

R Notebook: Multiple Regression Model of Student Academic Achievement

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April 6, 2017

Abstract

The interest of this study is in developing a prediction model of student success based on measured factors of success in Mathematics and Portuguese. Multiple regression is applied to develop a regression classifier based on student-provided factors that relate to living conditions and education conditions. Though regression tree modeling would appear at first to be the correct approach here, the number and high-cardinality nature of many of the variables in this data makes such an approach less feasible in practice.

```
set.seed(1)
library(car)
library(boot)
c <- read.table("student-por.csv",sep=";",header=TRUE)
c <- data.frame(c)
d <- read.table("student-mat.csv",sep=";",header=TRUE)
d <- data.frame(d)
e <- rbind(c,d)
```

Data Cleaning

Both Math and Portuguese sets are merged, alternate column titles are applied, and all student grades are averaged across three grade entries.

```
names(e) <- c("school","sex","age", "address","family size","parents cohab.", "mom's education",
             "dad's education","mom's job", "dad's job","reason", "guardian","travel", "study",
             "failures","education support","family support","paid","activities", "nursery","higher",
             "internet","romantic","family bond","free time","social","workday alch.","weekend alch.",
             "absences","Grade 1","Grade 2","Grade 3")

Grade <- (e$`Grade 1` + e$`Grade 2` + e$`Grade 3`) / 3
e$`Grade 1` <- NULL
e$`Grade 2` <- NULL
```

```
e$`Grade 3` <- NULL
e = cbind(e, Grade)
attach(e)
```

Exploratory Investigation

From initial inspection it is clear education success is to be quantified by

the Grade variable. Results of inspection indicate general normality of this output

variable. The class distributions of explanatory variables, ‘dad’s job’ and ‘mom’s job’

factors appear to show questionable value by inspection of the summary table.

This is indicated by the limited difference between class-levels, except for

the vaguely defined class, ‘other’, showing the survey question isn’t well-defined or

reliable an indicator. An inspection of the VIF’s (Variance Inflation Factors), of

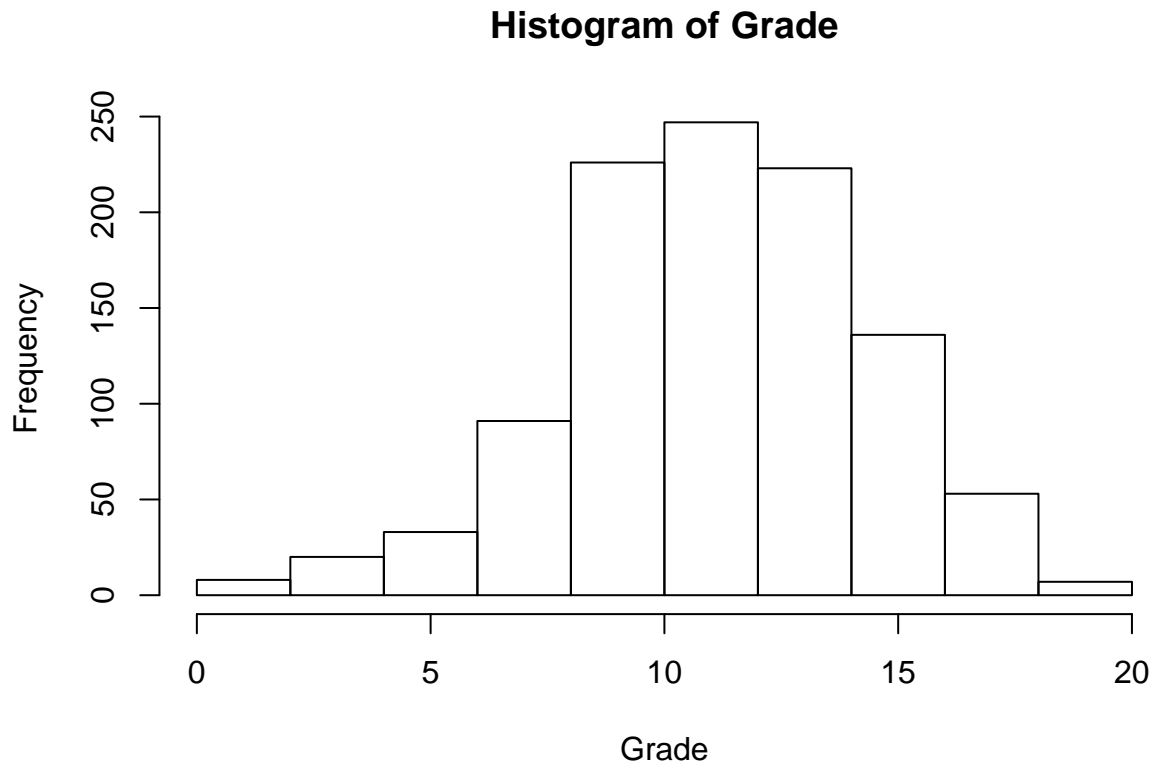
model parameters is performed to check for multicollinearity in the dataset.

```
summary(e)
```

```
##  school    sex      age      address family size parents cohab.
##  GP:772    F:591    Min.   :15.00    R:285   GT3:738     A:121
##  MS:272    M:453    1st Qu.:16.00    U:759   LE3:306     T:923
##                                     Median :17.00
##                                     Mean   :16.73
##                                     3rd Qu.:18.00
##                                     Max.   :22.00
##  mom's education dad's education    mom's job      dad's job
##  Min.   :0.000    Min.   :0.000    at_home :194    at_home : 62
##  1st Qu.:2.000    1st Qu.:1.000    health  : 82    health  : 41
##  Median :3.000    Median :2.000    other   :399    other   :584
##  Mean   :2.603    Mean   :2.388    services:239    services:292
##  3rd Qu.:4.000    3rd Qu.:3.000    teacher :130    teacher : 65
##  Max.   :4.000    Max.   :4.000
##          reason      guardian      travel      study
##  course      :430    father:243    Min.   :1.000    Min.   :1.00
##  home         :258    mother:728    1st Qu.:1.000    1st Qu.:1.00
##  other        :108    other : 73    Median :1.000    Median :2.00
##  reputation:248                    Mean   :1.523    Mean   :1.97
##                                     3rd Qu.:2.000    3rd Qu.:2.00
##                                     Max.   :4.000    Max.   :4.00
##          failures    education support family support    paid      activities
##  Min.   :0.0000    no :925          no :404          no :824    no :528
##  1st Qu.:0.0000    yes:119         yes:640         yes:220    yes:516
##  Median :0.0000
```

```
## Mean :0.2644
## 3rd Qu.:0.0000
## Max. :3.0000
## nursery higher internet romantic family bond free time
## no :209 no : 89 no :217 no :673 Min. :1.000 Min. :1.000
## yes:835 yes:955 yes:827 yes:371 1st Qu.:4.000 1st Qu.:3.000
## Median :4.000 Median :3.000
## Mean :3.936 Mean :3.201
## 3rd Qu.:5.000 3rd Qu.:4.000
## Max. :5.000 Max. :5.000
## social workday alch. weekend alch. health
## Min. :1.000 Min. :1.000 Min. :1.000 Min. :1.000
## 1st Qu.:2.000 1st Qu.:1.000 1st Qu.:1.000 1st Qu.:3.000
## Median :3.000 Median :1.000 Median :2.000 Median :4.000
## Mean :3.156 Mean :1.494 Mean :2.284 Mean :3.543
## 3rd Qu.:4.000 3rd Qu.:2.000 3rd Qu.:3.000 3rd Qu.:5.000
## Max. :5.000 Max. :5.000 Max. :5.000 Max. :5.000
## absences Grade
## Min. : 0.000 Min. : 1.333
## 1st Qu.: 0.000 1st Qu.: 9.333
## Median : 2.000 Median :11.333
## Mean : 4.435 Mean :11.267
## 3rd Qu.: 6.000 3rd Qu.:13.333
## Max. :75.000 Max. :19.333
```

```
hist(Grade)
```



```
str(e)
```

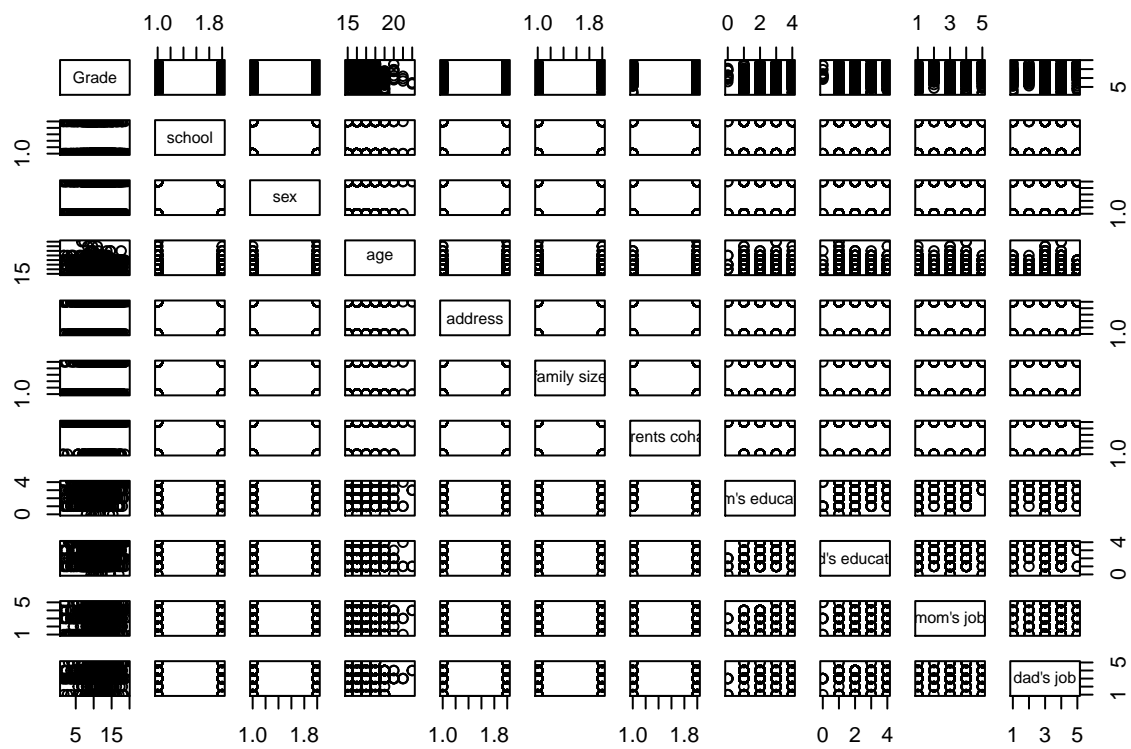
```
## 'data.frame':    1044 obs. of  31 variables:
## $ school          : Factor w/ 2 levels "GP","MS": 1 1 1 1 1 1 1 1 1 1 ...
## $ sex             : Factor w/ 2 levels "F","M": 1 1 1 1 1 2 2 1 2 2 ...
## $ age             : int  18 17 15 15 16 16 16 17 15 15 ...
## $ address         : Factor w/ 2 levels "R","U": 2 2 2 2 2 2 2 2 2 2 ...
## $ family size     : Factor w/ 2 levels "GT3","LE3": 1 1 2 1 1 2 2 1 2 1 ...
## $ parents cohab.  : Factor w/ 2 levels "A","T": 1 2 2 2 2 2 2 1 1 2 ...
## $ mom's education : int   4 1 1 4 3 4 2 4 3 3 ...
## $ dad's education : int   4 1 1 2 3 3 2 4 2 4 ...
## $ mom's job       : Factor w/ 5 levels "at_home","health",...: 1 1 1 2 3 4 3 3 4 3 ...
## $ dad's job       : Factor w/ 5 levels "at_home","health",...: 5 3 3 4 3 3 3 5 3 3 ...
## $ reason          : Factor w/ 4 levels "course","home",...: 1 1 3 2 2 4 2 2 2 2 ...
## $ guardian        : Factor w/ 3 levels "father","mother",...: 2 1 2 2 1 2 2 2 2 2 ...
## $ travel          : int   2 1 1 1 1 1 1 2 1 1 ...
## $ study           : int   2 2 2 3 2 2 2 2 2 2 ...
## $ failures        : int   0 0 0 0 0 0 0 0 0 0 ...
## $ education support: Factor w/ 2 levels "no","yes": 2 1 2 1 1 1 1 2 1 1 ...
## $ family support  : Factor w/ 2 levels "no","yes": 1 2 1 2 2 2 1 2 2 2 ...
## $ paid            : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
## $ activities      : Factor w/ 2 levels "no","yes": 1 1 1 2 1 2 1 1 1 2 ...
## $ nursery         : Factor w/ 2 levels "no","yes": 2 1 2 2 2 2 2 2 2 2 ...
## $ higher          : Factor w/ 2 levels "no","yes": 2 2 2 2 2 2 2 2 2 2 ...
## $ internet        : Factor w/ 2 levels "no","yes": 1 2 2 2 1 2 2 1 2 2 ...
## $ romantic        : Factor w/ 2 levels "no","yes": 1 1 1 2 1 1 1 1 1 1 ...
## $ family bond     : int   4 5 4 3 4 5 4 4 4 5 ...
## $ free time       : int   3 3 3 2 3 4 4 1 2 5 ...
## $ social          : int   4 3 2 2 2 2 4 4 2 1 ...
## $ workday alch.   : int   1 1 2 1 1 1 1 1 1 1 ...
## $ weekend alch.   : int   1 1 3 1 2 2 1 1 1 1 ...
## $ health          : int   3 3 3 5 5 5 3 1 1 5 ...
## $ absences        : int   4 2 6 0 0 6 0 2 0 0 ...
## $ Grade           : num  7.33 10.33 12.33 14 12.33 ...
```

```
names(e)
```

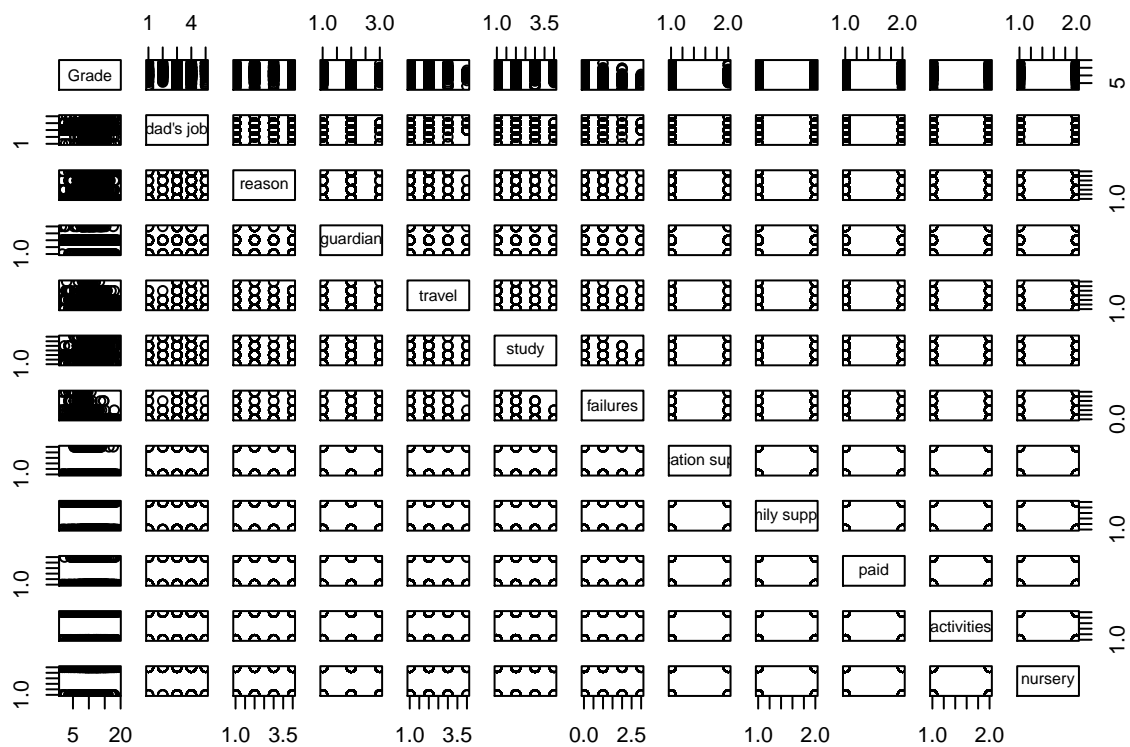
```
## [1] "school"          "sex"             "age"
## [4] "address"         "family size"     "parents cohab."
## [7] "mom's education" "dad's education" "mom's job"
## [10] "dad's job"       "reason"          "guardian"
## [13] "travel"          "study"           "failures"
## [16] "education support" "family support"  "paid"
## [19] "activities"      "nursery"         "higher"
## [22] "internet"        "romantic"        "family bond"
## [25] "free time"       "social"          "workday alch."
## [28] "weekend alch."   "health"          "absences"
## [31] "Grade"
```

```
x1 <- e[c(31, 1 : 10)]
```

```
pairs(x1)
```



```
x2 <- e[c(31, 10 : 20)]
pairs(x2)
```



```
x3 <- e[c(31, 20 : 30)]
pairs(x3)
```


Initial Fit: The Saturated Model

The following is a series of progressive model fits to find the best possible fit.

The saturated model cardinality is 30 variables. 10-fold CV is applied to MSE

estimation of the model performance on the test data.

```
names(e)

## [1] "school"          "sex"              "age"
## [4] "address"         "family size"      "parents cohab."
## [7] "mom's education" "dad's education"  "mom's job"
## [10] "dad's job"       "reason"           "guardian"
## [13] "travel"          "study"            "failures"
## [16] "education support" "family support"  "paid"
## [19] "activities"      "nursery"          "higher"
## [22] "internet"        "romantic"         "family bond"
## [25] "free time"       "social"           "workday alch."
## [28] "weekend alch."   "health"           "absences"
## [31] "Grade"

fit <- glm(Grade~., data = e)
MSE1 <- cv.glm(e, fit, K = 10)$delta[1]
summary(fit)

##
## Call:
## glm(formula = Grade ~ ., data = e)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -10.8517  -1.4833   0.1019   1.8281   7.8999
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    9.718585    1.641229   5.922 4.38e-09 ***
## schoolMS      -0.492338    0.235632  -2.089 0.036919 *
## sexM          -0.065729    0.202918  -0.324 0.746068
## age           0.030970    0.083072   0.373 0.709372
## addressU      0.240670    0.221106   1.088 0.276645
## `family size`LE3 0.369219    0.199709   1.849 0.064783 .
## `parents cohab.`T 0.023677    0.287473   0.082 0.934375
## `mom's education` 0.173160    0.126079   1.373 0.169925
## `dad's education` 0.042871    0.112327   0.382 0.702792
## `mom's job`health 0.934994    0.442614   2.112 0.034896 *
## `mom's job`other -0.020608    0.262211  -0.079 0.937372
## `mom's job`services 0.524154    0.310235   1.690 0.091426 .
## `mom's job`teacher -0.013337    0.410768  -0.032 0.974105
## `dad's job`health -0.057531    0.600577  -0.096 0.923704
## `dad's job`other -0.065647    0.386378  -0.170 0.865120
## `dad's job`services -0.247048    0.404383  -0.611 0.541386
## `dad's job`teacher 1.133663    0.538623   2.105 0.035562 *
## reasonhome     0.133123    0.229150   0.581 0.561410
```



```

## reasonother          0.066553   0.311433   0.214 0.830825
## reasonreputation     0.303609   0.239565   1.267 0.205329
## guardianmother      -0.220538   0.219213  -1.006 0.314636
## guardianother        0.217507   0.420273   0.518 0.604896
## travel               -0.094595   0.132621  -0.713 0.475841
## study                0.418159   0.115143   3.632 0.000296 ***
## failures             -1.476144   0.148519  -9.939 < 2e-16 ***
## `education support`yes -1.398765   0.286959  -4.874 1.27e-06 ***
## `family support`yes   -0.273525   0.188290  -1.453 0.146627
## paidyes              -0.768545   0.221702  -3.467 0.000549 ***
## activitiesyes         0.097293   0.181423   0.536 0.591887
## nurseryyes           -0.025260   0.222561  -0.113 0.909661
## higheryes            1.409229   0.341220   4.130 3.93e-05 ***
## internetyes          0.323375   0.233715   1.384 0.166780
## romanticyes          -0.448088   0.188898  -2.372 0.017874 *
## `family bond`         0.102933   0.096962   1.062 0.288680
## `free time`           0.032757   0.093005   0.352 0.724759
## social               -0.218046   0.089048  -2.449 0.014510 *
## `workday alch.`       -0.117328   0.128143  -0.916 0.360092
## `weekend alch.`       -0.008548   0.098360  -0.087 0.930768
## health               -0.156854   0.063972  -2.452 0.014378 *
## absences              -0.016961   0.014979  -1.132 0.257773
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 7.662112)
##
## Null deviance: 10806.2 on 1043 degrees of freedom
## Residual deviance: 7692.8 on 1004 degrees of freedom
## AIC: 5129.8
##
## Number of Fisher Scoring iterations: 2

```

A report on statistical significance of saturated model coefficients indicates significant ($p < 0.01$) predictors of Grade to be study, failures, education, support, paid, and higher.

MSE for 10-Fold CV of fit of saturated model:

```
MSE1
```

```
## [1] 7.988418
```

A check for multicollinearity by VIF shows negative results, indicating the potential for linear modelling success (conditioned on all GVIF values being less than 10).

```
vif(fit)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## school      1.457487 1      1.207264
## sex         1.378085 1      1.173919
## age        1.444359 1      1.201815
## address     1.322027 1      1.149794
## `family size` 1.125962 1      1.061114
## `parents cohab.` 1.153808 1      1.074155
## `mom's education` 2.738116 1      1.654725
## `dad's education` 2.077963 1      1.441514
## `mom's job` 2.713832 4      1.132916
## `dad's job` 1.890115 4      1.082832
## reason      1.427053 3      1.061060
## guardian    1.472356 2      1.101547
## travel      1.281912 1      1.132215
## study       1.256347 1      1.120869
## failures    1.292695 1      1.136968
## `education support` 1.133132 1      1.064487
## `family support` 1.145957 1      1.070494
## paid        1.113884 1      1.055407
## activities  1.121040 1      1.058792
## nursery     1.080640 1      1.039538
## higher      1.237127 1      1.112262
## internet    1.225436 1      1.106994
## romantic    1.113774 1      1.055355
## `family bond` 1.115004 1      1.055937
## `free time`  1.252843 1      1.119305
## social      1.433910 1      1.197460
## `workday alch.` 1.857976 1      1.363076
## `weekend alch.` 2.174975 1      1.474780
## health      1.130731 1      1.063359
## absences    1.177898 1      1.085310
```

Second Fit

A lower complexity model of 5 variables (reported significant from the saturated model report output) is fitted. All variables included are checked for significance

($p < 0.01$).

```
fit2 <- glm(Grade ~ study + failures + `education support` + paid + higher, data = e)
MSE2 <- cv.glm(e, fit2, K = 10)$delta[1]
summary(fit2)
```

```
##
## Call:
## glm(formula = Grade ~ study + failures + `education support` +
##      paid + higher, data = e)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -10.4849   -1.6574    0.0707    1.9185    7.9790
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      9.2697     0.3692  25.108 < 2e-16 ***
## study            0.4942     0.1091   4.530 6.57e-06 ***
## failures        -1.6364     0.1415 -11.566 < 2e-16 ***
## `education support`yes -1.2480     0.2796  -4.463 8.96e-06 ***
## paidyes         -0.6331     0.2193  -2.887 0.00397 **
## higheryes        1.8935     0.3368   5.622 2.42e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 8.158794)
##
##    Null deviance: 10806.2  on 1043  degrees of freedom
## Residual deviance:  8468.8  on 1038  degrees of freedom
## AIC: 5162.2
##
## Number of Fisher Scoring iterations: 2
```

10-Fold CV MSE estimate of Model II:

```
MSE2
```

```
## [1] 8.222127
```

This model shows negligible difference in MSE from the saturated model and contains

26 fewer predictors, thus indicating potential for out-of-sample performance.

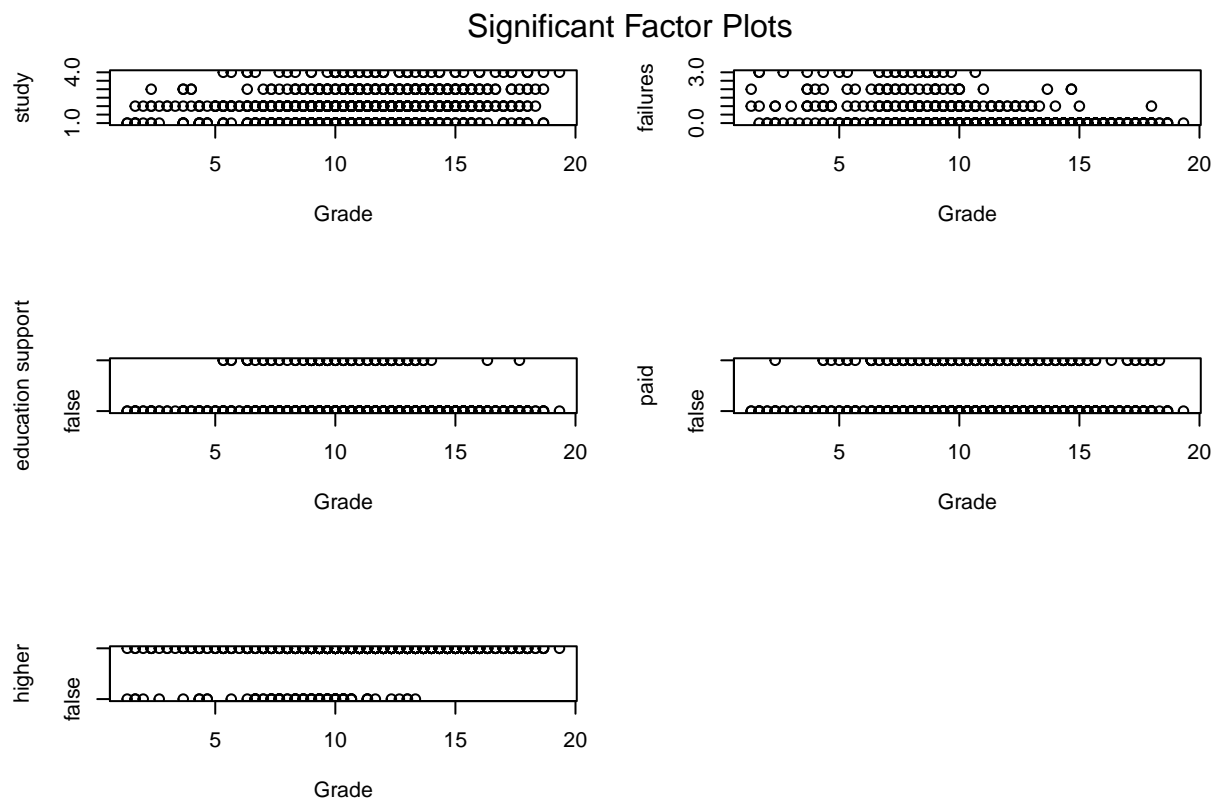
```
summary(fit2)
```

```
##
## Call:
## glm(formula = Grade ~ study + failures + `education support` +
##      paid + higher, data = e)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -10.4849   -1.6574    0.0707    1.9185    7.9790
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      9.2697     0.3692  25.108 < 2e-16 ***
## study            0.4942     0.1091   4.530 6.57e-06 ***
## failures        -1.6364     0.1415 -11.566 < 2e-16 ***
## `education support`yes -1.2480     0.2796  -4.463 8.96e-06 ***
## paidyes         -0.6331     0.2193  -2.887 0.00397 **
## higheryes        1.8935     0.3368   5.622 2.42e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## (Dispersion parameter for gaussian family taken to be 8.158794)
##
## Null deviance: 10806.2 on 1043 degrees of freedom
## Residual deviance: 8468.8 on 1038 degrees of freedom
## AIC: 5162.2
##
## Number of Fisher Scoring iterations: 2

par(mfrow = c(3, 2))

plot(Grade, study)
plot(Grade, failures)
plot(Grade, `education support`, yaxt='n')
axis(2, labels = c("false", "true"), at = c(1, 2))
plot(Grade, paid, yaxt='n')
axis(2, labels = c("false", "true"), at = c(1, 2))
plot(Grade, higher, yaxt='n')
axis(2, labels = c("false", "true"), at = c(1, 2))
mtext("Significant Factor Plots", side = 3, line = -3, outer = TRUE)
#dev.off()
```



Results

This results of this work should be seen as a starting point for more advanced studies

of success prediction in general education. They may hold significance for the source data's originating educational department. It appears strictly domain specific: general claims to any general predictive success of any derived models is not indicated. This view is surmised from the collected data and available documentation. The intent interpreted is to find a model of specific factors relevant to learning success that are shared between Mathematics and Portuguese, discussed in identical terms - identical variables are chosen for both data sets as collected from student surveys. This indicates an implicit assumption of the study, that a uniform learning measure exists between mathematics and language. This assumption appears to be latent in the work, the chosen factors themselves are more general, living-condition or non-subject specific. Though the apparent study objective appears to show a general-education predictive-intent, only two categories of education are represented in the data. It is apparent that, for the chosen causal-factors of study, the data is not sufficiently representative to address their generality. In addition, this study has limited data relative to the number of factors of interest, and the number of levels for the chosen factors included are also non-trivial, (the non-binary classes).

Conclusion

This work could be seen a good use of resources in determining how best to design future studies, specifically, what questions to exclude from study surveys in any future work. Results of this work indicate a reduction in the set of explanatory variables by a factor of 5. In regards to posing domain-specific questions that can be related

across different academic disciplines, a student's view of past achievement in each subject should be included. It is presumed that, generally, it should be assumed that student success should not be homogeneously classed - most students could show odd levels of success or failure across specific fields. Such a set of related predictors are expected to show a significant degree of statistical non-normality across subjects. This study shows one of the most predictive factors to be a student's past failure rate, generically defined. This factor should be split into multiple predictors of each academic subject category, if more education subject-categories are to be included in a re-designed study. It is expected that this set of related measures will act as a dominant predictor of general education success for an individual student.