

HEART ATTACK ANALYSIS

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DECISION TREE

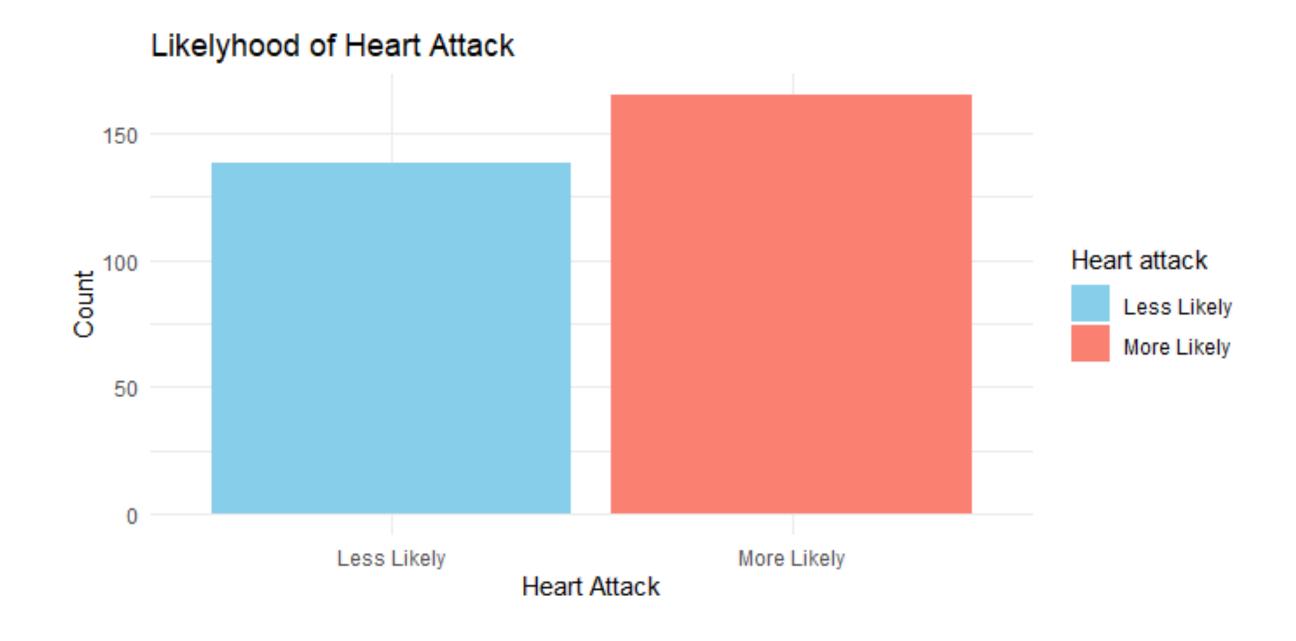
Exploratory Data Analysis





EDA

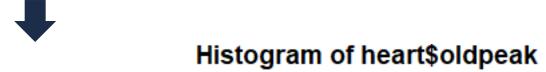
- The dataset is **balanced**
- There are no missing values
- There are no duplicates

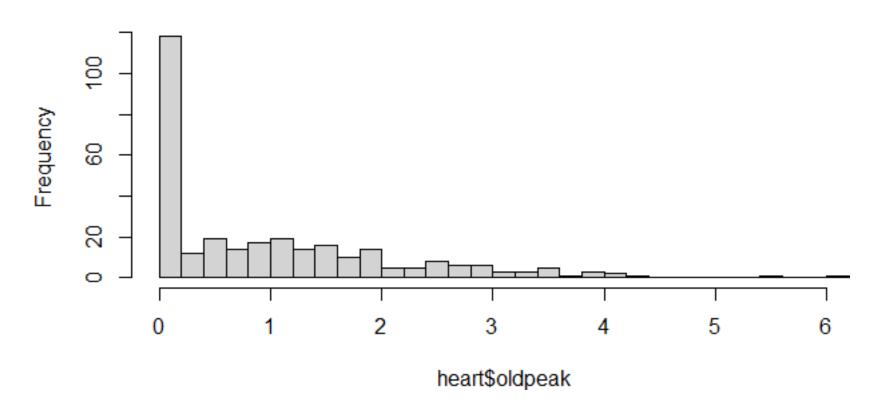


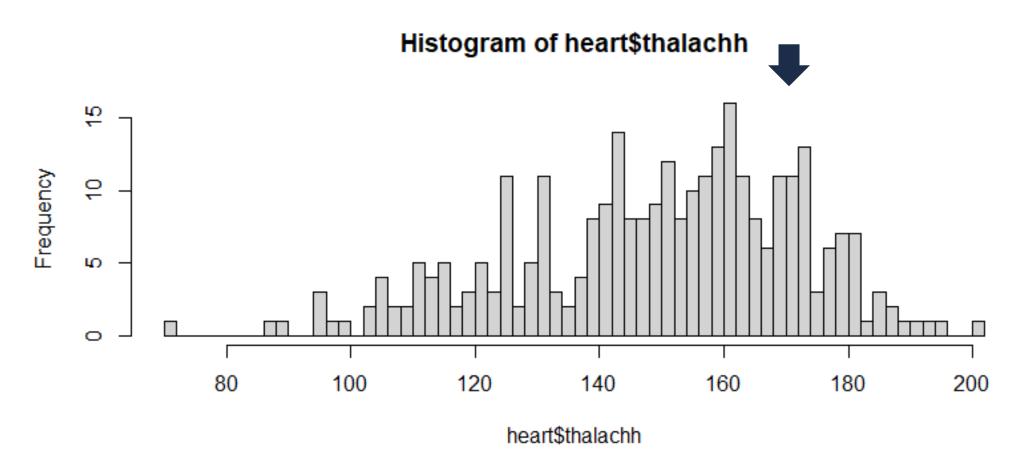


Univariate Analysis

• **Histograms** indicate normal distributions for most variables, except for "oldpeak" and "thalachh," which show left and right skewness, respectively







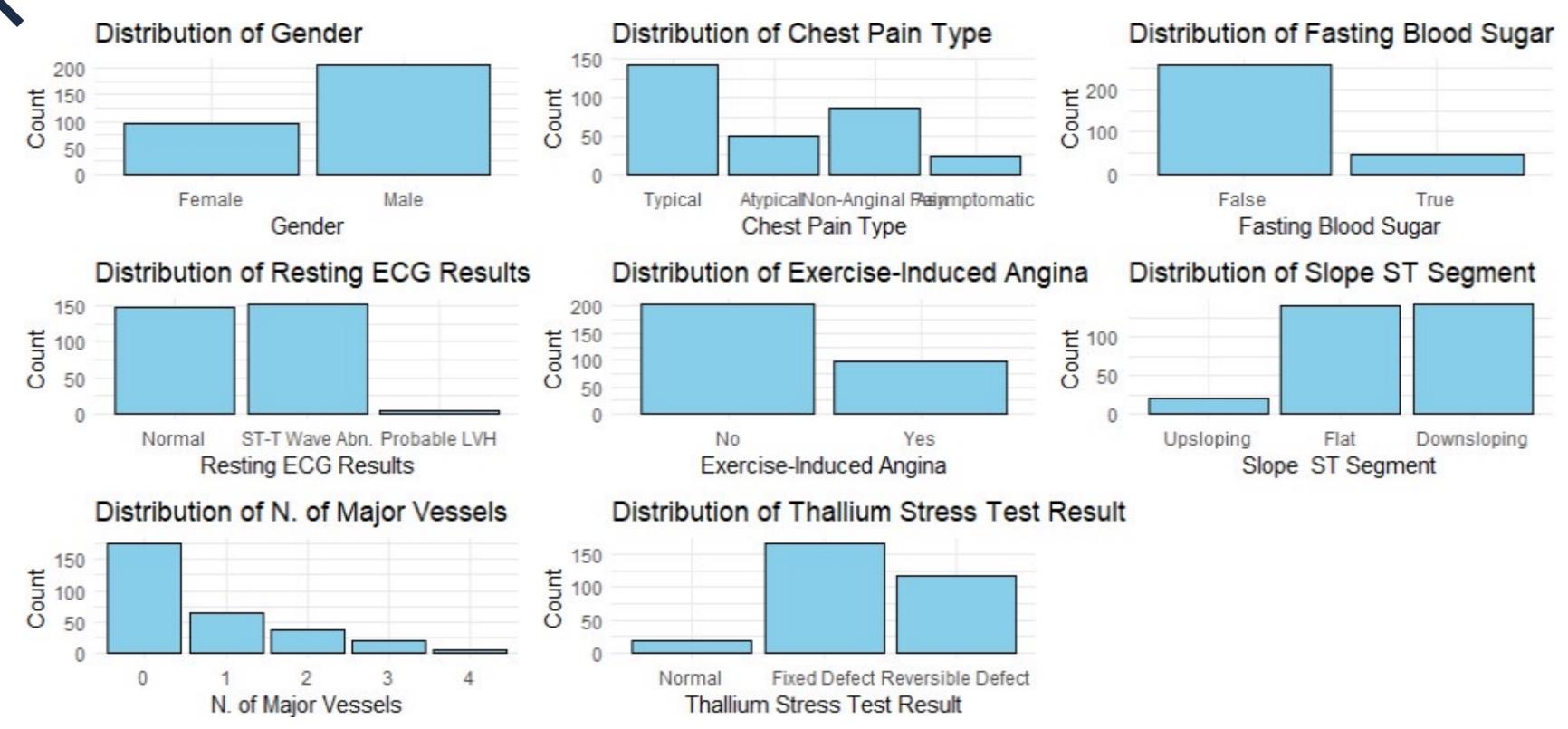


Univariate Analysis

Analyzing bar charts of categorical attributes:

- Gender imbalance with more males
- Resting ecg results show ST-T wave abnormality (type 1) as the most prevalent.

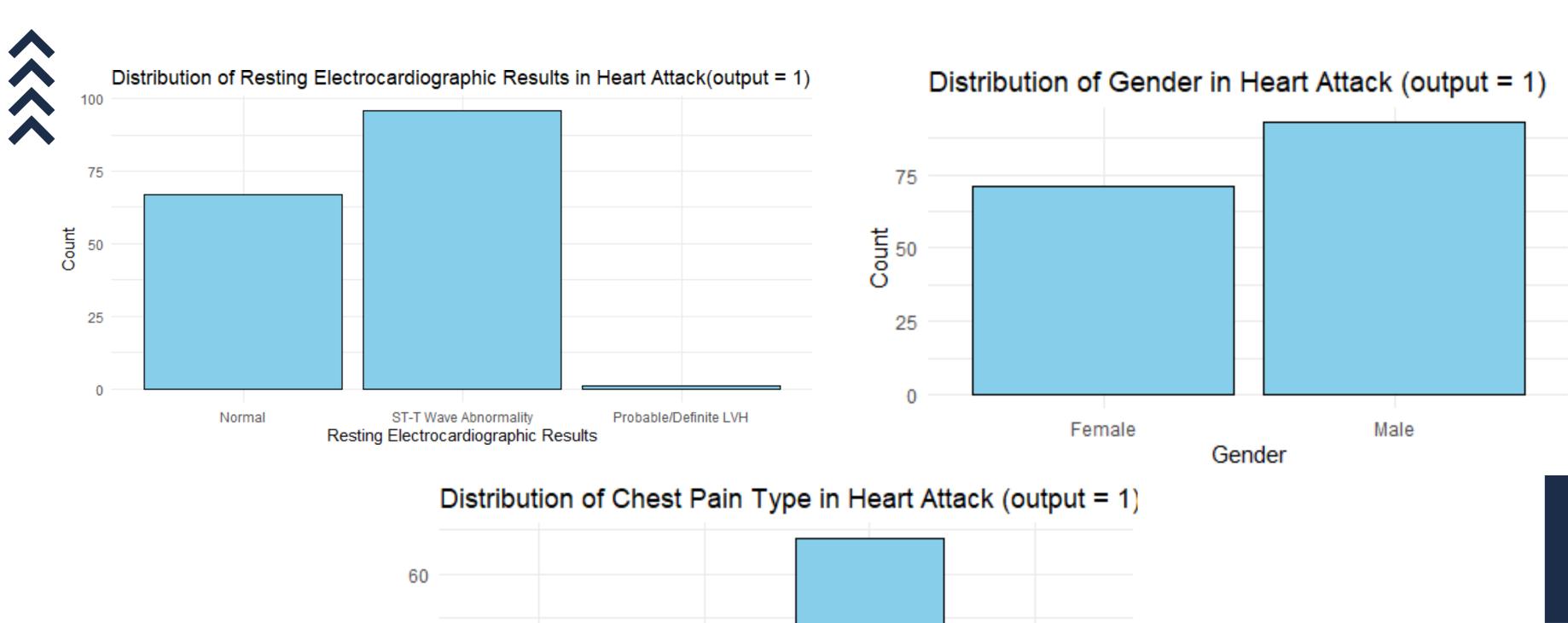


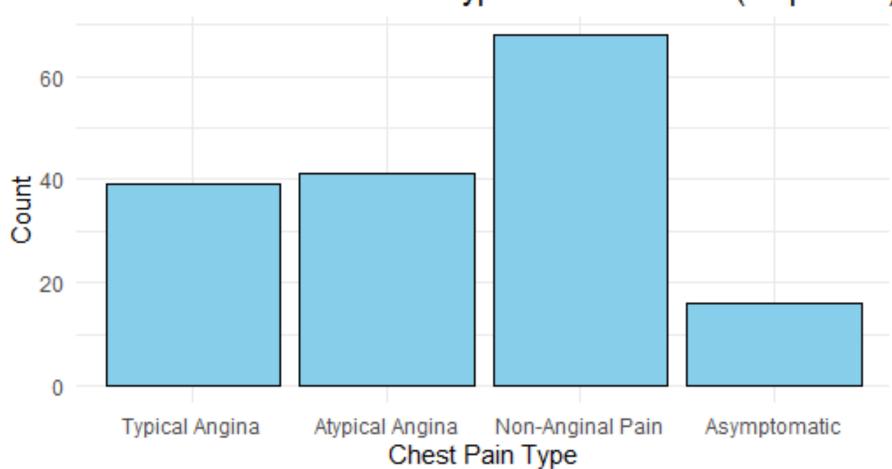




Bivariate Analysis

- Heart attack is more prevalent in males
- Individuals with a chest pain type (cp) equal to 3 (non-anginal) are more likely to have a heart attack
- Those with a rest ECG value of 1, indicating non-normal heartbeats, have a higher chance of heart attack







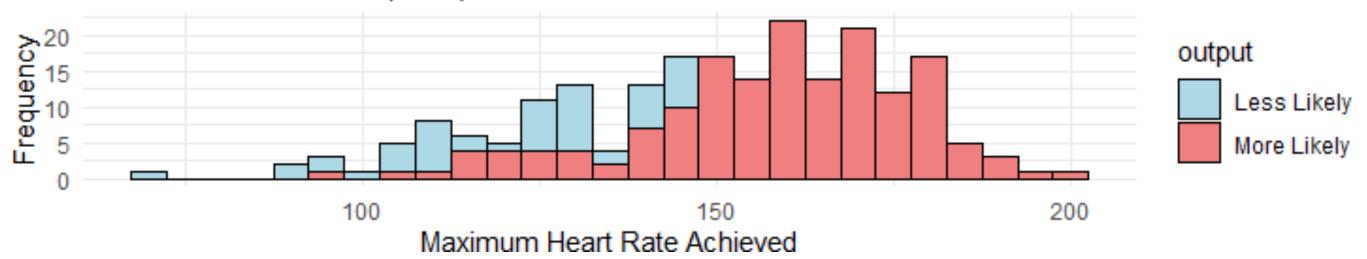
Bivariate Analysis

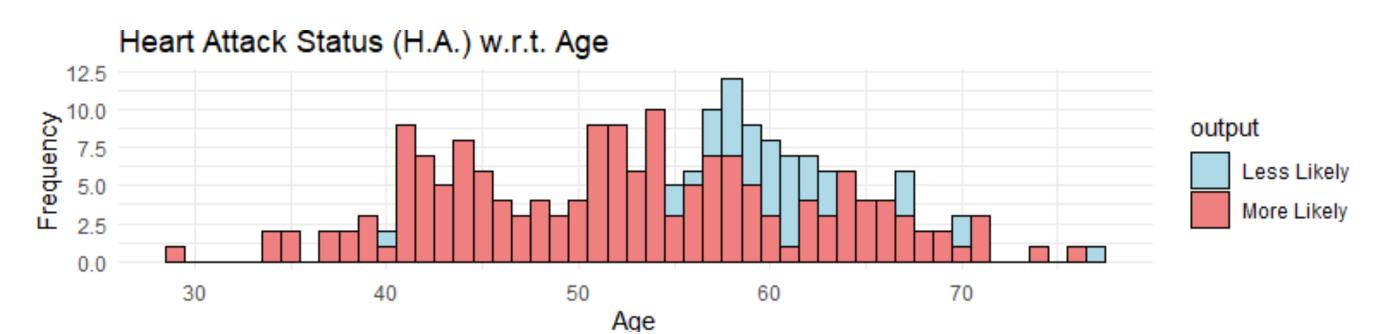
• Individuals in the middle age range (40 to 60 years) exhibit a higher likelihood of experiencing a heart attack.

• Previous peak (oldpeak) exhibits a negative correlation with the chances of experiencing a heart attack.



Heart Attack Status (H.A.) w.r.t. Maximum Heart Rate Achieved





Heart Attack Status (H.A.) w.r.t. Oldpeak

output
Less Likely

More Likely

oldpeak

Correlation



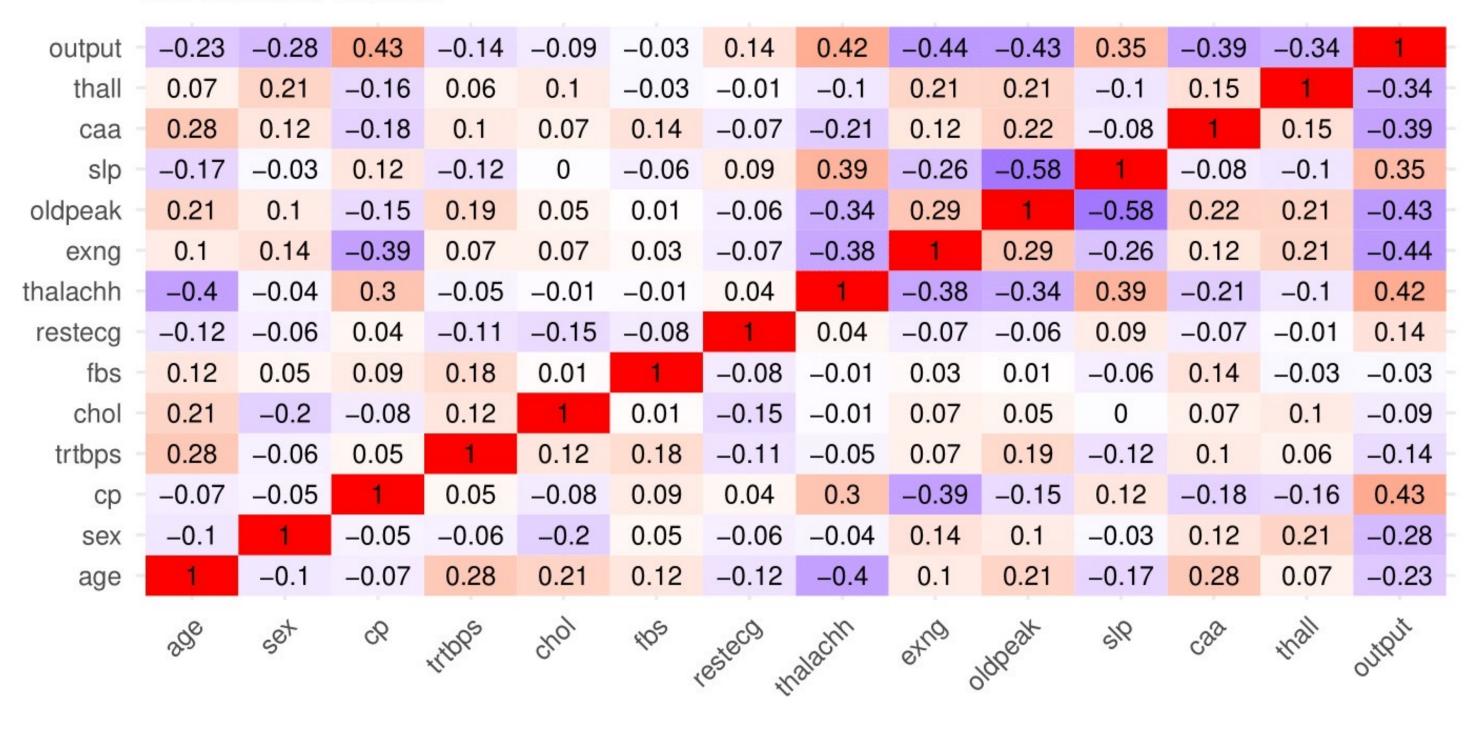


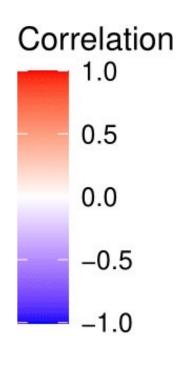
Correlation

- Positive Correlations with 'output' (Heart Attack):
- cp (Chest Pain Type): Strong positive correlation. Severity increase → Higher heart attack likelihood.
- Negative Correlations with 'output':
- exng (Exercise-Induced Angina): Negative correlation. Absence → Higher heart attack likelihood.
- Other Correlations:
- slp with oldpeak : Negative correlations. Certain ST segment patterns →Lower ST depression



Correlation Matrix





Principal Components Analisys

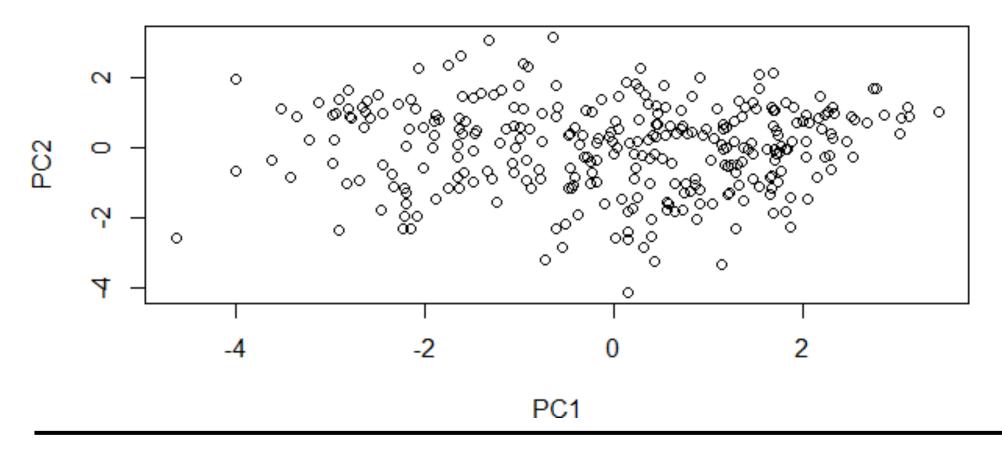




PCA

- The first 8 components (PC), capture 79.50% of the total variance in the original dataset.
- PC1: represents the most influential pattern in the data contributing to 21.25% of the total variance

PCA Results



Importance of components:

```
PC3
                                                         PC5
Standard deviation
                       1.6622 1.2396 1.10582 1.08681 1.01092
Proportion of Variance 0.2125 0.1182 0.09406 0.09086 0.07861
Cumulative Proportion 0.2125 0.3307
                                                         PC10
Standard deviation
                       0.98489 0.92885 0.88088 0.8479 0.78840
Proportion of Variance 0.07462 0.06637 0.05969 0.0553 0.04781
Cumulative Proportion 0.66890 0.73527 0.79495 0.8503 0.89807
                          PC11
                                         PC13
                       0.72808 0.65049 0.6098
Standard deviation
Proportion of Variance 0.04078 0.03255 0.0286
Cumulative Proportion 0.93885 0.97140 1.0000
```

Hirerachical Clustering

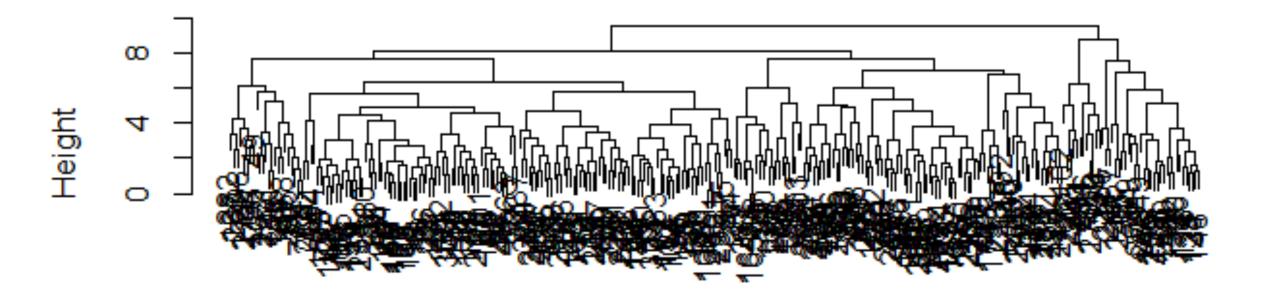




Hierachical Clustering

• There are 260 observations in Cluster 1 and 43 in Cluster 2

Cluster Dendrogram



heart_pc_dist hclust (*, "complete")

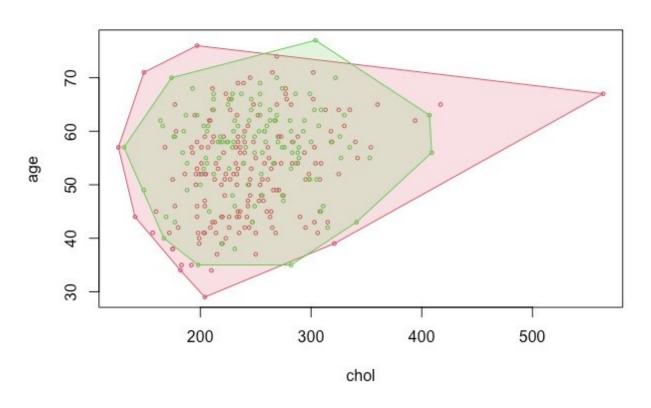
Prototype Clustering





K-Means and Fuzzy C-Means

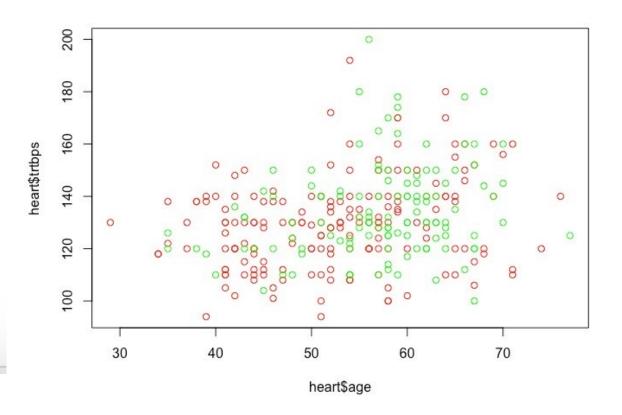
Convex Cluster Hulls



Memberships:

1 2
[1,] 0.4999270 0.5000730
[2,] 0.4994725 0.5005275
[3,] 0.4977166 0.5022834
[4,] 0.4968100 0.5031900
[5,] 0.4993047 0.5006953
[6,] 0.4988801 0.5011199
[7,] 0.4988390 0.5011610
[8,] 0.4976600 0.5023400
[9,] 0.4992600 0.5007400
[10,] 0.4981491 0.5018509
[11,] 0.4977643 0.5022357
[12,] 0.4972856 0.5027144
[13,] 0.4964204 0.5035796
[14,] 0.5000661 0.4999339

[15,] 0.4989450 0.5010550



Regression





Logistic regression

The first model has several variables that were marked as not significant, and therefore it was created a second model

```
glm(formula = output ~ age + sex + cp + trtbps + chol + fbs +
    restecg + thalachh + exng + oldpeak + slp + caa + thall,
    family = binomial, data = heart)
```

glm(formula = output ~ sex + cp + thalachh + exng + oldpeak +
 caa + thall, family = binomial, data = heart)

Coefficients:

```
Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.463553 1.481531 0.313 0.754366
        sex
        0.787179   0.174709   4.506   6.62e-06 ***
ср
        0.023665 0.008813 2.685 0.007248 **
thalachh
        exng
        -0.740612   0.182361   -4.061   4.88e-05 ***
oldpeak
        caa
thall
         -0.896269   0.274516   -3.265   0.001095 **
Signif. codes:
0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
```

Null deviance: 417.64 on 302 degrees of freedom

Residual deviance: 223.31 on 295 degrees of freedom

AIC: 239.31



> vif(logreg2)

sex cp thalachh exng oldpeak caa thall 1.089784 1.152667 1.136840 1.093343 1.110554 1.021568 1.027369

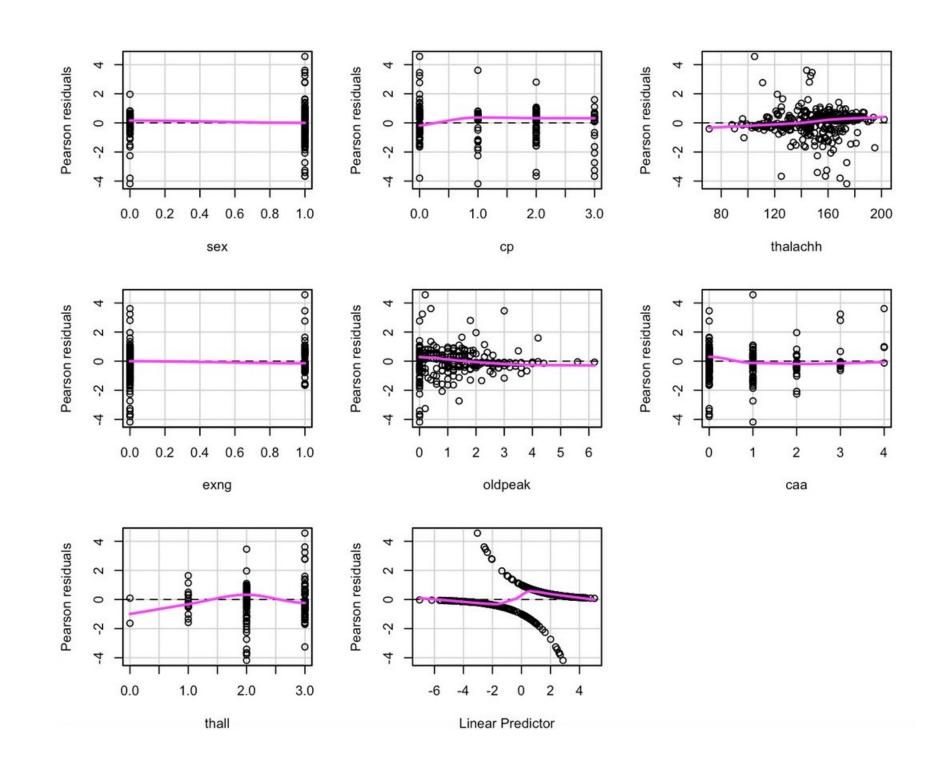
. .

Logistic regression

Some other observations can be made about the model

Normal Q-Q Plot

Theoretical Quantiles



Bayes Classifier





Bayes Classifier

We aimed to predict the occurrence of heart disease based on various factors using a Naive Bayes classifier

To assess the model's generalization performance, the dataset was randomly split into an 80% training set and a 20% testing set.

Features: sex, cp, thalachh, exng, oldpeak, caa, thall.

heart.pred4 0 1

0 24 9

1 0 28

[1] 0.852459



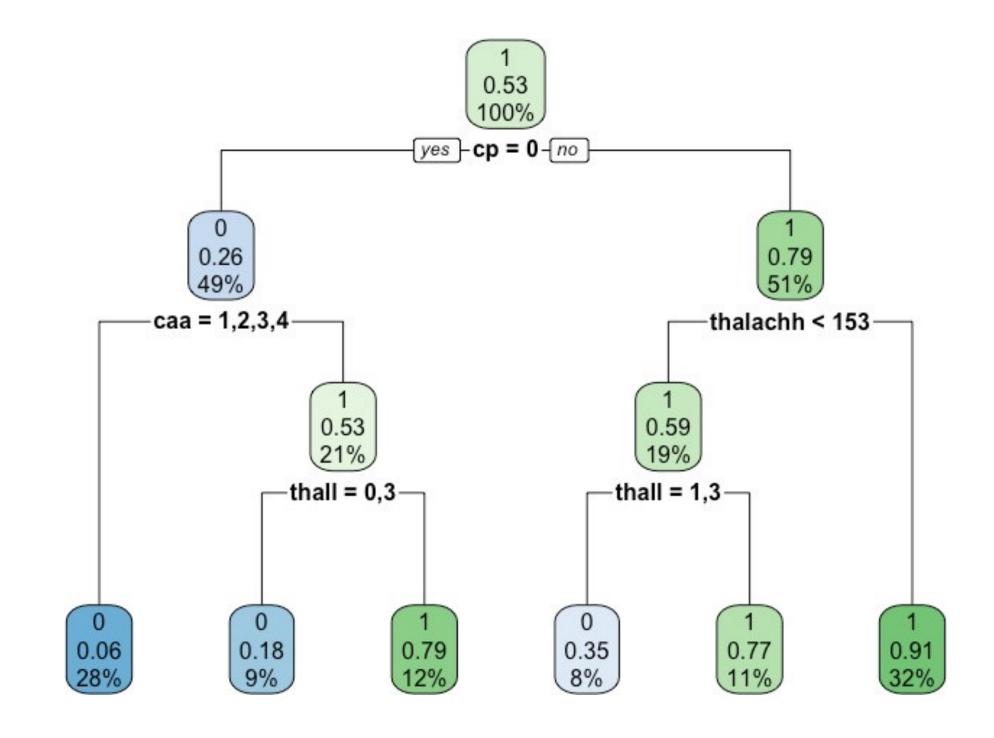
Decision Tree





Decision Tree

Here on the right, it is reported the decision tree that best represents the data with an overall accuracy of 80%.



THANK YOU!

for your attention