

# Nonlinear, Non-normal models

## Lecture 05.3: Determining your Distribution

Lauren Sullivan

Module: Linear, Nonlinear, and Mixed Effects Models

# Readings

## Required for class:

- ▶ NA

## Optional:

- ▶ Sullivan et al. 2016 *PLOS ONE*
- ▶ Bolker, B. *Ecological Models and Data in R - Ebook version*
- ▶ Brooks-Bartlett, J. *Probability concepts explained: Maximum likelihood estimation*

## What distribution to use?

Sometimes you are in a situation where you have your data, but you do not know what distribution fits your dependent variables ( $Y$ 's) and thus you don't know what approach to take for the rest of your analysis.

You need a method for determining which distribution fits your data most appropriately.

## Maximum Likelihood

To determine what distribution best fits your data, you need to use maximum likelihood estimation, which allows you to determine the *maximum likelihood estimates* (MLE) of the parameters of the potential distributions you are testing. These parameter estimates define the distribution so it **MOST LIKELY** fits the data.

NOTE: We try to maximize the log of the likelihood. But note that in most cases people *minimize* the negative log-likelihood instead of maximizing the positive log-likelihood.

# Data

Restored prairie experiment to understand how the presence/absence of herbivores alter the movement of the native Partridge Pea (*Chamaecrista fasciculata*) away from source locations.

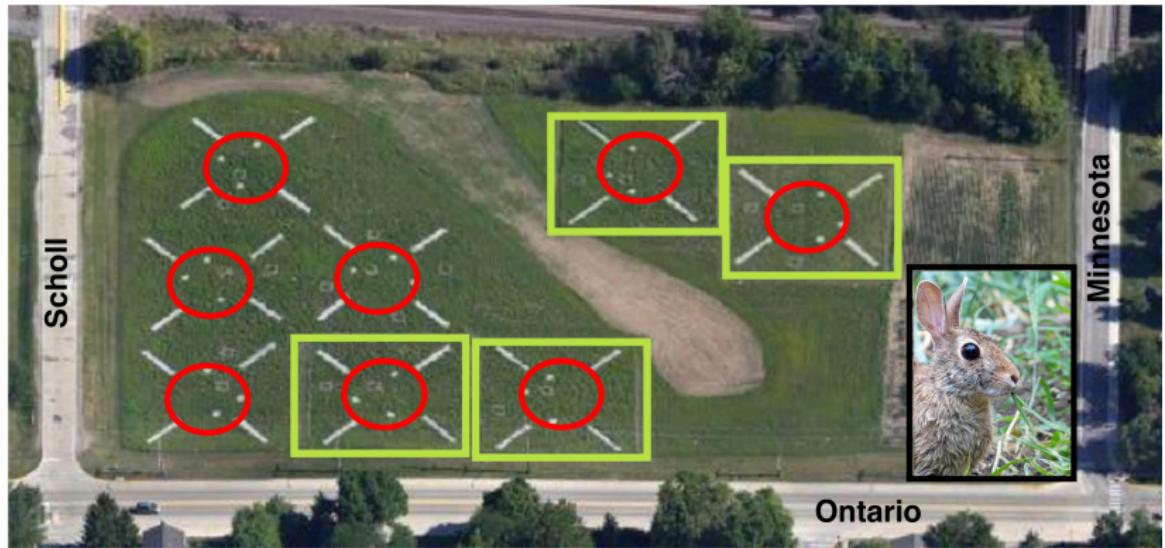
*Chamaecrista fasciculata*



Figure 1: From: Sullivan et al. 2016 PLOS ONE

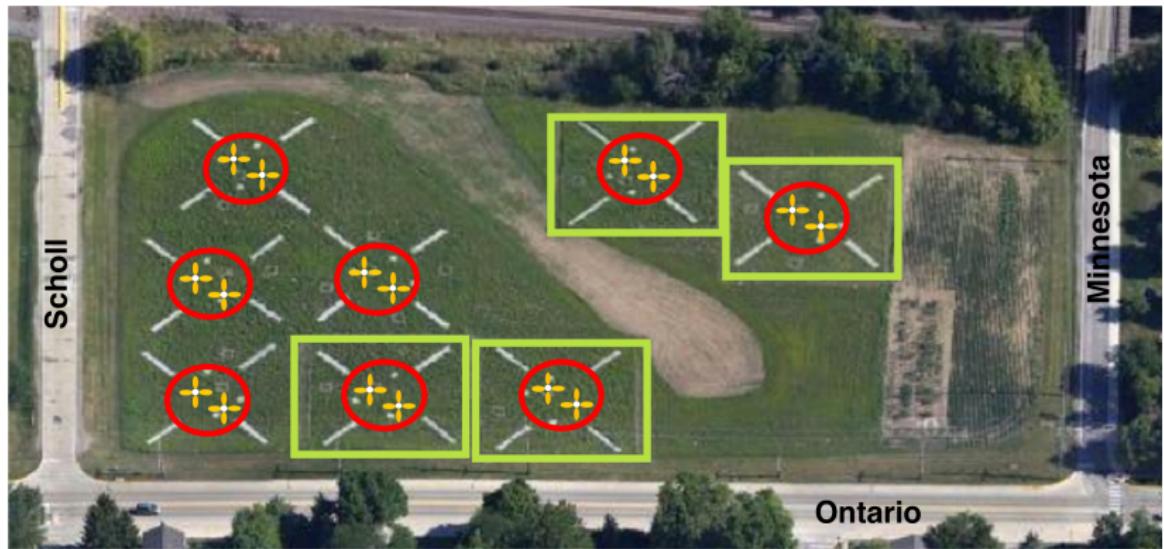
# Experimental Design

Have experimental units that either allow/deny herbivores access to the restored prairies.



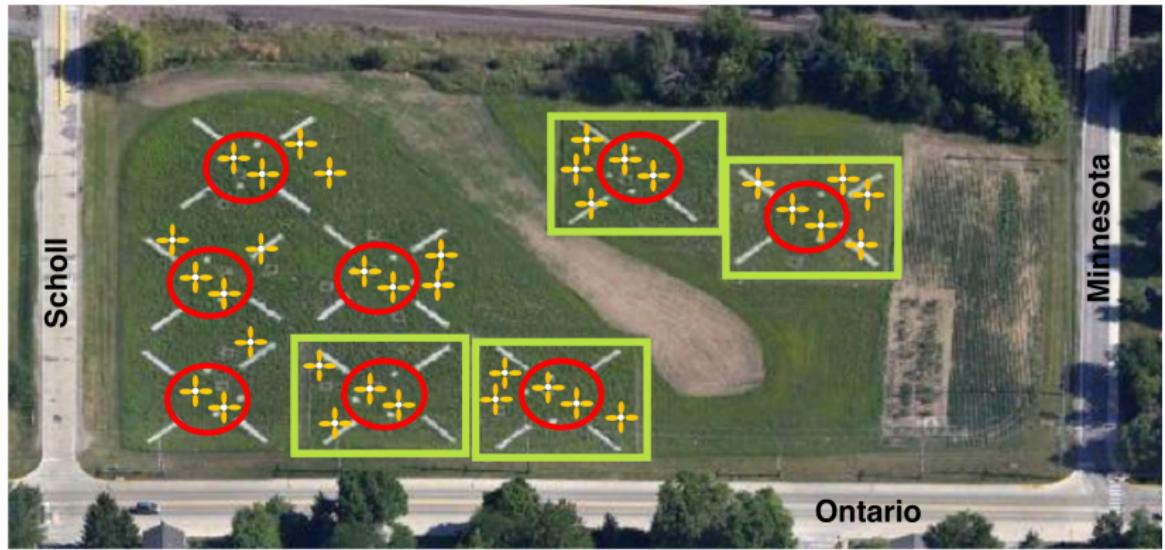
# Experimental Design

Plant Partridge Pea in known locations.

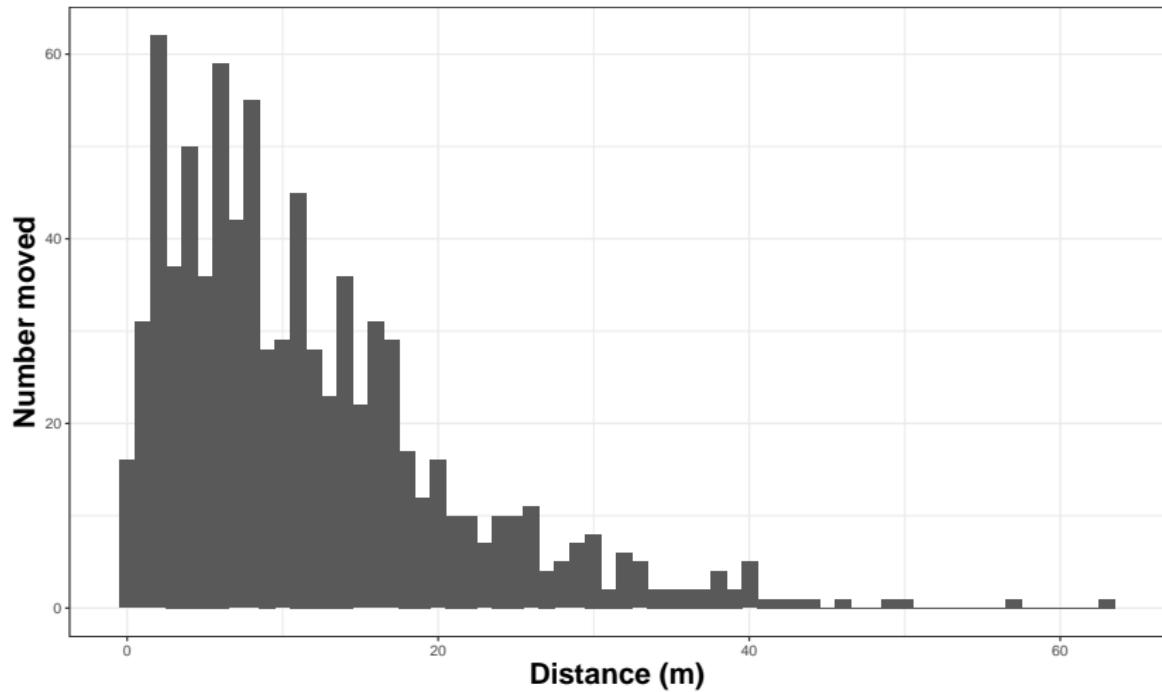


# Experimental Design

Measure how far away from the sources the new plants move and determine the shape of this distribution.



Graph the  $Y$ 's to see what shape they take.



## Fit different distributions with MLE - Normal

```
fit.norm.disc <- mle2(chafas$distance_.1bins~dnorm(mean=mu, sd=s),
                      start=list(mu=mean(chafas$distance_.1bins),
                                  s=sd(chafas$distance_.1bins)),
                      data=chafas)
summary(fit.norm.disc)

## Maximum likelihood estimation
##
## Call:
## mle2(minuslogl = chafas$distance_.1bins ~ dnorm(mean = mu, sd = s),
##       start = list(mu = mean(chafas$distance_.1bins), s = sd(chafas$distance_.
##       data = chafas)
##
## Coefficients:
##             Estimate Std. Error z value     Pr(z)
## mu    11.74002   0.32745 35.853 < 2.2e-16 ***
## s     9.41667   0.23154 40.669 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## -2 log L: 6055.989
```

## Fit different distributions with MLE - Exponential

```
fit.exp.disc<- mle2(chafas$distance_.1bins~dexp(rate=rate),
                      start=list(rate=11), data= chafas)
summary(fit.exp.disc)

## Maximum likelihood estimation
##
## Call:
## mle2(minuslogl = chafas$distance_.1bins ~ dexp(rate = rate),
##       start = list(rate = 11), data = chafas)
##
## Coefficients:
##             Estimate Std. Error z value    Pr(z)
## rate 0.0851962  0.0029626 28.758 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## -2 log L: 5727.808
```

## Fit different distributions with MLE - Poisson

```
fit.pois.disc<-mle2(chafas$distance_.1bins~dpois(lambda=1),
                      start=list(l=mean(chafas$distance_.1bins)),
                      data= chafas)
summary(fit.pois.disc)

## Maximum likelihood estimation
##
## Call:
## mle2(minuslogl = chafas$distance_.1bins ~ dpois(lambda = 1),
##       start = list(l = mean(chafas$distance_.1bins)), data = chafas)
##
## Coefficients:
##   Estimate Std. Error z value    Pr(z)
## l 11.74002   0.11915 98.534 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## -2 log L: 9031.689
```

## Fit different distributions with MLE - Negative Binomial

```
fit.nbinom.disc<-mle2(chafas$distance_.1bins~dnbinom(mu=m, size=s),
                        start=list(m=10, s=.1), data= chafas)
summary(fit.nbinom.disc)

## Maximum likelihood estimation
##
## Call:
## mle2(minuslogl = chafas$distance_.1bins ~ dnbinom(mu = m, size = s),
##       start = list(m = 10, s = 0.1), data = chafas)
##
## Coefficients:
##             Estimate Std. Error z value    Pr(z)
## m 11.74005     0.32578  36.036 < 2.2e-16 ***
## s  1.81273     0.10175  17.816 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## -2 log L: 5688.677
```

## Use AIC to determine the difference between models

```
AICtab(fit.norm.disc, fit.exp.disc, fit.pois.disc, fit.nbinom.disc)
```

```
##                   dAIC   df
## fit.nbinom.disc    0.0  2
## fit.exp.disc      37.1  1
## fit.norm.disc     367.3  2
## fit.pois.disc    3341.0  1
```

Graph the data and estimated distributions of your data based on likelihood estimates of parameters

fit of various distributions in relation to measured distance data

