$Introduction\ to\ Neural\ and\ Cognitive\ Modelling$

 $Assignment\ 4$

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 $For \ best \ viewing \ experience, \ use \ Google \ Colab$

<u>Click Here (https://colab.research.google.com/drive/1P-E1I1g6nS8PcqdeMobY6XN3SUohtrF4)</u>

Solution to Part 1

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

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

where
$$p(n) = \frac{1}{\sqrt{2\pi}(5)}.expigg(-rac{n^2}{2(5)^2}igg)$$

$$i. e p(n) pprox G(\mu = 0, \ \sigma = 5)$$

 $We\ have:$

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

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

$$\implies expig(-rac{S-0.25}{0.15}ig) = rac{50}{m-n-10} \,-\, 1$$

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

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

if we set m = 58, we get:

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

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

To compute n from S:

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

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:

$$rac{1}{\sqrt{2\pi}(5)} \cdot exp \Bigg(rac{-1}{2(5)^2} \Bigg(m \ - \ 10 \ - \ rac{50}{1 + exp \Big(-rac{S - 0.25}{0.15} \Big)} \Bigg)^2 \Bigg)$$

- We use the above relation to obtain L(S; 58)

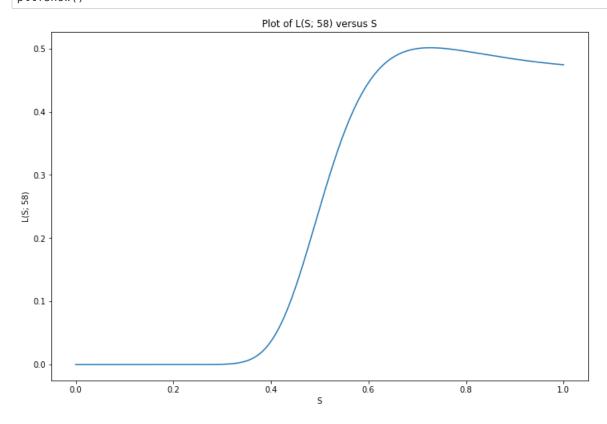
```
In [1]: import numpy as np
import matplotlib.pyplot as plt

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

def L(s, m = 58):
    # 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) for s in S_values]

fig = plt.figure(figsize=(12,8))
plt.xlabel('S')
plt.ylabel('L(S; 58)')
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

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

$$egin{array}{lll} ullet & A \ = \ rac{-1}{2(5)^2} igg(m \ - \ 10 \ - \ rac{50}{1 + expigg(- rac{S - 0.25}{0.15} igg)} igg)^{rac{1}{2}} \ ullet & B \ = \ igg(m \ - \ 10 \ - \ rac{50}{1 + expigg(- rac{S - 0.25}{0.15} igg)} igg) \ ullet & C \ = \ 1 \ + \ expigg(- rac{S - 0.25}{0.15} igg) \end{array}$$

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

$$\therefore \ p'(s) \ = \ rac{1}{\sqrt{2\pi}(5)}. \, exp(A). \, \Big(rac{-1}{2(5)^2}\Big).2. \, B. \, rac{+50}{C^2}. \, igg(exp\Big(-rac{S-0.25}{0.15}\Big)igg). rac{-S}{0.15}$$

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

$$p'(s) = 0$$

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

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

$$And: exp(A), rac{50}{C^2}, exp\Big(-rac{S-0.25}{0.15}\Big)
eq 0$$

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

Hence,

$$B = 0$$

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

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

$$\implies 1 \, + \, expig(-rac{S^*-0.25}{0.15}ig) = rac{50}{m-10}$$

$$\implies expig(-rac{S^*-0.25}{0.15}ig)=rac{50}{m-10}-1$$

$$\implies -rac{S^* - 0.25}{0.15} = ln \Big(rac{50}{m-10} - 1\Big)$$

$$\implies S^* = -rac{15}{100}. ln \Big(rac{50}{m-10} - 1\Big) + rac{25}{100}$$

```
In [2]: def get_S_optima(m):
    return -0.15 * np.log(50/48 - 1) + 0.25

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

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

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

 $S^* = 0.7267080745521916$ $L^* = 0.5013256549262001$ Setting m = 58:

$$S^* = -rac{15}{100}. ln \Big(rac{50}{48} - 1\Big) + rac{25}{100} = 0.72670807455$$

-is the required S that maximizes L(S; 58)

 $We \ verify \ using:$

- Estimating from the plot of L versus S
- ullet 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 ightarrow

 $S^* = 0.727$, and $L^* = 0.501$ are optimum values for S and L respectively.

Thank You