GeoCluster

A Latent Variable Generative Model for Continuous Space Geometric Clustering

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Introduction

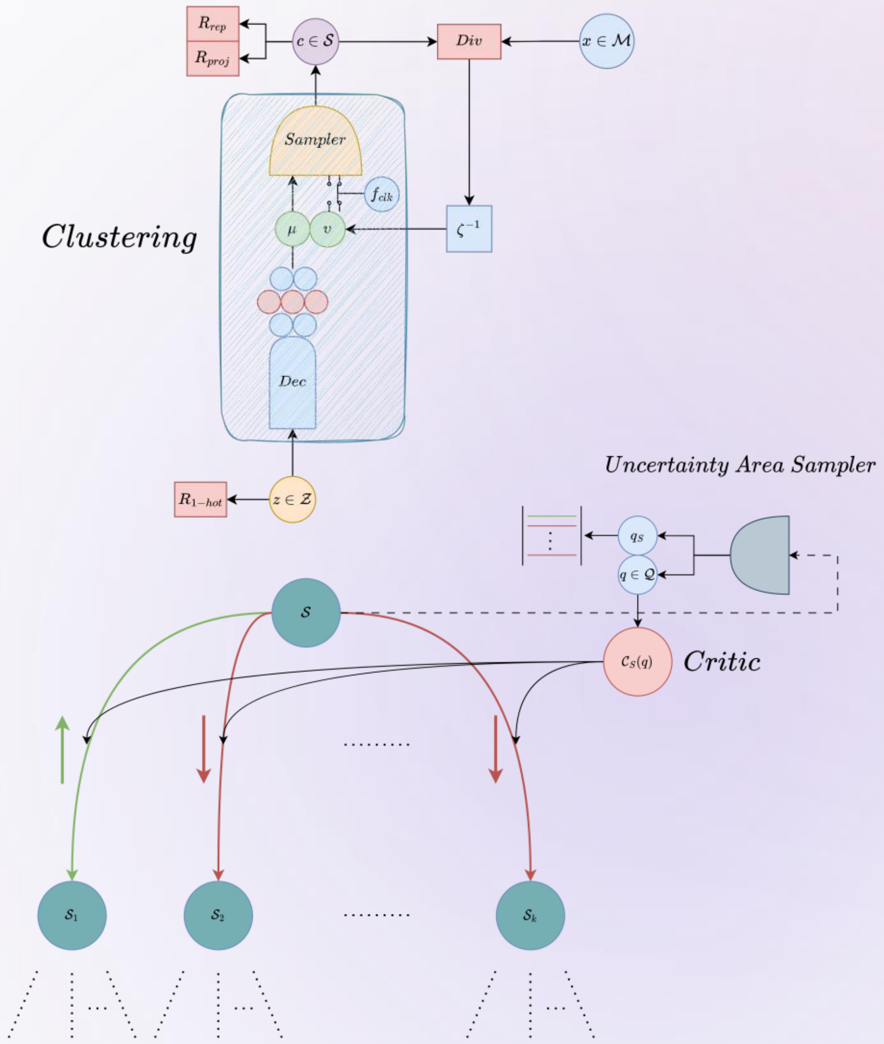
GeoCluster is a generative model that aims to partition the data space, while approximately preserving the original metric space. Applications may include:

- VLSI: maximum empty cube
- Robotics: path planning

GeoCluster Architecture

GeoCluster consists of two models:

- **Clustering**
  aims to partition the data space
- **Critic**
  aims to preserve the isometric properties of the original space



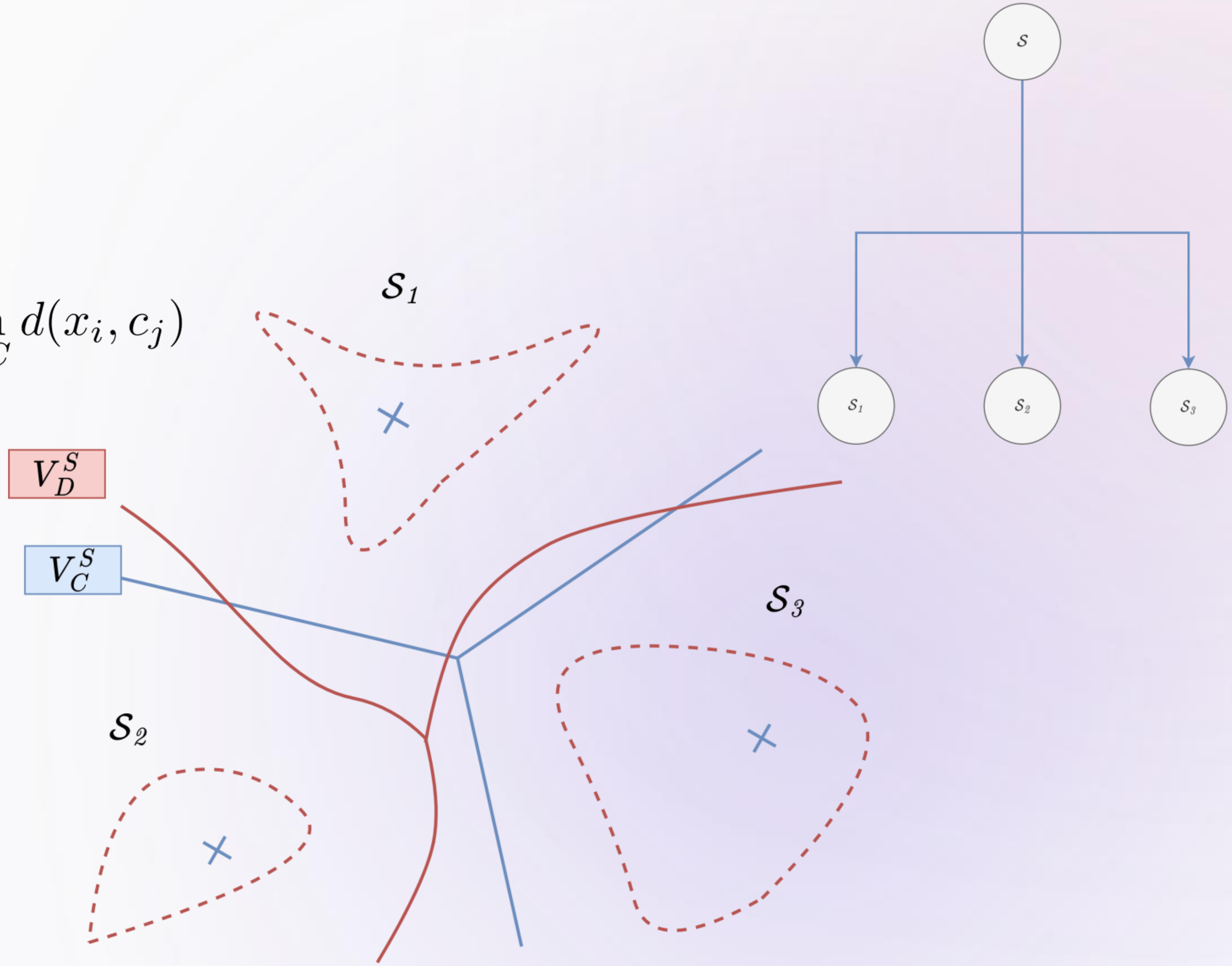
GeoCluster: Clustering

$$V_C = \{v_{c_1}, v_{c_2}, \cdots, v_{c_k}\} = \arg\min_C \sum_{i=1}^{n} \min_{c_j \in C} d(x_i, c_j)$$

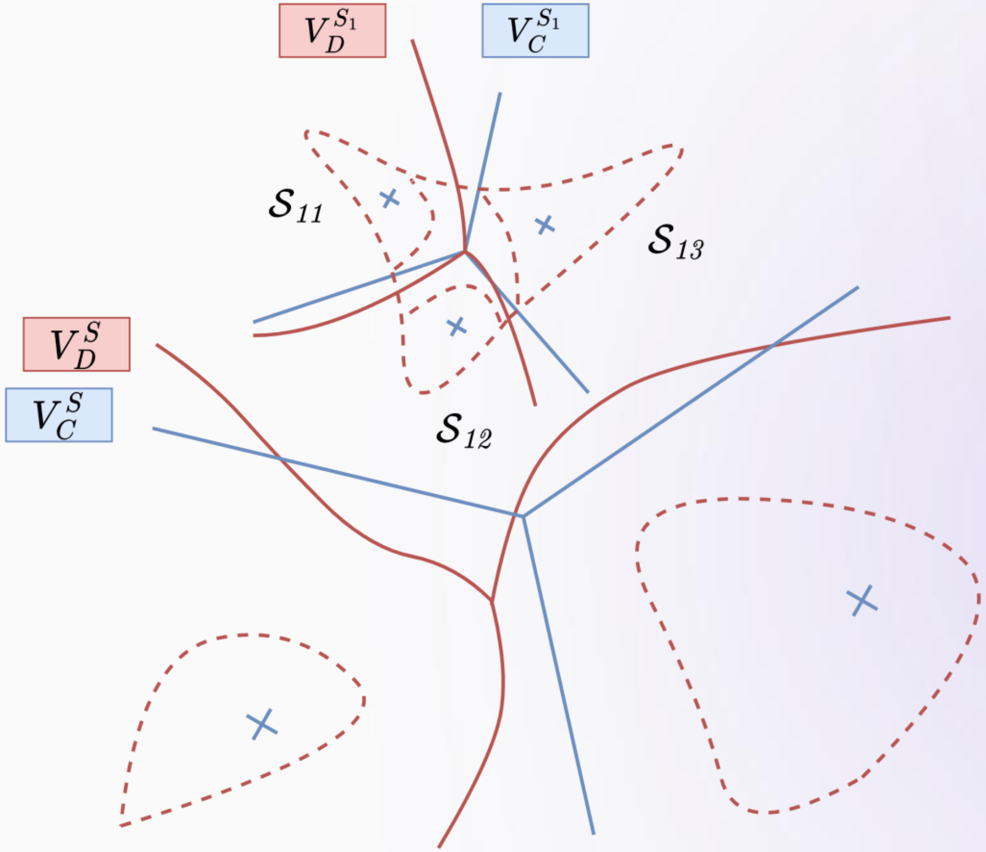
$$v_{c_i} = \{x \in S \mid \forall j \neq i, d(x, c_i) < d(x, c_j)\}$$

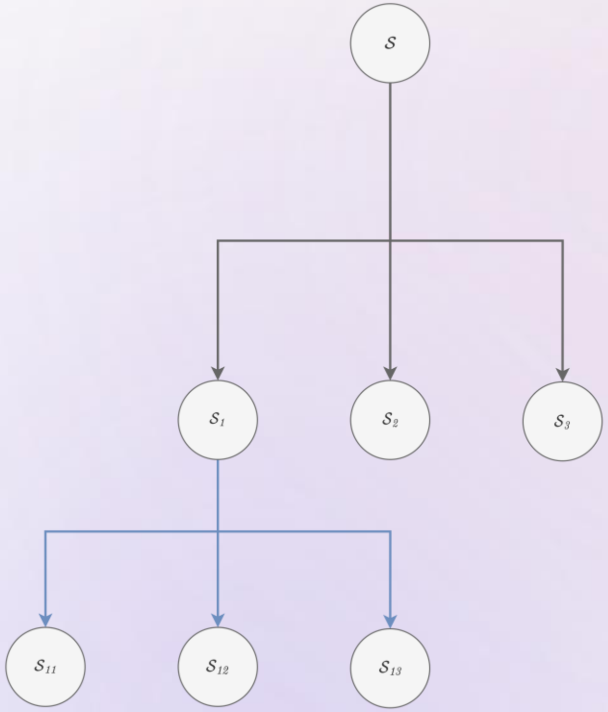
$$V_D = \{v_{d_1}, v_{d_2}, \cdots, v_{d_k}\}$$

$$v_{d_i} = \{x \in S \mid \forall j \neq i, d(x, d_i) < d(x, d_j)\}$$



GeoCluster: Hierarchical Clustering





GeoCluster: Uncertainty Area Sampler

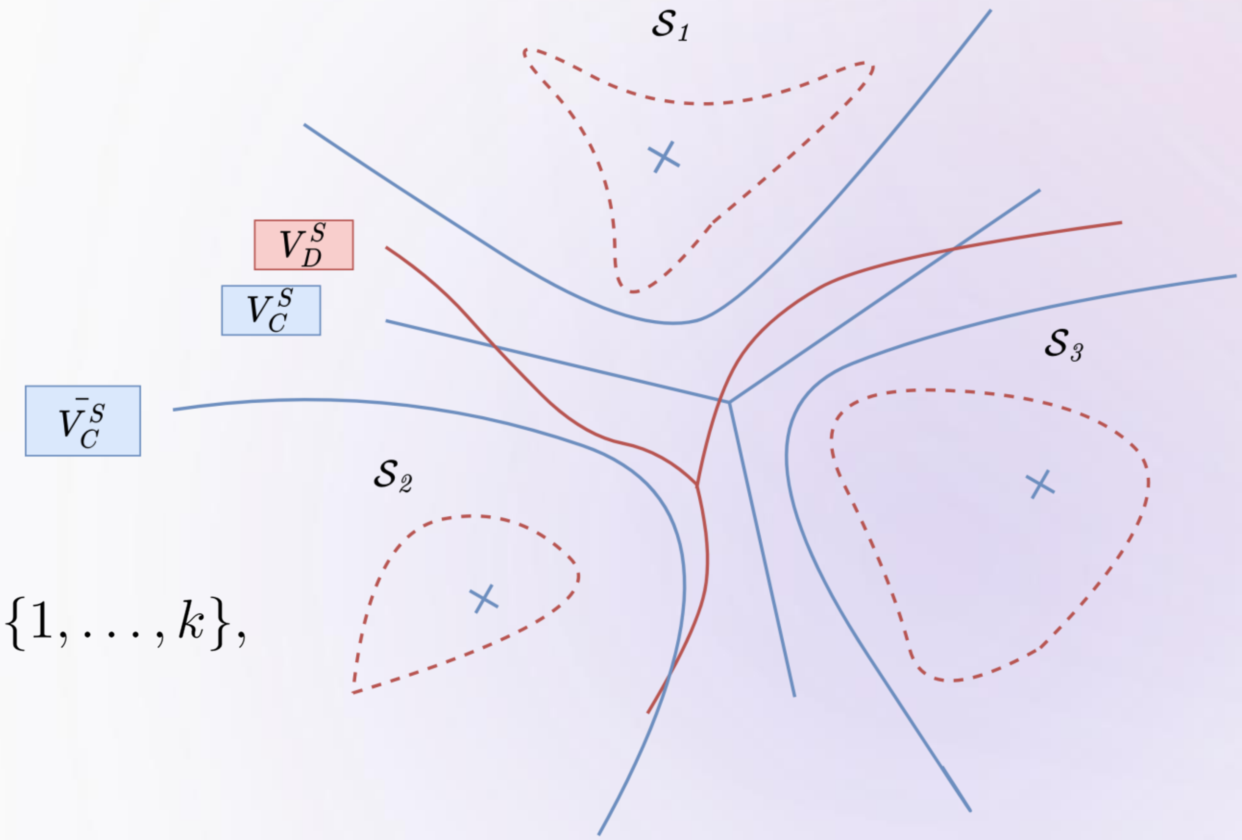
$$\tilde{V}_C = \{\tilde{v}_{c_1}, \tilde{v}_{c_2}, \cdots, \tilde{v}_{c_k}\}$$

$$\tilde{v}_{c_i} = \{(x, \mu_{c_i}(x)) \mid x \in S\}$$

$$\{\tilde{x}_i\}_{i=1}^{m} \sim \text{Uniform}(\tilde{V}_C)$$

$$\{\text{y}_i\}_{i=1}^{M}, \text{ such that } \forall i \in \{1, \ldots, M\}, \exists j \in \{1, \ldots, k\},$$

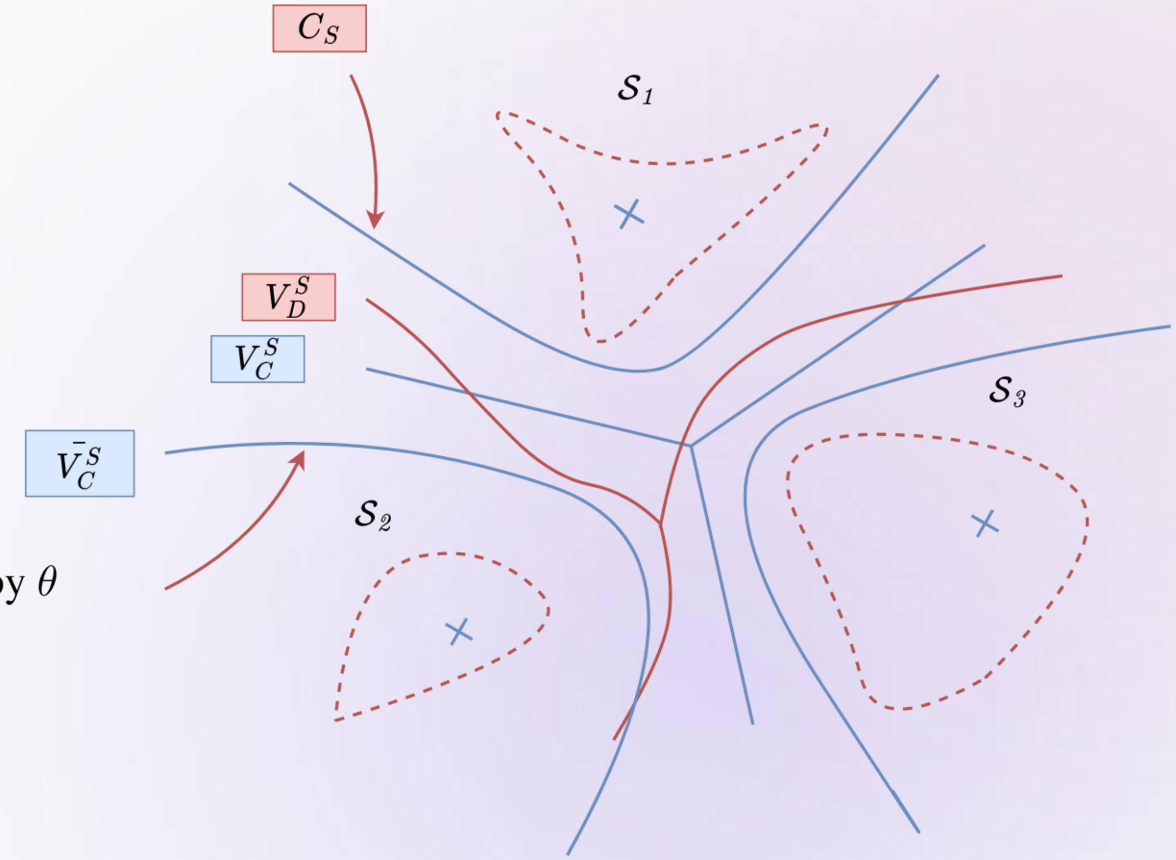
$$\text{where } y_i = j \text{ if } x_i \in v_{d_j}$$



GeoCluster: Critic

$$C_S = \arg\min_{\theta} \sum_{i=1}^{m} L(f_\theta(\tilde{x}_i), y_i)$$

- θ are the parameters of the critic neural network
- $f_\theta(\cdot)$ represents the critic neural network's function, parameterized by θ
- y_i is the true label of $\tilde{x}_i$ according to V_D
- L is a loss function



Results: Accuracy & Efficiency

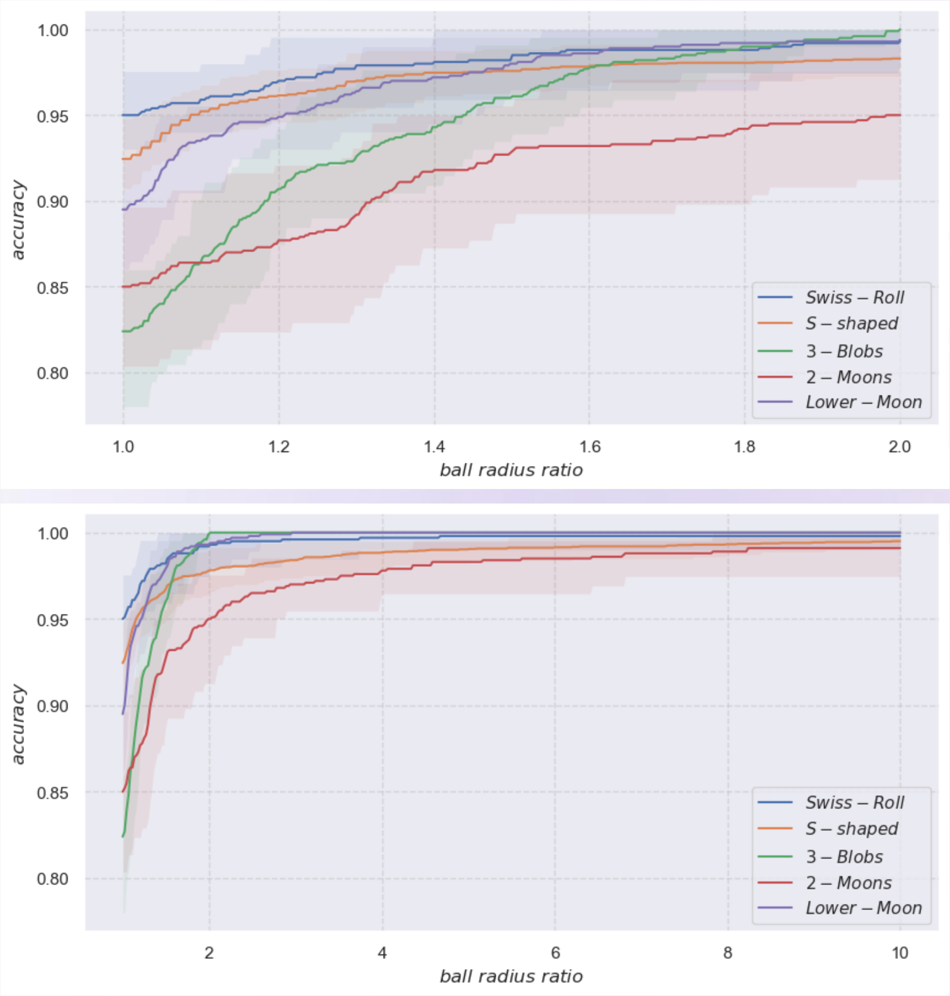
	Layer 1-2	Layer 2-3	Layer 3-4	Layer 4-5	Layer 5-6	Dimensions	Metric
Squares	82.8 ± 2.0	97.7 ± 0.7	99.8 ± 0.2	-	-	$\mathbb{R}^2$	L_∞
Cuboids	91.3 ± 0.8	87.9 ± 1.4	90.5 ± 2.4	93 ± 2.2	99.3 ± 0.7	$\mathbb{R}^3$	L_∞
Ellipses	95.7 ± 0.6	95.2 ± 1.1	97.7 ± 0.9	-	-	$\mathbb{R}^2$	L_2

	Top 1	*Top* 2	*Top* 5	*Top* 10	*Top* 1%	*Top* 5%	*Top* 10%
Squares	77.3 ± 2.3	79.1 ± 1.8	81.7 ± 2.4	83.4 ± 2.1	90.9 ± 2.0	99.7 ± 0.3	99.9 ± 0.1
Cuboids	61.9 ± 2.0	73.3 ± 1.6	85.3 ± 2.0	91.0 ± 1.2	99.0 ± 0.7	100	100
Ellipses	76.9 ± 1.6	79.3 ± 1.7	81.5 ± 1.8	83.8 ± 2.1	91.0 ± 0.9	98.4 ± 0.1	99.6 ± 0.4

Results: Accuracy & Efficiency

Continuous Soft-Accuracy, *“is our NN a good candidate, in terms of distance”*, measured for differently distributed 2D rectangles:

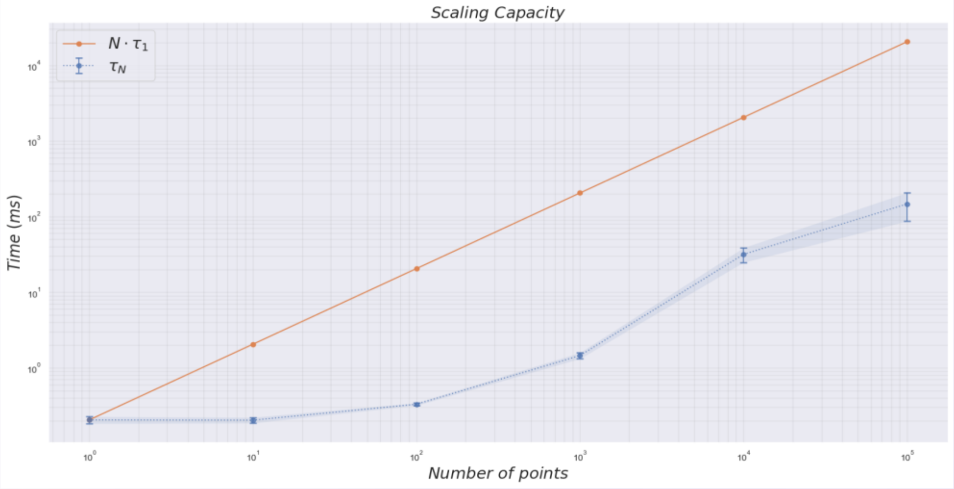
- Structure complexity does not decrease accuracy
- Complexity related decrease, converges @ ball = 2
- Data density seem to play a role

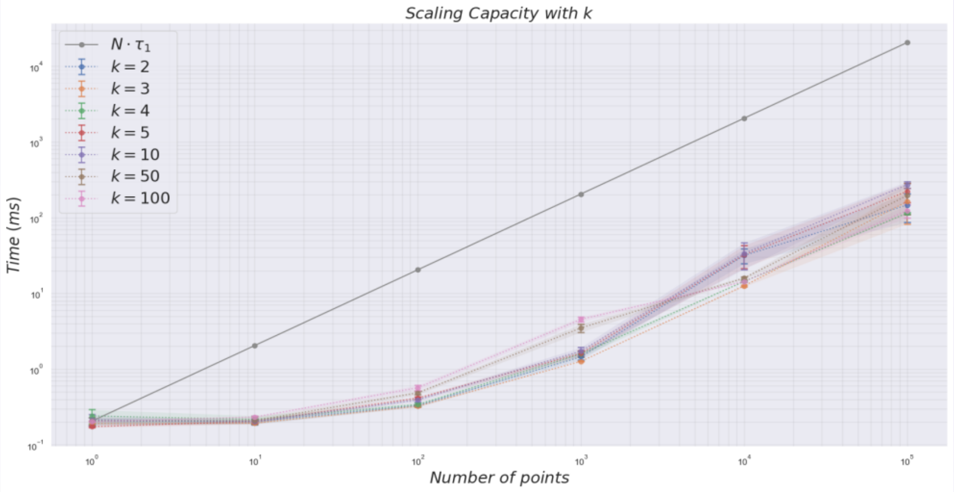


Results: Accuracy & Efficiency

Experimental average complexity is measured for N queries and m data:

- $N\tau_1 \rightarrow O(N log_k m)$
- $\tau_N \ll N\tau_1 \rightarrow O\left(\left\lceil\frac{N}{p}\right\rceil \log_k m\right), \tilde{p} = 100$
  p is due to parallelization
- $\tau_{N,1} \approx \tau_{N,k}\ \forall k \in \{2,3,4,5,10,50,100\}$

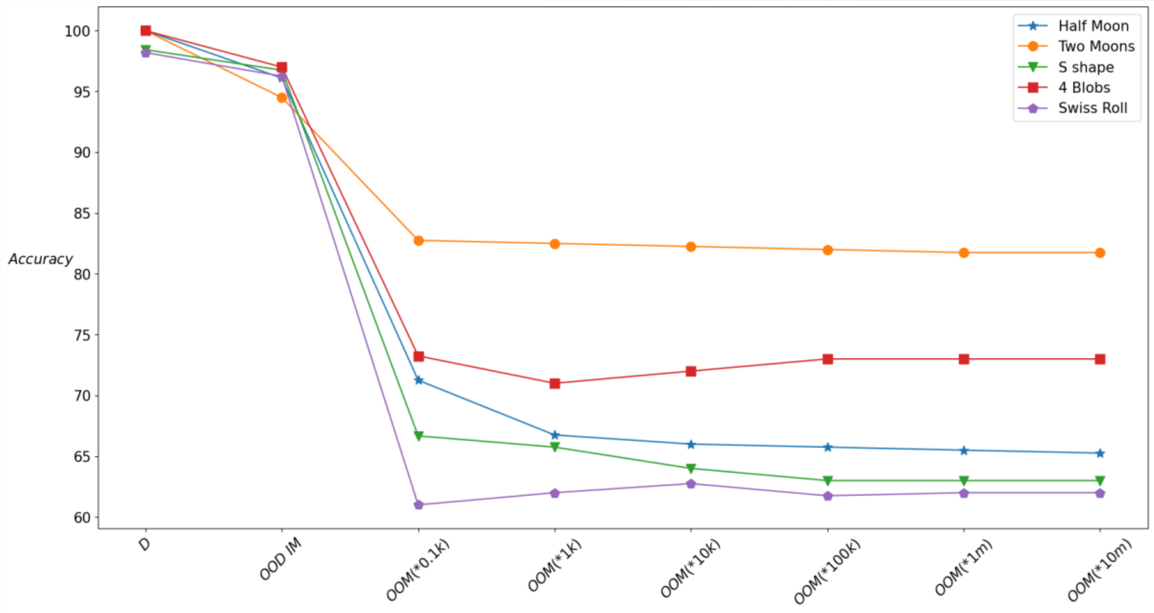


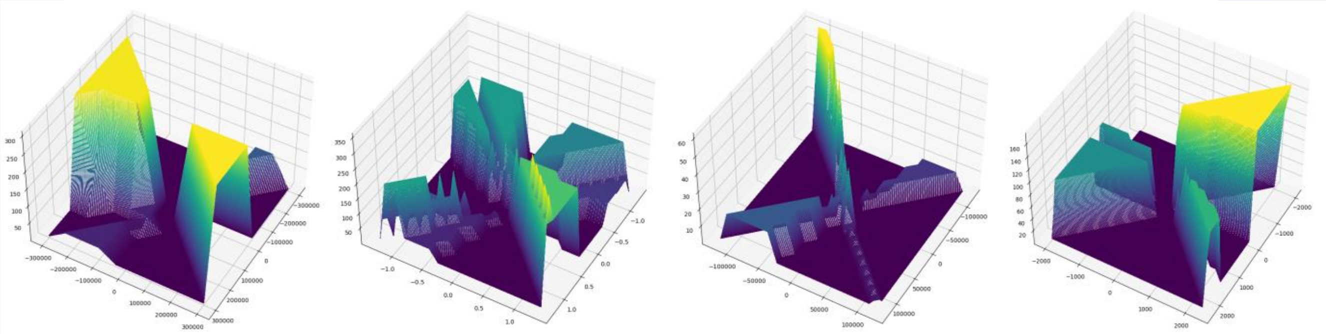


Results: Robustness

We measure the effectiveness of our model in approximating the nearest neighbor in out of distribution and out of manifold queries.

- Accuracy, drops, but converges as we move away
- Data structure seem to play a role in converged accuracy





Conclusions

- ✓ Clustering to partition space S
- ✓ Critic to preserve nearest neighbor information
- ✓ Hierarchical structure used for parsing
- ✓ Works for different data, metrics, and in 2,3 dimensions
- ✓ Fast due to neural network inherent parallelization abilities

Thank you

Minas Dioletis[1,7], *Ioannis Z. Emiris*[2,4], *George Ioannakis*[1], *Evanthia Papadopoulou*[5], *Thomas Pappas*[1], *Panagiotis Repouskos*[1], *Panagiotis Rigas*[1,2,3,†] *and Charalampos Tzamos*[1,6]

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