Exploring Image
Generation with Deep
Learning: Deep
Convolutional Generative
Adversarial Networks

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# UC San Diego

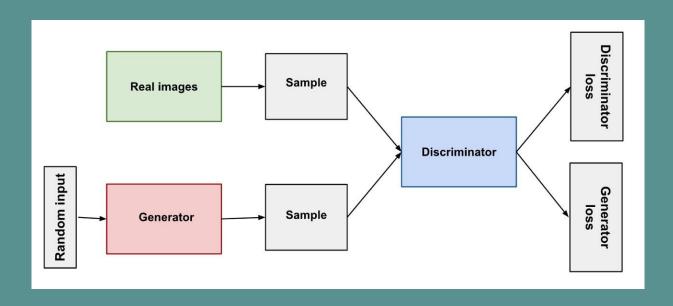
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## **Background**

# Generative Adversarial Networks (GAN)

- Generator
- Discriminator
- Adversarial Process
- CreatingRealistic Images

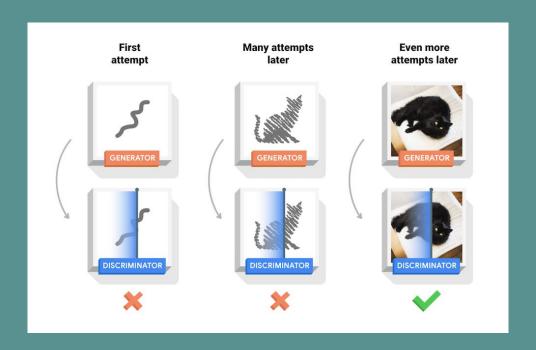


**GAN Architecture [4]** 

### Introduction & Motivation

# Deep Convolutional Generative Adversarial Network (DCGAN)

- Revisit the original DCGAN study (Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks, [2])
- Apply its methods to diverse datasets to explore the technique's effectiveness
- Goal is to understand its inner workings and identify its strengths and weaknesses.



DCGAN Example [5]

## **Approach & Methods**

- Data Loading & Preprocessing
- 2. Generator and Discriminator Architecture
- 3. Training & Loss Analysis
- 4. Image Generation Analysis

```
[9/10][2800/3166]
                        Loss D: 0.1270 Loss G: 6.9989
                                                       D(x): 0.9127
                                                                        D(G(z)): 0.0117 / 0.0036
[9/10][2850/3166]
                        Loss D: 0.1473 Loss G: 5.7211
                                                       D(x): 0.9611
                                                                        D(G(z)): 0.0866 / 0.0079
[9/10][2900/3166]
                        Loss D: 0.0800 Loss G: 4.4613
                                                        D(x): 0.9724
                                                                        D(G(z)): 0.0468 / 0.0201
                        Loss D: 0.0919 Loss G: 4.9013
                                                       D(x): 0.9352
[9/10][2950/3166]
                                                                        D(G(z)): 0.0168 / 0.0219
                                                       D(x): 0.9578
[9/10][3000/3166]
                        Loss D: 0.0559 Loss G: 5.3102
                                                                        D(G(z)): 0.0088 / 0.0115
                        Loss D: 0.0426 Loss G: 5.3165
                                                        D(x): 0.9767
[9/10][3050/3166]
                                                                        D(G(z)): 0.0173 / 0.0108
[9/10][3100/3166]
                        Loss D: 0.0479 Loss G: 5.7214
                                                        D(x): 0.9764
                                                                        D(G(z)): 0.0218 / 0.0081
                        Loss D: 0.0713 Loss G: 5.1483
[9/10][3150/3166]
                                                                        D(G(z)): 0.0121 / 0.0186
                                                        D(x): 0.9479
```

#### **DCGAN - Loss Probability**

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

DCGAN - Convolutional Layers Architecture

## **Experiments**

Apply the approach to diverse datasets.

### Three Datasets:

- 1. EMNIST
- 2. Celeb-A
- 3. CIFAR-10

Analyze results through metrics and image comparison.

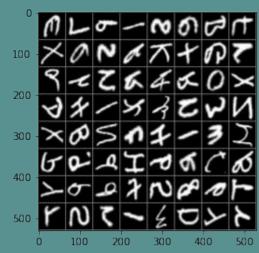




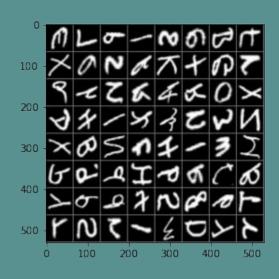


## **Experiments - EMNIST**

- Real and generated batch of images are identical
- Discriminator successfully recognizes real images
- Generator struggles to create realistic images







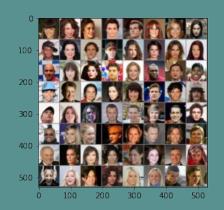
Generated Images

[10/10] [700/882] Loss_D:	0.0001	Loss_G:	9.8182	D(x):	1.0000	D(G(z)):	0.0001	/ 0.0001
[10/10] [750/882] Loss_D:	0.0000	Loss_G:	12.1525	D(x):	1.0000	D(G(z)):	0.0000	/ 0.0000
[10/10] [800/882] Loss_D:	0.0001	Loss_G:	9.9660	D(x):	0.9999	D(G(z)):	0.0001	/ 0.0000
[10/10] [850/882] Loss_D:	0.0003	Loss_G:	9.1757	D(x):	0.9998	D(G(z)):	0.0001	/ 0.0001

**Loss Metrics** 

## **Experiments - Celeb-A**

- Generated images appear disfigured
- Generator loss is relatively high
- Generator is not producing realistic images to deceive the Discriminator
- Discriminator performs well





#### Real Images

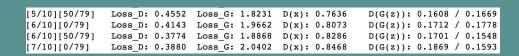
#### Generated Images

[9/10][2800/3166]	Loss_D: 0.1270	Loss_G: 6.9989	D(x): 0.9127	D(G(z)): 0.0117 / 0.0036
[9/10][2850/3166]	Loss_D: 0.1473	Loss_G: 5.7211	D(x): 0.9611	D(G(z)): 0.0866 / 0.0079
[9/10][2900/3166]	Loss_D: 0.0800	Loss_G: 4.4613	D(x): 0.9724	D(G(z)): 0.0468 / 0.0201
[9/10][2950/3166]	Loss_D: 0.0919	Loss_G: 4.9013	D(x): 0.9352	D(G(z)): 0.0168 / 0.0219
[9/10][3000/3166]	Loss_D: 0.0559	Loss_G: 5.3102	D(x): 0.9578	D(G(z)): 0.0088 / 0.0115
[9/10][3050/3166]	Loss_D: 0.0426	Loss_G: 5.3165	D(x): 0.9767	D(G(z)): 0.0173 / 0.0108
[9/10][3100/3166]	Loss_D: 0.0479	Loss_G: 5.7214	D(x): 0.9764	D(G(z)): 0.0218 / 0.0081
[9/10][3150/3166]	Loss_D: 0.0713	Loss_G: 5.1483	D(x): 0.9479	D(G(z)): 0.0121 / 0.0186

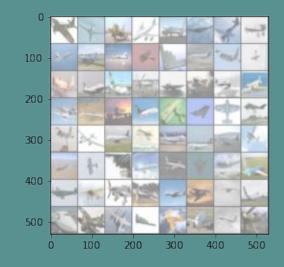
**Loss Metrics** 

## **Experiments - CIFAR-10**

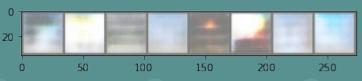
- Generated images lack a discernable object and appears smudgy
- Discriminator successfully recognizes real images
- Generator struggles to create realistic images



**Loss Metrics** 



**Real Images** 



Generated Images

## **Conclusion**

- Successfully re-implemented the DCGAN from the research paper.
- Did not have the best results compared to the research paper.
- Identified what requires further investigation with our experiments to improve our network.

# **Acknowledgements**

This presentation was completed for the final project of ECE 176:Introduction to Deep Learning & Applications.

Project Report and codebase can be found in our **GitHub repository**.



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#### References - Part 1

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[2] Radford Alec, Metz Luke, and Chintala Soumith. 2015. "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks." arXiv:1511.06434.

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[5] Deep convolutional generative Adversarial Network - Tensorflow. Retrieved March 17, 2023. <a href="https://www.tensorflow.org/tutorials/generative/dcgan">https://www.tensorflow.org/tutorials/generative/dcgan</a>

#### References - Part 2

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