

Using the method of Assignment 2 to approximate  $f'(x)$ .

First, by the method of calculus,  $f'(x) = \frac{-50x}{(1+25x^2)^2}$ , for all  $x \in [-1, 1]$ .

Point pick (uniformly), let  $y_n = f'(-1 + \frac{50}{n}) = \frac{-50(-1 + \frac{50}{n})}{[1 + 25(-1 + \frac{50}{n})^2]^2}$  for all  $n = 0, 1, 2, \dots, 100$ .

Construct tanh neural network with 3 layers. (一個隱藏層 with 20 個神經元)

$$\text{Loss: } L = \frac{1}{101} \sum_{n=0}^{100} (\hat{y}_n - y_n)^2.$$

Optimizer: SGD. (let  $r = \text{learning rate}$ )

★ Training process.

根據上面的 setting, 最初先使用  $r=0.1$  or  $r=0.3$  做嘗試, 發現  $r=0.1$  時, 速度過慢,

執行百次皆沒有太大的進展, 而  $r=0.3$  則是過大, 無法逼近。

最後, 選定  $r=0.22$  執行 500 次,  $r=0.1$  執行 500 次,  $r=0.05$  執行 500 次,  $r=0.01$  執行 500 次。

以下為 code (provide by discussing with ChatGPT), 和圖 (getting by google colab).

```
python
import torch
import torch.nn as nn
import torch.optim as optim
import matplotlib.pyplot as plt
import numpy as np

# 目標函數的一階導數
def runge_derivative(x):
    return -50 * x / (1 + 25 * x**2) ** 2

# 生成訓練資料
x_train = torch.linspace(-1, 1, 101).unsqueeze(1)
y_train = runge_derivative(x_train)

# 定義神經網路
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.hidden = nn.Linear(1, 20)
        self.output = nn.Linear(20, 1)
        self.act = torch.tanh

    def forward(self, x):
        return self.output(self.act(self.hidden(x)))

net = Net()
criterion = nn.MSELoss()
optimizer = optim.SGD(net.parameters(), lr=0.22) # 初始 lr

# 訓練參數
epochs = 2000
lr_schedule = [
    (0, 500, 0.22),
    (500, 1000, 0.10),
    (1000, 1500, 0.05),
    (1500, 2000, 0.01)
]

loss_history = []

for epoch in range(epochs):
    # 根據當前 epoch 調整學習率
    for start, end, lr in lr_schedule:
        if start <= epoch < end:
            for g in optimizer.param_groups:
                g['lr'] = lr

    # 前向傳播
    outputs = net(x_train)
    loss = criterion(outputs, y_train)

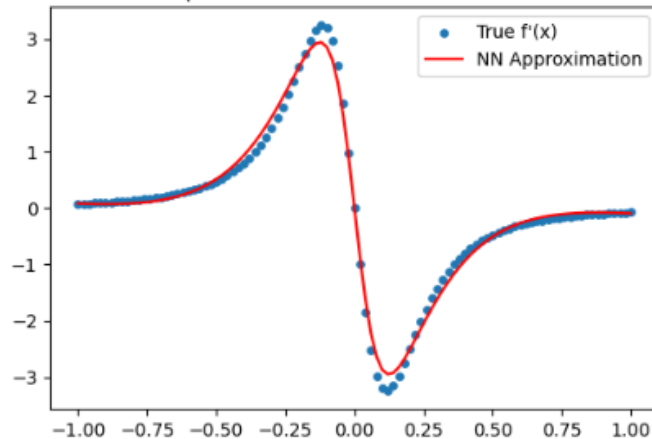
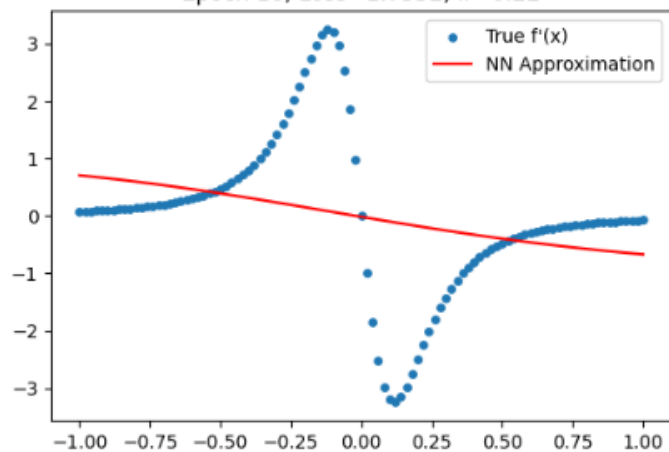
    # 反向傳播
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    loss_history.append(loss.item())

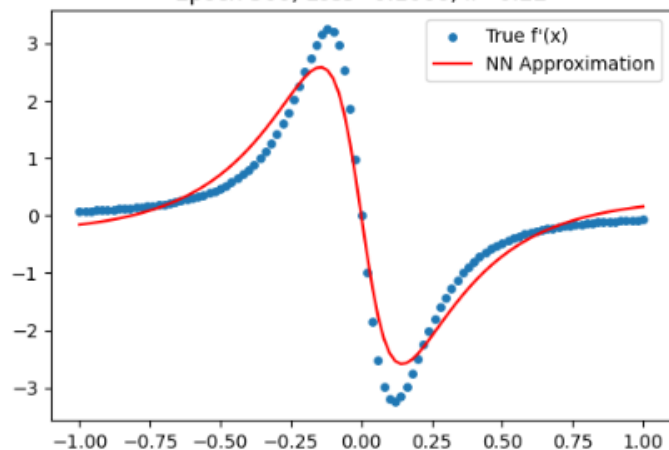
# 繪圖條件: 第 10 次 or 每 500 次
if (epoch+1) == 10 or (epoch+1) % 500 == 0:
    plt.figure(figsize=(6,4))
    plt.scatter(x_train.detach().numpy(), y_train.detach().numpy(), label="True f'(x)", s=15)
    plt.plot(x_train.detach().numpy(), outputs.detach().numpy(), 'r-', label="NN Approximation")
    # 找出當前 lr
    current_lr = optimizer.param_groups[0]['lr']
    plt.title(f"Epoch {epoch+1}, Loss={loss.item():.4f}, lr={current_lr}")
    plt.legend()
    plt.show()

# 最後輸出 Loss 曲線
plt.figure(figsize=(6,4))
plt.plot(loss_history)
plt.title("Loss Curve")
plt.xlabel("Epoch")
plt.ylabel("MSE Loss")
plt.show()
```

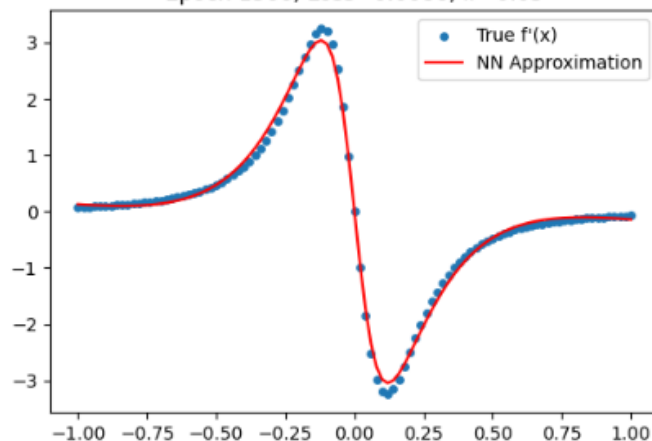
Epoch 10, Loss=1.7552, lr=0.22



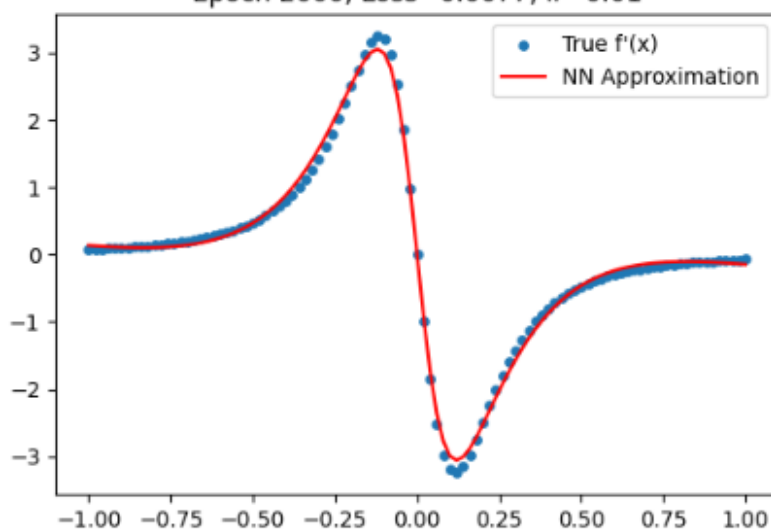
Epoch 500, Loss=0.1066, lr=0.22



Epoch 1500, Loss=0.0086, lr=0.05



Epoch 2000, Loss=0.0077, lr=0.01



## 第二题

要求同时逼近  $f(x)$ ,  $f'(x)$ .

我选择延用了大部分原本的设定. (tanh neural network)

单隐藏层 with 20 神经元.

$$L_f = \frac{1}{101} \sum_{h=0}^{100} (y_f - \hat{y}_f)^2 \quad L_{f'} = \frac{1}{101} \sum_{h=0}^{100} (y_{f'} - \hat{y}_{f'})^2$$

唯一較不同的是, I set a loss function with two component  $f(x), f'(x)$

$$\text{be defined as } L_{f,f'} = 0.5 L_f + 0.5 L_{f'}$$

是  $L_f, L_{f'}$  的加權平均。

Optimizer : SGD (  $r = \text{learning rate}$  ).

Training process.

有了前面兩次用經驗, 我初始便將  $r$  設定在 0.2 執行 100 ~ 300 次。

最後發現在 120 次的時候有最好的有效進展。

並且後面慢慢則嘗試, the final setting :  $r = 0.2$  , 120 times.

$r = 0.02$  , 120 times.

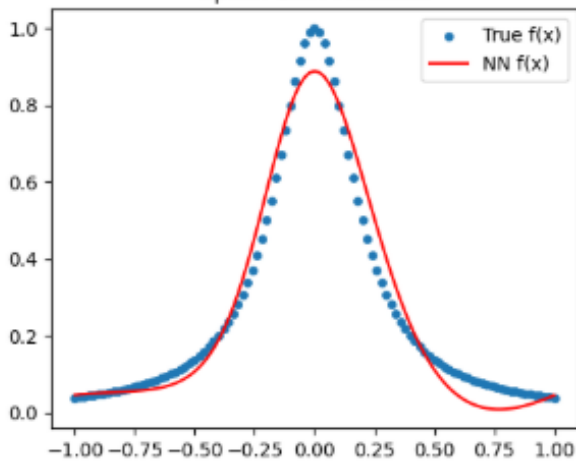
$r = 0.005$  , 240 times.

Processing picture | (因為設定相同, 使用的是幾乎一樣的 code, 就不再貼一次了)

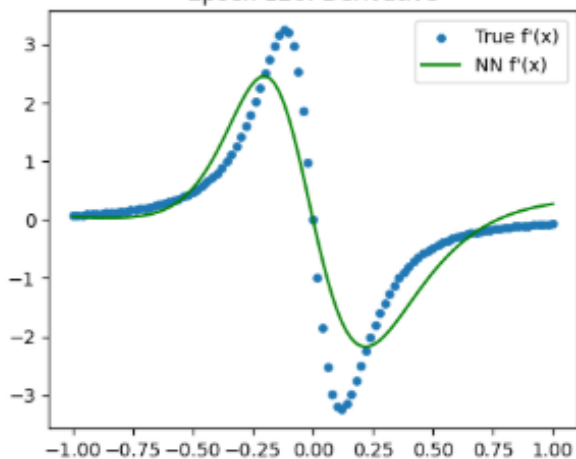
$r = 0.2 \downarrow$

Epoch 120: Loss\_f=0.0027, Loss\_df=0.3382, Loss\_total=0.1705

Epoch 120: Function



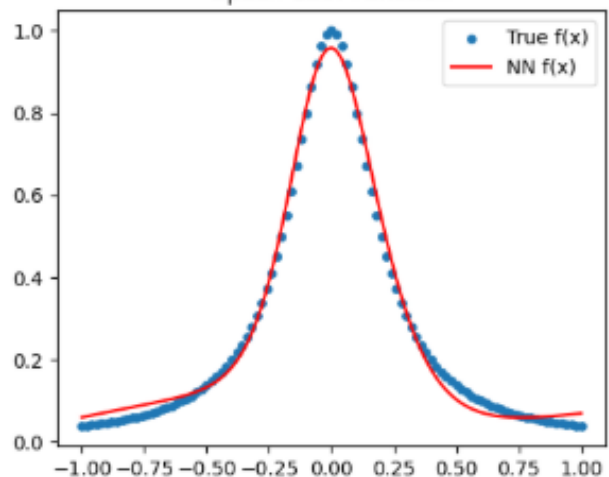
Epoch 120: Derivative



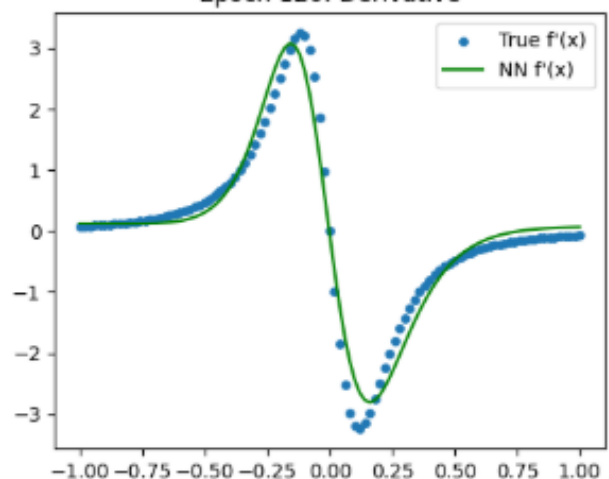
$r = 0.02 \downarrow$

Epoch 120: Loss\_f=0.0006, Loss\_df=0.0799, Loss\_total=0.0402

Epoch 120: Function



Epoch 120: Derivative



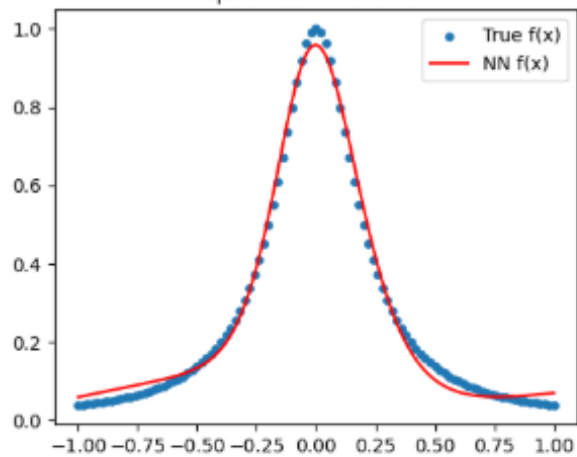
$$r = 0.005$$



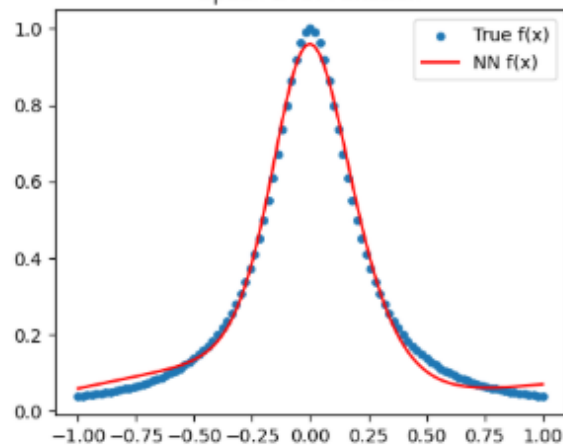
Epoch 120: Loss\_f=0.0005, Loss\_df=0.0772, Loss\_total=0.0389

Epoch 240: Loss\_f=0.0005, Loss\_df=0.0747, Loss\_total=0.0376

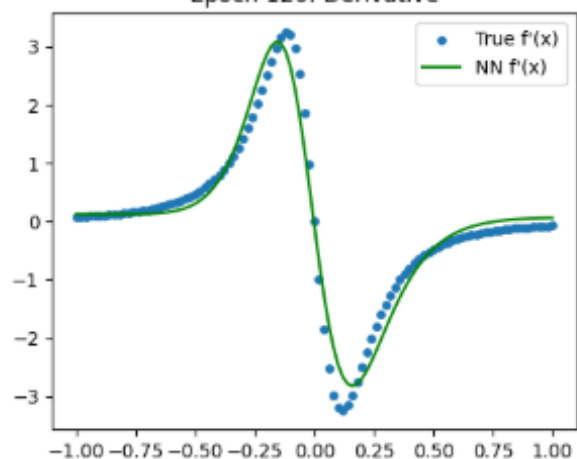
Epoch 120: Function



Epoch 240: Function



Epoch 120: Derivative



Epoch 240: Derivative

