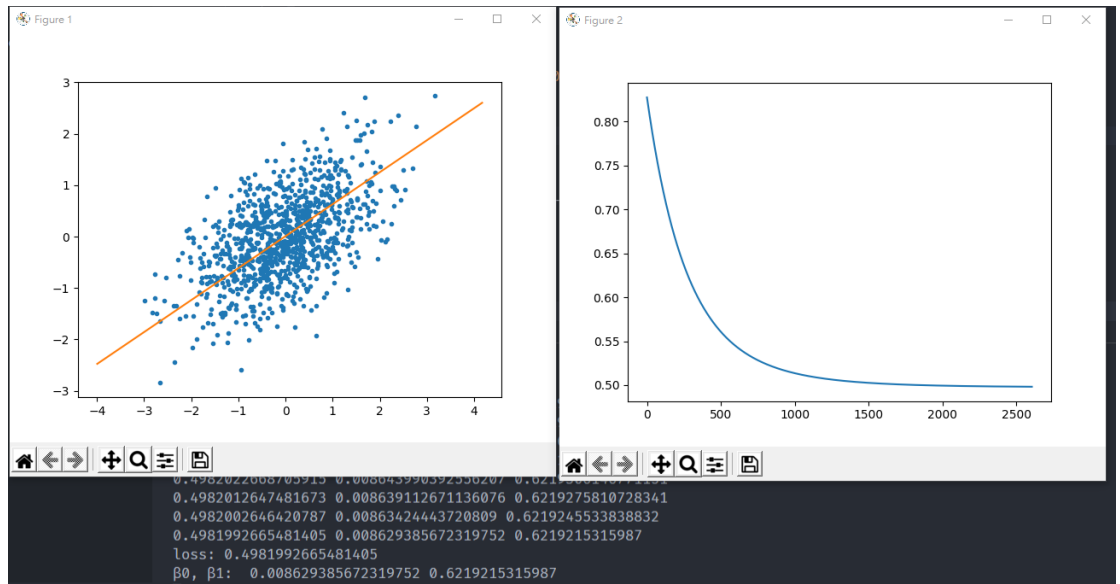


# Pattern Recognition, Homework 1

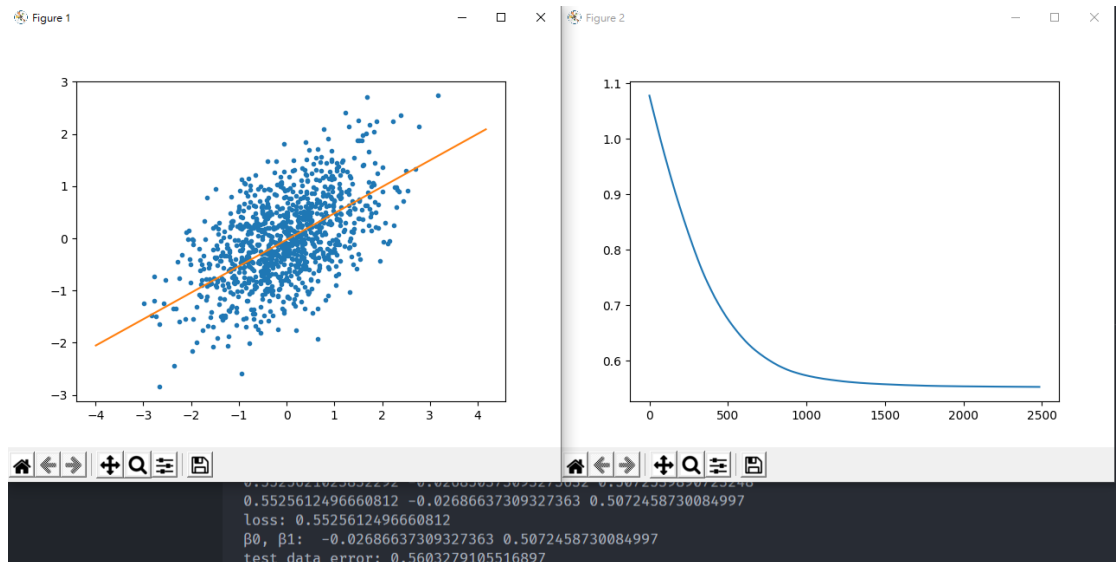
## 1. Part 1

- (1) Implement the linear regression model
- (2) Plot the learning curve of the training with both losses

### MSE



### MAE



- (3) mean square error and mean absolute error between your predictions and the ground truths on the testing data

MSE	MAE
0.5098033892530457	0.5603279105516897

- (4) the weights (  $\beta_1$  ) and intercepts (  $\beta_0$  ) of your linear model trained from both losses?

	MSE	MAE
$\beta_0$	0.008629385672319752	- 0.02686637309327363
$\beta_1$	0.6219215315987	0.5072458730084997

- (5) Please explain the difference between gradient descent, mini-batch gradient descent, and stochastic gradient descent?

- **gradient descent:**  
一次疊代(更新 **weight**) 就需要跑完全部的訓練資料。  
耗時較久，不過也較保險，可以避免只取到較邊緣的訓練資料導致訓練方向錯誤。
- **mini-batch gradient descent:**  
將資料集分成幾堆，一次疊代只需要跑完一堆就對 **weight** 進行更新。  
上下兩者的平衡。
- **stochastic gradient descent:**  
將資料分堆到極致，一次疊代只需要跑完一\*\*筆\*\*資料就對 **weight** 進行更新。  
收斂速度快，不過 **weight** 更新方向卻容易跳動( 因為訓練資料大部分都帶有誤差，只使用一筆資料訓練會將誤差對訓練方向的影響加到最大 )。

## 2. Part 2

(1)

$$\begin{aligned}
 \textcircled{1} P(\text{Guava}) &= P(\text{Guava} | \text{box} = R) \times P(\text{box} = R) \\
 &\quad + P(\text{Guava} | \text{box} = B) \times P(\text{box} = B) \\
 &\quad + P(\text{Guava} | \text{box} = G) \times P(\text{box} = G) \\
 &= (3/10) \times 0.2 + (2/4) \times 0.4 \\
 &\quad + (4/20) \times 0.4 \\
 &= 0.06 + 0.2 + 0.08 \\
 &= 0.34 \#
 \end{aligned}$$

$$\begin{aligned}
 \textcircled{2} P(\text{box} = B | \text{Apple}) &= P(\text{box} = B \& \text{Apple}) / P(\text{Apple}) \\
 &= 0.4 \times \frac{3}{4} / (0.2 \times \frac{3}{10} + 0.4 \times \frac{3}{4} + 0.4 \times \frac{12}{20}) \\
 &= 0.2 / (0.06 + 0.2 + 0.24) \\
 &= 0.2 / 0.5 \\
 &= 0.4 \#
 \end{aligned}$$

(2)

$$\begin{aligned}\text{var}(f) &= E\left[\left(f(x) - E(f(x))\right)^2\right] = E\left[f(x)^2 - 2f(x) \cdot E[f(x)] + E[f(x)]^2\right] \\ &= E\left[f(x)^2\right] - 2E\left[f(x)E[f(x)]\right] + E\left[E[f(x)]^2\right] \\ &= E\left[f(x)^2\right] - 2E[f(x)]E[f(x)] + E[f(x)]^2 \\ &= E\left[f(x)^2\right] - E[f(x)]^2\end{aligned}$$

(3)

$$\begin{aligned}& E_y\left[E_x[x|y]\right] \\ &= E_y\left[\sum_{x \in X} P(X=x|Y=y) \cdot x\right] \\ &= \sum_{y \in Y} P(Y=y) \left[\sum_{x \in X} P(X=x|Y=y) \cdot x\right] \\ &= \sum_{y \in Y} \sum_{x \in X} P(Y=y) P(X=x|Y=y) \cdot x \\ &= \sum_{y \in Y} \sum_{x \in X} P(X=x \& Y=y) \cdot x \\ &= \sum_{x \in X} P(X=x) \cdot x \\ &= E[x]\end{aligned}$$