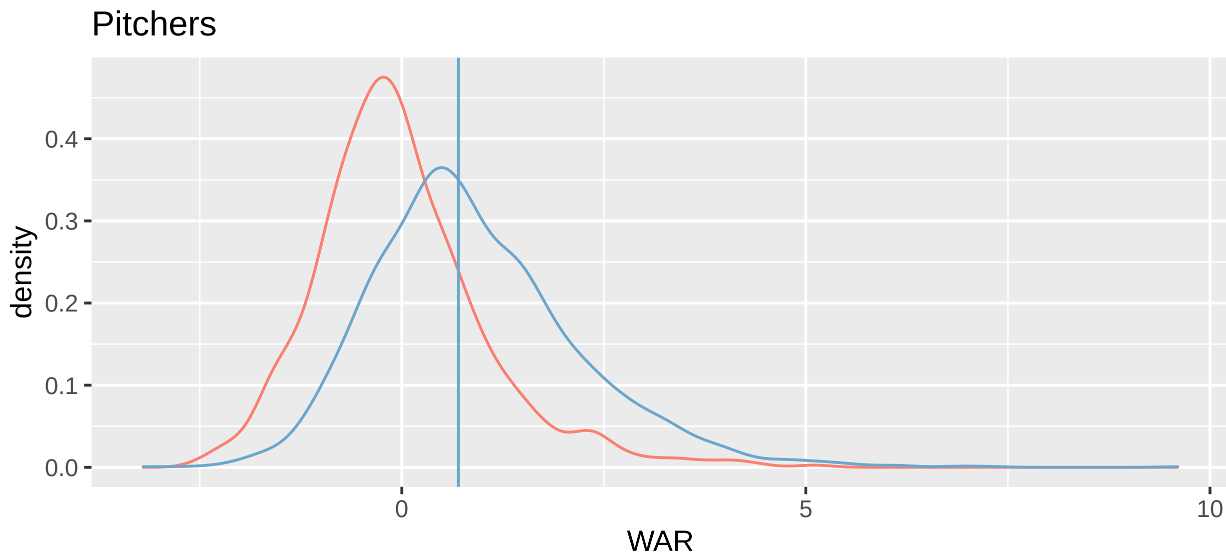
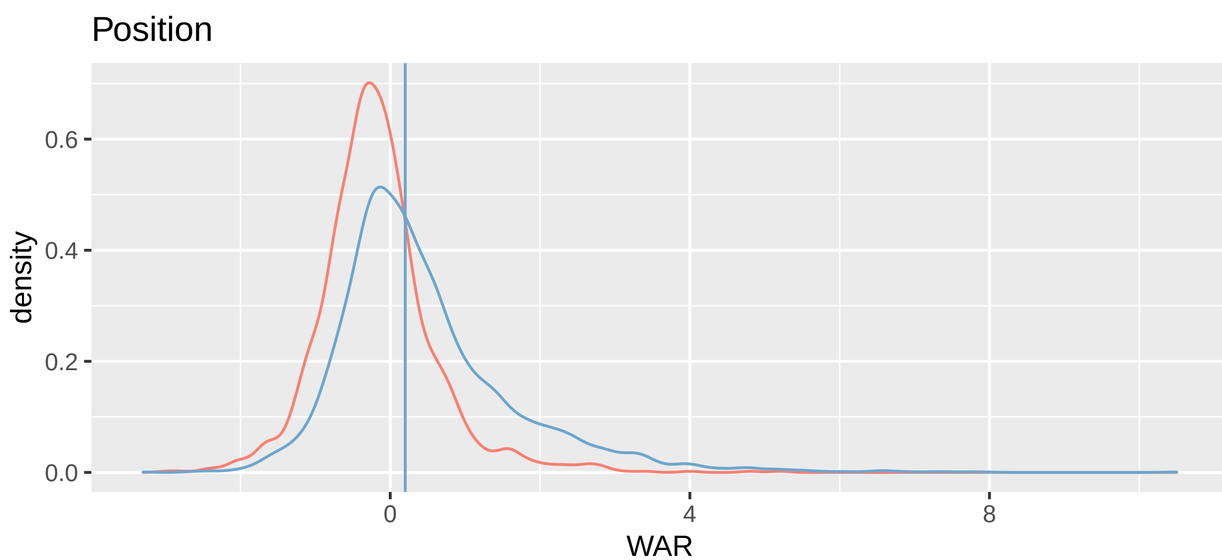
Modeling

Group 6

The Couldabeen Classification Problem





Counting Couldabeens

```r
#====================================#
#        Counting: Couldabeens      #
#====================================#
# Combine the threshold-classified retiree datasets
retirees <- rbind(pit_ret,pos_ret)
# Count couldabeens
couldabeens <- count_cbns(retirees)
```

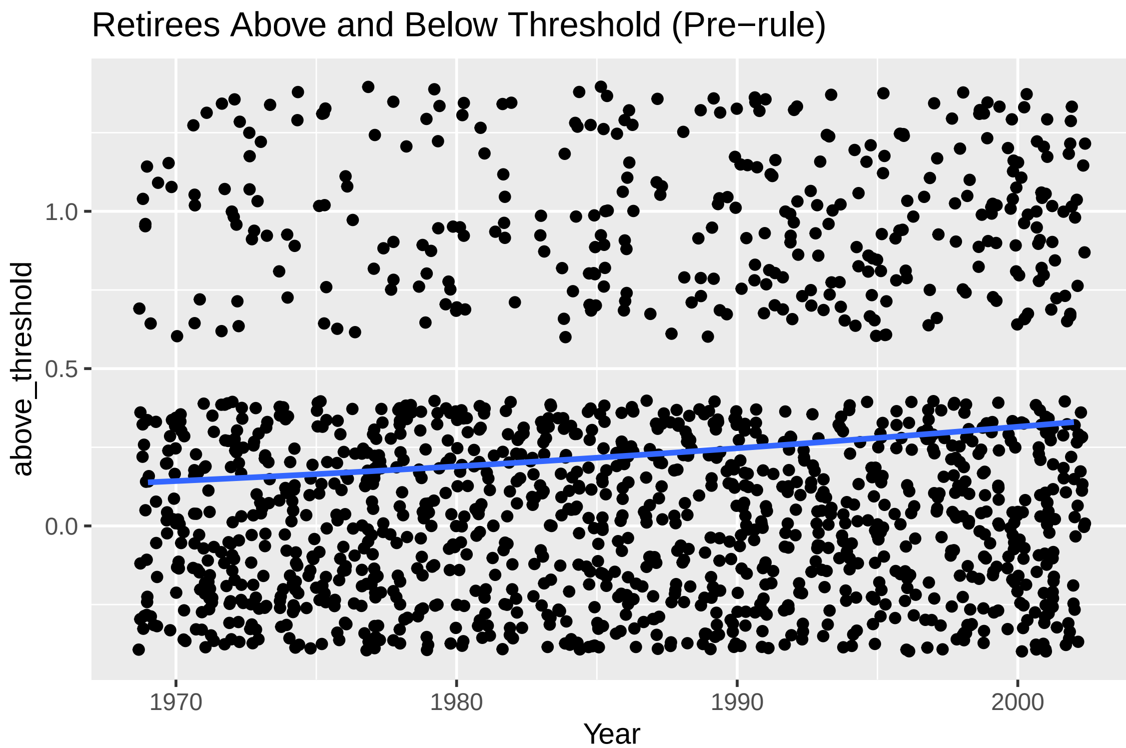
Our retirees dataframe looks like this:

```
##    WAR Year above_threshold
## 1  1.8 1972            TRUE
## 2  0.1 1974           FALSE
## 3  0.3 1976           FALSE
## 4 -0.5 1977           FALSE
## 5  0.4 1977           FALSE
## 6 -1.8 1974           FALSE
```

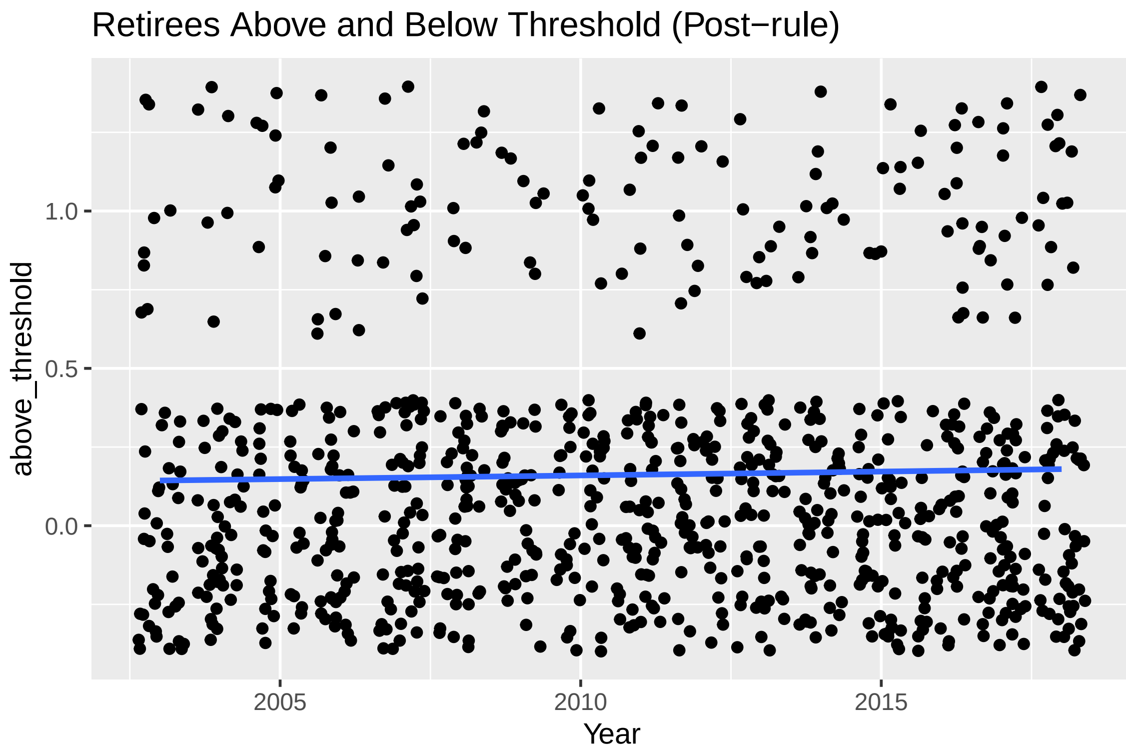
Our couldabeens dataframe looks like this:

```
## # A tibble: 6 x 2
##    Year  cbns
##   <dbl> <int>
## 1  1969     7
## 2  1970     3
## 3  1971     6
## 4  1972    10
## 5  1973     9
## 6  1974     6
```

First Look: A Logistic Model




```
##
## Call:
## glm(formula = above_threshold ~ Year, family = "binomial", data = dataset)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8949  -0.7642  -0.6479  -0.5547   1.9883
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -68.617412  12.853177  -5.339 9.37e-08 ***
## Year          0.033921   0.006465   5.247 1.55e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1583.3  on 1470  degrees of freedom
## Residual deviance: 1554.9  on 1469  degrees of freedom
## AIC: 1558.9
##
## Number of Fisher Scoring iterations: 4
```




```
##
## Call:
## glm(formula = above_threshold ~ Year, family = "binomial", data = dataset)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.6297  -0.6096  -0.5900  -0.5617   1.9697
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -37.46198   40.21840  -0.931    0.352
## Year          0.01781    0.02000   0.891    0.373
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 781.43  on 880  degrees of freedom
## Residual deviance: 780.63  on 879  degrees of freedom
## AIC: 784.63
##
## Number of Fisher Scoring iterations: 4
```

Computing Retiree Proportions

```
#====================================#
#      Proportions: Couldabeens     #
#====================================#
# Find number of retirees by year
num_retirees <- total_retirees_by_yr(df_pit_ret, df_pos_ret)
num_retirees <- data.frame(retirees = num_retirees$retirees)
# Append number of retirees that year
couldabeens <- cbind(couldabeens, num_retirees)
# Find proportion of couldabeens : retirees
couldabeens <- couldabeens %>% mutate(prop = cbns/retirees)
```

Here is what the proportion-appended couldabeen dataframe looks like:

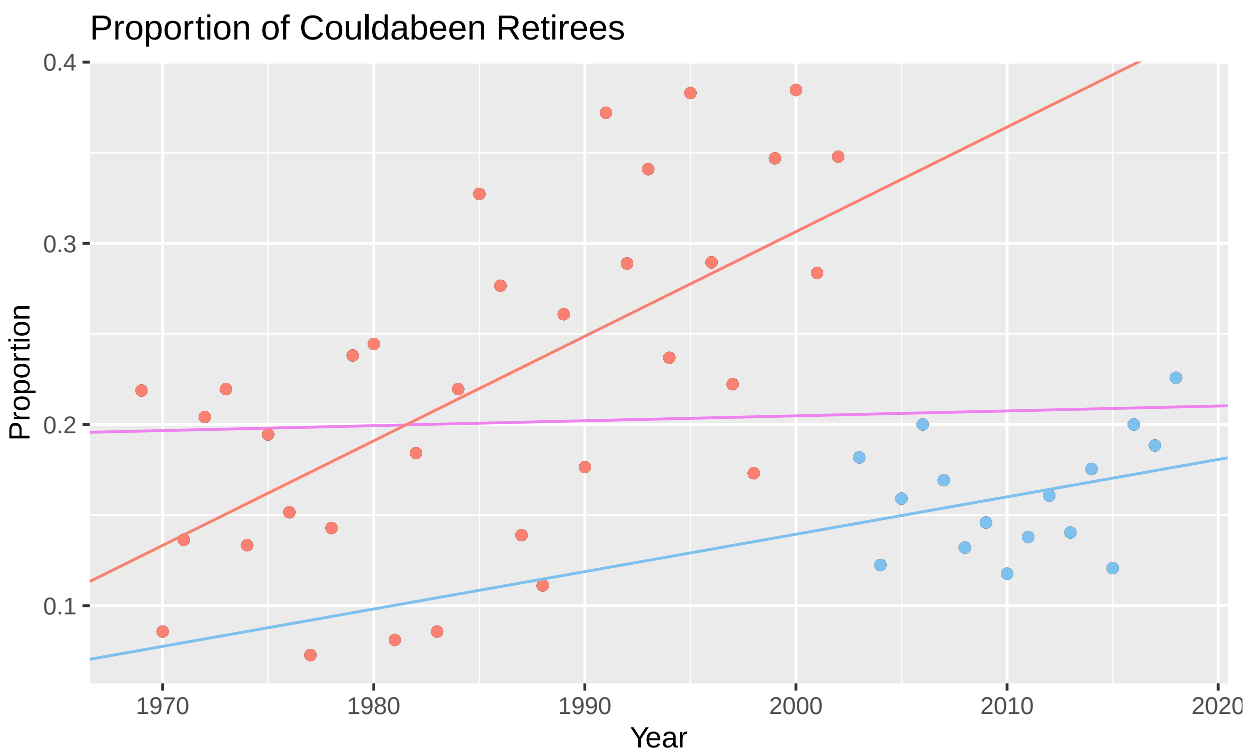
```
##   Year cbns retirees       prop
## 1 1969    7       32 0.21875000
## 2 1970    3       35 0.08571429
## 3 1971    6       44 0.13636364
## 4 1972   10       49 0.20408163
## 5 1973    9       41 0.21951220
## 6 1974    6       45 0.13333333
```

Year as Predictor: Linear Modeling

```r
#==================#
#     Modeling     #
#==================#
# Partition dataset into years before and after rule
couldabeens_pre <- prerule(couldabeens)
couldabeens_post <- postrule(couldabeens)
# Obtain linear model for pre-rule years
model_pre <- linear_model(couldabeens_pre)
coefs_pre <- model_pre$coefficients
# Obtain linear model for post-rule years
model_post <- linear_model(couldabeens_post)
coefs_post <- model_post$coefficients
# Obtain linear model for all years
model_comp <- linear_model(couldabeens)
coefs_comp <- model_comp$coefficients
```

Couldabeens: A Comprehensive Look

```
##
## Call:
## lm(formula = prop ~ I(Year), data = dataset)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.12581 -0.06211 -0.01833  0.04358  0.17984
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.3379371  1.6395066  -0.206    0.838
## I(Year)      0.0002714  0.0008224   0.330    0.743
##
## Residual standard error: 0.08392 on 48 degrees of freedom
## Multiple R-squared:  0.002263,   Adjusted R-squared:  -0.01852
## F-statistic: 0.1089 on 1 and 48 DF,  p-value: 0.7429
```



Couldabeens: Pre-rule Era (1969-2002)

```
##
## Call:
## lm(formula = prop ~ I(Year), data = dataset)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.126056 -0.044806  0.005781  0.053314  0.117608
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -11.238735   2.549750  -4.408  0.00011 ***
## I(Year)       0.005773   0.001284   4.495 8.56e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07346 on 32 degrees of freedom
## Multiple R-squared:  0.3871, Adjusted R-squared:  0.3679
## F-statistic: 20.21 on 1 and 32 DF,  p-value: 8.56e-05
```

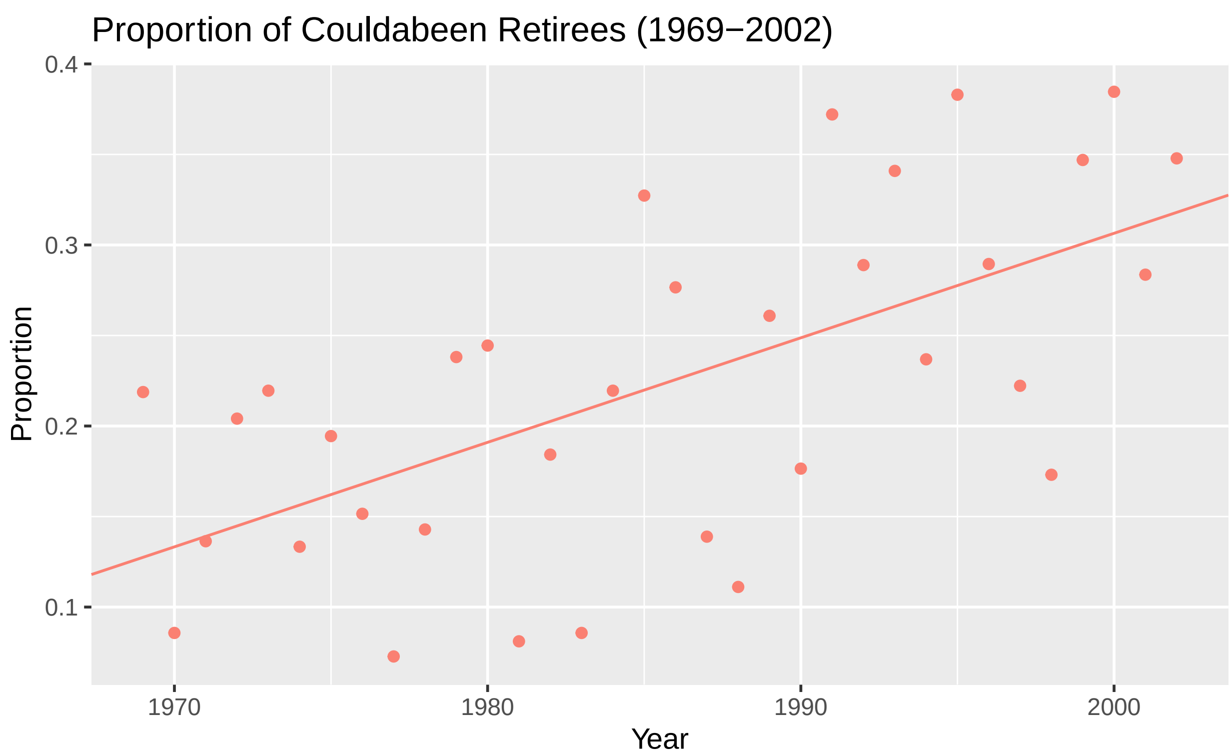


Figure 1: Proportion of Retirees who were Coulabeens prior to the implementation of the Luxury Tax

Couldabeens: Post-rule Era (2003-2018)

```
##
## Call:
## lm(formula = prop ~ I(Year), data = dataset)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.049689 -0.024453  0.001825  0.018410  0.049237
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.987717   3.481582  -1.145    0.271
## I(Year)      0.002064   0.001732   1.192    0.253
##
## Residual standard error: 0.03193 on 14 degrees of freedom
## Multiple R-squared:  0.09209,    Adjusted R-squared:  0.02724
## F-statistic:  1.42 on 1 and 14 DF,  p-value: 0.2532
```

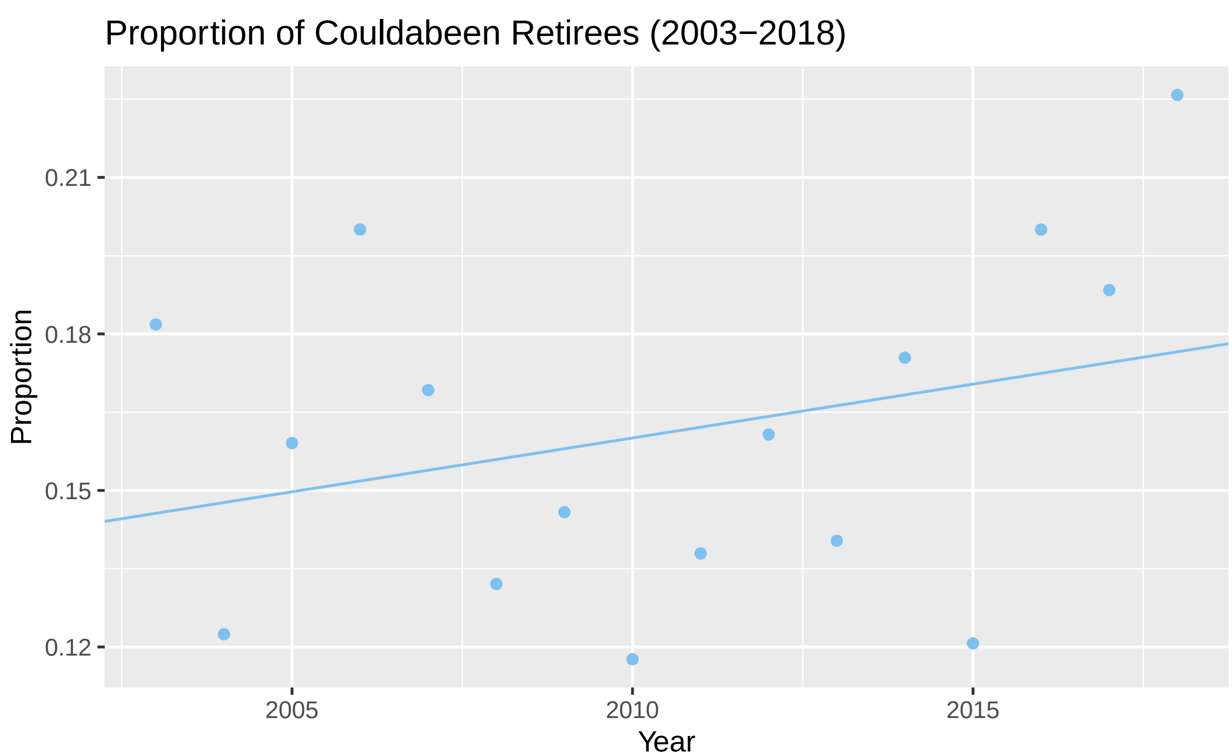


Figure 2: Proportion of Retirees who were Coulabeens after the implementation of the Luxury Tax

Quadratic Regression Model