CSCI 6521
Advanced Machine Learning I

Chapter 05: Paint

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Paint

- VAEs and GANs are able to learn a mapping between an underlying latent space and the original pixel space.
- By sampling from a distribution in the latent space, we can use the generative model to map this vector to a novel image in the pixel space.

A different application of generative models is in the field of *style transfer*:

- Here, our aim is to build a model that can transform an input base image in order to give the impression that it comes from the same collection as a given set of style images.
- This technique has clear commercial applications,
- and is now being used in computer graphics software, computer game design, and mobile phone applications.
- Some examples of this are shown in Figure 1 (see next slide).

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Figure 1: Style transfer examples†.

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- With style transfer, our aim isn't to model the underlying distribution of the style images,
- but instead to extract only the stylistic components from these images and embed these into the base image.
- We clearly cannot just merge the style images with the base image through interpolation,
- as the content of the style images would show through and the colors would become muddy and blurred.
- Moreover, it may be the style image set as a whole rather than one single image that captures the artist's style,
  - so, we need to find a way to allow the model to learn about style across a whole collection of images.
- We want to give the impression that the artist has used the base image as a guide to produce an original piece of artwork, complete with the same stylistic flair as other works in their collection.

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- We will learn how to build two different kinds of style transfer model
  - CycleGAN and
  - Neural Style Transfer
- and apply the techniques to our own photos and artwork.

Cycle-Consistent Adversarial Networks (CycleGAN)

- In paper #1, it was shown to train a model that could copy the style from a reference set of images onto a different image, without a training set of paired examples.

- Previous style transfer models, such as pix2pix (paper #2), required each image in the training set to exist in both the source and target domain.

  - While it is possible to manufacture this kind of dataset for some style problem settings (e.g., black and white to color photos, maps to satellite images), for others it is impossible.

- It would also take enormous effort to arrange photos of horses and zebras standing in identical positions.

- **Figure 4** (see next slide) shows the difference between the paired and unpaired datasets of pix2pix and CycleGAN, respectively

… CycleGAN

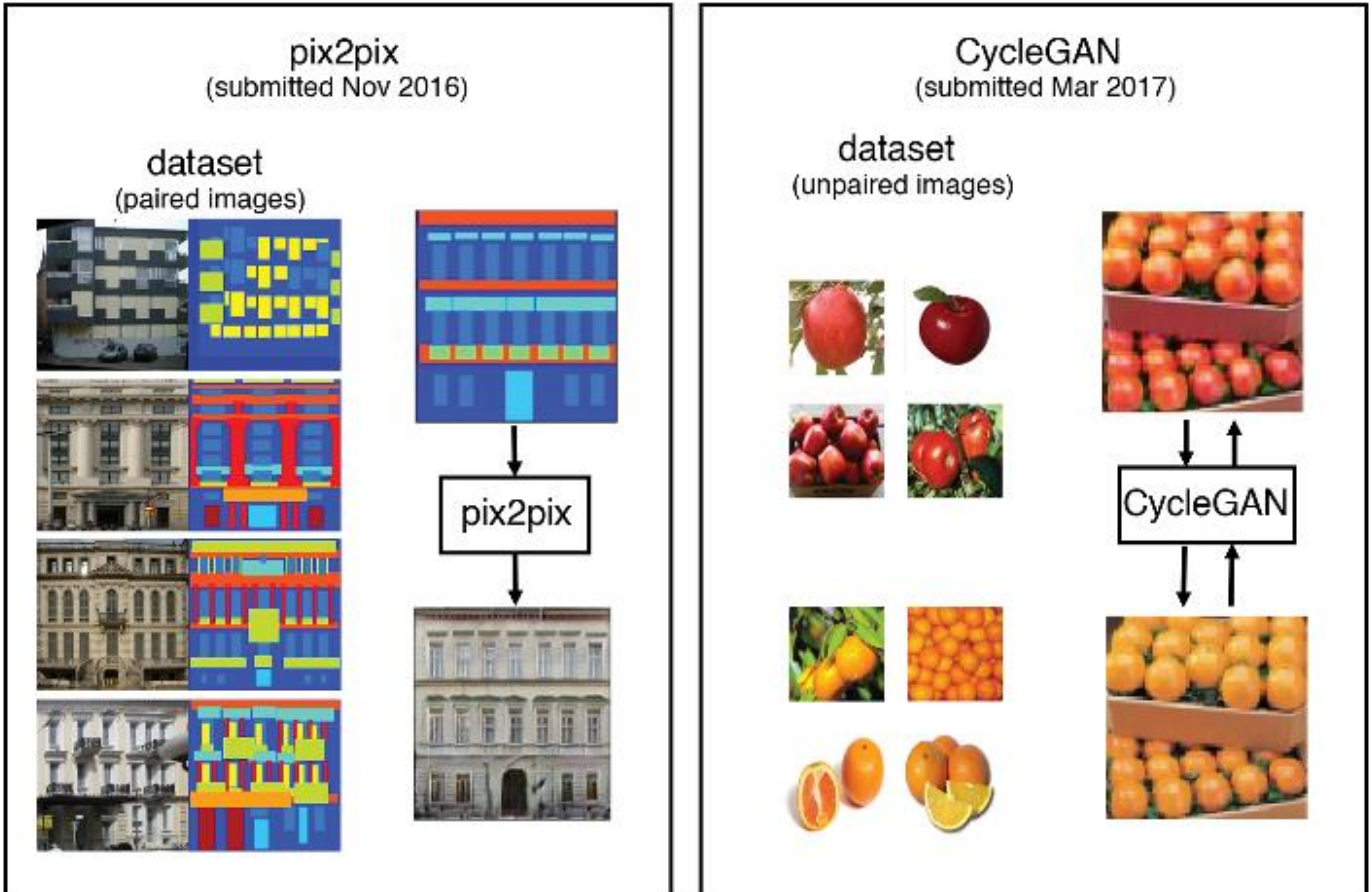

Figure 4: pix2pix dataset and domain mapping example.

… CycleGAN

- While pix2pix only works in one direction (from source to target),
- CycleGAN trains the model in both directions simultaneously,
  - so that the model learns to translate images from target to source as well as source to target.
  - This is a consequence of the model architecture, so you get the reverse direction for free.
- Let us now build and run a CycleGAN model in Keras (see Keras-GAN repository maintained by Erik Linder-Norén):
  - **See exercise**: #1_cyclegan_train.ipynb
- Creating a CycleGAN to Paint Like Monet:
  - **See exercise**:#2_Monet cyclegan
- Neural style transfer:
  - **See exercise**: #3_Neural style transfer

END.