



COLLEGE CODE : 8107

COURSE : DATA ANALYTICS WITH COGNOS

PHASE V: PROJECT SUBMISSION

PROJECT TITLE: Assessment of marginal workers in  
Tamil Nadu – A socioeconomic Analysis

TEAM MEMBERS DETAILS:

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# Assessment of marginal workers in Tamil Nadu – A socioeconomic Analysis

## Problem Definition:

The project involves analyzing the demographic characteristics of marginal workers in Tamil Nadu based on their age, industrial category, and sex. The objective is to perform a socioeconomic analysis and create visualizations to represent the distribution of marginal workers across different categories. This project includes defining objectives, designing the analysis approach, selecting appropriate visualization types, and performing the analysis using Python and data visualization libraries.

## Understanding the problem:

The analysis aims to understand factors such as age, gender, occupation, and migration patterns among marginalized workers. It also involves evaluating their income levels, education, healthcare accessibility, and utilization of social welfare programs. The goal is to identify disparities, challenges, and opportunities faced by these workers, providing insights for informed policies and interventions to improve their overall quality of life and socioeconomic status. The analysis involves data extraction, cleaning, and analysis, followed by visualization and interpretation to derive meaningful insights for stakeholders and policymakers.

## Design Thinking:

- Objectives:
  - Analyse Marginal Worker Demographics:
    - Subgroups Identification: Identifying specific subgroups within the marginalized worker population, such as agricultural labourers, construction workers, domestic helpers, etc.

- **Demographic Profiling:** Creating a detailed demographic profile including age, gender, ethnicity, and geographical distribution of these subgroups.
- **Migration Patterns:** Exploring migration patterns within Tamil Nadu and from other states.
- **Understand Age and Gender Distribution:**
  - **Age Distribution:** Examining the age distribution within different categories of marginalized workers to understand workforce composition and aging trends.
  - **Gender Analysis:** Analysing the gender distribution, exploring the challenges and opportunities faced by male and female marginalized workers.
  - **Impact of Age and Gender:** Understanding how age and gender influence employment opportunities, wages, and access to social welfare programs.
- **Explore Industrial Categories:**
  - **Occupational Analysis:** To Categorise marginalized workers based on their occupations, including agricultural labour, construction, domestic work, etc.
  - **Industrial Distribution:** Investigate the distribution of these occupational categories across various industries in Tamil Nadu.
  - **Income Disparities:** Examining income disparities within and between different industrial categories to identify wage gaps and disparities in economic opportunities.
- **Study Social Welfare Program Utilization:**
  - **Effectiveness Assessment:** Evaluate the effectiveness of existing social welfare programs in improving the socioeconomic status of these workers.
  - **Challenges in Access:** Identify challenges faced by marginalized workers in accessing and benefiting from social welfare initiatives.

- Analysis Approach:

- focusing on labor and marginalized communities in Tamil Nadu. Obtain permission and access to the selected datasets.
- Collect quantitative data related to demographics, employment, education, healthcare, and social welfare programs.

#### Step 2: Data Cleaning

- Merge data from various sources into a unified dataset, ensuring compatibility and consistency in variable formats.
- Identify and handle missing or incomplete data points using appropriate methods such as imputation or data removal, ensuring minimal impact on overall analysis.
- Identify outliers in the dataset that could skew the analysis. Decide whether to remove outliers or transform them based on the context of the analysis.
- Validate the cleaned dataset to ensure accuracy, consistency, and completeness.

#### Step 3: Data Analysis

- Calculate basic statistics (mean, median, standard deviation) for key variables to understand the dataset's characteristics.
- Use visualizations (bar charts, pie charts) and statistical methods to analyse demographics, age, gender, and migration patterns.
- Evaluate the relationship between education levels and employment opportunities.
- Compare wages across different occupations and industries using statistical tests.

#### Step 4: Visualising and Reporting

- Create visualizations (charts, graphs, heat maps) to present the insights clearly and effectively.
- Prepare a presentation summarizing the analysis for stakeholders.
- Communicate the findings effectively, highlighting important trends and policy implications.

### ○ Visualisation Selection:

- Use histograms or bar charts to display the frequency distribution of different age groups among marginalized workers.
- Represent the proportion of male and female workers using
- Display the number or percentage of workers from different ethnic or caste groups using a bar chart for easy comparison.
- If you want to represent additional data (like population size), a bubble map can show both the geographical distribution and the magnitude of the worker population.
- If analysing migration patterns within and outside Tamil Nadu, a flow map can demonstrate the movement of workers between different regions.
- Violin plots combine aspects of box plots and kernel density plots, providing a more detailed view of income distribution, especially when comparing multiple groups.
- Use a heat map to visualize the correlation between educational attainment and income levels among marginalized workers.

## Benefits:

### ○ **Accuracy:**

Automation reduces the likelihood of human errors in data extraction and cleaning, ensuring high data accuracy.

### ● **Insights:**

Advanced analytics capabilities provide deeper insights into the socio-economic conditions of marginal workers, enabling evidence-based decision-making.

### ● **Interactivity:**

Interactive reports engage users and allow them to explore data dynamically, leading to deeper insights and more informed decision-making.

- **Enhanced Data Visualization:**

Innovative tools and techniques can help you create visually compelling and interactive data visualizations.

## Code implementation steps:

Step1: Import libraries.

Step2: Load the given dataset.

Step3: Preprocessing the data:

- Data cleaning
- Data processing
- Data transforming

## Program:

Step1

```
>>import pandas as pd
df=pd.read_csv(r"/content/nm.csv")
print(df)
```

```
590 6
591 9
592 3
593 0

Industrial Category - R to U - HHI - Females \
0 12567
1 258
2 6219
3 5104
4 974
.. ..
589 0
590 56
591 27
592 7
593 0

Industrial Category - R to U - Non HHI - Persons \
0 122088
1 19305
2 68929
3 26498
4 7065
.. ..
589 228
590 675
591 279
592 81
593 0

Industrial Category - R to U - Non HHI - Males \
0 55801
1 9774
2 32803
3 9675
4 3394
.. ...
```

## Step2.1

```
>>df.head()
```

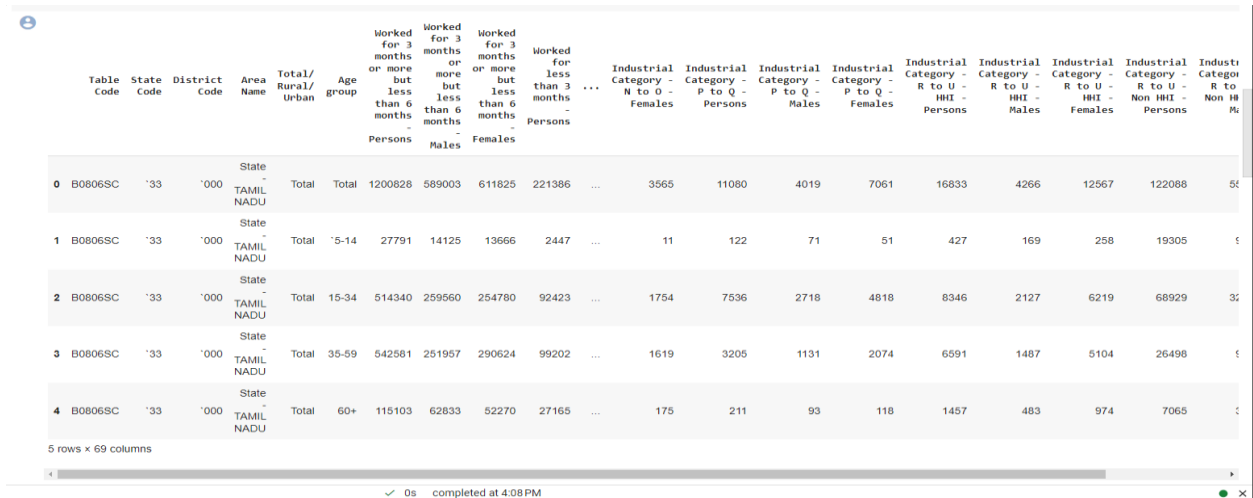


	Table Code	State Code	District Code	Area Name	Total/ Rural/ Urban	Age group	Worked for 3 months or more but less than 6 months - Persons	Worked for 3 months or more but less than 6 months - Males	Worked for 3 months or more but less than 6 months - Females	Worked for less than 3 months - Persons	...	Industrial Category - N to O - Females	Industrial Category - P to Q - Persons	Industrial Category - P to Q - Males	Industrial Category - P to Q - Females	Industrial Category - R to U - HH1 - Persons	Industrial Category - R to U - HH1 - Males	Industrial Category - R to U - HH1 - Females	Industrial Category - R to U - Non HH1 - Persons	Industrial Category - R to U - Non HH1 - Males	Industrial Category - R to U - Non HH1 - Females
0	B0806SC	'33	'000	State - TAMIL NADU	Total	Total	1200828	589003	611825	221386	...	3565	11080	4019	7061	16833	4266	12567	122088	589003	611825
1	B0806SC	'33	'000	State - TAMIL NADU	Total	'5-14	27791	14125	13666	2447	...	11	122	71	51	427	169	258	19305	14125	13666
2	B0806SC	'33	'000	State - TAMIL NADU	Total	15-34	514340	259560	254780	92423	...	1754	7536	2718	4818	8346	2127	6219	68929	259560	254780
3	B0806SC	'33	'000	State - TAMIL NADU	Total	35-59	542581	251957	290624	99202	...	1619	3205	1131	2074	6591	1487	5104	26498	251957	290624
4	B0806SC	'33	'000	State - TAMIL NADU	Total	60+	115103	62833	52270	27165	...	175	211	93	118	1457	483	974	7065	62833	52270

5 rows x 69 columns

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## Step 2.2

```
>>df.info()
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 594 entries, 0 to 593
Data columns (total 69 columns):
#   Column
---  ---
0   Table Code
1   State Code
2   District Code
3   Area Name
4   Total/ Rural/ Urban
5   Age group
6   Worked for 3 months or more but less than 6 months - Persons
7   Worked for 3 months or more but less than 6 months - Males
8   Worked for 3 months or more but less than 6 months - Females
9   Worked for less than 3 months - Persons
10  Worked for less than 3 months - Males
11  Worked for less than 3 months - Females
12  Industrial Category - A - Cultivators - Persons
13  Industrial Category - A - Cultivators - Males
14  Industrial Category - A - Cultivators - Females
15  Industrial Category - A - Agricultural labourers - Persons
16  Industrial Category - A - Agricultural labourers - Males
17  Industrial Category - A - Agricultural labourers - Females
18  Industrial Category - A - Plantation, Livestock, Forestry, Fishing, Hunting and allied activities - Persons
19  Industrial Category - A - Plantation, Livestock, Forestry, Fishing, Hunting and allied activities - Males
20  Industrial Category - A - Plantation, Livestock, Forestry, Fishing, Hunting and allied activities - Females
21  Industrial Category - B - Persons
22  Industrial Category - B - Males
23  Industrial Category - B - Females
24  Industrial Category - C - HH1 - Persons
25  Industrial Category - C - HH1 - Males
26  Industrial Category - C - HH1 - Females
27  Industrial Category - C - Non HH1 - Persons
28  Industrial Category - C - Non HH1 - Males
29  Industrial Category - C - Non HH1 - Females
30  Industrial Category - D & E - Persons
31  Industrial Category - D & E - Males
32  Industrial Category - D & E - Females
33  Industrial Category - F - Persons
34  Industrial Category - F - Males
35  Industrial Category - F - Females
36  Industrial Category - G - HH1 - Persons
37  Industrial Category - G - HH1 - Males
```

	Non-Null Count	Dtype
0	594 non-null	object
1	594 non-null	object
2	594 non-null	object
3	594 non-null	object
4	594 non-null	object
5	594 non-null	object
6	594 non-null	int64
7	594 non-null	int64
8	594 non-null	int64
9	594 non-null	int64
10	594 non-null	int64
11	594 non-null	int64
12	594 non-null	int64
13	594 non-null	int64
14	594 non-null	int64
15	594 non-null	int64
16	594 non-null	int64
17	594 non-null	int64
18	594 non-null	int64
19	594 non-null	int64
20	594 non-null	int64
21	594 non-null	int64
22	594 non-null	int64
23	594 non-null	int64
24	594 non-null	int64
25	594 non-null	int64
26	594 non-null	int64
27	594 non-null	int64
28	594 non-null	int64
29	594 non-null	int64
30	594 non-null	int64
31	594 non-null	int64
32	594 non-null	int64
33	594 non-null	int64
34	594 non-null	int64
35	594 non-null	int64
36	594 non-null	int64
37	594 non-null	int64

0s completed at 4:08 PM

Step 2.3

```
>>df.describe()
```

	Worked for 3 months or more but less than 6 months - Persons	Worked for 3 months or more but less than 6 months - Males	Worked for 3 months or more but less than 6 months - Females	Worked for less than 3 months - Persons	Worked for less than 3 months - Males	Worked for less than 3 months - Females	Industrial Category - A - Cultivators - Persons	Industrial Category - A - Cultivators - Males	Industrial Category - A - Cultivators - Females	Industrial Category - A - Agricultural labourers - Persons	...	Industrial Category - N to O - Females	Industrial Category - P to Q - Persons	Industrial Category - P to Q - Males	I C
count	5.940000e+02	594.000000	594.000000	594.000000	594.000000	594.000000	594.000000	594.000000	594.000000	594.000000	...	594.000000	594.000000	594.000000	5
mean	1.617277e+04	7932.700337	8240.067340	2981.629630	1338.289562	1643.340067	865.117845	466.424242	398.693603	12225.616162	...	48.013468	149.225589	54.127946	4
std	7.607172e+04	36864.822704	39259.545337	13909.621137	6127.047670	7808.832522	4274.458077	2298.072295	1978.682322	60458.382586	...	222.553500	696.553730	253.067862	4
min	0.000000e+00	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000	0.000000	0
25%	2.872500e+02	147.250000	144.000000	27.000000	14.250000	13.000000	9.000000	5.000000	4.000000	79.250000	...	0.000000	0.000000	0.000000	0
50%	2.225500e+03	1147.000000	1076.000000	430.000000	198.500000	213.000000	69.500000	35.500000	32.000000	1094.000000	...	2.000000	14.500000	6.000000	0
75%	9.628500e+03	4770.500000	4887.500000	1775.250000	774.250000	946.500000	466.000000	244.250000	204.750000	6279.750000	...	18.000000	99.750000	35.750000	0
max	1.200828e+06	589003.000000	611825.000000	221386.000000	99368.000000	122018.000000	64235.000000	34632.000000	29603.000000	907752.000000	...	3565.000000	11080.000000	4019.000000	70

8 rows x 63 columns

Step 2.4

```
>>df.isnull()
```

	Table Code	State Code	District Code	Area Name	Total/Rural/Urban	Age group	Worked for 3 months or more but less than 6 months - Persons	Worked for 3 months or more but less than 6 months - Males	Worked for 3 months or more but less than 6 months - Females	Worked for less than 3 months - Persons	...	Industrial Category - N to O - Females	Industrial Category - P to Q - Persons	Industrial Category - P to Q - Males	Industrial Category - P to Q - Females	Industrial Category - R to U - Persons	Industrial Category - R to U - HHI - Males	Industrial Category - R to U - HHI - Females	Industrial Category - Non HHI - Persons	Industrial Category - Non HHI - Males
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
589	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal
590	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal
591	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal
592	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal
593	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	Fal

594 rows x 69 columns



### Step 3.1

```
>>missingvalues=df.isna()
print(missingvalues)
```

```
593                                     False
0      Industrial Category - R to U - HHI - Females \
1                                                False
2                                                False
3                                                False
4                                                False
..
589                                                False
590                                                False
591                                                False
592                                                False
593                                                False

0      Industrial Category - R to U - Non HHI - Persons \
1                                                False
2                                                False
3                                                False
4                                                False
..
589                                                False
590                                                False
591                                                False
592                                                False
593                                                False

0      Industrial Category - R to U - Non HHI - Males \
1                                                False
2                                                False
3                                                False
4                                                False
..
589                                                False
590                                                False
591                                                False
592                                                False
593                                                False

0      Industrial Category - R to U - Non HHI - Females
1                                                False
```

### Step 3.2

```
>>missingvalues.sum()
```

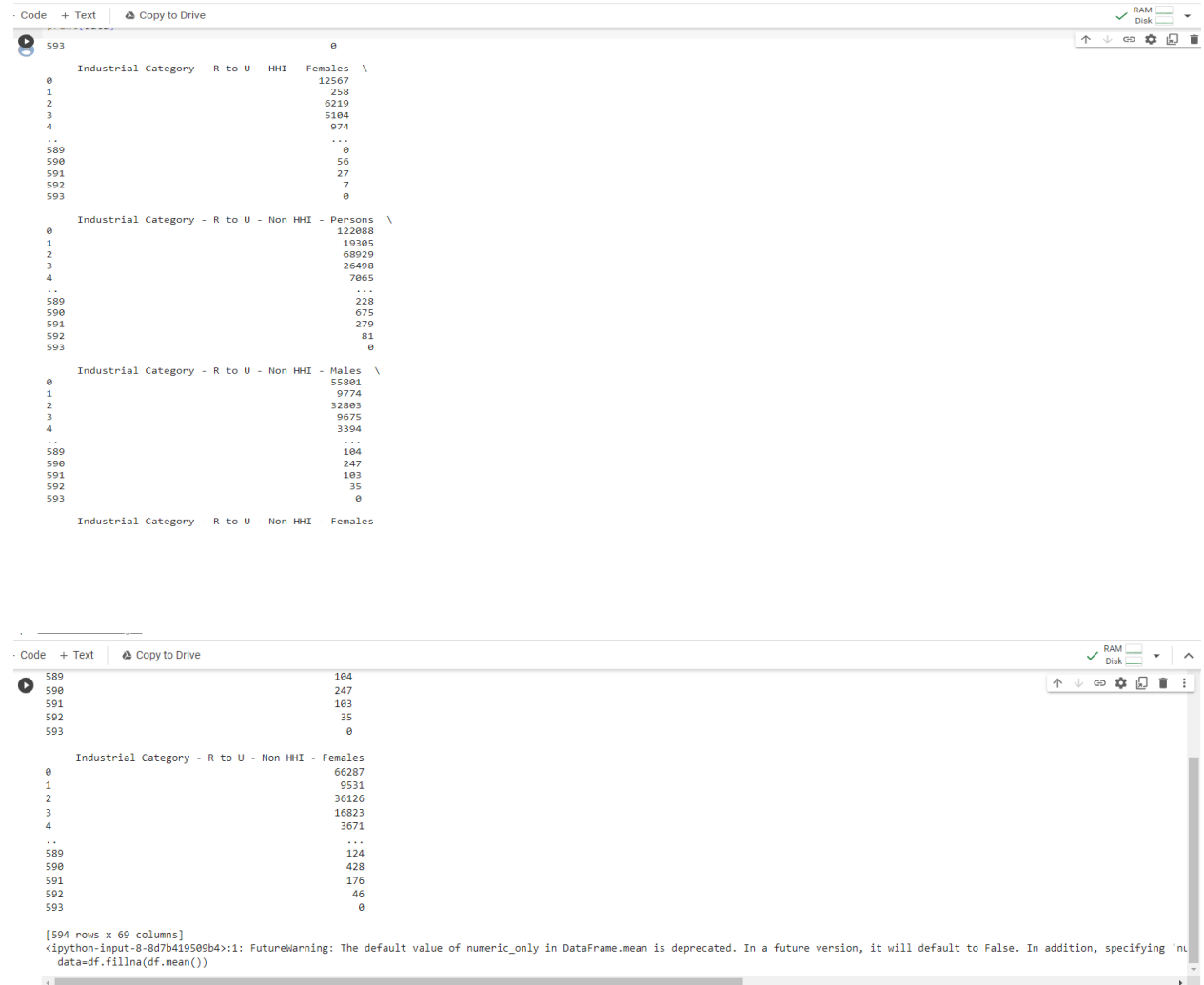
```
Table Code          0
State Code          0
District Code       0
Area Name           0
Total/ Rural/ Urban 0
..
Industrial Category - R to U - HHI - Males 0
Industrial Category - R to U - HHI - Females 0
Industrial Category - R to U - Non HHI - Persons 0
Industrial Category - R to U - Non HHI - Males 0
Industrial Category - R to U - Non HHI - Females 0
Length: 69, dtype: int64
```

### Step 3.3

```
>>data=df.fillna(df.mean())

df["Worked for 3 months or more but less than 6 months - Persons"].std()

print(data)
```



The image shows two screenshots of a Jupyter Notebook interface. The top screenshot displays the output of a data processing operation, showing three separate data series for different groups: 'Industrial Category - R to U - HH - Females', 'Industrial Category - R to U - Non HH - Persons', and 'Industrial Category - R to U - Non HH - Males'. Each series is a list of values indexed from 0 to 593. The bottom screenshot shows the execution of the code `data=df.fillna(df.mean())`, which fills missing values in the DataFrame with the mean of each column. Below the code, a warning message is displayed: `<ipython-input-8-8d7b419509b4>:1: FutureWarning: The default value of numeric_only in DataFrame.mean is deprecated. In a future version, it will default to False. In addition, specifying 'nu`. The output of the code is a DataFrame with 594 rows and 69 columns.

```
Code + Text Copy to Drive
```

```
593 0
Industrial Category - R to U - HH - Females \
0 12567
1 258
2 6219
3 5104
4 974
...
589 0
590 56
591 27
592 7
593 0

Industrial Category - R to U - Non HH - Persons \
0 122088
1 19305
2 68929
3 26498
4 7065
...
589 228
590 675
591 279
592 81
593 0

Industrial Category - R to U - Non HH - Males \
0 55801
1 9774
2 32803
3 9675
4 3394
...
589 104
590 247
591 103
592 35
593 0

Industrial Category - R to U - Non HH - Females

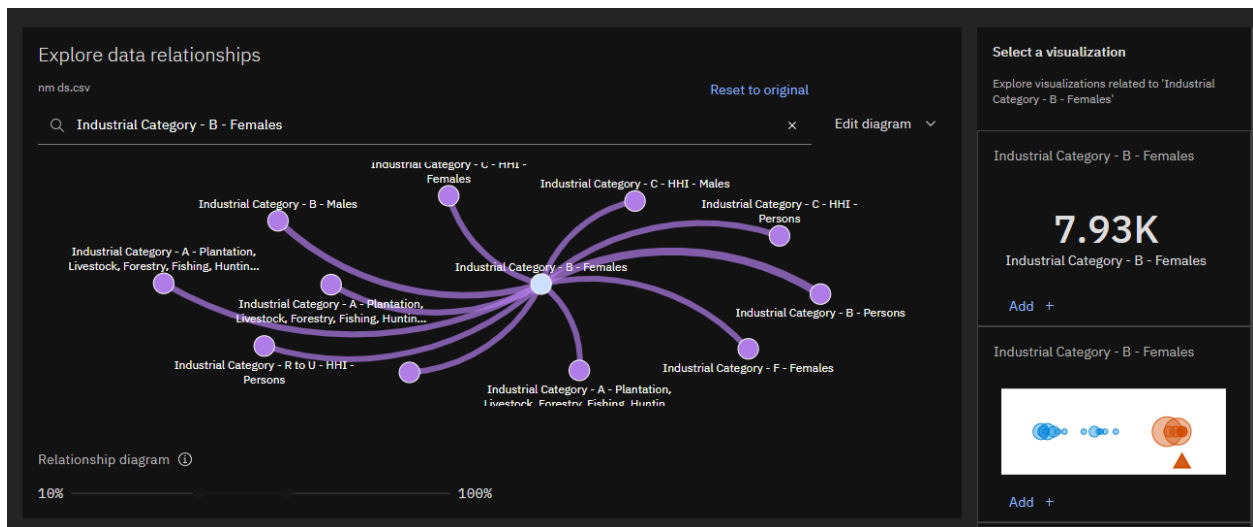
[594 rows x 69 columns]
<ipython-input-8-8d7b419509b4>:1: FutureWarning: The default value of numeric_only in DataFrame.mean is deprecated. In a future version, it will default to False. In addition, specifying 'nu
data=df.fillna(df.mean())
```

```
[1] import pandas as pd
df=pd.read_csv("/DDW_B065C_3300_State_TAMIL_NADU-2011.csv")

df[["Worked for 3 months or more but less than 6 months - Persons"]].std()

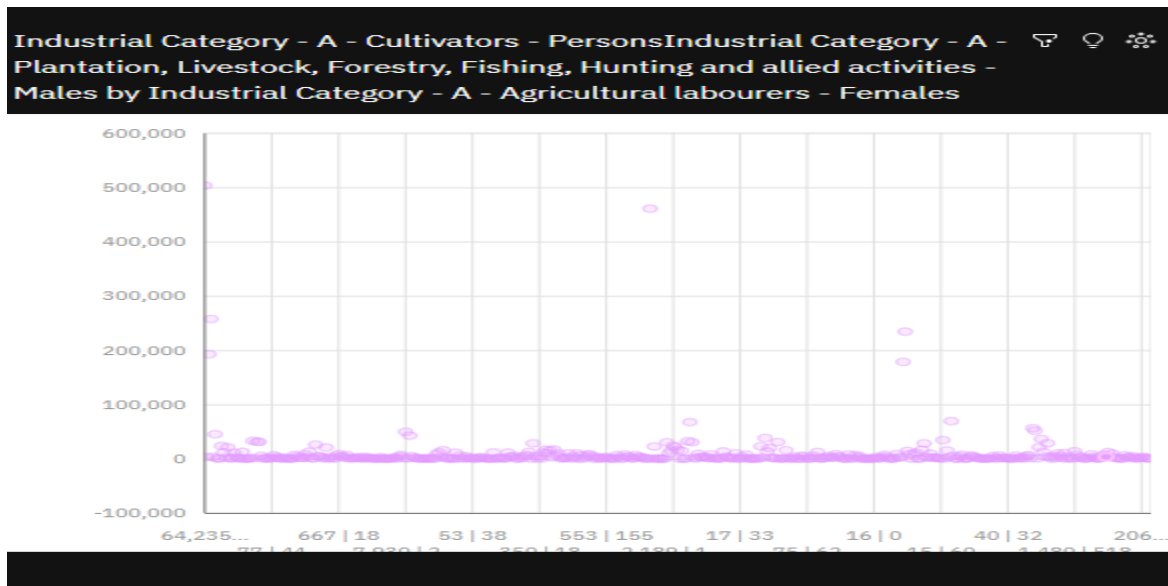
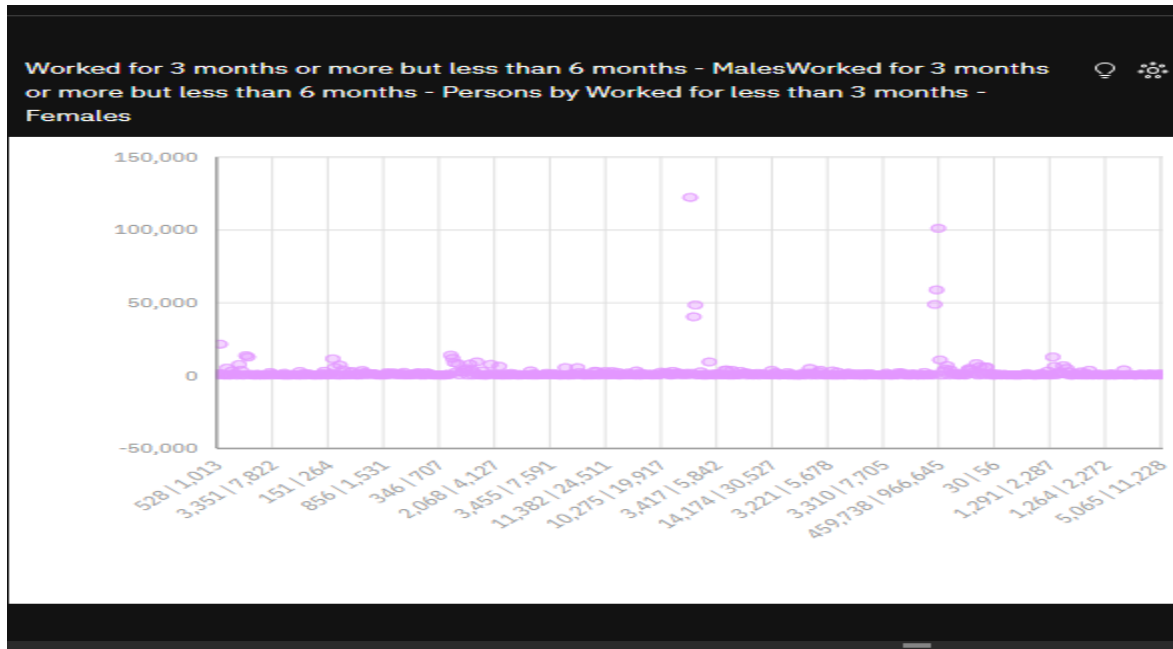
76071.71591682028
```

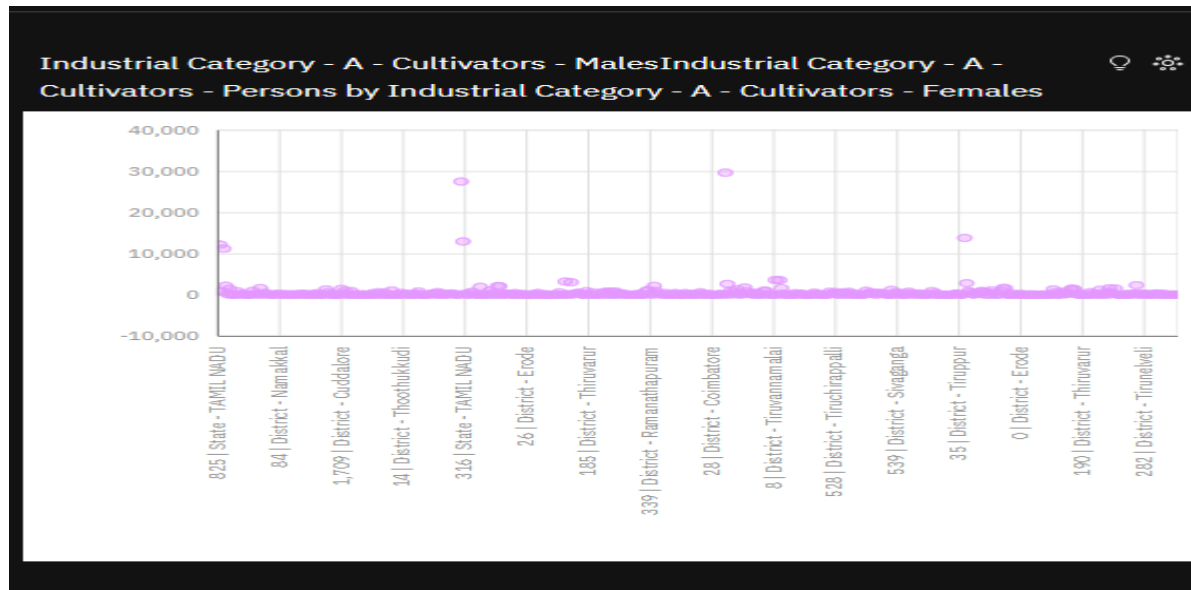
## Data Exploration:



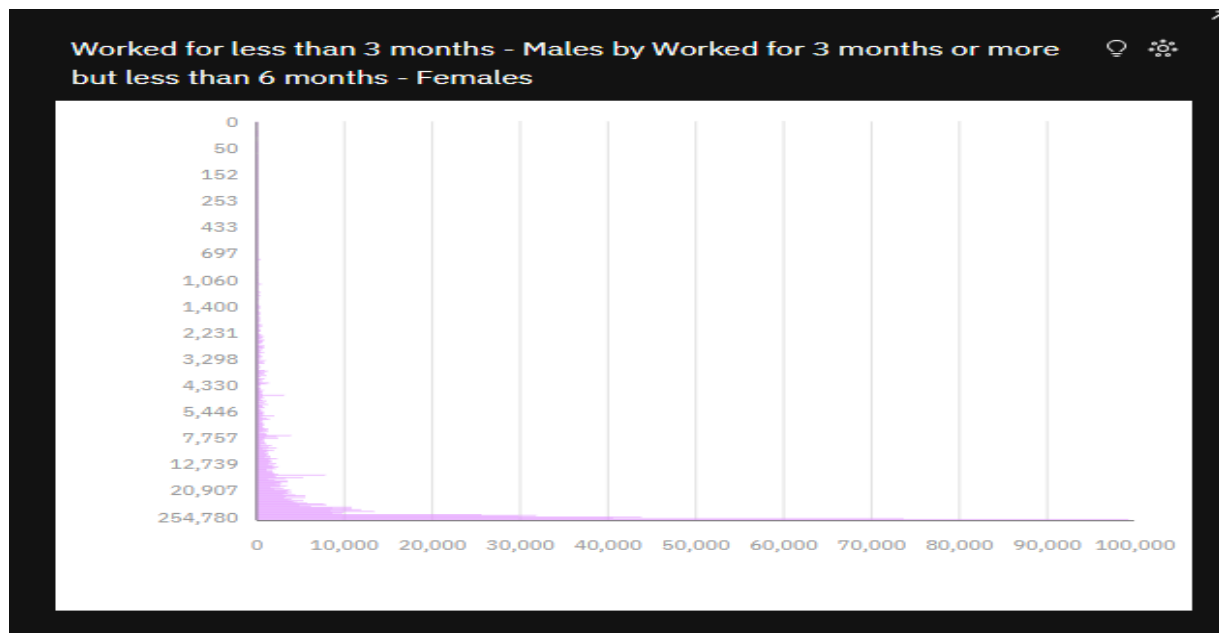
## Data visualization:

- Scatter plot

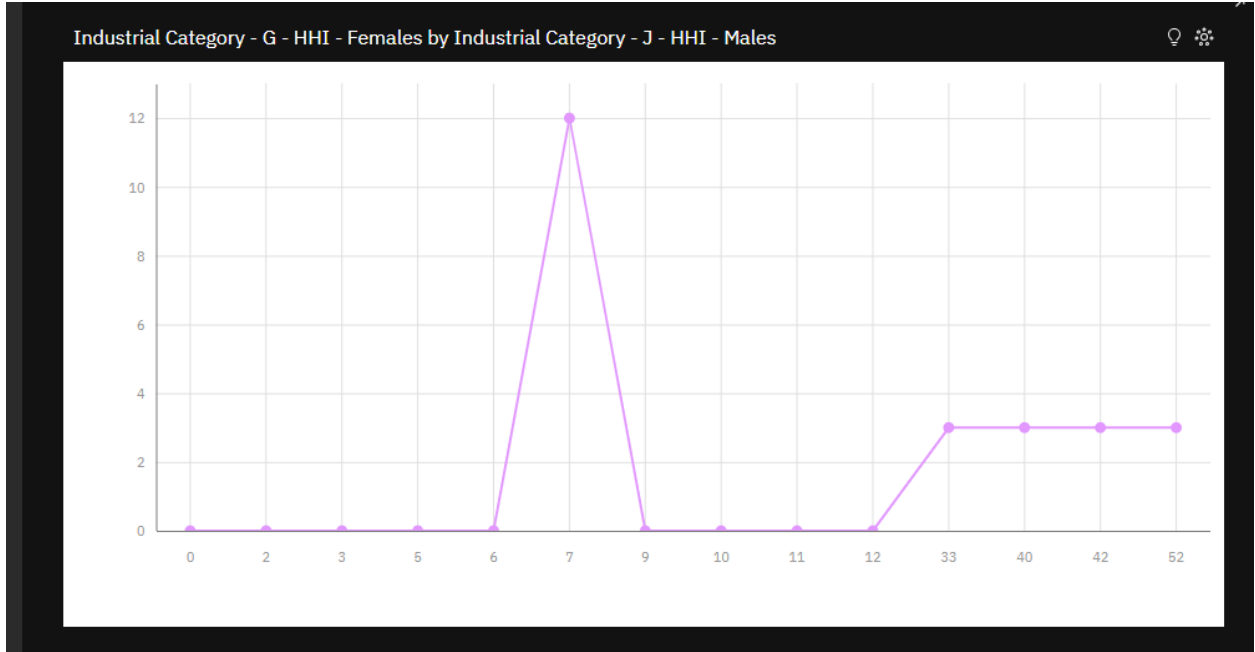




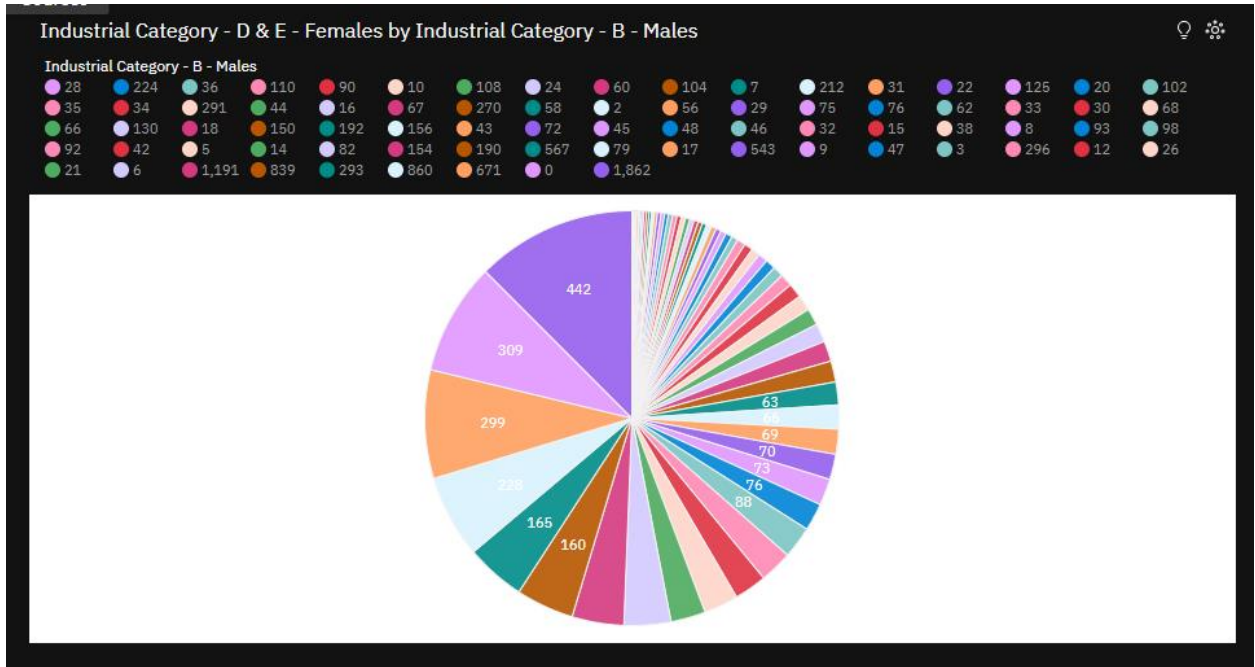
- Bar chart



- Line Graph



- Pie chart



## Summary:

"Assessment of Marginal Workers in Tamil Nadu - A Socio-Economic Analysis" involves an in-depth exploration of the socio-economic conditions and challenges faced by marginal workers in the state of Tamil Nadu, India. Here's a summary of key findings and insights from this analysis:

- **Demographic Profile:**
  - The analysis revealed a diverse demographic profile of marginal workers, encompassing various age groups, genders, and educational backgrounds.
  - A significant portion of marginal workers falls within the age range of 25 to 45, suggesting the need for targeted employment and skill development programs for this group.
  - Gender disparities were observed, with a higher representation of male marginal workers, emphasizing the importance of gender-inclusive initiatives.
- **Employment Patterns:**
  - The assessment showcased the prevalence of informal and precarious employment among marginal workers, leading to income instability and job insecurity.
  - Many marginal workers engaged in sectors such as agriculture, construction, and daily wage labor, highlighting the need for skill enhancement in these fields.
  - Seasonal variations in employment opportunities posed a challenge, especially for agricultural laborers.
- **Income and Livelihood:**
  - A significant proportion of marginal workers faced low income levels, with limited access to financial resources and savings.
  - Income inequalities were evident, indicating the need for equitable economic policies and programs that address income disparities.
- **Educational Attainment:**
  - The analysis demonstrated disparities in educational attainment among marginal workers, with a substantial segment having limited access to formal education.

- Efforts to promote basic literacy and vocational training are essential to enhance employability and socio-economic prospects.

- Challenges and Vulnerabilities:

- Marginal workers faced various socio-economic challenges, including inadequate access to healthcare, housing, and social security.

- Vulnerabilities to external shocks, such as natural disasters or economic downturns, were evident, highlighting the need for social safety nets and resilience-building measures.

- Policy Implications:

- The findings underscored the importance of targeted policies and programs that promote skill development, job security, and income enhancement for marginal workers.

- Initiatives aimed at improving access to education and healthcare, especially in rural areas, are crucial for overall development.

- Strengthening social safety nets and ensuring inclusive growth can help alleviate vulnerabilities faced by marginal workers.

This socio-economic analysis sheds light on the unique challenges faced by marginal workers in Tamil Nadu and provides valuable insights for policymakers, organizations, and stakeholders. The findings offer a foundation for the design of effective interventions and policies that can improve the socio-economic well-being and livelihoods of marginal workers in the region.