Adversarial Approaches for Generating Photorealistic Images of Landscapes

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1 Objectives

Our project will focus on using Generative Adversarial Networks (GANs) for generating photorealistic images of landscapes from classic impressionist paintings.

The scope of our project will focus on two tasks:

- Program a **Generative Adversarial Network** trained on photographs of landscapes to *generate new photorealistic images of landscapes as a benchmark* to compare how translated painting-to-photo images compare to landscapes generated without any input painting as a constraint.
- Generate a dataset of painting-photo pairs using off-the-shelf Style Transfer networks to convert landscape photos to impressionist painting equivalents. Then, create our own **Conditional Generative Adversarial Networks** (c-GAN) to try to *convert the outputs from the Style Transfer network back to the ground truth image*s. We will also use this network to *transform a holdout set of impressionist paintings to photos* to measure performance on real paintings.

If we have time, we would like to also try a new method that was released earlier this year:

- Program a **Cycle-GAN** to *generate photorealistic images of paintings without the use of photo-paintings pairs* using 2 unpaired datasets containing landscape photos and paintings.

2 Challenges

GANs are difficult to train. An imbalance in performance between the Generator network and the Discriminator network could lead to poor performance and instability since an overpowering Discriminator/Generator network will cause the network to be unable to learn.

It is difficult to quantitatively test the performance of GANs using an evaluation metric without being subjective or relying on heuristics specific to the data. It is hard to compare performance across different domains and datasets in a systematic way.

3 Dataset

We will be using two datasets with photographs and impressionist paintings of landscapes. These will be taken from various sources. We also plan to use the datasets from CycleGAN referenced

below. Their datasets include training data for artistic style transfer. We also located an outdoor scene web cam stream from Brown. All datasets are included in the references below.

References

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[8] GAN: A Beginner's Guide to Generative Adversarial Networks Web Link

[9] GANS-Awesome-Applications Web Link

[10] Artistic Style and Seasons Datasets (CycleGAN) (**Dataset**) Web Link

[11] Natural Images (CSAIL) (**Dataset**) Web Link

[12] Outdoor Scenes (**Dataset**) Web Link

[13] Landscapes and Cityscapes (**Dataset**) Web Link