The power of differentiation

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Topics

- The big idea: optimisation by following gradients
- Recap: what are gradients and how do we find them?
- Recap: Singular Value Decomposition and its applications
- Example: Computing SVD using gradients The Netflix Challenge

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 - How do we select those parameters?
- In deep learning/differentiable programming we typically define an objective function that we minimise (or maximise) with respect to those parameters
- This implies that we're looking for points at which the gradient of the objective function is zero w.r.t the parameters

The big idea: optimisation by following gradients
A simple 1D example

The big idea: optimisation by following gradients
A simple 2D example

The big idea: optimisation by following gradients

A more indicative example

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Recap: what are gradients and how do we find them?

The derivative in 1D

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$$\frac{dy}{dx} = 2x$$

Aside: numerical approximation of the derivative

 For numerical computation of gradients it is better to use a "centralised" definition of the gradient:

•
$$f'(a) = \lim_{h \to 0} \frac{f(a+h) - f(a-h)}{2h}$$

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 - $f'(a) = \lim_{h \to 0} \frac{f(a+h) f(a-h)}{2h}$
 - This is known as the symmetric difference quotient

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 - For small values of *h* this has less error than the standard one-sided difference quotient.

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- For numerical computation of gradients it is better to use a "centralised" definition of the gradient:
 - $f'(a) = \lim_{h \to 0} \frac{f(a+h) f(a-h)}{2h}$
 - This is known as the *symmetric difference quotient*
 - For small values of h this has less error than the standard one-sided difference quotient.
- If you are going to use this to estimate gradients you need to be aware of potential rounding errors due to floating point representations.
 - Calculating gradients this way using less than 64-bit precision is rarely going to be useful. (Numbers are not represented exactly, so even if h is represented exactly, x + h will probably not be)
 - You need to pick an appropriate *h* too small and the subtraction will have a large rounding error!

Recap: what are gradients and how do we find them? Derivatives of deeper functions

 Deep learning is all about optimising deeper functions; functions that are compositions of other functions

• e.g.
$$z = f \circ g(x) = f(g(x))$$

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- The chain rule of calculus tells us how to differentiate compositions of functions:

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Note that this is a silly example that just serves to demonstrate the principle!

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$$z = (x^2)^2 = y^2$$
 where $y = x^2$

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Example: differentiating $z = x^4$

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$$z = x^4$$

 $z = (x^2)^2 = y^2$ where $y = x^2$
 $\frac{dz}{dx} = \frac{dz}{dy} \frac{dy}{dx} = (2y)(2x) = (2x^2)(2x) = 4x^3$

Example: differentiating $z = x^4$

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$$z = x4$$

$$z = (x2)2 = y2 \text{ where } y = x2$$

$$\frac{dz}{dx} = \frac{dz}{dy} \frac{dy}{dx} = (2y)(2x) = (2x2)(2x) = 4x3$$

Equivalently, from first principles:

$$z = x^{4}$$

$$\frac{dz}{dx} = \lim_{h \to 0} \frac{(x+h)^{4} - x^{4}}{h}$$

$$\frac{dz}{dx} = \lim_{h \to 0} \frac{h^{4} + 4h^{3}x + 6h^{2}x^{2} + 4hx^{3} + x^{4} - x^{4}}{h}$$

$$\frac{dz}{dx} = \lim_{h \to 0} h^{3} + 4h^{2}x + 6hx^{2} + 4x^{3} = 4x^{3}$$

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Functions of multiple variables: partial differentiation

Functions of vectors and matrices: partial differentiation

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Example: Computing SVD using gradients - The Netflix Challenge