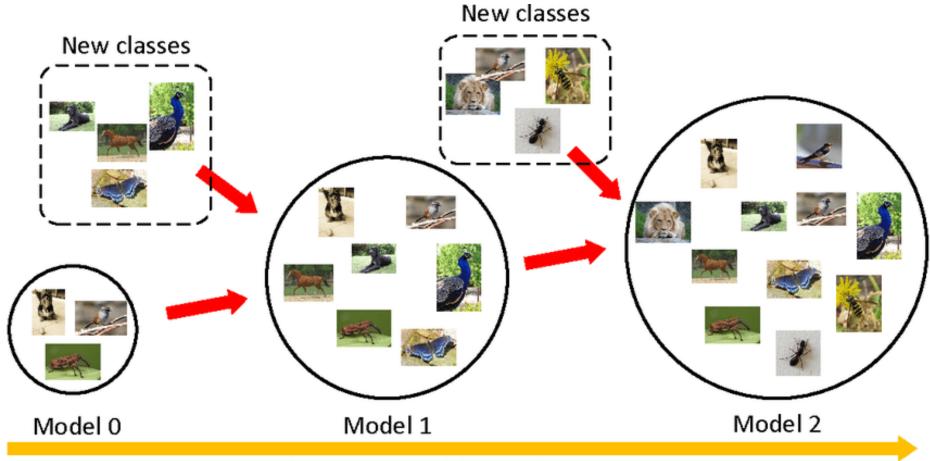
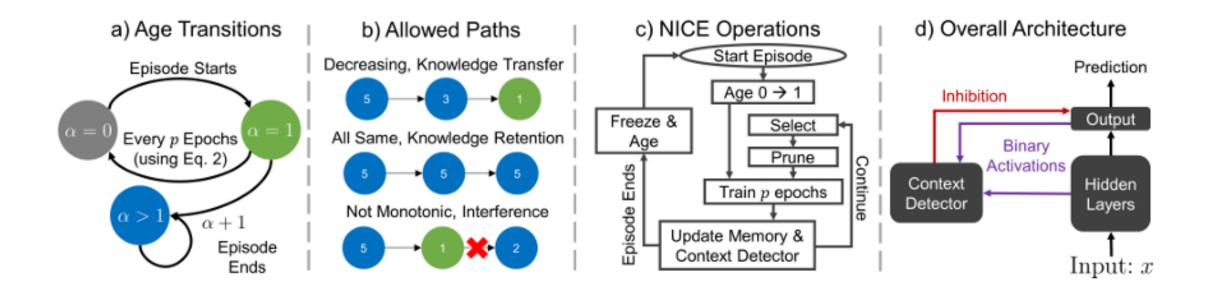
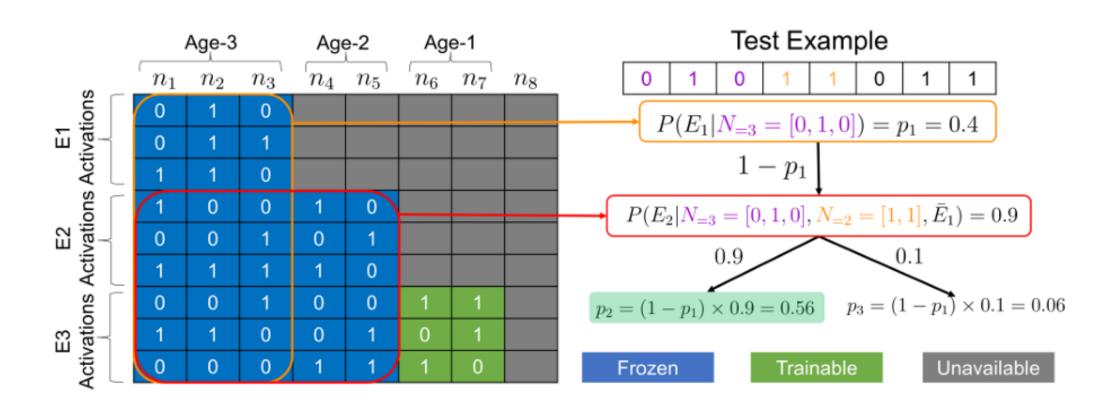
A20586593 Seonghwan Lim

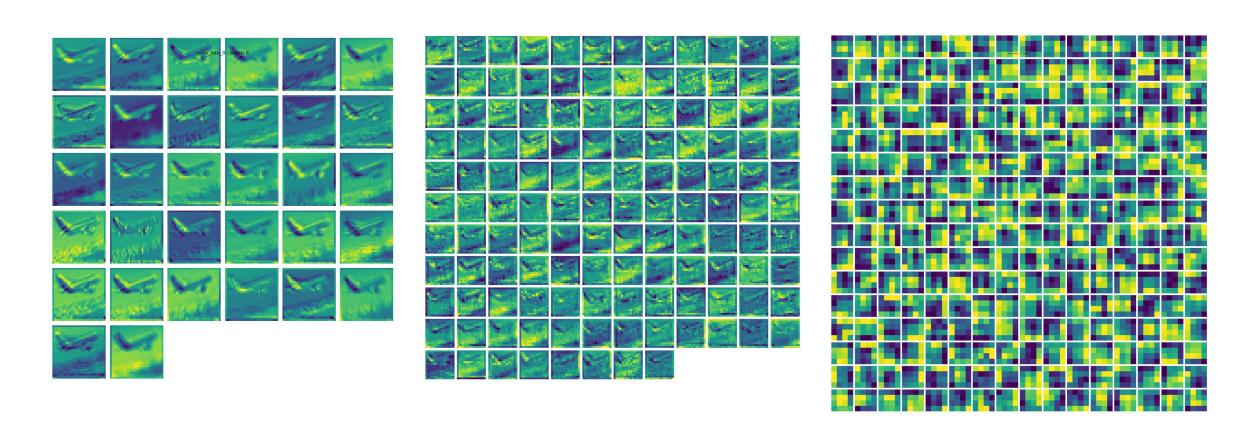
Class Incremental Learning

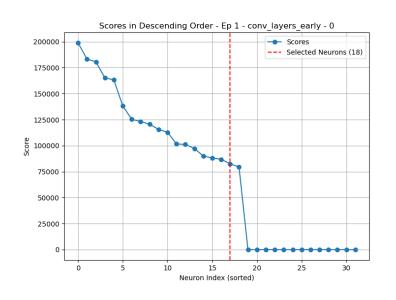


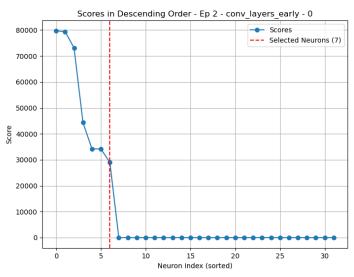
Incremental Learning

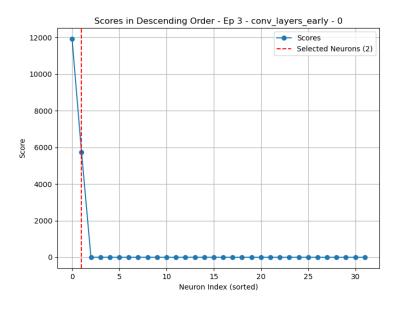






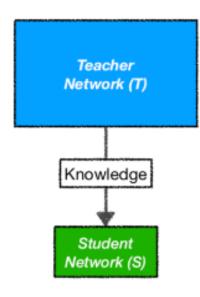






Introduction

Knowledge Distillation



1. Teacher Network (T)

- cumbersome model
 ex) ensemble / a large generalized model
- (pros) excellent performance
- (cons) computationally expansive
- can not be deployed when limited environments

2. Student Network (S)

- small model
- suitable for deployment
- (pros) fast inference
- (cons) lower performance than T

Key Loss Formula for Knowledge Distillation

$$L_{\text{total}} = \alpha \cdot L_{\text{CE}} + (1 - \alpha) \cdot L_{\text{KD}}$$

Where:

- \bullet $L_{\rm CE}$: Cross-Entropy Loss (difference between student model outputs and ground truth labels).
- ullet $L_{
 m KD}$: Knowledge Distillation Loss (difference between teacher and student output distributions).
- α: Balancing weight for L_{CE} and L_{KD}.
- T: Temperature for softening probability distributions.

Knowledge Distillation Loss (KD Loss)

$$L_{ ext{KD}} = T^2 \cdot ext{KL}ig(ext{Softmax}(rac{z_t}{T}) \,||\, ext{Softmax}(rac{z_s}{T})ig)$$

Where:

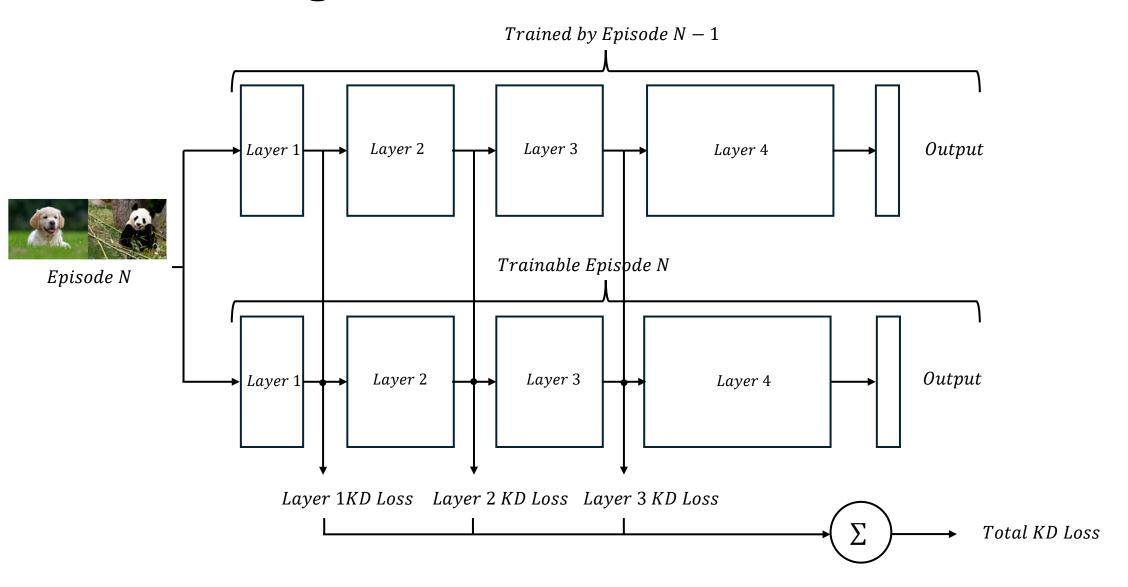
- z_t: Teacher model logits.
- z_s: Student model logits.
- KL Divergence: Measures the difference between two probability distributions.

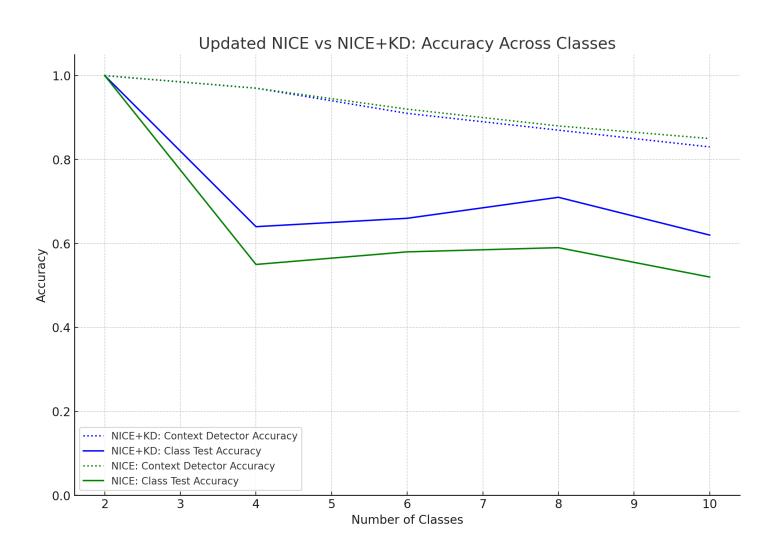
KL Divergence Formula

$$ext{KL}(P \,||\, Q) = \sum_i P(i) \cdot \log \left(rac{P(i)}{Q(i)}
ight)$$

Where:

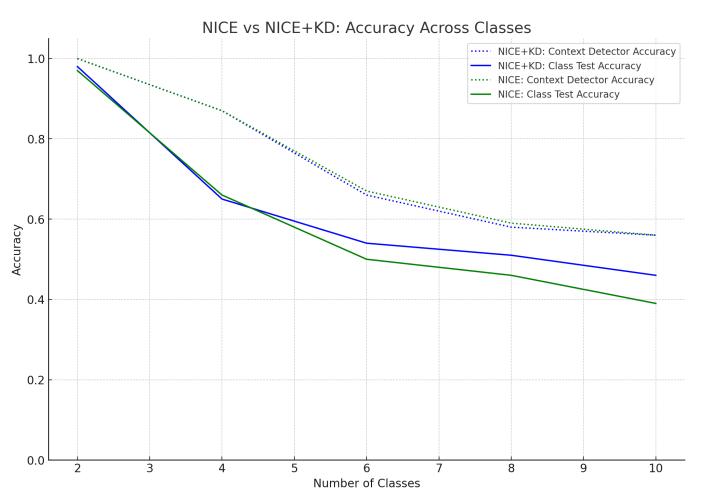
- P(i): The true probability distribution (e.g., teacher's softened output).
- Q(i): The approximate probability distribution (e.g., student's softened output).





Model: CNN_MNIST

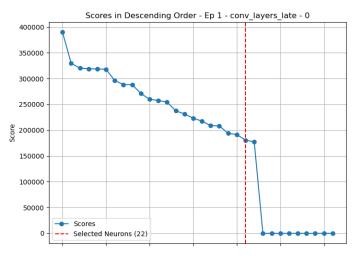
Data: MNIST

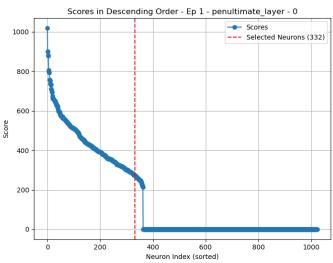


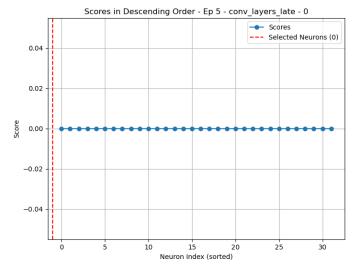
Model: VGG11 SLIM

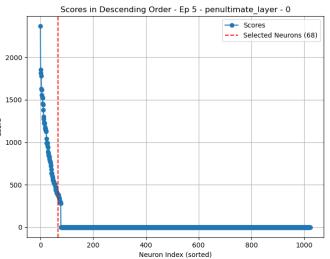
Data: CIFAR10

Future Works

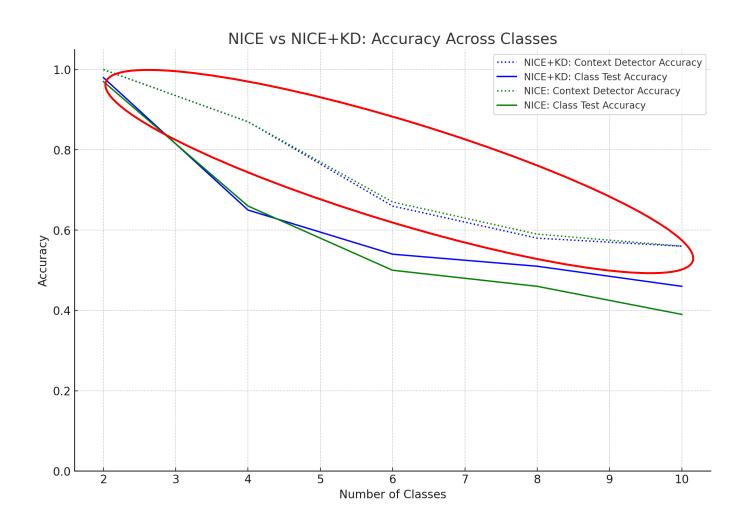








Future Works



Question

Thank You