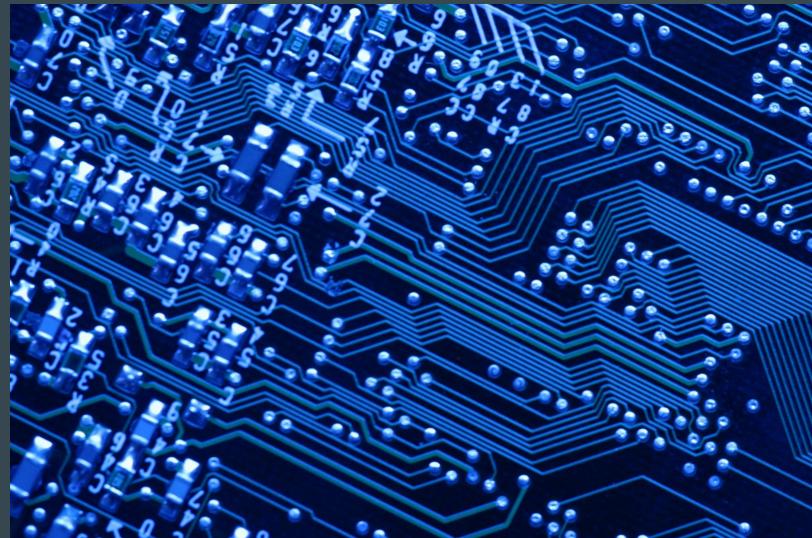
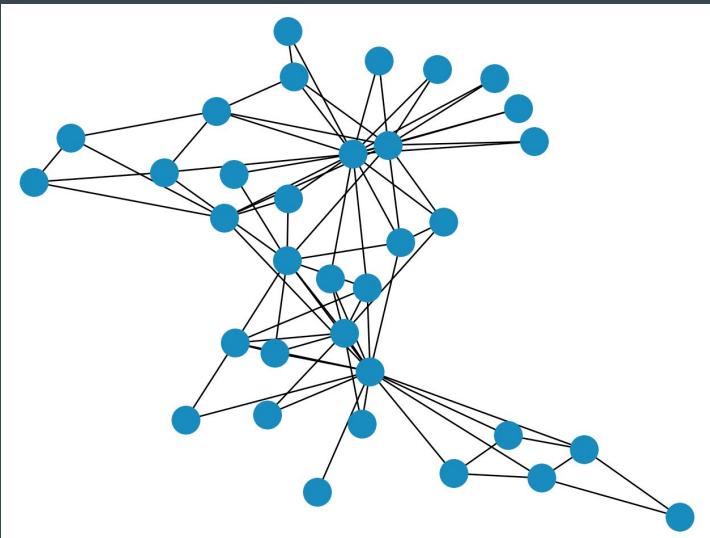


PyTorch Geometric to HLS

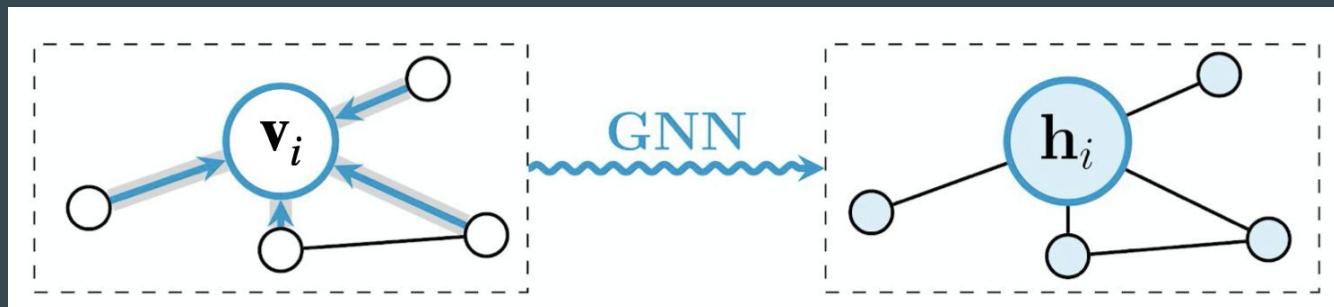
An hls4ml add-on for conversion of Graph Neural Networks



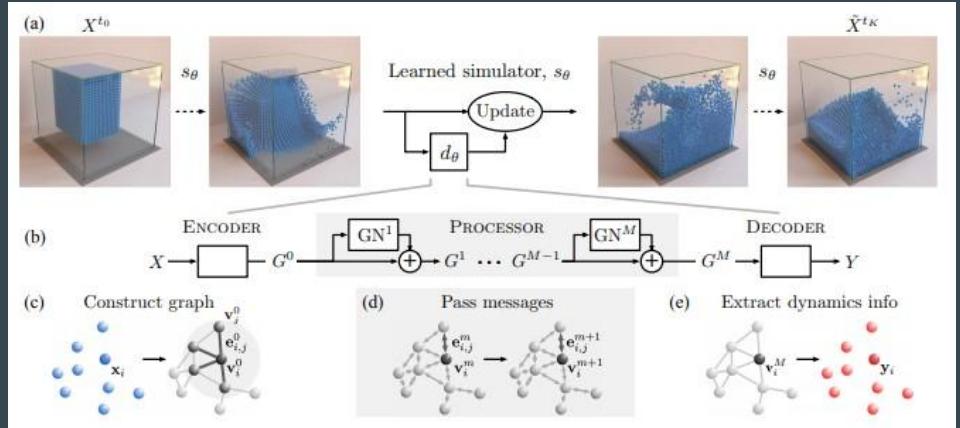
https://github.com/abdelabd/hls4ml/tree/pyg_to_hls_rebase

Graph Neural Networks

- $G = (V, E, \text{edge_index})$;
 - $V[i,j] = j\text{th attribute of } i\text{th vertex}$
 - $E[i,j] = j\text{th attribute of } i\text{th edge}$
 - $\text{edge_index}[0,i] = \text{the index of the sending node for the } i\text{th edge}$
 - $\text{edge_index}[1,i] = \text{the index of the receiving node for the } i\text{th edge}$
- We can represent arbitrary-dimensional objects as ‘nodes’
- We can represent arbitrary-dimensional relationships as ‘edges’
- Benefits: efficient encoding of context, generalizability, permutation invariance

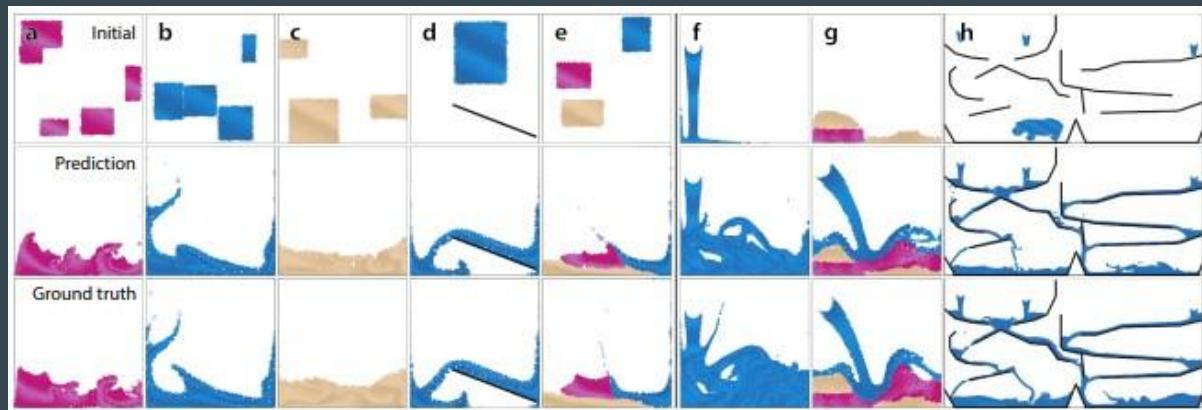


Generalizable, Contextual

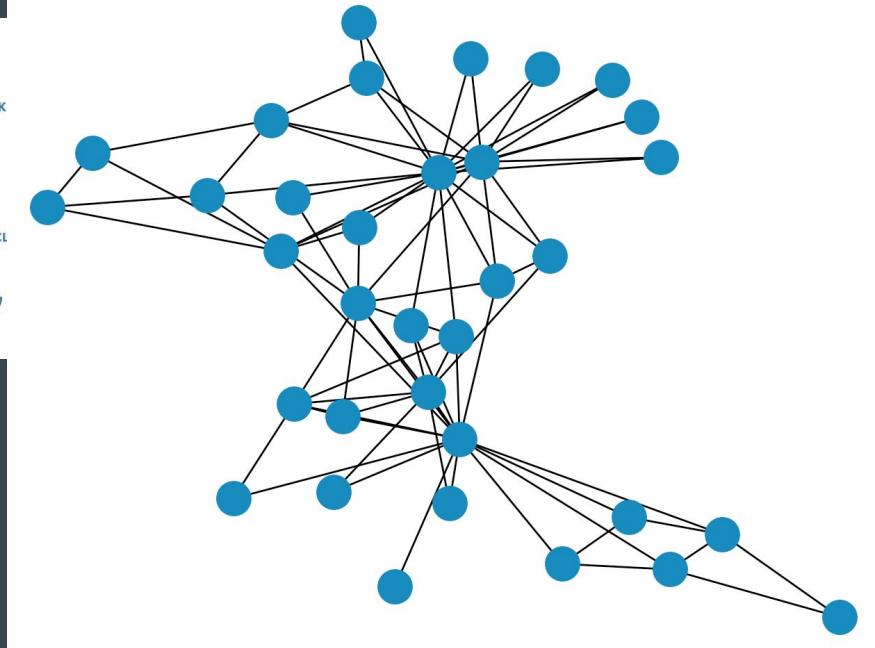
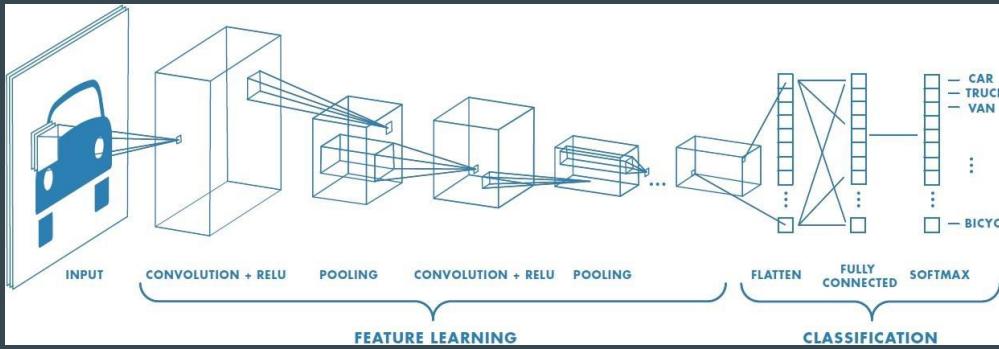


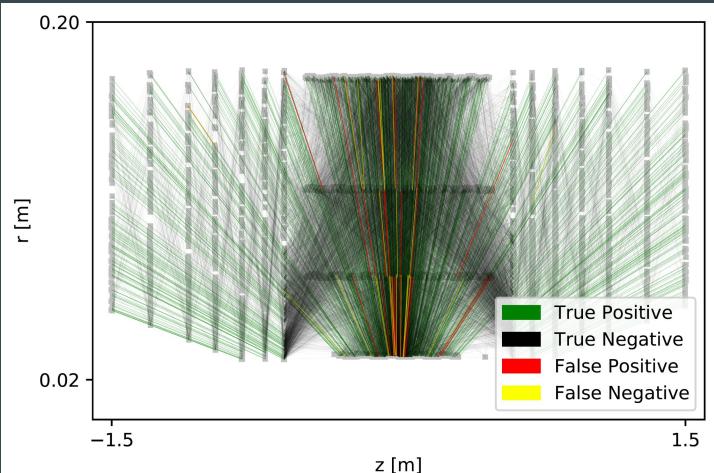
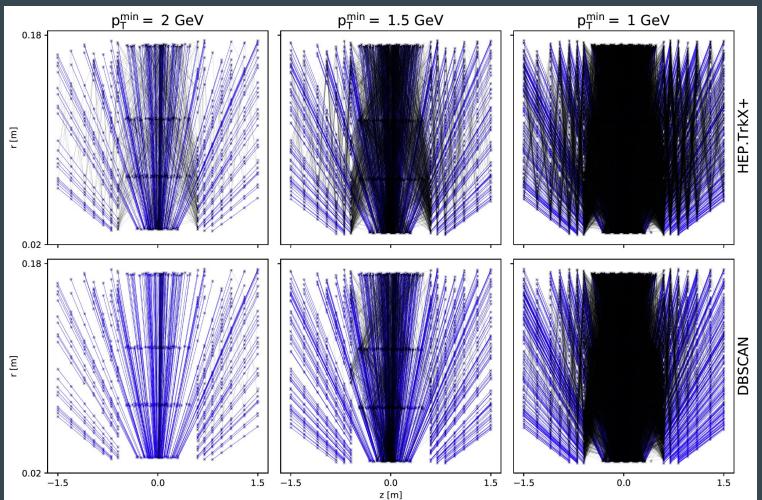
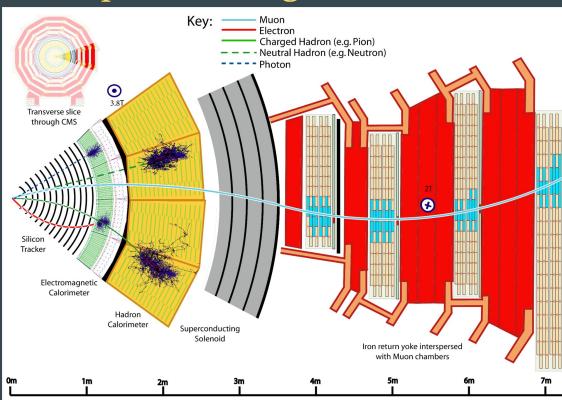
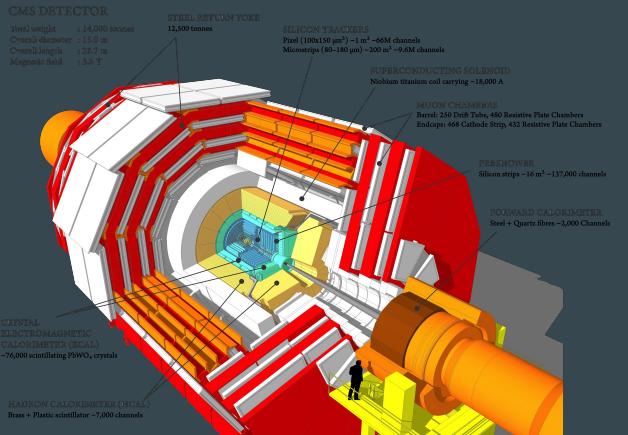
Learning to Simulate Complex Physics with Graph Networks, DeepMind 2020

<https://arxiv.org/abs/2002.09405>

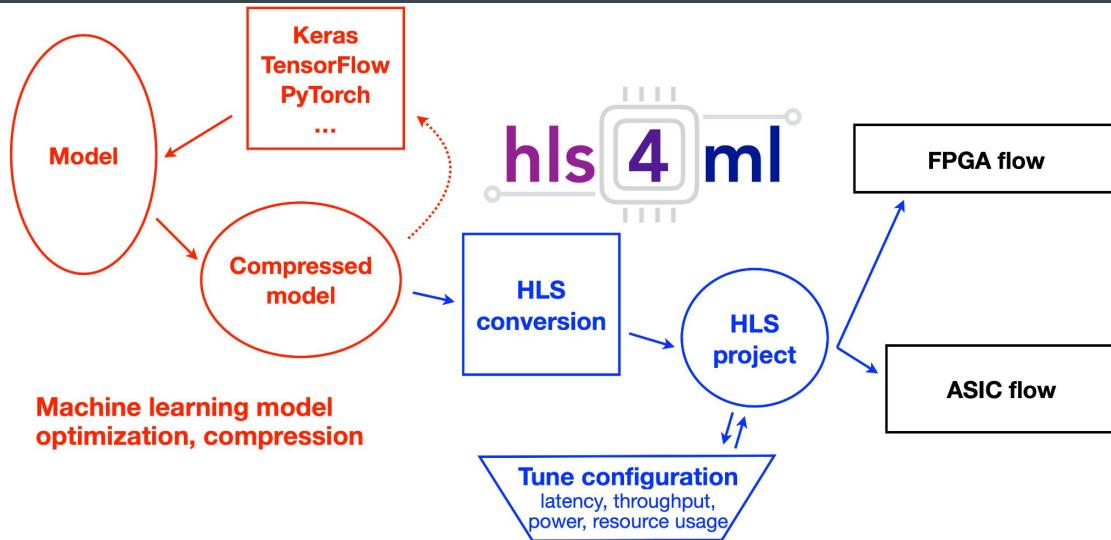
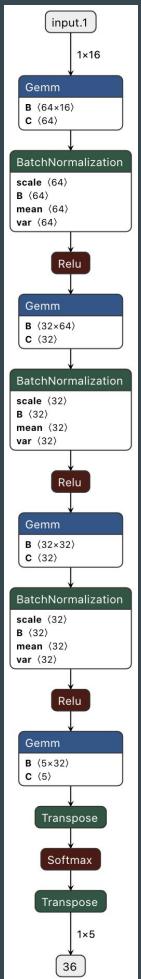


Permutation Invariant





hls4ml



See https://github.com/jmduarte/pytorch_dev_hls4ml/tree/commit_hls

```

layer2_t layer2_out[N_LAYER_2];
#pragma HLS ARRAY_PARTITION variable=layer2_out complete dim=0
nnet::dense<input_t, layer2_t, config2>(input1, layer2_out, w2, b2); // fc1

layer4_t layer4_out[N_LAYER_2];
#pragma HLS ARRAY_PARTITION variable=layer4_out complete dim=0
nnet::relu<layer2_t, layer4_t, ReLU_config4>(layer2_out, layer4_out); // act1

layer5_t layers5_out[N_LAYER_5];
#pragma HLS ARRAY_PARTITION variable=layer5_out complete dim=0
nnet::dense<layer4_t, layer5_t, config5>(layer4_out, layers5_out, w5, b5); // fc2

layer7_t layer7_out[N_LAYER_5];
#pragma HLS ARRAY_PARTITION variable=layer7_out complete dim=0
nnet::relu<layer5_t, layer7_t, ReLU_config7>(layer5_out, layer7_out); // act2

layer8_t layer8_out[N_LAYER_8];
#pragma HLS ARRAY_PARTITION variable=layer8_out complete dim=0
nnet::dense<layer7_t, layer8_t, config8>(layer7_out, layer8_out, w8, b8); // fc3

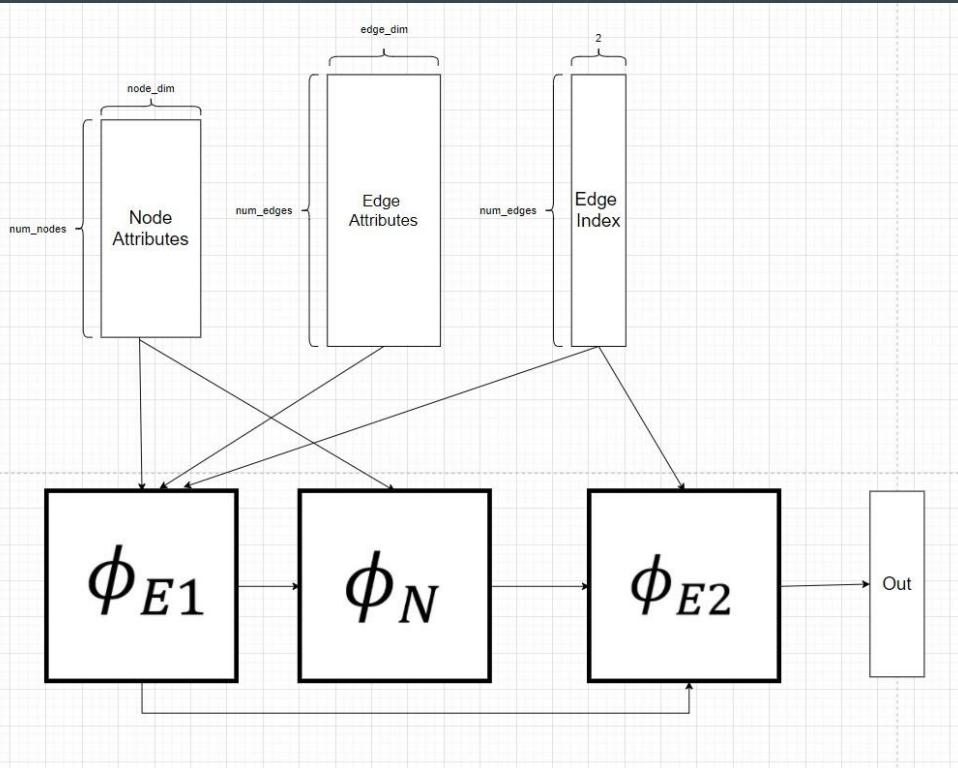
layer10_t layer10_out[N_LAYER_8];
#pragma HLS ARRAY_PARTITION variable=layer10_out complete dim=0
nnet::relu<layer8_t, layer10_t, ReLU_config10>(layer8_out, layer10_out); // act3

layer11_t layer11_out[N_LAYER_11];
#pragma HLS ARRAY_PARTITION variable=layer11_out complete dim=0
nnet::dense<layer10_t, layer11_t, config11>(layer10_out, layer11_out, w11, b11); // fc4

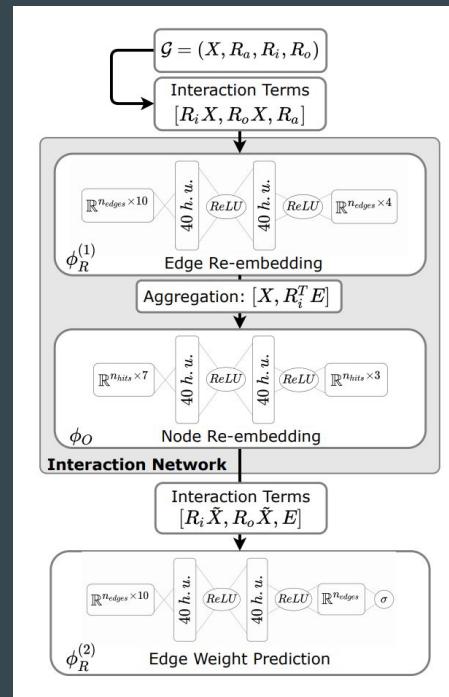
nnet::softmax<layer11_t, result_t, Softmax_config12>(layer11_out, layer12_out); // softmax
  
```

Graph Neural Networks: non-feedforward data flow

← Interaction Network



- <https://arxiv.org/abs/1612.00222>
- <https://arxiv.org/abs/2103.16701>
- https://github.com/GageDeZoort/interaction_network_paper



torch_geometric.nn.conv.MessagePassing

- Message → Aggregate → Update

```
def forward(self, data):#x, edge_index, edge_attr):
    x = data.x
    edge_index = data.edge_index
    edge_attr = data.edge_attr

    # Message
    x_i, x_j = x[edge_index[1]], x[edge_index[0]]
    msg_out = self.message(x_i, x_j, edge_attr) # self.message(edge_index, edge_attr)

    # Aggregate
    index = edge_index[1,:]
    ptr = None
    dim_size = x.shape[0]
    aggr_out = self.aggregate(msg_out, index, ptr, dim_size)

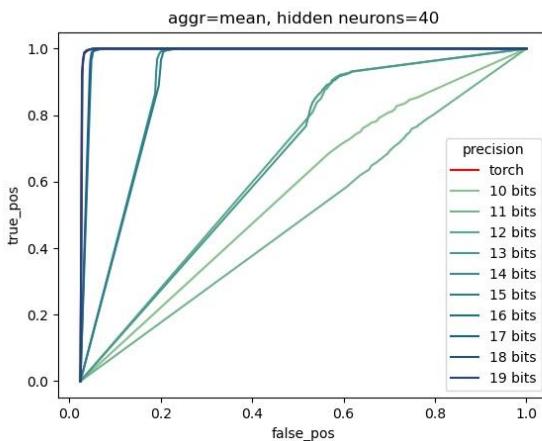
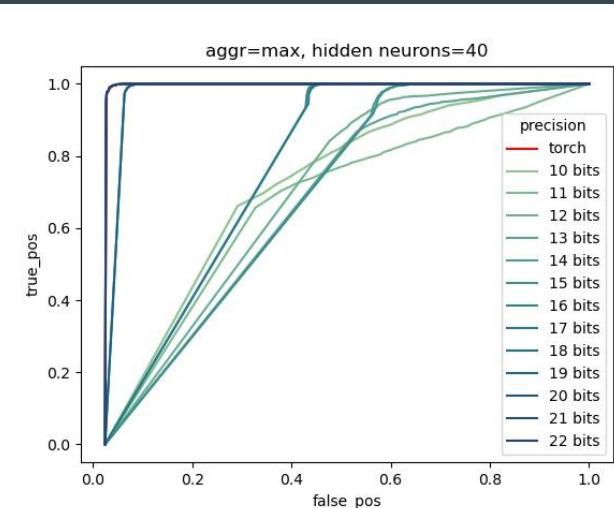
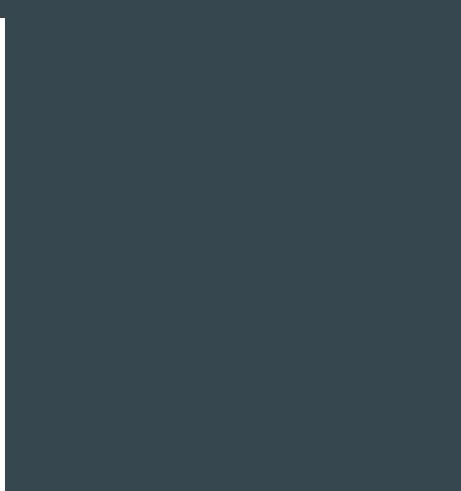
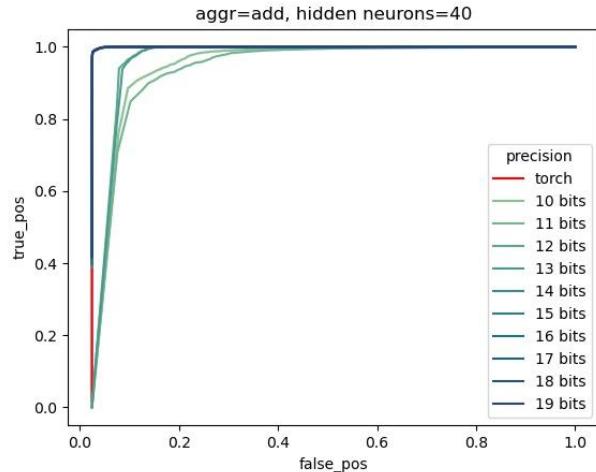
    # Update
    update_out = self.update(aggr_out, x)
    x_tilde = update_out

    #return update_out
    m2 = torch.cat([x_tilde[edge_index[1]],
                   x_tilde[edge_index[0]],
                   self.E], dim=1)
    return torch.sigmoid(self.R2(m2))
```

pyg_to_hls: EdgeBlock, NodeBlock, Aggregate

1. class GraphBlock(hls4ml.model.hls_layers.Layer): packages a torch *module* into a form that will be accepted as an HLS *layer*
2. class EdgeBlock(GraphBlock):
 - i. Inputs
 1. Node attributes
 2. Edge attributes
 3. Edge Index
 - ii. Function:
 1. For each edge:
 - a. <edge attributes, receiver-node attributes, sender-node attributes> → Neural Network → Edge predictions
 - b. Edge predictions → permutation-invariant aggregation → Aggregate edge predictions
 - iii. Outputs
 1. Edge predictions
 2. Aggregate edge predictions
2. class NodeBlock(GraphBlock):
 - i. Inputs
 1. Node attributes
 2. Aggregate edge attributes (or aggregate messages)
 - ii. Function:
 1. For each node:
 - a. <node attributes, aggregate attributes> → Neural Network → Node predictions
 - iii. Outputs
 1. Node predictions
3. class Aggregate(hls4ml.model.hls_layers.Layer):
 - a. Edge attributes → permutation-invariant aggregation → Aggregate edge attributes

Interaction Network Benchmarks



User-inputs

```
def pyg_to_hls(model, forward_dict, graph_dims,
               activate_final = None,
               fixed_precision_bits=16,
               fixed_precision_int_bits=6,
               int_precision_bits=16,
               int_precision_signed=False,
               output_dir = None):
```

```
# model.forward() dictionary
forward_dict = OrderedDict()
forward_dict["R1"] = "EdgeBlock"
forward_dict["0"] = "NodeBlock"
forward_dict["R2"] = "EdgeBlock"
```

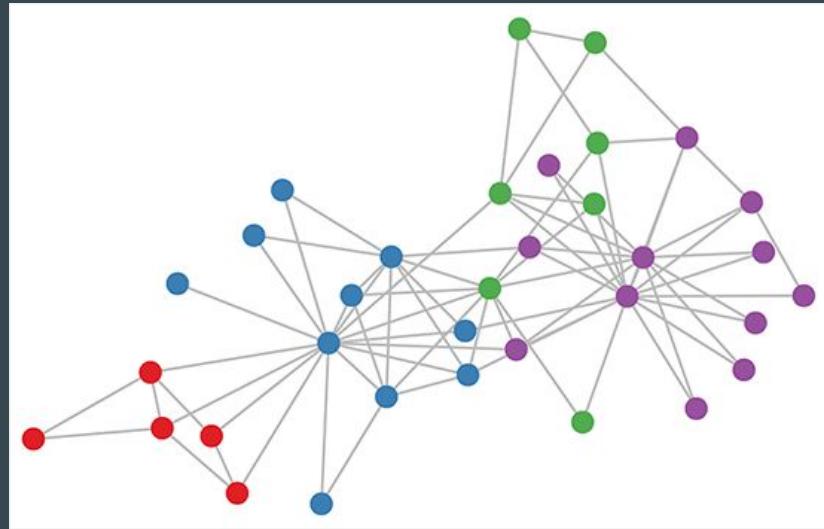
Graph padding and truncation

Hardware-implementation requires: n_nodes_max, n_edges_max

1. Truncation: removes true nodes, true edges, or both
 - a. Always bad
 - i. Fixes: Look for disconnected nodes, remove the least connected nodes first
 1. Compute ↗

2. Padding: adds dummy nodes, dummy edges, or both

 - a. sometimes bad
 - i. $n_nodes \geq n_nodes_max, n_edges < n_edges_max$
 1. Dummy edges must connect true nodes
 - b. sometimes alright
 - i. $n_nodes < n_nodes_max, n_edges \leq n_edges_max$
 1. Dummy nodes disconnected, or dummy nodes connected with dummy edges



Support yet to come

- Non-linear layers
- Arbitrary # of layers per block
 - Currently: 1-->4 layers
- Higher-degree neighbors for “Message” and “Aggregation”
 - Currently only first-degree neighbors
- Different “Message” schemes
 - Currently: `NN_input = concat(receiver attributes, sender attributes, edge attributes)`

About the author



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- B.A.: Physics, Economics @ U.Penn.
 - Graduation: August 2021
- Research Interests:
 - HEP, Astronomy, Applied ML for experimental Physics
 - Information theory, entropy and thermodynamics
 - Signal processing and hardware design
 - Graph Neural Networks and Graphical Causality
 - Reinforcement learning, Game Theoretic ML
- Hobbies:
 - Mountain biking, hiking, fishing
 - Basketball
 - Electric Guitar (noob)
- Applying to Physics and CS PhD programs!

← Abdelrahman Elabd