

HW1 講解

Couette flow(流體力學) and regression(回歸)

The most reliable way to
anticipate the future is to
understand the present.

John Naisbitt-1989

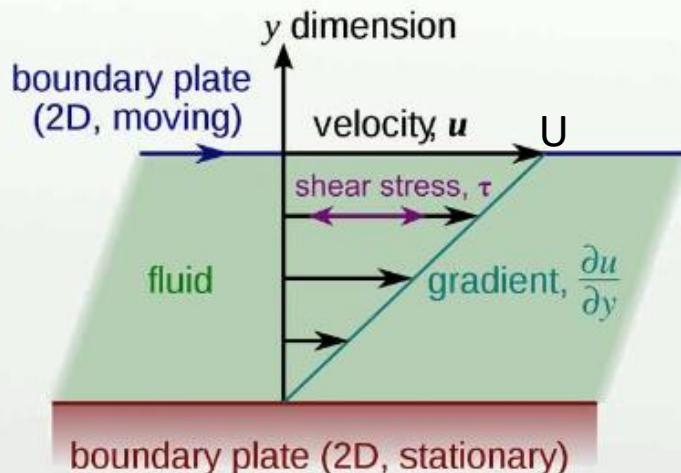
Couette flow

Derive from fluid mechanics

Couette flow

Navier-Stokes equation: $\rho(\mathbf{r}, t) \left[\frac{\partial \mathbf{u}(\mathbf{r}, t)}{\partial t} + \mathbf{u} \cdot \nabla \mathbf{u}(\mathbf{r}, t) \right] = \rho(\mathbf{r}, t) \mathbf{f}(\mathbf{r}, t) + \nabla \cdot \mathbf{T}$

Couette flow



https://en.wikipedia.org/wiki/File:Laminar_shear.svg

$$u = \frac{z}{H} U$$

Regression

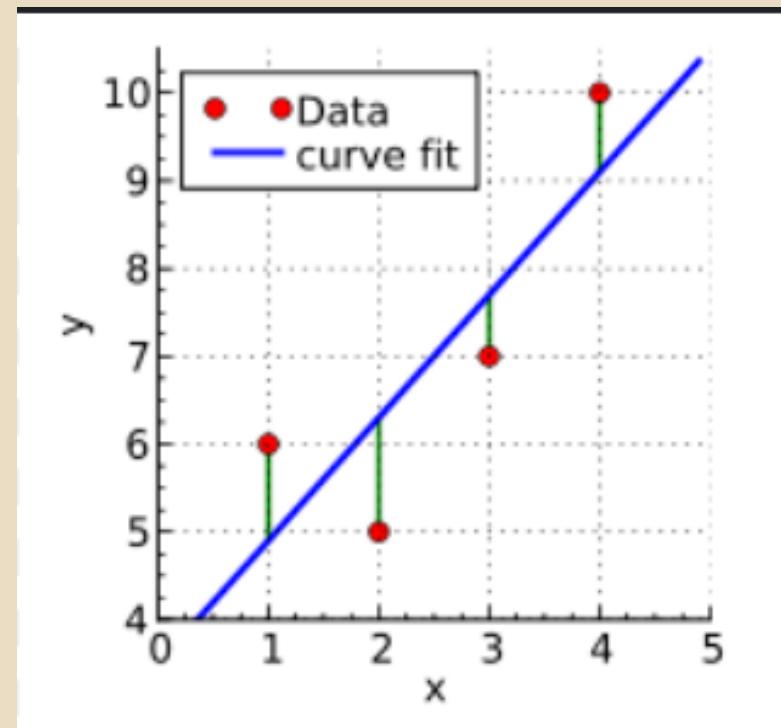
Curve fitting

最小平方法(線性)

$$y = wx + b$$

$$\min_{w,b} \sum_i (y - y_i)^2$$

Loss function



牛頓法→梯度下降法

$$x_{k+1} = x_k - lr \times f'(x_k)$$

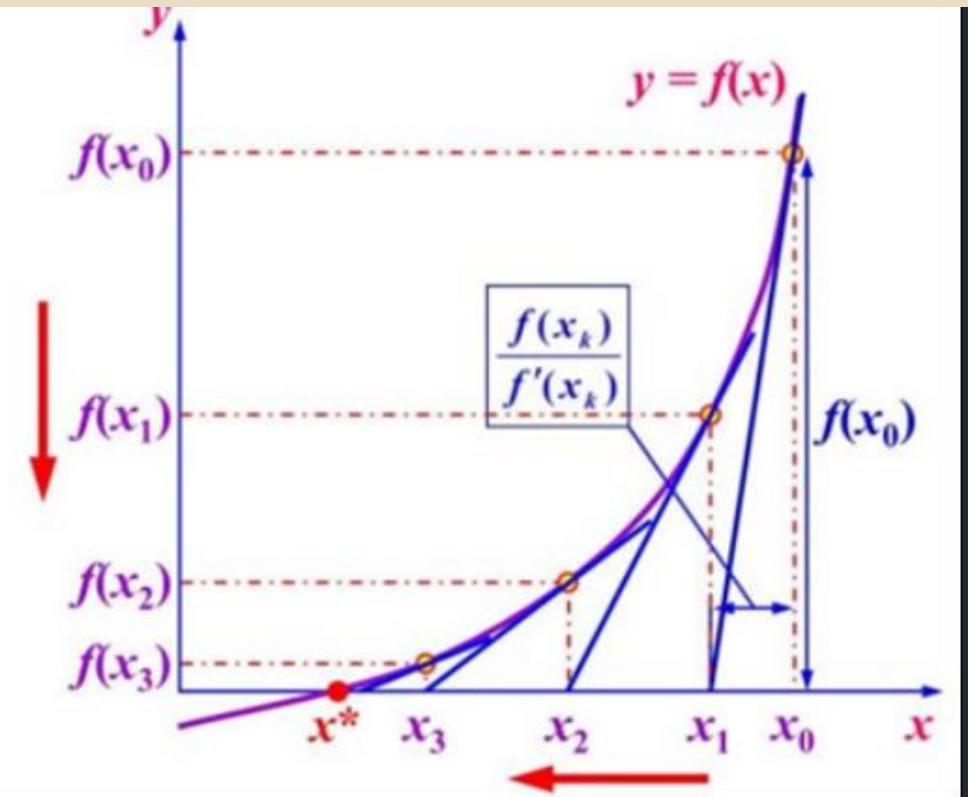
梯度下降法

$$f(x) = 0$$
$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

牛頓法

$$x_k \rightarrow x^*$$

$$f(x_k) \rightarrow 0$$



機器學習架構

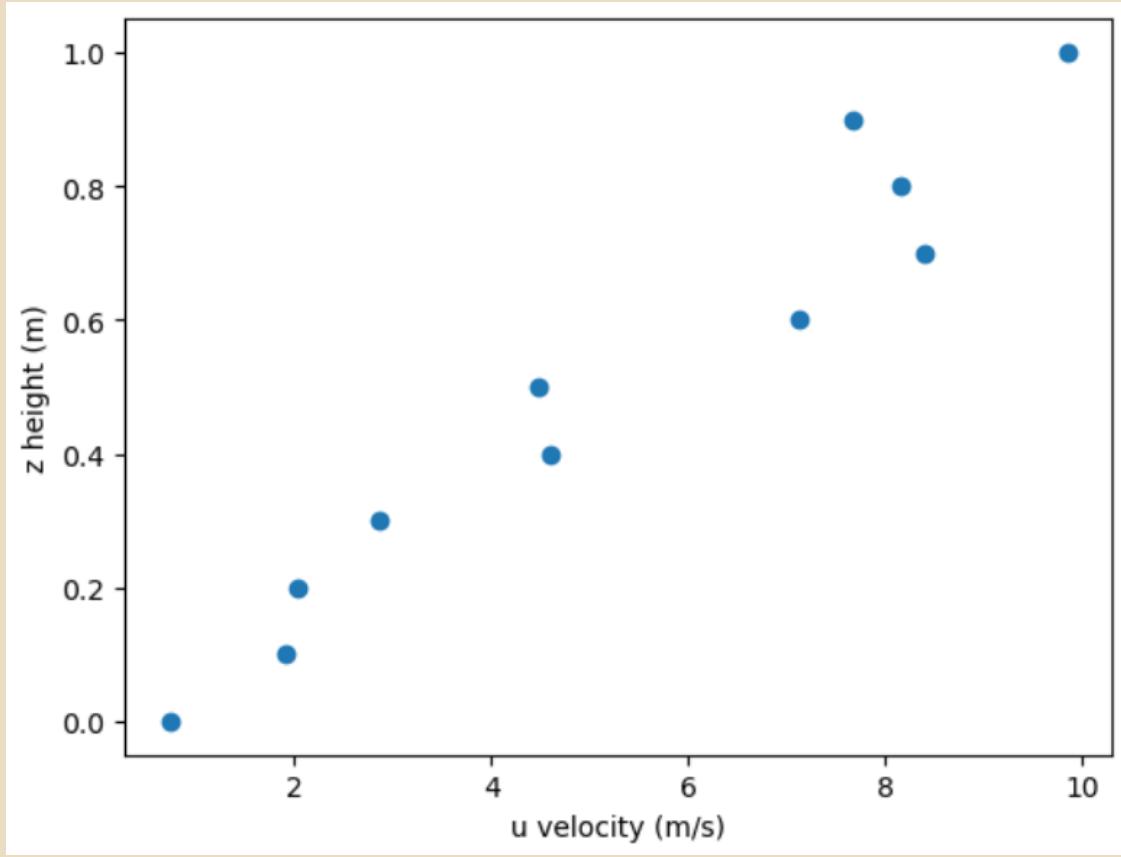
1. 使用線性模型: $u_p = z \times w + b$, 其中 u_p 為預測速度、 w 為權重 (weight)、 b 為偏位 (bias)。
2. 使用最小平方法做為損失函數 (loss function): $\text{loss_fn} = (u_p - u)^2$ (最小平方法)
3. 透過微分方式求得損失函數對 w 與 b 之梯度並結合學習率 (learning rate) 對 w 與 b 重複疊代進行最佳化 (optimization) (梯度下降法)

HW1

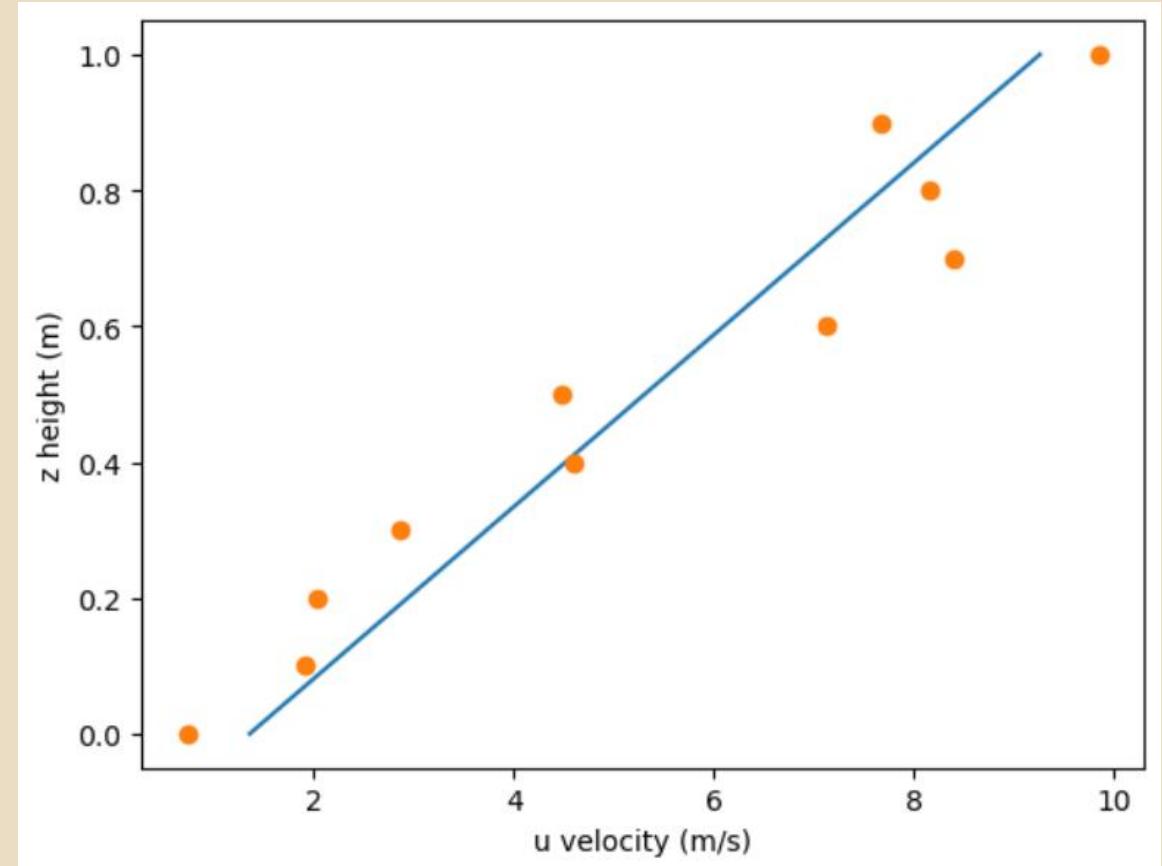
Curve fitting

Couette flow regression

Data



result



Basic level

Weight, bias, epoch, learning rate

```
''' Homework!!! You have to fill the number in this block to achieve basic grade '''
params=torch.tensor([xx, xx]) # weight and bias, arbitrary number
config={
    "number epoch": xxxx, # number of epoch, suggest from 100 to 50000
    "learning rate": xxxx, # learning rate, suggest from 1e-2 to 1e-5
}
```

Intermediate level

(1) 使用torch 背向傳播自動計算梯度(backward)與SGD優化器進行更新參數。

(2) 課堂上有提到使用L2 regularization可使weight之值降低，先將上述第一項任務完成，加入在其中加入L2 regularization。

```
'''Homework!!! Changing optimizer to this code,  
Additionally, implement L2 regularization code to achieve intermediate level'''  
#optimizer=optim.SGD([xxxx], xxxx, xxxx)
```

Training loop

```
#Parameters update  
def training(x,y,params,n_epoch,lr):  
    for epoch in range(1, n_epoch+1):  
        w, b=params  
        x_p=model(x,w,b)  
        loss=loss_fn(x_p,y)  
        grad=grad_fn(x_p,x,y)  
        params=optim(params,lr,grad)  
        '''Homework!!! Changing optimize step to this code to achieve intermediate level'''  
        #optimizer.zero_grad()  
        #train_loss.backward()  
        #optimizer.step()  
        print('Epoch: %d, Loss: %f' %(epoch, loss))  
    return params
```

Advanced level

- (1)為了解模型是否有(overfitting)之情形出現，可將訓練資料分成training set與validation set以檢查損失函數之下降情況判斷訓練是否過擬合。將資料透過任何方法分割成training set與validation set，並印出validation loss。
- (2)起透過增加一個變數early stop，讓validate loss若沒持續下降一定次數則提早停止訓練。

Hints:需使用函數或方法

shuffle_ind=**torch.randperm(num)** 回傳0至num-1之隨機排列

validate_ratio=**0.2** 為validation set佔所有dataset之比例

作業繳交

1. 將作業之code列印出紙本訂起來
2. 如果有做intermediate level/advanced level請特別標示出來
3. 請附上結果圖
4. 下周上課繳交

The most reliable way to
anticipate the future is to
create the future.

Lin-2024