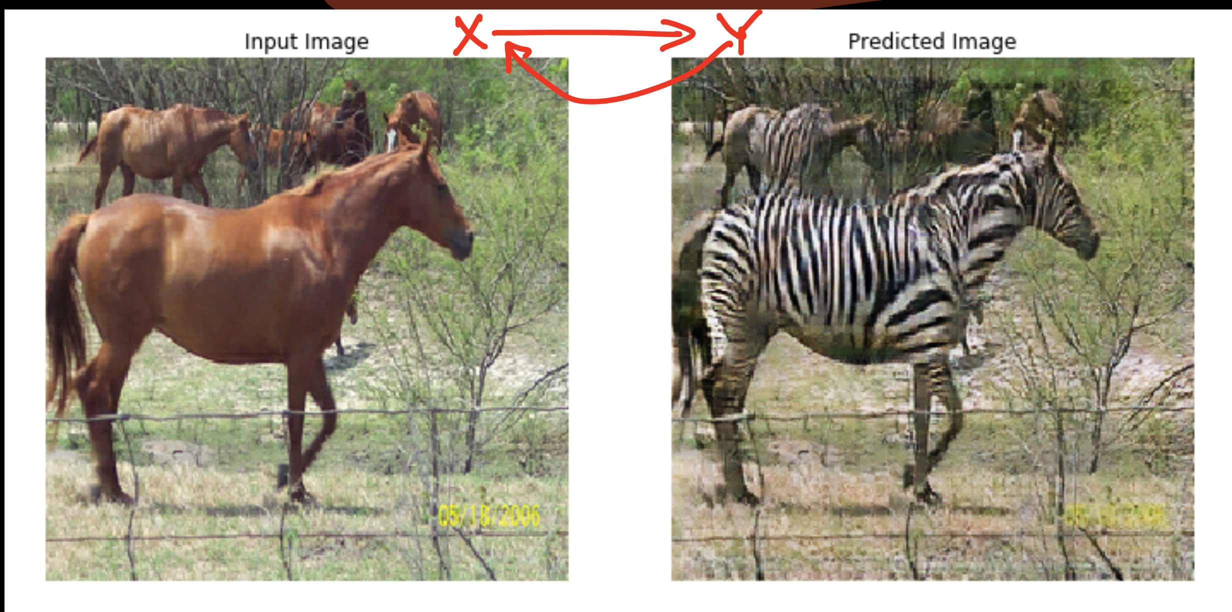
CYCLE GAN

Unpaired Image 2 Image transformation

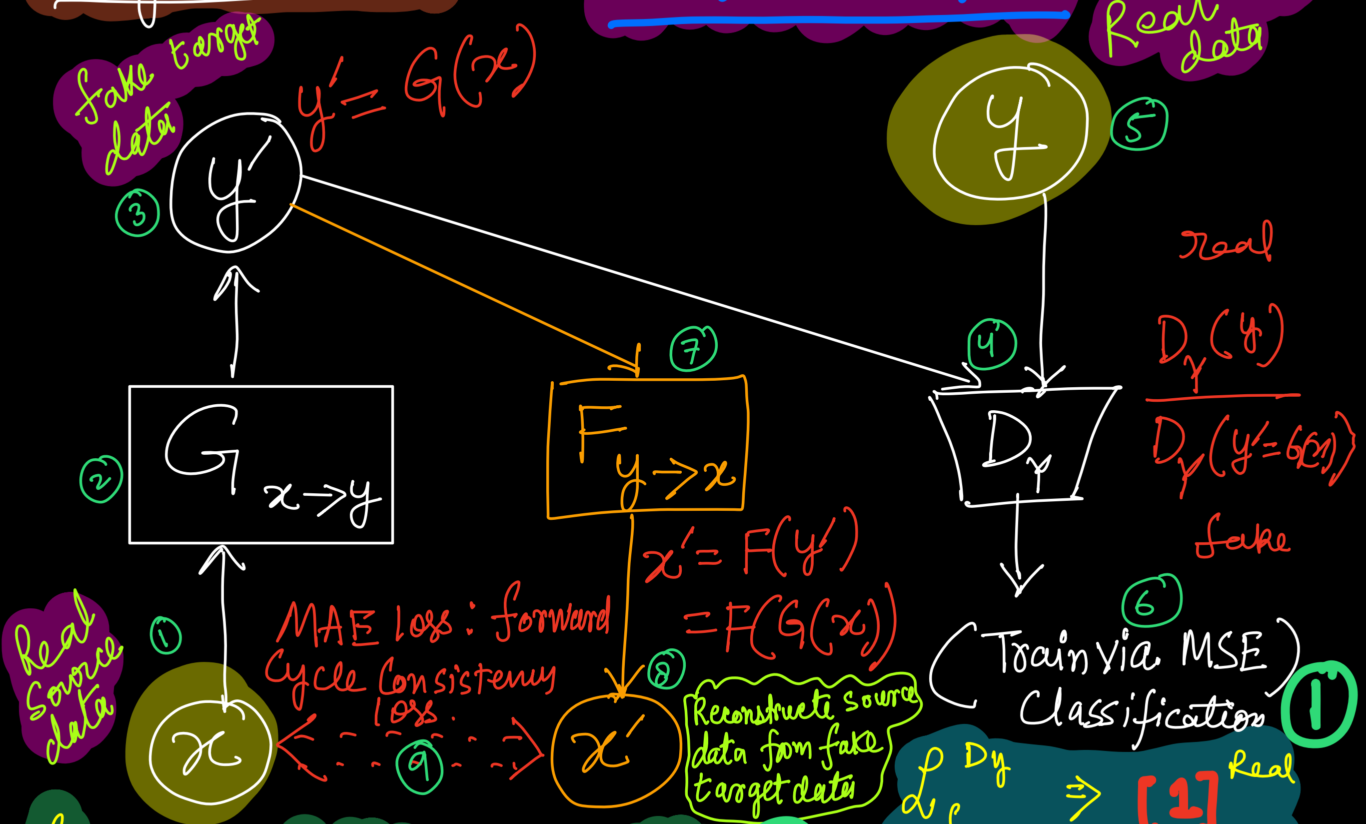


- Cross domain (X ⟶ Y)
- Image paring is not required
- Forward GAN (X→Y) and Backward GAN (Y–X) trained end2end.
- Along with adversarial loss it uses Cyclic consistency and Identity loss.

ICCV-2017, Citations so far [~12,500]

CycleGAN

Forward Cycle



(Train via MSE Classification) ①

$$\mathcal{L}^{D_y}_{\text{forward GAN}} \Rightarrow \underset{y \sim p_{data}(y)}{\mathbb{E}} [D_y(y) - 1]^2 + \underset{x \sim p_{data}(x)}{\mathbb{E}} [D_y(G(x))]^2$$

[1] Real

[0] fake

$$\mathcal{L}_{\text{for-cy}} = \underset{x \sim p_{data}(x)}{\mathbb{E}} \left[\| F(G(x)) - x \|_1 \right] \quad ③$$

(gives less blur as compared to L_2)

It ensures that original features of ⓧ should remain intact in ⓨ' & recoverable.

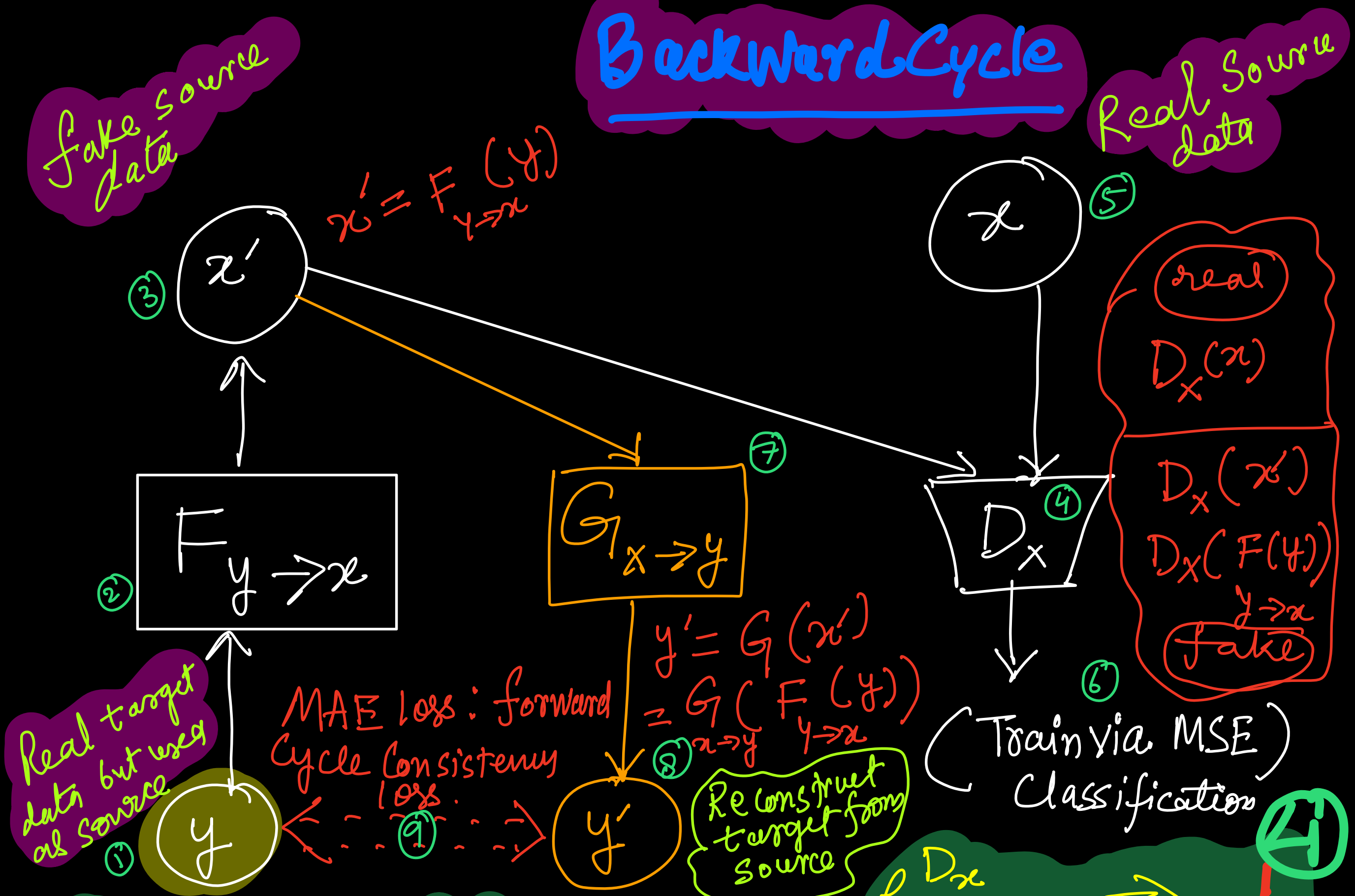
$$\mathcal{L}^{G_{x \to y}}_{\text{forward GAN}} \Rightarrow \underset{x \sim p_{data}(x)}{\mathbb{E}} \left(D_y(G(x)) - 1 \right)^2 \quad ②$$

Instead of BCE use MSE

It has ② GAN's
ⓐ $G_{x \to y}$ and D_y
ⓑ $F_{y \to x}$ & D_x
are Corresponding Gen/Dis (trained in adversarial manner.)

It is a Symmetric N/W (for/back) with reversed source & data.

Backward Cycle



$$\mathcal{L}_{back\text{-}cyc} = \mathbb{E}_{y\sim p_{data}(y)}\left[\| G(F(y)) - y \|_1\right] \quad 6$$

$$\mathcal{L}^{D_x}_{backward\text{-}GAN} \Rightarrow \mathbb{E}_{x\sim p_{data}(x)}\left[D_x(x) - 1\right]^2 + \mathbb{E}_{y\sim p_{data}(y)}\left[D_x(F(y))\right]^2 \quad 4$$

Real   Fake   0

$$\mathcal{L}^{F_{y\to x}}_{backward\text{-}GAN} = \mathbb{E}_{y\sim p_{data}(y)}\left[D_x(F(y)) - 1\right]^2 \quad 5$$

fake   1

$$L^{Discriminator}_{GAN} \Rightarrow 1 + 4$$

$$L^{Generator}_{GAN} \Rightarrow 2 + 5$$

$\lambda_1 = 1$ & $\lambda_2 = 10$

$$L_{cyc} = 3 + 6$$

$$L = \lambda_1 (L_{GAN}) + \lambda_2 (L_{cyc})$$

Several time it has been observed that proper Color Composition transfer is not successful in S → Target.

$$\mathcal{L}_{identity} = \mathbb{E}_{x \sim p_{data}(x)}\left[\| F(x) - x \|_1\right] + \mathbb{E}_{y \sim p_{data}(y)}\left[\| G(y) - y \|_1\right]$$

$$\boxed{\lambda_3 = 0.5}$$

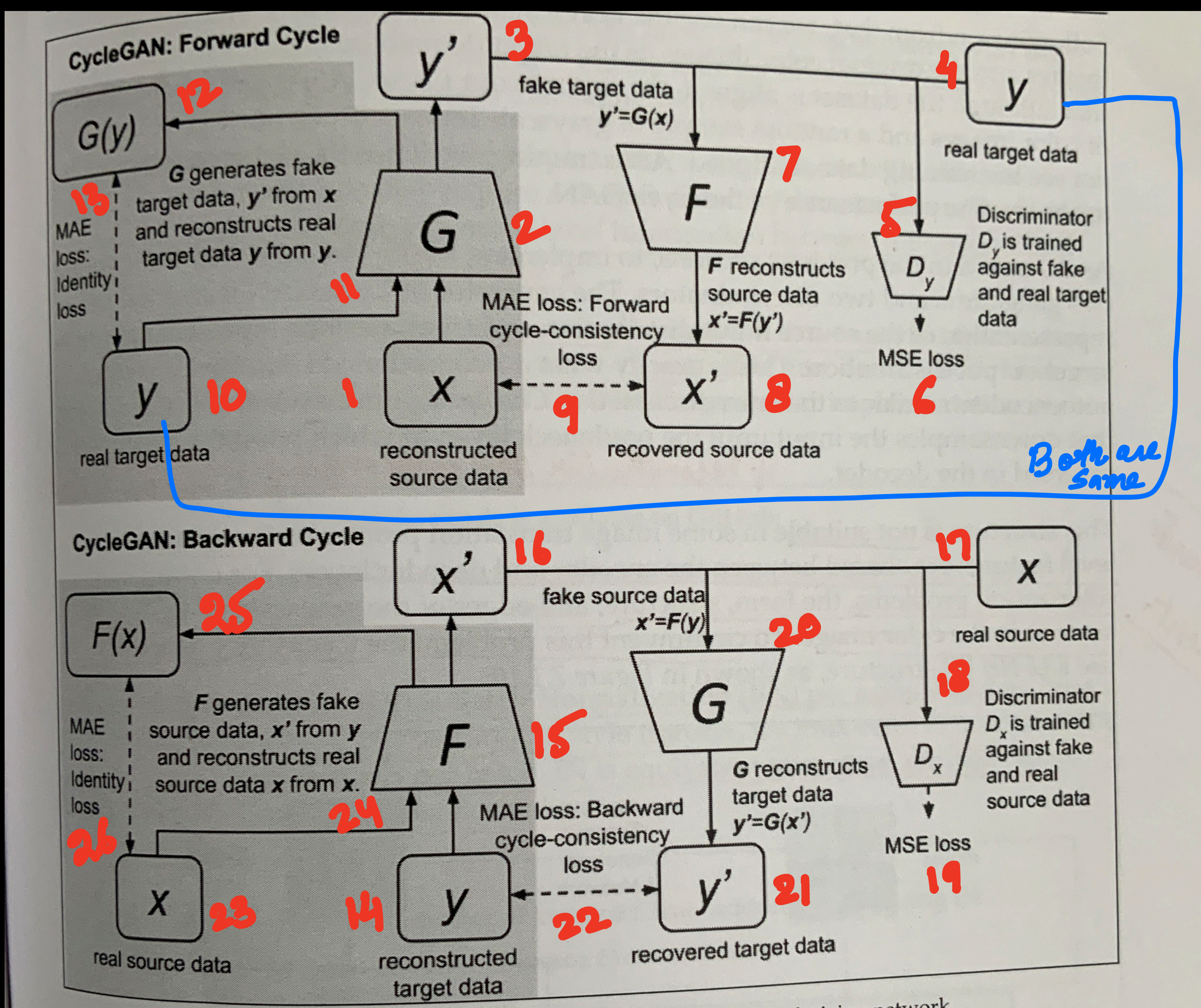


Figure taken from book " Advanced deep learning with Tensorflow2 and Keras " by Rowel Atienza. [follow the numbering].

Instead of using Binary Cross Entropy they have used MSE as suggested by LS-GAN.

(*) Its generator is obviously U-Net based which Concatenates encoder features to ensure feature sharing. Encoder does Instance normalization which is (BN) per sample.

(*) Discriminator utilizes PatchGAN Concept as deciding real/fake is inefficient in terms of parameters.

R/F	R/F
R/F	R/F

2x2 PatchGAN (non-overlapping patches)

(*) If X-domain dimension doesn't match Y-domain's dimension then either Identity loss need to be dropped or managed/ suitably defined.

(*) X & Y domains need to NOT very far and totally uncorrelated otherwise GAN learning may become unstable like Horse to Car

(*) Prediction of Cycle-GAN is Cyclic-consistent but don't ensure Semantic Consistency.

" generated samples may lost their semantic meaning during translation".

Hence "Cycle-Consistent Adversarial Domain Adaptation (CyCADA)" by Hoffman is proposed utilizing Semantic Consistency along with Cyclic Consistency.