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# Task : To predict the Dissolved Oygen using Linear Regression Model
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```
# importing necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import random as rnd
from sklearn import datasets
from sklearn import linear_model
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import RFE
```

```
# Read the data from csv file
df=pd.read_csv('Raw data.csv')
```

```
# printing the first five entries of a given dataset
df.head()
```

| | Time | Devicename | Temperature | TDS | PH | DO |
|---|---|---|---|---|---|---|
| 0 | Wed Jul 07 2021 14:15:09 GMT+0530 (India Stand... | 867378035207325 | 29.0625 | 0.0 | 13.61598 | 9.91 |
| 1 | Wed Jul 07 2021 14:16:14 GMT+0530 (India Stand... | 867378035207325 | 29.0625 | 0.0 | 13.12313 | 9.90 |
| 2 | Wed Jul 07 2021 14:17:18 GMT+0530 (India Stand... | 867378035207325 | 29.0000 | 0.0 | 13.55723 | 9.90 |
| | T+0530 | 867378035207325 | 29.0625 | 0.0 | 14.00000 | 9.90 |

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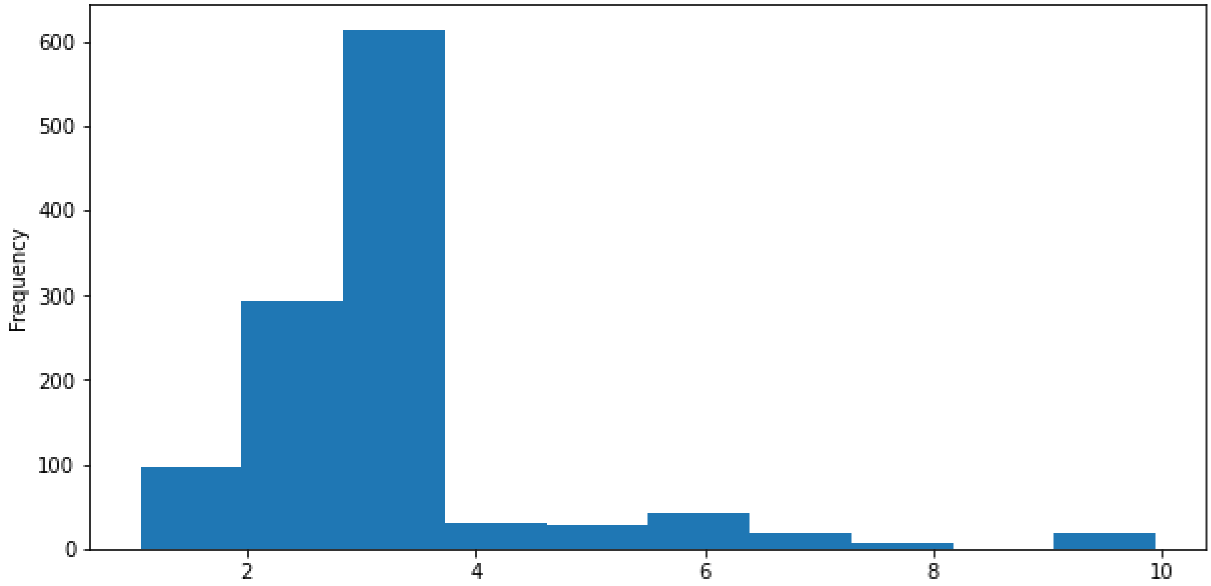
```
#Define the target y and non-target,learning variables[x] then removing non-numeric fields ['
df = df.drop(['Time','Devicename'],axis=1)
x = df.drop("DO",axis=1)
y = df["DO"]
df.head()
```

| | Temperature | TDS | PH | DO |
|---|---|---|---|---|
| 0 | 29.0625 | 0.0 | 13.61598 | 9.91 |
| 1 | 29.0625 | 0.0 | 13.12313 | 9.90 |
| 2 | 29.0000 | 0.0 | 13.55723 | 9.90 |
| 3 | 29.0625 | 0.0 | 14.00000 | 9.90 |
| 4 | 29.0625 | 0.0 | 14.00000 | 9.90 |

```
# Plot histogram of target/dependant variable (DO) to see distribution
plt.figure(figsize=(10,5))
df['DO'].plot(kind="hist")
```

```
<AxesSubplot:ylabel='Frequency'>
```



```
# Using Pearson Correlation {corr() function} plot all correlations (positive (0.5-1.0) and n
plt.figure(figsize=(9,8))
cor=df.corr()
sns.heatmap(cor,annot=True)
```

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<AxesSubplot:>
```

```
# Identifying positive correlation with target variable i.e., DO
target_corr=abs(cor["DO"])# DO is a target variable
positive_corr_target=target_corr[target_corr>(0.5)]
positive_corr_target
```

```
Temperature    0.669232
PH             0.702880
DO             1.000000
Name: DO, dtype: float64
```

```
# Detremining correlation between these fields Temperature and PH
print(df[["Temperature","PH"]].corr())
```

```
             Temperature        PH
Temperature     1.000000  0.650587
PH              0.650587  1.000000
```

```
# Drop unneceassary columns (TDS low correlation) and keep PH, DO and Temperature
df=df.drop(["TDS"],axis=1)
df.head()
```

|   | **Temperature** | **PH** | **DO** |
|---|---|---|---|
| **0** | 29.0625 | 13.61598 | 9.91 |
| **1** | 29.0625 | 13.12313 | 9.90 |
| **2** | 29.0000 | 13.55723 | 9.90 |
| **4** | 29.0625 | 14.00000 | 9.90 |

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```
#Create test and train variables using test_train_split from sklearn library
x_train,x_test,y_train,y_test=train_test_split(df,y,test_size=0.25)#test size is 25% of data
print(x_train.shape,y_train.shape)#862 members in test
print(x_test.shape,y_test.shape)#288 members in test
```

```
(862, 3) (862,)
(288, 3) (288,)
```

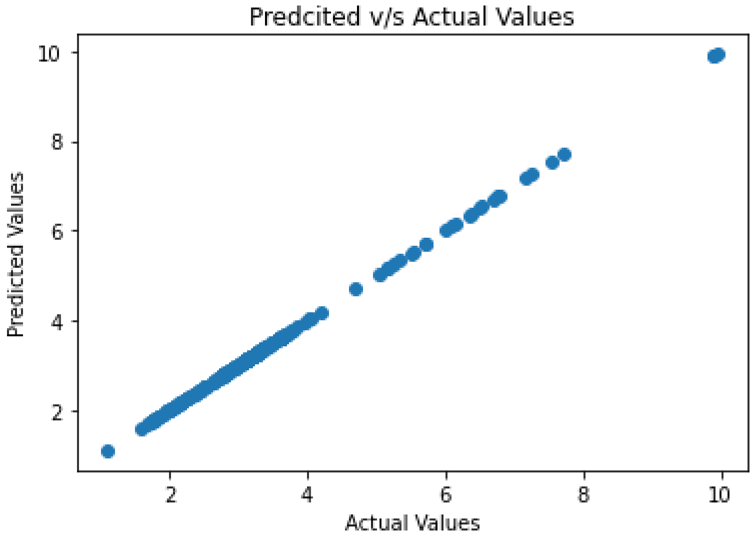
```
#Fitting the Linear Regression model - as all columns are numeric
lrm=linear_model.LinearRegression()
lrm_model=lrm.fit(x_train,y_train)
lrm_predictions=lrm.predict(x_test)
```

```
lrm_predictions[0:10]
```

```
array([2.65, 1.73, 2.27, 2.04, 3.78, 6.1 , 3.37, 3.24, 1.67, 3.31])
```

```
#Plot the predictions with a scatter plot
plt.scatter(y_test,lrm_predictions)
plt.title("Predcited v/s Actual Values")
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
```

```
Text(0, 0.5, 'Predicted Values')
```



```
print('Score:',lrm_model.score(x_test,y_test))
```

```
Score: 1.0
```

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```
dictors (non-dependant variables) into a single dataframe
df2['DO Actuals']=y_test
df2['DO Predictions']=lrm_predictions
```

```
df2.head()
```

| | Temperature | PH | DO | DO Actuals | DO Predictions |
|---|---|---|---|---|---|
| **202** | 25.8125 | 5.377826 | 2.65 | 2.65 | 2.65 |
| **812** | 26.1250 | 5.325606 | 1.73 | 1.73 | 1.73 |
| **221** | 25.8125 | 5.270116 | 2.27 | 2.27 | 2.27 |
| **805** | 26.1875 | 5.260324 | 2.04 | 2.04 | 2.04 |
| **966** | 25.0625 | 5.416993 | 3.78 | 3.78 | 3.78 |

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