(1) derive formulas to solve liner regression problems. $E(W_1, W_0 \mid \chi) = \frac{1}{N} \sum_{t=1}^{N} [r^t - (W_1 x^t + W_0)]^2$ 平均均方談差 推導 $W_1 = \frac{\sum_{i=1}^{r} x^{i} r^{i} - \overline{x} - \overline{r} N}{\sum_{i=1}^{r} (x^{i})^{i} - N\overline{x}^{i}} = \frac{\overline{x}^{i} - \overline{x}^{i}}{\overline{x}^{i} - \overline{x}^{i}}$ and $W_0 = \overline{r} - W_1 \overline{x}$ W 250A 1 = x a= yt, b = (W, x+wo) $g = \frac{1}{\sqrt{1}} \geq (\alpha - b)^2$ > 1/5 a-206+62 > 1/2 /2t - (2(rt) (W, xt+W))+ (W, xt+W)) → N5 r2t - 2rtw, χt - 2rtwo + Wix+ 2w, χtwo f Wo · · · (1) $\frac{1}{2} \frac{1}{dw_0} = 0 \Rightarrow \frac{y}{dw_0} = \frac{1}{11} \sum_{i=1}^{N} \frac{1}{2} 0 - 0 - 2 + \frac{1}{2} + 0 + 2 w_i x_i^{t} + 2 w_i^{t}$ 意义 机角板值=0 J = 1 5 + (-rt+ w, xt+ Wo) = 0 $\Rightarrow \sqrt{\sum_{i=1}^{t} + W_{i} \chi^{t} + W_{0}} = 0$ $\Rightarrow \sqrt{\sum_{i=1}^{t} + W_{i} \chi^{t} + \sqrt{W_{0}}} = 0$ $\Rightarrow W_0 = \frac{1}{N!} \geq -(-)^t + W_1 \chi^t$ $\neq W_0 = \sqrt{\sum_i \sum_i r^t - W_i \chi^t} \Rightarrow W_0 = \overline{r} - W_i \overline{\chi}$

再数(1) /故如, 心部和

$$\frac{1}{2} = 0 - 1 + 1 + 1 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2 + 0 + 2$$

$$\frac{g}{dw_1} = \frac{1}{N} \ge \lambda \left(-r^{\dagger} \chi^{\dagger} + \chi^{\dagger} W_1 + W_0 \chi^{\dagger}\right) = 0$$

$$\Rightarrow \frac{1}{N} \geq N_0 \chi^{\dagger} = \frac{1}{N} \geq r^{\dagger} \chi^{\dagger} - \chi^{2} N_1 = 0$$

$$\Rightarrow W_0: \frac{1}{N} \geq \chi^t = \frac{1}{N} \sum_{r} t_{\chi^t} + \frac{1}{N} \sum_{r} - \chi^{2t} W_1$$

$$\Rightarrow W_0 \cdot \overline{\chi} = \overline{M} + W_1 \cdot \overline{N} \ge -\chi^{2t}$$

$$\Rightarrow W_0 \cdot \overline{\chi} = \overline{W} - W_1 \cdot \overline{\chi}^{\perp}$$

$$\overline{\chi} W_0 = \overline{F} - W_1 \overline{\chi} / (f \lambda)$$

$$\Rightarrow (\overline{r} - W_1 \overline{\chi}) \overline{\chi} = \overline{r} \chi - W_1 \overline{\chi}^2$$

$$\Rightarrow \widehat{\chi} \widehat{r} - W_1 (\widehat{\chi})^2 - \widehat{r\chi} - W_1 \widehat{\chi}^2$$

$$\Rightarrow W_1(\overline{\chi^2} - (\overline{\chi})^2) = \gamma \overline{\chi} - \overline{\chi} \overline{\rho}$$

$$\Rightarrow W_{1} = \frac{r\bar{\chi} - \bar{\chi}\bar{\nu}}{\bar{\chi}^{2} - (\bar{\chi})^{2}} \#$$

(2-1) 利用 linear regression 預測攝影機拍攝之灰階值 對應之實際灰度值 預測 X=38(62, f(x)=?

資料點編號	座標(383,255)的灰階值	BM-7A 所量測輝度值
1	17703	1009
2	19079	1102
3	20620	1202
4	22181	1310
5	23632	1399
6	24911	1497
7	26371	1598
8	27986	1707
9	29467	1806
10	30960	1906

-	- 400	(///
11	32226	(x):7001
12	= 3 0000	2103
13	35146	2209
14	36572	2309
15	37929	2402
16	39274	2500
17	40610	2601
18	42063	2703
19	43332	2803
20	44696	2902
21	46154	3008

f(ス)= WiX+Wo,由證明1 and 2 得知

$$W_0 = \overline{\Gamma} - W_1 \overline{\chi}$$
, $W_1 = \frac{\overline{\chi} - \overline{\chi} \overline{r}}{\overline{\chi} - (\overline{\chi})}$

会 α = 拍攝之友階值, r=實際>液度值

$$\chi = \frac{1}{N} \times \chi = 32/23.04$$

$$f(38162) = 2427.95$$

$$f(21537) = 1259.92$$

$$f(50000) = 3259.66$$

(取到人数點第二位)

對應 python code

```
import numpy as np
         def get_w1(x, r): 2 usages
             x_bar = np.mean(x) >> 各自計算 で, ア(利用NP-Mean 算を均)
              return (np.mean(x * r) - x_bar * r_bar) / (np.mean(x ** 2) - x_bar ** 2)
             get_w0(x, r): 1 usage

return np.mean(r) - get_w1(x, r) * np.mean(x)

\frac{5 \cancel{\xi} + \cancel{k} \cancel{\xi} \cancel{\xi}}{\cancel{\xi}} = \frac{\cancel{\pi} - \cancel{\pi}}{\cancel{\pi}} - \cancel{\pi}
         def get_w0(x, r): 1 usage
                                                 ら数應到W。= 下一Wi え
         def f_{-} of f(x) = W (x + W)

(x, y) = 1 usage
              return w1 * x + w0
14
         if __name__ == "__main__":
             x = np.array([
                  17703, 19079, 20620, 22181, 23632, 24911, 26371, 27986, 29467, 30960,
                  32226, 33672, 35146, 36572, 37929, 39274, 40610, 42063, 43332, 44696,
             1) 与反陷值(拍摄)
             r = np.array([
                  1009, 1102, 1202, 1310, 1399, 1497, 1598, 1707, 1806, 1906,
                  2001, 2103, 2209, 2309, 2402,2500, 2601, 2703, 2803, 2902, 3008
             w1 = get_w1(x, r)
             w0 = get_w0(x, r)
             print(f"w1 = {w1:.2f}") >> Show calculated Wo and Wiprint(f"w0 = {w0:.2f}") >> Show calculated Wo and Wi
             for x in [38162, 21537, 50000]:→ X
                  print(f''f(\{x\}) = \{f_of_x(x, w1, w0): .2f\}'') \rightarrow \mathbb{R}_{X} / \mathbb{R}_{X}
```

```
w1 = 0.07

w0 = -253.22

f(38162) = 2427.95

f(21537) = 1259.92

f(50000) = 3259.66
```

←執行然音果

(2-2) 我出 MEDV 與鎮 13個特徵的各自 linear regressio 模型

各特徑殖實際意義

特徵 (Feature)	中文描述 (Chinese Description)
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CRIM 鄉鎮人均犯罪率

ZN 規劃為超過 25,000 平方英尺地塊的住宅用地比例

INDUS 每個鄉鎮非零售商業用地的比例

CHAS 查爾斯河虛擬變數 (若地塊毗鄰河流則為 1; 否則為 0)

NOX 一氧化氮濃度(百萬分之幾)

RM 每棟住宅的平均房間數

AGE 1940 年以前建造的自住單位比例

DIS 到波士頓五個就業中心的加權距離

RAD 輻射狀公路可達性指數

TAX 每 \$10,000 全值房產稅率

PTRATIO 鄉鎮師生比例

B $1000({
m Bk}-0.63)^2$ (其中 ${
m Bk}$ 為該鎮黑人比例)

LSTAT 人口中地位較低的百分比

MEDV 自住房屋的中位價值(以千美元計)

全 χ = MEDV, y = [cRIM~B] ⇒共13為且

CHAS RM AGE DIS RAD TAX B LSTAT

0.00632 18.00 2.310 0 0.5380 6.5750 65.20 4.0900 1 296.0 15.30 396.90 4.98 24.00

0.02731 0.00 7.070 0 0.4690 6.4210 78.90 4.9671 2 242.0 17.80 396.90 9.14 21.60

0.02739 0.00 7.070 0 0.4690 7.1850 61.10 4.9671 2 242.0 17.80 392.83 4.03 34.70

INDUS									5 m/3 AT 4 5					
									•					31
	6	0.02985	0.00	2.180	0	0.4580	6.4300	58.70	6.0622	3	222.0	18.70 394.12	5.21	28.70
	5	0.06905	0.00	2.180	0	0.4580	7.1470	54.20	6.0622	3	222.0	18.70 396.90	5.33	36.20
	4	0.03237	0.00	2.180	0	0.4580	6.9980	45.80	6.0622	3	222.0	18.70 394.63	2.94	33.40
	3	0.02729	0.00	7.070	0	0.4690	7.1850	61.10	4.9671	2	242.0	17.80 392.83	4.03	34.70
	2	0.02731	0.00	7.070	0	0.4690	6.4210	78.90	4.9671	2	242.0	17.80 396.90	9.14	21.60
	1	0.00632	18.00	2.310	U	0.5380	6.5750	65.20	4.0900	1	296.0	15.30 396.90	4.98	24.00

資料共506 筆由證明 1 and 2 可計算出 15 然且各自

PTRATIO

linear regression model f(x) = Wix+ Wo

利用程式計算出 13 組模行

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

def get_w1(x, r): 2 usages new*
x_bar = np.mean(x)
r_bar = np.mean(r)
return (np.mean(x * r) - x_bar * r_bar) / (np.mean(x ** 2) - x_bar ** 2)

def get_w0(x, r): 1 usage new*
return np.mean(r) - get_w1(x, r) * np.mean(x)

def f_of_x(x, w1, w0): 1 usage new*
return w1 * x + w0
```

```
if __name__ == "__main_
          "per capita crime rate by
                    "proportion of residential land zoned for lots over 25,000 sq.ft(ZN)",
                    "proportion of non-retail business acres per town(INDUS)",
                    "Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)[CHAS]",
                    "nitric oxides concentration (parts per 10 million)[NOX]",
                    "average number of rooms per dwelling(RM)",
                    "proportion of owner-occupied units built prior to 1940(AGE)",
                    "weighted distances to five Boston employment centres(DIS)",
                    "index of accessibility to radial highways(RAD)",
                    "full-value property-tax rate per $10,000(TAX)",
                    "pupil-teacher ratio by town(PTRATIO)",
                    "1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town[B]",
                    "% lower status of the population(LSTAT)",
                    "Median value of owner-occupied homes in $1000's(MEDV)"
         df = pd.read_csv( filepath_or_buffer: "housing.data", sep='\s+', names=features)

the pd. read_csv( filepath_or_buffer: "housing.data", sep='\s+', names=features)
         for feature in features[[-1]: 神氏 MEDV
                   print(f"Features: {feature}")
x = df[feature].values → [CRIM ~ LSTA] 特性 value → イ
                    r = df["Median value of owner-occupied homes in $1000's(MEDV)"].values
                   w1 = get_w1(x, r) \rightarrow \hat{c} + \hat{q} W_0 and W_1

w0 = get_w0(x, r) \rightarrow \hat{c} + \hat{q} W_0
                    print(f"w1: {w1:.2f}, w0: {w0:.2f}")
                    print(f''f(x) = \{w1:.2f\}x + \{w0:.2f\}'')
                    fig = plt.figure()
                    plt.scatter(x, r, color='lightpink', edgecolors='darkolivegreen')
                   plt.plot(*args: x, f_of_x(x, w1, w0), 'r-')
plt.xlabel(feature)

plt.ylabel("Modian value of the lines, plt.ylabel("Modian value of the
                    plt.ylabel("Median value of owner-occupied homes in $1000's(MEDV)")
                    plt.savefig(f"img/MEDV-{feature}.png")
                    print("---")
```

以下為13組特徵值所建立出的 Onear regression model(展示理小数>位)

```
Features: per capita crime rate by town(CRIM)
w1: -0.42, w0: 24.03
f(x) = -0.42x + 24.03
Features: proportion of residential land zoned for lots over 25,000 sq.ft(ZN)
w1: 0.14, w0: 20.92
f(x)=0.14x + 20.92
Features: proportion of non-retail business acres per town(INDUS)
w1: -0.65, w0: 29.75
f(x)=-0.65x + 29.75
Features: Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)[CHAS]
w1: 6.35, w0: 22.09
f(x)=6.35x + 22.09
Features: nitric oxides concentration (parts per 10 million)[NOX]
w1: -33.92, w0: 41.35
f(x) = -33.92x + 41.35
Features: average number of rooms per dwelling(RM)
w1: 9.10, w0: -34.67
f(x)=9.10x + -34.67
Features: proportion of owner-occupied units built prior to 1940(AGE)
w1: -0.12, w0: 30.98
f(x) = -0.12x + 30.98
Features: weighted distances to five Boston employment centres(DIS)
w1: 1.09, w0: 18.39
f(x)=1.09x + 18.39
Features: index of accessibility to radial highways(RAD)
w1: -0.40, w0: 26.38
f(x) = -0.40x + 26.38
Features: full-value property-tax rate per $10,000(TAX)
w1: -0.03, w0: 32.97
f(x) = -0.03x + 32.97
Features: pupil-teacher ratio by town(PTRATIO)
w1: -2.16, w0: 62.34
f(x) = -2.16x + 62.34
Features: 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town[B]
w1: 0.03, w0: 10.55
f(x)=0.03x + 10.55
Features: % lower status of the population(LSTAT)
w1: -0.95, w0: 34.55
f(x) = -0.95x + 34.55
```

以下多名MEDV 對名13個特徵值的 linear regression mule 1图





