19ZO02 Social And Economic Network Analysis

PROJECT REPORT

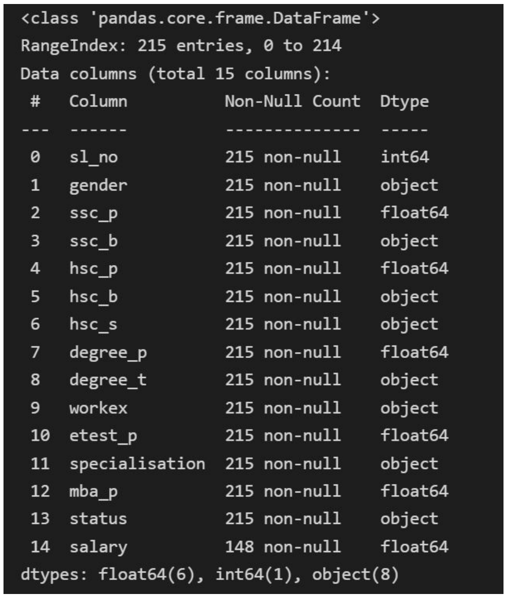
PROBLEM STATEMENT:

Unemployment has become a huge threat to the graduates in largely populated nations like India. In order to overcome the risk of getting struck in unemployment, many people choose domains that have lots of opportunities where job vacancies are huge and the scope of getting placed is higher. Thus, the fact that a student will get placed or not depends on his/her specialization of degree as well. Our problem statement is to analyze the placement data of students of a particular institution and draw some valuable insights like the department with highest placement percentage, the department with highest average salary etc. These inferences could guide freshers while they choose their specializations.

DATASET DESCRIPTION:

For our analysis, we took the placement data of Kaggle. This dataset consists of the placement data of students in campus recruitment. It includes details of students like secondary and higher secondary school percentage, their degree and specialization. It also includes their work experience and salary offered to them during their recruitment.

It contains about 215 rows with around 15 columns and so the shape of the dataset is 215*15. And some exploratory analyses were performed on the dataset. On analyzing we found that the dataset contains null values in the salary column, around 67 null values were present. They were replaced with 0 for calculating average salary. The datatypes of all the columns were analyzed in order to verify whether numerical columns are stored as numbers. Around 6 float columns, 8 categorical columns and 1 integer column was found.

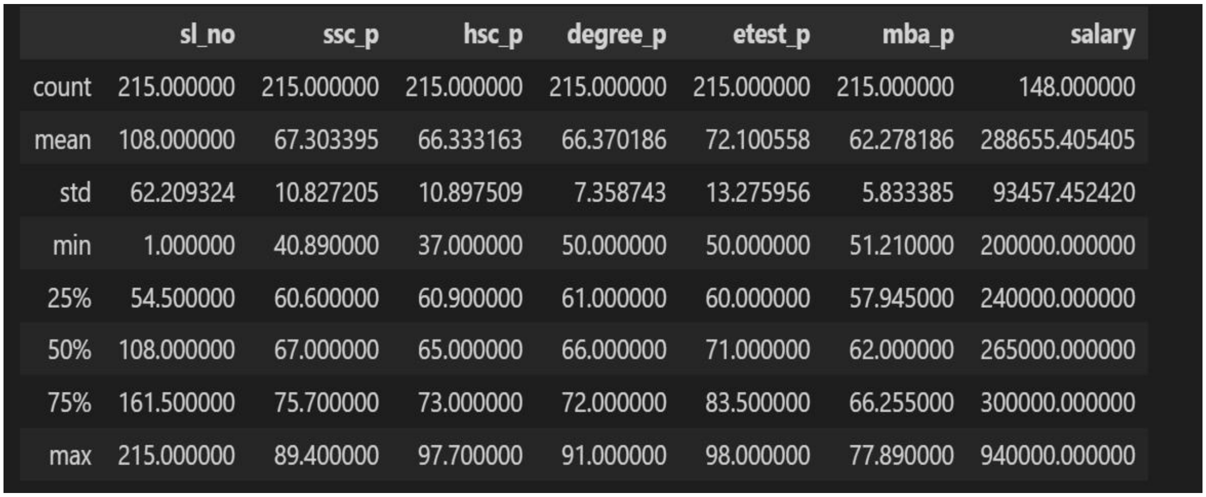


```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 215 entries, 0 to 214
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   sl_no           215 non-null    int64
 1   gender          215 non-null    object
 2   ssc_p           215 non-null    float64
 3   ssc_b           215 non-null    object
 4   hsc_p           215 non-null    float64
 5   hsc_b           215 non-null    object
 6   hsc_s           215 non-null    object
 7   degree_p        215 non-null    float64
 8   degree_t        215 non-null    object
 9   workex          215 non-null    object
 10  etest_p         215 non-null    float64
 11  specialisation  215 non-null    object
 12  mba_p           215 non-null    float64
 13  status          215 non-null    object
 14  salary          148 non-null    float64
dtypes: float64(6), int64(1), object(8)
```

Fig 1. Datatype description of individual columns

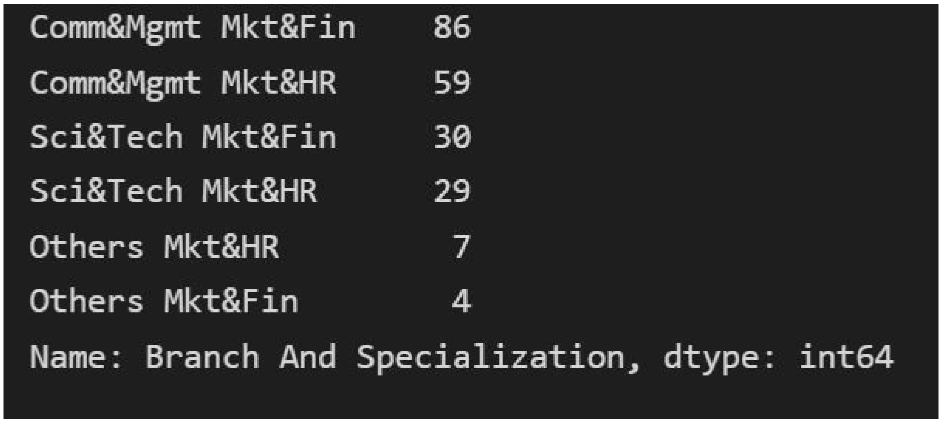
The dataset was further analyzed statistically to draw more insights. The mean, median and standard deviation of all the numerical columns was found to draw insights like range in which the salary column varies, the average salary of all the students irrespective of departments and further some more insights regarding the balanced nature of the dataset were drawn as well. It was observed that the dataset had the maximum count of about 86 people from "Commerce and Management" degree under "Market and Finance" specialization. In total there are about 6 different combinations of degree and specialization. The counts of students from other departments and specializations were analyzed as well.

DATASET URL: https://www.kaggle.com/code/secunsexto/placement-data/data



	sl_no	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
count	215.000000	215.000000	215.000000	215.000000	215.000000	215.000000	148.000000
mean	108.000000	67.303395	66.333163	66.370186	72.100558	62.278186	288655.405405
std	62.209324	10.827205	10.897509	7.358743	13.275956	5.833385	93457.452420
min	1.000000	40.890000	37.000000	50.000000	50.000000	51.210000	200000.000000
25%	54.500000	60.600000	60.900000	61.000000	60.000000	57.945000	240000.000000
50%	108.000000	67.000000	65.000000	66.000000	71.000000	62.000000	265000.000000
75%	161.500000	75.700000	73.000000	72.000000	83.500000	66.255000	300000.000000
max	215.000000	89.400000	97.700000	91.000000	98.000000	77.890000	940000.000000

Fig 2. Statistics of the Dataset



```
Comm&Mgmt Mkt&Fin    86
Comm&Mgmt Mkt&HR     59
Sci&Tech Mkt&Fin     30
Sci&Tech Mkt&HR      29
Others Mkt&HR         7
Others Mkt&Fin        4
Name: Branch And Specialization, dtype: int64
```

Fig 3. Number of records in each department - specializations

TOOLS USED:

In this section, we briefly discuss about the various tools and packages that we have used in order to accomplish our project

1. **NETWORKX**
   - **a.** This python package helps in creating graphs out of edges and nodes given in a csv file.
   - **b.** In order to visualize the various clusters in our dataset, we used this package to draw a simple graph that depicts the 6 different clusters that we mentioned earlier in fig 3
   - **c.** This package helped us to analyze the graph as well and some features like the average cluster co-efficient, diameter and the degree distribution were obtained. It was observed that the graph turned out to have infinite diameter since the graph is not fully connected

2. **MATPLOTLIB.PYPLOT**
   - **a.** This package is most widely used to plot bar graphs and other visualizations that help us plot clearly what we want.
   - **b.** We used this to plot the various departments versus the average salary and departments versus their placement percentage
   - **c.** This helped us to view visually the highest placement percentage and maximum average salary

3. **PANDAS**
   - **a.** This python package is used for processing csv (Comma Separated Values) files. The dataset is mostly available as .csv files
   - **b.** We used this to remove null values and clean our dataset. Also, we used pandas to create our own custom dataset from the original one for our convenience
   - **c.** We used pandas to perform exploratory analysis on the dataset for drawing more insights regarding the dataset.

CHALLENGES FACED:

1. Since the graph was not a fully connected one and edges were defined based on the department and specialization, link prediction became infeasible as links were static. So, we took cluster-based analyses.
2. To do cluster-based analyses, we had to brainstorm to decide on the valuable features that could give us valuable insights and whose analysis would be fruitful as well.
3. The raw dataset available was not suitable enough to consume directly. So, we had to clean and prepare the data before making our analysis

CONTRIBUTION OF TEAM MEMBERS:

Roll Number	Name	Contribution
19z247	Srivathssan VV	Cluster Analysis – Average Salary
19z253	Kousik Nibith Ram V P	Cluster Analysis – Maximum placement percentage
19z258	Vignesh M	Dataset Analysis
19z260	Vishwakjith I	Visualization graphs
20z432	Rajesh G	Graph Analysis

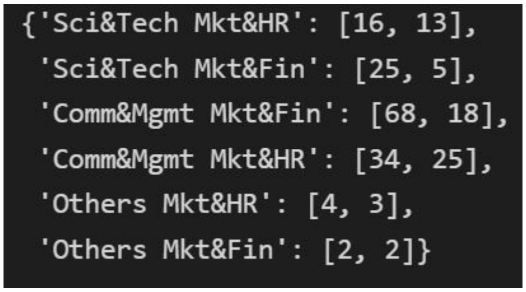
ANNEXURE 1: CODE:

```
#import statements
import networkx as nx
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
#Read csv files
df = pd.read_csv('Edges.csv')
df.head()
df.columns
#Create Graph From edge list
G = nx.from_pandas_edgelist(df,source='Source',target='Target')
plt.figure(figsize=(20,20))
nx.draw(G)
#Plot histogram
plt.hist([v for k,v in nx.degree(G)])
#print average clustering co efficient
nx.cluster.average_clustering(G)
#print diameter - infinite diameter
try:
    nx.diameter(G)
except Exception as e:
    print('Infinite Diameter')
#Conversion of graph to edge matrix for clustering
def graph_to_edge_matrix(G):
    edge_mat = np.zeros((len(G),len(G)),dtype=int)
    for node in G:
        for neighbor in G.neighbors(node):
            edge_mat[node-1][neighbor-1]=1
        edge_mat[node-1][node-1]=1
    return edge_mat
#Read csv for cluster analyses
df = pd.read_csv('Placement_Data_Full_Class.csv')
df.head()
df.columns
#Create custom dataset
dataset = {
    'Sl_no':[],
    'Branch And Specialization':[],
    'Placement Status':[],
    'Salary':[]
}
for index,row in df.iterrows():
    dataset['Sl_no'].append(row['sl_no'])
    dataset['Branch And Specialization'].append(row['degree_t']+' '+row['specialisation'])
    dataset['Placement Status'].append(row['status'])
    dataset['Salary'].append(row['salary'])
len(df)
len(dataset['Salary'])
#Dataset analysis
df.info()
#Statistical analysis
df.describe()
#null values checking
df.isna().sum()
#Creation of custom dataset
Dataframe = pd.DataFrame(dataset)
Dataframe.head()
Dataframe.isnull().sum()
#Filling of null values
```

```
Dataframe.fillna(value=0.0,inplace=True)

Dataframe.head()

#Printing count of students in each brnch and specialisation

Dataframe['Branch And Specialization'].value_counts()

#Count of students who are placed in  each department

lst={

   'Sci&Tech Mkt&HR':Dataframe[Dataframe['Branch And Specialization']=='Sci&Tech Mkt&HR']['Placement Status'].value_counts()[‘Placed’],

   'Sci&Tech Mkt&Fin':Dataframe[Dataframe['Branch And Specialization']=='Sci&Tech Mkt&Fin']['Placement Status'].value_counts()),

   'Comm&Mgmt Mkt&Fin':list(Dataframe[Dataframe['Branch And Specialization']=='Comm&Mgmt Mkt&Fin']['Placement Status'].value_counts()),

   'Comm&Mgmt Mkt&HR':list(Dataframe[Dataframe['Branch And Specialization']=='Comm&Mgmt Mkt&HR']['Placement Status'].value_counts()),

   'Others Mkt&HR':list(Dataframe[Dataframe['Branch And Specialization']=='Others Mkt&HR']['Placement Status'].value_counts()),

   'Others Mkt&Fin':list(Dataframe[Dataframe['Branch And Specialization']=='Others Mkt&Fin']['Placement Status'].value_counts()),}

avg_salary = []

# Average Salary of Sci&Tech Mkt&HR

avg_salary.append((Dataframe[Dataframe['Branch And Specialization']=='Sci&Tech Mkt&HR']['Salary'].sum()/len(Dataframe[Dataframe['Branch And Specialization']=='Sci&Tech Mkt&HR'])).round(2))

# Average Salary of Comm&Mgmt Mkt&Fin

avg_salary.append((Dataframe[Dataframe['Branch And Specialization']=='Comm&Mgmt Mkt&Fin']['Salary'].sum()/len(Dataframe[Dataframe['Branch And Specialization']=='Comm&Mgmt Mkt&Fin'])).round(2))

# Average Salary of Comm&Mgmt Mkt&HR

avg_salary.append((Dataframe[Dataframe['Branch And Specialization']=='Comm&Mgmt Mkt&HR']['Salary'].sum()/len(Dataframe[Dataframe['Branch And Specialization']=='Comm&Mgmt Mkt&HR'])).round(2))

# Average Salary of Sci&Tech Mkt&Fin

avg_salary.append((Dataframe[Dataframe['Branch And Specialization']=='Sci&Tech Mkt&Fin']['Salary'].sum()/len(Dataframe[Dataframe['Branch And Specialization']=='Sci&Tech Mkt&Fin'])).round(2))
```

```
# Average Salary of Others Mkt&HR.

avg_salary.append((Dataframe[Dataframe['Branch And Specialization']=='Others
Mkt&HR']['Salary'].sum()/len(Dataframe[Dataframe['Branch And Specialization']=='Others
Mkt&HR'])).round(2))

# Average Salary of Others Mkt&Fin

avg_salary.append((Dataframe[Dataframe['Branch And Specialization']=='Others
Mkt&Fin']['Salary'].sum()/len(Dataframe[Dataframe['Branch And Specialization']=='Others
Mkt&Fin'])).round(2))

#plotting dept vs placed students count

bxaxis = ['Sci&Tech Mkt&HR','Sci&Tech Mkt&Fin','Comm&Mgmt
Mkt&Fin','Comm&Mgmt Mkt&HR','Others Mkt&HR','Others Mkt&Fin']

byaxis = [lst[bxaxis[_]][1] for _ in range(len(lst))]

plt.figure(figsize=(14,5))

plt.bar(bxaxis, byaxis, color='g')

plt.title("Number of Placed Students")

plt.xlabel("Department")

plt.ylabel("Number of Students")

plt.show()

#plotting dept vs average salary

gxaxis = ['Sci&Tech Mkt&HR','Comm&Mgmt Mkt&Fin','Comm&Mgmt
Mkt&HR','Sci&Tech Mkt&Fin','Others Mkt&HR','Others Mkt&Fin']

plt.figure(figsize=(14,5))

plt.bar(gxaxis, avg_salary, color='b')

plt.title("Student's Average Salary")

plt.xlabel("Department")

plt.ylabel("Average Salary")

plt.show()

# Final Analysis

print("Hence from this analysis we can know that " +
gxaxis[avg_salary.index(max(avg_salary))] + " has high Average Salary")

print("Hence from this analysis we can know that " + bxaxis[byaxis.index(max(byaxis))] + "
has Highest Placement")
```

ANNEXURE 2: SNAPSHOTS:



```
{'Sci&Tech Mkt&HR': [16, 13],
 'Sci&Tech Mkt&Fin': [25, 5],
 'Comm&Mgmt Mkt&Fin': [68, 18],
 'Comm&Mgmt Mkt&HR': [34, 25],
 'Others Mkt&HR': [4, 3],
 'Others Mkt&Fin': [2, 2]}
```

Fig 4. Placement Count in each Department - Specialization

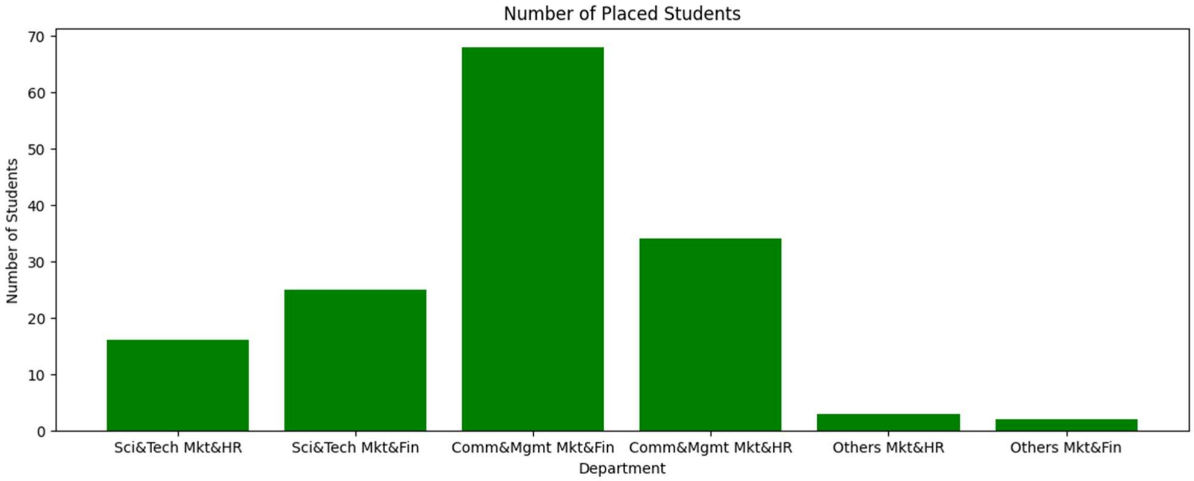


Fig 5. Department Vs Number of Placed Students

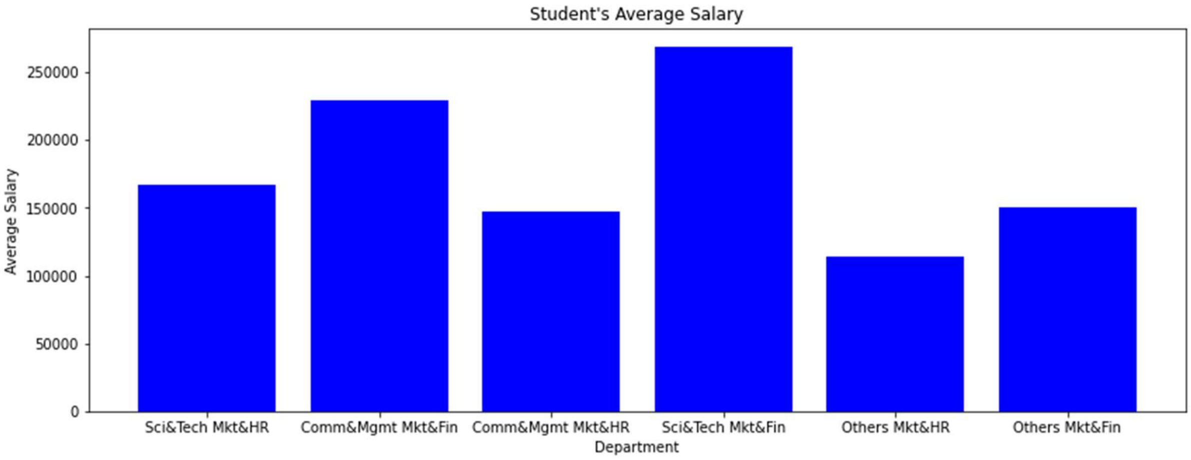
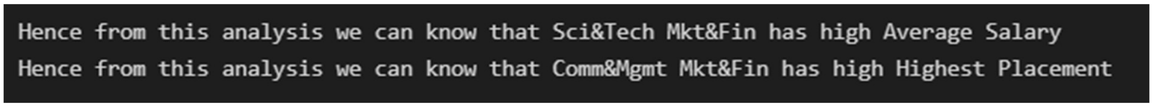


Fig 6. Department Vs Average Salary



```
Hence from this analysis we can know that Sci&Tech Mkt&Fin has high Average Salary
Hence from this analysis we can know that Comm&Mgmt Mkt&Fin has high Highest Placement
```

Fig 7. Final Inference

REFERENCES:

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