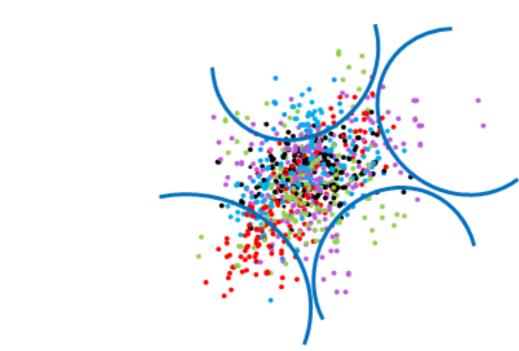
# GuCNet: A Guided Clustering-based Network for Improved Classification

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#### Introduction to Problem

- ► Task: Classification problem in vision data.
- ► Aim: Need to extract relevant features from patterns & project it onto an embedding space
- ► **Ensure:** Representations of each class of patterns are uniquely distinguishable.
- ► **Problem:** Semantic classification of challenging and highly-cluttered data is difficult.

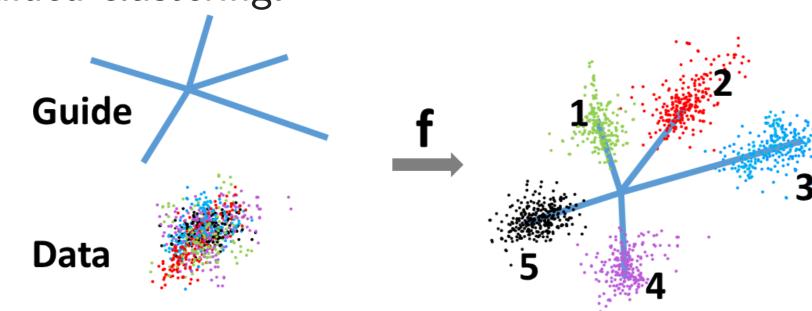


# **Guided Clustering**

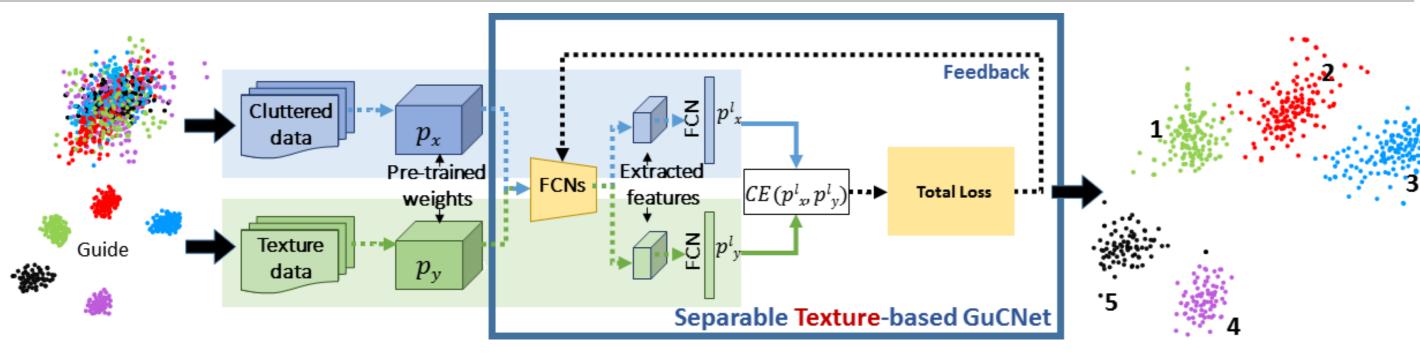
Many well-separable datasets are available.

Can we leverage the classifiability of any existing well separable dataset?

- ▶ Guide data (X): A well separable data.
- $\triangleright$  Cluttered data ( $\mathcal{Y}$ ): The cluttered dataset, which is to be classified.
- ► Embed class-wise features of the cluttered data to the distinct clusters of the guide data, to make them more separable.
- ► Therefore, guided-clustering.



# **Texture-based Guiding**

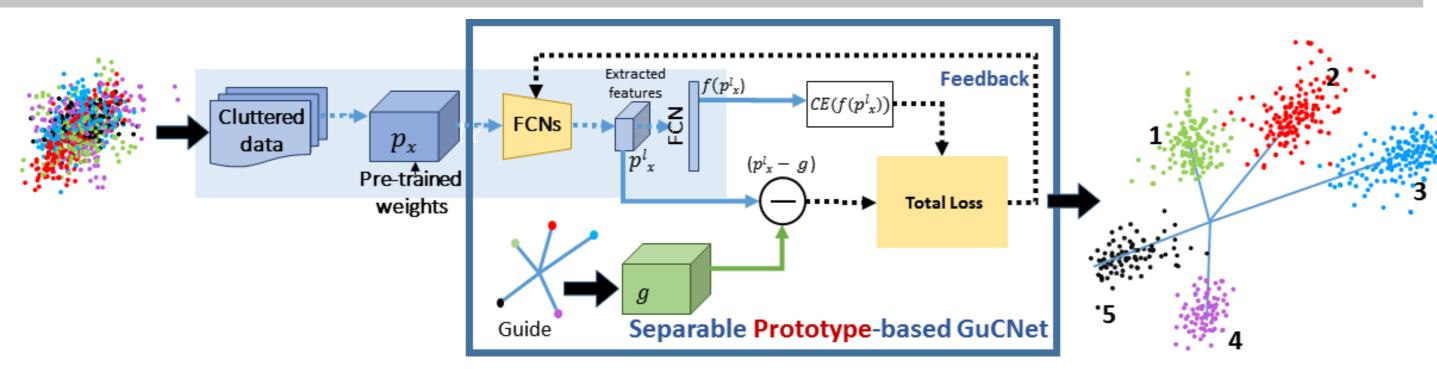


A well-separable data acts as a texture data.

We refer to the output of the convoluted features from  $\mathcal{X}$  and  $\mathcal{Y}$  as  $p_x^I$  and  $p_x^I$ , respectively.

- Extract initial level features from both data using a pre-trained network.
- Feed samples of class-c of both  $\mathcal X$  and  $\mathcal Y$  together as the same class label in the unified space.
- ightharpoonup Minimize cross-entropy loss:  $\mathcal{L}_{\mathsf{CE}} = \mathsf{CE}(p_x^I, p_v^I)$ .

# **Prototype-based Guiding**



If a well-separable data of *C*-class unavailable, we can also use a prototype-based guided clustering.

- Extract initial level features from cluttered data using a pre-trained network.
- ightharpoonup Choose K ( $K \geq C$ ) dimensional vectors (called prototypes g).
- ▶ Matching loss:  $(\mathcal{L}_{ml} = | p_x^l g |)$  to bring the dataset closer to the prototype vectors.
- $\blacktriangleright \text{ Minimize } \mathcal{L}_{\mathsf{ml}} = \mid p_{\mathsf{x}}^{l} g \mid + \mathsf{CE}(p_{\mathsf{x}}^{l}, p_{\mathsf{v}}^{l}).$

#### Results - RSSCN aerial scene dataset

Classification performance of the proposed GuCNet architecture on RSSCN dataset. Here baseline for guide data (MNIST) is 99.80%.

Model	Accuracy(%)	12 NANHOT		
VRGSIR	81.00%	$\mathcal{X}$ : MNIST		
AlexNet	88.80%			
CaffeNet	88.60%			
GoogleNet	79.80%			
VGG-M	87.30%			
VGG-VD16	85.60%	y: RSCCN		
Conv5-MSP5-FV	95.40%			
Baseline	88.39%			
GuCNet (Prototype)	97.36%			
GuCNet (Texture)	<b>99.11</b> %			

#### Results - LSUN Outdoor scene dataset

Classification performance on LSUN dataset with the same guide data.

Classification performance	te on LSUN dataset	with the same guide data.
Model	Accuracy(%)	V. MANIICT
Vanilla GAN	70.50%	$\mathcal{X}$ : MNIST
Labeled-samples	77.00%	
Hybrid GAN	83.20%	
Normal BN-Inception	90.40%	
Deeper BN-Inception	90.90%	
SJTU-ReadSense	90.40%	y: LSUN
SIAT MMLAB	91.60%	
Baseline	83.75%	
<b>GuCNet</b> (Prototype)	95.03%	
GuCNet (Texture)	94.86%	

# Results - TU-Berlin sketch dataset

Performance comparison on TU-Berlin dataset for classification accuracy. Here baseline accuracy for guide data is 84.54%.

Model	Accuracy(%)	
AlexNet-SVM	67.10%	$\mathcal{X}$ : TU-Berlin Images
AlexNet-Sketch	68.60%	
Sketch-A-Net SC	72.20%	
Sketch-A-Net-Hybrid	73.10%	
ResNet18-Hybrid	73.80%	
Alexnet-FC-GRU	79.95%	${\cal Y}$ : TU-Berlin Sketches
Zhang et. al.	82.95%	
Baseline	69.90%	
GuCNet (Prototype)	86.63%	
GuCNet (Texture)	89.26%	

# Some Interesting Ablation Study:

Effect of different types of co-binning of texture classes from guide set.

Dataset (TU-Berlin)	Accuracy(%)
Same class binning	89.26%
Dissimilar class binning	90.05%

Effect of separability of prototypes in terms of Hamming distance (H).

Datase	ı Sepa	ration (	n proto	types	
	w2vec	<b>H</b> = 2	$\frac{H_{\text{max}}}{2}$	$H_{\text{max}}$	
RSCCN	96.20%	96.02%	96.27%	97.36%	
LSUN	92.71%	94.60%	94.92%	95.03%	

# Conclusions

- ► Propose a simple guided clustering framework to get high performance in classification.
- Leverage the ease of separability of a guide dataset to improve the separability of a cluttered dataset.
- ▶ Pushes the embeddings of the data instances far apart in the semantic feature space while making the embedding space further discriminative.
- ► Established its efficacy on three challenging datasets and outperformed the state-of-the-art performance.