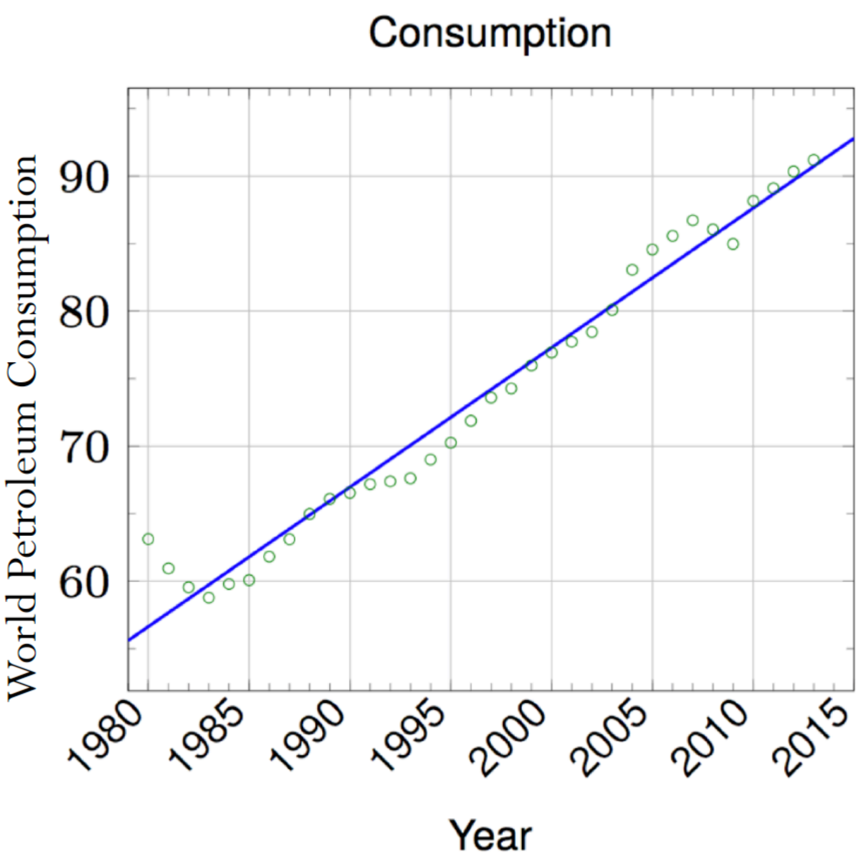
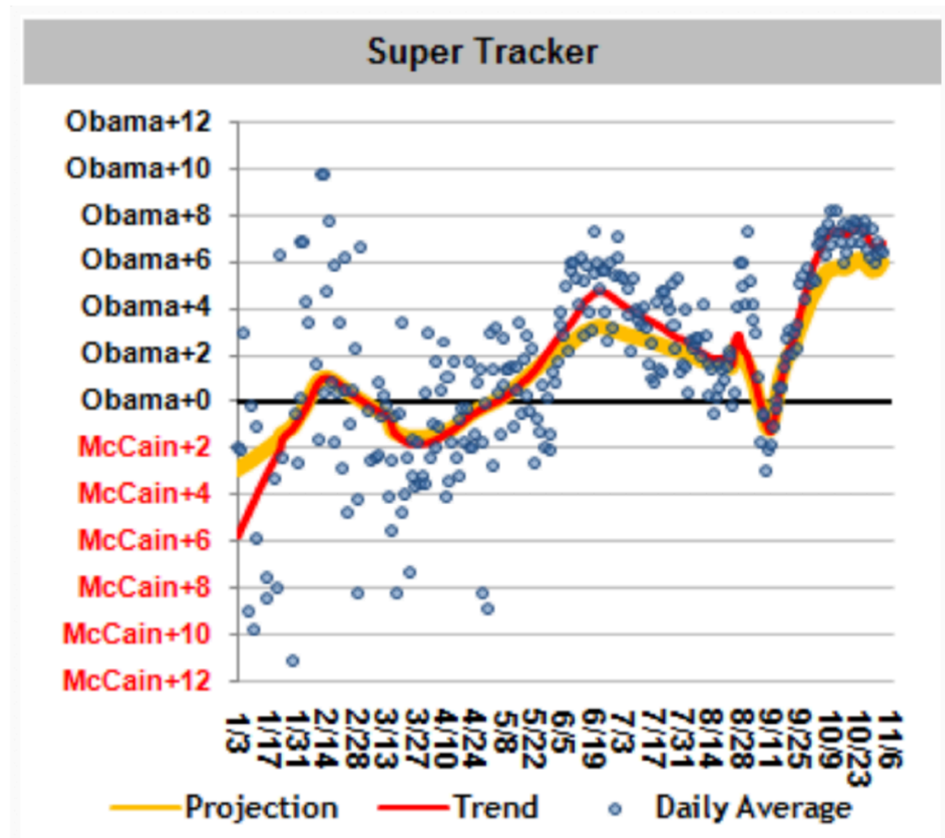
Least Squares and Data Fitting

Data fitting

How do we best fit a set of data points?





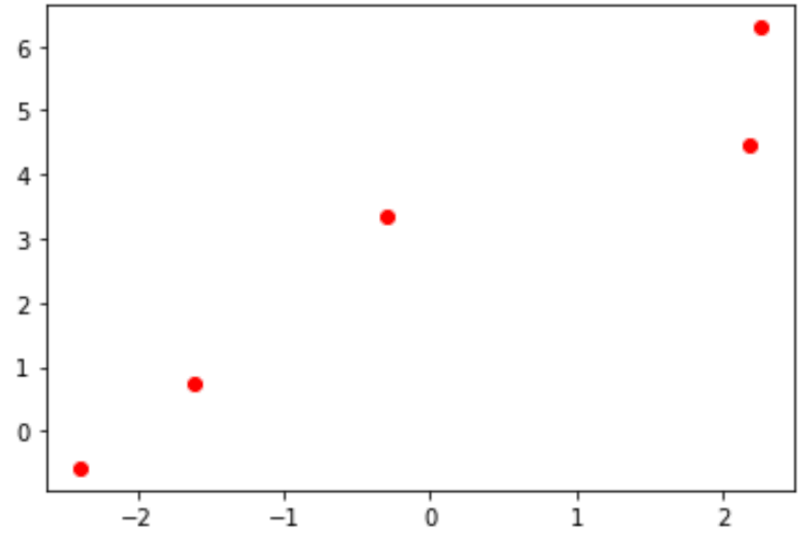
Linear Least Squares
1) Fitting with a line

Given m data points $\{\{t_1, y_1\}, \dots, \{t_m, y_m\}\}$, we want to find the function

$$y = x_o + x_1\, t$$

that best fit the data (or better, we want to find the coefficients x_o, x_1).

Thinking geometrically, we can think "what is the line that most nearly passes through all the points?"



Given m data points $\{\{t_1, y_1\}, \dots, \{t_m, y_m\}\}$, we want to find x_o and x_1 such that

$$y_i = x_o + x_1\, t_i \qquad \forall i \in [1, m]$$

or in matrix form:

$$\underset{m\times n}{\begin{bmatrix} 1 & t_1 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix}} \underset{n\times 1}{\begin{bmatrix} x_o \\ x_1 \end{bmatrix}} = \underset{m\times 1}{\begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix}} \qquad \boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{b}$$

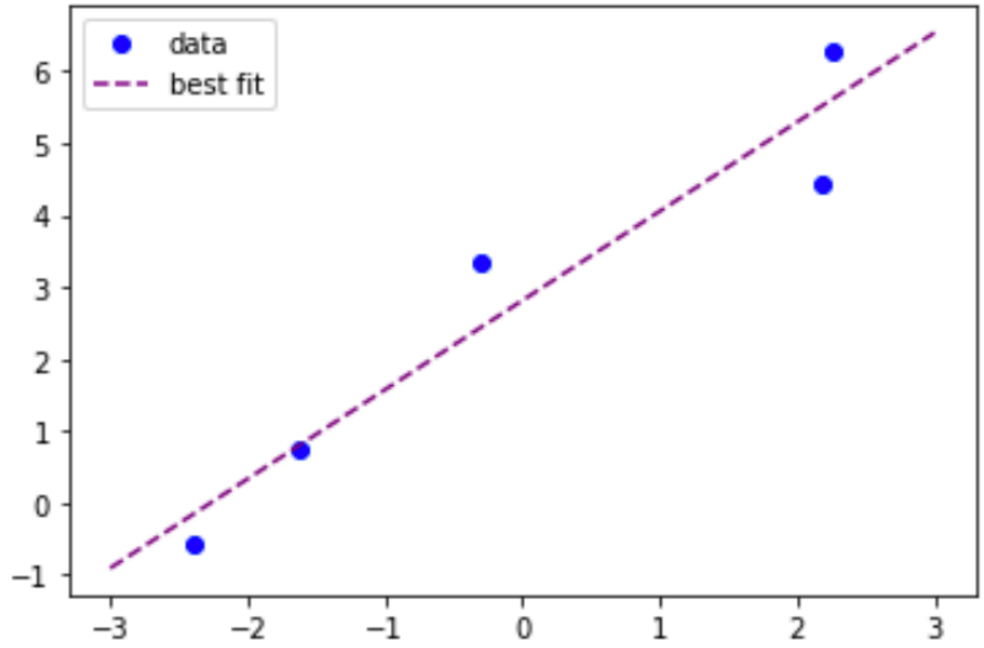
Note that this system of linear equations has more equations than unknowns – OVERDETERMINED SYSTEMS

We want to find the appropriate linear combination of the columns of $\boldsymbol{A}$ that makes up the vector $\boldsymbol{b}$.

If a solution exists that satisfies $\boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{b}$ then $\boldsymbol{b} \in range(\boldsymbol{A})$

Linear Least Squares

- In most cases, $\boldsymbol{b} \notin range(\boldsymbol{A})$ and $\boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{b}$ **does not have an exact solution**!



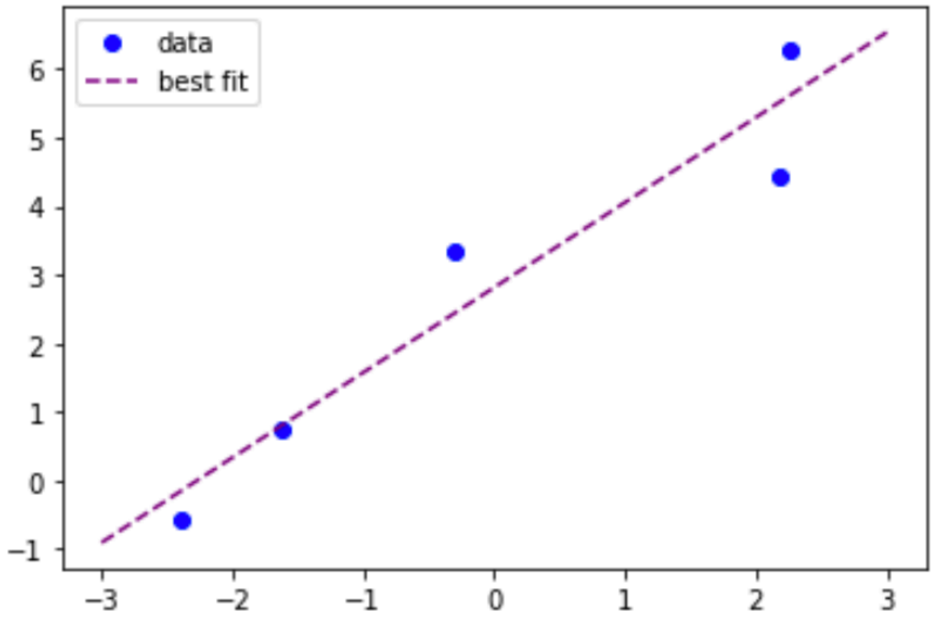
- Therefore, an overdetermined system is better expressed as

$$\boldsymbol{A}\,\boldsymbol{x} \cong \boldsymbol{b}$$

Linear Least Squares

- **Least Squares**: find the solution $\boldsymbol{x}$ that minimizes the residual

$$\boldsymbol{r} = \boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}$$



- Let's define the function ϕ as the square of the 2-norm of the residual

$$\phi(\boldsymbol{x}) = \|\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}\|_2^2$$

Linear Least Squares

- **Least Squares**: find the solution $\boldsymbol{x}$ that minimizes the residual

$$\boldsymbol{r} = \boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}$$

- Let's define the function ϕ as the square of the 2-norm of the residual

$$\phi(\boldsymbol{x}) = \|\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}\|_2^2$$

- Then the least squares problem becomes

$$\min_{\boldsymbol{x}} \phi\,(\boldsymbol{x})$$

- Suppose $\phi: \mathcal{R}^m \rightarrow \mathcal{R}$ is a smooth function, then $\phi(\boldsymbol{x})$ reaches a (local) maximum or minimum at a point $\boldsymbol{x}^* \in \mathcal{R}^m$ only if

$$\nabla\phi(\boldsymbol{x}^*) = 0$$

How to find the minimizer?

- To minimize the 2-norm of the residual vector

$$\min_{\boldsymbol{x}} \phi(\boldsymbol{x}) = \|\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}\|_2^2$$

$$\phi(\boldsymbol{x}) = (\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x})^T(\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x})$$

$$\nabla\phi(\boldsymbol{x}) = 2(\boldsymbol{A}^T\,\boldsymbol{b} - \boldsymbol{A}^T\boldsymbol{A}\,\boldsymbol{x})$$

Normal Equations – solve a linear system of equations

First order necessary condition:

$$\nabla\phi(\boldsymbol{x}) = 0 \rightarrow \boldsymbol{A}^T\,\boldsymbol{b} - \boldsymbol{A}^T\boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{0} \rightarrow \boldsymbol{A}^T\boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{A}^T\,\boldsymbol{b}$$

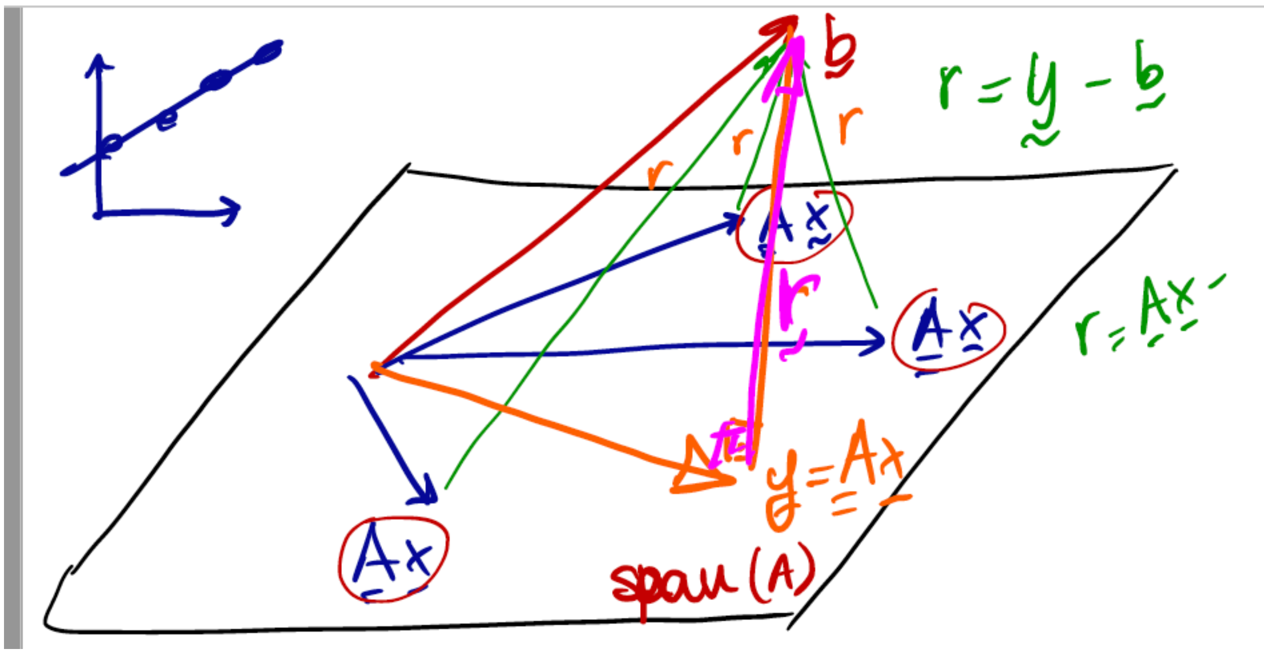
Second order sufficient condition:

$$D^2\phi(\boldsymbol{x}) = 2\boldsymbol{A}^T\boldsymbol{A}$$

$2\boldsymbol{A}^T\boldsymbol{A}$ **is a positive semi-definite matrix** → **the solution is a minimum**

Linear Least Squares (another approach)

- Find $\boldsymbol{y} = \boldsymbol{A}\,\boldsymbol{x}$ which is closest to the vector $\boldsymbol{b}$
- What is the vector $\boldsymbol{y} = \boldsymbol{A}\,\boldsymbol{x} \in range(\boldsymbol{A})$ that is closest to vector $\boldsymbol{y}$ in the Euclidean norm?



When $\boldsymbol{r} = \boldsymbol{b} - \boldsymbol{y} = \boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}$ is orthogonal to all columns of $\boldsymbol{A}$, then $\boldsymbol{y}$ is closest to $\boldsymbol{b}$

$$\boldsymbol{A}^T\boldsymbol{r} = \boldsymbol{A}^T(\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}) = 0 \longrightarrow \boldsymbol{A}^T\boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{A}^T\,\boldsymbol{b}$$

Summary:

- $\boldsymbol{A}$ is a $m \times n$ matrix, where $m > n$.
- m is the number of data pair points. n is the number of parameters of the "best fit" function.

- Linear Least Squares problem $\boldsymbol{A}\,\boldsymbol{x} \cong \boldsymbol{b}$ ***always*** has solution.

- The Linear Least Squares solution $\boldsymbol{x}$ minimizes the square of the 2-norm of the residual:

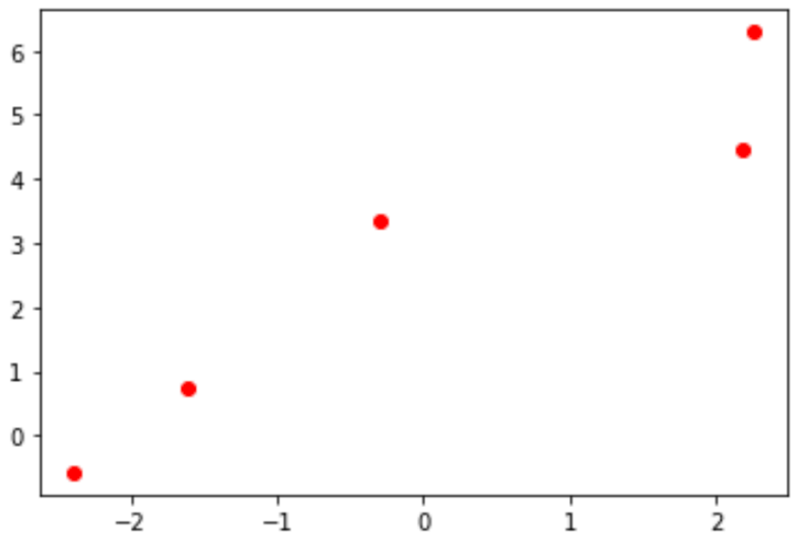
$$\min_{\boldsymbol{x}} \|\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}\|_2^2$$

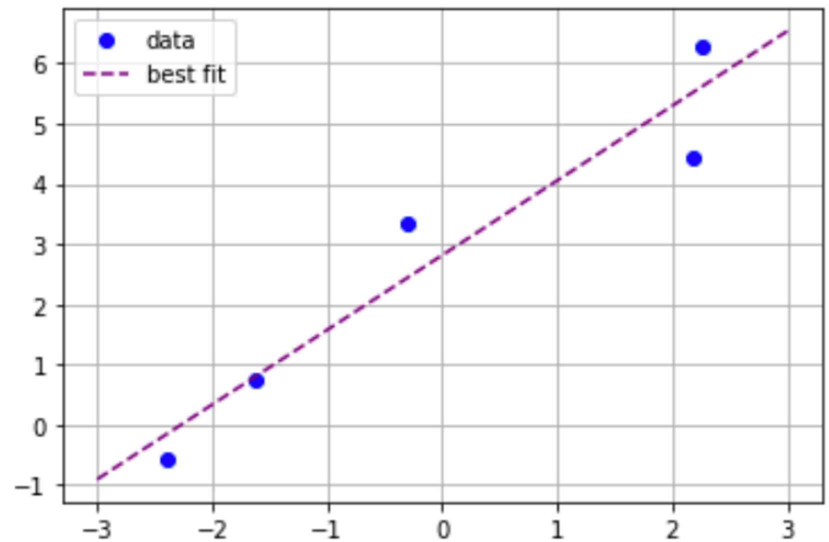
- One method to solve the minimization problem is to solve the system of **Normal Equations**

$$\boldsymbol{A}^T\boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{A}^T\,\boldsymbol{b}$$

- Let's see some examples and discuss the limitations of this method.

Example:






```
t
```

```
array([-1.61477467, -2.3970584 , -0.30372944,  2.26304537,  2.188127  ])
```

```
b
```

```
array([ 0.74112251, -0.57768693,  3.33523097,  6.29377547,  4.44786481])
```

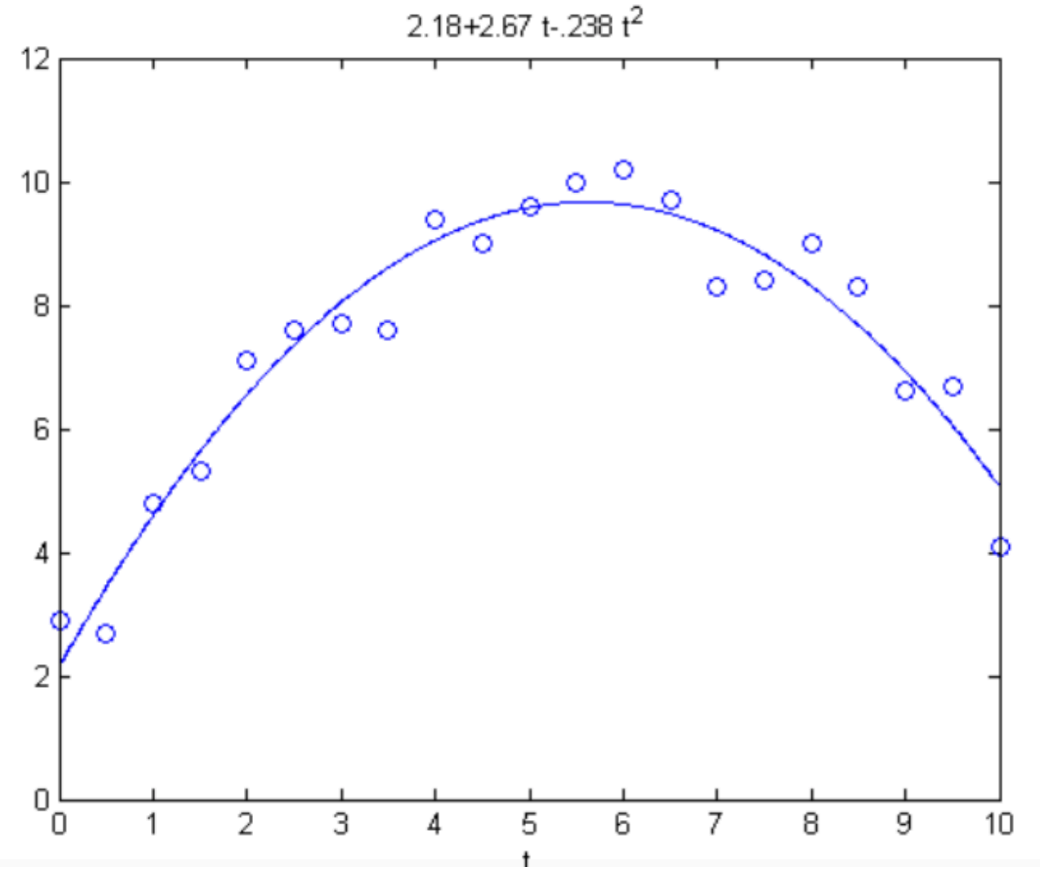
Solve: $\boldsymbol{A}^T \boldsymbol{A}\, \boldsymbol{x} = \boldsymbol{A}^T\, \boldsymbol{b}$

```
x
```

```
array([2.81441707, 1.24048133])
```

Data fitting - not always a line fit!

- Does not need to be a line! For example, here we are fitting the data using a quadratic curve.

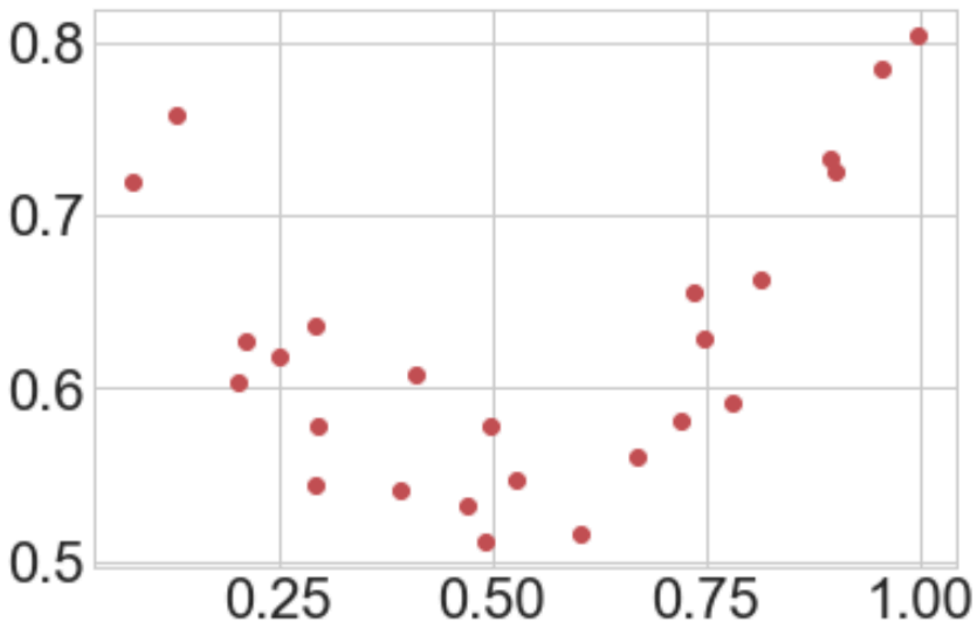


<u>Linear</u> Least Squares: The problem is **linear in its coefficients!**

Another examples

We want to find the coefficients of the quadratic function that best fits the data points:

$$y = x_0 + x_1\, t + x_2\, t^2$$

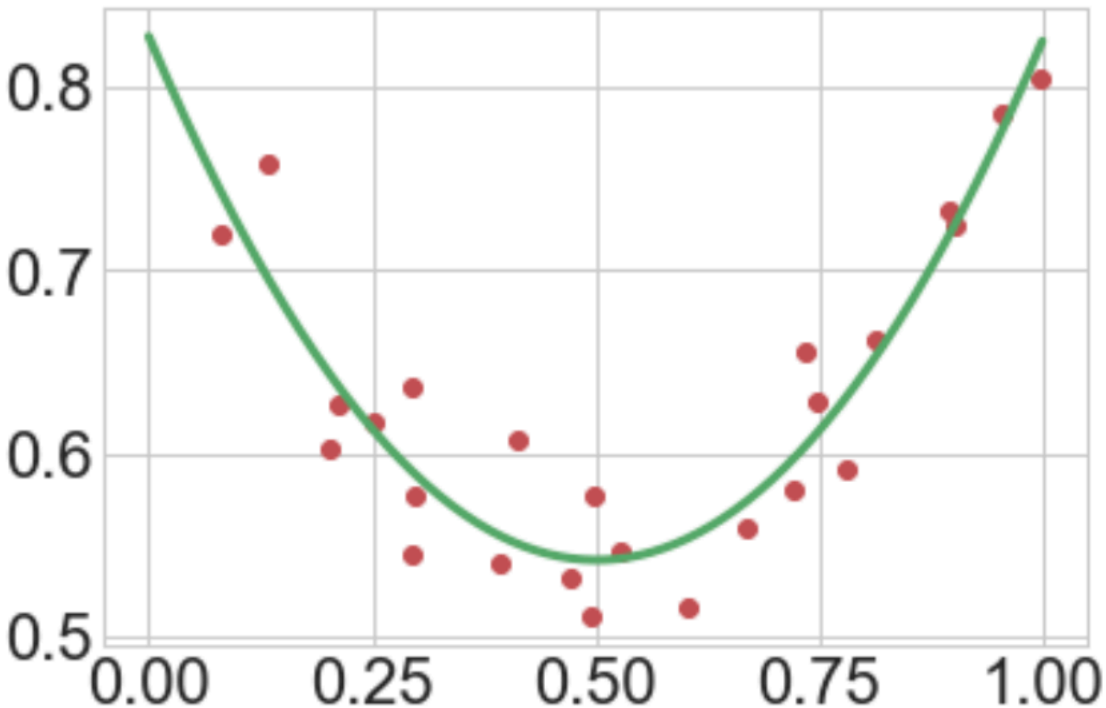


We would not want our "fit" curve to pass through the data points exactly as we are looking to model the general trend and not capture the noise.

Data fitting

$$\begin{bmatrix} 1 & t_1 & t_1^2 \\ \vdots & \vdots & \vdots \\ 1 & t_m & t_m^2 \end{bmatrix} \begin{bmatrix} x_o \\ x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix}$$

Solve: $\boldsymbol{A}^T \boldsymbol{A}\, \boldsymbol{x} = \boldsymbol{A}^T\, \boldsymbol{b}$



Which function is not suitable for linear least squares?

A) $y = a + b\,x + c\,x^2 + d\,x^3$
B) $y = x(a + b\,x + c\,x^2 + d\,x^3)$
C) $y = a\sin(x) + b/\cos(x)$
D) $y = a\sin(x) + x/\cos(bx)$
E) $y = a\,e^{-2x} + b\,e^{2x}$

Computational Cost

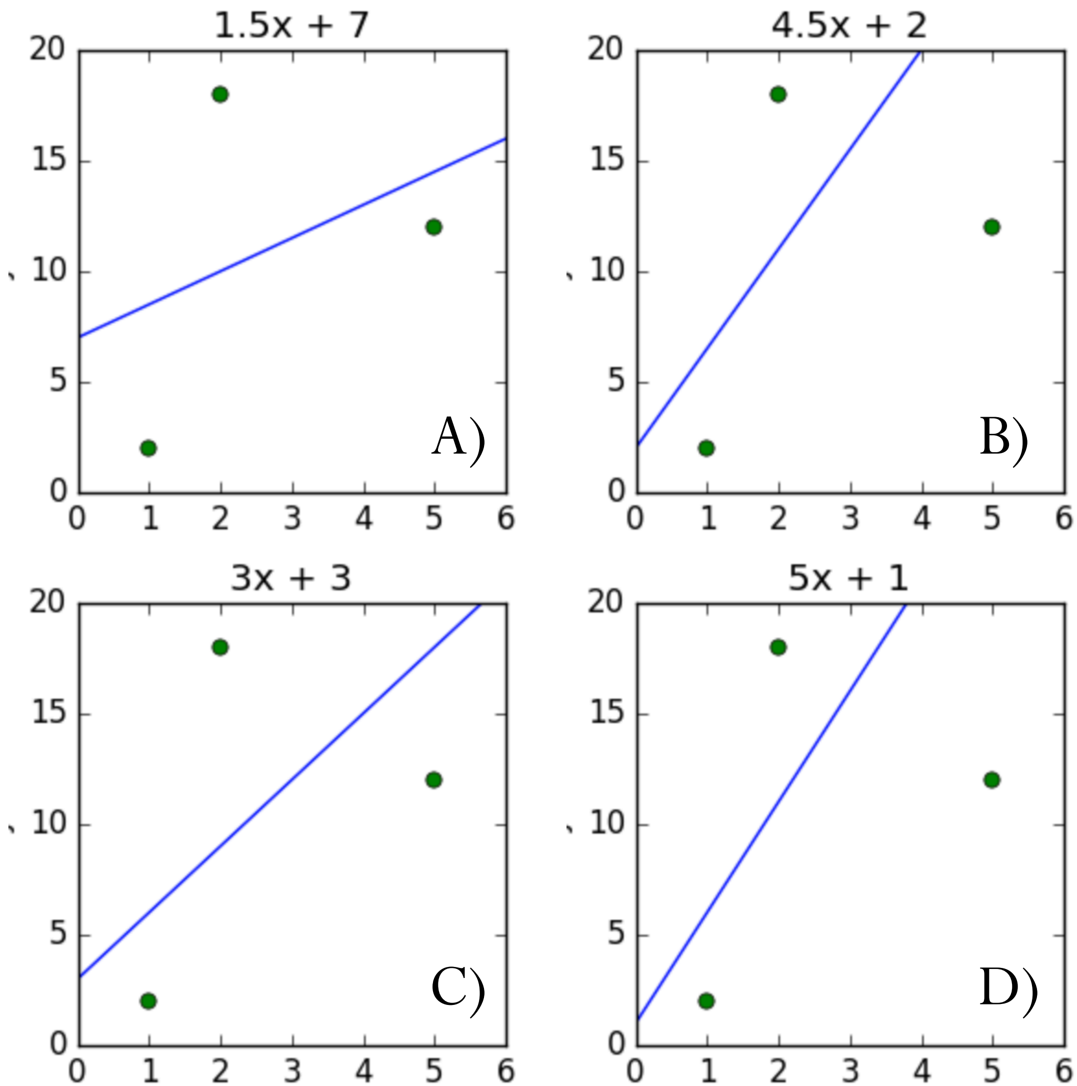
$$\boldsymbol{A}^T \boldsymbol{A}\, \boldsymbol{x} = \boldsymbol{A}^T\, \boldsymbol{b}$$

- Compute $\boldsymbol{A}^T \boldsymbol{A}$: $O(mn^2)$
- Factorize $\boldsymbol{A}^T \boldsymbol{A}$: LU $\rightarrow O\left(\frac{2}{3}n^3\right)$, Cholesky $\rightarrow O\left(\frac{1}{3}n^3\right)$
- Solve $O(n^2)$
- Since $m > n$ the overall cost is $O(mn^2)$

Short questions

Given the data in the table below, which of the plots shows the line of best fit in terms of least squares?

x	1	2	5
y	2	18	12



Short questions

Given the data in the table below, and the least squares model

$$y = c_1 + c_2 \sin(t\pi) + c_3 \sin(t\pi/2) + c_4 \sin(t\pi/4)$$

written in matrix form as

$$A \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix} \cong \mathbf{y}$$

determine the entry A_{23} of the matrix $\boldsymbol{A}$.
Note that indices start with 1.

A) -1.0
B) 1.0
C) $-$ 0.7
D) 0.7
E) 0.0

t_i	y_i
0.5	0.72
1.0	0.79
1.5	0.72
2.0	0.97
2.5	1.03
3.0	0.96
3.5	1.00

Solving Linear Least Squares with SVD

What we have learned so far…

$\boldsymbol{A}$ is a $m \times n$ matrix where $m > n$

(more points to fit than coefficient to be determined)

Normal Equations: $\boldsymbol{A}^T \boldsymbol{A}\, \boldsymbol{x} = \boldsymbol{A}^T\, \boldsymbol{b}$

- The solution $\boldsymbol{A}\, \boldsymbol{x} \cong \boldsymbol{b}$ is unique if and only if $rank(\mathbf{A}) = n$

($\boldsymbol{A}$ is full column rank)

- $rank(\mathbf{A}) = n$ → columns of $\boldsymbol{A}$ are ***linearly independent*** → n non-zero singular values → $\boldsymbol{A}^T\, \boldsymbol{A}$ has only positive eigenvalues → $\boldsymbol{A}^T \boldsymbol{A}$ is a symmetric and positive definite matrix → $\boldsymbol{A}^T \boldsymbol{A}$ is invertible

$$\boldsymbol{x} = (\boldsymbol{A}^T \boldsymbol{A})^{-1} \boldsymbol{A}^T\, \boldsymbol{b}$$

- If $rank(\mathbf{A}) < n$, then $\boldsymbol{A}$ is rank-deficient, and solution of linear least squares problem is ***not unique***.

Condition number for Normal Equations

Finding the least square solution of $\boldsymbol{A}\,\boldsymbol{x} \cong \boldsymbol{b}$ (where $\boldsymbol{A}$ is full rank matrix) using the Normal Equations

$$\boldsymbol{A}^T\boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{A}^T\,\boldsymbol{b}$$

has some advantages, since we are solving a square system of linear equations with a symmetric matrix (and hence it is possible to use decompositions such as Cholesky Factorization)

However, the normal equations tend to worsen the conditioning of the matrix.

$$cond(\boldsymbol{A}^T\boldsymbol{A}) = (cond(\boldsymbol{A}))^2$$

How can we solve the least square problem without squaring the condition of the matrix?

SVD to solve linear least squares problems

$\boldsymbol{A}$ is a $m{\times}n$ rectangular matrix where $m > n$, and hence the SVD decomposition is given by:

$$\boldsymbol{A} = \begin{pmatrix} \vdots & \cdots & \vdots \\ \boldsymbol{u}_1 & \cdots & \boldsymbol{u}_m \\ \vdots & \cdots & \vdots \end{pmatrix} \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \\ & & 0 \\ & & \vdots \\ & & 0 \end{pmatrix} \begin{pmatrix} \cdots & \mathbf{v}_1^T & \cdots \\ \vdots & \vdots & \vdots \\ \cdots & \mathbf{v}_n^T & \cdots \end{pmatrix}$$

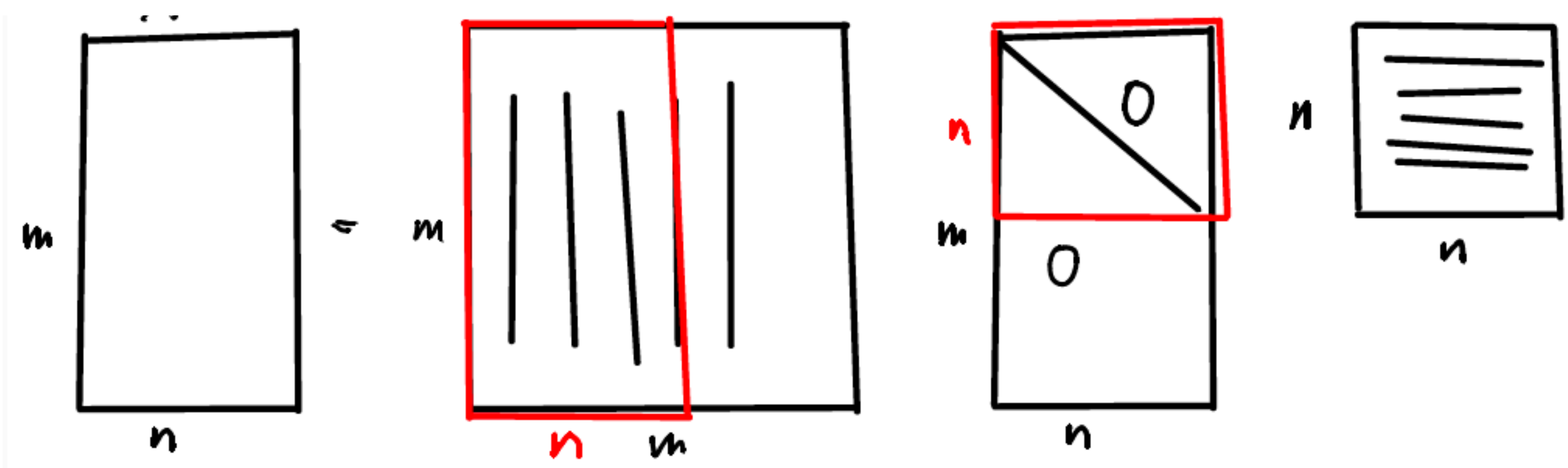
We want to find the least square solution of $\boldsymbol{A}\,\boldsymbol{x} \cong \boldsymbol{b}$, where $\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}$

or better expressed in reduced form: $\boldsymbol{A} = \boldsymbol{U}_R\ \boldsymbol{\Sigma}_{\boldsymbol{R}}\ \boldsymbol{V}^{\boldsymbol{T}}$

Recall Reduced SVD $\quad m > n$

$$\boldsymbol{A} = \boldsymbol{U}_R \, \boldsymbol{\Sigma}_R \, \boldsymbol{V}^T$$

$m \times n \qquad m \times n \qquad n \times n \qquad n \times n$



Shapes of the Reduced SVD

Suppose you compute a reduced SVD $A = U\Sigma V^T$ of a 10×14 matrix A. What will the shapes of U, Σ, and V be?

Hint: Remember the transpose on V!

The shape of U will be ☐ $\times$ ☐ .

The shape of Σ will be ☐ $\times$ ☐ .

The shape of V will be ☐ $\times$ ☐ .

SVD to solve linear least squares problems

$$\boldsymbol{A} = \boldsymbol{U}_R\ \boldsymbol{\Sigma}_R\ \boldsymbol{V}^T$$

$$\boldsymbol{A} = \begin{pmatrix} \vdots & \dots & \vdots \\ \boldsymbol{u}_1 & \dots & \boldsymbol{u}_n \\ \vdots & \dots & \vdots \end{pmatrix} \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{pmatrix} \begin{pmatrix} \dots & \mathbf{v}_1^T & \dots \\ \vdots & \vdots & \vdots \\ \dots & \mathbf{v}_n^T & \dots \end{pmatrix}$$

We want to find the least square solution of $\boldsymbol{A}\,\boldsymbol{x} \cong \boldsymbol{b}$, where $\boldsymbol{A} = \boldsymbol{U}_R\ \boldsymbol{\Sigma}_R\ \boldsymbol{V}^T$

Normal equations: $\boldsymbol{A}^T\boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{A}^T\,\boldsymbol{b} \longrightarrow (\boldsymbol{U}_R\ \boldsymbol{\Sigma}_R\ \boldsymbol{V}^T)^T(\boldsymbol{U}_R\ \boldsymbol{\Sigma}_R\ \boldsymbol{V}^T)\boldsymbol{x} = (\boldsymbol{U}_R\ \boldsymbol{\Sigma}_R\ \boldsymbol{V}^T)^T\boldsymbol{b}$

$$\boldsymbol{V}\,\boldsymbol{\Sigma}_R\boldsymbol{U}_R{}^T(\boldsymbol{U}_R\ \boldsymbol{\Sigma}_R\ \boldsymbol{V}^T)\boldsymbol{x} = \boldsymbol{V}\,\boldsymbol{\Sigma}_R\boldsymbol{U}_R{}^T\boldsymbol{b}$$

$$\boldsymbol{V}\,\boldsymbol{\Sigma}_R\,\boldsymbol{\Sigma}_R\ \boldsymbol{V}^T\boldsymbol{x} = \boldsymbol{V}\,\boldsymbol{\Sigma}_R\boldsymbol{U}_R{}^T\boldsymbol{b}$$

$$(\,\boldsymbol{\Sigma}_R\,)^2\ \boldsymbol{V}^T\boldsymbol{x} = \boldsymbol{\Sigma}_R\,\boldsymbol{U}_R{}^T\boldsymbol{b}$$

When can we take the inverse of the singular matrix?

$$(\boldsymbol{\Sigma_R})^2 \boldsymbol{V}^T \boldsymbol{x} = \boldsymbol{\Sigma_R} \boldsymbol{U}_R{}^T \boldsymbol{b}$$

1) <u>Full rank matrix</u> $(\sigma_i \neq 0 \ \forall i)$:

$\text{rank}(\boldsymbol{A}) = n$

$$\boldsymbol{V}^T \boldsymbol{x} = (\boldsymbol{\Sigma_R})^{-1} \boldsymbol{U}_R{}^T \boldsymbol{b}$$

Unique solution:

$$\boldsymbol{x} = \boldsymbol{V} (\boldsymbol{\Sigma_R})^{-1} \boldsymbol{U}_R{}^T \boldsymbol{b}$$

$n \times 1$ $n \times n$ $n \times n$ $n \times m$ $m \times 1$

2) <u>Rank deficient matrix</u> ($\text{rank}(\boldsymbol{A}) = r < n$)

$$(\boldsymbol{\Sigma_R})^2 \boldsymbol{V}^T \boldsymbol{x} = \boldsymbol{\Sigma_R} \boldsymbol{U}_R{}^T \boldsymbol{b}$$

Solution is not unique!!

Find solution $\boldsymbol{x}$ such that $\min_{\boldsymbol{x}} \phi(\boldsymbol{x}) = \|\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}\|_2^2$

and also $\min_{\boldsymbol{x}} \|\boldsymbol{x}\|_2$

2) Rank deficient matrix (continue)

We want to find the solution $\boldsymbol{x}$ that satisfies $(\boldsymbol{\Sigma_R})^2 \boldsymbol{V}^T \boldsymbol{x} = \boldsymbol{\Sigma_R} \boldsymbol{U_R}^T \boldsymbol{b}$ and also satisfies $\min_{\boldsymbol{x}} \|\boldsymbol{x}\|_2$

Change of variables: Set $\boldsymbol{V}^T \boldsymbol{x} = \boldsymbol{y}$ and then solve $\boldsymbol{\Sigma_R}\, \boldsymbol{y} = \boldsymbol{U_R}^T \boldsymbol{b}$ for the variable $\boldsymbol{y}$

$$\begin{pmatrix} \sigma_1 & & & & & \\ & \ddots & & & & \\ & & \sigma_r & & & \\ & & & 0 & & \\ & & & & \ddots & \\ & & & & & 0 \end{pmatrix} \begin{pmatrix} y_1 \\ \vdots \\ y_r \\ y_{r+1} \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} \boldsymbol{u}_1^T \boldsymbol{b} \\ \vdots \\ \boldsymbol{u}_r^T \boldsymbol{b} \\ \boldsymbol{u}_{r+1}^T \boldsymbol{b} \\ \vdots \\ \boldsymbol{u}_n^T \boldsymbol{b} \end{pmatrix}$$

$$y_i = \frac{\boldsymbol{u}_i^T \boldsymbol{b}}{\sigma_i} \qquad i = 1,2, \dots, r$$

What do we do when $i > r$?
Which choice of y_i will minimize

$$\|\boldsymbol{x}\|_2 = \|\boldsymbol{V}\, \boldsymbol{y}\|_2?$$

Set $y_i = 0, \qquad i = r + 1, \dots, n$

Evaluate

$$\boldsymbol{x} = \boldsymbol{V}\boldsymbol{y} = \begin{pmatrix} \vdots & \dots & \vdots \\ \boldsymbol{v}_1 & \dots & \boldsymbol{v}_n \\ \vdots & \dots & \vdots \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \Rightarrow \boldsymbol{x} = \sum_{i=1}^{n} y_i\, \boldsymbol{v_i} = \sum_{\substack{i=1 \\ \sigma_i \neq 0}}^{n} \frac{(\boldsymbol{u}_i^T \boldsymbol{b})}{\sigma_i} \boldsymbol{v_i}$$

Solving Least Squares Problem with SVD (summary)

Cost of SVD:
$O(m\,n^2)$

- Find $\boldsymbol{x}$ that satisfies $\min_{\boldsymbol{x}} \|\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}\|_2^2$
- Find $\boldsymbol{y}$ that satisfies $\min_{\boldsymbol{y}} \| \boldsymbol{\Sigma_R}\,\boldsymbol{y} - \boldsymbol{U_R}^T\boldsymbol{b}\,\|_2^2$
- Propose $\boldsymbol{y}$ that is solution of $\boldsymbol{\Sigma_R}\,\boldsymbol{y} = \boldsymbol{U_R}^T\boldsymbol{b}$

Cost:

- Evaluate: $\boldsymbol{z} = \boldsymbol{U_R}^T\boldsymbol{b}$ → $m\,n$
- Set: $y_i = \begin{cases} \frac{z_i}{\sigma_i}, & \text{if } \sigma_i \neq 0 \\ 0, \text{otherwise} \end{cases} \quad i = 1, \ldots, n$ → n
- Then compute $\boldsymbol{x} = \boldsymbol{V}\,\boldsymbol{y}$ → n^2

Solving Least Squares Problem with SVD (summary)

- If $\sigma_i \neq 0$ for $\forall i = 1, \ldots, n$, then the solution $\boldsymbol{y} = \boldsymbol{V} \, (\, \boldsymbol{\Sigma_R} \,)^{-1} \boldsymbol{U}_R{}^T \, \boldsymbol{b}$ is unique (and not a "choice").
- If at least one of the singular values is zero, then the proposed solution $\boldsymbol{y}$ is the one with the smallest 2-norm ($\|\boldsymbol{y}\|_2$ is minimal) that minimizes the 2-norm of the residual $\left\| \boldsymbol{\Sigma_R} \, \boldsymbol{y} - \boldsymbol{U}_R{}^T \boldsymbol{b} \right\|_2$
- Since $\|\boldsymbol{x}\|_2 = \|\boldsymbol{V} \, \boldsymbol{y}\|_2 = \|\boldsymbol{y}\|_2$, then the solution $\boldsymbol{x}$ is also the one with the smallest 2-norm ($\|\boldsymbol{x}\|_2$ is minimal) for all possible $\boldsymbol{x}$ for which $\|\boldsymbol{A}\boldsymbol{x} - \boldsymbol{b}\|_2$ is minimal.

Solving Least Squares Problem with SVD (summary)

Solve $\boldsymbol{A}\,\boldsymbol{x} \cong \boldsymbol{b}$ or $\boldsymbol{U}_R\,\boldsymbol{\Sigma}_{\boldsymbol{R}}\boldsymbol{V}^{\boldsymbol{T}}\boldsymbol{x} \cong \boldsymbol{b}$

$$\boldsymbol{x} \cong \boldsymbol{V}\,(\boldsymbol{\Sigma}_{\boldsymbol{R}})^{+}\,\boldsymbol{U}_R{}^{T}\,\boldsymbol{b}$$

Example:

Consider solving the least squares problem $\boldsymbol{A}\,\boldsymbol{x} \cong \boldsymbol{b}$, where the singular value decomposition of the matrix $\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{T}\boldsymbol{x}$ is:

$$\begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 & 0 \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 14 & 0 & 0 \\ 0 & 14 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{x} \cong \begin{bmatrix} 12 \\ 9 \\ 9 \\ 10 \end{bmatrix}$$

Determine $\|\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}\|_2$

Example

Suppose you have $\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}\boldsymbol{x}$ calculated. What is the cost of solving

$$\min_{\boldsymbol{x}} \|\boldsymbol{b} - \boldsymbol{A}\,\boldsymbol{x}\|_2^2 \;?$$

A) $O(n)$
B) $O(n^2)$
C) $O(mn)$
D) $O(m)$
E) $O(m^2)$