

REGRESSION

By:
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USING LINEAR REGRESSION TO PREDICT CONTINUOUS VARIABLE

	ENGINE SIZE	CYLINDERS	FUEL CONSUMPTION_COMB	CO2 EMISSIONS
0	2.0	4	8.5	196
1	2.4	4	9.6	221
2	1.6	4	5.9	136
3	3.5	6	11.1	255
4	3.5	6	10.6	244
5	3.5	6	10.0	230
6	3.5	6	10.1	232
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8	3.7	6	11.6	267
9	2.4	4	9.2	?

DEPENDENT VS INDEPENDENT VARIABLES

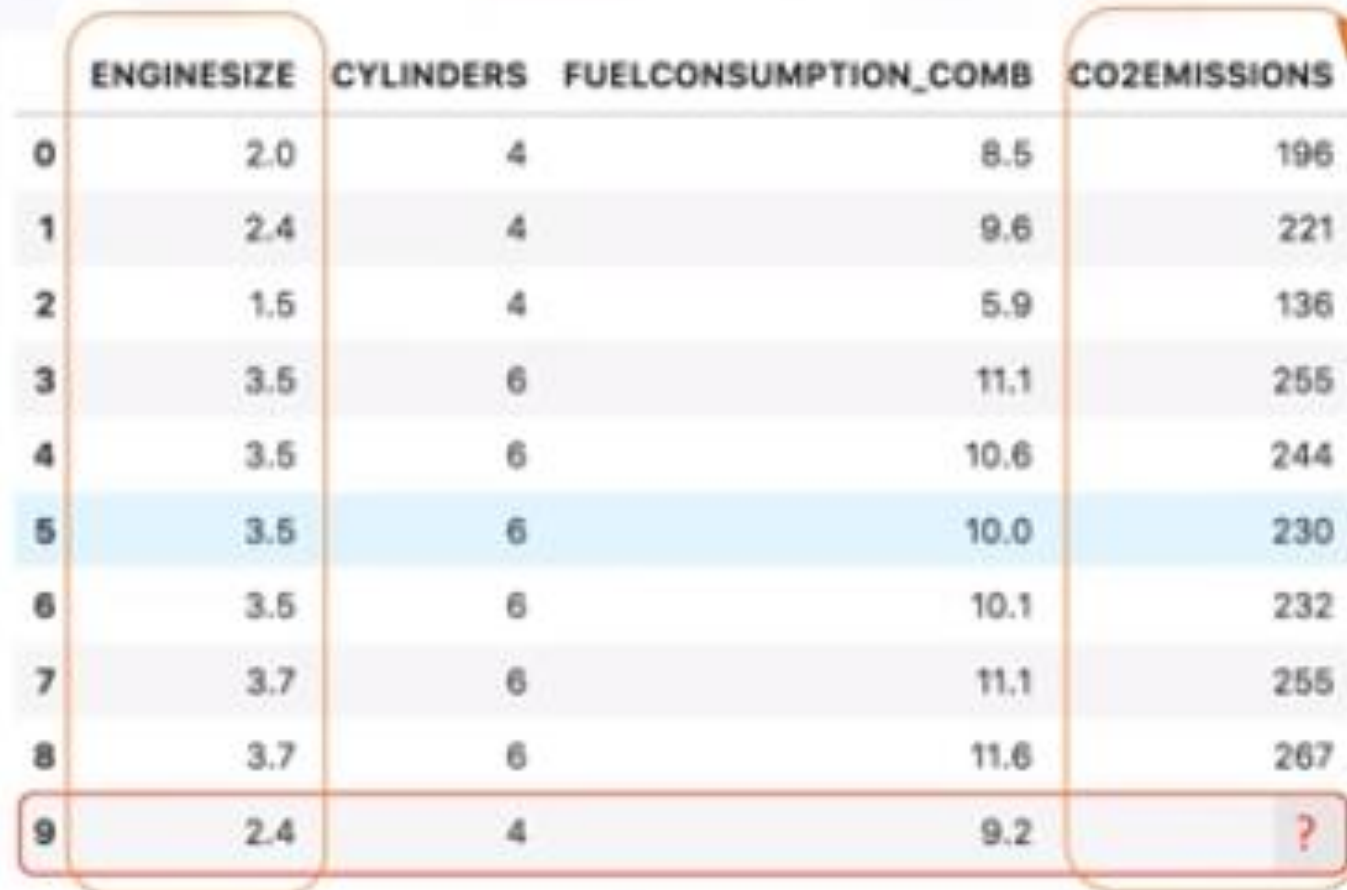
Y: Dependent variable

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X: Independent variable

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Continuous Values

REGRESSION TYPE

- SIMPLE LINEAR REGRESSION

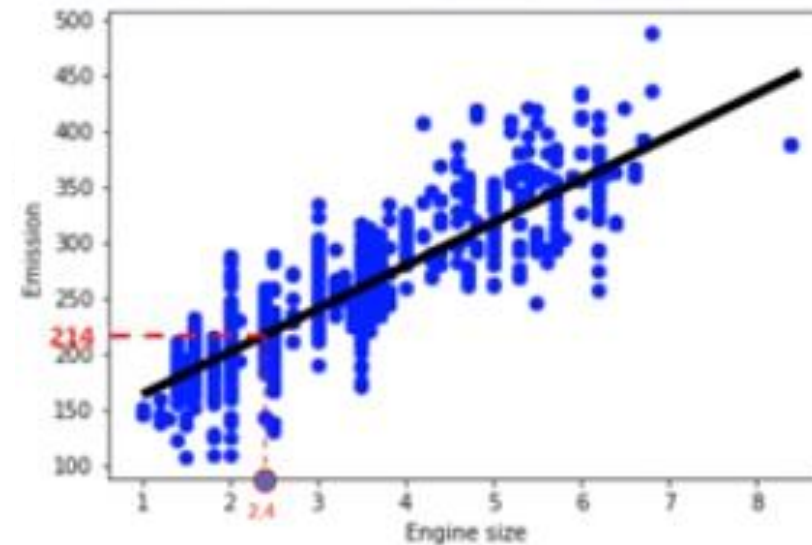
- Predict **co2emission** vs **EngineSize** of all cars
 - Independent variable (x): EngineSize
 - Dependent variable (y): co2emission

- MULTIPLE LINEAR REGRESSION

- Predict **co2emission** vs **EngineSize** and **Cylinders** of all cars
 - Independent variable (x): EngineSize, Cylinders, etc
 - Dependent variable (y): co2emission

SIMPLE LINEAR REGRESSION

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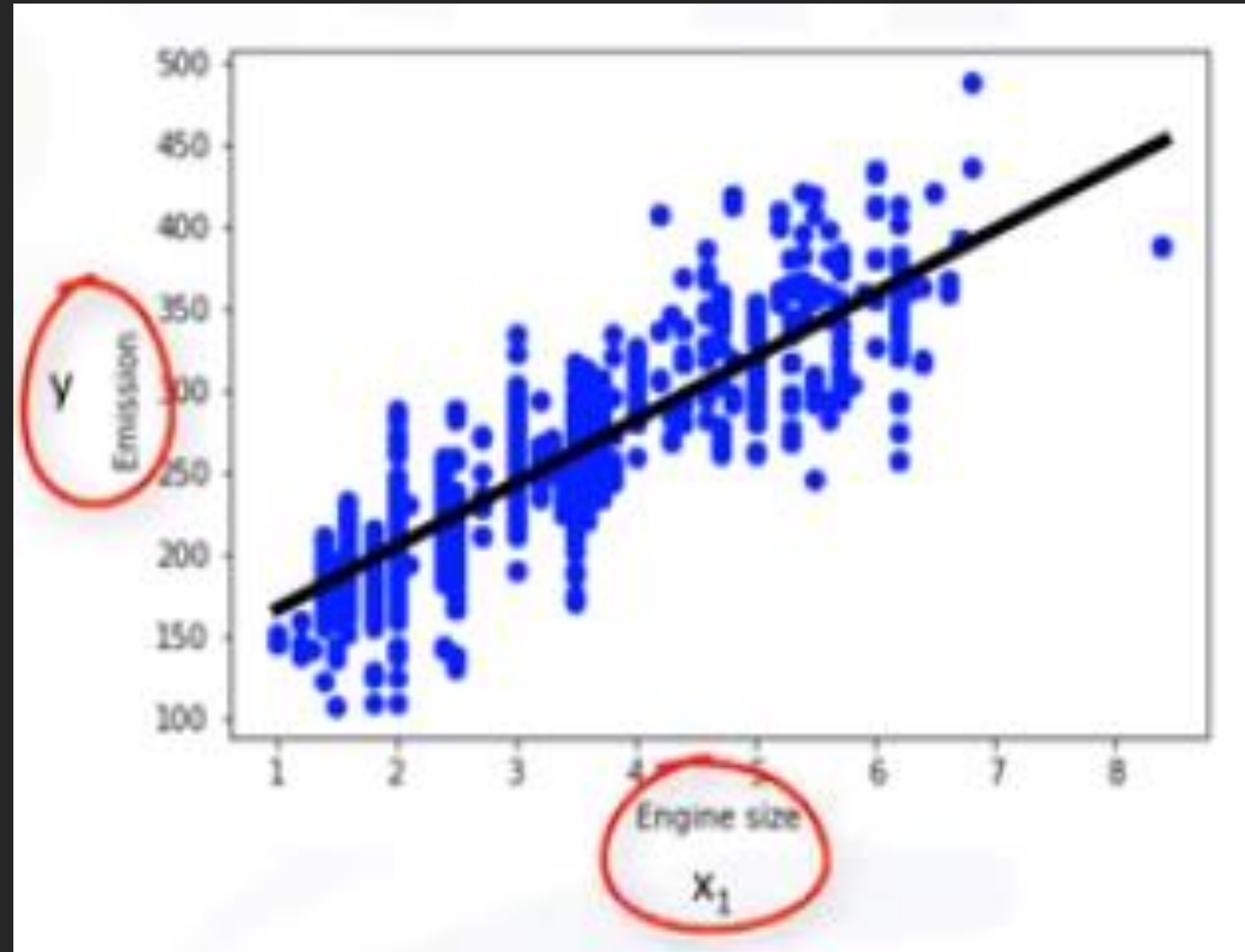
FITTING LINE

$$\hat{y} = \theta_0 + \theta_1 x_1$$

response variable

a single predictor

$$\hat{y} = \theta_0 + \theta_1 x_1$$



θ_0 and θ_1 are also called the coefficients of the linear equation. Slope and intercept respectively

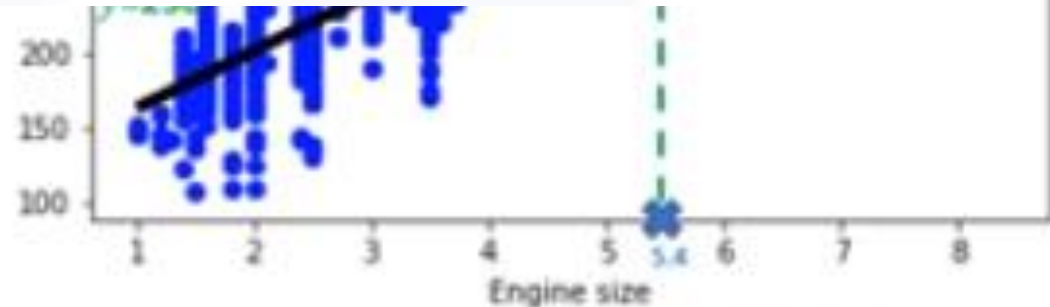
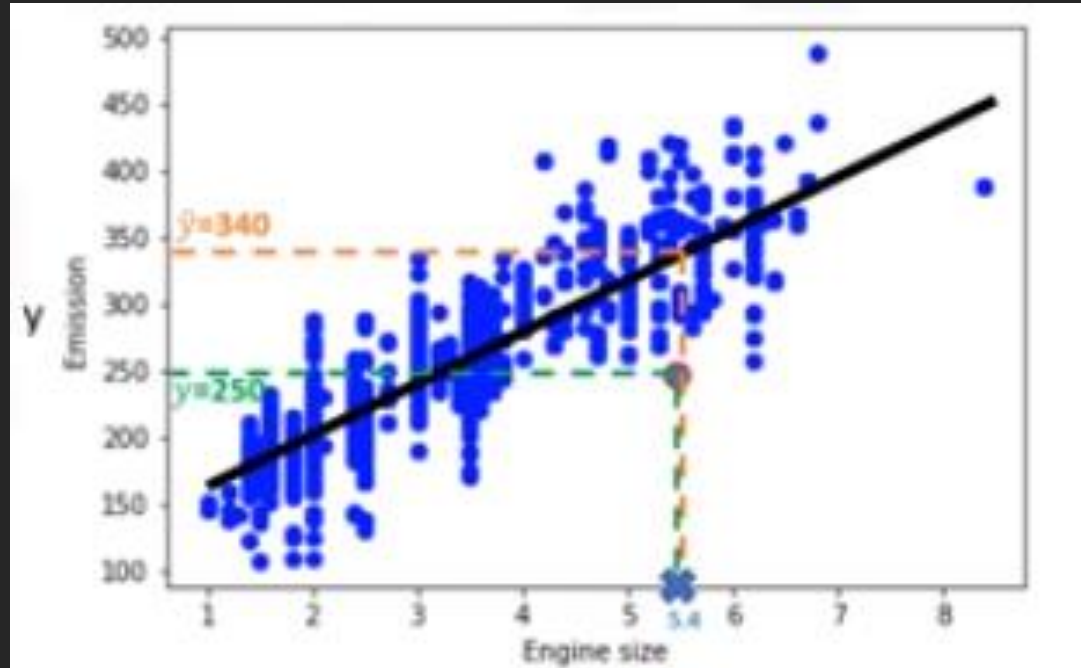
HOW TO FIND BEST FIT?

$$\begin{aligned}\text{Error} &= y - \hat{y} \\ &= 250 - 340 \\ &= -90\end{aligned}$$

This means our prediction line is not accurate.

This error is also called the residual error.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$



OBJECTIVE

- THE OBJECTIVE OF LINEAR REGRESSION IS TO MINIMIZE **THIS MSE EQUATION**, AND TO MINIMIZE IT, WE SHOULD FIND THE BEST PARAMETERS, θ_0 AND θ_1
- ACTUALLY, WE HAVE TWO OPTIONS HERE:
- OPTION 1 - WE CAN USE A MATHEMATIC APPROACH.
- OPTION 2 - WE CAN USE AN OPTIMIZATION APPROACH.

ESTIMATING THE PARAMETERS

$$\hat{y} = \theta_0 + \theta_1 x_1$$

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x_1 is indicated by a bracket on the ENGINE SIZE column (rows 4-8).
 y is indicated by a bracket on the CO2 EMISSIONS column (rows 4-8).

$$\theta_1 = \frac{\sum_{i=1}^s (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^s (x_i - \bar{x})^2}$$

$$\bar{x} = (2.0 + 2.4 + 1.5 + \dots) / 9 = 3.34$$

$$\bar{y} = (196 + 221 + 136 + \dots) / 9 = 256$$

$$\theta_1 = \frac{(2.0 - 3.34)(196 - 256) + (2.4 - 3.34)(221 - 256) + \dots}{(2.0 - 3.34)^2 + (2.4 - 3.34)^2 + \dots}$$

$$\theta_1 = 39$$

$$\theta_0 = 256 - 39 \cdot 3.34$$

$$\theta_0 = 125.74$$

PREDICTING WITH LINEAR REGRESSION

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$$\hat{y} = \theta_0 + \theta_1 x_1$$

$$\text{Co2Emission} = \theta_0 + \theta_1 \text{EngineSize}$$

$$\text{Co2Emission} = 125 + 39 \text{EngineSize}$$

$$\text{Co2Emission} = 125 + 39 \times 2.4$$

$$\text{Co2Emission} = \mathbf{218.6}$$

REGRESSION TYPE

- Predict **co2emission** vs **EngineSize** and **Cylinders** of all cars
 - Independent variable (x): EngineSize, Cylinders, etc
 - Dependent variable (y): co2emission

MULTIPLE LINEAR REGRESSION

EXAMPLES OF MLR

- Independent variables effectiveness on prediction

- Does revision time, test anxiety, lecture attendance and gender have any effect on the exam performance of students?

- Predicting impacts of changes

- How much does blood pressure go up (or down) for every unit increase (or decrease) in the BMI of a patient?

PREDICTING WITH MLR

$$\text{Co2 Em} = \theta_0 + \theta_1 \text{Engine size} + \theta_2 \text{Cylinders} + \dots$$

$$\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$$

$$\hat{y} = \theta^T X$$

$$\theta^T = [\theta_0, \theta_1, \theta_2, \dots]$$

$$X = \begin{bmatrix} 1 \\ x_1 \\ x_2 \\ \dots \end{bmatrix}$$

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- How to estimate θ ?

- Ordinary Least Squares

- Linear algebra operations

- Takes a long time for large datasets (10K+ rows)

- An optimization algorithm

- Gradient Descent

- Proper approach if you have a very large dataset

PREDICTING VALUES

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$$\theta^T = [125, 6.2, 14, \dots]$$

$$\hat{y} = 125 + 6.2x_1 + 14x_2 +$$

$$Co2Em = 125 + 6.2EngSize + 14Cylinders + \dots$$

$$Co2Em = 125 + 6.2 \times 2.4 + 14 \times 4 + \dots$$

$$Co2Em = 214.1$$

Q & A

- How to determine whether to use simple or multiple linear regression?

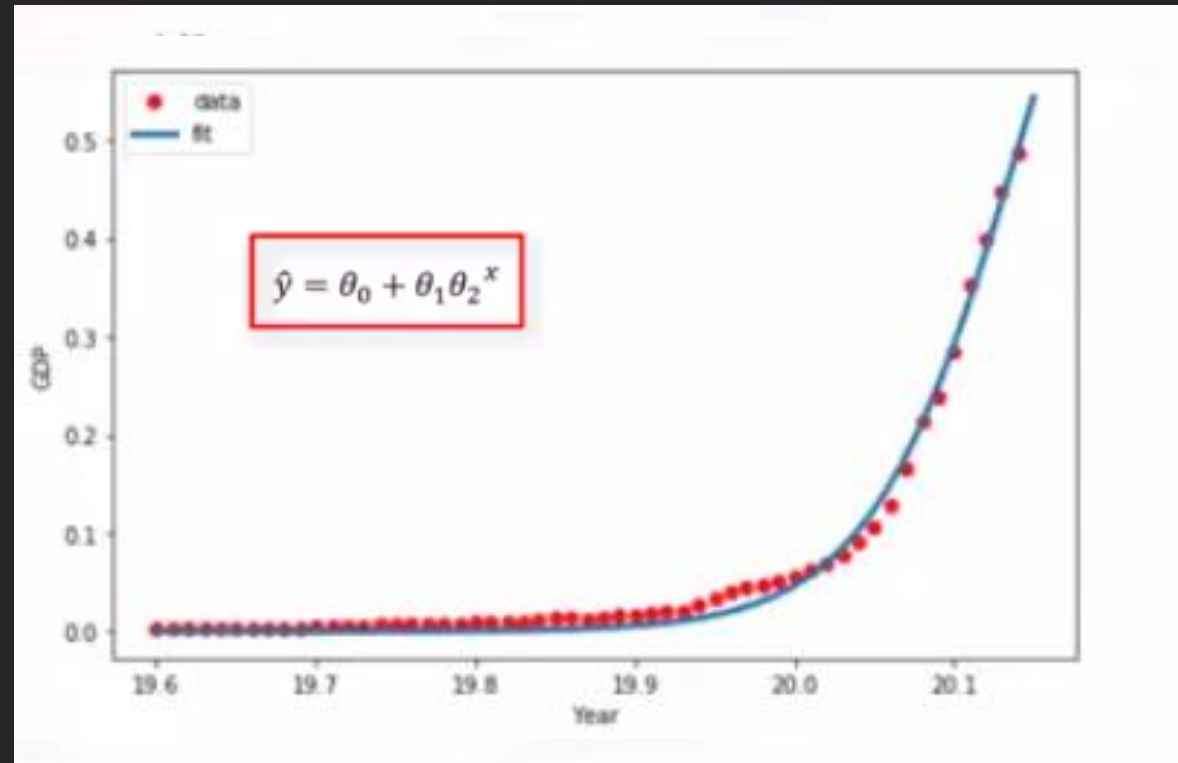
- How many independent variables should you use?

- Should the independent variable be continuous?

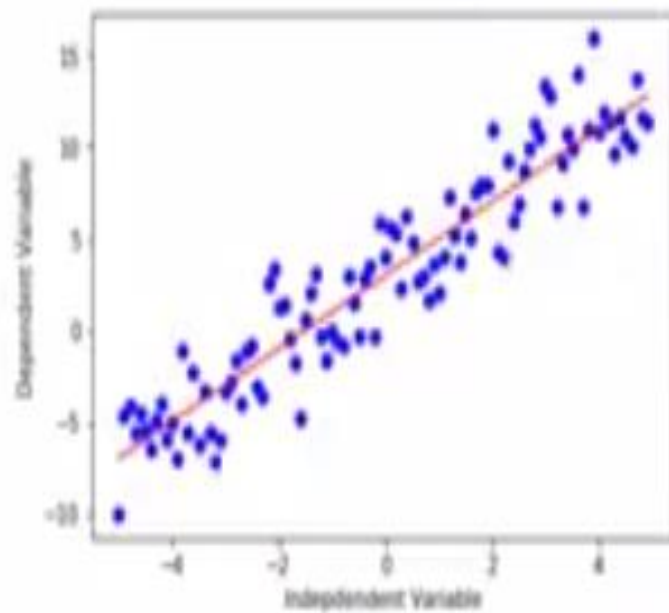
- What are the linear relationships between the dependent variable and the independent variables?

NON-LINEAR REGRESSION

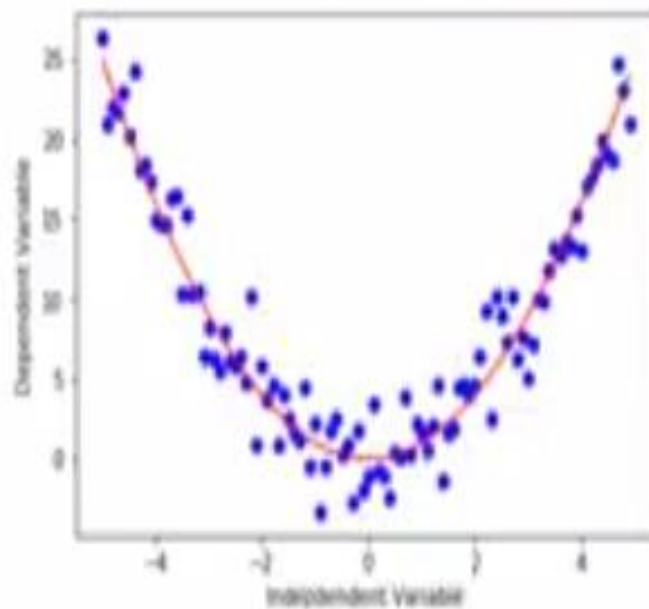
	Year	Value
0	1960	5.918412e+10
1	1961	4.955705e+10
2	1962	4.668518e+10
3	1963	5.009730e+10
4	1964	5.906225e+10
5	1965	6.970915e+10
6	1966	7.587943e+10
7	1967	7.205703e+10
8	1968	6.999350e+10
9	1969	7.871882e+10



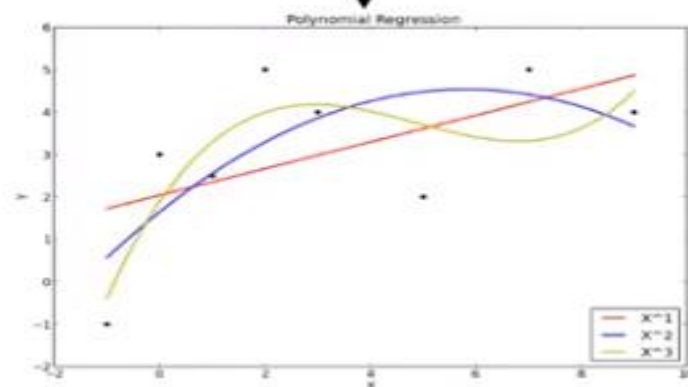
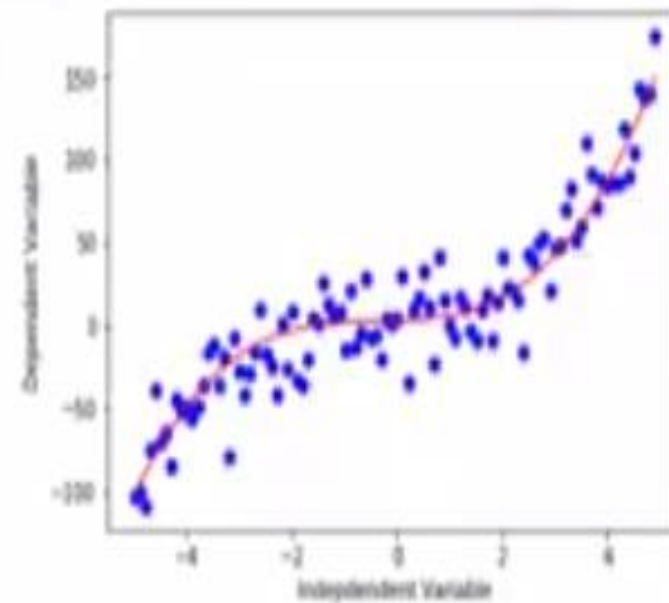
Linear Regression



Quadratic (Parabolic) Regression



Cubic Regression



NON-LINEAR REGRESSION

- To model non-linear relationship between the dependent variable and a set of independent variables
- \hat{y} must be a non-linear function of the parameters θ , not necessarily the features x

$$\hat{y} = \theta_0 + \theta_2^2 x$$

$$\hat{y} = \theta_0 + \theta_1 \theta_2^x$$

$$\hat{y} = \log(\theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3)$$

$$\hat{y} = \frac{\theta_0}{1 + \theta_1^{(x - \theta_2)}}$$

LINEAR VS NON LINEAR REGRESSION

- How can I know if a problem is linear or non-linear in an easy way?

- Inspect visually

It's best to plot bivariate plots of output variables with each input variable.

Also, you can calculate the correlation coefficient between independent and dependent variables, and if for all variables it is 0.7 or higher there is a linear tendency

- How should I model my data, if it displays non-linear on a scatter plot?

- Polynomial regression
- Non-linear regression model
- Transform your data

POLYNOMIAL VS NON-LINEAR REGRESSION

- POLYNOMIAL REGRESSION FITS A CURVE LINE TO YOUR DATA. A SIMPLE EXAMPLE OF A POLYNOMIAL WITH A DEGREE OF 3 CAN BE SHOWN AS:

$$\hat{y} = b_0 + b_1x^1 + b_2x^2 + b_3x^3$$

3rd degree polynomial regression

WHERE b_0 IS THE INTERCEPT OR BIAS UNIT AND b_1 TO b_3 ARE THE SLOPES OF EACH INDEPENDENT VALUE OF VARIABLE x .

IT SURE LOOKS LIKE A FEATURE SET FOR A MULTIPLE LINEAR REGRESSION RIGHT? JUST LIKE THE ONE BELOW, YES, IT DOES. INDEED A POLYNOMIAL REGRESSION IS A SPECIAL CASE OF MULTIPLE LINEAR REGRESSION, WITH THE MAIN IDEA OF 'HOW DO YOU SELECT YOUR FEATURES?'.

$$\hat{y} = b_0 + b_1x_1^1 + b_2x_2^2 + b_3x_3^3$$

3rd degree multiple linear regression 3 variables

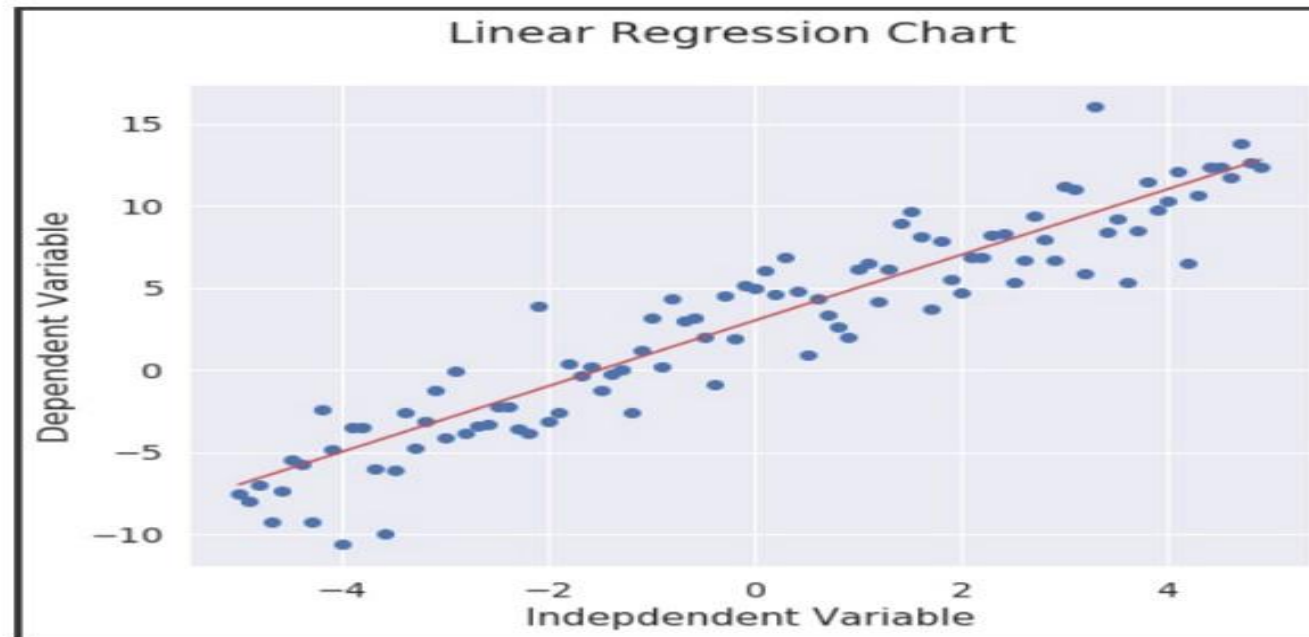
WHERE b_0 IS THE INTERCEPT OR BIAS UNIT AND b_1 TO b_3 ARE THE SLOPES OF EACH INDEPENDENT VARIABLE x_1 TO x_3

COMMON TYPES OF NON-LINEAR REGRESSION

- BEFORE WE GO ON, LET'S BRIEFLY LOOK AT LINEAR REGRESSION. IT IS OF THE EQUATION:

$$Y = B_0 + B_1X_1$$

LINEAR REGRESSION MODELS A RELATIONSHIP BETWEEN A DEPENDENT VARIABLE Y AND THE INDEPENDENT VARIABLE X . THIS RELATIONSHIP HAS A DEGREE OF 1.



1. CUBIC

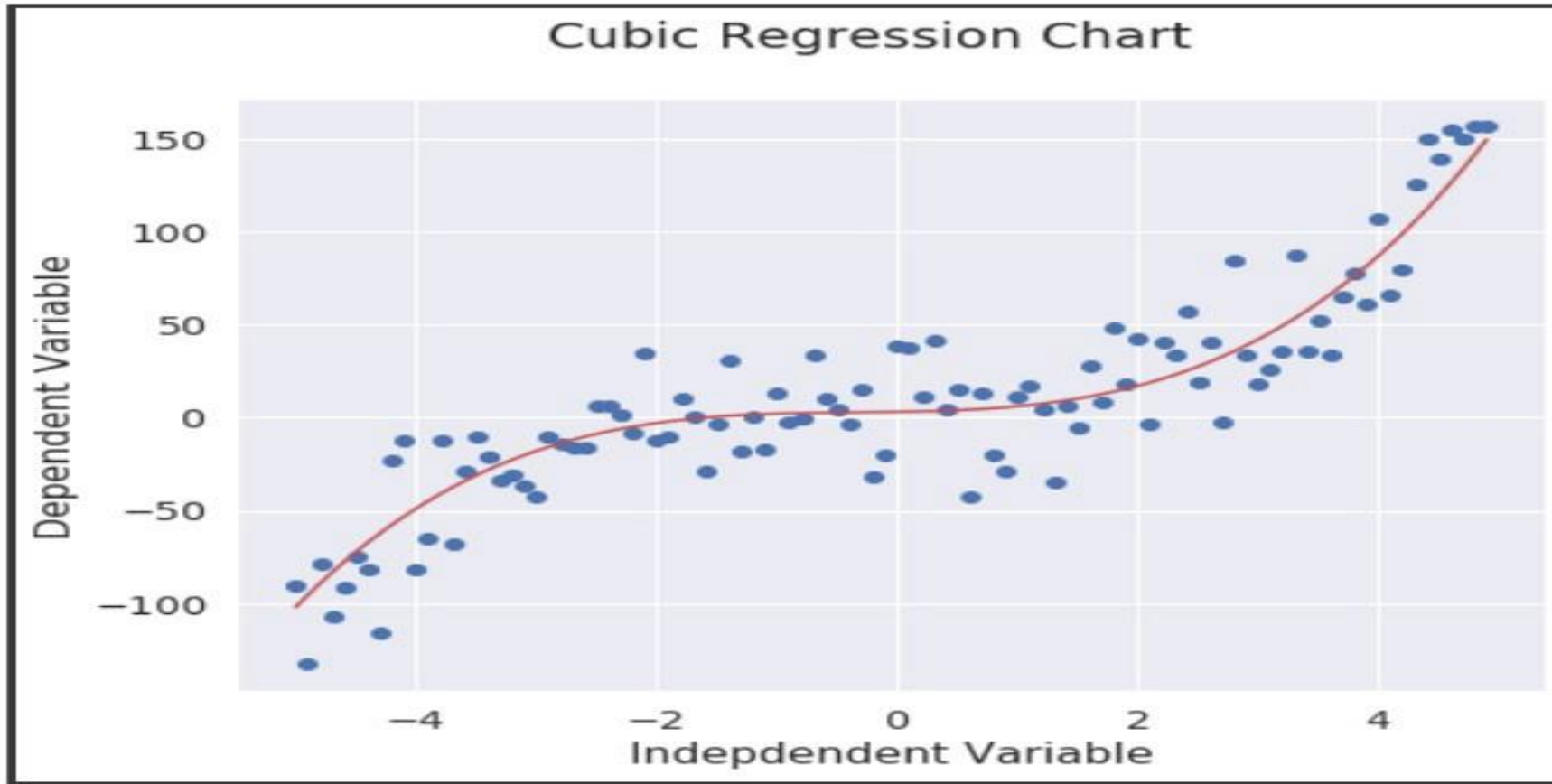
- A CUBIC FUNCTION IS OF THE FORM: \hat{y} IS EQUAL TO *INTERCEPT* PLUS VARIABLE x RAISED TO THE THIRD POWER PLUS x RAISED TO THE SECOND POWER AND SO ON. IT COULD ALSO BE IN REVERSE FROM 1ST POWER TO 3RD POWER
- THE GRAPH OF THIS FUNCTION IS NOT A STRAIGHT LINE OVER THE 2D PLANE.
- LET'S PLOT ONE, BUT FIRST, TAKE A LOOK AT THE CUBIC EQUATION BELOW.

$$\hat{y} = b_0 + 1(x^3) + 1(x^2) + 1(x^1)$$

Cubic Regression Equation

\hat{y} = intercept + x raised to power 3 + x raised to power 2 + x ...

SAMPLE CUBIC REGRESSION CHART



2. QUADRATIC

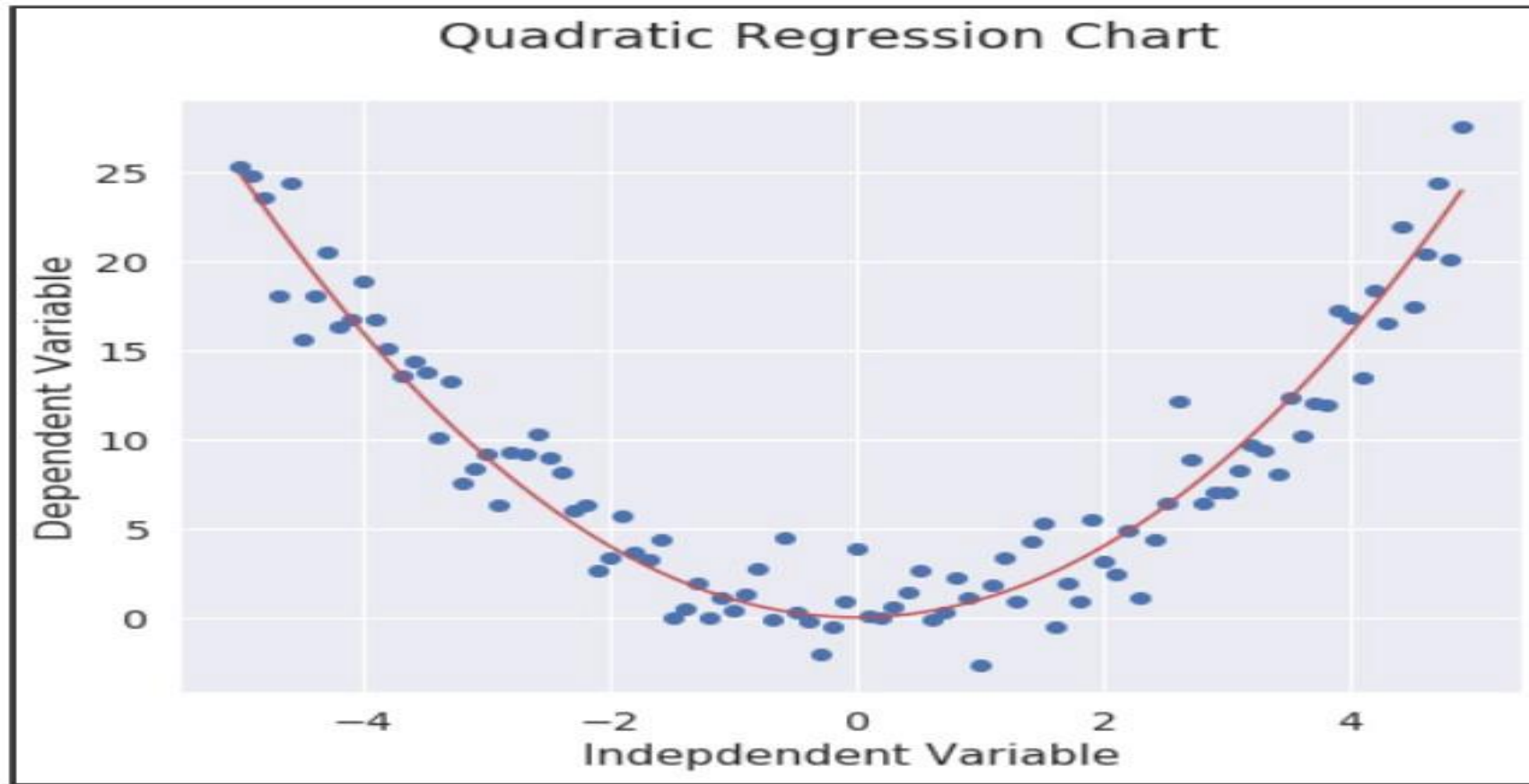
- A QUADRATIC FUNCTION IS OF THE EQUATION: \hat{Y} IS EQUAL TO VARIABLE X MULTIPLIED BY VARIABLE X OR RAISED TO THE POWER OF 2.

$$\hat{Y} = X^2$$

Quadratic Regression Equation

$$\hat{y} = X^2$$

SAMPLE QUADRATIC REGRESSION CHART



3. EXPONENTIAL

- AN EXPONENTIAL FUNCTION WITH BASE c IS DEFINED AS \hat{Y} IS EQUAL TO *INTERCEPT PLUS SLOPE* MULTIPLIED BY A CONSTANT(c) WHICH IS RAISED TO THE POWER OF VARIABLE X . SEE EXPRESSION BELOW.

$$\hat{Y} = a + bc^X$$

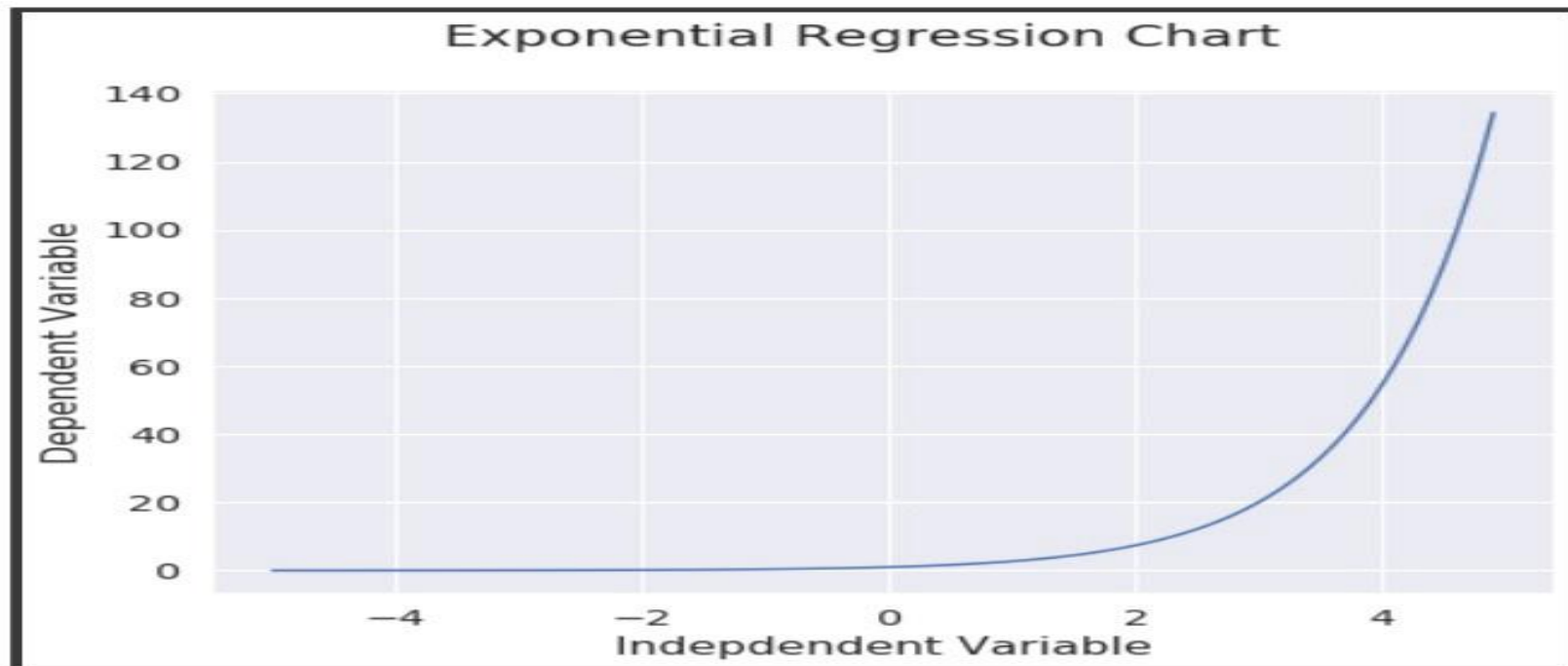
Exponential Regression Function

where $b \neq 0$, $c > 0 \neq 1$, x is a variable and a a real number and c is also a constant.

EXPONENTIAL MIGHT SEEM A BIT CONFUSING, BUT PLOTTING IT IS PRETTY STRAIGHT FORWARD.

SAMPLE EXPONENTIAL REGRESSION CHART

- SIMPLY APPLY THE `NUMPY.EXP()` FUNCTION AND PASS VARIABLE X AS ITS ARGUMENT IN THIS FORM: $Y_HAT = NP.EXP(X)$.
- THEN PLOT VARIABLE X ON THE X-AXIS AND VARIABLE Y ON THE Y-AXIS.



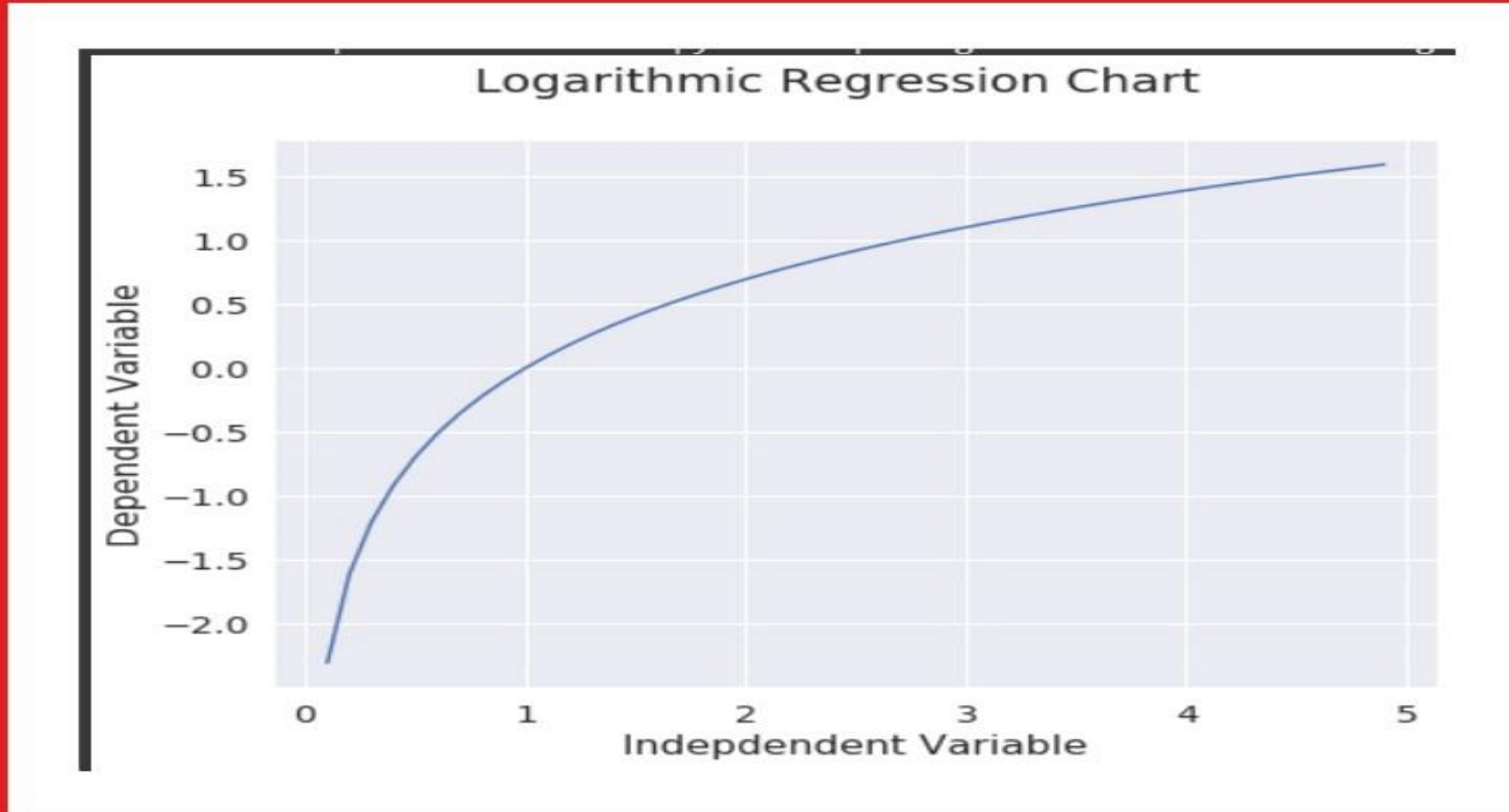
4. LOGARITHMIC

- IN LOGARITHMIC FUNCTION, \hat{Y} IS A RESULT OF APPLYING A LOGARITHMIC MAP ON VARIABLE X .
- IT IS ONE OF THE SIMPLEST EXPRESSIONS OF A LOGARITHMIC FUNCTION.

$$\hat{y} = \log(X)$$

Logarithmic Regression Equation

SAMPLE LOGARITHMIC REGRESSION CHART



5. SIGMOIDAL / LOGISTIC

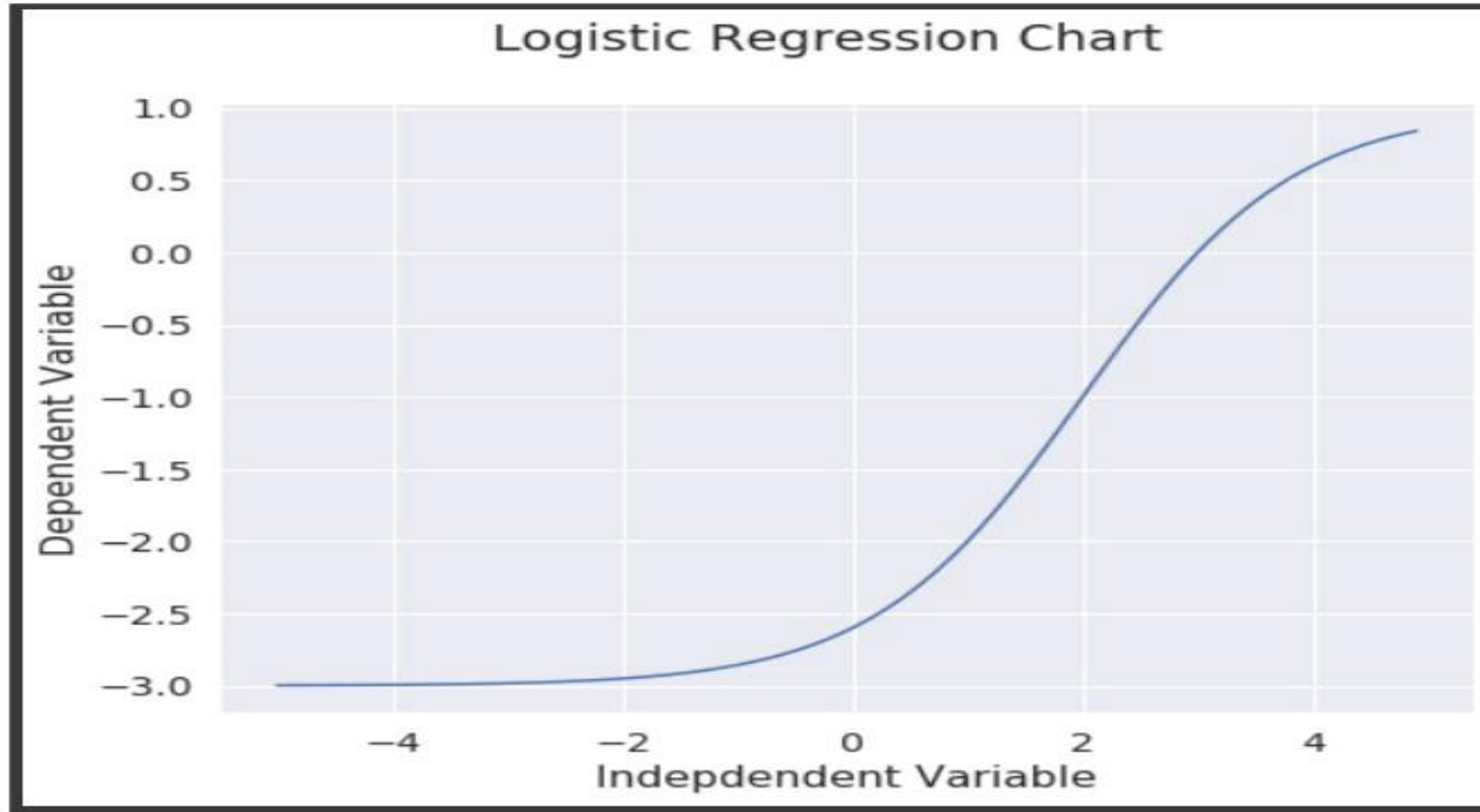
- LOGISTIC REGRESSION IS A VARIATION OF LINEAR REGRESSION, USEFUL WHEN THE OBSERVED DEPENDENT VARIABLE Y , IS A CATEGORICAL VARIABLE.
- IT FITS A SPECIAL S-SHAPED CURVE BY TAKING THE LINEAR REGRESSION AND TRANSFORMING THE NUMERIC ESTIMATES INTO A PROBABILITY SCORE, USING THE SIGMOID FUNCTION.

$$\hat{Y} = \frac{1}{1 + e^{\beta_1(X - \beta_2)}}$$

Logistic Regression Equation

β_1 controls the curves steepness, β_2 controls the curve on the x-axis.

SAMPLE LOGISTIC REGRESSION CHART



REMEMBER,

***IT IS IMPORTANT TO PICK A
REGRESSION MODEL THAT FITS THE
DATA SET THE BEST.***