Systolic Blood Pressure:
How High Can You Go?

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Overview

High SBP Rates

SBP measures the force your heart exerts on the arteries

High SBP Rates play a factor in determining cardiovascular disease

The results are interpreted for measures to prevent or lower high SBP.

Goals and Hypothesis

Goals

The goal is to find the most **significant health and social factors** that affect Systolic Blood Pressure in the BloodPressure.xlsx dataset.

Hypothesis

Based on initial data analysis:

It is predicted that smoking, alcohol use, bmi, stress and exercise have a significant relationship with SBP.

Data Cleaning Process

Step 1

Multi-collinear terms

- The alias() function was used to detect perfectly multicollinear terms.

Step 2

VIF

- VIF was used to identify multicollinearity, the BMI variable is multicollinear to height and weight.

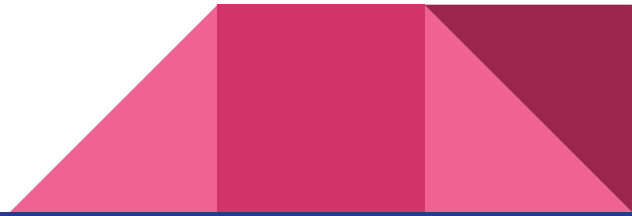
Step 3

Binary Categorical Variables

- Categorical Variables such as Gender, Married and Smoke were changed into binary values.
- NA values were checked for.

Unused Variables

- **Height, Weight and Overweight** were unused as they are already considered in the BMI variable.
- The **childbearing** factor was also unused as it is a **linear combination** of the gender variable.

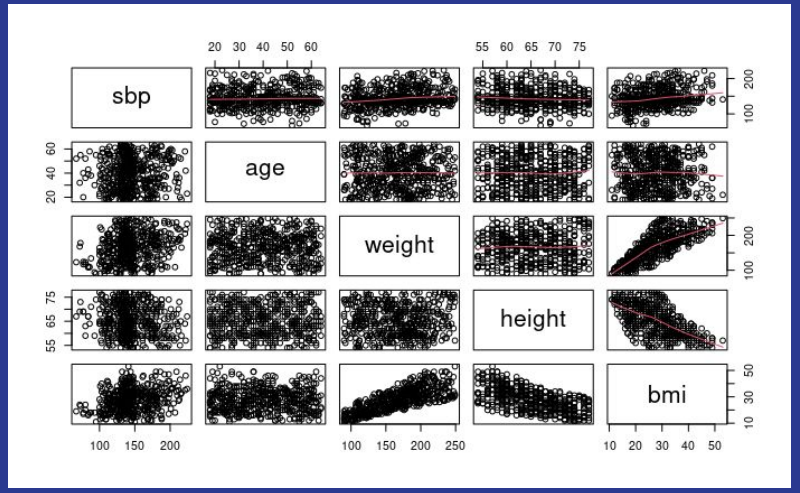


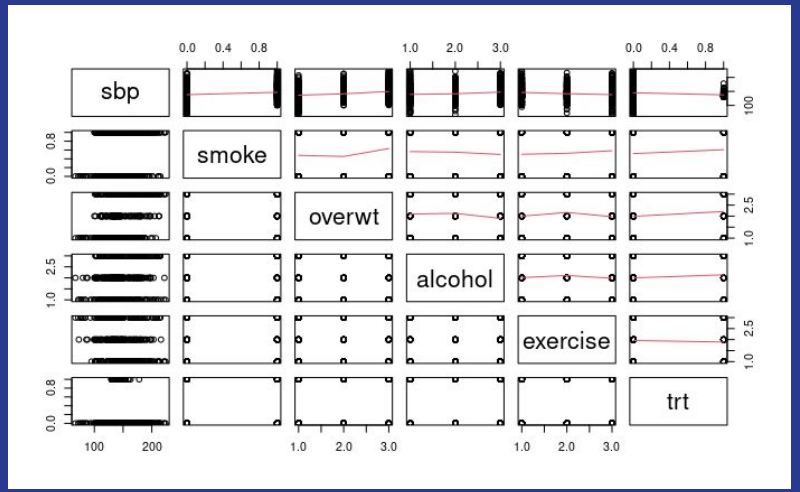
Scatterplot

It can be concluded that:

1. The factors: **smoke, alcohol, BMI** have a **positive** relation with SBP.

2. The factor **exercise and hypertension treatment** have a **negative** relation with SBP.

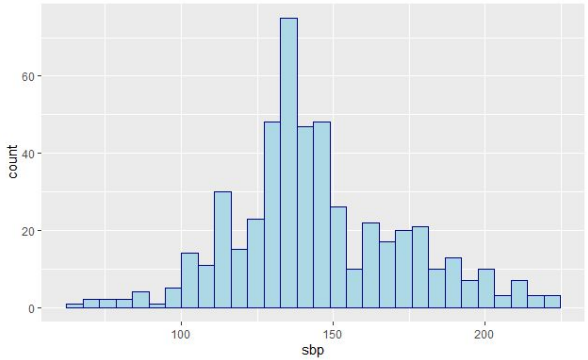


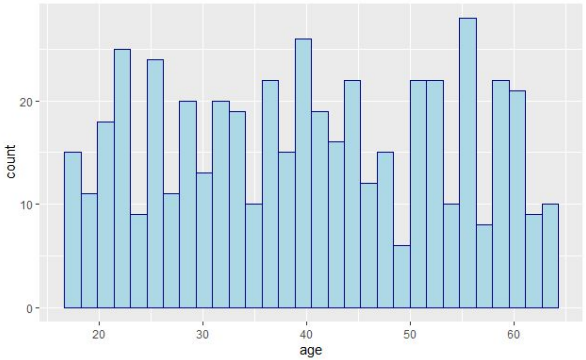


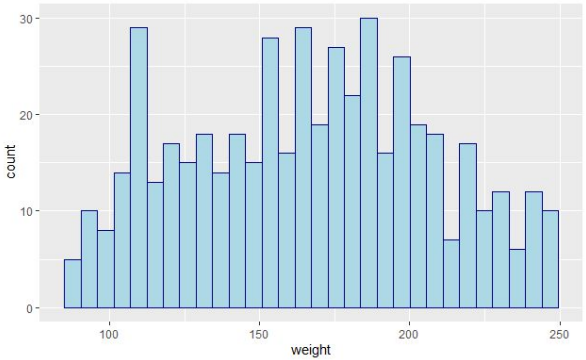
Correlation Matrix

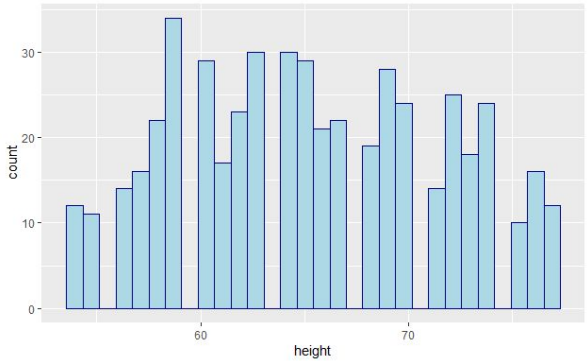
	sbp	gender	married	smoke	exercise	age	weight	height	overwt	race	alcohol	trt	bmi	stress	salt	chldbear	income	educatn
sbp	1.000	0.002	0.061	0.193	-0.145	0.037	0.230	-0.117	0.267	-0.008	0.133	-0.126	0.267	0.067	-0.029	0.025	0.046	-0.009
gender	0.002	1.000	-0.039	-0.045	-0.032	0.005	0.236	0.293	0.004	0.020	-0.089	0.063	0.000	0.031	0.009	-0.895	0.044	-0.109
married	0.061	-0.039	1.000	0.031	-0.036	-0.017	-0.081	0.017	-0.064	-0.069	0.073	-0.043	-0.077	-0.080	-0.054	0.039	-0.019	0.036
smoke	0.193	-0.045	0.031	1.000	0.060	-0.004	0.079	-0.069	0.122	-0.040	-0.049	0.063	0.106	0.029	-0.053	0.040	-0.088	-0.007
exercise	-0.145	-0.032	-0.036	0.060	1.000	0.048	0.025	0.045	-0.008	0.012	-0.012	-0.028	-0.018	-0.017	0.038	0.029	0.084	-0.031
age	0.037	0.005	-0.017	-0.004	0.048	1.000	-0.002	-0.001	0.050	-0.022	-0.094	0.035	0.002	0.040	0.052	-0.023	0.034	-0.020
weight	0.230	0.236	-0.081	0.079	0.025	-0.002	1.000	0.028	0.717	0.032	-0.105	0.121	0.768	0.057	-0.020	-0.207	0.010	-0.006
height	-0.117	0.293	0.017	-0.069	0.045	-0.001	0.028	1.000	-0.514	0.031	-0.062	0.014	-0.594	0.058	0.079	-0.269	0.039	0.033
overwt	0.267	0.004	-0.064	0.122	-0.008	0.050	0.717	-0.514	1.000	0.023	-0.084	0.093	0.889	0.034	-0.050	0.003	-0.023	-0.030
race	-0.008	0.020	-0.069	-0.040	0.012	-0.022	0.032	0.031	0.023	1.000	0.075	-0.076	0.003	0.075	-0.024	-0.052	0.054	0.080
alcohol	0.133	-0.089	0.073	-0.049	-0.012	-0.094	-0.105	-0.062	-0.084	0.075	1.000	0.063	-0.040	-0.029	-0.081	0.093	0.038	-0.039
trt	-0.126	0.063	-0.043	0.063	-0.028	0.035	0.121	0.014	0.093	-0.076	0.063	1.000	0.093	0.058	-0.025	-0.035	0.036	-0.011
bmi	0.267	0.000	-0.077	0.106	-0.018	0.002	0.768	-0.594	0.889	0.003	-0.040	0.093	1.000	0.003	-0.060	0.016	-0.006	-0.018
stress	0.067	0.031	-0.080	0.029	-0.017	0.040	0.057	0.058	0.034	0.075	-0.029	0.058	0.003	1.000	-0.029	-0.039	0.015	-0.009
salt	-0.029	0.009	-0.054	-0.053	0.038	0.052	-0.020	0.079	-0.050	-0.024	-0.081	-0.025	-0.060	-0.029	1.000	-0.025	0.010	-0.085
chldbear	0.025	-0.895	0.039	0.040	0.029	-0.023	-0.207	-0.269	0.003	-0.052	0.093	-0.035	0.016	-0.039	-0.025	1.000	0.002	0.115
income	0.046	0.044	-0.019	-0.088	0.084	0.034	0.010	0.039	-0.023	0.054	0.038	0.036	-0.006	0.015	0.010	0.002	1.000	-0.027
educatn	-0.009	-0.109	0.036	-0.007	-0.031	-0.020	-0.006	0.033	-0.030	0.080	-0.039	-0.011	-0.018	-0.009	-0.085	0.115	-0.027	1.000

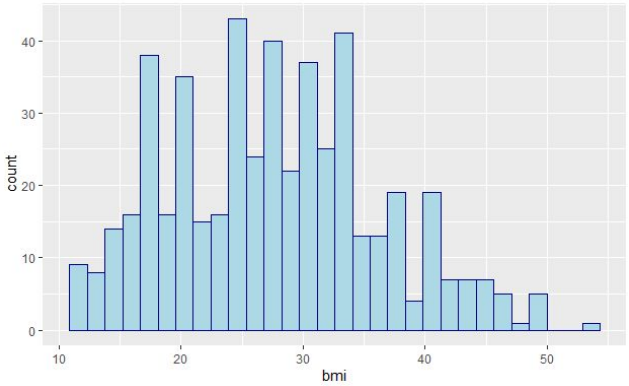
Quantitative Distributions





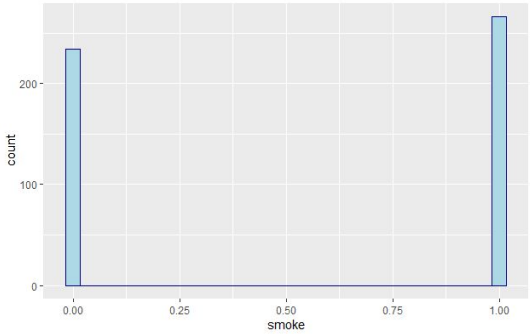


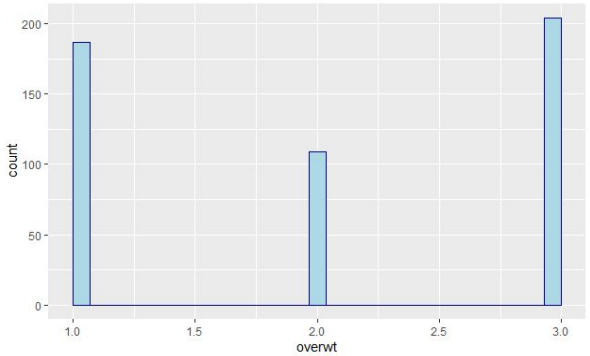


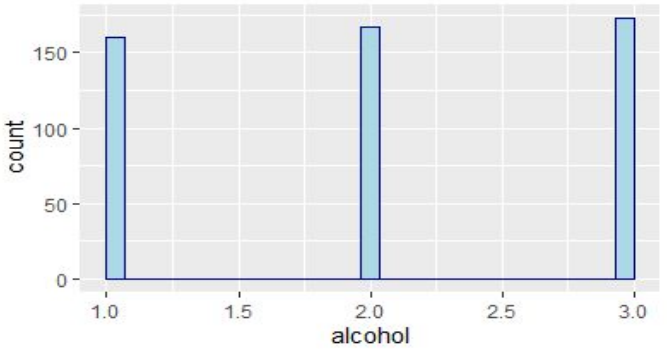


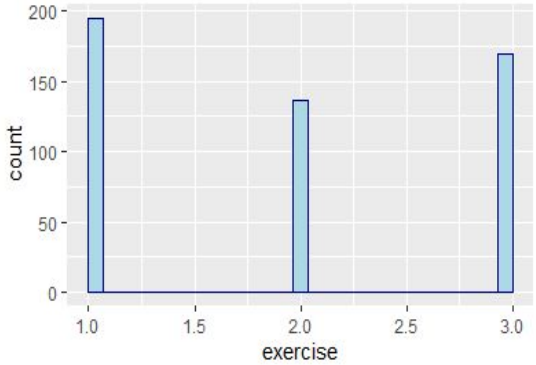
- Sbp, bmi normal
- Everything else roughly uniform

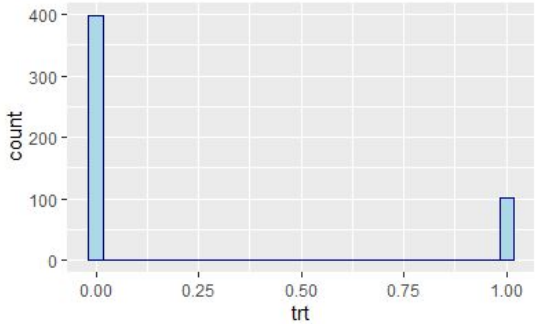
Categorical Distributions











- Everything evenly distributed / trt
- More overweight
- Not obvious bias within data

Model Selection

- Model selection
- Model significance
- Model interpretation
- Model validation

Model Selection

- Used the backwards StepAIC algorithm
- Interact quantitative variables with all qualitative variables
- Quantitative variables used:
  - Age
  - BMI (== Weight/Height^2)
- All categorical variables used
- Further selection done based on p-value significance

```
```{r echo=FALSE , include=FALSE}
fit <- lm(data = dat, formula = sbp ~ age*(factor(exercise)+factor(stress)+factor(salt)+factor(alcohol)+factor(smoke)+factor(gender)+factor(trt)+factor(married)+factor(race)+factor(income)+factor(educatn)) + bmi*(factor(exercise)+factor(stress)+factor(salt)+factor(alcohol)+factor(smoke)+factor(gender)+factor(trt)+factor(married)+factor(race)+factor(income)+factor(educatn)))

stepAIC(fit, direction="backward")
```
```

AIC is a statistic, based on SSE, used for model selection that penalizes a large amount of variables

Model Analysis

```
fit <- lm(formula = sbp ~ age + factor(exercise) + factor(stress) +
    factor(salt) + factor(alcohol) + factor(smoke) + factor(gender) +
    factor(trt) + factor(married) + bmi + age:factor(stress) +
    age:factor(gender) + factor(exercise):bmi + factor(salt):bmi +
    factor(trt):bmi, data = dat)
```

- Initial model from stepAIC

```
Residual standard error: 24.76 on 477 degrees of freedom
Multiple R-squared:  0.2525,    Adjusted R-squared:  0.218
F-statistic: 7.324 on 22 and 477 DF,  p-value: < 2.2e-16
```

- Once fitted, model overall very significant (p-val)
- Does not fit the data well (adjR^2)
  - Noise, seen in scatter-plot
  - Does not mean model is worthless

Coefficients using 100% of data

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	104.43132	10.97588	9.515	< 2e-16	***
age	0.09029	0.16896	0.534	0.593318	
factor(exercise)2	-14.39095	9.45903	-1.521	0.128823	
factor(exercise)3	-31.89574	9.08799	-3.510	0.000491	***
factor(stress)2	-0.37803	8.81681	-0.043	0.965819	
factor(stress)3	-10.61952	8.76562	-1.211	0.226305	
factor(salt)2	-0.87597	9.41027	-0.093	0.925874	
factor(salt)3	17.10853	9.06762	1.887	0.059798	.
factor(alcohol)2	1.61011	2.79974	0.575	0.565500	
factor(alcohol)3	11.42735	2.79787	4.084	5.18e-05	***
factor(smoke)1	11.24000	2.27519	4.940	1.08e-06	***
factor(gender)1	14.58584	7.15606	2.038	0.042076	*
factor(trt)1	20.35289	10.30989	1.974	0.048945	*
factor(married)1	3.72367	2.25750	1.649	0.099710	.
bmi	1.05592	0.26810	3.939	9.42e-05	***
age:factor(stress)2	0.06159	0.20926	0.294	0.768618	
age:factor(stress)3	0.40295	0.20846	1.933	0.053830	.
age:factor(gender)1	-0.32344	0.16838	-1.921	0.055333	.
factor(exercise)2:bmi	0.18961	0.31789	0.596	0.551145	
factor(exercise)3:bmi	0.79870	0.32112	2.487	0.013216	*
factor(salt)2:bmi	0.08413	0.32125	0.262	0.793522	
factor(salt)3:bmi	-0.59753	0.31476	-1.898	0.058253	.
factor(trt)1:bmi	-1.18829	0.34229	-3.472	0.000564	***

Model Significance

```
age                0.09029    0.16896    0.534 0.593318
factor(stress)2   -0.37803    8.81681   -0.043 0.965819
factor(stress)3  -10.61952    8.76562   -1.211 0.226305
```

The main effect of age, stress have high p-values.

- An f-test was run
  - H0: Beta_age = Beta_stress = 0
  - Ha: At least one not 0
- Unable to reject H0
- Slight improvement in adjR^2 after removal(0.02)

```
Model 1: sbp ~ factor(exercise) + factor(salt) + factor(alcohol) + factor(smoke) +
    factor(gender) + factor(trt) + factor(married) + bmi + age:factor(stress) +
    age:factor(gender) + factor(exercise):bmi + factor(salt):bmi +
    factor(trt):bmi
Model 2: sbp ~ age + factor(exercise) + factor(stress) + factor(salt) +
    factor(alcohol) + factor(smoke) + factor(gender) + factor(trt) +
    factor(married) + bmi + age:factor(stress) + age:factor(gender) +
    factor(exercise):bmi + factor(salt):bmi + factor(trt):bmi
  Res.Df    RSS Df Sum of Sq      F Pr(>F)
1    479 293497
2    477 292328  2    1169.2 0.9539  0.386
```

Model Interpretation

- There are still high p-values
  - Ex. Medium use of alcohol(p = 0.5522)
  - Doesn't mean alcohol not significant
  - High level of alcohol(p = 0.0000476)
- Some important covariates(alpha<0.1):
  - High levels of exercise □
  - High levels of alcohol use □
  - Smoking □
  - Salt □
  - BMI □
- Results match with hypothesis

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          101.4905     9.6296  10.539  < 2e-16 ***
factor(exercise)2    -14.9008     9.4509  -1.577 0.115536
factor(exercise)3    -31.9906     9.0500  -3.535 0.000448 ***
factor(salt)2         -0.8487     9.4026  -0.090 0.928113
factor(salt)3         17.3068     9.0656   1.909 0.056851 .
factor(alcohol)2       1.6577     2.7869   0.595 0.552244
factor(alcohol)3      11.4361     2.7863   4.104 4.76e-05 ***
factor(smoke)1        11.2001     2.2727   4.928 1.15e-06 ***
factor(gender)1       13.4850     7.1093   1.897 0.058455 .
factor(trt)1          20.9926    10.2851   2.041 0.041790 *
factor(married)1       3.7263     2.2567   1.651 0.099349 .
bmi                    1.0465     0.2680   3.905 0.000108 ***
age:factor(stress)1    0.1633     0.1239   1.318 0.188209
age:factor(stress)2    0.2145     0.1200   1.788 0.074390 .
age:factor(stress)3    0.3277     0.1197   2.736 0.006444 **
factor(gender)1:age   -0.3009     0.1675  -1.796 0.073129 .
factor(exercise)2:bmi  0.2035     0.3177   0.640 0.522203
factor(exercise)3:bmi  0.8011     0.3204   2.501 0.012732 *
factor(salt)2:bmi      0.0855     0.3211   0.266 0.790175
factor(salt)3:bmi     -0.6026     0.3147  -1.915 0.056099 .
factor(trt)1:bmi      -1.2029     0.3416  -3.522 0.000470 ***
```

Model Validation

- Data is split
  - **60**% testing
  - **40**% validation
- MSE = **627**
- MSPR = **717.2913**

Since MSE ≈ MSPR, the model is sound.

Model is not overfit and can generalize.

```
set.seed(123)
n = length(dat$sbp)*0.6
datIdx <- sample(1:length(dat$sbp), n, replace=FALSE)

trainingDat <- dat[datIdx,]
validationDat <- dat[-datIdx,]

fitTrain <- lm(formula = sbp ~ factor(exercise) +
    factor(salt) + factor(alcohol) + factor(smoke) + factor(gender) +
    factor(trt) + factor(married) + bmi + age:factor(stress) +
    age:factor(gender) + factor(exercise):bmi + factor(salt):bmi +
    factor(trt):bmi, data = trainingDat)

fitValidate <- lm(formula = sbp ~ factor(exercise) +
    factor(salt) + factor(alcohol) + factor(smoke) + factor(gender) +
    factor(trt) + factor(married) + bmi + age:factor(stress) +
    age:factor(gender) + factor(exercise):bmi + factor(salt):bmi +
    factor(trt):bmi, data = validationDat)

anova(fitTrain)

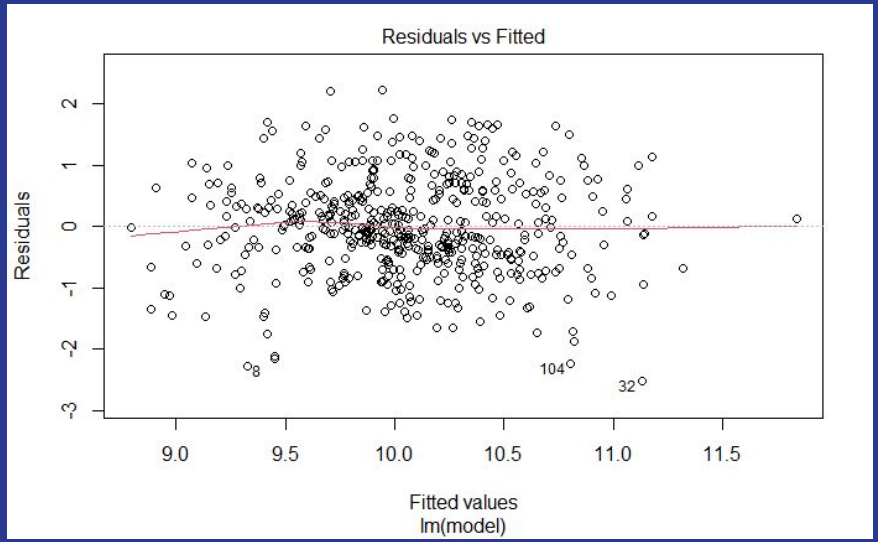
predictTrainWVal <- predict(fitValidate, trainingDat)
MSPR <- sum((trainingDat$sbp - predictTrainWVal)^2)/n
MSPR
```

Model Assumptions

- Linearity
- Normality
- Independence
- Constant Variance

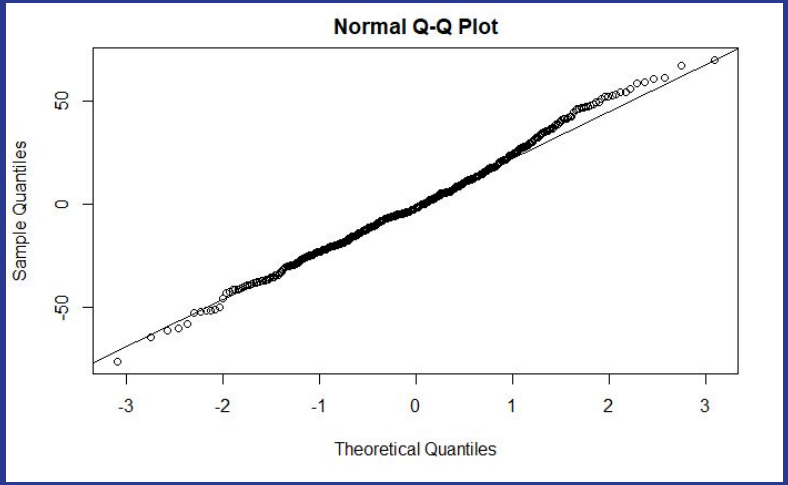
Linearity

- Relationship seems linear.
- **Cannot Reject** linearity.



Normality

- Normality Assumption seems to be satisfied
- P-value > 0.05
- QQ Plot




```
        Shapiro-Wilk normality test

data:  fit$residuals
W = 0.99446, p-value = 0.0672
```

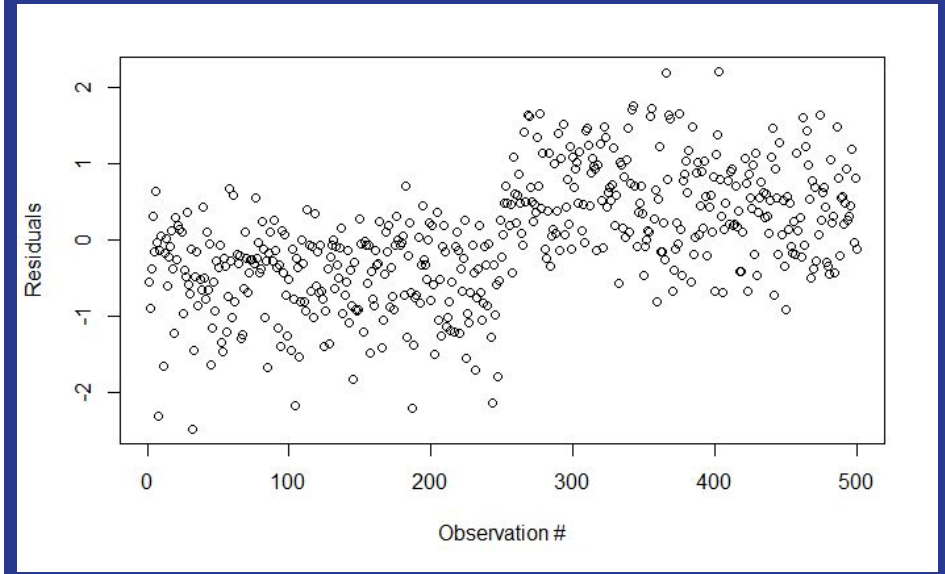
After Boxcox transformation

```
        Shapiro-Wilk normality test

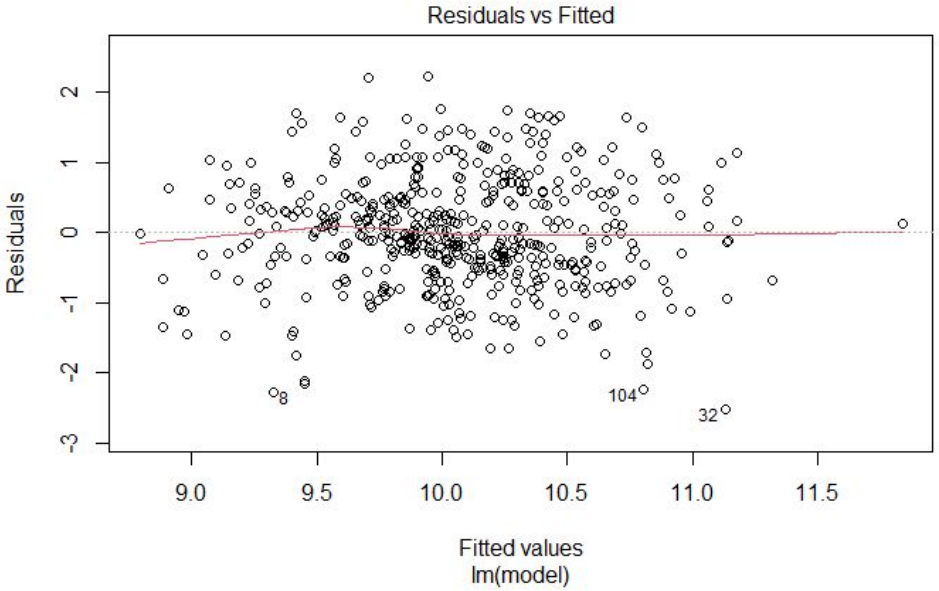
data:  fit$residuals
W = 0.99587, p-value = 0.2144
```

Independent Errors

- No obvious deviate pattern
- **Cannot reject** independent error terms



Model Assumptions - Heteroskedasticity




```
Breusch Pagan Test for Heteroskedasticity
-----------------------------------------
Ho: the variance is constant
Ha: the variance is not constant

                  Data
-----------------------------------------
Response : sbp^lambda
Variables: fitted values of sbp^lambda

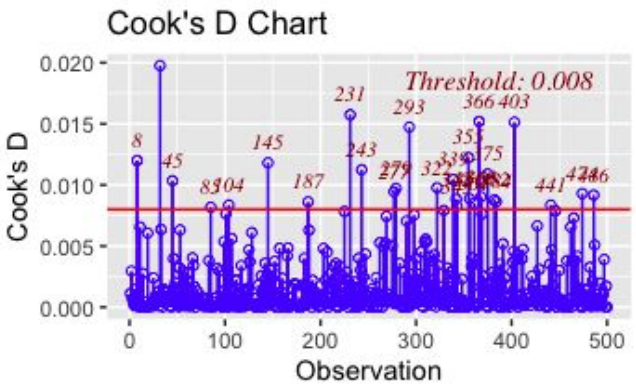
        Test Summary
-----------------------------------------
DF            =    1
Chi2          =    1.990896
Prob > Chi2   =    0.1582472
```

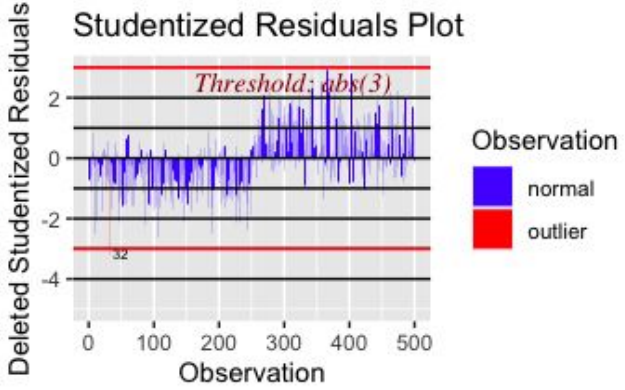
Cannot reject Homoscedasticity

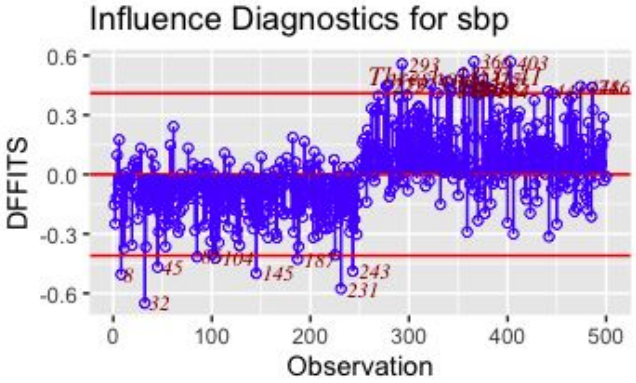
Outlier Detection

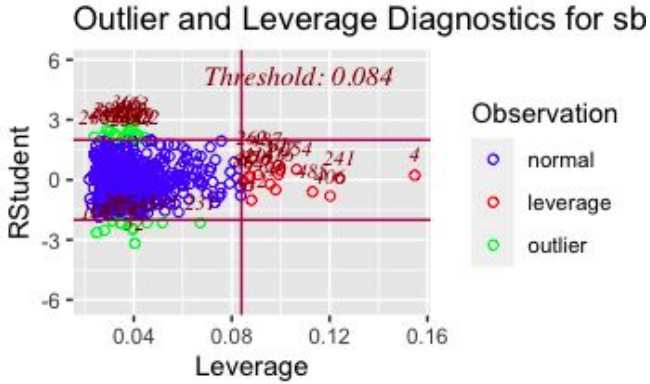
- Cook’s Distance
- Deleted Studentized Residuals
- DIFFITS
- Leverage

Outlier Detection Charts









Outliers

```
#deleted_stu_resid_outliers == NULL
#leverage_outliers == NULL
all_outliers=intersect(cook_outliers, dffits_outliers)
all_outliers
```

```
  [1]   8  32  45  85 104 145 187 231 243 277 279 293 322 339 342 343 355 356 361 366 368 375 382 384 403 441 474 486
```

Influential Points

```
striped_data = data[-all_outliers, ]
data = striped_data
summary(lm(formula = model, data = striped_data))$adj.r.squared
```

```
[1] 0.2825429
```

- Adjusted R-Squared is significantly higher than previous model (0.21)
- These points can be noted as **Influential Points**

Conclusion - Model Significance/Assumptions

- Low p-value, model is significant
- Low adjusted R^2, unknown variables
- The 627.0 = **MSE** ≈ **MSPR** = 717.29, not overfitting model
- The model also satisfies all the assumptions :
  - Constant Variance
  - Error Normality
  - Model Linearity

Conclusion - Model Interpretation

SBP are correlated with the following variables:

- High levels of exercise □
- High levels of alcohol use □
- Smoking □
- Hypertension Treatment □ (expected □)
- BMI □
- Age:Stress □
- Exercise:BMI □ (expected □)
- Hypertension Treatment:BMI □

Ways to Lower SBP

- When your SBP is high:
  - You are 4x more likely to die from a stroke
  - You are 3x more likely to die from heart disease

- Negative correlation with SBP:
  - Exercise
  - Healthy diet
  - Reduce smoking and Alcohol
  - Lower Weight

Questions?

Thank you :D