

# *Introduction to Neural and Cognitive Modelling*

## *Assignment 4*

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*For best viewing experience, use Google Colab*

**[Click Here \(https://colab.research.google.com/drive/1P-E1I1g6nS8PcqdeMobY6XN3SUohtrF4\)](https://colab.research.google.com/drive/1P-E1I1g6nS8PcqdeMobY6XN3SUohtrF4)**

# *Solution to Part 1*

$$m = r(S) + n$$

$$\implies m = 10 + \frac{50}{1 + \exp\left(-\frac{S-0.25}{0.15}\right)} + n$$

$$\text{where } p(n) = \frac{1}{\sqrt{2\pi}(5)} \cdot \exp\left(-\frac{n^2}{2(5)^2}\right)$$

$$\text{i.e } p(n) \approx G(\mu = 0, \sigma = 5)$$

*We have :*

$$\frac{50}{1 + \exp\left(-\frac{S-0.25}{0.15}\right)} = m - n - 10$$

$$\implies 1 + \exp\left(-\frac{S-0.25}{0.15}\right) = \frac{50}{m - n - 10}$$

$$\implies \exp\left(-\frac{S-0.25}{0.15}\right) = \frac{50}{m - n - 10} - 1$$

$$\implies -\frac{S-0.25}{0.15} = \ln\left(\frac{50}{m - n - 10} - 1\right)$$

$$\implies S = \frac{25}{100} - \frac{15}{100} \ln\left(\frac{50}{m - n - 10} - 1\right)$$

*if we set  $m = 58$ , we get :*

$$S = \frac{25}{100} - \frac{15}{100} \cdot \ln\left(\frac{50}{48 - n} - 1\right)$$

*Now,  $S \in [0, 1]$*

*To compute  $n$  from  $S$  :*

$$n = m - 10 - \frac{50}{1 + \exp\left(-\frac{S-0.25}{0.15}\right)}$$

*and with  $m$  set to 58,*

$$n = 48 - \frac{50}{1 + \exp\left(-\frac{S-0.25}{0.15}\right)}$$

*We have a Gaussian model for  $p(n)$ . Every  $S$  gives us a unique  $n$ . Thus, we can estimate  $L(S; m)$  as :*

$$\frac{1}{\sqrt{2\pi}(5)} \cdot \exp\left(\frac{-1}{2(5)^2} \left(m - 10 - \frac{50}{1 + \exp\left(-\frac{S-0.25}{0.15}\right)}\right)^2\right)$$

*– We use the above relation to obtain  $L(S; 58)$*

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

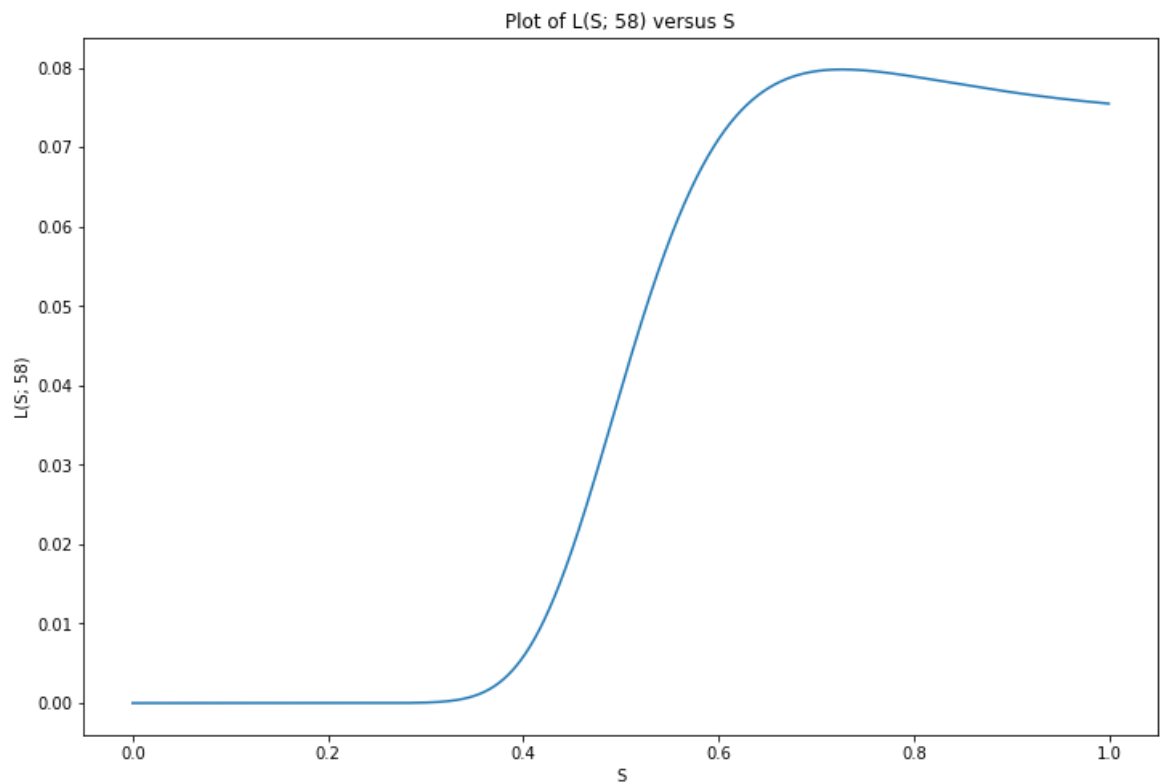
size = 10000
# Number of values used for plotting and estimations

def L(s, m):
    # Estimate the Likelihood L(S; m)
    calc = np.power((m - 10 - 50 / (1 + np.exp(-(s - 0.25) / 0.15))), 2) * (-1 / 50)
    return (1 / (5 * np.sqrt(2 * np.pi))) * np.exp(calc)

S_values = [(i / size) for i in range(size)]
L_values = [L(s, 58) for s in S_values]

fig = plt.figure(figsize=(12,8))
plt.xlabel('S')
plt.ylabel('L(S; 58)')
plt.title("Plot of L(S; 58) versus S")
plt.plot(S_values, L_values)
plt.show()

```



## Solution to Part 2

For ease of representation, let us define a few terms :

$$\begin{aligned} \bullet A &= \frac{-1}{2(5)^2} \left( m - 10 - \frac{50}{1 + \exp\left(-\frac{S-0.25}{0.15}\right)} \right)^2 \\ \bullet B &= \left( m - 10 - \frac{50}{1 + \exp\left(-\frac{S-0.25}{0.15}\right)} \right) \\ \bullet C &= 1 + \exp\left(-\frac{S-0.25}{0.15}\right) \end{aligned}$$

To estimate maximum likelihood, we differentiate  $p(S)$  w.r.t  $p$  :

$$\therefore p'(s) = \frac{1}{\sqrt{2\pi(5)}} \cdot \exp(A) \cdot \left( \frac{-1}{2(5)^2} \right) \cdot 2 \cdot B \cdot \frac{+50}{C^2} \cdot \left( \exp\left(-\frac{S-0.25}{0.15}\right) \right) \cdot \frac{-S}{0.15}$$

Now, we equate  $p'(s)$  to 0 to obtain critical points :

$$p'(s) = 0$$

$$\implies B = 0 \text{ or } S = 0$$

Note that :  $B = 0 \implies A = 0$

$$\text{And : } \exp(A), \frac{50}{C^2}, \exp\left(-\frac{S-0.25}{0.15}\right) \neq 0$$

Now,  $S = 0$  is a boundary point and  $L(0; 58) \approx 0$

Hence,

$$B = 0$$

$$\implies \left( m - 10 - \frac{50}{1 + \exp\left(-\frac{S^*-0.25}{0.15}\right)} \right) = 0$$

$$\implies \frac{50}{1 + \exp\left(-\frac{S^*-0.25}{0.15}\right)} = m - 10$$

$$\implies 1 + \exp\left(-\frac{S^*-0.25}{0.15}\right) = \frac{50}{m-10}$$

$$\implies \exp\left(-\frac{S^*-0.25}{0.15}\right) = \frac{50}{m-10} - 1$$

$$\implies -\frac{S^*-0.25}{0.15} = \ln\left(\frac{50}{m-10} - 1\right)$$

$$\implies S^* = -\frac{15}{100} \cdot \ln\left(\frac{50}{m-10} - 1\right) + \frac{25}{100}$$

```
In [2]: def get_S_optima(m):
        return -0.15 * np.log(50/(m - 10) - 1) + 0.25

        def get_maximum_likelihood(m):
            return L(get_S_optima(m), m)

        best_S = get_S_optima(58)
        best_ML = get_maximum_likelihood(58)

        print("S* = " + str(best_S))
        print("L* = " + str(best_ML))
```

```
S* = 0.7267080745521916
L* = 0.07978845608028655
```

Setting  $m = 58$  :

$$S^* = -\frac{15}{100} \cdot \ln\left(\frac{50}{48} - 1\right) + \frac{25}{100} = 0.72670807455$$

– is the required  $S$  that maximizes  $L(S; 58)$

We verify using :

- Estimating from the plot of  $L$  versus  $S$
- Iteratively checking computed  $L$  values to get an estimate of which  $S$  maximizes  $L$

```
In [3]: # Iteratively Checking L values to find which S maximizes L

def get_best_S_approx():
    position = np.argmax(np.asarray(L_values))
    return (position / size)

S_best_approx = get_best_S_approx()

print("An Approximation to S* using computed values: S*_approx = " + str(S_best_approx))

An Approximation to S* using computed values: S*_approx = 0.7267
```

– Clearly, everything checks out and  $\rightarrow$

$S^* = 0.7267$ ,  $L^* = 0.0798$  are optimum values for  $S$  and  $L$  respectively.

*Thank You*