ViCE: Improving Dense Representation Learning by Superpixelization and Contrasting Cluster Assignment

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Self-supervised dense representation learning

- Recent **self-supervised classification models** are better or equal to fully supervised models
- However, these methods are **ineffective for learning dense representations**
  - Typically reduce images into a **tiny feature 7x7 map** that discards precise spatial information about content
  - **Prohibitive computational demand** for contrastive learning methods [1] on high-resolution images

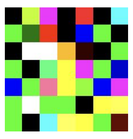
Regional decomposition by superpixels

- Decompose images into a **small set of visually coherent regions**
  - Adjacent similar pixels represent same semantics (no information loss)
  - Superpixel regions conform to image content (unlike grids)
- **Reduce computational complexity** by **O(1000)**
  - Improve efficiency of contrastive methods on high-resolution images
  - Experiments show that learning from high-resolution images is beneficial

1280x720 pixels ⇒ 921,600 pixels/vectors

Resnet50

Spatial information about content is lost

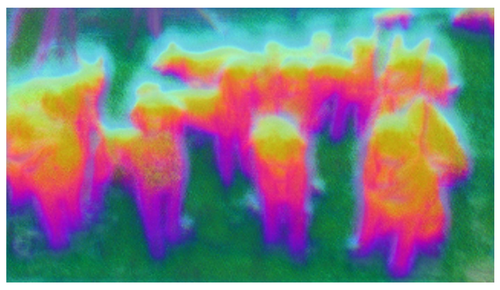


Embedding RGB visualizations (7x7)

Superpixelization

2304 vectors (99.75% reduction)

ViCE



Embedding RGB visualizations (1280x720)

ViCE: Visual Concept Embeddings

- View natural **images X** as a result of a **dense representation Z** of **latent visual concepts C = (c_1, … , c_K)** transformed by a **stochastic generative process f(X|Z)**
- Stochasticity: Assume a single latent Z representation maps to many potential images X
  - Same visual content but different pixel appearance
- Method: Learn an **approximative inverse function f'(Z|X)** and a **set C**

* Superpixels only used during training

Table 8: Average inference time for a high-resolution image

	Segmentation model	Cluster model	Linear model
[msec]	57	2395	15

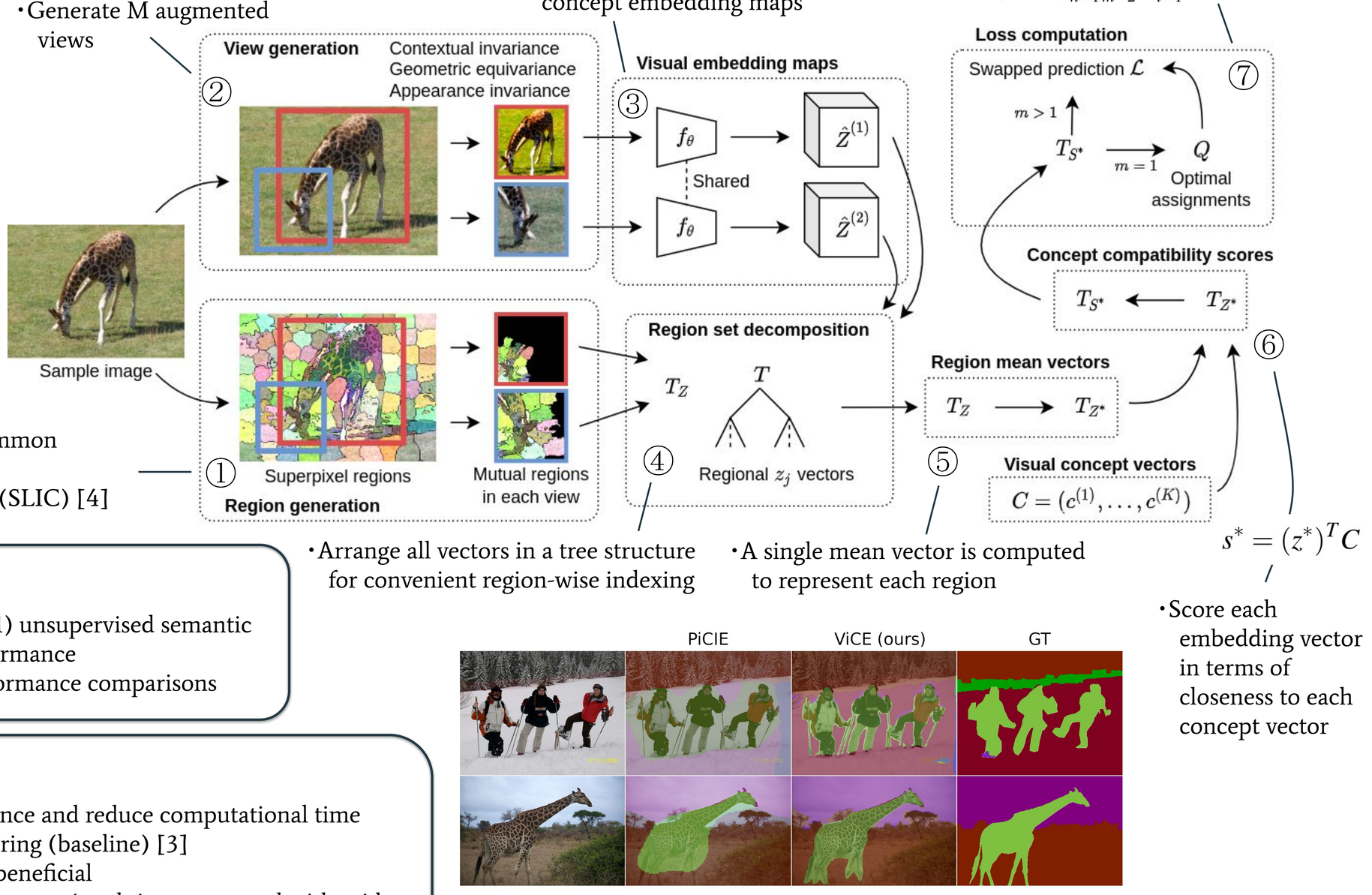
Learning method

Fundamental learning signals

- **Same content** with **different pixel appearance** by data augmentation [2,3]
- Semantic meaning from **spatial co-occurrence and context** (similar to learning word embeddings)

- Generate M augmented views
- Transform views into visual concept embedding maps
- Objective optimize the similarity of embeddings within all views, as well as the distribution of visual concepts

$$\mathcal{L}_{cl} = -\frac{1}{N(M-1)} \sum_{n=1}^{N} \sum_{m=2}^{M} \frac{1}{I} \sum_{i=1}^{I} q^{(i)} log\, \sigma \left(\frac{1}{\tau} s^{(i,m)*} \right)$$



- Partition image into I mutually common superpixel regions
- Simple Linear Iterative Clustering (SLIC) [4]

- Arrange all vectors in a tree structure for convenient region-wise indexing
- A single mean vector is computed to represent each region

$$s^* = (z^*)^T C$$

- Score each embedding vector in terms of closeness to each concept vector

Experiments

- Evaluate representation quality through 1) unsupervised semantic segmentation and 2) linear model performance
- Low-resolution and high-resolution performance comparisons

Results

- **Image decomposition** improves performance and reduce computational time
- **Online clustering** (ViCE) > Offline clustering (baseline) [3]
- Learning from **high-resolution images** is beneficial
- **Superpixels** improve performance and computational time compared with grids
- **General vision models** learn more useful embeddings also when comparing on a narrow domain

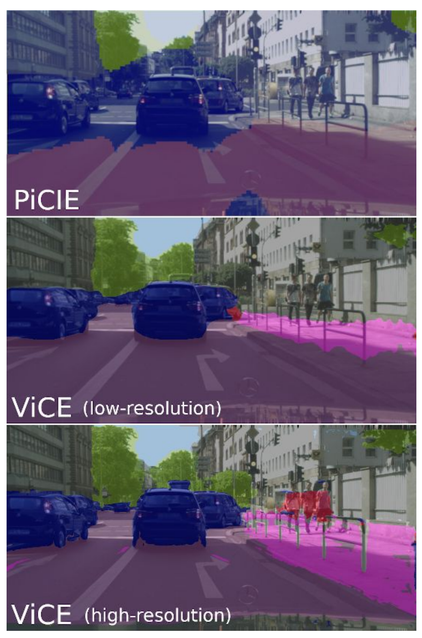


Table 1: Representation quality experiment results on low- and high-resolution images.

Model		mIoU	Acc.	Model		mIoU	Acc.
	COCO				*Cityscapes*		
ResNet50 [50]	C 27	8.9	24.60	ResNet50 [50]	C 27	-	-
MoCoV2 [22]	C 27	10.40	9.60	MoCoV2 [22]	C 27	-	-
DINO* [15]	C 27	9.60	30.50	DINO* [15]	C 27	-	-
IIC [56]	C 27	6.71	21.79	IIC [56]	C 27	6.35	47.88
PiCIE [23]	C 27	13.84	48.09	PiCIE [23]	C 27	12.31	65.50
	C 27◇	14.60	48.37		C 27◇	11.85	64.29
	C 27⋆	9.27	38.31		C 27⋆	8.80	82.48
	C 128⋆	10.75	49.81		C 128⋆	7.97	56.52
	C 256⋆	12.42	**66.02**		C 256⋆	12.71	**89.86**
	Linear	14.77	54.75		Linear	-	-
PiCIE+H [23]	C 27+100	14.40	50.0	PiCIE+H [23]	C 27+100	-	-
ViCE (low-res)	C 27	11.40	28.91	ViCE (low-res)	C 27	12.81	31.87
	C 27⋆	11.55	50.49		C 27⋆	19.52	80.34
	C 128⋆	16.66	52.33		C 128⋆	21.48	81.55
	C 256⋆	17.98	54.92		C 256⋆	21.24	81.72
	Linear	25.49	62.78		Linear	**31.55**	86.33
				No pretrain	Linear	24.84	82.99
ViCE (high-res)	C 256⋆	**21.77**	64.75	ViCE (high-res)	C 256⋆	**25.23**	84.28
	Linear	**29.38**	**68.16**		Linear	30.40	**87.0**
STEGO* [47]	C 27	28.20	56.90	STEGO* [47]	C 27	21.00	73.20
	Linear	41.00	76.10		Linear	-	-

C K: evaluation w. K clusters, ◇ reproduced results, ⋆ greedy assignment, ∗ ViT-based models

Conclusions

- Present a **new SOTA unsupervised semantic segmentation** method ViCE for learning to generate **dense embedding maps for high-resolution natural images**
- **Decomposing images** by superpixelization improves the effectiveness of classification-based self-supervised methods
- **Superpixels perform better** than conventional grid decomposition
- Hope our work will **raise interest in incorporating non-uniform image decomposition techniques** to improve other self-supervised computer vision methods including ViT-based models [5]

References: [1] Caron M. et al. NeurIPS, 2020 [2] Chen T. et al. ICML 2020 [3] Cho J. et al. CVPR 2021
[4] Achanta R. et al. PAMI, 2274-2285, 2012 [5] Caron M. et al. ICCV, 2021

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