# **Voltage Case Study**

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# **Objectives**

- Analyze Voltage vs Breakdown Time Case Study
- Lack of Fit F-test

# Case Study: Voltage vs Breakdown Time, a Controlled Experiment

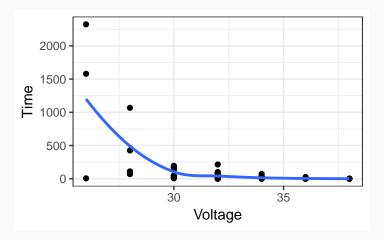
- Goal: study relationship between voltage and breakdown time of an electrical insulating fluid.
- The authors could control the voltage level of each trial.

```
library(Sleuth3)
data("case0802")
head(case0802)
```

```
##
        Time Voltage Group
        5.79
## 1
                  26 Group1
## 2 1579.52
                  26 Group1
## 3 2323.70
                  26 Group1
## 4
       68.85
                  28 Group2
## 5
     108.29
                  28 Group2
                  28 Groun?
## 6
      110 29
```

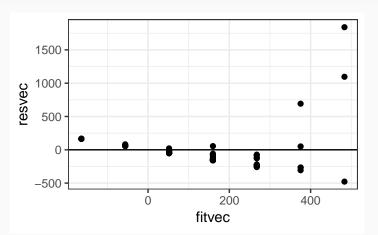
## Step 1: Make a plot

```
library(ggplot2)
qplot(Voltage, Time, data = case0802) +
geom_smooth(se = FALSE)
```



## Try an initial fit with a residual plot

```
lmout <- lm(Time ~ Voltage, data = case0802)
resvec <- resid(lmout)
fitvec <- fitted(lmout)
qplot(fitvec, resvec) + geom_hline(yintercept = 0)</pre>
```

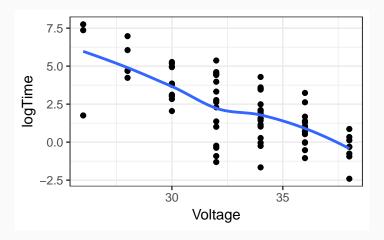


#### **Conclusion?**

- As the mean increases, the variability increases.
- We see a curved relationship between X and Y
- Clearly need a log-transformation

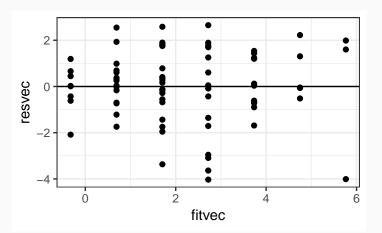
# Log-transformation and Re-plot

```
case0802$logTime <- log(case0802$Time)
qplot(Voltage, logTime, data = case0802) +
  geom_smooth(se = FALSE)</pre>
```



### Log-transformation and Residual Plot

```
lmout <- lm(logTime ~ Voltage, data = case0802)
resvec <- resid(lmout)
fitvec <- fitted(lmout)
qplot(fitvec, resvec) + geom_hline(yintercept = 0)</pre>
```



#### **Conclusion**

 $\, \blacksquare \,$  After the log-transformation, the data look pretty awesome.

# Formal test if there is a relationship

 There is clearly a relationship here, but you need to report p-values to get published, so . . .

```
sumout <- summary(lmout)
coef(sumout)

## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 18.9555 1.9100 9.924 3.052e-15
## Voltage -0.5074 0.0574 -8.840 3.340e-13
```

# More interesting are coefficient estimates with confidence intervals

## Interpret on Original Scale

- A one kV increase results in a  $\exp(-0.507) = 0.6$  multiplicative change in breakdown times.
- 95% confidence of

```
exp(confint(lmout)[2, ])
```

```
## 2.5 % 97.5 %
## 0.537 0.675
```

A one kV increase results in a 40% decrease in breakdown time,
 95% confidence interval of

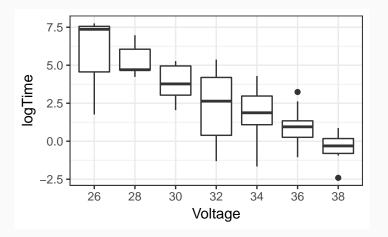
```
(1 - exp(confint(lmout)[2, ])) * 100
```

```
## 2.5 % 97.5 %
## 46.3 32.5
```

# Lack of Fit *F*-test

### We could have viewed this as an ANOVA problem

```
case0802$VoltageFac <- as.factor(case0802$Voltage)
qplot(VoltageFac, logTime, data = case0802, geom = "boxplo-
xlab("Voltage")</pre>
```

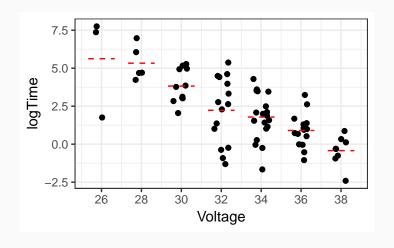


#### Which is better?

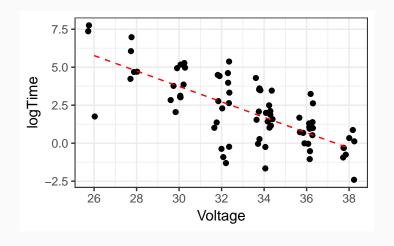
- If the linear model appears to fit fine, it is always preferred.
- You can interpolate with the linear model (not ANOVA).
- The linear model has easier interpretations.
- The linear model has fewer parameters
- We can formally test if the linear model does not fit using the F-testing strategy if we have replicates at given values of X

- $H_0: E[Y_i] = \beta_0 + \beta_1 X_i$  (mean is based on line)
- $H_A : E[Y_i] = \mu_j$  where  $X_i = j$  (mean is based on group)

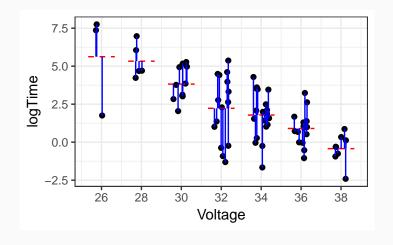
## **Full Model Estimates**



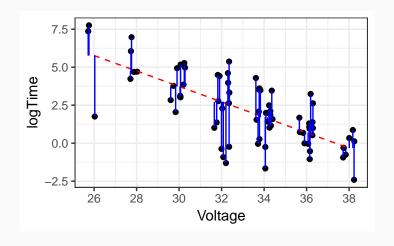
#### **Reduced Model Estimates**



## Residuals Fnder Full



#### Residuals Fnder Reduced



- $RSS_{full} = 173.7489$
- $df_{full} = n I = 76 7 = 69$

- $RSS_{full} = 173.7489$
- $df_{full} = n l = 76 7 = 69$
- $RSS_{reduced} = 180.0748$
- $df_{reduced} = n 2 = 76 2 = 74$

- $RSS_{full} = 173.7489$
- $df_{full} = n l = 76 7 = 69$
- $RSS_{reduced} = 180.0748$
- $df_{reduced} = n 2 = 76 2 = 74$
- $ESS = RSS_{reduced} RSS_{full} = 6.3259$
- $df_{extra} = df_{reduced} df_{full} = 74 69 5$

• 
$$RSS_{full} = 173.7489$$

• 
$$df_{full} = n - l = 76 - 7 = 69$$

• 
$$RSS_{reduced} = 180.0748$$

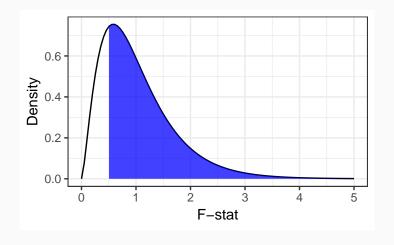
• 
$$df_{reduced} = n - 2 = 76 - 2 = 74$$

• 
$$ESS = RSS_{reduced} - RSS_{full} = 6.3259$$

• 
$$df_{extra} = df_{reduced} - df_{full} = 74 - 69 - 5$$

• 
$$F$$
-statistic =  $\frac{ESS/df_{extra}}{RSS_{full}/df_{full}} = 0.5024$ 

# Compare to an $\overline{F_{5,69}}$



## Calculate p-value

```
pf(0.5024, df1 = 5, df2 = 69, lower.tail = FALSE)
## [1] 0.7734
```

#### Lack of Fit in R

Create a factor variable

```
case0802$VoltageFac <- as.factor(case0802$Voltage)</pre>
```

Fit both the ANOVA and regression models

```
aout <- aov(logTime ~ VoltageFac, data = case0802)
lmout <- lm(logTime ~ Voltage, data = case0802)</pre>
```

#### Lack of Fit in R

anova(lmout, aout)

Use anova() to get ANOVA table

```
## Analysis of Variance Table
##
## Model 1: logTime ~ Voltage
## Model 2: logTime ~ VoltageFac
## Res.Df RSS Df Sum of Sq F Pr(>F)
## 1 74 180
## 2 69 174 5 6.33 0.5 0.77
```