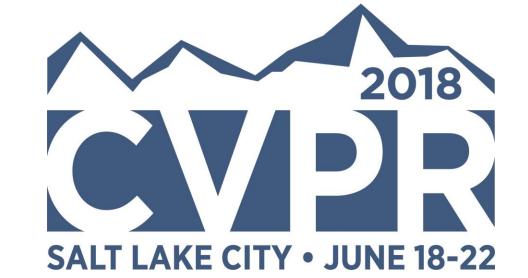




## FoldingNet: Point Cloud Auto-encoder via Deep Grid Deformation

Yaoqing Yang<sup>1</sup>, Chen Feng<sup>2</sup>, Yiru Shen<sup>3</sup>, Dong Tian<sup>2</sup>

<sup>1</sup>Carnegie Mellon University, <sup>2</sup>Mitsubishi Electric Research Laboratories, <sup>3</sup>Clemson University



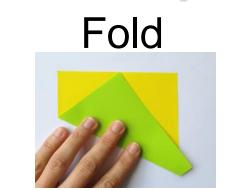
### **Problems and Motivations**

- How to generate unstructured point sets?
- How to utilize the 2D manifold structures of object surfaces?
- How to embed a point cloud into a compact representation?

#### Related Works

- Input representation: Voxel/Multi-view/Points/Mesh
- Existing decoder structures: Fully-connected/Image-based
- Ours: Folding-based auto-encoder from grid deformation

### 3D Unsupervised Learning using Paper Folding

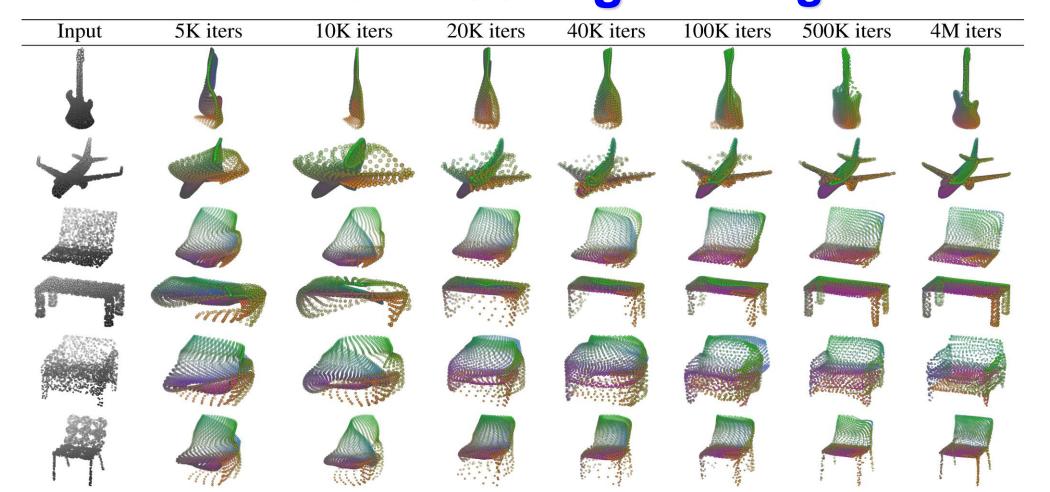




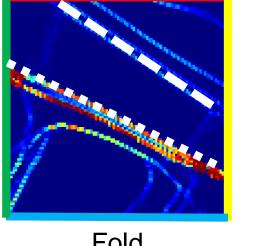


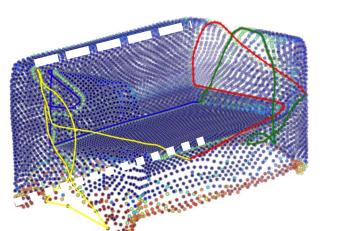


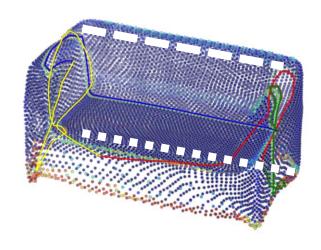
### **Learn to Fold Better during Training**

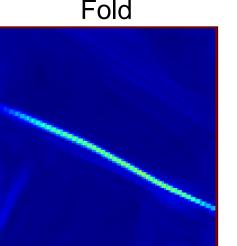


### **Neural Networks Learn to Fold/Tear/Stretch**

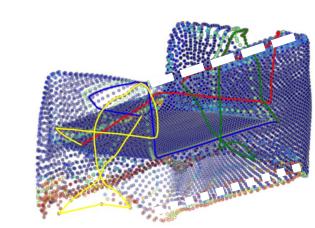


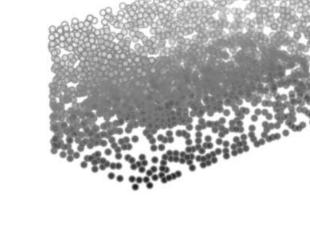




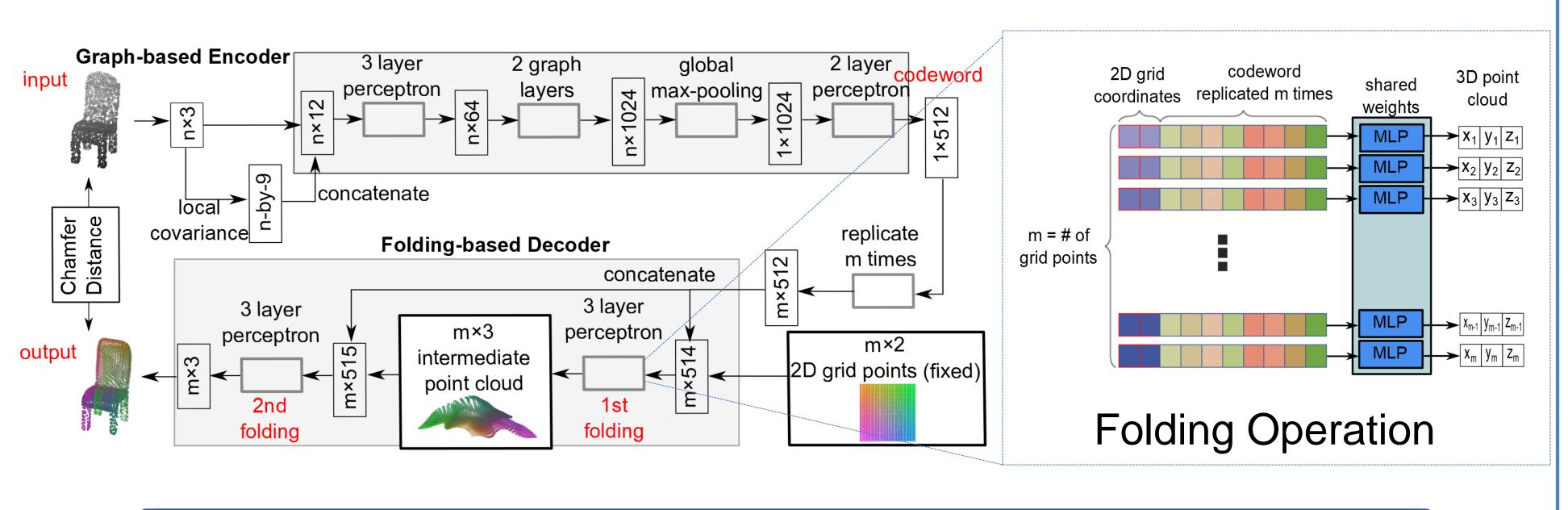


Tear/Stretch





### FoldingNet Architecture

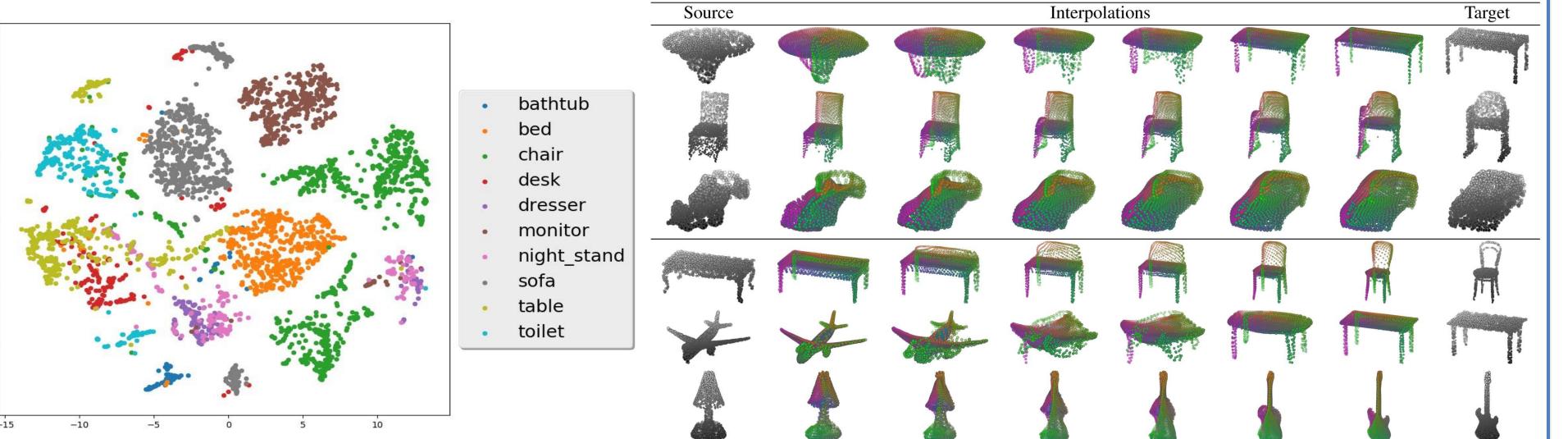


# Universal approximation theorem Different two-layer MLP can approximate different 2D → 3D mappings. Our theorem

A single two-layer MLP can be tuned by the input "codeword" to approximate any arbitrary 2D → 3D mapping.

### **Generate Useful Representations**

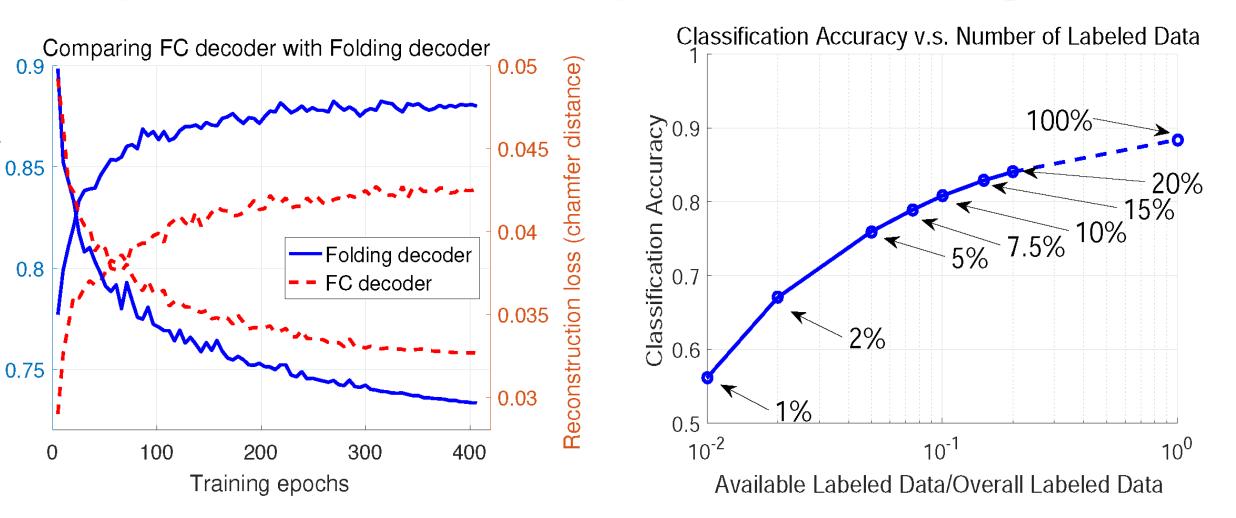
### Generate Meaningful Interpolations



Features extracted by FoldingNet are useful in clustering. The results are obtained by applying T-SNE on codewords.

Upper: same model categories
Lower: different model categories
Generated using a single FoldingNet

### **Unsupervised and Semi-supervised Learning**



### Transfer Learning Using Linear SVM on ModelNet40

Method	Accuracy
SPH [Kazhdan, Funkhouser, Rusinkiewicz]	68.2%
LFD [Chen, Tian, Shen, Ouhyoung]	75.5%
T-L Network [Girdhar, Fouhey, Rodriguez, Gupta]	74.4%
VConv-DAE [Sharma, Grau, Fritz]	75.5%
3D-Gan [ Wu, Zhang, Xue, Freeman, Tenenbaum]	83.3%
Latent-Gan [Achlioptas, Diamanti, Mitliagkas, Guibas]	85.7%
FoldingNet	88.4%

### **Ablation Study of the Decoder**

Grid Setting	# Folds	Test Cls. Acc.	Test Loss
Regular 2D	2	88.25%	0.0296
regular 2D	3	88.41%	0.0290
regular 1D	2	86.71%	0.0355
regular 3D	2	88.41%	0.0284
uniform 2D	2	87.12%	0.0321

### Different Folding Implementations

	Cls. Acc.	Test Loss	# Parameters
FoldingNet	88.41%	0.0296	1.0*10^6
Deconv	88.86%	0.0319	1.7*10^6