SQUID:
Deep Feature In-Painting for Unsupervised Anomaly Detection

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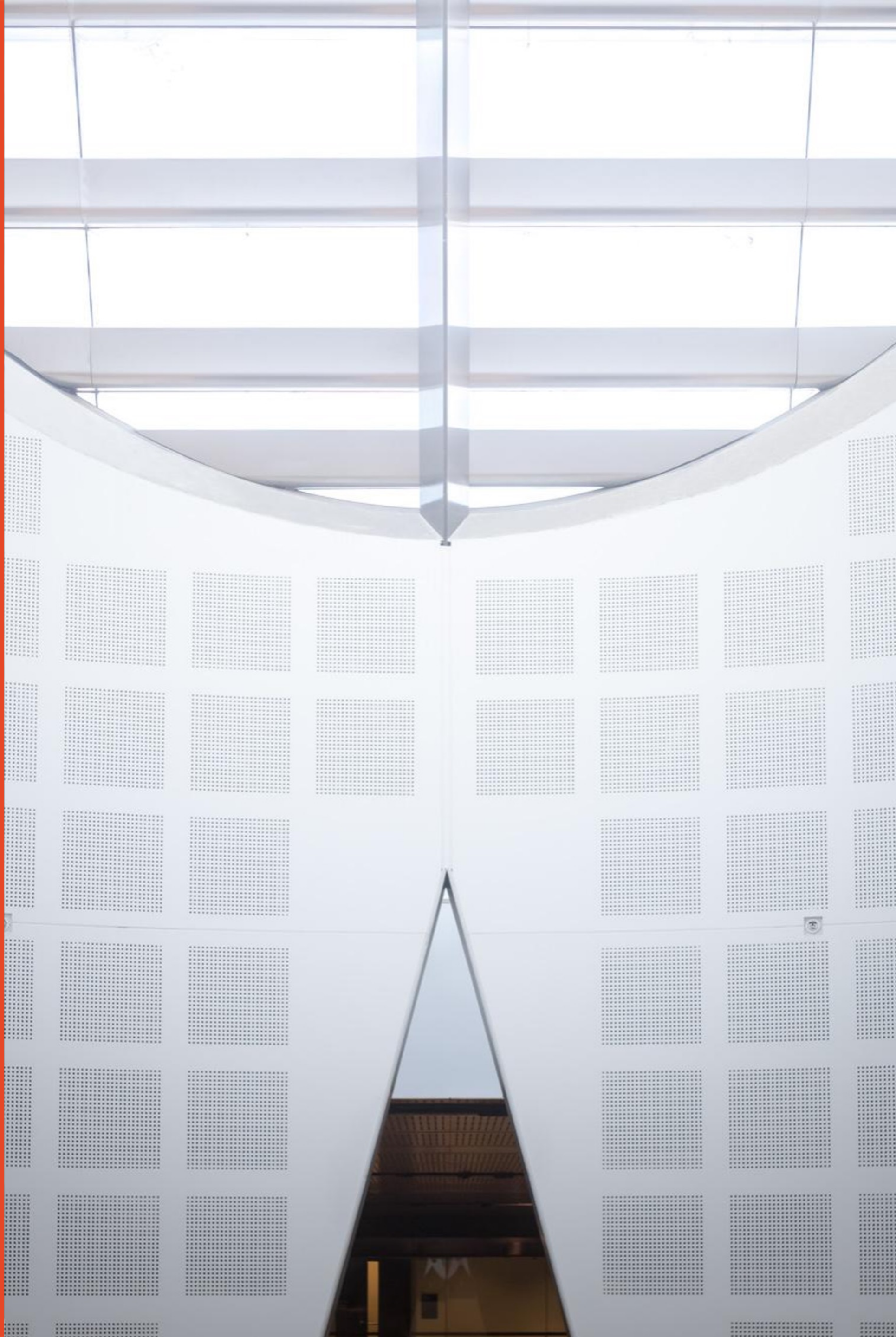


Outline

1. Motivation

2. Methodology

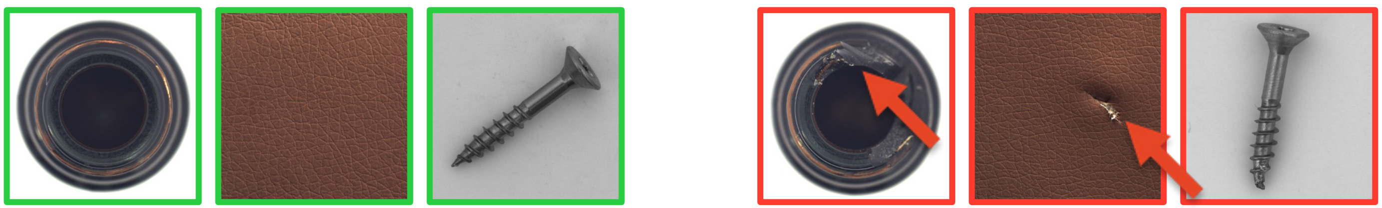
3. Results

4. Conclusion

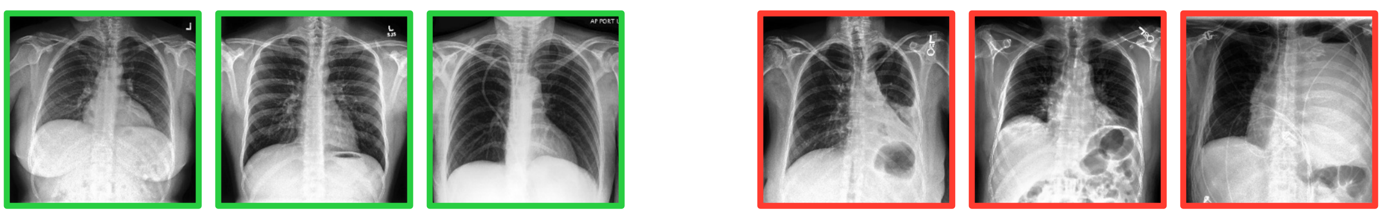
Motivation: Anomaly in Chest X-rays

Normal **Abnormal**

Anomaly Detection in Crowded Scenes
(photography images)



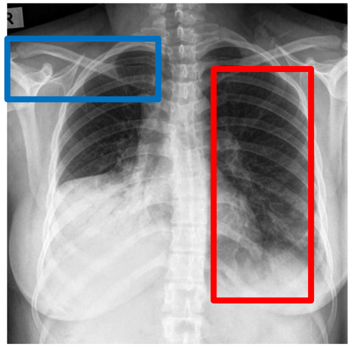
Anomaly Detection in Textures and Objects
(photography images)

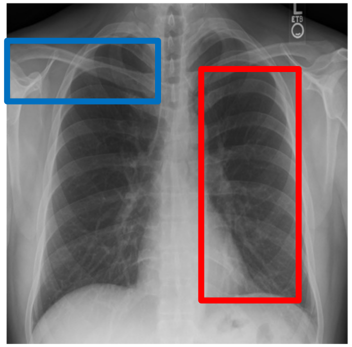


Anomaly Detection in Chest Anatomy
(**radiography images**)

Motivation: Unique Characteristics for Chest X-rays

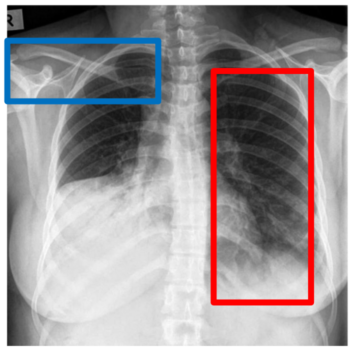
Radiography images

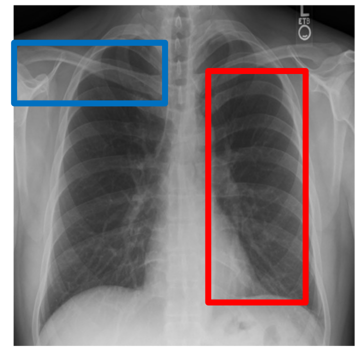




Motivation: Unique Characteristics for Chest X-rays

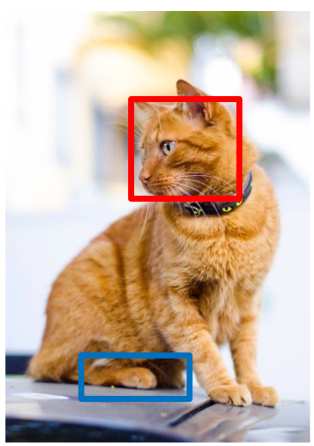
Radiography images

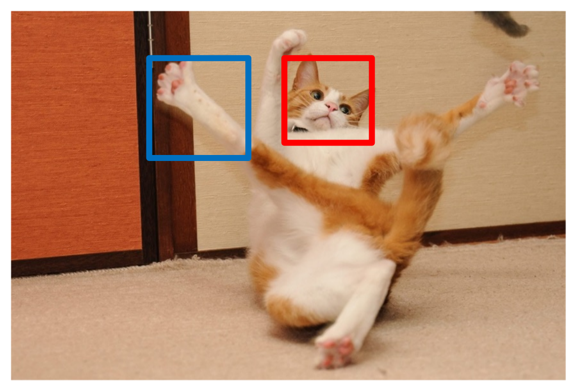




Consistent shapes/appearances and **fixed poses**.

Photography images





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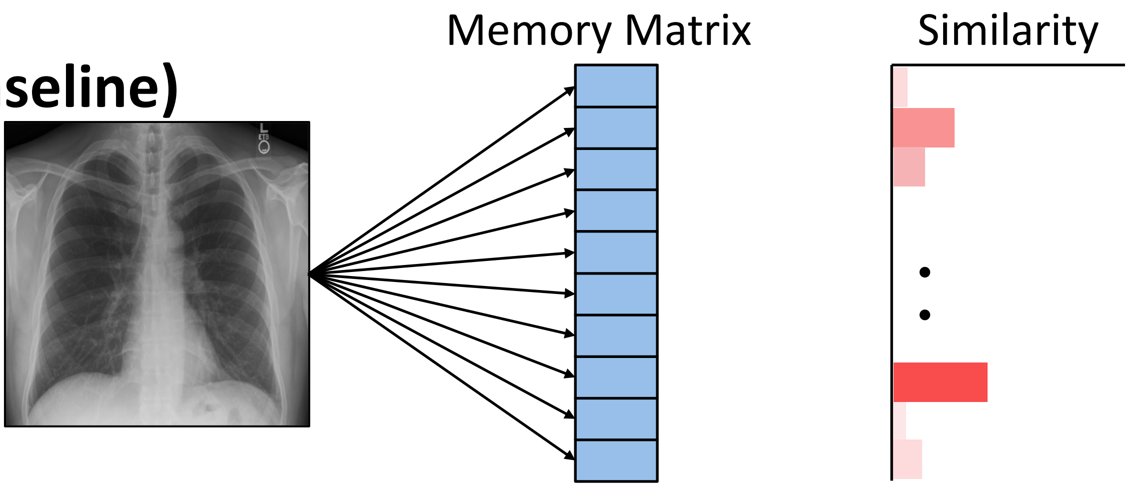
Methodology: Space-aware Memory

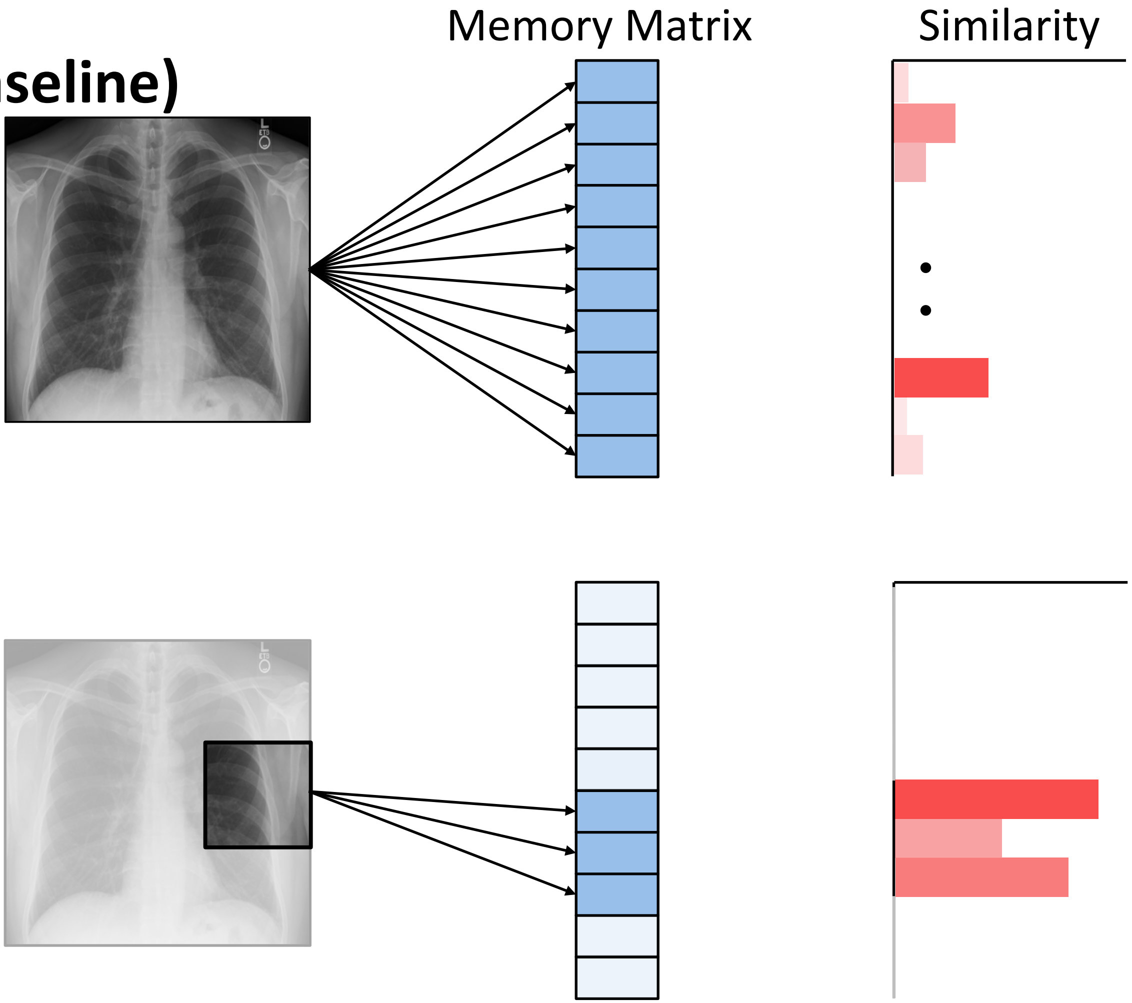
MemAE (Baseline)



Methodology: Space-aware Memory

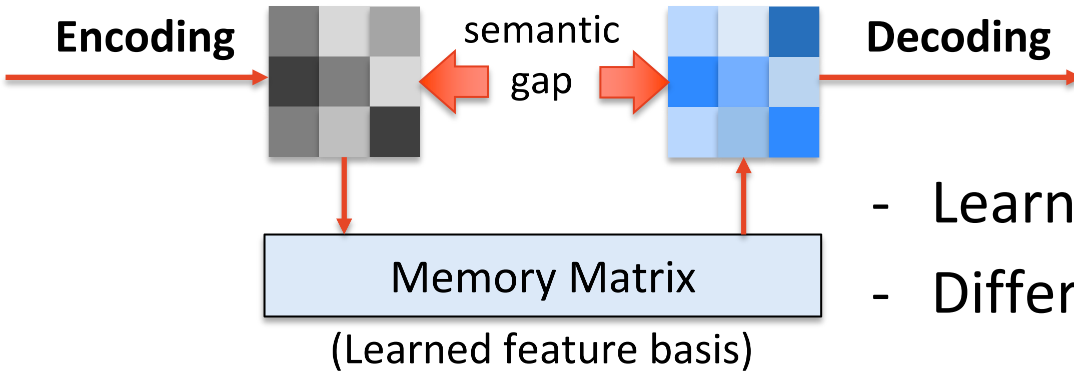
MemAE (Baseline)

Ours



Methodology: Memory Queue

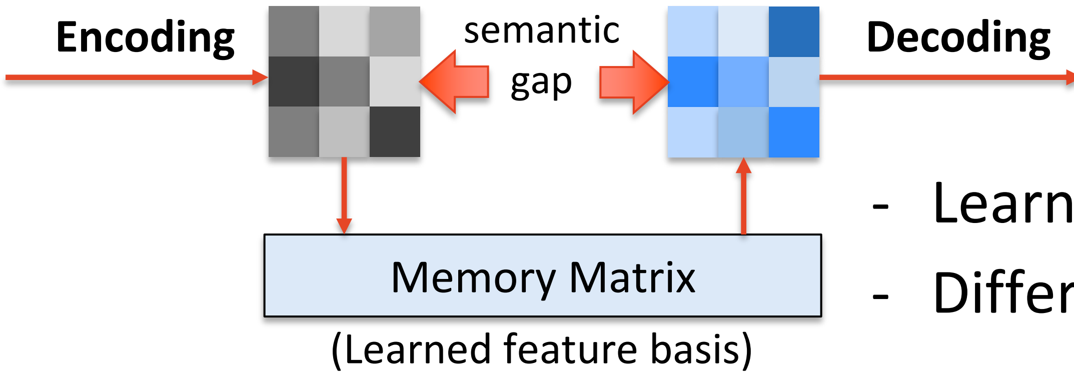
MemAE (Baseline)



- Learnable Matrix
- Different feature dist.

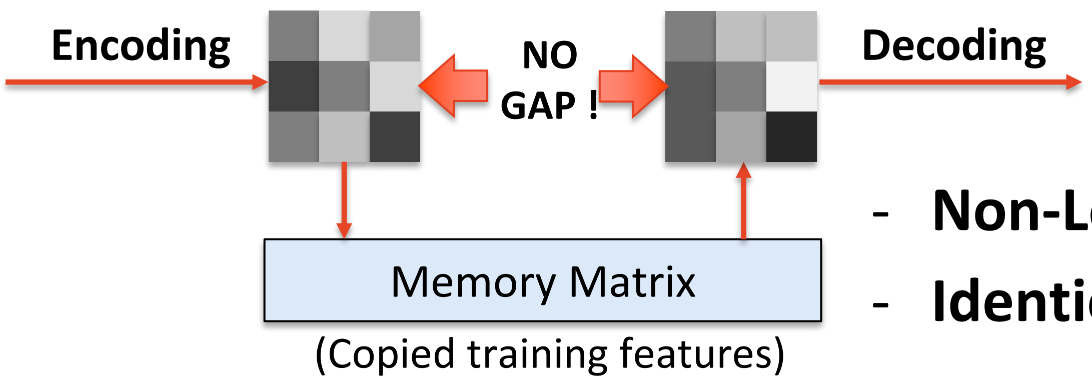
Methodology: Memory Queue

MemAE (Baseline)



- Learnable Matrix
- Different feature dist.

Ours

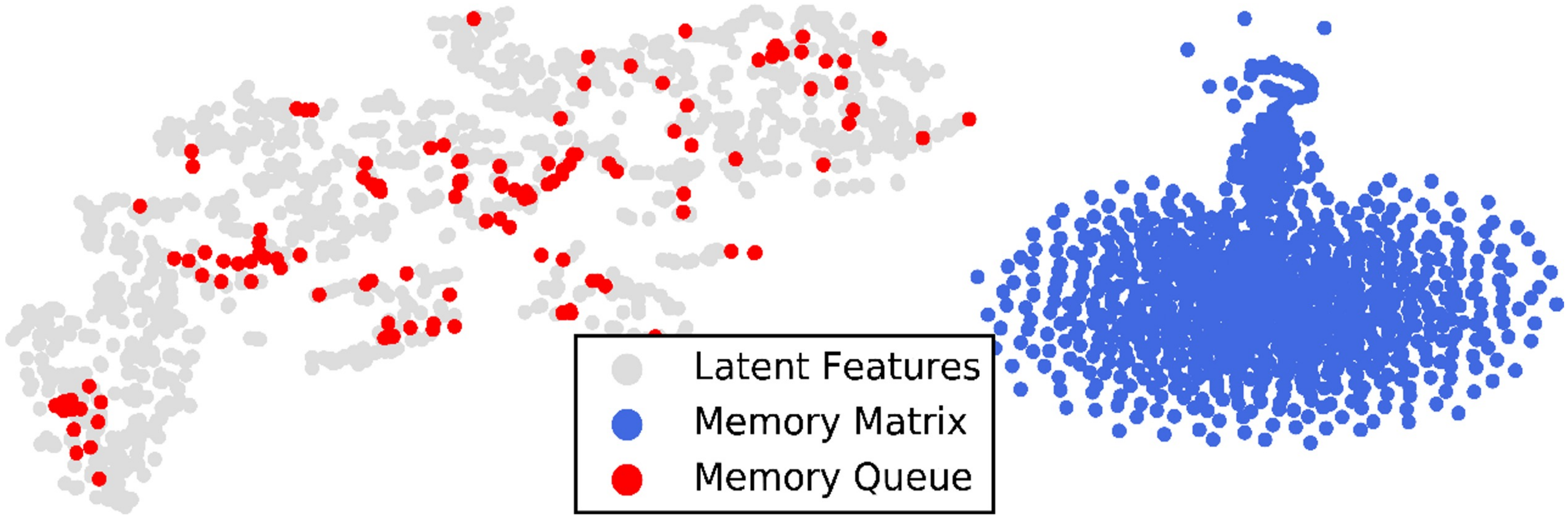


- **Non-Learnable** Matrix
- **Identical** feature dist.

How to prove?

Methodology: Memory Queue

t-SNE feature visualizations



Methodology: Memory Queue

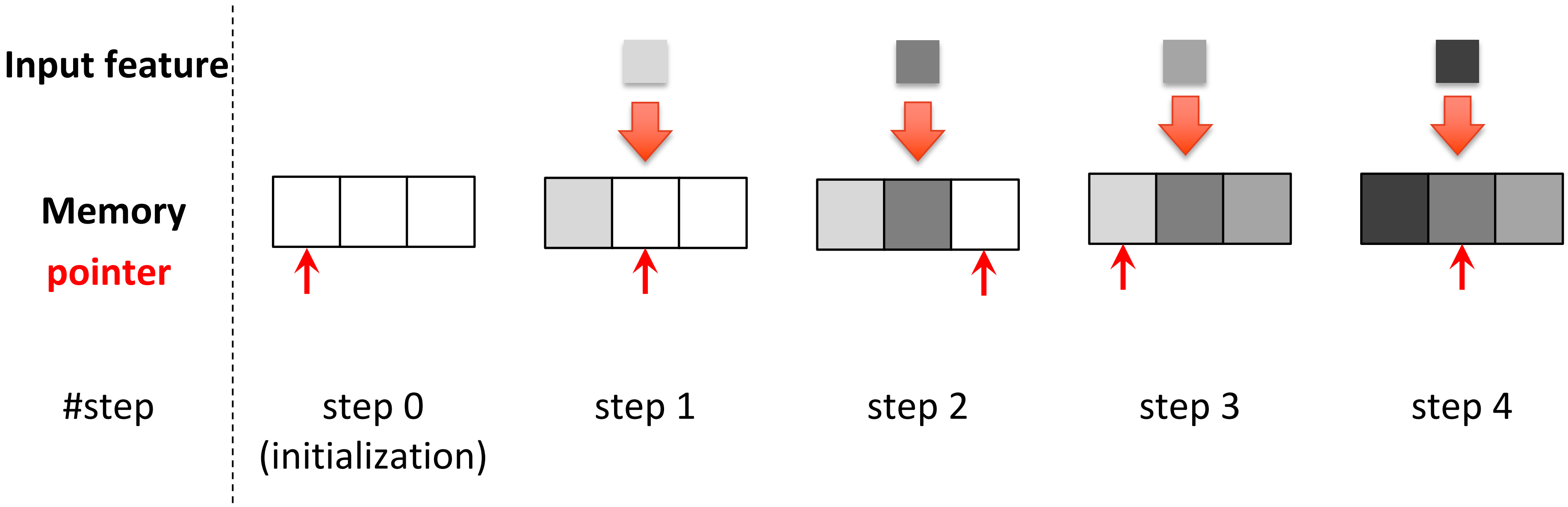
How to copy and paste?

- Memory matrix needs to be updated with most recent features.

- Refresh the entire matrix at every training step is inefficient. 

Methodology: Memory Queue

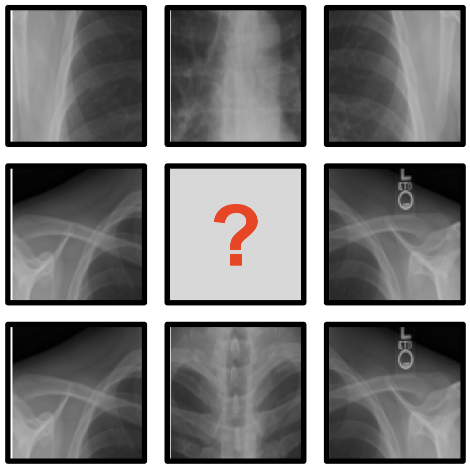
Memory Queue Processing



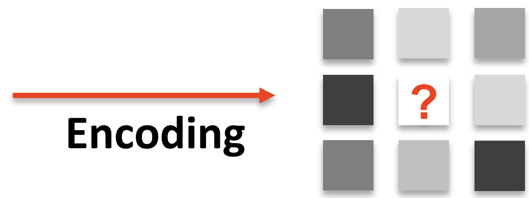
- First-in-first-out updating rule.
- Small learning rate helps.

Methodology: UAD as Feature-Space In-painting

Pixel-Space In-painting



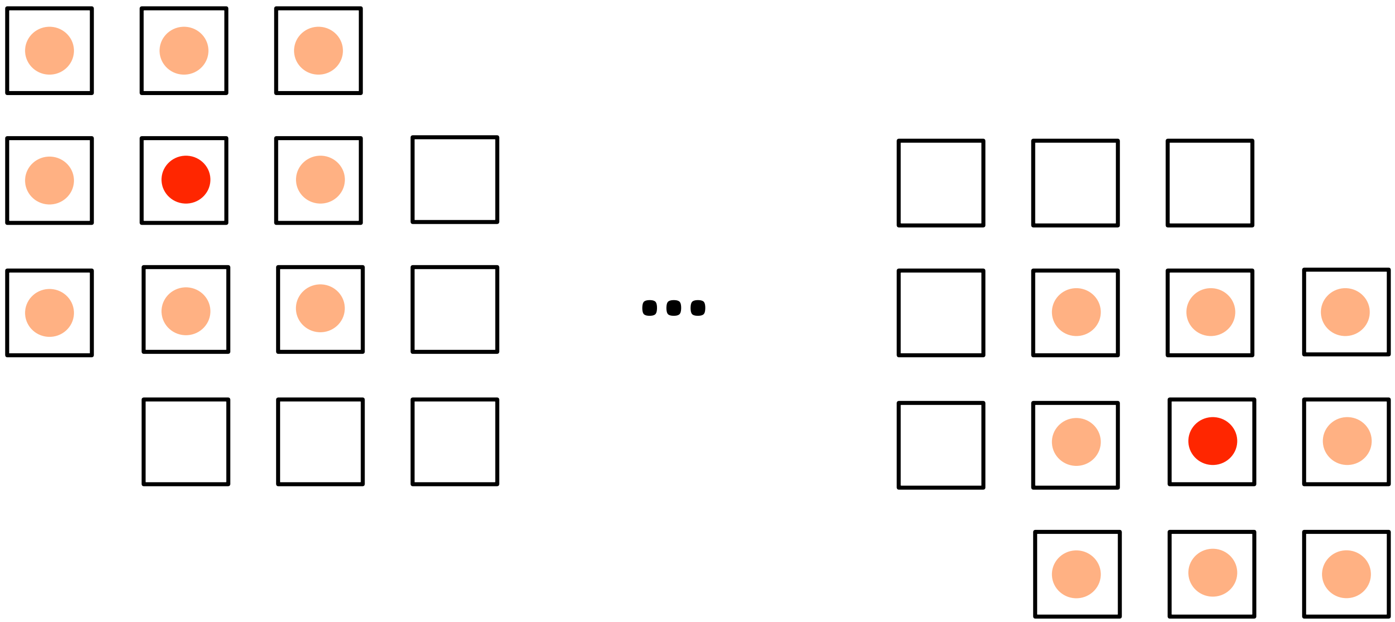
Feature-Space In-painting



Given the contextual information

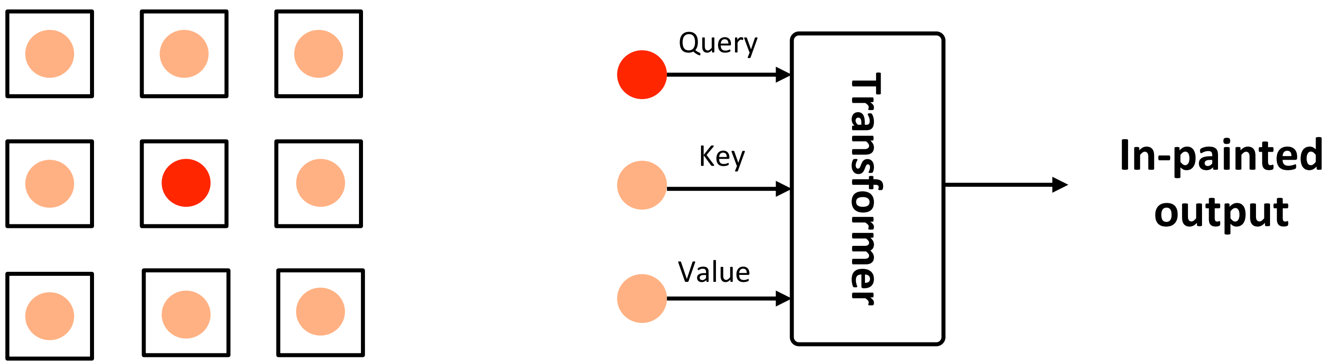
What does a normal patch look like?

Methodology: UAD as Feature-Space In-painting



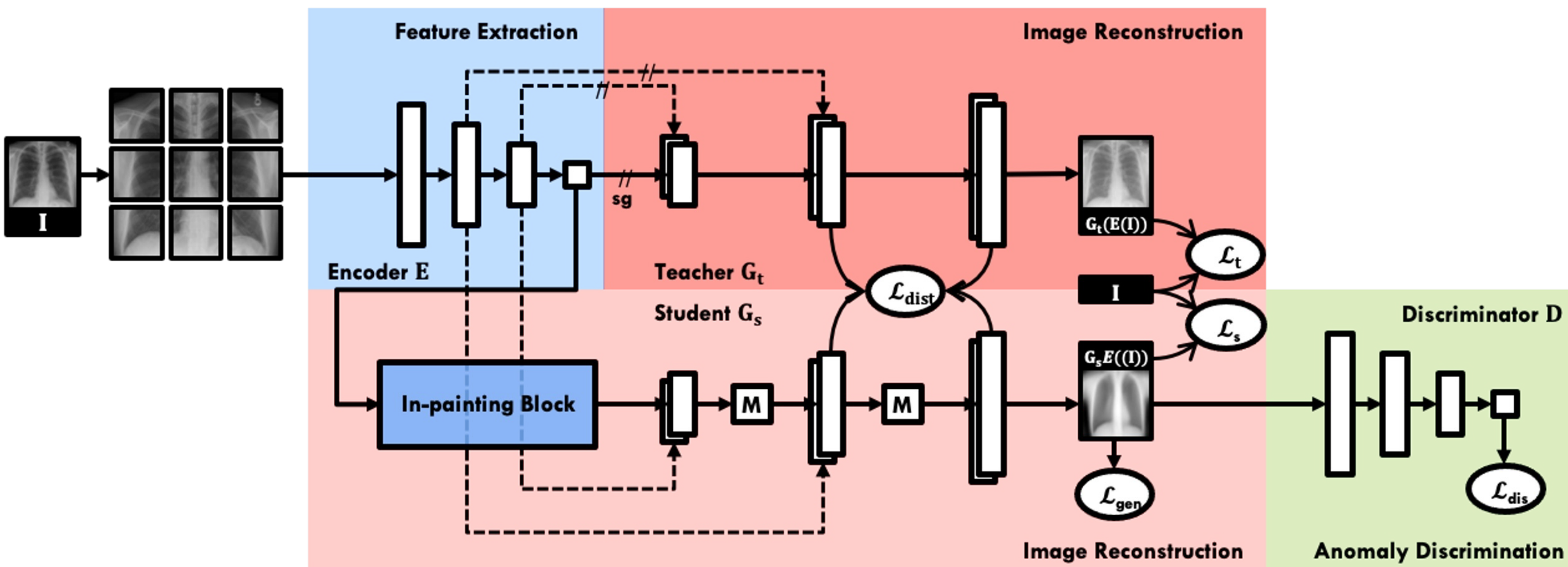
- Sliding window to traverse all patches
- Zero padding for out-of-range patches

Methodology: UAD as Feature-Space In-painting



Methodology: 🦑 SQUID 🦑

Space-aware memory **QU**eue for **I**n-painting and **D**etecting

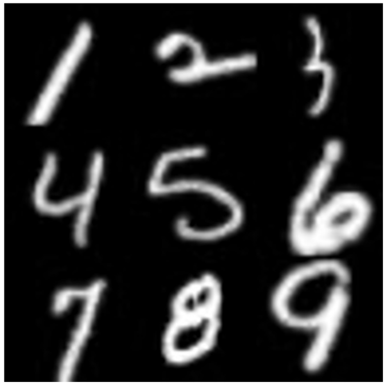


- GAN for adversarial learning
- Knowledge Distillation for regularization
- Generation quality as anomaly score
- Supervised by self-reconstruction losses.

Methodology: Creation of DigitAnatomy

Chest Anatomy

Digit Anatomy



Characteristics

- Consistent shape
- Fixed pose

Benefits

- Intuitive demos ✓
- Easy development/debug ✓

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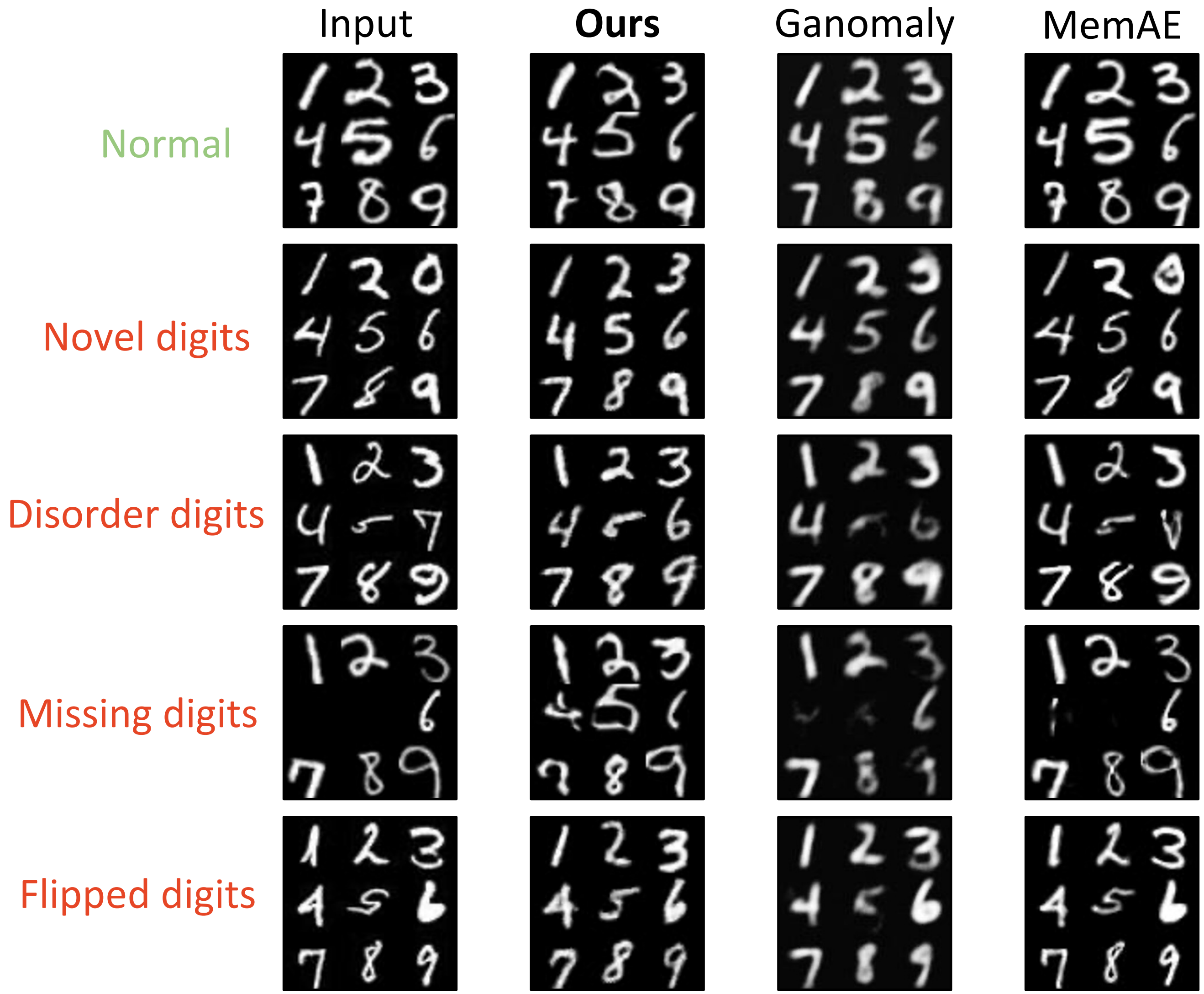
Results: Interpretations on DigitAnatomy



Results: Public Benchmarks

Quantitative Eval.

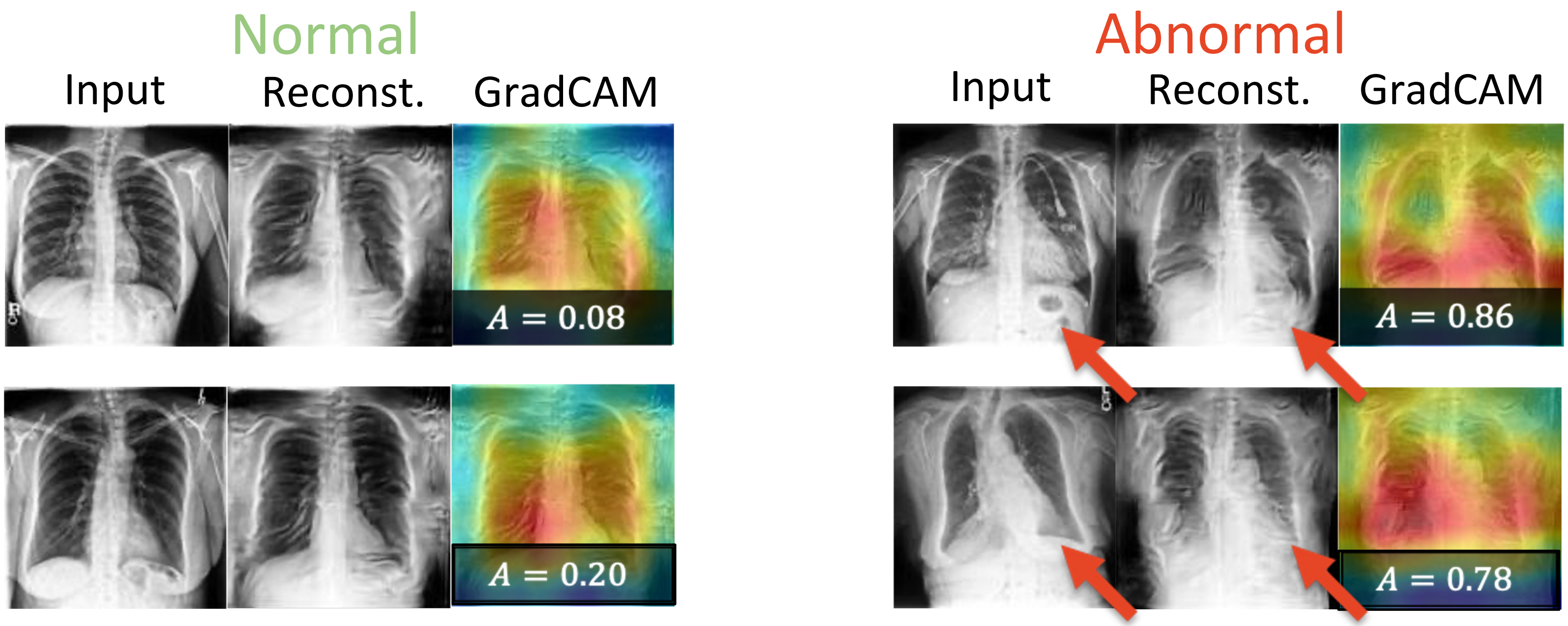
- AUC, Acc, F1 as metrics.
- Results of 3+ independent runs.
- >*5%AUC imp.* on ZhangLab.
- >*9%AUC imp.* on CheXpert.

ZhangLab	Ref & Year	AUC (%)	Acc (%)	F1 (%)
Auto-Encoder	-	59.9	63.4	77.2
VAE [35]	Arxiv'13	61.8	64.0	77.4
Ganomaly [1]	ACCV'18	78.0	70.0	79.0
f-AnoGAN [61]	MIA'19	75.5	74.0	81.0
MemAE [17]	ICCV'19	77.8±1.4	56.5±1.1	82.6±0.9
MNAD [53]	CVPR'20	77.3±0.9	73.6±0.7	79.3±1.1
SALAD [82]	TMI'21	82.7±0.8	75.9±0.9	82.1±0.3
CutPaste [40]	CVPR'21	73.6±3.9	64.0±6.5	72.3±8.9
PANDA [56]	CVPR'21	65.7±1.3	65.4±1.9	66.3±1.2
M-KD [59]	CVPR'21	74.1±2.6	69.1±0.2	62.3±8.4
IF 2D [50]	MICCAI'21	81.0±2.8	76.4±0.2	82.2±2.7
PaDiM [12]	ICPR'21	71.4±3.4	72.9±2.4	80.7±1.2
IGD [10]	AAAI'22	73.4±1.9	74.0±2.2	80.9±1.3
SQUID	-	**87.6±1.5**	**80.3±1.3**	**84.7±0.8**

CheXpert	Ref & Year	AUC (%)	Acc (%)	F1 (%)
Ganomaly [1]	ACCV'18	68.9±1.4	65.7±0.2	65.1±1.9
f-AnoGAN [61]	MIA'19	65.8±3.3	63.7±1.8	59.4±3.8
MemAE [17]	ICCV'19	54.3±4.0	55.6±1.4	53.3±7.0
CutPaste [40]	CVPR'21	65.5±2.2	62.7±2.0	60.3±4.6
PANDA [56]	CVPR'21	68.6±0.9	66.4±2.8	65.3±1.5
M-KD [59]	CVPR'21	69.8±1.6	66.0±2.5	63.6±5.7
SQUID	-	**78.1±5.1**	**71.9±3.8**	**75.9±5.7**

Results: Public Benchmarks

Qualitative Eval.



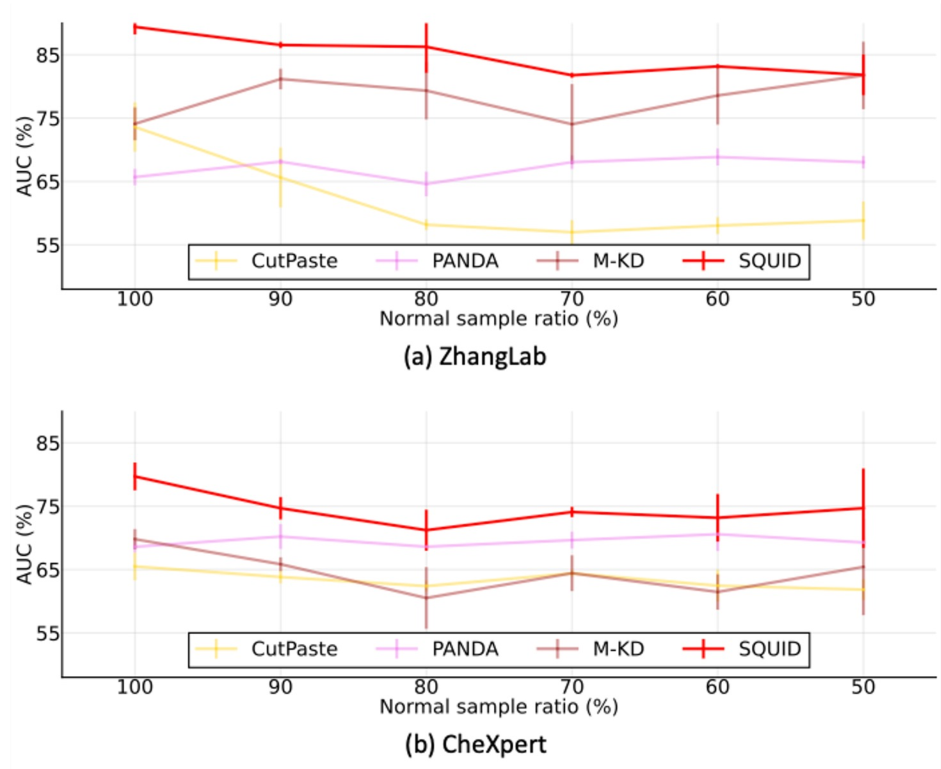
- Reconstructed normal images seem normal. ✓
- Reconstructed abnormal images seem normal. ✓
- Reconstructed normal/abnormal images have clear quality diff. ✓
- High anomaly score (A) for abnormal images, low for normal images. ✓

Results: True UAD Training

- Training dataset contains unknown data (normal/abnormal mixture).

- UAD algorithms should be robust to the mixed training.

- SQUID (red plots) yields the best robustness when the normal sample ratio >=*60%.*



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Conclusion

- Reformulated UAD as **feature-space in-painting**.
- Proposed **Space-aware Memory Queue** that caters to the unique characteristics of chest radiography.
- Designed multiple functional modules: **Gumbel Shrinkage, Masked Shortcut, Anomaly discrimination** that have never been explored in the UAD domain.
- Created the **DigitAnatomy** dataset to assist algorithm design in this domain.
- Achieved **SOTA performances** on three public benchmarks.
- Evaluated methods under the **real UAD training** settings for the first time.

Thank you!

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