FIT1043 Introduction to Data Science

Week 5

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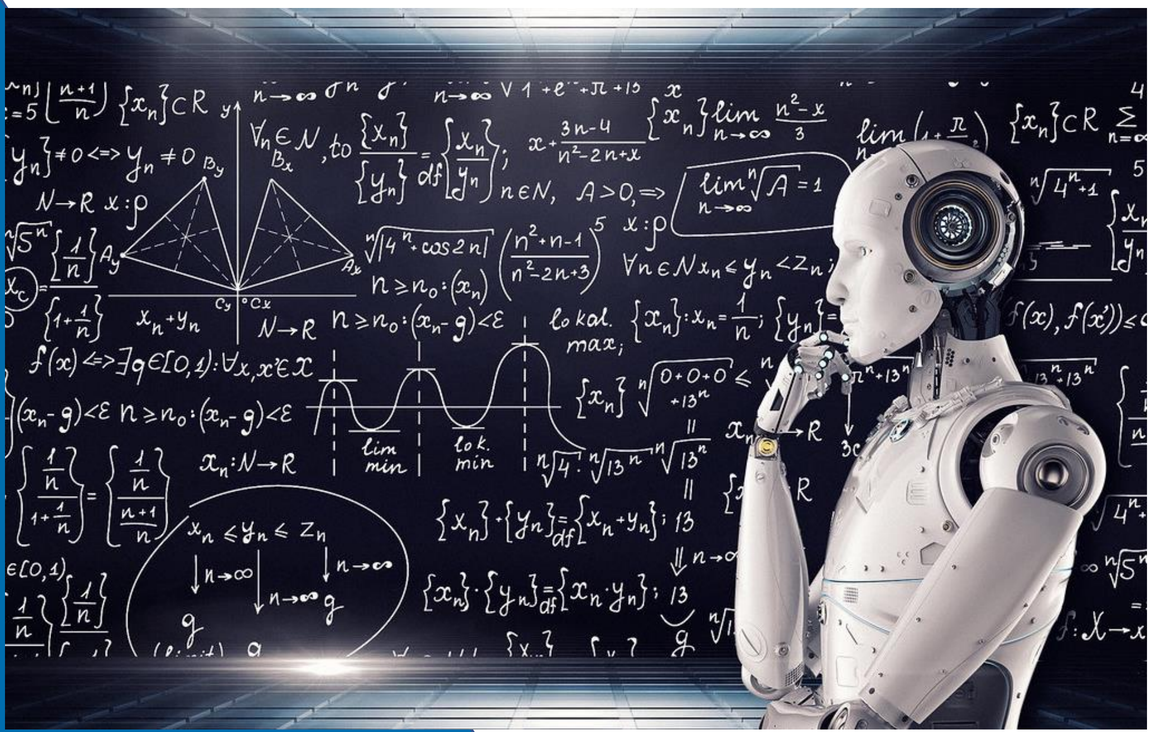
Monash University Malaysia

With materials from Wray Buntine, Mahsa Salehi

Introduction to Machine Learning



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Introduction to Machine Learning

What is Machine Learning?

- From Wikipedia: “…is the scientific study of **algorithms** and **statistical** models that computer systems use to perform a specific task without using explicit instructions, relying on **patterns** and **inference** instead.”

- From Emerj: “Machine Learning is the science of getting computers to learn and act like humans do, and improve their learning over time in autonomous fashion, by feeding them **data** and information in the form of **observations** and real-world interactions.

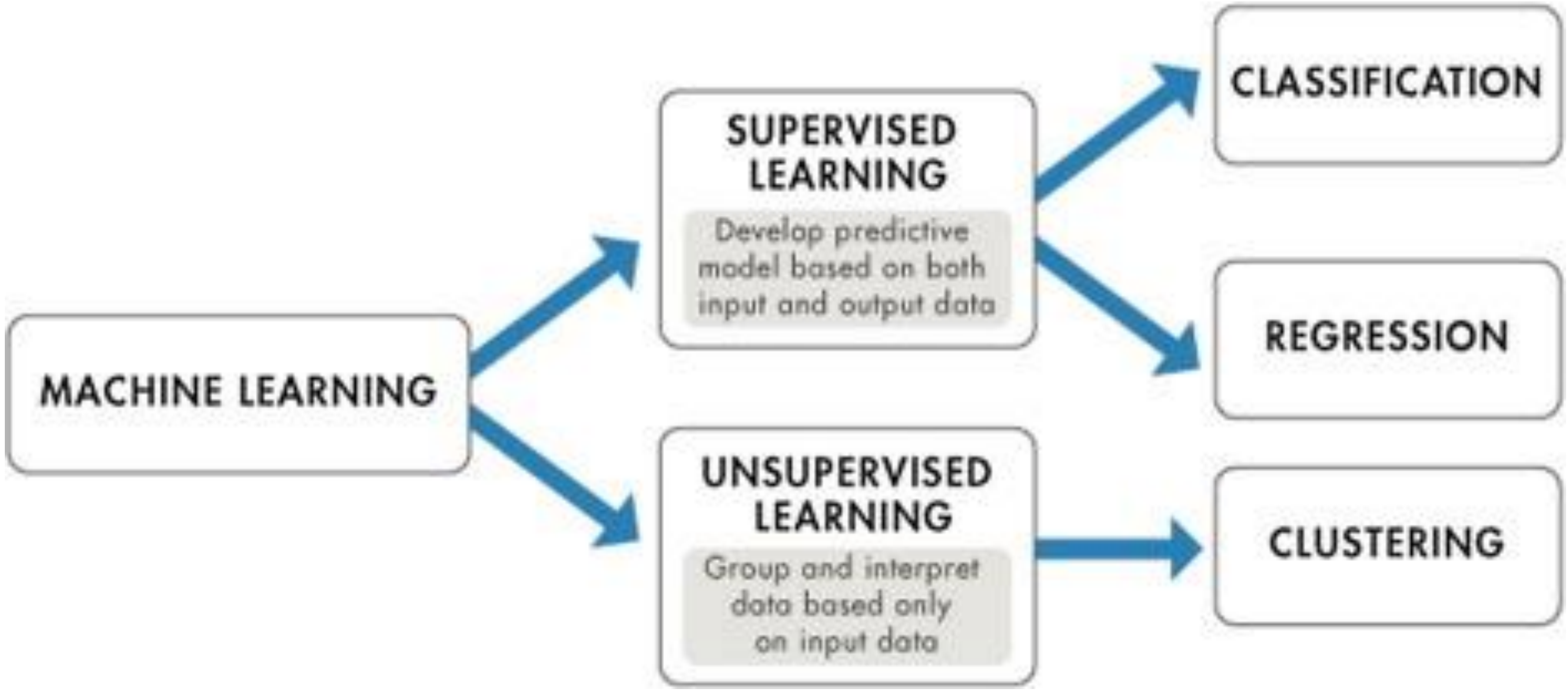
Introduction to Machine Learning

How to develop a Machine Learning model?

- Choose a measure of success
- Setting an evaluation protocol
- Developing a Benchmark Model
- Developing a Better Model and tuning its Hyperparameters

Learning Styles in ML Algorithms

Brownlee, J. (2016). Supervised and Unsupervised Machine Learning Algorithms



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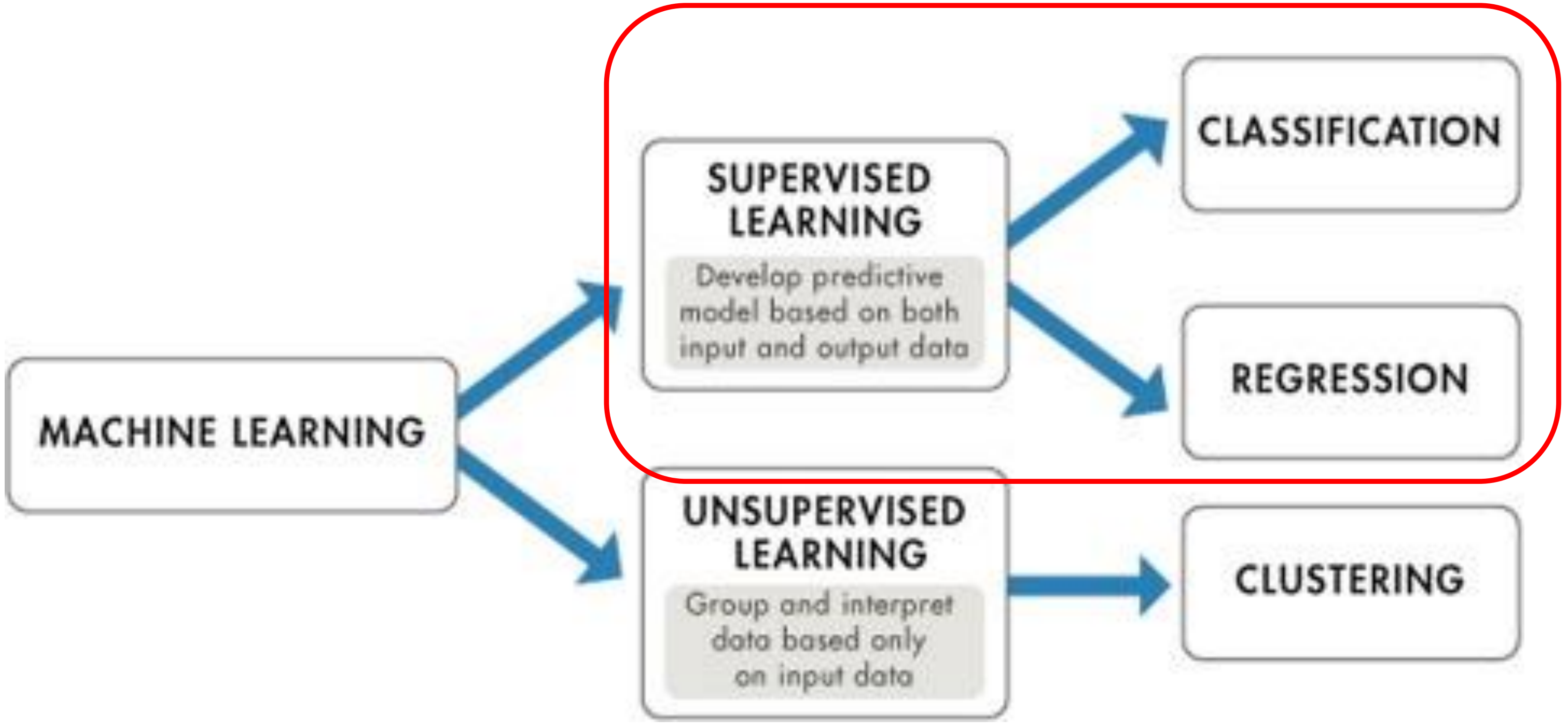

Learning Styles: *Supervised* ML

Brownlee J. (2016)

- All data is **labelled** and the algorithms learn to **predict** (infer) the output from the input data.
  - The goal is to approximate the mapping function so well that when you have new input data (x), you can predict the output variable (y) for that data.

- Example Problems:
  - Classification: The output variable is a category (e.g. “Red” or “Blue” for the Fish Classification)
  - Regression: The output variable is a real value (e.g. “dollars” or “weight”)

- Example Algorithms:
  - *Linear regression* for regression problems.
  - *Random forest (RF)* for classification and regression problems.
  - *Support vector machines (SVM)* for classification problems.

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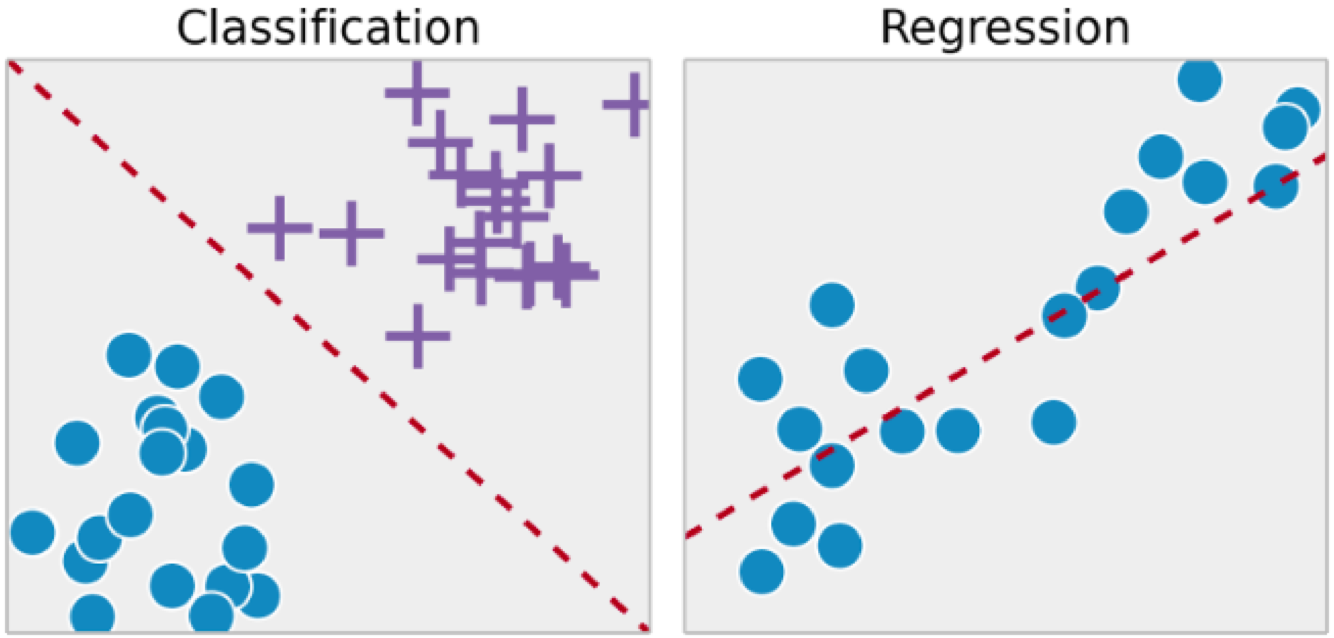
Learning Styles: Supervised ML

Brownlee J. (2016)



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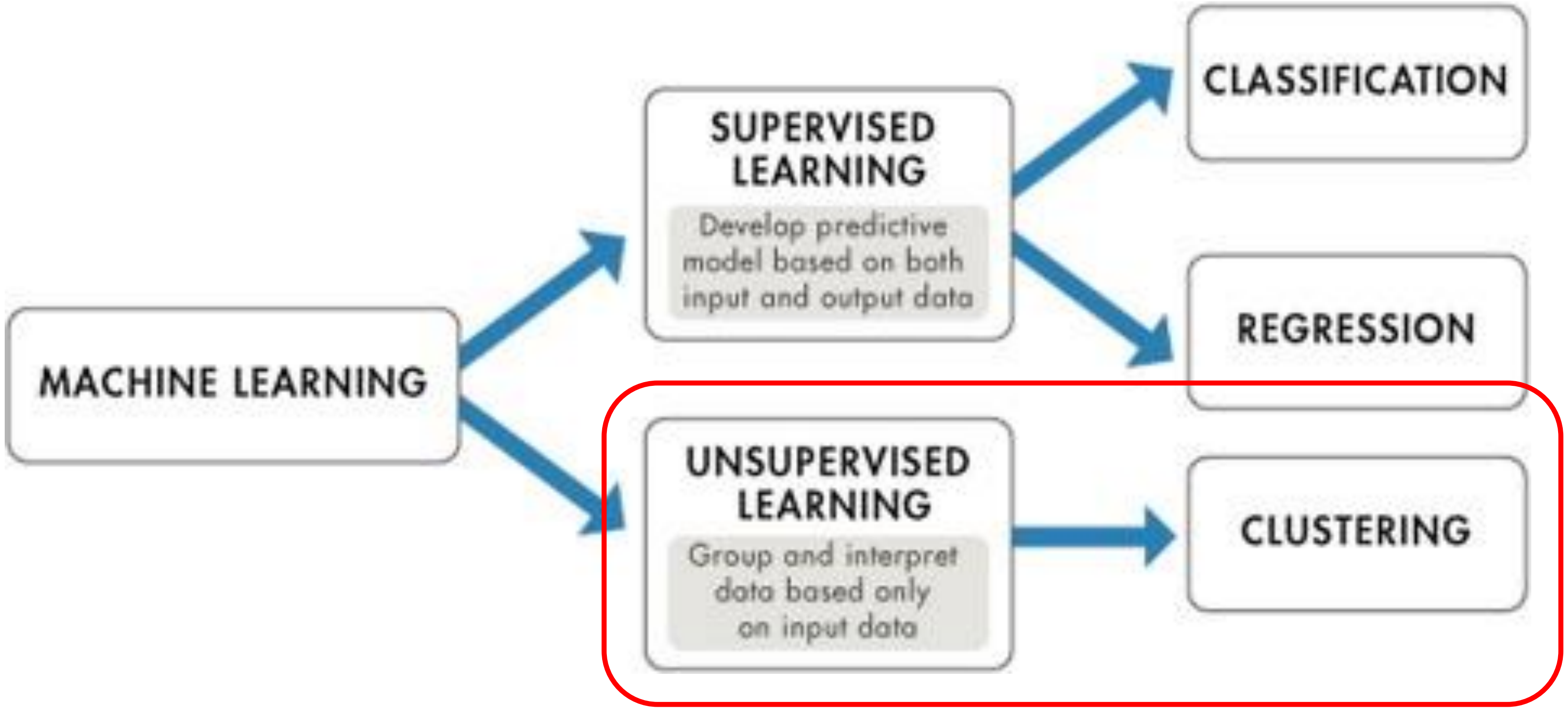

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Learning Styles: *Unsupervised* ML

Brownlee J. (2016)

- All data is **unlabelled** and the algorithms learn to inherent structure from the input data.
- The goal is to model the underlying structure or distribution in the data in order to learn more about the data.

- Example Problems: face similarity detection
  - Clustering: Discover the inherent groupings in the data (e.g. grouping customers by purchasing behaviour)
  - Association: Discover rules that describe large portions of your data (e.g. people that buy X also tend to buy Y)

- Example Algorithms:
  - *k-means* for clustering problems.
  - *Apriori* algorithm for association rule learning problems.

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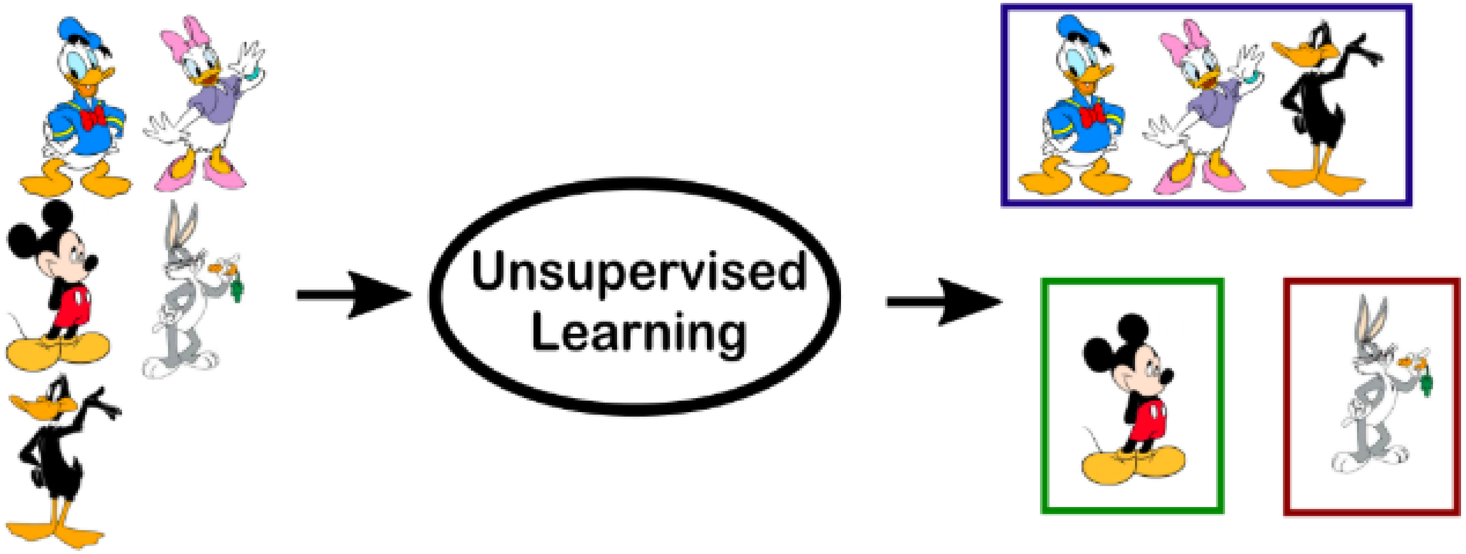
Learning Styles: *Unsupervised* ML

Brownlee J. (2016)



Theory of Data Analysis

Introduction to Learning Theory

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What is Learning Theory?

From Wikipedia:

(Computational) learning theory is a subfield of Artificial Intelligence devoted to ***studying the design and analysis of machine learning***.

Truth

Heart Disease Diagnosis

- For a single patient the “truth” can be measured directly
- How can you measure the “true” model?
    - Collect infinite data
    - But even if you can, it is a dynamic problem

Quality

To evaluate the quality of results derived from learning, we need notions of **value,** we will review quality and value using William Tell's Apple Shot (a Swiss folklore).

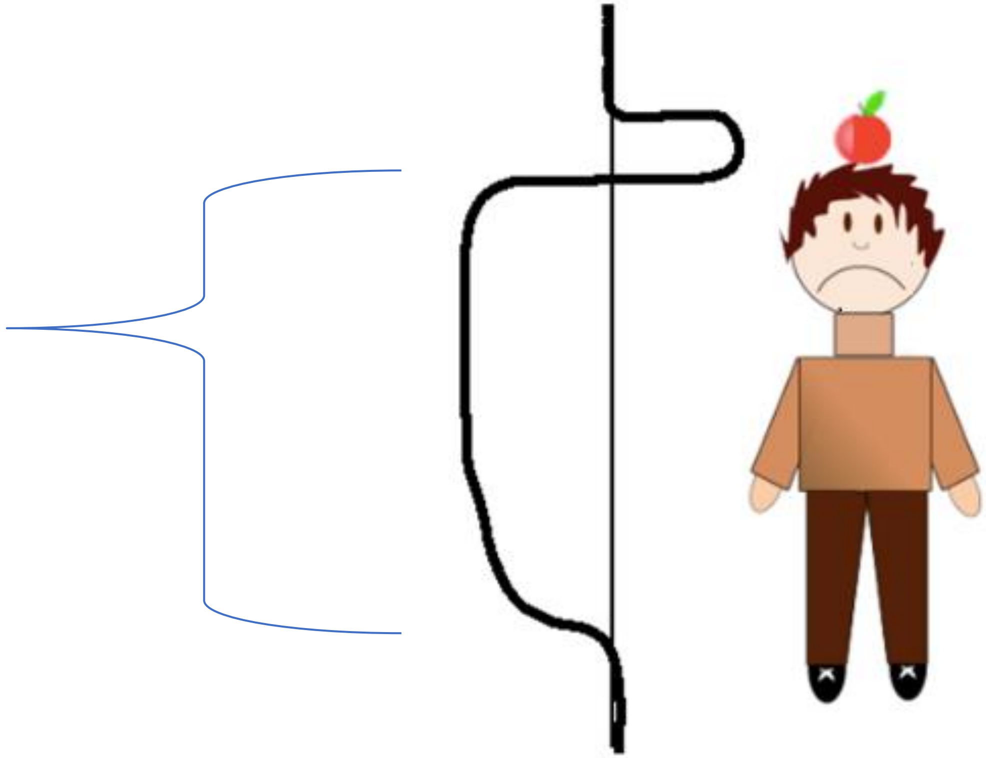
- William Tell forced to shoot the apple on his son's head

- If he strikes it, he gets both their freedom

William Tell's Apple Shot

This shows "value" as a function of height.

- Loss varies depending on where it strikes
- How do you compare loss of life versus gain of freedom?



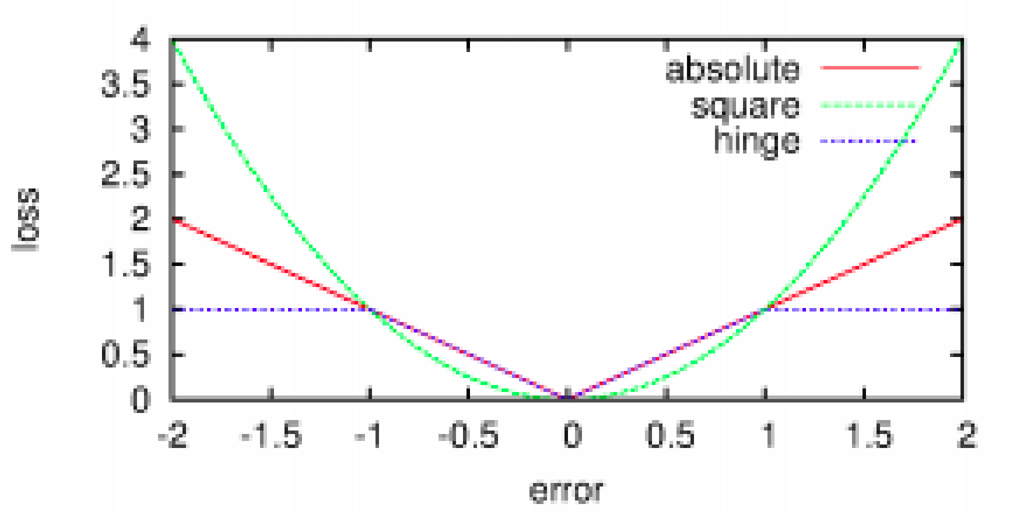
Quality

May be the consequence of your actions (making a prediction is a kind of action)

Can be measured on a positive or negative scale

Loss: positive when things are bad, negative (or zero) when they're good
Gain: positive when things are good, negative when they're not
Error: measure of "miss", sometimes a distance, but not a measure of quality

Quality is a Function of Error



Error measures the distance between the prediction and the actual value, where “0” means no error, prediction was exactly right.

We can convert error to a measure of quality using a loss function, e.g.:

absolute-error(x)	=	$\mid x \mid$	
square-error(x)	=	$x * x$	
hinge-error(x)	=	$\mid x \mid$,	if $\mid x \mid \leq 1$
			1 otherwise

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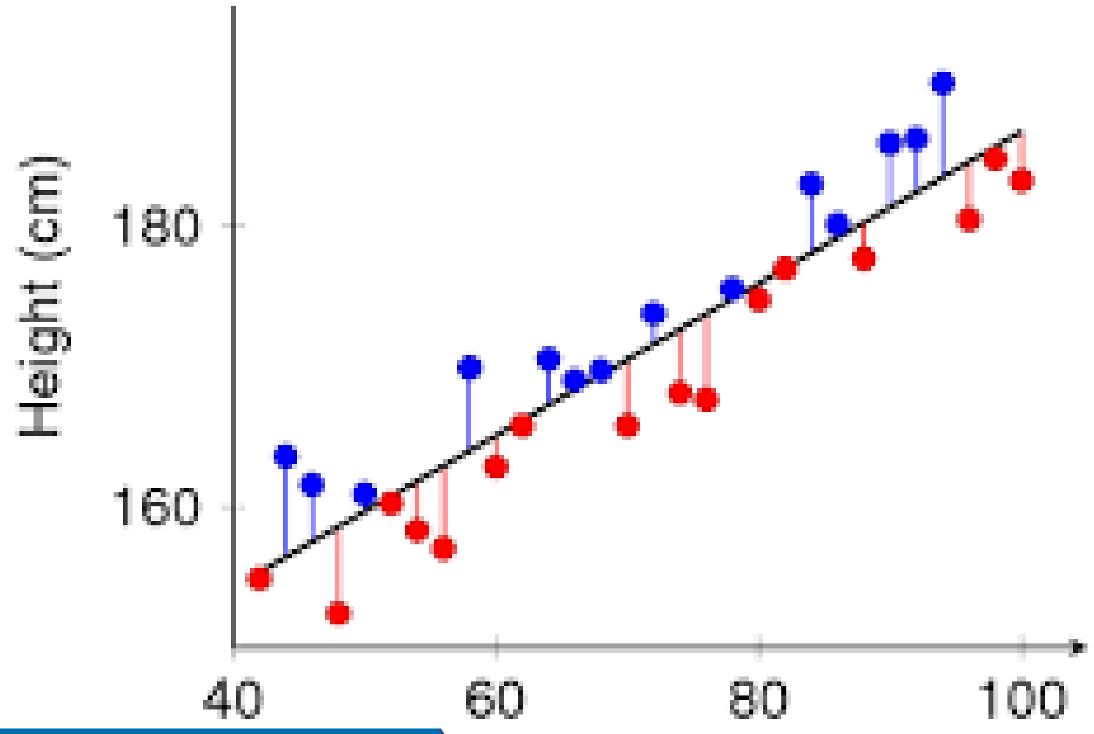
Regression



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Regression

$ $$ $$$ $$$$

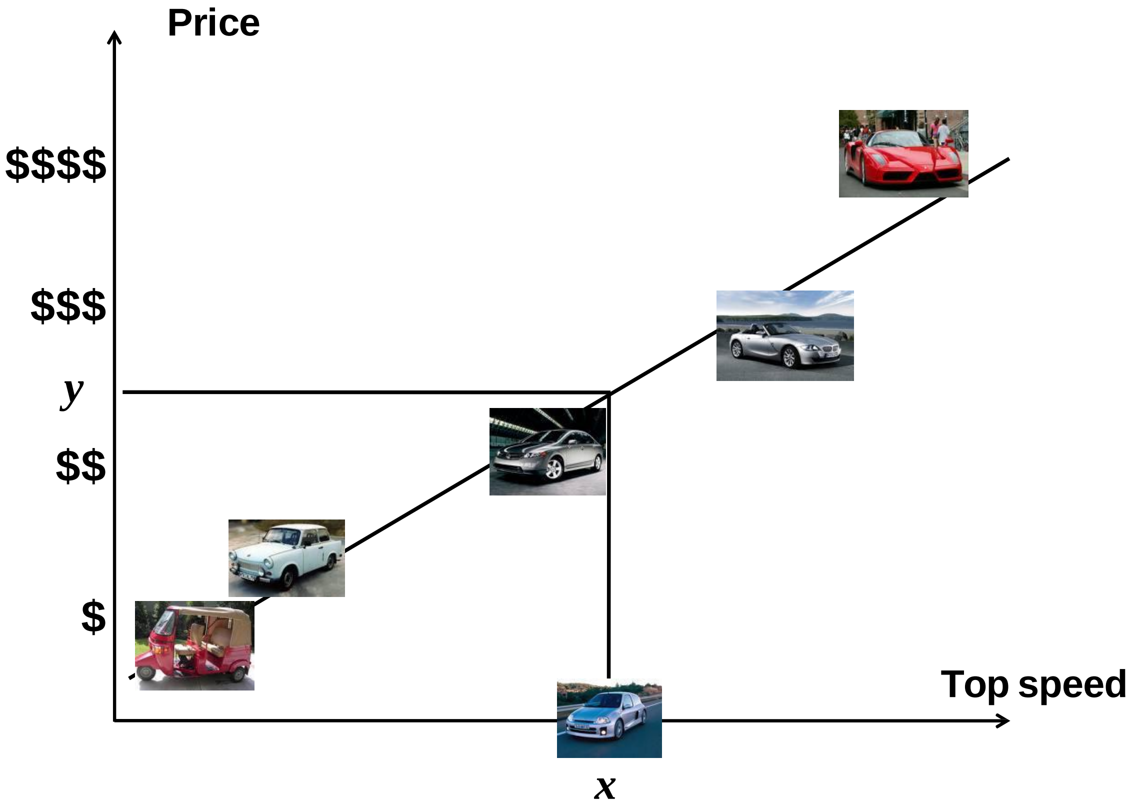
?

Regression

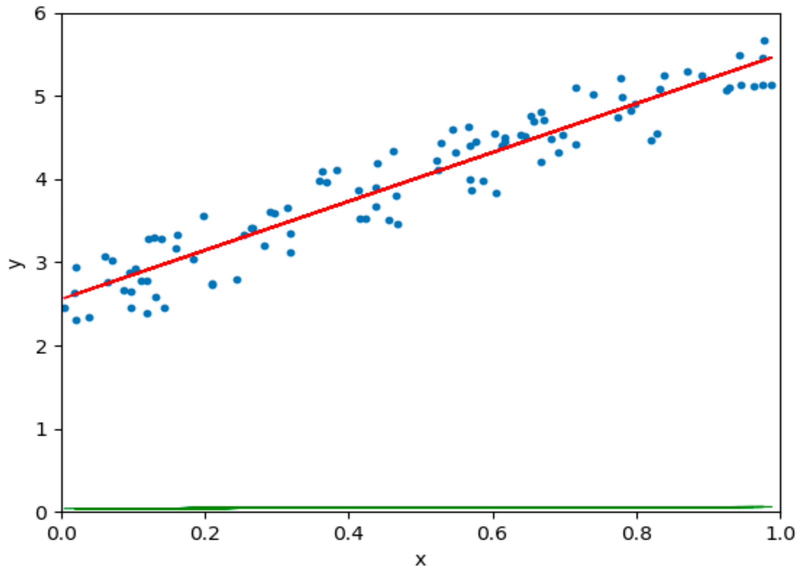
?

How much is this car worth?

Regression



Linear Regression



Regression fits a very simple equation to the data:

$$\hat{y}(x; \vec{a}) = a_0 + a_1 x$$

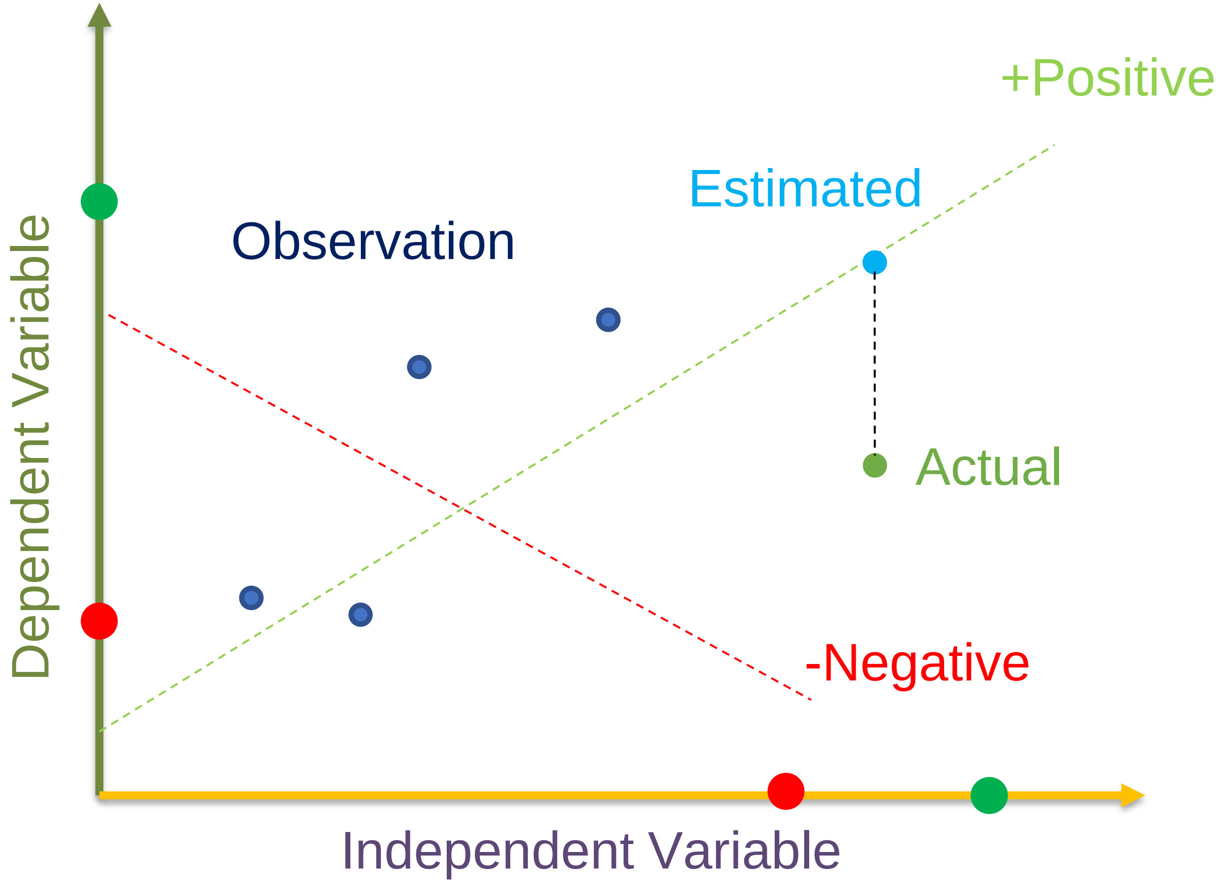
Data is shown with blue dots, red line is the "linear fitted model"

Here $\hat{y}(x; \vec{a})$ is the for prediction for y at the point x using the model parameters (a_0, a_1), i.e. the intercept and slope terms.

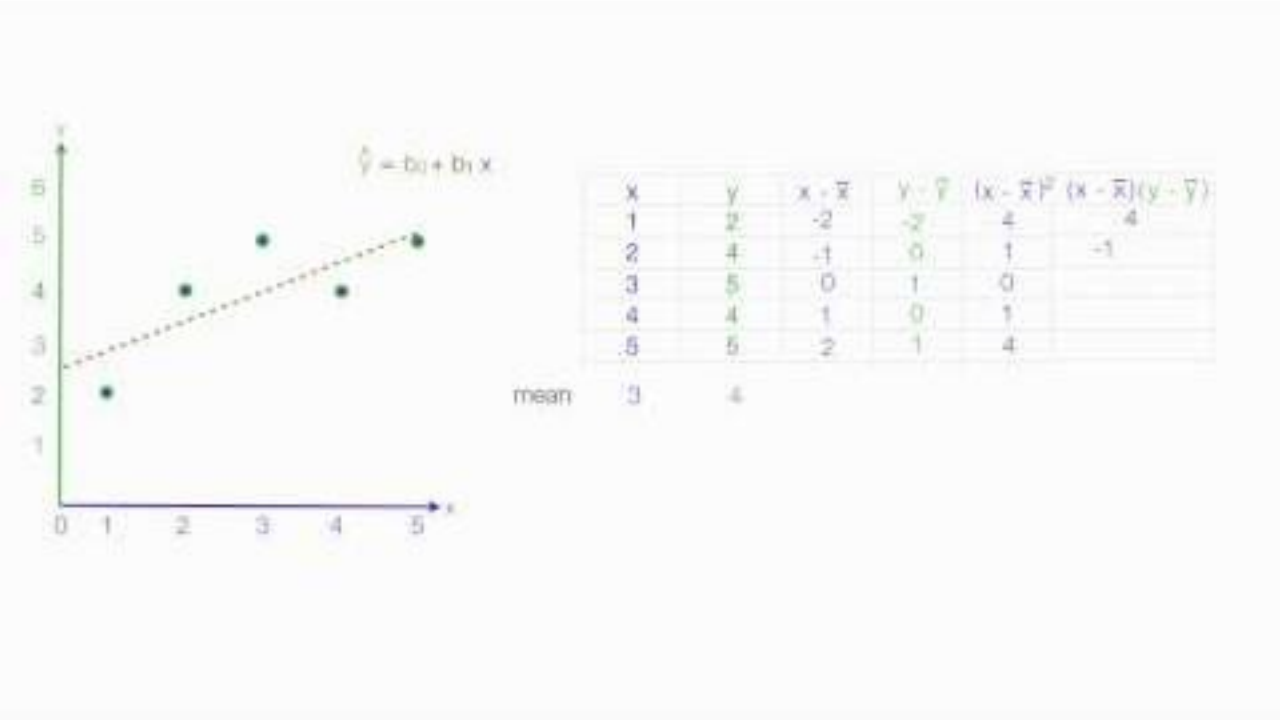
Given some data pairs (x_1, y_1), ...,(x_N , y_N), we fit a model by finding the vector $\vec{a}$ that minimises the loss function:

$$\text{mean square error} = MSE_{train} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}(x_i; \vec{a}) - y_i\right)^2$$

How to Calculate Linear Regression



How to Calculate Linear Regression



https://www.youtube.com/watch?v=JvS2triCgOY

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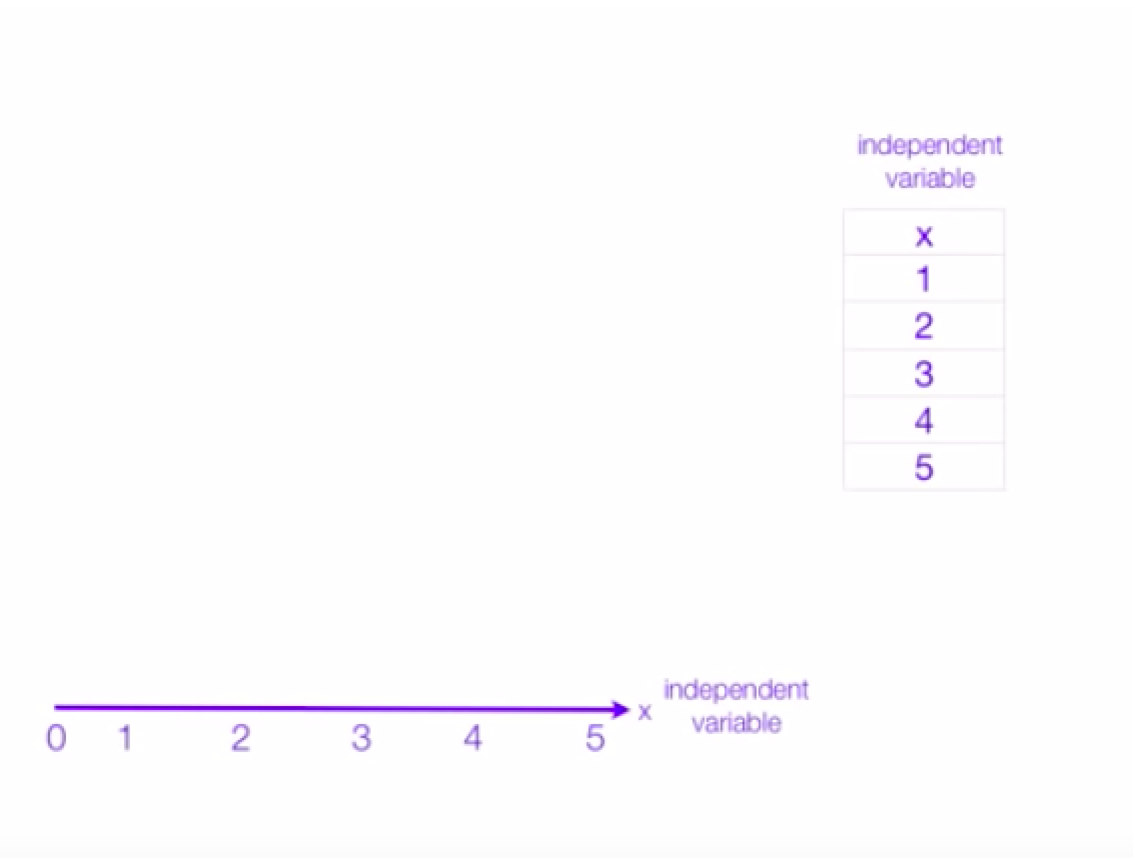

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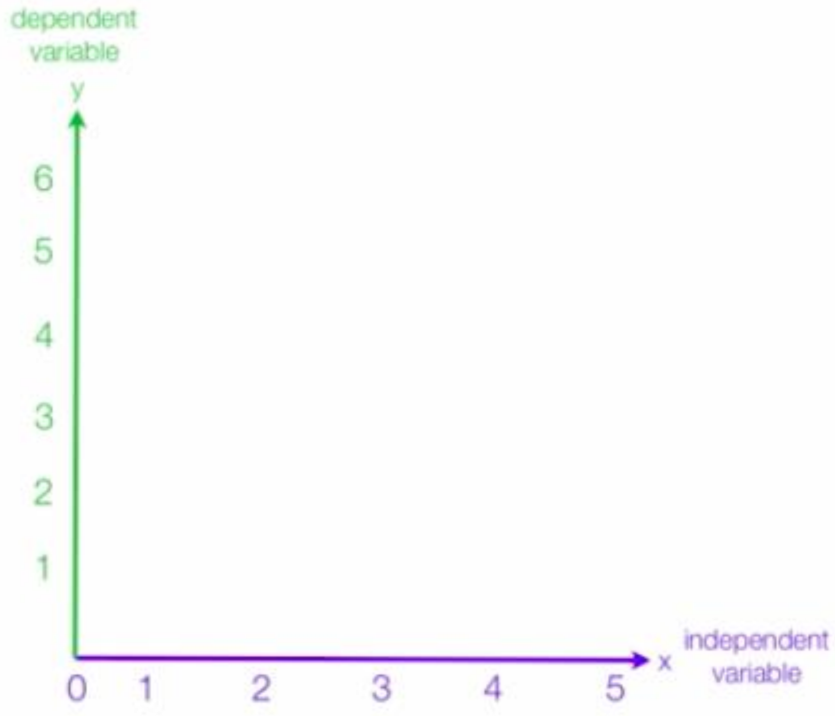

independent variable	dependent variable
x	y
1	2
2	4
3	5
4	4
5	5

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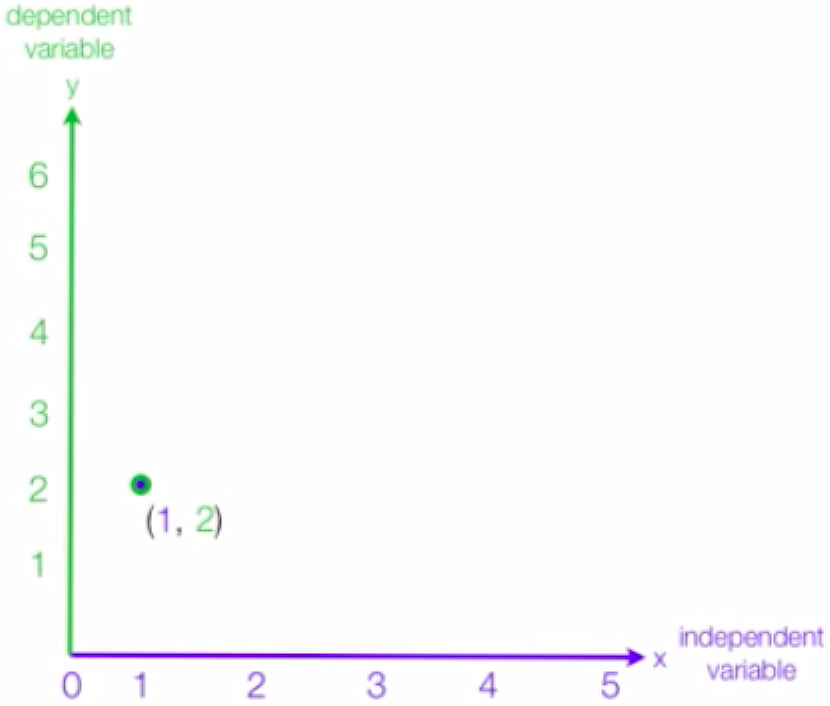
How to Calculate Linear Regression



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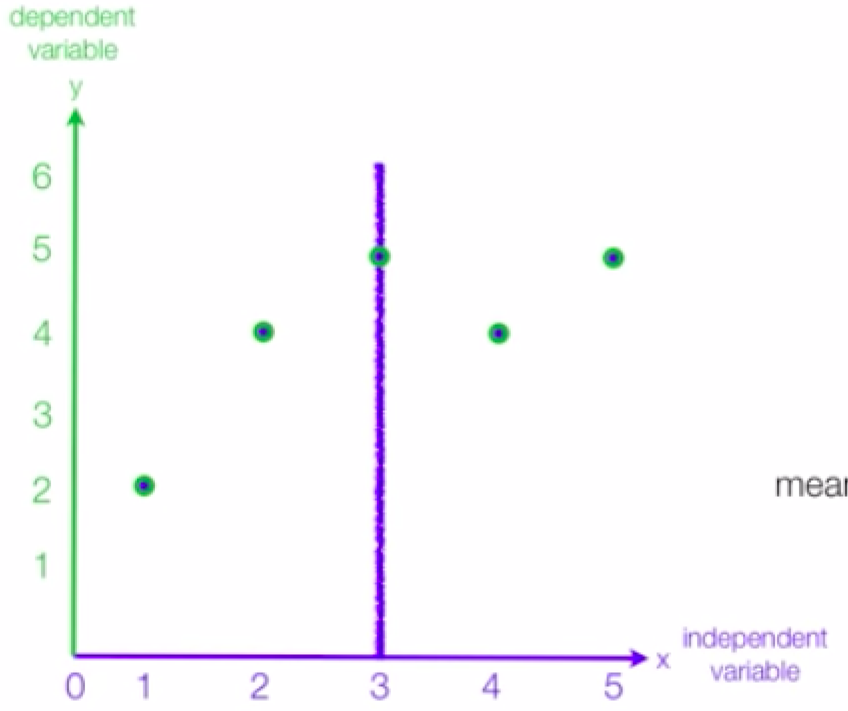

independent variable	dependent variable
x	y
1	2
2	4
3	5
4	4
5	5

mean 3

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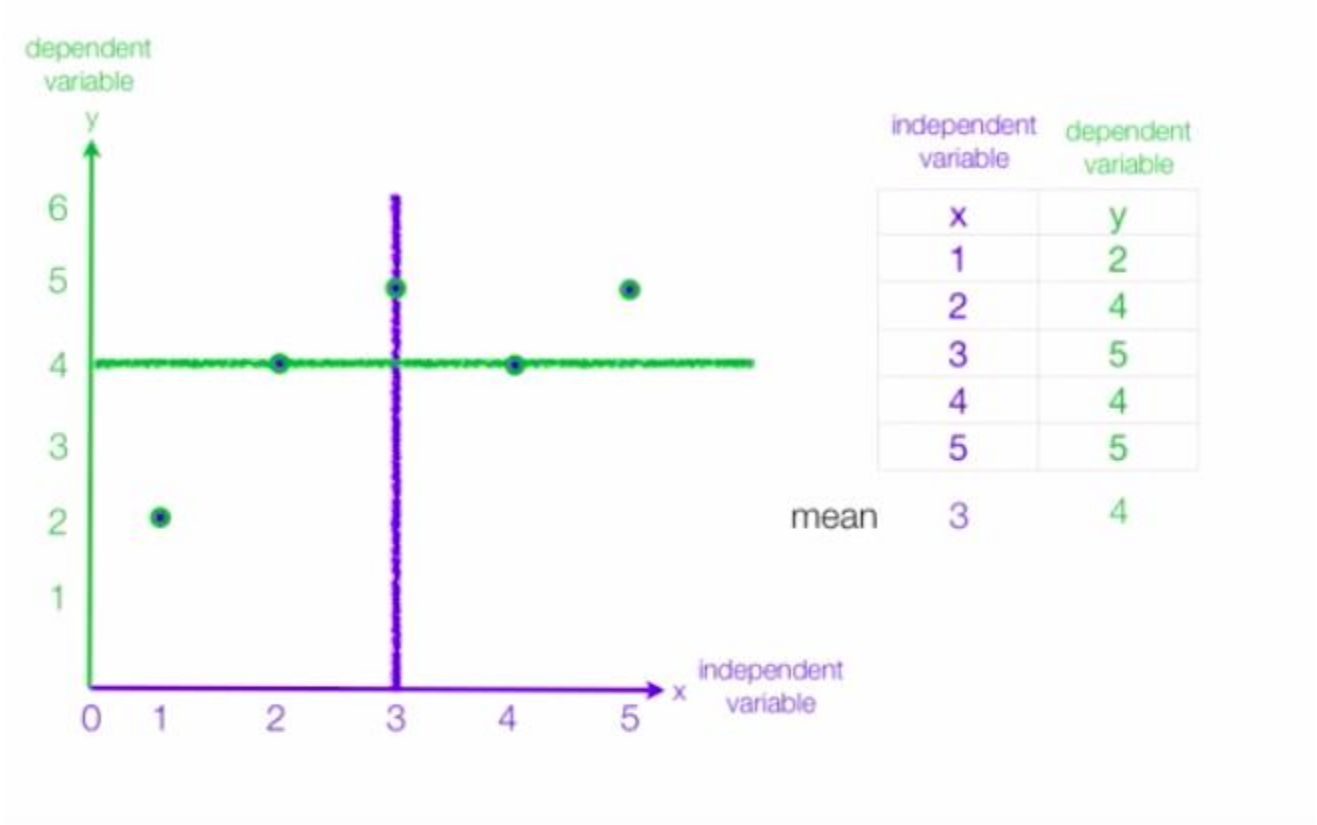
How to Calculate Linear Regression



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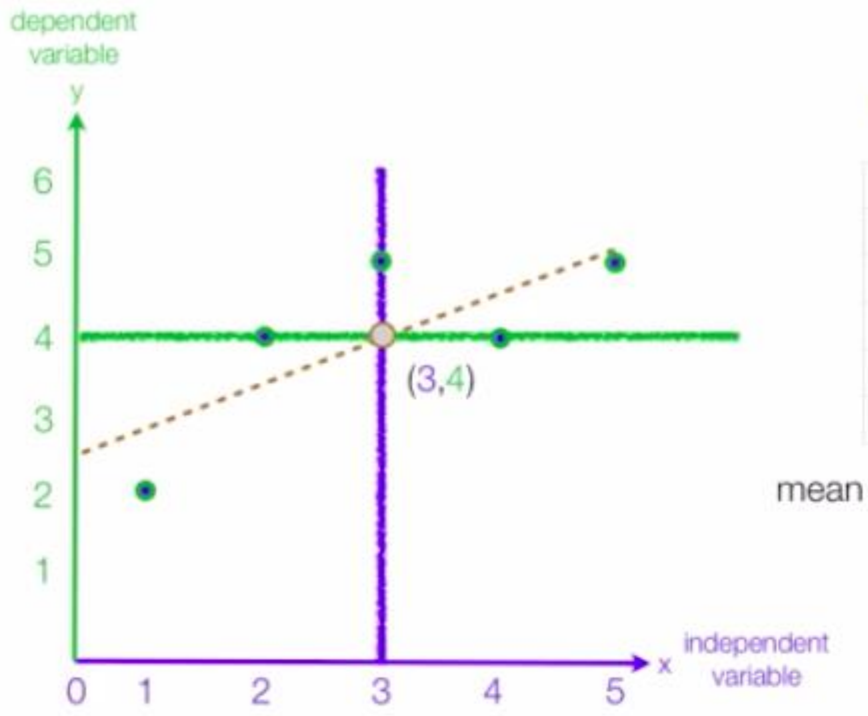

independent variable	dependent variable
x	y
1	2
2	4
3	5
4	4
5	5

mean

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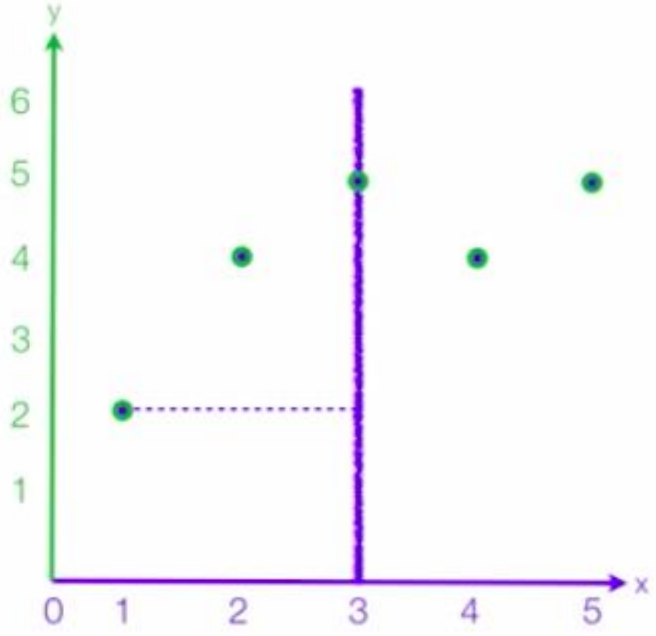
How to Calculate Linear Regression



	x	y	$x - \bar{x}$	
	1	2	1 - 3	
	2	4		
	3	5		
	4	4		
	5	5		
mean	3	4		

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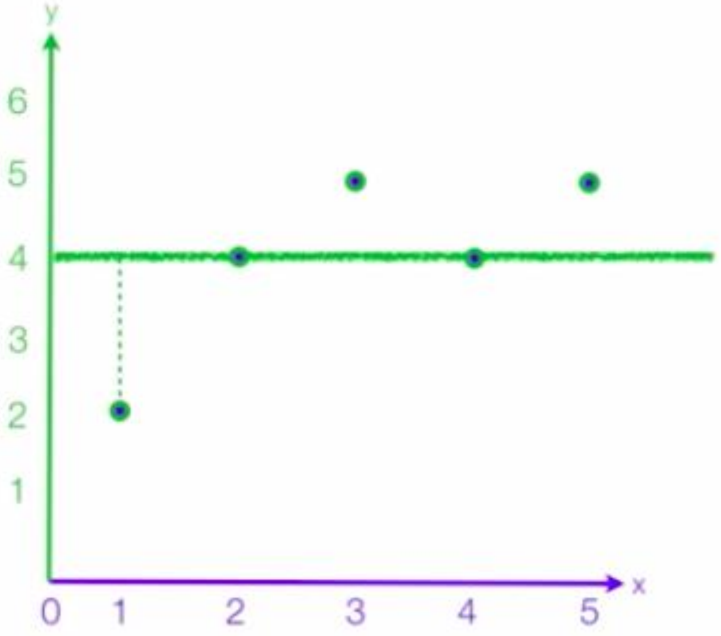
How to Calculate Linear Regression



	x	y	$x - \bar{x}$	$y - \bar{y}$
	1	2	-2	2 - 4
	2	4	-1	
	3	5	0	
	4	4	1	
	5	5	2	
mean	3	4		

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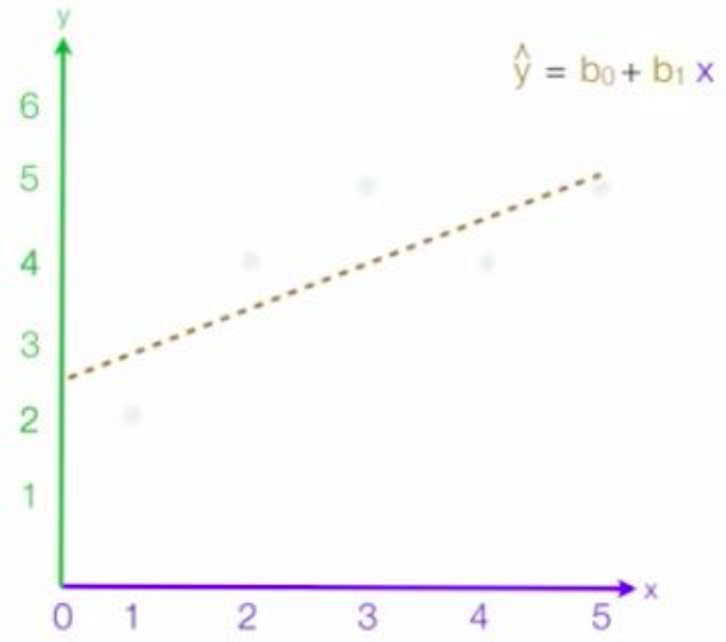
How to Calculate Linear Regression



x	y	$x - \bar{x}$	$y - \bar{y}$	$(x - \bar{x})^2$	$(x - \bar{x})(y - \bar{y})$
1	2	-2	-2	4	4
2	4	-1	0	1	0
3	5	0	1	0	0
4	4	1	0	1	0
5	5	2	1	4	2

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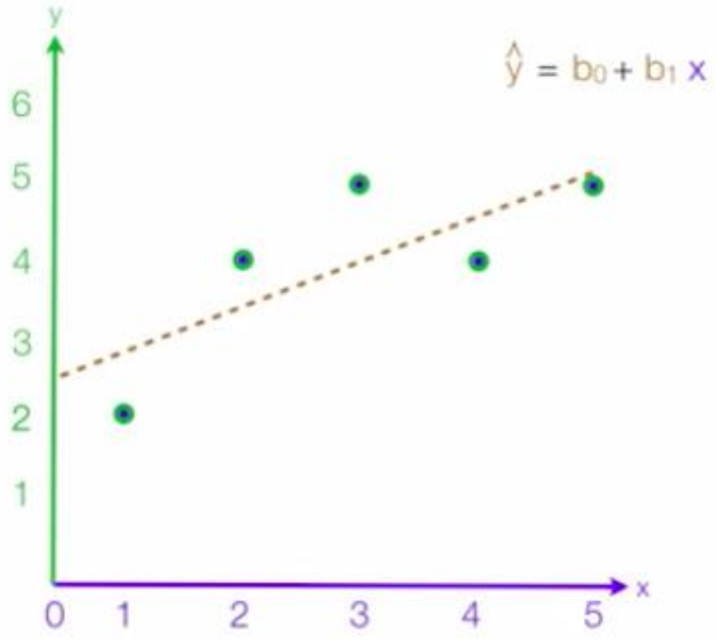
How to Calculate Linear Regression



	x	y	$x - \bar{x}$	$y - \bar{y}$	$(x - \bar{x})^2$	$(x - \bar{x})(y - \bar{y})$
	1	2	-2	-2	4	4
	2	4	-1	0	1	0
	3	5	0	1	0	0
	4	4	1	0	1	0
	5	5	2	1	4	2
					10	6
mean	3	4				

sum

$$b_1 = \frac{6}{10} = .6 = \frac{\Sigma(x - \bar{x})(y - \bar{y})}{\Sigma(x - \bar{x})^2}$$

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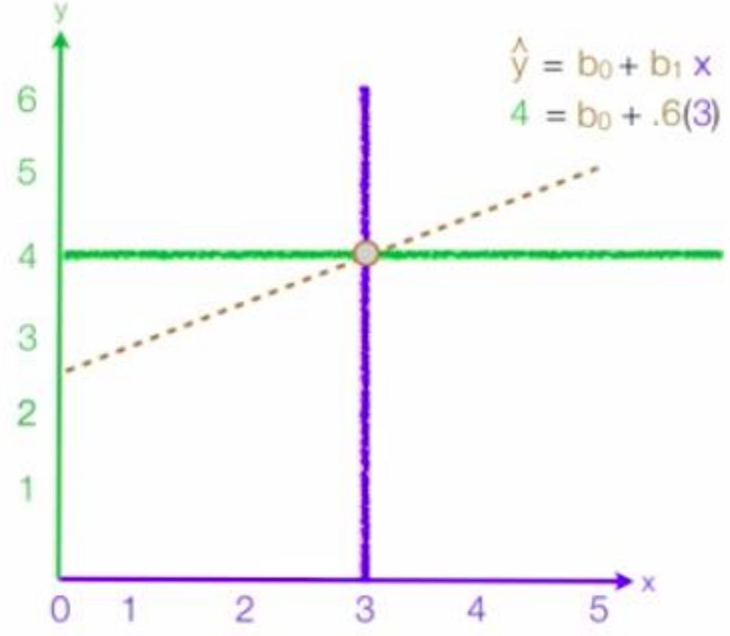
How to Calculate Linear Regression



$\hat{y} = b_0 + b_1 x$

$4 = b_0 + .6(3)$

x	y	$x - \bar{x}$	$y - \bar{y}$	$(x - \bar{x})^2$	$(x - \bar{x})(y - \bar{y})$
1	2	-2	-2	4	4
2	4	-1	0	1	0
3	5	0	1	0	0
4	4	1	0	1	0
5	5	2	1	4	2
				10	6
mean 3	4				

$$4 = b_0 + .6(3)$$

$$4 = b_0 + 1.8$$
$$-1.8 \quad\quad -1.8$$
$$2.2 = b_0$$

$$b_1 = \frac{6}{10} = .6 = \frac{\Sigma (x - \bar{x})(y - \bar{y})}{\Sigma (x - \bar{x})^2}$$

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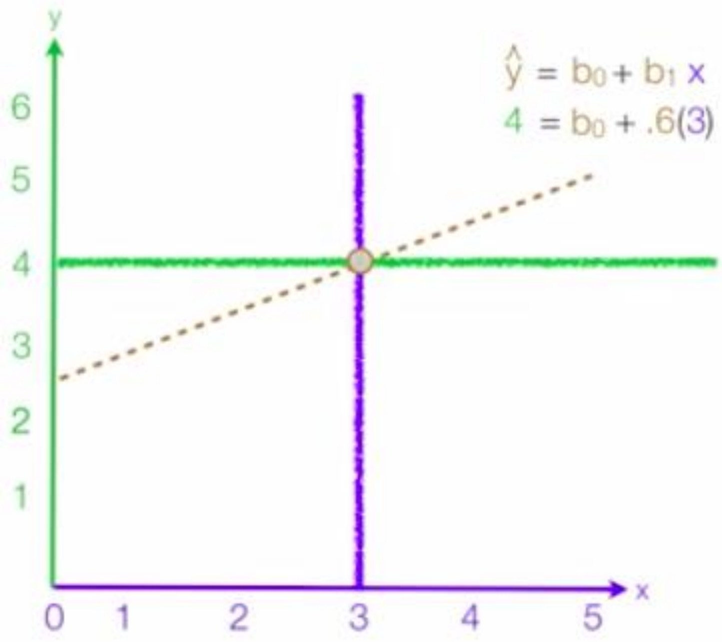
How to Calculate Linear Regression



$b_0 = 2.2$
$b_1 = .6$
$\hat{y} = 2.2 + .6x$

	x	y	$x - \bar{x}$	$y - \bar{y}$	$(x - \bar{x})^2$	$(x - \bar{x})(y - \bar{y})$
	1	2	-2	-2	4	4
	2	4	-1	0	1	0
	3	5	0	1	0	0
	4	4	1	0	1	0
	5	5	2	1	4	2
					10	6
mean	3	4				

$4 = b_0 + .6(3)$

$4 = b_0 + \cancel{1.8}$

$-1.8 \quad \cancel{-1.8}$

$2.2 = b_0$

$$b_1 = \frac{6}{10} = .6 = \frac{\Sigma(x - \bar{x})(y - \bar{y})}{\Sigma(x - \bar{x})^2}$$

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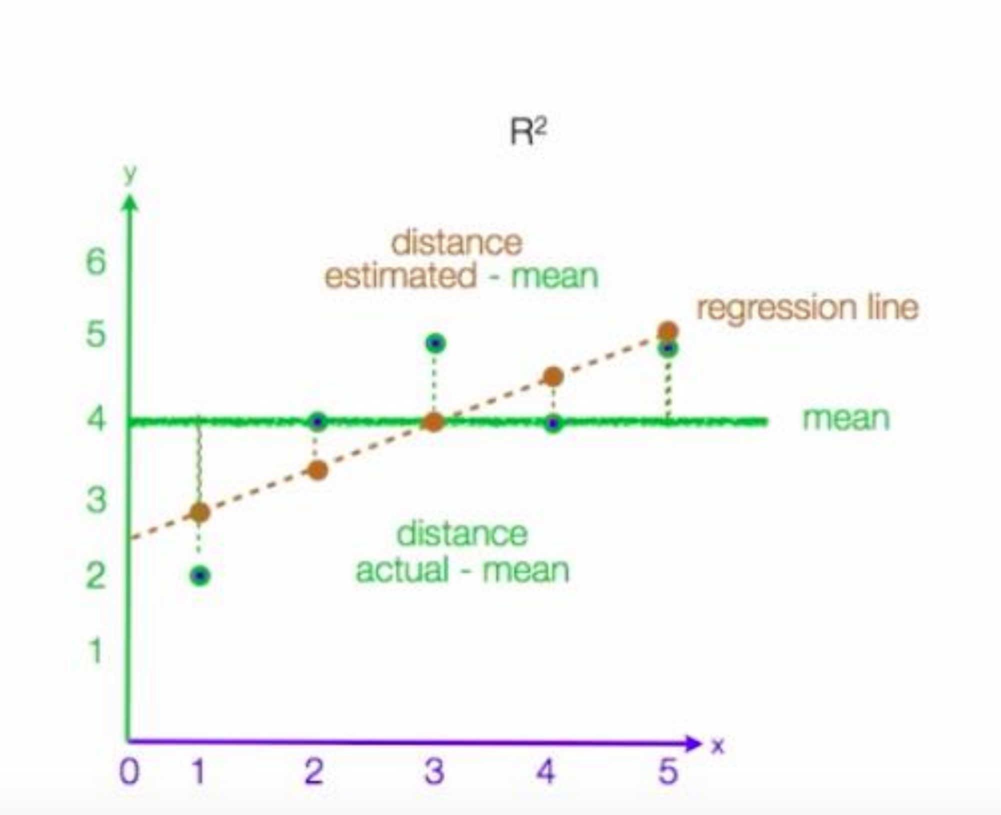
How to Calculate Linear Regression



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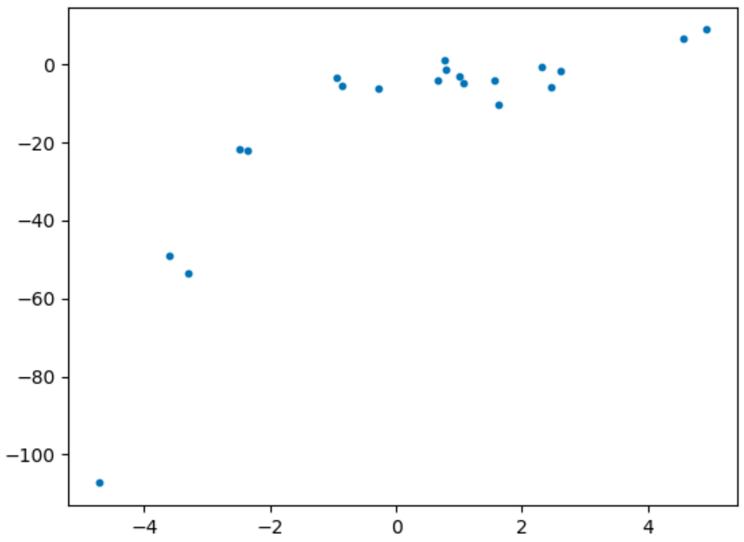
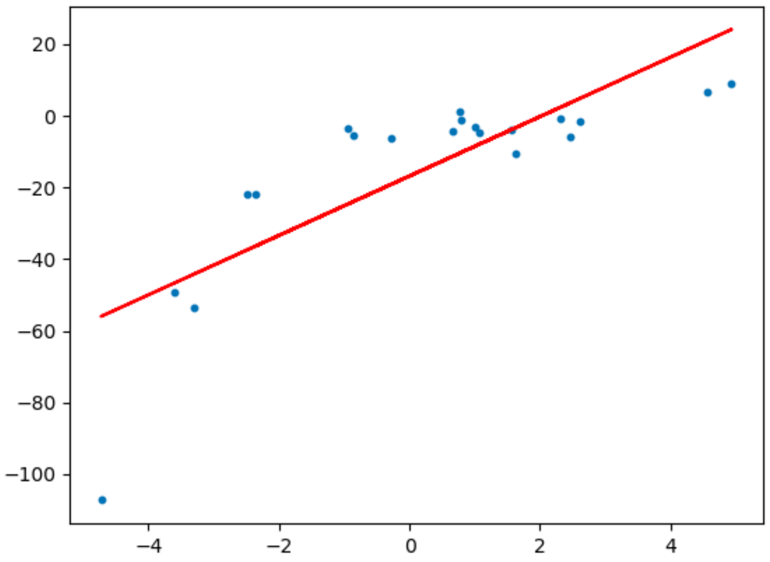
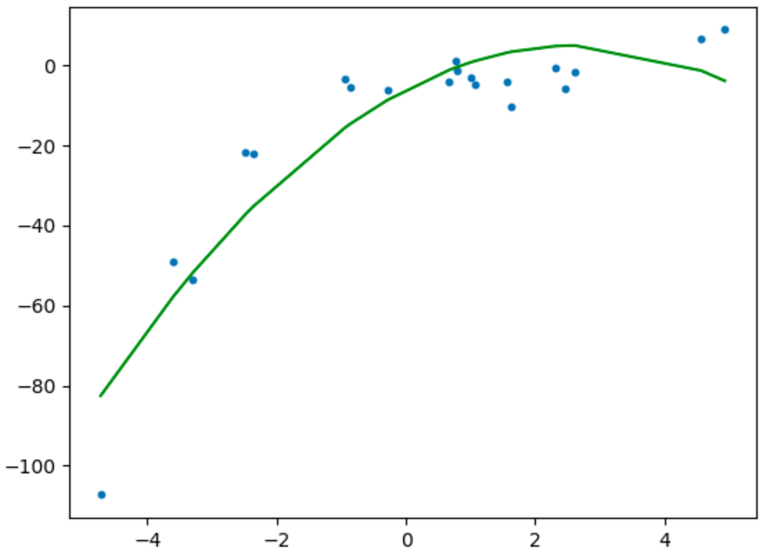
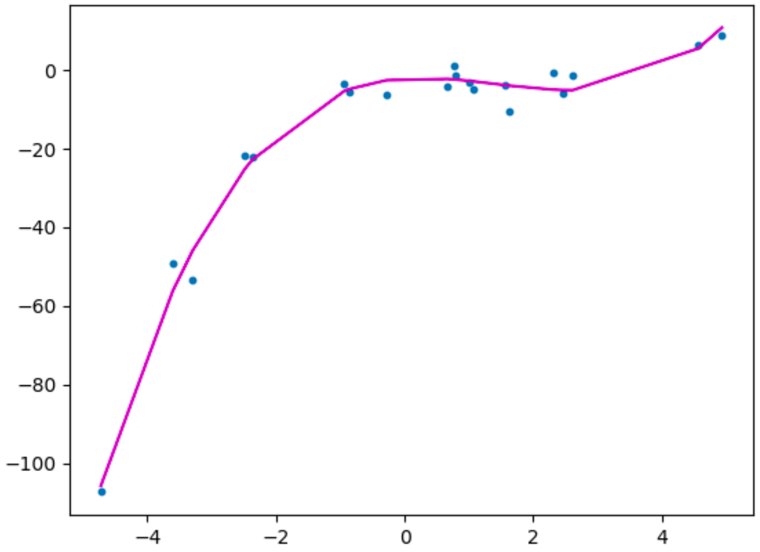
Polynomial Regression



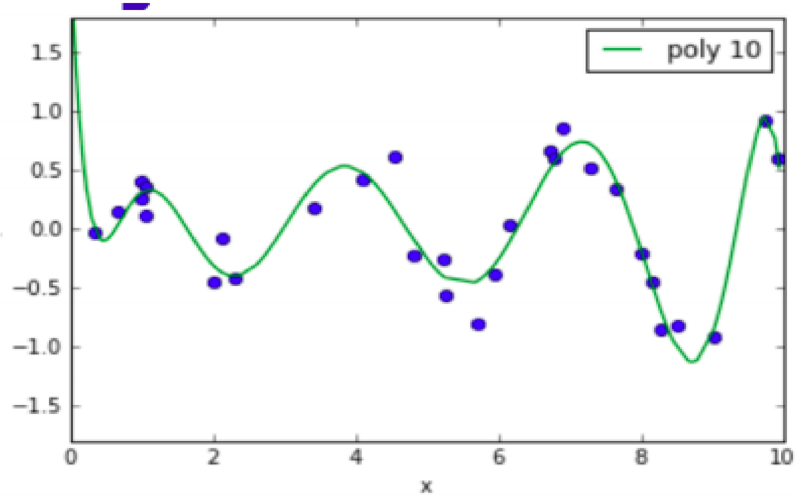






Polynomial Regression

- Data is shown with blue dots, green line is the "polynomial fitted model"



- **Polynomial regression** uses the same linear regression infrastructure to fit a higher order polynomial. In this case we fit a 10-th order polynomial:

$$\hat{y}(x;\vec{a}) = a_0 + a_1 x + a_2 x^2 + \ldots a_9 x^9 + a_{10} x^{10} = \sum_{i=0}^{10} a_i x^i$$

- By finding the vector $\vec{a}$ that for a given set of data pairs $(x_1, y_1), \ldots, (x_N, y_N)$ minimises the loss function:

$$\text{mean square error} = MSE_{train} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}(x_i;\vec{a}) - y_i\right)^2$$

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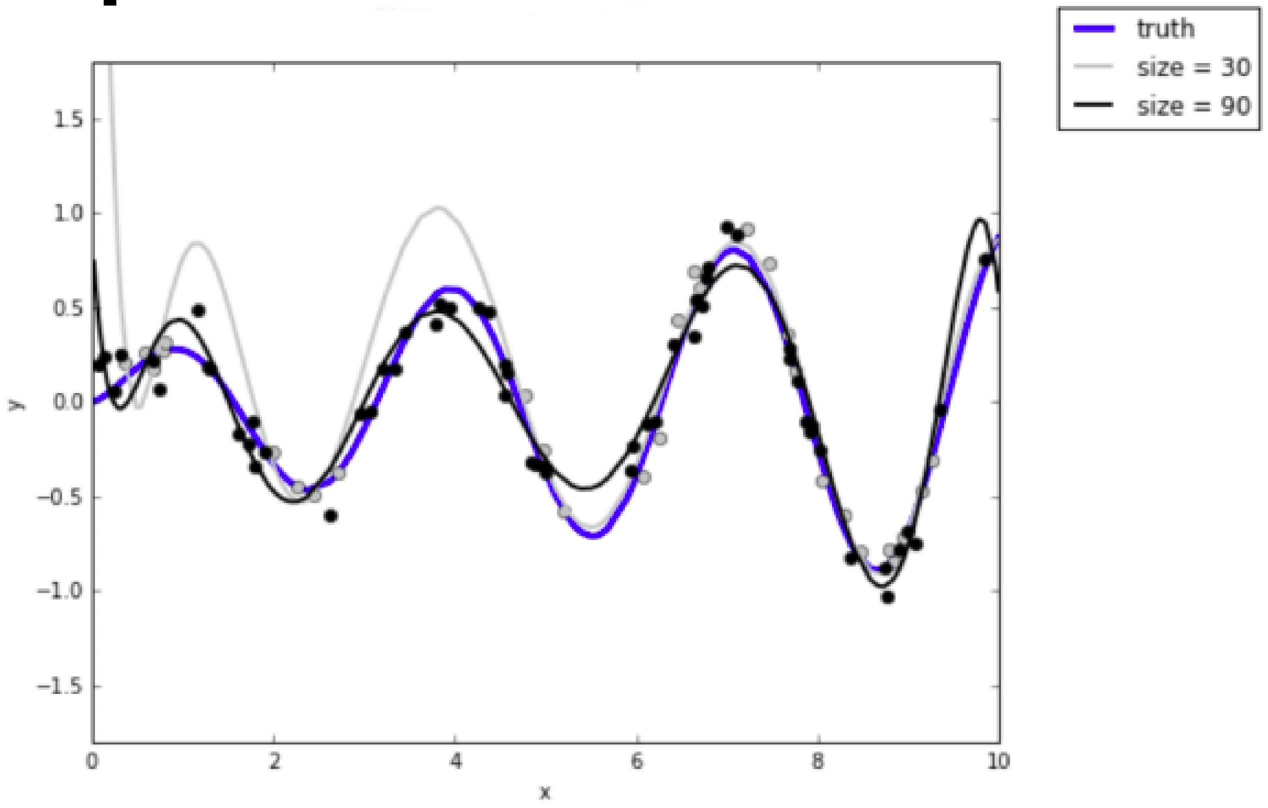
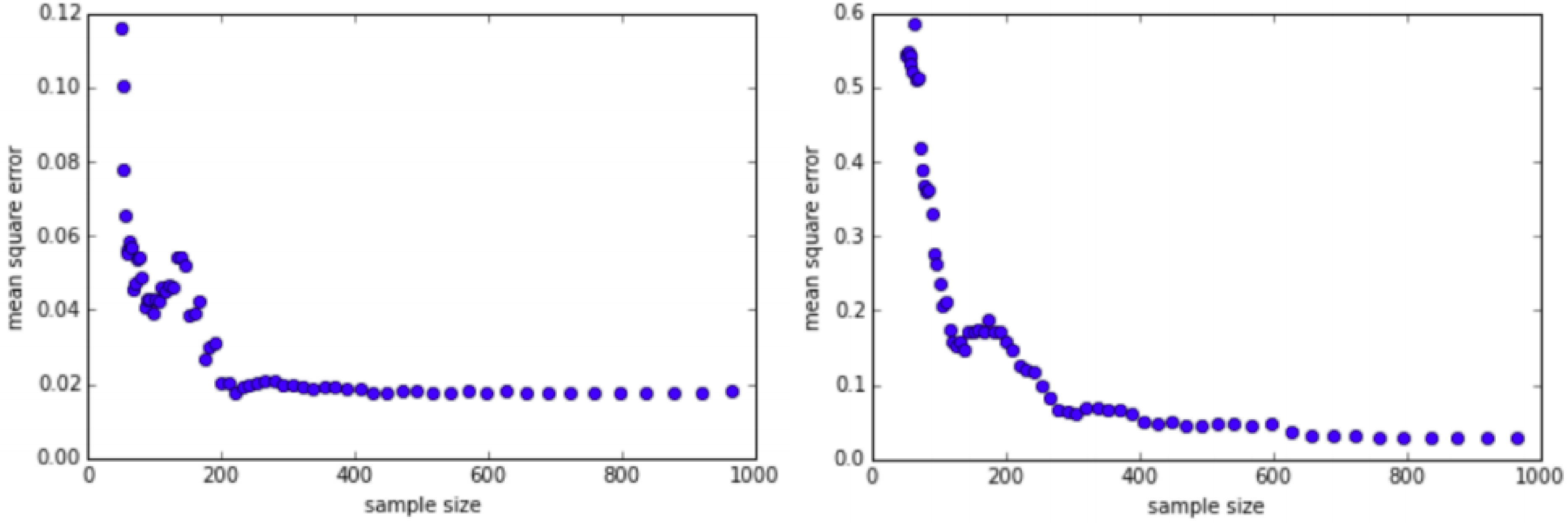
More Data Improves the Fit



- Blue line is true model that generated the data (before noise was added).
- Grey curve is model fit to 30 data points
- Black curve is model fit to 90 data points

In general, more data means better fit

More Data Improves the Fit



MSE decreases as the amount of training data grows

- These plots are called **learning curves**
- Different learning algorithms exhibit different behaviour (rate of decay)

Home Activities

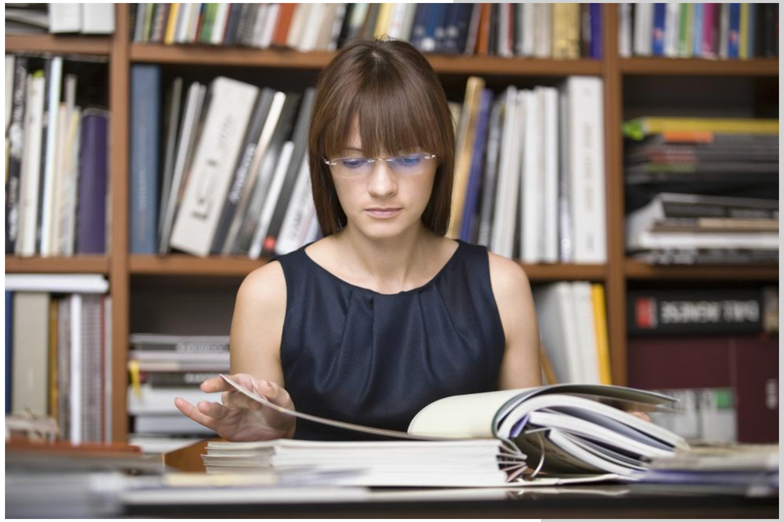
Suggested Activities for the week

Videos

Watch David Longstreet's easy to follow video on regression and on Calculate R^2 using regression analysis.

Reading

Read pages 16 – 18 of Jason Brownlee, "Master Machine Learning Algorithms: discover how they work and implement them from scratch", 2016



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Recap: Learning Outcomes

Week

By the end of this week you should be able to:

- Explain what are models and predictive models
- Analyse predictive models in different examples
- Understand how to evaluate predictive models
- **Analyse how to estimate linear regression model**
- Apply linear regression and polynomial regression on different data sets using Python