ST3009: Statistical Methods for Computer Science

Week 9 Assignment - Senán d'Art - 17329580

Q1

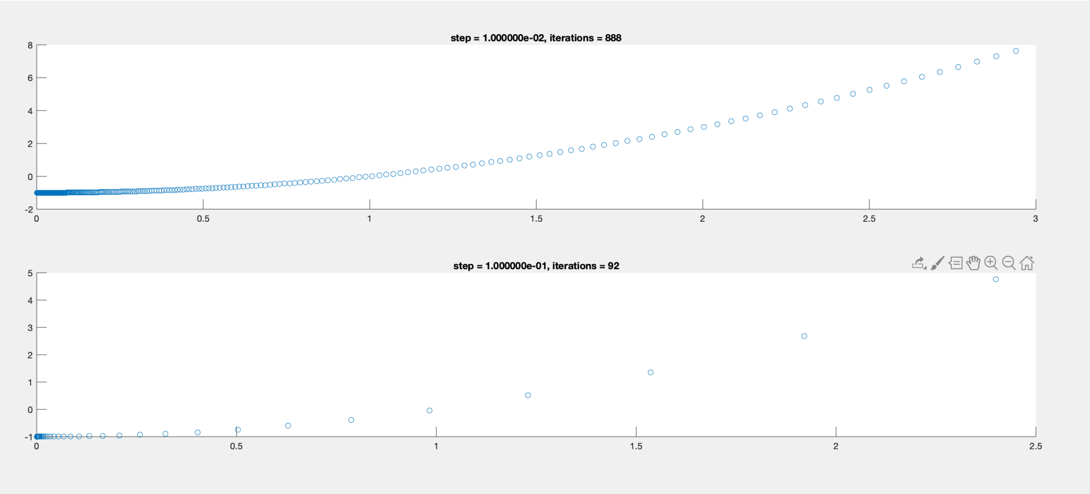
(a)

The following function returns the minimum of the function for a given step (α) value.

```
function min = q1_a(step)
    accuracy = 0.000000001;

    i = 0;
    j = 0;
    nx = 3;
    while abs(nx - j) > accuracy
        j = nx;
        nx = j - (step * (2*j));
        i = i + 1;
    end
    min = j^2 - 1;
    disp(i);
end
```

(b)

By plotting the value at each of the steps the following graphs were created:



When $\alpha = 0.01$, the minimum is acheived in 888 steps.
When $\alpha = 0.1$, the minimum is acheived in 92 steps.
When $\alpha = 1$, the minimum is overshot and the code will not reach it as the steps are too large.

Out of the 3 values here, $\alpha = 0.1$ is the most optimal as it reaches the minimum without the large overhead of the smaller number. The largest value ($\alpha = 1$) is useless as it does not reach the minimum.

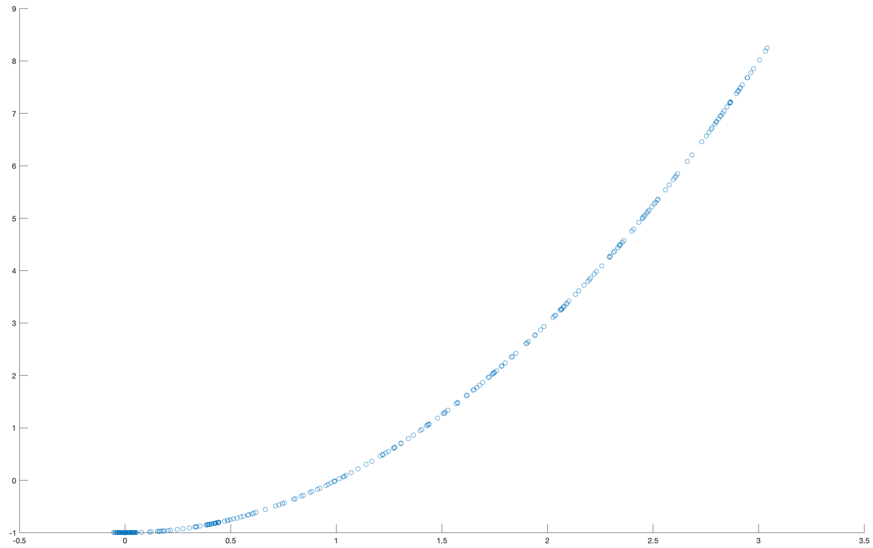
(c)

The following code was used:

```
function m = q1c()
    step = 0.1;
    accuracy = 0.00001;

    rng(0);

    ix = [];
    iy = [];
    i = 0;
    x = 0;
    nx = 3;
    while abs(nx - x) > accuracy
        x = nx;

        y = f(x);
        ny = y;
        while ny >= y
            nx = x + ((rand() - 0.5) * step);
            ny = f(nx);
            i = i + 1;
            ix(i) = nx;
```

```
            iy(i) = ny;
        end
    end
    m = f(x);

    disp(i);
    scatter(ix, iy)
end

function y = f(x)
    y = x^2 - 1;
end
```

The resulting graph looked like this:



(d)

By changing the random seed value at the start, different timing was observed. In the case of the graph above, it took ~16,000 iterations to reach the minimum. However the number of iterations varied between 33 (lowest observed) and $52,000$ (highest observed). This highlights some of the charactaristics of this approach: it is very random and the time taken to complete the operation depends heavily on the initial random seed. It is also difficult to predict the performance as it can vary greatly.

Q2

(a)

We can assign a value to each review, in this case we assign the value of 1 to a positive review and a value of -1 to a negative review.

Each review can be written as a vector:

$$pred = sign(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + ... + +\theta_n x_n)$$

Where θ_n is the weight applied to each element, x_n is the number of times a word appears in the review.
In this case $pred$ is the prediction (positive or negative).

To calculate θ_n we need to apply a cost function and iterate through possible values to find the values which are most accurate (train the model).

When trained, we can apply the vector representing a review to the weighted vector we are using. Then based on if the result is positive or negative, we can predict the sentiment of the review.

(b)

Assumptions:

- We assume that the relationship is linear, ie. there do not exist multiple minimums in our cost function which could result in a different result (we could find a local minimum but not a global minimum).
- We also assume that the set of reviews selected is representative of all reviews. If there are biases in the sample data, these will be reflected in the predictions.

(c)

- Take subsets of the training data (with replacement).
- Train model using this data.
- Log the parameter values (θ).
- Repeat many times.

This should allow us to get a confidence interval for each of the words in the review. It must be repeated many times in order to build up a decently accurate spread of values.
By comparing the confidence of each of the words in a review and their weights, we can predict a certain level of confidence for that review.