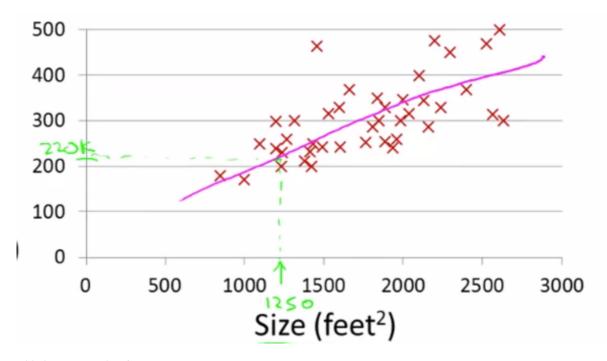
Model and Cost Function

Let's take an example of a sample dataset which contains the housing prices in a particular city.



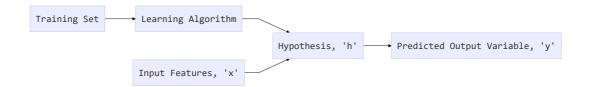
This is an example of:

- Supervised Learning: Given the "correct answer" for each example in the dataset
- Regression Problem: Objective is to predict real-valued output

Size in $ft^2(x)$	Price in \$100 (y)
2104 (x ⁽¹⁾)	460 (y ⁽¹⁾)
1416 (x ⁽²⁾)	232 (y ⁽²⁾)
$1534 (x^{(3)})$	315 (y ⁽³⁾)
852 (x ⁽⁴⁾)	178 (y ⁽⁴⁾)

Notation:

- m: Number of training examples
- *x's*: "Input" Variable
- *y's*: "Output" Variable
- (x, y): Single Training Example
- $(x^{(i)}, y^{(i)})$: $i^{(th)}$ Training Example



What is Hypothesis?

It maps from input features to output variables. It can be represented as

$$h_{ heta}(x) = heta_0 + heta_1 x$$

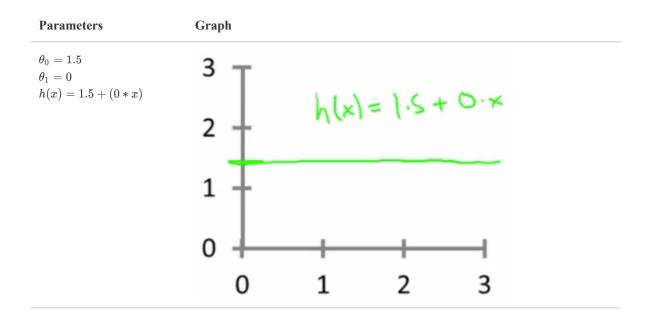
The shorthand notation for the above equation is

$$h(x) = heta_0 + heta_1 x$$

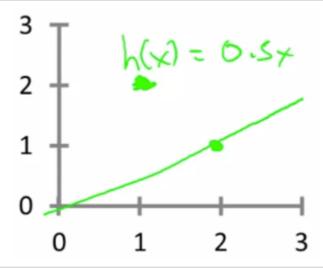
Here, θ_0 and θ_1 are the parameters



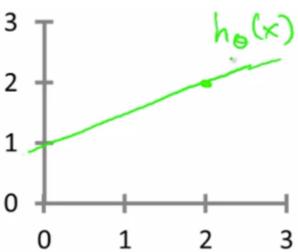
The black line represents the Hypothesis. This model is called **Univariate Linear Regression** or *Linear Regression with One Variable*. Below are some of the examples for certain values of the parameters θ_0 and θ_1 .



$$egin{aligned} heta_0 &= 0 \ heta_1 &= 0.5 \ h(x) &= 0 + (0.5*x) \end{aligned}$$



$$egin{aligned} heta_0 &= 1 \ heta_1 &= 0.5 \ h(x) &= 1 + (0.5*x) \end{aligned}$$



Choosing the Values of θ_0 and θ_1

- Choose θ_0 and θ_1 so that $h_{\theta}(x)$ is close to y for our training examples
- Formulation:

$$minimize_{ heta_0 heta_1}rac{1}{2m}\sum_{i=1}^m(h_ heta(x^{(i)})-y^{(i)})$$

Where,

- $lacksquare h_{ heta}(x^{(i)}) = heta_0 + heta_1 x^{(i)}$
- m =Number of training examples
- Cost Function (Squared Error Function):

$$J(heta_0, heta_1) = rac{1}{2m} \sum_{i=1}^m (h_ heta(x^{(i)}) - y^{(i)})^2$$

■ Therefore, in Linear Regression, the goal is:

$$minimize_{ heta_0 heta_1}J(heta_0, heta_1)$$