CycleGAN

Presentation prepared by Piotr Gugnowski

About research paper

Title: Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

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Field of study

Image-to-Image Translation

A task is to learn a translation based given image set.

Unpaired dataset

Usually Image-to-Image translation is based on learning from paired images set.

Unfortunately paired data is not always available.

CycleGAN don’t need that requirement to be met, and its goal is learn how to map input image form that belongs to some domain to look like image from other domain.

Why would we need to train Image translator on unpaired data?

Lack of data

There are situations where a person can imagine an image in a different style, but it never existed or was never saved.

Human imagination is infinite

Monet painting into photo

Limitations

Input and output scenes should have similar shaper.

For example it will fail in transforming dogs to cats and *vice versa*.

Limited control on how transformation will be applied, we can just adjust input image.

Important ideas

Generative Adversarial Networks

Great in image generation, editing, feature learning, etc.

Contains generator and discriminator that are trying to trick each other. In result they both gradually get better in their tasks.

Based on **adversarial loss** that forces generated images to be indistinguishable from images from real images.

Cycle consistency

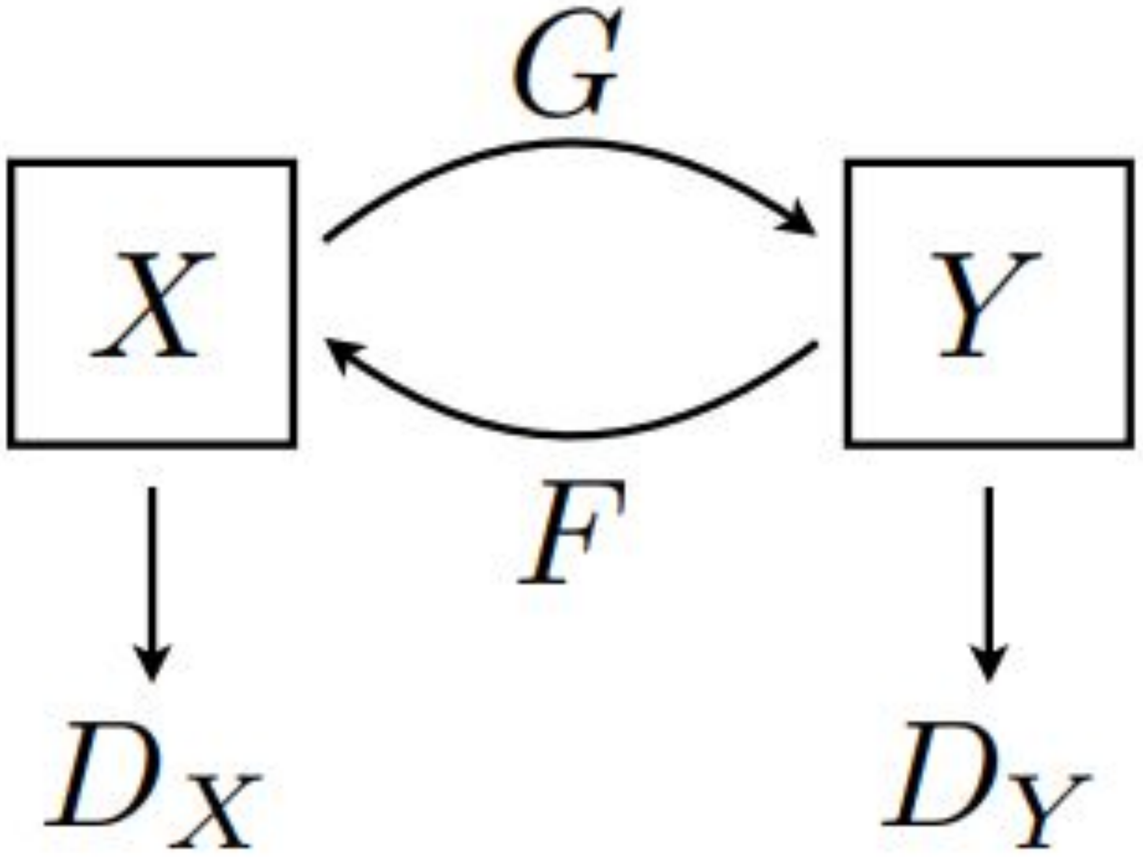
In this method of Image-to-Image translation we want generators from both GANs to be consistent with each other.

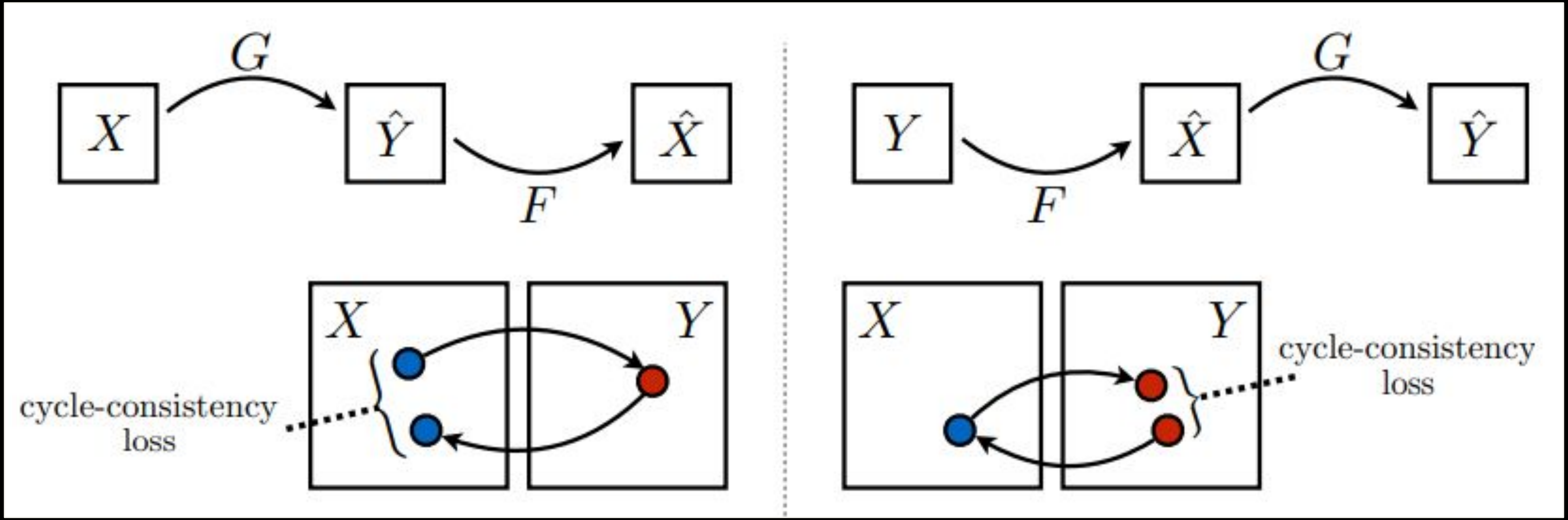
To achieve this translating model needs to have **cycle consistency loss** applied to its objectives.

Two cooperating GANs

The output from one GAN is the input for the other GAN.

It does not guarantee that the model will keep original input features.
Model collapse can occur and input images will be just transformed into one of images from the target domain.





It occurs that **cycle consistency** requirement causes generators to keep original scene recognizable in the transformed image. Both side cycle consistency is required.

Formulation

1. Adversarial Loss

$$\mathcal{L}_{GAN}(G, D_Y, X, Y) = E_{y\sim p_{data}(y)}[\log D_Y(y)] + E_{x\sim p_{data}(x)}[\log(1 - D_Y(G(x)))]$$

2. Cycle Consistency Loss

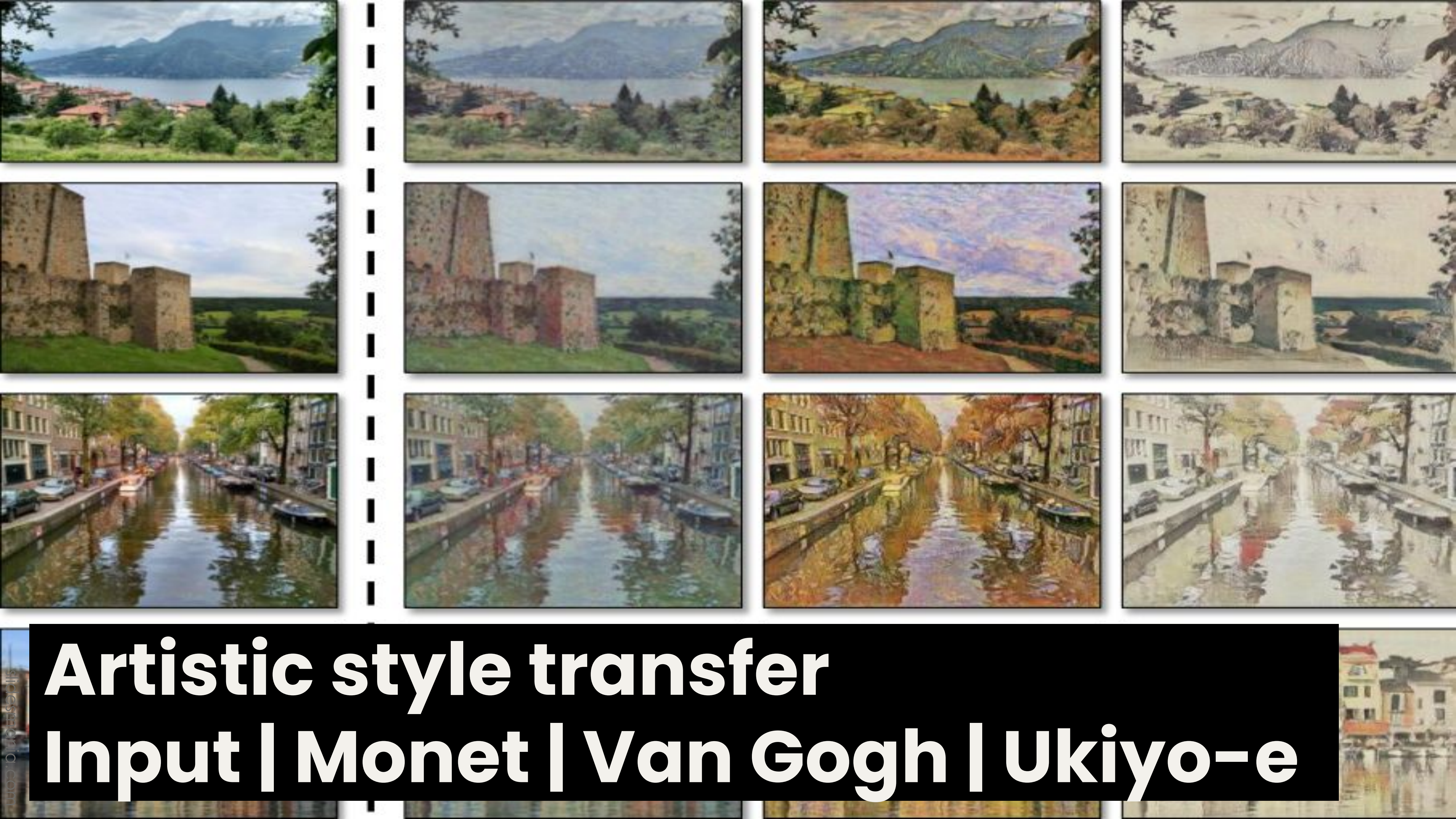
$$\mathcal{L}_{cyc}(G, F) = E_{x\sim p_{data}(x)}[\|F(G(x)) - x\|_1] + E_{y\sim p_{data}(y)}[\|G(F(y)) - y\|_1],$$

3. Full Objective

$$\mathcal{L}(G, F, D_X, D_Y) = \mathcal{L}_{GAN}(G, D_Y, X, Y) + \mathcal{L}_{GAN}(F, D_X, Y, X) + \lambda\mathcal{L}_{cyc}(G, F)$$

Applications

…that are useful



Artistic style transfer
Input | Monet | Van Gogh | Ukiyo-e

Object transfiguration

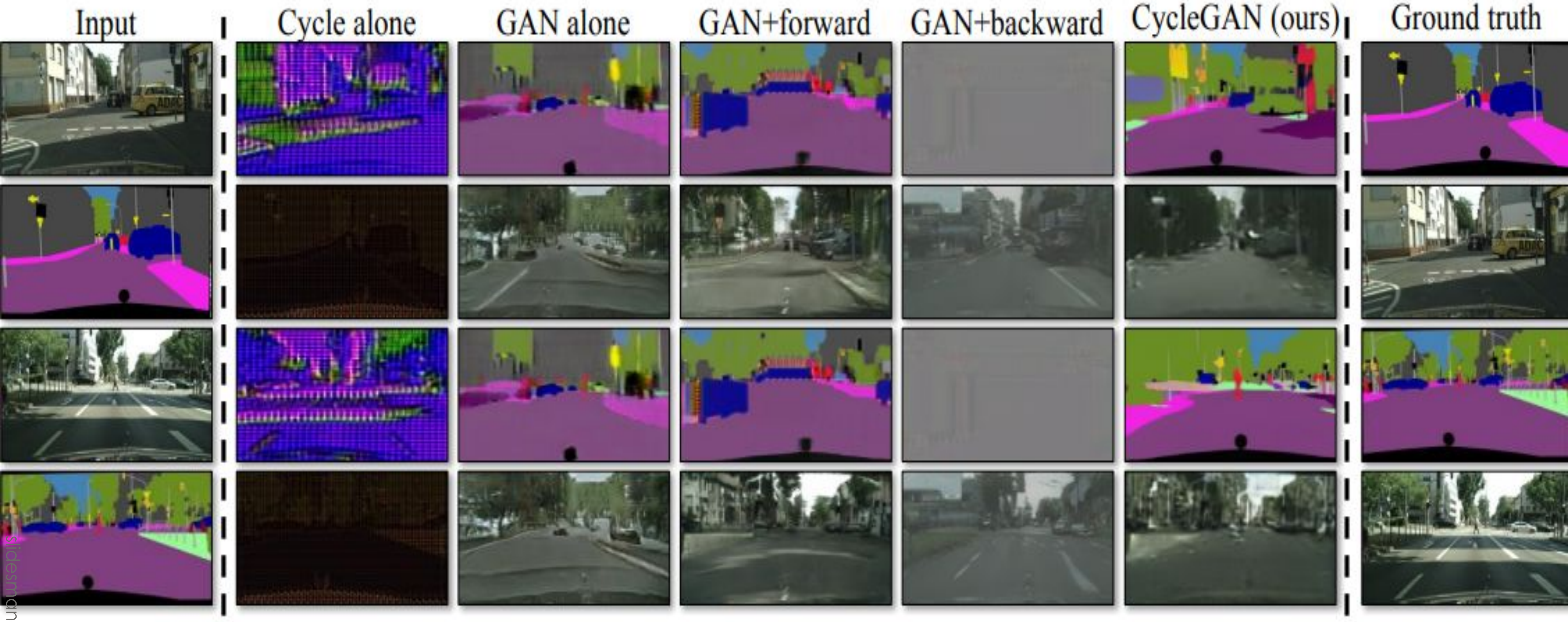
Season transfer

Photo from painting

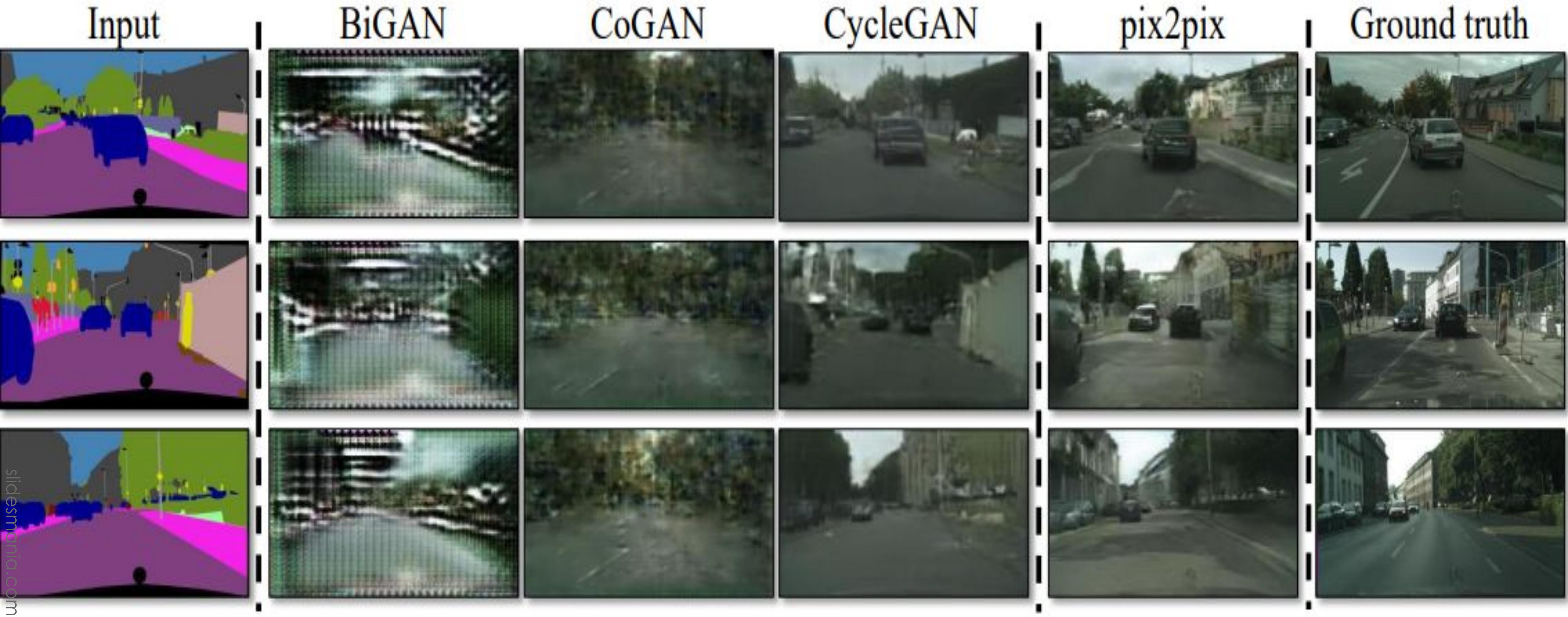
Model analysis

comparison & formula correctness

Truncated variants of model



Other image mapping methods




Input
BiGAN
CoGAN
CycleGAN
pix2pix
Ground truth
slidesmania.com

Thank you!

Do you have any questions?

Ask them via

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or in person.