Let  $X_i \sim_{i.i.d.} Poisson(\lambda)$ . Find the MLE for  $\lambda$ .

We first need to write down the joint density of the samples  $X_i$ , given as the product of their respective densities (because they are independent)

$$L(X_1, \dots, X_n) = \prod_i \frac{\lambda^{x_i} e^{-\lambda}}{x_i!}$$

$$= \frac{\lambda^{\sum_i x_i} e^{-n\lambda}}{\prod_i x_i!}$$
(2)

$$=\frac{\lambda^{\sum_{i}x_{i}}e^{-n\lambda}}{\prod_{i}x_{i}!}\tag{2}$$

This is a case, as most are, where taking the logarithm of the density simplifies things greatly. We see that:

$$\log(L) = \sum_{i} x_{i} \cdot \log(\lambda) - \lambda n - \log(\prod_{i} x_{i}!). \tag{3}$$

The final step is to differentiate with respect to  $\lambda$ :

$$\frac{\partial}{\partial \lambda} \log(L) = \sum_{i} x_{i} \cdot \frac{1}{\lambda} - n \tag{4}$$

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$$\frac{\partial}{\partial \lambda} \log(L) = \sum_{i} x_{i} \cdot \frac{1}{\lambda} - n \tag{4}$$

Which we then set to zero:

$$\sum_{i} x_{i} \cdot \frac{1}{\widehat{\lambda}} = n \tag{5}$$

$$\widehat{\lambda} = \frac{1}{n} \sum_{i} x_{i}.$$
(6)

And so this is just the average of the samples.

So, if we observe the values 2, 4, 5, and 7 and believe that they come from a Poisson distribution, a good estimator of the rate  $\lambda$  is:

$$\widehat{\lambda} = \frac{1}{4} (2 + 4 + 5 + 7)$$

$$= 4.5$$
(8)

Let  $X_i \sim_{i.i.d.} Geometric(p)$ . Find the MLE for p.

We again need to write down the joint density of the samples  $X_i$ :

$$L(X_1, \dots, X_n) = \prod_{i} (1 - p)^{x_i - 1} \cdot p$$

$$= (1 - p)^{\sum_{i} x_i - n} \cdot p^n$$
(10)

And we again take the logarithm of the density to simplify:

$$\log(L) = (\sum_{i} x_i - n) \log(1 - p) + n \log(p)$$

(11)

And then differentiate with respect to *p*:

$$\frac{\partial}{\partial \lambda} \log(L) = \frac{n}{p} - \frac{\sum_{i} x_i - n}{1 - p}$$

(12)

And then differentiate with respect to p:

$$\frac{\partial}{\partial \lambda} \log(L) = \frac{n}{p} - \frac{\sum_{i} x_i - n}{1 - p}$$

Which we then set to zero:

$$\frac{n}{\widehat{p}} = \frac{\sum_{i} x_i - n}{1 - \widehat{p}}$$

$$\frac{1}{\widehat{p}} = \frac{1}{1 - \widehat{p}}$$

$$p(1 - \widehat{p}) = \widehat{p}(\sum r_i - r_i)$$

$$n(1 - \widehat{p}) = \widehat{p}(\sum_{i} x_{i} - n)$$
$$n - n\widehat{p} = \widehat{p}\sum_{i} x_{i} - \widehat{p}n$$

$$n - n\widehat{p} = \widehat{p} \sum_{i} x_{i}$$
$$n = \widehat{p} \sum_{i} x_{i}$$

$$n-n\widehat{p} =$$

(12)

(13)

(14)

(15)

And so this gives the estimator:

$$\widehat{p} = \frac{n}{\sum_{i} x_{i}} \tag{17}$$

Does this make sense? (it should!)

If we observe the number of free throws a basketball player makes before missing one, and get the data points 10, 8, 12, and 2, a good estimator for how often they miss a free throw would be:

$$\widehat{p} = \frac{4}{10 + 8 + 12 + 2}$$

$$= 0.125$$
(19)

Or, in other words, they make aroun 87.5% of their throws.