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A Data-driven Cloud Classification Framework Based on a Rotationally Invariant Autoencoder

Takuya Kurihana[1,4], Elisabeth Moyer[3,4], Rebecca Willett[1,2], and Ian Foster[1,5]

Contact: tkurihana@uchicago.edu

1.Department of Computer Science, University of Chicago; 2. Department of Statistics, University of Chicago; 3. Department of Geoscience, University of Chicago; 4. Center for Robust Decision Making on Climate and Energy Policy (RDCEP); 5. Argonne National Laboratory

Unsupervised Cloud Classification (CC) enables novel classification

Supervised cloud classification restricts models in artificial predefined category e.g. WMO, ISCCP

Issue of artificial cloud category:

- Effective for "classic" examples or deterministic definition
- Non-functional for intermediate / complex cloud types
- Mean cloud properties do not capture relevant physics and spatial information

Rotation-Invariant (RI) Autoencoder

- Adapt shift-transform invariant autoencoder (Matuso et.al 2017) to map different orientations of identical inputs into an uniform orientation (Cloud class is independent to its orientation!)
- Rotation dependence problem in autoencoder

$$L = \lambda_{\rm inv} L_{\rm inv} + \lambda_{\rm res} L_{\rm res}$$

- *Transform-Invariant loss*

$$L_{\rm inv} = \frac{1}{N}\sum_{x \in S}\sum_{i} ||\hat{x} - D(E(T_{\theta_i}(x)))||_2^2$$

- *Restoration loss*

$$L_{\rm res} = \sum_{x \in S} \min_{i} ||T_{\theta_i}(x) - \hat{x}||_2^2$$

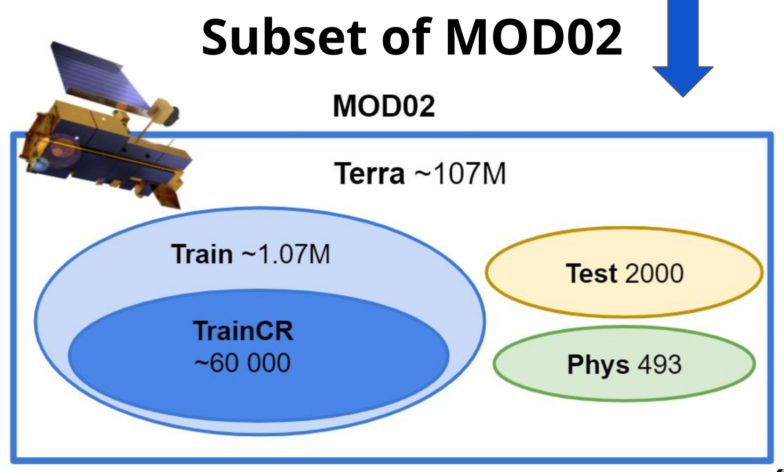
D: Decoder
E: Encoder
I: Input
N: Number of rotation angles
L: Loss
S: Set of images in a mini-batch
T_{θ_i}: Rotation operator by θ_i degree

Use of MODIS Satellite Data

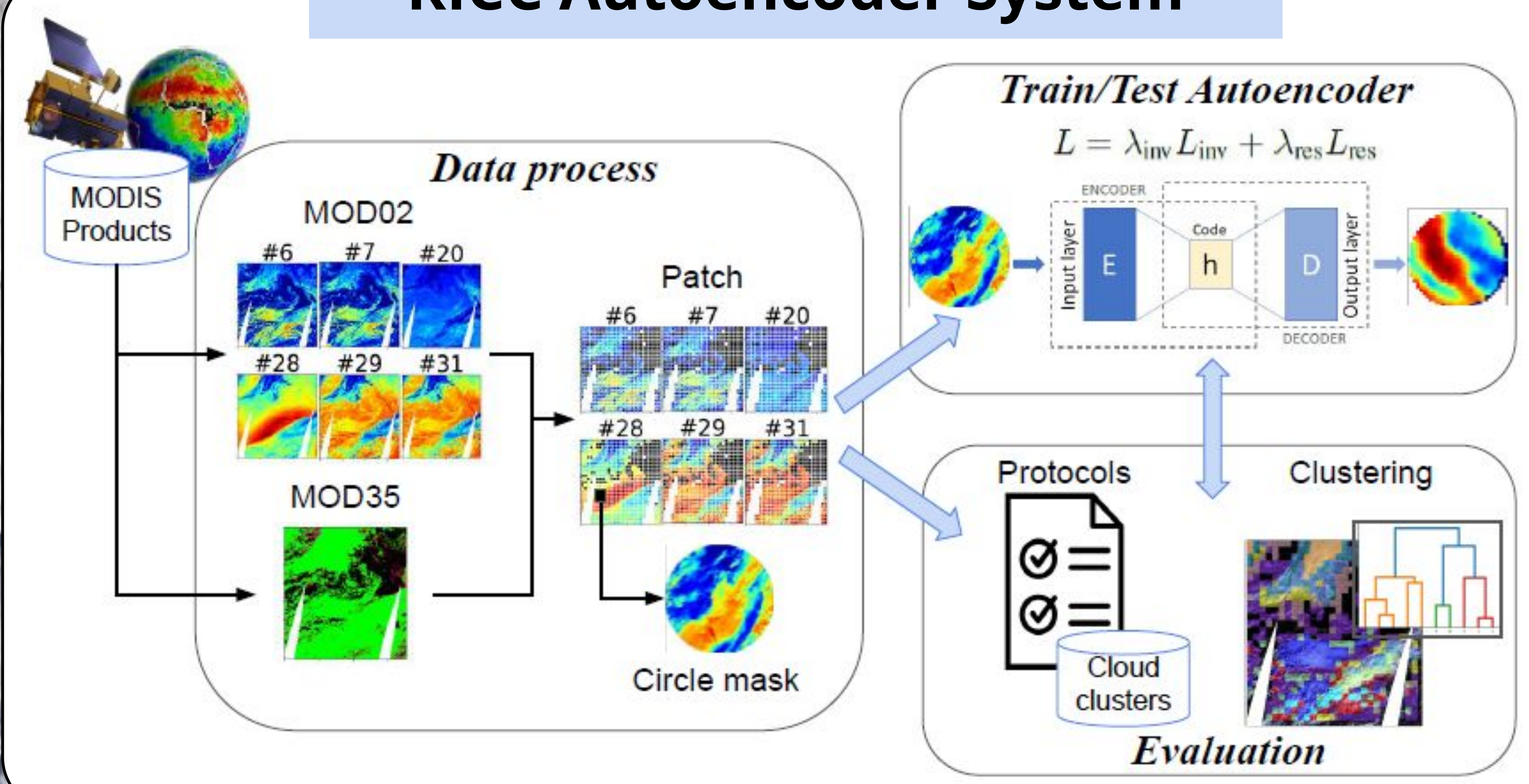
Product	Description	Band
MOD02	S/w infrared (1.230-1.250 μm)	5
	S/w infrared (1.628-1.652 μm)	6
	S/w infrared (2.105-2.155 μm)	7
	L/w thermal infrared (3.660-3.840 μm)	20
	L/w thermal infrared (7.175-7.475 μm)	28
	L/w thermal infrared (8.400-8.700 μm)	29
	L/w thermal infrared (10.780-11.280 μm)	31
MOD35	Cloud mask	
MOD06	Cloud optical thickness	
	Cloud top pressure	
	Cloud phase infrared	
	Cloud effective radius	

MOD02: Use for train and test data
MOD35: Detect cloud pixels
MOD06: Evaluate physical association

Subset of MOD02



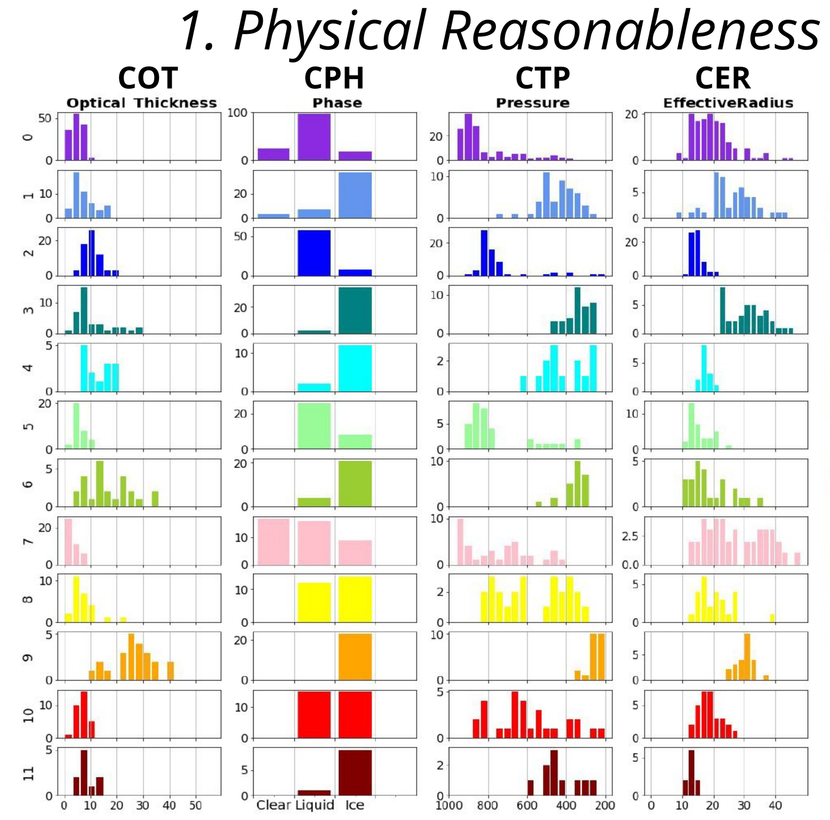
RICC Autoencoder System



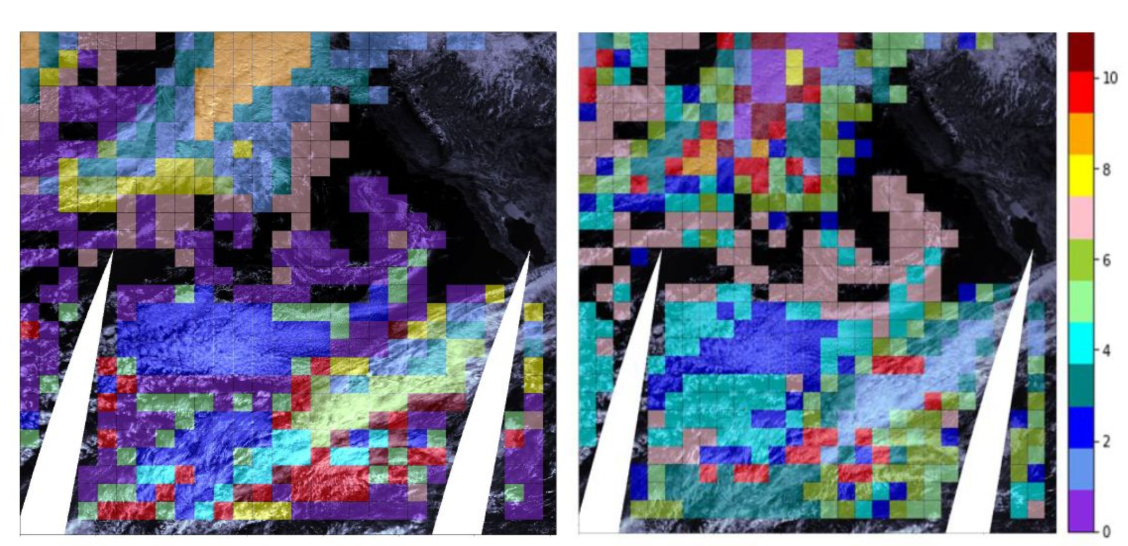
Validation of RICC

- Design four protocols for evaluating the meteorological utility of the novel clusters produced by RICC system
- Tested RICC system on *Phys* & *Test* dataset (see data section) to validate whether our RICC system satisfies our evaluation protocols
- Results show physically reasonable, spatially coherent, cohesive in latent space and rotational invariant

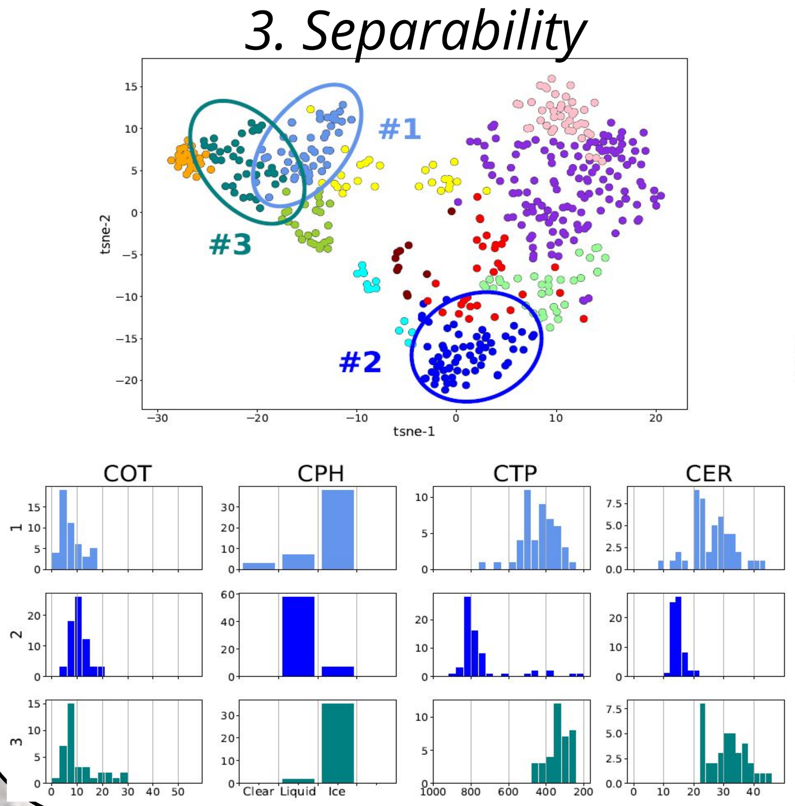
1. Physical Reasonableness



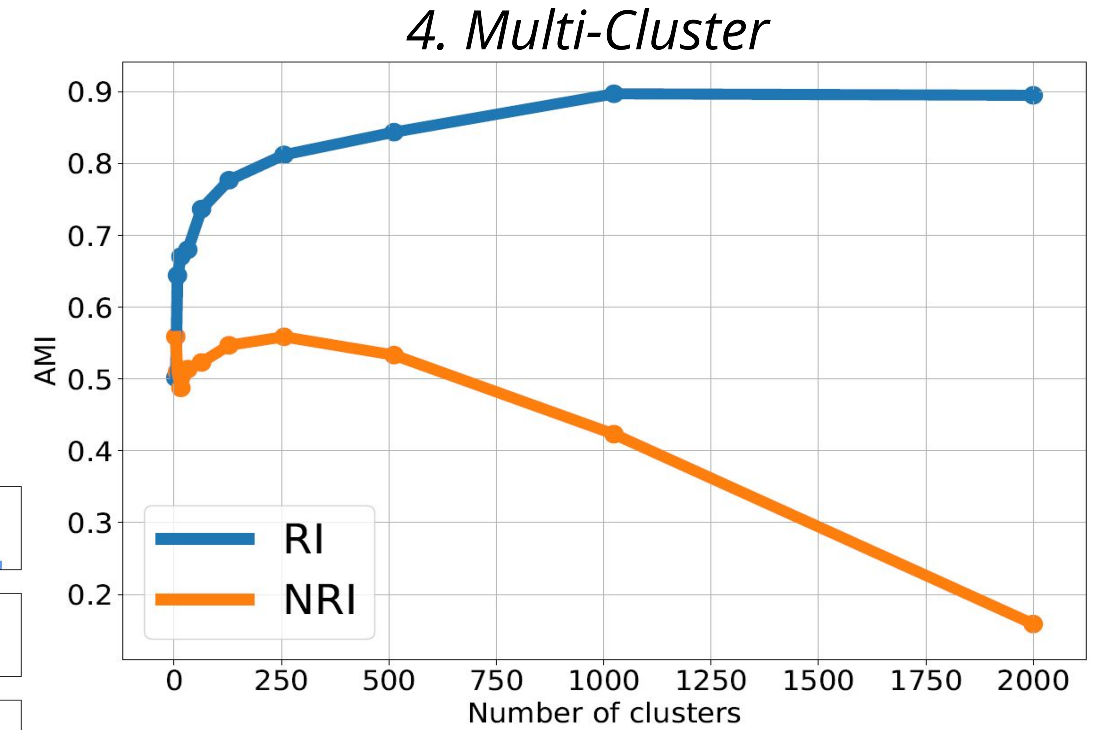
2. Spatial Coherence



3. Separability



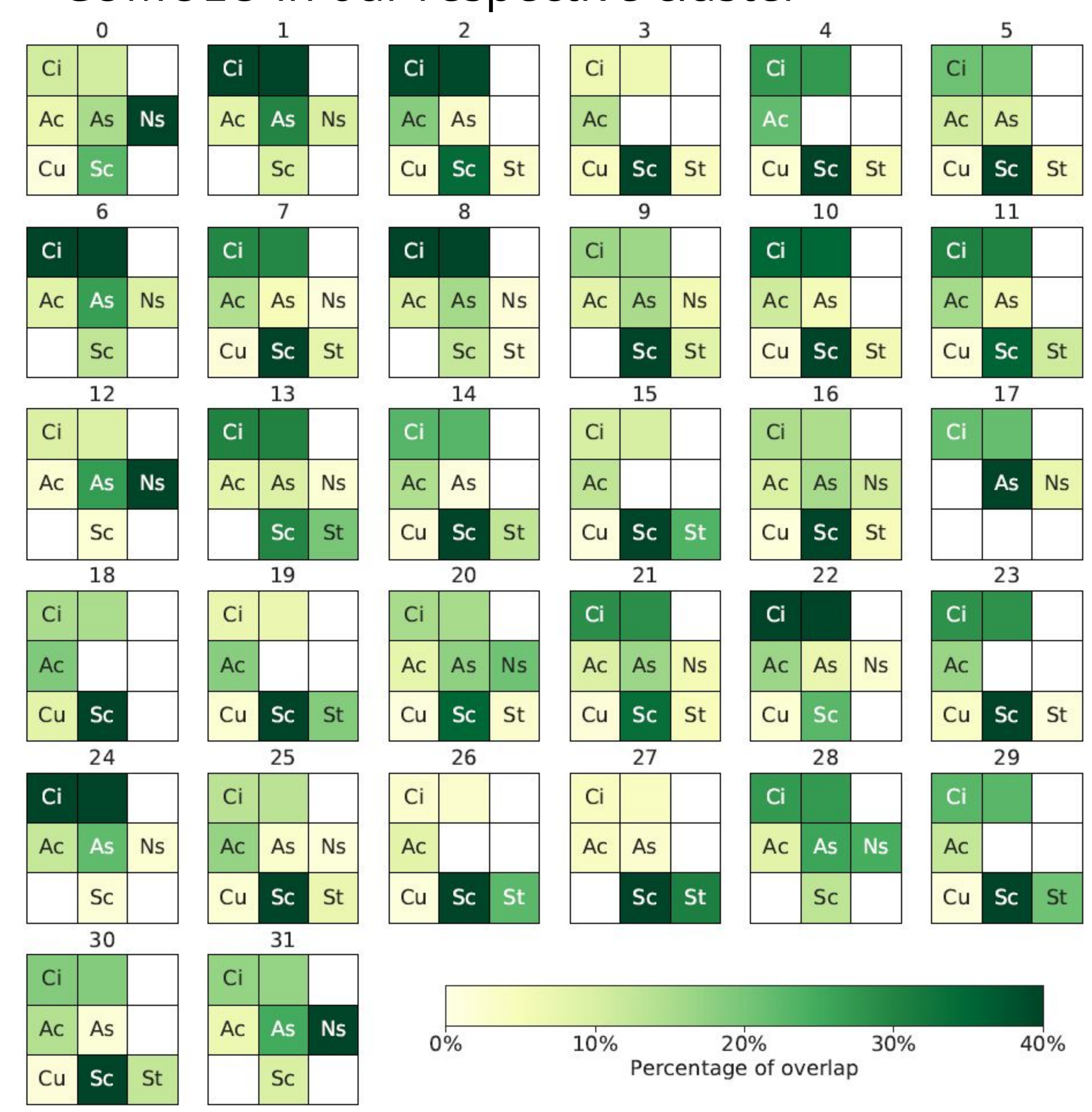
4. Multi-Cluster



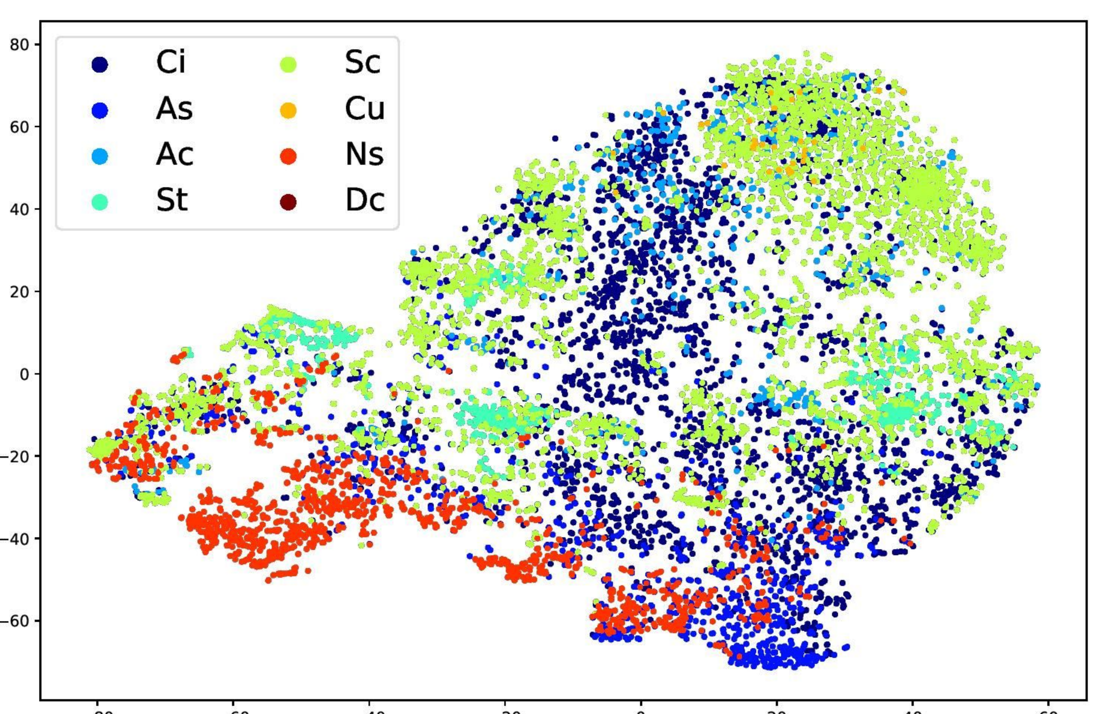
NRI: Non-RI autoencoder (Kurihana et al. 2019)

Comparison with CUMULO

- Compared resultant cloud classes obtained with unsupervised and supervised classifier
- Use CUMULO dataset (Zantedeschi et. al 2019)
- Computed percentage of categories of CUMULO in our respective cluster



Structure of latent representation produced by RICC, colored by the most frequent CUMULO category within the patch



Take-Away Points

- Address rotation dependence problem to cloud image
- Yield physically reasonable, spatially coherent which learns spatial and rotation invariant features