

Cross-domain Correspondence Learning for Exemplar-based Image Translation (CoCosNet)

CVPR 2020 oral

Pan Zhang, Bo Zhang, Dong Chen, Lu Yuan, Fang Wen



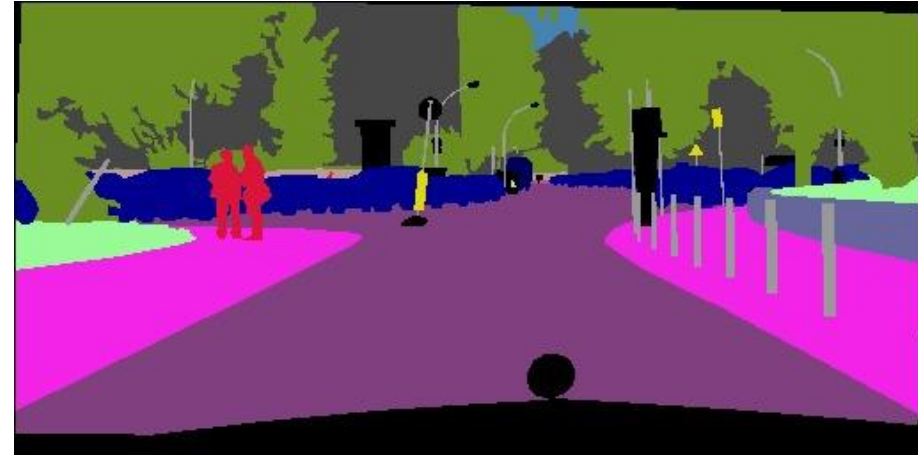
Prior image translation methods

- Lack of fine-grain controllability



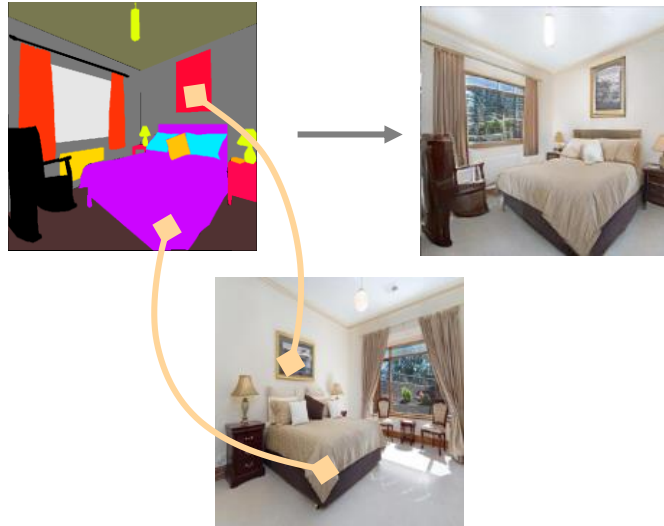
Edge → shoes
(MUNIT, ECCV 2018)

- Significant artifacts in complex scenes



SPADe, CVPR 2019

Proposed exemplar-based solution



- Instance-level style control
- Significantly improve the image quality
- General translation solution

Mask to image



Edge to face

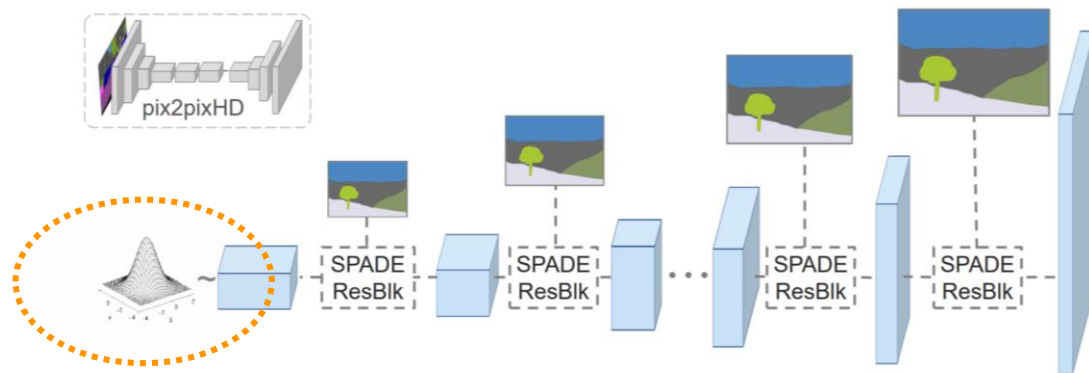


Pose synthesis

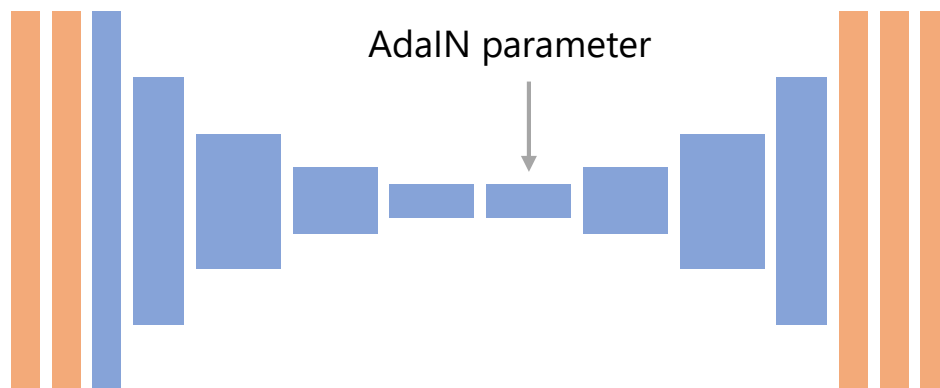


Relation with exemplar-based methods

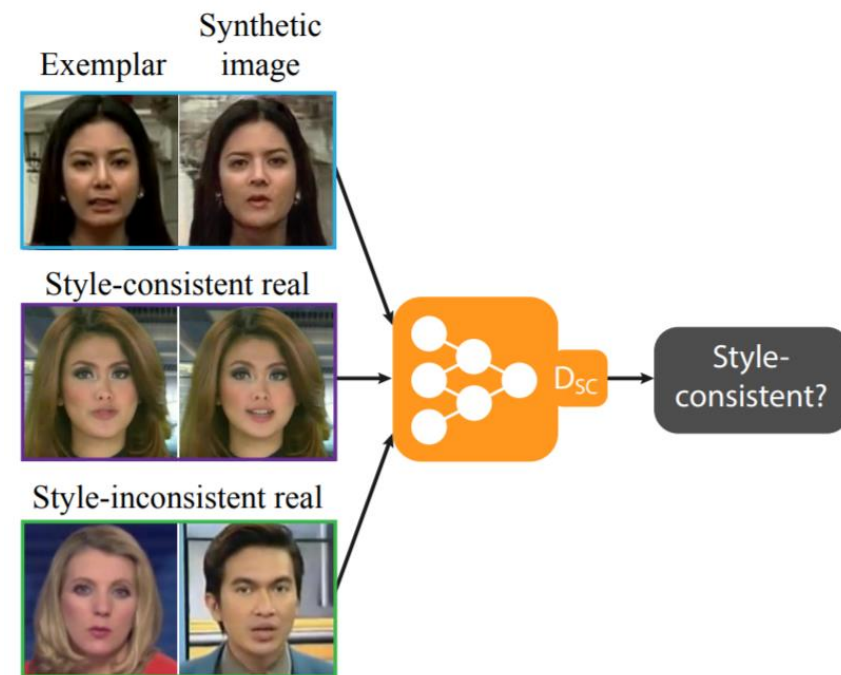
Embed style with latent space



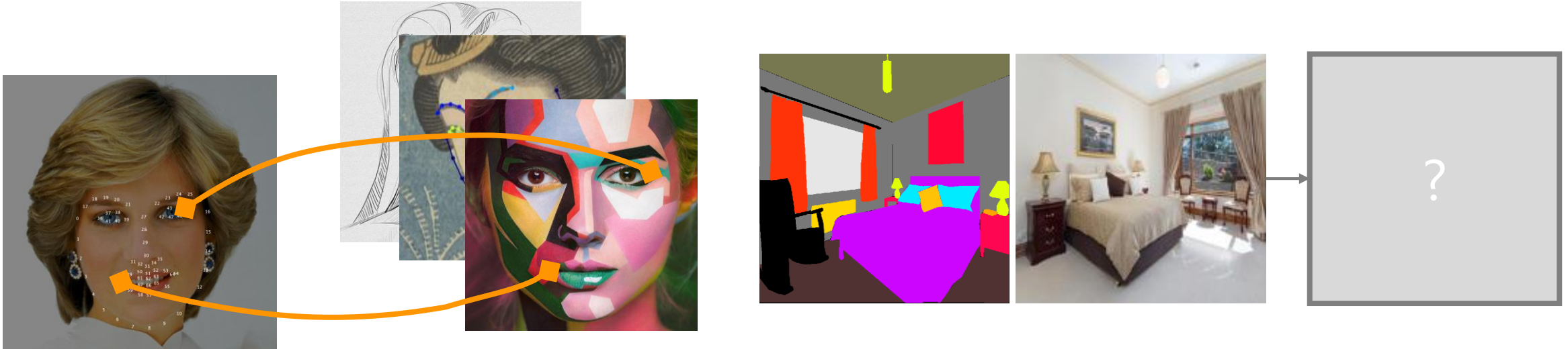
Style injection during AdaIN



Style discriminator



Motivation



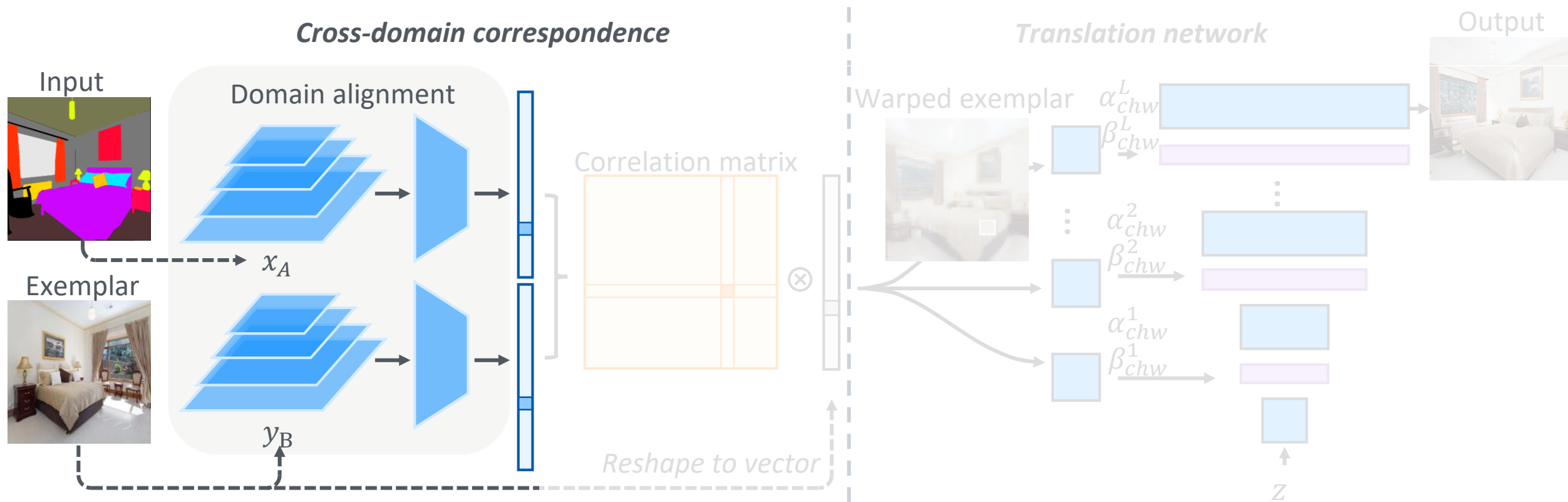
How to establish correspondence for heterogeneous images?



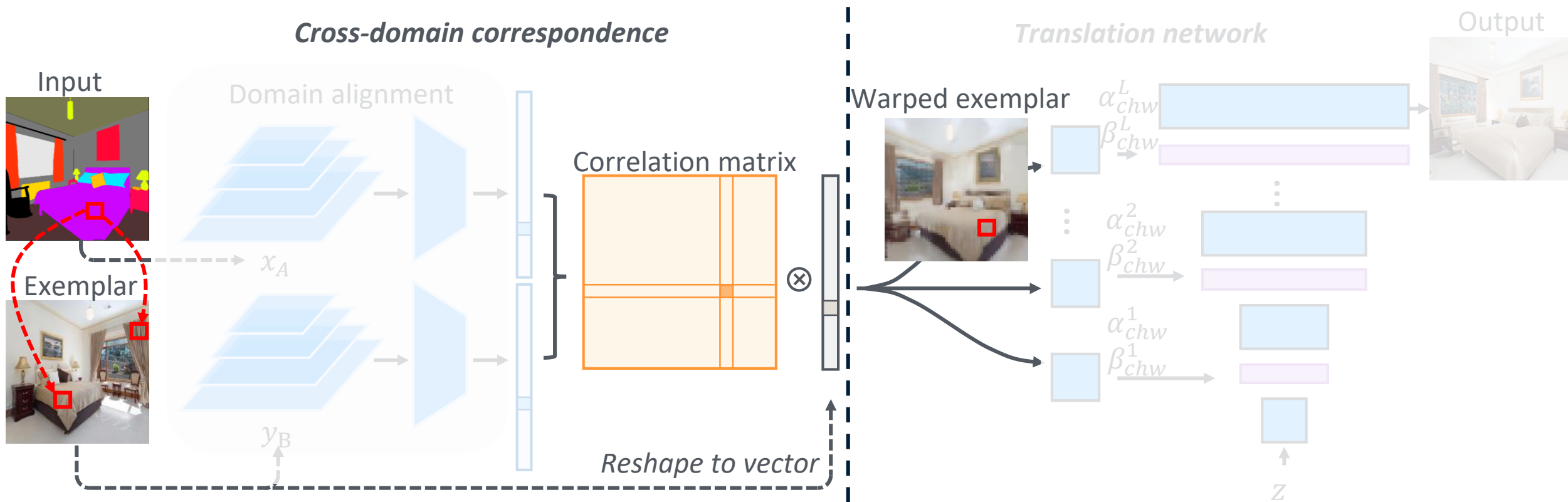
What is the desired translation output given an exemplar?

Facilitate each other

Framework

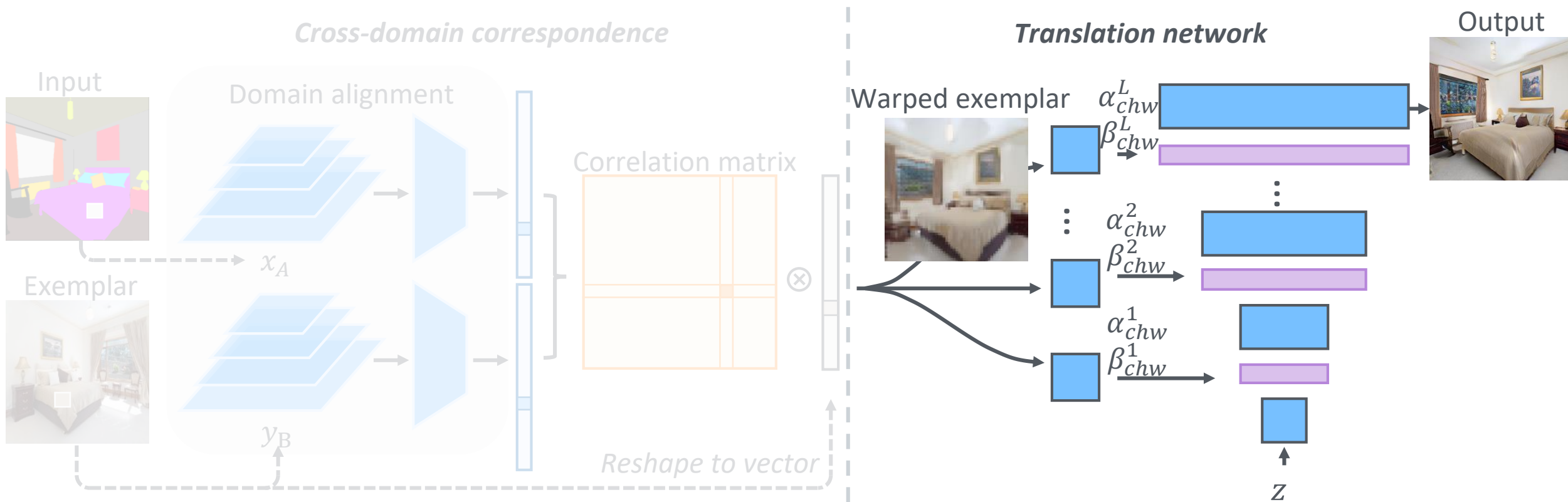


Framework



Framework

$$\alpha_{h,w}^i(r_{y \rightarrow x}) \times \frac{F_{c,h,w}^i - \mu_{h,w}^i}{\sigma_{h,w}^i} + \beta_{h,w}^i(r_{y \rightarrow x}),$$



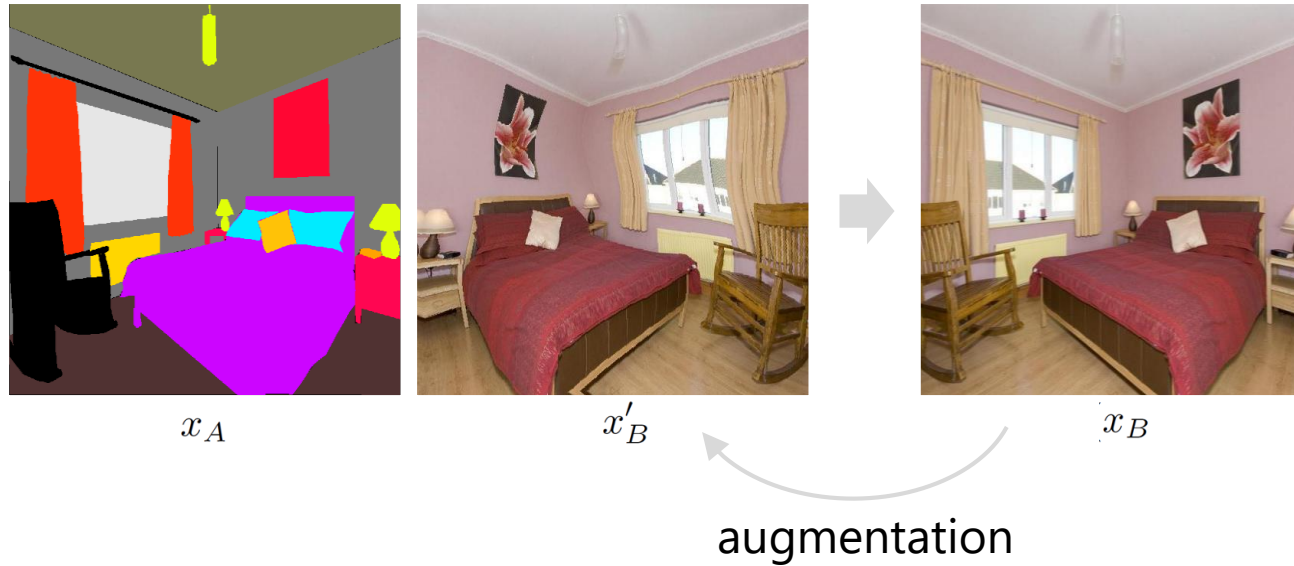
Loss

Translation network

Pseudo exemplar loss:

$$\mathcal{L}_{feat} = \sum_l \lambda_l \|\phi_l(\mathcal{G}(x_A, x'_B)) - \phi_l(x_B)\|_1,$$

Pseudo exemplar pairs



Loss

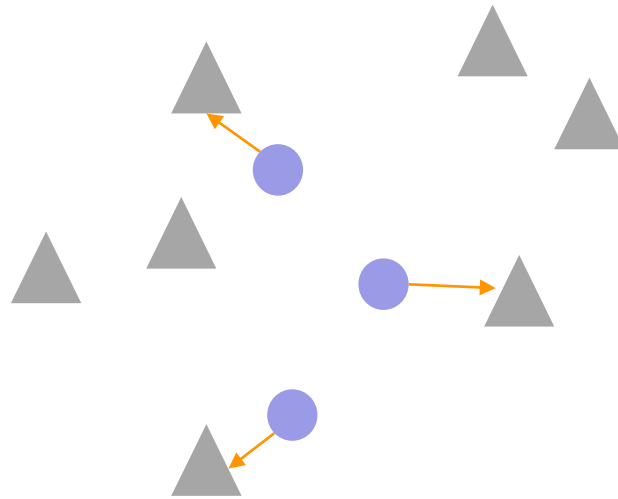
Translation network

Contextual loss: let the output to mimic the appearance of the semantically corresponding patches of the exemplar.

$$\mathcal{L}_{context} =$$

$$\sum_l \omega_l \left[-\log \left(\frac{1}{n_l} \sum_i \max_j A^l(\phi_i^l(\hat{x}_B), \phi_j^l(y_B)) \right) \right],$$

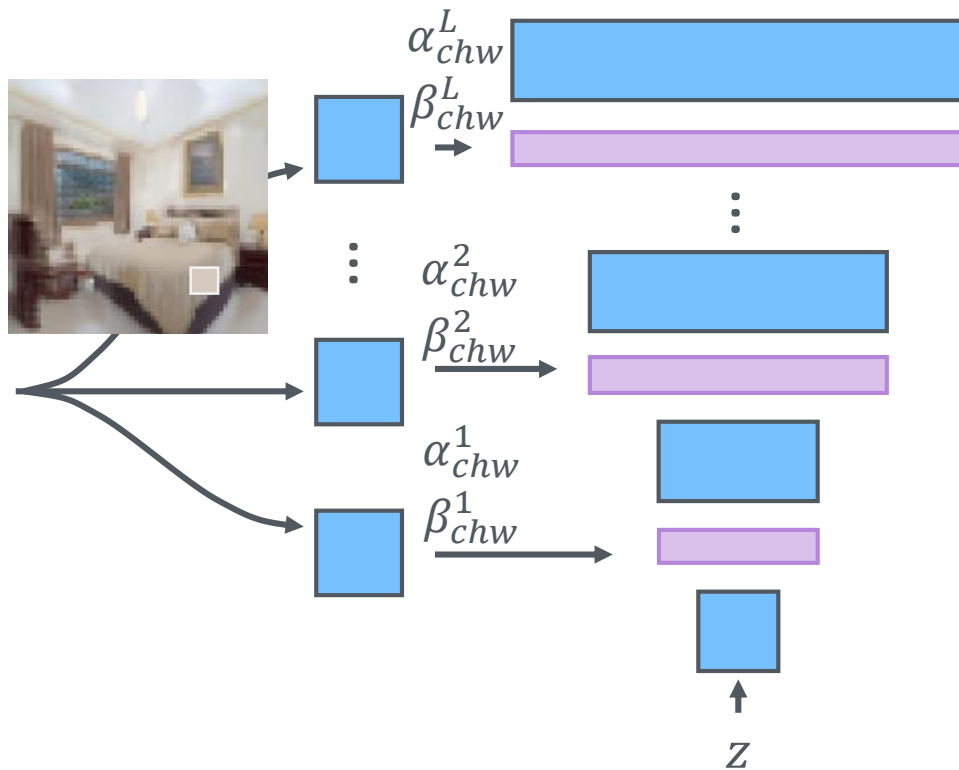
pairwise affinities in the VGG feature space



Loss

Translation network

Translation network



Perceptual loss: the output should maintain the semantics as the input

$$\mathcal{L}_{perc} = \|\phi_l(\hat{x}_B) - \phi_l(x_B)\|_1.$$

Adversarial loss: make the output as realistic as possible

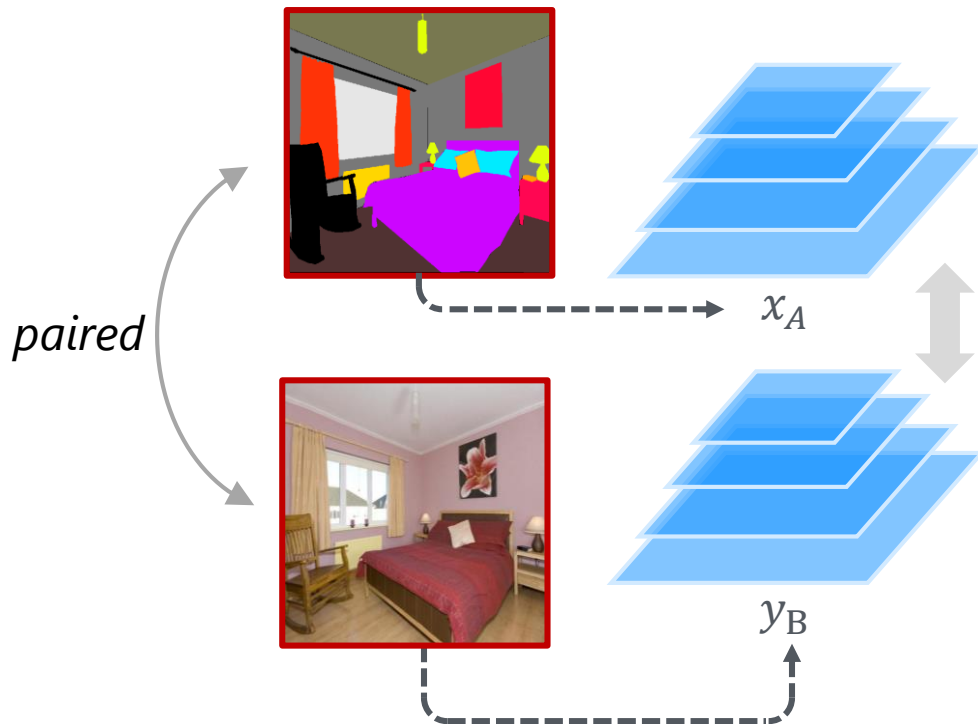
$$\mathcal{L}_{adv}^{\mathcal{D}} = -\mathbb{E}[h(\mathcal{D}(y_B))] - \mathbb{E}[h(-\mathcal{D}(\mathcal{G}(x_A, y_B)))]$$

$$\mathcal{L}_{adv}^{\mathcal{G}} = -\mathbb{E}[\mathcal{D}(\mathcal{G}(x_A, y_B))],$$

Loss

Cross-domain correspondence network

Domain adversarial

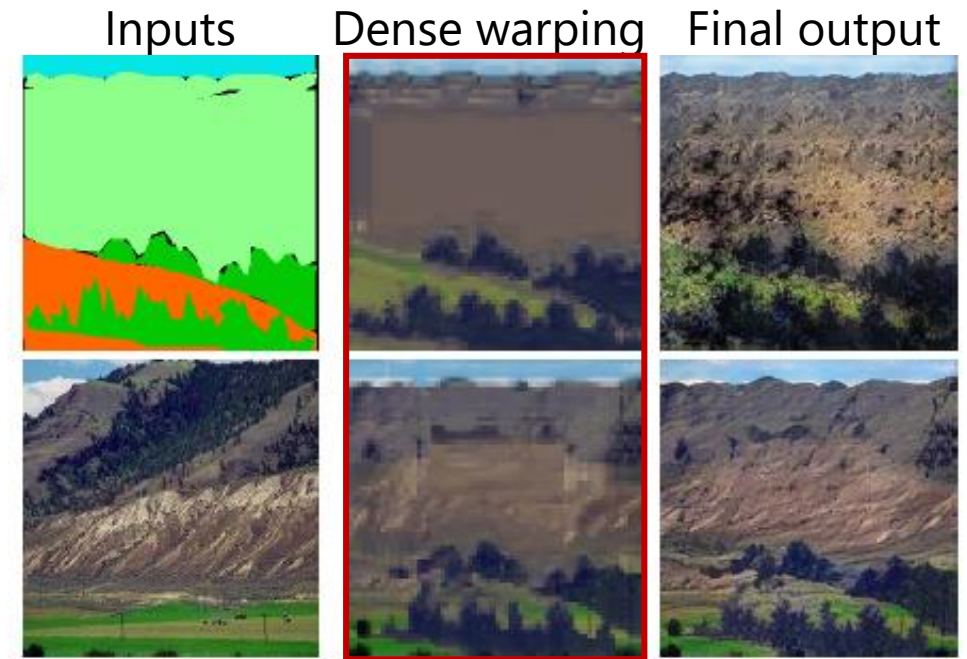


Domain alignment loss: the embeddings of inputs should lie in the same domain

$$\mathcal{L}_{domain}^{\ell_1} = \|\mathcal{F}_{A \rightarrow S}(x_A) - \mathcal{F}_{B \rightarrow S}(x_B)\|_1$$

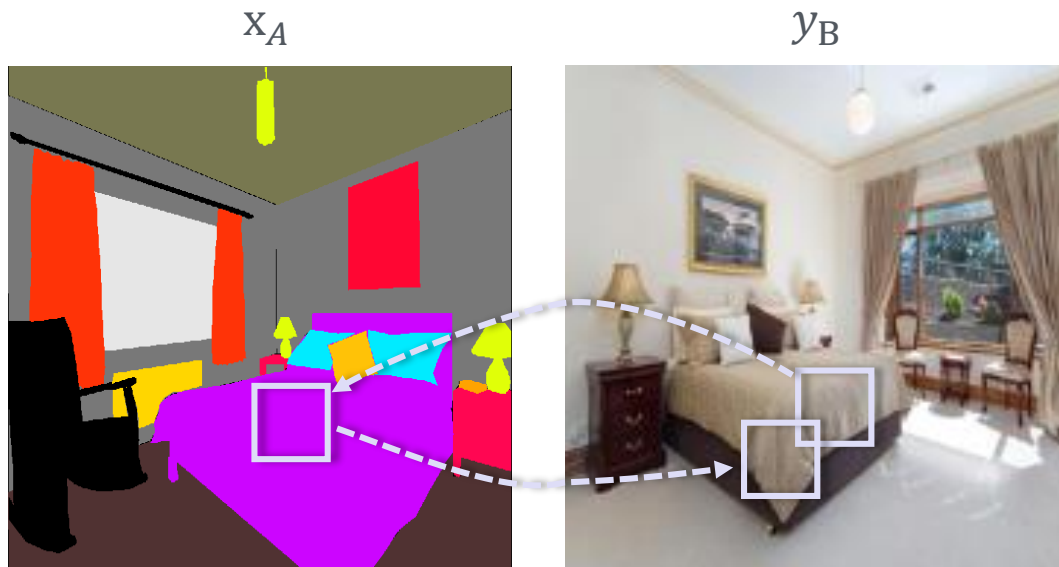
w/o $\mathcal{L}_{domain}^{\ell_1}$

w/ $\mathcal{L}_{domain}^{\ell_1}$



Loss

Cross-domain correspondence network



Cycle warping regularization:

$$\mathcal{L}_{reg} = \|r_{y \rightarrow x \rightarrow y} - y_B\|_1,$$

Inputs Dense warping Final output

w/o \mathcal{L}_{reg}



w/ \mathcal{L}_{reg}



Total loss

$$\mathcal{L}_{\theta} = \min_{\mathcal{F}, \mathcal{T}, \mathcal{G}} \max_{\mathcal{D}} \psi_1 \mathcal{L}_{feat} + \psi_2 \mathcal{L}_{perc} + \psi_3 \mathcal{L}_{context} \\ + \psi_4 \mathcal{L}_{adv}^{\mathcal{G}} + \psi_5 \mathcal{L}_{domain}^{\ell_1} + \psi_6 \mathcal{L}_{reg},$$

- Pseudo exemplar pairs:
 - VGG feature matching
- Real exemplar pairs:
 - Perceptual loss
 - Contextual loss
- Adversarial loss:
 - hinge loss
 - Discriminator feature matching
- Domain alignment loss
 - Domain l1 loss
- Correspondence regularization
 - Cyclic warping loss

Comparison with state-of-the-art

Input



SPADE (CVPR 2019)



Ours

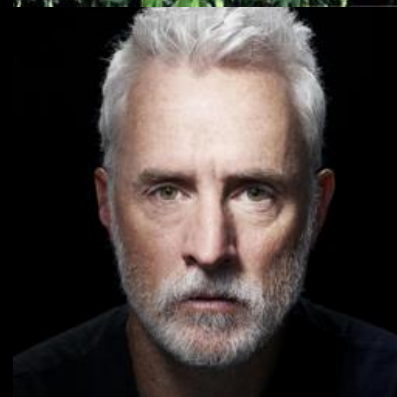
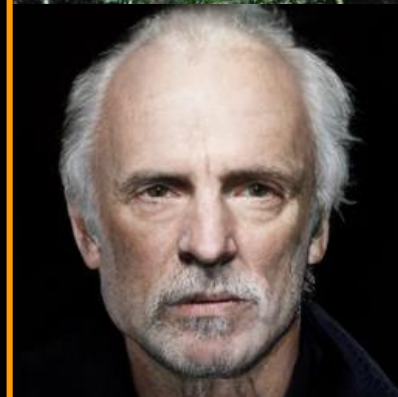
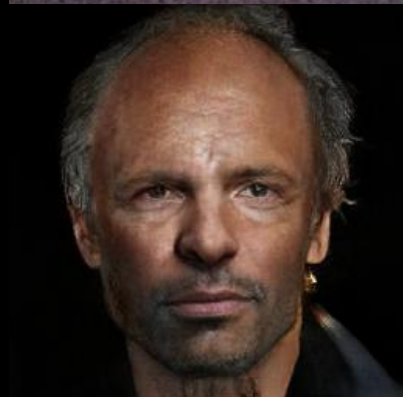


Exemplar

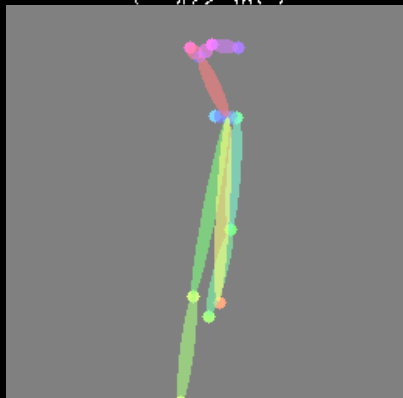


FID (lower is better)

33.9 → 26.4

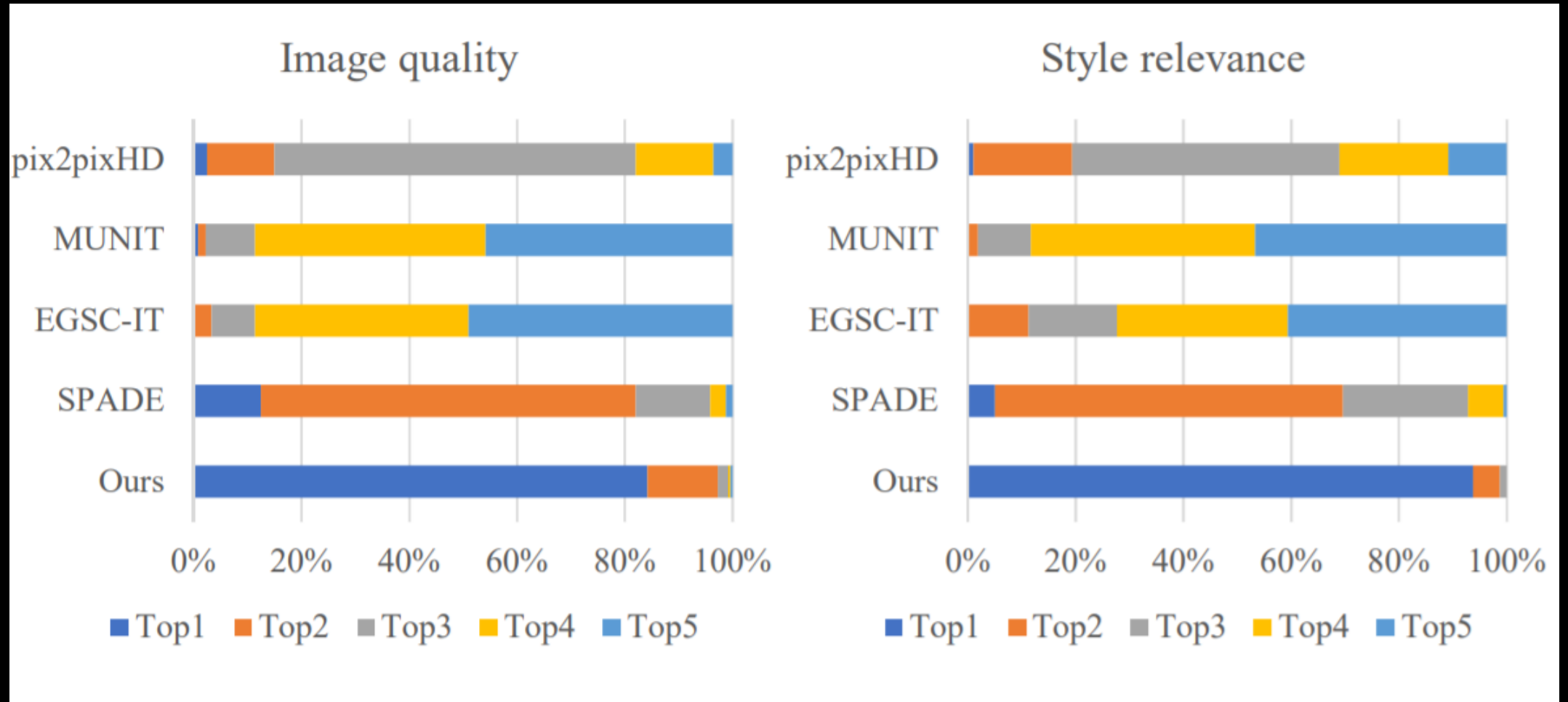


31.5 → 14.3



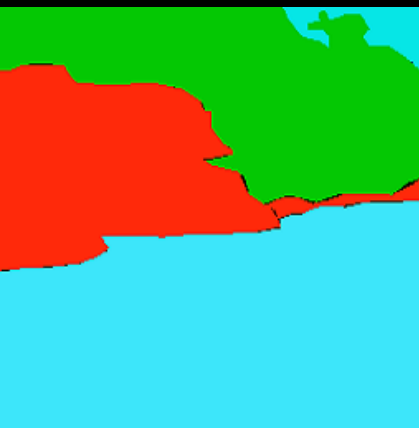
36.2 → 14.4

User preference



Results on ADE20k

Input



Output



Exemplar



Input



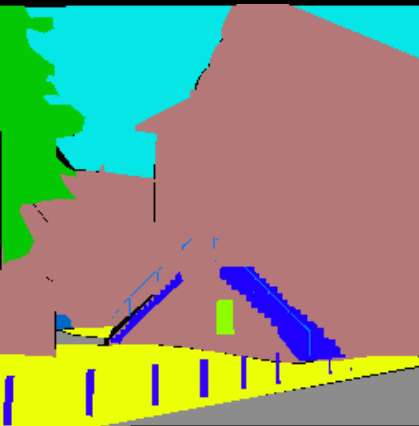
Output



Exemplar



Input



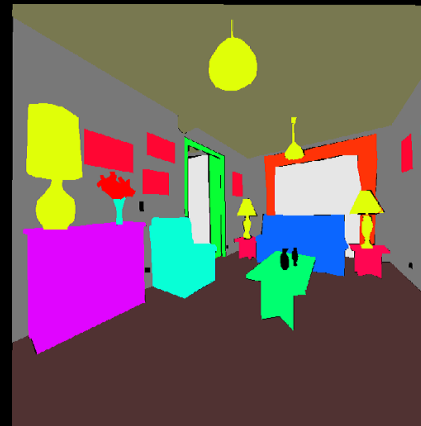
Output



Exemplar



Input



Output



Exemplar



Results on Celeb-A

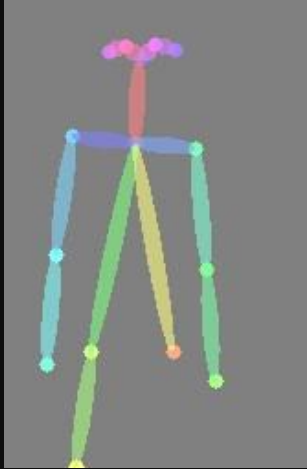


Results on Deepfashion



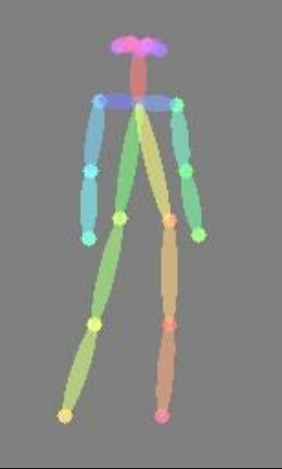
Exemplar

Input

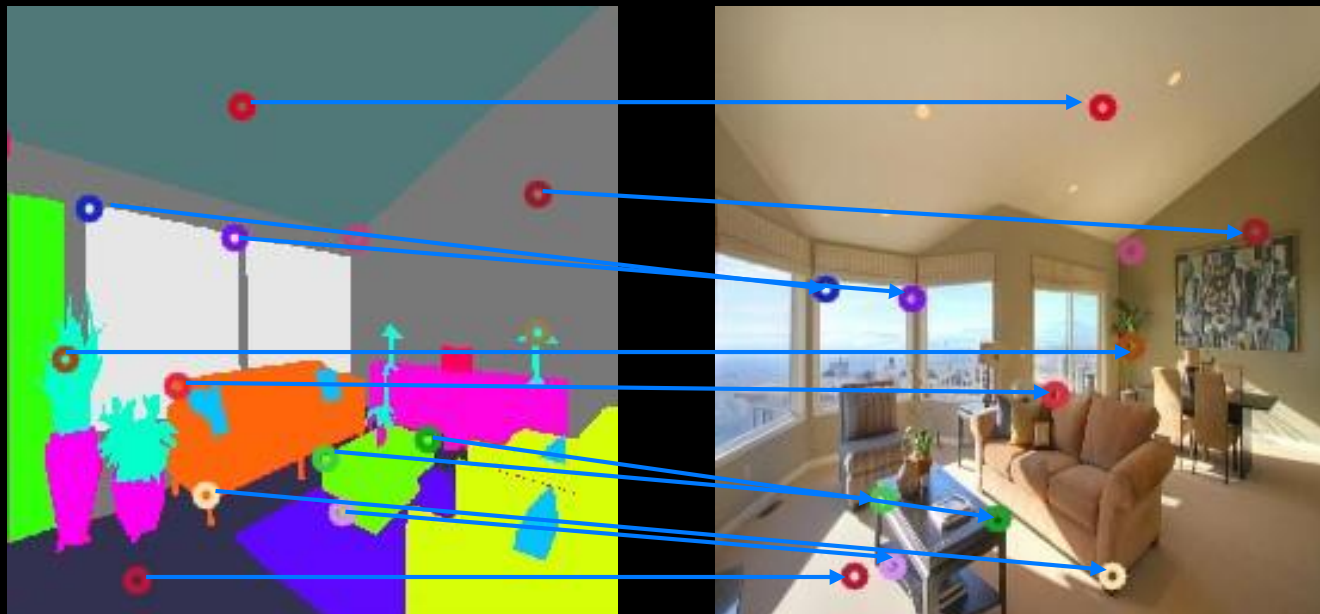


Exemplar

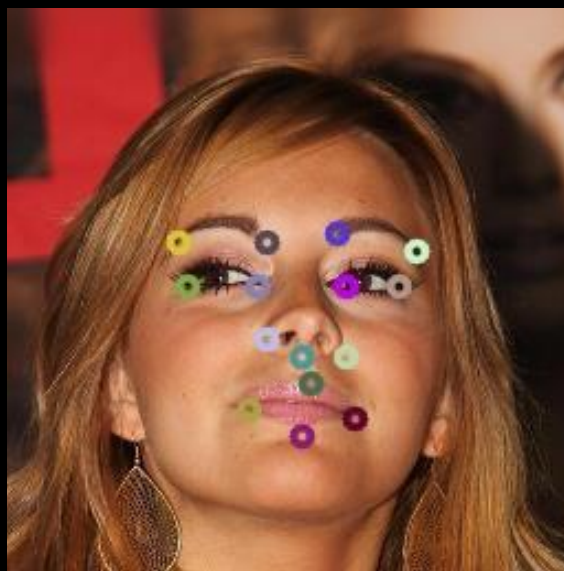
Input



Cross-domain correspondence

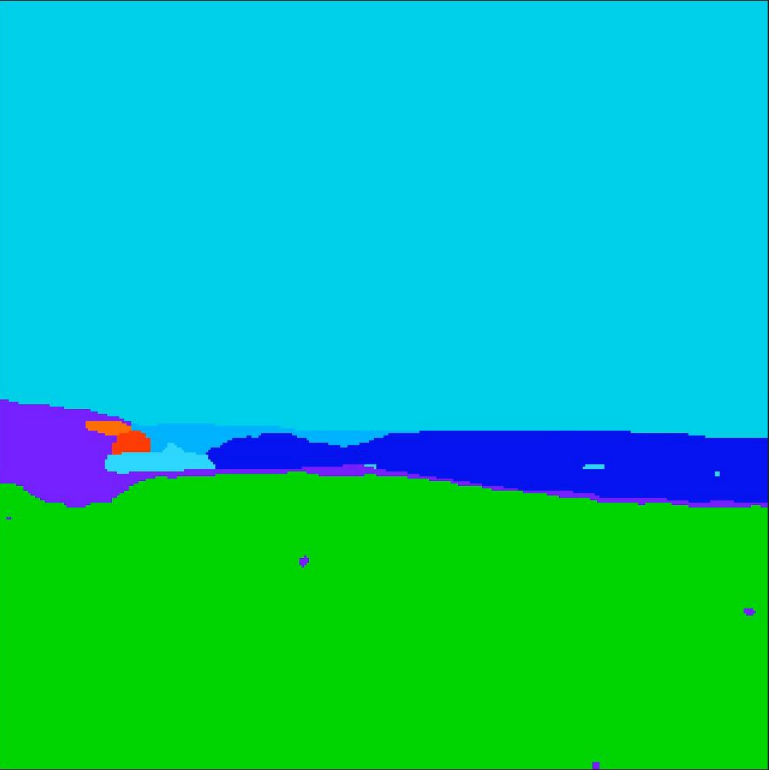


Weak supervised learning !



Application: interactive painter

Canvas



road

rock

water

sand

sea

sky

grass

mount

tree

Load Painting

Save Painting

Draw


Fill

Undo

Redo

Clean


Synthesis



Translate

Save

Reference



Open Reference

Retrieve

Clean

road rock water sand sea sky grass mount tree

Load Painting Save Painting Draw Fill

Undo Redo Clean

Translate

Save

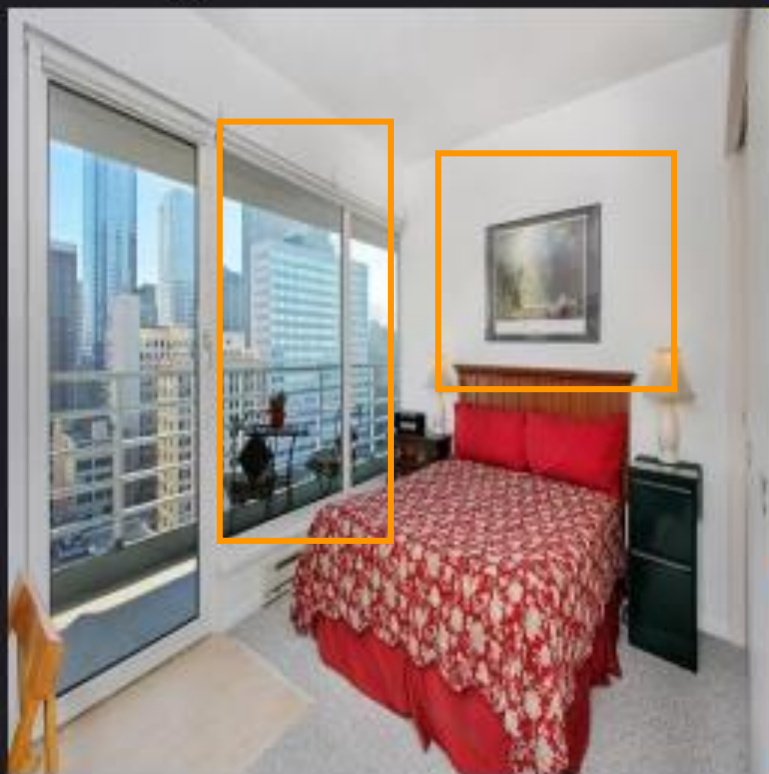
Open Reference

Retrieve

Clean

Application: image editing

▼ Ori image



Load

Inpainting : Off

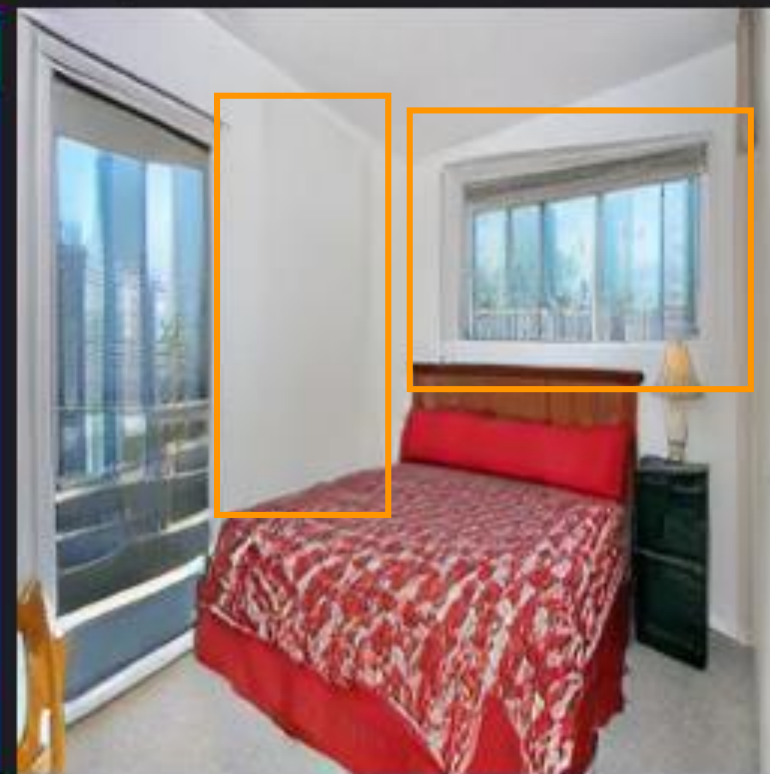
▼ Label



Undo

Redo

▼ Output



Synthesis

Save

Application: image editing

▼ Ori image



Load

Inpainting : Off

▼ Label



Undo

Redo

▼ Output

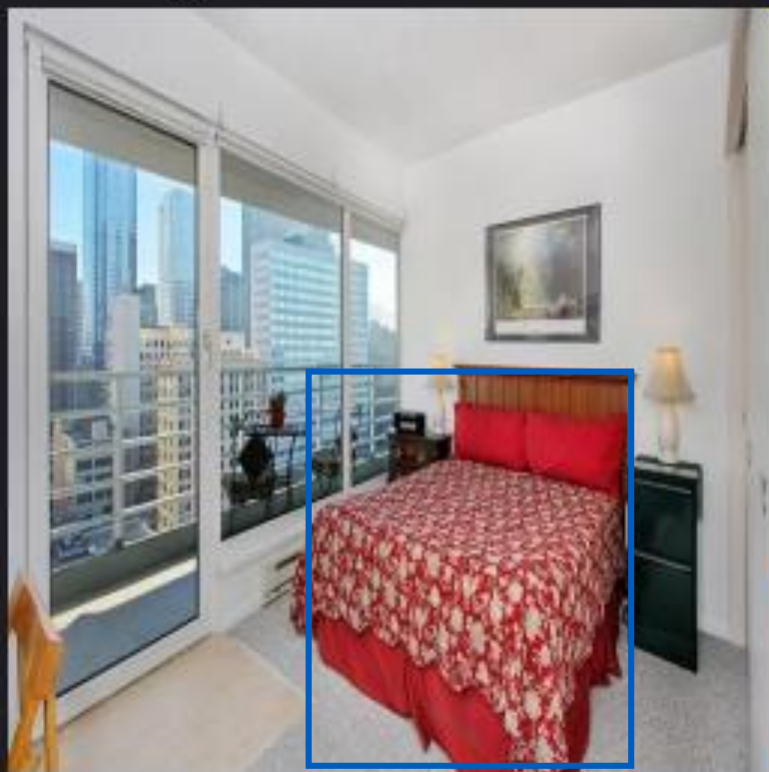


Synthesis

Save

Application: image editing

▼ Ori image



Load

Inpainting : Off

▼ Label



Undo

Redo

▼ Output



Synthesis

Save

Application: makeup transfer



Thank you!



Project webpage: <https://panzhang0212.github.io/CoCosNet/>
Code will be released soon.

Bringing photo back to life, CVPR 2020 oral
Project page: http://raywzy.com/Old_Photo/

