أكاديمية سدايا
SDAIA Academy

Classification Models

Employee Promotion

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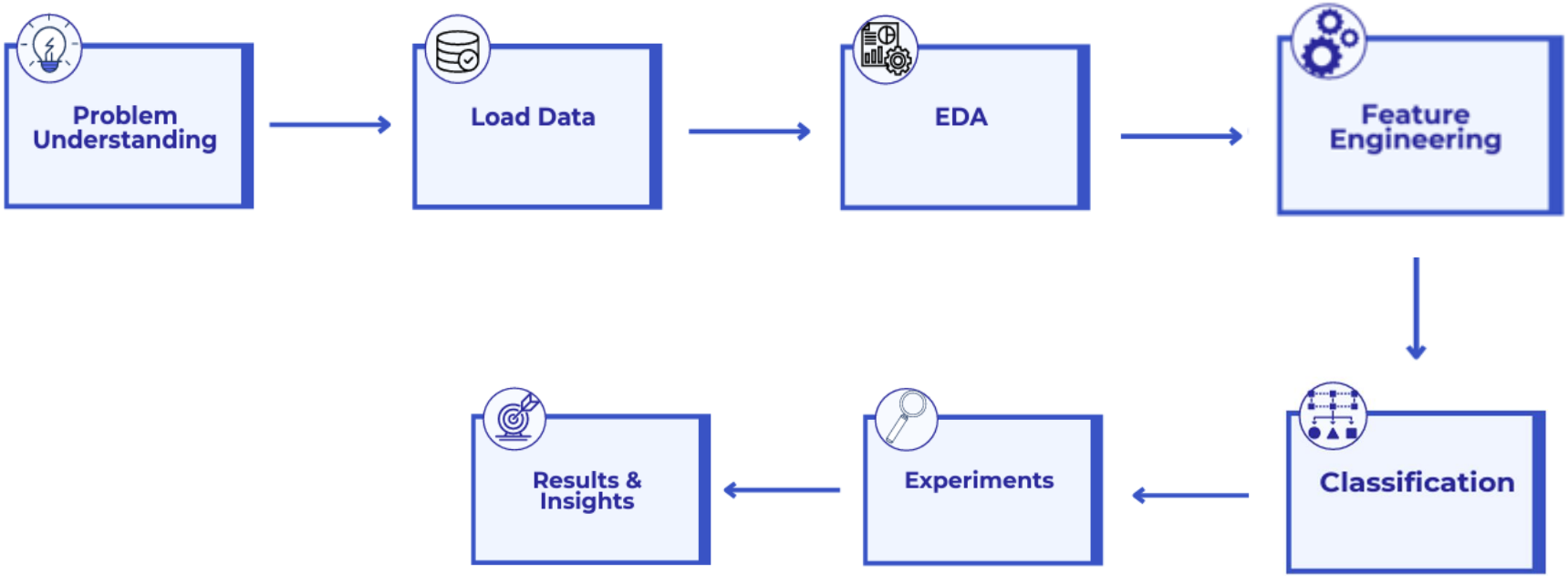
INTRODUCTION

There are many companies trying to determine which employees are eligible for a promotion by a certain evaluation, and with thousands of employees, this is delaying the transition to new positions. Hence, the company needs to help identify the qualified candidates at a particular checkpoint so that they can speed up the entire promotion cycle.

INSPIRATION

We try predict whether a potential promote at checkpoint in the test set will be promoted or not after the evaluation process.

Methodology



Dataset

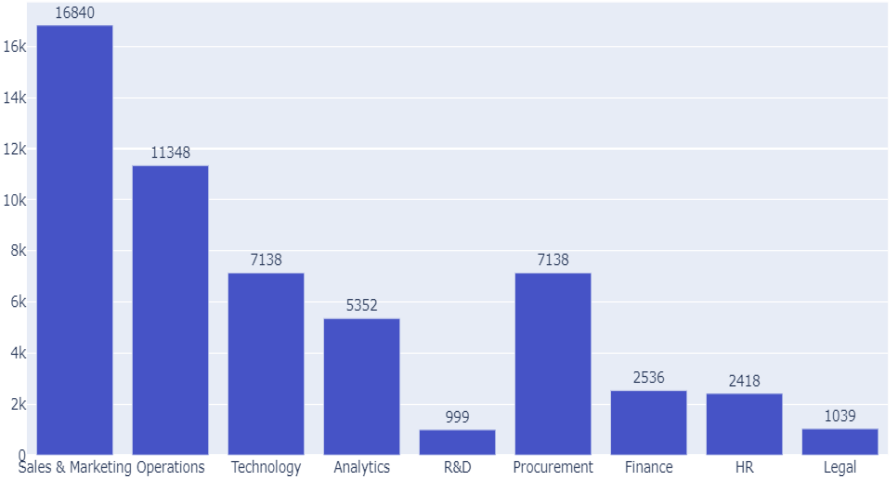
Source	**HR Analytics: Employee Promotion Data** *It was uploaded in Kaggle.com*
Records	**54808 Employee Records**
Features	**13 Features** *id , department, education, gender, lenght_of_service,… etc.*
Target	**Predict the eligible candidates for promotion**

Dataset

Name of Columns	Describtion	Type
Employee_id	Unique ID for employee	int64
department	Department of employee	object
region	Region of employment (unordered)	object
Education	Education Level	object
Gender	Gender of Employee	object
recruitment_channel	Channel of recruitment for employee	object
no_of_trainings	no of other trainings completed in previous year on soft skills, technical skills etc.	int64
age	Age of Employee	int64
previous_year_rating	Employee Rating for the previous year	float64
length_of_service	Length of service in years	int64
awards_won?	if awards won during previous year then 1 else 0	int64
avg_training_score	Average score in current training evaluations	int64
is_promoted	Recommended for promotion (Target)	int64

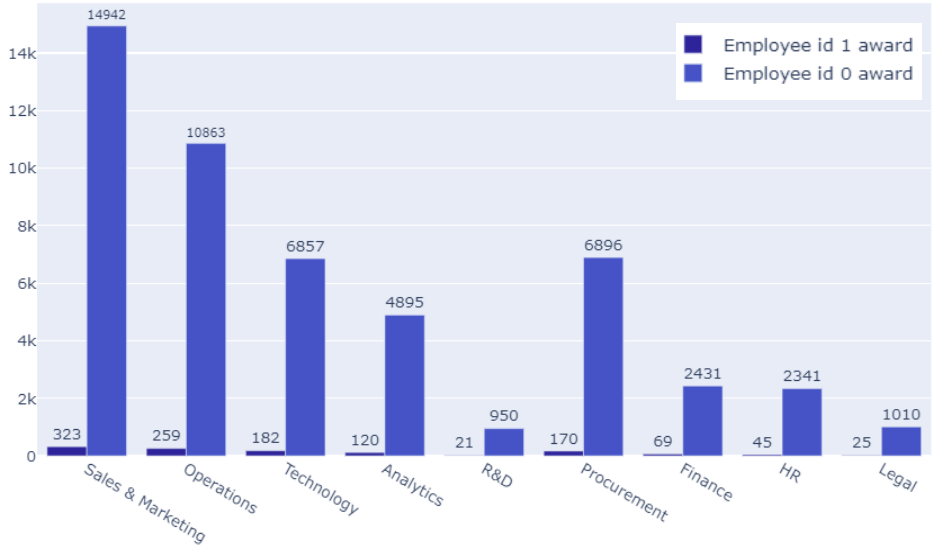
Exploratory Data Analysis

Distribution of Employees in Different Departments



The highest number of department on dataframe is about 16840 in Sales & marketing and the lowest number is about 999 in R&D

The highest number of award by departement



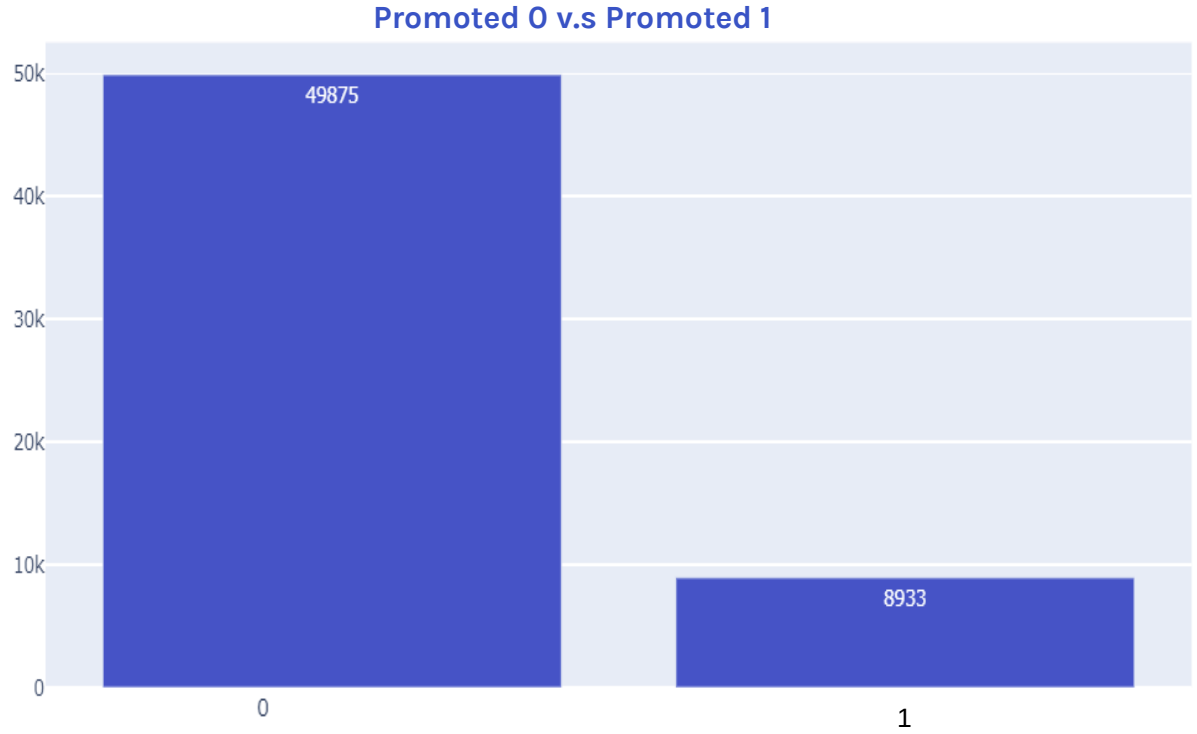
The highest number of award by departement on dataframe is about 323 in Sales & marketing and the lowest number is about 25 in Legal

Features Engineering

Convert Categorical Columns to label Variables

Resulted in decreasing the models' scores.

Data Imbalance



Number Of Observation

54808

Number Of Promoted 1

49875

Number Of Promoted 0

4933

Event rate 8.2 %

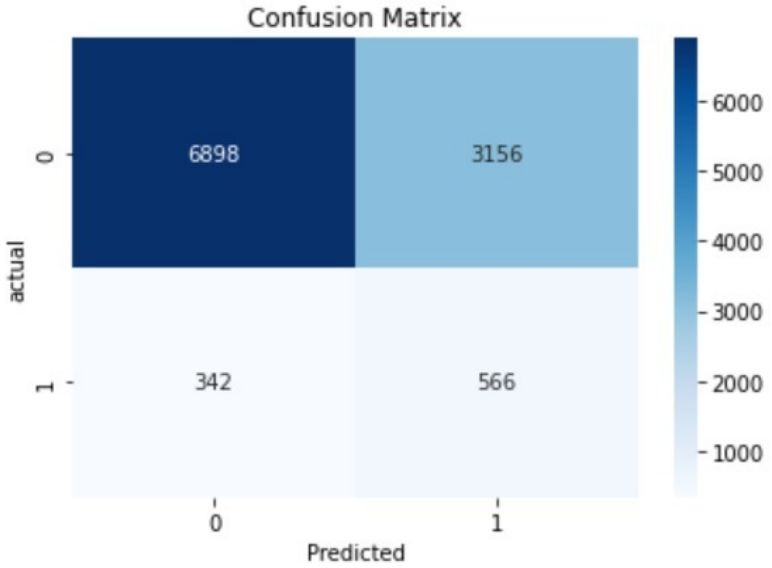
Data Imbalance

Approache for Imbalanced Data

Resampling Technique:

- Random Over-Sampling

Logistic Regression()



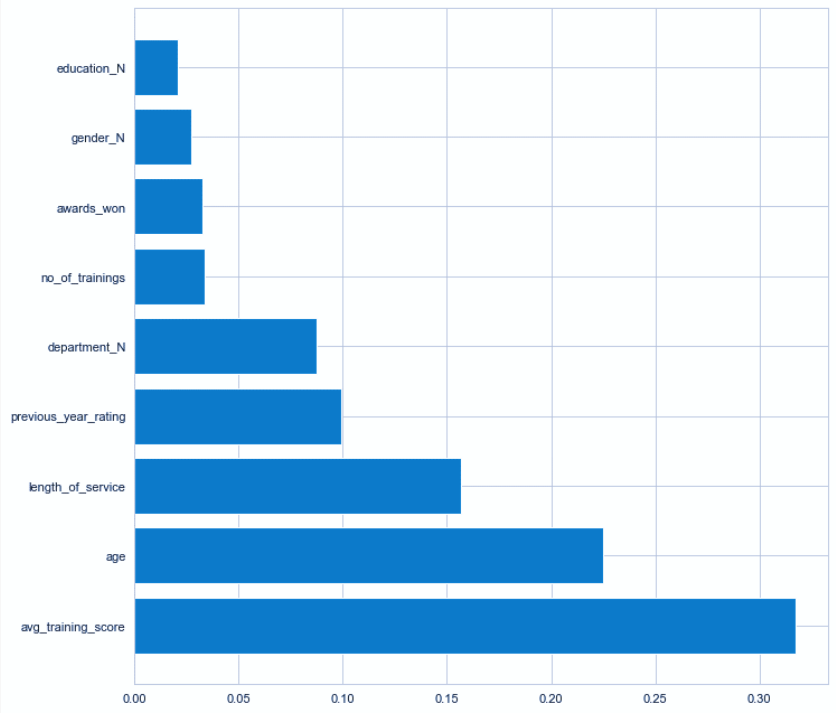
Testing Scores

Accuracy	=	68.08
Precision	=	15.20
Recall	=	62.33
F-1	=	24.44

	precision	recall	f1	support
0	0.95	0.69	0.80	1054
1	0.15	0.62	0.24	908
accuracy			0.68	10962
macro avg	0.55	0.65	0.52	10962
weighted avg	0.89	0.68	0.75	10962

Feature importance

for random forest



low Feature importance

- Education_N
- Gender_N
- Awards_won

Experiments

Classifier		Accuracy	Precision	Recall	F-1
KNN	Validation	65.31	11.37	46.72	18.29
	Test	64.92	11.48	45.53	18.34
Logistic Regression	Validation	63	12.74	58.89	20.96
	Test	63.31	13.20	58.10	21.51
Random Forest	Validation	62	12.75	60.39	21
	Test	62	13	59.75	21.54
XGBoost	Validation	52.91	11.77	71.87	20.23
	Test	53.48	11.96	68.90	20.38
LGBM	Validation	65.96	12.53	51.77	20.18
	Test	66.33	13.23	52	21
Stacking	Validation	92	85.56	9.52	17.14
	Test	75	13	32.74	18.53

Split Data

60% train, 20% Validation
20% test

Resampling Technique

Random Over-Sampling

Experiments

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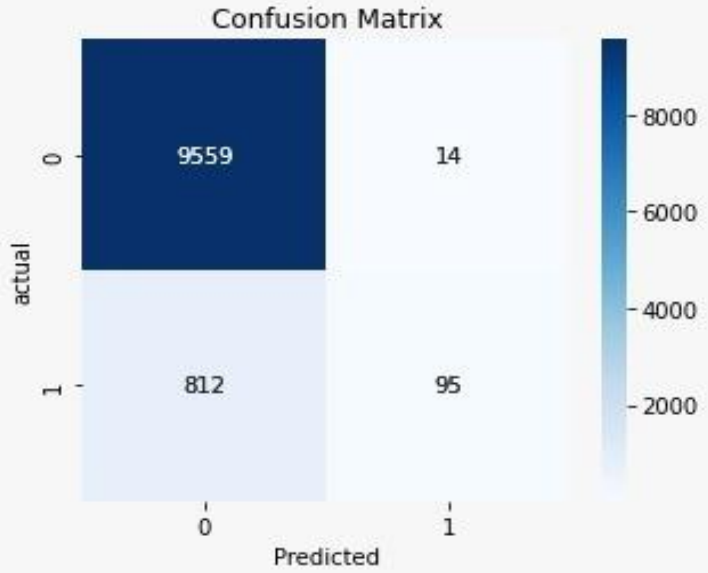
Resampling Technique

Random Over-Sampling

XGBoost (Imbalanced)

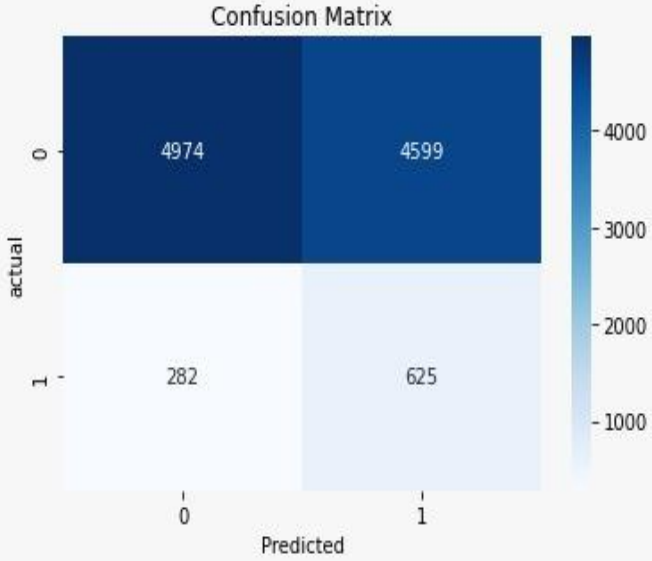


Testing Scores

Accuracy = 92.12
Precision = 87.16
Recall = 10.5
F-1 = 19

	precision	recall	f1	support
0	0.92	1.00	0.96	9573
1	0.87	0.10	0.19	907
accuracy			0.92	10480
macro avg	0.90	0.55	0.57	10480
weighted avg	0.92	0.92	0.89	10480

XGBoost (balanced)



Testing Scores

Accuracy	=	53.43
Precision	=	12
Recall	=	69
F-1	=	20.4

	precision	recall	f1	support
0	0.95	0.52	0.67	9573
1	0.12	0.69	0.20	907
accuracy			0.53	10480
macro avg	0.53	060	0.44	10480
weighted avg	0.87	0.53	0.63	10480

Conclusion

1. **Classifier Performance Metrics of interest**
   Accuracy, Recall, Precision, F-1
2. **Random over-sampling for Handling Imbalance Data**
3. **XGBoost is the Best Classifier for this dataset**
   With Accuracy = 53.43 , precision = 12 , recall = 69 , F-1 = 20.4

Future work

1. **Correcting errors, if any**
2. **Work on tuning the classifiers more, and try other classifiers**

Tools

Jupyter Notebook

Scikit-learn

Seaborn

Python Programming Language

Plotly

Pandas

Thank You

Dr. Patrick Saoud

For Everything!

Thank You!

Any Question?

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