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Unsupervised Abnormality Detection through Mixed Structure Regularization (MSR) in Deep Sparse Auto-encoders

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innovation + you

Supervised learning

Cars

Motorcycles

Testing:
What is this?

Slide source: Andrew Ng, ECCV 2010

Supervised learning in the medical setting

- Insufficient amounts of annotated data
- Expensive data
- Annotations are not just labels
- A lot of categories with similar properties
- Etc…

Cars

Motorcycles

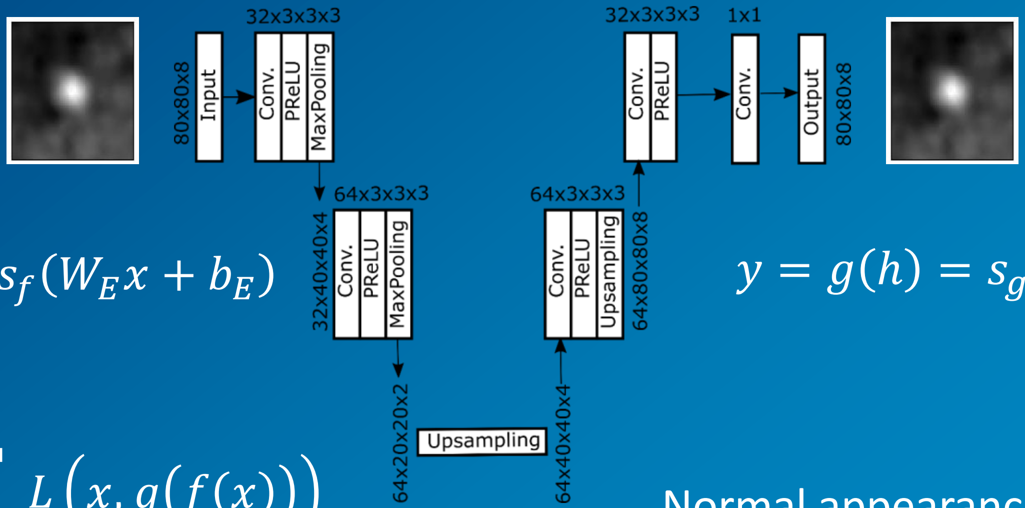
Testing:
What is this?

Unsupervised learning in the medical setting

Key idea:

1. Model normal appearance using auto-encoders by training with normal data only

$$h = f(x) = s_f(W_E x + b_E)$$



$$y = g(h) = s_g(W_D h + b_D)$$

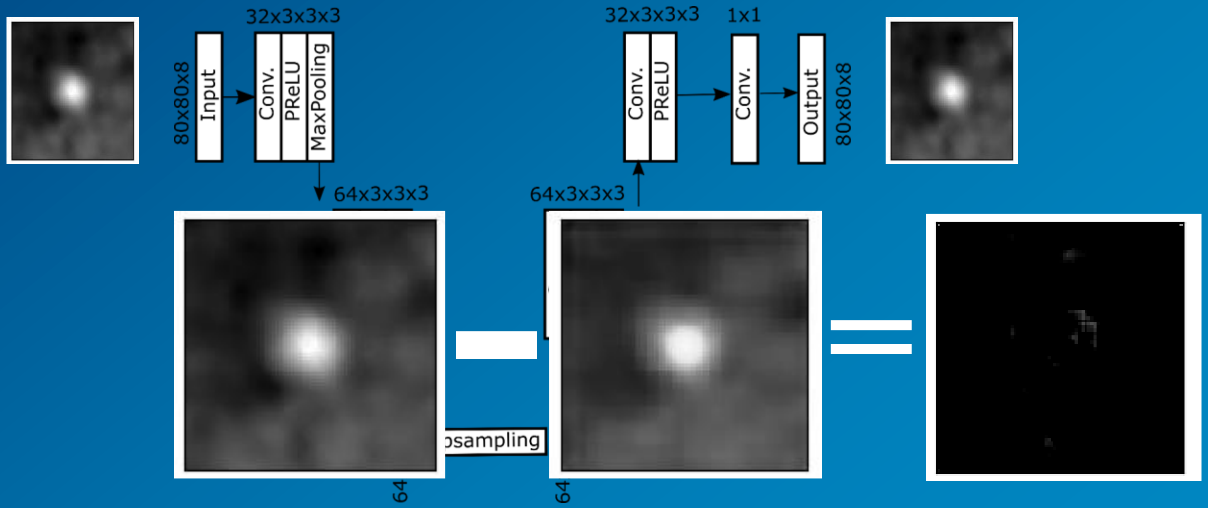
$$\hat{\theta} = \arg\min_{\theta} \sum_{x \in D_n} L\left(x, g\left(f(x)\right)\right)$$

Normal appearance model

Unsupervised learning in the medical setting

Key idea:

1. Model normal appearance using auto-encoders by training with normal data only
2. Given an image, measure its abnormality as the auto-encoder reconstruction error



Decision: normal

Unsupervised learning in the medical setting

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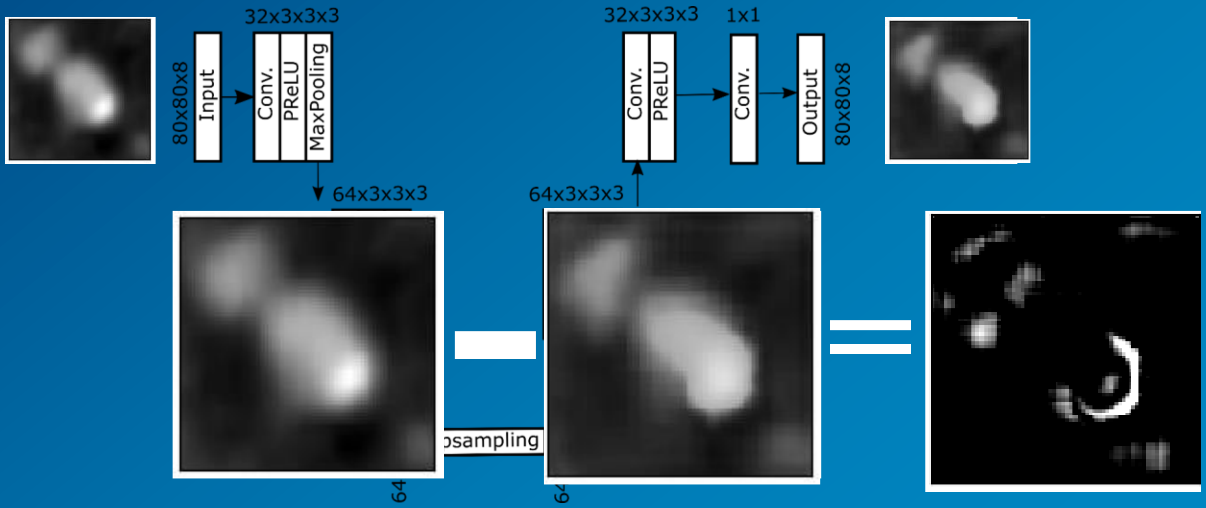

Decision: mild stenosis

Unsupervised learning in the medical setting

Key idea:

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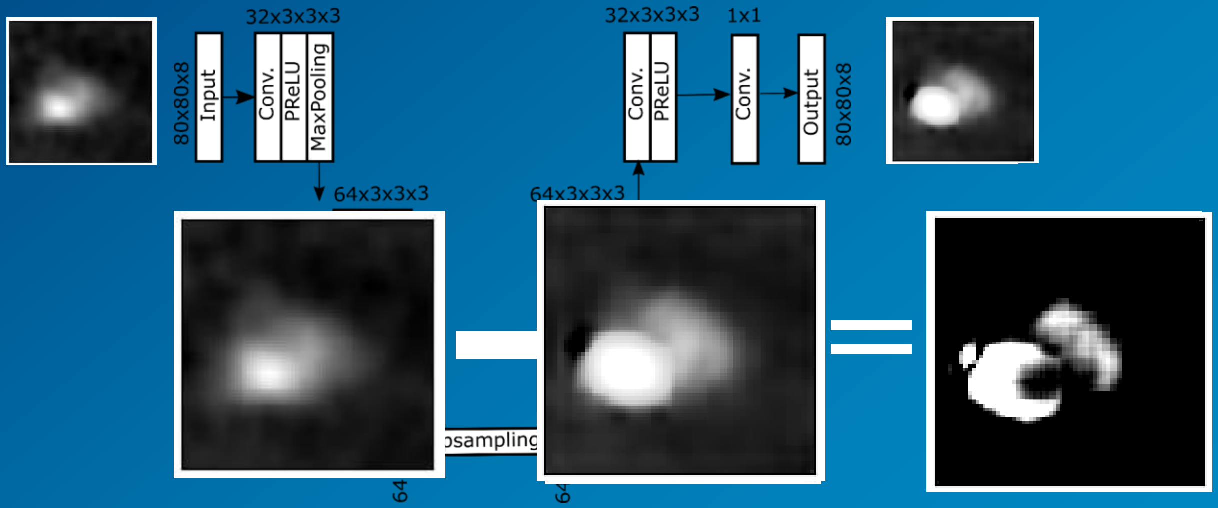
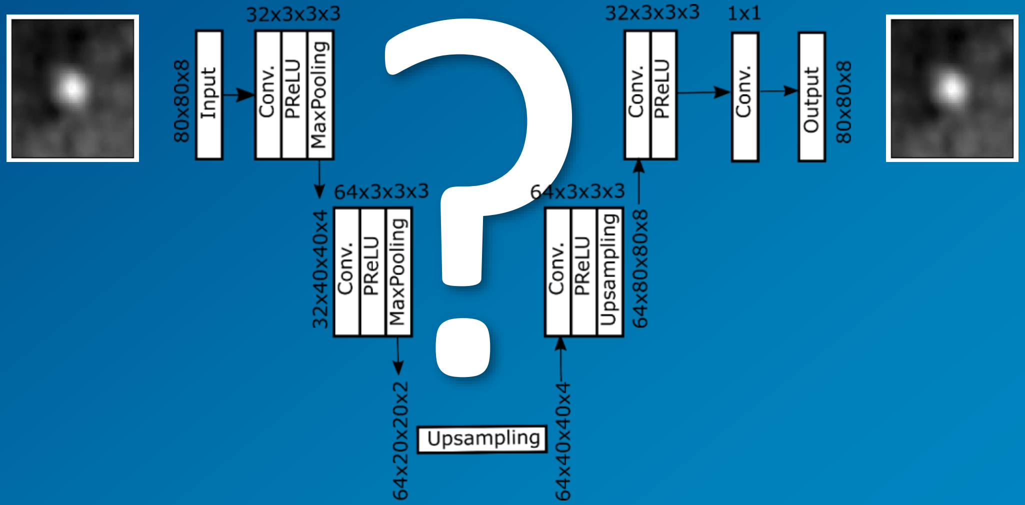


Decision: severe stenosis

Unsupervised learning in the medical setting

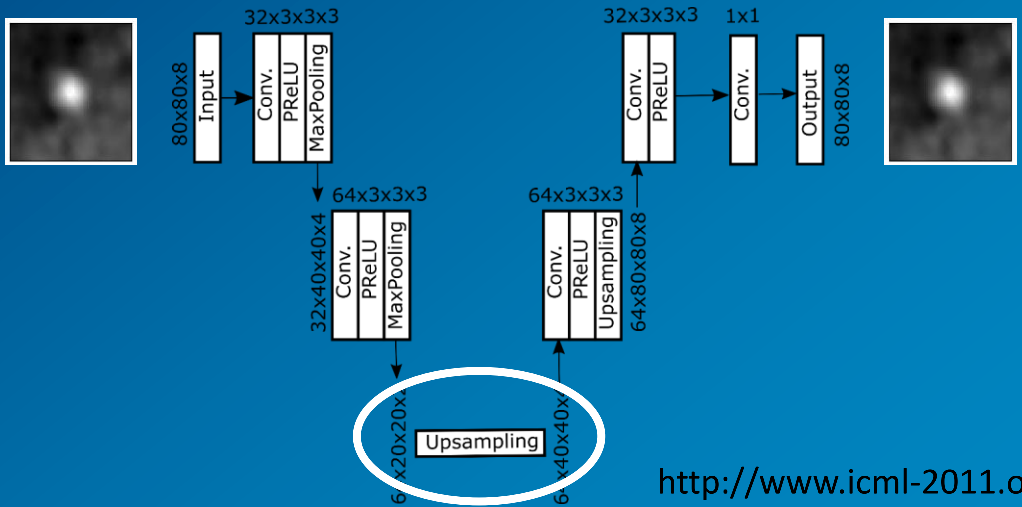
The challenge: How to encourage the auto-encoder to learn useful representation?



Unsupervised learning in the medical setting

The challenge: How to encourage the auto-encoder to learn useful representation?

Contractive auto-encoder: limit the number of parameters in the bottleneck



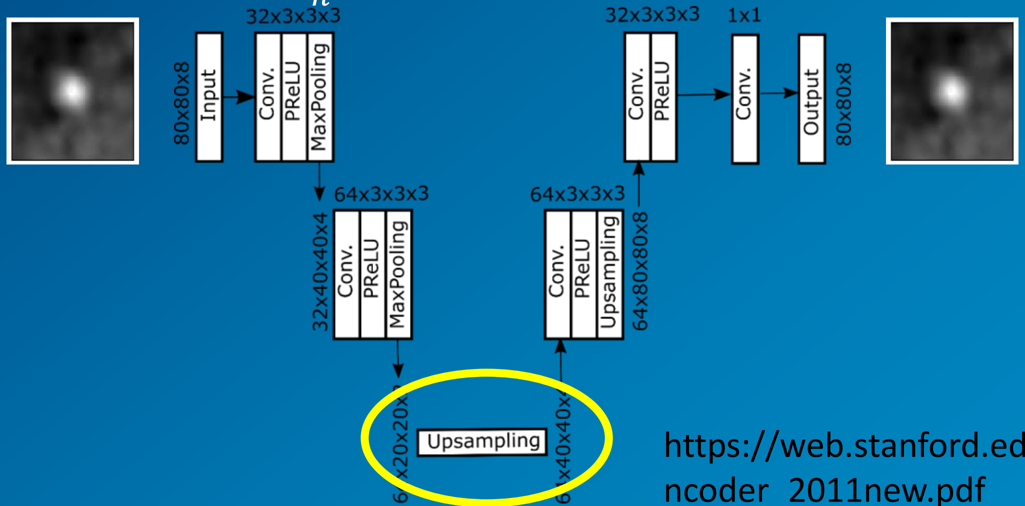
http://www.icml-2011.org/papers/455_icmlpaper.pdf

Unsupervised learning in the medical setting

The challenge: How to encourage the auto-encoder to learn useful representation?

Sparse auto-encoder: encourage sparse representation

$$\hat{\theta} = \arg\min_{\theta} \sum_{x \in D_n} L\left(x, g\left(f(x)\right)\right) + \lambda R(W) + \gamma S\left(f(x)\right)$$



https://web.stanford.edu/class/cs294a/sparseAutoencoder_2011new.pdf

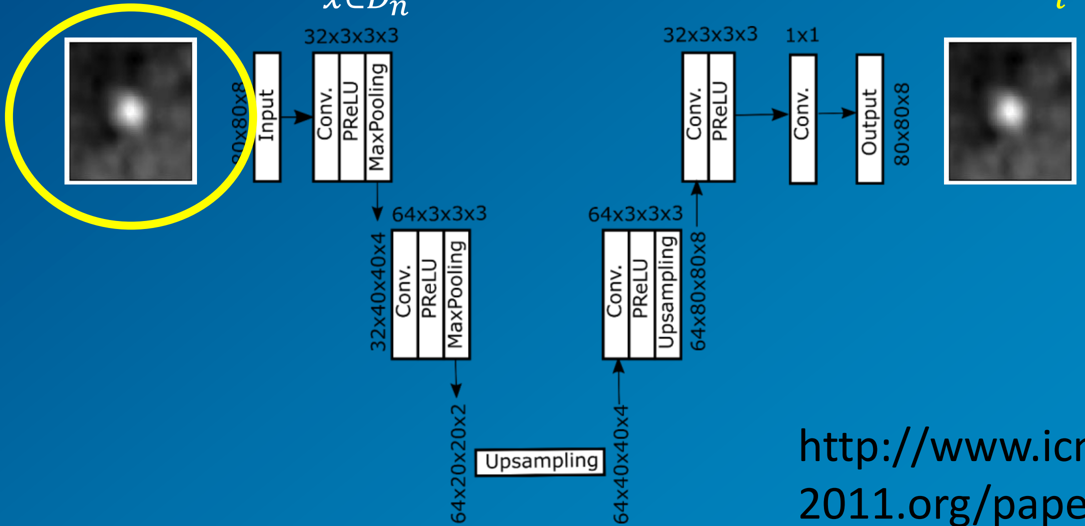
Unsupervised learning in the medical setting

The challenge: How to encourage the auto-encoder to learn useful representation?

Denoising auto-encoder: add random noise to the input data at each training iteration

$$\hat{\theta} = \arg\min_{\theta} \sum_{x \in D_n} L\left(x, g\left(f\left(\tilde{x}\right)\right)\right) + \lambda R(W)$$

$\tilde{x} = x + z_i,$
$z_i \sim \mathcal{N}(0,1).$



http://www.icml-2011.org/papers/455_icmlpaper.pdf

Unsupervised learning in the medical setting

The challenge: How to encourage the auto-encoder to learn useful representation?

The mixed structure regularization: mix the input with randomly structure sampled from the training dataset in addition to noise and sparsity terms

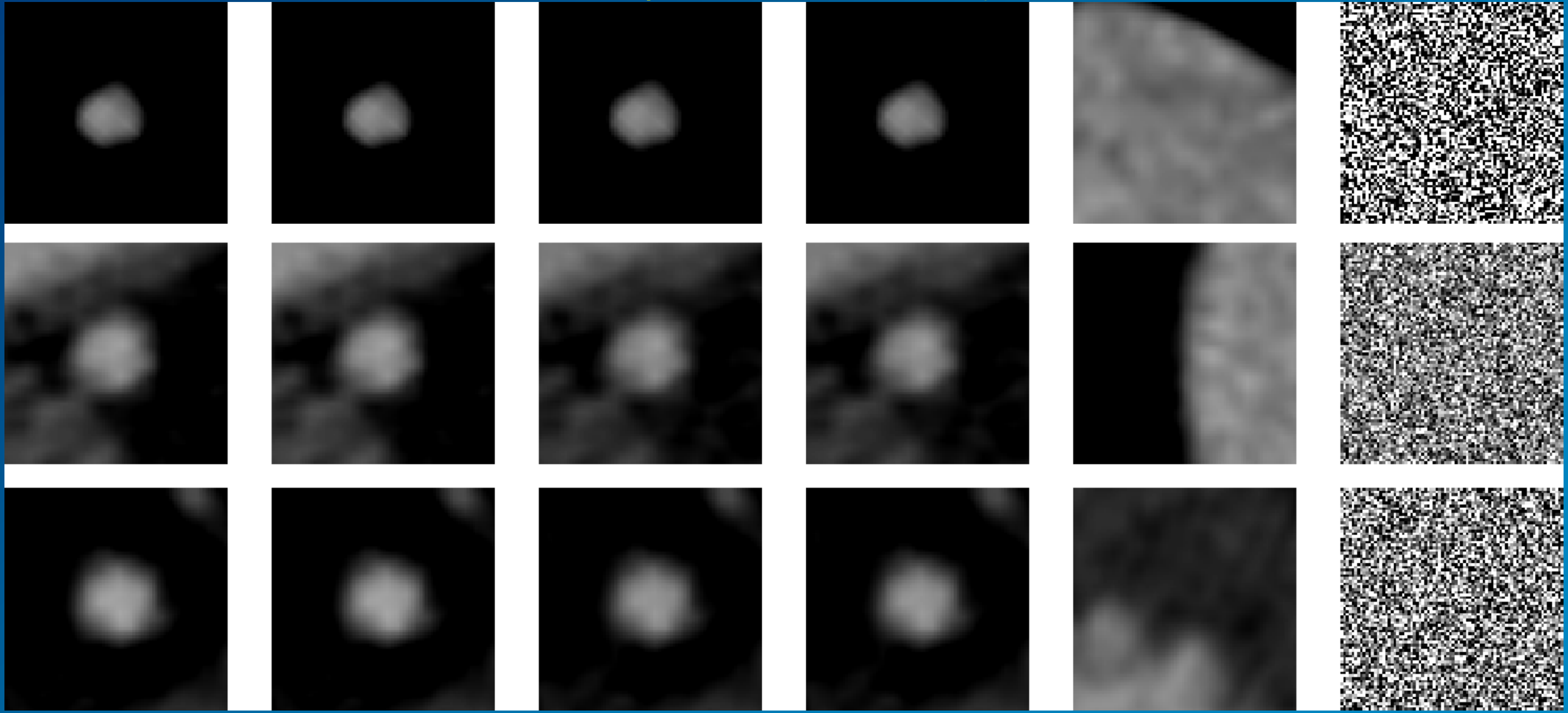
$$\hat{\theta} = \arg\min_{\theta} \sum_{x \in D_n} L\left(x, g\left(f\left(\tilde{\tilde{x}}\right)\right)\right) + \lambda R(W) + \gamma S\big(f(x)\big)$$

$$\tilde{\tilde{x}} = (1-\alpha)x + \alpha x_r + z_i, \qquad z_i \sim \mathcal{N}(0, \sigma).$$

https://arxiv.org/abs/1902.11036

Auto-encoder inputs

x	$x + z_i$, $z_i \sim \mathcal{N}(0,1)$	$(1-\alpha)x + \alpha x_r$	$(1-\alpha)x + \alpha x_r + z_i$	x_r	z_i



Coronary Artery Disease (CAD)

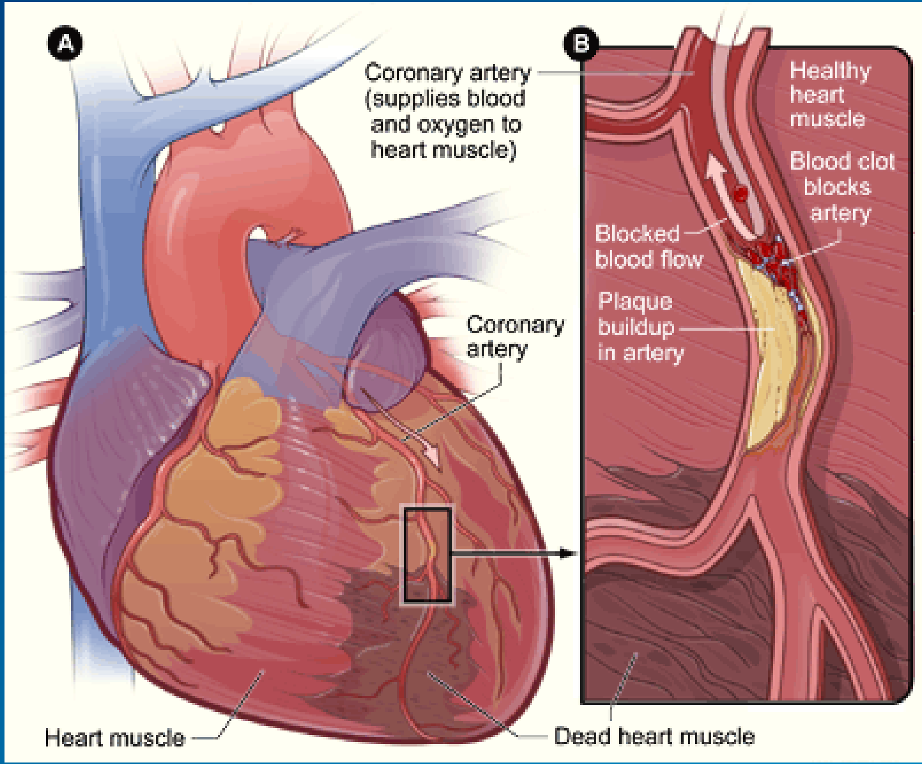
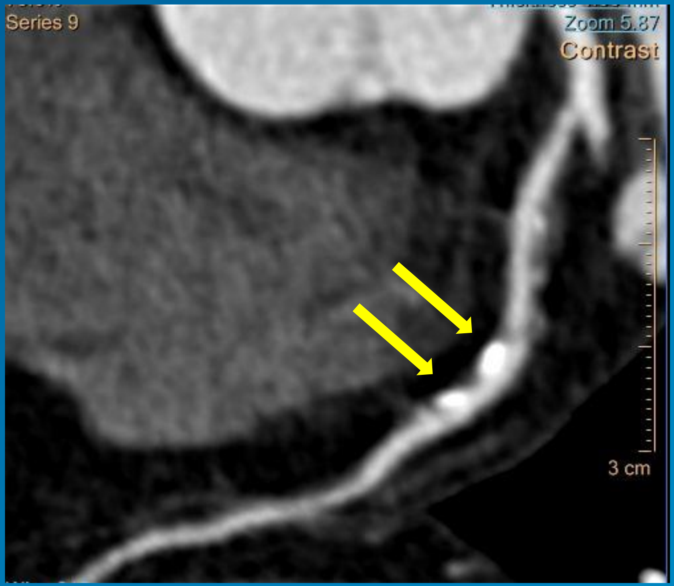


Image source: http://www.nhlbi.nih.gov/health/health-topics/topics/cad/signs

Evaluating chest pain by Coronary Computed Tomography angiography (CCTA)

Coronary CTA has a high sensitivity and high negative predictive value for diagnosis of obstructive CAD by detecting anatomical narrowing in the coronaries

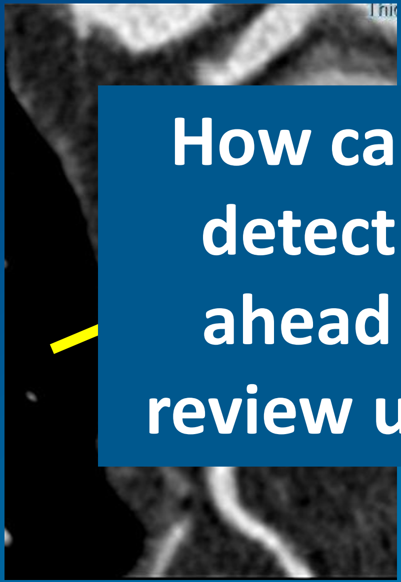
Soft plaque (darker)



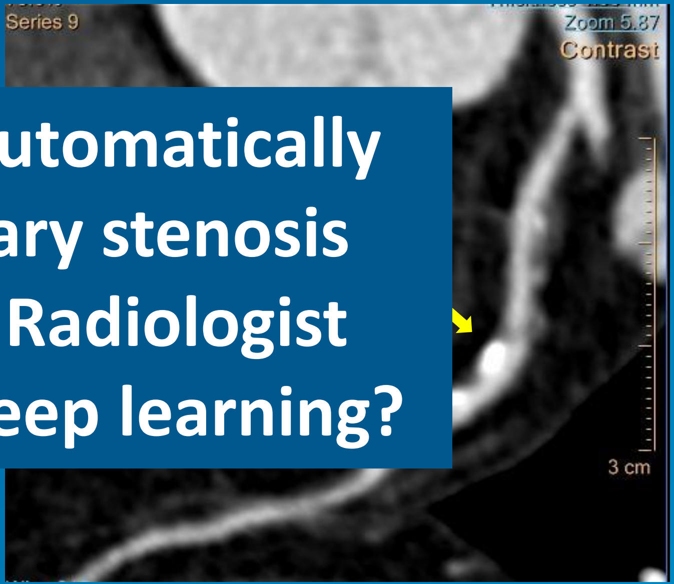
Calcified plaque (brighter)

Evaluating chest pain by Coronary Computed Tomography angiography (CCTA)

Coronary CTA has a high sensitivity and high negative predictive value for diagnosis of obstructive CAD by detecting anatomical narrowing in the coronaries



Soft plaque (darker)



Calcified plaque (brighter)

How can we automatically detect coronary stenosis ahead of the Radiologist review using deep learning?

MSR for abnormality detection

SUBJECTS:
90 CCTA datasets
Philips Brilliance (64/iCT)
48 Helical; 42 Axial

Processing:
Centerline extraction, Automatic lumen and wall segmentation (iCWLS)
Cross-sectional stenosis grading

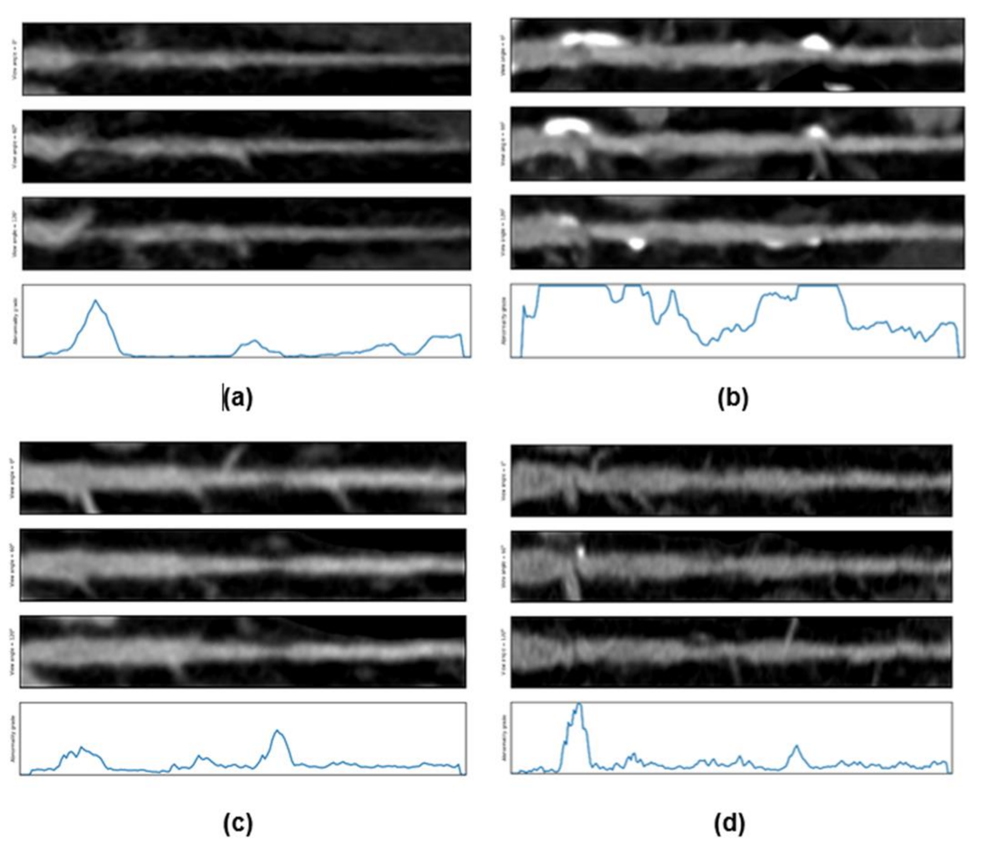
Training:
(cross-sections<20% stenosis)

Normal representation

Task 1:
distinguishing between healthy and disease cross-sections (<20% vs >70% stenosis)

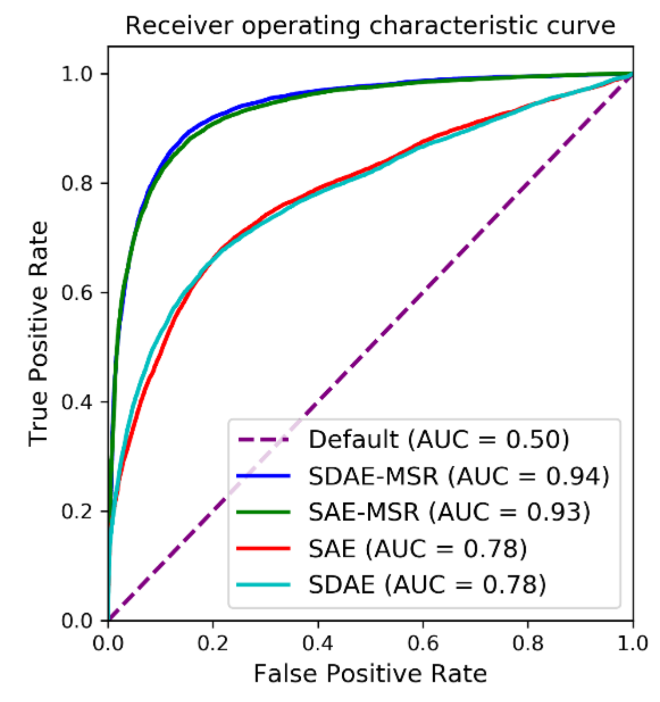
Task 2:
Detecting cross-sections with stenosis > 40%

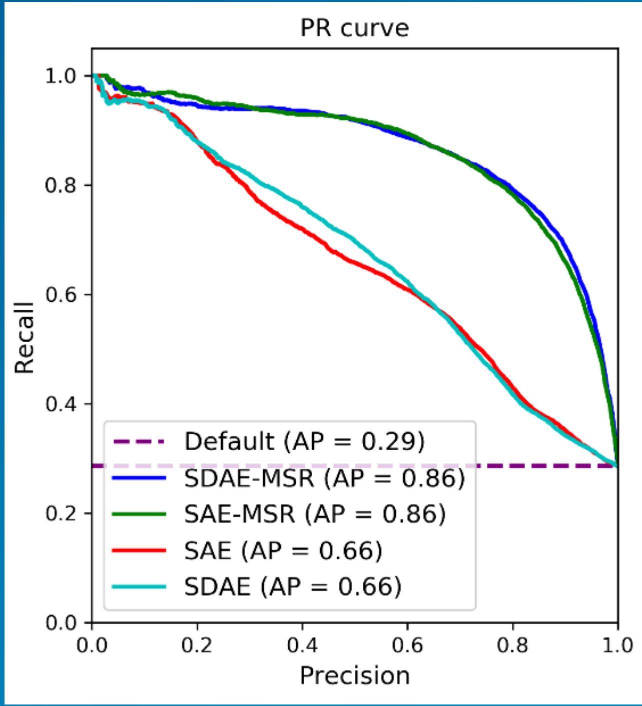
Examples



Distinguishing between healthy and disease cross-sections (<20% vs >70% stenosis)

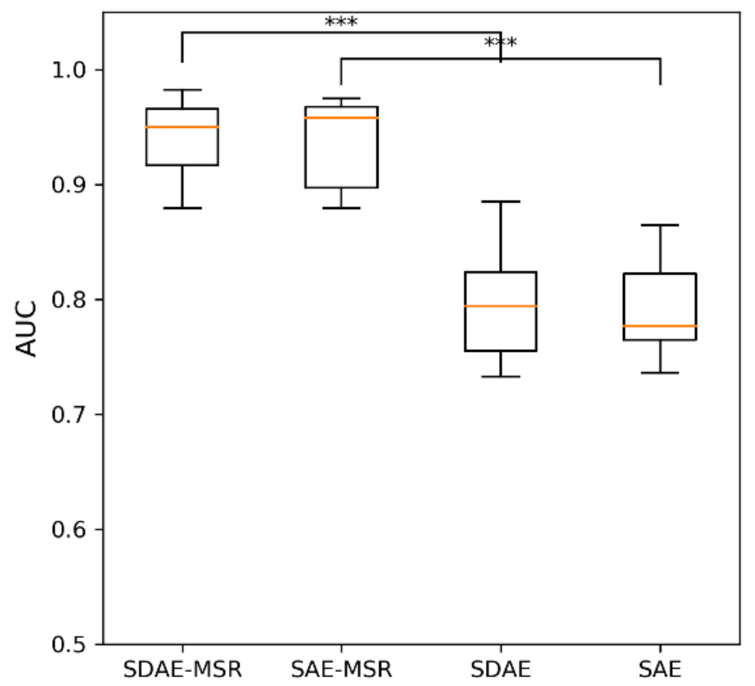
Aggregated performance curves

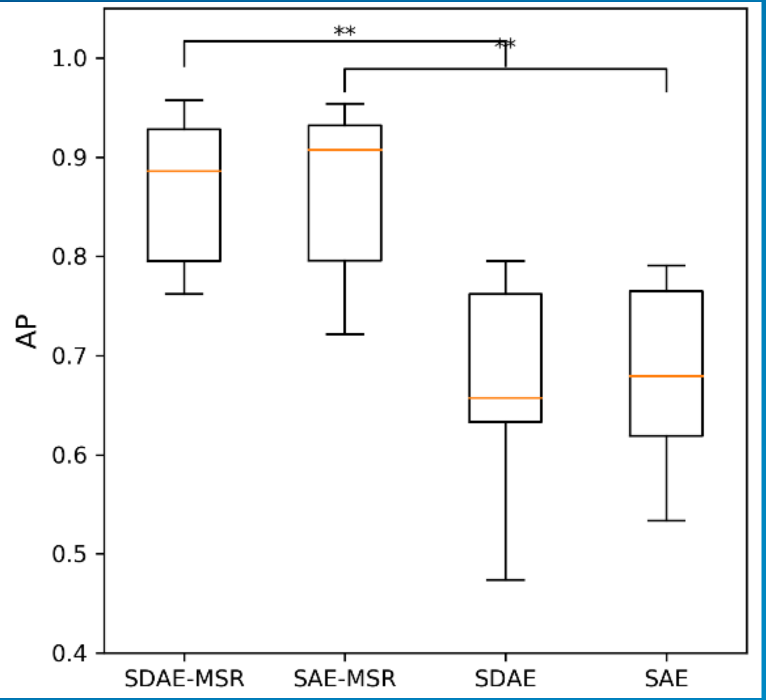




Distinguishing between healthy and disease cross-sections (<20% vs >70% stenosis)

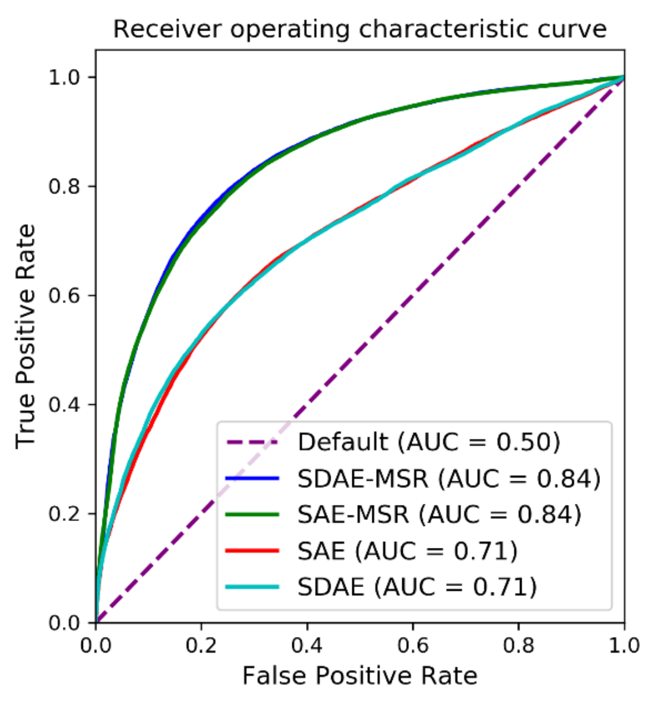
CV scores distribution

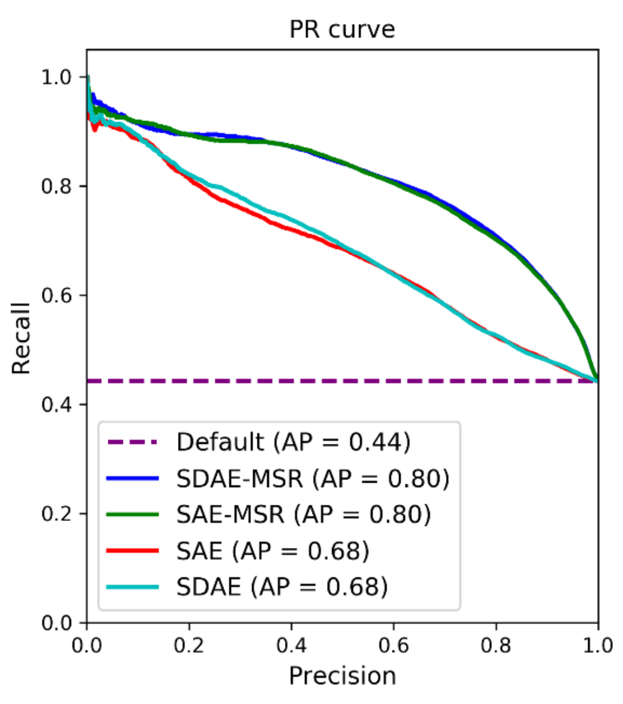




Detecting cross-sections with stenosis > 40%

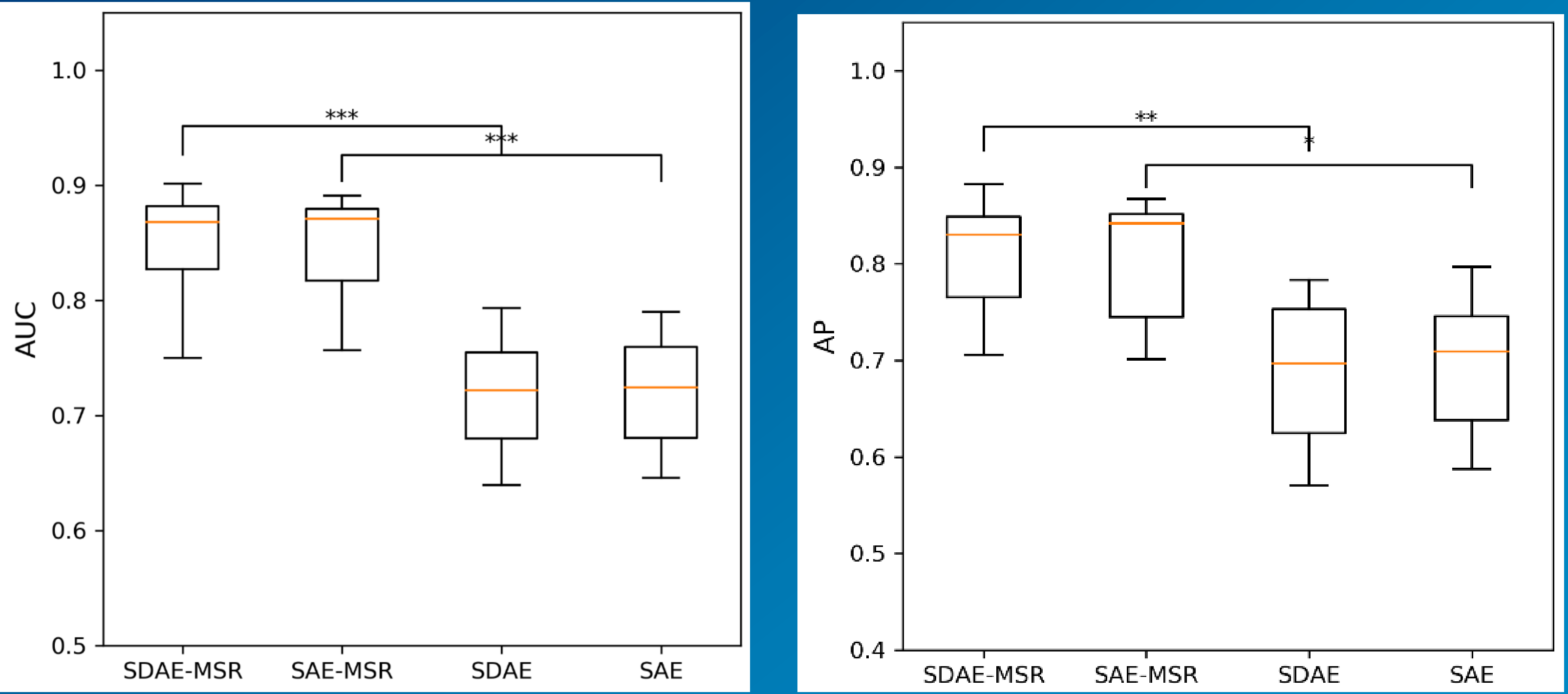
Aggregated performance curves





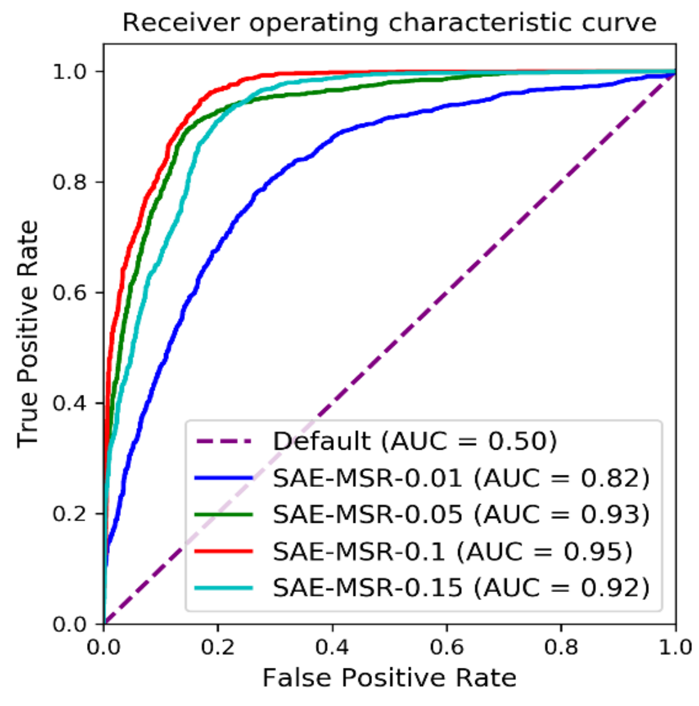
Detecting cross-sections with stenosis > 40%

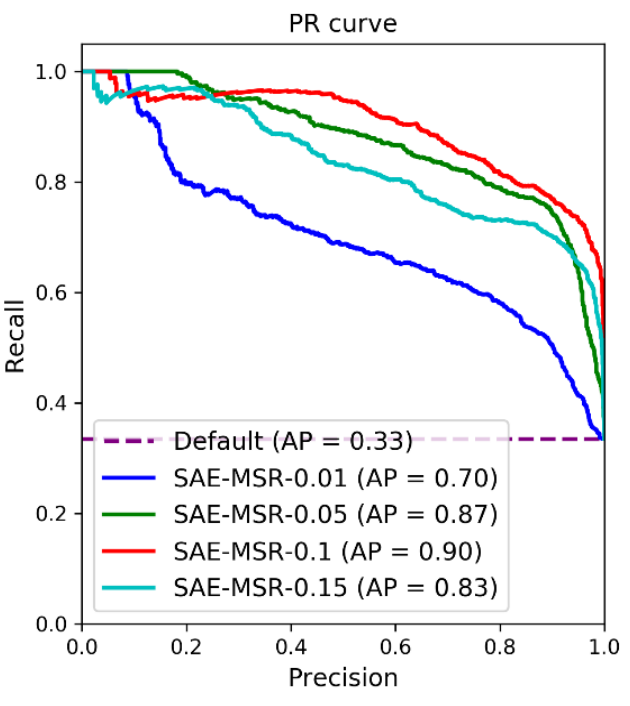
CV scores distribution



Impact of the mixed structure weighting parameter

Distinguish between healthy and disease cross-sections (<20% vs >70% stenosis)





Summary

Auto-encoders can learn useful representation of normal appearance of medical images

Abnormalities can be detected as outliers in the normal appearance model

Mixed structure regularization has the potential to improve the capacity of auto-encoders to learn underlying useful representations in addition to common techniques

Mixed structure regularization with appropriate weight can be used as an additional data augmentation technique in multiple deep-learning tasks

More information

See our detailed paper at:

https://arxiv.org/abs/1902.11036

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Research Article

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Abstract

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