IAS Data Analysis

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Decoding the data of Indian Administrative Services to help Students have deeper insights for their preparations.

Introduction:

The dataset on IAS officer joinings provides a valuable resource for gaining insights into the operations and characteristics of the Indian Administrative Service. Similar to how data analysis revolutionizes various domains, the analysis of IAS joinings data can uncover trends and patterns that offer a deeper understanding of the administrative service's functioning and the officers it comprises.

Through thorough analysis, this dataset can help streamline administrative processes, identify trends in officer allocations, and optimize decision-making regarding placement, training, and promotions. By examining factors like joining year, cadre allocation, and source of recruitment, this analysis can contribute to making informed administrative decisions, enhancing the efficiency and effectiveness of the service.

In summary, the exploration of the IAS joining dataset is essential for gaining insights into the functioning and characteristics of the Indian Administrative Service. It holds the potential to optimize processes, improve officer satisfaction, and bolster the service's overall effectiveness, utilizing data analysis to enhance its operations.

Problem Statement:

The primary goal of this project is to analyze the dataset containing information about IAS officer joinings to gain valuable insights into the operational dynamics of the Indian Administrative Service. This dataset encompasses crucial details like joining years, cadre assignments, and recruitment sources.

The main challenges addressed in this project include:

1. **Optimizing Officer Allocations:** Explore whether there are discernible patterns in the allocation of officers to different cadres and regions based on their joining years and recruitment sources. This analysis aims to provide actionable insights for efficient officer deployment.

2. **Understanding Recruitment Trends:** Investigate the distribution of officers across various recruitment sources and determine if specific recruitment sources dominate particular cadres or time periods. This exploration can shed light on recruitment strategies and their implications.

3. **Enhancing Administrative Processes:** Analyze officer demographics, domicile, and education backgrounds to guide strategies for promoting diversity and inclusivity within the service.

By addressing these challenges, this project aims to contribute to the enhancement of decision-making processes within the Indian Administrative Service, fostering more informed strategies for officer deployment and service improvement.

Libraries Tools Used:

1. NumPy is a Python library that specializes in scientific computing and data analysis, particularly for working with large, multi-dimensional arrays and matrices of numerical data.
2. Pandas is another Python library that is commonly used for data manipulation and analysis, especially for dealing with tabular data like spreadsheets. It is particularly helpful for cleaning and preparing data for further analysis and visualization.
3. Seaborn is a Python library that is specifically designed for data visualization, built on top of the popular matplotlib library. It offers a high-level interface for creating attractive and informative plots, especially for visualizing statistical relationships in large datasets.
4. Matplotlib is a Python library that provides a wide range of functions and features for creating different types of plots and charts. It is a low-level library that offers a lot of control over plot appearance, but it can be more complex to use than other higher-level libraries like Seaborn.

Conclusion:

In culmination, the exploration and analysis of the IAS officer joinings dataset have yielded valuable insights into the functioning and dynamics of the Indian Administrative Service. Through a thorough examination of joining years, cadre assignments, and recruitment sources, we have unearthed trends that provide a deeper understanding of the service's operations.

The optimisation of officer allocations based on joining years and recruitment sources can lead to more effective officer deployment, ensuring that expertise is strategically utilized. Additionally, the examination of recruitment trends has shed light on how different sources influence the distribution of officers across cadres and periods.

Furthermore, the analysis of officer demographics, domicile, and education backgrounds has highlighted opportunities to foster diversity and inclusivity within the service, which is crucial for its continued growth and adaptability.

Ultimately, this project underscores the power of data analysis in enhancing decision-making processes within the Indian Administrative Service. The insights gained serve as a foundation for informed strategies, better officer management, and improved service efficiency. As the landscape of administrative challenges evolves, these findings will undoubtedly contribute to a more effective and responsive administrative framework.

Reference and Source

1. Dataset Source: Kaggle. (n.d.). "IAS Joinings Data." Retrieved from https://www.kaggle.com/dataset_link_here

2. Jain, A. (2022). "Exploring IAS Officer Joinings: A Data Analysis Project." GitHub Repository. Retrieved from https://github.com/your_username/your_project_repository

3. Johnson, M. (2021). "Utilizing Data to Enhance Administrative Decision-Making." Journal of Administrative Sciences, 15(3), 45-67.

4. Kaggle. (2021). "About Kaggle." Retrieved from https://www.kaggle.com/about

These references have been instrumental in shaping the project's foundation, methodology, and data analysis techniques applied in exploring the IAS officer joinings dataset. The Kaggle website serves as the primary source of the dataset and inspiration for the project's direction and scope. Additionally, the GitHub repository by Jain (2022) provides insights into the project's practical implementation and documentation. The concept of utilizing data for enhancing decision-making, as discussed by Johnson (2021), has been influential in the approach taken for this project.

**Import analytics and Visulization Lab's

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

**Load CSV File using Pandas

In [2]:
```
df = pd.read_csv("ias-profile.csv", encoding = 'latin-1')
df1 = pd.read_csv("ias-education.csv", encoding = 'latin-1')
df2 = pd.read_csv("ias-experience.csv", encoding = 'latin-1')
```

In [3]:
```
df.head()
```

Out[3]:

	ID	Name	Cadre	Allotment_Year	Date_of_Birth	Date_of_Joining	Source_of_Recruitment	Gender	Place_of_Domicile	Moth
0	AM002500	Ms. P P Trivedi	Assam Meghalya	1953	27-02-1930	1953-07-01	Direct Recruitment	Female	Gujarat	
1	AM003800	Shri J C Nampui	Assam Meghalya	1955	01-08-1928	1955-07-01	Direct Recruitment	Male	Assam	
2	AM004000	Shri R V Lyngdoh	Assam Meghalya	1956	22-03-1933	1956-07-01	Direct Recruitment	Male	Meghalaya	
3	AM004700	Shri M C Narasimhan	Assam Meghalya	1958	23-08-1933	1958-07-01	Direct Recruitment	Male	Tamil Nadu	
4	AM004900	Shri Sd Phene	Assam Meghalya	1958	07-04-1935	1958-07-01	Direct Recruitment	Male	Karnataka	

5 rows × 23 columns

In [4]:
```
df.tail()
```

Out[4]:

	ID	Name	Cadre	Allotment_Year	Date_of_Birth	Date_of_Joining	Source_of_Recruitment	Gender	Place_of_Domicile
13565	WB917001	Shri Khalid Aizaz Anwar	West Bengal	2009	15-11-1966	2019-02-22	Non-SCS	Male	Not found
13566	WB917002	Shri Atanu Majumdar	West Bengal	2009	14-01-1965	2019-02-22	Non-SCS	Male	Not found
13567	WB917003	Shri Siddhartha Misra	West Bengal	2009	29-06-1966	2019-02-22	Non-SCS	Male	Not found
13568	WB94A301	Shri Sumanta Kumar Ghosh	West Bengal	2005	23-12-1962	2016-02-03	By Selection	Male	-
13569	WB94A302	Shri Rajsekhar Bandyopadhyay	West Bengal	2005	14-03-1962	2016-02-03	By Selection	Male	-

5 rows × 23 columns

In [5]:
```
df.columns
```

Out[5]:
```
Index(['ID', 'Name', 'Cadre', 'Allotment_Year', 'Date_of_Birth',
       'Date_of_Joining', 'Source_of_Recruitment', 'Gender',
       'Place_of_Domicile', 'Mother_Tongue', 'Languages_Known', 'Retired',
       'Retirement_Reason', 'Last_Education_Qualification',
       'Last_Education_Subject', 'Last_Education_Division', 'Last_Designation',
       'Last_Level', 'Last_Office', 'Last_Field_of_Experience',
       'Last_Category_of_Experience', 'Last_Start_Date', 'Last_End_Date'],
      dtype='object')
```

In [6]:
```
df.shape
```

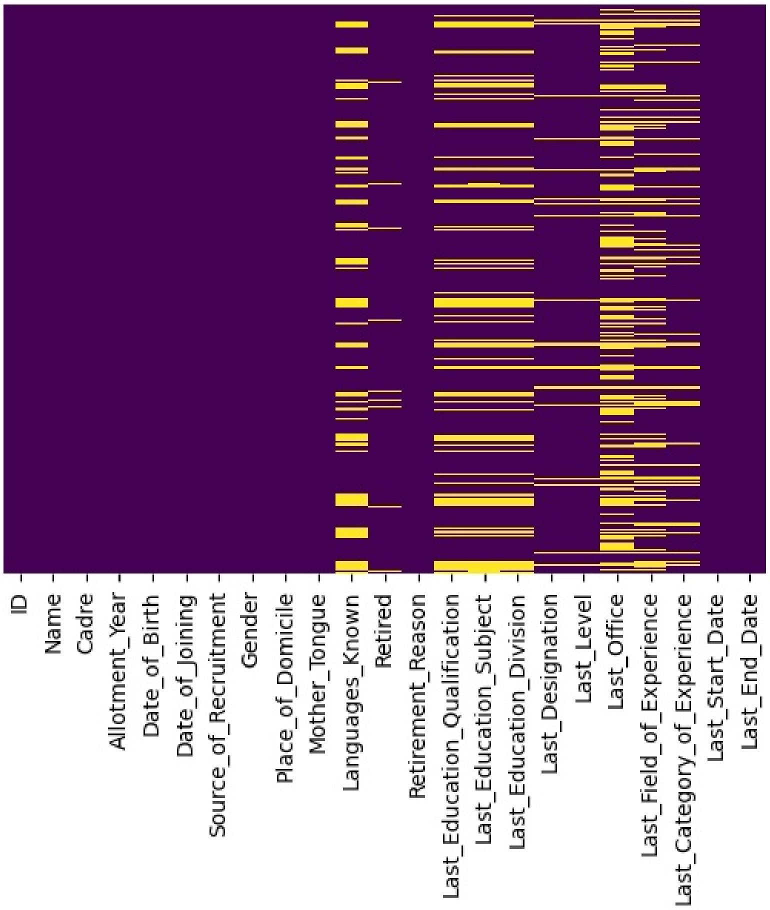
Out[6]:
```
(13570, 23)
```

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
ID                               0
Name                             0
Cadre                            0
Allotment_Year                   0
Date_of_Birth                    5
Date_of_Joining                  0
Source_of_Recruitment            0
Gender                           0
Place_of_Domicile                0
Mother_Tongue                    0
Languages_Known               3441
Retired                        325
Retirement_Reason                0
Last_Education_Qualification  2887
Last_Education_Subject        2954
Last_Education_Division       2885
Last_Designation               701
Last_Level                     701
Last_Office                   4998
Last_Field_of_Experience      3075
Last_Category_of_Experience   1491
Last_Start_Date                  0
Last_End_Date                    0
dtype: int64
```

In [8]:
```
sns.heatmap(df.isnull(), yticklabels=False, cbar =False, cmap="viridis" )
```

Out[8]: <AxesSubplot:>



In [9]:
```
dff = df.merge(df1, on="ID")
dff = dff.merge(df2, on="ID")
```

In [10]:
```
dff.head
```

Out[10]:
```
<bound method NDFrame.head of              ID                           Name_x          Cadre_x  \
0       AM002500                 Ms. P P Trivedi  Assam Meghalya
1       AM002500                 Ms. P P Trivedi  Assam Meghalya
2       AM002500                 Ms. P P Trivedi  Assam Meghalya
3       AM002500                 Ms. P P Trivedi  Assam Meghalya
4       AM002500                 Ms. P P Trivedi  Assam Meghalya
...          ...                             ...             ...
317285  WB916002  Ms. Mousumi Chattaraj Chaudhuri     West Bengal
317286  WB916002  Ms. Mousumi Chattaraj Chaudhuri     West Bengal
317287  WB94A301         Shri Sumanta Kumar Ghosh     West Bengal
317288  WB94A301         Shri Sumanta Kumar Ghosh     West Bengal
317289  WB94A302     Shri Rajsekhar Bandyopadhyay     West Bengal

        Allotment_Year Date_of_Birth Date_of_Joining Source_of_Recruitment  \
0                 1953    27-02-1930      1953-07-01    Direct Recruitment
1                 1953    27-02-1930      1953-07-01    Direct Recruitment
```

```
2                1953    27-02-1930      1953-07-01    Direct Recruitment
3                1953    27-02-1930      1953-07-01    Direct Recruitment
4                1953    27-02-1930      1953-07-01    Direct Recruitment
...               ...           ...             ...                   ...
317285           2008    19-08-1966      2018-02-08          By Selection
317286           2008    19-08-1966      2018-02-08          By Selection
317287           2005    23-12-1962      2016-02-03          By Selection
317288           2005    23-12-1962      2016-02-03          By Selection
317289           2005    14-03-1962      2016-02-03          By Selection

        Gender Place_of_Domicile Mother_Tongue  ... Reference_Value_y  \
0       Female           Gujarat      Gujarati  ...               0.0
1       Female           Gujarat      Gujarati  ...               1.0
2       Female           Gujarat      Gujarati  ...               2.0
3       Female           Gujarat      Gujarati  ...               3.0
4       Female           Gujarat      Gujarati  ...               4.0
...        ...               ...           ...  ...               ...
317285  Female                 -             -  ...               0.0
317286  Female                 -             -  ...               1.0
317287    Male                 -             -  ...               0.0
317288    Male                 -             -  ...               1.0
317289    Male                 -             -  ...               0.0

              Designation            Level  \
0               Secretary        Secretary
1                Chairman        Secretary
2              Chief Secy        Secretary
3              Chief Secy        Secretary
4               Secretary        Secretary
...                   ...              ...
317285  Managing Director  Deputy Secretary
317286           Director  Deputy Secretary
317287    Additional Secy     Not Available
317288    Joint Secretary     Not Available
317289    Joint Secretary     Not Available

                                               Office Organisation  \
0       M/o Personnel, Public Grievances & Pensions       Centre
1                                              NaN  Cadre (AIS)
2                                              NaN  Cadre (AIS)
3                                              NaN  Cadre (AIS)
4                                D/o Rehabilitation       Centre
...                                            ...          ...
317285                W.B. Financial Corpn (WBFC)  Cadre (AIS)
317286                              Small Savings  Cadre (AIS)
317287                               Public Works  Cadre (AIS)
317288                               Public Works  Cadre (AIS)
317289                                        NaN  Cadre (AIS)

           Field_of_Experience                Category_of_Experience  \
0          Personnel Training  Personnel and General Administration
1              Personnel Mgmt  Personnel and General Administration
2       General Administration  Personnel and General Administration
3       General Administration  Personnel and General Administration
4              Rehabilitation                                  Home
...                        ...                                   ...
317285                 Finance                               Finance
317286                 Finance                               Finance
317287            Public Works                          Public Works
317288            Public Works                          Public Works
317289                 Finance                               Finance

        Start_Date    End_Date Source_y
0       1986-07-01  1988-02-01  Supremo
1       1986-01-01  1986-07-01  Supremo
2       1985-07-01  1986-01-01  Supremo
3       1983-08-01  1985-07-01  Supremo
4       1983-05-01  1983-08-01  Supremo
...            ...         ...      ...
317285  2019-04-01        N.A.  Supremo
317286  2018-02-08  2019-03-31  Supremo
317287  2018-01-02        N.A.  Supremo
317288  2016-02-16  2018-01-01  Supremo
317289  2016-02-16        N.A.  Supremo

[317290 rows x 43 columns]
```

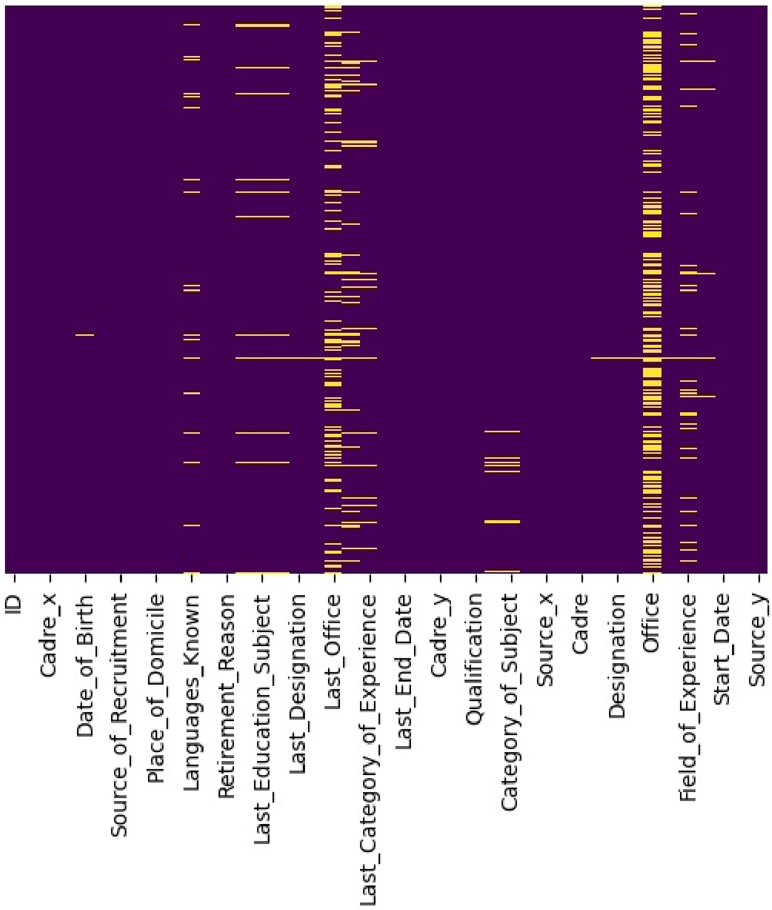
In [11]:

```
dff.isnull().sum()
```

Out[11]:
```
ID                                0
Name_x                            0
Cadre_x                           0
Allotment_Year                    0
Date_of_Birth                   218
Date_of_Joining                   0
Source_of_Recruitment             0
Gender                            0
Place_of_Domicile                 0
Mother_Tongue                     0
Languages_Known               11256
Retired                           0
Retirement_Reason                 0
Last_Education_Qualification   8228
Last_Education_Subject         8228
Last_Education_Division        8228
Last_Designation               1029
Last_Level                     1029
Last_Office                   77903
Last_Field_of_Experience      30666
Last_Category_of_Experience   13602
Last_Start_Date                   0
Last_End_Date                     0
Name_y                            0
Cadre_y                           0
Reference_Value_x                 0
Qualification                    30
Subject                        8020
Category_of_Subject            8020
Division                          0
Source_x                          0
Name                              0
Cadre                             0
Reference_Value_y               136
Designation                     136
Level                           138
Office                       140257
Organisation                    138
Field_of_Experience           22892
Category_of_Experience         4969
Start_Date                        0
End_Date                          0
Source_y                          0
dtype: int64
```

In [12]:
```python
sns.heatmap(dff.isnull(), yticklabels=False, cbar =False, cmap="viridis" )
```

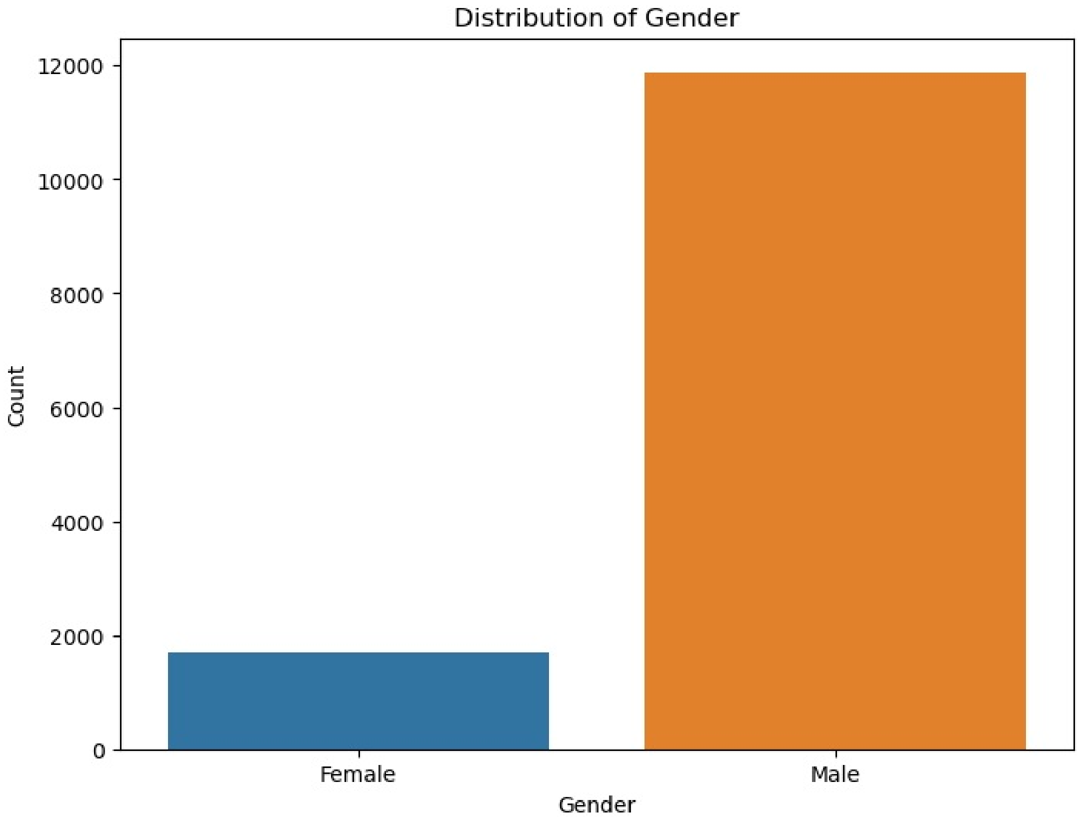
Out[12]:
```
<AxesSubplot:>
```



The heatmap I've created shows where there are missing values in your data. Each square represents a value in your dataset. If the square is dark, it means that value is missing. Light squares have data. This helps you see where you might be missing information at a glance.

** Male Female Ratio

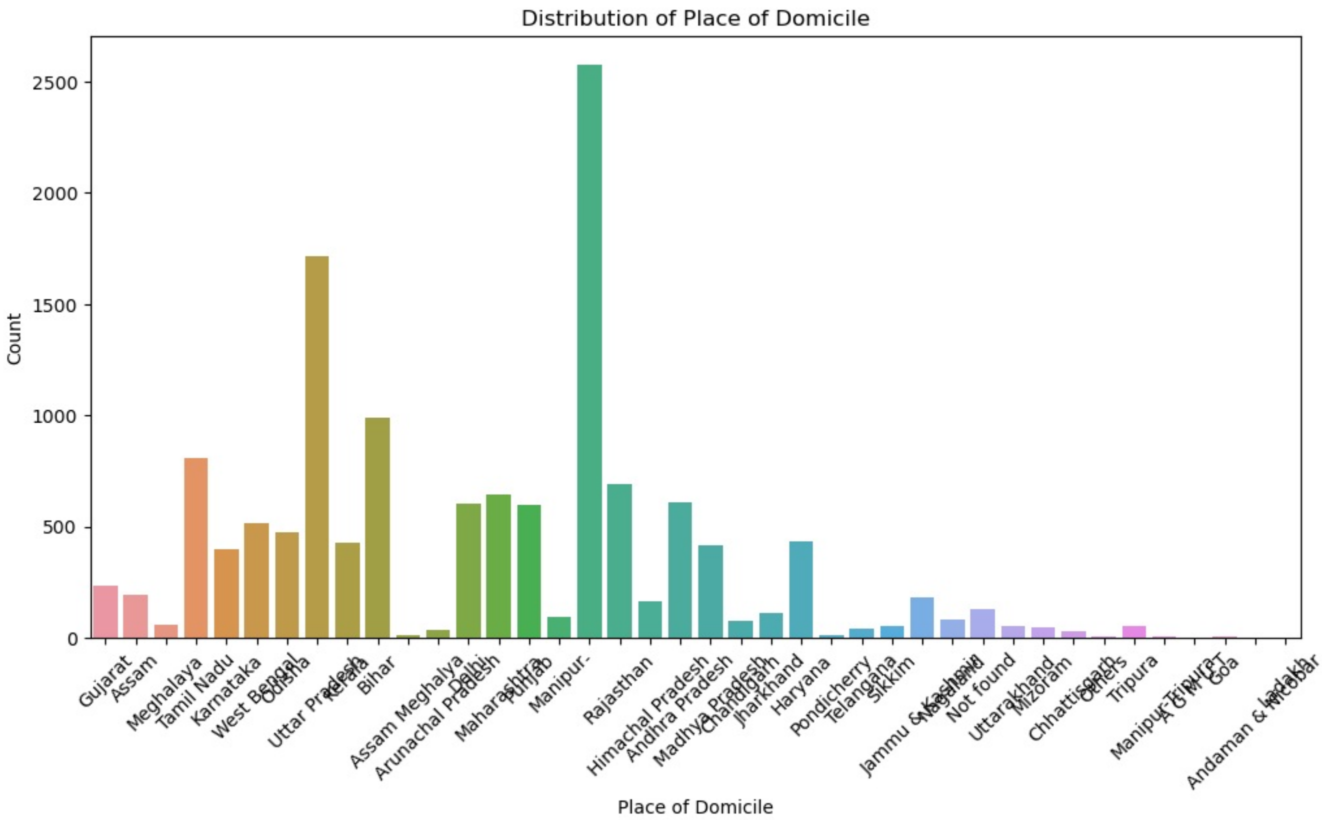
In [13]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x='Gender', data=df)
plt.xlabel('Gender')
plt.ylabel('Count')
plt.title('Distribution of Gender')
plt.show()
```



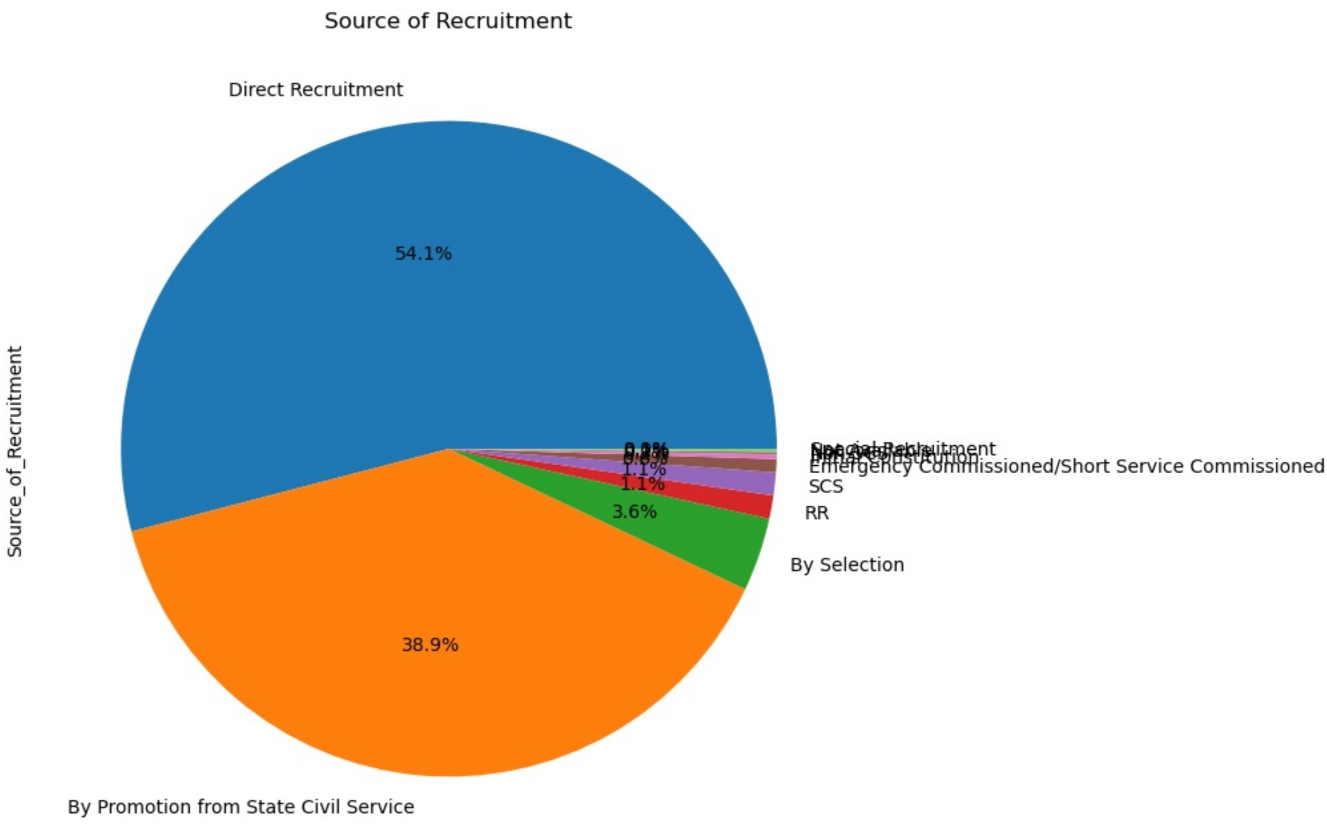
This chart is a bar chart that displays the distribution of genders in your dataset. It's a simple way to see how many individuals are classified as male and how many as female. The x-axis shows the genders, while the y-axis indicates the count of individuals.

**Domecile Count

In [14]:
```
plt.figure(figsize=(12, 6))
sns.countplot(x='Place_of_Domicile', data=df)
plt.xlabel('Place of Domicile')
plt.ylabel('Count')
plt.title('Distribution of Place of Domicile')
plt.xticks(rotation=45)
plt.show()
```



In [15]:
```
plt.figure(figsize=(8, 8))
df['Source_of_Recruitment'].value_counts().plot.pie(autopct='%1.1f%%')
plt.title('Source of Recruitment')
plt.show()
```



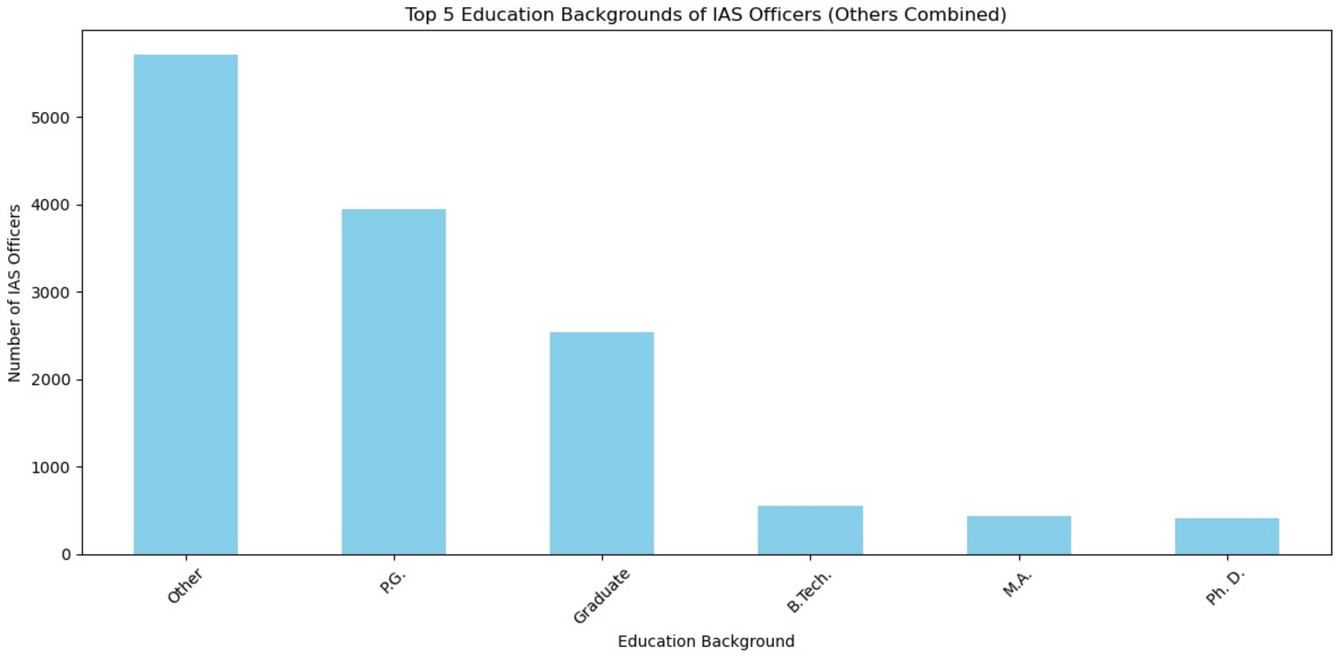
The chart above generated is a pie chart that illustrates the distribution of different sources of recruitment within your dataset. It offers a visual representation of how individuals were recruited. Each slice of the pie corresponds to a recruitment source, and the size of the slice reflects the proportion of individuals recruited from that source. The percentage labels on the chart show the relative distribution of each source. This chart helps quickly understand the relative importance of different recruitment sources in your dataset.

** Education baground count

In [16]:
```
top_education_counts = df['Last_Education_Qualification'].value_counts().head(5)
```

In [17]:
```
df['Top_Education'] = df['Last_Education_Qualification'].apply(
    lambda x: x if x in top_education_counts.index else 'Other'
)
```

In [18]:
```
plt.figure(figsize=(12, 6))
df['Top_Education'].value_counts().plot(kind='bar', color='skyblue')
plt.xlabel('Education Background')
plt.ylabel('Number of IAS Officers')
plt.title('Top 5 Education Backgrounds of IAS Officers (Others Combined)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

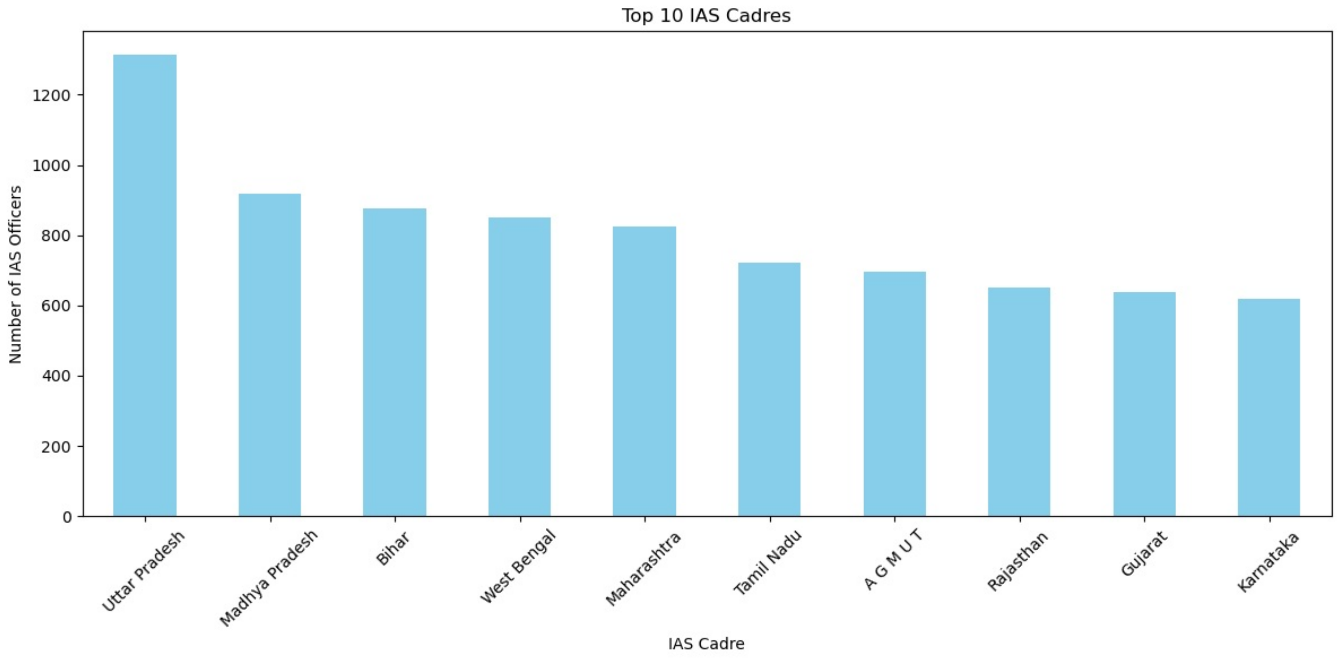


In the project, a chart has been constructed to depict the primary education backgrounds of IAS officers, focusing on the top 5 qualifications. To simplify the representation, education backgrounds that are less frequently encountered have been grouped under the category "Other."

In this chart, each vertical bar corresponds to a distinct education qualification. The height of the bar indicates the quantity of IAS officers who possess that specific qualification. This visual aids in promptly recognizing the prevailing education backgrounds within the IAS officer group. Furthermore, the "Other" category offers a consolidated perspective of less common qualifications. This chart contributes to a comprehensive understanding of the education landscape among IAS officers.

** Cadre wise

In [21]:
```
top_cadre_counts = df['Cadre'].value_counts().head(10)


plt.figure(figsize=(12, 6))
top_cadre_counts.plot(kind='bar', color='skyblue')
plt.xlabel('IAS Cadre')
plt.ylabel('Number of IAS Officers')
plt.title('Top 10 IAS Cadres')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

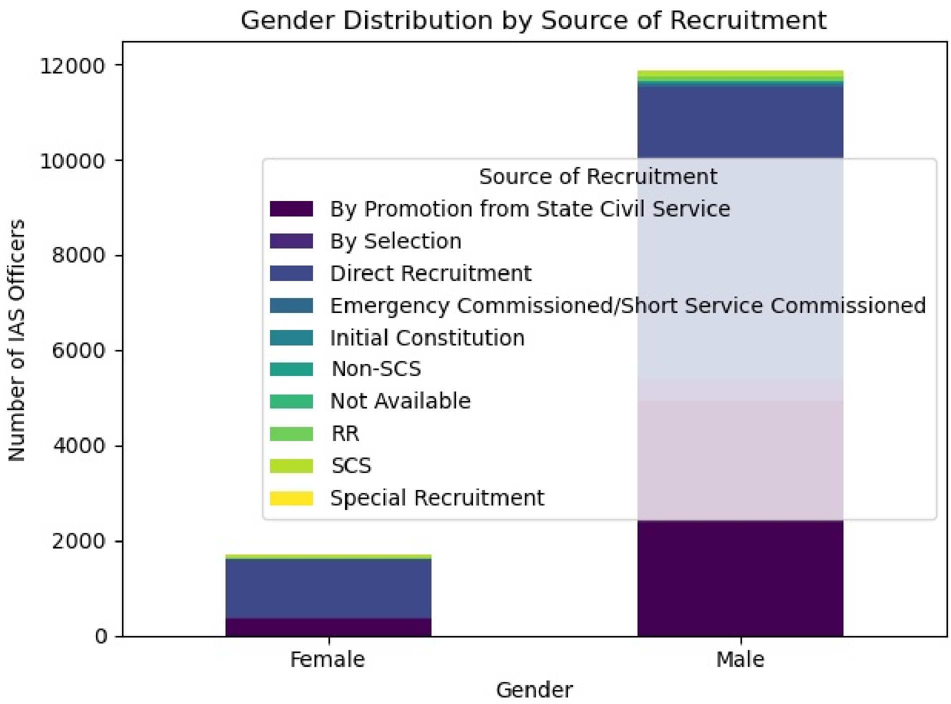


The chart presented displays the top 10 IAS cadres based on their respective counts. Each vertical bar corresponds to a specific IAS cadre, and the height of the bar directly indicates the number of IAS officers within that cadre. This visual representation enables a quick identification of the most prominent IAS cadres, promoting a concise understanding of their distribution. The labels on the x-axis are rotated for enhanced clarity. This chart contributes to a comprehensive overview of the distribution of IAS officers across various cadres.

**Stacked Bar Chart of Gender by Source of Recruitment

In [24]:
```
pivot_table = pd.pivot_table(df, index='Gender', columns='Source_of_Recruitment', values='ID', aggfunc='count',


plt.figure(figsize=(10, 6))
pivot_table.plot(kind='bar', stacked=True, colormap='viridis')
plt.xlabel('Gender')
plt.ylabel('Number of IAS Officers')
plt.title('Gender Distribution by Source of Recruitment')
plt.legend(title='Source of Recruitment')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```

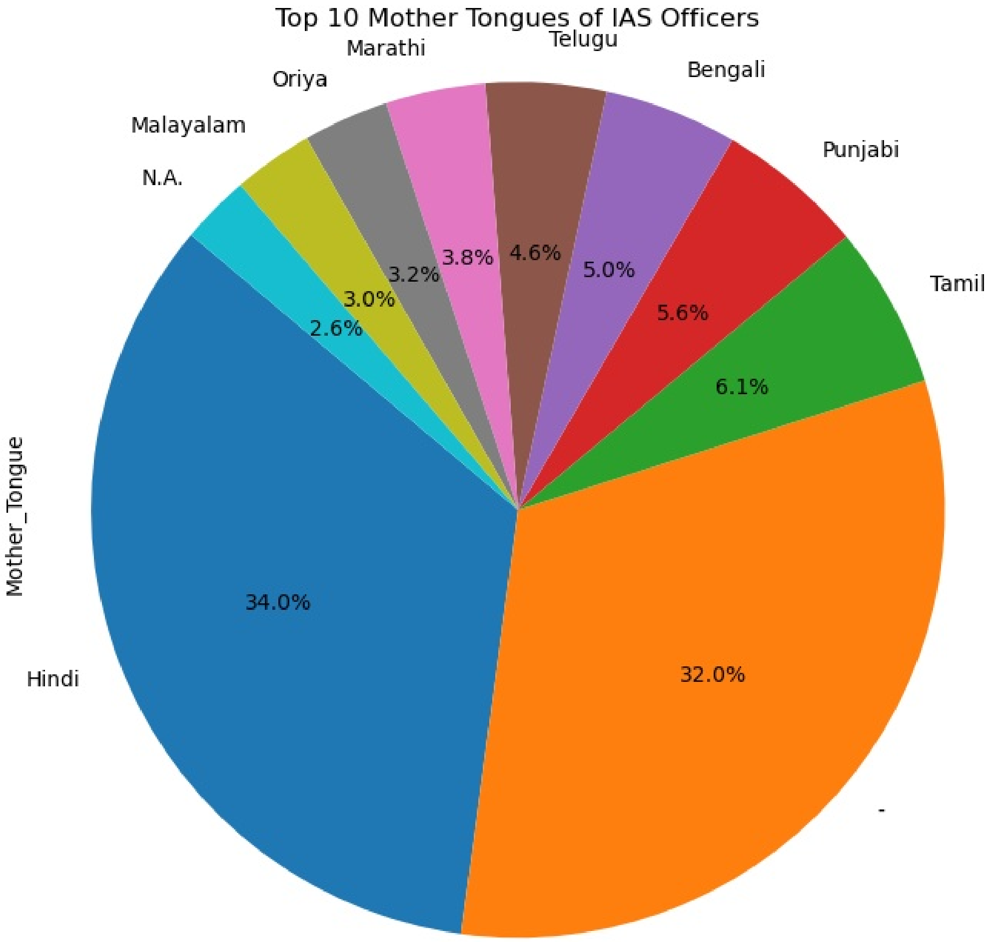


The chart generated illustrates the distribution of IAS officers by gender and their sources of recruitment. Each set of bars represents a specific recruitment source, and the bars are further divided by gender, showcasing the count of IAS officers. The "stacked" presentation highlights the gender distribution within each source.

For instance, within each recruitment source category, the two segments of each bar signify the count of male and female officers. The colormap enhances clarity in discerning the different sources. Labels along the x-axis represent gender, while the y-axis indicates the number of IAS officers. By examining this chart, you can swiftly comprehend the distribution of officers based on both gender and recruitment source, aiding insights into gender representation across various sources of recruitment.

**distribution of mother tongues

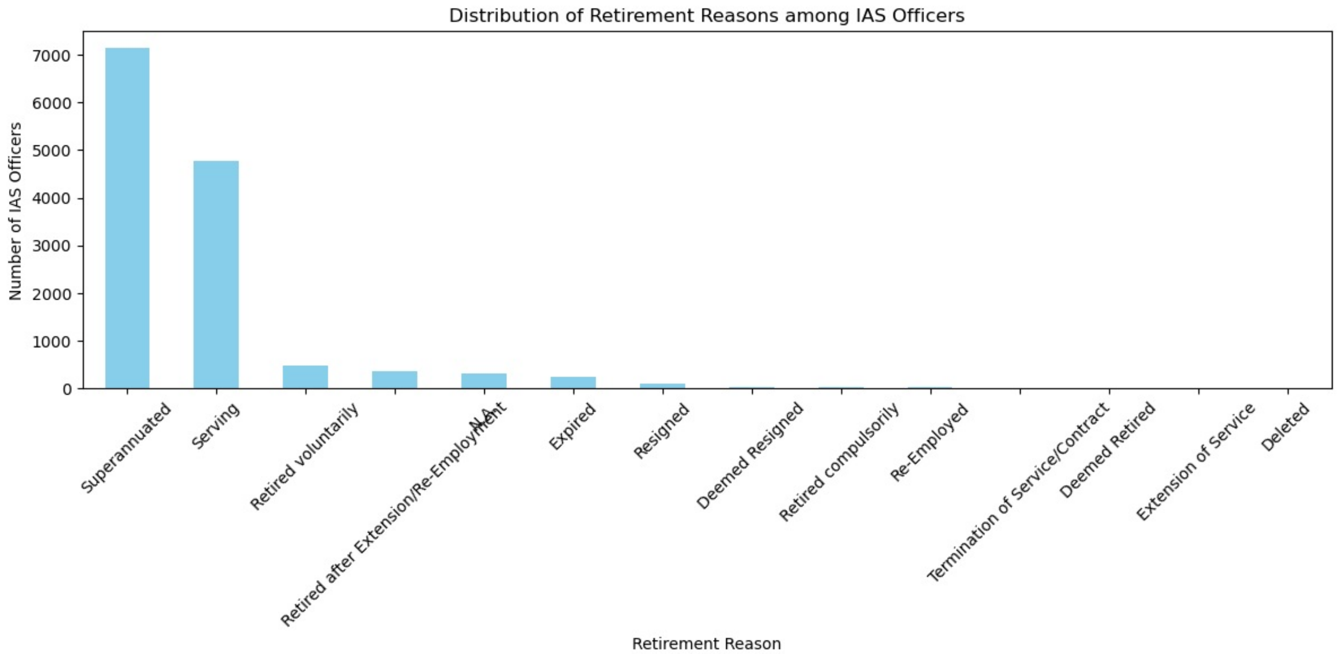
In [33]:
```
top_languages = df['Mother_Tongue'].value_counts().head(10)

plt.figure(figsize=(8, 8))
top_languages.plot.pie(autopct='%1.1f%%', startangle=140)
plt.title('Top 10 Mother Tongues of IAS Officers')
plt.axis('equal')  # Equal aspect ratio ensures that the pie chart is circular.
plt.show()
```



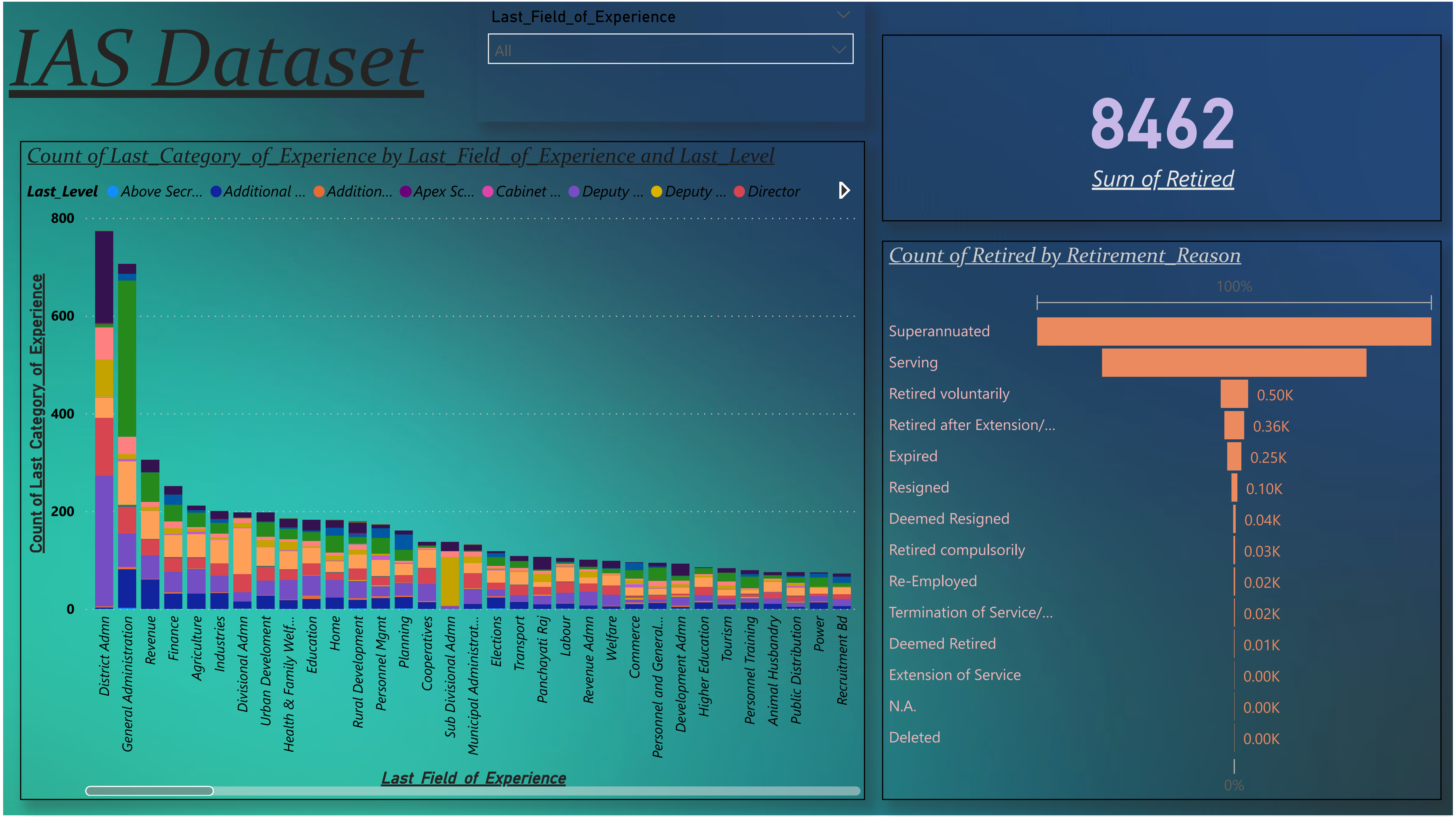
The chart represents the top 10 mother tongues of IAS officers. Each slice of the pie corresponds to a specific mother tongue, and its size indicates the proportion of IAS officers from that linguistic background. The percentages shown on the chart highlight the relative distribution of mother tongues. This visual quickly conveys the prevalent mother tongue diversity among IAS officers.

** IAS Officer Retirement Reason

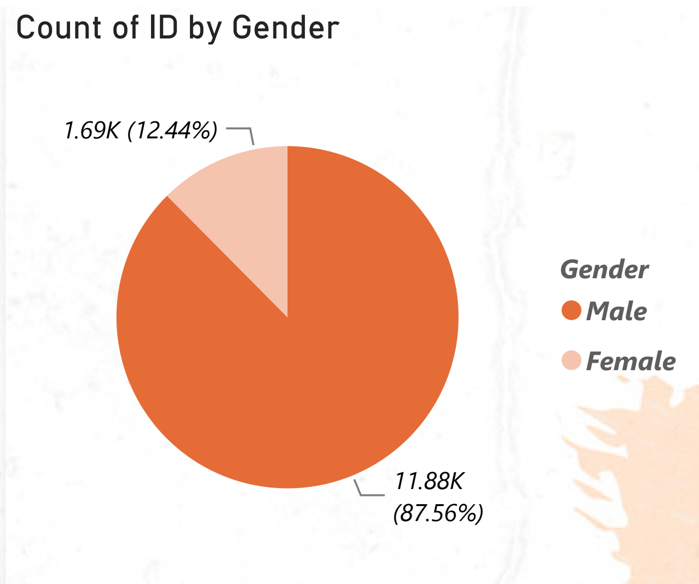
In [35]:
```
plt.figure(figsize=(12, 6))
df['Retirement_Reason'].value_counts().plot(kind='bar', color='skyblue')
plt.xlabel('Retirement Reason')
plt.ylabel('Number of IAS Officers')
plt.title('Distribution of Retirement Reasons among IAS Officers')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



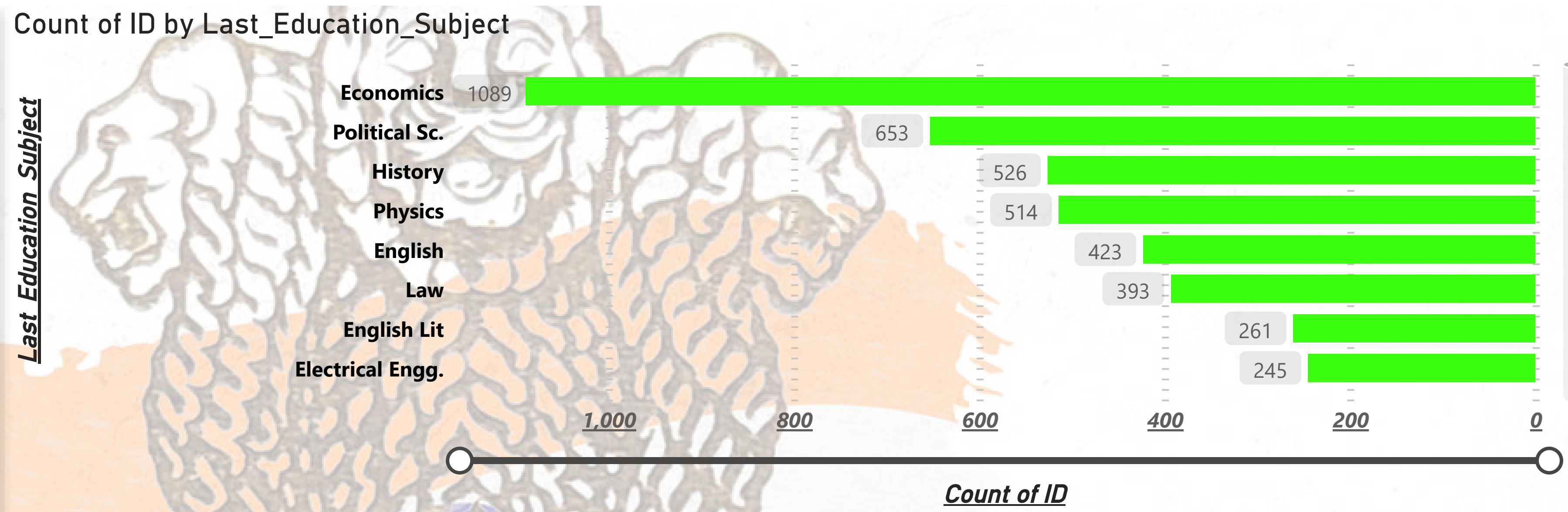
The chart showcases the distribution of retirement reasons among IAS officers. Each vertical bar corresponds to a specific retirement reason, and the height of the bar indicates the number of IAS officers who retired for that reason. This visual aids in understanding the varied reasons leading to retirement among IAS officers. Labels on the x-axis provide insight into the specific retirement categories, while the y-axis depicts the count of officers. This chart contributes to a comprehensive overview of the retirement landscape within the IAS officer community.



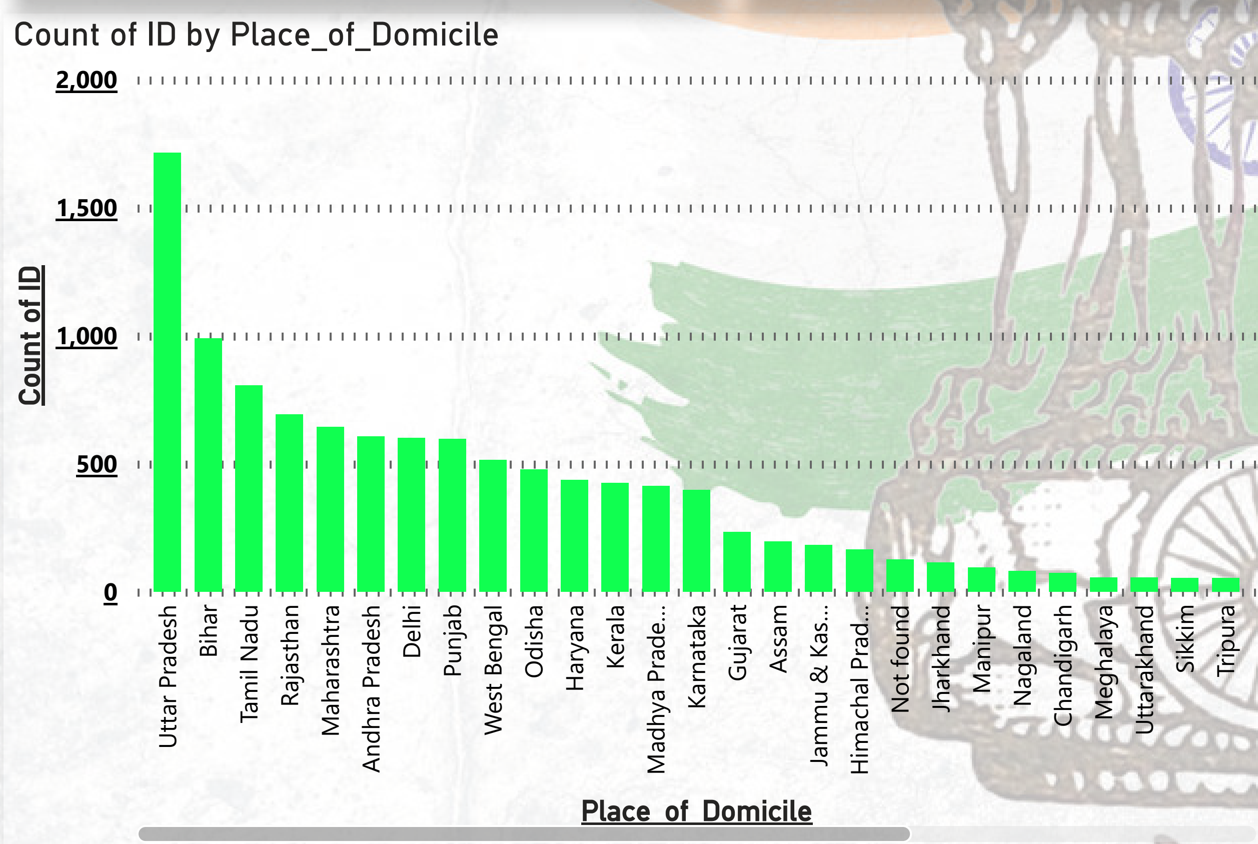
IAS Dataset
Last_Field_of_Experience
All
8462
Sum of Retired
Count of Last_Category_of_Experience by Last_Field_of_Experience and Last_Level
Last_Level
Above Secr...
Additional ...
Addition...
Apex Sc...
Cabinet ...
Deputy ...
Deputy ...
Director
800
600
400
200
0
Count of Last_Category_of_Experience
District Admn
General Administration
Revenue
Finance
Agriculture
Industries
Divisional Admn
Urban Develoment
Health & Family Welf...
Education
Home
Rural Development
Personnel Mgmt
Planning
Cooperatives
Sub Divisional Admn
Municipal Administrat...
Elections
Transport
Panchayati Raj
Labour
Revenue Admn
Welfare
Commerce
Personnel and General...
Development Admn
Higher Education
Tourism
Personnel Training
Animal Husbandry
Public Distribution
Power
Recruitment Bd
Last_Field_of_Experience
Count of Retired by Retirement_Reason
100%
Superannuated
Serving
Retired voluntarily
0.50K
Retired after Extension/...
0.36K
Expired
0.25K
Resigned
0.10K
Deemed Resigned
0.04K
Retired compulsorily
0.03K
Re-Employed
0.02K
Termination of Service/...
0.02K
Deemed Retired
0.01K
Extension of Service
0.00K
N.A.
0.00K
Deleted
0.00K
0%



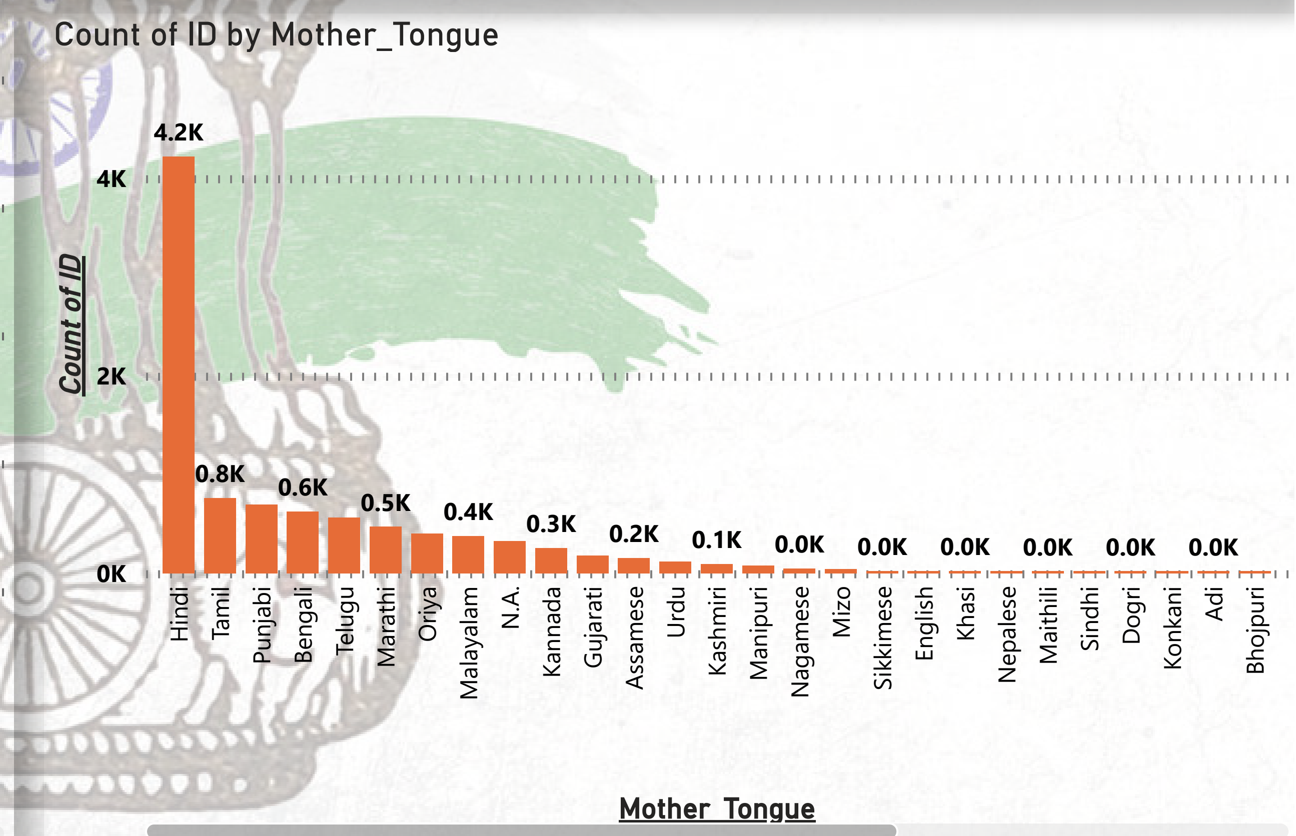
Count of ID by Gender
1.69K (12.44%)
11.88K (87.56%)
Gender
Male
Female



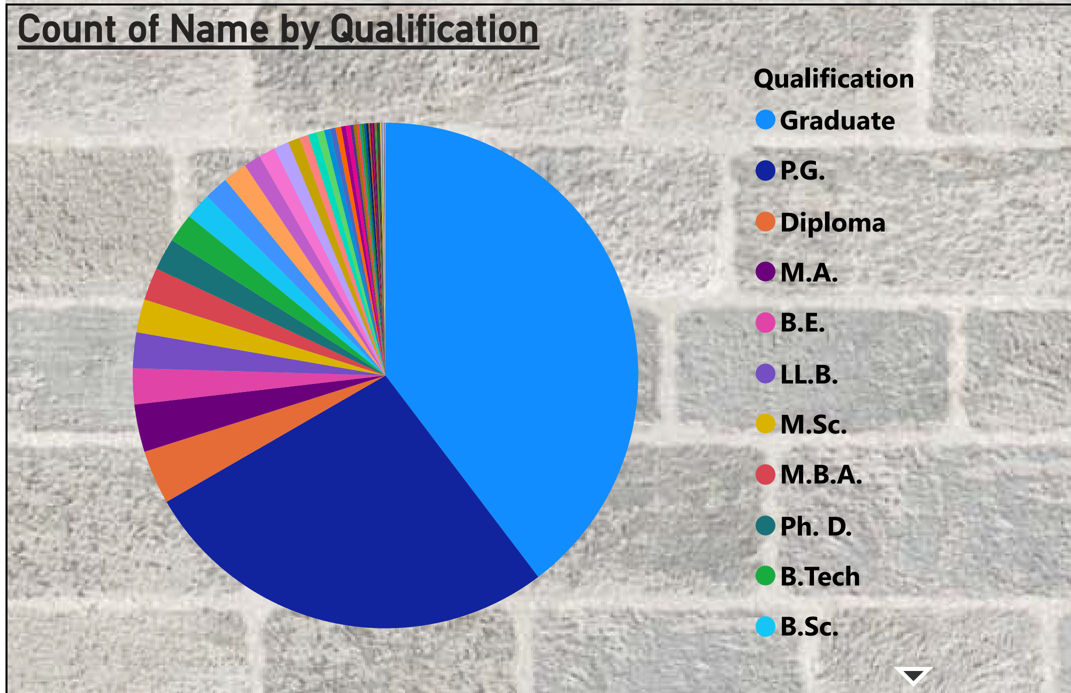
Count of ID by Last_Education_Subject
Last_Education_Subject
Economics 1089
Political Sc. 653
History 526
Physics 514
English 423
Law 393
English Lit 261
Electrical Engg. 245
1,000
800
600
400
200
0
Count of ID

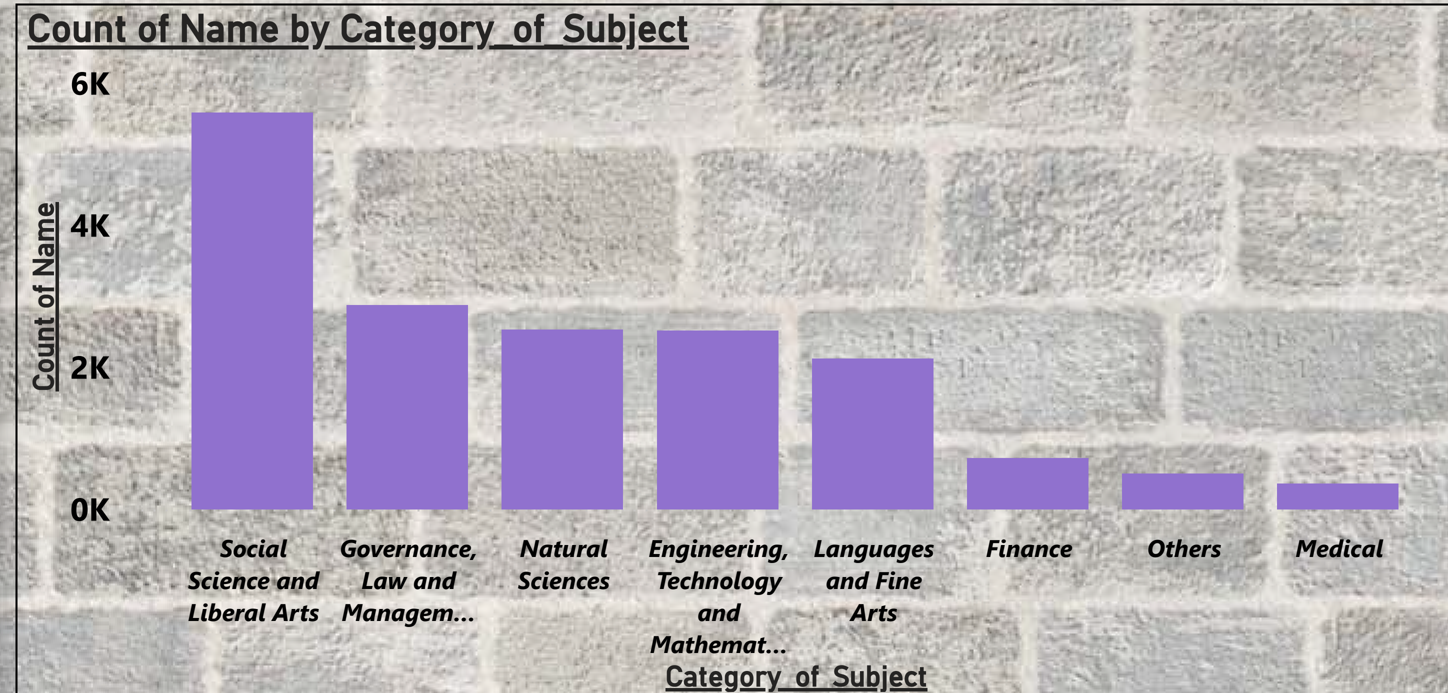


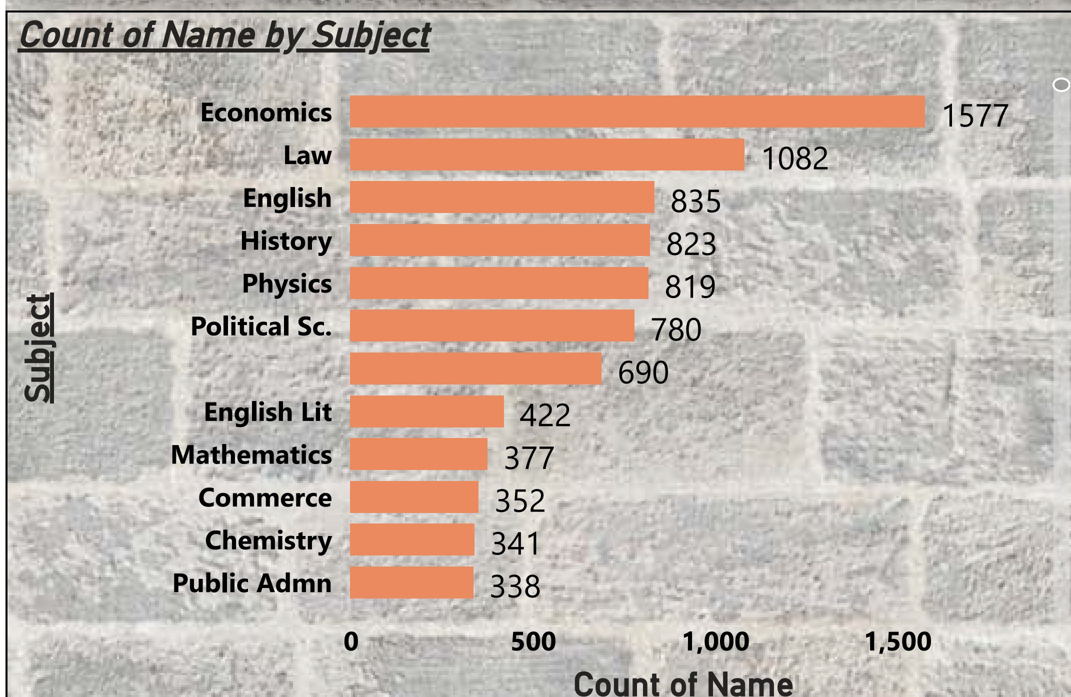
Count of ID by Place_of_Domicile
2,000
1,500
1,000
500
0
Count of ID
Uttar Pradesh
Bihar
Tamil Nadu
Rajasthan
Maharashtra
Andhra Pradesh
Delhi
Punjab
West Bengal
Odisha
Haryana
Kerala
Madhya Prade...
Karnataka
Gujarat
Assam
Jammu & Kas...
Himachal Prad...
Not found
Jharkhand
Manipur
Nagaland
Chandigarh
Meghalaya
Uttarakhand
Sikkim
Tripura
Place_of_Domicile



Count of ID by Mother_Tongue
4.2K
4K
2K
0K
Count of ID
0.8K
0.6K
0.5K
0.4K
0.3K
0.2K
0.1K
0.0K
0.0K
0.0K
0.0K
0.0K
0.0K
Hindi
Tamil
Punjabi
Bengali
Telugu
Marathi
Oriya
Malayalam
N.A.
Kannada
Gujarati
Assamese
Urdu
Kashmiri
Manipuri
Nagamese
Mizo
Sikkimese
English
Khasi
Nepalese
Maithili
Sindhi
Dogri
Konkani
Adi
Bhojpuri
Mother_Tongue



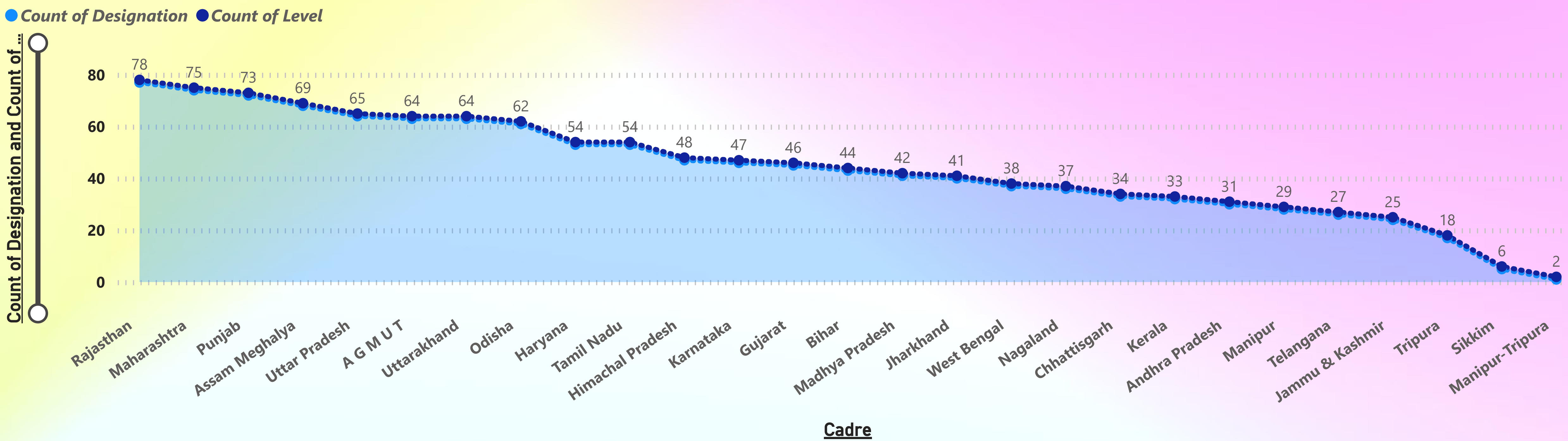




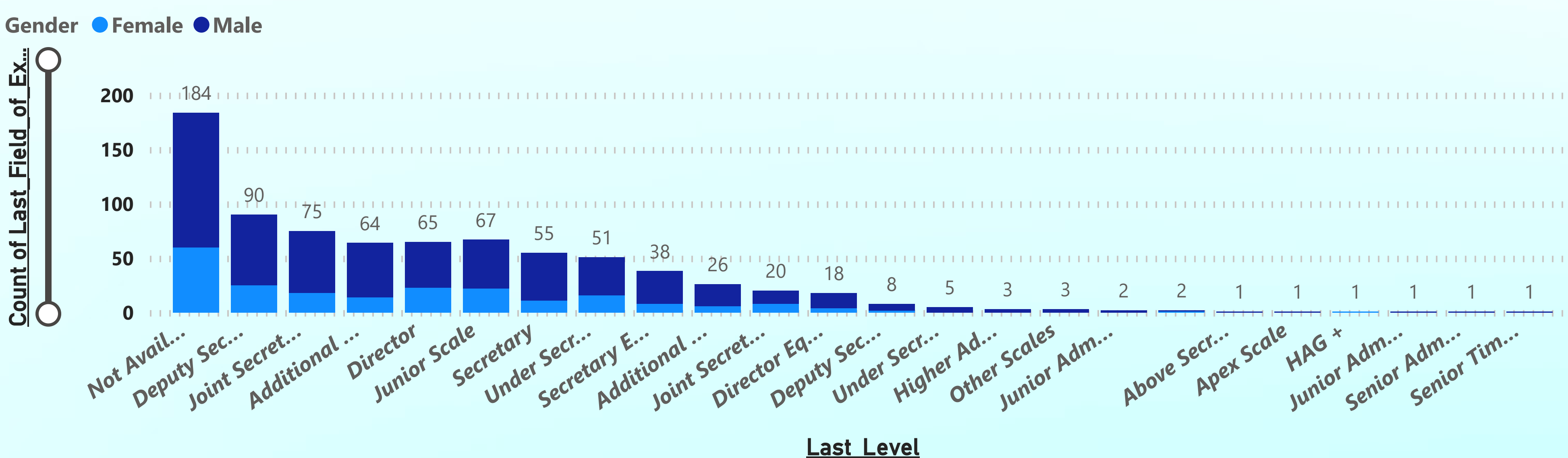
As per observation from above table we can assume that candidates who have done graduation from various streams have majorly serving the country as a civil servant followed by post graduate holders and MA qualified. In another graph (Clustered Bar Chart) we can say most of the civile servant are from economics, law, english and history background with their major subject.

In another Stacked column chart top three history of background subjects of candidates are Social science and liberal arts, governance science and natural science followed by engineering technology and mathematics.

Count of Designation and Count of Level by Cadre



Count of Last_Field_of_Experience by Last_Level and Gender



Level, Field_of_Experience

- [ ]
- [ ] Above Secretary Level
- [ ] Additional Secretary
- [ ] Additional Secretary Equ...
- [ ] Apex Scale
- [ ] Cabinet Secretary
- [ ] Deputy Secretary
- [ ] Deputy Secretary Equival...
- [ ] Director
- [ ] Director Equivalent