

LINEAR REGRESSION



simpli|learn



Profit Estimation of a Company

A Venture Capital firm is trying to understand which companies should they invest

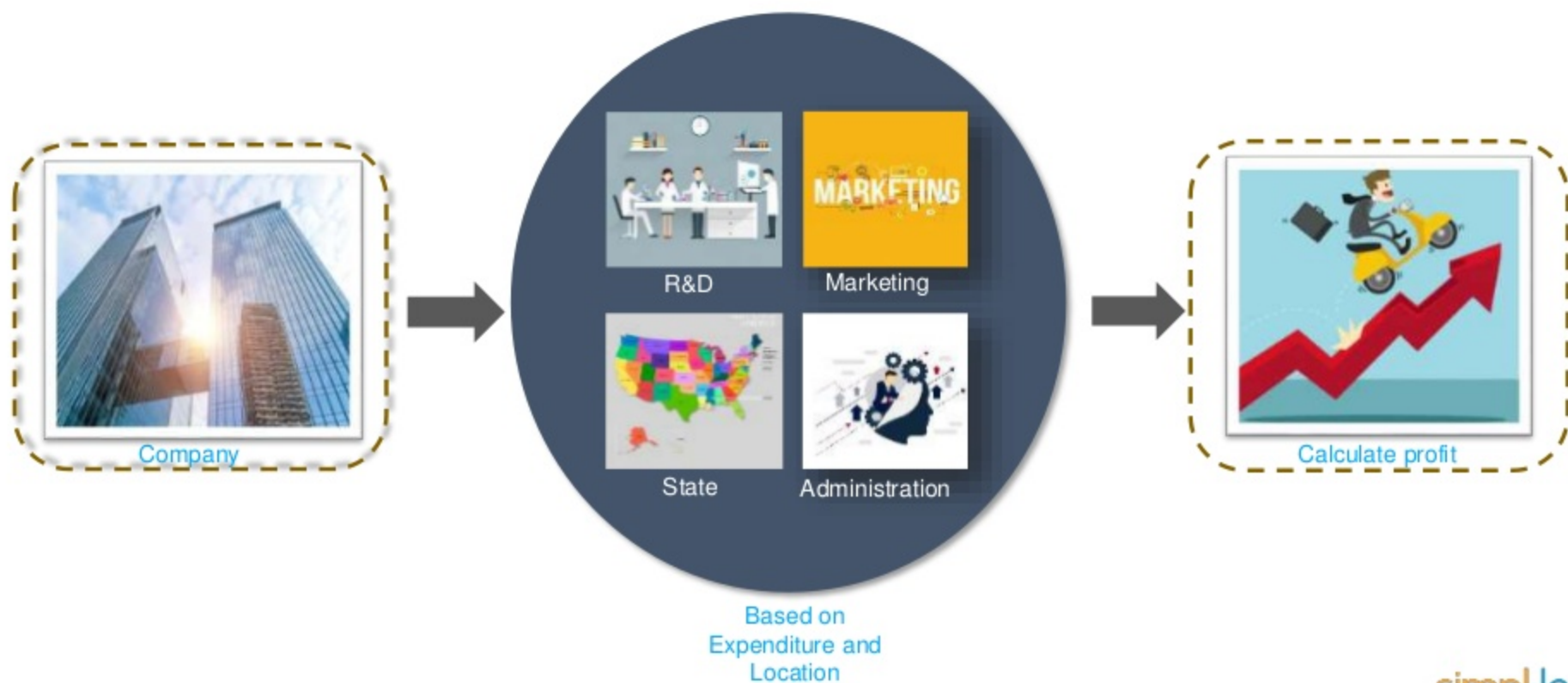


Venture Capital firm

Profit Estimation of a Company

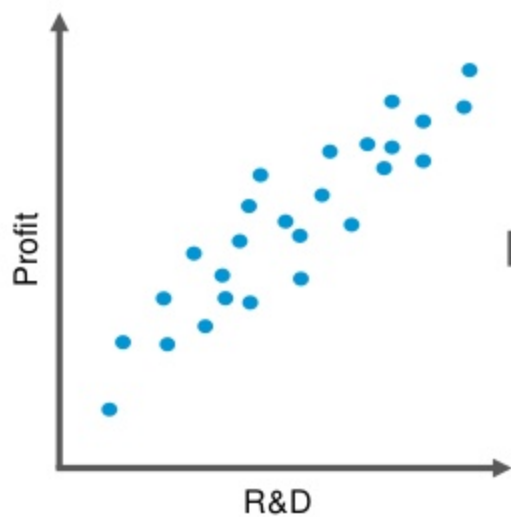


Profit Estimation of a Company

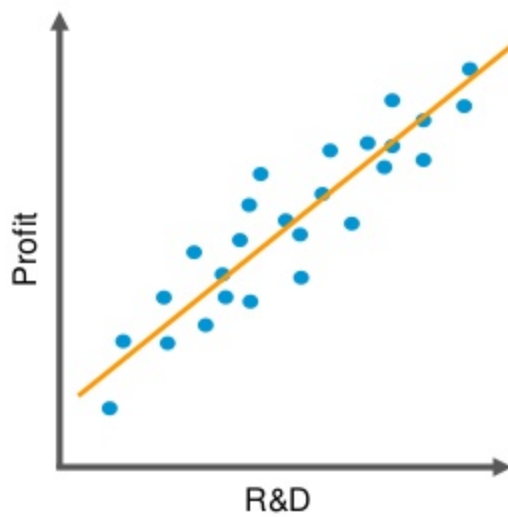


Profit Estimation of a Company

For simplicity, let's consider a single variable (R&D) and find out which companies to invest in



Plotting profit based on R&D expenditure



Prediction line to estimate profit



Companies spending more on R&D make good profit, let's invest in them

What's in it for you?

- ▶ Introduction to Machine Learning
- ▶ Machine Learning Algorithms
- ▶ Applications of Linear Regression
- ▶ Understanding Linear Regression
- ▶ Multiple Linear Regression
- ▶ Use Case – Profit Estimation of Companies



A close-up photograph of a white robotic arm with a gripper. The gripper is holding a light-colored wooden block that has a circular hole and a square hole. The background is a solid dark brown color.

Introduction to Machine Learning

Introduction to Machine Learning

Based on the amount of rainfall, how much would be the crop yield?



Crop Field



Based on Rainfall



Predict crop yield

Independent and Dependent Variables

Independent variable

A variable whose value does not change by the effect of other variables and is used to manipulate the dependent variable. It is often denoted as **X**.

Dependent variable

A variable whose value changes when there is any manipulation in the values of independent variables. It is often denoted as **Y**.

In our example:



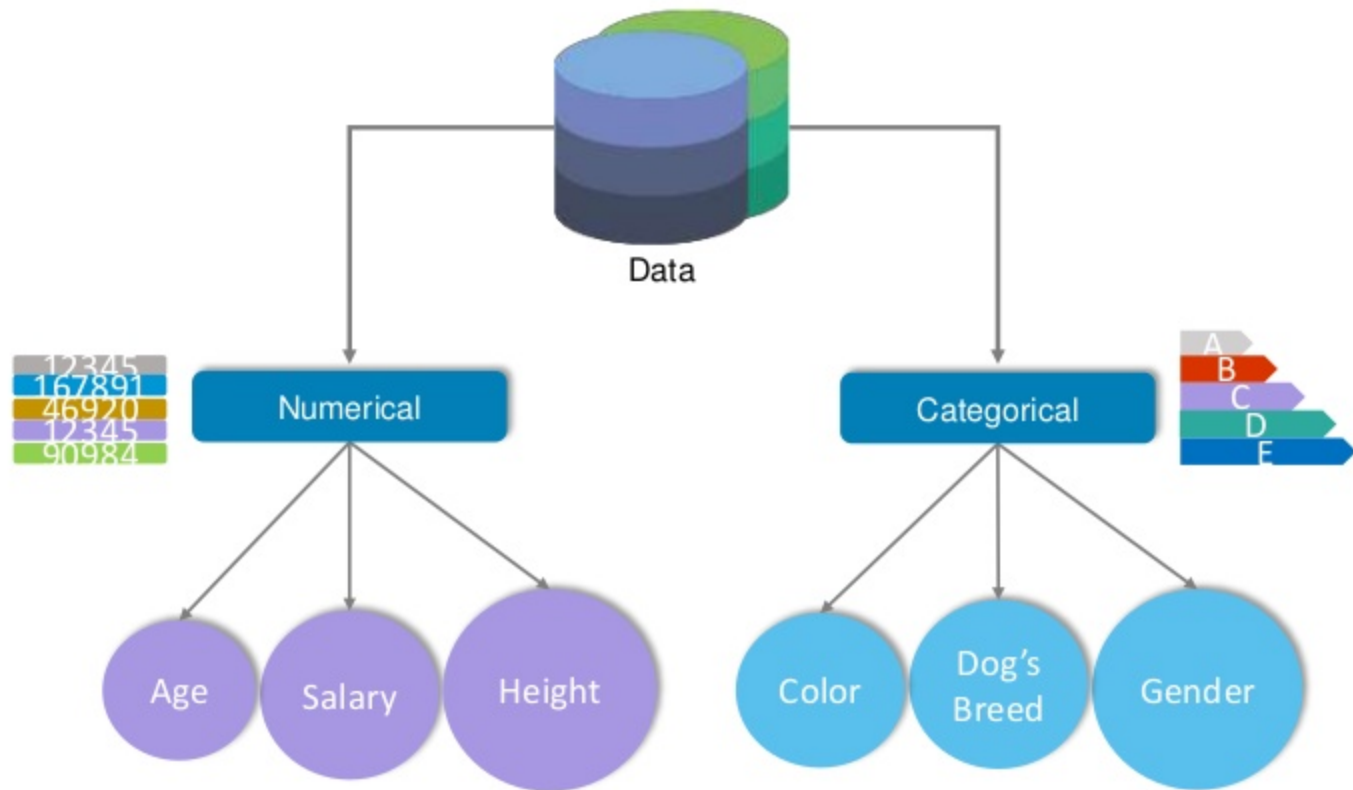
Rainfall – Independent variable

Crop yield depends on the amount of rainfall received

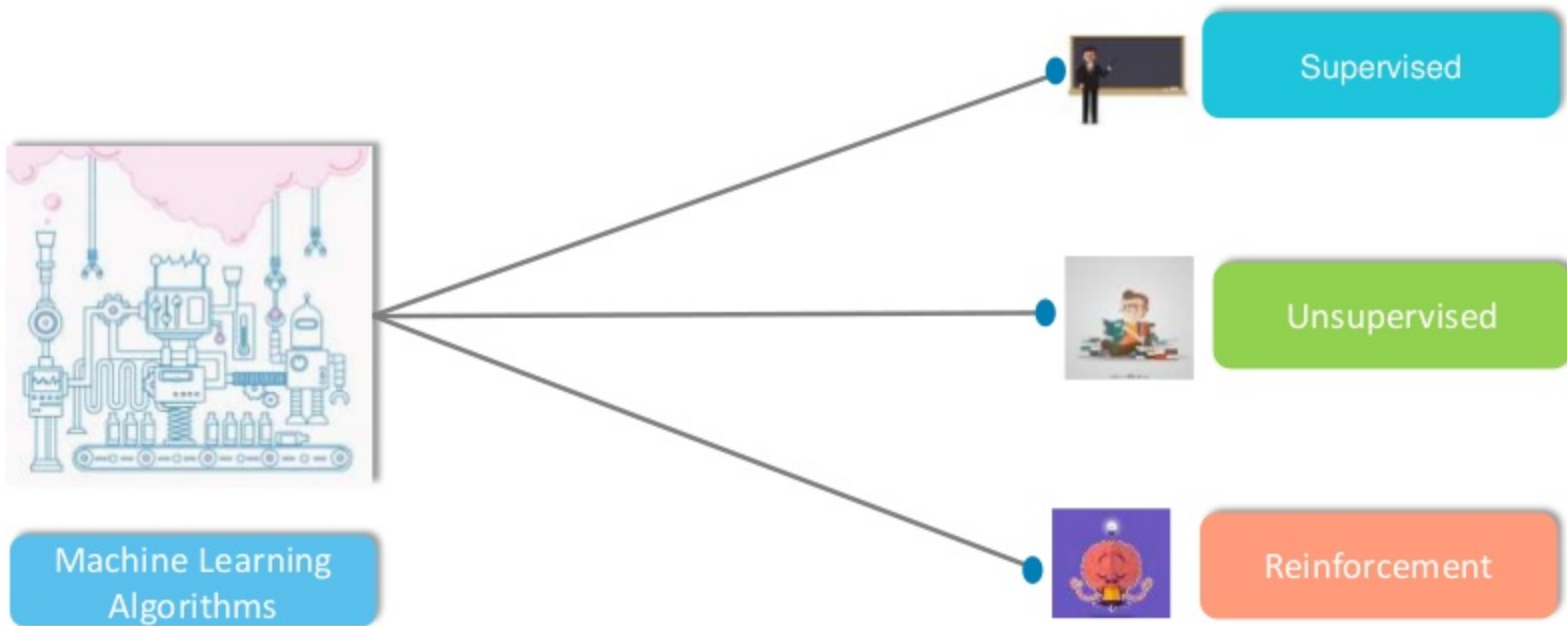


Crop yield – Dependent variable

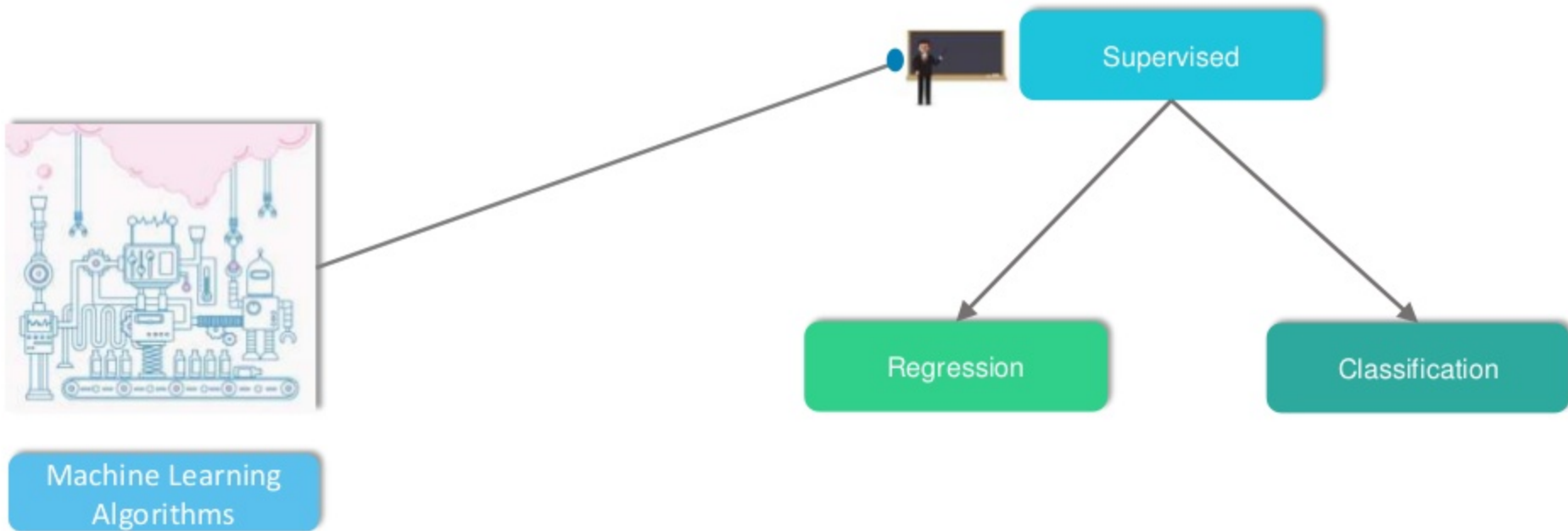
Numerical and Categorical Values



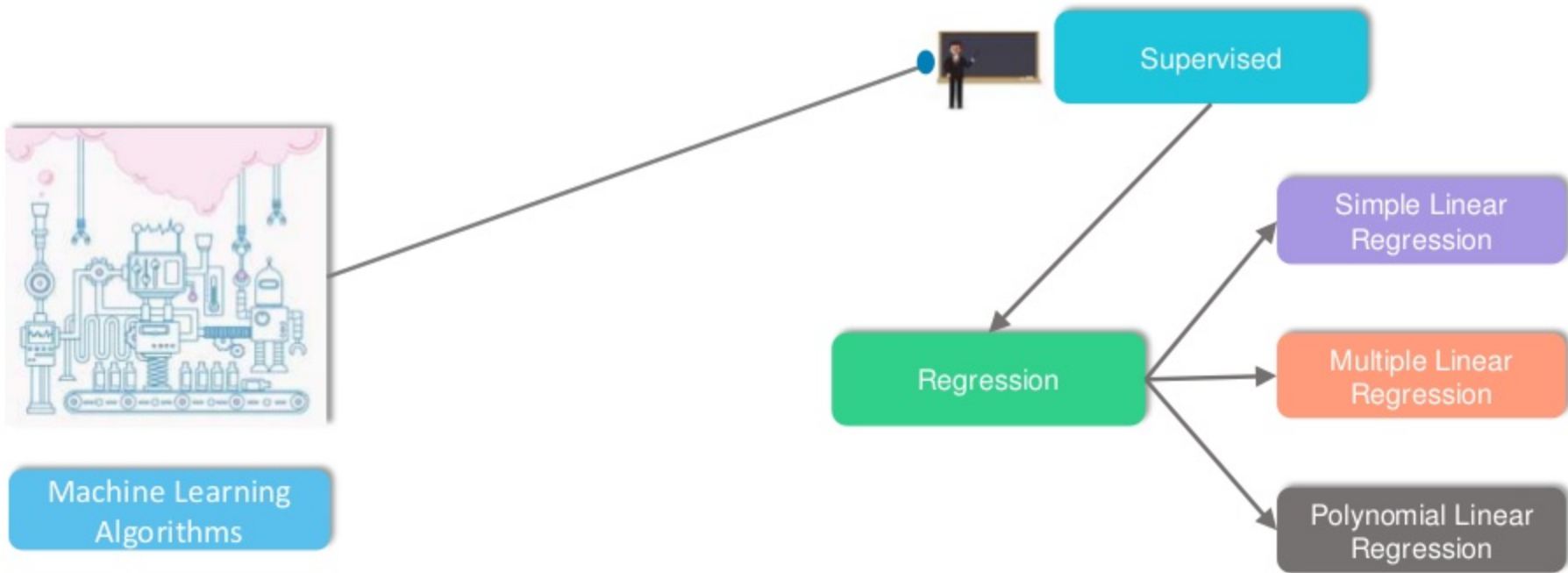
Machine Learning Algorithms



Machine Learning Algorithms



Machine Learning Algorithms



A robotic arm with a gripper is shown holding a black cylindrical object. The arm is positioned over a wooden block that has several different shaped holes, including a circular one and a square one. The background is a solid dark color.

Applications of Linear Regression

Applications of Linear Regression



Economic Growth

Used to determine the Economic Growth of a country or a state in the coming quarter, can also be used to predict the GDP of a country

Applications of Linear Regression



Product price

Can be used to predict what would be the price of a product in the future

Applications of Linear Regression



Housing sales

To estimate the number of houses a builder would sell and at what price in the coming months

Applications of Linear Regression



Score Prediction

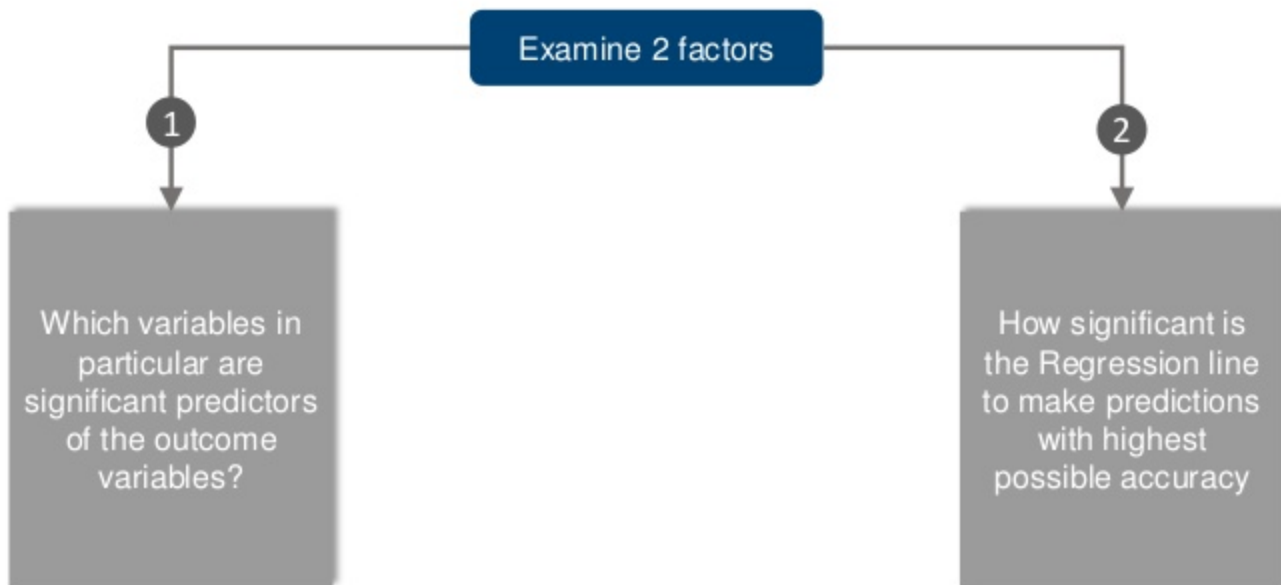
To predict the number of runs a player would score in the coming matches based on previous performance

A close-up photograph of a white robotic arm with a gripper. The gripper is holding a light-colored wooden block that has a circular hole cut into it. The background is a soft, out-of-focus grey. An orange banner is overlaid across the middle of the image, containing the title text.

Understanding Linear Regression

Understanding Linear Regression

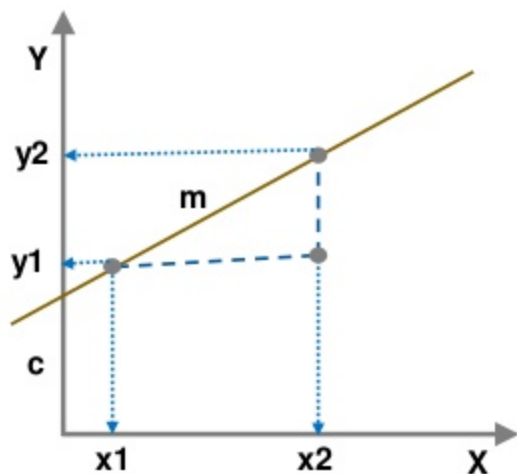
Linear Regression is a statistical model used to predict the relationship between independent and dependent variables.



Regression Equation

The simplest form of a simple linear regression equation with one dependent and one independent variable is represented by:

$$y = m * x + c$$



y ---> Dependent Variable

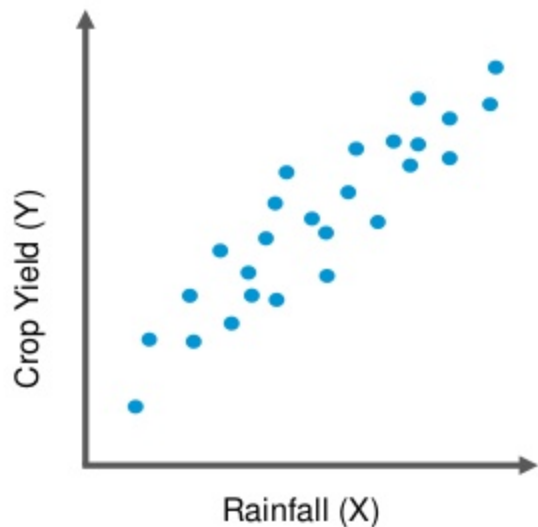
x ---> Independent Variable

m ---> Slope of the line

c ---> Coefficient of the line

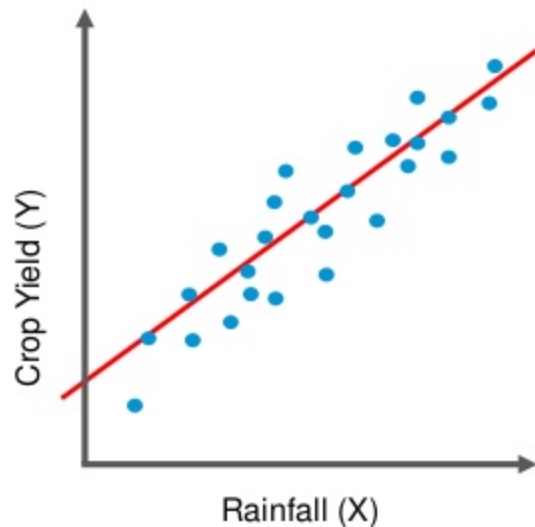
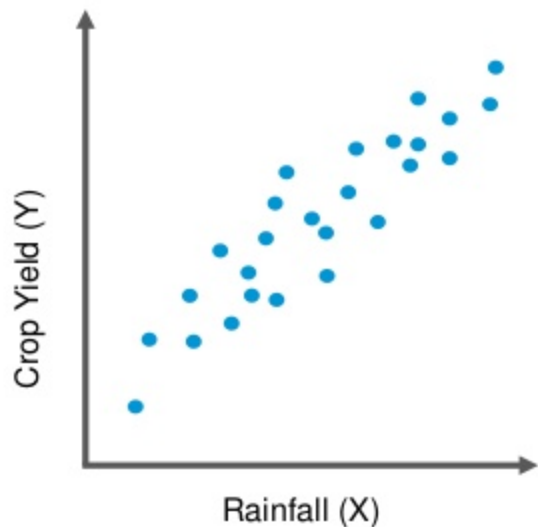
$$m = \frac{y2 - y1}{x2 - x1}$$

Prediction using the Regression line



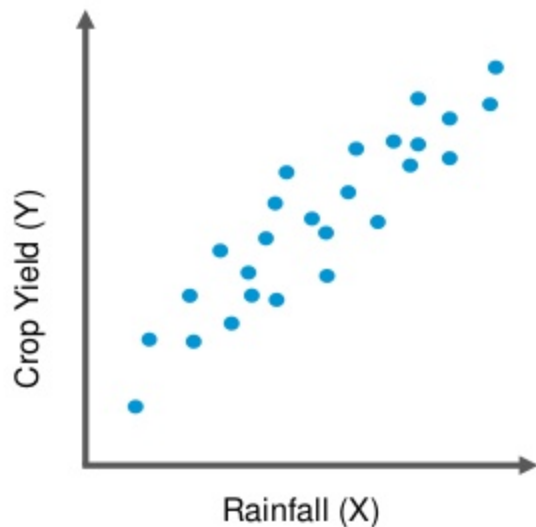
Plotting the amount of Crop Yield based on the amount of Rainfall

Prediction using the Regression line

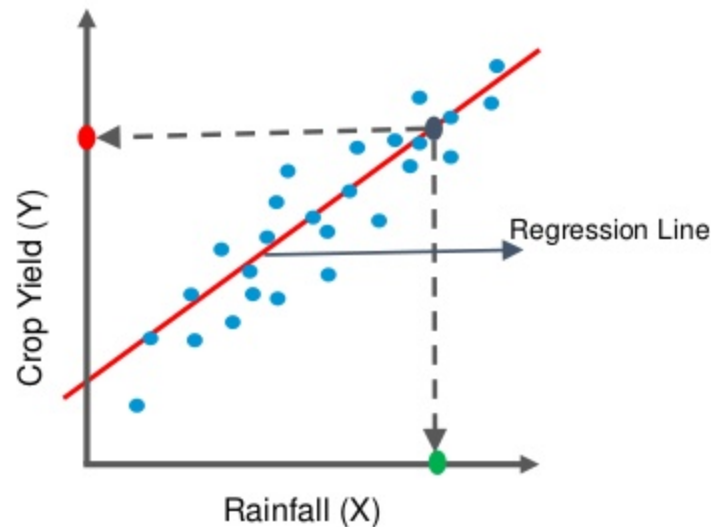


Plotting the amount of Crop Yield based on the amount of Rainfall

Prediction using the Regression line



Plotting the amount of Crop Yield based on the amount of Rainfall

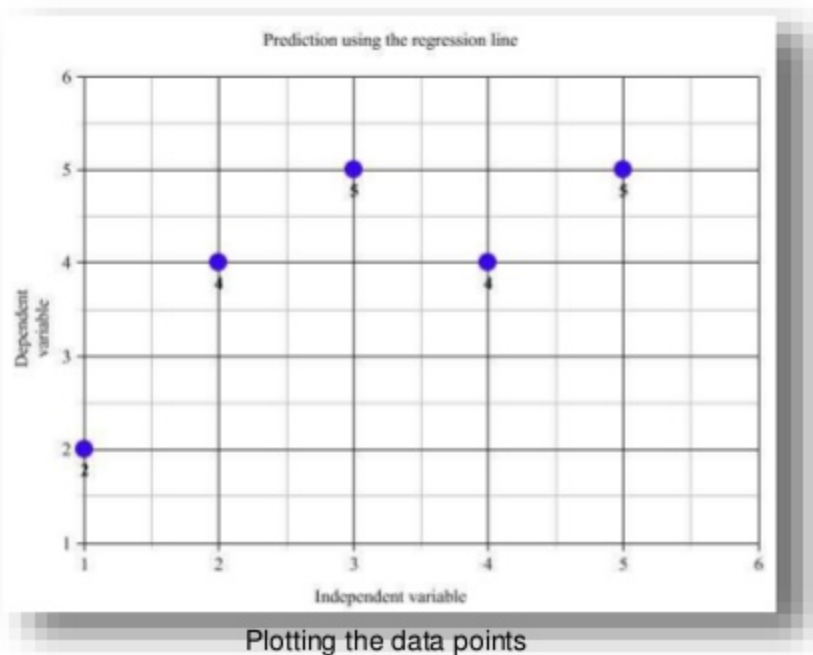


The Red point on the Y axis is the amount of Crop Yield you can expect for some amount of Rainfall (X) represented by Green dot

Intuition behind the Regression line

Lets consider a sample dataset with 5 rows and find out how to draw the regression line

Independent variable	Dependent variable
X	Y
1	2
2	4
3	5
4	4
5	5



Intuition behind the Regression line

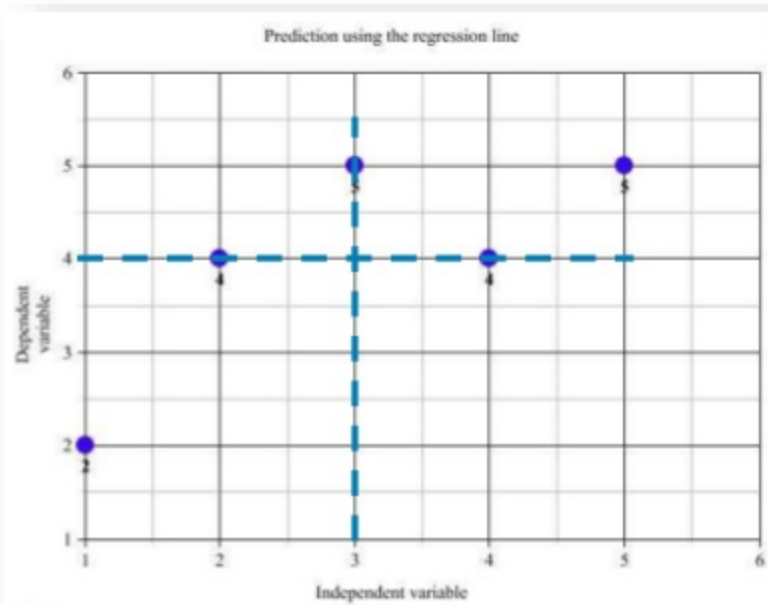
Calculate the mean of X and Y and plot the values

Independent variable	Dependent variable
X	Y
1	2
2	4
3	5
4	4
5	5

Mean

3

4



Plotting the mean of X and Y

Intuition behind the Regression line

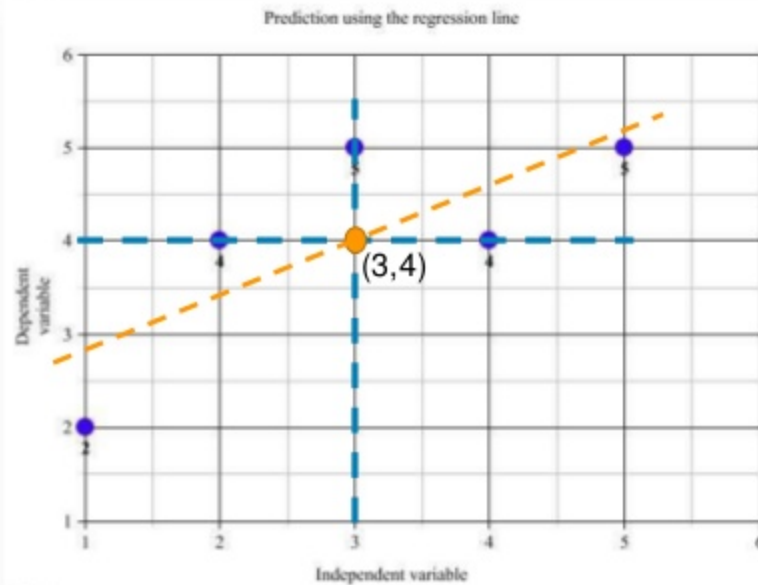
Regression line should ideally pass through the mean of X and Y

Independent variable	Dependent variable
X	Y
1	2
2	4
3	5
4	4
5	5

Mean

3

4



Regression line

Intuition behind the Regression line

Drawing the equation of the Regression line

Σ

X	Y	(X ²)	(Y ²)	(X*Y)
1	2	1	4	2
2	4	4	16	8
3	5	9	25	15
4	4	16	16	16
5	5	25	25	25
$\Sigma = 15$	$\Sigma = 20$	$\Sigma = 55$	$\Sigma = 86$	$\Sigma = 66$

$$\begin{aligned}
 Y &= m * X + c \\
 &= 0.6 * 3 + 2.2 \\
 &= 4
 \end{aligned}$$

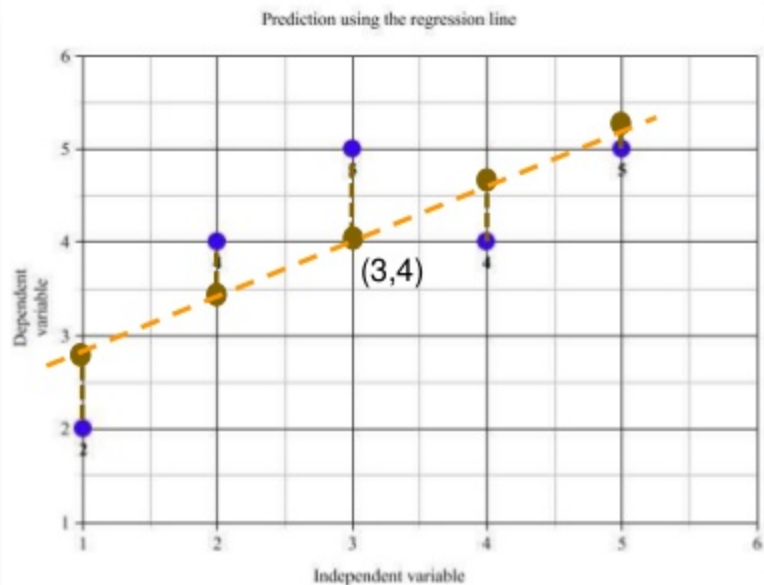
Linear equation is represented as $Y = mX + c$

$$m = \frac{((n * \Sigma X * Y)) - ((\Sigma X) * (\Sigma Y))}{((n * \Sigma X^2) - (\Sigma X)^2)} = \frac{((5 * 66) - (15 * 20))}{((5 * 55) - (225))} = 0.6$$

$$c = \frac{((\Sigma Y) * \Sigma X) - (\Sigma X * \Sigma Y)}{((n * \Sigma X^2) - (\Sigma X)^2)} = 2.2$$

Intuition behind the Regression line

Lets find out the predicted values of Y for corresponding values of X using the linear equation where $m=0.6$ and $c=2.2$



Y_{pred}

$$Y = 0.6 * 1 + 2.2 = 2.8$$

$$Y = 0.6 * 2 + 2.2 = 3.4$$

$$Y = 0.6 * 3 + 2.2 = 4$$

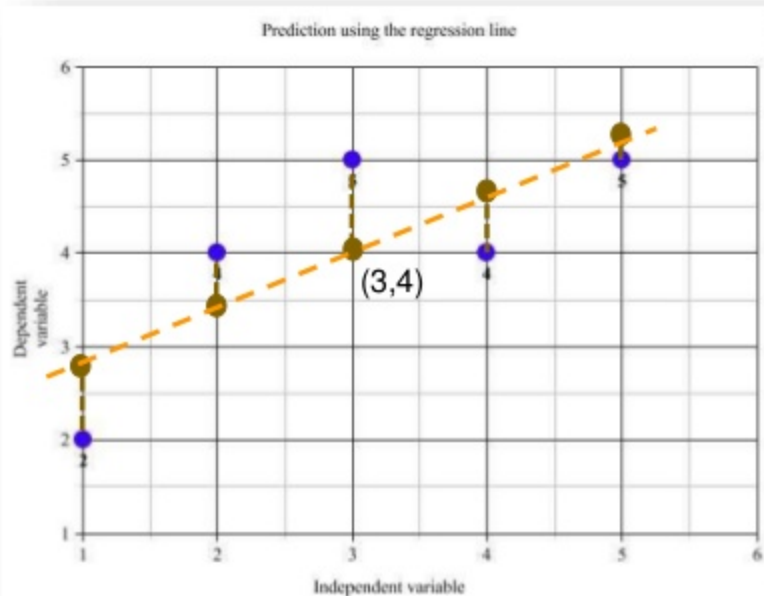
$$Y = 0.6 * 4 + 2.2 = 4.6$$

$$Y = 0.6 * 5 + 2.2 = 5.2$$

Here the blue points represent the **actual Y values** and the brown points represent the **predicted Y values**. The distance between the actual and predicted values are known as **residuals or errors**. The best fit line should have the least sum of squares of these errors also known as **e square**.

Intuition behind the Regression line

Lets find out the predicted values of Y for corresponding values of X using the linear equation where $m=0.6$ and $c=2.2$



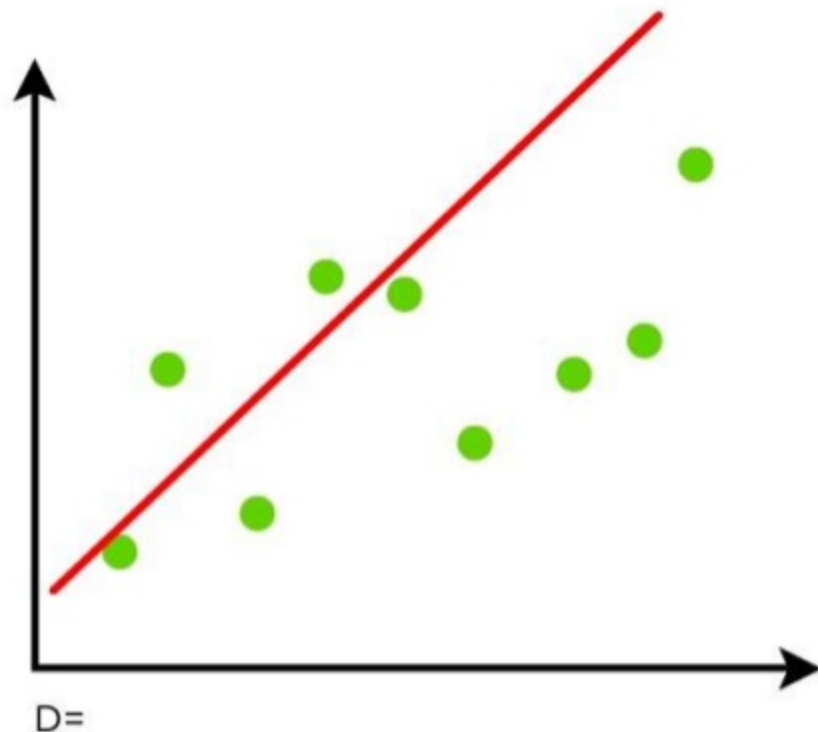
X	Y	Y_{pred}	$(Y - Y_{\text{pred}})$	$(Y - Y_{\text{pred}})^2$
1	2	2.8	-0.8	0.64
2	4	3.4	0.6	0.36
3	5	4	1	1
4	4	4.6	-0.6	0.36
5	5	5.2	-0.2	0.04

$$\sum = 2.4$$

The sum of squared errors for this regression line is 2.4. We check this error for each line and conclude the best fit line having the least square value.

Finding the Best fit line

Minimizing the Distance: There are lots of ways to minimize the distance between the line and the data points like Sum of Squared errors, Sum of Absolute errors, Root Mean Square error etc.



We keep moving this line through the data points to make sure the Best fit line has the least square distance between the data points and the regression line

A close-up photograph of a white robotic arm with a gripper. The gripper is holding a light-colored wooden block that has a circular hole cut into it. The background is a soft, out-of-focus grey. An orange banner is overlaid across the middle of the image, containing the text 'Multiple Linear Regression'.

Multiple Linear Regression

Multiple Linear Regression

Simple Linear Regression

$$Y = m * x + c$$

Multiple Linear Regression

Independent variables (IDV's)

$$Y = m_1 * x_1 + m_2 * x_2 + m_3 * x_3 + + m_n * x_n + c$$

Dependent variable (DV)

$m_1, m_2, m_3, \dots, m_n$

Slopes

Coefficient

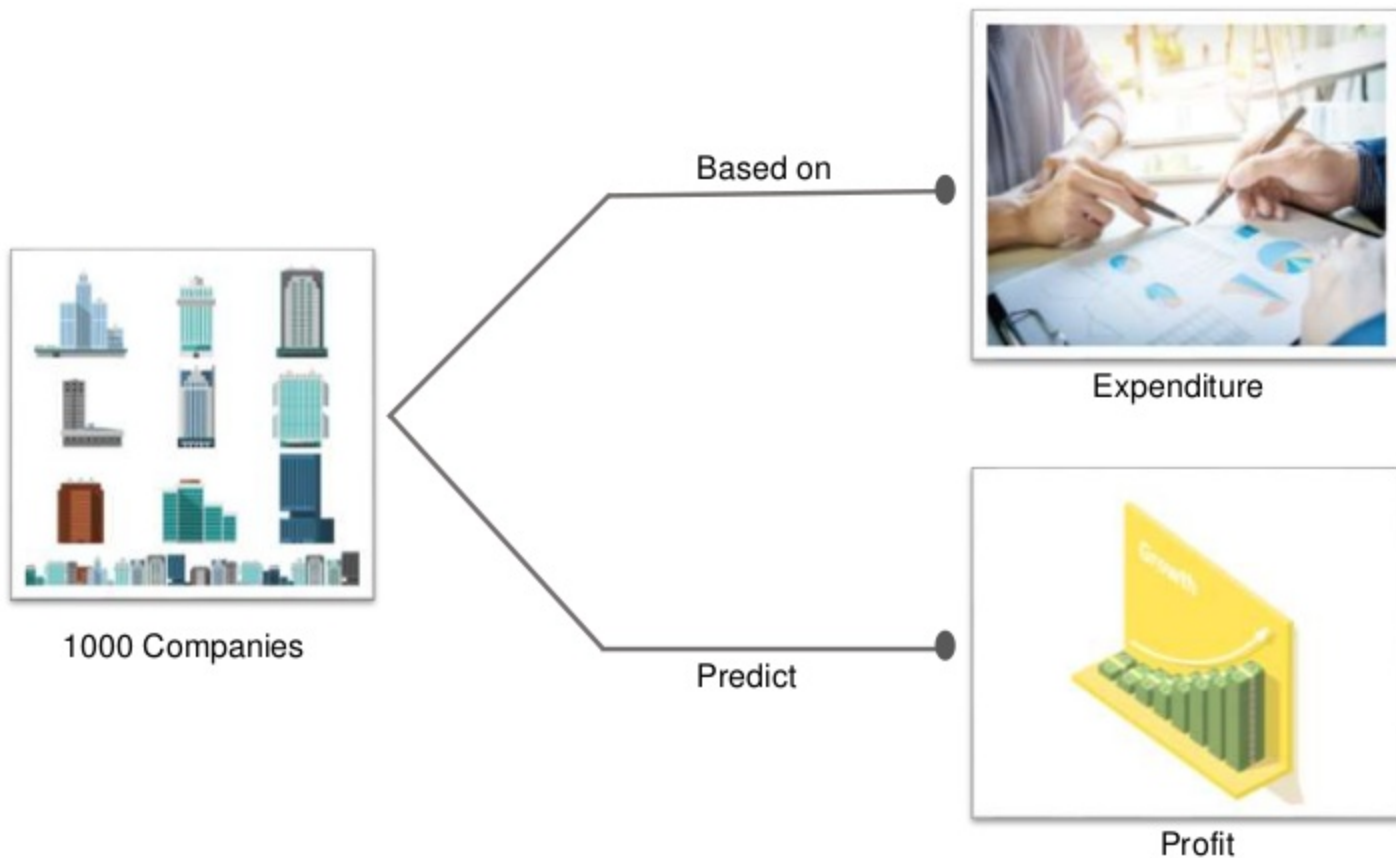
A close-up photograph of a white robotic arm with a gripper. The gripper is holding a light-colored wooden block that has a circular hole cut into it. The background is a soft, out-of-focus grey. An orange banner is overlaid across the middle of the image, containing the title text.

Implementation of Linear Regression

Use case implementation of Linear Regression



Use case implementation of Linear Regression



Use case implementation of Linear Regression

Predicting **Profit** of 1000 companies based on the attributes mentioned in the figure:

Profit
Estimation

Use case implementation of Linear Regression

Predicting **Profit** of 1000 companies based on the attributes mentioned in the figure:



Use case implementation of Linear Regression

Predicting **Profit** of 1000 companies based on the attributes mentioned in the figure:



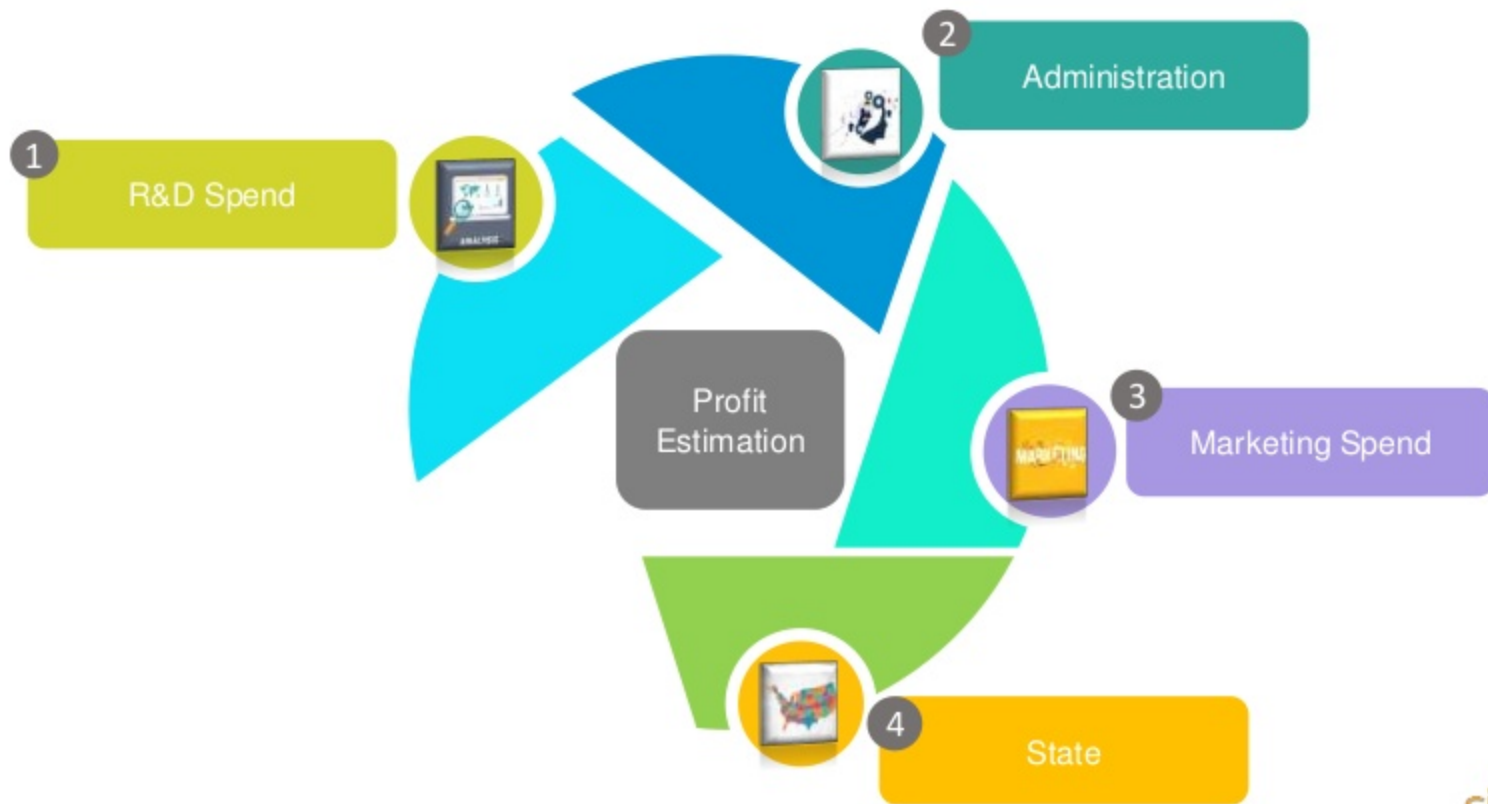
Use case implementation of Linear Regression

Predicting **Profit** of 1000 companies based on the attributes mentioned in the figure:



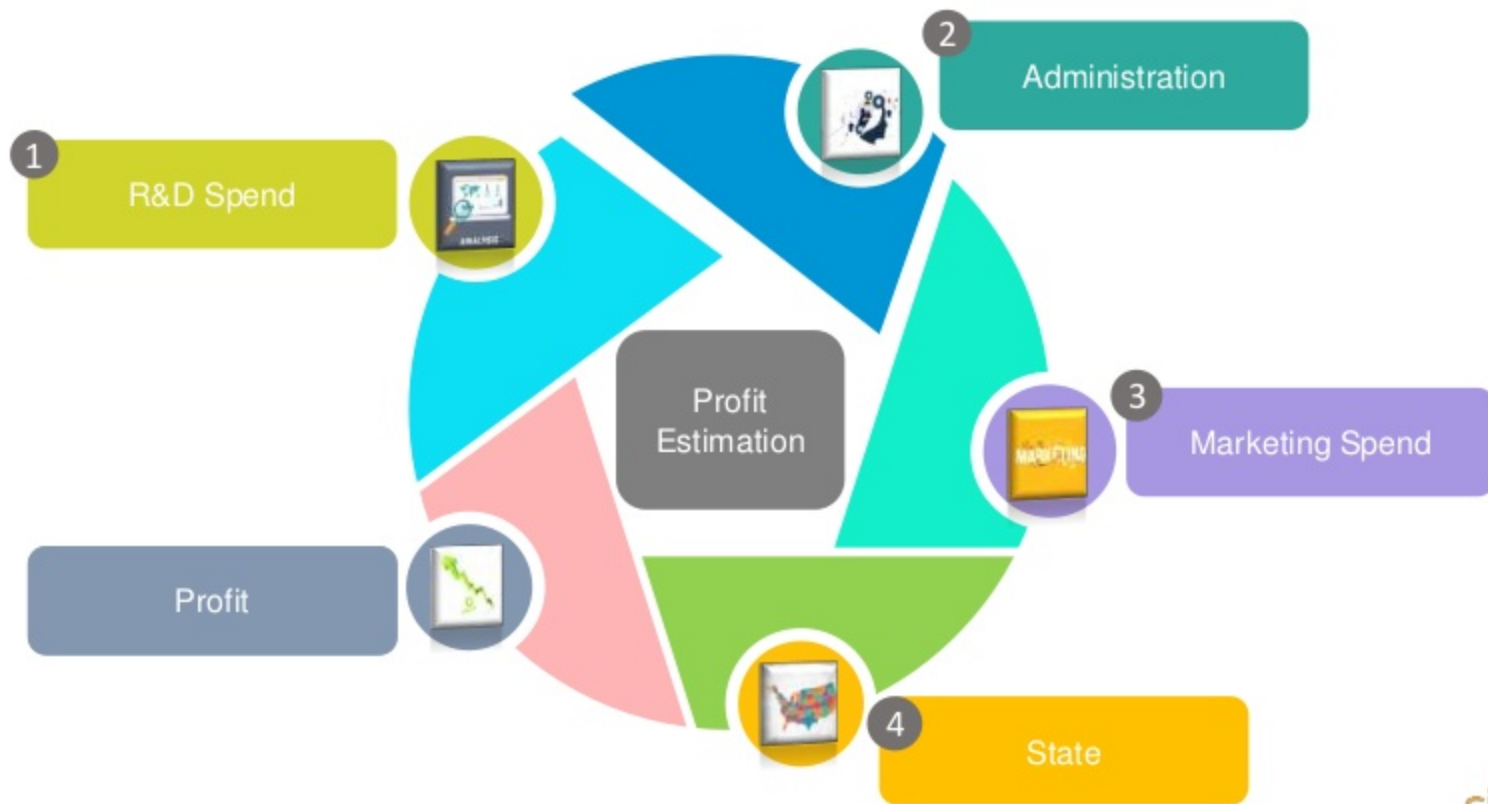
Use case implementation of Linear Regression

Predicting **Profit** of 1000 companies based on the attributes mentioned in the figure:



Use case implementation of Linear Regression

Predicting **Profit** of 1000 companies based on the attributes mentioned in the figure:



Use case implementation of Linear Regression

Predicting **Profit** of 1000 companies based on the attributes mentioned in the figure:



Use case implementation of Linear Regression

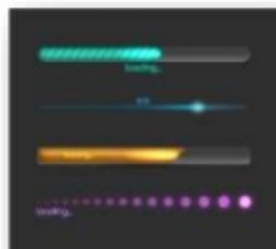
1. Import the libraries:



```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
%matplotlib inline
```

Use case implementation of Linear Regression

2. Load the Dataset and extract independent and dependent variables:



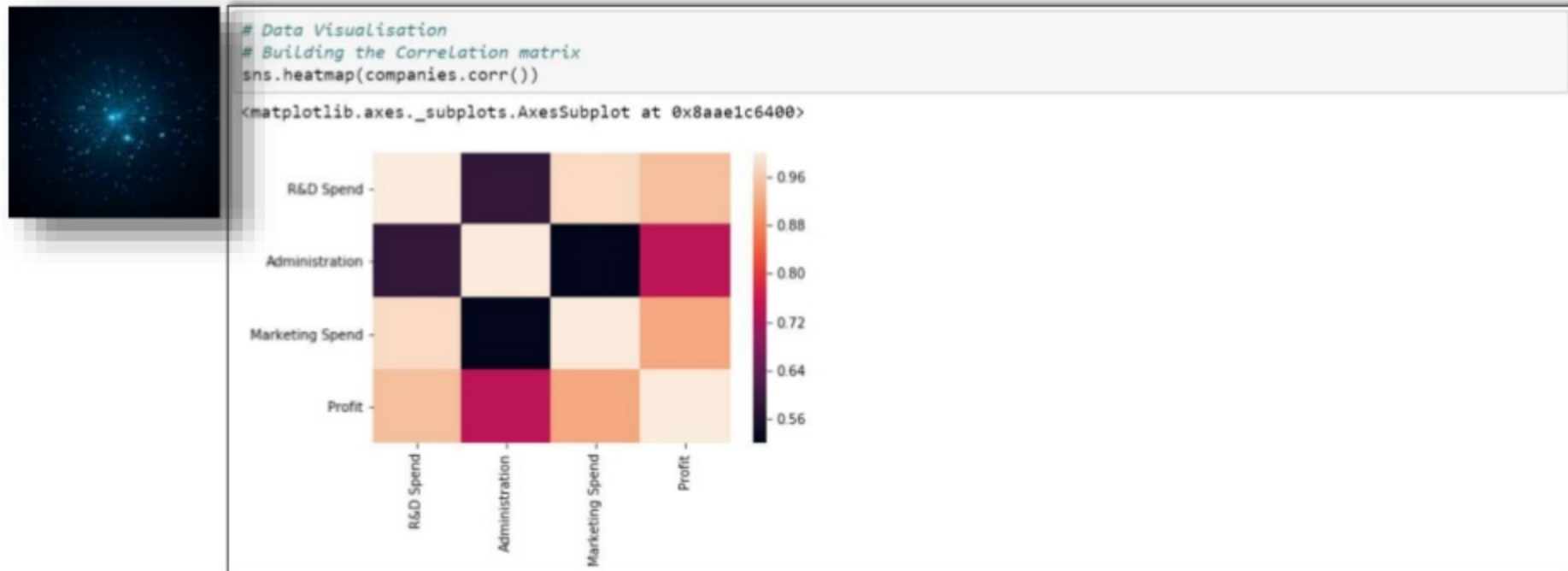
```
# Importing the dataset and Extracting the Independent and Dependent variables
companies = pd.read_csv('C:/Users/avijeet.biswal/Desktop/1000_Companies.csv')
X = companies.iloc[:, :-1].values
y = companies.iloc[:, 4].values
```

```
companies.head()
```

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94

Use case implementation of Linear Regression

3. Data Visualization:



Use case implementation of Linear Regression

4. Encoding Categorical Data:



```
# Encoding categorical data
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
labelencoder = LabelEncoder()
X[:, 3] = labelencoder.fit_transform(X[:, 3])
onehotencoder = OneHotEncoder(categorical_features = [3])
X = onehotencoder.fit_transform(X).toarray()
```

5. Avoiding Dummy Variable Trap:



```
# Avoiding the Dummy Variable Trap
X = X[:, 1:]
```

Use case implementation of Linear Regression

6. Splitting the data into Train and Test set:



```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

7. Fitting Multiple Linear Regression Model to Training set:



```
# Fitting Multiple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
model_fit = LinearRegression()
model_fit.fit(X_train, y_train)

LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

Use case implementation of Linear Regression

8. Predicting the Test set results:



```
# Predicting the Test set results
y_pred = regressor.predict(X_test)
y_pred
array([ 89790.61532915,  88427.07187361,  94894.67836972,
        175680.86725611,  83411.73042088, 110571.90200074,
        132145.22936439,  91473.37719686, 164597.05380606,
        53222.82667401,  66950.19050989, 150566.43987005,
        126915.20858596,  59337.8597105 , 177513.91053062,
        75316.28143051, 118248.14406603, 164574.40699902,
        170937.2898107 , 182069.11645084, 118845.03252689,
        85669.95112229, 180992.59396144,  84145.08220145,
        105005.83769214, 101233.56772747,  53831.07669091,
        56881.41475224,  68896.39346905, 210040.00765883,
        120778.72270894, 111724.87157654, 101487.90541518,
        137959.02649624,  63969.95996743, 108857.91214126,
        186014.72531988, 171442.64130747, 174644.26529205,
        117671.49128195,  96731.37857433, 165452.25779409,
        107724.34331255,  50194.54176913, 116513.89532179,
        58632.4898682 , 158416.4682761 ,  78541.48521609,
        159727.66671743, 131137.87699644, 184880.70924516,
        174609.0826688 ,  93745.66352059,  78341.13383418,
        180745.9043908 ,  84461.61490552, 142900.90602903,
        170618.44098397,  84365.09530839, 105307.3716218 ,
        141660.07290787,  52527.34340442, 141842.9626416 ,
        139176.27973195,  98294.52669666, 113586.86790969,])
```


Use case implementation of Linear Regression

9. Calculating the Coefficients and Intercepts:



```
# Calculating the Coefficients
print(regressor.coef_)

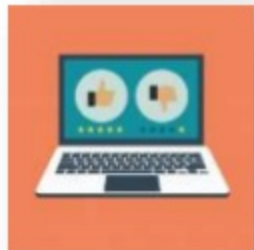
[ -8.80536598e+02  -6.98169073e+02   5.25845857e-01   8.44390881e-01
  1.07574255e-01]

# Calculating the Intercept
print(regressor.intercept_)

-51035.229724
```

Use case implementation of Linear Regression

10. Evaluating the model:



```
# Calculating the R squared value
from sklearn.metrics import r2_score
r2_score(y_test, y_pred)

0.91126958922688628
```

R squared value of 0.91 proves the model is a good model

Use case summary



We successfully trained our model with certain predictors and estimated the profit of companies using linear regression

Key Takeaways

Introduction to Machine Learning?

Based on the amount of crops how much should be the crop price?



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Numerical and Categorical Values



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Applications of Linear Regression



Linear Regression is used to predict numerical values.

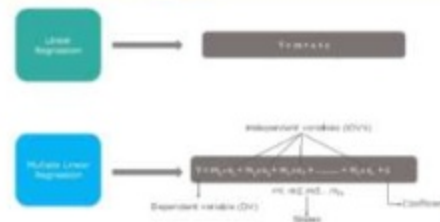
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Use case implementation of Linear Regression



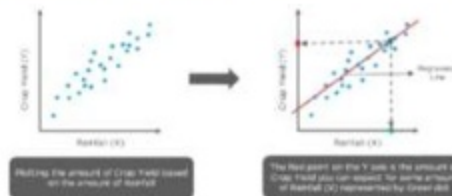
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Multiple Linear Regression



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Prediction using the Regression line



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The background image shows two hands shaking in a firm grip over a desk. On the desk, there are several sheets of paper, some with writing, and a clear glass. The scene is dimly lit, with a warm, slightly blurred background suggesting an office or meeting environment. An orange banner with the text 'THANK YOU' is centered over the hands.

THANK YOU

For more information, visit

www.simplilearn.com

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