

# INTRODUCTION TO OPTIMISATION

Spring 2022

Prerequisites:

- matrix computations
- multivariate calculus



# MATRIX COMPUTATIONS

$$\begin{cases} ax + by = b_1 \\ cx + dy = b_2 \end{cases}$$

$$\Leftrightarrow A \begin{pmatrix} x \\ y \end{pmatrix} = b \quad ; \quad A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}, \quad b = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$$

$$A \in \mathbb{R}^{2 \times 2}, \quad b \in \mathbb{R}^2$$

$$\begin{aligned} \text{Inner product: } \underline{a} \cdot \underline{b} &= (\alpha_1 \underline{i} + \alpha_2 \underline{j} + \alpha_3 \underline{k}) \cdot (\beta_1 \underline{i} + \beta_2 \underline{j} + \beta_3 \underline{k}) \\ &= \sum_{i=1}^3 \alpha_i \beta_i \end{aligned}$$

$$\begin{aligned} \text{In matrix form: } a &= (\alpha_1 \quad \alpha_2 \quad \alpha_3)^T \\ b &= (\beta_1 \quad \beta_2 \quad \beta_3)^T \\ a^T b &= \sum \alpha_i \beta_i \end{aligned}$$

# GEOMETRY

Equation of a plane:  $\mathbb{R}^3$

$$\underline{n} \cdot (\underline{r} - \underline{r}_0) = 0$$

$\underline{n}$  is the normal;  $\underline{r}_0$  a point on the plane

$$\underline{r} = x \underline{i} + y \underline{j} + z \underline{k}$$

Coordinate form:  $c_1 x + c_2 y + c_3 z = d$

$$\left. \begin{array}{l} \underline{n} \Rightarrow n = (c_1 \ c_2 \ c_3)^T \\ \underline{r} \Rightarrow r = (x \ y \ z)^T \\ \underline{r}_0 \Rightarrow r_0 = (x_0 \ y_0 \ z_0)^T \end{array} \right\} n^T r = n^T r_0 = d$$

This notation is agnostic to the dimension:  $\mathbb{R}^n$  ok.



What about a line in space?

— There are no coordinate form expressions:

A line in space is the intersection of two planes.

SURFACE :  $z = f(x, y)$

Gradient :  $\nabla f = \frac{\partial f}{\partial x} \underline{i} + \frac{\partial f}{\partial y} \underline{j}$

Example :  $z = ax + by$

$$\nabla f = a \underline{i} + b \underline{j}$$

Fix  $z$  ; Constant (intercept changes)

Gradient is the normal to the line.

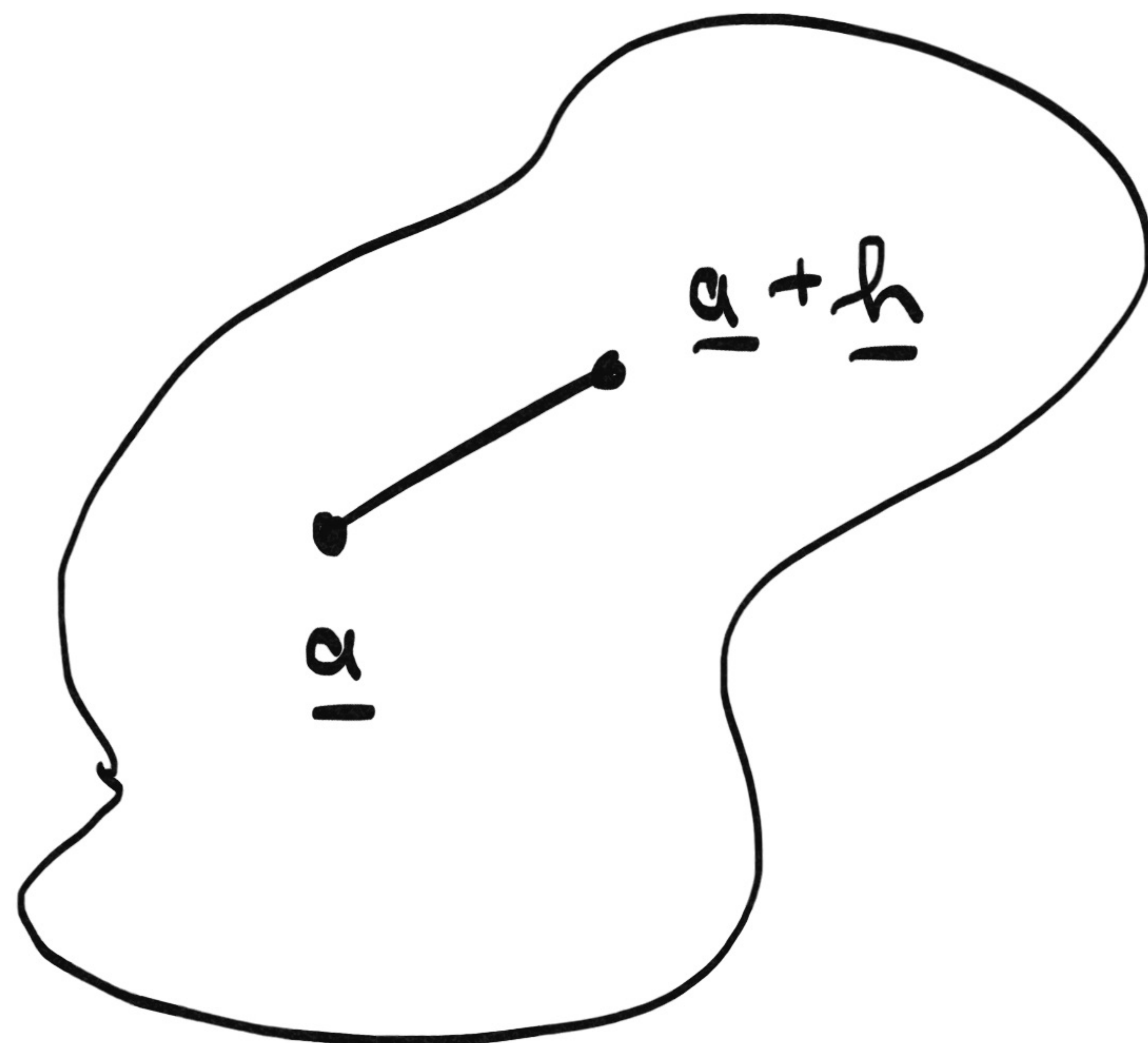
## TANGENT PLANE

$$z = f(x, y) \quad ; \quad \text{Point } (a, b)$$

$$z = f(a, b) + \frac{\partial f}{\partial x}(x - a) + \frac{\partial f}{\partial y}(y - b)$$

$$\Rightarrow \text{normal: } \underline{n} = \frac{\partial f}{\partial x} \underline{i} + \frac{\partial f}{\partial y} \underline{j} - \underline{k}$$

## TAYLOR



$$f(\underline{a} + \underline{h}) \approx$$

$$\sum_{j=0}^{\infty} \frac{(\underline{h} \cdot \nabla)^j f(\underline{a})}{j!}$$

$m=1$  : Tangent plane!



2<sup>nd</sup> ORDER (with abusing the notation)

$$f(\underline{x} + \underline{h}) \approx f(\underline{x}) + \underline{h} \cdot \nabla f(\underline{x}) + \frac{1}{2} \underline{h} H_f(\underline{x}) \underline{h}^T$$

$$H_f(\underline{x}) = \begin{pmatrix} \frac{\partial^2}{\partial x_1^2} f(\underline{x}) & \frac{\partial^2}{\partial x_2 \partial x_1} f(\underline{x}) & \dots & \frac{\partial^2}{\partial x_n \partial x_1} f(\underline{x}) \\ \frac{\partial^2}{\partial x_1 \partial x_2} f(\underline{x}) & \frac{\partial^2}{\partial x_2^2} f(\underline{x}) & \dots & \\ \vdots & & \ddots & \\ \frac{\partial^2}{\partial x_1 \partial x_n} f(\underline{x}) & & & \frac{\partial^2}{\partial x_n^2} f(\underline{x}) \end{pmatrix}$$

The Hessian : Real & Symmetric

It is positive definite if all eigenvalues are positive ;  $\lambda_i > 0$

Negative definite :  $\lambda_i < 0$

Indefinite, otherwise



# LAGRANGE : Constrained Optimisation

For instance: maximise  $f(x,y)$  subject to  
 $g(x,y) = C$

Lagrange function :

$$L(x,y,\lambda) = f(x,y) + \lambda g(x,y)$$

$\nabla L(x,y,\lambda) = 0$  are the critical points.

$\lambda$  is the Lagrange multiplier.

Geometric interpretation :

$$\nabla f(x,y) \parallel \nabla g(x,y)$$

for the problem to have a solution.



# NOTATION (YET ANOTHER LANGUAGE)

Problem P :  $\min f(x)$

$$\text{s.t. : } g_i(x) \leq 0, \quad i = 1, \dots, m$$

$$h_j(x) = 0, \quad j = 1, \dots, l$$

$$x \in \underline{X}$$

$x \in \mathbb{R}^n$  : decision variables

$f : \mathbb{R}^n \rightarrow \mathbb{R}$  : objective function

$\underline{X} \subseteq \mathbb{R}^n$  : ground set (physical constraints)

$g_i, h_j : \mathbb{R}^n \rightarrow \mathbb{R}$  : constraint functions

$g_i \leq 0$  : inequality constraints

$h_j = 0$  : equality constraints