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The Surprising Effectiveness of Linear Unsupervised Image-to-Image Translation

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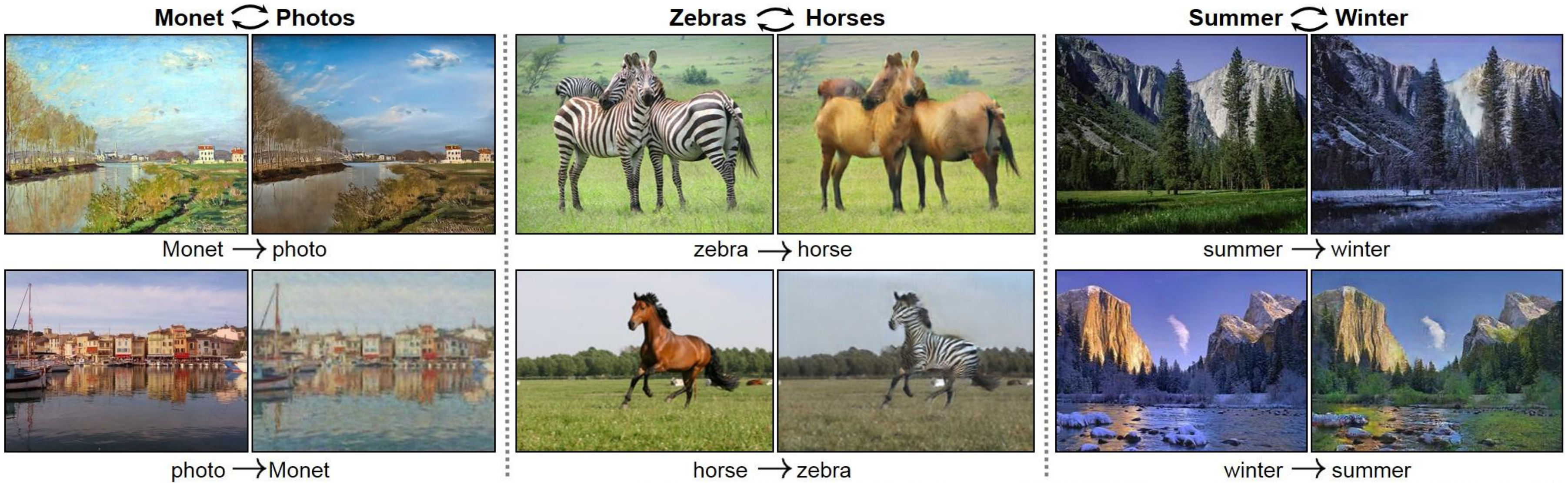
https://github.com/eitanrich/lin-im2im

Unsupervised Domain Translation (UDT)

- **Input**: datasets D_A, D_B sampled from the *marginals* $P(A), P(B)$ of some joint distribution $P(A, B)$
- **Task**: Learn $P(B|A)$

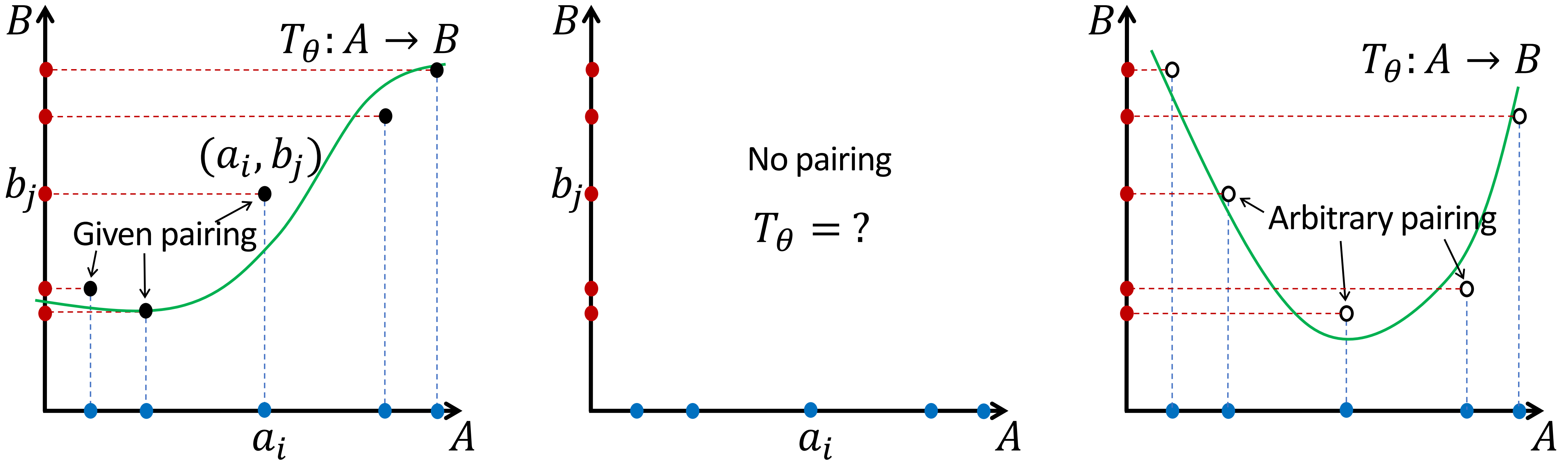


Unsupervised im2im domain pairs used in CycleGAN [1]

[1] Zhu et al, Unpaired image-to-image translation using cycle-consistent adversarial networks, ICCV 2017

UDT is ill-posed !

- Toy example: $A, B \subset \mathbb{R}$.
  Without matching pairs, any arbitrary pairing defines a valid transformation:

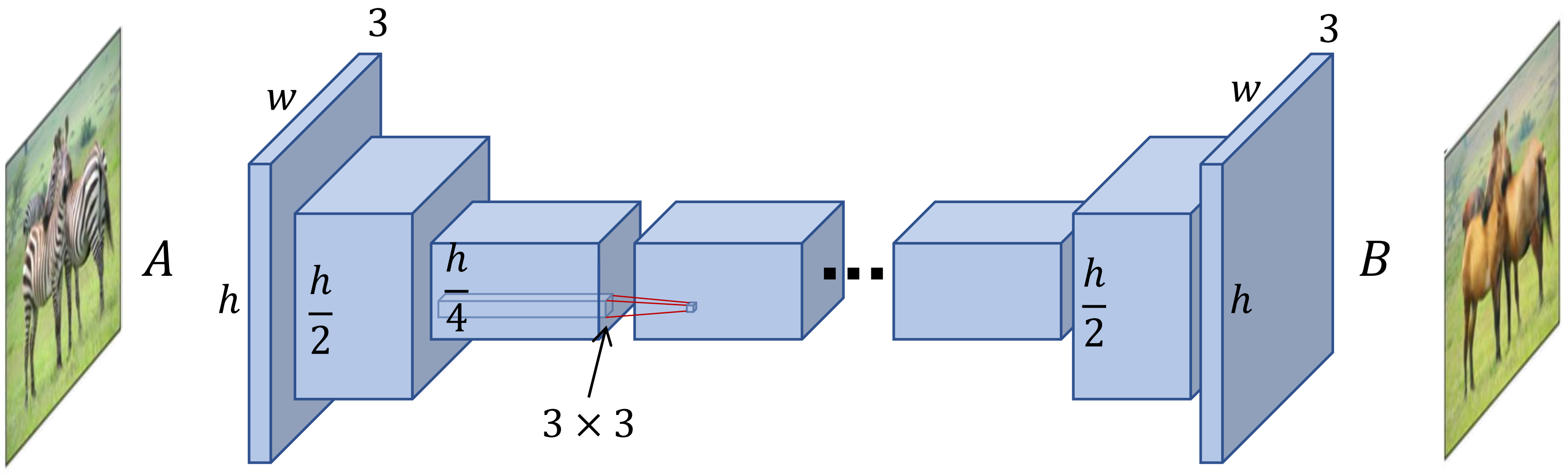


- So how does CycleGAN, MUNIT [2], … work?

[2] Huang et al, Multimodal unsupervised image-to-image translation, ECCV 2018

Locality bias: problem + architecture

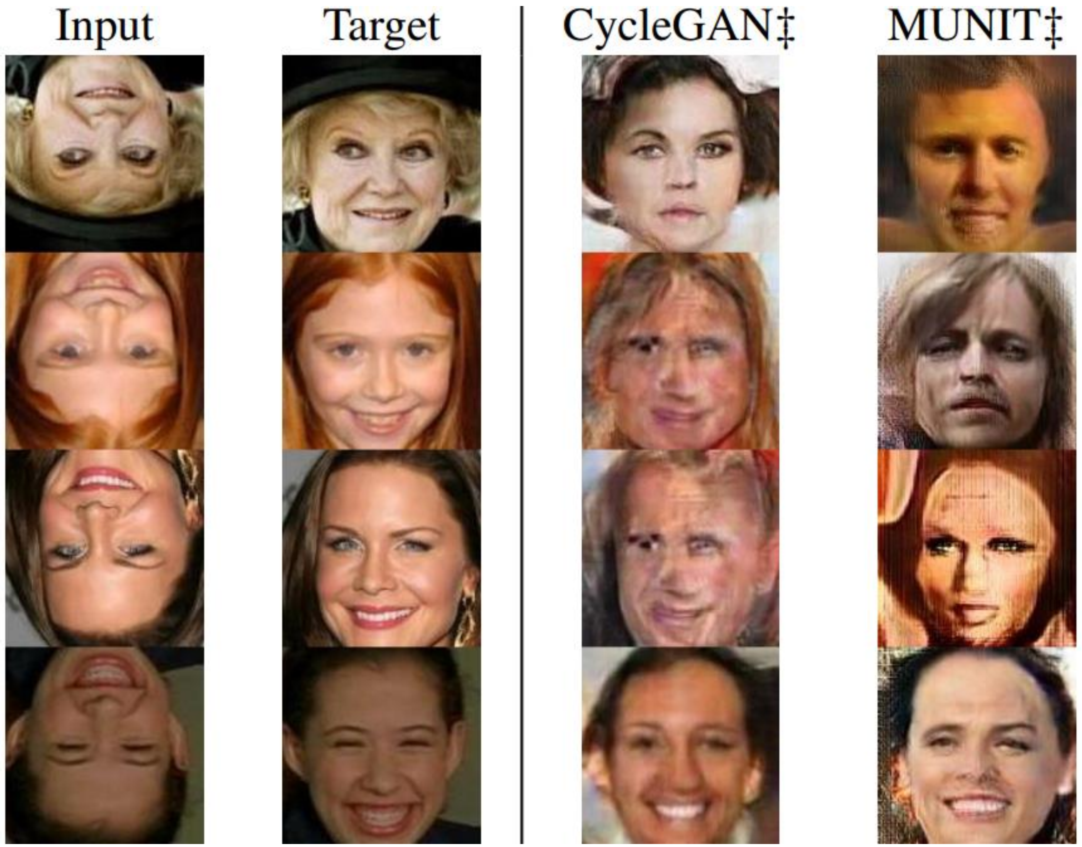
- CycleGAN, … use an autoencoder bottleneck with a large spatial size and small convolution kernels:



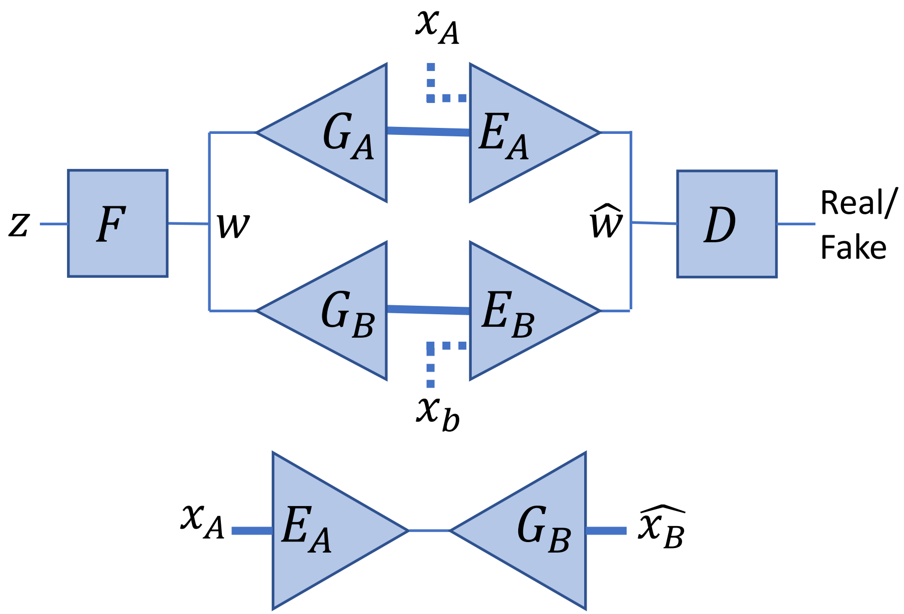
- What happens if we remove the bias?

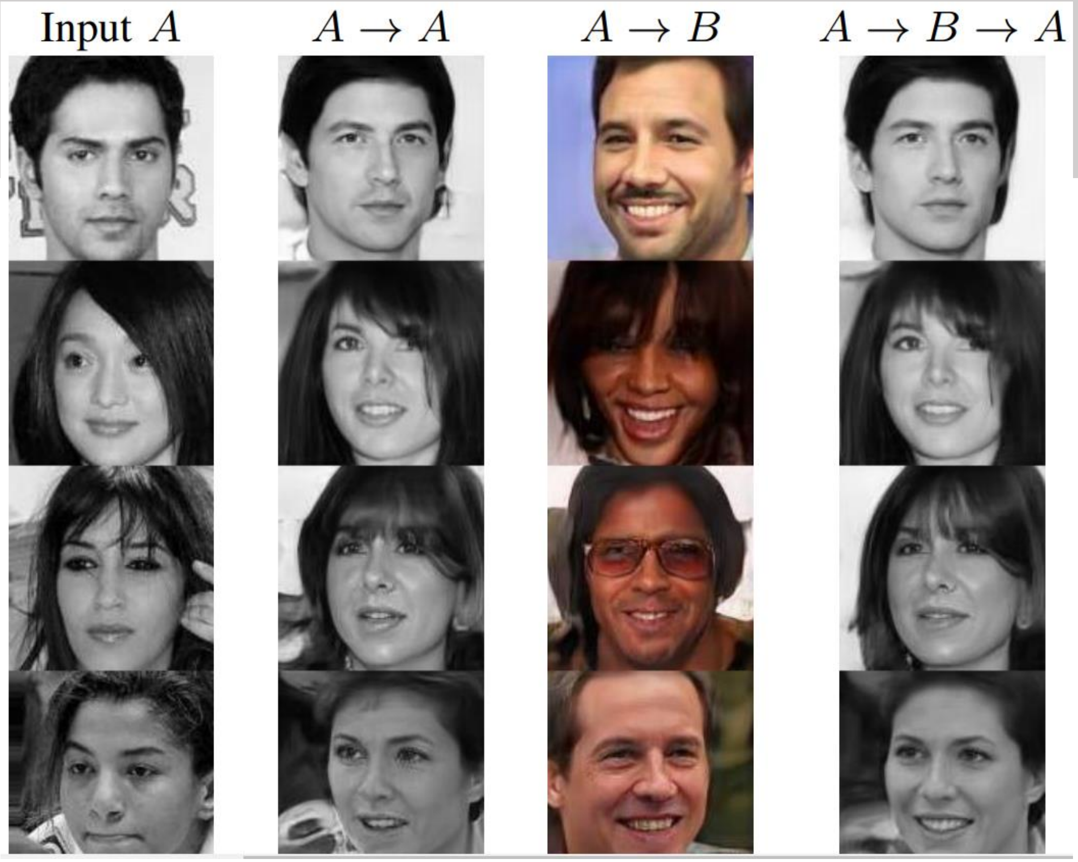
Nonlocal problem

- CycleGAN and MUNIT fail to learn a simple nonlocal problem like *vertical flip:*



Nonlocal architecture





- We construct a UDT model w/o locality bias using StyleGAN / ALAE [3] (top: training configuration, bottom: inference).
- The architecture converges to an <u>arbitrary</u> solution, even for a simple problem like image colorization.

[3] Pidhorskyi et al, Adversarial latent autoencoders, CVPR 2020

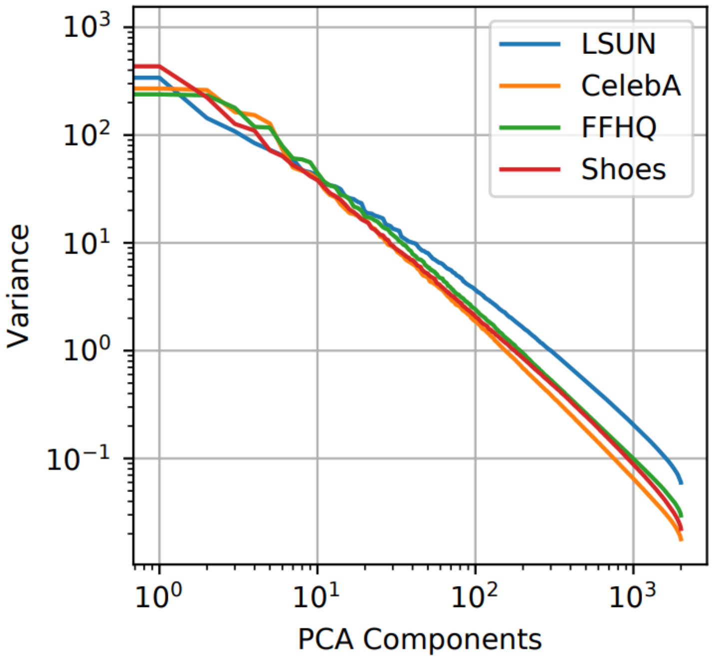
Linear, orthogonal image-to-image translation

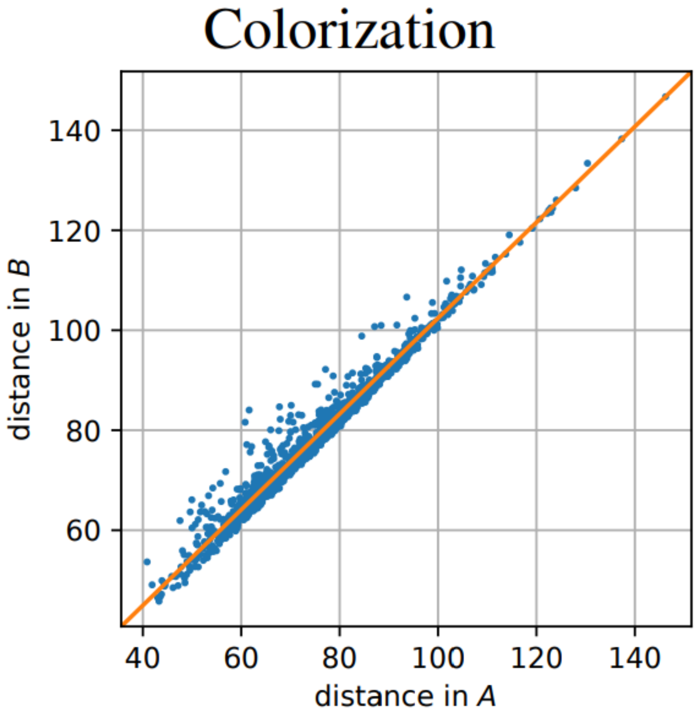
- Find $T: A \to B$ ($b = Ta$) such that $TT' = T'T = I$
- Challenges:
  - T is very large
  - Unsupervised learning scheme?
  - Expressiveness?

Solution: Learn a linear transformation in *PCA space*

$$T = W_B Q W_A'$$

r principal components of D_B — learned $r \times r$ orthogonal matrix — r principal components of D_A

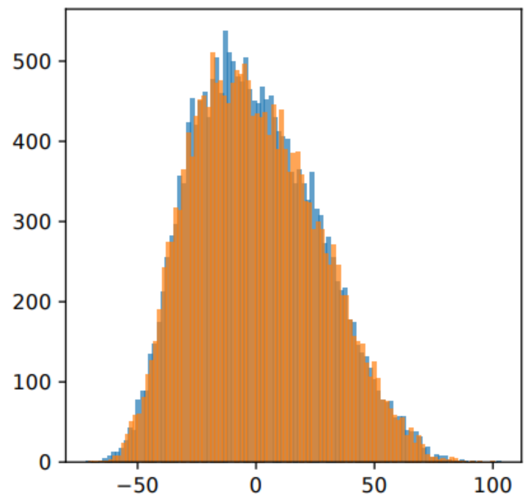


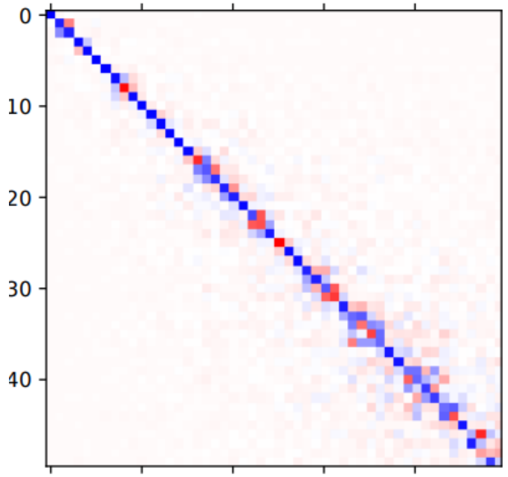


Natural images are well represented by relatively few PCA components ($r \ll d$).

Many real tasks like colorization are close to being distance-preserving.

Learning method: Procrustes + ICP[4,5] in PCA space





PCA ambiguity is resolved via skewness.
Target Q is close to identity.

Algorithm 1: Orthogonal UDT in PCA subspace

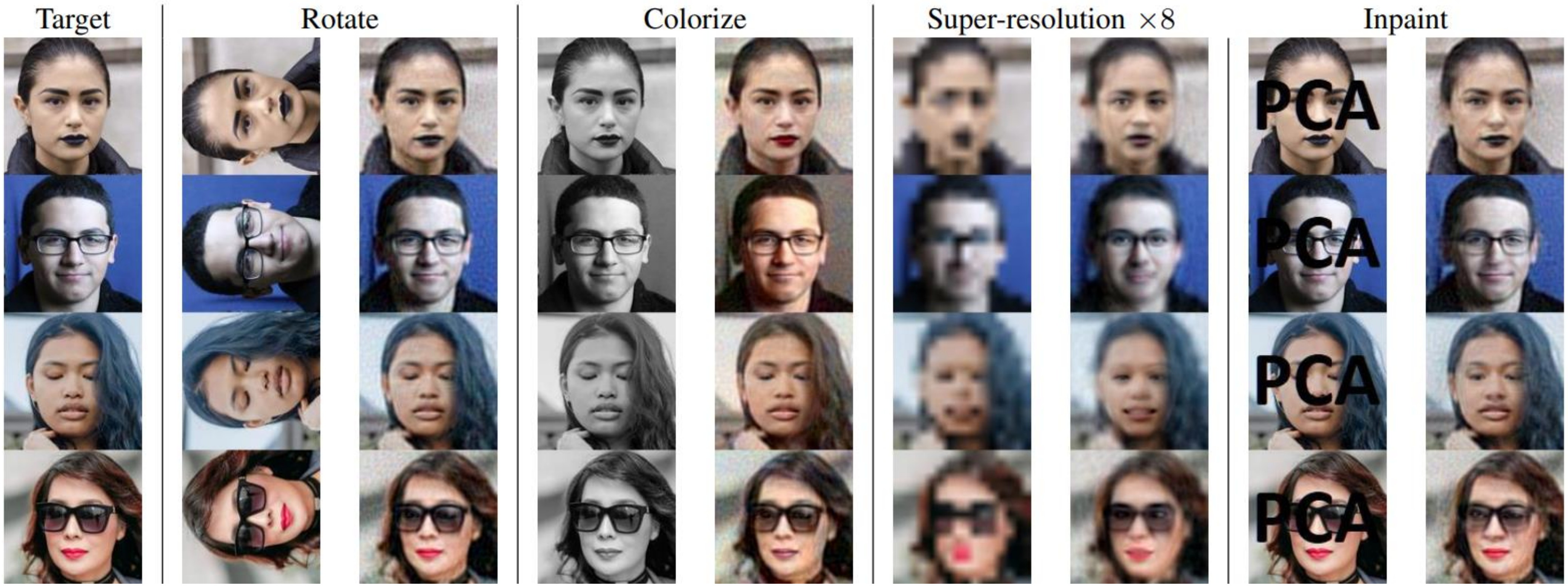
Input: $\mathcal{D}_A = \{x_1^A, \dots x_n^A\}$, $\mathcal{D}_B = \{x_1^B, \dots x_m^B\}$, r
Result: Orthogonal transformation $T : A \rightarrow B$

Compute W_A, W_B: r principal components of $\mathcal{D}_A, \mathcal{D}_B$
Fix eigenvectors sign for positive skew
Compute PCA embedding $\{z_1^A, \dots z_n^A\}$, $\{z_1^B, \dots z_m^B\}$
Initialize $Q \leftarrow I$
while *not converged* **do**
    $A \leftarrow \emptyset$, $B \leftarrow \emptyset$
    for $i \leftarrow 1$ ***to*** n **do**
        $j \leftarrow \arg\min_{j'} ||z_i^A Q - z_{j'}^B||$
        $k \leftarrow \arg\min_{k'} ||z_{k'}^A Q - z_j^B||$
        if $k = i$ **then**
            A.insert-row(z_i^A), B.insert-row(z_j^B)
    $U, S, V \leftarrow \mathrm{SVD}(A^T B)$
    $Q \leftarrow UV$
return $T \leftarrow W_A^T Q W_B$

[4] Besl et al, Method for registration of 3-d shapes, 1992
[5] Hoshen and Wolf, Non-adversarial unsupervised word translation, 2018

Results

Task	CycleGAN‡			MUNIT‡			Ours‡			Ours†		
	MSE	SSIM	T[h]	MSE	SSIM	T[h]	MSE	SSIM	T[h]	MSE	SSIM	T[h]
CelebA-colorize	0.0066	**0.914**	49	0.0256	0.750	52	**0.0043**	0.883	**0.04**	0.0071	0.761	0.04
CelebA-vflip	0.1167	0.358	43	0.1084	0.333	48	**0.0012**	**0.917**	**0.04**	0.0041	0.780	0.04
FFHQ-rot90	0.1267	0.302	39	0.1220	0.268	39	**0.0023**	**0.870**	**0.05**	0.0335	0.381	0.05



Conclusion

- UDT is in general ill-posed.
- SOTA unsupervised im2im methods rely on locality bias.
- Our approach - linear orthogonal transformations - can be learned in a few seconds and works well for many true relations.