Learning Semantics-enriched Representation via Self-discovery, Self-classification, and Self-restoration

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Project page: github.com/JLiangLab/SemanticGenesis

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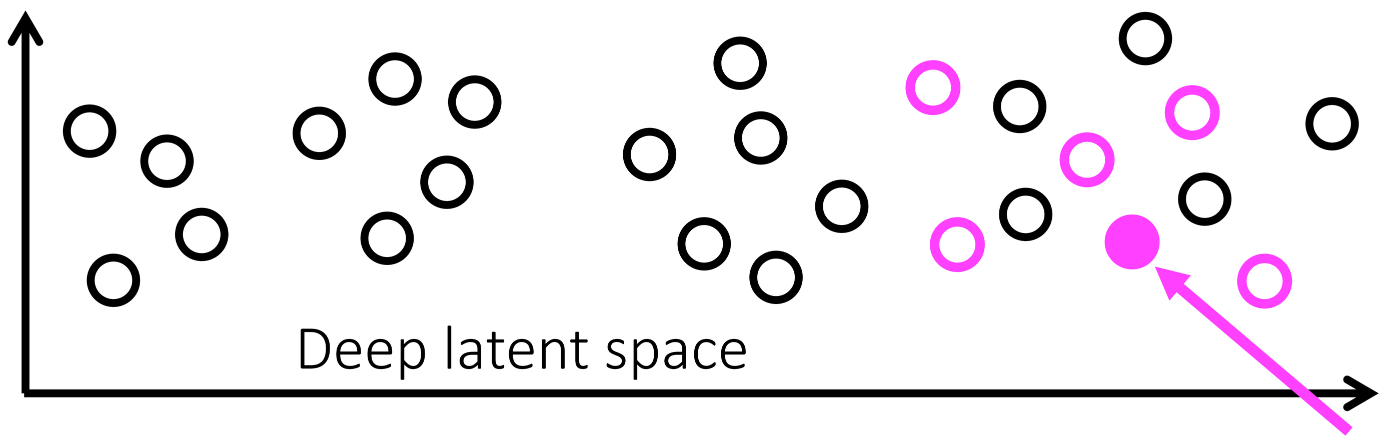
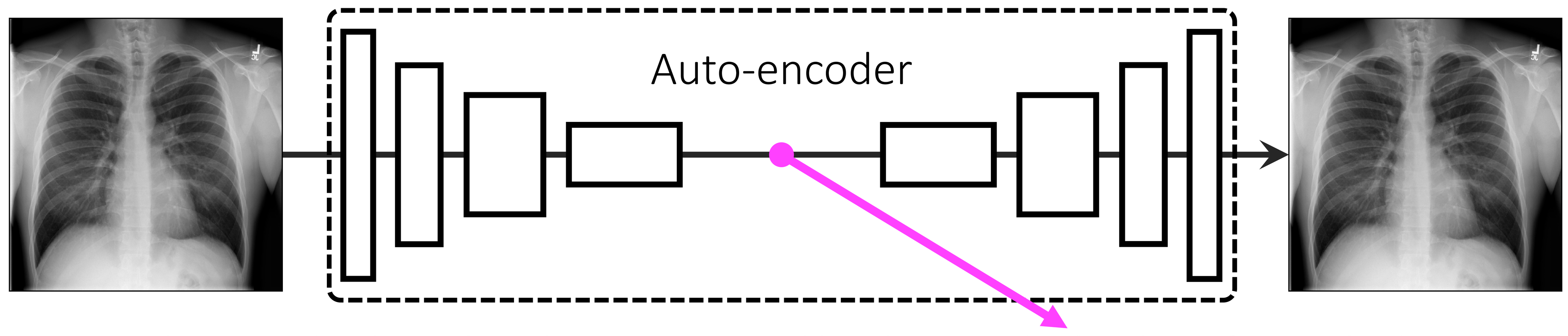
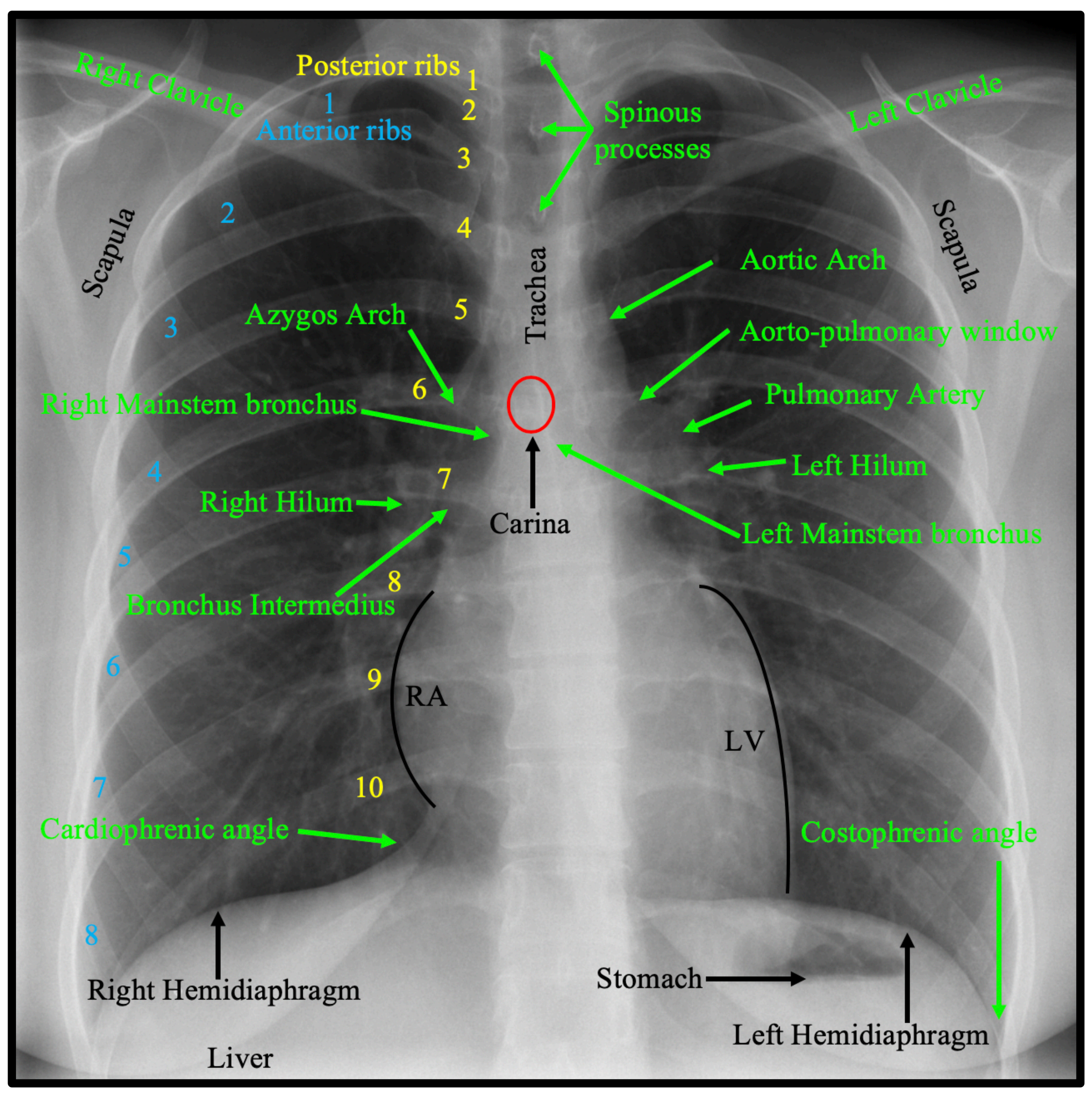
Motivation: Medical imaging follows protocols for defined clinical purposes, generating images of similar anatomy across patients and yielding recurring anatomical patterns across images. These recurring patterns are naturally associated with rich semantic knowledge about human body, offering unique potential to foster deep semantic representation learning and leading to semantically more powerful models.

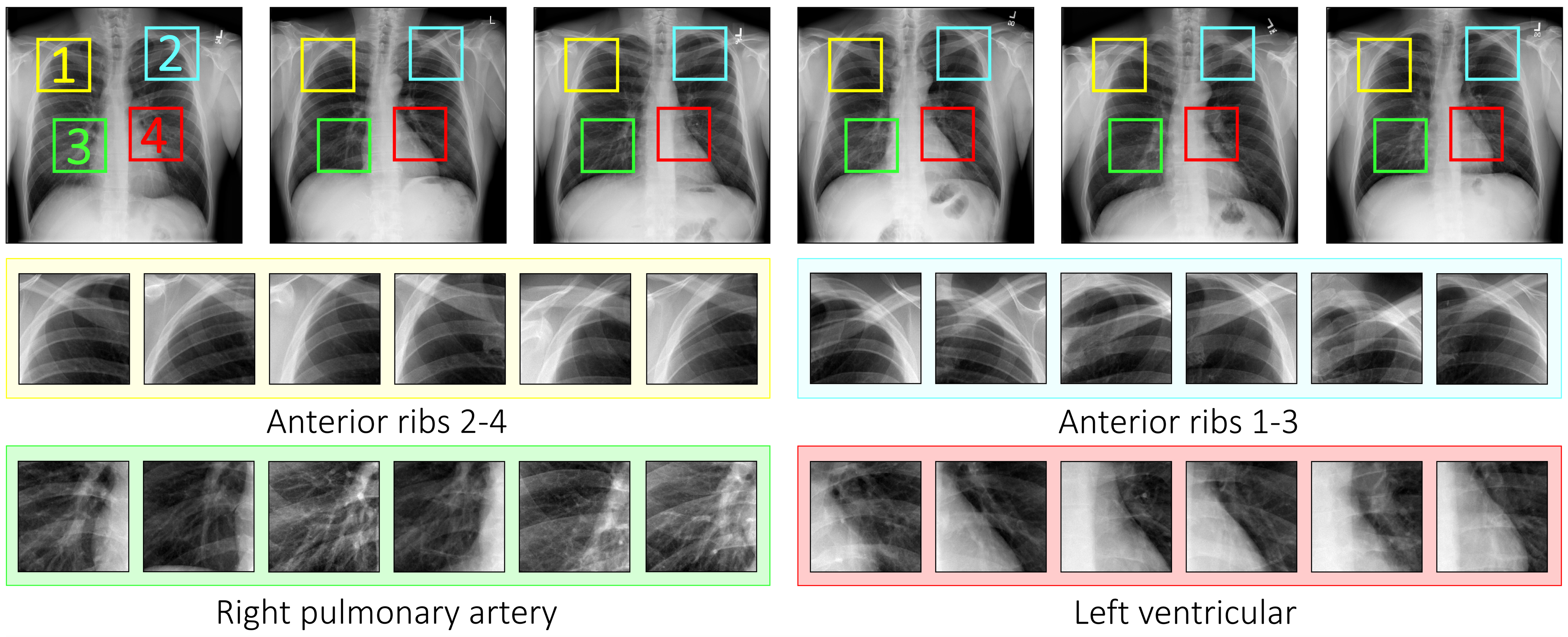
Question: *How to exploit the semantics imbedded in recurring anatomical patterns to enrich self-supervised representation learning?*





5 examples randomly selected from the top nearest neighbors based on the **deep latent features** for the reference



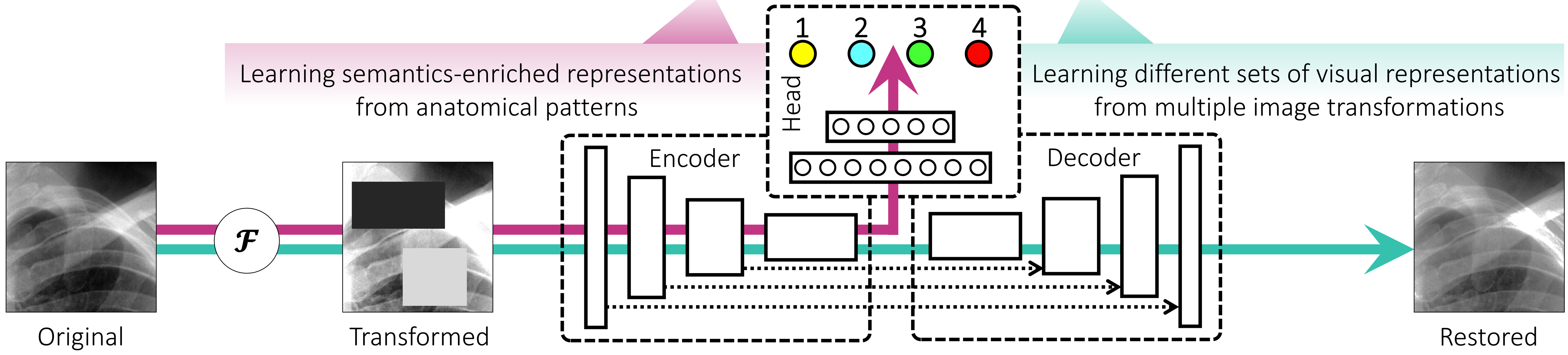


Discovering similar anatomical patterns across different patients automatically

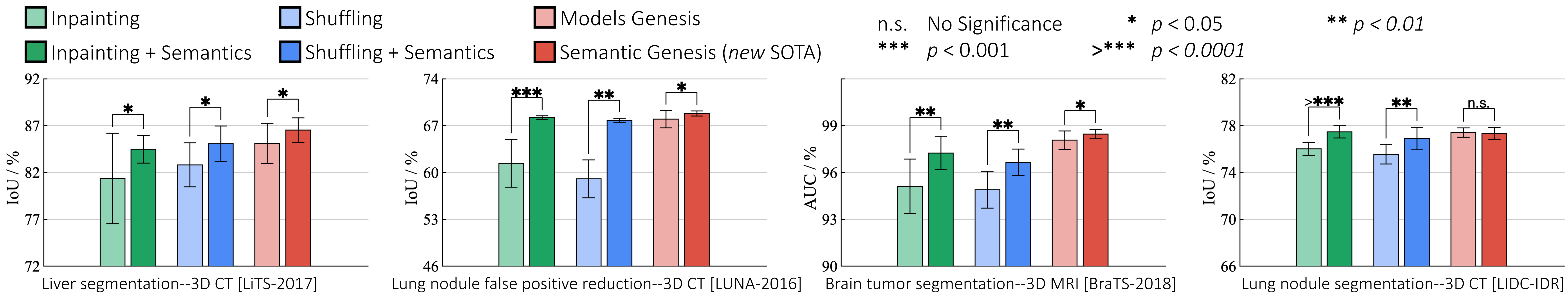
Semantic Genesis

A collection of pre-trained 3D deep models

Learning semantics-enriched representation by (a) self-discovery, (b) self-classification, and (c) self-restoration of anatomical patterns



Result I: Learning semantics, as an add-on, enriches existing self-supervised learning approaches



Result II: Semantic Genesis outperforms existing pre-trained models for 3D medical image analysis

Task / Method	Modality	Metric	Scratch	MedicalNet	I3D	Inpainting	Shuffling	Rubik's Cube	Self-restoration	Self-classification	Semantic Genesis
Lung nodule false positive reduction	CT	AUC	94.25±5.07	95.80±0.51	98.26±0.27	95.12±1.74	94.90±1.18	96.24±1.27	98.07±0.59	97.49±0.45	**98.46±0.30**
Lung nodule segmentation	CT	IoU	74.05±1.97	75.68±0.32	71.58±0.55	76.02±0.55	75.55±0.82	72.87±0.16	**77.41±0.40**	76.93±0.87	77.33±0.52
Liver segmentation	CT	IoU	79.76±5.42	85.52±0.58	70.65±4.26	81.36±4.83	82.82±2.35	75.59±0.20	85.10±2.15	84.14±1.78	**86.53±1.30**
Brain tumor segmentation	MRI	IoU	59.87±4.04	66.09±1.35	67.83±0.75	61.38±3.84	59.05±2.83	62.75±1.93	67.96±1.29	64.02±0.98	**68.82±0.38**

The best methods are **bolded** while the others are highlighted in red if they achieve equivalent performance compared with the best one (i.e., p > 0.05).

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