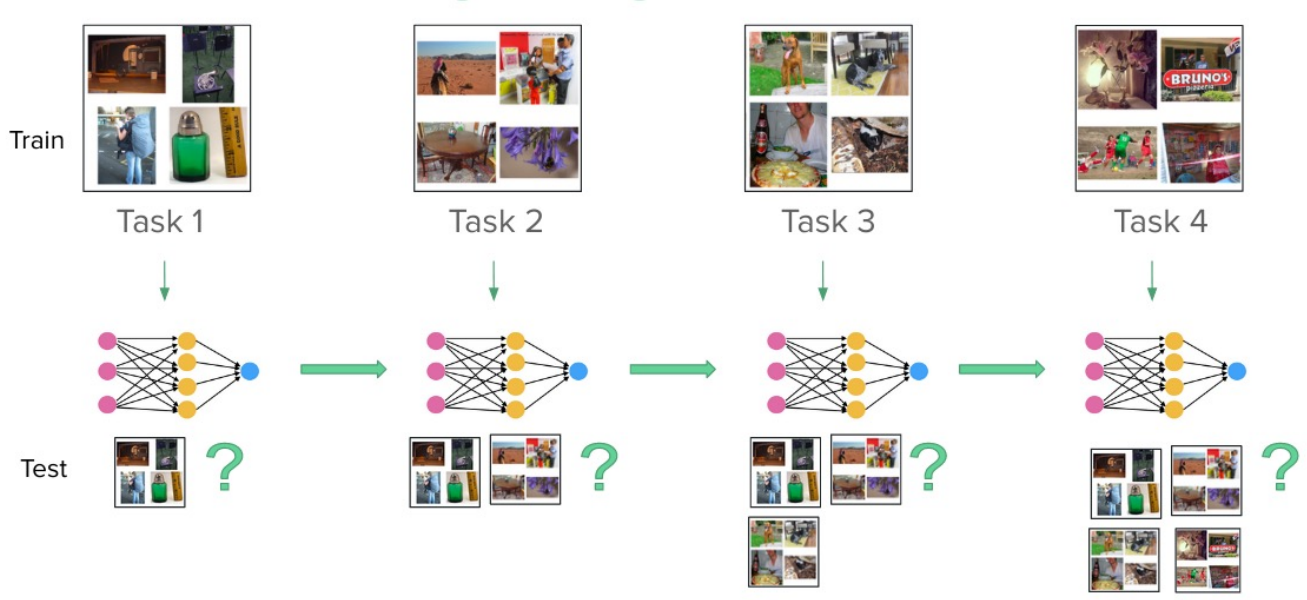
La MAML

Continual learning (CL) problem involves training models with limited capacity to perform well on a set of an unknown number of *sequentially arriving tasks*. Data re not i.i.d when they arrive sequentially.



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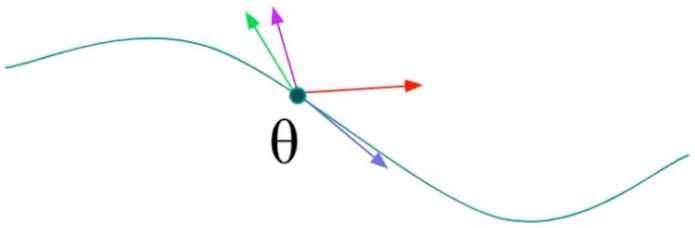
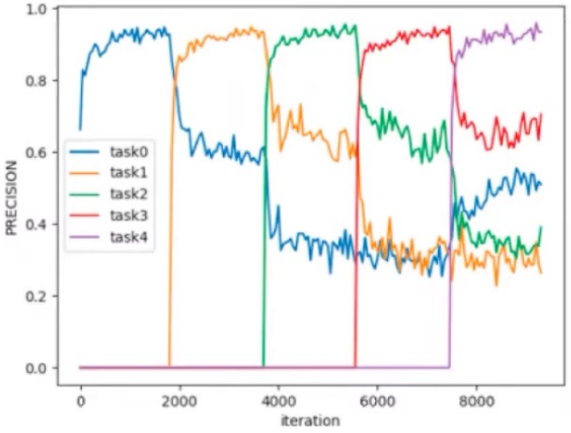
Potential issue: forget all tasks (intefreference)

Catastrophic Forgetting

Gradient directions for various tasks at any time *t*





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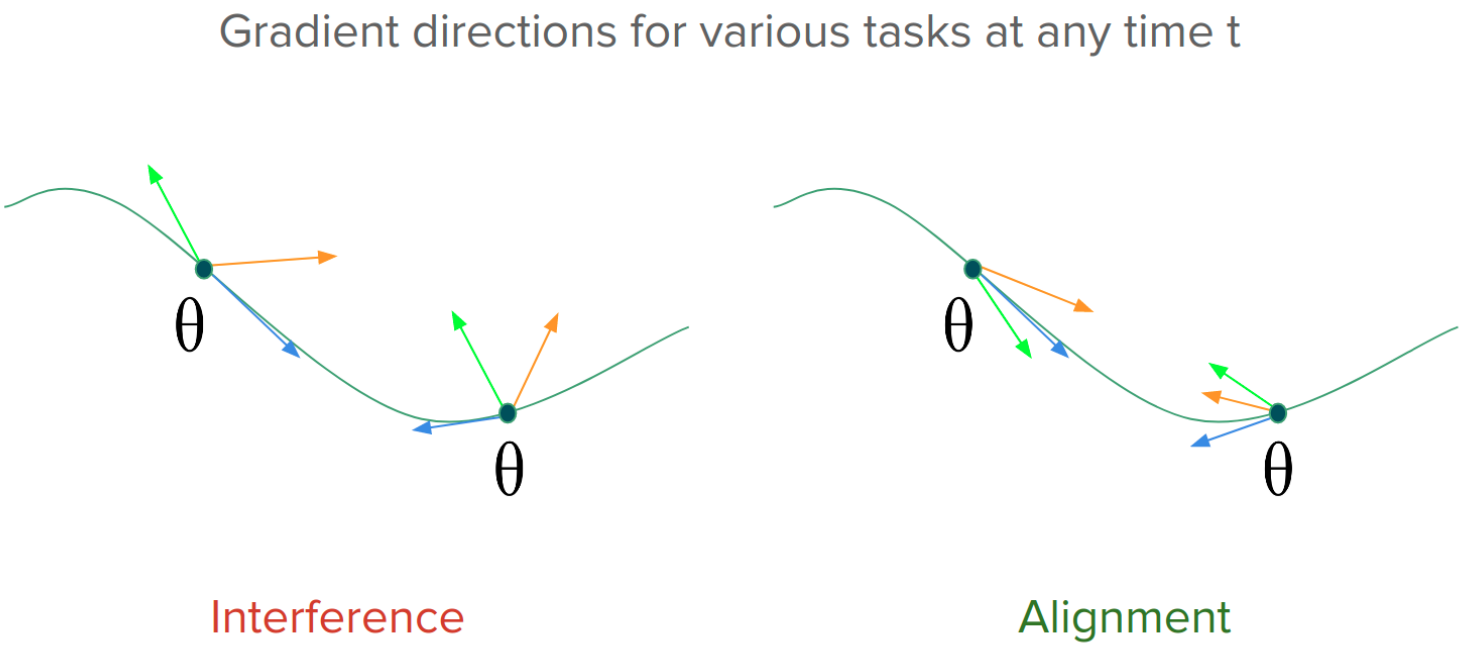
MetaLearning

Potential issue: forget all tasks (interference), gradient-alignment is essential to make shared progress on task-wise objectives under limited availability of training-data.



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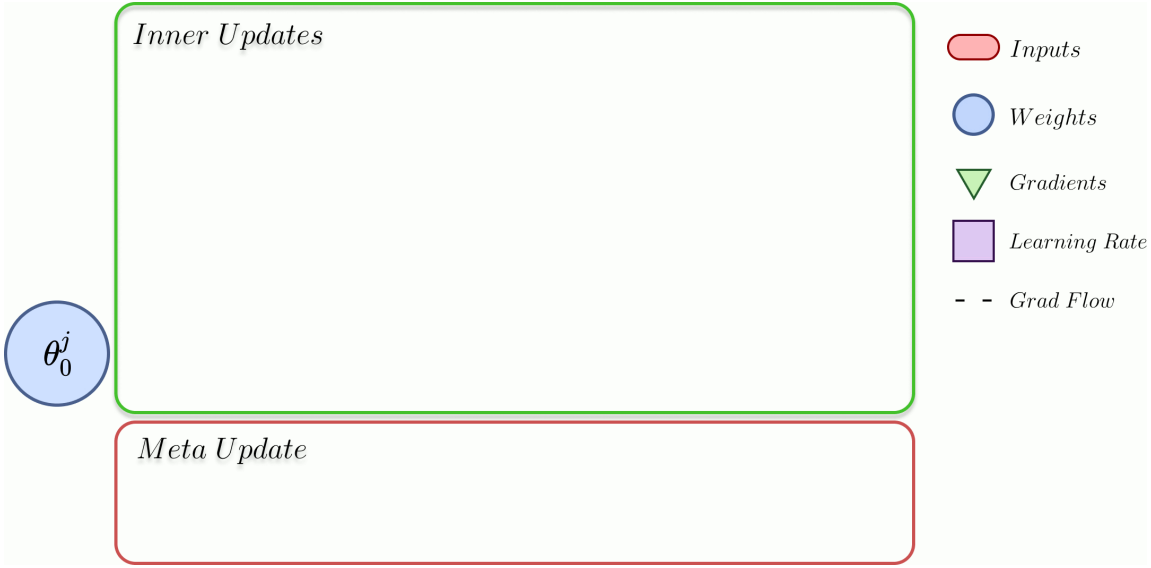
La MAML

La-MAML algorithm: For every batch of data, the initial weights undergo a series of k fast updates to obtain θjk (here $j = 0$), which is evaluated against a meta-loss to backpropagate gradients with respect to the weights $\theta 00$ and learning rates $\alpha 0$. First $\alpha 0$ is updated to $\alpha 1$ which is then used to update $\theta 00$ to $\theta 10$. The blue boxes indicate fast weights while the green boxes indicate gradients for the slow updates. LRs and weights are updated in an asynchronous manner.



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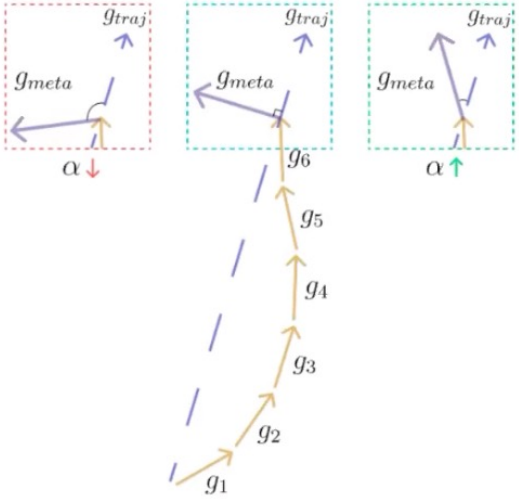
La MAML

Gradient of Learning rates (alpha) :

$$g_{\mathrm{MAML}}(\alpha) = \frac{\partial}{\partial \alpha} L_m(\theta_k)$$
$$= \left(\frac{\partial}{\partial \theta_k} L_m(\theta_k)\right)\left(-\sum_{i=0}^{k-1} \frac{\partial}{\partial \theta_i} L_i(\theta_i)\right)$$

Outer Gradient — Inner Gradient

Old + New Tasks — New Task



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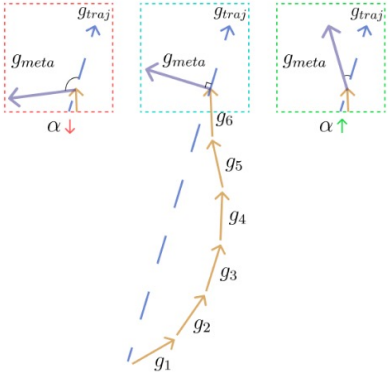
La MAML

Updating the network weights and LRs asynchronously in the meta-update
Two losses to simulate continual learning in the inner loop and test forgetting in the outer loop is referred to as the Online-Aware Meta Learning objective.

Algorithm 1 La-MAML : Look-ahead MAML

Input: Network weights θ, LRs α, inner objective ℓ, meta objective L, learning rate for $\alpha : \eta$
$j \leftarrow 0$, $R \leftarrow \{\}$ ▷ Initialise Replay Buffer
for $t := 1$ **to** T **do**
  for $ep := 1$ **to** num_{epochs} **do**
    for batch b **in** $(X^t, Y^t) \sim D_t$ **do**
      $k \leftarrow sizeof(b)$
      $b_m \leftarrow Sample(R) \cup b$
      for $n = 0$ **to** $k - 1$ **do**
        Push $b[k']$ to R with reservoir sampling
        $\theta^j_{k'+1} \leftarrow \theta^j_{k'} - \alpha^j \cdot \nabla_{\theta^j_{k'}}$
      end for
      $\alpha^{j+1} \leftarrow \alpha^j - \eta \nabla_{\alpha^j} L_t(\theta^j_k, b_m)$
      $\theta^{j+1}_0 \leftarrow \theta^j_0 - max(0, \alpha^{j+1}) \cdot \nabla_{\theta^j_0} L_t(\theta^j_k, b_m)$
      $j \leftarrow j + 1$
    end for
  end for
end for



(a)
(b)

Figure 2: Different scenarios for the alignment of g_{traj} (blue dashed line) and g_{meta}, going from interference (left) to alignment (right). Yellow arrows denote the *inner updates*. The LR α increases (decreases) when gradients align (interfere).

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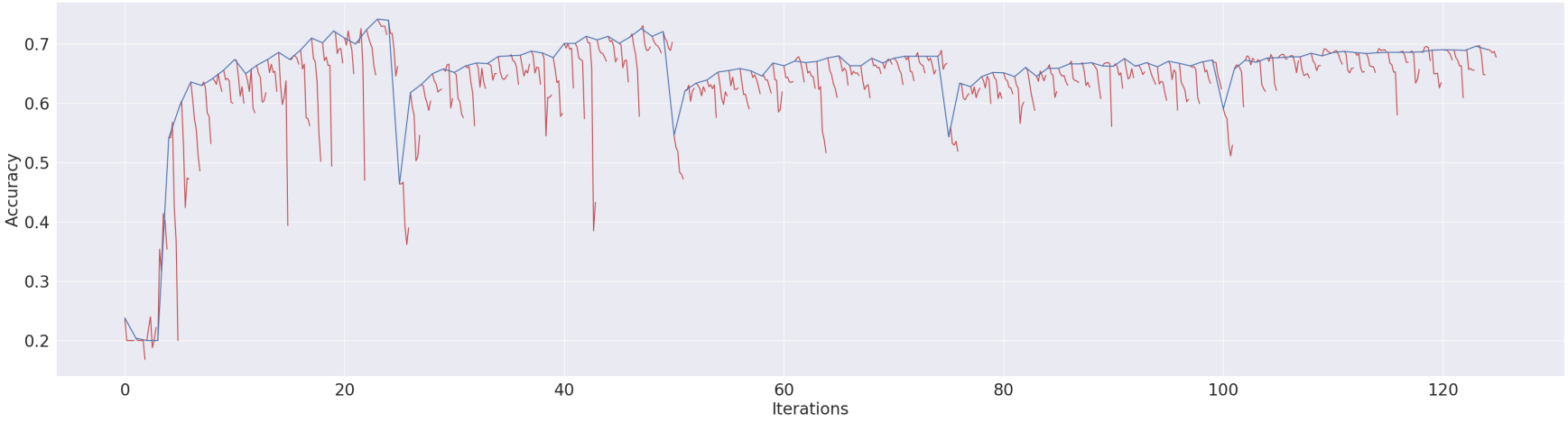
La MAML

Updating the network weights and LRs asynchronously in the meta-update
Two losses to simulate continual learning in the inner loop and test forgetting in the outer loop is referred to as the Online-Aware Meta Learning objective.



Retained Accuracy (RA) for La-MAML plotted every 25 meta-updates

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Reinforcement-Learning

Reinforcement learning

Example for video games

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Reinforcement learning

Example for walking robots

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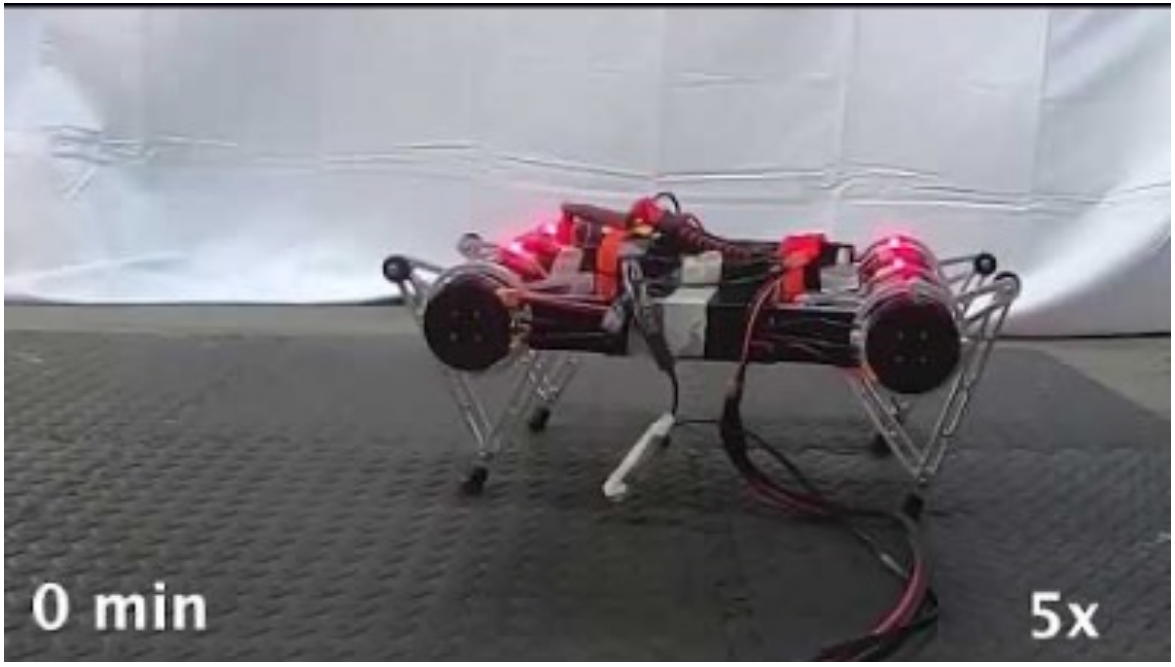
Reinforcement learning

Example for walking robots



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Reinforcement learning: learning from rewards

- The **Reward** Rt defines the goal of an RL problem.
- Gives the **agent** a sense of what is good and bad.
- A reward of a higher magnitude is better.
- Usually a function of **environment** state (situation).

- Explore and exploit:

  Reinforcement Learning is like trial and error
- The agent should **explore** the environment to search for better policies.
- After the selection of the optimal **policy**, the agent maximizes the rewards.
  - Exploration finds more information about the environment.
  - Exploitation uses known information to maximize reward.

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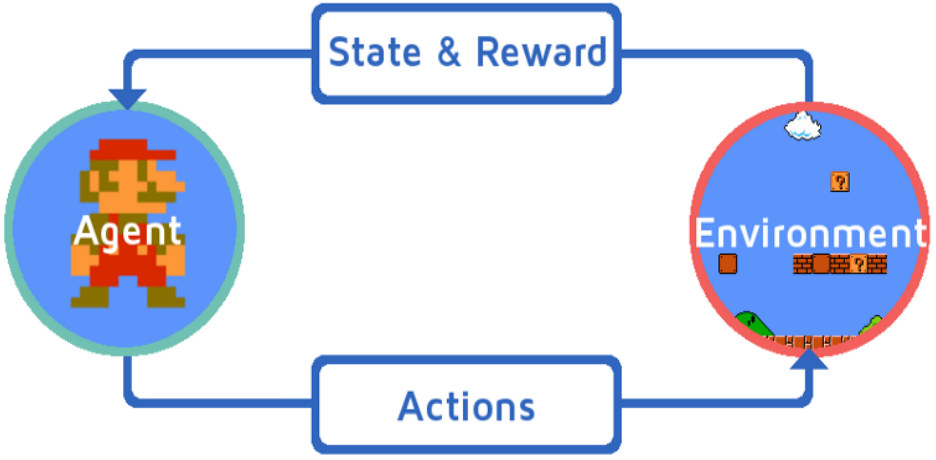
Reinforcement learning: learning from rewards

- The RL Agent receives **state S^0** from the **environment** i.e. Mario
- Based on that **state S^0,** the RL agent takes an **action A^0**, say — our RL agent moves right. Initially, this is random.
- Now, the environment is in a new state **S^1** (new frame from Mario or the game engine)
- Environment gives some **reward R^1** to the RL agent. It probably gives a +1 because the agent is not dead yet.
- This RL loop continues until we are dead or we reach our destination, and it continuously outputs a sequence of **state, action and reward.**
- Aim of our RL agent is to maximize the reward



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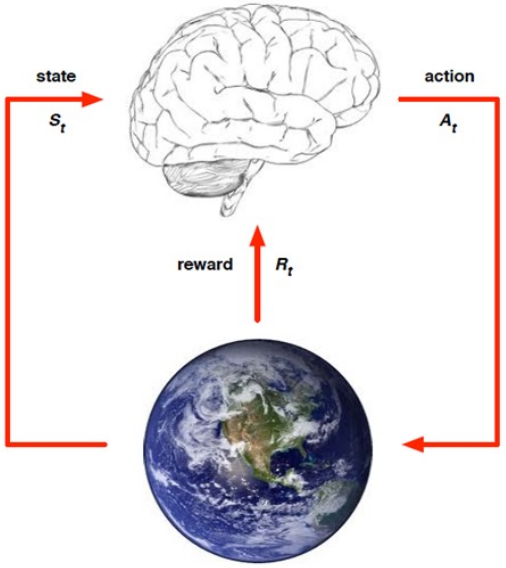
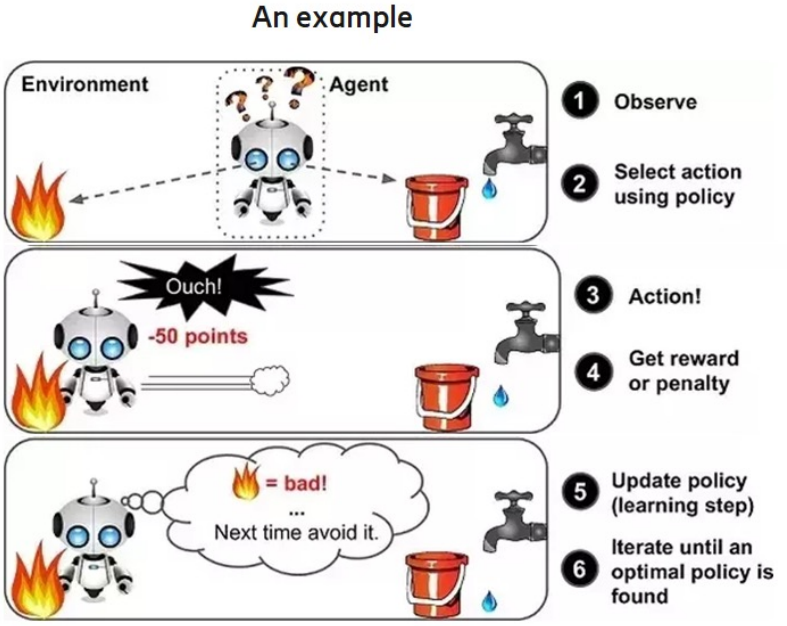
Example





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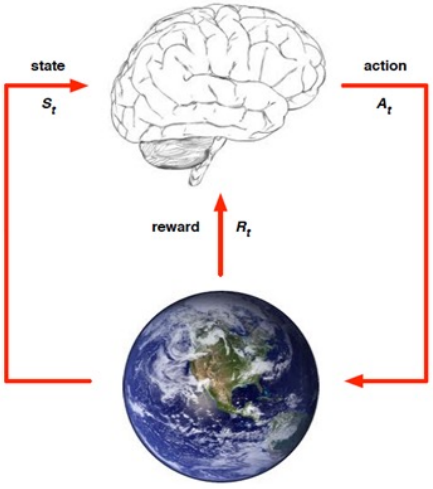
RL Agent Basics

- An RL agent may include one or more of these components
  - Policy: agent's behaviour function
  - Value function: how good is each state and/or action
  - Model: agent's representation of the environment



Characteristics

What makes reinforcement learning different from other machine learning paradigms?

- There is no supervisor, only a *reward* signal
- Feedback is delayed, not instantaneous
- Time really matters (sequential, non i.i.d data)
- Agent's actions affect the subsequent data it receives

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Reward maximization

•The cumulative rewards at each time step with the respective action is written as:

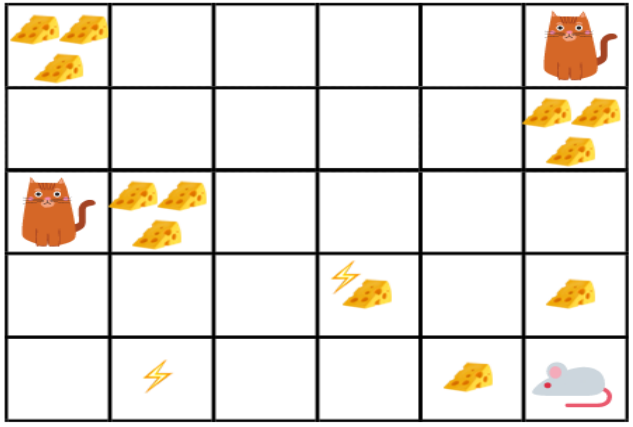
$$G_t = \sum_{k=0}^{T} R_{t+k+1}$$

•But discounting might be important: reward "closer" might be discounted (like yield/rate)

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} where \gamma \in [0,1)$$

$$R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} \ldots$$

- Sigma (Sum up)
- Discount rate
- Rewards received at each state
- Expanded form of the Equation



Better eat everything before being eaten by cat

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Reinforcement learning approaches

1. Policy-based approach

   Mapping each state to the best action (deterministic or stochastic- gives a distribution)

   $$a = \pi(s)$$

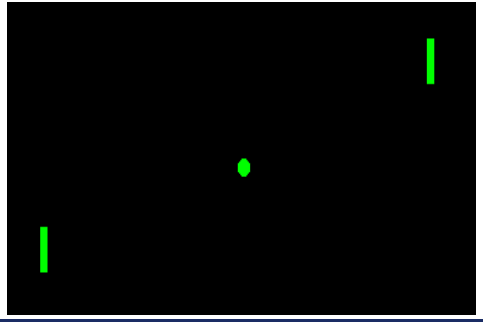
   a: actions. S: state, π : Policy function

2. Value-based

   optimize the value function: maximum expected future reward

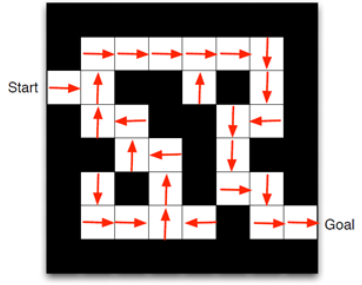
$$v_\pi(s) = \mathbb{E}_\pi \left[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots \mid S_t = s \right]$$

Expected | Reward discounted | Given that state



Policy, Value Function & Model

- A policy is the agent's behaviour
- It is a map from state to action, e.g.
- Deterministic policy: $a = \pi(s)$
- Stochastic policy: $\pi(a|s) = \mathbb{P}[A_t = a|S_t = s]$

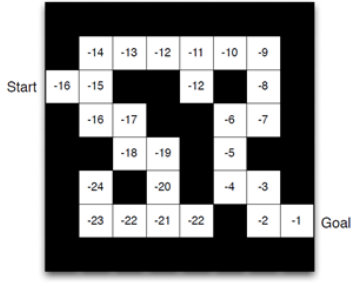


Policy

- Arrows represent policy $\pi(s)$ for each state s

- Value function is a prediction of future reward
- Used to evaluate the goodness/badness of states
- And therefore to select between actions, e.g.

$$v_\pi(s) = \mathbb{E}_\pi \left[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots \mid S_t = s \right]$$

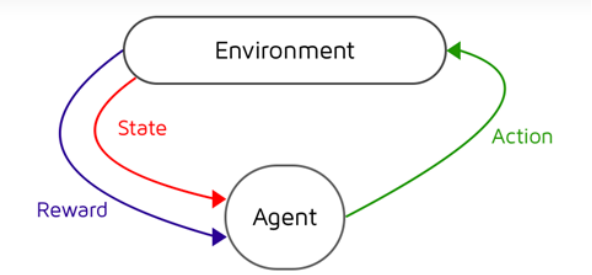


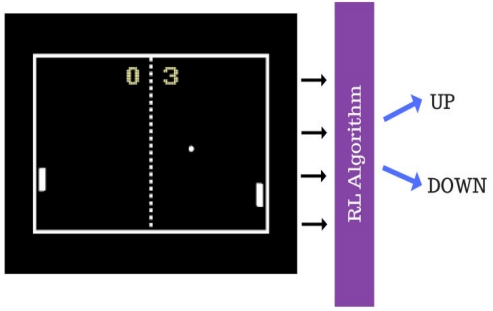
Value Function

- Numbers represent value $v_\pi(s)$ of each state s

Reinforcement learning approaches

Not all actions were bad, maybe only last moves





Do not discard entire sequence by only weight last ones negatively (due to sparsity in reward setting).