For each of the following problems, provide your answer and show the steps taken to solve the problem.

Problem 1. Maximum Likelihood Estimation (50 points) Given a dataset $\{x1, x2, ..., xN\}$ of size N, derive the maximum likelihood estimate (as a function of x1, ..., xN) for: (a) The lower and upper limits, a and b, of a uniform distribution,

 $f(x; a, b) = {$

$$\frac{1}{b-a}$$
, if $a \le x \le b$
0, otherwise

1.

(assuming each $xi \in R$). Show all of your work. (25 points)

to find the upper limit of a uniform distribution we have:

$$egin{aligned} b_{MLE} &= argmax P_b(x_1, x_2, \dots, x_N) \ &= argmax \prod_{i=1}^N rac{1}{b-a} \ &= argmax (rac{1}{b-a})^N \end{aligned}$$

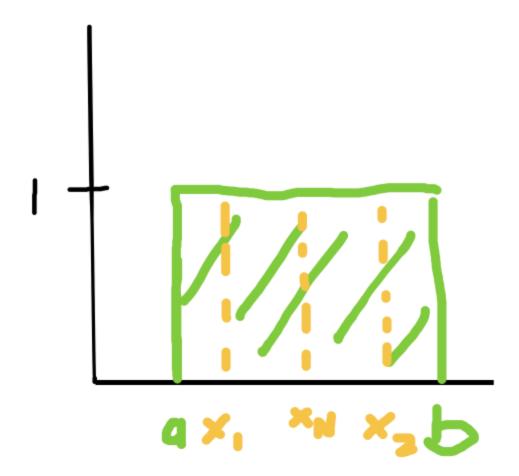
From this expression we can see that the larger b, the larger the maximum likelihood estimation. Therefore, we can conclude that $b = \max(x_{i})$

Similarly for the lower limit,

$$egin{aligned} a_{MLE} &= argmax P_a(x_1, x_2, \dots, x_N) \ &= argmax \prod_{i=1}^N rac{1}{b-a} \ &= argmax (rac{1}{b-a})^N \end{aligned}$$

The smaller a the larger the MLE, Therefore, we can conclude that $a=min(x_i)$

To test this, we can draw the uniform distribution and some x values:



uniform distribution

If some value of x was greater than b, the probability would be 0 and if some value of x was less than a, the probability would also be 0. Therefore to maximize the likelihood, we want all values of x to fall within the range a and b.

b. The λ parameter of a Poisson distribution,

$$f(x;\lambda) = egin{cases} rac{e^{-\lambda}\lambda^x}{x!}, & ext{if } x \geq 0 \ 0, & ext{if } x < 0 \end{cases}$$

(assuming each $xi \ge 0$). Show all of your work. (25 points) Hints: (i) plotting some sample data may be helpful and calculus should not be required (a); (ii) maximizing the log likelihood provides the same parameter values and often provides a simpler path to a solution (b); (iii) log(ab) = log a + log b; (iv) log e a = a.

$$l(\lambda|x) = p(x|\lambda) = \prod_{i=1}^N p(x_i|\lambda) = \prod_{i=1}^N e^{-\lambda} rac{\lambda}{x!}$$

Then, take the log likelihood

$$egin{align} L(\lambda|x) &= logl(\lambda|x) = \sum_{i=1}^{N} logp(x_i|\lambda) \ &= \sum_{i=1}^{N} loge^{-\lambda} rac{\lambda^x}{x!} \ &= \sum_{i=1}^{N} loge^{-\lambda} + log\lambda^x - logx! \ &= -\lambda \sum_{i=1}^{N} + xlog\lambda - logx! \ MLE &= \lambda^* = argmax_{\lambda} L(\lambda|x) \ &= -\lambda \sum_{i=1}^{N} + xlog\lambda - logx! \ \end{pmatrix}$$

Problem 2. Bayesian Parameter Estimation (50 points) The density function of an exponential distribution is given by $f_{\lambda}(x)=\lambda e^{-\lambda x}$. The MLE for the parameter λ can be calculated as $\lambda=\frac{n}{\sum_i x_i}$. We will now consider Bayesian parameter estimation for this distribution.

a. Using a prior distribution from the Gamma distribution, $f_{\alpha,\beta}(\lambda)=\frac{\beta^{\alpha}\lambda^{\alpha-1}e^{-\lambda\beta}}{\Gamma(\alpha)}$, with parameters α and β , show that the posterior distribution for λ , after updating using three datapoints x1, x2, x3, is also a Gamma distribution and show its new parameter values, α 0 and β 0, in terms of α , β , x1, x2, and x3. (25 points)

$$egin{split} p(x_1,x_2,x_3\mid\lambda) &= \lambda^3 e^{-\lambda(x_1+x_2+x_3)} \ \ p(\lambda\mid x_1,x_2,x_3) &\propto p(x_1,x_2,x_3\mid\lambda)\cdot p(\lambda) \end{split}$$

substituting the prior and likelihood functions we get:

$$p(\lambda \mid x_1, x_2, x_3) \propto rac{eta^lpha}{\Gamma(lpha)} \lambda^{lpha - 1} e^{-\lambda eta} \cdot \lambda^3 e^{-\lambda(x_1 + x_2 + x_3)}$$

which simplifies to:

$$p(\lambda \mid x_1, x_2, x_3) \propto rac{eta^lpha}{\Gamma(lpha)} \lambda^{lpha + 2 - 1} e^{-\lambda(eta + x_1 + x_2 + x_3)}$$

and we get the parameter values as:

$$lpha_0=lpha+2$$
 $eta_0=eta+x_1+x_2+x_3$

b. If our prior parameters are $\alpha=2$ and $\beta=1$, and our data sample consists of x1 = 3.7, x2 = 4.5, x3 = 4.8: Compute the posterior probability of a new datapoint x4 = 3.8 under the fully Bayesian estimation of λ . You can either leave your answer in terms of the Gamma function, or provide the exact answer. (13 points) Hints: (i) You shouldn't have to solve the complicated integral; (ii) Since the Gamma distribution normalizes to 1, R λ λ α -1 e $-\lambda\beta$ d λ = $\Gamma(\alpha)$ $\beta\alpha$; (iii) The Gamma function is related to the factorial function as $\Gamma(x) = (x-1)!$ for positive integers x.

$$lpha_0 = 2 + 2 = 4$$
 $eta_0 = 1 + 3.7 + 4.5 + 4.8 = 14$

To compute x_4 , plug α_0 β_0 and x_4 into the density function

$$f(\lambda \mid lpha_0, eta_0) = rac{\Gamma(lpha_0)}{eta_0^{lpha_0}} \lambda^{lpha_0 - 1} e^{-eta_0 \lambda}$$

so we get:

$$f(\lambda \mid 4,14) = rac{\Gamma(4)}{14^4} \cdot (3.8)^{4-1} e^{-14\cdot 3.8}$$

c. If we have the same prior and datapoints as in (b), what is the probability of a new datapoint x4 = 3.8 using maximum a posteriori estimation of λ ? (12 points) Hint: (i) The mode of the Gamma distribution (i.e., the λ that attains its maximal probability) is $\alpha-1$