LOGISTIC CLASSIFICATION AND SOFTMAX

REMINDER Logistic and softmax

LOGISTIC

- Probabilistic interpretation of the two-class linear classification.
- Classifier:

$$\mathbf{h}_{\mathbf{w}}(\mathbf{x}) = p(C_1|\mathbf{x}) = \sigma(\mathbf{w}^{\mathrm{T}}\mathbf{x})$$
 where $\sigma(a) = \frac{1}{1 + \exp(-a)}$ (logistic function).

• Training:

$$\max_{\mathbf{w}} p(\mathbf{y}|\mathbf{w})$$

where

$$p(\mathbf{y}|\mathbf{w}) = \prod_{n=1}^{N} h^{(n)} y^{(n)} \cdot \left(1 - h^{(n)}\right)^{\left(1 - y^{(n)}\right)}$$
Real label of *n*th datapoint of *n*th datapoint

SOFTMAX

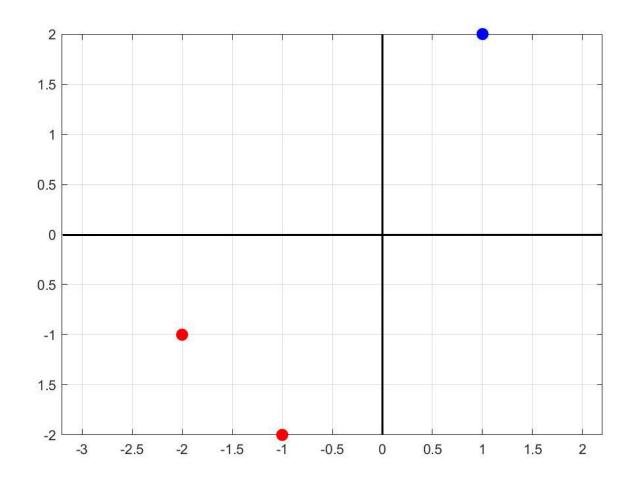
Likelihood

EXERCISE 2

LOGISTIC CLASSIFICATION

Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

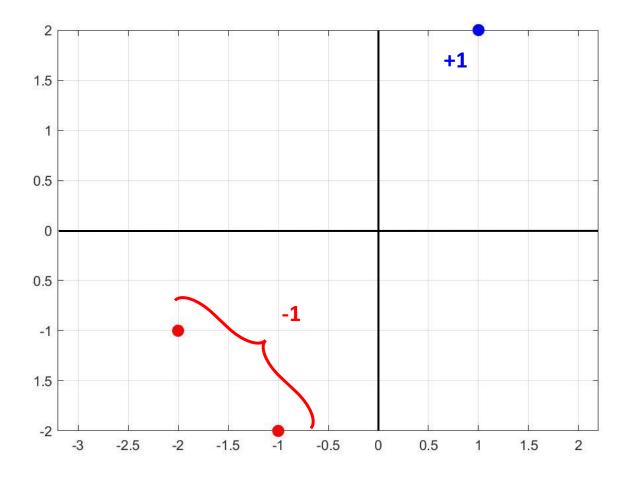
(a) Plot the points and write the parametric form of a logistic classifier $h_w(x)$. What is the difference with a linear classifier?



$$h_{\mathbf{w}}(\mathbf{x}) = ?$$

Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

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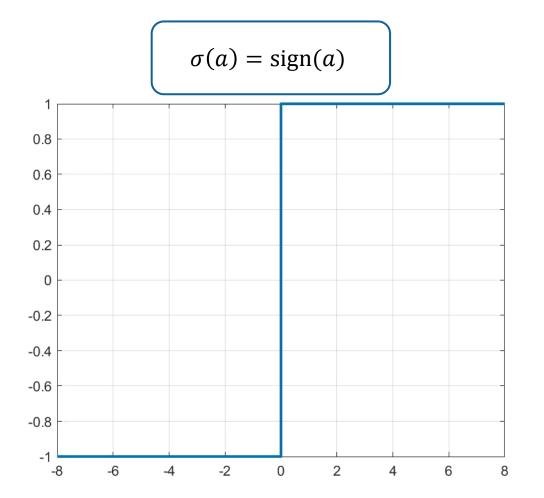
$$h_{\mathbf{w}}(\mathbf{x}) = \sigma(\mathbf{w}^{\mathrm{T}}\mathbf{x})$$

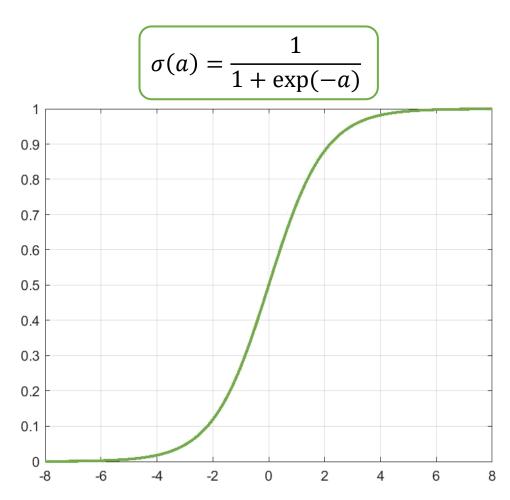
where
$$\mathbf{w}^{\mathrm{T}}\mathbf{x} = w_0 + w_1x_1 + w_2x_2$$

and $\sigma(a) = \frac{1}{1 + \exp(-a)}$

Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

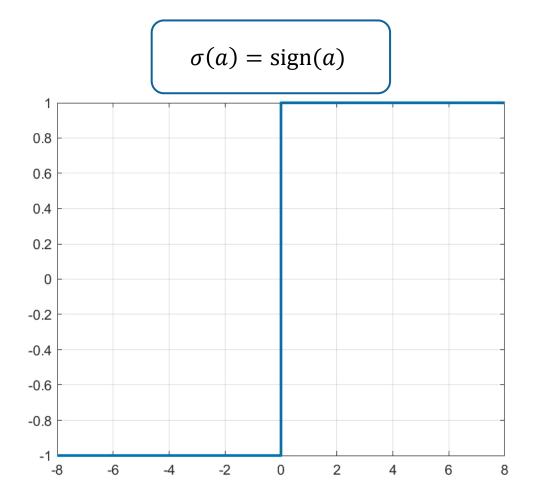
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Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

(b) Labels 1 and -1 are not adequate when solving a two-class problem with logistic regression. Why? Which labels should we choose?



$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

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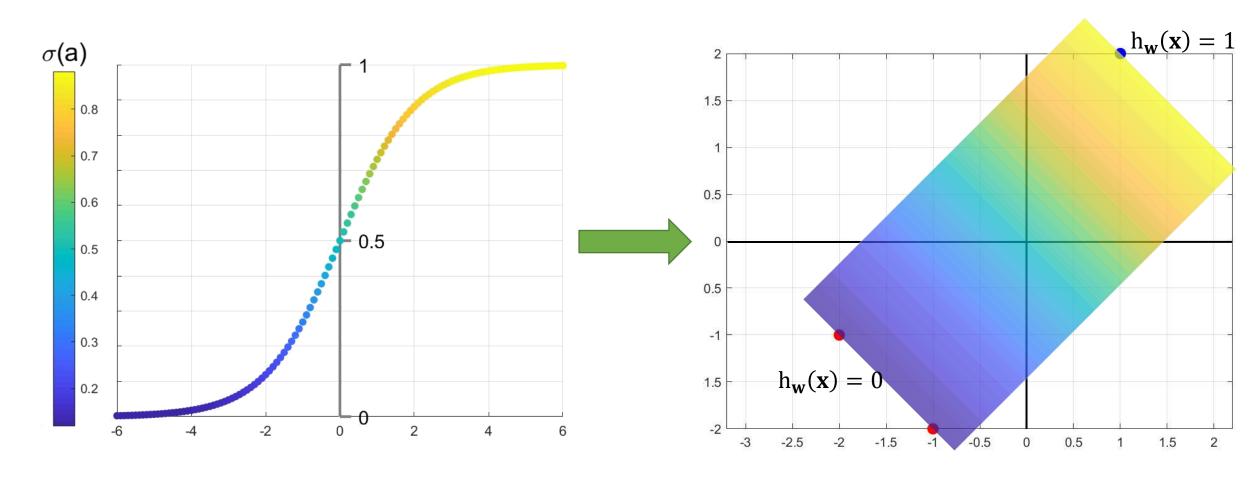
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$$h_{\mathbf{w}}(\mathbf{x}) = \sigma(\mathbf{w}^{\mathrm{T}}\mathbf{x})$$

Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

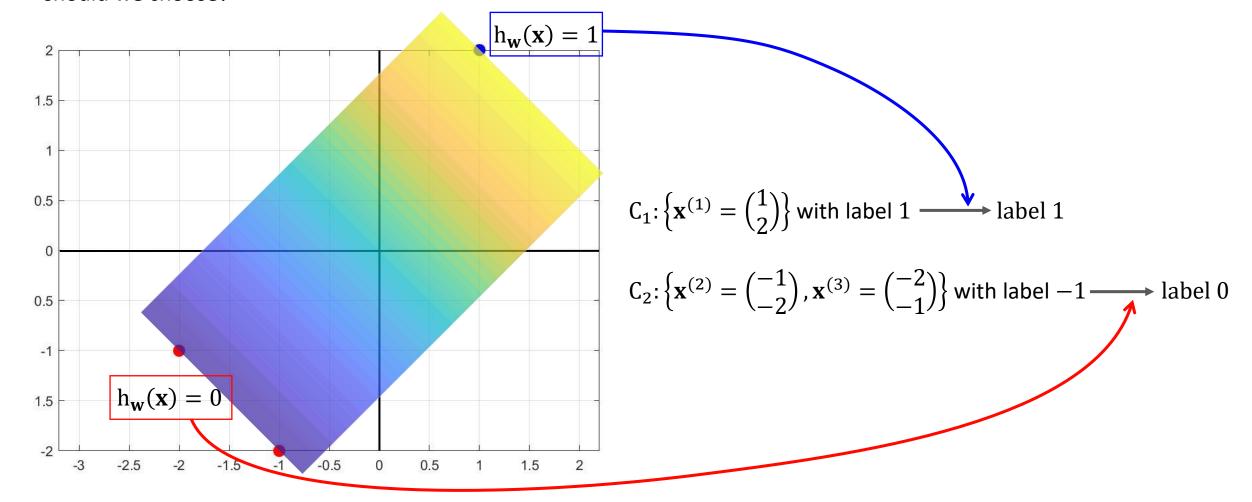
(b) Labels 1 and -1 are not adequate when solving a two-class problem with logistic regression. Why? Which labels should we choose?



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(c) Write the error function that is minimized when estimating the logistic classifier that separates the given data and develop it.

$$\mathbb{E}(\mathbf{w}) = ?$$

Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

(c) Write the error function that is minimized when estimating the logistic classifier that separates the given data and develop it.

$$\max_{\mathbf{w}} p(\mathbf{y}|\mathbf{w}) \quad \text{where} \quad p(\mathbf{y}|\mathbf{w}) = \prod_{n=1}^{N} h^{(n)} \mathbf{y}^{(n)} \cdot \left(1 - h^{(n)}\right)^{\left(1 - \mathbf{y}^{(n)}\right)}$$

is equivalent to

$$h^{(n)} = h_{\mathbf{w}}(\mathbf{x}^{(n)}) = \sigma(\mathbf{w}^{\mathrm{T}}\mathbf{x}^{(n)}) = \frac{1}{1 + \exp(\mathbf{w}^{\mathrm{T}}\mathbf{x}^{(n)})}$$

the prediction of the nth point

$$\min_{\mathbf{w}} \mathbb{E}(\mathbf{w}) \qquad \text{where} \qquad \mathbb{E}(\mathbf{w}) = -\ln p(\mathbf{y}|\mathbf{w}) = -\sum_{n=1}^{N} y^{(n)} \cdot \ln h^{(n)} + \left(1 - y^{(n)}\right) \ln \left(1 - h^{(n)}\right)$$

Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

(d) (Optional) Derive the expression of the error from the previous exercise with respect to the weight vector.

$$\mathbb{E}(\mathbf{w}) = -\ln p(\mathbf{y}|\mathbf{w}) = -\sum_{n=1}^{N} y^{(n)} \cdot \ln h^{(n)} + (1 - y^{(n)}) \ln(1 - h^{(n)})$$

$$\frac{\partial \mathbb{E}(\mathbf{w})}{\partial \mathbf{w}} = ? \qquad \dots \text{OPTIONAL HOMEWORK } \dots$$

Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

(e) (Jupyter) Generate a gradient descend algorithm with ridge regression. To do so, you only have to add to the gradient an extra term λw , where λ is the regularization parameter. Plot the data and the resulting linear classifier in the same figure.



Until convergence:

Update:
$$\mathbf{w}_{new} = \mathbf{w}_{old} - \alpha \frac{\partial \mathbb{E}(\mathbf{w})}{\partial \mathbf{w}} \mathbf{w} = \mathbf{w}_{old}$$

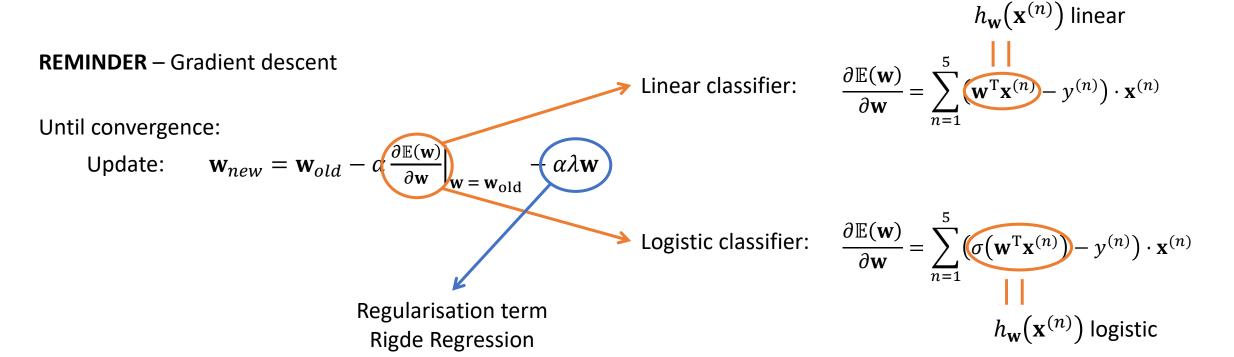
Linear classifier:
$$\frac{\partial \mathbb{E}(\mathbf{w})}{\partial \mathbf{w}} = \sum_{n=1}^{5} (\mathbf{w}^{T} \mathbf{x}^{(n)} - y^{(n)}) \cdot \mathbf{x}^{(n)}$$

 $h_{\mathbf{w}}(\mathbf{x}^{(n)})$ linear

Logistic classifier:
$$\frac{\partial \mathbb{E}(\mathbf{w})}{\partial \mathbf{w}} = \sum_{n=1}^{5} (\sigma(\mathbf{w}^{\mathsf{T}}\mathbf{x}^{(n)}) - y^{(n)}) \cdot \mathbf{x}^{(n)}$$
$$| | h_{\mathbf{w}}(\mathbf{x}^{(n)}) | \text{ logistic}$$

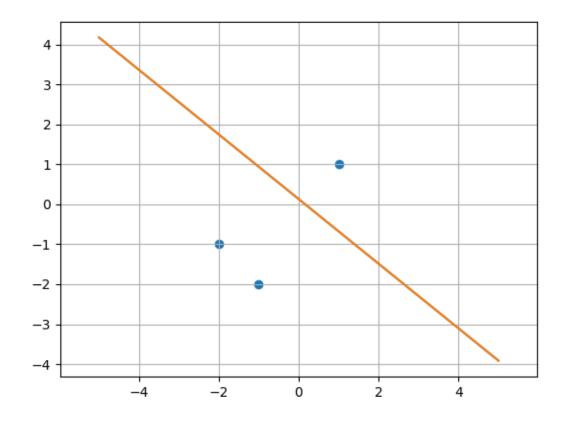
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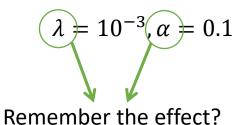
(e) (Jupyter) Generate a gradient descend algorithm with ridge regression. To do so, you only have to add to the gradient an extra term $\lambda \mathbf{w}$, where λ is the regularization parameter. Plot the data and the resulting linear classifier in the same figure.



Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

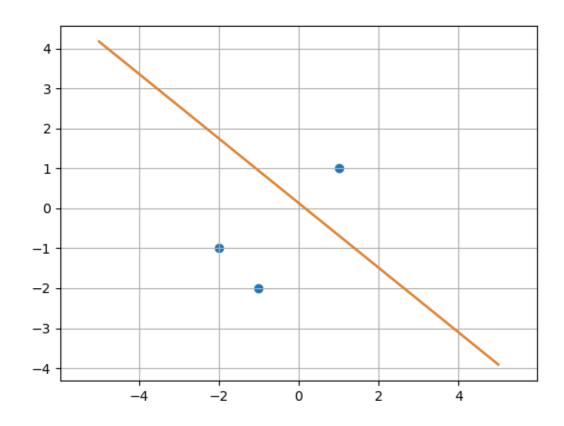
(e) (Jupyter) Generate a gradient descend algorithm with ridge regression. To do so, you only have to add to the gradient an extra term $\lambda \mathbf{w}$, where λ is the regularization parameter. Plot the data and the resulting linear classifier in the same figure.





Consider two classes: the class C_1 : $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}\right\}$ with label 1 and C_2 : $\left\{\mathbf{x}^{(2)} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} -2 \\ -1 \end{pmatrix}\right\}$ with label -1

(f) (Jupyter, Optional) Estimate the logistic classifier using the function sklearn.linear model.LogisticRegression. Draw the data points and the resulting linear classier in the same figure.



Should be similar to ours.

Even tough it will depend on the regularisation parameter λ and the learning rate α .

EXERCISE 3

SOFTMAX CLASSIFICATION

REMINDER Logistic and softmax

LOGISTIC

- **Probabilistic** interpretation of the **two-class** linear classification.
- Classifier:

$$h_{\mathbf{w}}(\mathbf{x}) = p(C_1|\mathbf{x}) = \sigma(\mathbf{w}^{\mathrm{T}}\mathbf{x})$$
where $\sigma(a) = \frac{1}{1 + \exp(-a)}$ (logistic function).

Training:

$$\min_{\mathbf{w}} \mathbb{E}(\mathbf{w})$$

where

$$\mathbb{E}(\mathbf{w}) = -\sum_{n=1}^{N} y^{(n)} \cdot \ln h^{(n)} + (1 - y^{(n)}) \ln(1 - h^{(n)})$$
Log-likelihood

SOFTMAX

- **Generalisation** of the logistic to multi-class classification.
- Classifier:

assign **x** to class
$$C_k$$
 if $h_k(x) > h_l(x) \forall l \neq k$

where

$$h_k(\mathbf{x}) = p(C_k|\mathbf{x}) = \frac{\exp(\mathbf{w}_k^T\mathbf{x})}{\sum_{j=1}^K \exp(\mathbf{w}_j^T\mathbf{x})}.$$
 Softmax

function

Training:

$$\min_{\mathbf{w}} \mathbb{E}(\mathbf{w})$$

where

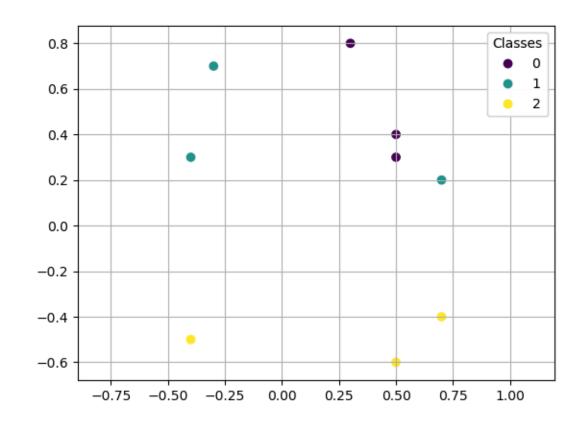
$$\mathbb{E}(\mathbf{w}) = -\sum_{n=1}^{N} \sum_{k=1}^{K} y_k^{(n)} \cdot \ln h_k^{(n)}$$
Cross-entropy

Consider three classes:

Class 0
$$C_0$$
: $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{\mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{\mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$



Assume that the values obtained for the three discriminants are $\mathbf{w}_0 = \begin{pmatrix} -0.3 \\ 0.87 \\ 1.47 \end{pmatrix}$, $\mathbf{w}_1 = \begin{pmatrix} -0.01 \\ 0.58 \\ 1.02 \end{pmatrix}$ and $\mathbf{w}_2 = \begin{pmatrix} 0.43 \\ -1.90 \\ 0.33 \end{pmatrix}$

(a) Draw the points and codify the class of the vectors according to 1 - of - K encoding.

$$1 - \text{of} - K$$
 encoding for class j , target output $y = (0, ..., 0, 1, 0, ..., 0)$
a.k.a hot encoding or dummy encoding j th coefficient

Class 0
$$C_0$$
: $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}, \longrightarrow \mathbf{y}^{(1)} = \mathbf{y}^{(2)} = \mathbf{y}^{(3)} = ?$
Class 1 C_1 : $\left\{\mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}, \longrightarrow \mathbf{y}^{(4)} = \mathbf{y}^{(5)} = \mathbf{y}^{(6)} = ?$
Class 2 C_2 : $\left\{\mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\} \longrightarrow \mathbf{y}^{(7)} = \mathbf{y}^{(8)} = \mathbf{y}^{(9)} = ?$

(a) Draw the points and codify the class of the vectors according to 1 - of - K encoding.

$$1 - \text{of} - K$$
 encoding for class j , target output $y = (0, ..., 0, 1, 0, ..., 0)$

$$j \text{th coefficient}$$

Class 0 C₀:
$$\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}, \longrightarrow \mathbf{y}^{(1)} = \mathbf{y}^{(2)} = \mathbf{y}^{(3)} = (1,0,0)^{\mathrm{T}}$$

Class 1 C₁: $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}, \longrightarrow \mathbf{y}^{(4)} = \mathbf{y}^{(5)} = \mathbf{y}^{(6)} = (0,1,0)^{\mathrm{T}}$

Class 2 C₂: $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\} \longrightarrow \mathbf{y}^{(7)} = \mathbf{y}^{(8)} = \mathbf{y}^{(9)} = (0,0,1)^{\mathrm{T}}$

Class 0
$$C_0$$
: $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{\mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{\mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

(b) Determine at which class the calculated softmax will classify the points raw the points $\mathbf{x}^{(1)}$, $\mathbf{x}^{(4)}$ and $\mathbf{x}^{(7)}$.

REMINDER – Softmax

$$h_k(\mathbf{x}) = p(C_k|\mathbf{x}) = \frac{\exp(\mathbf{w}_k^T\mathbf{x})}{\sum_{j=1}^K \exp(\mathbf{w}_j^T\mathbf{x})} \quad \forall k = 0,1,2$$
Probability of \mathbf{x} of being class k .

We classify the point **x** to the class with **higher probability**.

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

(b) Determine at which class the calculated softmax will classify the points raw the points $\mathbf{x}^{(1)}$, $\mathbf{x}^{(4)}$ and $\mathbf{x}^{(7)}$.

REMINDER – Softmax

$$p(C_k|\mathbf{x}) = \frac{\exp(\mathbf{w}_k^T \mathbf{x})}{\sum_{i=1}^K \exp(\mathbf{w}_i^T \mathbf{x})} \quad \forall k = 0,1,2$$

Efficient way of computing softmax output

$$\mathbf{w}_{0}^{T}\mathbf{x}$$

$$\mathbf{w}_{1}^{T}\mathbf{x}$$

$$\mathbf{w}_{1}^{T}\mathbf{x}$$

$$\mathbf{w}_{2}^{T}\mathbf{x}$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

(b) Determine at which class the calculated softmax will classify the points raw the points $\mathbf{x}^{(1)}$, $\mathbf{x}^{(4)}$ and $\mathbf{x}^{(7)}$.

1

$$\begin{pmatrix} \mathbf{w}_0^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathrm{T}} \mathbf{x}^{(1)} \end{pmatrix} = \begin{pmatrix} \cdots & \mathbf{w}_0^{\mathrm{T}} & \cdots \\ \cdots & \mathbf{w}_1^{\mathrm{T}} & \cdots \\ \cdots & \mathbf{w}_2^{\mathrm{T}} & \cdots \end{pmatrix} \cdot \mathbf{x}^{(1)} = ?$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

Bias term:
$$\mathbf{w}^{T}\mathbf{x} = (w_{0} + w_{1}x_{1} + w_{2}x_{2})$$

$$\begin{pmatrix} \mathbf{w}_{0}^{T}\mathbf{x}^{(1)} \\ \mathbf{w}_{1}^{T}\mathbf{x}^{(1)} \\ \mathbf{w}_{2}^{T}\mathbf{x}^{(1)} \end{pmatrix} = \begin{pmatrix} \cdots & \mathbf{w}_{0}^{T} & \cdots \\ \cdots & \mathbf{w}_{1}^{T} & \cdots \\ \cdots & \mathbf{w}_{2}^{T} & \cdots \end{pmatrix} \cdot \mathbf{x}^{(1)} = \begin{pmatrix} -0.3 & 0.87 & 1.47 \\ -0.01 & 0.58 & 1.02 \\ 0.43 & -1.90 & 0.33 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 0.5 \\ 0.4 \end{pmatrix} = \begin{pmatrix} 0.72 \\ 0.69 \\ -0.39 \end{pmatrix}$$

Bias term:
$$\mathbf{w}^{T}\mathbf{x} = w_{0} + w_{1}x_{1} + w_{2}x_{2}$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

$$\exp\begin{pmatrix} \mathbf{w}_0^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathrm{T}} \mathbf{x}^{(1)} \end{pmatrix} = ?$$

$$\begin{pmatrix} \mathbf{w}_0^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathrm{T}} \mathbf{x}^{(1)} \end{pmatrix} = \begin{pmatrix} 0.72 \\ 0.69 \\ -0.39 \end{pmatrix}$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

$$\exp\begin{pmatrix} \mathbf{w}_0^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathrm{T}} \mathbf{x}^{(1)} \\ \dots \mathbf{T}_{-1}(1) \end{pmatrix} = \begin{pmatrix} 2.06 \\ 1.99 \\ 0.68 \end{pmatrix}$$

$$\begin{pmatrix} \mathbf{w}_0^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathrm{T}} \mathbf{x}^{(1)} \end{pmatrix} = \begin{pmatrix} 0.72 \\ 0.69 \\ -0.39 \end{pmatrix}$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

$$\exp\begin{pmatrix} \mathbf{w}_0^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathrm{T}} \mathbf{x}^{(1)} \end{pmatrix} = \begin{pmatrix} 2.06 \\ 1.99 \\ 0.68 \end{pmatrix}$$

sum
$$\left[\exp \begin{pmatrix} \mathbf{w}_0^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathrm{T}} \mathbf{x}^{(1)} \end{pmatrix} \right] = ?$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

$$\exp\begin{pmatrix} \mathbf{w}_0^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathrm{T}} \mathbf{x}^{(1)} \end{pmatrix} = \begin{pmatrix} 2.06 \\ 1.99 \\ 0.68 \end{pmatrix}$$

sum
$$\left[\exp \begin{pmatrix} \mathbf{w}_0^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathrm{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathrm{T}} \mathbf{x}^{(1)} \end{pmatrix} \right] = 2.06 + 1.99 + 0.68 = 4.73$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

$$\begin{pmatrix} p(C_0|\mathbf{x}^{(1)}) \\ p(C_1|\mathbf{x}^{(1)}) \\ p(C_2|\mathbf{x}^{(1)}) \end{pmatrix} = \frac{\exp\begin{pmatrix} \mathbf{w}_0^T\mathbf{x}^{(1)} \\ \mathbf{w}_1^T\mathbf{x}^{(1)} \\ \mathbf{w}_2^T\mathbf{x}^{(1)} \end{pmatrix}}{\sup \left[\exp\begin{pmatrix} \mathbf{w}_0^T\mathbf{x}^{(1)} \\ \mathbf{w}_1^T\mathbf{x}^{(1)} \\ \mathbf{w}_2^T\mathbf{x}^{(1)} \end{pmatrix} \right]} = ?$$

$$\exp\begin{pmatrix} \mathbf{w}_0^{\mathsf{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathsf{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathsf{T}} \mathbf{x}^{(1)} \end{pmatrix} = \begin{pmatrix} 2.06 \\ 1.99 \\ 0.68 \end{pmatrix} \qquad \sup\left[\exp\begin{pmatrix} \mathbf{w}_0^{\mathsf{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_1^{\mathsf{T}} \mathbf{x}^{(1)} \\ \mathbf{w}_2^{\mathsf{T}} \mathbf{x}^{(1)} \end{pmatrix} \right] = 4.73$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

(b) Determine at which class the calculated softmax will classify the points raw the points
$$\mathbf{x}^{(1)}$$
, $\mathbf{x}^{(4)}$ and $\mathbf{x}^{(7)}$.

$$\begin{pmatrix} p(\mathcal{C}_0|\mathbf{x}^{(1)}) \\ p(\mathcal{C}_1|\mathbf{x}^{(1)}) \\ p(\mathcal{C}_2|\mathbf{x}^{(1)}) \end{pmatrix} = \frac{\exp\begin{pmatrix} \mathbf{w}_0^T\mathbf{x}^{(1)} \\ \mathbf{w}_1^T\mathbf{x}^{(1)} \\ \mathbf{w}_2^T\mathbf{x}^{(1)} \end{pmatrix}}{\sup \left[\exp\begin{pmatrix} \mathbf{w}_0^T\mathbf{x}^{(1)} \\ \mathbf{w}_1^T\mathbf{x}^{(1)} \\ \mathbf{w}_2^T\mathbf{x}^{(1)} \end{pmatrix} \right]} = \begin{pmatrix} \frac{2.06}{4.73} \\ \frac{4.73}{0.68} \\ \frac{0.44}{4.73} \end{pmatrix} = \begin{pmatrix} \frac{0.44}{0.42} \\ 0.14 \end{pmatrix}$$
The largest probability is for class 0, then, this classifier would assign $\mathbf{x}^{(1)}$ to class 0.

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

(b) Determine at which class the calculated softmax will classify the points raw the points $\mathbf{x}^{(1)}$, $\mathbf{x}^{(4)}$ and $\mathbf{x}^{(7)}$.

Repeat for $\mathbf{x}^{(4)}$ and $\mathbf{x}^{(7)}$...

$$\begin{pmatrix} p(C_0|\mathbf{x}^{(4)}) \\ p(C_1|\mathbf{x}^{(4)}) \\ p(C_2|\mathbf{x}^{(4)}) \end{pmatrix} = \begin{pmatrix} 0.15 \\ 0.19 \\ 0.66 \end{pmatrix}$$
$$\mathbf{x}^{(4)} \text{ to class 2}$$

$$\begin{pmatrix} p(C_0|\mathbf{x}^{(7)}) \\ p(C_1|\mathbf{x}^{(7)}) \\ p(C_2|\mathbf{x}^{(7)}) \end{pmatrix} = \begin{pmatrix} 0.36 \\ 0.47 \\ 0.17 \end{pmatrix}$$
$$\mathbf{x}^{(7)} \text{ to class } 1$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

(c) Calculate and plot the discriminant surfaces.

REMINDER – Discriminant surfaces (DS)

DS between class j and class k (DS_{jk}):

$$\mathrm{DS}_{jk} = \{\mathbf{x} \mid g_j(\mathbf{x}) = g_k(\mathbf{x})\}$$
 where $g_k(\mathbf{x}) = \mathbf{w}_k^\mathrm{T}\mathbf{x}$ (analogously for j)

The set of points \mathbf{x} that satisfy the condition $g_j(\mathbf{x}) = g_k(\mathbf{x})$.

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

$$\mathbf{w}_{0} = \begin{pmatrix} -0.3 \\ 0.87 \\ 1.47 \end{pmatrix}, \mathbf{w}_{1} = \begin{pmatrix} -0.01 \\ 0.58 \\ 1.02 \end{pmatrix}$$
$$\mathbf{w}_{2} = \begin{pmatrix} 0.43 \\ -1.90 \\ 0.33 \end{pmatrix}$$

(c) Calculate and plot the discriminant surfaces.

$$g_k(\mathbf{x}) = \mathbf{w}_k^{\mathrm{T}} \mathbf{x}$$

$$DS_{01} = \{ \mathbf{x} \mid g_0(\mathbf{x}) = g_1(\mathbf{x}) \} = \{ \mathbf{x} \mid ? \}$$

$$DS_{02} = \{ \mathbf{x} \mid g_0(\mathbf{x}) = g_2(\mathbf{x}) \} = \{ \mathbf{x} \mid ? \}$$

$$DS_{12} = \{ \mathbf{x} \mid g_1(\mathbf{x}) = g_2(\mathbf{x}) \} = \{ \mathbf{x} \mid ? \}$$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

$$\mathbf{w}_{0} = \begin{pmatrix} -0.3 \\ 0.87 \\ 1.47 \end{pmatrix}, \mathbf{w}_{1} = \begin{pmatrix} -0.01 \\ 0.58 \\ 1.02 \end{pmatrix}$$
$$\mathbf{w}_{2} = \begin{pmatrix} 0.43 \\ -1.90 \\ 0.33 \end{pmatrix}$$

(c) Calculate and plot the discriminant surfaces.

$$g_k(\mathbf{x}) = \mathbf{w}_k^{\mathrm{T}} \mathbf{x}$$

$$DS_{01} = \{\mathbf{x} \mid g_0(\mathbf{x}) = g_1(\mathbf{x})\} = \{\mathbf{x} \mid -0.3 + 0.87x_1 + 1.47x_2 = -0.01 + 0.58x_1 + 1.02x_2\}$$

$$= \{\mathbf{x} \mid -0.29 + 0.29x_1 + 0.45x_2 = 0\}$$

$$DS_{02} = \{\mathbf{x} \mid g_0(\mathbf{x}) = g_2(\mathbf{x})\} = \{\mathbf{x} \mid -0.73 + 2.77x_1 + 1.14x_2 = 0\}$$

$$DS_{02} = \{g_0(x) - g_2(x) = 0\}$$

$$DS_{03} = \{g_0(x) - g_2(x) = 0\}$$

$$DS_{04} = \{g_0(x) - g_1(x) = 0\}$$

$$\text{Then if } DS_{01} > 0 \Rightarrow g_0 > g_1$$

$$\text{if } DS_{01} < 0 \Rightarrow g_0 < g_1$$

$$\text{if } DS_{01} < 0 \Rightarrow g_0 < g_1$$

 $DS_{12} = \{g_1(x) - g_2(x) = 0\}$

Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

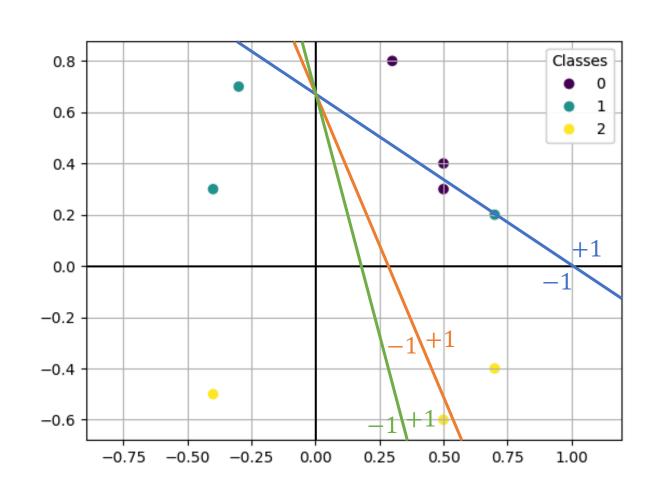
$$\mathbf{w}_{0} = \begin{pmatrix} -0.3 \\ 0.87 \\ 1.47 \end{pmatrix}, \mathbf{w}_{1} = \begin{pmatrix} -0.01 \\ 0.58 \\ 1.02 \end{pmatrix}$$
$$\mathbf{w}_{2} = \begin{pmatrix} 0.43 \\ -1.90 \\ 0.33 \end{pmatrix}$$

(c) Calculate and plot the discriminant surfaces.

$$DS_{01} = \{ \mathbf{x} \mid -0.29 + 0.29x_1 + 0.45x_2 = 0 \}$$

$$DS_{02} = \{ \mathbf{x} \mid -0.73 + 2.77x_1 + 1.14x_2 = 0 \}$$

$$DS_{12} = \{ \mathbf{x} \mid -0.44 + 2.48x_1 + 0.69x_2 = 0 \}$$



Class 0
$$C_0$$
: $\left\{ \mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,

Class 1 C_1 : $\left\{ \mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,

Class 2 C_2 : $\left\{ \mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

(d) Calculate the error for the given solutions.

REMINDER – CROSS-ENTROPY

$$\mathbb{E}(\mathbf{w}_0,\mathbf{w}_1,\mathbf{w}_2) = -\sum_{n=1}^N \sum_{k=1}^K y_k^{(n)} \cdot \ln h_k^{(n)} \qquad \text{where} \qquad \begin{cases} y_k^{(n)} \left\{ = 1 & \text{if } \mathbf{x}^{(n)} \text{ belongs to class } k \\ = 0 & \text{otherwise} \end{cases} \\ h_k^{(n)} = p(C_k | \mathbf{x}^{(n)}) \qquad \qquad \text{Alreading exercises} \end{cases}$$

$$y_k^{(n)} \begin{cases} = 1 & if \mathbf{x}^{(n)} \text{ belongs to class } k \\ = 0 & \text{otherwise} \end{cases}$$

$$h_k^{(n)} = p(C_k | \mathbf{x}^{(n)})$$
 Already computed in exercise b

Class 0
$$C_0$$
: $\left\{\mathbf{x}^{(1)} = \begin{pmatrix} 0.5 \\ 0.4 \end{pmatrix}, \mathbf{x}^{(2)} = \begin{pmatrix} 0.8 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(3)} = \begin{pmatrix} 0.3 \\ 0.8 \end{pmatrix} \right\}$,
Class 1 C_1 : $\left\{\mathbf{x}^{(4)} = \begin{pmatrix} -0.4 \\ 0.3 \end{pmatrix}, \mathbf{x}^{(5)} = \begin{pmatrix} -0.3 \\ 0.7 \end{pmatrix}, \mathbf{x}^{(6)} = \begin{pmatrix} 0.7 \\ 0.2 \end{pmatrix} \right\}$,
Class 2 C_2 : $\left\{\mathbf{x}^{(7)} = \begin{pmatrix} 0.7 \\ -0.4 \end{pmatrix}, \mathbf{x}^{(8)} = \begin{pmatrix} 0.5 \\ -0.6 \end{pmatrix}, \mathbf{x}^{(9)} = \begin{pmatrix} -0.4 \\ -0.5 \end{pmatrix} \right\}$

(d) Calculate the error for the given solutions.

REMINDER – CROSS-ENTROPY

$$\mathbb{E}(\mathbf{w}_{0}, \mathbf{w}_{1}, \mathbf{w}_{2}) = -\sum_{n=1}^{N} \sum_{k=1}^{K} y_{k}^{(n)} \cdot \ln h_{k}^{(n)} = -\sum_{n=1}^{N} \mathbf{y}^{(n)^{\mathrm{T}}} \cdot \ln \mathbf{h}^{(n)} = -(1 \quad 0 \quad 0) \begin{pmatrix} \ln p(\mathcal{C}_{0}|\mathbf{x}^{(1)}) \\ \ln p(\mathcal{C}_{1}|\mathbf{x}^{(1)}) \\ \ln p(\mathcal{C}_{2}|\mathbf{x}^{(1)}) \end{pmatrix} - \dots = 9.55$$