Binary Logistic Regression

Conway

```
## Warning: package 'knitr' was built under R version 3.5.3
```

Prompt

The data are based on a mock jury study conducted by Shari Diamond and Jonathan Casper. Subjects (N = 100) watched a videotaped sentencing phase trial in which the defendant had already been found guilty. The issue for the jurors to decide was whether the defendant deserved the death penalty. These data were collected "pre-deliberation"" (i.e., each juror was asked to provide his/her vote on the death penalty verdict, then the jurors met as a group to decide the overall jury verdict).The initial individual verdicts are given in this data set. Verdict is dummy coded: 0 = life sentence, 1 = death penalty.

Load packages and import data

```r
# Load packages
library(pacman)
```

```
## Warning: package 'pacman' was built under R version 3.5.3
```

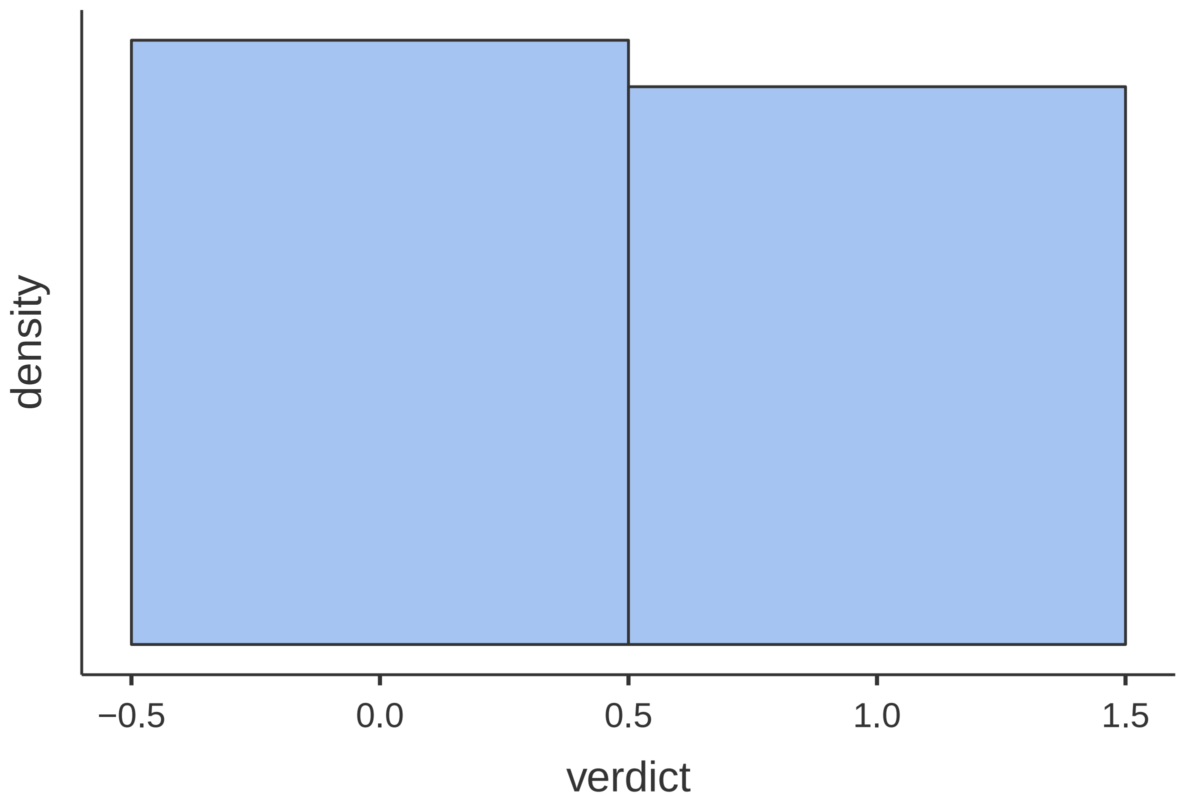
```r
p_load(psych, jmv, aod, QuantPsyc, ggeffects, ggplot2)

# Import data
BL <- read.csv("https://www.dropbox.com/s/hd43va8a7hjfj27/Diamond.csv?dl=1")
```

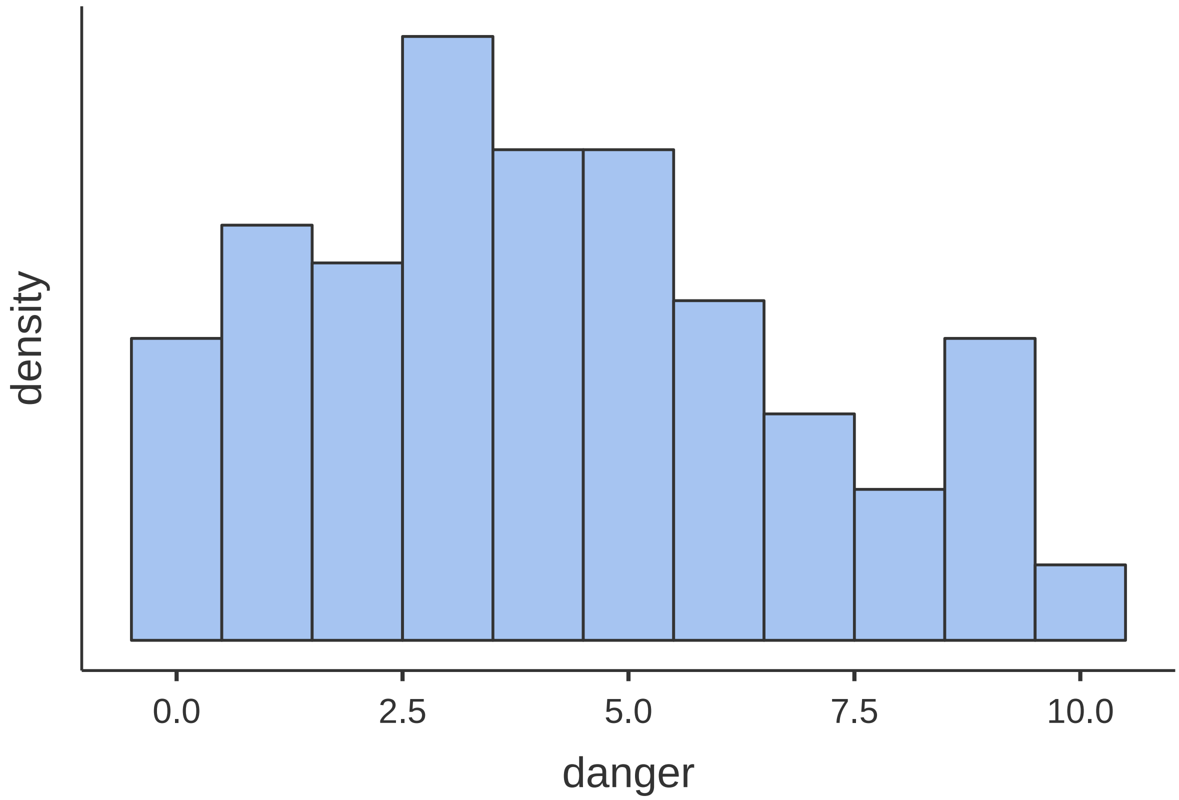
Descriptive statistics

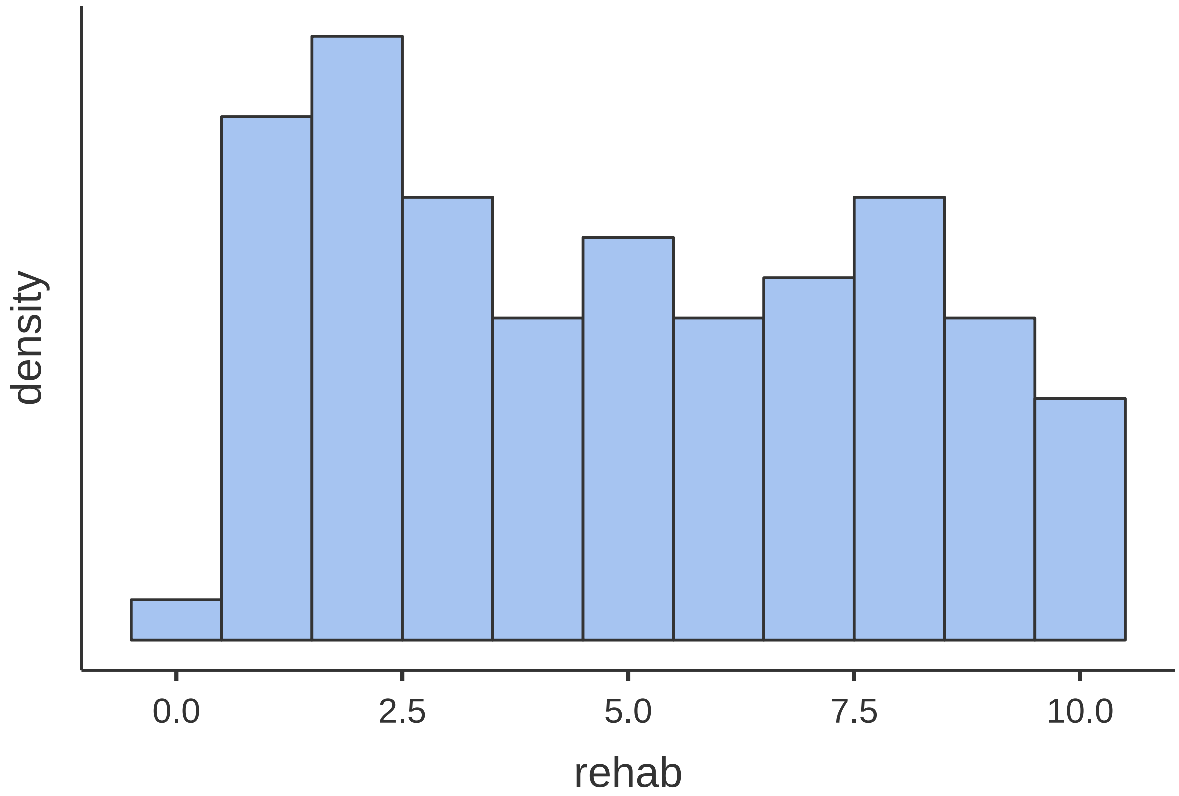
```r
# Descriptive statistics
# Including the binary outcome so we can see the frequencies (prints below Descriptives table)
# baseline classification success is equal to the reference frequency for Retention (No = 2)

desc <- descriptives(data = BL,
                     vars = c('verdict', 'danger', 'rehab', 'punish', 'gendet', 'specdet', 'incap'),
                     sd = TRUE,
                     skew = TRUE,
                     kurt = TRUE,
                     freq = TRUE,
                     hist = TRUE)
desc
```

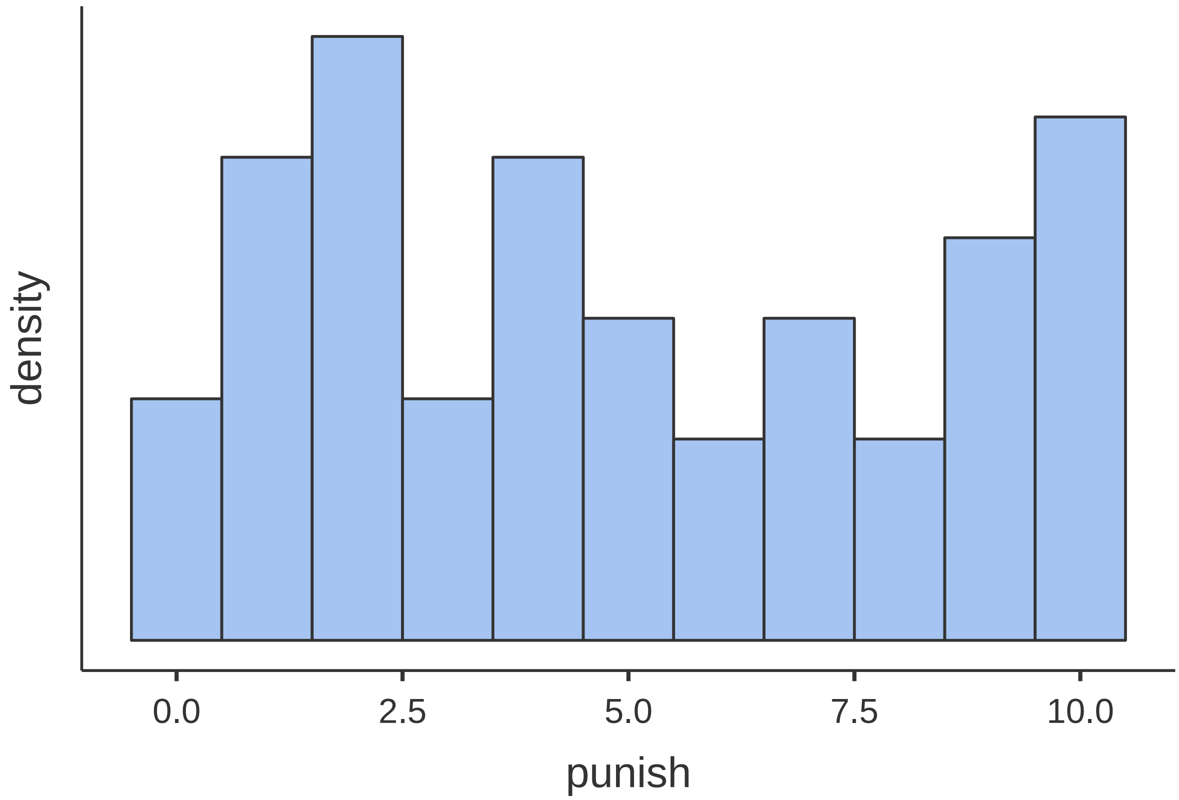
```
##
##  DESCRIPTIVES
##
##  Descriptives
##  -----------------------------------------------------------------------------------------
##                           verdict    danger    rehab    punish    gendet    specdet    incap
##  -----------------------------------------------------------------------------------------
##    N                          100       100      100       100       100        100      100
##    Missing                      0         0        0         0         0          0        0
##    Mean                     0.480      4.16     4.89      4.94      5.17       4.76     4.92
##    Median                    0.00      4.00     5.00      4.00      5.00       4.00     5.00
##    Standard deviation       0.502      2.70     2.91      3.30      3.10       3.01     3.13
##    Minimum                      0         0        0         0         0          0        0
```

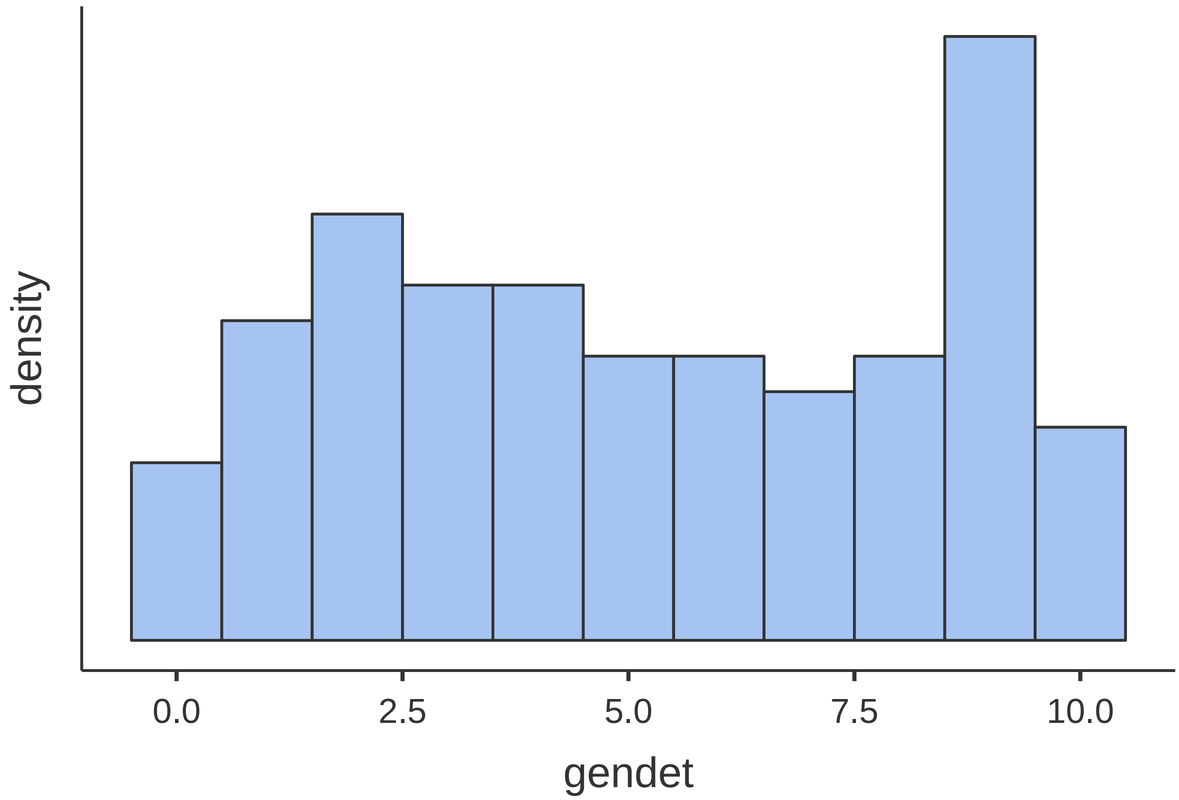
```
##    Maximum                          1         10        10         10          10          10         10
##    Skewness                    0.0813      0.360     0.191      0.195     0.00548       0.113     0.0856
##    Std. error skewness          0.241      0.241     0.241      0.241       0.241       0.241      0.241
##    Kurtosis                     -2.03     -0.690     -1.25      -1.33       -1.33       -1.19      -1.03
##    Std. error kurtosis          0.478      0.478     0.478      0.478       0.478       0.478      0.478
##  -----------------------------------------------------------------------------------------------------
##
##
##  FREQUENCIES
##
##  Frequencies of verdict
##  --------------------------------------------------
##    Levels    Counts    % of Total    Cumulative %
##  --------------------------------------------------
##    0             52          52.0            52.0
##    1             48          48.0           100.0
##  --------------------------------------------------
```

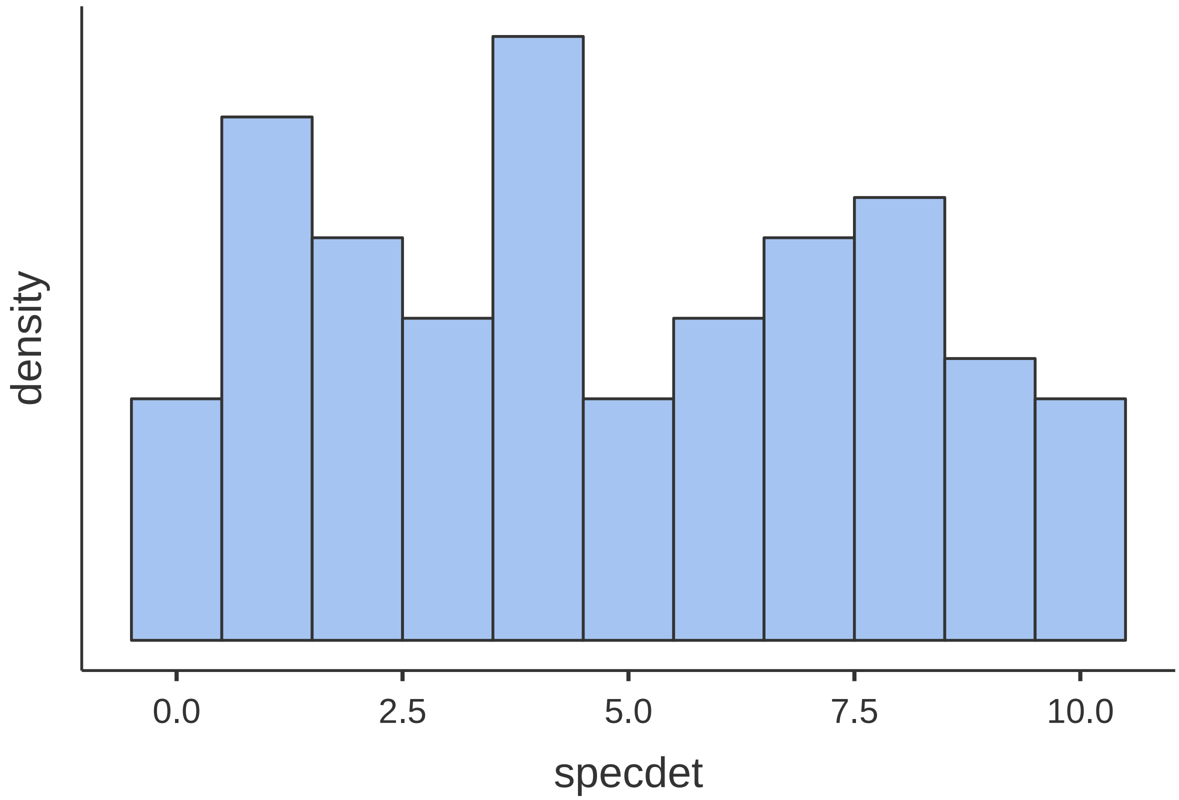


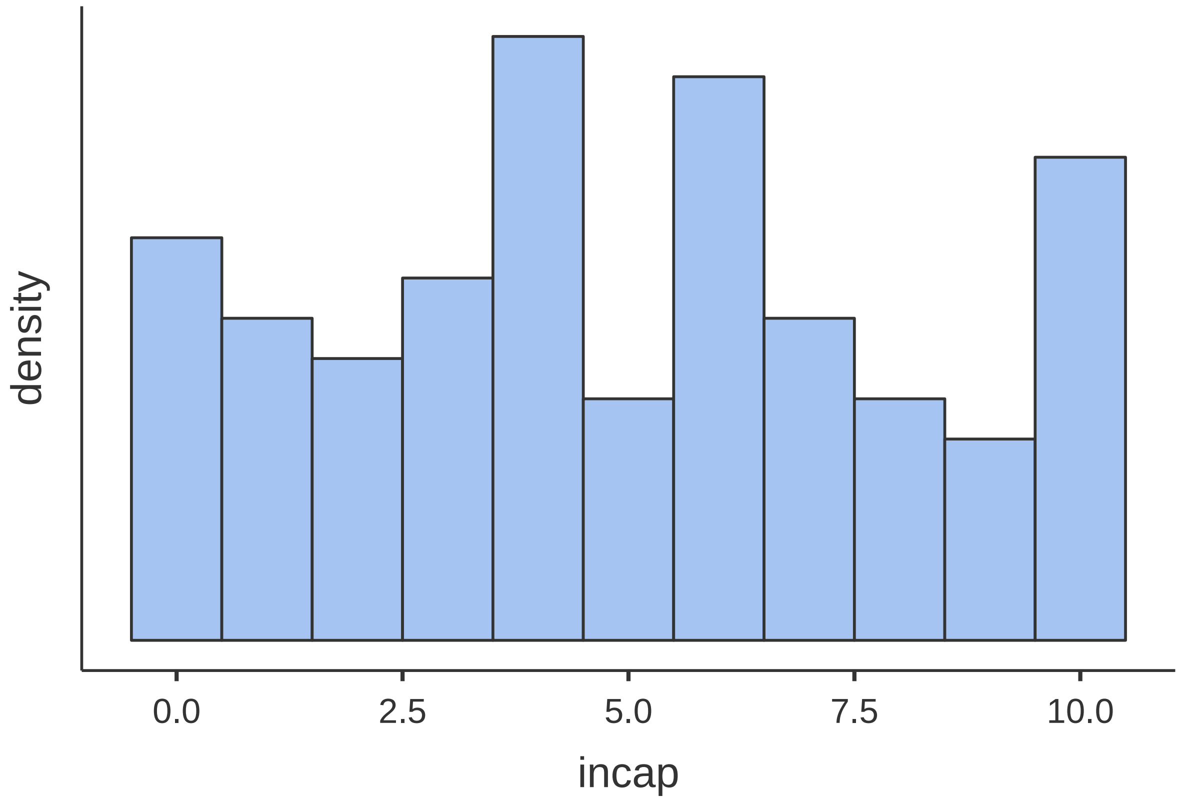

density
0.0
2.5
5.0
7.5
10.0
danger


density
0.0
2.5
5.0
7.5
10.0
rehab


density
0.0
2.5
5.0
7.5
10.0
punish


density
0.0
2.5
5.0
7.5
10.0
gendet


density
0.0
2.5
5.0
7.5
10.0
specdet



Assumptions 1. Independence of Observations 2. Predictor Variables Normally Distributed 3. Multicollinearity

Correlations

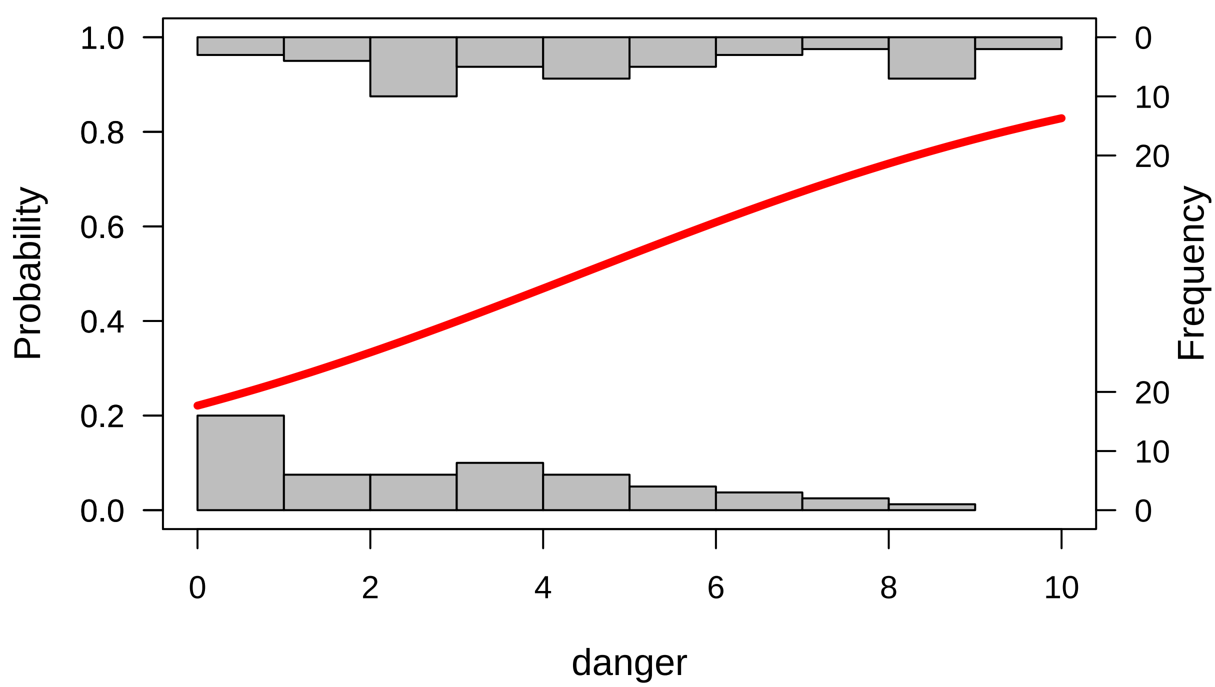
```
# Correlation
cortable <- corrMatrix(data = BL,
                      vars = c('verdict', 'danger', 'rehab', 'punish', 'gendet', 'specdet', 'incap'),
                      flag = TRUE)
cortable
```

```
##
##  CORRELATION MATRIX
##
##  Correlation Matrix
##  ----------------------------------------------------------------------------------------------------
##                              verdict    danger     rehab      punish     gendet     specdet    incap
##  ----------------------------------------------------------------------------------------------------
##    verdict    Pearson's r                0.346     -0.226      0.042      0.232      0.057      0.070
##               p-value                   < .001      0.024      0.679      0.020      0.574      0.491
##
##    danger     Pearson's r                          -0.087     -0.101      0.038      0.083      0.124
##               p-value                               0.392      0.317      0.709      0.411      0.221
##
##    rehab      Pearson's r                                      0.073      0.091      0.002     -0.014
##               p-value                                          0.472      0.365      0.988      0.888
##
##    punish     Pearson's r                                                 0.023      0.016     -0.107
```

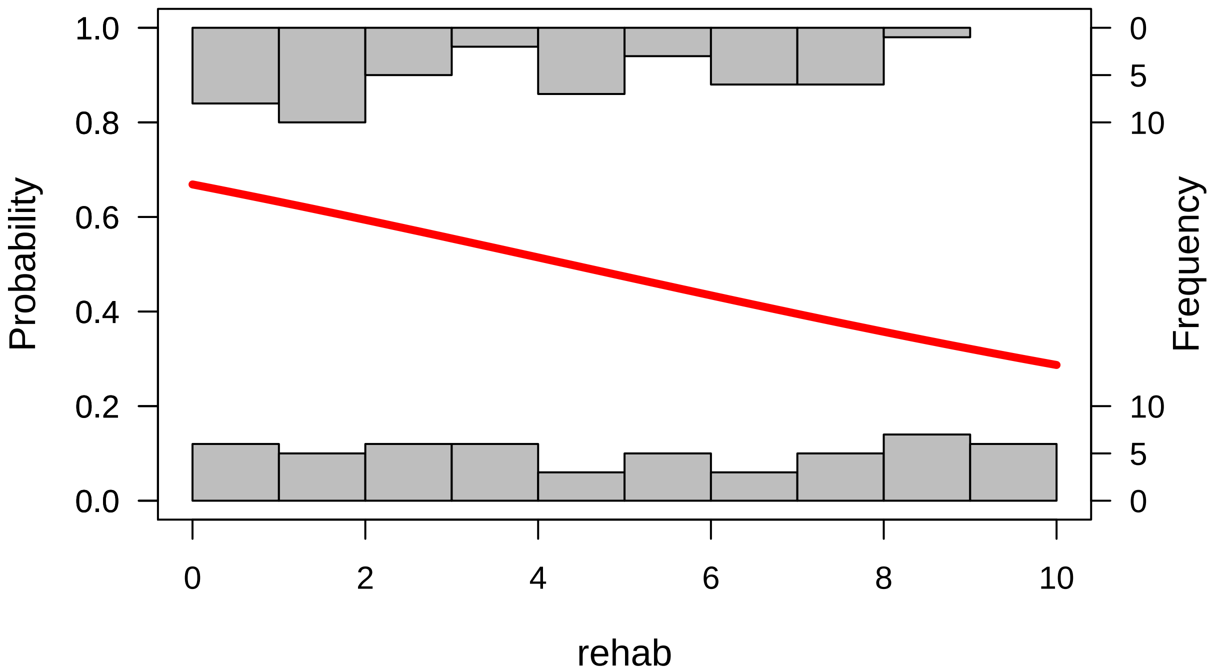
```
##              p-value                                               0.823      0.876     0.290
##
##    gendet    Pearson's r                                                      0.094     0.112
##              p-value                                                          0.352     0.269
##
##    specdet   Pearson's r                                                               -0.064
##              p-value                                                                    0.526
##
##    incap     Pearson's r
##              p-value
## ------------------------------------------------------------------------------------------------
##    Note. * p < .05, ** p < .01, *** p < .001
```

Logistic Plots

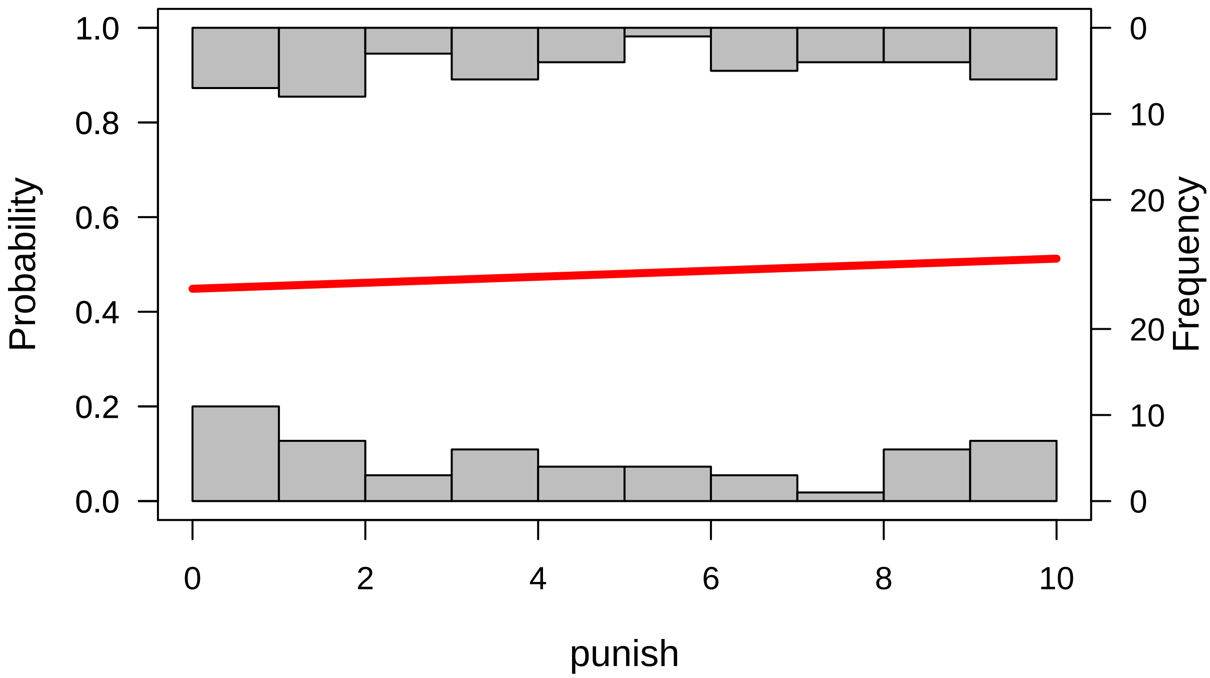
```r
p_load(popbio)
logi.hist.plot(BL$danger, BL$verdict, boxp=FALSE, type="hist", col="gray", xlabel = "danger")
```



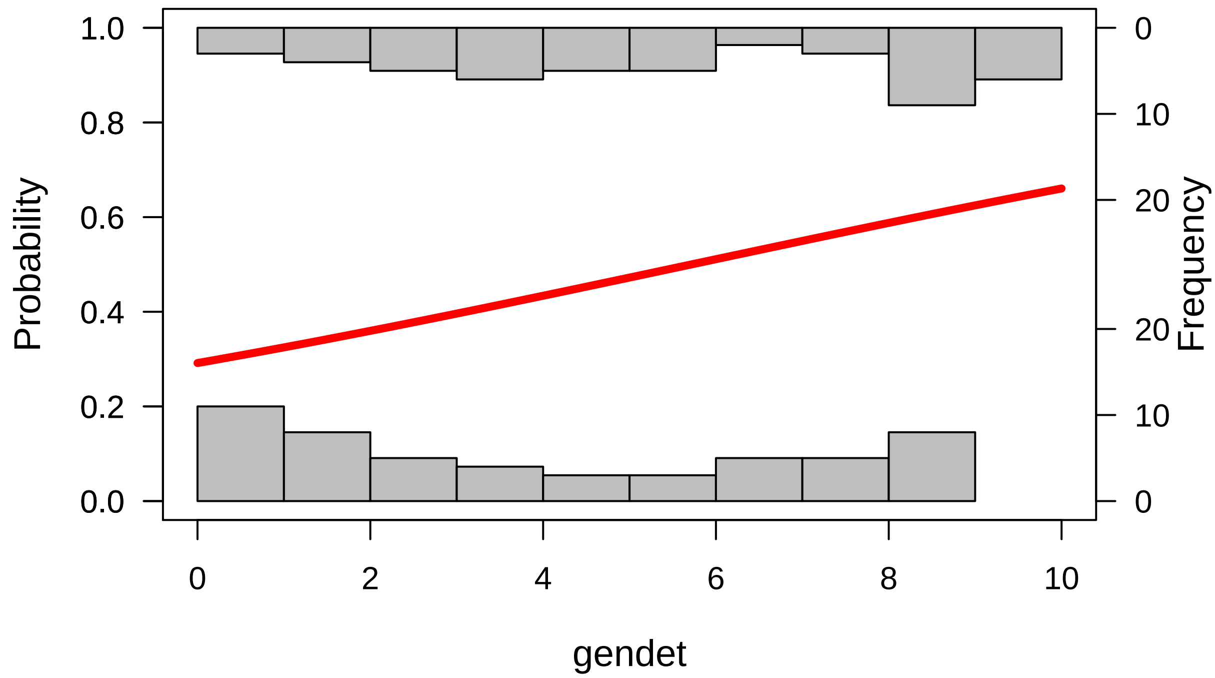

```r
logi.hist.plot(BL$rehab, BL$verdict, boxp=FALSE, type="hist", col="gray", xlabel = "rehab")
```



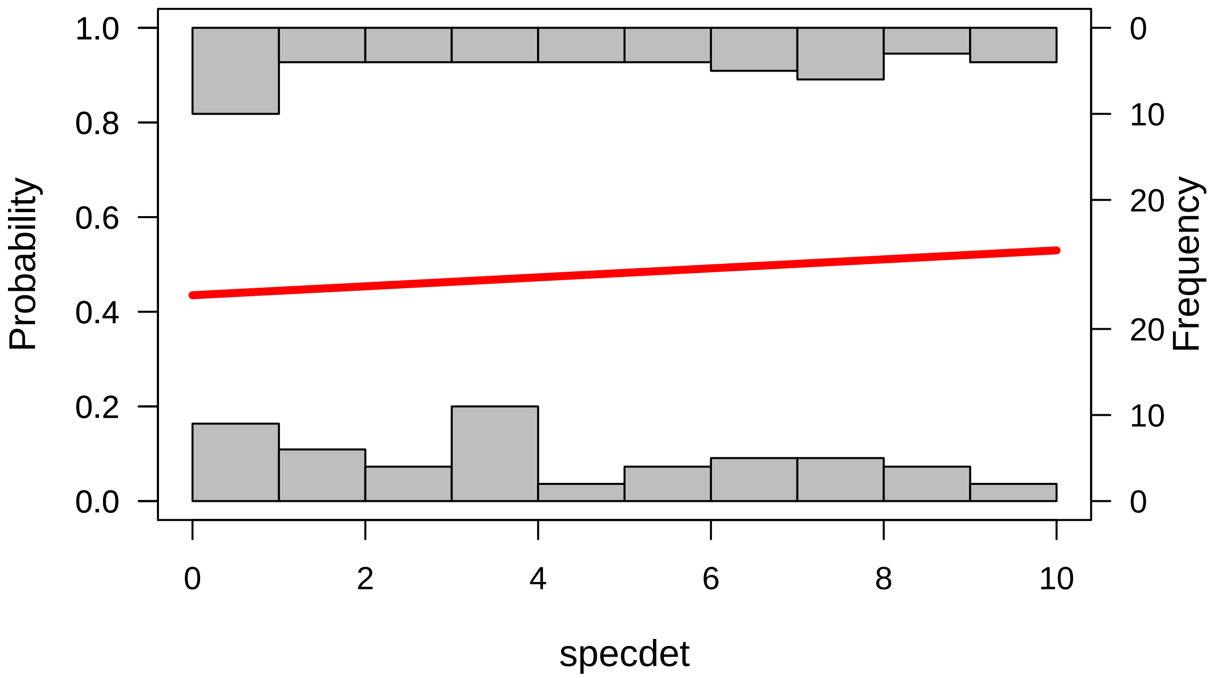

```
logi.hist.plot(BL$punish, BL$verdict, boxp=FALSE, type="hist", col="gray", xlabel = "punish")
```



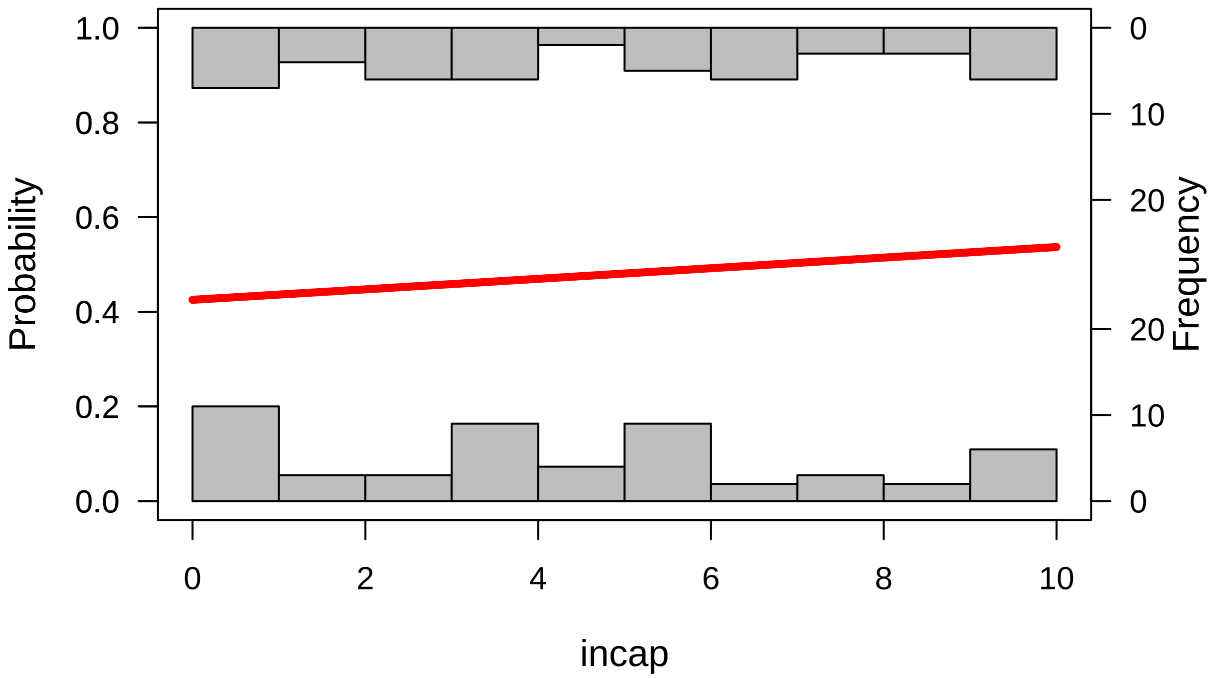

```
logi.hist.plot(BL$gendet, BL$verdict, boxp=FALSE, type="hist", col="gray", xlabel = "gendet")
```




```
logi.hist.plot(BL$specdet, BL$verdict, boxp=FALSE, type="hist", col="gray", xlabel = "specdet")
```




```
logi.hist.plot(BL$incap, BL$verdict, boxp=FALSE, type="hist", col="gray", xlabel = "incap")
```



BiLoRe Models

```
# Null model
# Null deviance = Chi squared for the model
# df = N - (# of parameters)
model0 <- glm(BL$verdict ~ 1, family = binomial)
summary(model0)
```

```
##
## Call:
## glm(formula = BL$verdict ~ 1, family = binomial)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.144   -1.144   -1.144    1.212    1.212
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.08004    0.20016    -0.4    0.689
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 138.47  on 99  degrees of freedom
## Residual deviance: 138.47  on 99  degrees of freedom
## AIC: 140.47
##
## Number of Fisher Scoring iterations: 3
```

```r
print("Logit")
```

```
## [1] "Logit"
```

```r
coef(model0)
```

```
## (Intercept)
## -0.08004271
```

```r
model0.odds <- exp(coef(model0)) #converts coefficient to odds [P(outcome)/(1-P(outcome))]
print("Odds")
```

```
## [1] "Odds"
```

```r
model0.odds
```

```
## (Intercept)
##   0.9230769
```

```r
model0.probs <- model0.odds / (1 + model0.odds) #
print("Probabilities")
```

```
## [1] "Probabilities"
```

```r
model0.probs
```

```
## (Intercept)
##        0.48
```

```r
print("Columns = Observed, Rows = Predicted")
```

```
## [1] "Columns = Observed, Rows = Predicted"
```

```r
print("Null model")
```

```
## [1] "Null model"
```

```r
ClassLog(model0, BL$verdict) # classification success under the null model (baseline)
```

```
## $rawtab
##        resp
##          0  1
##   FALSE 52 48
##
## $classtab
##        resp
##         0 1
##   FALSE 1 1
##
## $overall
## [1] 0.52
##
## $mcFadden
## [1] 2.220446e-16
```

```r
# Model with predictors specific to the defendent.
# when odds ratio < 1 just flip (invert) the result(in relation to "no" instead of in relation to "yes"
# AIC is used to compare non-nested models for fit (lower means better fit)
# top chi-squared indicates the change of chi-squared vs the null model (Deviance + chi squared)
```

```r
model1.jmv <- jmv::logRegBin(
  data = BL,
  dep = verdict,
  covs = vars(danger, specdet, incap, rehab, punish, gendet),
  blocks = list(
    list(
      'danger',
      'specdet',
      'incap')),
  refLevels = list(
    list(
      var = 'verdict',
      ref = '0')),
  modelTest = TRUE,
  OR = TRUE,
  class = TRUE,
  acc = TRUE,
  collin = TRUE)

model1.jmv
```

```
##
##  BINOMIAL LOGISTIC REGRESSION
##
##  Model Fit Measures
##  -------------------------------------------------------------
##    Model    Deviance    AIC    R²-McF    <U+03C7>²     df    p
##  -------------------------------------------------------------
##        1         126    134    0.0916    12.7     3    0.005
##  -------------------------------------------------------------
##
##
##  MODEL SPECIFIC RESULTS
##
##  MODEL 1
##
##  Model Coefficients
##  ----------------------------------------------------------------------
##    Predictor    Estimate    SE        Z         p        Odds ratio
##  ----------------------------------------------------------------------
##    Intercept     -1.4592    0.6289    -2.320    0.020         0.232
##    danger         0.2786    0.0868     3.208    0.001         1.321
##    specdet        0.0228    0.0719     0.316    0.752         1.023
##    incap          0.0220    0.0696     0.316    0.752         1.022
##  ----------------------------------------------------------------------
##    Note. Estimates represent the log odds of "verdict = 1" vs.
##    "verdict = 0"
##
##
##  ASSUMPTION CHECKS
##
##  Collinearity Statistics
##  --------------------------------
##                VIF     Tolerance
```

```
## --------------------------------
##   danger     1.01        0.986
##   specdet    1.01        0.988
##   incap      1.02        0.984
## --------------------------------
##
##
## PREDICTION
##
## Classification Table   verdict
## -------------------------------------
##   Observed    0     1     % Correct
## -------------------------------------
##          0    34    18         65.4
##          1    21    27         56.2
## -------------------------------------
##   Note. The cut-off value is set
##   to 0.5
##
##
## Predictive Measures
## -------------------
##   Accuracy
## -------------------
##      0.610
## -------------------
##   Note. The
##   cut-off value
##   is set to 0.5
```

```r
# Model with predictors about the criminal justice system.

#Multicollinearity

#Tolerance = 1 - R squared --> for our purpose < .4 is bad
#VIF = 1/Tolerance
#  Small VIF values indicates low correlation among variables under ideal conditions
#Multicollinearity occurs when two or more predictors in the model are correlated and provide redundant

model2.jmv <- jmv::logRegBin(
  data = BL,
  dep = verdict,
  covs = vars(danger, specdet, incap, rehab, punish, gendet),
  blocks = list(
    list(
      'rehab',
      'punish',
      'gendet')),
  refLevels = list(
    list(
      var = 'verdict',
      ref = '0')),
  modelTest = TRUE,
  OR = TRUE,
```

```r
  class = TRUE,
  acc = TRUE,
  collin = TRUE)

model2.jmv
```

```
##
##  BINOMIAL LOGISTIC REGRESSION
##
##  Model Fit Measures
##  -------------------------------------------------------------
##    Model    Deviance    AIC    R²-McF    <U+03C7>²      df    p
##  -------------------------------------------------------------
##        1         126    134    0.0901    12.5      3    0.006
##  -------------------------------------------------------------
##
##
##  MODEL SPECIFIC RESULTS
##
##  MODEL 1
##
##  Model Coefficients
##  --------------------------------------------------------------------
##    Predictor    Estimate    SE        Z         p         Odds ratio
##  --------------------------------------------------------------------
##    Intercept     -0.2619    0.5875    -0.446    0.656          0.770
##    rehab         -0.1946    0.0770    -2.527    0.011          0.823
##    punish         0.0373    0.0650     0.575    0.566          1.038
##    gendet         0.1830    0.0720     2.540    0.011          1.201
##  --------------------------------------------------------------------
##    Note. Estimates represent the log odds of "verdict = 1" vs.
##    "verdict = 0"
##
##
##  ASSUMPTION CHECKS
##
##  Collinearity Statistics
##  -------------------------------
##             VIF     Tolerance
##  -------------------------------
##    rehab     1.06        0.944
##    punish    1.01        0.991
##    gendet    1.05        0.952
##  -------------------------------
##
##
##  PREDICTION
##
##  Classification Table   verdict
##  -------------------------------------
##    Observed    0     1     % Correct
##  -------------------------------------
##           0    39    13         75.0
##           1    22    26         54.2
```

```
## -------------------------------------
##    Note. The cut-off value is set
##    to 0.5
##
##
##  Predictive Measures
##  -------------------
##    Accuracy
##  -------------------
##       0.650
##  -------------------
##    Note. The
##    cut-off value
##    is set to 0.5
```

```r
# Model with all predictors

model3.jmv <- jmv::logRegBin(
  data = BL,
  dep = verdict,
  covs = vars(danger, specdet, incap, rehab, punish, gendet),
  blocks = list(
    list(
      'danger',
      'specdet',
      'incap',
      'rehab',
      'punish',
      'gendet')),
  refLevels = list(
    list(
      var = 'verdict',
      ref = '0')),
  modelTest = TRUE,
  OR = TRUE,
  class = TRUE,
  acc = TRUE,
  collin = TRUE)

model3.jmv
```

```
##
##  BINOMIAL LOGISTIC REGRESSION
##
##  Model Fit Measures
##  -------------------------------------------------------------
##    Model    Deviance    AIC    R²-McF    <U+03C7>²     df    p
##  -------------------------------------------------------------
##        1         114    128     0.176    24.4      6    < .001
##  -------------------------------------------------------------
##
##
##  MODEL SPECIFIC RESULTS
##
##  MODEL 1
```

```
##
## Model Coefficients
## ----------------------------------------------------------------------
##   Predictor    Estimate    SE        Z          p        Odds ratio
## ----------------------------------------------------------------------
##   Intercept    -1.74758    0.9173    -1.9052    0.057         0.174
##   danger        0.29339    0.0929     3.1575    0.002         1.341
##   specdet       0.00590    0.0786     0.0751    0.940         1.006
##   incap         0.00353    0.0759     0.0465    0.963         1.004
##   rehab        -0.18784    0.0814    -2.3077    0.021         0.829
##   punish        0.07012    0.0711     0.9861    0.324         1.073
##   gendet        0.18574    0.0773     2.4019    0.016         1.204
## ----------------------------------------------------------------------
##   Note. Estimates represent the log odds of "verdict = 1" vs.
##   "verdict = 0"
##
##
## ASSUMPTION CHECKS
##
## Collinearity Statistics
## --------------------------------
##              VIF     Tolerance
## --------------------------------
##   danger     1.07        0.933
##   specdet    1.02        0.977
##   incap      1.05        0.955
##   rehab      1.04        0.957
##   punish     1.06        0.941
##   gendet     1.06        0.948
## --------------------------------
##
##
## PREDICTION
##
## Classification Table   verdict
## -------------------------------------
##   Observed    0     1     % Correct
## -------------------------------------
##          0    39    13         75.0
##          1    16    32         66.7
## -------------------------------------
##   Note. The cut-off value is set
##   to 0.5
##
##
## Predictive Measures
## ------------------
##   Accuracy
## ------------------
##      0.710
## ------------------
##   Note. The
##   cut-off value
##   is set to 0.5
```

Model Comparison

```
# Model1 vs. Model3
# This is a similar set up to multiple regression in terms of the code, so if you know you will be runn

modelcomp.jmv <- jmv::logRegBin(
  data = BL,
  dep = verdict,
  covs = vars(danger, specdet, incap, rehab, punish, gendet),
  blocks = list(
    list(
      'danger',
      'specdet',
      'incap'),
    list(
      'rehab',
      'punish',
      'gendet')),
  refLevels = list(
    list(
      var = 'verdict',
      ref = '0')),
  modelTest = TRUE,
  OR = TRUE,
  class = TRUE,
  acc = TRUE,
  collin = TRUE)

modelcomp.jmv
```

```
##
##  BINOMIAL LOGISTIC REGRESSION
##
##  Model Fit Measures
##  --------------------------------------------------------------
##    Model    Deviance    AIC    R²-McF    <U+03C7>²      df    p
##  --------------------------------------------------------------
##        1         126    134    0.0916    12.7     3     0.005
##        2         114    128    0.1763    24.4     6    < .001
##  --------------------------------------------------------------
##
##
##  Model Comparisons
##  ----------------------------------------------
##    Model         Model    <U+03C7>²      df    p
##  ----------------------------------------------
##        1    -        2    11.7     3    0.008
##  ----------------------------------------------
##
##
##  MODEL SPECIFIC RESULTS
##
##  MODEL 1
##
##  Model Coefficients
```

```
## ------------------------------------------------------------------
##   Predictor    Estimate    SE        Z         p        Odds ratio
## ------------------------------------------------------------------
##   Intercept     -1.4592    0.6289    -2.320    0.020         0.232
##   danger         0.2786    0.0868     3.208    0.001         1.321
##   specdet        0.0228    0.0719     0.316    0.752         1.023
##   incap          0.0220    0.0696     0.316    0.752         1.022
## ------------------------------------------------------------------
##   Note. Estimates represent the log odds of "verdict = 1" vs.
##   "verdict = 0"
##
##
## ASSUMPTION CHECKS
##
## Collinearity Statistics
## --------------------------------
##              VIF     Tolerance
## --------------------------------
##   danger     1.01        0.986
##   specdet    1.01        0.988
##   incap      1.02        0.984
## --------------------------------
##
##
## PREDICTION
##
## Classification Table   verdict
## -------------------------------------
##   Observed    0     1     % Correct
## -------------------------------------
##          0    34    18         65.4
##          1    21    27         56.2
## -------------------------------------
##   Note. The cut-off value is set
##   to 0.5
##
##
## Predictive Measures
## ------------------
##   Accuracy
## ------------------
##      0.610
## ------------------
##   Note. The
##   cut-off value
##   is set to 0.5
##
##
## MODEL 2
##
## Model Coefficients
## -------------------------------------------------------------------
##   Predictor    Estimate    SE        Z          p        Odds ratio
## -------------------------------------------------------------------
```

```
##    Intercept    -1.74758    0.9173    -1.9052    0.057          0.174
##    danger        0.29339    0.0929     3.1575    0.002          1.341
##    specdet       0.00590    0.0786     0.0751    0.940          1.006
##    incap         0.00353    0.0759     0.0465    0.963          1.004
##    rehab        -0.18784    0.0814    -2.3077    0.021          0.829
##    punish        0.07012    0.0711     0.9861    0.324          1.073
##    gendet        0.18574    0.0773     2.4019    0.016          1.204
##  ---------------------------------------------------------------------
##    Note. Estimates represent the log odds of "verdict = 1" vs.
##    "verdict = 0"
##
##
##  ASSUMPTION CHECKS
##
##  Collinearity Statistics
##  --------------------------------
##               VIF     Tolerance
##  --------------------------------
##    danger     1.07        0.933
##    specdet    1.02        0.977
##    incap      1.05        0.955
##    rehab      1.04        0.957
##    punish     1.06        0.941
##    gendet     1.06        0.948
##  --------------------------------
##
##
##  PREDICTION
##
##  Classification Table   verdict
##  -------------------------------------
##    Observed    0     1     % Correct
##  -------------------------------------
##           0    39    13         75.0
##           1    16    32         66.7
##  -------------------------------------
##    Note. The cut-off value is set
##    to 0.5
##
##
##  Predictive Measures
##  -------------------
##    Accuracy
##  -------------------
##       0.710
##  -------------------
##    Note. The
##    cut-off value
##    is set to 0.5
```

Center Predictors

```r
BL$dangerC <- BL$danger - mean(BL$danger)
BL$rehabC <- BL$rehab - mean(BL$rehab)
BL$punishC <- BL$punish - mean(BL$punish)
```

```r
BL$gendetC <- BL$gendet - mean(BL$gendet)
BL$specdetC <- BL$specdet - mean(BL$specdet)
BL$incapC <- BL$incap - mean(BL$incap)
```

Re-run model with all predictors and run parsimonious model.

```r
#remove not significant predictors

finalmodel.jmv <- logRegBin(
  data = BL,
  dep = verdict,
  covs = vars(dangerC, specdetC, incapC, rehabC, punishC, gendetC),
  blocks = list(
    list(
      'dangerC', # significant predictors only
      'rehabC',
      'gendetC'),
    list(
      'specdetC', # full model
      'incapC',
      'punishC')),
  refLevels = list(
    list(
      var = 'verdict',
      ref = '0')),
  modelTest = TRUE,
  OR = TRUE,
  class = TRUE,
  acc = TRUE,
  collin = TRUE)

finalmodel.jmv
```

```
##
##  BINOMIAL LOGISTIC REGRESSION
##
##  Model Fit Measures
##  --------------------------------------------------------------
##    Model    Deviance    AIC    R²-McF    <U+03C7>²      df    p
##  --------------------------------------------------------------
##        1         115    123     0.169    23.4     3    < .001
##        2         114    128     0.176    24.4     6    < .001
##  --------------------------------------------------------------
##
##
##  Model Comparisons
##  ----------------------------------------------
##    Model         Model    <U+03C7>²      df    p
##  ----------------------------------------------
##        1    -        2    1.00     3    0.801
##  ----------------------------------------------
##
##
##  MODEL SPECIFIC RESULTS
```

```
##
##  MODEL 1
##
##  Model Coefficients
##  ------------------------------------------------------------------
##    Predictor    Estimate    SE        Z         p        Odds ratio
##  ------------------------------------------------------------------
##    Intercept     -0.0955    0.2263    -0.422    0.673         0.909
##    dangerC        0.2797    0.0888     3.151    0.002         1.323
##    rehabC        -0.1807    0.0806    -2.242    0.025         0.835
##    gendetC        0.1881    0.0765     2.460    0.014         1.207
##  ------------------------------------------------------------------
##    Note. Estimates represent the log odds of "verdict = 1" vs.
##    "verdict = 0"
##
##
##  ASSUMPTION CHECKS
##
##  Collinearity Statistics
##  -------------------------------
##               VIF     Tolerance
##  -------------------------------
##    dangerC    1.01        0.992
##    rehabC     1.03        0.972
##    gendetC    1.04        0.964
##  -------------------------------
##
##
##  PREDICTION
##
##  Classification Table   verdict
##  ------------------------------------
##    Observed    0     1     % Correct
##  ------------------------------------
##           0    37    15         71.2
##           1    16    32         66.7
##  ------------------------------------
##    Note. The cut-off value is set
##    to 0.5
##
##
##  Predictive Measures
##  -------------------
##    Accuracy
##  -------------------
##       0.690
##  -------------------
##    Note. The
##    cut-off value
##    is set to 0.5
##
##
##  MODEL 2
##
```

```
## Model Coefficients
## ------------------------------------------------------------------
##   Predictor    Estimate    SE        Z          p        Odds ratio
## ------------------------------------------------------------------
##   Intercept    -0.09352    0.2277    -0.4108    0.681         0.911
##   dangerC       0.29339    0.0929     3.1575    0.002         1.341
##   rehabC       -0.18784    0.0814    -2.3077    0.021         0.829
##   gendetC       0.18574    0.0773     2.4019    0.016         1.204
##   specdetC      0.00590    0.0786     0.0751    0.940         1.006
##   incapC        0.00353    0.0759     0.0465    0.963         1.004
##   punishC       0.07012    0.0711     0.9861    0.324         1.073
## ------------------------------------------------------------------
##   Note. Estimates represent the log odds of "verdict = 1" vs.
##   "verdict = 0"
##
##
## ASSUMPTION CHECKS
##
## Collinearity Statistics
## ---------------------------------
##              VIF     Tolerance
## ---------------------------------
##   dangerC     1.07        0.933
##   rehabC      1.04        0.957
##   gendetC     1.06        0.948
##   specdetC    1.02        0.977
##   incapC      1.05        0.955
##   punishC     1.06        0.941
## ---------------------------------
##
##
## PREDICTION
##
## Classification Table   verdict
## -------------------------------------
##   Observed    0     1     % Correct
## -------------------------------------
##          0    39    13         75.0
##          1    16    32         66.7
## -------------------------------------
##   Note. The cut-off value is set
##   to 0.5
##
##
## Predictive Measures
## ------------------
##   Accuracy
## ------------------
##      0.710
## ------------------
##   Note. The
##   cut-off value
##   is set to 0.5
```

Use regression equation to calculate predicted logit, odds, and probability

```
# Let D = danger, R = rehab, G = gendet
D = 10
R = 0
G = 10

predlogit <- -.096 + (.278*D) + (-.181*R) + (.188*G)
predodds <- exp(predlogit)
predprob <- predodds / (1 + predodds)

predlogit
```

```
## [1] 4.564
```

```
predodds
```

```
## [1] 95.96658
```

```
predprob
```

```
## [1] 0.9896872
```