Question 2

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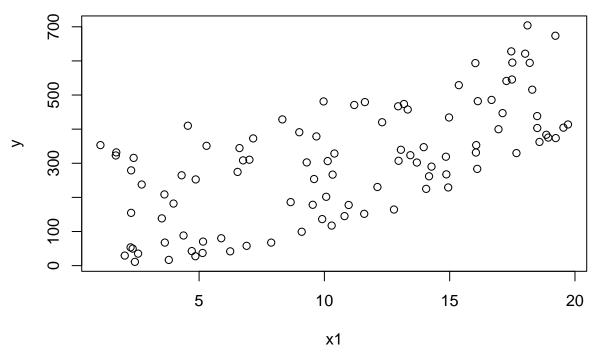
2b.

In general, a nonlinear trend can look fairly linear when data contain noise. For example, the following code plots data generated from $y = f(x1, x2) = x_1^2 + x_2^2 + \epsilon$, where $\epsilon \sim N(0, 0.02^2)$.

```
set.seed(390)
n <- 100
# simulate 20 values from uniform(0,1)
x1 = runif(n,1,20)
x2= runif(n,1,20)

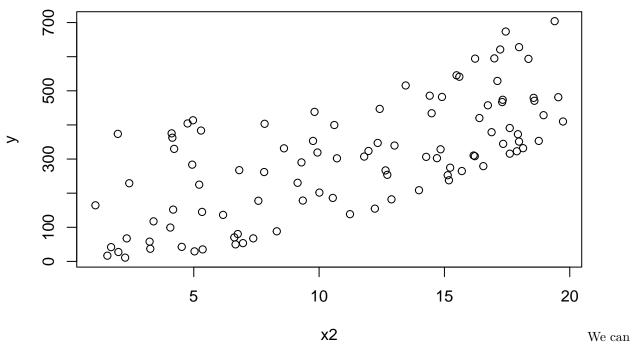
y = x1^2+x2*x2+rnorm(20,sd=0.02)
plot(y~x1, main = " Marginal plot of y vs x1", xlab = "x1", ylab = "y")</pre>
```

Marginal plot of y vs x1



```
plot(y~x2,main = " Marginal plot of y vs x2", xlab = "x2", ylab = "y")
```

Marginal plot of y vs x2



see clearly form the marginal plots showing a linear trend but the overall model that generated the y values is nonlinear in x. We can see from the joint marginal plot that the are jointly nonlinear.

Question 2

 \mathbf{a}

```
# simulate data
n <- 100
x <- runif(n, 1, 10)
beta_0 <- 3
beta_1 <- 2
sigma <- 3

# Generate y values based on the original model
epsilon <- rnorm(n, mean = 0, sd = sigma * x)
y <- beta_0 + beta_1 * x + epsilon

# transformations
y_prime <- y / x
x_prime <- 1 / x

# Check the variance of y_prime
var_y_prime <- var(y_prime)
print(sqrt(var_y_prime))</pre>
```

[1] 3.430146

We can see that variance of y' is very close to the initial σ

 \mathbf{c}

This is equivalent to OLS estimate because using the weights on the original data is like doing a $\frac{y}{x}$ transformation. We can see from the coefficients that there is not much change.

```
# wls model
fit_wls \leftarrow lm(y ~ x, weights = 1 / x^2)
# OLS model
fit_ols_trans <- lm(y_prime ~ x_prime)</pre>
# Compare the coefficients
summary(fit_wls)$coefficients
               Estimate Std. Error t value
                                                  Pr(>|t|)
## (Intercept) 4.089974 2.2529295 1.815402 0.0725203966
## x
               2.193610  0.6439473  3.406505  0.0009555446
summary(fit_ols_trans)$coefficients
               Estimate Std. Error t value
                                                  Pr(>|t|)
## (Intercept) 2.193610  0.6439473  3.406505  0.0009555446
## x_prime
               4.089974 2.2529295 1.815402 0.0725203966
```

Question 3

```
library(faraway)
pander::pander(head(pipeline))
```

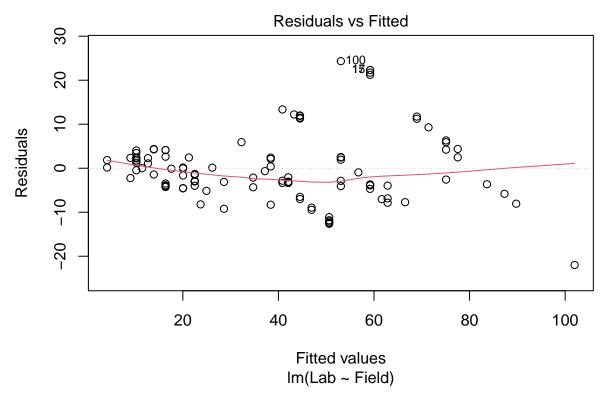
Field	Lab	Batch
18	20.2	1
38	56	1
15	12.5	1
20	21.2	1
18	15.5	1
36	39	1

a.

Fitting a linear model by regressing Lab on Field as;

```
fit_lm <- lm( Lab ~ Field, data = pipeline)

plot(fit_lm, which = 1)</pre>
```



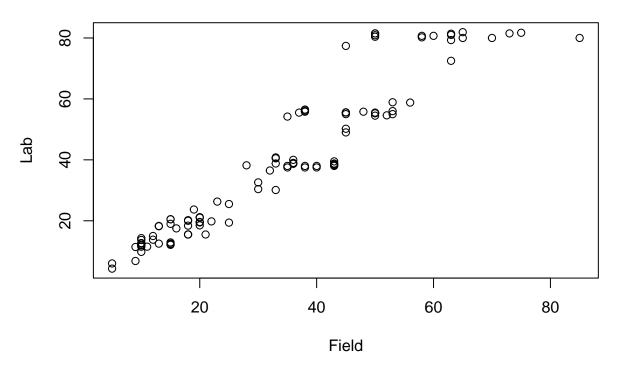
We can see from the residual vs fitted plot that linearity assumption is checked but the residuals have a funnel like pattern. As x increases the variability increases.

b

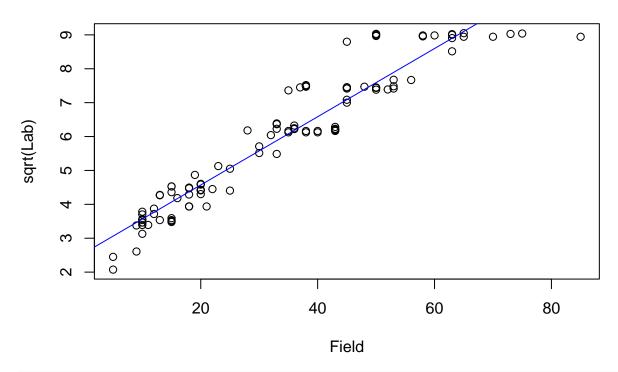
```
i = order(pipeline$Field)
npipe = pipeline[i,]
ff = gl(12,9)[-108]
meanfield = unlist(lapply(split(npipe$Field,ff),mean))
varlab = unlist(lapply(split(npipe$Lab,ff),var))
# Remove last point
meanfield <- meanfield[-length(meanfield)]</pre>
varlab <- varlab[-length(varlab)]</pre>
# Log transform
log_meanfield <- log(meanfield)</pre>
log_varlab <- log(varlab)</pre>
# model
var_model <- lm(log_varlab ~ log_meanfield)</pre>
summary(var_model)
##
## Call:
## lm(formula = log_varlab ~ log_meanfield)
##
```

```
## Residuals:
                 1Q Median
##
       Min
                                   30
## -1.00477 -0.42268 0.05989 0.37854 0.93815
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
                -1.9352
                          1.0929 -1.771 0.110403
## (Intercept)
                 1.6707
## log_meanfield
                             0.3296 5.070 0.000672 ***
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 0.657 on 9 degrees of freedom
## Multiple R-squared: 0.7406, Adjusted R-squared: 0.7118
## F-statistic: 25.7 on 1 and 9 DF, p-value: 0.0006723
# Extract coefficients for a0 and a1
## take exp because of the log
a0 <- exp(coef(var_model)[1])
## slope - a1
a1 <- coef(var_model)[2]
# WLS as the inverse
predicted_variance <- a0 * (pipeline$Field ^ a1)</pre>
weights <- 1 / predicted_variance</pre>
# Perform WLS regression of Lab on Field using the calculated weights
wls_model <- lm(Lab ~ Field, data = pipeline, weights = weights)</pre>
summary(wls model)
##
## Call:
## lm(formula = Lab ~ Field, data = pipeline, weights = weights)
## Weighted Residuals:
      Min
              1Q Median
                               3Q
                                      Max
## -1.7432 -0.6719 -0.2493 0.5967 2.7275
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.05530
                          0.69765 - 1.513
                                             0.133
                          0.03401 34.984
## Field
               1.18963
                                            <2e-16 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 0.9846 on 105 degrees of freedom
## Multiple R-squared: 0.921, Adjusted R-squared: 0.9202
## F-statistic: 1224 on 1 and 105 DF, p-value: < 2.2e-16
# Assuming the pipeline dataset is available with columns Field and Lab
# Initial Scatter Plot
plot(pipeline$Field, pipeline$Lab, main = "Original Plot of Lab vs Field",
    xlab = "Field", ylab = "Lab")
```

Original Plot of Lab vs Field

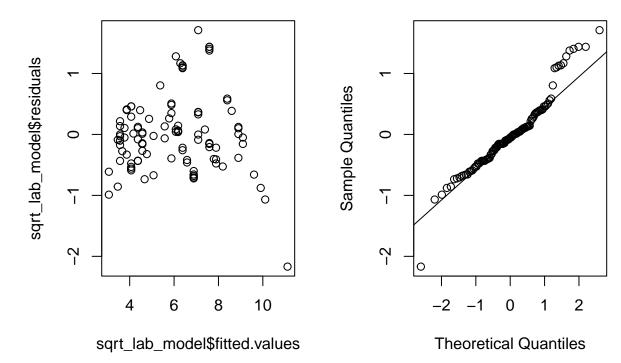


Square Root Transformation of Lab vs Field

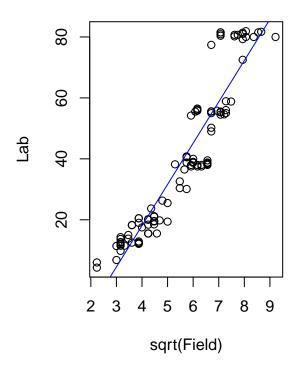


```
# Diagnostic plots for sqrt(Lab) vs Field
par(mfrow = c(1, 2))
plot(sqrt_lab_model$fitted.values, sqrt_lab_model$residuals, main = "Residuals vs Fitted (sqrt(Lab))")
qqnorm(sqrt_lab_model$residuals, main = "QQ Plot of Residuals (sqrt(Lab))")
qqline(sqrt_lab_model$residuals)
```

Residuals vs Fitted (sqrt(Lab)) QQ Plot of Residuals (sqrt(Lab))

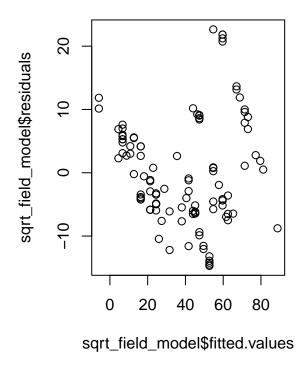


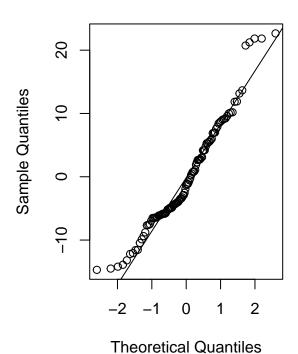
quare Root Transformation of Field



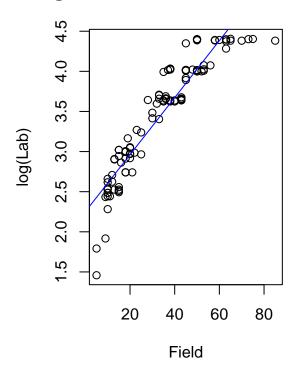
plot(sqrt_field_model\$fitted.values, sqrt_field_model\$residuals, main = "Residuals vs Fitted (sqrt(Field
qqnorm(sqrt_field_model\$residuals, main = "QQ Plot of Residuals (sqrt(Field))")
qqline(sqrt_field_model\$residuals)

Residuals vs Fitted (sqrt(Field)) QQ Plot of Residuals (sqrt(Field))





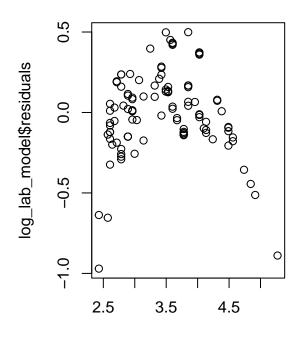
Log Transformation of Lab vs Fie

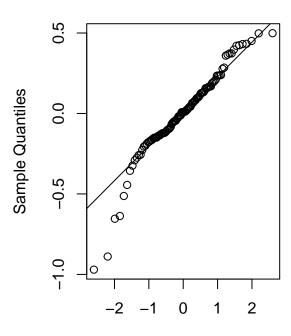


```
plot(log_lab_model$fitted.values, log_lab_model$residuals, main = "Residuals vs Fitted (log(Lab))")
qqnorm(log_lab_model$residuals, main = "QQ Plot of Residuals (log(Lab))")
qqline(log_lab_model$residuals)
```

Residuals vs Fitted (log(Lab))

QQ Plot of Residuals (log(Lab))

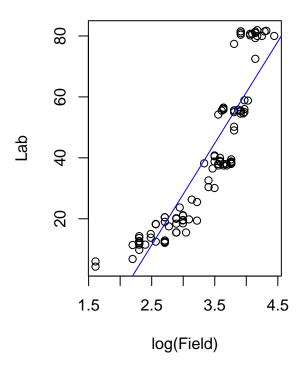




log_lab_model\$fitted.values

Theoretical Quantiles

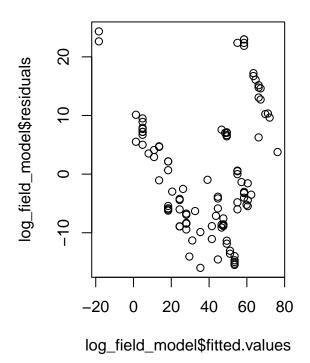
Log Transformation of Field vs La

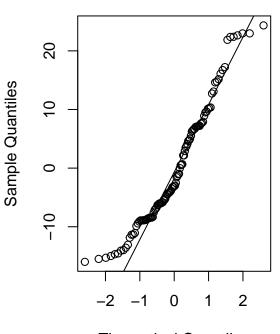


plot(log_field_model\$fitted.values, log_field_model\$residuals, main = "Residuals vs Fitted (log(Field))
qqnorm(log_field_model\$residuals, main = "QQ Plot of Residuals (log(Field))")
qqline(log_field_model\$residuals)

Residuals vs Fitted (log(Field))

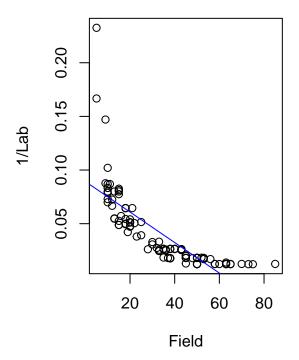
QQ Plot of Residuals (log(Field)





Theoretical Quantiles

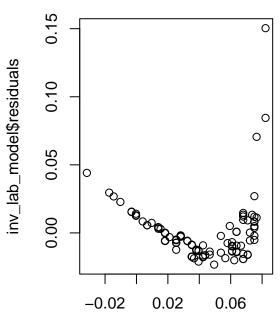
Inverse Transformation of Lab vs F

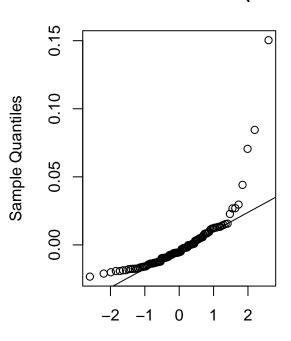


```
plot(inv_lab_model$fitted.values, inv_lab_model$residuals, main = "Residuals vs Fitted (1/Lab)")
qqnorm(inv_lab_model$residuals, main = "QQ Plot of Residuals (1/Lab)")
qqline(inv_lab_model$residuals)
```

Residuals vs Fitted (1/Lab)

QQ Plot of Residuals (1/Lab)

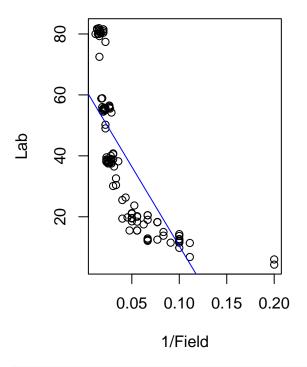




inv_lab_model\$fitted.values

Theoretical Quantiles

Inverse Transformation of Field vs

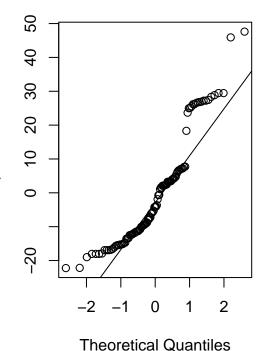


plot(inv_field_model\$fitted.values, inv_field_model\$residuals, main = "Residuals vs Fitted (1/Field)") qqnorm(inv_field_model\$residuals, main = "QQ Plot of Residuals (1/Field)") qqline(inv_field_model\$residuals)

Residuals vs Fitted (1/Field)

50 8 4 inv_field_model\$residuals 30 20 10 0 -20 -400 20 40 60 inv_field_model\$fitted.values

QQ Plot of Residuals (1/Field)



Sample Quantiles

```
# Reset plotting layout
par(mfrow = c(1, 1))
```