

University Recommendation System For Masters in USA

A Knowledge Discovery & Data Mining Project with Machine Learning Prediction

Dataframe

Student Profile Dataset

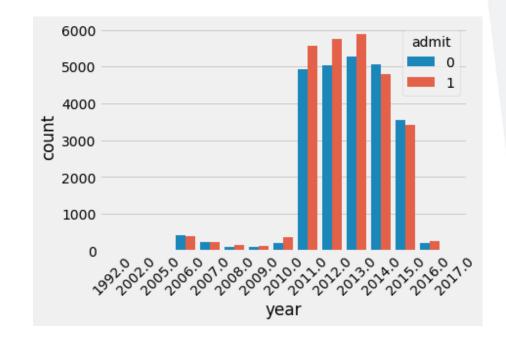
	userName	major	researchExp	industryExp	specialization	toefiScore pr	rogram	department	toeffEssay	internExp	greV gr	reQ userProfileLin	k journalPub	s grea	topperCgpa termA	ndYear	confPubs	ugCollege	gmatA	egpa g	matQ cgp	a Scale	vreng	univName a	amit
1750	nas_judee	Electrical and Computer Engineering	0	0 0	Digital VLSI Comp Arch	101.0	WS	EEE	Chemistry	NaN	3.0 10	2.0 16	8 http://www.edulix.com/unisearch/user.php?uid=2.	0.0	4.0	0	Pall - 2015	BITS Plani	NaN	8.00	8.0	10	NaN	University of Wisconsin Madison	0
2646	Arun_Leo	Computer Science	0	0	Neticorici	100.0	WS	8 Tech	information Technology	NaN	0.0 49	0.0 74	0 http://www.edulix.com/unisearch/user.phg?uid=1	0.0	3.5	8.89	Fall - 2012 Madras II	strute of Technology	NaN	8.14	NaN	10	14204	University of Texas Dallas	1.
10495	han_judee	Electrical and Computer Engineering	0	0.0	Digital VLSI Comp Arch	101.0	MS	EEE	Chemistry	NaN	3.0 15	2.0 16	8 http://www.edutix.com/unisearch/user.php?uid=2	0.0	40	0	FMI - 2015	DITS Plani	NaN	8.00	0.0	10	NW	University of Southern California	0
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26456	han_judee	Electrical and Computer Engineering	0	0.0	Digital VLSI Comp Arch	101.0	MS	EEE	Chemistry	NaN	3.0 15	2.0 16	8 http://www.edulix.com/unisearch/user.php?uid=2	0.0	4.0	0	Fall - 2010	BITS Plani	NaN	8.00	8.9	10	NaN	Purdue University	0
26794	savey911	environmental engineering	0	0	NaN	107.0	MS	Civil Engg	Nahi	NaN	0.0 15	9.0 15	8 http://www.edulix.com/unisearch/user.php?uid=1	0.0) Nan	81	Fall - 2014	Nagpur University	NaN :	58.00	NaN	100	NaN	Purdue Liniversity	0
27500	Arun_Leo	Computer Science	0	0	Networks	100.0	MS	6 Tech	information Technology	Nen	0.0 49	0.0 74	D http://www.eduio.com/univearch/user.php?uid=1.	0.0	3.5	8.89	Fall - 2012 Madres In	withrie of Sechnology	NaN	8.14	Nahi	30	Nan	Oteo State University Columbus	0

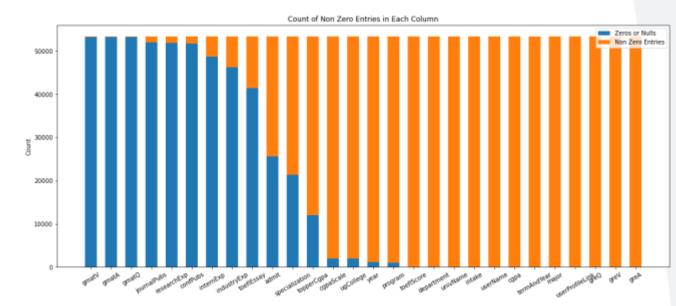
QS World Ranking Dataset

R	Rank institutio	n location code	location	ar score	ar rank	er score	er rank	fsr score	fsr rank	cpf score	cpf rank	ifr score	ifr rank	isr score	isr rank	irn score	irn rank	ger score	ger rank	score scaled
0	1 Massachusetts Institute of Technology (MIT	US	United States	100.0	5	100.0	4	100.0	14	100.0	5	100.0	54	90.0	109	96.1	58	100.0	3	100
1	2 University of Cambridg	e UK	United Kingdom	100.0	2	100.0	2	100.0	11	92.3	55	100.0	60	96.3	70	99.5	6	100.0	9	98.8
2	3 Stanford Universit	y US	United States	100.0	4	100.0	5	100.0	6	99.9	9	99.8	74	60.3	235	96.3	55	100.0	2	98.5
3	4 University of Oxfor	d UK	United Kingdom	100.0	3	100.0	3	100.0	8	90.0	64	98.8	101	98.4	54	99.9	3	100.0	7	98.4
4	5 Harvard Universit	y US	United States	100.0	1	100.0	1	99.4	35	100.0	2	76.9	228	66.9	212	100.0	1	100.0	1	97.6

Exploratory Data Analysis (EDA)

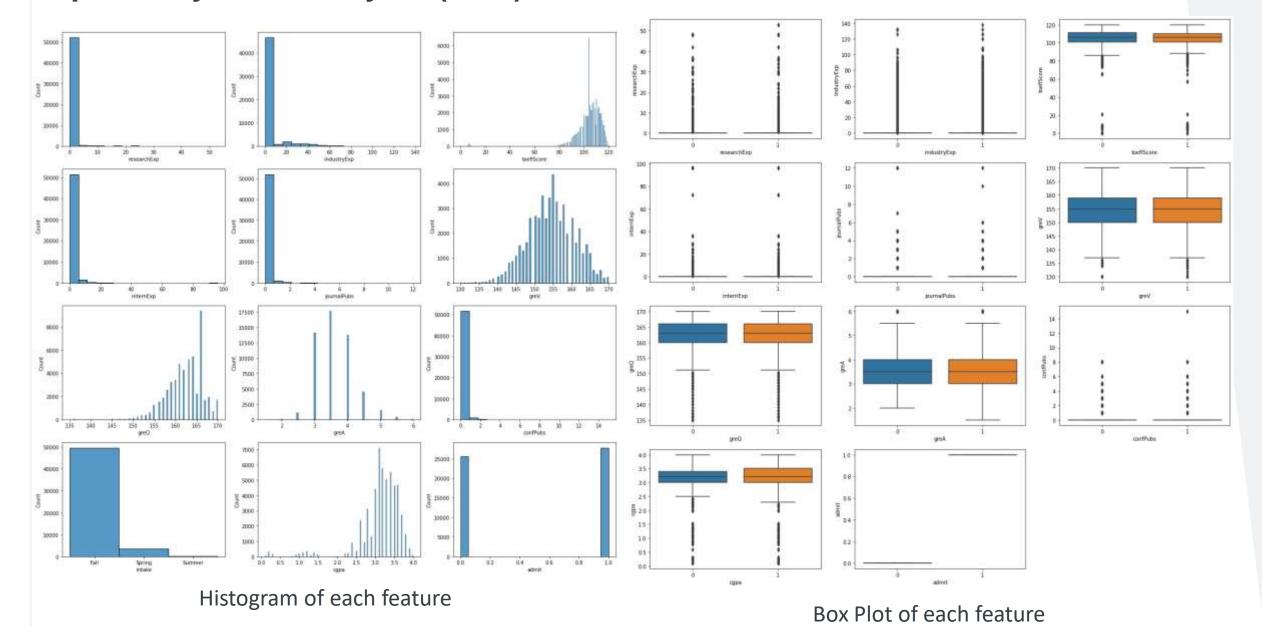
- •Null values in gmatA were 53203, gmatV were 53208 and gmatQ were significantly high.
- •TOEFL essay had a total of 41448 null values.
- •The data was shifted towards the left and was irregularly placed.
- •CGPA was given in different scales like 0,4,5,10 and 100.
- Few GRE scores data followed previous marking system.





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Exploratory Data Analysis (EDA)



Data cleaning

- Manual grouping of majors column and brought it down from 245 unique majors to 34.
- Converting GRE scores to the current scoring system.
- Shifting of misaligned data from columns.
- Identifying and removing irrelevant and less significant features.
- Filling of null values with either mean or mode.
- Restricting the dataset to MS values.
- Converting CGPA to 4 scale.
- Dropping rows with significant null values.
- Removing of outliers.

	old	newQ	newV
0	800	166	170
1	790	164	170
2	780	163	170
3	770	161	170
4	760	160	170

For Column: toeflScore -> Range: 83.0 To 128.0 Total outliers removed: 597

For Column: greV -> Range: 132.0 To 177.0 Total outliers removed: 8

For Column: greQ -> Range: 148.0 To 178.0 Total outliers removed: 229

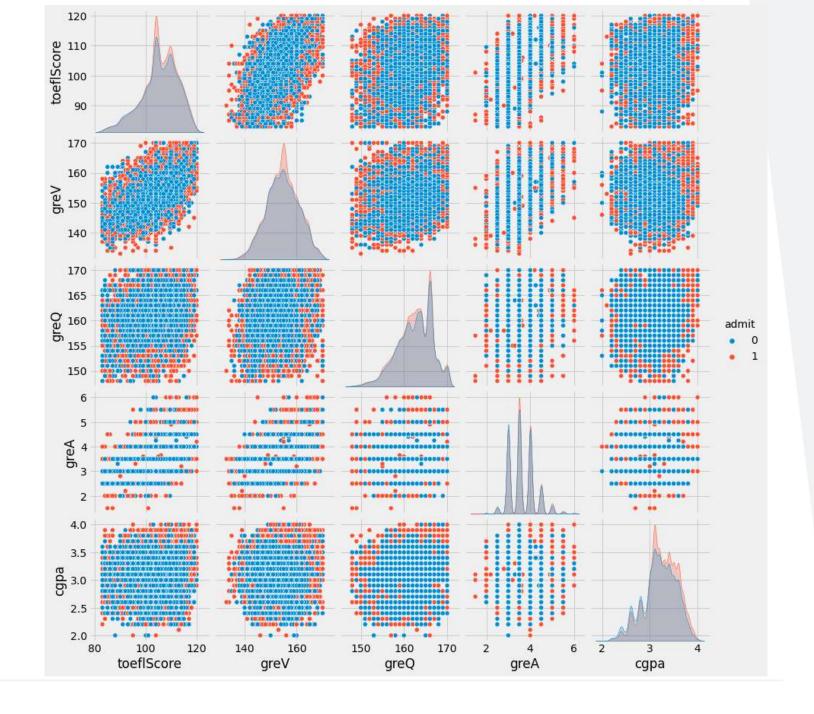
For Column: greA -> Range: 1.0 To 6.0 Total outliers removed: 0

For Column: cgpa -> Range: 2.0 To 4.5 Total outliers removed: 1877

Pair plots

- Pair plots visually plots each of the numeric feature against other features.
- Shows relationship between pairs of features.
- Represents data based on target feature.

Data is linearly not separable



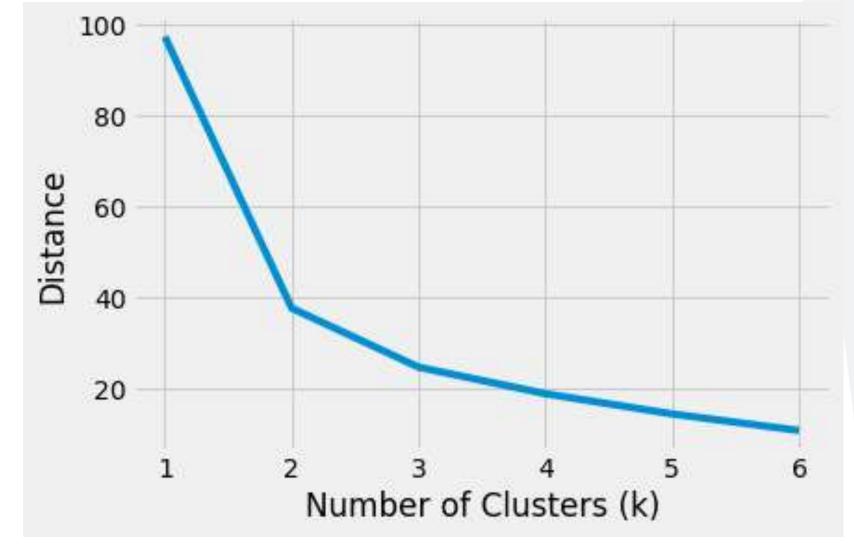
Clustering

- Used World ranking dataset from QS website.
- Filtered the data to universities in US.
- Dropped scores columns and kept ranks for better analysis.
- Performed Min-Max Scaling.
- Performed PCA on the dataset to help with visualisation.
- Schools were classified into tiers.



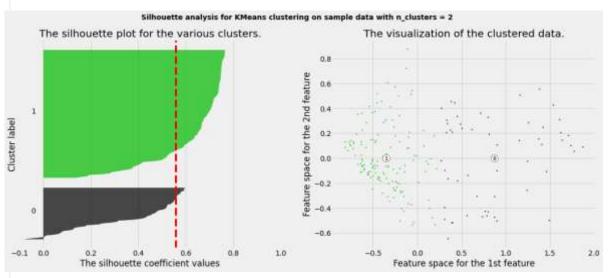
Cluster Analysis

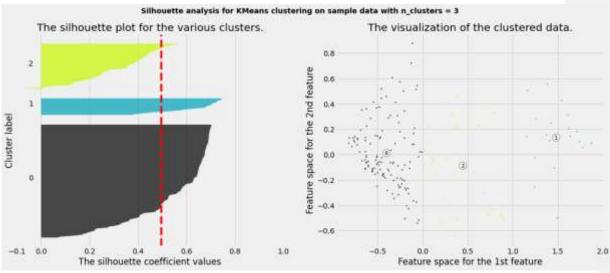
- Sum of squared distances of samples to their closest cluster center.
- Trade off between number of clusters and inertia.
- Elbow curve shows
 k=2 can produce
 better results.

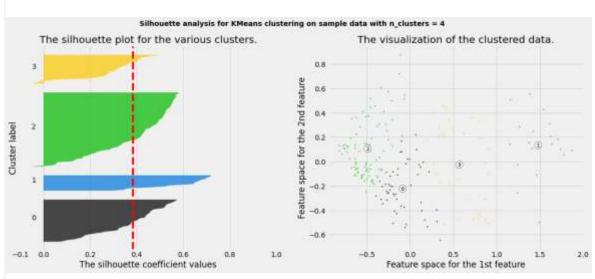


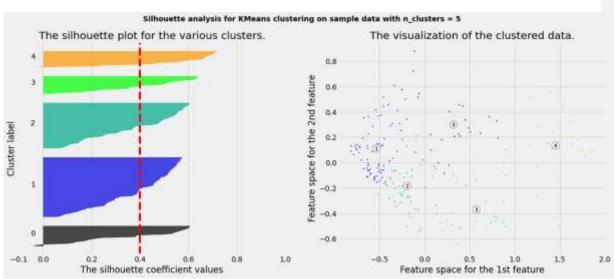
Elbow plot for K-Means inertia

Cluster Analysis



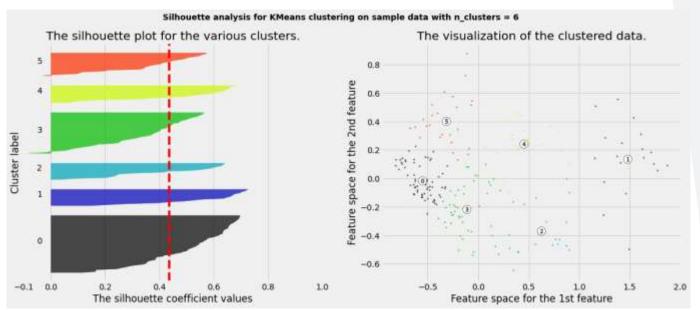


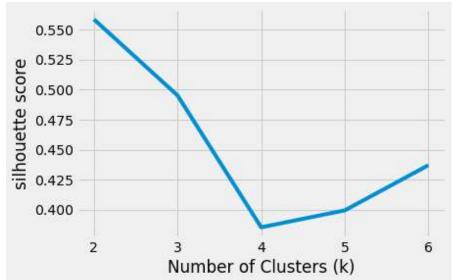




Cluster Analysis

- Compares how a point is similar to it's own cluster compared to other clusters.
- The value of the silhouette ranges between [1, -1]
- A high value indicates that the object is well matched to its own cluster and poorly matched to neighbouring clusters.





Clustering Results

Tier 1: Tier 2:

Worcester Polytechnic Institute

Wayne State University

Virginia Polytechnic Institute and State University

University of Utah

University of Texas Dallas

University of Texas Arlington

University of North Carolina Charlotte

University of Illinois Chicago

University of Colorado Boulder

University of Cincinnati

University of California Santa Cruz

University of Arizona

Syracuse University

SUNY Stony Brook

SUNY Buffalo

Rutgers University New Brunswick/Piscataway

North Carolina State University

New Jersey Institute of Technology

George Mason University

Clemson University

University of Wisconsin Madison

University of Washington

University of Texas Austin

University of Southern California

University of Pennsylvania

University of North Carolina Chapel Hill

University of Minnesota Twin Cities

University of Michigan Ann Arbor

University of Massachusetts Amherst

University of Maryland College Park

University of Illinois Urbana-Champaign

University of Florida

University of California Santa Barbara

University of California San Diego

University of California Los Angeles

University of California Irvine

University of California Davis

Texas A and M University College Station

Stanford University

Purdue University

Princeton University

Ohio State University Columbus

Northwestern University

Northeastern University

New York University

Massachusetts Institute of Technology

Johns Hopkins University

Harvard University

Georgia Institute of Technology

Cornell University

Columbia University

Carnegie Mellon University

California Institute of Technology

Arizona State University

Algorithms Applied

- KNN
- Random Forest
- Naive Baye's
- Logistic Regression
- Support Vector Machines
- Linear Discriminant Analysis



Final transformations - I

Splitting

- •Splitting the data based on it's cluster.
- •Splitting the data into 30% test data and 70% train data.

Min-Max scaling

•Normalising data between 0 and 1.

Upscaling

- •Uses bootstrapping with replacement.
- •Creates a random resampling of data.
- •Upscaling the admit rows since it's below the 65% of majority class.

Label encoding

- •Converts text categorical data into numerical data.
- •Each unique category gets a unique numerical value.



Initial testing results

PREDICTION FOR CLUSTER 0

	accuracy_score	precision_score	recall_score	f1_score
SVM	0.623638	0.629170	0.923096	0.748305
KNN	0.611077	0.656352	0.752060	0.700954
LR	0.628632	0.636220	0.904370	0.746958
LDA	0.629237	0.636427	0.905618	0.747527
Naive Bayes	0.622730	0.646568	0.832709	0.727928
Random Forest	0.598366	0.656257	0.708365	0.681316

PREDICTION FOR CLUSTER 1

	accuracy_score	precision_score	recall_score	f1_score
SVM	0.599161	0.607824	0.320443	0.419649
KNN	0.590766	0.572724	0.374581	0.452930
LR	0.565349	0.544701	0.237175	0.330460
LDA	0.565466	0.544917	0.237690	0.331000
Naive Bayes	0.554390	0.520940	0.182779	0.270611
Random Forest	0.572345	0.530911	0.467131	0.496983

Without university Name

PREDICTION FOR CLUSTER 0

	accuracy_score	precision_score	recall_score	f1_score
SVM	0.751513	0.765919	0.851021	0.806231
KNN	0.739709	0.763194	0.828600	0.794553
LR	0.638620	0.644817	0.901844	0.751973
LDA	0.639074	0.644955	0.902840	0.752414
Naive Bayes	0.640738	0.657753	0.851769	0.742293
Random Forest	0.724425	0.749602	0.820379	0.783395

PREDICTION FOR CLUSTER 1

	accuracy_score	precision_score	recall_score	f1_score
SVM	0.731608	0.706752	0.669397	0.687568
KNN	0.721231	0.703715	0.635835	0.668055
LR	0.598461	0.571549	0.358879	0.440909
LDA	0.598694	0.571909	0.359408	0.441415
Naive Bayes	0.599977	0.583215	0.326903	0.418967
Random Forest	0.694415	0.666571	0.614958	0.639725

With University Name

Final transformations - II

One hot encoding

Why

- Not to have any bias added to the data.
- Improves accuracy of the model.

What

- It represents text data numerically.
- Converts unique values into different features.

When

- We have nominal categorical data.
- When curse of dimensionality doesn't effect model accuracy.



Results with one hot encoding

- •These algorithms were applied on both the clusters.
- •SVM had the best accuracy for both cluster 0 and cluster 1.
- •We also added KNN and random forest for further analysis.

PREDICTION FOR CLUSTER 0

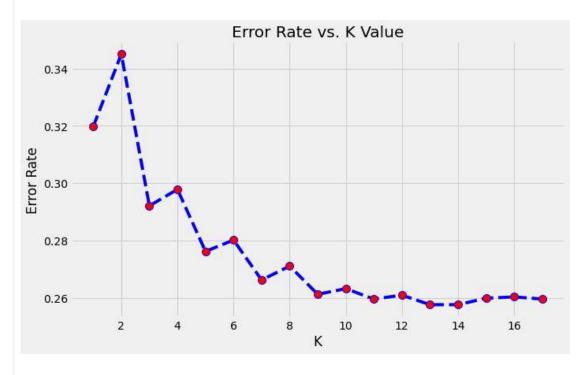
	accuracy_score	precision_score	recall_score	f1_score
SVM	0.756356	0.772953	0.849404	0.809377
KNN	0.743039	0.768715	0.826789	0.796695
LR	0.718069	0.740058	0.827783	0.781466
LDA	0.718069	0.739951	0.828032	0.781518
Naive Bayes	0.429782	0.849727	0.077286	0.141686
Random Forest	0.743493	0.768133	0.829026	0.797418

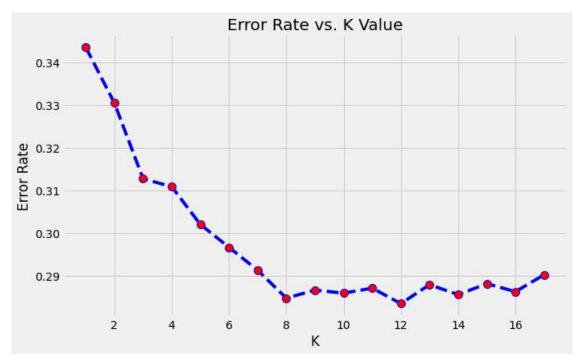
PREDICTION FOR CLUSTER 1

	accuracy_score	precision_score	recall_score	f1_score
SVM	0.726711	0.698038	0.656944	0.676868
KNN	0.719133	0.688209	0.649719	0.668410
LR	0.703743	0.676610	0.613059	0.643268
LDA	0.702227	0.674845	0.610918	0.641292
Naive Bayes	0.649878	0.615846	0.522077	0.565098
Random Forest	0.711321	0.679170	0.639550	0.658765

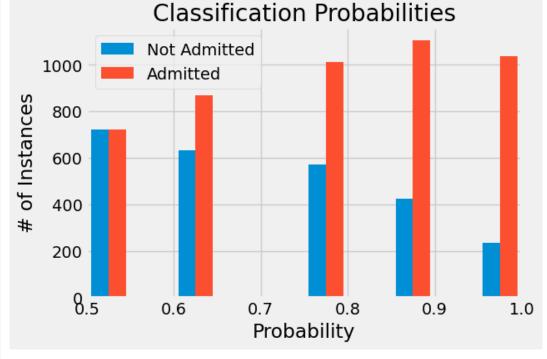
Hyper Parameter Tuning

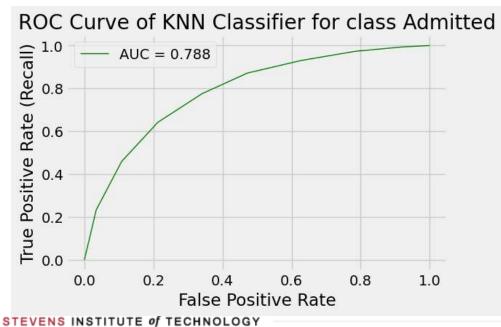
KNN

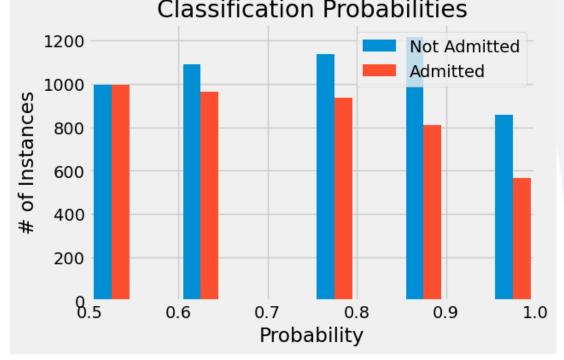


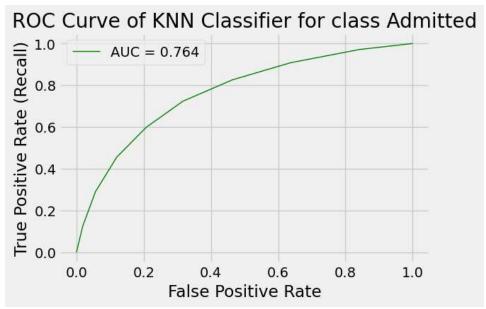


Tier 1 Tier 2







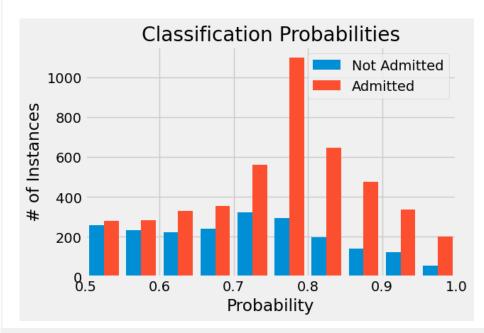


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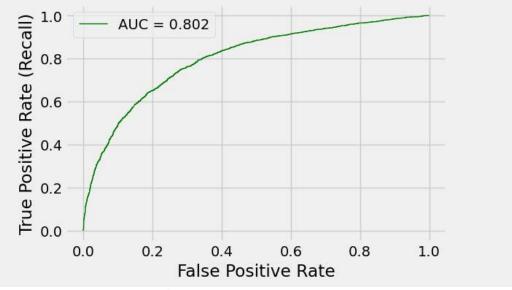
Tier 2

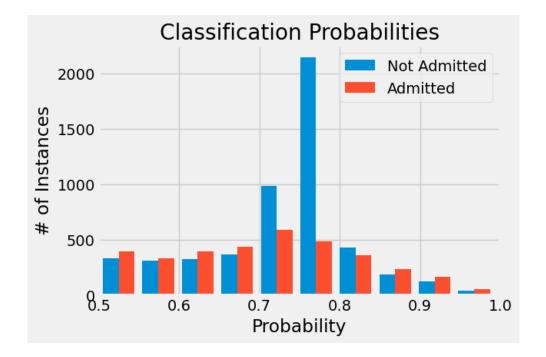
18

SVM

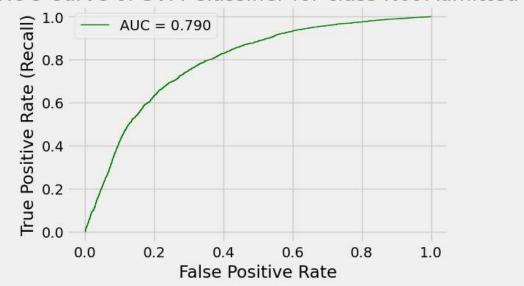


ROC Curve of SVM Classifier for class Not Admitted





ROC Curve of SVM Classifier for class Not Admitted

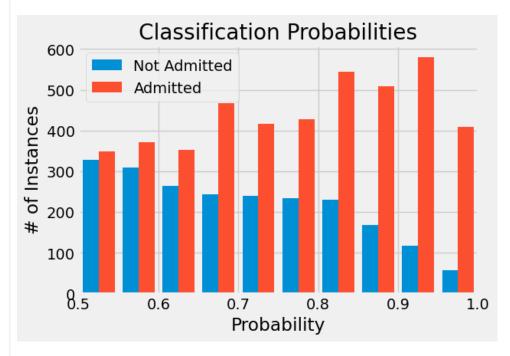


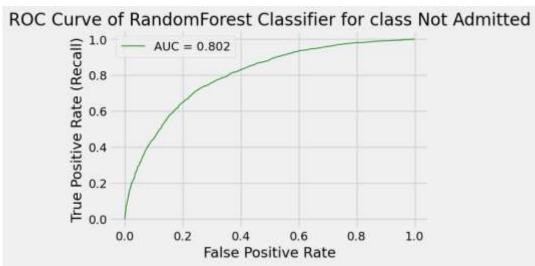
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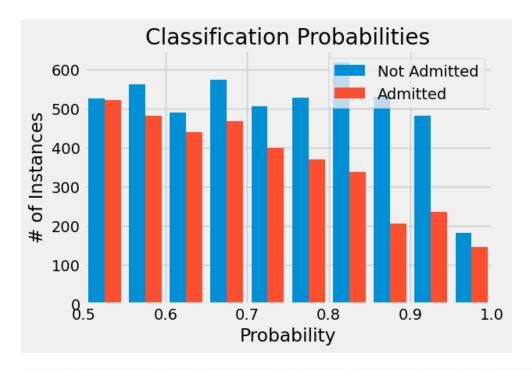
Tier 1

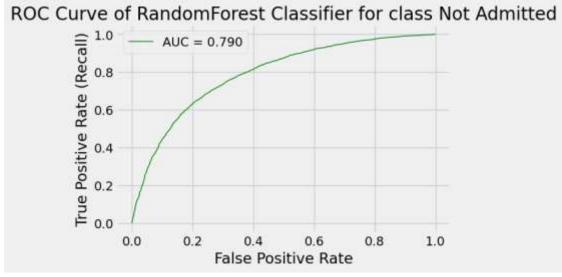
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Random Forest





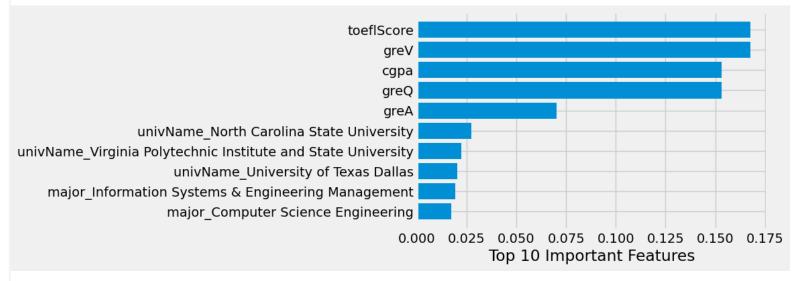




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 Tier 1

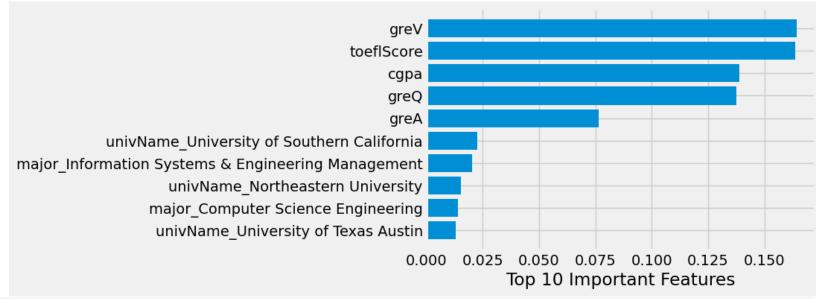
Tier 2

Top 10 important features



Tier 1





Final Results

KNN

Prediction for tier 1 Universities

	precision	recall	f1-score	support
0	0.65	0.66	0.65	2539
1.	0.78	0.78	0.78	4069
accuracy			0.73	6608
macro avg	0.72	0.72	0.72	6608
weighted avg	0.73	0.73	0.73	6608

Prediction for tier 2 Universities

	precision	recall	f1-score	support
0	0.71	0.79	0.75	4741
1	0.70	0.60	0.65	3836
accuracy			0.71	8577
macro avg	0.70	0.70	0.70	8577
weighted avg	0.71	0.71	0.70	8577

Final Hyper parameters: K=8, leaf_size= 30, weights='uniform', p= 2

Final Results

SVM

Prediction for tier 1 Universities

Prediction for tier 2 Universities

	precision	recall	f1-score	support		precision	recall	f1-score	support
0 1	0.70 0.77	0.60 0.84	0.64 0.80	2536 4072	0 1	0.74 0.71	0.79 0.65	0.77 0.68	4785 3792
accuracy macro avg weighted avg	0.74 0.74	0.72 0.75	0.75 0.72 0.74	6608 6608	accuracy macro avg weighted avg	0.73 0.73	0.72 0.73	0.73 0.72 0.73	8577 8577 8577

Random Forest

Final Hyper parameters: C=1, gamma=1, kernel='poly'

Prediction for tier 1 Universities

Prediction for tier 2 Universities

	precision	recall	f1-score	support		precision	recall	f1-score	support
0 1	0.69 0.77	0.60 0.83	0.64 0.80	2536 4072	0 1	0.74 0.70	0.77 0.66	0.76 0.68	4785 3792
accuracy macro avg weighted avg	0.73 0.74	0.71 0.74	0.74 0.72 0.74	6608 6608 6608	accuracy macro avg weighted avg	0.72 0.72	0.72 0.72	0.72 0.72 0.72	8577 8577 8577

Final Hyper parameters: 'bootstrap': True, 'max_depth': None, 'max_features': 'auto', 'n_estimators': 500

Final Insights

- Always analyse the data instead of directly dropping it.
- Necessary to visualise the data to gain better insights.
- Data pre-processing has the biggest impact in model accuracy.
- Test different encoding methods to check if it helps.
- Clustering of data can enhance performance.
- Always check if hyper parameter tuning helps your model.
- Our profiles are evaluated holistically, therefore your SOP and LOR matters.
- Each university is unique in their own way of evaluating candidates.







THANK YOU