Deep Feature In-painting for Unsupervised Anomaly Detection in Radiography Images

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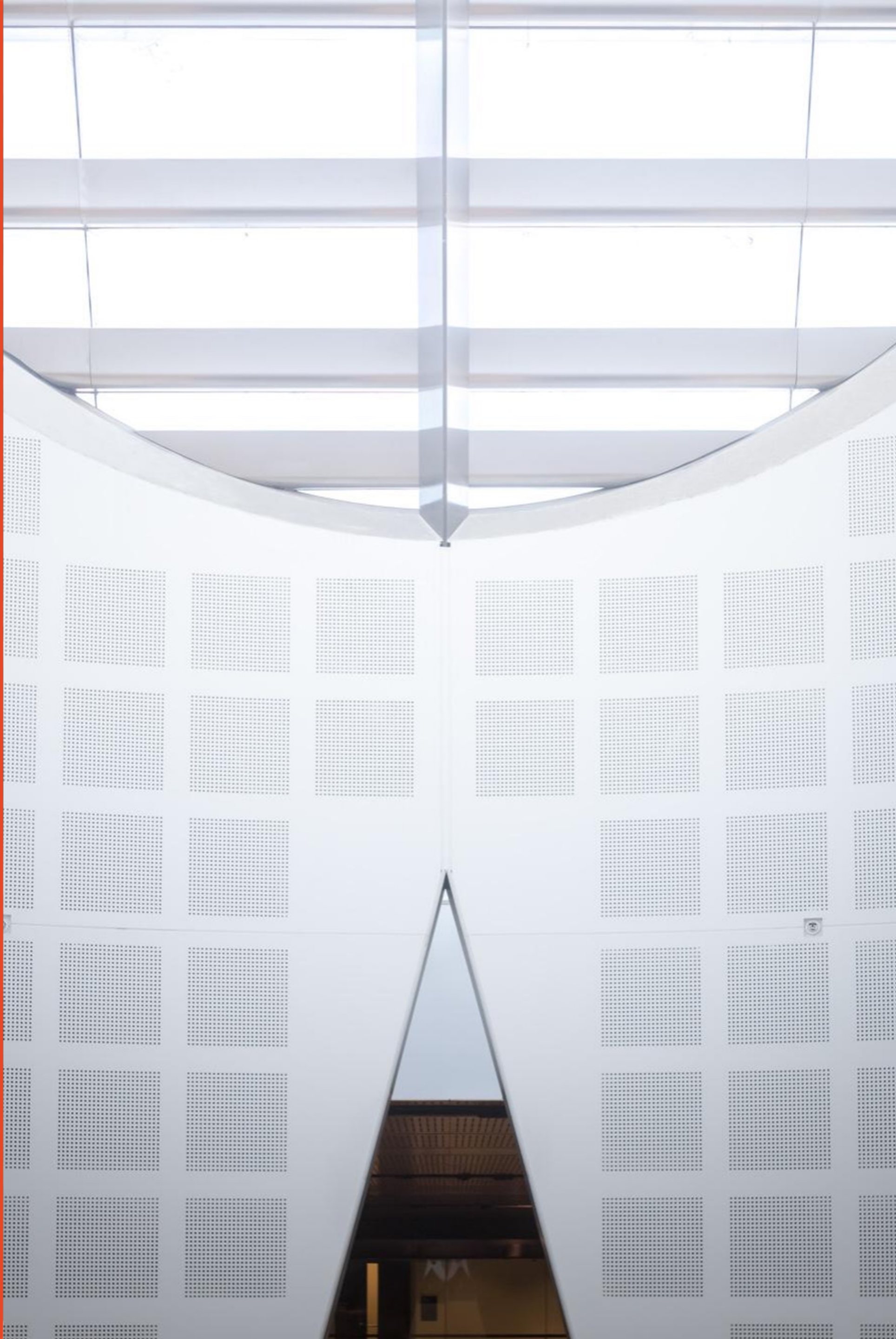
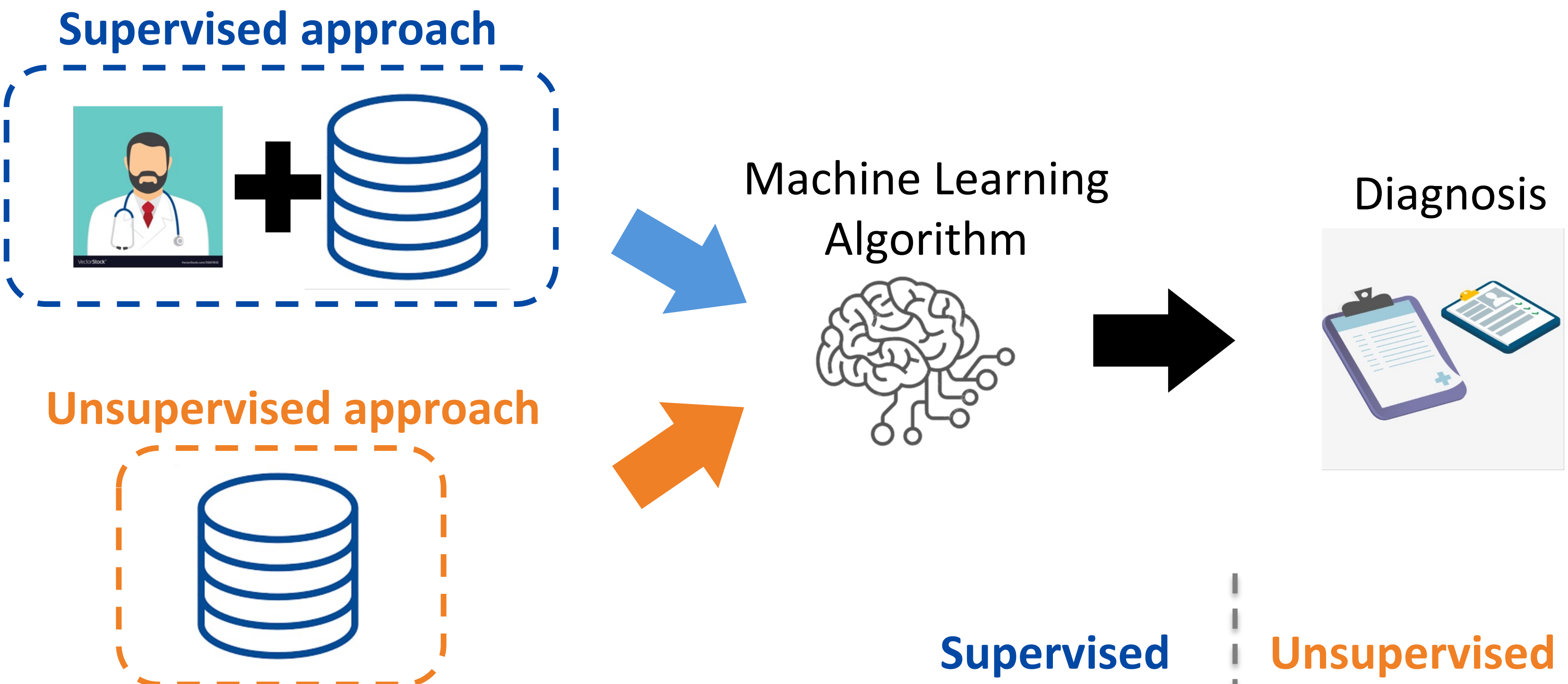


Outline

Motivation: Why ML for Medical Imaging?

- **Faster diagnosis/treatment.** ✓
- **Less human intervention.** ✓
- **Saves more lives.** ✓

Motivation: Why Unsupervised Learning?



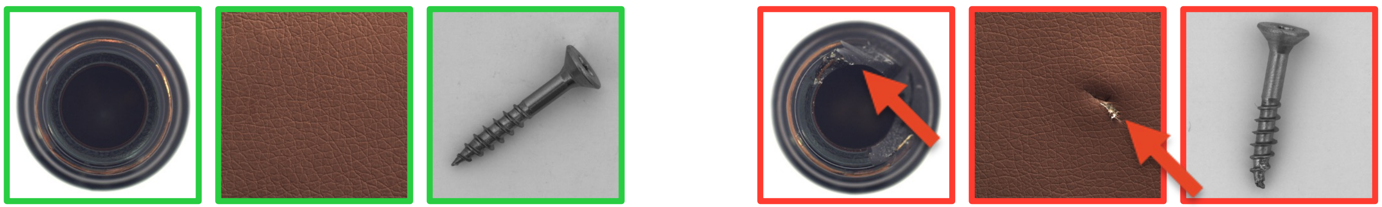
	Supervised	Unsupervised	
✗	Paired ground truth	**ZERO** ground truth needed	✓
✗	Human intelligence + Machine intelligence	Machine intelligence **ONLY**	✓

Motivation: Anomaly in Chest X-rays

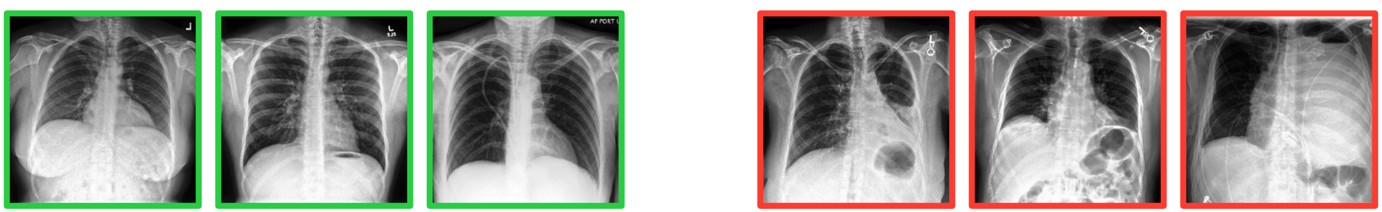
Normal

Abnormal

Anomaly Detection in Crowded Scenes
(photography images)



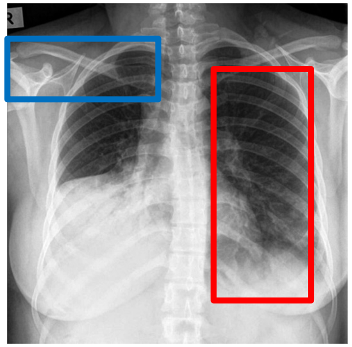
Anomaly Detection in Textures and Objects
(photography images)

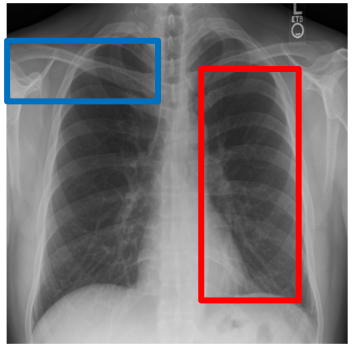


Anomaly Detection in Chest Anatomy
(**radiography images**)

Motivation: Unique Characteristics for Chest X-rays

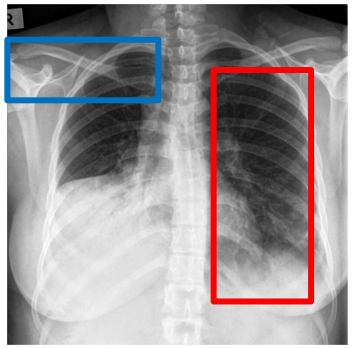
Radiography images

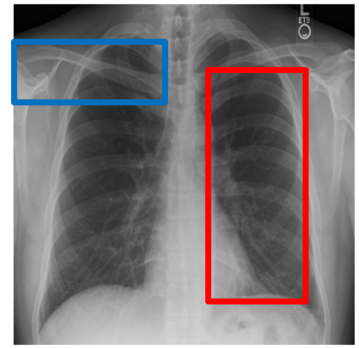




Motivation: Unique Characteristics for Chest X-rays

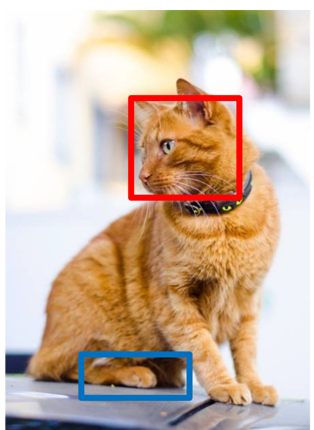
Radiography images

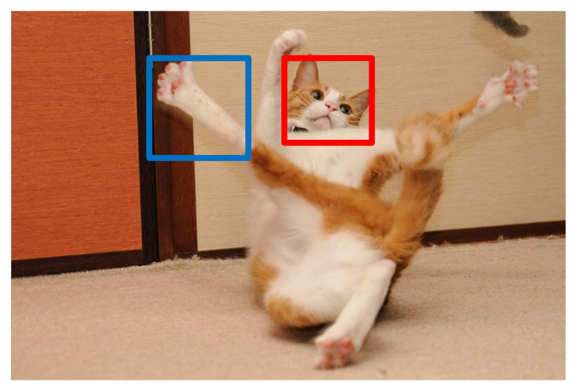




Consistent shapes/appearances and **fixed poses**.

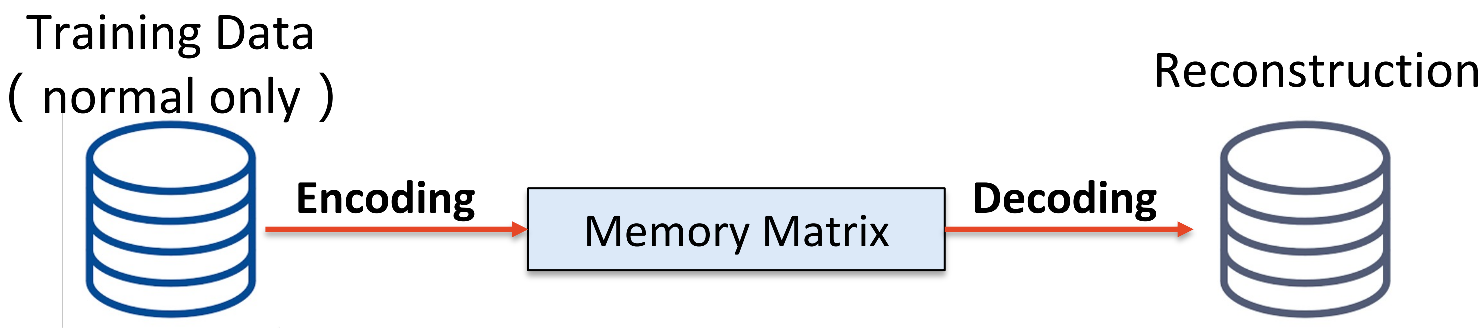
Photography images





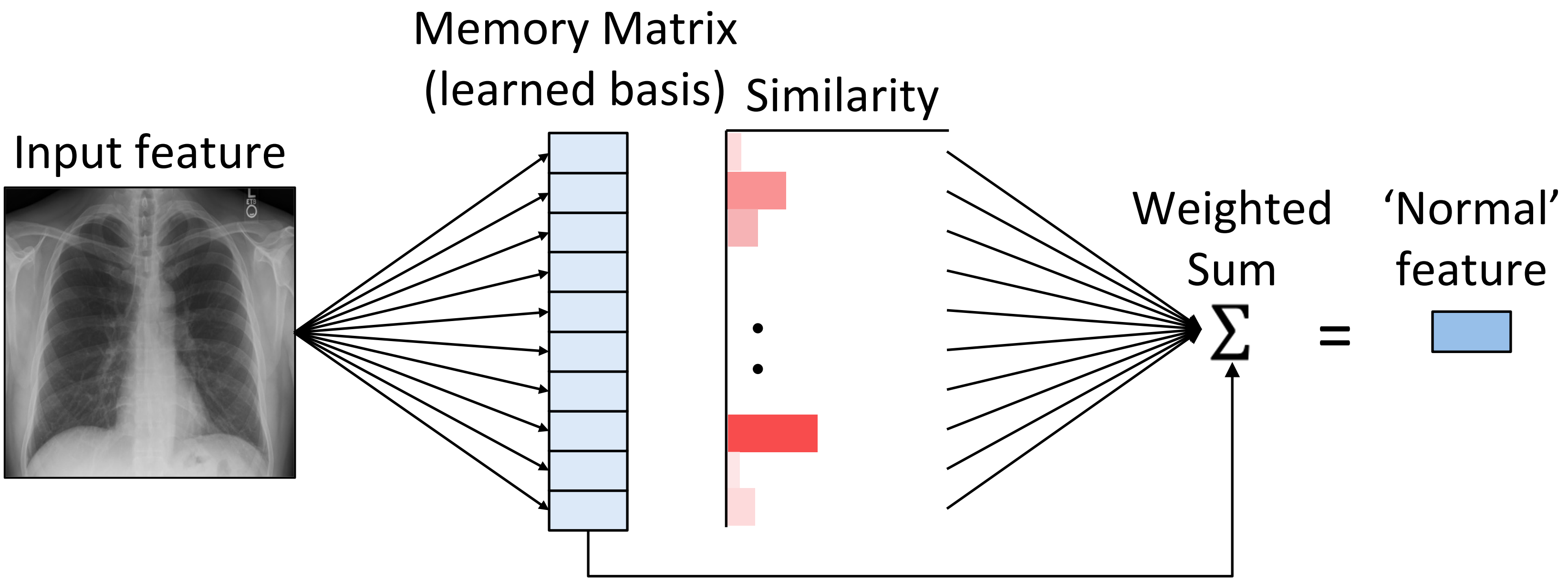
Outline

Literature: Baseline – MemAE (Gong *etal.*, ICCV 2019)



Literature: Baseline – MemAE (Gong *etal.*, ICCV 2019)

Feature Augmentation



Outline

1. Motivation
2. Background & Literature
3. **Problem Definition**
4. Methodology
5. Results
6. Discussion
7. Conclusion

Problem Definition & Objectives

Algorithm Robustness	Robust to pixel distortions, mixed training dataset.
Methodology novelty	Proposal of multiple new techniques and strategies
Methodology Interpretability	Creation of an intuitive dataset to better interpretate ideas
Performance superiority	SOTA performances on public and challenging benchmarks
Evaluation correctness	Evaluation under the TRUE UAD protocol with the best results.

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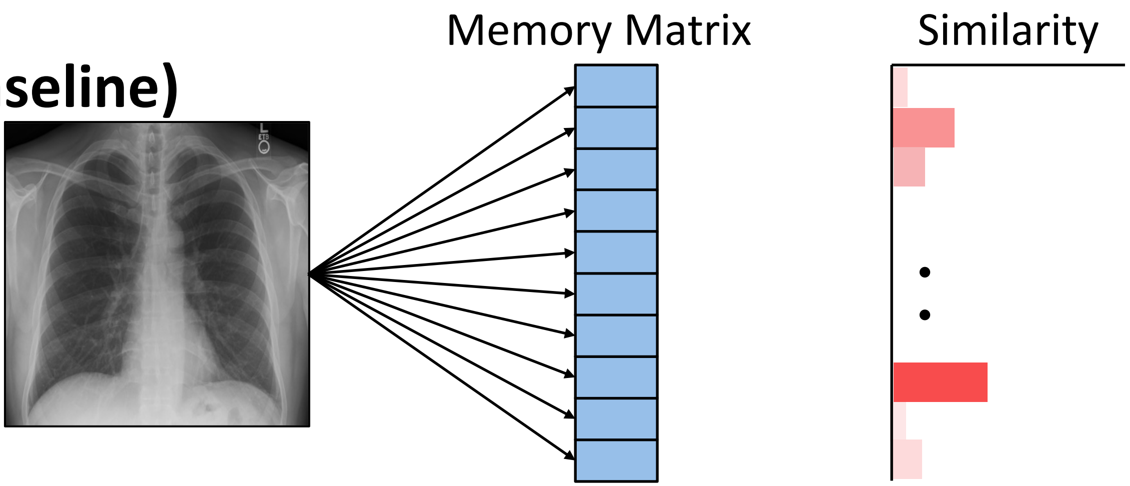
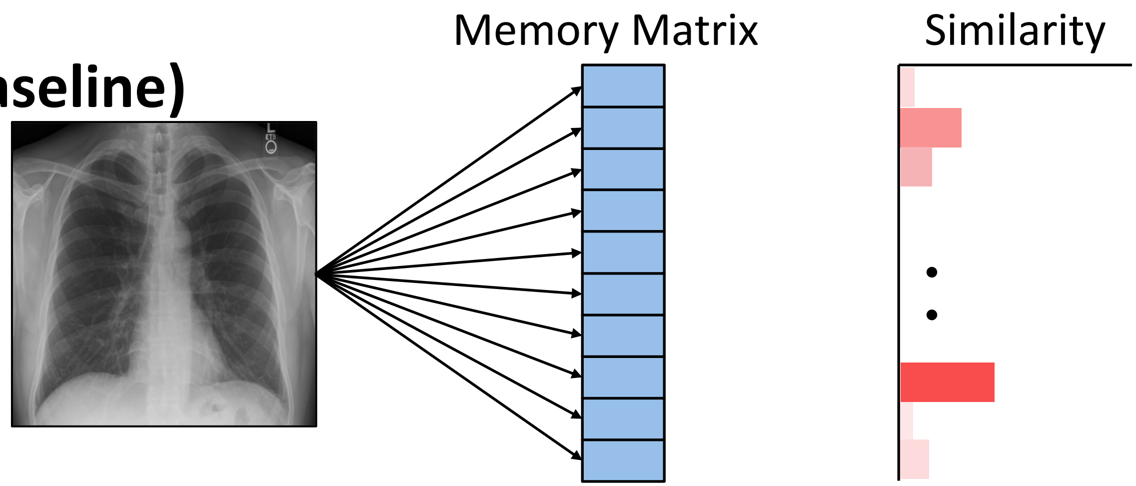
Methodology: Space-aware Memory

MemAE (Baseline)

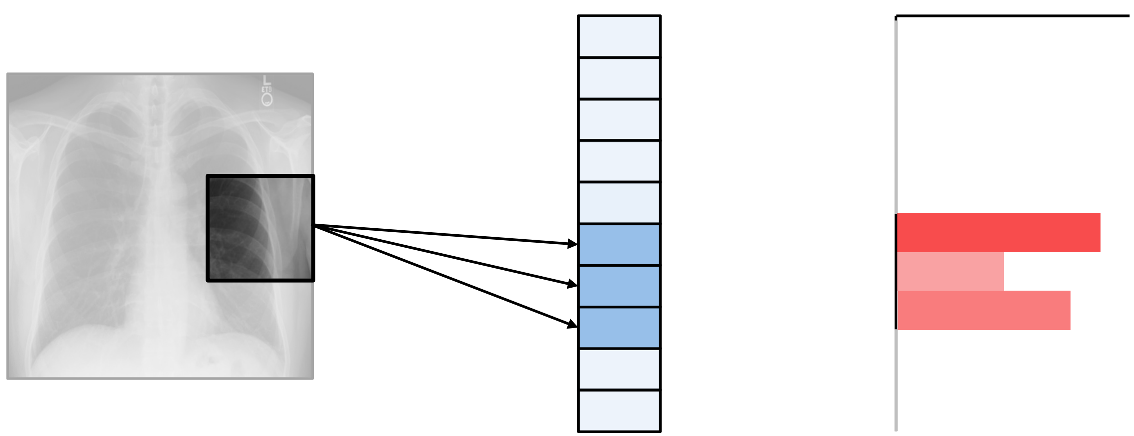


Methodology: Space-aware Memory

MemAE (Baseline)

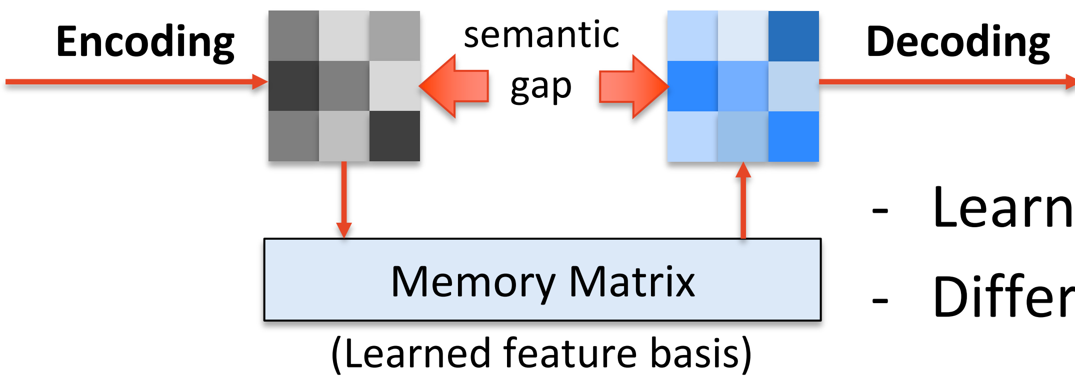


Ours



Methodology: Memory Queue

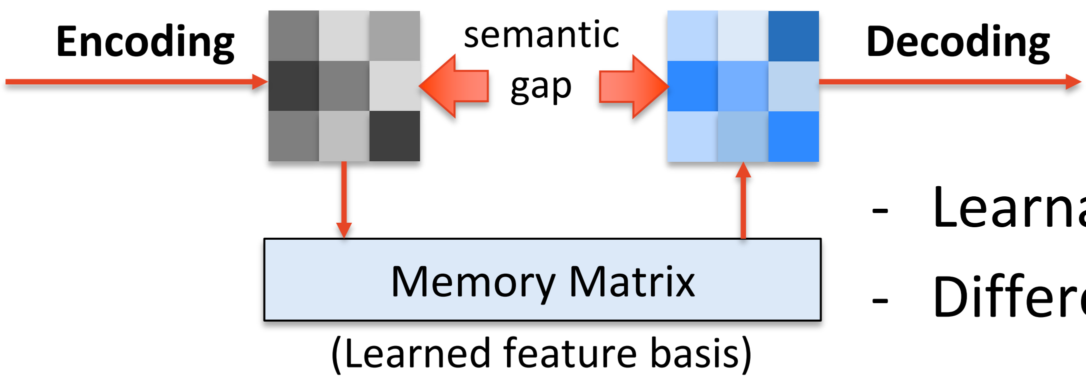
MemAE (Baseline)



- Learnable Matrix
- Different feature dist.

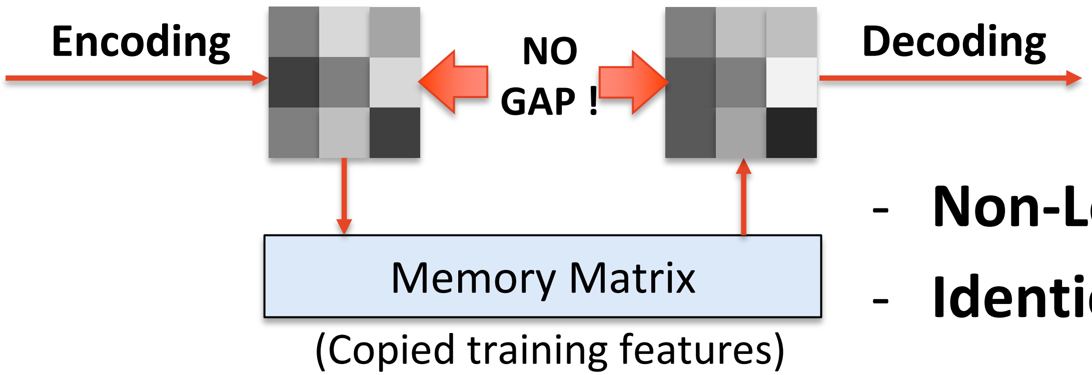
Methodology: Memory Queue

MemAE (Baseline)



- Learnable Matrix
- Different feature dist.

Ours

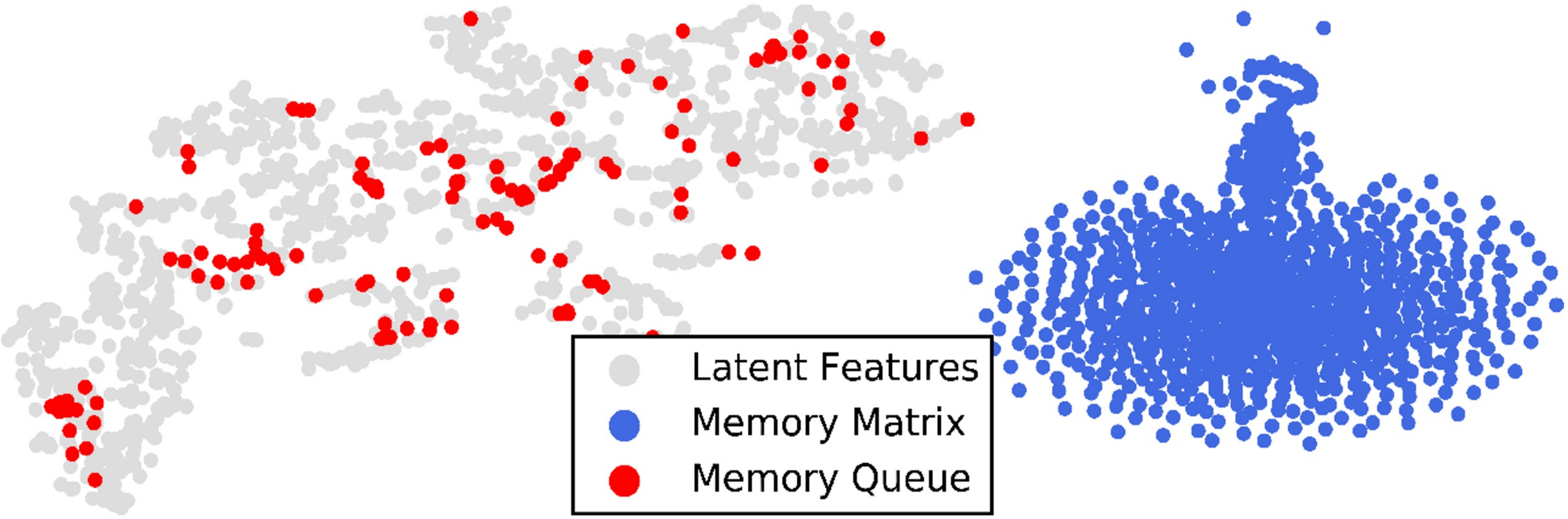


- **Non-Learnable** Matrix
- **Identical** feature dist.

How to prove?

Methodology: Memory Queue

t-SNE feature visualizations



Methodology: Memory Queue

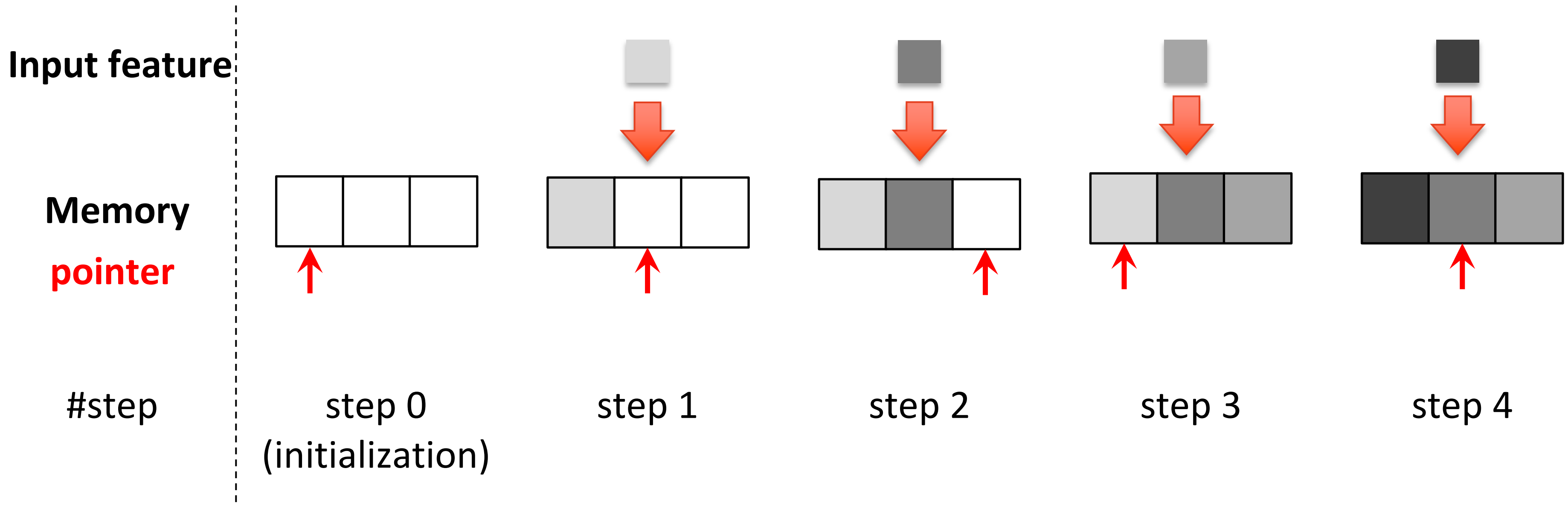
How to copy and paste?

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

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

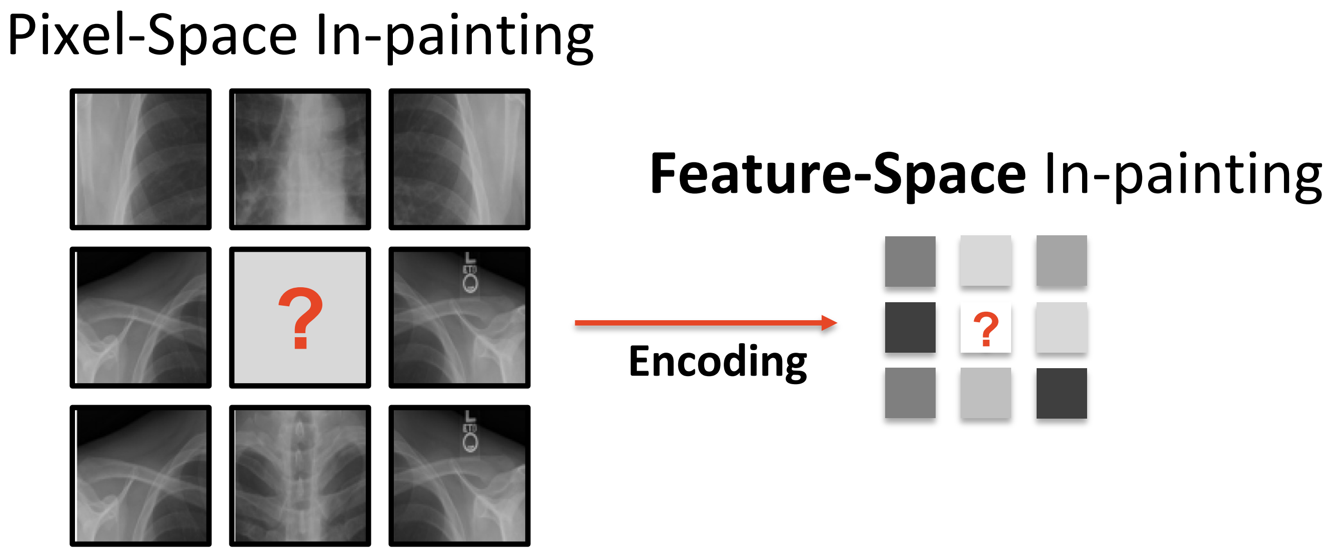
Methodology: Memory Queue

Memory Queue Processing



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

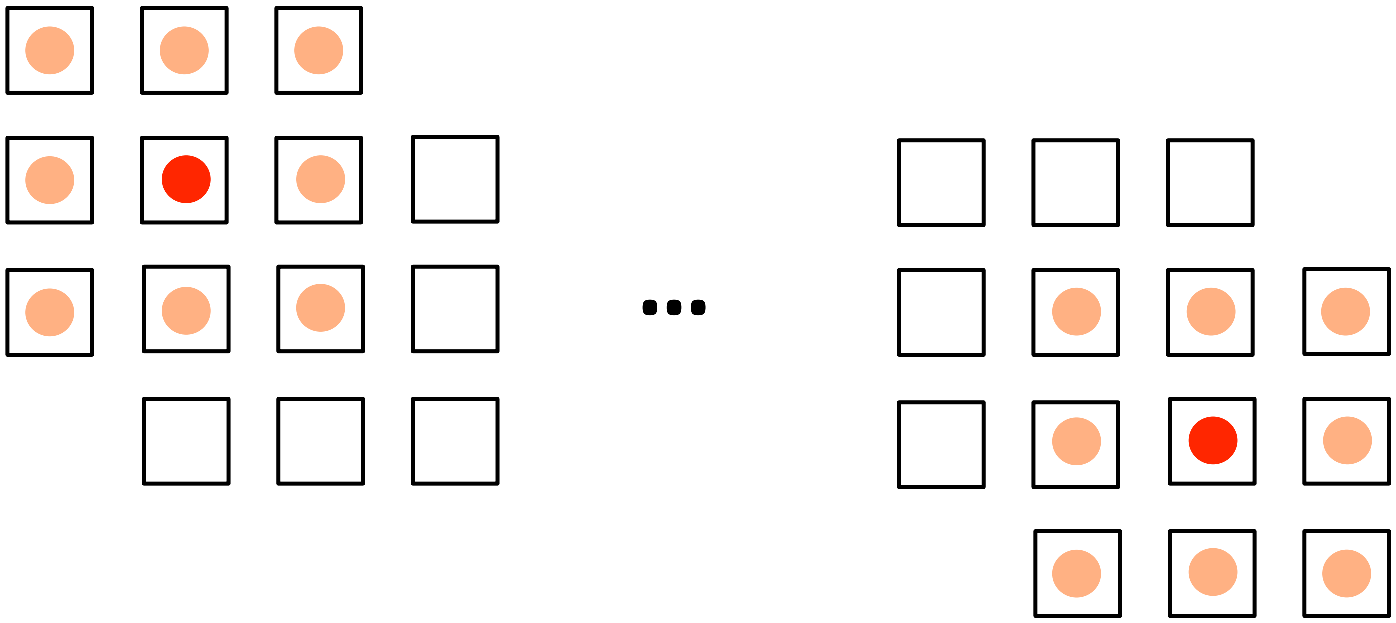
Methodology: UAD as Feature-Space In-painting



Given the contextual information

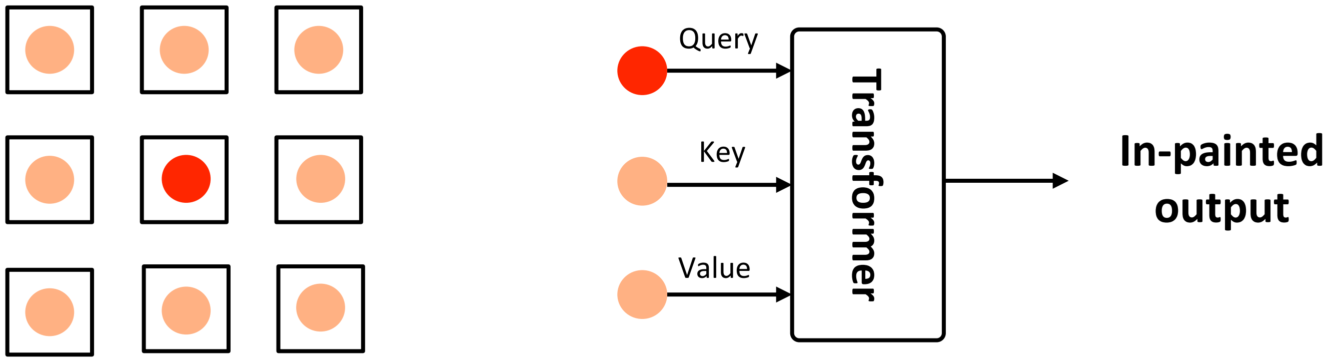
What does a normal patch look like?

Methodology: UAD as Feature-Space In-painting

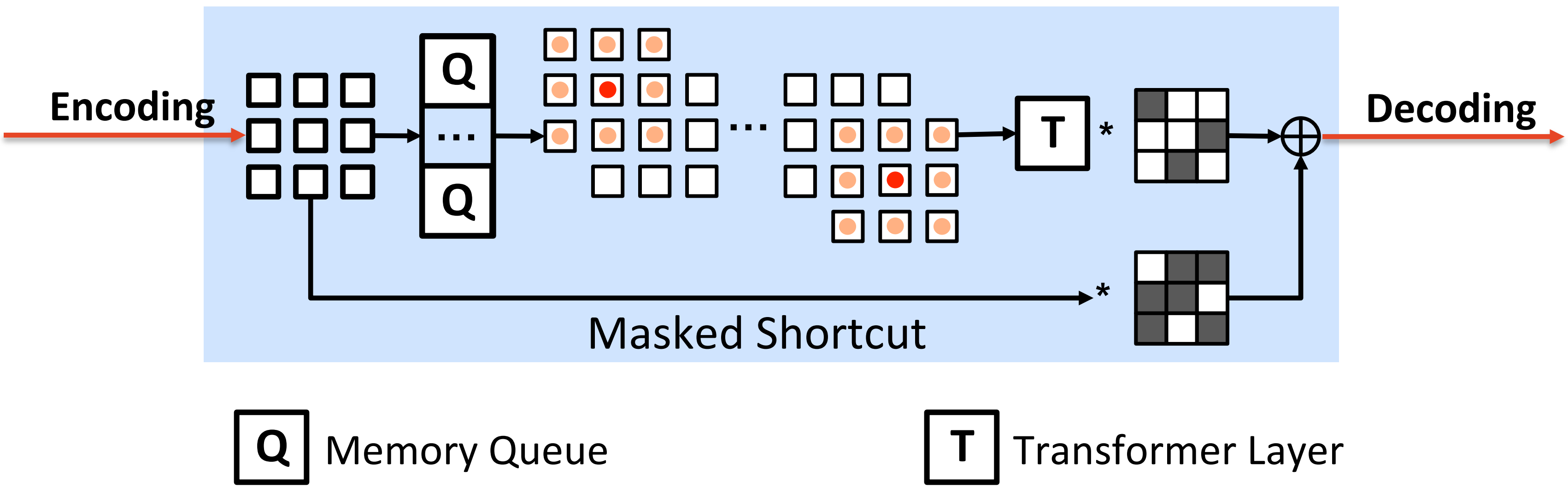


- Sliding window to traverse all patches
- Zero padding for out-of-range patches

Methodology: UAD as Feature-Space In-painting

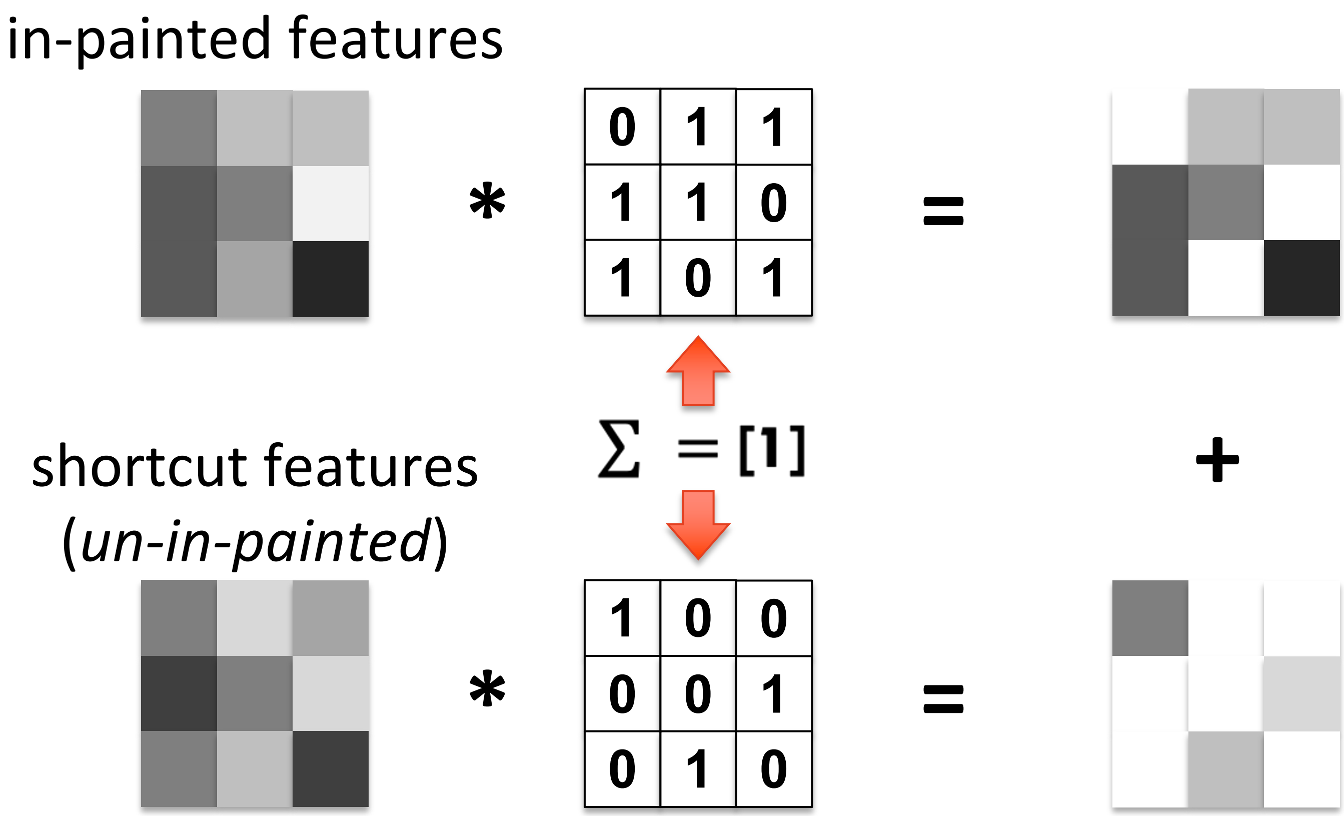


Methodology: In-painting Block



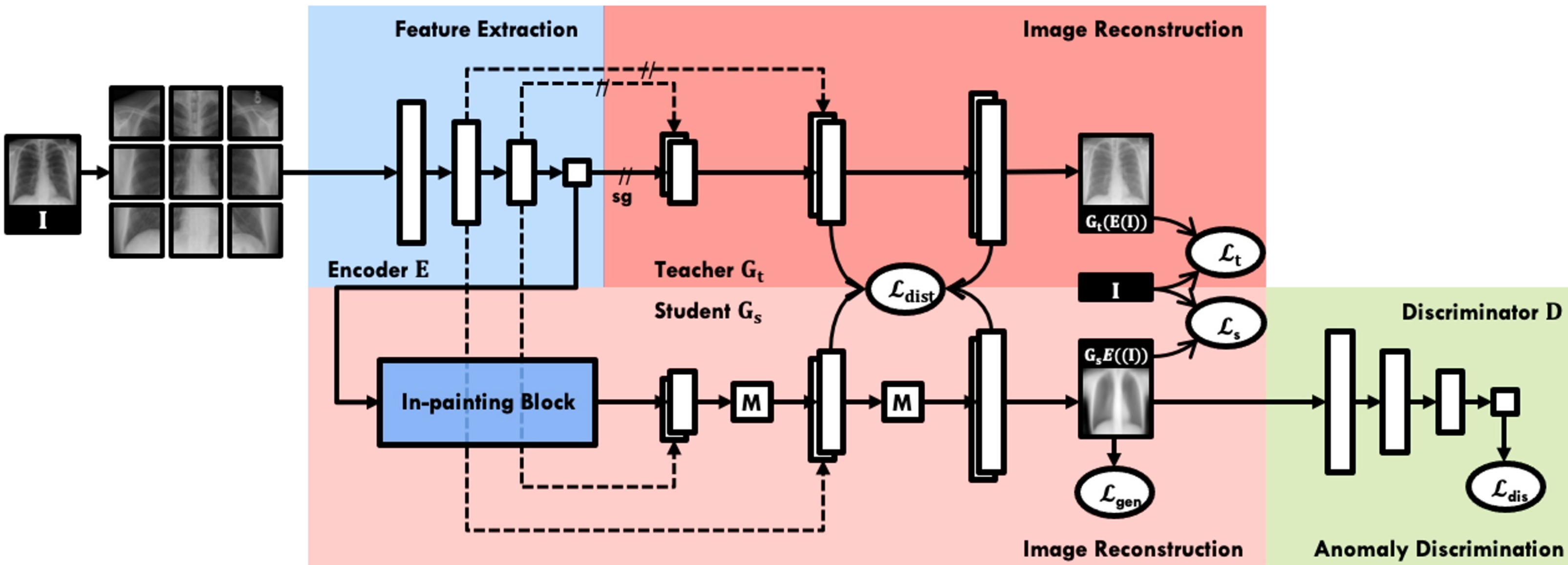
- Use shortcut for gradient preservation and better feature aggregation.
- Naive identity shortcut leads to degenerations.

Methodology: Masked Shortcut



Methodology: 🦑 SQUID 🦑

Space-aware memory QUeue for In-painting and Detecting

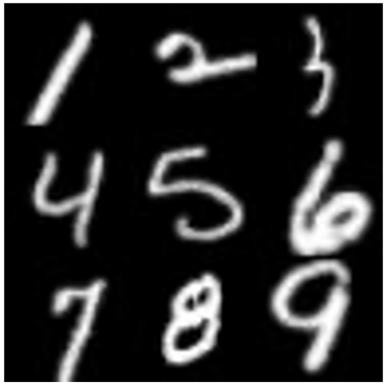


- GAN for adversarial learning
- Knowledge Distillation for regularization
- Generation quality as anomaly score
- Supervised by self-reconstruction losses.

Methodology: Creation of DigitAnatomy

Chest Anatomy

Digit Anatomy



Characteristics

- Consistent shape
- Fixed pose

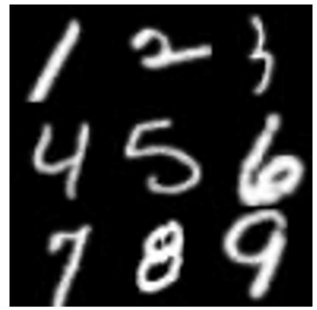
Benefits

- Intuitive demos ✓
- Easy development/debug ✓

Methodology: Creation of DigitAnatomy

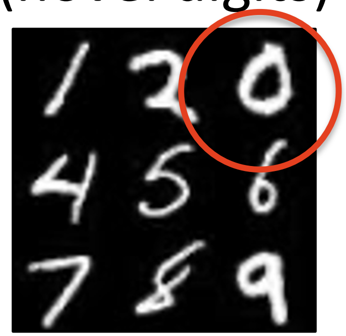
Normal

(1-9 in order)



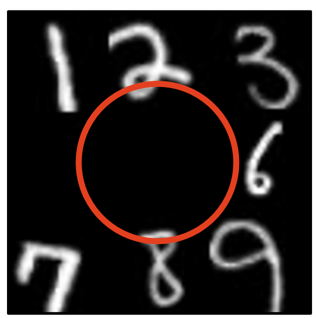
Abnormal

(novel digits)



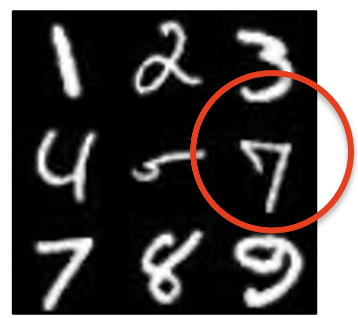
Abnormal

(missing digits)



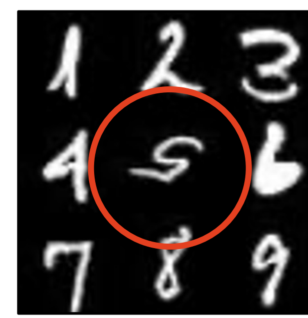
Abnormal

(disorder digits)



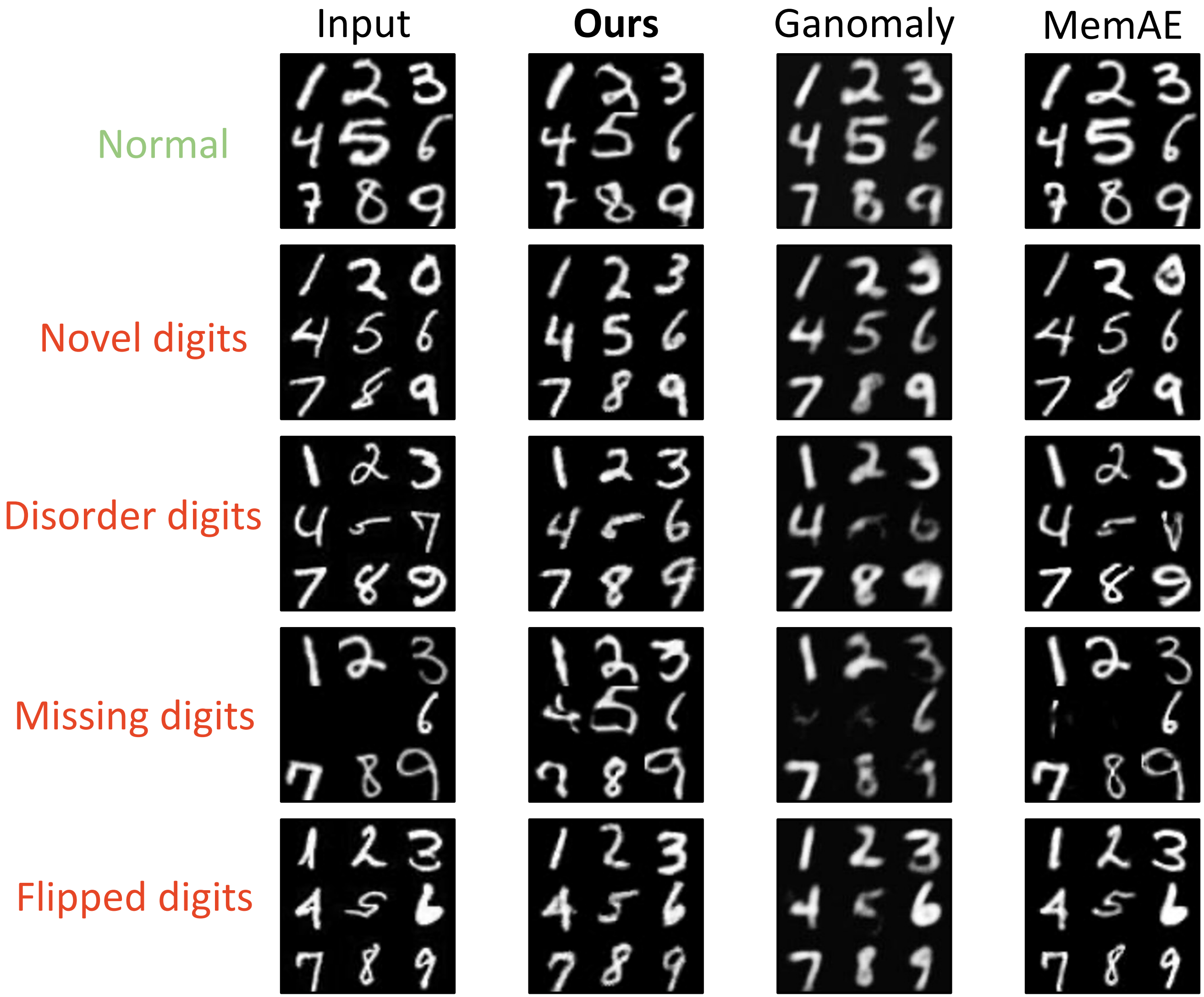
Abnormal

(flipped digits)



Outline

Results: Interpretations on DigitAnatomy



Results: Public Benchmarks

Zhang Lab Chest X-ray Dataset:

Disease include: *Pneumonia*.

Stanford CheXpert:

Disease include: *Cardiomegaly, Enlarged Cardiomegaly, Lung Lesion, Lung Opacity, Edema, Consolidation, Pneumonia, Atelectasis, Pneumothorax, Pleural Effusion, Pleural Other, Fracture.*

	ZhangLab	CheXpert
Train set (pos./neg.)	3783 / 1249	21171 / 4999
Val. set (pos./neg.)	100 / 100	19 / 14
Test set (pos./neg.)	390 / 234	250 / 250
#Anomalies	1	12
Difficulty level	⭐⭐	⭐⭐⭐

Results: Public Benchmarks

Quantitative Eval.

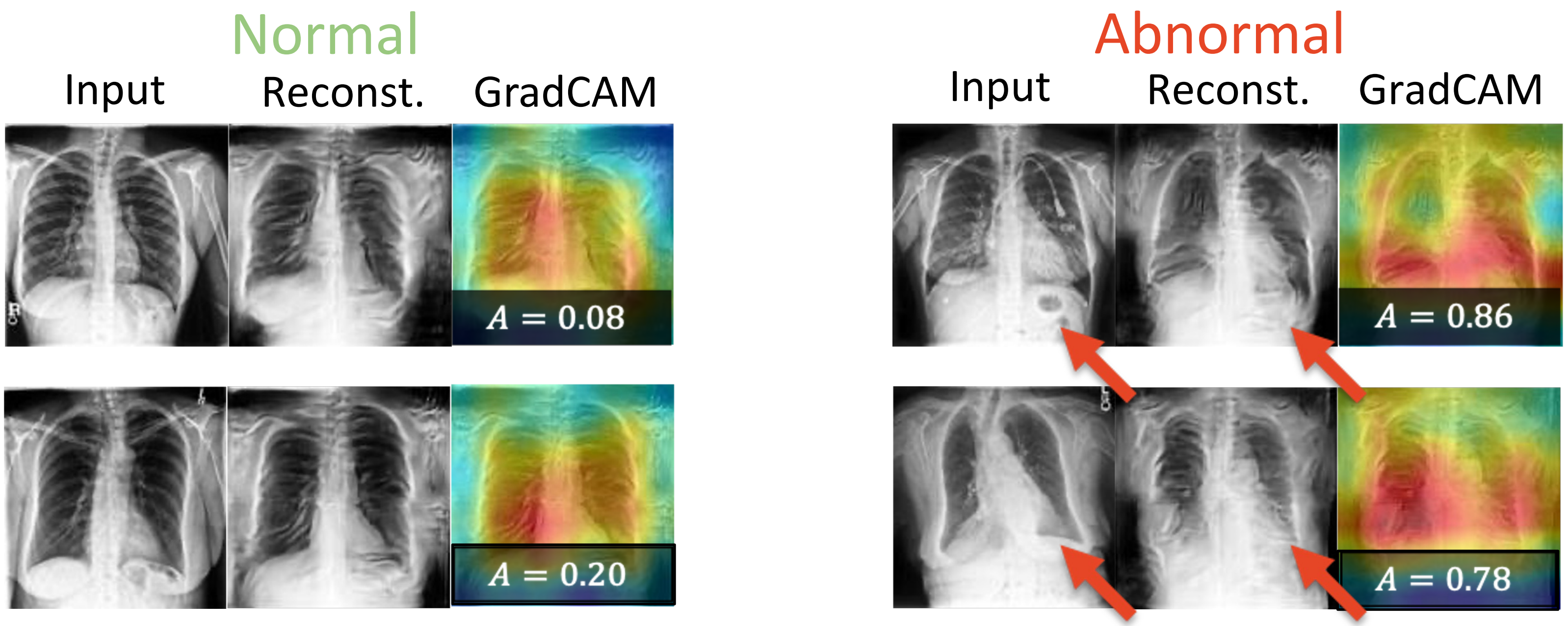
- AUC, Acc, F1 as metrics.
- Results of 3+ independent runs.
- >*5%AUC imp.* on ZhangLab.
- >*9%AUC imp.* on CheXpert.

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. ✓

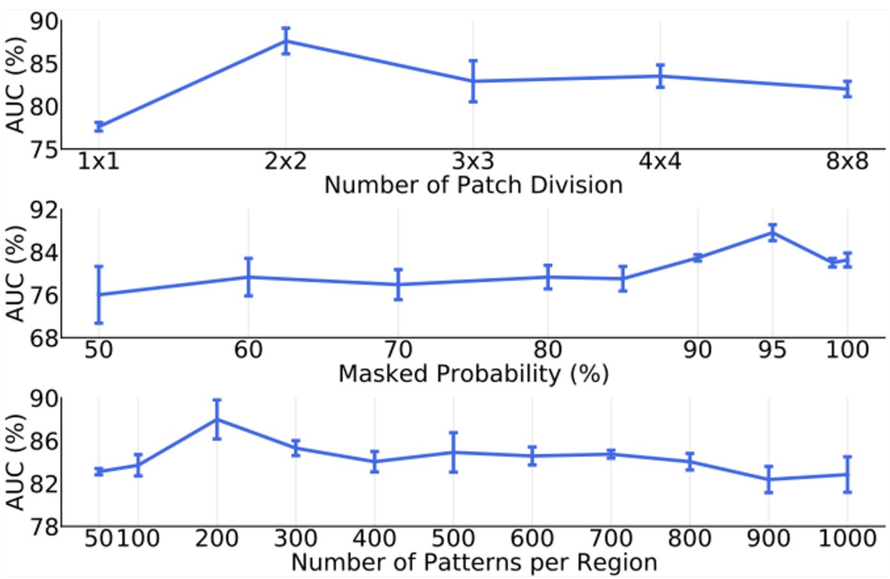
Results: Ablation Studies

Component Studies

TABLE 4.4. Component studies indicate that the overall performance benefits from all of the components in SQUID. The ablation study is conducted on the ZhangLab dataset.

Method	AUC(%)	Acc(%)	F1(%)
w/o Space-aware Memory	77.6±0.5	75.5±0.5	82.5±0.6
w/o In-painting Block	80.9±2.1	75.8±1.5	81.6±1.3
w/o Skip Connection	79.5±1.6	73.0±1.4	78.8±0.5
w/o Hierarchical Memory	82.9±1.2	77.4±1.1	81.2±0.5
w/o Knowledge Distillation	85.4±0.8	79.5±0.7	83.5±0.8
w/o Stop Gradient	85.0±4.3	77.6±2.8	79.8±1.6
w/o Gumbel Shrinkage	86.2±3.3	80.5±3.2	85.4±2.1
Full SQUID	**87.6±1.5**	**80.3±1.3**	**84.7±0.8**

Hyper-param. Studies

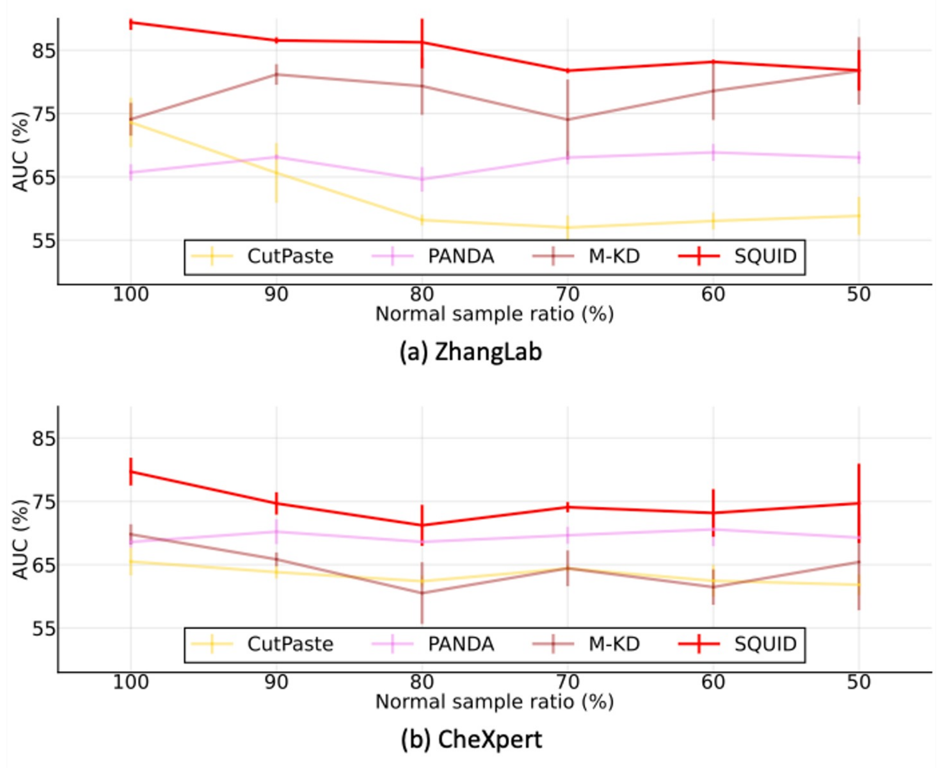


Results: True UAD Training

- 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%.*



(a) ZhangLab

(b) CheXpert

Outline

Discussion

Limitations & Future Work

- **Complex framework.**
  - Reuse networks/layers.
  - Better skip connections.

- **Inefficient inference.**
  - Lighter-weight backbone/operators.
  - Network pruning/quantization/compression.

- **Inaccurate pixel-wise anomaly detection.**
  - Feature-space residual.
  - In-painting + data augmentation.

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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.

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- Tiange Xiang, Yixiao Zhang, Yongyi Lu, Alan Yuille, Chaoyi Zhang, Weidong Cai, Zongwei Zhou, “Feature-level In-painting for Unsupervised Anomaly Detection in Radiography Images", Sub- mitted to *Medical Image Analysis*, 2022. (Under Review)

Thank you!

Any questions ?

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