## Working with neural networks at CERN

**Roope Niemi** 



### Who I am & how I got here

- Sotungin lukio 2008-2011
- 2012-2017: non-IT work
- 2017-2022: Studies at University of Helsinki, Kumpula (Computer Science, Data Science)
- 2021-2024: Work at Nokia, applying to CERN a few times
- September 2024 → Software engineer / data scientist (QUEST) at CERN



### What I do

- Optimize neural networks for hardware, so they are fast and accurate → design methods to train compressed neural networks
- Programming with Python, read scientific papers, implement algorithms from them and compare them to other algorithms. Possibly improve them

```
S_g(w,s) := \operatorname{sign}(w) \cdot \operatorname{ReLU}(|w| - g(s))
```

```
class STR(PruningLayer):
def __init__(self, config, layer, out_size):
    super(STR, self).__init__()
    self.config = config
    threshold_size = get_threshold_size(config, out_size, layer.weight.shape)
    self.s = nn.Parameter(torch.ones(threshold_size) * -self.config.threshold_init)
    self.g = torch.sigmoid
```

```
def forward(self, weight):
"""
sign(W) * ReLu(|W| - g(s))
"""
mask = self.get_mask(weight)
return torch.sign(weight) * mask.view(weight.shape)
```

def get\_mask(self, weight):

return torch.relu(torch.abs(weight).view(weight.shape[0], -1) - self.g(self.s))





#### Triggers

- A lot of data from particle collisions. ATLAS has data volume of over 60TB/s
- Use triggers to save only relevant data. Has to be quick, but sensitive enough to signs of rare processes
- Selection based on heuristics such as energy, charge, direction, momentum
- Use neural networks to get better results than traditional rule-based methods?
- A good neural network means nothing if it cannot be run efficiently in hardware







#### **Neural networks**

- Neural networks learn from data
- Can be trained to do tasks such as classification, text, image or video generation, regression, pattern recognition











#### **Neural networks**

- Everything is numbers
- Neural networks produce an output by doing mathematical operations such as multiplication and addition



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#### Expected output **Neural networks** A numerical value for Input Output difference between Calculate error of Neural In the beginning, the neural expected output and prediction network network output network produces outputs that make no sense Repeat **During training the neural** network learns to produce better Calculate effect Update parameters to of each parameter to outputs improve output the output Partial derivatives, Gradient descent chain rule Local Minima Global Minimum



#### **Neural networks**

- Bigger neural networks can be more powerful, but slow
- In limited-resource or low-latency environments, this won't do.
- Use compression to make them faster and use fewer resources

Comp	oressi	on
Ар	pilea	



### **Compressing neural networks**

- Restrict parameters to be one of 2,4,16,256 etc. values
- Teach neural network to work with fewer parameters

PR. MC		
	16 values256 values	

64 112 991 = 11110100100100100101011111 = 26 bits 25 812 = 110010011010100 = 15 bits 54 = 110110 = 6 bits

min	-1
max	0.9921875
mean	0.03131510416666667
std	0.2122100147954903
sparsity	91.7%

99	93	1	•	85	79	55	= 99 x 85 + 93 x 79 + 1 x 55 = 15817
99	93	0	•	85	79	55	= 99 x 85 + 93 x 79 + 0 x 55 = 15762

### **Optimizing (compressed) neural networks**

- Hyperparameters: a set of parameters that configure the neural network architecture and how it is trained
- Neural networks are a black box. Training can take a long time. Have to wait until training ends to see how well a set of hyperparameters work automate
- With compressed neural networks that run directly on hardware, have to also consider requirements by hardware





## Al use cases



### **Track reconstruction**

#### **Offline:**

- spacepoint formation
- track seeding
- track following
- track fitting
- **Online:** 
  - pattern recognition
  - latency O(10)us

**Neural networks** 



Current environment inside ATLAS

at LHC



Expected environment inside ATLAS at HL-LHC





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## Jet tagging

- Identify the type of the particle that initiates the jet.
- Challenge: particles can radiate, radiated particles produce more particles
- Neural network: -
- use measured particle properties and particle pair interactions to identify particle types



#### **Anomaly detection**

- What if the trigger discards events that show new physics?
- Same input as Global Trigger, has to run in 50ns
- Find events that are very unusual









## L0 Muon trigger

#### For cases with reduced RPC performance:

- Pattern recognition neural networks, distinguish muon hits from backgrounds
- Momentum estimation

Event Image





Signal

# Additional







