Multilinear Regression

```
\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n
```

```
In [20]: N columns = ['Homework','Midterm','Final']
data = pd.DataFrame({
    "Homework": [95,70,80,100,70],
    "Midterm": [90,60,80,80,85],
    "Final": [93,66,85,60,90]

},index=['Alice','Bob','Clare','David','Eve'])
data.head()
```

Out[20]:

	Homework	Midterm	Final
Alice	95	90	93
Bob	70	60	66
Clare	80	80	85
David	100	80	60
Eve	70	85	90

```
In [21]:  print(np.corrcoef(data['Homework'],data['Final'])[0,1])
```

-0.1771490677357476

```
In [22]:  print(np.corrcoef(data['Midterm'],data['Final'])[0,1])
```

0.6700743886411277

2.0

[95 90]

```
In [24]:

y1 = data.loc['Alice',['Final']].values

               print(y1)
               [93]
              theta = np.array([2.0,0.2,0.8])
In [25]:
               print(theta)
               [2. 0.2 0.8]
              prediction = 2.0 + 0.2*x1[0] + 0.8*x1[1]
In [26]:
               print(prediction)
              93.0
In [27]:
              squared_error = (prediction - y1)**2
               print(squared_error)
               [0.]
In [28]:
              def get_squared_error(data,name,theta):
                   x = data.loc[name,['Homework','Midterm']].values
                   y = data.loc[name,['Final']].values
                   prediction = theta[0] + theta[1]*x[0] + theta[2]*x[1]
                   squared error = (prediction-y)**2
                   return squared error
               get_squared_error(data, "Bob", theta)
    Out[28]: array([4.])
In [29]:
              all errors = [get squared error(data,name,theta)for name in data.index]
           print(all errors)
               [array([0.]), array([4.]), array([9.]), array([676.]), array([36.])]
In [30]:
           M mse = np.mean(all_errors)
               print('MSE: ',mse)
               print("RMSE: ",np.sqrt(mse))
              MSE: 145.0
               RMSE: 12.041594578792296
          Multilinear Regression: Normal Equation
          \hat{\boldsymbol{\theta}} = \left(\mathbf{X}^T \cdot \mathbf{X}\right)^{-1} \cdot \mathbf{X}^T \cdot \mathbf{y}.
```

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```
In [34]:

    m,n = data.shape

             X = np.hstack([np.ones([m,1]),data[['Homework','Midterm']].values])
             print(X)
                      95.
                           90.]
                 1.
                 1.
                     70.
                           60.1
                     80.
                           80.]
                 1. 100.
                           80.]
                 1.
                     70.
                           85.]]
             y = data[['Final']].values
In [32]: ▶
             print(y)
             [[93]
              [66]
              [85]
              [60]
              [90]]
In [35]:
             num = X.T.dot(x)
             theta opt = np.linalg.inv(num).dot(X.T.dot(y))
             print(theta_opt)
             [[35.
              [-0.71627907]
              [ 1.30697674]]
In [38]:
             all_errors = [get_squared_error(data,name,theta_opt)for name in data.index]
             mse = np.mean(all_errors)
             rmse = np.sqrt(mse)
             print("MSE: ",mse)
             print("RMSE: ",rmse)
             MSE: 36.82790697674422
```

RMSE: 6.068600083770903

Multilinear Regression: Gradient Descent

$$\hat{\theta} \leftarrow \hat{\theta} - r \cdot \frac{\partial J(\hat{\theta})}{\partial \theta}.$$

· The partial derivative of the cost function is given by

$$\frac{\partial J(\hat{\theta})}{\partial \theta} = \frac{2}{m} \cdot \mathbf{X}^T \cdot (\mathbf{X} \cdot \theta - \mathbf{y}).$$

- Verify the formula of partial derivative assuming there is one input feature.
- End iteration if certain stop criteria is reached, such as:
 - Value of $\hat{\theta}$ becomes stable.
 - · Certain iteration amount is reached.

```
In [42]:
             m,n=data.shape
             theta_hat = np.random.rand(n,1)
             print(theta_hat)
             [[0.76272655]
              [0.59038968]
              [0.14812814]]
In [47]:
             X2 = np.hstack([np.ones([m,1]),data[['Homework','Midterm']].values/100])
             y2 = y
             print(X2)
             [[1.
                    0.95 0.9 ]
                    0.7 0.6 ]
              [1.
              [1.
                    0.8 0.8 ]
                          0.8 ]
              [1.
                    1.
              [1.
                    0.7 0.85]]
In [48]:
             num_iter = 6000
             r = 0.05
             MSEs = []
             for iter in range(num iter):
                 gradient = (X2.T).dot(X2.dot(theta_hat)-y2)*2/m
                 theta_hat -= r*gradient
                 MSE = 1/m*(X2.dot(theta_hat)-y2).T.dot(X2.dot(theta_hat)-y2)
                 MSEs.append(MSE[0,0])
             print(theta_hat)
             [[ 36.31043372]
              [-69.94711093]
              [127.28166283]]
In [49]:
             MSE
   Out[49]: array([[36.92103962]])
```

```
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In [50]:
              plt.plot(range(num_iter),MSEs)
              plt.ylim(0,200)
    Out[50]: (0, 200)
               200
               175
               150
               125
               100
                75
                50
                25
                 0
                          1000
                                 2000
                                        3000
                                               4000
                                                      5000
                                                              6000
              from sklearn.linear_model import LinearRegression
In [51]:
              model lr = LinearRegression()
              model_lr.fit(data[['Homework','Midterm']],data['Final'])
    Out[51]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Fa
              lse)
In [52]:
          model_lr.intercept_,model_lr.coef_
```

Out[52]: (35.00000000000004, array([-0.71627907, 1.30697674]))