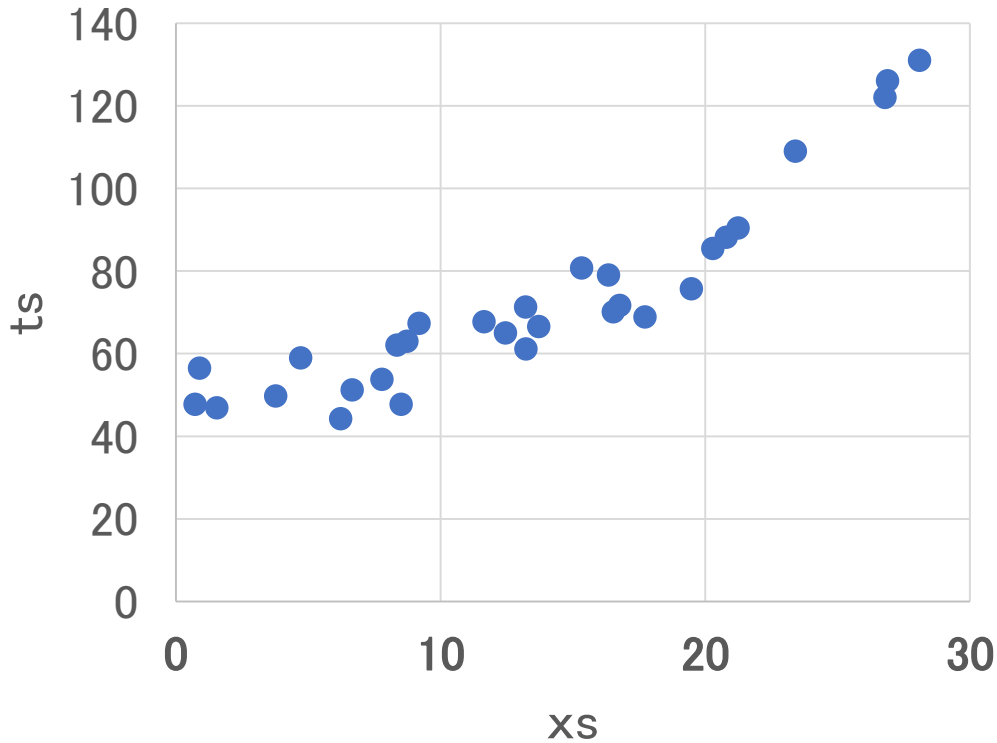
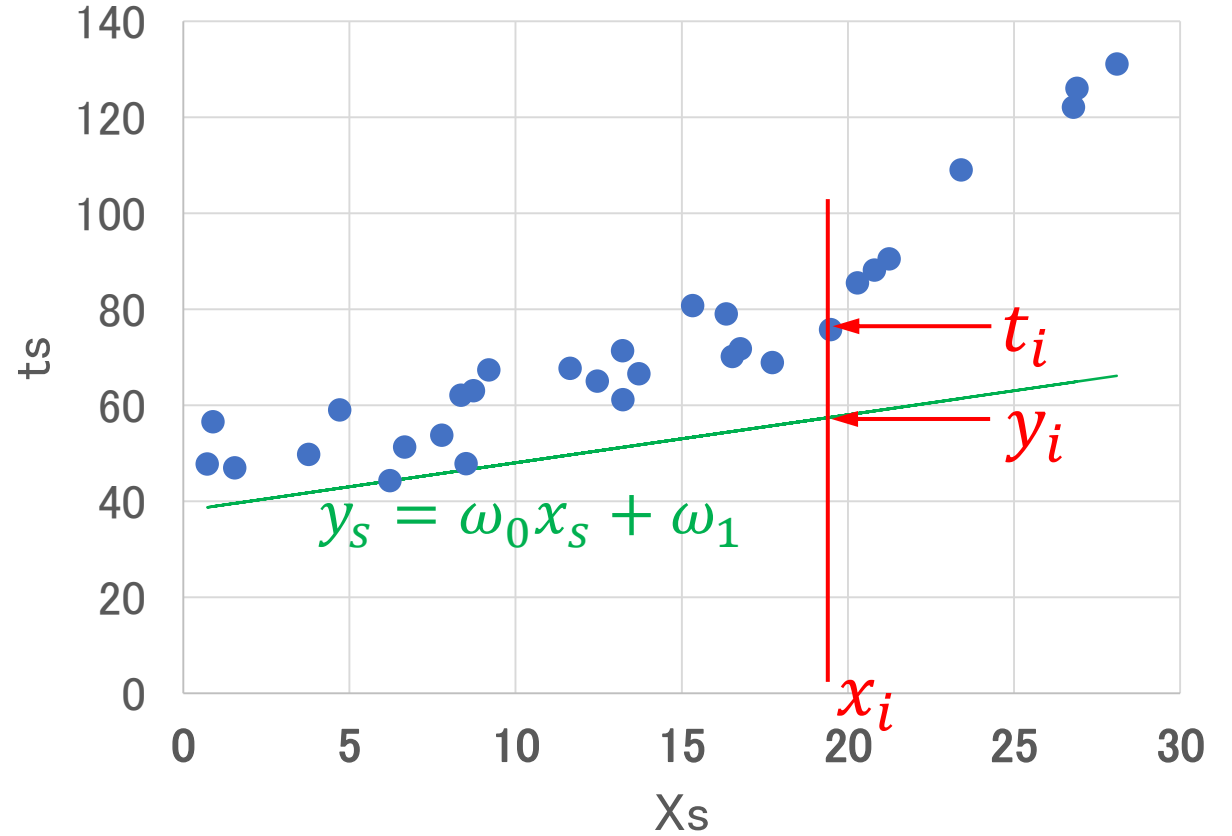


データ

```
xs [16.524 21.244 8.727 15.325 26.788 26.889 3.768 6.217 1.544 13.224  
0.896 13.705 19.474 8.355 20.288 17.726 0.719 16.766 7.778 12.453  
8.506 20.794 13.214 4.706 16.339 23.409 9.191 6.659 11.639 28.092]  
ts [70.135 90.464 63.033 80.721 122.065 126.031 49.769 44.271 46.926  
61.163 56.516 66.573 75.741 62.075 85.447 68.883 47.736 71.724  
53.774 65.007 47.788 88.152 71.328 59.019 79.008 109.037 67.342  
51.264 67.704 131.06 ]
```



線形回帰



$$J = \frac{1}{n} \{ (t_0 - y_0)^2 + (t_1 - y_1)^2 + \dots \}$$
$$= \frac{1}{n} \sum_{i=0}^{n-1} (t_i - y_i)^2$$

平均二乗誤差 (MSE: mean squared error)

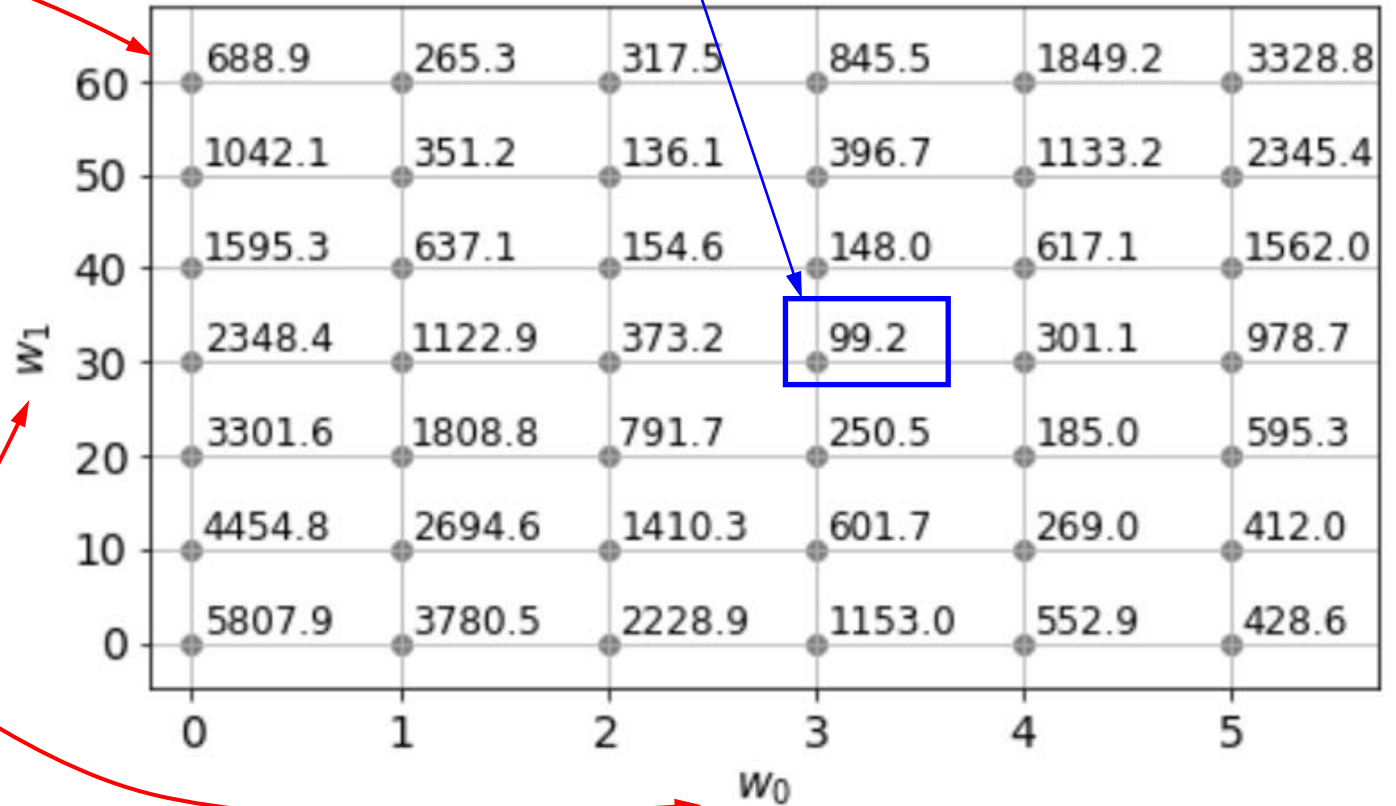
平均二乗誤差 (MSE) のマトリクス

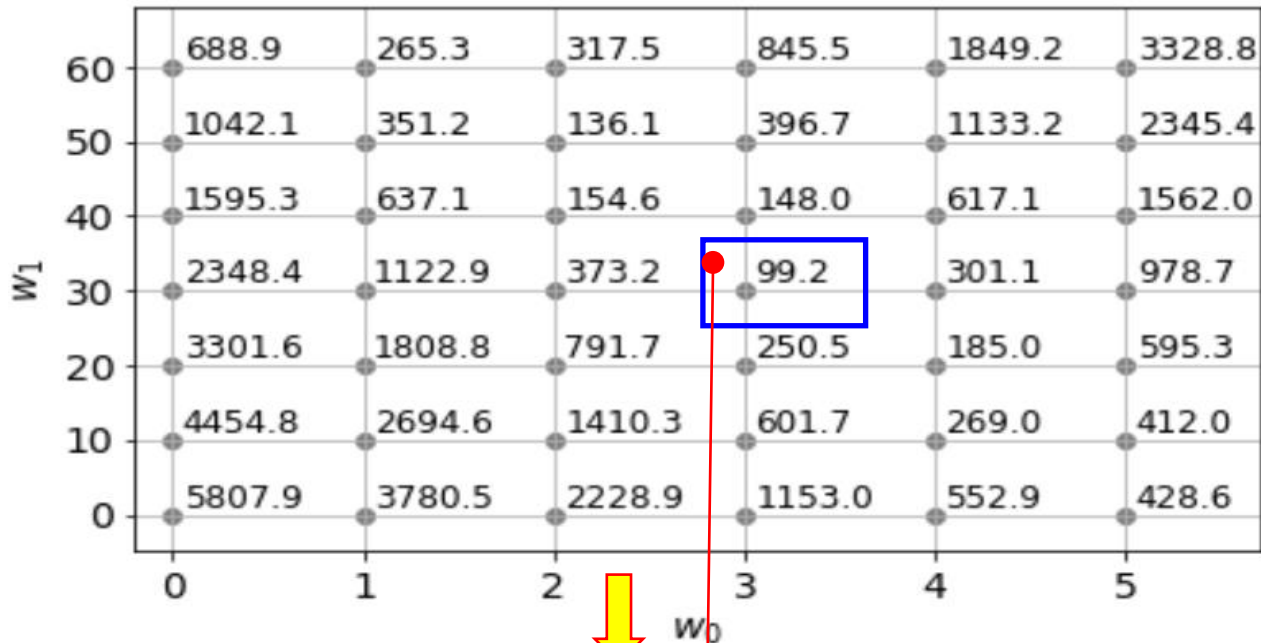
MSE が極小になるのは？

$$x_s = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{n-1} \end{bmatrix} \quad t_s = \begin{bmatrix} t_0 \\ t_1 \\ \vdots \\ t_{n-1} \end{bmatrix}$$

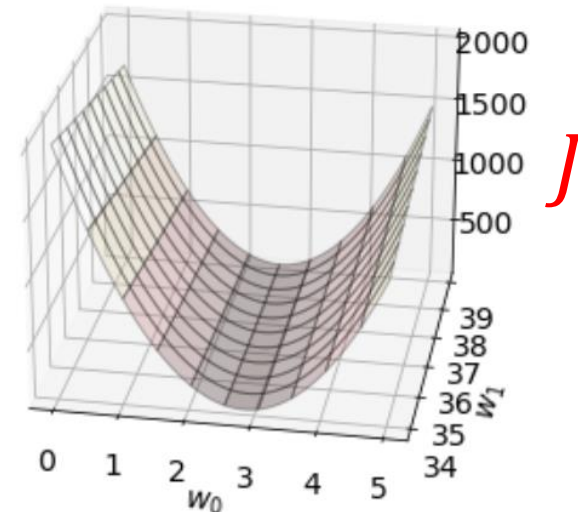
$$y_s = \omega_0 x_s + \omega_1$$

$$J = \frac{1}{n} \{ (t_0 - y_0)^2 + (t_1 - y_1)^2 + \dots \}$$
$$= \frac{1}{n} \sum_{i=0}^{n-1} (t_i - y_i)^2$$

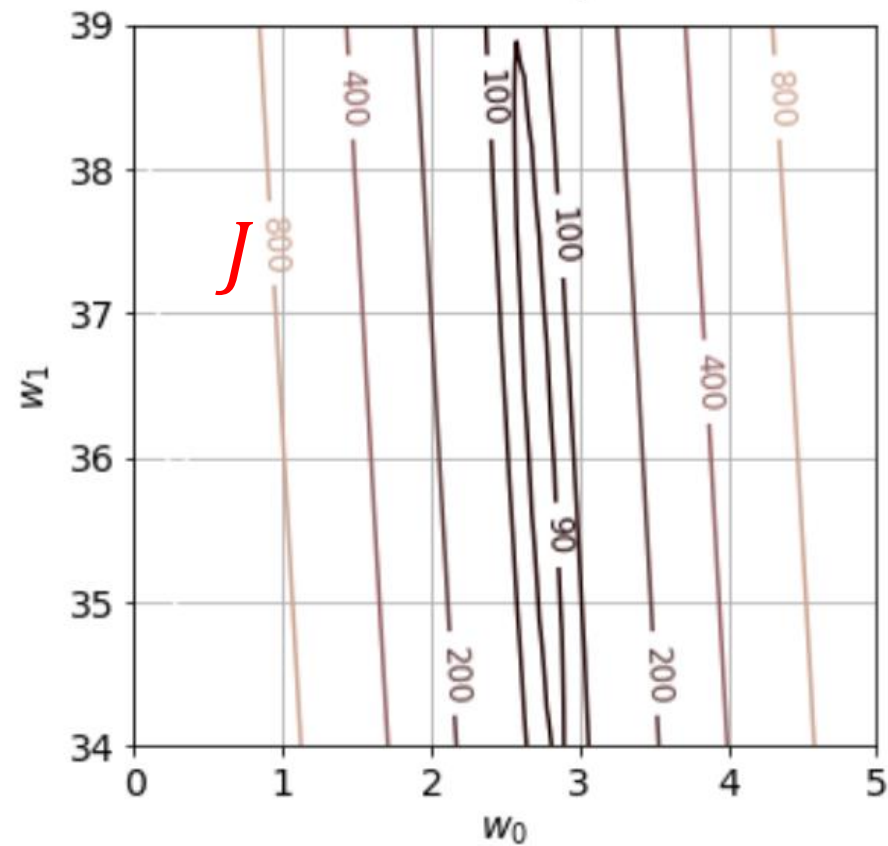
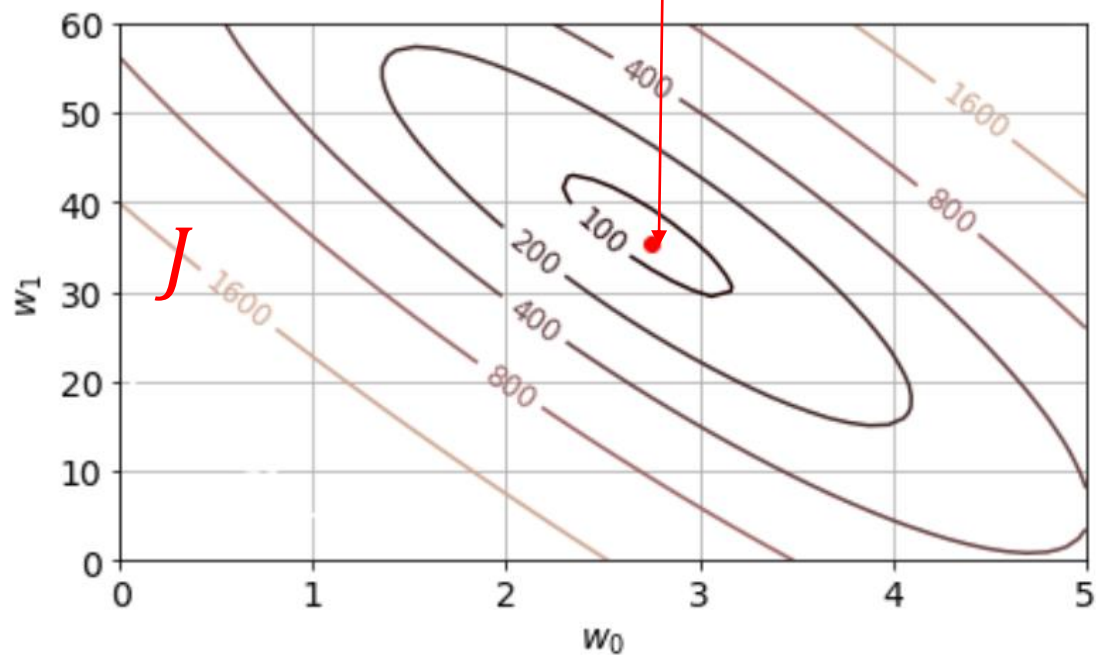




3次元で描くと

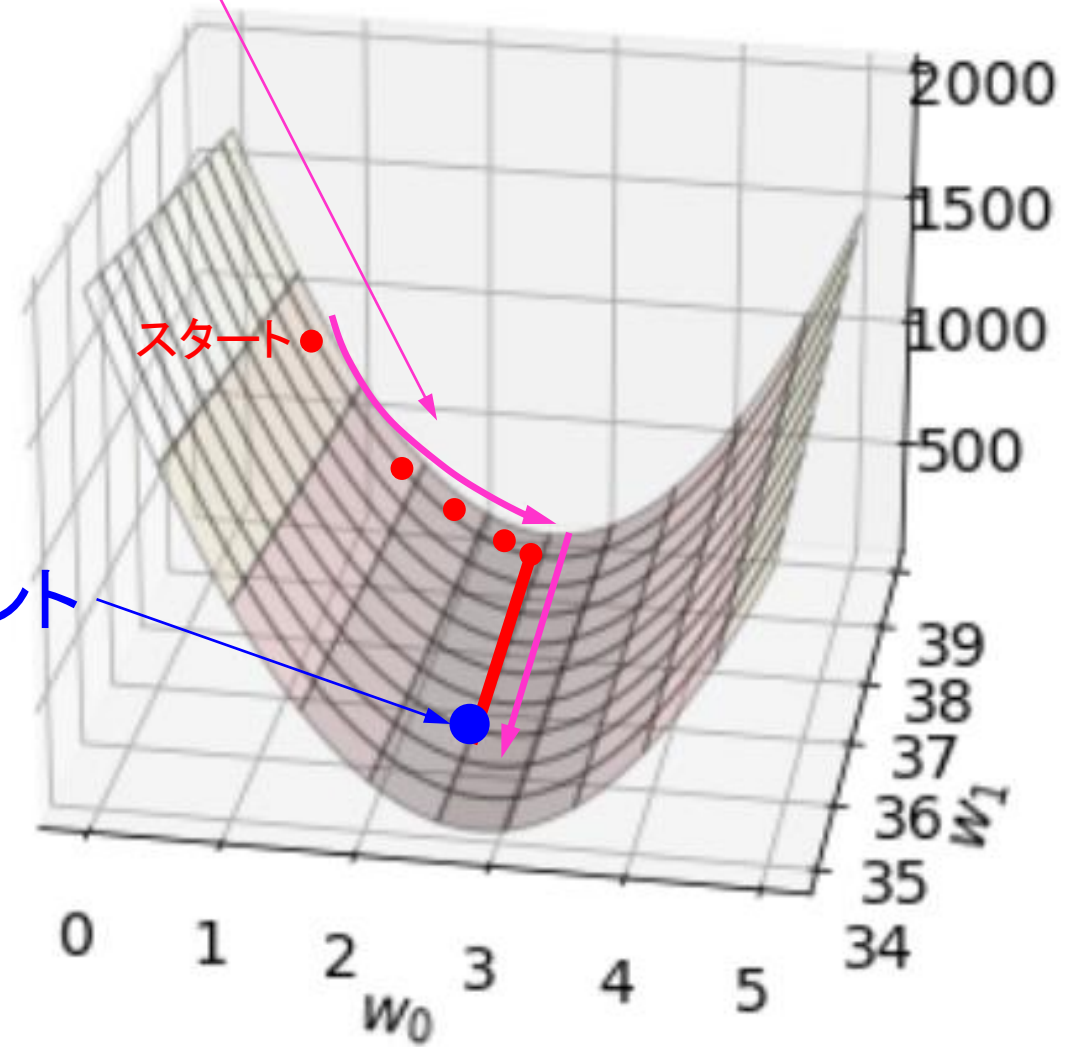
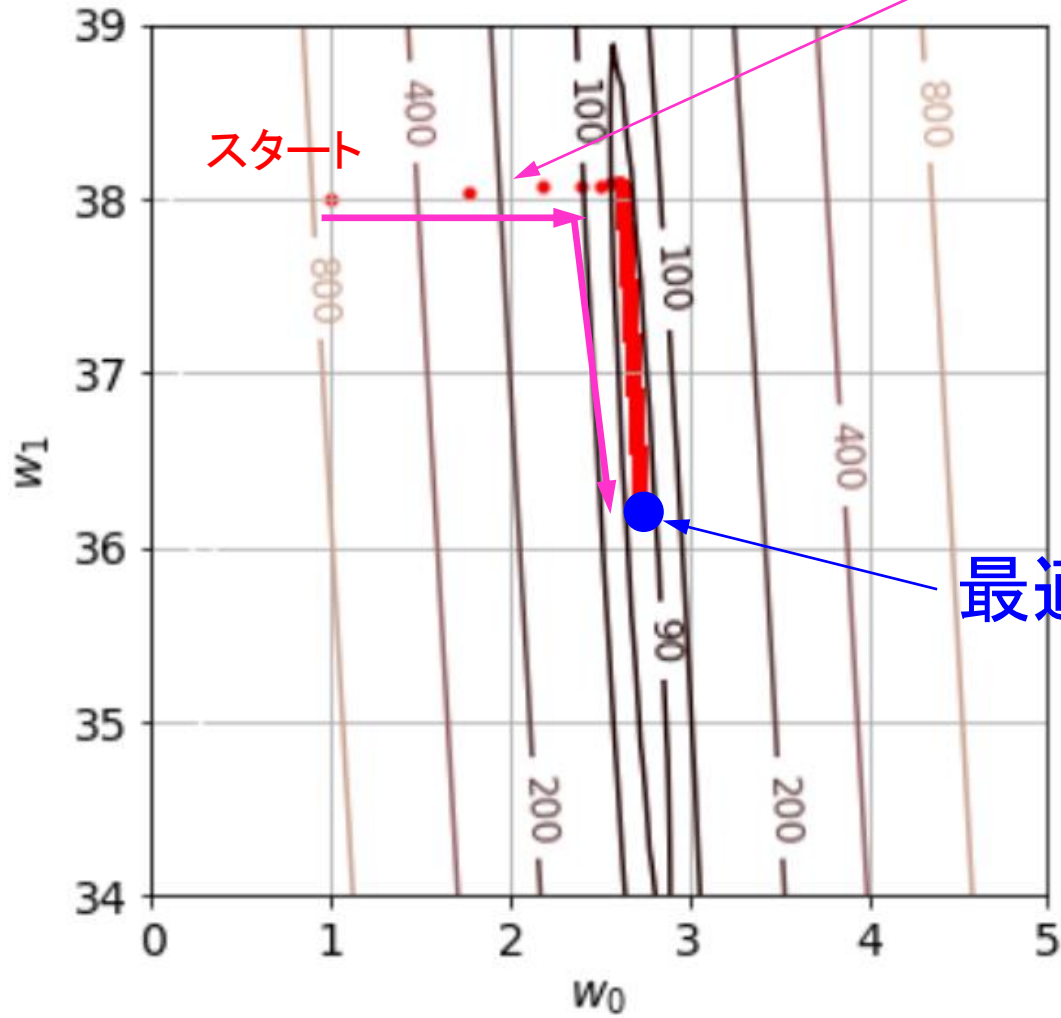


グリッドサーチ: $w_0=2.755$, $w_1=35.510$ のとき最小MSE 88.391



最大勾配の方向に移動

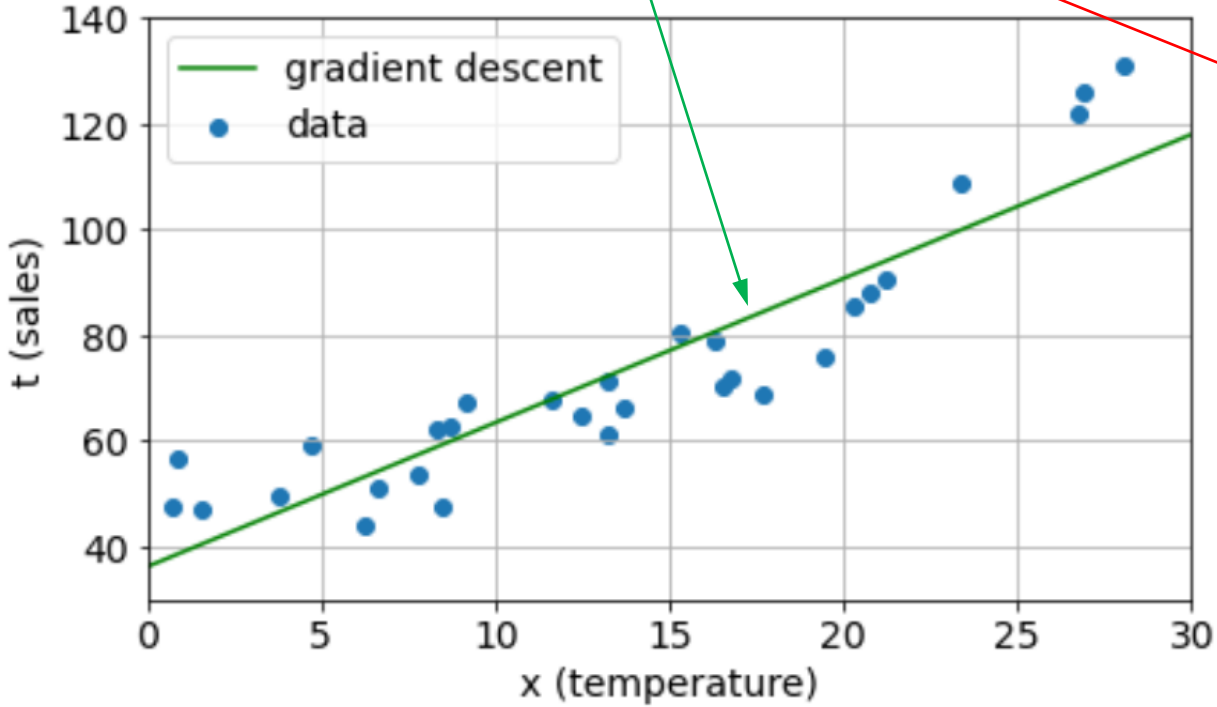
勾配法: $w_0=2.726$, $w_1=36.234$ のとき最小MSE 88.236



最適ポイントの ω_0 と ω_1 を代入して線形回帰式

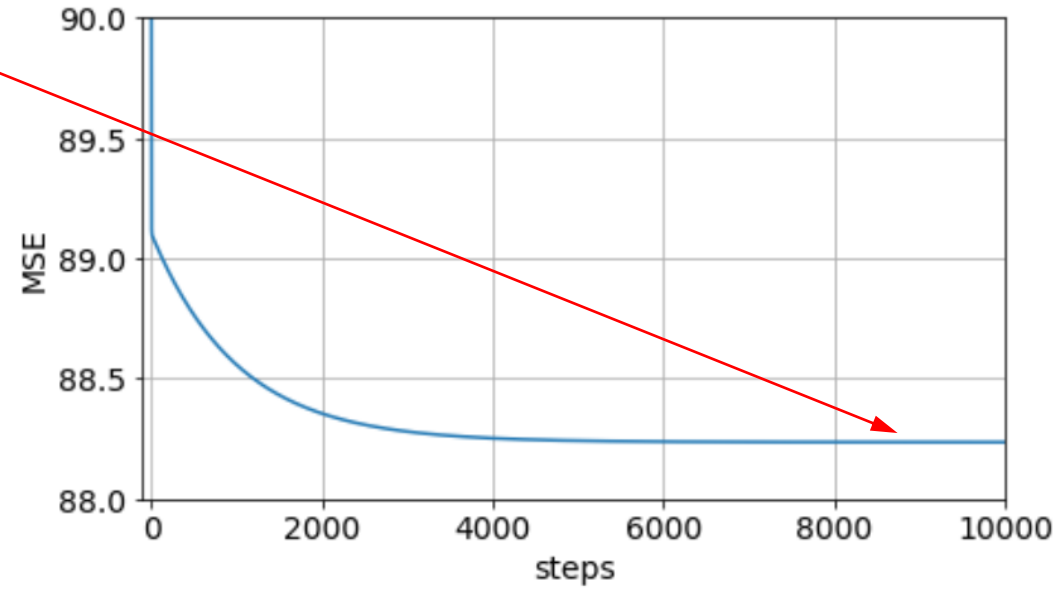
$$y = \omega_0 x + \omega_1$$

勾配法: $w_0=2.726$, $w_1=36.234$ のとき最小MSE 88.236



学習曲線

最小MSE = 88.24



$$x = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{n-1} \end{bmatrix} \quad t = \begin{bmatrix} t_0 \\ t_1 \\ \vdots \\ t_{n-1} \end{bmatrix}$$

解析解: $w_0=2.726$, $w_1=36.221$ のとき最小MSE 88.236

$$\begin{bmatrix} t_0 \\ t_1 \\ \vdots \\ t_{n-1} \end{bmatrix} = \begin{bmatrix} x_0 & 1 \\ x_1 & 1 \\ \vdots & \vdots \\ x_{n-1} & 1 \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \end{bmatrix}$$

代数法: **996 μ s**

勾配法: **714ms**

$$t = x w$$

$$x^T t = x^T x w$$

$$(x^T x)^{-1} x^T t = (x^T x)^{-1} x^T x w \\ = w$$

$$w = (x^T x)^{-1} x^T t$$

ムーア・ペンローズの疑似逆行列