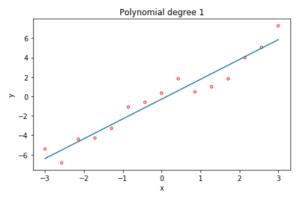
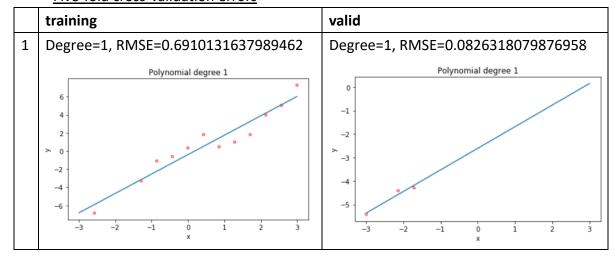
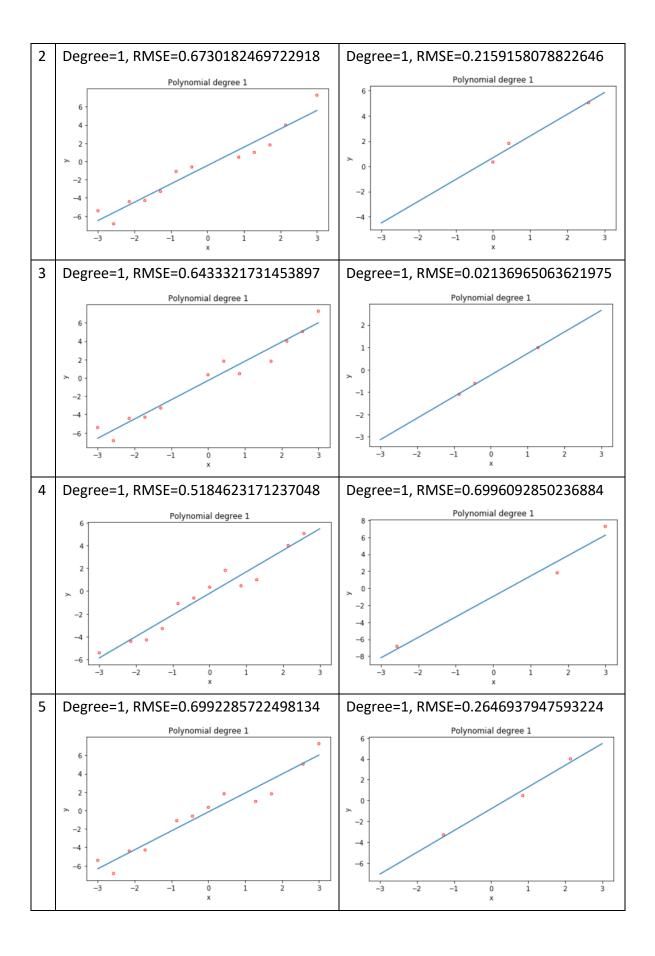
- Execution description: steps how to execute your codes.
- ➤ 使用 Colab, ctrl+F9 執行。
- ▶ 將參數存放於 Parameter 可以修改 num points, num points=15。
- 多數調整好後,Generate Samples 利用 linspace 函數調整 sample 產生的區間(np.linespace(0, 1)在 0 到 1 間均勻產生 num\_points 個 sample, np.linespace(-3, 3)在-3 到 3 間均勻產生 num points 個 sample)。
- ▶ 產生 sample 後,plot.scatter 將生成的 sample 繪製成二維散布圖。
- > 調整 regression 中的 degree 顯示 linear regression(degree=1)和 polynomial regression(degree=5, degree=10, degree=14)的 fitting plot。
- ▶ 調整 Imda 來做正則化(Imda=0, Imda=0.001/m, Imda=1/m, Imda=1000/m)。
- Experimental results: As specified in the assignment
- Perform Linear Regression. Show the fitting plot, the training error, and the five-fold cross-validation errors.

Degree=1, RMSE=0.6608466592234012



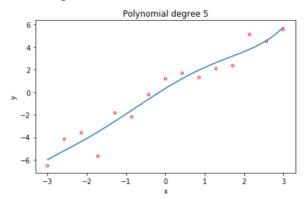
Five-fold cross-validation errors



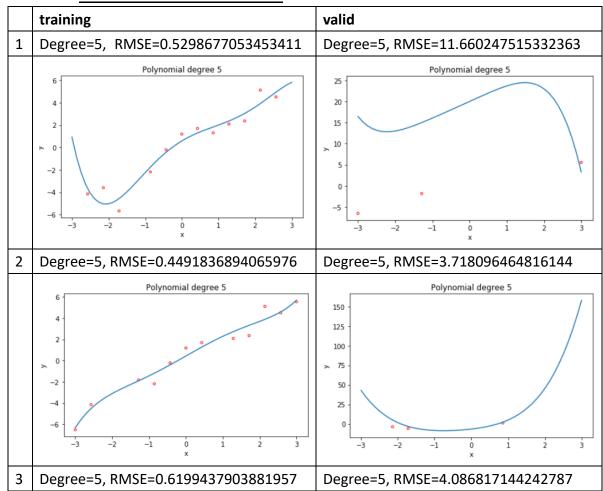


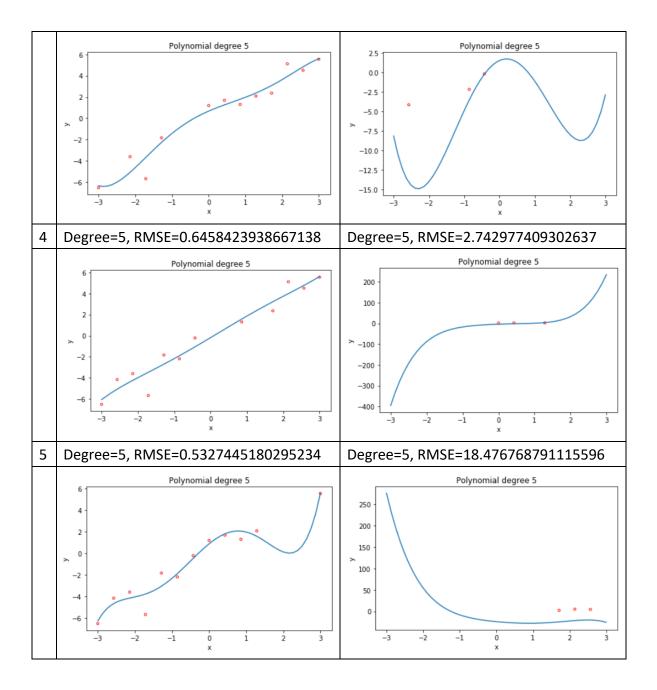
- Perform Polynomial Regression with degree 5, 10 and 14, respectively. For each case, show the fitting plot, the training error, and the five-fold cross-validation errors. (Hint: Arrange the polynomial regression equation as follows and solve the model parameter vector w.)
  - Degree=5

Degree=5, RMSE=0.6283404445398233



Five-fold cross-validation errors

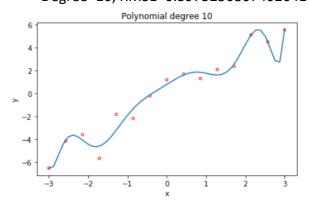


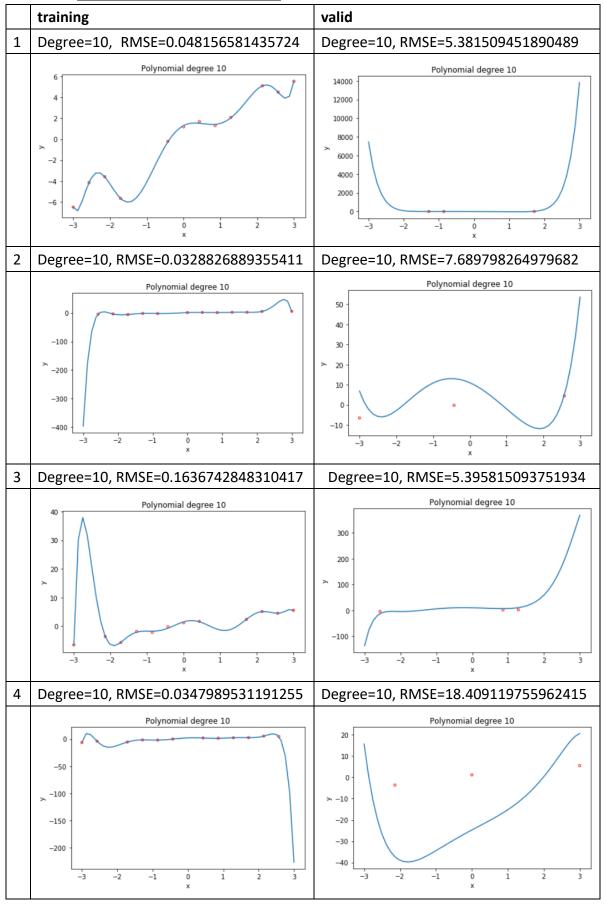


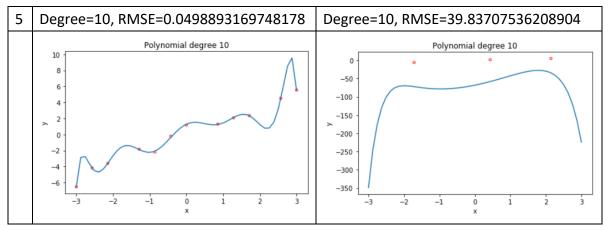
■ Degree=10

<u>Training error</u>

#### Degree=10, RMSE=0.3975256867402641

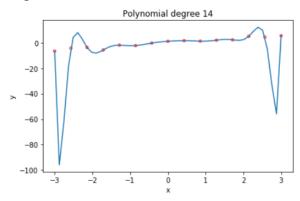




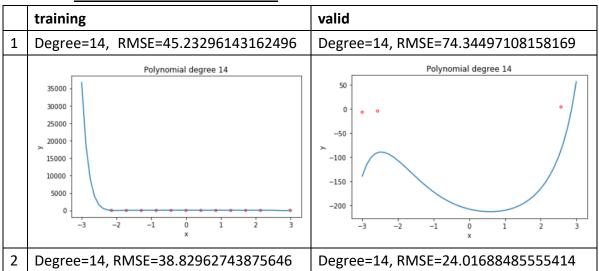


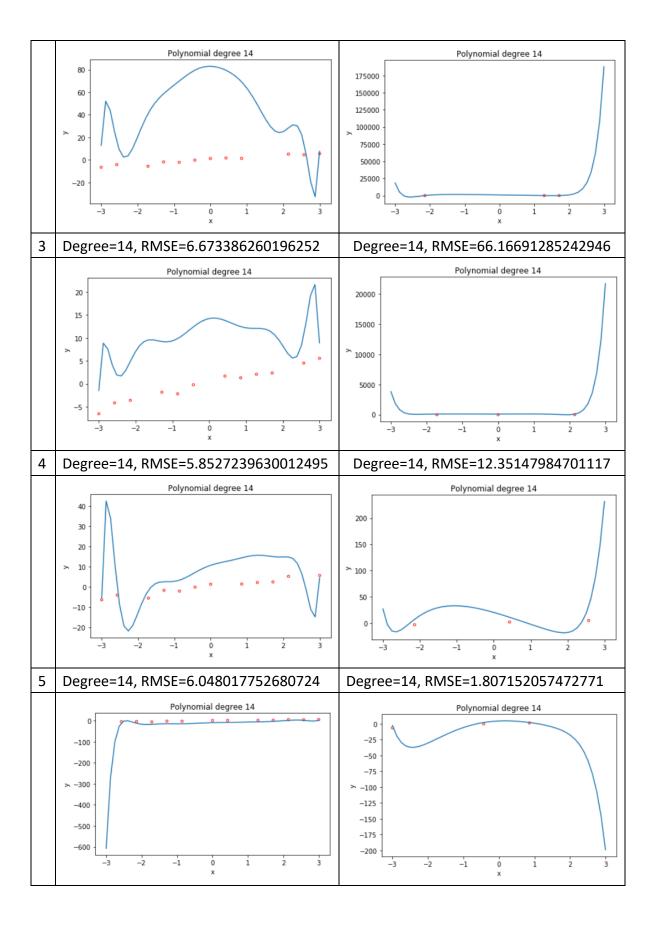
■ Degree=14

Degree=14, RMSE=7.136053752255e-06



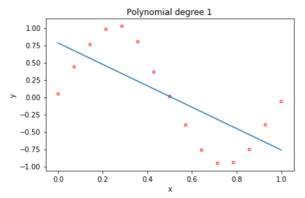
Five-fold cross-validation errors



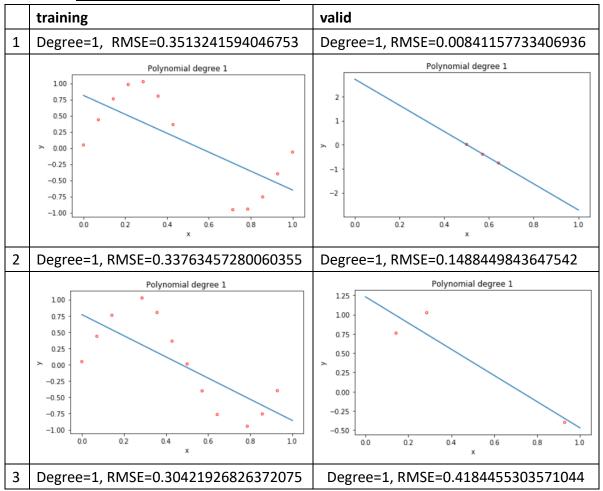


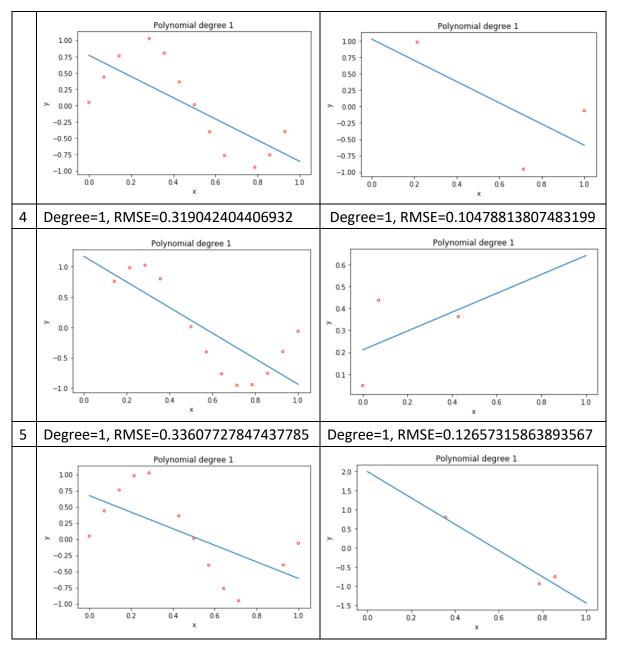
- Change the model to  $y = \sin(2\pi x) + \epsilon$  with the noise  $\epsilon \sim N(0, 0.04)$  and (equal spacing)  $x \in [0, 1]$ . Then repeat those stated in 2) and 3). Compare the results with linear/polynomial regression on different datasets.
  - Degree=1

Degree=1, RMSE=0.3381117366078396



Five-fold cross-validation errors

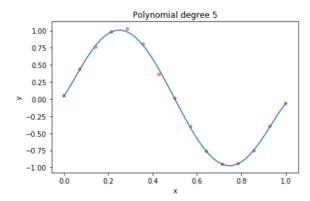


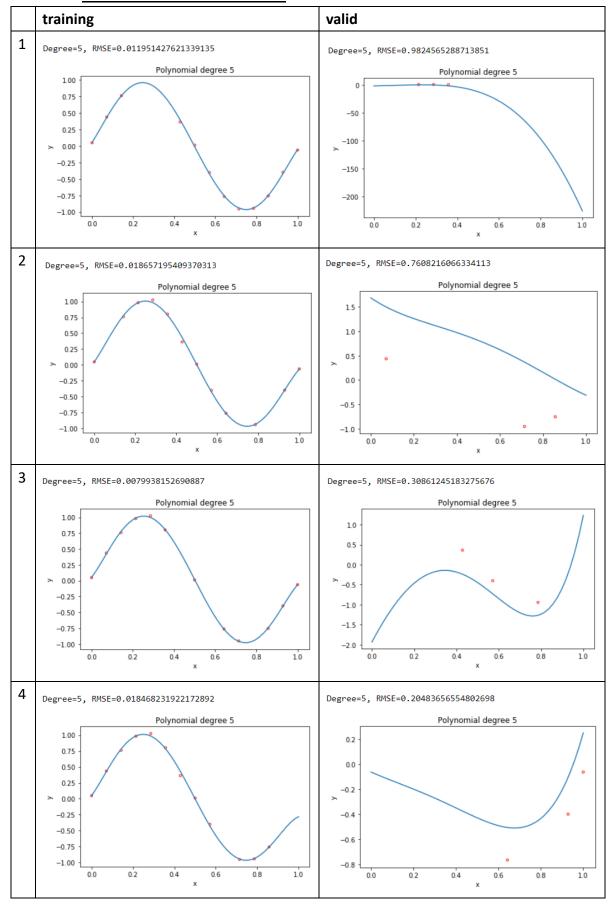


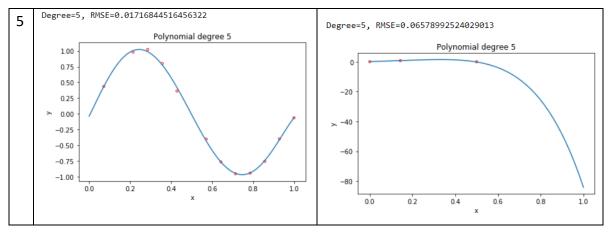
# ■ Degree=5

### **Training error**

Degree=5, RMSE=0.017025404734936914



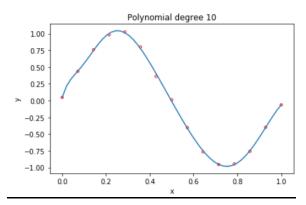


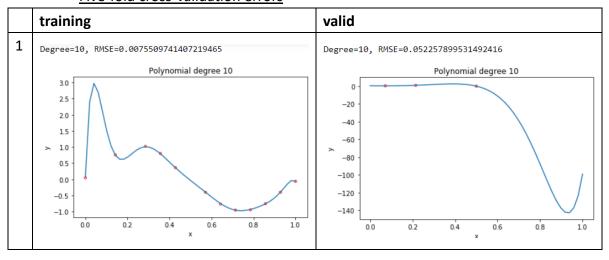


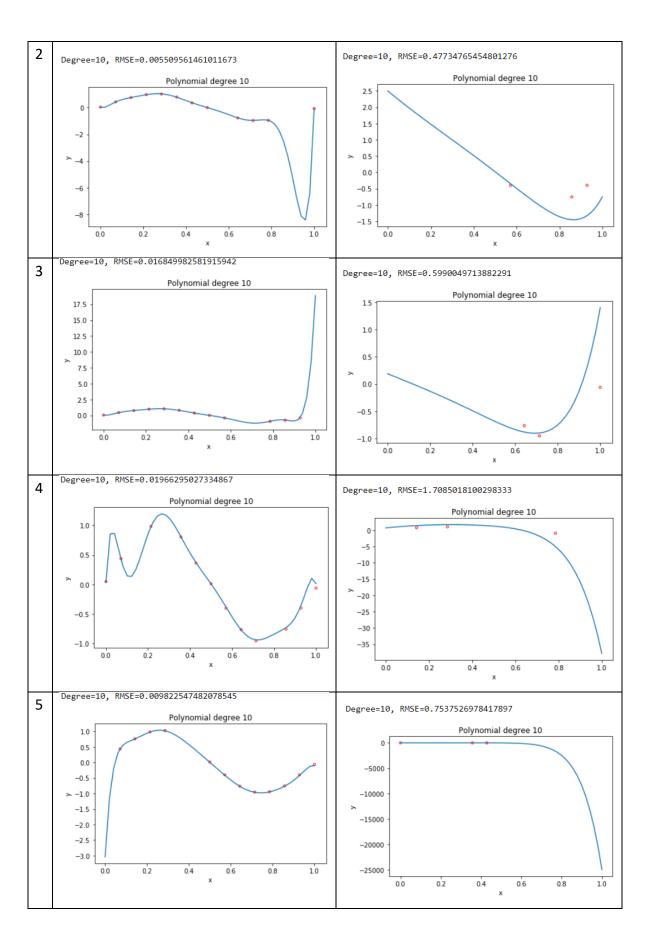
## ■ Degree=10

#### **Training error**

Degree=10, RMSE=0.011747387744402643



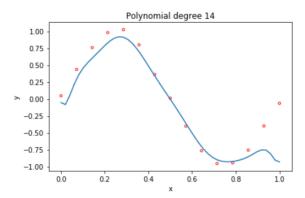


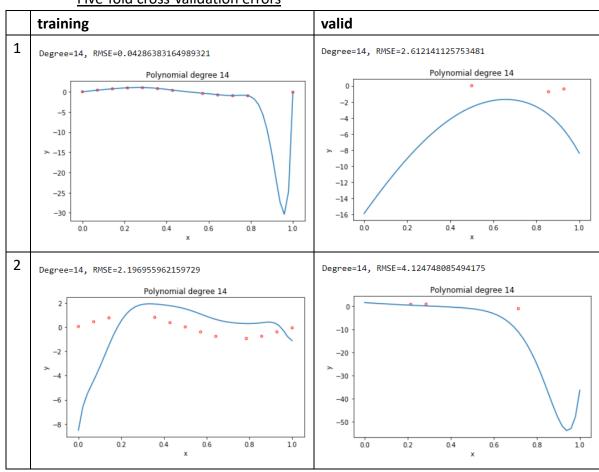


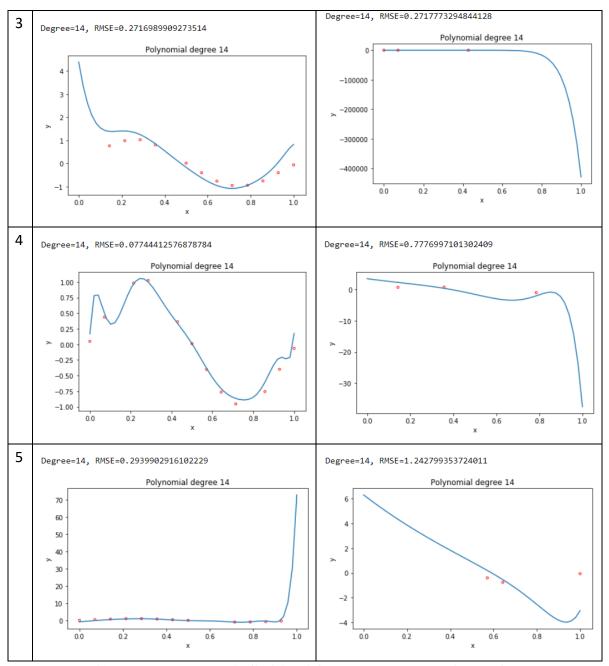
## ■ Degree=14

### **Training error**

Degree=14, RMSE=0.18215695742583007

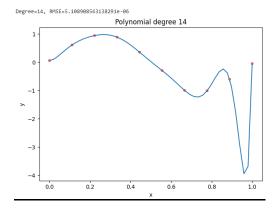


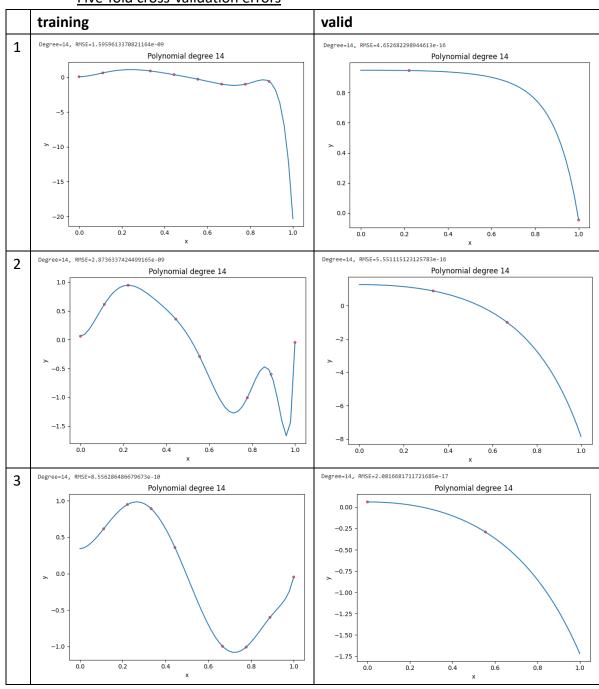


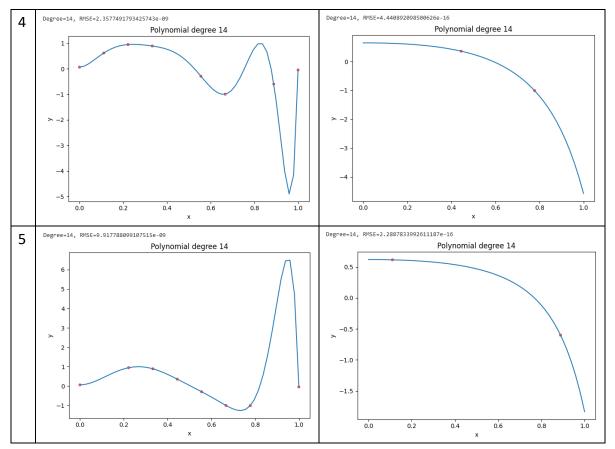


■ 比較: linear regression 對曲線類型的 dataset(Ex: sin)不適用,應用 polynomial regression 解決曲線類型的 dataset。

- Following 4), perform polynomial regression with degree 14 by varying the number of training data points m = 10, 80, 320. Show the five-fold cross-validation errors and the fitting plots. Compare the results to those in 4).
  - m=10
    Training error



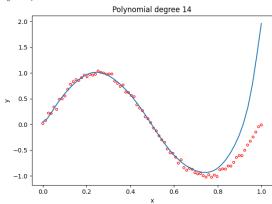




### ■ m=80

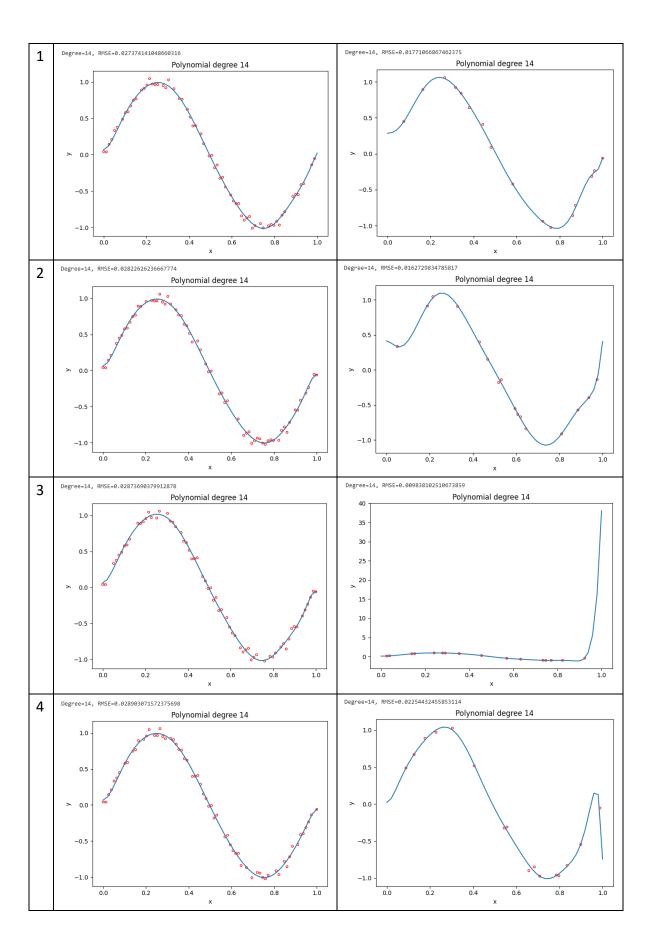
### Training error

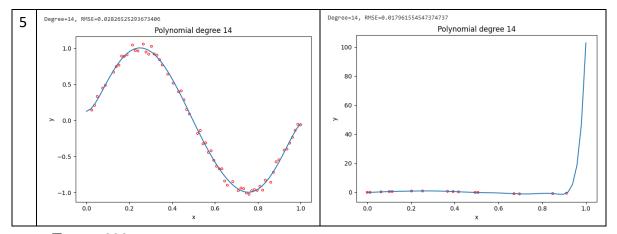
Degree=14, RMSE=0.2750086613851848



Five-fold cross-validation errors

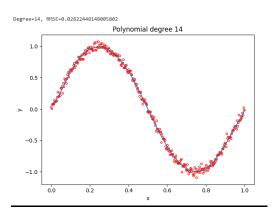
training	valid
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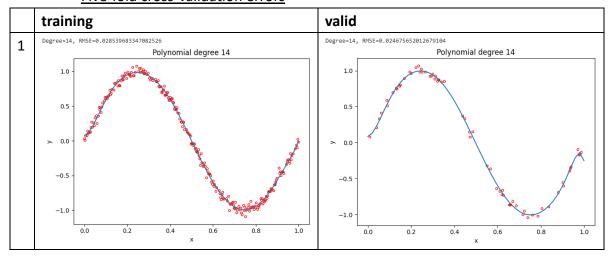


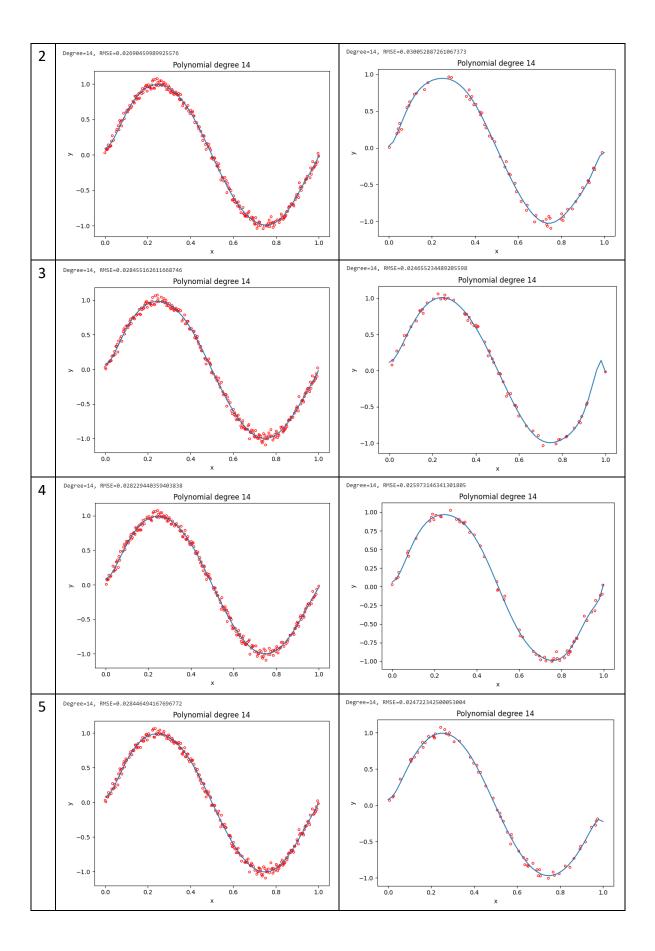


### ■ m=320

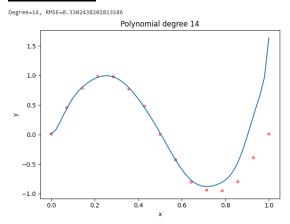
### **Training error**



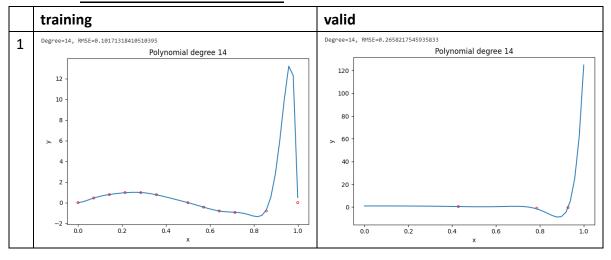


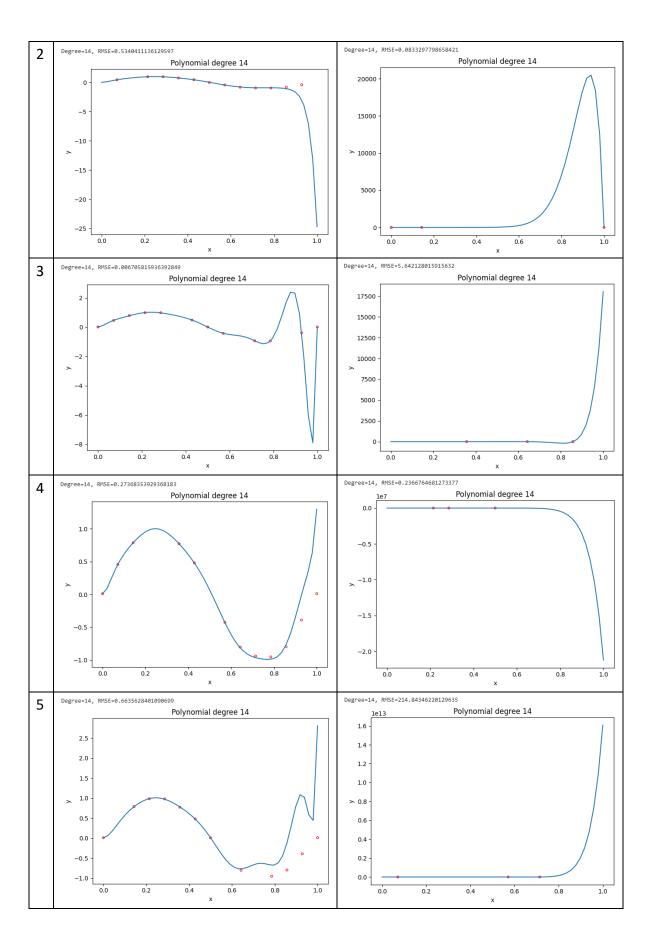


- 比較: m=10 時,因為 data 很少,所以模型遇到沒看過的資料時會隨機 猜測,導致預測結果不如預期。對比 m=320 的波形明顯可看出在 num\_point 數量多的情況下模型預測準確率較 num\_point 少的高很 多。
- Following 4), perform polynomial regression of degree 14 via regularization. Compare the results by setting  $\lambda = 0$ , 0.001/m, 1/m, 1000/m, where m = 15 is the number of data points (with x = 0, 1/(m-1), 2/(m-1), . . . , 1). Show the five-fold cross-validation errors and the fitting plots.
  - λ= 0



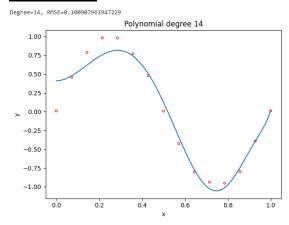
Five-fold cross-validation errors

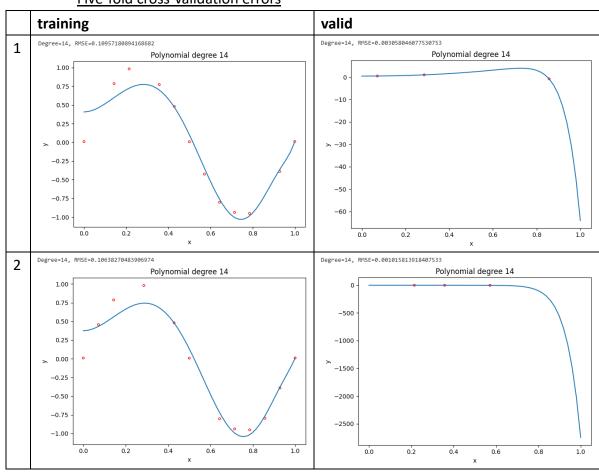


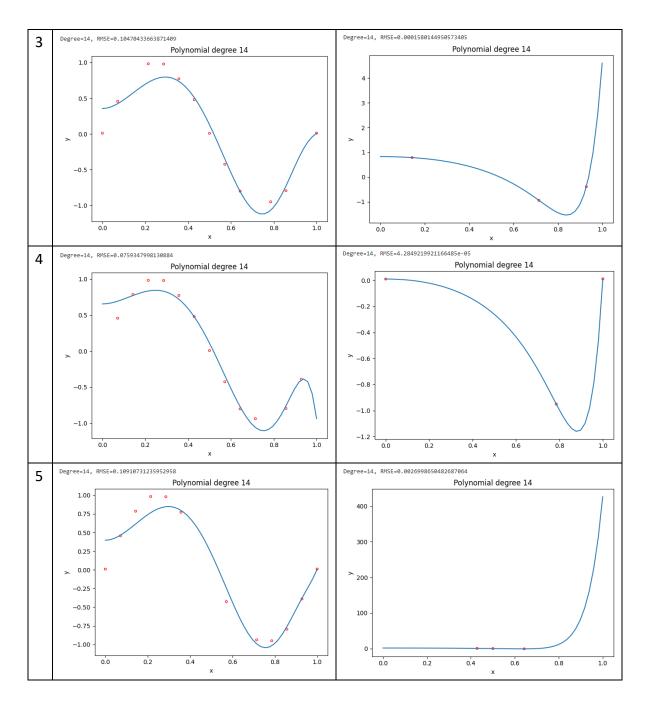


## ■ \(\lambda = 0.001/15\)

### **Training error**

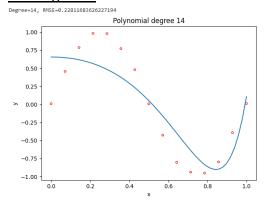


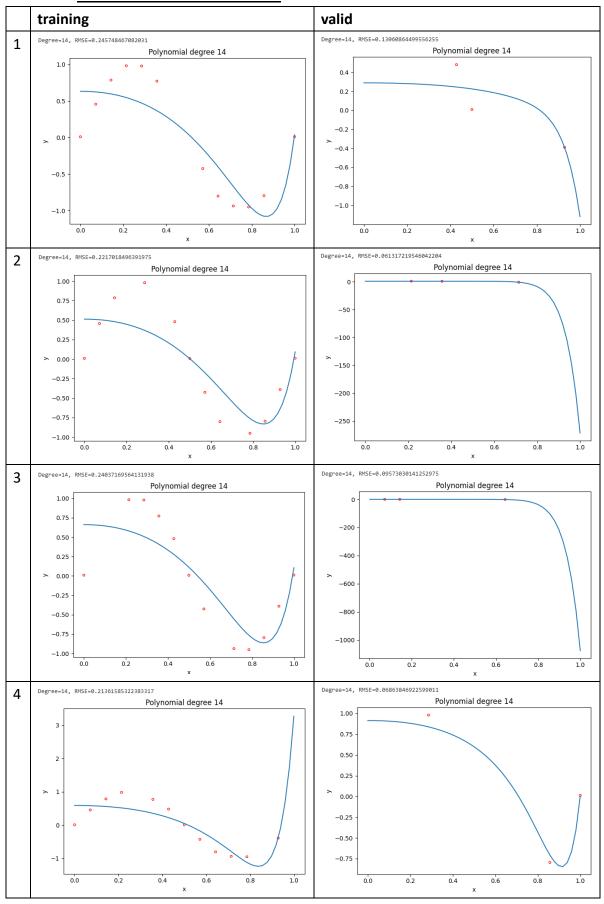


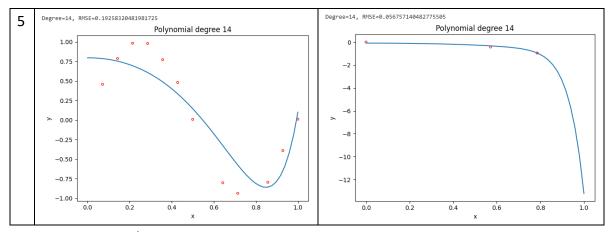


## ■ λ= 1/15

#### <u>Training error</u>

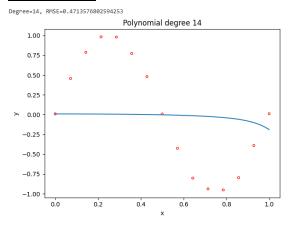


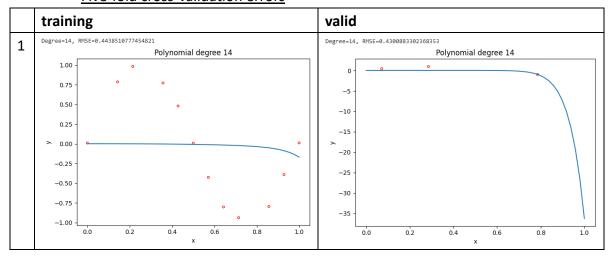


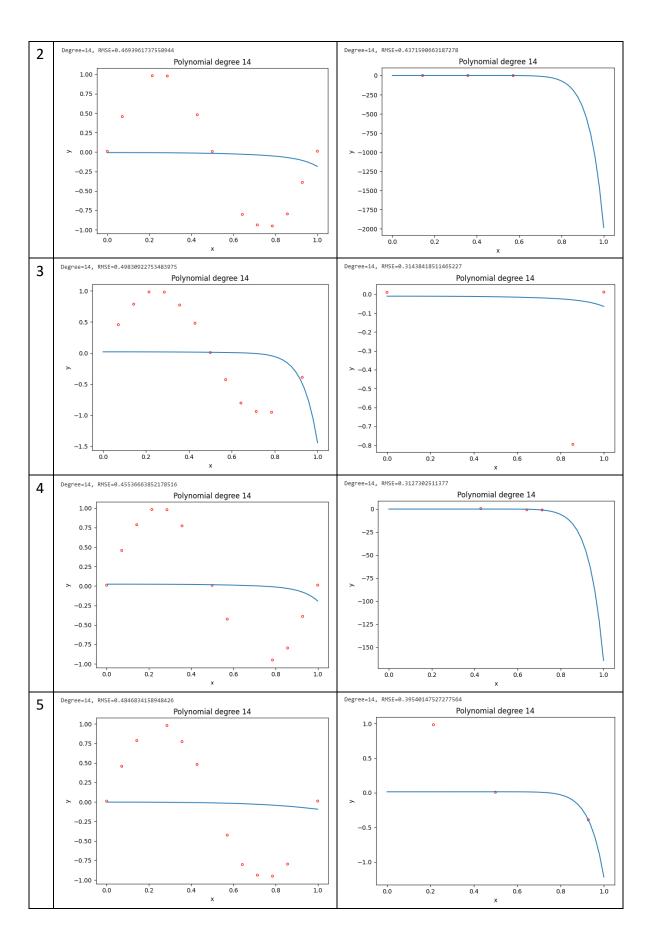


## 

#### **Training error**

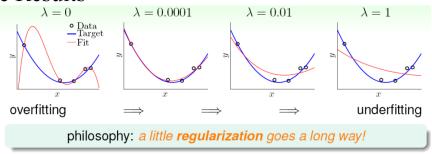






- Conclusion: The observation from your results.
  - ➤ Linear regression 只適用於線性關係的資料,但當我們的資料是非線性的就必須用 polynomial regression 才能畫出最佳擬合線。龐大的資料集在做 five-fold 時,比較不會因資料量不足找不到逆矩陣而出現錯誤,但過少的資料集也可能造成訓練資料不足,因而導致 overfitting。
  - 》 改變  $\lambda$  值,  $\lambda$  =0 時模型無法彈性的做出判斷 (模型複雜度太高),由擬合圖可看出有 overfitting 的問題;  $\lambda$  =1000/m 時彈性過大因此模型無法判斷所學習的資料,由擬合圖看出有 underfitting 的問題;  $\lambda$  =0.001/m 最為精準,能畫出最佳擬合線。

## The Results



實驗結果完全符合課堂簡報中的結果。

• Discussion: The questions or the difficulties you met during the implementation.

原本以為是因為點太少而一直出現找不到逆矩陣的問題

```
86
87 def _raise_linalgerror_singular(err, flag):
---> 88 raise LinAlgError("Singular matrix")
89
90 def _raise_linalgerror_nonposdef(err, flag):
LinAlgError: Singular matrix
```

將 np.linalg.inv 改成 np.linalg.pinv。

參考資料: https://blog.csdn.net/weixin 43977640/article/details/109908976