DS-GA.3001 Embodied Learning and Vision

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NYU

Spring 2025

embodied-learning-vision-course.github.io

Lecture Slides for Note Taking

Module 5:
Continual Learning,
Few-Shot Learning, Meta-Learning

Why Continual Learning?

- The world is not a dataset that allows you to get IID samples.

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- The world keeps changing and evolving.

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- The world is not a dataset that allows you to get IID samples.
- The world keeps changing and evolving.
- Online vs. Continual
  - Online means that samples arrive in a streaming / temporal partial order, but they may still come from a static distribution.

$$\theta_t = f(x_t, \theta_{t-1}) \quad x_{1:T} \sim \mathcal{X}$$

  - Example: Online reinforcement learning, trajectory roll out is online, but the environment is the same.
  - Continual learning means that there will be distribution shift.

What is Continual Learning?

- Distribution shift: Forgetting
  - Learning on A and then B, results in worse performance on A.

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  - Leverage the similarity between tasks.

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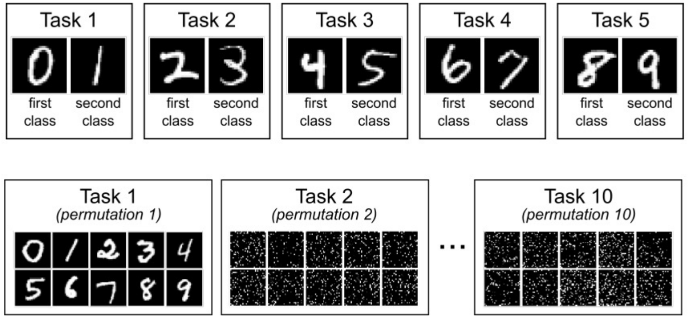
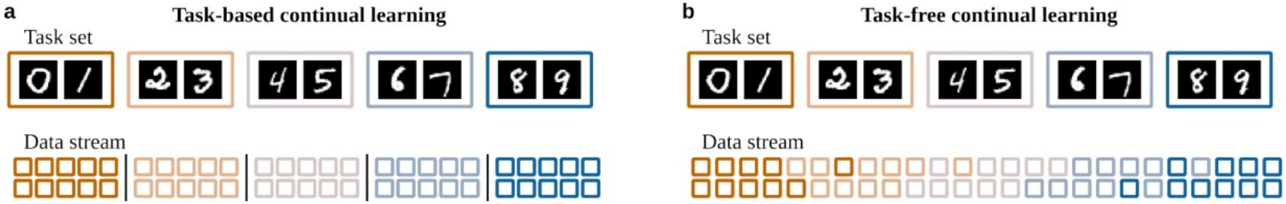
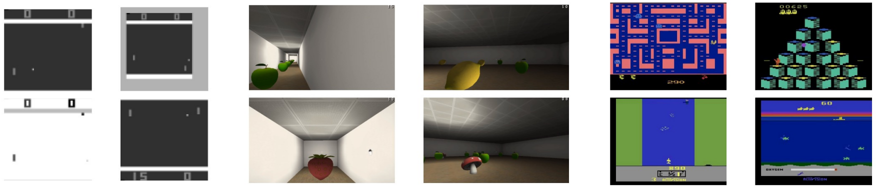
  - Leverage the similarity between tasks.
- Compositionality
  - Learning A and B first, and then learning tasks with composed A+B.
- Incremental/curriculum Learning
  - Learning A->B->C is easier than at random order.

Continual Learning

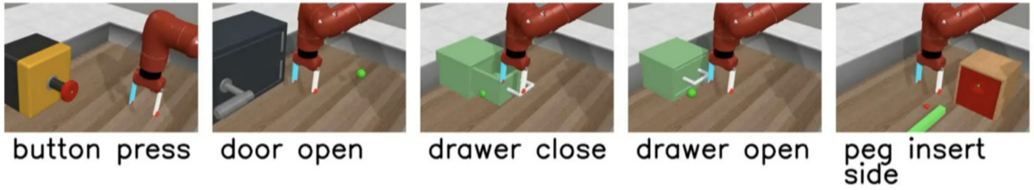
- Learning a sequence of tasks without looking back.







(a) Pong variants (b) Labyrinth games (c) Atari games



van de Ven et al. Continual learning and catastrophic forgetting. arXiv 2024.
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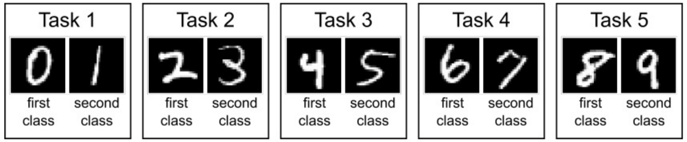
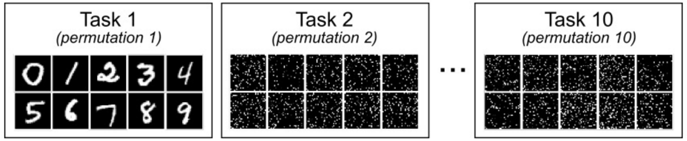
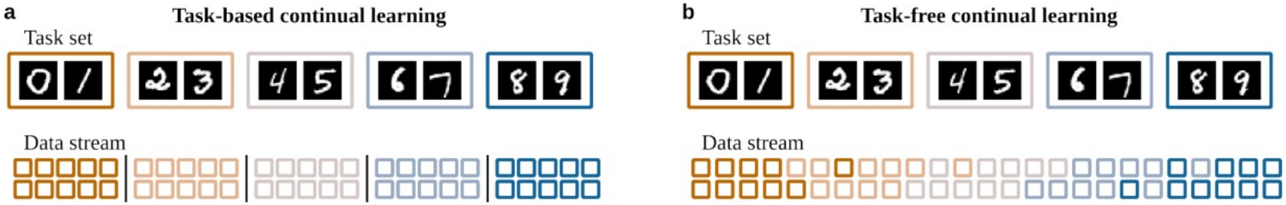
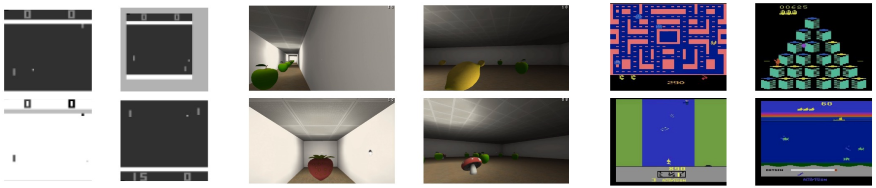
Continual Learning

- Learning a sequence of tasks without looking back.
- Goal is to do well on all of the tasks at the end.









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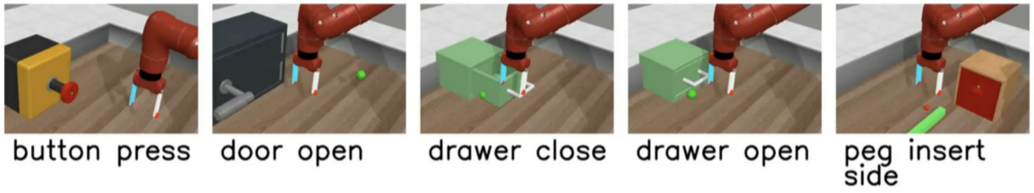

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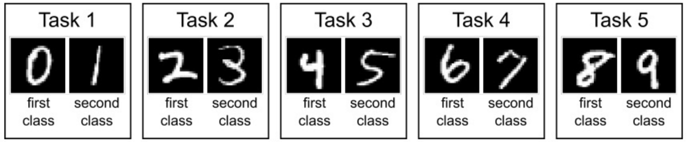
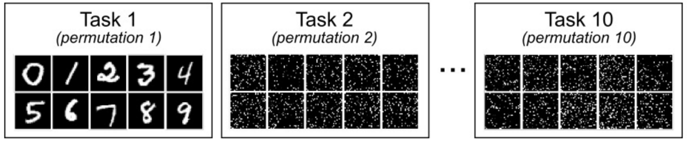
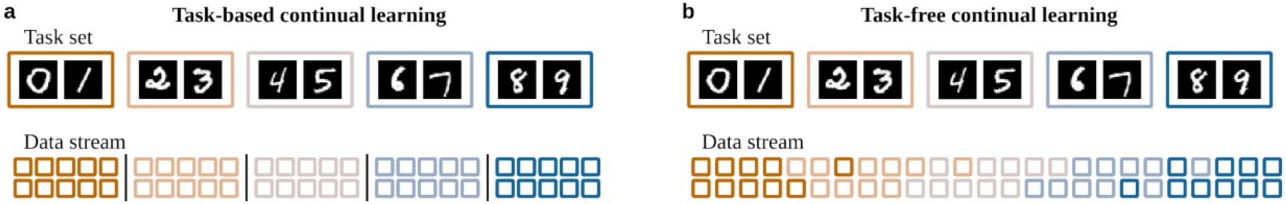
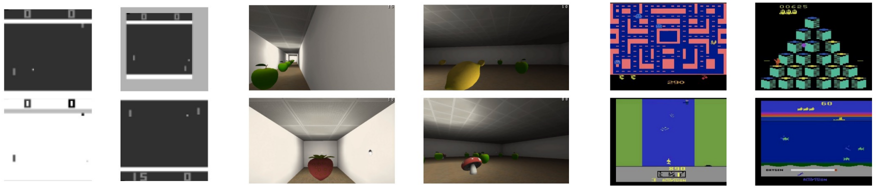
Continual Learning

- Learning a sequence of tasks without looking back.
- Goal is to do well on all of the tasks at the end.
- Task boundary









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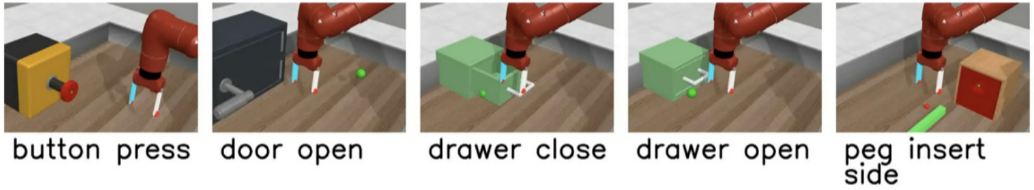

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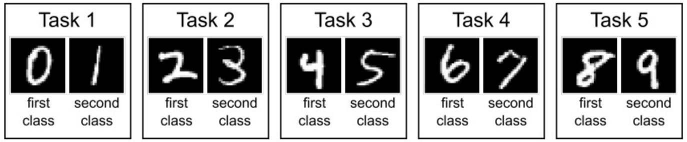
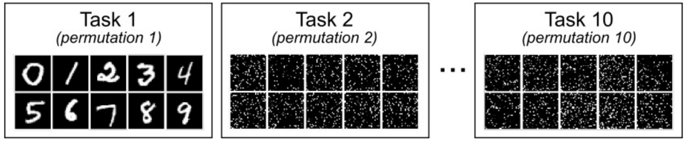
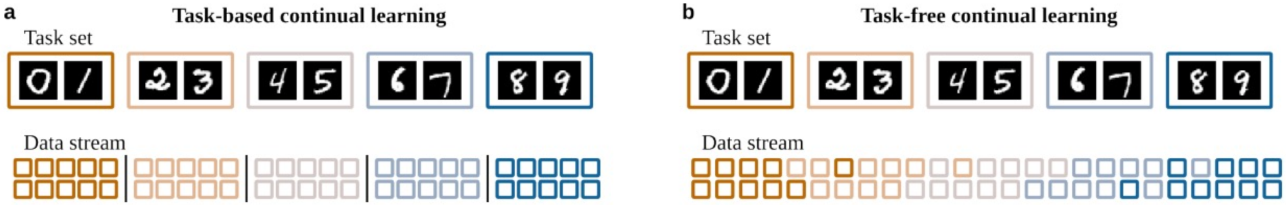
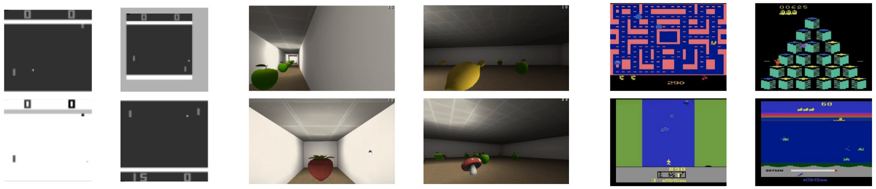
Continual Learning

- Learning a sequence of tasks without looking back.
- Goal is to do well on all of the tasks at the end.
- Task boundary
- Memory constraints









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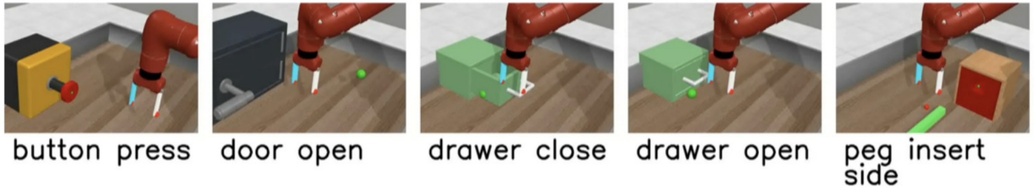

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Parameter Regularization

- Over-completeness Assumption. A multitude of models can reach equivalent performance.

$$\mathcal{S}_A = \{\theta \mid \ell_A(\theta) < \epsilon\}$$

$$\mathcal{S}_A \cap \mathcal{S}_B \neq \emptyset$$

Kirkpatrick et al. *Overcoming catastrophic forgetting in neural networks.* PNAS 2017.

Parameter Regularization

- Over-completeness Assumption. A multitude of models can reach equivalent performance.
- What is left is to efficiently find the intersection between A and B.

$$p(\theta \mid \mathcal{D}_A) = \mathcal{N}(\theta; \theta^*, \Sigma)$$

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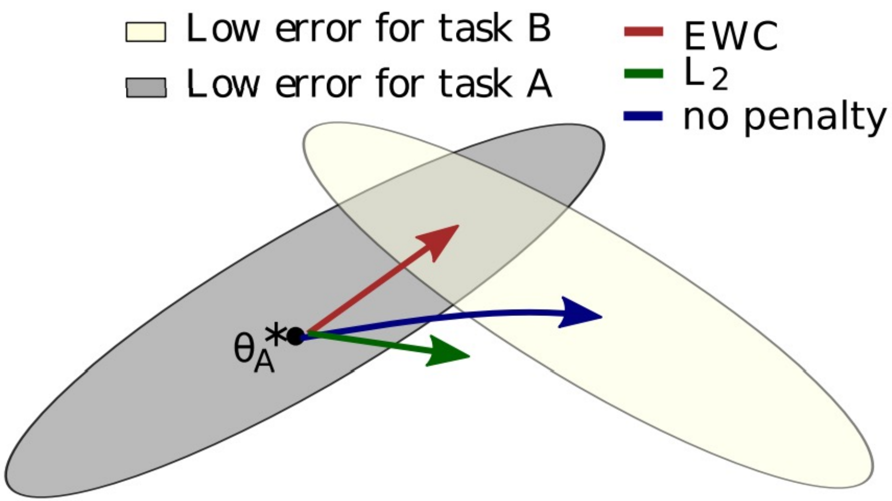
$$p(\theta \mid \mathcal{D}_A) = \mathcal{N}(\theta; \theta^*, \Sigma)$$

- Elastic Weight Consolidation (EWC):

$$\mathcal{L}(\theta) = \mathcal{L}_B(\theta) + \sum_i \frac{\lambda}{2} F_i (\theta_i - \theta^*_{A,i})^2$$



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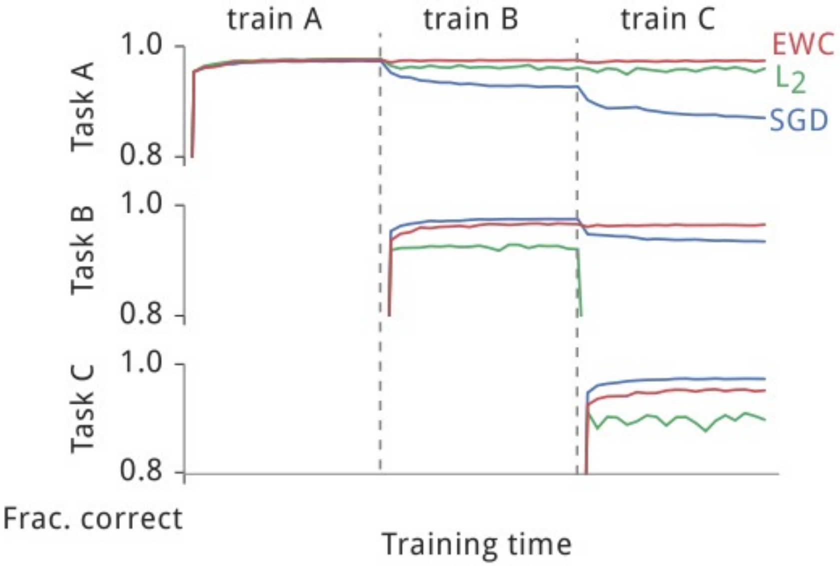
Computing Fisher

- At the end of each epoch, compute the gradient squared:

$$F_i = \left(\frac{d\mathcal{L}}{d\theta_i} \right)^2$$



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- At the end of each epoch, compute the gradient squared:
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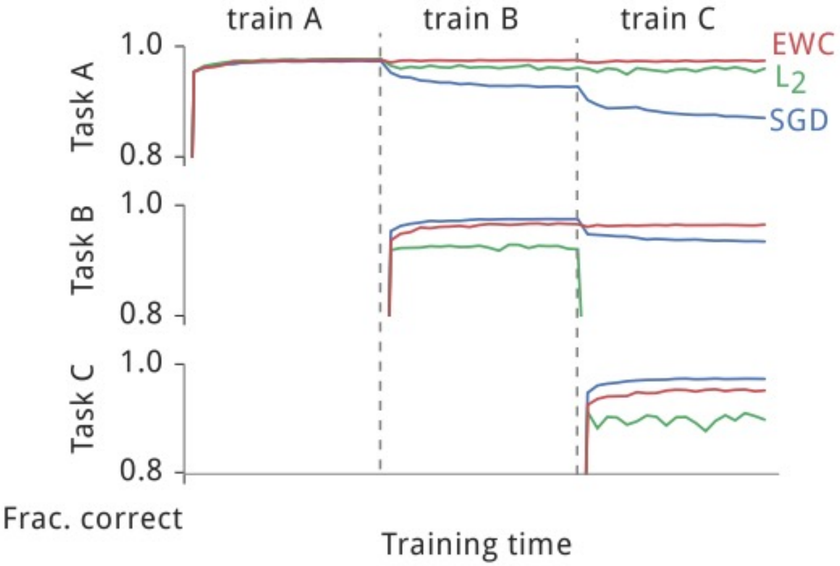
- Measures the sensitivity on each parameter dimension.



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Computing Fisher

- At the end of each epoch, compute the gradient squared:

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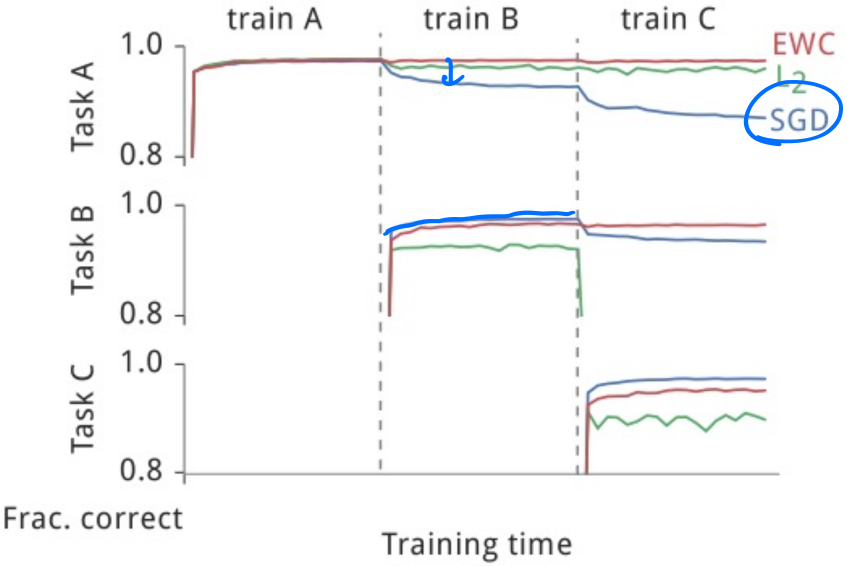
- Measures the sensitivity on each parameter dimension.
- You can also accumulate an online estimate.



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Variational Continual Learning (VCL)

- Bayesian formulation:

$$p(\boldsymbol{\theta} \mid \mathcal{D}_{1:T}) \propto p(\boldsymbol{\theta}) \prod_{t=1}^{T} p(\mathcal{D}_t \mid \boldsymbol{\theta}) \propto p(\boldsymbol{\theta} \mid \mathcal{D}_{1:T-1}) p(\mathcal{D}_T \mid \boldsymbol{\theta}).$$

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- Variational approach:

$$\boxed{q_t(\boldsymbol{\theta})} = \underset{q \in \mathcal{Q}}{\operatorname{argmin}} \operatorname{KL}\left(q(\boldsymbol{\theta}) \parallel \frac{1}{Z_t} \boxed{q_{t-1}(\boldsymbol{\theta})} \boxed{p(\mathcal{D}_t \mid \boldsymbol{\theta})}\right).$$

likelihood for the current dataset.

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Nguyen et al. Variational Continual Learning. ICLR 2018.

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θ_t

F_i

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$$q_t(\boldsymbol{\theta}) = \prod_{d=1}^{D} \mathcal{N}(\theta_{t,d}; \mu_{t,d}, \sigma^2_{t,d}).$$

d^2

- Compare to EWC: Maintains uncertainty throughout training.

Nguyen et al. Variational Continual Learning. ICLR 2018.

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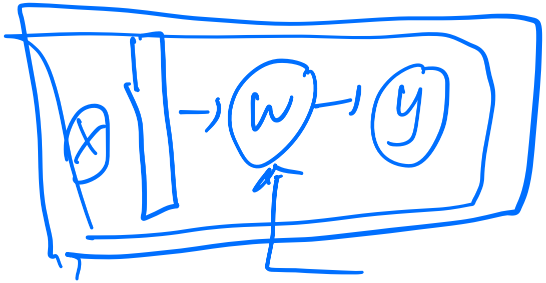
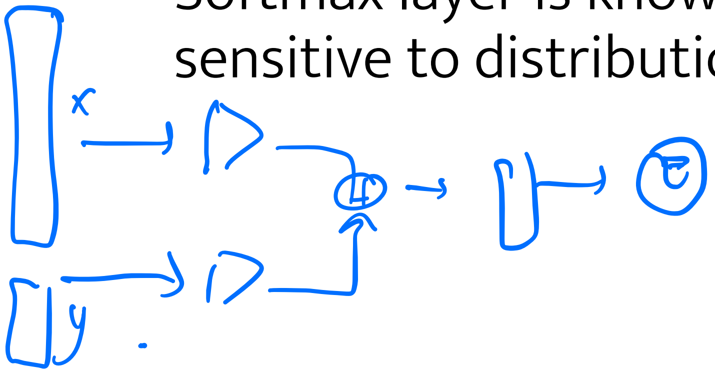
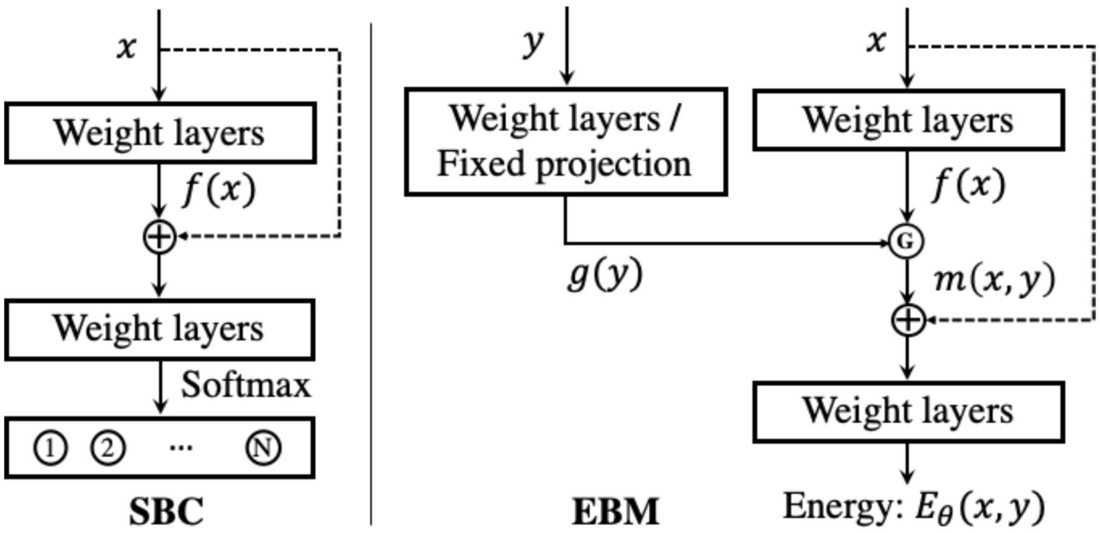


EBM for Continual Learning

$E(x, y).$

- Softmax layer is known to be sensitive to distribution shift.





Li et al. Energy-Based Models for Continual Learning. CoLLAs 2022.

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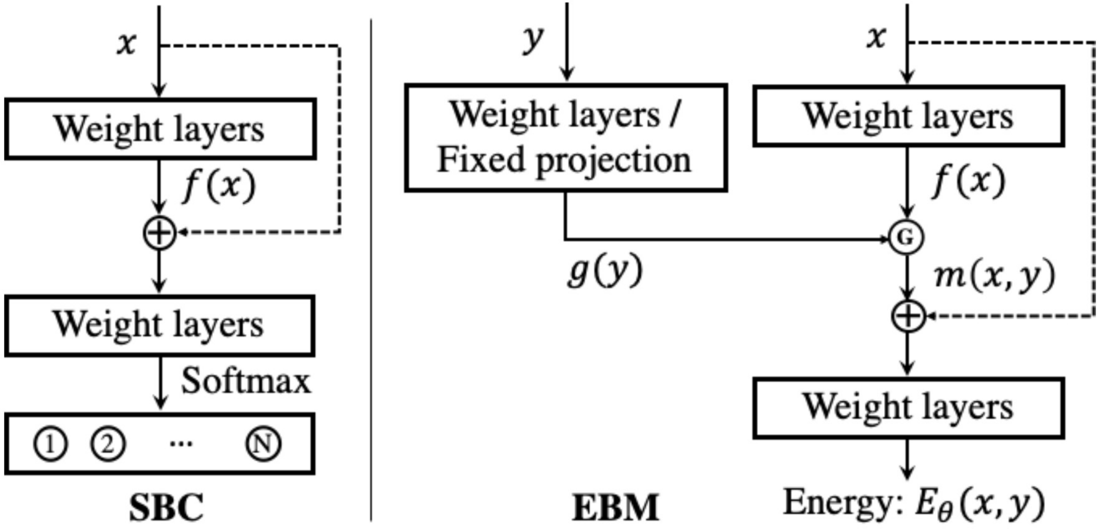
EBM for Continual Learning

- Softmax layer is known to be sensitive to distribution shift.
- A common approach is to use nearest mean classifier.



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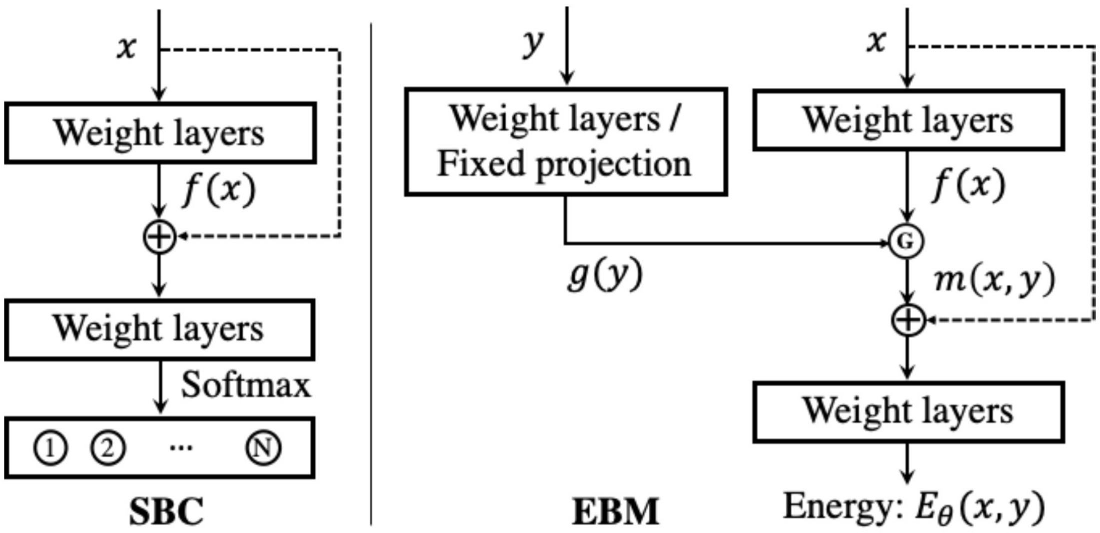

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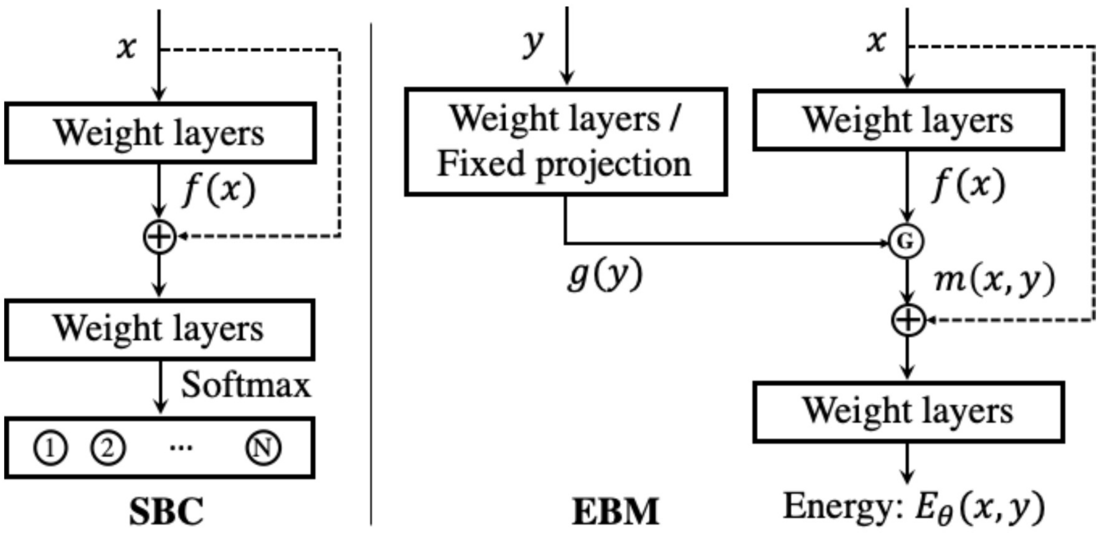
EBM for Continual Learning

- Softmax layer is known to be sensitive to distribution shift.
- A common approach is to use nearest mean classifier.
- Can be generalized to EBMs
- Energy between inputs and labels:

$$m(\mathbf{x}, y) = G(f(\mathbf{x}), g(y))$$

$$L_{CD}(\theta) = \mathbb{E}_{(\mathbf{x},y,y^-)\sim p_D}[E_\theta(\mathbf{x}, y) - E_\theta(\mathbf{x}, y^-)].$$



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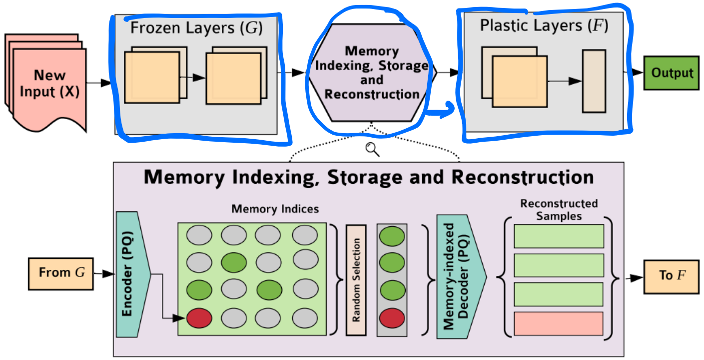
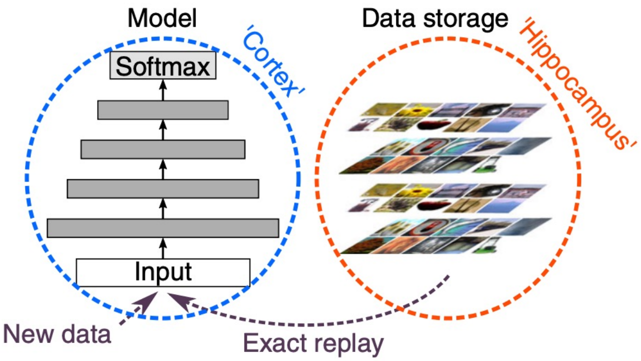
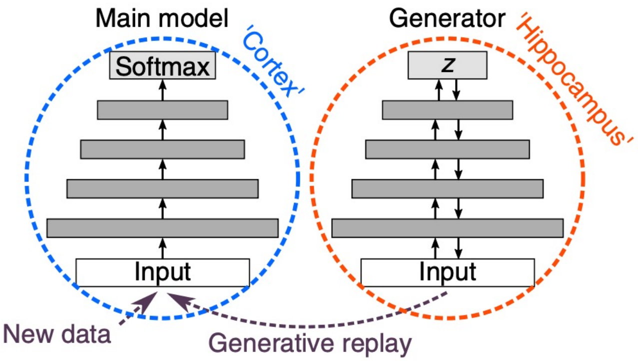


Replay

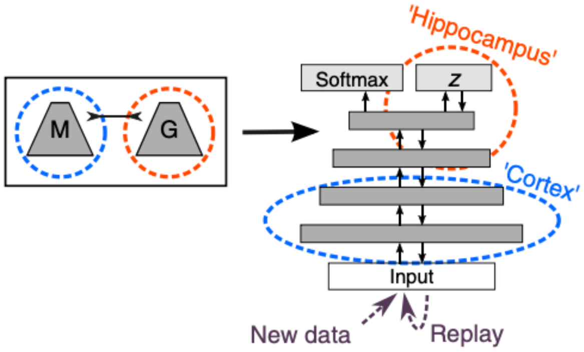
- Store raw data, representations, or train a generative model

Generative replay.





Feedback Connections



Rebuffi et al. iCaRL: Incremental Classifier and Representation Learning. CVPR 2017.
van de Ven et al. Brain-inspired replay for continual learning with artificial neural networks. Nature communications 2020.
Hayes et al. REMIND Your Neural Network to Prevent Catastrophic Forgetting. ECCV 2020.

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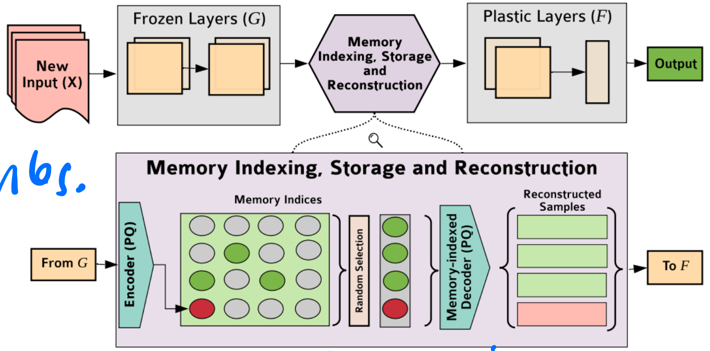
reservoir sampling.

beginning high prob. storing samples.

Replay



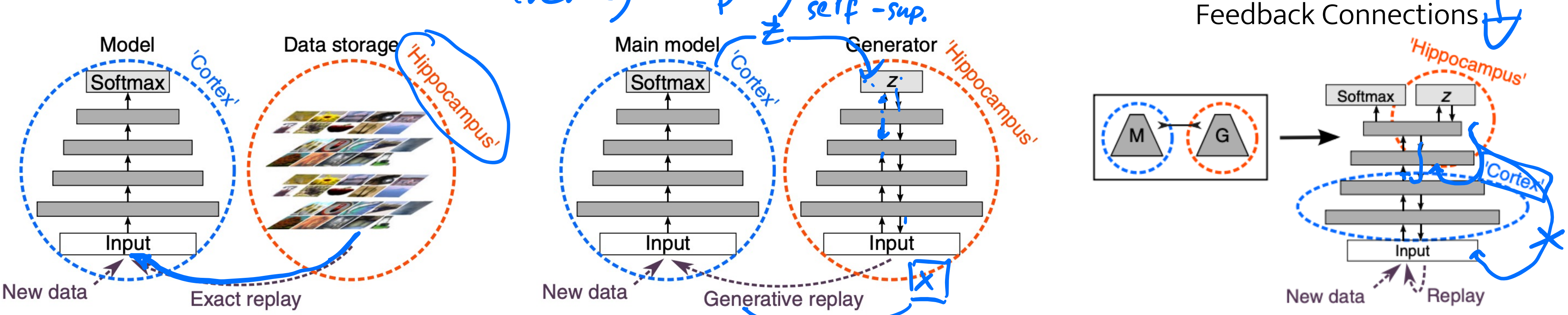
Closer to avg representation.

- Store raw data, representations, or train a generative model
- Coreset selection $\mu \leftarrow \frac{1}{n} \sum_{x \in X} \varphi(x)$ $p_k \leftarrow \underset{x \in X}{\operatorname{argmin}} \|\mu - \frac{1}{k}[\varphi(x) + \sum_{j=1}^{k-1} \varphi(p_j)]\|.$

average rep

classification

self-sup.



reconstruction.

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Knowledge Distillation

- Instead of saving the data points, we can also save the previous model checkpoint.

train

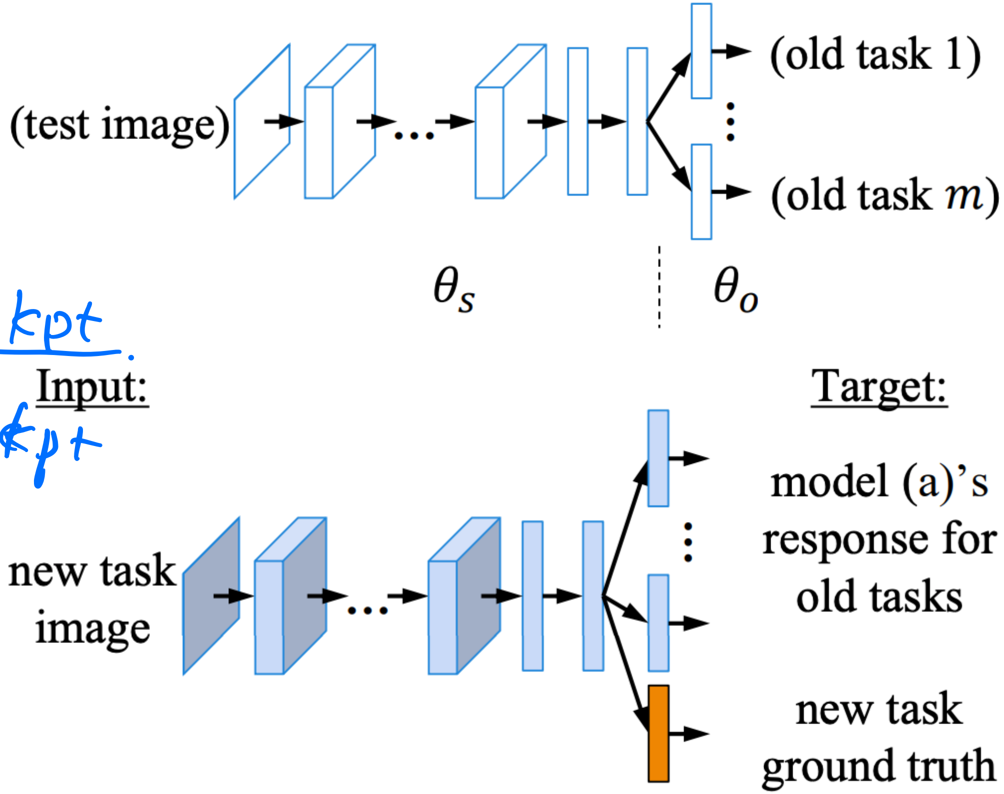
$y_o = f(x_n; \theta_o)$. old ckpt

$\hat{y}_o = f(x_n; \theta_n)$. new ckpt

$\mathcal{L}(y_o, \hat{y}_o)$

new data

$y_n = f(x_n, \theta_n)$



Li & Hoiem. Learning without Forgetting. ECCV 2016.

Knowledge Distillation

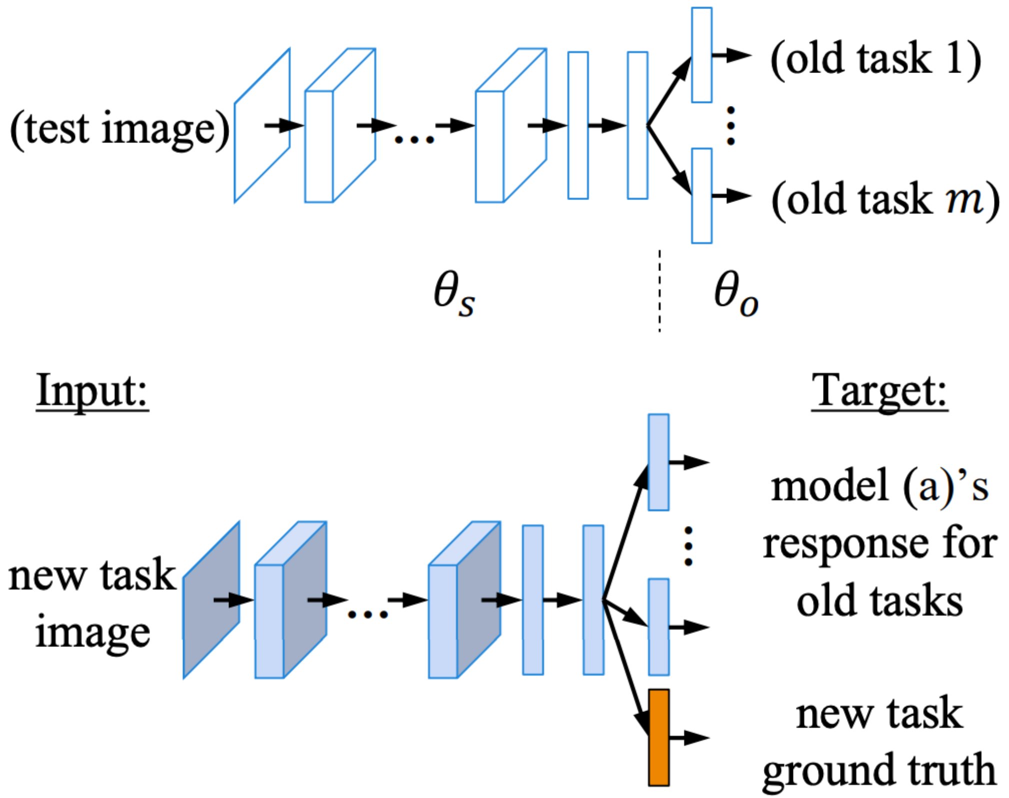
- Instead of saving the data points, we can also save the previous model checkpoint.

$$y_o = f(x_n; \theta_o).$$

$$\hat{y}_o = f(x_n; \theta_n).$$

$$\mathcal{L}(y_o, \hat{y}_o)$$

- Use new data points and old weights to "distill"



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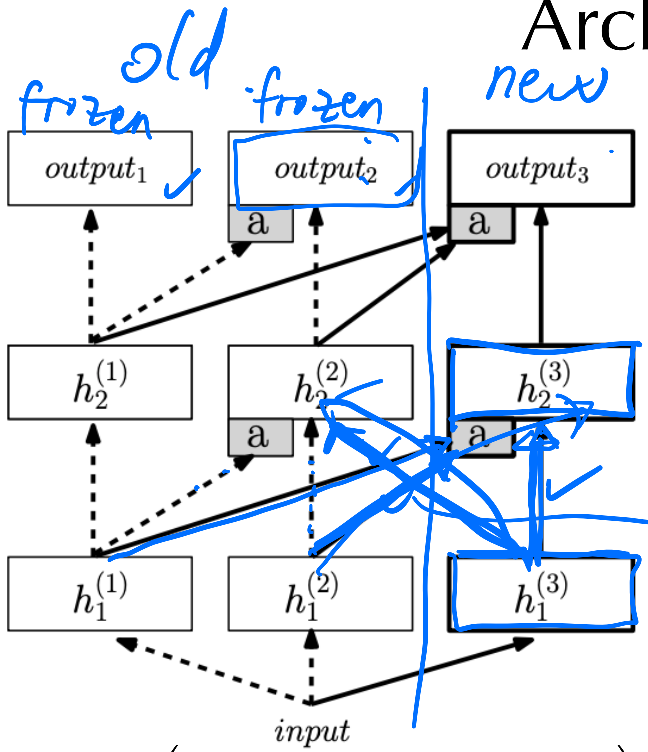
Architecture Expansion

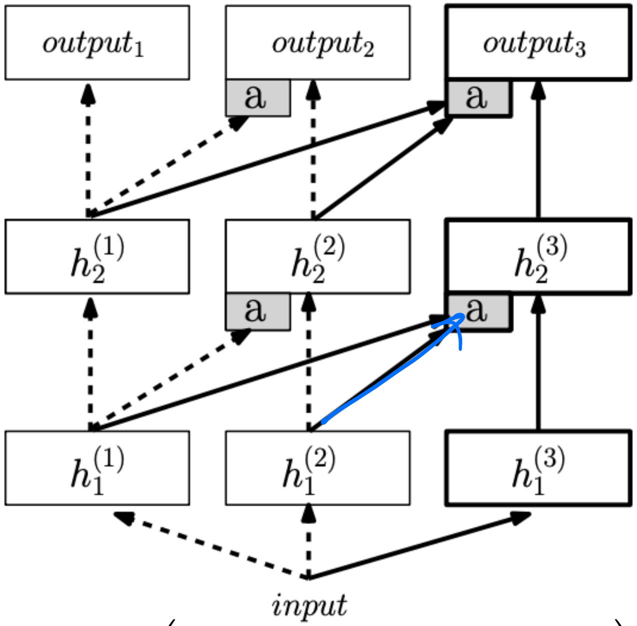


leverage knowledge from previous tasks.

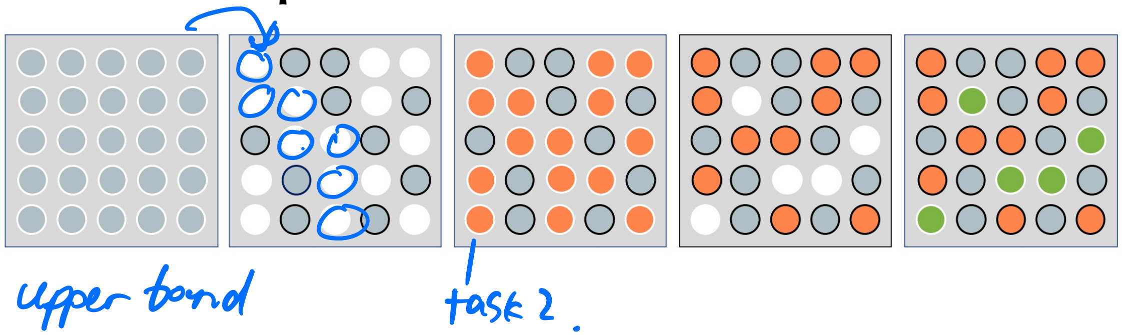
$$h_i^{(k)} = f\left(W_i^{(k)} h_{i-1}^{(k)} + \sum_{j<k} U_i^{(k:j)} h_{i-1}^{(j)}\right).$$

Rusu et al. Progressive Neural Networks. NIPS 2016 Deep Learning Symposium.
PackNet: Adding Multiple Tasks to a Single Network by Iterative Pruning. CVPR 2018.
Yoon et al. Lifelong Learning with Dynamically Expandable Networks. ICLR 2018.

Architecture Expansion



$$h_i^{(k)} = f\left(W_i^{(k)} h_{i-1}^{(k)} + \sum_{j<k} U_i^{(k:j)} h_{i-1}^{(j)}\right).$$



Rusu et al. Progressive Neural Networks. NIPS 2016 Deep Learning Symposium.
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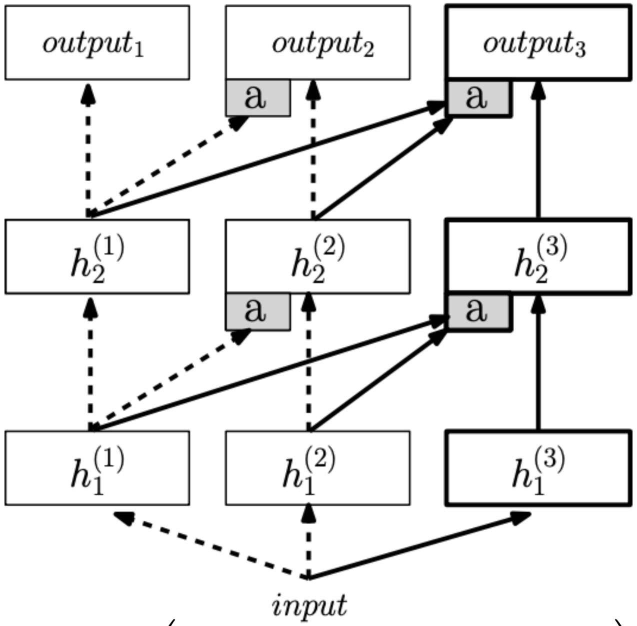

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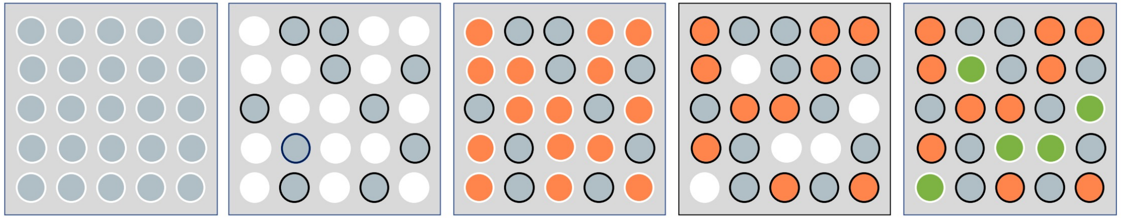

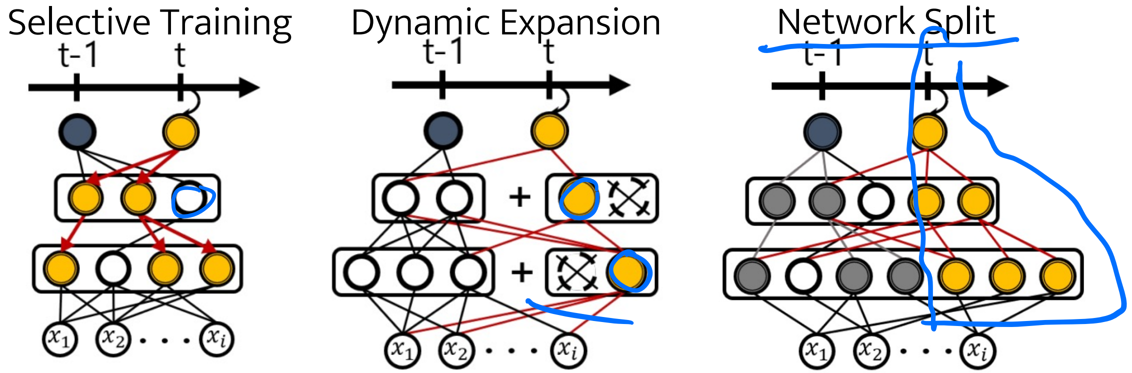

Selective Training

$$\mathcal{L}(\boldsymbol{W}_L^t, \boldsymbol{W}_{1:L-1}^{t-1}, \mathcal{D}_t) + \mu\|\boldsymbol{W}_L^t\|_1$$

Dynamic Expansion

Group sparsity

$$\mathcal{L}(\boldsymbol{W}_l^{\mathcal{N}}, \boldsymbol{W}_l^{t-1}, \mathcal{D}_t) + \mu\|\boldsymbol{W}_l^{\mathcal{N}}\|_1 + \gamma \sum_g \|\boldsymbol{W}_{l,g}^{\mathcal{N}}\|_2$$

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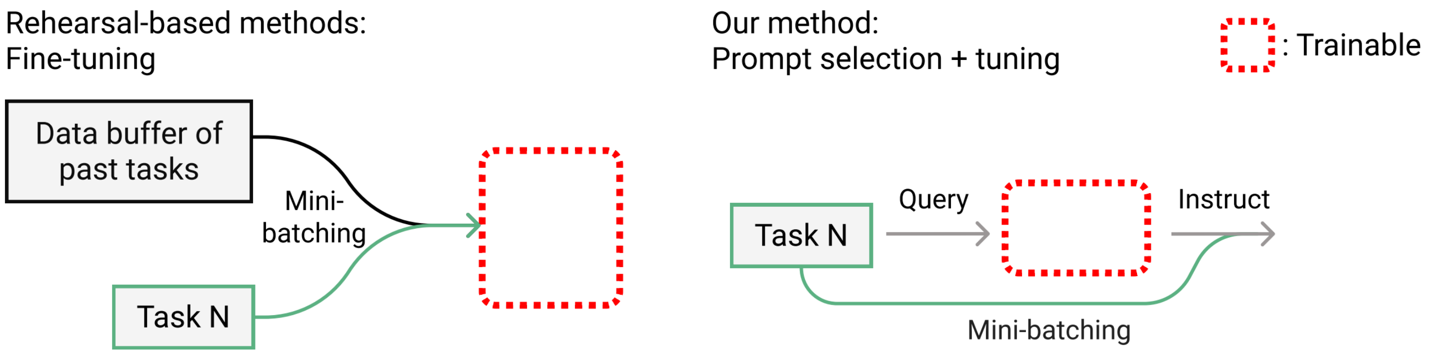
Adapting Pretrained Models

- Pretrained models have general knowledge that can be adapted to a continual stream of tasks.



Wang et al. Learning to Prompt for Continual Learning. CVPR 2022.

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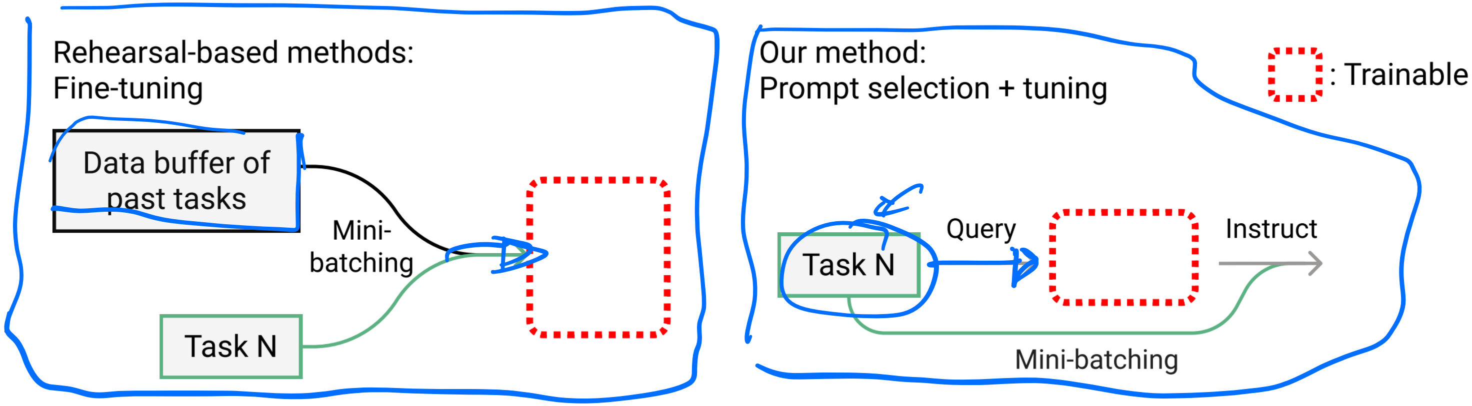

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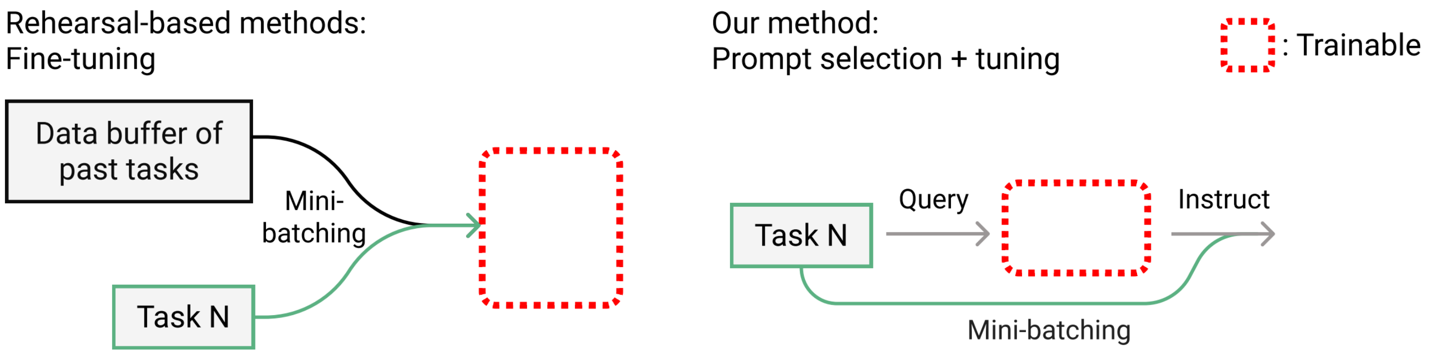
Adapting Pretrained Models

- Pretrained models have general knowledge that can be adapted to a continual stream of tasks.
- Learn adaptation parameters for each task and store these as “task embeddings.”
- Main model is frozen.



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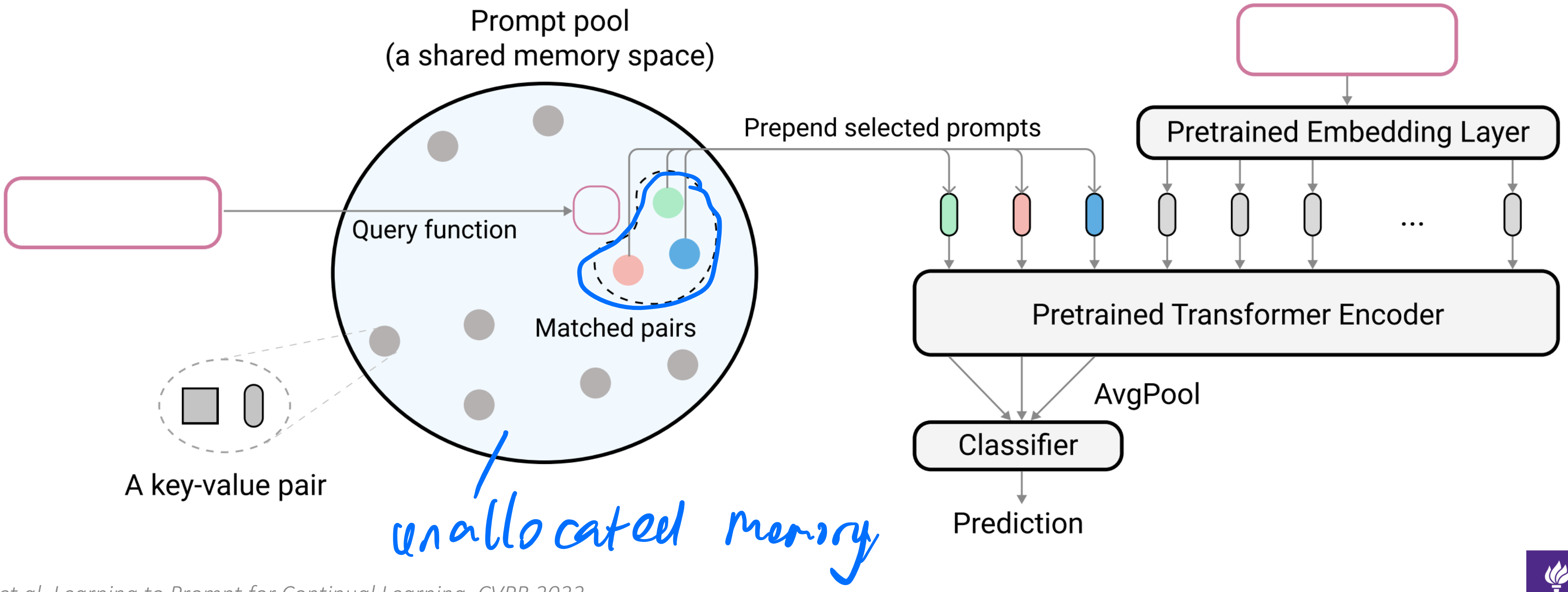
Learning to Prompt

Prompt pool (slot memory)

$$\{(k_1, p_1), \ldots, (k_M, p_M)\}$$



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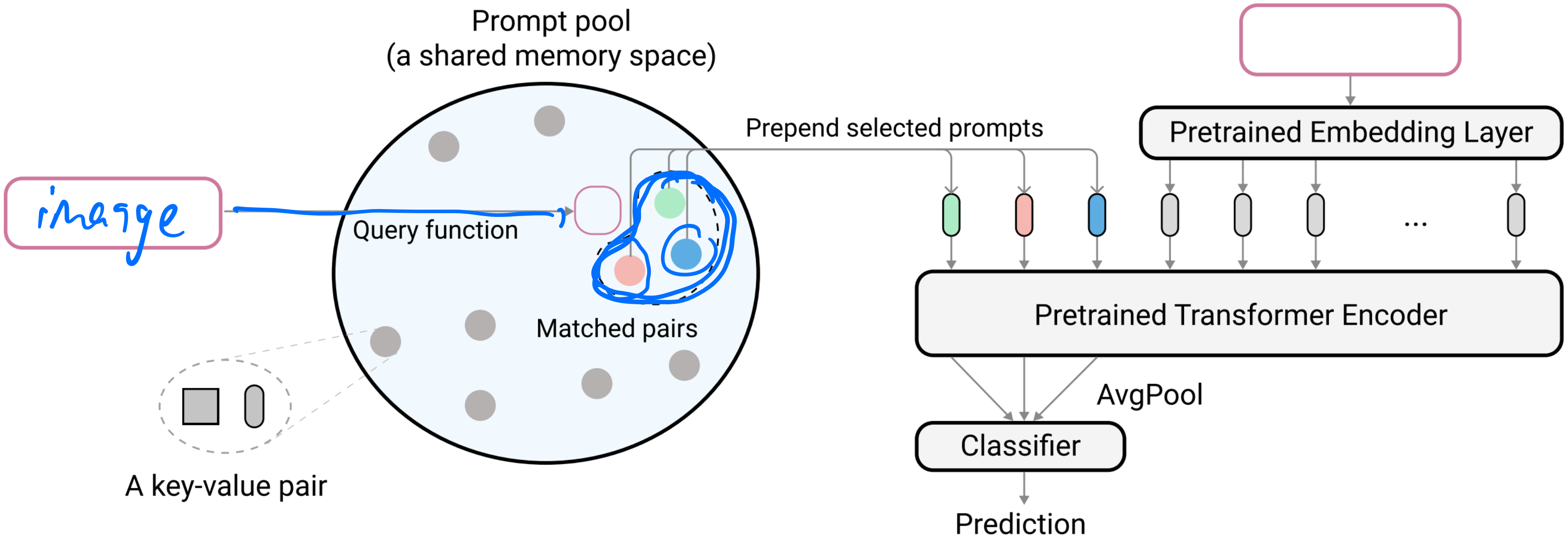
$$K_s = \text{argmin}_{\mathcal{S}} \sum_{i \in \mathcal{S}} \gamma(q(x), k_i)$$



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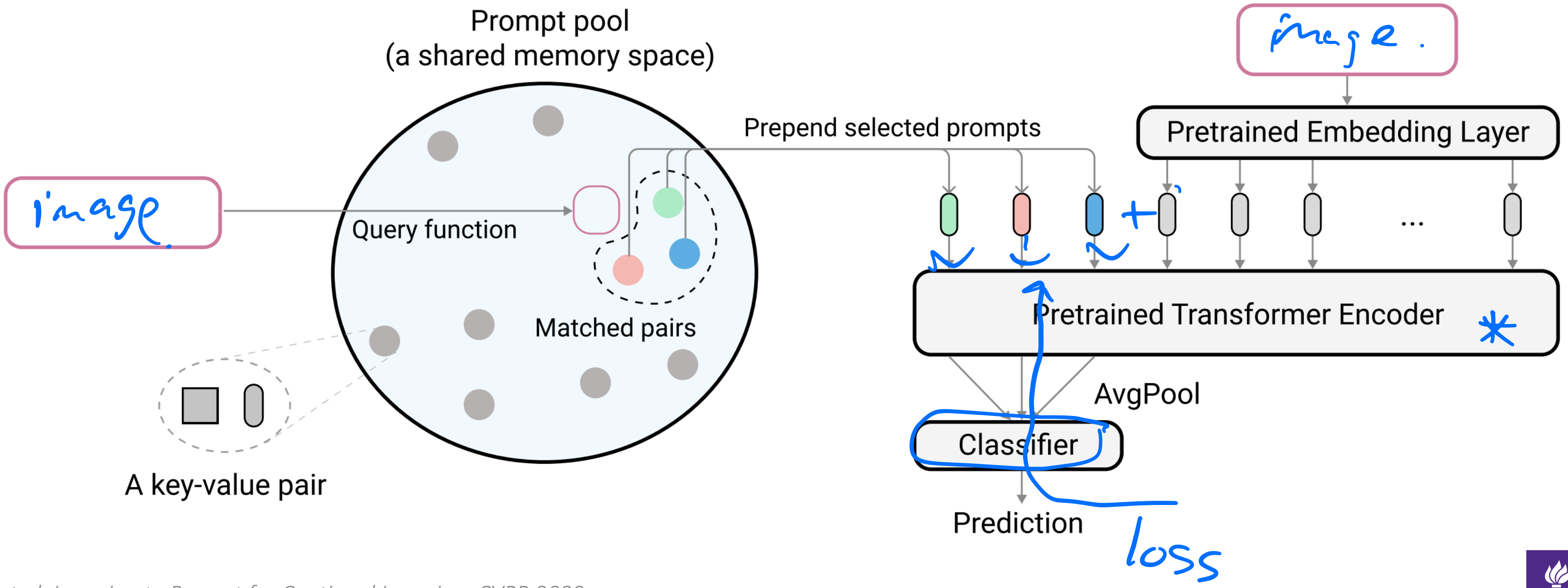
$$\min_{P,K,\phi} \mathcal{L}(g_\phi(x), y) + \lambda \sum_{i \in K_s} \gamma(q(x), k_i)$$

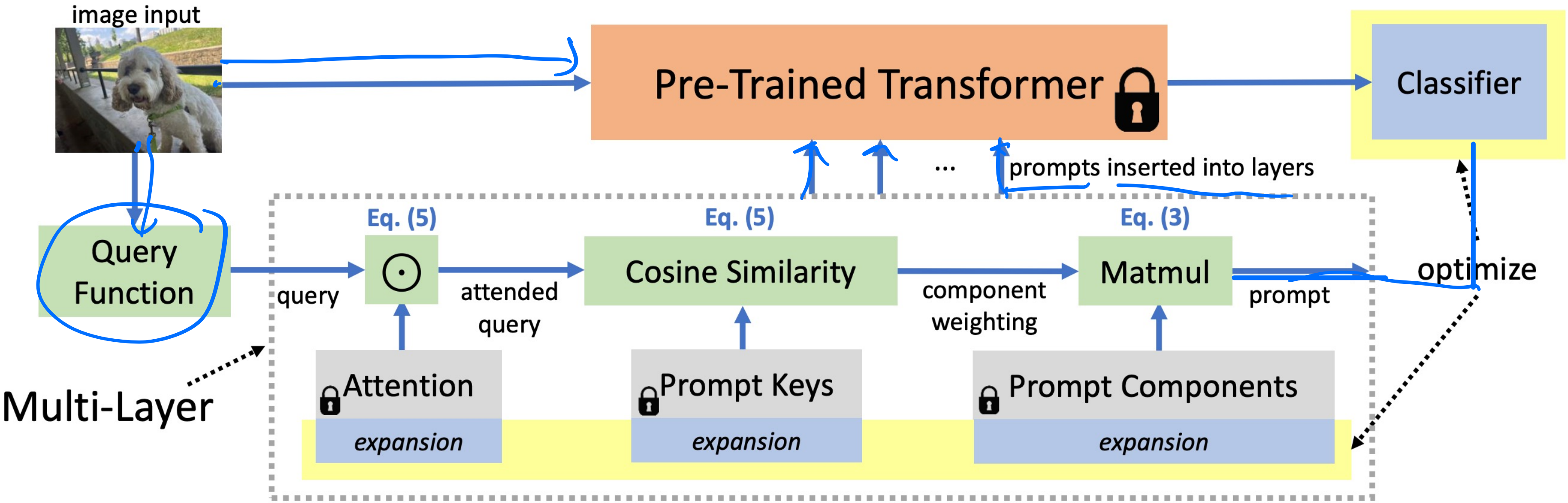


Wang et al. Learning to Prompt for Continual Learning. CVPR 2022.

Learned Prompt Query

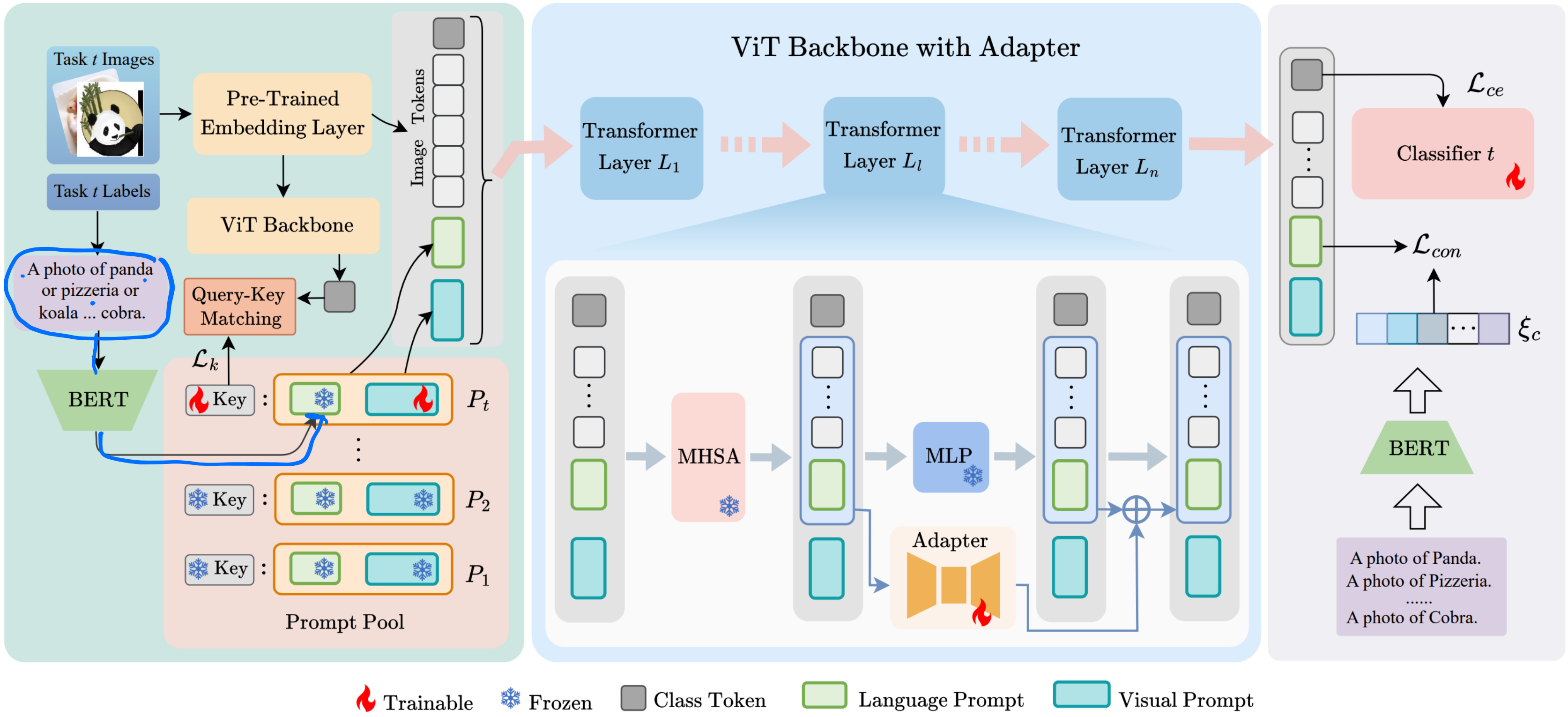
- The query function can be end-to-end learned.

$$\alpha = \{\gamma(q(x) \odot A_1, K_1), \ldots, \gamma(q(x) \odot A_M, K_M)\}$$



Smith et al. CODA-Prompt: COntinual Decomposed Attention-based Prompting for Rehearsal-Free Continual Learning. CVPR 2023.

Multimodal Semantic Prompts



Yin et al. Adapter-Enhanced Semantic Prompting for Continual Learning. arXiv 2024.

Continual Learning and Memory

forgetting.

- Fragility of feedforward gradient descent of the entire networks

Continual Learning and Memory

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memory.

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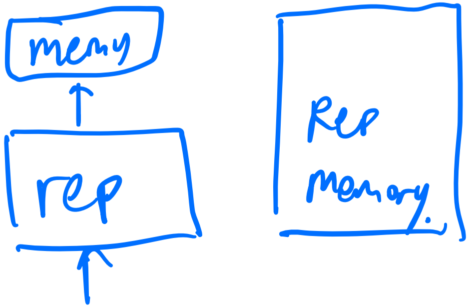
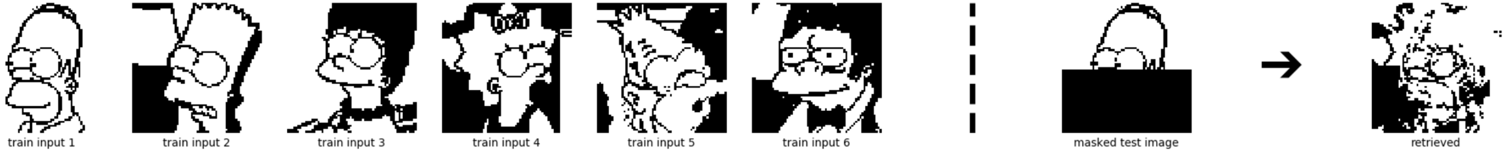
Continual Learning and Memory

- Fragility of feedforward gradient descent of the entire networks
- If we have representations ready, continual learning is just memorizing a sequence of new tasks.
- In prompting approaches:
  - prompt pool = memory
  - pretrained network = representations
- But what if representations also need to be built sequentially?
- It’s also plausible that representations are just “deeper memory.”



Associative Memory

- Memory aims to store content for easy retrieval



Krotov & Hopfield. Dense Associative Memory for Pattern Recognition. NIPS 2016.
https://ml-jku.github.io/hopfield-layers/

Associative Memory

- Memory aims to store content for easy retrieval
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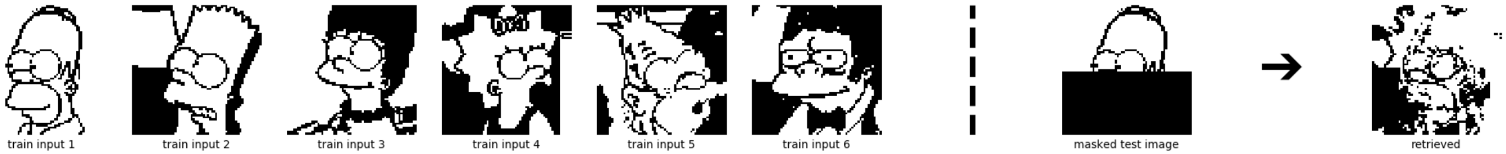

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$$E = -\frac{1}{2}\sum_{i,j=1}^{N} s_i \boxed{W_{ij}} s_j . \qquad W_{ij} = \sum_{k=1}^{K} \xi_i^k \xi_j^k .$$

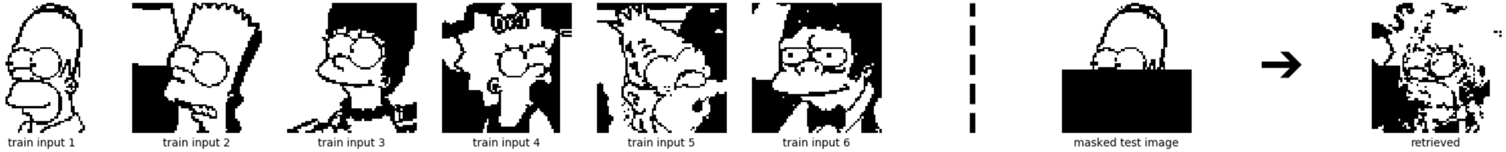
"Superposition" of k slots
Hebbian learning

$s = \xi$

stored patterns.

retrieval.

ξ stored. pattern.



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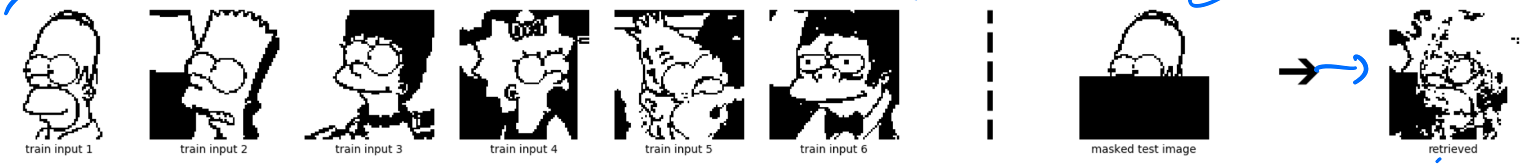
  - When presented with a new pattern the network should respond with a stored memory which most closely resembles the input.

Stored patterns



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"Superposition" of k slots
Hebbian learning

binary.

  - When presented with a new pattern the network should respond with a stored memory which most closely resembles the input.
  - Retrieval: $\boxed{s_i = \mathrm{sign}\left(\sum_j W_{ij} s_j\right)}$ Storage: $C \approx \frac{d}{2\log(d)} = 0.14d.$

100.

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Memory Duality

- Duality with a feedforward network.

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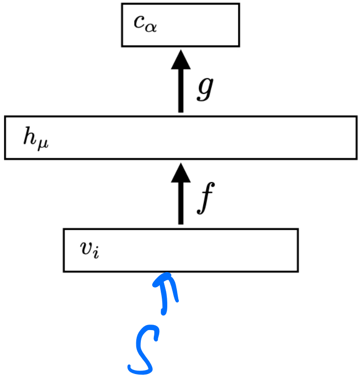

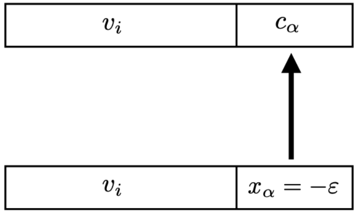

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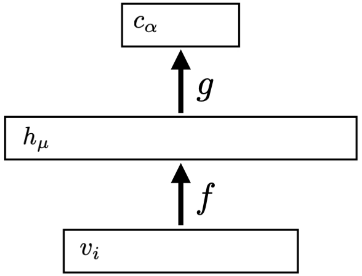

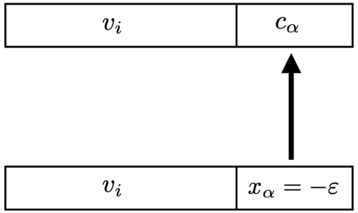

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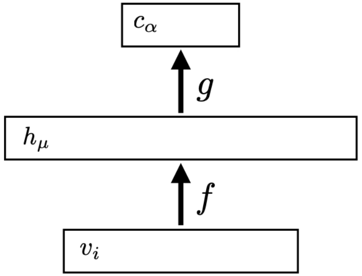
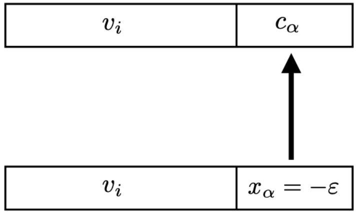
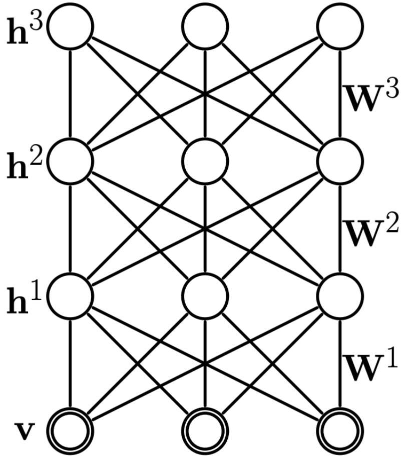




Deep Boltzmann Machine



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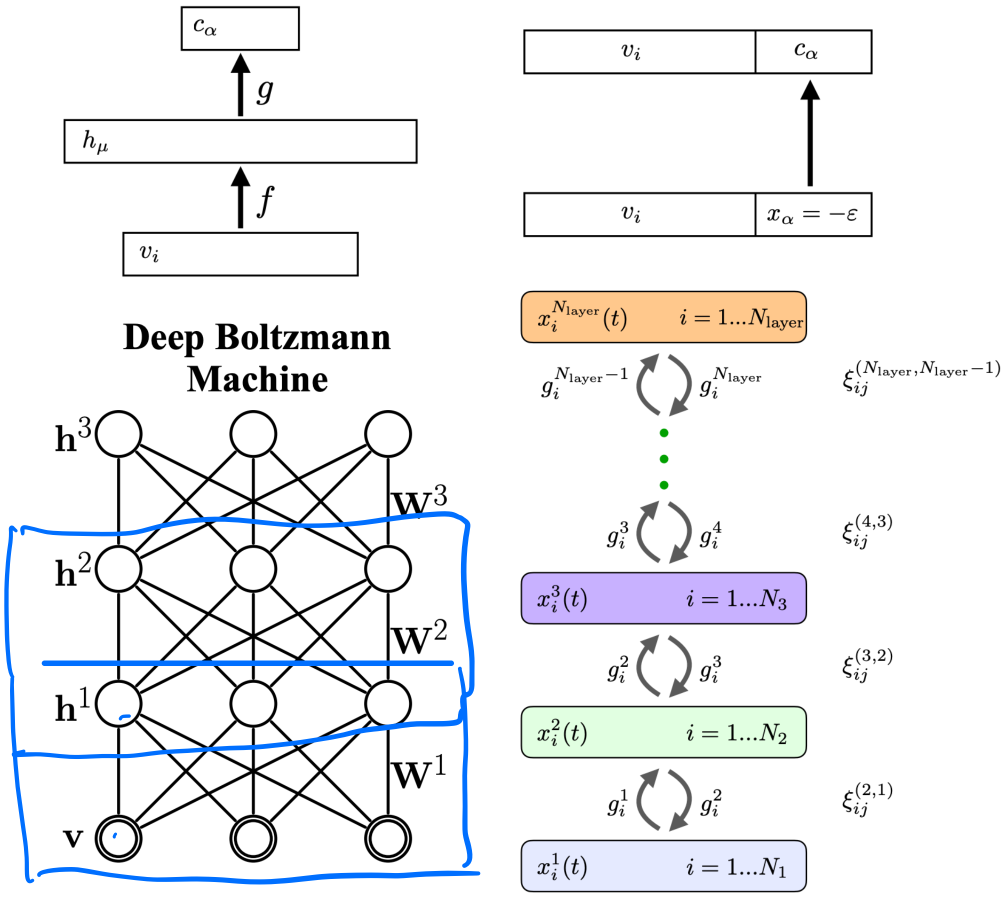

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Relation to Transformers

- General form:

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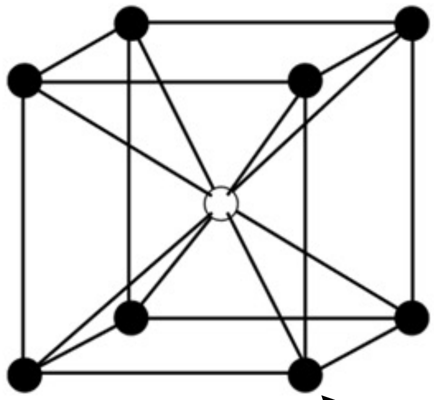
Stored patterns

retrieved vector

Relation to Transformers



- General form:

$$E = -\sum_k F\Big(\sum_i \xi_i^k s_i\Big).$$

- When $F(z) = z^2$ it gives the classic HN.

$$\nabla_{s_i} E = \boxed{-\sum_j W_{ij} s_j}$$

$$s_i \leftarrow \mathrm{sign}\big(\textstyle\sum_j W_{ij} s_j\big)$$

Ramsauer et al. Hopfield Networks is All You Need. ICLR 2021.

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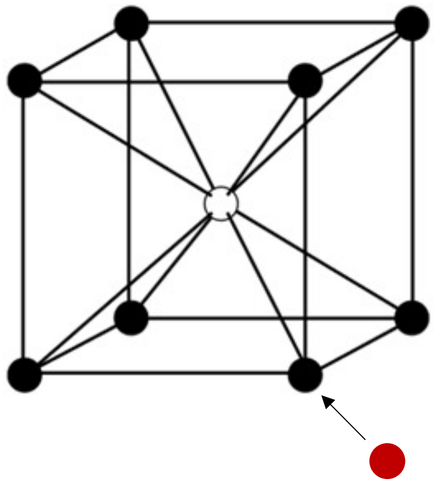

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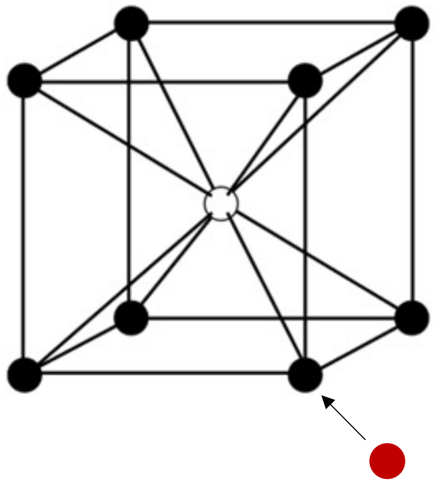

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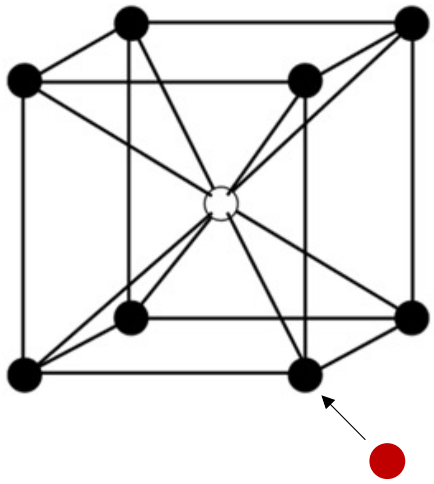

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$\xi\xi^\top$

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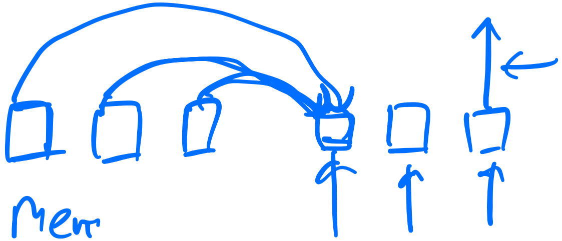

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Mem

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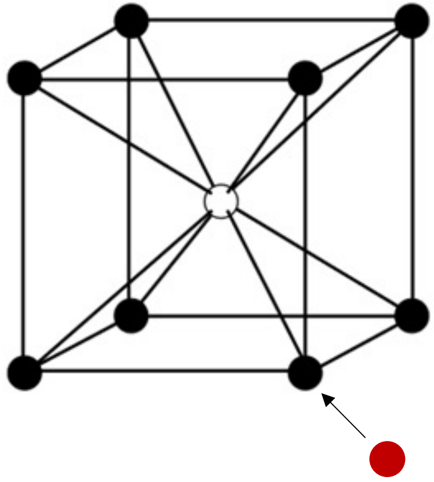
1 step.

$$E = -\mathrm{logsumexp}(\beta, \boldsymbol{\Xi}^\top \boldsymbol{s}) + \frac{1}{2} \boldsymbol{s}^\top \boldsymbol{s} + \beta^{-1} \log N + \frac{1}{2} M^2.$$



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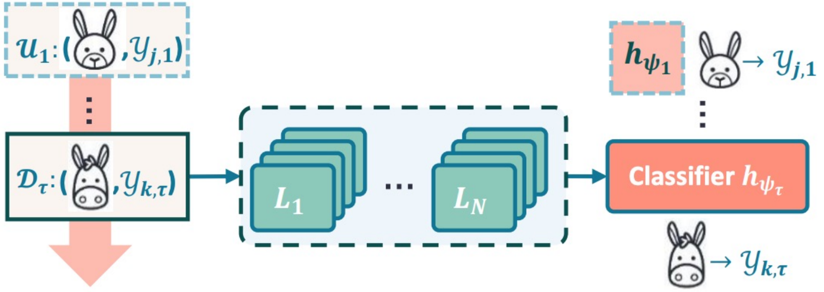
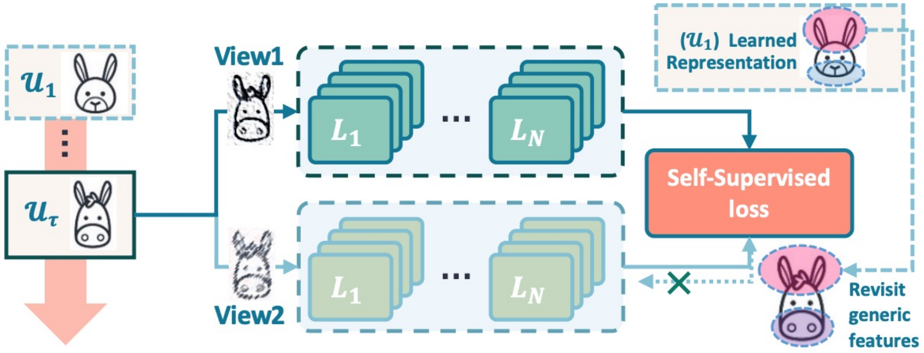
Continual Self-Supervised Learning

- Learning from a stream of unlabeled inputs.



SUPERVISED CONTINUAL LEARNING (SCL)

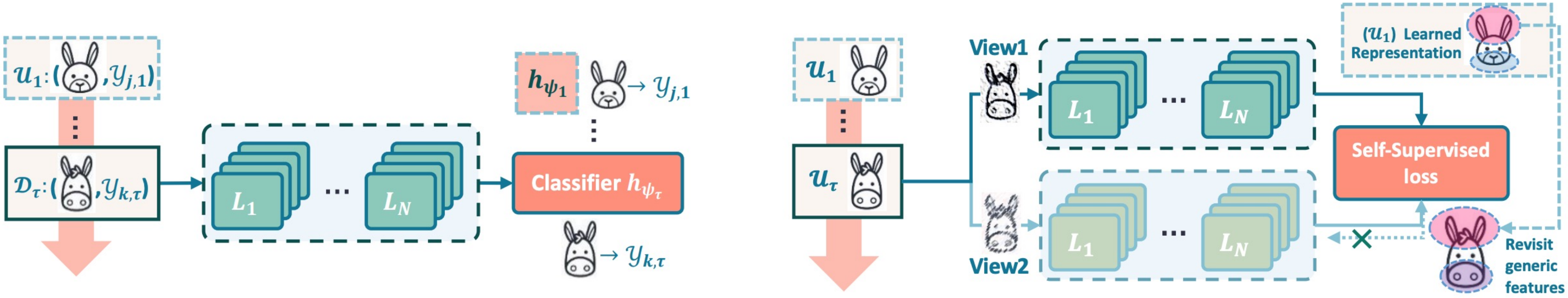


UNSUPERVISED CONTINUAL LEARNING (UCL)

Madaan et al. Representational Continuity for Unsupervised Continual Learning. ICLR 2022.

Continual Self-Supervised Learning

- Learning from a stream of unlabeled inputs.
- Bring SSL to the dynamic world.



SUPERVISED CONTINUAL LEARNING (SCL)

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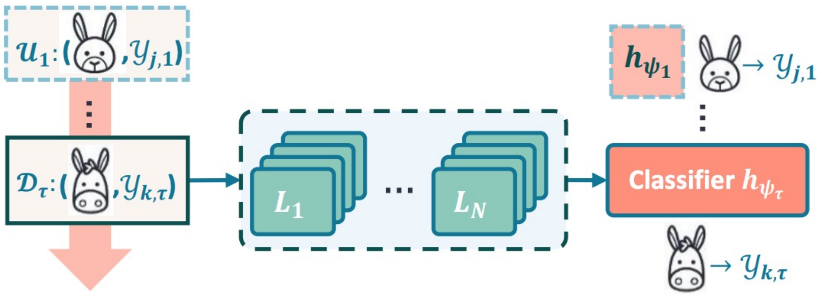
Continual Self-Supervised Learning

- Learning from a stream of unlabeled inputs.
- Bring SSL to the dynamic world.
- SSL can still suffer from distributional shifts.



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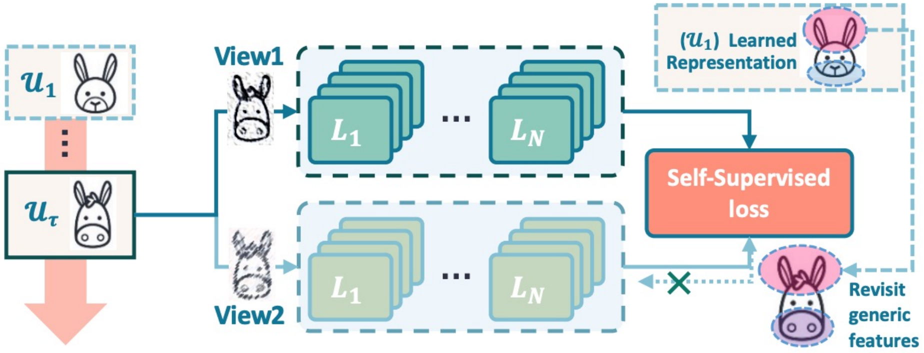

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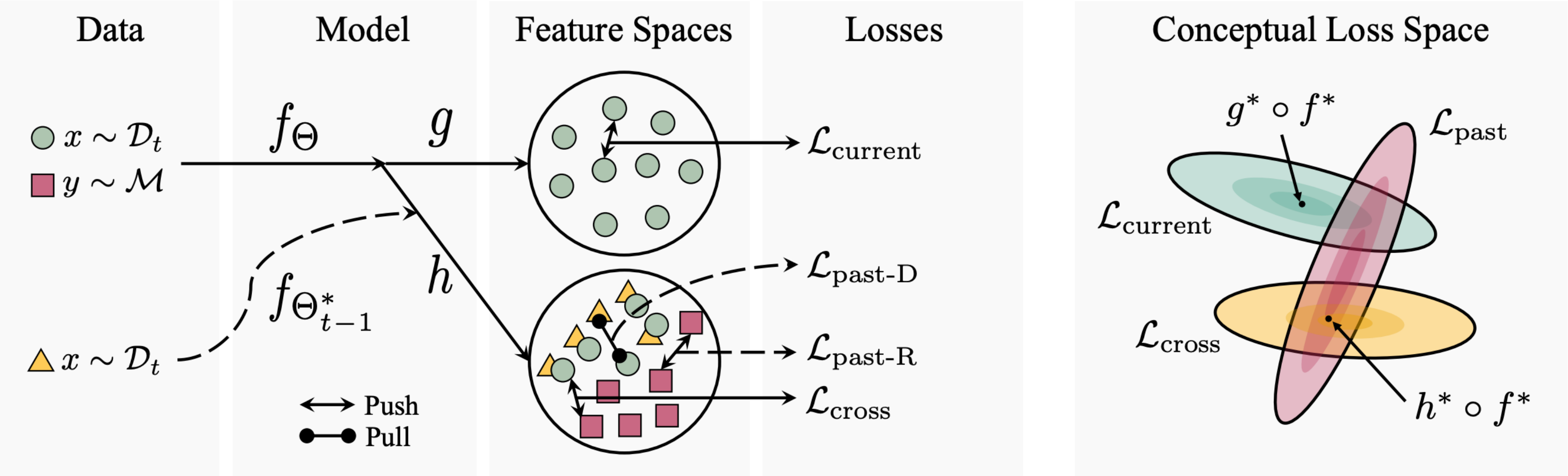
Continual Self-Supervised Learning

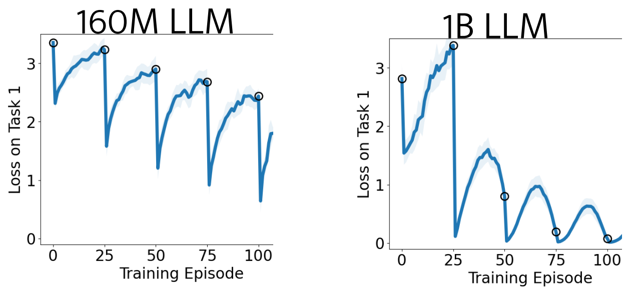
- Integrating learning objectives of both past and present.

$$\underbrace{\mathcal{L}(X; g \circ f_t)}_{\text{Current}} + \underbrace{\mathcal{L}(X, X; h \circ f_{t-1}, h \circ f_t)}_{\text{Past (Distillation)}} + \underbrace{\mathcal{L}(Y; h \circ f_t)}_{\text{Past (Replay)}} + \underbrace{\mathcal{L}(X, Y; h \circ f_t)}_{\text{Cross-Consolidation}}$$



Zhang et al. Integrating Present and Past in Unsupervised Continual Learning. CoLLAs 2024.

Outlooks

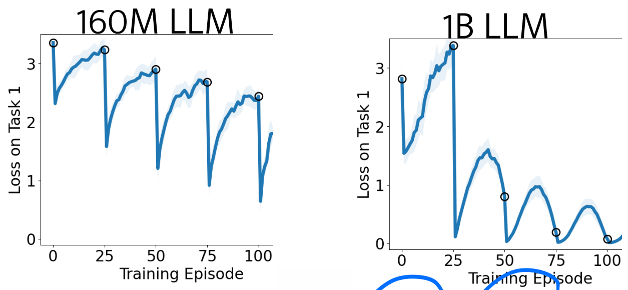


- Understand continual learning at scale

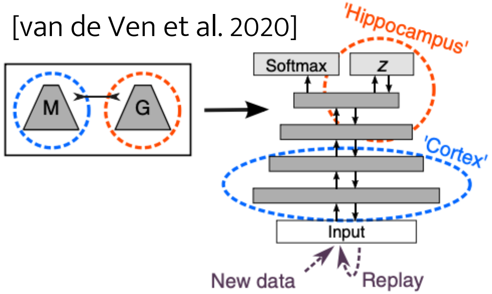
[Mayo et al. 2023]

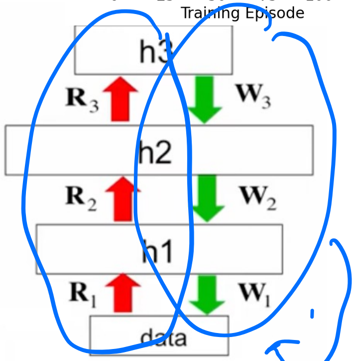
Outlooks

- Understand continual learning at scale
- Unified learning architecture, objective and replay, role of sleep



[van de Ven et al. 2020]





[Hinton et al. 1995]

[Mayo et al. 2023]

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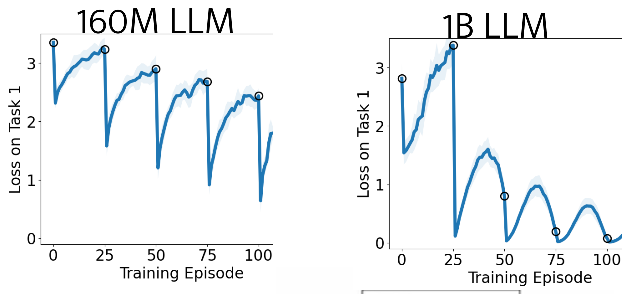
Outlooks

- Understand continual learning at scale
- Unified learning architecture, objective and replay, role of sleep
- Continual learning with real world structure



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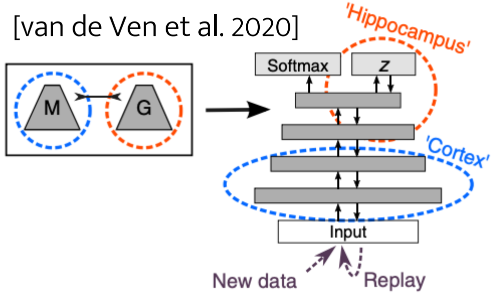

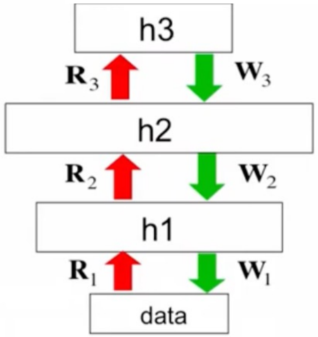

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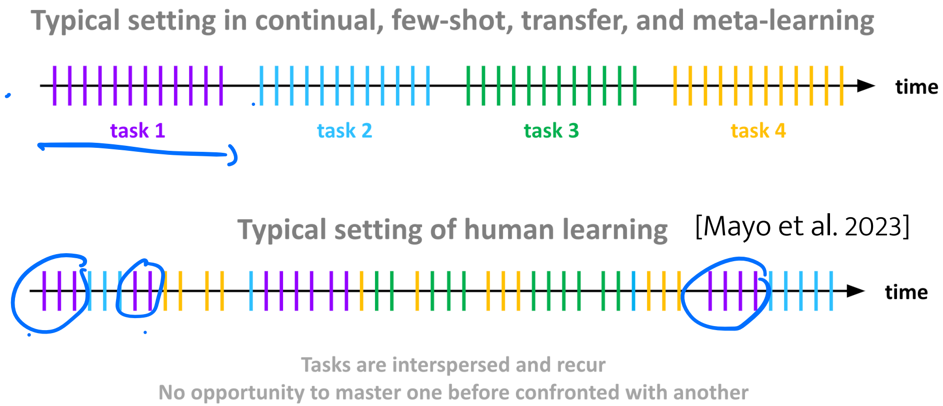

[Mayo et al. 2023]

Summary: Continual Learning

- Regularization, Distillation, Architecture Expansion/Isolation

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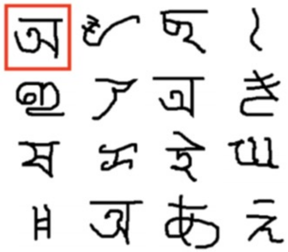
- Regularization, Distillation, Architecture Expansion/Isolation
- Frozen representation: prompt learning
- Integration of memory and representations
- Combination with self-supervised learning
- Exploration of multimodal continual learning from embodied environments

Few-Shot Learning and Meta-Learning

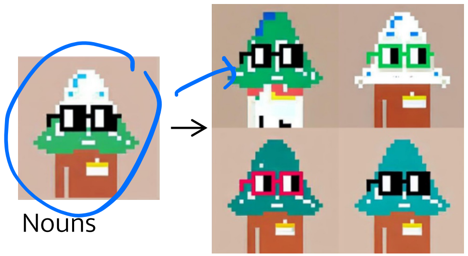
Few-Shot Learning (FSL)

- Humans can quickly learn new concepts with a few examples.
- Learning in embodied agents also needs to be adaptive and swift.
- Examples: Recognize new objects, perform new skills, map new areas, etc.



[Lake et al. 2011]

[Ren et al. 2018]



[Lu et al. 2024]

FSL: General Setup

- Quickly learn a task (learning episode) with very few number of training examples and get evaluated on a set of test examples.

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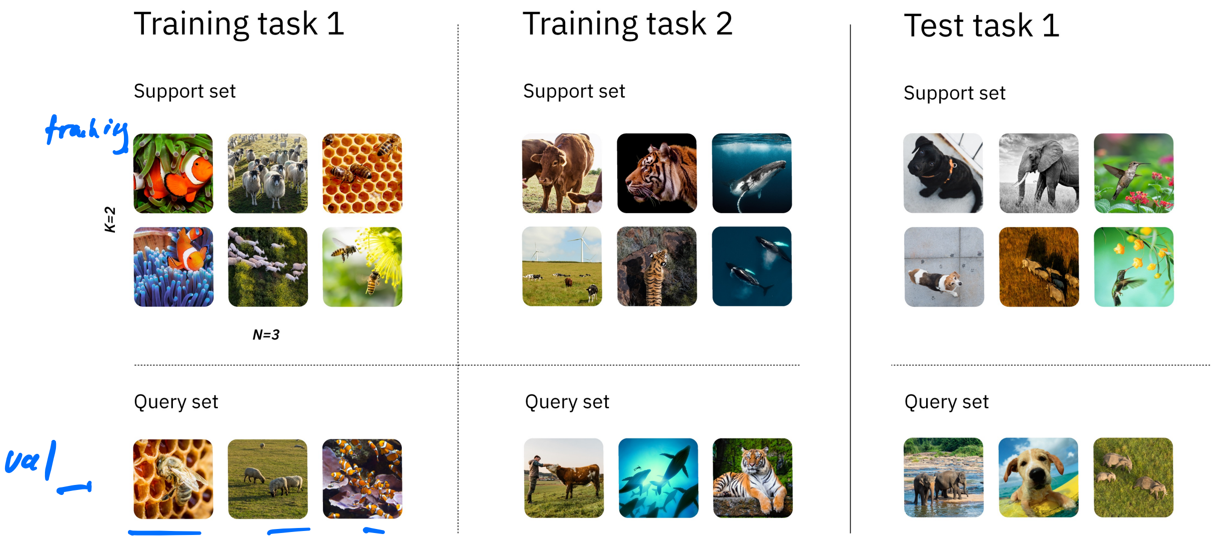
- During training, going through many episodes of the same structure.



https://www.ibm.com/think/topics/few-shot-learning

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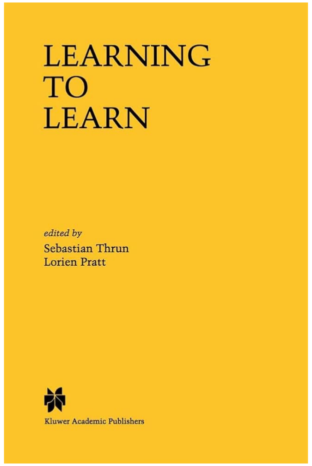
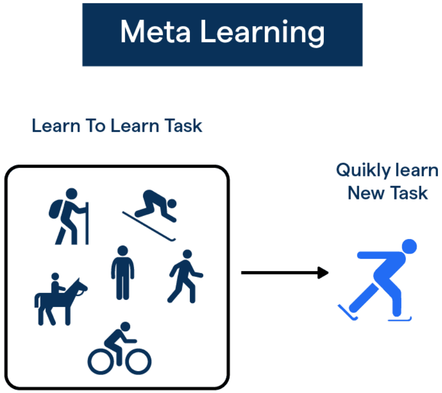
Learning to Learn

- Conceptually, we'd like to generalize new learning experiences.





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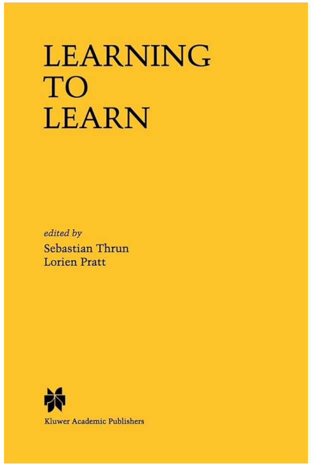
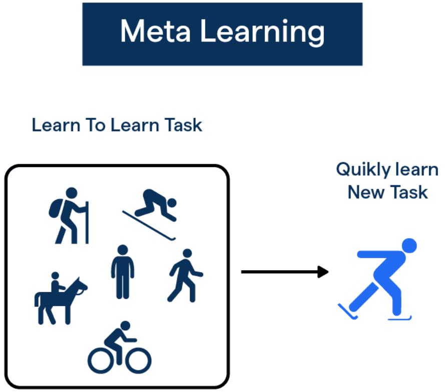
Learning to Learn

- Conceptually, we'd like to generalize new learning experiences.
- 1 learning experience = 1 training example





T_1 T_2 . . . T_N

Learning to Learn

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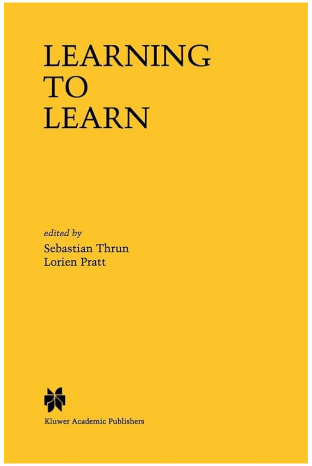
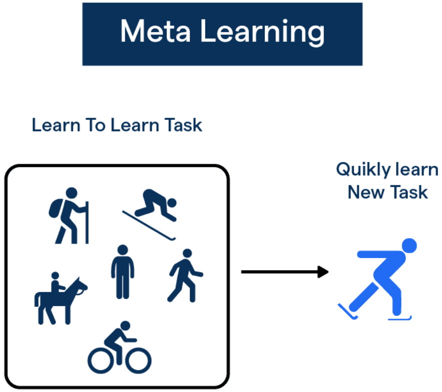
- Related to multi-task learning





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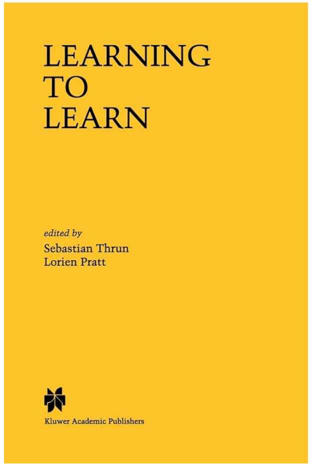
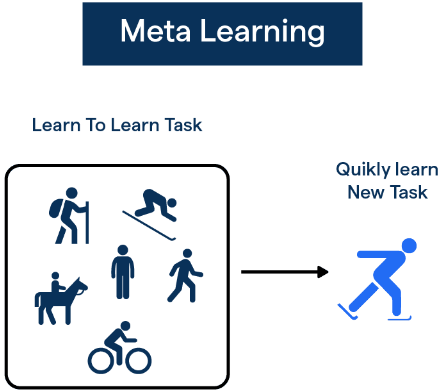
    - Optimizer
    - Initialization
    - Architecture
    - Representations
    - Abstraction of tasks





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- What can be meta-learned?
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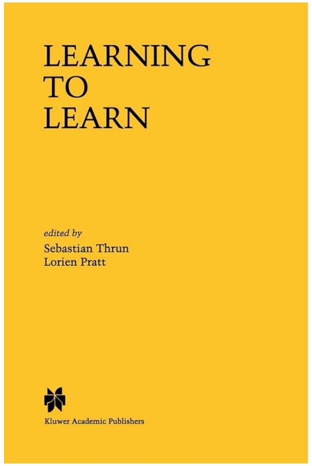
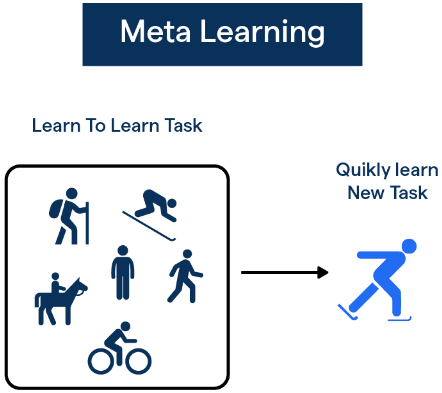
    - Abstraction of tasks
- Discover learning algorithms that support FSL.





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Meta-Optimization (Bi-level Optimization)

- One can formulate meta-learning as a meta-optimization problem.

$$\min_{\lambda} \mathop{\mathbb{E}}_{D \sim \mathcal{D}} \boxed{\min_{\theta} \mathop{\mathbb{E}}_{x \sim D} \mathcal{L}(x; \theta, \lambda).}$$

hyperparameter

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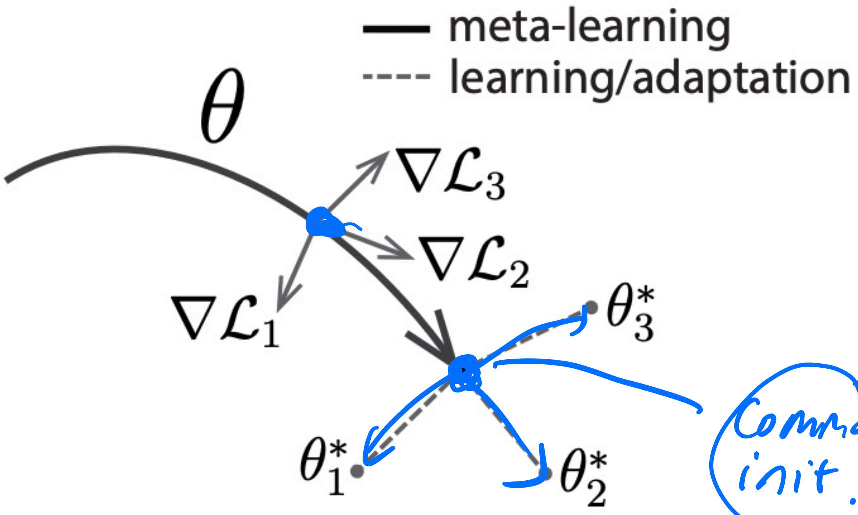
- Need to optimize through the inner optimization.
  - BPTT
  - Fixed point (implicit differentiation)
  - Zeroth order optimization
- Short-horizon bias: Optimal actions in the next few steps may not be optimal in the long run.
  - Example: Lowering learning rate will always result in short-term gains.

MAML (Truncated Optimization)

- For few-shot learning, short horizon is actually needed.
- Unroll the gradient graph for a few iterations.
- MAML (Model-agnostic meta-learning)



Common init.

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**

Finn et al. Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. ICML 2017.

Hypernetworks, Best Response Functions

- Another way to "amortize" the optimization is to use a network to predict the optimal inner parameters.

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- Best response function: $\boxed{w^*} = \operatorname{argmin}_w \mathcal{L}_T(\boxed{\lambda}, w)$. $\lambda^* = \operatorname{argmin}_\lambda \mathcal{L}(\lambda, w^*)$.

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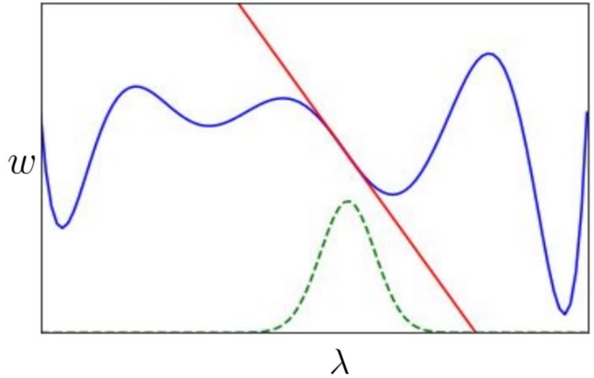

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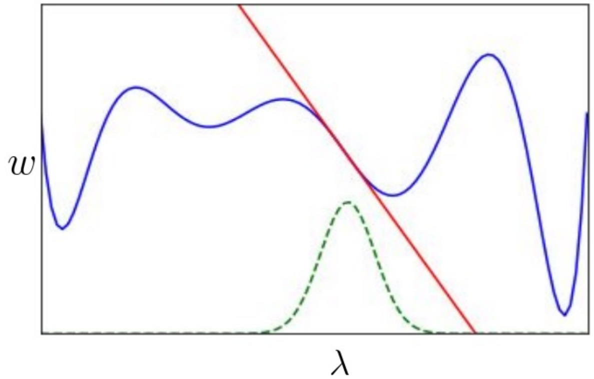

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approx. inner loop.

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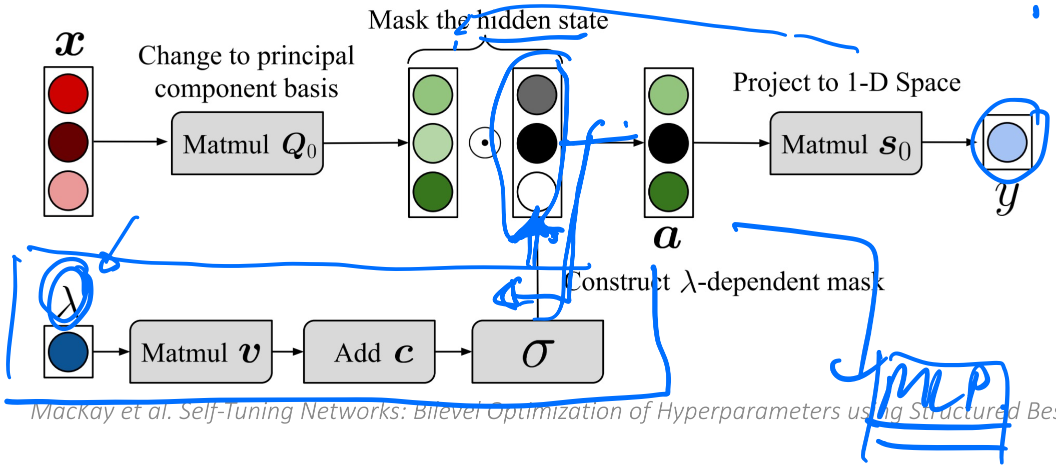

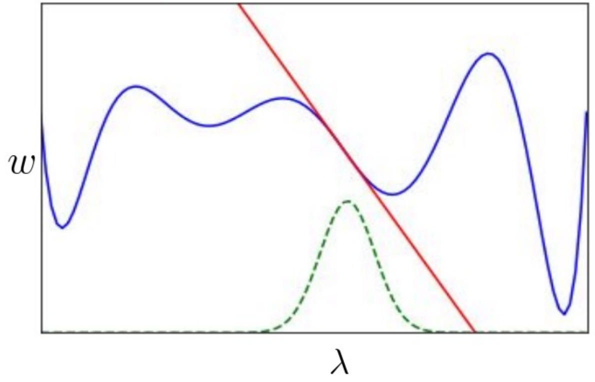

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Representation and Memory

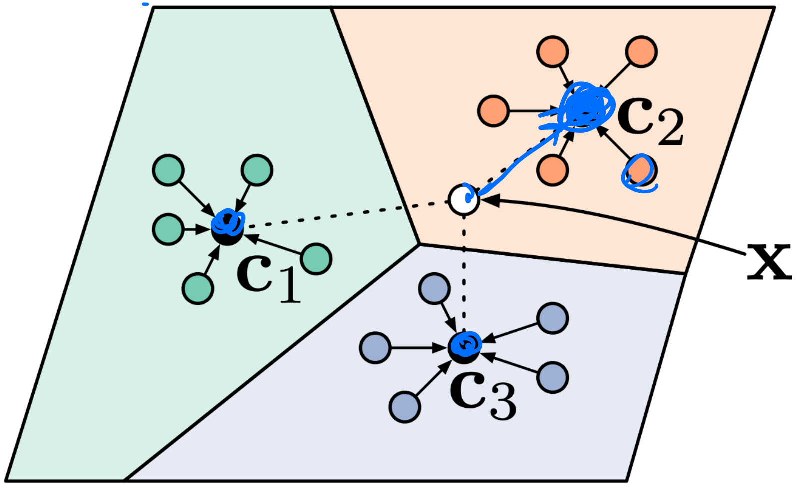
- Prototypical Network: Few-shot Classification

Snell et al. Prototypical Networks for Few-shot Learning. NIPS 2017.
Allen et al. Infinite Mixture Prototypes for Few-Shot Learning. ICML 2019.

Representation and Memory

- Prototypical Network: Few-shot Classification
- Prototype = Avg. representation of a class

$$\mathbf{p}_k = \frac{1}{|S_k|} \sum_{(\mathbf{x},y)\in S_k} f_\phi(\mathbf{x}_i).$$



$$p(y = k \mid \mathbf{x}) = \mathrm{softmax}(-d(f_\phi(\mathbf{x}), \mathbf{p}_k)).$$

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Representation and Memory

- Prototypical Network: Few-shot Classification
- Prototype = Avg. representation of a class
- 1 example = exemplar-based. Can be in between.

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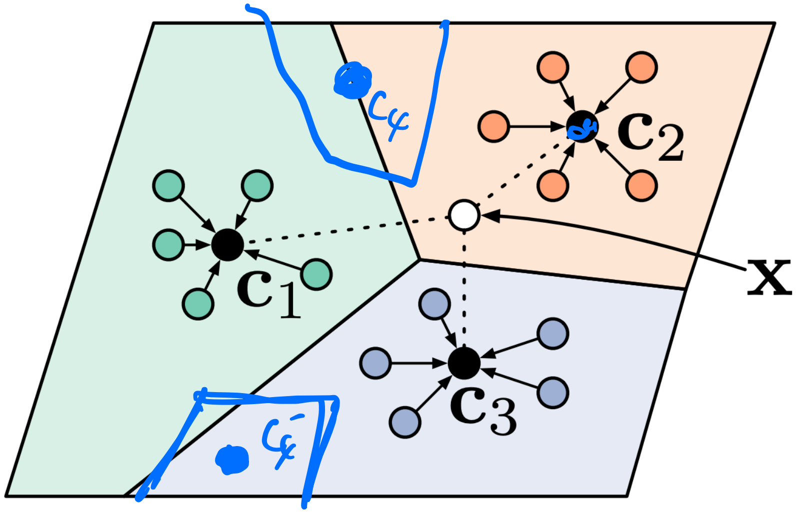

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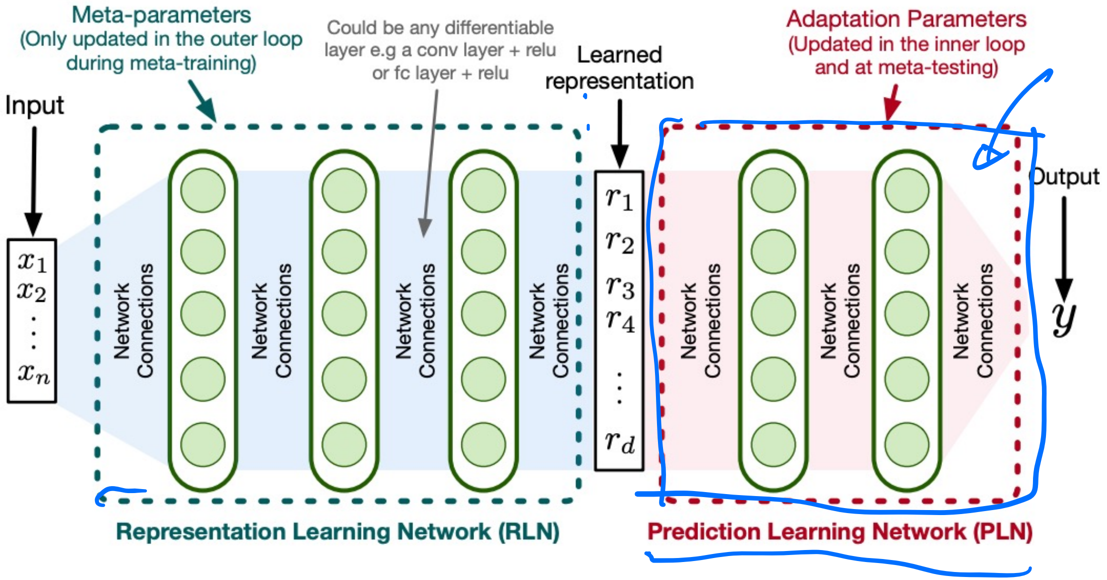
Representation and Memory

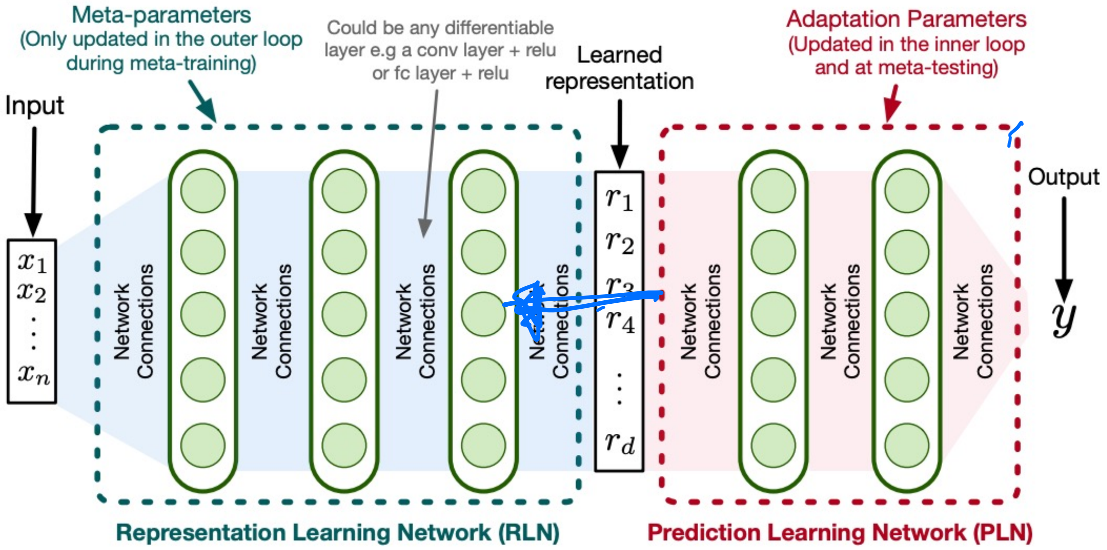
- Representation vs. Memory Layers



Javed & White. Meta-Learning Representations for Continual Learning. NeurIPS 2019.

Representation and Memory

- Representation vs. Memory Layers
- Learning to continually learn



Algorithm 2: Meta-Training : OML

Require: $p(\mathcal{T})$: distribution over CLP problems
Require: α, β: step size hyperparameters

randomly initialize θ
while not done **do**
  randomly initialize W
  Sample CLP problem $\mathcal{T}_i \sim p(\mathcal{T})$
  Sample $\mathcal{S}_{train}$ from $p(\mathcal{S}_k|\mathcal{T}_i)$
  $W_0 = W$
  for $j = 1, 2, \ldots, k$ **do**
    $(X_j, Y_j) = \mathcal{S}_{train}[j]$
    $W_j = W_{j-1} - \alpha \nabla_{W_{j-1}} \ell_i(f_{\theta, W_{j-1}}(X_j), Y_j)$
  end for
  Sample S_{test} from $p(\mathcal{S}_k|\mathcal{T}_i)$
  Update $\theta \leftarrow \theta - \beta \nabla_\theta \ell_i(f_{\theta, W_k}(S_{test}[:, 0]), S_{test}[:, 1])$
end while

Javed & White. Meta-Learning Representations for Continual Learning. NeurIPS 2019.

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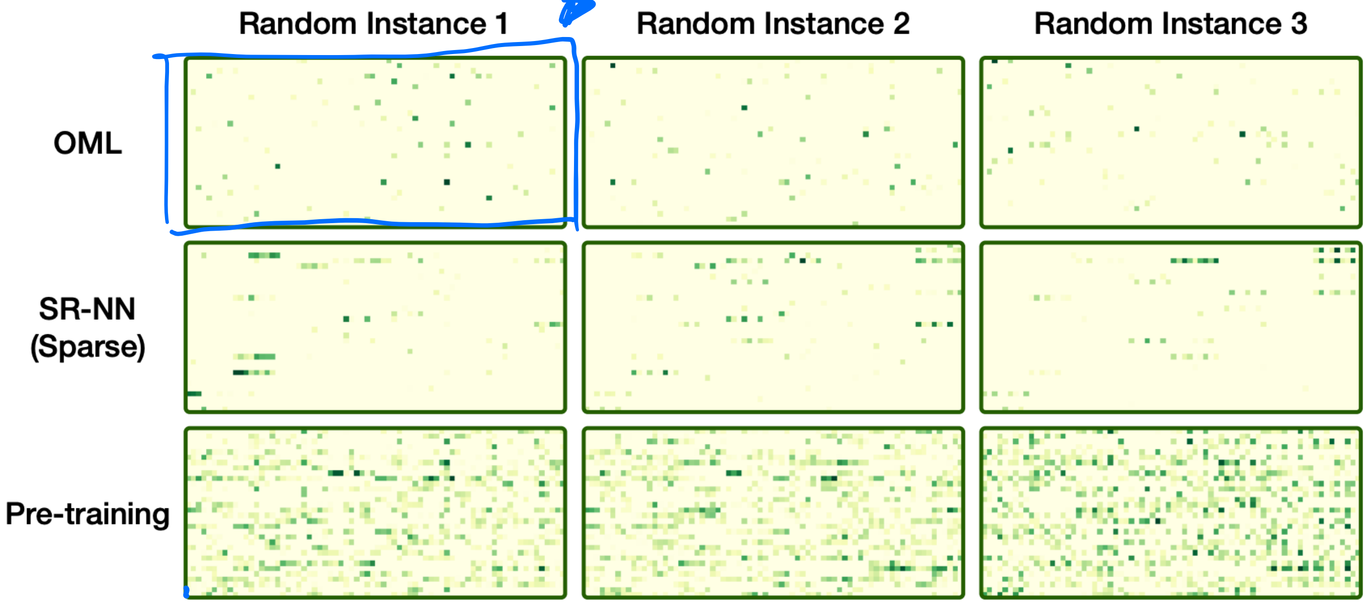
Representation and Memory

- Meta-learning leads to sparse representation suitable for continual learning.



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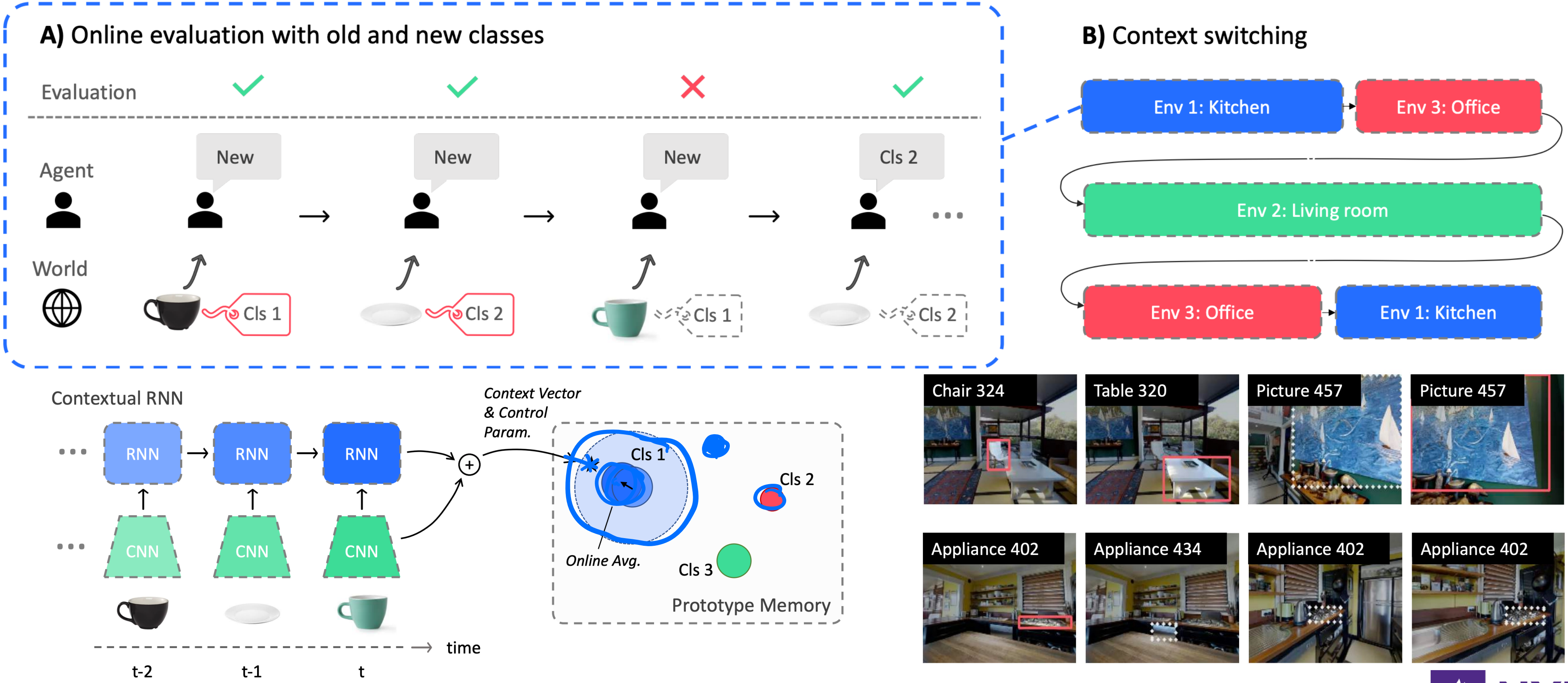
Online Continual Few-Shot Learning



Ren et al. Wandering Within a World: Online Contextualized Few-Shot Learning. ICLR 2021.

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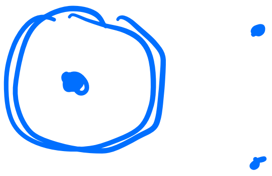
- Learning contextual representations (for context shifts).
- Learning to output unknowns.



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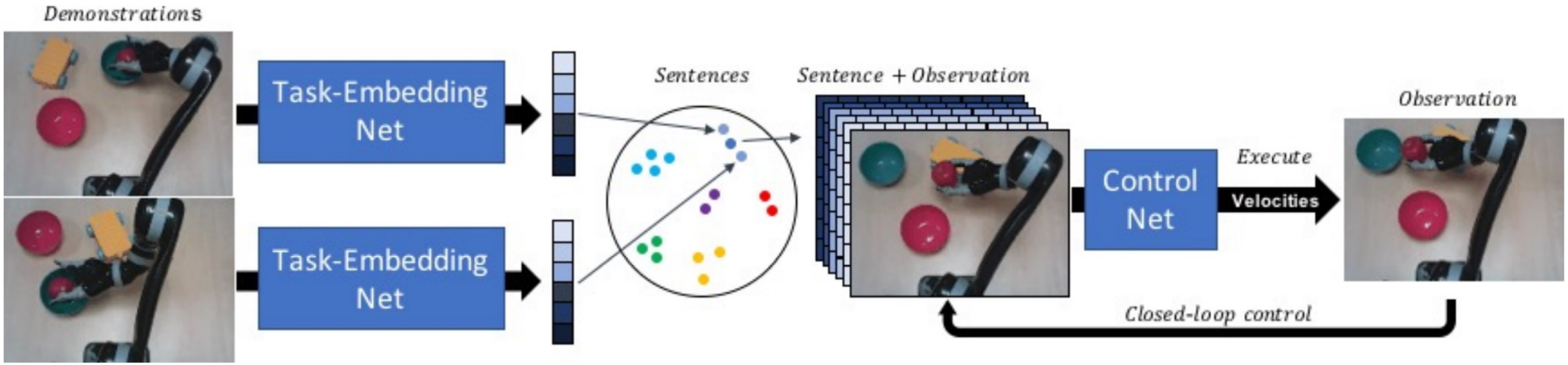
Few-Shot Imitation Learning

- The idea of prototype learning can also be applied to skill learning.



Finn et al. One-Shot Visual Imitation Learning via Meta-Learning. CoRL 2017.
James et al. Task-Embedded Control Networks for Few-Shot Imitation Learning. CoRL 2018.

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Few-Shot Imitation Learning

- The idea of prototype learning can also be applied to skill learning.
- Embedding learning:

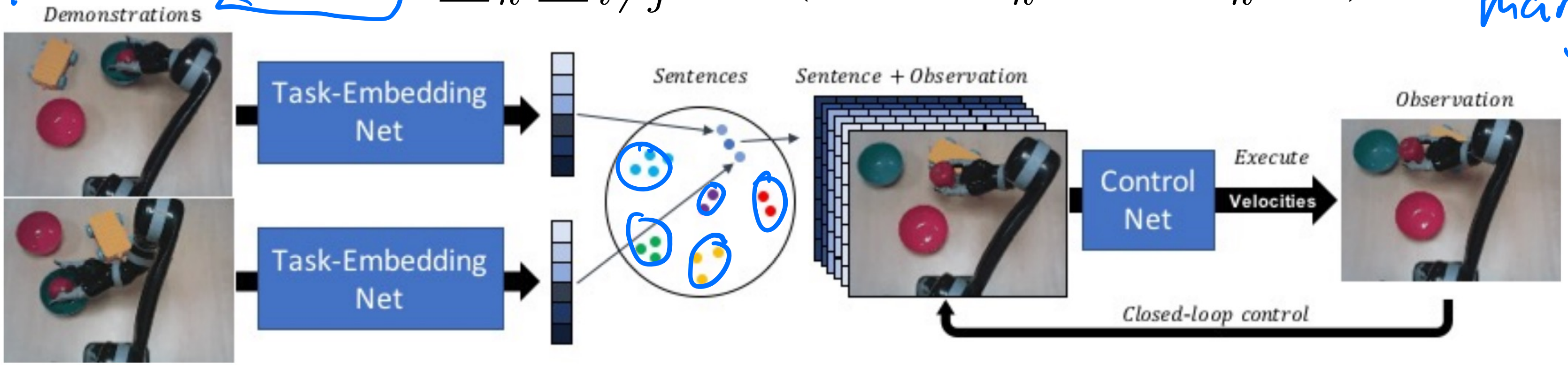
traj.

$$s^j = \frac{1}{K}\sum_{\tau_k^j \in \mathcal{T}^j} \boxed{f_\theta(\tau_k^j)}. \qquad \tilde{s}^j = s^j / \|s^j\|.$$

prototype.

$$\boxed{\mathcal{L}_{emb}} = \sum_k \sum_{i \neq j} \max(0, \Delta - \tilde{s}_k^j \cdot \tilde{s}^j + \tilde{s}_k^j \cdot \tilde{s}^i).$$

max-margin



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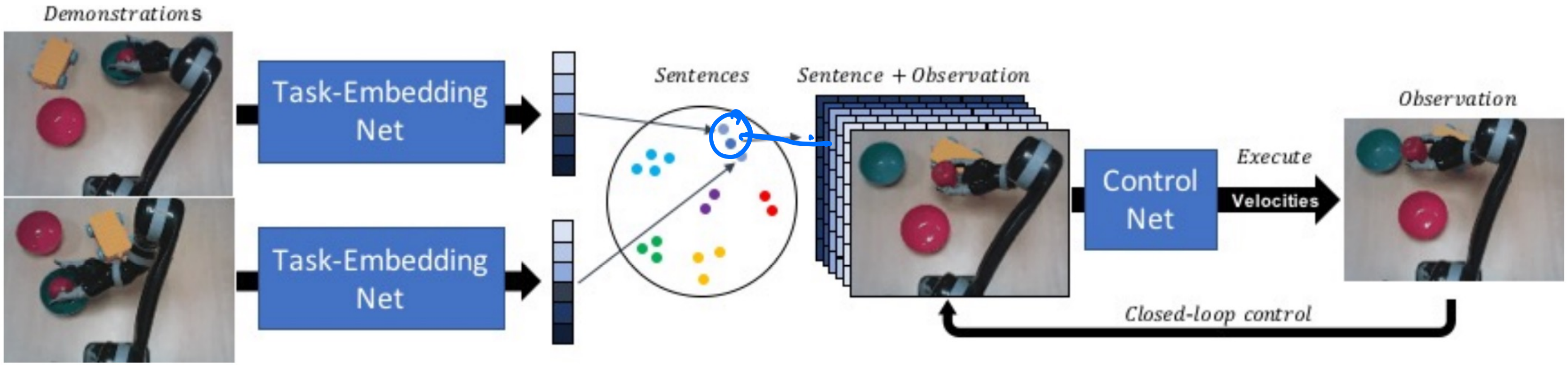
Few-Shot Imitation Learning

- Control learning:

$$\mathcal{L}_{ctr} = \sum_j \sum_{(o,a)\in\tau^j} \|\underbrace{\pi(o, s^j)}_{\text{Output}} - \underbrace{a}_{\text{action.}}\|_2^2$$



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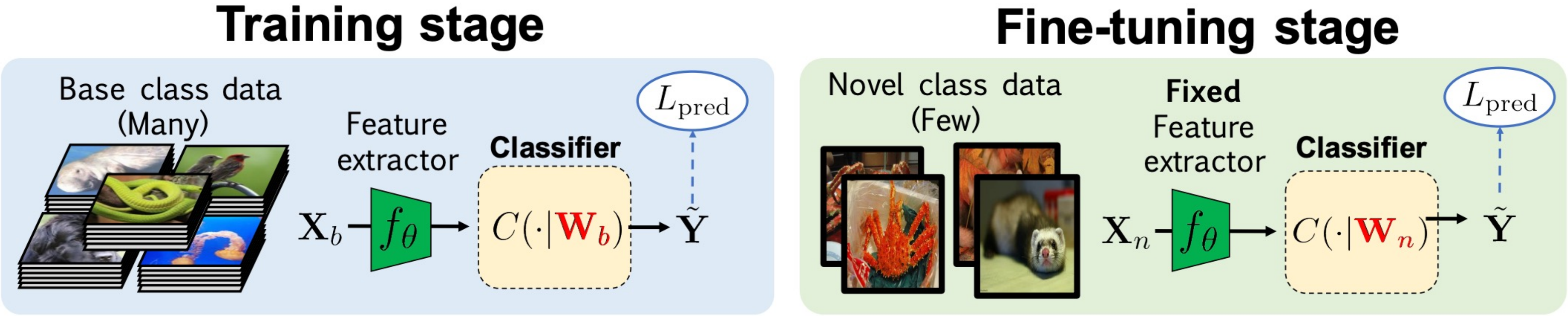
Leveraging Pretrained Representations

- Need a strong pretrained network.



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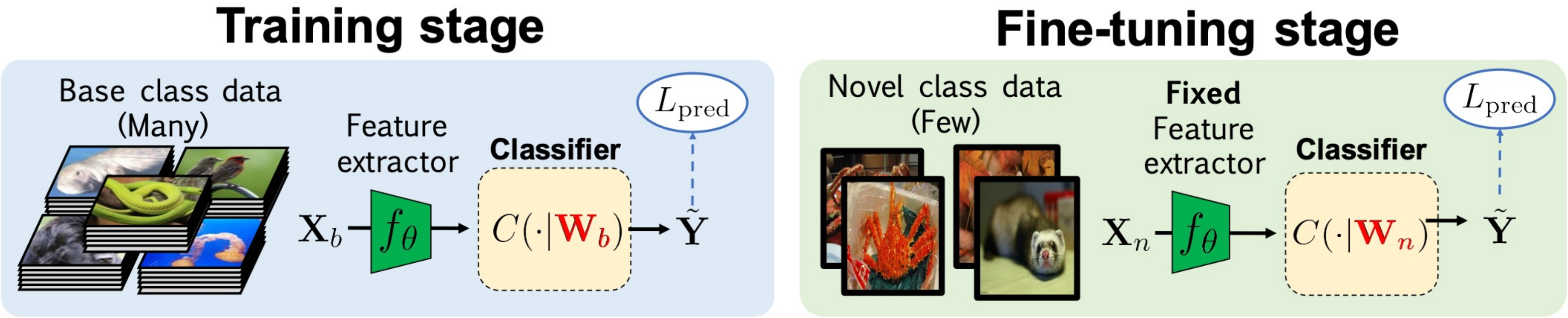

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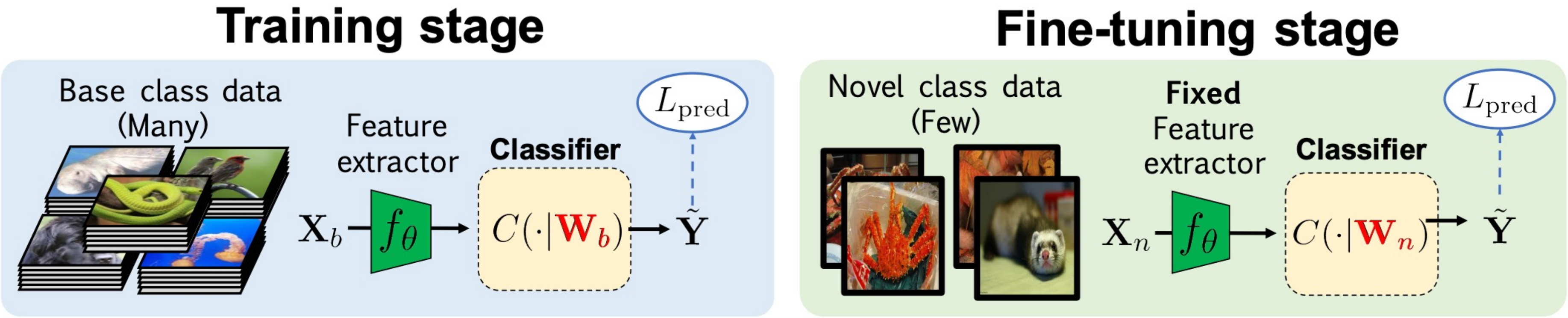
Leveraging Pretrained Representations

- Need a strong pretrained network.
- Works well for few-shot classification.
- Once again proves that representation is crucial.



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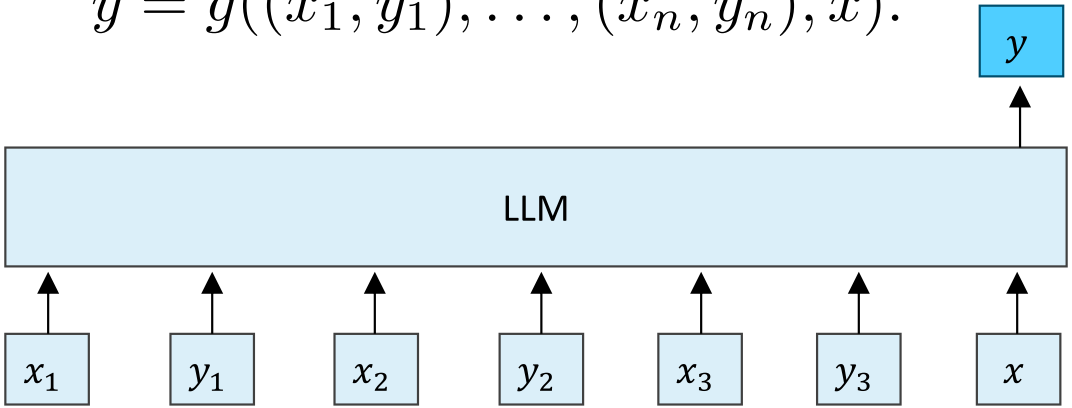
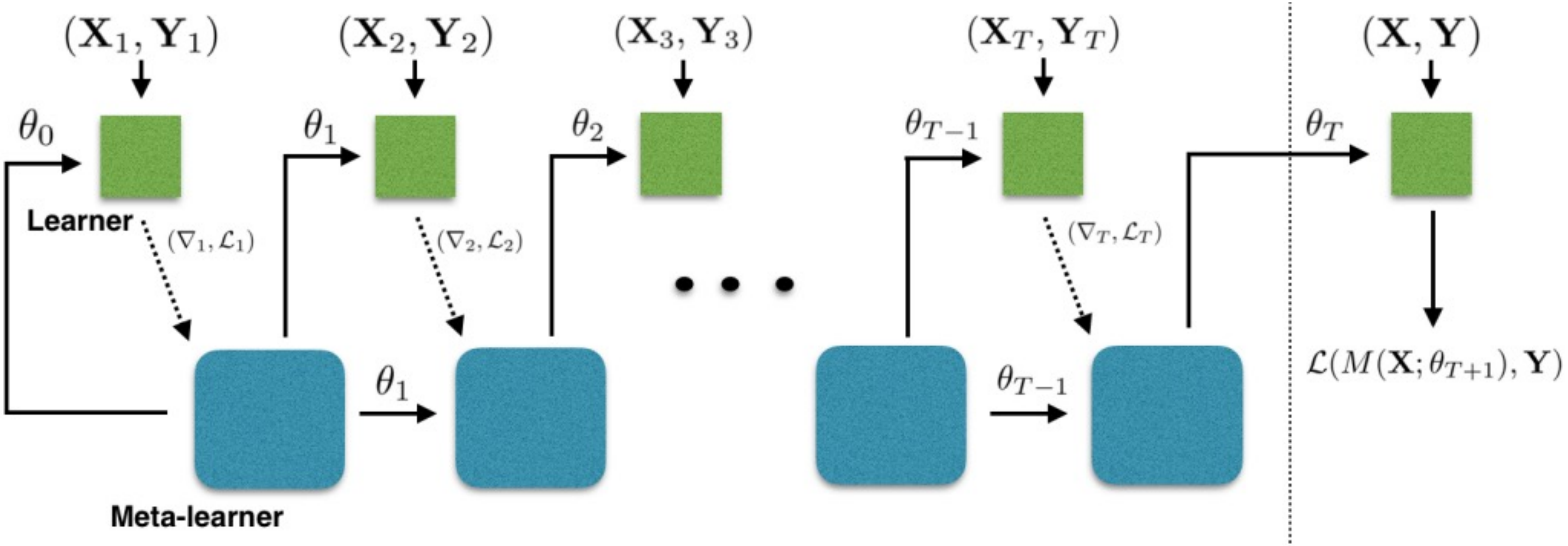
- Traditionally, learning through parameters θ.
- ICL does not optimize any parameters, just put the training data in the context.
- Inner optimization loop done in a sequence model (RNN, Transformer, etc.)

$$y = g((x_1, y_1), \ldots, (x_n, y_n), x).$$



Meta-Learning LSTM

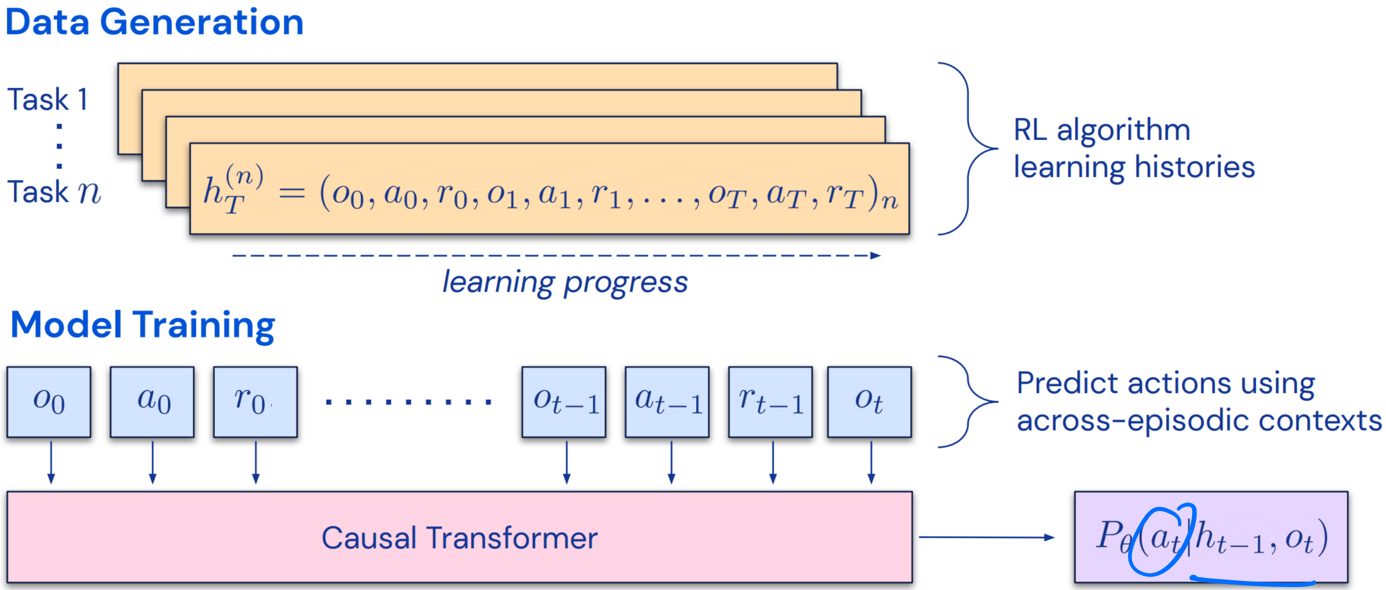
- An earlier sequential meta-learning paradigm before ICL.
- Using hidden states as "parameters"



Ravi & Larochelle. Optimization as a Model for Few-Shot Learning. ICLR 2017.

In-Context RL

- Use sequences of Obervation (o_t), Action (a_t) and Reward (r_t) generated by standard RL algorithms.



Laskin et al. In-context Reinforcement Learning with Algorithm Distillation ICLR 2023.

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Test-Time Tuning/Adaptation

- Context Retrieval, e.g. nearest neighbors
- Finetuning on examples
  - Full finetuning
  - Low-rank adaptation
  - Prompt tuning
- Self-supervision objectives

Summary: Towards Embodied Learning Agents

- A modularized but differentiable end-to-end architecture
  - Perception
  - Prediction
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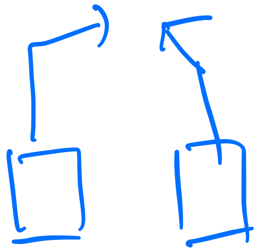

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  - Optimization / fixed point iteration
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  - Learning inductive biases, learning to learn

Topic Presentations

	Component 1	Component 2
Week 7 (Mar 6)	Continual Learning, Few-shot Learning (1 hr)	**Deep Learning for Structured Prediction** Tanishq Sardana, Qing Mu, Owais Shuja
Week 8 (Mar 13)	Guest Lecture – Prof. Wei-Chiu Ma (1 hr)	**3D Vision and Mapping** Sihang Li, Kanishkha Jaisankar, Denis Mbey Akola, Zijin Hu
Week 9 (Mar 20)	**SSL and Object Discovery** Anurup Naskar, Dahye Kim, Sal Yeung, Surbhi (1.5 hr)	**World Model 1** Sidhartha Reddy Potu, Andrew Deur
Week 11 (Apr 3)	**World Model 2** Pratyaksh Prabhav Rao, Sergey Sedov, Rooholla Khorrambakht	**End-to-End Planning** Raman Kumar Jha, Jovita Gandhi, Sushma Mareddy, Mrunal Sarvaiya
Week 12 (Apr 10)	**Continual Learning** Akshay Raman, Amey Joshi, Zifan Zhao	**Few-Shot Learning** Ellen Su, Xu Zhang, Swarali Borde
Week 13 (Apr 17)	Guest Lecture – Dr. Andrei Barsan (1hr)	**LLM Agents** Solim LeGris, Ravan Budda, Dan Zhao, Sunidhi Tandel

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Project Presentations

Week 14 (Apr 24)	Project Presentations (7 teams)
Week 15 (May 1)	Project Presentations (7 teams)

- Apr 10: Sign up for a presentation slot. Week 14 Presenters get 2% bonus. First come first serve.
- Project topics and proposals to be shared in the class.

Today

- Tanishq Sardana: Segment Anything
- Qing Mu: DETR: End-to-End Object Detection
- Owais Saad Shuja: Latent Diffusion Models
- Discussion