

Predict Students Dropout and Academic Success

SIC 603

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Agenda

- Motivation
- | Targeted audience
- About the problem
- I Understanding the data
- I EDA & Visualization
- | Preprocessing
- | Modeling
- I Final Results
- | Future Improvements
- Conclusion

1. Motivation

1. Motivation

Why is it important to Predict Students Dropout and Academic Success?

Predicting student dropout helps identify at-risk students, enabling timely support from educators. This fosters resilient environments and reduces dropout rates, positively impacting communities. By prioritizing academic success, we inspire lifelong learning and empower students to change their life trajectories.

2. Targeted audience

2. Targeted Audience







3. About the problem

3. About the problem

In a bustling city, a vibrant university attracted diverse students, each with unique backgrounds and challenges. A rich dataset captured their stories, highlighting factors like marital status, application modes, and courses chosen, reflecting their aspirations. This data revealed patterns of success and struggle, particularly showing that single and evening students faced more obstacles.

4. Understanding the data

4. Understanding the data

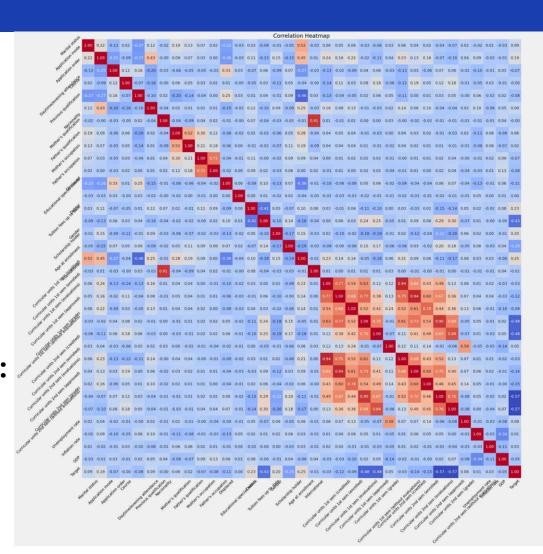
Our data consists of 37 features, here's the most important ones.

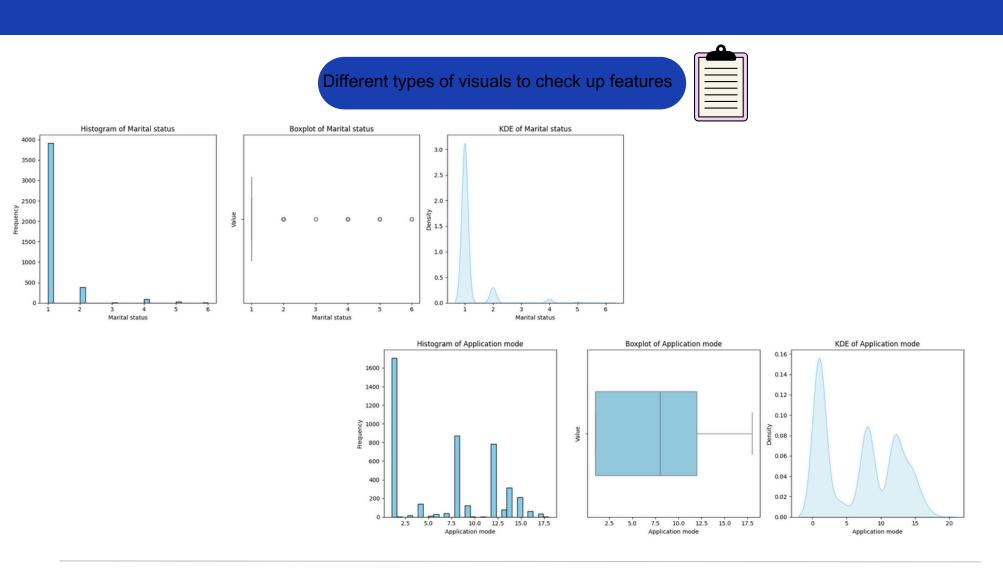
- Marital Status: The marital status of the student (e.g., single, married, divorced).
- **Application Mode**: Refers to the mode or type of application the student submitted to enroll in the course.
- **Application Order**: Indicates the order in which the student applied for the course. For example, whether it was the student's first, second, or third choice.
- **Course**: The course or degree program the student is enrolled in (e.g., Computer Science, Engineering, etc.).
- **Daytime/Evening Attendance**: Specifies whether the student attends the course during the day or in the evening, representing their attendance schedule.
- **Previous Qualification**: The type of academic qualification the student had before enrolling in the course (e.g., high school diploma, vocational training).
- **Previous Qualification (Grade)**: The final grade or score associated with the student's previous qualification.
- **Nationality**: The nationality of the student.
- Mother's Qualification: The highest academic qualification attained by the student's mother.
- Father's Qualification: The highest academic qualification attained by the student's father.

Correlation between features

Strongest correlation with target:

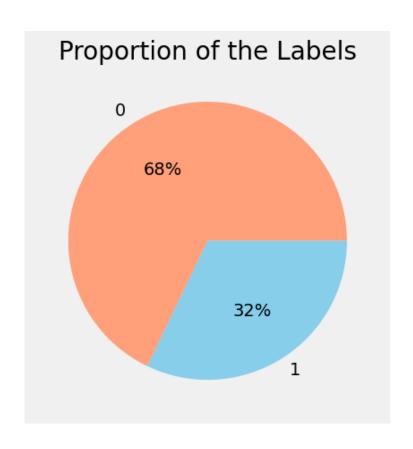
Curricular units 2nd sem (grade) 0.571792 Curricular units 2nd sem (approved) 0.569500 Curricular units 1st sem (grade) 0.480669

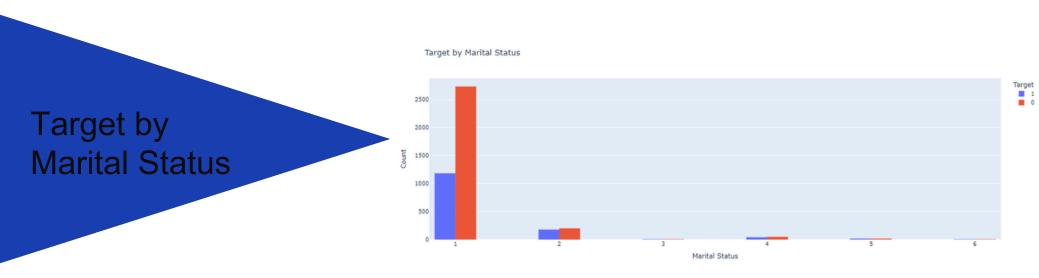




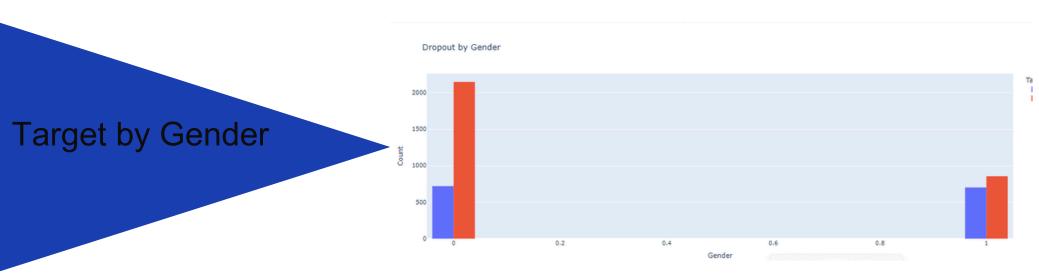
Target column distribution

imbalanced data





Single Individuals are more likely to have dropped out



Females are more likely to have dropped out

Encoding

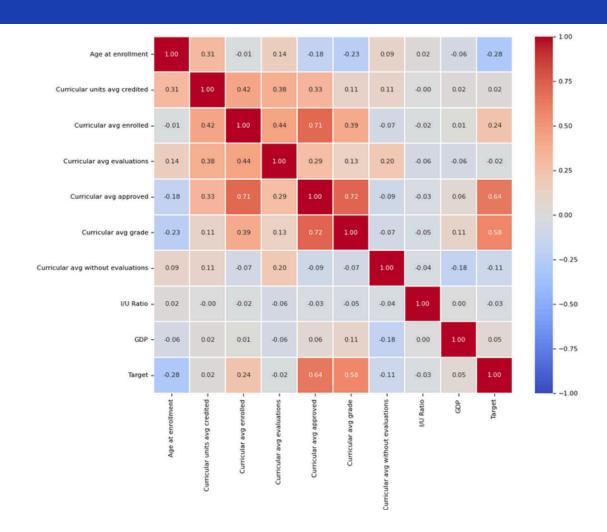
We did some encoding and mapping to our nominal and categorical columns such as one hot encoding and label encoding.

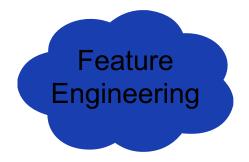
Feature Engineering

We started by dropping some unnecessary columns such as Nacionality, International and Educational special needs

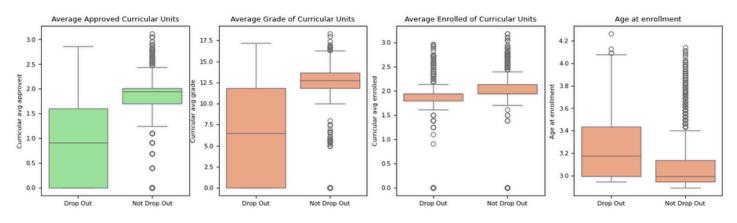
Then, we decided to create a new feature that represents inflation to unemployment ratio instead of the two features.

Finally, we created some features that represents the average of some features such as grades, evaluations and courses enrolled.









it's pretty obvious that no drop out student should have 0 credits, so we should drop them

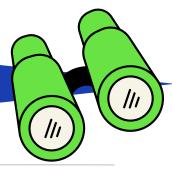
Data
Transformation
and Scaling

From the EDA part, we could see that we have some skewed features, so we used log transformation to cure skewed features.

Then, we used standard scaling for our classification models, and robust scaling for clustering.



Now, let's dive into our models performance!

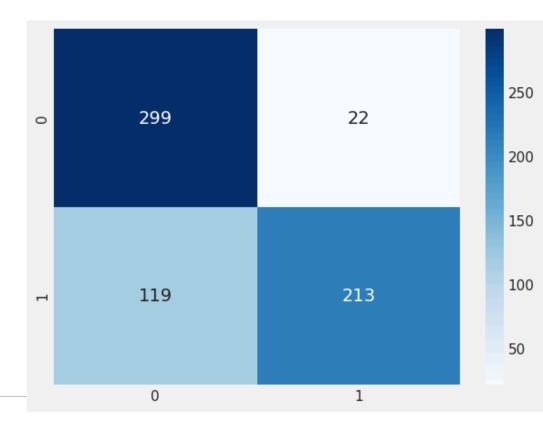


We will discuss these models and compare the results of each:

- . Logistic Regression
- . KNN
- . SVM
- . Random Forest
- . Naive Bayes
- . Decision Tree
- . AdaBoost Classifier with GridSearch and without
- . GradeintBoost Classifier with GridSearch and without
- . XGBoost Classifier with GridSearch and without

Naive Bayes

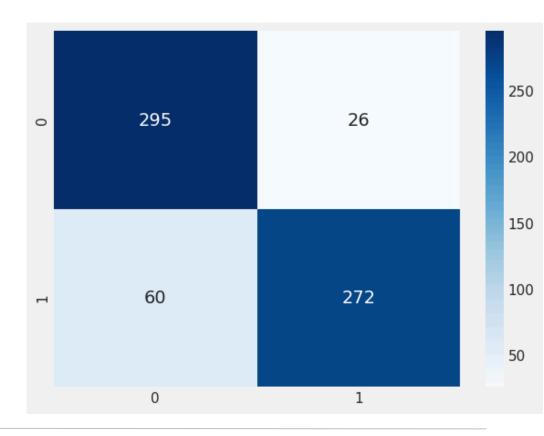
Validatio Test Accu	n Accu iracy:	0.77628120 uracy: 0.748 0.784073506	466257668 8912711			
		Report for				
CIGSSITIC	acton	precision				
		precision	recall	T1-Score	Support	
	0.0	0.70	0.94	0.81	1498	
		0.92				
	1.0	0.52	0.02	0.74	1340	
accur	acy			0.78	3044	
macro	ave	0.81	0.78	0.77	3044	
weighted		0.81				
meagneed		0.01	0.70	0.,,	5511	
		Report for				
		precision			support	
		precision		.1 500.0	Suppor E	
	0.0	0.67	0.93	0.78	315	
	1.0	0.89	0.58	0.71	337	
accur	acv			0.75	652	
macro	avg	0.78	0.75	0.74	652	
		0.79			652	
	0					
classific	ation	Report for	Test Set:			
		precision			support	
		p. cc131011	7 00021	. 2-30010	Juppor C	
	0.0	0.72	0.93	0.81	321	
	1.0	0.91	0.64	0.75	332	
accur	acy			0.78	653	
macro	avg	0.81	0.79	0.78	653	
weighted		0.81	0.78	0.78	653	



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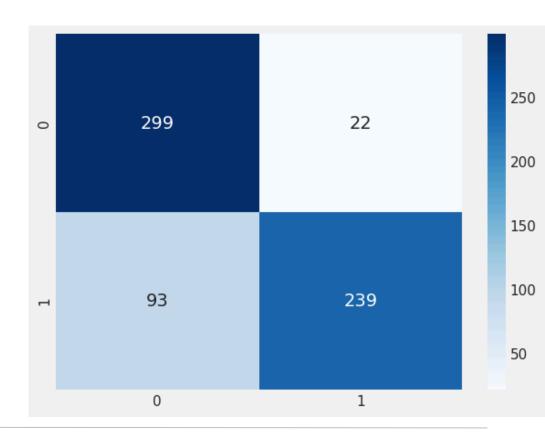
Logistic Regression

Validation Acc Test Accuracy:	Train Accuracy: 0.8610381077529566 Validation Accuracy: 0.8496932515337423 Test Accuracy: 0.8683001531393568							
Classification								
	precision	recall	f1-score	support				
0.0	0.83	0.90	0.86	1492				
	0.90							
1.0	0.50	0.02	0.00	1540				
accuracy			0.86					
macro avg	0.86	0.86	0.86	3044				
weighted avg	0.86	0.86	0.86	3044				
==========								
Classification	Report for	Validatio	n Set:					
	precision			support				
	pi cc1310ii	1 CC011	11-30010	Suppor C				
				245				
	0.82							
1.0	0.89	0.81	0.85	337				
accuracy			0.85	652				
macro avg	0.85	0.85	0.85	652				
weighted avg								
mergineed dvg	0.05	0.05	0.05	032				
Classification								
	precision	recall	f1-score	support				
0.0	0.83	0.92	0.87	321				
1.0	0.91	0.82	0.86	332				
accuracy			0.87	653				
	0.07	0.07						
	0.87							
weighted avg	0.87	0.87	0.87	653				



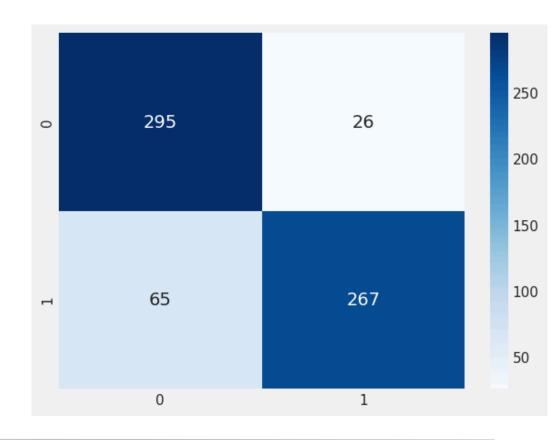
KNN

	Train Accuracy: 0.8350854139290408								
Validation Accuracy: 0.799079754601227 Test Accuracy: 0.8238897396630934									
	163. Actually, 6,623669735063934								
Classific	Classification Report for Train Set:								
		precision	recall	f1-score	support				
		0.78							
	1.0	0.92	0.74	0.82	1546				
accur	acv			0.84	3044				
		0.85	0.84						
	_	0.85							
-	-								
Classific	ation	Report for							
		precision	recall	f1-score	support				
	a a	0.74	0 01	a 01	215				
		0.89							
	1.0	0.05	0.03	0.76	337				
accur	acy			0.80	652				
macro	avg	0.81	0.80	0.80	652				
		0.82							
-	-								
Classific	ation	Report for							
		precision	recall	f1-score	support				
	0.0	0.76	0.93	0.84	321				
		0.92							
accur	acy			0.82	653				
macro	avg	0.84	0.83	0.82	653				
weighted	avg	0.84	0.82	0.82	653				



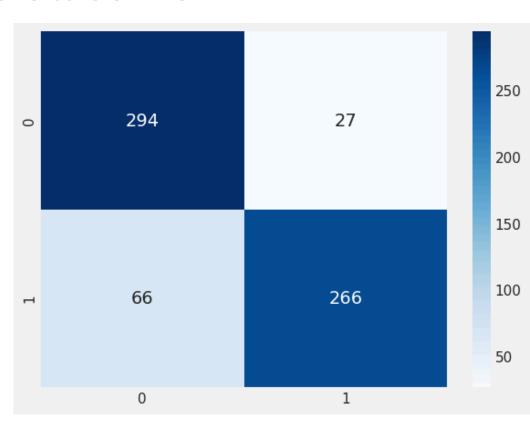
SVM

Train Accuracy: 0.864323258869908 Validation Accuracy: 0.8573619631901841 Test Accuracy: 0.8606431852986217								
		Report for precision	Train Set	:				
		0.83						
	1.0	0.91	0.82	0.86	1546			
accu macro weighted	avg	0.87 0.87	0.87 0.86	0.86	3044 3044 3044			
Classific	cation	Report for	validatio	======= n				
C1033111	cucion	precision			support			
		0.00	0.00	0.00	245			
		0.82 0.90						
	racy			0.86				
		0.86						
weighted	avg	0.86	0.86	0.86	652			
Classifi	cation	Report for						
		precision	recall	†1-score	support			
		0.82						
		0.91						
accu	racv			0.86	653			
		0.87	0.86					
		0.87			653			
_	-							



AdaBoost Classifier

Validation Test Acco	Train Accuracy: 0.8488830486202366 Validation Accuracy: 0.8466257668711656 Test Accuracy: 0.8575803981623277							
		Report for						
C10331110	Lacion	precision			support			
	0.0	0.80	0.91	0.86	1498			
		0.90						
accur	racy			0.85	3044			
macro	avg	0.85	0.85	0.85	3044			
		0.86						
-	-							
		Report for						
		precision			support			
	0.0	0.80	0.92	0.85	315			
	1.0	0.91	0.78	0.84	337			
accur	racy			0.85	652			
macro	avg	0.85	0.85					
		0.86						
		Report for			=======			
		precision			support			
	2.0	0.82	0.02	0.00	221			
	1.0	0.91	0.80	0.85	332			
accur	racy			0.86	653			
macro	avg	0.86	0.86	0.86	653			
weighted		0.86	0.86	0.86	653			



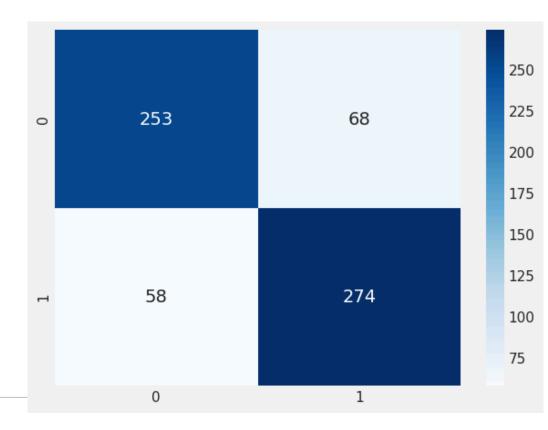
Decision Tree

Train Accuracy: 1.0

Validation Accuracy: 0.7837423312883436

Test Accuracy: 0.8070444104134763

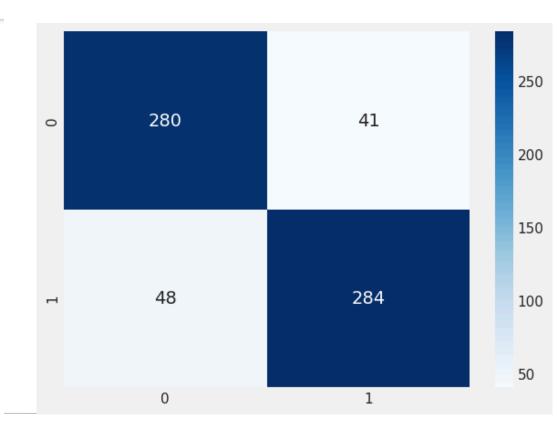
Classification	Report for	Train Set	:		
	precision	recall	f1-score	support	
0.0	1.00	1.00	1.00	1498	
	1.00				
accuracy			1.00	3044	
macro avg	1.00	1.00	1.00	3044	
weighted avg					
Classification	n Report for	Validatio	n Set:		
	precision	recall	f1-score	support	
0.0	0.77	0.79	0.78	315	
1.0	0.80	0.78	0.79	337	
accuracy			0.78	652	
macro avg	0.78	0.78	0.78	652	
weighted avg	0.78	0.78	0.78	652	
Classification	Report for	Test Set:			
	precision	recall	f1-score	support	
	-				
0.0	0.81	0.79	0.80	321	
1.0	0.80	0.83	0.81	332	
accuracy			0.81	653	
	0.81	0.81	0.81	653	
weighted avg	0.81	0.81	0.81	653	
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GradientBoost Classifier

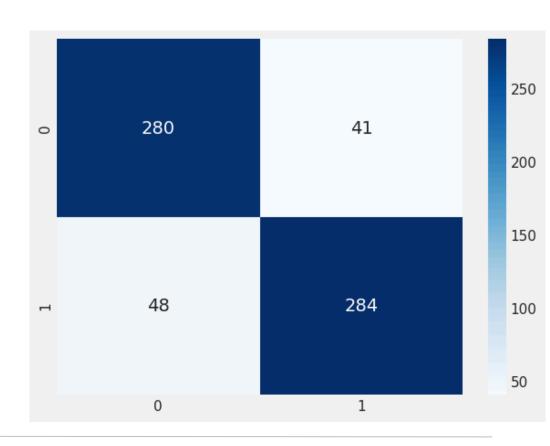
Validatio Test Accu	Train Accuracy: 0.8837056504599211 Validation Accuracy: 0.843558282208589 Test Accuracy: 0.8637059724349158							
		Report for						
CIGSSITIO	acton	precision			support			
	0.0	0.85	0.92	0.89	1498			
	1.0	0.92						
accur				0.88				
macro	avg	0.89	0.88	0.88	3044			
weighted	avg	0.89	0.88	0.88	3044			
Classific	ation	Report for	Validatio	n Set:				
		precision	recall	f1-score	support			
	0.0	0.81	0.89	0.85	315			
	1.0	0.89	0.80	0.84	337			
266111	22.51/			0.84	CE2			
accur		0.85	0.05					
		0.85						
weighted	uvg	0.05	0.04	0.07	652			
Classific	ation	Report for		_				
		precision	recall	f1-score	support			
	0.0	0.85	0.87	0.86	321			
	1.0	0.87	0.86	0.86	332			
accur	racv			0.86	653			
macro	ava	0.86	0 06	0.00	653			
weighted	avg	0.86	0.86	0.86	653			
mergilled	uvg	0.00	0.00	0.00	333			



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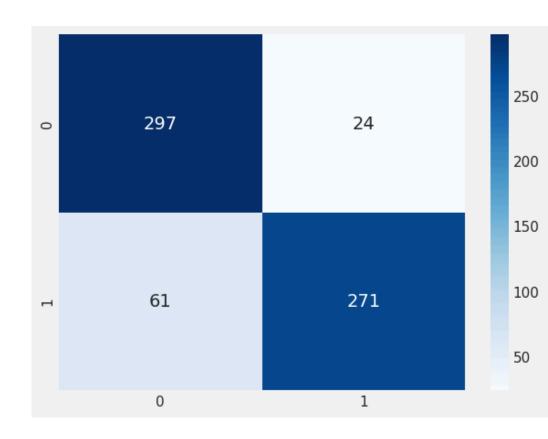
AdaBoost Classifier with GridSearch

Best AdaBoost Classifier parameters: {'algorithm': 'SAMME.R', 'n_estimators': 200} Train Accuracy: 0.8837056504599211 Validation Accuracy: 0.843558282208589 Test Accuracy: 0.8637059724349158								
Classification Report for Train Set:								
precision recall f1-score support								
0.0 0.85 0.92 0.89 1498								
1.0 0.92 0.85 0.88 1546								
accuracy 0.88 3044								
macro avg 0.89 0.88 0.88 3044								
weighted avg 0.89 0.88 0.88 3044								
Classification Report for Validation Set:								
precision recall f1-score support								
0.0 0.81 0.89 0.85 315								
1.0 0.89 0.80 0.84 337								
accuracy 0.84 652								
macro ave 0.85 0.85 0.84 652								
weighted avg 0.85 0.84 0.84 652								
weighted avg								
Classification Report for Test Set:								
precision recall f1-score support								
0.0 0.85 0.87 0.86 321								
1.0 0.87 0.86 0.86 332								
accuracy 0.86 653								
macro avg 0.86 0.86 0.86 653								



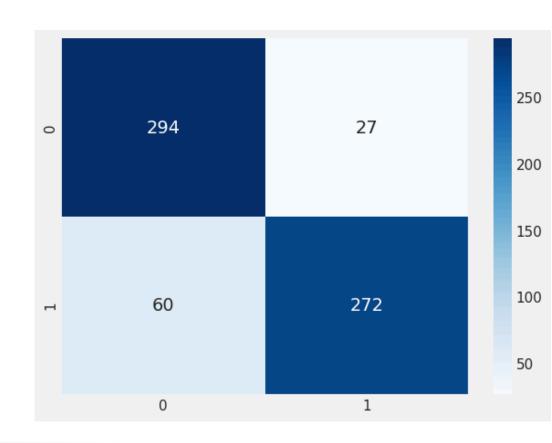
XGBoost Classifier

Train Accuracy: 0.8912614980289093 Validation Accuracy: 0.8374233128834356 Test Accuracy: 0.8698315467075038							
		Report for T					
C1033111	cacion	precision			support		
		0.85 0.94					
	avg	0.90 0.90			3044		
classifi		Report for V	 /alidatio				
C1055111	Cacton	precision			support		
		0.85 0.83					
weighted	avg avg	0.84 0.84	0.84	0.84	652 652		
		Report for T precision	rest Set:				
	0.0 1.0	0.83 0.92	0.93 0.82	0.87 0.86	321 332		
	avg	0.87 0.87			653		



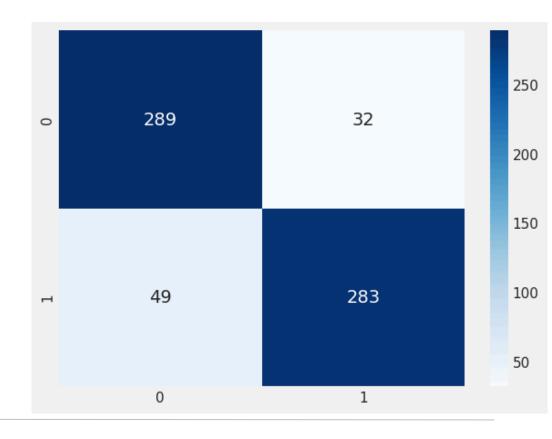
XGBoostClassifier with GridSearch

Best XGBoost parameters: {'gamma': 0.1, 'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 100} Train Accuracy: 0.8915900131406045 Validation Accuracy: 0.8358895705521472 Test Accuracy: 0.8667687595712098								
Classification								
CIGSSITICACION	precision			support				
0.0	0.85	0.94	0.90	1498				
	0.94							
accuracy			0.89	3044				
macro avg	0.90	0.89	0.89	3044				
weighted avg	0.90	0.89	0.89	3044				
Classification								
	precision	recall	f1-score	support				
0.0	0.85	0.00	0.02	215				
	0.82							
1.0	0.02	0.0/	0.05	337				
accuracy			0.84	652				
macro avg	0.84	0.83		652				
weighted avg								
Classification								
	precision	recall	f1-score	support				
	0.83							
1.0	0.91	0.82	0.86	332				
accuracy				653				
macro avg weighted avg	0.87	0.87 0.87						
weighten avg	0.8/	0.8/	0.8/	653				



GradientBoost Classifier with GridSearch

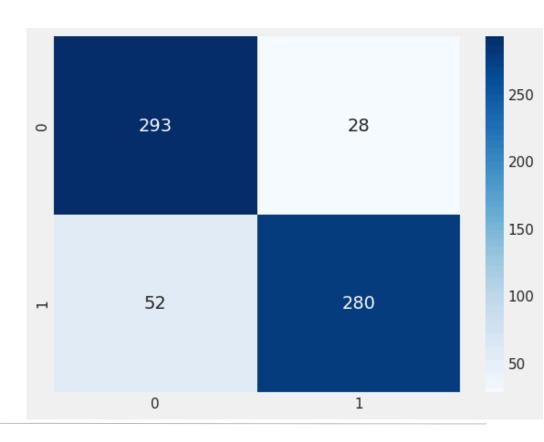
Best Gradient Boosting parameters: {'max_depth': 3, 'n_estimators': 200} Train Accuracy: 0.9250985545335085 Validation Accuracy: 0.838957055214724 Test Accuracy: 0.8759571209800919							
Classification							
CIGSSITICACIO	precision			support			
0.0	0.90	0.96	0.93	1498			
	0.96						
accuracy			0.93				
	0.93						
weighted avg	0.93	0.93	0.93	3044			
Classification							
CIGSSITICACIO	precision			support			
	pi ecision	recarr	11-30016	Suppor C			
0.0	0.80	0.89	0.84	315			
	0.89						
accuracy			0.84	652			
	0.84						
weighted avg	0.84	0.84	0.84	652			
Classificatio							
Classificatio	n keport for precision			support			
	bisectation	Lecall	11-5C01'6	20ppor-C			
0.0	0.86	0.90	0.88	321			
1.0							
accuracy			0.88	653			
macro avg	0.88	0.88	0.88	653			
weighted avg	0.88	0.88	0.88	653	_		



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Random Forest

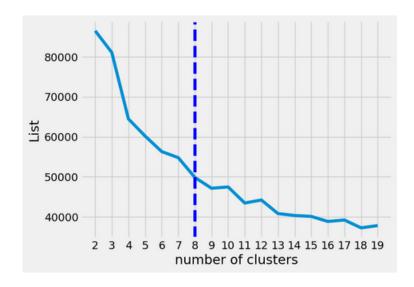
Train Accuracy: 1.0 Validation Accuracy: 0.8542944785276073 Test Accuracy: 0.877488514548239							
		Report for 1					
C1022111	Lacton						
		precision	recall	f1-score	support		
		1 00	1 00	1 00	4400		
		1.00	1.00	1.00	1498		
	1.0	1.00	1.00	1.00	1546		
				4 00	2044		
accui					3044		
macro	avg	1.00 1.00	1.00	1.00	3044		
weighted	avg	1.00	1.00	1.00	3044		
Classifi	cation	Report for \					
		precision	recall	f1-score	support		
	0.0	0.81	0.92	0.86	315		
	1.0	0.91	0.80	0.85	337		
accui	racv			0.85	652		
macro		0.86	0.86				
		0.86					
weighted	uvg	0.00	0.03	0.05	032		
Classification Report for Test Set:							
C1033111	cucion	precision			support		
		precision	recuir	11-30016	Suppor C		
	0.0	0.85	0.91	0.88	321		
		0.91					
	1.0	0.51	0.04	0.00	332		
accui	cacv			0.88	653		
macro		0.88	a 00				
weighted		0.88					
MetRuren	avg	0.88	0.88	0.88	653		

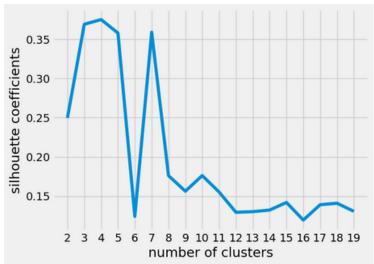




We preferred to work with robust scaled data in this part.

1.KMeans

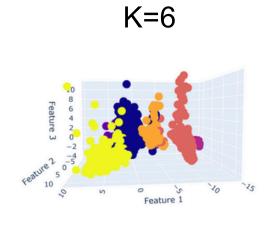




1.KMeans

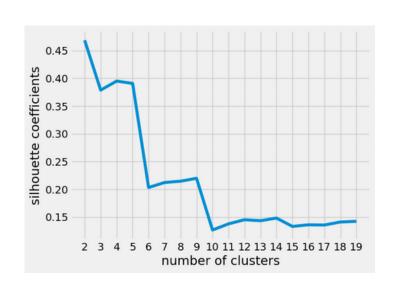
Clustering

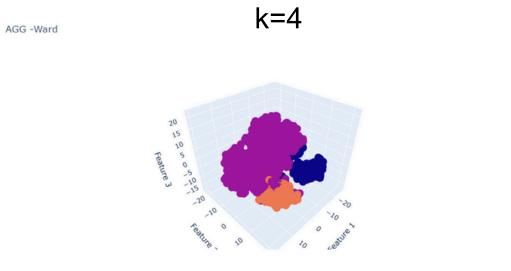
Kmeans



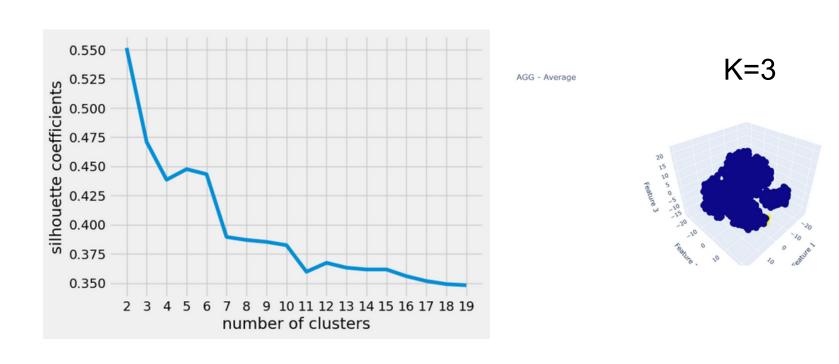


2.Agglomerative Clustering Ward

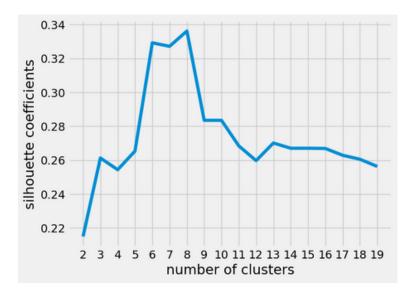




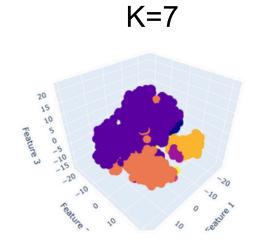
2.Agglomerative Clustering Average



2.Agglomerative Clustering Complete



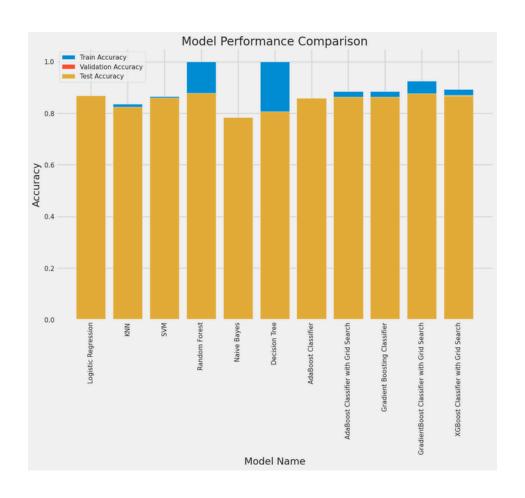
AGG - Complete



Labels

8. Final results

8. Final Results



Best Model is: Random Forest Classifier

9. Conclusion

9. Conclusion

Early Detection of Student Dropout Trends

 The analysis of the student performance dataset aims to help universities and schools identify students at risk of academic dropout. By predicting student trends early, educational institutions can intervene with personalized solutions to improve academic outcomes.

•

In this project, several machine learning models were explored, with Random
Forest being the most effective model. Despite a slight overfitting issue, the
model achieved an accuracy of 87.75%, making it a reliable tool for predicting
students likely to drop out.

9. Conclusion

Early Detection of Student Dropout Trends

Key takeaways include:

- Early intervention is crucial for helping at-risk students.
- Data driven insights enable educational institutions to develop tailored support programs.
- Random Forest can serve as the primary model for student performance prediction with continuous tuning to mitigate overfitting.

By leveraging such models, schools and universities can improve retention rates and provide timely support to students who may need additional academic assistance.

10.Future imporvments

10. Future improvements

We could enhance our deployment by making the student only enter their ID

The clustering part could be much better with some optimization.

Any Questions?



Team work

Name	Contribution		
Salma Sherif	StoryTelling, introduction, Second part of Modeling		
Ashraf Saber	EDA, Preprocessing, Conclusion		
Mahmoud Wahban	First part of Modeling, Clustering		



Thank you

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