# Deep Learning and Practice - Lab2 report

## Introduction

### Deep image prior

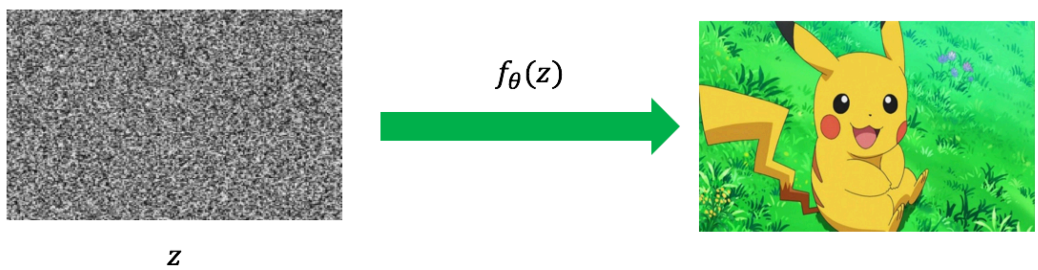
透過 CNN 去學習圖像中的特徵 (e.g. 紋路) 來進行圖片的還原，像是去除雜訊、圖片修復 … 等。

相較於一般的 Learning，此方法事前不需要準備大量的 training data，每一次以 Random vector 作為 Model input，待修復的圖像作為 Loss function (MSE) 中要去 fit 的對象，透過 Gradient descent 去不斷 update 參數後，即可漸漸學習到該圖像特徵，在**特定的迭代次數**下終止訓練，再輸入 Random vector 後即可得到修復後的圖像。

在特定的迭代次數下，CNN 學習到了圖像中較自然、明顯的特徵，進而可輸出不含雜訊、缺陷的圖像。

$$x = f_{\theta}(\mathrm{z})$$

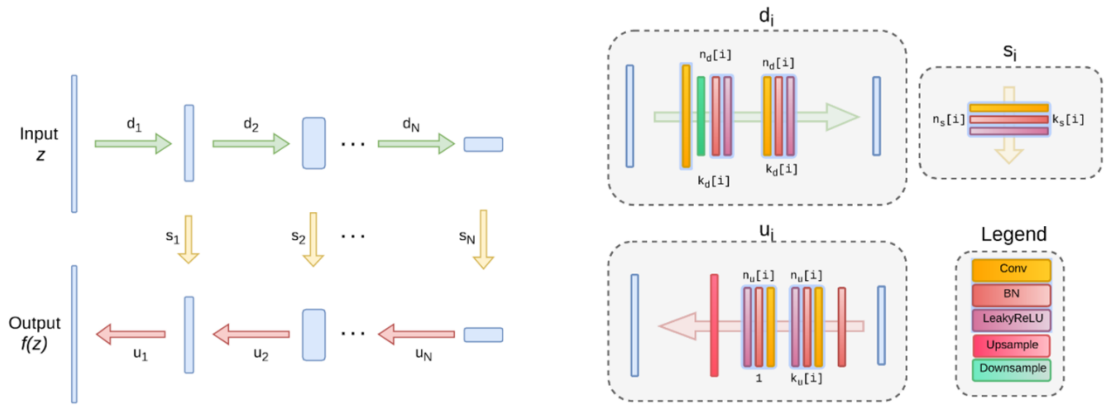
z = random vector ; x = image ; $\theta = parameters\ to\ learn$




## Experiment setup

### 1. Model detail

使用 decoder-encoder 結構，中間穿插一些 skip connection，對輸入圖像先進行 down sampling 後再 up sampling 回來。




# 2. Parameters

## ■ Requirement 1 - **A parametrization with high noise impedance**

- Input channels : 3 ; Size : Image width * Image height
- Down sampling units output channels = [8 , 16, 32, 64, 128]
- Up sampling units output channels = [8, 16, 32, 64, 128]
- Skip units output channels = [0, 0, 0, 4, 4]
- Down sampling units kernel size = [3, 3, 3, 3, 3]
- Up sampling kernel units size = [3, 3, 3, ,3, 3]
- Skip units kernel size = [NA, NA, NA, 1, 1]
- Iteration times : 2400
- Learning rate : 0.01
- Optimizer : Adam
- Up sampling method : bilinear
- Activation function : LeakyReLU
- Loss function :

$$\|f_\theta(z) - x_0\|^2$$

## ■ Requirement 2 - **Blind image denoising**

- Input channels : 32 ; Size : Image width * Image height
- Down sampling units output channels = [128 , 128, 128, 128, 128]
- Up sampling units output channels = [128, 128, 128, 128, 128]
- Skip units output channels = [4, 4, 4, 4, 4]
- Down sampling units kernel size = [3, 3, 3, 3, 3]
- Up sampling kernel units size = [3, 3, 3, ,3, 3]

- Skip units kernel size = [1, 1, 1, 1, 1]
- Iteration times : 1800
- Learning rate : 0.01
- Optimizer : Adam
- Up sampling method : bilinear
- Activation function : LeakyReLU
- Loss function :

$$\|f_\theta(z) - x_0\|^2$$

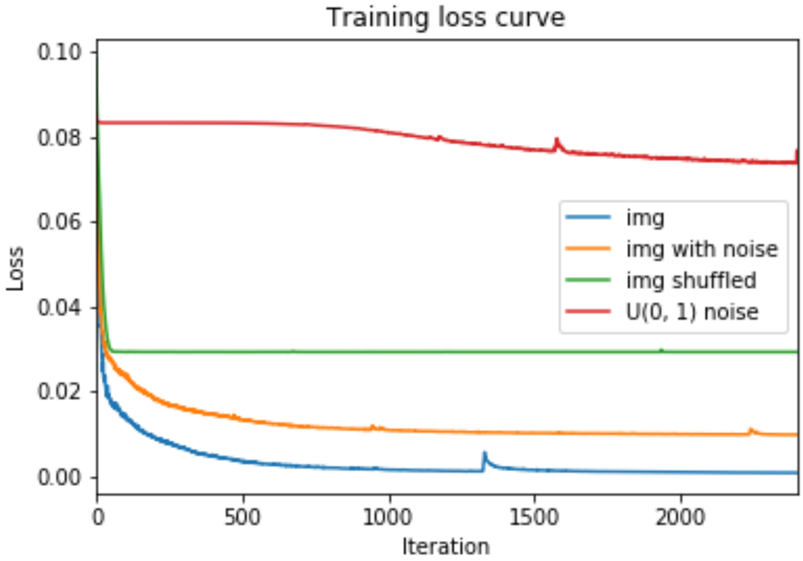
## ■ Requirement 3 - **Blind super-resolution**

- Input channels : 32 ; Size : Image width * Image height
- Down sampling units output channels = [128 , 128, 128, 128, 128]
- Up sampling units output channels = [128, 128, 128, 128, 128]
- Skip units output channels = [4, 4, 4, 4, 4]
- Down sampling units kernel size = [3, 3, 3, 3, 3]
- Up sampling kernel units size = [3, 3, 3, ,3, 3]
- Skip units kernel size = [1, 1, 1, 1, 1]
- Iteration times : 2000
- Learning rate : 0.01
- Optimizer : Adam
- Up sampling method : bilinear
- Activation function : LeakyReLU
- Loss function :

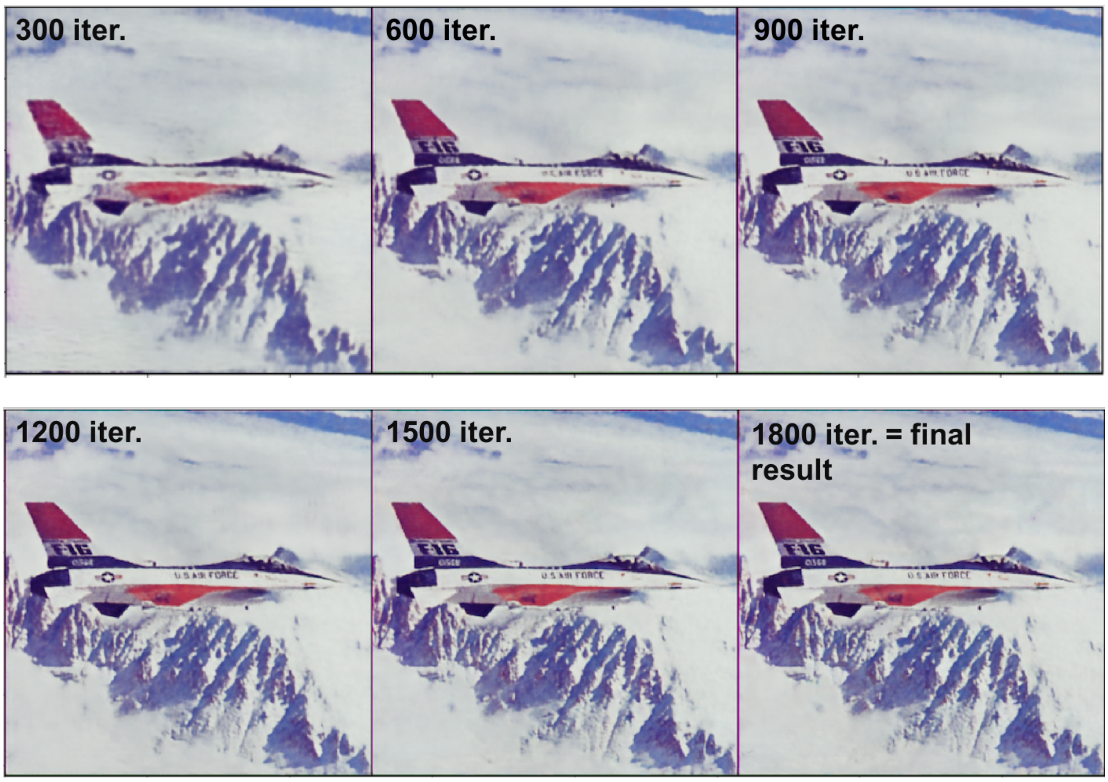
$$\|ds(f_\theta(z)) - x_0)\|^2$$

# Result

## ■ Requirement 1




## ■ Requirement 2

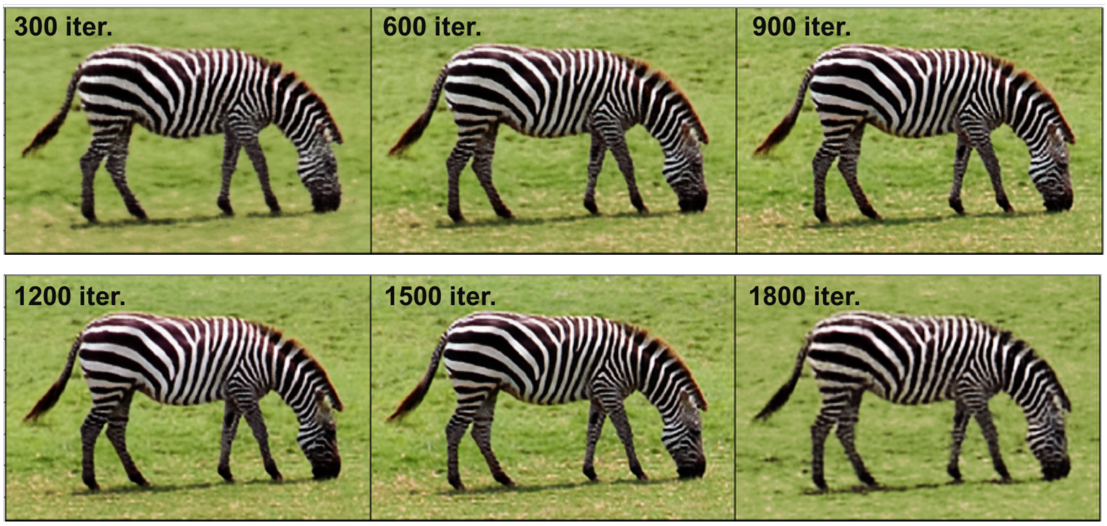


PSNR = 30.499

```
dl2018@dl2018-BM5275-BM5375-BM5675:~/Lab2$ python3 denoising.py
Before PSNR:20.364061838193976

Number of params: 2217831
Starting optimization with ADAM
Iteration 01799    Loss 0.009642
After PSNR :30.49940599123646
```

## Requirement 3





PSNR = 23.13

```
dl2018@dl2018-BM5275-BM5375-BM5675:~/Lab2$ python3 super-resolution.py
HR and LR resolutions: (576, 384), (144, 96)
PSNR bicubic: 23.1048   PSNR nearest: 20.8212
Starting optimization with ADAM
Result PSNR:23.13093518764635.253   PSNR_HR 23.056
```

# Discussion

## 對 Noise 有著 High-impedance

由 Requirement 1 的實驗可知，目標圖像為較接近自然圖像的情況下(圖像有一定的規律, e.g. Pure image or image with some noise)，model 學習的速度較快，當圖像沒有一定規律(e.g. 經過 shuffle 的自然圖像 or 全雜訊的圖像)，model 學習的速度較慢，這也再次說明了 CNN 圖像修復的能力，CNN 會先學習到圖像中一些較「規律」的部分，之後才會進而去學到較細節、不規律的部分，也就是對雜訊有著較高的阻抗能力。因此在特定的迭代次數下終止訓練，即可得到修復後的圖片。

# Reference


[1] https://github.com/DmitryUlyanov/deep-image-prior

[2] https://blog.csdn.net/edogawachia/article/details/78745067

[3] https://blog.csdn.net/muyiyushan/article/details/79093806

[4] http://www.cnblogs.com/shouhuxianjian/p/8006847.html