Analyzing Factors Influencing Academic Success and Dropouts in Higher Education

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Motivation

Transitioning from secondary to higher education poses a significant challenge to students

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Transitioning from secondary to higher education poses a significant challenge to students

- potentially leading to academic failure and dropouts
- negatively affecting students, the school, and parents

Research question

What factors are the most predictive of student graduate outcomes in higher education?

Literature review

- Beaulac & Rosenthal (2019) predict whether students will complete their program based on college course grades with random forests

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  Accuracy of 78.84%
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  Accuracy for boosting (73%) is higher than for random forests (72%)

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Data set

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```{r}
colnames(student_data)
```

```
 [1] "Marital Status"                                 "Application mode"
 [3] "Application order"                              "Course_Enrolled"
 [5] "Daytime/evening attendance"                     "Previous qualification"
 [7] "Previous qualification (grade)"                 "Nationality"
 [9] "Mother's qualification"                         "Father's qualification"
[11] "Mother's occupation"                            "Father's occupation"
[13] "Admission grade"                                "Displaced"
[15] "Educational special needs"                      "Debtor"
[17] "Tuition fees up to date"                        "Gender"
[19] "Scholarship holder"                             "Age at enrollment"
[21] "International"                                  "Curricular units 1st sem (credited)"
[23] "Curricular units 1st sem (enrolled)"            "Curricular units 1st sem (evaluations)"
[25] "Curricular units 1st sem (approved)"            "Curricular units 1st sem (grade)"
[27] "Curricular units 1st sem (without evaluations)" "Curricular units 2nd sem (credited)"
[29] "Curricular units 2nd sem (enrolled)"            "Curricular units 2nd sem (evaluations)"
[31] "Curricular units 2nd sem (approved)"            "Curricular units 2nd sem (grade)"
[33] "Curricular units 2nd sem (without evaluations)" "Unemployment rate"
[35] "Inflation rate"                                 "GDP"
[37] "Target"
```

Data processing

Our data preparation steps include:

- Checking for missing values

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- Checking for missing values
- Converting categorical variables to factor type
- Simplifying complex categorical variables into fewer levels

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Goal

- Familiarize with the data

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- Visualize relationships between features and target

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- Visualize relationships between features and target
- Potentially form assumptions about the strongest predictors

Method

- Data visualization:
    - Histograms
    - Boxplots, Barplots

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  - Histograms
  - Boxplots, Barplots
- Statistical Methods:
  - Five-number summaries
  - Correlation matrix

Results

- Combine early college performance metrics from semester-based to yearly

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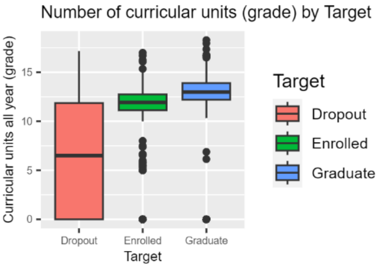
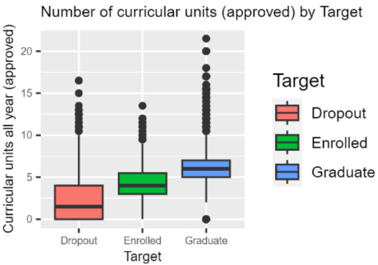
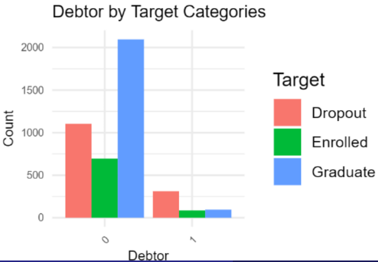
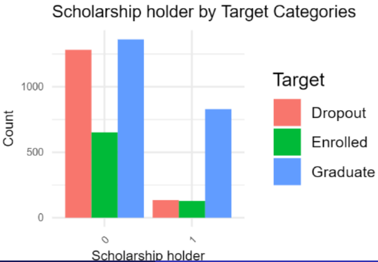
- Identify some potential strong predictors among the features

Results (cont.)









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Model building

- Our dependent variable is a three-class categorical variable

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  - `Dropout`, `Enrolled`, and `Graduate`
- We are also concerned with the task of inference
- We will use two classification models:
  - random forests
  - boosted trees

Random forest

- We use `randomForest` package

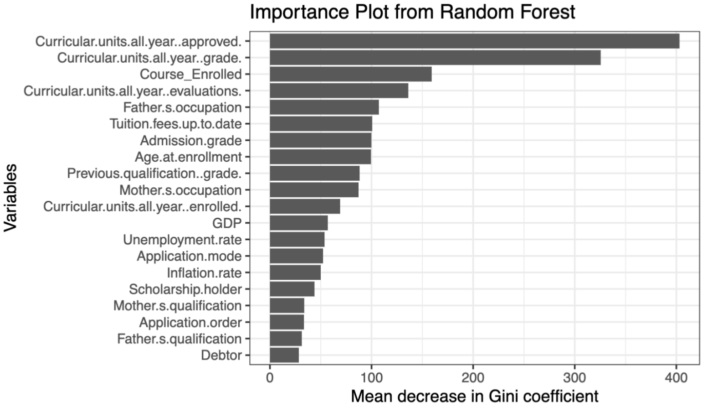
```
```{r}
library(randomForest)
set.seed(2024)
rf_mod <- randomForest(Target ~., train_student, ntree = 250, mtry = 5)
rf_mod
```
```

```
Call:
 randomForest(formula = Target ~ ., data = train_student, ntree = 250,      mtry = 5)
               Type of random forest: classification
                     Number of trees: 250
No. of variables tried at each split: 5

        OOB estimate of  error rate: 22.69%
Confusion matrix:
         Dropout Enrolled Graduate class.error
Dropout      872       82      178  0.22968198
Enrolled     152      202      270  0.67628205
Graduate      59       55     1638  0.06506849
```

Random forest (cont.)

- `ntree = 250, mtry = 5`



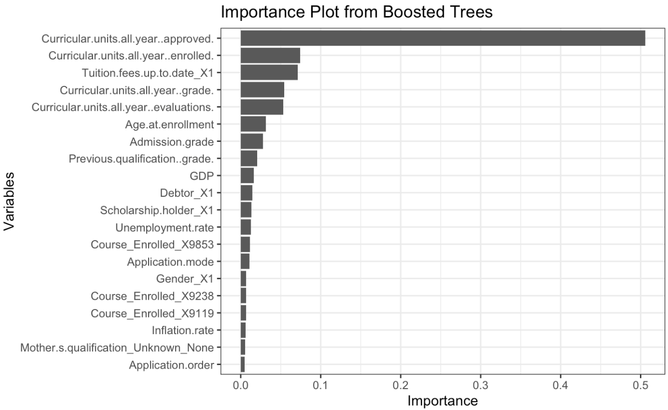
- `accuracy = 77.48%`

Boosted trees

- We use `tidymodels` package
- set engine "`xgboost`"

Boosted trees (cont.)

- `trees = 250, min_n = 10, tree_depth = 5, learn_rate = 0.4`



- `accuracy = 77.82%`

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Conclusions

- Strongest predictors of college dropouts: first-year performance metrics (the number of curricular units approved, enrolled, grades, and evaluations), tuition fee payment status, age at enrollment.

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Conclusions

- Strongest predictors of college dropouts: first-year performance metrics (the number of curricular units approved, enrolled, grades, and evaluations), tuition fee payment status, age at enrollment.
- Significantly strong: the average number of credits approved per semester
  → Build upon Martins et al. (2021), confirming the importance of first-year college performance metrics
  → Our accuracy (78%), surpasses those of the authors' models (73%)

Limitations

- Random Forest and Boosted Trees are computationally intensive

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- Potentially non-optimal parameter settings
- Limited data which affects generalizability
- Class imbalance for the response variable, which might lead to higher error

Areas for Further Research

- Inclusion of aspects related to social life on campus

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- Inclusion of aspects related to social life on campus
- Replicate the study at various institutions to enhance representativeness

References

Beaulac, C., & Rosenthal, J. S. (2019). Predicting University Students' Academic Success and Major Using Random Forests. In *Research in Higher Education*, *60*(7), 1048-1064. https://doi.org/10.1007/s11162-019-09546-y

Martins, M. V., Tolledo, D., Machado, J., Baptista, L. M., & Realinho, V. (2021). Early Prediction of Student's Performance in Higher Education: A Case Study. In *Trends and Applications in Information Systems and Technologies*, *1*, 166-175. https://doi.org/10.1007/978-3-030-72657-7$_1$6