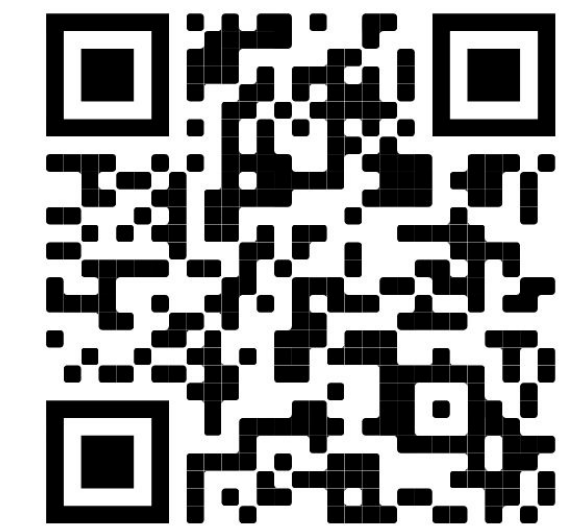




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# Generating Natural Images with Direct Patch Distributions Matching

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Code & Live demo



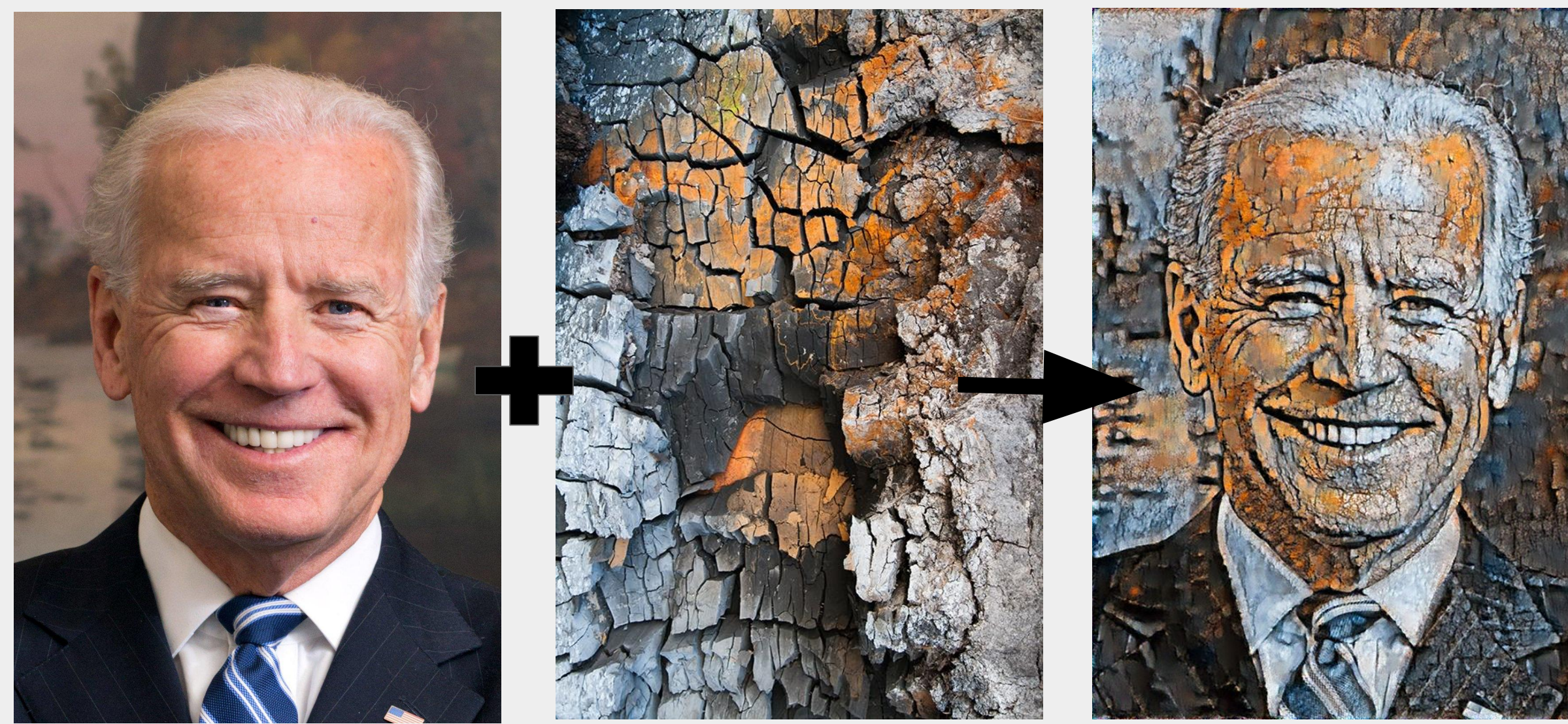
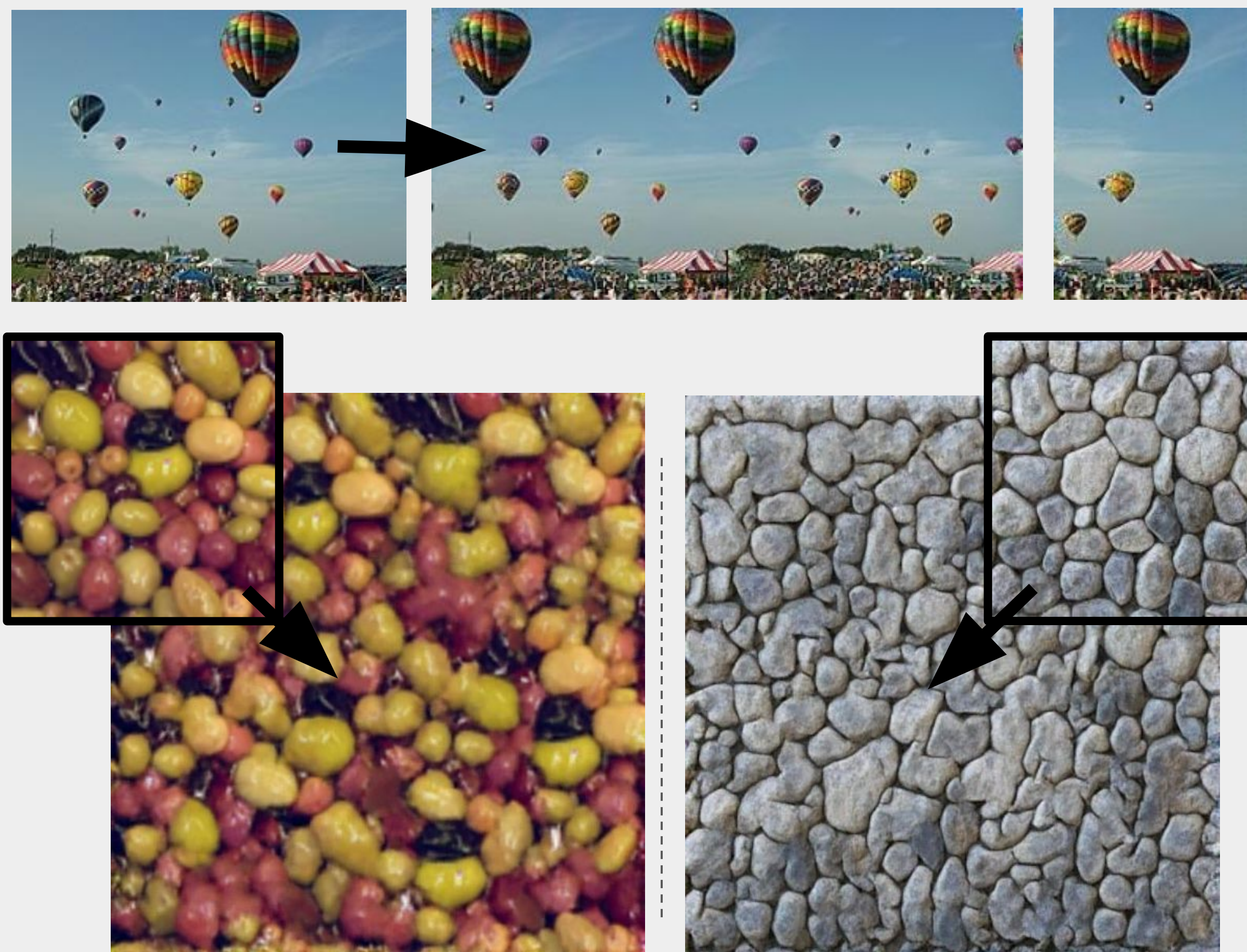
## Overview

### Abstract

By efficiently matching the distribution of patches between images we can solve a broad spectrum of single-image generative tasks without training a per-image GAN or computing patch nearest neighbors.

### Single image generative models

In a wide variety of tasks a model needs to capture the statistics of a single reference image in order to resample or manipulate it.



## References

- Simakov, Denis, et al. "Summarizing visual data using bidirectional similarity." *2008 IEEE Conference on Computer Vision and Pattern Recognition*. IEEE, 2008.
- Shaham, Tamar Rott, Tali Dekel, and Tomer Michaeli. "Singan: Learning a generative model from a single natural image." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.
- Granot, Niv, et al. "Drop the gan: In defense of patches nearest neighbors as single image generative models." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.

## Method

### Patch distribution matching:

Many single image generative models try to match the patch distribution of a reference image using objectives like the Bidirectional similarity or patch-discriminators.

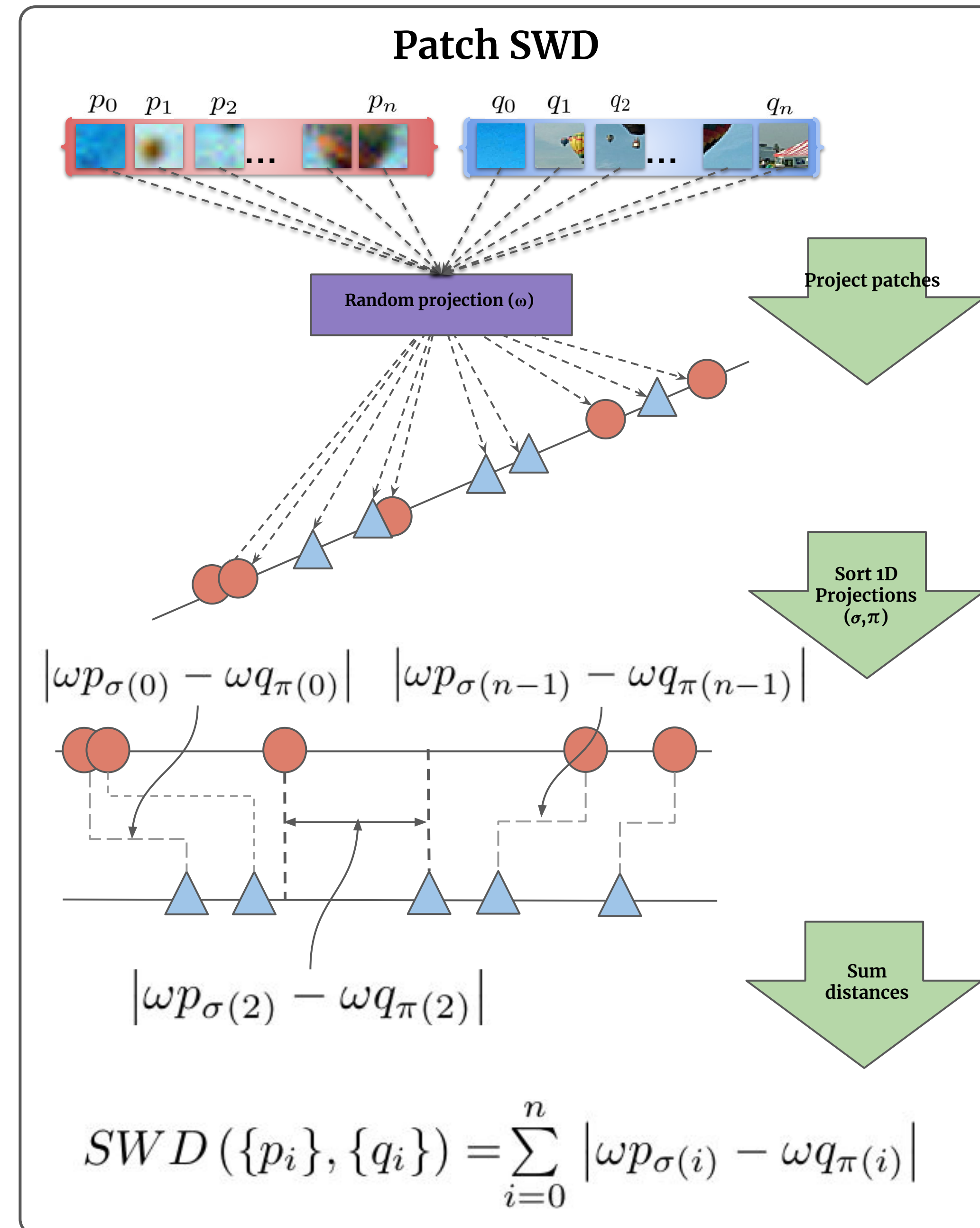
We use efficiently compute the SWD between patches using 2d convolutions:

**Algorithm 1** GPDM.  
**Input:** Target image  $x$ , initial guess  $\hat{y}$ , learning rate  $\beta$   
**Output:** Optimized image  $y$

```

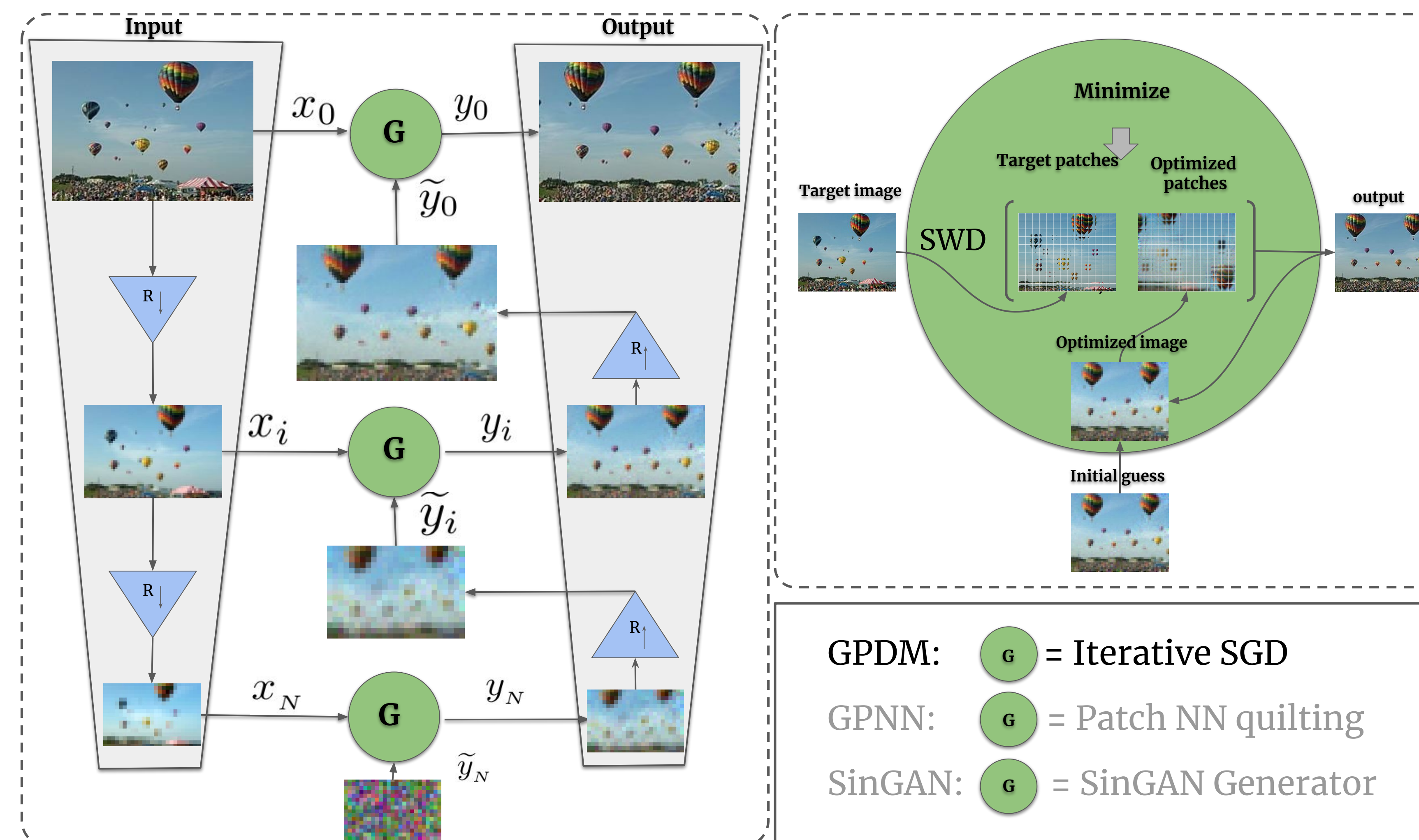
1:  $y \leftarrow \hat{y}$ 
2: while not converged do
3:    $L \leftarrow 0$ 
4:   for  $i=1, k$  do
5:      $\omega \sim N(0, \sigma I)$ 
6:      $\omega \leftarrow \text{unflat}(\frac{\omega}{\|\omega\|})$ 
7:      $p \leftarrow \text{flat}(\text{conv2d}(x, \omega))$ 
8:      $q \leftarrow \text{flat}(\text{conv2d}(y, \omega))$ 
9:      $L \leftarrow L + \frac{1}{k} |\text{sort}(p) - \text{sort}(q)|$ 
10:  end for
11:   $y \leftarrow y - \beta \nabla_y L$ 
12: end while

```



### Synthesis proces:

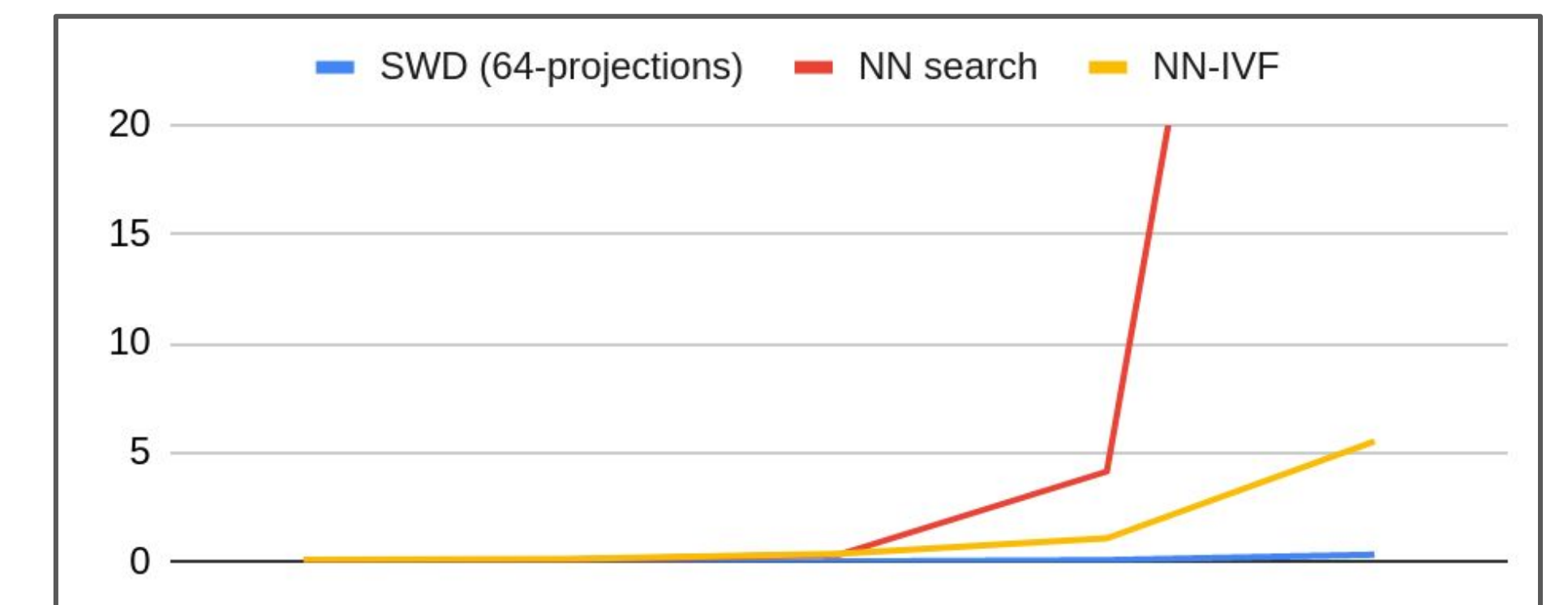
We synthesis an image in a multi-scale manner: at each level an initial guess is optimize to match the patch distribution of the scaled reference imag.



## Results

### Computation efficiency

Our method scales more efficiently with the size of the image. Computing SWD is  $O(n \log(n))$  while nearest-neighbor based approaches scale quadratically



### Comparison to other methods:

We visually and quantitatively compare our to other method. GPDM compares to GPNN outperforms SinGAN.

