Abstract

Deep anomaly detection (AD) aims to provide robust and efficient classifiers for one-class and unbalanced settings. However, current AD models still struggle on edge-case normal samples and are often unable to keep high performance over different scales of anomalies. Moreover, there currently does not exist a unified framework efficiently covering both one-class and unbalanced learnings. In the light of these limitations, we introduce a new two-stage anomaly detector which memorizes during training multi-scale normal prototypes to compute an anomaly deviation score. First, we simultaneously learn representations and memory modules on multiple scales using a novel memory-augmented contrastive learning. Then, we train an anomaly distance detector on the spatial deviation maps between prototypes and observations. Our model highly improves the state-of-the-art performance on a wide range of object, style, and local anomalies with up to 50% error relative improvement on CIFAR-100. It is also the first model to keep high performance across the one-class and unbalanced settings.

1. Introduction

Detecting observations straying apart from a well defined normal baseline consistently lies at the center of many modern machine learning challenges. Given the complexity of the anomalous class and the high cost of obtaining labeled anomalies, this task of anomaly detection differs quite a lot from classical binary classification. This accordingly gave birth to many deep anomaly detection (AD) methods producing more stable results given an extremely unbalanced training dataset. Deep AD has been successful in various applications such as in fraud detection [18], medical imaging [51], video surveillance [16] or defect detection [48].

However, existing anomaly detection models still present some limitations. (1) There is a hard trade-off between remembering edge-case normal samples and remaining generalizable enough toward anomalies. This lack of normal sample memorization often leads to high false reject rates on harder samples. (2) These models tend to focus on either local low-scale anomalies or global object oriented anomalies but fail to combine both. Current models often remain highly dataset-dependent and do not explicitly use multi-scaling. (3) AD lacks an efficient unified framework which could easily tackle one-class (OC) and semi-supervised (SS) detection. Indeed, existing methods are either introduced as one-class or semi-supervised detectors, with different specialized approaches and set of hyper-parameters.

In the light of these limitations, we introduce in this paper a novel two-stage AD model named AnoMem which memorizes during training multi-scale normal class prototypes to compute an anomaly deviation score at several scales. Unlike previous memory bank equipped methods [21, 42], our normal memory layers cover the normal class at multiple scales and not only improve anomaly detection but also the quality of the learned representations. Additionally, by using the modern Hopfield layers for memorization, our method is much more efficient than nearest neighbor anomaly detectors [4, 23]. These detectors require keeping the whole normal set, while ours can learn the most representative samples with a fixed size. Through extensive experiments, we demonstrate that our method significantly outperforms all previous anomaly detectors using memory.

Our main contributions in this paper are the following:

- We propose to integrate memory modules into contrastive learning to remember normal class prototypes during training. In the first stage, we simultaneously learn representations using contrastive learning and memory modules, allowing for effective normal sample memorization. In the second stage, we learn to detect anomalies using the memorized prototypes. When additional anom-
lous samples are available, we train an anomaly distance detector on the spatial deviation maps between prototypes and observations. To our best knowledge, AnoMem is the first working well in both OC and SS settings with a few anomalies, making it unifying method.

- AnoMem is further improved by using multi-scale normal prototypes in both representation learning and AD stage. We introduce a novel way to efficiently memorize 2D features maps spatially. This enables our model to accurately detect low-scale, texture-oriented anomalies and higher-scale, object-oriented anomalies (multi-scale AD).
- We validate the efficiency of our method and compare it with Sota methods on one-vs-all, out-of-distribution (OoD) and face anti-spoofing detection. We improve detection with up to 50% error relative improvement on object anomalies and 14% on face anti-spoofing.

2. Related work

2.1. Memory modules

A memory module should achieve two main operations: (i) writing inside a memory from a given set of samples (remembering) and (ii) recovering from a partial or corrupted input the most similar sample in its memory with minimal error (recalling). Most of the time, memory modules will differ on the amount of images they can memorize given a model size and the average reconstruction error.

A simple memory module is the nearest neighbor queue. Given a maximum size $M$, it stores the last $M$ samples representations in the queue. To remember an incomplete input $x$, it retrieves the nearest neighbor from the queue.

A more effective memory module is the modern Hopfield layer [44]. It represents the memory as a learnable matrix of weights $X \in \mathbb{R}^{d \times N_{Mem}}$ and retrieves samples by recursively applying the following formula until convergence:

$$\xi^{t+1} = \text{softmax}(\beta \xi^t X^T) X^T$$

where $\xi^{(0)}$ is the query vector and $\beta$ is the inverse temperature. Its form is similar to the attention mechanism in transformers, except it reapplies the self-attention until convergence. This layer has a very high memory capacity and remember samples with very low redundancy [44]. Subsequently, we call this layer a Hopfield layer of size $N_{Mem}$.

2.2. Anomaly detection (AD)

AD is a binary classification problem where the normal class is usually well-defined as being sampled from a distribution $p_{norm}$, whereas the anomaly class is implicitly defined as anything not normal. The anomaly class is significantly broader and more complex than the normal class, creating a natural imbalance between the required amount of normal data and anomalous data. We call semi-supervised AD (SSAD) the setting where a small additional set of anomalies $X_{anom}$ is available. In one-class AD (OC-AD), only normal samples $X_{norm}$ are used for training.

There exist several families of approaches for OC-AD. Pretext task methods learn to solve on the normal data an auxiliary task [5, 27–29], different from AD task. The inferred anomaly score describes how well the auxiliary task is performed on the input. Similarly, two-stage methods consist of a representation learning step and an anomaly score estimation step. After learning an encoder on normal data using self-supervised learning [8, 11, 57, 64] or an encoder pre-trained on massive additional datasets [45, 46, 61], the anomaly score is computed with a simple OC classifier on the latent space [35, 54, 55]. The methods [4, 23] have used a nearest neighbor queue to fetch the closest prototypical normal samples inside the latent space. The mean $L_2$ distance to these samples is then used as the anomaly score.

Density estimation methods tackle the estimation of the distribution $p_{norm}$ by using deep high-dimensional density estimators such as normalizing-flows [34], likelihood ratio methods [47], variational models [14] or more recently diffusion models [40, 60]. Reconstruction methods measure the reconstruction error of a bottleneck encoder-decoder, trained using denoising autoencoders [43, 52] or two-way GANs [1, 2, 37, 58]. Some works used memory in the latent space of an auto-encoder [21, 42] for AD. During training the latent memory weights are learned to achieve optimal reconstruction on the normal class. Then, the reconstruction is performed from the memory closest fetched latent vector. More recently, knowledge distillation methods have been adapted to AD by using the representation discrepancy of anomalies in the teacher-student model [12, 15].

SSAD mainly revolves around two-stage methods and anomaly distance methods. We note however that some recent work has tried to generalize pretext task to SSAD [29]. In the SSAD two-stage methods, a supervised classifier with the anomalous samples is trained in the second stage instead of the aforementioned one-class estimator [24]. Distance methods directly use a distance to a centroid as the anomaly score and learn the model to maximize the anomaly distance on anomalous samples and minimize it on normal samples [30, 49]. To the best of our knowledge, no SSAD methods in the literature use any kind of memory mechanism for the anomaly score computation.

We also note that there is a closely related task of anomaly localization (AL), which goal is to produce an anomaly heatmap. AL datasets range from defect localization [6] to surveillance video abnormal event detection [39]. Specialized methods targeting localization [35, 62] have been introduced to efficiently solve this task.

2.3. Contrastive learning

Contrastive learning is a self-supervised representation learning method. It operates on the basis of two principles:
(1) two different images should yield dissimilar representations, and (2) two different views of the same image should yield similar representations. The views of an image are characterized by a set of transformations $\mathcal{T}$. There have been many methods enforcing these two principles: SimCLR [9], Barlow-Twins [64] and VICReg [3] with a siamese network, MoCo [25] with a negative sample bank, BYOL [22] and SimSiam [10] with a teacher-student network or SwAV [7] with contrastive clusters. While some contrastive methods such as SimCLR and MoCo require negatives samples, other such as BYOL, SimSiam and SwAV do not.

In the simplest formulation, the pairs of representations to contrast are only considered from two views of a batch augmented by transformations $(t, t')$. In SimCLR, the following loss is minimized on those two batches:

$$L_{CO} = \frac{1}{2B} \sum_{k=1}^{B} \ell_{NTX}(z_k, z'_k) + \ell_{NTX}(z'_k, z_k)$$

where $z, z'$ are the last features of the two augmented batches and $\ell_{NTX}$ is the Normalized Temperature-scaled Cross Entropy Loss (NT-Xent). In practice, minimizing $L_{CO}$ will yield representations with the most angular spread variance, while retaining angular invariance in regards to $\mathcal{T}$.

Memory mechanisms can also be used into contrastive learning as proposed in [17,32]. During training, the positive and negative pairs are augmented with the samples nearest neighbors from a memory queue. This allows the method to reach better performance for smaller batch sizes.

3. Proposed method

Sec.3.1 first details a novel training procedure to simultaneously learn an encoder representations and a set of multi-scale normal class prototypes. Sec. 3.2 then presents how to use the encoder and the normal prototypes to train a one-class or unbalanced anomaly detector in a unified framework. Our model training is fully summarized in Fig. 2.

Notation. Let $\mathcal{X} = \{(x_k, y_k)\}_{k}$ be a training dataset made of normal samples ($y_k = 1$) and potentially of anomalies ($y_k = 0$). We use a backbone network $f: \mathbb{R}^{H \times W \times C} \rightarrow \mathbb{R}^D$ composed of several stages $f^{(1)}, \ldots, f^{(S)}$ such that the dimensions of the $s^{th}$ scale feature map are $H^{(s)} \times W^{(s)} \times C^{(s)}$. We note $z^{(s)} = f^{(s)} \circ \cdots \circ f^{(1)}(x)$.

3.1. Memorizing normal class prototypes

In this section, we first introduce how memory modules can be used in the contrastive learning scheme to provide robust and representative normal class prototypes. Then we generalize our idea to several scales throughout the encoder.

Foremost, we choose to apply a contrastive learning type method rather than other unsupervised learning schemes, as it produces better representations with very few labeled data [13]. We also favor self-supervised learning on the normal data rather than using a pre-trained encoder on generic datasets which often performs poorly on data with a significant distribution shift. In order to learn unsupervised representations and a set of normal prototypes, we could sequentially apply contrastive learning then perform k-means clusterisation and use the cluster centroids as the normal prototypes. However this approach has two main flaws. First, the representation learning step and the construction of prototypes are completely separated. Indeed, it has been shown in several contrastive learning methods [7,17] that the inclusion of a few representative samples in the negative examples can significantly improve the representation quality, and alleviate the need for large batches. Moreover, the resulting k-means prototypes do not often cover atypi-
regularization loss which ensures that the variance of the learned representations is low. We explicitly introduce the anomalous and normal labels in the multi-view batch, where \( p \) covers any representation inside the multi-view batch, \( \tau \) is a temperature hyper-parameter and \( \cos(\cdot, \cdot) \) is the cosine similarity. In contrast with existing two-stage AD methods, we explicitly introduce the anomalous and normal labels from the very first step of representation learning.

### Variance loss as regularization

Our procedure can be prone to representation collapse during the first epochs. Indeed, we observed that the dynamic contrastive loss and the randomly initialized memory layer can occasionally lead to a collapse of all prototypes to a single point during the first epochs. To prevent this, we introduce an additional regularization loss which ensures the variance of the retrieved memory samples does not reach zero:

\[
\mathcal{L}_V(z, y) = -\frac{1}{\sum_k y_k} \sum_{k=1}^B y_k \sqrt{\text{Var}[\text{Mem}(z_k, y_k)]}
\]

### Multi-scale contrasted memory

To gather information from several scales, we apply our contrasted memory loss not only to the flattened 1D output \( z \) of our encoder but also to \( S \) intermediate layer 3D feature maps \( z^{(1)}, \ldots, z^{(S)} \).

We add after each scale representation \( z^{(s)} \) a memory layer \( \text{HF}^{(s)} \) to effectively capture multi-scale normal prototypes. However, memorizing the full 3D map as a single flattened vector would not be ideal. Indeed, at lower scales we are interested in memorizing local patterns regardless of their position. Moreover, the memory would span across a space of very high dimensions. Therefore, 3D intermediate maps are viewed as a collection of \( H^{(s)}W^{(s)} \) 1D feature vectors \( z_{ij}^{(s)} \) rather than a single flattened 1D vector. This is equivalent to remembering the image as patches.

Since earlier features map will have a high resolution, the computational cost and memory usage of such approach can quickly explode. Thus, we only apply our contrasted memory loss on a random sample with ratio \( \mu^{(s)} \) of the available vectors on the \( s \)th scale.

Our multi-scale contrasted memory loss becomes

\[
\mathcal{L}_{\text{COM-MS}} = \frac{1}{S} \sum_{s=1}^S \sum_{i,j \in \Omega^{(s)}} \lambda^{(s)} \left[ \lambda_V \mathcal{L}_V(z_{ij}^{(s)}, y) + \lambda^{(s)} \mathcal{L}_{\text{COM}}(z_{ij}^{(s)}, z_{ij}^{(s)}, y) \right]
\]

where \( \lambda_V \) controls the impact of the variance loss, \( \lambda^{(s)} \) controls the importance of the \( s \)th scale, and \( \Omega^{(s)} \) is a random sample without replacement of \( [H^{(s)}W^{(s)}] \) points from \([1, H^{(s)}] \times [1, W^{(s)}] \). We choose to put more confidence on the latest stages which are more semantically meaningful than earlier scales, meaning that \( \lambda^{(1)} < \cdots < \lambda^{(S)} \).

We simultaneously minimize this loss on all of the encoder stages and the memory layers’ weights. An overview of this first stage is given in Fig. 2a, and its algorithm is presented in Alg. 1. Compared to previous memory bank equipped anomaly detectors [4, 21, 23, 42], our model is the first to memorize the normal class at several scales allowing it to be more robust to anomalous sizes. Moreover, the use of normal memory does not only improve anomaly detection but also the quality of the learned representations, as will be discussed in Sec. 4.4.
3.2. Multi-scale normal prototype deviation

In this second step of training, our goal is to compute an anomaly score given the pre-trained encoder \( f \) and the multi-scale normal memory layers \( HF^{(1)}, \ldots, HF^{(5)} \).

For each scale \( s \), we consider the difference \( \Delta^{(s)} \) between the encoder feature map \( z^{(s)} \) and its recollection from the \( s \)th memory layer. The recollection process consists in spatially applying the memory layer to each \( C^{(s)} \) depth 1D vector:

\[
\Delta^{(s)} = z^{(s)} - HF^{(s)}(z^{(s)})
\]

where \((HF(z))_{i,j} = HF(z_{i,j})\).

One-class AD. In this case, we use the \( L_2 \) norm of the difference map as an anomaly score for each scale and no further training is required:

\[
s_a^{(s)}(x) = \|\Delta^{(s)}\|_2
\]

Semi-supervised AD. We use the additional labeled data to train \( S \) scale-specific classifiers on the difference map \( \Delta^{(s)} \). Each classifier is first composed of an average pooling layer \( \phi \) followed by a two-layer MLP \( g^{(s)} \) with a single scalar output. \( \phi \) reduces the spatial resolution of \( \Delta^{(s)} \), to prevent using very large layers on earlier scales. The output of \( g^{(s)} \) directly corresponds to the \( s \)th scale anomaly distance:

\[
s_a^{(s)}(x) = g^{(s)} \circ \phi(\Delta^{(s)})
\]

Each scale-specific classifier is trained using the intermediate features of the same normal and anomalous samples used during the first step along their labels. The training procedure is similar to other distance-based anomaly detectors [30, 49] where the objective is to obtain small distances for normal samples while keeping high distances on anomalies. We note that our model is the first to introduce memory prototypes learned during representation learning into the anomaly distance learning. The distance constraint is enforced via a double-hinge distance loss:

\[
\ell_{\text{dist}}(d,y) = y \cdot \max\left(d - 1 - \frac{1}{M}, 0\right) + (1-y) \cdot \max\left(M - d, 0\right)
\]

where \( d \) is the anomaly distance for a given sample, and \( M \) controls the size of the margin around the unit ball frontier. Using this loss, both normal samples and anomalous features will be correctly separated without encouraging anomalous features to be pushed toward infinity. Our second stage supervised loss is the following

\[
L_{\text{SUP}} = \frac{1}{S \cdot B} \sum_{k=1}^{B} \sum_{s=1}^{S} \ell_{\text{dist}}(g^{(s)} \circ \phi(\Delta^{(s)}), y_k)
\]

Finally, all scale anomaly scores are merged using a sum weighted by the confidence parameters \( \lambda^{(s)} \):

\[
s_a(x) = \frac{1}{\sum_{s} \lambda^{(s)}} \sum_{s} \lambda^{(s)} \cdot s_a^{(s)}(x)
\]
Table 1: Comparison with SoTA methods over several datasets using the AUC in the one-vs-all protocol. The three blocks respectively contain one-class, semi-supervised and methods usable in both settings. AnoMem is the best performing unified model. Underline indicates the overall best result, bold indicates the best semi-supervised method (We re-evaluated Elsa, DP-VAE, SSAD, GOAD and ARNet on CIFAR100 and CUB-200).

| Models \ $\gamma$ | AUROC (%) | CUB-200 | CIFAR-10 | CIFAR-100 |
|-------------------|-----------|---------|----------|-----------|
|                   | 0. 0.01 0.05 0.10 | 0. 0.01 0.05 0.10 | 0. 0.01 0.05 0.10 |
| MemAE [21]        | 59.6      | 60.9    | 57.4     |
| OC-SVM [53]       | 76.3      | 64.7    | 62.6     |
| PIAD [58]         | 63.5      | 79.9    | 78.8     |
| GOAD [5]          | 66.6      | 88.2    | 74.5     |
| MHIRot [27]       | 77.6      | 89.5    | 83.6     |
| Reverse Distillation [15] | -         | 86.5    | -        |
| SSD [54]          | -         | 90.0    | 85.1     |
| CSI [57]          | 52.4      | 94.3    | 85.8     |
| Supervised        | 53.1      | 58.6    | 62.4     |
| SS-DGM [31]       | -         | -       | -        |
| Elsa [24]         | 77.8      | 81.3    | 82.9     |
| DeepSAD [49]      | 53.9      | 62.7    | 63.4     |
| DP-VAE [14]       | 61.7      | 65.4    | 67.2     |
| AnoMem (ours)     | 81.4      | 84.1    | 85.3     |

4.3. Comparison to the state-of-the-art

4.3.1 One-vs-all

This section compares AnoMem with SoTA AD methods on the one-vs-all protocol, in the one-class setting and the semi-supervised setting when possible.

Considered one-class methods are hybrid models [53], reconstruction error generative model [58], the knowledge distillation method [18], pretext tasks methods [5, 27], and the two-stage method [57]. We also consider semi-supervised methods such as density estimation methods [31], and two-stage AD [24]. To further show the disadvantages of classical binary classification, we also include a classical deep classifier trained with batch balancing between normal samples and anomalies. Lastly, unified methods usable in both one-class and semi-supervised learning are included with the reconstruction error model [14], and direct anomaly distance models [49]. For a fair comparison in the same conditions, we take the existing implementations or re-implement and evaluate ourselves all one-class methods, except [5, 19, 57]. The results are presented in Tab. 1.

First of all, we can notice the classical supervised approach falls far behind anomaly detectors on all datasets. This highlights the importance of specialized AD models, as classical models are likely to overfit on anomalies.

Furthermore, AnoMem overall performs significantly better than all considered detectors on various datasets with up to 62% relative error improvement on CIFAR-10 and $\gamma = 0.01$. Although performance greatly increases with more anomalous data, it remains highly competitive with only normal samples. In the OC setting, AnoMem outperforms all methods specialized for OC including pretext
task methods, reconstruction error methods and by far hybrid methods. The usage of memory in AnoMem is much more efficient than the memory for reconstruction used in MemAE. Indeed, while we learn the memory through contrastive learning, MemAE and others [21, 42] learned it via the pixel-wise reconstruction loss. Their normal prototypes are much more constrained and therefore less semantically rich and generalizable. For SSAD, AnoMem reduces SoTA error gap on nearly all anomalous data ratio. Its multi-scale anomaly detectors allow capturing more fine-grained anomalies as we can see in the CUB-200 results.

Finally, AnoMem performs very well in both OC and SSAD while other unified methods generally fail in the OC setting. In this regard, AnoMem is to the best of our knowledge the first efficient unified anomaly detector. We also note that the change from OCAD to SSAD in our model was done with minimal hyperparameter tuning. This is due to the first training step being shared between OC and SS settings.

4.3.2 Out-of-Distribution (OoD) detection

In Tab. 2, we compare AnoMem to SoTA models with CIFAR-10 as ID dataset and OoD datasets SVHN, LSUN and CIFAR-100. Our model keeps among the best performance with a relative error improvement of 37% with the second best performing method on the challenging CIFAR-10 vs CIFAR-100. AnoMem performs similarly well as the SoTA baseline CSI [57], however the latter mainly relies during inference on keeping in memory the entire training set features. This results in a very high memory footprint on huge training sets, while our model ingeniously learns a fixed size memory. Moreover, CSI often performs poorly on datasets with a few training normal samples as can be seen on one-vs-all CUB-200 (50 images per class) results.

It is also worth noting that algorithms in [36, 46] obtain higher performance on this task, however, they rely on models pretrained on an additional large-scale dataset such as ImageNet-21K [50]. Therefore, comparing directly those methods to AnoMem, being trained from scratch on a smaller dataset, is not fair as there is an overlap in nature of the pre-training samples used in [36] and anomalous samples to be detected.

Finally, we note that in this protocol the normal class is composed of several sub-classes. This shows the ability of our memory modules to cover multi-modal normal cues.

4.3.3 Face presentation attack detection (FPAD)

Tab. 3 compares our model on the FPAD intra-dataset cross-type protocol with SoTA methods presented in Sec. 4.3.1. Without any further tuning for face data, our method improves FPAD performance on WMCA with an error relative improvements of up to 14% on paper prints. It outperforms existing anomaly detectors on all unseen attack type, including the OC setting. We can also notice that it reduces the error gap between coarse attacks (PM, FM) and harder fine-grained attacks (PP, SR) thanks to its multi-scale AD.

4.4. Ablation study

In this section we study the impact of the multi-scale memory layers in the two training stages and show they are essential to our model performance.

First, we evaluate using linear evaluation on CIFAR-10 and CIFAR-100 how the memory affects the contrastive learning of the encoder representations. As we can see in Tab. 4(a), the inclusion of the memory layers on the first branch drastically improves the quality of the encoder representations. We hypothesis that, as shown in [17], the inclusion of prototypical samples in one of the branch allows to contrast positive images against representative negatives. This alleviates the need for large batch size, and highly reduces the multi-scale contrastive learning memory usage.

To support the importance of memory during AD, we compare the performance of the anomaly detector with k-means centroids or with the normal prototypes learned during the first stage. In the first case, we train the anomaly detectors with the same procedure but instead of fetching the Hopfield layer output we use the closest k-means centroid. The results on CIFAR datasets are presented in Tab. 4(b).
4.6. Spatial sampling ratios

Sampling ratios \( r \) are introduced during the first step in order to reduce the amount of patterns considered in the contrastive loss, and consequently the similarity matrix size. In low scales, we can expect nearby samples to be quite similar. Therefore, it is not as detrimental to the training to skip some of the available patterns.

To guide our choice of sampling ratio, we measure our anomaly detection AUC with various sampling ratio and anomalous data ratio \( \gamma \). Since the last scale feature maps are spatially very small, we only vary the first scale ratio \( r(1) \) and set \( r(2) = 1 \). The batch size if fixed throughout the experiments. The results are displayed in Sec. 4.6. We can see that low sampling ratios (\( \gamma < 0.3 \)) significantly decrease the AD performance. However the gain in performance for higher ratios is generally not worth the additional computational cost: by more than doubling the amount of sampled patterns, we only increase the relative AUC by 2%.

![Figure 3: Memory experiments on CIFAR-10.](image)

![Figure 4: Sampling ratio experiments on CIFAR-10.](image)

5. Conclusion and future work

In this paper, we present a new two-stage anomaly detection model which memorizes normal class prototypes in order to compute an anomaly deviation score. By introducing normal memory layers in a contrastive learning setting, we can first jointly learn the encoder representations and a set of normal prototypes. This improves the quality of the learned representations, and allows a strong memorization of normal samples. The normal prototypes are then used to train a simple detector in a unified framework for one-class or semi-supervised AD. Furthermore, we extend these prototypes to several scales making our model more robust to different anomaly sizes. Finally, we assess its performance on a wide array of dataset containing object, style and local anomalies. AnoMem greatly outperforms SoTA performance on all datasets and different anomalous data regimes.

For future work, we could explore the use of multi-scale anomaly score for anomaly localization. Indeed, in the one-class setting of our model we could merge the several scale anomaly maps into a single heatmap.
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