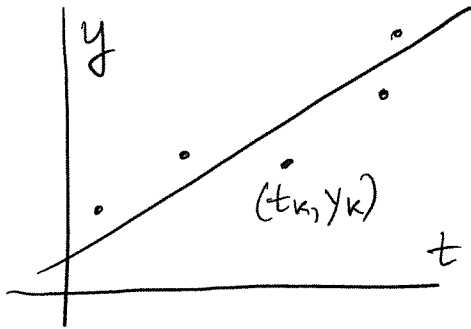


Sec. 3.8. Least squares (LS) solution to inconsistent l.s.

16-1

① LS fit to data



Suppose we have data points that exhibit a nearly linear dependence

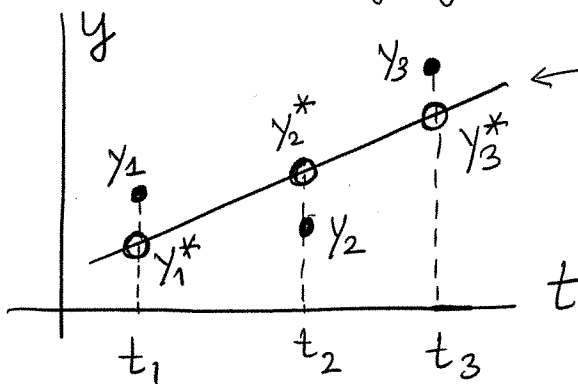
$$y \approx a_0 + a_1 t.$$

↑
"approximately equal"

Q1: How can we find a_0, a_1 such that this straight line is the best fit to the data points?

Q2: What is "the best fit"?

We answer Q2 first, considering just three points not lying on the same line.



$$y_{\text{best}}(t) = a_0 + a_1 t.$$

Let $y_k^* = y_{\text{best}}(t_k)$,

so that y_1^*, y_2^*, y_3^*

do lie on the same line.

We call this line the best (linear) fit if:

$$\boxed{\sum_{k=1}^{\# \text{ of points}} (y_k - y_k^*)^2 = \min} \quad (\star)$$

Since it makes the sum of **squares** of the deviations **the least**, it is called the **Least Squares (LS) fit**.

② LS approximation to the data
and LS sol'n of an inconsistent l.s.

Ex. 1 Find the best (=LS) linear fit to 3 points: $(t_1, y_1), (t_2, y_2), (t_3, y_3)$.

Sol'n: 1) seek $y_{\text{best}} = a_0 + a_1 t$, where a_0, a_1 are to be found.

$$\text{@ } (t_1, y_1): a_0 \cdot 1 + a_1 \cdot t_1 \text{ "="" } y_1$$

$$\text{@ } (t_2, y_2): a_0 \cdot 1 + a_1 \cdot t_2 \text{ "="" } y_2$$

$$\text{@ } (t_3, y_3): a_0 \cdot 1 + a_1 \cdot t_3 \text{ "="" } y_3$$

Note: We wrote "=", not =, because we cannot expect that all three points will fall on the same line. So, "=" means 'approximates', not 'strictly equals'.

The previous system in matrix form is:

$$\left[\underbrace{\begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}}_{\underline{A_1}}, \underbrace{\begin{pmatrix} t_1 \\ t_2 \\ t_3 \end{pmatrix}}_{\underline{A_2}} \right] \underbrace{\begin{pmatrix} a_0 \\ a_1 \end{pmatrix}}_{\substack{\underline{x} \\ \uparrow \\ \text{unknown}}} \text{ "="" } \underbrace{\begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix}}_{\underline{y}}, \Rightarrow$$

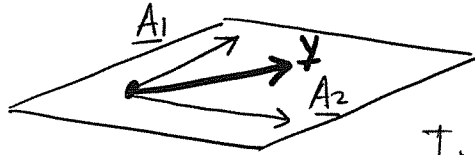
$$[\underline{A_1}, \underline{A_2}] \cdot \underline{x} \text{ "="" } \underline{y} \Leftrightarrow \underline{A} \underline{x} \text{ "="" } \underline{y}.$$

Using the key formula, we can also write it as:

$$x_1 \underline{A_1} + x_2 \underline{A_2} \text{ "="" } \underline{y} \quad (*)$$

There are two possibilities with respect to the above equation:

(a)

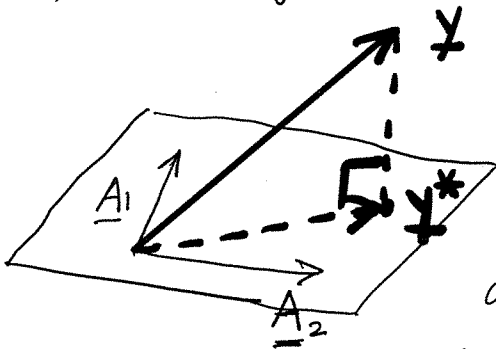


y lies in the plane made by \underline{A}_1 & \underline{A}_2 .

I.e., it is in $Sp(\{\underline{A}_1, \underline{A}_2\})$,

\Rightarrow equation **(*)** on p. 16-2 is consistent. We know how to solve it (use REF). But, this situation is special, not generic; it would imply that the 3 pts in the original problem happen to be on the same straight line.

(b) The generic case is when y is **not** in



the plane made by

\underline{A}_1 and \underline{A}_2 . Then y

is not in $Sp(\{\underline{A}_1, \underline{A}_2\})$,

and l.s. **(*)** is inconsistent.

Then, instead of ~~solving~~ it,

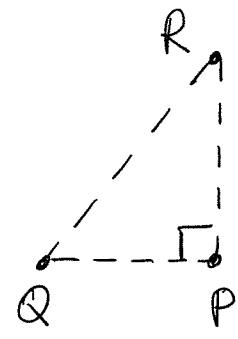
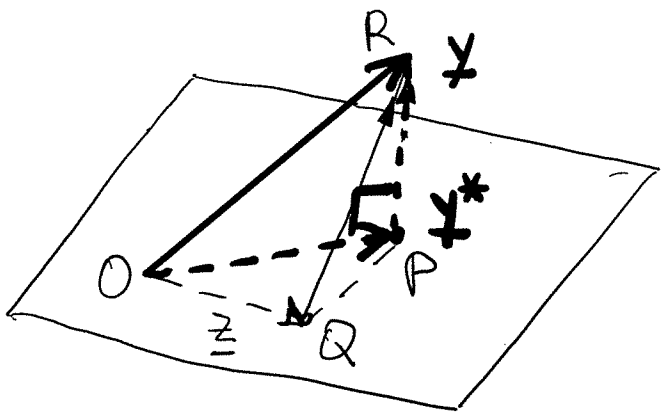
which is impossible, we will do the next best thing,

which is possible: solve

$$x_1 \underline{A}_1 + x_2 \underline{A}_2 = \underline{y}^*, \quad (**)$$

where \underline{y}^* is the projection of y on the plane made by $(\underline{A}_1, \underline{A}_2)$ (i.e., \underline{y}^* is in $Sp(\{\underline{A}_1, \underline{A}_2\})$).

• Why is this \underline{y}^* the best approximation to y ?



Consider any other vector \underline{z} in the same plane.

Note that: $\vec{PR} = \underline{y} - \underline{y}^*$
 $\vec{QR} = \underline{y} - \underline{z}$.

Then: $\|\vec{PR}\|$ = distance between \underline{y} and \underline{y}^* ,
 $\|\vec{QR}\|$ = distance between \underline{y} and \underline{z} .

Now look at the ΔRPQ in the right figure above. The angle $\angle P = 90^\circ$ because $\vec{PR} \perp$ plane and hence $\vec{PR} \perp$ any line in this plane.

From this right ΔRPQ , it is clear that $\|\vec{PR}\| < \|\vec{QR}\|$, so distance from \underline{y} is the shortest to \underline{y}^* among all vectors \underline{z} in that plane.

Note 1: We have shown that

$$\|\vec{PR}\| \equiv \|\underline{y} - \underline{y}^*\| = \min.$$

However, $\underline{y} = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix}$, $\underline{y}^* = \begin{pmatrix} y_1^* \\ y_2^* \\ y_3^* \end{pmatrix}$, where y_k^* are the values marked with "o" in figure on p. 16-1. (Since all y_k^* lie on the same line, the l.s. $A\underline{x} = \underline{y}^*$ is consistent, as we've seen above from another perspective.)

But then $\sum_{k=1}^3 (y_k - y_k^*)^2 = \|\underline{y} - \underline{y}^*\|^2 = \min$, which agrees with formula (*) on p. 16-1 and justifies name 'LS'.

Note 2: Vector y^* is called the LS approximation to the data (i.e., to y).

We will now use y^* to find \underline{x} , the LS solution to the consistent l.s. $A\underline{x} = y^*$.

So, we need to find y^* . Recall:

- $\vec{PR} = y - y^*$
- $\vec{PR} \perp$ plane made by $\underline{A}_1, \underline{A}_2$; $\Rightarrow \vec{PR} \perp \underline{A}_1, \underline{A}_2$.

Write this using linear algebra:

$$\begin{cases} \underline{A}_1^T (y - y^*) = 0 \\ \underline{A}_2^T (y - y^*) = 0 \end{cases} \Rightarrow \begin{bmatrix} \underline{A}_1^T \\ \underline{A}_2^T \end{bmatrix} (y - y^*) = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \Rightarrow$$

$$A^T \cdot (y - y^*) = \underline{0} \Rightarrow \boxed{A^T y = A^T y^*}$$

Unfortunately, this gives us $A^T y^*$, not y^* (and remember that you cannot cancel A^T on both sides of the above equation).

So, we proceed as follows:

$$A^T (A \underline{x} = y^*) \Rightarrow \underbrace{A^T(A \underline{x})}_{\text{matrix}} = A^T y^* = \underbrace{A^T y}_{\text{vector}}$$

$$\Rightarrow \boxed{(A^T A) \underline{x} = A^T y}$$

The LS solution to the inconsistent

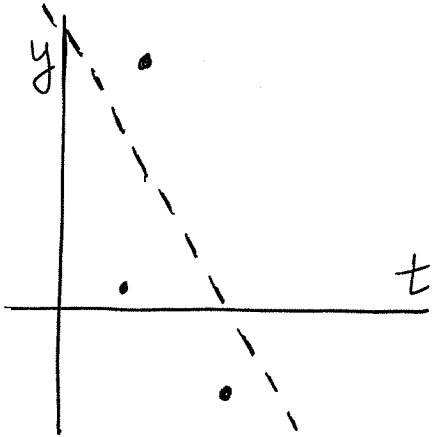
l.s. $A \underline{x} = y$.

The Normal equation

Ex. 2 (= Ex. 1 with numbers)

Find the best (= LS) linear fit through:

$(4, -2), (2, 6), (3/2, 1/2)$.



Sol'n: a) Seeking

$$y_{\text{best}} = a_0 + a_1 t \leftarrow \text{linear}$$

1) Setup:

@ $(4, -2)$: $a_0 \cdot 1 + a_1 \cdot 4 = -2$

@ $(2, 6)$: $a_0 \cdot 1 + a_1 \cdot 2 = 6$

@ $(\frac{3}{2}, \frac{1}{2})$: $a_0 \cdot 1 + a_1 \cdot \frac{3}{2} = \frac{1}{2}$

Matrix form:

$$\underbrace{\begin{pmatrix} 1 & 4 \\ 1 & 2 \\ 1 & 3/2 \end{pmatrix}}_A \underbrace{\begin{pmatrix} a_0 \\ a_1 \end{pmatrix}}_x = \underbrace{\begin{pmatrix} -2 \\ 6 \\ 1/2 \end{pmatrix}}_y$$

2) Compute the ingredients of the Normal Equation:

$$A^T A = \begin{pmatrix} 1 & 1 & 1 \\ 4 & 2 & 3/2 \end{pmatrix} \begin{pmatrix} 1 & 4 \\ 1 & 2 \\ 1 & 3/2 \end{pmatrix} = \begin{pmatrix} 3 & 15/2 \\ 15/2 & 89/4 \end{pmatrix}$$

$$A^T y = \begin{pmatrix} 1 & 1 & 1 \\ 4 & 2 & 3/2 \end{pmatrix} \begin{pmatrix} -2 \\ 6 \\ 1/2 \end{pmatrix} = \begin{pmatrix} 9/2 \\ 19/4 \end{pmatrix}$$

3) Solve the Normal Equation $(A^T A)x = A^T y$:

$$\begin{pmatrix} 3 & 15/2 \\ 15/2 & 89/4 \end{pmatrix} x = \begin{pmatrix} 9/2 \\ 19/4 \end{pmatrix} \xrightarrow{\text{REF}} x = \begin{pmatrix} a_0 \\ a_1 \end{pmatrix} = \begin{pmatrix} 43/7 \\ -13/7 \end{pmatrix}$$

Answer:

$$y_{\text{best}} = \frac{43}{7} - \frac{13}{7} t \quad (\approx 6 - 2t)$$

Needed only for the caveat described later.

3) Discussion

Generalization 1 Exactly the same approach can be used to find LS polynomial fits (e.g., quadratic): $y_{best} = a_0 + a_1 t + a_2 t^2$.

MUST SEE Ex. 4 in textbook.

Generalization 2 Exactly the same approach can be used if instead of a linear combination of t^n (i.e., a polynomial), we use any other set of functions for a LS fit.

Ex. 3 Approximation of a function by sines and cosines (a Fourier series)

seek

$y_{best} = a_0 + a_1 \cos t + a_2 \sin t + a_3 \cos 2t + a_4 \sin 2t$
to fit through points $(t_1, y_1), \dots, (t_m, y_m)$.

Follow exactly the same approach as in Ex. 1:

@ (t_1, y_1) : $a_0 \cdot 1 + a_1 \cdot \cos t_1 + a_2 \cdot \sin t_1 + a_3 \cos 2t_1 + a_4 \sin 2t_1 = y_1$
⋮
⋮
⋮
@ (t_m, y_m) : $a_0 \cdot 1 + a_1 \cdot \cos t_m + a_2 \cdot \sin t_m + a_3 \cos 2t_m + a_4 \sin 2t_m = y_m$

In matrix form:

$$\underbrace{\begin{pmatrix} 1 & \cos t_1 & \sin t_1 & \cos 2t_1 & \sin 2t_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \cos t_m & \sin t_m & \cos 2t_m & \sin 2t_m \end{pmatrix}}_A \underbrace{\begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{pmatrix}}_x = \underbrace{\begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}}_y$$

Solve the normal equation $(A^T A)x = A^T y$.

Caveat Let us revisit Ex. 2.

In setting up the 3rd equation there, we had fractions $\frac{3}{2}$ and $\frac{1}{2}$. Since most of us do not like fractions, we can multiply that equation by 2. Then:

$$\begin{array}{l}
 1 \cdot a_0 + 4a_1 = -2 \\
 1 \cdot a_0 + 2a_1 = 6 \\
 2 \cdot a_0 + 3a_1 = 1
 \end{array}
 \Rightarrow
 \underbrace{\begin{pmatrix} 1 & 4 \\ 1 & 2 \\ 2 & 3 \end{pmatrix}}_{A_{new}}
 \underline{x} = \underbrace{\begin{pmatrix} -2 \\ 6 \\ 1 \end{pmatrix}}_{\underline{y}_{new}}
 \Rightarrow$$

solve the new Normal Eq. $A_{new}^T A_{new} \underline{x} = A_{new}^T \underline{y}_{new}$.

$$\Rightarrow \underline{x} = \begin{pmatrix} 3 \\ -1 \end{pmatrix} \Rightarrow \begin{pmatrix} 6 & 12 \\ 12 & 29 \end{pmatrix} \begin{pmatrix} 6 \\ 7 \end{pmatrix}$$

$(y_{best})_{new} = 3 - t$. Compare this with:

$(y_{best})_{ex.2} \approx 6 - 2t$. They are very different!

① How come ?? ② And, which one is "correct"?

Resolution: Note that in Ex. 2, we solved a problem equivalent to minimizing this sum of squares:

$$((a_0 + a_1 \cdot 4) - (-2))^2 + ((a_0 + a_1 \cdot 2) - 6)^2 + ((a_0 + a_1 \cdot \frac{3}{2}) - \frac{1}{2})^2 = \min.$$

However, on this page we minimized a **different** sum:

$$\boxed{\text{same term}} + \boxed{\text{same term}} + \underbrace{(2a_0 + 3a_1 - 1)^2}_{\text{different term}} = \min$$

We weighed this term \rightarrow **④** $(a_0 + \frac{3}{2}a_1 - \frac{1}{2})^2$ much heavier than in Ex. 2, and 4 times heavier than the other two terms.

I.e., our new LS will have to pass much closer to point 3 than to points 1 & 2. This contradicts our original intention to treat all points equally.

Moral: When setting up a LS inconsistent l.s., do **NOT multiply any equation by anything except "1"**.