

Translating Images to Images with Generative Adversarial Networks

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Image-to-Image Translation

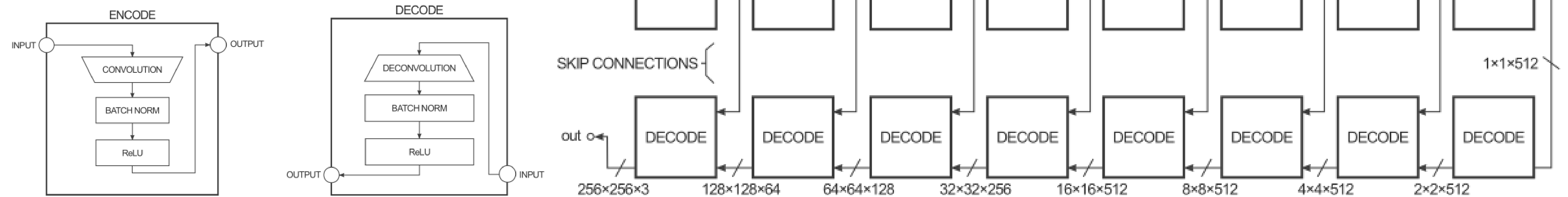
What is the problem?

Many computer vision problems can be seen as converting one type of image to another type. After all, images can be represented in all sorts of formats.



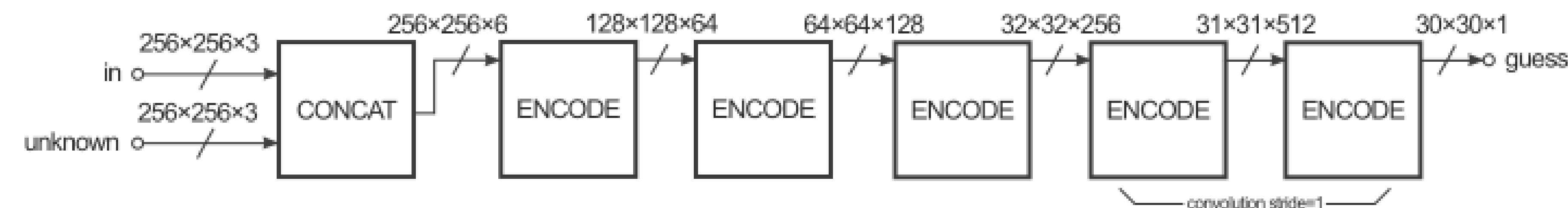
Generator Network

- U-net architecture
- Skip connections to pass on information from lower layers
- Take in image, generate new image



Discriminator Network

- PatchGAN architecture
- Take in pair of images, decide if real or fake
- Automatic loss function to make generated images more realistic



Training Outline

1. Get batch of conditional data and real data
2. Use batch of conditional data to generate fake data
3. Train discriminator using real/conditional image pair and fake/conditional image pair
4. Train whole GAN network using conditional images
5. Repeat for a certain number of epochs

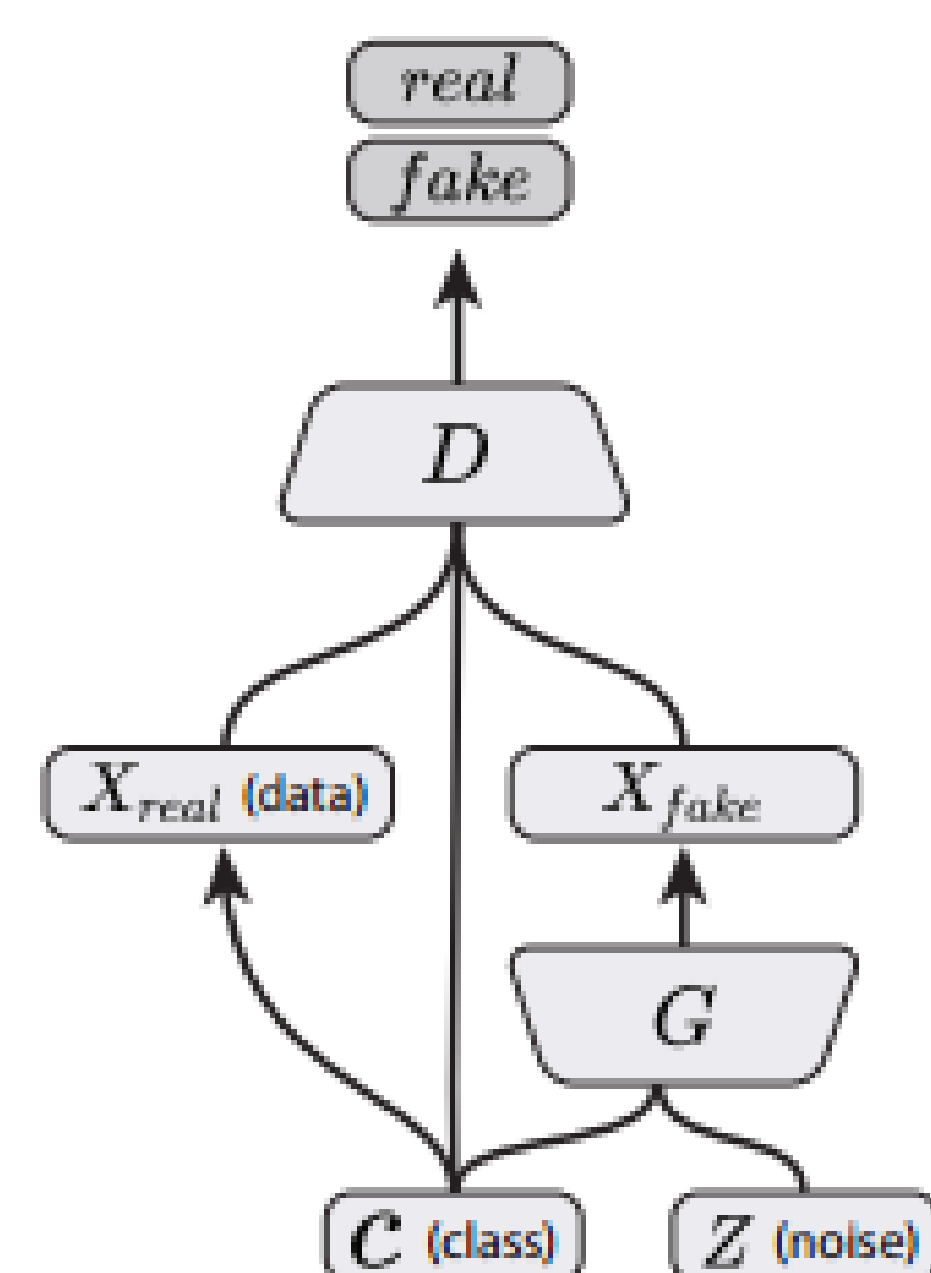
Generative Adversarial Networks

GANs

- Composed of two networks: a discriminator and generator network that compete.
- The discriminator's goal is to determine if the input image is real or fake.
- The generator's goal is to generate new images to fool the discriminator.

Conditional GANs (cGANs)

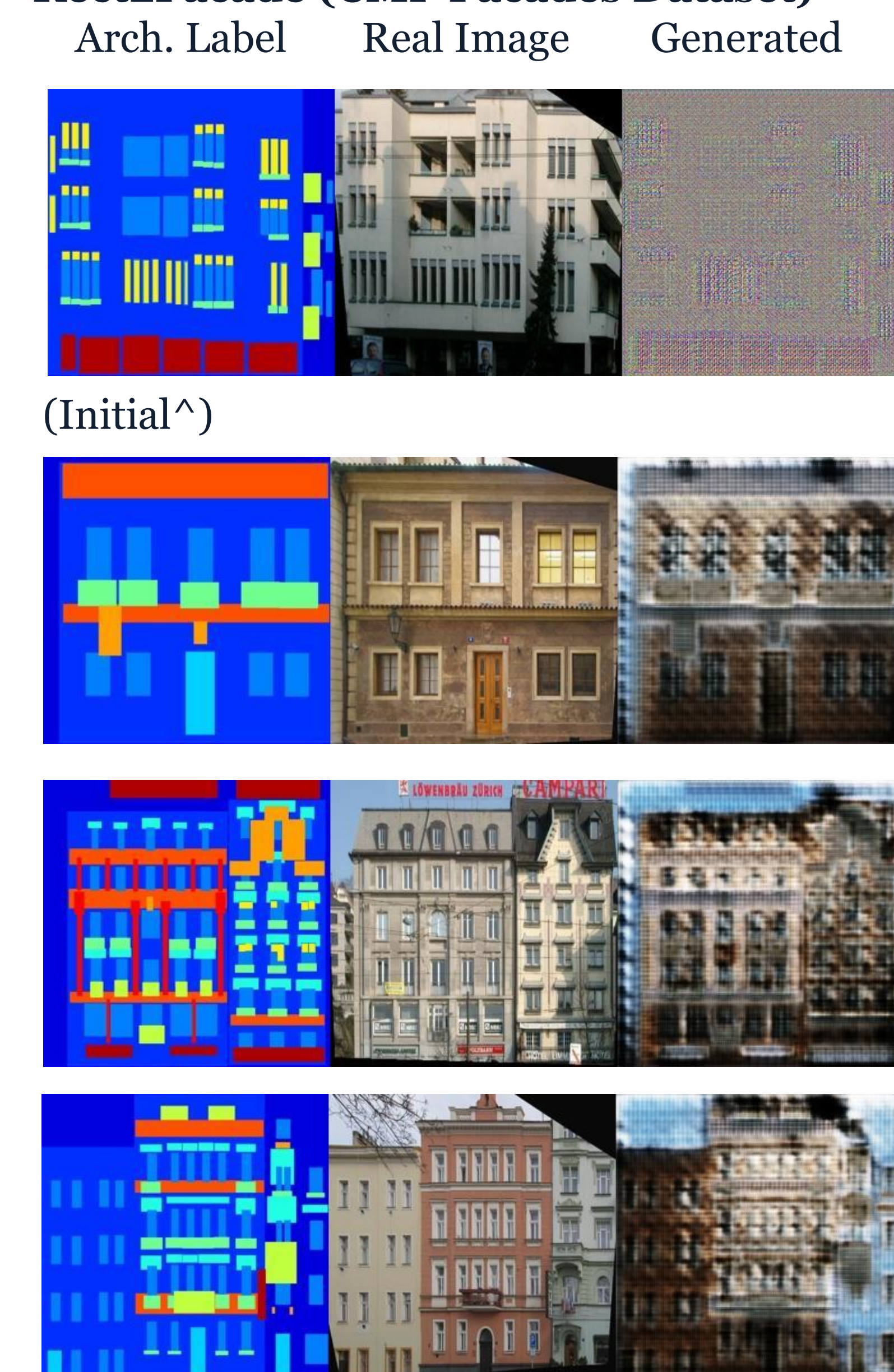
Variation of GANs. Adds conditional information.



Conditional GAN
(Mirza & Osindero, 2014)

Results

Rect2Facade (CMP Facades Dataset)



Edge2Nike (Zappos50k Dataset)



Conclusions

- Overall results are quite satisfactory
- Challenges: balancing GAN training
- Improvements: train for more epochs, larger batch size
- Applications: colorizing images, reconstructing images from edges, photos from label maps, day to night, images to word embedding

Acknowledgements

Networks trained on GTX960 (1GB)
Intel Core i5-4460

Online images from:
<https://affinelayer.com/pix2pix/>
<https://arxiv.org/pdf/1610.09585.pdf>