

Goals and Motivation

- General domain transfer has applications like drawing between different domains and producing new data
- Our aim here is to create a general domain transfer model which maps samples from one domain to another. We aim to transfer samples from one

domain to another in an unsupervised while preserving manner, correspondences between the samples.

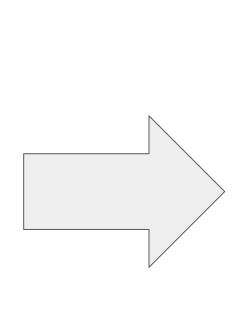
Our Problem

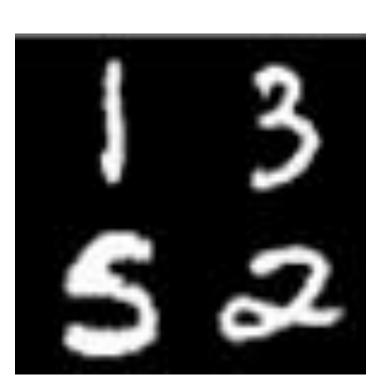
Source

Target



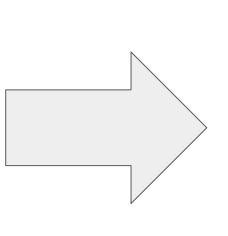
SVHN





MNIST







MS Celeb

Bitmoji

- Given a sample in the SVHN Domain, generate corresponding the sample
- person's face, generate their • Given a corresponding Bitmoji sample

References

[1] Y. Taigman, A. Polyak, and L. Wolf. Unsupervised cross-domain image generation. arXiv preprint arXiv:1611.02200, 2016. [2] Xinru Hua, Davis Rempe, and Haotian Zhang, Unsupervised Cross-Domain Image Generation, Technical Report, Stanford University

Unsupervised Cross-Domain Image Generation Girish Chandar G | S Deepak Narayanan | Sammed S Kagi | Shivji Bhagat

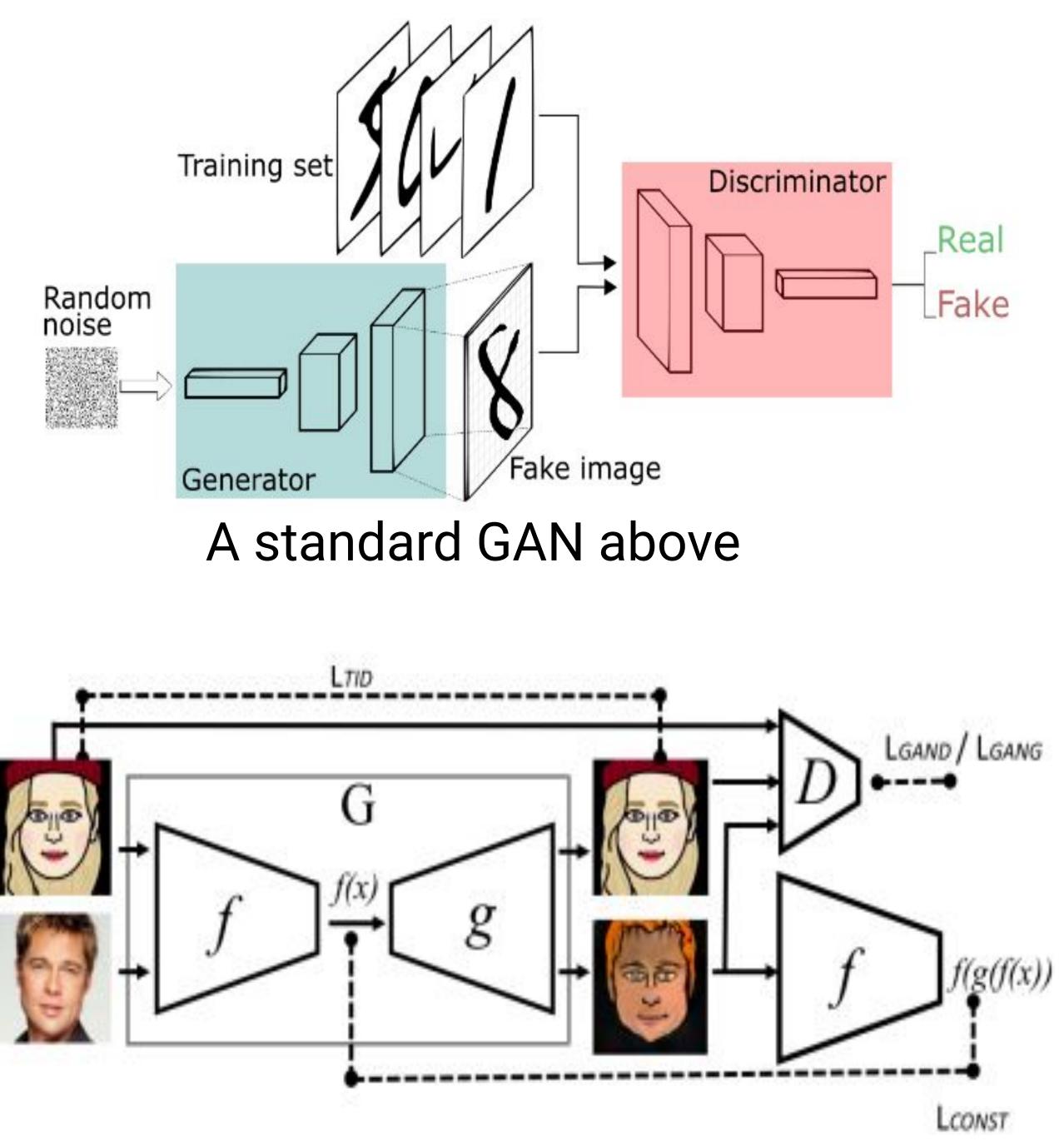
varied analogies

the



MNIST

Use a modified GAN to somehow capture the requirements of the task at hand.



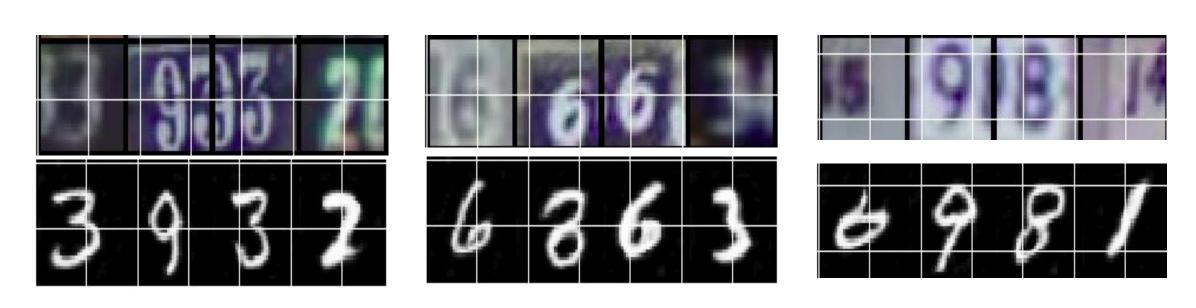
Major differences in the architectures

- Input to the generator is the output of a feature encoder unlike the standard GAN, to which the input is a noise vector.
- Additional loss functions to impose feature constancy and identity across domains
- Constancy and Identity ensure one to one correspondence
- Usage of a ternary discriminative function

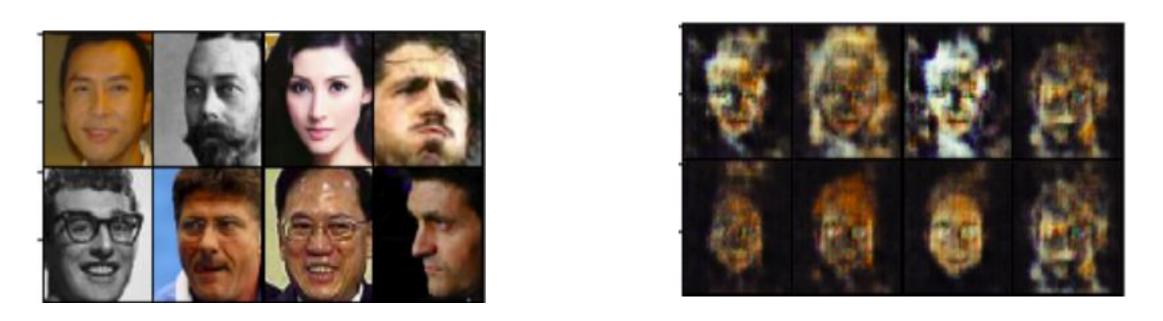
Approach

Results and Discussion

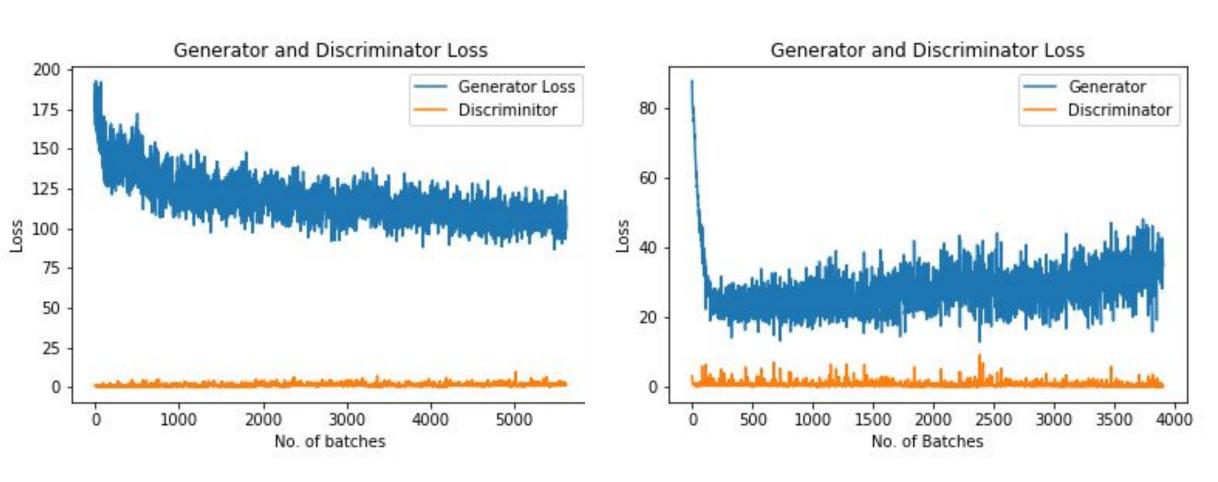
Accuracy of 77.67% on SVHN to MNIST conversion



Face Transfer



Loss function plots for the best transfers SVHN to MNIST MS-Celeb to Bitmoji



Conclusions and Discussions

- times.
- same for a number.
- digit transfer case.

Acknowledgements

We would like to thank Prof. Nipun Batra and our TA Mr. Shubham Singh for their continued inputs and support during the course of the project.

1. Training a GAN is a very difficult process. We had the issue of mode collapse multiple

2. Learning a feature encoder for a face is a much more complex task than learning the

3. It was difficult for us to get visually pleasing results for the face transfer model. Even after trying out multiple architectures for the generator and discriminator we couldn't generate realistic images, as we could, in the