# Modeling Student Exam Performance

A study of performance of students in school examinations as a function of social, demographic and behavioral variables

**Chris Lawson, Alberto Salvarese, Utkarsh Mujumdar, Jeffrey Gordon**

# Problem Description

Education is highly regarded as a key factor for a long-term economic achievement.

To guarantee equal opportunities, a society should therefore invest more on the education, developing  a school system able to understand and fill the gaps in different students' background, and guarantee a fair educational path

s have improved, there are realities that still
s in the educational system

**Goal**: Try to evaluate which features contribute the most in determining students' academic success, to have a better understanding on where to intervene to guarantee fairness

# Dataset

Source

Grades of students from two secondary schools in Portugal in the subjects of Mathematics and Portuguese language, collected in 2008[1]

Features

School
Gender
Age
House Type
Family Size

Demographic

Mother's/Father's Education
Mother's/Father's Occupation
Parent's Cohabitation
Internet access
Family Support

Social/Economic

Studytime
Freetime
Participation in a romantic relationship
Frequency of going out
Alcohol Consumption

Behavioral

Target

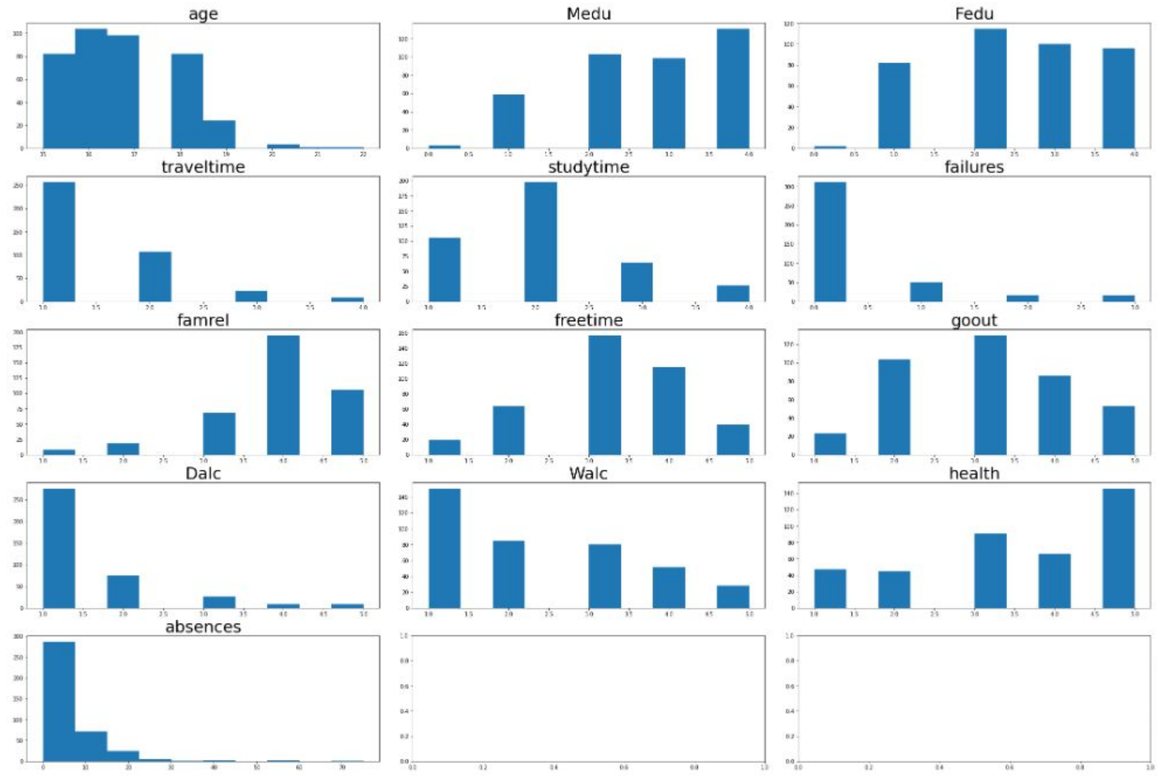
**G3**

Final Grade obtained in the respective subject (Mathematics/ Portuguese)

1: P.Cortez, A. Silva, *Using Data Mining to Predict Secondary Student Performance*, http://www3.dsi.uminho.pt/pcortez/student.pdf

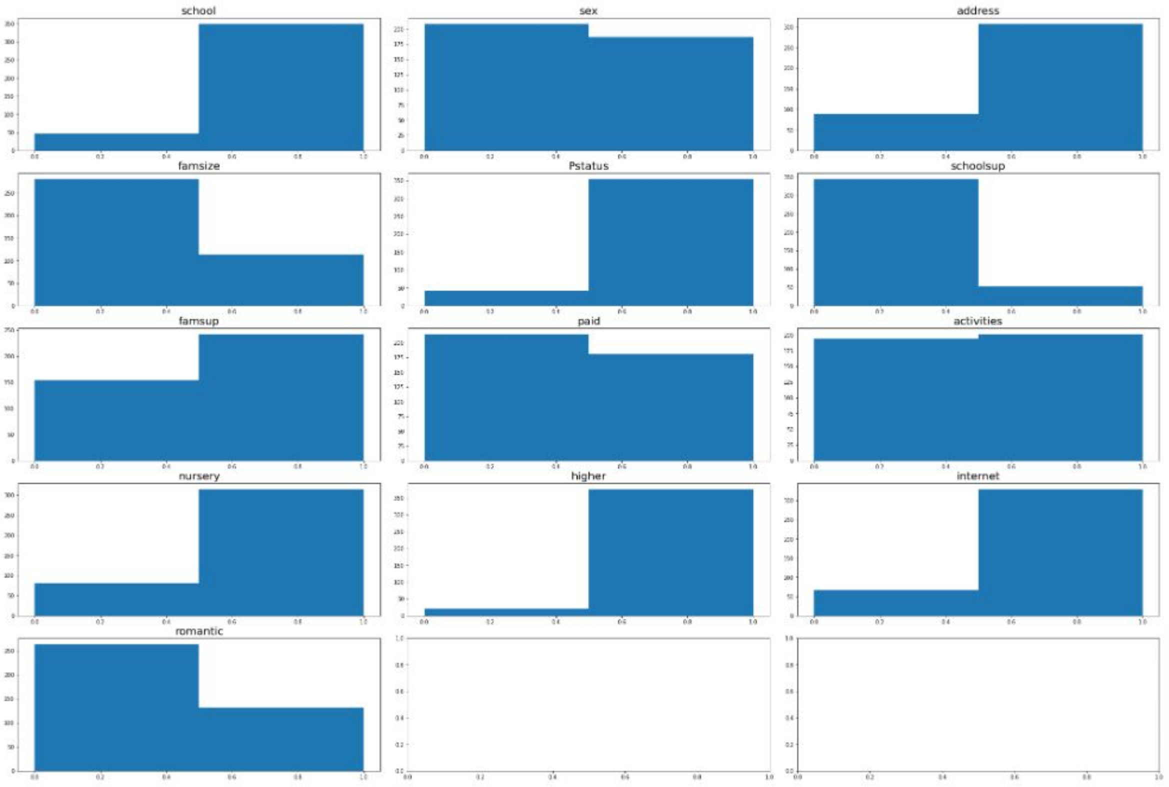
# Feature Exploration

Distributions of numeric variables



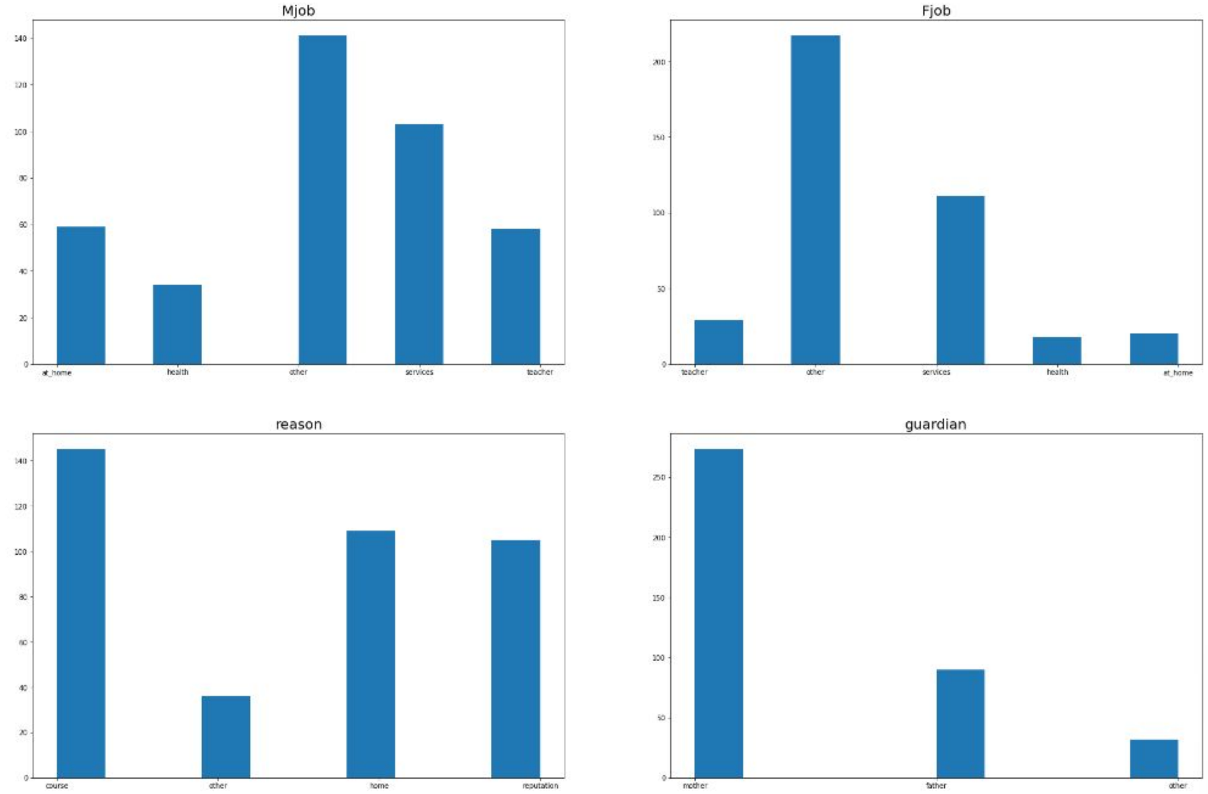
# Feature Exploration

Distributions of categorical variables



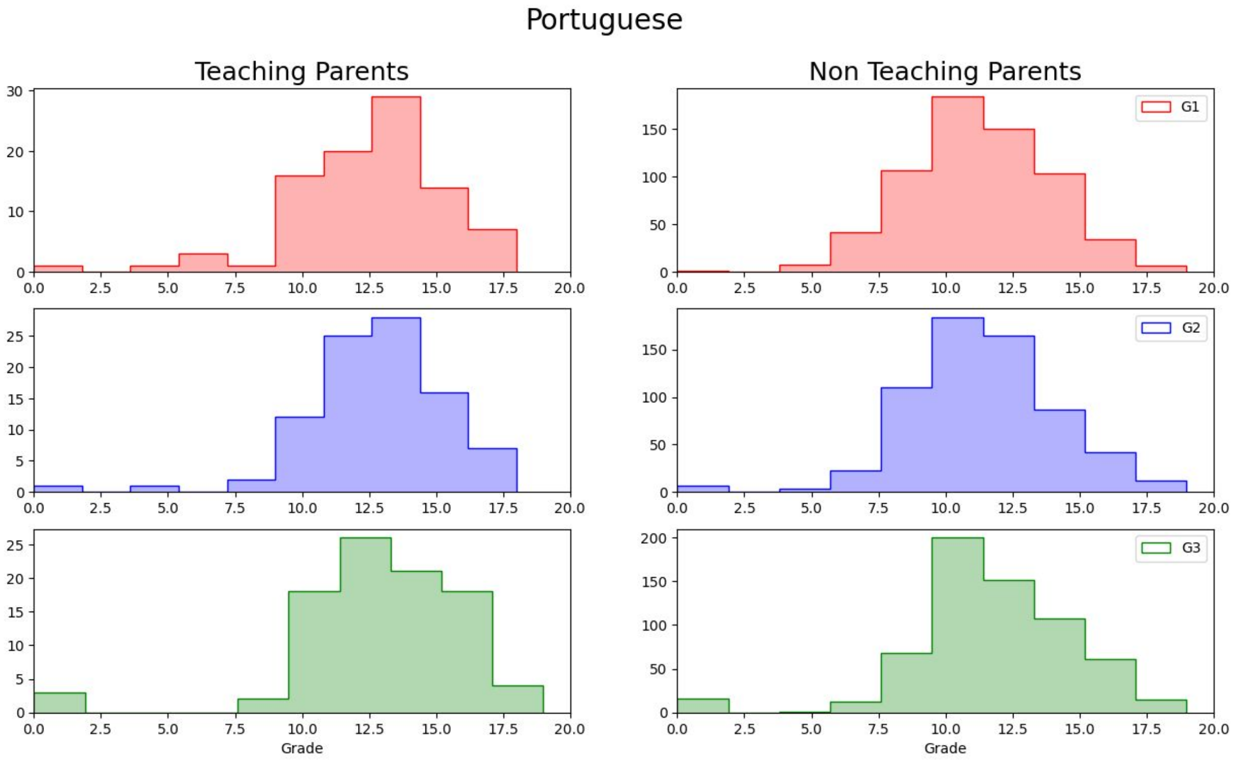
# Feature Exploration

Distributions of categorical variables (contd)



# Feature Exploration

Comparison of grades for students having at least one parent who is a teacher vs students having no parents as teachers



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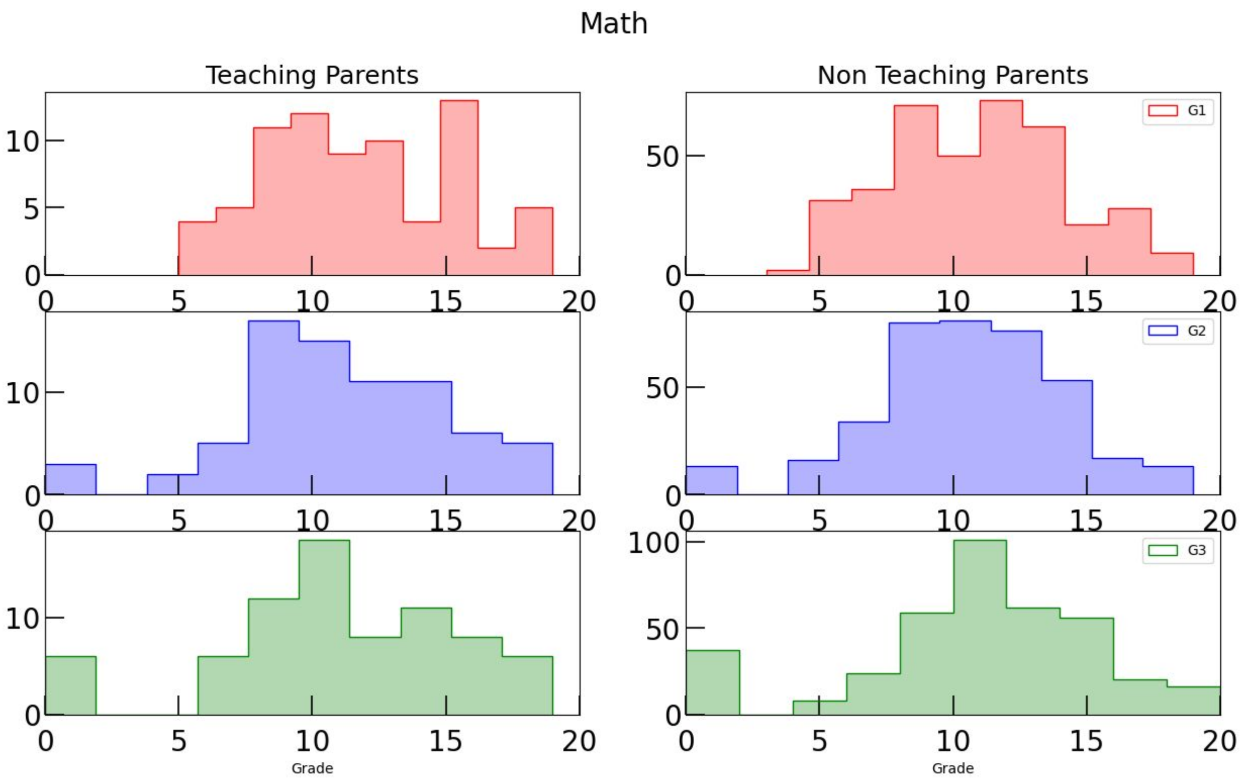
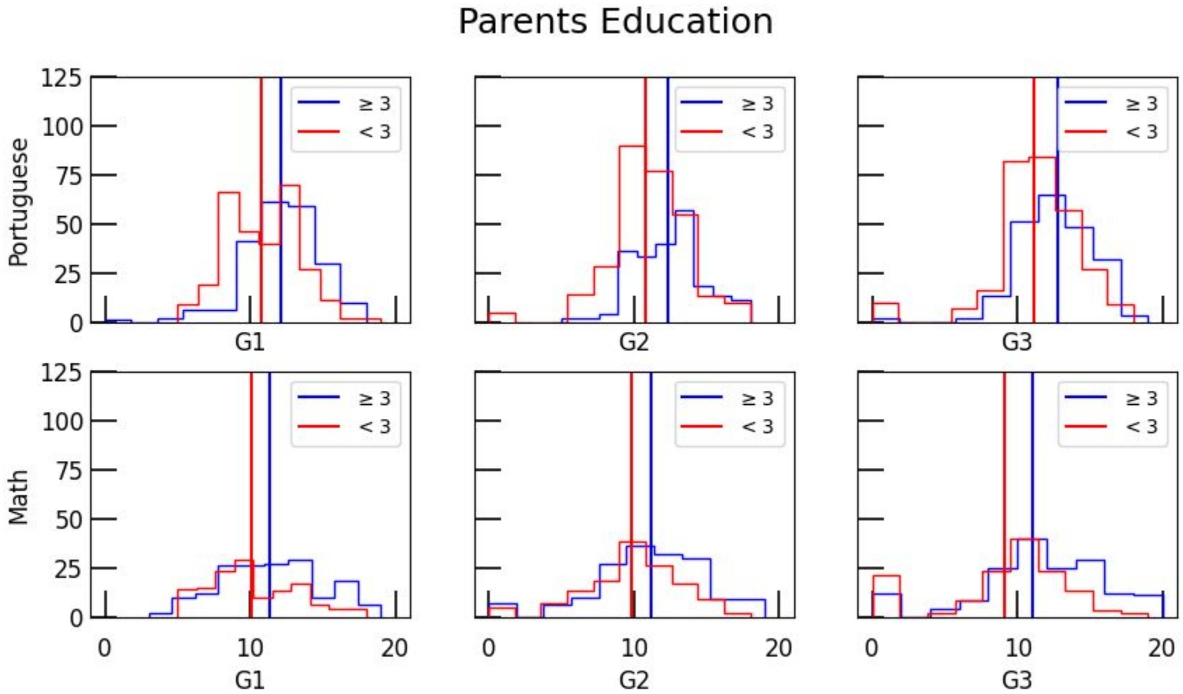


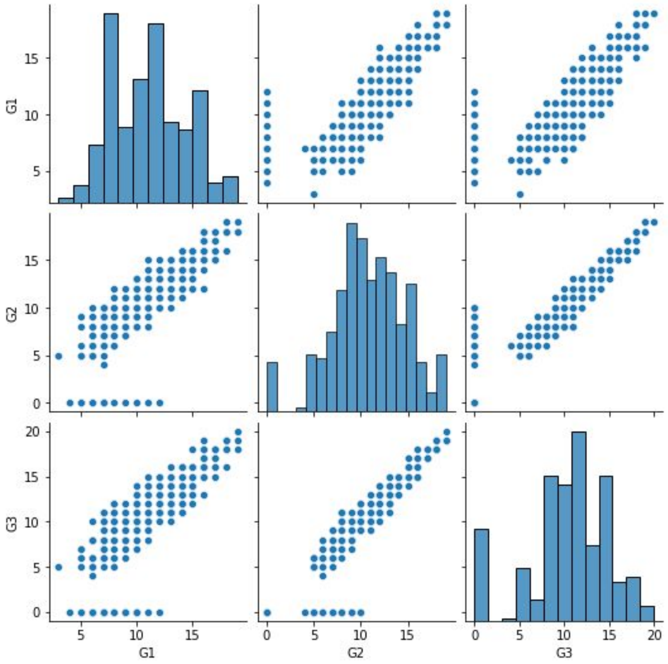
# Feature Exploration

Effect of parents education on the student’s grades in Math & Portuguese
>=3: Secondary education or Higher
<3: Lower than secondary education



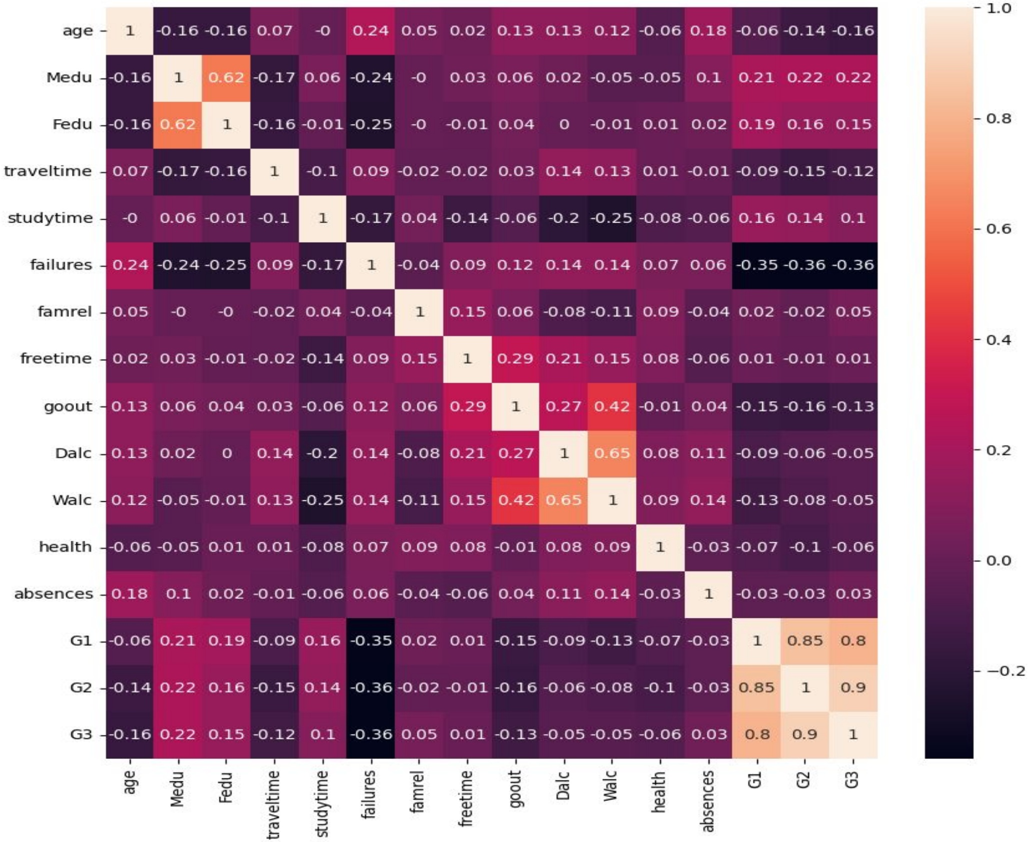
# Feature Exploration

Correlations between grades G1, G2 and G3 for the Math subject

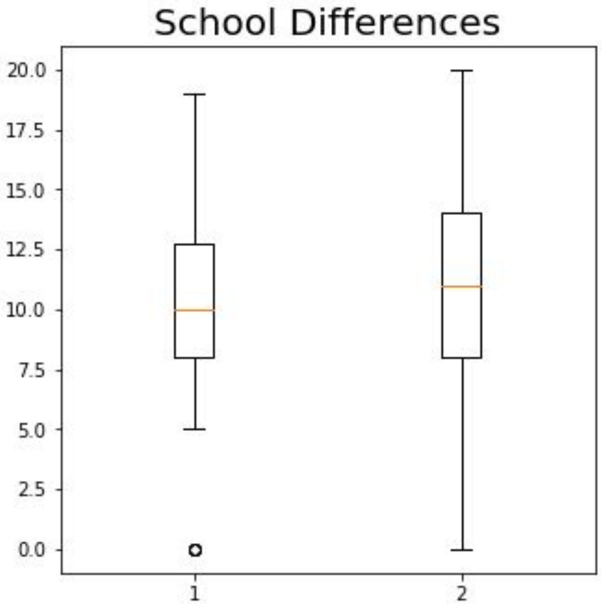


# Feature Exploration

Correlation matrix of all numeric features

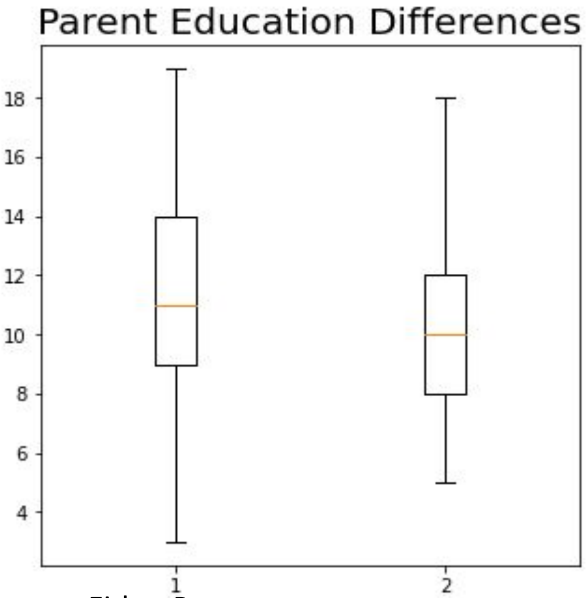


# Feature Exploration




School A School B

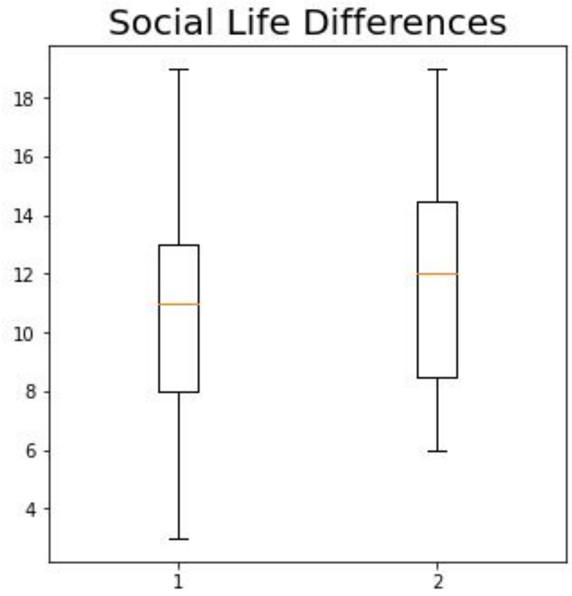

Has Teacher Parent Neither Parent



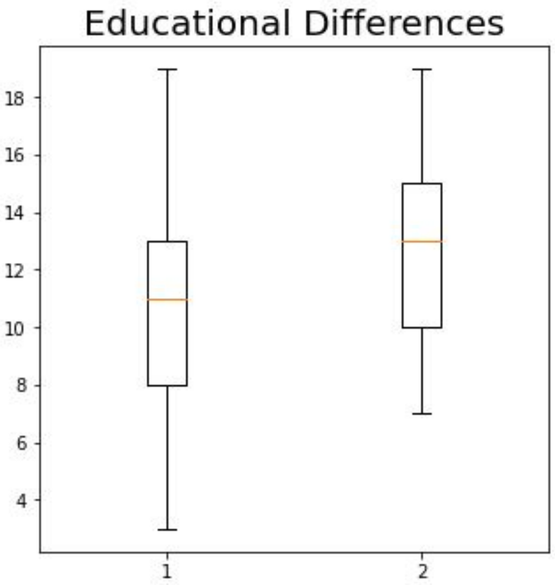

Either Parent Graduated HS or higher

Neither Parent Graduated

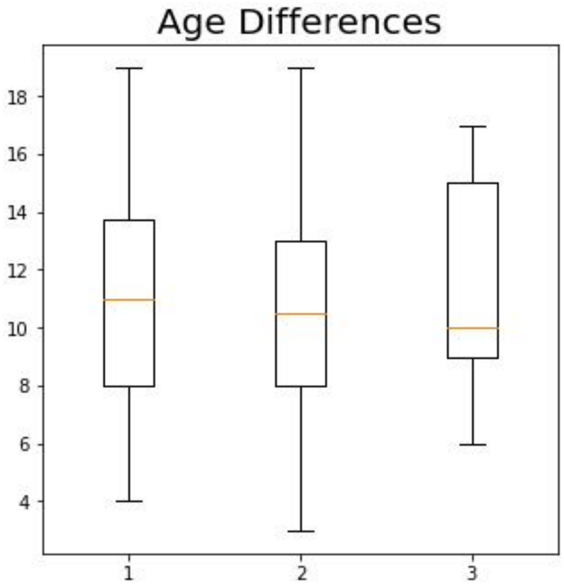
# Feature Exploration




Goes out More    Goes less More

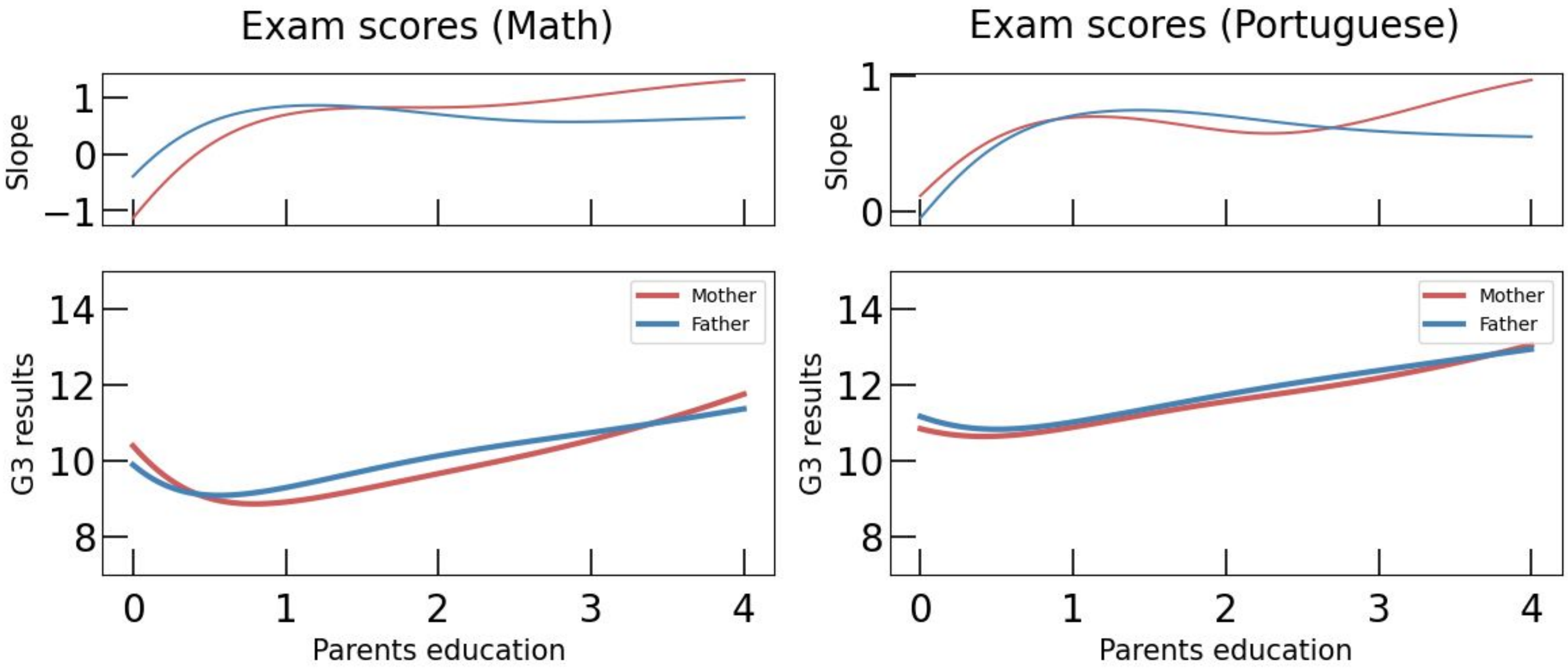



Higher failures, absences    Less failure absences




17)    [17, 20)    [20,

# Feature Exploration



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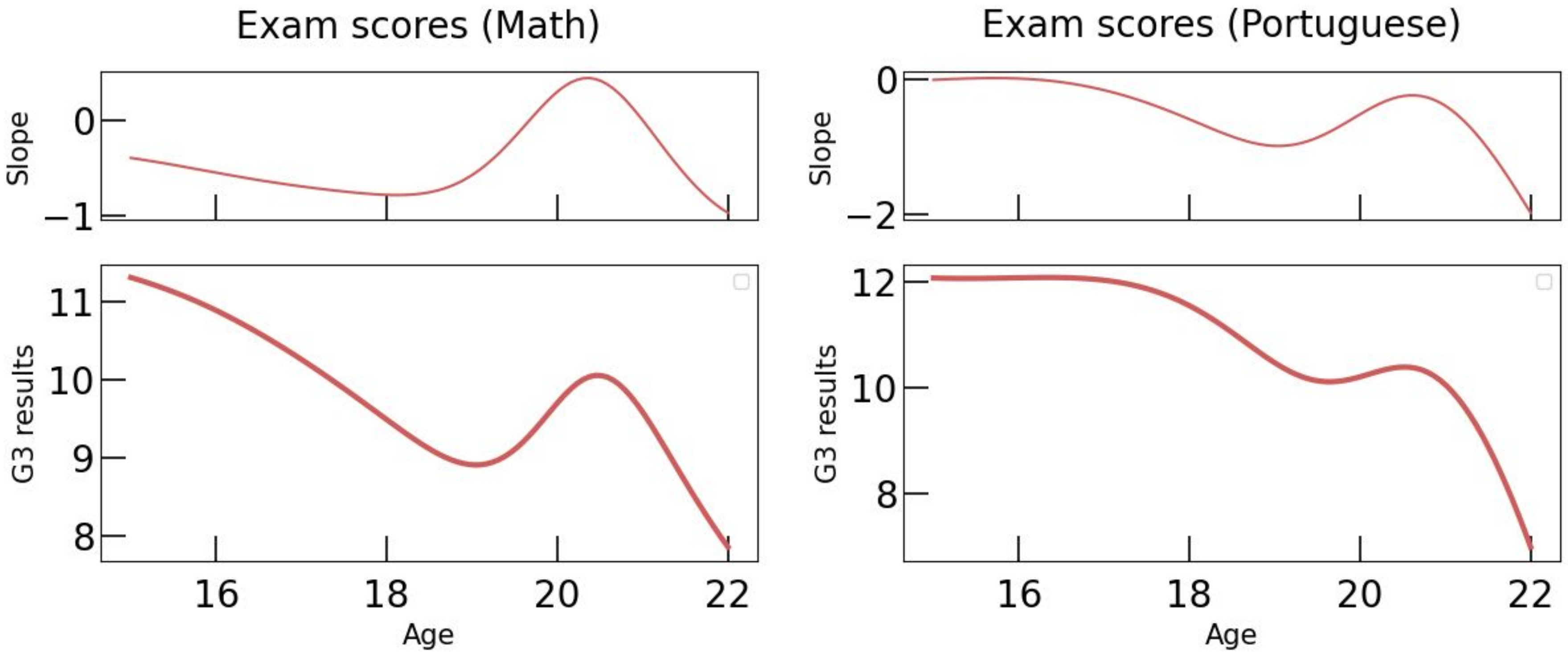

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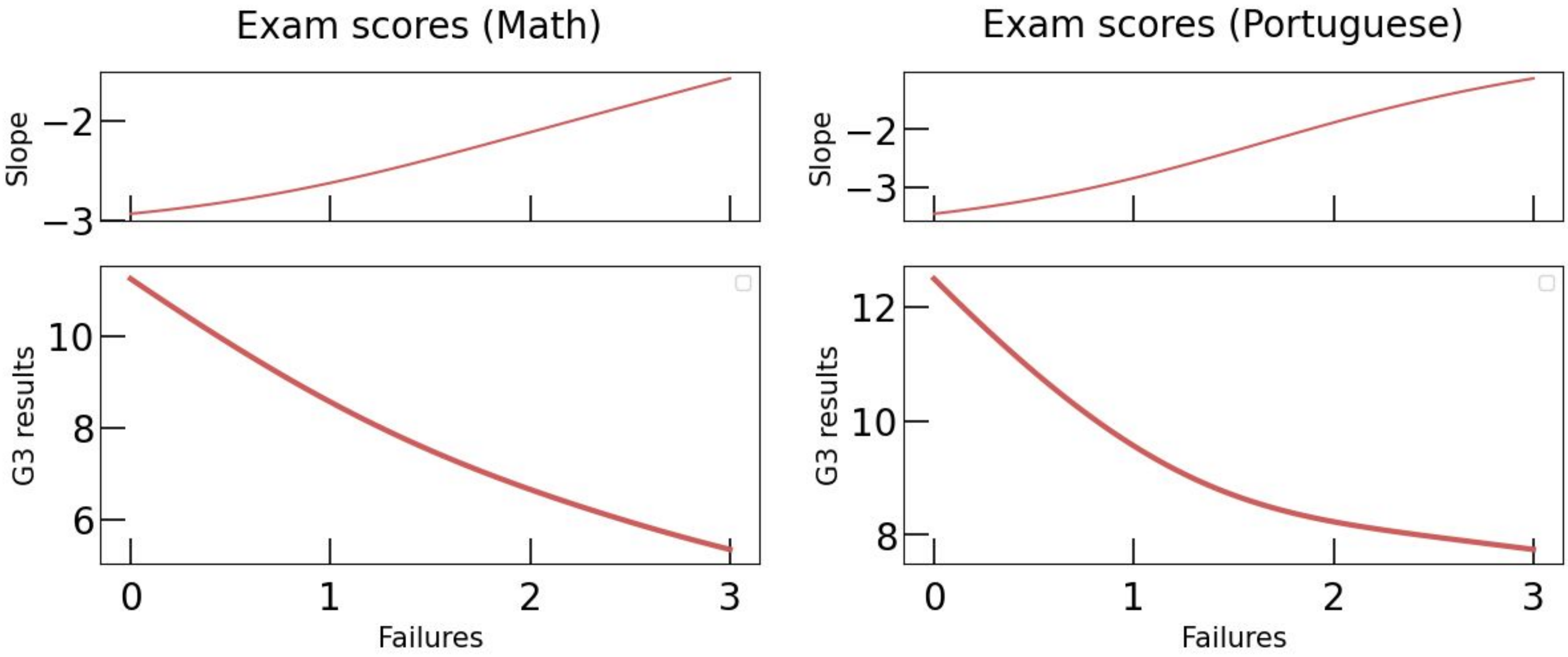


# Feature Engineering

Stratifying data with respect to three variables: ‘Student quality’, ‘School’, and ‘Absences’

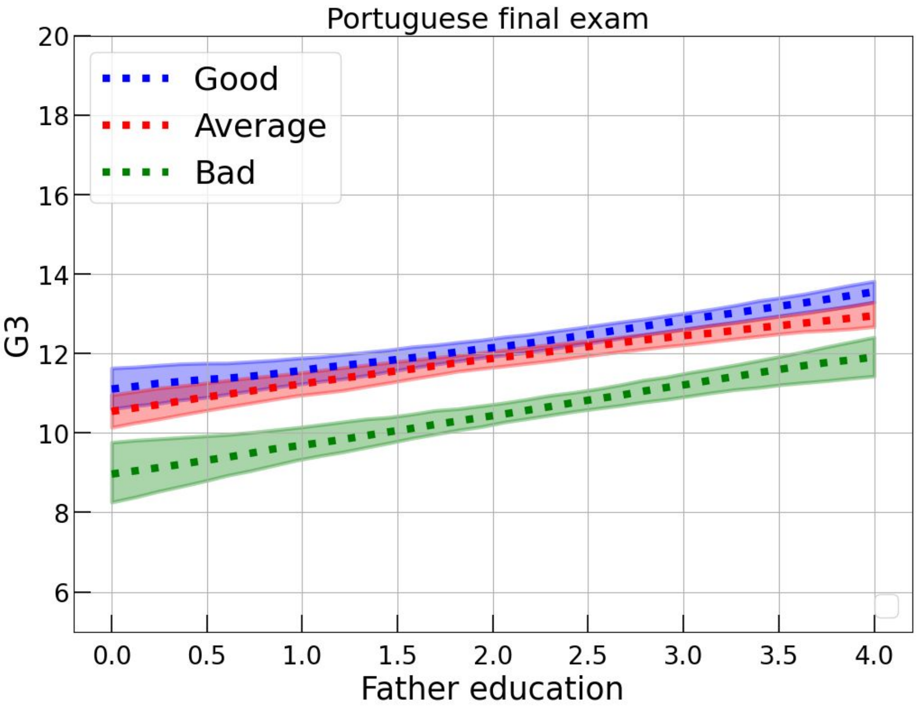
**Student quality**: sum of (normalized) absences, hours going out, daily alcohol, and weekend alcohol consumption

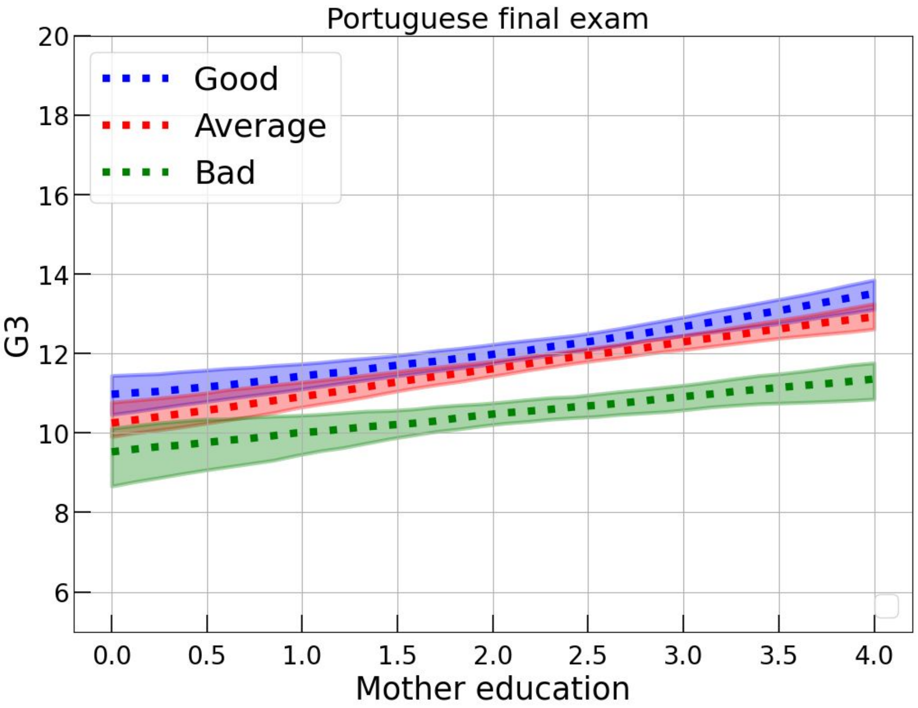
‘**Good student**’: from 0 to 1; ‘**Average**’: from 1.1 to mean+std; ‘**Bad**’: above mean+std

**School**: students enrolled in Gabriel Pereira or Mousinho da Silveira

**Absences**: from 0 to 5; from 5 to 20; above 20

# Feature Exploration



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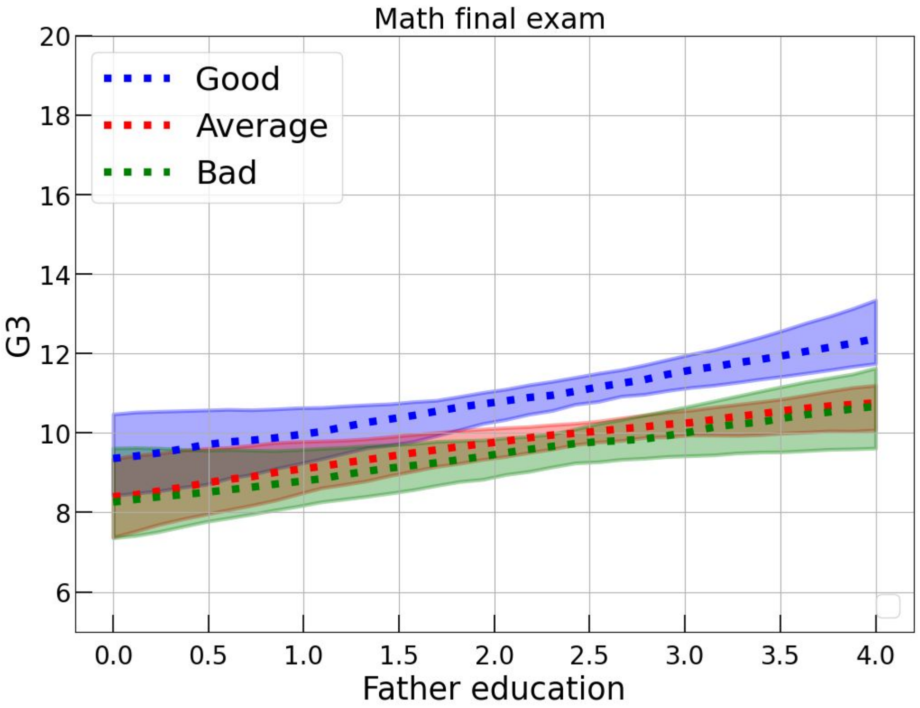


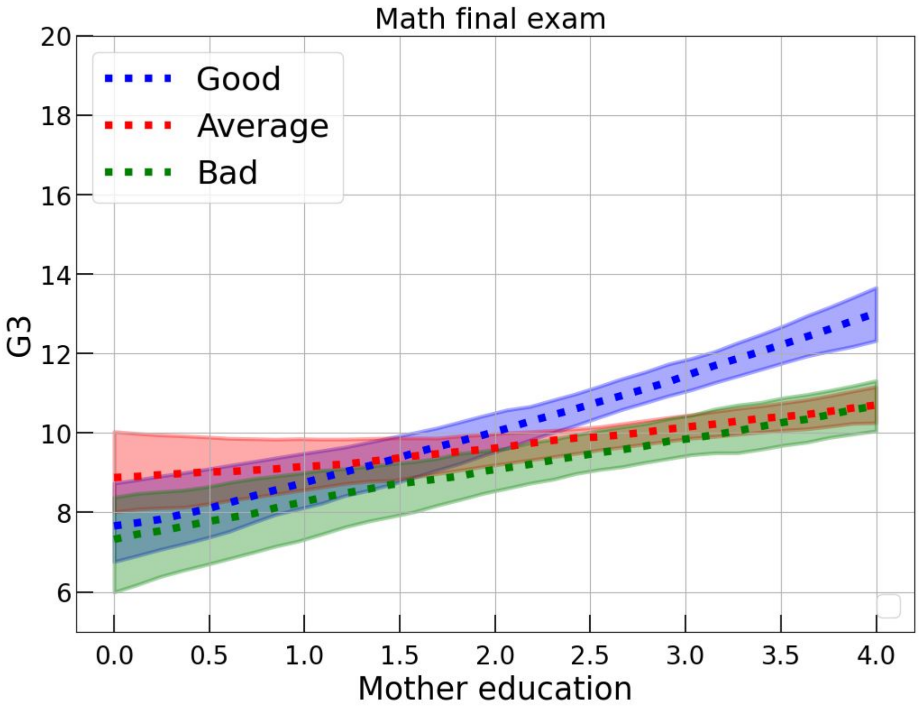

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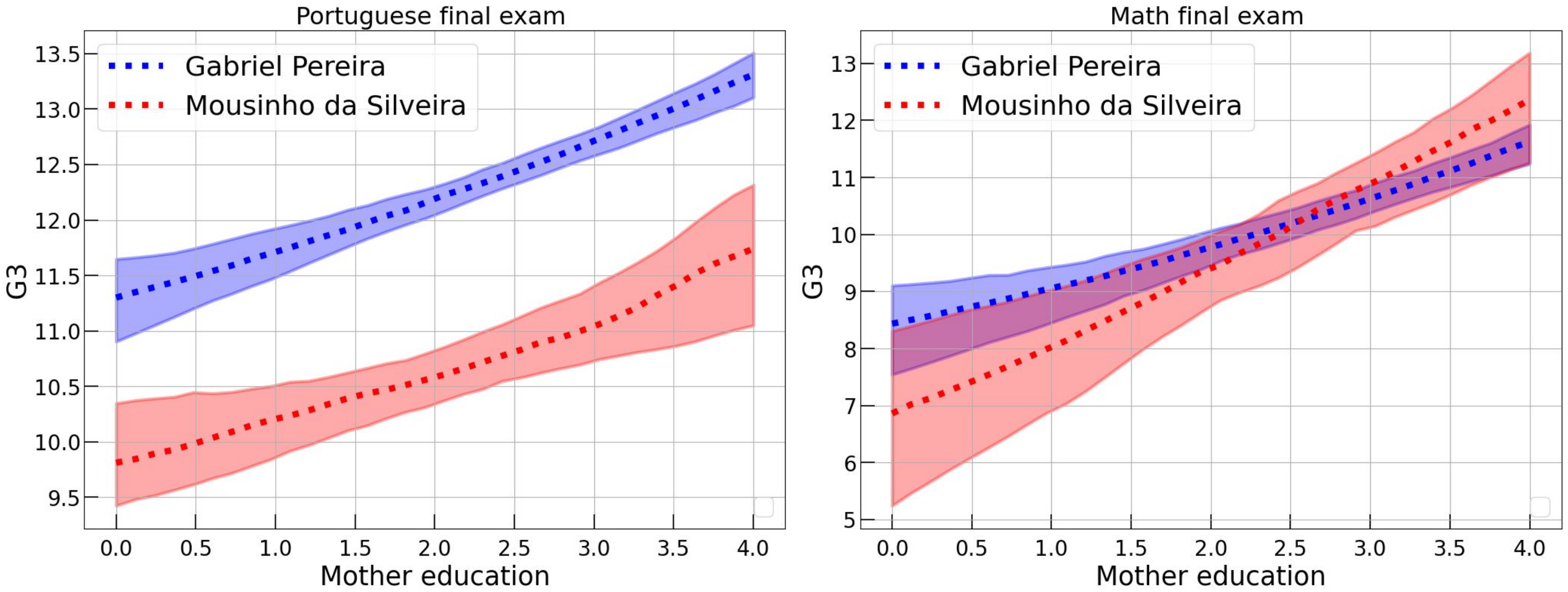

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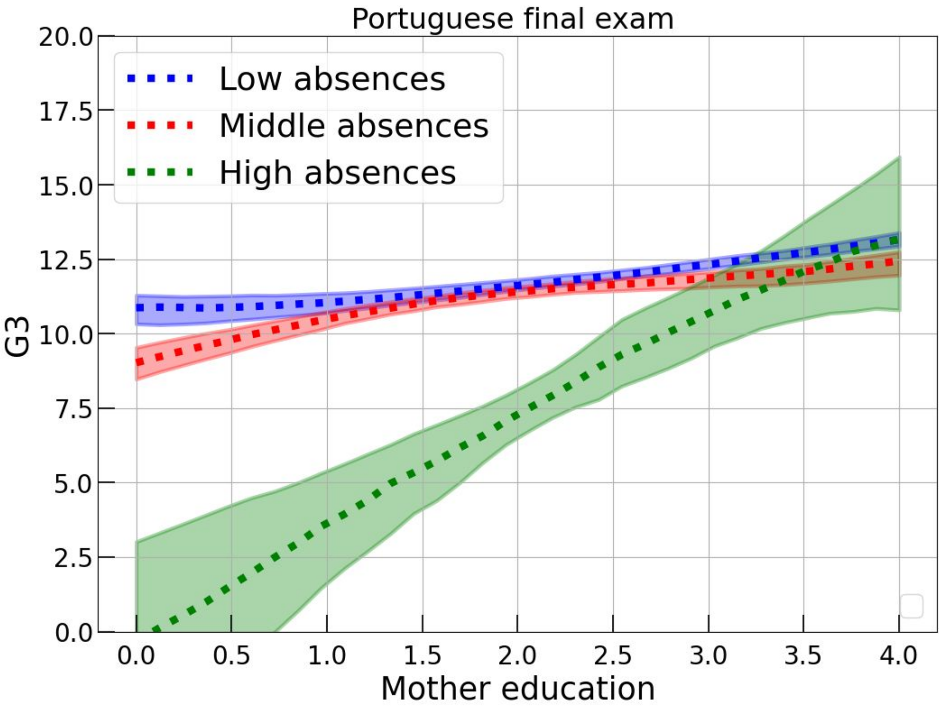
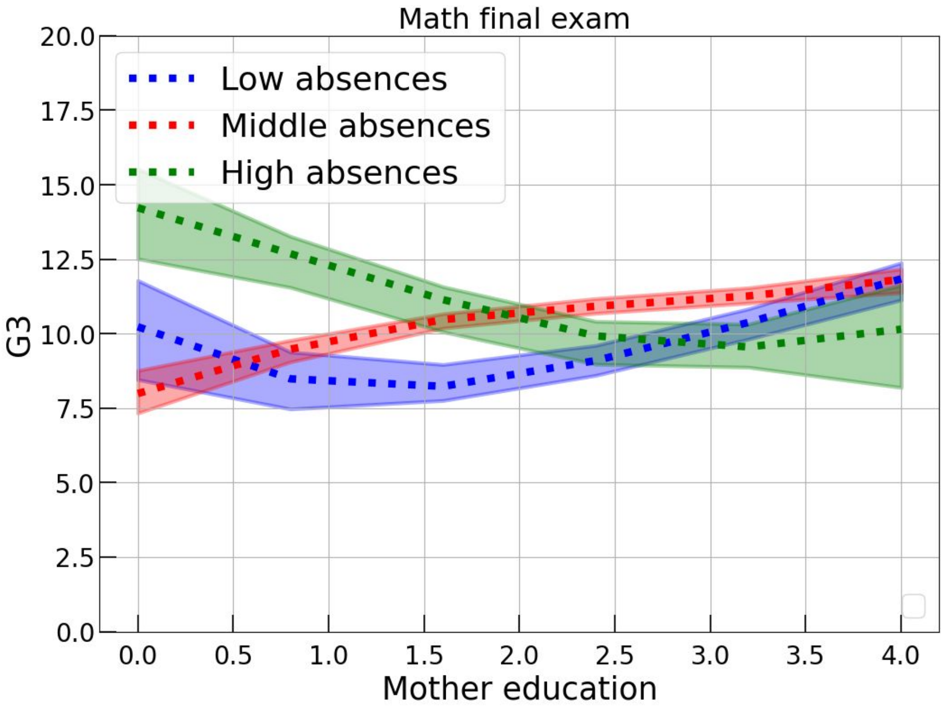


# Project Hypothesis

- Has the school students are enrolled in an impact on their results?
- Does the parents’ education have an influence on the grades students receive?
- Does having parents that worked as a teacher (one or both) have a positive influence on the grades they received?
- Does the age the students have an influence on their exam results?
- Is there a correlation between any of the after school variables (romantic, freetime, going out etc) that have an impact on student performance?

# Modeling

First round of regression models applied:

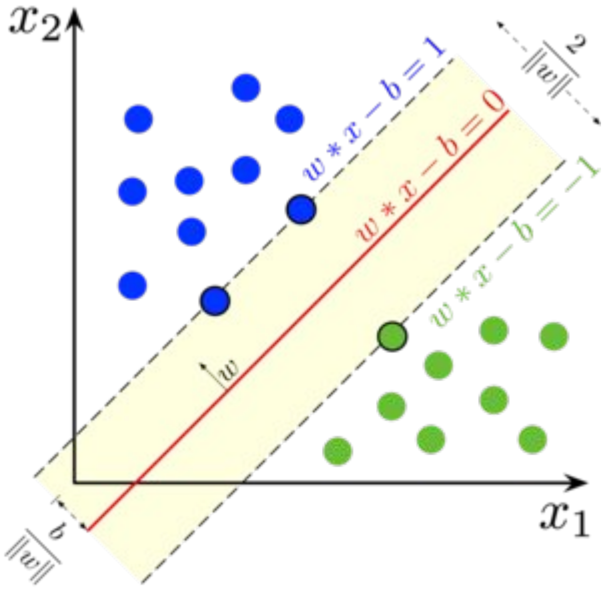
- Linear
- SVM

Kernel Type Models

- Gaussian Process
- Kernel Ridge

Ensemble type Models

- Decision Tree
- Random Forest



# Modeling

Feature Manipulation:

1) Categorical variables were OHEd
2) Features dropped:
   a) Reason
   b) School
   c) Guardian
   d) Father Education
   e) Weekday Alcohol Consumption
3) Will only use G3 as a target variable

Data Manipulation:

1) Base Models with Specific Hypertuning
2) Scaling Features
3) Feature Reduction (PCA)

Each step included modifications from previous steps

# Modeling

Model Specific Hypertuning parameters:

- Gaussian Process:
  - Default Kernel (Constant * RBF)
  - Dot + White kernels
  - RBF + White kernels
- Kernel Ridge:
  - Linear kernel
  - Polynomial kernel
  - RBF kernel
  - Sigmoid kernel
  - Alpha between 0 and 1 in 0.1 increments
- SVM:
  - Same kernels as KR
  - Degree from 0 to 12
- Decision Tree
  - Max Depth between 5 and 20 in 5 increments
  - Max Features between 5 and 15 in 5 increments
  - Min leaf samples between 5 and 20 in 5 increments
- Random Forest
  - Same as Decision Tree

# GAN + Predictor Network

- **GAN**: Generator and Discriminator Neural Network Models
- **Generator (4 Feed Forward + ReLU)**
  - Receives random noise as input
  - When trained, outputs fake data similar to the actual data
- **Discriminator (4 Feed Forward + ReLU + Sigmoid)**
  - Receives samples as input
  - Classifies the data as fake/generated, or real
- **Minimax Game** - Trained Simultaneously using one another
- **Predictor Network (4 Feed Forward + ReLU)**
  - Receives samples as input
  - Outputs the predicted G3 Score
- **Goal**: See if a deep learning approach would give us any significant results/decent models, which would provide us with more insight into the data as a whole

# Validation Techniques

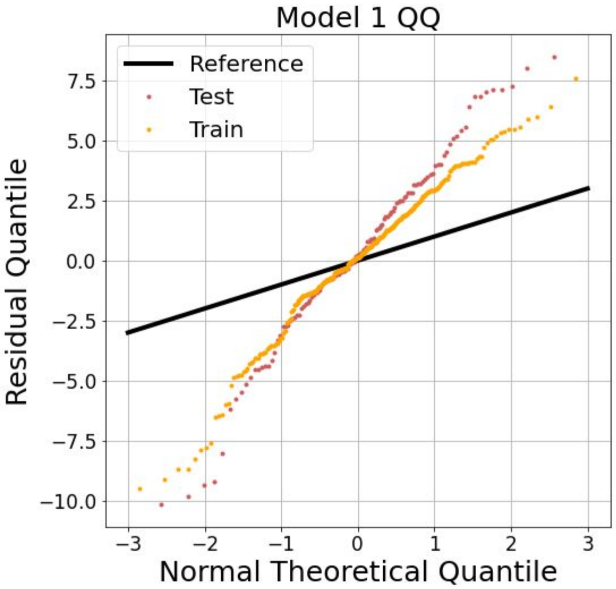
For each model the following validation techniques were used:

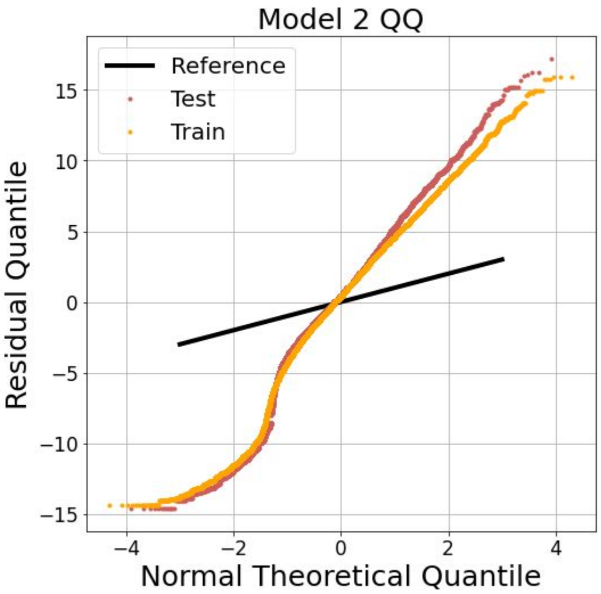
- 10-fold validation
- QQ plots
- Scoring Metric: MSE

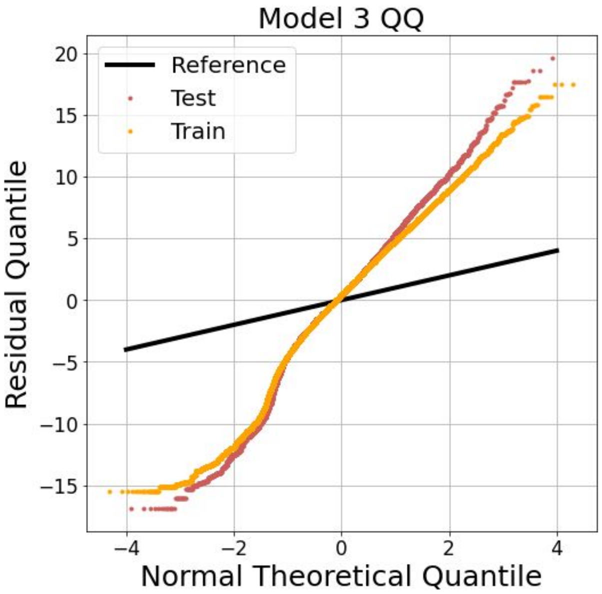
# Results

| Model + Dataset | MSE | Standard Deviation |
|---|---|---|
| Random Forest (Scaled) | 17.403 | 6.398 |
| Gaussian Process (Base) | 18.814 | 7.977 |
| Gaussian Process (All) | 19.228 | 8.000 |
| Gaussian Process (Scaled) | 19.228 | 8.000 |
| Linear (Base) | 19.44 | 8.030 |
| Linear (Scaled) | 19.45 | 8.036 |

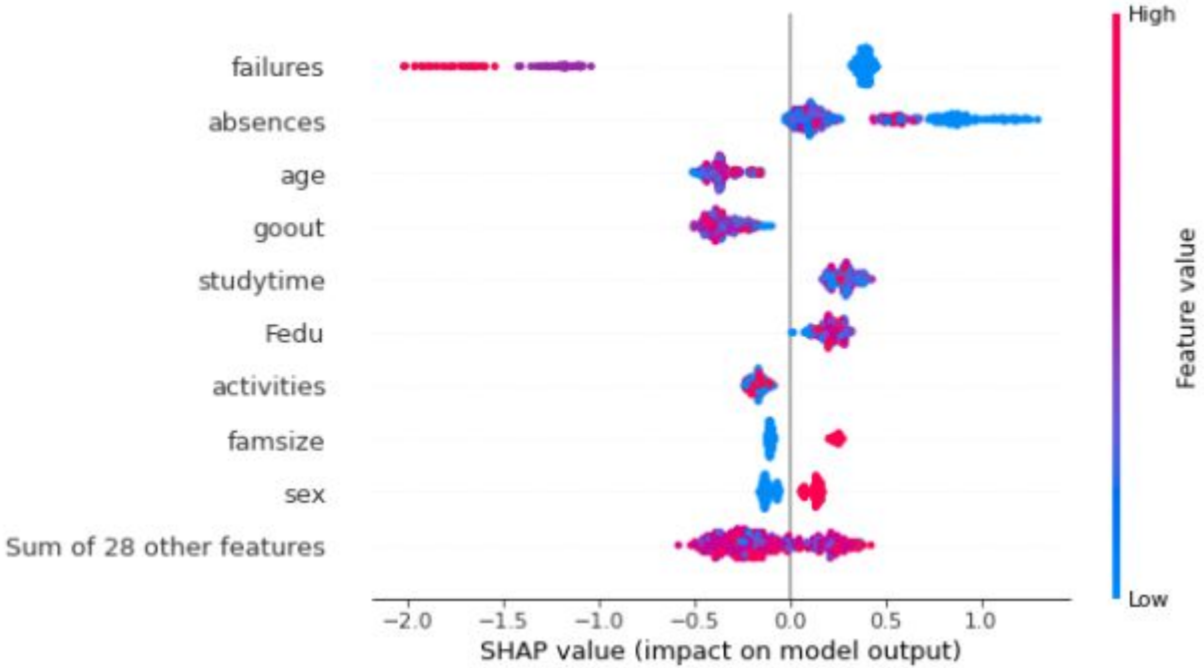
# Results


Model 1 QQ
Reference
Test
Train
Residual Quantile
Normal Theoretical Quantile
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
−3
−2
−1
0
1
2
3


Model 2 QQ
Reference
Test
Train
Residual Quantile
Normal Theoretical Quantile
15
10
5
0
−5
−10
−15
−4
−2
0
2
4

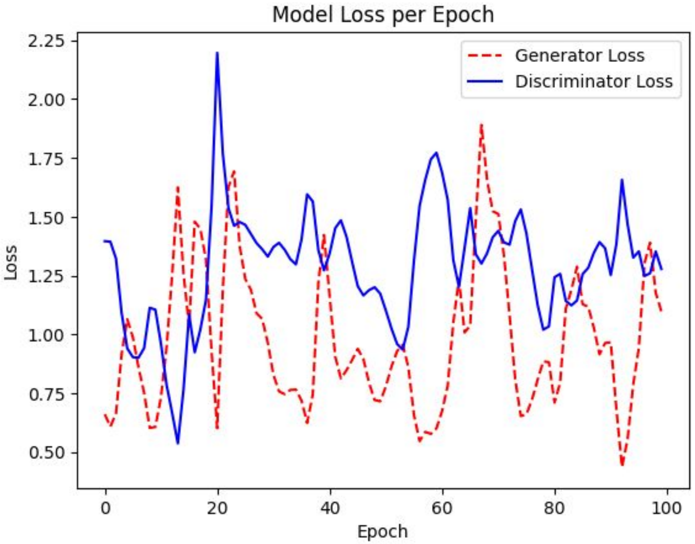

Model 3 QQ
Reference
Test
Train
Residual Quantile
Normal Theoretical Quantile
20
15
10
5
0
−5
−10
−15
−4
−2
0
2
4

# Results - SHAP

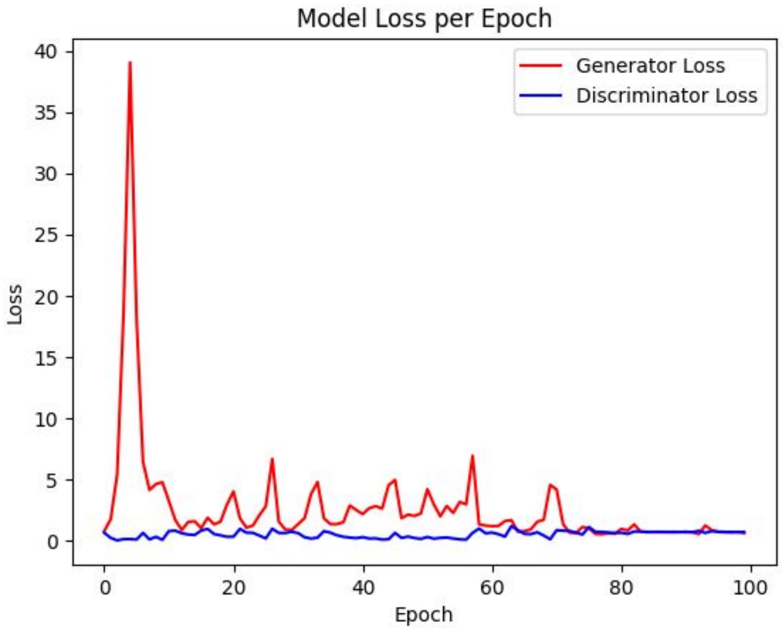


# GAN Results

Initial GAN Loss Curves




Final GAN Curve

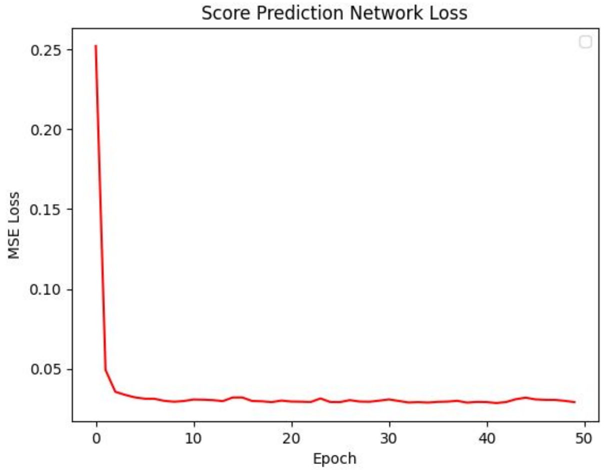


# GAN Interpretation

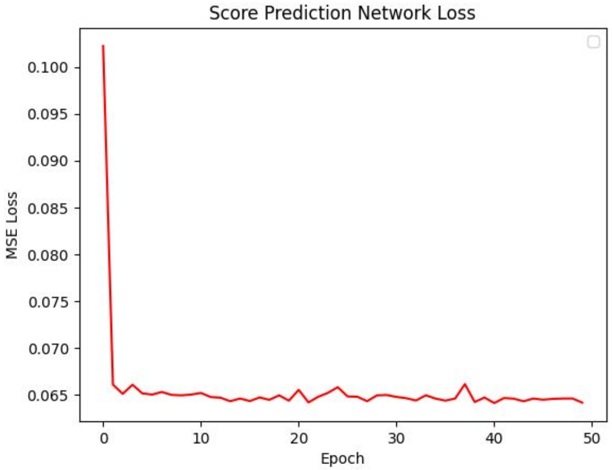
- Best BCE Loss found was in the .59 - .69 range for both models
- Large oscillation and divergence due to the minimax between models being one sided most of the time (discriminator was improved much faster than generator or vice versa, hinders training)
- You generally want to see a small bit of divergence, until both models reach an equilibrium
- Our model reaching equilibrium while still having a decently high BCE Loss tells us that the generator couldn’t find the underlying distribution of the real data, so there's nothing pushing the discriminator to improve

# Predictor Network

Trained on Real Data (.029 Loss)




Trained on Real + Fake Data (.064 Loss)




- Good loss value w/ real data, slightly worse with real and generated data, as expected
- The steep and early loss decrease given a very low learning rate tells us:
  - Model had too easy of a time learning to predict the score
  - Model is too complex and overfitting, or the features aren't good predictors of the score
  - However with simple models, convergence didn't happen

# Thoughts

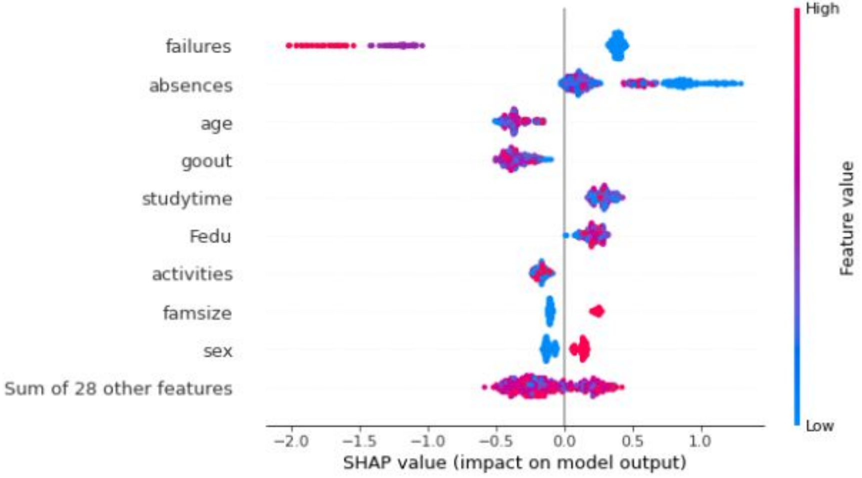
- All in all, the neural network models performed mediocre and is most likely not a good fit for the data
- Generator could be used to generate more diverse data, therefore giving the networks something to find patterns in
- Future Improvements:
  - Cross Validation
  - More generated data
  - More optimal models through hyperparameter tuning and training methods

# Discussion

- Best model - Random Forest
  - Could have potentially have been overfit

- Questionable Q-Q plots
- SHAP corresponds with our hypothesis

- Limitations
  - Treating categorical variables as numerical
  - Disproportionate group sizes



# Conclusion

- Best model
  - Random Forest

- Hypothesis 1 - School Influence
  - **Plausible**
- Hypothesis 2 - Parent's Education
  - **True**
- Hypothesis 3 - Parent's Job
  - **Plausible**
- Hypothesis 4 - Student Age
  - **True**
- Hypothesis 5 - After-school life
  - **Plausible**
- Final Conclusion:
  - Academic Features are most important

Important Features coincide with paper over this dataset

# Contribution

| Name | Contribution |
|---|---|
| Alberto Salvarese | 100 |
| Chris Lawson | 100 |
| Jeffrey Gordon | 100 |
| Utkarsh Mujumdar | 100 |