# Least squares Sample Subtitle

Juan V. Vía

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### Showing why least squares

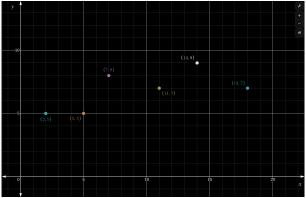
We have a variable y. We know that it's dependent of another variable x in some way. But we don't know how, exactly. So we go to the field and measure certain points. Those that we can reach. Six of them.

$$(2,5), (5,5), (7,8), (11,7), (14,9), (18,7)$$

That is: at x = 2 we measure y = 5, at x = 5 we measure y = 5 again, but at x = 7 we got y = 8, and so on.

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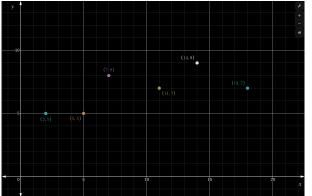
Back to desk we plot these points.



There is a model lurking in these points? A line perhaps?

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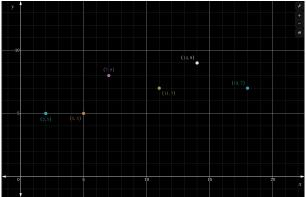
Let's start by tracing a line wich "best fit" that data



Why a line? To warm the modeling machine in our minds we are considering a line, a one degree polynomial.

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What line to plot? How to choose that line?



Enter the math...

#### Showing why least squares

A very common way to express a line in the plane is isolating y as a polynomial function of x:

$$y = mx + b$$

From this equation we can see that m is the *slope* of the line and b is the y-intercept (the value of y when x = 0).

Will be handy for us to write this equation using vector notation:

$$y = \begin{bmatrix} x & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix}$$

And switching terms:

$$\begin{bmatrix} x & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = y$$

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Ok. Fine. This form

$$\begin{bmatrix} x & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = y$$

will be a useful one because we know x and y in six points. For example take the first point (2,5)

$$\begin{bmatrix} 2 & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = 5$$

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And yes, your guess is true. We can incorporate the second point (5,5) and get

$$\begin{bmatrix} 2 & 1 \\ 5 & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} 5 \\ 5 \end{bmatrix}$$

Doing the product you can workout m and b from this equation. m=0 and b=5. Because the matrix is square. And invertible by the way.

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Going further, incorporate the third point.

$$\begin{bmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} 5 \\ 5 \\ 8 \end{bmatrix}$$

This invalidate the previous result. m cannot be 0 more. Neither b with 5.

Actually, henceforth the equation is over-determined and have no solution.

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Fourth point.

$$\begin{bmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \\ 11 & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} 5 \\ 5 \\ 8 \\ 7 \end{bmatrix}$$

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Fifth point.

$$\begin{bmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \\ 11 & 1 \\ 14 & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} 5 \\ 5 \\ 8 \\ 7 \\ 9 \end{bmatrix}$$

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Sixth and last point.

$$\begin{bmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \\ 11 & 1 \\ 14 & 1 \\ 18 & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} 5 \\ 8 \\ 7 \\ 9 \\ 7 \end{bmatrix}$$

This is the equation derived from our measurement.

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Time to name things.

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Call A to the matrix

$$A = \begin{bmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \\ 11 & 1 \\ 14 & 1 \\ 18 & 1 \end{bmatrix}$$

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Call x to the column vector

$$x = \begin{bmatrix} m \\ b \end{bmatrix}$$

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Call b to the column vector

$$b = \begin{bmatrix} 5 \\ 5 \\ 8 \\ 7 \\ 9 \\ 7 \end{bmatrix}$$

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Thus, the equation

$$\begin{bmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \\ 11 & 1 \\ 14 & 1 \\ 18 & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} 5 \\ 5 \\ 8 \\ 7 \\ 9 \\ 7 \end{bmatrix}$$

becomes

$$Ax = b$$

### Showing why least squares

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$$||Ax - b|| \neq 0$$

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$$||Ax - b|| \neq 0$$

We need the least squares approximate solution

#### Showing why least squares

In the least squares approximate solution of Ax = b we, provided that  $||Ax - b|| \neq 0$ , select x that the *norm* of the *residual* r = Ax - b is minimal.

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It's all there: http://vmls-book.stanford.edu/ and in many other sources. The least squares approximate solution is very known.

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Let's see it.

Showing why least squares

All start with our equation Ax = b.

Showing why least squares

Take the original matrix A:

$$A = \begin{bmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \\ 11 & 1 \\ 14 & 1 \\ 18 & 1 \end{bmatrix}$$

### Showing why least squares

Take the original matrix A:

$$A = \begin{bmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \\ 11 & 1 \\ 14 & 1 \\ 18 & 1 \end{bmatrix}$$

Transpose it, and get  $A^{T}$ :

$$A^{\mathsf{T}} = \begin{bmatrix} 2 & 5 & 7 & 11 & 14 & 18 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

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Multiply  $A^{\mathsf{T}}$  by A

$$A^{\mathsf{T}}A = \begin{bmatrix} 2 & 5 & 7 & 11 & 14 & 18 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \\ 11 & 1 \\ 14 & 1 \\ 18 & 1 \end{bmatrix} = \begin{bmatrix} 719 & 57 \\ 57 & 6 \end{bmatrix}$$

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Invert the product

$$(A^{\mathsf{T}}A)^{-1} = \begin{bmatrix} 719 & 57 \\ 57 & 6 \end{bmatrix}^{-1} = \begin{bmatrix} \frac{2}{355} & -\frac{19}{355} \\ -\frac{19}{355} & \frac{719}{1065} \end{bmatrix}$$

#### Showing why least squares

Multiply inverse and transpose

$$(A^{\mathsf{T}}A)^{-1}A^{\mathsf{T}} = \begin{bmatrix} \frac{2}{355} & -\frac{19}{355} \\ -\frac{19}{355} & \frac{719}{1065} \end{bmatrix} \begin{bmatrix} 2 & 5 & 7 & 11 & 14 & 18 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} -\frac{3}{71} & -\frac{9}{355} & -\frac{1}{71} & \frac{3}{355} & \frac{9}{355} & \frac{17}{355} \\ \frac{121}{213} & \frac{434}{1065} & \frac{64}{213} & \frac{92}{1065} & -\frac{79}{1065} & -\frac{307}{1065} \end{bmatrix}$$

Let's call this product  $(A^{T}A)^{-1}A^{T}$  the *pseudo-inverse* 

Showing why least squares

Finally multiply the pseudo-inverse by b

$$x = (A^{\mathsf{T}}A)^{-1}A^{\mathsf{T}}b \tag{1}$$

$$= \begin{bmatrix} -\frac{3}{71} & -\frac{9}{355} & -\frac{1}{71} & \frac{3}{355} & \frac{9}{355} & \frac{17}{355} \\ \frac{121}{213} & \frac{434}{1065} & \frac{64}{213} & \frac{92}{1065} & -\frac{79}{1065} & -\frac{307}{1065} \end{bmatrix} \begin{bmatrix} 5\\8\\7\\9\\7 \end{bmatrix}$$
(2)

$$= \begin{bmatrix} \frac{61}{355} \\ \frac{5539}{1065} \end{bmatrix} \tag{3}$$

$$= \begin{bmatrix} 0.171831 \\ 5.20094 \end{bmatrix} \tag{4}$$

### Showing why least squares

That's it

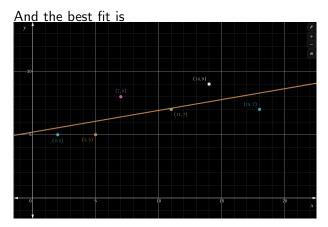
$$x = \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} \frac{61}{355} \\ \frac{5539}{1065} \end{bmatrix} \text{ or } \begin{bmatrix} 0.171831 \\ 5.20094 \end{bmatrix}$$

and m = 0.171831and b = 5.20094and the line is

$$y = 0.171831x + 5.20094$$

and that is the line which best fit our data points.

Showing why least squares



### Recapitulation

You have a bunch of data points and suspect that a polynomial function y = Ax + B from this points is a good model.

You build a matrix A and a vector b from the polynomial and the points.

The polynomial coefficients are a vector x so Ax = bThen  $x = (A^{\mathsf{T}}A)^{-1}A^{\mathsf{T}}b$ 

Don't worry, its XXI century

So the key is calculate  $x = (A^{\mathsf{T}}A)^{-1}A^{\mathsf{T}}b$ . But you don't need to do this by hand like Gauss did. See the code, in this case Javascript code, using the mathjs package.

```
const { multiply, transpose, inv, matrix, format } =
   require( "mathjs")
const solve = (A. b) \Rightarrow \{
  const transposed = transpose(A)
  const product = multiply(transposed, A)
  const inverse = inv(product)
  const pseudoInverse = multiply(inverse, transposed)
                     = multiply(pseudoInverse, b)
  const x
  return x
const A = matrix([[2,1],[5,1],[7,1],[11,1],[14,1],[18,1]))
const b = matrix([5,5,8,7,9,7])
console.log(format(solve(A, b),5))
```

The polynomial function

Get a terminal and do the magic

### The polynomial function

### Get a terminal and do the magic

```
$ node ls.js
[0.17183, 5.2009]
```

### Going further

Mind blowing is coming

To avert catastrophic damage in our brains it's time to rename things

In the example we found a line y = mx + b, now:

m becomes a<sub>1</sub>

b becomes a<sub>0</sub>

x becomes  $x_1$ 

y remains the same

The found line, then, becomes

$$y = a_1 x_1 + a_0 = 0.17183 x_1 + 5.2009$$

Nothing has changed, only the names.

### The polynomial function

In the example we picked a line for regression.

A line in a plane can be expressed as a polynomial function  $P(x_1)$  where y (the dependent variable, a real number) is a function of  $x_1$  (the independent variable, a real number)

$$y: \mathbb{R} \to \mathbb{R} = P(x_1) = a_1x_1 + a_0$$

But there are others  $P(x_1)$ s, for example:

$$y \colon \mathbb{R} \to \mathbb{R} = P(x_1) = a_2 x_1^2 + a_1 x_1 + a_0$$

What about using that quadratic function as the model for the measured points?

Let's see...

#### A curve as a model

That is the curve:  $y = a_2x_1^2 + a_1x_1 + a_0$ And those are the points: (2,5), (5,5), (7,8), (11,7), (14,9), (18,7)Replacing  $x_1$  and y in each point, and switching terms:

$$a_2x_1^2 + a_1x_1 + a_0 = 5$$