脸部妆容迁移！速览几篇用GAN来做的论文

bryant 机器学习与生成对抗网络 2019-11-26

Makeup transfer妆容迁移，常用于将参考图像的妆容迁移到目标人脸上。实际上也是一种风格迁移。下面整理了几篇妆容迁移的论文。笔者已经下载打包好论文，大家有兴趣可以关注微信公众号“学点诗歌和AI知识”回复“妆容迁移”获得论文的网盘下载地址哦。

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1. 2018CVPR：PairedCycleGAN: Asymmetric Style Transfer for Applying and Removing Makeup

基于cycleGAN来进行上妆或者去妆。不要求成对的数据训练，值得注意的是，上妆的G输入不仅仅是素颜图像，包括妆后参照图像。其中训练时要眼、鼻、嘴、眉毛等切图像块，最后再用泊松融合。

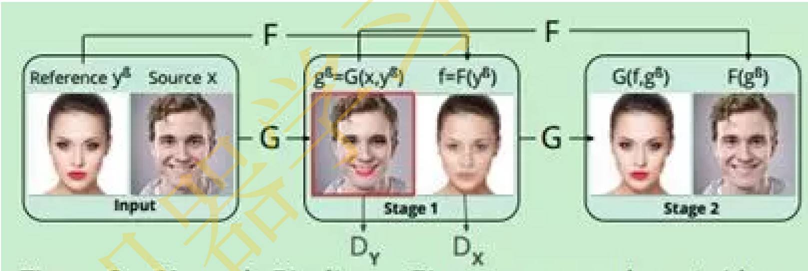
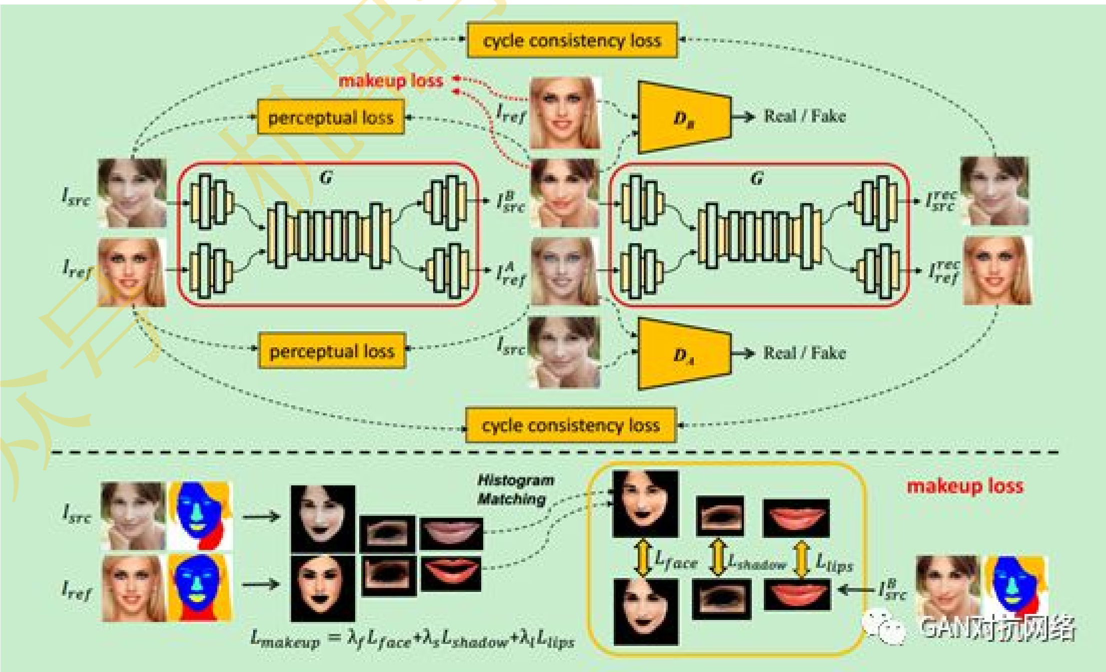


Figure 2: Network Pipeline. Given a source photo (without makeup) and a makeup reference, our system simultaneously learns a makeup transfer function G and a makeup removal function F. The result of the first stage can be viewed as a pair output by image analogy, and can serve as input for the second stage. We compare the output from the second stage with the source to measure identity preservation and style consistency.

2. BeautyGAN: Instance-level Facial Makeup Transfer with Deep Generative Adversarial Network

主页： http://liusi-group.com/projects/BeautyGAN



3. BEHOLDER-GAN: GENERATION AND BEAUTIFICATION OF FACIAL IMAGES WITH CONDITIONING ON THEIR BEAUTY

LEVEL

作者训练了一个可以根据“颜值分数”生成人脸的模型。另外，提出的方法也可以美化人脸，提高颜值。

Fig. 1: Generated faces. Each row has the same latent vector but is conditioned on a different beauty score (left to right - least attractive to most attractive). The generated sequences reveal human preferences and biases: for e plGAN对抗网络es turn into younger ones, masculine faces turn into feminine, and darker skin to brighter.

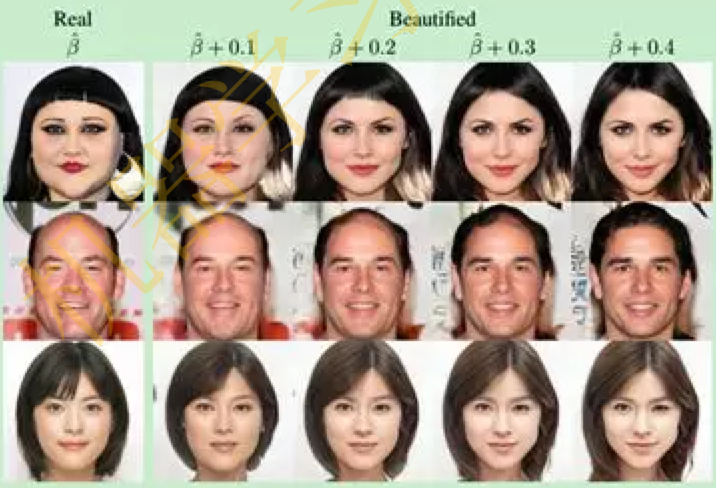


Fig. 2: Beautification of real faces. Left column are the input real faces. To the right are the beautified images with an increasing beauty level ($\hat{\beta}$ is the recovered real face beauty). For $\hat{\beta}+0.1$ we observe reasonable beautification. When further increasing the beauty level it seems that the person identity is not preserved. For privacy and ethical reasons, efGAN对抗网络ng the real faces together with their predicted beauty scores.

4. Disentangled Makeup Transfer with Generative Adversarial Network

关注的点更多，如上妆的多样性等。

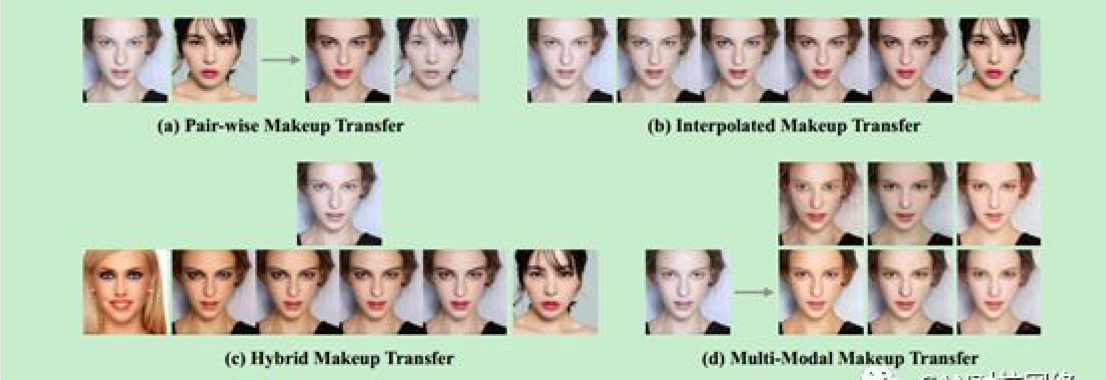
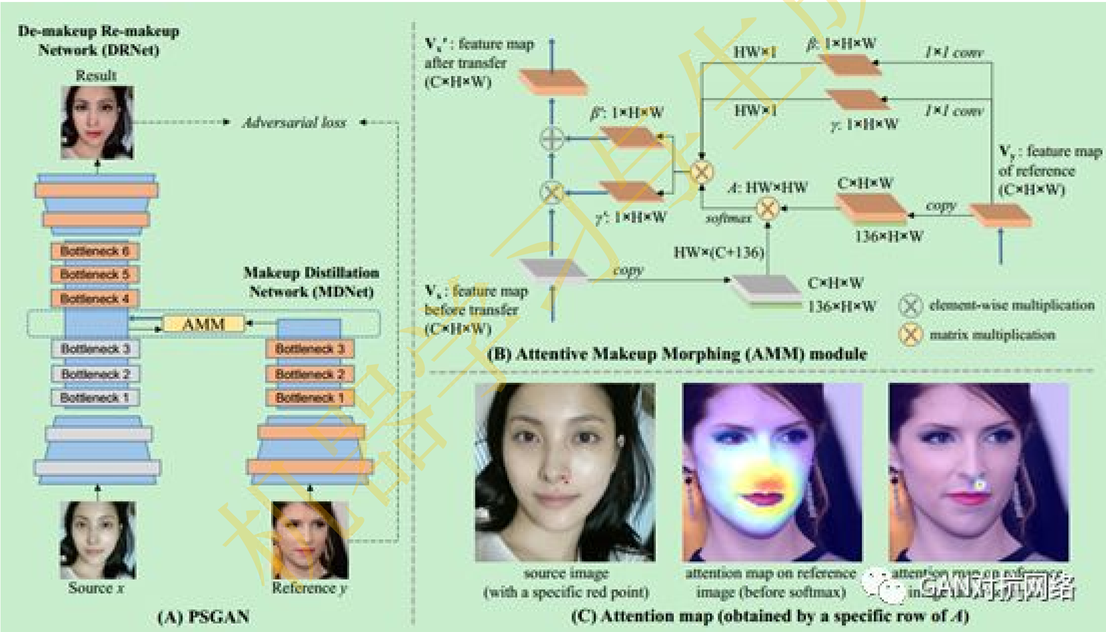


Figure 1: Different scenarios of makeup transfer. Most related researches only focus on the pair-wise makeup transfer. In contrast, our model can achieve all of them.

5. PSGAN: Pose-Robust Spatial-Aware GAN for Customizable Makeup Transfer

关注不同姿态/脸部朝向上妆的鲁棒性。



6. Semi-supervised Eye Makeup Transfer by Swapping Learned Representation

关注眼妆，并专门制作了一个眼妆数据集。

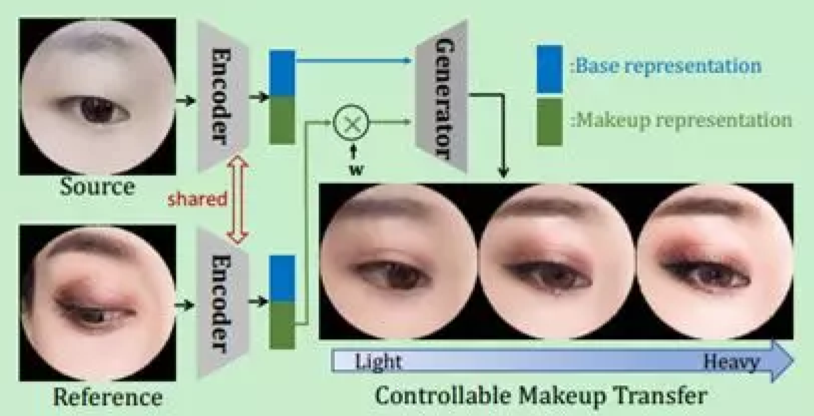


Figure 1: At inference stage, the source image can present eye makeup styles of the reference image with controllable makeup degree. The weight **w** is gradually increased to demonstrate that the makeup degree can be controlled conveniently

7. LADN: Local Adversarial Disentangling Network forFacial Makeup and De-Makeup

关注生成更高质量细节，多个重叠、局部判别器进行对抗训练。

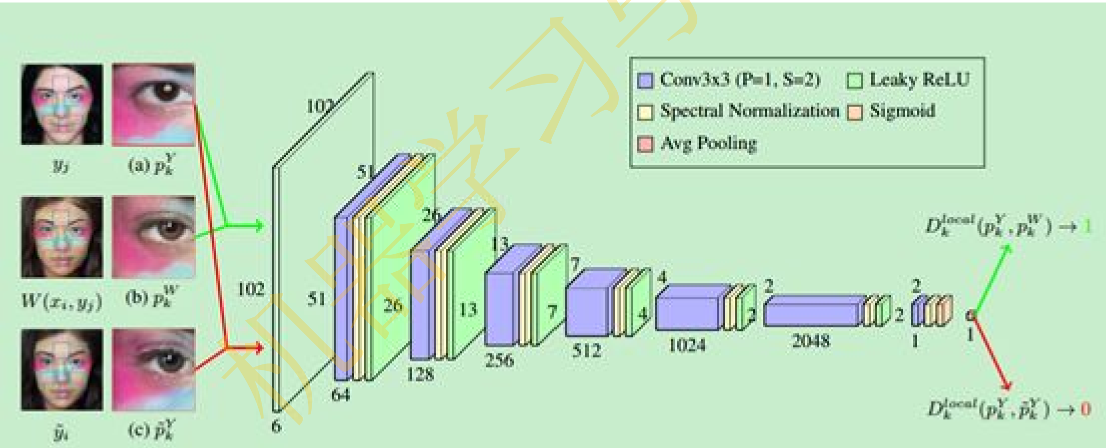


Figure 3: Local Patches and Local Discriminators. The local patches p_k^Y, p_k^W and $\tilde{p}_k^Y$ (of size 102 × 102 × 3) are respectively cropped from the makeup reference, the warping result and the generated image. Pairs of p_k^Y, p_k^W are concatenated along the color channel and fed into the local discriminator as positive examples, while those of p_k^Y, $\tilde{p}_k^Y$ as negative ones. Each local discriminator is comprised of six 3 × 3 convolutional layers (padding=1, stride=2) with spectral normalization layers and leaky ReLU layers as shown. After the last layer of spectral normalization, the 2 × 2 × 1 feature vector is passed to a sigmoid module and then averaged to pro[illegible] which is the output indicating the probability of input pair possessing the same makeup style.

8. 2019 CVPR BeautyGlow: On-Demand Makeup Transfer Framework with Reversible Generative Network

用的不是GAN而是Glow来做，作者认为这样可以按需更精准地把控妆容程度。

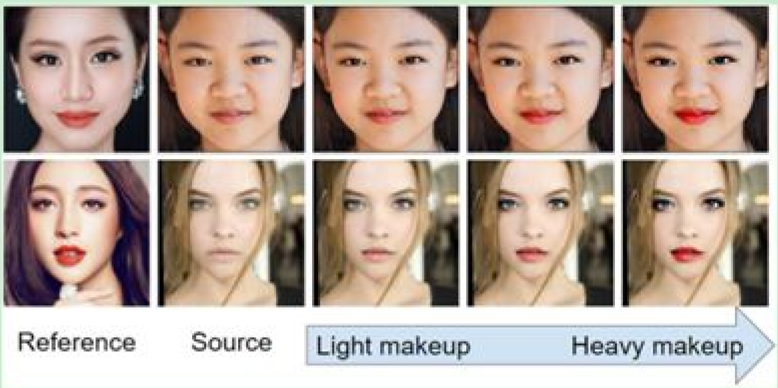


Figure 1: *The makeup features such as eyeshadows and lip gloss are extracted from reference makeup images and are transferred to source non-makeup images. The lightness of the makeup can be tuned by adjusting the magnification in the latent space.*

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