Measures of Success:

Determining the most significant predictors of student achievement

An analysis of student achievement data in secondary education of two Portuguese schools courtesy of UC Irvine Machine Learning Repository

Seth Dalmacio, Rachel Brown, Talibah Timothy, Liliana Perez Diaz, Nedal Rashid



Project Overview

In this project we sought to answer, what are the most important predictors that will determine whether a student passes or fails?

Our Methodology:

- Clean data
- 2. Use a classification algorithm (Logistic regression, K-Means Clustering, etc) to determine the variables that appear to have the most impact on student achievement
- 3. Create and train a model to predict student outcomes
- 4. Visualize findings
- 5. Evaluate model performance

Dataset Used: https://archive.ics.uci.edu/dataset/320/student+performance

Tools Used: Pandas, Matplotlib, Seaborn, Scikit learn

Data cleaned to ensure consistency and usability

Purpose: Ensure the dataset is consistent, understandable, and ready for analysis by removing irrelevant or redundant data and handling missing values.



Remove

Remove unnecessary columns identity those that do not contribute to analysis

Rename

Make column names more consistent and descriptive

Address inconsistencies

Handle missing or inconsistent values; check for missing data and either fill in with suitable value or drop

Scale

Normalize and scale numerical features

Export

Export cleaned dataset for use in analysis

Data cleaned to ensure consistency and usability

Before cleaning

```
school;sex;age;address;famsize;Pstatus;Medu;Fedu;Mjob;Fjob;reason;guardian;traveltime;studytime;failures;schoolsup;famsup;paid;activities;nursery;h
GP;"F";18;"U";"GT3";"A";4;4;"at_home";"teacher";"course";"mother";2;2;0;"yes";"no";"no";"no";"yes";"yes";"no";"no";4;3;4;1;1;3;6;"5";6";6
GP;"F";17;"U";"GT3";"T";1;1;"at_home";"other";"course";"father";1;2;0;"no";"yes";"no";"yes";"yes";"yes";"no";5;3;3;1;1;3;4;"5";5";6
GP;"F";15;"U";"LE3";"T";1;1;"at_home";"other";"other";"mother";1;2;3;"yes";"no";"yes";"yes";"yes";"yes";"no";4;3;2;2;3;3;10;"7";8";10
GP;"F";15;"U";"GT3";"T";4;2;"health";"services";"home";"mother";1;3;0;"no";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"yes";"ye
```

After cleaning

school	sex	age	Parent_st	Mother_Ec Father	_Ed Mjob	Fjob	reason	traveltime Study	_Tim failure:	s	schoolsur famsup	paid	activities	nursery	higher	internet
GP	F		18 A	4	4 at_home	teacher	course	2	2	0	1 ()	0 ()	1	1 0
GP	F		17 T	1	1 at_home	other	course	1	2	0	0	1	0 ()	0	1 1
GP	F		15 T	1	1 at_home	other	other	1	2	3	1 ()	1 ()	1	1 1
GP	F		15 T	4	2 health	services	home	1	3	0	0	1	1 :	L	1	1 1
GP	F		16 T	3	3 other	other	home	1	2	0	0	1	1 ()	1	1 0
GP	M		16 T	4	3 services	other	reputatio	r 1	2	0	0	1	1 :	L I	1	1 1
GP	M		16 T	2	2 other	other	home	1	2	0	0 ()	0 ()	1	1 1

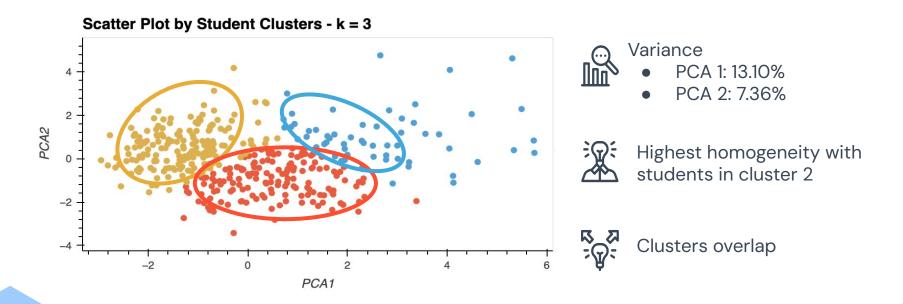
Data cleaned to ensure consistency

```
[1]: import pandas as pd
     from sklearn.preprocessing import MinMaxScaler
[2]: # Load the dataset
    data = pd.read_csv('Resources/student-mat.csv', delimiter=';')
[3]: # Remove unnecessary columns
    columns_to_remove = ["G1", "G2", "Walc", "address", "famrel", "Dalc", "guardian", "famsize"]
     data.drop(columns=[col for col in columns to remove if col in data.columns], errors='ignore', inplace=True)
[4]: # Rename columns
     data.rename(columns={"G3": "final_grade", "studytime": "Study_Time_Hours", "Fedu": "Father_Edu", "Medu": "Mother_Edu", "Pstatus"
[5]: # Convert 'yes'/'no' to 0's and 1's
    binary columns = ['schoolsup', 'famsup', 'paid', 'activities', 'nursery', 'higher', 'internet', 'romantic']
     for col in binary columns:
        if col in data.columns:
             data[col] = data[col].map({'yes': 1, 'no': 0})
[6]: # Handle missing values: Fill with mean for 'absences'
     if 'absences' in data.columns:
         data['absences'].fillna(data['absences'].mean(), inplace=True)
```

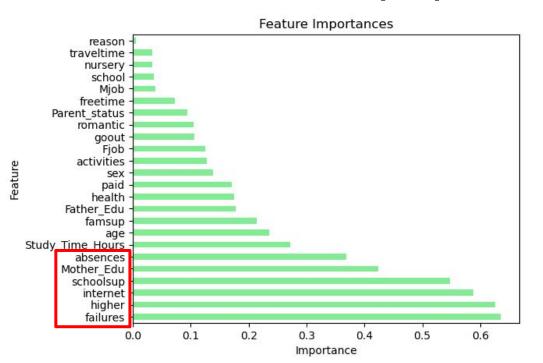
- Clean Data
- Rename columns
- Remove columns
- Prepare data for for rest of the steps



Clusters only explain ~20% of variance

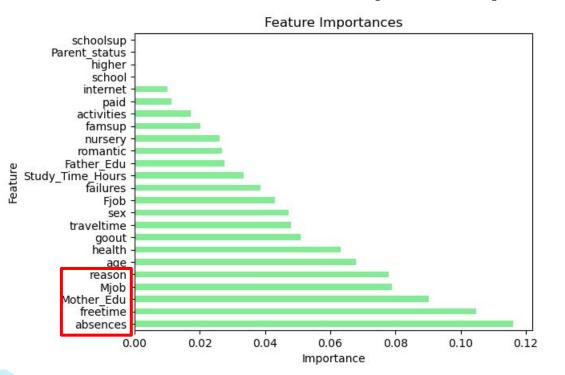


Logistic regression shows past failures, desire for higher ed, internet access may be predictors of success



		Coefficient
11	failures	0.637093
17	higher	0.625623
18	internet	0.586423
12	schoolsup	0.546977
4	Mother_Edu	0.424645
23	absences	0.368176
10	Study_Time_Hours	0.272150
2	age	0.235348
13	famsup	0.214005
5	Father_Edu	0.177268
22	health	0.175581
14	paid	0.170889
1	sex	0.138447
15	activities	0.127860
7	Fjob	0.125328
21	goout	0.106399
19	romantic	0.104248
3	Parent_status	0.093528
20	freetime	0.073369
6	Mjob	0.039472
0	school	0.035761
16	nursery	0.033901
9	traveltime	0.033049
8	reason	0.005652

Decision Trees reveal absences, free time, and mother's education level to be potential predictors of success



		_
	Feature	Importance
23	absences	0.116200
20	freetime	0.104882
4	Mother_Edu	0.090366
6	Mjob	0.079067
8	reason	0.077947
2	age	0.067986
22	health	0.063255
21	goout	0.050796
9	traveltime	0.048039
1	sex	0.047128
7	Fjob	0.043158
11	failures	0.038519
10	Study_Time_Hours	0.033431
5	Father_Edu	0.027494
19	romantic	0.026718
16	nursery	0.026166
13	famsup	0.020151
15	activities	0.017273
14	paid	0.011335
18	internet	0.010087
0	school	0.000000
17	higher	0.000000
3	Parent_status	0.000000
12	schoolsup	0.000000

Model correctly classified around 71% of cases, may be some bias toward positive predictions

Confusion Matrix

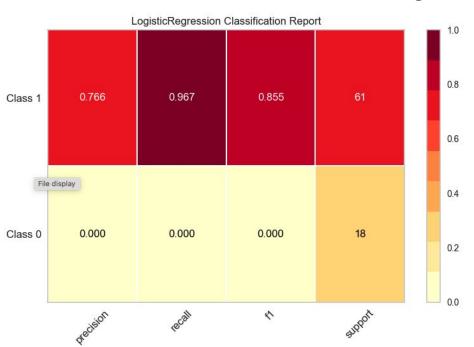
	Predicted 0	Predicted 1	
Actual 0	5	16	O = low success
Actual 1	13	65	1 = high success

Accuracy Score: 0.70707070707071

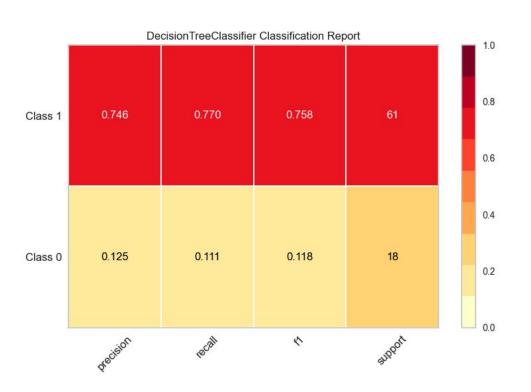
Classification Report

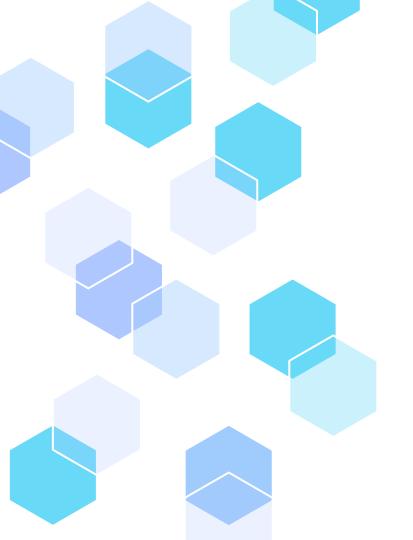
Classificat	.10	precision	recall	f1-score	support
	0	0.28	0.24	0.26	21
	1	0.80	0.83	0.82	78
accurac	су			0.71	99
macro av	/g	0.54	0.54	0.54	99
weighted av	/g	0.69	0.71	0.70	99

Model shows strong bias toward predicting positive cases but struggles significantly with negative cases suggesting potential imbalance issues in the training data



Decision Tree shows slightly more balanced performance between classes, though still poor for Class 0





Thank you!

Questions?

Resources

Data

https://archive.ics.uci.edu/dataset/320/student+performance