## Matters of Discussion[ML] <u>Linear regression</u>

- Simple & Multiple linear regression

- Estimating the regression equation

- prediction variable selection in linear regression

## **ML** in Simple Linear Regression

Simple linear regression is what you can use when you have one independent variable[X] and one dependent variable [Y].

$$Y = \beta_0 + \beta_1 X$$

- While training the model:
- x: input training data (univariate one input variable(parameter))
- y: labels to data (supervised learning)
- e.g.-For Given Height(X), predict the Weight (Y);

## ML in Multiple linear regression

- Multiple linear regression is what you can use when you have a bunch of different independent variables or predictor variables [X1,X2,..Xn] and one dependent variable or response variable[Y].
- The multiple linear regression explains the relationship between one continuous dependent variable (y) and two or more independent variables (x1, x2, x3... etc).

#### Cont...

- Multiple Input Factors and One predicted O/P.
- ❖ Dimension reduction technique may be used to filter out the good set of independent variables [Input Factors ]that influence on the dependent variable[Y].
- ✓ Predictive variable Y or O/P.
- Eye disease type prediction[predicted O/P] based on input disease symptoms [input factors].

#### Regression problem in machine learning

- A regression can have real valued or discrete input variables.
- Regression models are used to predict a continuous value.
- Predicting prices of a house given the features of house like size, price etc. is one of the common examples of Regression.

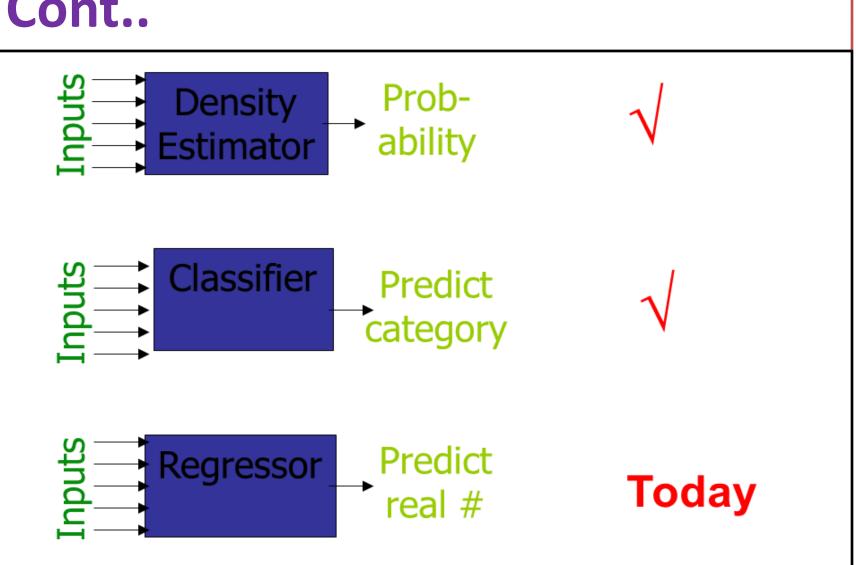
#### Continuous variables are simply running numbers.

Categorical variables are categories.

categorical: Well, I'm tall and smart

continuous: Well, I'm 180 cm and have an IQ of 126

## Cont...

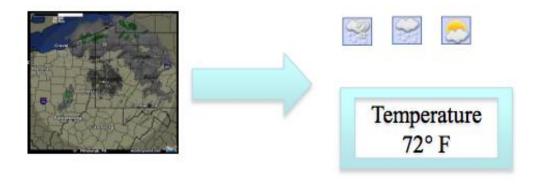


## Regression examples

#### Stock market

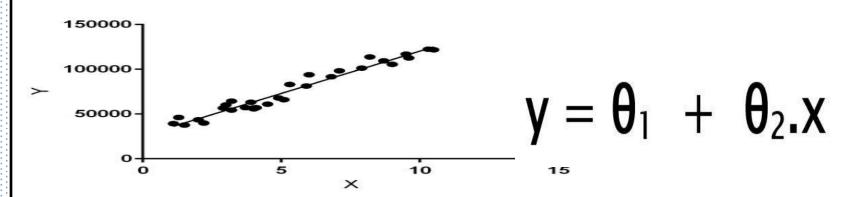
# | No. 12, 1800 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 | 10, 180 |

#### Weather prediction



Predict the temperature at any given location

#### Hypothesis function for Linear Regression



#### When training the model -

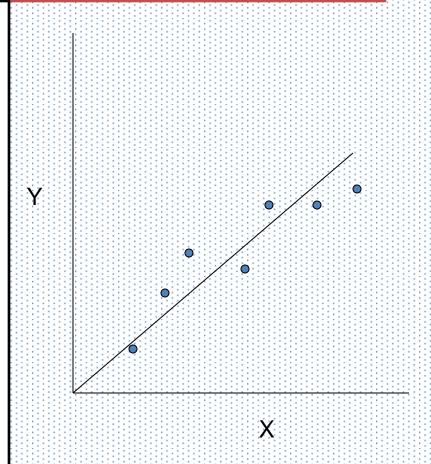
- it fits the best line to predict the value of y for a given value of x. The model gets the best regression fit line by finding the best  $\theta$ 1 and  $\theta$ 2 values.
- $\triangleright$  01: intercept
- $\triangleright$   $\theta$ 2: coefficient of x
- **Φ** Once we find the best θ1 and θ2 values, we get the best fit line. So when we are finally using our model for prediction, it will predict the value of y for the input value of x.

## **Linear regression Applications**

Given an input x we would like to compute an output y

#### For example:

- Predict height from age
- Predict Google's price from Yahoo's price
- Predict distance from wall from sensors



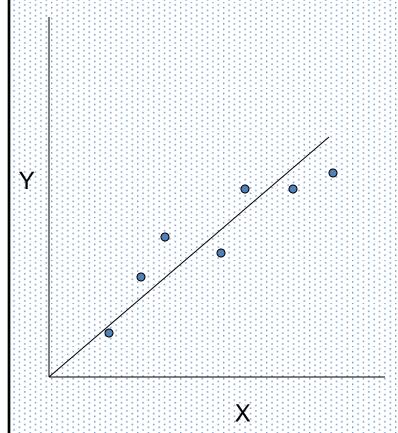
Compiled By: Dr. Nilamadhab Mishra [(PhD- CSIE) Taiwan]

## Linear regression in ML

- Given an input x we would like to compute an output y
- In linear regression we assume that y and x are related with the following equation:

What we are Observed values trying to predict  $v = wx + \varepsilon$ 

where w is a parameter and  $\epsilon$  represents measurement or other noise

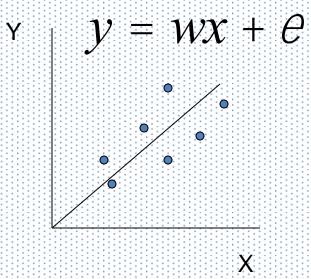


## Linear regression in ML

- •Our goal is to estimate w from a training data of  $\langle x_i, y_i \rangle$  pairs
- Optimization goal: minimize squared error (least squares):

$$\operatorname{arg\,min}_{w} \mathop{\stackrel{\circ}{\text{d}}}_{i} (y_{i} - wx_{i})^{2}$$

- Why least squares?
- minimizes squared distance between measurements and predicted line.



## Solving linear regression

- To optimize:
- We just take the derivative w.r.t. to w ....

prediction

$$\frac{\P}{\P w} \mathop{\mathring{a}}_{i} (y_{i} - wx_{i})^{2} = 2 \mathop{\mathring{a}}_{i} - x_{i} (y_{i} - wx_{i})$$

#### Training data of <xi,yi> pairs

## Solving linear regression

- To optimize closed form:
- We just take the derivative w.r.t. to w and set to 0:

$$\frac{\P}{\P w} \mathring{a} (y_i - wx_i)^2 = 2 \mathring{a} - x_i (y_i - wx_i) \triangleright$$

$$2 \mathring{a}_i x_i (y_i - wx_i) = 0 \quad \triangleright \quad 2 \mathring{a}_i x_i y_i - 2 \mathring{a}_i wx_i x_i = 0$$

**Training data of <xi,yi> pairs** 

$$\mathring{\mathbf{a}} x_i y_i = \mathring{\mathbf{a}} w x_i^2 \quad \triangleright$$

$$w = \frac{\mathring{a} x_i y_i}{\mathring{a} x_i^2}$$

## Implementation logic

```
# observations
  x = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
  y = np.array([1, 3, 2, 5, 7, 8, 8, 9, 10, 12])
  # estimating coefficients
  b = estimate coef(x, y)
  print("Estimated coefficients:\nb 0 = \{\mathcal{E}\}\
      \nb_1 = \{w\}''.format(b[0], b[1])
```

## **Analysis**

$$y = wx + \varepsilon$$

Estimated coefficients:

$$\varepsilon$$
 = -0.0586206896552

$$w = 1.45747126437$$

The linear regression model -----

$$y = 1.45747126437 \times + (-0.0586206896552)$$

#### **Cost function(J) of Linear Regression Model**

Cost function(J) of Linear Regression is the Root Mean Squared Error (RMSE) between predicted y value (predicted) and true y value (y).

$$J = rac{1}{n} \sum_{i=1}^n (pred_i - y_i)^2$$

Reduced Cost function (minimizing RMSE value)

Best value of w and  $\varepsilon$  should be estimated that minimize the error between predicted y value (predicted) and true y value (y).

## Steps to Establish a Regression

- 1) Carry out the experiment of gathering a sample of observed values of height and corresponding weight.
- 2) Create a relationship model using the lm() functions in R.
- 3) Find the coefficients from the model created and create the mathematical equation using these
- 4) To predict the weight of new persons, use the predict() function in R.

#### 1. Input Data

# Values of height

151, 174, 138, 186, 128, 136, 179, 163, 152, 131

# Values of weight.

63, 81, 56, 91, 47, 57, 76, 72, 62, 48

2. lm() Function - creates the relationship model between the predictor and the response variable.

Im(formula,data)

formula is a symbol presenting the relation between x and y. data is the vector on which the formula will be applied.

#### Cont..

#### Create Relationship Model & get the Coefficients

```
# Apply the lm() function. relation <- lm(y~x) print(relation)
```

N.B- " $x \sim y$ " meaning that x and y are of the same order of magnitude.

#### 3. O/P----Coefficients:

Find the coefficients from the model created and create the mathematical equation using these

$$Y = 0.6746 x + (-38.4551)$$

#### 4. use the predict() function in R.

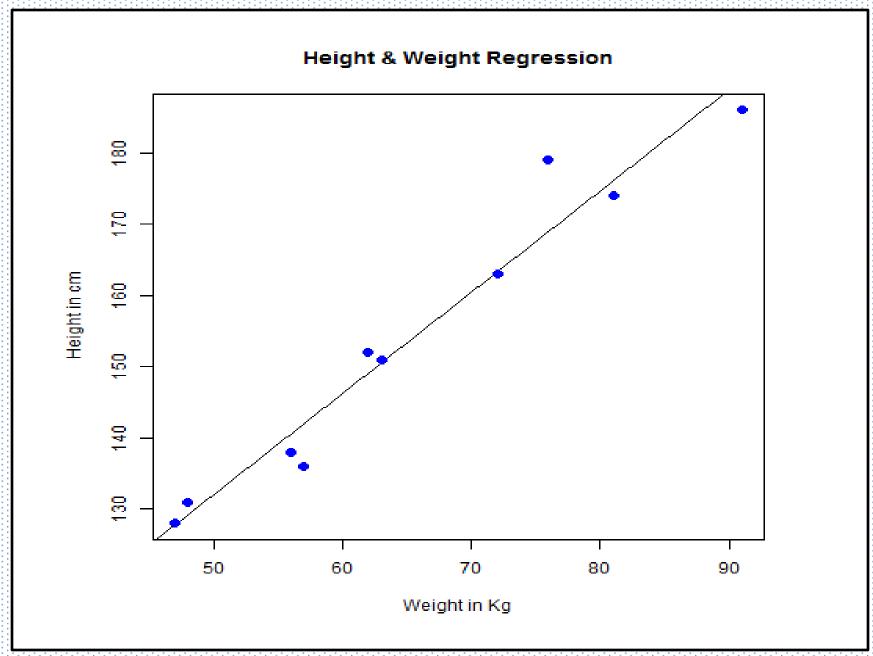
predict(object, newdata)

object is the formula which is already created using the lm() function.

newdata is the vector containing the new value for predictor variable.

```
Predict the weight of new persons
# The predictor vector.
x <- c(151, 174, 138, 186, 128, 136, 179, 163, 152, 131)
# The resposne vector.
y < -c(63, 81, 56, 91, 47, 57, 76, 72, 62, 48)
# Apply the lm() function.
relation <- lm(y^x)
# Find weight of a person with height 170.
a \leftarrow data.frame(x = 170)
result <- predict(relation,a)
print(result)
                                       P-- 76.22869
```

```
# Create the predictor and response variable.
x <- c(151, 174, 138, 186, 128, 136, 179, 163, 152, 131)
y <- c(63, 81, 56, 91, 47, 57, 76, 72, 62, 48)
relation <- lm(y^x)
# Give the chart file a name.
png(file = "linearregression.png")
# Plot the chart.
plot(y,x,col = "blue",main = "Height & Weight Regression",
abline(lm(x^y)),cex = 1.3,pch = 16,xlab = "Weight in Kg",ylab =
"Height in cm")
```



## **ACTIVITY -7( LAB-03)**

Consider any dataset and Implement and investigate the Linear regression algorithm, and analyze the results in details.

### **ACTIVITY-08**

Formulate Hypothesis function for Linear Regression and Investigate the computational analysis of linear regression model to estimate the coefficients for any real world application.



# Cheers For the Great Patience! Query Please?