THE UNIVERSITY of EDINBURGH
informatics

Advanced Robotics

2 – Intro to optimisation - least-squares minimisation
15 Sep 2025

Steve Tonneau - School of Informatics
University of Edinburgh

Course objective (reminder):

Control a robot in an environment such that it accomplishes a motion task

Model of the robot (and the environment)

- Geometry / Dynamics state   Let's start with this
- Constraints (collisions, forces etc)

Mathematical definition of a task as a (differentiable) function

- $f(q) = 0$ means the task is satisfied

Motion generated using an optimal control formulation

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Control a robot in an environment such that it accomplishes a motion task

Model of the robot (and the environment)

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Let's start with this...
... But before that ... Let's talk about optimisation (just a bit)

- Constraints (collisions, forces etc)

Mathematical definition of a task as a (differentiable) function

- f(q) = 0 means the task is satisfied

Motion generated using an optimal control formulation

Lecture objective:

Starting from well-known notions from secondary school:

- ❑ Progressively get familiar with the concept of optimisation
- ❑ Brush-off basic Matrix operations

Your objectives for the lecture:

- ❑ The concept of minimising an objective through gradient analysis
- ❑ The notion of constraint (we probably won’t have time)

NB: Today’s techniques don’t work in most cases in robotics (because of non linearities)

This is a new lecture based on last year’s observations

Any feedback is welcome. This lecture might not seem like a robotics one but it is.

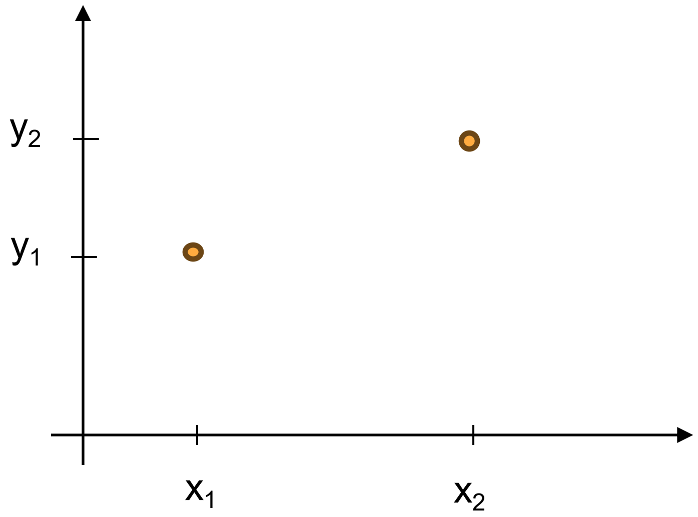
Back to secondary school

Given two samples (x_1,y_1) and (x_2,y_2) reconstruct a trajectory $y=f(x)$

- Assuming f(x) is *linear* (follows a line)

Example of application – 1D robot

- x axis is time
- y axis is position
- (x,y) state punctually estimated using on board-sensing => noise



How do we solve this ?

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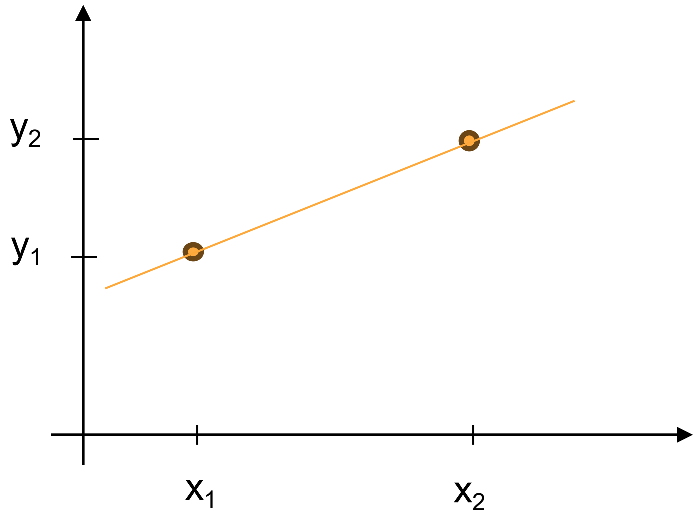
Let's work on the board. Solution on slides afterwards



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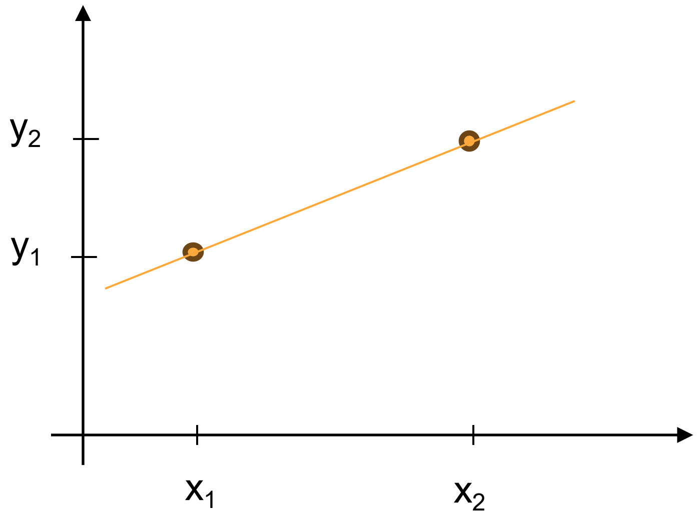
$$\Rightarrow \begin{aligned} y_1 &= w_0 x_1 + w_1 \\ y_2 &= w_0 x_2 + w_1 \end{aligned}$$

The unknown is $\mathbf{w} = [w_0, w_1] \in \mathbb{R}^2$ vectors in lower case bold



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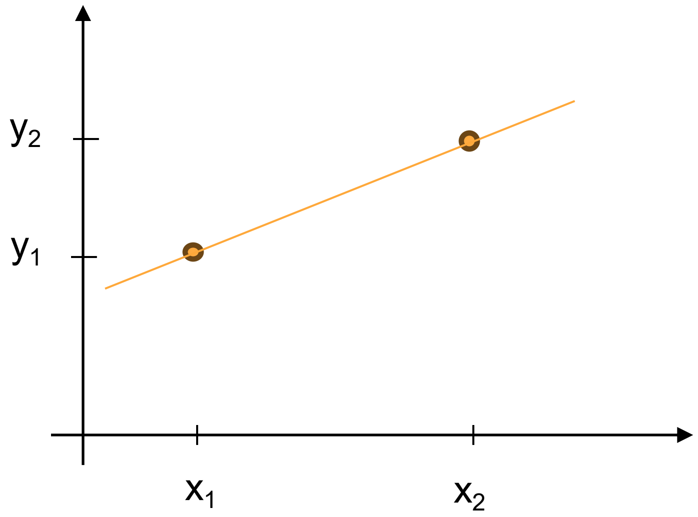
$$y_1 - y_2 = w_0(x_1 - x_2)$$

$$\boxed{\begin{aligned} w_0 &= \frac{y_1 - y_2}{x_1 - x_2} \\ w_1 &= y_1 - w_0 x_1 \end{aligned}}$$



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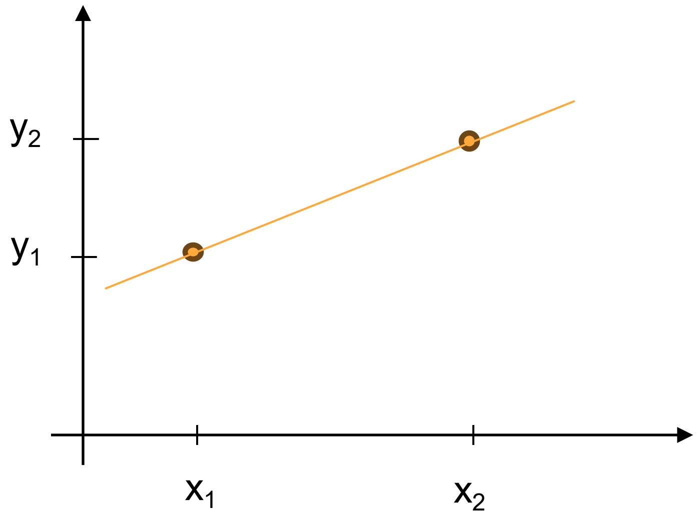

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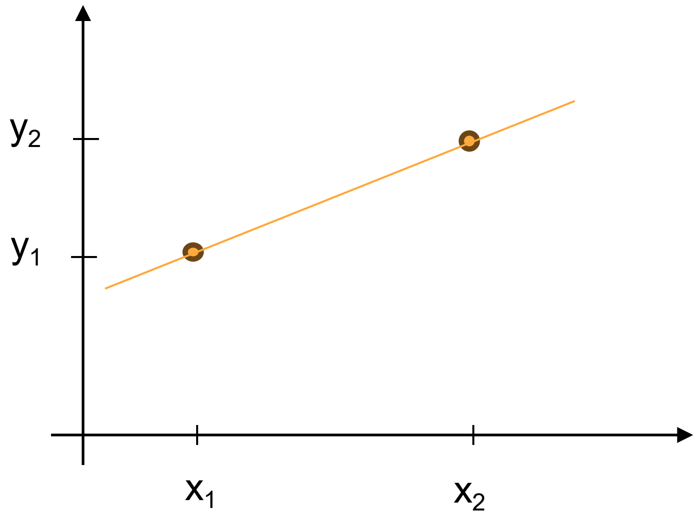
Matrices in **upper** case bold



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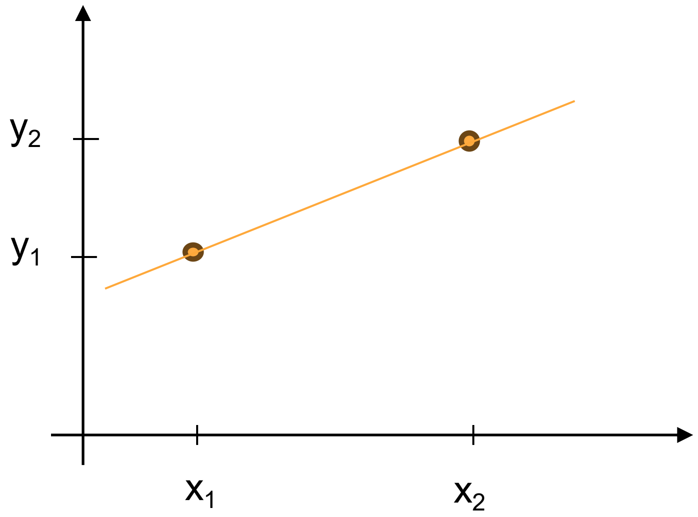

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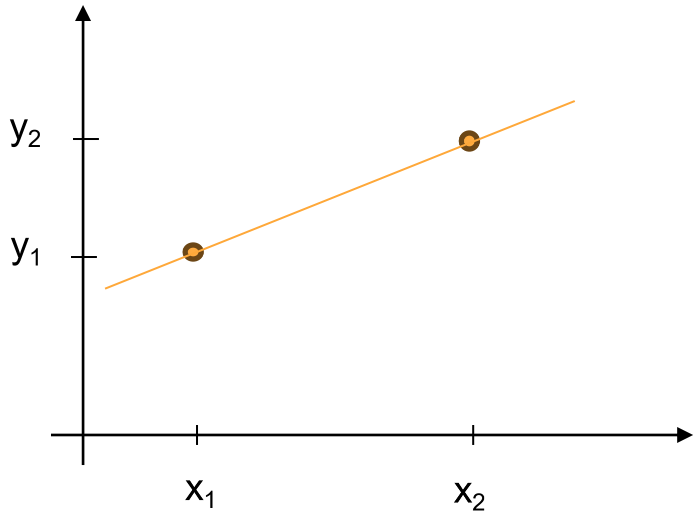
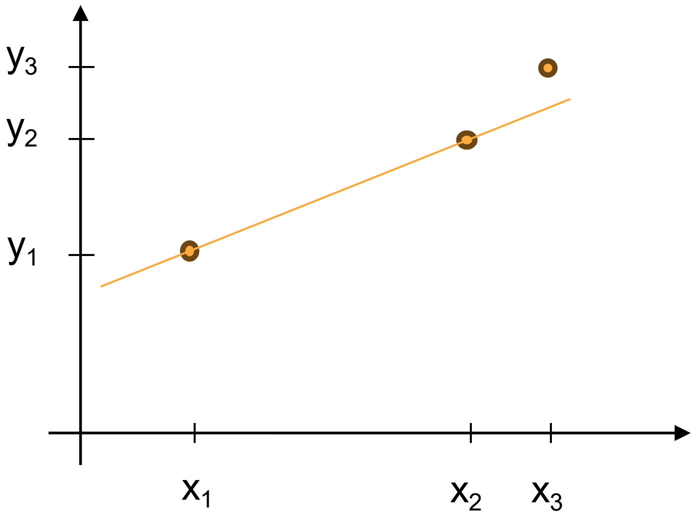


What if X is not invertible?

Exercise: calculate the inverse of X and check that you find the desired solution

What if we consider n > 2 samples? ⌛

- ❑ Noisy sensors / actuators => not all points on a line

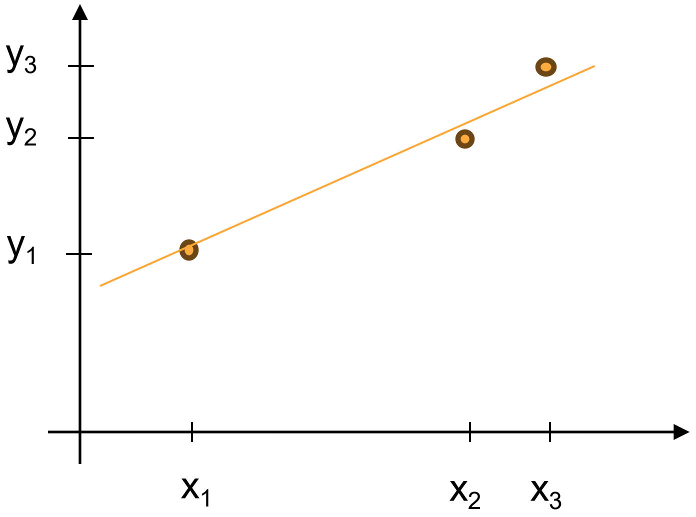


Optimising an objective

- Try to approximate "as best as possible":

  Minimise cost / error OR maximise a reward (same thing)

- What objective?
  - If perfect match exists, we want this
  - On average all points are "close enough"



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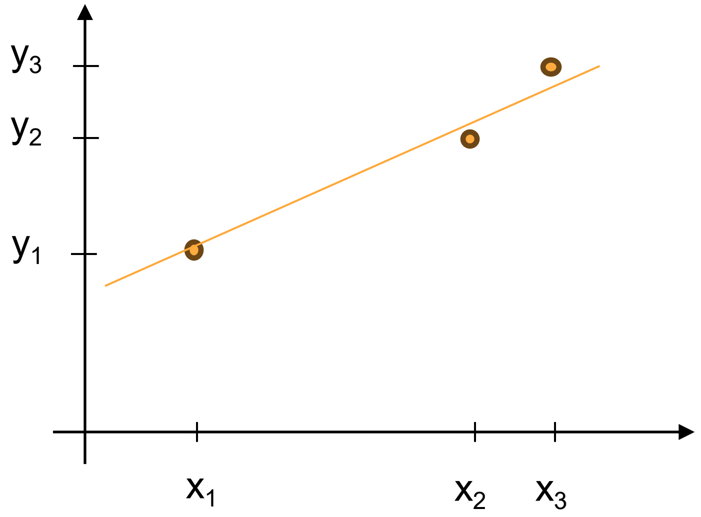


- ❑ Minimise the residual error between sample and line prediction:

$$r_i = y_i - (w_0 x_i + w_1), \forall i = \{1, \ldots, n\}$$

Square it to deal with negative values:

$$l(\mathbf{w}) = \sum_{i=1}^{n} r_i^2$$

Does this satisfy our objectives?

How to minimise l(w)?

- Minimise $l(\mathbf{w}) = \sum_{i=1}^{n} r_i^2$ where $r_i = y_i - (w_0 x_i + w_1), \forall i = \{1, \dots, n\}$

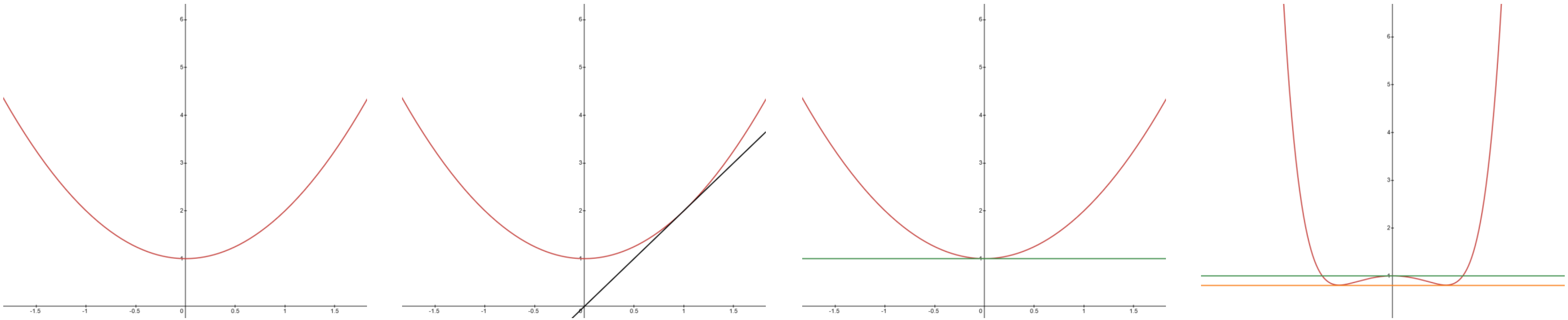
- Matrix form is

$$\underbrace{\begin{bmatrix} r_1 \\ \dots \\ r_n \end{bmatrix}}_{\mathbf{r}} = \underbrace{\begin{bmatrix} y_1 \\ \dots \\ y_n \end{bmatrix}}_{\mathbf{y}} - \underbrace{\begin{bmatrix} x_1 & 1 \\ \dots & \\ x_n & 1 \end{bmatrix}}_{\mathbf{X}} \underbrace{\begin{bmatrix} w_0 \\ w_1 \end{bmatrix}}_{\mathbf{w}}$$

- We thus want to find the minimum of $l(\mathbf{w}) = \mathbf{r}^T\mathbf{r} = (\mathbf{y} - \mathbf{X}\mathbf{w})^T(\mathbf{y} - \mathbf{X}\mathbf{w})$

How to minimise l(**w**)?

- Necessary (not sufficient) condition for a minimum: gradient is **0** (stationary point)



To minimise l(**w**) we compute the gradient

$$\nabla_{\mathbf{w}} l(\mathbf{w}) = \frac{d}{d\mathbf{w}}(\mathbf{r}^T \mathbf{r}) = \left[\frac{\partial l}{\partial w_0}, \frac{\partial l}{\partial w_1} \right] \in \mathbb{R}^2$$

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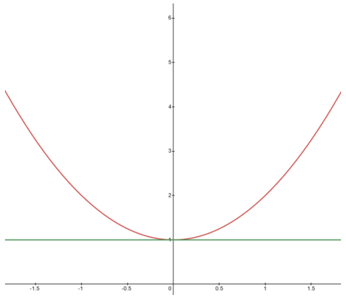
Objective: set this gradient to 0



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<u>Chain rule:</u>

$$\frac{d}{dx} f(g(x)) = f'(g(x)) \cdot g'(x)$$

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$$\frac{d\mathbf{r}}{d\mathbf{w}} = \frac{d}{d\mathbf{w}}(\mathbf{y} - \mathbf{X}\mathbf{w})$$

$$= \frac{d}{d\mathbf{w}}(-\mathbf{X}\mathbf{w})$$

$$\frac{d}{d\mathbf{w}}(\mathbf{r}^T\mathbf{r}) = 2\mathbf{r}^T\frac{d\mathbf{r}}{d\mathbf{w}}$$

$$\frac{d\mathbf{r}}{d\mathbf{w}} = -\mathbf{X}$$

To minimise l($\mathbf{w}$) we compute the gradient

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$$\frac{d\mathbf{r}}{d\mathbf{w}} = -\mathbf{X}$$

$$\frac{\partial}{\partial\mathbf{w}}(\mathbf{r}^T\mathbf{r}) = 2\mathbf{r}^T(-\mathbf{X})$$
$$= 2(\mathbf{y} - \mathbf{X}\mathbf{w})^T(-\mathbf{X})$$

Optimum at gradient = 0

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Transpose of a scalar is equal to the scalar

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$$(\mathbf{A}\mathbf{B})^T = \mathbf{B}^T\mathbf{A}^T, (\mathbf{A}^T)^T = A$$

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$$\mathbf{w} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}$$

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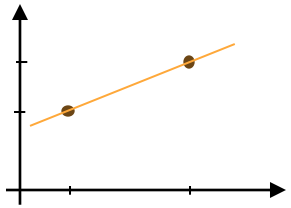

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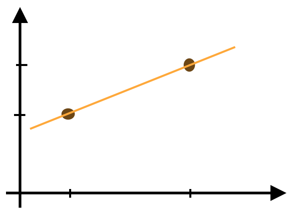

Exact vs approximate solution depends
on whether X is invertible!
Although pseudo-inverse not always defined (underconstrained)

In conclusion

- Optimisation is essentially working with the gradients of a function
  - Setting it to 0 does not guarantee global optimum (except in some cases)
  - We need to be able to invert matrices / approximate something close enough
- Least squares is a widely used technique
  - Constraints require extra work => Can we set constraints into the cost ?
  - Inversion is really a problem (numerical instability)
- Exercice. What is y=f(y) is a polynomial of degree 3 (or higher) ? Would unconstrained least square still work?

Homework for next week

- ❑ Self run the python tutorial if you need
- ❑ Make sure your environment is setup on DICE and run tutorial 0
- ❑ Ask questions on ~~Piazza~~ EdStem if you do not understand something