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CodedVTR: **Code**book-based Sparse **V**oxel **TR**ansformer with Geometric Guidance

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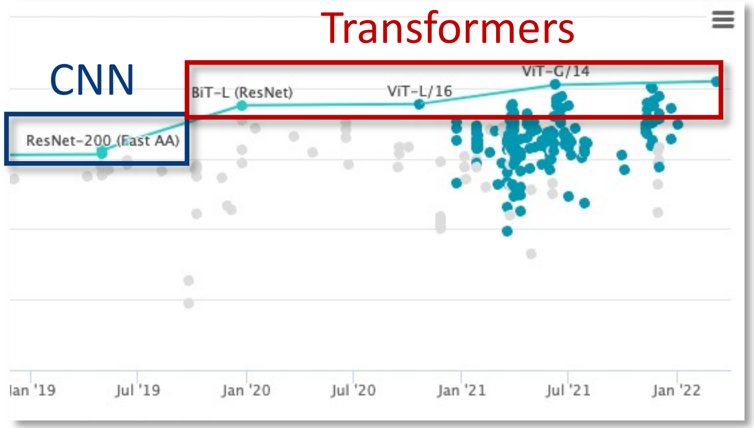
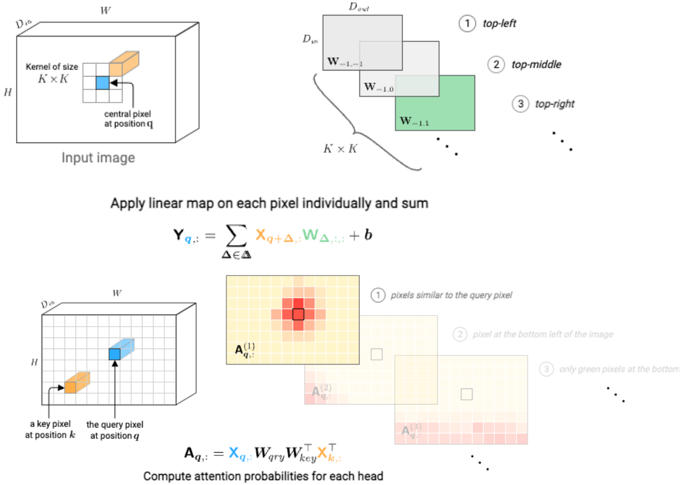
Background

- **Transformers outperform CNN** and achieve SOTA in many vision tasks
- Transformer's superiority:
  - Less inductive bias -> Better representation power



Performance of ImageNet1K Classification[1]



Self-Attention could **approximate** Conv,
And it is a **more generalized form** of Conv[2]

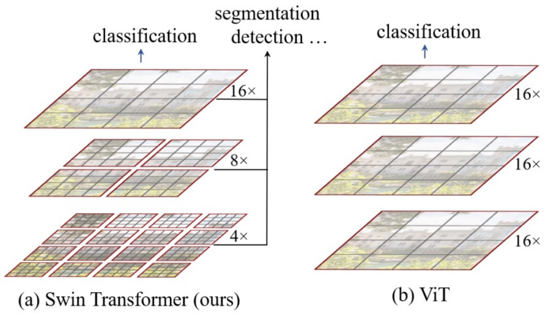
[1] ImageNet Benchmark (Image Classification) | Papers With Code
[2] Cordonnier, J., Loukas, A., & Jaggi, M. (2020). On the Relationship between Self-Attention and Convolutional Layers. ArXiv, abs/1911.03584.

Background

- **Transformer's Problem:** harder to optimize and generalize
  - Rely on large-scale pretraining, **overfits** when directly trained on smaller dataset
  - Slow convergence & sensitive to hyperparameters (LR, initialization, data-aug…)
- **Solution:** introduce domain-specific inductive bias

> *" When directly trained on the ImageNet, ViT yields modest accuracies of a few points below ResNets of comparable size " [1]*

ViT[1] requires large-scale pretraining to outperform ResNets

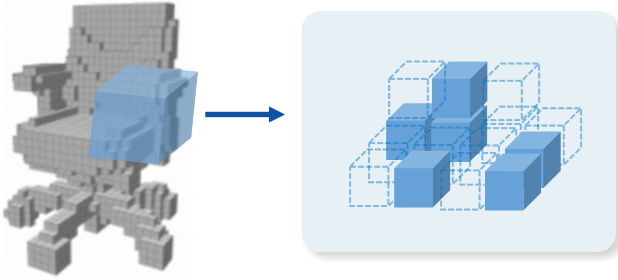


Swin Transformer[2] uses **hierarchical window-based local** aggregation

[1] Dosovitskiy, Alexey et al. "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale." ArXiv abs/2010.11929 (2021): n. pag.
[2] Liu, Ze et al. "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows." 2021 IEEE/CVF International Conference on Computer Vision (ICCV) (2021): 9992-10002.

Background

- Introducing transformer into 3D Domain: The generalization issue is aggravated
  - 3D Data (Sparse Voxel) has unique properties (sparse & irregular)
  - Relatively limited data scale



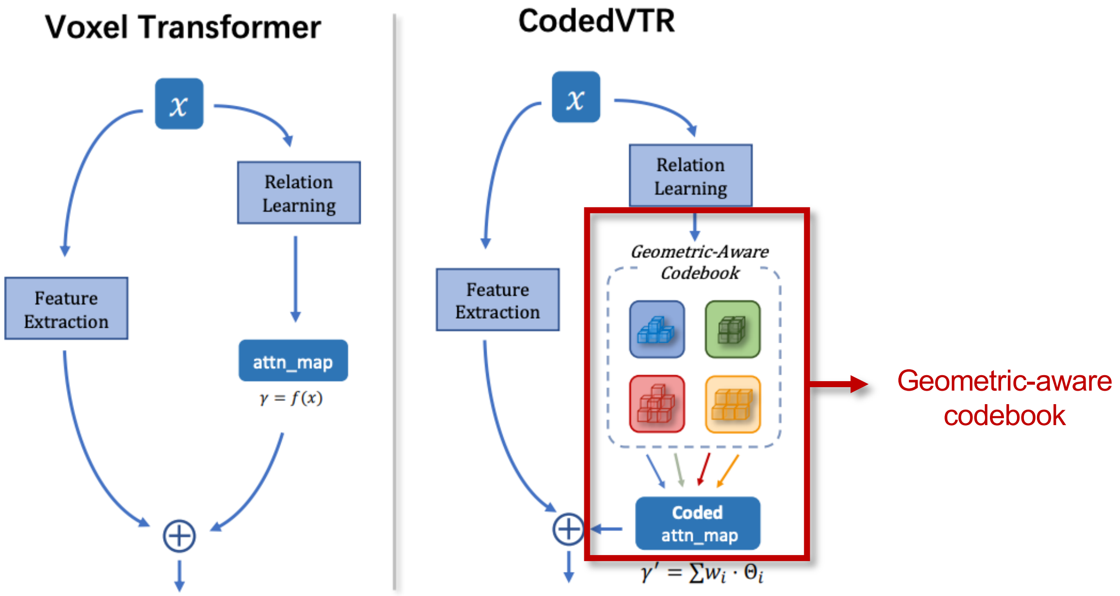
Voxel's unique properties:
sparse and irregular

Dataset	Method (Model)		Params	mIOU
ScanNet	Convolution	Minkowski-M	7M	67.3%
		Minkowski-L	11M	72.4%
	Transformer	PointTransformer	6M	58.6% (-8.7%)
		VoTR (Mink-M)	7M	62.5% (-4.8%)
		VoTR (Mink-L)	11M	66.1% (-6.3%)
SemanticKITTI	Convolution	Minkowski-M	7M	58.9%
		Minkowsk-L	11M	61.1%
	Transformer	VoTR (Mink-M) †	7M	56.5% (-2.4%)
		VoTR (Mink-L)	11M	58.2% (-2.9%)

Simply employ transformer
fails to outperform CNN

Contribution

- **Key**: alleviate the generalization issue
- **CodedVTR:** introduce **geometric-aware codebook**
  - Codebook-based attention
  - Geometric-aware attention

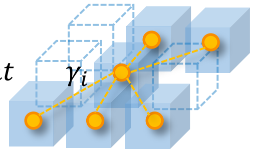


Motivation

- **Comparison of conv and transformer** (with local self-attention)
  - The attention weight generation:

Activation x

Attention Weight γ_i

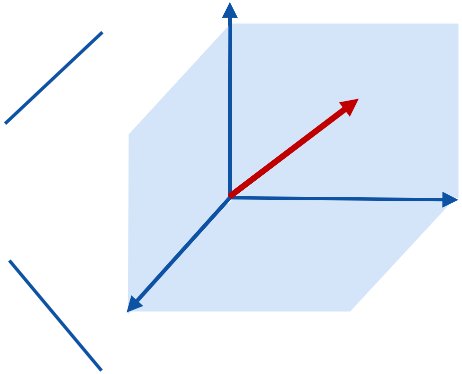


Attention Span (*Local Neighborhood* Φ)

$$y = \sum_i^{\Phi} \gamma_i \cdot g(x_i)$$

$$\gamma = f(x)$$

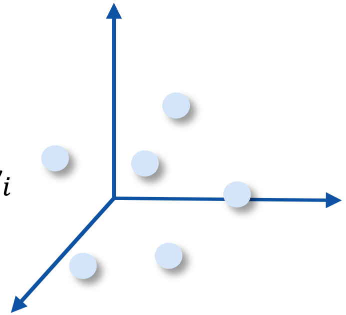
Self-attention



Learn the whole continuous space $f(x)$ ***of dimension:*** $N(\Phi)$

Convolution

$$\gamma = w_i$$



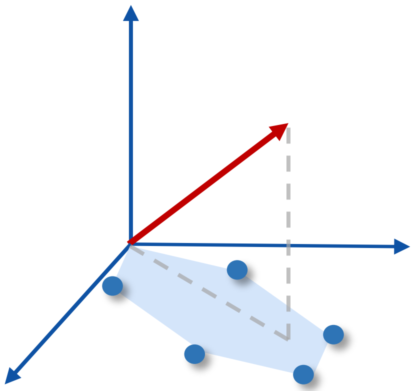
Learn some weights w_i *on anchor points*

Methodology

- **Codebook-based attention:** encode the attn-weight with codebook elements

$$f(x) \sim f_d(x) = \sum w_i \theta_i$$

- Codebook elements θ_i could be viewed as:
  - attention weight "Prototypes"
  - a set of basis that span a subspace
- **Project** the attention learning in the subspace
- **Regularization** – helps generalization



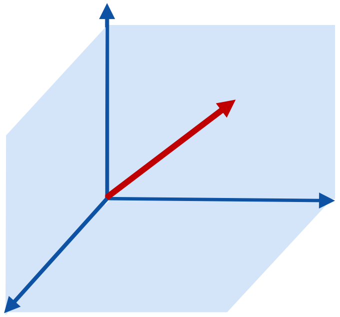
Learn the subspace $f_d(x)$
of dim: $N(\Theta) < N(\Phi)$

Methodology

- Codebook-based attention is an **intermediate state** of self-attention and convolution

Self-Attention

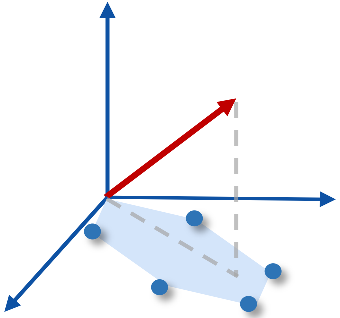
$$\gamma = f(x)$$



$$N(\Theta) = \infty$$

Codebook-based Self-Attention

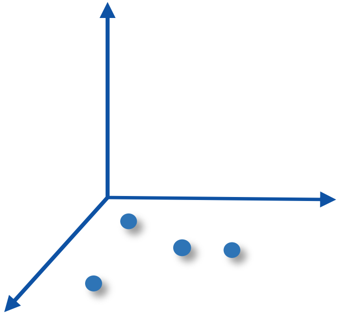
$$\gamma = f_d(x) = \sum w_i \, \theta_i$$



$$N(\Theta)$$

Convolution

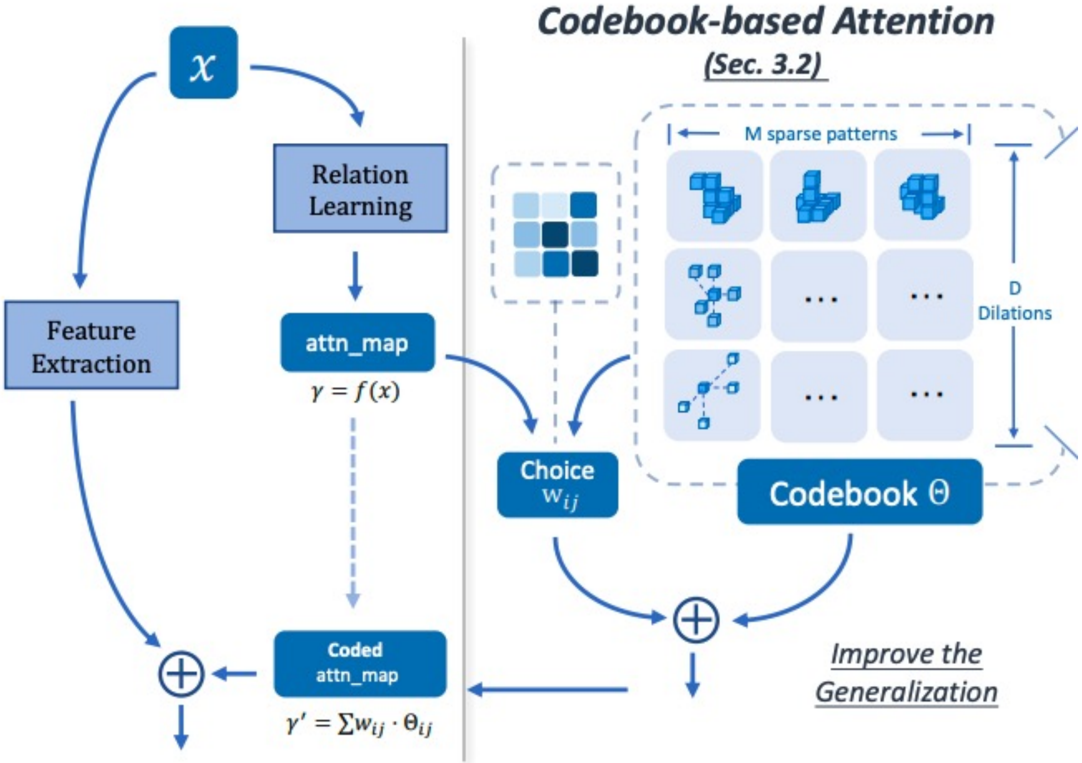
$$\gamma = w_i$$



$$N(\Theta)=1$$

Methodology

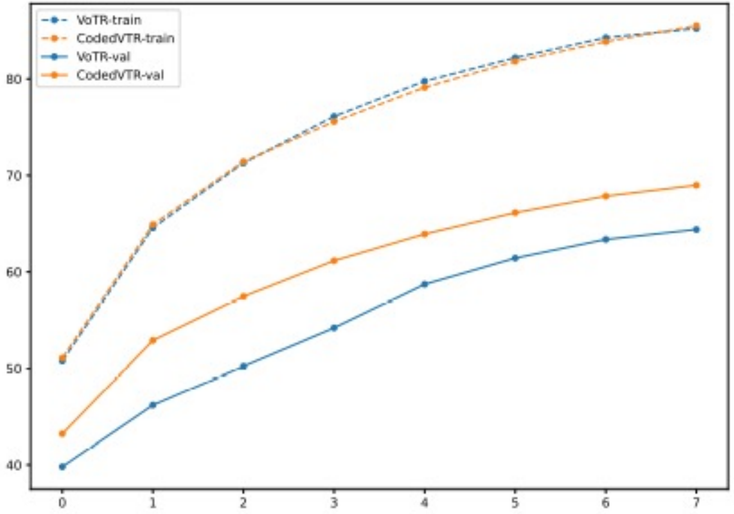
- Codebook Design



Experimental Results

- Results of Codebook Design

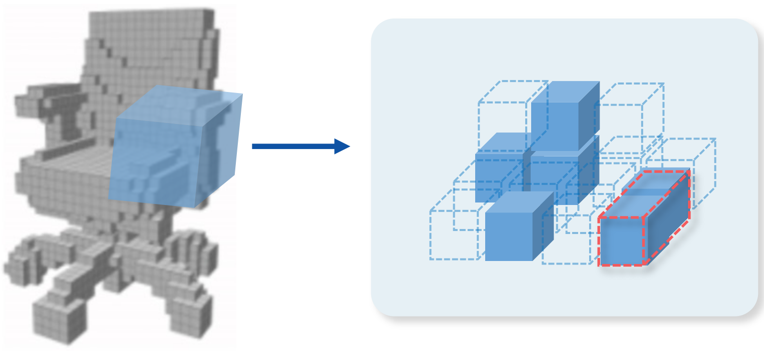
$N(\Phi)$	mIOU
1	57.1%
4	58.5%
24	**60.4%**
48	58.1%

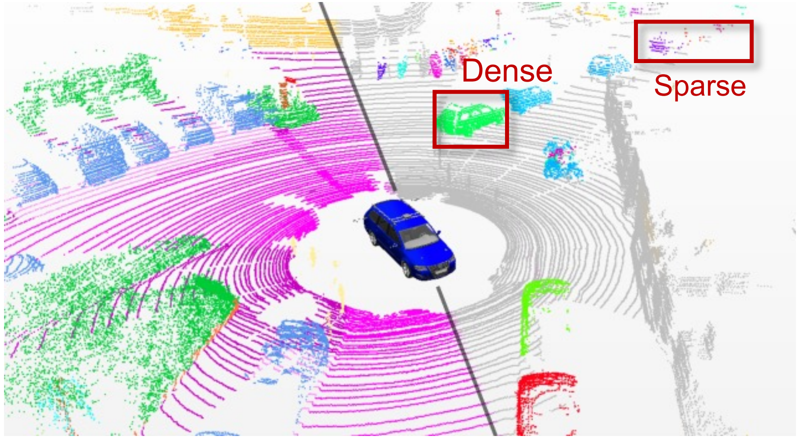


CodedVTR helps generalization

Methodology

- 3D data’s unique properties -> Geometric-aware attention



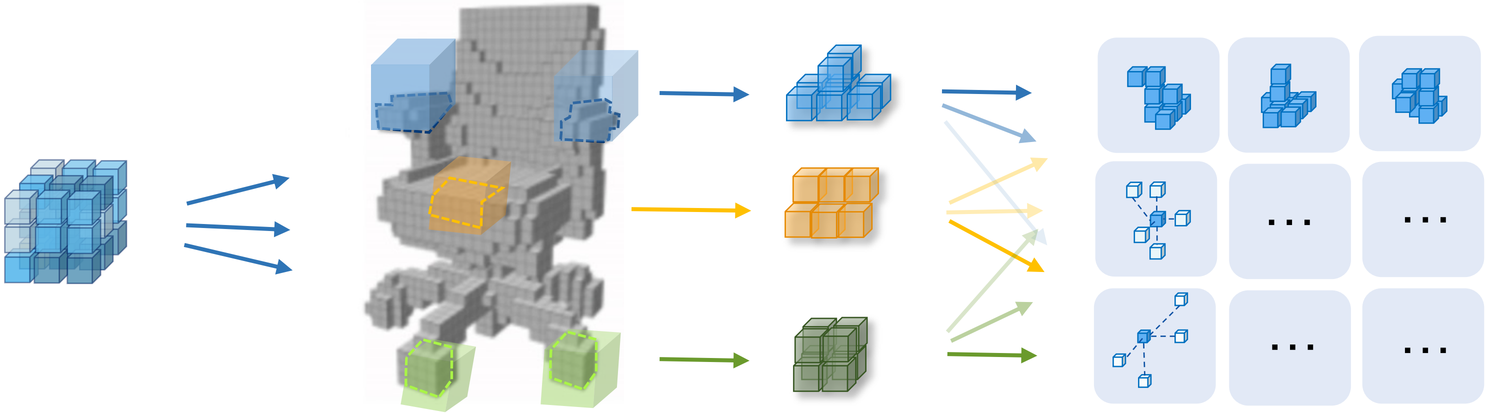


Sparsity & Varying geometric shape

Varying densities (outdoor)

Methodology

- Geometric-aware attention
  - Geo-shape: assign different geometric shapes for codebook elements
  - Geo-guide: encourage attention to match the input's sparse pattern



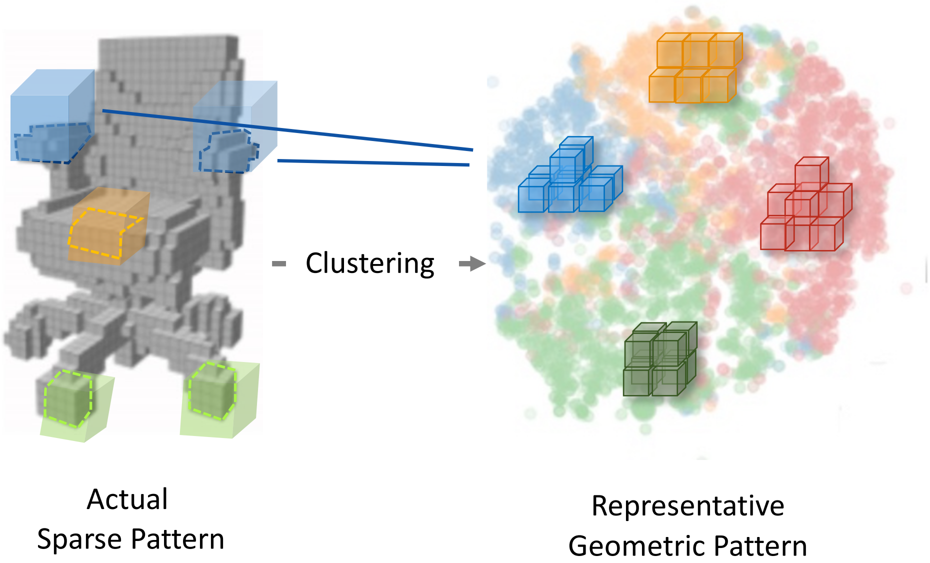
Same convolution weight

Different input voxel sparse pattern

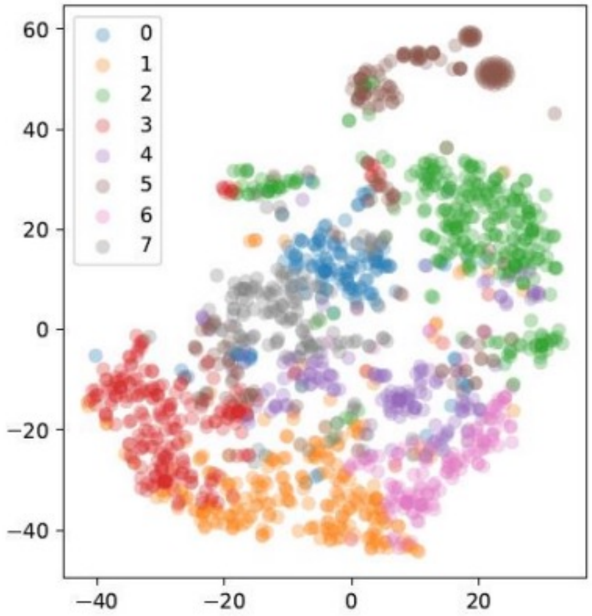
Different geometric shapes codebook-elements

Methodology

- How to determine geometric shape?
  - Adopt **k-means clustering** to get 8 representative sparse pattern in 3 dilations

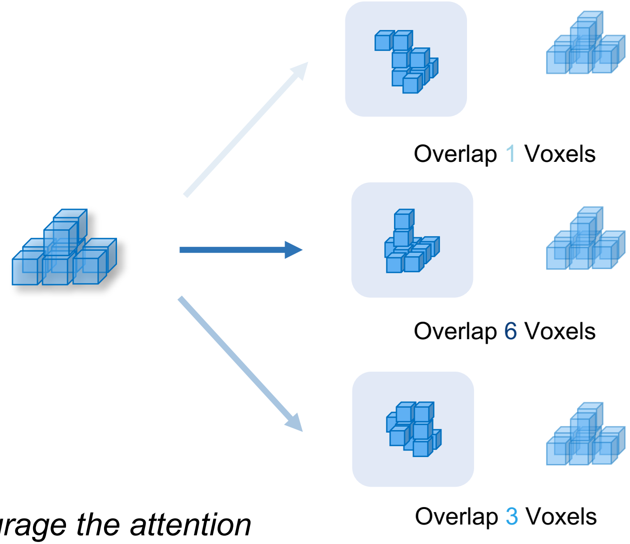


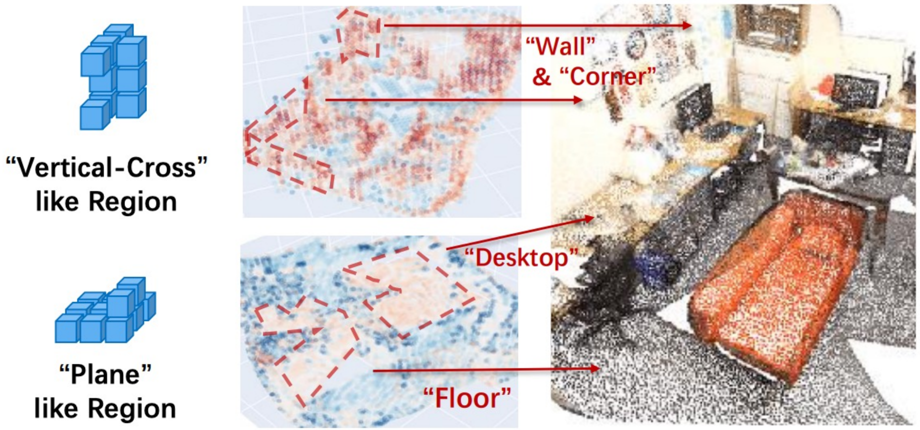
Clustering t-SNE Visualization



Methodology

- How to adopt geometric guide?
  - Regularize the attention with “mismatch code”

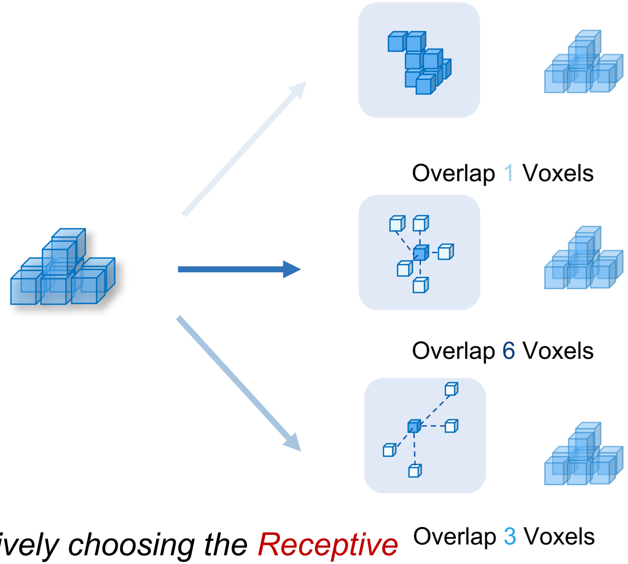




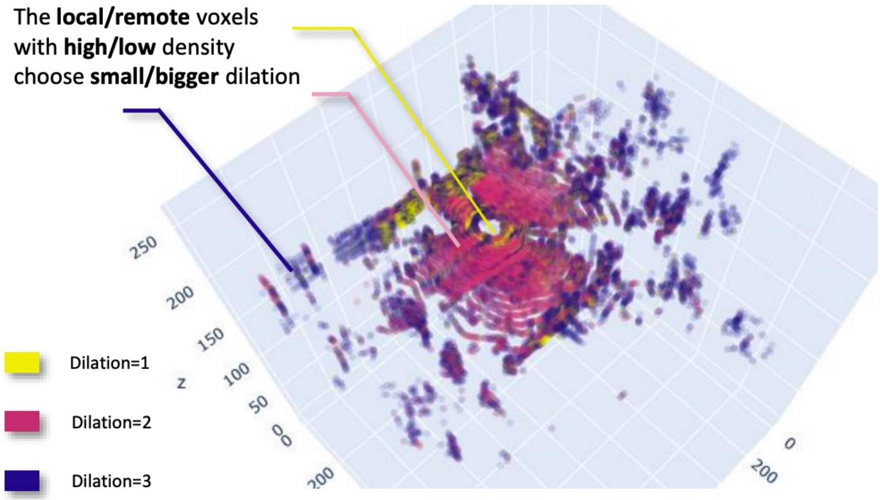
Encourage the attention
To lean to matching geometric shape

Methodology

- How to adopt geometric guide?
  - Regularize the attention with “mismatch code”



Adaptively choosing the Receptive Field for different densities

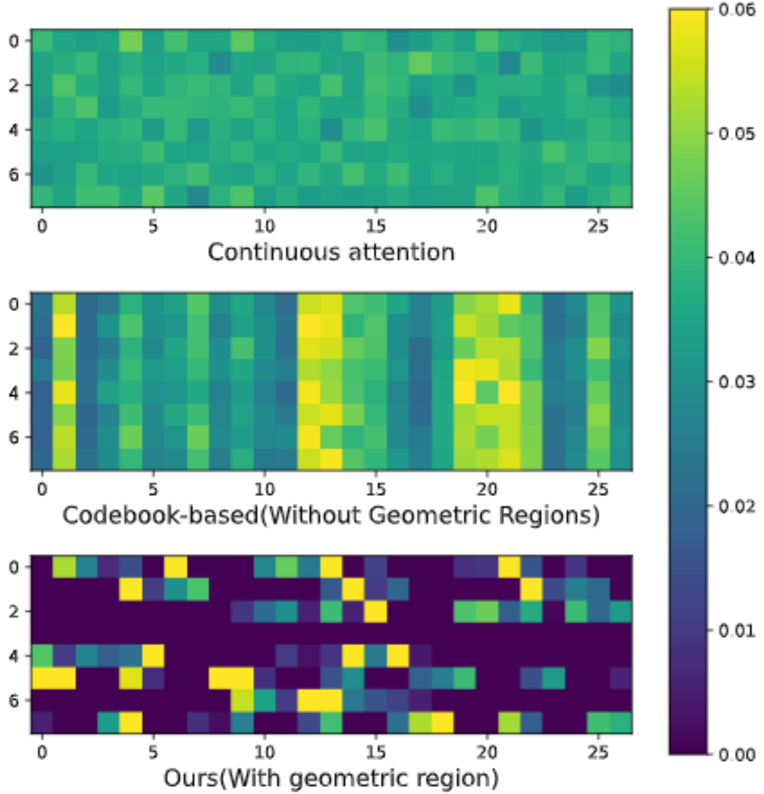


Experimental Results

Naïve self-attention
(Uniform Attention Map)

Codebook-based self-attention
(Similar attention map)

Geometric-aware self-attention
(Meaningful attention map)



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		CodedVTR (Mink-L)	11M	**73.0%**(+0.6%)
SemanticKITTI	Convolution	Minkowski-M	7M	58.9%
		Minkowsk-L	11M	61.1%
		SPVCNN	8M	60.7%
	Transformer	CodedVTR (Mink-M)	7M	**60.4%** (+0.5)
		CodedVTR (Mink-L)	11M	**63.2%** (+2.1%)
		CodedVTR (SPVCNN)	8M	**61.8%**(+1.1%)
Nuscenes	Convolution	Minkowski-M	7M	66.5%
		Minkowsk-L	7M	69.4%
	Transformer	CodedVTR (Mink-M)	7M	**69.9%** (+3.4%)
		CodedVTR (Mink-L)	11M	**72.5%** (+3.1%)