# Generating logo images with Generative Adversarial Networks

Hristo Todorov Hristo Kanev Scientific advisors: Dr. Stoyan Vellev

August 14, 2020

### Introduction

- What are we trying to achieve?
- How are we trying to achieve it?
- What is the main question we want to answer?

#### Dataset

- Large Logo Dataset (LLD)
- Composed of over 600 000 high-quality diverse images
- Can be used freely for academic purposes



Figure: Sample images from the dataset

# Generative Adversarial Networks

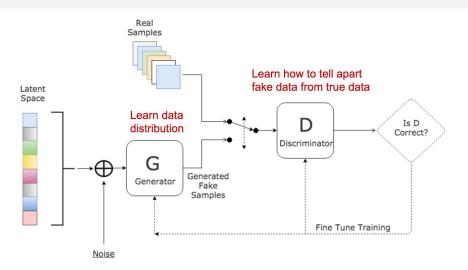


Figure: Architecture of a GAN



# Training a Generative Adversarial Network

- Trained via backpropagation no need for any Markov chains
- Really unstable to train
- The loss (cost) function heavily affects the training process

# Binary cross-entropy

$$\min_{G} \max_{D} V(D,G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_{z}(z)}[\log(1 - D(G(z)))] \tag{1}$$

#### Least Squares Loss

$$\min_{D} V_{LSGAN} = \frac{1}{2} \mathbb{E}_{x \sim p_{data}(x)} [(D(x) - 1)^{2}] + \frac{1}{2} \mathbb{E}_{z \sim p_{z}(z)} [(D(G(z))^{2}]$$
 (2)

$$\min_{G} V_{LSGAN} = \frac{1}{2} \mathbb{E}_{z \sim p_z(z)} [(D(G(z))^2]$$
 (3)

#### Wasserstein Generative Adversarial Network

- Minimal changes to the architecture of the discriminator
- Harder to train
- No sign of vanishing gradients and mode collapse

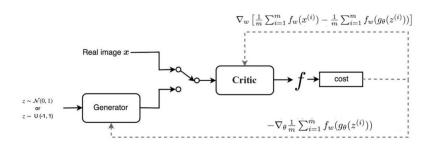


Figure: Architecture of a WGAN



# Conditional Generative Adversarial Network

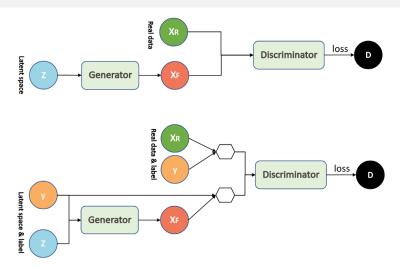


Figure: Comparison between a regular GAN and a CGAN

# Feature extraction via Transfer learning

- Transfer learning using a neural network trained at solving one problem to solve different, but similar problem
- VGG16 convolutional neural network trained at classifying objects from the famous dataset ImageNet

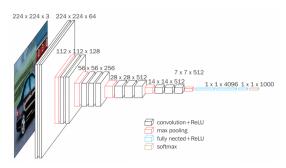


Figure: Architecture of VGG16 - deep convolutional neural network with 16 layers

### Feature extraction via autoencoder

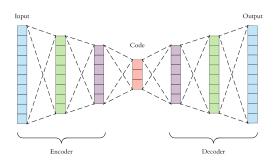


Figure: Architecture of an autoencoder

$$\phi: X \to F \tag{4}$$

$$\psi: F \to X \tag{5}$$

$$\phi, \psi = \underset{\phi, \psi}{\arg \min} \|X - (\psi \circ \phi)X\|^2 \tag{6}$$

# K-means Clustering

By using K-means clustering, we can group the images and create synthetic labels. Images that have more in common that they do with the other images will have the same label.

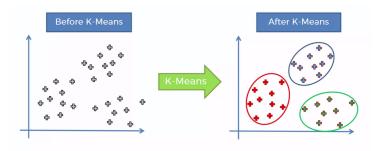


Figure: K-means clustering example

# Image Processing Algorithms

- Blurring
- Complementing
- Color changing
- Denoising Autoencoder

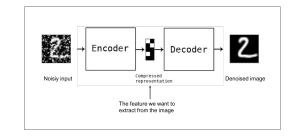


Figure: Architecture of a Denoising Autoencoder

# Implementation

- Python 3
- Tensorflow 2.0
- NumPy
- OpenCV
- Matplotlib
- Scikit-learn
- PIL
- Django
- HTML
- CSS
- JavaScript
- Nvidia CUDA















# Results



Figure: Sample of generated images

## Conclusion & Future Work

#### **Conclusion:**

- Pleasurable results, although graphic designers still cannot be completely replaced
- Room for further improvements

#### Future plans:

- Train the neural networks for more iterations
- Implement new image processing algorithms
- Expand the research into other UI elements such as pictograms

#### Personal contribution

- Architecture + hyperparameter tuning
- Development of a system, capable of producing great results
- Clarification and addressing of the main challenges in UI elements synthesis

# Demo

https://calliope.pythonanywhere.com

# Thank you for your attention! Any questions?