

Section 3.3

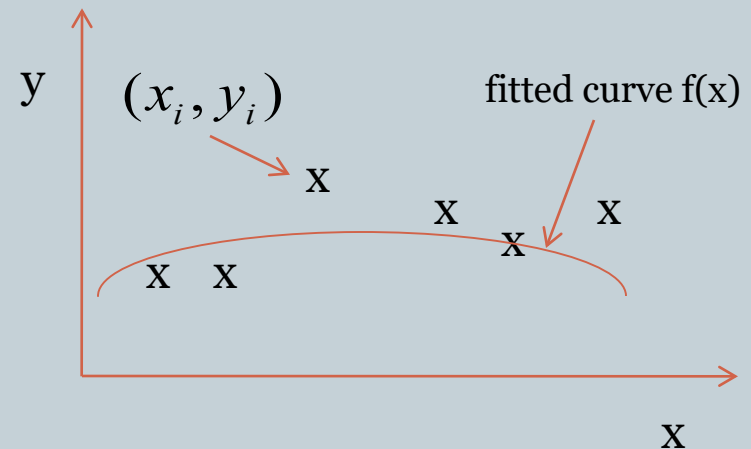
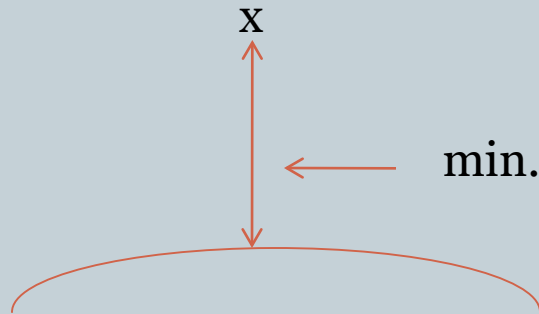
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LEAST SQUARE DATA FITTING

Least Square Fitting Model

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Given a set of data points $(x_i, y_i)_{i=1}^N$, we need to find a model $f(x)$ best fit the data points, and $f(x_i)$ is as close to y_i as possible.



Error of the Model

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We measure the accuracy of the model by comparing $f(x_i)$ with y_i .

To find the error made at the points:

	ERROR =
1-norm	$\sum_{i=1}^N f(x_i) - y_i $
2-norm	$\sum_{i=1}^N (f(x_i) - y_i)^2$
∞ -norm	$\max f(x_i) - y_i \quad 1 \leq i \leq N$

Note: the 2-norm is more desirable because differentiability is smoother than the others.

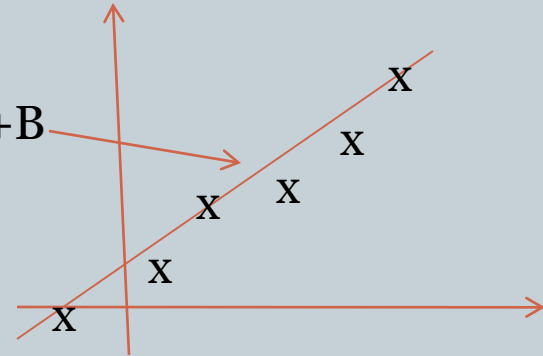
Line fitting

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The goal is to find:

1. slope **A**
2. *y*-intercept **B**

$$y(x)=Ax+B$$



so the error is as small as possible.

Note that for each set of (A,B), we can measure its performance. Namely, the square error:

$$E(A,B)=\sum_{i=1}^N (f(x_i)-y_i)^2 \underset{\substack{\text{line fit} \\ f(x)=Ax+B}}{=} \sum_{i=1}^N (Ax_i+B-y_i)^2 \leftarrow \text{Square error}$$

Least Square Error

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Remarks:

The optimal (A^*, B^*) will yield the Least Square Error(LSE)

$E(A, B) = \sum_{i=1}^N (Ax_i + B - y_i)^2$ is a 2-variables function

To find extreme of $F(x, y)$

1. Find the critical points, set $\frac{\partial F}{\partial x} = 0$ & $\frac{\partial F}{\partial y} = 0 \Rightarrow (x^*, y^*)$

2. Form $D(x, y) = F_{xx}(x, y)F_{yy}(x, y) - F_{xy}^2(x, y)$

To find critical points:

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$$\frac{\partial E}{\partial A} = \sum_{i=1}^N 2(Ax_i + B - y_i)x_i = 0 \Rightarrow A = \frac{\sum x_i^2}{\sum x_i^2 + \sum x_i} + B \frac{\sum x_i}{\sum x_i^2 + \sum x_i} = \frac{\sum x_i y_i}{\sum x_i^2 + \sum x_i} \dots (1)$$

$$\frac{\partial E}{\partial B} = 2 \sum_{i=1}^N (Ax_i + B - y_i) \cdot 1 = 0 \Rightarrow B = \frac{1}{N} \sum y_i - \frac{1}{N} A \sum x_i \dots \dots \dots (2)$$

Substitute (2) into (1) :

To find critical points:



$$A^* = \frac{\sum x_i y_i - \frac{1}{N} \sum x_i \sum y_i}{\sum x_i^2 - \frac{1}{N} (\sum x_i)^2} \dots\dots\dots (3)$$

$$B^* = \frac{\frac{1}{N} (\sum x_i)^2 \sum y_i - (\sum x_i y_i) \sum x_i}{\sum x_i^2 - \frac{1}{N} (\sum x_i)^2} \dots\dots\dots (4)$$

To minimal error, we show that

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$$D(A^*, B^*) > 0 \text{ \& } E_{AA}(A^*, B^*) > 0$$

$$E_{AA} = \frac{\partial}{\partial A} (2 \sum A x_i^2 + B x_i - x_i y_i) = 2 \sum x_i^2$$

$$E_{BB} = \frac{\partial}{\partial B} (2 \sum A x_i + B N - \sum y_i) = 2N$$

$$E_{AB} = 2 \sum x_i$$

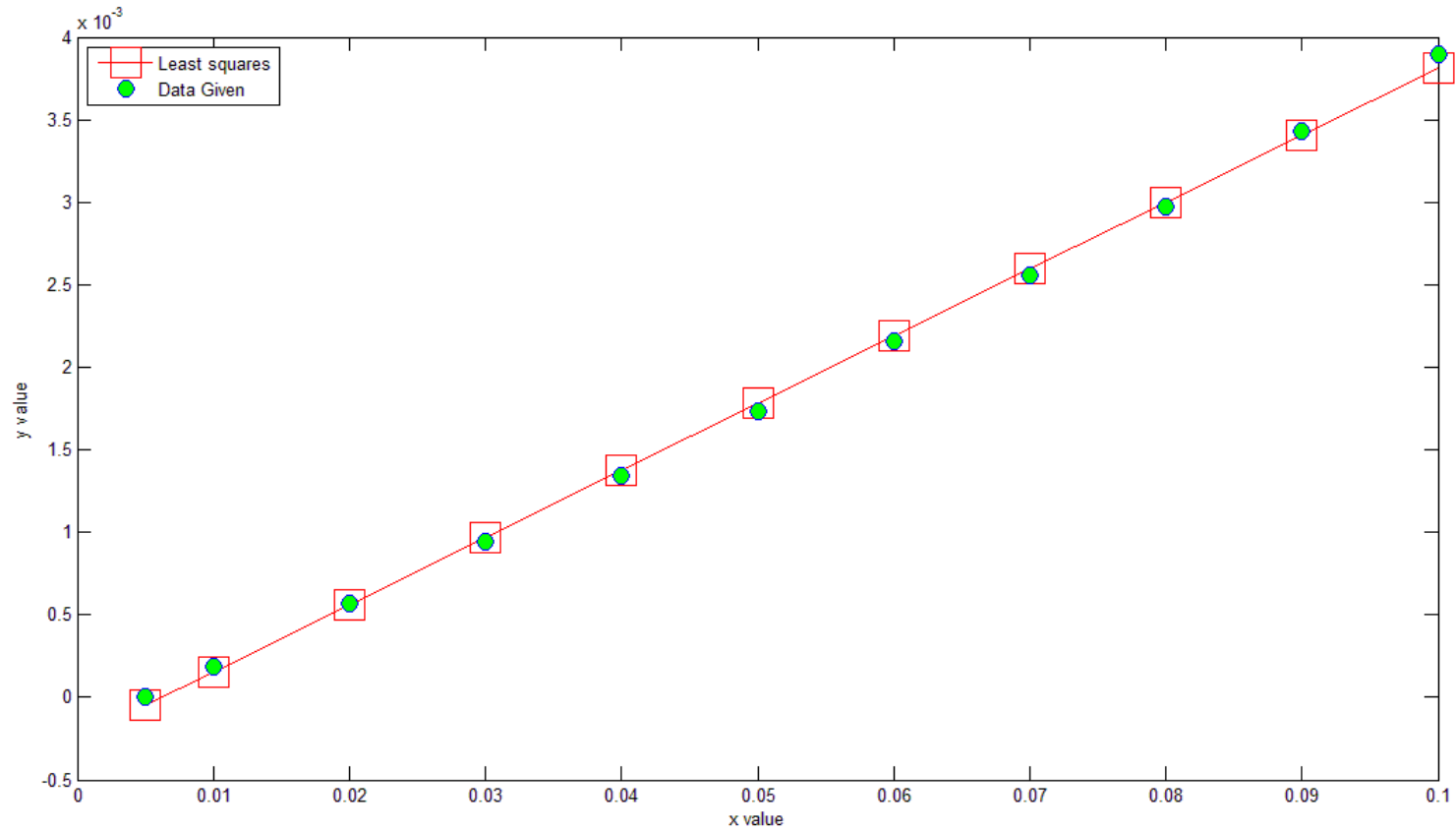
Matlab –Line fit

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- $x = [\dots];$
- $y = [\dots];$
- $a = x;$
- $b = y;$
- $[A,B] = \text{mylinefit}(x,y)$
- $y = B + A * x;$
- $\text{plot}(x,y, '-rs');$ hold on
- $\text{plot}(a,b, 'bo');$ hold on
- $\text{title}(\dots)$
- $\text{ylabel}('y \text{ value}')$
- $\text{xlabel}('x \text{ value}')$
- $\text{legend}('Least \text{ squares}', 'Data \text{ Given}', 2)$

Linefit Graph

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Homework:

1. Prove that $D(A^*, B^*) > 0$

2. For a one-parameter fit $f(x) = Ax$, derive the formulation

for the optimal A^* such that $E(A) = \sum_{i=1}^N (Ax_i - y_i)^2$ yields the

least mean square error

3. Write a MATLAB function that takes in $(x_i, y_i)_{i=1}^N$ and returns A^*

4. Section 3.3 # 7a, 8b, 9a