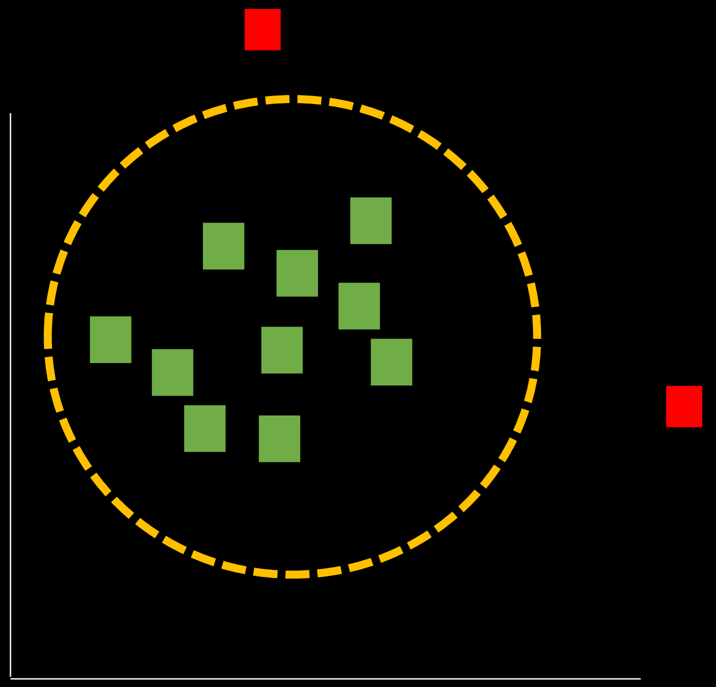
What is Visual Anomaly Detection

Normal

Anomaly

The problem formulation

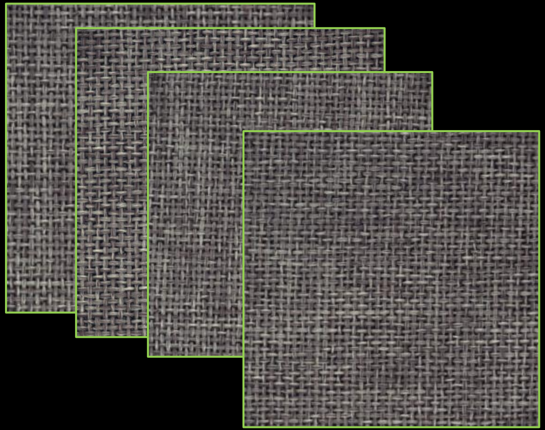


Out of distribution detection

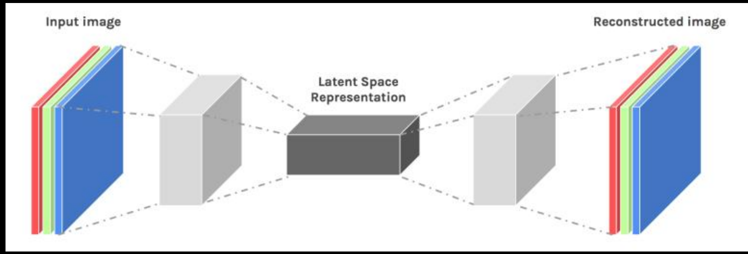
We do not use classification algorithms

We use anomaly detection

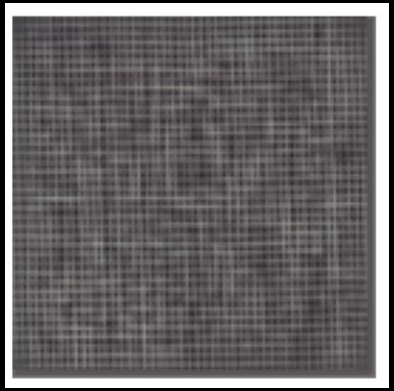
The naïve method



Normal



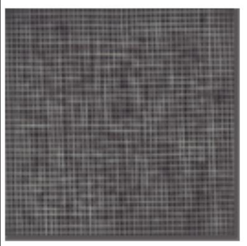
Autoencoder



Reconstruction

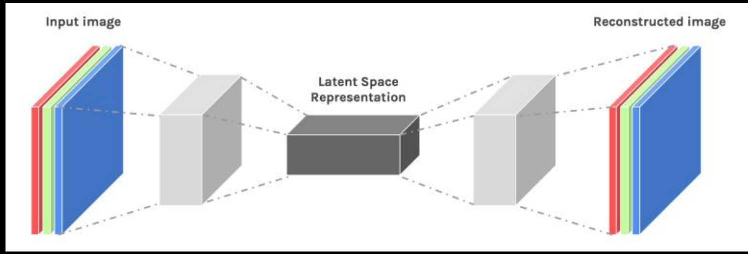
Tensor of shape (3,256,256)

Tensor of shape (3,256,256)

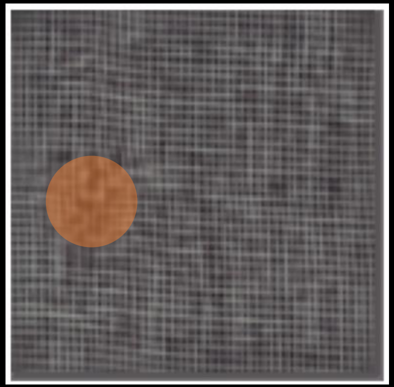
Anomaly Score = MSE( - )

Why this out of distribution task is so difficult ?

Abnormal



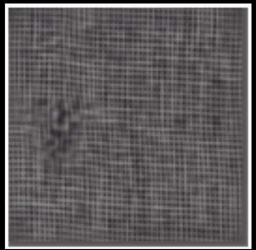
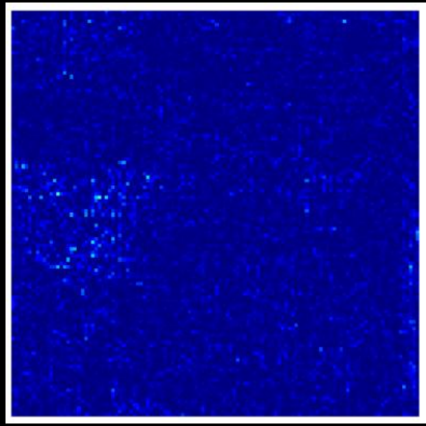
Autoencoder



Reconstruction

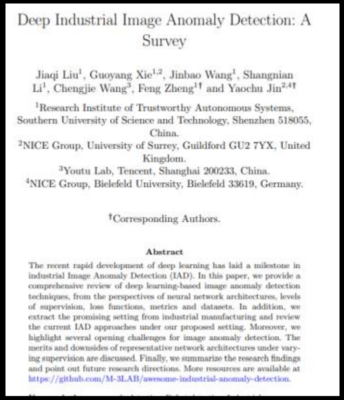
Tensor of shape (3,256,256)

Tensor of shape (3,256,256)

Anomaly Score = MSE( - ) = 

Tensor of shape (1,256,256)

Resources


Deep Industrial Image Anomaly Detection: A Survey

Jiaqi Liu[1], Guoyang Xie[1,2], Jinbao Wang[1], Shangnian Li[1], Chengjie Wang[3], Feng Zheng[1†] and Yaochu Jin[2,4†]

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[2]NICE Group, University of Surrey, Guildford GU2 7YX, United Kingdom.
[3]Youtu Lab, Tencent, Shanghai 200233, China.
[4]NICE Group, Bielefeld University, Bielefeld 33619, Germany.

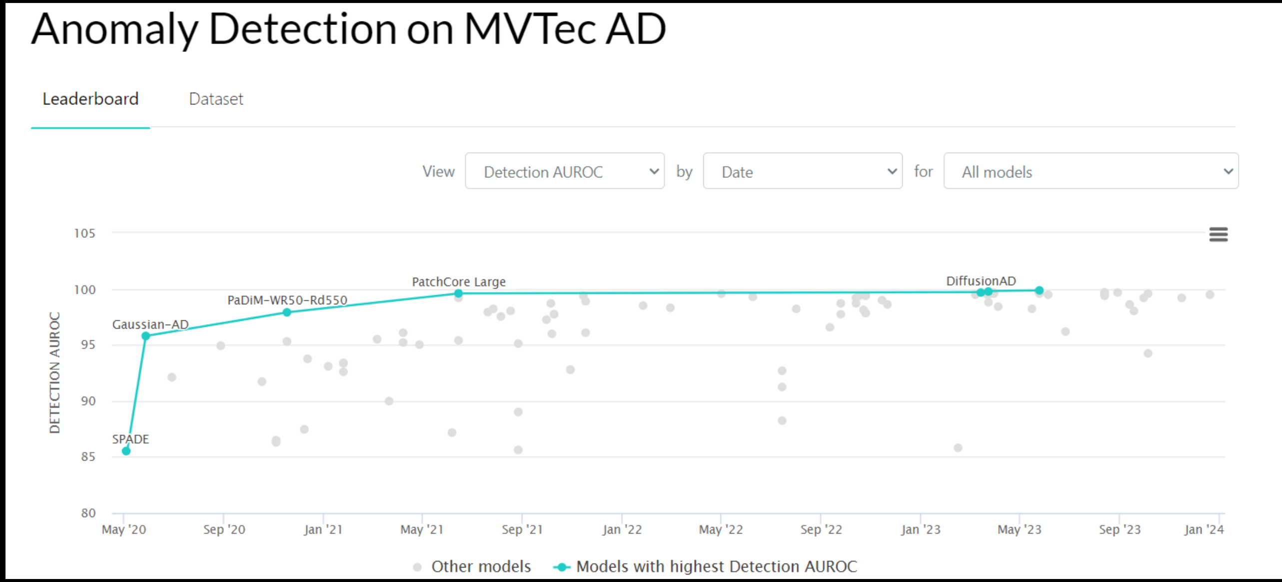
[†]Corresponding Authors.

Abstract

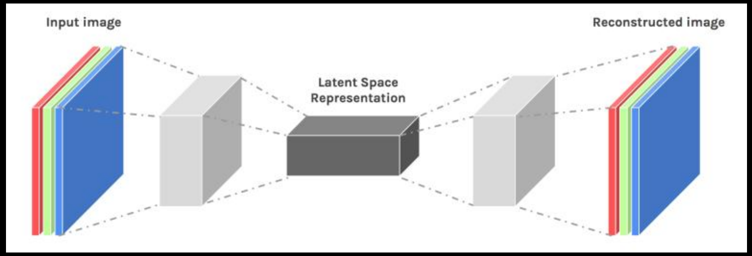
The recent rapid development of deep learning has laid a milestone in industrial Image Anomaly Detection (IAD). In this paper, we provide a comprehensive review of deep learning-based image anomaly detection techniques, from the perspectives of neural network architectures, levels of supervision, loss functions, metrics and datasets. In addition, we extract the promising setting from industrial manufacturing and review the current IAD approaches under our proposed setting. Moreover, we highlight several opening challenges for image anomaly detection. The merits and downsides of representative network architectures under varying supervision are discussed. Finally, we summarize the research findings and point out future research directions. More resources are available at https://github.com/M-3LAB/awesome-industrial-anomaly-detection.

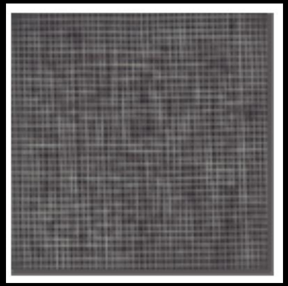
- **Deep Industrial Image Anomaly Detection: A Survey**

- Data Set – https://www.mvtec.com/company/research/datasets/mvtec-ad



Convolution and Transposed Convolution

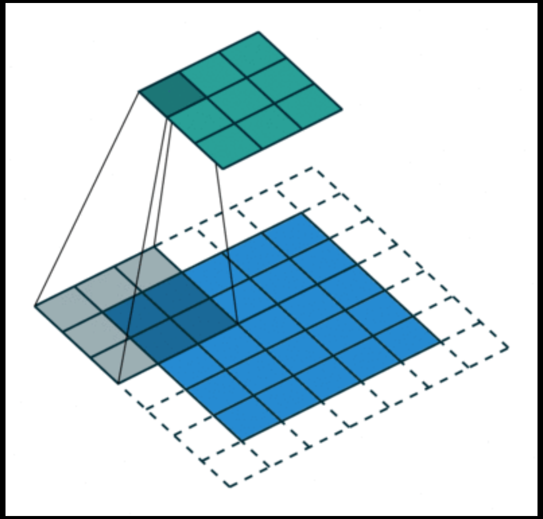


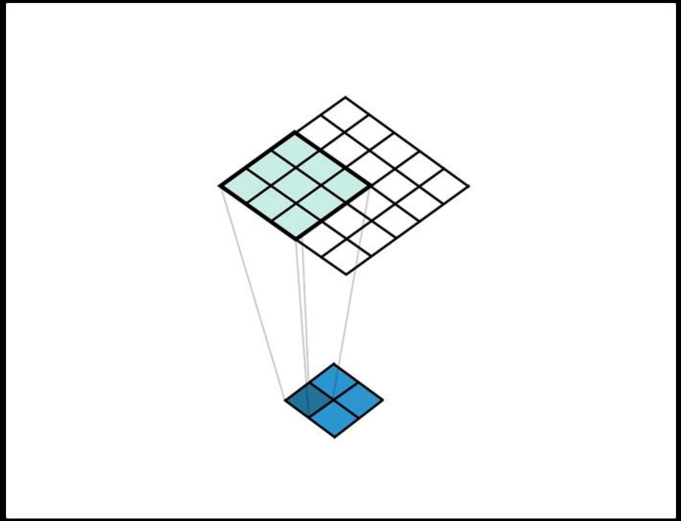


Normal

Autoencoder

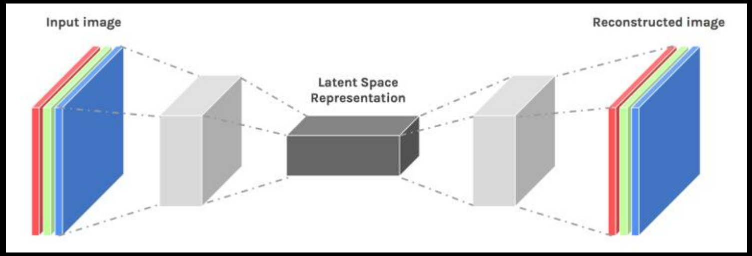
Reconstruction



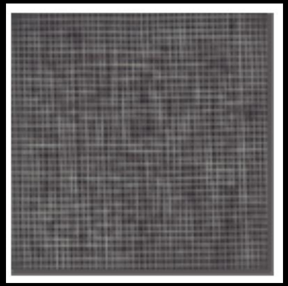


Convolution and Transposed Convolution

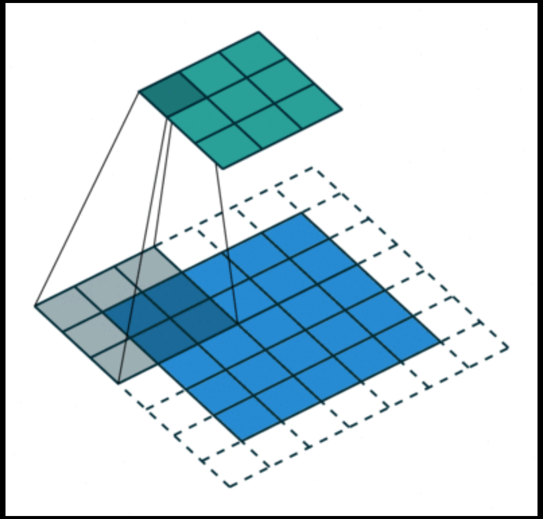
Normal

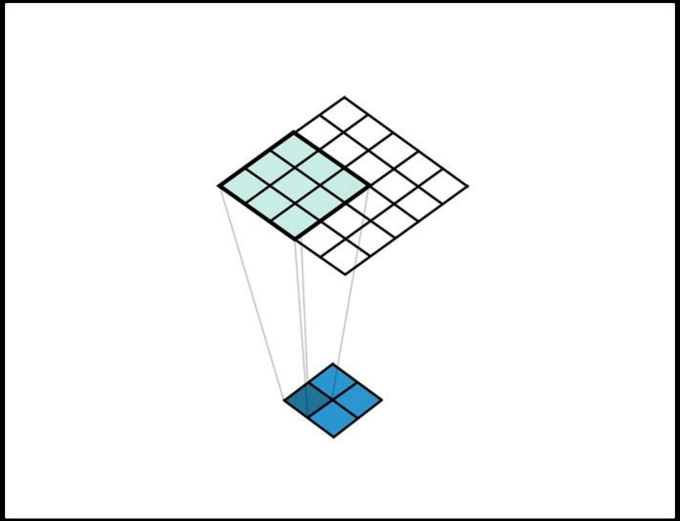


Autoencoder

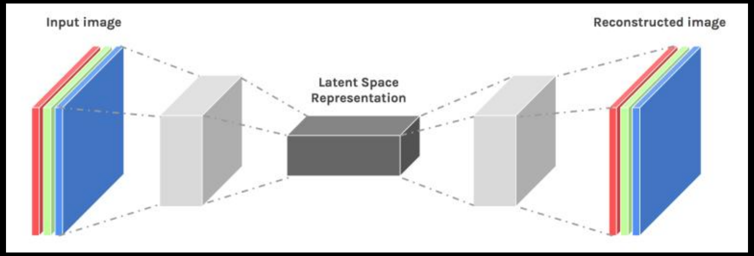


Reconstruction

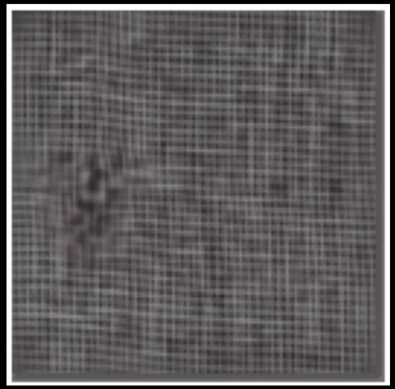




Abnormal



Autoencoder

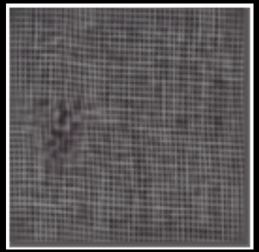
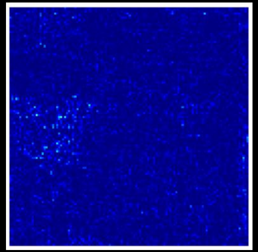


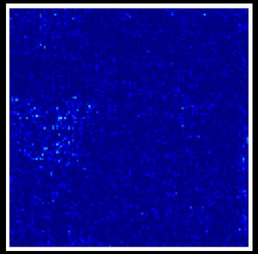
Reconstruction

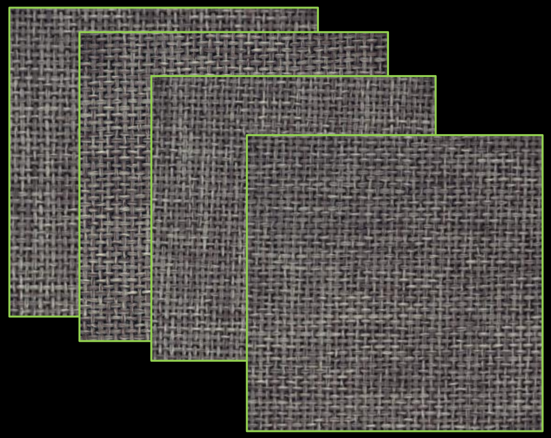
Tensor of shape (3,256,256)

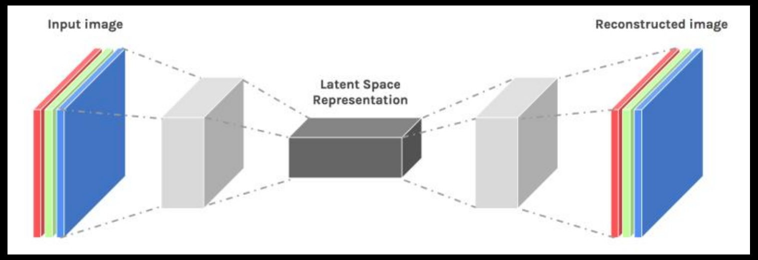
Tensor of shape (3,256,256)

Tensor of shape (1,256,256)

Anomaly Map = MSE( - ) = 

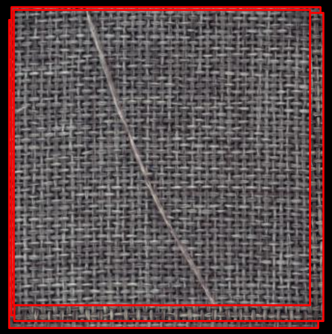
Anomaly Score = MEAN() = 0.334 (a single number)

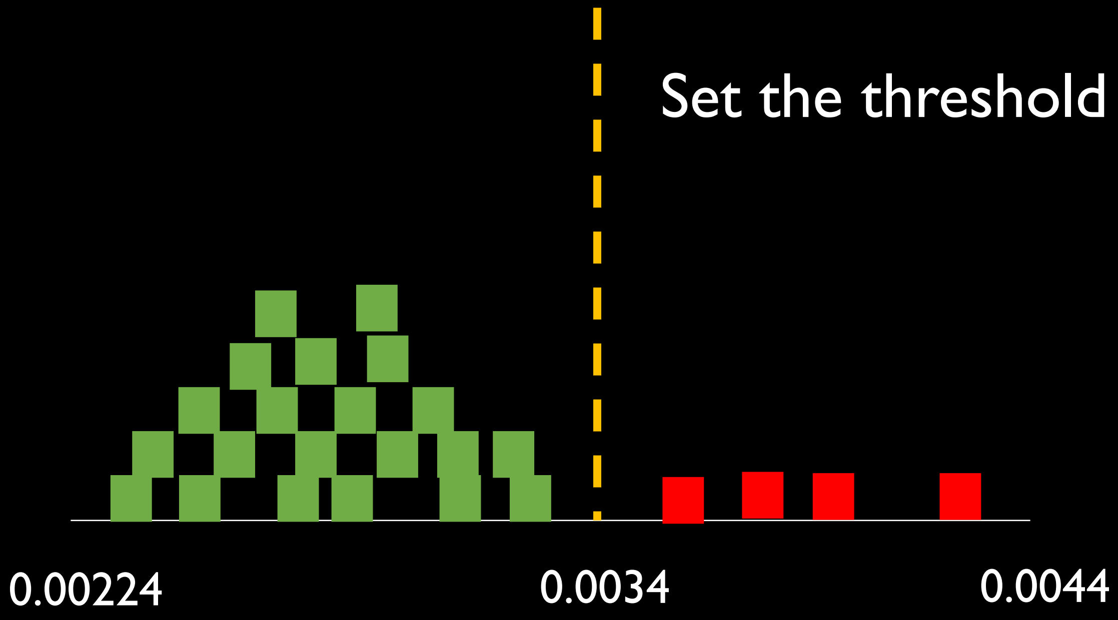




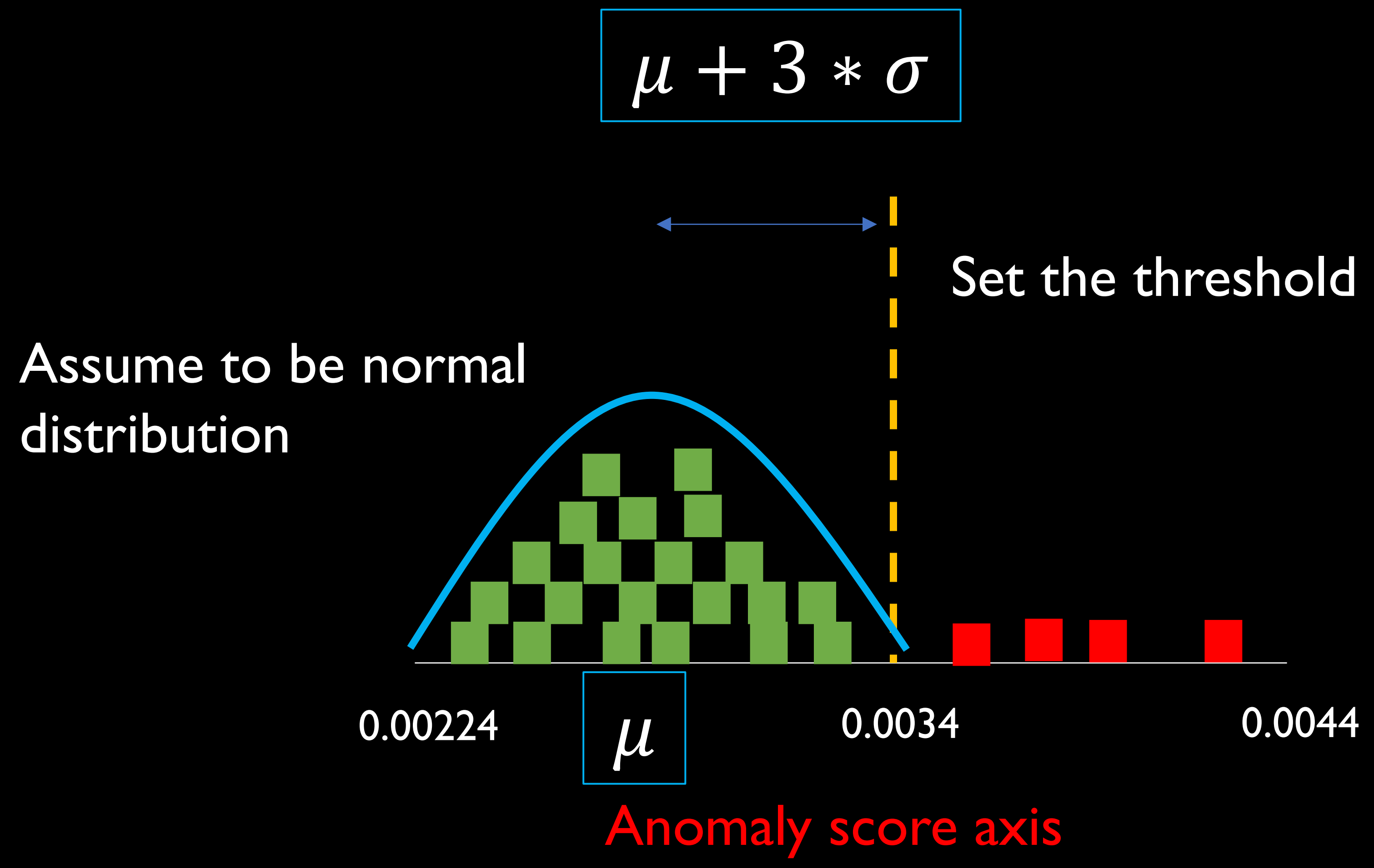
Autoencoder

Anomaly score

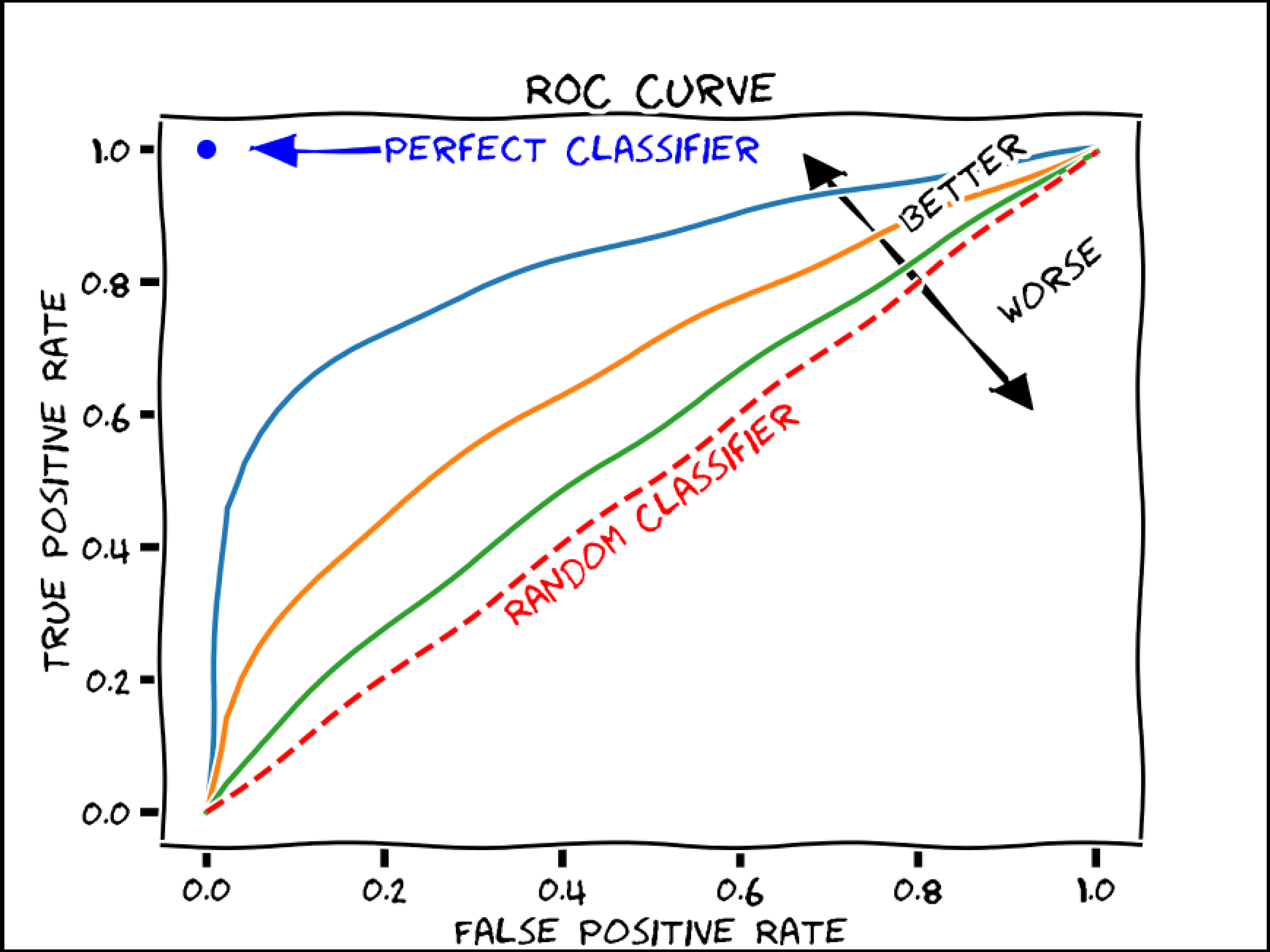




Anomaly score axis



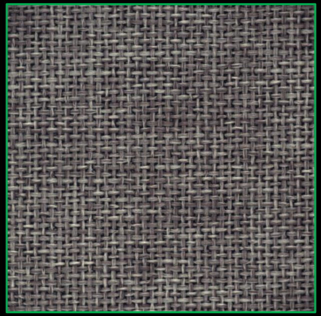
$\mu + 3 * \sigma$
Set the threshold
Assume to be normal distribution
0.00224
μ
0.0034
0.0044
Anomaly score axis


ROC CURVE
PERFECT CLASSIFIER
BETTER
WORSE
RANDOM CLASSIFIER
TRUE POSITIVE RATE
FALSE POSITIVE RATE
0.0
0.2
0.4
0.6
0.8
1.0

Real life example of industrial data

Normal

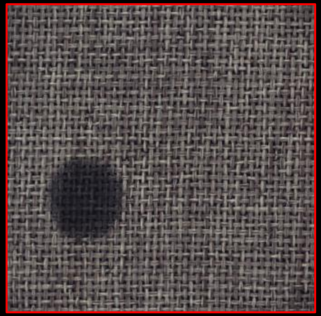
Very high number of images

Abnormal

Very low number of images






DFR: Deep Feature Reconstruction for Unsupervised Anomaly Segmentation

Jie Yang, Yong Shi, ZhiQuan Qi

***Abstract*—Automatic detecting anomalous regions in images of objects or textures without priors of the anomalies is challenging, especially when the anomalies appear in very small areas of the images, making difficult-to-detect visual variations, such as defects on manufacturing products. This paper proposes an effective unsupervised anomaly segmentation approach that can detect and segments out the anomalies in small and confined regions of images. Concretely, we develop a multi-scale regional feature generator which can generate multiple spatial context-aware representations from pre-trained deep convolutional networks for every subregion of an image. The regional representations not only describe the local characteristics of corresponding regions but also encode their multiple spatial context information, making them discriminative and very beneficial for anomaly detection. Leveraging these descriptive regional features, we then design a deep yet efficient convolutional autoencoder and detect anomalous regions within images via fast feature reconstruction. Our method is simple yet effective and efficient. It advances the state-of-the-art performances on several benchmark datasets and shows great potential for real applications.**

***Index Terms*—Anomaly detection, anomaly segmentation, regional representation, feature reconstruction.**

I. Introduction

UNSUPERVISED anomaly segmentation aims at precisely detecting and localizing anomalous regions within images solely via prior knowledge from the anomaly-free images. This task is significant especially in smart manufacturing processes for ensuring qualified products, such as automatically inspecting and screening defective or flawed products. In these inspection scenarios, it is usually preferable to train machine learning models only with normal images of the products alone to detect the anomalies. Since industrial processes are generally optimized to produce least unqualified samples, it might be impossible to collect a sufficient amount or even a few of defective samples. More importantly, because all sorts of anomalies or defects would possibly occur during manufacturing, a detection model solely trained on limited

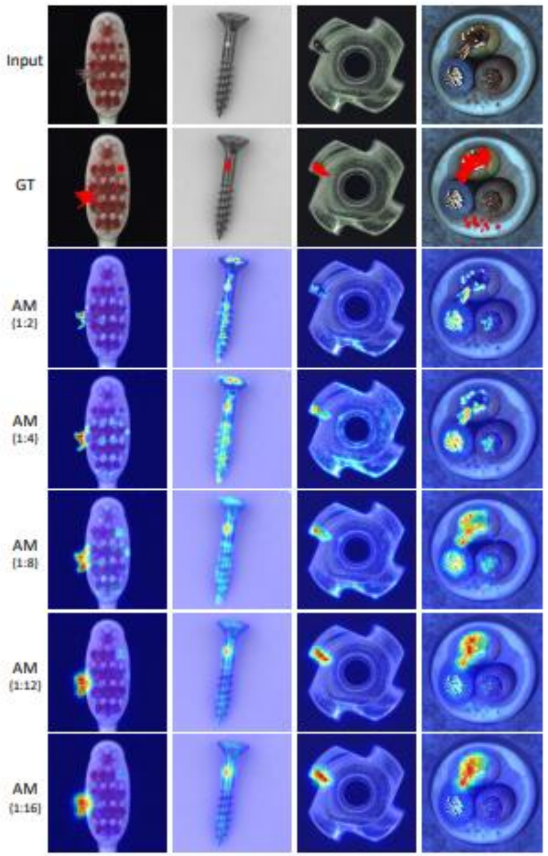
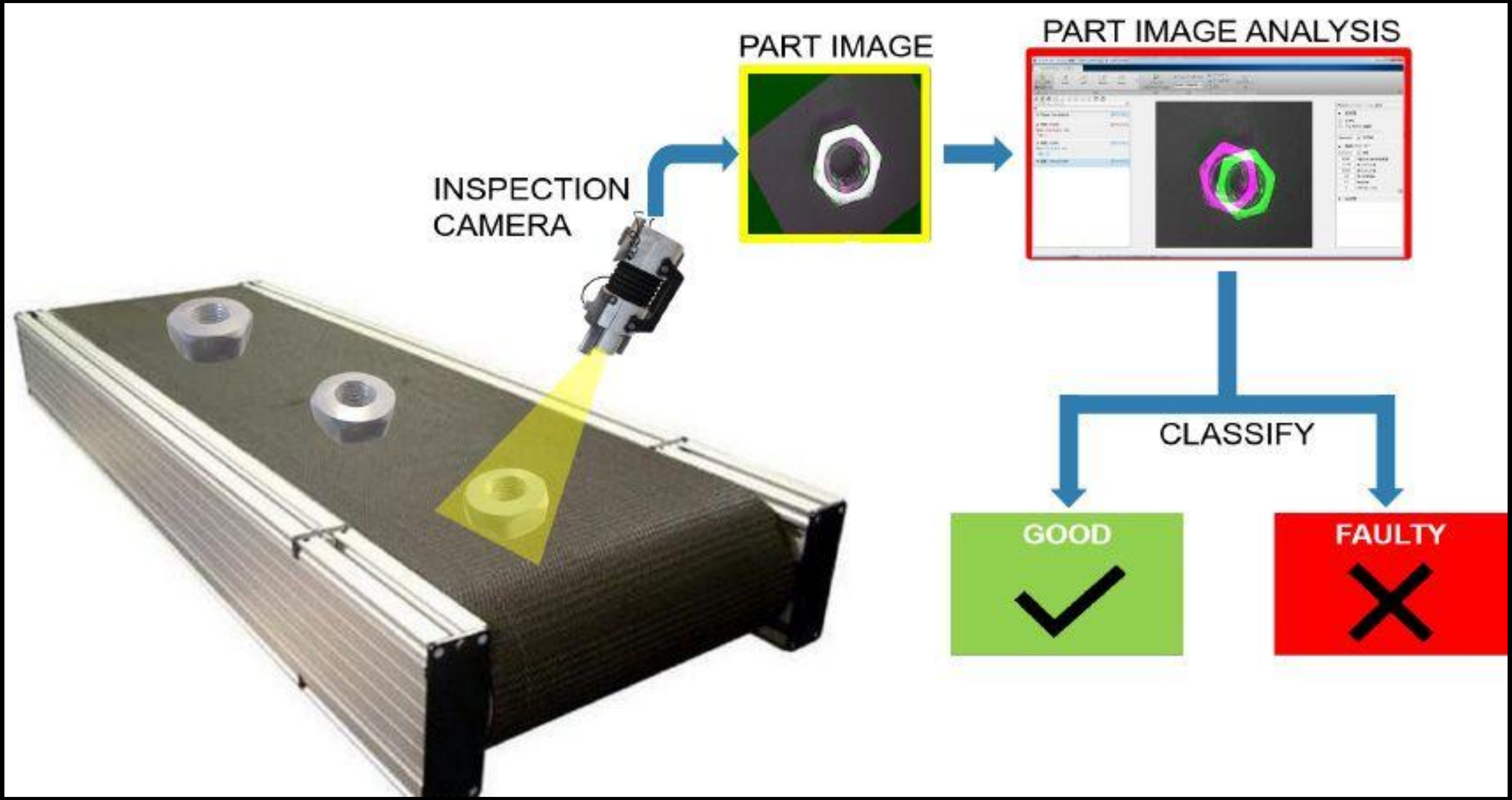
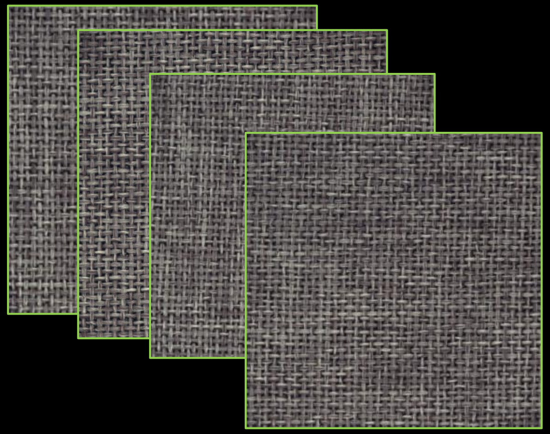


Fig. 1. Qualitative results of our anomaly detection method with increasing feature scales on the MVTec AD dataset. Input: input image. AM $\{1{:}l\}$: anomaly map of our approach where representation scales from 1 to l are leveraged. Note that in AM red regions correspond to high score for anomaly.

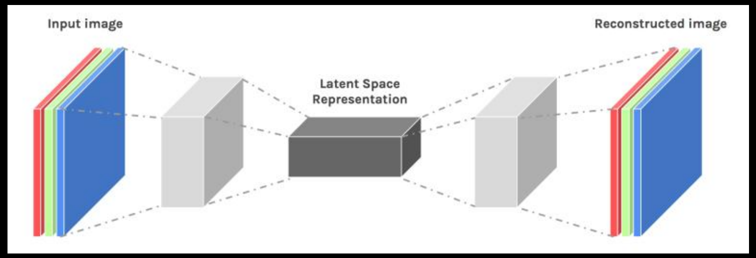
Application in the industry (inspection during production)



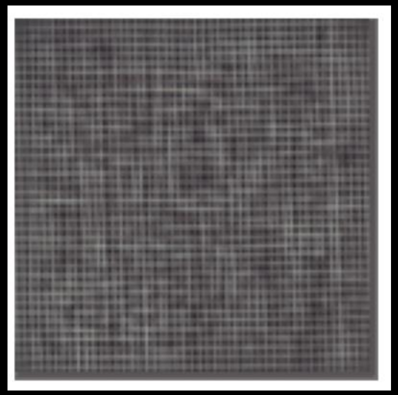
The naïve method



Normal



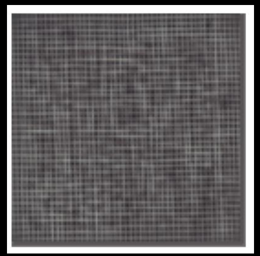
Autoencoder



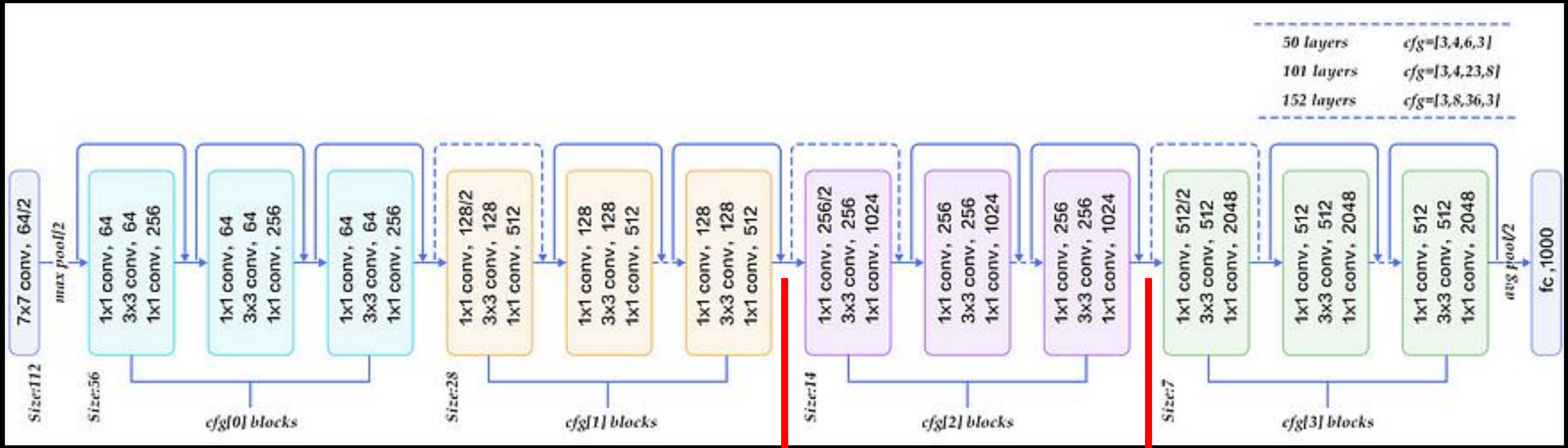
Reconstruction

Tensor of shape (3,256,256)

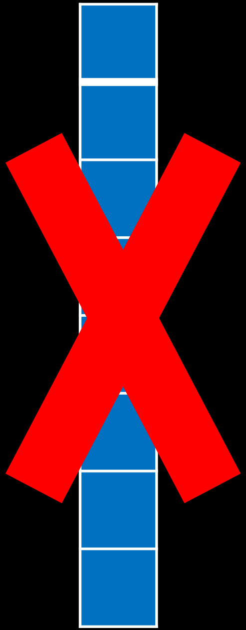
Tensor of shape (3,256,256)

Anomaly Score = MSE( - )

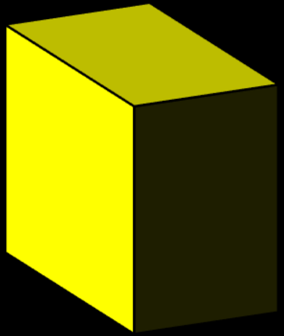
Normal



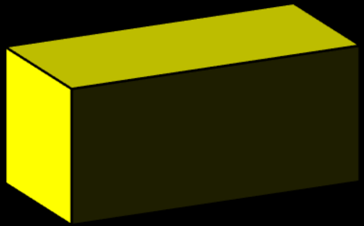
Pretrained resnet 50 model



(2048)

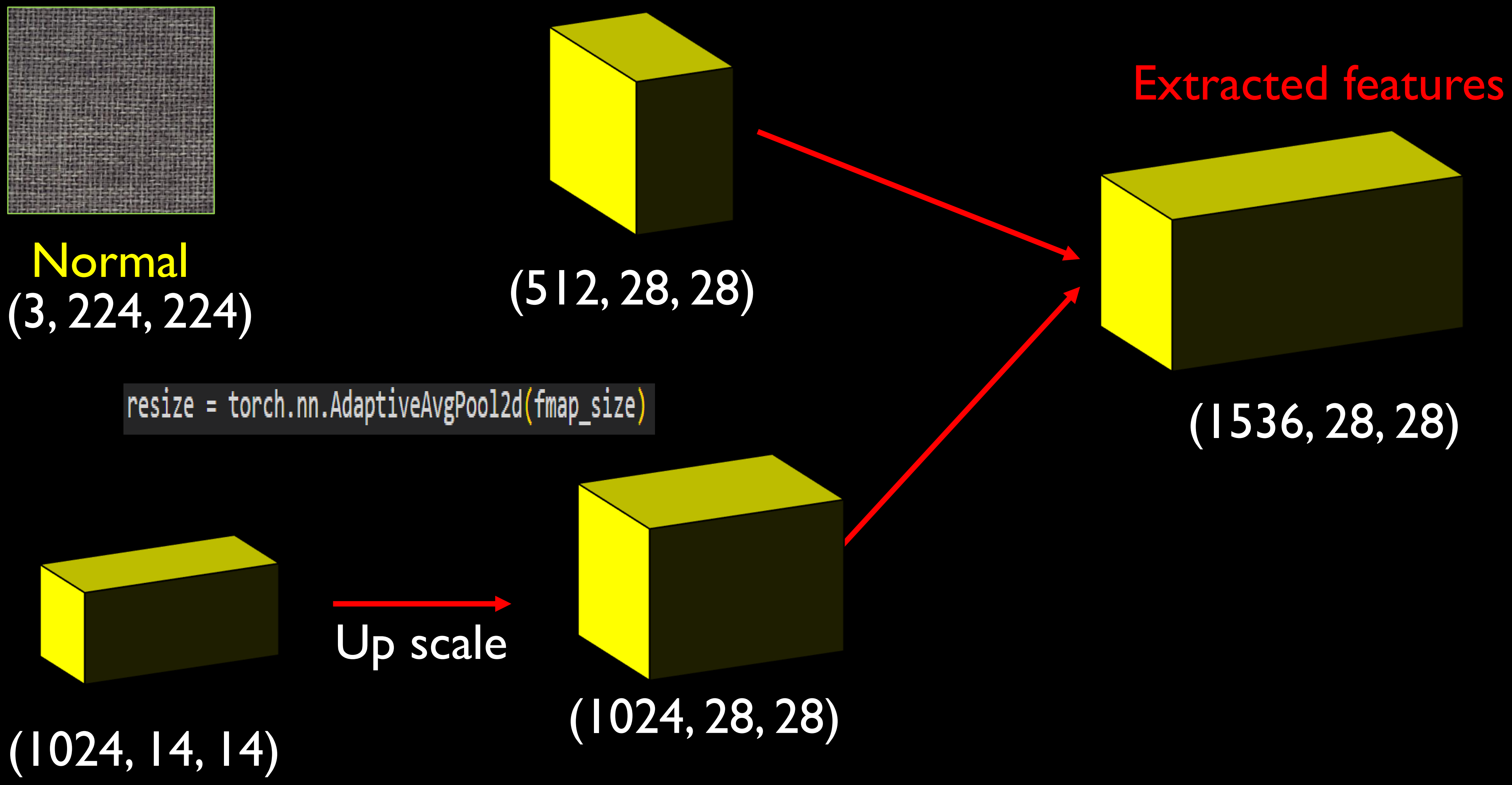


(512, 28, 28)

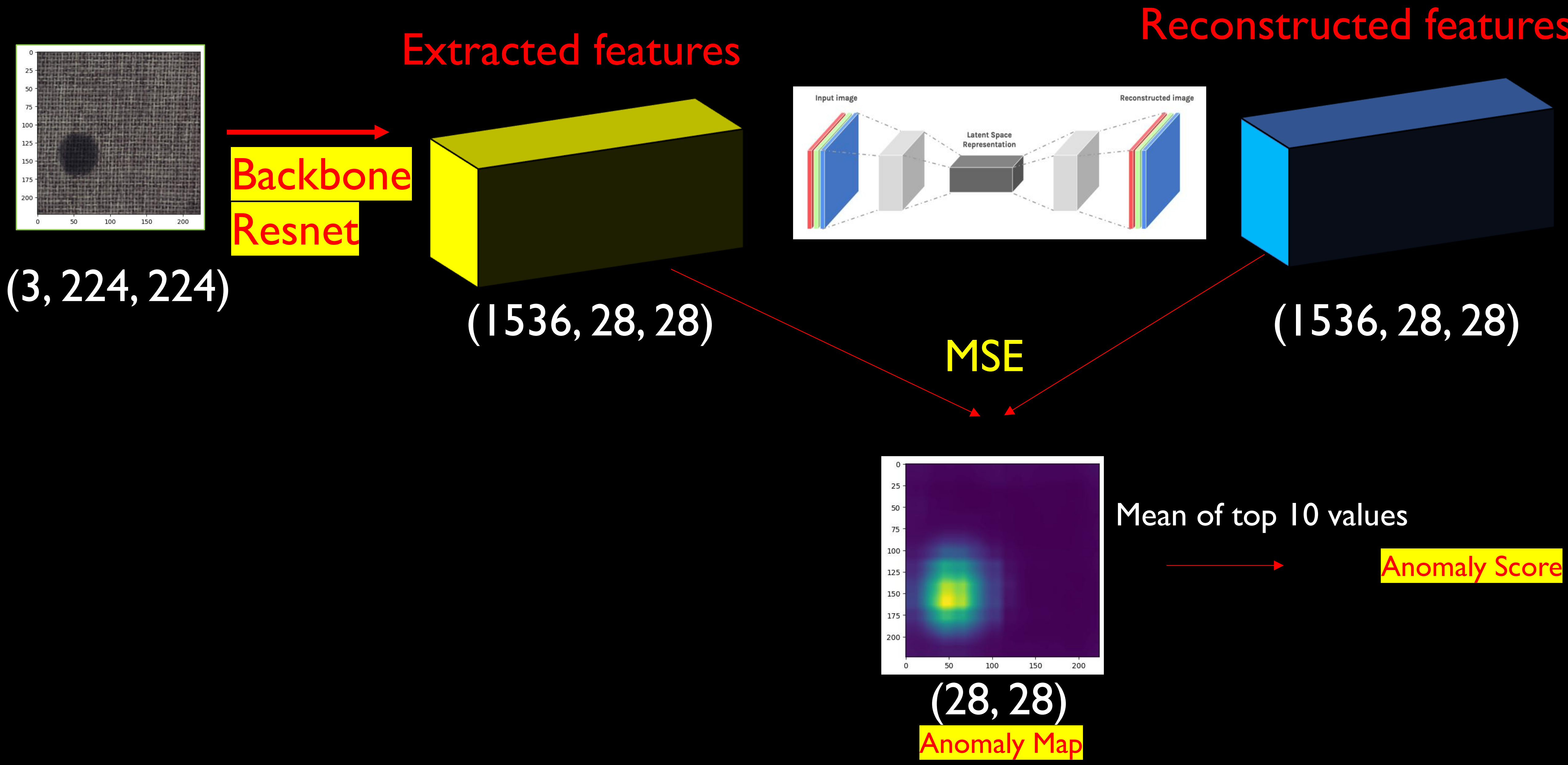


(1024, 14, 14)

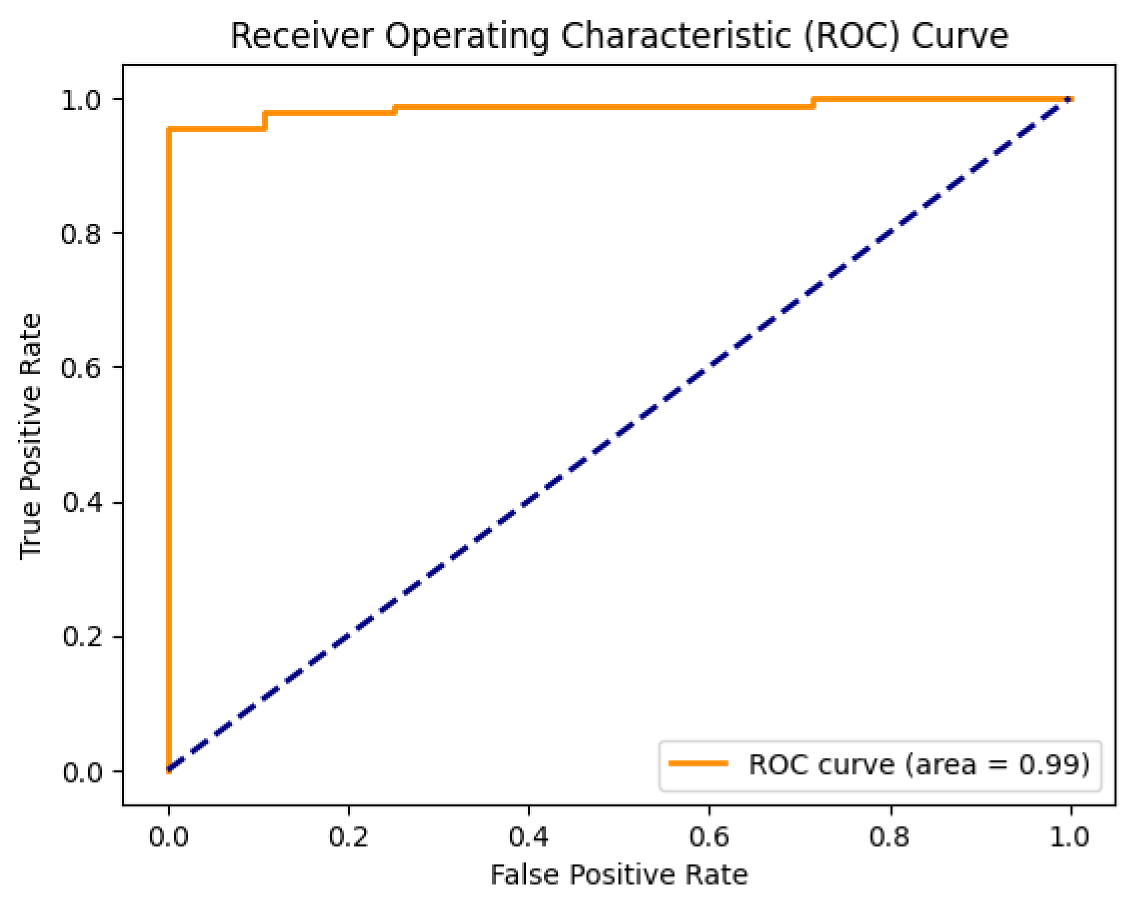
How to aggregate the features



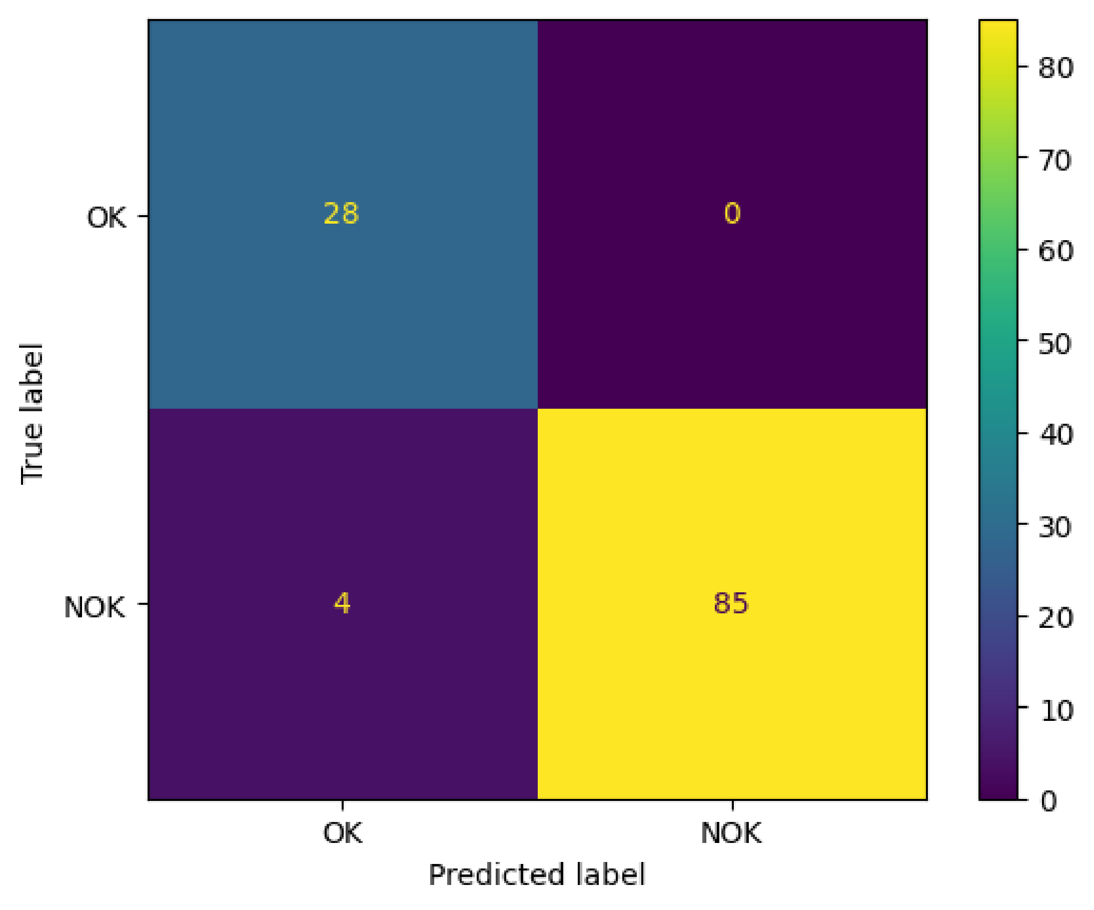
How to train an autoencoder



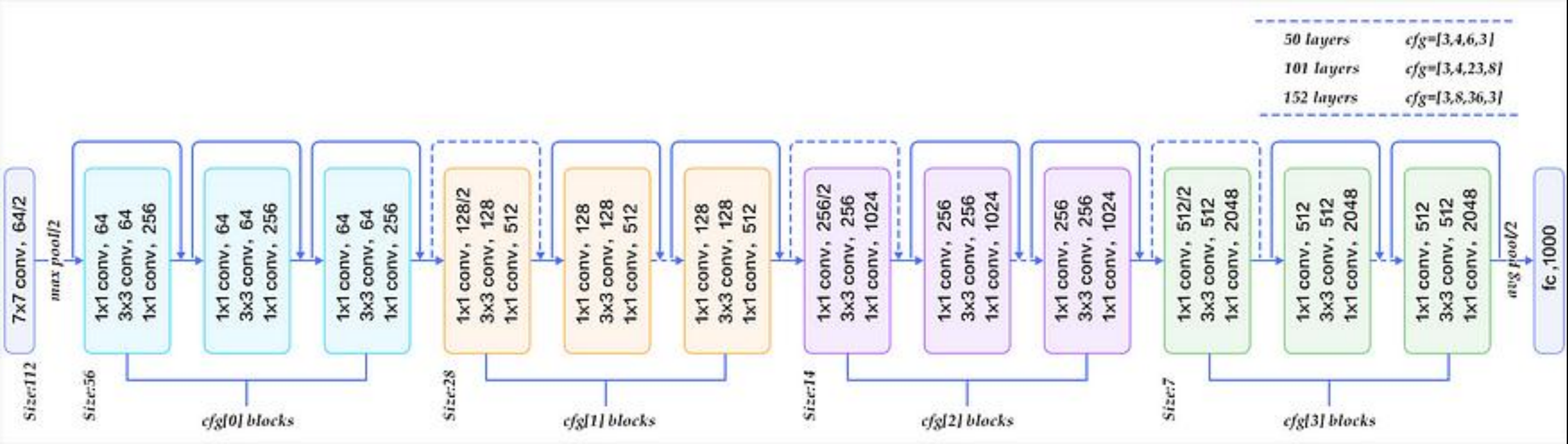
Results



Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (area = 0.99)



True label
Predicted label
OK
NOK
28
0
4
85
0
10
20
30
40
50
60
70
80


50 layers cfg=[3,4,6,3]
101 layers cfg=[3,4,23,8]
152 layers cfg=[3,8,36,3]
7x7 conv, 64/2
max pool/2
Size:112
Size:56
1x1 conv, 64
3x3 conv, 64
1x1 conv, 256
cfg[0] blocks
Size:28
1x1 conv, 128/2
3x3 conv, 128
1x1 conv, 512
1x1 conv, 128
3x3 conv, 128
1x1 conv, 512
cfg[1] blocks
Size:14
1x1 conv, 256/2
3x3 conv, 256
1x1 conv, 1024
1x1 conv, 256
3x3 conv, 256
1x1 conv, 1024
cfg[2] blocks
Size:7
1x1 conv, 512/2
3x3 conv, 512
1x1 conv, 2048
1x1 conv, 512
3x3 conv, 512
1x1 conv, 2048
cfg[3] blocks
avg pool/2
fc ,1000

Towards Total Recall in Industrial Anomaly Detection

Karsten Roth[1,*], Latha Pemula[2], Joaquin Zepeda[2], Bernhard Schölkopf[2], Thomas Brox[2], Peter Gehler[2]
[1]University of Tübingen [2]Amazon AWS

Abstract

Being able to spot defective parts is a critical component in large-scale industrial manufacturing. A particular challenge that we address in this work is the cold-start problem: fit a model using nominal (non-defective) example images only. While handcrafted solutions per class are possible, the goal is to build systems that work well simultaneously on many different tasks automatically. The best peforming approaches combine embeddings from ImageNet models with an outlier detection model. In this paper, we extend on this line of work and propose ***PatchCore****, which uses a maximally representative memory bank of nominal patch-features. PatchCore offers competitive inference times while achieving state-of-the-art performance for both detection and localization. On the challenging, widely used MVTec AD benchmark PatchCore achieves an image-level anomaly detection AUROC score of up to* 99.6%*, more than halving the error compared to the next best competitor. We fur-*

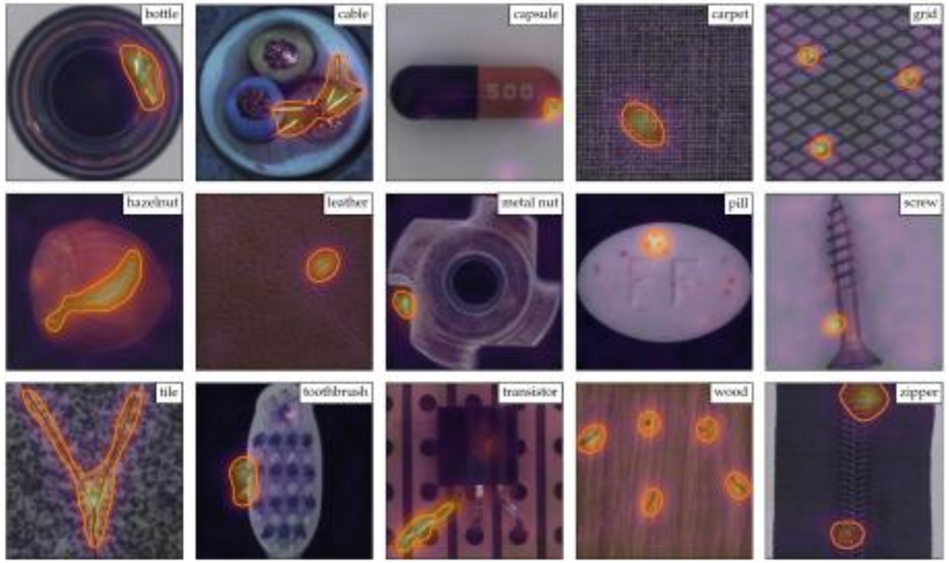
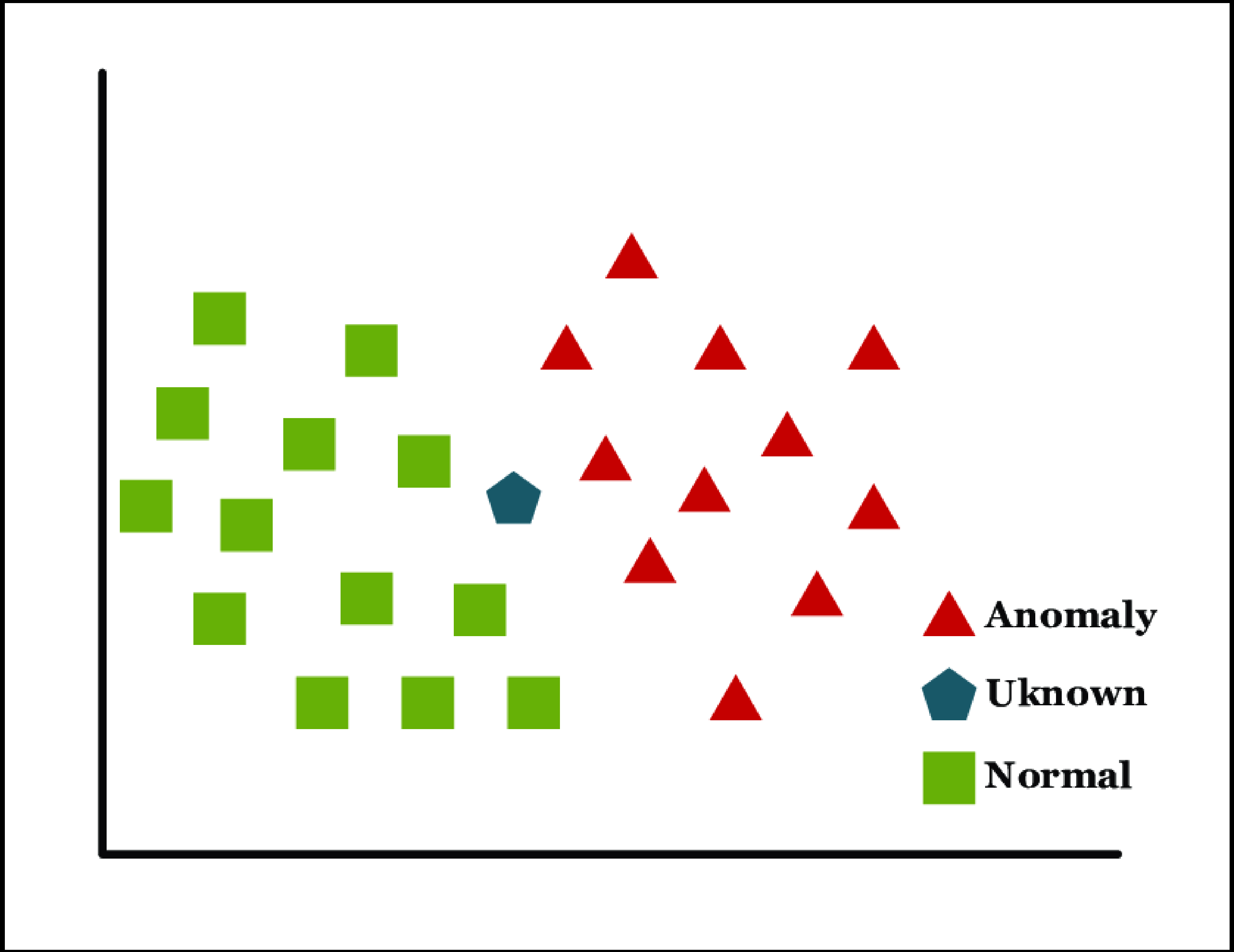
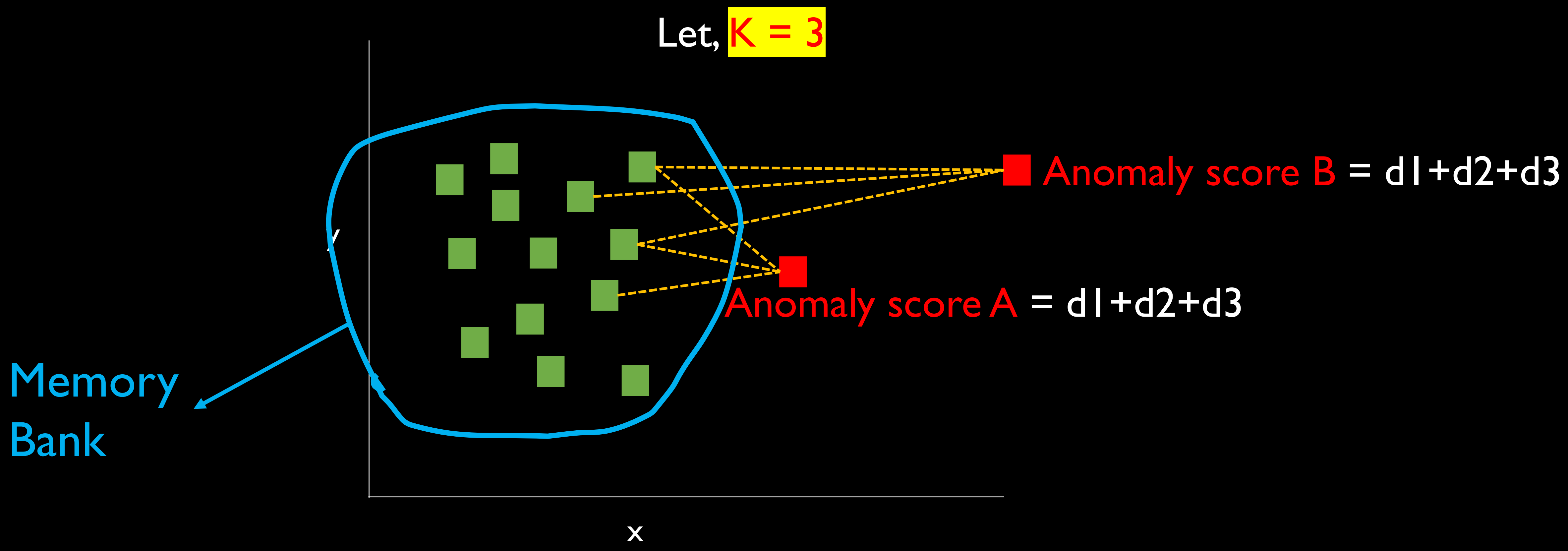


Figure 1. Examples from the MVTec benchmark datasets. Superimposed on the images are the segmentation results from *PatchCore*. The orange boundary denotes anomaly contours of actual segmentation maps for anomalies such as broken glass, scratches, burns or structural changes in blue-orange color gradients.

K nearest neighbours



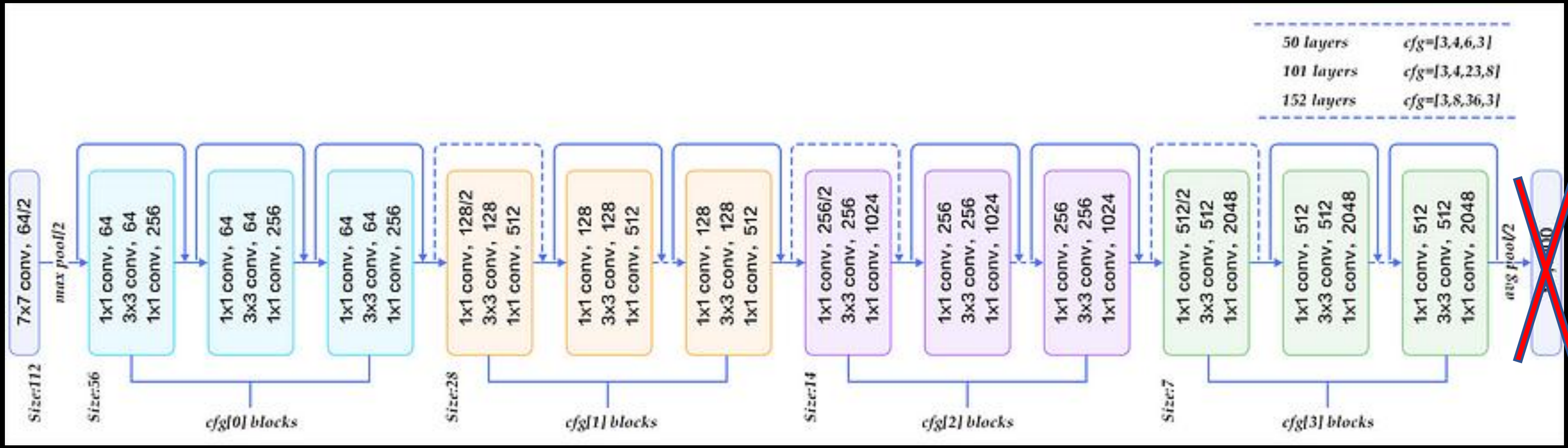
K nearest neighbours for anomaly detection



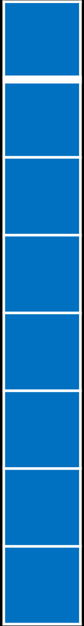
Anomaly score B > Anomaly Score A

Normal

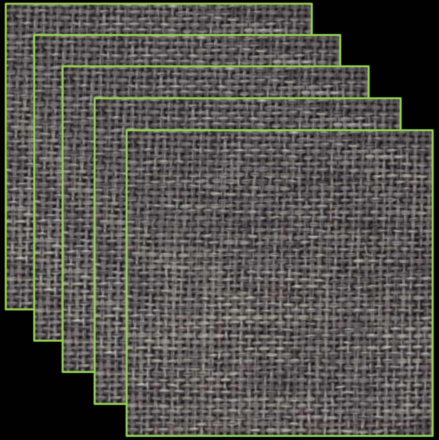
(3, 224, 224)



Pretrained Resnet-50 model



(2048)



(100, 3, 224, 224)

Memory Bank

	1	2	…	2048
1				
2				
…				
100				

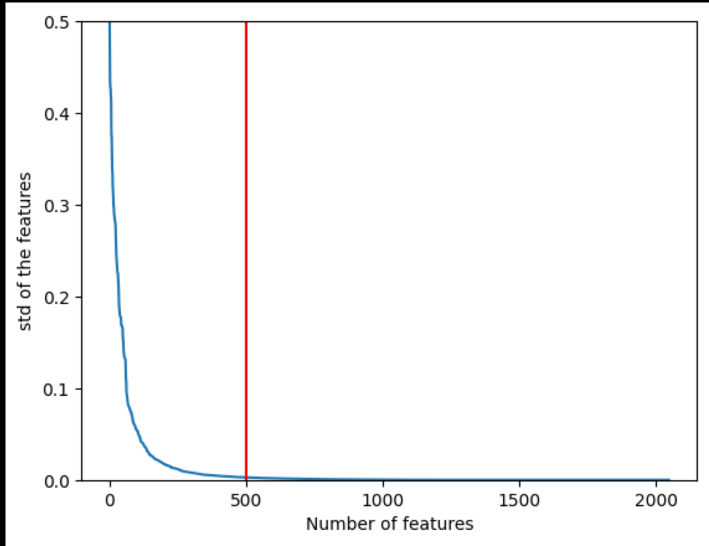
(100, 2048)

	1	2	…	2048
1				
2				
…				
100				
std	σ_1	σ_2	…	σ_{2048}

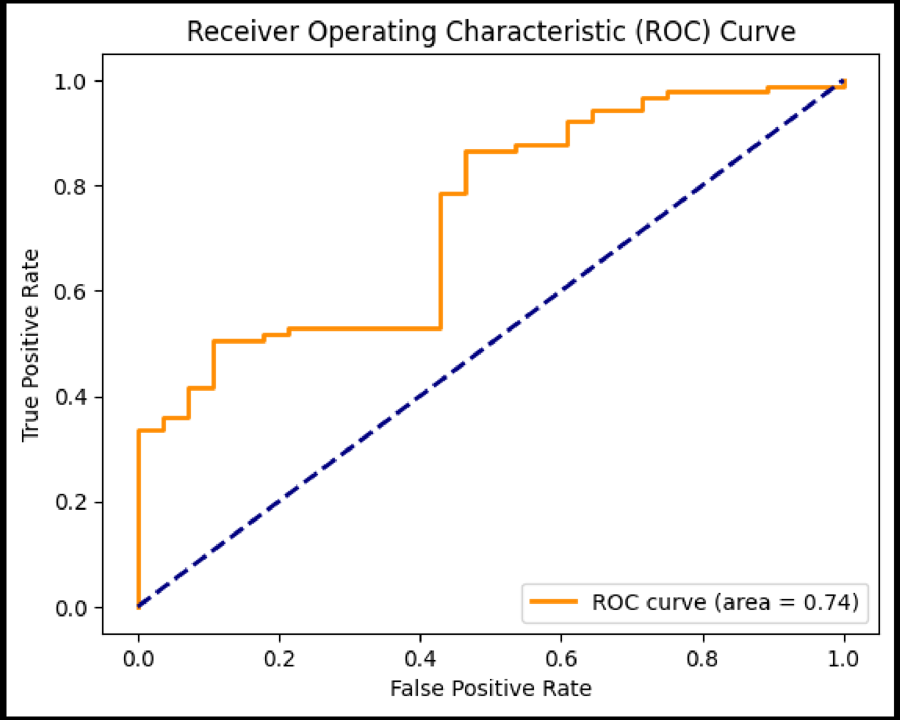
Memory Bank

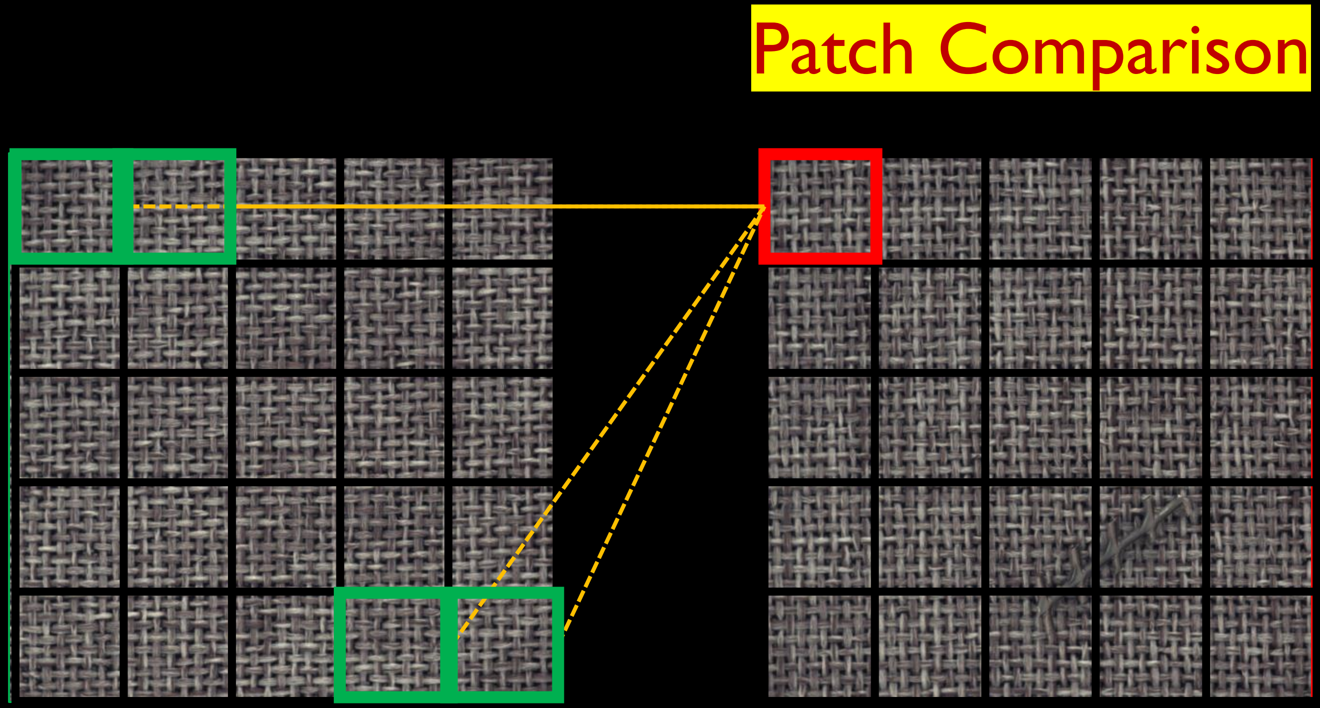
	1	2	…	500
1				
2				
…				
100				

Select 500 columns having high variance

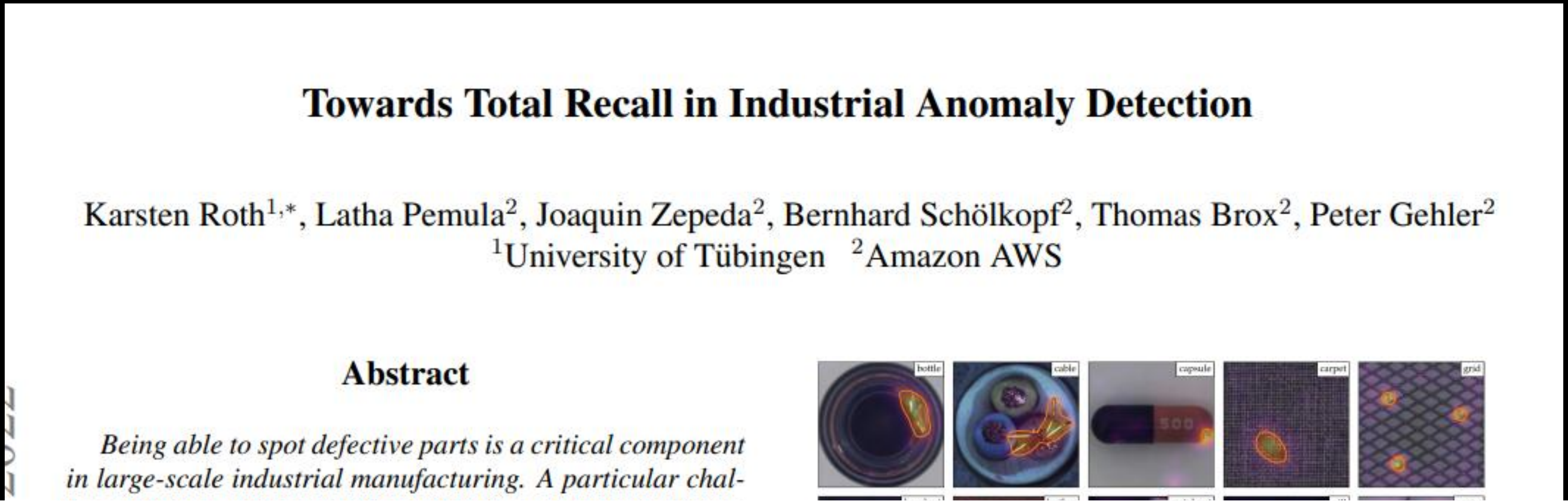


But The results are not very good





Part -2 of PatchCore explanation`



Towards Total Recall in Industrial Anomaly Detection

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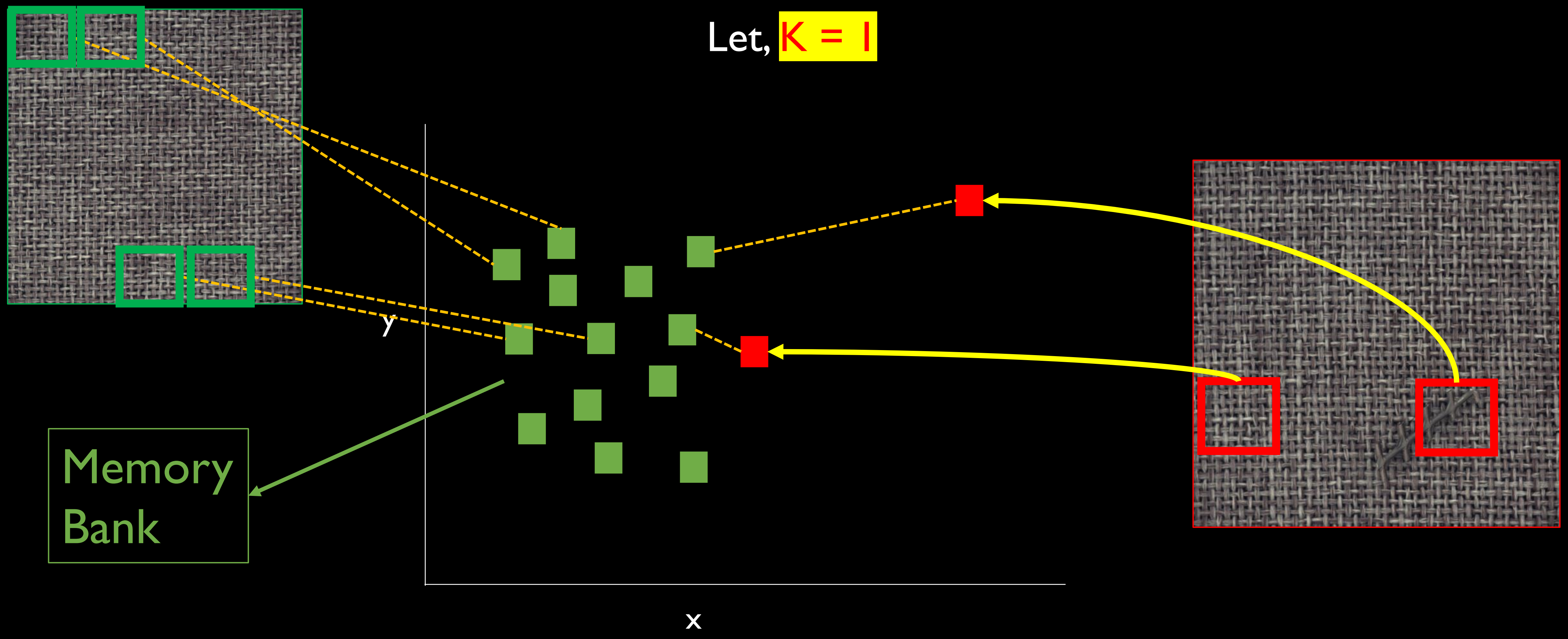
Abstract

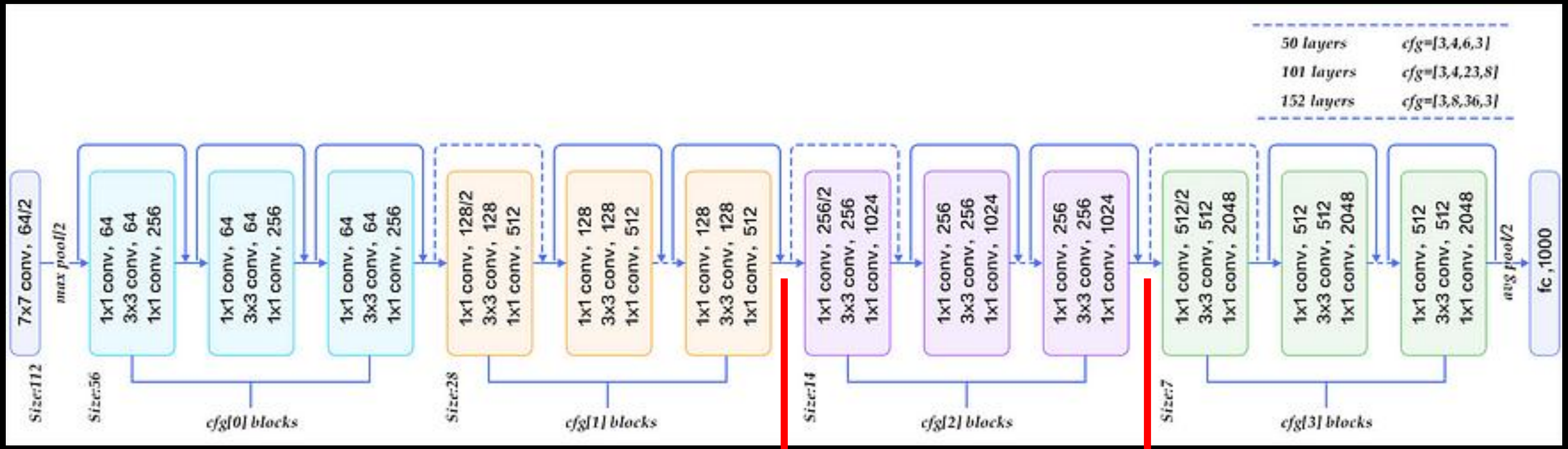
Being able to spot defective parts is a critical component in large-scale industrial manufacturing. A particular chal-

K nearest neighbours for anomaly detection

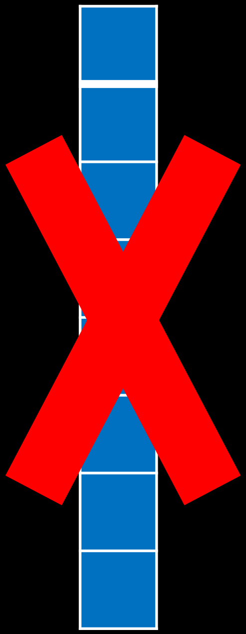
Let, K = 1



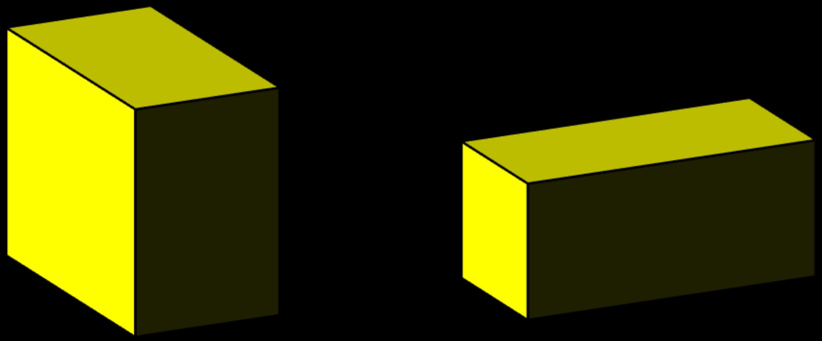
Normal



Pretrained resnet 50 model

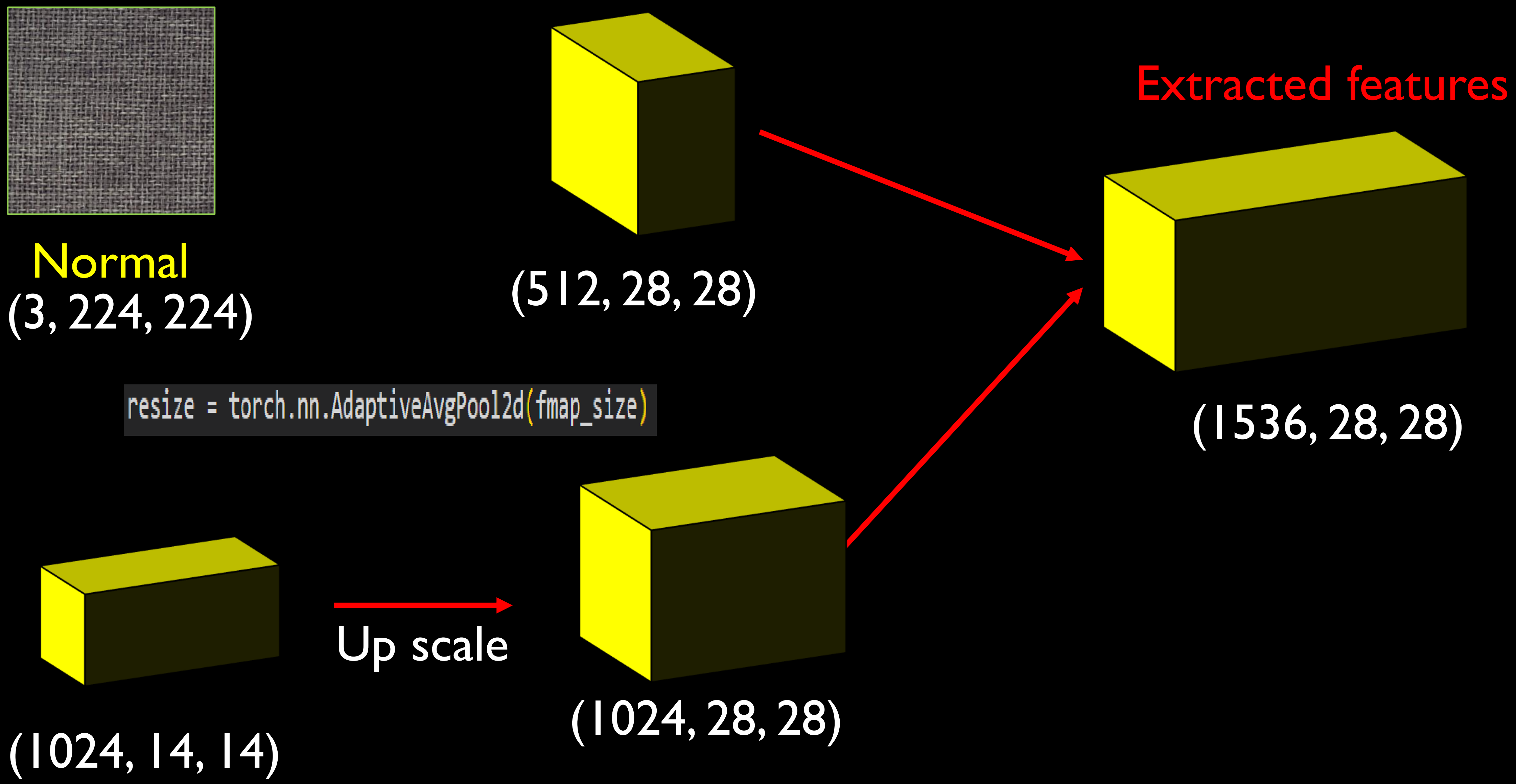


(2048)

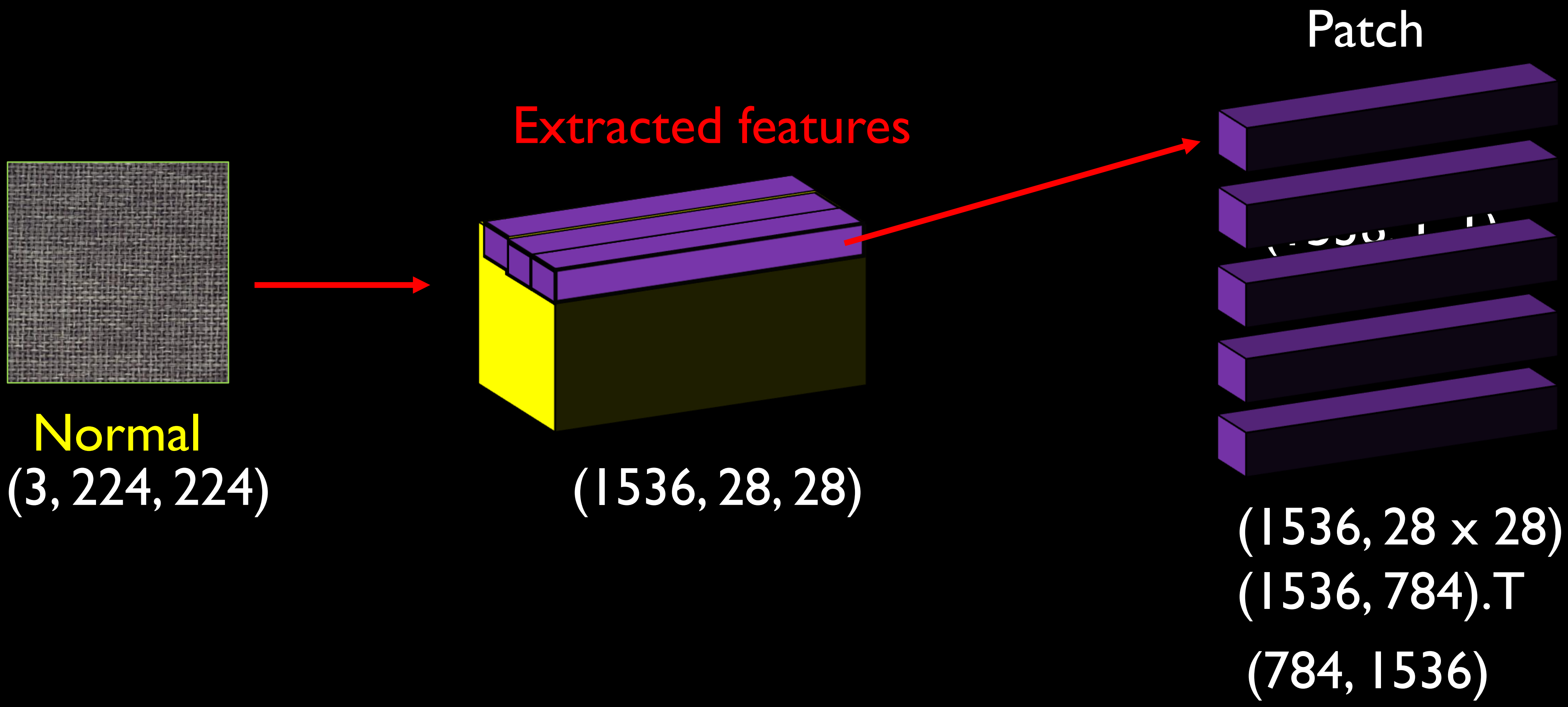


(512, 28, 28) (1024, 14, 14)

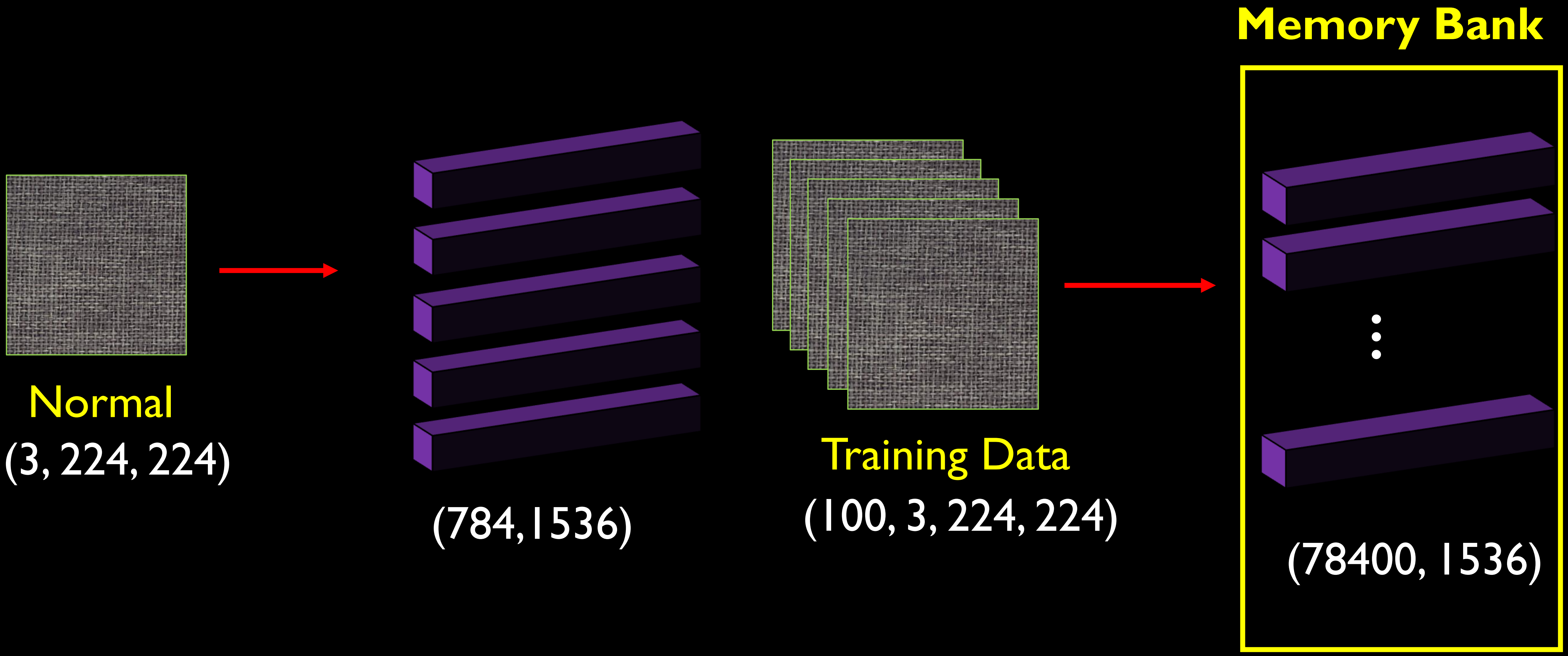
How to aggregate the features



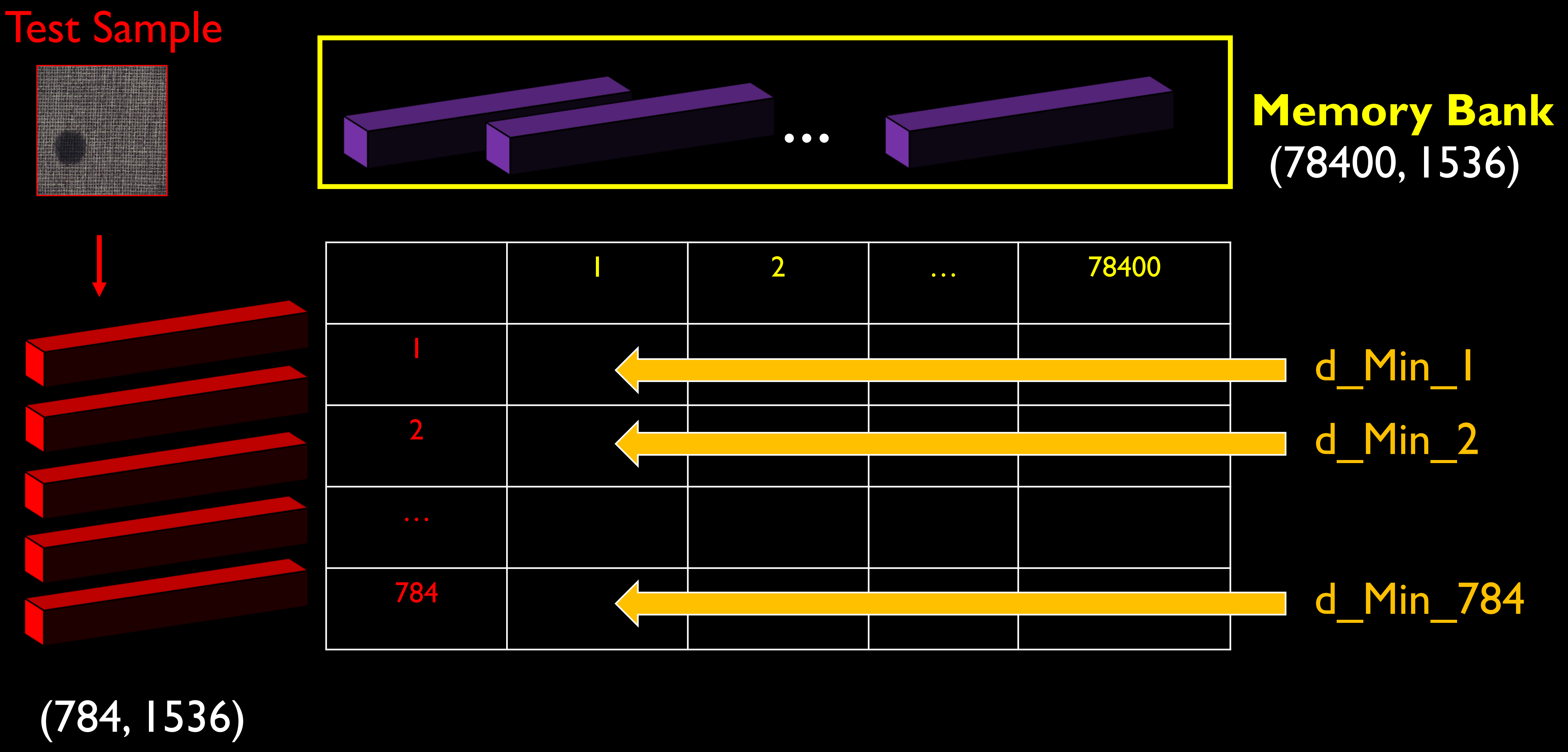
Patch Features



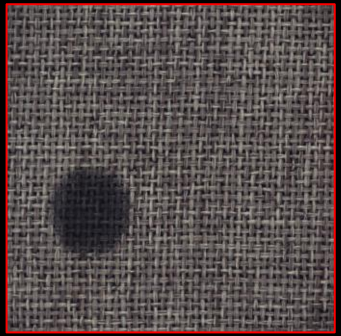
Memory Bank of Patches



Anomaly Detection with Memory Bank



Test Sample



Distance_score

d_Min_1

d_Min_2

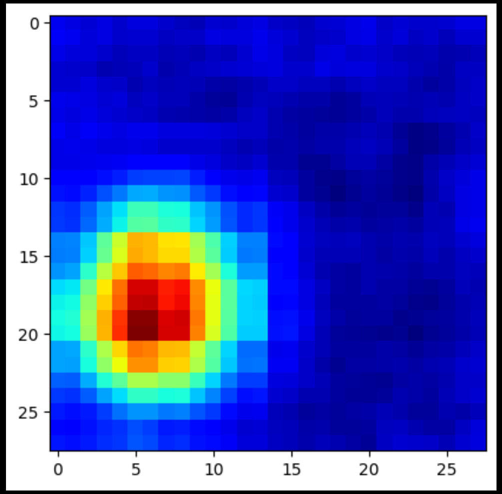
⋮

d_Min_784

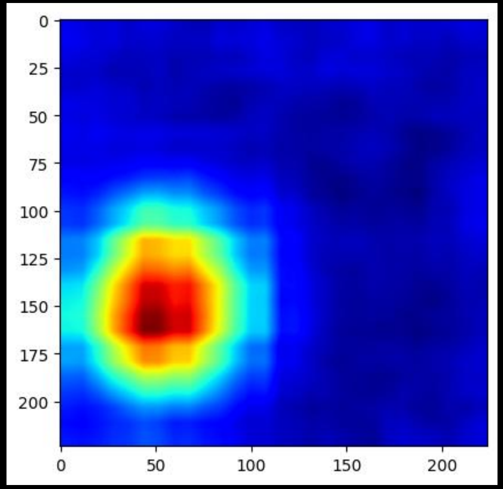
Max

Anomaly Score (s_star)

Reshape



(28 x 28)



(224 x 224)