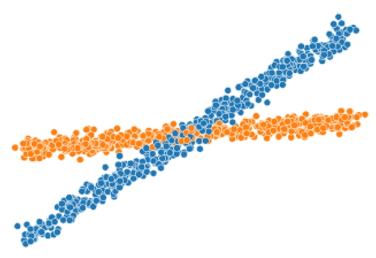
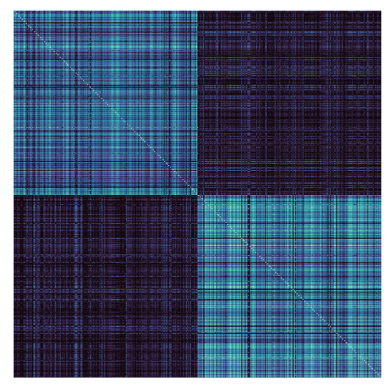
Learning Self-Expression Metrics for Scalable and Inductive Subspace Clustering

Introduction

- Subspace Clustering
  - Points are sampled from a union of subspaces
  - Goal: Assign points to subspace clusters
- Self-Expressiveness
  - Point = Linear combination of other points from same subspace
  - Directly learn coefficients
  - Coefficients can be used to derive quadratic subspace affinity matrix
  - Use spectral clustering to derive cluster labels
- Non-linearity
  - Add autoencoder to learn latent space for clustering [1]
- Challenges
  - Quadratic overhead by coefficient matrix
  - Models are transductive, cannot cluster-out-of-sample data



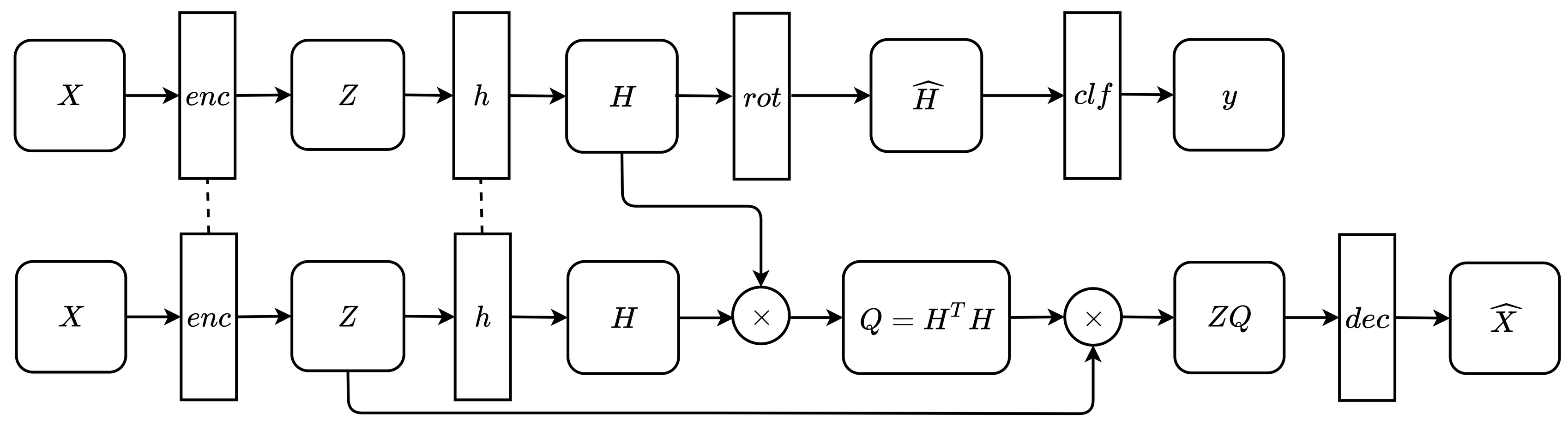


$$\min_{C \in \mathbb{R}^{N \times N}} \frac{1}{2}\|C\|_F^2 + \frac{\lambda}{2}\|X - XC\|_F^2$$

- Contributions
  - Use siamese network to learn affinity function → **constant memory**
  - Combine with classifier → **model is inductive**
  - Provable subspace recovery → **no loss in expressive power**

Siamese Subspace Clustering Networks

- Dot products of embeddings H = self-expression coefficients
  - Independent clusters in this space are orthogonal
  - Independent: Sum of subspace dimensions $\leq$ dimension of their span
- Rotate clusters into axis-aligned subspaces
  - Multiply with orthonormal matrix R, optimized on Stiefel manifold [2]
- Cluster assignment based on orthogonal projection distance
- Multi-step training
  1. Train with self-expressive and autoencoder loss
  2. Get pseudo-labels with spectral clustering
  3. Train classifier with cross-entropy loss
- Future work: No SC, triplet loss, joint training



Experiments

- Preliminary results on MNIST
  - Transductive clustering of 10,000 test images
  - Out-of-sample clustering of 60,000 training images
- Competitive performance at dramatic parameter/GPU-memory reduction due to siamese network and mini-batch training
- Reliable clustering of OoS-data without memory overhead, DSC-Net would require >39GB (not inductive)
- Code is available [3]

	ACC	ARI	NMI	#Parameters	GPU-Memory (GB)
DSC-Net [1]	63.54 ± 0.00	57.42 ± 0.00	$\mathbf{72.34 \pm 0.00}$	$100,014,991$	2.71
SSCN	$\mathbf{67.98 \pm 3.40}$	$\mathbf{58.53 \pm 3.34}$	69.48 ± 2.38	$\mathbf{66,291}$ $(\mathbf{-99.93\%})$	$\mathbf{0.19}$ $(\mathbf{-92.96\%})$
SSCN-OoS	67.39 ± 3.38	57.10 ± 3.27	67.16 ± 2.34	$66,291$	0.19

[1] Pan Ji et al. "Deep subspace clustering networks". In: *NeurIPS* (2017).

[2] Jun Li, Li Fuxin, and Sinisa Todorovic. "Efficient Riemannian optimization on the Stiefel manifold via the Cayley transform". In: *ICLR* (2020).

[3] `https://github.com/buschju/sscn`.

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