Least Squares Generative Adversarial Networks (LSGAN) for Image Generation

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Problem Formulation

The Generated Adversarial Network (GAN) features a generator and discriminator working in tangent, with the discriminator trained to evaluate the authenticity of images and the generator trying to trick it. In doing so, the generator is able to learn to produce authentic-seeming images.

Objective: Though GAN's have proven useful in computer vision, in this project we demonstrate that modifying the loss function to use least square loss improves stability and quality of images, as evaluated on the Fashion-MNIST dataset.

Architecture

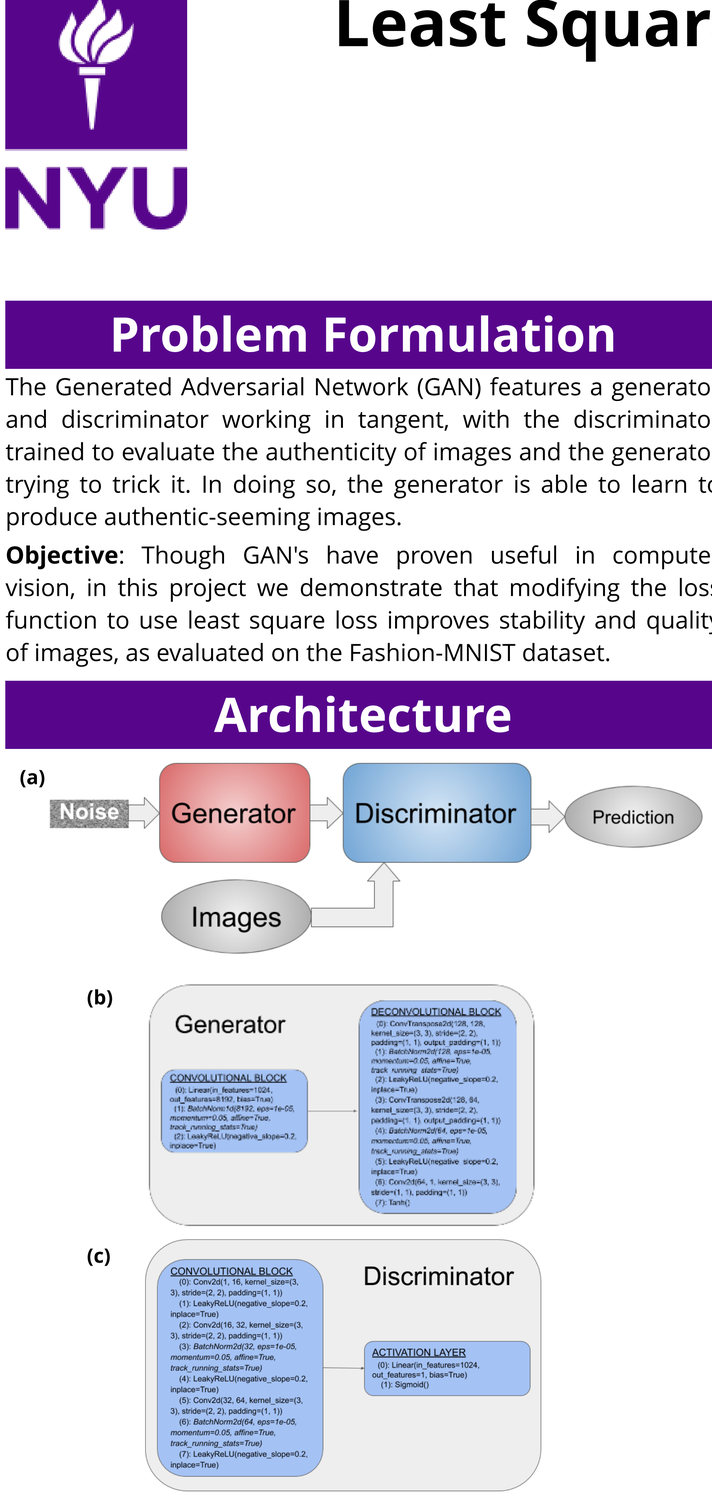

Figure 3 GAN architecture. (a) Basic architecture of a GAN. **(b)** Our best Generator architecture. **(c)** Our best Discriminator architecture. The italicized BatchNorm layer in (b) and (c) was an optional layer we experimented on.

Generated Images

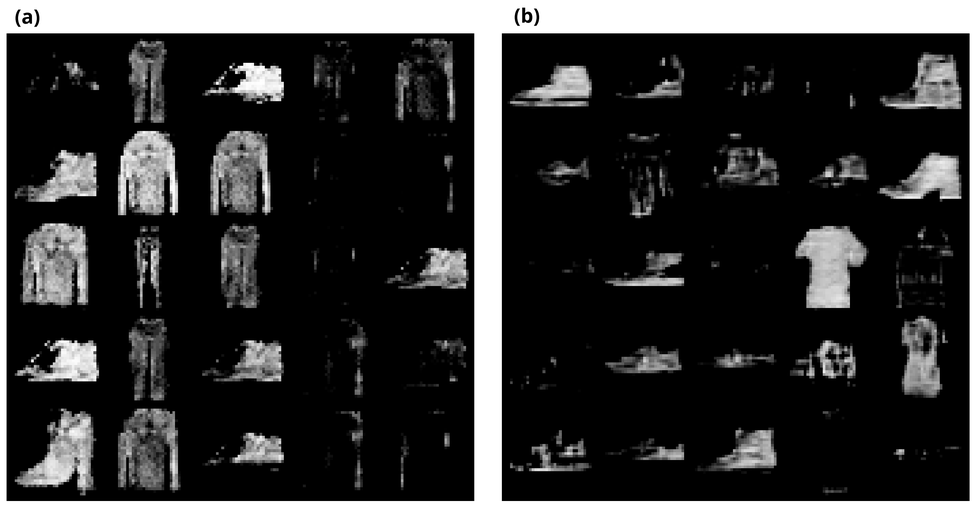

Figure 1 GAN-generated images. (a) Images generated by GAN using batch normalization. **(b)** Images generated by GAN without batch normalization.

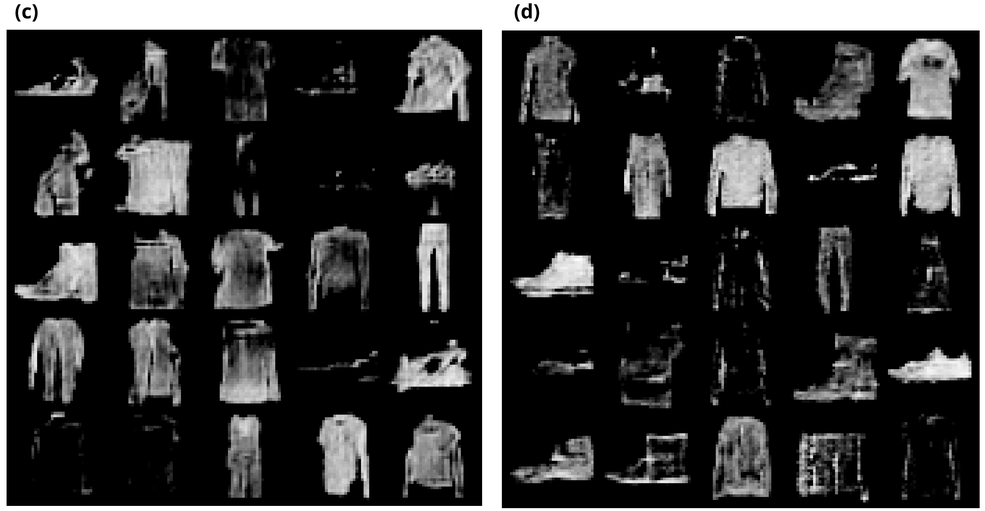

Figure 2 LSGAN-generated images. (a) Images generated by LSGAN using batch normalization. **(b)** Images generated by LSGAN without batch normalization

Results

Models	No Batch Norm	Batch Norm (Momentum = 0.1)	Batch Norm (Momentum = 0.05)
GAN	**66.73**	**144.43**	**347.65**
LSGAN	**48.72**	**74.12**	**144.11**

Table 1: FID scores for each model. The Frechet Inception Distance (FID) is a metric allowing us to compare the similarity between a set of real and generated images.

Discussion

- In terms of both quality of images generated and FID score, we observed that the LSGAN without batch normalization performed best.
- Although we experimented with different values for momentum, batch normalization ultimately never improved performance.
- We reduced the complexity of our architecture to prevent "mode collapse", wherein the generator is unable to improve itself.

Future Work

For future work, our group is interested in seeing if it is possible to extend this analysis to more complex image datasets. Additionally, applying a semi-supervised approach by passing image metadata or labels to the model may prove beneficial.

References

Goodfellow et al. "Generative Adversarial Networks" https://arxiv.org/abs/1406.2661

Mao et al. "Least Squares Generative Adversarial Networks" https://arxiv.org/pdf/1611.04076.pdf

Huesel et a. "GANs Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium"https://arxiv.org/abs/1606.03498

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