Regression
Lesson 3a

Kevin Zollicoffer

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Introduction

Regression assignment 3a using R

The complete source for this assigment is available on Github:

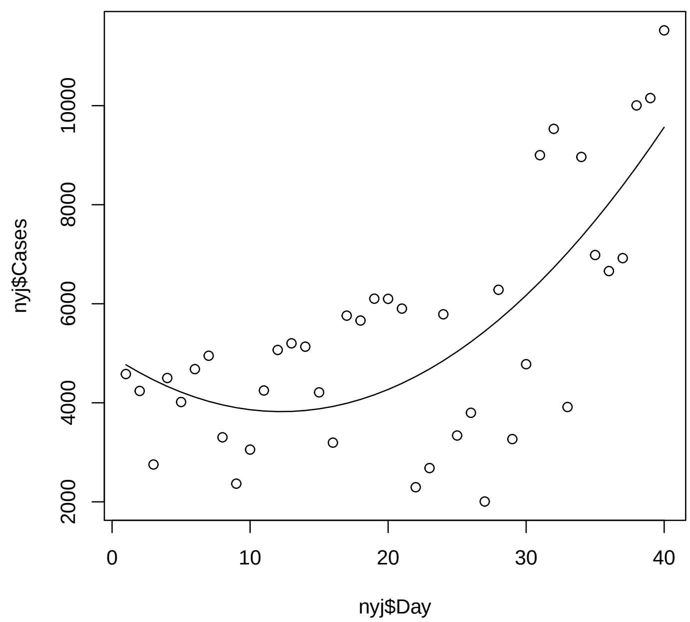
`https://github.com/zollie/PASS-Regression-Assignment3a`

Problem 4.1

```
> nyj <- read.csv("~/R/PASS/Regression/Assignment3a/nyjuice.csv")
> nyj$DaySq <- nyj$Day**2
> attach(nyj)
```

a

```
> plot(nyj$Day, nyj$Cases)
> model <- lm(Cases ~ Day + DaySq)
> newX <- seq(min(nyj$Day), max(nyj$Day), length=nrow(nyj))
> newXsq <- newX**2
> lines(newX, predict(model, newdata=data.frame(Day=newX, Xsq=newXsq)))
```



b

```
> model_simp <- lm(Cases ~ Day)
> summary(model_simp)

Call:
lm(formula = Cases ~ Day)

Residuals:
    Min      1Q  Median      3Q     Max
-4115.0 -1118.1   305.4  1152.6  3799.6

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   2802.4      604.7   4.634 4.13e-05 ***
Day            123.0       25.7   4.783 2.61e-05 ***
---
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1

Residual standard error: 1877 on 38 degrees of freedom
Multiple R-squared:  0.3758,	Adjusted R-squared:  0.3594
F-statistic: 22.88 on 1 and 38 DF,  p-value: 2.606e-05
```

$\hat{Y} = 2802.4 + Day123$

c

```
> summary(model)

Call:
lm(formula = Cases ~ Day + DaySq)

Residuals:
    Min      1Q  Median      3Q     Max 
-3435.9 -1401.3   251.3  1310.1  2801.7 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4944.221    829.601   5.960 7.12e-07 ***
Day         -183.029     93.319  -1.961  0.05740 .  
DaySq          7.463      2.207   3.381  0.00172 ** 
---
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1

Residual standard error: 1662 on 37 degrees of freedom
Multiple R-squared:  0.5232,	Adjusted R-squared:  0.4974 
F-statistic:  20.3 on 2 and 37 DF,  p-value: 1.122e-06
```

$\hat{Y} = 4944.221 - Day183.029 + DaySq7.463$

c

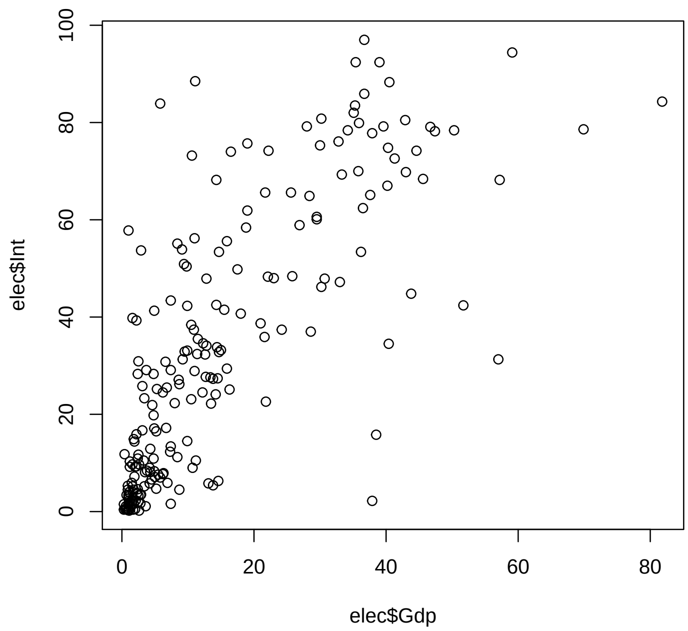
$H_0 : DaySq = 0$
$H_a : DaySq \neq 0$

The p-value for DaySq is 0.00172 $<$ .05 therefore, we reject the H_0 as it appears there is statistical eveidence to support H_a

Problem 4.3

The data are scatter plotted first for visual inspection.

```
> options(scipen=999)
> elec <- read.csv("~/R/PASS/Regression/Assignment3a/internet.csv")
> plot(elec$Gdp, elec$Int)
```



This data is highly skewed to the right. We drop the two extreme outliers from the data.

```
> max2 <- order(elec$Gdp,decreasing=T)[1:2]
> elec2 <- elec[-max2,]
> attach(elec2)
```

Next, 3 models are examaned.

```
> model.A <- lm(Int ~ Gdp)
> summary(model.A)

Call:
lm(formula = Int ~ Gdp)

Residuals:
    Min      1Q  Median      3Q     Max
-64.353 -11.079  -3.247   9.184  64.137

Coefficients:
            Estimate Std. Error t value             Pr(>|t|)
(Intercept) 11.30877    1.72759   6.546       0.000000000453 ***
Gdp          1.45763    0.08495  17.158 < 0.0000000000000002 ***
---
```

```
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1

Residual standard error: 17.85 on 208 degrees of freedom
Multiple R-squared:  0.586,	Adjusted R-squared:  0.584
F-statistic: 294.4 on 1 and 208 DF,  p-value: < 0.00000000000000022
```

```
> model.B <- lm(log(Int) ~ log(Gdp))
> summary(model.B)
```

```
Call:
lm(formula = log(Int) ~ log(Gdp))

Residuals:
    Min      1Q  Median      3Q     Max 
-3.4847 -0.3929  0.0805  0.4740  3.0290 

Coefficients:
            Estimate Std. Error t value             Pr(>|t|)    
(Intercept)  1.02800    0.11623   8.845 0.000000000000000397 ***
log(Gdp)     0.88670    0.04891  18.130 < 0.0000000000000002 ***
---
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1

Residual standard error: 0.9078 on 208 degrees of freedom
Multiple R-squared:  0.6125,	Adjusted R-squared:  0.6106 
F-statistic: 328.7 on 1 and 208 DF,  p-value: < 0.00000000000000022
```

```
> elec2$Gdp_C <- elec2$Gdp**.5
> elec2$Int_C <- elec2$Int**.5
> model.C <- lm(Int_C ~ Gdp_C, data=elec2)
> summary(model.C)
```

```
Call:
lm(formula = Int_C ~ Gdp_C, data = elec2)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.7722 -1.0818 -0.0734  0.9538  5.1862 

Coefficients:
            Estimate Std. Error t value             Pr(>|t|)    
(Intercept)  1.28408    0.22632   5.674         0.0000000464 ***
Gdp_C        1.13240    0.05993  18.896 < 0.0000000000000002 ***
---
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1

Residual standard error: 1.629 on 208 degrees of freedom
```

```
Multiple R-squared:  0.6319,	Adjusted R-squared:  0.6301
F-statistic: 357.1 on 1 and 208 DF,  p-value: < 0.00000000000000022
```

The log_e transformations had the lowest standard error, however the power transform had the highest R^2. A forth model was tried thart takes the power of .5 for the response, and the log of the predictor, Gdp

```
> model.D <- lm(Int_C ~ log(Gdp), data=elec2)
> summary(model.D)

Call:
lm(formula = Int_C ~ log(Gdp), data = elec2)

Residuals:
    Min      1Q  Median      3Q     Max
-6.2480 -0.9576  0.0962  1.0249  5.9594

Coefficients:
            Estimate Std. Error t value             Pr(>|t|)
(Intercept)  1.64325    0.20483   8.022   0.0000000000000746 ***
log(Gdp)     1.67484    0.08619  19.432 < 0.0000000000000002 ***
---
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1

Residual standard error: 1.6 on 208 degrees of freedom
Multiple R-squared:  0.6448,	Adjusted R-squared:  0.6431
F-statistic: 377.6 on 1 and 208 DF,  p-value: < 0.00000000000000022
```

This model has the highest R^2, although it may be more troublesome to interpret.

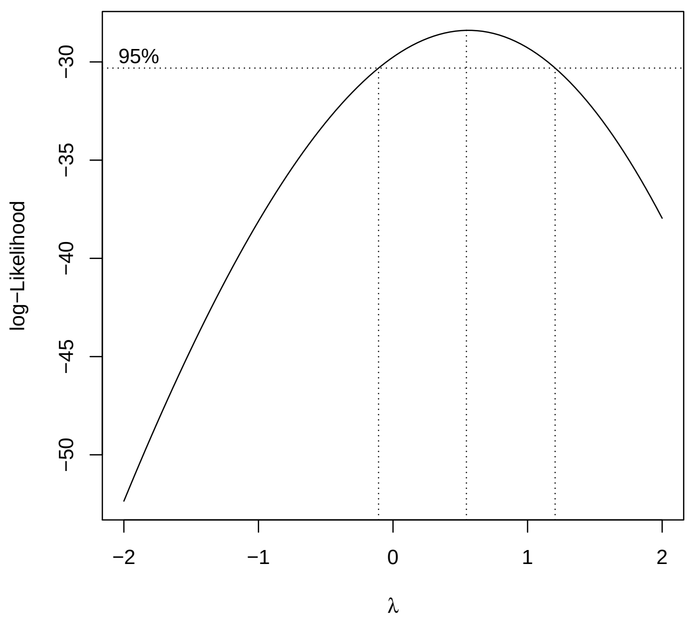
Conclusion

In this case I would choose model.B of the 4 evaluated due to it's ease of interpretation and relatively high R^2 and low standard error compared to the other 3 models.

Boxcox

I attempted touse boxcox, but was unsure how to interret it so left it out of the above.

```
> library(MASS)
> boxcox(model, plotit=TRUE)
>
```


95%
log−Likelihood
−30
−35
−40
−45
−50
−2
−1
0
1
2
λ