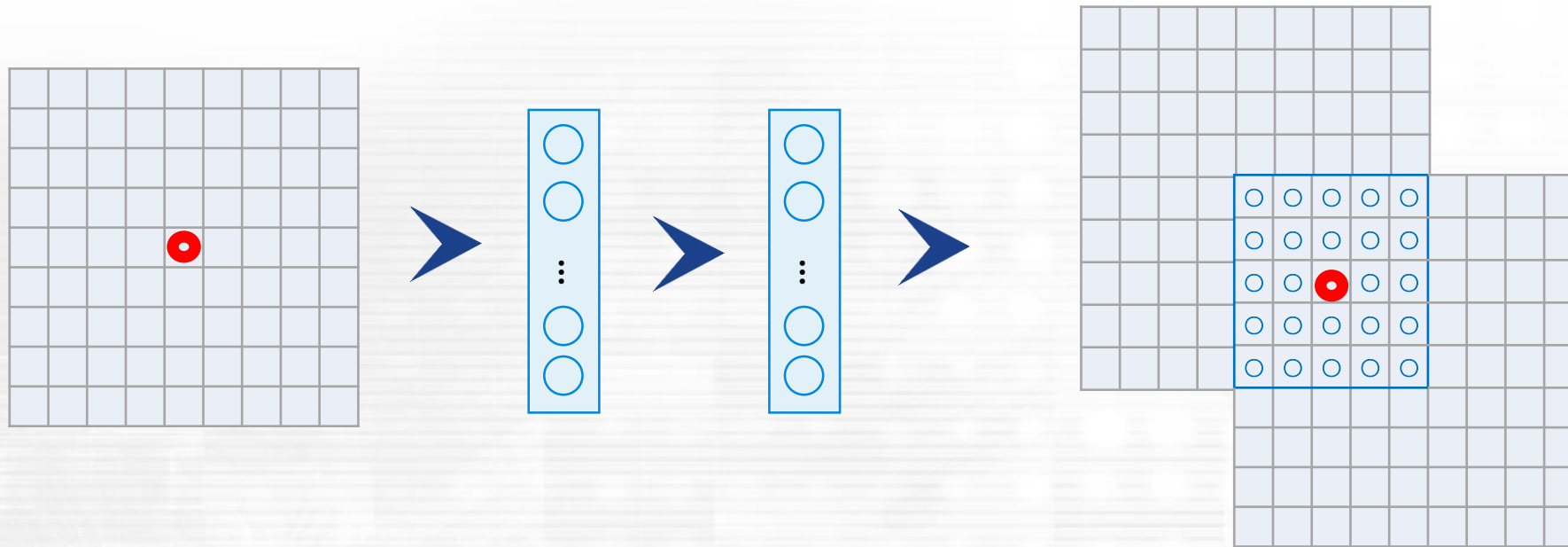
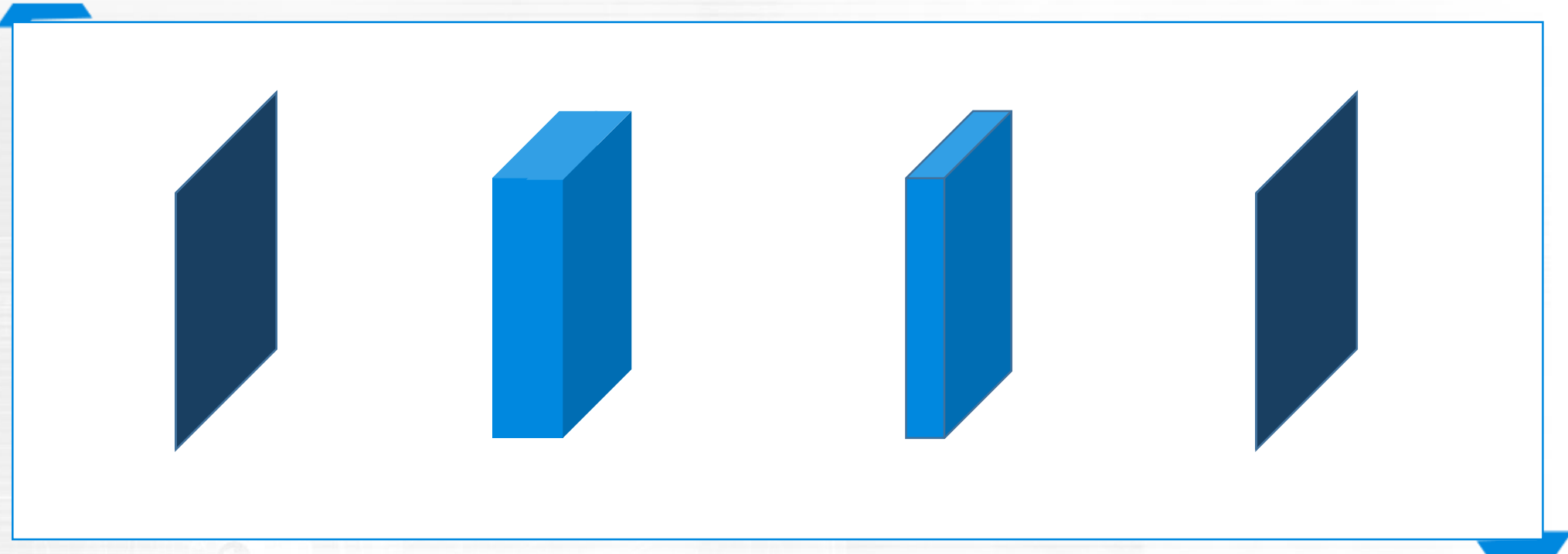

Super-Resolution using CNN



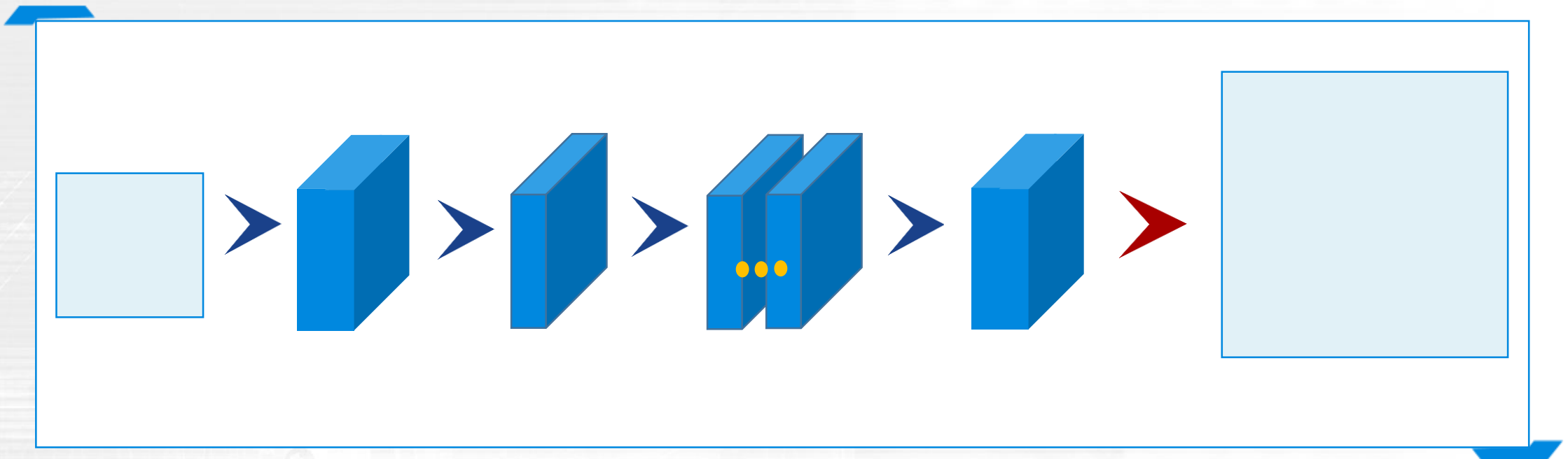
Super-Resolution using CNN



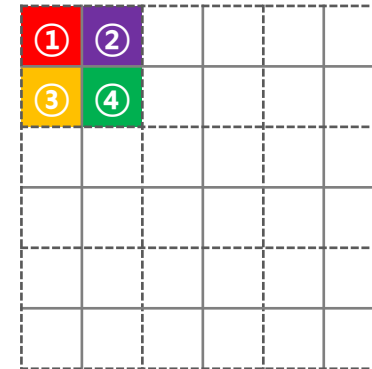
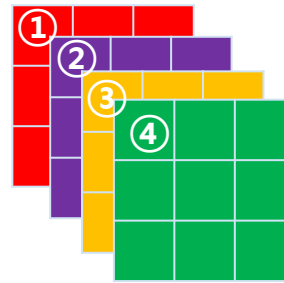
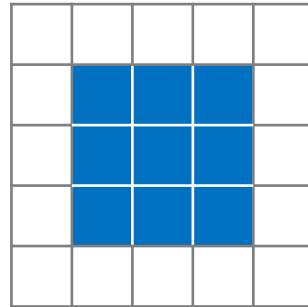
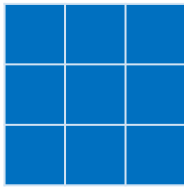
Super-Resolution using CNN



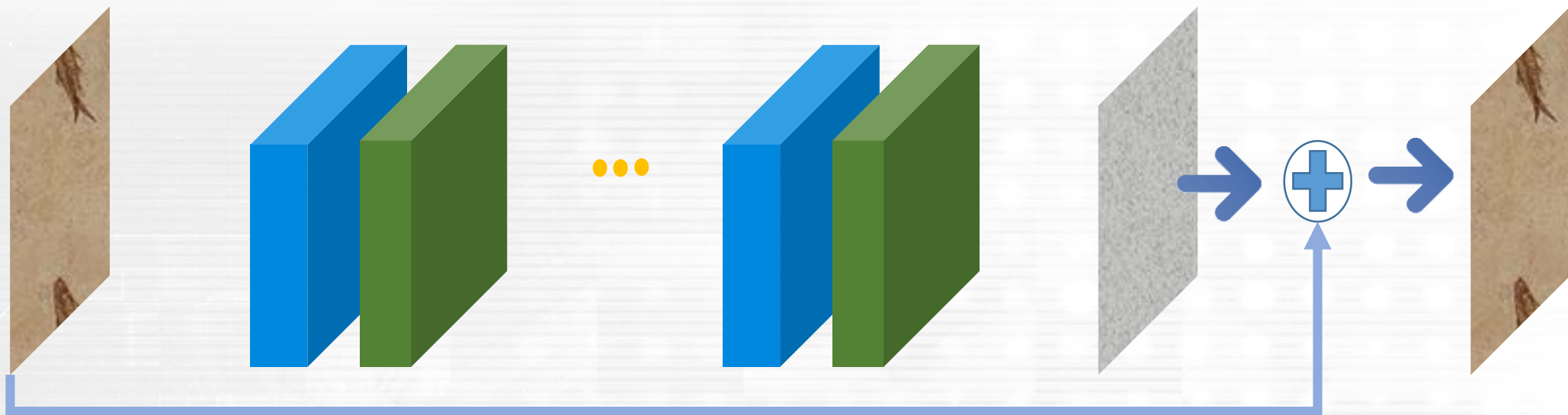
Fast SRCNN



Sub-Pixel CNN

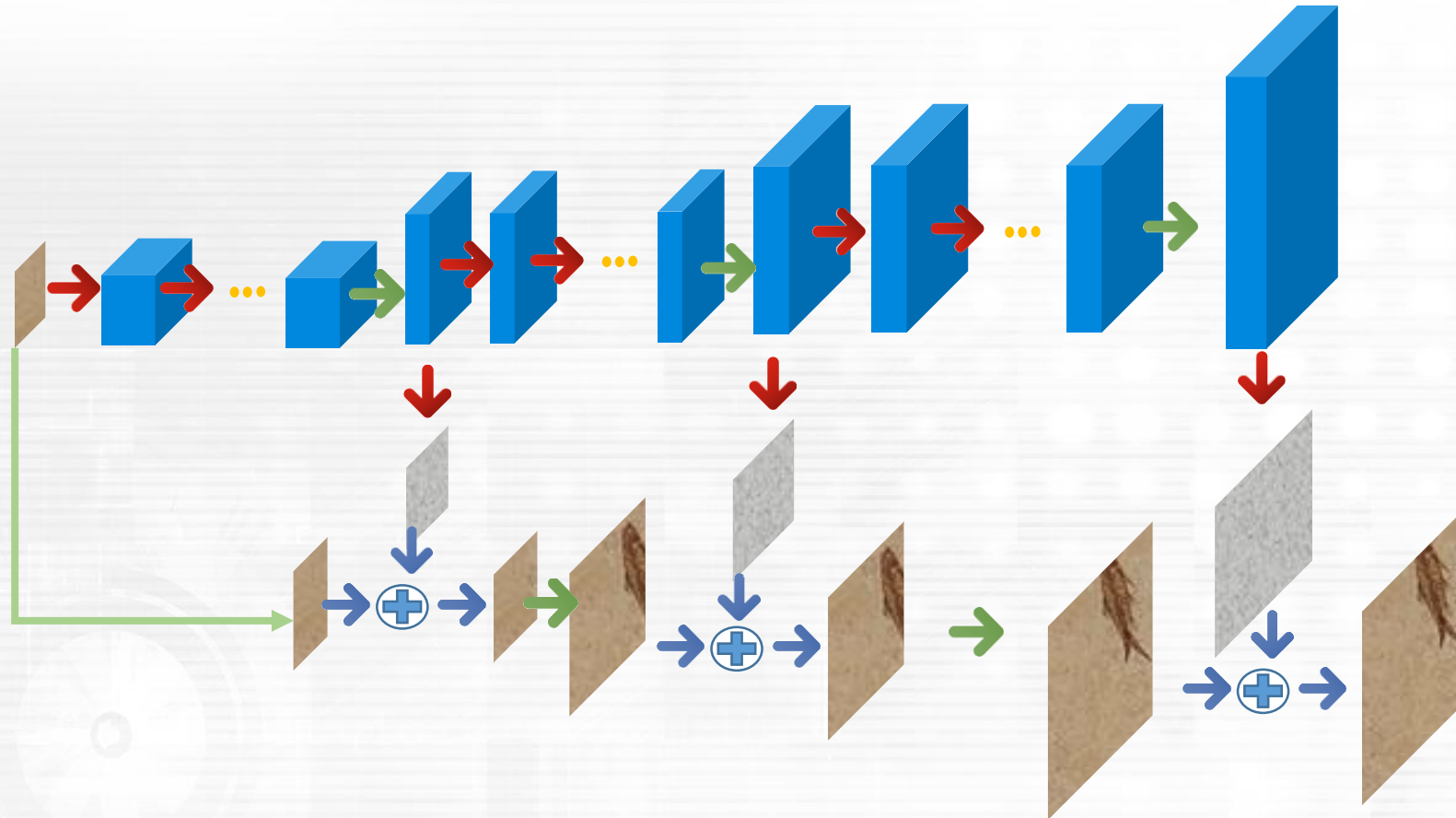


Deep CNN for Super Resolution

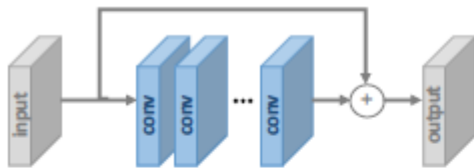


Gradient Clipping

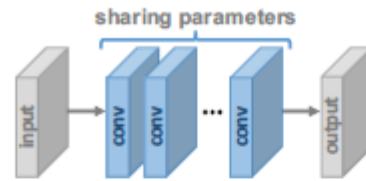
Laplacian Pyramid Network



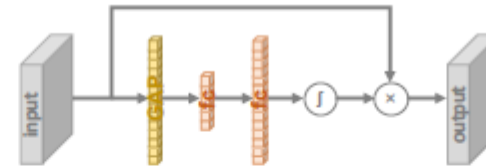
Deep Networks



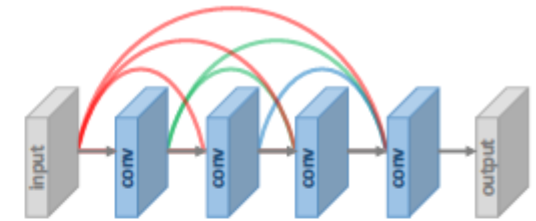
(a) Residual learning



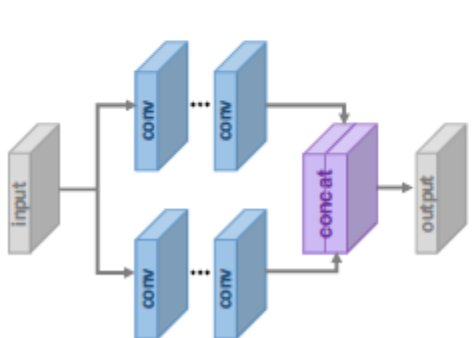
(b) Recursive learning



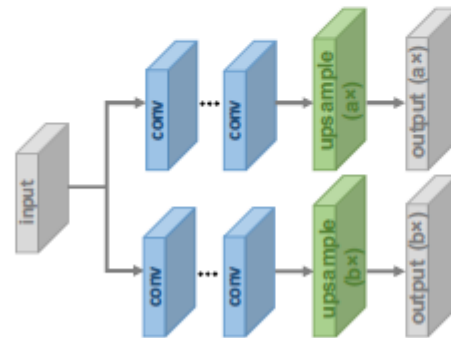
(c) Channel attention



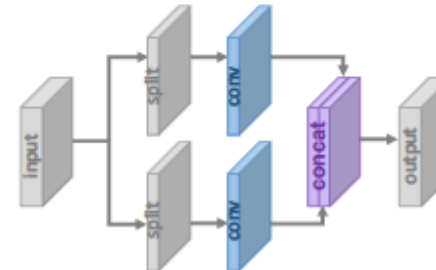
(d) Dense connections



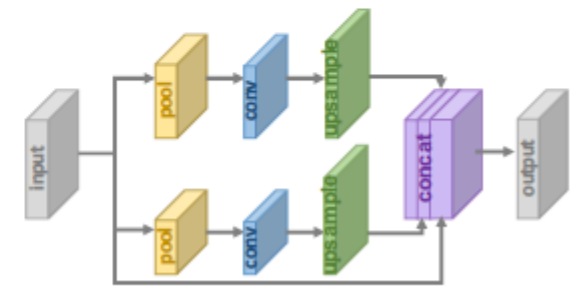
(e) Local multi-path learning



(f) Scale-specific multi-path learning

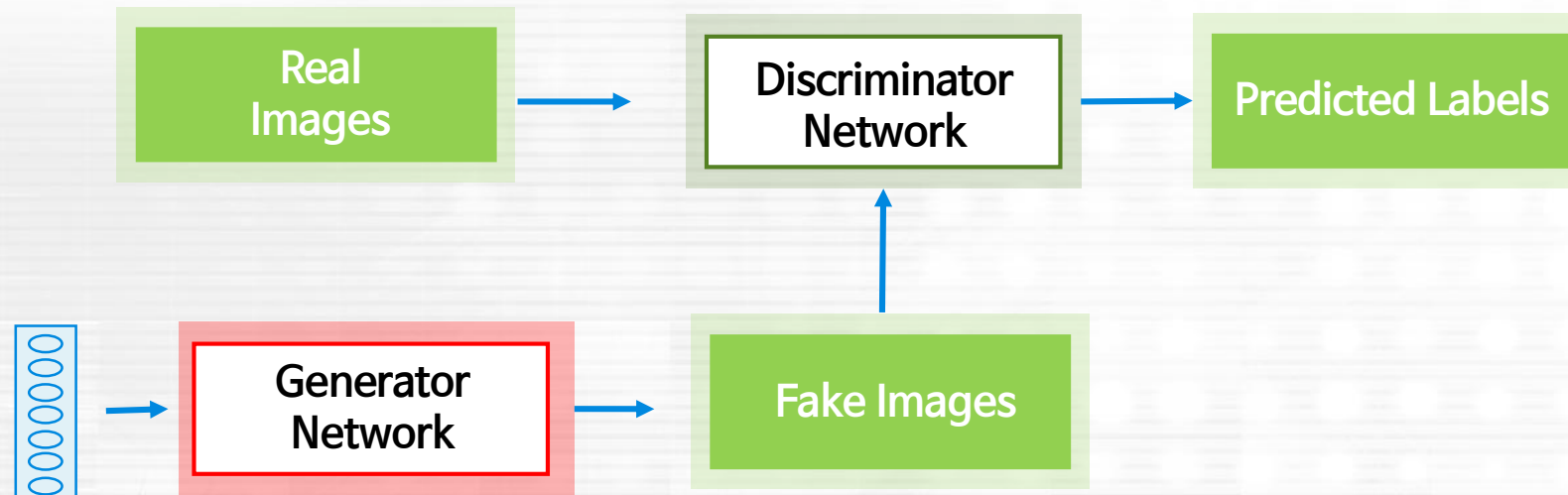


(g) Group convolution



(h) Pyramid pooling

Generative Adversarial Network



$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

Conditional GAN

Conditional GAN

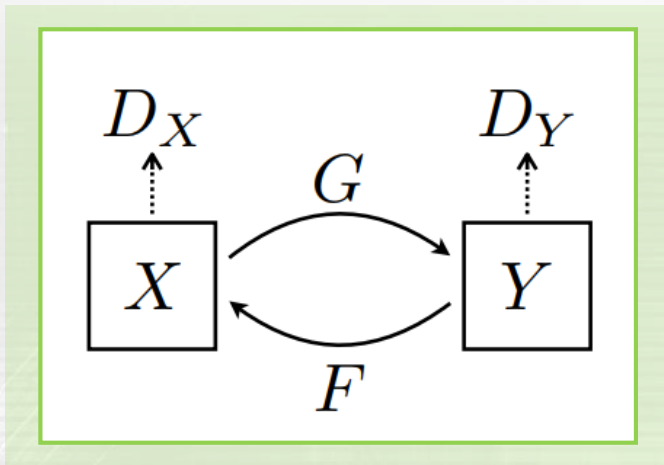
$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}_y[\log D(y)] + \mathbb{E}_{x,z}[\log(1 - D(G(x, z)))]$$

$$\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{x,y}[\log D(x, y)] + \mathbb{E}_{x,z}[\log(1 - D(x, G(x, z)))]$$

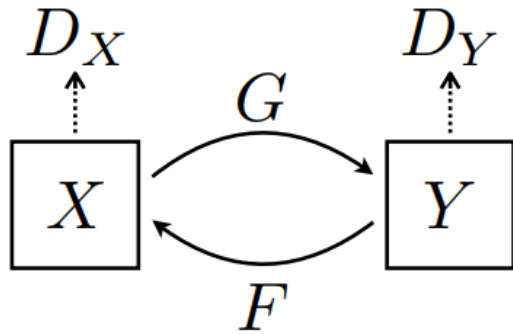
$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x, z)\|_1]$$

$$G^* = \arg \min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G)$$

Cycle GAN



Cycle GAN



$$G^*, F^* = \arg \min_{G, F} \max_{D_X, D_Y} \mathcal{L}(G, F, D_X, D_Y)$$

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

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

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

GAN for Super Resolution



GAN for Super Resolution

$$l_{MSE}^{SR} = \frac{1}{r^2 WH} \sum_{x=1}^{rW} \sum_{y=1}^{rH} (I_{x,y}^{HR} - G_{\theta_G}(I^{LR})_{x,y})^2$$

$$l_{VGG/i,j}^{SR} = \frac{1}{W_{i,j} H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\phi_{i,j}(I^{HR})_{x,y}) - \phi_{i,j}(G_{\theta_G}(I^{LR})_{x,y})^2$$

$$l_{Gen}^{SR} = \sum_{n=1}^N -\log D_{\theta_D}(G_{\theta_G}(I^{LR}))$$

Medical Image Super-Resolution

- MRI super-resolution
- CT reconstruction

Medical Image Synthesis

- MRI - PET generation
- Data generation for better training model

Metrics for Image Quality

- Peak Signal to Noise Ratio (PSNR)

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX_I^2}{MSE} \right) = 20 \cdot \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right) = 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE)$$

Metrics for Image Quality

- Structural Similarity Index (SSIM)

$$l(x, y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \quad c(x, y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \quad s(x, y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

$$SSIM(x, y) = [l(x, y)^\alpha c(x, y)^\beta s(x, y)^\gamma] \quad c_3 = c_2/2$$

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Metrics for Image Quality

- Mean Opinion Score (MOS)