Derive MLE estimator for parameters of normal distribution. Estimate  $\mu$  and  $\sigma^2$  for observed values: 10,2; 11,5; 9,7; 10,8; 11,1; 9,9 and 10,6.

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{\frac{-(x-\mu)}{2\sigma^2}}$$

Consider a mixture of two normal distributions with  $\mu_1 \neq \mu_2$  how would the likelihood function change?

$$\hat{y}_{1} = 10,5429$$

$$\hat{y}_{2} = 0,362449$$

Formulate likelihood and log-likelihood function for *n* IID 2-parametric exponentially distributed random variables. Derive MLE estimator for both parameters and estimate them for observed values: 6,5; 2,9; 1,3; 3,7; 3,4; 7,8; 7,1; 4,1; 4,8; 6,1. PDF for exponential distribution:

$$f(x) = \begin{cases} \lambda e^{-\lambda(x-a)} & x > a \\ 0 & \text{otherwise} \end{cases}$$

Exponential distribution can be used as a model for "time to failure". Find a way to incorporate surviving parts into likelihood function.

$$\bar{x} = 4, 77 \rightarrow \hat{\lambda} = 0,288$$

min  $(x_1) = 1,3$ 

1) 
$$L(\sigma_{1}\sigma^{2}) = \prod_{i=1}^{N} \frac{1}{N_{i}\sigma^{2}} \cdot \frac{1}{N_{i}\sigma^{2}} \cdot \frac{1}{N_{i}\sigma^{2}}) = \frac{1}{N_{i}\sigma^{2}} \left[ \ln \left( \frac{1}{N_{i}\sigma^{2}} \right) + \ln \left( \frac{1}{\sigma} \right) + \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \right] = \frac{N_{i}}{N_{i}\sigma^{2}} \left[ \ln \left( \frac{1}{N_{i}\sigma^{2}} \right) + \ln \left( \frac{1}{\sigma} \right) + \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \right] = \frac{N_{i}}{N_{i}\sigma^{2}} \left[ \ln \left( \frac{1}{N_{i}\sigma^{2}} \right) + \ln \left( \frac{1}{\sigma} \right) - \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \right] = \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \left[ \ln \left( \frac{1}{N_{i}\sigma^{2}} \right) + \ln \left( \frac{1}{\sigma} \right) - \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \right] = \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \left[ \ln \left( \frac{1}{N_{i}\sigma^{2}} \right) + \ln \left( \frac{1}{\sigma} \right) + \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \right] = \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \left[ \ln \left( \frac{1}{N_{i}\sigma^{2}} \right) + \ln \left( \frac{1}{N_{i}\sigma^{2}} \right) + \ln \left( \frac{1}{N_{i}\sigma^{2}} \right) + \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \right] = \frac{N_{i}\sigma^{2}}{N_{i}\sigma^{2}} \left[ \ln \left( \frac{1}{N_{i}\sigma^{2}} \right) + \ln \left( \frac{1}{$$

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 case  $x_c$  jeth fungoval

Necense:  $L(\lambda; \alpha) = \prod_{x \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \prod_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \prod_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \prod_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \prod_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \prod_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \prod_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y \in A} \frac{\lambda(x_c - \alpha)}{\lambda(x_c - \alpha)} = \sum_{y$ 

Amount of latecomers into MSP lessons can be viewed as a random variable with Poisson distribution (see PMF). Derive MLE for parameter \( \) and estimate lambda given following observations from last year: \( 1, 2, 4; 2, 1, 4; 1, 1, 3, 5, 5. \)

$$p(x) = \frac{\lambda^x}{x!}e^{-\lambda}$$

Where  $x \in \mathbb{N} \cup \{0\}$ 

1) 
$$L(\lambda) = \frac{\pi}{1 \times 1} \frac{\lambda^{x_{i}}}{\lambda^{x_{i}}} = \lambda$$

$$\frac{\partial L}{\partial \lambda} = \frac{\sum_{i=1}^{n} x_{i}}{\lambda^{x_{i}}} - \lambda \qquad -\sum_{i=1}^{n} x_{i} \ln(\lambda) - \sum_{i=1}^{n} (x_{i}!) - \lambda \lambda$$

$$\overline{x} = 2.4$$

## Ronus

Try to estimate population size of some species via capture-recapture scheme. Capture-recapture uses hypergeometric distribution vith PMF:

$$p(x) = \frac{\binom{M}{x} \binom{N-M}{n-x}}{\binom{N}{n}}$$

python cod

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