hw0

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1 HW 0 - Ishaan Sathaye

1.1 Section A: Theory

Take derivative with respect to x in the following equations.

1. $f(x) = log(1/x)$

- $f'(x) = -1/x$

2. $f(x) = x^2 + 3x + 17$

- $f'(x) = 2x + 3$

3. $f(x) = xy + e^{x^2+y+5}$

- $f'(x) = y + 2xe^{x^2+y+5}$

Take derivative with respect to y in the following equations.

1. $f(y) = log(y/x)$

- $f(y) - log(y) - log(x)$
- $f'(y) = 1/y$

2. $f(y) = xy + e^{x^2+y+5}$

- $f'(y) = x + e^{x^2+y+5}$

1.2 Section B: Coding

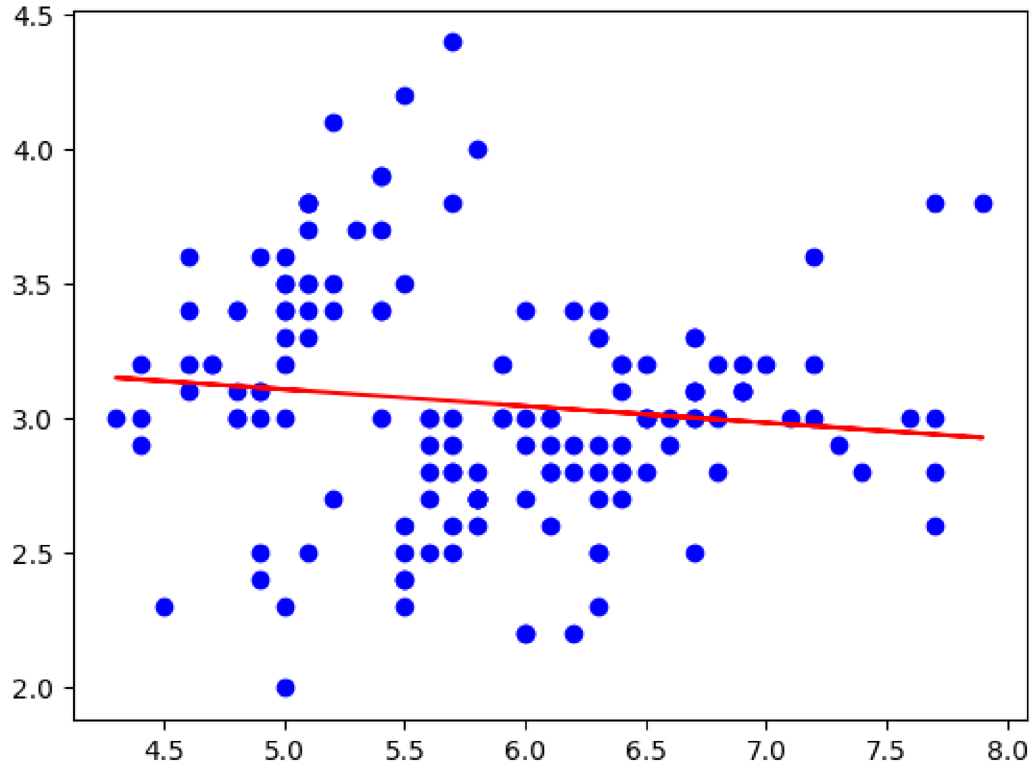
[1]:
```
# 1. Implement a Function from scratch to fit a simple linear regression

import numpy as np

def estimate_coefs_slr(x, y, intercept=True):
    x = np.array(x)
    y = np.array(y)

    x_bar = np.mean(x)
    y_bar = np.mean(y)

    cov_xy = np.cov(x, y, ddof=1)[0, 1]
    var_x = np.var(x, ddof=1)
```

```
    beta_1 = cov_xy / var_x

    if intercept:
        beta_0 = y_bar - beta_1 * x_bar
    else:
        beta_0 = 0

    return beta_0, beta_1
```

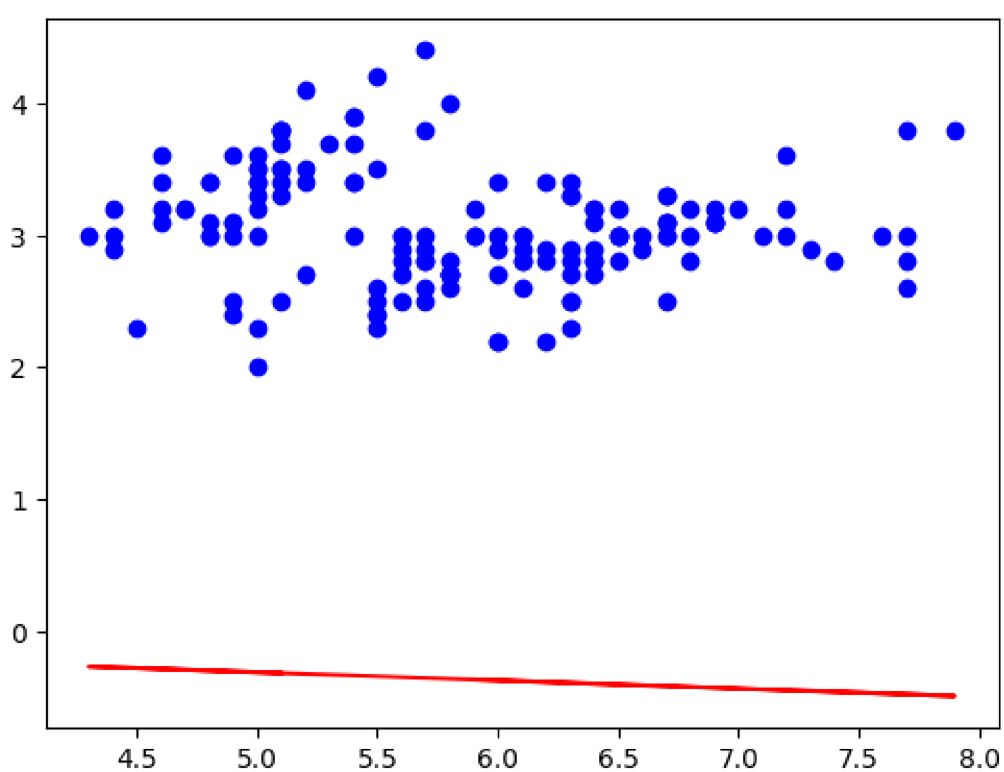
[2]:
```
# 2. Implement a function that first a simple linear regression on data and␣
 ↪predicts the y-vales

def predict_slr(x, y, intercept=True):
    beta_0, beta_1 = estimate_coefs_slr(x, y, intercept)
    y_hat = [beta_0 + beta_1 * i for i in x]
    return y_hat
```

[3]:
```
# 3. Write a function that fits a simple linear regression on data, predicts␣
 ↪the y-vales and plots teh predicted values and real values.

def plot_predictions_slr(x, y, intercept=True):
    import matplotlib.pyplot as plt
    y_hat = predict_slr(x, y, intercept)
    plt.scatter(x, y, color='blue')
    plt.plot(x, y_hat, color='red')
    plt.show()
```

[4]:
```
# 4. Demonstrate the success of all 3 of your functions, with and without the␣
 ↪intercept term, on a simple dataset.

from sklearn.datasets import load_iris
import pandas as pd

iris = load_iris()
df = pd.DataFrame(iris['data'], columns=iris['feature_names'])

x = df['sepal length (cm)']
y = df['sepal width (cm)']

plot_predictions_slr(x, y, intercept=True)
plot_predictions_slr(x, y, intercept=False)
```



4.5
4.0
3.5
3.0
2.5
2.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0



4
3
2
1
0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0

1.3 Section C: Concepts

The vector containing both derivatives is called the gradient.

1. What is the equation for the gradient for the equation in A.3 and A.5?

$f(x) = xy + e^{x^2+y+5}$ - $\nabla f(x, y) = [y + 2xe^{x^2+y+5}, x + e^{x^2+y+5}]$

$f(y) = xy + e^{x^2+y+5}$ - $\nabla f(x, y) = [y + 2xe^{x^2+y+5}, x + e^{x^2+y+5}]$

2. What is the value of the gradient of the equation from A.3 and A.5, evaluated at x = 7 and y = 10?

$f(x) = xy + e^{x^2+y+5}$ - $\nabla f(x = 7, y = 10) = [10 + 2 * 7e^{7^2+10+5}, 7 + e^{7^2+10+5}]$ - $\nabla f(x = 7, y = 10) = [10 + 2 * 7e^{64}, 7 + e^{64}]$

3. For loops are not needed in any of the functions to compute each individual predicted y value because the functions are vectorized. Since both x and y are vectors, the operations are performed element-wise. This is why the functions are able to compute the predicted y values for all x values at once.

4. No, a plot of predictions from any machine learning model we fit on data will not look like a straight line. The plot of predictions from the linear regression model looks like a straight line because the model is a linear. However, most machine learning models are not linear and have non-linear features, which is why the predictions will not look like a straight line.

1.4 Section D: Reading Assignment

If my focus was prediction, what I would prioritize would be achieving just a high accuracy of the model and a less focus on interpretability or simplicity. I would use validation to see how well the model does on unseen data and even use other techniques such as neural networks or random forests.

If my focus was interpretation, what I would need to prioritize would be understanding the relationship between house size and price and this would be through a simpler model. Simple linear regression would be better here because it is easier to interpret and understand the relationship between the two variables. I would also look at the coefficients of the model to understand the relationship between the two variables.