GuCNet: A Guided Clustering-based Network for Improved Classification

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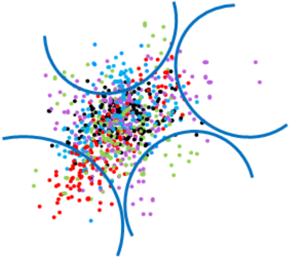
International Conference on Pattern Recognition, 2021

Introduction to Problem

- 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.
- Semantic classification of challenging and highly-cluttered data is difficult.

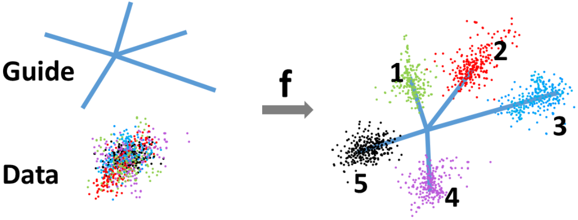


Guided Clustering

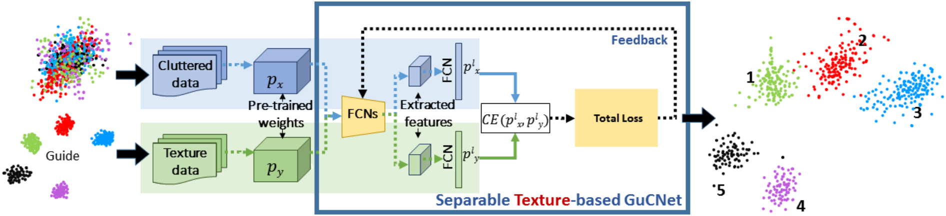
Many well-separable datasets are available.

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

- **Guide data ($\mathcal{X}$):** A well separable data.
- **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.



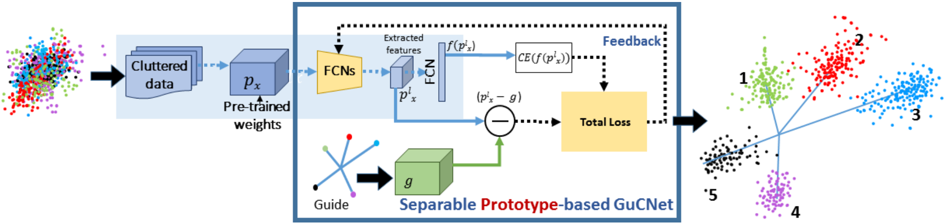
1. Separable Texture-based Guiding



A well-separable data acts as a texture data.

- 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.
- Minimize cross-entropy $\mathcal{L}_{\mathrm{CE}} = \mathrm{CE}(p^l_x, p^l_y)$.

2. Separable Prototype-based Guiding



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

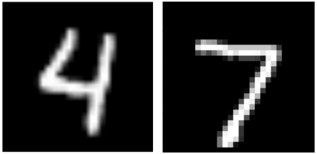
- Extract initial level features from cluttered data using a pre-trained network.
- Choose K ($K \geq C$) dimensional vectors (called *prototypes* g).
- **Matching loss:** ($\mathcal{L}_{\text{ml}} = \mid p_x^l - g \mid$) to bring the dataset closer to the prototype vectors.
- Minimize $\mathcal{L}_{\text{ml}}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

Results - RSSCN aerial scene dataset

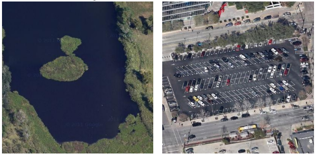
Classification performance of the proposed GuCNet architecture on RSSCN dataset. Here baseline for guide data (MNIST) is 99.80%.

Model	Accuracy(%)
LLC (CH)	79.94%
SpLSA (SIFT)	79.37%
VLAD (SIFT)	79.34%
RGSIR	81.00%
AlexNet	88.80%
CaffeNet	88.60%
GoogleNet	79.80%
VGG-M	87.30%
VGG-VD16	85.60%
Conv5-MSP5-FV	95.40%
Baseline	88.39%
GuCNet (Prototype)	**97.36%**
GuCNet (Texture)	**99.11%**

$\mathcal{X}$: MNIST



$\mathcal{Y}$: RSCCN

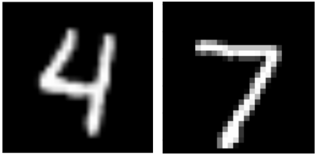


Results - LSUN Outdoor scene dataset

Classification performance of GuCNet on LSUN dataset with the same guide data.

Model	Accuracy(%)
Vanilla GAN	70.50%
Labeled-samples	77.00%
ds-cube	83.00%
Hybrid GAN	83.20%
Normal BN-Inception+scene n/w	90.40%
Deeper BN-Inception+scene n/w	90.90%
SJTU-ReadSense	90.40%
SIAT MMLAB	91.60%
Baseline	83.75%
GuCNet (Prototype)	**95.03%**
GuCNet (Texture)	**94.86%**

$\mathcal{X}$: MNIST



$\mathcal{Y}$: LSUN

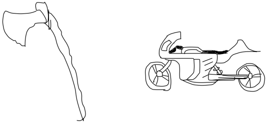
Results - TU-Berlin sketch dataset

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

Model	**Accuracy(%)**
AlexNet-SVM	67.10%
AlexNet-Sketch	68.60%
Sketch-A-Net SC	72.20%
Sketch-A-Net-Hybrid	73.10%
ResNet18-Hybrid	73.80%
Humans	73.10%
Sketch-A-Net-Hybrid	77.00%
Sketch-A-Net	77.00%
Alexnet-FC-GRU	79.95%
Zhang *et. al.*	82.95%
Baseline	69.90%
GuCNet (Prototype)	**86.63%**
GuCNet (Texture)	**89.26%**

$\mathcal{X}$: TU-Berlin Images

$\mathcal{Y}$: TU-Berlin Sketches



Some Interesting Ablation Study:

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

Dataset (TU-Berlin)	**Accuracy(%)**
GuCNet (Texture):	
Same class binning	89.26%
Dissimilar class binning	90.05%

Table: Effect of separability of prototypes in terms of Hamming distance (H) on GuCNet performance.

Dataset	**Separation of prototypes**			
	w2vec	$H = 2$	$\frac{H_{\text{max}}}{2}$	H_{max}
GuCNet (Prototype):				
RSCCN dataset	96.20%	96.02%	96.27%	97.36%
LSUN dataset	92.71%	94.60%	94.92%	95.03%

Conclusion

- We propose a very simple yet novel guided clustering 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.
- **Future work:** Can try to match the distributions of the two datasets and study the performance.

Thank You