# Unsupervised Cross-Domain Image Generation

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## Introduction and Motivation

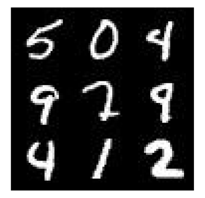
- We explore the fundamental problem of **general domain transfer** by replicating a recent method presented in "Unsupervised Cross-Domain Image Generation" [1]. This method **maps a sample from one domain to a similar sample in a different domain** using a generative adversarial network (GAN) in an unsupervised fashion.
- We attempt to replicate this method in two visual application areas - digits and faces - and perform additional analysis on various components of the approach. **We achieve similar visual results for digits but not faces**, finding that the training procedure is crucial to a successful GAN implementation.

## Data Collection

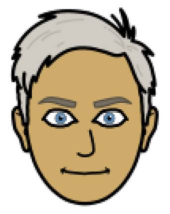
- For digit transfer, we use images from the Street View House Numbers (SVHN) dataset [2] and MNIST database of handwritten digits [3].
- For face transfer, we use a subset of the MS-Celeb-1M dataset [4] and **our own dataset of emojis we created using Bitmoji** [5].
- Digit and face images are resized to (32, 32) and (96, 96) respectively, and all images are normalized to [-1, 1].

| Application | Name | Size | Type |
|---|---|---|---|
| Digit Transfer: | SVHN | 531,131 | RGB |
| | MNIST | 60,000 | Grayscale |
| Face Transfer: | MS-Celeb-1M | 912,224 | RGB |
| | Bitmoji | 1,000,000 | RGB |

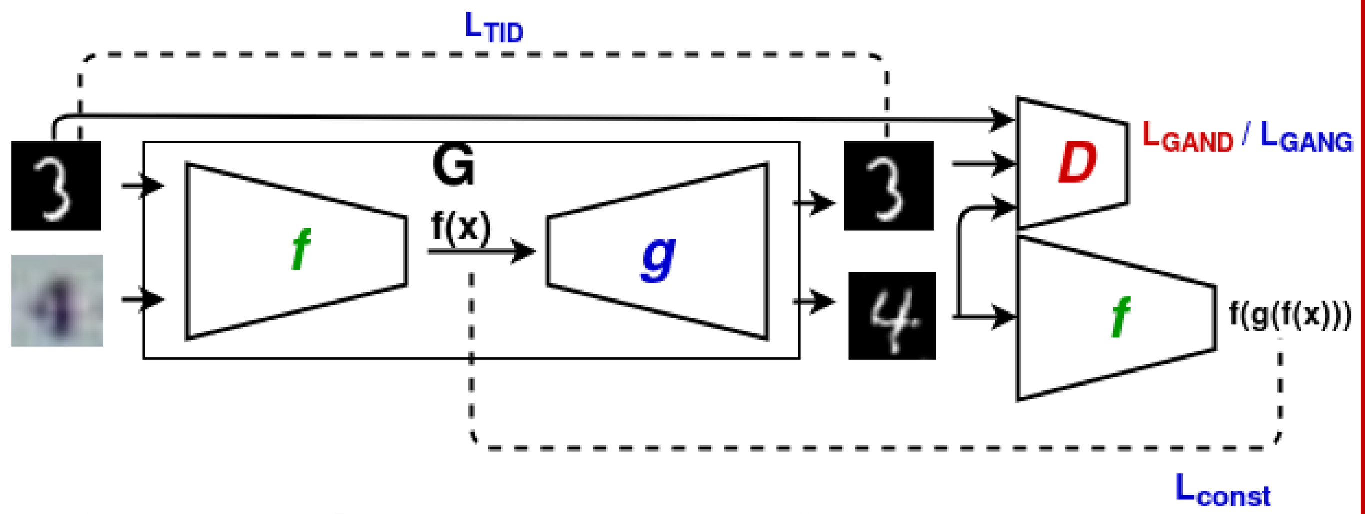

SVHN


MNIST


Face


Bitmoji

## Model Architecture and Loss




- ***f*** - encodes an image into a feature vector
- ***g*** - generates an image from feature vector
- ***D*** - classifies each image into three classes

➢ Discriminator loss:

$$L_D = -\sum_{x\in\mathbf{s}} \log D_1(g(f(x))) - \sum_{x\in\mathbf{t}} \log D_2(g(f(x))) - \sum_{x\in\mathbf{t}} \log D_3(x)$$

➢ Generator loss:

$$L_G = L_{GANG} + \alpha L_{Const} + \beta L_{TID} + \gamma L_{TV}$$

$$L_{GANG} = -\sum_{x\in\mathbf{s}} \log D_3(g(f(x))) - \sum_{x\in\mathbf{t}} \log D_3(g(f(x)))$$

$$L_{CONST} = \sum_{x\in\mathbf{s}} d(f(x), f(g(f(x))))$$

$$L_{TID} = \sum_{x\in\mathbf{t}} d_2(x, G(x))$$

## Results


Fig. 1: SVHN → MNIST

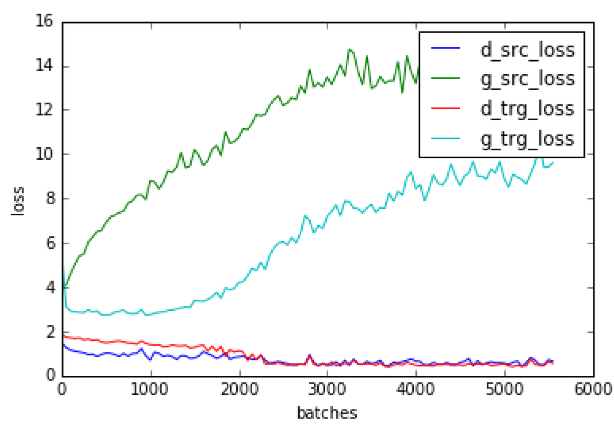


Fig. 2: Loss curve during training

| | Training set | Test set |
|---|---|---|
| Our best model | 81.50% | 74.50% |
| No $L_{const}$ | 22.06% | 18.85% |
| Cross entropy for $L_{const}$ | 96.92% | 91.09% |
| Referenced paper | N/A | 90.66% |

Table 1: Accuracy comparison

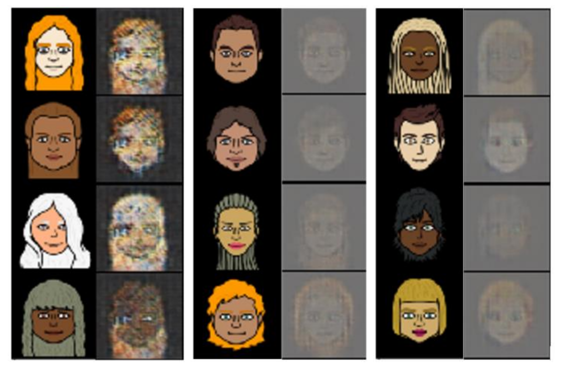

(a) (b) (c)

Fig. 3: Encoding ability of *f* using (a) MSE, (b) cosine similarity, and (c) combined loss

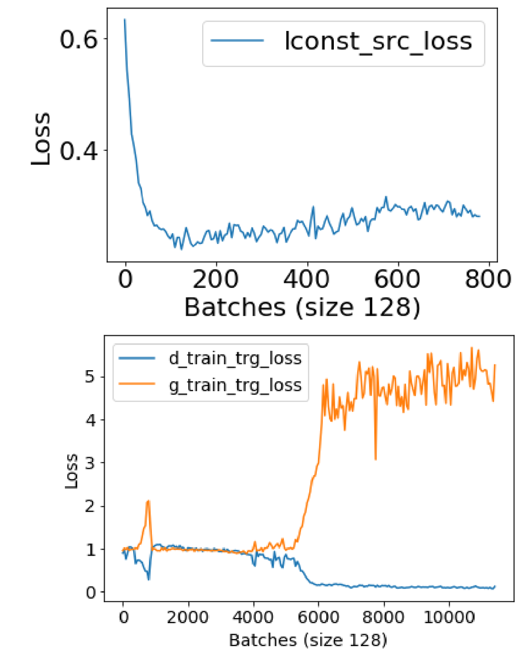


Fig. 4: Problematic loss curves


Fig. 5: Face → Emoji

## Discussion and Additional Analysis

### Best result (digit transfer)

- We trained our best model (Fig. 1 and Fig. 2) for 12 epochs using extra training set of SVHN and training set of MNIST on Google Cloud (8 Intel Broadwell CPUs and 1 NVIDIA Tesla P100 GPU).
- For quantitative evaluation, we judged our transfer results using an MNIST classifier (Table 1).

### GAN training strategies

- ***Balance of discriminator and generator*** - the methods we tried include: a) Train generator more than discriminator, b) Hyperparameter settings, c) Lower bound on discriminator loss, and d) Model architecture.
- ***Normalization*** – standard normal vs. transform to [-1, 1]. Tanh as the last layer of generator.
- ***Avoid sparse gradients*** - downsampling with maxpool vs. strided convolution. LeakyReLU vs. ReLU in discriminator.
- ***Optimization parameters*** – learning rate schedule, SGD vs. Adam, weight decay.

### Effectiveness of $L_{const}$

- ***Without $L_{const}$*** - generated digits are clear but obviously lack correspondence.
- ***Cross entropy loss for $L_{const}$*** - between transferred images and labels of original images. Easily achieved similarly excellent digit transfer performance to the referenced paper, but challenges idea of an "unsupervised" method.

## References

[1] Y. Taigman, A. Polyak, L. Wolf, Unsupervised Cross-Domain Image Generation, arXiv preprint arXiv:1611.02200 (2016).
[2] N., Yuval, T. Wang, A. Coates, A. Bissacco, B. Wu, A. Y. Ng, Reading digits in natural images with unsupervised feature learning, In NIPS workshop on deep learning and unsupervised feature learning, vol. 2011, no. 2, p. 5, 2011.
[3] Y. LeCun, The MNIST database of handwritten digits, http://yann. lecun. com/exdb/mnist/ (1998).
[4] Y. Guo, L. Zhang, Y. Hu, X. He, J. Gao, A Dataset and Benchmark for Large Scale Face Recognition, European Conference on Computer Vision, 2016
[5] https://www.bitmoji.com/