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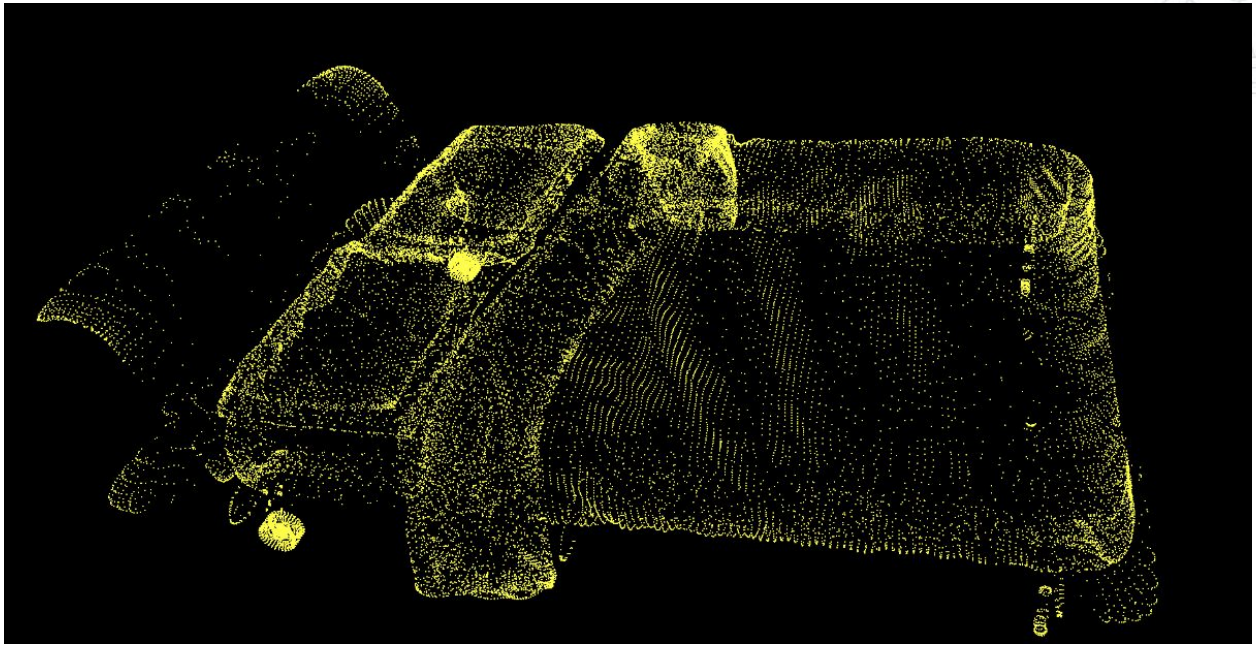
3D Point Cloud Classification

using
Graph Neural Networks

https://github.com/DishaJindal/Point-Cloud-Classification

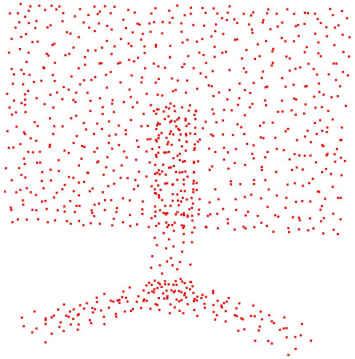
3D Point Cloud



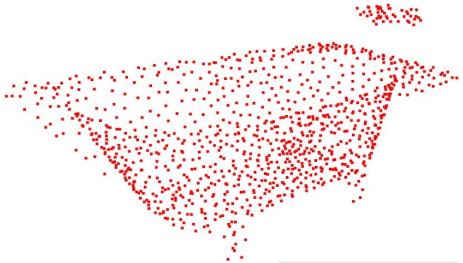
ModelNet 10 Classes..

Chair

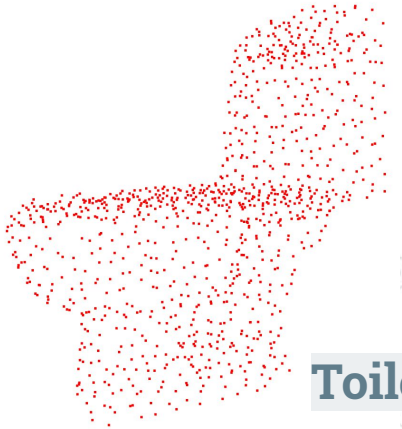
Night Stand



Monitor



Bathtub



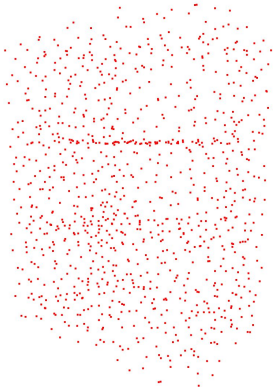
Toilet

ModelNet 10 Classes..

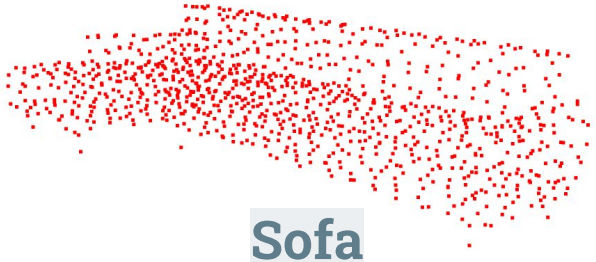
Desk

Bed

Table



Dresser



Sofa

Challenges with 3D Point Cloud Classification

3D Point Clouds do not have the same regularities or symmetries like 2D data

When represented as graphs, the vertices do not have the same number of neighbors

Some earlier approaches:

- Process a collection of 2D images instead
- Bin the points into voxels

How Graph Neural Networks help?

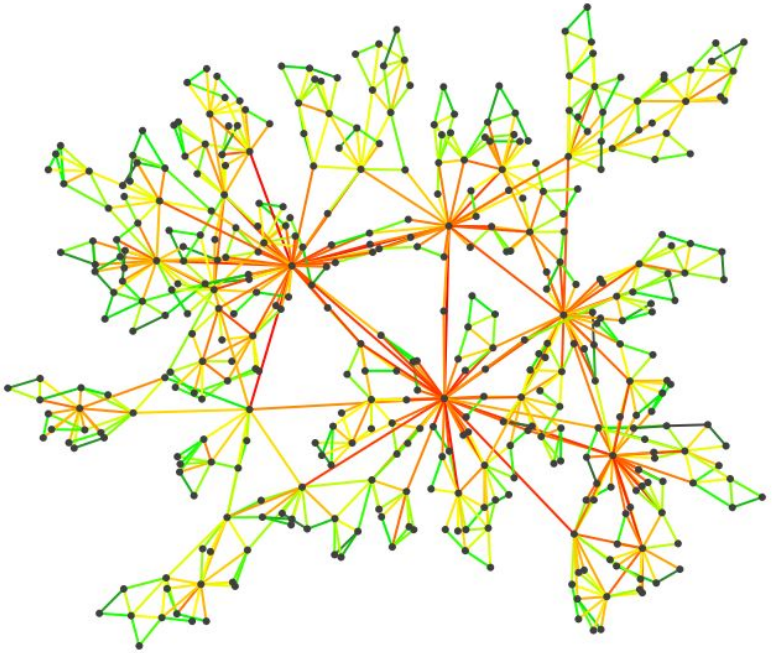
Directly using the point cloud data to tackle the 3D classification problem is an research topic

Graph CNN extend traditional CNN to handle data that is supported on a graph

The architecture has novel localized graph convolutions and two graph downsampling operations

It learns a latent signature summarizing each point cloud at different receptive fields

Graph Construction



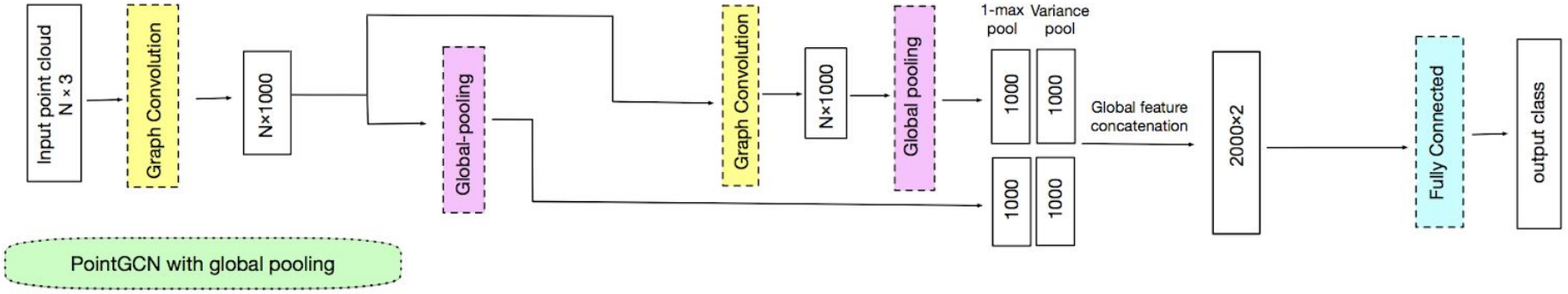
CPU Construction Time

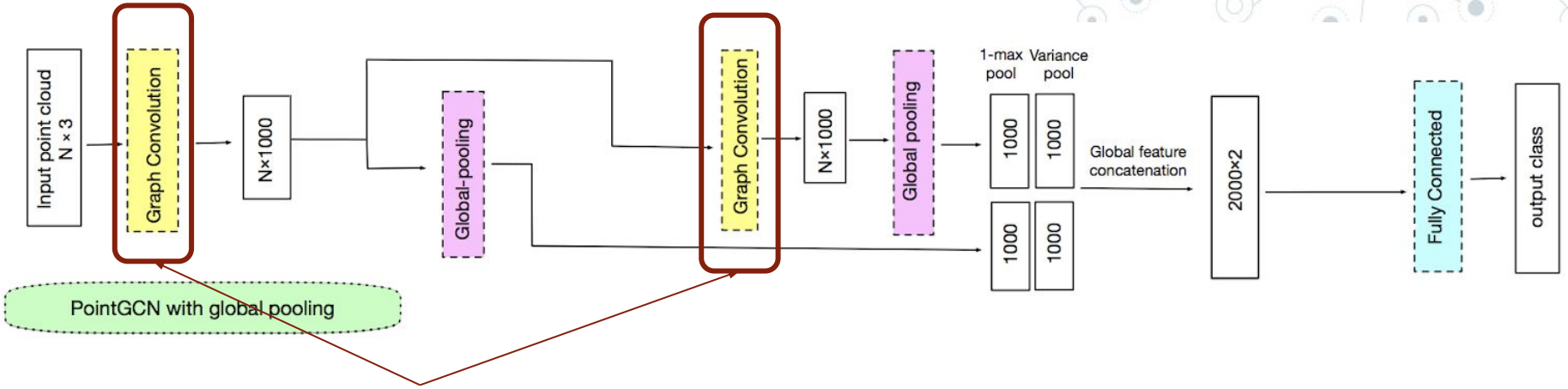
9409076 µs

GPU Construction Time

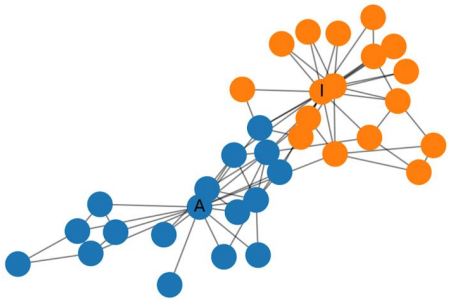
19 µs

Model Architecture

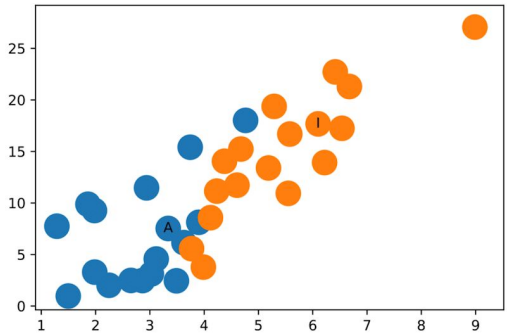


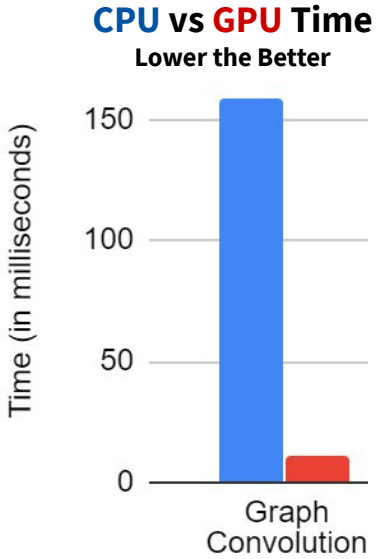


Graph Convolution Layers

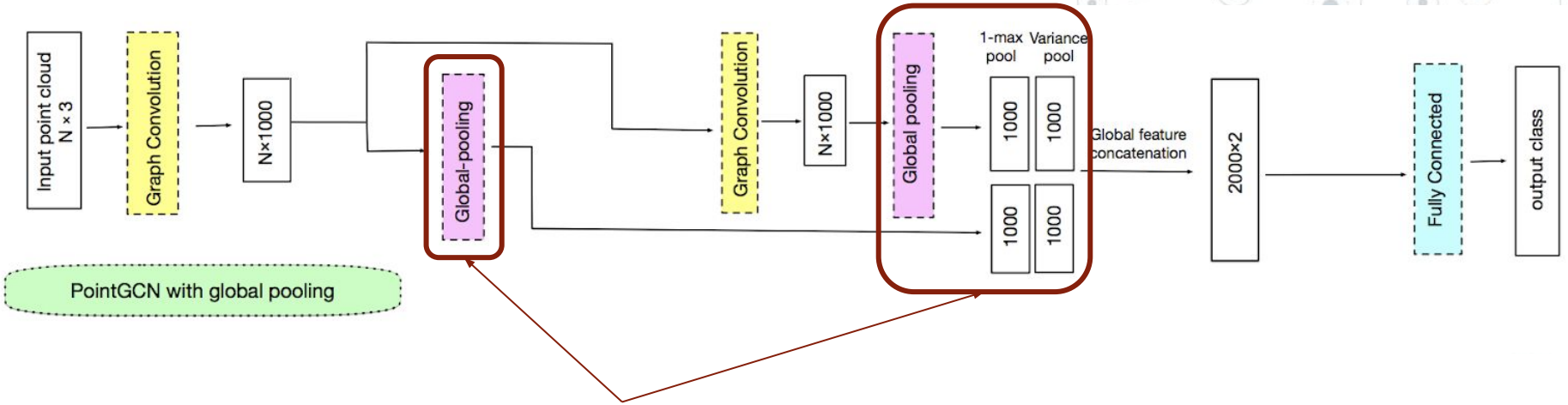


Graph Convolutional Network

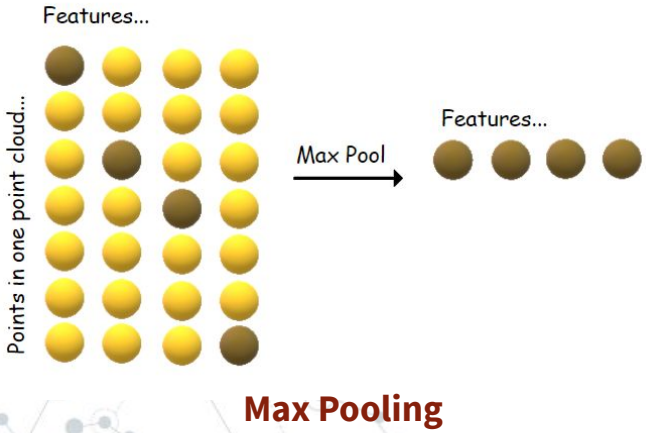




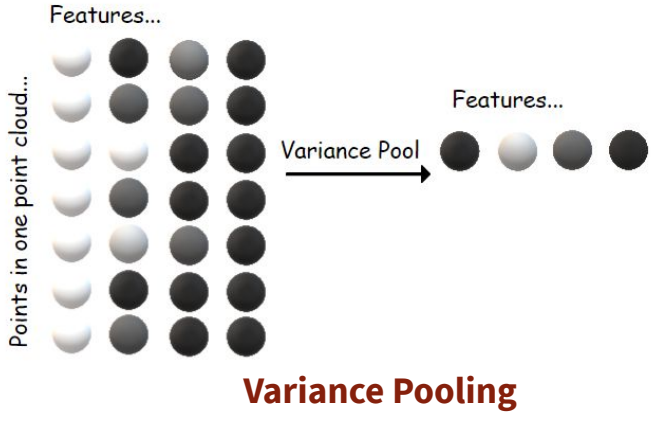
Reference: https://towardsdatascience.com/how-to-do-deep-learning-on-graphs-with-graph-convolutional-networks-7d2250723780



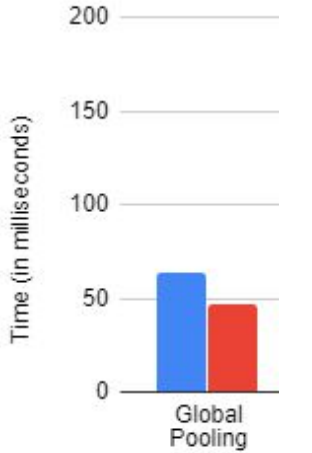
Global Pooling Layers

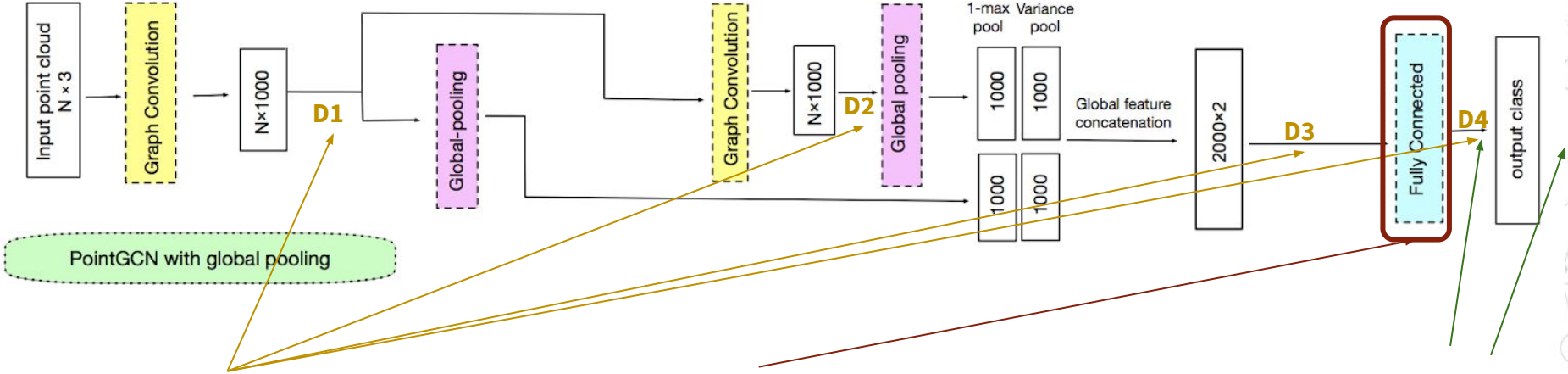


Max Pooling

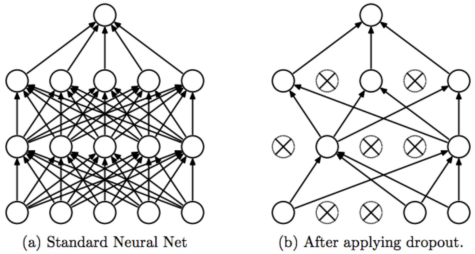


Variance Pooling

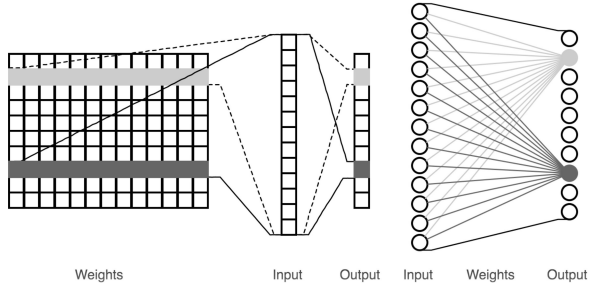




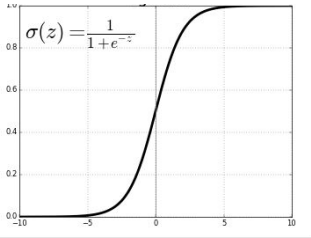
Dropout Layers



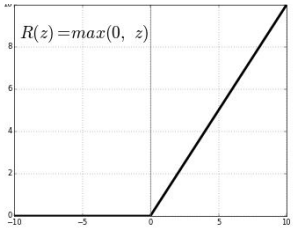
Fully Connected Layer



Activation Functions



Softmax

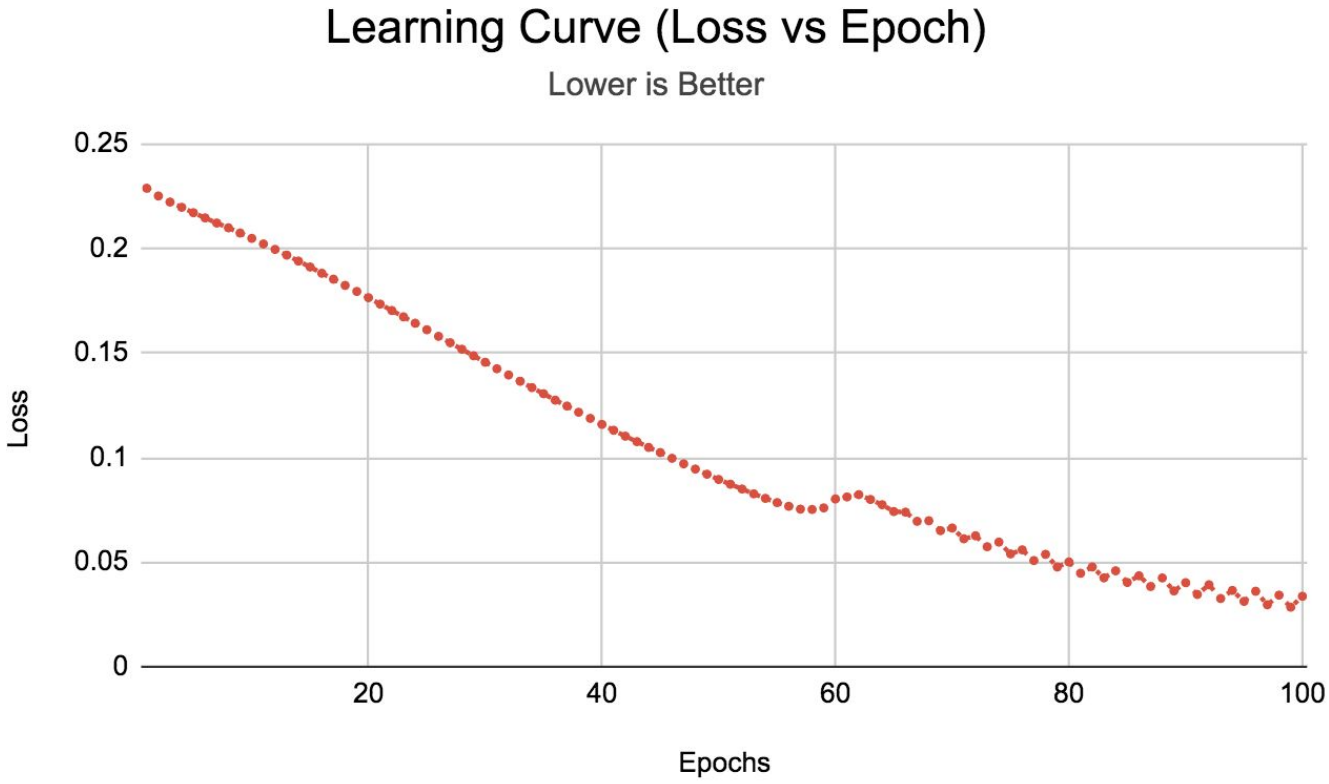


ReLU

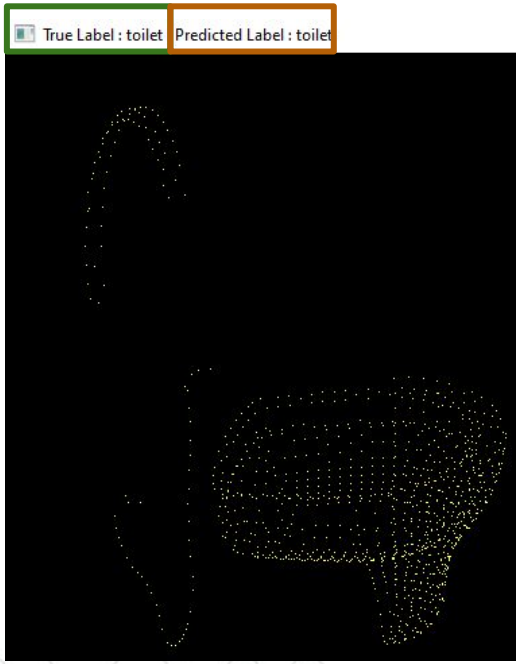
Dropout : https://medium.com/@amarbudhiraja/https-medium-com-amarbudhiraja-learning-less-to-learn-better-dropout-in-deep-machine-learning-74334da4bfc5
FCL : https://www.oreilly.com/library/view/machine-learning-with/9781787121515/79694e8a-e30d-4b30-9b59-abcb2c436182.xhtml
Activations : https://medium.com/@himanshuxd/activation-functions-sigmoid-relu-leaky-relu-and-softmax-basics-for-neural-networks-and-deep-8d9c70eed91e

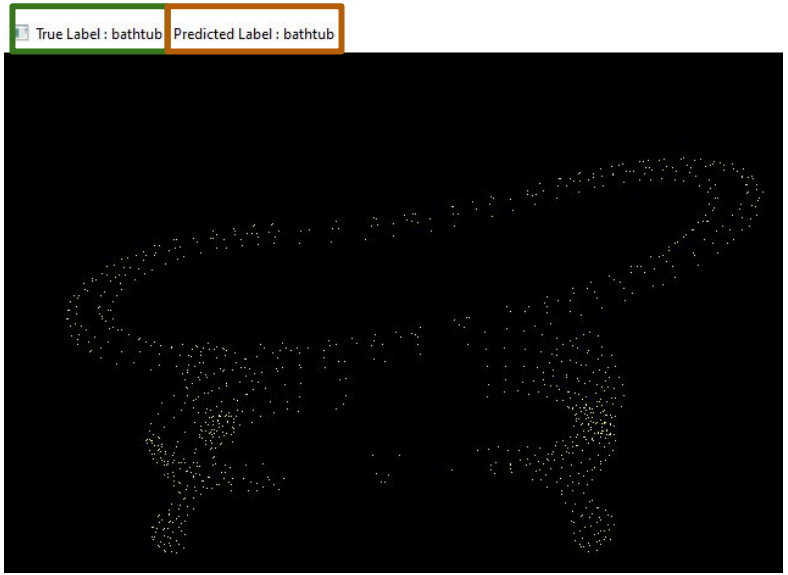
How does the model perform?

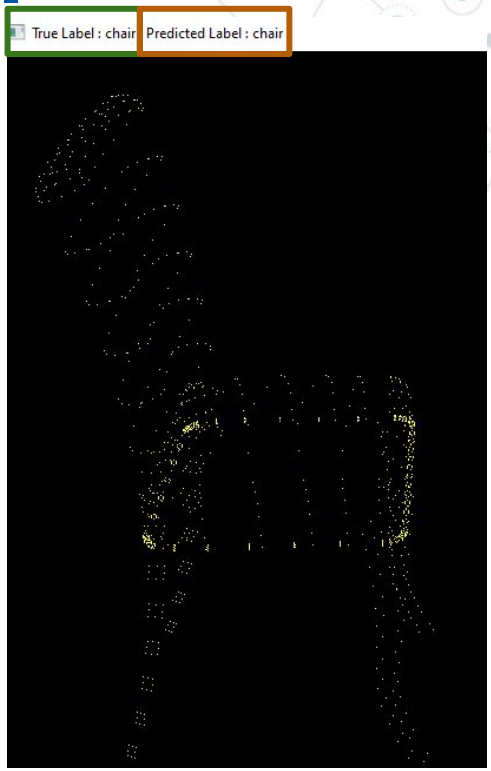
It learns...


Learning Curve (Loss vs Epoch)
Lower is Better
0.25
0.2
0.15
0.1
0.05
0
Loss
20
40
60
80
100
Epochs

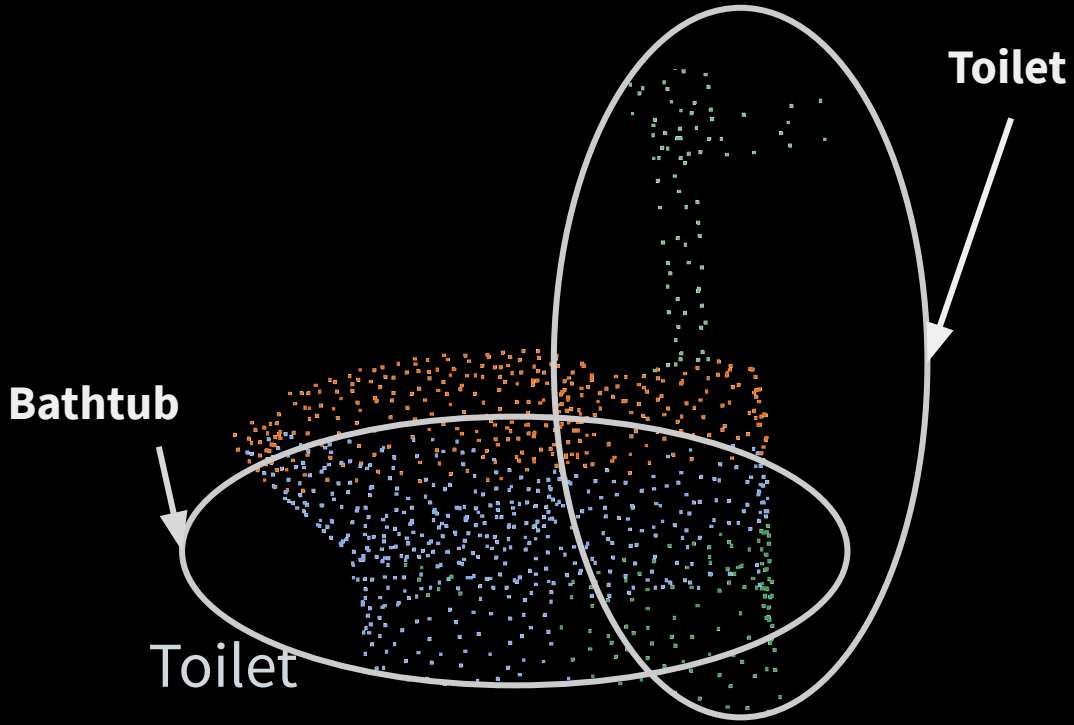
It classifies 3D Point Clouds..

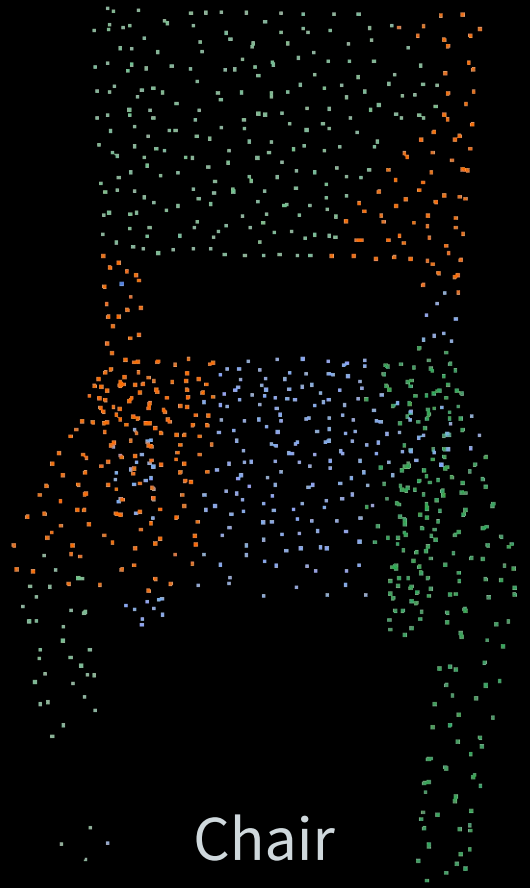






It can do point wise classification...





Bathtub Bed Chair Desk Dresser Monitor Night Stand Sofa Table Toilet

How fast is it?

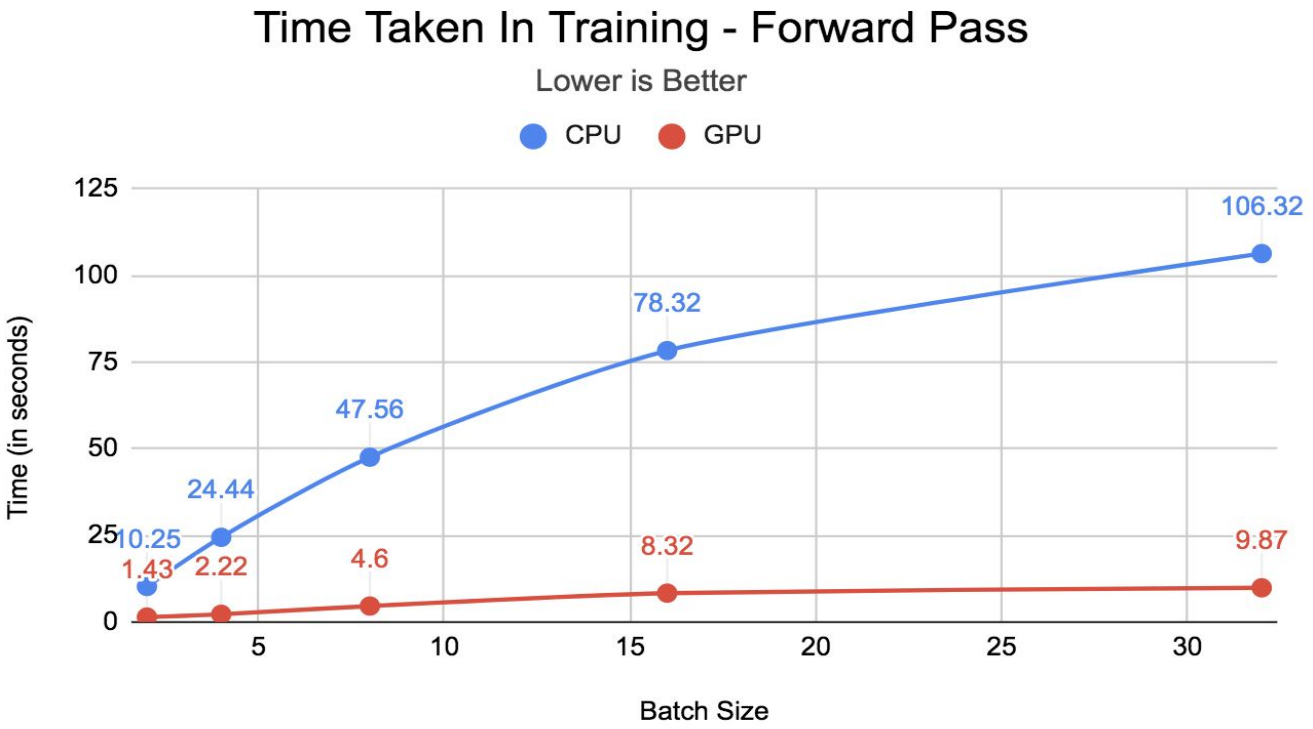
CPU vs GPU

Recording speeded up 200 times

Recording speeded up 10 times

How much Better?

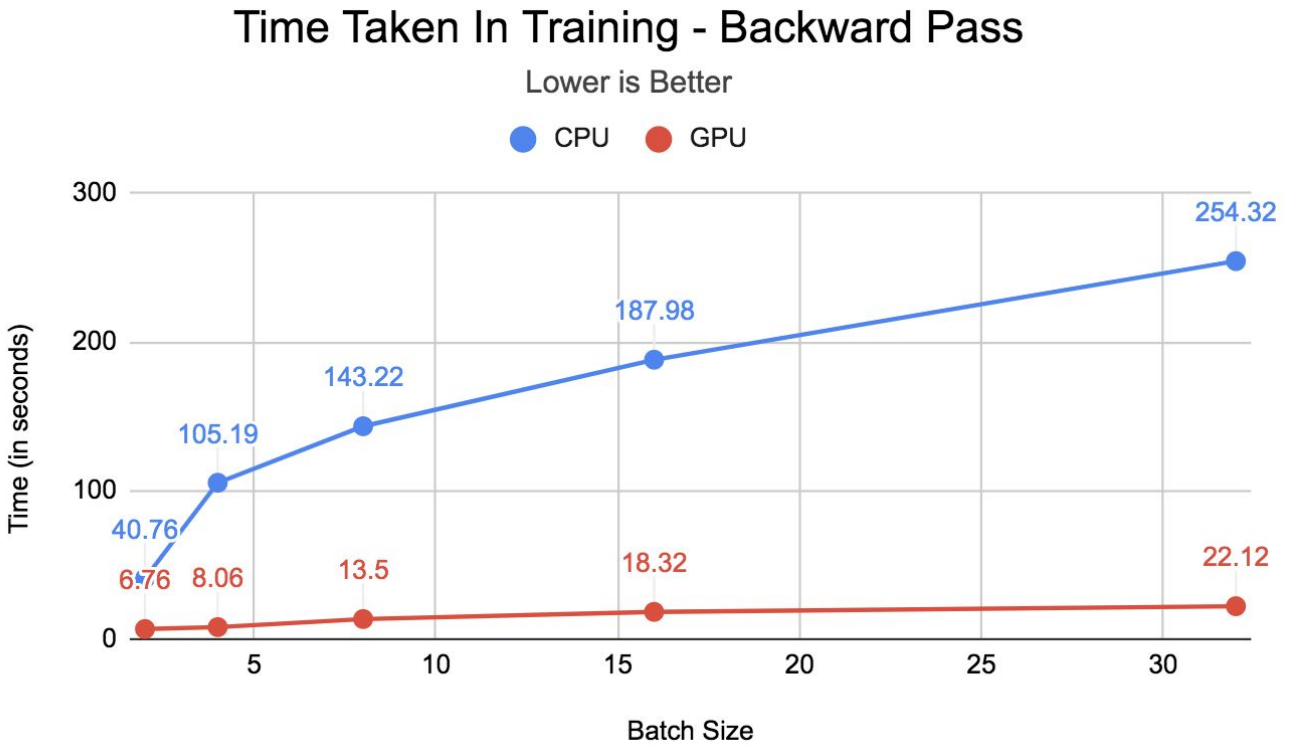
Forward Pass ✔



How much Better?

Forward Pass ✅

Backward Pass ✅



How much Better?

Forward Pass ✅

Backward Pass ✅

Inference ✅

982 ms

CPU Inference Time

111 ms

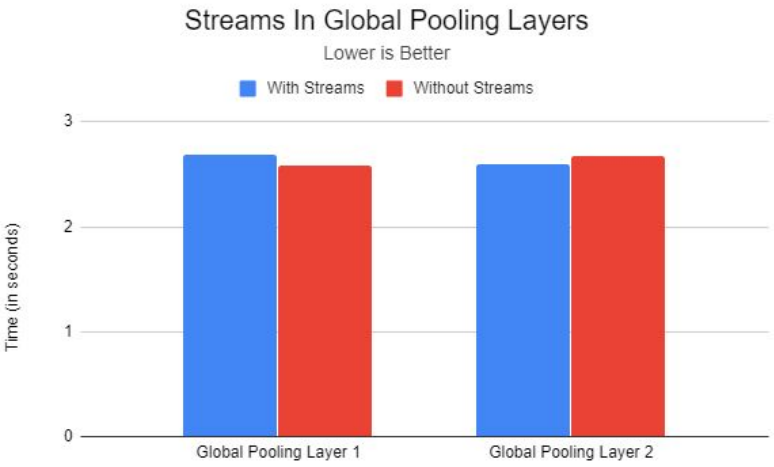
GPU Inference Time

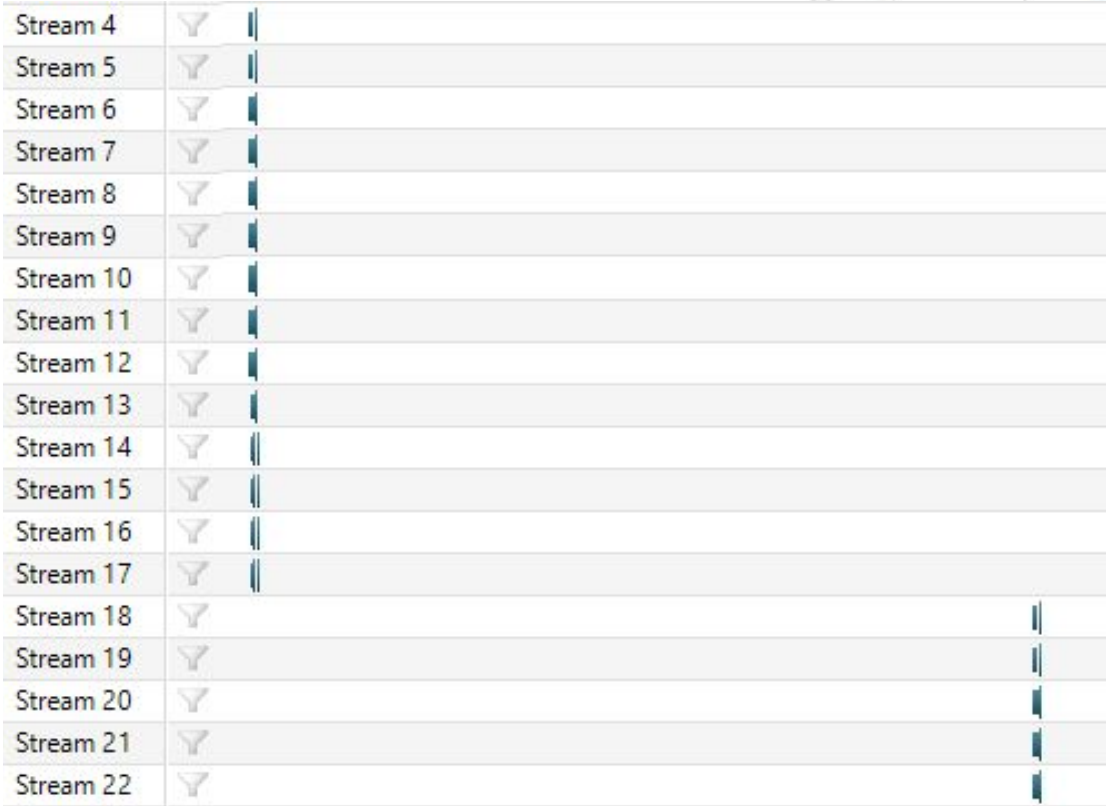
9x

Speed-up!

Not all experiments worked as expected...

Streams


Streams In Global Pooling Layers
Lower is Better
With Streams
Without Streams
Time (in seconds)
3
2
1
0
Global Pooling Layer 1
Global Pooling Layer 2


Stream 4
Stream 5
Stream 6
Stream 7
Stream 8
Stream 9
Stream 10
Stream 11
Stream 12
Stream 13
Stream 14
Stream 15
Stream 16
Stream 17
Stream 18
Stream 19
Stream 20
Stream 21
Stream 22

Learnings..

- No universal optimizations! Optimized reduction did not work well for small data
- Do your math properly! Else you end up with things like Kronecker product (which results in a 10^6x10^6 sized matrix ~ 2^{14} gb)
- Memory Leaks!

Credits..

Special thanks to,

- Yingxue Zhang and Michael Rabbat - Authors of the paper: A GRAPH-CNN FOR 3D POINT CLOUD CLASSIFICATION
- Tim Kaldewey (NVIDIA) for motivating us to experiment with streams.
- Our shadow team - Chhavi Sharma

Thanks!

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