Hw14
Lifelong Learning

ML TAs

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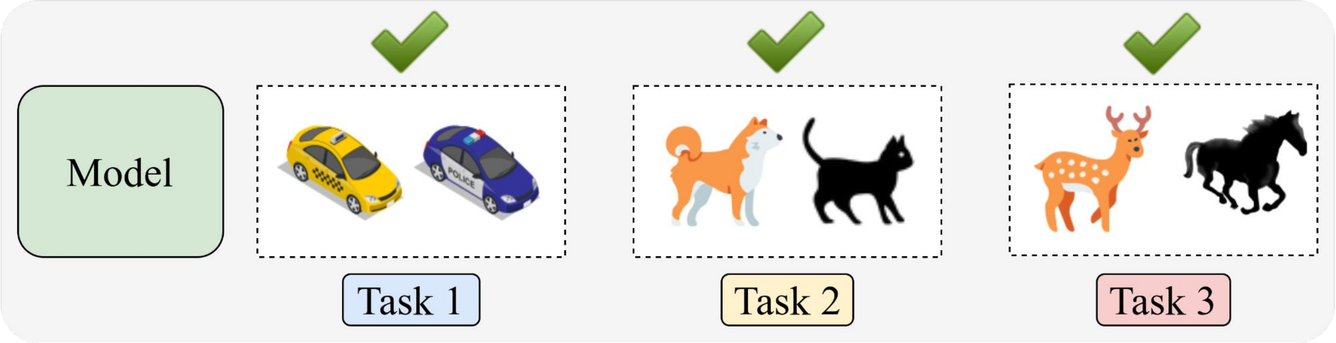
Outline

- Introduction
- Dataset
- Sample Code
- COOL Quiz
- Grading
- Submission

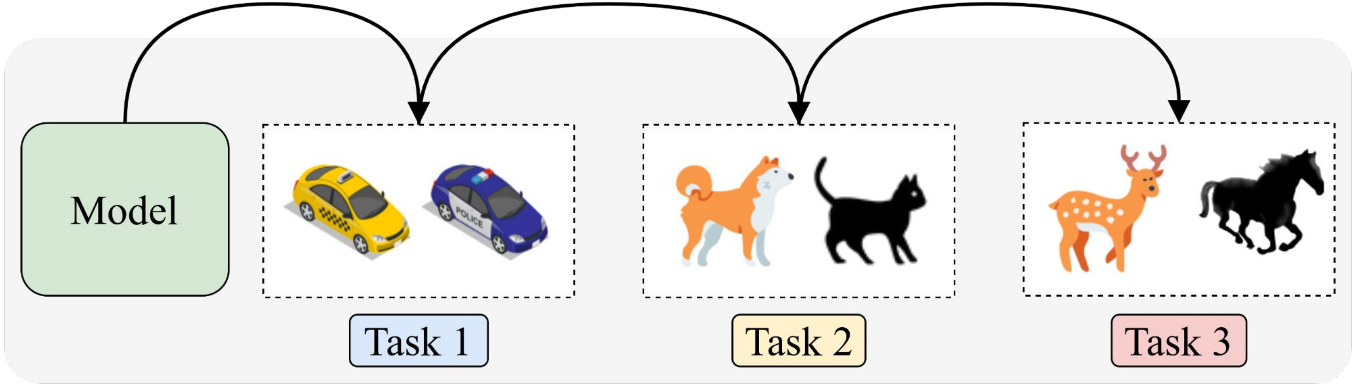
Introduction - LifeLong Learning

Goal: A model can beat all task!



Introduction - LifeLong Learning

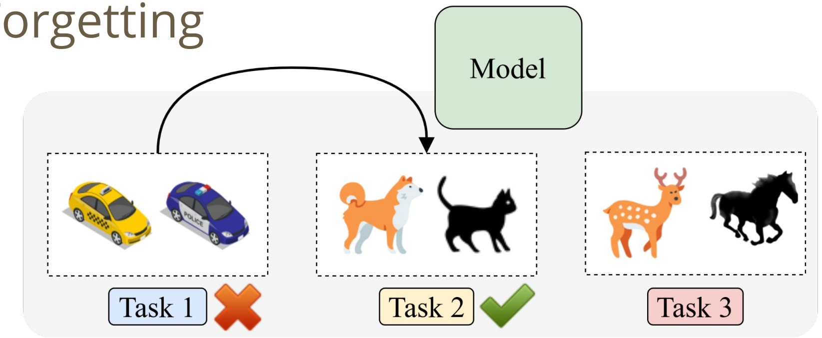
Condition: Model Sequentially Learn Different Task! (In Training Time)



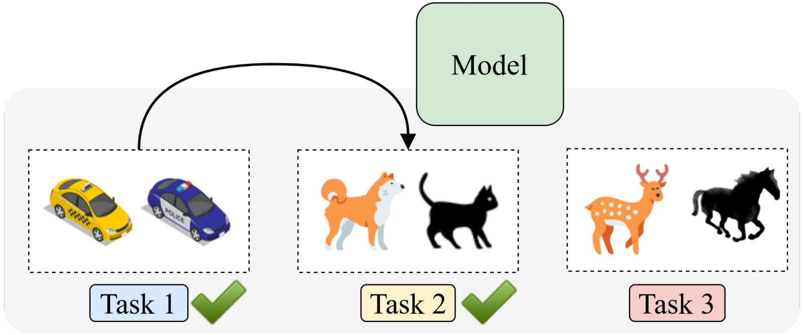
Introduction - LifeLong Learning

KeyPoint: Avoid Catastrophic Forgetting

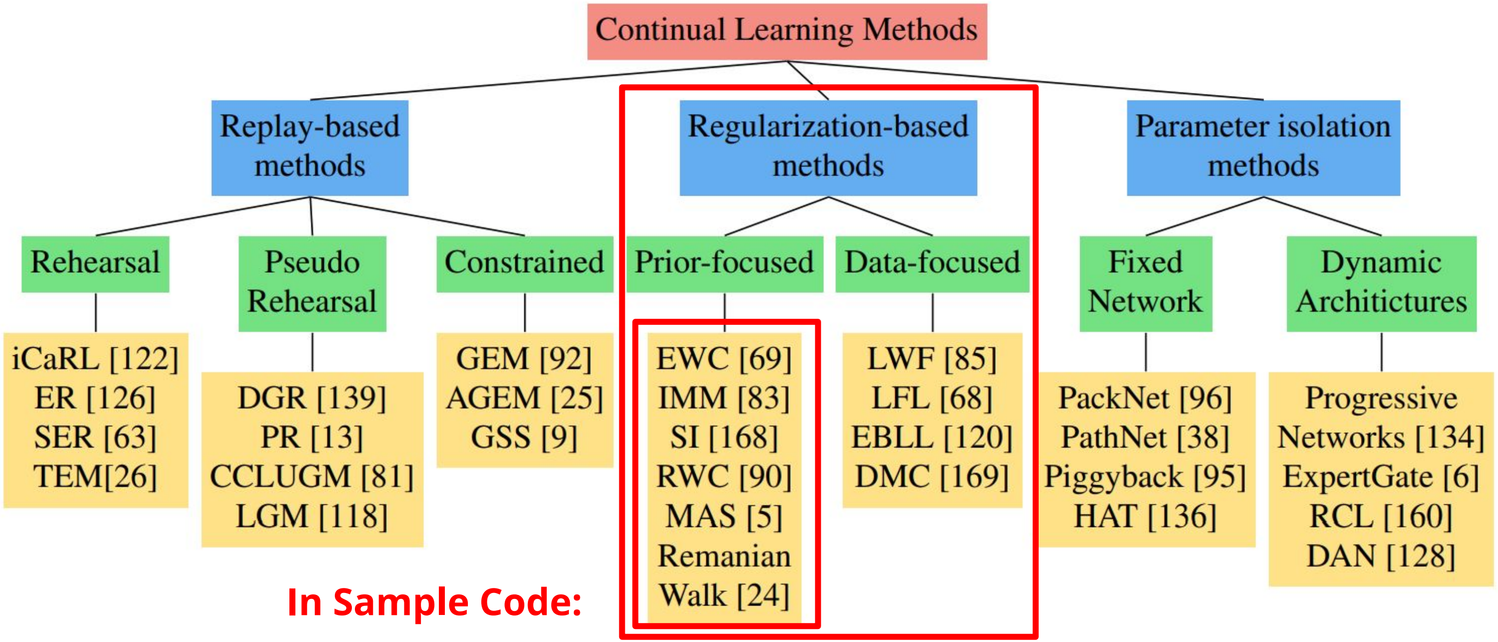
Catastrophic Forgetting



Avoid Catastrophic Forgetting

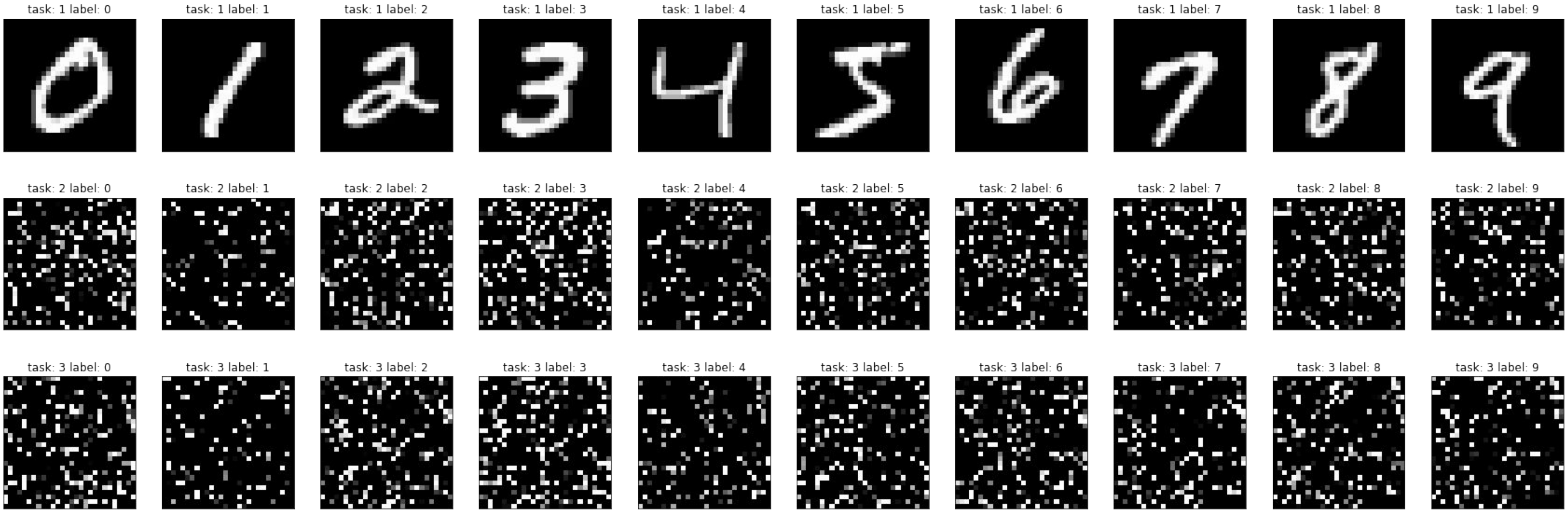


Introduction



Dataset

Permuted MNIST

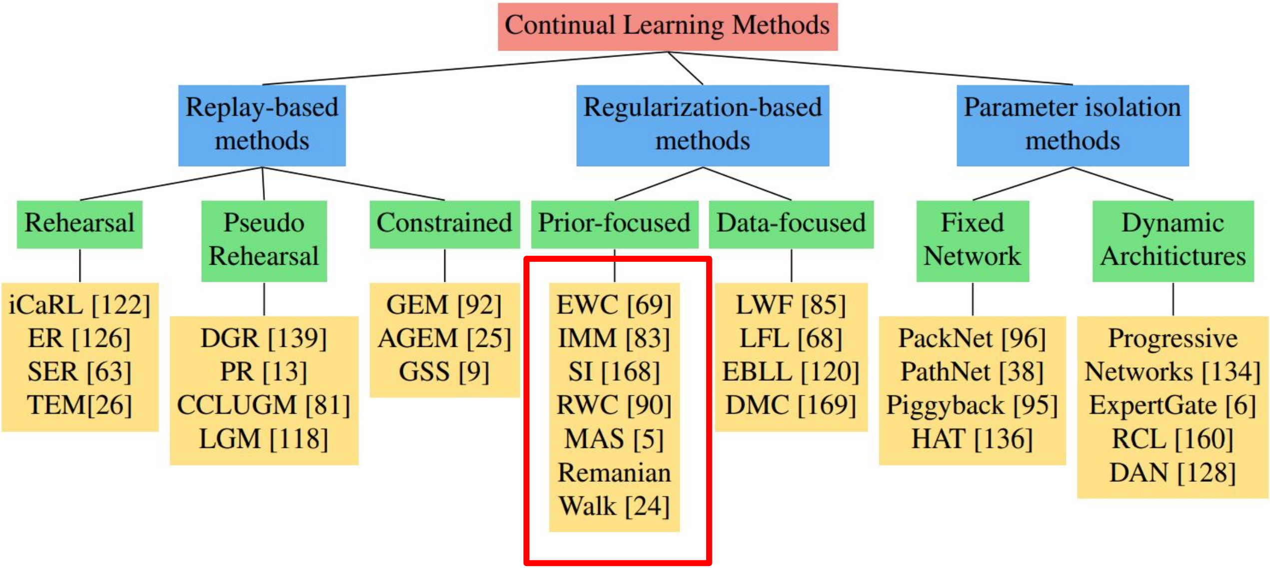


Sample Code - Training Detail

- 5 task / Each task has 10 epoches for training.
- Each method cost ~20 minutes for training model.
- CoLab Link (copy to your drive first! Don’t simply run colab.)

Sample Code - Methods

- Baseline
- EWC
- MAS
- SI
- RWalk
- SCP



Sample Code - Guideline

- Utility
- Visualization
- Methods

Sample Code

- Utility
  - Permutation
  - Dataloader and Training Argument
  - Model
  - train
  - evaluate
  - evaluate metric
- Visualization
- Methods

Sample Code

- Utility
  - Permutation
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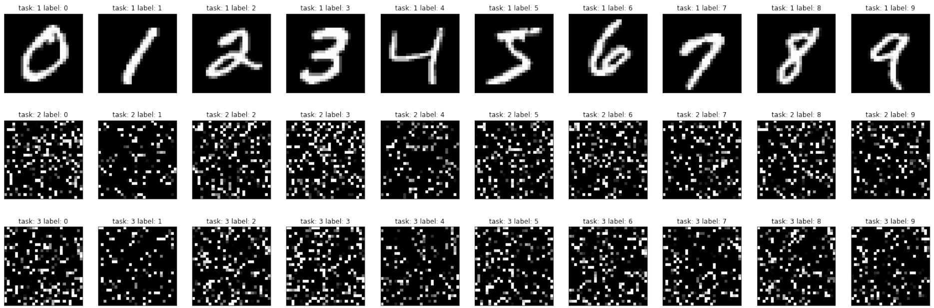
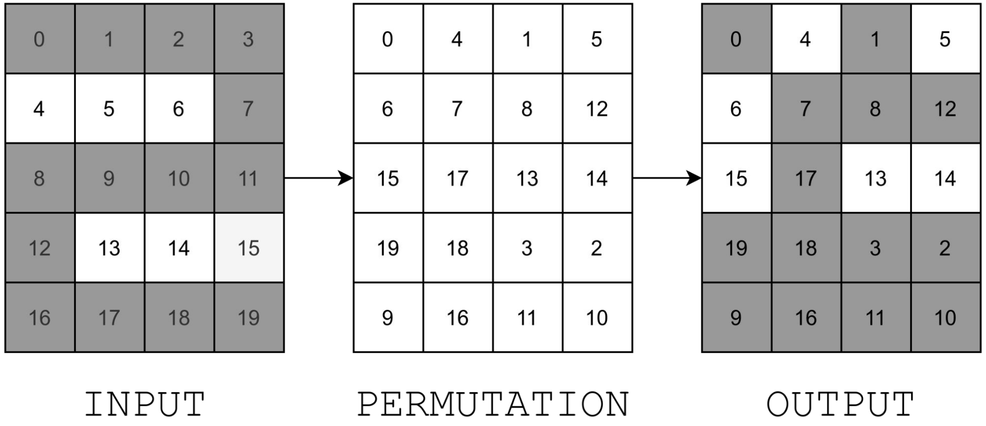




5 PERMUTATION = 5 TASK

Sample Code

- Utility
  - Permutation
  - Dataloader an
  - Model
  - train
  - evaluate
  - evaluate metric
- Visualization
- Methods

Fixed model size!

```
Model(
  (fc1): Linear(in_features=784, out_features=1024, bias=True)
  (fc2): Linear(in_features=1024, out_features=512, bias=True)
  (fc3): Linear(in_features=512, out_features=256, bias=True)
  (fc4): Linear(in_features=256, out_features=10, bias=True)
  (relu): ReLU()
)
```

Sample Code

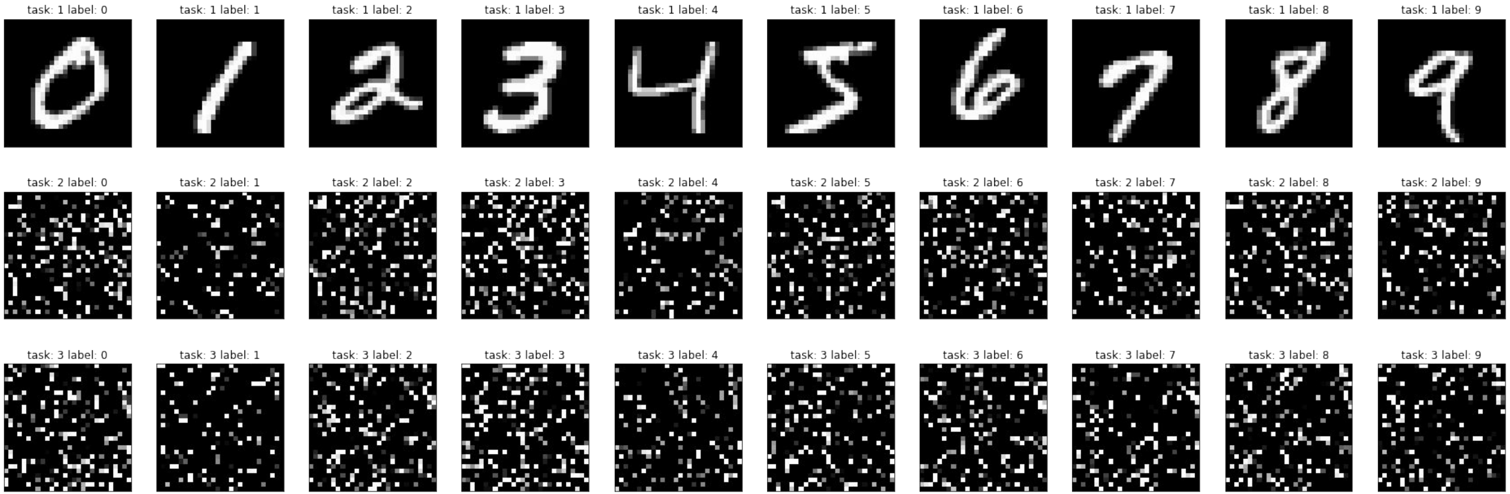
- Utility
  - Permutation
  - Dataloader and Training Argument
  - Model
  - train
  - evaluate
  - evaluate metric
- Visualization
- Methods

In k th task:

$$AverageAccuracy_k = \frac{1}{k}\Sigma_{j=1}^{k} a_{k,j}$$

Sample Code

- Utility
- Visualization
- Methods



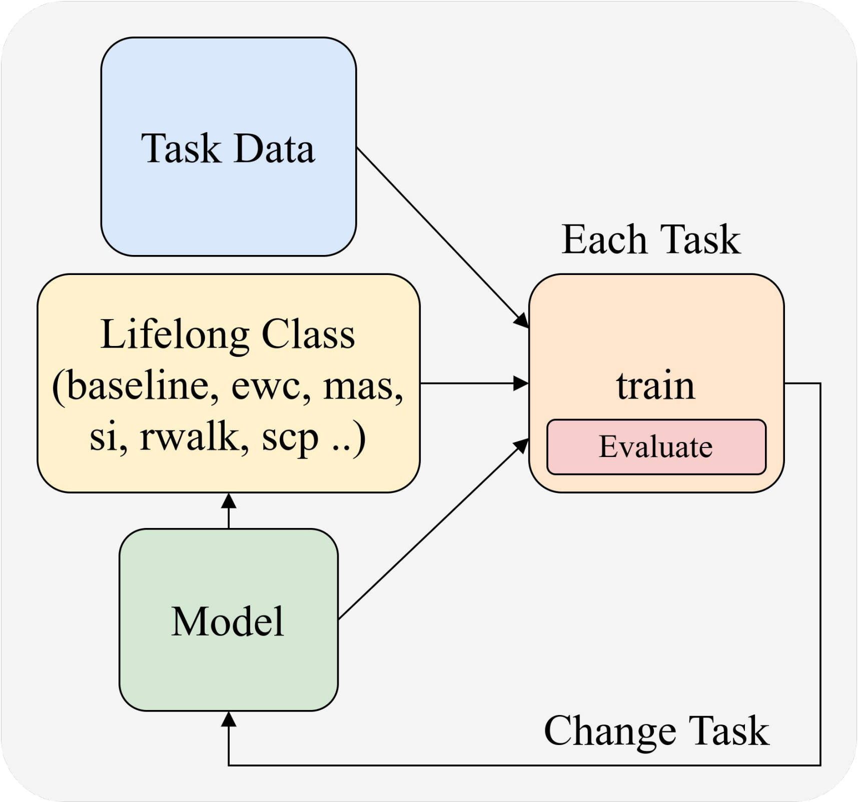
Sample Code - Guideline

- Utility
- Visualization
- Methods
  - Baseline
  - EWC
  - MAS
  - SI
  - RWalk
  - SCP

Baseline

Sequentially Train

Training Pipeline:



Lifelong learning class

Lifelong Class
(baseline, ewc, mas,
si, rwalk, scp ..)

```python
class baseline(object):
    """
    baseline technique: do nothing in regularization term [initialize and all weight is zero]
    """
    def __init__(self, model, dataloaders, device):

        self.model = model
        self.dataloaders = dataloaders
        self.device = device

        self.params = {n: p for n, p in self.model.named_parameters() if p.requires_grad} #extract all parameters in models
        self.p_old = {} # store current parameters
        self._precision_matrices = self._calculate_importance() # generate weight matrix

        for n, p in self.params.items():
            self.p_old[n] = p.clone().detach() # keep the old parameter in self.p_old

    def _calculate_importance(self):
        precision_matrices = {}
        for n, p in self.params.items(): # initialize weight matrix (fill zero)
            precision_matrices[n] = p.clone().detach().fill_(0)

        return precision_matrices

    def penalty(self, model: nn.Module):
        loss = 0
        for n, p in model.named_parameters():
            _loss = self._precision_matrices[n] * (p - self.p_old[n]) ** 2
            loss += _loss.sum()
        return loss

    def update(self, model):
        # do nothing
        return
```

Lifelong learning class

Lifelong Class
(baseline, ewc, mas,
si, rwalk, scp ..)

train

```python
class baseline(object):
    """
    baseline technique: do nothing in regularization term [initialize and all weight is zero]
    """
    def __init__(self, model, dataloaders, device):

        self.model = model
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        return loss

    def update(self, model):
        # do nothing
        return
```

EWC - Elastic Weight Consolidation

1. You need to know how to generate Guardiance weight from EWC!
2. Do this method need to use label ?
3. Hint: (trace the class ewc and its calculate_importance function)

Paper Link: https://arxiv.org/pdf/1612.00796.pdf

MAS - Memory Aware Synapse

1. You need to know how to generate Guardiance weight from MAS!
2. Do this method need to use label ?
3. Hint: (trace the class mas and its calculate_importance function)

Paper Link: https://arxiv.org/abs/1711.09601

SI - Synaptic Intelligence

1. You need to know how to generate Guardiance weight from SI!
2. Do this method need to use label ?
3. Hint: (Accumulated loss change in each update step)

Paper Link: https://arxiv.org/abs/1703.04200, Talk Slide

SI - Main Idea

$$L(\theta) = L_2(\theta) + c\sum_i \Omega_i \left(\theta_i - \boxed{\theta^*_{1,i}}\right)^2$$

From learning trajectory

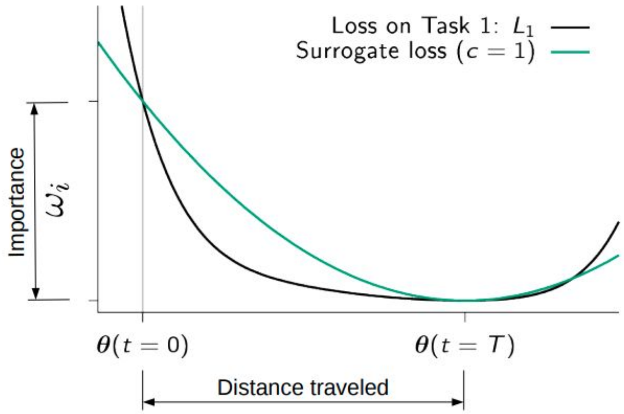
Parameter importance on-line from learning trajectory!

Picture comes from: [Talk Slide]

SI - Abstract

Leveraging per-parameter importance for continual learning

$$L(\theta) = L_2(\theta) + c\sum_i \Omega_i \left(\theta_i - \theta^*_{1,i}\right)^2 \qquad \boxed{\Omega_i \equiv \frac{\omega_i}{(\Delta_i)^2 + \epsilon}}$$



Picture comes from: [Talk Slide]

SI - Method

Total change in loss is given by the path integral over the gradient field

$$\int_C \boldsymbol{g}(\boldsymbol{\theta}(t))d\boldsymbol{\theta} = \int_{t_0}^{t_1} \boldsymbol{g}(\boldsymbol{\theta}(t)) \cdot \boldsymbol{\theta}'(t)dt = L(t_1) - L(t_0)$$

$$= \sum_k \int_{t_0}^{t_1} g_k(t)\theta'_k(t)dt \equiv -\sum_k \omega_k$$

- Is a parameter-specific quantity
- Can be computed on-line during training (running sum)

$\boldsymbol{g}$: Gradient

$\boldsymbol{\theta}$: Parameters

$\boldsymbol{\theta}'$: Updates

Natural way of assigning credit for a global change to local parameters

$$L(t_1) - L(t_0) = -\sum_k \omega_k^{\mu}$$

Picture comes from: [Talk Slide]

RWalk - Remanian Walk

1. Trace class rwalk and its update function!
2. Do this method need to use label ?
3. Hint:(The code is similar to two method which mentioned in sample code)

Paper Link: https://arxiv.org/abs/1801.10112

SCP - Sliced Cramer Preservation

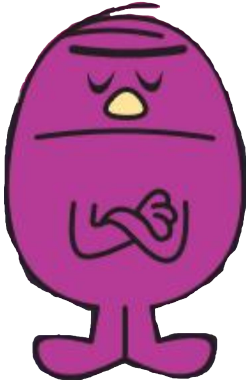
1.Paper Link: https://openreview.net/pdf?id=BJge3TNKwH

2.Do this method need to use label ?

SCP - Main Idea

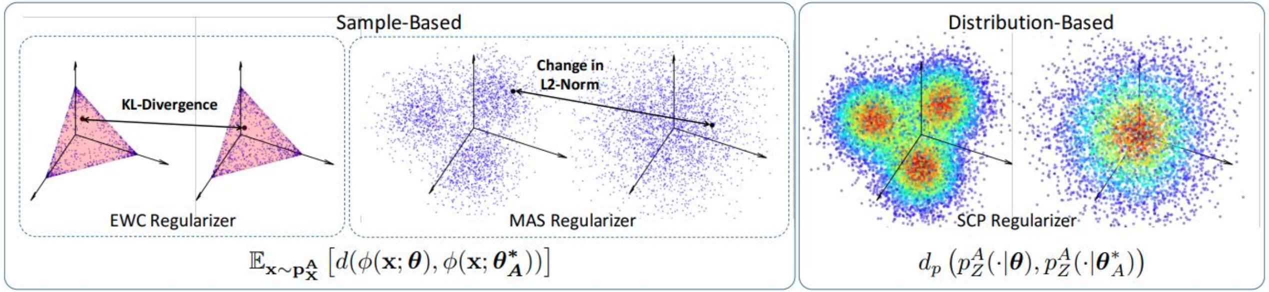
- Propose Distributed-based Distance to prevent fast intransigence and avoid overestimate the importance of parameter.

intransigence



Model do not want to learn new task,
and it just keep old task performance

SCP - Sliced Cramer Preservation (Hint)

1. 

Paper Link: https://openreview.net/pdf?id=BJge3TNKwH

COOL Quiz

- 25 multiple choice questions
- Basic Concept & Dataset : 4 Questions
- Sample Code: 15 Questions
  - EWC: 3 Questions
  - MAS: 3 Questions
  - SI: 3 Questions
  - Remanian Walk: 3 Questions
  - Sliced Cramer Preservation: 3 Questions
- Other Methods & scenario: 6 Questions
  - ICaRL, LwF, GEM, DGR
  - Three Scenario

Grading

- All Questions (0.4pt)
- You have to choose ALL the correct answers for each question
- Warning: The answers in NTU Cool are not correct, NTU grading score before deadline is not the final grading score.
- Please do not select the choice depends on the grading score.

Submission

- No late submission!
- We can only pick the last submission!
- Deadline: 2021/07/02 23:59
- Warning: The answers in NTU Cool are not correct, NTU grading score before deadline is not the final grading score.
- Please do not select the choice depends on the grading score.

Links

- CoLab Link
- NTU Cool Multiple Choice Question
- Warning: The answers in NTU Cool are not correct, NTU grading score before deadline is not the real grading score.
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If any questions, you can ask us via...

- NTU COOL (recommended)
  - https://cool.ntu.edu.tw/courses/4793
- Email
  - ntu-ml-2021spring-ta@googlegroups.com
  - The title must begin with “[HW14]”
- TA hours
  - Each Monday 19:00~21:00 線上
  - Each Friday 13:30~14:20 線上
  - Each Friday During Class