Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import sklearn
```

In [2]:
```
df = pd.read_csv(r"F:\Datasets\Machine Learning (Codes and Data Files)\Data\MBA Salary.csv")
```

In [4]:
```
len(df)
```

Out[4]: 50

In [5]:
```
df.info()
```

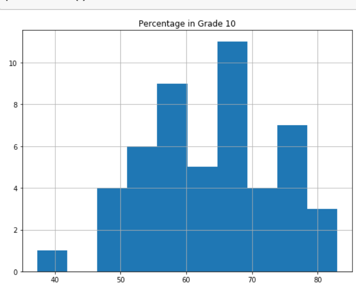
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 3 columns):
S. No.                    50 non-null int64
Percentage in Grade 10    50 non-null float64
Salary                    50 non-null int64
dtypes: float64(1), int64(2)
memory usage: 1.3 KB
```

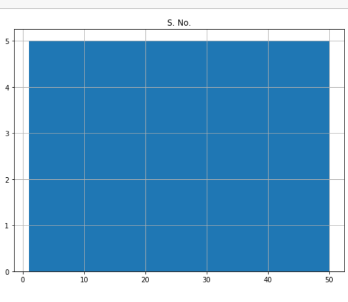
In [7]:
```
df.describe()
```

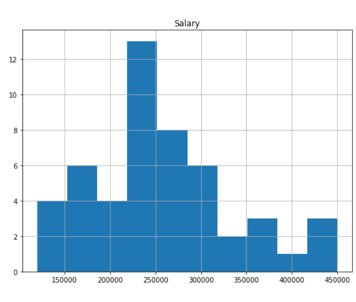
Out[7]:

	S. No.	Percentage in Grade 10	Salary
count	50.00000	50.000000	50.000000
mean	25.50000	63.922400	258192.000000
std	14.57738	9.859937	76715.790993
min	1.00000	37.330000	120000.000000
25%	13.25000	57.685000	204500.000000
50%	25.50000	64.700000	250000.000000
75%	37.75000	70.000000	300000.000000
max	50.00000	83.000000	450000.000000

In [12]:
```
df.hist(figsize=(20,15))
plt.show()
```







Building the SLM

In [13]:
```
import statsmodels.api as sm
```

Adding Values for X and Y

In [14]:
```
X = sm.add_constant(df["Percentage in Grade 10"] )
```

```
C:\Users\LENOVO\Anaconda3\lib\site-packages\numpy\core\fromnumeric.py:2389: FutureWarning: Me
thod .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

In [17]:
```
X.head()
```

Out[17]:

	const	Percentage in Grade 10
0	1.0	62.00
1	1.0	76.33
2	1.0	72.00
3	1.0	60.00
4	1.0	61.00

In [18]:
```
Y = df["Salary"]
```

In [19]:
```
Y.head()
```

Out[19]:
```
0    270000
1    200000
2    240000
3    250000
4    180000
Name: Salary, dtype: int64
```

Splitting the Dataset into Training and Validation Sets

In [20]:
```
from sklearn.model_selection import train_test_split
```

In [21]:
```
train_X, test_X, train_y, test_y = train_test_split( X, Y, train_size = 0.8, random_state =
100 )
```

Fitting the Model using ols method

In [22]:
```
mba_salary_lm = sm.OLS( train_y, train_X ).fit()
```

In [24]:
```
mba_salary_lm.params
```

Out[24]:
```
const                     30587.285652
Percentage in Grade 10     3560.587383
dtype: float64
```

MODEL DIAGNOSTICS

It is important to validate the regression model to ensure its validity and goodness of fit before it can be used for practical applications. The following measures are used to validate the simple linear regression models:

1. Co-efficient of determination (R-squared).
2. Hypothesis test for the regression coefficient.
3. Analysis of variance for overall model validity (important for multiple linear regression).
4. Residual analysis to validate the regression model assumptions.
5. Outlier analysis, since the presence of outliers can significantly impact the regression parameters.

In [25]:
```
mba_salary_lm.summary2()
```

Out[25]:

Model:	OLS	Adj. R-squared:	0.190
Dependent Variable:	Salary	AIC:	1008.8680
Date:	2021-07-07 02:03	BIC:	1012.2458
No. Observations:	40	Log-Likelihood:	-502.43
Df Model:	1	F-statistic:	10.16
Df Residuals:	38	Prob (F-statistic):	0.00287
R-squared:	0.211	Scale:	5.0121e+09

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
const	30587.2857	71869.4497	0.4256	0.6728	-114904.8089	176079.3802
Percentage in Grade 10	3560.5874	1116.9258	3.1878	0.0029	1299.4892	5821.6855

Omnibus:	2.048	Durbin-Watson:	2.611
Prob(Omnibus):	0.359	Jarque-Bera (JB):	1.724
Skew:	0.369	Prob(JB):	0.422
Kurtosis:	2.300	Condition No.:	413

From the summary output shown above, we can infer the following:

1. The model R-squared value is 0.211, that is, the model explains 21.1% of the variation in salary.
2. The p-value for the t-test is 0.0029 which indicates that there is a statistically significant relationship (at significance value a = 0.05) between the feature, percentage in grade 10, and salary. Also, the probability value of F-statistic of the model is 0.0029 which indicates that the overall model is statistically significant. Note that, in a simple linear regression, the p-value for t-test and F-test will be the same since the null hypothesis is the same. (Also F = t2 in the case of SLR.)

The co-efficient of determination (R-squared) has the following properties:

1. The value of R-squared lies between 0 and 1.
2. Mathematically, R-squared (R2) is square of correlation coefficient (R2 = r2), where r is the Pearson correlation co-efficient.
3. Higher R-squared indicates better fit; however, one should be careful about the spurious relationship.

Residual Analysis

Residuals or errors are the difference between the actual value of the outcome variable and the predicted value ( ) Y Y i i - . Residual (error) analysis is important to check whether the assumptions of regression models have been satisfied. It is performed to check the following:

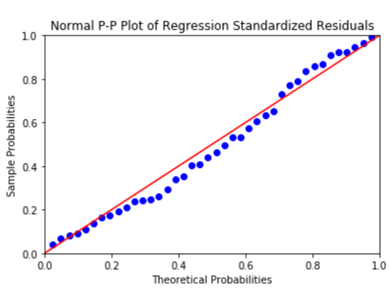
1. The residuals are normally distributed.
2. Variance of residual is constant (homoscedasticity).
3. The functional form of regression is correctly specified.
4. THere are no outliers.

1) Check for Normal Distribution of Residual

In [27]:
```
import matplotlib.pyplot as plt
import seaborn as sn
%matplotlib inline
```

In [31]:
```
mba_salary_resid = mba_salary_lm.resid
probplot = sm.ProbPlot(mba_salary_resid)
plt.figure( figsize = (8, 6))
probplot.ppplot( line="45" )
plt.title( "Normal P-P Plot of Regression Standardized Residuals" )
plt.show()
```

```
<Figure size 576x432 with 0 Axes>
```



The normality of residuals can be checked using the probability−probability plot (P-P plot). P-P plot compares the cumulative distribution function of two probability distributions against each other. In the current context, we use the P-P plot to check whether the distribution of the residuals matches with that of a normal distribution. In Python, ProbPlot() method on statsmodel draws the P-P plot as shown in Figure

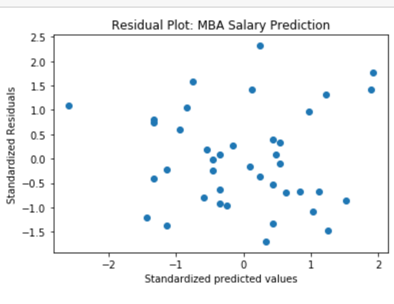
In Figure, the diagonal line is the cumulative distribution of a normal distribution, whereas the dots represent the cumulative distribution of the residuals. Since the dots are close to the diagonal line, we can conclude that the residuals follow an approximate normal distribution (we need only an approximate normal distribution).

2) Test of Homoscedasticity

An important assumption of the regression model is that the residuals have constant variance (homoscedasticity) across different values of the predicted value (Y). The homoscedasticity can be observed by drawing a residual plot, which is a plot between standardized residual value and standardized predicted value. If there is heteroscedasticity (non-constant variance of residuals), then a funnel type shape in the residual plot can be expected. A non-constant variance of the residuals is known as heteroscedasticity. The following custom method get_standardized_values() creates the standardized values of a series of values (variable). It subtracts values from mean and divides by standard deviation of the variable.

In [33]:
```
def get_standardized_values( vals ):
    return (vals - vals.mean())/vals.std()
```

In [34]:
```
plt.scatter( get_standardized_values( mba_salary_lm.fittedvalues ),
get_standardized_values( mba_salary_resid ))
plt.title( "Residual Plot: MBA Salary Prediction");
plt.xlabel( "Standardized predicted values" )
plt.ylabel( "Standardized Residuals" );
```



It can be observed in Figure that the residuals are random and have no funnel shape, which means the residuals have constant variance (homoscedasticity).

3) Outlier Analysis

Outliers are observations whose values show a large deviation from the mean value. Presence of an outlier can have a significant influence on the values of regression coefficients. Thus, it is important to identify the existence of outliers in the data. The following distance measures are useful in identifying influential observations:

1. Z-Score
2. Mahalanobis Distance
3. Cook's Distance
4. Leverage Values

a) Z-Score

In [36]:
```
from scipy.stats import zscore
```

In [38]:
```
mba_salary_df = df
```

In [39]:
```
mba_salary_df["z_score_salary"] = zscore( mba_salary_df.Salary )
```

In [41]:
```
mba_salary_df.head()
```

Out[41]:

	S. No.	Percentage in Grade 10	Salary	z_score_salary
0	1	62.00	270000	0.155481
1	2	76.33	200000	-0.766241
2	3	72.00	240000	-0.239543
3	4	60.00	250000	-0.107868
4	5	61.00	180000	-1.029590

In [42]:
```
mba_salary_df[ (mba_salary_df.z_score_salary > 3.0) | (mba_salary_df.z_score_salary < -3.0)
]
```

Out[42]:

S. No.	Percentage in Grade 10	Salary	z_score_salary

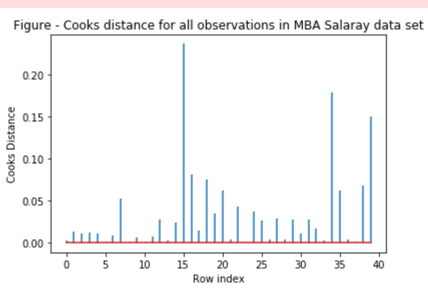
So, there are no observations that are outliers as per the Z-score.

b) Cook's Distance

Cook's distance measures how much the predicted value of the dependent variable changes for all the observations in the sample when a particular observation is excluded from the sample for the estimation of regression parameters. A Cook's distance value of more than 1 indicates highly influential observation. Python code for calculating Cook's distance is provided below. In this get_influence() returns the influence of observations in the model and cook_distance variable provides Cook's distance measures. Then the distances can be plotted against the observation index to find out which observations are influential.

In [46]:
```
mba_influence = mba_salary_lm.get_influence()
(c, p) = mba_influence.cooks_distance
plt.stem(np.arange( len( train_X) ), np.round( c, 3 ), markerfmt="," )
plt.title( "Figure - Cooks distance for all observations in MBA Salaray data set" )
plt.xlabel("Row index")
plt.ylabel("Cooks Distance")
plt.show()
```

```
C:\Users\LENOVO\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: UserWarning: In Matplotl
ib 3.3 individual lines on a stem plot will be added as a LineCollection instead of individua
l lines. This significantly improves the performance of a stem plot. To remove this warning a
nd switch to the new behaviour, set the "use_line_collection" keyword argument to True.
  This is separate from the ipykernel package so we can avoid doing imports until
```

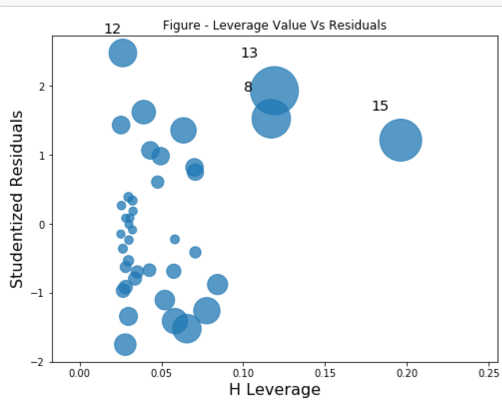


From Figure, it can be observed that none of the observations' Cook's distance exceed 1 and hence none of them are outliers.

c) Leverage Values

Leverage value of an observation measures the influence of that observation on the overall fit of the regression function and is related to the Mahalanobis distance. Leverage value of more than 3(k + 1)/n is treated as highly influential observation, where k is the number of features in the model and n is the sample size. statsmodels.graphics.regressionplots module provides influence_plot() which draws a plot between standardized residuals and leverage value. Mostly, the observations with high leverage value (as mentioned above) and high residuals [more than value 3(k + 1)/n] can be removed from the training

In [47]:
```
from statsmodels.graphics.regressionplots import influence_plot
fig, ax = plt.subplots( figsize=(8,6) )
influence_plot( mba_salary_lm, ax = ax )
plt.title("Figure - Leverage Value Vs Residuals")
plt.show()
```



In Figure, the size of the circle is proportional to the product of residual and leverage value. The larger the circle, the larger is the residual and hence influence of the observation.

Making Prediction and Measuring Accuracy

Ideally, the prediction should be made on the validation (or test) data and the accuracy of prediction should be evaluated.

1) Predicting using the Validation Set

The model variable has a method predict(), which takes the X parameters and returns the predicted values.

In [48]:
```
pred_y = mba_salary_lm.predict( test_X )
```

2) Finding R-Squared and RMSE

Several measures can be used for measuring the accuracy of prediction. Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are some of the frequently used measures. sklearn.metrics has r2_score and mean_squared_error for measuring R-squared and MSE values. We need to take the square root of the MSE value to get RMSE value. Both the methods take predicted Y values and actual Y values to calculate the accuracy measures. Numpy module has sqrt method to calculate the square root of a value.

In [49]:
```
from sklearn.metrics import r2_score, mean_squared_error
```

In [50]:
```
#r squared
np.abs(r2_score(test_y, pred_y))
```

Out[50]: 0.15664584974230378

So, the model only explains 15.6% of the variance in the validation set.

In [52]:
```
np.sqrt(mean_squared_error(test_y, pred_y))
```

Out[52]: 73458.04348346894

RMSE means the average error the model makes in predicting the outcome. The smaller the value of RMSE, the better the model is.

3) Calculating Prediction Intervals

The regression equation gives us the point estimate of the outcome variable for a given value of the independent variable. In many applications, we would be interested in knowing the interval estimate of Yi for a given value of explanatory variable. wls_prediction_std() returns the prediction interval while making a prediction. It takes significance value (a) to calculate the interval. An a-value of 0.1 returns the prediction at confidence interval of 90%. The code for calculating prediction interval is as follows:

In [54]:
```
from statsmodels.sandbox.regression.predstd import wls_prediction_std

# Predict the y values
pred_y = mba_salary_lm.predict( test_X )

# Predict the low and high interval values for y
_, pred_y_low, pred_y_high = wls_prediction_std( mba_salary_lm, test_X, alpha = 0.1)

# Store all the values in a dataframe
pred_y_df = pd.DataFrame( { "grade_10_perc": test_X["Percentage in Grade 10"], "pred_y": pre
d_y, "pred_y_left": pred_y_low, "pred_y_right": pred_y_high } )
```

In [55]:
```
pred_y_df[0:10]
```

Out[55]:

	grade_10_perc	pred_y	pred_y_left	pred_y_right
6	70.0	279828.402452	158379.832044	401276.972860
36	68.0	272707.227686	151576.715020	393837.740352
37	52.0	215737.829560	92950.942395	338524.716726
28	58.0	237101.353858	115806.869618	358395.838097
43	74.5	295851.045675	173266.083342	418436.008008
49	60.8	247070.998530	126117.560983	368024.436076
5	55.0	226419.591709	104507.444388	348331.739030
33	78.0	308313.101515	184450.060488	432176.142542
20	63.0	254904.290772	134057.999258	375750.582286
42	74.4	295494.986937	172941.528691	418048.445182

In [ ]: