הפקולטה להנדסת
חשמל ומחשבים
ע"ש אנדרו וארנה ויטרבי

SIPL
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TECHNION
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Creating Image Segmentation Maps Using GANs

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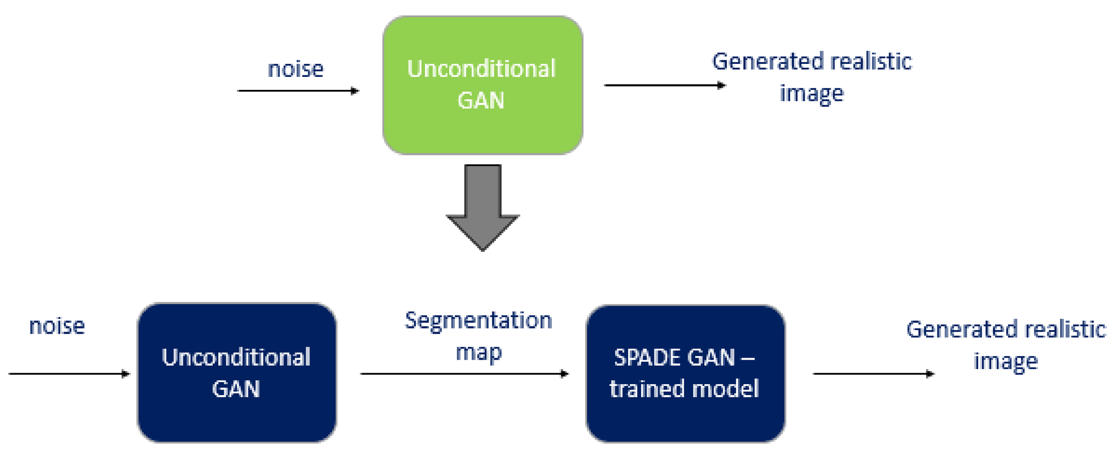
Introduction

- The use of GAN has drastically affected low-level vision in graphics, particularly in tasks related to image creation and image-to-image translation.
- With the success of GANs we will produce segmentation maps. With these maps and with the help of the generative model we can get a semantic understanding of the data set and even create completely new scenes.

Goals

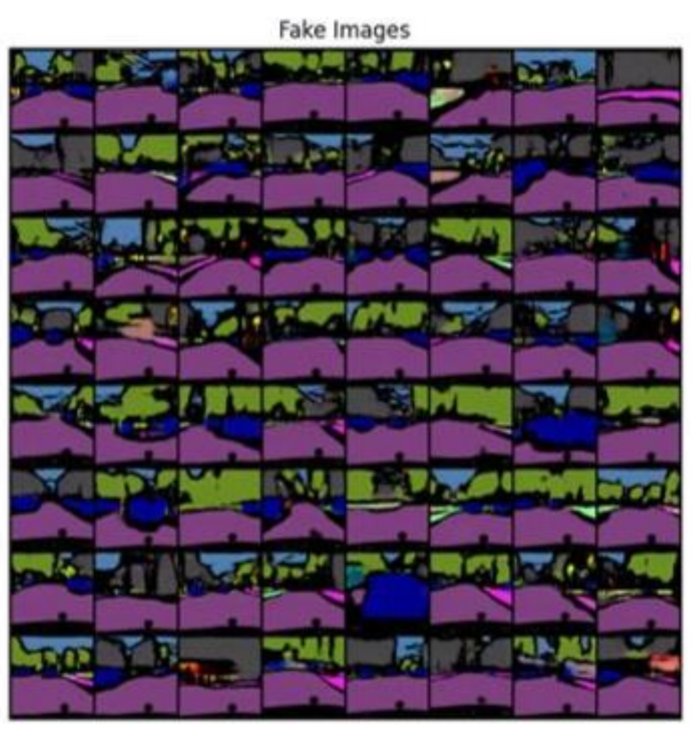
- The project goal is to create segmentation maps using unconditional GANs in order to use those images in another GAN which will create a realistic street image.
- Instead of generating street images directly from one GAN, our training process will have two stages:
  1. We will create a segmentation images of streets using styleGAN.
  2. We will use those images as an input for existing GAN (SPADE) that create and add a layer of texture to a segmentation images to create a realistic picture.



Project scheme

DCGAN

- In order to understand and learn about GANs, we used existing DCGAN that works for 3x64x64 face images and tried it on our data.

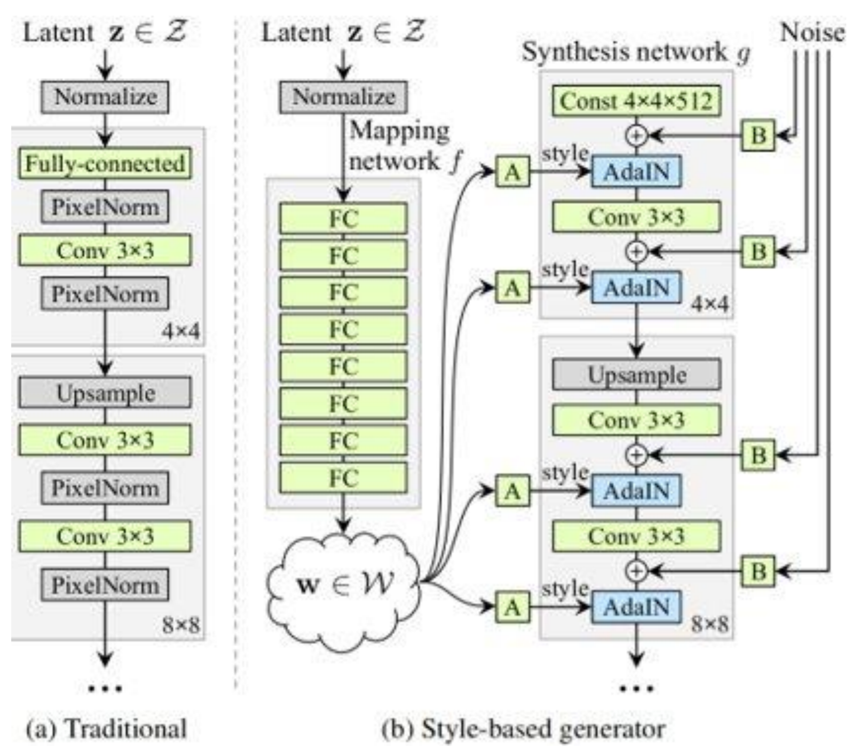


DCGAN results

- Problems with DCGAN Results:
  1. Distorted dashboard symbol
  2. No human are shown, only “redish” stains
  3. Places where the color is not uniform

StyleGAN

- StyleGAN not only allows for a better understanding of the generated output, but also produces images that look more authentic than previously generated images.



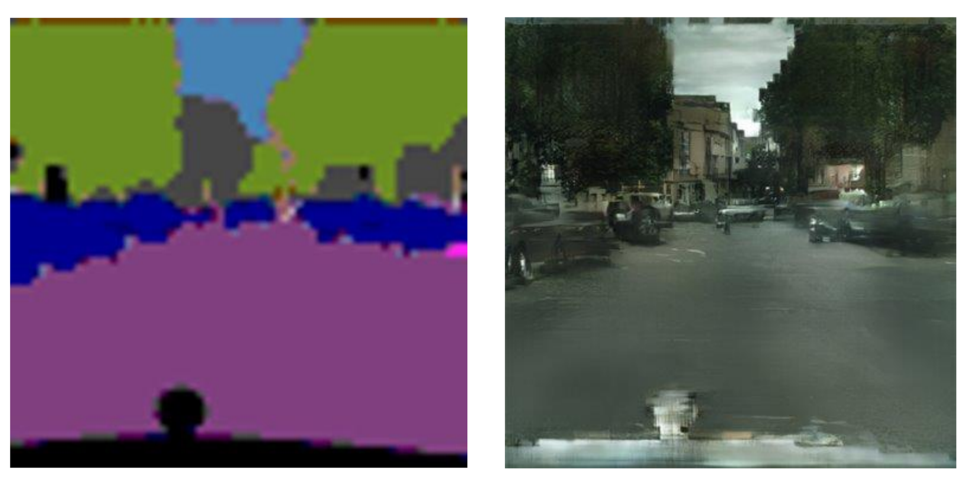
Traditional generator vs styleGAN generator

- <u>The Changes to the model include:</u>
  - Progressive growing.
  - The use of a mapping network to map points in latent space to an intermediate latent space.
  - The use of the intermediate latent space to control style at each point in the generator model.
  - The introduction to noise as a source of variation at each point in the generator model.

StyleGAN results

SPADE

- SPADE stands for spatially-adaptive normalization, a simple but effective layer for synthesizing photorealistic images given an input semantic layout.
- In order to use SPADE we had to do some adjustments:
  - Conversion of each pixel to the closest pixel value among the segmentation map options.
  - Create Label Map from the segmentation map.



StyleGAN and SPADE results

Comparison

- We compare our results to the use of only unconditional gan by using the same styleGAN model on the realistic images.

Unconditional gan results

FID

- For the evaluation of the performance of GANs at image generation, we will use the “Frechet Inception Distance” (FID) .
- FID captures the similarity of generated images to real ones better than the Inception Score.
- A lower FID indicates better-quality images; conversely, a higher score indicates a lower-quality image and the relationship may be linear.

$$\mathrm{FID} = |\mu - \mu_w|^2 + \mathrm{tr}(\Sigma + \Sigma_w - 2(\Sigma\Sigma_w)^{1/2}).$$

FID equation

Results

		FID
Our segmention map	original segmentation map	245.989
Our images after SPADE	Original realistic images	179.463
Images styleGan generation	Original realistic images	247.257

FID comparison table

Conclusions

- We created successful segmentation images of streets using styleGAN.
- We used these images as an input for existing GAN (SPADE) that created and added a layer of texture to a segmentation images to create a realistic picture.
- Our two-step process produced better results from the unconditional GAN alone.
- Two-step process simplifies the image generation process.

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