assig2-logistic-post-1

February 19, 2024

0.1 Logistic Regression - Gradient Descent

In this part you will build a logistic regression model using Numpy and doing gradient descent. You should complete the following cells (those with comments and no code).

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
```

[2]:
```
# read data
import pandas as pd
from sklearn.preprocessing import add_dummy_feature

data = pd.read_csv('https://raw.githubusercontent.com/thomouvic/SENG474/main/
↪data/exams_admitted.csv')
print(data.head())
```

```
       exam1      exam2  admitted
0  34.623660  78.024693         0
1  30.286711  43.894998         0
2  35.847409  72.902198         0
3  60.182599  86.308552         1
4  79.032736  75.344376         1
```

[3]:
```
# extract X and y from data
# use features 'exam1' and 'exam2' for X
# use feature 'admitted' for y
# use pandas.DataFrame.values to convert to numpy arrays
X = data[['exam1', 'exam2']].values
y = data[['admitted']].values
```

[4]:
```
# normalize X
# use scikit-learn's built-in function MinMaxScaler
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X = scaler.fit_transform(X)
```

[5]:
```python
# add a dummy feature for the intercept
# use scikit-learn's built-in function add_dummy_feature
from sklearn.preprocessing import add_dummy_feature

X = add_dummy_feature(X)
```

[6]:
```python
# set m (number of training examples) and n (number of features)
# use the shape attribute of X
m, n = X.shape
```

[9]:
```python
# initialize theta to zeros
theta = np.zeros((n, 1))
```

[15]:
```python
# define sigmoid function
def sigmoid(z):
  return 1 / (1 + np.exp(-z))

# test your sigmoid function on the value 0, should return 0.5
print(sigmoid(0))
```

```
0.5
```

[16]:
```python
# create a hypothesis function called h that takes in:
# theta, an instance x, and returns the hypothesis
# the hypothesis is the sigmoid of x@theta
# use the @ operator for matrix multiplication
def h(theta, x):
  return sigmoid(x @ theta)

# test your hypothesis function on the first instance of X, should return [[0.
 ↪5]]
print(h(theta, X[0]))

# the above function is vectorized
# for example, if instead of a single instance x, we have a matrix X of shape␣
 ↪(m,n)
# then the hypothesis is a vector of shape (m,1)
# where each element is the hypothesis for the corresponding row of X
# test it on the first 5 instances of X, should return an array of 0.5's
print(h(theta, X[:5]))
```

```
[0.5]
[[0.5]
 [0.5]
 [0.5]
 [0.5]
 [0.5]]
```

[23]:
```
# create a function called J that takes in theta, X, y, and returns the cost
# the cost is the average of the log loss over the training examples
# the log loss for a single example is␣
↪-y*log(h(theta,x))-(1-y)*log(1-h(theta,x))
# the cost is the average of the log loss over the training examples
# use the np.mean function to compute the average
# use the np.log function to compute the log
# use the @ operator to compute matrix multiplication
# use a vectorized implementation, do not use a for loop over the training␣
↪examples
# use the hypothesis function h defined above
def J(theta, X, y):
  return np.mean(-y * np.log(h(theta, X)) - (1 - y) * np.log(1 - h(theta, X)))


# test your cost function on the initial all-zero theta, should return 0.
↪6931471805599453
print(J(theta, X, y))
```

```
0.6931471805599453
```

[28]:
```
# create a function called gradient that takes in theta, X, y, and returns the␣
↪gradient
# the gradient is the average of the gradient over the training examples
# use the hypothesis function h defined above
# use a vectorized implementation, do not use a for loop over the training␣
↪examples
# use the @ operator to compute matrix multiplication
# use the np.mean function to compute the average
# use the formula for the gradient given in the lecture
# the vectorized formula is X.T@(h(theta,X)-y)/m

def gradient(theta, X, y):
  return X.T @ (h(theta, X) - y) / m


# test your gradient function on the initial theta
print(gradient(theta, X, y))
```

```
[[-0.1       ]
 [-0.12904484]
 [-0.12015491]]
```

[29]:
```
# create a function called 'fit' that takes in:
# X, y, alpha, num_iters, initial theta,
# and returns: final theta, and J_history
# inside the function:
```

```
# initialize theta to the initial theta
# initialize J_history to an empty list
# for each iteration, using a for loop over num_iters:
# update theta by subtracting alpha times the gradient (using the gradient␣
↪function defined above)
# compute the cost J using the cost function defined above and append it to␣
↪J_history
# return final theta, and J_history
def fit(X, y, alpha, num_iters, initial_theta):
  theta = initial_theta
  J_history = []
  for i in range(num_iters):
    theta = theta - alpha * gradient(theta, X, y)
    J_history.append(J(theta, X, y))
  return theta, J_history


# create a function called predict that takes in:
# theta, and an array X_new of instances,
# and returns the predictions
# threshold the hypothesis at 0.5
# use the hypothesis function h defined above
def predict(theta, X_new):
  return h(theta, X_new) >= 0.5
```

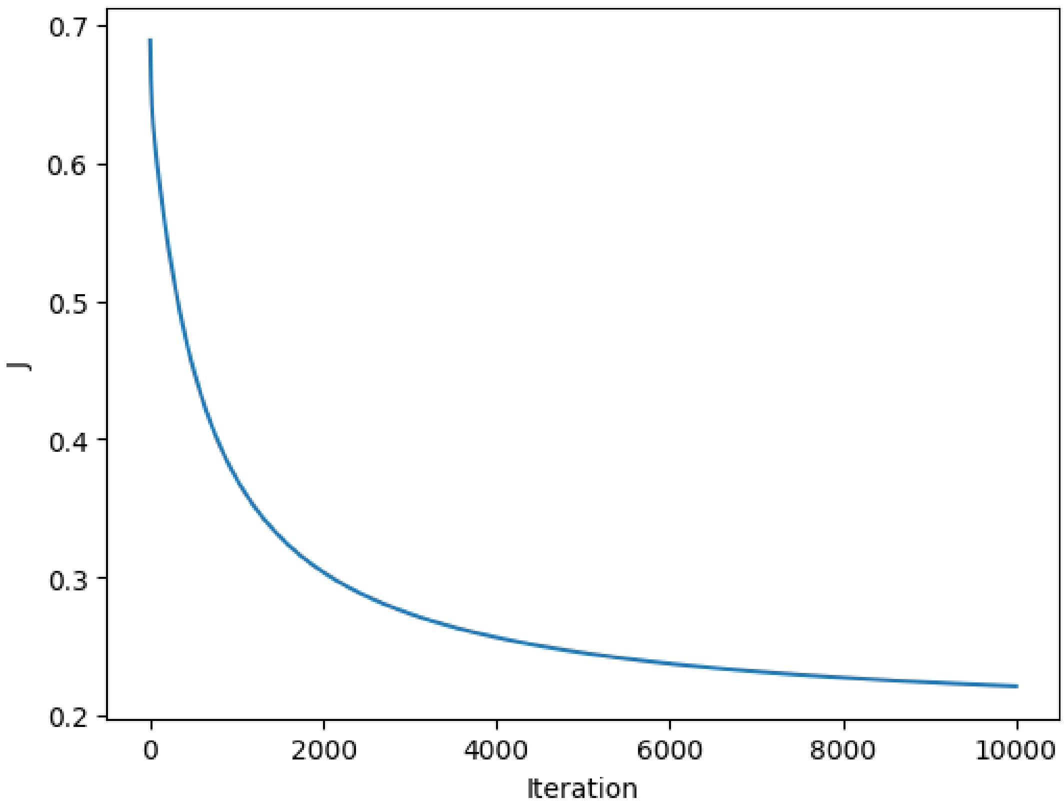
[30]:
```
# call fit() with the following arguments:
# X, y, alpha=0.1, num_iters=10000, initial_theta=np.zeros((n,1))
# store the returned values in theta, J_history
# uncomment the following line to call fit()

theta, J_history = fit(X, y, alpha=0.1, num_iters=10000, initial_theta=np.
↪zeros((n,1)))

# plot the cost over the iterations stored in J_history
# you should see the cost decreasing
# uncomment the following lines to plot the cost

plt.plot(J_history)
plt.xlabel('Iteration')
plt.ylabel('J')
```

[30]:
```
Text(0, 0.5, 'J')
```



[31]:

```
# plot the data points
# use a scatter plot
# use the first feature for the x-axis, the second feature for the y-axis
# use the actual labels for the color, c=y[:,0]
# uncomment the following line to plot the data points
plt.scatter(X[:,1],X[:,2],c=y[:,0])


# plot the decision boundary
# the decision boundary is the line where the hypothesis is 0.5
# the hypothesis is 0.5 when x@theta=0
# so the decision boundary is the line where x@theta=0
# this is a line in the x1,x2 plane

# for plotting the decision boundary, we need two points
# create two x1 values, say 0 and 1 (since we scaled to [0,1])
# then calculate the corresponding x2 values
# using the decision boundary equation
# uncomment the following lines to plot the decision boundary
two_x1 = np.array([0, 1])
two_x2 = -(theta[0] + theta[1] * two_x1) / theta[2]
```

```
# plot the decision boundary as a k-- line. k-- is black dashed line
plt.plot(two_x1, two_x2, "k--", linewidth=3)
```

[31]: [<matplotlib.lines.Line2D at 0x7826dd4a6680>]