Image-Image Domain Adaptation with Preserved Self-Similarity and Domain-Dissimilarity for Person Re-identification

Weijian Deng

Overview

- Thanks for giving me the opportunity to talk about our work
- This talk covers
  - Generative adversarial network (GAN)
  - CycleGAN
  - SPGAN (our)

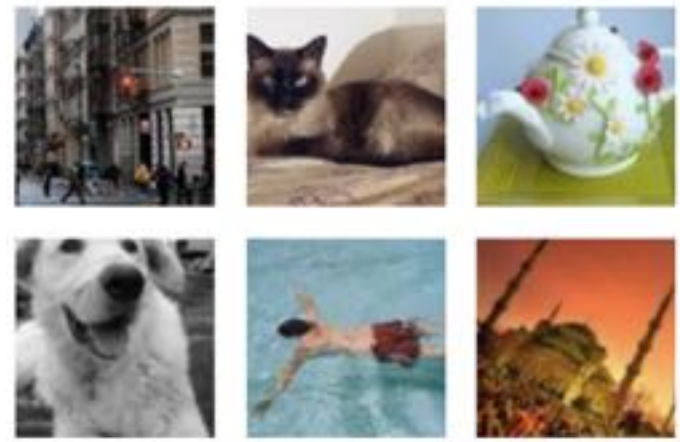
Generative model

What I cannot create, I do not understand

—Richard Feynman

Generative model

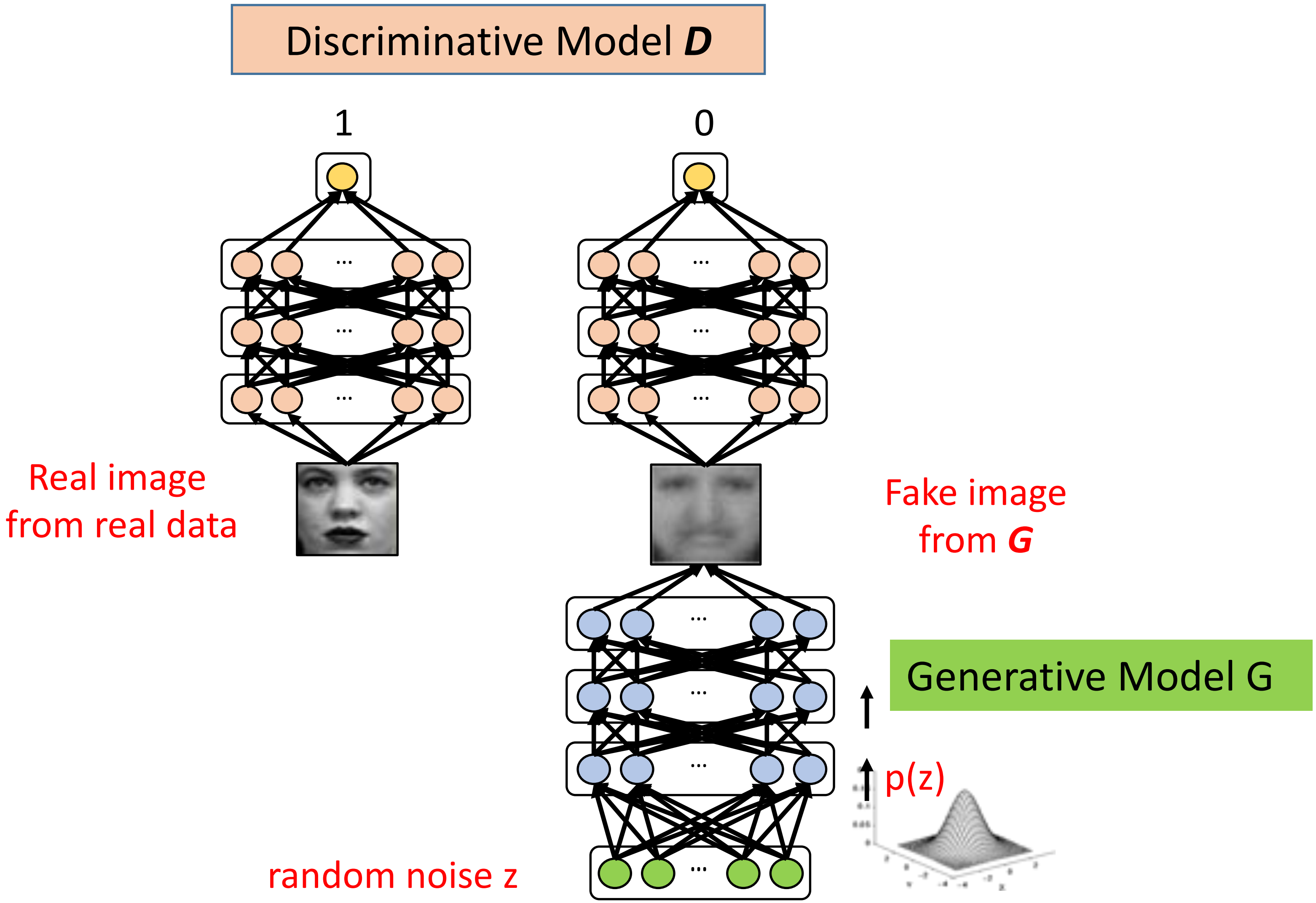
Real images distribution
$P_{data}(x)$



generated images distribution
$P_G(x)$

We want to learn $P_G(x)$ similar to $P_{data}(x)$

Generative adversarial network (GAN)



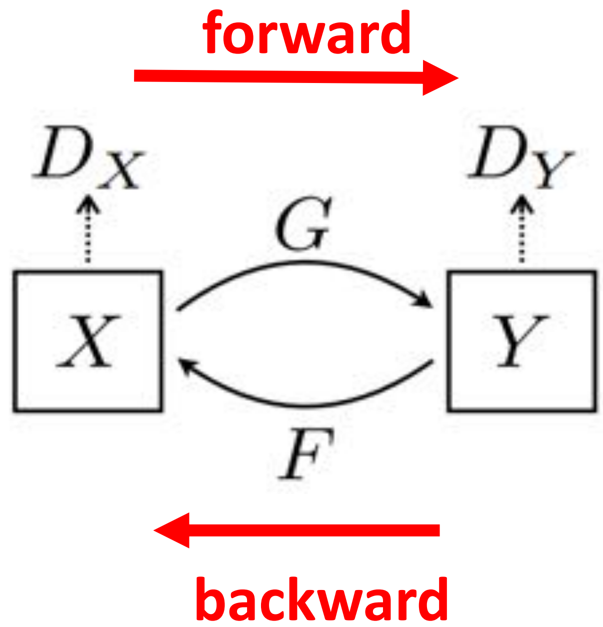
Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

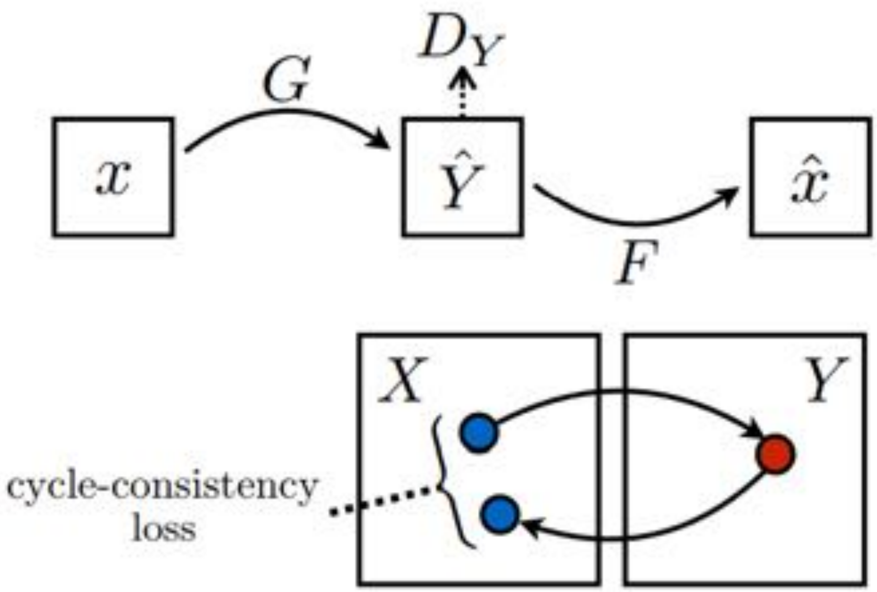
CycleGAN

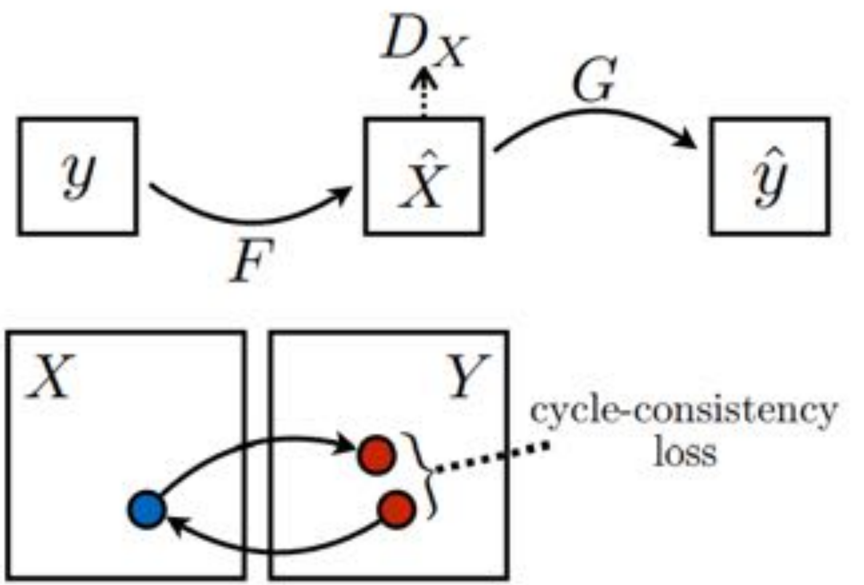
Horse → zebra

Zhu, etal. Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks In ICCV 2017

CycleGAN

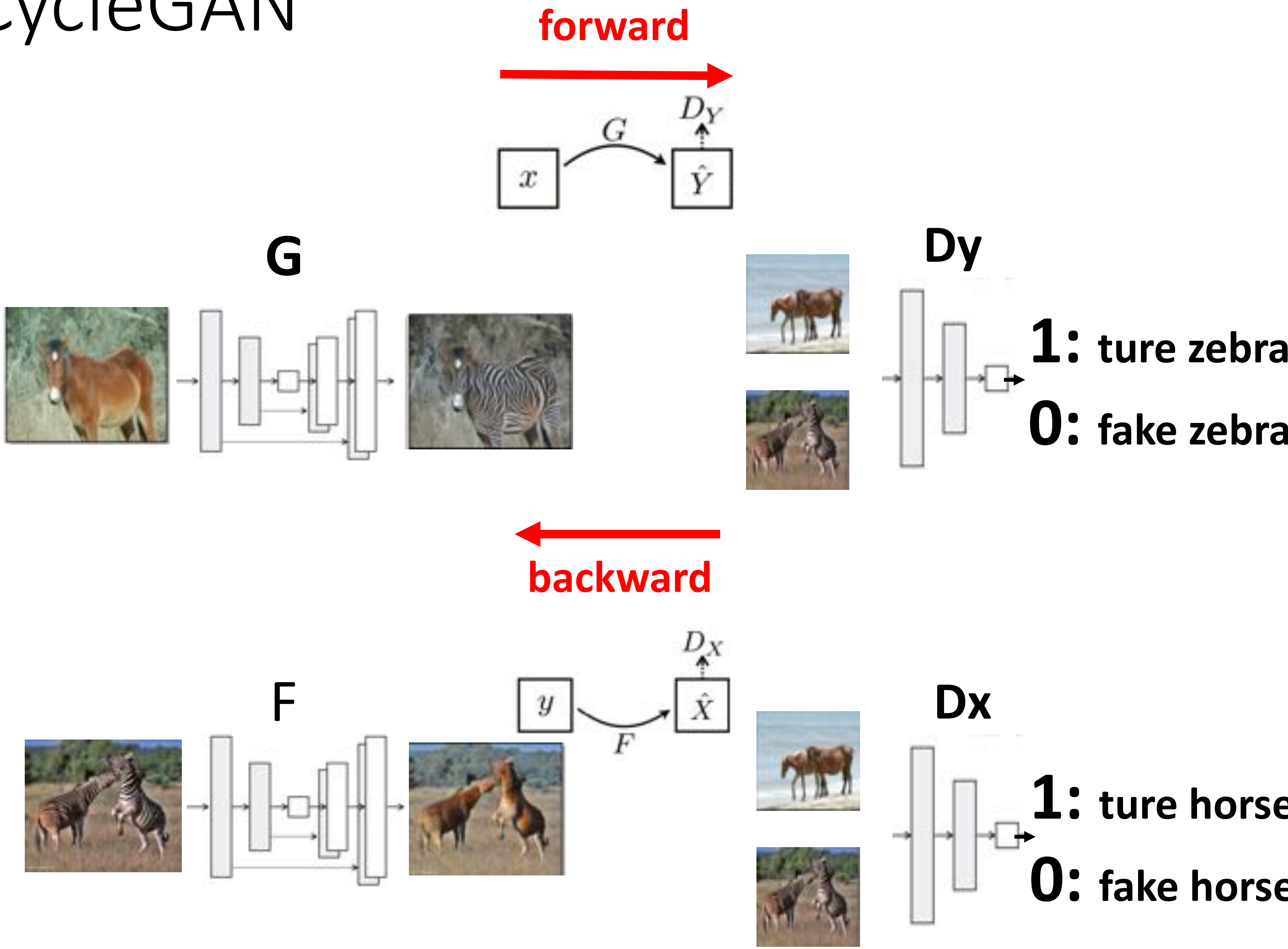






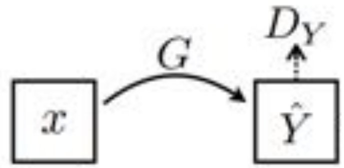
Zhu, etal. Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks In ICCV 2017

CycleGAN

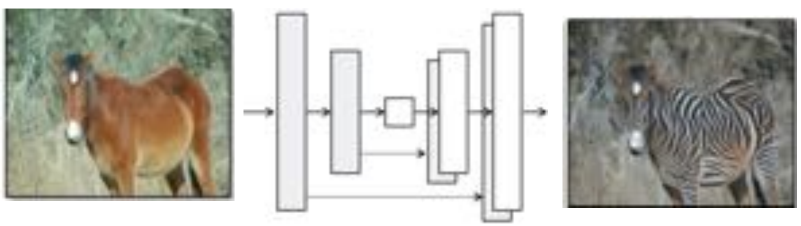

forward
D_Y
G
x
$\hat{Y}$
G
Dy
1: ture zebra
0: fake zebra
backward
D_X
F
y
$\hat{X}$
F
Dx
1: ture horse
0: fake horse

CycleGAN

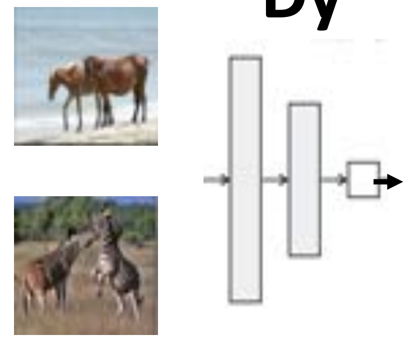
forward



G



Dy

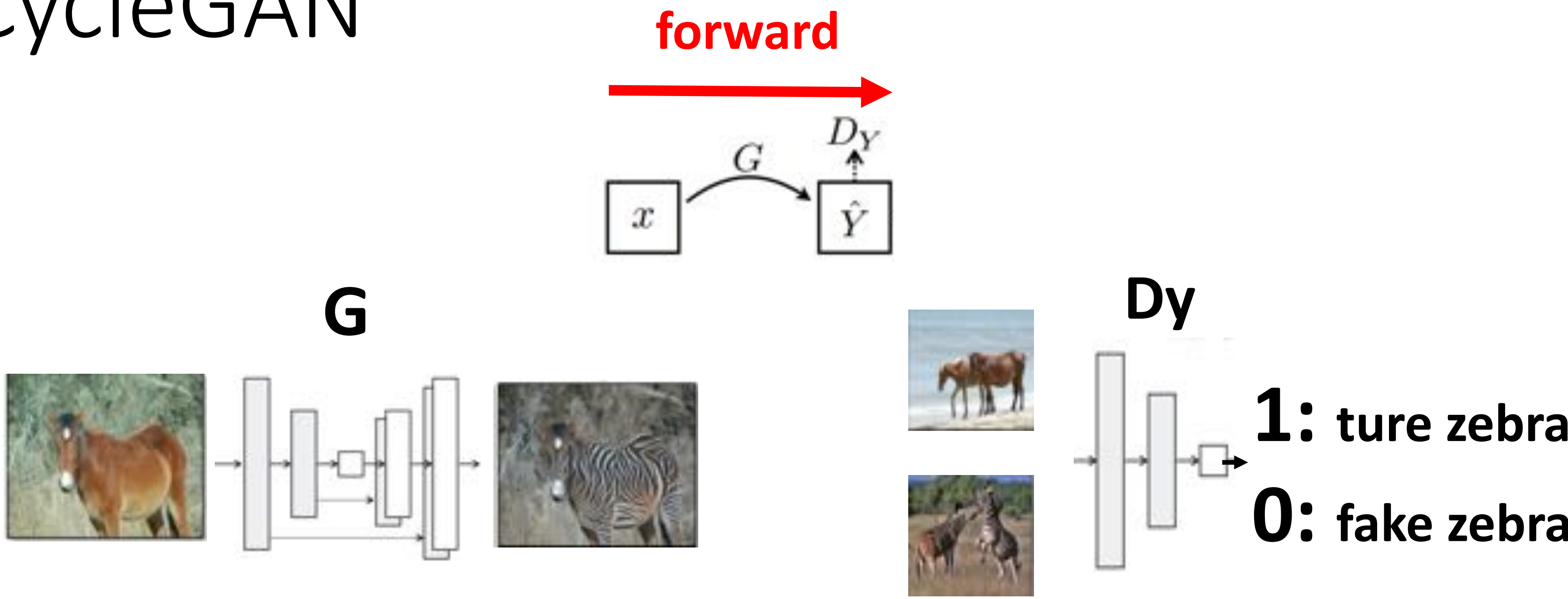


1: ture zebra

0: fake zebra

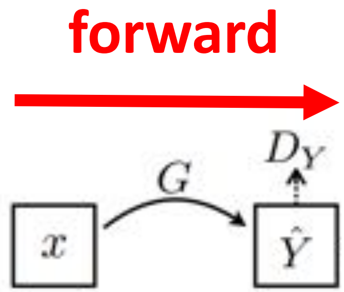
Minmax game

CycleGAN



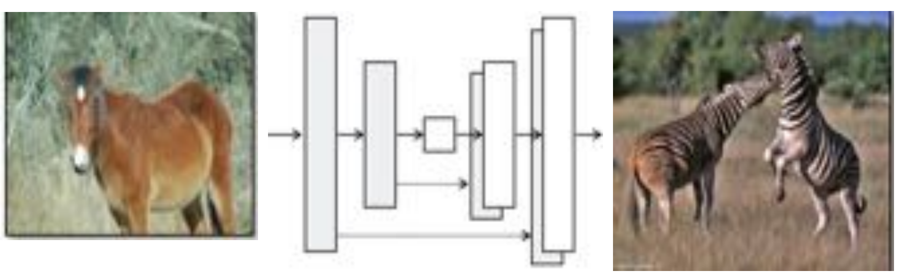
Q? minmax function is enough?

CycleGAN

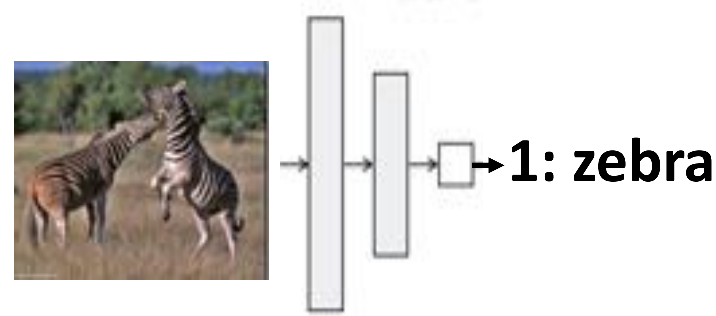


Q? minmax function is enough?

G

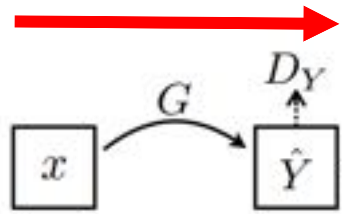


Dy



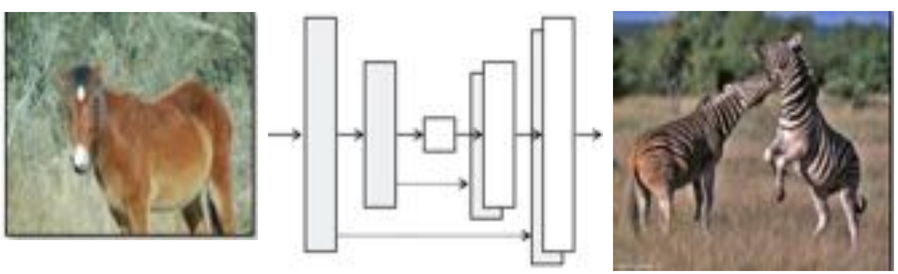
CycleGAN

forward

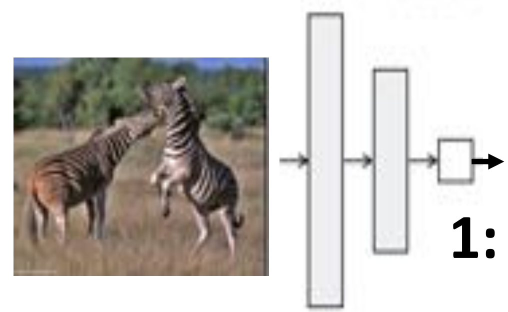


Q? minmax function is enough?
Content is changed!

G



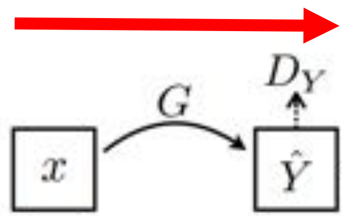
Dy



1: ture zebra

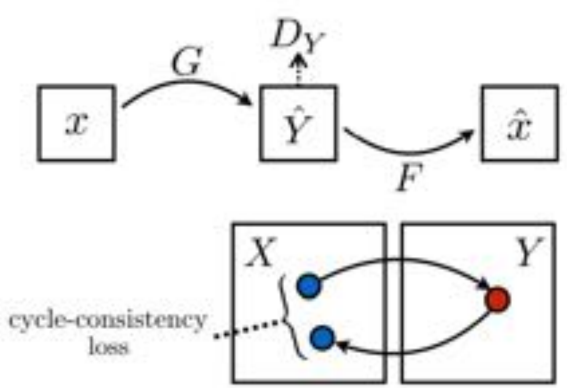
CycleGAN

forward



Q? minmax function is enough?

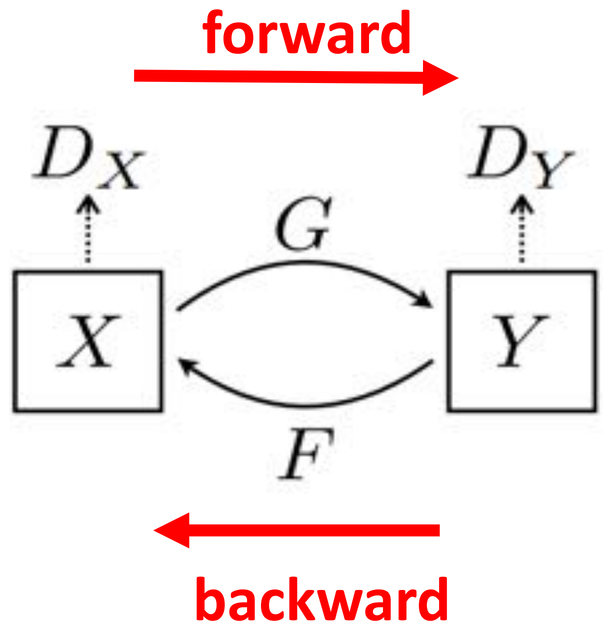
Content is changed!

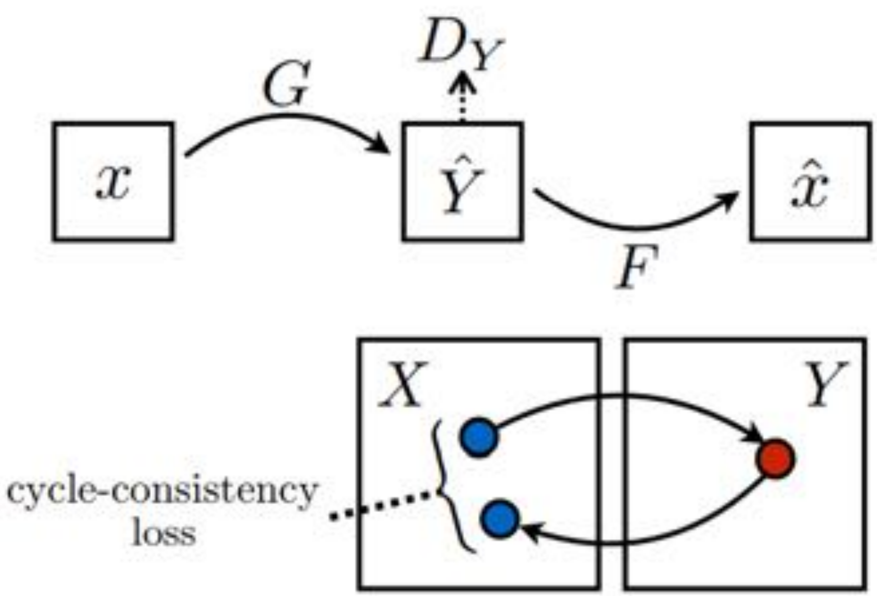


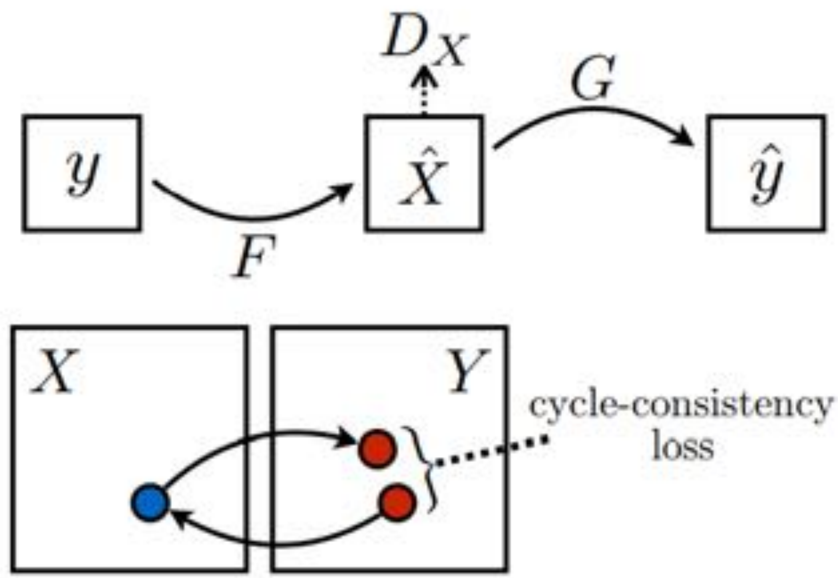
Cycle-consistency loss

Preserve the content

CycleGAN

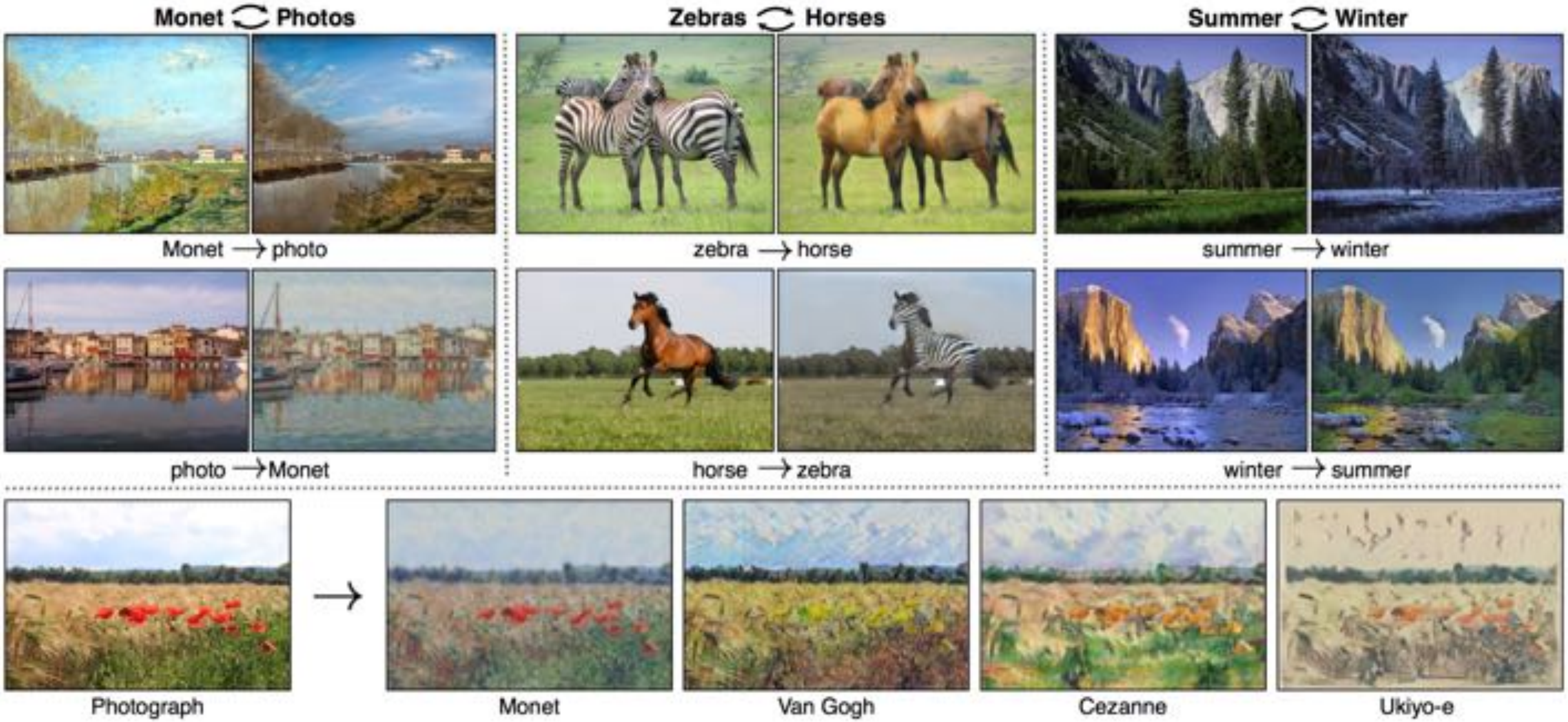






Zhu, etal. Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks In ICCV 2017

CycleGAN



Zhu, etal. Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks In ICCV 2017

SPGAN (Similarity Preserving GAN)

Duke images

Market images

Person re-identification (re-ID) models trained on one dataset often **fail to generalize** well to another due to **dataset bias**

Big drop!

76.8% →43.1%

(train on market)

Deng,etal. Image-Image Domain Adaptation with Preserved Self-Similarity and Domain-Dissimilarity for Person Re-identification. In CVPR 2018.

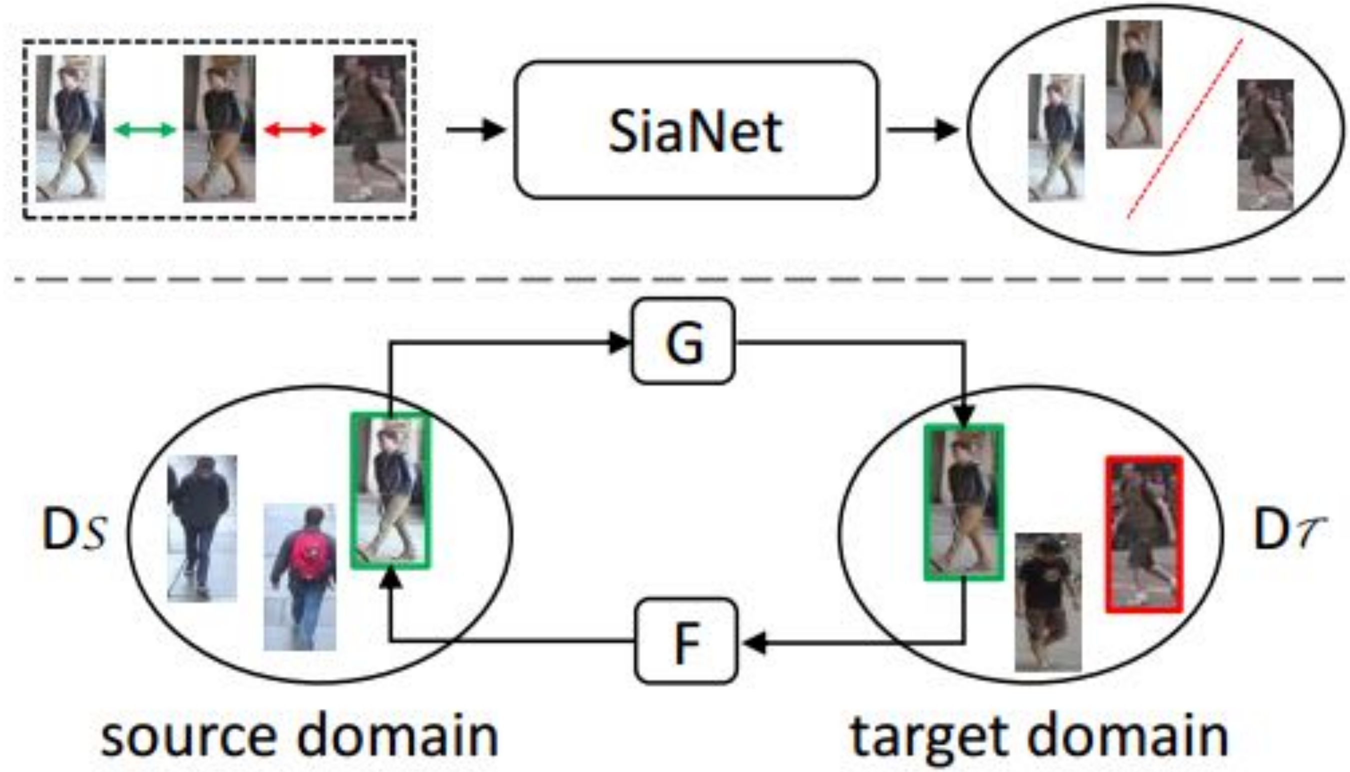
SPGAN (Similarity Preserving GAN)

"Learning via translation" framework

Step 1: source-target image translation **Step 2**: feature learning

Deng,etal. Image-Image Domain Adaptation with Preserved Self-Similarity and Domain-Dissimilarity for Person Re-identification. In CVPR 2018.

SPGAN (Similarity Preserving GAN)

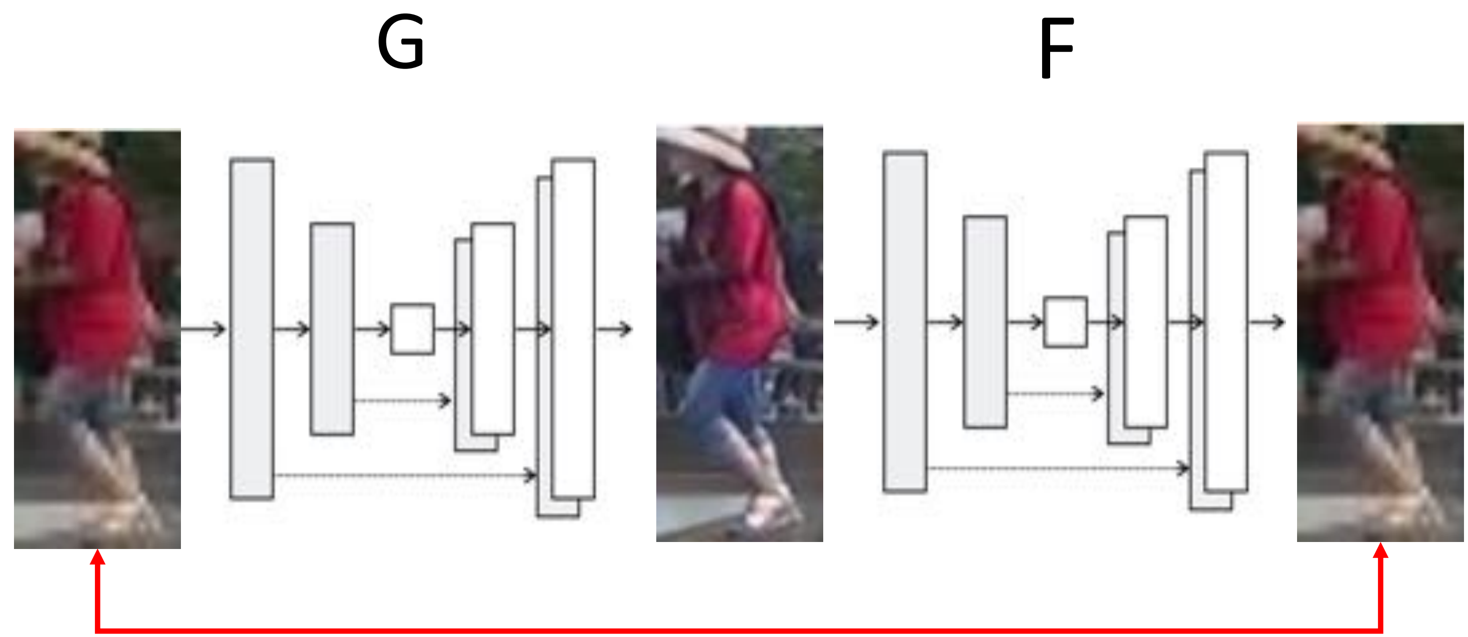


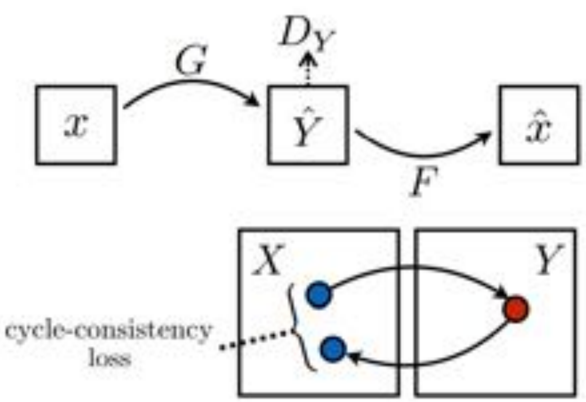
Source domain: images from one dataset **duke**
Target domain: images from another dataset **market**

Note that two datasets contain different classes/ IDs

Deng,etal. Image-Image Domain Adaptation with Preserved Self-Similarity and Domain-Dissimilarity for Person Re-identification. In CVPR 2018.

SPGAN

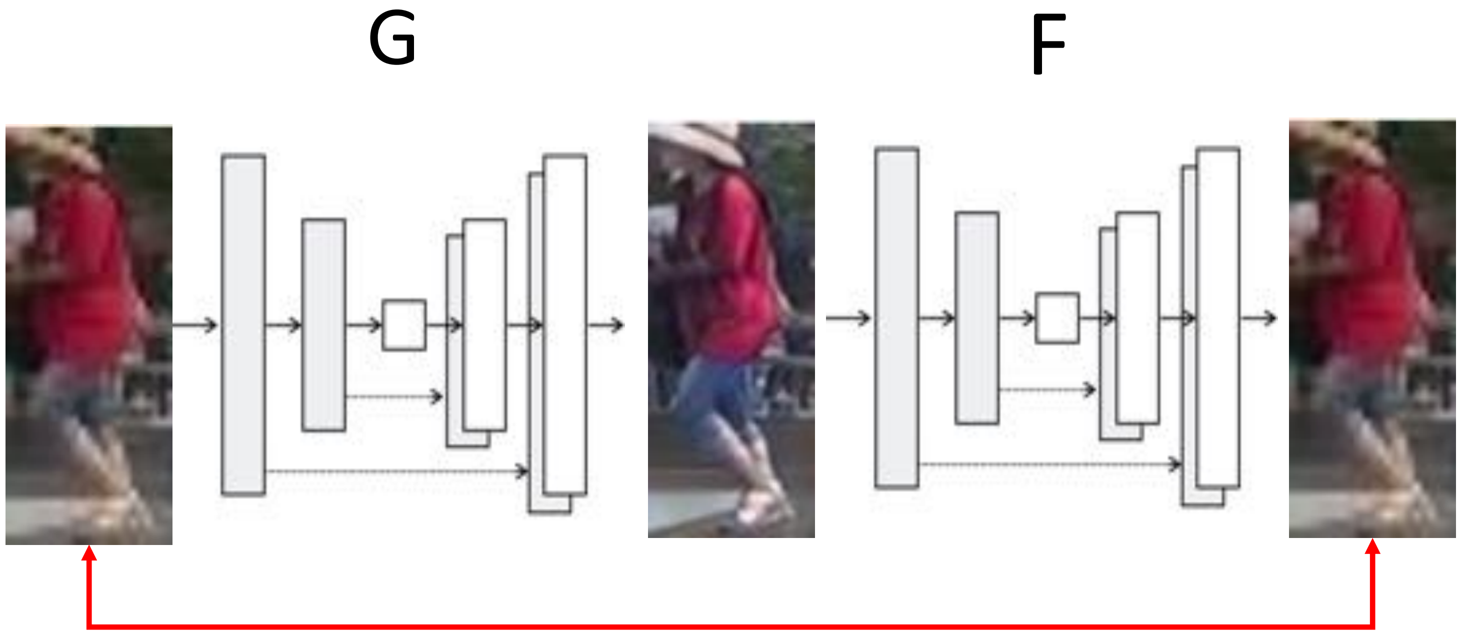


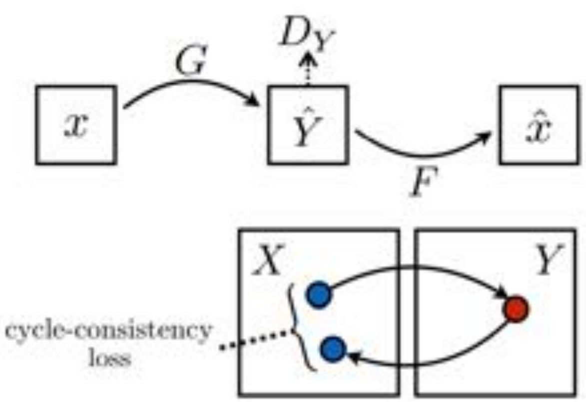


Cycle-consistency loss

Preserve the content

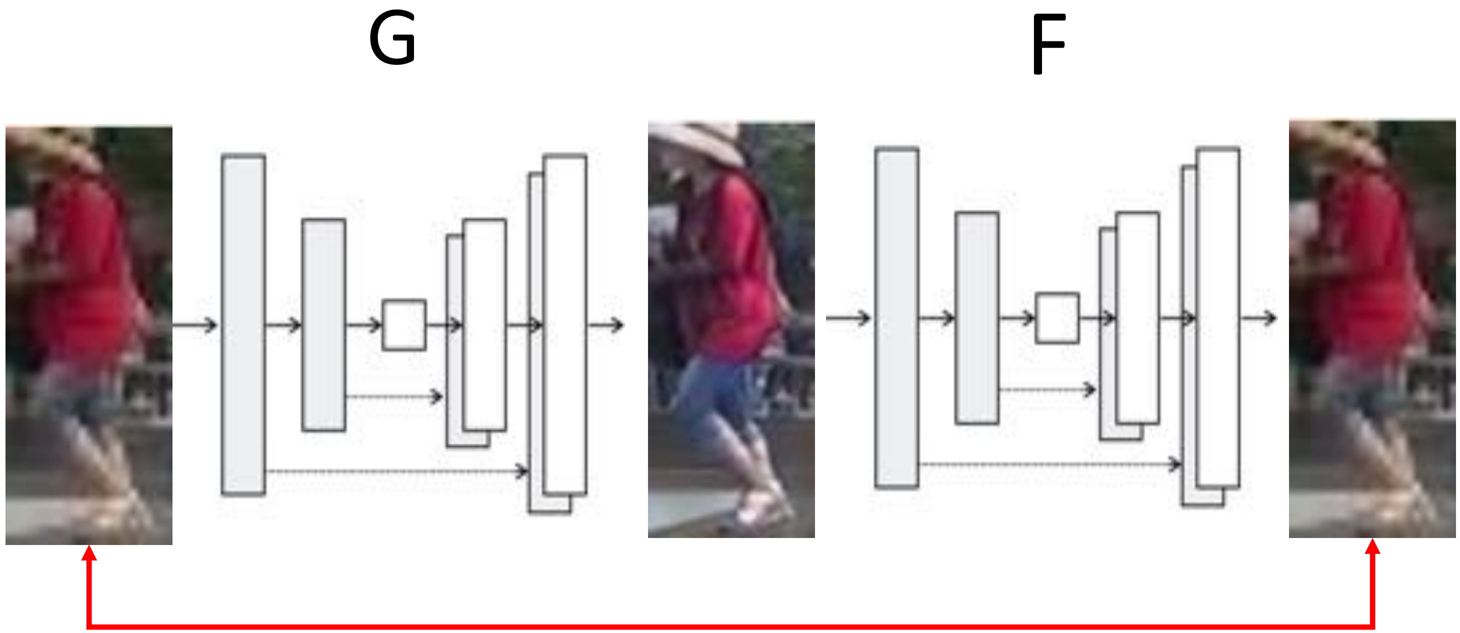
SPGAN



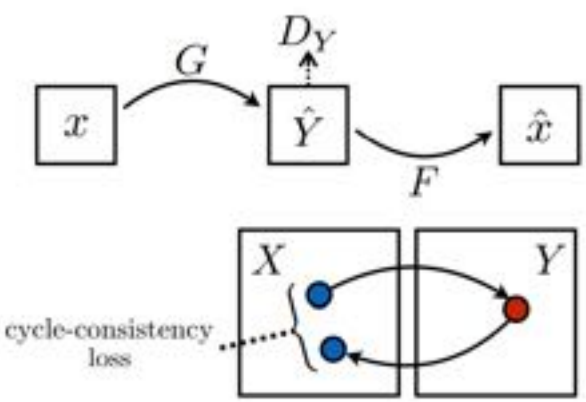


Q: cycle-consistency loss is enough?

SPGAN



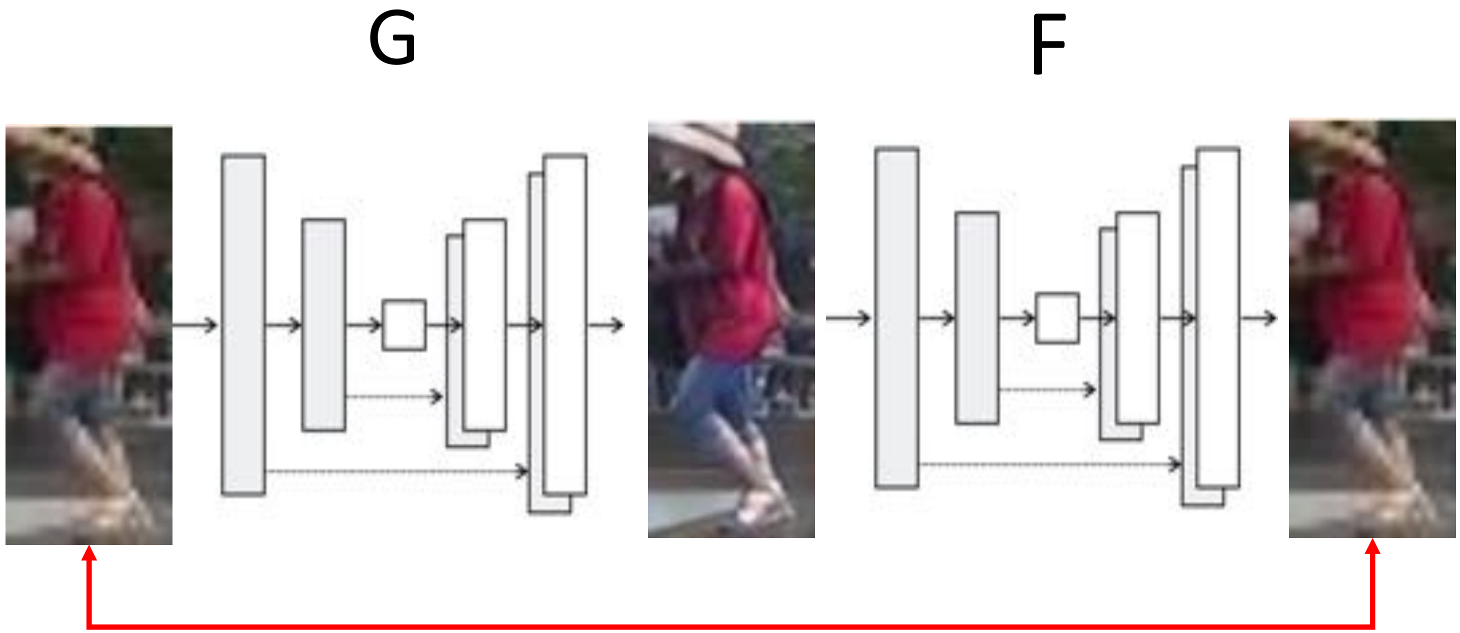
Q: cycle-consistency loss is enough?



The translated image is used for learning feature/ training a classifier.

Thus, identity information should be preserved

SPGAN

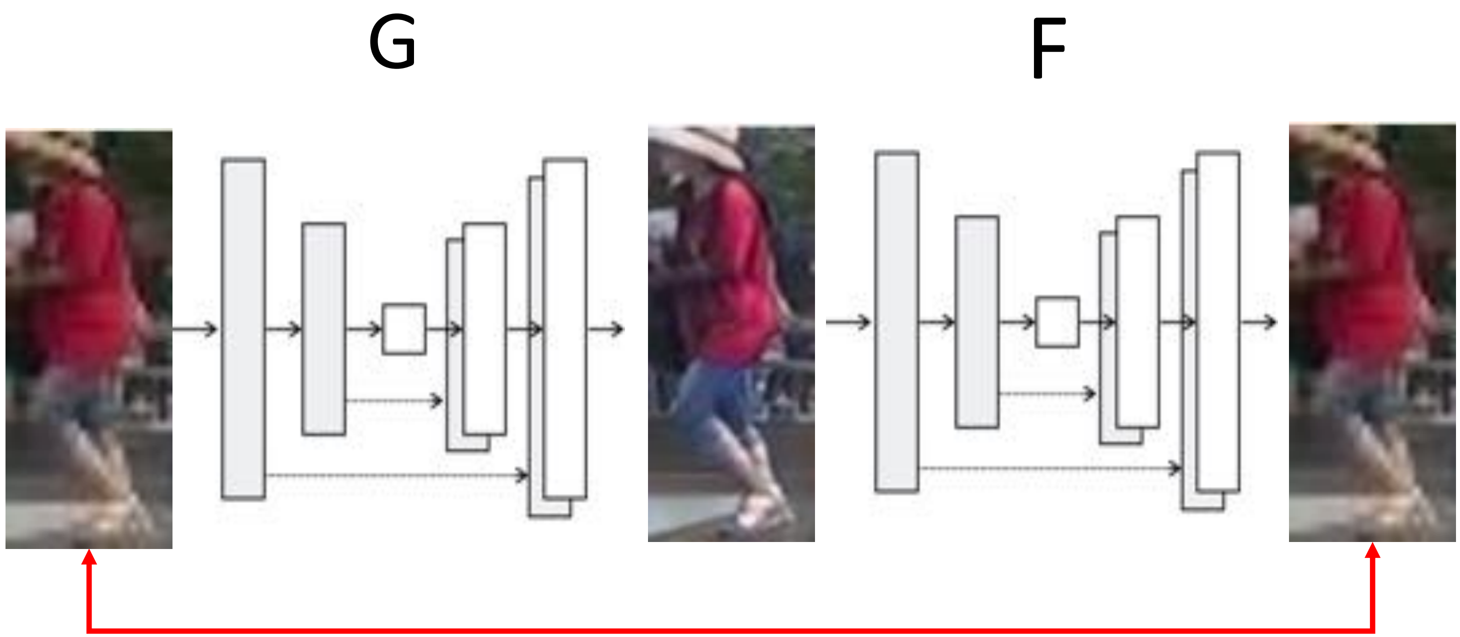


identity information should be preserved

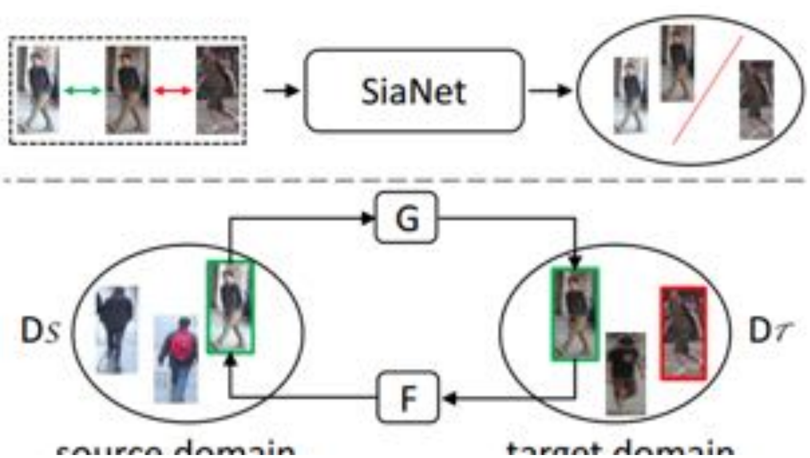
New unsupervised constraints:

1) the translated image should be **close** to its original image at feature space; (similarity)
2) The translated images should be **not close** to target images (dissimilarity)

SPGAN



identity information should be preserved



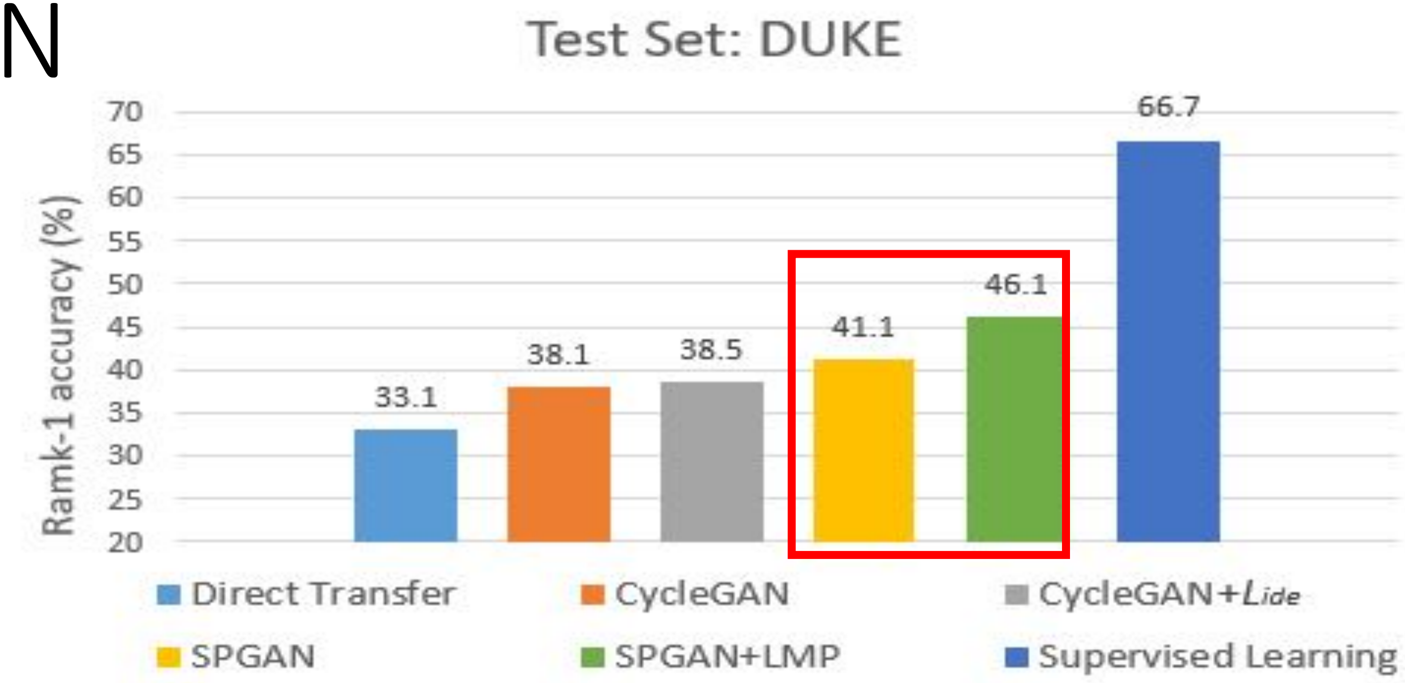
New unsupervised constraints:

1) **the translated image should be close to its original image at feature space; (similarity)**
2) **The translated images should be not close to target images (dissimilarity)**

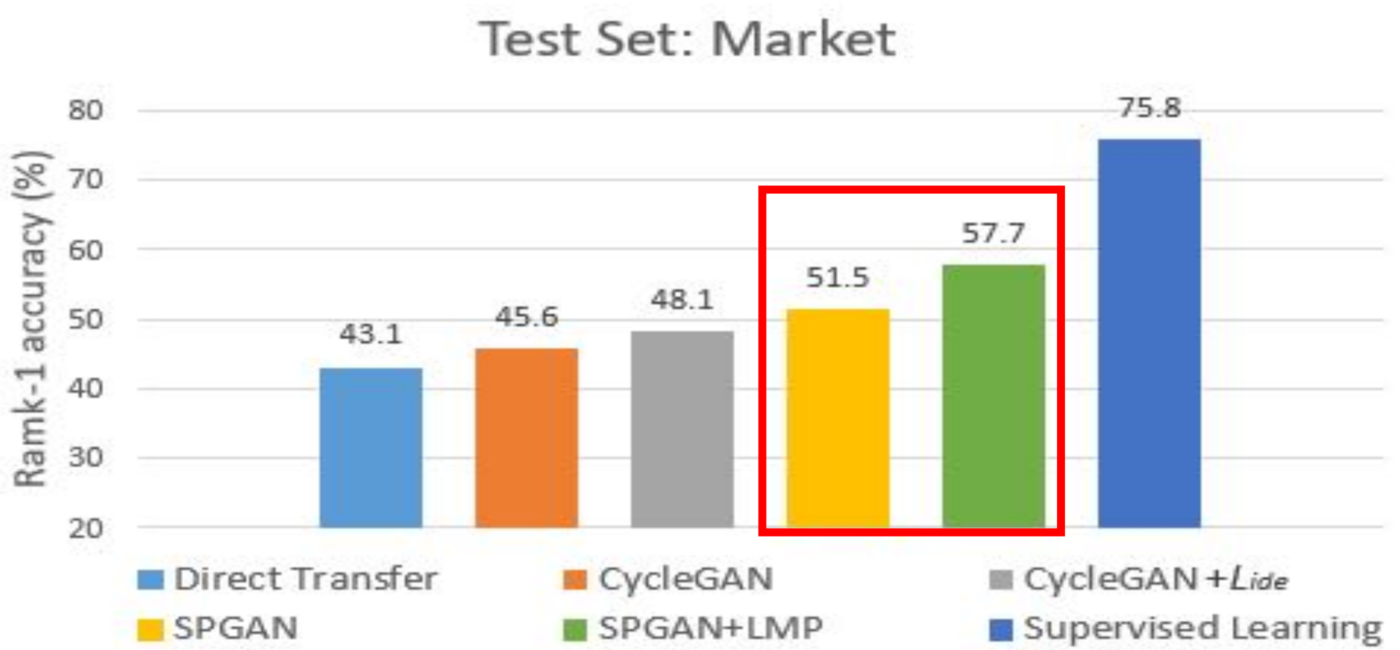
SPGAN

Visual examples

SPGAN



Test Set: DUKE
Ramk-1 accuracy (%)
70
65
60
55
50
45
40
35
30
25
20
33.1
38.1
38.5
41.1
46.1
66.7
Direct Transfer
CycleGAN
CycleGAN+Lide
SPGAN
SPGAN+LMP
Supervised Learning



Test Set: Market
Ramk-1 accuracy (%)
80
70
60
50
40
30
20
43.1
45.6
48.1
51.5
57.7
75.8
Direct Transfer
CycleGAN
CycleGAN+Lide
SPGAN
SPGAN+LMP
Supervised Learning

Thank you