# PairedCycleGAN: Asymmetric Style Transfer for Applying and Removing Makeup

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## Abstract

*This paper introduces an automatic method for editing a portrait photo so that the subject appears to be wearing makeup in the style of another person in a reference photo. Our unsupervised learning approach relies on a new framework of cycle-consistent generative adversarial networks. Different from the image domain transfer problem, our style transfer problem involves two asymmetric functions: a forward function encodes example-based style transfer, whereas a backward function removes the style. We construct two coupled networks to implement these functions one that transfers makeup style and a second that can remove makeup such that the output of their successive application to an input photo will match the input. The learned style network can then quickly apply an arbitrary makeup style to an arbitrary photo. We demonstrate the effectiveness on a broad range of portraits and styles.[3]*


## 1. Introduction

Digital photo manipulation now plays a central role in portraiture. Professional tools allow photographers to adjust lighting, remove blemishes, or move wisps of hair. Whimsical applications let novices add cartoon elements like a party hat or clown nose, or to turn photos into drawings and paintings. Some tools like Taaz [2] and PortraitPro [1] can digitally add makeup to a person in a photo, but the styles are limited to a collection of preset configurations and/or a set of parameters that adjust specific features like lip color.

This paper introduces a way to digitally add makeup to a photo of a person, where the style of the makeup is provided in an example photo of a different person (Figure 1). One challenge is that it is difficult to acquire a dataset of photo triplets from which to learn: the source photo, the reference makeup photo, and the ground truth output (which preserves identity of the source and style of the reference). Previous work on style transfer avoids the need for such a training set by defining the style and content loss functions based on deep features trained by neural networks [4],[5],[6]. While those approaches can produce good results for stylization of imagery in general, they do not work well for adding various makeup styles to faces. A second challenge, specific to our makeup problem, is that people are highly sensitive to visual artifacts in rendered faces. A potential solution is to restrict the stylization range so as to define a specific color transformation space (such as affine transformations), or so as to preserve edges [6],[7],[5]. Unfortunately, this approach limits the range of makeup, because many styles include features that would violate the edge preservation property such as elongated eyelashes or dark eye liner.

Inspired by recent successful photorealistic style transfer based on generative adversarial networks (GANs), we take an unsupervised learning approach that builds on the CycleGAN architecture of Zhu *et al.*[8]. CycleGAN can transfer images between two domains by training on two sets of images, one from each domain. For our application, CycleGAN could in principle learn to apply a general make-you-look-good makeup to a no-makeup face, but it would not replicate a specific example makeup style.

## References


[1] Portrait pro - easy photo editing software. http://www.portraitprofessional.com/. 1

[2] Taaz virtual makeover and hairstyles. http://www.taaz.com/. 1

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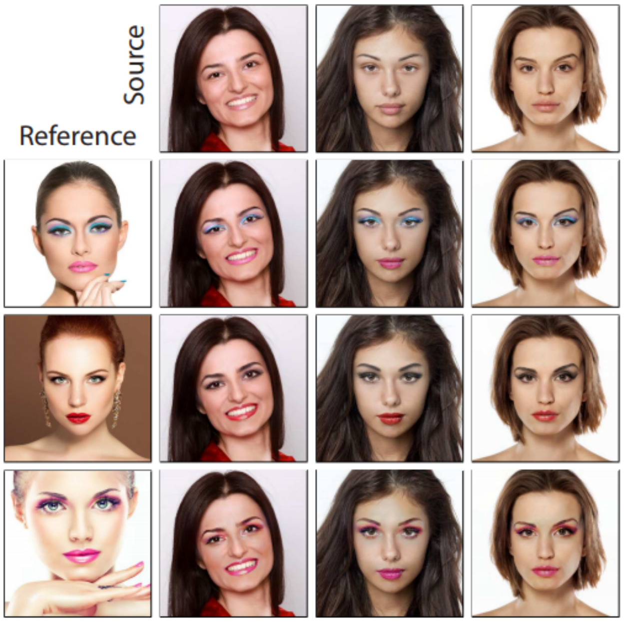


Figure 1. Three source photos (top row) are each modified to match makeup styles in three reference photos (left column) to produce nine different outputs (3 × 3 lower right).

[7] F. Luan, S. Paris, E. Shechtman, and K. Bala. Deep photo style transfer. *arXiv preprint arXiv:1703.07511*, 2017. 1

[8] J. Zhu, T. Park, P. Isola, and A. A. Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. *arXiv preprint arXiv:1703.10593*, 2017. 1