R Project : Heat attack

Load libraries

```
library(tidyverse)
library(caret)
library(RColorBrewer)
library(corrplot)
```

Data preparation

Import dataset

```
df <- read.csv("heart.csv")
```

Check df's structure

```
str(df)
```

```
## 'data.frame':    303 obs. of  14 variables:
##  $ age     : int  63 37 41 56 57 57 56 44 52 57 ...
##  $ sex     : int  1 1 0 1 0 1 0 1 1 1 ...
##  $ cp      : int  3 2 1 1 0 0 1 1 2 2 ...
##  $ trtbps  : int  145 130 130 120 120 140 140 120 172 150 ...
##  $ chol    : int  233 250 204 236 354 192 294 263 199 168 ...
##  $ fbs     : int  1 0 0 0 0 0 0 0 1 0 ...
##  $ restecg : int  0 1 0 1 1 1 0 1 1 1 ...
##  $ thalachh: int  150 187 172 178 163 148 153 173 162 174 ...
##  $ exng    : int  0 0 0 0 1 0 0 0 0 0 ...
##  $ oldpeak : num  2.3 3.5 1.4 0.8 0.6 0.4 1.3 0 0.5 1.6 ...
##  $ slp     : int  0 0 2 2 2 1 1 2 2 2 ...
##  $ caa     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ thall   : int  1 2 2 2 2 1 2 3 3 2 ...
##  $ output  : int  1 1 1 1 1 1 1 1 1 1 ...
```

Check missing value

```
colSums(is.na(df))
```

```
##      age      sex       cp   trtbps     chol      fbs  restecg thalachh
##        0        0        0        0        0        0        0        0
##     exng  oldpeak      slp      caa    thall   output
##        0        0        0        0        0        0
```

Check and remove duplicated value

```
df[duplicated(df)|duplicated(df,fromLast = TRUE),]
```

```
##     age sex cp trtbps chol fbs restecg thalachh exng oldpeak slp caa thall
## 164  38   1  2    138  175   0       1      173    0       0   2   4     2
## 165  38   1  2    138  175   0       1      173    0       0   2   4     2
##     output
## 164      1
## 165      1
```

```
df <- df[!duplicated(df),]
```

Data transformation

```
df$sex <- factor(df$sex,
                 levels = c(0,1),
                 labels = c("F","M"))

df$output <- factor(df$output,
                 levels = c(0,1),
                 labels = c("0","1"))
df$cp <- as.factor(df$cp)
df$restecg <- as.factor(df$restecg)
```

Summary of dataset

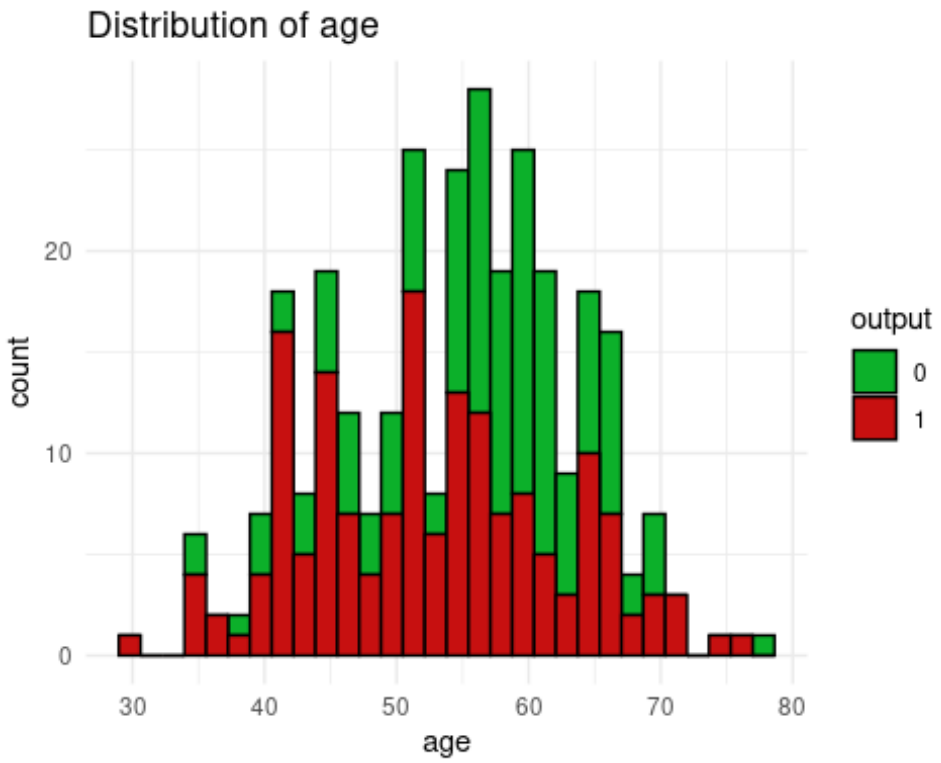
```
summary(df)
```

```
##       age        sex     cp          trtbps           chol
##  Min.   :29.00   F: 96   0:143   Min.   : 94.0   Min.   :126.0
##  1st Qu.:48.00   M:206   1: 50   1st Qu.:120.0   1st Qu.:211.0
##  Median :55.50           2: 86   Median :130.0   Median :240.5
##  Mean   :54.42           3: 23   Mean   :131.6   Mean   :246.5
##  3rd Qu.:61.00                   3rd Qu.:140.0   3rd Qu.:274.8
##  Max.   :77.00                   Max.   :200.0   Max.   :564.0
##       fbs        restecg    thalachh          exng          oldpeak
##  Min.   :0.000   0:147   Min.   : 71.0   Min.   :0.0000   Min.   :0.000
##  1st Qu.:0.000   1:151   1st Qu.:133.2   1st Qu.:0.0000   1st Qu.:0.000
##  Median :0.000   2:  4   Median :152.5   Median :0.0000   Median :0.800
##  Mean   :0.149           Mean   :149.6   Mean   :0.3278   Mean   :1.043
##  3rd Qu.:0.000           3rd Qu.:166.0   3rd Qu.:1.0000   3rd Qu.:1.600
##  Max.   :1.000           Max.   :202.0   Max.   :1.0000   Max.   :6.200
##       slp             caa             thall       output
##  Min.   :0.000   Min.   :0.0000   Min.   :0.000   0:138
##  1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:2.000   1:164
##  Median :1.000   Median :0.0000   Median :2.000
##  Mean   :1.397   Mean   :0.7185   Mean   :2.315
##  3rd Qu.:2.000   3rd Qu.:1.0000   3rd Qu.:3.000
##  Max.   :2.000   Max.   :4.0000   Max.   :3.000
```

Exploratory data analysis

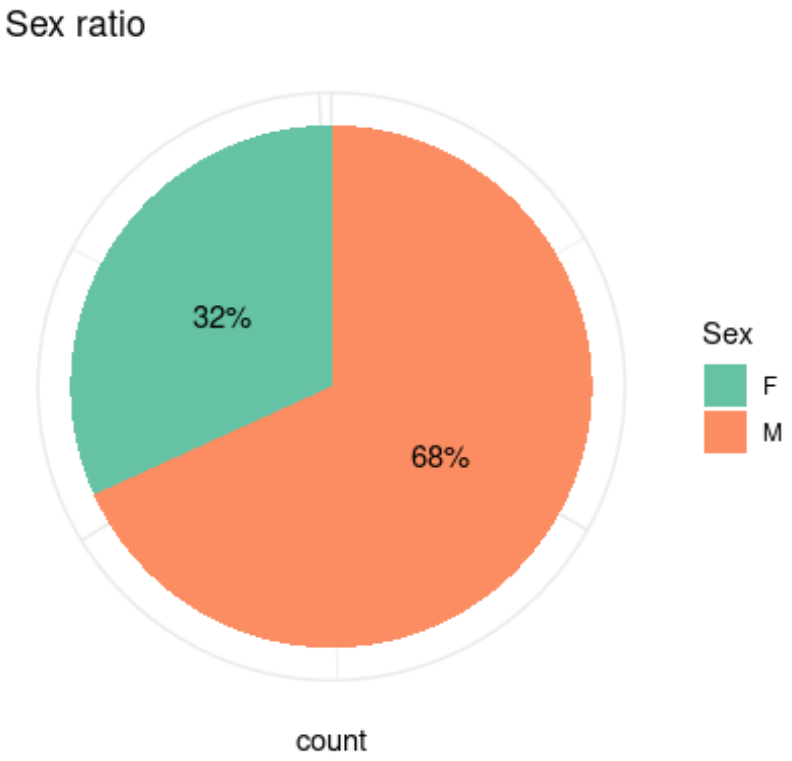
Age distribution

```
ggplot(data = df, aes(x = age, fill = output)) +
  geom_histogram(bins = 30, color = "black" ) +
  theme_minimal() +
  labs(title = "Distribution of age") +
  scale_fill_manual(values= c("#0cb02a", "#c71010"))
```



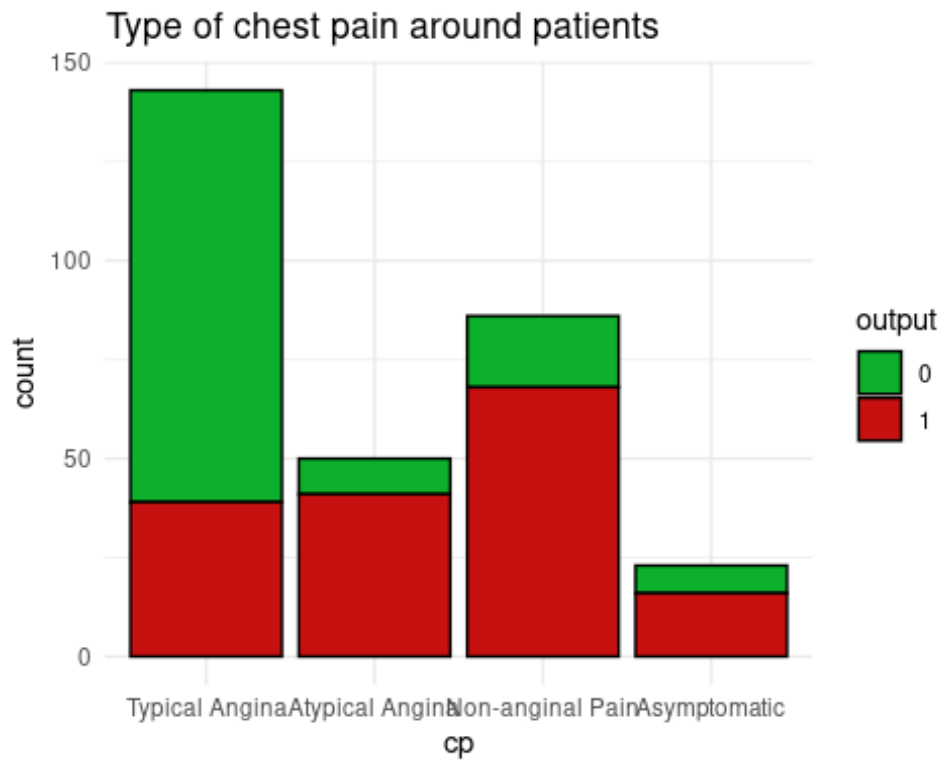
Sex ratio

```
ggplot(df, aes(x = "", y = after_stat(count), fill = sex)) +
  geom_bar(stat = "count", width = 1 ) +
  coord_polar("y", start = 0) +
  theme_minimal() +
  labs(title = "Sex ratio", fill = "Sex", x = NULL ) +
  scale_fill_brewer(palette = "Set2") +
  theme(axis.text.x = element_blank()) +
  geom_text(aes(label = paste0(round((after_stat(count) / sum(after_stat(coun
t))) * 100), "%")), position = position_stack(vjust = 0.5), stat = "count")
```



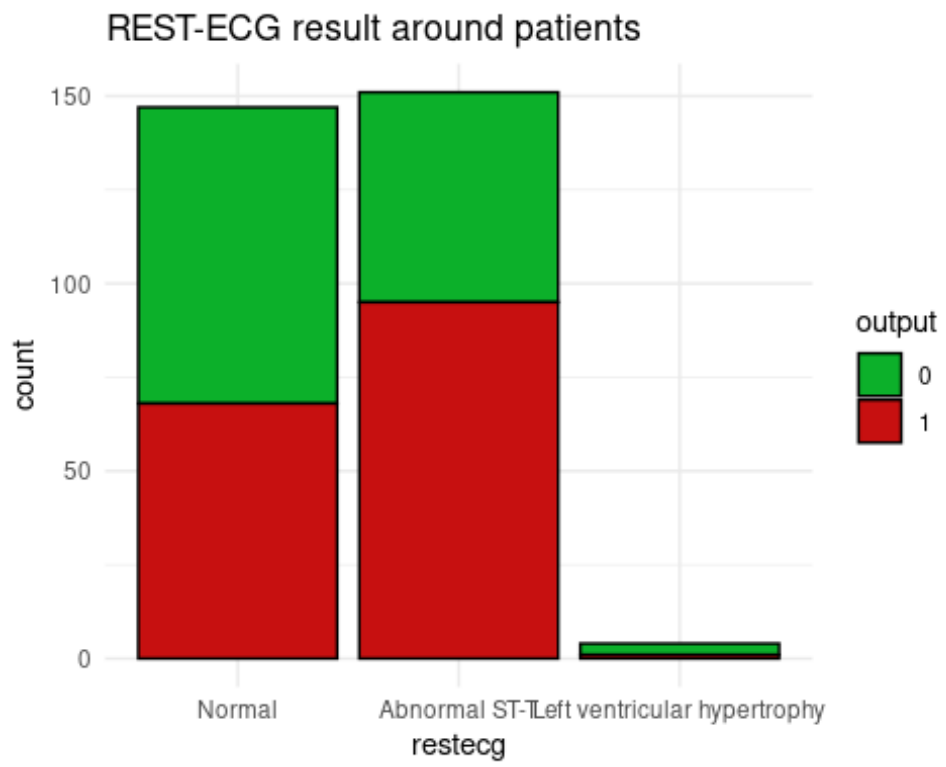
Type of chest pain around patients

```
ggplot(df, aes(x= cp, fill = output)) +
  geom_bar(color = "black") +
  theme_minimal() +
  labs(title = "Type of chest pain around patients") +
  scale_fill_manual(values= c("#0cb02a", "#c71010")) +
  scale_x_discrete(labels = c("Typical Angina", "Atypical Angina", "Non-angin
al Pain", "Asymptomatic"))
```



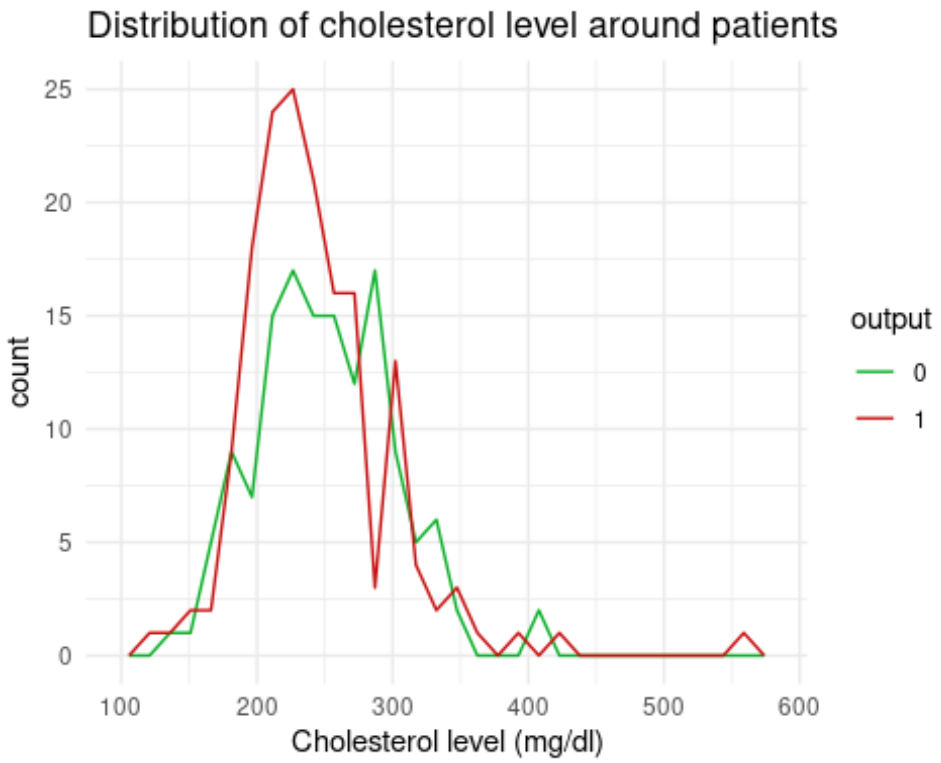
Resting electrocardiographic results around patients

```
ggplot(df, aes(x= restecg, fill = output)) +
  geom_bar(color = "black") +
  theme_minimal() +
  labs(title = "REST-ECG result around patients") +
  scale_fill_manual(values= c("#0cb02a", "#c71010")) +
  scale_x_discrete(labels = c("Normal", "Abnormal ST-T", "Left ventricular hy
pertrophy"))
```



Heat rate around patients

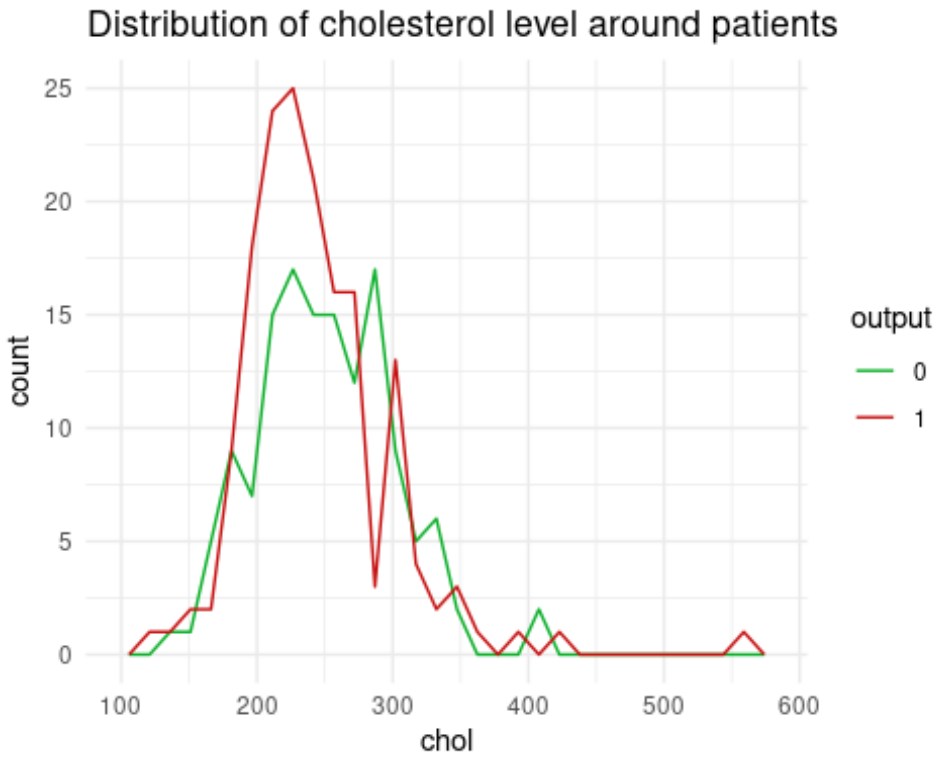
```
ggplot(df, aes(x = chol, color = output)) +
  geom_freqpoly() +
  scale_color_manual(values= c("#0cb02a", "#c71010")) +
  labs(title = "Distribution of cholesterol level around patients") +
  xlab("Cholesterol level (mg/dl)")+
  theme_minimal()
```



Cholestoral level aroud patients

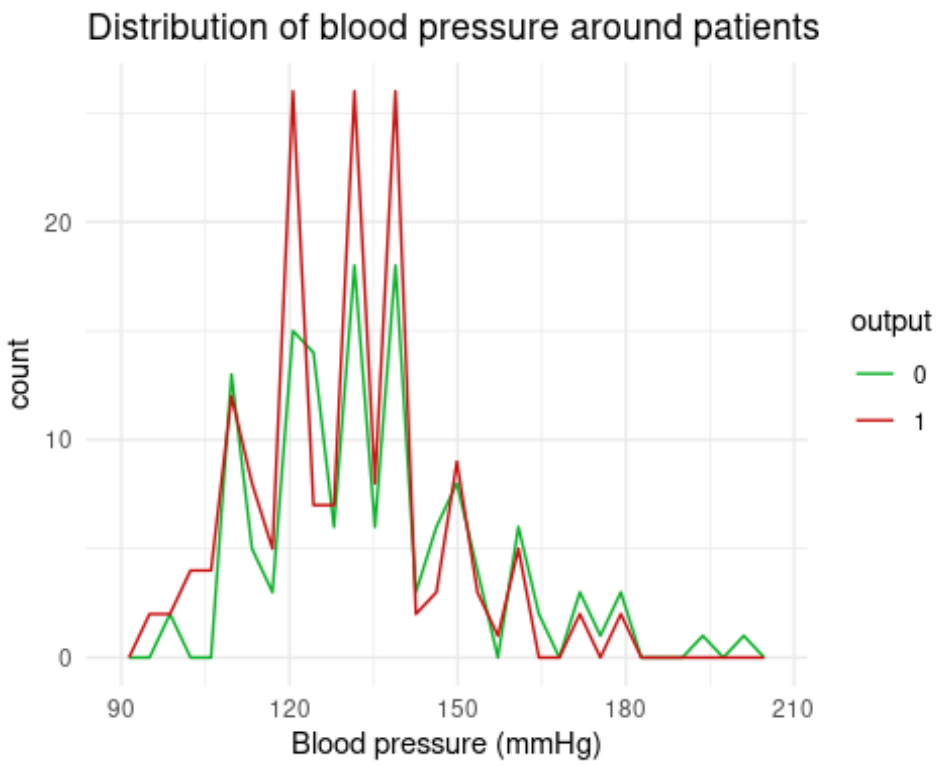
```
ggplot(df, aes(x = chol, color = output)) +
  geom_freqpoly() +
  scale_color_manual(values= c("#0cb02a", "#c71010")) +
  labs(title = "Distribution of cholesterol level around patients") +
  theme_minimal()

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Blood pressure level aroud patients

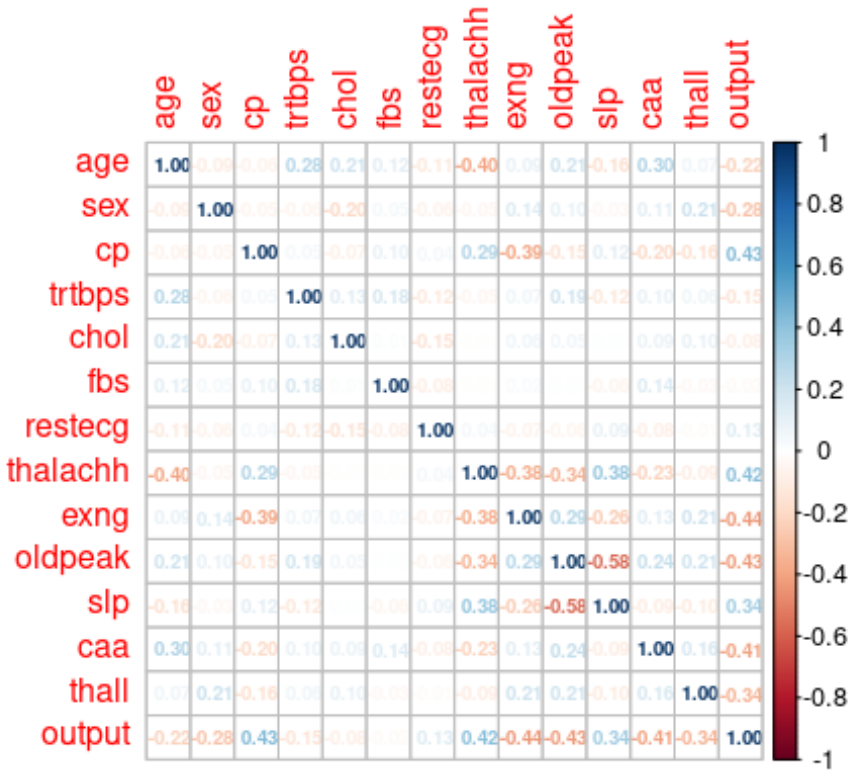
```
ggplot(df, aes(x = trtbps , color = output)) +
  geom_freqpoly() +
  scale_color_manual(values= c("#0cb02a", "#c71010")) +
  labs(title = "Distribution of blood pressure around patients") +
  xlab("Blood pressure (mmHg)")+
  theme_minimal()
```



Correlation matrix

```
# Calculate the correlation matrix
corr_matrix <- cor(df)

# Create a correlation heat map
corrplot(corr_matrix, method= "number", number.cex = 0.6 )
```



Prediction model

Split data

```
split_data <- function(df, train_size = 0.8) {
  set.seed(42)
  n <- nrow(df)
  id <- sample(1:n, size = n*train_size)
  train_df <- df[id,]
  test_df <- df[-id,]
  return(list(train = train_df, test = test_df))
}

prep_data <- split_data(df)
train_data <- prep_data[[1]]
test_data <- prep_data[[2]]
```

Logistic regression

Train model

```
set.seed(25)
ctrl <- trainControl(
  method = "cv",
  number = 5,
  verboseIter =  TRUE
)

lgt_model <- train(output ~ .,
                   data = train_data,
                   method = "glm",
                   preProcess = c("center", "scale"),
                   trControl = ctrl)
```

Model evaluation

```
# Train data
p <- predict(lgt_model)
confusionMatrix(p, train_data$output,
                    positive = "0",
                    mode = "prec_recall")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0  88  12
##          1  21 120
##
##                Accuracy : 0.8631
##                  95% CI : (0.8131, 0.9038)
##     No Information Rate : 0.5477
##     P-Value [Acc > NIR] : <2e-16
```

```
##
##                  Kappa : 0.7216
##
##  Mcnemar's Test P-Value : 0.1637
##
##               Precision : 0.8800
##                  Recall : 0.8073
##                      F1 : 0.8421
##              Prevalence : 0.4523
##          Detection Rate : 0.3651
##    Detection Prevalence : 0.4149
##       Balanced Accuracy : 0.8582
##
##        'Positive' Class : 0
##
```

```r
# Test data
p <- predict(lgt_model, newdata = test_data)
confusionMatrix(p, test_data$output,
                positive = "0",
                mode = "prec_recall")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 19  4
##          1 10 28
##
##                Accuracy : 0.7705
##                  95% CI : (0.645, 0.8685)
##     No Information Rate : 0.5246
##     P-Value [Acc > NIR] : 6.666e-05
##
##                   Kappa : 0.5354
##
##  Mcnemar's Test P-Value : 0.1814
##
##               Precision : 0.8261
##                  Recall : 0.6552
##                      F1 : 0.7308
##              Prevalence : 0.4754
##          Detection Rate : 0.3115
##    Detection Prevalence : 0.3770
##       Balanced Accuracy : 0.7651
##
##        'Positive' Class : 0
##
```

Logistic regression with ridge and lasso

Train model

```
set.seed(25)
ctrl <- trainControl(
  method = "cv",
  number = 5,
  verboseIter =  TRUE
)

my_grid <- expand.grid(alpha = 0:1,
                       lambda = seq(0.0005, 0.05, length = 20))
glmnet_model <- train(output~ .,
                      data = train_data,
                      method = "glmnet",
                      preProcess = c("center", "scale"),
                      tunGrid = my_grid,
                      trControl = ctrl)
```

Model evaluation

```
# Train data
p <- predict(glmnet_model)
confusionMatrix(p, train_data$output,
                positive = "0",
                mode = "prec_recall")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0  83  10
##          1  26 122
##
##                Accuracy : 0.8506
##                  95% CI : (0.7992, 0.8931)
##     No Information Rate : 0.5477
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.6946
##
##  Mcnemar's Test P-Value : 0.01242
##
##               Precision : 0.8925
##                  Recall : 0.7615
##                      F1 : 0.8218
##              Prevalence : 0.4523
##          Detection Rate : 0.3444
##    Detection Prevalence : 0.3859
##       Balanced Accuracy : 0.8429
##
```

```
##        'Positive' Class : 0
##

# Test data
p <- predict(glmnet_model, newdata = test_data)
confusionMatrix(p, test_data$output,
                positive = "0",
                mode = "prec_recall")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 19  1
##          1 10 31
##
##                Accuracy : 0.8197
##                  95% CI : (0.7002, 0.9064)
##     No Information Rate : 0.5246
##     P-Value [Acc > NIR] : 1.492e-06
##
##                   Kappa : 0.6331
##
##  Mcnemar's Test P-Value : 0.01586
##
##               Precision : 0.9500
##                  Recall : 0.6552
##                      F1 : 0.7755
##              Prevalence : 0.4754
##          Detection Rate : 0.3115
##    Detection Prevalence : 0.3279
##       Balanced Accuracy : 0.8120
##
##        'Positive' Class : 0
##
```

KNN model

Train model

```
set.seed(25)
ctrl <- trainControl(
  method = "cv",
  number = 5,
  verboseIter =  TRUE
)

knn_model <- train(output ~ .,
                   data = train_data,
                   method = "knn",
                   preProcess = c("center", "scale"),
                   trControl = ctrl)
```

Model evaluation

```
# Train data
p <- predict(knn_model)
confusionMatrix(p, train_data$output,
                   positive = "0",
                   mode = "prec_recall")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0  92  12
##          1  17 120
##
##                Accuracy : 0.8797
##                  95% CI : (0.8318, 0.9179)
##     No Information Rate : 0.5477
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.7561
##
##  Mcnemar's Test P-Value : 0.4576
##
##               Precision : 0.8846
##                  Recall : 0.8440
##                      F1 : 0.8638
##              Prevalence : 0.4523
##          Detection Rate : 0.3817
##    Detection Prevalence : 0.4315
##       Balanced Accuracy : 0.8766
##
##        'Positive' Class : 0
##
```

```r
# Test data
p <- predict(knn_model, newdata = test_data)
confusionMatrix(p, test_data$output,
                positive = "0",
                mode = "prec_recall")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 22  4
##          1  7 28
##
##                Accuracy : 0.8197
##                  95% CI : (0.7002, 0.9064)
##     No Information Rate : 0.5246
##     P-Value [Acc > NIR] : 1.492e-06
##
##                   Kappa : 0.6367
##
##  Mcnemar's Test P-Value : 0.5465
##
##               Precision : 0.8462
##                  Recall : 0.7586
##                      F1 : 0.8000
##              Prevalence : 0.4754
##          Detection Rate : 0.3607
##    Detection Prevalence : 0.4262
##       Balanced Accuracy : 0.8168
##
##        'Positive' Class : 0
##
```

Decision tree model

Train model

```
set.seed(25)
ctrl <- trainControl(
  method = "cv",
  number = 5,
  verboseIter =  TRUE
)

rpart_model <- train(output~ .,
                     data = train_data,
                     method = "rpart",
                     preProcess = c("center", "scale"),
                     tuneGrid = expand.grid(cp = c(0.02, 0.0001, 0.25)),
                     trControl = ctrl)
```

Model evaluation

```
# Train data
p <- predict(rpart_model)
confusionMatrix(p, train_data$output,
                positive = "0",
                mode = "prec_recall")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0  89  14
##          1  20 118
##
##                Accuracy : 0.8589
##                  95% CI : (0.8085, 0.9003)
##     No Information Rate : 0.5477
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.7139
##
##  Mcnemar's Test P-Value : 0.3912
##
##               Precision : 0.8641
##                  Recall : 0.8165
##                      F1 : 0.8396
##              Prevalence : 0.4523
##          Detection Rate : 0.3693
##    Detection Prevalence : 0.4274
##       Balanced Accuracy : 0.8552
##
##        'Positive' Class : 0
##
```

```r
# Test data
p <- predict(rpart_model, newdata = test_data)
confusionMatrix(p, test_data$output,
                positive = "0",
                mode = "prec_recall")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 19  3
##          1 10 29
##
##                Accuracy : 0.7869
##                  95% CI : (0.6632, 0.8814)
##     No Information Rate : 0.5246
##     P-Value [Acc > NIR] : 2.064e-05
##
##                   Kappa : 0.5678
##
##  Mcnemar's Test P-Value : 0.09609
##
##               Precision : 0.8636
##                  Recall : 0.6552
##                      F1 : 0.7451
##              Prevalence : 0.4754
##          Detection Rate : 0.3115
##    Detection Prevalence : 0.3607
##       Balanced Accuracy : 0.7807
##
##        'Positive' Class : 0
##
```

Random forest model

Train model

```
set.seed(25)
ctrl <- trainControl(
  method = "cv",
  number = 5,
  verboseIter =  TRUE
)

mtry_grid <- data.frame(mtry = 2:13)
rf_model <- train(output~ .,
                  data = train_data,
                  method = "rf",
                  preProcess = c("center", "scale"),
                  tuneGrid = mtry_grid,
                  trControl = ctrl)
```

Model evaluation

```
# Train data
p <- predict(rf_model)
confusionMatrix(p, train_data$output,
                positive = "0",
                mode = "prec_recall")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 108   0
##          1   1 132
##
##                Accuracy : 0.9959
##                  95% CI : (0.9771, 0.9999)
##     No Information Rate : 0.5477
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.9916
##
##  Mcnemar's Test P-Value : 1
##
##               Precision : 1.0000
##                  Recall : 0.9908
##                      F1 : 0.9954
##              Prevalence : 0.4523
##          Detection Rate : 0.4481
##    Detection Prevalence : 0.4481
##       Balanced Accuracy : 0.9954
##
```

```
##        'Positive' Class : 0
##

# Test data
p <- predict(rf_model, newdata = test_data)
confusionMatrix(p, test_data$output,
                positive = "0",
                mode = "prec_recall")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 21  2
##          1  8 30
##
##                Accuracy : 0.8361
##                  95% CI : (0.7191, 0.9185)
##     No Information Rate : 0.5246
##     P-Value [Acc > NIR] : 3.442e-07
##
##                   Kappa : 0.6681
##
##  Mcnemar's Test P-Value : 0.1138
##
##               Precision : 0.9130
##                  Recall : 0.7241
##                      F1 : 0.8077
##              Prevalence : 0.4754
##          Detection Rate : 0.3443
##    Detection Prevalence : 0.3770
##       Balanced Accuracy : 0.8308
##
##        'Positive' Class : 0
##
```

Model comparision

```
list_models = list(Lgt = lgt_model,
                   Glm = glmnet_model,
                   Knn = knn_model,
                   DecisionTree = rpart_model,
                   RandomForest = rf_model)
results = resamples(list_models)
summary(results)
```

```
##
## Call:
## summary.resamples(object = results)
##
## Models: Lgt, Glm, Knn, DecisionTree, RandomForest
## Number of resamples: 5
##
## Accuracy
##                   Min.   1st Qu.    Median      Mean   3rd Qu.      Max. N
A's
## Lgt          0.7083333 0.7708333 0.8571429 0.8255952 0.8750000 0.9166667
0
## Glm          0.7291667 0.7708333 0.8775510 0.8421769 0.8958333 0.9375000
0
## Knn          0.7708333 0.7916667 0.8541667 0.8380102 0.8775510 0.8958333
0
## DecisionTree 0.6041667 0.6875000 0.7916667 0.7506803 0.8333333 0.8367347
0
## RandomForest 0.7291667 0.7500000 0.8163265 0.8132653 0.8750000 0.8958333
0
##
## Kappa
##                   Min.   1st Qu.    Median      Mean   3rd Qu.      Max. N
A's
## Lgt          0.4000000 0.5368421 0.7100592 0.6448136 0.7464789 0.8306878
0
## Glm          0.4448399 0.5368421 0.7504244 0.6784865 0.7879859 0.8723404
0
## Knn          0.5335689 0.5833333 0.7052632 0.6728329 0.7525253 0.7894737
0
## DecisionTree 0.1943463 0.3856655 0.5862069 0.5014801 0.6683938 0.6727880
0
## RandomForest 0.4564460 0.4893617 0.6240409 0.6212392 0.7446809 0.7916667
0
```