

# Evolution Strategies for Approximating Gradients

CMPUT 328

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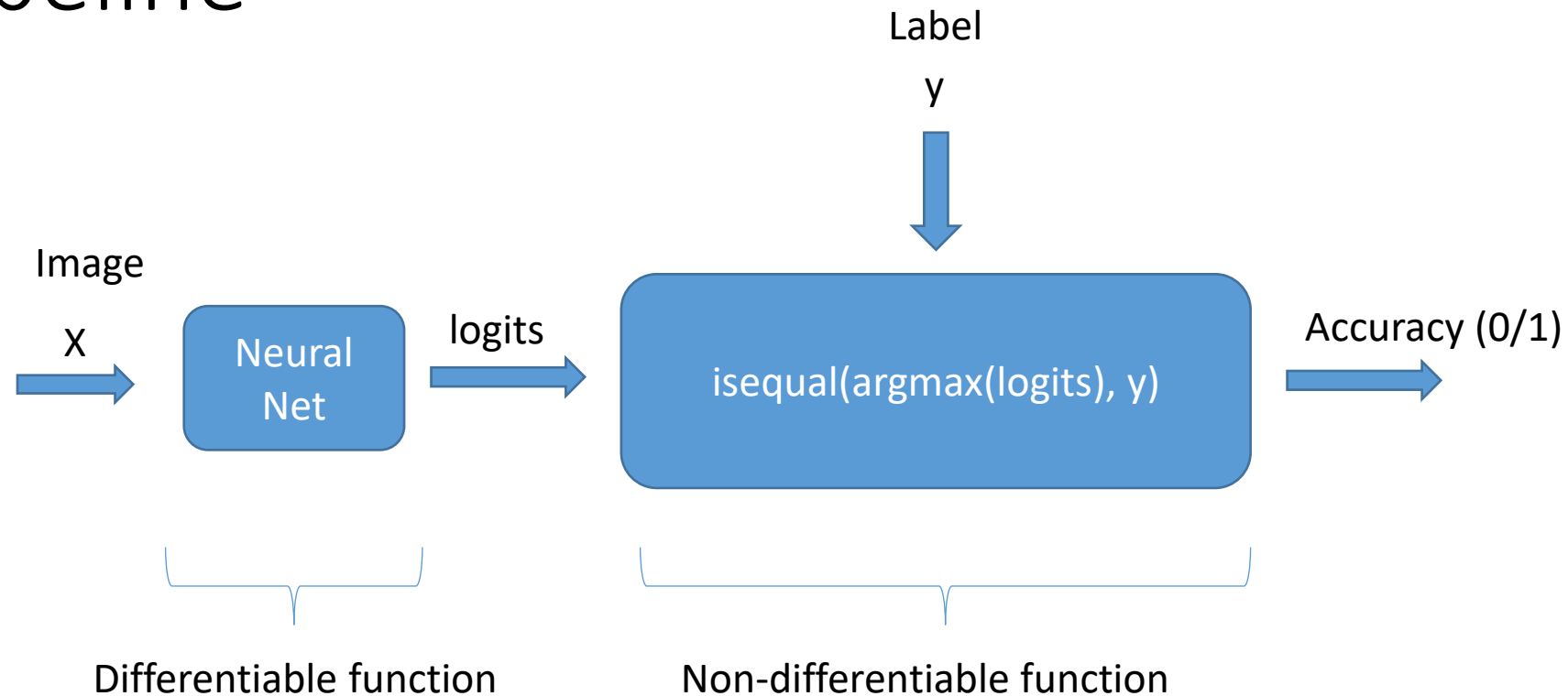
# Differentiable Programming

- Our familiar example is neural networks: parameterized differentiable function
- Software packages use chain rules to compute derivatives to backpropagate for learning parameters
- Differentiable pipeline can be more general than neural net
- In fact, any program where each computation is a differentiable function can make use of auto derivative
- PyTorch and Eager mode of TensorFlow use this kind of “auto-diff”
- This framework is called “differentiable programming”
- Differentiable programming is more general than deep learning or neural network

# More general differentiable programming?

- What if you have a function that is non-differentiable within a processing pipeline?
- How do we compute derivative across a non-differentiable function?
- We can apply a type of sampling technique called “evolution strategies” (ES) to overcome this kind of obstacles
- ES has been applied as a powerful alternative to reinforcement learning recently (<https://arxiv.org/abs/1703.03864>)
- I will show here how we can use ES in an image classification pipeline, where a part of the pipeline is non-differentiable

# Motivating example: An image classification pipeline



Goal: maximize accuracy by optimizing parameters of the neural net

We cannot apply chain rule or auto-diff, because a part of the pipeline is non-differentiable

# Evolution strategies to approximate gradient

- Apply ES to compute approximate gradient of logits
- Push gradient of logits backward to neural net for chain-rule or auto-diff
- A hybrid method: apply chain rule to differentiable parts and apply ES to non-differentiable parts

# Algorithm for approximate gradient computation by ES

- Initialize  $g$  to a zero vector
- For  $n=1, 2, \dots, N$ 
  - Sample a vector  $q_n$  from a zero-mean Gaussian of variance  $t$
  - Compute accuracy as  $f_n = \text{isequal}(\text{argmax}(\text{logits} + q_n), y)$
  - Update gradient vector:  $g = g + f_n q_n$
- Return  $g / (tN)$  as approximate gradient of logits

# Disadvantages

- ES is not sample efficient: if logits is a very long vector,  $N$  needs to be a really large integer, leading to slow or poor optimization
- How to choose the variance parameter  $t$ ?