

LEENet: Learned Early Exit Network

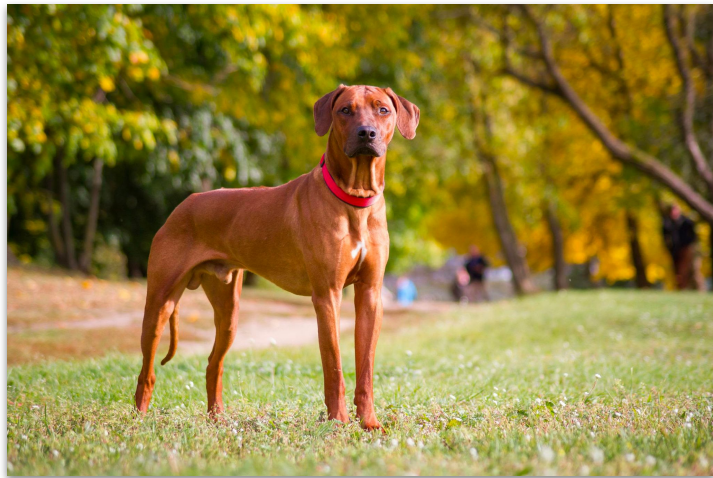
Learning Optimal Early Exit Policy for Efficiency Improvements in DNNs

Austin Chemelli, Anthony Wong, Blake Sanie, Dylan Mace, Dylan Small, Nic Zacharis

Project Motivation & Background

Introduction

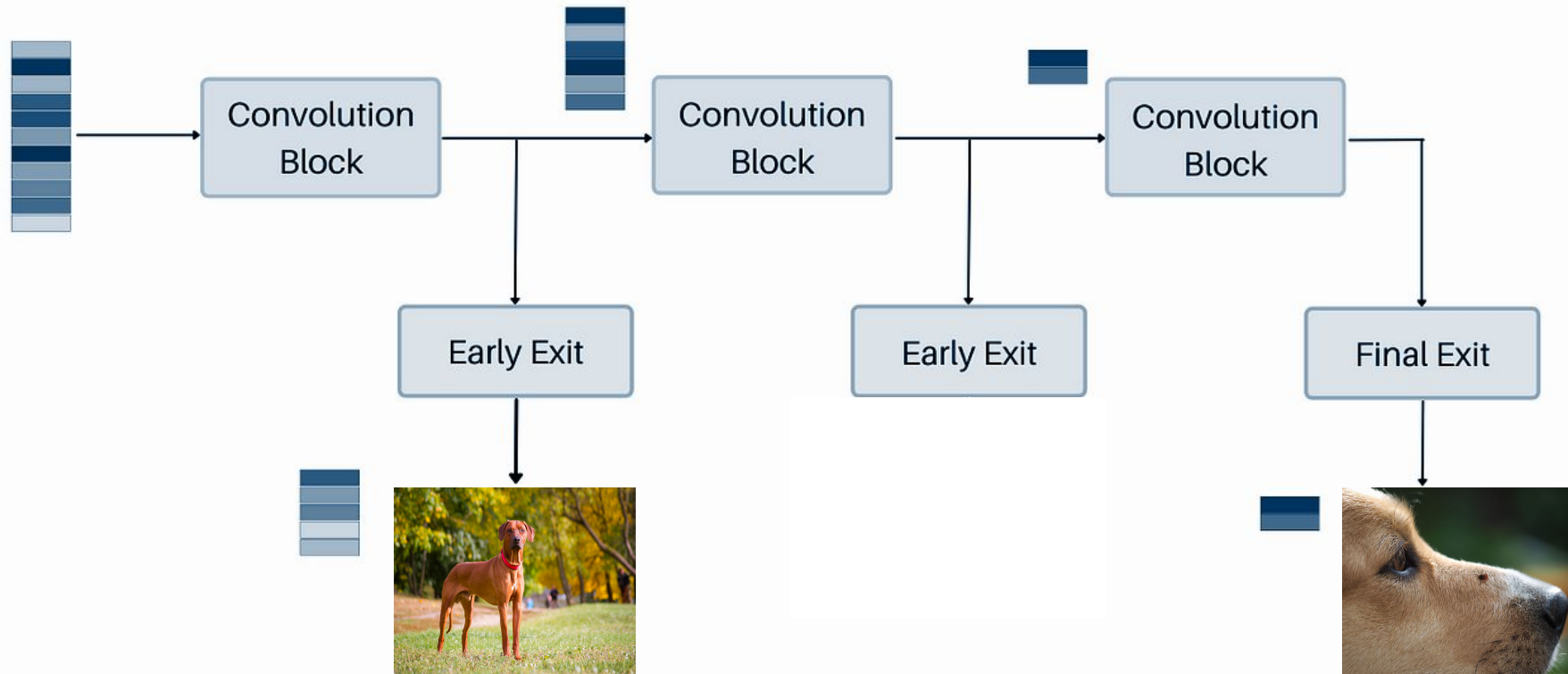
- Suppose we have two images that we want to classify:



- The right image is harder to classify
- Current ML models use the same parameters/computations for all images

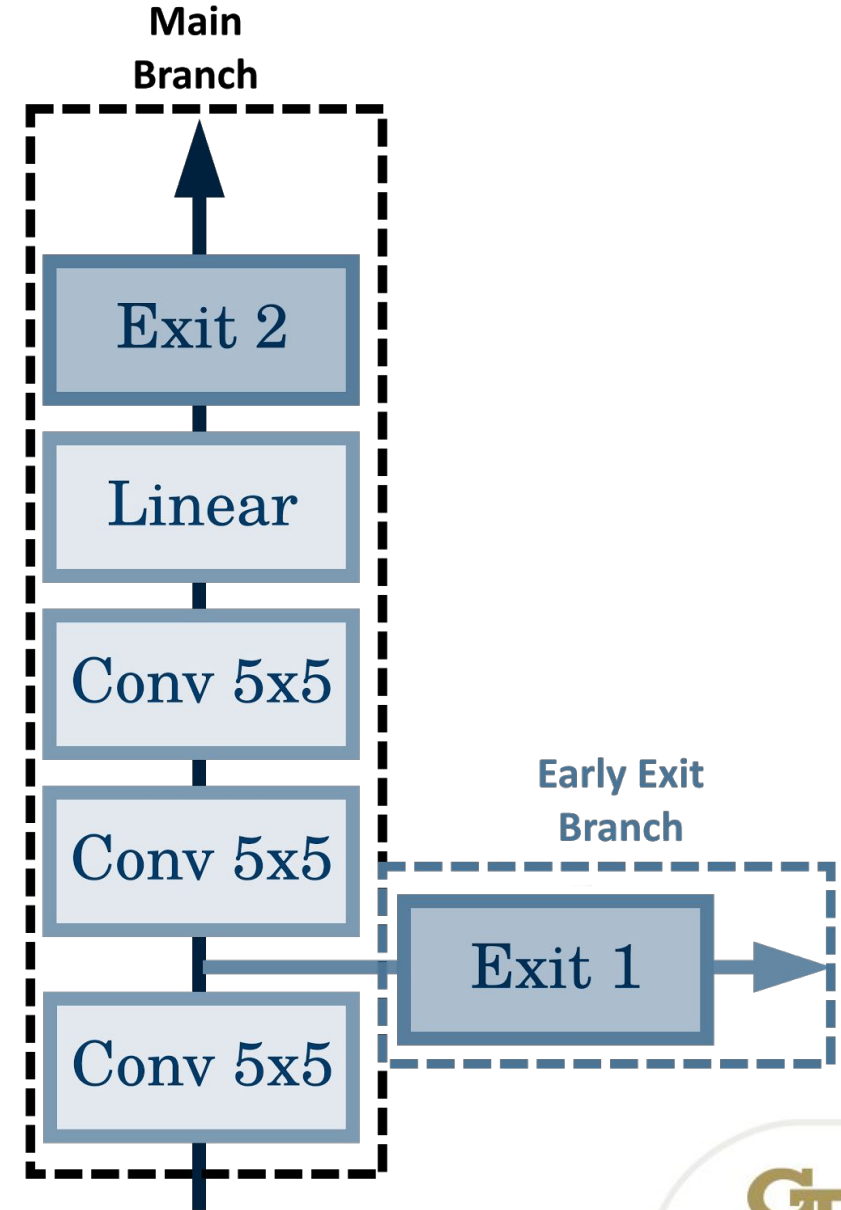
What is Early Exit?

- Place classifiers at **multiple** locations throughout the model
- At each potential exit, a **confidence value** dictates whether to use the exit
 - If threshold met, classify image



Problem Domain

- How many exit layers to insert?
- Where to insert possible new exits?
- How to teach a model when to use each exit?

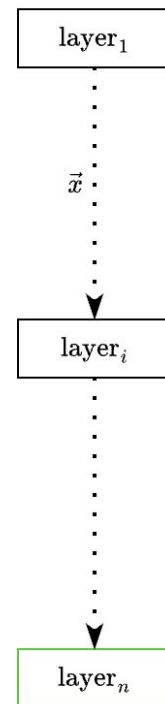


Project Information

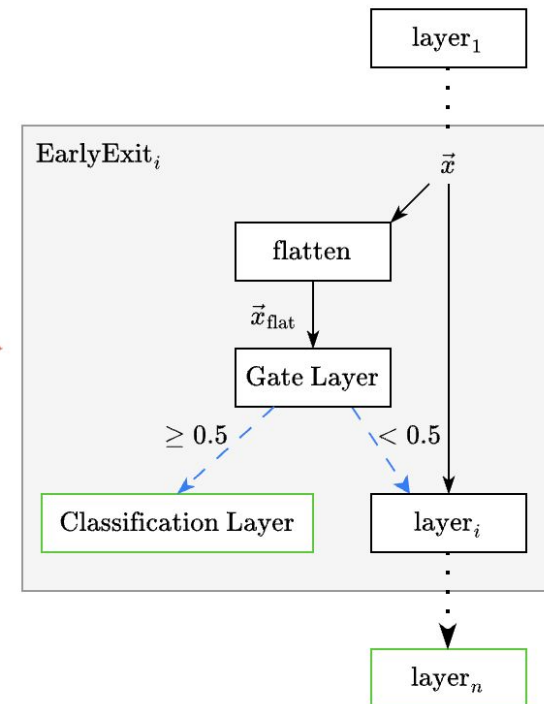
Our Approach

- Remove all manual exit confidences
- Insert “gate layer” to decide whether to exit
- Learn gate layer parameters to optimize accuracy/cost tradeoff
- Insert hyperparameters for tuning tradeoff

Base Model



Extended with Early Exit



Legend

Produces \mathbb{R}^m Logits

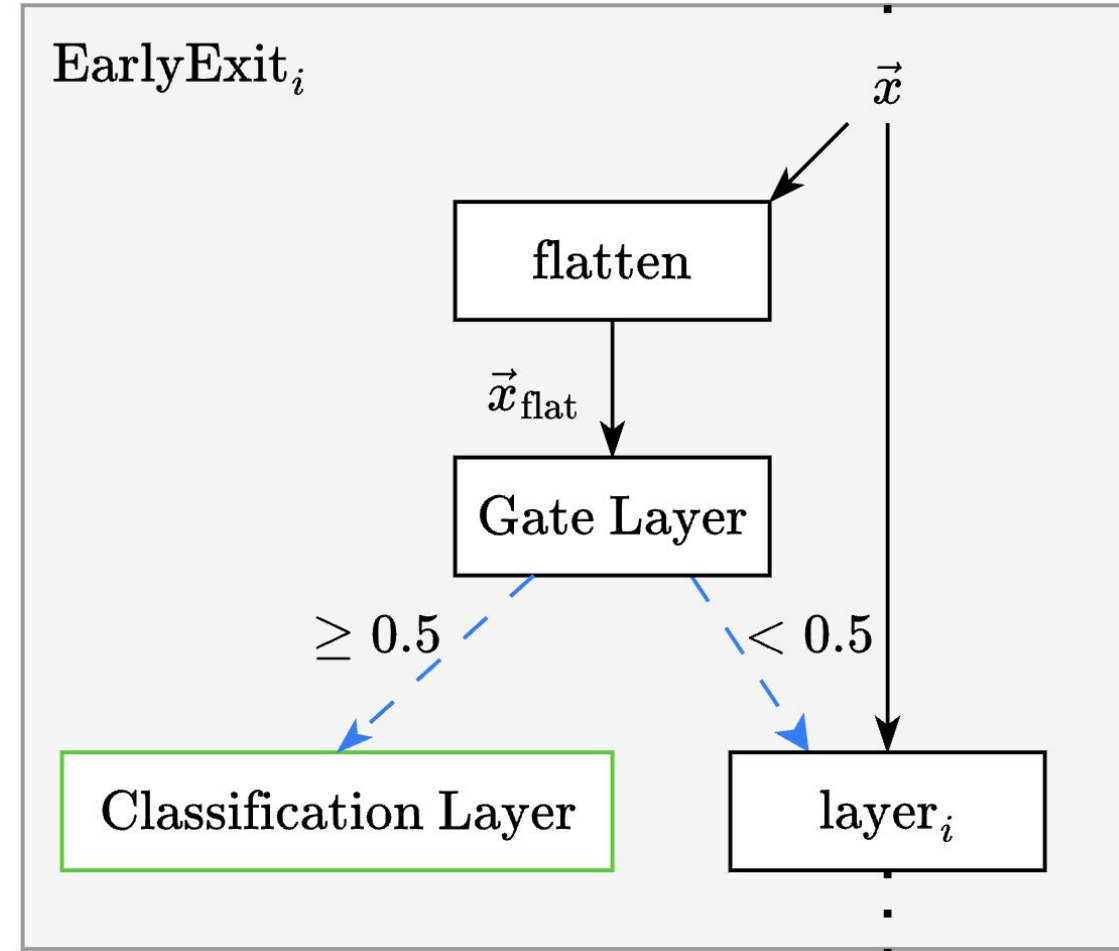
Indirect layer descentance
.....>

Direct layer descentance
—————>

Conditional branch
- - - - ->

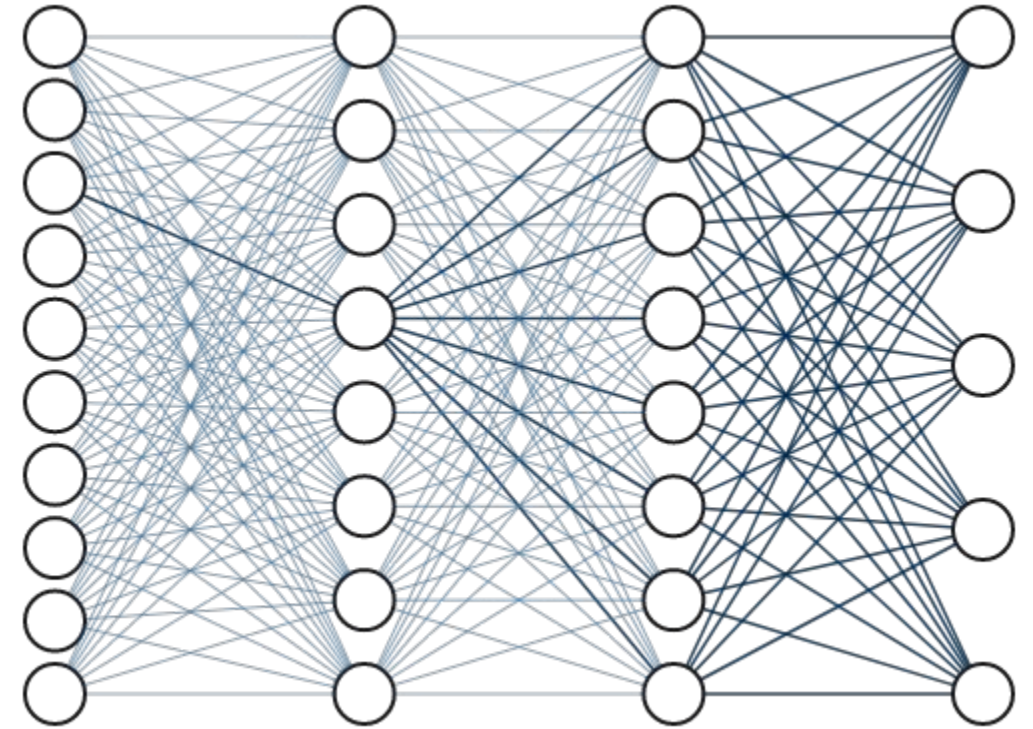
Our Approach (cont.)

- Input gets flattened
 - Output Size: (n,)
- Dot product with gate layer parameters
 - Output Size: (1,)
- Decide whether to exit
 - Gate layer output above threshold
- If exit, classify n input to logits
 - Output Size: (n_classes,)
- If not exit, feed through original network



Training Process

- Train each early exit classifier
 - These can be trained individually since they are unrelated
 - **Loss:** Categorical Cross Entropy
- Train final classification layer
 - This is just transfer learning onto your dataset
 - **Loss:** Categorical Cross Entropy
- Train gate layers
 - These have to be trained at the same time
 - **Loss:** Custom Loss Function (next slides)



Custom Gate Loss Function

$$\text{loss} = \frac{1 - \alpha}{n} \left[\sum_{(X, y, \hat{y}, g)} \left(\sum_{i=0}^{|g|} \left(\text{CE}(y, \hat{y}_i) \cdot g_i \prod_{j=0}^{i-1} \bar{g}_j \right) \right) \right] + \left[\sum_{(X, y, \hat{y}, g)} \left(\sum_{i=0}^{|g|} \left(\text{costs}_i \cdot g_i \prod_{j=0}^{i-1} \bar{g}_j \right) + \text{costs}_{|g|} \prod_{j=0}^{|g|} \bar{g}_j \right) \right] \frac{\alpha}{n}$$

Minimize CE (Maximize Accuracy)

Minimize Computational Cost (Maximize Efficiency)

Control Weighting of Accuracy + Cost

Maximizing Accuracy

- Iterate over all images in the batch
- Calculate product summed over all gates:
 - Cross Entropy loss of:
 - \mathbf{y} : true classification
 - $\hat{\mathbf{y}}_i$: predicted classification logits from gate i
 - Probability of exiting at gate i:
 - \mathbf{g}_i : exit confidence for gate i (larger means more confident)
 - $\bar{\mathbf{g}}_j$: forward confidence for gate j (equal to $1-\mathbf{g}_i$)

$$\left[\sum_{(X,y,\hat{y},g)} \left(\sum_{i=0}^{|g|} \left(\text{CE}(y, \hat{y}_i) \cdot g_i \prod_{j=0}^{i-1} \bar{g}_j \right) \right) \right]$$

Minimize this term for higher net model accuracy

Maximizing Efficiency

$$\left[\sum_{(X,y,\hat{y},g)} \left(\sum_{i=0}^{|g|} \left(\text{costs}_i \cdot g_i \prod_{j=0}^{i-1} \bar{g}_j \right) + \text{costs}_{|g|} \prod_{j=0}^{|g|} \bar{g}_j \right) \right]$$

- Iterate over all images in the batch
- Calculate product summed over all gates:
 - Cost of exiting at gate i:
 - Derived as % **parameters utilized**
 - Value ranges from **(0, 1]**
 - Probability of exiting at gate i:
 - g_i : exit confidence for gate i (larger means more confident)
 - \bar{g}_j : forward confidence for gate j (equal to $1-g_i$)

Minimize this term for lower net inference cost

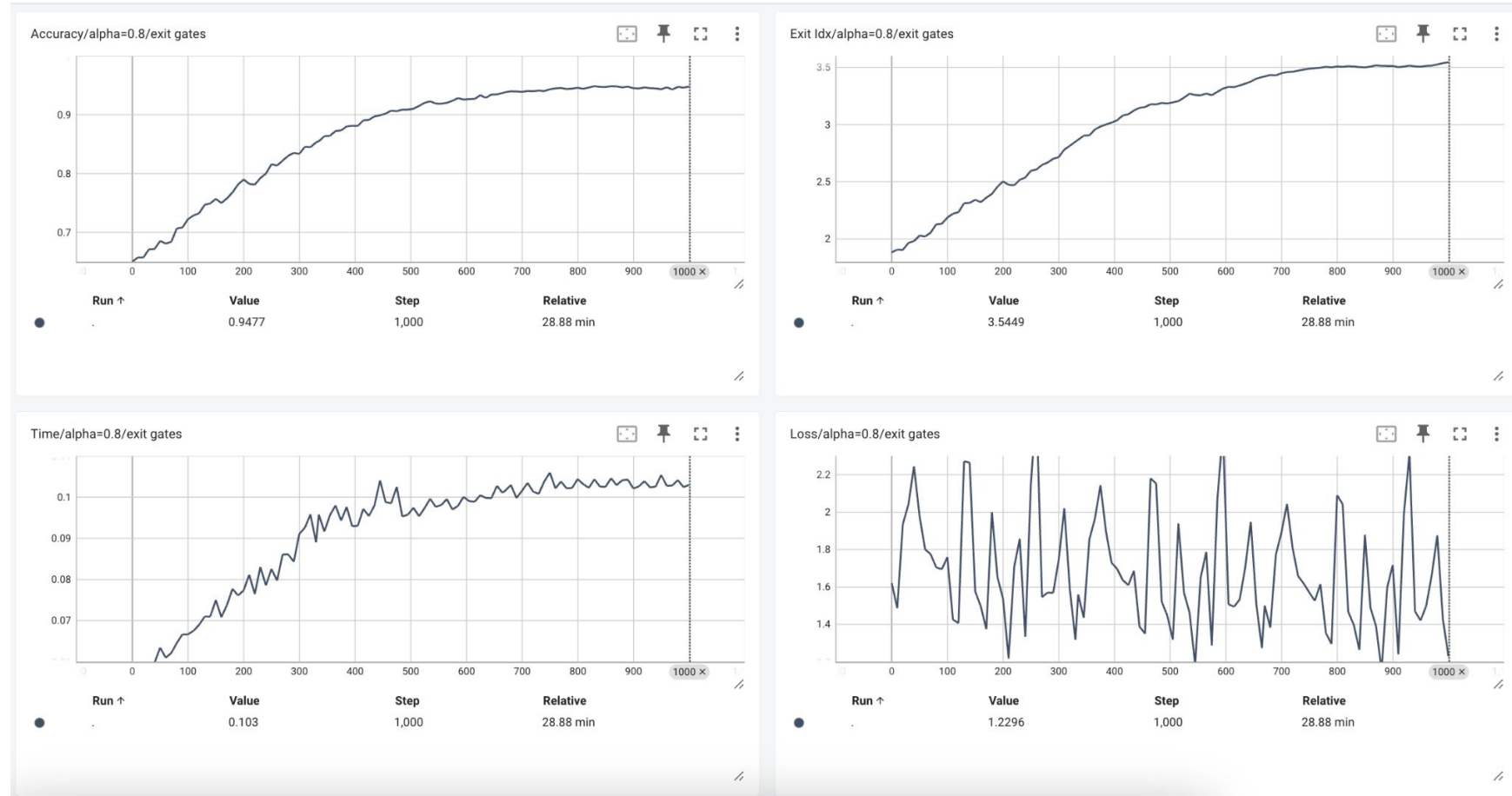
Initial Results + Remaining Work

Initial Results (ResNet50/ImageNetTE, $\alpha=0.8$)

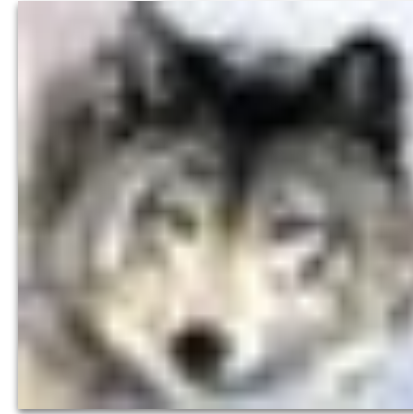
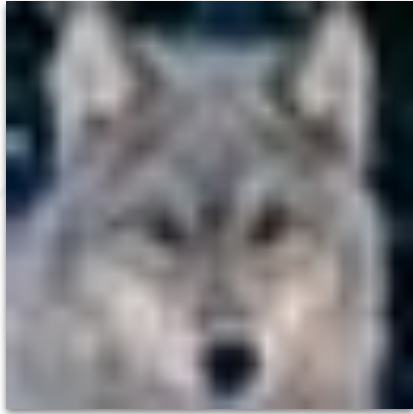
25%
Time
Savings

50%
Cost
Reduction

5%
Accuracy
Drop

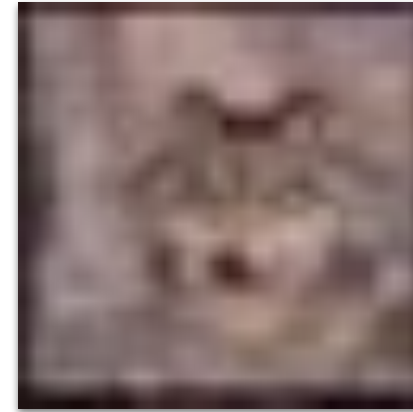
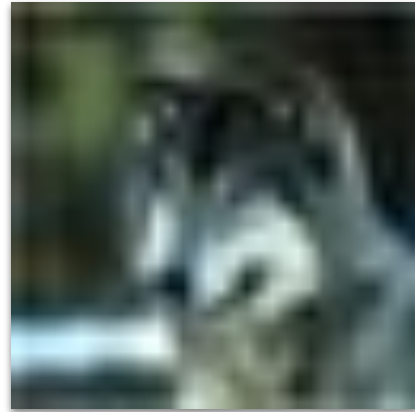


Correct Examples: Wolf (VGG11/CIFAR100, $\alpha=0.6$)



Exit 2 of 5

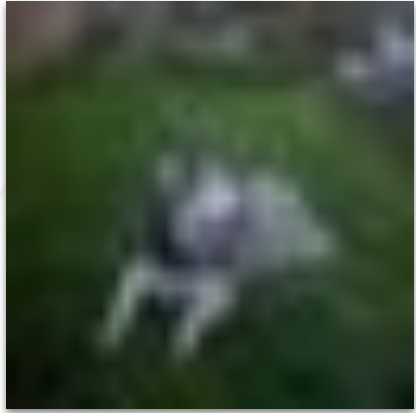
Consistent Face Scale
and Position



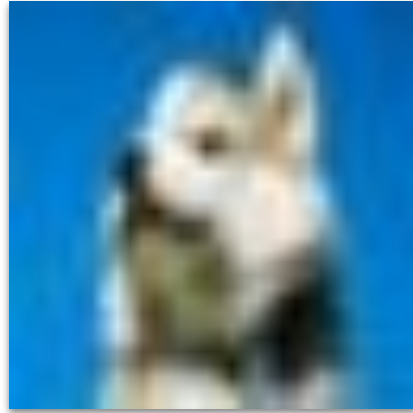
Exit 3 of 5

Discoloration, scale
and position variation

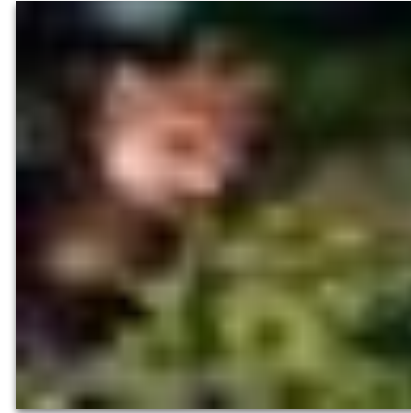
Incorrect Examples: Wolf (VGG11/CIFAR100, $\alpha=0.6$)



Fox



Seal



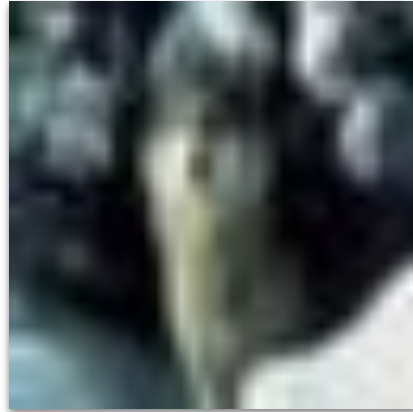
Fox

Exit 2 of 5

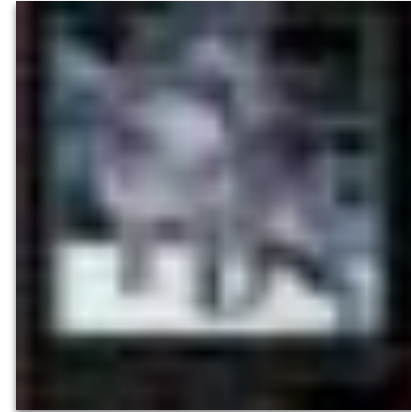
Subject/background interference



Rabbit



Flatfish



Turtle

Exit 3 of 5

Misleading subject representation

Next Steps

- Code cleaning + implementation improvements
- Pushing Time Savings
 - Multithreading gate and classification layers
 - Changing gate and classifier architectures
- Image Augmentations
- Configure training on more powerful computers (GPUs, Pace, etc.)
- Calculate trendlines when varying α
 - Average model accuracy
 - Average exit location
 - Average computation time
 - Average computation cost
- Train on a large set of different datasets/ML models
 - AlexNet, MSDNet,
- Calculate scaling scores based upon dataset size
- Continue to do comparison studies with previous work