Week 4 - Regression Analysis - Python

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1 Data Warehousing and Data Mining

1.1 Labs

1.1.1 Prepared by Gilroy Gordon

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1.1.2 Week 3 - Regression Analysis in Python

Additional Reference Resources:
http://scikit-learn.org/stable/modules/linear_model.html

1.2 Objectives

```
 > Data Transformation
 > Data Mining
      > Linear Regression
 > Model Evaluation and Prediction
      > Train/Test Split - 70/30
 > Presentation
      > Scatter Plot
```

1.3 Import required libraries and acquire data

NB. The data required was retrieved from the required text for this course. This should assist you in following the concepts from the book better

```
In [2]: # import required libraries
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
```

```
In [3]: data_path = './data/Creditcardprom.csv' # Path to data file
        data = pd.read_csv(data_path)
        data
```

```
Out[3]:    Income Range Magazine Promo Watch Promo Life Ins Promo Credit Card Ins.  \
        0      40-50,000            Yes          No             No               No
        1      30-40,000            Yes         Yes            Yes               No
        2      40-50,000             No          No             No               No
        3      30-40,000            Yes         Yes            Yes              Yes
        4      50-60,000            Yes          No            Yes               No
        5      20-30,000             No          No             No               No
        6      30-40,000            Yes          No            Yes              Yes
        7      20-30,000             No         Yes             No               No
        8      30-40,000            Yes          No             No               No
        9      30-40,000            Yes         Yes            Yes               No
        10     40-50,000             No         Yes            Yes               No
        11     20-30,000             No         Yes            Yes               No
        12     50-60,000            Yes         Yes            Yes               No
        13     40-50,000             No         Yes             No               No
        14     20-30,000             No          No            Yes              Yes

               Sex  Age
        0      Male   45
        1    Female   40
        2      Male   42
        3      Male   43
        4    Female   38
        5    Female   55
        6      Male   35
        7      Male   27
        8      Male   43
        9    Female   41
        10   Female   43
        11     Male   29
        12   Female   39
        13     Male   55
        14   Female   19
```

```
In [4]: # What columns are in the data set ? Do they have spaces that I should consider
        data.columns
```

```
Out[4]: Index(['Income Range', 'Magazine Promo', 'Watch Promo', 'Life Ins Promo',
               'Credit Card Ins.', 'Sex', 'Age'],
              dtype='object')
```

1.4 Aim: Can we determine a person's age based on the other factors?

age = a(Income Range) + b(Magazine Promo) + c(Watch Promo) + d(Life Ins Promo)+ e(Credit Card Ins.) + f(Sex)

The coefficients a-f, what are they? What is the relationship between the variables? Does multicolinearity exist?

I have created a function below `create_label_encoder_dict` to assist with this. The function accepts a dataframe object and uses the `LabelEncoder` class from `sklearn.preprocessing` to encode (dummy encoding) or transform non-numerical columns to numbers. Finally it returns a dictionary object of all the encoders created for each column.

The LabelEncoder is a useful resource as it not only automatically transforms all values in a column but also keeps a track of what values were transformed from. i.e. It will change all `Female` to `0` and all `Male` to `1`

```
In [7]: def create_label_encoder_dict(df):
            from sklearn.preprocessing import LabelEncoder

            label_encoder_dict = {}
            for column in df.columns:
                # Only create encoder for categorical data types
                if not np.issubdtype(df[column].dtype, np.number) and column != 'Age':
                    label_encoder_dict[column]= LabelEncoder().fit(df[column])
            return label_encoder_dict
```

```
In [9]: label_encoders = create_label_encoder_dict(data)
        print("Encoded Values for each Label")
        print("="*32)
        for column in label_encoders:
            print("="*32)
            print('Encoder(%s) = %s' % (column, label_encoders[column].classes_ ))
            print(pd.DataFrame([range(0,len(label_encoders[column].classes_))], columns=label_en
```

```
Encoded Values for each Label
================================
================================
Encoder(Sex) = ['Female' 'Male']
        Encoded Values
Female               0
Male                 1
================================
Encoder(Income Range) = ['20-30,000' '30-40,000' '40-50,000' '50-60,000']
           Encoded Values
20-30,000               0
30-40,000               1
40-50,000               2
50-60,000               3
================================
Encoder(Magazine Promo) = ['No' 'Yes']
     Encoded Values
No                0
Yes               1
================================
```

```
Encoder(Watch Promo) = ['No' 'Yes']
     Encoded Values
No                0
Yes               1
================================
Encoder(Life Ins Promo) = ['No' 'Yes']
     Encoded Values
No                0
Yes               1
================================
Encoder(Credit Card Ins.) = ['No' 'Yes']
     Encoded Values
No                0
Yes               1
```

In [11]:
```python
# Apply each encoder to the data set to obtain transformed values
data2 = data.copy() # create copy of initial data set
for column in data2.columns:
    if column in label_encoders:
        data2[column] = label_encoders[column].transform(data2[column])

print("Transformed data set")
print("="*32)
data2
```

```
Transformed data set
================================
```

Out[11]:
```
    Income Range  Magazine Promo  Watch Promo  Life Ins Promo  \
0              2               1            0               0
1              1               1            1               1
2              2               0            0               0
3              1               1            1               1
4              3               1            0               1
5              0               0            0               0
6              1               1            0               1
7              0               0            1               0
8              1               1            0               0
9              1               1            1               1
10             2               0            1               1
11             0               0            1               1
12             3               1            1               1
13             2               0            1               0
14             0               0            0               1

    Credit Card Ins.  Sex  Age
```

```
0                    0    1   45
1                    0    0   40
2                    0    1   42
3                    1    1   43
4                    0    0   38
5                    0    0   55
6                    1    1   35
7                    0    1   27
8                    0    1   43
9                    0    0   41
10                   0    0   43
11                   0    1   29
12                   0    0   39
13                   0    1   55
14                   1    0   19
```

```
In [16]: # separate our data into dependent (Y) and independent(X) variables
         X_data = data2[['Income Range','Sex','Life Ins Promo','Magazine Promo', 'Watch Promo']]
         Y_data = data2['Age']
```

1.5 70/30 Train Test Split

We will split the data using a 70/30 split. i.e. 70% of the data will be randomly chosen to train the model and 30% will be used to evaluate the model

```
In [17]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(X_data, Y_data, test_size=0.30)

In [14]: # Import linear model package (has several regression classes)
         from sklearn import linear_model

In [15]: # Create an instance of linear regression
         reg = linear_model.LinearRegression()

In [32]: reg.fit(X_train,y_train)

Out[32]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)

In [33]: reg.coef_

Out[33]: array([  4.20886076,  -8.43037975, -17.51898734,   5.5       ,
                  8.26582278])

In [34]: X_train.columns

Out[34]: Index(['Income Range', 'Sex', 'Life Ins Promo', 'Magazine Promo',
                'Watch Promo'],
               dtype='object')

In [35]: print("Regression Coefficients")
         pd.DataFrame(reg.coef_,index=X_train.columns,columns=["Coefficient"])
```

Regression Coefficients

Out[35]:

	Coefficient
Income Range	4.208861
Sex	-8.430380
Life Ins Promo	-17.518987
Magazine Promo	5.500000
Watch Promo	8.265823

In [36]:
```
# Intercept
reg.intercept_
```

Out[36]: 42.658227848101255

In [42]:
```
# Make predictions using the testing set
test_predicted = reg.predict(X_test)
test_predicted
```

Out[42]: array([26.41772152, 48.14556962, 51.53164557, 43.11392405, 42.64556962])

In [43]:
```
from sklearn.metrics import mean_squared_error, r2_score
```

In [44]:
```
# The mean squared error
print("Mean squared error: %.2f" % mean_squared_error(y_test, test_predicted))
```

```
Mean squared error: 50.14
```

In [45]:
```
# Explained variance score: 1 is perfect prediction
# R squared
print('Variance score: %.2f' % r2_score(y_test, test_predicted))
```

```
Variance score: -3.57
```

In [47]:
```
help(reg.score)
```

```
Help on method score in module sklearn.base:

score(X, y, sample_weight=None) method of sklearn.linear_model.base.LinearRegression instance
    Returns the coefficient of determination R^2 of the prediction.

    The coefficient R^2 is defined as (1 - u/v), where u is the residual
    sum of squares ((y_true - y_pred) ** 2).sum() and v is the total
    sum of squares ((y_true - y_true.mean()) ** 2).sum().
    The best possible score is 1.0 and it can be negative (because the
    model can be arbitrarily worse). A constant model that always
    predicts the expected value of y, disregarding the input features,
    would get a R^2 score of 0.0.
```

```
    Parameters
    ----------
    X : array-like, shape = (n_samples, n_features)
        Test samples.

    y : array-like, shape = (n_samples) or (n_samples, n_outputs)
        True values for X.

    sample_weight : array-like, shape = [n_samples], optional
        Sample weights.

    Returns
    -------
    score : float
        R^2 of self.predict(X) wrt. y.
```

```
In [48]: reg.score(X_test,y_test)

Out[48]: -3.5749185396313994
```

1.5.1 Visualizations

It's difficult to plat a scatter plot with so many dimensions
How about Dimensionality Reduction?
One such method - Principal Component Analysis

```
In [50]: from sklearn.decomposition import PCA

In [51]: pca = PCA(n_components=1)

In [53]: pca.fit(data2[X_train.columns])

Out[53]: PCA(copy=True, iterated_power='auto', n_components=1, random_state=None,
           svd_solver='auto', tol=0.0, whiten=False)

In [54]: pca.components_

Out[54]: array([[ 0.96117326, -0.10803145,  0.08602344,  0.23885282, -0.0049457 ]])

In [55]: pca.n_features_

Out[55]: 5

In [56]: pca.n_components_

Out[56]: 1
```

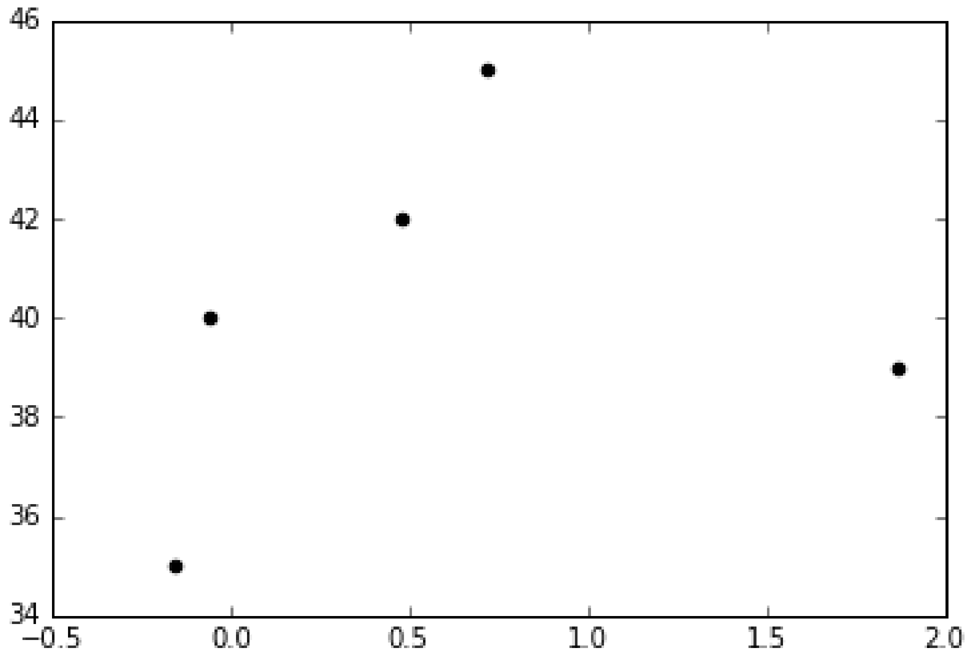
Now that we can reduce our components(factors/features) let us plot (X against y)

```
In [59]: #Again :
         X_test
```

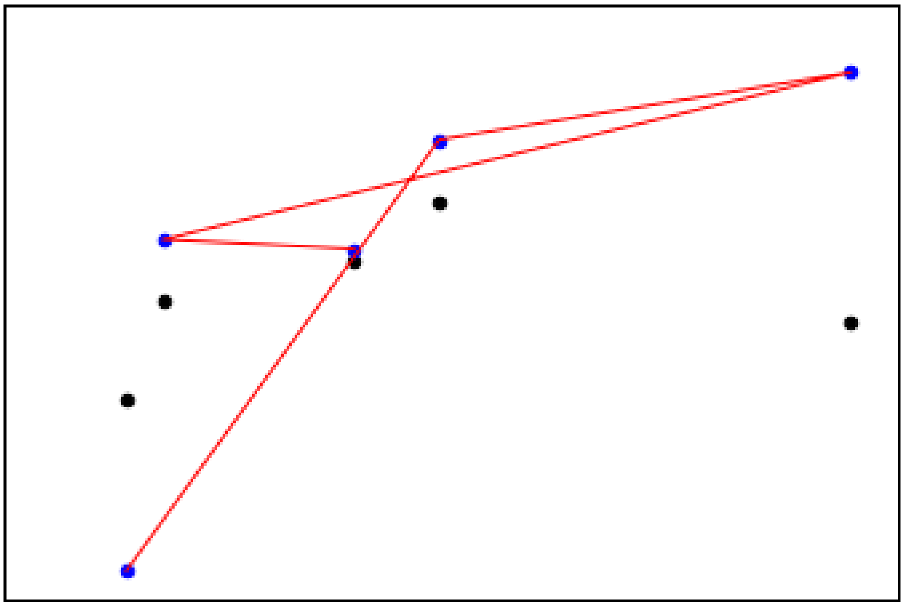
Out[59]:

	Income Range	Sex	Life Ins Promo	Magazine Promo	Watch Promo
6	1	1	1	1	0
0	2	1	0	1	0
12	3	0	1	1	1
1	1	0	1	1	1
2	2	1	0	0	0

```
In [60]: X_reduced = pca.transform(X_test)
         X_reduced

Out[60]: array([[-0.15821581],
                [ 0.71693401],
                [ 1.86721646],
                [-0.05513007],
                [ 0.47808119]])

In [61]: plt.scatter(X_reduced, y_test,  color='black')

Out[61]: <matplotlib.collections.PathCollection at 0x7f402752ed68>
```



```
In [64]: plt.scatter(X_reduced, y_test,  color='black')
         plt.scatter(X_reduced, test_predicted, color='blue')
         plt.plot(X_reduced, test_predicted, color='red',linewidth=1)

         plt.xticks(())
         plt.yticks(())

         plt.show()
```



1.6 Not very insightful? Let us discuss this in class