Architecture-Based Approaches in Continual Learning

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Introduction

Problem Definition

Continual Learning (CL): learning a sequence of tasks $t = 1, \cdots, N$ in order, with datasets $D^t = \{x^t, y^t\}$

Task-Incremental Learning (TIL): continual learning scenario, aim to train a model that performs well on all learned tasks

$$\max_f \sum_{t=1}^{N} \text{metric}(f(x^t), y^t), \{x^t, y^t\} \in D^t$$

Key assumptions when training and testing task t:

- No access to the whole data from previous tasks $1, \cdots, t-1$
- Testing on all seen tasks $1, \cdots, t$
- For TIL testing, task ID t of each test sample is known by the model. Otherwise, it is **task-agnostic testing**

Existing Approaches for TIL

Replay-based Approaches

- Prevent forgetting by storing parts of the data from previous tasks
- Replay algorithms use them to consolidate previous knowledge
- E.g. iCaRL, GEM, DER, DGR ...

Regularization-based Approaches

- Add regularization terms constructed using information about previous tasks to the loss function when training new tasks
- E.g. LwF, EWC, SI, IMM, VCL, ...

Architecture-based Approaches (what we are talking about)

- Dedicate network parameters in different parts of the network to different tasks
- Keep the parameters for previous tasks from being significantly changed
- E.g. Progressive Networks, PackNet, DEN, Piggyback, HAT, CPG, UCL, ...

Existing Approaches for TIL

Optimization-based Approaches

- Explicitly design and manipulate the optimization step
- For example, project the gradient not to interfere previous tasks
- E.g. GEM, A-GEM, OWM, OGD, GPM, RGO, TAG, ...

Representation-based Approaches

- Use special architecture or training procedure to create powerful representations
- Inspired from self-supervised learning, large-scale pre-training like LLMs
- E.g. Co2L, DualNet, prompt-based approaches (L2P, CODAPrompt, ...), CPT (continual pre-training)...

Architecture-based Approaches

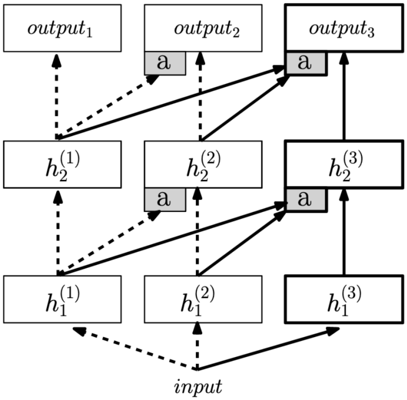
Architecture-based Approaches

- Leverages the separability characteristic of the neural network architecture
- Treat the network as decomposable resources for tasks, rather than as a whole
- Dedicate different parts of a neural network to different tasks to minimize the inter-task interference
- Focus on reducing representational overlap between tasks

The "part" of a network can be regarded in various ways:

- **Modular Networks**: play around network modules like layers, blocks
- **Parameter Allocation**: allocate group of parameters or neurons to task as a subnet
- **Model Decomposition**: decompose network from various aspects into shared and task-specific components

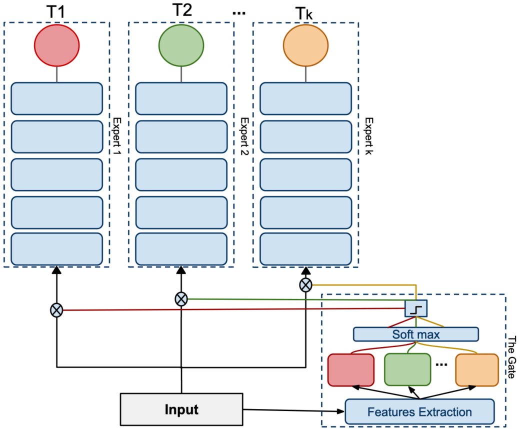
Modular Networks: Progessive Networks



Progressive Networks, 2016

- Expand the network with new column module for each new task
- Linearly increasing model memory
- Similar to independent training: train a independent network for each task

Modular Networks: Progessive Networks



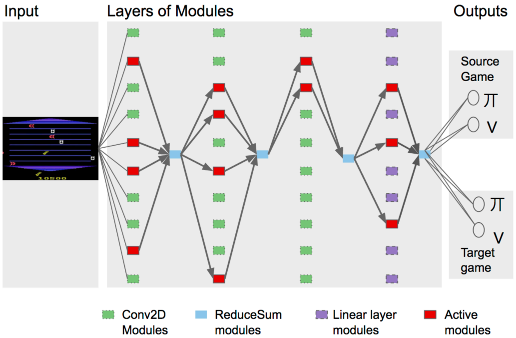
Expert Gate, 2017

- A new independent expert (network) for each new task
- Similar to independent training but work in task-agnostic testing
- A gate works as the task ID selector at test time
- The gate is a network learned through the task sequence

Modular Networks: PathNet

PathNet, 2017

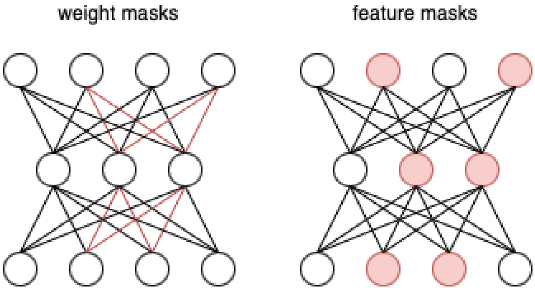
- Prepare a large pool of modules for the algorithm to select from
- Several options in each module position, concatenated and form a subnet for a task
- Choose the path by tournament genetic algorithm between different paths during the training of a task



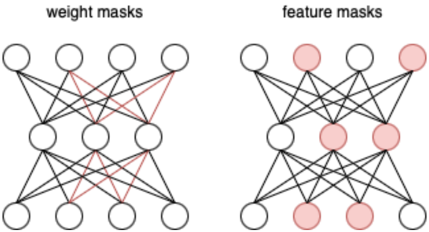
Parameter Allocation: Overview

Parameter Allocation

- Refines the level of modules to parameters or neurons
- Selects a collection of parameters or neurons to allocate to each task
- Also forms a subnet for the task



Parameter Allocation: Overview



- Weight masks are way greater than feature masks in scale
- Should keep a decent amount of neurons in each layer

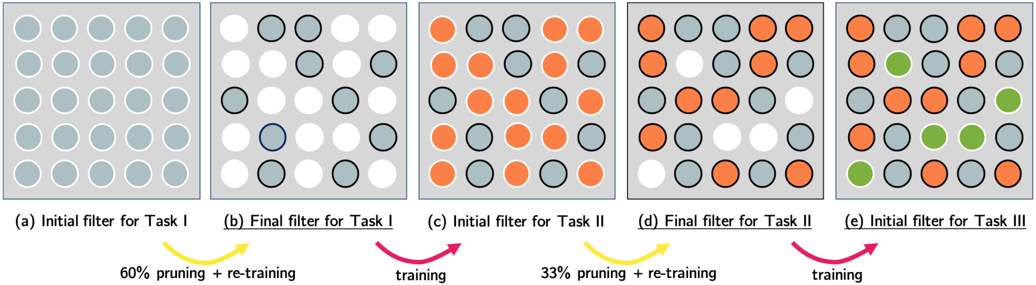
Parameter Allocation methods differ in ways:

- Methods to allocate
  - Manually set through hyperparameters
  - Learned together with the learning process
- Application of masks during training
  - Forward pass
  - Backward pass
  - Parameter update step
- Application of masks during testing
  - Most methods fix the selected subnet after trained on their belonged task and use it as the only model to predict for that task during testing

Parameter Allocation: PackNet

PackNet, 2018

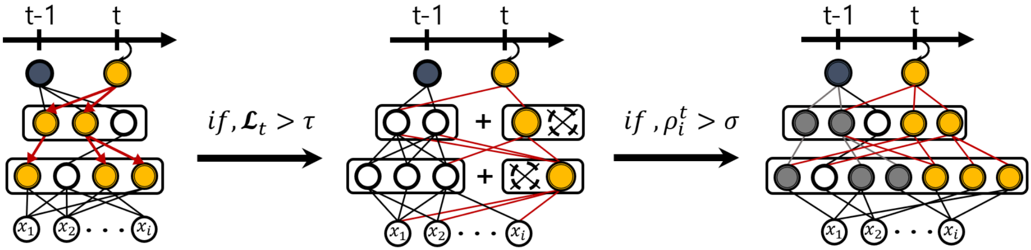
- Select non-overlapping weight masks and allocate them to tasks
- Fix masked parameters once trained until testing using the subnet
- Post-hoc selection by pruning (by absolute values of weights) after training
- Retraining after pruning as network structure changes
- Manually allocation by percentage hyperparameters



Parameter Allocation: DEN

DEN (Dynamically Expandable Networks), 2018

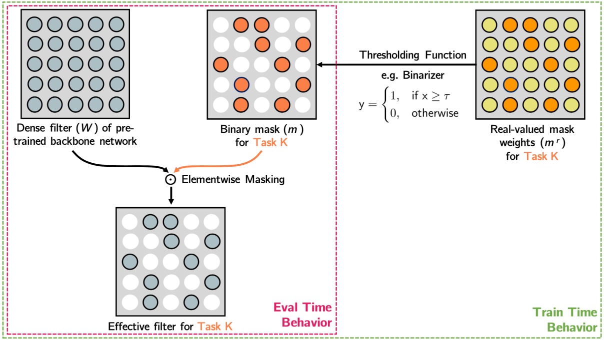
- Find the important neurons as feature masks for testing, and duplicate
- Find by training with equally L2 regularisation, whose connected parameters change a lot are important
- Dynamic network expansion when performance can't be improved, prune after
- The training selects their own important neurons by L1 regularised training, then only train them by L2 regularisation
- Manually allocation by threshold hyperparameters, slightly better than percentage



Parameter Allocation: Piggyback

Piggyback, 2018

- Learnable allocation: binary masks are gated from real values which is differentiable and can be learned together with parameters
- Still binary during test
- Sacrifices with the network parameters fixed, reduced representation ability



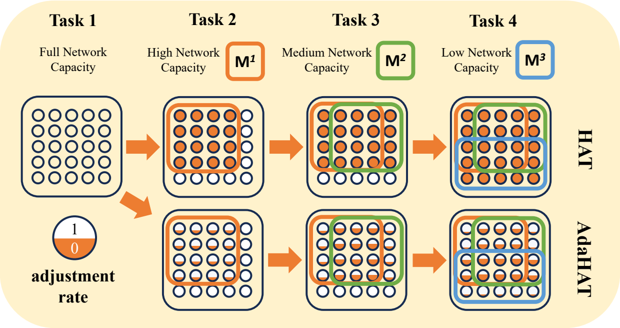
SupSup, 2020

- Extends to task-agnostic testing

Parameter Allocation: HAT

HAT (Hard Attention to the Task), 2018

- Masks and parameters are both learnable
- Fix masked parameters once trained until testing using the subnet
- Sparsity regularization for masks



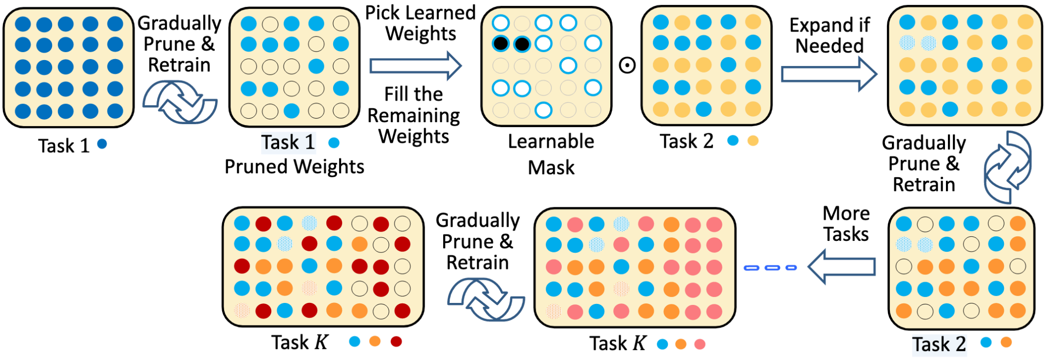
AdaHAT, 2024 (my work)

- Allow minor adaptive adjustment to masked parameters

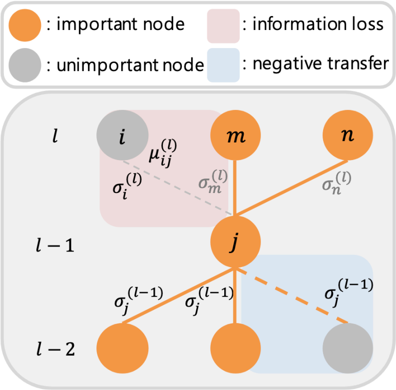
Parameter Allocation: CPG

CPG (Compacting, Picking and Growing), 2019

- Post-hoc pruning and retraining + network expanding + learnable masks (on previous weights)



Parameter Allocation: UCL



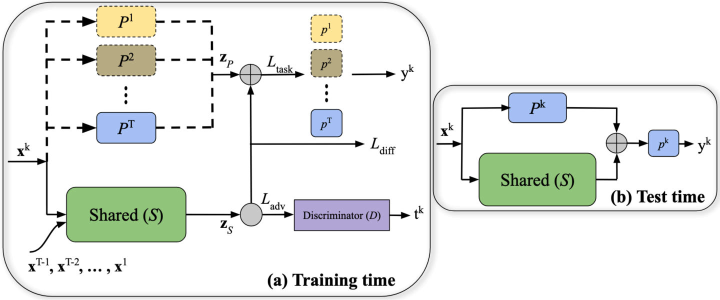
UCL (Uncertainty-based Continual Learning), 2019

- Identify the important neurons by uncertainty measure derived from Bayesian learning theory
- Apply different regularisation to the weights by neuron importance
- the important neurons only work in training
- The identification of important neurons is soft controlled by coefficient hyperparameters (σ_{init}) in the regularisation terms
- More like a regularisation-based but incorporate architecture-based ideas

Model Decomposition: ACL

ACL (Adversarial Continual Learning), 2020

- Shared and task-specific, modules, features
- Shared module is adversarially trained with the discriminator to generate task-invariant features. The discriminator predicts task labels



Model Decomposition: APD

APD (Additive Parameter Decomposition), 2020

- Decomposes the parameter matrix of a layer mathematically:

$$\theta_t = \sigma \odot \mathcal{M}_t + \tau_t, \mathcal{M}_t = \mathsf{Sigmoid}(\mathbf{v}_t)$$

- Apply different regularisation strategies to shared σ and task-specific $\tau_t, \mathbf{v}_t$

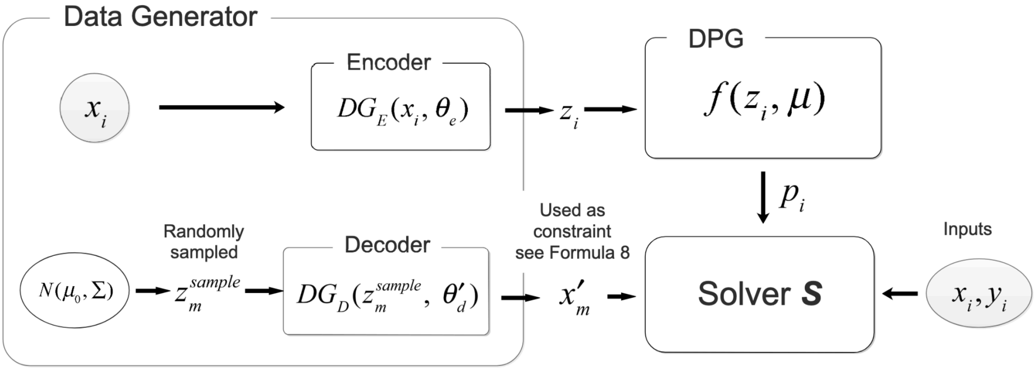
$$\min_{\sigma, \tau_t, \mathbf{v}_t} \mathcal{L}\left(\{\sigma \otimes \mathcal{M}_t + \tau_t\}; \mathcal{D}_t\right) + \lambda_1 \left\|\tau_t\right\|_1 + \lambda_2 \left\|\sigma - \sigma^{(t-1)}\right\|_2^2$$

1. Shared parameters σ not deviate far from the previous
2. The capacity of task-specific τ_t to be as small as possible, by making it sparse

Model Decomposition: PGMA

PGMA (Parameter Generation and Model Adaptation), 2019

- Task-specific parameters p_t are generated by DPG (dynamic parameter generator)
- Shared parameters θ_0 (in solver S) adapt itself to task t with the generated task-specific p_t



Challenges

Challenge: Network Capacity and Plasticity

Network Capacity Problem

- Any fixed model will eventually get full and lead to the performance drop, given the potentially infinite task sequence
- Become explicit in architecture-based approaches
- Can be solved by taking shortcuts to expand the networks, but it is not fair

Stability-Plasticity Trade-Off

- Continual learning seeks to trade off the balance between stability and plasticity
- Approaches that fix part of model for previous tasks are lack of plasticity by stressing too much stability
- Others whichever has task shared components still face the classic catastrophic forgetting problem, which is a result of lack of stability
- They both lead to a bad average performance

Thank You

Thank you for your attention!

Please feel free to ask any questions.

Check out the post in my blog for complete narratives of this pre!

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