PREDICTING PORTUGESE SECONDARY SCHOOL STUDENT PERFORMANCE

https://github.com/annieptba/data1030_project.git

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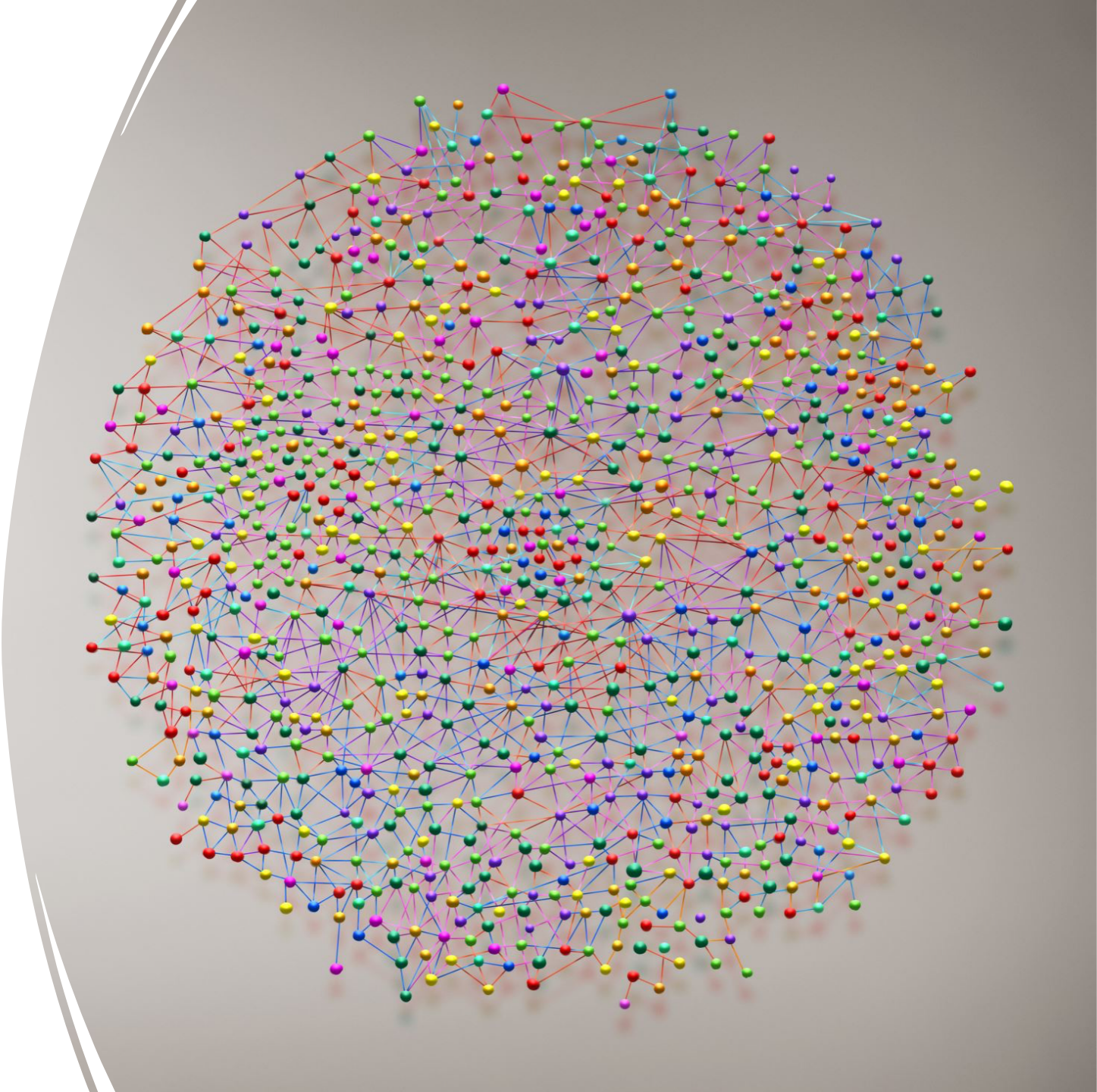
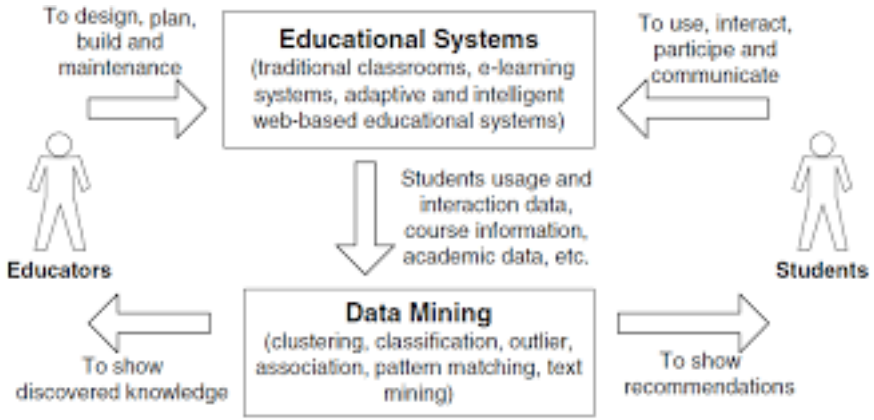
December 4th, 2020



CONTENT OVERVIEW



- 1. Recap - Intro and EDA
- 2. Cross validation
- 3. Results
- 4. Outlook

1. RECAP

Problem:

Classification: classify students' final performance (categorical values 'pass' - >=10, 'fail', <10) using first and second period grades and other social, economic, and education factors

EDA Recap: initially focus more on social factors (romantic status, alcohol consumption, etc), now focus more on features that are most important as shown by the model

Preprocessing Recap: generate pass_fail feature as target variable, drop G3, use train_test_split and KfopId split, apply OneHotEncoder, MinMaxEncoder, LabelEncoder

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Data overview and source

https://archive.ics.uci.edu/ml/datasets/student+performance

1,044 instances (students) including 395 Mathematics class students and 649 Portuguese language class students

33 features

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Implications:

What type of courses can be offered to attract more students? Is it possible to predict student performance?

What are the factors that affect student achievement?

My model explores these similar questions but look further into demographic factors such as family support, romantic relationships, alcohol consumption, and internet access.

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Original research:

Project: "Using Data Mining To Predict Secondary School Student Performance" by Cortez and Silva in 2008

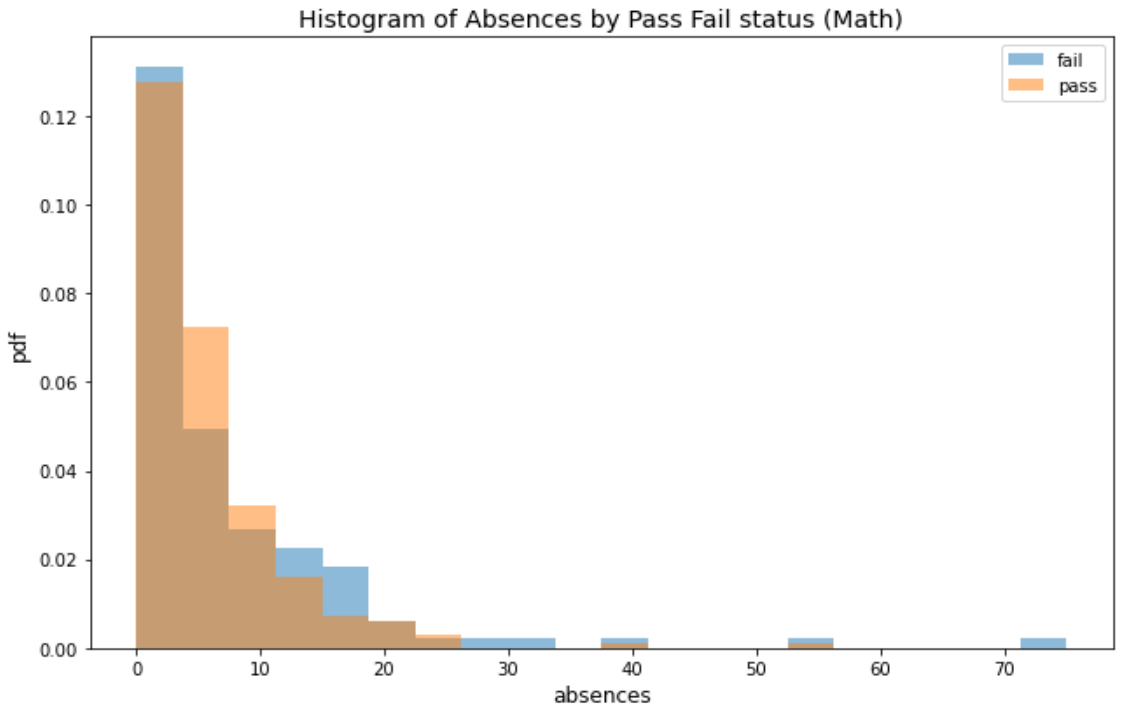
Method: binary classification (pass/fail), classification with 5 levels (I very good → V insufficient), regression, with a numeric output that ranges between (0%) and (100%)

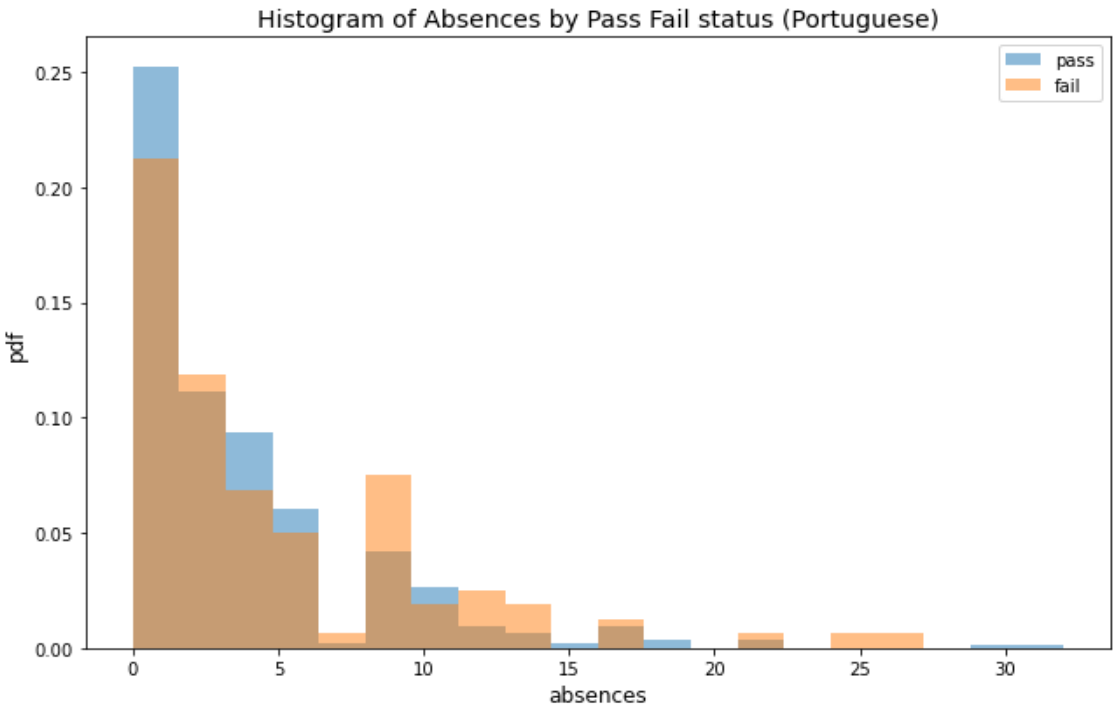
Result: students' final grades can be predicted by the first and/or second school period grades and also other relevant features

EDA - PASS FAIL STATUS AND ABSENCES

- Students have more absences in Math than Portuguese → students may be less interested or struggle more with this subject
- More students who had higher absences were able to pass Portuguese than Math, which again suggests that Math is harder than Portuguese for the students

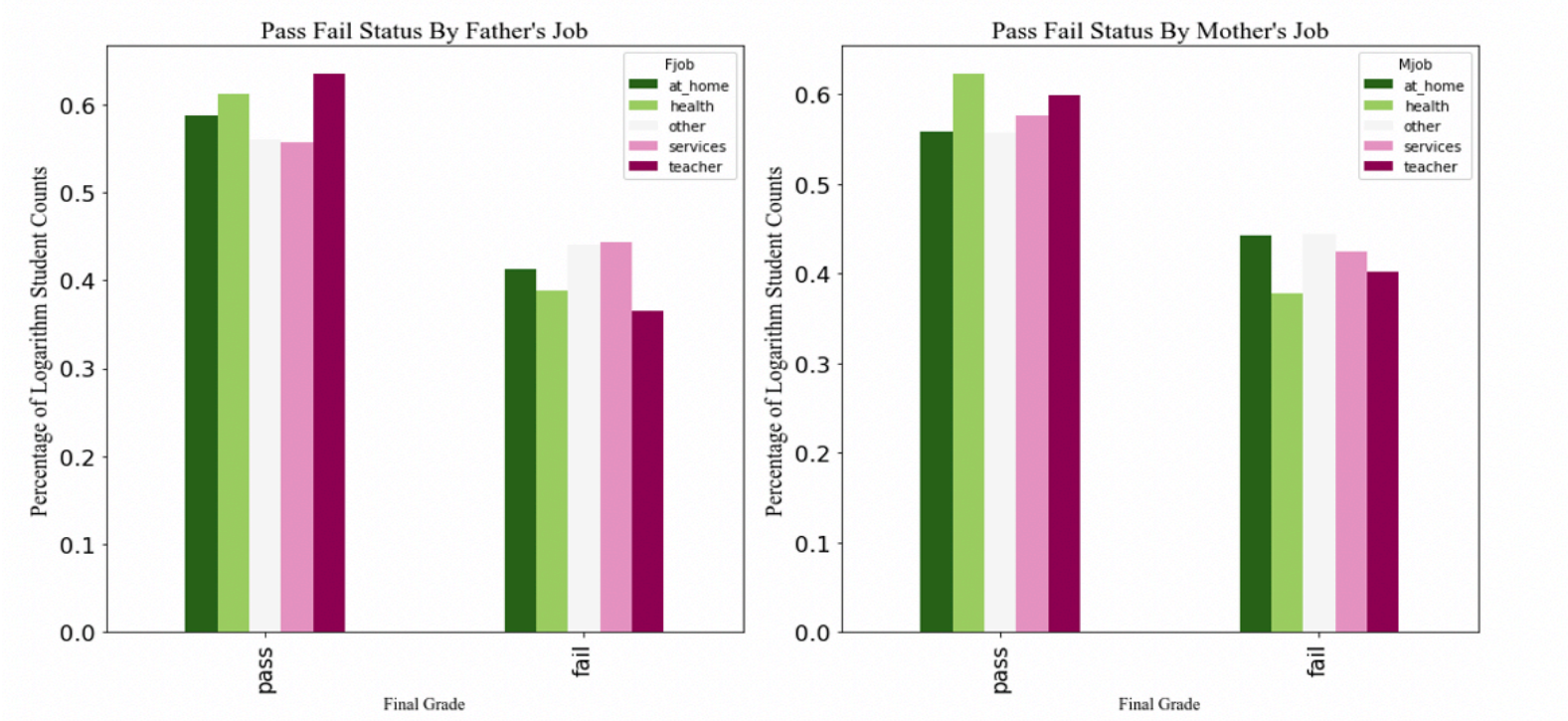
- why students are absent more in Math
- how or if they are struggling with the subject,
- what can be done to improve





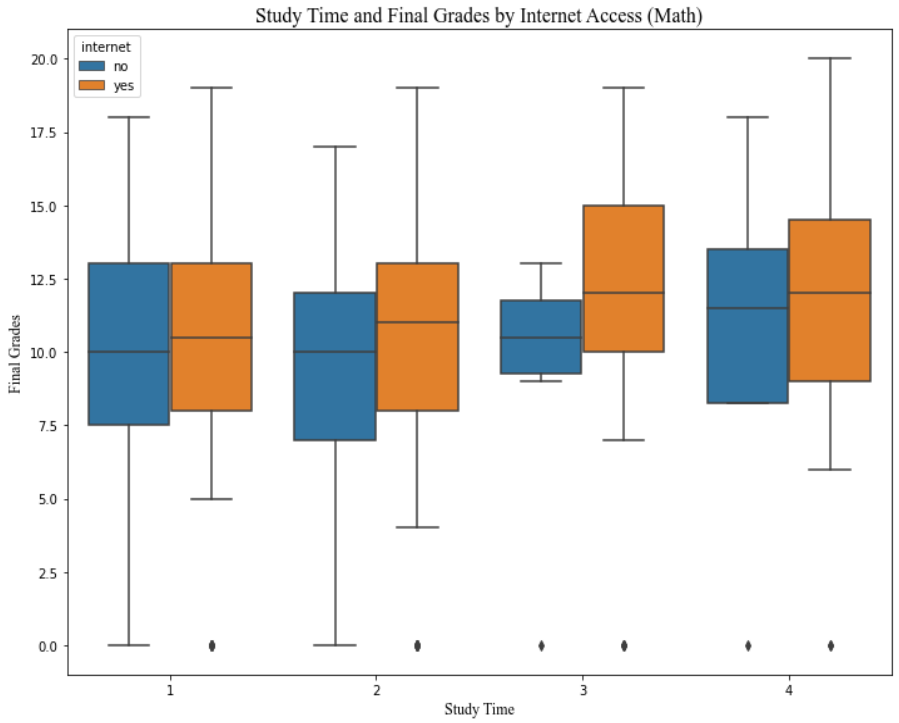
EDA - PASS FAIL STATUS AND PARENTS' JOBS

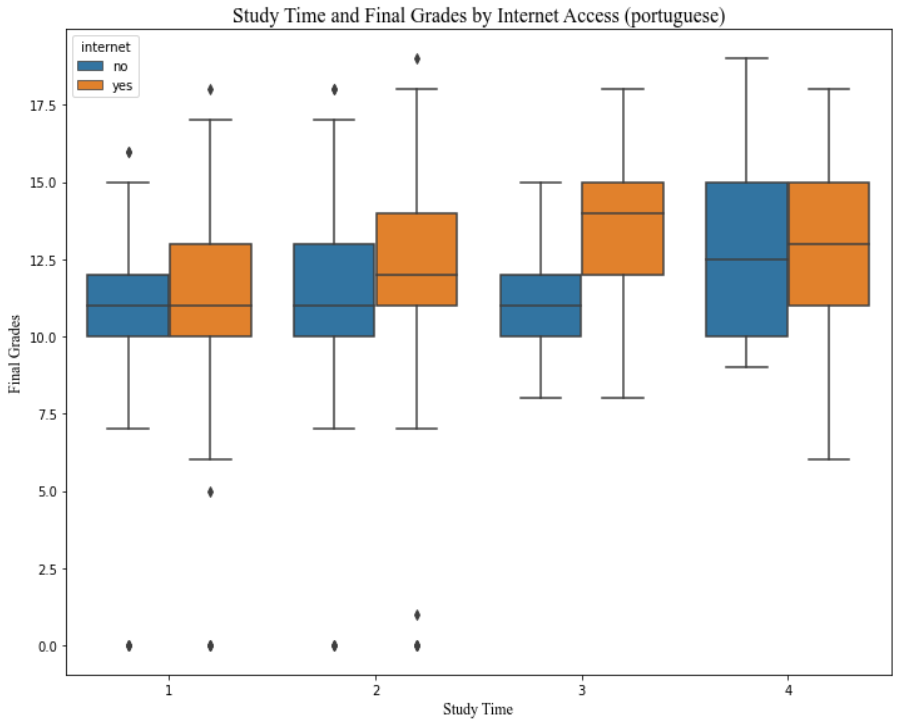
- correlation between the parents' job and students' performance
- more students pass if their parents are in a "highly educated" field, such as health or teacher and vice versa.
- there isn't a significant different between the number of students who pass and fail with respect to the mother or father's job, which suggests that both parents' jobs are equally important.
- suggests some degree of socioeconomic inequality in education



EDA - STUDYTIME, FINAL GRADE, INTERNET ACCESS

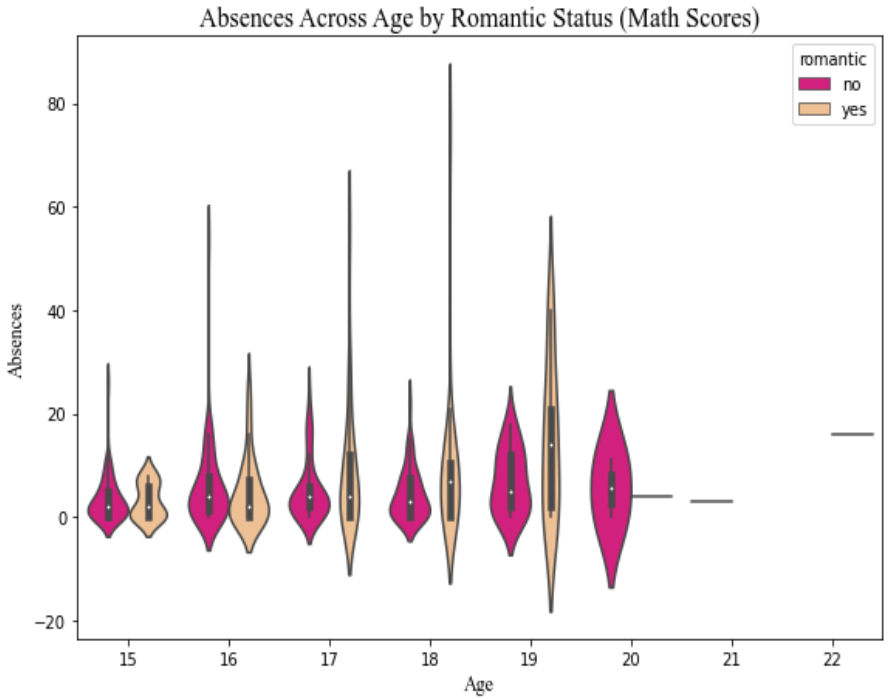
- students who have internet have higher grades than those who don't → internet is quite important for studying.
- for students who study less in both subjects, there is a smaller difference in the final grades between those who don't have internet and those who do compared to students who study more → strong students are more effective at using the internet for studying
- →needs to be more research into what the students do on the Internet, how much time do they dedicate their internet use to studying, and how schools can assist students in using the Internet for more education purposes.

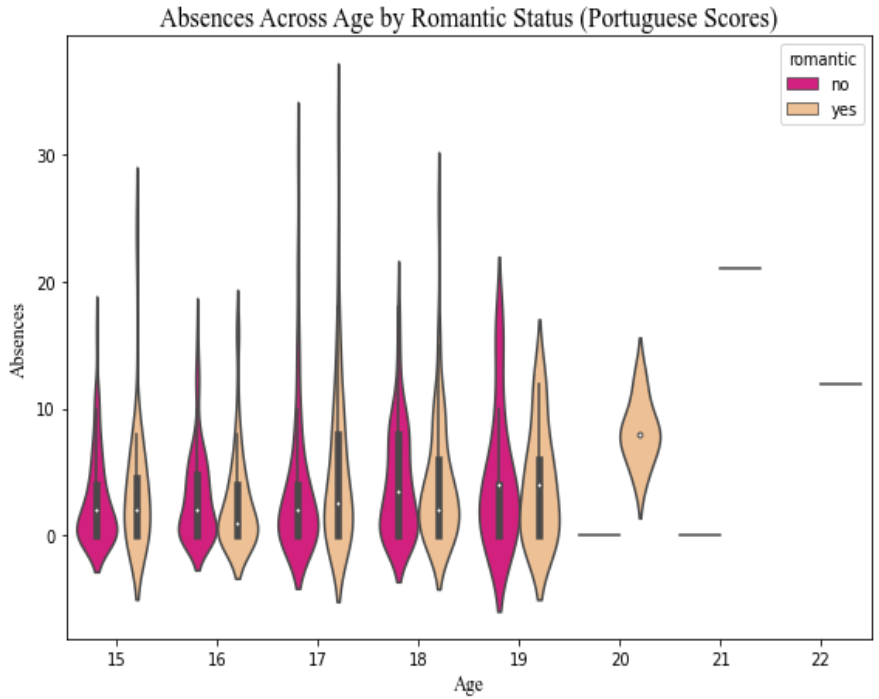




EDA - ABSENCES, AGE, ROMANCE

- students who are in a relationship have more absences than those who don't. → suggests that relationships can distract students from school.
- In math, students between 17 - 19 years old have the most absences and are in a relationship more.
- In Portuguese, there are more students who are in a relationship than Math, and these students also have more absences → suggests that either students in Math are more "disciplined" or math is harder and require students to study more.





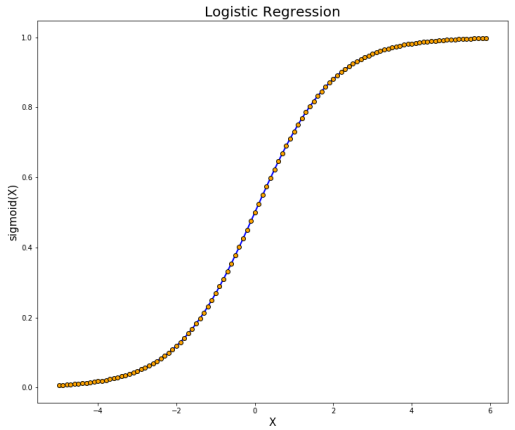
2. CROSS VALIDATION - MACHINE LEARNIJG MODELS & FEATURE IMPORTANCES

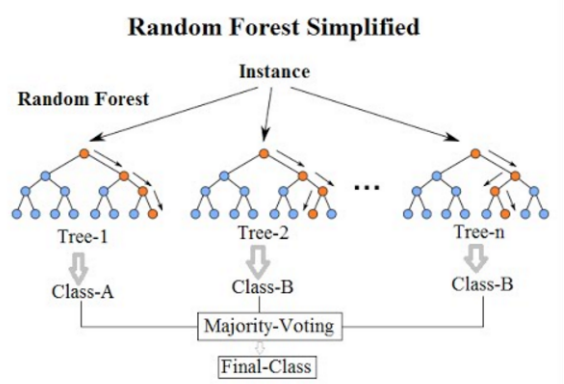
Figure: Splitting & Preprocessing Results

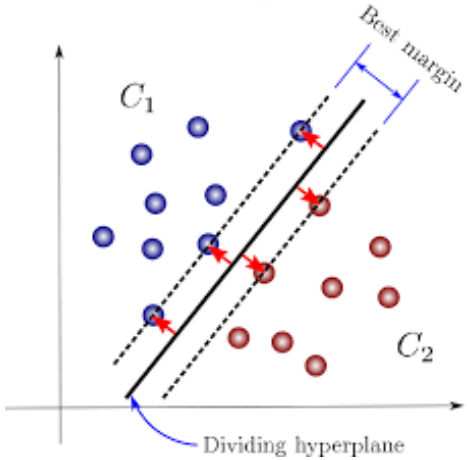
	Math (all score)	Math (no midterm 2 scores)	Math (no midterm 1&2 scores)	Portuguese (all score)	Portuguese (no midterm 2 scores)	Portuguese (no midterm 1&2 scores)
Total points	395 points	395 points	395 points	649 pointts	649 point	649 points
Test Set (0.2)	79 points	79 points	79 points	130 points	130 points	130 points
Train Set	252-253 points	252-253 points	252-253 points	252-253 points	252-253 points	252-253 points
Validation Set	63-64 points	63-64 points	63-64 points	63-64 points	63-64 points	63-64 points
OneHotEncoder	17 features	18 features	19 features	20 features	21 features	22 features
MinMax Encoder	4 features	3 features	2 features	4 features	3 features	2 features
Columns Before Encoding (Exclusing G3, Including Pass_Fail)	33 features	32 features	31 features	33 features	32 features	31 features
Columns After Encoding (Exclusing G3, Including Pass_Fail)	47 features	46 features	45 features	47 features	46 features	45 features

- Create an additional feature called "pass_fail" which denotes that a student fail if their score us below 10 and pass if otherwise.
- 3 sub-models: Model 1 consists of all midterm and final scores, Model 2 consists of only the first midterm scores and final scores, and Model 3 consists of no midterm and only final scores
- Splitting: Both data sets are IID, relatively small, and don't have group structure, time series, and missing values → basic train_test_split (0.2 test size), and a KFold split
- Preprocessing: ordinal features already encoded, OneHotEncoder on the remaining non-bounded/ranked, categorical features and the MixMaxEncoder on the bounded continuous features, LabelEncoder on the target variable
- choose accuracy score because my datasets are both balanced (0.671 Class 1 for Math and 0.846 Class 1 for Portuguese)
- measure uncertainties due to splitting and non-deterministic ML models, I loop through 10 random states and calculate the mean and standard deviation of the test scores
- additional cross-validation confusion matrix and ROC curve
- developed an ML pipeline using K-Fold Cross Validation (GridSearchCV)

2. CROSS VALIDATION- MACHINE LEARNIJG MODELS & FEATURE IMPORTANCES







- 3 ML algorithms: logistic regression, random forest classifier, support vector classifier.
- Hyperparameter tuning
  - LogisticRegression(penalty='l1', solver='saga', max_iter=10000, random_state = 20)
    - Tune: 'logisticregression__C': np.logspace(-2,2, num=8)
  - RandomForestClassifier(n_estimators = 100,random_state=random_state)
    - Tune: 'randomforestclassifier__max_depth': np.linspace(2,30,num=9,dtype=int)
    - Tune: 'randomforestclassifier__max_features': np.linspace(0.25,1,5)
  - SVC(random_state = 20)
    - Tune 'svc__C': np.logspace(-3,4,num=8)
    - Tune: 'svc__gamma': np.logspace(-3,4,num=8)
- Feature importance
  - LR: perturbation, linear coefficients, SHAP (LinearExplainer).
  - RFC: perturbation, random forest metrics, SHAP (TreeExplainer).
  - SVC: perturbation and SHAP (KernelExplainer).

3. RESULTS -MODEL PERFORMANCE

- highest accuracy from Model 1 because the algo have more score information to leverage from to predict the performance, accuracy score erodes over Model 2 and Model 3 because the algo have less score information to predict from.
- Model 2 performs pretty well, and its results fit into an academic context because it allows schools and teachers to identify weak students early on to take necessary actions

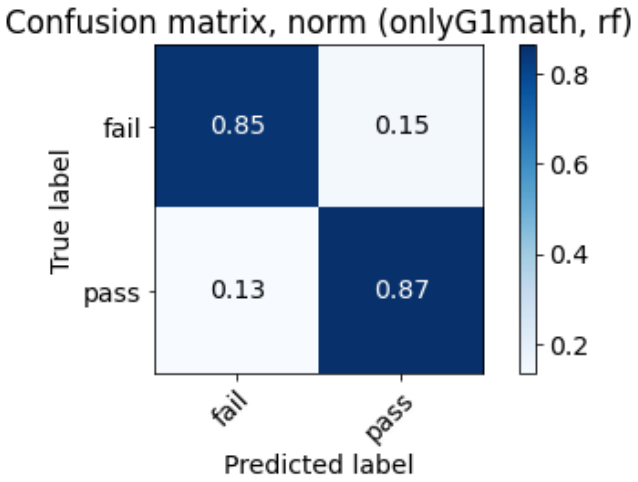
Sub-model (2-class)	ML Model	Baseline	Mean Accuracy	Std Accuracy	Std Above Baseline	Best Parameters	Best Model
Math (all score)	LR	0.671	0.919	0.019	13.059	C = 0.5179	Logistic Regression/ Random Forest Classification
	RFC		0.916	0.02	12.256	max_depth = 5, max_features = 0.625	
	SVC		0.905	0.024	9.755	C = 10000, gamma = 0.001	
Math (no midterm 2 scores)	LR		0.838	0.036	4.642	C = 26.827	Random Forest Classification (but All 3 Models Perform Quite Similarly)
	RFC		0.849	0.037	4.814	max_depth = 9, max_features = 0.625	
	SVC		0.841	0.04	4.253	C = 10000, gamma = 0.001	
Math (no midterm 1&2 scores)	LR		0.67	0.062	-0.014	C = 0.01	Support Vector Classification (but All 3 Models Perform Quite Similarly)
	RFC		0.676	0.056	0.091	max_depth = 2, max_features = 0.25	
	SVC		0.68	0.055	0.166	C = 100, gamma = 1	
Portuguese (all score)	LR	0.846	0.931	0.02	4.254	C = 1.93	Logistic Regression/ Random Forest Classification
	RFC		0.932	0.018	4.782	max_depth = 2, max_features = 0.4375	
	SVC		0.925	0.023	3.438	C = 10000, gamma = 0.001	
Portuguese (no midterm 2 scores)	LR		0.889	0.02	2.154	C = 100	Random Forest Classification
	RFC		0.915	0.022	3.14	max_depth = 2, max_features = 0.625	
	SVC		0.875	0.024	1.212	C = 1000, gamma = 0.001	
Portuguese (no midterm 1&2 scores)	LR		0.84	0.031	-0.191	C = 0.01	All 3 Models Perform Quite Similarly
	RFC		0.841	0.032	-0.154	max_depth = 2, max_features = 0.25	
	SVC		0.84	0.031	-0.191	C = 1, gamma = 10	

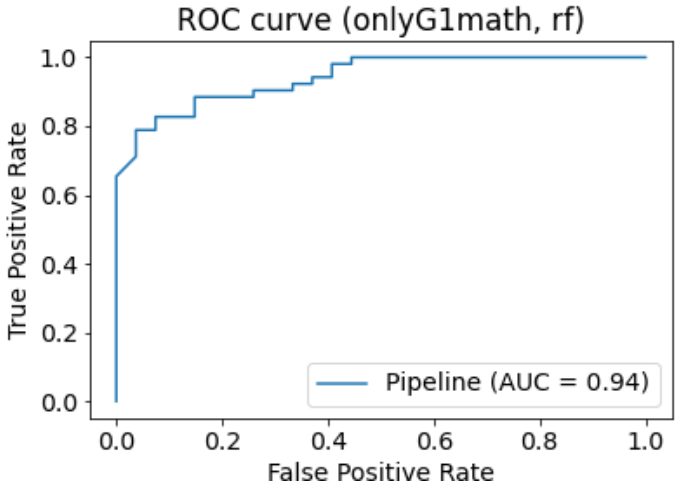
3. RESULTS - CONFUSION MATRICES AND ROC CURVES

- Model 2 is quite accurate and allows the most actionable insights for educators to help teachers improve students performance before it's too close to the end of the semester
- Display Random Forest Classification's Confusion Matrix and ROC Curves for Model 2 for both the Math and Portuguese dataset because these were the best models

Math, Model 2:

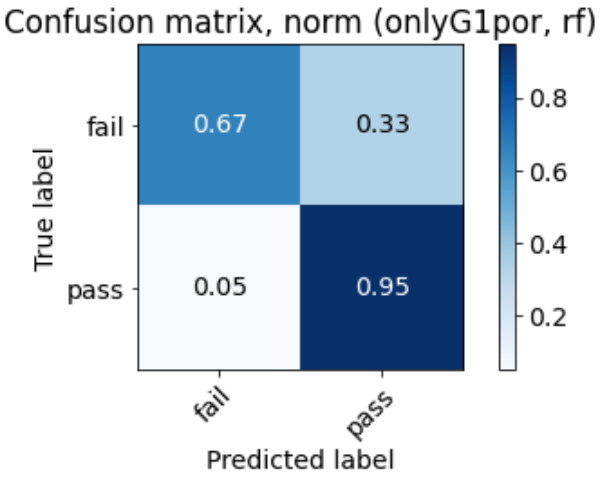
- Random Forest Classification (n_estimators = 100, random_state = 42, max_depth = 9, max_features = 0.625)
- Test accuracy: 0.924

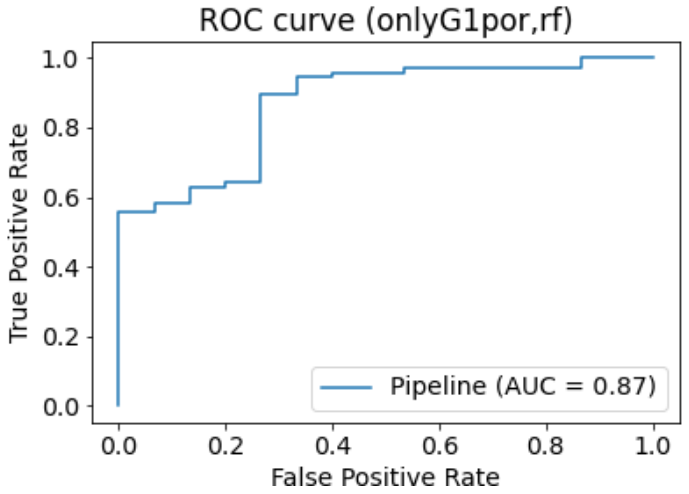




Portuguese Model 2:

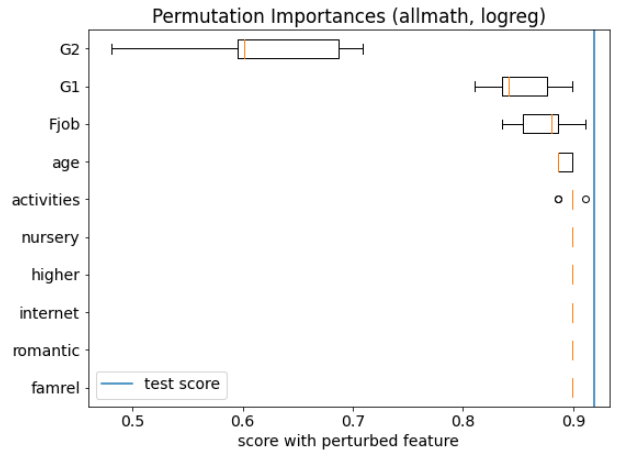
- Random Forest Classification (n_estimators = 100, random_state = 42, max_depth = 2 max_features = 0.625)
- Test accuracy: 0.954

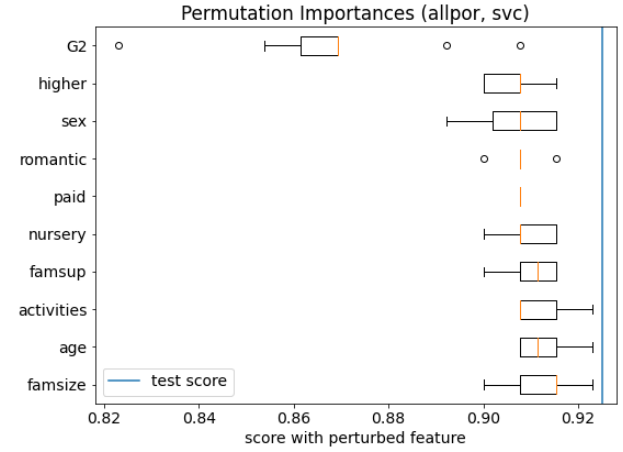


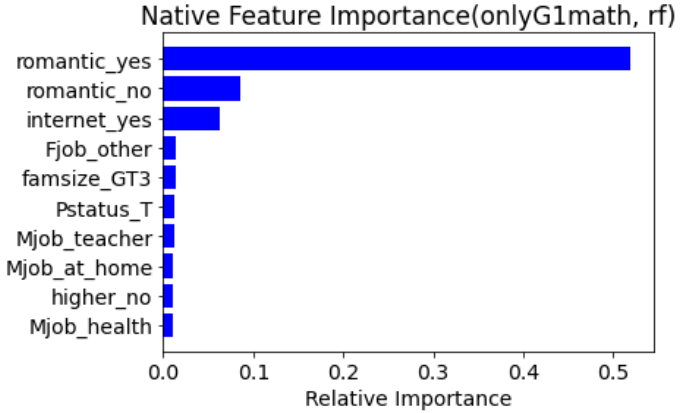


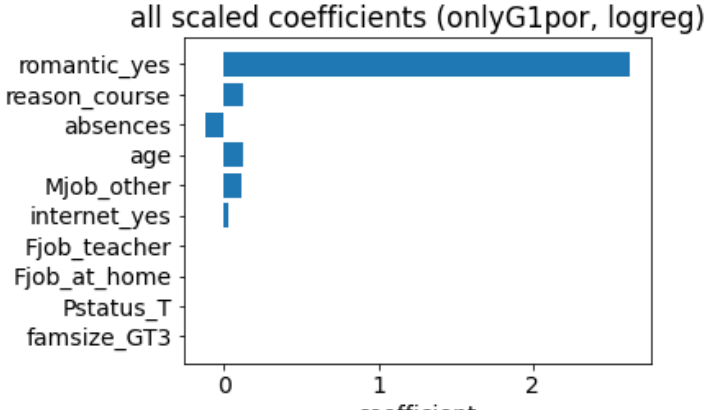
3. RESULTS - FEATURE IMPORTANCES (GLOBAL)

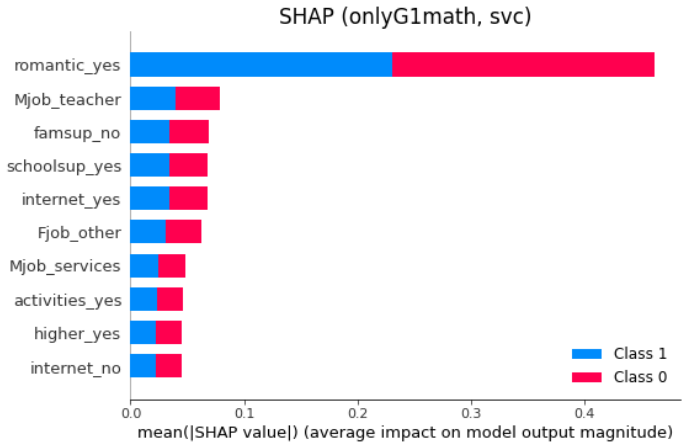
- Features importance varies by model, but there are some commonality.
- For Models 1 and 2, the midterm scores are the most important features.
- Other important features are **romantic status, internet access, the jobs of the parents, absences, and school supplement and fam supplement.**
- Some of the **least important features are health, family size & relationship, and travel time.**
- Educators should focus on helping students navigate adolescent relationships in a way that could positively impact their performance, work closely with parents of students who have weak performance, and provide more supplement when necessary.

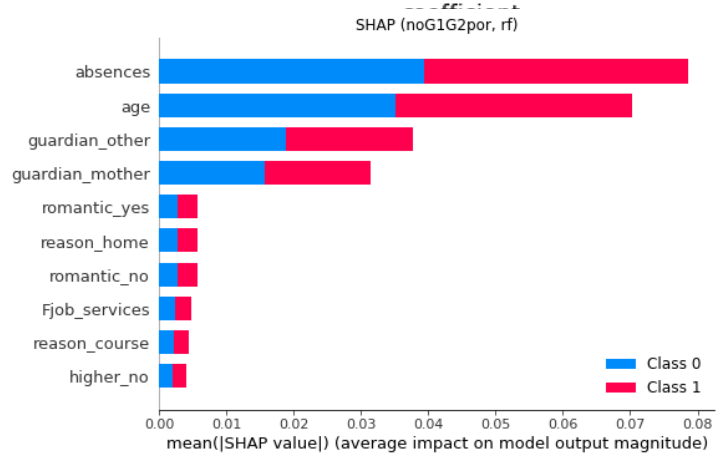












4. OUTLOOK

- **Weak spots:** used all features for prediction
- **Improvement suggestions:** feature selection, feature engineering, multi-class classification, more complex ML models such as XGBoost, PCA, KNN, etc.
- **Additional info:** homework scores, school attitude, prior exposure to the subject, enjoyment of the subjects, more continuous or ordinal features, students' performance in more countries, more holistic measures of academic performance, such as average grades across the school year or school attitude should be considered.