

Linear regression

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Contents

Review of vector/matrix notation and linear algebra

A regression model

Linear regression

Gradient descent

Stochastic Gradient Descent

Regularisation

Scalar and vectors

标量, 标量

- A **scalar** is just a numeric value like 0.9 or -18.7 .
- Scalars are usually denoted as lower case letters like x or a .
- A **vector** is an ordered list of scalar values. Sometimes we refer to these scalar values of the vector as **attributes** or **entries** of the vector.
- Vectors are usually denoted by bold lowercase letters like \mathbf{x} or \mathbf{y} .

Vectors

- A vector can appear sometimes written as a row vector, e.g.

$$\mathbf{x} = [x_1, x_2, x_3, x_4, x_5]$$

Or as a column vector

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}$$

- In this module, **ALL vectors will be column vectors by default.** So, when you see a vector, e.g. \mathbf{x} , \mathbf{y} , \mathbf{z} always think this vector has a column-wise shape.

Matrices

- A **matrix** is a rectangular array of scalars arranged in rows and columns.
- Matrices are usually denoted by bold uppercase letters, e.g. **X** or **Y**.
- The following matrix has three rows and two columns

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ x_{31} & x_{32} \end{bmatrix}$$

- The entries in the matrix above are of the form x_{ij} , where the first subindex i indicates the row of the element and the second subindex j indicates the column.

Matrix transpose

- Let \mathbf{X} be a matrix with elements x_{ij} .
- The transpose of a matrix \mathbf{X} is a new matrix \mathbf{X}^\top with elements x_{ji} .

$$\mathbf{X} = \begin{bmatrix} 4.1 & -5.6 \\ -2.6 & 7.9 \\ 3.5 & 1.8 \end{bmatrix}, \quad \mathbf{X}^\top = \begin{bmatrix} 4.1 & -2.6 & 3.5 \\ -5.6 & 7.9 & 1.8 \end{bmatrix}$$

Matrix multiplication

- Let **A** be a matrix with entries a_{ik} of dimensions $p \times q$.
- Let **B** be a matrix with entries b_{kj} of dimensions $t \times s$.
- Matrix multiplication of the form **AB** is only possible if $q = t$.
- If this is the case, the matrix **C** = **AB** has dimensions $p \times s$ with entries

$$c_{ij} = \sum_k a_{ik} b_{kj}.$$

Transpose of a product

- Let \mathbf{w} be a vector of dimensions $d \times 1$. Let \mathbf{X} be a matrix with dimensions $n \times d$.
- The transpose of the product \mathbf{Xw} , $(\mathbf{Xw})^\top$ is

$$(\mathbf{Xw})^\top = \mathbf{w}^\top \mathbf{X}^\top.$$

How to prove that? (Linear Algebra)

- We can apply this result to a product of several matrices

$$\begin{aligned}(\mathbf{ABCD})^\top &= ((\mathbf{AB})(\mathbf{CD}))^\top \\&= (\mathbf{CD})^\top (\mathbf{AB})^\top \\&= \mathbf{D}^\top \mathbf{C}^\top \mathbf{B}^\top \mathbf{A}^\top.\end{aligned}$$

From a scalar operation to a vector operation

- It is usually desirable to transform a scalar operation into a vector operation.
- When coding scalar operations, we require making use of loops, which can be expensive.
- In contrast, vector operations are handled efficiently by low-level routines already included in modules like numpy.

Example

Write the following scalar operation into a vector/matrix form

$$\begin{aligned}
 i=1: & \left(y_1 - \sum_{j=1}^d x_{1j} w_j \right)^2 \\
 & \vdots \\
 & \left(y_n - \sum_{j=1}^d x_{nj} w_j \right)^2
 \end{aligned}
 \rightarrow
 \begin{aligned}
 & \sum_{i=1}^n (y_i - \sum_{j=1}^d x_{ij} w_j)^2 \\
 & \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} - \begin{pmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \dots & x_{n,d} \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{pmatrix}
 \end{aligned}$$

$\begin{pmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \dots & x_{n,d} \end{pmatrix} = \begin{matrix} 1 \times d \\ d \times d \end{matrix}$

$y_1 - x_1 w$
 $\rightarrow y_2 - x_2 w$
 \vdots
 $y_n - x_n w$

$\rightarrow Y - wX$

$\rightarrow \sum_{j=1}^d x_{nj} w_j$

Answer (I)

- The sum above can be written as

$$\begin{aligned}\sum_{i=1}^n (y_i - \sum_{j=1}^d x_{ij} w_j)^2 &= (y_1 - \sum_{j=1}^d x_{1j} w_j)(y_1 - \sum_{j=1}^d x_{1j} w_j) \\ &\quad + \dots \\ &\quad + (y_n - \sum_{j=1}^d x_{nj} w_j)(y_n - \sum_{j=1}^d x_{nj} w_j).\end{aligned}$$

- Let us define a vector \mathbf{v} of dimensions $n \times 1$ with entries given as

$$(y_i - \sum_{j=1}^d x_{ij} w_j).$$

Answer (II)

- The product of vectors $\mathbf{v}^\top \mathbf{v}$ gives the same result than the required sum,

$$\begin{aligned}\mathbf{v}^\top \mathbf{v} &= \left[(y_1 - \sum_{j=1}^d x_{1j} w_j) \quad \cdots \quad (y_n - \sum_{j=1}^d x_{nj} w_j) \right] \begin{bmatrix} (y_1 - \sum_{j=1}^d x_{1j} w_j) \\ \vdots \\ (y_n - \sum_{j=1}^d x_{nj} w_j) \end{bmatrix} \\ &= \sum_{i=1}^n (y_i - \sum_{j=1}^d x_{ij} w_j)^2.\end{aligned}$$

- How do we express the elements in \mathbf{v} with vectors and matrices?

Answer (III)

- For a fixed i , x_{i1}, \dots, x_{id} can be grouped into a vector \mathbf{x}_i^\top .
- The internal sums in the entries of \mathbf{v} can then be written as

$$\sum_{j=1}^d x_{ij} w_j = \mathbf{x}_i^\top \mathbf{w} = \begin{bmatrix} x_{i1} & x_{i2} & \cdots & x_{id} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix}$$

- We can now write \mathbf{v} as

$$\mathbf{v} = \begin{bmatrix} y_1 - \mathbf{x}_1^\top \mathbf{w} \\ \vdots \\ y_n - \mathbf{x}_n^\top \mathbf{w} \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} - \begin{bmatrix} \mathbf{x}_1^\top \mathbf{w} \\ \vdots \\ \mathbf{x}_n^\top \mathbf{w} \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} - \begin{bmatrix} \mathbf{x}_1^\top \\ \vdots \\ \mathbf{x}_n^\top \end{bmatrix} \mathbf{w}$$

Y - wX.

- We can group the scalars y_1, \dots, y_n into a vector \mathbf{y} .
- We can group the row vectors $\mathbf{x}_1^\top, \dots, \mathbf{x}_n^\top$ into a matrix \mathbf{X} .

Answer (IV)

□ It means that $\mathbf{v} = \mathbf{y} - \mathbf{X}\mathbf{w}$.

□ Finally

$$\sum_{i=1}^n (y_i - \sum_{j=1}^d x_{ij} w_j)^2 = \mathbf{v}^\top \mathbf{v} = (\mathbf{y} - \mathbf{X}\mathbf{w})^\top (\mathbf{y} - \mathbf{X}\mathbf{w}).$$

Two common types of products

- ❑ **Inner product.** The inner product between two vectors results in a scalar.
- ❑ Let \mathbf{x} and \mathbf{y} be vectors of dimension $m \times 1$. The inner product is given as

the first x determine the row and second y determine the column.

inner

$$\mathbf{x}^T \mathbf{y} = \sum_{i=1}^m x_i y_i$$

$m \times 1 \cdot 1 \times m \rightarrow 1 \times 1$

- ❑ **Outer product.** The outer product between two vectors results in a matrix.
- ❑ Let \mathbf{x} be a vector of dimension $m \times 1$ and \mathbf{y} a vector of dimension $p \times 1$. The outer product is given as

outer

$$\mathbf{xy}^T = \begin{bmatrix} x_1 y_1 & \cdots & x_1 y_p \\ x_2 y_1 & \cdots & x_2 y_p \\ \vdots & \vdots & \vdots \\ x_m y_1 & \cdots & x_m y_p \end{bmatrix}$$

$m \times 1 \cdot 1 \times p = m \times p$

Differentiating a function in a vector/matrix form (I)

- We will see cases in which a function $f(\mathbf{w})$ depends on some parameters grouped in a vector \mathbf{w} .
- We would like to find the vector of parameters \mathbf{w} that maximise $f(\mathbf{w})$.

- For example, suppose $f(\mathbf{w})$ is defined as
- $$f(\mathbf{w}) = \sum_{i=1}^d w_i x_i.$$
- Handwritten notes and diagrams illustrating the function definition:
- Top right: $w_1 x_1 + w_2 x_2 + \dots + w_d x_d \leftrightarrow 1 \times d \times 1$
 - Middle right: $[w_1 \dots w_d] \cdot \begin{bmatrix} x_1 \\ \vdots \\ x_d \end{bmatrix}$ or $(x_1 \dots x_d) \begin{bmatrix} w_1 \\ \vdots \\ w_d \end{bmatrix}$
 - Below the first vector: \downarrow $\mathbf{w} \cdot \mathbf{x}$
 - Below the second vector: $\text{or } \mathbf{x}^T \mathbf{w}.$

- We can group the scalars x_1, \dots, x_d into \mathbf{x} . Likewise for \mathbf{w} .
- According to what we saw before, we can write $f(\mathbf{w})$ as $f(\mathbf{w}) = \mathbf{x}^T \mathbf{w}$.

Differentiating a function in a vector/matrix form (II)

- For a fixed \mathbf{x} , we are interested in computing the gradient of $f(\mathbf{w})$ with respect to \mathbf{w}

$$\frac{df(\mathbf{w})}{d\mathbf{w}} = \begin{bmatrix} \frac{\partial f(\mathbf{w})}{\partial w_1} \\ \vdots \\ \frac{\partial f(\mathbf{w})}{\partial w_d} \end{bmatrix} = \begin{bmatrix} x_1 \\ \vdots \\ x_d \end{bmatrix} = \mathbf{x}.$$

- Some useful identities when differentiating with respect to a vector

$$\mathbf{x} = [x_1, x_2, \dots, x_d]^T$$

$$\mathbf{w}^T \mathbf{x} = w_1 x_1 + w_2 x_2 + w_3 x_3 + \dots + w_d x_d$$

$$(w^T \mathbf{x}) d\mathbf{w} = x_1 + x_2 + \dots + x_d = \mathbf{x}$$

$$\mathbf{w}^T \cdot \mathbf{w} = w_1 \cdot w_1 + \dots + w_d \cdot w_d$$

$$(w^T w) d\mathbf{w} = w_1^2 d\mathbf{w} + \dots + w_d^2 d\mathbf{w} = 2w_1 + 2w_2 + \dots + 2w_d = 2\mathbf{w}.$$

$f(\mathbf{w})$	$\frac{df(\mathbf{w})}{d\mathbf{w}}$
$\mathbf{w}^T \mathbf{x}$	\mathbf{x}
$\mathbf{x}^T \mathbf{w}$	\mathbf{x}
$\mathbf{w}^T \mathbf{w}$	$2\mathbf{w}$
$\mathbf{w}^T \mathbf{C} \mathbf{w}$	$2\mathbf{C} \mathbf{w}$

easy to comprehend

Identity matrix and the inverse of a matrix

- ✓ ☒ The identity matrix of size N is a square matrix with ones on the main diagonal and zeros elsewhere, e.g.,

$$\mathbf{I}_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

- ☐ The inverse matrix of a matrix \mathbf{A} of dimensions $d \times d$, denoted as \mathbf{A}^{-1} , satisfies

$$\mathbf{A}\mathbf{A}^{-1} = \mathbf{A}^{-1}\mathbf{A} = \mathbf{I}_d$$

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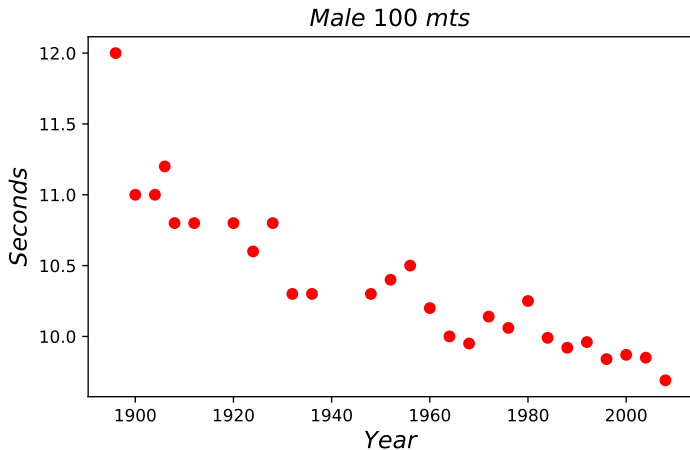
Regularisation

Olympic 100m Data



Image from Wikimedia Commons <http://bit.ly/191adDC>.

Dataset



Model

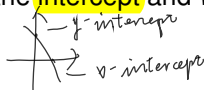
- We will use a linear model $f(x, \mathbf{w})$ to predict y , where y is the time in seconds and x the year of the competition.

1-dimension Gradient

- The linear model is given as

$$f(x, \mathbf{w}) = w_0 + w_1 x,$$

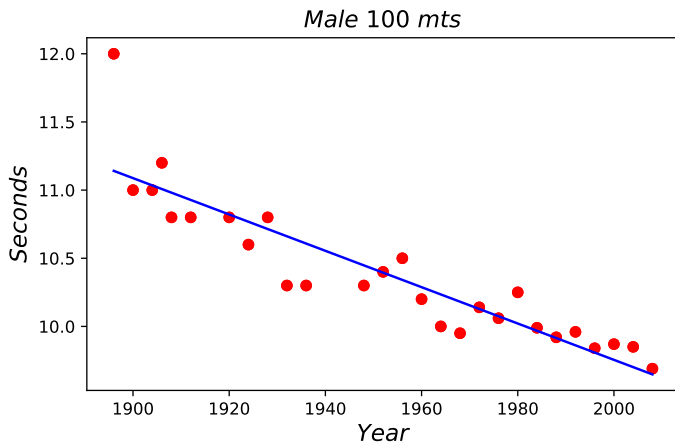
where w_0 is the **intercept** and w_1 is the **slope**.



- We use **w** to refer both to w_0 and w_1 .

$$\begin{Bmatrix} w_0 \\ w_1 \end{Bmatrix}$$

Data and model



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Linear model

- a build-up model to lengthen the old data to make it able to accomplish prediction

- A simple model for regression consists in using a linear combination of the attributes to predict the output

Very like the formula to calculate the Expectations Value
Similar to: $f(\mathbf{x}, \mathbf{w}) = w_0 + w_1 x_1 + \dots + w_D x_D, \rightarrow (x)$

where w_0, w_1, \dots, w_D are the parameters of the regression model.

- The term w_0 is the **bias term** or **intercept**, e.g. $f(\mathbf{0}, \mathbf{w}) = w_0$.

- The expression above can be written in a vectorial form

$$f(\mathbf{x}, \mathbf{w}) = \mathbf{w}^T \mathbf{x}.$$

$1 \times D \quad D \times 1 \rightarrow 1 \times 1.$

$w^T \cdot x \rightarrow [w_0, w_1, \dots, w_D] \begin{bmatrix} 1 \\ x_1 \\ x_2 \\ \vdots \\ x_D \end{bmatrix}$

where we have defined $\mathbf{w} = [w_0, w_1, \dots, w_D]^T$ and $\mathbf{x} = [1, x_1, \dots, x_D]^T$.

- Notice that $x_0 = 1$. $x_0 \cdot w_0 \rightarrow \text{intercept}$

Parenthesis: Gaussian pdf

- The Gaussian pdf has the form

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$$p(y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{(y - \mu)^2}{2\sigma^2} \right\}.$$

$$P(y) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \cdot \left(\frac{y - \mu}{\sigma} \right)^2}$$

$P(Y=y)$: the probability of Event y happen

- A Gaussian pdf requires two parameters μ and σ^2 , the mean and the variance of the RV Y .

- We denote the Gaussian pdf as $p(y|\mu, \sigma^2) = \mathcal{N}(y|\mu, \sigma^2)$ or $y \sim \mathcal{N}(\mu, \sigma^2)$.

$$P(y|\mu, \sigma^2) = \mathcal{N}(y|\mu, \sigma^2)$$

$$\text{or } y \sim \mathcal{N}(\mu, \sigma^2) \checkmark$$

mass \leftrightarrow discrete

probability density function \rightarrow continuous

μ : mean or expectation of the distribution.
 σ : Standard deviation
 σ^2 : variance of the distribution

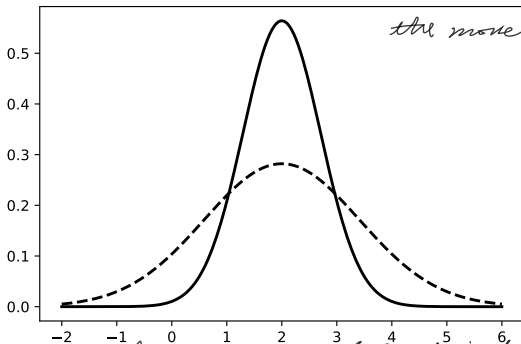
Parenthesis: Gaussian pdf

The mean of the three Gaussians is $\mu = 2$ and the variances are $\sigma^2 = 0.5$ (solid), and $\sigma^2 = 2$ (dashed).

$\sigma^2 \uparrow$

$\sigma^2 \uparrow$, difference between

x and μ \uparrow
the more wavy it is.



σ^2 : describes to how much degree each sample is difference from
(variance) the sum of the mean value
expectations value

Gaussian regression model (I) *build connections*

- We use a Gaussian regression model to relate the inputs and outputs

$$y = f(\mathbf{x}, \mathbf{w}) + \epsilon,$$

target
attribution

noises

f(x, w) = w_i

where $\epsilon \sim \mathcal{N}(0, \sigma^2)$.

- It assumes that each output y_i that we observe can be explained as the prediction of an underlying model, $f(\mathbf{x}_i, \mathbf{w})$ **plus** a noise term ϵ_i .
- For a fixed \mathbf{x} and a fixed \mathbf{w} , $f(\mathbf{x}, \mathbf{w})$ is a **constant**, then *why add?*

$$\underbrace{w_1 \cdot w_i}_{\text{constant}} \text{ or } \underbrace{w_0}_{\text{constant}} \text{ or } \underbrace{x_1 w_1}_{\text{constant}} \text{ or } \dots \underbrace{x_n w_n}_{\text{constant}} \rightarrow \text{constant over all}$$

$$y = \text{constant} + \epsilon,$$

where ϵ is a continuous RV.

- What is the pdf for y ? (we are adding a constant to a Gaussian RV)

Expectation
M is pi · x

$$E\{y\} = E\{\text{constant} + \epsilon\} = \text{constant} \quad \leftarrow \text{M: the constant's Exp value is itself}$$

J

$$\text{var}\{y\} = \text{var}\{\text{constant}\} + \text{var}\{\epsilon\} = \sigma^2 \quad \leftarrow \sigma^2$$

Gaussian regression model (II)

- This means that

about the μ : mean or average or Expected Value

$$y \sim \mathcal{N}(\text{constant}, \sigma^2),$$

1. for continuous RV: $E(X) = \int_{\mathcal{R}} x \cdot f(x) \cdot dx$

where we said constant was $f(\mathbf{x}, \mathbf{w})$, this is,

2. for discrete case: (finite)

$$E(X) = \sum_{i=1}^K x_i \cdot p_i$$

✓ \hookrightarrow Special Case: usually refer to average.

* μ : expectation value when $p_i = \frac{1}{n}$

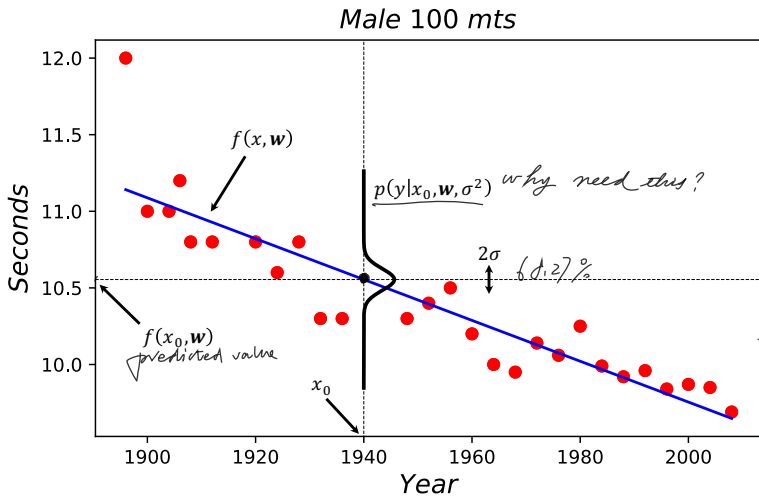
$$E(X) = \frac{\sum x_i}{n}$$

- Because we assumed that \mathbf{x} and \mathbf{w} are given, we can also write

$$p(y|\mathbf{x}, \mathbf{w}, \sigma^2) = \mathcal{N}(y|f(\mathbf{x}, \mathbf{w}), \sigma^2).$$

- If we knew the value for \mathbf{w} , once we have a new \mathbf{x}_* , we can predict the output as $f(\mathbf{x}_*, \mathbf{w})$.
- σ^2 tells us the noise variance.

Gaussian regression model (III)



How do we estimate \mathbf{w} ? (I)

- We start with a training dataset $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)$.

- We assume that the random variables Y_1, \dots, Y_N are independent, *they do not interfere with each other*
 $P(y_1/x_1, y_2/x_2, \dots, y_N/x_N)$
$$p(y_1, \dots, y_N | \mathbf{x}_1, \dots, \mathbf{x}_N) = p(y_1 | \mathbf{x}_1) \cdots p(y_N | \mathbf{x}_N) = \prod_{n=1}^N p(y_n | \mathbf{x}_n).$$
 $P(y/x)$

- We also **assume** *why to have this could form as for a Normal distribution* that the RVs Y_1, \dots, Y_N follow an *identical* distribution, Gaussian in this case

$$p(y_n | \mathbf{x}_n, \mathbf{w}, \sigma^2) = \mathcal{N}(y_n | f(\mathbf{x}_n, \mathbf{w}), \sigma^2) = \mathcal{N}(y_n | \mathbf{w}^\top \mathbf{x}_n, \sigma^2).$$

$\begin{bmatrix} w_0, w_1, \dots, w_n \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}$

$= \frac{w_0 + w_1 x_1 + w_2 x_2 + \dots + w_n x_n}{\mu : \text{the Expect Value}}$

- Both assumptions go by the name of the *iid* assumption, *independent and identically distributed*.

How do we estimate \mathbf{w} ? (II)

- Putting both assumptions together, we get

$$p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2) = \prod_{n=1}^N p(y_n | \mathbf{x}_n, \mathbf{w}, \sigma^2) = \prod_{n=1}^N \mathcal{N}(y_n | \mathbf{w}^\top \mathbf{x}_n, \sigma^2),$$

where $\mathbf{y} = [y_1, \dots, y_N]^\top \in \mathbb{R}^{N \times 1}$ and $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_N]^\top \in \mathbb{R}^{N \times (D+1)}$.

The expression above can then be written as

$$p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2) = \prod_{n=1}^N \mathcal{N}(y_n | \mathbf{w}^\top \mathbf{x}_n, \sigma^2),$$

$$= \prod_{n=1}^N \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{(y_n - \mathbf{w}^\top \mathbf{x}_n)^2}{2\sigma^2} \right\}.$$

$$= \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{n=1}^N (y_n - \mathbf{w}^\top \mathbf{x}_n)^2 \right\}.$$

How do we estimate \mathbf{w} ? (III)

- When we look at a Gaussian pdf, like

$$p(y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{(y - \mu)^2}{2\sigma^2} \right\},$$

we assume that both μ and σ^2 are given. In this case, the pdf follows all the properties we reviewed before.

- The same is true for

$$p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2) = \prod_{n=1}^N p(y_n|\mathbf{x}_n, \mathbf{w}, \sigma^2) = \prod_{n=1}^N \mathcal{N}(y_n|\mathbf{w}^\top \mathbf{x}_n, \sigma^2).$$

Similar to 11

- Given $\mathbf{w}^\top \mathbf{x}_n$ and σ^2 , then each $p(y_n|\mathbf{x}_n, \mathbf{w}, \sigma^2)$ is a pdf.
- A different approach would be to say: I have some data for $\{y_n\}_{n=1}^N$ and $\{\mathbf{x}_n\}_{n=1}^N$ but
 - “I don’t know what is \mathbf{w}^\top (therefore I don’t know what is $\mathbf{w}^\top \mathbf{x}_n$)”
 - “I don’t know what is σ^2 ”.

How do we estimate \mathbf{w} ? (IV)

- With y_n and \mathbf{x}_n given but with unknown values for \mathbf{w} and σ^2 , each $p(y_n|\mathbf{x}_n, \mathbf{w}, \sigma^2)$ is not a pdf anymore.
- In that case, the function

$$\underset{\text{Probability}}{p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2)} = \prod_{n=1}^N \mathcal{N}(y_n|\mathbf{w}^\top \mathbf{x}_n, \sigma^2), \quad 0 \leq p < 1$$

receives the name of a **likelihood function**.

- We can think of a likelihood function as a function of the parameters \mathbf{w} and σ^2 ,

$$g(\mathbf{w}, \sigma^2) = p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2),$$

- And subsequently, we can use **multivariate calculus** to find the values of \mathbf{w}, σ^2 that **maximise** $g(\mathbf{w}, \sigma^2)$.
- In statistics this is known as the *maximum-likelihood* (ML) criterion to estimate parameters.

\mathbf{w}

How do we estimate \mathbf{w} ? (V)

- Given \mathbf{y}, \mathbf{X} , we use the ML criterion to find the parameters \mathbf{w} and σ^2 that maximise

$$p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2) = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{n=1}^N (y_n - \mathbf{w}^\top \mathbf{x}_n)^2 \right\}.$$

- In practice, we prefer to maximise the log of the likelihood $p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2)$,

$$\begin{aligned} LL(\mathbf{w}, \sigma^2) &= \log p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2) \\ &= -\frac{N}{2} \log(2\pi) - \frac{N}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum_{n=1}^N (y_n - \mathbf{w}^\top \mathbf{x}_n)^2. \end{aligned}$$

- Consistency of the ML criterion** If data was really generated according to the probability we specified, the correct parameters will be recovered in the limit as $N \rightarrow \infty$.

Connection with the sum of squared errors

- If we multiply $LL(\mathbf{w}, \sigma^2)$ by minus one, we get

$$E(\mathbf{w}, \sigma^2) = -\log p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2) \propto \sum_{n=1}^N (y_n - \mathbf{w}^\top \mathbf{x}_n)^2.$$

- The ML criterion for this model has a close connection with the sum-of-squared errors used in non-probabilistic formulations of linear regression.
- Maximising the log-likelihood function is equivalent to minimising the sum-of-squares errors.
- Notice that the log is a monotonic function, meaning that if we find \mathbf{w}, σ^2 that maximise $g(\mathbf{w}, \sigma^2)$, those will also maximise $\log(g(\mathbf{w}, \sigma^2))$.

Normal equation (I)

- Let us find an estimate for \mathbf{w} .
- From what we saw before,

$$LL(\mathbf{w}, \sigma^2) = -\frac{N}{2} \log(2\pi) - \frac{N}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum_{n=1}^N (y_n - \mathbf{w}^\top \mathbf{x}_n)^2.$$

- Using what we reviewed in the section on vector/matrix notation, it can be shown that this expression can be written in a vectorial form as

$$LL(\mathbf{w}, \sigma^2) = -\frac{N}{2} \log(2\pi) - \frac{N}{2} \log \sigma^2 - \frac{1}{2\sigma^2} (\mathbf{y} - \mathbf{X}\mathbf{w})^\top (\mathbf{y} - \mathbf{X}\mathbf{w})$$

- Let us focus on the term $(\mathbf{y} - \mathbf{X}\mathbf{w})^\top (\mathbf{y} - \mathbf{X}\mathbf{w})$,

$$(\mathbf{y} - \mathbf{X}\mathbf{w})^\top (\mathbf{y} - \mathbf{X}\mathbf{w}) = \mathbf{y}^\top \mathbf{y} - \mathbf{w}^\top \mathbf{X}^\top \mathbf{y} - \mathbf{y}^\top \mathbf{X}\mathbf{w} + \mathbf{w}^\top \mathbf{X}^\top \mathbf{X}\mathbf{w}$$

Normal equation (II)

- We can find the \mathbf{w} that maximises $LL(\mathbf{w}, \sigma^2)$ by taking the gradient $\frac{dLL(\mathbf{w}, \sigma^2)}{d\mathbf{w}}$, equating to zero and solving for \mathbf{w} .

- Taking the gradient of each term in $LL(\mathbf{w}, \sigma^2)$ wrt \mathbf{w} , we get

$$\frac{d}{d\mathbf{w}} \left[-\frac{N}{2} \log(2\pi) \right] = 0, \quad \frac{d}{d\mathbf{w}} \left[-\frac{N}{2} \log \sigma^2 \right] = 0, \quad \frac{d}{d\mathbf{w}} \left[-\frac{1}{2\sigma^2} \mathbf{y}^\top \mathbf{y} \right] = 0,$$

$$\frac{d}{d\mathbf{w}} \left[\frac{1}{2\sigma^2} \mathbf{w}^\top \mathbf{X}^\top \mathbf{y} \right] = \frac{1}{2\sigma^2} \mathbf{X}^\top \mathbf{y},$$

$$\frac{d}{d\mathbf{w}} \left[\frac{1}{2\sigma^2} \mathbf{y}^\top \mathbf{X} \mathbf{w} \right] = \frac{1}{2\sigma^2} \mathbf{X}^\top \mathbf{y}$$

$$\frac{d}{d\mathbf{w}} \left[-\frac{1}{2\sigma^2} \mathbf{w}^\top \mathbf{X}^\top \mathbf{X} \mathbf{w} \right] = -\frac{1}{2\sigma^2} 2\mathbf{X}^\top \mathbf{X} \mathbf{w}$$

Normal equation (III)

- Putting these terms together, we get

$$\begin{aligned}\frac{d}{d\mathbf{w}} LL(\mathbf{w}, \sigma^2) &= \frac{1}{2\sigma^2} \mathbf{X}^\top \mathbf{y} + \frac{1}{2\sigma^2} \mathbf{X}^\top \mathbf{y} - \frac{1}{2\sigma^2} 2\mathbf{X}^\top \mathbf{X} \mathbf{w} \\ &= \frac{1}{\sigma^2} \mathbf{X}^\top \mathbf{y} - \frac{1}{\sigma^2} \mathbf{X}^\top \mathbf{X} \mathbf{w}\end{aligned}$$

- Now, equating to zero and solving for \mathbf{w} , we get

$$\begin{aligned}\frac{1}{\sigma^2} \mathbf{X}^\top \mathbf{y} - \frac{1}{\sigma^2} \mathbf{X}^\top \mathbf{X} \mathbf{w} &= \mathbf{0} \\ \mathbf{X}^\top \mathbf{X} \mathbf{w} &= \mathbf{X}^\top \mathbf{y} \\ \mathbf{w}_* &= (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y}.\end{aligned}$$

- The expression for \mathbf{w}_* is known as the *normal equation*.
- The solution for \mathbf{w}^* exists if we can compute $(\mathbf{X}^\top \mathbf{X})^{-1}$.
- The inverse can be computed as long as $\mathbf{X}^\top \mathbf{X}$ is non-singular (e.g. determinant different from zero, or has full-rank).

Solving for σ_*^2

- Following a similar procedure, it can be shown that the ML solution for σ_*^2 is given as

$$\sigma_*^2 = \frac{1}{N}(\mathbf{y} - \mathbf{X}\mathbf{w}_*)^\top (\mathbf{y} - \mathbf{X}\mathbf{w}_*).$$

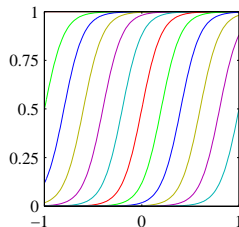
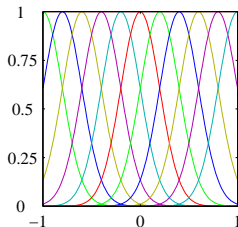
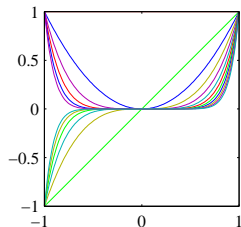
Basis functions

- The model that is linear in \mathbf{x} only allows linear relationships between \mathbf{x} and y .
- We can extend the model to describe non-linear relationships between the inputs and the output by using basis functions, non-linear mappings from inputs to outputs.
- However, we keep the linear relationship of y wrt \mathbf{w} for tractability.
- The predictive model follows as $f(\mathbf{x}, \mathbf{w})$

$$f(\mathbf{x}, \mathbf{w}) = w_0 + \sum_{i=1}^M w_i \phi_i(\mathbf{x}) = \mathbf{w}^\top \boldsymbol{\phi}(\mathbf{x}),$$

where $\phi_i(\mathbf{x})$ are basis functions and we have $M + 1$ parameters for the vector \mathbf{w} and $\boldsymbol{\phi}(\mathbf{x}) = [1, \phi_1(\mathbf{x}), \dots, \phi_M(\mathbf{x})]^\top$.

Examples of basis functions



Polynomial: $\phi_i(x) = x^i$.

Exponential: $\phi_i(x) = \exp\left\{-\frac{(x-\mu_i)^2}{2s^2}\right\}$

Sigmoidal: $\phi_i(x) = \sigma\left(\frac{x-\mu_i}{s}\right)$, $\sigma(a) = 1/(1 + \exp(-a))$.

Transforming the input using the basis functions

- As an example, let us use polynomial basis functions to predict y , the time in seconds in the 100 mt Olympics competition.
- For each x (year of the competition), we now compute the vector of polynomial basis functions

$$\phi(x) = \begin{bmatrix} 1 \\ x \\ x^2 \\ x^3 \\ \vdots \\ x^M \end{bmatrix}$$

- We have converted the unidimensional input feature x into a higher dimensional feature representation $\phi(x) \in R^{M+1}$.

Normal equations with a design matrix

- Given \mathbf{X} , we first compute a new design matrix Φ ,

$$\Phi = \begin{bmatrix} \phi(\mathbf{x}_1)^\top \\ \phi(\mathbf{x}_2)^\top \\ \vdots \\ \phi(\mathbf{x}_N)^\top \end{bmatrix} = \begin{bmatrix} \phi_0(\mathbf{x}_1) & \phi_1(\mathbf{x}_1) & \cdots & \phi_M(\mathbf{x}_1) \\ \phi_0(\mathbf{x}_2) & \phi_1(\mathbf{x}_2) & \cdots & \phi_M(\mathbf{x}_2) \\ \vdots & \vdots & \cdots & \vdots \\ \phi_0(\mathbf{x}_N) & \phi_1(\mathbf{x}_N) & \cdots & \phi_M(\mathbf{x}_N) \end{bmatrix}$$

- We now can use (\mathbf{y}, Φ) and write the Gaussian linear regression problem

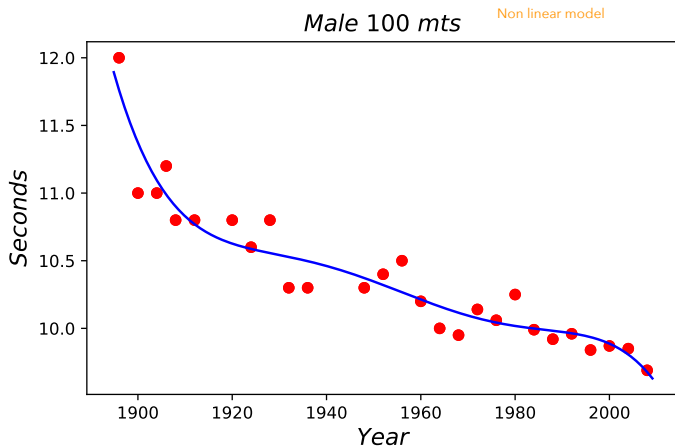
$$p(\mathbf{y}|\mathbf{X}, \mathbf{w}, \sigma^2) = \prod_{n=1}^N \mathcal{N}(y_n | \mathbf{w}^\top \phi_n, \sigma^2),$$

where $\phi_n = \phi(\mathbf{x}_n)$.

- Using the ML criterion, we arrive to the following normal equation

$$\mathbf{w}_* = (\Phi^\top \Phi)^{-1} \Phi^\top \mathbf{y}.$$

Olympic 100-mt data with $M = 5$



Alternative to find \mathbf{w}

different ways of finding \mathbf{w}

- ❑ For solving the normal equation, we need to invert $\mathbf{X}^T \mathbf{X}$.
- ❑ This inversion has a computational complexity between $\mathcal{O}((D+1)^{2.4})$ to $\mathcal{O}((D+1)^3)$ (depending on the implementation).
- ❑ The normal equation is linear regarding the number of instances in the training data, $\mathcal{O}(N)$.
- ❑ It can handle a large training set as long as it fits in memory.
- ❑ Alternatively, we can use iterative optimisation in cases with a large number of features and too many instances to fit in memory.

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General problem

- We are given a function $h(\mathbf{w})$, where $\mathbf{w} \in \mathbb{R}^p$.
- Aim: to find a value for \mathbf{w} that minimises $h(\mathbf{w})$.
- Use an iterative procedure

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \eta \mathbf{d}_k,$$

where \mathbf{d}_k is known as the search direction and it is such that

$$h(\mathbf{w}_{k+1}) < h(\mathbf{w}_k).$$

- The parameter η is known as the **step size** or **learning rate**.

Gradient descent

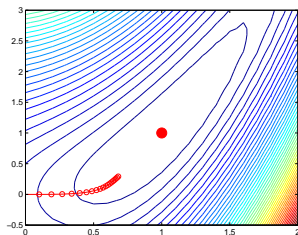
- Also known as **steepest descent**.
- It assumes that $\mathbf{d}_k = -\mathbf{g}_k$, where $\mathbf{g}_k = \mathbf{g}(\mathbf{w}_k)$.
- It can be written like

$$\mathbf{w}_{k+1} = \mathbf{w}_k - \eta \mathbf{g}_k.$$

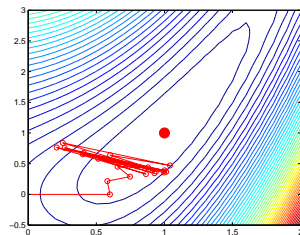
- Perhaps, the simplest algorithm for unconstrained optimisation.

Step size

- The main issue in gradient descent is how to set the step size.
- If it is too small, convergence will be very slow. If it is too large, the method can fail to converge at all.



(a)



(b)

Figure: The function to optimise is $h(w_1, w_2) = 0.5(w_1^2 - w_2^2) + 0.5(w_1 - 1)^2$. The minimum is at (1, 1). In (a) $\eta = 0.1$. In (b) $\eta = 0.6$.

Alternatives to choose the step size η

- ❑ Line search methods (there are different alternatives).
- ❑ Line search methods may use search directions other than the steepest descent direction.
- ❑ Conjugate gradient (method of choice for quadratic objectives $g(\mathbf{w}) = \mathbf{w}^\top \mathbf{A} \mathbf{w}$).
- ❑ Use a *Newton* search direction.

Gradient descent for linear regression (I)

- For simplicity, let us assume that the objective function $h(\mathbf{w})$ corresponds to the mean squared error

$$E(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N (y_n - \mathbf{w}^\top \mathbf{x}_n)^2.$$

- We could also minimise the negative $LL(\mathbf{w})$ instead.

- We write the update equation as

$$\mathbf{w}_{k+1} = \mathbf{w}_k - \eta \left. \frac{d}{d\mathbf{w}} E(\mathbf{w}) \right|_{\mathbf{w}=\mathbf{w}_k}.$$

Gradient descent for linear regression (II)

- Computing the gradient for $E(\mathbf{w})$, we get

$$\frac{d}{d\mathbf{w}} E(\mathbf{w}) = \frac{2}{N} \sum_{n=1}^N (\mathbf{w}^\top \mathbf{x}_n - y_n) \mathbf{x}_n = \frac{2}{N} \mathbf{X}^\top (\mathbf{X}\mathbf{w} - \mathbf{y}).$$

- The update equation follows as

$$\mathbf{w}_{k+1} = \mathbf{w}_k - \eta \frac{2}{N} \mathbf{X}^\top (\mathbf{X}\mathbf{w}_k - \mathbf{y}).$$

- The computation of the gradient involves using the whole dataset (\mathbf{X}, \mathbf{y}) at every step.
- For this reason, this algorithm is known as *batch gradient descent*.

Gradient descent and feature scaling

- Always normalise the features if using gradient descent.
- Gradient descent converges faster if all features have a similar scale.
- If the attributes are in very different scales, it may take a long time to converge.

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Online learning and large datasets

- Traditionally in machine learning, the gradient \mathbf{g}_k is computed using the whole dataset $\mathcal{D} = \{\mathbf{x}_n, y_n\}_{n=1}^N$.
- There are settings, though, where only a subset of the data can be used.
- **Online learning**: the instances (\mathbf{x}_n, y_n) appear one at a time.
- **Large datasets**: computing the exact value for \mathbf{g}_k would be expensive, if not impossible.

Stochastic gradient descent (I)

- In stochastic gradient descent (SGD), the gradient \mathbf{g}_k is computed using a subset of the instances available.
- The word update when new instances added **stochastic** refers to the fact that the value for \mathbf{g}_k will depend on the subset of the instances chosen for computation.

Stochastic gradient descent (II)

- In the stochastic setting, a better estimate can be found if the gradient is computed using

$$\mathbf{g}_k = \frac{1}{|S|} \sum_{i \in S} \mathbf{g}_{k,i},$$

where $S \in \mathcal{D}$, $|S|$ is the cardinality of S , and $\mathbf{g}_{k,i}$ is the gradient at iteration k computed using the instance (\mathbf{x}_i, y_i) .

- This setting is called *mini-batch gradient descent*.

Step size in SGD

- Choosing the value of η is particularly important in SGD since there is no easy way to compute it.
- Usually the value of η will depend on the iteration k , η_k .
- It should follow the **Robbins-Monro** conditions

$$\sum_{k=1}^{\infty} \eta_k = \infty, \quad \sum_{k=1}^{\infty} \eta_k^2 < \infty.$$

- Various formulas for η_k can be used

$$\eta_k = \frac{1}{k}, \quad \eta_k = \frac{1}{(\tau_0 + k)^\kappa},$$

where τ_0 slows down early iterations and $\kappa \in (0.5, 1]$.

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What is regularisation?

- It refers to a technique used for preventing overfitting in a predictive model.
- It consists in adding a term (a regulariser) to the objective function that encourages simpler solutions.
- With regularisation, the objective function for linear regression would be

$$h(\mathbf{w}) = E(\mathbf{w}) + \lambda R(\mathbf{w}),$$

where $R(\mathbf{w})$ is the regularisation term and λ the regularisation parameter.

- In the expression for $h(\mathbf{w})$, we can use the negative $LL(\mathbf{w})$ instead of $E(\mathbf{w})$.
- If $\lambda = 0$, we get $h(\mathbf{w}) = E(\mathbf{w})$.

Different types of regularisation

- The objective function for linear regression would be

$$h(\mathbf{w}) = E(\mathbf{w}) + \lambda R(\mathbf{w}),$$

where $R(\mathbf{w})$ follows as

$$R(\mathbf{w}) = \alpha \|\mathbf{w}\|_1 + (1 - \alpha) \frac{1}{2} \|\mathbf{w}\|_2^2,$$

where $\|\mathbf{w}\|_1 = \sum_{m=1}^p |w_m|$, and $\|\mathbf{w}\|_2^2 = \sum_{m=1}^p w_m^2$.

lasso regularisation

- If $\alpha = 1$, we get ℓ_1 regularisation.
- If $\alpha = 0$, we get ℓ_2 regularisation. Rich regression
- If $0 < \alpha < 1$, we get the elastic net regularisation.

Ridge regression or ℓ_2 regularisation

- In ridge regression, $\alpha = 0$,

$$h(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N (y_n - \mathbf{w}^\top \mathbf{x}_n)^2 + \frac{\lambda}{2} \mathbf{w}^\top \mathbf{w},$$

- It can be shown that an optimal solution for \mathbf{w}_* is given as

$$\mathbf{w}_* = \left(\mathbf{X}^\top \mathbf{X} + \frac{\lambda N}{2} \mathbf{I} \right)^{-1} \mathbf{X}^\top \mathbf{y}.$$

- Notice that we can also use iterative procedure for optimising $h(\mathbf{w})$ either through batch gradient decent, SGD or mini-batch SGD.