Software Engineering: OOP illustrated through Density Estimating Neural Networks
GANs

Albert Montillo, Son Nguyen

UTSouthwestern

Departments: Lyda Hill Department of Bioinformatics, Radiology, and Advanced Imaging Research Center

SWE course

Lyda Hill Department of Bioinformatics

Outline

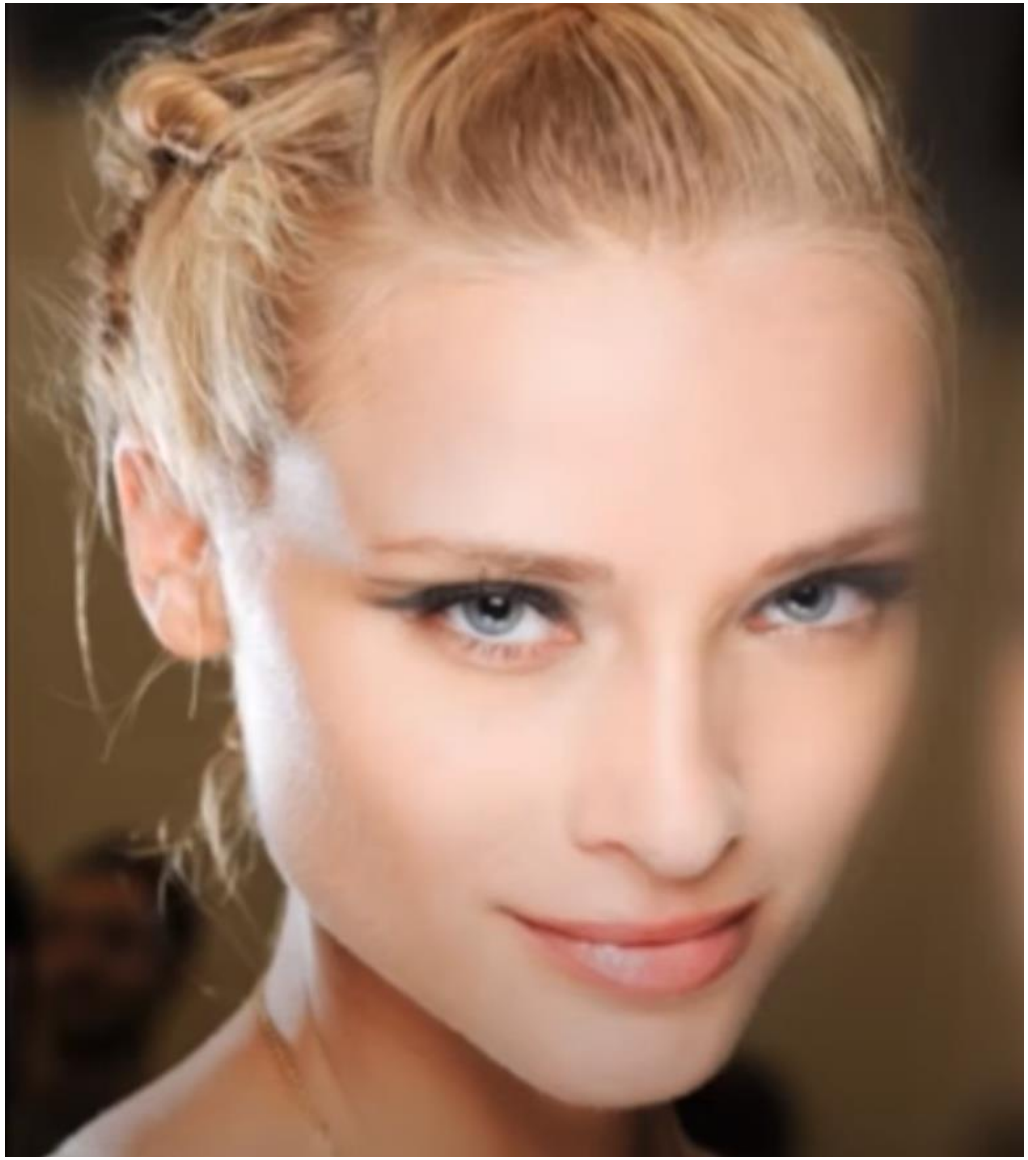
1. **Monday : Object Oriented Variational Autoencoders (VAEs)**
   1. Self study read the slides (Monday_VAE..pptx) on your own
   2. Start the exercise described on slides 47-54
   3. Any concerns: email TAs and/or bring questions to Tuesday morning lecture

2. **Tuesday**
   1. Ask your residual questions about VAEs after having attempted exercise Monday
   2. New topic: Object Oriented Generative Adversarial Networks (GANs)
   3. New topic: Symbolic debugger: cond breakpoints and call stack traversal

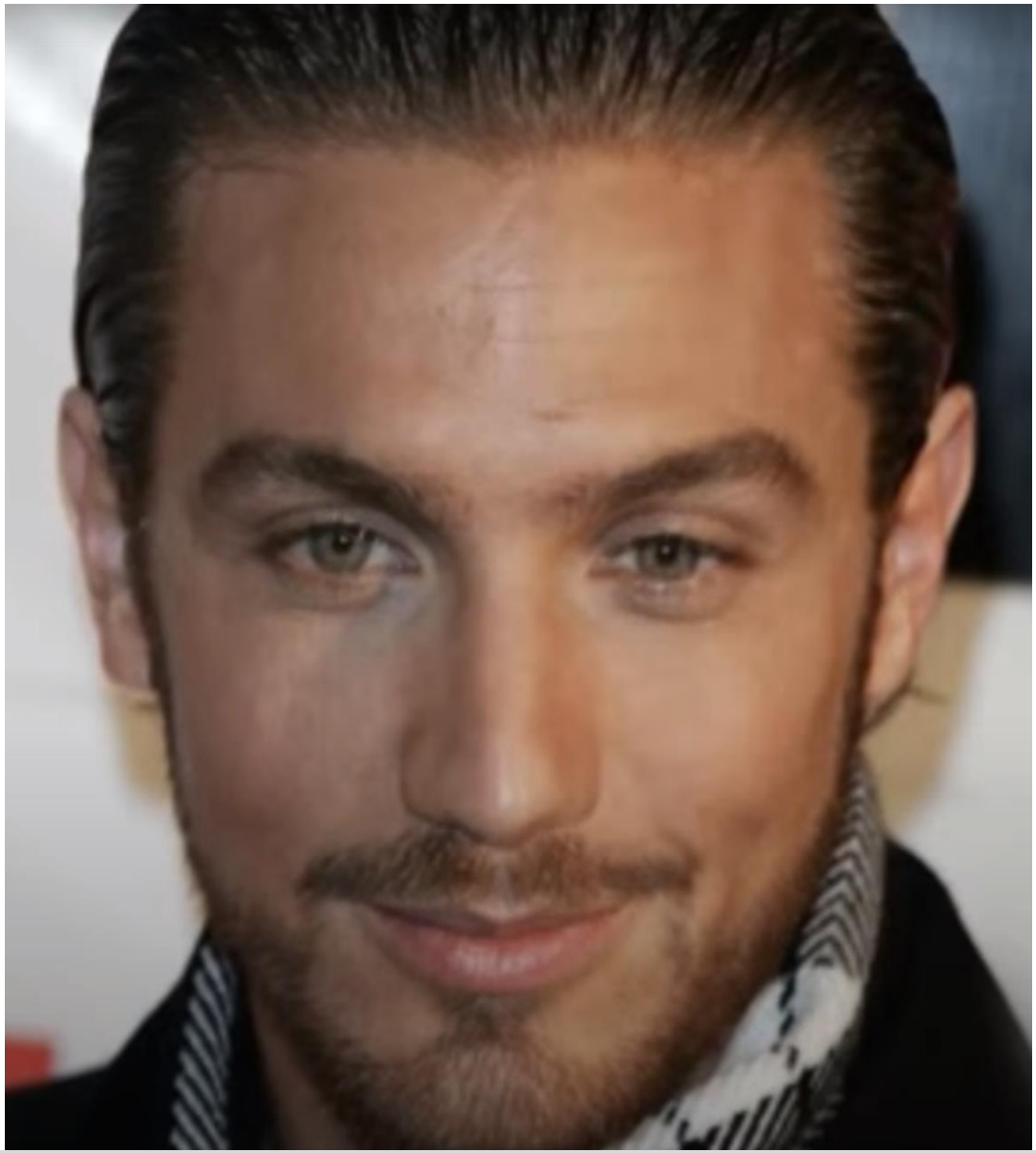
3. **Wednesday**
   1. Review observations on VAEs and GANs
   2. New topic: Object Oriented ***conditional*** VAEs (cVAE) and ***Auxillary Classifier*** GANs (AKA cGAN or acGAN)
   3. New topic: Motivate a possible combination of cVAE and cGAN

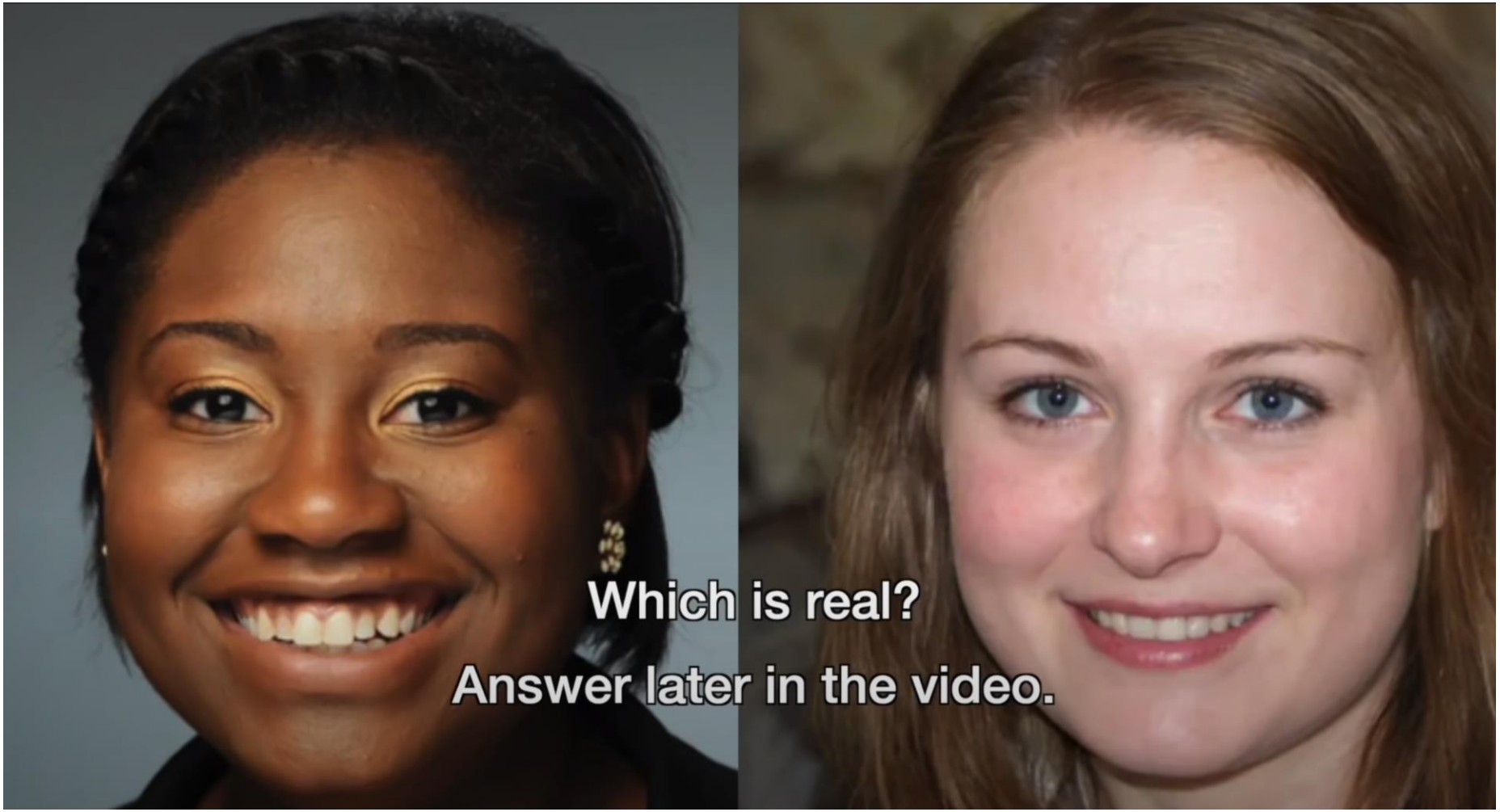
4. **Thursday**
   1. Review cVAE, cGAN observations
   2. Review cVAE-cGAN code
   3. New topic: Hyperparameter optimization
   4. New topic: training curve and latent space traversal and visualization

Who is this?



Who is this?





https://www.youtube.com/watch?v=ixgFtjfO_7Q&t=52s&ab_channel=DigitalEngine

https://www.youtube.com/watch?v=ixgFtjfO_7Q&t=52s&ab_channel=DigitalEngine

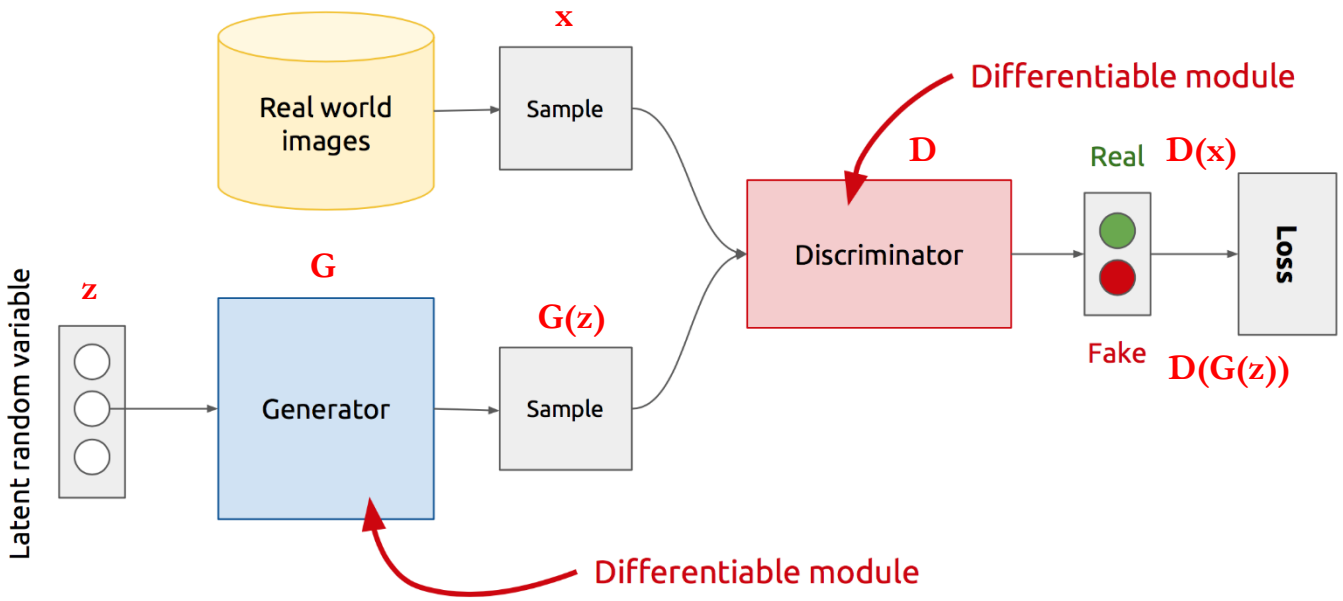
Generative Adversarial Networks (GANs)

- **Introduced in 2014 by Ian Goodfellow**
- **Why do we need GANs? What are they useful for?**
  - **To generate new data for augmentation when labeled training data is scarce**
  - **To generate new data to be used as is (to understand a density)**
- **Why is it adversarial?**
  - **It is a competition between 2 components**
  - **Generator (counterfeiter) produces fake data by mimicking real data**
  - **Discriminator (cop) … distinguishes real from fake data (to catch the counterfeiter)**
- **Discriminator's loss (inability to discriminate reals from fakes) is passed to the Generator as an objective function**

Steps to train a GAN

1. Define the problem
2. Define the GAN architecture
3. Train Discriminator to distinguish real from fake data
4. Train Generator to synthesize new data
5. Repeat steps 3 and 4 until convergence
6. When training is finished, synthesize new data from generator

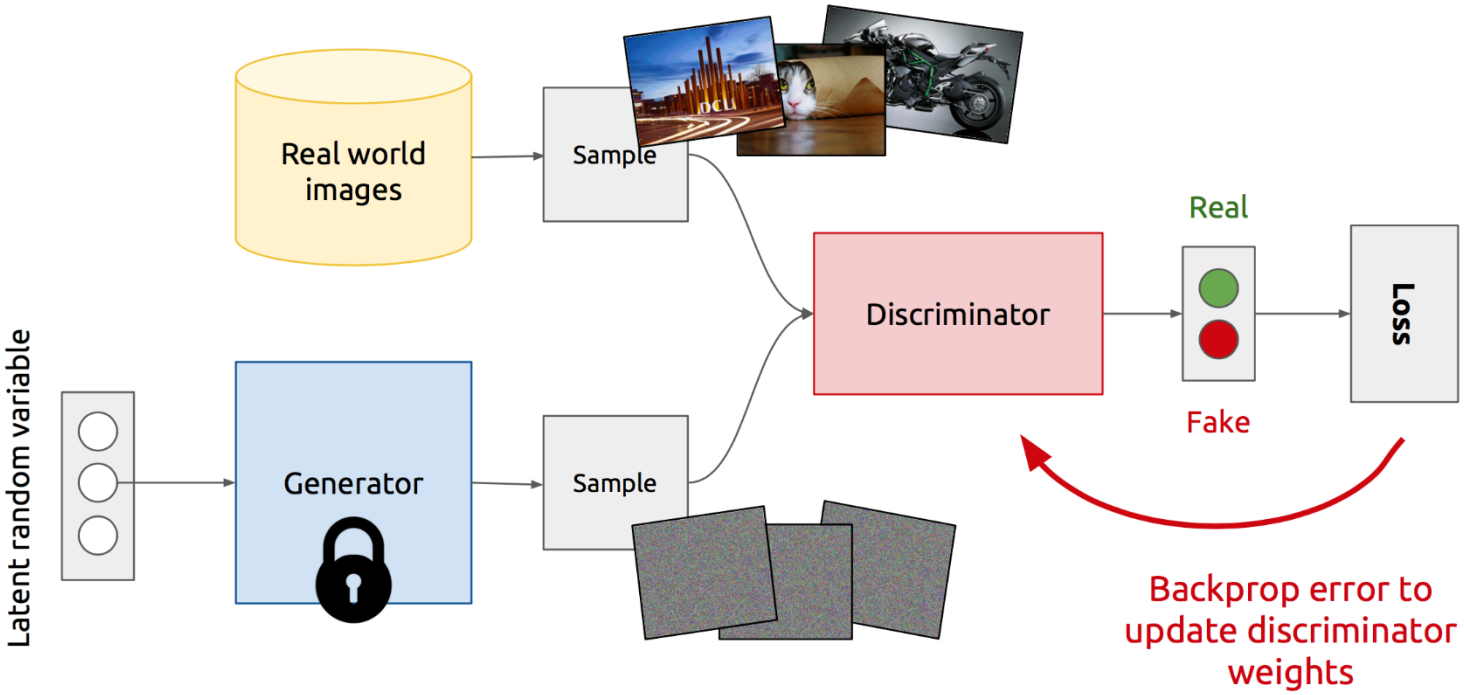
Architecture of a GAN



- **Z** is some random noise (Gaussian/Uniform).
- **Z** can be thought as the latent representation of the image.

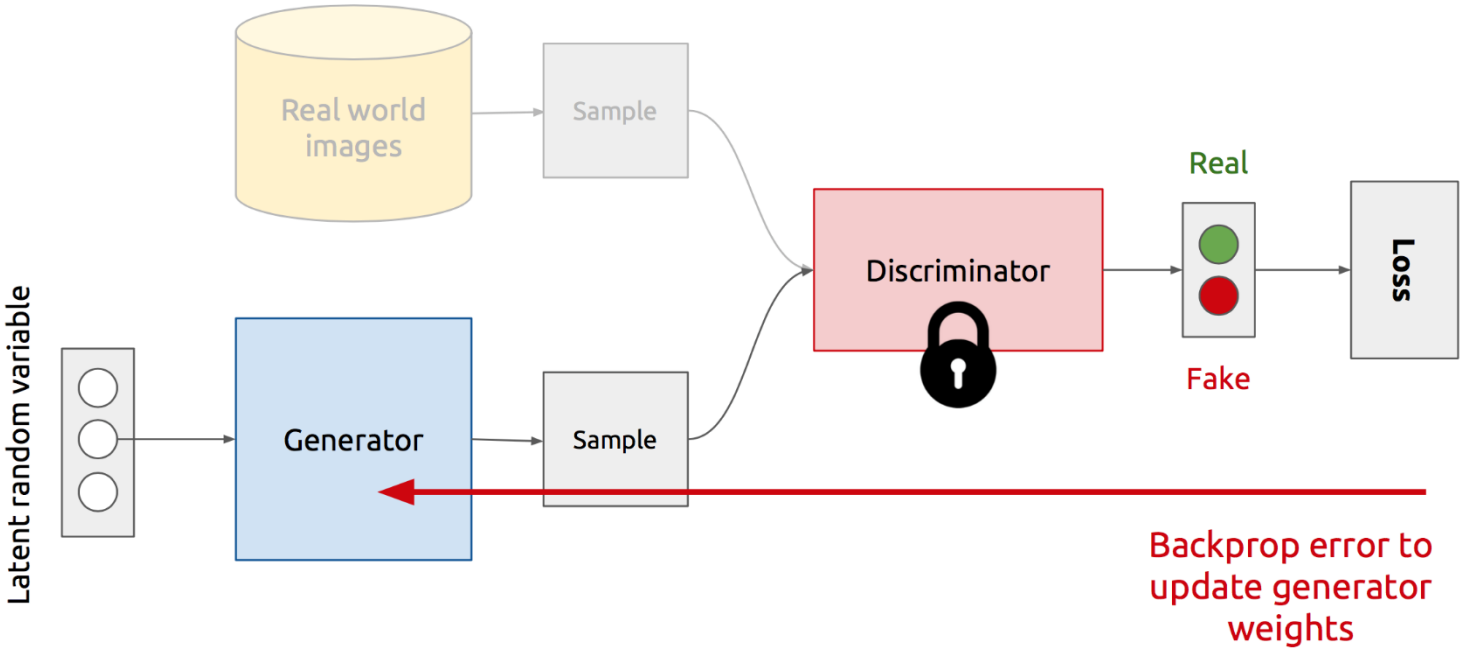
https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016

Discriminator training



https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016

Generator training



https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016

Formulation of the GAN

$$\min_G \max_D V(D, G)$$

It is formulated as a minimax game, where:

- **The Discriminator is trying to maximize its reward $V(D, G)$**
- **The Generator is trying to minimize Discriminator's reward (or maximize its loss)**

$$V(D, G) = \mathbb{E}_{x \sim p(x)}[\log D(x)] + \mathbb{E}_{z \sim q(z)}[\log(1 - D(G(z)))]$$

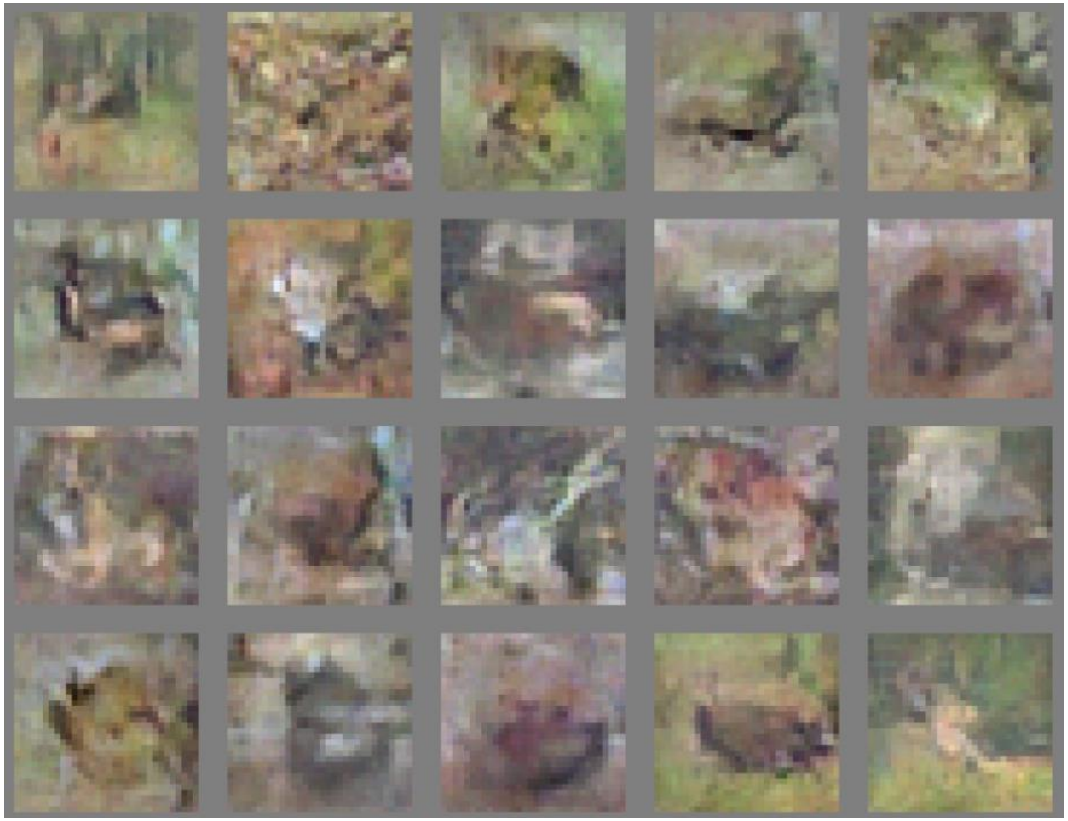
The Nash equilibrium of this particular game is achieved at:

- $P_{data}(x) = P_{gen}(x) \ \ \forall x$
- $\mathbf{D}(x) = \frac{1}{2} \ \ \forall x$

Adapted from http://slazebni.cs.illinois.edu/spring17/lec11_gan.pptx

Steps to train a GAN

CIFAR



Goodfellow, Ian, et al. **"Generative adversarial nets."** *Advances in neural information processing systems*. 2014.

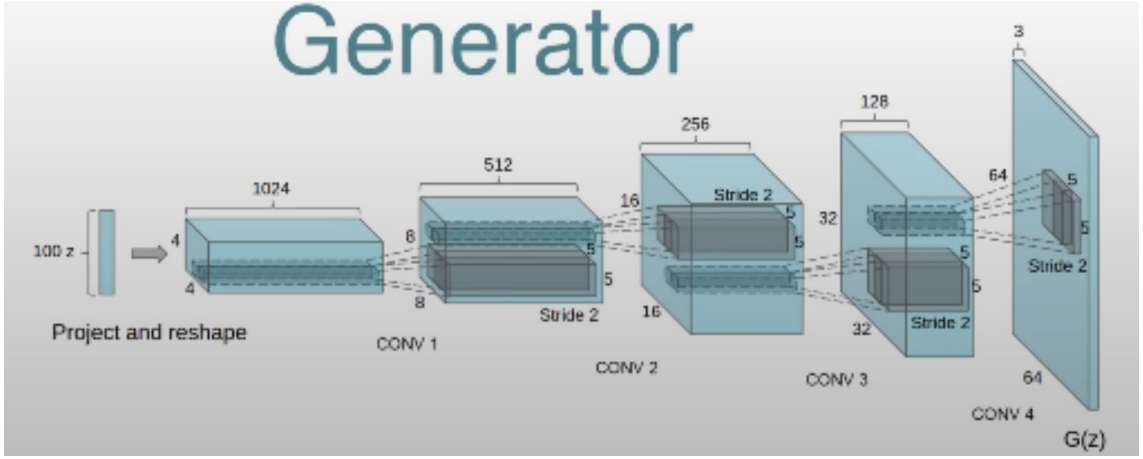
Steps to train a GAN

DCGAN: Bedroom images

Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv:1511.06434 (2015).

Deep convolutional GANs (DCGANs)

Architecture



Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv:1511.06434 (2015).

Key ideas:

- Replace dense fully connected hidden layers with transposed convolutions
  - **Generator:** Strided transposed convolutions

- **Inside Generator**
  - Use ReLU for hidden layers
  - Use Sigmoid for the output layer

Deep convolutional GANs (DCGANs)

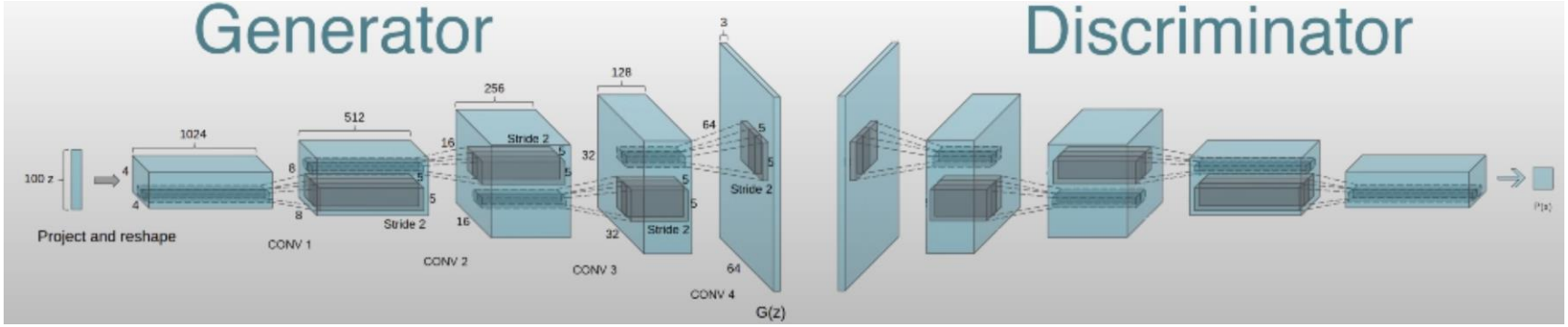
Architecture

Key ideas:

- Replace dense fully connected hidden layers with **convolutions**
  - **Discriminator:** Strided **convolutions**
- Use Batch normalization after every layer
- **Inside Discriminator**
  - Use ReLU for hidden layers
  - Use Sigmoid for the output layer
- Output is probability of **real** image (authenticity classifier)

Deep convolutional GANs (DCGANs)

Architecture



Key ideas:

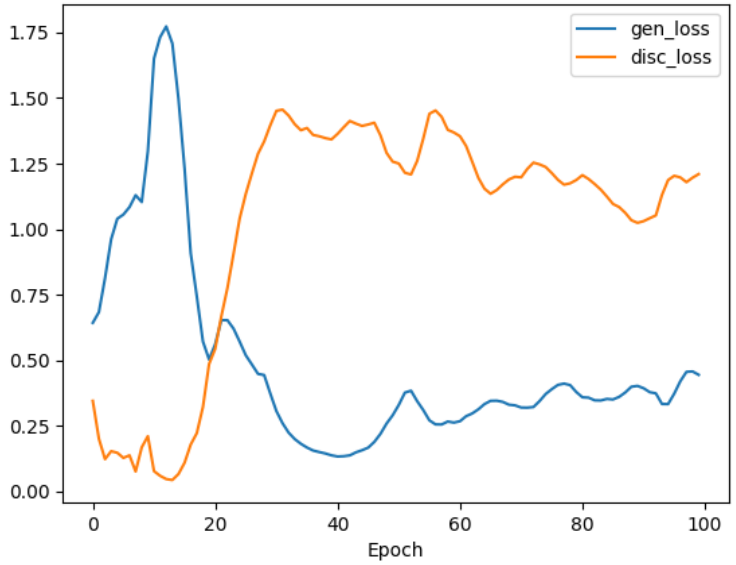
- Generator constructs an image from a random input (Z) with same dimensions as real images
- Discriminator receives images from real data and from generated
- Compatible networks
  - Generator produces images of a given size
  - Discriminator analyzes images of that same size
- There is no weight tying (as there can be in an autoencoder).
- Freedom to construct Discriminator with different depth, so long as it is compatible with Generator

Challenges when implementing GANs

1. Divergence

- Generated images get worse and worse with more training
- Reason: the learning rate for the Generator and Discriminator networks are not properly balanced
- Solutions:
  - decrease the discriminator learning rate to help achieve the necessary balance via hyperparameter optimization
    - Manual: graduate student descent
    - Automated: e.g., Bayesian Optimization
  - add noise to the real/fake labels when training the discriminator to restrain its learning.

- Example from GAN trained on AD. Required decreasing discriminator LR to 10% of the generator LR to get equilibrium in the losses. The two losses don't need to be equal in magnitude as long as they each stay roughly flat.

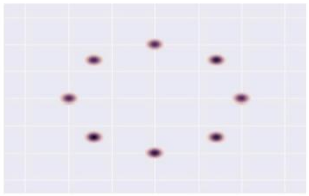


Challenges when implementing GANs

2. Mode collapse

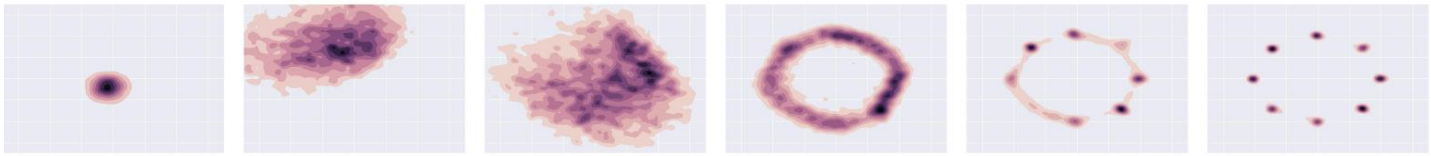
- **Example: given that real examples come from a 2D Gaussian Distribution (with 8 modes)**

Target



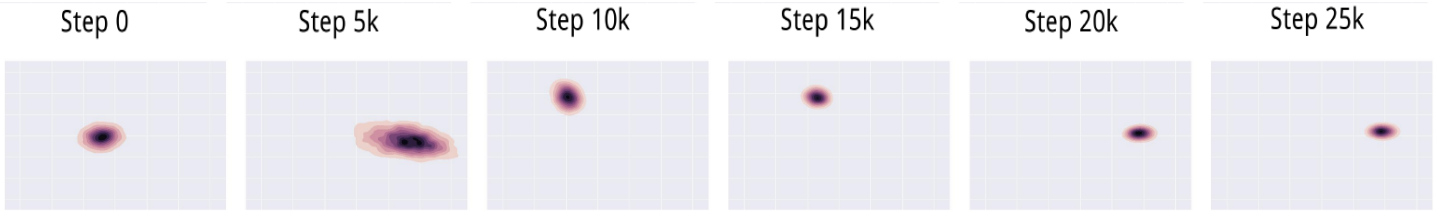
- **You would expect your GAN to evolve to learn to generate a distribution more and more like the true multimodal one:**

Expected



- **Instead: Generator fails to output diverse samples**
  - **During training generated samples move from one mode to another and fail to capture all the modes .. Thus, you don't get diversity in the generated samples**

Output



Metz, Luke, et al. **"Unrolled Generative Adversarial Networks."** arXiv preprint arXiv:1611.02163 (2016).

Challenges when implementing GANs

Solution: reward sample diversity

At Mode Collapse,

- **Generator produces good samples, but a very few of them.**
- **Thus, Discriminator can't tag them as fake.**

To address this problem,

- **Let the Discriminator know about this edge-case.**

More formally,

- **Let the Discriminator look at an entire mini-batch instead of single examples: the mini batch from one source (database), and from the other source (generator)**
- **If there is lack of diversity in a source, it will mark the examples as fake (we ensure that the database examples are always diverse)**

Thus,

- **Generator will be forced to produce diverse samples.**

Salimans, Tim, et al. "Improved techniques for training gans." *Advances in Neural Information Processing Systems*. 2016.

Why use GANs for Generation?

Can be trained using back-propagation for Neural Network based Generator/Discriminator functions.

Sharp images can be generated.

Fast to sample from the model distribution: *single* forward pass generates a *single* sample.

GANs Reading List

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y. Generative adversarial nets, NIPS (2014).

Goodfellow, Ian NIPS 2016 Tutorial: Generative Adversarial Networks, NIPS (2016).

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

Salimans, T., Goodfellow, I., Zaremba, W., Cheung, V., Radford, A., & Chen, X. Improved techniques for training gans. NIPS (2016).

Chen, X., Duan, Y., Houthooft, R., Schulman, J., Sutskever, I., & Abbeel, P. InfoGAN: Interpretable Representation Learning by Information Maximization Generative Adversarial Nets, NIPS (2016).

Zhao, Junbo, Michael Mathieu, and Yann LeCun. Energy-based generative adversarial network. arXiv preprint arXiv:1609.03126 (2016).

Mirza, Mehdi, and Simon Osindero. Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784 (2014).

Liu, Ming-Yu, and Oncel Tuzel. Coupled generative adversarial networks. NIPS (2016).

Denton, E.L., Chintala, S. and Fergus, R., 2015. Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks. NIPS (2015)

Dumoulin, V., Belghazi, I., Poole, B., Lamb, A., Arjovsky, M., Mastropietro, O., & Courville, A. Adversarially learned inference. arXiv preprint arXiv:1606.00704 (2016).

Applications:

Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. Image-to-image translation with conditional adversarial networks. arXiv preprint arXiv:1611.07004. (2016).

Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., & Lee, H. Generative adversarial text to image synthesis. JMLR (2016).

Antipov, G., Baccouche, M., & Dugelay, J. L. (2017). Face Aging With Conditional Generative Adversarial Networks. arXiv preprint arXiv:1702.01983.

Exercise on object oriented GANs

Walk through of Exercise on GANs

1. **Introduce the GAN code:**
    1. **Everyone: git clone the code the repo**
        1. **cd to the folder of your local git repo in ~trainXX**
        2. **The code that you are to complete is in …/vaegan/gan.py**

    2. **Then Walk through the structure of gan.py**

    3. **Walk through today's caller program:**
        1. **train_gan_mnist.ipynb**

Overview of the train_gan notebook

- **Given a complete notebook to run a GAN (train_gan_mnist.ipynb)**
- **Given a *partially* complete GAN (gan.py)**
- **Your job:**
  - **Understand the calling code in the notebook (.ipynb)**
  - **Understand the partial gan.py**
  - **We will review together what is missing and you will work on it together.**
- **Once you are done, test your GAN.**
- **Write down what you observe.**

Structure of the GAN code file: gan.py

Standard GAN

- **Generator module**
  - **class Generator(tf.keras.Model)**
- **Discriminator module**
  - **class Discriminator(ft.keras.Model)**
- **GAN model**
  - **Contains one Generator and one Discriminator**

Structure of the Generator module

- **Class Generator(tf.keras.Model)**

- **Methods**
  - **__init__() … define the layers that you wish to use in the forward pass**
  - **call() …. Define the forward pass.**
  - **get_config() and from_config() … helper methods that allow loading and saving trained models.**

Structure of the Discriminator module

- **Class Discriminator(tf.keras.Model)**

- **Methods**
  - **__init__() … define the layers that you wish to use in the forward pass**
  - **call() …. Define the forward pass.**
  - **get_config() and from_config() … helper methods that allow loading and saving trained models.**

Some programming tips

- **self.attribute … self refers to the current instance of the class.**

- **How forward pass is expressed:**
  - **x=inputs**
  - **x = self.layerName1(x)**
  - **x = self.layerName2(x)**

  Now x contains the inputs transformed by the two layers.

Some programming tips

What are some helpful functions to help you understand what to do next?

variable.shape is your friend

```
Z.shape returns the dimensions of the variable, Z
```

whos variable is also your friend

```
>> %whos
  Name          Size                Bytes  Class     Attributes
  Z           300x2                  4800  double
```

Think about these questions:

- **You may observe something like this during training. It is to be expected. What happens with longer training?**

- **What do you observe about the appearance of the strokes of the digits?**
- **In the plots of the training curves, what is happening to the generator and discriminator losses? What does that signify? Practical implication?**
- **What pros and cons of GAN final results do you observe over VAE final results?**

Acknowledgements


Albert Montillo, PhD, PI


Son Nguyen, PhD Postdoc


Alex Treacher PhD student

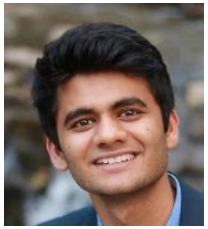

Aixa Andrade Hernandez, MS, PhD student


Austin Marckx PhD student


Krishna Chitta Res. Sci.

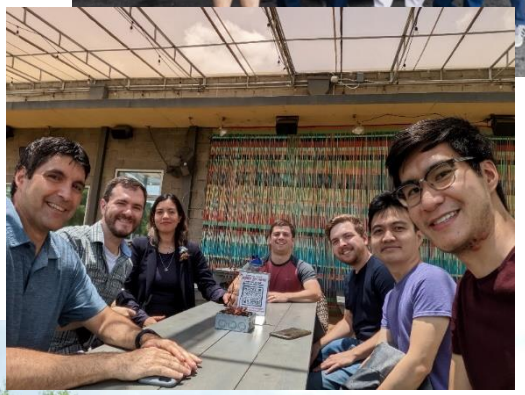
---------- Recent Alumni ----------


Atef Ali Undergrad


Vyom Raval, BS MD/PhD


Kevin Nguyen MD/PhD student


Cooper Mellema MD/PhD student



Lab Funding

- **NIH/ NIGMS R01** ***Correcting Biases in Deep Learning***
- **King Foundation (PI) : Quantitative AD diagnostics.**
- **Lyda Hill Foundation (PI): Quantitative prognostics of Parkinson's disease**
- **NIH/ NIA R01 Blood Biomarkers for Alzheimer's and Parkinson's**
- **TARCC : Texas Alzheimer's Research and Care Consortium.**
- **NIH / NINDS F31 fellowship : Causal connectivity biomarkers for neurological disorders**

Thank you!

Email: **Albert.Montillo@UTSouthwestern.edu**
Github: https://github.com/DeepLearningForPrecisionHealthLab

MegNET …. Artifact suppression
BLENDS …. fMRI augmentation
Antidepressant-Reward-fMRI …. response prediction
Parkinson-Severity-rsfMRI … disease trajectory prediction