PuppetGAN: Cross-Domain Image Manipulation by Demonstration

Ben Usman 1,2, Nick Dufour 1,2, Kate Saenko 2, Chris Bregler 1
1 Google AI 2 Boston University

Our model can manipulate a single specific attribute of a real image A using a synthetic reference B.

Unsupervised Cross-Domain Adaptation produces entangled representations (e.g. CycleGAN).
Unsupervised Cross-Domain Disentanglement might disentangle wrong attributes (e.g. MUNIT).
Supervised Single-Domain Disentanglement fails to generalize to a different domain (e.g. InfoGAN, Cycle-Consistent VAE).

Existing Supervised Cross-Domain Disentanglement Methods yield degenerate solution that ignore parts of the learned embeddings (e.g. DiDA).
The PuppetGAN model is more resilient against such degenerate solution.

The proposed compositional consistency loss ensures that both embedding components are used during image generation.

Other techniques we used:
- reconstruction and cycle losses
- adversarial domain alignment
- regularization with instance noise

Other findings reported in the paper:
- disentanglement quality metrics
- failure case analysis
- input outlier robustness
- comparison to other models

Model | Disentanglement quality (MNIST ↔ Rendered Digits) | Size | Rotation
---|---|---|---
| Acc | r_{adv}^\alpha | r_{adv}^\beta | V_{rot} | Acc | r_{adv}^\alpha | r_{adv}^\beta | V_{rot}
PuppetGAN | 0.73 | 0.85 | 0.02 | 0.02 | 0.97 | 0.40 | 0.11 | 0.01
CycleGAN [28] | 0.10 | 0.28 | 0.06 | 0.28 | 0.11 | 0.54 | 0.37 | 0.33
DiDA [2] | 0.71 | 0.18 | 0.09 | 0.02 | 0.86 | 0.04 | 0.35 | 0.02
MUNIT [10] | 0.96 | 0.06 | 0.09 | 0.01 | 1.00 | 0.00 | 0.15 | 0.01
Cycle-VAE [8] | 0.17 | 0.22 | 0.16 | 0.01 | 0.29 | 0.45 | 0.10 | 0.01
PuppetGAN† | 0.64 | 0.28 | 0.07 | 0.01 | 0.10 | 0.06 | 0.04 | 0.01

† larger discrepancy in attribute distributions between A and B ⇒ lower disentanglement quality