Logistic regression

🔶 Logistic regression is an algorithm that can help us answering yes or no questions by predicting the probability something happening or not happening.

🔶 Logistic regression is a classification algorithm despite its name has regression in it. It predicts two binary dependent output either as 0 or 1 based on the input variables.

🔶The regression in its name means we are using the same algorithm as used in linear regression. The difference is that the output is mapped using a logistic/sigmoid function so that it will be in a range between 0 and 1. Any output value < 0.5 will be classified as 0 and any value >= 0.5 will be classified as 1.

🔶 In this notebook, the logistic regression algorithm is coded step by step following:

Logistic regression

Hypothesis: $h_\theta(x) = \sigma(\theta^T x) = \dfrac{1}{1+e^{-\theta^T x}}$

parameters/weights: $\theta = [\theta_0, \theta_1, \theta_2 \cdots \theta_n]$

Cost function: $J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^i \log(h_\theta(x^i)) + (1-y^i)\log(1-h_\theta(x^i))]$

Find the parameters that'll minimize $J(\theta)$: Gradient Descent

- Start with Random θ
- Update the weights until reach minimum of $J(\theta)$

$$\theta_j = \theta_j - \alpha \sum_{i=1}^{m}(h_\theta(x^i) - y^i)\, x_j^i$$

Note: All the weights should be updated simultaneously

$$h_\theta(x) = \frac{1}{1+e^{-\theta^T x}}$$

Import libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

Coding the algorithm

In [2]:
```
class LogisticRegression():
    def __init__(self, x, y):
```

```
        x0 = np.ones((x.shape[0],1)) # add the bias term
        x = np.append(x0, x, axis=1) # append the bias to the input variable
        self.x = x
        self.y = y
        self.m = x.shape[0]
        self.n = x.shape[1]
        self.theta = np.random.randn(self.n) # initialize the weights with random num

    def sigmoid(self, z):
        return 1/(1+np.exp(-z))

    def CostFunction(self):
        self.h = self.sigmoid(np.matmul(self.x, self.theta)) # calculate the hypothes
        self.J = (-1/self.m) * np.sum( self.y*np.log(self.h) + (1-self.y)*np.log(1 -
#         print (self.J)
        return self.h, self.J

    def GradientDescent(self, epoch=10, alpha=0.01):
        self.cost_history = []
        self.theta_history = []
        for i in range(epoch):
            h, J = self.CostFunction()
            self.cost_history.append(J)
            self.theta_history.append(self.theta)
            self.theta = self.theta - alpha / self.m * np.dot(self.x.T, h-self.y)
        pass

    def Theta(self):
        return self.theta

    def CostHistory(self):
        return self.cost_history

    def ThetaHistory(self):
        return self.theta_history

    def predict(self, x_test, y_test):
        x0 = np.ones((x_test.shape[0],1))
        x_test = np.append(x0, x_test, axis=1)
        self.y_pred = self.sigmoid(np.matmul(x_test, self.theta))
        self.y_pred[self.y_pred>=0.5] = 1
        self.y_pred[self.y_pred<0.5] = 0
        self.test_accuracy = (self.y_pred == y_test).sum()/ len(y_test)*100
        return self.y_pred.astype(int), self.test_accuracy
```

In [3]:

```
# feature scaling is not used in this notebook, coded for fun.
class FeatureScaler():
    def __init__(self, x):
        self.x = x.copy().astype(float)
    def FitTransform(self):
        n = self.x.shape[1]
        for i in range(n):
            xi = self.x[:,i]
            xi_scaled = (xi - xi.mean()) / (xi.max() - xi.min())
```

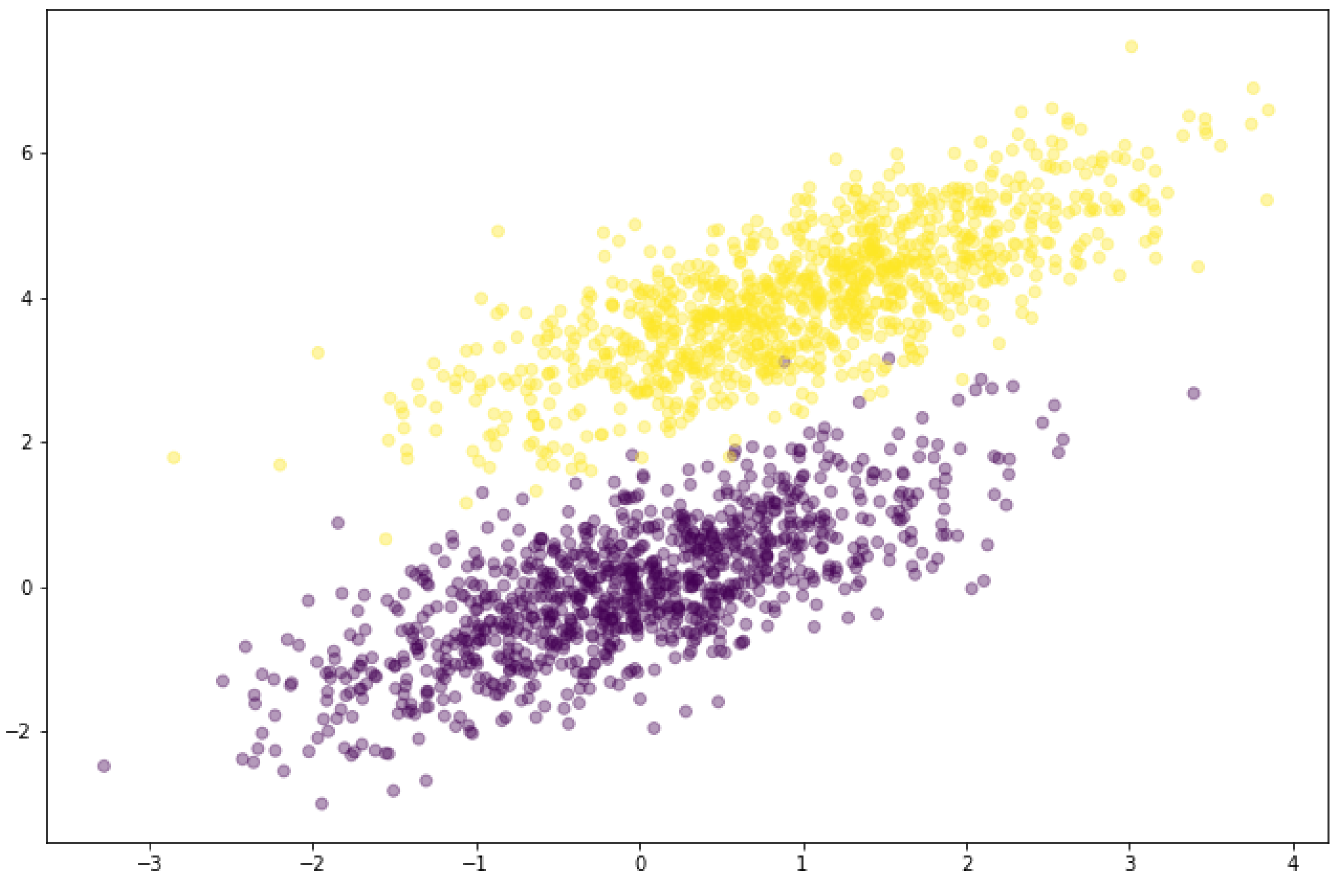
```
            self.x[:,i] = xi_scaled
        return self.x
```

Simulating data

The data used in this notebook are simulated using np.random.multivariate_normal to create two seperable features. Credit to git repo

In [4]:

```
np.random.seed(42)
num_observations = 1000

x1 = np.random.multivariate_normal([0, 0], [[1, .75],[.75, 1]], num_observations)
x2 = np.random.multivariate_normal([1, 4], [[1, .75],[.75, 1]], num_observations)
features = np.vstack((x1, x2)).astype(np.float32)
labels = np.hstack((np.zeros(num_observations),
                              np.ones(num_observations)))

#Displaying the output

plt.figure(figsize=(12,8))
plt.scatter(features[:, 0], features[:, 1], c = labels, alpha = .4)
plt.show()
```



Split data to train and test dataset

In [5]:

```
df = pd.DataFrame()
```

In [6]:

```
df['feature_1'] = features[:,0]
df['feature_2'] = features[:,1]
df['label'] = labels.astype(int)
```

In [7]:

```
df.head()
```

Out[7]:

	feature_1	feature_2	label
0	-0.415750	-0.513517	0
1	-1.144330	-0.067385	0
2	0.301810	0.136251	0
3	-1.748547	-1.205889	0
4	0.247329	0.630977	0

In [8]:

```
df = df.sample(frac=1, random_state=42).reset_index(drop=True)
```

In [9]:

```
train_frac = 0.7
train_size = int(df.shape[0] * train_frac)
x = np.array(df.iloc[:,0:2])
y = np.array(df.iloc[:,2])
x_train = x[0:train_size,:]
y_train = y[0:train_size]
x_test = x[train_size:,:]
y_test = y[train_size:]
```

In [10]:

```
print ('training size is {}\ntest size is {}'.format(x_train.shape[0], x_test.shape[0
```

```
training size is 1400
test size is 600
```

Initialize the model

In [11]:

```
clf = LogisticRegression(x_train, y_train)
```

Predict using gradient descent method

In [12]:

```
epoch = 1000
alpha = 0.5
clf.GradientDescent(epoch, alpha)
y_pred_train, train_error = clf.predict(x_train,y_train)
y_pred_test, accuracy = clf.predict(x_test,y_test)
theta = clf.Theta()
```

In [13]:

```
# print the test data, predicted test data and the error
print('y_test\n {}\n\ny_pred_test\n {}\n\ntest accuracy (%) {}\n\ntheta {}'
```

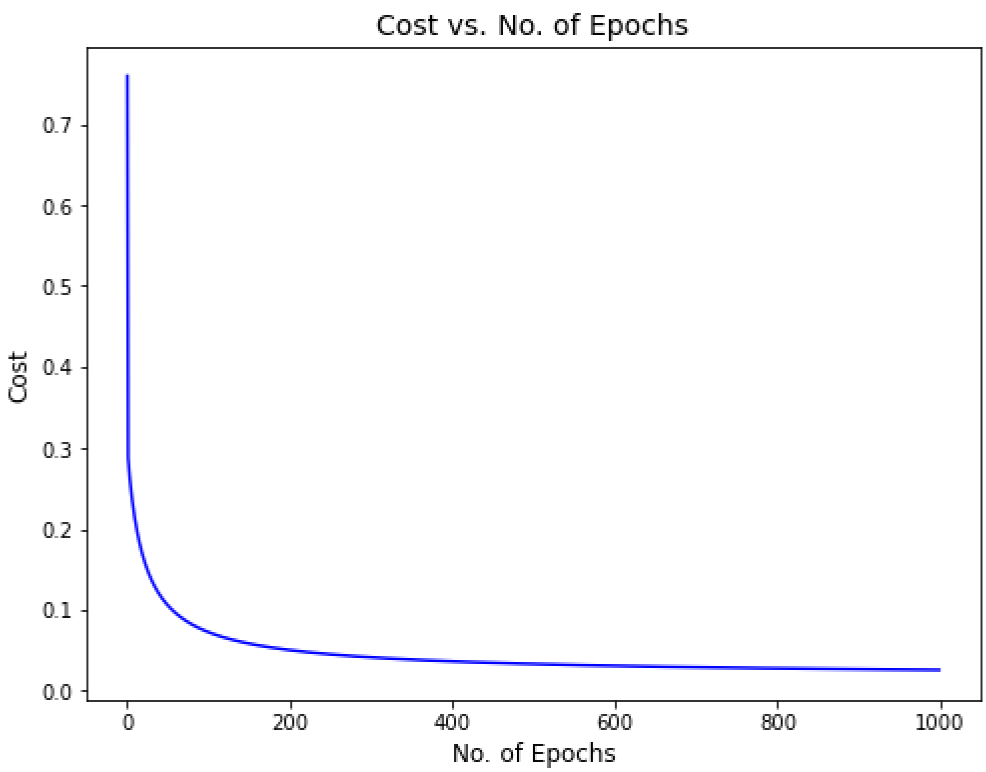
```
    .format(y_test[0:20], y_pred_test[0:20], accuracy, theta))
```

```
y_test
 [0 0 0 1 1 1 0 1 1 0 0 0 0 1 0 0 1 1 0 1]

y_pred_test
 [0 0 0 1 1 1 0 1 1 0 0 0 0 1 0 0 1 1 0 1]

test accuracy (%) 99.5

theta [-6.51769471 -1.92665152  3.77311985]
```

Visulize cost vs epochs

In [14]:

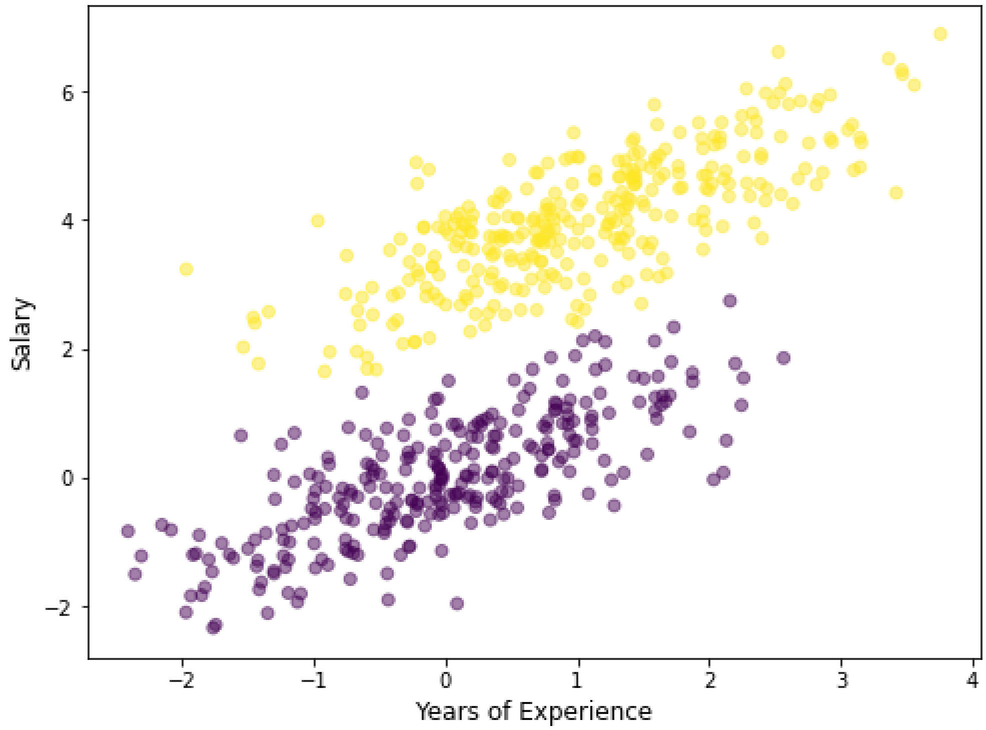
```
cost = clf.CostHistory()
fig = plt.figure(figsize=(8,6))
plt.plot(range(epoch), cost, c='b')
plt.title('Cost vs. No. of Epochs', fontsize=14)
plt.xlabel('No. of Epochs', fontsize=12)
plt.ylabel('Cost', fontsize=12)
plt.show()
```



Visulize fitted results using both method

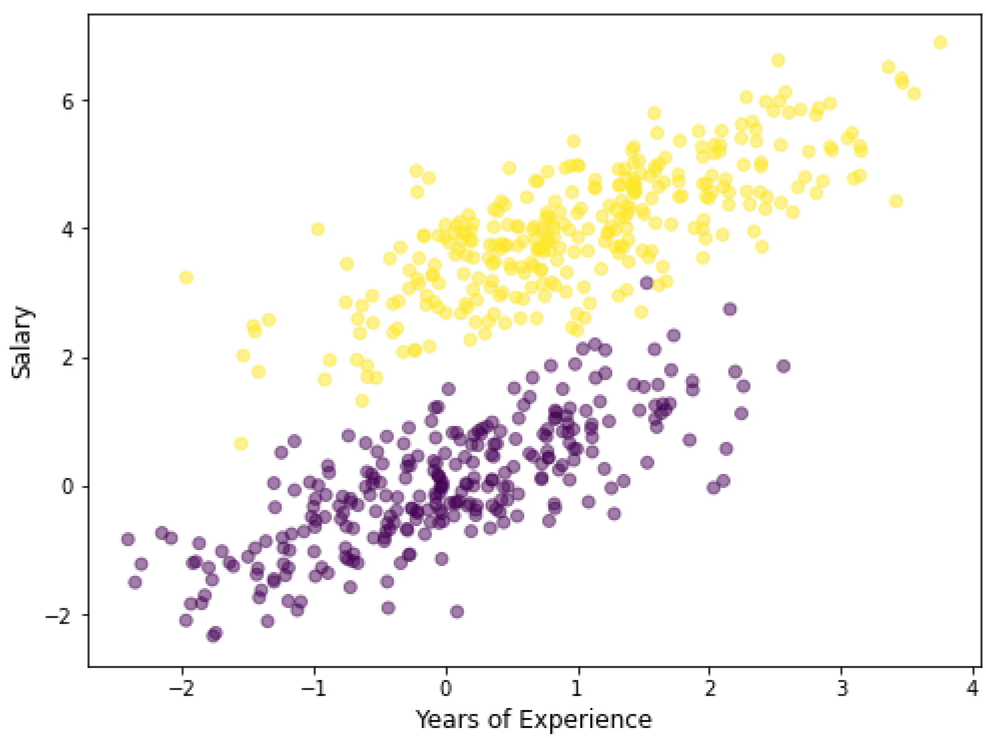
In [15]:

```
fig = plt.figure(figsize=(8,6))
plt.scatter(x_test[:,0], x_test[:,1], c=y_pred_test, alpha = .5)
plt.title('', fontsize=14)
plt.xlabel('Years of Experience', fontsize=12)
plt.ylabel('Salary', fontsize=12)
plt.show()
```



In [16]:

```
fig = plt.figure(figsize=(8,6))
plt.scatter(x_test[:,0], x_test[:,1], c=y_test, alpha = .5)
plt.title('', fontsize=14)
plt.xlabel('Years of Experience', fontsize=12)
plt.ylabel('Salary', fontsize=12)
plt.show()
```



In [ ]: