Learning with Non-Stationary Streaming Data: A Beginner's Guide to Continual Learning

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Continual Learning and Related Concepts

The Scope

Machine Learning Paradigms

- How the data distribute and the way that they are allowed to be used
- How the model is evaluated
- Without looking into what types of data are
- E.g., supervised / unsupervised learning, reinforcement learning, transfer learning

Scenario

- The real-world applications
- E.g., image classification, object detection, machine translation

Continual Learning (CL)

- A.k.a. **Lifelong Learning**, **Incremental Learning**, **Sequential Learning**
- A machine learning paradigm involving multiple tasks

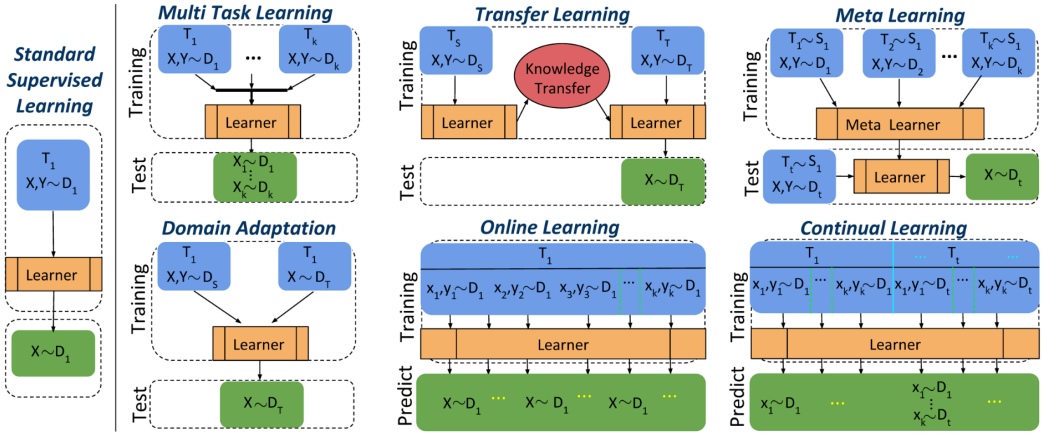
Definition of Continual Learning

> ***Continual learning*** *is a machine learning paradigm where an algorithm receives the data from tasks sequentially without the access to previous ones to learn a model that performs the best for all tasks.*

Key Features:

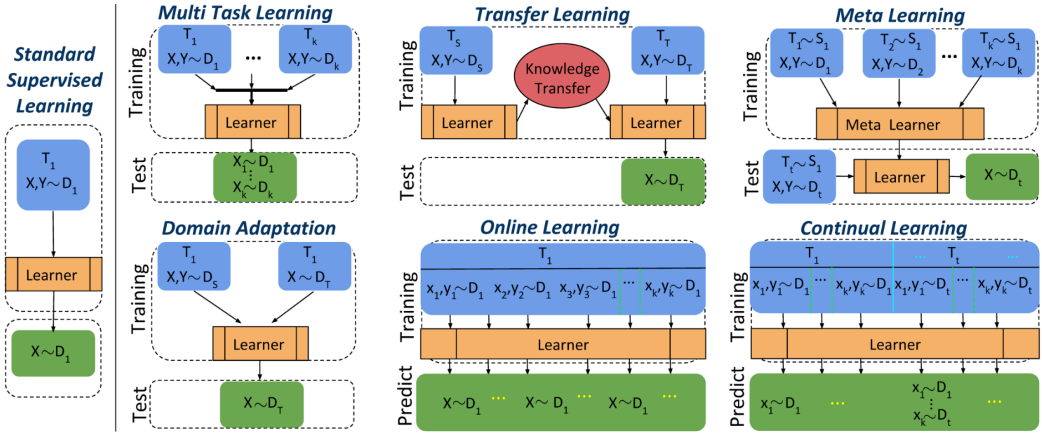
- Sequential tasks
  - Non-stationary data: tasks from different distributions *(difficult!)*
- Test for all tasks *(difficult!)*
- No access to previous task's data
  - Practical considerations: huge memory cost / potential violence to privacy
  - It's not joint training. Problems: computation cost, induction bias
- Infinite sequence of tasks
  - Never know the future challenges

Differences From Other Paradigms



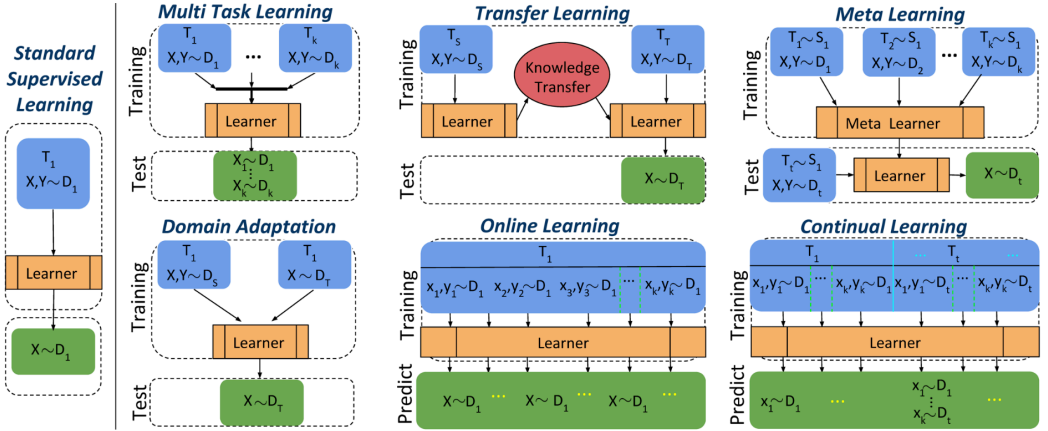
- **Standard Supervised Learning**: continual learning with one task

Differences From Other Paradigms



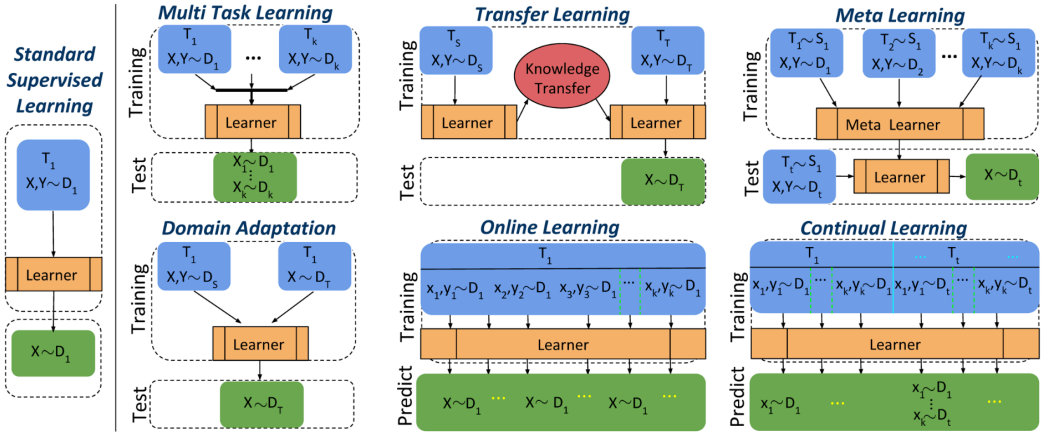
- **Multi-Task Learning**: tasks sequentially $\rightarrow$ at the same time

Differences From Other Paradigms



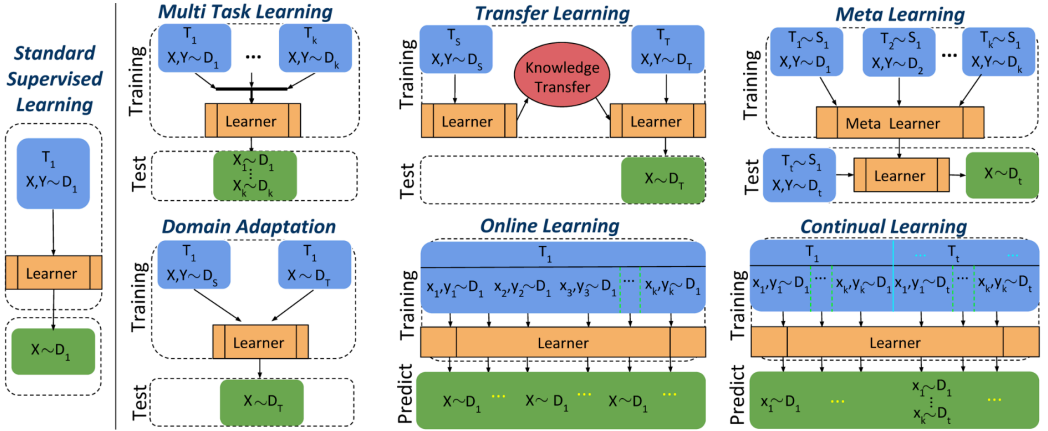
- **Transfer Learning** / **Domain Adaptation**: 2 tasks, test for all tasks → for the second task

Differences From Other Paradigms



- **Online Learning**: single-task paradigm, data are from same distribution

Differences From Other Paradigms



- **Meta Learning**: test for all tasks $\rightarrow$ for unseen new tasks, learn to learn with meta learner

Why Continual?

One of the most important feature in human learning is to learn and adapt new knowledge continuously without forgetting previous knowledge.

$$\Downarrow$$

Standard deep learning process (*No!*)

$$\Downarrow$$

Continual Learning is born for it (*Yes!*)

Fit in any real world application s facing a continuous stream of non-stationary data when it's a bad idea to retrain from scratch.

Potential Applications

Continual learning is still in its early age without so many examples of applications due to its difficulty, but it is a highly potential solution to any real-world applications.

- In Robotics
  - Robotic agents are naturally playground for continual learning because of they interact with real world, and some might say CL is born for robotics
  - Various scenarios like object detection, segmentation, reinforcement learning which face the non-stationary data challenges.
- In Autonomous Driving
  - The environment and driving conditions are constantly changing, like weather, traffic, objects
- In Finance
  - For example, anomaly detection in auditing: a company might face different patterns of frauds in their financial quarters or years.
  - Other applications: algorithm trading, portfolio selection, financial forecasting, credit scoring.
- In CV, NLP, recommendation systems, health care, etc.

Continual Learning Classification and Formal Definitions

Formal Definition of Continual Learning Classification

In **continual learning classification problem**, we have:

- Tasks: $t = 1, 2, \cdots$
- Training data of tasks: $\mathcal{D}_{\text{train}}^{(t)} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N_t} \in (\mathcal{X}^{(t)}, \mathcal{Y}^{(t)})$
- Testing data of tasks as well: $\mathcal{D}_{\text{test}}^{(t)} \in (\mathcal{X}^{(t)}, \mathcal{Y}^{(t)})$

We aim to develop an algorithm which trains the model $f^{(t-1)}$ to $f^{(t)}$ at the time for task t:

- With access to $\mathcal{D}_{\text{train}}^{(t)}$ only
- To perform well on all seen tasks $\mathcal{D}_{\text{test}}^{(1)}, \cdots, \mathcal{D}_{\text{test}}^{(t)}$

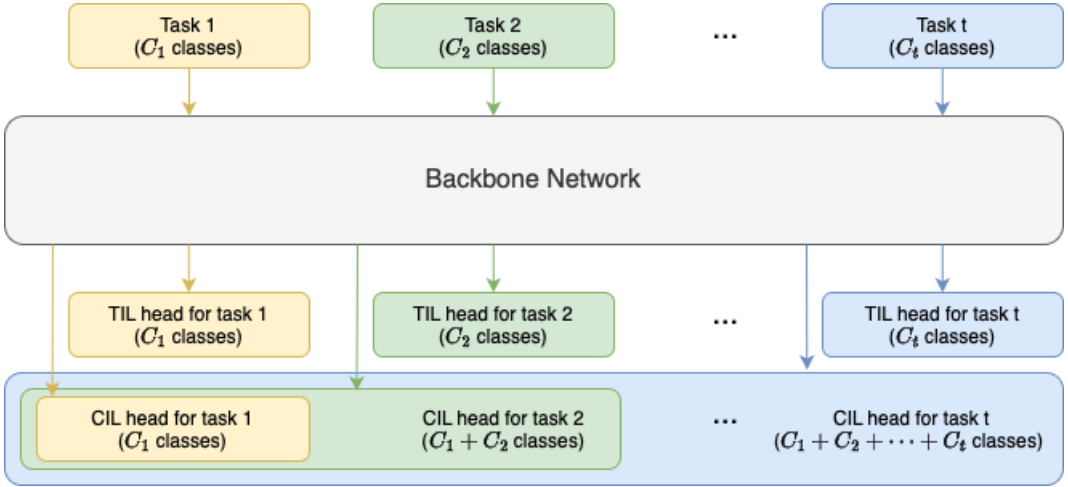
The Multi-head Classifier

CL Model = Backbone Network + Multi-head Classifier

Multi-head classifier

- Output heads assigned to different tasks
- A head = simply a linear output layer outputing logits of classes
- New head is initialised and trained along with backbone as new task come in

The Multi-head Classifier



TIL vs CIL

Task-Incremental Learning (TIL)

- Known task ID during testing: $(\mathbf{x}, y, t) \in (\mathcal{X}^{(t)}, \mathcal{Y}^{(t)})$
- Output heads are segregated, without considering other tasks
- A-level analogy: separately conducted exams, students know which subject is tested on.

Class-Incremental Learning (CIL)

- Classes from all tasks to predict from: $(\mathbf{x}, y) \in (\mathcal{X}^{(1)} \cup \cdots \cup \mathcal{X}^{(t)}, \mathcal{Y}^{(1)} \cup \cdots \cup \mathcal{Y}^{(t)})$, without known task ID
- Incremental evolving output heads
- A-level analogy: one crazily huge exam including and mixing all subjects
- Much more difficult than TIL!

TIL vs CIL

More paradigms:

- **Task-agnostic testing**: TIL without known test ID. the model has to figure out the test ID by itself
- **Task-agnostic continual learning**: eliminate the task boundary

The Challenges: From Examples of the Baseline Algorithms

Logistics

- 2 naive baseline algorithms
- Evaluated on a simple 10-task CL dataset
- Analyse the results and introduce the challenges faced by CL

Before that, I give a tour around:

- Where to evaluate the algorithms: the construction of CL datasets
- How to evaluate the algorithms: the metrics that CL cares about

How to Construct CL Dataset: Permute, Split, Combine

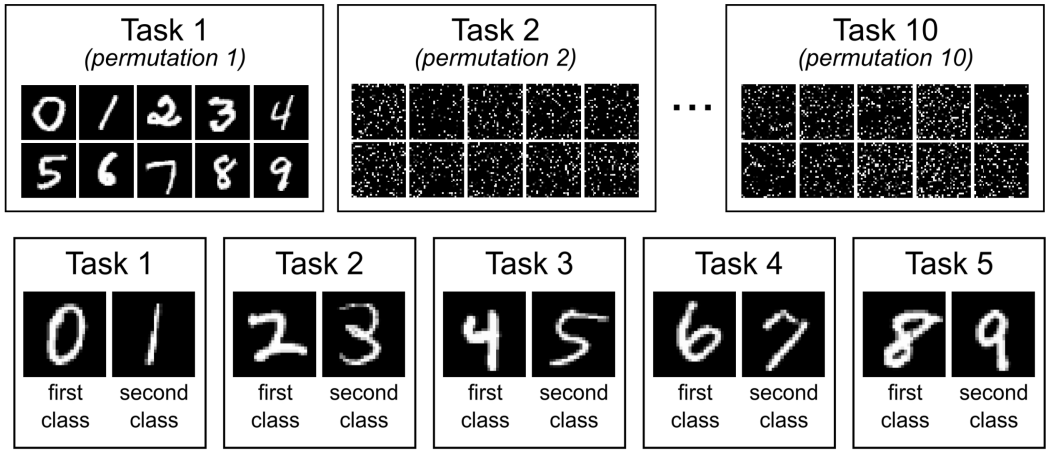
Combine

- From different sources of ML datasets, each serving as a task
- Be aware varied input dimensions
- E.g., HAT on a sequence from 8 datasets: CIFAR10, CIFAR100, FaceScrub, FashionMNIST, NotMNIST, MNIST, SVHN, and TrafficSigns.

Constructed from one dataset:

- **Permute**: permute image pixels in the original dataset under a same certain way to get for a task
- **Split**: split the original dataset by group of classess to form subsets for different tasks

How to Construct CL Dataset: Permute, Split, Combine



Metrics: What CL Cares About

The lower triangular matrix: the main result

$$\begin{matrix} a_{1,1} & & & \cdots \\ a_{2,1} & a_{2,2} & & \cdots \\ a_{3,1} & a_{3,2} & a_{3,3} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{matrix}$$

- $a_{t,\tau}$: the accuracy of $f^{(t)}$ after training task t, testing on task τ testset $\mathcal{D}_{\text{test}}^{(\tau)}$

Average Accuracy (AA)

$$\text{AA}_t = \frac{1}{t} \sum_{\tau=1}^{t} a_{t,\tau}$$

- The main performance metric to make effort to improve

Metrics: What CL Cares About

Backward Transfer (BWT)

$$\mathrm{BWT}_t = \frac{1}{t-1} \sum_{\tau=1}^{t-1} \left(a_{t,\tau} - a_{\tau,\tau} \right)$$

- Forgetting measure: summed up drop in performance on previously learned tasks
- Stability measure: how stable the model changed after training new tasks

Forward Transfer (FWT)

$$\mathrm{FWT}_t = \frac{1}{t-1} \sum_{\tau=2}^{t} \left(a_{\tau,\tau} - a_{\tau}^{I} \right)$$

- a_{τ}^{I}: the performance of reference model, trained with task τ alone
- CL could have achieved better performance as reference model without considering preventing forgetting on previous tasks
- Plasticity measure: summed up difference from reference model – the most plausible model

Finetuning and Fix: the Baselines

Two naive baselines for continual learning paradigm:

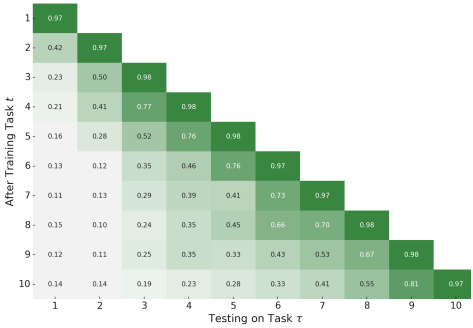
Finetuning (or SGD)

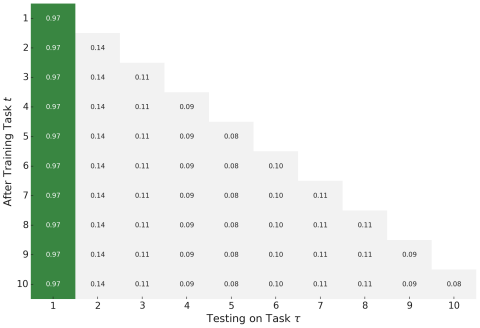
- Simply initialise from the model learned from last task
- Take no action to prevent forgetting, let it go

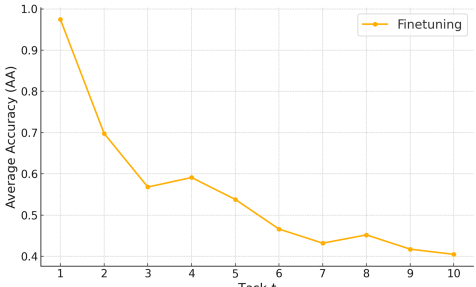
Fix

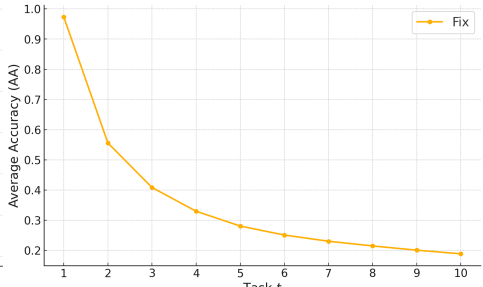
- Fix the model from being updated after training first task
- The other way around which tries to fully prevent forgetting

Finetuning and Fix: the Baselines









Challenge 1: Catastrophic Forgetting

Catastrophic Forgetting

- Previous knowledge can hardly be preserved within neural networks after convergence to a different data distribution
- Finetuning suffers the most
- The main problem that most CL alogirthms make effort to address

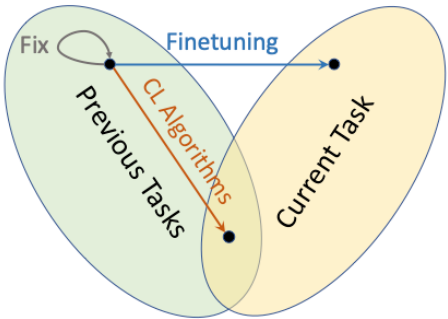
> **Tip**
>
> In CIL, forgetting is even more catastrophic because of the lack of negative examples, which shows CIL is much more difficult than TIL.

However, CL is not all about catastrophic forgetting. It is just one side of the coin.

Challenge 2: Stability-Plasticity Dilemma

The Problem of the Other Extreme

- Fully prevent forgetting = promote too much stability $\rightarrow$ completely lose plasticity
- As we can see in the extreme effort of Fix, both two extremes lead to bad average performance



Stability-Plasticity Dilemma

- The model cannot achieve both stability and plasticity at the same time
- CL algorithms have to trade-off the balance of stability-plasticity

Challenge 3: Network Capacity

Network Capacity Problem

- Any fixed model will eventually get full as infinite tasks arrive
- Cannot select a proper-sized network beforehand under the infinte task assumption

The network: *fixed* or *expanded*?

Independent Learning

- A prohibited way to do continual learning
- Fully expanded network capacity, causing linear increasing model memory cost
- Achieve the best performance as the reference models. Not fair!

The metrics taking into account model memory cost?

Classic Methodology

Replay-based Approaches

- In CL definition: no access to the previous data
- Mainly due to a data memory issue
- Still allow storing a small amount of previous data

Replay-based Approaches:

- Store a small amount of representations of previous data
- Try to mimic the previous task distribution
- Leverage them by replay mechanisms

Two steps for Replayed Data:

- Sampling:
  - Manually select by certain importance measure
  - Generated by generative model (pseudo replay)
  - Some samples features to store (feature replay)
- Utilizing:
  - Replayed data are not enough to be mixed and trained with new data
  - Mechanism like knowledge distillation, optimization constraints

Regularisation-based Approaches

- Add regularisation for preventing forgetting to loss function:

$$\min_{\theta} \mathcal{L}^{(t)}(\theta) = \mathcal{L}^{(t)}_{\text{cls}}(\theta) + \lambda R(\theta)$$

$$\mathcal{L}^{(t)}_{\text{cls}}(\theta) = \sum_{(\mathbf{x},y)\in\mathcal{D}^{(t)}_{\text{train}}} l(f(\mathbf{x};\theta), y)$$

- Regularisation parameter λ: hyperparameter, controlling the intensity of preventing forgetting, or the scale to balance stability-plasticity trade-off

Regularisation-based Approaches

Weight Regularisation

- The naive way:

$$R(\theta) = \sum_i \left(\theta_i - \theta_i^{(t-1)}\right)^2 = \|\theta - \theta^{(t-1)}\|^2$$

- With parameter importance:

$$R(\theta) = \sum_i \omega_i \left(\theta_i - \theta_i^{(t-1)}\right)^2$$

- In EWC, 2017:

$$\omega_i = F_i = \frac{1}{N_t} \sum_{(\mathbf{x},y)\in\mathcal{D}_{\text{train}}^{(t-1)}} \left[\frac{\partial l(f^{(t-1)}(\mathbf{x},\theta), y)}{\partial \theta_i}\right]^2$$

Regularisation-based Approaches

Feature Regularisation

- Implicitly regularise the parameters by constraining features
- The naive way (LwF, 2016):

$$R_{\text{LWF}}(\theta) = \sum_{(\mathbf{x},y)\in\mathcal{D}_{\text{train}}^{(t)}} l(f(\mathbf{x};\theta), f(\mathbf{x};\theta^{(t-1)}))$$

Architecture-based Approaches

Architecture-based Approaches

- A distintly different strategy that decomposes the network
- Dedicate different parts of a neural network to different tasks
- Minimize the inter-task interference
- Leverages the separability characteristic of the neural network architecture

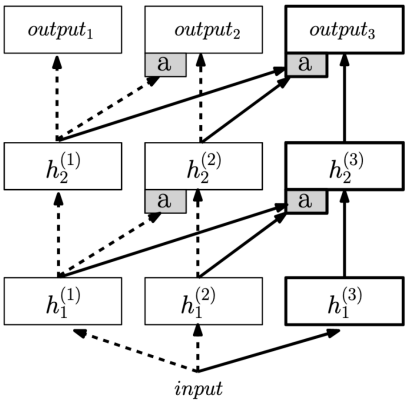
How to define “parts”:

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

Challenges:

- Network capacity becomes explicit
- Tend to fix part of model for previous tasks, stress stability, lack plasticity

Architecture-based Approaches



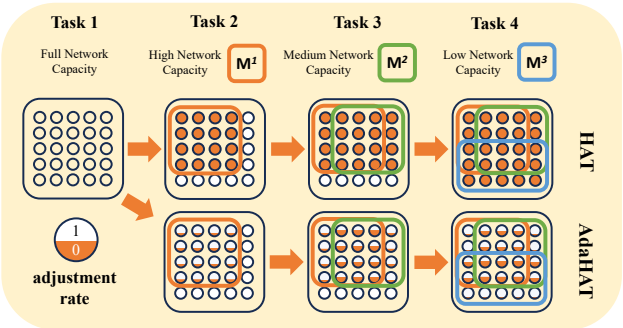
Progressive Networks, 2016

- 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

Architecture-based Approaches

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



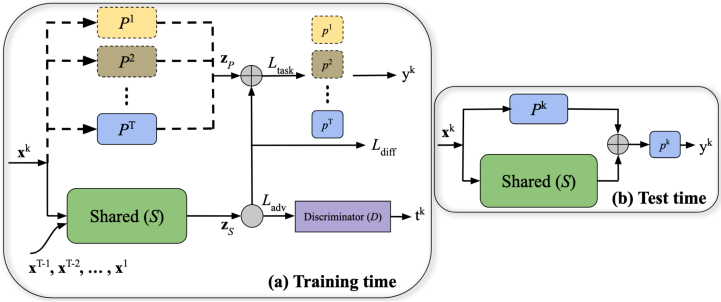
AdaHAT, 2024 (my work)

- Allow minor adaptive adjustment to masked parameters

Architecture-based Approaches

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



Optimization-based Approaches

Optimization-based Approaches

- Explicitly design and manipulate the optimization step
- Often involves direct modification of the gradients

Orthogonal gradients projection:

- Project the gradient g to the direction g' orthogonal to the previous space
- Prevent interfering previous tasks in the gradient descent level

The orthogonal projection: Gram-Schmidt formulas

$$u_1 = v_1,\ u_k = v_k - \sum_{i=1}^{k-1} \text{proj}u_i(v_k),\ \text{proj}u_i(v_k) = \frac{v_k \cdot u_i}{u_i \cdot u_i} u_i$$

New Trends in Continual Learning

Continual Learning + Self-Supervised Learning

Self-Supervised Learning (SSL)

- Can help models learn more generalized representations, essential for continual learning to prevent forgetting
- E.g. DualNet
  - Divide into fast and slow network → task-specific and shared
  - Slow network is meant for generalized representations using the SSL loss Barlow Twins

Contrastive Learning

- Contrastive loss encourages similar representations for samples considered similar, distinct representations for samples regarded as contrasting
- E.g. Co2L (Contrastive Continual Learning)
  - Contrast the new task with the previous task
  - Pushes them to become separate in the representation space to prevent forgetting

Continual Learning + Pre-trained Models

Finetuning for downstream continual learning

- Become popular along with per-trained models like Transformer, BERT
- Shared = pre-trained model, task-specific = finetuning for each task in CL

Prompt-based continual learning

- Prompt doesn't need updating parameters, solves the problem of cost to finetune
- Become popular along with larger pre-trained models like GPT
- Shared = pre-trained model, task-specific = prompts for each task in CL
- E.g. L2P (Learning to Prompt for Continual Learning)
  - Select the most relevant prompts from a pool}
  - Instance-wise query mechanism to retrieve prompt, task-agnostic}

Continual Pre-Training (CPT)

- Solve the continual learning problem of pre-training model itself

Other Trends

Extended Paradigms:

- Few-Shot Continual Learning (FSCL)
- Unsupervised Continual Learning (UCL)
- Online Continual Learning (OCL)

Thank You

Thank you for your attention!

Please feel free to ask any questions or reach out to me at:

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