Machine Learning

1. Supervised
2. Unsupervised
3. Reinforcement

Regression

1. Linear Regression
2. Multiple Regression
3. Polynomial

HW

- differentiate between regression and classification

Hands on Simple Linear Regression

importing libs

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

import dataset

```
# from google.colab import files
# uploaded = files.upload()
# D5data1.csv

import os
```

```
os.chdir(r'C:\Users\surya\Downloads\PG-DBDA-Mar23\Datasets')
os.getcwd()
```

```
'C:\\Users\\surya\\Downloads\\PG-DBDA-Mar23\\Datasets'
```

```
dataset = pd.read_csv('D5data1.csv')
dataset.head()
```

	YearsExperience	Salary
0	1.1	39343.0
1	1.3	46205.0
2	1.5	37731.0
3	2.0	43525.0
4	2.2	39891.0

```
dataset.shape
```

```
(30, 2)
```

```
dataset.describe()
```

	YearsExperience	Salary
count	30.000000	30.000000
mean	5.313333	76003.000000
std	2.837888	27414.429785
min	1.100000	37731.000000
25%	3.200000	56720.750000
50%	4.700000	65237.000000
75%	7.700000	100544.750000
max	10.500000	122391.000000

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
```

```
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   YearsExperience  30 non-null     float64
 1   Salary           30 non-null     float64
dtypes: float64(2)
memory usage: 608.0 bytes
```

define x & Y

```
# independent var
x = dataset.iloc[ : , :-1].values
x[:5]
```

```
array([[1.1],
       [1.3],
       [1.5],
       [2. ],
       [2.2]])
```

```
# dependent var
y = dataset.iloc[ : , -1].values
y[:5]
```

```
array([39343., 46205., 37731., 43525., 39891.])
```

Splitting

- Splitting the training data & testing data

```
from sklearn.model_selection import train_test_split
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=1/3, random_state=0)
```

```
x_train[:5]
```

```
array([[2.9],
       [5.1],
       [3.2],
       [4.5],
       [8.2]])
```

```
y_train[:5]
```

```
array([ 56642.,  66029.,  64445.,  61111., 113812.])
```

Modeling

- Modeling the Simple Linear Regression Model

```
from sklearn.linear_model import LinearRegression
```

```
regressor = LinearRegression()
```

Training

- Training the Simple Linear Regression Model

```
regressor.fit(x_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

Prediction

- predicting the test data

```
y_pred = regressor.predict(x_test)
y_pred[:5]
```

```
array([ 40835.10590871, 123079.39940819,  65134.55626083,  63265.36777221,
       115602.64545369])
```

Visualize

- visualize the Training dataset

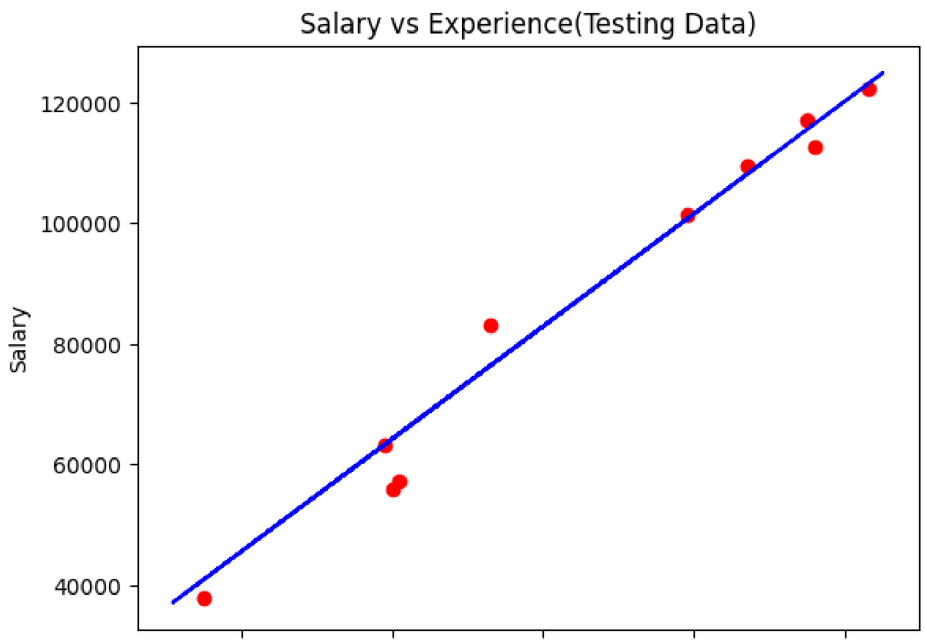
Cross-Validation: training data vs predicted data

```
plt.scatter(x_train, y_train, color='red')
# training data points
```

```
plt.plot(x_train, regressor.predict(x_train), color='blue')
# predicted data line
plt.title('Salary vs Experience(Training data)')
plt.xlabel('Experience')
plt.ylabel('Salary')
plt.show()
```

Cross-Validation: testing data vs predicted data

```
plt.scatter(x_test, y_test, color='red')
# testing data points
plt.plot(x_train, regressor.predict(x_train), color='blue')
# predicted data line
plt.title('Salary vs Experience(Testing Data)')
plt.xlabel('Experience')
plt.ylabel('Salary')
plt.show()
```



Prediction

```
print(regressor.predict([[31]]))
# prediction with custom input
```

```
[316540.40798082]
```

Evaluation

Regressor Coefficient

```
b = regressor.coef_
# Regressor Coefficient property
b
```

```
array([9345.94244312])
```

y intercept

```
a = regressor.intercept_
# y intercept property
a
```

```
26816.192244031183
```

Mean Square Error (MSE)

```
from sklearn.metrics import mean_squared_error
```

```
mean_squared_error(y_test, y_pred)
# Mean Square Error (MSE)
```

```
21026037.329511296
```

r2_score

- R-Squared

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

```
r2_score(y_test, y_pred)
```

```
0.9749154407708353
```

Regression Summary

```
import statsmodels.api as sm
```

```
x_stats = sm.add_constant(x_train)
```

```
regsummary = sm.OLS(y_train, x_stats).fit()
print(regsummary.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.938
Model:                            OLS   Adj. R-squared:                  0.935
Method:                 Least Squares   F-statistic:                     273.2
Date:                Mon, 24 Jul 2023   Prob (F-statistic):           2.51e-12
```

```
Time:                        23:27:10   Log-Likelihood:                -202.60
No. Observations:                  20   AIC:                             409.2
Df Residuals:                      18   BIC:                             411.2
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       2.682e+04   3033.148      8.841      0.000    2.04e+04    3.32e+04
x1          9345.9424    565.420     16.529      0.000    8158.040    1.05e+04
==============================================================================
Omnibus:                        2.688   Durbin-Watson:                   2.684
Prob(Omnibus):                  0.261   Jarque-Bera (JB):                1.386
Skew:                           0.305   Prob(JB):                        0.500
Kurtosis:                       1.864   Cond. No.                         11.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

R-Squared

- coefficient of determination
- using OLS Regression model for Linear regression

```
regsummary.rsquared_adj
```

```
0.9347561124721737
```

Hands on Multiple Linear Regression

importing libs

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

import dataset

```
# from google.colab import files
# uploaded = files.upload()
```

```
# D5data2.csv

import os
os.chdir(r'C:\Users\surya\Downloads\PG-DBDA-Mar23\Datasets')
os.getcwd()
```

```
'C:\\Users\\surya\\Downloads\\PG-DBDA-Mar23\\Datasets'
```

```
dataset = pd.read_csv('D5data2.csv')
dataset.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

```
dataset.shape
```

```
(50, 5)
```

```
dataset.describe()
```

	R&D Spend	Administration	Marketing Spend	Profit
count	50.000000	50.000000	50.000000	50.000000
mean	73721.615600	121344.639600	211025.097800	112012.639200
std	45902.256482	28017.802755	122290.310726	40306.180338
min	0.000000	51283.140000	0.000000	14681.400000
25%	39936.370000	103730.875000	129300.132500	90138.902500
50%	73051.080000	122699.795000	212716.240000	107978.190000
75%	101602.800000	144842.180000	299469.085000	139765.977500
max	165349.200000	182645.560000	471784.100000	192261.830000

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   R&D Spend        50 non-null     float64
 1   Administration   50 non-null     float64
 2   Marketing Spend  50 non-null     float64
 3   State            50 non-null     object 
 4   Profit           50 non-null     float64
dtypes: float64(4), object(1)
memory usage: 2.1+ KB
```

define X & Y

```
# independent vars
x = dataset.iloc[ : ,  : -1].values
x[:5]
```

```
array([[165349.2, 136897.8, 471784.1, 'New York'],
       [162597.7, 151377.59, 443898.53, 'California'],
       [153441.51, 101145.55, 407934.54, 'Florida'],
       [144372.41, 118671.85, 383199.62, 'New York'],
       [142107.34, 91391.77, 366168.42, 'Florida']], dtype=object)
```

```
# dependent var
y = dataset.iloc[ : , -1].values
y[:5]
```

```
array([192261.83, 191792.06, 191050.39, 182901.99, 166187.94])
```

Transformation

OneHotEncoder & ColumnTransformer

```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
```

```
ct = ColumnTransformer(transformers=[('encode', OneHotEncoder(), [3])], remainder='passthrough')
```

```
x = np.array(ct.fit_transform(x))
```

```
x[:5]
```

```
array([[0.0, 0.0, 1.0, 165349.2, 136897.8, 471784.1],
       [1.0, 0.0, 0.0, 162597.7, 151377.59, 443898.53],
       [0.0, 1.0, 0.0, 153441.51, 101145.55, 407934.54],
       [0.0, 0.0, 1.0, 144372.41, 118671.85, 383199.62],
       [0.0, 1.0, 0.0, 142107.34, 91391.77, 366168.42]], dtype=object)
```

Splitting

```
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)
```

```
x_train[:5]
```

```
array([[0.0, 1.0, 0.0, 55493.95, 103057.49, 214634.81],
       [0.0, 0.0, 1.0, 46014.02, 85047.44, 205517.64],
       [0.0, 1.0, 0.0, 75328.87, 144135.98, 134050.07],
       [1.0, 0.0, 0.0, 46426.07, 157693.92, 210797.67],
       [0.0, 1.0, 0.0, 91749.16, 114175.79, 294919.57]], dtype=object)
```

Modeling

```
from sklearn.linear_model import LinearRegression
```

```
regressor = LinearRegression()
```

Training

```
regressor.fit(x_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

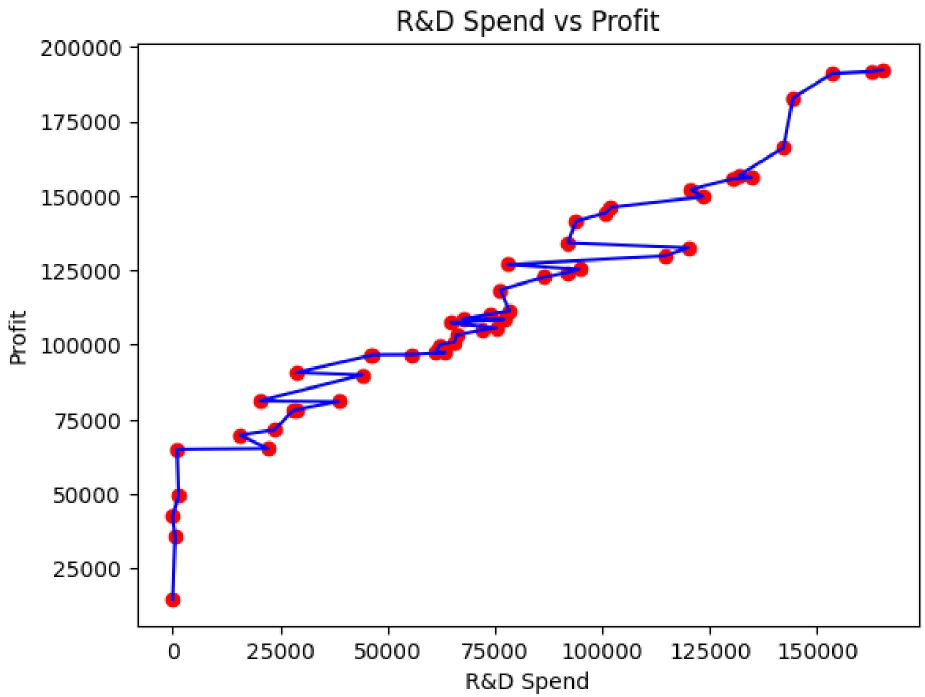
Prediction

```
y_pred = regressor.predict(x_test)
# prediction from testing data
y_pred[:5]
```

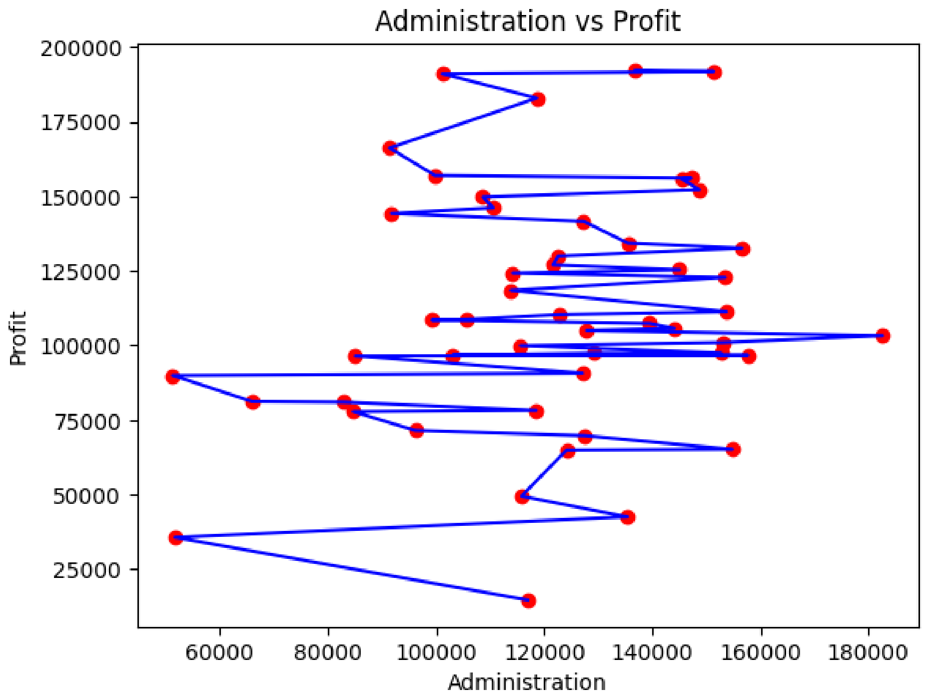
```
array([103015.20159796, 132582.27760815, 132447.73845174,  71976.09851258,
       178537.48221056])
```

visualization

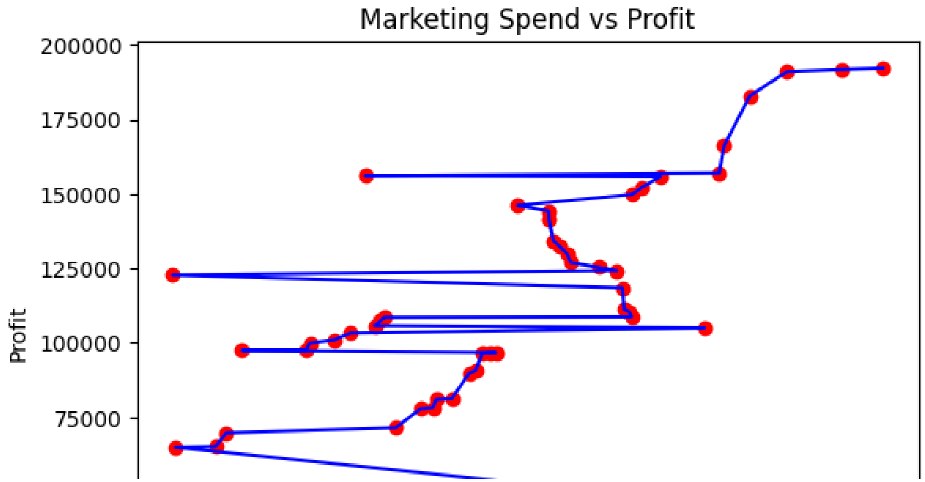
```
plt.scatter(dataset['R&D Spend'], dataset['Profit'], color='red')
plt.plot(dataset['R&D Spend'], dataset['Profit'], color='blue') # actual dataset
plt.title('R&D Spend vs Profit')
plt.xlabel('R&D Spend')
plt.ylabel('Profit')
plt.show()
```



```
plt.scatter(dataset['Administration'], dataset['Profit'], color='red')
plt.plot(dataset['Administration'], dataset['Profit'], color='blue') # actual dataset
plt.title('Administration vs Profit')
plt.xlabel('Administration')
plt.ylabel('Profit')
plt.show()
```




```
plt.scatter(dataset['Marketing Spend'], dataset['Profit'], color='red')
plt.plot(dataset['Marketing Spend'], dataset['Profit'], color='blue') # actual dataset
plt.title('Marketing Spend vs Profit')
plt.xlabel('Marketing Spend')
plt.ylabel('Profit')
plt.show()
```



Hands on Polynomial Linear Regression

- first start with building the linear regression model, then move to build polynomial regression model
- prone to outliers
- degree is most important

importing libs

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

import dataset

```
# from google.colab import files
# uploaded = files.upload()
# D5data4.csv

import os
os.chdir(r'C:\Users\surya\Downloads\PG-DBDA-Mar23\Datasets')
os.getcwd()
```

```
'C:\\Users\\surya\\Downloads\\PG-DBDA-Mar23\\Datasets'
```

```
dataset = pd.read_csv('D5data4.csv')
dataset.head()
```

	Position	Level	Salary
0	Business Analyst	1	45000
1	Junior Consultant	2	50000
2	Senior Consultant	3	60000
3	Manager	4	80000
4	Country Manager	5	110000

```
dataset.shape
```

```
(10, 3)
```

```
dataset.describe()
```

	Level	Salary
count	10.00000	10.000000
mean	5.50000	249500.000000
std	3.02765	299373.883668
min	1.00000	45000.000000
25%	3.25000	65000.000000
50%	5.50000	130000.000000
75%	7.75000	275000.000000
max	10.00000	1000000.000000

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   Position  10 non-null     object
 1   Level     10 non-null     int64 
 2   Salary    10 non-null     int64 
```

```
dtypes: int64(2), object(1)
memory usage: 368.0+ bytes
```

define X & Y

```
# independent vars
x = dataset.iloc[ : ,  1:2].values
x[:5]
```

```
array([[1],
       [2],
       [3],
       [4],
       [5]], dtype=int64)
```

```
# dependent vars
y = dataset.iloc[ : , -1].values
y[:5]
```

```
array([ 45000,  50000,  60000,  80000, 110000], dtype=int64)
```

Splitting

```
from sklearn.model_selection import train_test_split
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=0)
```

```
x_train[:5]
```

```
array([[10],
       [ 2],
       [ 7],
       [ 8],
       [ 4]], dtype=int64)
```

```
y_train[:5]
```

```
array([1000000,   50000,  200000,  300000,   80000], dtype=int64)
```

transformation

```
# from sklearn.preprocessing import LabelEncoder
```

```
# labelencoder = LabelEncoder()
# x[:, 0] = labelencoder.fit_transform(x[:, 0])
```

```
# from sklearn.compose import ColumnTransformer
# from sklearn.preprocessing import OneHotEncoder
```

```
# ct = ColumnTransformer([('encode', OneHotEncoder(), [0])], remainder='passthrough')
# x = np.array(ct.fit_transform(x))
```

```
# x[:5]
```

Linear model (for comparison)

Modeling Linear Model

```
from sklearn.linear_model import LinearRegression
```

```
lin_reg = LinearRegression()
```

Training Linear Model

```
lin_reg.fit(x, y)
```

```
▾ LinearRegression
LinearRegression()
```

Polynomial Modeling

Modeling Polynomial Model

```
from sklearn.preprocessing import PolynomialFeatures
```

```
poly_reg = PolynomialFeatures(degree=4)
# degree = number of features
```

Training Polynomial Model on `x`

```
x_poly = poly_reg.fit_transform(x)
```

Modeling Linear Model

```
lin_reg2 = LinearRegression()
```

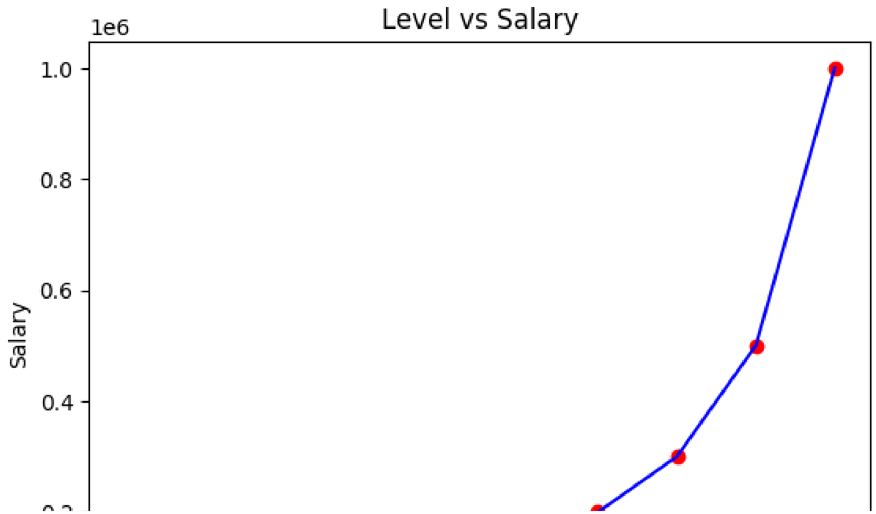
Training Linear Model On Polynomial Model

```
lin_reg2.fit(x_poly, y)
```

```
▾ LinearRegression
LinearRegression()
```

Visualization

```
plt.scatter(x, y, color='red')
plt.plot(x, y, color='blue') # actual dataset
plt.title('Level vs Salary')
plt.xlabel('Level')
plt.ylabel('Salary')
plt.show()
```



HW:

```
Build the Regression Model for Linear, MultiLinear and Polynomial Regression
Use dataset:
--------------
a.    Day5data3.csv and
b.    Ecommerce Customer.txt
```

```

```