

# [Re] Local alignment statistics - Regression analysis by Altchul and Gish 1996

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## Introduction

This script replicates the regression analysis discussed in Altschul and Gish (1996). It assumed you have Tab 1 already loaded into memory OR load it using the code below.

Regression analysis is used to calculate K and lambda from mu (u) and the sequence lengths. The starting point is the following equation:

Plain text version of equation:

$$\mu = (\ln(m \times n \times K))/\lambda$$

Rendered version of equation.

$$\mu = \frac{\ln(m * n * K)}{\lambda}$$

Altschul and Gish (1996) indicate that this equation can be re-arranged into a linear equation of the form  $y = M X x + b$

where

- y is mu (the response or dependent variable)
- M is the slope
- x is  $\ln(m \times n)$  (the predictor or independent variable)
- b is the intercept

This gives us  $y = M X x + b$   $\mu = (1 / \lambda) X \ln(m \times n) + \ln(K)/\lambda$

From our simulations we will input sequences of length m and length n, and we will get out a distribution of scores. From the distribution of scores we'll be able to estimate mu. We can then make a scatter plot of mu versus  $\ln(m \times n)$  and use linear regression to estimate a line of best fit of the form  $y = M X x + b$ . The parameters for this line, M and b, can then be re-arranged algebraically to estimate lambda and  $\ln(K)$

$$M = 1/\lambda$$

which rearranges to

$$M * \lambda = 1$$

and then

$$\lambda = 1/M.$$

So, the inverse of the slope from our regression will give us lambda.

Once we have lambda, we can solve for K

$$b = \ln(K)/\lambda$$

$$b X \lambda = \ln(K)$$

$$\exp(b X \lambda) = \exp(\ln(K))$$

$$\exp(b \times \lambda) = K$$

We just got  $\lambda$  above, so we plug that value into the equation and get  $K$ .

We can see how the original linear equation gets converted by recalling that  $\ln(a \times b) = \ln(a) + \ln(b)$

Therefore,  $\ln(m \times n \times K)$  can be rearranged to  $\ln(K) + \ln(m \times n)$

So, starting with  $\mu = (\ln(m \times n \times K))/\lambda$

We apply the addition rule of logs we just outlined  $\mu = (\ln(m \times n) + \ln(K))/\lambda$

and we get  $\mu = \ln(m \times n)/\lambda + \ln(K)/\lambda$

which is equivalent to

$$\mu = (1/\lambda) \times \ln(m \times n) + \ln(K)/\lambda$$

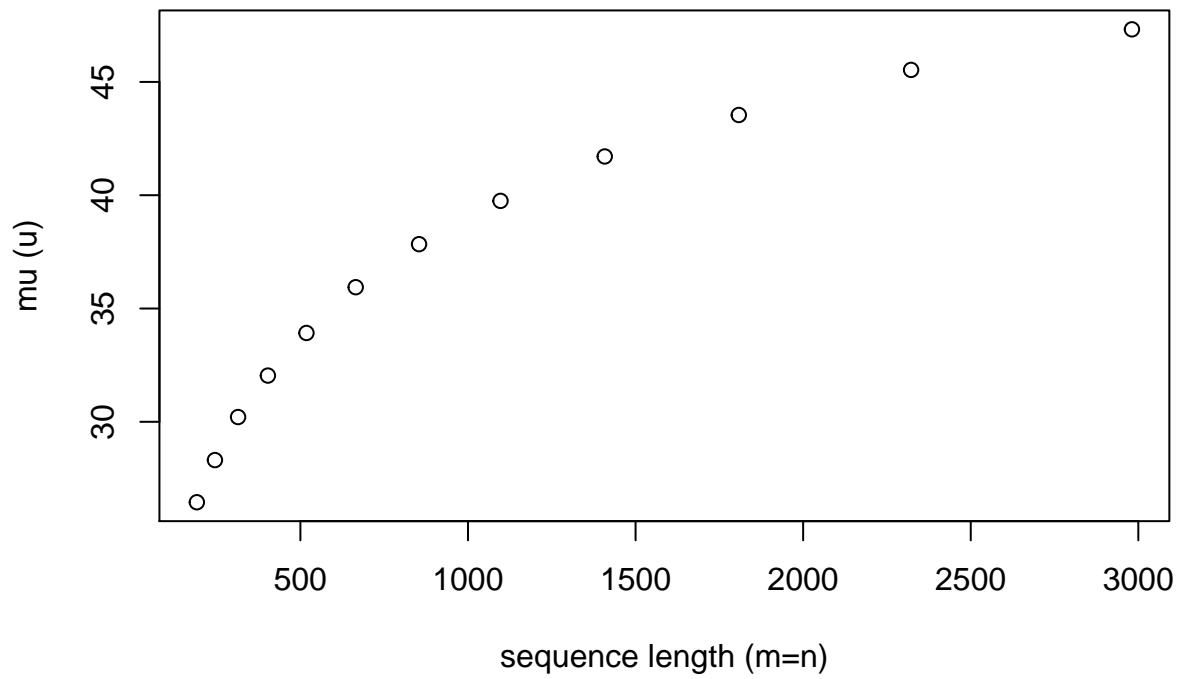
## Load Table 1

```
table1 <- read.csv(file = "table1.csv")
```

## Regression analysis

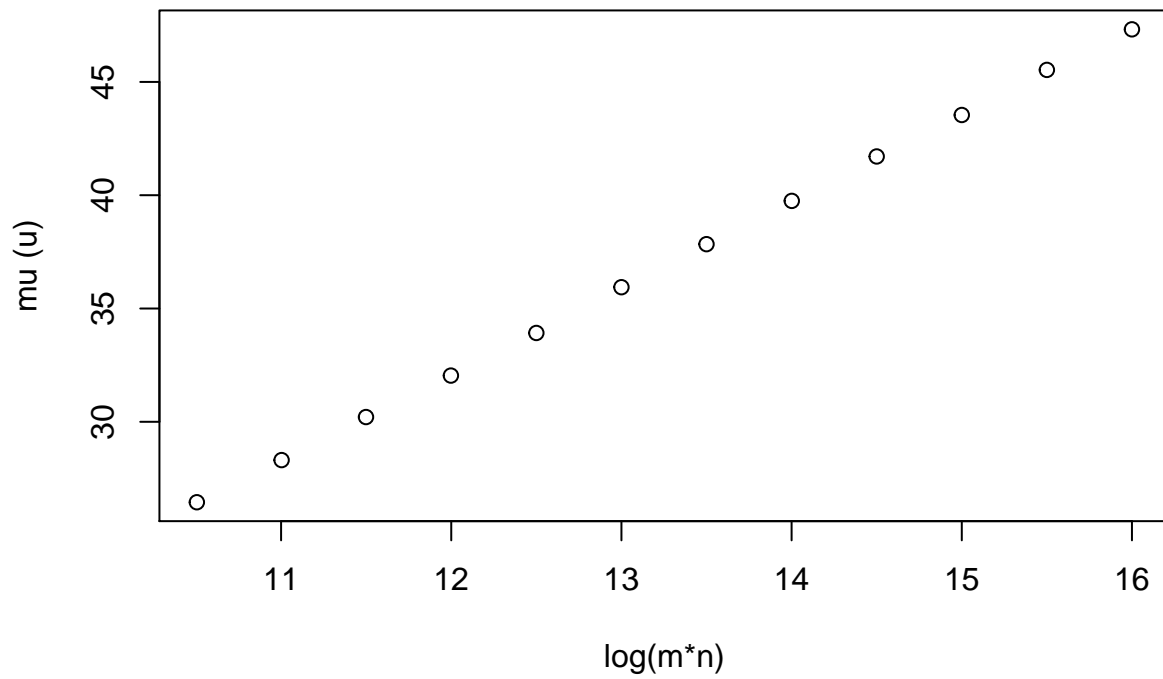
There is a non-linear relationship between length of the simulated sequences and the estimate of  $\mu$

```
plot(table1$u ~ table1$mn,  
     xlab = "sequence length (m=n)",  
     ylab = "mu (u)")
```



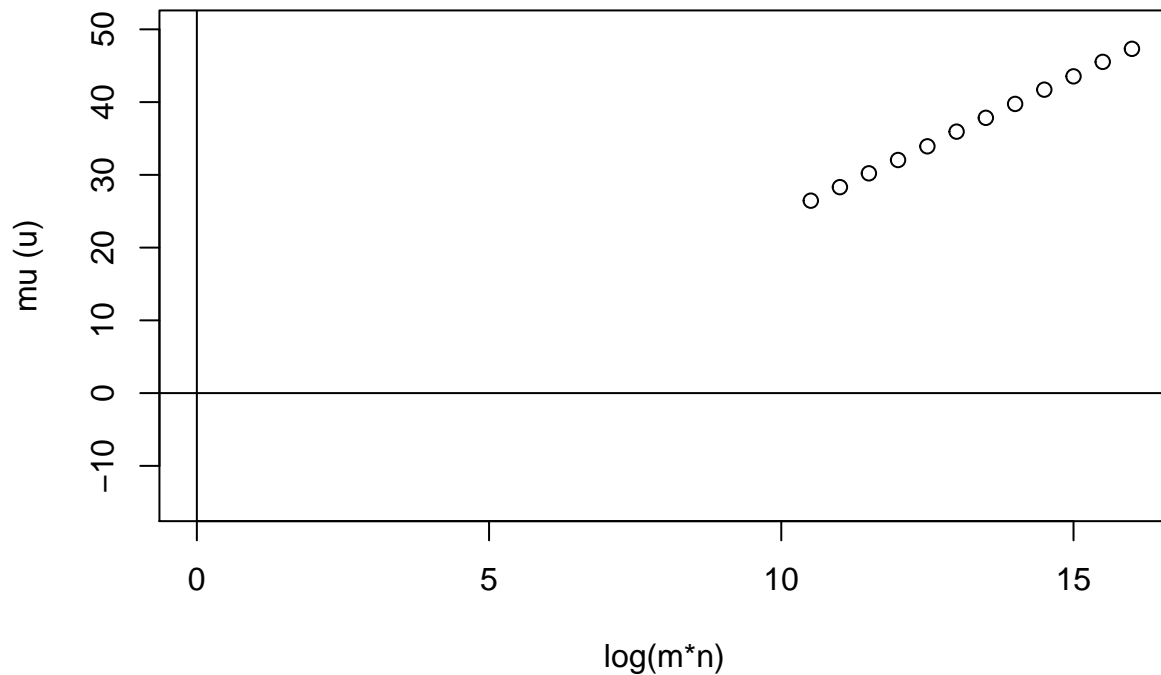
Taking the log of  $m \cdot n$  (the search space)

```
plot(table1$u ~ table1$ln.nm,  
      xlab = "log(m*n)",  
      ylab = "mu (u)")
```



Plot  $\log(m \cdot n)$  vs  $u$ , with the axes adjusted so the origin ( $x = 0$ ,  $y = 0$ ) is visible.

```
plot(table1$u ~ table1$ln.nm,  
     xlim = c(0,16),  
     ylim = c(-15,50),  
     xlab = "log(m*n)",  
     ylab = "mu (u)")  
abline(h = 0)  
abline(v = 0)
```



Linear regression using `lm()`

```
# linear regression
lin.reg <- lm(u ~ ln.nm, data = table1)
```

```
# look at output
summary(lin.reg)
```

```
##
## Call:
## lm(formula = u ~ ln.nm, data = table1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.095304 -0.027192  0.008233  0.024556  0.063545
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -13.697825   0.115689  -118.4   <2e-16 ***
## ln.nm         3.817050   0.008658   440.9   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.05174 on 10 degrees of freedom
## Multiple R-squared:  0.9999, Adjusted R-squared:  0.9999
## F-statistic: 1.944e+05 on 1 and 10 DF, p-value: < 2.2e-16
```

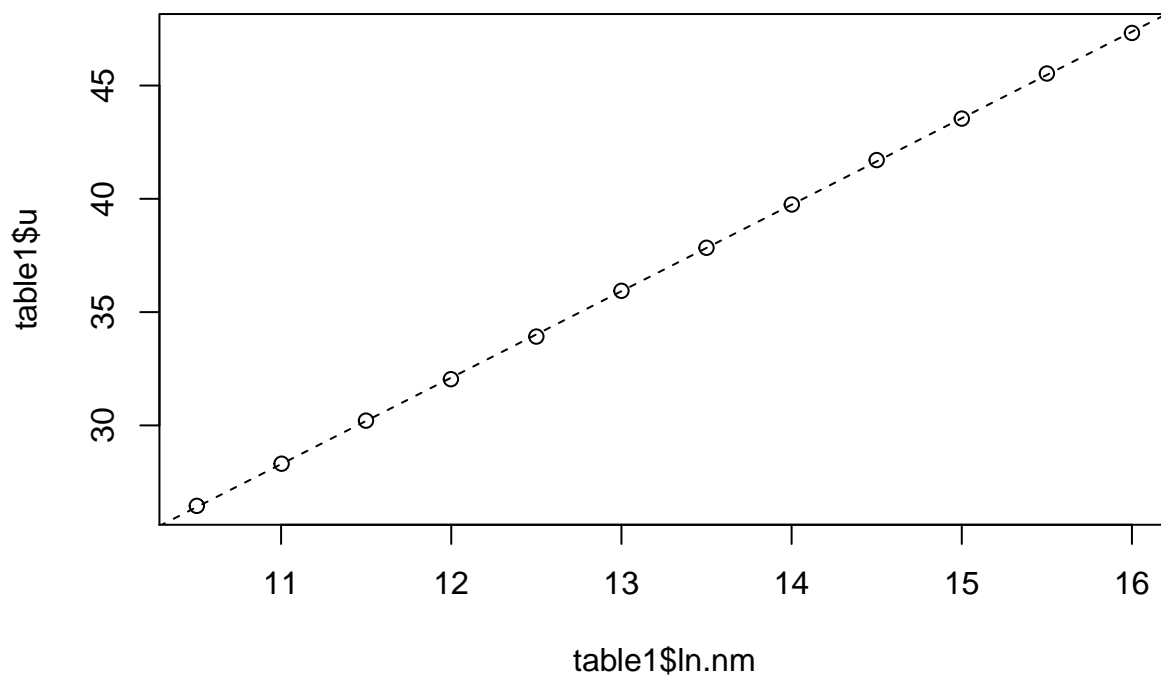
```
# look at intercept and slope
coef(lin.reg)
```

```
## (Intercept)      ln.nm
##   -13.69782     3.81705
```

Plot regression line on plot scaled normally

```
# plot data; no adjusted to xlim or ylim
plot(table1$u ~ table1$ln.nm)

# add regression line
abline(lin.reg, lty = 2)
```



Plot regression line on plot scaled with origin visible

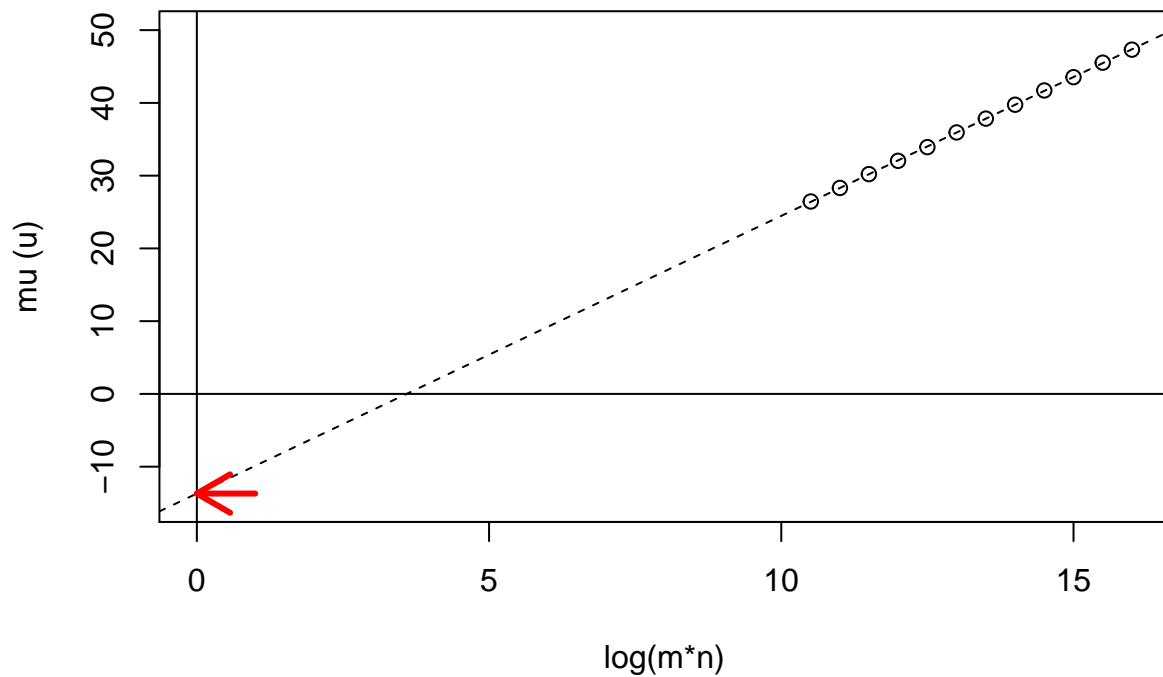
```
# plot data
plot(table1$u ~ table1$ln.nm,
      xlim = c(0,16),
      ylim = c(-15,50),
      xlab = "log(m*n)",
      ylab = "mu (u)")

#add regression line
abline(lin.reg, lty = 2)

#add reference lines
abline(h = 0)
```

```
abline(v = 0)

# show where y intercept is
arrows(x1 = 0,
       x0 = 1,
       y0 = -13.69782,
       y1 = -13.69782 ,length = 0.2, lwd = 3, col = 2)
```



Extract parameters from linear regression

```
#y = M*x + b
#y = M*ln(m*n) + b
# M = slope
# b = intercept
b <- coef(lin.reg)[1] #intercept; ln(K)/lambda
M <- coef(lin.reg)[2] #slope; 1/lambda

# M = 1 / lambda
# re-arrange to:
# M*lambda = 1
# lambda = 1/M
lambda <- 1/M # 0.261 reported in original paper
lambda

## ln.nm
```

```
## 0.2619824
#  $b = \ln(K)/\lambda$ 
#  $b*\lambda = \ln(K)$ 
#  $\exp(b*\lambda) = K$ 
K <- exp(b*lambda) # 0.026 reported in Table 2
K
```

```
## (Intercept)
## 0.0276373
```

## Advanced/Optional: Regression analysis on “edged-corrected” length

This is same idea as above, except using the “edge-corrected” distances discussed by Altschul and Gish. This reduces the discrepancies between the results of their experiment and theoretical predictions.

```
lin.reg2 <- lm(u ~ ln.n.m., data = table1)
summary(lin.reg2)

##
## Call:
## lm(formula = u ~ ln.n.m., data = table1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.125323 -0.025757 -0.000993  0.025927  0.118919
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -11.32176    0.15454  -73.26 5.48e-15 ***
## ln.n.m.       3.67345    0.01167  314.80 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07246 on 10 degrees of freedom
## Multiple R-squared:  0.9999, Adjusted R-squared:  0.9999
## F-statistic: 9.91e+04 on 1 and 10 DF, p-value: < 2.2e-16

b2 <- coef(lin.reg2)[1] #intercept;  $\ln(K)/\lambda$ 
M2 <- coef(lin.reg2)[2] #slope;  $1/\lambda$ 

lambda2 <- 1/M2 # 0.261 reported in original paper
lambda2

## ln.n.m.
## 0.2722238

K2 <- exp(b2*lambda2) # 0.026 reported in Table 2
K2

## (Intercept)
## 0.045865
```