

Project Proposal

- ★ Our goal is to create an Early Warning System for At-Risk Students.
- ★ The education dataset, collected via school reports and questionnaires, consists of over 600 individual data instances from two Portuguese classes including attributes such as
 - demographics
 - o grades
 - social factors
 - support
- ★ We're hoping to identify problem areas within students' environments and potentially reduce the total drop-out rate.

Key Questions: Potential Risk Factors

- extra educational support
- higher-educated parents
 - health
 - social tendencies



Methodology

Data Model
Implementation

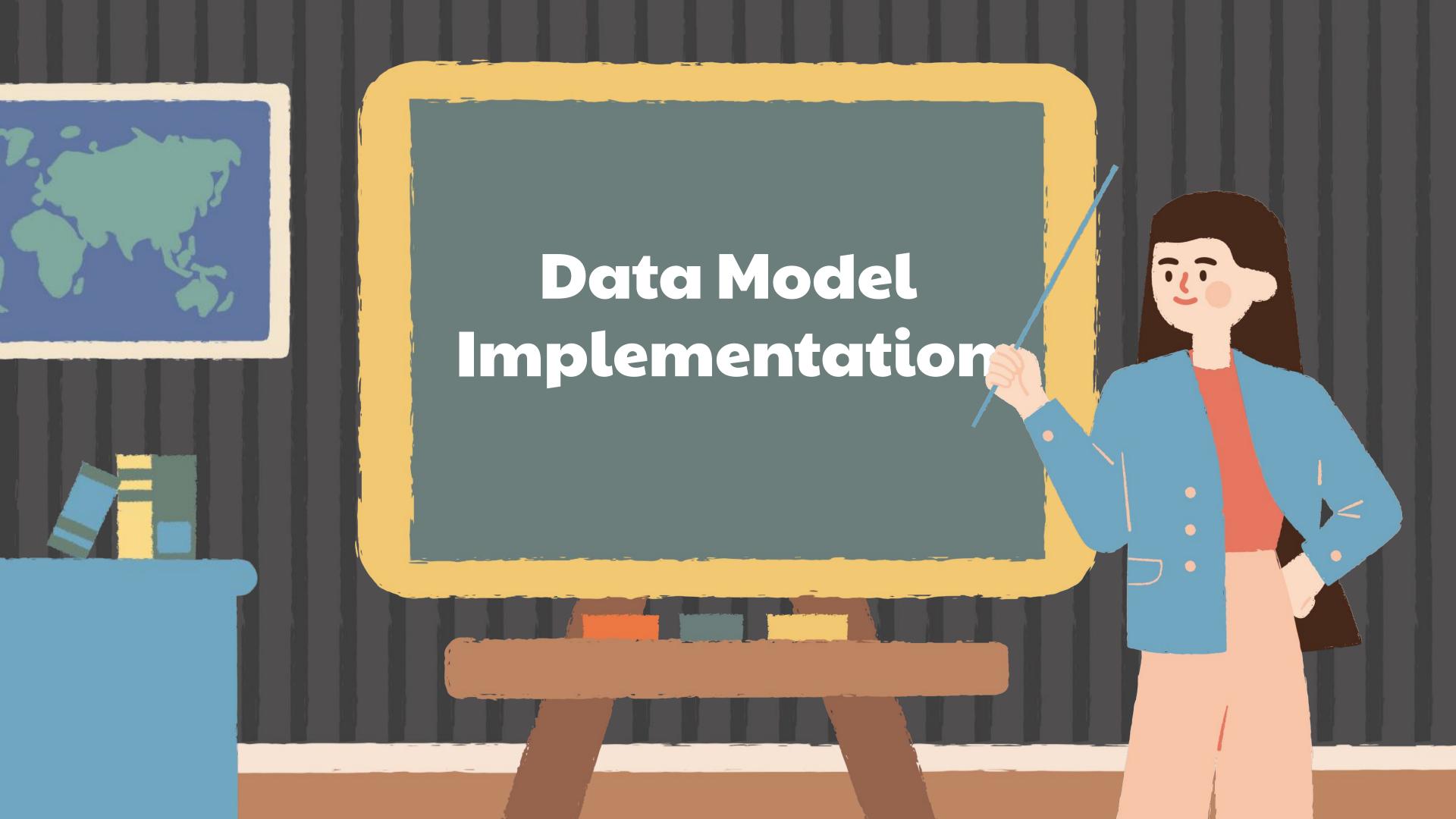
Data Model
Optimization

Prediction & Visualization

- cleaned two CSVs (math class data, Portuguese class data)
- SQLite database creation

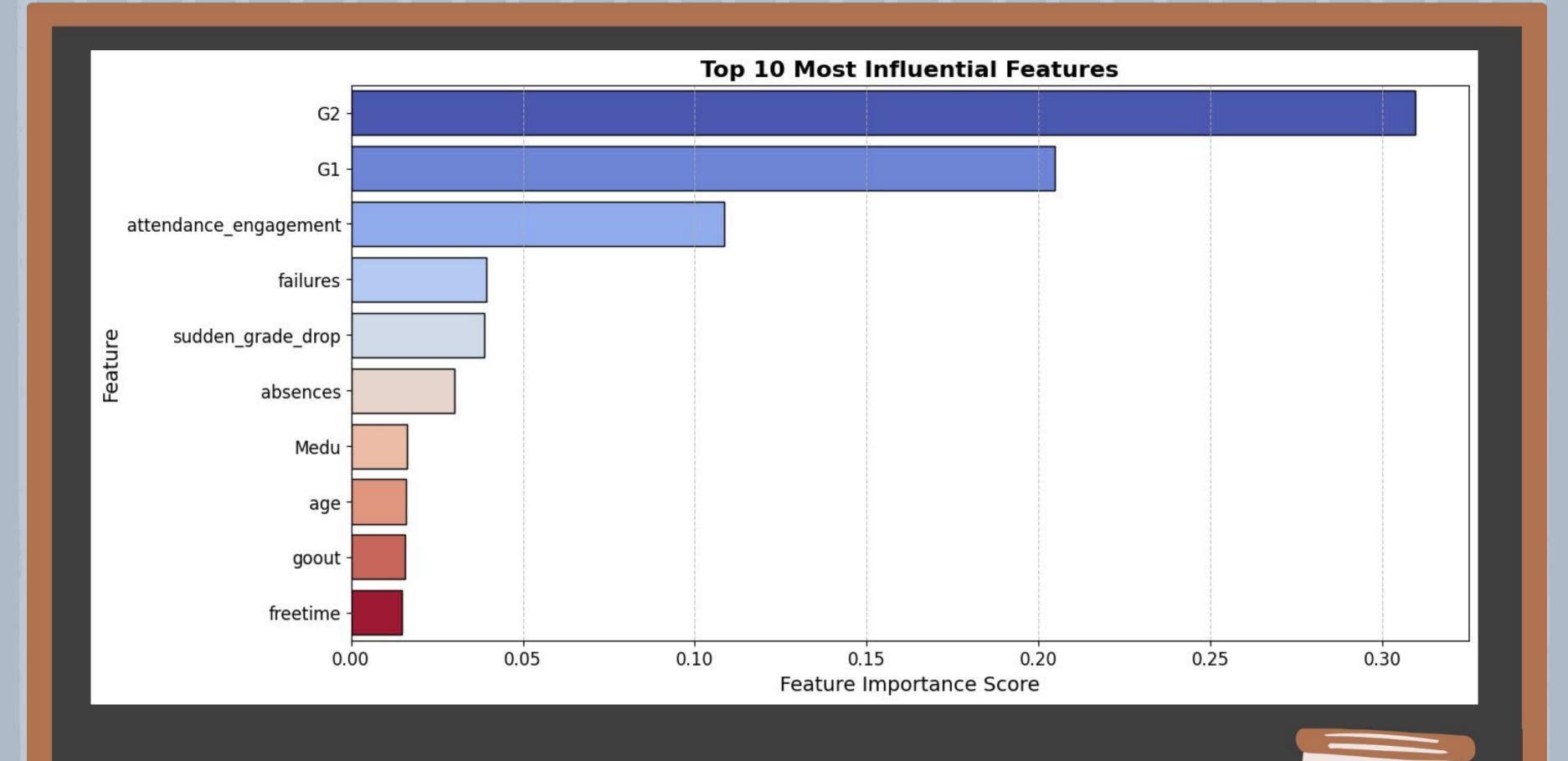
- feature engineering
- multilabel classification
 - modifying target
 - experimenting with model type





Process

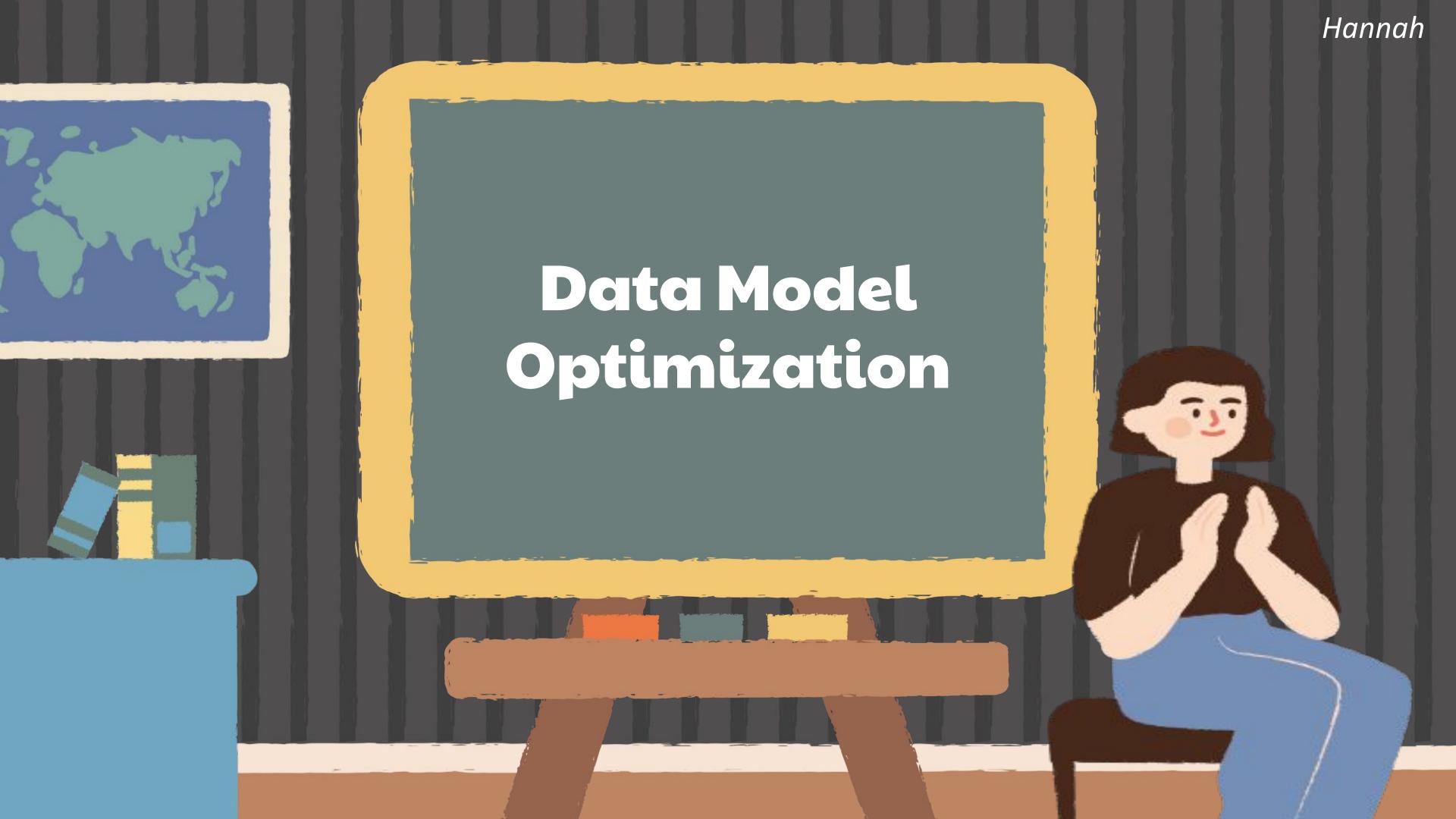
- Minimal cleaning
- Feature Engineering
 - Attendance Engagement (Balances absences with grades)
 - Sudden Grade Drop (from G1 to G2)
 - Low Engagement Flag (Flags students whose engagements levels are in the highest quartile)
- Model Types
 - Logistic Regression Baseline
 - Decision Tree Baseline
- Predictions



Classification Report for Baseline

Accuracy: 0.803		722		
Classification	Report:			
Р	recision	recall	f1-score	support
0	0.71	0.78	0.74	46
1	0.84	0.82	0.83	122
2	0.82	0.78	0.80	41
accuracy			0.80	209
macro avg	0.79	0.79	0.79	209
weighted avg	0.81	0.80	0.80	209
р	recision	recall	f1-score	support
0	0.71	0.78	0.74	46
1	0.84	0.82	0.83	122
2	0.82	0.78	0.80	41
accuracy			0.80	209
macro avg	0.79	0.79	0.79	209
weighted avg	0.81	0.80	0.80	209

Baseline Log	istic Regress	ion Model	Evaluation	n:
Accuracy: 0.8	8468899521531	1		
Classification	on Report:			
	precision	recall	f1-score	support
0	0.74	0.87	0.80	46
1	0.90	0.83	0.86	122
2	0.84	0.88	0.86	41
accuracy			0.85	209
macro avg	0.83	0.86	0.84	209
weighted avg	0.85	0.85	0.85	209
	precision	recall	f1-score	support
0	0.74	0.87	0.80	46
1	0.90	0.83	0.86	122
2	0.84	0.88	0.86	41
accuracy			0.85	209
macro avg	0.83	0.86	0.84	209
weighted avg	0.85	0.85	0.85	209



Process

- Feature Engineering
 - Extra Support
 - Health
 - Parent Education
 - Social Tendencies
- Experimenting with different targets
 - G3 (final grade)
 - creating a risk category (multiclass labels)

- Experimenting with Model Types
 - Logistic Regression
 - ✓ Highest accuracy (99%)
 - Decision Tree
 - ✓ Highest accuracy (100%)
 - Random Forest
 - Pruned Forest
 - ✓ Highest accuracy (85.65%)

Hannah

Optimizations 1-3 focused on engineering features, yielding 90%+ accuracy.

Optimization 4 focused on modifying the multiclass labels (based on final grades) from three to **four risk categories** and making this the **new target**.



- 0 'at risk'
- 1 'low risk'
- 2 'moderate risk'
- 3 'not at risk'

Logistic Regression Model Evaluation: Accuracy: 0.9904306220095693 Classification Report:

	precision	recall	f1-score	support
0	1.00	(0.96)	0.98	46
1	0.97	1.00	0.98	61
2	1.00	1.00	1.00	61
3	1.00	1.00	1.00	41
	S-activistics.	1100000000		
accuracy			0.99	209
macro avg	0.99	0.99	0.99	209
weighted avg	0.99	0.99	0.99	209

- performs well at classifying 'moderate risk' and 'not at risk' students
- missed some 'at risk' students leading to false-positives for 'low risk' students.



Decision Tree Model Evaluation:

Accuracy: 1.0

Classification Report:

	precision	recall	+1-score	support
0	1.00	1.00	1.00	46
1	1.00	1.00	1.00	61
2	1.00	1.00	1.00	61
3	1.00	1.00	1.00	41
accuracy			1.00	209
macro avg	1.00	1.00	1.00	209
weighted avg	1.00	1.00	1.00	209



The 100% accuracy here may reflect a complex or non-linear dataset.

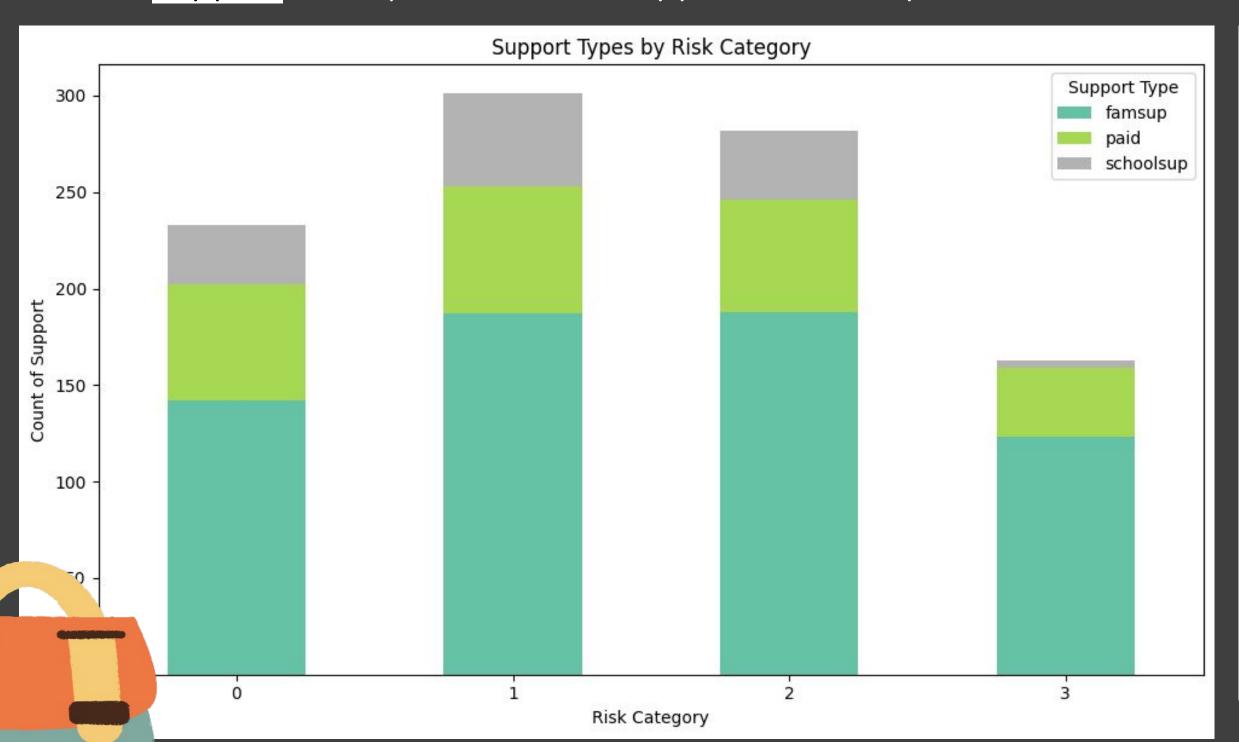
Extra support features didn't make a significant difference.





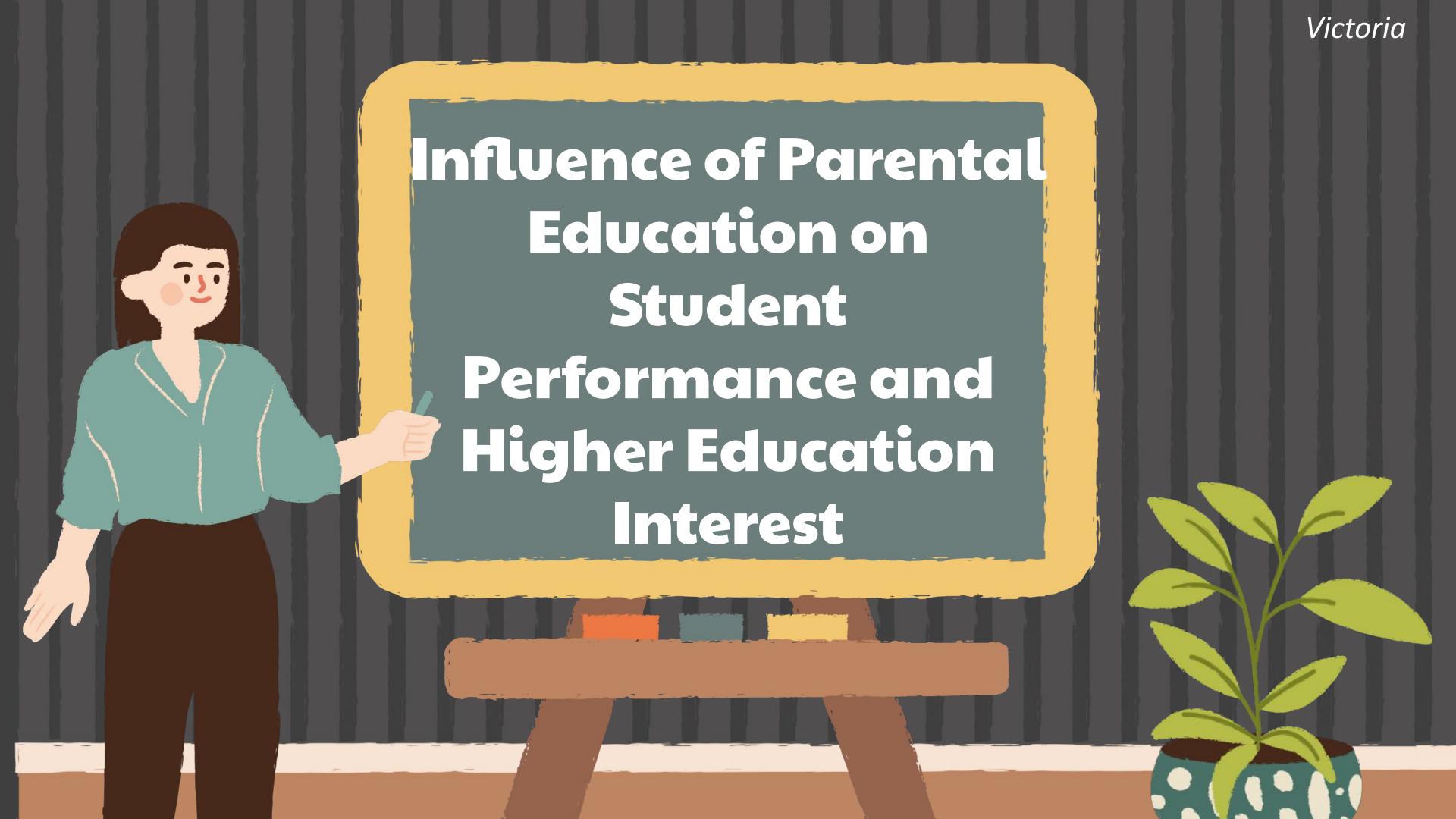
Hannah

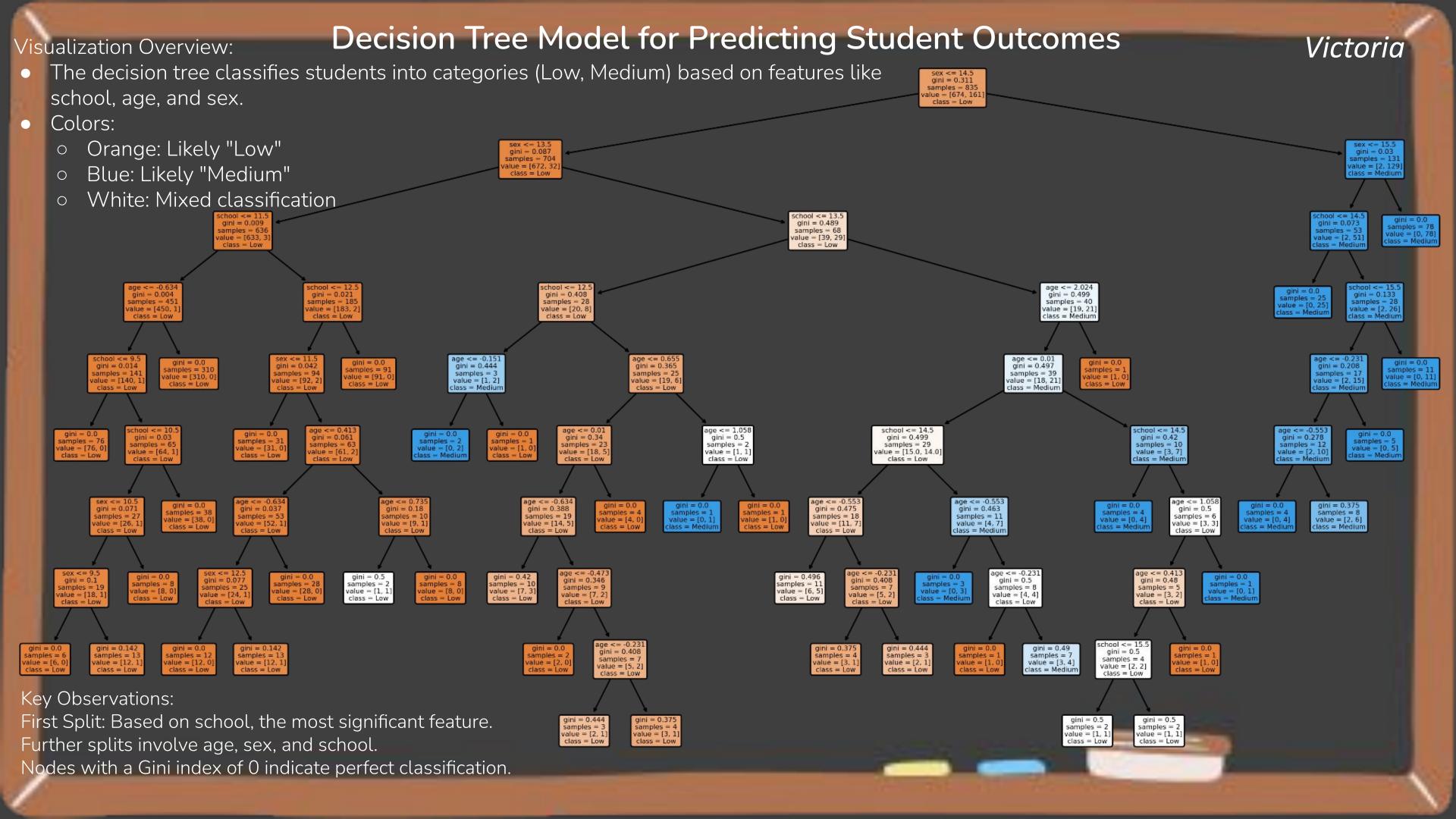
Is there a relationship between a student being at-risk and access to extra educational support, family educational support, or extra paid classes within the course subject?



Students identified as being 'at risk' receive

- more total support than 'not at risk students'
- less than
 'moderate' and
 'low risk' students.







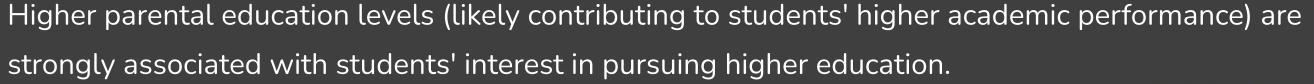
Do students with higher-educated parents perform better in final exams (G3)?

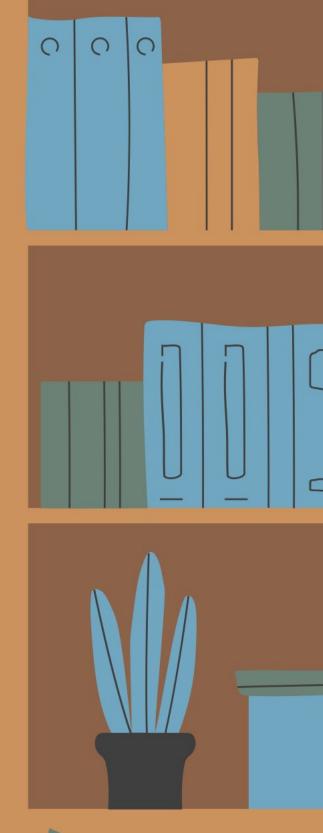


Do they show stronger interest in higher education?

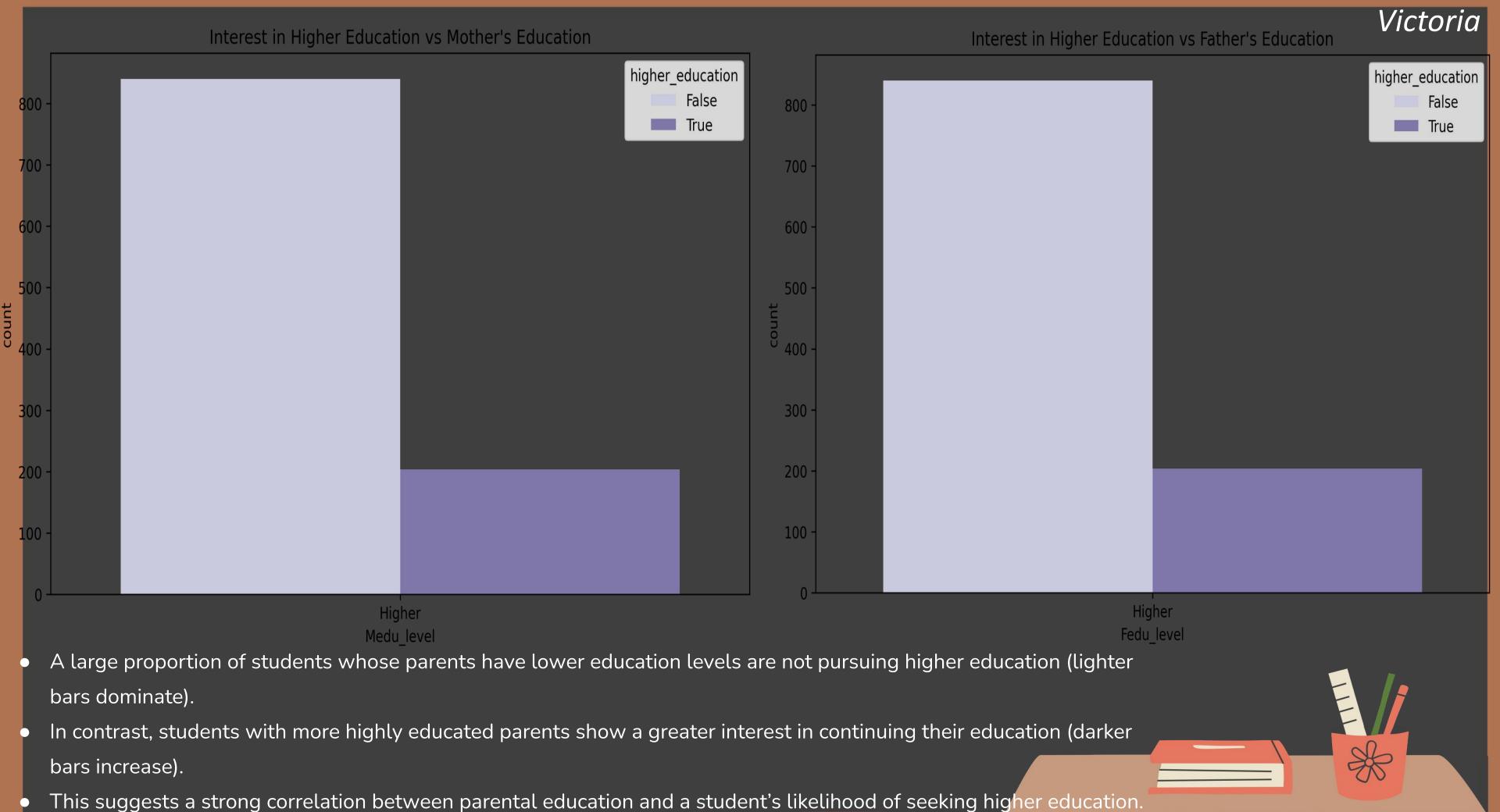
Key Takeaways:

- Class 0 (Not Pursuing Higher Education):
 - > 100% precision & recall no false negatives 🚀
- Class 1 (Pursuing Higher Education):
 - > 100% precision all predicted students belong to this class
 - > 86% recall some students may be missed (false negatives) 🗘
- ❖ F1-Score Insights:
 - High F1-scores for both classes
 - \triangleright Slight preference for precision in predicting higher education students \mathbf{H}







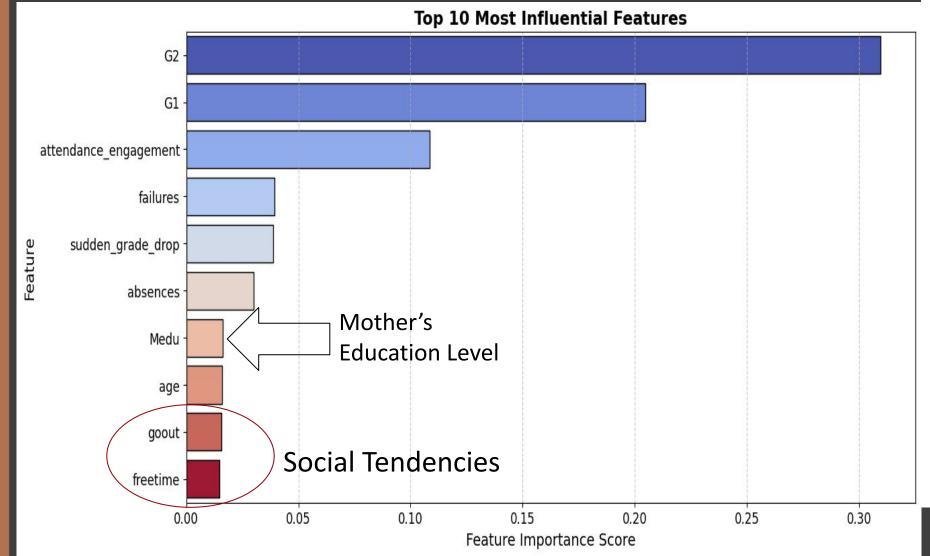


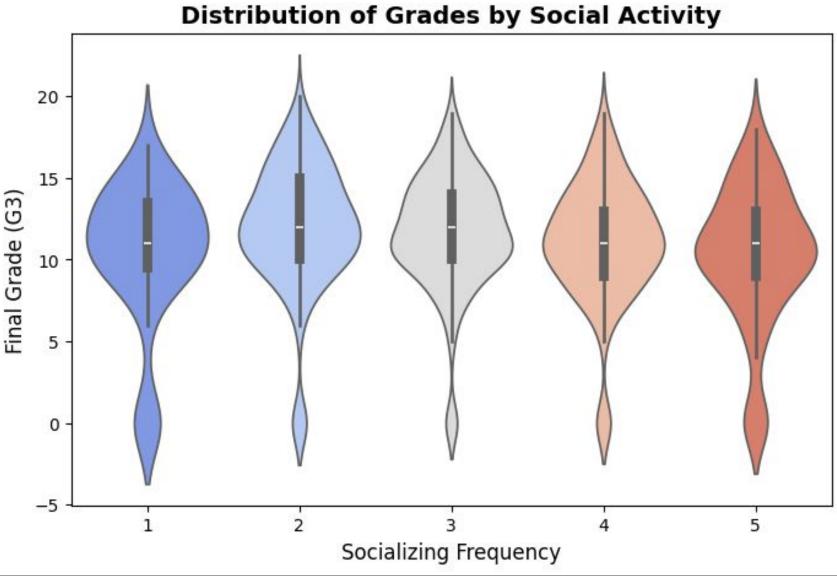


Social Tendencies and their correlations

What impact do certain social tendencies have on the students' likelihood to succeed? (e.g. Frequency of alcoholic consumption, social lives, extracurricular activities,

romantic relationships, etc.)



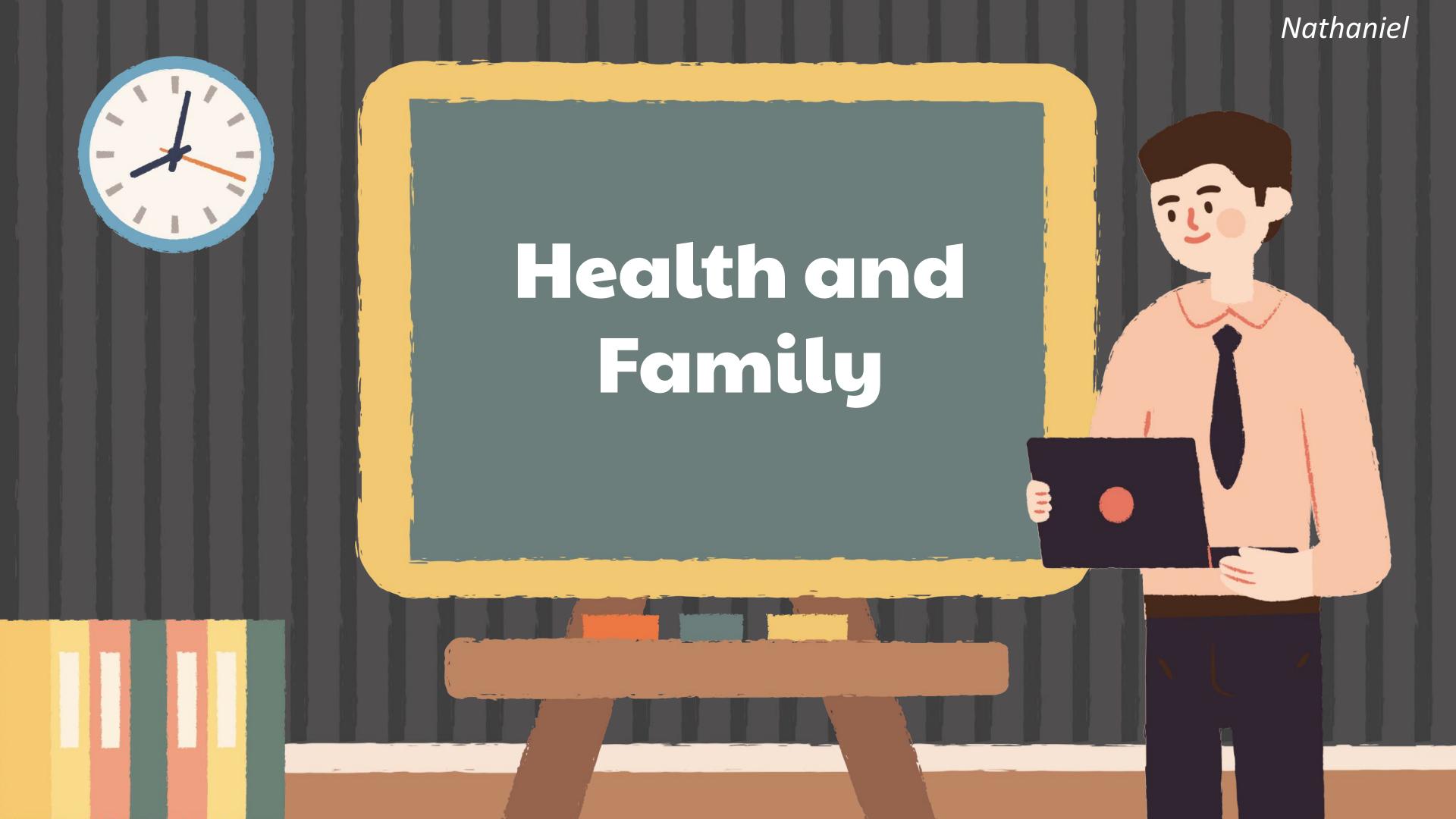




Social Tendencies and their correlations

Ethan

Academic & Social Factors										1.0					
G1 -	1.00	0.86	0.81	-0.15	-0.14	0.21	-0.37	-0.09	0.04	-0.05	-0.10	-0.06			1.0
G2 -	0.86	1.00	0.91	-0.13	-0.13	0.18	-0.38	-0.09	0.04	-0.07	-0.11	-0.09		- (0.8
G3 -	0.81	0.91	1.00	-0.13	-0.12	0.16	-0.38	-0.05	0.05	-0.06	-0.10	-0.08			
Dalc -	-0.15	-0.13	-0.13	1.00	0.63	-0.16	0.12	0.13	-0.08	0.14	0.25	0.07		- (0.6
Walc -	-0.14	-0.13	-0.12	0.63	1.00	-0.23	0.11	0.14	-0.10	0.13	0.40	0.11			
studytime -	0.21	0.18	0.16	-0.16	-0.23	1.00	-0.15	-0.08	0.01	-0.09	-0.07	-0.06		- (0.4
failures -	-0.37	-0.38	-0.38	0.12	0.11	-0.15	1.00	0.10	-0.05	0.10	0.07	0.05		_ (0.2
absences -	-0.09	-0.09	-0.05	0.13	0.14	-0.08	0.10	1.00	-0.06	-0.03	0.06	-0.03			0.2
famrel -	0.04	0.04	0.05	-0.08	-0.10	0.01	-0.05	-0.06	1.00	0.14	0.08	0.10		- (0.0
freetime -	-0.05	-0.07	-0.06	0.14	0.13	-0.09	0.10	-0.03	0.14	1.00	0.32	0.08			
goout -	-0.10	-0.11	-0.10	0.25	0.40	-0.07	0.07	0.06	0.08	0.32	1.00	-0.01		-	-0.2
health -	-0.06	-0.09	-0.08	0.07	0.11	-0.06	0.05	-0.03	0.10	0.08	-0.01	1.00			
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Nathaniel

How does health impact a person's likelihood to succeed?

01

Does poor health often result in more absences and poorer grades?

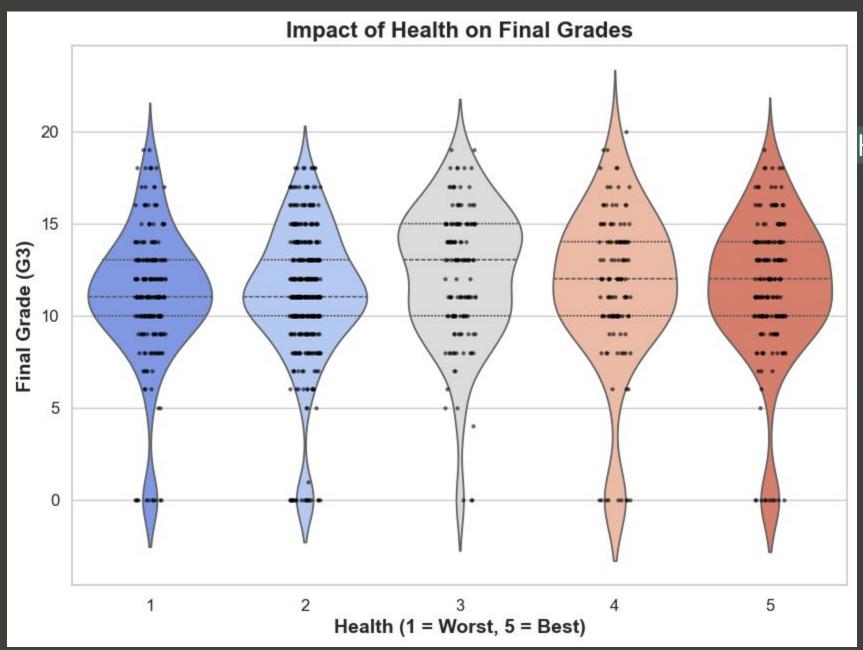
02

Is there a high incidence of absence and failure among students classified in poor health?

03

Is there a correlation between health and quality of family relationships?

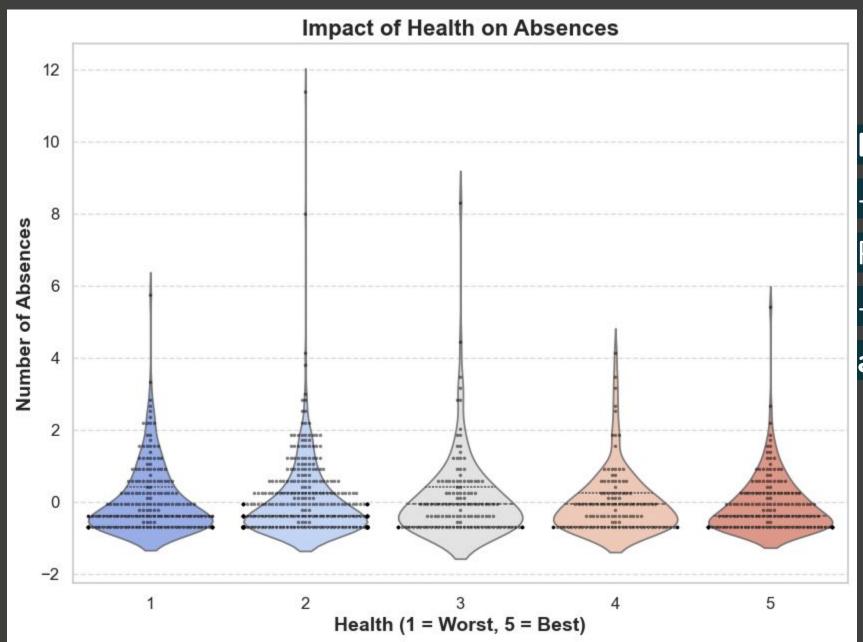
Nathaniel



Health & Success

- There is a weak negative correlation with grades (ρ = -0.081, ρ = 0.009), suggesting that poor health slightly lowers grades.
- Conclusion: While health may have some impact, it is not the main predictor of success.





Health and Absences

- No strong correlation **(ρ = -0.034, ρ = 0.267)** \rightarrow

Poor health **does not** increase absences.

- **Conclusion:** Health **affects grades more than attendance**.





Dep. Vari	lable:	f	amrel	R-squa	red:		0.011
Model:			OLS	1,4(2,07)	-squared:		0.010
Method:		Least Sq	uares	F-stat	istic:		11.42
Date:		Tue, 18 Mar	2025	Prob ((F-statistic)	1	0.000755
Time:		18:	31:13	Log-Li	kelihood:		-1475.7
No. Obser	vations:		1044	AIC:			2955.
Df Residu	uals:		1042	BIC:			2965.
Df Model:			1				
Covariand	ce Type:	nonr	obust				
	coe	f std err		t	P> t	[0.025	0.975]
const	-3.469e-17	0.031	-1.1	3e-15	1.000	-0.060	0.060
health	0.104	0.031		3.379	0.001	0.044	0.165
====== Omnibus:	-=======	 15	===== 5.627	 Durbir	:======= n-Watson:	=======	1.952
Prob(Omni	lbus):		0.000		-Bera (JB):		240.357
Skew:			1.008				6.41e-53
Kurtosis:			4.207				1.00

Health & Family Relationships

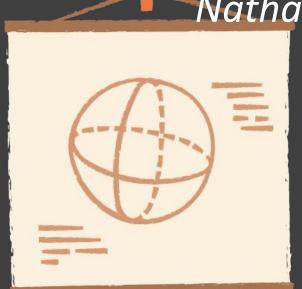
- Weak positive correlation **($\rho = 0.090$, p = 0.0037)** \rightarrow

Healthier students report better family relationships.

Conclusion: Family support may contribute to both better
 health and academic success.

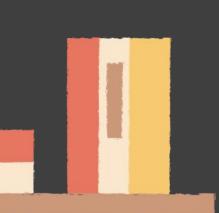


Implications



If schools want to identify at risk students, they should be looking at:

- ✓ grades
- ✓ attendance
- ✓ mother's education



Summary & Conclusions



- ★ Successfully optimized our baseline model
- ★ A Decision Tree Model was most accurate
 - Less linear relationships
 - Some features heavily skewed the chances of a student being at risk
- ★ We realized that we could have made a features prediction earlier on to ensure we were analyzing the most impactful features

