

# Problem Set 5

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## 1 References and License

We are answering questions in the material from MIT OpenCourseWare course 18.05, Introduction to Probabil-

ity and Statistics.

In this document we are answering questions Orloff and Bloom ask in [1].

Please see the references section for detailed citation information.

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We use documentation in to write the L<sup>A</sup>T<sub>E</sub>Xsource code for this document.

## 2 Fit line to data

In this section we answer questions about a random variable  $Y$  drawn from the random variable  $Y_i \sim ax_i + b + \epsilon_i$ , where  $\epsilon_i$  is a random variable with mean 0 and variance  $\sigma^2$ .

Orloff and Bloom grant us that the  $\epsilon_i$  are independent.

### 2.1 Likelihood function

We derive the likelihood function  $f(y_i | a, b, x_i, \sigma)$ .

To derive  $f$  we assume  $x_i, y_i$ , and  $\sigma$  are known values.

It is of paramount importance to note:

$$\epsilon_i \sim N(0, \sigma). \tag{1}$$

We then look at the random variable:

$$Y_i = ax_i + b + \epsilon_i \tag{2}$$

$\epsilon_i$  is a random variable that follows a normal distribution. In the context of this discussion, it is not a fixed value, its value depends on what we choose for  $a$ , and  $b$ . Keep in mind that we are trying to find values for  $a$ , and  $b$  that maximize the likelihood of the linear relationship between  $X$  and  $Y$ .

So, if  $\epsilon_i \sim N(0, \sigma^2)$ , then

$$ax_i + b + \epsilon_i \sim N(ax_i + b, \sigma^2). \tag{3}$$

That is, since  $\epsilon_i$  is a random variable with mean 0, then the random variable  $ax_i + b + \epsilon_i$  will have mean  $ax_i + b$ . Orloff and Bloom show this in [2]. In this case we are treating  $ax_i + b$  as constants. This is really confusing, because we are trying to find values for  $a$  and  $b$  that maximize a probability. So we are considering varying values of  $a$  and  $b$  so that we find the best values for them. However, assuming we choose values for  $a$  and  $b$ , then  $ax_i + b + \epsilon_i$  will have mean  $ax_i + b$ .

In order to make the leap to a probability density function that we are going to maximize, we cite the reasoning Orloff and Bloom give in [3], section 4.

Then the likelihood function  $f_i$  for one point  $(x_i, y_i)$  is:

$$f_i(y_i \mid x_i, a, b, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y_i - (ax_i + b))^2}{2\sigma^2}}. \quad (4)$$

The likelihood function  $f$  of all points is the product of the function above for all values of  $x_i$ , and  $y_i$ :

$$f = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y_i - (ax_i + b))^2}{2\sigma^2}}. \quad (5)$$

We can rewrite the product above as:

$$f(y_i \mid x_i, a, b, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\sum_{i=1}^n (y_i - ax_i + b))^2}{2\sigma^2}}. \quad (6)$$

The right hand side of the equation above is the likelihood function.

## 2.2 Likelihood and log-likelihood functions for particular values

We suppose we have the following data:

$(1, 8), (3, 2), (5, 1)$ .

We write down the likelihood and log likelihood functions for these data:

$$f(y_i \mid x_i, a, b, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(8 - (a+b))^2 + (2 - (3a+b))^2 + (1 - (5a+b))^2}{2\sigma^2}}. \quad (7)$$

$$\ln(f(y_i | x_i, a, b, \sigma)) = \ln\left(\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(8-(a+b))^2 + (2-(3a+b))^2 + (1-(5a+b))^2}{2\sigma^2}}\right). \quad (8)$$

We simplify the right hand side of the equation above in several steps:

$$\ln(f(y_i | x_i, a, b, \sigma)) = \ln\left(\frac{1}{\sqrt{2\pi}\sigma}\right) + \ln\left(e^{-\frac{(8-(a+b))^2 + (2-(3a+b))^2 + (1-(5a+b))^2}{2\sigma^2}}\right) \quad (9)$$

$$\begin{aligned} \ln(f(y_i | x_i, a, b, \sigma)) &= \ln\left(\frac{1}{\sqrt{2\pi}\sigma}\right) + \\ &\frac{-\left((8-(a+b))^2 + (2-(3a+b))^2 + (1-(5a+b))^2\right)}{2\sigma^2} \ln(e). \end{aligned} \quad (10)$$

$$\ln(f(y_i | x_i, a, b, \sigma)) = \ln\left(\frac{1}{\sqrt{2\pi}\sigma}\right) + \frac{\left(-(8-(a+b))^2 + (2-(3a+b))^2\right)}{2\sigma^2} \quad (11)$$

### 2.2.1 General formulation

We gave the general formulation for the likelihood function above:

$$f(y_i, a, b, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\sum_{i=1}^n (y_i - ax_i + b))^2}{2\sigma^2}}. \quad (12)$$

Note we have removed the  $x_i$  from the left hand side of the equation as a function parameter because the  $x_i$  are constants.

We obtain the log likelihood function applying the natural logarithm function to both sides of the equation above, and then simplifying using the laws of logarithms.

$$\ln(f(y_i, a, b, \sigma)) = \ln\left(\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\sum_{i=1}^n (y_i - ax_i + b))^2}{2\sigma^2}}\right). \quad (13)$$

$$\ln(f(y_i, a, b, \sigma)) = \ln\left(\frac{1}{\sqrt{2\pi}\sigma}\right) + \ln\left(e^{-\frac{(\sum_{i=1}^n (y_i - ax_i + b))^2}{2\sigma^2}}\right). \quad (14)$$

$$\ln(f(y_i, a, b, \sigma)) = \ln\left(\frac{1}{\sqrt{2\pi}\sigma}\right) + \ln\left(e^{-\frac{(\sum_{i=1}^n (y_i - ax_i + b))^2}{2\sigma^2}}\right). \quad (15)$$

$$\ln(f(y_i, a, b, \sigma)) = \ln\left(\frac{1}{\sqrt{2\pi}\sigma}\right) - \frac{(\sum_{i=1}^n (y_i - ax_i + b))^2}{2\sigma^2}. \quad (16)$$

### 2.3 Maximum likelihood estimates for $a$ , and $b$

For this problem, Orloff and Bloom allow us to assume that  $\sigma$  is a constant, known value. They ask us to find the maximum likelihood estimates for  $a$ , and  $b$ , under these circumstances.

In this case, we will be working with partial derivatives of

$$\ln(f(y_i |, a, b, \sigma)) = \ln\left(\frac{1}{\sqrt{2\pi}\sigma}\right) + \frac{\left(-(8 - (a + b))^2 + (2 - (3a + b))^2 + (1 - (4a + 2b))^2\right)}{2\sigma^2} \quad (17)$$

At this point we have an exercise in calculus and linear algebra to obtain two equations in two unknowns by setting the partial derivatives of the function  $f$  above with respect to  $a$ , and  $b$  to zero, and then solving the system for  $a$  and  $b$ .

$$\frac{\delta a}{\delta f} \ln(f(y_i |, a, b, \sigma)) = \frac{-2(8 - (a + b)) - 2(6)(2 - (3a + b)) - 2(5)(1 - (4a + 2b))}{2\sigma^2} \quad (18)$$

## References

- [1] Jeremy Orloff and Jonathan Bloom. *18.05 Problem Set 5, Spring 2014*. Available at [https://ocw.mit.edu/courses/mathematics/18-05-introduction-to-probability-and-statistics-spring-2014/assignments/MIT18\\_05S14\\_ps5.pdf](https://ocw.mit.edu/courses/mathematics/18-05-introduction-to-probability-and-statistics-spring-2014/assignments/MIT18_05S14_ps5.pdf) (Spring 2014).
- [2] Jeremy Orloff and Jonathan Bloom. *Expectation, Variance and Standard Deviation for Continuous Random Variables Class 6, 18.05, Spring 2014* Jeremy Orloff and Jonathan Bloom. Available at [https://ocw.mit.edu/courses/mathematics/18-05-introduction-to-probability-and-statistics-spring-2014/readings/MIT18\\_05S14\\_Reading6a.pdf](https://ocw.mit.edu/courses/mathematics/18-05-introduction-to-probability-and-statistics-spring-2014/readings/MIT18_05S14_Reading6a.pdf) (Spring 2014).
- [3] Jeremy Orloff and Jonathan Bloom. *Maximum Likelihood Estimates Class 10, 18.05* Jeremy Orloff and Jonathan Bloom. Available at [https://ocw.mit.edu/courses/mathematics/18-05-introduction-to-probability-and-statistics-spring-2014/readings/MIT18\\_05S14\\_Reading10b.pdf](https://ocw.mit.edu/courses/mathematics/18-05-introduction-to-probability-and-statistics-spring-2014/readings/MIT18_05S14_Reading10b.pdf) (Spring 2014).