Logistic Regression

Dominik Glandorf

2023-01-31

Data preparation

Load data

```
setwd("~/EWS")
source("read_data.R")
students = get_student_sub()
terms = get_term_features()
```

See available columns

```
attr(students,"spec")
```

```
## cols(
##   mellon_id = col_double(),
##   first_code = col_double(),
##   last_code = col_double(),
##   num_terms = col_double(),
##   first_year = col_double(),
##   first_term = col_double(),
##   first_month = col_double(),
##   first_term_desc = col_character(),
##   last_year = col_double(),
##   last_term = col_character(),
##   last_term_desc = col_character(),
##   last_month = col_double(),
##   number_of_years = col_double(),
##   birth_year = col_double(),
##   birth_month = col_double(),
##   age_at_enrolment = col_double(),
##   start_as_freshman = col_logical(),
##   appl_status = col_character(),
##   uc_total_score = col_double(),
##   uc_read_score = col_double(),
##   uc_writing_score = col_double(),
##   uc_math_score = col_double(),
##   number_ap = col_double(),
##   passed_ap_abs = col_double(),
##   passed_ap_rel = col_double(),
##   best_ap = col_double(),
##   avg_ap = col_double(),
##   graduated = col_logical(),
##   dropout = col_logical(),
##   admitdate = col_character(),
##   female = col_logical(),
##   int_student = col_double(),
##   ethnicity = col_character(),
##   first_generation = col_double(),
##   low_income = col_logical(),
##   father_edu_level_code = col_double(),
##   mother_edu_level_code = col_double(),
##   ell = col_double(),
##   single_parent = col_double(),
##   foster_care = col_double(),
##   household_size_app = col_double(),
##   distance_from_home = col_double(),
##   sport_at_admission = col_character(),
##   cal_res_at_app = col_character(),
##   hs_gpa = col_double(),
##   toefl_score = col_double(),
##   ielts_score = col_double()
## )
```

Create dataframe for model

```
predictors = c("age_at_enrolment",
               "uc_total_score",
               "uc_math_score",
               "uc_read_score",
               "uc_writing_score",
               "number_ap",
               "passed_ap_rel",
               "best_ap",
               "avg_ap",
               "int_student",
               "ethnicity",
               "first_generation",
               "low_income",
               "father_edu_level_code",
               "mother_edu_level_code",
               "ell",
               "single_parent",
               "foster_care",
               "household_size_app",
               "distance_from_home",
               "sport_at_admission",
               "cal_res_at_app",
               "hs_gpa")
dat = students %>% select(all_of(c(predictors, "dropout")))
```

Strategy for missing categorical values: Create a missing category. Also, merge/exclude categories that are rare.

```
dat$low_income[is.na(dat$low_income)]=F
dat$household_size_app[dat$household_size_app>6] = 6
dat$father_edu_level_code[dat$father_edu_level_code==4]=NA
saa = table(dat$sport_at_admission)
dat$sport_at_admission[dat$sport_at_admission %in% names(saa[saa<nrow(dat)/1000])] = "other"
categorical_cols <- c("int_student","ethnicity","first_generation","father_edu_level_code","mother_edu_
dat[categorical_cols] <- lapply(dat[categorical_cols], as.character)
dat[categorical_cols][is.na(dat[categorical_cols])] = "unknown"

dat = dat[complete.cases(dat),]
dat[categorical_cols] <- lapply(dat[categorical_cols], as.factor)

#for (c in categorical_cols) {
#  print(table(dat[,c]))
#}
```

We now include 0.355025 of the dataset.

Model estimation

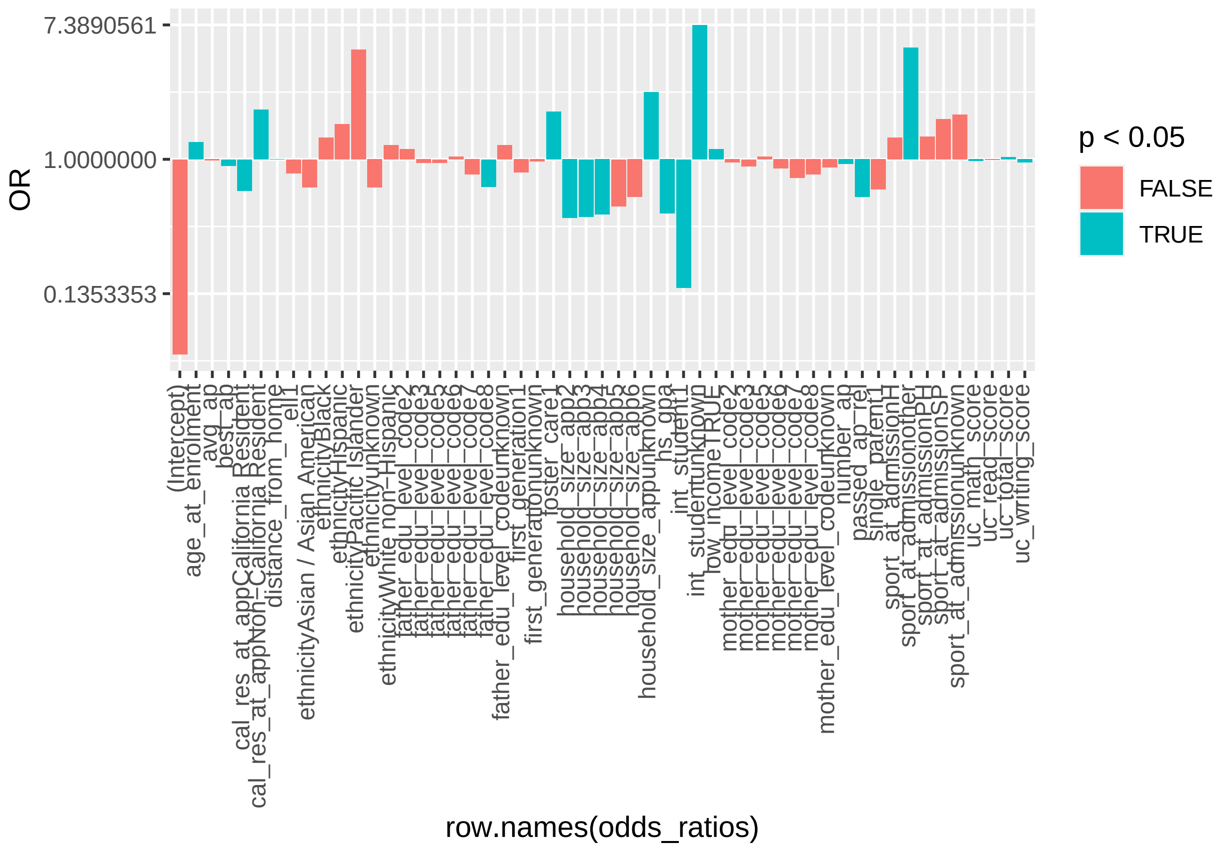
First, split into training and test data

```
sample <- sample(c(TRUE, FALSE), nrow(dat), replace=TRUE, prob=c(0.7,0.3))
train <- dat[sample, ]
test <- dat[!sample, ]
```

```
log.reg.fit = glm(dropout ~ ., train, family = 'binomial')
#summary(log.reg.fit)
```

Effects

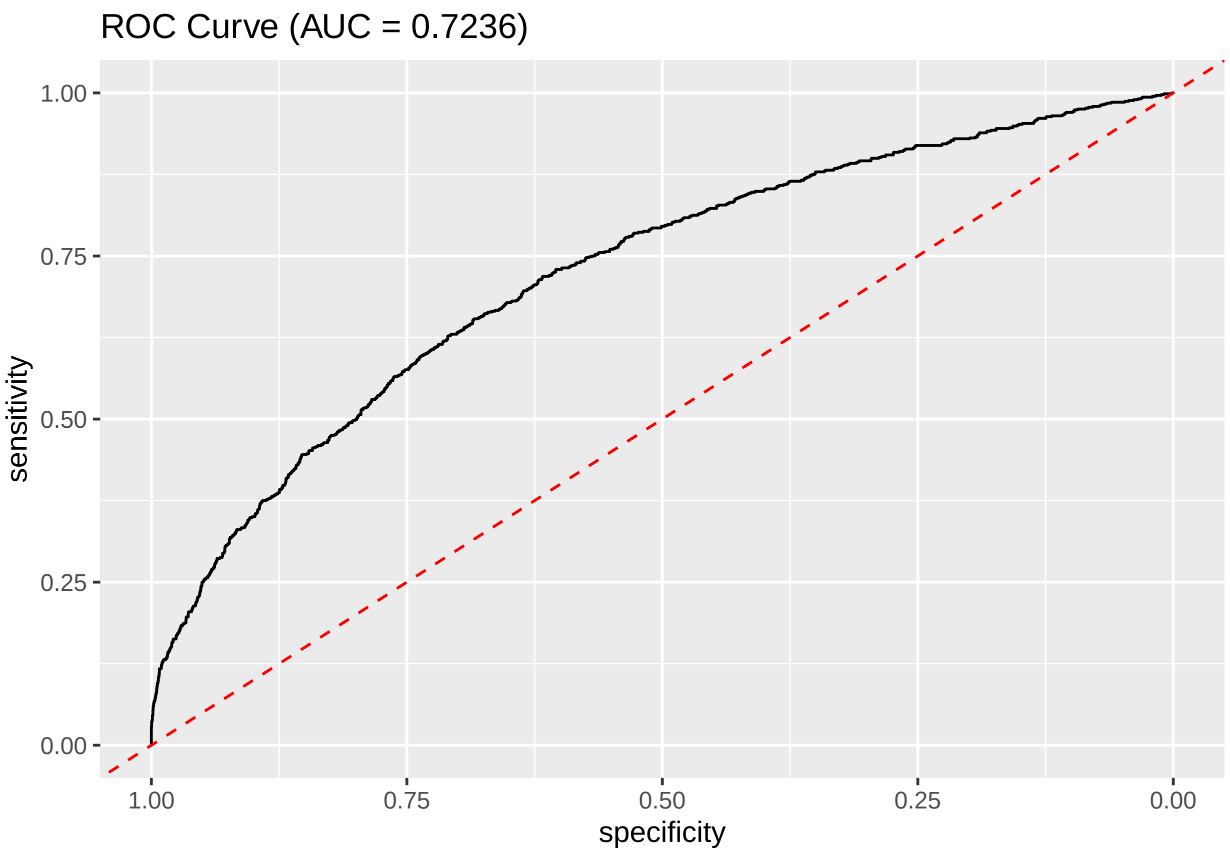
```
odds_ratios = data.frame(OR=exp(log.reg.fit$coefficients),
                         p=coef(summary(log.reg.fit))[,4])
ggplot(odds_ratios, aes(x=row.names(odds_ratios),y=OR, fill=p<0.05))+
  geom_bar(stat="identity") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.25, hjust=1)) +
  scale_y_continuous(trans='log')
```



# Model evaluation

```
dropout_prob = predict(log.reg.fit, test, type = "response") # response outputs the prob instead of log

rocobj <- roc(test$dropout, dropout_prob)
auc <- round(auc(test$dropout, dropout_prob),4)
ggroc(rocobj) +
  ggtitle(paste0('ROC Curve ', '(AUC = ', auc, ')')) +
  geom_abline(intercept = 1, slope = 1, color = "red", linetype = "dashed")
```



### Including term level variables We have to decide until which term we include the variables and then only predict students that are not already dropped out.

```
attr(terms, "spec")
```

```
## cols(
##   mellon_id = col_double(),
##   term_code = col_double(),
##   term_num = col_double(),
##   units_completed = col_double(),
##   cumulative_units_completed = col_double(),
##   cum_avg_credits = col_double(),
##   units_completed.rel_term_num = col_double(),
##   cum_avg_credits.rel_term_num = col_double(),
##   units_completed.rel_major = col_double(),
##   cum_avg_credits.rel_major = col_double(),
##   units_completed.rel_major_termnum = col_double(),
##   cum_avg_credits.rel_major_termnum = col_double(),
##   major_1 = col_character(),
##   school_1 = col_character(),
##   num_majors = col_double()
## )
```

```
students = merge(students, terms%>%filter(term_num==1)%>%select(mellon_id,major_1), by="mellon_id")
```