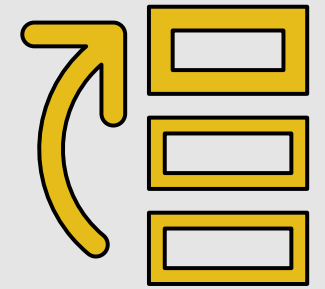


Multilevel Modeling for the Uninitiated

BERDC Special Topics Talk 13



DaCCoTA

DAKOTA COMMUNITY COLLABORATIVE
ON TRANSLATIONAL ACTIVITY

Dr. Mark Williamson
Biostatistics, Epidemiology,
and Research Design Core

Opening

Goal: Gaze at the expansive rafters of multilevel modeling

- ✧ Definitions and common types *'A View from Above'*
- ✧ Designing and setting up models *'Blueprints and Bricks'*
- ✧ Results and Caveats *'Opening the Doors Carefully'*
- ✧ Conceptual Examples *'An Awe in-Spiring Tour'*
- ✧ Worked Examples *'Going the Distance'*

Before Moving On:

Pre-test: https://und.qualtrics.com/jfe/form/SV_4VDpoMi8o7fkiTs

R code: https://med.und.edu/daccota/_files/docs/berdc_docs/multilevel_modeling_rcode.txt

SAS code: https://med.und.edu/daccota/_files/docs/berdc_docs/multilevel_modeling_sascode.txt

Definitions

- ✿ “A multilevel model is a statistical model applied to data collected at more than one level in order to elucidate relationships at more than one level” [1-2]
- ✿ Put simply, multiple levels of data
- ✿ Also known as: Linear Mixed Models, Mixed Effects Models, Hierarchical Models, Nested Models, Repeated Measures Models, Random Effects Models, Random Coefficient Models... [3]
- ✿ Always have both fixed and random effects

Types

Two broad **approaches**:

- ✦ Multiple regression
- ✦ Structural Equation Modeling (SEM)

Three basic **classes**:

- ✦ Unconstrained (null)
- ✦ Random Intercepts
- ✦ Random Intercepts and Slopes

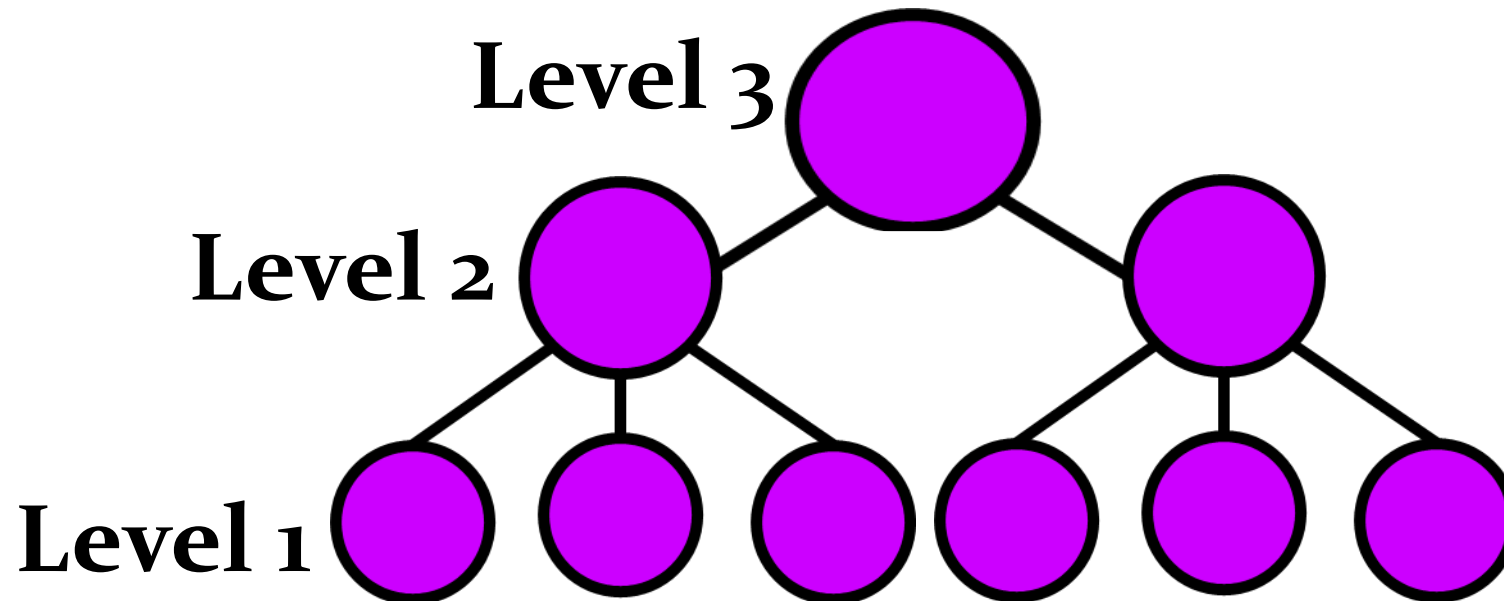
Common **Extensions**:

- ✦ 3-Level Models
- ✦ Non-normal
- ✦ Longitudinal
- ✦ Meta-analysis

Levels

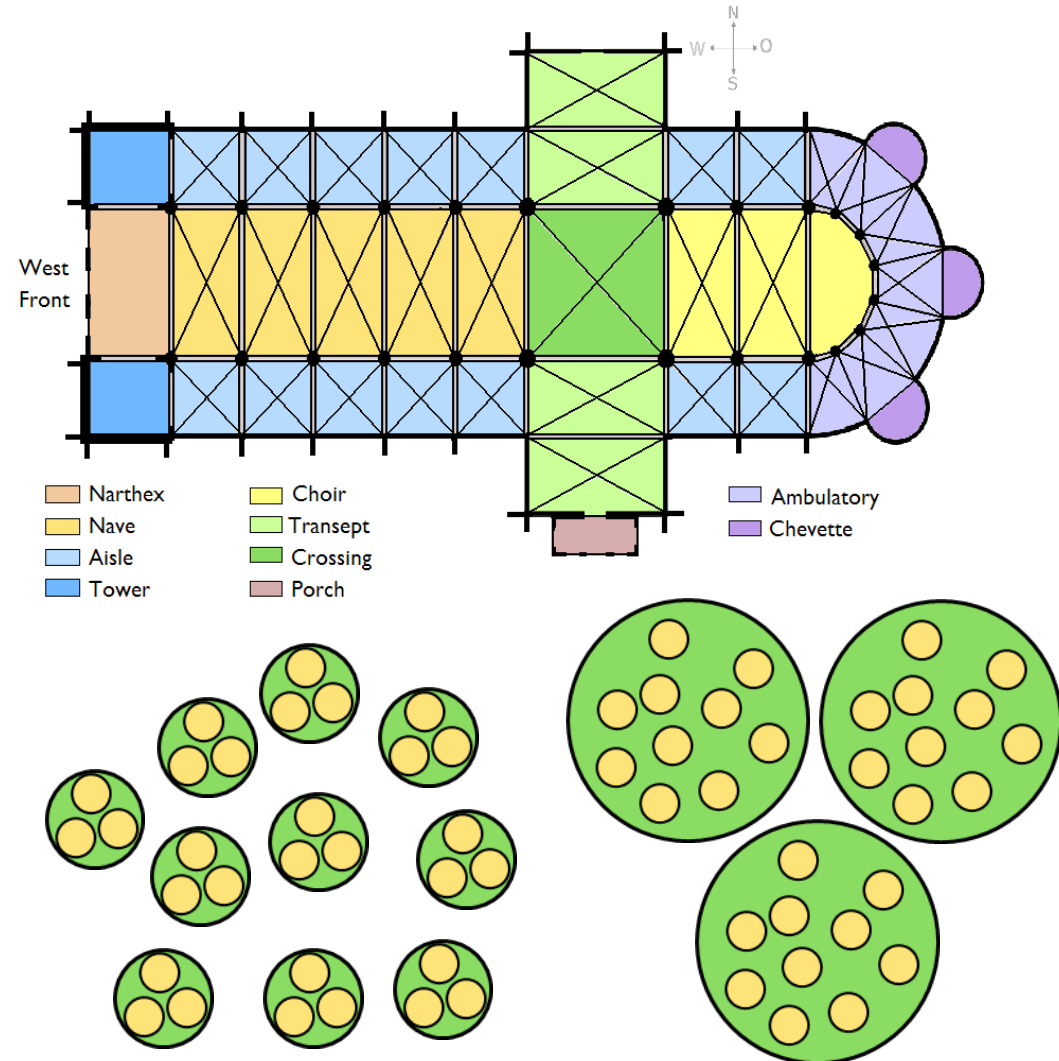
Examples of Levels:

- ✧ Basic 2-Level: Individuals nested in Classes
- ✧ 3-Level: Individuals nested in Classes nested in Schools
- ✧ Longitudinal: Repeated measurements nested in Individuals



Design 1

- ✧ Study Design Blueprint[4]
- ✧ Sample representation (L1, L2, ...)
- ✧ Number of groups (L2 cluster size)
- ✧ Cohort vs. Cross-sectional
- ✧ Randomization (experimental)
- ✧ Data Design
- ✧ Levels
- ✧ Variables



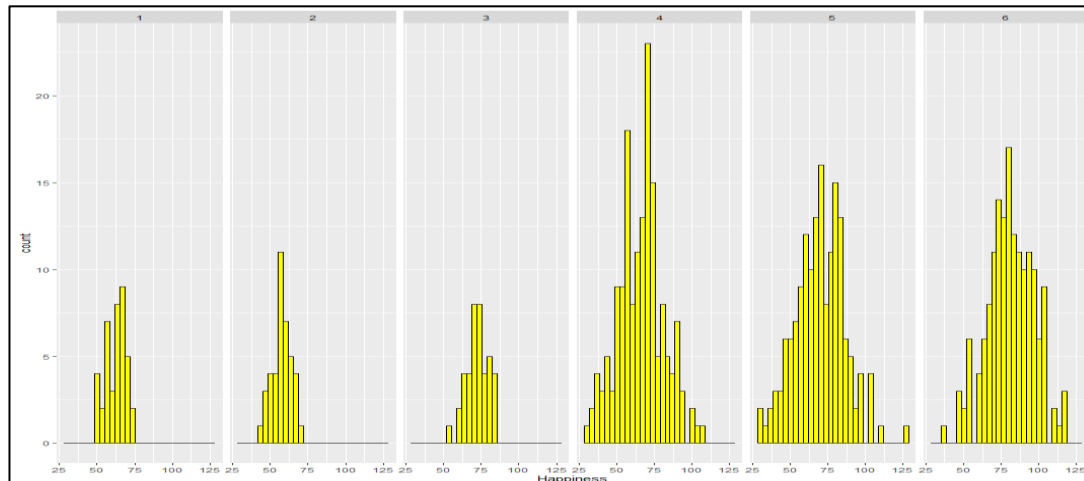
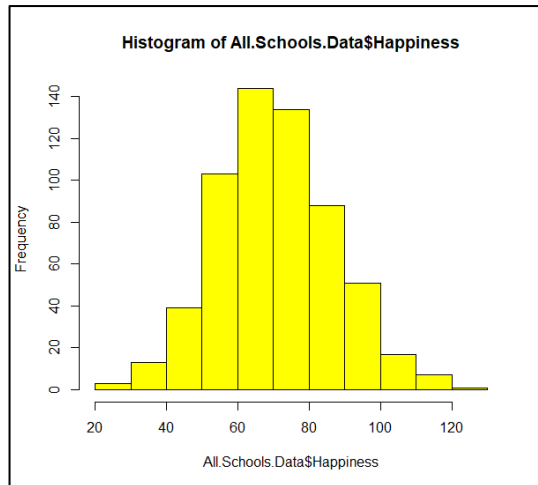
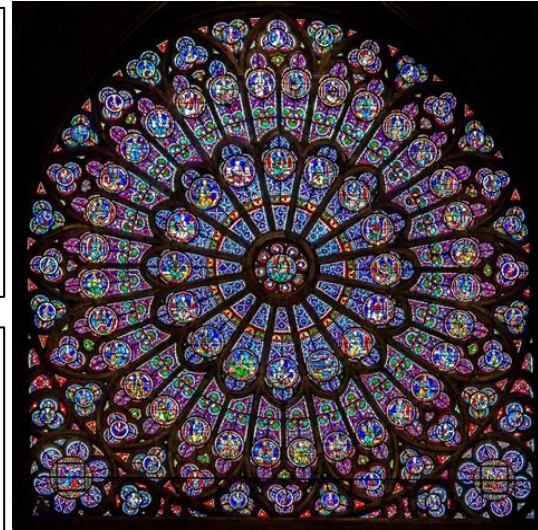
Design 2

Visualizing Data [5]

- ★ Samples and Summaries
- ★ Histograms
- ★ Correlation
- ★ Scatter plots
- ★ Spaghetti plots

##	Happiness	Friends	GPA	StudentID
## 1	54.60136	12.741917	2.744812	1
## 2	64.21655	8.870604	1.473716	2
## 3	62.91056	10.726257	2.077085	3
## 4	66.52306	11.265725	2.936896	4
## 5	57.07570	10.808537	3.327470	5
## 6	68.82087	9.787751	2.690941	6

Happiness	Friends	GPA	StudentID	School
Min. : 29.36	Min. : -0.1076	Min. : 1.001	Min. : 1.0	Min. : 1.0
1st Qu.: 59.21	1st Qu.: 4.0221	1st Qu.: 1.633	1st Qu.: 150.8	1st Qu.: 4.0
Median : 69.88	Median : 5.4308	Median : 2.458	Median : 300.5	Median : 5.0
Mean : 70.68	Mean : 5.9057	Mean : 2.454	Mean : 300.5	Mean : 4.4
3rd Qu.: 81.38	3rd Qu.: 7.5602	3rd Qu.: 3.267	3rd Qu.: 450.2	3rd Qu.: 6.0
Max. : 126.32	Max. : 15.4038	Max. : 3.998	Max. : 600.0	Max. : 6.0



Design 2

Visualizing Data [5]

Samples and Summaries

Histograms

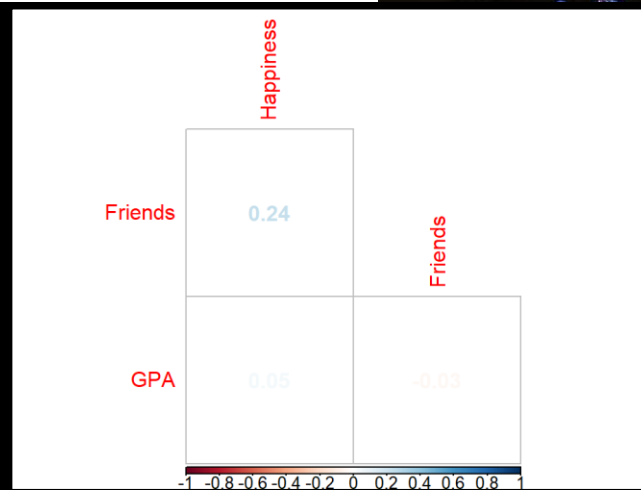
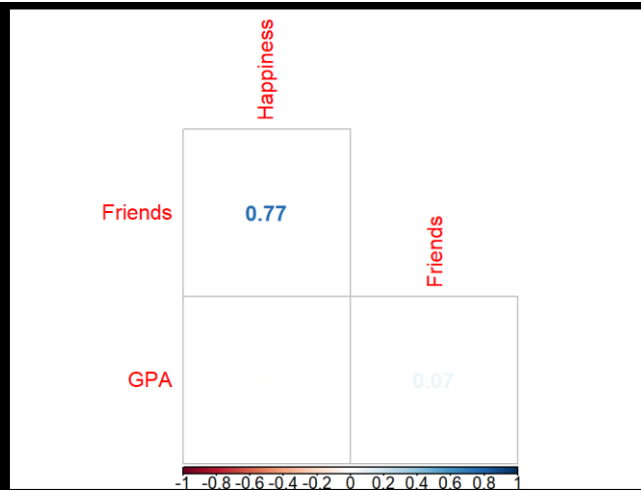
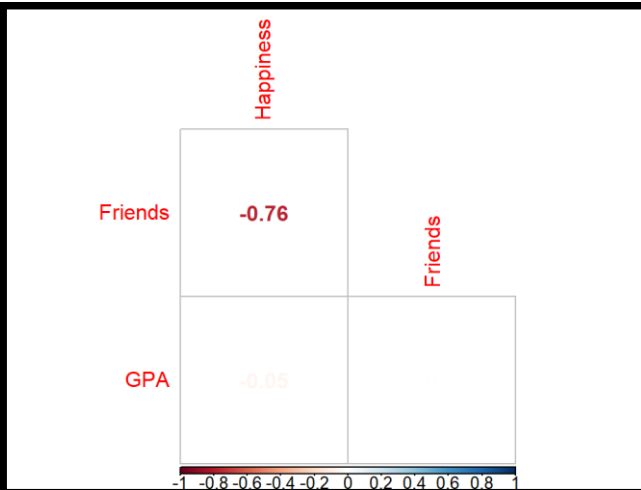
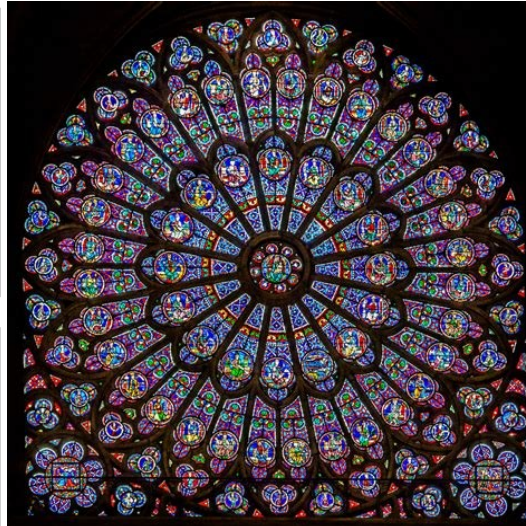
Correlation

Scatter plots

Spaghetti plots

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Median : 69.88	Median : 5.4308	Median :2.458	Median :300.5	Median :5.0
Mean : 70.68	Mean : 5.9057	Mean :2.454	Mean :300.5	Mean :4.4
3rd Qu.: 81.38	3rd Qu.: 7.5602	3rd Qu.:3.267	3rd Qu.:450.2	3rd Qu.:6.0
Max. :126.32	Max. :15.4038	Max. :3.998	Max. :600.0	Max. :6.0



Design 2

Visualizing Data [5]

Samples and Summaries

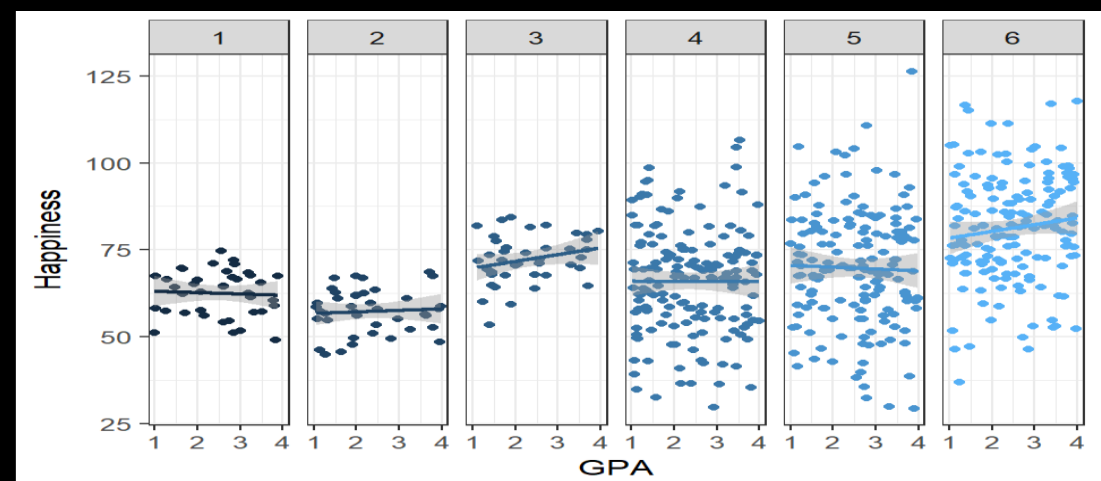
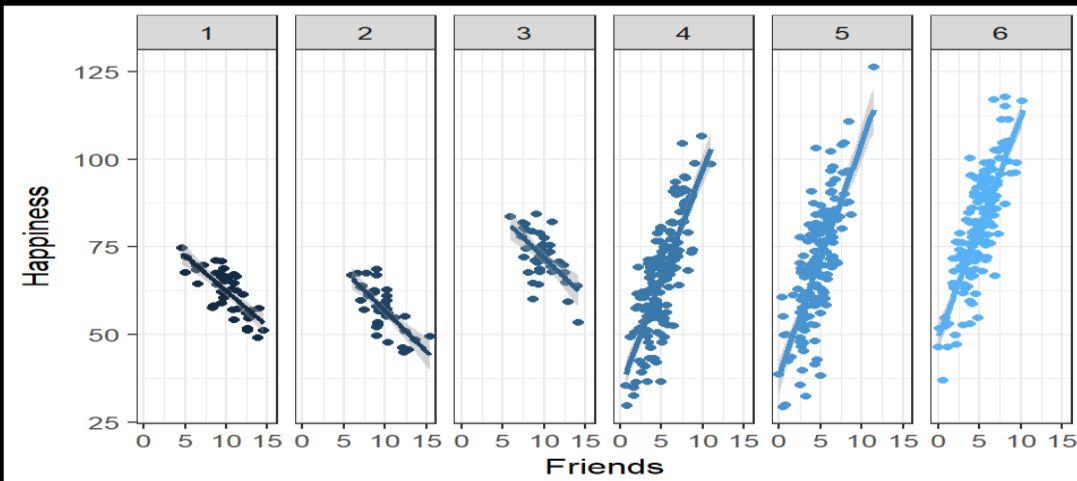
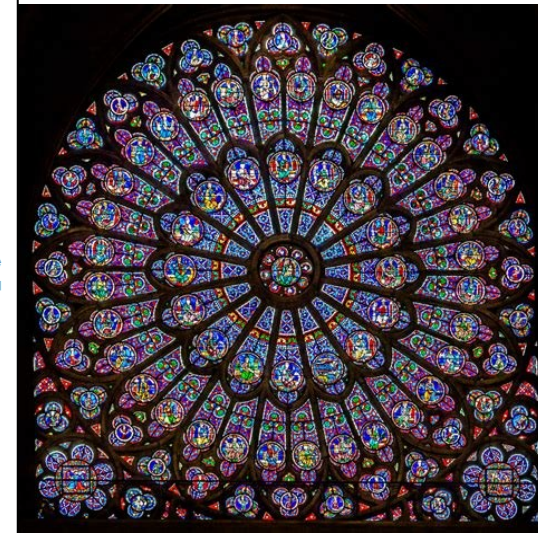
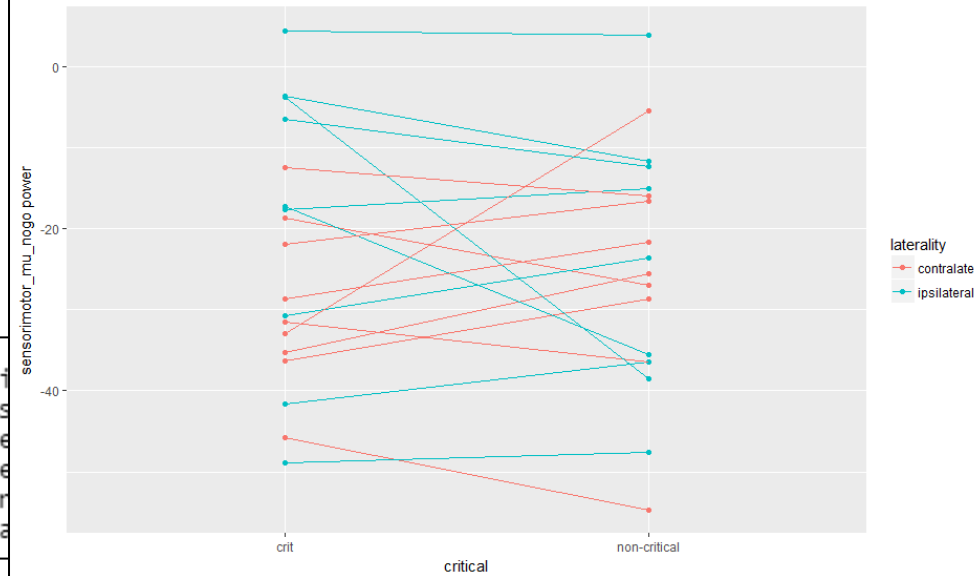
Histograms

Correlation

Scatter plots

Spaghetti plots

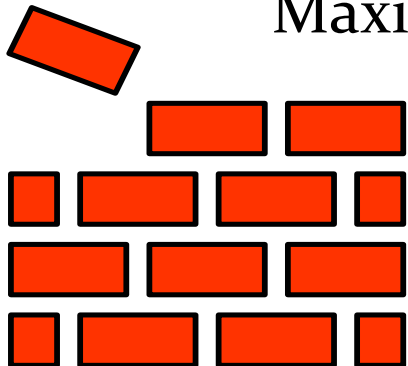
Happiness	
Min.	: 29.36
1st Qu.	: 59.21
Median	: 69.88
Mean	: 70.68
3rd Qu.	: 81.38
Max.	: 126.32



Setup 1

✧ Crafting Model [6-7]

- ✧ From bottom up (no 'best' approach)
- ✧ Formulate equation (if that helps you)
- ✧ Fixed/Random Intercepts & Slopes
- ✧ Centering
- ✧ Covariance matrices
- ✧ Maximum Likelihood (ML) versus Restricted Maximum Likelihood (REML)



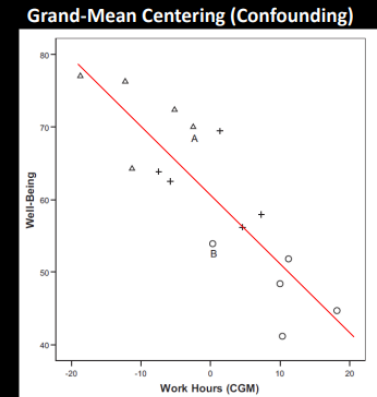
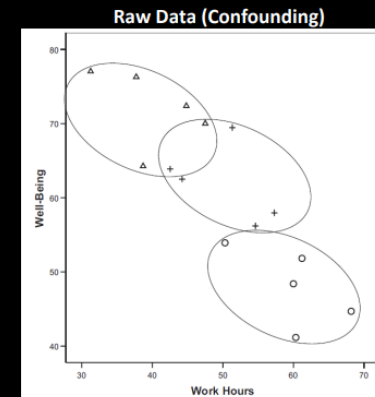
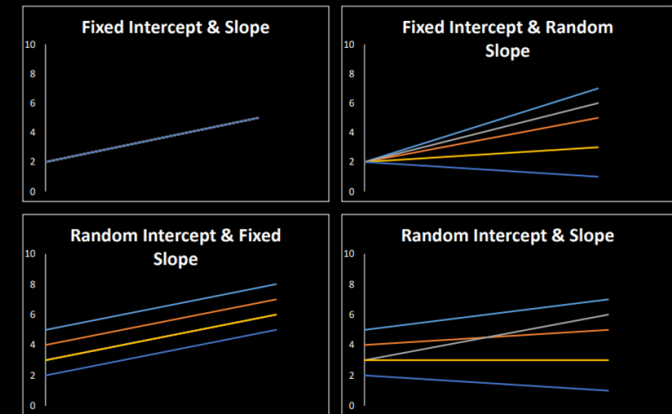
$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

Random Effects

Spaghetti Plots



Setup 2

Getting your computer to do your whims [7]

Sample Syntax: R

2-LEVEL

- Lmer

```
model <- lmer(DV ~ Predictor1 + (1 + Predictor1|ID), data=data, na.action = "na.exclude")
summary(model)
```

- nlme

```
model <- lme(DV ~ Predictor1, random = ~Predictor1|ID, na.action = "na.exclude", data=data)
summary(model)
```

Sample Syntax: R

3-LEVEL

- Lmer

```
model <- lmer(DV ~ Predictor1 + (1 + Predictor1|ID:DAY) + (1 + Predictor1|ID), data=data, na.action = "na.exclude")
summary(model)
```

- nlme

```
model <- lme(DV ~ Predictor1, random = list(ID = ~Predictor1, DAY = ~Predictor1), na.action = "na.exclude", data=data)
summary(model)
```

Sample Syntax: R

CROSS-CLASSIFIED

- Lmer

```
model <- lmer(DV ~ Predictor1 + (1 + Predictor1|ID) + (1 + Predictor1|Target), data=data, na.action = "na.exclude")
summary(model)
```

- nlme

Crossed models are slow

Sample Syntax: SAS

2-Level

```
PROC MIXED data=data COVTEST;
CLASS ID;
MODEL DV = Predictor1/CL S DDFM=satterth;
RANDOM INTERCEPT Predictor1 / SUB=ID TYPE=UN;
RUN;
```

Sample Syntax: SAS

3-Level

```
PROC MIXED data=data COVTEST;
CLASS DAY ID;
MODEL DV = Predictor1/CL S DDFM=satterth;
RANDOM INTERCEPT Predictor1 / SUB=DAY(ID) TYPE=UN;
RANDOM INTERCEPT Predictor1 / SUB=ID TYPE=UN;
RUN;
```

Sample Syntax: SAS

CROSS-CLASSIFIED

```
PROC MIXED data=data COVTEST;
CLASS ID TARGET;
MODEL DV = Predictor1/CL S DDFM=satterth;
RANDOM INTERCEPT Predictor1 / SUB=ID TYPE=UN;
RANDOM INTERCEPT Predictor1 / SUB=TARGET TYPE=UN;
RUN;
```

Analyzing Results

- ✿ Fixed Effects
- ✿ Coefficients
- ✿ Significance
- ✿ Random Effects
- ✿ Overall Model
- ✿ AIC or BIC
- ✿ Chi-Sq. /DF

```
## Linear mixed model fit by maximum likelihood ['lmerMod']
## Formula: Happiness ~ Friends.C + GPA.C + (1 + Friends.C | School)
## Data: All.Schools.Data
##
##      AIC      BIC    logLik deviance df.resid
## 4438.4 4469.2 -2212.2 4424.4    593
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.6347 -0.6060  0.0229  0.6675  3.7765
##
## Random effects:
## Groups Name Variance Std.Dev. Corr
## School (Intercept) 42.14 6.492
## Friends.C 17.94 4.235 0.51
## Residual 86.37 9.294
##
## Number of obs: 600, groups: School, 6
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept) 75.3044 2.7888 27.003
## Friends.C 2.1566 1.7431 1.237
## GPA.C 0.4235 0.4271 0.991
##
## Correlation of Fixed Effects:
##              (Intr) Frnd.C
## Friends.C 0.454
## GPA.C 0.002 0.001
```

```
The GLIMMIX Procedure

Convergence criterion (PCONV=1.11022E-8) satisfied.

Fit Statistics

-2 Log Pseudo-Likelihood    40985.43
Generalized Chi-Square      6980.42
Gener. Chi-Square / DF      0.81

Covariance Parameter Estimates

Cov Parm      Subject      Estimate      Standard
Intercept     SCHOOLID     1.1400      0.1094

Solutions for Fixed Effects

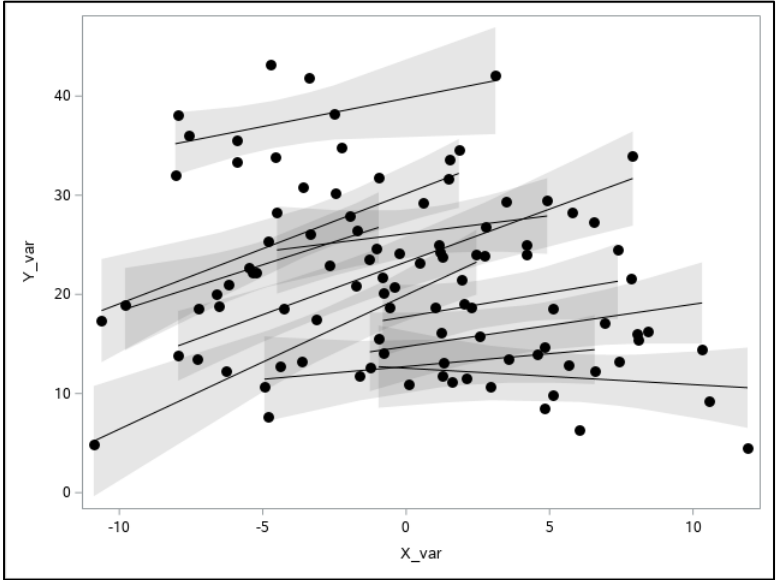
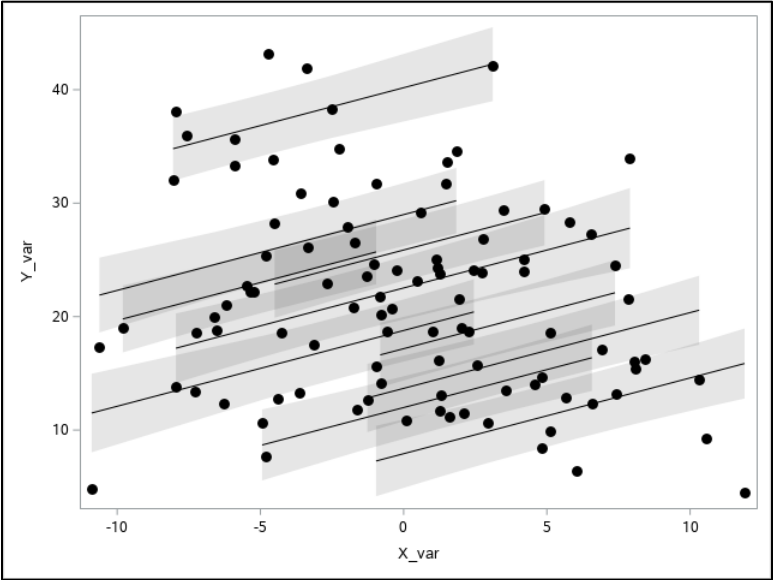
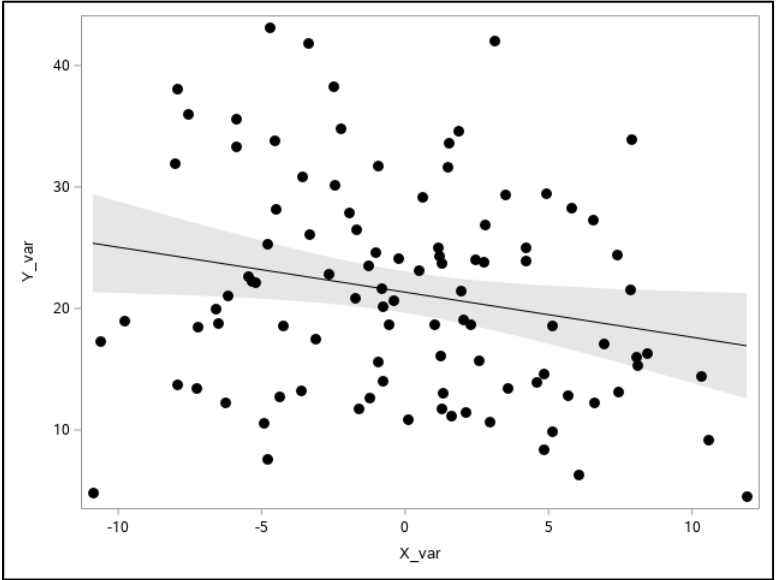
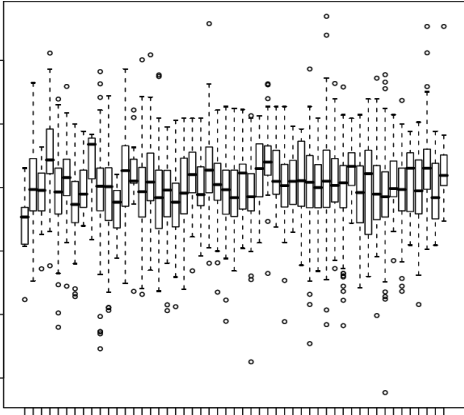
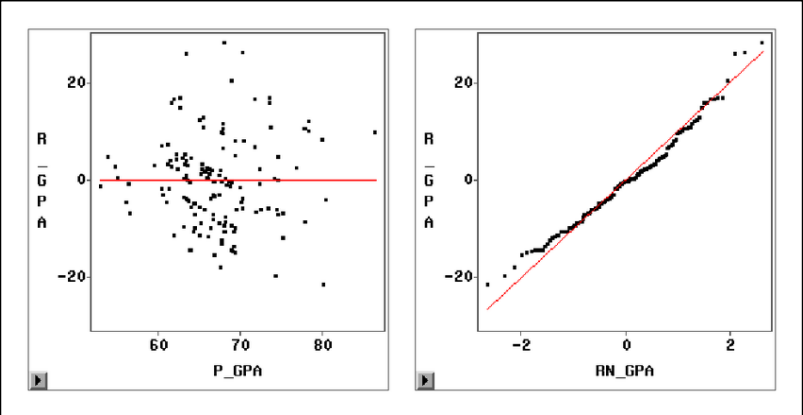
Effect          Estimate      Standard
Intercept       -1.9594      0.07137
SEX              0.4668      0.06306

Type III Tests of Fixed Effects

Effect          Num      Den      F Value      Pr > F
SEX              1      8170      54.80      <.0001
```

Analyzing Results 2

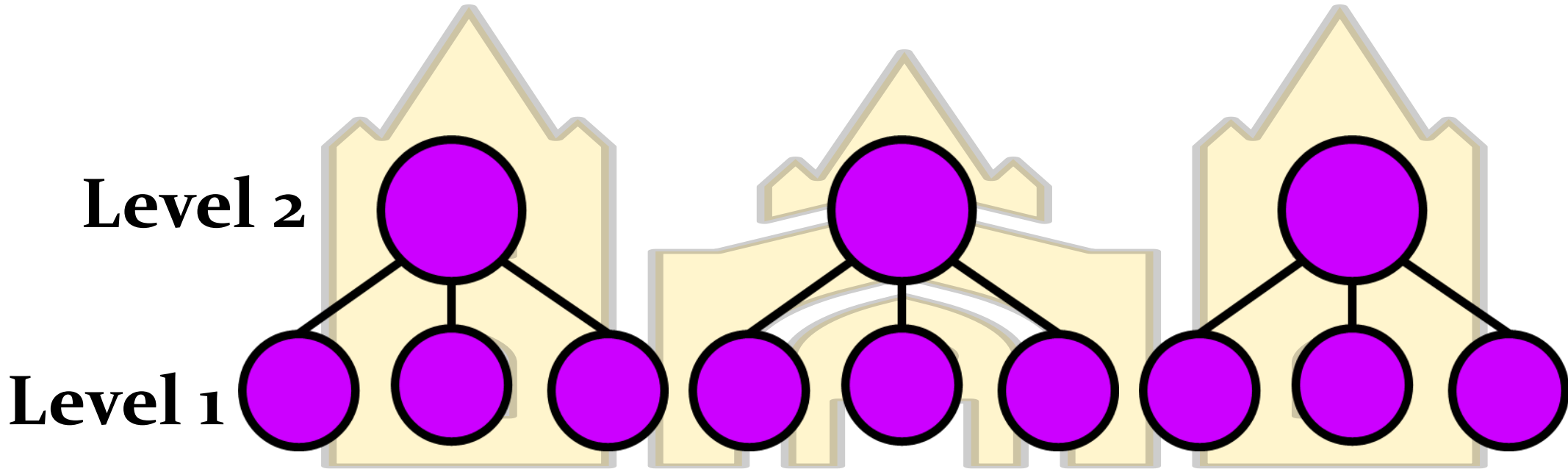
- Residuals
- QQ-plots
- Scatter plots with regression lines



Caveats & Concerns

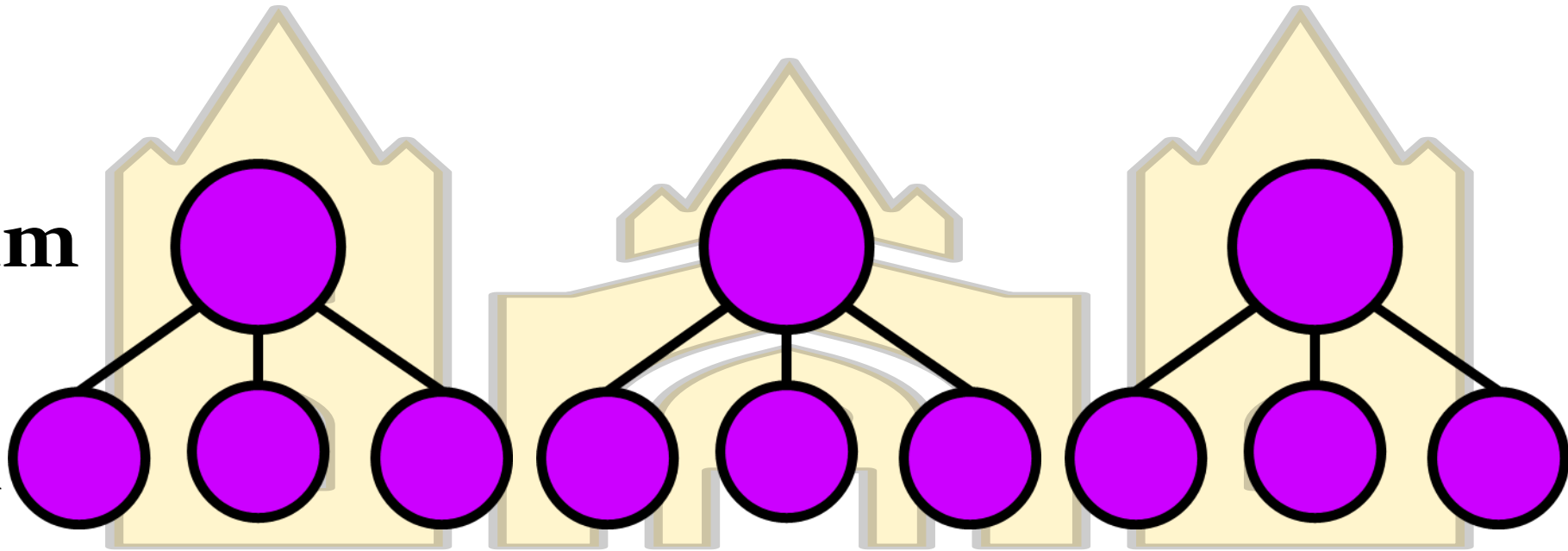
- ✿ When and when not [8]
 - ✿ **Yes:** correlated groupings (clusters), longitudinal
 - ✿ **No:** ICC too low, fixed effects approach good enough
 - ✿ Empirical, statistical, and theoretical justifications
- ✿ Reminders
 - ✿ Can treat intercepts and slopes as outcomes of level-2 predictors
 - ✿ Centering, covariance structures, and other options should be examined
 - ✿ Beware of non-normality

Conceptual Examples



Conceptual Examples

Team

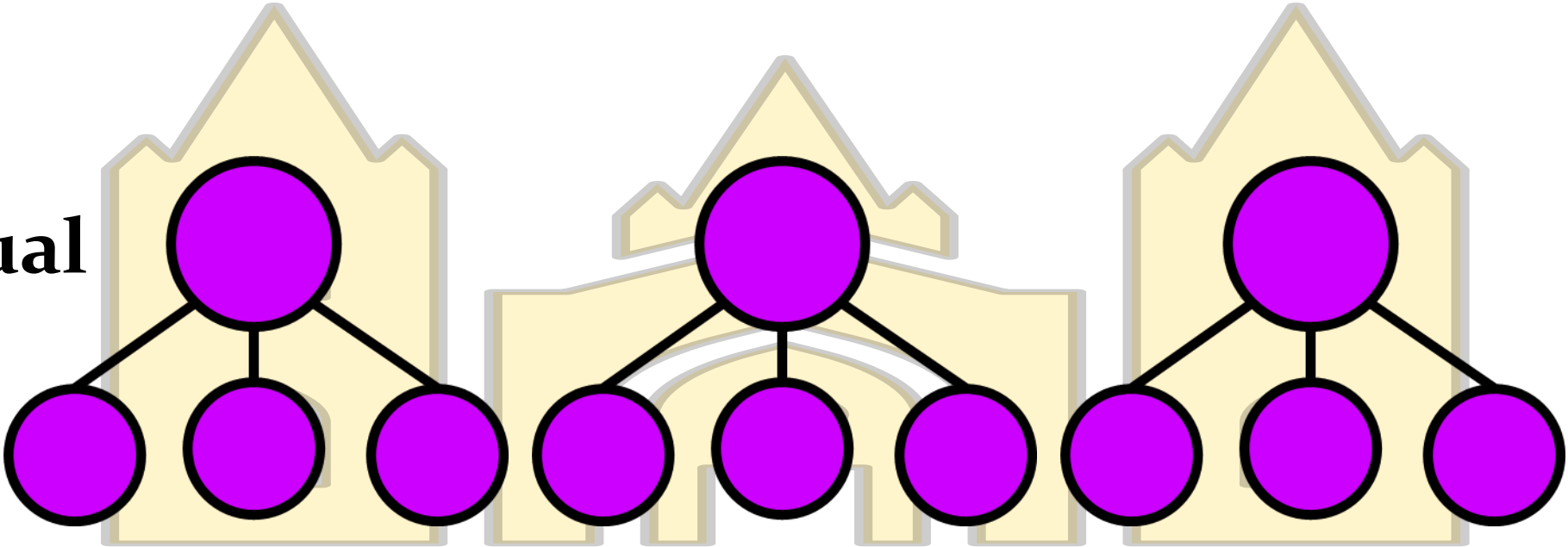


Individual

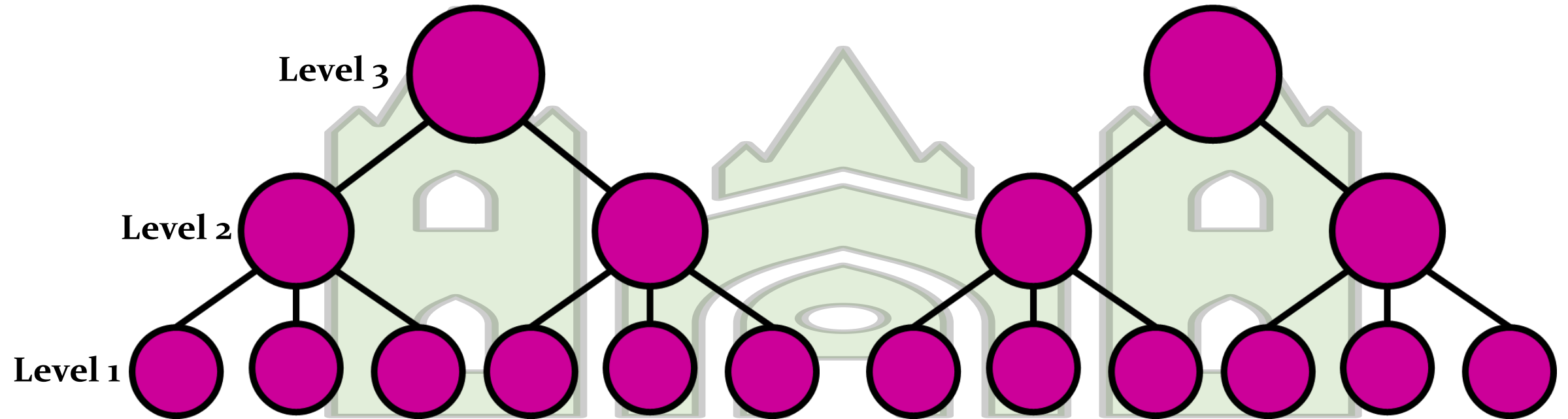
Conceptual Examples

Individual

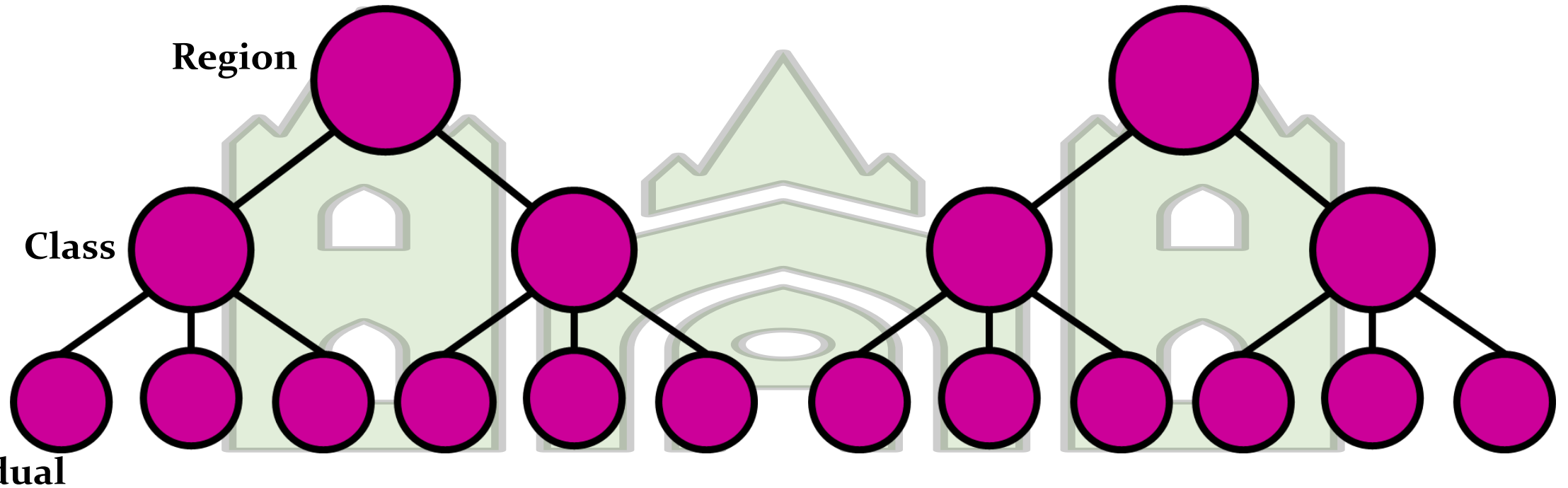
Day



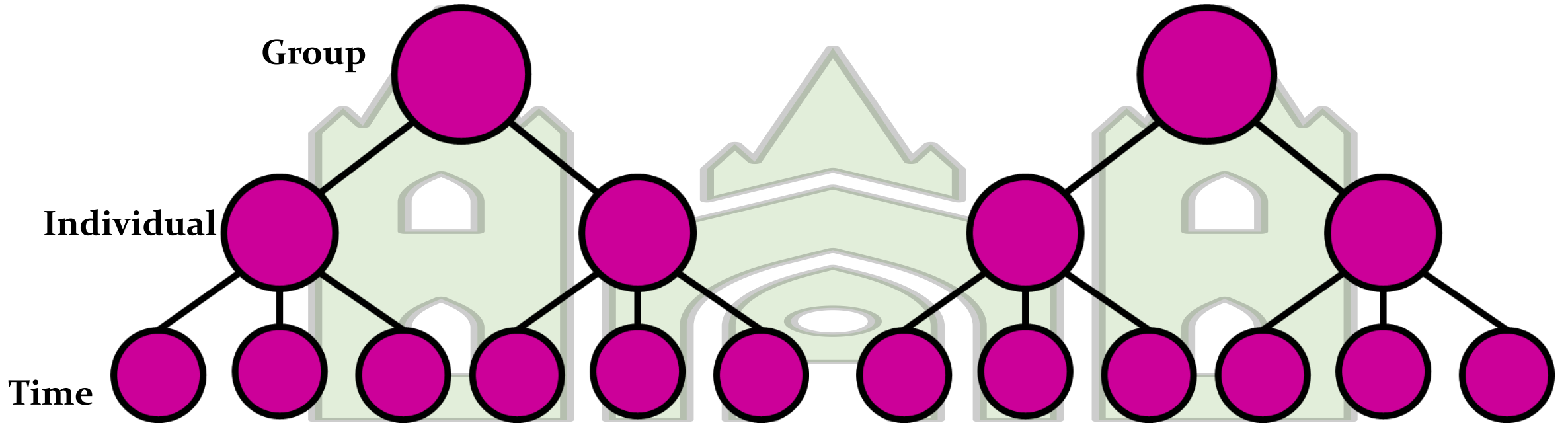
Conceptual Examples



Conceptual Examples

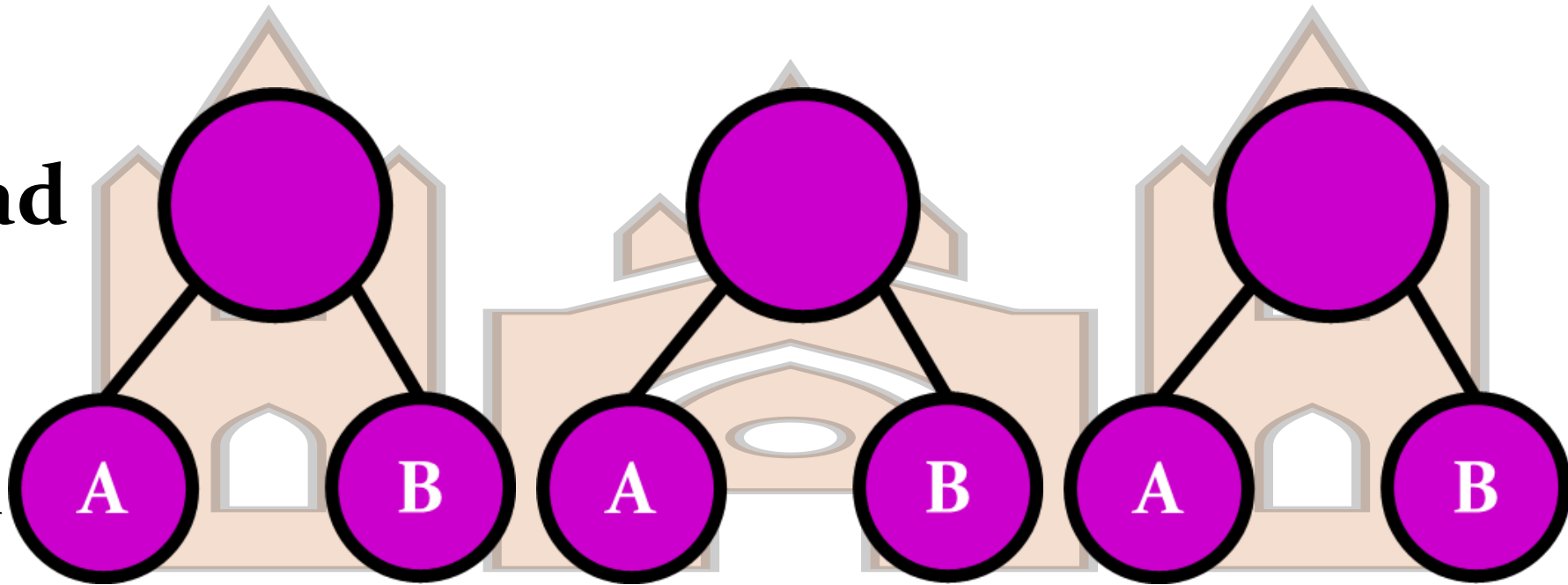


Conceptual Examples



Conceptual Examples

Dyad



Individual

Worked Examples

R and SAS

- ✿ Example 1: Fire Damage and Knights
- ✿ Example 2: Fire Damage and Archers
- ✿ Example 3: Dragon Hits and Arrows
- ✿ Example 4: Dragon Gold and Training

Example 1: Fire Damage and Knights

Dataset Creation

- <https://ademos.people.uic.edu/Chapter16.html> [9]
- Parameters different across England and France
- 10 Regions (5 E, 5 F), each with knights and archers
- Knights and archers centered
- Fire damage as function of knights

	Fire_Damage	Knights	Archers	Region	Knights.C	Archers.C
1	47.09645	10.427925	8.508462	1	-0.39715575	0.6401865
2	27.62843	10.959316	11.843101	1	0.13423551	3.9748253
3	26.85106	10.175657	11.500109	1	-0.64942335	3.6318333
4	56.58726	10.887717	4.982892	1	0.06263626	-2.8853835
5	67.97403	9.274324	3.918132	1	-1.55075660	-3.9501436
6	37.26558	10.245348	10.000532	1	-0.57973270	2.1322562

Example 1: Fire Damage and Knights

Model 1: Knight Standard Regression

R

```
>D1_M1 <-lm(Fire_Damage ~ Knights.C,  
data=Dragon1)  
>summary(D1_M1)  
>ggplot(data=Dragon1,  
aes(x=Knights.C, y=Fire_Damage)) +  
geom_point() +  
geom_smooth(method=lm, color="red")
```

SAS

```
PROC GLIMMIX data=Dragon1 method=MMPL;  
model Fire_Damage=Knights_C/s;  
output out=D1M1_pred pred lcl ucl;  
PROC SORT data=D1M1_pred;  
by Knights_C;  
PROC SGPLOT data=D1M1_pred noautolegend;  
band x=Knights_C lower=lcl upper=ucl;  
scatter x=Knights_C y=Fire_Damage;  
series x=Knights_C y=pred;
```


Example 1: Fire Damage and Knights

Model 1: Knight Standard Regression

Call:

```
lm(formula = Fire_Damage ~ Knights.C, data = Dragon1)
```

Residuals:

```
   Min    1Q  Median    3Q   Max
-35.049 -11.422 -2.464  10.182  48.416
```

Coefficients:

```
      Estimate Std. Error t value Pr(>|t|)
(Intercept)  42.6837    1.6140  26.445 < 2e-16 ***
Knights.C    -3.1590    0.6919  -4.565 1.45e-05 ***
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 16.14 on 98 degrees of freedom
 Multiple R-squared: 0.1754, Adjusted R-squared: 0.167
 F-statistic: 20.84 on 1 and 98 DF, p-value: 1.449e-05

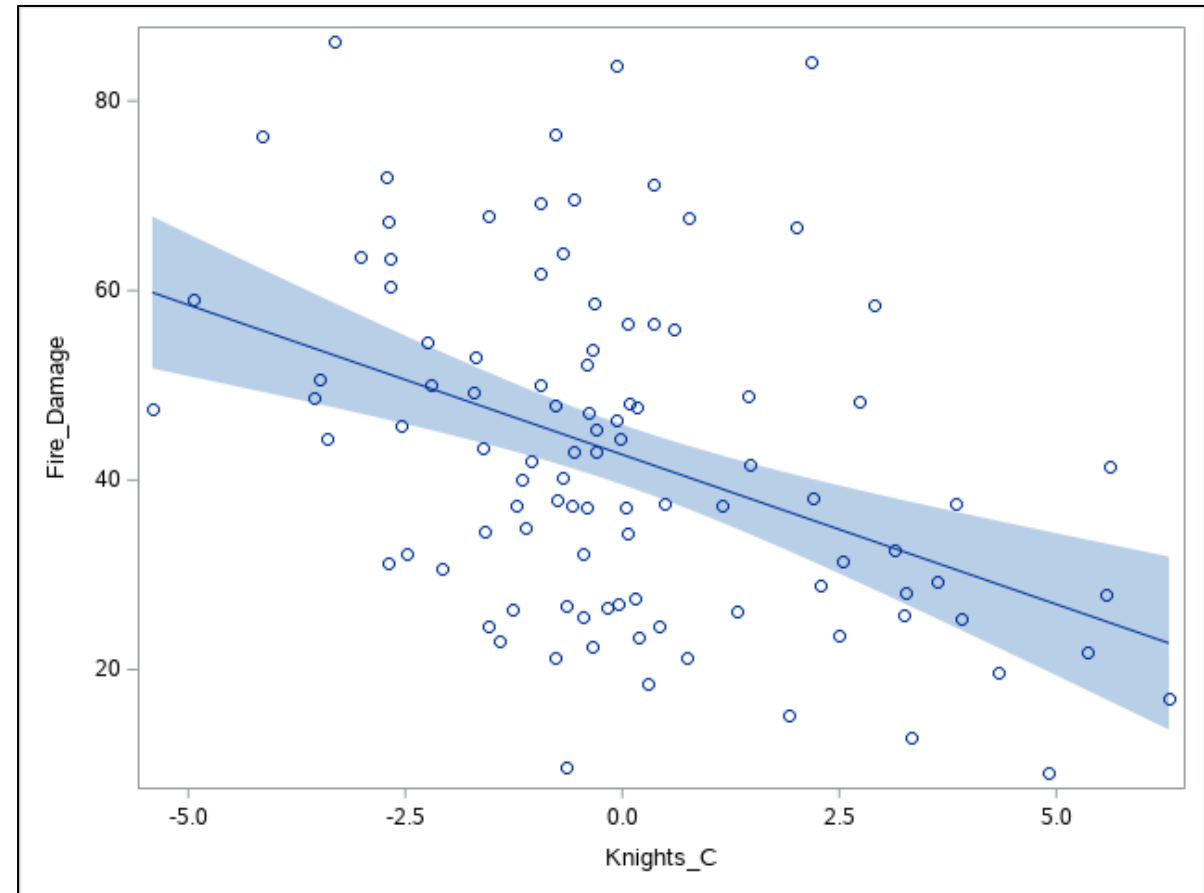
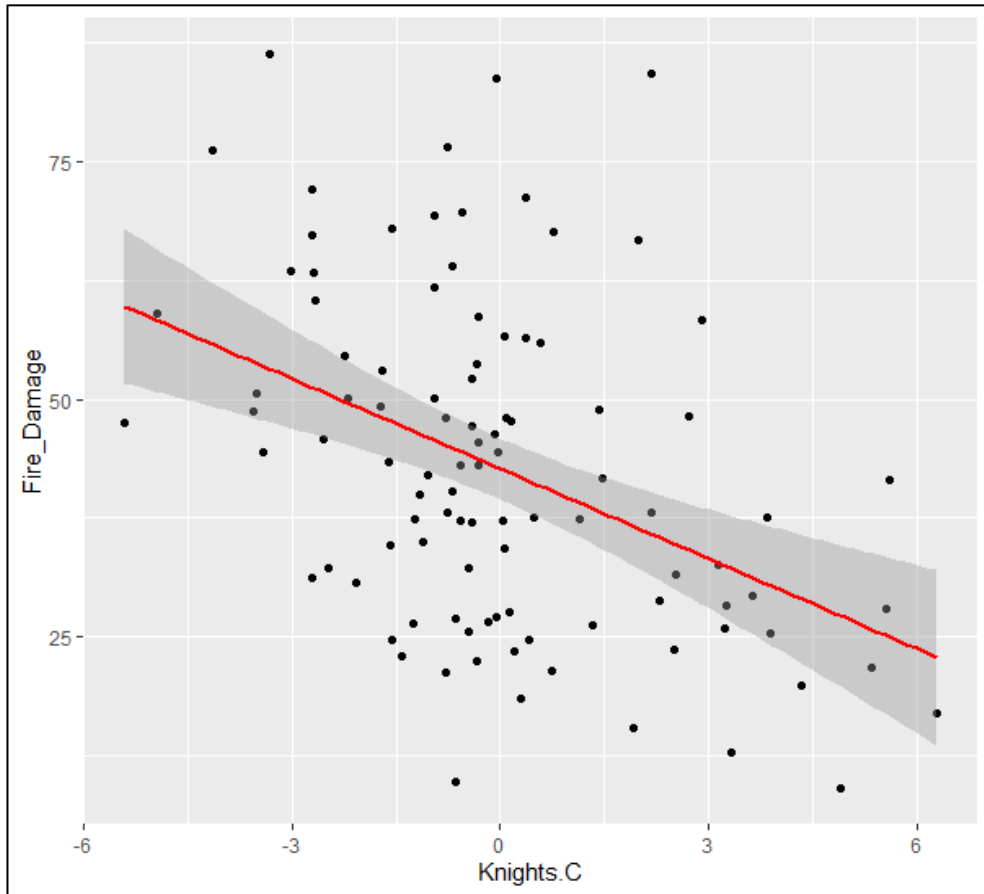
Fit Statistics	
-2 Log Likelihood	838.03
AIC (smaller is better)	844.03
AICC (smaller is better)	844.28
BIC (smaller is better)	851.85
CAIC (smaller is better)	854.85
HQIC (smaller is better)	847.19
Pearson Chi-Square	25530.03
Pearson Chi-Square / DF	255.30

Parameter Estimates					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	42.6840	1.5978	98	26.71	<.0001
Knights_C	-3.1590	0.6850	98	-4.61	<.0001
Scale	255.30	36.1049	.	.	.

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Knights_C	1	98	21.27	<.0001

Example 1: Fire Damage and Knights

Model 1: Knight Standard Regression



Example 1: Fire Damage and Knights

Model 2: Knight Level-2 Random Intercepts

R

```
>D1_M2 <-lmer(Fire_Damage ~ Knights.C + (1|Region),  
data=Dragon1, REML=F)  
>summary(D1_M2)  
>Dragon1$Fire_Damage_KPred <-predict(D1_M2,  
newdata=Dragon1)  
  
>ggplot(data=Dragon1, aes(x=Knights.C, y=Fire_Damage_KPred,  
group=Region)) +  
  geom_point(aes(color=Region))+  
  geom_smooth(method='lm', se=TRUE, aes(colour=Region))+  
  xlab("Knights") + ylab("Predicted Fire Damage")+  
  theme(legend.position = "none")
```

SAS

```
PROC GLIMMIX data=Dragon1 method=MMPL;  
  class Region;  
  model Fire_Damage=Knights_C/s;  
  random Region;  
  output out=D1M2_pred pred lcl ucl;  
PROC SORT data=D1M2_pred;  
  by Knights_C;  
PROC SGPLOT data=D1M2_pred noautolegend;  
  band x=Knights_C lower=lcl  
  upper=ucl/group=Region transparency=.90;  
  scatter x=Knights_C  
  y=Fire_Damage/group=Region;  
  series x=Knights_C y=pred/group=Region;
```

Example 1: Fire Damage and Knights

Model 2: Knight Level-2 Random Intercepts

Linear mixed model fit by maximum likelihood ['lmerMod']
 Formula: Fire_Damage ~ Knights.C + (1 | Region)
 Data: Dragon1

AIC	BIC	logLik	deviance	df.resid
752.7	763.2	-372.4	744.7	96

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.88811	-0.50811	-0.01185	0.61301	2.80776

Random effects:

Groups	Name	Variance	Std.Dev.
Region	(Intercept)	184.29	13.575
	Residual	72.38	8.508

Number of obs: 100, groups: Region, 10

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	42.6837	4.3764	9.753
Knights.C	-2.6581	0.4072	-6.527

Correlation of Fixed Effects:

(Intr)
Knights.C 0.000

Fit Statistics	
-2 Log Likelihood	744.74
AIC (smaller is better)	752.74
AICC (smaller is better)	753.16
BIC (smaller is better)	753.95
CAIC (smaller is better)	757.95
HQIC (smaller is better)	751.41
Generalized Chi-Square	7237.87
Gener. Chi-Square / DF	72.38

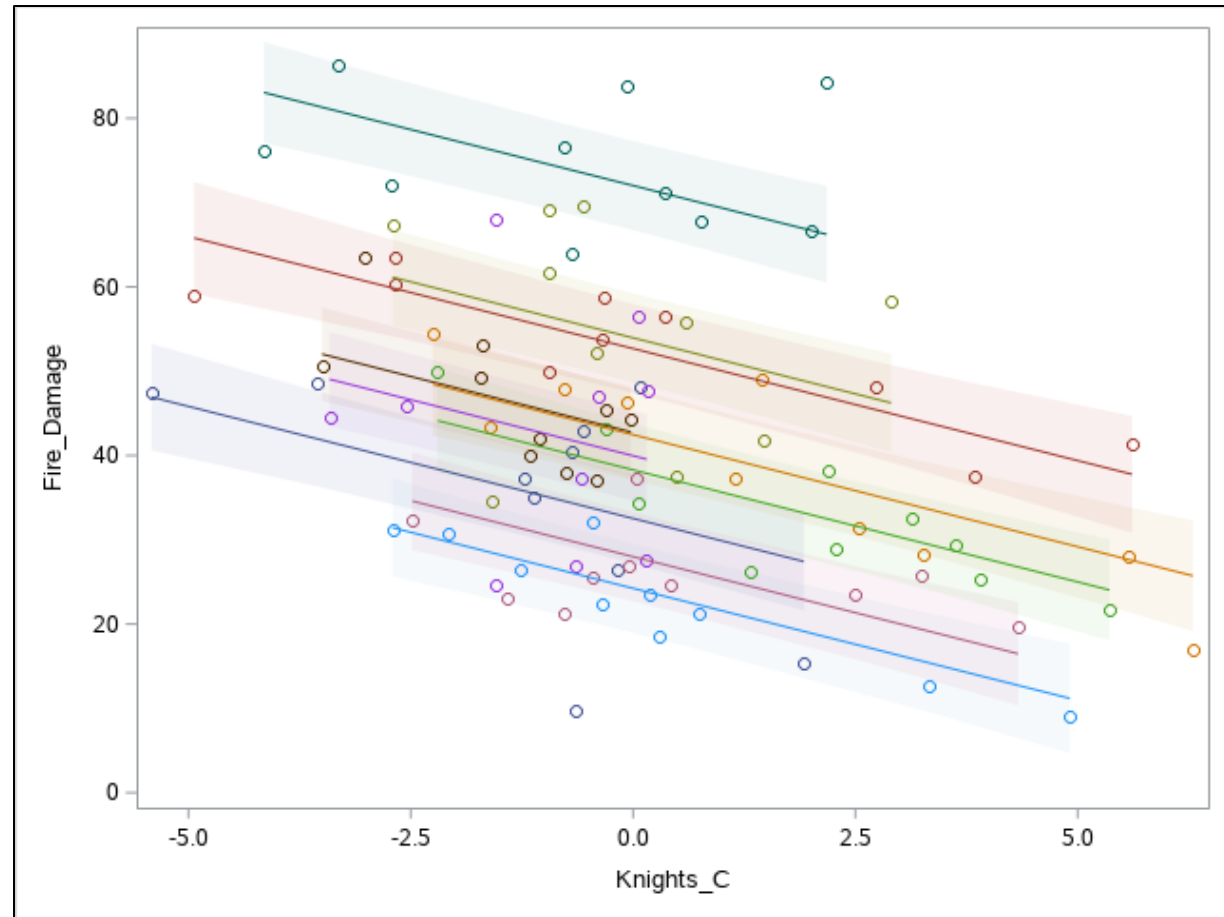
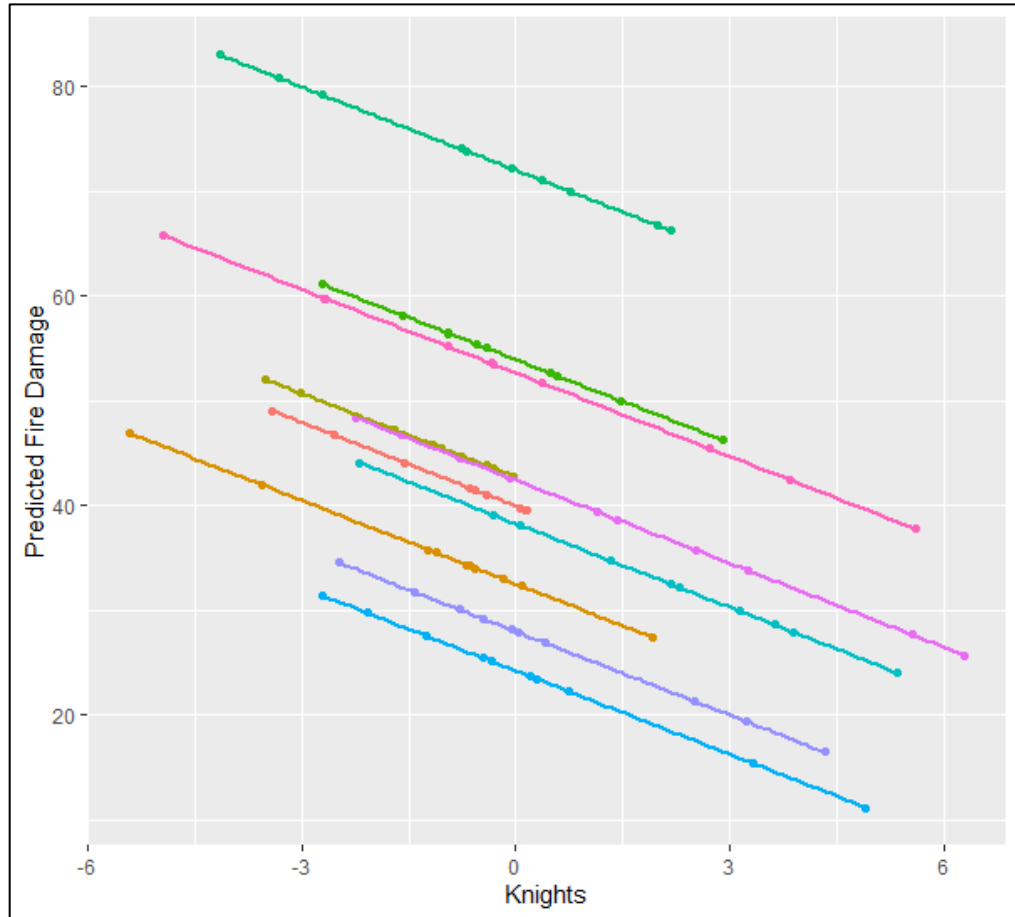
Covariance Parameter Estimates		
Cov Parm	Estimate	Standard Error
Region	184.29	85.6901
Residual	72.3787	10.7900

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	42.6839	4.3763	9	9.75	<.0001
Knights_C	-2.6581	0.4072	89	-6.53	<.0001

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Knights_C	1	89	42.60	<.0001

Example 1: Fire Damage and Knights

Model 2: Knight Level-2 Random Intercepts



Example 1: Fire Damage and Knights

Model 3: Knight Level-2 Random Intercepts and Slopes

R

```
>D1_M3 <-lmer(Fire_Damage ~ Knights.C + (Knights.C|Region),
data=Dragon1, REML=F)
>summary(D1_M3)

>Dragon1$Fire_Damage_KPred2 <-predict(D1_M3,
newdata=Dragon1)

>ggplot(data=Dragon1, aes(x=Knights.C, y=Fire_Damage_KPred2,
group=Region)) +
  geom_point(aes(color=Region))+
  geom_smooth(method='lm', se=TRUE, aes(colour=Region))+
  xlab("Knights") + ylab("Fire Damage")+
  theme(legend.position = "none")
```

SAS

```
PROC GLIMMIX data=Dragon1 method=MMPL;
  class Region;
  model Fire_Damage=Knights_C/s;
  random intercept Knights_C/subject = Region;
  output out=D1M3_pred pred lcl ucl;
PROC SORT data=D1M3_pred;
  by Knights_C;
PROC SGPLOT data=D1M3_pred noautolegend;
  band x=Knights_C lower=lcl
upper=ucl/group=Region transparency=.90;
  scatter x=Knights_C
y=Fire_Damage/group=Region;
  series x=Knights_C y=pred/group=Region;
```

Example 1: Fire Damage and Knights

Model 3: Knight Level-2 Random Intercepts and Slopes

Linear mixed model fit by maximum likelihood ['lmerMod']
 Formula: Fire_Damage ~ Knights.C + (Knights.C | Region)
 Data: Dragon1

AIC BIC logLik deviance df.resid
 755.5 771.1 -371.8 743.5 94

Scaled residuals:
 Min 1Q Median 3Q Max
 -2.87825 -0.50982 -0.06848 0.62848 2.81394

Random effects:
 Groups Name Variance Std.Dev. Corr
 Region (Intercept) 187.7426 13.7019
 Knights.C 0.2129 0.4615 1.00
 Residual 71.2306 8.4398
 Number of obs: 100, groups: Region, 10

Fixed effects:
 Estimate Std. Error t value
 (Intercept) 42.7731 4.4145 9.689
 Knights.C -2.6722 0.4339 -6.159

Correlation of Fixed Effects:
 (Intr)
 Knights.C 0.333
 optimizer (nloptwrap) convergence code: 0 (OK)
 boundary (singular) fit: see ?isSingular

Fit Statistics	
-2 Log Likelihood	744.74
AIC (smaller is better)	752.74
AICC (smaller is better)	753.16
BIC (smaller is better)	753.95
CAIC (smaller is better)	757.95
HQIC (smaller is better)	751.41
Generalized Chi-Square	7237.87
Gener. Chi-Square / DF	72.38

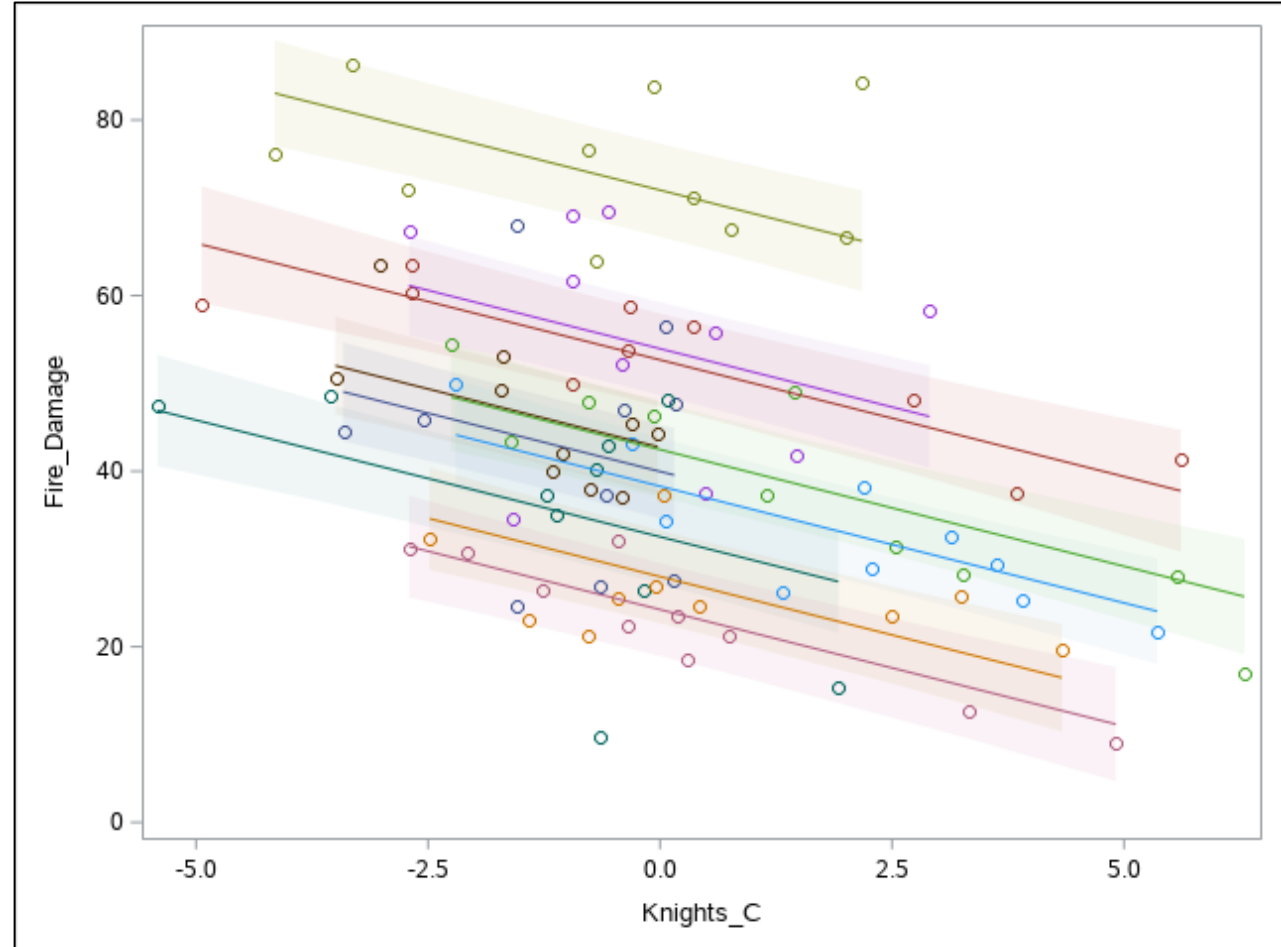
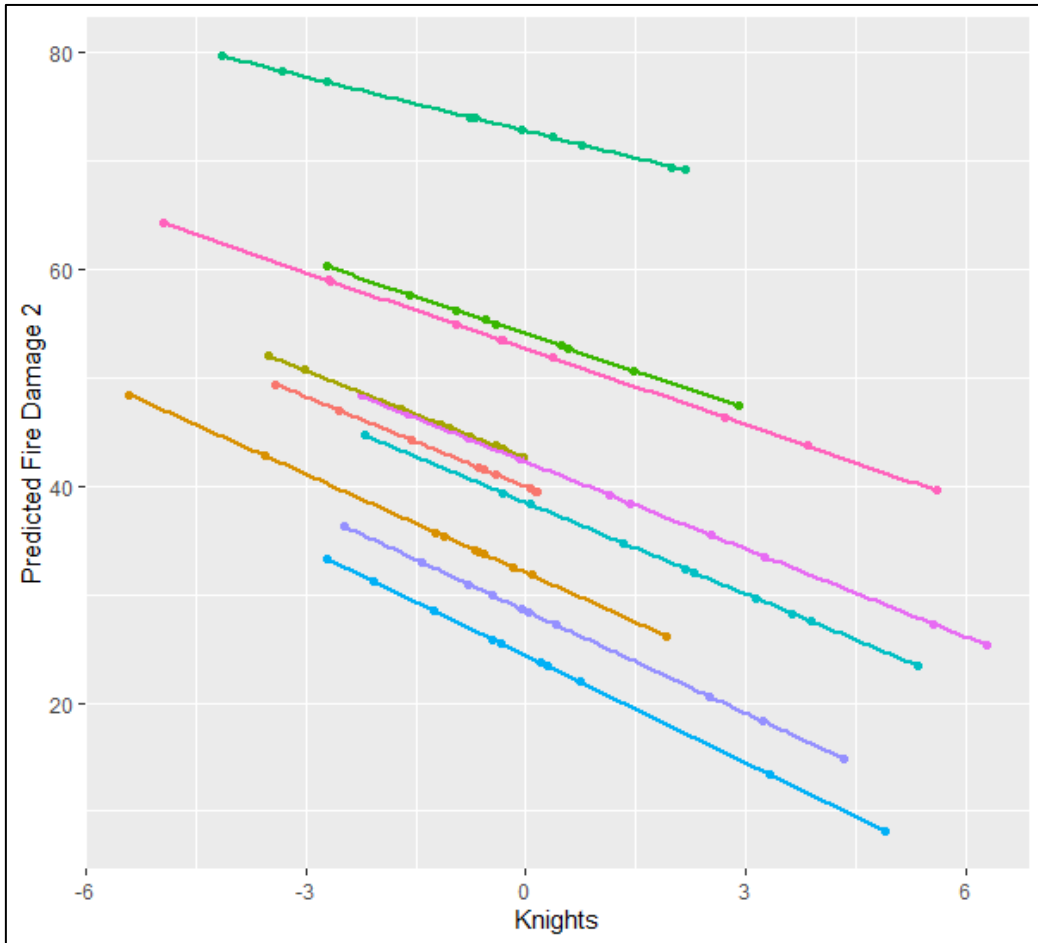
Covariance Parameter Estimates			
Cov Parm	Subject	Estimate	Standard Error
Intercept	Region	184.29	85.6906
Knights_C	Region	0	.
Residual		72.3787	10.7900

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	42.6839	4.3764	9	9.75	<.0001
Knights_C	-2.6581	0.4072	9	-6.53	0.0001

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Knights_C	1	9	42.60	0.0001

Example 1: Fire Damage and Knights

Model 3: Knight Level-2 Random Intercepts and Slopes



Example 2: Fire Damage and Archers

Model 1: Archer Standard Regression

R

```
>D2_M1 <-lm(Fire_Damage ~ Archers.C,  
data=Dragon1)  
>summary(D2_M1)  
  
>ggplot(data=Dragon1,  
aes(x=Archers.C, y=Fire_Damage)) +  
geom_point() +geom_smooth(method=lm,  
color="red")
```

SAS

```
PROC GLIMMIX data=Dragon1 method=MMPL;  
model Fire_Damage=Archers_C/s;  
output out=D2M1_pred pred lcl ucl;  
PROC SORT data=D2M1_pred;  
by Archers_C;  
PROC SGPLOT data=D2M1_pred noautolegend;  
band x=Archers_C lower=lcl upper=ucl;  
scatter x=Archers_C y=Fire_Damage;  
series x=Archers_C y=pred;
```

Example 2: Fire Damage and Archers

Model 1: Archer Standard Regression

Call:
 lm(formula = Fire_Damage ~ Archers.C, data = Dragon1)

Residuals:
 Min 1Q Median 3Q Max
 -41.077 -12.787 -2.217 11.727 43.842

Coefficients:
 Estimate Std. Error t value Pr(>|t|)
 (Intercept) 42.6837 1.7361 24.586 <2e-16 ***
 Archers.C 1.4808 0.6818 2.172 0.0323 *

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 17.36 on 98 degrees of freedom
 Multiple R-squared: 0.04592, Adjusted R-squared: 0.03619
 F-statistic: 4.717 on 1 and 98 DF, p-value: 0.03227

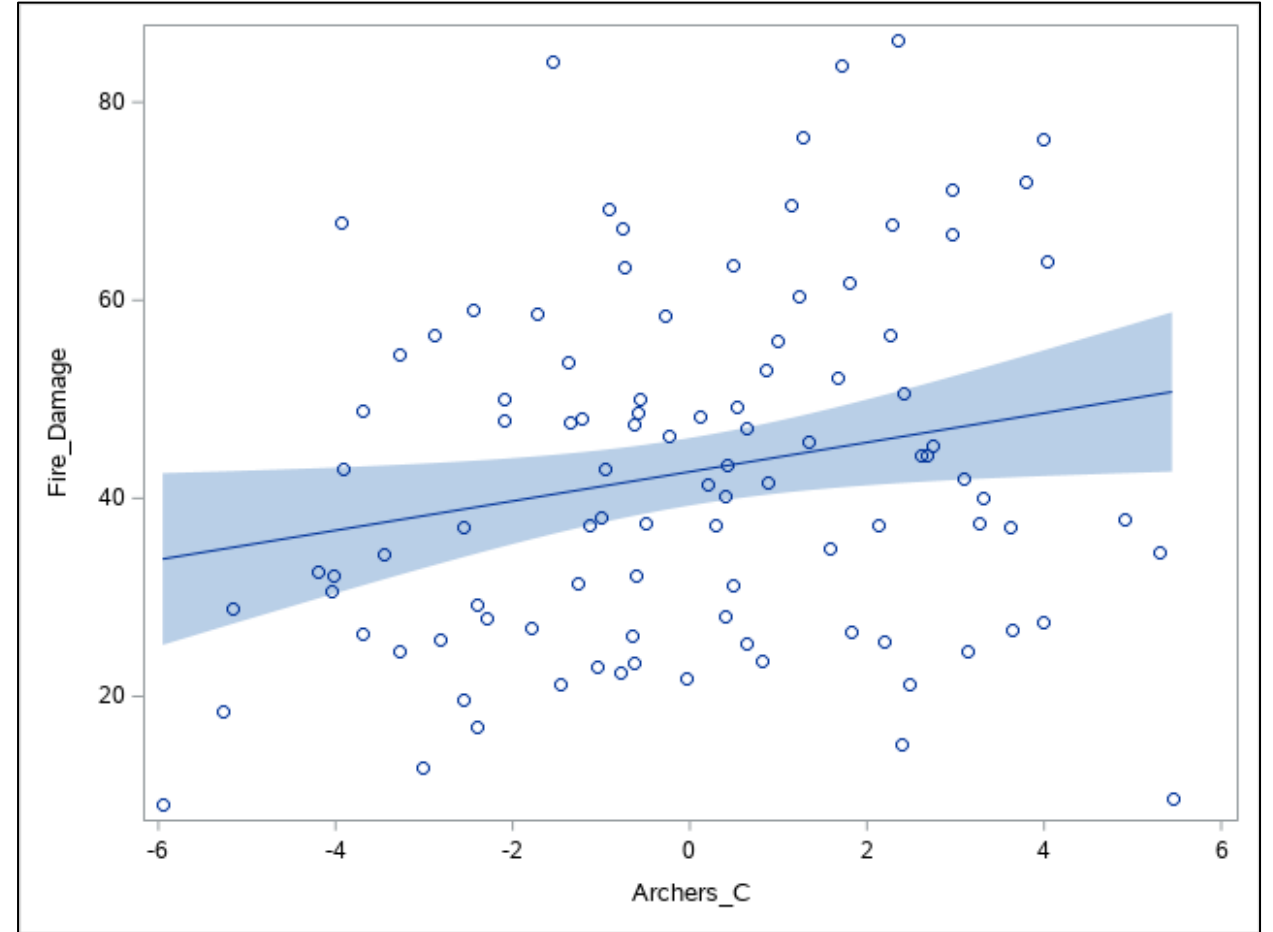
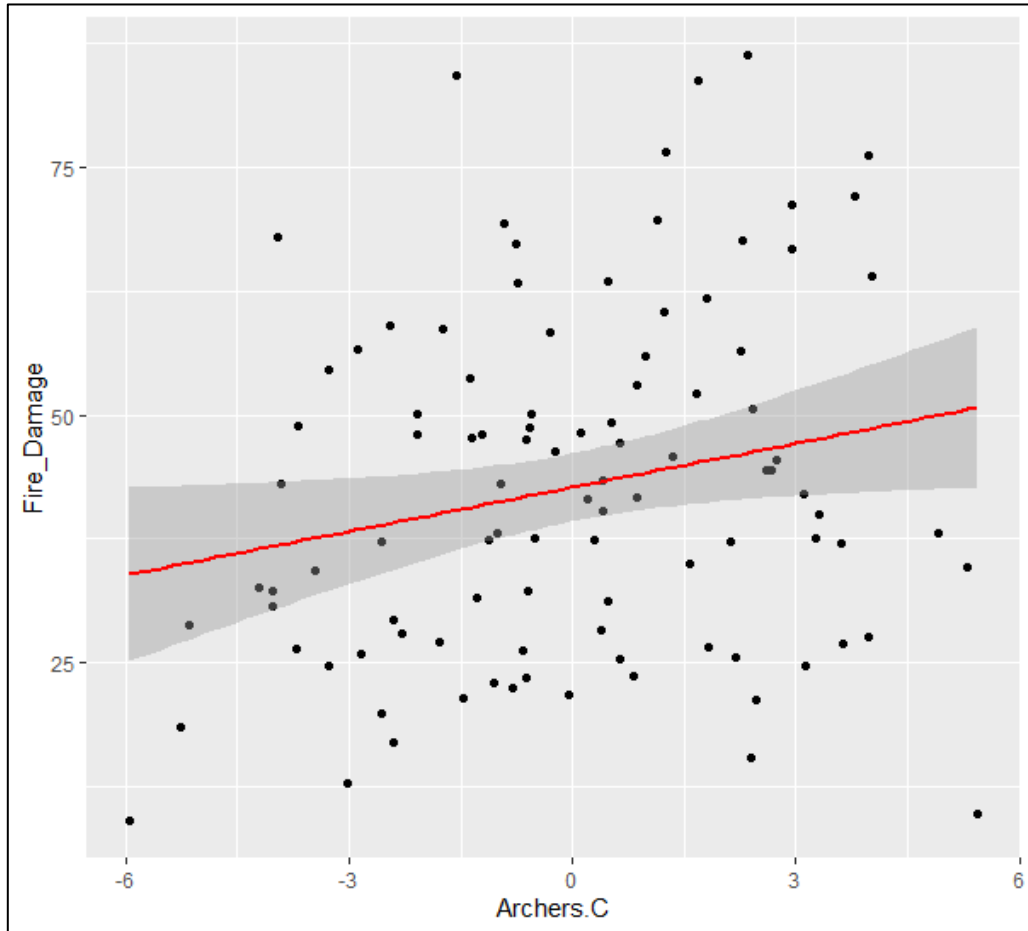
Fit Statistics	
-2 Log Likelihood	852.61
AIC (smaller is better)	858.61
AICC (smaller is better)	858.86
BIC (smaller is better)	866.43
CAIC (smaller is better)	869.43
HQIC (smaller is better)	861.78
Pearson Chi-Square	29538.20
Pearson Chi-Square / DF	295.38

Parameter Estimates					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	42.6833	1.7187	98	24.84	<.0001
Archers_C	1.4808	0.6749	98	2.19	0.0306
Scale	295.38	41.7733	.	.	.

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Archers_C	1	98	4.81	0.0306

Example 2: Fire Damage and Archers

Model 1: Archer Standard Regression



Example 2: Fire Damage and Archers

Model 2: Archer Level-2 Random Intercepts

R

```
>D2_M2 <-lmer(Fire_Damage ~ Archers.C + (1|Region),  
data=Dragon1, REML=F)  
>summary(D2_M2)  
  
>Dragon1$Fire_Damage_APred <-predict(D2_M2,  
newdata=Dragon1)  
  
>ggplot(data=Dragon1, aes(x=Archers.C, y=Fire_Damage_APred,  
group=Region)) +  
  geom_point(aes(color=Region))+  
  geom_smooth(method='lm', se=TRUE, aes(colour=Region))+  
  xlab("Archers") + ylab("Fire Damage")+  
  theme(legend.position = "none")
```

SAS

```
PROC GLIMMIX data=Dragon1 method=MMPL;  
  class Region;  
  model Fire_Damage=Archers_C/s;  
  random Region;  
  output out=D2M2_pred pred lcl ucl;  
PROC SORT data=D2M2_pred;  
  by Knights_C;  
PROC SGPLOT data=D2M2_pred noautolegend;  
  band x=Archers_C lower=lcl  
  upper=ucl/group=Region transparency=.90;  
  scatter x=Archers_C  
y=Fire_Damage/group=Region;  
  series x=Archers_C y=pred/group=Region;
```

Example 2: Fire Damage and Archers

Model 2: Archer Level-2 Random Intercepts

Linear mixed model fit by maximum likelihood ['lmerMod']
 Formula: Fire_Damage ~ Archers.C + (1 | Region)
 Data: Dragon1

AIC	BIC	logLik	deviance	df.resid
762.3	772.7	-377.1	754.3	96

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.74765	-0.65590	0.00371	0.73893	1.96885

Random effects:

Groups	Name	Variance	Std.Dev.
Region	(Intercept)	331.68	18.212
Residual		75.53	8.691

Number of obs: 100, groups: Region, 10

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	42.6837	5.8244	7.328
Archers.C	-2.6720	0.4705	-5.679

Correlation of Fixed Effects:

(Intr)
Archers.C 0.000

Fit Statistics	
-2 Log Likelihood	754.29
AIC (smaller is better)	762.29
AICC (smaller is better)	762.71
BIC (smaller is better)	763.50
CAIC (smaller is better)	767.50
HQIC (smaller is better)	760.96
Generalized Chi-Square	7552.79
Gener. Chi-Square / DF	75.53

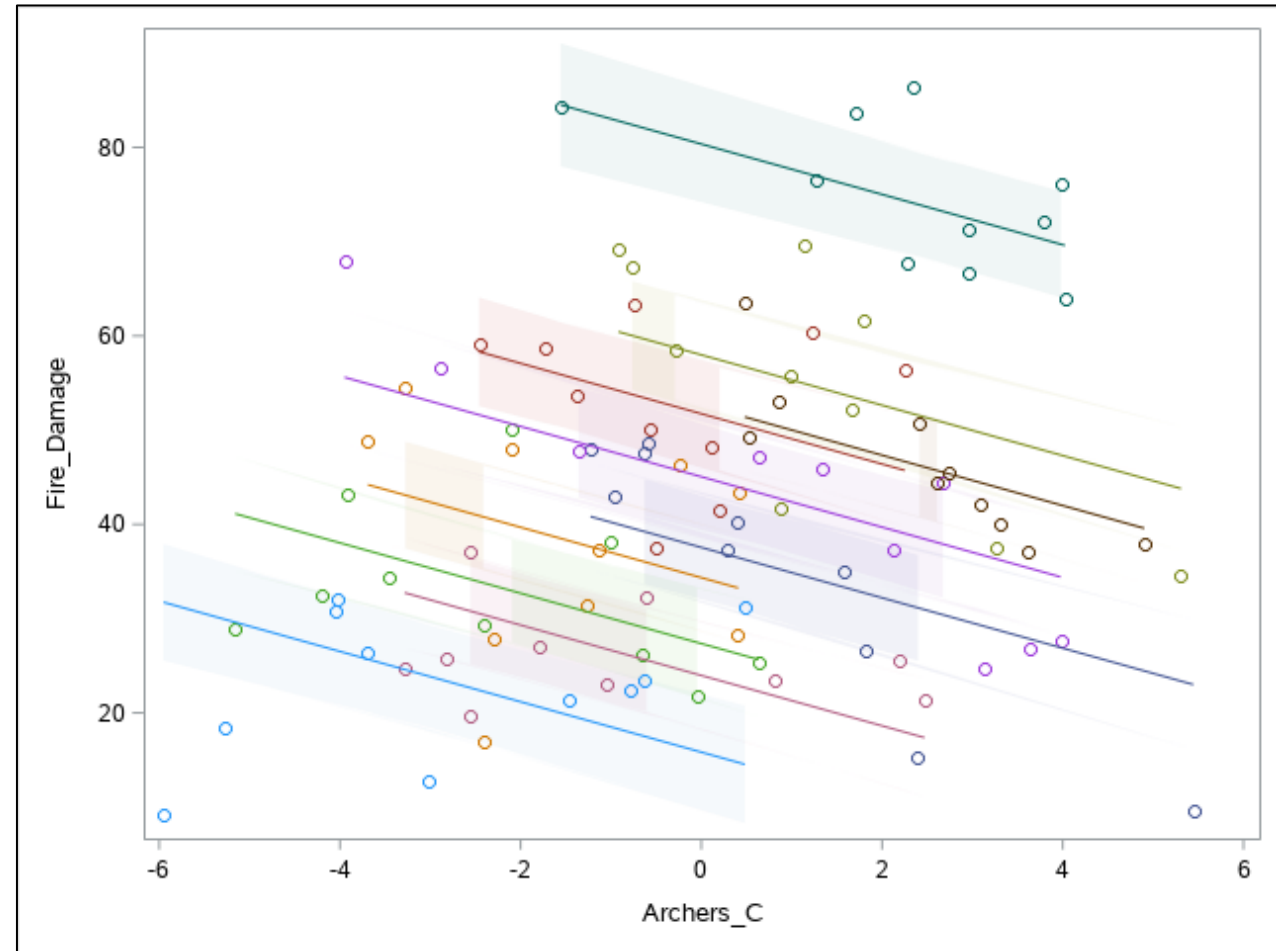
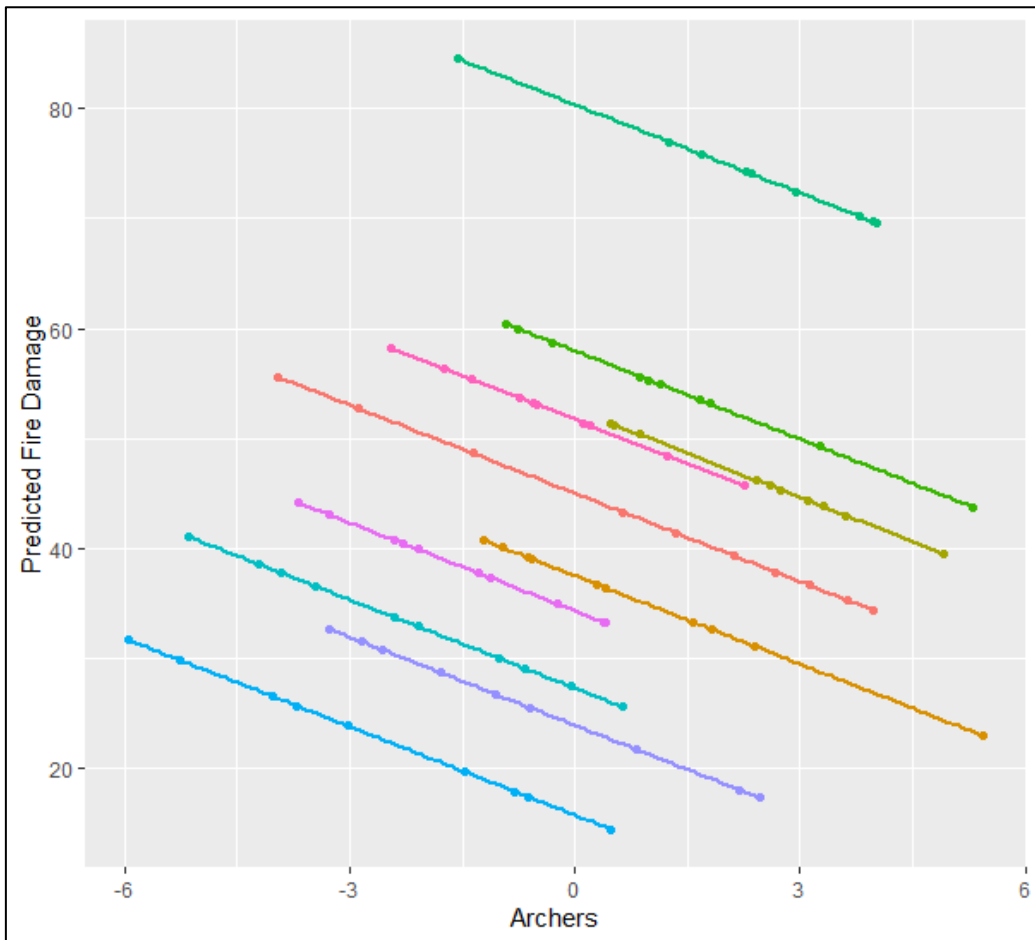
Covariance Parameter Estimates		
Cov Parm	Estimate	Standard Error
Region	331.68	154.00
Residual	75.5279	11.2779

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	42.6845	5.8244	9	7.33	<.0001
Archers_C	-2.6720	0.4705	89	-5.68	<.0001

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Archers_C	1	89	32.25	<.0001

Example 2: Fire Damage and Archers

Model 2: Archer Level-2 Random Intercepts



Example 2: Fire Damage and Archers

Model 3: Archer Level-2 Random Intercepts and Slopes

R

```
>D2_M3 <-lmer(Fire_Damage ~ Archers.C + (Archers.C|Region),  
data=Dragon1, REML=F)  
>summary(D2_M3)  
  
>Dragon1$Fire_Damage_APred2 <-predict(D2_M3,  
newdata=Dragon1)  
  
>ggplot(data=Dragon1, aes(x=Archers.C, y=Fire_Damage_APred2,  
group=Region)) +  
  geom_point(aes(color=Region))+  
  geom_smooth(method='lm', se=TRUE, aes(colour=Region))+  
  xlab("Archers") + ylab("Fire Damage")+  
  theme(legend.position = "none")
```

SAS

```
PROC GLIMMIX data=Dragon1 method=MMPL;  
  class Region;  
  model Fire_Damage=Archers_C/s;  
  random intercept Archers/subject = Region;  
  output out=D2M3_pred pred lcl ucl;  
PROC SORT data=D2M3_pred;  
  by Archers_C;  
PROC SGPLOT data=D2M3_pred noautolegend;  
  band x=Archers_C lower=lcl  
  upper=ucl/group=Region transparency=.90;  
  scatter x=Archers_C  
  y=Fire_Damage/group=Region;  
  series x=Archers_C y=pred/group=Region;
```

Example 2: Fire Damage and Archers

Model 3: Archer Level-2 Random Intercepts and Slopes

Linear mixed model fit by maximum likelihood ['lmerMod']
 Formula: Fire_Damage ~ Archers.C + (Archers.C | Region)
 Data: Dragon1

AIC	BIC	logLik	deviance	df.resid
752.1	767.7	-370.0	740.1	94

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.0279	-0.4983	-0.1237	0.6095	2.2319

Random effects:

Groups	Name	Variance	Std.Dev.	Corr
Region	(Intercept)	297.280	17.242	
	Archers.C	4.398	2.097	-0.50
Residual		58.172	7.627	

Number of obs: 100, groups: Region, 10

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	45.2840	5.5414	8.172
Archers.C	-2.6568	0.7941	-3.346

Correlation of Fixed Effects:

(Intr)	
Archers.C	-0.418

Fit Statistics	
-2 Log Likelihood	742.01
AIC (smaller is better)	752.01
AICC (smaller is better)	752.65
BIC (smaller is better)	753.52
CAIC (smaller is better)	758.52
HQIC (smaller is better)	750.35
Generalized Chi-Square	5849.44
Gener. Chi-Square / DF	58.49

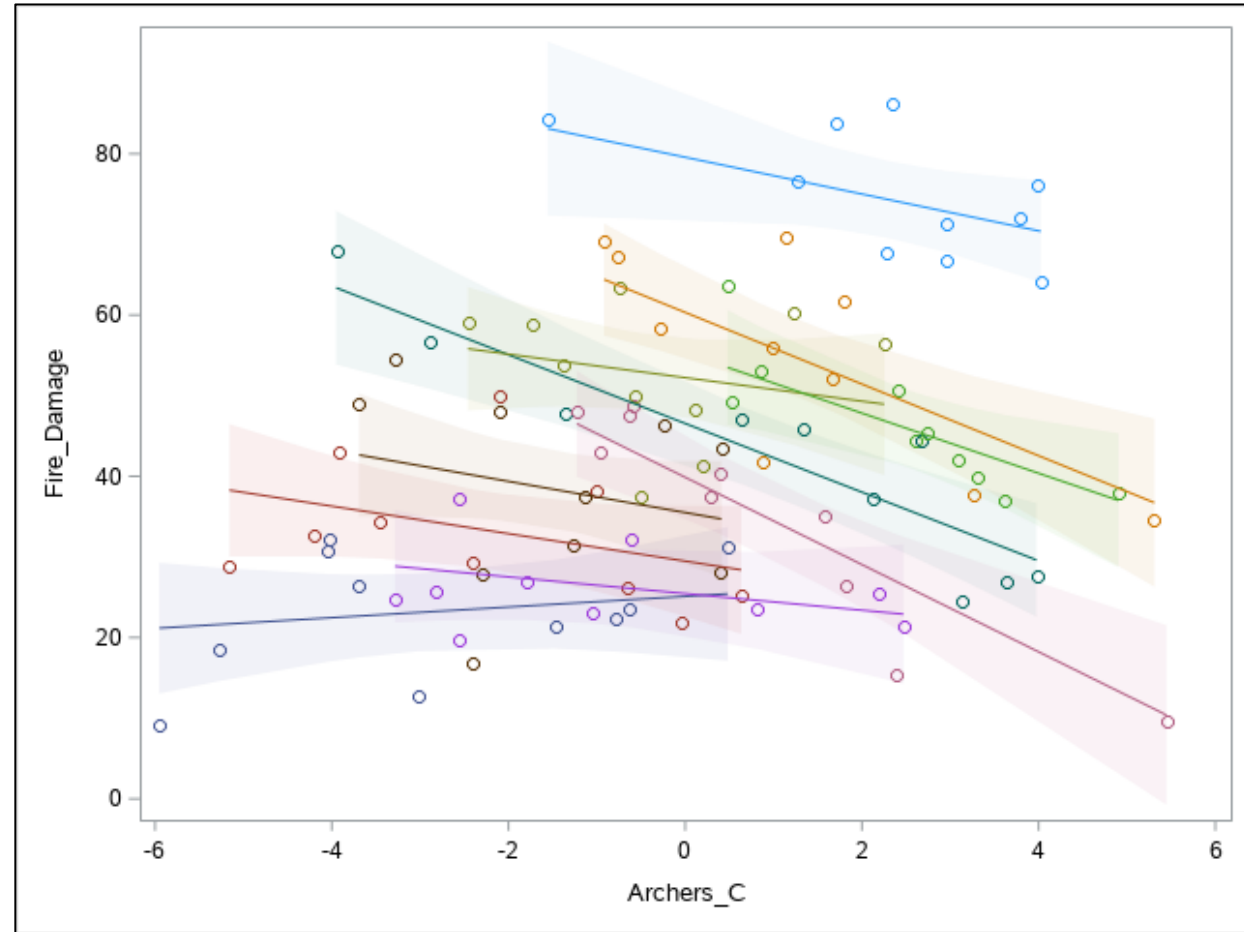
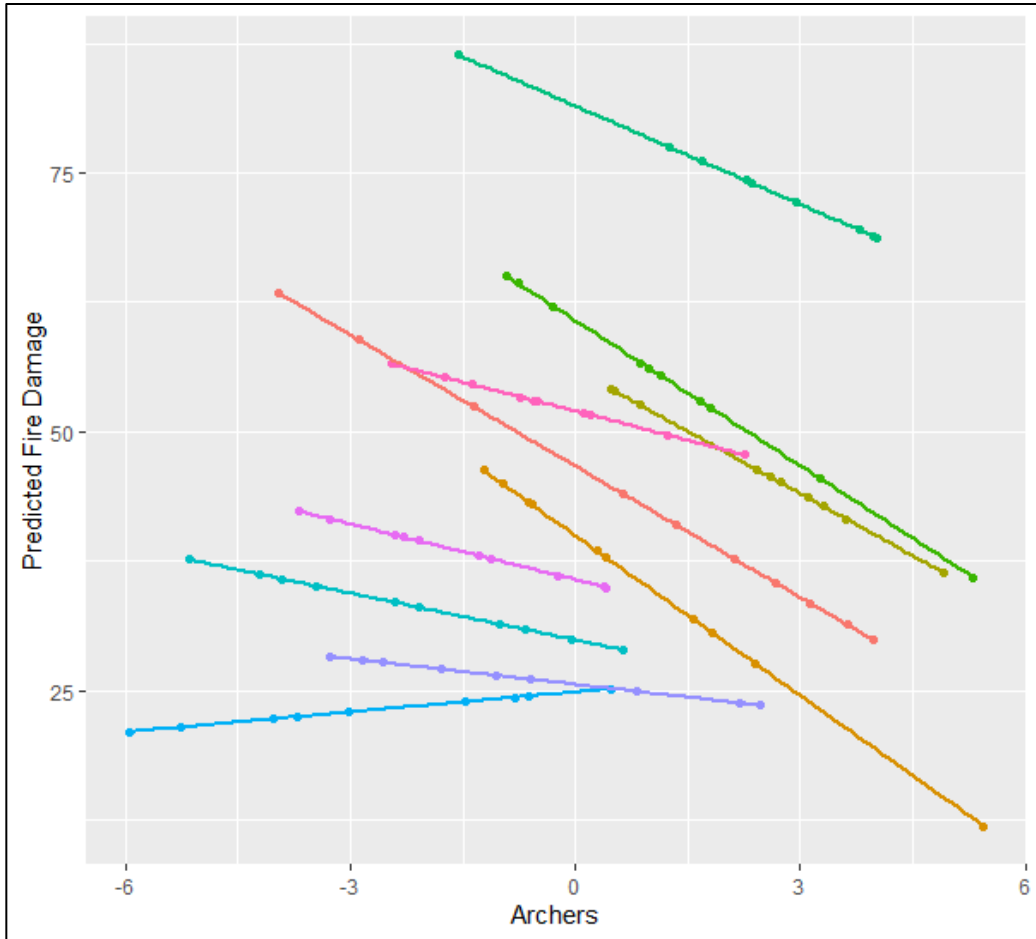
Covariance Parameter Estimates			
Cov Parm	Subject	Estimate	Standard Error
Intercept	Region	282.39	132.55
Archers_C	Region	4.4534	2.7237
Residual		58.4944	9.1638

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	44.9369	5.4090	9	8.31	<.0001
Archers_C	-2.5597	0.7991	9	-3.20	0.0108

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Archers_C	1	9	10.26	0.0108

Example 2: Fire Damage and Archers

Model 3: Archer Level-2 Random Intercepts and Slopes



Example 3: Dragon Hits and Arrows

Dataset Creation

- <https://data.princeton.edu/pop510/lang2> [10]
- Got data and transformed it to fit the dragon theme

```
>testds <- read.dta("https://data.princeton.edu/pop510/snijders.dta")
```

```
>testds2 <-testds[testds$schoolnr<100,] #Subset
```

```
#langpost <-DragonHit
```

```
#iavc <-ArrowNumber
```

```
#schoolnr <-Cathedral
```

```
>Dragon2 <-data.frame("DragonHit"=testds2$langpost/5,  
  "Arrows.C"=testds2$iq_verb*5-mean(testds2$iq_verb*5),  
  "Cathedral"=testds2$schoolnr)
```

```
>head(Dragon2)
```

	DragonHit	Arrows.C	Cathedral
1	9.2	16.056511	1
2	9.0	13.556511	1
3	6.6	-11.443489	1
4	9.2	-3.943489	1
5	4.0	-18.943489	1
6	6.0	-11.443489	1

Example 3: Dragon Hits and Arrows

Model 1: Arrow Standard Regression

R

```
>D3_M1 <- lm(DragonHit ~ Arrows.C,  
             data=Dragon2)  
  
>summary(D3_M1)  
  
>ggplot(data=Dragon2, aes(x=Arrows.C,  
                          y=DragonHit)) +  
  geom_point() +  
  geom_smooth(method=lm, color="red")
```

SAS

```
PROC GLIMMIX data=Dragon2 method=MMPL;  
  model DragonHit=Arrows_C/s;  
  output out=D3M1_pred pred lcl ucl;  
PROC SORT data=D3M1_pred;  
  by Arrows_C;  
PROC SGPLOT data=D3M1_pred noautolegend;  
  band x=Arrows_C lower=lcl upper=ucl;  
  scatter x=Arrows_C y=DragonHit;  
  series x=Arrows_C y=pred;
```

Example 3: Dragon Hits and Arrows

Model 1: Arrow Standard Regression

Call:

```
lm(formula = DragonHit ~ Arrows.C, data = Dragon2)
```

Residuals:

```
   Min    1Q  Median    3Q   Max
-4.5474 -0.9384  0.0877  1.0616  3.2003
```

Coefficients:

```
      Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.874939  0.050464  156.05 <2e-16 ***
Arrows.C     0.109550  0.004652   23.55 <2e-16 ***
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.44 on 812 degrees of freedom

Multiple R-squared: 0.4058, Adjusted R-squared: 0.4051

F-statistic: 554.6 on 1 and 812 DF, p-value: < 2.2e-16

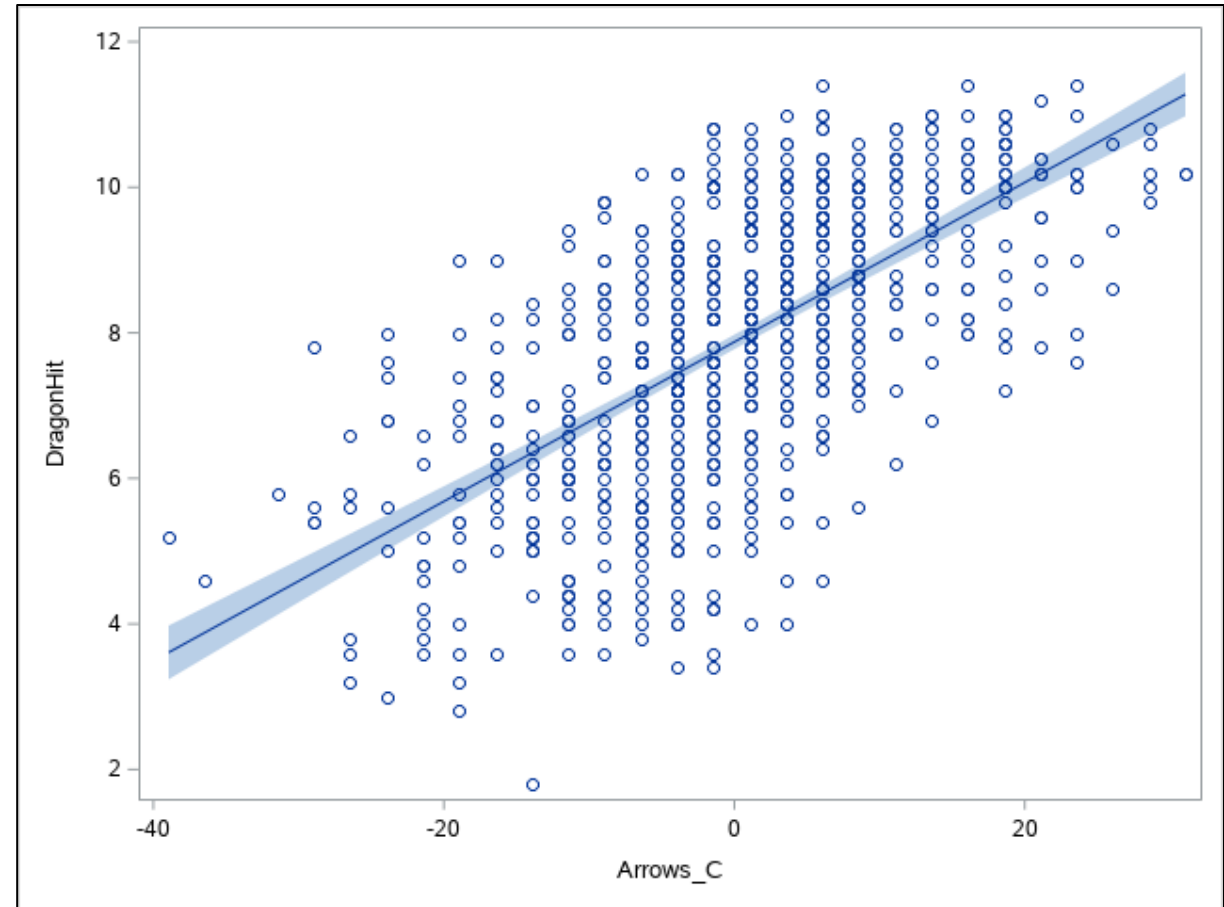
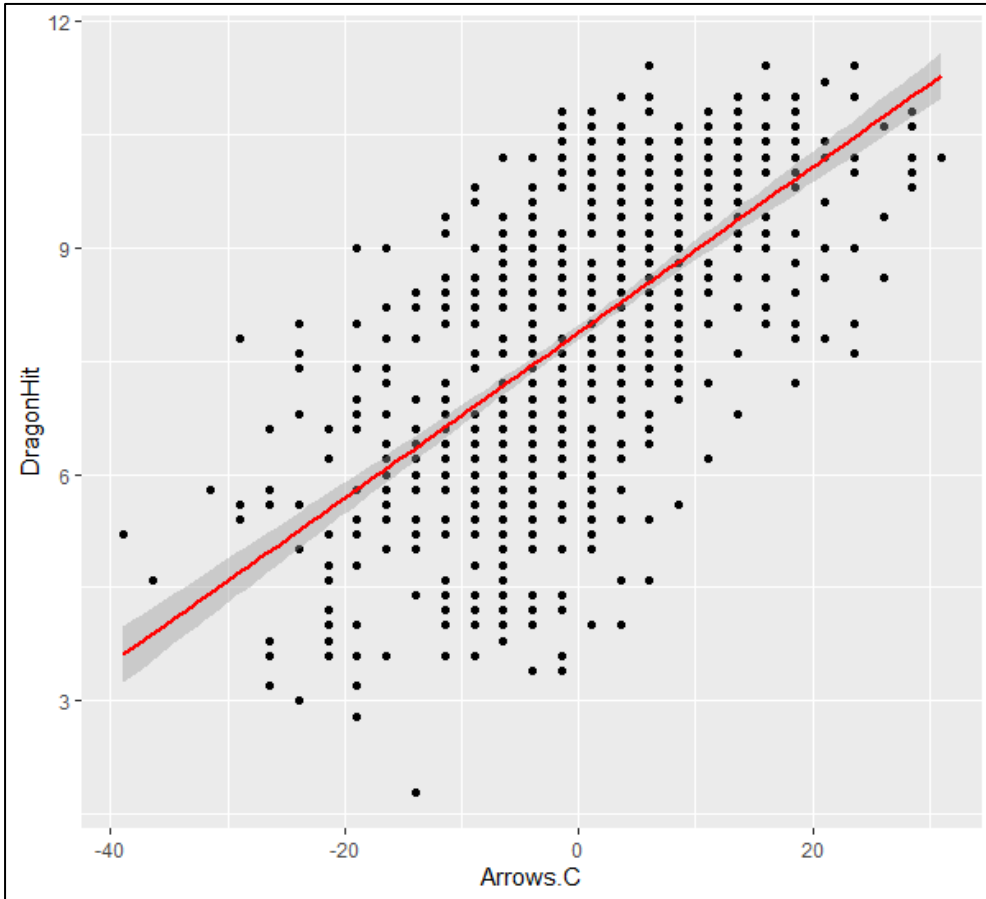
Fit Statistics	
-2 Log Likelihood	2901.40
AIC (smaller is better)	2907.40
AICC (smaller is better)	2907.43
BIC (smaller is better)	2921.51
CAIC (smaller is better)	2924.51
HQIC (smaller is better)	2912.82
Pearson Chi-Square	1683.22
Pearson Chi-Square / DF	2.07

Parameter Estimates					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	7.8749	0.05040	812	156.24	<.0001
Arrows_C	0.1095	0.004646	812	23.58	<.0001
Scale	2.0678	0.1025	.	.	.

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Arrows_C	1	812	555.95	<.0001

Example 3: Dragon Hits and Arrows

Model 1: Arrow Standard Regression



Example 3: Dragon Hits and Arrows

Model 2: Arrow Level-2 Random Intercepts

R

```
>D3_M2 <- lmer(DragonHit ~ Arrows.C + (1|Cathedral),  
data=Dragon2, REML=F)  
  
>summary(D3_M2)  
  
>Dragon2$DragonHit_Pred <-predict(D3_M2,  
newdata=Dragon2)  
  
>ggplot(data=Dragon2, aes(x=Arrows.C, y=DragonHit_Pred,  
group=Cathedral)) +  
  geom_point(aes(color=Cathedral))+  
  geom_smooth(method='lm', se=F, aes(colour=Cathedral))+  
  xlab("Arrows") + ylab("Dragon Hits")+  
  theme(legend.position = "none")
```

SAS

```
PROC GLIMMIX data=Dragon2 method=MMPL;  
  class Cathedral;  
  model DragonHit=Arrows_C/s;  
  random Cathedral;  
  output out=D3M2_pred pred lcl ucl;  
PROC SORT data=D3M2_pred;  
  by Arrows_C;  
PROC SGPLOT data=D3M2_pred noautolegend;  
  band x=Arrows_C lower=lcl  
  upper=ucl/group=Cathedral transparency=.90;  
  scatter x=Arrows_C y=DragonHit;  
  series x=Arrows_C y=pred/group=Cathedral;
```

Example 3: Dragon Hits and Arrows

Model 2: Arrow Level-2 Random Intercepts

Linear mixed model fit by maximum likelihood ['lmerMod']
 Formula: DragonHit ~ Arrows.C + (1 | Cathedral)
 Data: Dragon2

AIC	BIC	logLik	deviance	df.resid
2839.4	2858.2	-1415.7	2831.4	810

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.2753	-0.6202	0.0361	0.7280	2.1384

Random effects:

Groups	Name	Variance	Std.Dev.
Cathedral	(Intercept)	0.3328	0.5769
Residual		1.7507	1.3231

Number of obs: 814, groups: Cathedral, 46

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	7.818114	0.098527	79.35
Arrows.C	0.103365	0.004584	22.55

Correlation of Fixed Effects:
 (Intr)
 Arrows.C 0.023

Fit Statistics	
-2 Log Likelihood	2831.38
AIC (smaller is better)	2839.38
AICC (smaller is better)	2839.43
BIC (smaller is better)	2846.69
CAIC (smaller is better)	2850.69
HQIC (smaller is better)	2842.12
Generalized Chi-Square	1425.08
Gener. Chi-Square / DF	1.75

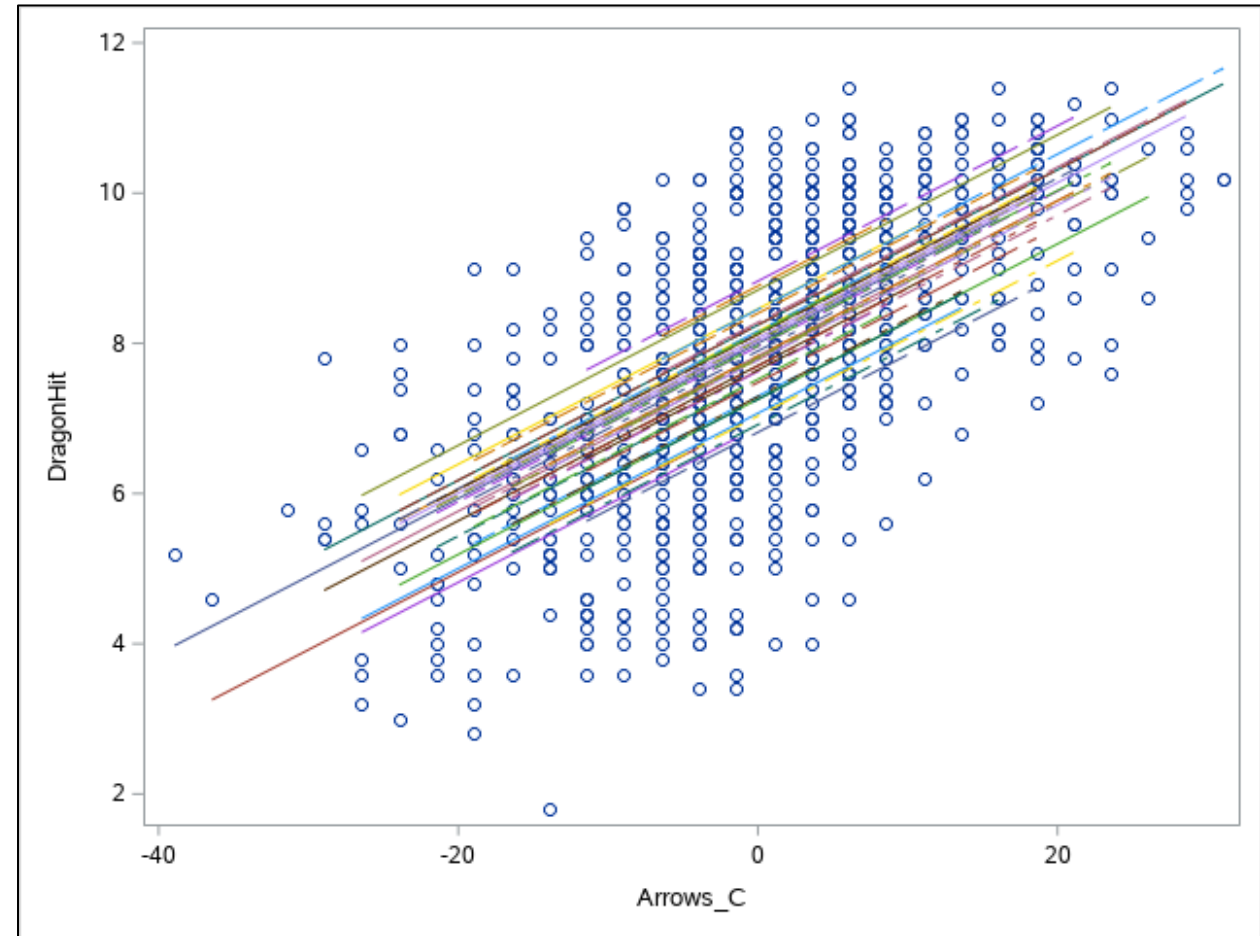
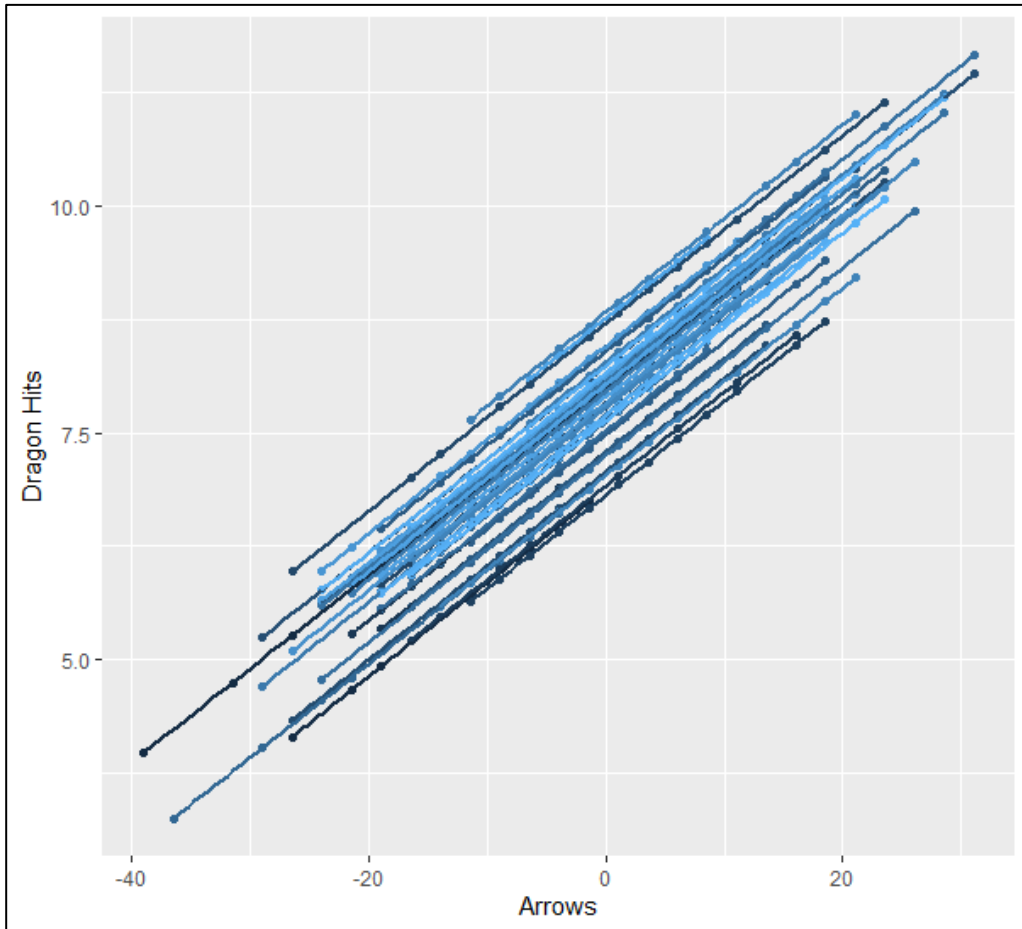
Covariance Parameter Estimates		
Cov Parm	Estimate	Standard Error
Cathedral	0.3328	0.09537
Residual	1.7507	0.08946

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	7.8181	0.09853	45	79.35	<.0001
Arrows_C	0.1034	0.004584	767	22.55	<.0001

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Arrows_C	1	767	508.49	<.0001

Example 3: Dragon Hits and Arrows

Model 2: Arrow Level-2 Random Intercepts



Example 3: Dragon Hits and Arrows

Model 3: Arrow Level-2 Random Intercepts and Slopes

R

```
>D3_M3 <- lmer(DragonHit ~ Arrows.C +  
(Arrows.C | Cathedral), data=Dragon2, REML=F)
```

```
summary(D3_M3)
```

```
>Dragon2$DragonHit_Pred2 <- predict(D3_M3,  
newdata=Dragon2)
```

```
>ggplot(data=Dragon2, aes(x=Arrows.C, y=DragonHit_Pred2,  
group=Cathedral)) +  
geom_point(aes(color=Cathedral))+  
geom_smooth(method='lm', se=F, aes(colour=Cathedral))+  
xlab("Arrows") + ylab("Dragon Hits")+  
theme(legend.position = "none")
```

SAS

```
PROC GLIMMIX data=Dragon2 method=MMPL;  
class Cathedral;  
model DragonHit=Arrows_C/s;  
random intercept Arrows_C/subject=Cathedral;  
output out=D3M3_pred pred lcl ucl;  
PROC SORT data=D3M3_pred;  
by Arrows_C;  
PROC SGPLOT data=D3M3_pred noautolegend;  
band x=Arrows_C lower=lcl  
upper=ucl/group=Cathedral transparency=.90;  
scatter x=Arrows_C y=DragonHit;  
series x=Arrows_C y=pred/group=Cathedral;
```

Example 3: Dragon Hits and Arrows

Model 3: Arrow Level-2 Random Intercepts and Slopes

Linear mixed model fit by maximum likelihood ['lmerMod']
 Formula: DragonHit ~ Arrows.C + (Arrows.C | Cathedral)
 Data: Dragon2

AIC	BIC	logLik	deviance	df.resid
2838.5	2866.7	-1413.2	2826.5	808

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.2454	-0.6294	0.0523	0.7400	2.3003

Random effects:

Groups	Name	Variance	Std.Dev.	Corr
Cathedral	(Intercept)	0.3354974	0.57922	
	Arrows.C	0.0001697	0.01303	-1.00
	Residual	1.7340747	1.31684	

Number of obs: 814, groups: Cathedral, 46

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	7.83793	0.09843	79.62
Arrows.C	0.10428	0.00492	21.20

Correlation of Fixed Effects:

	(Intr)
Arrows.C	-0.345

optimizer (nloptwrap) convergence code: 0 (OK)
 boundary (singular) fit: see ?isSingular

Fit Statistics	
-2 Log Likelihood	2831.33
AIC (smaller is better)	2841.33
AICC (smaller is better)	2841.40
BIC (smaller is better)	2850.47
CAIC (smaller is better)	2855.47
HQIC (smaller is better)	2844.75
Generalized Chi-Square	1420.78
Gener. Chi-Square / DF	1.75

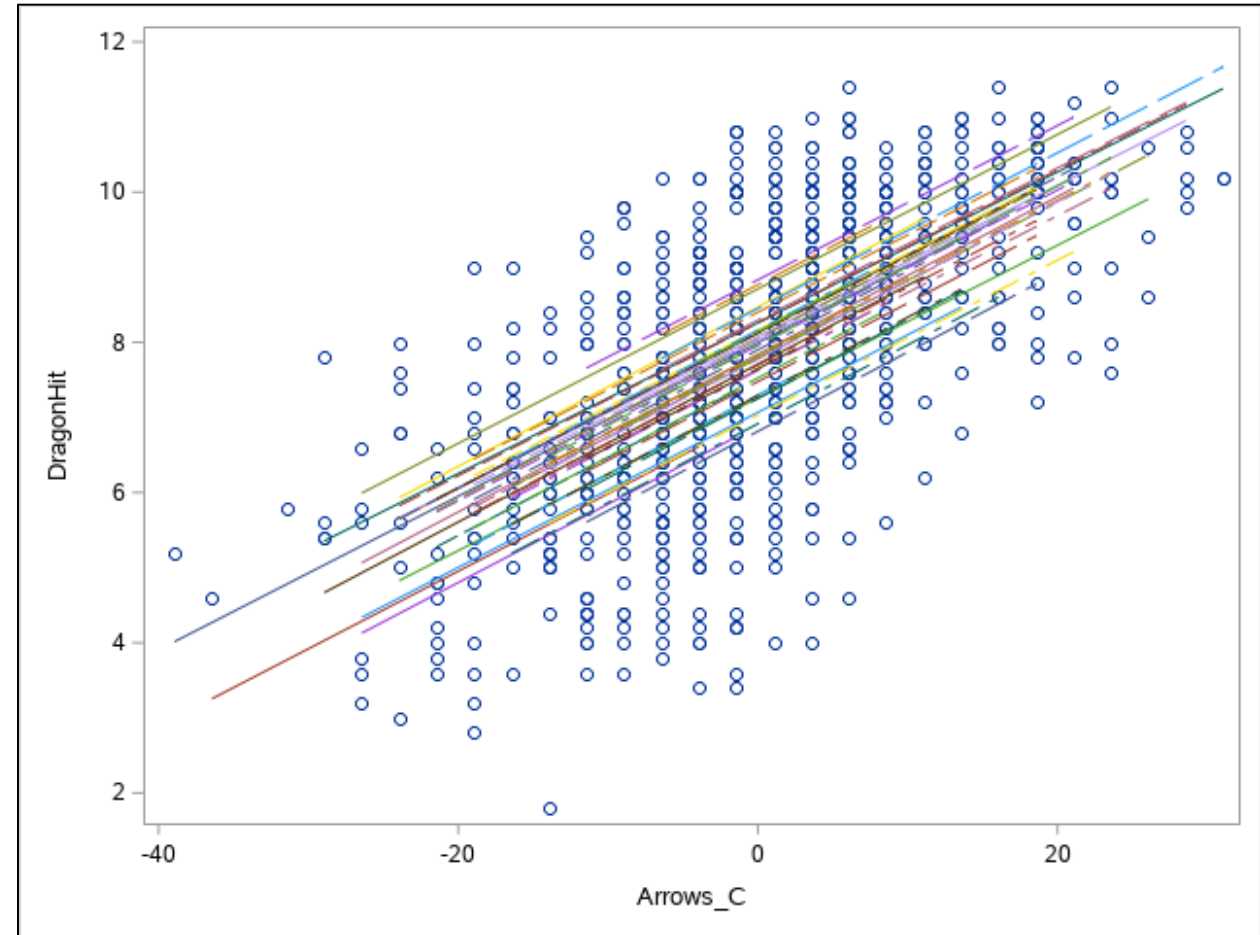
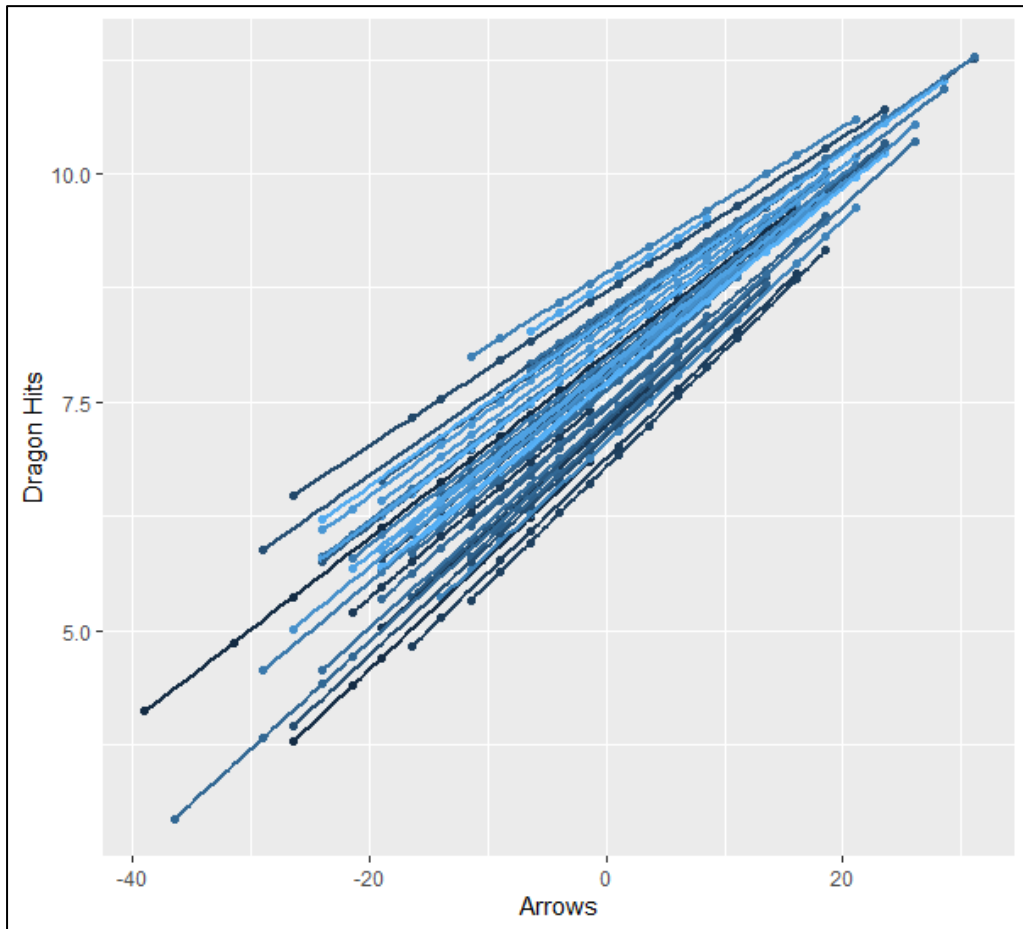
Covariance Parameter Estimates			
Cov Parm	Subject	Estimate	Standard Error
Intercept	Cathedral	0.3347	0.09641
Arrows_C	Cathedral	0.000045	0.000213
Residual		1.7454	0.09224

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	7.8204	0.09882	45	79.14	<.0001
Arrows_C	0.1037	0.004712	45	22.00	<.0001

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
Arrows_C	1	45	484.14	<.0001

Example 3: Dragon Hits and Arrows

Model 3: Arrow Level-2 Random Intercepts and Slopes



Example 4: Dragon Gold and Training

Dataset Creation

- <https://alexanderdemos.org/Mixed5.html> [11]
- Got data and transformed it to fit the dragon theme

```
>setwd("C:/Users/Mark.Williamson.2/Desktop/Williamson Data/R/R_data/2022  
Data")
```

```
>testds3 <-read.csv("Sim3level.csv")
```

```
>head(testds3)
```

```
#Math<- Dragon_gold
```

```
#ActiveTime <-TrainingTime
```

```
#StudentID<- Knight
```

```
#Classroom<- Commander
```

```
#School <-Cathedral
```

```
DragonGold TrainingTime KnightID Commander Cathedral TrainingTime.C Commander.2
```

```
1 55.4 0.7 1 1 C1 -4.140351 C1:1
```

```
2 54.3 0.8 2 1 C1 -4.040351 C1:1
```

```
3 61.4 1.3 3 1 C1 -3.540351 C1:1
```

```
4 56.1 7.5 4 1 C1 2.659649 C1:1
```

```
5 53.3 0.4 5 1 C1 -4.440351 C1:1
```

```
6 58.0 6.9 6 1 C1 2.059649 C1:1
```

```
>Dragon3 <-data.frame("DragonGold"=testds3$Math,  
"TrainingTime"=testds3$ActiveTime,  
"KnightID"=testds3$StudentID,  
"Commander"=testds3$Classroom, "Cathedral"=testds3$School)
```

Example 4: Dragon Gold and Training

Model 1: Training Standard Regression

R

```
>D4_M1 <- lm(DragonGold ~ TrainingTime.C,  
             data=Dragon3)  
>summary(D4_M1)  
  
>ggplot(data=Dragon3, aes(x=TrainingTime.C,  
                           y=DragonGold)) +  
  geom_point() +  
  geom_smooth(method=lm, color="red")
```

SAS

```
PROC GLIMMIX data=Dragon3 method=MMPL;  
  model DragonGold=TrainingTime_C/s;  
  output out=D4M1_pred pred lcl ucl;  
PROC SORT data=D4M1_pred;  
  by TrainingTime_C;  
PROC SGPLOT data=D4M1_pred noautolegend;  
  band x=TrainingTime_C  
      lower=lcl upper=ucl;  
  scatter x=TrainingTime_C y=DragonGold;  
  series x=TrainingTime_C y=pred;
```

Example 4: Dragon Gold and Training

Model 1: Training Standard Regression

Call:

```
lm(formula = DragonGold ~ TrainingTime.C, data = Dragon3)
```

Residuals:

```
   Min     1Q  Median     3Q    Max
-29.503 -7.641 -1.626  6.771 37.919
```

Coefficients:

```
      Estimate Std. Error t value Pr(>|t|)
(Intercept)  42.9605    0.4658  92.239 <2e-16 ***
TrainingTime.C  1.4648    0.1573   9.314 <2e-16 ***
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 11.12 on 568 degrees of freedom
Multiple R-squared: 0.1325, Adjusted R-squared: 0.131
F-statistic: 86.75 on 1 and 568 DF, p-value: < 2.2e-16

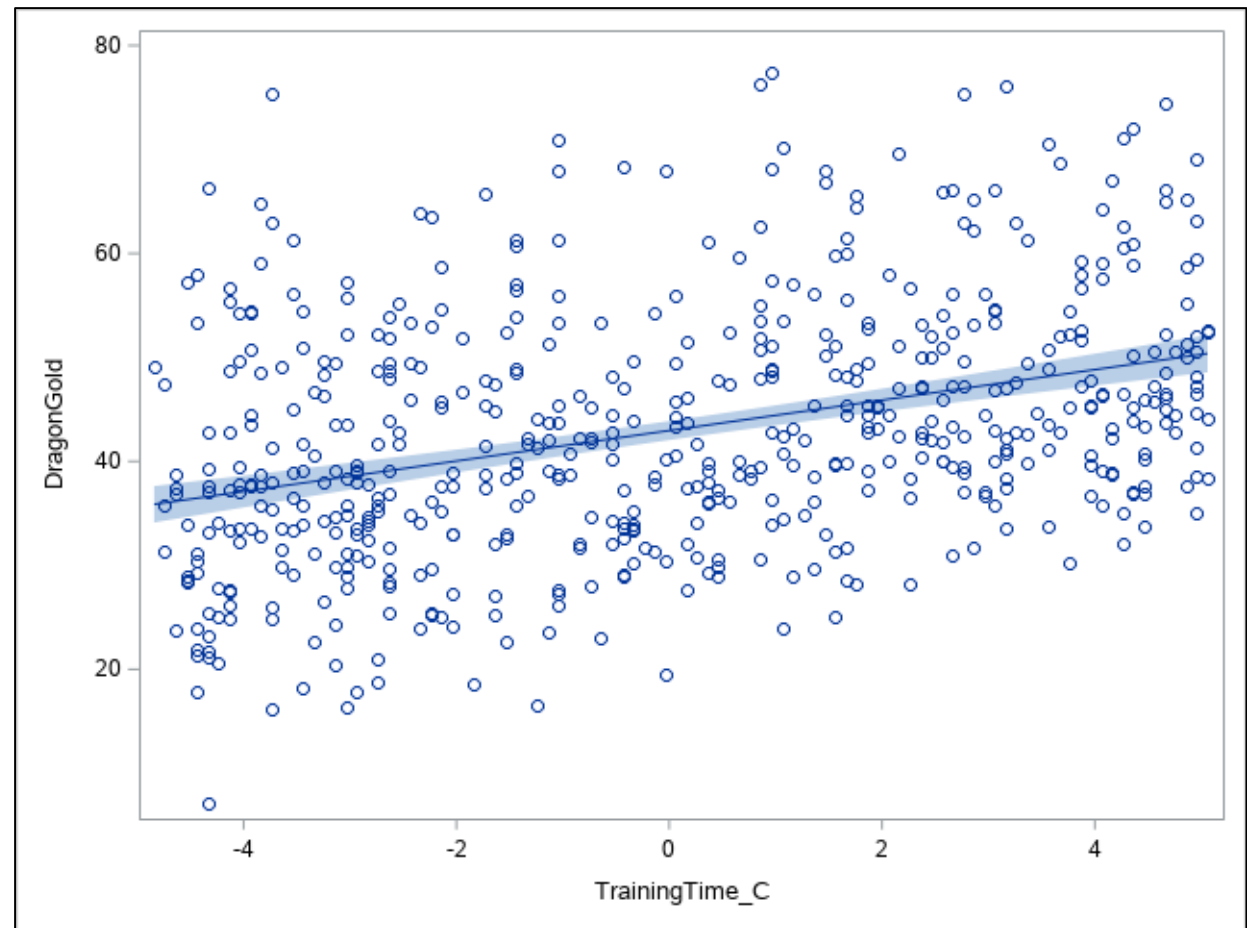
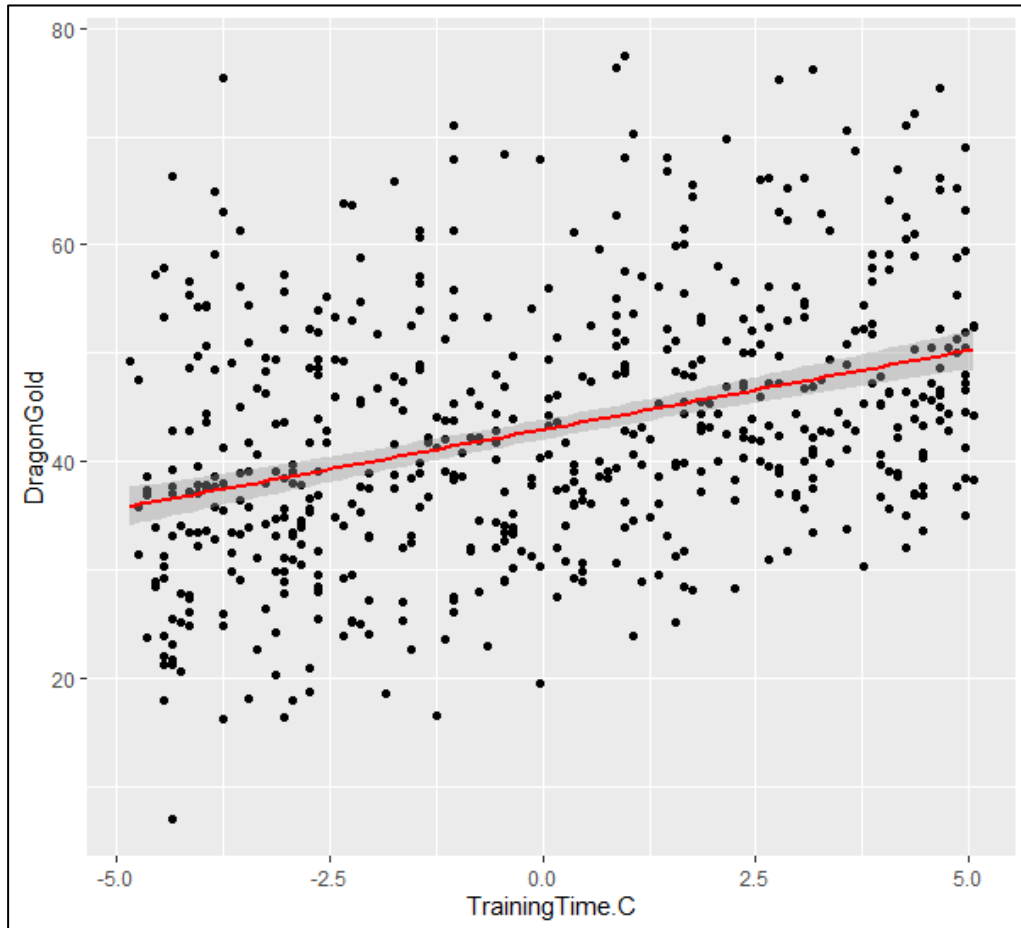
Fit Statistics	
-2 Log Likelihood	4361.53
AIC (smaller is better)	4367.53
AICC (smaller is better)	4367.57
BIC (smaller is better)	4380.57
CAIC (smaller is better)	4383.57
HQIC (smaller is better)	4372.62
Pearson Chi-Square	70232.45
Pearson Chi-Square / DF	123.21

Parameter Estimates					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	42.9605	0.4649	568	92.40	<.0001
TrainingTime_C	1.4648	0.1570	568	9.33	<.0001
Scale	123.21	7.2986	.	.	.

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
TrainingTime_C	1	568	87.06	<.0001

Example 4: Dragon Gold and Training

Model 1: Training Standard Regression



Example 4: Dragon Gold and Training

Model 2: Training Level-2 Random Intercepts

R

```
>D4_M2 <- lmer(DragonGold ~ TrainingTime.C + (1|Commander.2),  
data=Dragon3, REML=F)  
>summary(D4_M2)  
  
>Dragon3$DragonGold_Pred <-predict(D4_M2, newdata=Dragon3)  
  
>ggplot(data=Dragon3, aes(x=TrainingTime.C, y=DragonGold_Pred,  
group=Commander.2)) +  
  geom_point(aes(color=Commander.2))+  
  geom_smooth(method='lm', se=F, aes(colour=Commander.2))+  
  xlab("Training Time") + ylab("Dragon Gold")+  
  theme(legend.position = "none")
```

SAS

```
PROC GLIMMIX data=Dragon3 method=MMPL;  
  class Commander_2;  
  model DragonGold=TrainingTime_C/s;  
  random Commander_2;  
  output out=D4M2_pred pred lcl ucl;  
PROC SORT data=D4M2_pred;  
  by TrainingTime_C;  
PROC SGPLOT data=D4M2_pred noautolegend;  
  band x=TrainingTime_C lower=lcl  
  upper=ucl/group=Commander_2  
      transparency=.90;  
  scatter x=TrainingTime_C y=DragonGold;  
  series x=TrainingTime_C  
  y=pred/group=Commander_2;
```


Example 4: Dragon Gold and Training

Model 2: Training Level-2 Random Intercepts

Linear mixed model fit by maximum likelihood ['lmerMod']
 Formula: DragonGold ~ TrainingTime.C + (1 | Commander.2)
 Data: Dragon3

AIC BIC logLik deviance df.resid
 3401.4 3418.8 -1696.7 3393.4 566

Scaled residuals:
 Min 1Q Median 3Q Max
 -3.3097 -0.6559 -0.0453 0.6428 3.1190

Random effects:
 Groups Name Variance Std.Dev.
 Commander.2 (Intercept) 109.16 10.448
 Residual 17.54 4.189
 Number of obs: 570, groups: Commander.2, 30

Fixed effects:
 Estimate Std. Error t value
 (Intercept) 43.99163 1.91588 22.96
 TrainingTime.C 1.49248 0.06064 24.61

Correlation of Fixed Effects:
 (Intr)
 TrainngTm.C 0.000

Fit Statistics	
-2 Log Likelihood	3393.45
AIC (smaller is better)	3401.45
AICC (smaller is better)	3401.52
BIC (smaller is better)	3407.05
CAIC (smaller is better)	3411.05
HQIC (smaller is better)	3403.24
Generalized Chi-Square	10000.17
Gener. Chi-Square / DF	17.54

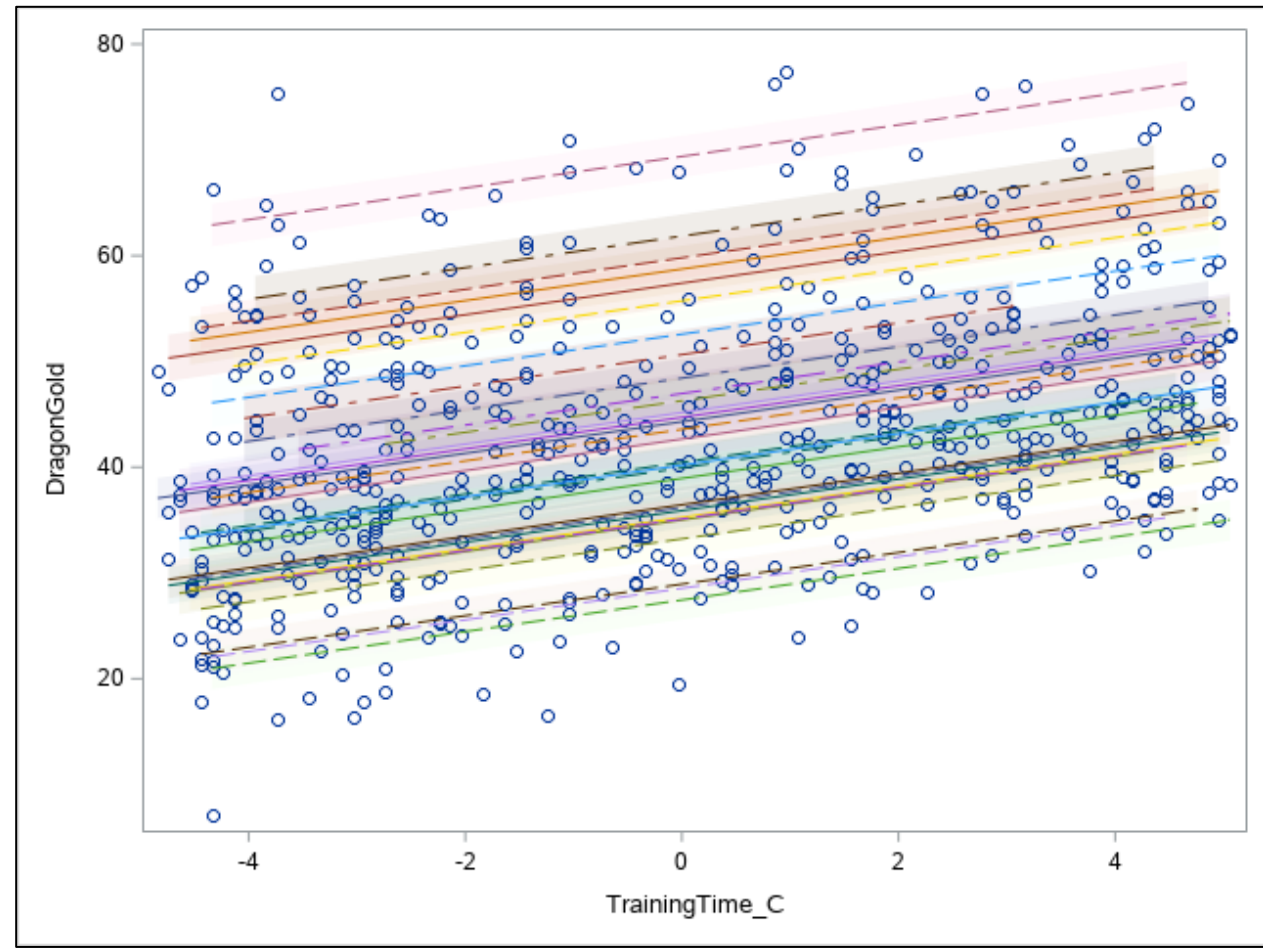
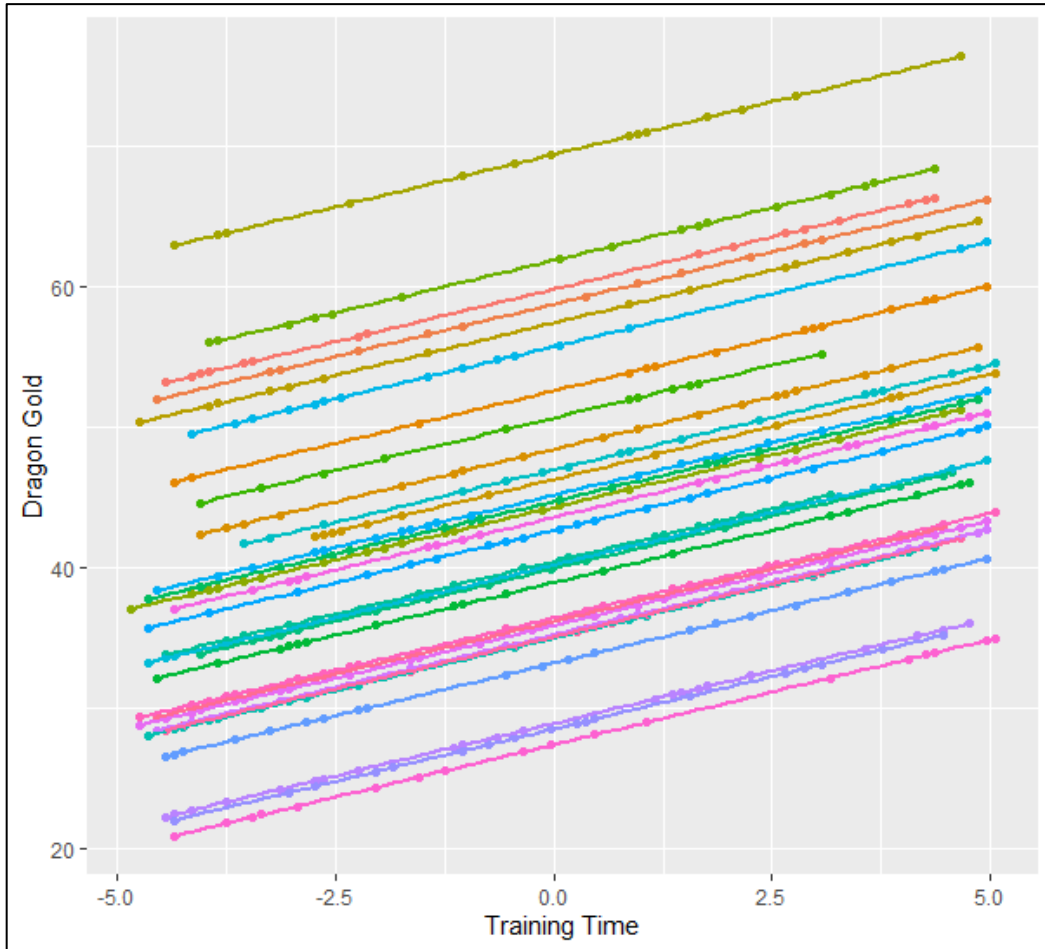
Covariance Parameter Estimates		
Cov Parm	Estimate	Standard Error
Commander_2	109.16	28.4361
Residual	17.5442	1.0677

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	43.9916	1.9159	29	22.96	<.0001
TrainingTime_C	1.4925	0.06064	539	24.61	<.0001

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
TrainingTime_C	1	539	605.84	<.0001

Example 4: Dragon Gold and Training

Model 2: Training Level-2 Random Intercepts



Example 4: Dragon Gold and Training

Model 3: Training Level-3 Random Intercepts

R

```
>D4_M3.1 <- lmer(DragonGold ~ TrainingTime.C +  
  (1|Cathedral) + (1|Commander.2),  
  data=Dragon3, REML=F)  
  
>summary(D4_M3.1)  
  
>D4_M3.2 <- lmer(DragonGold ~ TrainingTime.C +  
  (1|Cathedral) + (1|Cathedral:Commander),  
  data=Dragon3, REML=F)  
  
>summary(D4_M3.2)
```

SAS

```
PROC SGPLOT data=D4M3_pred noautolegend;  
  where Cathedral='C2';  
  band x=TrainingTime_C lower=lcl  
  upper=ucl/group=Commander_2 transparency=.90;  
  scatter x=TrainingTime_C y=DragonGold;  
  series x=TrainingTime_C y=pred/group=Commander_2;  
  yaxis ranges=(0-80); title "C2";  
  
PROC SGPLOT data=D4M3_pred noautolegend;  
  where Cathedral='C3'; title "C2";  
  band x=TrainingTime_C lower=lcl  
  upper=ucl/group=Commander_2 transparency=.90;  
  scatter x=TrainingTime_C y=DragonGold;  
  series x=TrainingTime_C y=pred/group=Commander_2;  
  yaxis ranges=(0-80); title "C3";  
  yaxis ranges=(0-80), title C1 ,
```

Example 4: Dragon Gold and Training

Model 3: Training Level-3 Random Intercepts

Linear mixed model fit by maximum likelihood ['lmerMod']
 Formula: DragonGold ~ TrainingTime.C + (1 | Cathedral) + (1 | Cathedral:Commander)
 Data: Dragon3

AIC	BIC	logLik	deviance	df.resid
3384.9	3406.7	-1687.5	3374.9	565

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.3181	-0.6554	-0.0496	0.6355	3.0840

Random effects:

Groups	Name	Variance	Std.Dev.
Cathedral:Commander	(Intercept)	44.67	6.684
Cathedral	(Intercept)	60.43	7.774
Residual		17.54	4.189

Number of obs: 570, groups: Cathedral:Commander, 30; Cathedral, 3

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	44.44829	4.65891	9.54
TrainingTime.C	1.49291	0.06062	24.63

Correlation of Fixed Effects:
 (Intr)
 TrainngTm.C 0.000

Fit Statistics	
-2 Log Likelihood	3393.45
AIC (smaller is better)	3401.45
AICC (smaller is better)	3401.52
BIC (smaller is better)	3407.05
CAIC (smaller is better)	3411.05
HQIC (smaller is better)	3403.24
Generalized Chi-Square	10000.17
Gener. Chi-Square / DF	17.54

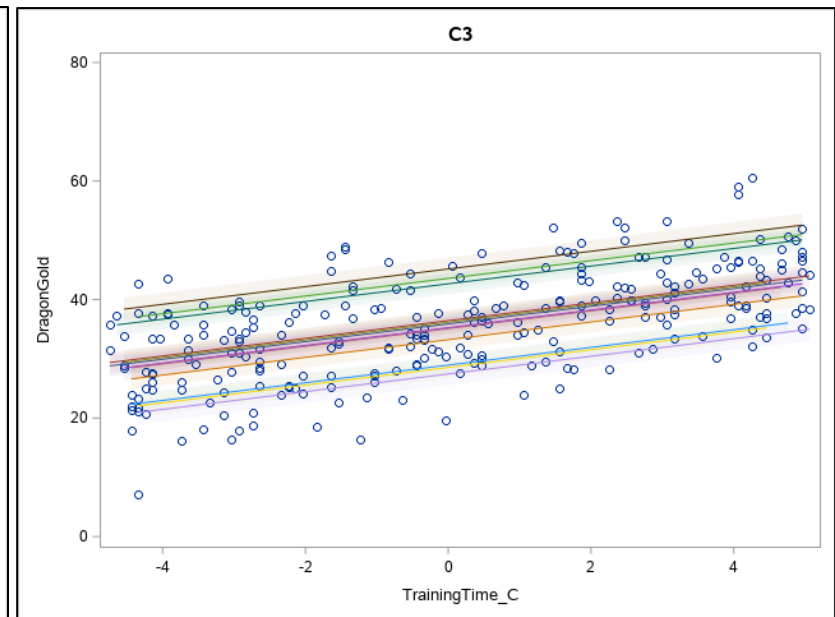
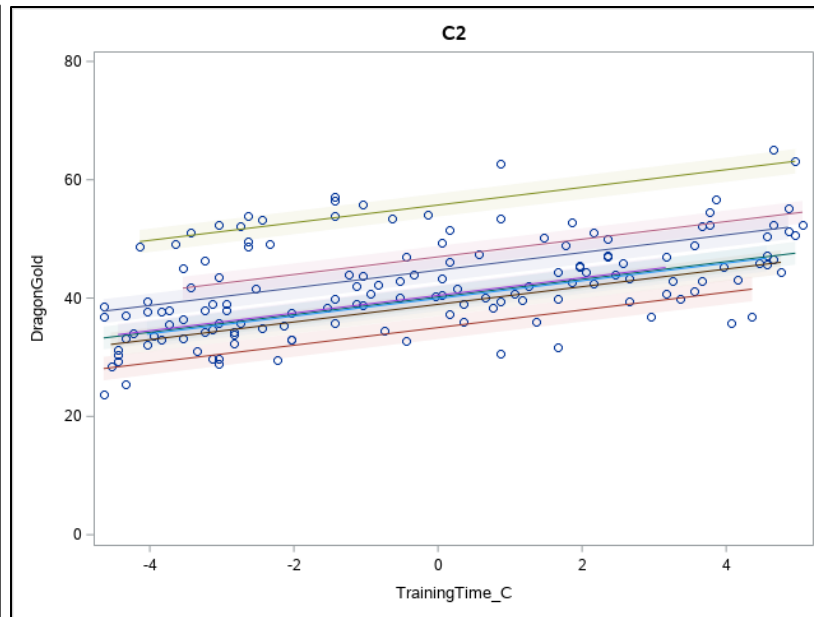
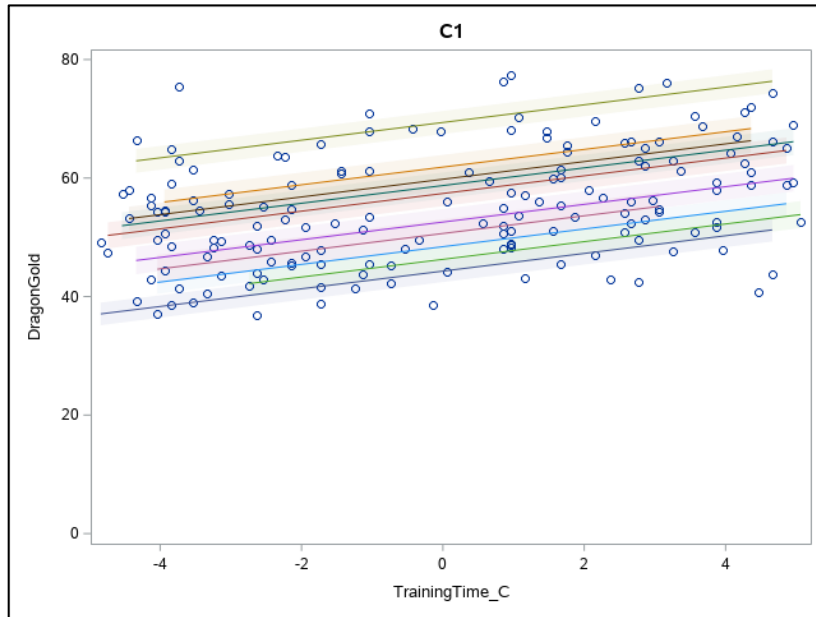
Covariance Parameter Estimates		
Cov Parm	Estimate	Standard Error
Commander(Cathedral)	109.16	28.4361
Residual	17.5442	1.0677

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	43.9916	1.9159	29	22.96	<.0001
TrainingTime_C	1.4925	0.06064	539	24.61	<.0001

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
TrainingTime_C	1	539	605.84	<.0001

Example 4: Dragon Gold and Training

Model 3: Training Level-2 Random Intercepts and Slopes



Example 4: Dragon Gold and Training

Model 4: Training Level-3 Random Intercepts and Slopes

R

```
>D4_M4 <- lmer(DragonGold ~ TrainingTime.C +  
(1+TrainingTime.C | Cathedral) +  
  (1+TrainingTime.C | Cathedral:Commander), data=Dragon3,  
REML=F)  
>summary(D4_M4)  
>Dragon3$DragonGold_Pred2 <- predict(D4_M4, newdata=Dragon3)  
  
>ggplot(data=Dragon3, aes(x=TrainingTime.C, y=DragonGold_Pred2,  
  group=Commander)) +  
  facet_grid(~Cathedral) + geom_point(aes(color=Commander))+  
  geom_smooth(method='lm', se=F, aes(colour=Commander))+  
  xlab("Training Time") + ylab("Dragon Gold")+  
  theme(legend.position = "none")
```

SAS

```
PROC SGPLOT data=D4M4_pred noautolegend;  
  where Cathedral='C2';  
  band x=TrainingTime_C lower=lcl  
  upper=ucl/group=Commander transparency=.90;  
  scatter x=TrainingTime_C y=DragonGold;  
  series x=TrainingTime_C y=pred/group=Commander;  
  yaxis ranges=(0-80); title "C2";  
  
PROC SGPLOT data=D4M4_pred noautolegend;  
  where Cathedral='C3';  
  band x=TrainingTime_C lower=lcl  
  upper=ucl/group=Commander transparency=.90;  
  scatter x=TrainingTime_C y=DragonGold;  
  series x=TrainingTime_C y=pred/group=Commander;  
  yaxis ranges=(0-80); title "C3";
```

Example 4: Dragon Gold and Training

Model 4: Training Level-3 Random Intercepts and Slopes

Linear mixed model fit by maximum likelihood [lmerMod]
 Formula: DragonGold ~ TrainingTime.C + ((1 | Cathedral) + (0 + TrainingTime.C | Cathedral)) + (1 + TrainingTime.C | Cathedral:Commander)
 Data: Dragon3

AIC BIC logLik deviance df.resid
 3353.7 3388.5 -1668.9 3337.7 562

Scaled residuals:
 Min 1Q Median 3Q Max
 -3.03150 -0.64800 -0.02983 0.65167 2.97169

Random effects:
 Groups Name Variance Std.Dev. Corr
 Cathedral.Commander (Intercept) 46.05782 6.7866
 TrainingTime.C 0.17298 0.4159 0.14
 Cathedral TrainingTime.C 0.06047 0.2459
 Cathedral.1 (Intercept) 62.33496 7.8952
 Residual 15.36809 3.9202
 Number of obs: 570, groups: Cathedral:Commander, 30; Cathedral, 3

Fixed effects:
 Estimate Std. Error t value
 (Intercept) 44.3677 4.7311 9.378
 TrainingTime.C 1.4418 0.1719 8.385

Correlation of Fixed Effects:
 (Intr)
 TrainngTm.C 0.016

Fit Statistics	
-2 Log Likelihood	3338.03
AIC (smaller is better)	3352.03
AICC (smaller is better)	3352.22
BIC (smaller is better)	3345.72
CAIC (smaller is better)	3352.72
HQIC (smaller is better)	3339.34
Generalized Chi-Square	8763.03
Gener. Chi-Square / DF	15.37

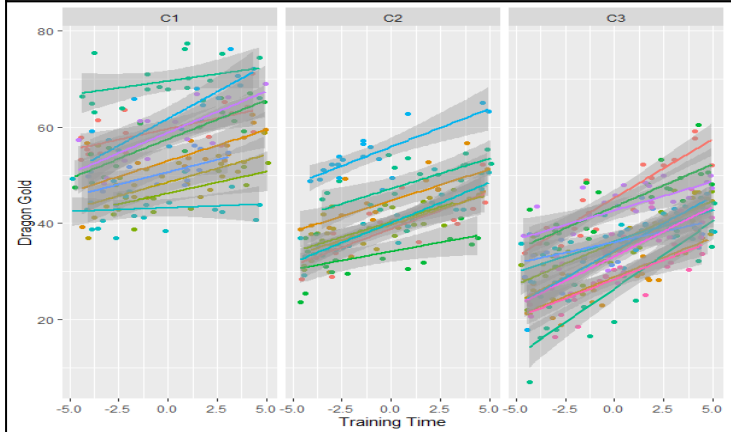
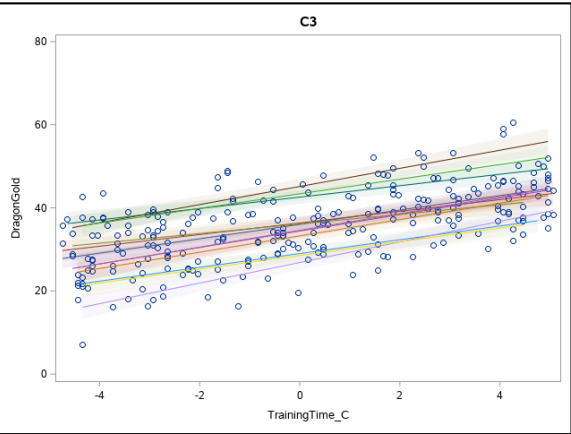
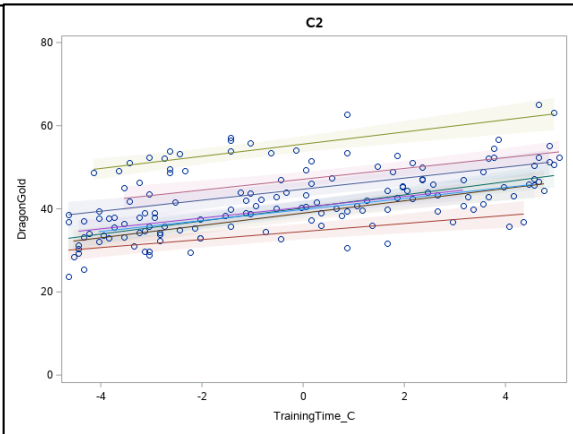
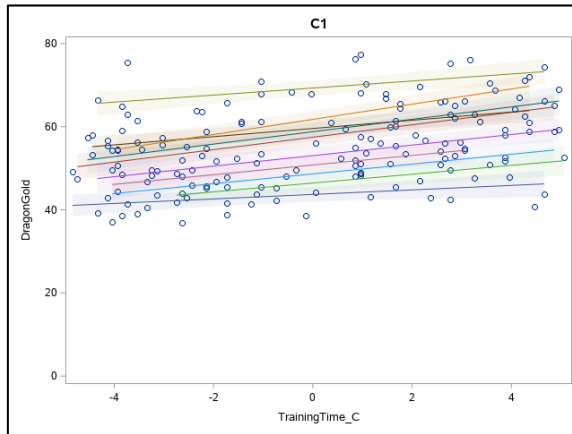
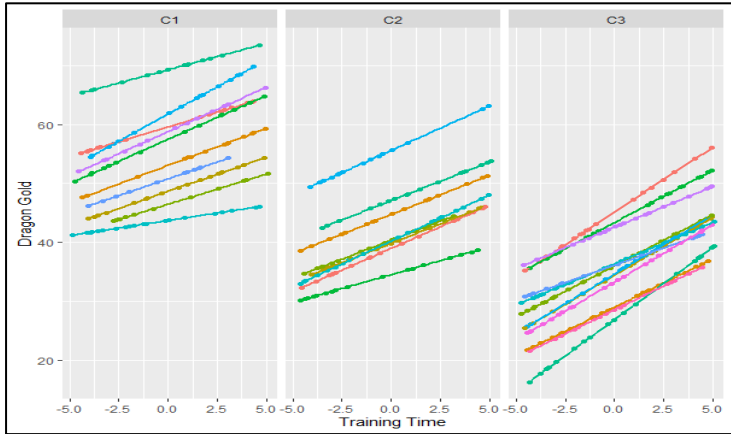
Covariance Parameter Estimates			
Cov Parm	Subject	Estimate	Standard Error
Intercept	Commander(Cathedral)	46.1129	12.7761
TrainingTime_C	Commander(Cathedral)	0.1722	0.07246
Intercept	Cathedral	60.5906	53.0752
TrainingTime_C	Cathedral	0.05829	0.06830
Residual		15.3737	0.9618

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	44.3533	4.6694	0	9.50	.
TrainingTime_C	1.4425	0.1697	0	8.50	.

Type III Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
TrainingTime_C	1	0	72.22	.

Example 4: Dragon Gold and Training

Model 4: Training Level-3 Random Intercepts and Slopes



Conclusions

- ✦ Multilevel modeling deals with data that have non-independent grouping (aka, multi-levels, nesting, hierarchies, etc..)
- ✦ Not all regressions require multilevel modeling
- ✦ Always include fixed and random effects
- ✦ Intercepts and slopes can be made random
- ✦ With careful planning and attention, sophisticated results are possible

Please take the post-test and survey:

Post-test: https://und.qualtrics.com/jfe/form/SV_erinW9wUcC9xrZI

Survey: https://und.qualtrics.com/jfe/form/SV_1FwNCWiobpKVadw

References

- [1] **Multilevel Modeling (Douglas A. Luke)**
- [2] **<https://www.biostat.jhsph.edu/~fdominic/teaching/bio656/lectures/1.intro.pdf>**
- [3] **<https://www.apa.org/science/about/psa/2017/01/multilevel-modelling>**
- [4] **Multilevel Modeling: Methodological Advances, Issues, and Applications (Steven P. Reise & Naihua Duan)**
- [5] **<https://ademos.people.uic.edu/Chapter16.html>**
- [6] **https://en.wikipedia.org/wiki/Multilevel_model**
- [7] **https://sites.lsa.umich.edu/whirl/wp-content/uploads/sites/792/2020/11/MLMWorkshopSlides_UofT_Fall2019.pdf**
- [8] **<http://www.stat.columbia.edu/~gelman/research/published/multi2.pdf>**
- [9] **<https://ademos.people.uic.edu/Chapter16.html>**
- [10] **<https://data.princeton.edu/pop510/lang2>**
- [11] **<https://alexanderdemos.org/Mixed5.html>**

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