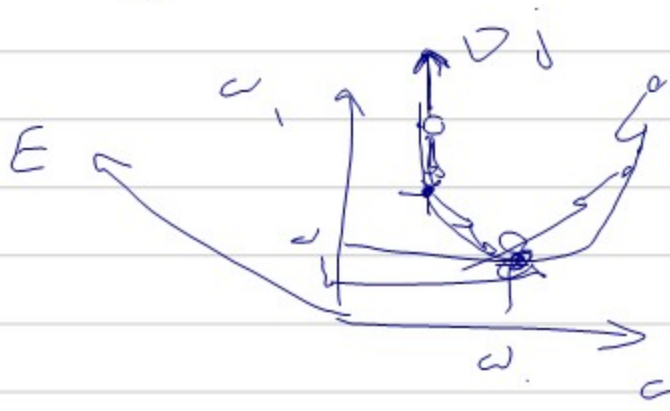


GD

المسألة

$$\underbrace{JSE}_{\underbrace{J}} = \underbrace{\frac{1}{n} \sum (y^{(i)} - \hat{y}^{(i)}|^2)}_{\underbrace{\quad}} \left\{ \begin{array}{l} \frac{\partial J}{\partial w} \\ \frac{\partial J}{\partial w_i} \end{array} \right.$$



Gradient descent

$$J(w_0, w_1, \dots, w_n) \rightarrow \left\{ \begin{array}{l} \frac{\partial J}{\partial w} \\ \frac{\partial J}{\partial w_i} \\ \frac{\partial J}{\partial w_n} \end{array} \right\} \rightarrow \nabla J$$

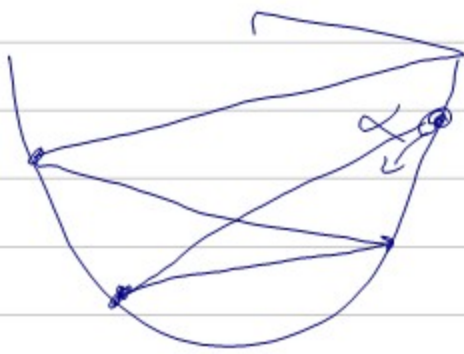
$$w = w_0, w_1, \dots, w_n \leftarrow \text{random}$$

GD المبدأ

For steps in $\textcircled{100}$:

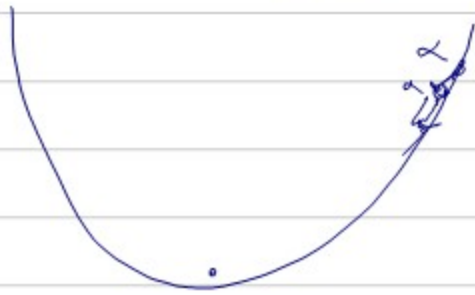
$$w_{\text{new}} = \underbrace{w_{\text{old}}}_{\text{descend}} - \alpha \nabla J$$

$\alpha \rightarrow$ learning rate



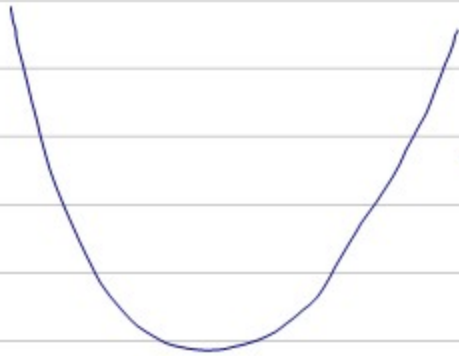
$\alpha \uparrow$ cost \downarrow
 $\alpha \downarrow$ cost \uparrow

$\alpha \downarrow$ cost \uparrow
 $\alpha \downarrow$ cost \downarrow



epoch

Parameter
 Hyperparameter



Convex



Non-Convex

local optimum

Global optimum

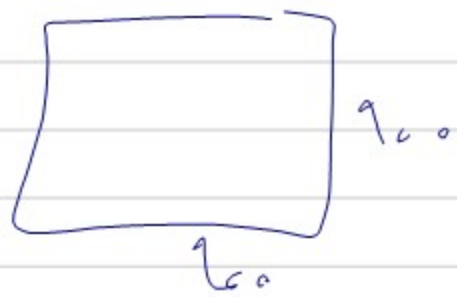
$$W_{t+1} = W_t + \alpha \nabla J(W_t)$$

\nearrow G Ascend \searrow G Descend

3 اشکالی که وجود دارد

① Batch Gradient Descent

در هر بار تمام داده‌ها را می‌بینیم
بسیار کند

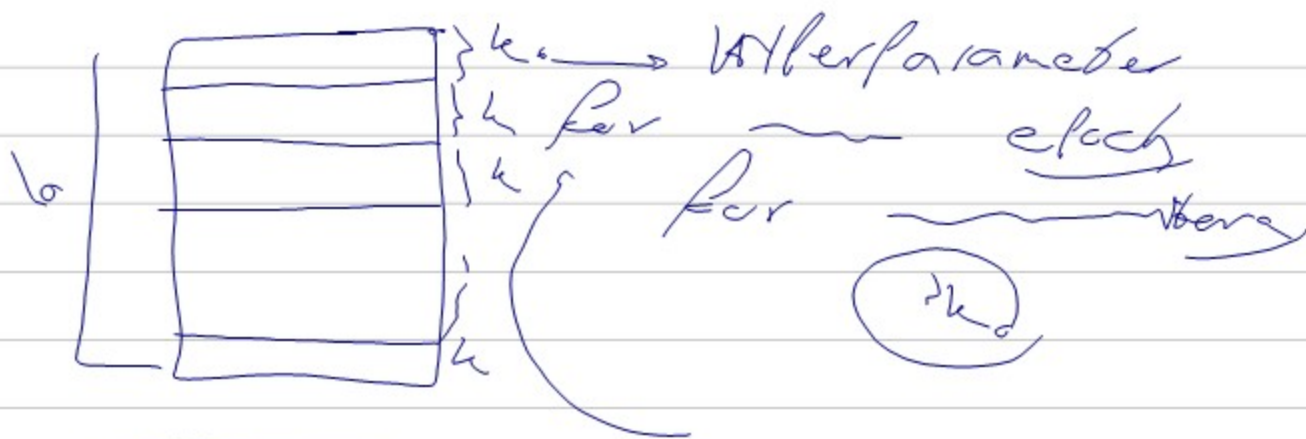


کند

② Stochastic GD

در هر بار یک نمونه را می‌بینیم
آهسته / کند

③ mini batch GD



$$\omega_{\text{F+9}} = \omega^+ - \alpha \times \nabla j$$

$$ME = \sum_b (\hat{y}^{(n)} - y^{(n)})^2 / m$$

$$\nabla j \left\{ \begin{array}{l} \frac{\partial j}{\partial \omega_0} = \sum (\omega_0 + \omega_n - y) / m \\ \frac{\partial j}{\partial \omega_1} = \sum (\omega_1 + \omega_n - y) / m \end{array} \right.$$

$$\omega_0 = \omega_0^+ - \alpha \frac{\partial j}{\partial \omega_0}$$

$$\omega_1^+ = \omega_1^+ - \alpha \frac{\partial j}{\partial \omega_1}$$

linear_model
from sklearn.model_selection import

(PIP) scikit-learn
install

LinearRegression

model = LinearRegression()

model.fit(x_train, y_train)

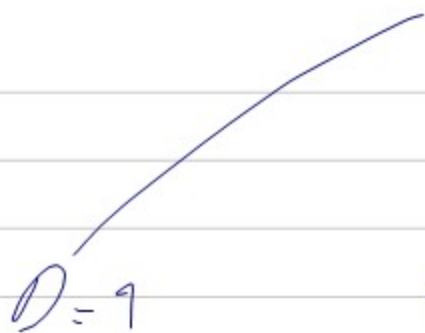
y_pred = model.predict(x_test)

from sklearn.model_selection import
train_test_split

x_train, x_test, y_train, y_test = train_test_split
(x, y, test_size=0.2,)

20% به عنوان داده تست

random_state = 10



linear classification

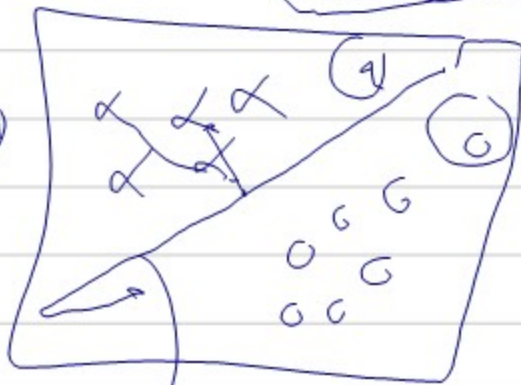
classification

$$x \mapsto y \in \{0, 1\}$$

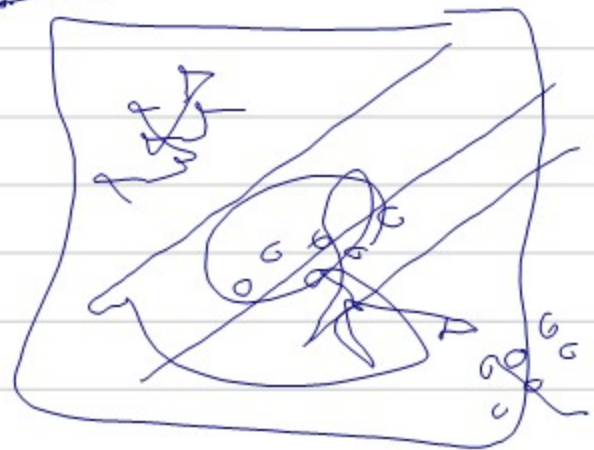
Regression

$$x \mapsto y \in \mathbb{R}$$

$$\omega_0 + \omega_1 x_1 + \omega_2 x_2 = 0$$



$g(x)$



$g_1(x)$

$g_2(x)$

$\left\{ \begin{array}{l} C_1 \\ C_2 \end{array} \right.$

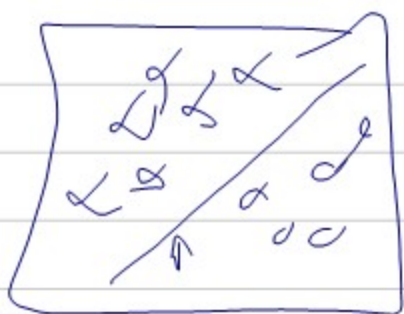
$$\text{if } g_1(x) > g_2(x)$$

otherwise

~~⊗~~

k -class

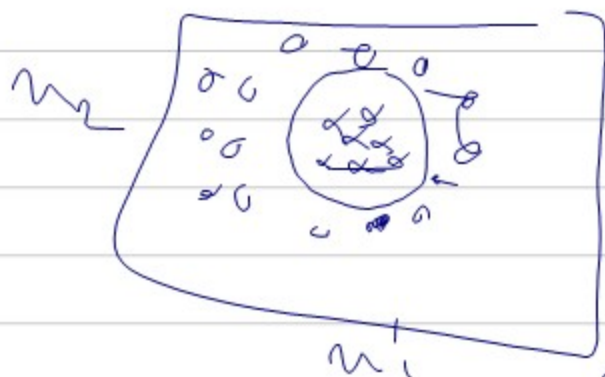
$$\hat{y} = \arg \max_i g_i(x)$$



$$D \leq 1$$

$$1 + u_1^2 + u_2^2 \approx$$

$$u_1^2 + u_2^2 = 1$$

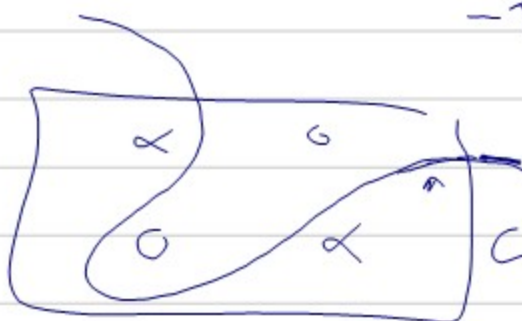


$$D = 2$$

$$\begin{bmatrix} 1 & u_1 & u_2 & u_1^2 & u_2^2 \\ 1 & u_1 & u_2 & u_1^2 & u_2^2 \\ 1 & u_1 & u_2 & u_1^2 & u_2^2 \end{bmatrix}$$

$$\omega_0 + \omega_1 u_1 + \omega_2 u_2 + \omega_3 u_1^2 + \omega_4 u_2^2$$

$$D = 3$$



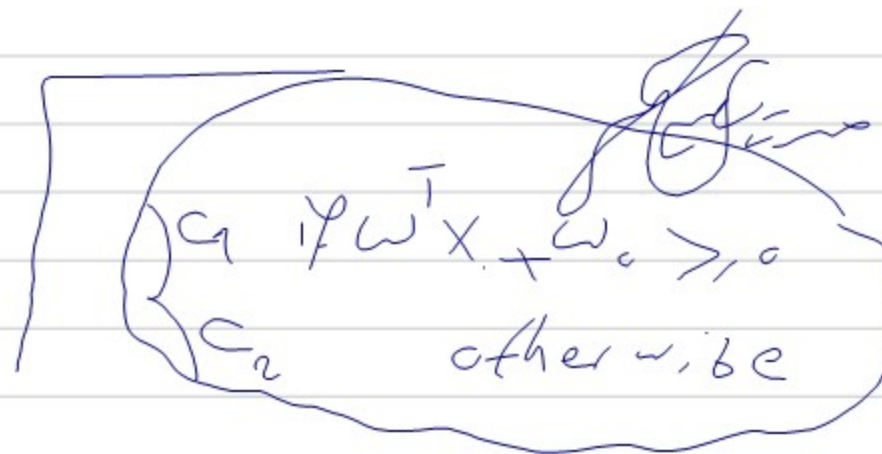
$$\omega \{ \text{class } 1 \}$$

$$f(u) > 0 \Rightarrow 0$$

$$\omega_0 + \omega_1 u_1 + \omega_2 u_2 + \dots + \omega_D u_D = 0$$

Decision

boundary

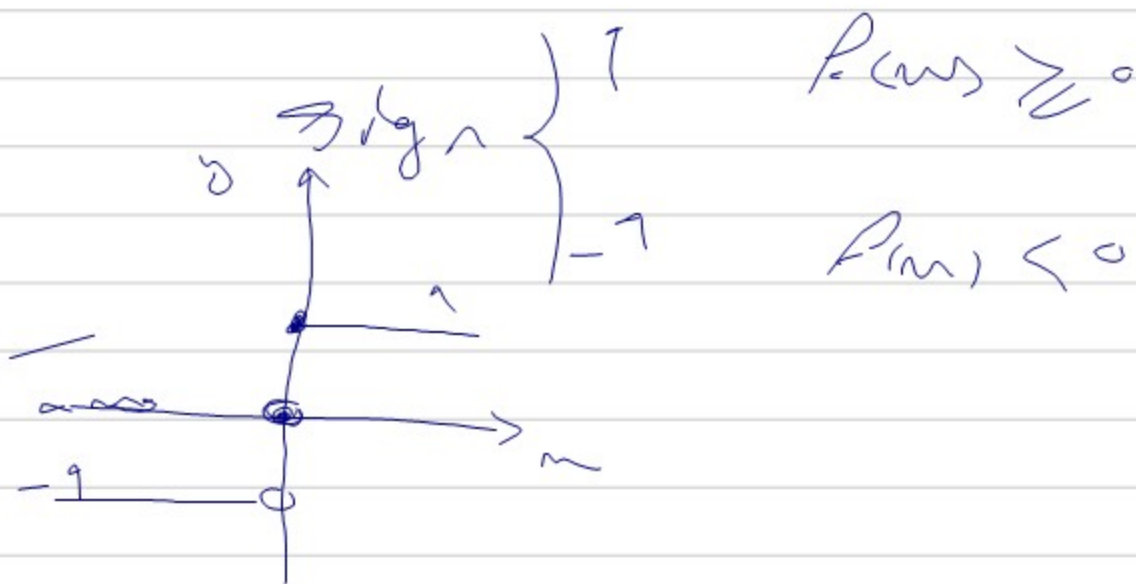
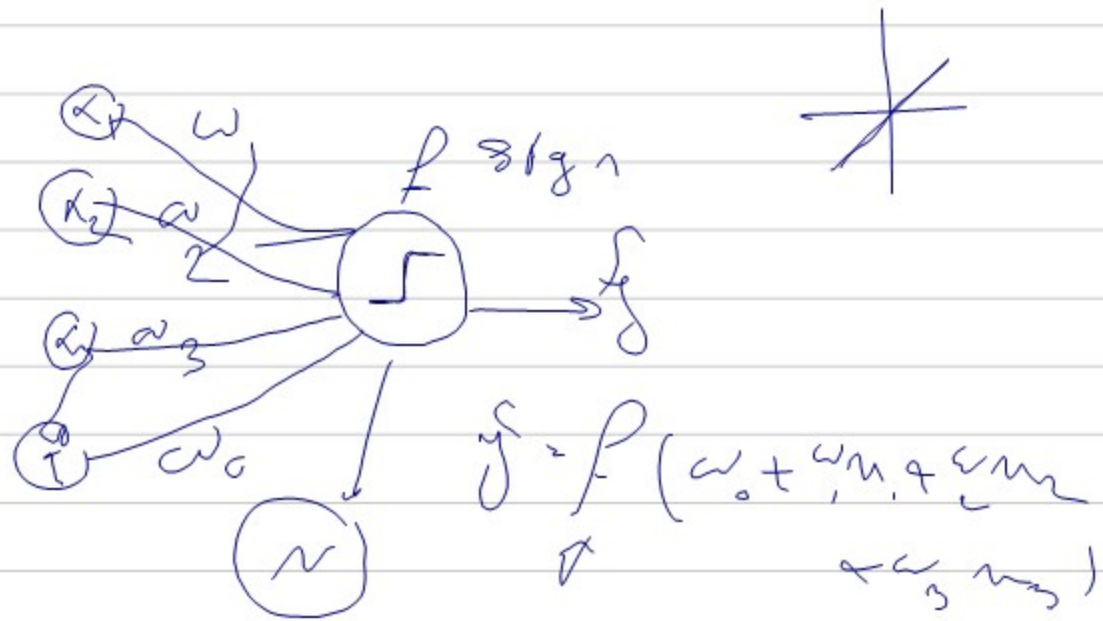
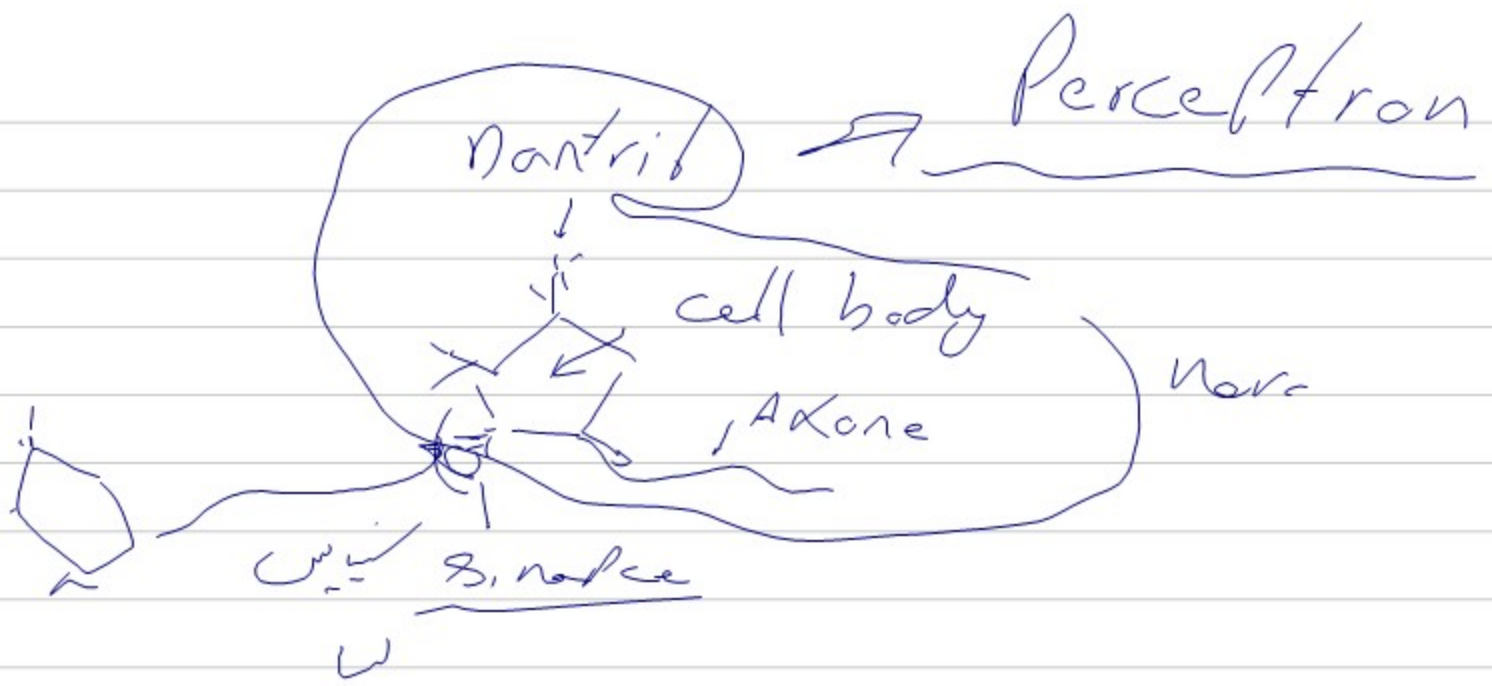


$$c_1 \text{ if } \omega^T x + \omega_0 \geq 0$$

$$c_2 \text{ otherwise}$$

$$x \in [1, u_1, u_2, \dots]$$

$$\omega \in [\omega_0, \omega_1, \omega_2, \dots]$$



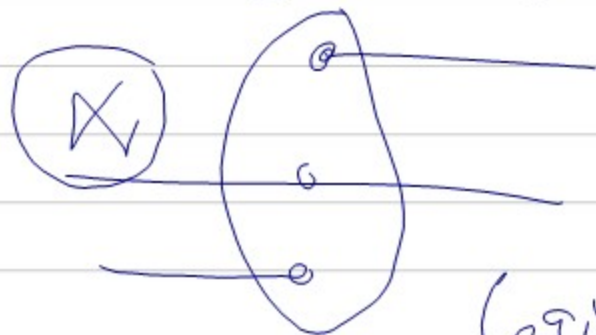
$$f = \text{Sigmoid}(\omega \cdot x_n)$$

msE

$$\sum \frac{(y - \hat{y})^2}{n}$$

0

$\omega \cdot x_n$



Logistic regression

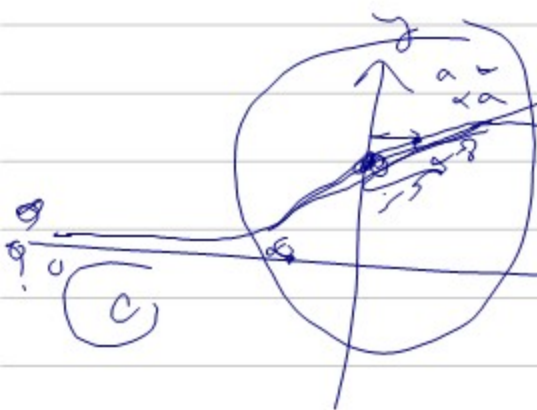
Activation function

~~Sigmoid~~

Sigmoid

$\omega \cdot x_n$

$(0, 1)$



Sigmoid

$$\sigma(\omega^T x) = \frac{1}{1 + e^{-\omega^T x}}$$

$$\sum \frac{(y - \delta(\omega^2 x))}{m}^2$$

$$\nabla J \left[\frac{\partial L}{\partial \omega} \right]$$

$$y = \frac{(n - \text{rank}_y)}{n_{\text{max}} - \text{rank}_y}$$

Preproc
 MinMaxScaler (1)

from sklearn.preprocessing import
 MinMaxScaler

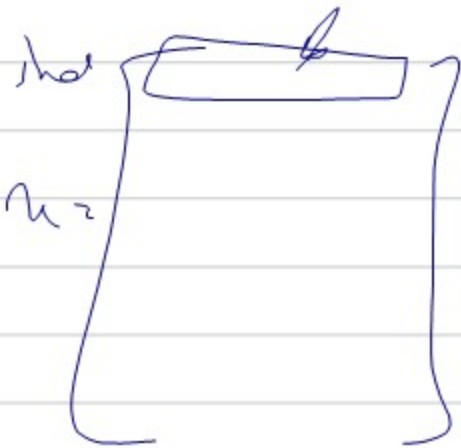
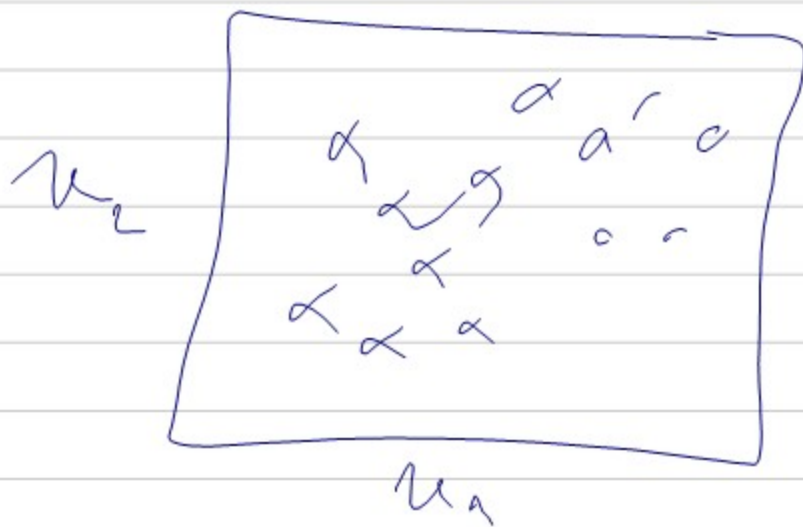
`scd = MinMaxScaler()`

`scd = scd.fit_transformer(x_train)`
`x_test`

تاریخ: Standard Scaler ②
 معینیت و دایریت

$$y = \frac{(x - \text{mean})}{\text{std}}$$

Standard deviation



$0 \Rightarrow 1, 1 \Rightarrow 0$
 $0 \Rightarrow 0, 1 \Rightarrow 1$

Confusion matrix

$2 \times 2 \Rightarrow 2 \times 2$

\hat{P}
 \hat{y}

$t=y$

	$\hat{y}=0$	$\hat{y}=1$
$y=0$	4 TP	2 FN
$y=1$	1 FP	3 TN

$\Rightarrow P_{ie}$

$$ACC = \frac{TP + TN}{TP + FP + FN + TN}$$

sensitivity $\gamma = \frac{TP}{TP + FN}$

precision $= \frac{TP}{TP + FP}$ ✓