

Machine Learning

Supplementary Material of Lecture 2

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Aside - finding maxima and minima

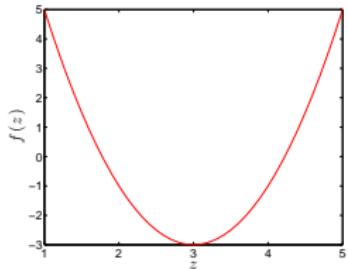
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$$\operatorname{argmin}_z f(z), \quad f(z) = 2z^2 - 12z + 15.$$

Aside - finding maxima and minima

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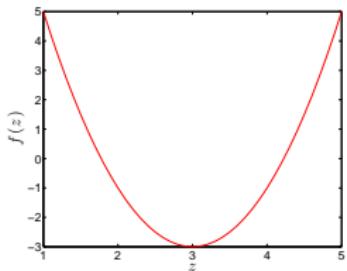
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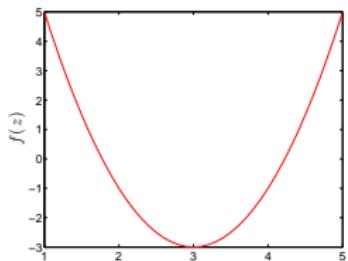


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Aside - finding maxima and minima

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At a minimum (or a maximum), the gradient must be zero.

The gradient is given by the first derivative of the function:

$$\frac{df(z)}{dz} = 4z - 12$$

Setting to zero and solving for z

$$4z - 12 = 0, \quad z = 12/4 = 3$$

Finding maxima and minima

Introduction

k. yuan

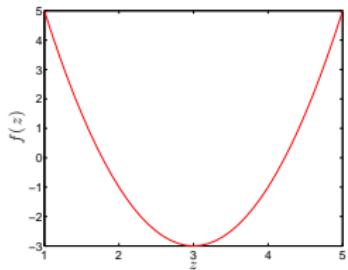
Optimisation

Optimising our function

The Olympic
model

- ▶ So, we know that the gradient is 0 at $z = 3$.
- ▶ How do we know if it is a minimum or a maximum?

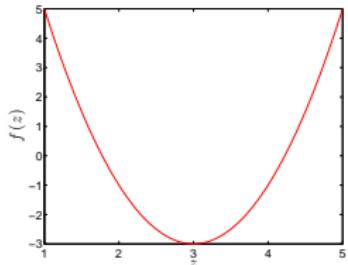
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At a minimum, the gradient must be increasing.

Finding maxima and minima

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At a minimum, the gradient must be increasing.

Taking the second derivative:

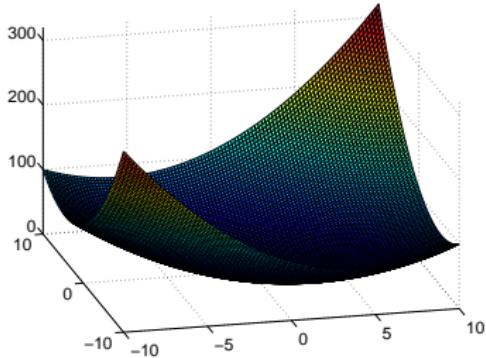
$$\begin{aligned}\frac{df(z)}{dz} &= 4z - 12 \\ \frac{d^2z}{dz^2} &= 4\end{aligned}$$

The gradient is always increasing. Therefore, we have found a minimum and it is the only minimum.

Finding maxima and minima

What about functions of more than one variable?

$$\operatorname{argmin}_{y,z} f(y, z), \quad f(y, z) = y^2 + z^2 + y + z + yz$$



We now use *partial derivatives*, $\frac{\partial f}{\partial z}$ and $\frac{\partial f}{\partial y}$

When calculating the partial derivative with respect to y we assume everything else (including z) is a constant.

$$\frac{\partial f}{\partial y} = 2y + 1 + z, \quad \frac{\partial f}{\partial z} = 2z + 1 + y$$

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To find a potential minimum, set both to zero and solve for y and z :

$$\begin{aligned}y &= -\frac{1}{3} \\z &= -\frac{1}{3}.\end{aligned}$$

To make sure its a minimum, check second derivatives:

$$\frac{\partial^2 f}{\partial y^2} = 2, \quad \frac{\partial^2 f}{\partial z^2} = 2.$$

Both are positive so we have a minimum.

Back to our function

$$\mathcal{L} = \frac{1}{N} \sum_{n=1}^N (t_n - f(x_n; w_0, w_1))^2.$$

Now, recall that:

$$f(x_n; w_0, w_1) = w_0 + w_1 x$$

So:

$$\operatorname{argmin}_{w_0, w_1} \mathcal{L} = \operatorname{argmin}_{w_0, w_1} \frac{1}{N} \sum_{n=1}^N (t_n - w_0 - w_1 x_n)^2$$

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We need to find $\frac{\partial \mathcal{L}}{\partial w_0}$ and $\frac{\partial \mathcal{L}}{\partial w_1}$, do some algebra, and we'll have expressions for the *best* values!

Differentiating the loss

- ▶ Taking partial derivatives with respect to w_0 and w_1 :

$$\mathcal{L} = \frac{1}{N} \sum_{n=1}^N (t_n - w_0 - w_1 x_n)^2$$

$$\frac{\partial \mathcal{L}}{\partial w_0} = -\frac{2}{N} \sum_{n=1}^N (t_n - w_0 - w_1 x_n)$$

$$\frac{\partial \mathcal{L}}{\partial w_1} = -\frac{2}{N} \sum_{n=1}^N x_n (t_n - w_0 - w_1 x_n)$$

Two useful differentiation identities

$$\frac{\partial}{\partial w_0} \left(\sum_{n=1}^N f_n(w_0) \right) = \sum_{n=1}^N \frac{\partial f_n(w_0)}{\partial w_0}$$

$$\frac{\partial}{\partial w_0} (f(w_0)^2) = 2f(w_0) \frac{\partial f(w_0)}{\partial w_0}$$

$$\frac{\partial \mathcal{L}}{\partial w_0} = -\frac{2}{N} \sum_{n=1}^N (t_n - w_0 - w_1 x_n)$$

$$0 = -\frac{2}{N} \sum_{n=1}^N (t_n - w_0 - w_1 x_n)$$

$$\frac{2}{N} \sum_{n=1}^N w_0 = \frac{2}{N} \sum_{n=1}^N t_n - \frac{2}{N} \sum_{n=1}^N w_1 x_n$$

$$w_0 = \bar{t} - w_1 \bar{x}$$

Where

$$\bar{t} = \frac{1}{N} \sum_{n=1}^N t_n, \quad \bar{x} = \frac{1}{N} \sum_{n=1}^N x_n$$

$$\frac{\partial \mathcal{L}}{\partial w_1} = -\frac{2}{N} \sum_{n=1}^N x_n(t_n - w_0 - w_1 x_n)$$

$$0 = -\frac{2}{N} \sum_{n=1}^N x_n(t_n - w_0 - w_1 x_n)$$

$$w_1 \frac{1}{N} \sum_{n=1}^N x_n^2 = \frac{1}{N} \sum_{n=1}^N x_n t_n - w_0 \frac{1}{N} \sum_{n=1}^N x_n$$

$$w_1 \overline{x^2} = \overline{xt} - w_0 \overline{x}$$

Where

$$\overline{x^2} = \frac{1}{N} \sum_{n=1}^N x_n^2, \quad \overline{xt} = \frac{1}{N} \sum_{n=1}^N x_n t_n$$

Substituting:

Substituting our expression for w_0 into that for w_1 :

$$\begin{aligned} w_0 &= \bar{t} - w_1 \bar{x} \\ w_1 \overline{x^2} &= \overline{xt} - w_0 \bar{x} \\ w_1 \overline{x^2} &= \overline{xt} - \bar{x}(\bar{t} - w_1 \bar{x}) \\ w_1 &= \frac{\overline{xt} - \bar{x}\bar{t}}{\bar{x}^2 - (\bar{x})^2} \end{aligned}$$

So, to summarise:

$$w_1 = \frac{\overline{xt} - \bar{x}\bar{t}}{\bar{x}^2 - (\bar{x})^2}, \quad w_0 = \bar{t} - w_1 \bar{x}$$

Note that $\overline{xt} \neq \bar{x}\bar{t}$ and $\overline{x^2} \neq (\bar{x})^2$.

Olympic data

n	x_n	t_n	$x_n t_n$	x_n^2
1	1896	12.00	22752.0	3.5948e+06
2	1900	11.00	20900.0	3.6100e+06
3	1904	11.00	20944.0	3.6252e+06
:	:	:	:	:
26	2004	9.85	19739.4	4.0160e+06
27	2008	9.69	19457.5	4.0321e+06
$(1/N) \sum_{n=1}^N$	1952.37	10.39	20268.1	3.8130e+06
	\bar{x}	\bar{t}	\bar{xt}	$\bar{x^2}$

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Substituting these values into our expressions gives:

$$w_1 = -0.0133, \quad w_0 = 36.416$$