Binary classification problems

Logistic regression from a neural networks perspective

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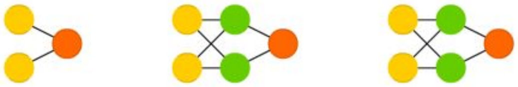
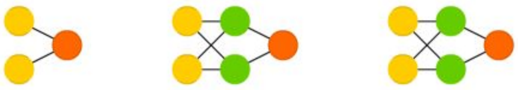
Binary classification problems

- the response variable **y** is **qualitative** and takes up one of two values
- binary traits (e.g. cases/controls, resistant/susceptible, true/false, etc.)
- **y** = **label** (a.k.a. dependent variable)
- **X** = matrix of **features** (continuous, categorical)

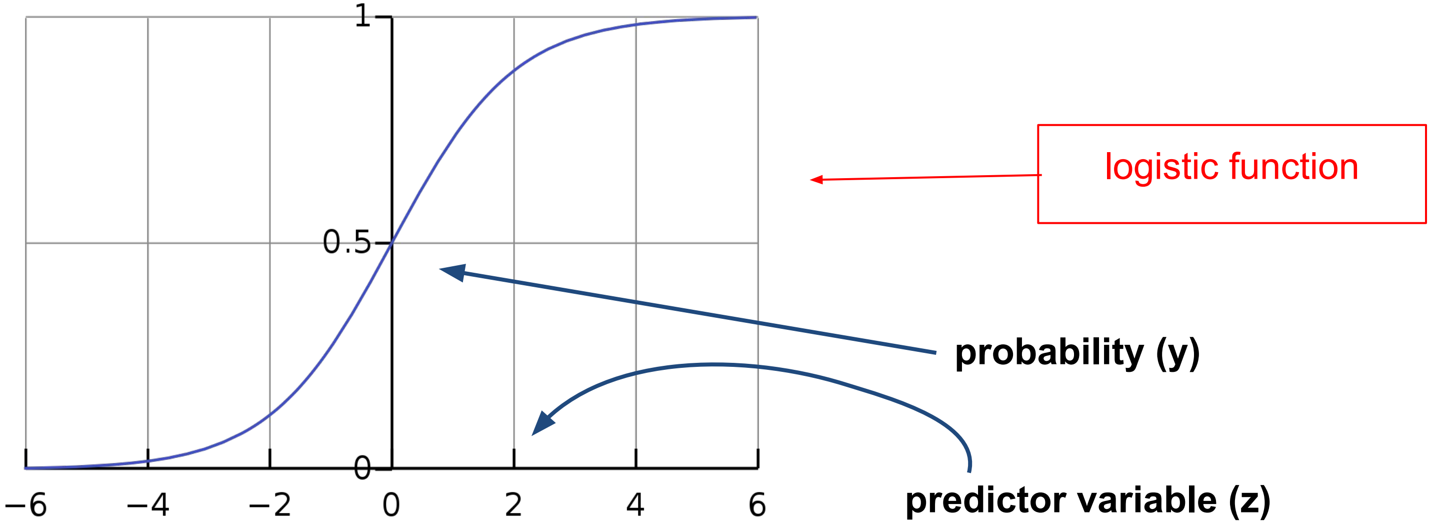


Binary classification problems

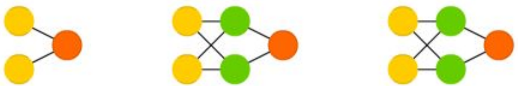
- the response variable **y** is **qualitative** and takes up one of two values
- binary traits (e.g. cases/controls, resistant/susceptible, true/false, etc.)
- **y** = **label** (a.k.a. dependent variable)
- **X** = matrix of **features** (continuous, categorical)
- we don't model the response directly, rather its **probability**: **P(y=1|x)**
- probabilities lie in [0,1] (not +/- infinity)



Binary classification problems



$$\frac{1}{1+e^{-z}} = \frac{1}{1+\frac{1}{e^z}} = \frac{e^z}{1+e^z}$$

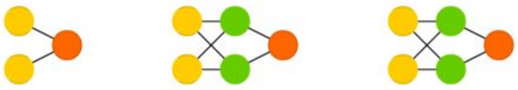


Logistic regression

- the logistic function is the basis for **logistic regression**
- **P(y=1|x)**
- **Z = β_0+β_1x**

$$P(y=1|x)=\sigma(z)=\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}$$

we see here the familiar **model coefficients** (from linear regression) to be estimated and then used for predictions



Logistic regression

odds

- a little bit of algebra:

$$\sigma(z) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}} \longrightarrow \frac{\sigma(z)}{1-\sigma(z)} = e^{\beta_0+\beta_1 x}$$

Logistic regression

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odds

$$\sigma(z) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}} \longrightarrow \frac{\sigma(z)}{1-\sigma(z)} = e^{\beta_0+\beta_1 x}$$

log(odds): logit

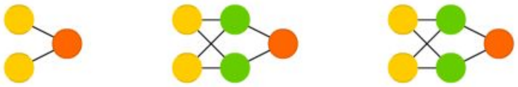
$$log\left(\frac{\sigma(z)}{1-\sigma(z)}\right) = logit(\sigma(z)) = \beta_0 + \beta_1 x$$

Logistic regression

- the **logit function** (log(odds)) is the **link function** between a linear expression of X and the probabilities of Y
- linear X expression (β_0+β_1x) → logit scale (continuous)
- logistic function: converts values on the logit scale back to probabilities

$$\begin{cases} logit(\sigma(z)) = \beta_0 + \beta_1 x \\ \sigma(\beta_0 + \beta_1 x) = P(y = 1|x) \end{cases}$$

our objective!



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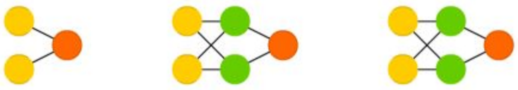
$$\begin{cases} logit(\sigma(z)) = \beta_0 + \beta_1 x \\ \sigma(\beta_0 + \beta_1 x) = P(y = 1|x) \end{cases}$$

Rings a bell?



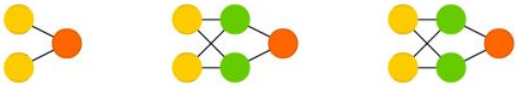
Estimating the coefficients

how do we obtain the model coefficients β?

- we need to define a **cost function** and then minimise it

observations	predictions
y	$\hat{y} = \sigma(\beta_0 + \beta_1 x)$

difference between observed and predicted values



Estimating the coefficients

how do we obtain the model coefficients β?

- we need to define a **cost function** and then minimise it
- $\hat{y} = \sigma(z)$

$$J(\beta) = \mathrm{Cost}\left(\hat{y}, y\right) = -\left(y \cdot log(\hat{y}) + (1 - y) \cdot log(1 - \hat{y})\right)$$

Cost function for logistic regression

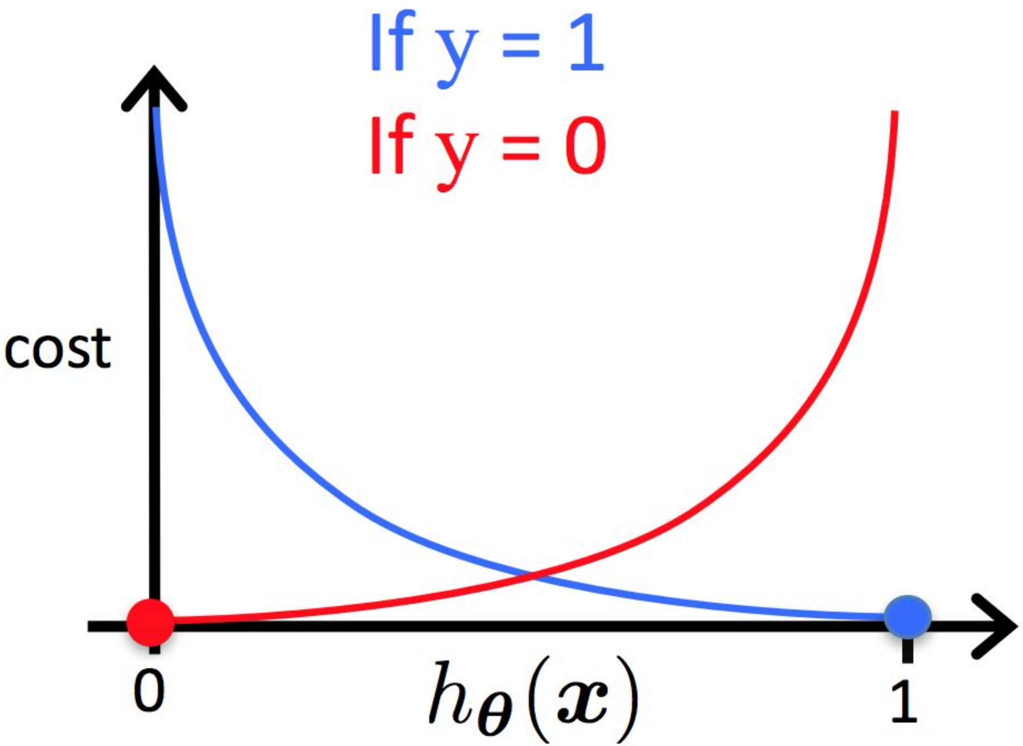
$$J(\beta) = \text{Cost}\,(\hat{y}, y) = -\,(y \cdot log(\hat{y}) + \cancel{(1 - y) \cdot log(1 - \hat{y})})$$

<u>if y = 1</u>

- y_hat → 1, cost → 0
- y_hat → 0 (but y = 1), cost → infinity

the opposite holds if y = 0

Cost function for logistic regression



From: https://datascience.stackexchange.com/questions/40982/logistic-regression-cost-function

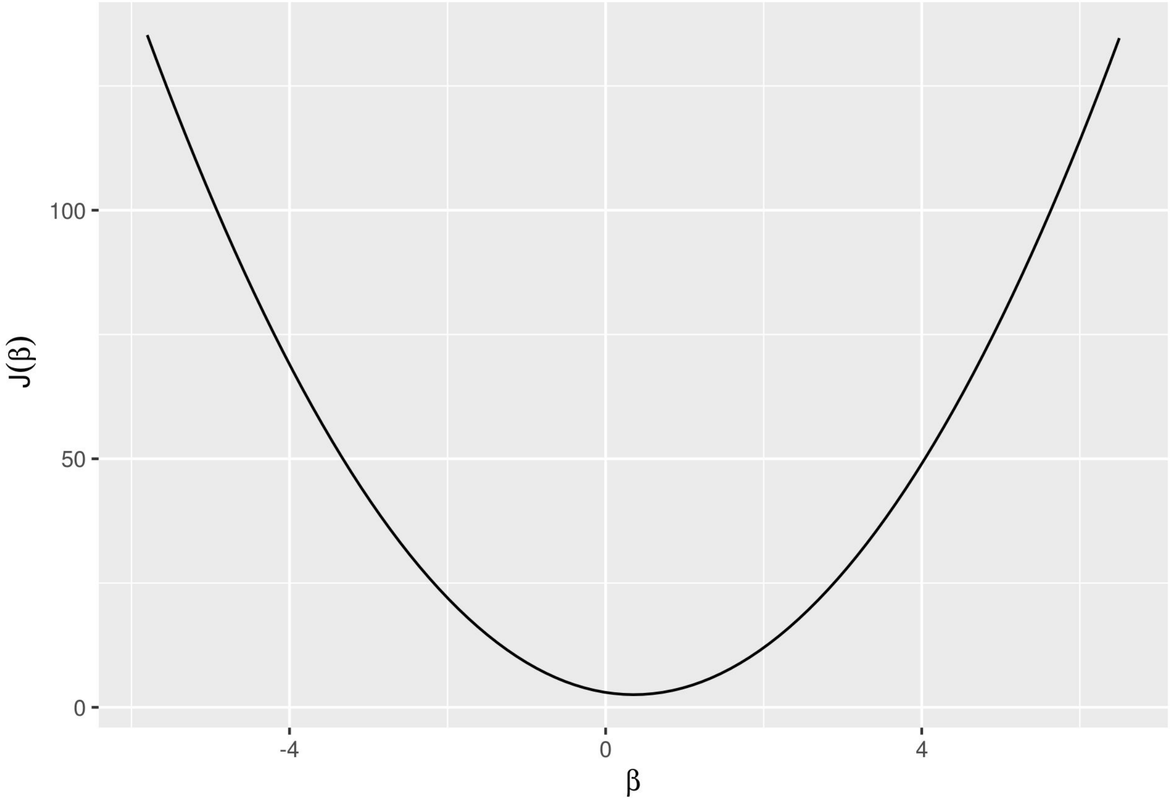
Minimising the cost function

$$\begin{cases} J(\beta) = -\left(y \cdot log(\hat{y}) + (1 - y) \cdot log(1 - \hat{y})\right) \\ \underset{\beta}{\text{minimize}}\, J(\beta) \end{cases}$$

Minimising the cost function

- the defined cost function is convex
- can be minimised by **gradient descent**
- machine learning perspective: gradient descent is a general algorithm to solve models
- alternatively:
    - maximum likelihood
    - non-linear least squares

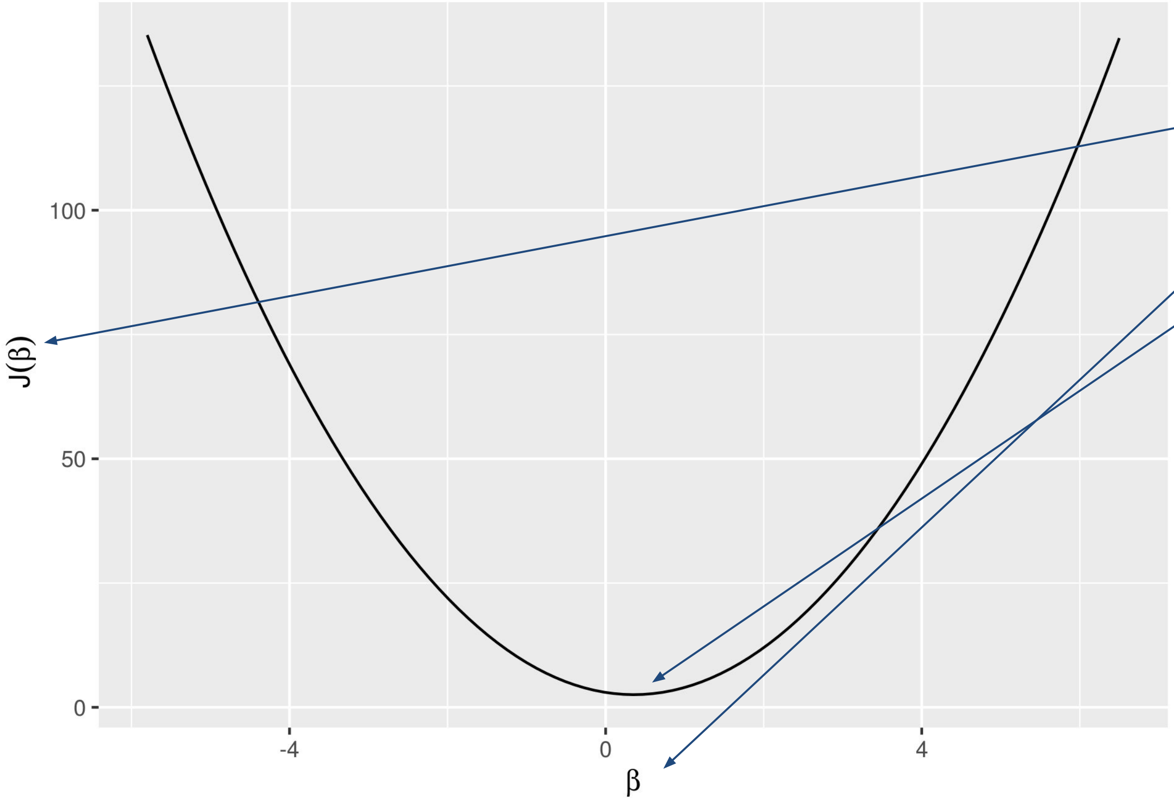
Minimise the cost function



Simple logistic regression (1 parameter):

$$z = \beta \cdot x$$

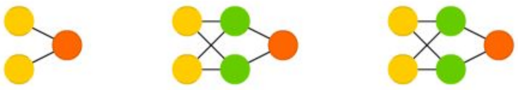
Minimise the cost function



1. loss function
2. model parameters
3. minimum

Simple logistic regression (1 parameter):

$$z = \beta \cdot x$$

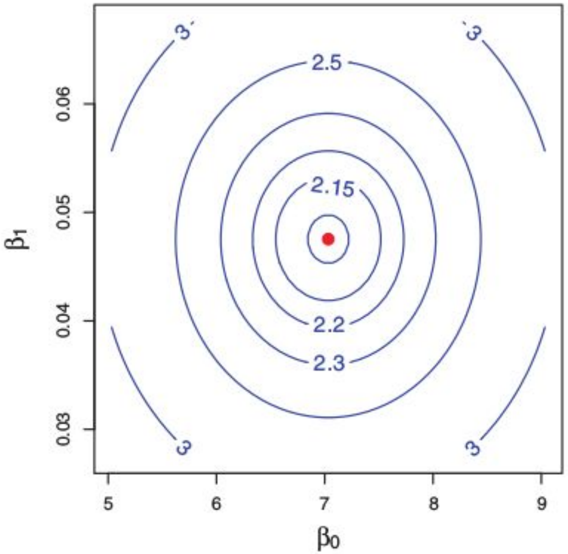


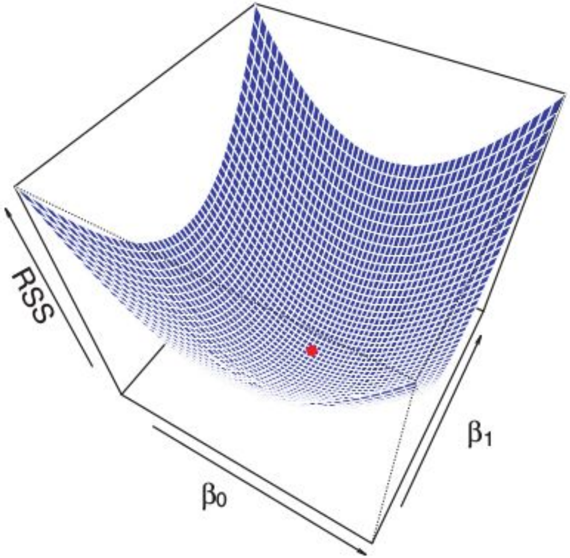
Minimise the cost function

Multiple logistic regression

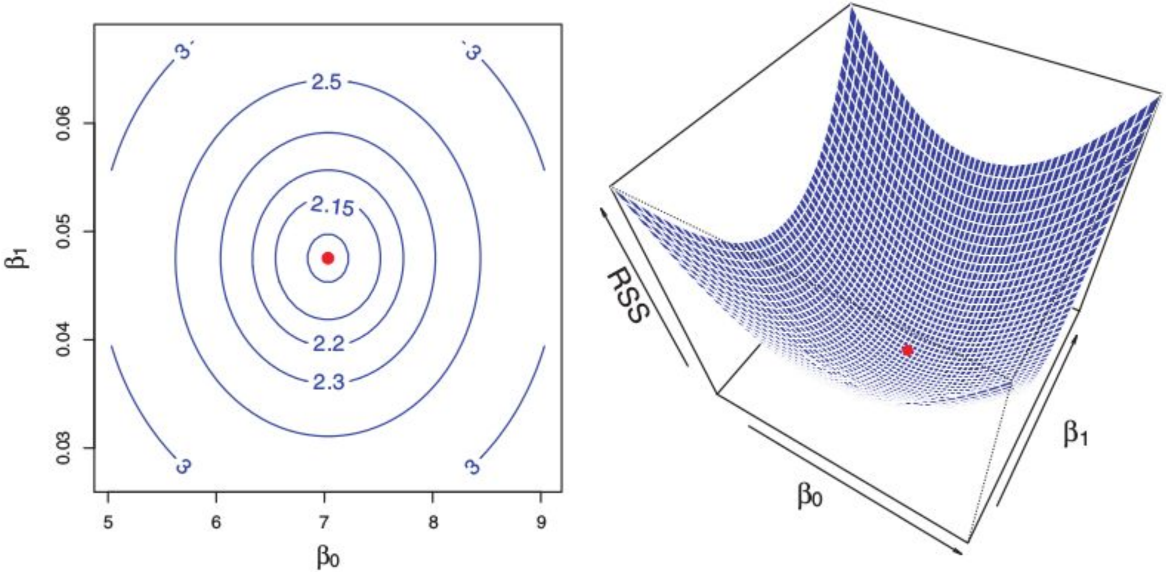
(e.g. 2 parameters):

$$y = \beta_0 + \beta_1 \cdot x$$





Minimise the cost function



Multiple logistic regression

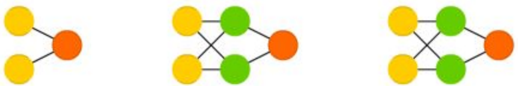
(e.g. 2 parameters):

$$y = \beta_0 + \beta_1 \cdot x$$

Multiple logistic regression (> 2

parameters):

→ m-dimensional hyperspace

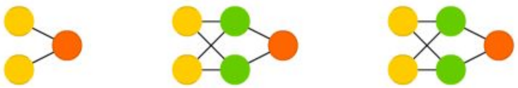


Cost function: finding the minimum?

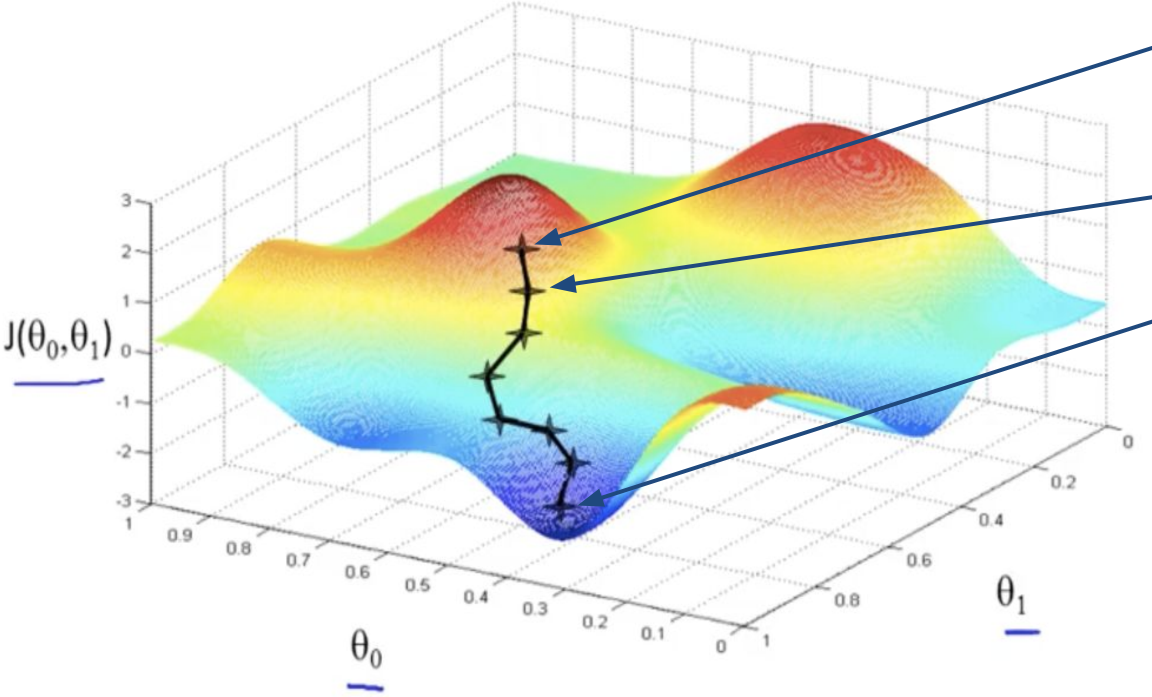
Gradient Descent:

$$\underset{\beta}{\text{minimize}}\, J(\beta)$$

1. Start with initial values for β : (initialisation)
2. Change β in the direction of reducing J(β) : (descent)
3. Stop when the minimum is reached : (minimisation)



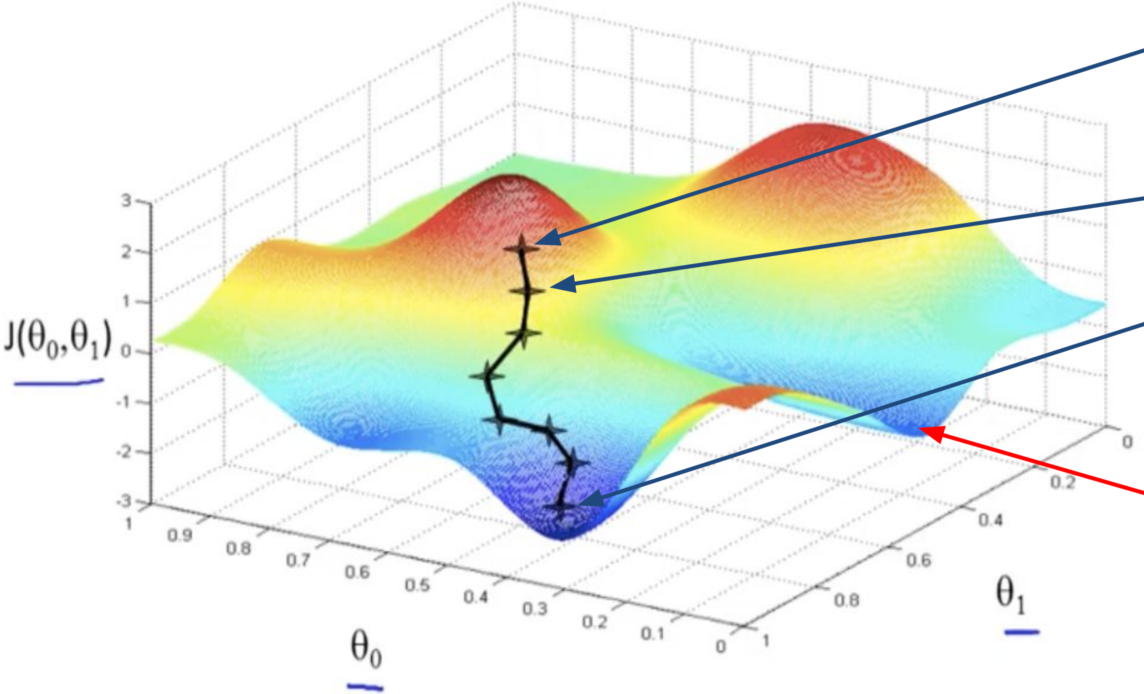
Gradient descent



1. starting point (initialisation)
2. find the steepest direction around the starting point
3. take one step in this direction
4. repeat until convergence (local minimum)

Source: Andrew Ng
https://medium.com/@DBCerigo/on-why-gradient-descent-is-even-needed-25160197a635

Gradient descent



1. starting point (initialisation)
2. find the steepest direction around the starting point
3. take one step in this direction
4. repeat until convergence (local minimum)

changing initialisation may lead to a different local minimum!

Source: Andrew Ng
https://medium.com/@DBCerigo/on-why-gradient-descent-is-even-needed-25160197a635

Gradient descent

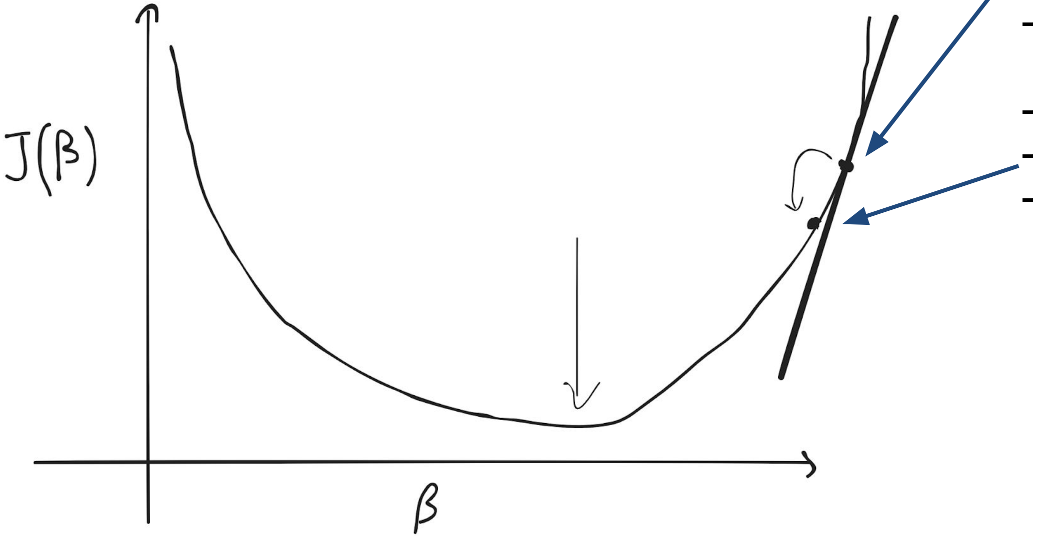
$$\beta_j := \beta_j - \alpha \frac{\partial}{\partial \beta_j} J(\beta)$$

assignment operator

learning rate (size of the steps)

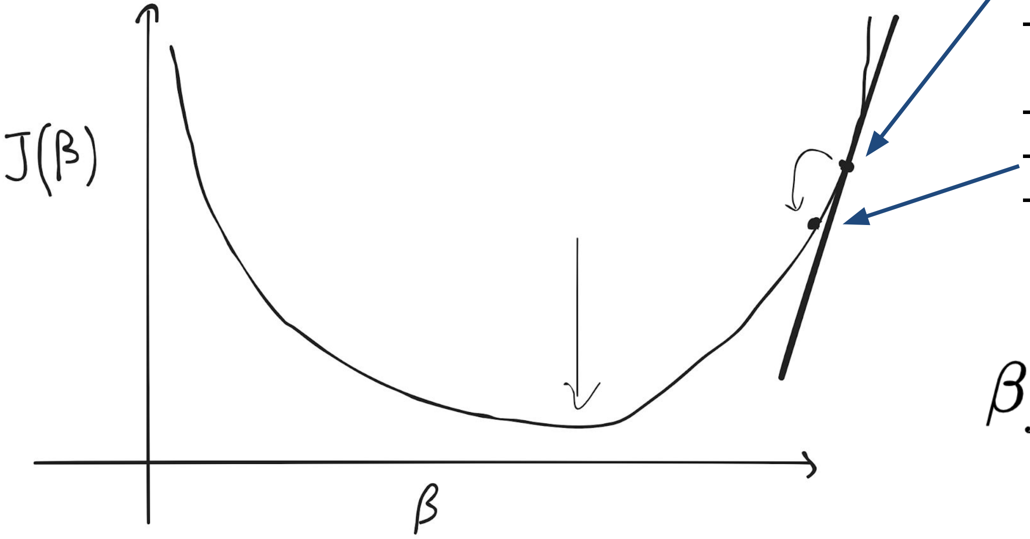
Partial derivative of J(**β**) with respect to $\boldsymbol{\beta}_j$

Gradient descent



- starting point (initial value for β)
- calculate the (partial) derivative in that point
- $\rightarrow$ positive slope
- update the value for β
- repeat

Gradient descent

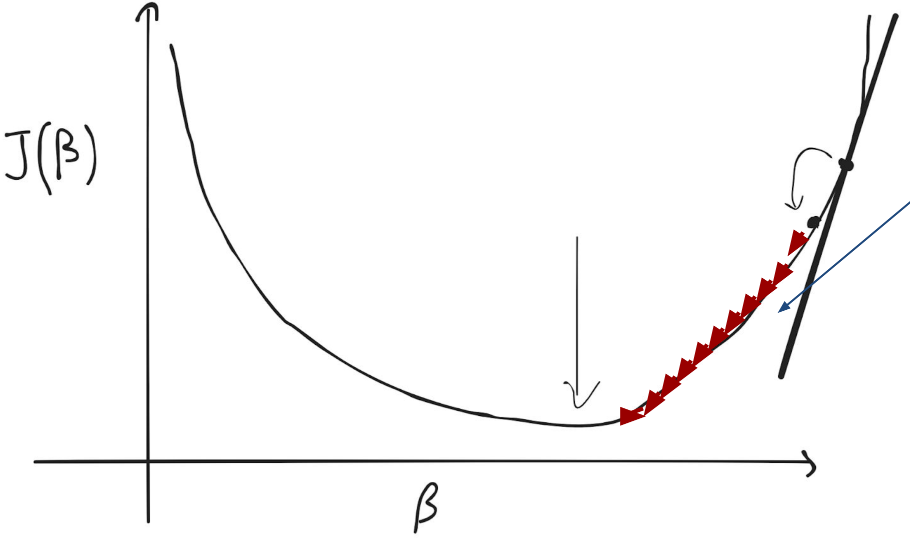


- starting point (initial value for β)
- calculate the (partial) derivative in that point
- → positive slope
- **update** the value for β
- repeat

$$\beta_j := \beta_j - \alpha \frac{\partial}{\partial \beta_j} J(\beta)$$

- positive slope → reducing the value of β (and the other way around)

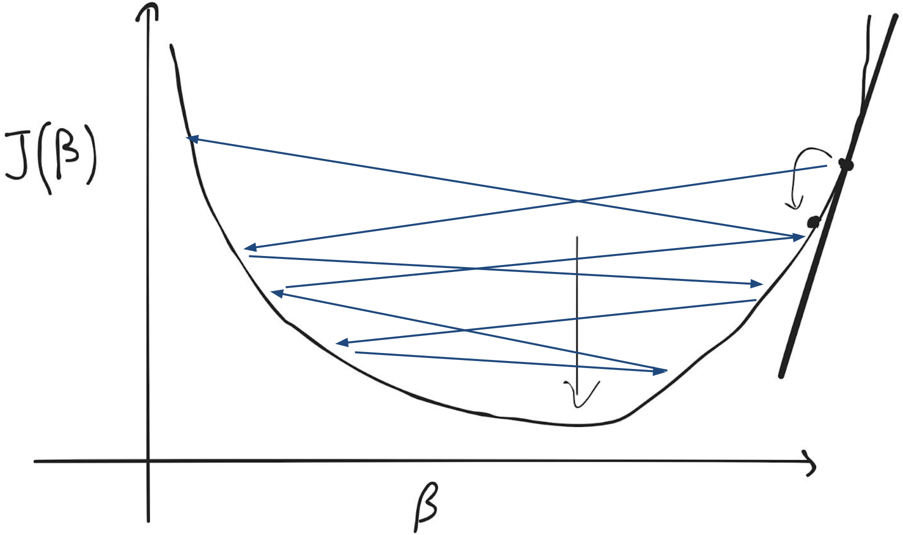
Gradient descent



- α controls the size of the updating step
- small $\alpha \rightarrow$ slow descent

$$\beta_j := \beta_j - \alpha \frac{\partial}{\partial \beta_j} J(\beta)$$

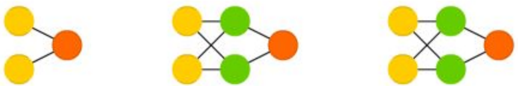
Gradient descent



- α controls the size of the updating step
- large $\alpha \rightarrow$ overshooting: failure to converge

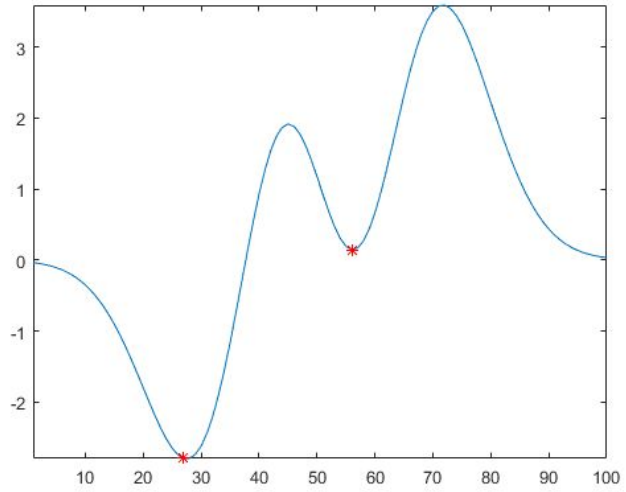
$$\beta_j := \beta_j - \alpha \frac{\partial}{\partial \beta_j} J(\beta)$$

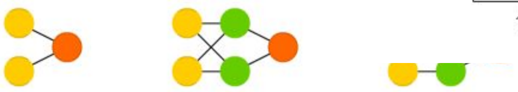
made with ziteboard



Gradient descent - recap

- general method to **solve machine learning models** (e.g. multiple linear regression)
- optimise (minimise) the cost function → **optimiser**
- importance of the **learning rate**
- local minimum → **momentum**





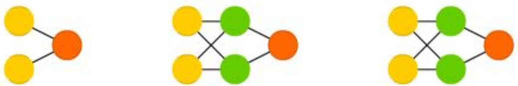
Logistic regression - recap

1) $$z = w \cdot x + b$$

introduce **w** (weight) as parameter (+ b): NN notation

2) $$\hat{y} = \sigma(z)$$

3) $$J(w) = -\left(y \cdot log(\hat{y}) + (1 - y) \cdot log(1 - \hat{y})\right)$$



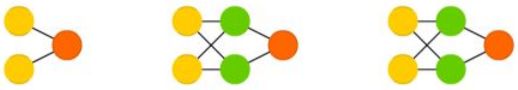
Logistic regression - recap

1) $z = w \cdot x + b$

2) $\hat{y} = \sigma(z)$

3) $J(w)$

forward propagation



Logistic regression - recap

backward propagation

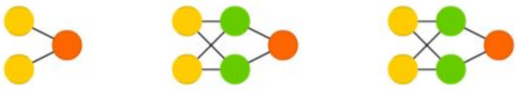
$$\frac{\partial \hat{y}}{\partial z} \qquad \frac{\partial J}{\partial \hat{y}}$$

$$z = w \cdot x + b$$

$$\hat{y} = \sigma(z)$$

$$J(w)$$

forward propagation



Logistic regression - recap

backward propagation

$$\frac{\partial \hat{y}}{\partial z}$$

$$\frac{\partial J}{\partial \hat{y}}$$

$$z = w \cdot x + b$$

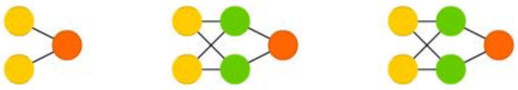
$$\hat{y} = \sigma(z)$$

$$J(w)$$

forward propagation

$$\frac{\partial J}{\partial z} = \frac{\partial J}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z}$$

chain rule



Logistic regression - recap

$$\frac{\partial J}{\partial z} = \frac{\partial J}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z}$$

$$\frac{\partial J}{\partial w_1} = \frac{\partial J}{\partial z} \cdot x_1$$

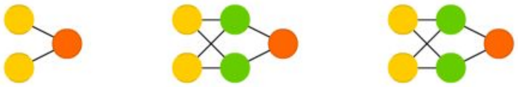
$$\frac{\partial J}{\partial w_2} = \frac{\partial J}{\partial z} \cdot x_2$$

$$\frac{\partial J}{\partial b} = \frac{\partial J}{\partial z}$$

$$\left.\begin{aligned} w_1 &:= w_1 - \alpha \frac{\partial J}{\partial w_1} \\ w_2 &:= w_2 - \alpha \frac{\partial J}{\partial w_2} \\ b &:= b - \alpha \frac{\partial J}{\partial b} \end{aligned}\right\} \text{updating step}$$

Take away message

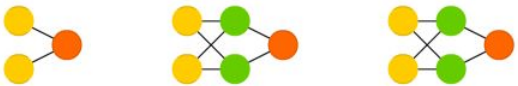
- **back propagation** is a way (algorithm) to calculate partial derivatives (of the cost function with respect to the parameters) easily and efficiently
- partial derivatives are then used to **update** the values of the **parameters**
- in this way **gradient descent** can work to minimise the **cost function** and **estimate** the best values for the **parameters**
- this is very important to efficiently learn the weights (parameters) of deep neural networks



Binary classification: measuring performance

- the most common metric to measure the performance of a binary classifier is the **error rate**:

$$\frac{1}{n}\sum_{i=1}^{n} I(y \neq \hat{y})$$



Confusion matrix

		True observation	
		1	0
Prediction	1	TP	FP
	0	FN	TN

- **FPR** = FP/(FP+TN)
- **FNR** = FN/(FN+TP)
- TER = (FN+FP)/(FN+FP+TN+TP)

Confusion matrix

		True observation	
		1	0
Prediction	1	TP	FP
	0	FN	TN

Not only total error rate!

- **FPR** = FP/(FP+TN)
- **FNR** = FN/(FN+TP)
- TER = (FN+FP)/(FN+FP+TN+TP)

Logistic regression

- demonstration 04a
- exercise 04a.1

→ code_04a_logistic_regression.ipynb