Lab 10. Binary logistic regression

Libraries

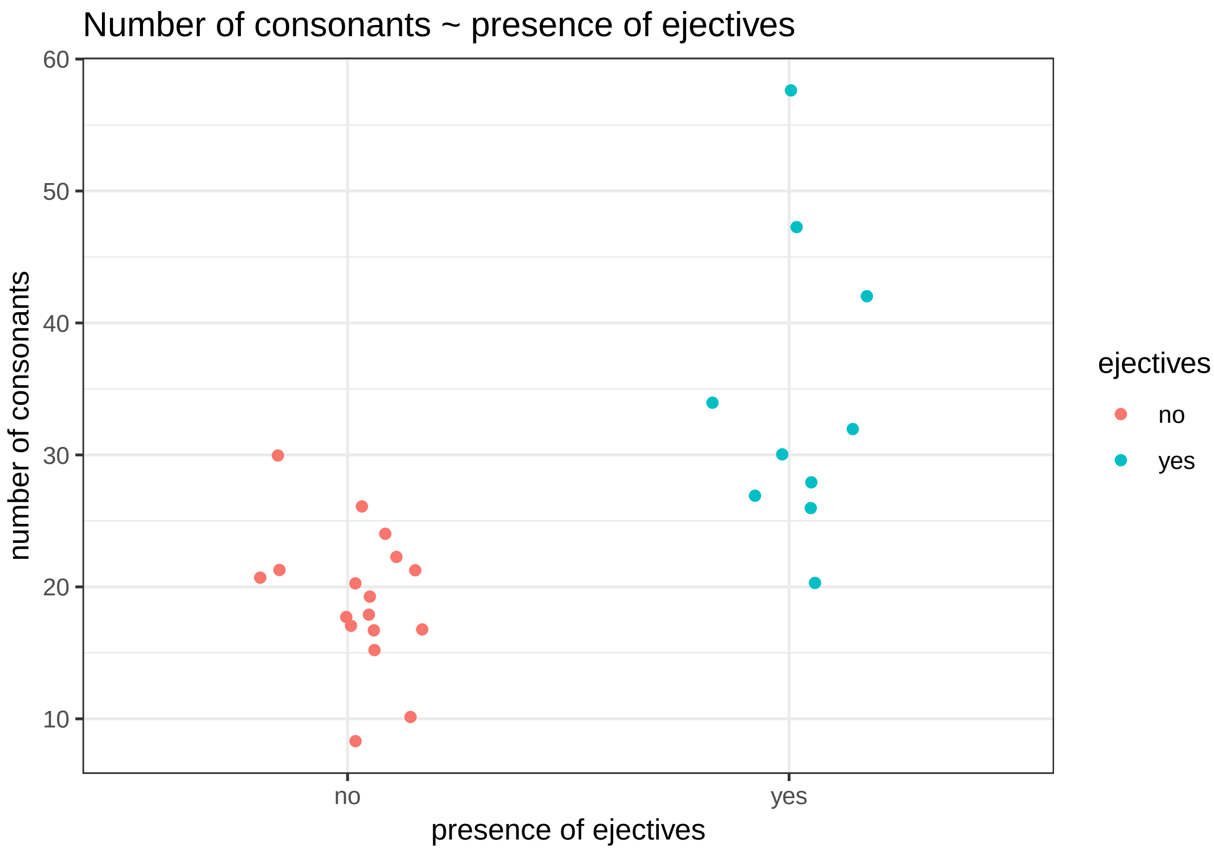
```
library(tidyverse)
library(stats) # glm() function for logit regression models
library(caret) # library to calculate confusion matrix and agreement
library(pROC) # library to draw ROC curves
```

1 Logit model with one numeric predictor

It is interesting to know whether the languages with more consonants are more likely to have ejective sounds. So we collected data from phonological database LAPSyD: http://goo.gl/0btfKa.

1.1 Data summary

```
ej_cons <- read.csv("https://agricolamz.github.io/2018-MAG_R_course/data/correlation_regressions_ejecti
ej_cons %>%
  ggplot(aes(ejectives, n.cons.lapsyd, color = ejectives))+
  geom_jitter(width = 0.2)+
  labs(title = "Number of consonants ~ presence of ejectives",
       x = "presence of ejectives",
       y = "number of consonants")+
  theme_bw()
```



1.2 Model without predictors

```
fit1 <- glm(ejectives~1, data = ej_cons, family = "binomial")
summary(fit1)
```

```
##
## Call:
## glm(formula = ejectives ~ 1, family = "binomial", data = ej_cons)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9619  -0.9619  -0.9619   1.4094   1.4094
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.5306     0.3985  -1.331    0.183
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 35.594  on 26  degrees of freedom
## Residual deviance: 35.594  on 26  degrees of freedom
## AIC: 37.594
##
## Number of Fisher Scoring iterations: 4
```

How we get this estimate value?

```r
table(ej_cons$ejectives)
```

```
##
##  no yes
##  17  10
```

```r
log(10/17)
```

```
## [1] -0.5306283
```

What does this model say? This model says that if we have no predictors and take some language it has $\frac{1}{(1+e^{0.5306283})} = 0.37037$ probability to have ejectives.

```r
1/(1+exp(0.5306283))
```

```
## [1] 0.3703704
```

1.3 Model with numeric predictor

```r
fit2 <- glm(ejectives~n.cons.lapsyd, data = ej_cons, family = "binomial")
summary(fit2)
```

```
##
## Call:
## glm(formula = ejectives ~ n.cons.lapsyd, family = "binomial",
##     data = ej_cons)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8317  -0.4742  -0.2481   0.1914   2.1997
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -9.9204     3.7699  -2.631   0.0085 **
## n.cons.lapsyd   0.3797     0.1495   2.540   0.0111 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 35.594  on 26  degrees of freedom
## Residual deviance: 16.202  on 25  degrees of freedom
## AIC: 20.202
##
## Number of Fisher Scoring iterations: 6
```

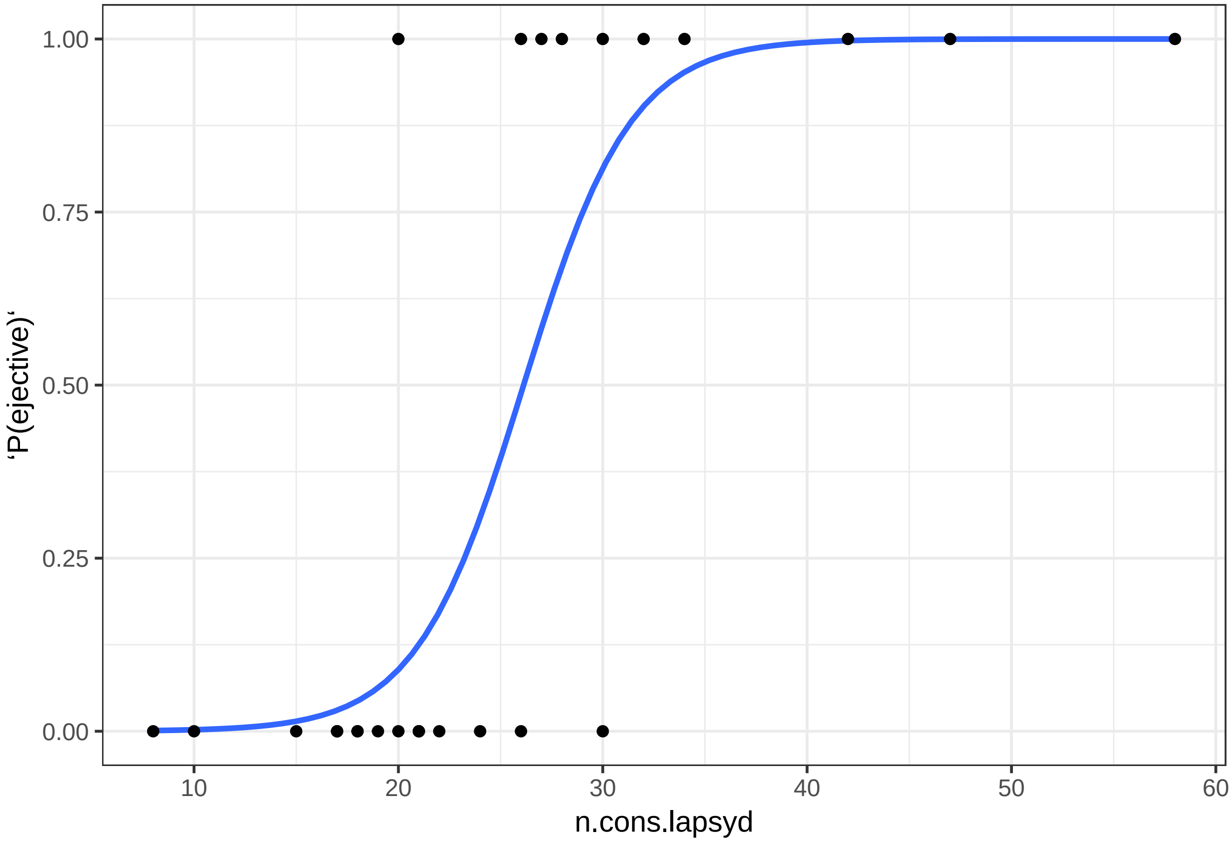
What does this model say? This model says:

$$\log(odds(ej)) = \beta_o + \beta_1 \times n.cons.lapsyd = -9.9204 + 0.3797 \times n.cons.lapsyd$$

Lets visualize our model:

```r
ej_cons %>%
  mutate(`P(ejective)` = as.numeric(ejectives) - 1) %>%
  ggplot(aes(x = n.cons.lapsyd, y = `P(ejective)`))+
```

```r
  geom_smooth(method = "glm", method.args = list(family = "binomial"), se = FALSE) +
  geom_point()+
  theme_bw()
```



So probability for a language that have 30 consonants will be

$$\log(odds(ej)) = -9.9204 + 0.3797 \times 30 = 1.4706$$

$$P(ej) = \frac{1.47061}{1 + 1.4706} = 0.8131486$$

1.4 predict()

```r
new.df <- data.frame(n.cons.lapsyd = c(30, 55, 34, 10))
predict(fit2, new.df) # odds
```

```
##         1         2         3         4
##  1.470850 10.963579  2.989686 -6.123334
```

```r
predict(fit2, new.df, type = "response") # probabilities
```

```
##           1           2           3           4
## 0.813186486 0.999982679 0.952106011 0.002186347
```

```r
predict(fit2, new.df, type = "response", se.fit = TRUE) # probabilities and confidense interval
```

```
## $fit
```

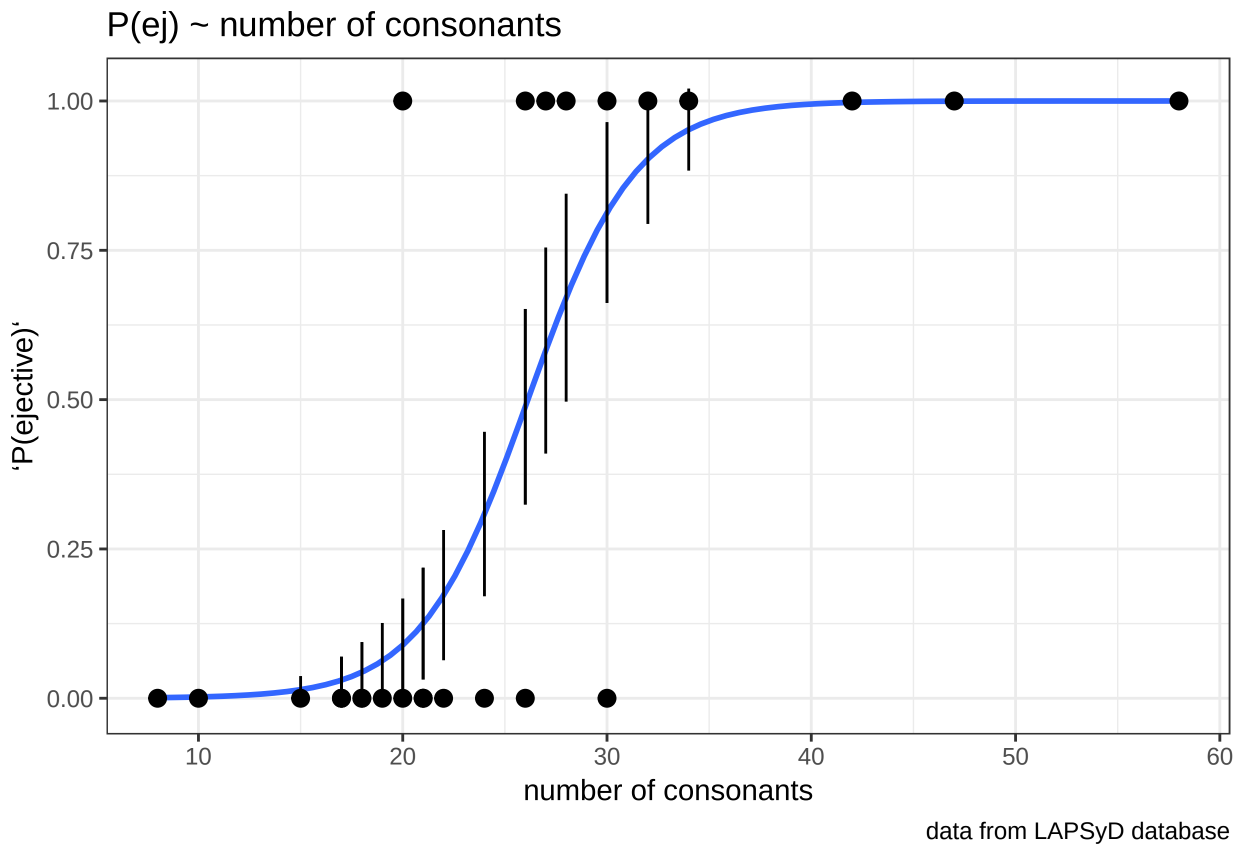
```
##           1           2           3           4 
## 0.813186486 0.999982679 0.952106011 0.002186347 
## 
## $se.fit
##            1            2            3            4 
## 1.512886e-01 7.882842e-05 6.869366e-02 5.038557e-03 
## 
## $residual.scale
## [1] 1
```

So we actually can create a plot with confidense intervals.

```
ej_cons_ci <- cbind.data.frame(ej_cons, predict(fit2, ej_cons, type = "response", se.fit = TRUE)[1:2])
ej_cons_ci
```

```
##          name n.cons.lapsyd ejectives         fit       se.fit
## 1     Turkish            24        no 0.308443627 1.376976e-01
## 2      Korean            21        no 0.124931874 9.358363e-02
## 3        Tiwi            21        no 0.124931874 9.358363e-02
## 4      Kpelle            22        no 0.172669632 1.090491e-01
## 5        Tulu            21        no 0.124931874 9.358363e-02
## 6  Mapudungun            20        no 0.088972775 7.806484e-02
## 7       Kiowa            19        no 0.062623081 6.341445e-02
## 8     Guarani            18        no 0.043702625 5.034610e-02
## 9    Japanese            15        no 0.014417525 2.278884e-02
## 10      Batak            17        no 0.030313786 3.921885e-02
## 11     Yoruba            18        no 0.043702625 5.034610e-02
## 12    Finnish            17        no 0.030313786 3.921885e-02
## 13  Kayardild            17        no 0.030313786 3.921885e-02
## 14   Hawaiian             8        no 0.001024268 2.658820e-03
## 15      Maori            10        no 0.002186347 5.038557e-03
## 16  Hungarian            26        no 0.488005505 1.637595e-01
## 17    Kannada            30        no 0.813186486 1.512886e-01
## 18   Georgean            28       yes 0.670717326 1.740778e-01
## 19     Ingush            34       yes 0.952106011 6.869366e-02
## 20     Abkhaz            58       yes 0.999994456 2.769836e-05
## 21    Amharic            32       yes 0.902934848 1.088031e-01
## 22    Sandawe            47       yes 0.999638868 1.216840e-03
## 23    Tlingit            42       yes 0.997593950 6.337117e-03
## 24     Lakota            30       yes 0.813186486 1.512886e-01
## 25    Yucatec            20       yes 0.088972775 7.806484e-02
## 26     Aymara            27       yes 0.582178309 1.725265e-01
## 27       Pomo            26       yes 0.488005505 1.637595e-01
```

```
ej_cons_ci %>%
  mutate(`P(ejective)` = as.numeric(ejectives) - 1) %>%
  ggplot(aes(x = n.cons.lapsyd, y = `P(ejective)`))+
  geom_smooth(method = "glm", method.args = list(family = "binomial"), se = FALSE)+
  geom_point() +
  geom_pointrange(aes(x = n.cons.lapsyd, ymin = fit - se.fit, ymax = fit + se.fit))+
  labs(title = "P(ej) ~ number of consonants",
       x = "number of consonants",
       caption = "data from LAPSyD database")+
  theme_bw()
```



2. Choice betweeen two constructions in Russian

The Russian verb *gruzit'* 'load' is special for three reasons. First, this verb has two syntactic constructions it can appear in, second, it has three perfective counterparts with the prefixes *NA-*, *PO-*, and *ZA-* that do not add to its lexical meaning (and thus can be cosidered Natural Perfectives), and third all three Natural Perfectives can also use both constructions.

The two constructions that *gruzit'* 'load' can appear in are called the '"THEME-object" construction and the '"GOAL-object" construction, and this phenomenon is known in many languages as Locative Alternation. We can illustrate these two constructions in Russian with the following examples:

- THEME-object: *gruzit' jaschiki*.ACC *na telegu*(PP) 'load the boxes.THEME onto the cart.GOAL'. The goal appears in a prepositional phrase in the theme-object construction, usually with the preposition *na* `onto' or _v_into`'.
- GOAL-object: *gruzit' telegu*.ACC *jaschikami*.INS 'load the cart.GOAL with boxes.THEME'. The theme in the GOAL-object construction appears in the instrumental case. *gruzit'*

The verb 'load' uses not just one, but three prefixes to form Natural Perfectives: *NA-*, *ZA-*, and *PO-*. Collectively we call these four verbs (the simplex and the three Natural Perfectives) '"the 'load' verbs". All three Natural Perfectives can appear in both the THEME-object and the GOAL-object constructions. Janda et al. 2013, chapter 4 explores whether the choice of prefix makes a difference in the distribution of the THEME-object and GOAL-object constructions. Along with the prefixes, they test whether the passive construction (ie. construction with passive participle) and omission of the prepositional phrase (ie. reduced construction) could motivate the choice between the THEME-object and GOAL-object constructions.

The dataset: There are 1920 lines of data, each corresponding to one of the examples extracted from the Russian National Corpus. The dataset includes four variables:

* CONSTRUCTION: This is our dependent variable, and it has two values, `theme`, and `goal`.
* VERB: This is an independent variable, and it has four values, `\_zero` (for the unprefixed verb *gruzit'* 'load'), `na`, `za`, and `po` (for the three prefixed variants).
* REDUCED: This is an independent variable, and it has two values, yes and no. This refers to whether the construction was reduced (`yes`) or full (`no`).
* PARTICIPLE: This is an independent variable, and it has two values, yes and no. This refers to whether the construction was passive (`yes`) or active (`no`).

Source: Trolling repository References: Janda et al. (2013), Why Russian aspectual prefixes aren't empty: prefixes as verb classifiers. Bloomington, IN: Slavica Publishers.

2.1 Data summary

```
loaddata = read.csv('https://raw.githubusercontent.com/LingData2019/LingData/master/data/loaddata.csv')
summary(loaddata)
```

```
##  CONSTRUCTION    VERB      REDUCED    PARTICIPLE
##  goal : 871   _zero:393   no :1353   no : 895
##  theme:1049   na   :368   yes: 567   yes:1025
##                po   :703
##                za   :456
```

2.2 Formulate your hypothesis, what motivates the choice between two constructions?

2.3 Fit the simplest logistic regression model using `VERB` as the only factor.

```
# use glm() in the following way: fit <- glm(Dependent_variable ~ Factor_variable(s), family = binomial
load.glm <- glm(CONSTRUCTION ~ VERB, family=binomial, data=loaddata)
print(summary(load.glm))
```

```
##
## Call:
## glm(formula = CONSTRUCTION ~ VERB, family = binomial, data = loaddata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.3036  -0.7235   0.0925   0.0925   2.1692
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.1274     0.1011   1.260    0.208
## VERBna       -2.3802     0.2044 -11.643   <2e-16 ***
## VERBpo        5.3251     0.5873   9.066   <2e-16 ***
## VERBza       -1.3342     0.1503  -8.877   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2645.2  on 1919  degrees of freedom
```

```
## Residual deviance: 1305.3  on 1916  degrees of freedom
## AIC: 1313.3
##
## Number of Fisher Scoring iterations: 8
```

2.4 Formulate the results of your analysis as text:

```

```

2.5 Add more factors to your model, one by one.

Note that we do not consider possible interactions here yet.

```
load.glm1 <- glm(CONSTRUCTION ~ VERB + REDUCED, family=binomial, data=loaddata)
print(summary(load.glm1))
```

```
##
## Call:
## glm(formula = CONSTRUCTION ~ VERB + REDUCED, family = binomial,
##     data = loaddata)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -3.16027  -0.63733   0.08946   0.08946   2.31723
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.3086     0.1132   2.727 0.006399 **
## VERBna       -2.3906     0.2054 -11.636  < 2e-16 ***
## VERBpo        5.2104     0.5881   8.859  < 2e-16 ***
## VERBza       -1.2673     0.1519  -8.343  < 2e-16 ***
## REDUCEDyes   -0.5321     0.1445  -3.682 0.000231 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2645.2  on 1919  degrees of freedom
## Residual deviance: 1291.5  on 1915  degrees of freedom
## AIC: 1301.5
##
## Number of Fisher Scoring iterations: 8
```

```
load.glm2 <- glm(CONSTRUCTION ~ VERB + REDUCED + PARTICIPLE, family=binomial, data=loaddata)
print(summary(load.glm2))
```

```
##
## Call:
## glm(formula = CONSTRUCTION ~ VERB + REDUCED + PARTICIPLE, family = binomial,
##     data = loaddata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.9999  -0.2447   0.0173   0.1116   3.0746
```

```
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)       1.2315     0.1513   8.137 4.07e-16 ***
## VERBna           -2.2183     0.2331  -9.515  < 2e-16 ***
## VERBpo            7.5756     0.6447  11.751  < 2e-16 ***
## VERBza           -0.9941     0.1842  -5.398 6.75e-08 ***
## REDUCEDyes       -0.8078     0.1728  -4.676 2.93e-06 ***
## PARTICIPLEyes    -3.7309     0.2900 -12.867  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2645.16  on 1919  degrees of freedom
## Residual deviance:  928.19  on 1914  degrees of freedom
## AIC: 940.19
##
## Number of Fisher Scoring iterations: 8
```

2.6 Which model fits your data the best according to AIC?

Note that this model should include only significant factors.

AIC (Akaike Information Criterion) is a goodness-of-fit measure to compare the models with different number of predictors. It penalizes a model for having too many predictors. The smaller AIC, the better.

```
Name of the model:
AIC:
```

2.7 Fit the model with all factors and all possible interactions.

Hint: Dependent_variable ~ Factor1 * Factor2 * Factor3 (the same as: Factor1 + Factor2 + Factor3 + Factor1:Factor2 + … + Factor1:Factor2:Factor3)

```r
load.glm3 <- glm(CONSTRUCTION ~ VERB * REDUCED * PARTICIPLE, family=binomial, data=loaddata)
print(summary(load.glm3))
```

```
##
## Call:
## glm(formula = CONSTRUCTION ~ VERB * REDUCED * PARTICIPLE, family = binomial,
##     data = loaddata)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.77494  -0.26308   0.00008   0.00008   3.13218
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                         1.4542     0.1963   7.407 1.29e-13 ***
## VERBna                             -2.4069     0.2998  -8.029 9.85e-16 ***
## VERBpo                             18.1118   747.4556   0.024 0.980668
## VERBza                             -1.4225     0.2651  -5.365 8.10e-08 ***
## REDUCEDyes                         -1.0202     0.2727  -3.741 0.000183 ***
```

```
## PARTICIPLEyes                        -5.9541     1.0245  -5.812 6.19e-09 ***
## VERBna:REDUCEDyes                     0.1576     0.5402   0.292 0.770515
## VERBpo:REDUCEDyes                   -14.7172   747.4563  -0.020 0.984291
## VERBza:REDUCEDyes                     0.4384     0.3984   1.101 0.271097
## VERBna:PARTICIPLEyes                  2.0089     1.4520   1.383 0.166519
## VERBpo:PARTICIPLEyes                  5.9541   910.7860   0.007 0.994784
## VERBza:PARTICIPLEyes                  3.1602     1.1219   2.817 0.004849 **
## REDUCEDyes:PARTICIPLEyes            -14.0461  2688.5034  -0.005 0.995831
## VERBna:REDUCEDyes:PARTICIPLEyes       0.2405  2927.9353   0.000 0.999934
## VERBpo:REDUCEDyes:PARTICIPLEyes      12.5200  2838.5881   0.004 0.996481
## VERBza:REDUCEDyes:PARTICIPLEyes      14.0436  2688.5035   0.005 0.995832
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2645.16  on 1919  degrees of freedom
## Residual deviance:  893.46  on 1904  degrees of freedom
## AIC: 925.46
##
## Number of Fisher Scoring iterations: 18
```

2.8 Remove all insignificant interactions and report the minimal optimal model here:

```r
load.glm4 <- glm(CONSTRUCTION ~ VERB + REDUCED + PARTICIPLE + VERB:PARTICIPLE, family=binomial, data=loa
print(summary(load.glm4))
```

```
##
## Call:
## glm(formula = CONSTRUCTION ~ VERB + REDUCED + PARTICIPLE + VERB:PARTICIPLE,
##     family = binomial, data = loaddata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.1261  -0.2414   0.0790   0.0914   3.2058
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)            1.3872     0.1616   8.584  < 2e-16 ***
## VERBna                -2.3336     0.2446  -9.539  < 2e-16 ***
## VERBpo                 4.3806     1.0118   4.330 1.49e-05 ***
## VERBza                -1.2416     0.1981  -6.267 3.68e-10 ***
## REDUCEDyes            -0.8891     0.1748  -5.085 3.67e-07 ***
## PARTICIPLEyes         -5.9579     1.0169  -5.859 4.66e-09 ***
## VERBna:PARTICIPLEyes   1.7717     1.4415   1.229 0.219043
## VERBpo:PARTICIPLEyes   5.6670     1.5926   3.558 0.000373 ***
## VERBza:PARTICIPLEyes   3.1804     1.0729   2.964 0.003034 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2645.16  on 1919  degrees of freedom
```

```
## Residual deviance:  906.69  on 1911  degrees of freedom
## AIC: 924.69
##
## Number of Fisher Scoring iterations: 8
```

2.9 Check the 95% confidence intevals of the estimated coefficients.

Use confint(model_name) to calculate them.

```
print("These are the confidence interval values:")
```

```
## [1] "These are the confidence interval values:"
```

```
confint(load.glm4)
```

```
## Waiting for profiling to be done...

##                            2.5 %     97.5 %
## (Intercept)             1.077659  1.7120139
## VERBna                 -2.825357 -1.8647411
## VERBpo                  2.859036  7.2560372
## VERBza                 -1.634089 -0.8567527
## REDUCEDyes             -1.235253 -0.5492324
## PARTICIPLEyes          -8.838291 -4.4202915
## VERBna:PARTICIPLEyes -1.494244  5.0379696
## VERBpo:PARTICIPLEyes  2.219574  9.1864343
## VERBza:PARTICIPLEyes  1.461953  6.1140973
```

If a 95% confidence interval contains zero, this indicates that the corresponding effect is not significant. You can also use `exp(confint(...))` to obtain simple odds ratios. The confidence interval of a significant effect based on simple odds ratios should not include 1.

2.10 Report the odds of success for each predictor variable.

Use exp(model_name$coefficients)

```
print("These are the odds of success for each predictor variable:")
```

```
## [1] "These are the odds of success for each predictor variable:"
```

```
print(exp(load.glm$coefficients))
```

```
##   (Intercept)        VERBna        VERBpo        VERBza
##    1.13586957    0.09253272 205.42264752    0.26336237
```

2.11 Additional code: stepwise selection of variables

See examples from Levshina 2015: m0.glm <- glm(Aux ~ 1, data = doenLaten, family = binomial) m.fw <- step(m0.glm, direction = "forward", scope = ~ Causation + EPTrans + Country)

m.glm <- glm(Aux ~ Causation + EPTrans + Country, data = doenLaten, family = binomial) m.bw <- step(m.glm, direction = "backward")

```
load.glm0 <- glm(CONSTRUCTION ~ 1, family=binomial, data=loaddata)
load.glm.fw <- step(load.glm0, direction = "forward", scope = ~ VERB + REDUCED + PARTICIPLE)
```

```
## Start:  AIC=2647.16
## CONSTRUCTION ~ 1
##
##              Df Deviance    AIC
## + VERB        3   1305.3 1313.3
## + REDUCED     1   2470.5 2474.5
## + PARTICIPLE  1   2559.9 2563.9
## <none>            2645.2 2647.2
##
## Step:  AIC=1313.31
## CONSTRUCTION ~ VERB
##
##              Df Deviance     AIC
## + PARTICIPLE  1   950.73  960.73
## + REDUCED     1  1291.51 1301.51
## <none>           1305.31 1313.31
##
## Step:  AIC=960.73
## CONSTRUCTION ~ VERB + PARTICIPLE
##
##           Df Deviance    AIC
## + REDUCED  1   928.19 940.19
## <none>         950.73 960.73
##
## Step:  AIC=940.19
## CONSTRUCTION ~ VERB + PARTICIPLE + REDUCED
```

```
load.glm.bw <- step(load.glm2, direction = "backward")
```

```
## Start:  AIC=940.19
## CONSTRUCTION ~ VERB + REDUCED + PARTICIPLE
##
##              Df Deviance     AIC
## <none>            928.19  940.19
## - REDUCED     1   950.73  960.73
## - PARTICIPLE  1  1291.51 1301.51
## - VERB        3  2353.91 2359.91
```

2.12 Additional code: variables' importance

```
library(caret)
varImp(load.glm4)
```

```
##                       Overall
## VERBna               9.538879
## VERBpo               4.329559
## VERBza               6.267175
## REDUCEDyes           5.085227
## PARTICIPLEyes        5.858903
## VERBna:PARTICIPLEyes 1.229077
## VERBpo:PARTICIPLEyes 3.558238
## VERBza:PARTICIPLEyes 2.964285
```

2.13 Model accuracy

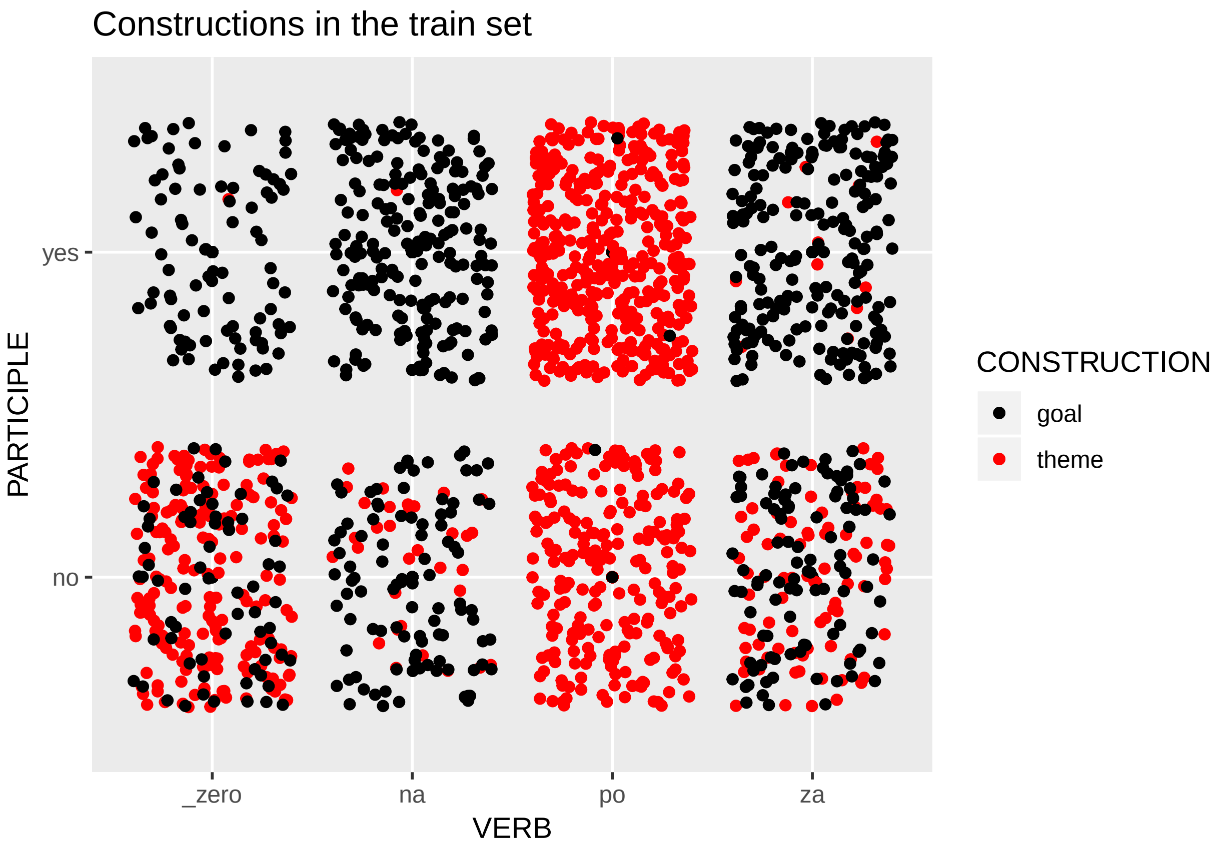
Dividing data into training and test sets

The rule of thumb is to use 10% or 20% or 25% data points as a test set (usually not less than 20 data points). The model will be trained on the remaining data.

```
set.seed(42)
load.test.index <- sample(1:nrow(loaddata), size=floor(nrow(loaddata)/10)) # select 10% random points,
paste0("The test set size: ", floor(nrow(loaddata)/10), ". The training set size: ", nrow(loaddata)-flo
```

```
## [1] "The test set size: 192. The training set size: 1728."
```

```
load.test <- loaddata[load.test.index,]
load.train <- loaddata[-load.test.index,]
load.train %>%
  ggplot(aes(x=VERB, y=PARTICIPLE, col=CONSTRUCTION)) +
  scale_color_manual(values=c("black", "red")) +
  geom_point() +
  geom_jitter() +
  ggtitle("Constructions in the train set")
```




```
load.test %>%
  ggplot(aes(x=VERB, y=PARTICIPLE, col=CONSTRUCTION)) +
  scale_color_manual(values=c("black", "red")) +
  geom_point() +
  geom_jitter() +
  ggtitle("Constructions in the test set")
```

- Training the model on the train set, making prediction on the test set

```
load.glm5 <- glm(CONSTRUCTION ~ VERB + REDUCED + PARTICIPLE + VERB:PARTICIPLE, family="binomial", data=
#print(summary(load.glm5))
load.glm5.link.scores <- predict(load.glm5, newdata=load.test, type="link")
load.glm5.response.scores <- predict(load.glm5, newdata=load.test, type="response")
load.glm5.scores <- data.frame(link=load.glm5.link.scores,
                               response=load.glm5.response.scores,
                               construction_obs=load.test$CONSTRUCTION,
                               stringsAsFactors=FALSE)
```

Confusion matrix and accuracy

Confusion matrix counts the cases of correctly predicted classes as well as the cases of misclassification (false positives and false negatives) . **Accuracy** are the counts on the backslash diagonal divided by the total counts.

```
load.test %>%
  count(CONSTRUCTION, VERB, REDUCED, PARTICIPLE) %>%
  select(-n, -CONSTRUCTION) %>%
  unique() ->
  load.test.pdata

load.test.pdata %>%
  predict(load.glm5, newdata = ., type = "response") ->
  load.test.pdata$PREDICTION

load.test.pdata %>%
```

```
  arrange(PREDICTION)
```

```
## # A tibble: 16 x 4
##    VERB  REDUCED PARTICIPLE PREDICTION
##    <fct> <fct>   <fct>           <dbl>
##  1 na    yes     yes           0.00265
##  2 _zero yes     yes           0.00510
##  3 na    no      yes           0.00637
##  4 _zero no      yes           0.0122
##  5 za    yes     yes           0.0321
##  6 za    no      yes           0.0741
##  7 na    yes     no            0.147
##  8 na    no      no            0.294
##  9 za    yes     no            0.332
## 10 za    no      no            0.546
## 11 _zero yes     no            0.634
## 12 _zero no      no            0.807
## 13 po    yes     yes           0.989
## 14 po    yes     no            0.992
## 15 po    no      yes           0.995
## 16 po    no      no            0.996
```

```
load.test.pdata %>%
  arrange(desc(PREDICTION))
```

```
## # A tibble: 16 x 4
##    VERB  REDUCED PARTICIPLE PREDICTION
##    <fct> <fct>   <fct>           <dbl>
##  1 po    no      no            0.996
##  2 po    no      yes           0.995
##  3 po    yes     no            0.992
##  4 po    yes     yes           0.989
##  5 _zero no      no            0.807
##  6 _zero yes     no            0.634
##  7 za    no      no            0.546
##  8 za    yes     no            0.332
##  9 na    no      no            0.294
## 10 na    yes     no            0.147
## 11 za    no      yes           0.0741
## 12 za    yes     yes           0.0321
## 13 _zero no      yes           0.0122
## 14 na    no      yes           0.00637
## 15 _zero yes     yes           0.00510
## 16 na    yes     yes           0.00265
```

```
v <- rep(NA, nrow(load.glm5.scores))
v <- ifelse(load.glm5.scores$response >= .5, "theme", "goal")
load.glm5.scores$construction_pred <- as.factor(v)

confusionMatrix(data = load.glm5.scores$construction_pred, reference = load.glm5.scores$construction_obs
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction goal theme
```

```
##      goal    86     3
##      theme   13    90
##
##                Accuracy : 0.9167
##                  95% CI : (0.8682, 0.9516)
##     No Information Rate : 0.5156
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.8337
##
##  Mcnemar's Test P-Value : 0.02445
##
##             Sensitivity : 0.9677
##             Specificity : 0.8687
##          Pos Pred Value : 0.8738
##          Neg Pred Value : 0.9663
##              Prevalence : 0.4844
##          Detection Rate : 0.4688
##    Detection Prevalence : 0.5365
##       Balanced Accuracy : 0.9182
##
##        'Positive' Class : theme
##
```

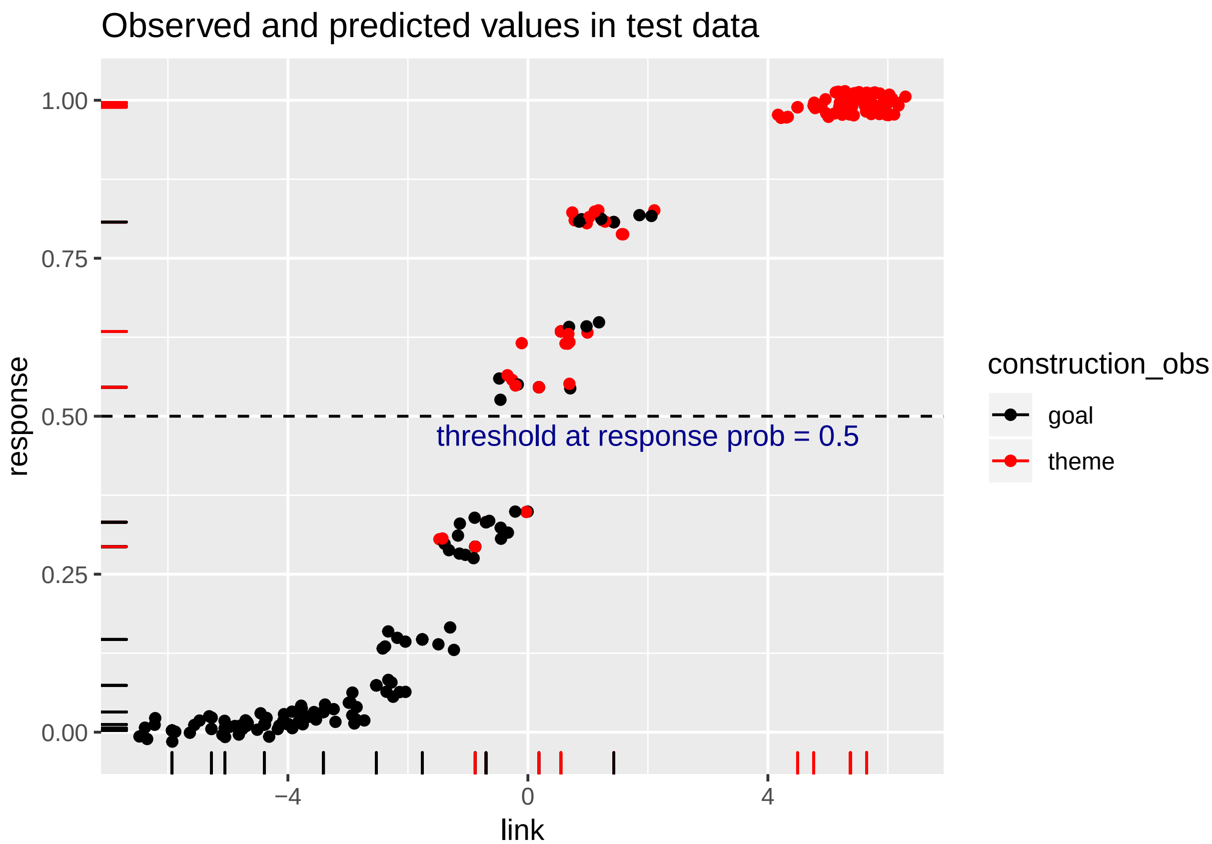
Inspect false positives and false negatives

```
data.frame(load.test, response = load.glm5.scores$response, predicted = load.glm5.scores$construction_p
  arrange(predicted, response)
```

```
##    CONSTRUCTION  VERB REDUCED PARTICIPLE  response predicted
## 1         theme    na      no         no 0.2935676      goal
## 2         theme    na      no         no 0.2935676      goal
## 3         theme    za     yes         no 0.3322976      goal
## 4          goal    za      no         no 0.5458472     theme
## 5          goal    za      no         no 0.5458472     theme
## 6          goal    za      no         no 0.5458472     theme
## 7          goal    za      no         no 0.5458472     theme
## 8          goal _zero     yes         no 0.6342141     theme
## 9          goal _zero     yes         no 0.6342141     theme
## 10         goal _zero     yes         no 0.6342141     theme
## 11         goal _zero      no         no 0.8072214     theme
## 12         goal _zero      no         no 0.8072214     theme
## 13         goal _zero      no         no 0.8072214     theme
## 14         goal _zero      no         no 0.8072214     theme
## 15         goal _zero      no         no 0.8072214     theme
## 16         goal _zero      no         no 0.8072214     theme
```

```
load.glm5.scores %>%
  ggplot(aes(x=link, y=response, col=construction_obs)) +
  scale_color_manual(values=c("black", "red")) +
  geom_point() +
  geom_rug() +
  geom_jitter(width=.7, height=.02) +
  geom_hline(yintercept=0.5, linetype="dashed") +
```

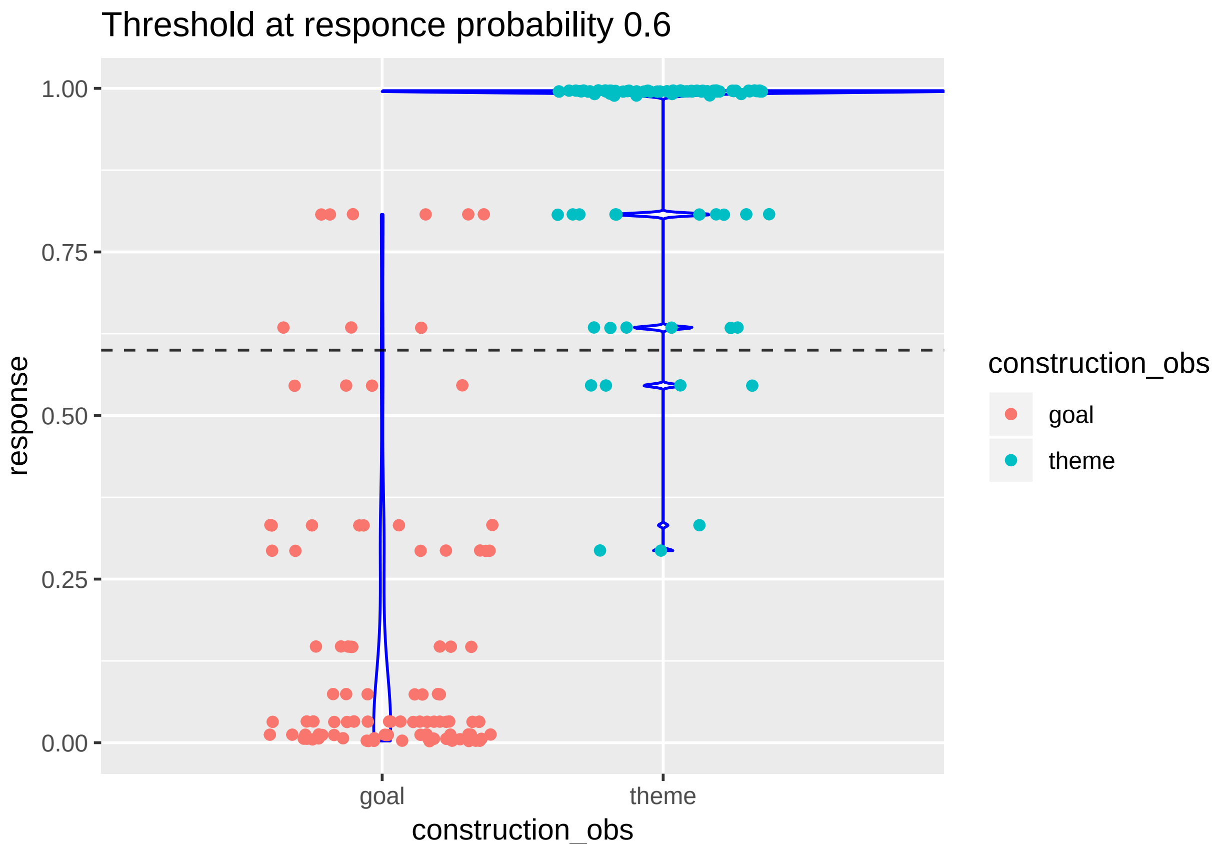
```
  annotate(geom="text", x=2, y=0.47, label="threshold at response prob = 0.5", color="darkblue") +
  ggtitle("Observed and predicted values in test data")
```



Yet another way to plot observed and predicted variables:

```
  ggplot(data=load.glm5.scores, aes(x=construction_obs, y=response)) +
    geom_violin(fill=rgb(1,1,1,alpha=0.6), color="blue", width = 2) +
    geom_jitter(aes(color = construction_obs)) +
    geom_hline(yintercept=0.6, linetype="dashed", alpha=0.8) +
#    scale_color_discrete(name = "type") +
    labs(title="Threshold at responce probability 0.6")
```

```
## Warning: position_dodge requires non-overlapping x intervals
```



At the threshold 0.6, there are 8 false positives (predicted as "theme" whereas the observed class is "goal") and 7 false negatives (predicted as "goal" whereas the observed class is "theme"). The violin plots show that the distribution of response probabilities within each class is quite good (most of the "goal" response probs are below 0.2, most of the "theme" response probs equal 1).

2.14 AUC (area under the ROC curve)

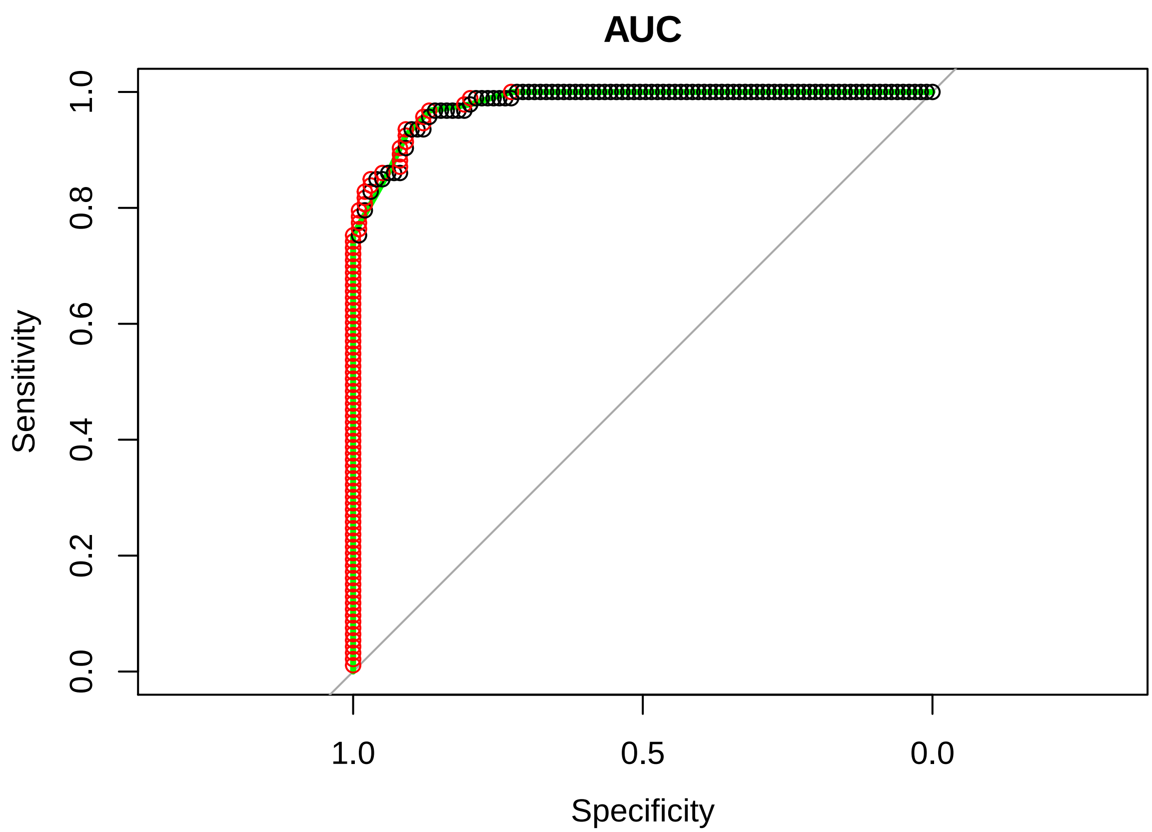
The ROC* curve shows the trade off between the rate at which you can correctly predict something (True Positive rate) with the rate of incorrectly predicting something (False Positive rate). The curve starts in the bottom left corner and uses an ordered vector of prediction scores (e.g. `load.glm5.scores$response` above, ordered) to take the next step. Each time the curve "sees" the positive value (e.g. `"goal"`) in the observed output it moves up (northward), and each time it sees the negative value (e.g. "theme") it takes a step right (eastward). Ideally, if we only have true positives and true negatives predicted by the model, the curve will move up till the top left corner and then move right till the top right corner.

The area under the ROC curve (AUC) ranges from 0.50 to 1.00, where 0.50 is considered a random prediction, 0.70 is a borderline case, and 0.80 and above indicates that the model does a good job in discriminating between the two output values. The closer the ROC gets to the optimal point of perfect prediction in the top left corner the closer the AUC gets to 1.
*ROC stands for Receiver Operating Characteristics. Read more: https://www.r-bloggers.com/illustrated-guide-to-roc-and-auc/.

```
load.glm5.roc <- roc(load.test$CONSTRUCTION, load.glm5.response.scores, direction="<")
plot(load.glm5.roc, col="green", lwd=3, main="AUC")

simple_roc <- function(labels, scores){
  labels <- labels[order(scores, decreasing=TRUE)]
```

```
  data.frame(TPR=cumsum(labels)/sum(labels), FPR=cumsum(!labels)/sum(!labels), labels)
} #TPR - True Positive Ratio, FPR - False Positive Ratio
load.glm5.simple.roc <- simple_roc(load.test$CONSTRUCTION=="theme", load.glm5.link.scores)
with(load.glm5.simple.roc, points(1 - FPR, TPR, col=1 + labels))
```




```
auc(load.glm5.roc)
```

```
## Area under the curve: 0.9802
```