

In-class Discussion and Problem Set (after lecture 1)

LSA 2013, LI539
Mixed Effect Models

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Getting Help

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Questions
and
Discussion

Linearity
assumption

Predictor
coding

Continuous
predictors

Binary
categorical
predictors

- **Subscribe to ling-R-lang:** `https://mailman.ucsd.edu/mailman/listinfo/ling-r-lang-l`
- **In R: try `?foo` or `help(foo)` first**
- **Ask your neighbor (during problem sets) or the class.**

The linear predictor

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- Recall that for the **LM**:

$$\eta = I(\mu) = E(\mathbf{y}) = \alpha + \beta_1 \mathbf{x}_1 + \cdots + \beta_n \mathbf{x}_n$$

... and for **GLM**, more generally, η is a linear combination of the predictors $\{\mathbf{x}_i\}$:

$$\eta = \alpha + \beta_1 \mathbf{x}_1 + \cdots + \beta_n \mathbf{x}_n \quad (\text{linear predictor})$$

The linearity assumption

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$$y = \underbrace{\beta_0 x_0 + \dots + \beta_n x_n}_{\text{Predicted Mean}} + \underbrace{\epsilon}_{\text{Noise} \sim N(0, \sigma_\epsilon)}$$

Questions

- What does the linearity assumption made by **AN(C)OVA** and the **LM** mean?

The linearity assumption

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$$\mathbf{y} = \underbrace{\beta_0 \mathbf{x}_0 + \dots + \beta_n \mathbf{x}_n}_{\text{Predicted Mean}} + \underbrace{\epsilon}_{\text{Noise} \sim N(0, \sigma_\epsilon)}$$

Questions

- What does the linearity assumption made by **AN(C)OVA** and the **LM** mean?
- When we use these models, do we assume that the output is linear in the input variables (i.e., that the input variables are linearly related to the outcome)? Do we assume that the outcome is linear in the parameter estimates?

The linearity assumption

$$y = \underbrace{\beta_0 x_0 + \dots + \beta_n x_n}_{\text{Predicted Mean}} + \underbrace{\epsilon}_{\text{Noise} \sim N(0, \sigma_\epsilon)}$$

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Questions

- Are the following, well-formed linear models?

$$RT = \alpha$$

$$RT = \alpha + \beta_1 \text{Frequency}$$

$$RT = \beta_1 \text{Frequency}$$

$$RT = \beta_1 \log_{10} \text{Frequency}$$

$$RT = \alpha + \beta_1 \text{Frequency}^2 + \beta_2 \text{Frequency}^3$$

$$RT = \alpha + \beta_1 \text{Frequency} * \text{DerivEntropy}$$

$$RT = \alpha + \beta_1 \text{Frequency}^{\beta_2}$$

$$RT = \frac{\beta_1}{\text{Frequency}^{2/3}}$$

Visualization

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```
library(languageR)
```

```
data(lexdec)
```

```
g = glm(RT ~ I(Frequency^2) + I(Frequency^3), data=lexdec)
```

```
summary(g)$coefficients
```

```
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    6.5271408  0.0259644 251.388 0.000000
## I(Frequency^2) -0.0090349  0.0031069  -2.908 0.003686
## I(Frequency^3)  0.0005876  0.0003969   1.480 0.138936
```

```
library(ggplot2)
```

```
ggplot(lexdec, aes(x=I(Frequency^2), y=RT)) +
```

```
  geom_point() +
```

```
  geom_abline(
```

```
    intercept = coef(g)['(Intercept)'],
```

```
    slope = coef(g)['I(Frequency^2)'],
```

```
    color = "blue")
```

```
ggplot(lexdec, aes(x=I(Frequency^3), y=RT)) +
```

```
  geom_point() +
```

```
  geom_abline(
```

```
    intercept = coef(g)['(Intercept)'],
```

```
    slope = coef(g)['I(Frequency^3)'],
```

```
    color = "red")
```

Linear in the coefficients (and transformed predictors)

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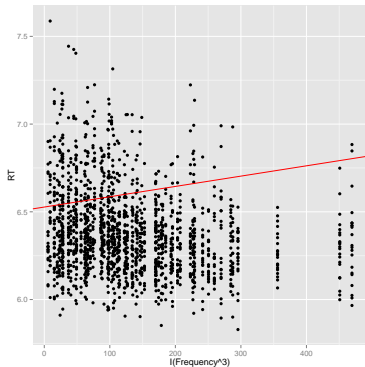
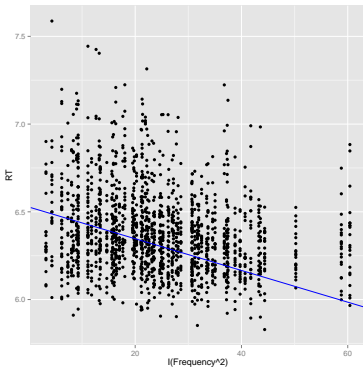
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Non-linear in the input variables

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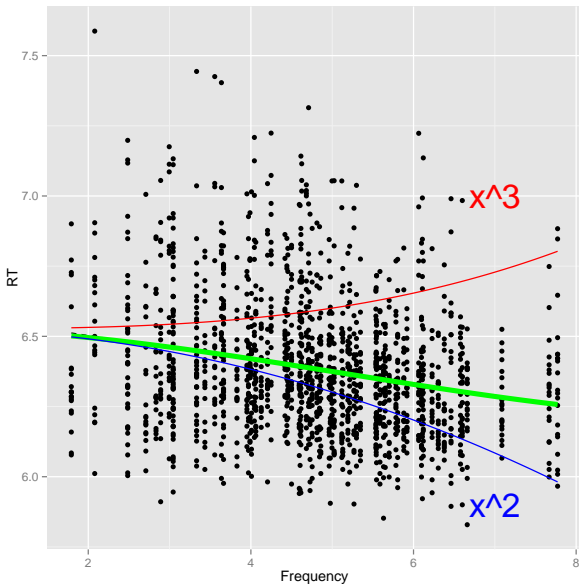
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Centering a continuous variable

Task

- Analyze the effects of `Frequency` and `Trial` on RTs in the `lexdec` data set.

```
summary(glm(RT ~ Frequency + Trial, data= lexdec))
```

- Then center both predictors (i.e., remove their mean out of them). Save these new predictors under a new name in `lexdec`, e.g.

```
lexdec$cFrequency = lexdec$Frequency - mean(lexdec$Frequency)  
summary(lexdec[,c('Frequency', 'cFrequency')])
```

```
##      Frequency      cFrequency  
## Min.      :1.79    Min.      : -2.9594  
## 1st Qu.:3.95    1st Qu.: -0.7999  
## Median :4.75    Median :  0.0025  
## Mean   :4.75    Mean   :  0.0000  
## 3rd Qu.:5.65    3rd Qu.:  0.9014  
## Max.   :7.77    Max.   :  3.0208
```

- Rerun the model with the new centered predictors. What changes and what doesn't change?

Centering a continuous variable

Task

- Now, let's do the same when there's also an interaction in the model:

```
summary(glm(RT ~ Frequency * Trial, data= lexdec))$coefficients

##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    6.6761129   5.403e-02 123.568 0.000e+00
## Frequency     -0.0544937   1.103e-02  -4.939 8.635e-07
## Trial          -0.0008211   4.609e-04  -1.781 7.502e-02
## Frequency:Trial 0.0001084   9.416e-05   1.152 2.496e-01
```

- Compare the models with uncentered and centered predictors.

```
# Beyond the coefficients, another interesting thing to compare is
# the models predictions (the predicted RTs)
g1 = glm(RT ~ Frequency * Trial, data= lexdec)
g2 = glm(RT ~ cFrequency * cTrial, data= lexdec)

# if the models make the same prediction the difference in their
# predictions should be zero
predict(g1) - predict(g2)
```

Task

- Analyze the effects of NativeLanguage, Sex, and their interaction on RTs in the lexdec data set.

```
summary(glm(RT ~ NativeLanguage * Sex, data= lexdec))$coefficients
```

- Now change the ordering of the levels for NativeLanguage, so the model compares 'native' against 'non-natives', rather than the other way around. Rerun the model and compare.

```
# by default R assumes alphanumeric ordering of factor levels  
# but we can always change that by explicitly stating what  
# order we would like:  
lexdec$NativeLanguage =  
  factor(lexdec$NativeLanguage, levels=c('Other', 'English'))  
  
# Btw, c() is simply referring to a vector in R. They can  
# contain numbers, strings, or any (combination) of other  
# objects, e.g. c(4, "seven", "Hans the Wurst", c(log(2), "hai"))
```

- Let's go through what just happened.

ANOVA-coded 2x2

Task

- Now, use sum/effect/ANOVA/contrast-coding for the two predictors (NativeLanguage and Sex) and repeat the analysis

```
# confirm that the default contrast was treatment-coding, e.g.
contrasts(lexdec$Sex)

##      M
## F 0
## M 1

# change contrasts
contrasts(lexdec$Sex) = contr.sum(2)
contrasts(lexdec$Sex)

##      [,1]
## F      1
## M     -1

# notice that default sum-coding in R assigns 1 to the
# alphanumericly first level and -1 to the second level

# let's label the contrast so that we don't get confused
# (cbind() makes a matrix out of multiple vectors; in this
# case 1 vector, but it allows us to label the columns/vectors)
contrasts(lexdec$Sex) = cbind("Male" = c(-1, 1))
```

ANOVA-coded 2x2

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Task

- Compare the output of a 2x2 GLM under a) default treatment-coding, b) default sum-coding, c) halved sum-coding:

```
contrasts(lexdec$Sex) = contr.sum(2) / 2
contrasts(lexdec$Sex)

##      [,1]
## F    0.5
## M   -0.5

contrasts(lexdec$NativeLanguage) = contr.sum(2) / 2
contrasts(lexdec$NativeLanguage)

##           [,1]
## Other      0.5
## English  -0.5
```