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Sparse Generative Adversarial Networks

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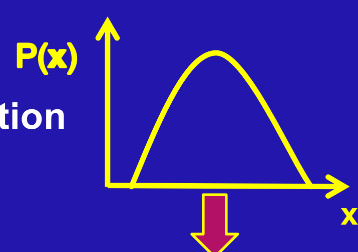
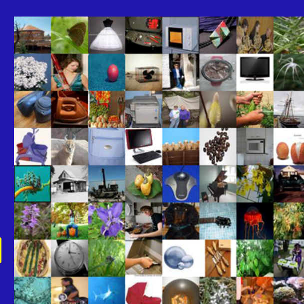
Generative Modeling

- Density estimation





Training examples

Gen. Adv. Nets

- Sample generation

Model samples

Generative Adversarial Networks

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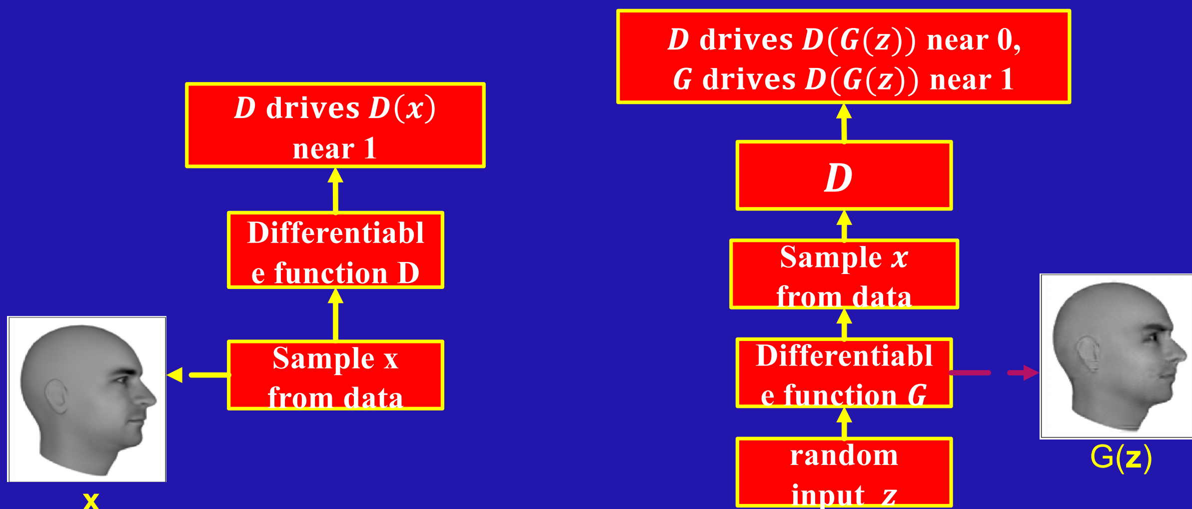

Lotter, William, Gabriel Kreiman, and David Cox. "Unsupervised learning of visual structure using predictive generative networks." arXiv preprint arXiv:1511.06380 (2015).

Minimax Game

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$$\min_{G} \max_{D} \mathbb{E}_{\boldsymbol{x}\sim p_{\boldsymbol{x}}} [\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}} [\log(1 - D(G(\boldsymbol{z})))]$$

for i in range (n):
- select a mini batch of the real samples $\boldsymbol{X}$
- create random vectors $\boldsymbol{Z}$
- generate fake samples $G_{\omega_i}(\boldsymbol{Z})$
- $\theta_{i+1} \leftarrow \theta_i - \eta\, \nabla_\theta L^D$
- $\omega_{i+1} \leftarrow \omega_i - \eta\, \nabla_\omega L^G$

Wasserstein GAN

- Replacing the Jenson-Shannon divergence $JS(p_x \,||\, p_g)$ with the earth-mover's distance $W(p_x, p_g)$,

$$\min_{G} \max_{D \in \mathcal{D}} \mathbb{E}_{x \sim p_x}\left[D(x)\right] - \mathbb{E}_{z \sim p_z}\left[D\big(G(z)\big)\right],$$

Where $\mathcal{D}$ is the set of 1-Lipschitz functions.

- When good convergence is achieved, reasonably good results obtained
- Problems with events of catastrophic failures happen and reduce the reliability/robustness

Generative Network

$$\boldsymbol{z} \in \mathbb{R}^n \qquad \boldsymbol{z} \sim N(0, \boldsymbol{I}_{n \times n})$$

$$G(\boldsymbol{z}) \in \mathbb{R}^k \qquad G(\boldsymbol{z}) \in \mathbb{R}^{(512 \times 512 \times 3)}$$

$$\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix} \qquad \begin{bmatrix} G(z)_1 \\ G(z)_2 \\ \vdots \\ \vdots \\ \vdots \\ G(z)_k \end{bmatrix}$$

A generative network is a function that takes a random vector $z \in \mathbb{R}^n$ and generates a sample vector $G(z) \in \mathbb{R}^k$, $k \gg n$.

Generated images

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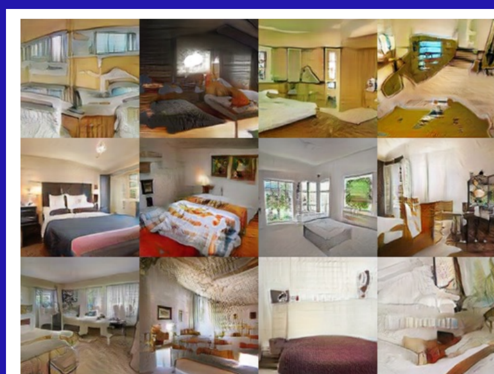
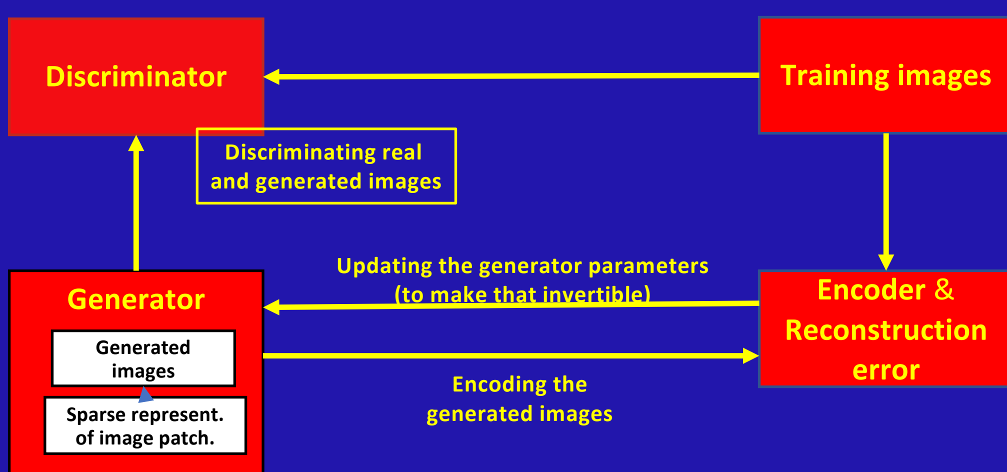
Successful



Unsuccessful

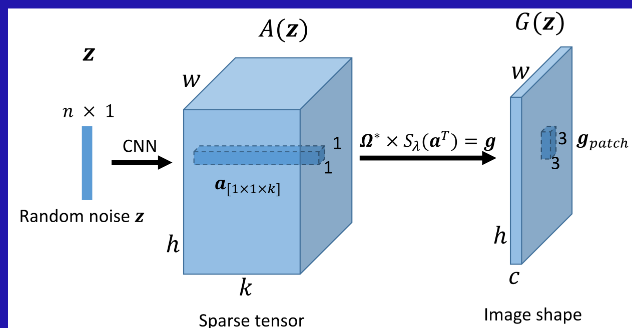
Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434.

New Approach in a nutshell



Sparse Generator Network

- **Avoid potentially singular features by regularization**

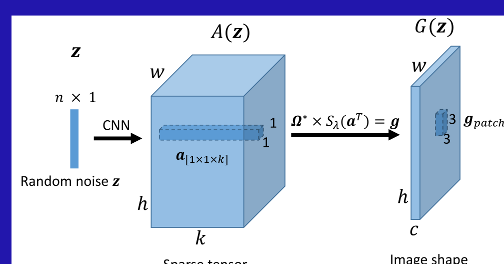


- **A deep neural network that generates a vector of sparse coefficients $S(z)$ from a random input noise vector z.**
- **These coefficients are used as a representation of the image patches resulting from for example a Lasso model,**

Sparse Generator Network

- **The image patches can be simply computed by multiplying the coefficients by a pre-trained dictionary Ω^*.**

- **Training dictionary Ω^*:**

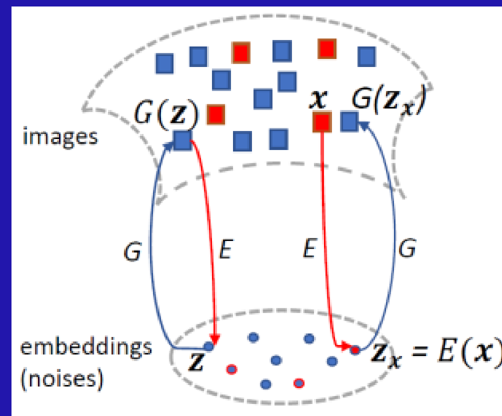


$$\{\boldsymbol{\Omega}^*, \boldsymbol{R}\} = \underset{\boldsymbol{\Omega},\, \boldsymbol{R}}{\boldsymbol{arg\ min}}\ ||\boldsymbol{G} - \boldsymbol{\Omega}\ \boldsymbol{R}||_F^2 + \boldsymbol{\lambda}||\boldsymbol{R}||_1\,, \quad \boldsymbol{\Omega} \in \boldsymbol{\mathcal{C}},$$

$\boldsymbol{g_i} \in \boldsymbol{R^m}$ $\boldsymbol{i} \in \{1, .., s\}$ are vectorized image patches as columns of a matrix $\boldsymbol{G}$.

An Encoder Network

- Ensuring the map $G(z)$ is rich and can generate a wide variety of real-world images,
- Verifying that it is injective to provide additional robustness to mode-collapse



$$\phi^* = \arg\min_{\phi} \mathbb{E}_{z\sim p_z} ||E_\phi(G(z)) - z||_2$$

Sparse Generative Adversarial Network

$$\min_{G} \max_{D\in\mathcal{D}} \mathbb{E}_{x\sim p_x}[D(x)] - \mathbb{E}_{z\sim p_z}[D(G(z))] + \mathbb{E}_{x\sim p_x}[||G(E^*(x)) - x||_2^2]$$

st: $$E^* \in \arg\min_{E} \mathbb{E}_{z\sim p_z}[||E(G(z)) - z||_2^2]$$

where $\mathcal{D}$ is the set of 1-Lipschitz functions.

Sparse Generative Adversarial Network

$$L_D = \mathbb{E}_{z\sim p_z}[D(G(z))] - \mathbb{E}_{x\sim p_x}[D(x)] + \lambda \mathbb{E}_{\hat{x}\sim p_{\hat{x}}}[(||\nabla_{\hat{x}} D(\hat{x})||_2 - 1)^2],$$

$$L_G = -\mathbb{E}_{z\sim p_z}[D(G(z))],$$

$$L_R = \mathbb{E}_{x\sim p_x}[||G(E^*(x)) - x||_2^2]$$

st: $$E^* \in \arg\min_E \mathbb{E}_{z\sim p_z}[||E(G(z)) - z||_2^2]$$

Sparse GAN Framework, 3-players

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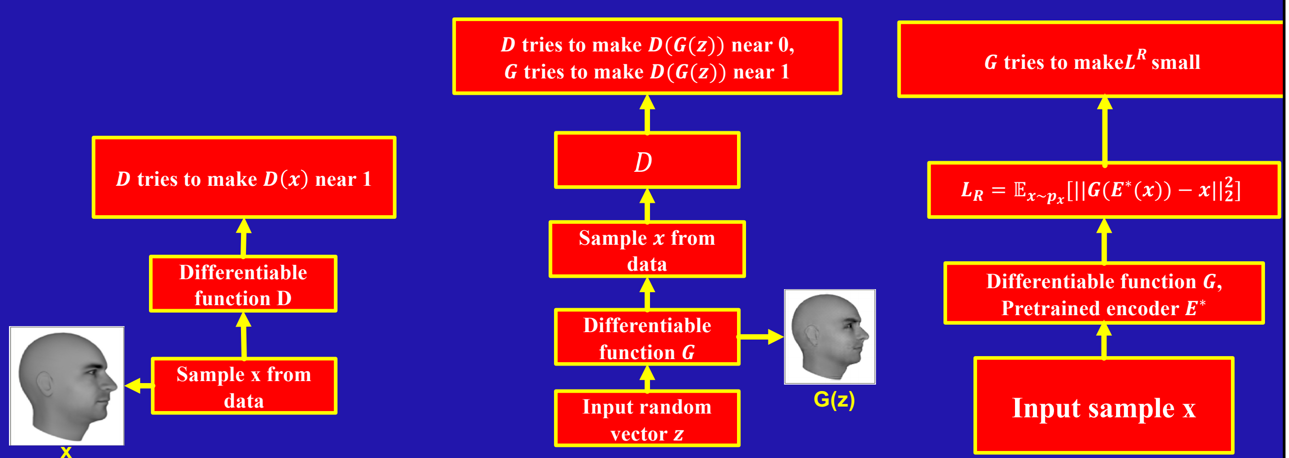


Results

Inception score

Inception score on CIFAR10 images without residual blocks in generator

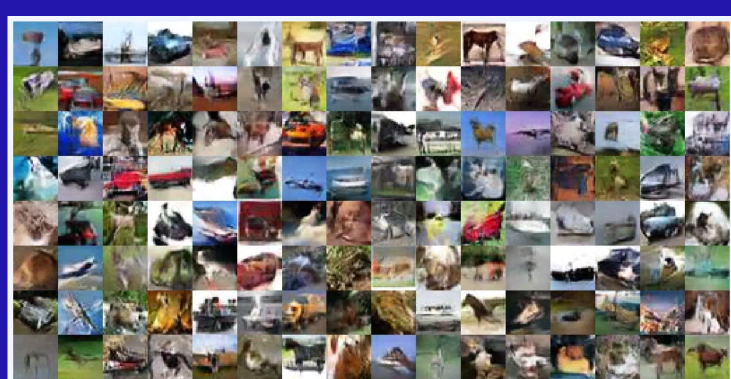
Method	score	SPGAN	SPGAN recon.
ALI [7]	5.36	-	-
BEGAN [2]	5.62	-	-
WGAN [1]	5.76	6.1	6.6
Im-WGAN [11]	5.92	6.2	6.7

Inception score

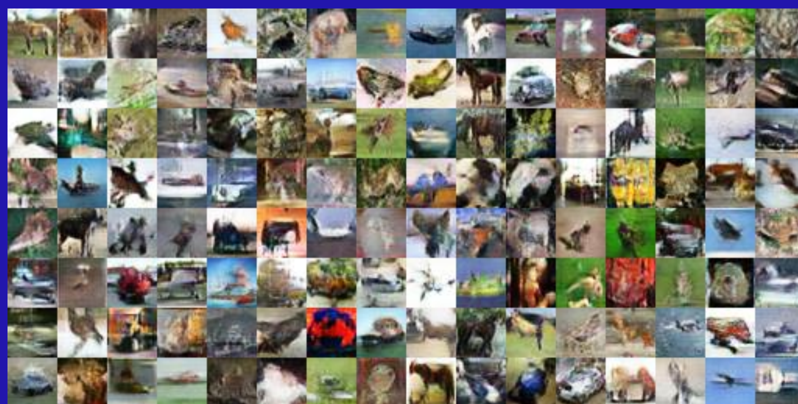
Inception score on CIFAR10 images with residual blocks in generator

Method	score	SPGAN	SPGAN recon.
ALI [7]	5.36	-	-
BEGAN [2]	5.62	-	-
WGAN [1]	7.73	7.85	7.88
Im-WGAN [11]	7.86	7.93	7.95

Produced images from cifar10 dataset:

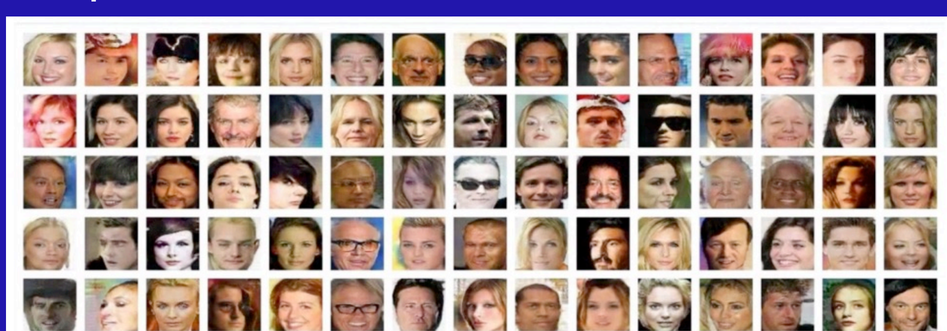


Produced images from cifar10 dataset:



Generated images using celebrity face dataset

Proposed method



Generated images using celebrity face dataset

Improved WGAN method

Conclusion

- An enhanced more robust GAN architecture, which generates images from patches obtained through a UoS model.
- A third player, called "reconstructor" to ensure high variability of the output images.
- The idea can be generalized to an arbitrary number of layers in different datasets.