Class Constrained CycleGAN

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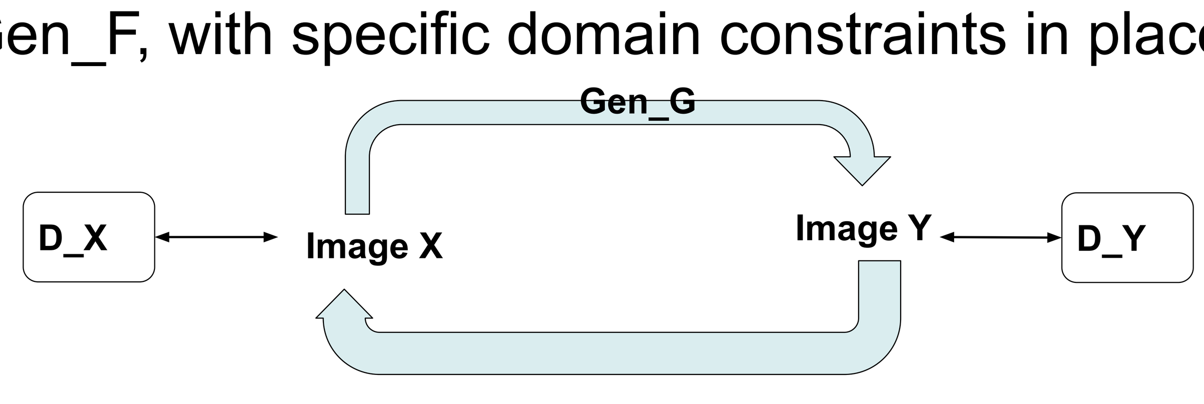
Abstract

Translating images from one domain to another domain is an active research area. The state of the art CycleGANs are capable of translating from domain A to domain B, with high accuracy. Recent research have shown the capabilities of CycleGAN to produce clear and large images.

Our project utilizes a class constrained mechanism in the CycleGAN, that lets the user to train on multiple domain transformations on the same CycleGAN. This approach allows us to test the transitive nature of the CycleGAN i.e., CycleGAN trained to translate from Domain A to Domain B, as well as, from Domain B to Domain C, is capable of understanding the features important for translating Domain A to Domain C without any prior mapped training. This opens a new realm for utilizing CycleGANs for feature based conditioned image generation.

Setup for Class Constrained CycleGAN

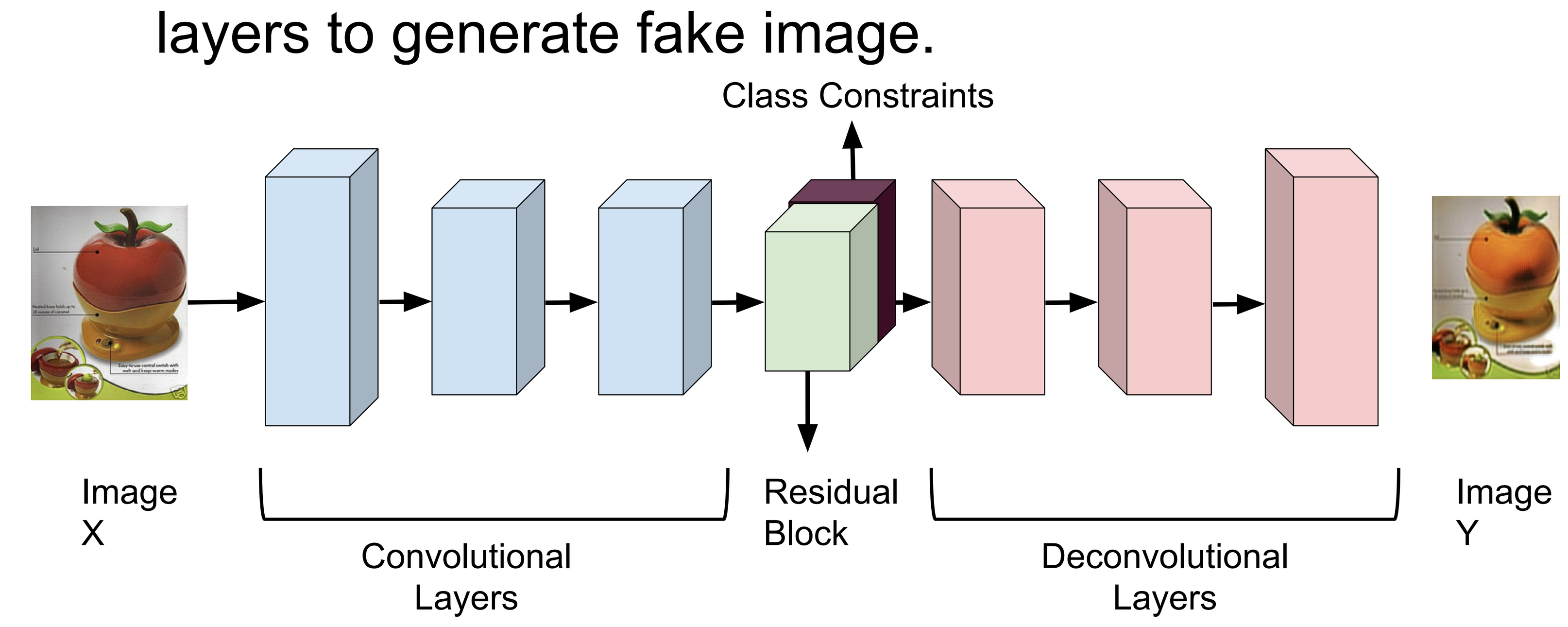
- The input for the forward CycleGAN (Gen_G) is an image of domain X and feature vector of the domain Y. Gen_G generates fake_image_Y.
- Using generated fake_image_Y we calculate Gen_G loss, by making the discriminator D_Y believe fake_image_Y is a real image of domain Y.
- Inversely, we train discriminator D_Y, with the real images and the fake image of domain Y.
- The same process is carried out in reverse to translate images from domain Y to domain X, using generator (Gen_F) and discriminator D_X.
- Cycle-consistency is an assumption that, the imageX that is used as the basis for generating fake_image_Y through Gen_G, must be comparable to the image generated using fake_image_Y as the base through Gen_F, with specific domain constraints in place.



- For testing the transitive nature of the class constrained CycleGAN, we used three domains: domain X,Y,Z. We trained the translations from domain X to domain Y, also the translations from domain Y to domain Z on the same CycleGAN. The trained CycleGAN was capable of translating images from domain X to domain Z(and vice versa), without previous paired training.

Generator

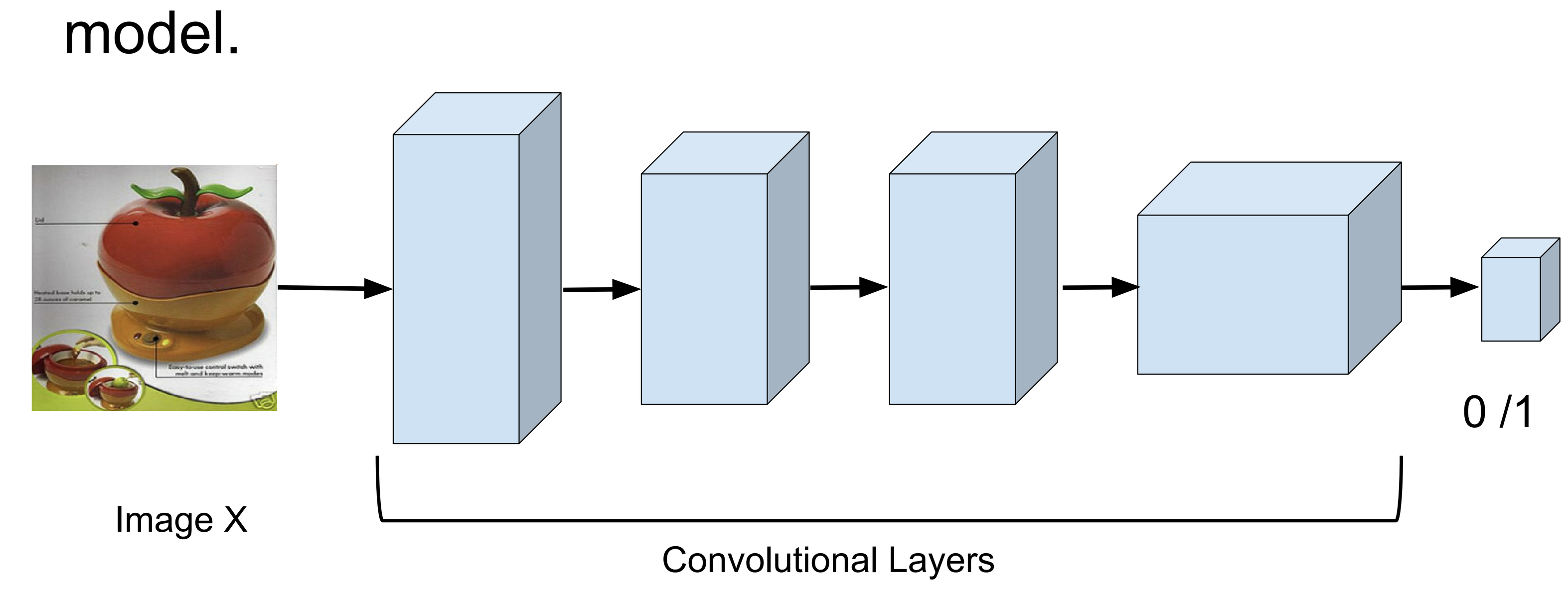
- **Encoder**
  - A series of Convolutional layers that reduces an image_X to a resnet block with a 256 feature representation of image_X.
- **Transformer**
  - Appends the class features as one hot encoding to the resnet block and updates the generated images conditioned on the class.
- **Decoder**
  - Builds back the low level features back from the transformed feature vector using deconvolutional layers to generate fake image.



Discriminator

Discriminator takes an image as input and classifies it into one of two classes : fake or real image.

The discriminator extracts the features from the input image. It makes a decision, if a image belonging to a specific class, if it is real or fake. This decision is then used in the Generator to adjust its weights and tune the model.



Losses

- **Cycle loss** : Loss in cycle-consistency when trying to generate back the original image_X, from the fake_image_Y, using back_cycle_GAN (F) and vice versa.

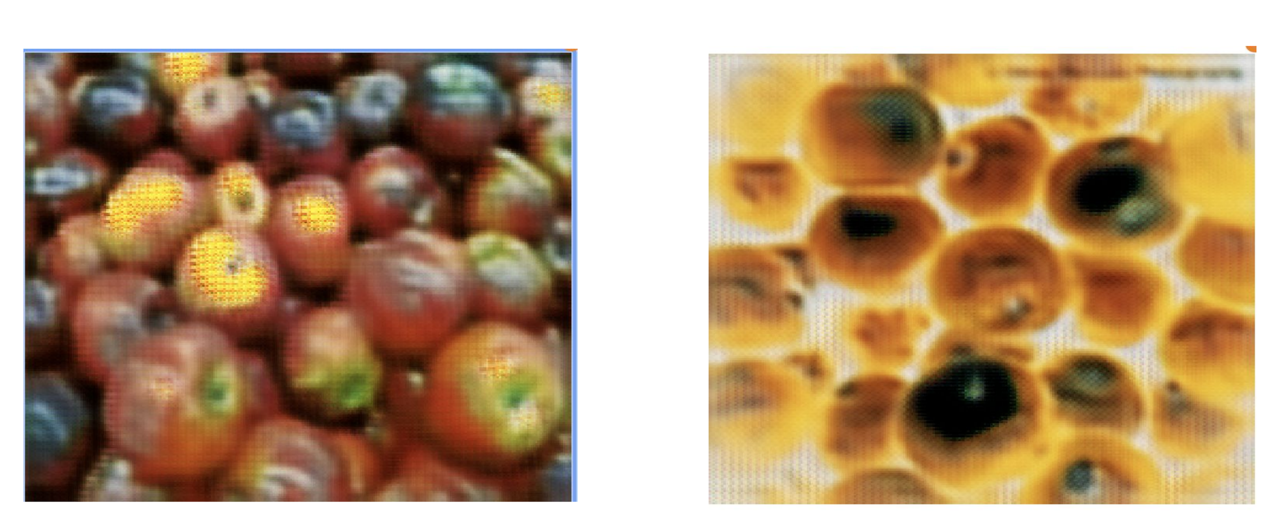
- **G loss, F loss** : GAN loss generated by trying to make the discriminator believe that the generated fake image is the real image for a given class, by sending it to the discriminator.

  G_loss = G_gan_loss + forward_cycle_loss
  F_loss = F_gan_loss + backward_cycle_loss

- **D_X, D_Y discriminator loss** : Discriminator that returns the total loss, when trying to classify fake generated and real image conditioned on a class(mean_squared_error)

Evaluation and Outputs

These are our test trained on Apple<->Oranges and Oranges<->Mangoes, and trying to generate apples from mangoes, and vice versa.



Apples to Mangoes (Transitive property using class constraints)

Since these are a from of unsupervised learning, we do not have a gold standard to compare our generated images. We are experimenting on various evaluation metrics for unsupervised learning.

References

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