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1 Title:

Unsupervised Cross-Domain Image Generation

2 Summary:

This paper proposes domain transfer network to transfer samples from source domain to analogous samples in target domain in an unpaired setting. Analogy is defined through f-constancy i.e. a given function f should be invariant to the transfer function. Further, when f is mapping to embedding space, the paper proposes to learn the transfer function from the embedding itself. A combination of loss functions are proposed and ablations are provided. Visually appealing results on Celeba-emoji transfer and SOTA domain adaptation results on SVHN-MNIST transfer demonstrate the method's effectiveness.

3 Strengths:

i) We have flexibility in choosing the type of f. It's like a prior that we impose. For example, we can apply this method to domain adaptation as well as to style transfer by choosing f. ii) Although GAN loss is used, the identity and f-constancy ensure that mode collapse doesn't happen as a fewer modes cannot satisfy identity or a suitable chosen f iii) Domain adaptation using DTN transferred images shown to work well as compared to other adversarial approaches that perform feature adaptation.

4 Weaknesses:

i) The choice of loss functions are not sufficiently justified. For instance, multi-class discriminator is used for GANs, but no citation or explanation is provided. Similarly, the use of f in generator is not clearly explained except empirical results demonstrate huge advantages on SVHN-MNIST task. ii) The choice of f matters a lot as it determines how the images are related in both the domains. However, ablations are not presented on various choices of f. iii) SOTA domain adaptation results are presented only on one dataset. Similarly, good results on various tasks are presented but each task is explored only in single setting

5 Analysis of Experiments:

i) Ablations in Table 1. on SVHN-MNIST task, show that f and GAN work synchronously and dropping either leads to huge drop in performance. Also, each individual loss component seems to have a positive impact. ii) Table 2. shows that domain adaptation task through the generated images works well on SVHN-MNIST achieving SOTA (84.44%) while using a nearest neighbour classifier in contrast with DANN (73.85%) iii) Figure 3. shows unseen source images are transferred well provided their analogous target images are seen and not vice-versa i.e. GAN loss prevents unseen target images, while identity loss on target ensures some transfer happens even on unseen source images. iv) Appendix D shows the network failing to produce realistic looking faces from emojis.

6 Possible Extensions:

Theoretical and experimental exploration of choice of f and its impact on domain transfer. For example, can we control the degree of transfer by controlling f and can we vary f to interpolate across domains in a meaningful way? Note that f is like a prior. Detailed experiments of this method on multiple datasets, and extensions on each task touched upon in this paper namely, missing classes, domain adaptation and transfer, style transfer.