



# Introduction to Linear Regression



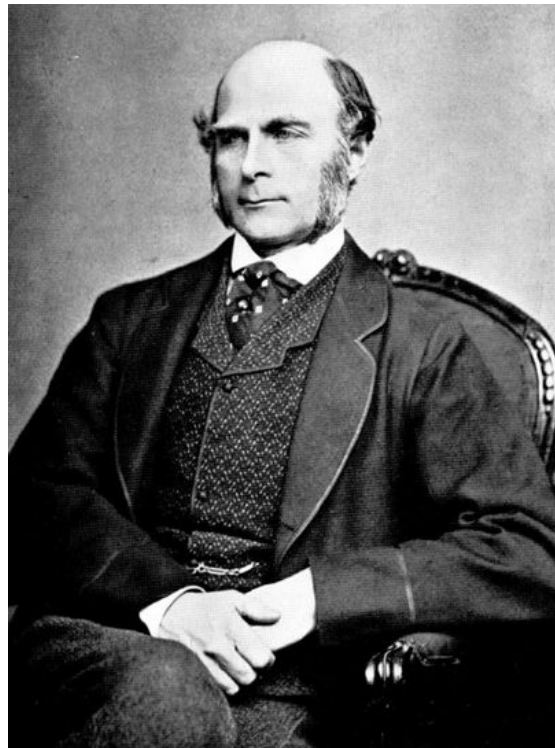
# Reading Assignment

Chapters 2 & 3 of  
**Introduction to Statistical Learning**  
By Gareth James, et al.



# History

This all started in the 1800s with a guy named **Francis Galton**. Galton was studying the relationship between parents and their children. In particular, he investigated the relationship between the heights of fathers and their sons.

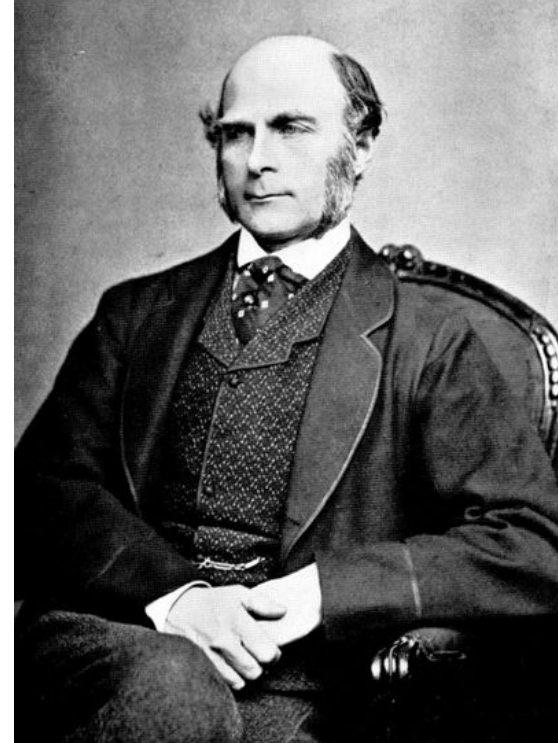




# History

What he discovered was that a man's son tended to be roughly as tall as his father.

However Galton's breakthrough was that the son's height **tended to be closer to the overall average** height of all people.

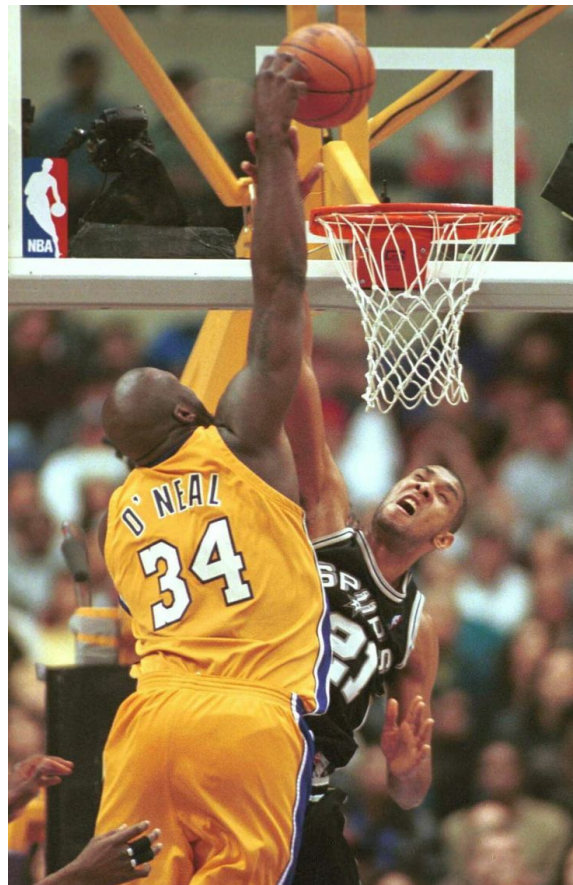




## Example

Let's take **Shaquille O'Neal** as an example. Shaq is really tall: 7ft 1in (2.2 meters).

If Shaq has a son, chances are he'll be pretty tall too. However, Shaq is such an anomaly that there is also a very good chance that his son will be **not be as tall as Shaq**.

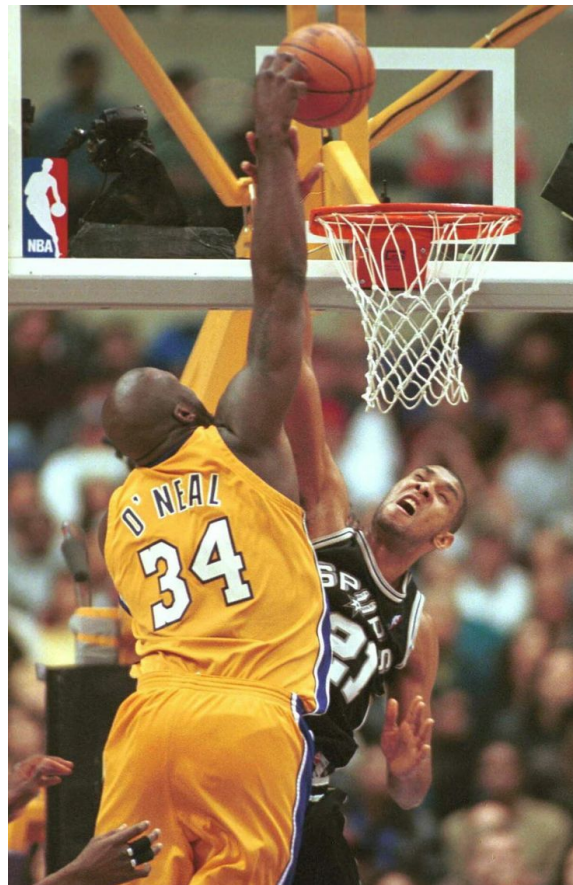




## Example

Turns out this is the case:  
Shaq's son is pretty tall (6 ft 7 in), but not nearly as tall as his dad.

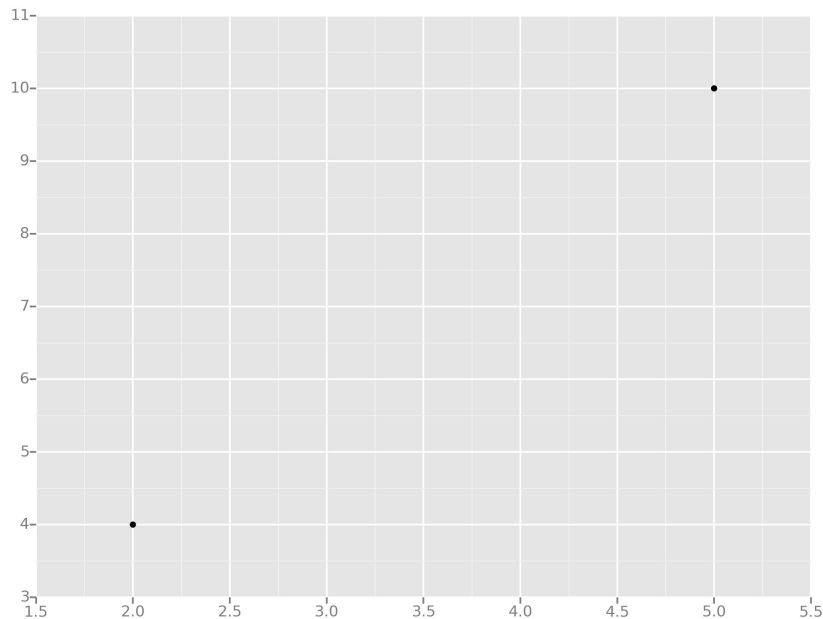
Galton called this phenomenon **regression**, as in "A father's son's height tends to regress (or drift towards) the mean (average) height."





## Example

Let's take the simplest possible example: calculating a regression with only 2 data points.

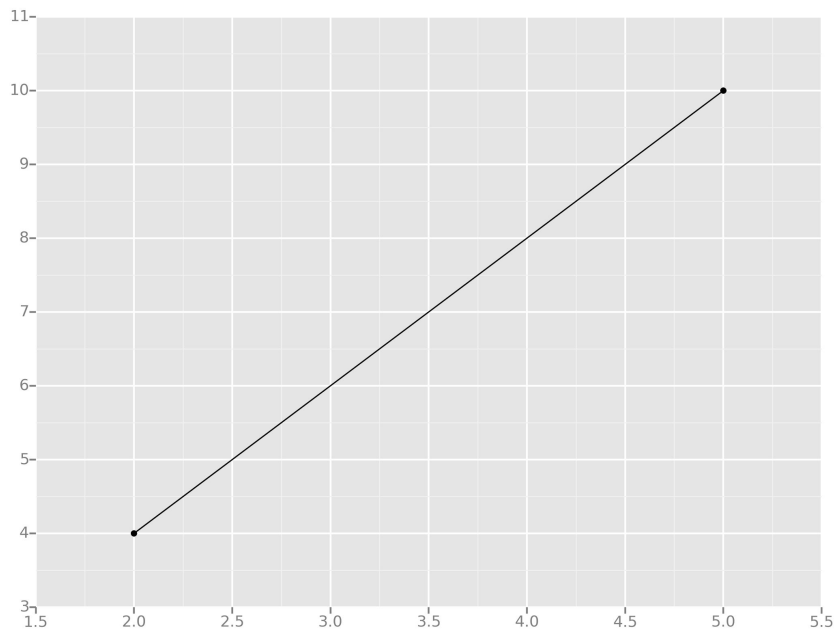




## Example

All we're trying to do when we calculate our regression line is draw a line that's as close to every dot as possible.

For classic linear regression, or "Least Squares Method", you only measure the closeness in the "up and down" direction



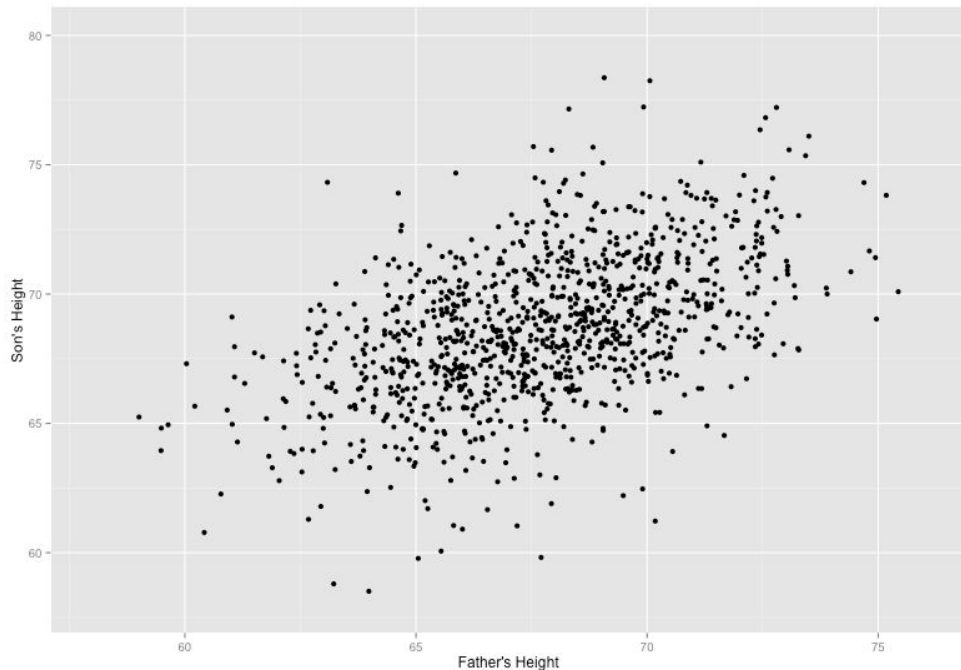




## Example

Now wouldn't it be great if we could apply this same concept to a graph with more than just two data points?

By doing this, we could take multiple men and their son's heights and do things like tell a man how tall we expect his son to be...before he even has a son!

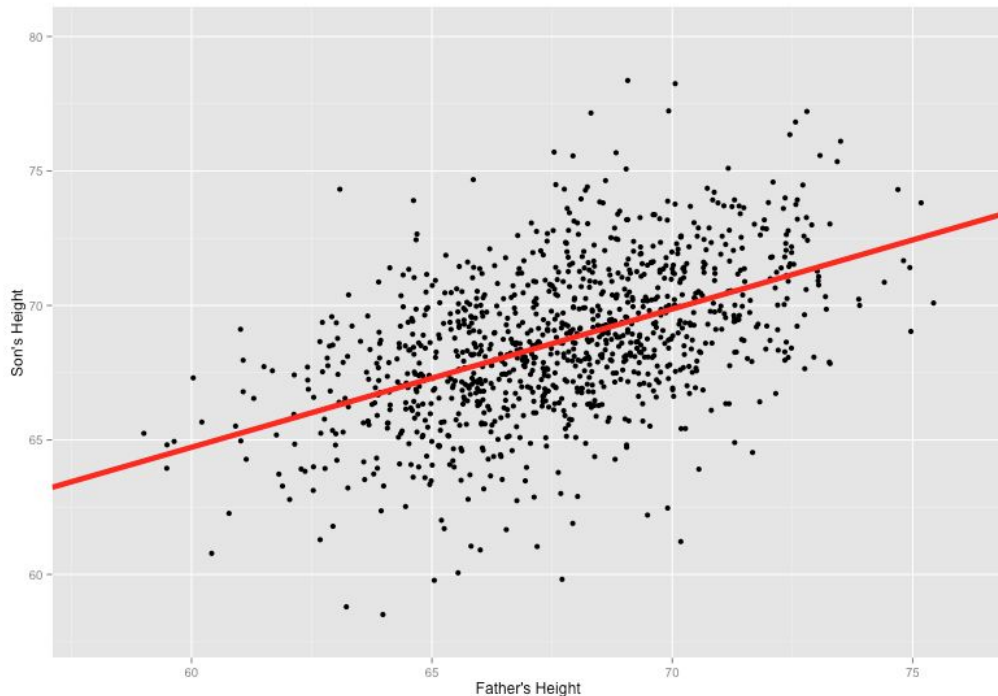




## Example

Our goal with linear regression is to **minimize the vertical distance** between all the data points and our line.

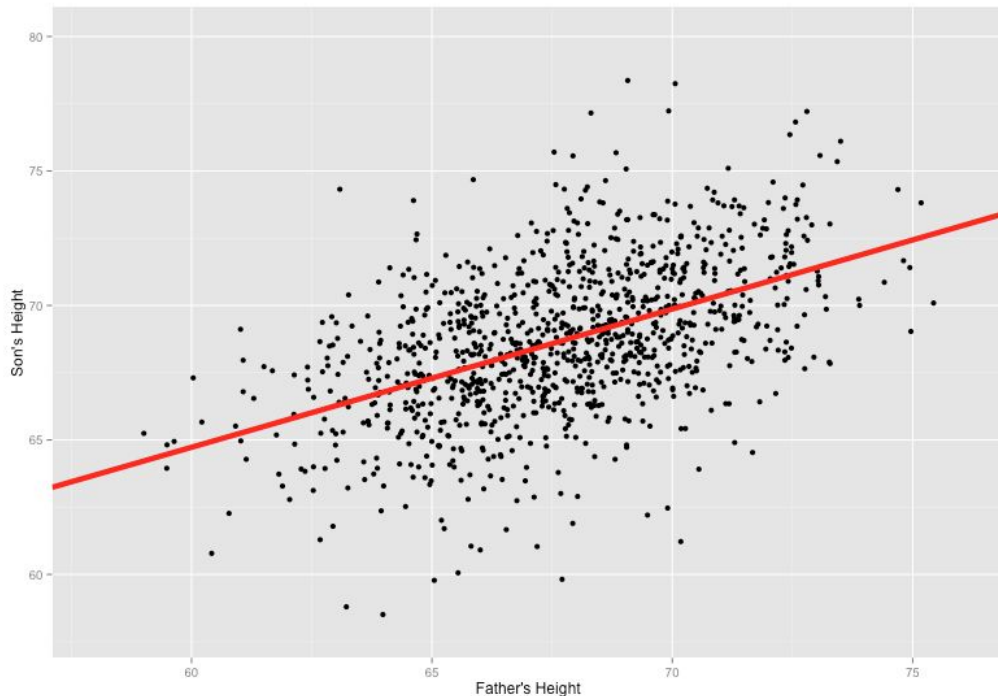
So in determining the **best line**, we are attempting to minimize the distance between **all** the points and their distance to our line.





## Example

There are lots of different ways to minimize this, (sum of squared errors, sum of absolute errors, etc), but all these methods have a general goal of minimizing this distance.

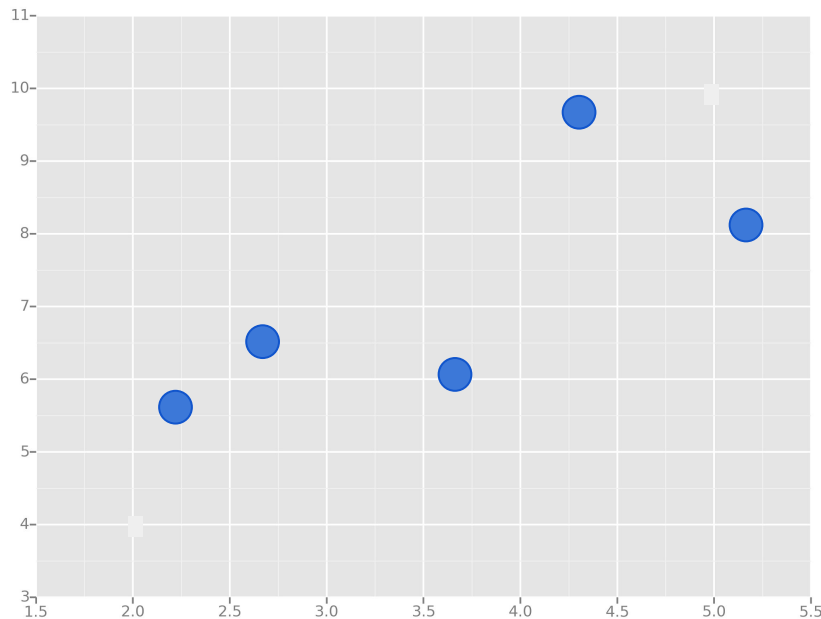




## Example

For example, one of the most popular methods is the least squares method.

Here we have blue data points along an x and y axis.

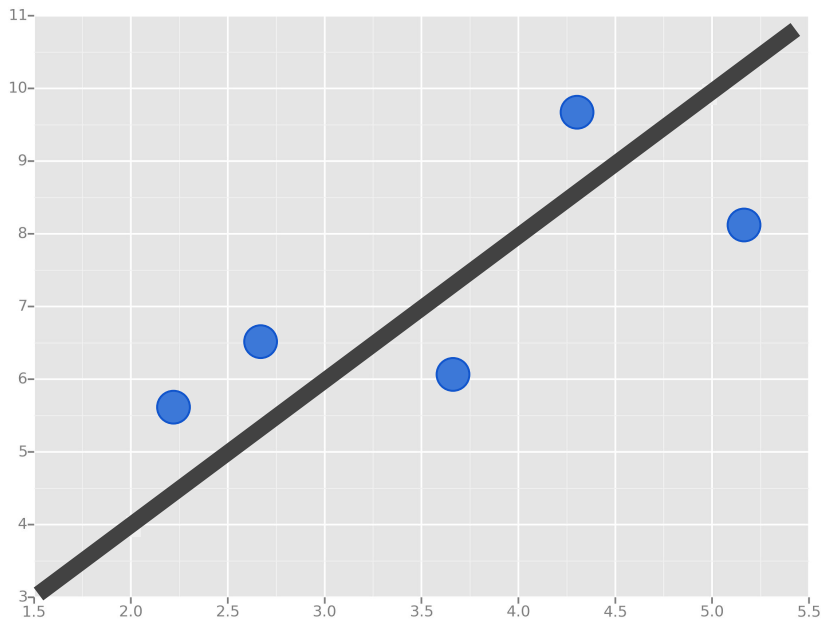




## Example

Now we want to fit a linear regression line.

The question is, how do we decide which line is the best fitting one?

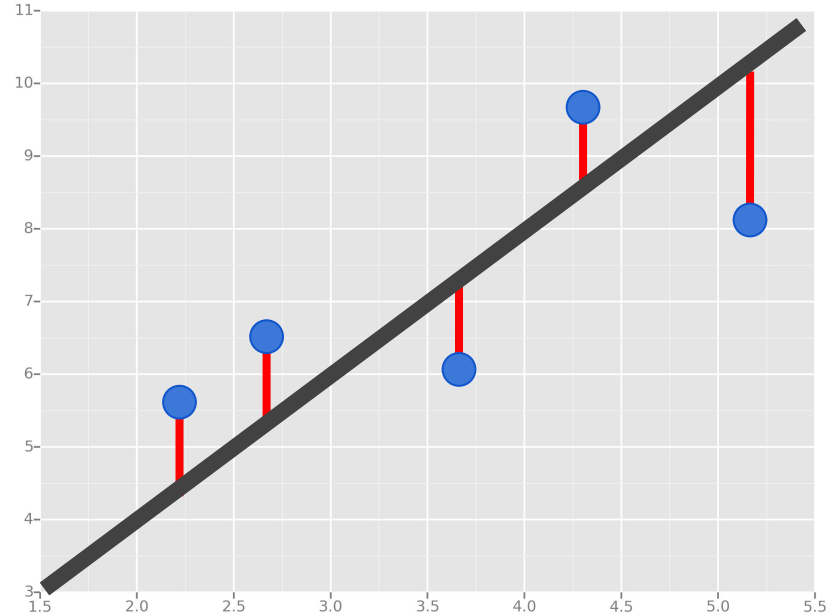




## Example

We'll use the Least Squares Method, which is fitted by minimizing the ***sum of squares of the residuals***.

The residuals for an observation is the difference between the observation (the y-value) and the fitted line.





## Example with Python

In the next lecture we'll use SciKit-Learn and Python to create a linear regression model.

Then you'll have your own portfolio project exercise and afterwards we'll go over the solutions to that project.



## Example with Python

See you in the next lecture!