Non Linear modelling (22IM10040)

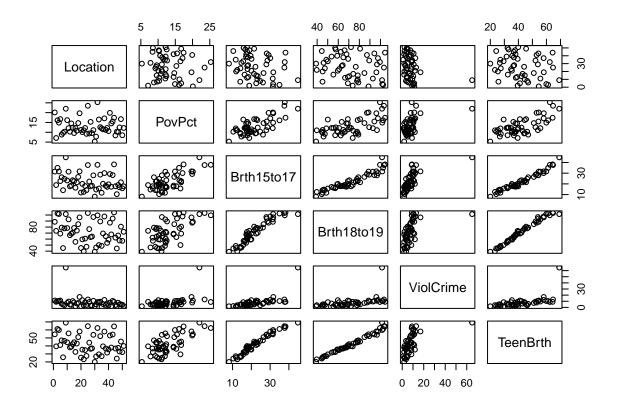
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2025-03-19

head(df)

##		Location	PovPct	Brth15to17	Brth18to19	ViolCrime	TeenBrth
##	1	Alabama	20.1	31.5	88.7	11.2	54.5
##	2	Alaska	7.1	18.9	73.7	9.1	39.5
##	3	Arizona	16.1	35.0	102.5	10.4	61.2
##	4	Arkansas	14.9	31.6	101.7	10.4	59.9
##	5	${\tt California}$	16.7	22.6	69.1	11.2	41.1
##	6	Colorado	8.8	26.2	79.1	5.8	47.0

plot(df)



```
library(ggplot2)
library(reshape2)

# Reshape data for ggplot

df_melt <- melt(df, id.vars = "Location") # Assuming 'Product_id' is categorical

# Create boxplots

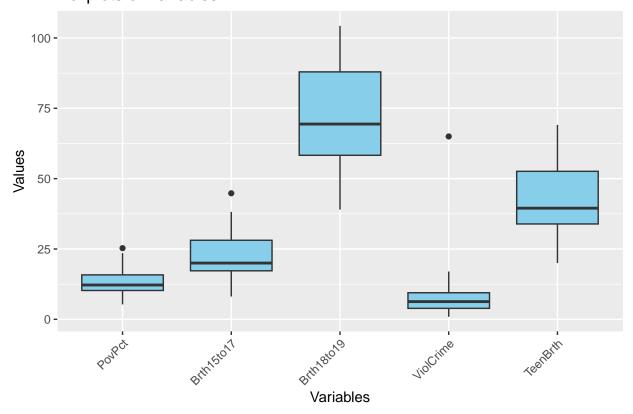
ggplot(df_melt, aes(x = variable, y = value)) +

geom_boxplot(fill = "skyblue") +

theme(axis.text.x = element_text(angle = 45, hjust = 1)) +

labs(title = "Boxplots of Variables", x = "Variables", y = "Values")</pre>
```

Boxplots of Variables



```
colSums(is.na(df)) # Shows the count of missing values in each column
```

```
## Location PovPct Brth15to17 Brth18to19 ViolCrime TeenBrth ## 0 0 0 0 0 0 0
```

unique(df\$Location)

```
## [1] "Alabama" "Alaska" "Arizona"

## [4] "Arkansas" "California" "Colorado"

## [7] "Connecticut" "Delaware" "District_of_Columbia"

## [10] "Florida" "Georgia" "Hawaii"

## [13] "Idaho" "Illinois" "Indiana"
```

```
## [16] "Iowa"
                                 "Kansas"
                                                         "Kentucky"
## [19] "Louisiana"
                                 "Maine"
                                                         "Maryland"
                                 "Michigan"
## [22] "Massachusetts"
                                                         "Minnesota"
## [25] "Mississippi"
                                 "Missouri"
                                                         "Montana"
## [28] "Nebraska"
                                 "Nevada"
                                                         "New Hampshire"
## [31] "New Jersey"
                                "New Mexico"
                                                         "New York"
## [34] "North Carolina"
                                 "North Dakota"
                                                         "Ohio"
## [37] "Oklahoma"
                                 "Oregon"
                                                         "Pennsylvania"
## [40] "Rhode Island"
                                 "South_Carolina"
                                                         "South Dakota"
## [43] "Tennessee"
                                 "Texas"
                                                         "Utah"
## [46] "Vermont"
                                 "Virginia"
                                                         "Washington"
## [49] "West_Virginia"
                                 "Wisconsin"
                                                         "Wyoming"
dim(df)
```

[1] 51 6

Since we can see that there are 51 different location , so it will not impact the model so we will drop this column

```
# Drop the 'Location' column
df <- df[, !names(df) %in% "Location"]</pre>
linmodel <- lm(PovPct~. , data = df) # Fitting a linear model</pre>
summary(linmodel)
##
## Call:
## lm(formula = PovPct ~ ., data = df)
##
## Residuals:
      Min
                1Q Median
                                3Q
                                       Max
## -5.5239 -1.9763 -0.1048 1.6729 5.6012
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 6.22349
                          1.82549
                                    3.409 0.00136 **
## Brth15to17 -0.45769
                          0.44681 -1.024 0.31102
## Brth18to19 -0.82144
                          0.27311 -3.008 0.00426 **
## ViolCrime
              -0.07786
                          0.06683 -1.165 0.24997
## TeenBrth
              1.81957
                          0.66635
                                    2.731 0.00893 **
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 2.773 on 46 degrees of freedom
## Multiple R-squared: 0.6132, Adjusted R-squared: 0.5796
## F-statistic: 18.23 on 4 and 46 DF, p-value: 4.916e-09
```

```
# Load necessary library
library(ggplot2)
# Fit polynomial regression models for different degrees
fit1 <- lm(PovPct ~ poly(Brth15to17, 1, raw = TRUE), data = df) # Linear
fit2 <- lm(PovPct ~ poly(Brth15to17, 2, raw = TRUE), data = df) # Quadratic
fit3 <- lm(PovPct ~ poly(Brth15to17, 3, raw = TRUE), data = df) # Cubic
fit4 <- lm(PovPct ~ poly(Brth15to17, 4, raw = TRUE), data = df) # Quartic
anova(fit1, fit2, fit3, fit4)
## Analysis of Variance Table
##
## Model 1: PovPct ~ poly(Brth15to17, 1, raw = TRUE)
## Model 2: PovPct ~ poly(Brth15to17, 2, raw = TRUE)
## Model 3: PovPct ~ poly(Brth15to17, 3, raw = TRUE)
## Model 4: PovPct ~ poly(Brth15to17, 4, raw = TRUE)
    Res.Df
              RSS Df Sum of Sq
                                    F Pr(>F)
## 1
        49 426.88
        48 409.38 1
## 2
                        17.496 2.1663 0.14788
## 3
        47 409.38 1
                        0.000 0.0000 0.99649
## 4
        46 371.52 1
                        37.864 4.6882 0.03559 *
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
# Fit polynomial regression models for different degrees
fit1 <- lm(PovPct ~ poly(TeenBrth, 1, raw = TRUE), data = df) # Linear
fit2 <- lm(PovPct ~ poly(TeenBrth, 2, raw = TRUE), data = df) # Quadratic
fit3 <- lm(PovPct ~ poly(TeenBrth, 3, raw = TRUE), data = df) # Cubic</pre>
fit4 <- lm(PovPct ~ poly(TeenBrth, 4, raw = TRUE), data = df) # Quartic
anova(fit1, fit2, fit3, fit4)
## Analysis of Variance Table
## Model 1: PovPct ~ poly(TeenBrth, 1, raw = TRUE)
## Model 2: PovPct ~ poly(TeenBrth, 2, raw = TRUE)
## Model 3: PovPct ~ poly(TeenBrth, 3, raw = TRUE)
## Model 4: PovPct ~ poly(TeenBrth, 4, raw = TRUE)
## Res.Df
              RSS Df Sum of Sq
                                    F Pr(>F)
## 1
        49 462.30
                        40.870 4.8867 0.03208 *
## 2
        48 421.43 1
## 3
        47 406.27 1
                        15.162 1.8129 0.18476
## 4
        46 384.72 1
                        21.547 2.5763 0.11532
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
AIC(fit1, fit2, fit3, fit4) # Lower AIC is better
       df
               ATC
## fit1 3 263.1553
## fit2 4 260.4348
## fit3 5 260.5661
## fit4 6 259.7868
```

```
summary(fit1)$adj.r.squared

## [1] 0.4842952

summary(fit2)$adj.r.squared

## [1] 0.5200923

summary(fit3)$adj.r.squared

## [1] 0.5275148

summary(fit4)$adj.r.squared

## [1] 0.5428474
```

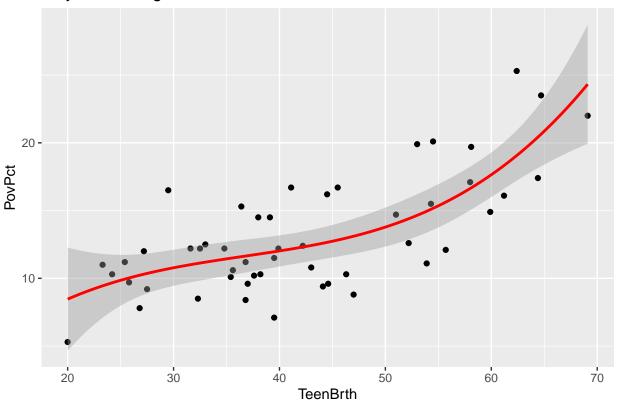
stat_smooth(method = "lm", formula = y ~ poly(x, 3, raw = TRUE), color = "red") +

labs(title = "Polynomial Regression Fit", x = "TeenBrth", y = "PovPct")

Polynomial Regression Fit

ggplot(df, aes(x = TeenBrth, y = PovPct)) +

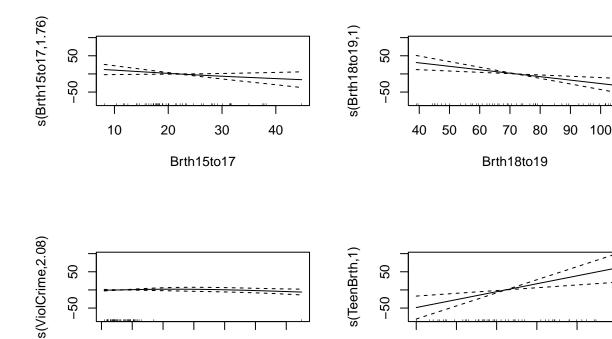
geom_point() +



```
library(splines) # For spline regression
              # For Generalized Additive Model (GAM)
library(mgcv)
## Warning: package 'mgcv' was built under R version 4.4.3
## Loading required package: nlme
## This is mgcv 1.9-1. For overview type 'help("mgcv-package")'.
library(ggplot2)
                 # For visualization
# Fit a spline model with 3 knots
fit_spline_3 <- lm(PovPct ~ bs(TeenBrth, knots = c(10, 20, 30)), data = df)
# Fit a spline model with 5 knots
fit_spline_5 <- lm(PovPct \sim bs(TeenBrth, knots = c(10, 15, 20, 25, 30)), data = df)
# Compare models
anova(fit_spline_3, fit_spline_5)
## Analysis of Variance Table
##
## Model 1: PovPct \sim bs(TeenBrth, knots = c(10, 20, 30))
## Model 2: PovPct ~ bs(TeenBrth, knots = c(10, 15, 20, 25, 30))
   Res.Df
              RSS Df Sum of Sq
                                    F Pr(>F)
## 1
        46 389.09
        45 388.74 1
                       0.34999 0.0405 0.8414
## 2
# Fit a GAM model using smoothing splines
gam_fit <- gam(PovPct ~ s(Brth15to17) + s(Brth18to19) + s(ViolCrime) + s(TeenBrth), data = df)
# Summary of the model
summary(gam_fit)
## Family: gaussian
## Link function: identity
## Formula:
## PovPct ~ s(Brth15to17) + s(Brth18to19) + s(ViolCrime) + s(TeenBrth)
## Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 13.1176
                           0.3777
                                   34.73 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
                   edf Ref.df
                                   F p-value
## s(Brth15to17) 1.7630 2.2300 1.624 0.20315
## s(Brth18to19) 0.9999 0.9999 10.432 0.00235 **
```

```
## s(ViolCrime) 2.0816 2.1533 1.698 0.16608
## s(TeenBrth) 0.9999 0.9999 9.471 0.00359 **
## ---
## Signif. codes: 0 '*** 0.001 '** 0.05 '.' 0.1 ' ' 1
##
## Rank: 36/37
## R-sq.(adj) = 0.602 Deviance explained = 64.9%
## GCV = 8.4029 Scale est. = 7.2752 n = 51

# Visualize the effect of each predictor
plot(gam_fit, pages = 1, se = TRUE)
```

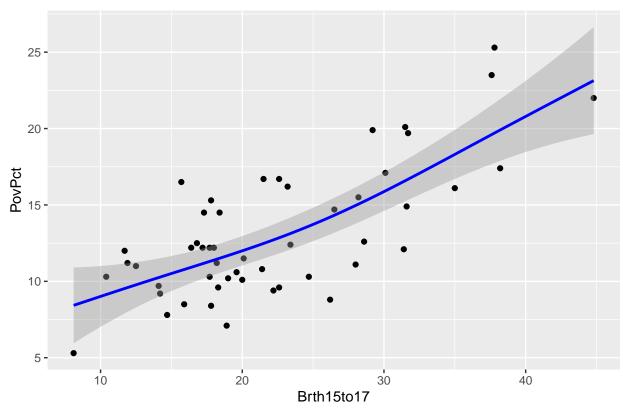


ViolCrime

```
ggplot(df, aes(x = Brth15to17, y = PovPct)) +
geom_point() +
geom_smooth(method = "gam", formula = y ~ s(x), color = "blue") +
labs(title = "GAM Fit for PovPct", x = "Brth15to17", y = "PovPct")
```

TeenBrth

GAM Fit for PovPct



R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

Note that the echo = FALSE parameter was added to the code chunk to prevent printing of the R code that generated the plot.