Week 13 Activity: GLMs

Now reconsider the willow tit dataset and consider modeling not just the presence / absence of birds, but directly modeling the number of birds observed in each spatial region.

```
birds <- read.csv('http://math.montana.edu/ahoegh/teaching/stat491/data/willowtit2013_count.csv')
head(birds) %>% kable()
```

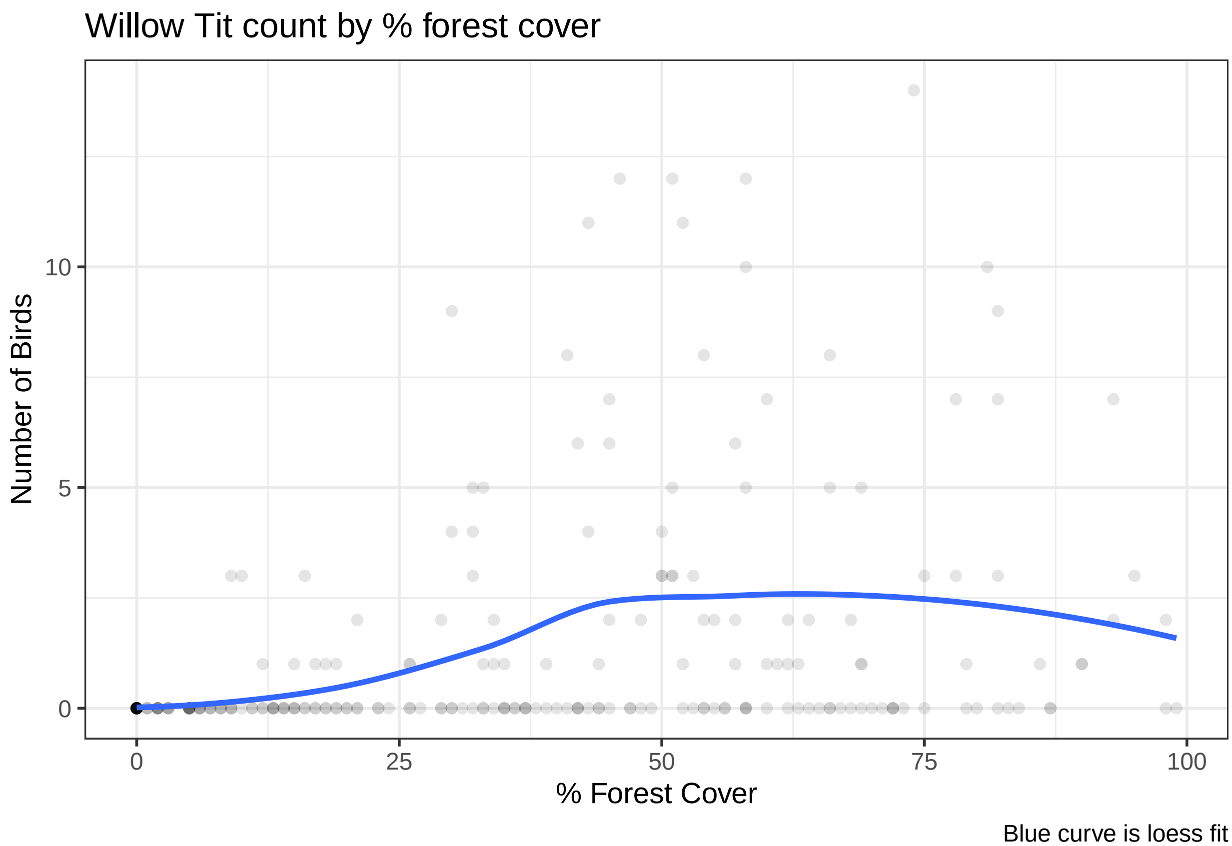
siteID	elev	rlength	forest	bird.count	searchDuration
Q001	450	6.4	3	0	160
Q002	450	5.5	21	0	190
Q003	1050	4.3	32	3	150
Q004	950	4.5	9	0	180
Q005	1150	5.4	35	0	200
Q006	550	3.6	2	0	115

This dataset contains 242 sites and 6 variables:

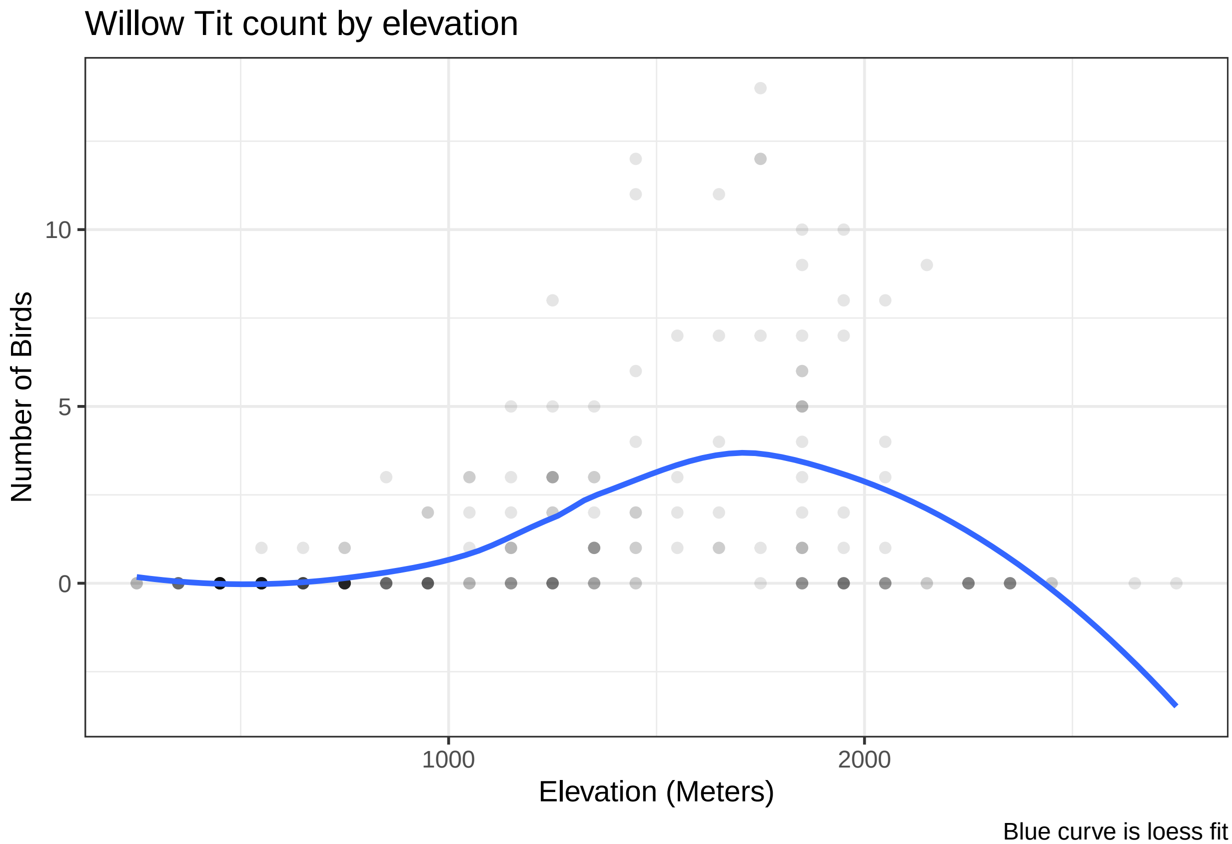
```
- siteID, a unique identifier for the site, some were not sampled during this period
- elev, mean elevation of the quadrant in meters
- rlength, the length of the route walked by the birdwatcher, in kilometers
- forest, percent forest cover
- bird.count, number of birds identified
- searchDuration, time birdwatcher spent searching the site, in minutes
```

1. Data Visualization Create two figures that explore `bird.count` as a function of forest cover percentage (`forest`) and elevation (`elev`) data visualization that

```
birds %>% ggplot(aes(y = bird.count, x = forest)) + geom_point(alpha = .1) +
  geom_smooth(method ='loess', formula = "y ~ x", se = F) + theme_bw() +
  ggtitle('Willow Tit count by % forest cover') +
  ylab('Number of Birds') + xlab("% Forest Cover") +
  labs(caption = 'Blue curve is loess fit')
```




```
birds %>% ggplot(aes(y = bird.count, x = elev)) + geom_point(alpha = .1) +
  geom_smooth(method ='loess', formula = "y ~ x", se = F) + theme_bw() +
  ggtitle('Willow Tit count by elevation') +
  ylab('Number of Birds') + xlab("Elevation (Meters)") +
  labs(caption = 'Blue curve is loess fit')
```



2. Model Specification Using a Poisson regression model, clearly write out the model to understand how forest cover and elevation impact bird count.

$$count_i \sim Poisson(\mu_i) \tag{1}$$

$$\log(\mu_i) = \beta_0 + \beta_1 x_{elev} + \beta_2 x_{elev}^2 + \beta_3 x_{forest} + \beta_4 x_{forest}^2 \tag{2}$$

Note: variables will be standardized for this analysis.

3. Priors Describe and justify the necessary priors for this model.

I anticipate these values being small, so normal priors centered at zero with variance of 100 will be sufficient and minimally informative)

4. Fit MCMC Fit the JAGS code for this model. You will have to put this together following the specification in the previous examples, but the following statement can be used for the sampling model portion.

```
model.string <- 'model {
  for (i in 1:Ntotal) {
    y[i] ~ dpois(mu[i])
    mu[i] <- exp(beta0 + sum( beta[1:Nx] * x[i,1:Nx] ))
  }
  # priors inserted here
  beta0 ~ dnorm(0,1/5^2)
```

```
  for (j in 1:Nx){
    beta[j] ~ dnorm(0, 1/100^2)
  }
}'


birds <- birds %>%
  mutate(std_elev = (elev - mean(elev)) / sd(elev),
         std_elev_sq = std_elev^2,
         std_forest = (forest - mean(forest)) / sd(forest),
         std_forest_sq = std_forest^2)


# Fit Model
jags.poiss <-  jags.model(textConnection(model.string),
                data=list(y=birds$bird.count, Ntotal=nrow(birds), Nx = 4,
                x= birds[,c('std_elev','std_elev_sq','std_forest','std_forest_sq')]),
                             n.chains =2, n.adapt = 5000)
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 242
##    Unobserved stochastic nodes: 5
##    Total graph size: 2313
##
## Initializing model
```

```
update(jags.poiss, 10000)
samples <- coda.samples(jags.poiss, variable.names = c('beta','beta0'), n.iter = 10000)

summary(samples)
```

```
##
## Iterations = 15001:25000
## Thinning interval = 1
## Number of chains = 2
## Sample size per chain = 10000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##             Mean      SD  Naive SE Time-series SE
## beta[1]  2.34966 0.23392 0.0016541       0.009800
## beta[2] -1.03219 0.18933 0.0013388       0.007664
## beta[3]  1.37509 0.13300 0.0009405       0.003686
## beta[4] -0.70027 0.08609 0.0006087       0.002193
## beta0    0.06101 0.11644 0.0008234       0.002628
##
## 2. Quantiles for each variable:
##
##            2.5%     25%     50%     75%   97.5%
## beta[1]  1.9307  2.18994  2.33473  2.4948  2.8490
```

```
## beta[2] -1.4298 -1.15420 -1.02390 -0.9028 -0.6873
## beta[3]  1.1214  1.28287  1.37327  1.4642  1.6455
## beta[4] -0.8732 -0.75711 -0.69980 -0.6419 -0.5338
## beta0   -0.1745 -0.01491  0.06382  0.1406  0.2834
```

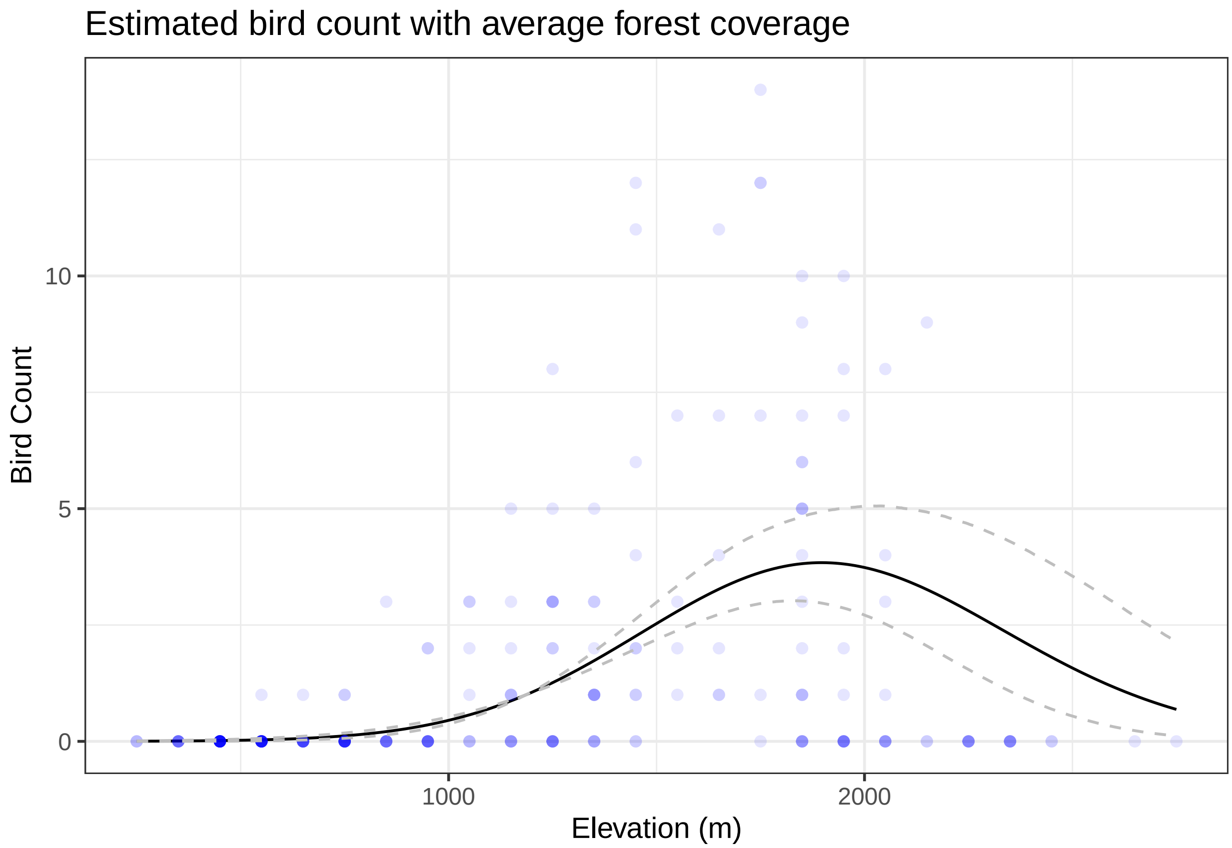
```
summary(glm(bird.count ~ std_elev + std_elev_sq + std_forest + std_forest_sq, family=poisson, data=birds
```

```
##
## Call:
## glm(formula = bird.count ~ std_elev + std_elev_sq + std_forest +
##     std_forest_sq, family = poisson, data = birds)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.4216  -0.7049  -0.2639  -0.0478   3.4696
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.07211    0.11653   0.619    0.536
## std_elev       2.32176    0.22672  10.241  < 2e-16 ***
## std_elev_sq   -1.01020    0.18229  -5.542 3.00e-08 ***
## std_forest     1.36736    0.13227  10.337  < 2e-16 ***
## std_forest_sq -0.69504    0.08482  -8.194 2.52e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 908.78  on 241  degrees of freedom
## Residual deviance: 308.86  on 237  degrees of freedom
## AIC: 557.92
##
## Number of Fisher Scoring iterations: 6
```

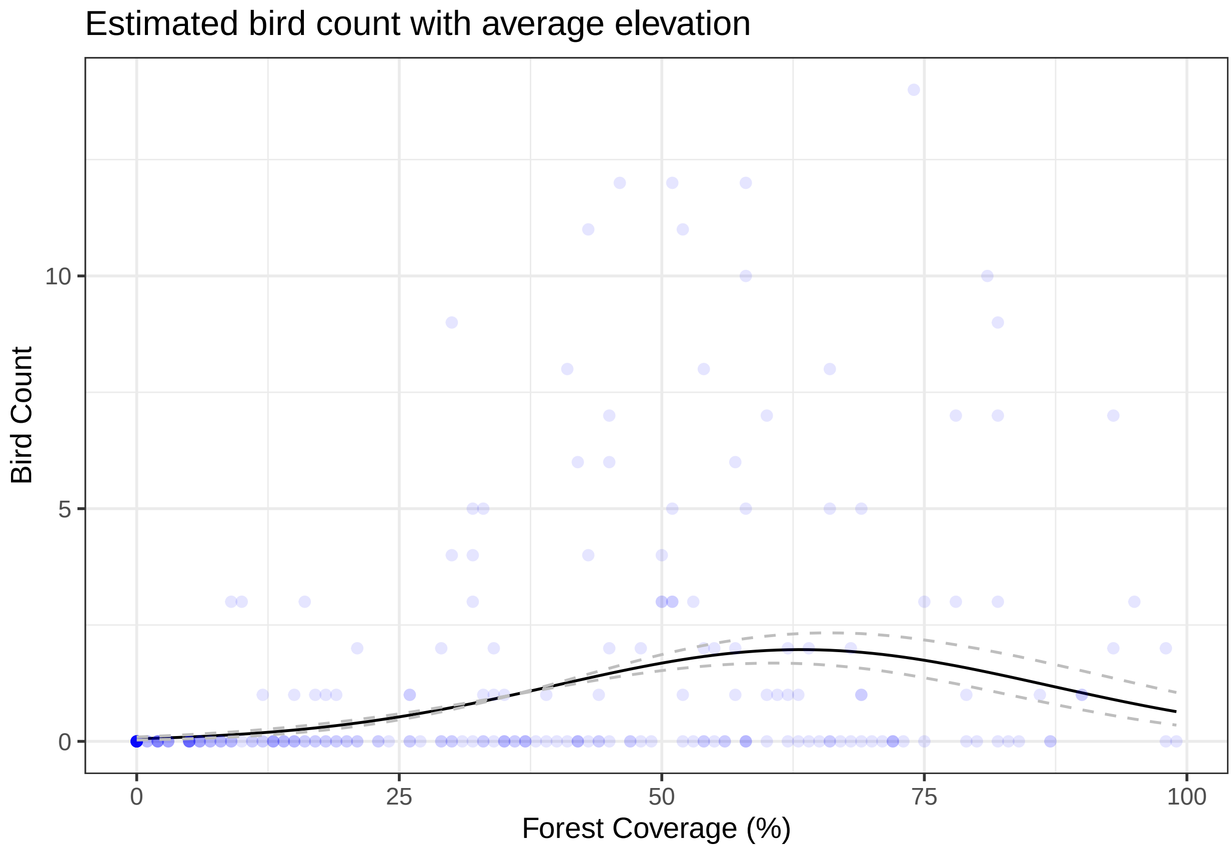
5. Summarize inferences from model Talk about the model and discuss which and how predictor variables influence the observed bird count.

With squared terms, the interpretation of coefficients is a little more complicated. However, we can start with the intercept.

- β_0: can be interpreted as the expected bird count for an average elevation (1186 meters) and average forest coverage (36%). In particular $\exp(\beta_0) = 1.0701059$ (0.8, 1.3)
- For an average forest coverage, the mean impact of elevation can be visualized as



- For an average elevation, the impact of forest coverage can be visualized as


Estimated bird count with average elevation
Bird Count
10
5
0
0
25
50
75
100
Forest Coverage (%)