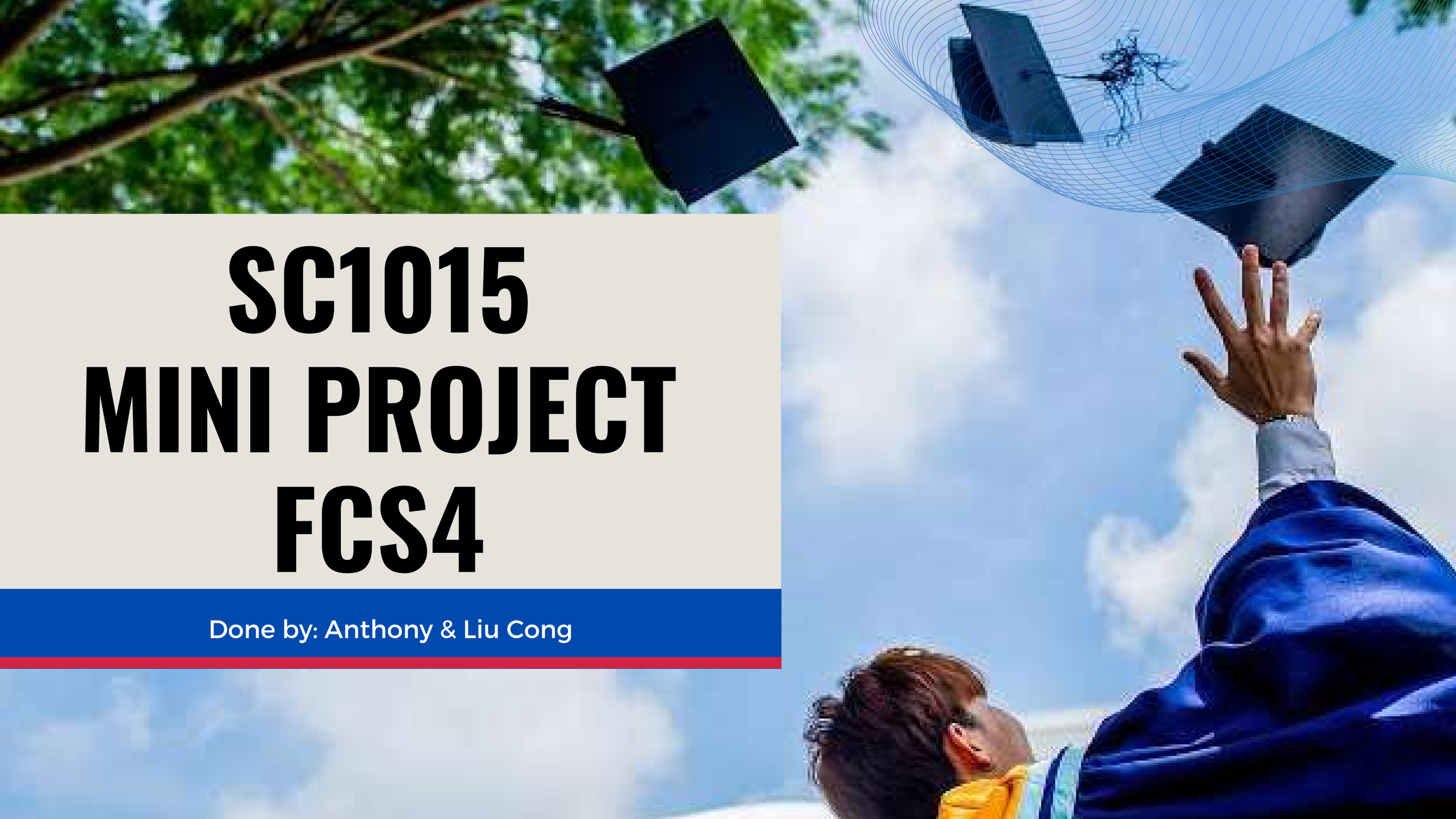


SC1015 MINI PROJECT FCS4

Done by: Anthony & Liu Cong

EMERGENCE OF AI

ARE AI REPLACING US?

THEREFORE...

OUR PROJECT

We aim to predict the employability of fresh graduates with Bachelor's, from Computer Science and IT related background, in the US

01 FINDING DATASETS

STEP 1 : Finding Datasets

kaggle

- The 1st dataset: 700 fresh graduates with their placement status
- The 2nd dataset: The ranking of universities from across 114 locations

STEP 1 : Finding Datasets

```
jobData
```

	id	name	gender	age	degree	stream	college_name	placement_status	salary	gpa	years_of_experience
0	1	John Doe	Male	25	Bachelor's	Computer Science	Harvard University	Placed	60000	3.7	2.0
1	2	Jane Smith	Female	24	Bachelor's	Electrical Engineering	Massachusetts Institute of Technology	Placed	65000	3.6	1.0
2	3	Michael Johnson	Male	26	Bachelor's	Mechanical Engineering	Stanford University	Placed	58000	3.8	3.0
3	4	Emily Davis	Female	23	Bachelor's	Information Technology	Yale University	Not Placed	0	3.5	2.0
4	5	David Brown	Male	24	Bachelor's	Computer Science	Princeton University	Placed	62000	3.9	2.0
...	...	...	...	...	...	...	...	...	...	...	...
695	696	Lucas Taylor	Male	23	Bachelor's	Computer Science	University of Washington	Placed	67000	3.8	3.0
696	697	Emma Martinez	Female	26	Bachelor's	Electronics and Communication	University of California--Berkeley	Placed	66000	3.9	3.0
697	698	Aiden Davis	Male	24	Bachelor's	Computer Science	University of Illinois--Urbana-Champaign	Placed	65000	3.8	3.0
698	699	Mia Wilson	Female	23	Bachelor's	Electrical Engineering	University of Colorado--Boulder	Placed	66000	3.7	2.0
699	700	Jack Garcia	Male	26	Bachelor's	Information Technology	University of North Carolina--Chapel Hill	Not Placed	0	3.6	1.0

700 rows × 11 columns

The 1st dataset

STEP 1 : Finding Datasets

```
jobData.describe()
```

	id	age	salary	gpa	years_of_experience
count	700.00000	700.000000	700.000000	700.000000	699.000000
mean	350.50000	24.411429	52474.285714	3.750429	2.177396
std	202.21688	1.164268	25160.331005	0.121212	0.779393
min	1.00000	23.000000	0.000000	3.400000	1.000000
25%	175.75000	23.000000	61000.000000	3.700000	2.000000
50%	350.50000	24.000000	64000.000000	3.800000	2.000000
75%	525.25000	26.000000	66000.000000	3.900000	3.000000
max	700.00000	26.000000	68000.000000	3.900000	3.000000

The 1st dataset

STEP 1 : Finding Datasets

```
uniRankings.head()
```

	2024 RANK	2023 RANK	Institution Name	Country Code	Country	SIZE	FOCUS	RES.	AGE	STATUS	...	International Faculty Rank	International Students Score	International Students Rank	International Research Network Score	Inter R N
0	rank display	rank display2	institution	location code	location	size	focus	research	age band	status	...	ifr rank	isr score	isr rank	irn score	
1	1	1	Massachusetts Institute of Technology (MIT)	US	United States	M	CO	VH	5	B	...	56	88.2	128	94.3	
2	2	2	University of Cambridge	UK	United Kingdom	L	FC	VH	5	A	...	64	95.8	85	99.9	
3	3	4	University of Oxford	UK	United Kingdom	L	FC	VH	5	A	...	110	98.2	60	100.0	
4	4	5	Harvard University	US	United States	L	FC	VH	5	B	...	210	66.8	223	100.0	

The 2nd dataset

02 PREPARATION AND CLEANING OF DATA

STEP 2: Prepration

1 Removal of erroneous data.

2 Standardisation of naming convention

3 Merged the datasets and dropping of the unnecessary data.

4 Encoding of categorical values

STEP 2: Prepration

```
jobData.isnull().sum()
```

```
id                    0
name                  0
gender                0
age                   0
degree                0
stream                0
college_name          0
placement_status      0
salary                0
gpa                   0
years_of_experience   1
dtype: int64
```

```
jobData[jobData['years_of_experience'].isnull()] # seeing the null row
jobData=jobData.dropna() # dropping the null row
jobData
```

	id	name	gender	age	degree	stream	college_name	placement_status	salary	gpa	years_of_experience
0	1	John Doe	Male	25	Bachelor's	Computer Science	Harvard University	Placed	60000	3.7	2.0
1	2	Jane Smith	Female	24	Bachelor's	Electrical Engineering	Massachusetts Institute of Technology	Placed	65000	3.6	1.0
2	3	Michael Johnson	Male	26	Bachelor's	Mechanical Engineering	Stanford University	Placed	58000	3.8	3.0
3	4	Emily Davis	Female	23	Bachelor's	Information Technology	Yale University	Not Placed	0	3.5	2.0
4	5	David Brown	Male	24	Bachelor's	Computer Science	Princeton University	Placed	62000	3.9	2.0
...	...	...	...	...	...	...	...	...	...	...	...
695	696	Lucas Taylor	Male	23	Bachelor's	Computer Science	University of Washington	Placed	67000	3.8	3.0
696	697	Emma Martinez	Female	26	Bachelor's	Electronics and Communication	University of California--Berkeley	Placed	66000	3.9	3.0
697	698	Aiden Davis	Male	24	Bachelor's	Computer Science	University of Illinois--Urbana-Champaign	Placed	65000	3.8	3.0
698	699	Mia Wilson	Female	23	Bachelor's	Electrical Engineering	University of Colorado--Boulder	Placed	66000	3.7	2.0
699	700	Jack Garcia	Male	26	Bachelor's	Information Technology	University of North Carolina--Chapel Hill	Not Placed	0	3.6	1.0

699 rows × 11 columns

STEP 2: Preparation & Cleaning

1 Removal of erroneous data.

2 Standardisation of naming convention

3 Merged the datasets and dropping of the unnecessary data.

4 Encoding of categorical values

STEP 2: Preparation & Cleaning

Dataset 1:

- Massachusetts Institute of Technology
- University of California--Los Angeles
- University of Illinois--Urbana-Champaign

Dataset 2:

- Massachusetts Institute of Technology (MIT)
- University of California, Los Angeles (UCLA)
- University of Illinois at Urbana-Champaign

STEP 2: Preparation & Cleaning

1 Removal of erroneous data

2 Standardisation of naming convention

3 Merged the datasets and dropping of the unnecessary data

4 Encoding of categorical values

STEP 2: Preparation & Cleaning

	id	name	gender	age	degree	stream	college_name	placement_status	salary	gpa	years_of_experience
0	1	John Doe	Male	25	Bachelor's	Computer Science	Harvard University	Placed	60000	3.7	2.0
1	2	Jane Smith	Female	24	Bachelor's	Electrical Engineering	Massachusetts Institute of Technology	Placed	65000	3.6	1.0
2	3	Michael Johnson	Male	26	Bachelor's	Mechanical Engineering	Stanford University	Placed	58000	3.8	3.0
3	4	Emily Davis	Female	23	Bachelor's	Information Technology	Yale University	Not Placed	0	3.5	2.0
4	5	David Brown	Male	24	Bachelor's	Computer Science	Princeton University	Placed	62000	3.9	2.0

id	name	gender	age	degree	stream	college_name	placement_status	salary	gpa	years_of_experience	ranking
1	John Doe	Male	25	Bachelor's	Computer Science	Harvard University	Placed	60000	3.7	2.0	4
2	Jane Smith	Female	24	Bachelor's	Electrical Engineering	Massachusetts Institute of Technology	Placed	65000	3.6	1.0	1
3	Michael Johnson	Male	26	Bachelor's	Mechanical Engineering	Stanford University	Placed	58000	3.8	3.0	5
4	Emily Davis	Female	23	Bachelor's	Information Technology	Yale University	Not Placed	0	3.5	2.0	16
5	David Brown	Male	24	Bachelor's	Computer Science	Princeton University	Placed	62000	3.9	2.0	17

STEP 2: Preparation & Cleaning

id	name	gender	age	degree	stream	college_name	placement_status	salary	gpa	years_of_experience	ranking
1	John Doe	Male	25	Bachelor's	Computer Science	Harvard University	Placed	60000	3.7	2.0	4
2	Jane Smith	Female	24	Bachelor's	Electrical Engineering	Massachusetts Institute of Technology	Placed	65000	3.6	1.0	1
3	Michael Johnson	Male	26	Bachelor's	Mechanical Engineering	Stanford University	Placed	58000	3.8	3.0	5
4	Emily Davis	Female	23	Bachelor's	Information Technology	Yale University	Not Placed	0	3.5	2.0	16
5	David Brown	Male	24	Bachelor's	Computer Science	Princeton University	Placed	62000	3.9	2.0	17

	id	gender	age	stream	college_name	placement_status	salary	gpa	years_of_experience	ranking
0	1	Male	25	Computer Science	Harvard University	Placed	60000	3.7	2.0	4
3	4	Female	23	Information Technology	Yale University	Not Placed	0	3.5	2.0	16
4	5	Male	24	Computer Science	Princeton University	Placed	62000	3.9	2.0	17
6	7	Male	26	Information Technology	California Institute of Technology	Placed	59000	3.8	3.0	15
7	8	Female	24	Computer Science	University of Chicago	Not Placed	0	3.6	2.0	11

STEP 2: Preparation & Cleaning

1 Removal of erroneous data

2 Standardisation of naming convention

3 Merged the datasets and dropping of the unnecessary data

4 Encoding of categorical values

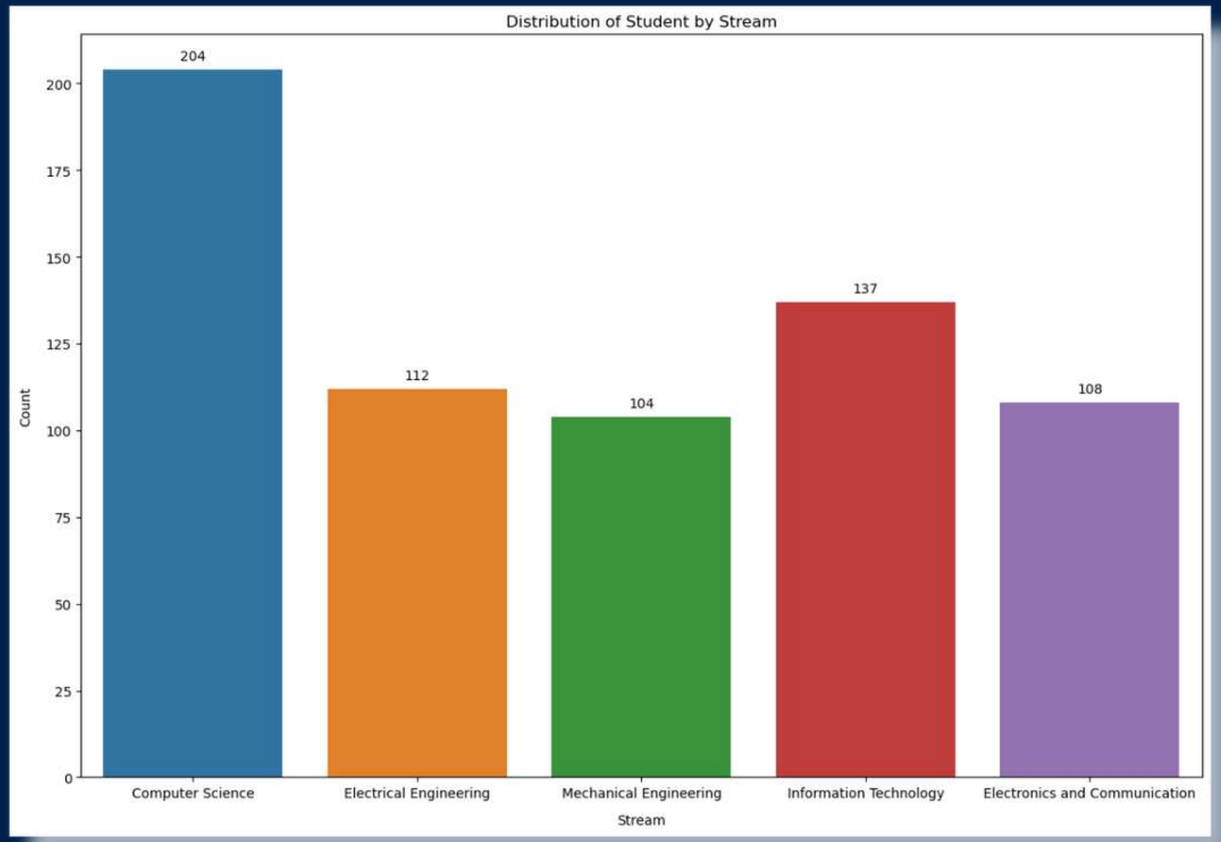
STEP 2: Preparation & Cleaning

	id	gender	age	stream	college_name	placement_status	salary	gpa	years_of_experience	ranking
0	1	1	25	0	4	1	60000	3.7	2.0	4
3	4	0	23	1	33	0	0	3.5	2.0	16
4	5	1	24	0	5	1	62000	3.9	2.0	17
6	7	1	26	1	1	1	59000	3.8	3.0	15
7	8	0	24	0	12	0	0	3.6	2.0	11
...	...	...	...	...	...	...	...	...	...	...
691	692	1	25	0	29	1	63000	3.6	1.0	520
693	694	1	26	1	21	1	67000	3.9	3.0	33
695	696	1	23	0	31	1	67000	3.8	3.0	63
697	698	1	24	0	18	1	65000	3.8	3.0	64
699	700	1	26	1	23	0	0	3.6	1.0	132

341 rows × 10 columns

03 INSIGHTS GENERATION

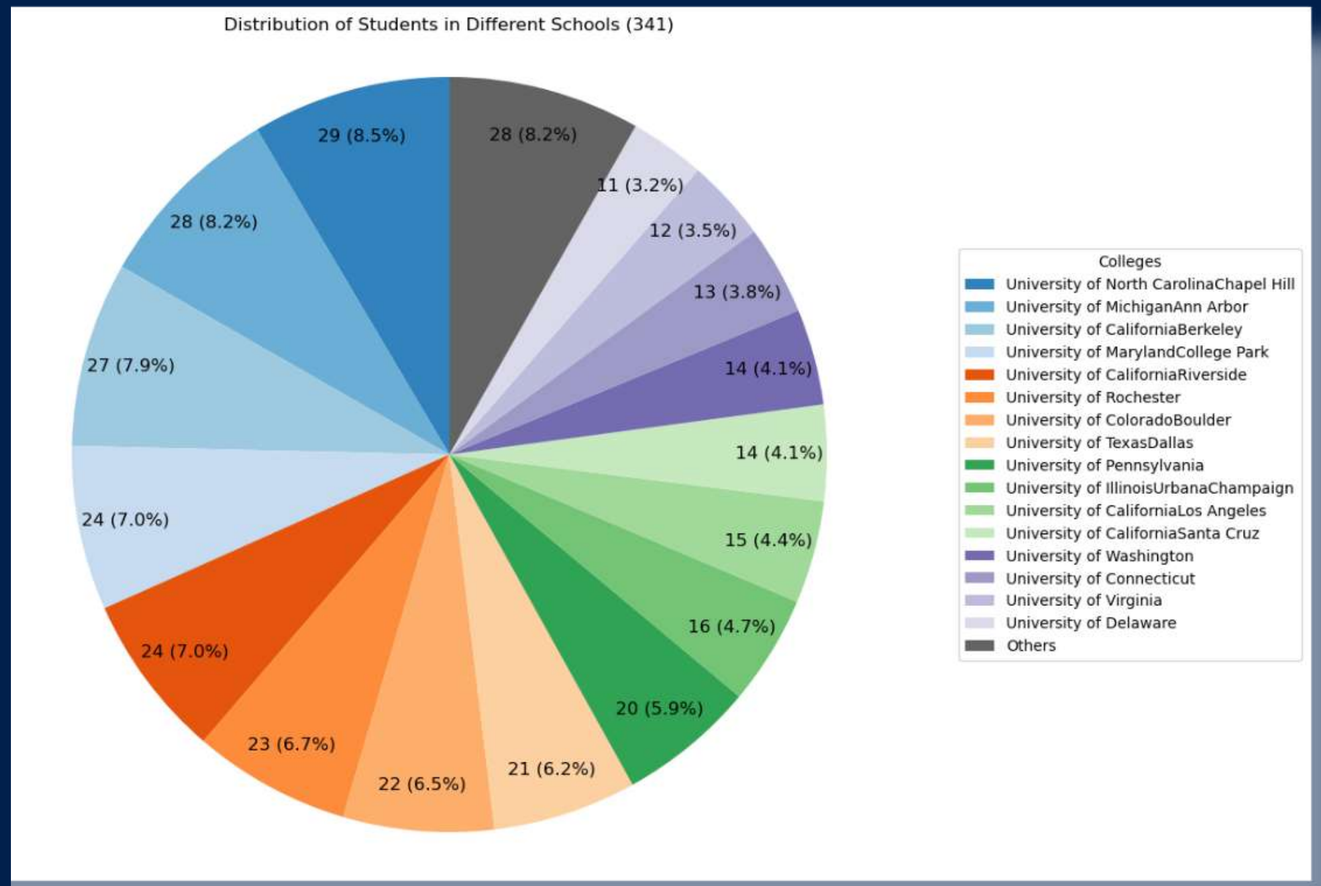
Basic Insights
Distribution of Student by Stream



Primarily focusing on the data from these 2 streams:

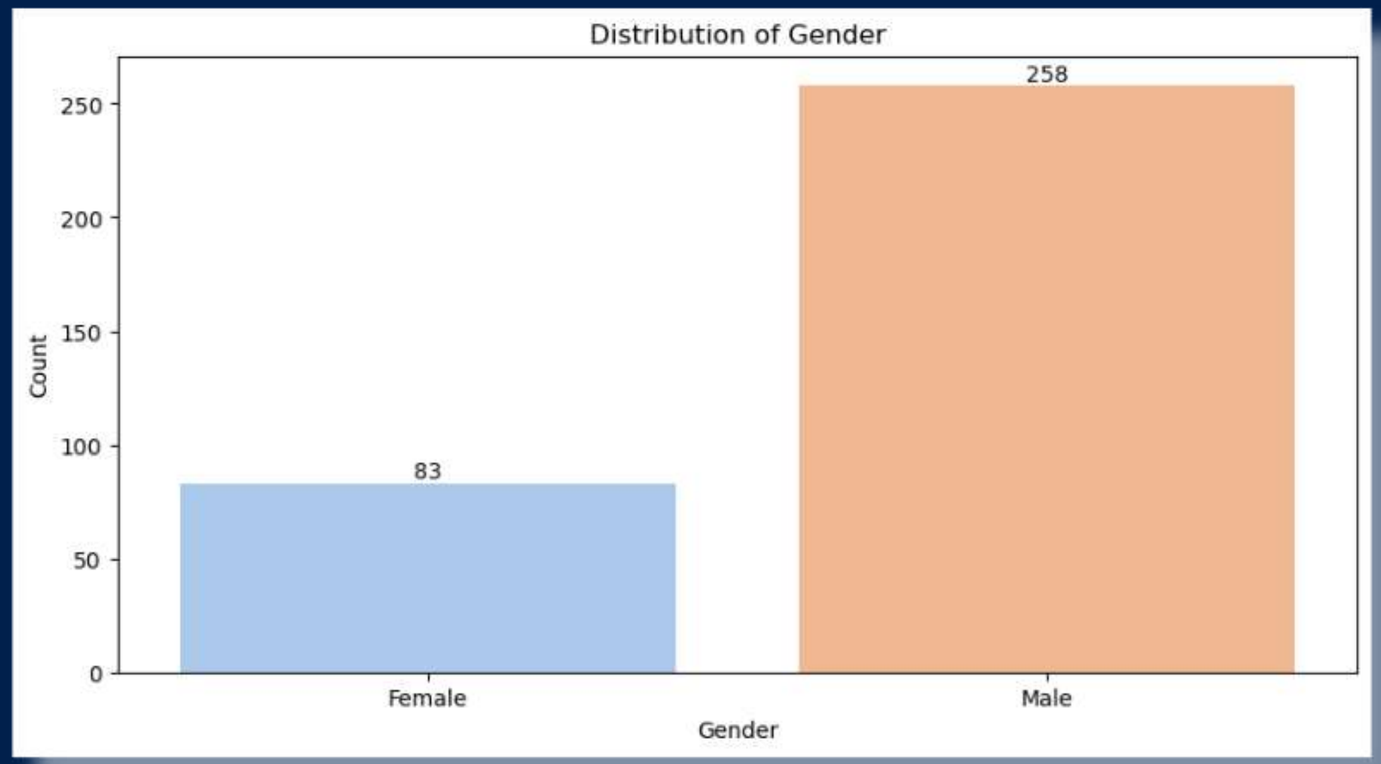
- Computer Science: 204 Students
- Information Technology: 137 Students

Basic Insights
Distribution by Colleges



For simplicity, colleges that fell below the threshold of 3% are grouped together for easy visualisation

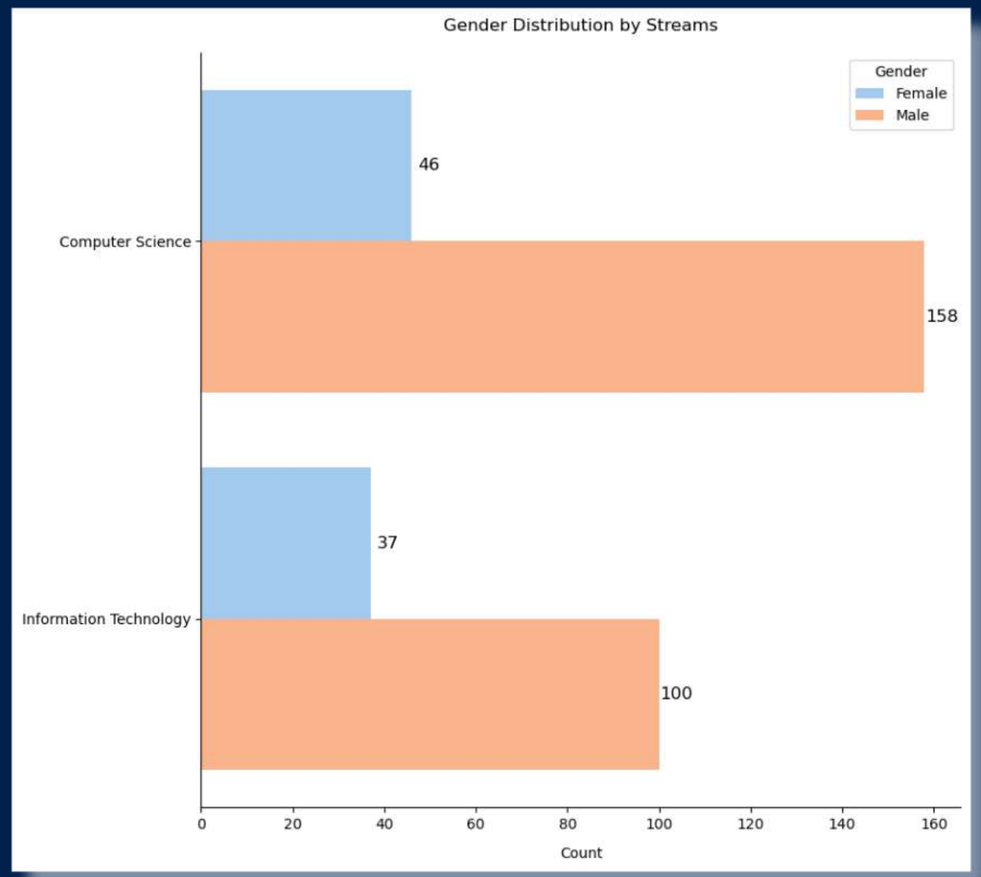
Basic Insights
Distribution by Gender (Dataset)



- Out of 341 graduates:
  - 83 identified as female
  - 258 identified as male

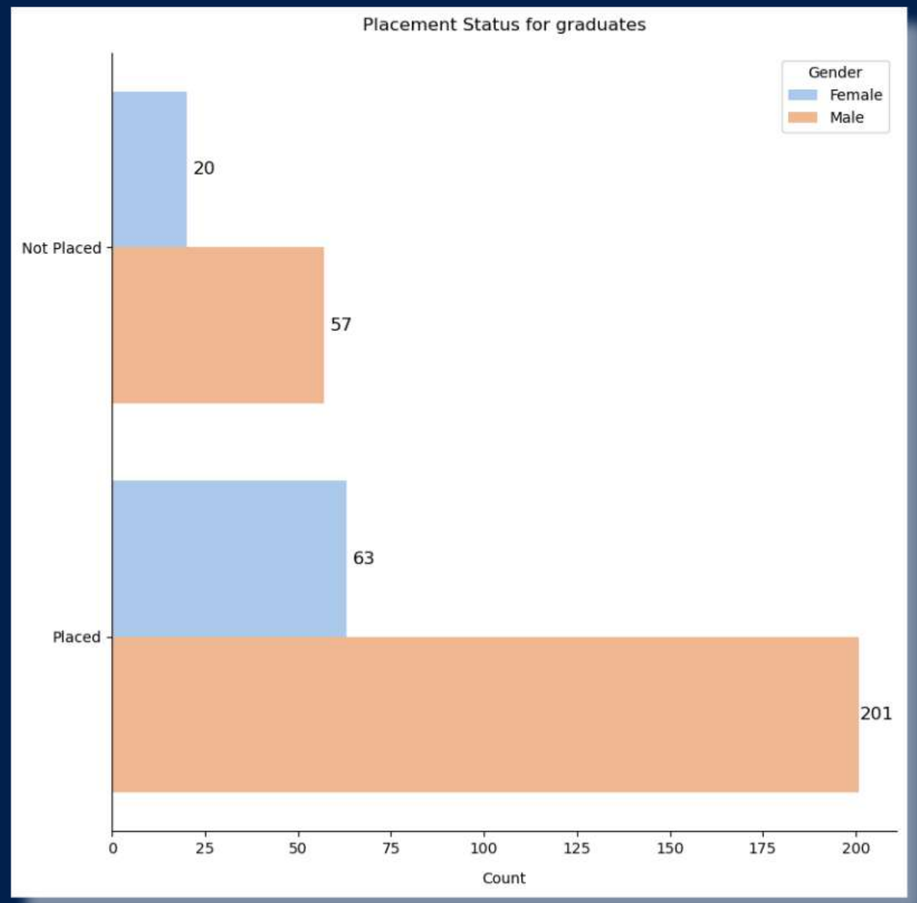
- Discovered a gender imbalance in the dataset

Basic Insights
Distribution by Gender (Streams)



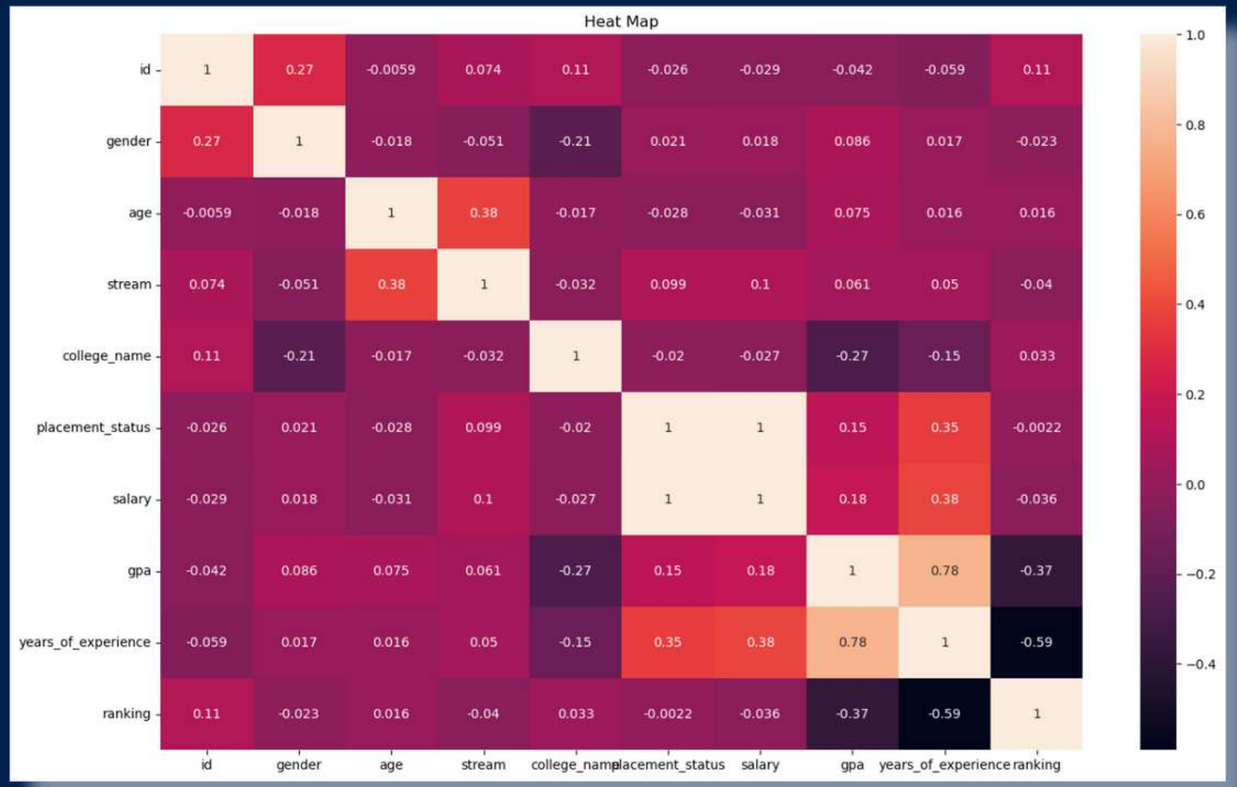
- 46 Female in Computer Science, 37 Female in Information Technology
- 158 Male in Computer Science, 100 Male in Information Technology

Basic Insights
Distribution by Gender (Placement Status)



- 24% of Female gradutes do not have a placement
- 22% of Male graduates do not have a placement

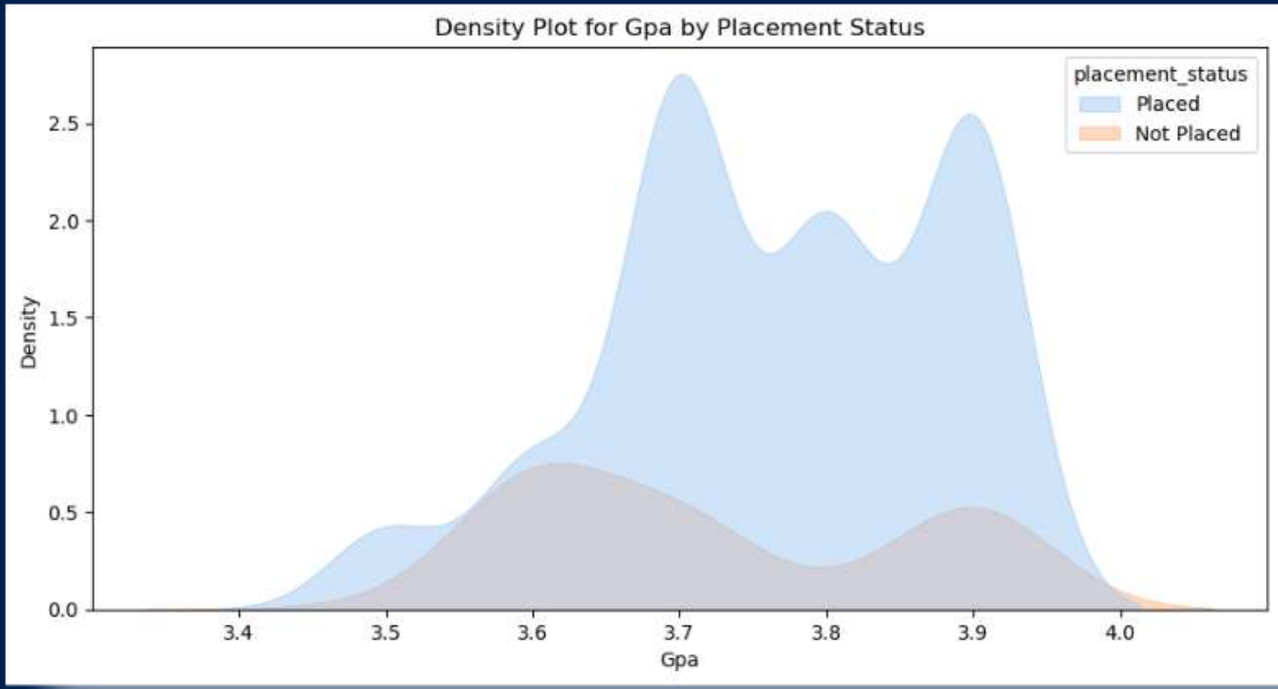
Exploratory Analysis
Heat Map

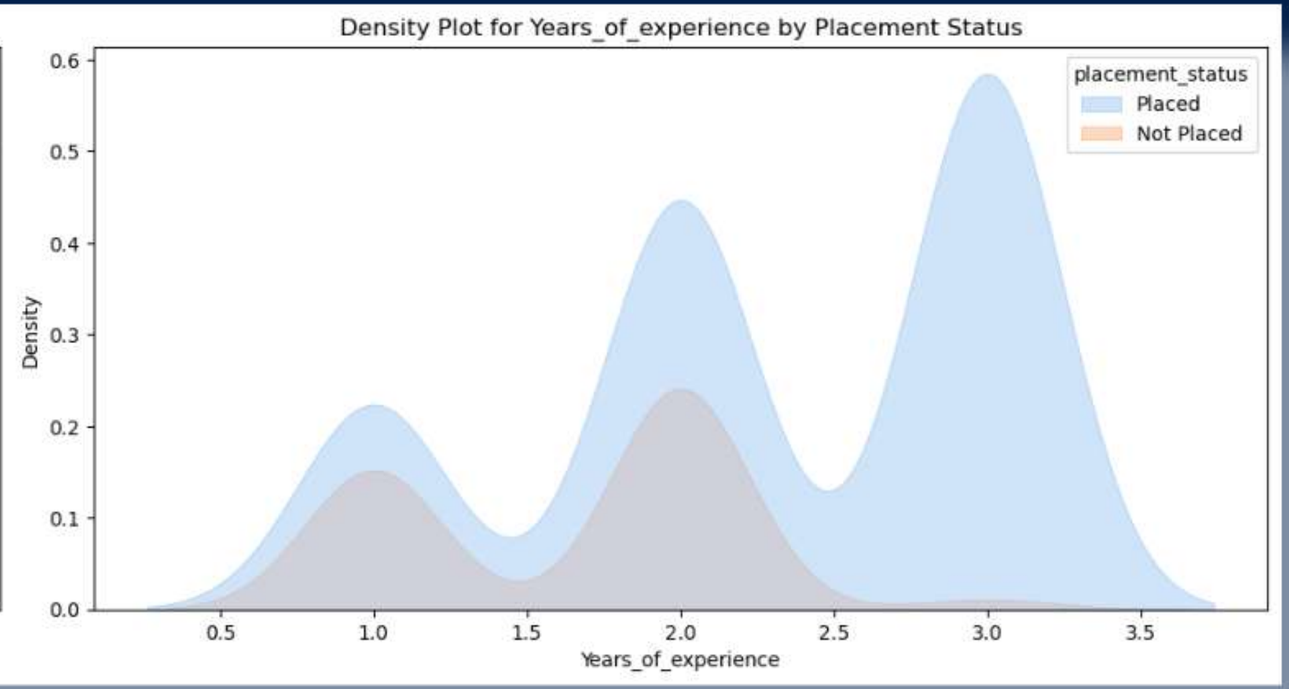


Correlation to Placement Status

- Gender, Stream, GPA (0.15) and Years of Experience (0.38) are positively correlated
- College Name and Age are negatively correlated

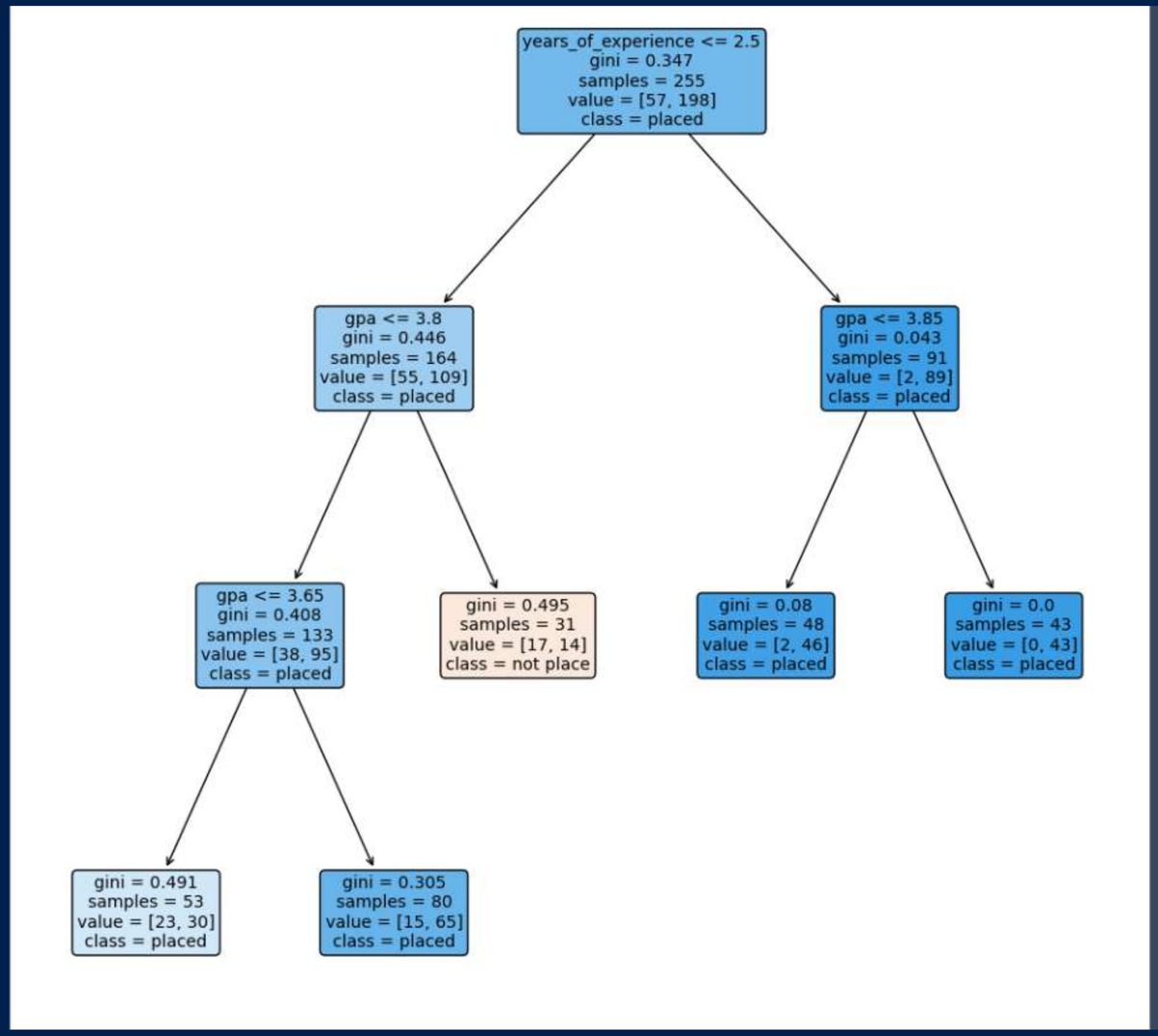
Exploratory Analysis
KDE





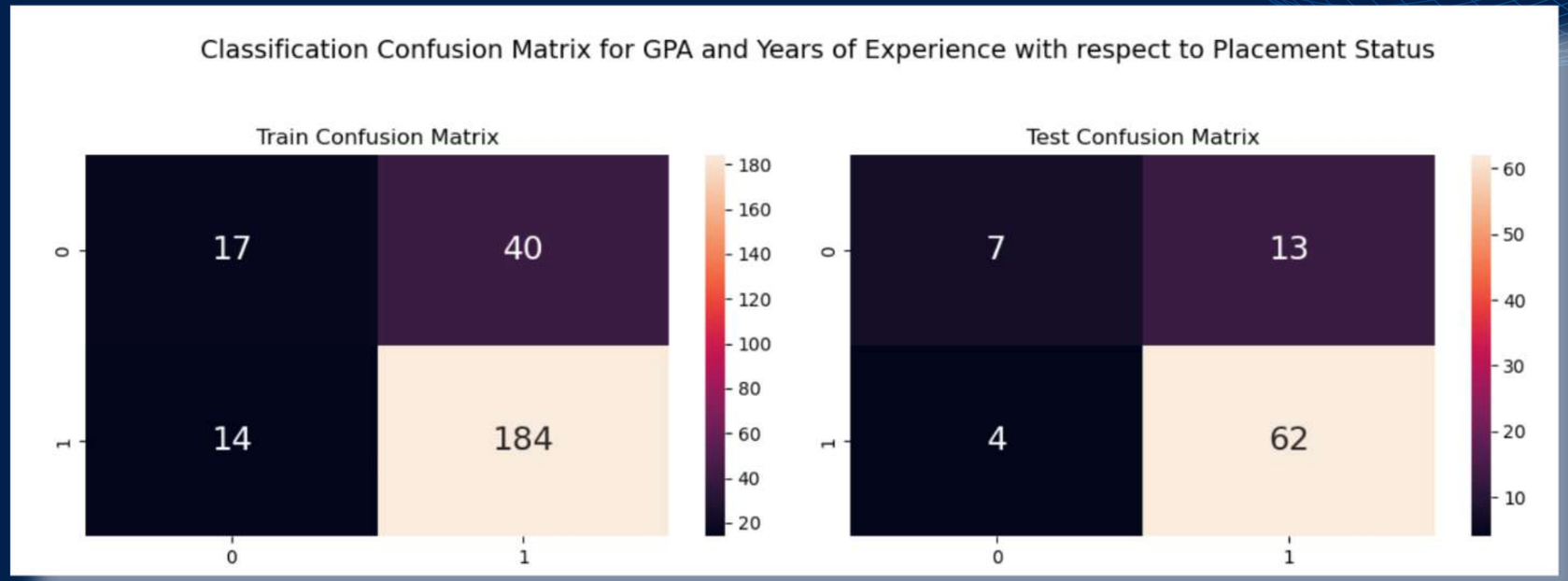
Majority with Placement Status has a GPA >= 3.65 and/or Year of Experience >= 1.5

Exploratory Analysis
Decision Tree Classifier model



- **Years of Experience >= 2.5 and GPA > 3.8 will have be placed**

Exploratory Analysis

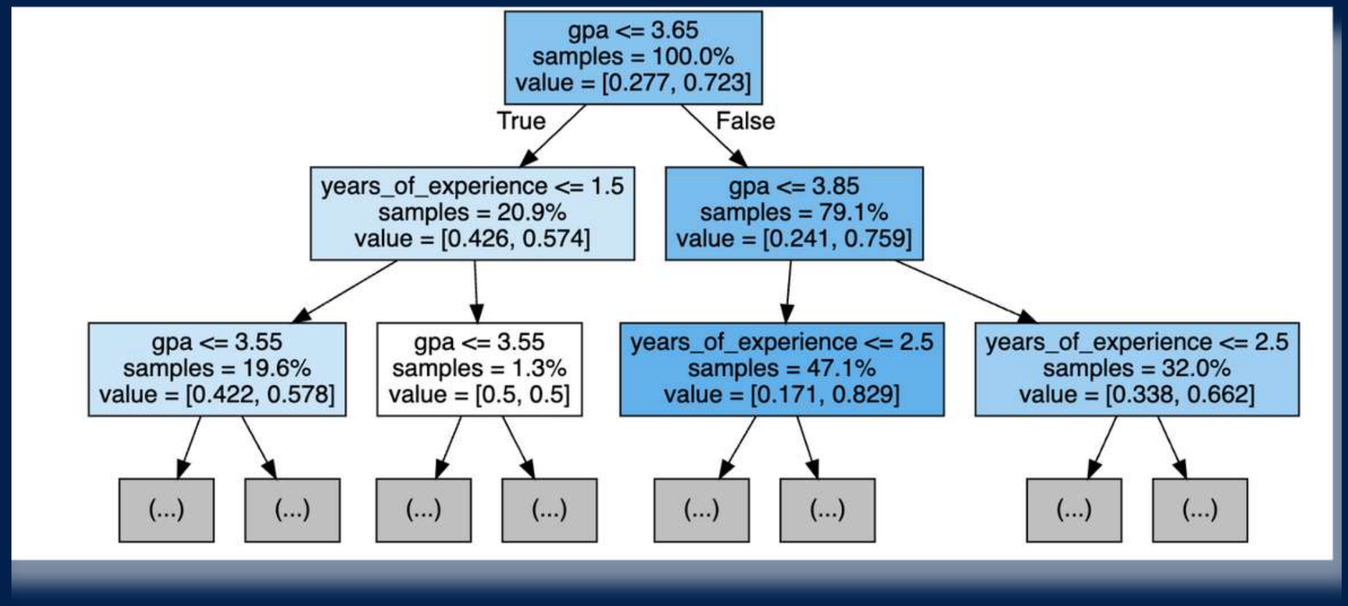


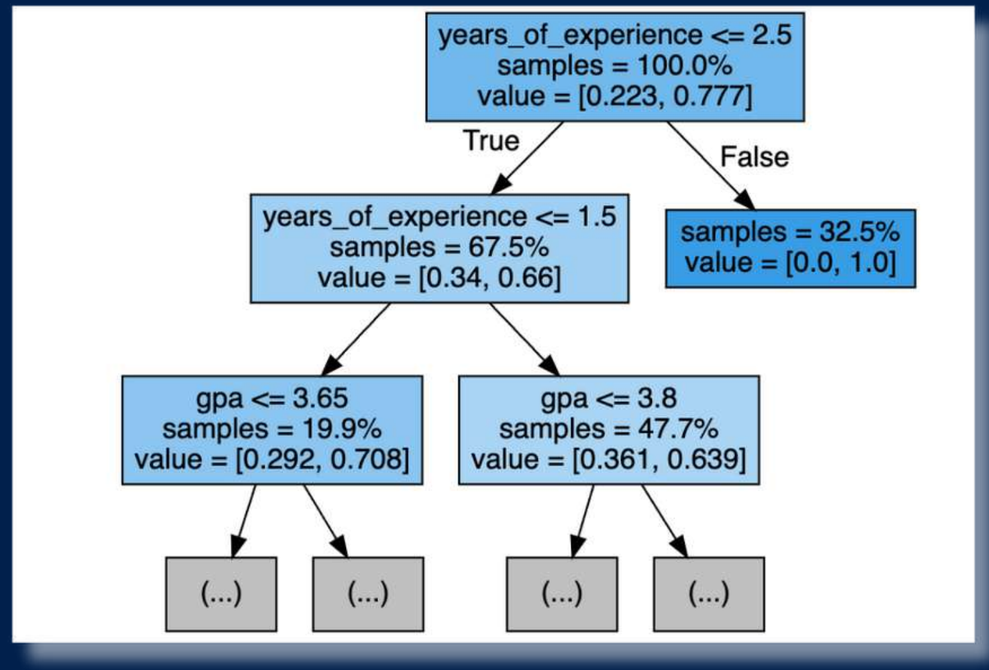

```
Goodness of Fit of Model          Train Dataset
Classification Accuracy           : 0.788235294117647

Goodness of Fit of Model          Test Dataset
Classification Accuracy           : 0.8023255813953488
```

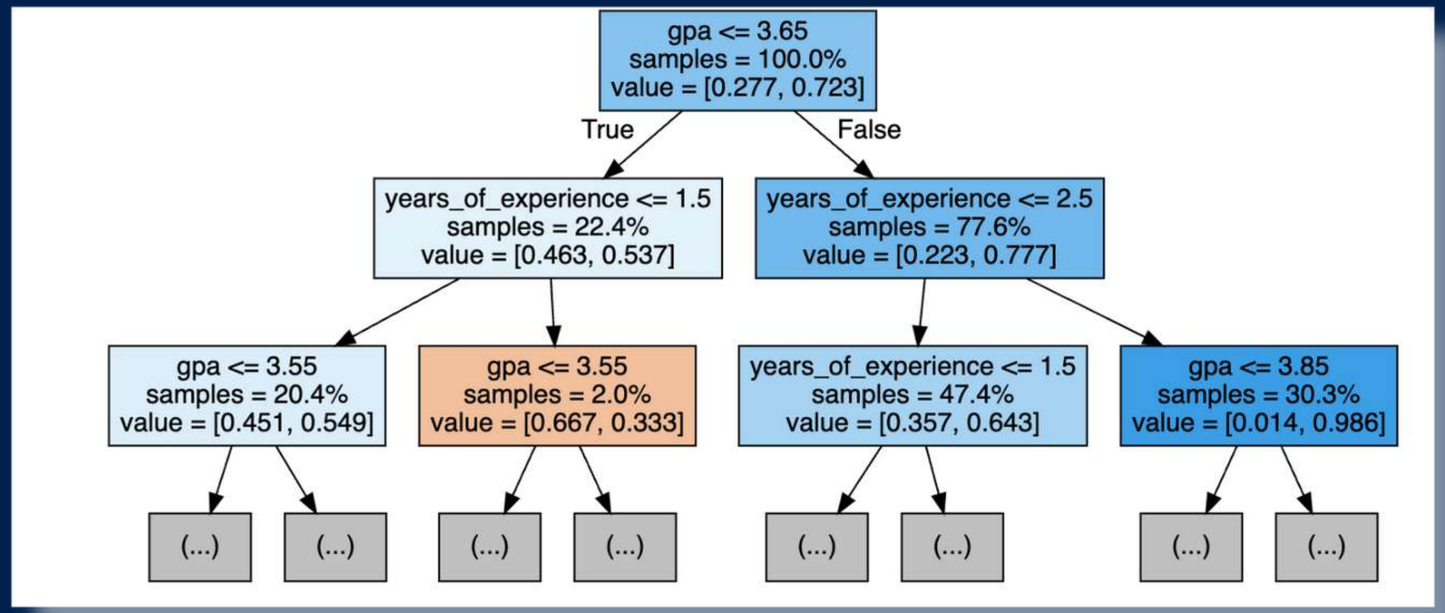
Overall the Decision Tree Classifier attained a fairly good classification result

Exploratory Analysis
Random Forest Classification Model



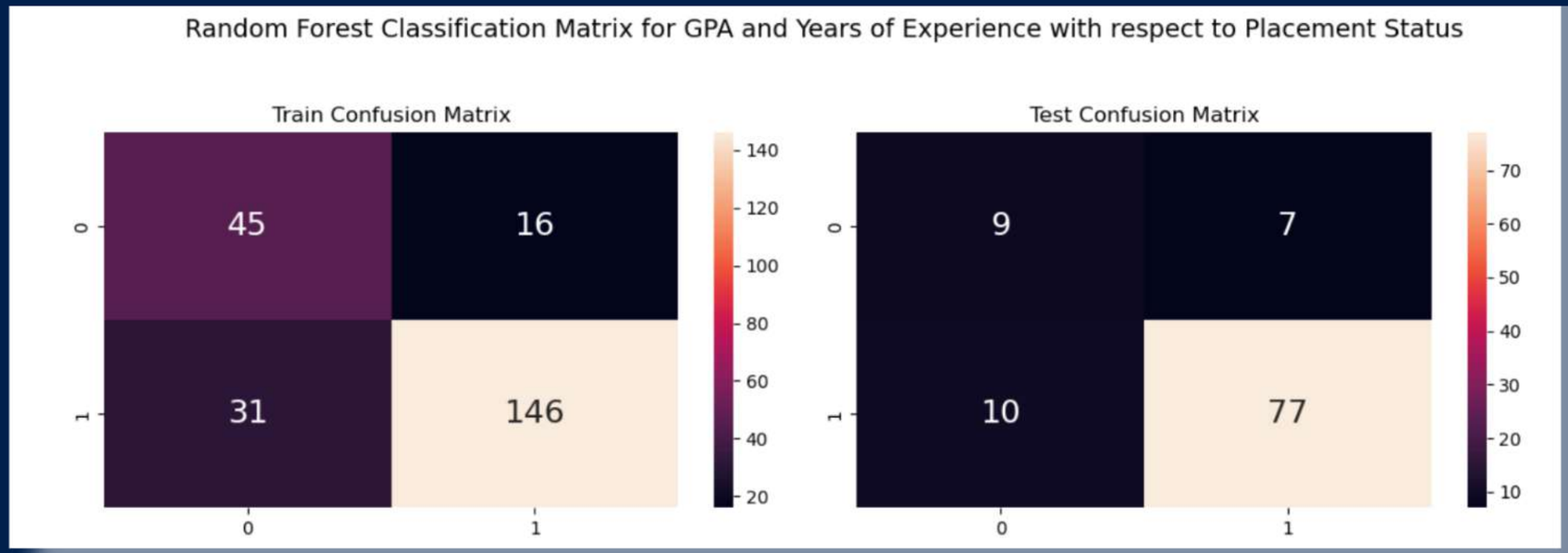


Exploratory Analysis



Clear that those with higher GPA and work experience will likely have a placement

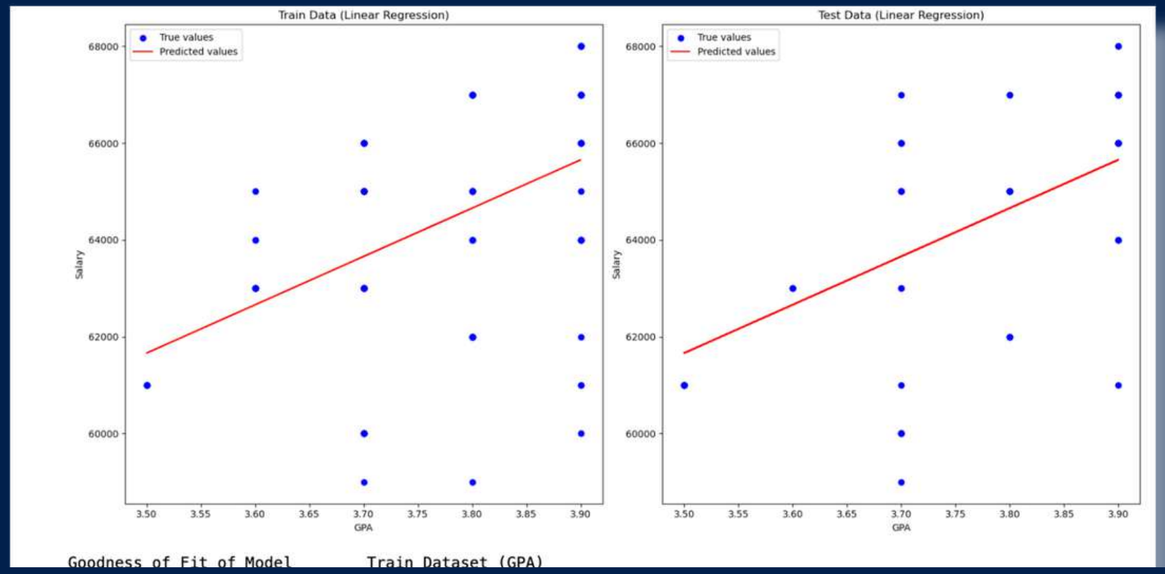
Exploratory Analysis

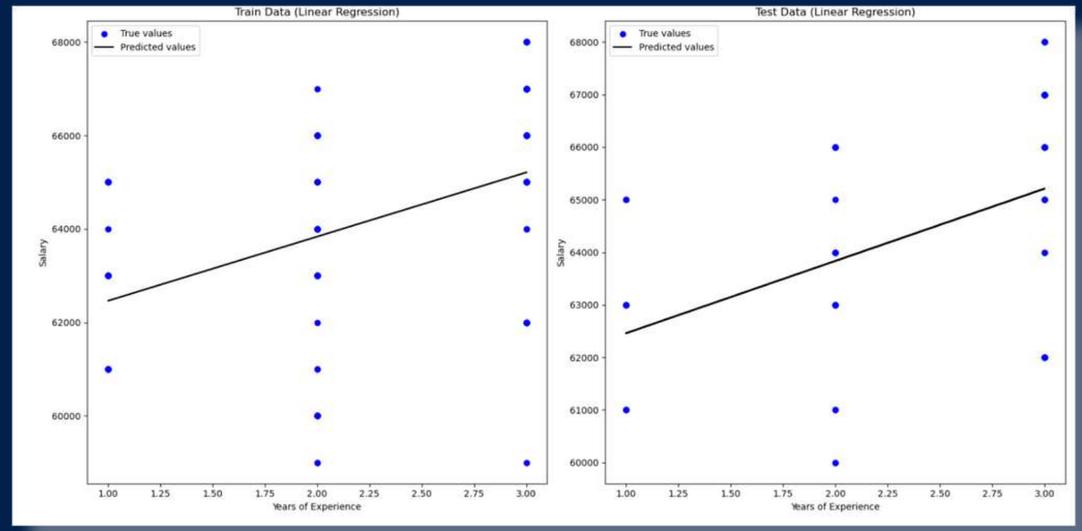



```
Random Forest Classifier Accuracy for train data: 0.8025210084033614
Random Forest Classifier Accuracy for test data: 0.8349514563106796
```

Overall the Random Forest Classifier attained a better classification result as compared to Decision Tree Classifier due to its benefits

Exploratory Analysis
Linear Regression





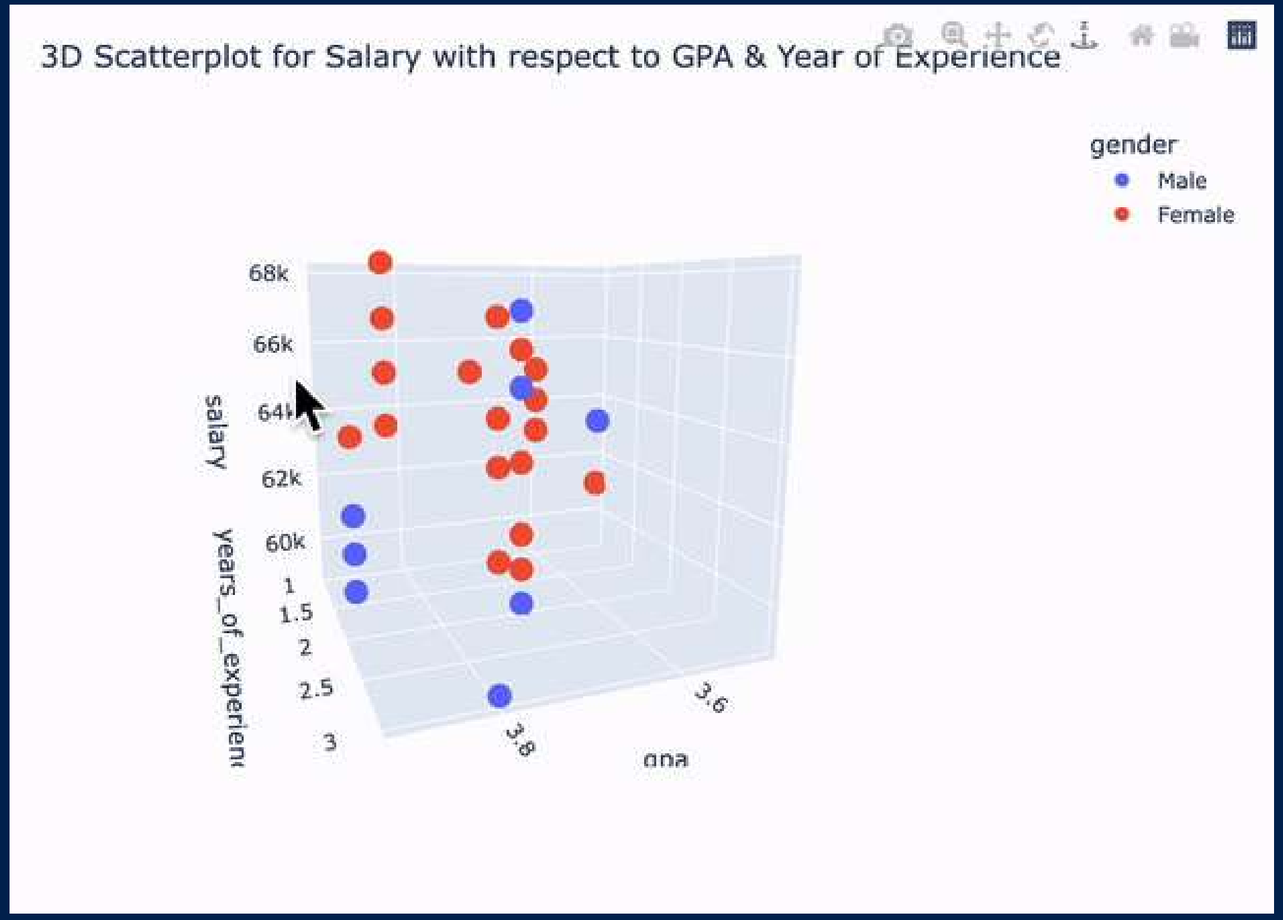

```
Goodness of Fit of Model          Train Dataset (GPA)
Explained Variance (R^2)          : 0.23103913217027627
Mean Squared Error (MSE)          : 3831545.040437954

Goodness of Fit of Model          Test Dataset (GPA)
Explained Variance (R^2)          : 0.40948814463837147
Mean Squared Error (MSE)          : 3625086.667636664
```

```
Goodness of Fit of Model          Train Dataset (Years of Experience)
Explained Variance (R^2)          : 0.20198960218852746
Mean Squared Error (MSE)          : 4278039.212509988

Goodness of Fit of Model          Test Dataset (Years of Experience)
Explained Variance (R^2)          : 0.2323871735373102
Mean Squared Error (MSE)          : 3771276.8822607957
```

Exploratory Analysis
3D Scatterplot



Higher GPA and/or Years of Experience = Higher Salary

SUMMARY

1) College ranking, gender, and age have minimal impact on placement

2) GPA and experience influence placement and salary

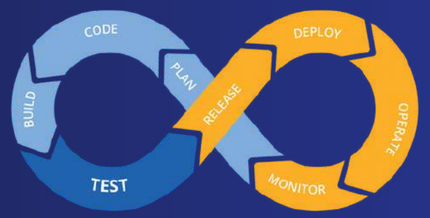
RECOMMENDATION

Go Beyond GPA:

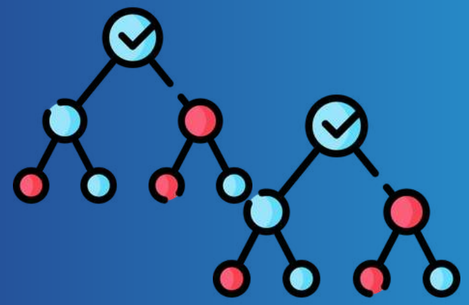
Factors Influencing Placement

- **Side projects**
- **Internships**
- **Hackathons**
- **Leetcode practice**

Key takeaway



1. Utilizing Github for CICD



2. Application of Random Forest Classification Model

3. Significance of Data Preparation

THANK YOU!