INF283 | Weekly Exercise 02 | Regression

Table of Contents:

1. Univariate Linear Regression

Linear Regression with Gradient Descent

In [1]:

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

Finding the mean squared error (MSE)

In [2]:

```
# We are now going to define a function which takes the parameters (w0 and w1) of
# a line and then finds the mean-squared error between the user-specified points
# and the line.
def compute_error_for_line_given_points(w0, w1, points):
    totalError = 0
    for i in range(0, len(points)):
        x = points[i, 0]
        y = points[i, 1]
        # accumulate 'sum of square' errors in totalError variable
        totalError += (y - (w1 * x + w0)) ** 2
    # find mean of sum of squared errors
    mse = totalError/len(points)
    return mse

# N.B.: Students who wish to do this excercise in R should implement this function in R
 themselves
```

Gradient Descent

In [3]:

```
def step_gradient(w0_current, w1_current, points, learningRate):
    #initialize the partial derivatives for the cummlative sum
    w0_par_der = 0
    w1_par_der = 0

    n = len(points)

    # computation for the summation
    for i in range(0, len(points)):
        x = points[i, 0]
        y = points[i, 1]
        # partial derivative (of MSE) with respect to w0
        w0_par_der += (y - ((w1_current * x) + w0_current))
        # partial derivative (of MSE) with respect to w1
        w1_par_der += x * (y - ((w1_current * x) + w0_current))

    # multiplcation of summation results with -2/n
    w0_par_der = -(2/n) * w0_par_der
        # partial derivative (of MSE) with respect to w1
    w1_par_der = -(2/n) * w1_par_der

    # make a gradient vector from the partial derivatives
    gradient_mse = np.array([w0_par_der, w1_par_der])

    # make a vector of weights
    weight_vector = np.array([w0_current, w1_current])

    # update rule for weights
    updated_weight_vector = weight_vector - (learningRate * gradient_mse)

    # return the updated weight vector as a list
    return np.ndarray.tolist(updated_weight_vector)

# N.B. Students who wish to do this excercise in R should implement this function in R
 themselves
```

Running Gradient Descent Iteratively

In [4]:

```
def gradient_descent_runner(points, starting_w0, starting_w1, learning_rate, num_iterat
ions):
    w0 = starting_w0
    w1 = starting_w1
    for i in range(num_iterations):
        w0, w1 = step_gradient(w0, w1, points, learning_rate)
        mse = compute_error_for_line_given_points(w0, w1, points)
        print(f'Iteration {i+1}: w0={w0:0.5f}, w1={w1:0.5f}, mse={mse:0.5f}')
    return [w0, w1, mse]
# N.B.: Students who wish to do this exercise in R should implement this function in R
 themselves
```

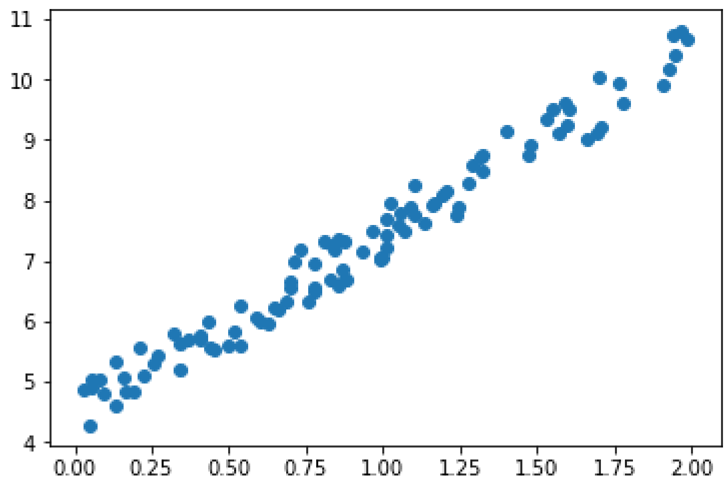
Bringing it all together

In [5]:

```
np.random.seed(2)

# generate 100 x values from 0 to 2 randomly, then sort them in ascending order
X = 2 * np.random.rand(100, 1)
X.sort(axis=0)

# generate y values and add noise to it
y = 4 + 3 * X + np.random.rand(100, 1)

# let us plot the data
plt.scatter(X, y)
```

Out[5]:

```
<matplotlib.collections.PathCollection at 0x269541d7fd0>
```



In [8]:

```
# combine the x and y values into a single array called points
points = np.column_stack((X, y))

num_iterations = 100
learning_rate = 0.1
initial_w0 = 0 # initial y-intercept guess
initial_w1 = 0 # initial slope guess
early_stop = 0.00064
[w0, w1, mse] = gradient_descent_runner_early_stop(points, initial_w0, initial_w1, lear
ning_rate, num_iterations, early_stop)
```

```
Iteration 1: w0=1.44691, w1=1.50194, mse=20.14308
Iteration 2: w0=2.32806, w1=2.39849, mse=7.47831
Iteration 3: w0=2.86801, w1=2.93046, mse=2.87255
Iteration 4: w0=3.20208, w1=3.24295, mse=1.19394
Iteration 5: w0=3.41183, w1=3.42341, mse=0.57873
Iteration 6: w0=3.54643, w1=3.52453, mse=0.35003
Iteration 7: w0=3.63550, w1=3.57805, mse=0.26199
Iteration 8: w0=3.69691, w1=3.60309, mse=0.22532
Iteration 9: w0=3.74143, w1=3.61118, mse=0.20757
Iteration 10: w0=3.77555, w1=3.60925, mse=0.19693
Iteration 11: w0=3.80321, w1=3.60148, mse=0.18912
Iteration 12: w0=3.82676, w1=3.59037, mse=0.18255
Iteration 13: w0=3.84765, w1=3.57743, mse=0.17664
Iteration 14: w0=3.86674, w1=3.56358, mse=0.17117
Iteration 15: w0=3.88456, w1=3.54934, mse=0.16604
Iteration 16: w0=3.90144, w1=3.53503, mse=0.16122
Iteration 17: w0=3.91758, w1=3.52085, mse=0.15667
Iteration 18: w0=3.93309, w1=3.50690, mse=0.15238
Iteration 19: w0=3.94807, w1=3.49325, mse=0.14833
Iteration 20: w0=3.96257, w1=3.47992, mse=0.14451
Iteration 21: w0=3.97662, w1=3.46694, mse=0.14090
Iteration 22: w0=3.99025, w1=3.45430, mse=0.13750
Iteration 23: w0=4.00348, w1=3.44201, mse=0.13428
Iteration 24: w0=4.01632, w1=3.43005, mse=0.13125
Iteration 25: w0=4.02880, w1=3.41844, mse=0.12838
Iteration 26: w0=4.04092, w1=3.40715, mse=0.12568
Iteration 27: w0=4.05269, w1=3.39618, mse=0.12313
Iteration 28: w0=4.06412, w1=3.38552, mse=0.12072
Iteration 29: w0=4.07523, w1=3.37516, mse=0.11844
Iteration 30: w0=4.08603, w1=3.36510, mse=0.11630
Iteration 31: w0=4.09651, w1=3.35533, mse=0.11427
Iteration 32: w0=4.10670, w1=3.34583, mse=0.11236
Iteration 33: w0=4.11660, w1=3.33660, mse=0.11055
Iteration 34: w0=4.12622, w1=3.32763, mse=0.10885
Iteration 35: w0=4.13556, w1=3.31892, mse=0.10724
Iteration 36: w0=4.14464, w1=3.31046, mse=0.10572
Iteration 37: w0=4.15346, w1=3.30223, mse=0.10429
Iteration 38: w0=4.16203, w1=3.29424, mse=0.10293
Iteration 39: w0=4.17035, w1=3.28648, mse=0.10166
Iteration 40: w0=4.17844, w1=3.27894, mse=0.10045
Iteration 41: w0=4.18630, w1=3.27162, mse=0.09931
Iteration 42: w0=4.19393, w1=3.26450, mse=0.09824
Iteration 43: w0=4.20135, w1=3.25758, mse=0.09722
Iteration 44: w0=4.20856, w1=3.25086, mse=0.09627
Iteration 45: w0=4.21556, w1=3.24433, mse=0.09536
Iteration 46: w0=4.22236, w1=3.23799, mse=0.09451
Iteration 47: w0=4.22897, w1=3.23183, mse=0.09371
Iteration 48: w0=4.23539, w1=3.22584, mse=0.09295
Iteration 49: w0=4.24163, w1=3.22002, mse=0.09223
Iteration 50: w0=4.24769, w1=3.21437, mse=0.09155
```

Exercise 1.1

In [7]:

```
# TODO:
# Paste your code below for the modified gradient_descent_runner_early_stop function
def gradient_descent_runner_early_stop(points, starting_w0, starting_w1, learning_rate,
 num_iterations, early_stop):
    w0 = starting_w0
    w1 = starting_w1
    mse_t0 = 1e4 # Set to a high number for case 0
    for i in range(num_iterations):
        w0, w1 = step_gradient(w0, w1, points, learning_rate)
        mse_t1 = compute_error_for_line_given_points(w0, w1, points)
        if(mse_t0 - mse_t1 < early_stop):
            break;
        else:
            print(f'Iteration {i+1}: w0={w0:0.5f}, w1={w1:0.5f}, mse={mse_t1:0.5f}')
            mse_t0 = mse_t1
    return [w0, w1, mse_t0]
# N.B.: Students who wish to do this exercise in R should implement this function in R
 themselves
```

Exercise 1.2

In the program above we had set the learning rate to 0.1. Using the original `gradient_descent_runner` function, first set the number of iterations to 100. Then try to run the code with two different values of learning rates:

1. a learning rate of 0.001
2. a learning rate of 1

Explain what you observe.

In [9]:

```
%%capture
num_iterations = 100
learning_rate = [1, 1e-3]
initial_w0 = 0 # initial y-intercept guess
initial_w1 = 0 # initial slope guess
for lr in learning_rate:
    print("--------------------" + "\n" + "Learning rate: " + str(lr))
    [w0, w1, mse] = gradient_descent_runner(points, initial_w0, initial_w1, lr, num_ite
rations)
```

TODO

> When learning rate is set to 1 the mse (drastically) increases. </br> When learning rate is set to 0.001 the mse decreases, however it decreases slowly. </br> Conclusion: Learning rate = 1 is too high, while learning rate = 0.001 is too low.

Exercise 1.3

In [10]:

```
# TODO
# Write your solution here
shape = X.shape
obj_type = X.dtype
ones = np.ones((shape), obj_type)
X_ones = np.hstack((X, ones))
```

In [11]:

```
X_trans = X_ones.T
```

In [12]:

```
X_trans_times_X = X_trans.dot(X_ones)
```

In [13]:

```
from numpy.linalg import inv
```

In [14]:

```
X_T_times_X__inv = inv(X_trans_times_X)
```

In [15]:

```
w_hat = ((X_T_times_X__inv.dot(X_trans)).dot(y))
```

In [16]:

```
w_hat
```

Out[16]:

```
array([[3.02129039],
       [4.45478709]])
```

It seems like the values are more or less the same, so both methods obviously work.

Exercise 1.4

To brush up your calculus skills, derive the partial derivate of MSE that has *L2* penalty term included in it. In other words, we want you compute the following partial derivatives:

$$\frac{\partial}{\partial w_0}\left(\frac{1}{n}\sum_{i=1}^{n}[y_i - (w_1 x_i + w_0)]^2 + \lambda {w_0}^2\right)$$

$$\frac{\partial}{\partial w_1}\left(\frac{1}{n}\sum_{i=1}^{n}[y_i - (w_1 x_i + w_0)]^2 + \lambda {w_1}^2\right)$$

What to submit ¶

A derivation of both the gradient equations.

$$\frac{\partial}{\partial w_0}\left(\frac{1}{n}\sum_{i=1}^{n}[y_i - (w_1 x_i + w_0)]^2 + \lambda \cdot {w_0}^2\right) = \underline{-\frac{2}{n}\left(\sum_{i=1}^{n} y_i - (w_1 x_i + w_0) + 2\lambda w_0\right)}$$

$$\frac{\partial}{\partial w_1}\left(\frac{1}{n}\sum_{i=1}^{n}[y_i - (w_1 x_i + w_0)]^2 + \lambda \cdot {w_1}^2\right) = \underline{-\frac{2}{n}\left(\sum_{i=1}^{n} y_i - (w_1 x_i + w_0) + 2\lambda w_1\right)}$$

Linear Regression with *sklearn* Machine Learning Library

In [17]:

```
# import LinearRegression class from sklearn.linear_model module
from sklearn.linear_model import LinearRegression

# make a lin_reg object form the LinearRegression class
lin_reg = LinearRegression()

# use the fit method of LinearRegression class to fit a straight line through the data
lin_reg.fit(X, y)
```

Out[17]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=Fals
e)
```

In [18]:

```
print('slope w1:', lin_reg.coef_)
print('y-intercept w0:', lin_reg.intercept_)
```

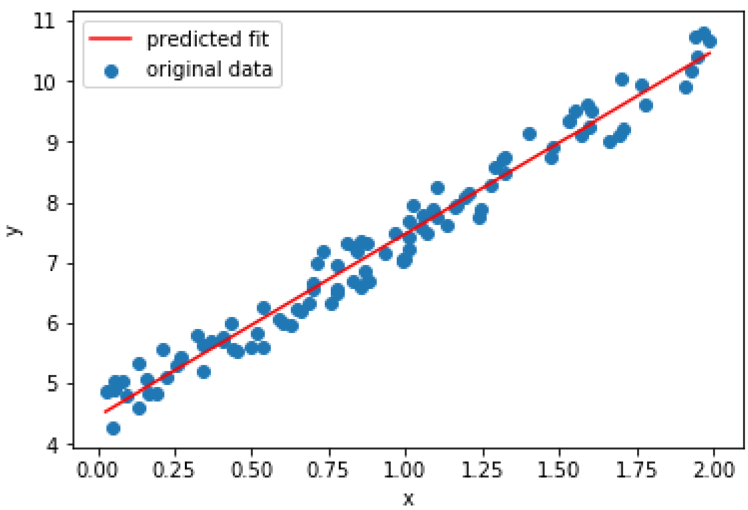
```
slope w1: [[3.02129039]]
y-intercept w0: [4.45478709]
```

In [19]:

```
# plot the original data points as a scatter plot
plt.scatter(X, y, label='original data')

# plot the line that fits these points. Use the values of m and b as provided by the fi
t method
y_ = lin_reg.coef_*X + lin_reg.intercept_

# you can also get y_ by using the predict method. Uncomment the line below:
#y_ = lin_reg.predict(X)

plt.plot(X, y_, color='r', label='predicted fit')
plt.xlabel('x'); plt.ylabel('y')
plt.legend(loc='best')
```

Out[19]:

```
<matplotlib.legend.Legend at 0x26955ba9630>
```



Exercise 1.5

1. The *fit* method from the **sklearn library** seems to give more or less the same values for *b* and *m* as "my" implementation of the **Normal Equation**

In [20]:

```
# Answer to 2.
test_data_point = 3
pred_value = float(lin_reg.predict(test_data_point))
actual_value = 4 + 3*test_data_point
print("Predicted value: " + str(pred_value) + '\n' + "Actual value: " + str(actual_valu
e))
```

```
Predicted value: 13.518658256328946
Actual value: 13
```

Pretty fair prediction

2. Multivariate Linear Regression

In [21]:

```
# make a dataframe of the data
df = pd.read_csv('movies.csv')

# show first five rows of df
df.head(n=5)
```

Out[21]:

	revenue	production_cost	promotional_cost	book_sales
0	85.099998	8.5	5.100000	4.7
1	106.300003	12.9	5.800000	8.8
2	50.200001	5.2	2.100000	15.1
3	130.600006	10.7	8.399999	12.2
4	54.799999	3.1	2.900000	10.6

In [22]:

```
# Extract the first column and set it to the output or dependent varaible y
y = df[['revenue']]

# Remove the first column and set the rest of the dataframe to X. This is the set of in
depedent variables
X = df.drop(columns=['revenue'])

# show first five rows of X
X.head(n=5)
```

Out[22]:

	production_cost	promotional_cost	book_sales
0	8.5	5.100000	4.7
1	12.9	5.800000	8.8
2	5.2	2.100000	15.1
3	10.7	8.399999	12.2
4	3.1	2.900000	10.6

In [23]:

```
# show first five rows of y
y.head(n=5)
```

Out[23]:

	revenue
0	85.099998
1	106.300003
2	50.200001
3	130.600006
4	54.799999

In [24]:

```
from sklearn.linear_model import LinearRegression

# make a lin_reg object form the LinearRegression class
lin_reg = LinearRegression()

# use the fit method of LinearRegression class to fit a straight line through the data
lin_reg.fit(X, y)

# Display the learned parameters
lin_reg.intercept_, lin_reg.coef_
```

Out[24]:

```
(array([7.67602854]), array([[3.66160401, 7.62105126, 0.82846807]]))
```

Exercise 2.1

In [25]:

```
## TODO
## Write your code here
prod_c = 23
prom_c = 12
book_s = 10
X_test = np.array([prod_c, prom_c, book_s]).reshape(1, -1)
lin_reg.predict(X_test)
```

Out[25]:

```
array([[191.6302165]])
```

Multivariate Regression with Polynomial basis

In [26]:

```
# define the number of points to generate as k
k = 100

# define a seed value. It is important to define the seed value
# so that the random numbers generated are the same every time
# this code is executed.
np.random.seed(10)

# generate k x-axis values from -3 to +3
X = 6 * np.random.rand(k, 1) - 3

# sort the numbers in ascending order. This helps when we are plotting the data.
# Without this line, your plots will be all jumbled up
X.sort(axis=0)

# generate k y-axis values
y = 0.5 * X**2 + X + 2 + np.random.rand(k, 1)
```

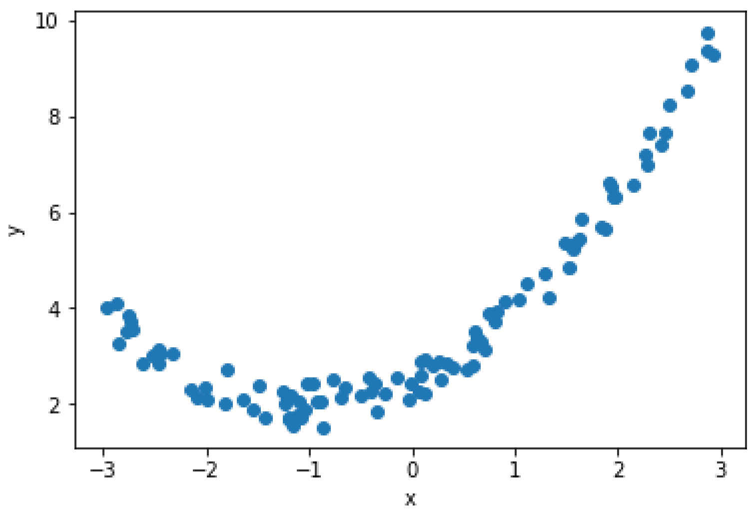
Let us now plot the data:

In [27]:

```
plt.scatter(X, y)
plt.xlabel('x'); plt.ylabel('y')
```

Out[27]:

```
Text(0,0.5,'y')
```



In [28]:

```
from sklearn.preprocessing import PolynomialFeatures

poly_features = PolynomialFeatures(degree=15, include_bias=False)

# generate polyonimal features upto degree 2 from the vector X
X_poly = poly_features.fit_transform(X)
```

In [29]:

```
# display 4 original data points
X[1:5]
```

Out[29]:

```
array([[-2.8754883 ],
       [-2.84760131],
       [-2.7643094 ],
       [-2.76024475]])
```

In [30]:

```
# Display the transformed data.
# You will now see the original X data alongside its corresponding 2nd-degree polynomia
l feature
X_poly[1:5]
```

Out[30]:

```
array([[-2.87548830e+00,  8.26843299e+00, -2.37757823e+01,
         6.83669840e+01, -1.96588463e+02,  5.65287826e+02,
        -1.62547853e+03,  4.67404451e+03, -1.34401603e+04,
         3.86470238e+04, -1.11129065e+05,  3.19550326e+05,
        -9.18863225e+05,  2.64218046e+06, -7.59755900e+06],
       [-2.84760131e+00,  8.10883321e+00, -2.30907240e+01,
         6.57531760e+01, -1.87238830e+02,  5.33181537e+02,
        -1.51828844e+03,  4.32348015e+03, -1.23115477e+04,
         3.50583794e+04, -9.98322871e+04,  2.84282551e+05,
        -8.09523365e+05,  2.30519979e+06, -6.56428994e+06],
       [-2.76430940e+00,  7.64140644e+00, -2.11232116e+01,
         5.83910924e+01, -1.61411045e+02,  4.46190069e+02,
        -1.23340740e+03,  3.40951967e+03, -9.42496726e+03,
         2.60535256e+04, -7.20200055e+04,  1.99085578e+05,
        -5.50334134e+05,  1.52129382e+06, -4.20532680e+06],
       [-2.76024475e+00,  7.61895107e+00, -2.10301697e+01,
         5.80484154e+01, -1.60227834e+02,  4.42268036e+02,
        -1.22076802e+03,  3.36961853e+03, -9.30097184e+03,
         2.56729587e+04, -7.08636494e+04,  1.95601016e+05,
        -5.39906677e+05,  1.49027457e+06, -4.11352255e+06]])
```

In [31]:

```
lin_reg = LinearRegression()

# Now we fit a linear model to the X_poly (the transformed features set) and y
lin_reg.fit(X_poly, y)

# show the values of intercept and learned co-efficients
lin_reg.intercept_, lin_reg.coef_
```

Out[31]:

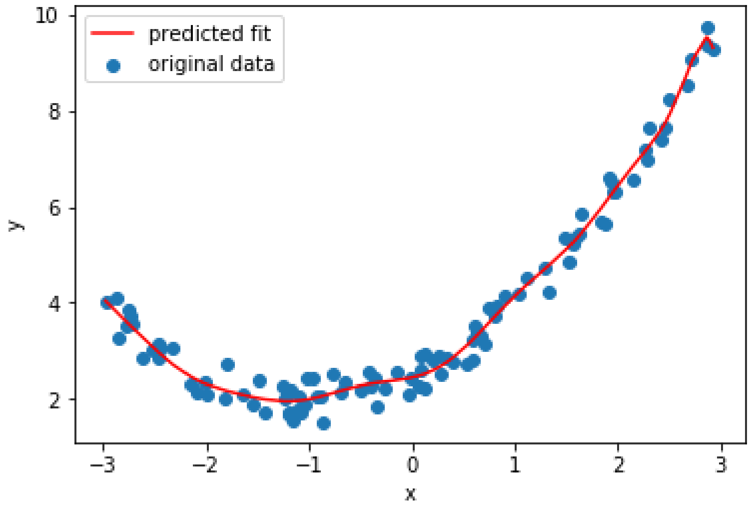
```
(array([2.43771889]),
 array([[ 4.70240062e-01,  9.81483416e-01,  1.45901724e+00,
         -5.43920910e-01, -1.30913386e+00,  2.30186856e-01,
          5.62777734e-01, -4.49943278e-02, -1.28760085e-01,
          3.53201168e-03,  1.58848833e-02,  1.15315775e-05,
         -9.84782281e-04, -1.01041607e-05,  2.36325364e-05]]))
```

In [32]:

```
y_ = lin_reg.predict(X_poly)

plt.scatter(X, y, label='original data')
plt.plot(X, y_, color='r', label='predicted fit')
plt.legend(loc='best')

plt.xlabel('x')
plt.ylabel('y')
```

Out[32]:

```
Text(0,0.5,'y')
```



Regularization with Ridge Penalty

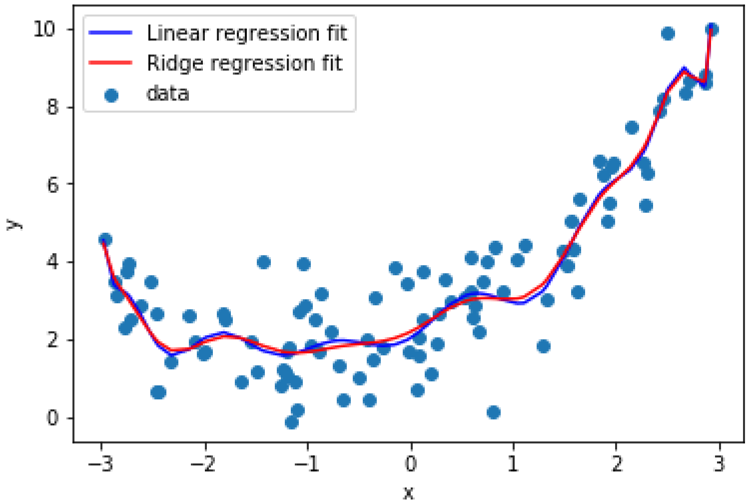
In [33]:

```
from sklearn.linear_model import Ridge
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures

# define the number of points to generate
k = 100
np.random.seed(10)

# generate k x-axis values from -3 to +3
X = 6 * np.random.rand(k, 1) - 3
X.sort(axis=0)

# generate k y-axis values
y = 0.5 * X**2 + X + 2 + np.random.randn(k, 1)

# Create polynomial feature (degree 15)
poly_features = PolynomialFeatures(degree=15, include_bias=False)
X_poly = poly_features.fit_transform(X)

# Create Ridge regression object from Ridge class
ridge_reg = Ridge(alpha=5e-2)
# Fit data using Ridge regression
ridge_reg.fit(X_poly, y)

# Create Linear regression object from LinearRegress class (this is just for compariso
n)
lin_reg = LinearRegression()
# Fit data using Linear regression
lin_reg.fit(X_poly, y)

y_predict_ridge = ridge_reg.predict(X_poly)
y_predict_linear = lin_reg.predict(X_poly)

plt.scatter(X, y, label='data')
plt.plot(X, y_predict_linear, color='b', label='Linear regression fit')
plt.plot(X, y_predict_ridge, color='r', label='Ridge regression fit')

plt.xlabel('x')
plt.ylabel('y')

plt.legend(loc='best')
```

```
C:\Users\Sindr\Anaconda3\lib\site-packages\sklearn\linear_model\ridge.py:1
12: LinAlgWarning: scipy.linalg.solve
Ill-conditioned matrix detected. Result is not guaranteed to be accurate.
Reciprocal condition number9.211483e-17
  overwrite_a=True).T
```

Out[33]:

```
<matplotlib.legend.Legend at 0x26955f7d898>
```



Exercise 2.2

TODO

> Observing that when changing(/decreasing) the **regularization parameter** the model starts overfitting

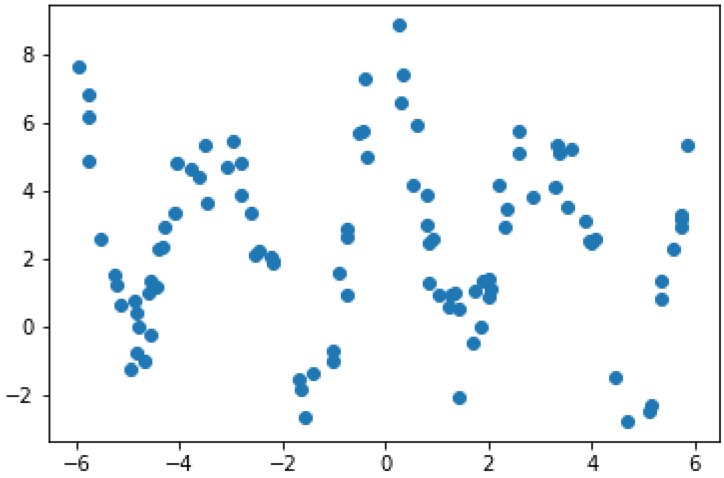
Linear Regression with Radial Basis Functions

In [34]:

```
# Set random seed
np.random.seed(0)
m = 100

# Create random set of m x values between -6 and +6
X = np.random.rand(m, 1)*12 - 6
X.sort(axis =0)

# Create a non-linear dataset with random noise
y = 0.5*np.cos(X) + np.sin(X) + 4*np.cos(2*X) + np.exp(np.cos(3*X)) + 3*np.random.rand(
m,1)

# plot it
plt.scatter(X, y)
```

Out[34]:

```
<matplotlib.collections.PathCollection at 0x26955fe5fd0>
```

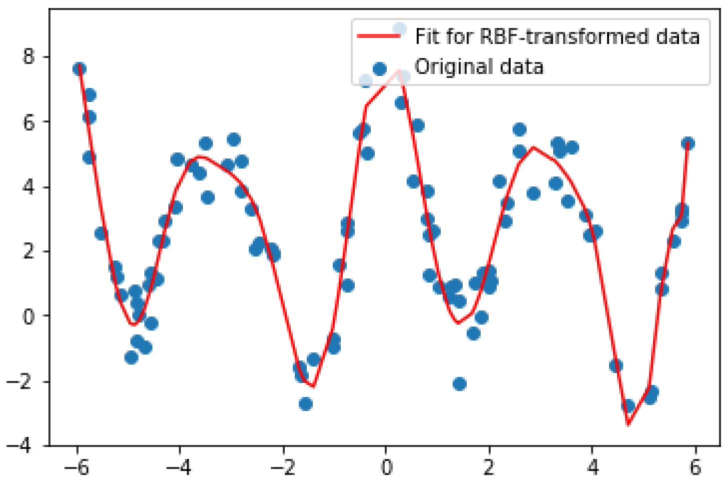


In [35]:

```
from sklearn.metrics.pairwise import rbf_kernel
from sklearn.linear_model import LinearRegression

# find the transformation of X using Radial Basis Functions
# Each point in X is now modeled as vector of 100 values.
# See the X_RBF.shape and X_RBF to find how rbf_kernel transformed
# the original datapoints
X_RBF = rbf_kernel(X, X, gamma=0.1)

# Fit a linear regression model to the RBF-transformed data
clf = LinearRegression()
clf.fit(X_RBF, y)

# find the predicted values
y_= clf.predict(X_RBF)

# plot original data and predicted fit
plt.scatter(X, y, label='Original data')
plt.plot(X, y_, color='r', label='Fit for RBF-transformed data')
plt.legend(loc='best')
```

Out[35]:

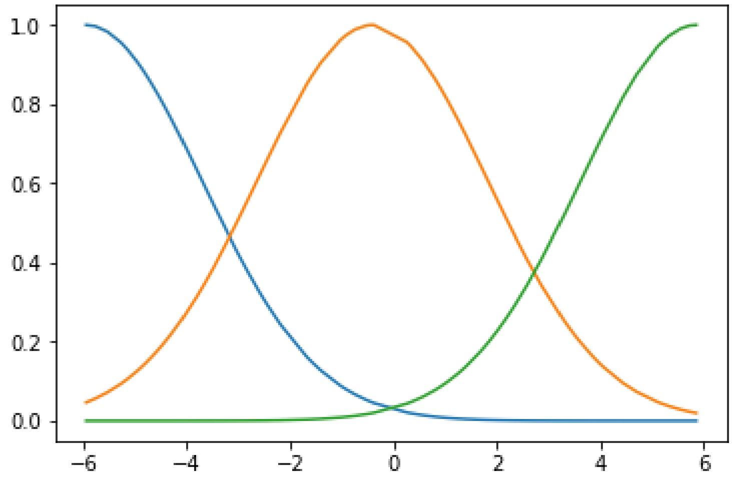
```
<matplotlib.legend.Legend at 0x26958529048>
```



Exercise 2.3

In [36]:

```
# TODO
# Paste your solution here
X_RBF_0th = X_RBF[0]
X_RBF_49th = X_RBF[49]
X_RBF_99th = X_RBF[99]
ans = np.array([X_RBF_0th, X_RBF_49th, X_RBF_99th])

plt.plot(X, ans.T)
plt.show()
```



3. Logistic Regression

In [37]:

```
from sklearn import datasets
iris = datasets.load_iris()

# iris is a dictionary of key-value pairs. Each key-value pairs contains some informati
on about the dataset.
# Lets display a list of these keys and see what they hold
list(iris.keys())
```

Out[37]:

```
['data', 'target', 'target_names', 'DESCR', 'feature_names']
```

In [38]:

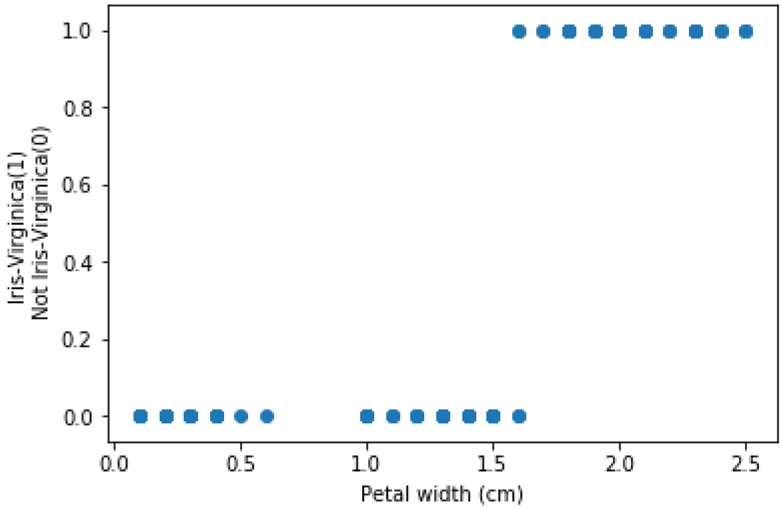
```
# Let us get the petal width. It is present in the 4th column of data
X = iris["data"][:, 3:]
X.sort(axis=0)

# Lets define a binaray variable that encodes whether a flower is Iris-Virginca or not
# Iris_virginca flower is encoded as a 2 in target
y = (iris["target"] == 2).astype(np.int) # 1 if Iris-Virginica, else 0
```

In [39]:

```
plt.scatter(X, y)
plt.xlabel('Petal width (cm)')
plt.ylabel('Iris-Virginica(1) \n Not Iris-Virginica(0)')
```

Out[39]:

```
Text(0,0.5,'Iris-Virginica(1) \n Not Iris-Virginica(0)')
```

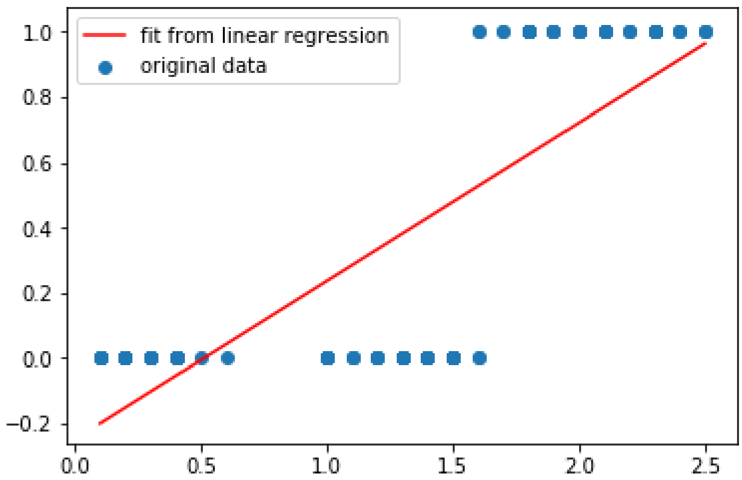


In [40]:

```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(X, y)
y_ = lin_reg.predict(X)

plt.scatter(X, y, label='original data')
plt.plot(X, y_, color='r', label='fit from linear regression')
plt.legend(loc='best')
```

Out[40]:

```
<matplotlib.legend.Legend at 0x26958593c18>
```



In [41]:

```
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression()
log_reg.fit(X, y)
```

Out[41]:

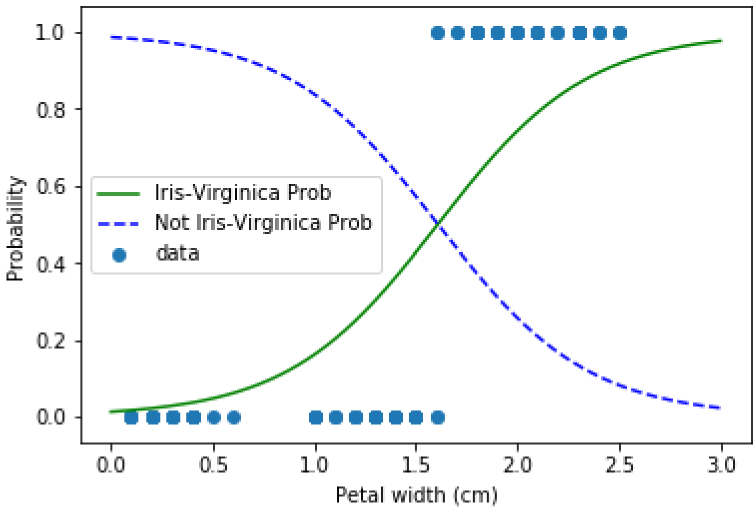
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=Tru
e,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

In [42]:

```
# we generate X_new which is vector of closely spaced points form 0 to 3
# This vector will help us plot the model
X_new = np.linspace(0, 3, 1000).reshape(-1, 1)

# make a vector of prediction probablity values for all datapoints in X_new
y_proba = log_reg.predict_proba(X_new)

plt.plot(X_new, y_proba[:, 1], "g-", label="Iris-Virginica Prob")
plt.plot(X_new, y_proba[:, 0], "b--", label="Not Iris-Virginica Prob")
plt.scatter(X, y, label='data')

plt.xlabel('Petal width (cm)')
plt.ylabel('Probability')
plt.legend(loc='best')
```

Out[42]:

```
<matplotlib.legend.Legend at 0x26958614e48>
```



In [43]:

```
log_reg.predict([[1.7]])
```

Out[43]:

```
array([1])
```

In [44]:

```
log_reg.predict_proba([[1.7]])
```

Out[44]:

```
array([[0.43834057, 0.56165943]])
```

Exercise 3.1

In [45]:

```
multiclass_logreg_obj = LogisticRegression(multi_class="multinomial", solver="lbfgs", C
=10)
# let us get the petal width. It is present in the 4th column of data
X = iris["data"][:, [2,3]]
y = iris["target"]
```

In [46]:

```
print(X.shape)
print(y.shape)
```

```
(150, 2)
(150,)
```

In [47]:

```
df = pd.DataFrame(X, columns=[iris.feature_names[2], iris.feature_names[3]])
```

In [48]:

```
print(df.head())
```

```
   petal length (cm)  petal width (cm)
0                1.4               0.1
1                1.4               0.1
2                1.3               0.1
3                1.5               0.1
4                1.4               0.1
```

In [49]:

```
multiclass_logreg_obj.fit(X, y)
```

Out[49]:

```
LogisticRegression(C=10, class_weight=None, dual=False, fit_intercept=Tru
e,
          intercept_scaling=1, max_iter=100, multi_class='multinomial',
          n_jobs=1, penalty='l2', random_state=None, solver='lbfgs',
          tol=0.0001, verbose=0, warm_start=False)
```

In [69]:

```
X_new = np.array([1, 0.1], ndmin=2)
prediction = multiclass_logreg_obj.predict(X_new)
pred_class = prediction[0]
pred_prob = multiclass_logreg_obj.predict_proba(X_new)
pred_prob_class = (pred_prob[0][pred_class])
print('Prediction {}'.format(prediction) + ', with a probability of: {}'.format(pred_pr
ob_class))
```

```
Prediction [0], with a probability of: 0.9995796959204409
```