COURSE LABORATORY MANUAL

1. EXPERIMENT NO: 10

2. TITLE: **LOCALLY WEIGHTED REGRESSION ALGORITHM**

3. LEARNING OBJECTIVES:

- Make use of Data sets in implementing the machine learning algorithms.
- Implement ML concepts and algorithms in Python

4. AIM:

- Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

5. THEORY:

- Given a dataset X, y, we attempt to find a linear model h(x) that minimizes residual sum of squared errors. The solution is given by Normal equations.
- Linear model can only fit a straight line, however, it can be empowered by polynomial features to get more powerful models. Still, we have to decide and fix the number and types of features ahead.
- Alternate approach is given by locally weighted regression.
- Given a dataset X, y, we attempt to find a model h(x) that minimizes residual sum of weighted squared errors.
- The weights are given by a kernel function which can be chosen arbitrarily and in my case I chose a Gaussian kernel.
- The solution is very similar to Normal equations, we only need to insert diagonal weight matrix W.

Algorithm

```
def local_regression(x0, X, Y, tau):
    # add bias term
    x0 = np.r_[1, x0]
    X = np.c_[np.ones(len(X)), X]

    # fit model: normal equations with kernel
    xw = X.T * radial_kernel(x0, X, tau)
    beta = np.linalg.pinv(xw @ X) @ xw @ Y

    # predict value
    return x0 @ beta
def radial_kernel(x0, X, tau):
    return np.exp(np.sum((X - x0) ** 2, axis=1) / (-2 * tau * tau))
```

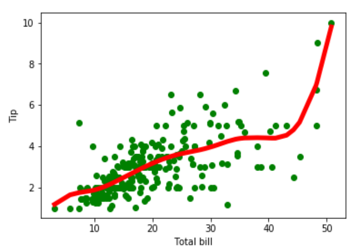
6. PROCEDURE / PROGRAMME :

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

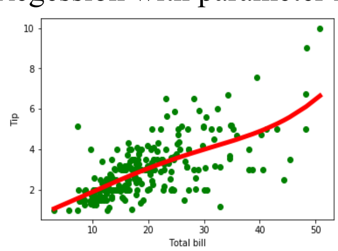
```
def kernel(point,xmat, k):
    m,n = np.shape(xmat)
    weights = np.mat(np.eye((m))) # eye - identity matrix
    for j in range(m):
        diff = point - X[j]
        weights[j,j] = np.exp(diff*diff.T/(-2.0*k**2))
    return weights

def localWeight(point,xmat,ymat,k):
    wei = kernel(point,xmat,k)
    W = (X.T*(wei*X)).I*(X.T*(wei*ymat.T))
    return W

def localWeightRegression(xmat,ymat,k):
    m,n = np.shape(xmat)
    ypred = np.zeros(m)
    for i in range(m):
        ypred[i] = xmat[i]*localWeight(xmat[i],xmat,ymat,k)
    return ypred

def graphPlot(X,ypred):
    sortindex = X[:,1].argsort(0) #argsort - index of the smallest
    xsort = X[sortindex][:,0]
    fig = plt.figure()
    ax = fig.add_subplot(1,1,1)
    ax.scatter(bill,tip, color='green')
    ax.plot(xsort[:,1],ypred[sortindex], color = 'red', linewidth=5)
    plt.xlabel('Total bill')
    plt.ylabel('Tip')
    plt.show();

# load data points
data = pd.read_csv('data10_tips.csv')
bill = np.array(data.total_bill) # We use only Bill amount and Tips data
tip  = np.array(data.tip)

mbill = np.mat(bill) # .mat will convert nd array is converted in 2D array
mtip = np.mat(tip)
m= np.shape(mbill)[1]
one = np.mat(np.ones(m))
X = np.hstack((one.T,mbill.T)) # 244 rows, 2 cols

# increase k to get smooth curves
ypred = localWeightRegression(X,mtip,3)
graphPlot(X,ypred)
```

7. RESULTS & CONCLUSIONS:

Regession with parameter k = 3



Regession with parameter k = 9



8. LEARNING OUTCOMES :

- To understand and implement linear regression and analyse the results with change in the parameters

9. APPLICATION AREAS:

- Demand anaysis in business
- Optimization of business processes
- Forecasting

10. REMARKS: