# ALGO_1. Linear Regression

- Linear regression uses the relationship between the data-points to draw a straight line through all them.
- This line can be used to predict future values.

```
#necesary imports
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import pickle
```

```
data = pd.read_csv('1_Advertising 41.csv')
data.head()
```

| | Unnamed: 0 | TV | radio | newspaper | sales |
|---|---|---|---|---|---|
| 0 | 1 | 230.1 | 37.8 | 69.2 | 22.1 |
| 1 | 2 | 44.5 | 39.3 | 45.1 | 10.4 |
| 2 | 3 | 17.2 | 45.9 | 69.3 | 9.3 |
| 3 | 4 | 151.5 | 41.3 | 58.5 | 18.5 |
| 4 | 5 | 180.8 | 10.8 | 58.4 | 12.9 |

```
data.shape
```

```
(200, 5)
```

```
data.info() # print the summary of DataFrame
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  200 non-null    int64  
 1   TV          200 non-null    float64
 2   radio       200 non-null    float64
 3   newspaper   200 non-null    float64
 4   sales       200 non-null    float64
dtypes: float64(4), int64(1)
memory usage: 7.9 KB
```

```
data.isna().sum() # finding no. of NaNs in DataFrame
```

```
Unnamed: 0    0
TV            0
radio         0
newspaper     0
sales         0
dtype: int64
```

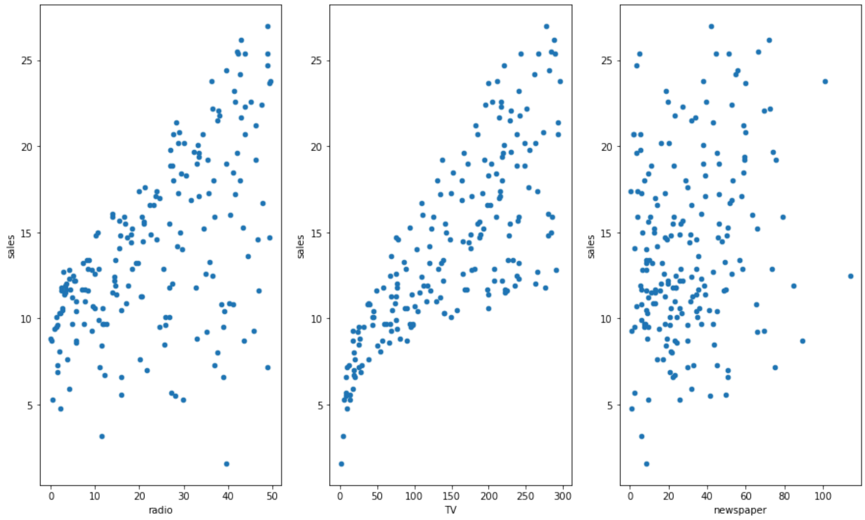
**Now, Let's see the relationship between the feature and targeted column (CORRELATION)**

```
# Visualize the relationship between the features and targeted column using 'Scatter plot':

fig,axs = plt.subplots(1,3)

data.plot(kind = 'scatter', x = 'TV', y = 'sales', ax = axs[1], figsize = (15,9))
data.plot(kind = 'scatter', x = 'radio', y = 'sales', ax = axs[0])
data.plot(kind = 'scatter', x = 'newspaper', y = 'sales', ax = axs[2])

# optionally used for Saving the Visualization (into your system) purpose only.
fig.savefig('testdata.jpg')
```




**Observations from above scatter plot:-**

- TV: Strong positive relationship.
- Radio: Positive relationship.
- Newspaper: Negative relationship.

**BEST FIT LINE:-** (good: If less residual)

- x: input | y: prediction/output | **y = mx + b**
- BEST FIT LINE must be **close to (or) covers most** of the data points of the plot.
- find ***m = ?***
- find ***b = ?***

**Actual data - Predicted data = Residual value**

## NOTE:

- **to avoid value of residual becoming zero** we use to **square them and then add**.(**eliminates negative effect** on calculation)
- **Gradient Descent :** learns and **reduces the Residual** to find best pattern.

```
# SLR as 1feature and 1 label
#create X = feature & Y = Label
X = data[['TV']]
Y = data.sales # Y : Actual Value.

# follow the usual sklearn pattern: import, instantiate, fit

from sklearn.linear_model import LinearRegression # import
lm = LinearRegression() # instantiate
lm.fit(X,Y) # .fit : used to train the model.
```

```
▾ LinearRegression
LinearRegression()
```

```
# print intercept(constant) & Coefficient(slope):


print(lm.intercept_) # b: intercept of y-axis
```

```
7.032593549127693
```

```
print(lm.coef_) # (Coefficient of x (or) slope: TV = 0.04753664 * sales
```

```
[0.04753664]
```

```
# Beta1 = slope = coef_ of x

# ONE Unit increase wrt sales is called Coef


# calculate the prediction if expence on TV ad is $50k=x.
y = lm.coef_ *50 + lm.intercept_
y
```

```
array([9.40942557])
```

```
# calculate the prediction if expence on TV ad is $50k.
y = 0.047537*50 + 7.032594
y
```

```
9.409444
```

Thus, we can predict sales of **9409 units** in that market.

Let's do the same using code.

```
# creating DataFrame, if $50k is expended on TV ad.
#X_new = pd.DataFrame({'TV': [50]}) # expence on TV ad is $50k.
#X_new
```

```
# use the model to predict new value.
lm.predict([[50]])
```

```
C:\Users\Lenovo\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but LinearRegres
  warnings.warn(
array([9.40942557])
```

```
import warnings # Filtering warnings
warnings.filterwarnings('ignore')
```

```
# use the model to predict new value.
lm.predict([[50]])
```

```
array([9.40942557])
```

```
# calculated prediction (if expence on TV ad is $50k) is 61% correct.(to be studied thereafter)
# 61% -> r2_score
```

## How Least Squares Line changes, based on input data (Demo only)

- [www.desmos.com/calculator/jwquvmikhr](www.desmos.com/calculator/jwquvmikhr)

# MODEL CONFIDENCE

**How well does the Model Fit the Data ?**

- how well system learns or trains itself (to predict) on percentage basis.

**R^2 statistics**

- The closer the value of R^2 wrt 1, the better the model fits our data. If R^2 comes below Zero(which is a possibility) that means the model is so bad, that it is performing even worse than the average best fit line.

**Metric to check model performance (r2_score)**

- Metric: Evaluating tools or techniques performance , E.g.: R^2 statistics(one of the tools).

```
from sklearn.metrics import r2_score
```

```
X.head(3) # X = feature(TV)-- "x"
```

| | TV |
|---|---|
| 0 | 230.1 |
| 1 | 44.5 |
| 2 | 17.2 |

```
Y.head(3) # Y: Actual value(Sales)-- "y"
```

```
0    22.1
1    10.4
2     9.3
Name: sales, dtype: float64
```

```
# pass all tv records and predict sales due to TV ads only.

predicted_sales_TV = lm.predict(X) # PREDICTED VALUES-- "y(hat)"

predicted_sales_TV = pd.DataFrame(predicted_sales_TV)
predicted_sales_TV.head()
# Y^: Predicted value(predicted_sales_TV),
```

| | 0 |
|---|---|
| 0 | 17.970775 |
| 1 | 9.147974 |
| 2 | 7.850224 |
| 3 | 14.234395 |
| 4 | 15.627218 |

```
# Let's compare original sales numbers (Y) with our model predicted sales (Y^).

r2_score(y_true = Y, y_pred = predicted_sales_TV)
```

```
0.611875050850071
```

- Our Model's prediction is 61% correct.
- Earlier, calculated prediction (if expence on TV ad is $50k) is also 61% correct.

**Simple Linear Regression:** only one feature used to predict.(like till here on 'TV' is used).***--R^2***

**Multiple Linear Regression:** more than 1 feature is used for prediction. (like from here on 'TV, Radio & News Paper' will be used).***--Adjusted R^2 statistics***

**Adjusted R^2 statistics:** (pulls down the values of R^2 statistics)

```
# N= No. of Rows or Samples
# P= No. of Columns or features or predictions.

#- -> .shape-> (no. of rows, no. of columns)
```

```
# Create X & y.
X = data[['TV','radio','newspaper']]
y = data['sales']

lm = LinearRegression() # Multiple Linear Regression
lm.fit(X,y)
```

```
▾ LinearRegression
LinearRegression()
```

```
# Print b & m (printing best fit line):

print('Intercept : ->',lm.intercept_)
print('TV : ->',lm.coef_[0])
print('radio : ->',lm.coef_[1])
print('newspaper : ->',lm.coef_[2])
```

```
Intercept : -> 2.9388893694594085
TV : -> 0.045764645455397615
```

```
radio : -> 0.18853001691820448
newspaper : -> -0.0010374930424763007
```

**observation:**

- By "increasing investment" by 1Unit, the "sales" increased by that coef_.

**Observation:**

- TV: Strong positive relationship.
- Radio: Positive relationship.
- Newspaper: Negative relationship.

## Feature Selection

How do one can decide **which feature have to be included** in a linear model? Here's one idea:

- Check if the R-squared value goes up when you add new predictors to the model.

```
#preparing data for R2_score on TV & Radio as we can see they are positively related (coef).
X= data[['TV',"radio"]] # features
y= data.sales # Labels

# let's train the model
lm.fit(X,y)

# Check the R2_score.

predicted_sales= lm.predict(X)
r2_score(y,predicted_sales)
```

```
0.8971942610828956
```

```
#Let's do the same taking all the features.
X= data[['TV',"radio",'newspaper']] # features
y= data.sales # Labels

# let's train the model
lm.fit(X,y)

# Check the R2_score.

predicted_sales= lm.predict(X)
r2_score(y,predicted_sales)
```

```
0.8972106381789522
```

**Observation**:

- TV- 61%
- TV+Radio- 89.719% ~ 89.72%
- TV+Radio+newspaper- 89.721% ~ 89.72%
- **Newspaper has very least contribution wrt our label.**

```
Start coding or generate with AI.
```

```
Start coding or generate with AI.
```

```
Start coding or generate with AI.
```

```
Start coding or generate with AI.
```