Deep Learning Project: Synthesis

Generating images by training Generative Adversarial Networks (GANs)

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GENERATIVE ADVERSARIAL NETWORKS

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- Can we measure the quality of the **discriminator** by removing the real/fake classifier and feeding the convolutional features into a new classifier? This would show that the model learned general, useful features.
- Is it possible to show that there are dedicated parts of the **generator** that control properties of its output? In other words, do we reach some vector arithmetics on the input vector noise.

Training experiences

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- With our GPU time it was not possible to reach nearly a good classification accuracy as they did in the papers.
- Training on celebA worked well and we got some nice results for the vector arithmetics.

Theory

GENERATIVE ADVERSARIAL NETWORKS

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- The job of the **generator** is to spawn fake images that look like the training images.
- The job of the **discriminator** is to look at an image and output whether or not it is a real training image or a fake image from the generator.

Discriminator Notation

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- Here, since we are dealing with images the input to $D(x)$ is an image of HWC size $3x64x64$.
- Intuitively, $D(x)$ should be HIGH when x comes from training data and LOW when x comes from the generator.

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- $G(z)$ represents the generator function which maps the latent vector z to data-space.
- The goal of G is to estimate the distribution that the training data comes from p_{data} so it can generate fake samples from that estimated distribution p_g.
- So, $D(G(z))$ is the probability (scalar) that the output of the generator G is a real image.

Training by playing a MinMax game

- As described in Goodfellows paper, D and G play a **MinMax game** in which D tries to maximize the probability it correctly classifies reals and fakes ($\log D(x)$), and G tries to minimize the probability that D will predict its outputs are fake ($\log(1 - D(G(x)))$).

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- The GAN **loss function** is:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 D(G(x)))]$$

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- In theory, the solution to this **MinMax** game is where $p_g = p_{data}$ and the discriminator guesses randomly if the inputs are real or fake.

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- The **generator** is comprised of convolutional-transpose layers, batch norm layers, and ReLU activations.
- The input is a latent vector, z, that is drawn from a standard normal distribution and the output is a $3x64x64$ RGB image.

STRUCTURE OF THE DCGAN NETWORK

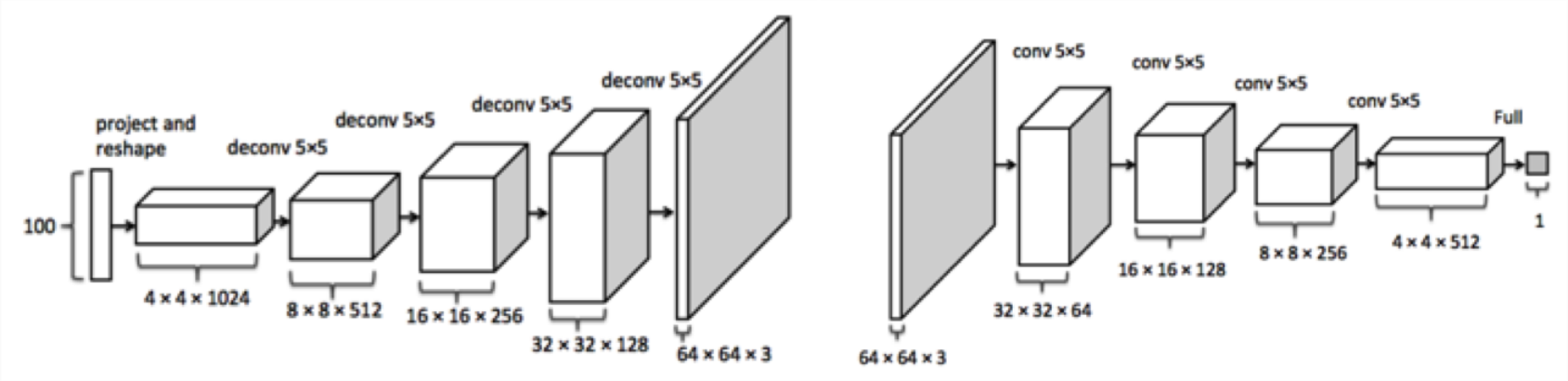

Figure 1: DCGAN network

Experiment 1: Classification of Food-101

CLASSIFICATION ON FOOD-101

The Data:

- IMAGENET-1K: pictures of 1000 different objects
- food-101: 101.000 images in 101 different food categories

The Experiment:

- Train a DCGAN on the IMAGENET-1K dataset. Use the discriminator as feature extractor for food-101.
- Use the output of all the convolutional layers of the discriminator as feature extractor and train a linear SVM on food-101.

RESULTS CLASSIFICATION ON FOOD-101

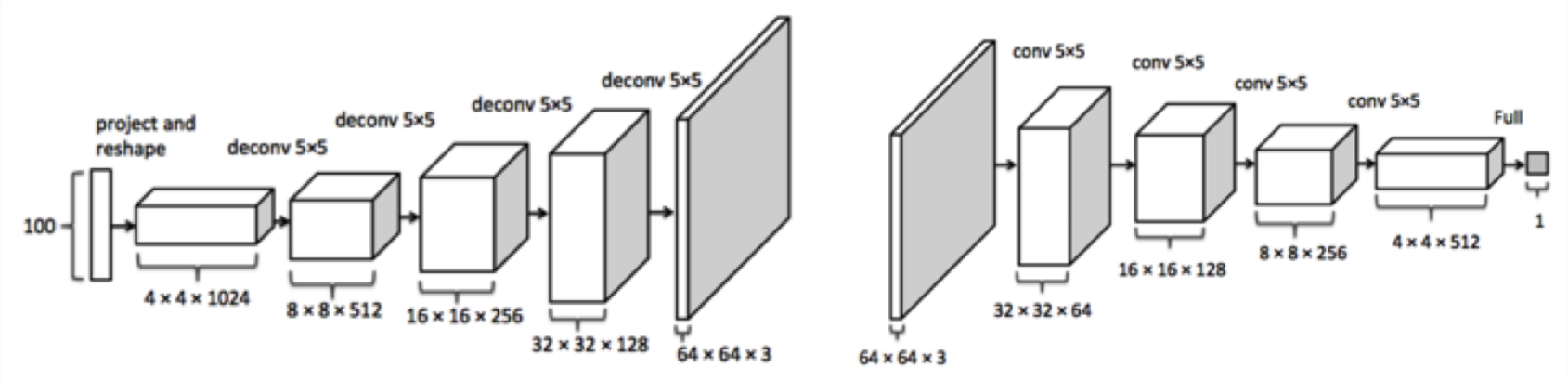

Figure 2: DCGAN network

Questions?