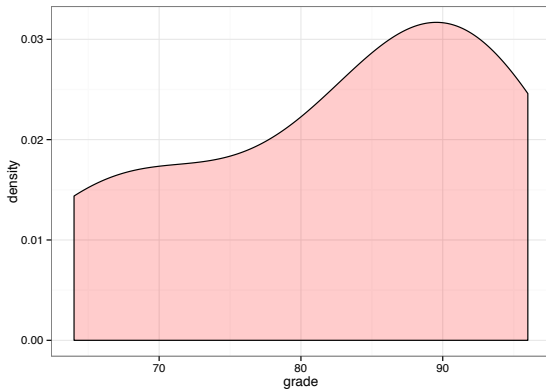
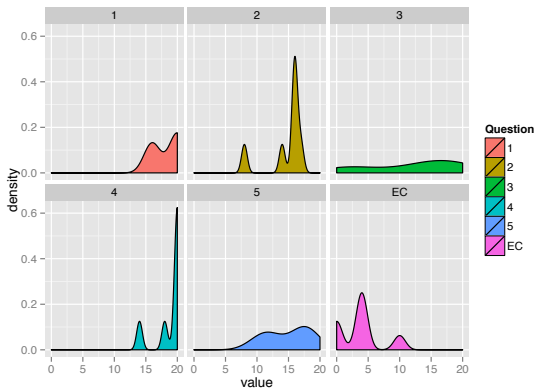


You all Did Fine

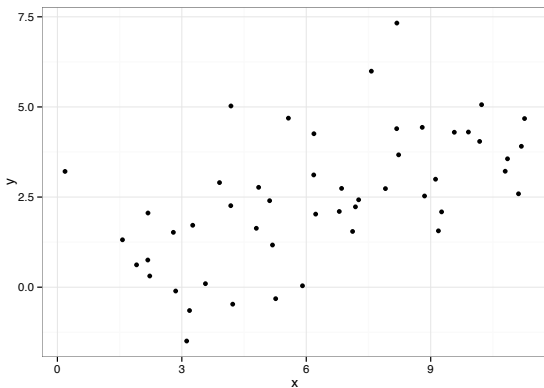


Main Issues were Power & Confidence Intervals of Non-Normal Regression

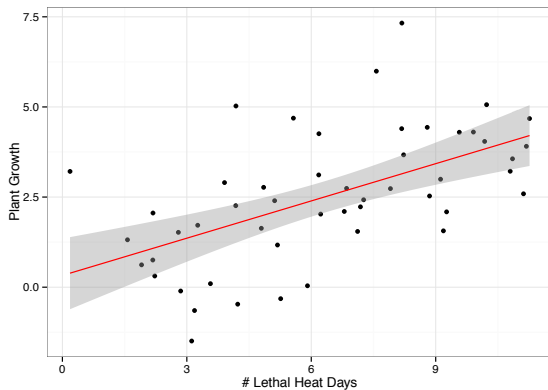


Observational Study Design

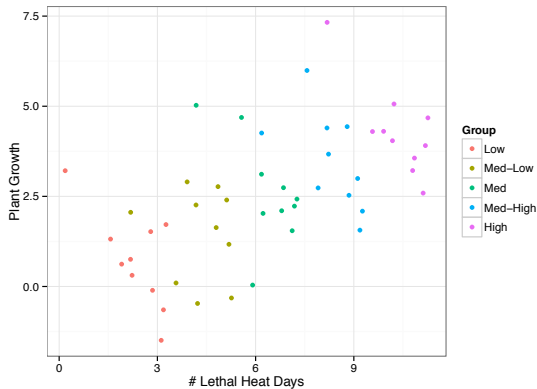
Problem: What if An Observed Relationship Doesn't Make Sense?



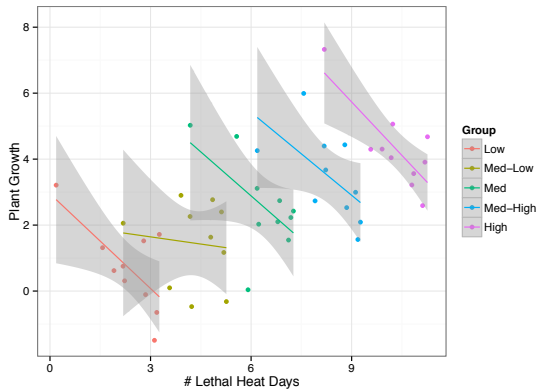
Problem: What if An Observed Relationship Doesn't Make Sense



Covariates can Change Results



Simpson's Paradox

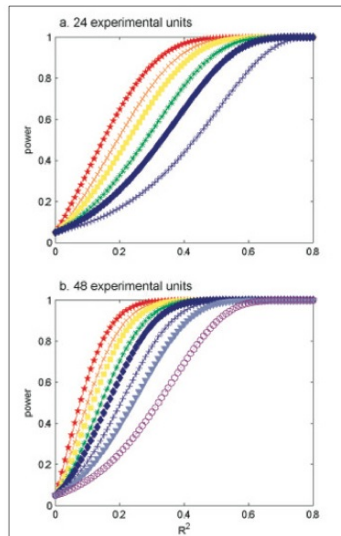


ANOVA v. Regression for Experiments

Regression Design and ANOVA Design have the Same Model

- ▶ $Y = BX + e$ underlies both
- ▶ F-Test for both examines variation explained
- ▶ BUT Regression has fewer parameters to sample size

For Linear Relationships, More Power from Regression



- ANOVA: 2 treatments; Regression: 1 factor
- ANOVA: 3 treatments
- ANOVA: 4 treatments; Regression: 2 factors
- ANOVA: 6 treatments
- ANOVA: 8 treatments
- ANOVA: 12 treatments
- ANOVA: 16 treatments
- ANOVA: 24 treatments

A Simulation Approach to ANOVA and Regression Power

```
getY <- function(x) rnorm(length(x), x , 10)

#two approaches
x<-1:24
xAnova<-rep(seq(1,24,length.out=6),4)
```

A Simulation Approach to ANOVA and Regression Power

```
powFunc <- function(predictor, n.sims=500, a=F, fun=getY){  
  pvec <- sapply(1:n.sims, function(i) {  
    y <-fun(predictor)  
  
    #run either a regression or categorical model  
    if(a){  
      alm <- lm(y~I(factor(predictor)))  
    }else{  
      alm <- lm(y~predictor)  
    }  
  
    #get p from an f test  
    anova(alm)[1,5]  
  } )  
  
  #power  
  1 - sum(pvec > 0.05)/n.sims  
}
```

Yes, Regression More Powerful

```
set.seed(100)
powFunc(x)

# [1] 0.914

powFunc(xAnova, a=T)

# [1] 0.712
```

What if the Relationship is Nonlinear

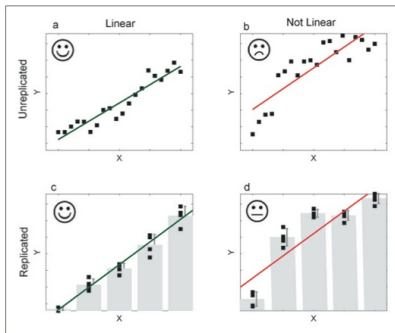
```
getYSat <- function(x) rnorm(length(x), -2/x, 0.7)
#
powFunc(x, fun=getYSat)

# [1] 0.39

powFunc(xAnova, a=T, fun=getYSat)

# [1] 0.918
```

Replicated Regression or Other Options



Nonlinear Least Squares an option, GLM if Heteroskedasticity exists