Graph Convolution

A: Adjacency Matrix

U: Feature Matrix

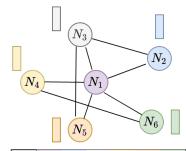
W: Weight Matrix/ Filter

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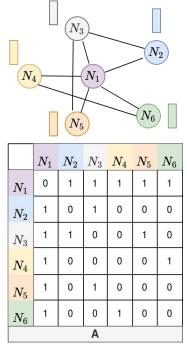
	N_1	N_2	N_3	N_4	N_5	N_6
N_1	0	1	1	1	1	1
N_2	1	0	1	0	0	0
N_3	1	1	0	0	1	0
N_4	1	0	0	0	0	1
N_5	1	0	1	0	0	0
N_6	1	0	0	1	0	0
Α						

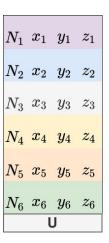
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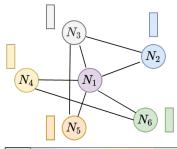


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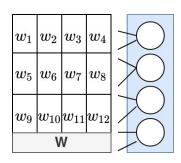
U: Feature Matrix

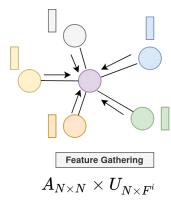
W: Weight Matrix/ Filter

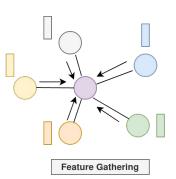


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Α						

N_1	x_1	y_1	z_1		
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N_5	x_5	y_5	z_5		
N_6	x_6	y_6	z_6		
U					



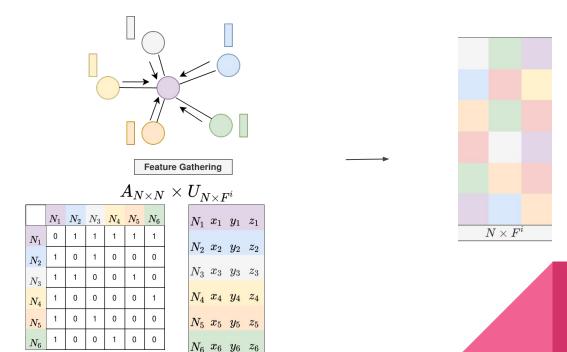


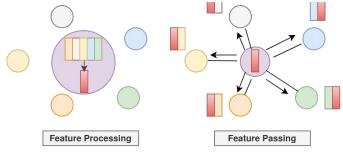


$A_{N imes N}$	×	$U_{N imes F^i}$
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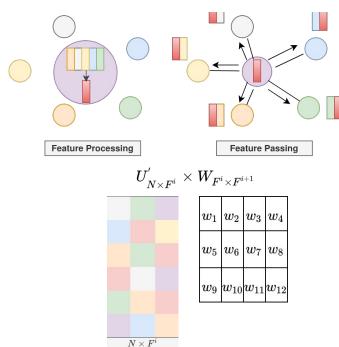
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1	, ,, ,		
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N_4	x_4	y_4	z_4
N_5	x_5	y_5	z_5
N_6	x_6	y_6	z_6

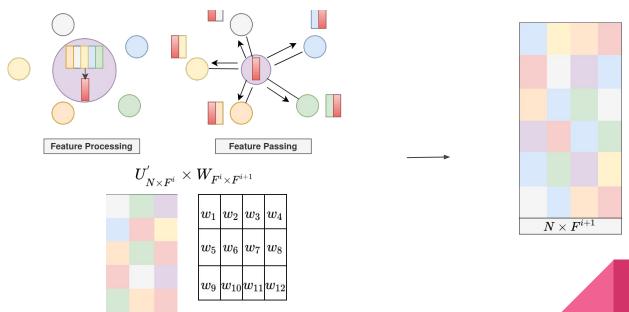




$$U_{N imes F^i}^{'} imes W_{F^i imes F^{i+1}}$$



Graph Convolution



 $N \times F^i$

Graph Convolution

$$F^{i+1} = \sigma(A_{N imes N} U_{N imes F^i} W^i_{F^i imes F^{i+1}})$$

Here σ is non-linearity in the network. It can be relu, leaky-relu, sigmoid e.t.c. For our work we have considered leaky-relu function.

- It measures the distance between two point set
- o In our case point set contains distinct tuple values which represent (x, y, z) coordinates of 3D point cloud shape. Ex: S1 = $\{(xi, yi, zi)\}$ and S2 = $\{(x'j, y'j, z'j)\}$

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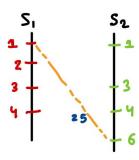
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Ex:
$$S1 = \{1, 2, 3, 4\}$$
 and $S2 = \{3, 4, 1, 6\}$

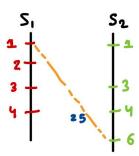


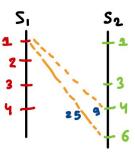


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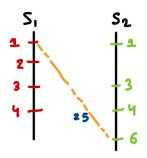


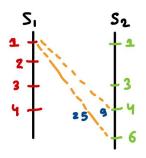
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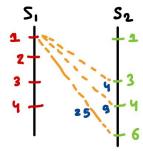




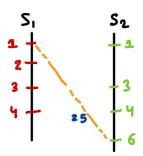
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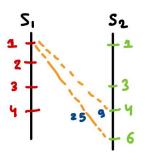


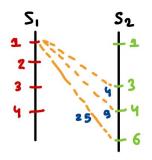


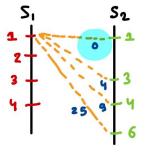


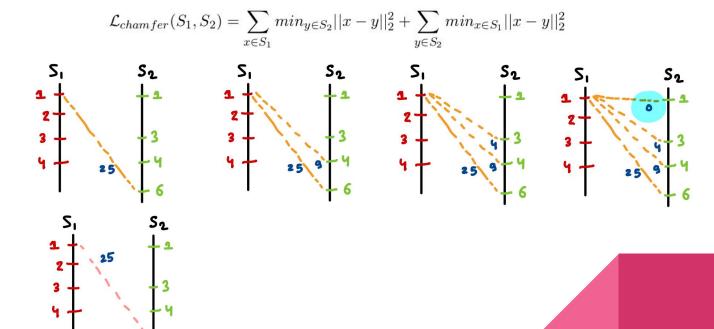
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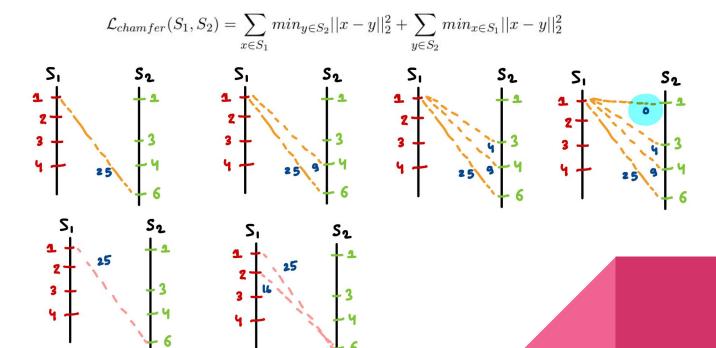


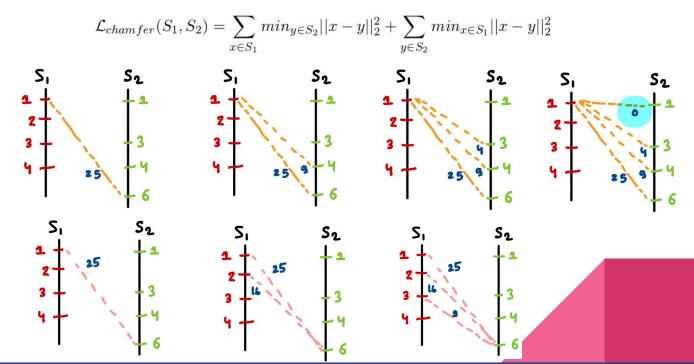


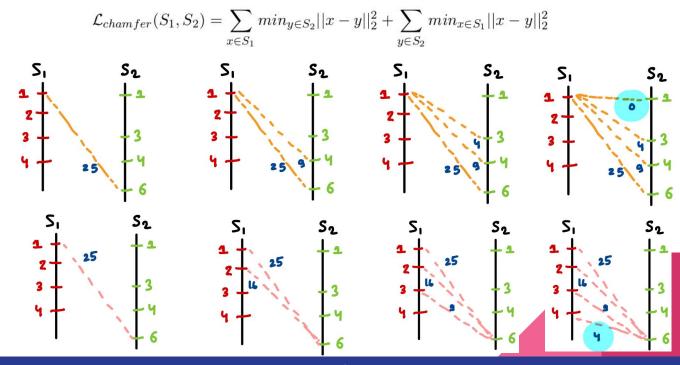












Chamfer Distance

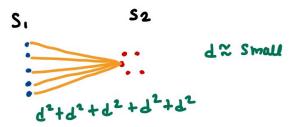
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In case of 3D coordinates

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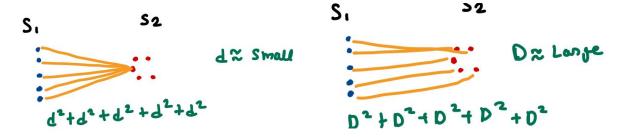
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- Frechet Inception Distance [3] and Frechet Point Cloud [1]
 - FID is use to evaluate the quality of target image with respect to reference image.
 - FPD is use to evaluate the quality of target point cloud with respect to reference point cloud.
 - These both are the metrics for evaluation and comparison of the deep learning models.
 - We use FID in image generation GAN to evaluate the quality of image generated by the GAN model.
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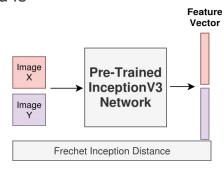
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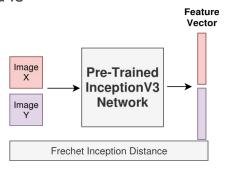
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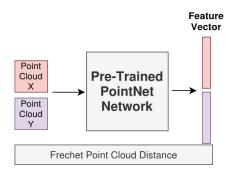
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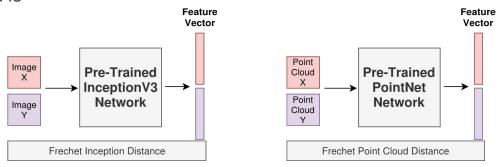


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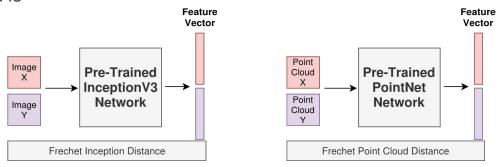
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$$|FD = \left|\left|\mu_X - \mu_Y
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Lower the Frechet Distance better the generated result is.

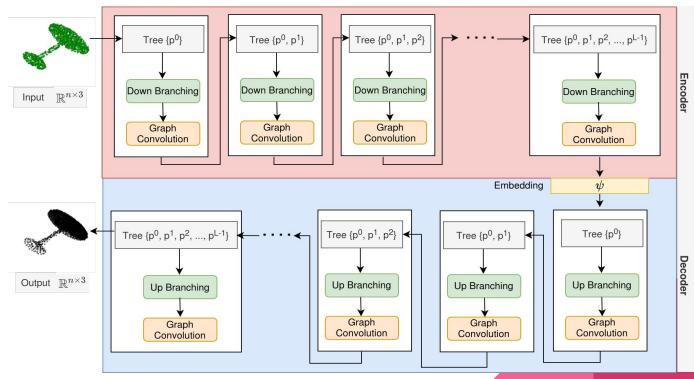
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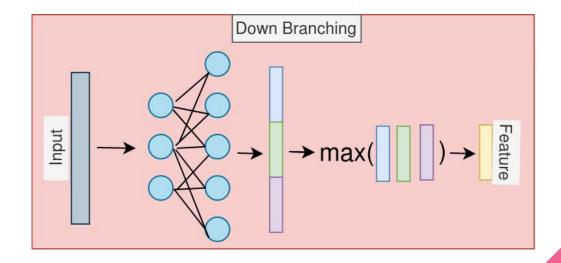
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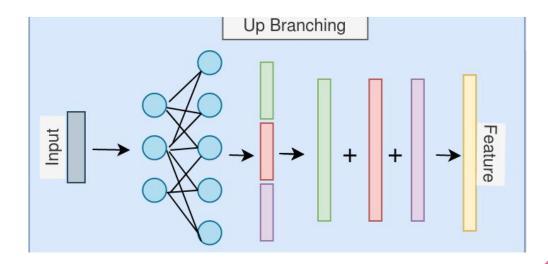
Proposed TreeGCN-ED Model



- Proposed TreeGCN-ED Model
 - Down Branching



- Proposed TreeGCN-ED Model
 - Up Branching



- Loss Function
 - Chamfer distance function is used to train complete TreeGCN-ED model.

- Dataset
 - ShapenetBenchmarkV0 [5]
 - Specifically we trained our model on 2 classes [chair and table]

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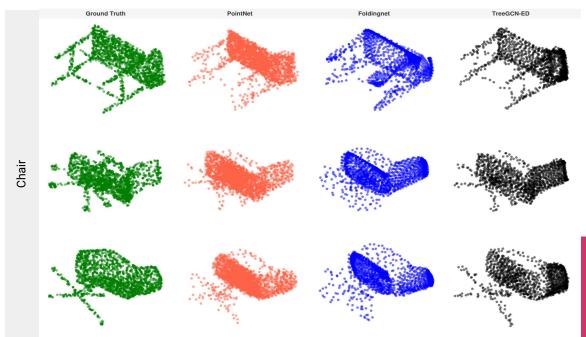
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- **Result and Comparison**
 - **Quantitative Results**

Class	Models	CD	FPD
Table	PointNet-ED [6]	20.89	11849.31
	FoldingNet [7]	0.93	26.04
	TreeGCN-ED	0.70	11.77
Chair	PointNet-ED [6]	12.25	3810.69
	FoldingNet [7]	0.99	17.64
	TreeGCN-ED	0.76	7.60

- Result and Comparison
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