DAV REPORT: DEVELOPER ANALYSIS

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SEMESTER-V

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ACKNOWLEDGEMENT

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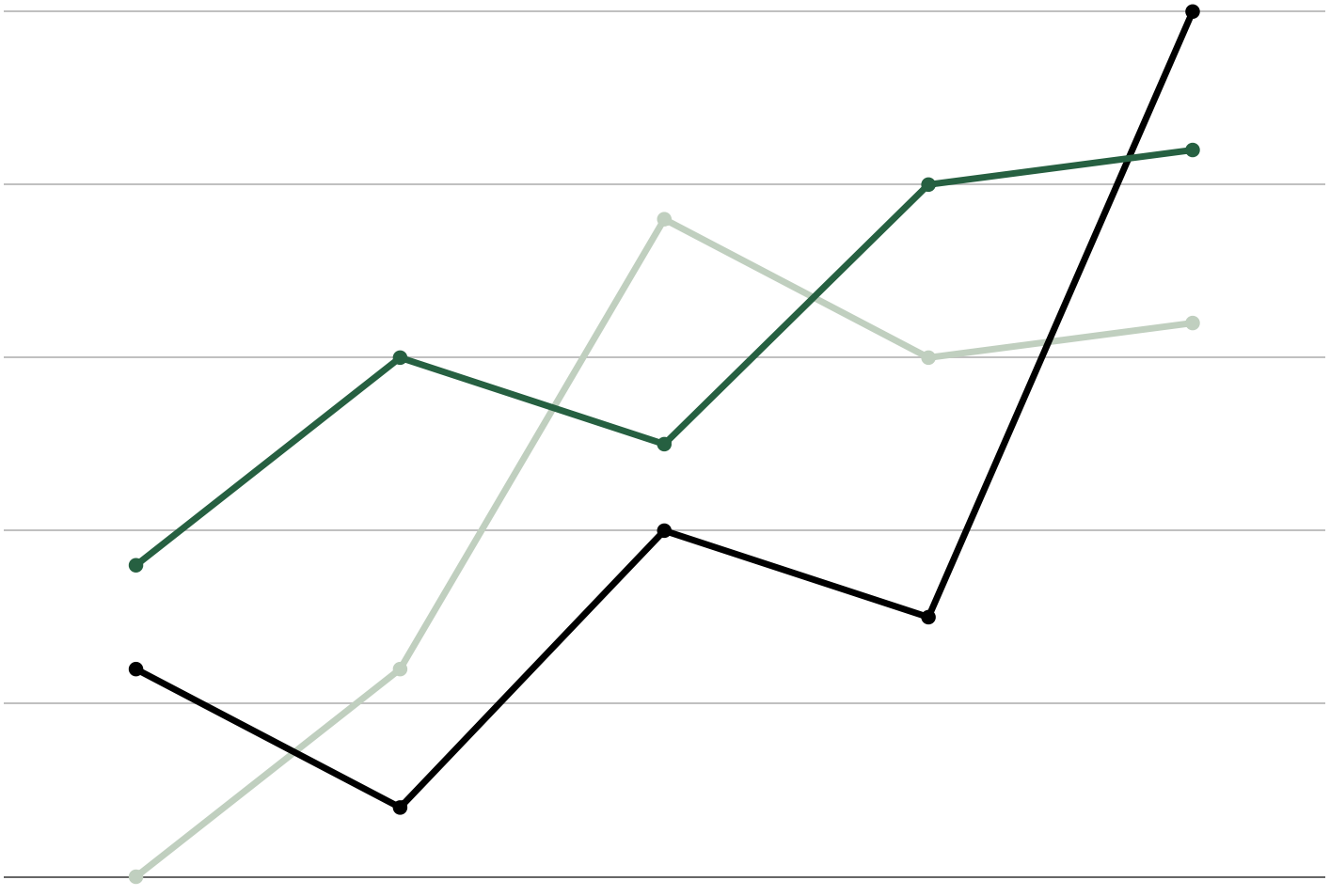
We would also like to extend our gratitude to our College Principal **Dr. Madhu Pruthi** wholeheartedly, for providing us the facility that was required.



Preface

This report has been prepared as part our Data Analysis and Visualization project, part of BSc. Computer Science Hons Semester V. This report is prepared with the view to include all the details regarding the project that we have carried out.

The initial portion is the overview of the Project. The dataset taken in consideration is about the Developers on Stackoverflow. This report includes the analysis of different columns. Analysis includes ,'How Years Coded Job affects Developers' Salary, Job Satisfaction, Career Satisfaction etc. Also it includes which language is the most popular one worldwide as well as in India.

In this project, We have plotted different types of graphs using multiple libraries in Python for ease of understanding. Thus, as you go ahead, the report will reveal minute details of the work that we have done in our project.

Github Repository Link :https://github.com/g-4-gagan/Developer-data-analysis

Overview

The Developer Analysis Dataset originally named as “Stack Overflow Survey” has been taken from Kaggle. The dataset informs us about developers' qualifications, the country in which they reside, their specialization, in their satisfaction in careers and jobs and salaries in their respective fields. The dataset also describes the developers’ favorite databases, programming languages, and IDE.

This dataset gives us insight into whether the country they belong to plays a significant role in their satisfaction of jobs and opportunities. The dataset informs us about how important are skills such as adapting to newer technology, problem-solving and proper education for propelling into a career of a developer.

Dimensions

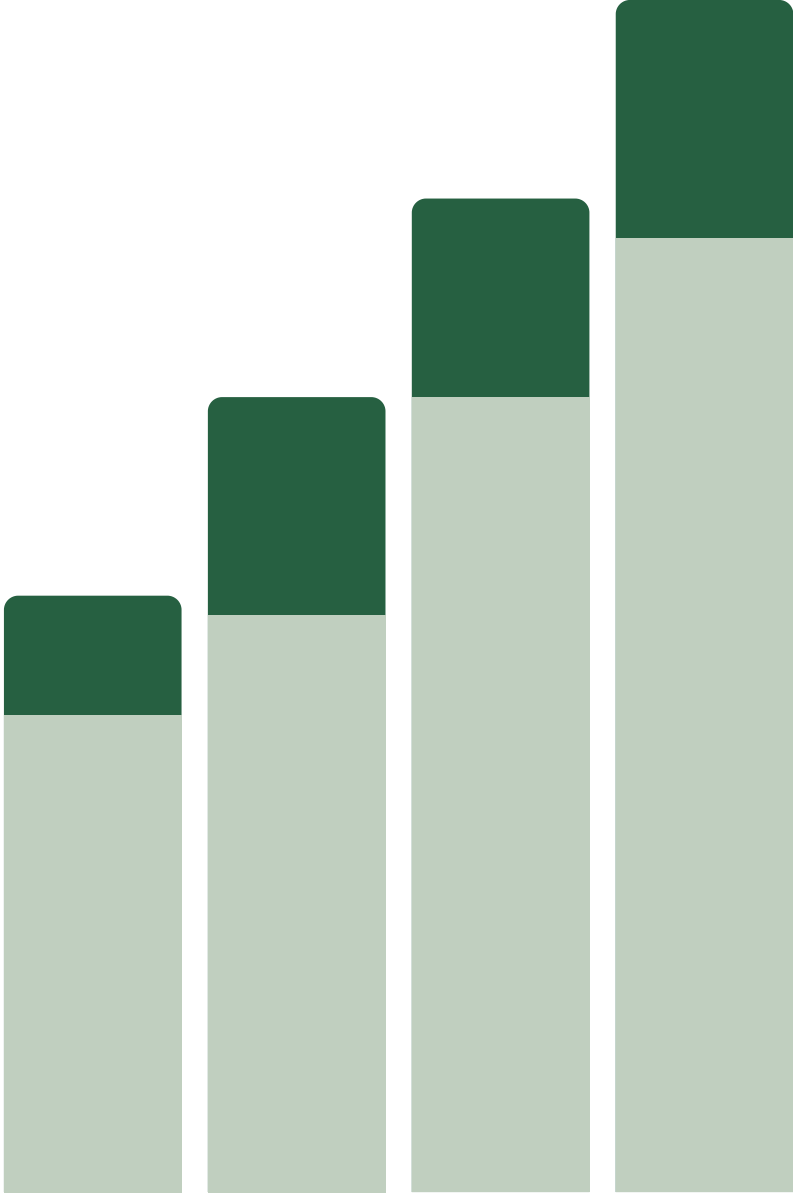
51392 Rows X 54 Columns

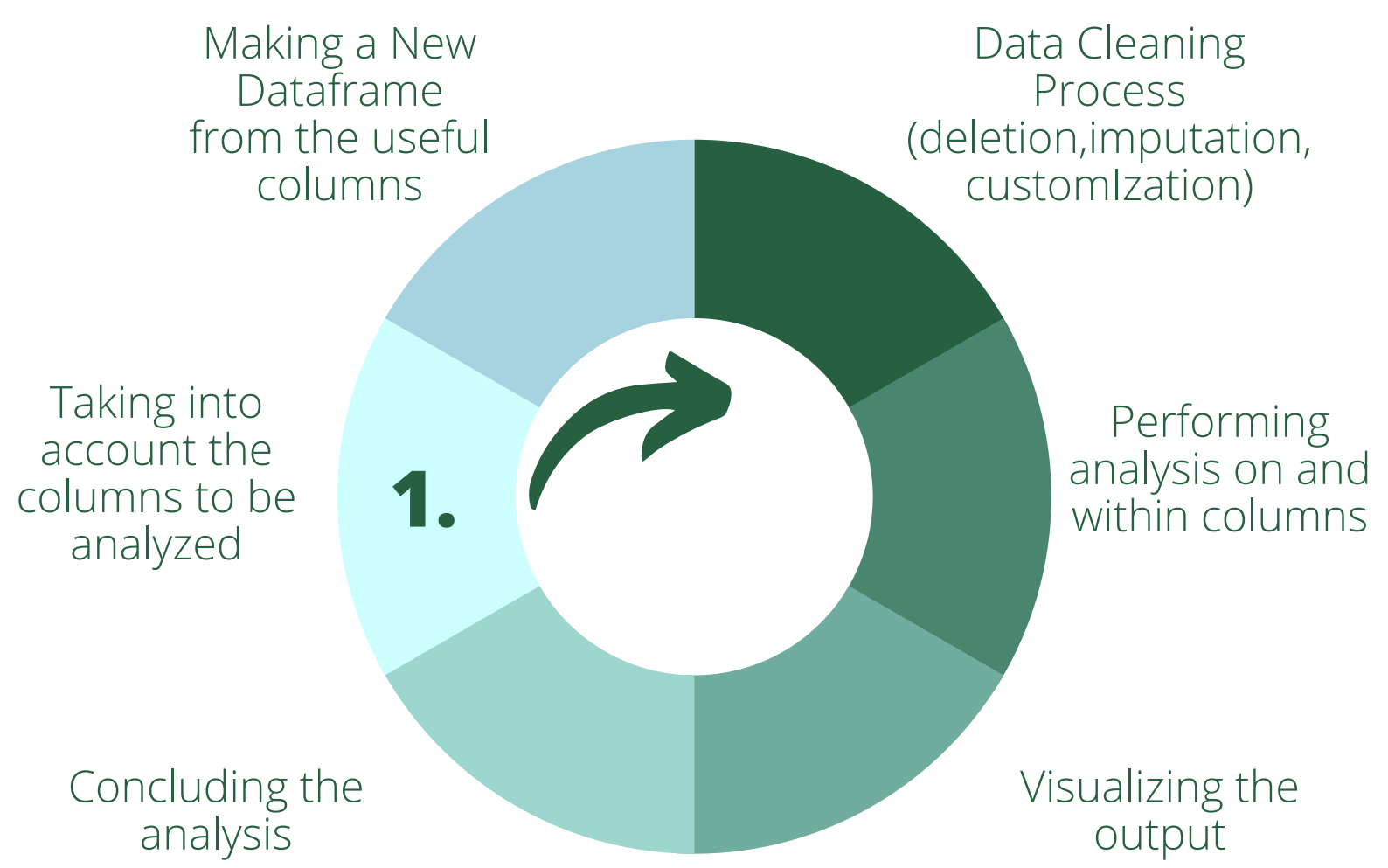
Problem statement

To find the average salaries for developers, based on different programming languages, databases etc. that they have studied and form a relationship between their qualifications, specializations and current jobs with respect to their current salaries

vision

To create a tool for people to help them find the most relatable programming language based on the languages already studied by them





Insights.

Taken From	Kaggle
Language	Python
Software	Jupyter Notebook
Libraries	1. Numpy 2. Pandas 3. Matplotlib 4. Seaborn 5. Plotly

Columns

Respondent
Professional
ProgramHobby
Country
University
EmploymentStatus
FormalEducation
MajorUndergrad
YearsCodedJob
DeveloperType
NonDeveloperType
CareerSatisfaction
JobSatisfaction
ProblemSolving
LearningNewTech
JobSecurity
DiversityImportant
SeriousWork
WorkPayCare
ChallengeMyself

LastNewJob
Assess_Scoring
ImportantBenefits
JobProfile
LearnedHiring
Overpaid
EducationImportant
EducationTypes
WorkStart
HaveWorkedLanguage
WantWorkLanguage
HaveWorkedDatabase
WantWorkDatabase
HaveWorkedPlatform
WantWorkPlatform
IDE
Gender
Auditory Environment
HighestEducationParents
Salary
ExpectedSalary

AssessJobIndustry
AssessJobRole
AssessJobExp
AssessJobDept
AssessJobTech
AssessJobProjects
AssessJobCompensation
AssessJobOffice
AssessJobCommute
AssessJobRemote
AssessJobProfDevel
AssessJobDiversity
AssessJobProduct
AssessJobFinances

A Glance at the Dataset

Respondent	Professional	ProgramHobby	Country	University	EmploymentStatus	FormalEducation	MajorUndergrad	YearsCodedJob	DeveloperType	NonDeveloperType
1	Student	Yes, both	United States	No	Not employed, and not looking for work	Secondary school	NaN	NaN	NaN	.
2	Student	Yes, both	United Kingdom	Yes, full-time	Employed part-time	Some college/university study without earning ...	Computer science or software engineering	NaN	NaN	NaN
3	Professional developer	Yes, both	United Kingdom	No	Employed full-time	Bachelor's degree	Computer science or software engineering	20 or more years	Other	NaN

CareerSatisfaction	JobSatisfaction	ProblemSolving	LearningNewTech	JobSecurity	DiversityImportant	SeriousWork	WorkPayCare	ChallengeMyself	LastNewJob
NaN	NaN	Strongly agree	Agree	Strongly agree	Agree	Strongly agree	Strongly disagree	Agree	Not applicable/ never
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
8.0	9.0	Strongly agree	Strongly agree	Agree	Strongly agree	Agree	Disagree	Agree	NaN

ImportantBenefits	JobProfile	LearnedHiring	Overpaid	EducationImportant	EducationTypes	WorkStart	HaveWorkedLanguage	WantWorkLanguage	HaveWorkedDatabase
Stock options; Vacation/days off; Remote options	Other	NaN	NaN	NaN	Online course; Open source contributions	6:00 AM	Swift	Swift	NaN
NaN	Other	Some other way	NaN	NaN	Online course; Self-taught; Hackathon; Open so...	10:00 AM	JavaScript; Python; Ruby; SQL	Java; Python; Ruby; SQL	MySQL; SQLite
NaN	NaN	NaN	Neither underpaid nor overpaid	Not very important	Self-taught; Coding competition; Hackathon; Op...	9:00 AM	Java; PHP; Python	C; Python; Rust	MySQL

WantWorkDatabase	HaveWorkedPlatform	WantWorkPlatform	IDE	AuditoryEnvironment	Gender	HighestEducationParents	Salary	ExpectedSalary	Access_Scorin
NaN	iOS	iOS	Atom; Xcode	Turn on some music	Male	High school	NaN	NaN	30.
MySQL; SQLite	Amazon Web Services (AWS)	Linux Desktop; Raspberry Pi; Amazon Web Servic...	Atom; Notepad++; Vim; PyCharm; RubyMine; Visua...	Put on some ambient sounds (e.g. whale songs, ...	Male	A master's degree	NaN	37500.0	0.
NaN	NaN	NaN	Sublime Text; Vim; IntelliJ	Turn on some music	Male	A professional degree	113750.000000	NaN	0.

Things to Analyze :

1. Different kinds of developers that exist
2. Developer Count from Different Countries
3. Developer Gender Ratio
4. Developers' Career Satisfaction vs Salary
5. Preferred Programming Language
6. Preferred Database
7. Preferred Platform to work on
8. Time to Start Work in different Countries
9. Auditory Environment's role in coding
10. Work Pay Care in Developers
11. Developers' satisfaction of Job

and much more....

Importing Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
import chart_studio.plotly as py
from plotly.offline import download_plotlyjs, init_notebook_mode,plot ,iplot
init_notebook_mode(connected=True)
import plotly.graph_objs as go
```

PANDAS

Pandas is built on top of two core Python libraries—matplotlib for data visualization and NumPy for mathematical operations.

- This library offers data manipulation and data operations for numerical tables and time series.
- Easily handles missing data
- It uses Series for one-dimensional data structure and Data Frame for multi-dimensional data structure
- It provides an efficient way to slice the data
- It provides a flexible way to merge, concatenate or reshape the data
- It includes a powerful time series tool to work with

NUMPY

- NumPy is a Python library used to perform mathematical and statistical operations with arrays.
- It also has functions for working in domain of linear algebra, Fourier transform, and matrices like isnan() , arange() , reshape() ,and many more...

MATPLOTLIB

- Explicitly create figures and axes, and call methods on them .
- Rely on pyplot to automatically create and manage the figures and axes, and use pyplot functions for plotting.
- Plots like Bar Graph, Histogram, Scatterplot, Area plot, Pie plot etc. are used.

SEABORN

- It is used for data visualization and exploratory data analysis.
- Seaborn works easily with dataframes and the Pandas library. The graphs created can also be customized easily.
- Plots like Heatmap , Histogram , Bar Plot , Factor Plot , Density Plots,etc are used.

PLOTLY

- It s a graphing library designed especially for data scientists, engineers, and programmers to easily visualize trends in their data using Python, R, Matlab, or Javascript.
- It enables Python users to create beautiful interactive web-based visualizations that can be displayed in Jupyter notebooks, saved to standalone HTML files, or served as part of pure Python-built web applications using Dash.

Salary vs Years Coded

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

In [2]:
```
df = pd.read_csv("Analysis_file.csv",low_memory = False, index_col='Respondent')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 51392 entries, 1 to 51392
Data columns (total 53 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Professional            51392 non-null  object
 1   ProgramHobby            51392 non-null  object
 2   Country                 51392 non-null  object
 3   University              51392 non-null  object
 4   EmploymentStatus        51392 non-null  object
 5   FormalEducation         51392 non-null  object
 6   MajorUndergrad          42841 non-null  object
 7   YearsCodedJob           40891 non-null  object
 8   DeveloperType           36125 non-null  object
 9   NonDeveloperType        4891 non-null   object
 10  CareerSatisfaction      42695 non-null  float64
 11  JobSatisfaction         40376 non-null  float64
 12  ProblemSolving          31293 non-null  object
 13  LearningNewTech         31304 non-null  object
 14  JobSecurity             31240 non-null  object
 15  DiversityImportant      30903 non-null  object
 16  SeriousWork             31014 non-null  object
 17  WorkPayCare             30965 non-null  object
 18  ChallengeMyself         30971 non-null  object
 19  LastNewJob              32710 non-null  object
 20  AssessJobIndustry       22130 non-null  object
```

Imputing the Salary Column

In [4]:
```
df['Salary'].count()
```

Out[4]:
```
12891
```

In [5]:
```
df['YearsCodedJob'].dropna().unique()
```

Out[5]:
```
array(['20 or more years', '9 to 10 years', '10 to 11 years',
       '8 to 9 years', '7 to 8 years', '11 to 12 years', '17 to 18 years',
       '15 to 16 years', '1 to 2 years', '3 to 4 years', '12 to 13 years',
       'Less than a year', '5 to 6 years', '16 to 17 years',
       '13 to 14 years', '6 to 7 years', '2 to 3 years', '4 to 5 years',
       '14 to 15 years', '18 to 19 years', '19 to 20 years'], dtype=object)
```

In [6]:
```
avg_salary = dict()
for x in df['YearsCodedJob'].dropna().unique():
    avg_salary[x] = df[df['YearsCodedJob']==x]['Salary'].mean()
```

In [7]:
```
avg_salary
```

Out[7]:
```
{'20 or more years': 98128.09747715948,
 '9 to 10 years': 63120.608545548384,
 '10 to 11 years': 67455.78263092662,
 '8 to 9 years': 66454.53546474078,
 '7 to 8 years': 58952.900695846074,
 '11 to 12 years': 71432.17525788138,
 '17 to 18 years': 87996.92497548716,
 '15 to 16 years': 79883.65565306017,
 '1 to 2 years': 34152.737761066004,
 '3 to 4 years': 44545.60036265642,
 '12 to 13 years': 82845.42494629917,
 'Less than a year': 33298.75204458008,
 '5 to 6 years': 52440.94312624933,
 '16 to 17 years': 77528.61148028531,
 '13 to 14 years': 75496.373677403,
 '6 to 7 years': 57454.15413633074
```

In [8]:
```
def impute_Salary(cols):
    Salary = cols[0]
    ycj = cols[1]

    if(pd.isnull(Salary)):
        if(pd.notnull(ycj)):
            return avg_salary[ycj]
    return Salary
```

In [9]:
```
df['Salary'] = df[["Salary","YearsCodedJob"]].apply(impute_Salary,axis=1)
```

In [10]:
```
df['Salary'].count()
```

Out[10]:
```
40948
```

In [11]:
```
df[['YearsCodedJob','Salary']].head(10)
```

Out[11]:

Respondent	YearsCodedJob	Salary
1	NaN	NaN
2	NaN	NaN
3	20 or more years	113750.000000
4	9 to 10 years	63120.608546
5	10 to 11 years	67455.782631
6	NaN	NaN
7	8 to 9 years	66454.535465
8	7 to 8 years	58952.900696
9	7 to 8 years	58952.900696

Imputing 'YearsCodedJob' Column

In [12]:
```
df['YearsCodedJob'].unique()
```

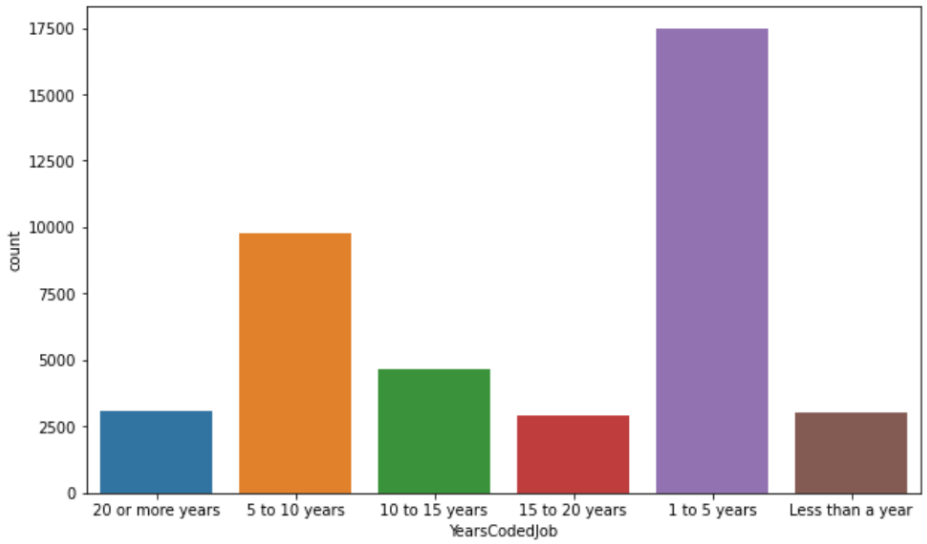
Out[12]:
```
array([nan, '20 or more years', '9 to 10 years', '10 to 11 years',
       '8 to 9 years', '7 to 8 years', '11 to 12 years', '17 to 18 years',
       '15 to 16 years', '1 to 2 years', '3 to 4 years', '12 to 13 years',
       'Less than a year', '5 to 6 years', '16 to 17 years',
       '13 to 14 years', '6 to 7 years', '2 to 3 years', '4 to 5 years',
       '14 to 15 years', '18 to 19 years', '19 to 20 years'], dtype=object)
```

In [13]:
```
def decrease_ycj_cat(x):
    if(x == '1 to 2 years' or x == '2 to 3 years' or x == '3 to 4 years'or x== '4 to 5 years'):
        return '1 to 5 years'

    elif(x == '5 to 6 years' or x == '6 to 7 years'or x== '7 to 8 years' or x == '8 to 9 years' or x== '9 to 10 years' ):
        return '5 to 10 years'

    elif(x == '10 to 11 years' or x=='11 to 12 years' or x=='12 to 13 years' or x== '13 to 14 years'or x=='14 to 15 years' ):
        return '10 to 15 years'

    elif(x=='15 to 16 years'or x== '16 to 17 years'or x=='17 to 18 years'or x== '18 to 19 years'or x=='19 to 20 years'):
        return '15 to 20 years'

    else:
        return x
```

In [14]:
```
df["YearsCodedJob"] = df["YearsCodedJob"].apply(decrease_ycj_cat)
```

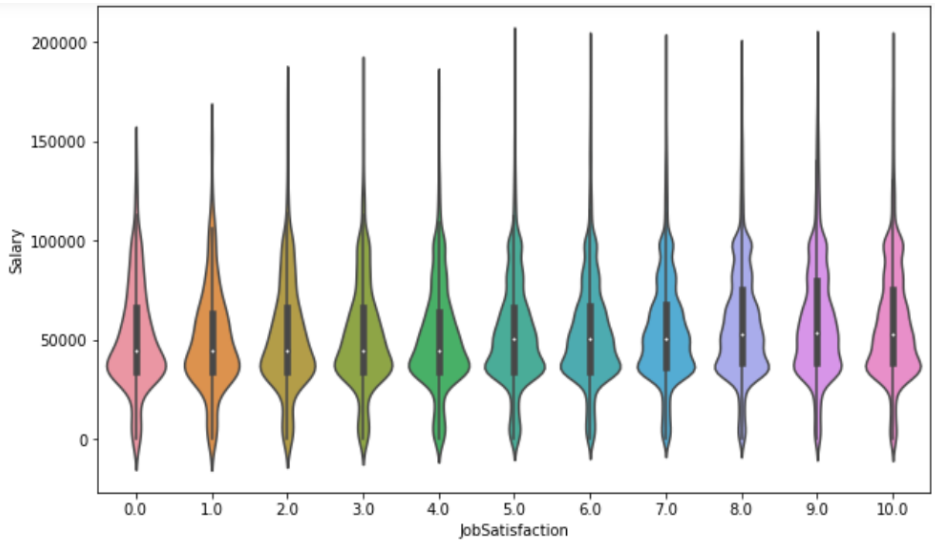
In [15]:
```
plt.figure(figsize =(10,6))
sns.countplot(df["YearsCodedJob"])
```

Out[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x9fbbef8>
```



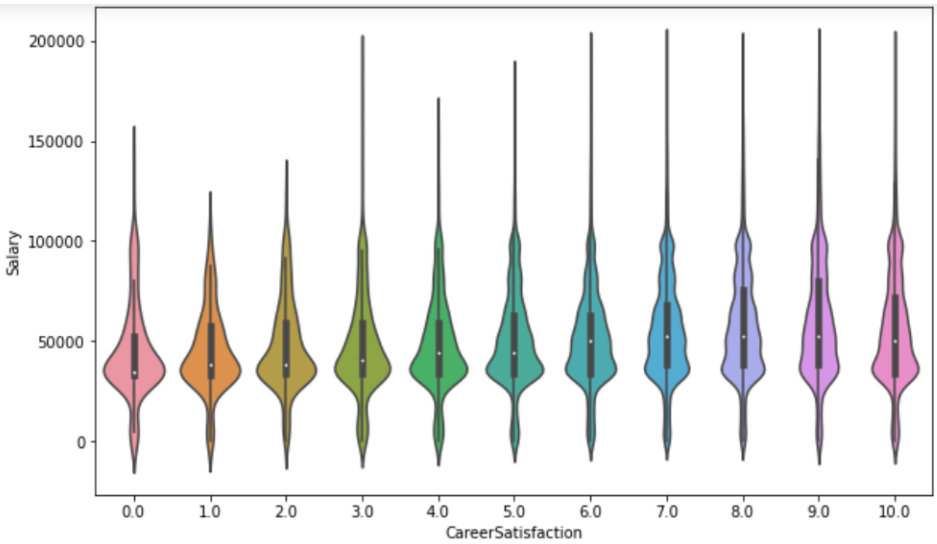
In [16]:
```
#df.to_csv('updatedDatasets/Update1.csv')
```

In [17]:
```
plt.figure(figsize =(10,6))
sns.violinplot(data=df,y='Salary',x='JobSatisfaction')
```



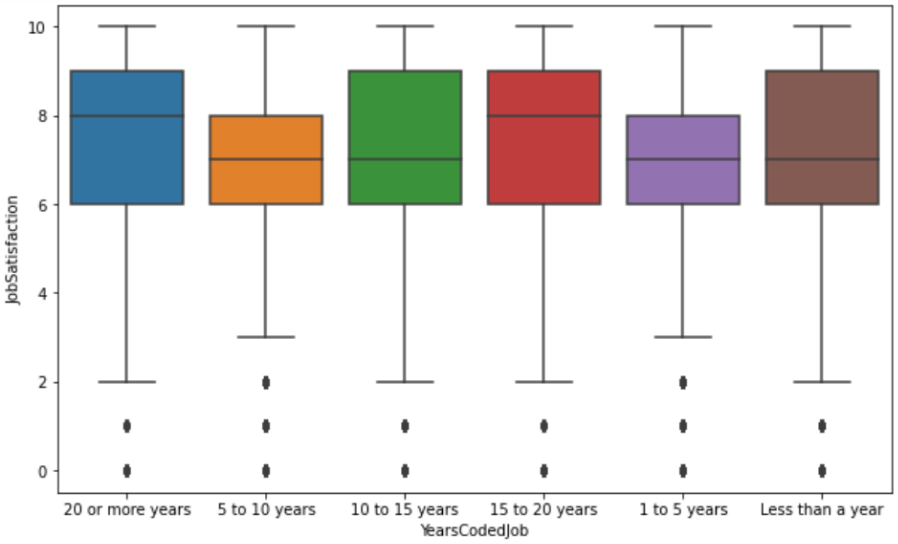
In [18]:
```
plt.figure(figsize =(10,6))
sns.violinplot(data=df,y='Salary',x='CareerSatisfaction')
```

Out[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xa849d60>
```



In [19]:
```
plt.figure(figsize =(10,6))
sns.boxplot(data=df,x='YearsCodedJob',y='JobSatisfaction')
```

Out[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xc35b598>
```



In [20]:
```
plt.figure(figsize =(10,6))
sns.boxplot(data=df,x='YearsCodedJob',y='CareerSatisfaction')
```

Out[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xcb75a18>
```

Assess_Score

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

In [2]:
```
df = pd.read_csv('updatedDatasets/Update1.csv')
```

In [3]:
```
df['AssessJobIndustry'].unique()
```

Out[3]:
```
array(['Very important', nan, 'Somewhat important', 'Important',
       'Not very important', 'Not at all important'], dtype=object)
```

In [4]:
```
df.iloc[:,21:35].head()
```

Out[4]:

	AssessJobIndustry	AssessJobRole	AssessJobExp	AssessJobDept	AssessJobTech	AssessJobProjects	AssessJobCompensation	AssessJobOffice	AssessJ
0	Very important	Very important	Important	Very important	Very important	Very important	Important	Very important	V
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	Somewhat important	Somewhat important	Somewhat important	Important	Important	Very important	Important	Very important	
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

In [5]:
```
pd.DataFrame(df['AssessJobIndustry'].value_counts())
```

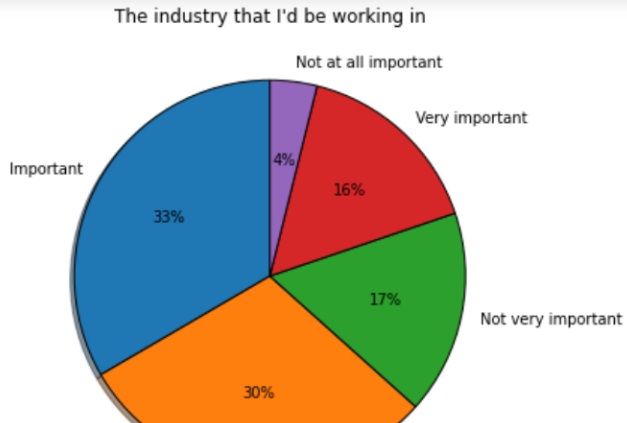
Out[5]:

	AssessJobIndustry
Important	7391
Somewhat important	6637
Not very important	3721
Very important	3521
Not at all important	860

In [6]:
```
#When you're assessing potential jobs to apply to, how important are each of the following to you?
#AssessjobIndustry : The industry that I'd be working in
#AssessJobRole : The specific role or job title I'd be applying for
#AssessJobExp : The experience level called for in the job description
#AssessJobDept : The specific department or team I'd be working on
#AssessJobTech : The languages, frameworks, and other technologies I'd be working with
#AssessJobProjects : How projects are managed at the company or organization
#AssessJobCompensation : The compensation and benefits offered
#AssessJobOffice : The office environment I'd be working in
#AssessJobCommute :  The amount of time I'd have to spend commuting
#AssessJobRemote :  The opportunity to work from home/remotely
#AssessJobProfDevel : Opportunities for professional development
#AssessJobDiversity : The diversity of the company or organization
#AssessJobProduct : How widely used or impactful the product or service I'd be working on is
#AssessJobFinances : The financial performance or funding status of the company or organization
```

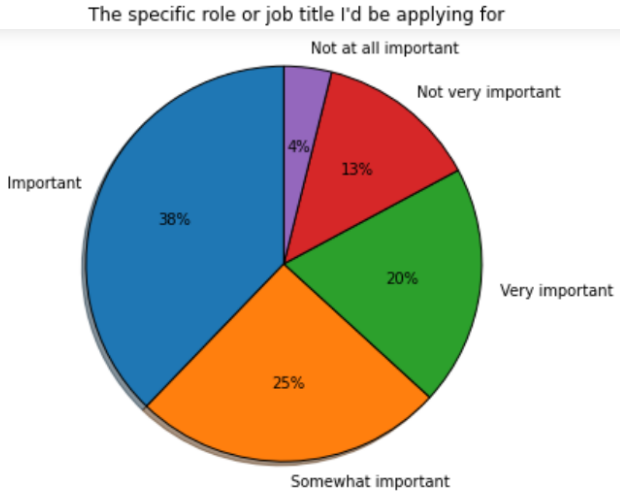
In [7]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobIndustry'].value_counts(), labels = df['AssessJobIndustry'].value_counts().index,
        startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The industry that I'd be working in")
```

Out[7]:
```
Text(0.5, 1.0, "The industry that I'd be working in")
```



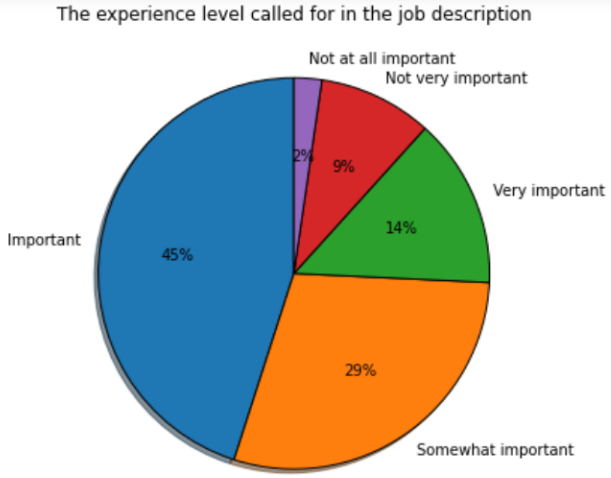
In [8]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobRole'].value_counts(), labels = df['AssessJobRole'].value_counts().index,
        startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The specific role or job title I'd be applying for")
```

Out[8]: Text(0.5, 1.0, "The specific role or job title I'd be applying for")



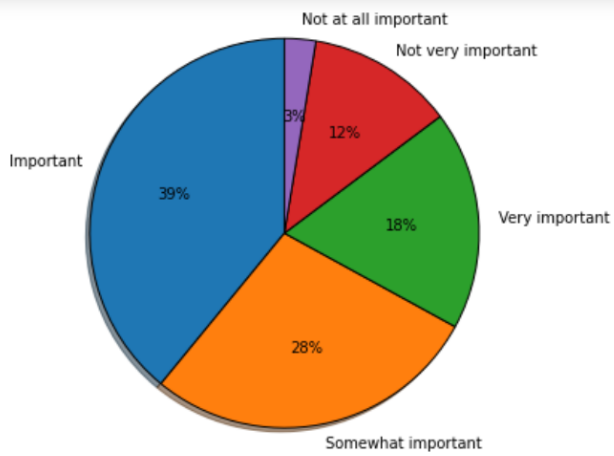
In [9]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobExp'].value_counts(), labels = df['AssessJobExp'].value_counts().index,
        startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The experience level called for in the job description")
```

Out[9]: Text(0.5, 1.0, 'The experience level called for in the job description')



In [10]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobDept'].value_counts(), labels = df['AssessJobDept'].value_counts().index,
        startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The specific department or team I'd be working on")
```

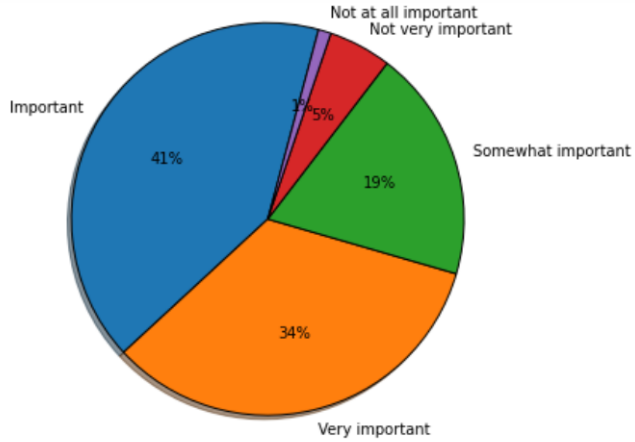
Out[10]: Text(0.5, 1.0, "The specific department or team I'd be working on")



In [11]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobTech'].value_counts(), labels = df['AssessJobTech'].value_counts().index,
        startangle=75, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The languages, frameworks, and other technologies I'd be working with")
```

Out[11]:
```
Text(0.5, 1.0, "The languages, frameworks, and other technologies I'd be working with")
```

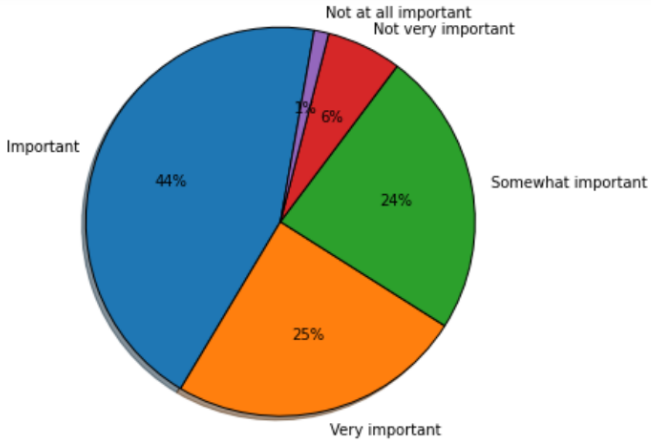
The languages, frameworks, and other technologies I'd be working with



In [12]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobProjects'].value_counts(), labels = df['AssessJobProjects'].value_counts().index,
        startangle=80, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("How projects are managed at the company or organization")
```

Out[12]:
```
Text(0.5, 1.0, 'How projects are managed at the company or organization')
```

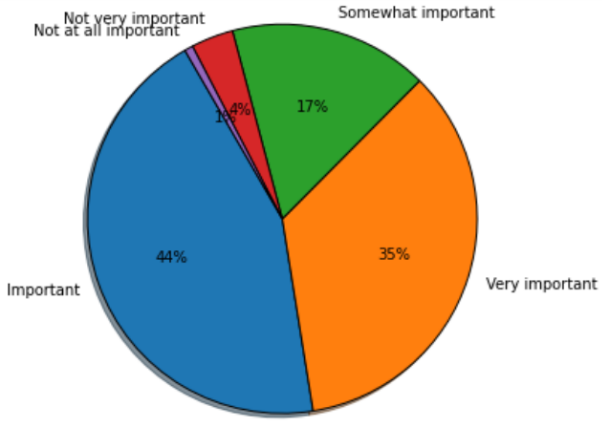
How projects are managed at the company or organization



In [13]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobCompensation'].value_counts(), labels = df['AssessJobCompensation'].value_counts().index,
        startangle=120, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The compensation and benefits offered")
```

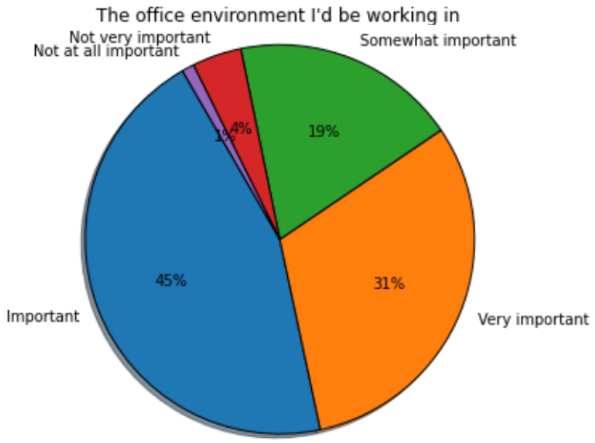
Out[13]:
```
Text(0.5, 1.0, 'The compensation and benefits offered')
```

The compensation and benefits offered



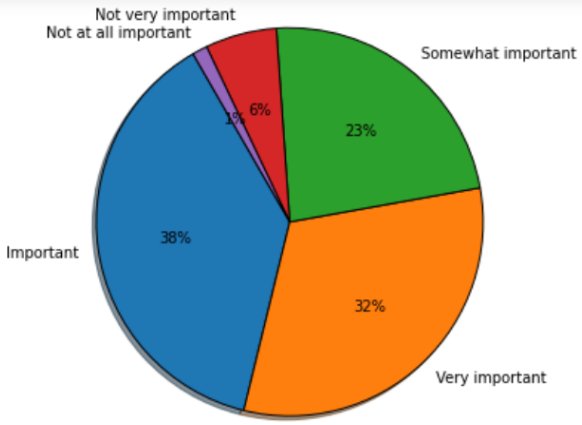
In [14]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobOffice'].value_counts(), labels = df['AssessJobOffice'].value_counts().index,
        startangle=120, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The office environment I'd be working in")
```

Out[14]:
```
Text(0.5, 1.0, "The office environment I'd be working in")
```



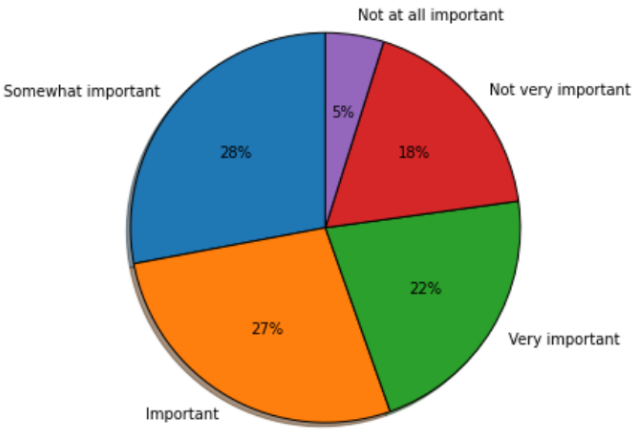
In [15]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobCommute'].value_counts(), labels = df['AssessJobCommute'].value_counts().index,
        startangle=120, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The amount of time I'd have to spend commuting")
```

Out[15]:
```
Text(0.5, 1.0, "The amount of time I'd have to spend commuting")
```



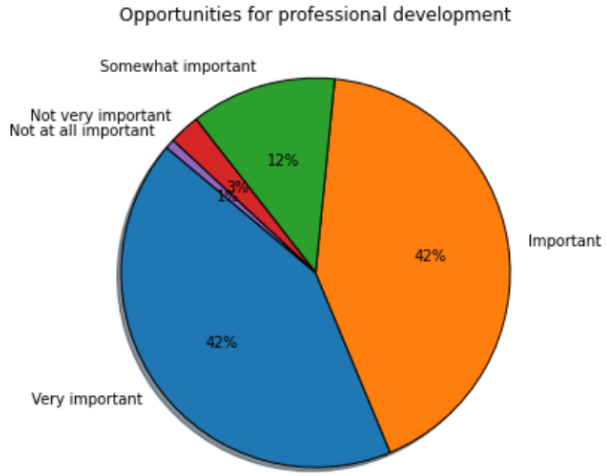
In [16]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobRemote'].value_counts(), labels = df['AssessJobRemote'].value_counts().index,
        startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The opportunity to work from home/remotely")
```

Out[16]:
```
Text(0.5, 1.0, 'The opportunity to work from home/remotely')
```



In [17]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobProfDevel'].value_counts(), labels = df['AssessJobProfDevel'].value_counts().index,
        startangle=140, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("Opportunities for professional development")
```

Out[17]:
```
Text(0.5, 1.0, 'Opportunities for professional development')
```

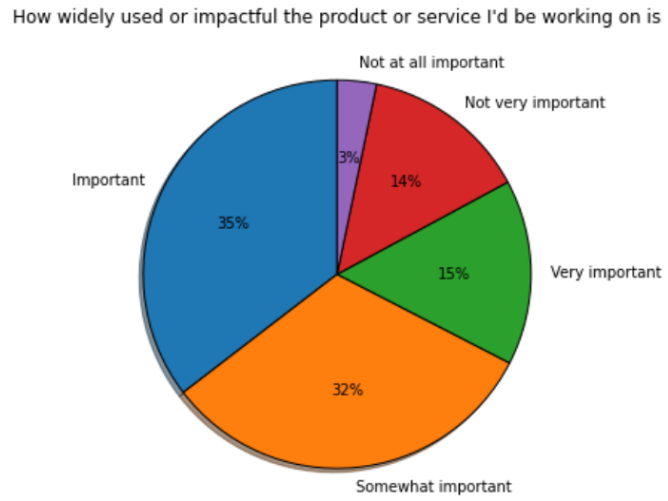


In [18]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobDiversity'].value_counts(), labels = df['AssessJobDiversity'].value_counts().index,
        startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The diversity of the company or organization")
```

Out[18]:
```
Text(0.5, 1.0, 'The diversity of the company or organization')
```

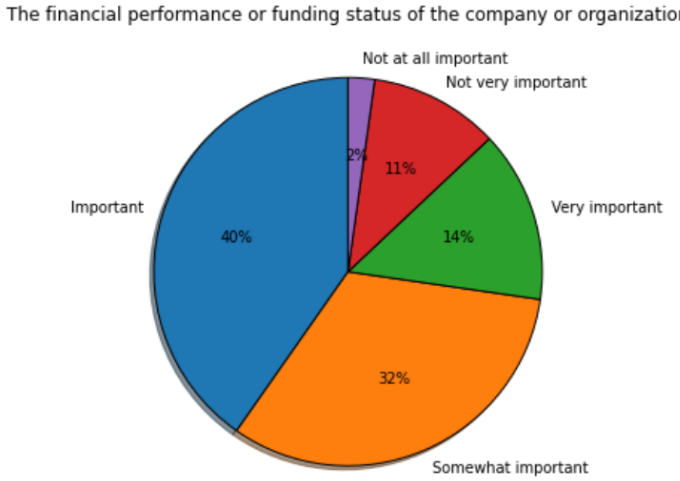
In [19]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobProduct'].value_counts(), labels = df['AssessJobProduct'].value_counts().index,
        startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("How widely used or impactful the product or service I'd be working on is")
```

Out[19]:
```
Text(0.5, 1.0, "How widely used or impactful the product or service I'd be working on is")
```



In [20]:
```
plt.figure(figsize=(10,6))
plt.pie(df['AssessJobFinances'].value_counts(), labels = df['AssessJobFinances'].value_counts().index,
        startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("The financial performance or funding status of the company or organization")
```

Out[20]:
```
Text(0.5, 1.0, 'The financial performance or funding status of the company or organization')
```



In [21]:
```
def assess_score(cols):
    score = 0

    for x in cols:
        if pd.isnull(x):
            score += 0
        elif x == 'Not at all important':
            score += 0.5
        elif x == 'Not very important':
            score += 1
        elif x == 'Somewhat important':
            score += 1.5
        elif x == 'Important':
            score += 2
        else:
            score += 2.5

    return score
```

In [22]:
```
temp = df.iloc[:,21:35].apply(assess_score,axis=1)
```

In [23]:
```
temp.head(3)
```

Out[23]:
```
0    30.5
1     0.0
2     0.0
dtype: float64
```

In [24]:
```
df['Assess_Scoring']=temp
```

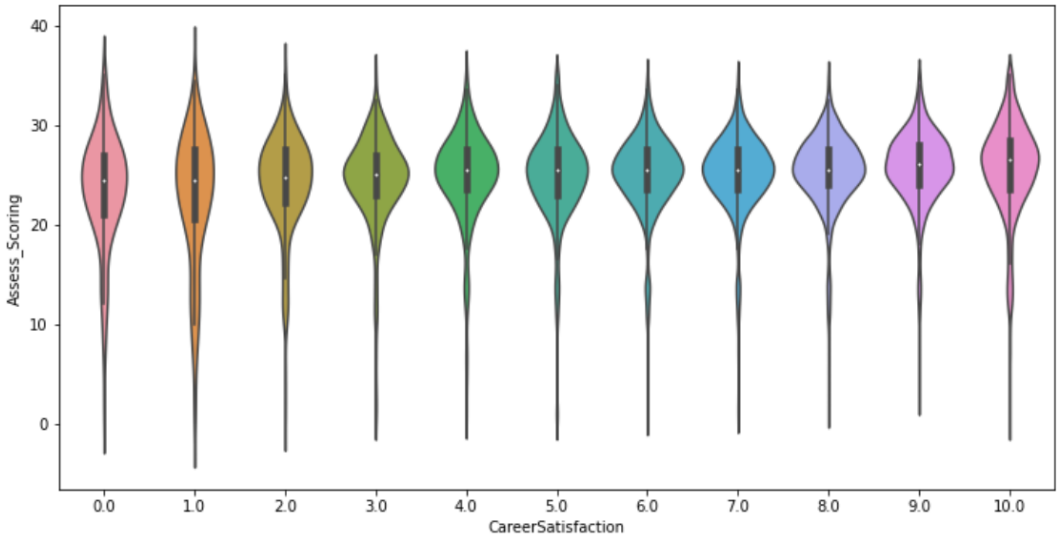
In [25]:
```
temp=df.drop(df.iloc[:,21:35],axis=1)
temp['Assess_Scoring'].replace({0:np.nan}, inplace=True)
```

In [26]:
```
temp[temp['Assess_Scoring']!=0]['Assess_Scoring'].count()
```

Out[26]:
```
22689
```

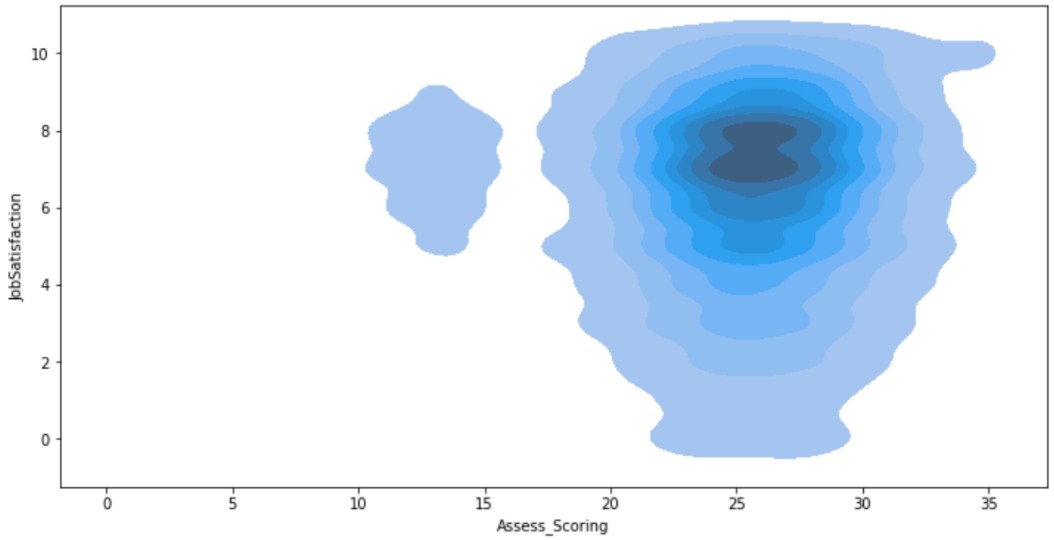
In [27]:
```
plt.figure(figsize =(12,6))
sns.violinplot(data=temp,y='Assess_Scoring',x='CareerSatisfaction')
```

Out[27]:
```
<AxesSubplot:xlabel='CareerSatisfaction', ylabel='Assess_Scoring'>
```



In [28]:
```
plt.figure(figsize =(12,6))
sns.kdeplot(data=temp,x='Assess_Scoring',y='JobSatisfaction',fill=True, common_norm=False, palette="crest",)
```

Out[28]:
```
<AxesSubplot:xlabel='Assess_Scoring', ylabel='JobSatisfaction'>
```



In [30]:
```
temp.to_csv('updatedDatasets/Update2.csv',index=False)
```

In [21]:
```
def assess_score(cols):
    score = 0

    for x in cols:
        if pd.isnull(x):
            score += 0
        elif x == 'Not at all important':
            score += 0.5
        elif x == 'Not very important':
            score += 1
        elif x == 'Somewhat important':
            score += 1.5
        elif x == 'Important':
            score += 2
        else:
            score += 2.5

    return score
```

In [23]:
```
temp = df.iloc[:,21:35].apply(assess_score,axis=1)
```

In [24]:
```
temp[:5]
```

Out[24]:
```
0    30.5
1     0.0
2     0.0
3    28.5
4     0.0
dtype: float64
```

In [25]:
```
df['Assess_Scoring']=temp
```

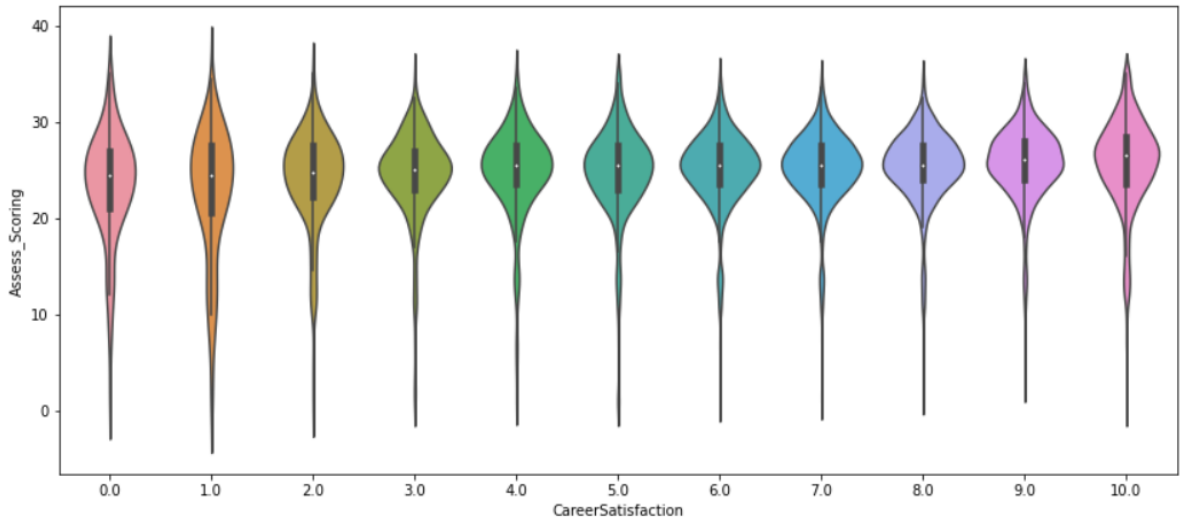
In [26]:
```
temp=df.drop(df.iloc[:,21:35],axis=1)
temp['Assess_Scoring'].replace({0:np.nan}, inplace=True)
```

In [27]:
```
temp[temp['Assess_Scoring']!=0]['Assess_Scoring'].count()
```

Out[27]:
```
22689
```

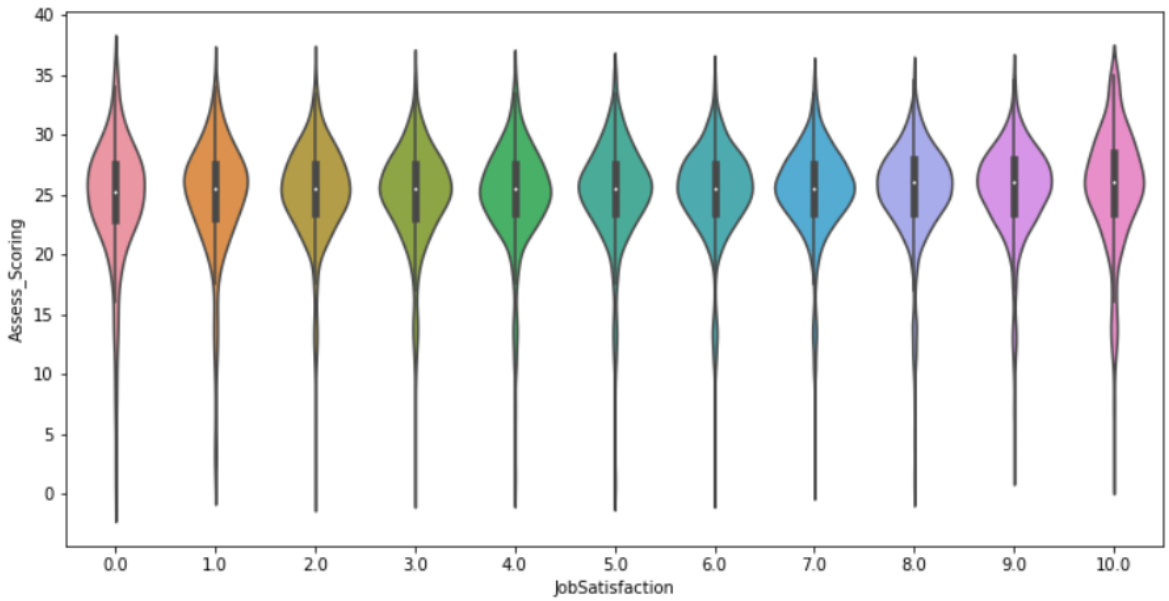
In [28]:
```
plt.figure(figsize =(14,6))
sns.violinplot(data=temp,y='Assess_Scoring',x='CareerSatisfaction')
```

Out[28]: <AxesSubplot:xlabel='CareerSatisfaction', ylabel='Assess_Scoring'>



In [29]:
```
plt.figure(figsize =(12,6))
sns.violinplot(data=temp,y='Assess_Scoring',x='JobSatisfaction')
```

Out[29]: <AxesSubplot:xlabel='JobSatisfaction', ylabel='Assess_Scoring'>



In [30]:
```
temp.to_csv('updatedDatasets/Update2.csv',index=False)
```

Gender Analysis

```
In [2]: df = pd.read_csv('updatedDatasets/Update2.csv')
```

```
In [22]: df['Gender'].unique()
```

```
Out[22]: array(['Male', nan, 'Female', 'Gender non-conforming', 'Other',
                'Male; Gender non-conforming', 'Female; Transgender',
                'Male; Female', 'Male; Other', 'Transgender',
                'Transgender; Gender non-conforming',
                'Female; Gender non-conforming',
                'Male; Female; Transgender; Gender non-conforming; Other',
                'Male; Female; Transgender', 'Male; Female; Other',
                'Male; Female; Transgender; Gender non-conforming',
                'Male; Transgender', 'Female; Transgender; Gender non-conforming',
                'Gender non-conforming; Other',
                'Male; Female; Gender non-conforming', 'Female; Other',
                'Male; Transgender; Gender non-conforming', 'Transgender; Other',
                'Male; Gender non-conforming; Other',
                'Female; Gender non-conforming; Other',
                'Male; Female; Gender non-conforming; Other',
                'Female; Transgender; Other',
                'Female; Transgender; Gender non-conforming; Other',
                'Male; Transgender; Other', 'Male; Female; Transgender; Other'],
               dtype=object)
```

```
In [23]: df['Gender'].nunique()
```

```
Out[23]: 29
```

Segregation/Cleaning Gender Column

Making Following Categories : Male , Female , NaN , Other

Other contains:Transgender, Gender non-conforming

```
In [24]: def gender_sortner(x):
             if(x == 'Male' or x== 'Female' or pd.isna(x)):
                 return x
             else:
                 return 'Other'
         df["Gender"] = df["Gender"].apply(gender_sortner)
```

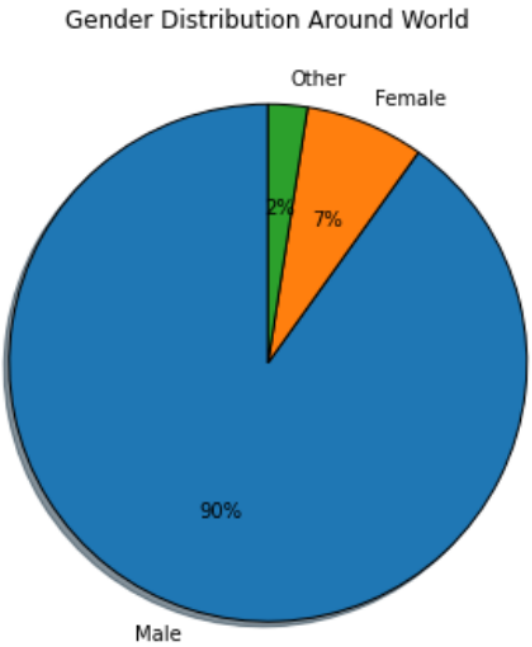
```
In [25]: df['Gender'].unique()
```

```
Out[25]: array(['Male', nan, 'Female', 'Other'], dtype=object)
```

```
In [26]: gender_groupby = df.groupby('Gender')
```

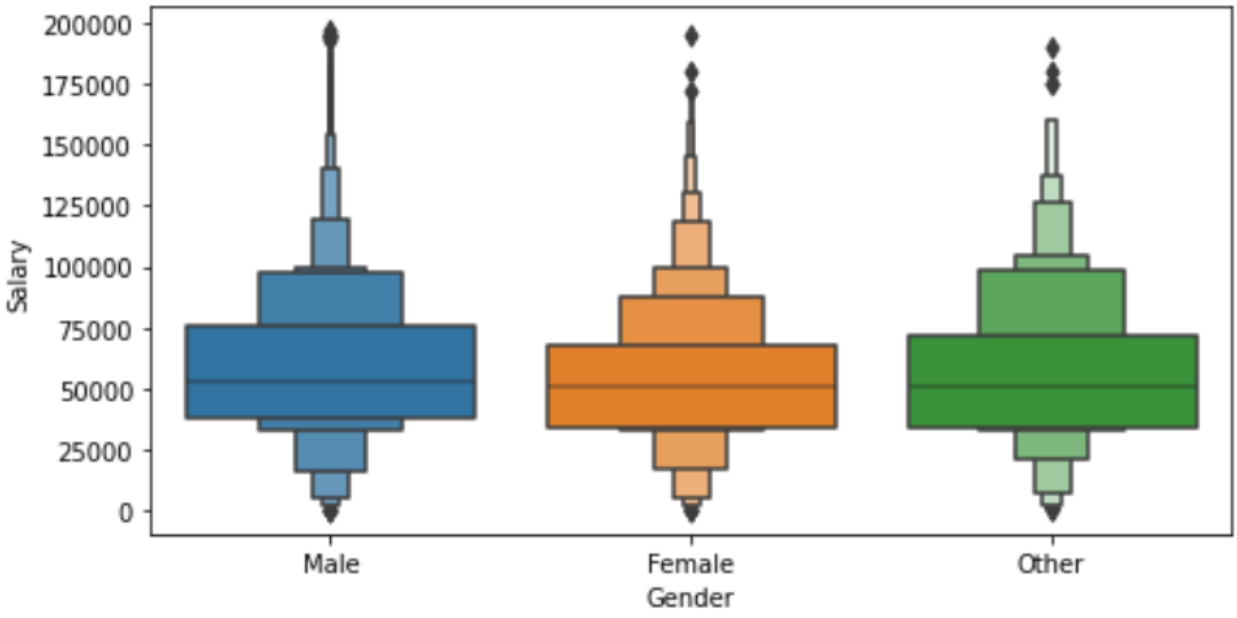
```
In [8]: plt.figure(figsize=(10,6))
        plt.pie(df['Gender'].value_counts(), labels = df['Gender'].value_counts().index,
                startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
        plt.title("Gender Distribution Around World")
```

```
Out[8]: Text(0.5, 1.0, 'Gender Distribution Around World')
```




```
In [9]: plt.figure(figsize=(8,4))
        sns.boxenplot(x='Gender',y='Salary',data=df)
```

```
Out[9]: <AxesSubplot:xlabel='Gender', ylabel='Salary'>
```




```
In [10]: gender_groupby['Salary'].mean()
```

```
Out[10]: Gender
         Female    54346.519630
         Male      57497.391317
         Other     56838.943817
         Name: Salary, dtype: float64
```

Worldwide Analysis

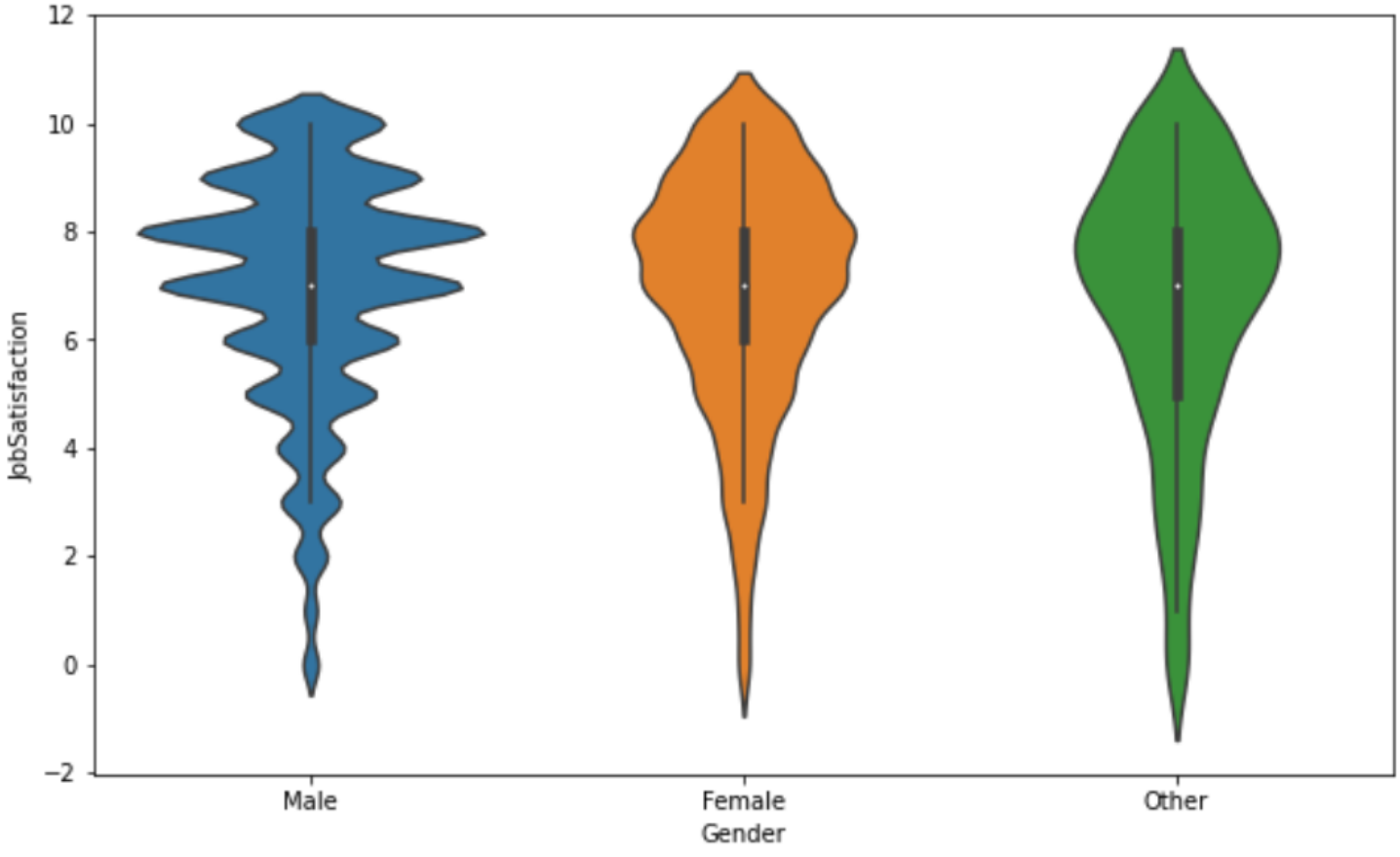
In [17]:
```
gender_groupby['JobSatisfaction'].mean()
```

Out[17]:
```
Gender
Female    6.936620
Male      7.004372
Other     6.735751
Name: JobSatisfaction, dtype: float64
```

In [18]:
```
gender_groupby['JobSatisfaction'].count()
```

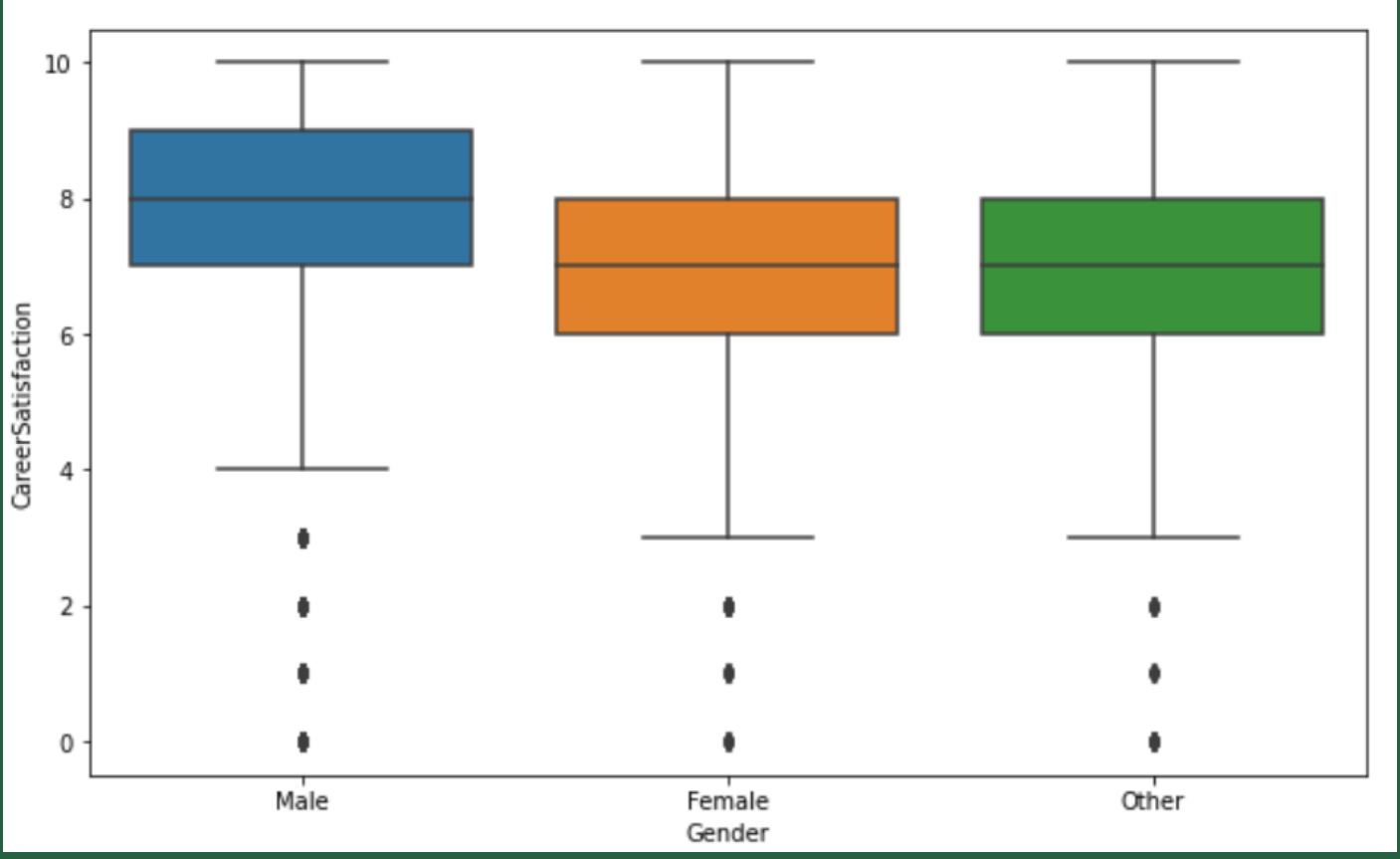
Out[18]:
```
Gender
Female     2130
Male      26306
Other       579
Name: JobSatisfaction, dtype: int64
```

In [19]:
```
plt.figure(figsize=(15,8))
ax=sns.countplot(data=df,x='JobSatisfaction',hue='Gender')
plt.xticks(rotation=45)
for p in ax.patches:
    ax.annotate(format(p.get_height()),(p.get_x(),p.get_height()+0.6))
plt.title(" WORLD  WIDE  JOB  SATISFACTION ")
```



Worldwide Career Satisfaction

```
In [14]: gender_groupby['CareerSatisfaction'].count()

Out[14]: Gender
         Female     2237
         Male      27582
         Other       660
         Name: CareerSatisfaction, dtype: int64

In [38]: gender_groupby['CareerSatisfaction'].mean()

Out[38]: Gender
         Female    7.185069
         Male      7.394061
         Other     6.924242
         Name: CareerSatisfaction, dtype: float64

In [16]: plt.figure(figsize=(10,6))
         sns.boxplot(data=df,x='Gender',y='CareerSatisfaction')

Out[16]: <AxesSubplot:xlabel='Gender', ylabel='CareerSatisfaction'>
```



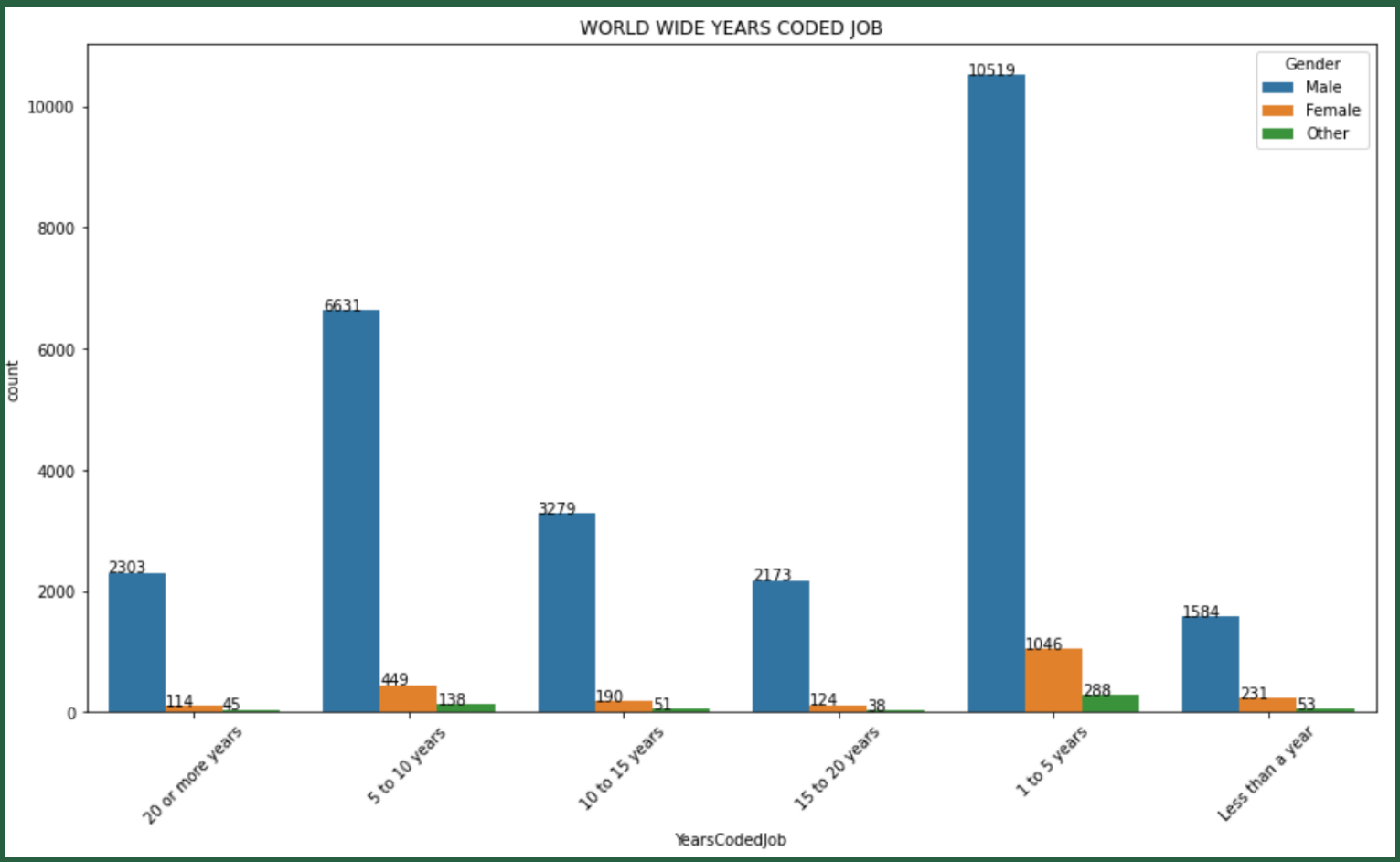
Worldwide Years Coded Job

```
In [17]: gender_groupby['YearsCodedJob'].count()
```

```
Out[17]: Gender
         Female     2154
         Male      26489
         Other       613
         Name: YearsCodedJob, dtype: int64
```

```
In [36]: plt.figure(figsize=(15,8))
         ax=sns.countplot(data=df,x='YearsCodedJob',hue='Gender')
         plt.xticks(rotation=45)
         for p in ax.patches:
             ax.annotate(format(p.get_height()),(p.get_x(),p.get_height()+0.6))
         plt.title("WORLD WIDE YEARS CODED JOB")
```

```
Out[36]: Text(0.5, 1.0, 'WORLD WIDE YEARS CODED JOB')
```

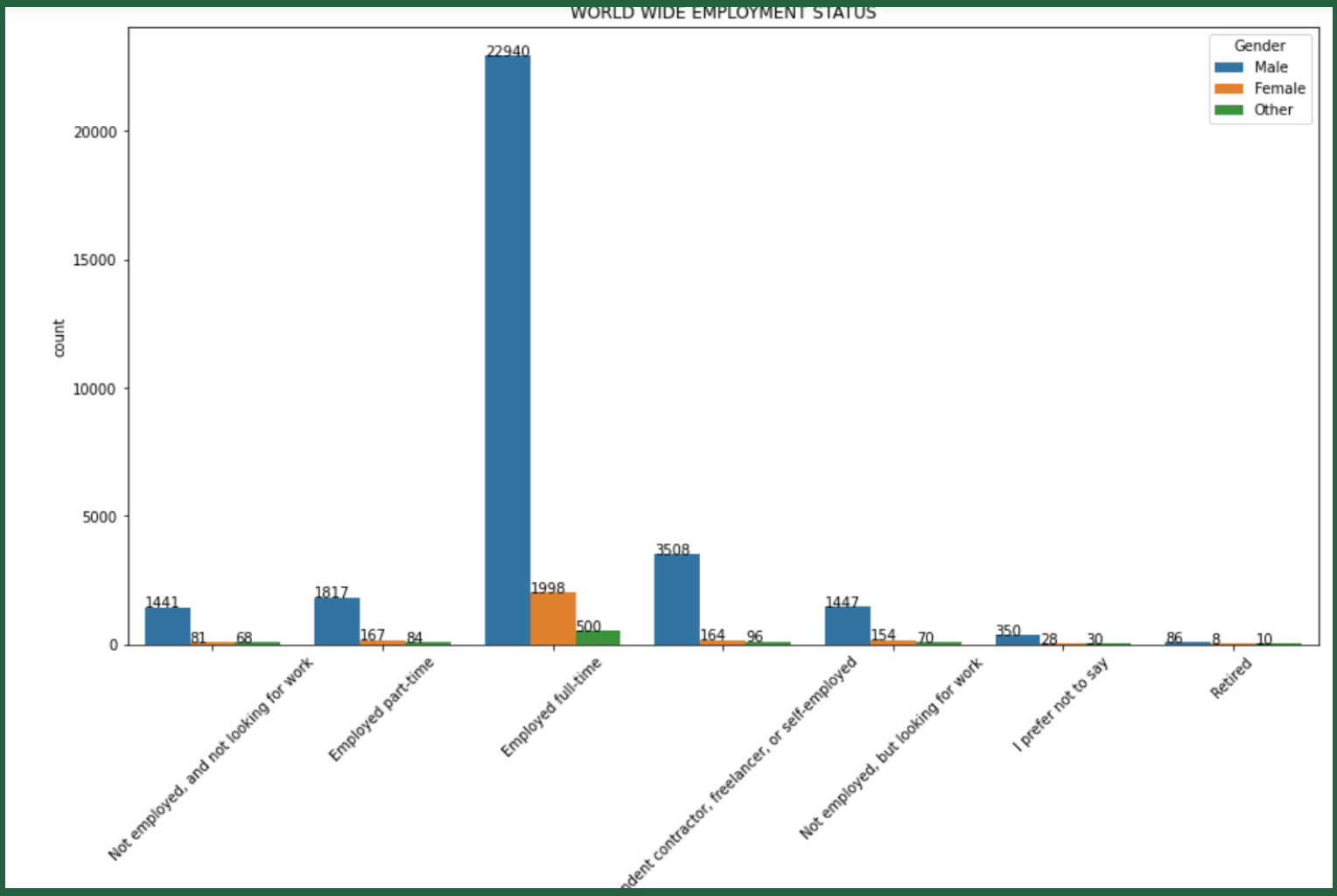


Worldwide Employment Status

```
In [19]: gender_groupby['EmploymentStatus'].count()
```

```
Out[19]: Gender
         Female     2600
         Male      31589
         Other       858
         Name: EmploymentStatus, dtype: int64
```

```
In [20]: plt.figure(figsize=(15,8))
         ax=sns.countplot(data=df,x='EmploymentStatus',hue='Gender')
         plt.xticks(rotation=45)
         for p in ax.patches:
             ax.annotate(format(p.get_height()),(p.get_x(),p.get_height()+0.6))
             plt.title("WORLD WIDE EMPLOYMENT STATUS")
```



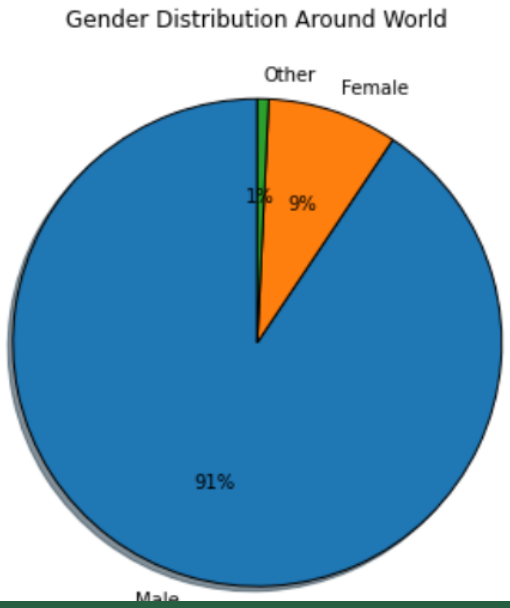
Gender Analysis India

In [21]:
```
df_india=df[df['Country']=='India']
gender_groupby_India = df_india.groupby('Gender')
gender_groupby_India['Salary'].mean()
```

Out[21]:
```
Gender
Female    33297.340313
Male      33225.401283
Other     33158.461985
Name: Salary, dtype: float64
```

In [22]:
```
plt.figure(figsize=(10,6))
plt.pie(df_india['Gender'].value_counts(), labels = df_india['Gender'].value_counts().index,
        startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("Gender Distribution Around World")
```

Out[22]:
```
Text(0.5, 1.0, 'Gender Distribution Around World')
```

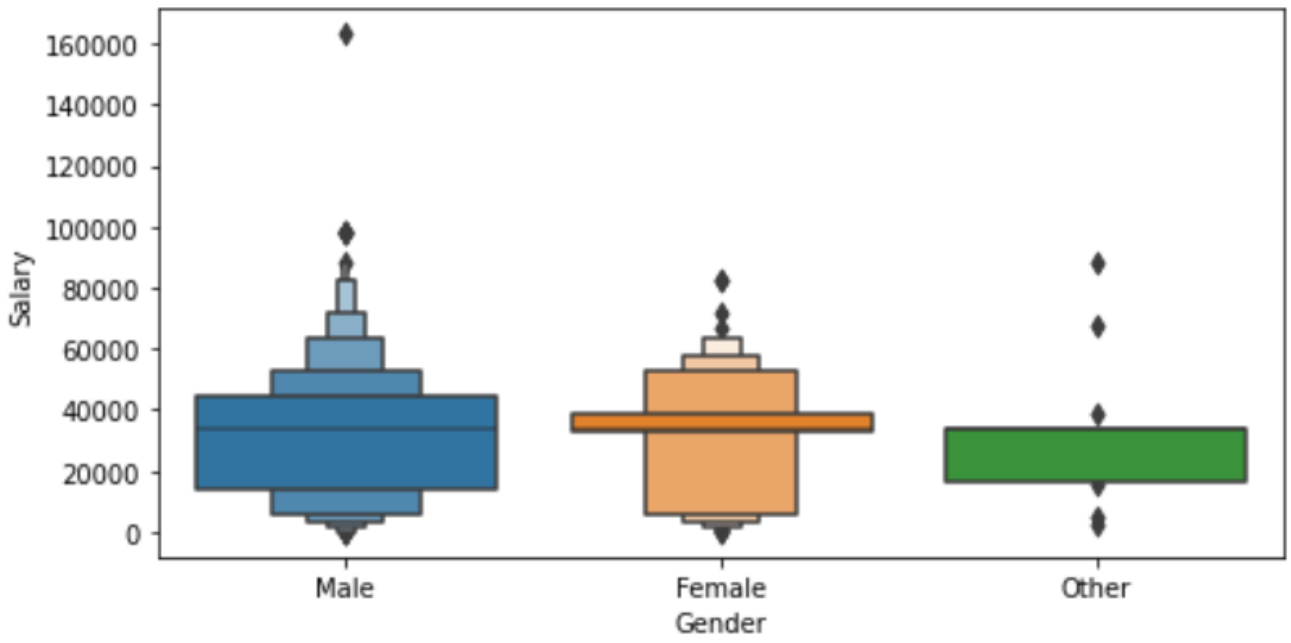


In [23]:
```
gender_groupby_India['Salary'].mean()
```

Out[23]:
```
Gender
Female    33297.340313
Male      33225.401283
Other     33158.461985
Name: Salary, dtype: float64
```

In [24]:
```
plt.figure(figsize=(8,4))
sns.boxenplot(x='Gender',y='Salary',data=df_india)
```

Out[24]:
```
<AxesSubplot:xlabel='Gender', ylabel='Salary'>
```



In [26]:
```
gender_groupby_India['Assess_Scoring'].mean()
```

Out[26]:
```
Gender
Female    27.200000
Male      26.681507
Other     22.923077
Name: Assess_Scoring, dtype: float64
```

In [27]:
```
plt.figure(figsize=(10,6))
sns.violinplot(data=df_india,x='Gender',y='Assess_Scoring')
plt.title("  I N D I A   A S S E S S  S C O R E  ")
```

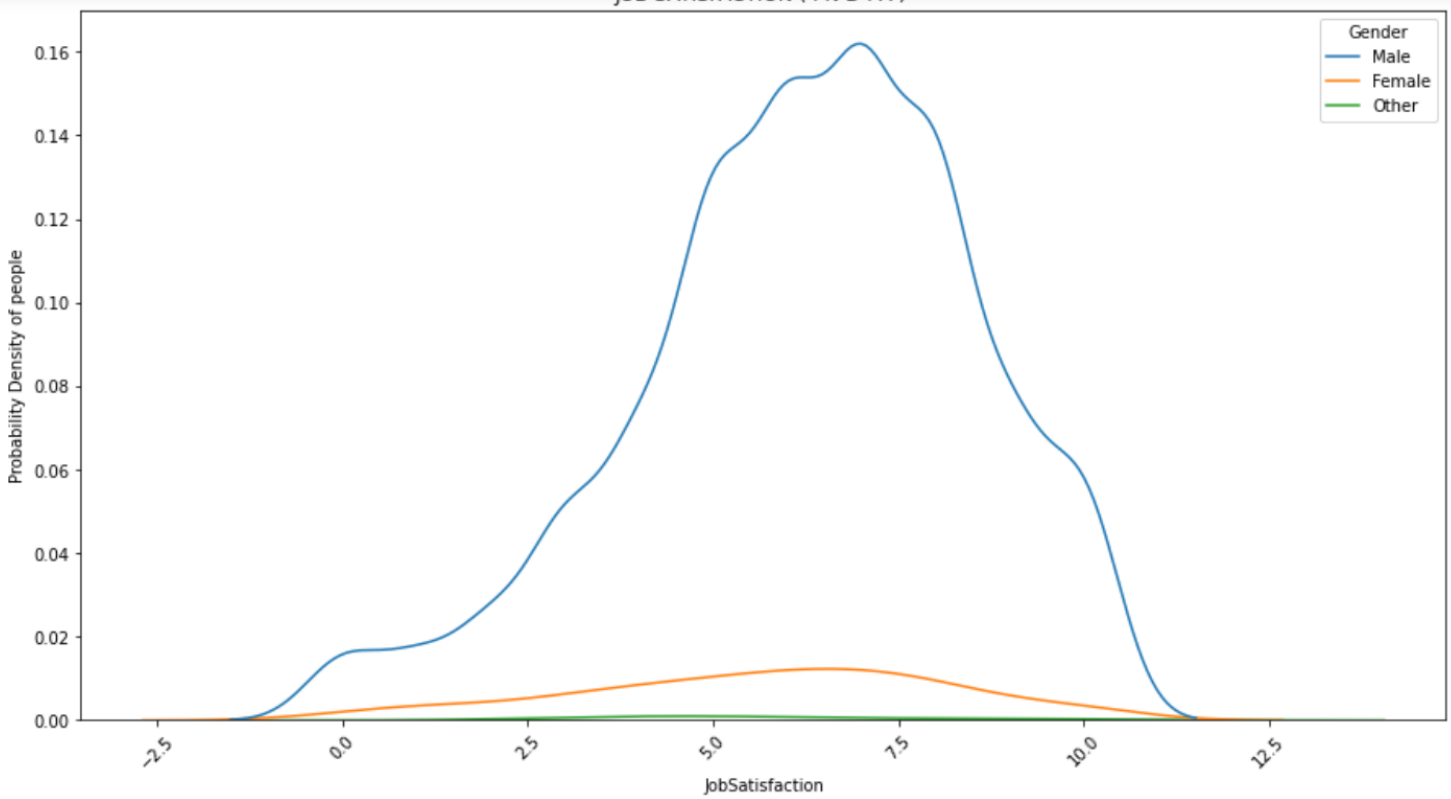
Out[27]:
```
Text(0.5, 1.0, '  I N D I A   A S S E S S  S C O R E  ')
```

In [28]:
```
gender_groupby_India['JobSatisfaction'].mean()
```

Out[28]:
```
Gender
Female    5.648485
Male      6.222639
Other     5.750000
Name: JobSatisfaction, dtype: float64
```

In [29]:
```
plt.figure(figsize=(15,8))
ax=sns.kdeplot(data=df_india,x='JobSatisfaction',hue='Gender')
plt.xticks(rotation=45)
for p in ax.patches:
    ax.annotate(format(p.get_height()),(p.get_x(),p.get_height()+0.6))
plt.title("JOB SATISFACTION ( I N D I A ) ")
plt.ylabel("Probability Density of people")
```

Out[29]:
```
Text(0, 0.5, 'Probability Density of people')
```

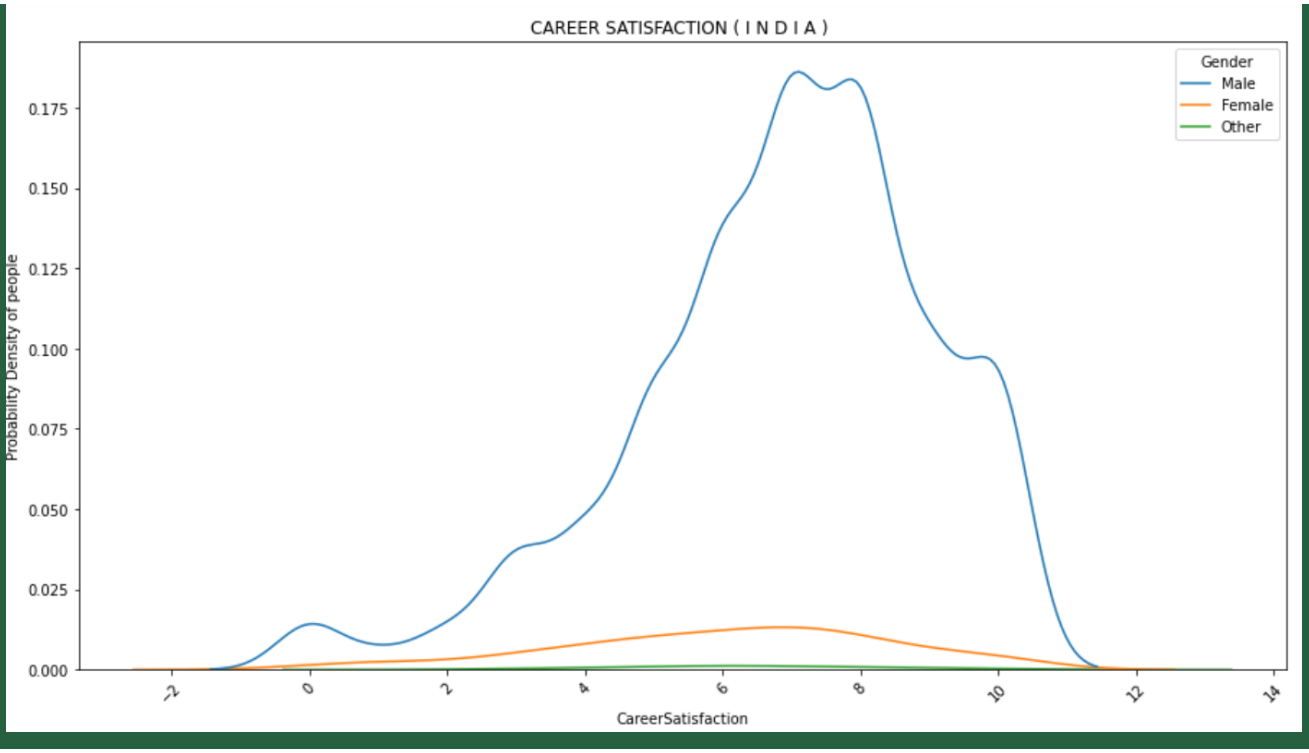


[30]:
```
gender_groupby_India['CareerSatisfaction'].mean()
```

[30]:
```
Gender
Female    6.028736
Male      6.856557
Other     6.428571
```

In [31]:
```
plt.figure(figsize=(15,8))
ax=sns.kdeplot(data=df_india,x='CareerSatisfaction',hue='Gender')
plt.xticks(rotation=45)
for p in ax.patches:
    ax.annotate(format(p.get_height()),(p.get_x(),p.get_height()+0.6))
plt.title("CAREER SATISFACTION ( I N D I A ) ")
plt.ylabel("Probability Density of people")
```

Out[31]:
```
Text(0, 0.5, 'Probability Density of people')
```



In [32]:
```
df.to_csv('updatedDatasets/Update3.csv',index=False)
df_india.to_csv('updatedDatasets/UpdatedIndia.csv',index=False)
```

Country

In [2]:
```
df = pd.read_csv('updatedDatasets/Update3.csv',index_col='Respondent')
```

In [3]:
```
df['Country'].nunique()
```

Out[3]:
```
201
```

In [4]:
```
country_groupby = df.groupby('Country')
```

In [5]:
```
country_avaerage_salary = pd.DataFrame(country_groupby['Salary'].mean())
country_avaerage_salary.sort_values('Salary',ascending=False).head()
```

Out[5]:

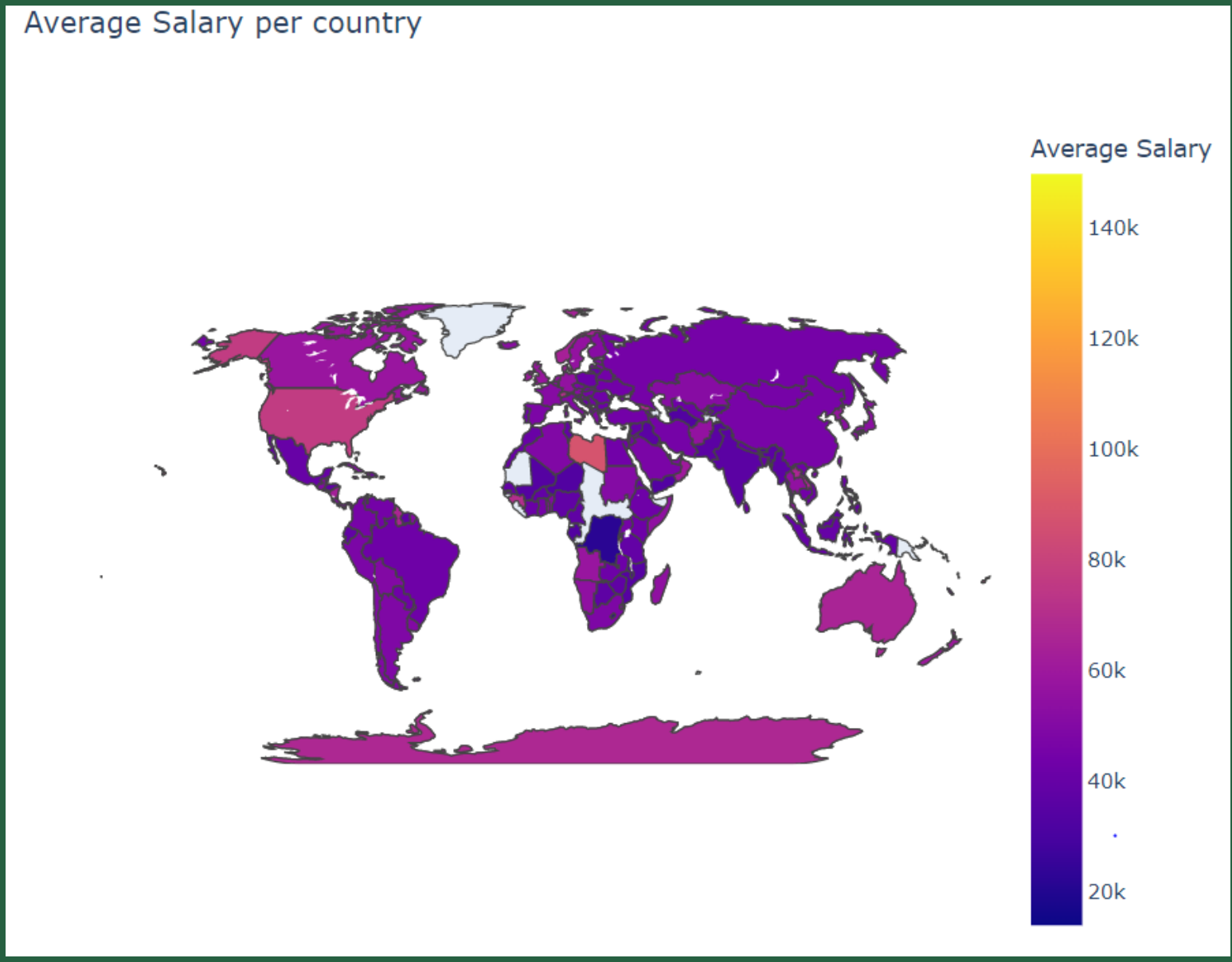
	Salary
Country	
Bermuda	150000.000000
Anguilla	100000.000000
American Samoa	98128.097477
Burundi	98128.097477
Libya	87996.924975

In [6]:
```
import chart_studio.plotly as py
from plotly.offline import download_plotlyjs, init_notebook_mode,plot ,iplot
init_notebook_mode(connected=True)
import plotly.graph_objs as go
```

In [7]:
```
data = dict(type='choropleth',
       locations=country_avaerage_salary.index,
       locationmode='country names',
       z = country_avaerage_salary['Salary'],
       colorbar = {'title':'Average Salary'})
```

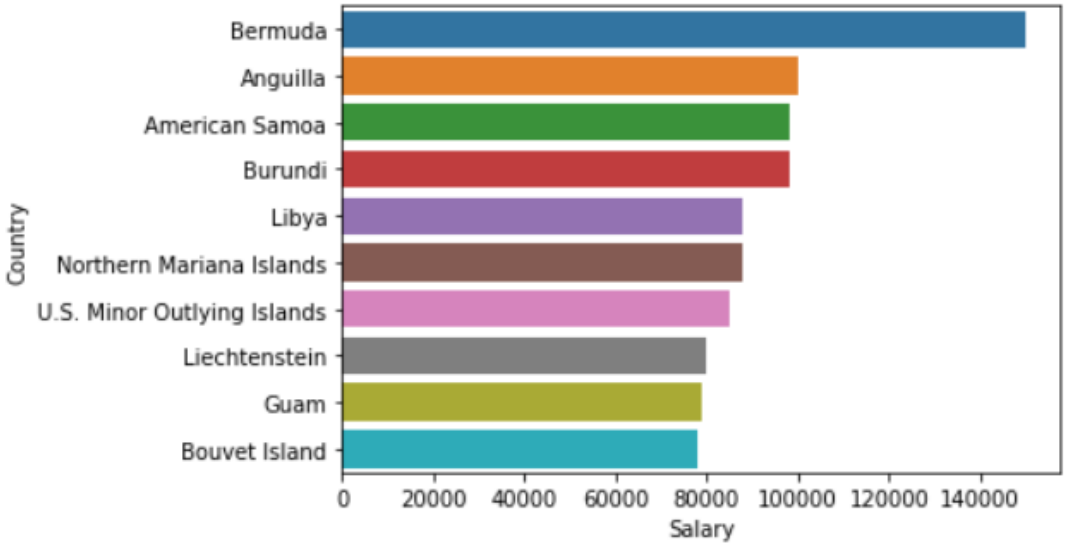
In [8]:
```
layout = dict(title='Average Salary per country',
             geo = dict(showframe=False,
                        projection={'type':'natural earth'}))
```

```
In [9]: choromap = go.Figure(data= [data],layout=layout)

In [10]: iplot(choromap)
```



In [11]:
```
temp = country_avaerage_salary.sort_values('Salary',ascending=False).head(10)
sns.barplot(x=temp['Salary'],y=temp.index)
```

Out[11]: <AxesSubplot:xlabel='Salary', ylabel='Country'>



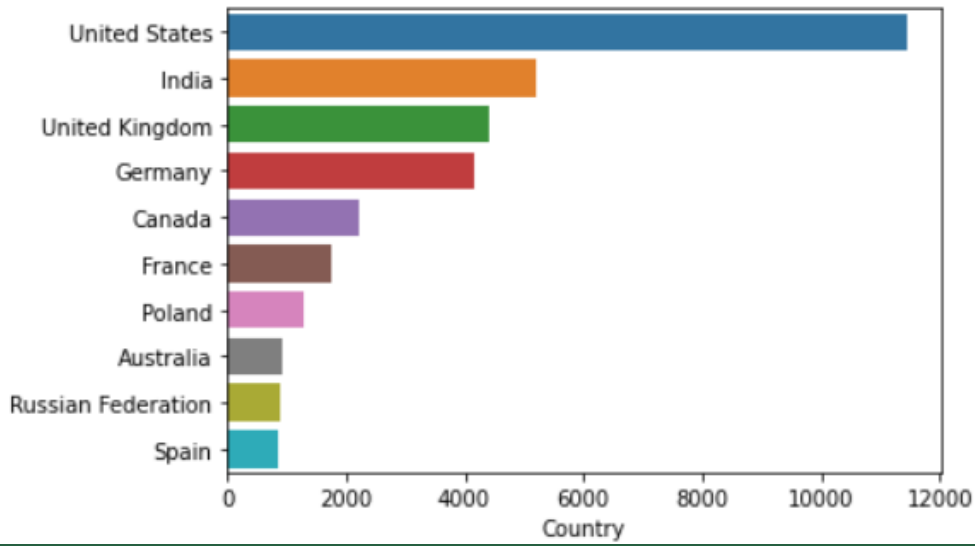
In [12]:
```
country = pd.DataFrame(df.Country.value_counts())
country.sort_values('Country',ascending=False).head()
```

Out[12]:

	Country
United States	11455
India	5197
United Kingdom	4395
Germany	4143
Canada	2233

In [13]:
```
temp = country.sort_values('Country',ascending=False).head(10)
sns.barplot(x=temp['Country'],y=temp.index)
```

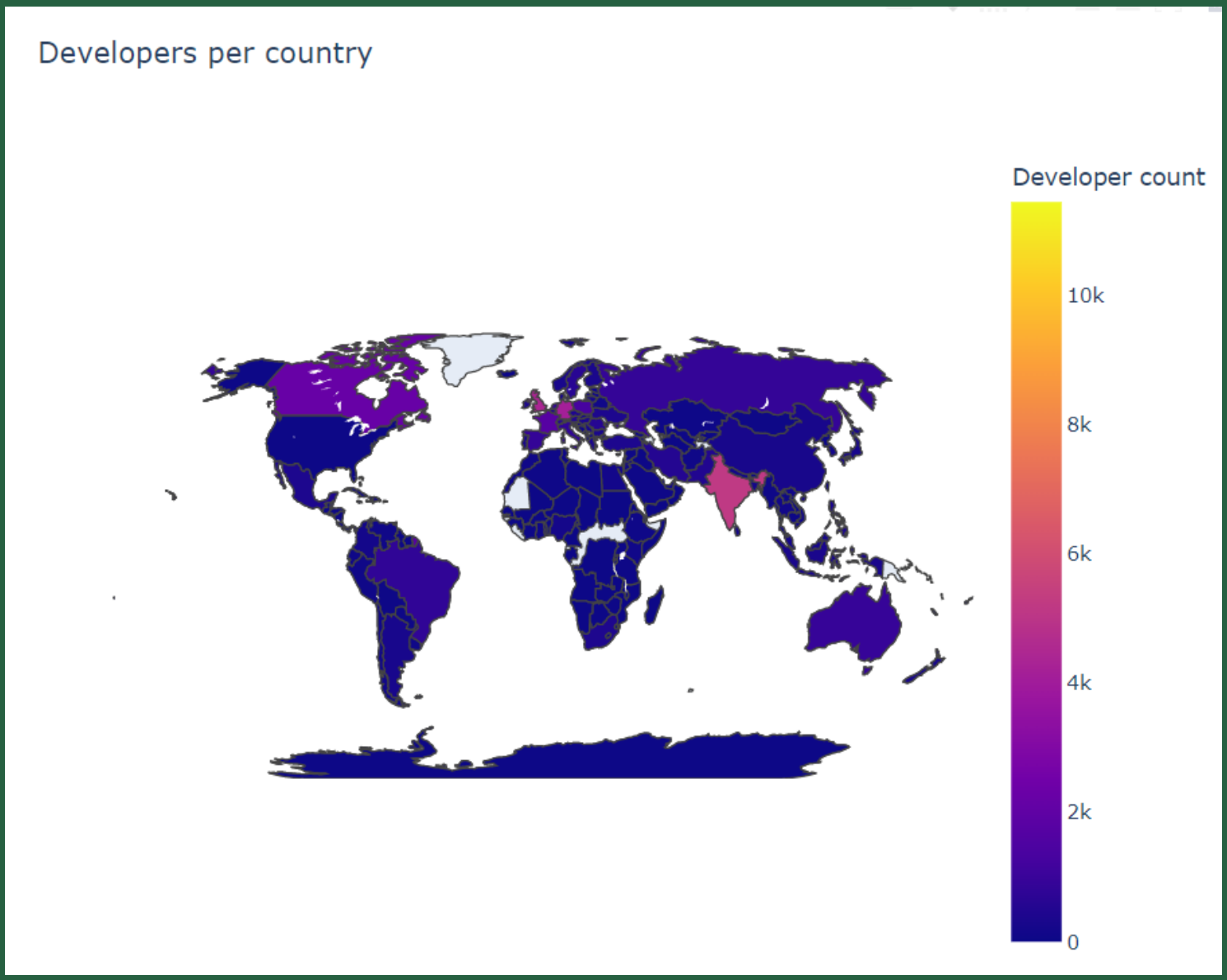
Out[13]: <AxesSubplot:xlabel='Country'>



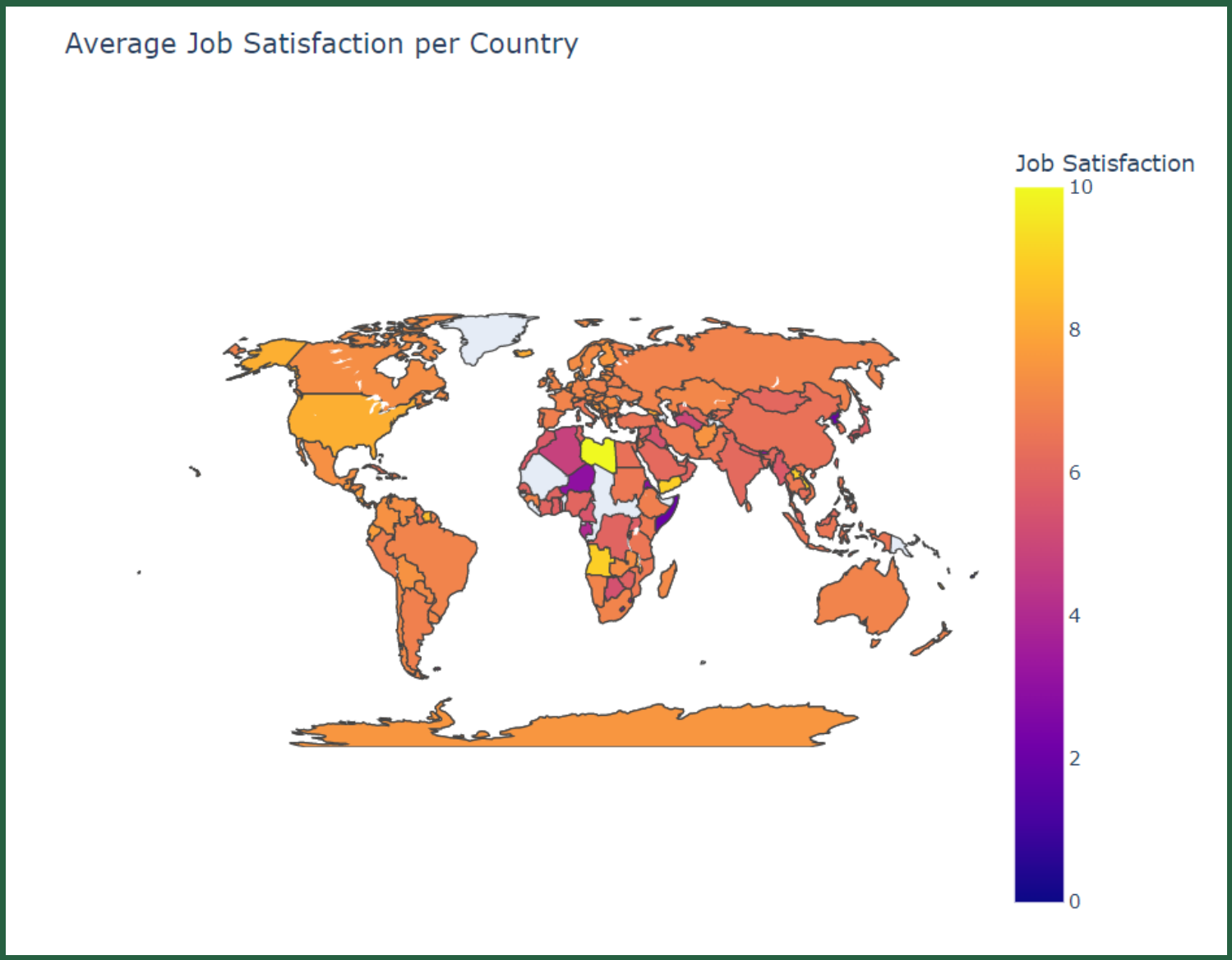
In [14]:
```
data = dict(type='choropleth',
       locations=country.index,
       locationmode='country names',
       z = country['Country'],
       text = country.index,
       colorbar = {'title':'Developer count'})
```

In [15]:
```
layout = dict(title='Developers per country',
             geo = dict(showframe=False,
                        projection={'type':'natural earth'}))
```

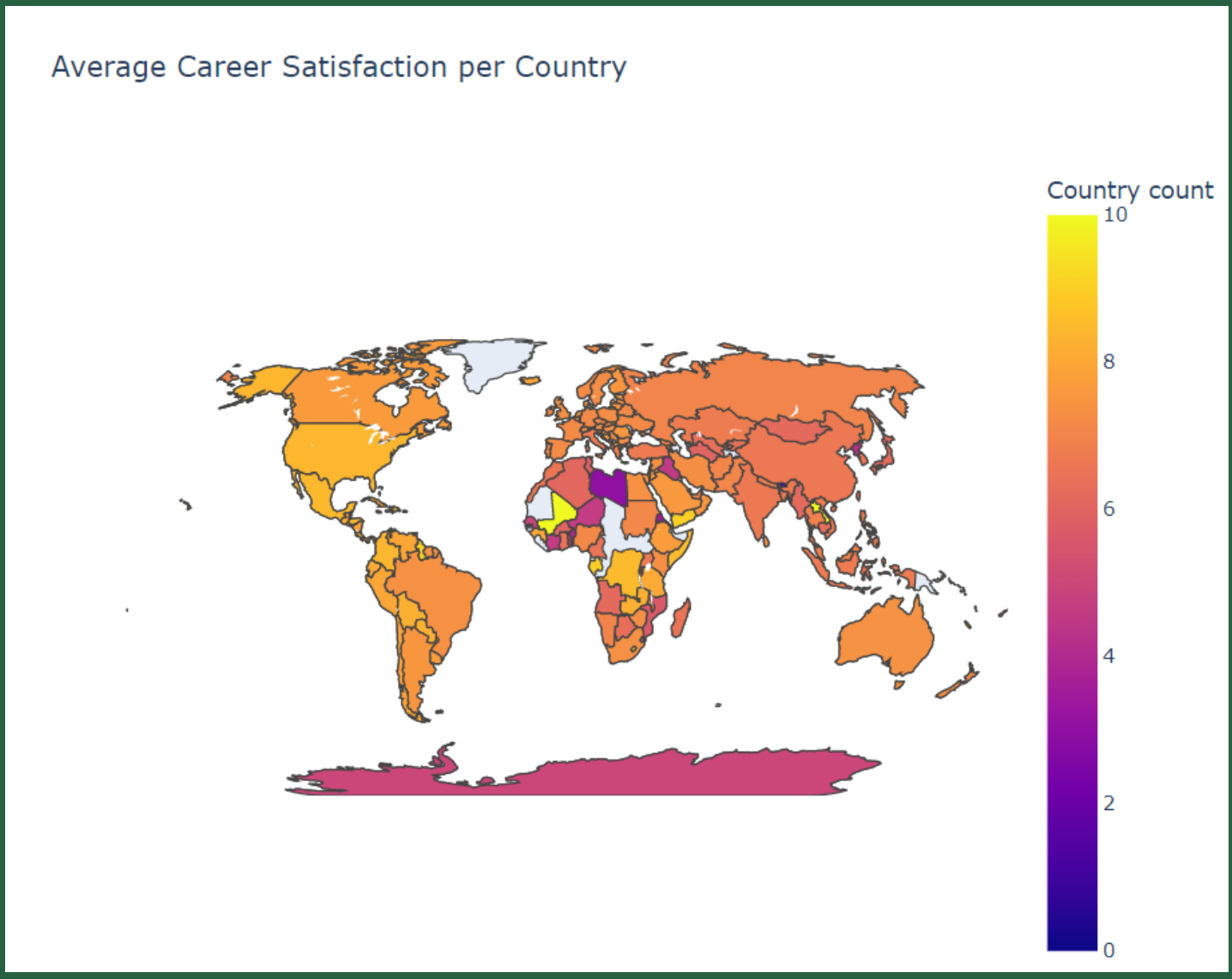
In [16]:
```
choromap2 = go.Figure(data= [data],layout=layout)
iplot(choromap2)
```



In [17]:
```
data = dict(type='choropleth',
       locations=country_groupby['Salary'].mean().index,
       locationmode='country names',
       z = country_groupby['JobSatisfaction'].mean(),
       colorbar = {'title':'Job Satisfaction'})
layout = dict(title='Average Job Satisfaction per Country',
             geo = dict(showframe=False,
                        projection={'type':'natural earth'}))
choromap3 = go.Figure(data= [data],layout=layout)
iplot(choromap3)
```



In [18]:
```
data = dict(type='choropleth',
       locations=country_groupby['Salary'].mean().index,
       locationmode='country names',
       z = country_groupby['CareerSatisfaction'].mean(),
       colorbar = {'title':'Country count'})
layout = dict(title='Average Career Satisfaction per Country',
             geo = dict(showframe=False,
                        projection={'type':'natural earth'}))
choromap3 = go.Figure(data= [data],layout=layout)
iplot(choromap3)
```



Top IDEs Preferred

In [2]:
```
data = pd.read_csv("updatedDatasets/Update3.csv")
```

In [3]:
```
dataT = data[data['IDE'].notna()]
```

In [4]:
```
dataT.head(1)
```

Out[4]:

	Respondent	Professional	ProgramHobby	Country	University	EmploymentStatus	FormalEducation	MajorUndergrad	YearsCodedJob	DeveloperType	...	Wa
0	1	Student	Yes, both	United States	No	Not employed, and not looking for work	Secondary school	NaN	NaN	NaN	...	

1 rows × 41 columns

[IDE] Segregation, Cleaning and Analysis

In [5]:
```
A = {}
J = list()
for i in dataT['IDE']:
    x = i
    x = str(x)
    L = x.split(';')

    for k in L:
        J.append(k.strip())
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1;
    J.clear()
```

In [7]:
```
D1=pd.Series(A,name='IDE Users')
```

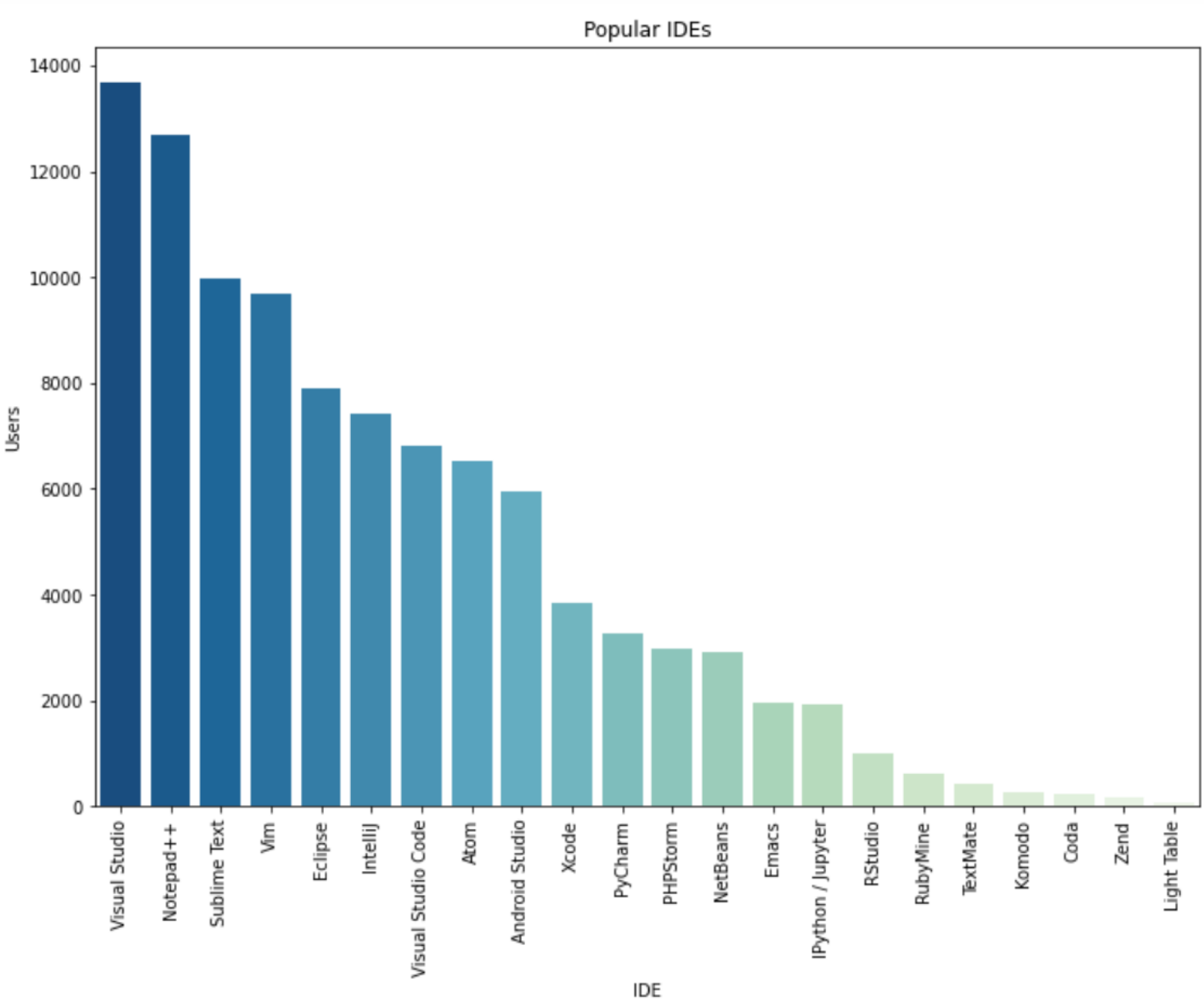
In [8]:
```
D1 =D1.to_frame()
```

In [9]:
```
D1=D1.reset_index(level=0)
```

In [10]:
```
D1.columns=['IDE','Users']
```

In [11]:
```
D1 = D1.sort_values(by='Users',ascending=False)
```

In [12]:
```
fig, ax = plt.subplots()
fig.set_size_inches(11.7, 8.27)
s.barplot(data=D1,x='IDE',y='Users',order=D1['IDE'],palette='GnBu_r')
plt.title('Popular IDEs')
plt.xticks(rotation=90)
plt.show()
```



Top Programming Languages

In [30]:
```
dataT=data[data['HaveWorkedLanguage'].notna()]
```

In [31]:
```
A = {}
J = list()
for i in dataT['HaveWorkedLanguage']:
    x = i
    x = str(x)
    L = x.split(';')

    for k in L:
        J.append(k.strip())
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1;
    J.clear()
```

In [16]:
```
D2 = pd.Series(A, name = 'Languages Already Worked')
```

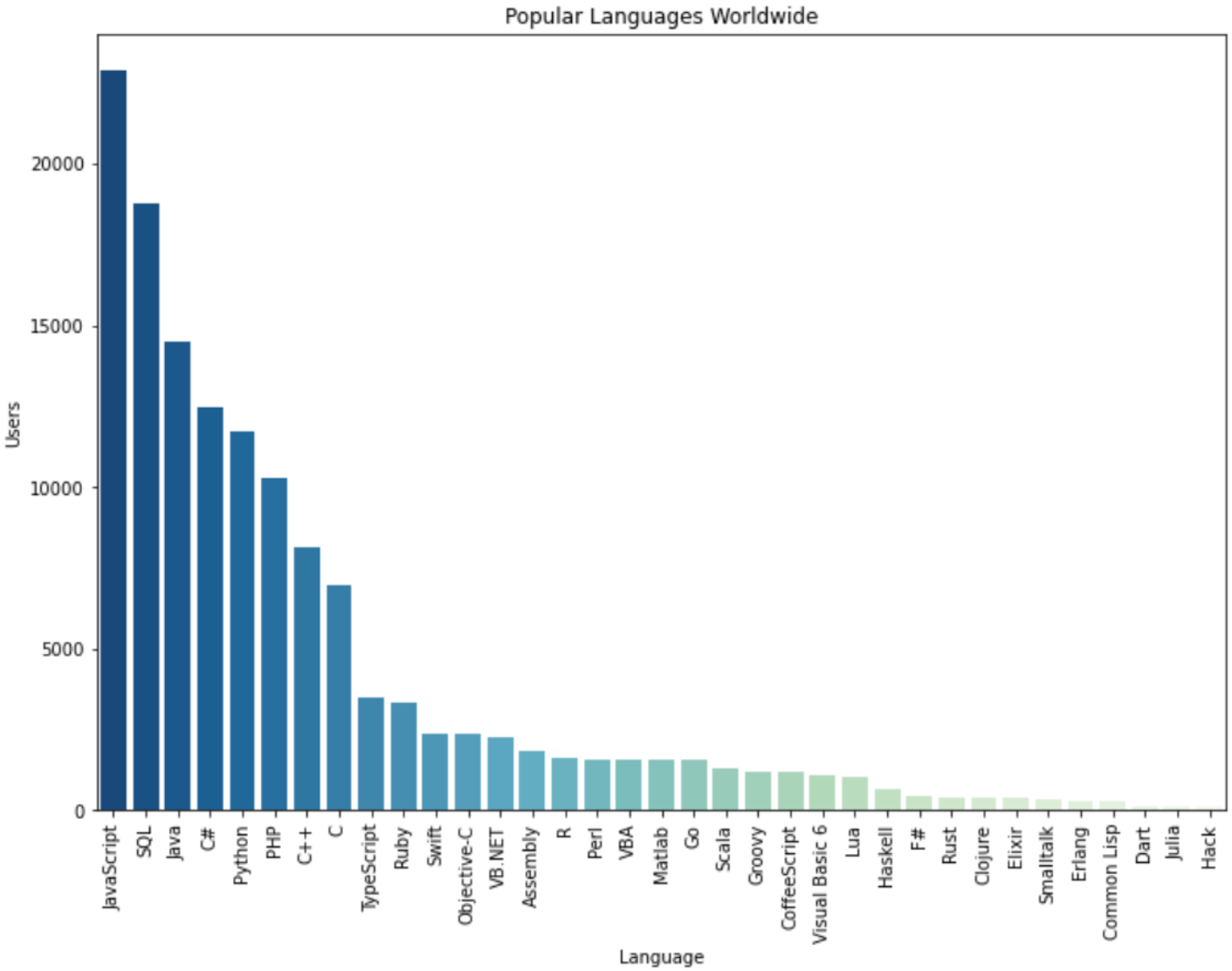
In [32]:
```
D2 = D2.to_frame()
```

In [33]:
```
D2 = D2.reset_index(level=0)
```

In [34]:
```
D2.columns=['Language','Users']
```

In [35]:
```
D2 = D2.sort_values(by='Users',ascending=False)
```

In [36]:
```
fig, ax = plt.subplots()
fig.set_size_inches(11.7, 8.27)
s.barplot(data=D2,x='Language',y='Users',palette='GnBu_r')
plt.xticks(rotation=90)
plt.title('Popular Languages Worldwide')
plt.show()
```



Language vs Salary

In [ ]:
```
D=dict()
J=list()
for i in range(len(data)):
    x=data.iloc[i]['HaveWorkedLanguage']
    J=str(x).split('; ')
    if pd.isna(data.iloc[i]['Salary']):
            continue
    for v in J:
        if v not in D:
            D[v]=[1,data.iloc[i]['Salary']]
        else:
            D[v][0]=D[v][0]+1
            D[v][1]=D[v][1]+data.iloc[i]['Salary']
        J.clear()
```

In [ ]:
```
D.pop('nan')
D
```

In [ ]:
```
temp = pd.DataFrame(D).transpose()
temp.columns = ['Count','TotalSalary']
temp.head()
```

In [ ]:
```
temp['AvgSalary']=temp['TotalSalary']/temp['Count']
temp.drop('TotalSalary',axis=1,inplace=True)
temp.head()
```

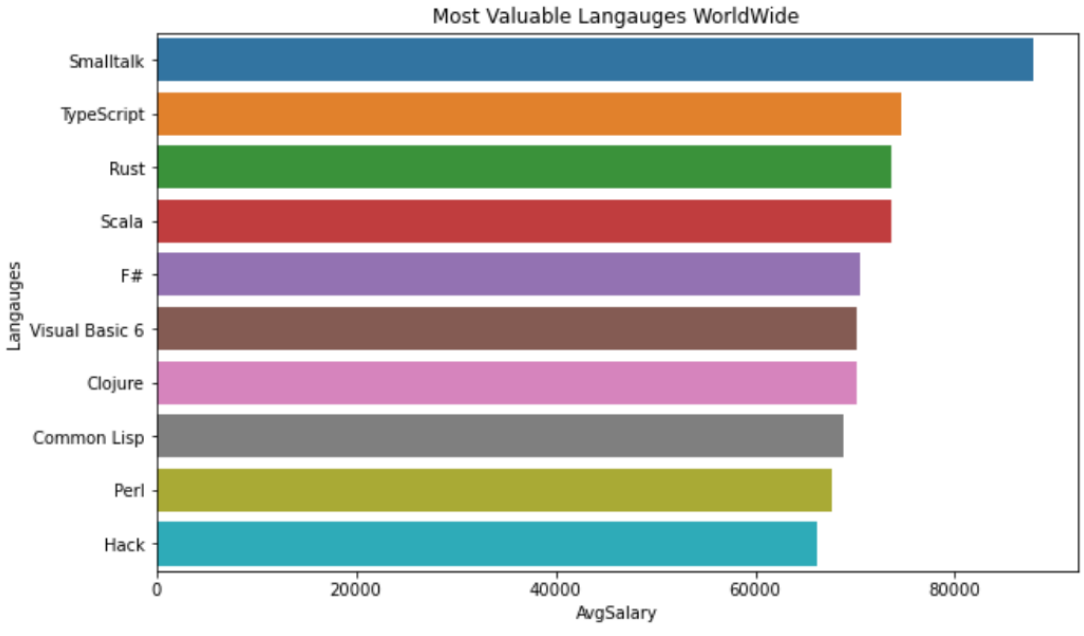
In [ ]:
```
temp.reset_index(inplace=True)
temp.sort_values('AvgSalary',ascending=False).head()
```

In [42]:
```
temp.reset_index(inplace=True)
temp.sort_values('AvgSalary',ascending=False).head()
```

Out[42]:

	index	Count	AvgSalary
29	Smalltalk	62.0	87855.410630
34	TypeScript	7.0	74606.885120
23	Rust	4.0	73693.728036
19	Scala	46.0	73582.858016
32	F#	23.0	70469.940540

In [43]:
```
plt.figure(figsize=(10,6))
s.barplot(y='index',x='AvgSalary',data=temp.sort_values('AvgSalary',ascending=False).head(10))
plt.title('Most Valuable Langauges WorldWide')
plt.ylabel('Langauges')
plt.show()
```



Popular Databases

In [49]:
```
dataT = data[data['HaveWorkedDatabase'].notna()]
```

In [50]:
```
A = {}
J = list()
for i in dataT['HaveWorkedDatabase']:
    x = i
    x = str(x)
    L = x.split(';')

    for k in L:
        J.append(k.strip())
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1;
    J.clear()
```

In [51]:
```
A
```

Out[51]:
```
{'MySQL': 16375,
 'SQLite': 7838,
 'MongoDB': 6192,
 'Redis': 4143,
 'SQL Server': 11358,
 'PostgreSQL': 7815,
 'Oracle': 4874,
 'Cassandra': 906}
```

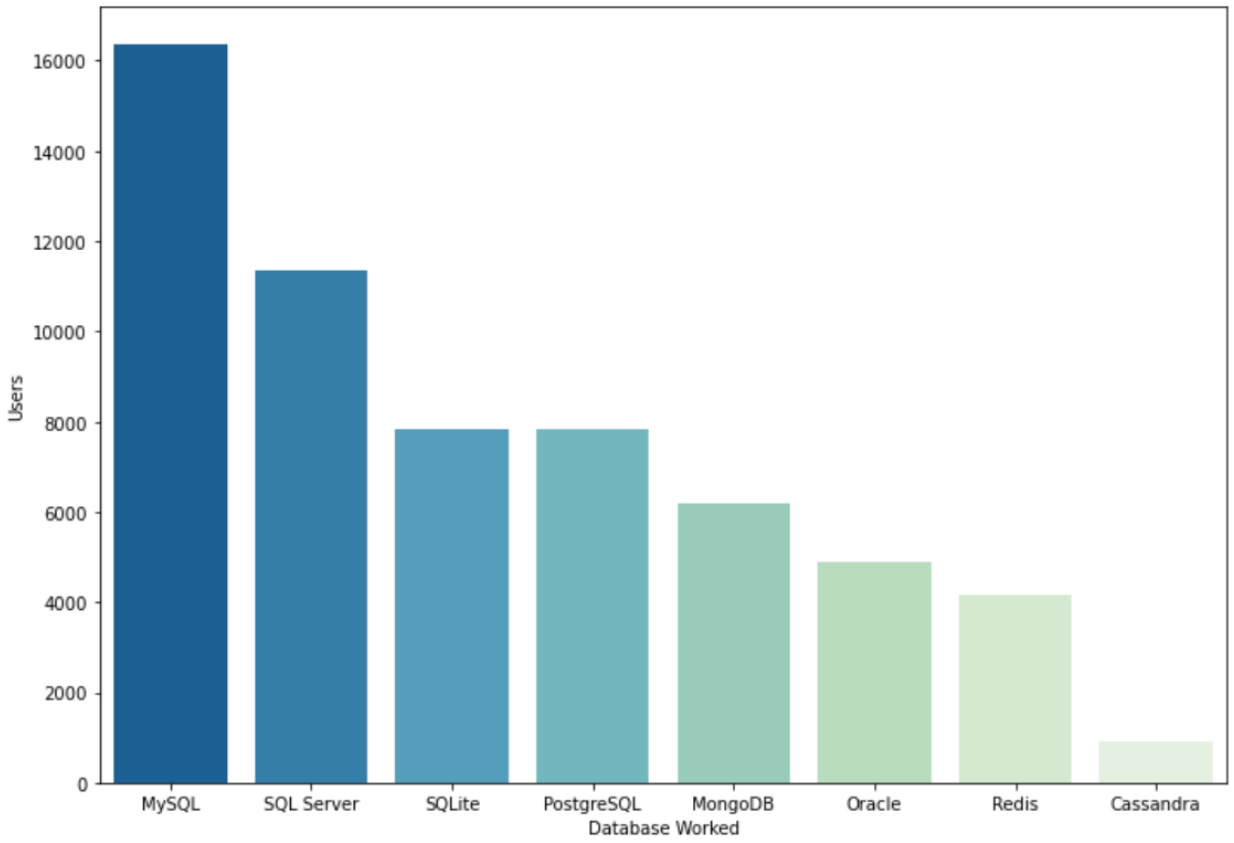
In [52]:
```
D4= pd.Series(A,name="Have Worked Database")
```

In [54]:
```
D4 = D4.to_frame()
```

In [55]:
```
D4 =D4.reset_index(level=0)
```

In [56]:
```
D4.columns=['Database Worked','Users']
```

In [57]:
```
D4 = D4.sort_values(by='Users',ascending=False)
fig,ax = plt.subplots()
fig.set_size_inches(11.7, 8.27)
s.barplot(data=D4,x='Database Worked',y ='Users',palette='GnBu_r')
```



Popular Platforms

In [58]:
```
dataT = data[data['HaveWorkedPlatform'].notna()]
```

In [59]:
```
A = {}
J = list()
for i in dataT['HaveWorkedPlatform']:
    x = i
    x = str(x)
    L = x.split(';')

    for k in L:
        J.append(k.strip())
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1;
    J.clear()
```

In [63]:
```
D6 = pd.Series(A,name ='Have Worked Platform')
```

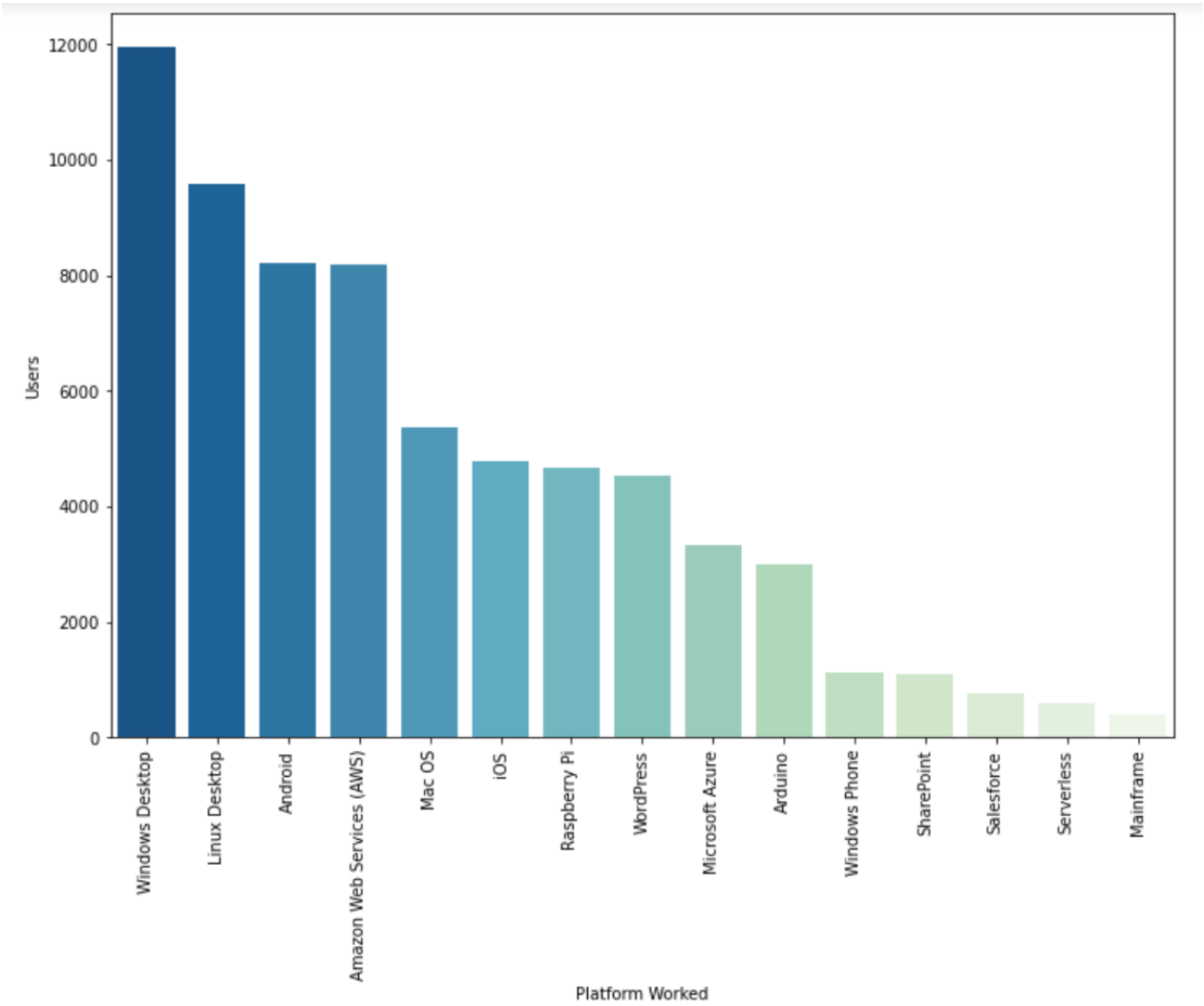
In [65]:
```
D6= D6.to_frame()
```

In [66]:
```
D6=D6.reset_index(level=0)
```

In [67]:
```
D6.columns=['Platform Worked','Users']
```

In [68]:
```
D6=D6.sort_values(by='Users',ascending=False)
```

In [69]:
```
fig,ax = plt.subplots()
fig.set_size_inches(11.8,8.27)
s.barplot(data=D6,x='Platform Worked',y='Users',palette='GnBu_r')
plt.xticks(rotation=90)
```



Important Benefits

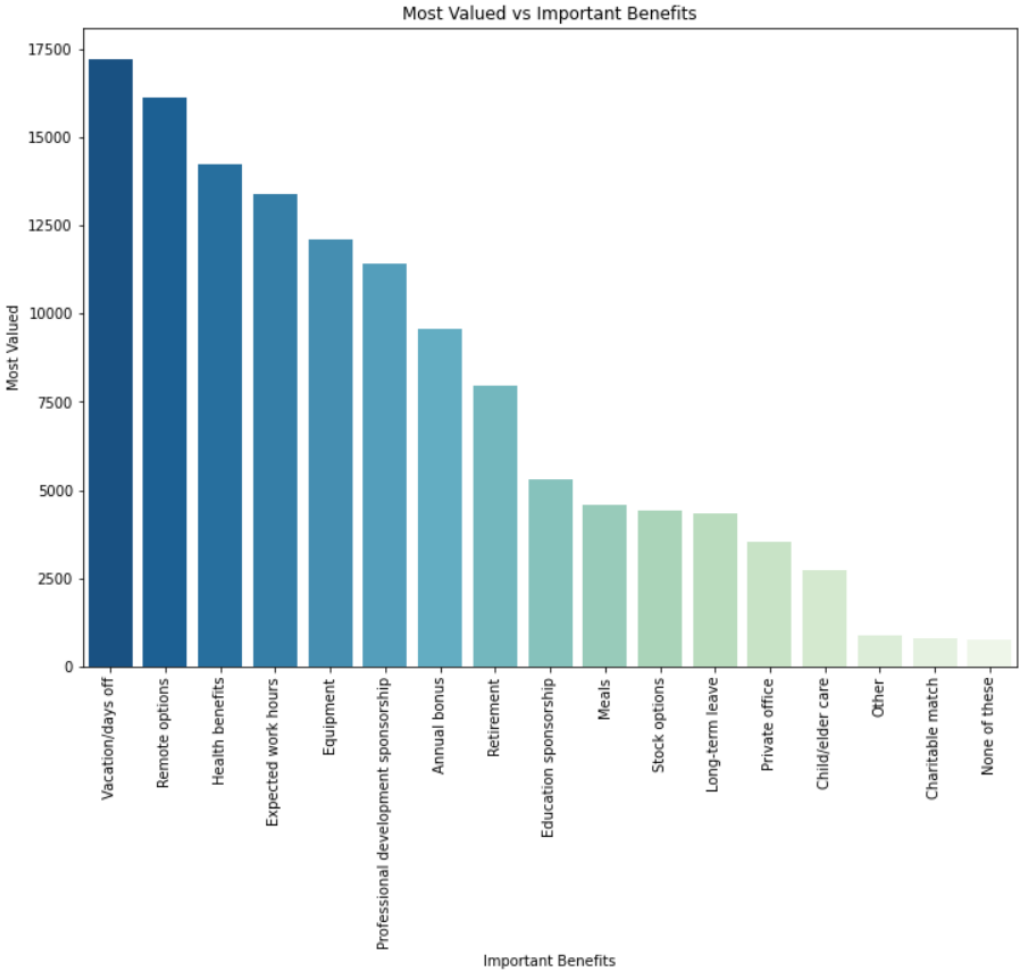
In [2]:
```
data = pd.read_csv("updatedDatasets/Update3.csv")
```

ImportantBenefits Analysis

In [3]:
```
A=dict()
J=list()
for i in data['ImportantBenefits']:
    x=i
    x=str(x)
    J=x.split('; ')
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1
    J.clear()
```

In [4]:
```
D8 = pd.Series(A,name="Important Benefits")
D8 = D8.drop('nan')
D8 = D8.to_frame()
D8 = D8.reset_index(level=0)
D8.columns=['Important Benefits','Most Valued']
D8 = D8.sort_values(by='Most Valued',ascending=False)
```

In [5]:
```
fig,ax = plt.subplots()
fig.set_size_inches(11.8,8.27)
s.barplot(data=D8,x='Important Benefits',y='Most Valued',palette='GnBu_r')
plt.xticks(rotation=90)
plt.title('Most Valued vs Important Benefits')
```

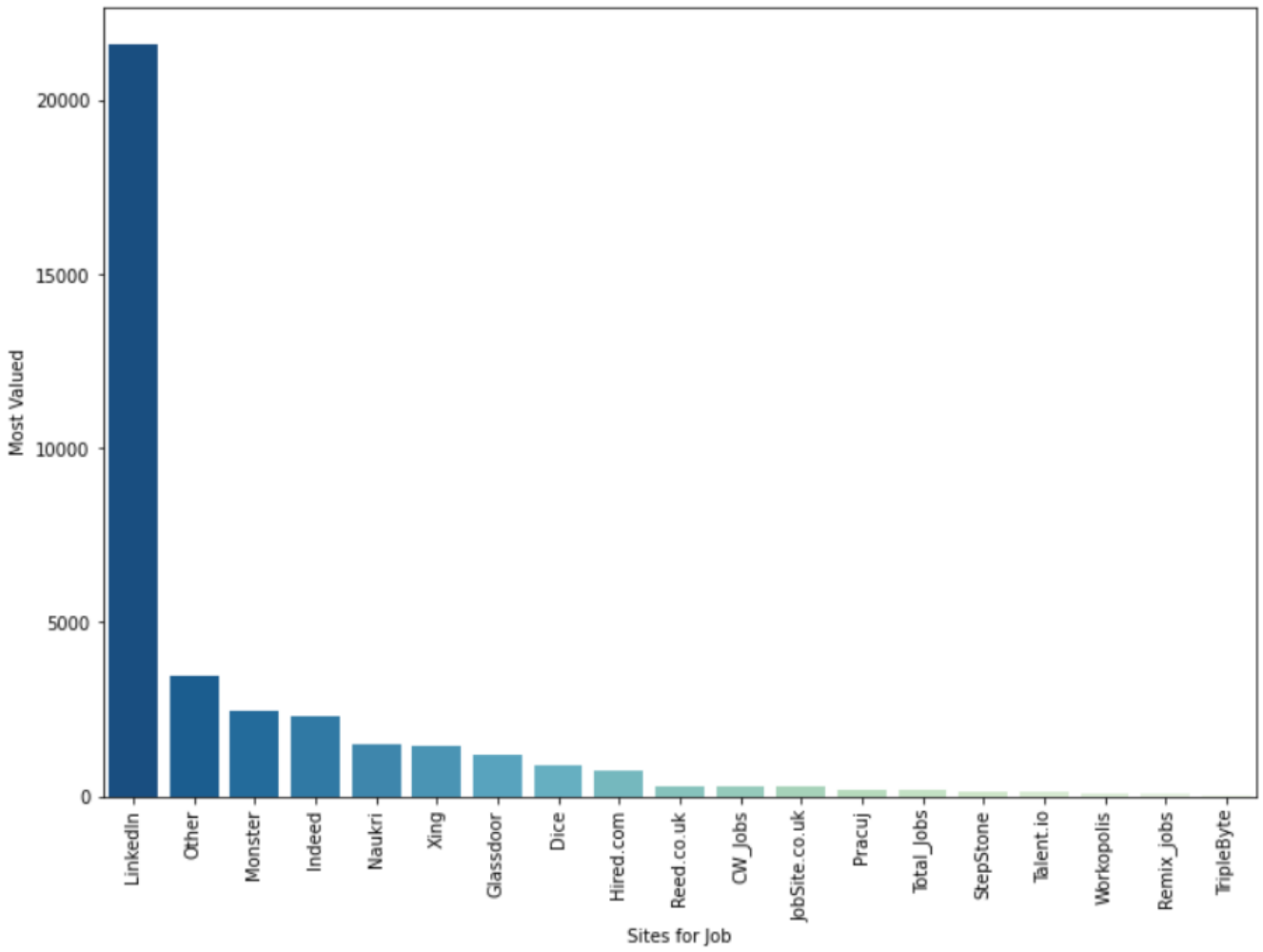


Job Profile

In [6]:
```
A=dict()
J=list()
for i in data['JobProfile']:
    x=i
    x=str(x)
    J=x.split('; ')
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1
    J.clear()
```

In [7]:
```
D9 = pd.Series(A,name="Job Profile Sites")
D9 = D9.drop('nan')
D9 = D9.to_frame()
D9 = D9.reset_index(level=0)
D9.columns=['Sites for Job','Most Valued']
D9 = D9.sort_values(by='Most Valued',ascending=False)
```

In [8]:
```
fig,ax = plt.subplots()
fig.set_size_inches(11.8,8.27)
s.barplot(data=D9,x='Sites for Job',y='Most Valued',palette='GnBu_r')
plt.xticks(rotation=90)
plt.title('Sites For Job vs Most Valued')
```

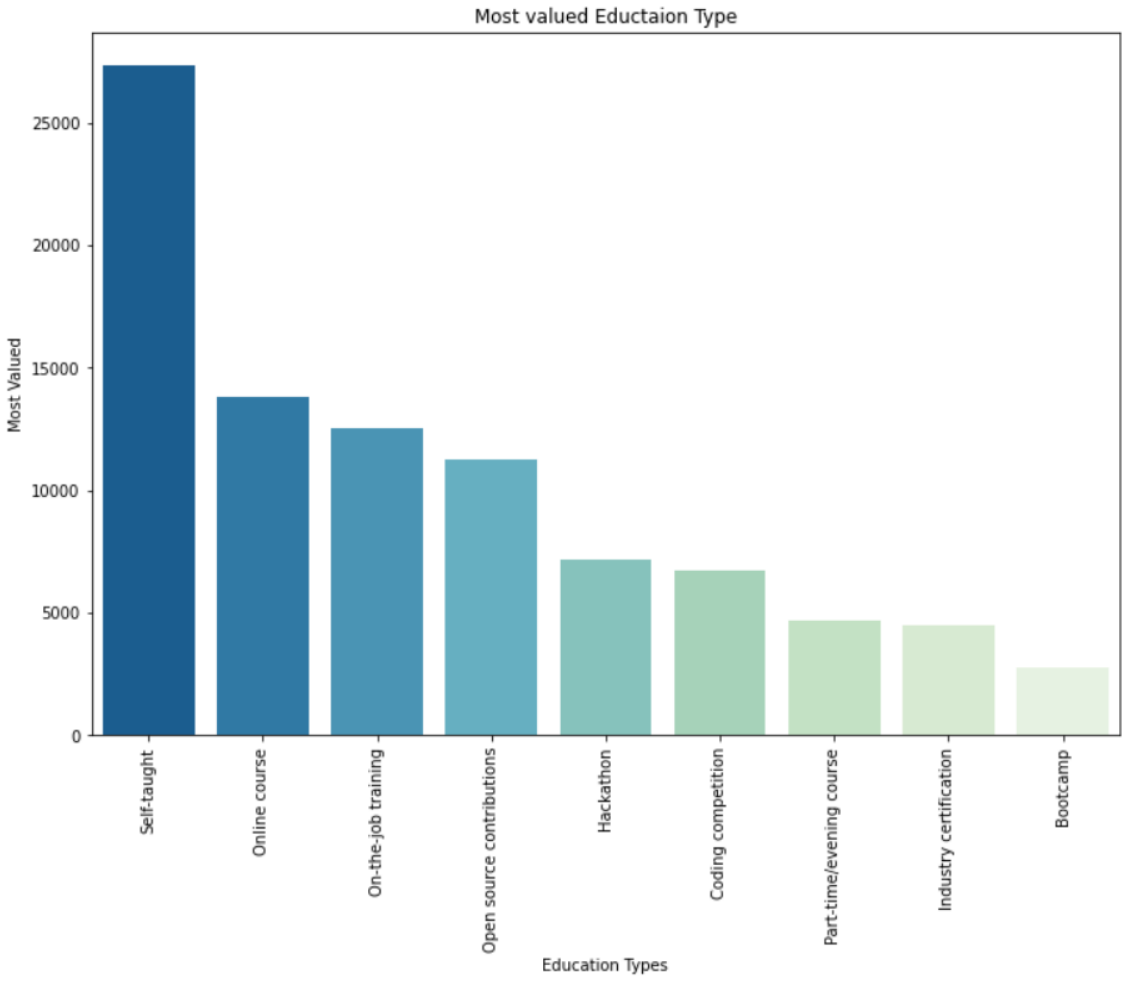


Education Types

In [9]:
```
A=dict()
J=list()
for i in data['EducationTypes']:
    x=i
    x=str(x)
    J=x.split('; ')
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1
    J.clear()
```

In [10]:
```
D10 = pd.Series(A,name="Education Types")
D10 = D10.drop('nan')
D10 = D10.to_frame()
D10 = D10.reset_index(level=0)
D10.columns=['Education Types','Most Valued']
D10 = D10.sort_values(by='Most Valued',ascending=False)
```

In [11]:
```
fig,ax = plt.subplots()
fig.set_size_inches(11.8,8.27)
s.barplot(data=D10, x='Education Types' ,y='Most Valued' ,palette='GnBu_r')
plt.xticks(rotation=90)
plt.title('Most valued Eductaion Type')
```

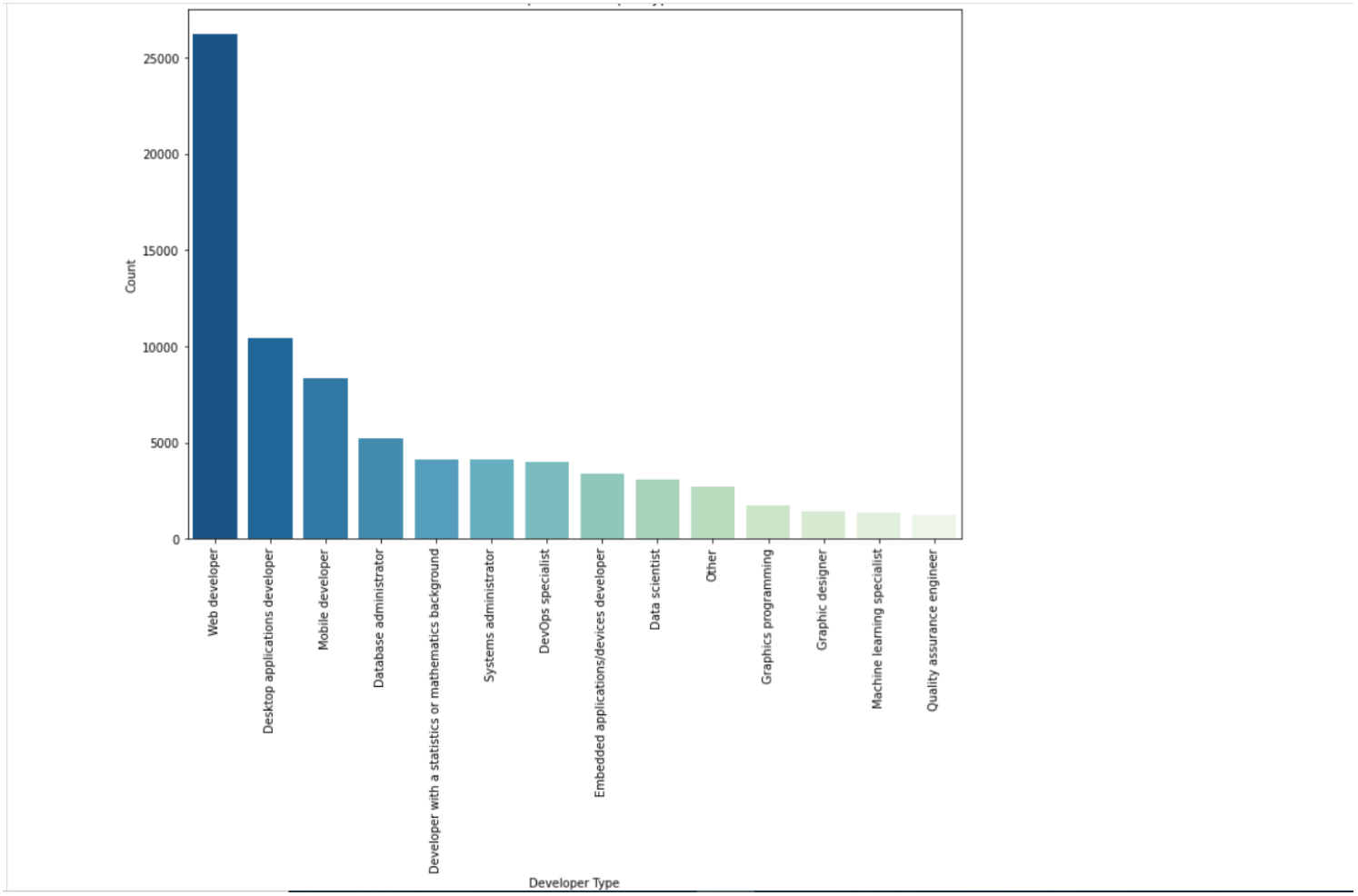


Developer Type

In [12]:
```
A=dict()
J=list()
for i in data['DeveloperType']:
    x=i
    x=str(x)
    J=x.split('; ')
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1
    J.clear()
```

In [13]:
```
D11=pd.Series(A,name='Developer Type')
D11=D11.drop('nan')
D11=D11.to_frame()
D11=D11.reset_index(level=0)
D11.columns=['Developer Type','Count']
D11=D11.sort_values(by='Count',ascending=False)
```

In [14]:
```
fig,ax = plt.subplots()
fig.set_size_inches(11.8,8.27)
s.barplot(data=D11, x='Developer Type' ,y='Count' ,palette='GnBu_r')
plt.xticks(rotation=90)
plt.title('Most Popular Developer Type')
```



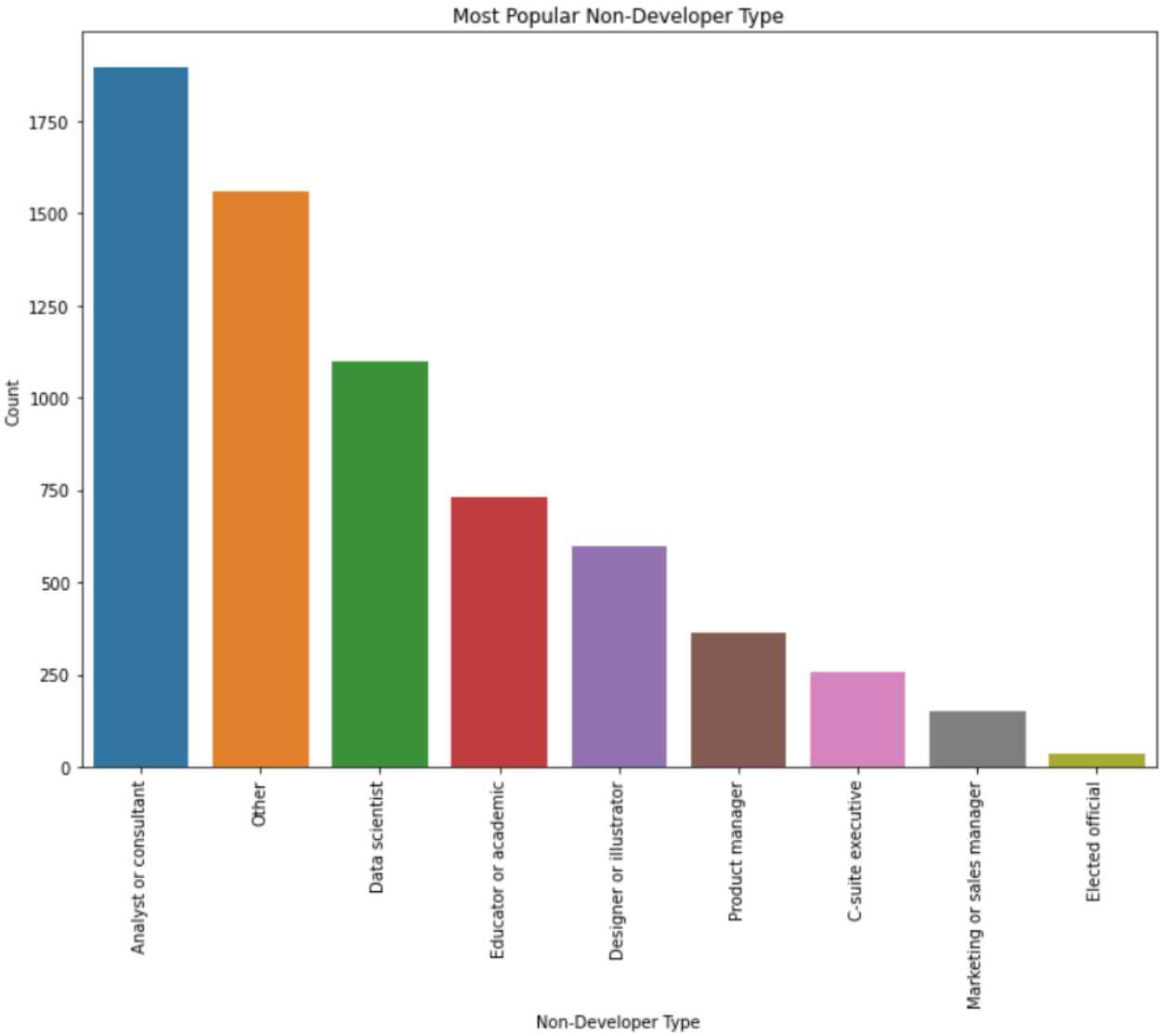
Non-Developer

In [15]:
```
A=dict()
J=list()
for i in data['NonDeveloperType']:
    x=i
    x=str(x)
    J=x.split('; ')
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1
    J.clear()
A
```

Out[15]:
```
{'.': 1,
 'nan': 46501,
 'Data scientist': 1100,
 'Other': 1558,
 'C-suite executive': 257,
 'Product manager': 365,
 'Educator or academic': 732,
 'Analyst or consultant': 1897,
 'Marketing or sales manager': 152,
 'Designer or illustrator': 600,
 'Elected official': 34}
```

In [16]:
```
D12=pd.Series(A,name='Non-Developer Type')
D12=D12.drop('nan')
D12=D12.drop('.')
D12=D12.to_frame()
D12=D12.reset_index(level=0)
D12.columns=['Non-Developer Type','Count']
D12=D12.sort_values(by='Count',ascending=False)
```

In [17]:
```
fig,ax=plt.subplots()
fig.set_size_inches(11.8,8.27)
s.barplot(data=D12,x='Non-Developer Type',y='Count')
D12=D12.sort_values(by='Count',ascending=False)
plt.xticks(rotation=90)
plt.title('Most Popular Non-Developer Type')
```


Most Popular Non-Developer Type
Count
1750
1500
1250
1000
750
500
250
0
Analyst or consultant
Other
Data scientist
Educator or academic
Designer or illustrator
Product manager
C-suite executive
Marketing or sales manager
Elected official
Non-Developer Type

Language Recommendation

In [3]:
```
A = {}
J = list()
for i in df['HaveWorkedLanguage']:
    x = i
    x = str(x)
    L = x.split(';')

    for k in L:
        J.append(k.strip())
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1;
    J.clear()
```

In [4]:
```
A.pop('nan')
A
```

Out[4]:
```
{'Swift': 2368,
 'JavaScript': 22875,
 'Python': 11704,
 'Ruby': 3324,
 'SQL': 18754,
 'Java': 14524,
```

In [5]:
```
temp = []
for x in df['HaveWorkedLanguage']:
    if pd.isna(x)== False:
        temp1 = []
        J = []
        L = x.split(';')
        for k in L:
            J.append(k.strip())
        for y in list(A.keys()):
            if (y in J):
                temp1.append(1)
            else:
                temp1.append(0)
        temp.append(temp1)
```

In [6]:
```
ab = pd.DataFrame(data=temp,columns=list(A.keys()))
ab.head()
```

Out[6]:

	Swift	JavaScript	Python	Ruby	SQL	Java	PHP	Matlab	R	Rust	...	Lua	VBA	Groovy	Go	Smalltalk	Visual Basic 6	Common Lisp	Dart	Julia	Hack
0	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	1	1	1	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	0	0	1	0	0	1	1	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	1	0	1	0	0	1	1	0	...	0	0	0	0	0	0	0	0	0	0
4	0	1	0	0	0	0	1	0	0	1	...	0	0	0	0	0	0	0	0	0	0

5 rows × 35 columns

In [7]:
```
python = ab['Python']
python.head()
```

Out[7]:
```
0    0
1    1
2    1
3    1
4    0
Name: Python, dtype: int64
```

In [8]:
```
similar_to_python = ab.corrwith(python)
corr_python = pd.DataFrame(similar_to_python,columns=['correlation'])
corr_python.dropna(inplace=True)
corr_python.sort_values('correlation',ascending=False).head(10)
```

Out[8]:

	correlation
Python	1.000000
C	0.184977
C++	0.169447
R	0.142893
Matlab	0.136947
Assembly	0.109696
Go	0.108960
Lua	0.100857
Perl	0.090786
Haskell	0.078823

In [9]:
```
ab2 = pd.DataFrame(list(A.items()),columns=['Language','Count'])
ab2.head()
```

Out[9]:

	Language	Count
0	Swift	2368
1	JavaScript	22875
2	Python	11704
3	Ruby	3324
4	SQL	18754

In [10]:
```
corr_python = pd.merge(corr_python,ab2,left_index=True,right_on='Language')
corr_python.head()
```

Out[10]:

	correlation	Language	Count
0	0.017209	Swift	2368
1	-0.041113	JavaScript	22875
2	1.000000	Python	11704
3	0.069663	Ruby	3324
4	-0.025430	SQL	18754

In [11]:
```
corr_python.set_index('Language').head()
```

Out[11]:

Language	correlation	Count
Swift	0.017209	2368
JavaScript	-0.041113	22875
Python	1.000000	11704
Ruby	0.069663	3324
SQL	-0.025430	18754

In [12]:
```
corr_python[corr_python['Count']>1000].sort_values('correlation',ascending=False).head(10)
```

Out[12]:

	correlation	Language	Count
2	1.000000	Python	11704
17	0.184977	C	6974
18	0.169447	C++	8155
8	0.142893	R	1634
7	0.136947	Matlab	1569
19	0.109696	Assembly	1823

Database Recommendation

In [13]:
```
A = {}
J = list()
for i in df['HaveWorkedDatabase']:
    x = i
    x = str(x)
    L = x.split(';')

    for k in L:
        J.append(k.strip())
    for v in J:
        if v not in A:
            A[v]=1
        else:
            A[v]=A[v]+1;
    J.clear()
```

In [14]:
```
A.pop('nan')
A
```

Out[14]:
```
{'MySQL': 16375,
 'SQLite': 7838,
 'MongoDB': 6192,
 'Redis': 4143,
 'SQL Server': 11358,
 'PostgreSQL': 7815,
 'Oracle': 4874
```

In [15]:
```
temp = []
for x in df['HaveWorkedDatabase']:
    if pd.isna(x)== False:
        temp1 = []
        J = []
        L = x.split(';')
        for k in L:
            J.append(k.strip())
        for y in list(A.keys()):
            if (y in J):
                temp1.append(1)
            else:
                temp1.append(0)
        temp.append(temp1)
```

In [16]:
```
ab = pd.DataFrame(data=temp,columns=list(A.keys()))
ab.head()
```

Out[16]:

	MySQL	SQLite	MongoDB	Redis	SQL Server	PostgreSQL	Oracle	Cassandra
0	1	1	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0
2	1	1	1	1	1	0	0	0
3	1	0	0	0	0	0	0	0
4	0	1	0	0	0	0	0	0

In [17]:
```
mysql = ab['MySQL']
mysql.head()
```

Out[17]:
```
0    1
1    1
2    1
3    1
4    0
Name: MySQL, dtype: int64
```

In [18]:
```
similar_to_mysql = ab.corrwith(mysql)
corr_mysql = pd.DataFrame(similar_to_mysql,columns=['correlation'])
corr_mysql.dropna(inplace=True)
corr_mysql.sort_values('correlation',ascending=False).head(3)
```

Out[18]:

	correlation
MySQL	1.000000
SQLite	0.075484
Redis	0.040005

In [19]:
```
ab2 = pd.DataFrame(list(A.items()),columns=['Databases','Count'])
ab2.head()
```

Out[19]:

	Databases	Count
0	MySQL	16375
1	SQLite	7838
2	MongoDB	6192
3	Redis	4143
4	SQL Server	11358

In [20]:
```
corr_mysql = pd.merge(corr_mysql,ab2,left_index=True,right_on='Databases')
corr_mysql.head()
```

Out[20]:

	correlation	Databases	Count
0	1.000000	MySQL	16375
1	0.075484	SQLite	7838
2	0.038457	MongoDB	6192
3	0.040005	Redis	4143
4	-0.205809	SQL Server	11358

In [21]:
```
corr_mysql.set_index('Databases').head()
```

Out[21]:

Databases	correlation	Count
MySQL	1.000000	16375
SQLite	0.075484	7838
MongoDB	0.038457	6192
Redis	0.040005	4143
SQL Server	-0.205809	11358

In [22]:
```
corr_mysql[corr_mysql['Count']>2000].sort_values('correlation',ascending=False).head(3)
```

Out[22]:

	correlation	Databases	Count
0	1.000000	MySQL	16375
1	0.075484	SQLite	7838
3	0.040005	Redis	4143

Auditory Environment

```
In [3]: df['AuditoryEnvironment'].unique()
```

```
Out[3]: array(['Turn on some music',
                'Put on some ambient sounds (e.g. whale songs, forest sounds)',
                nan, 'Keep the room absolutely quiet', 'Something else',
                'Put on a movie or TV show', 'Turn on the news or talk radio'],
               dtype=object)
```

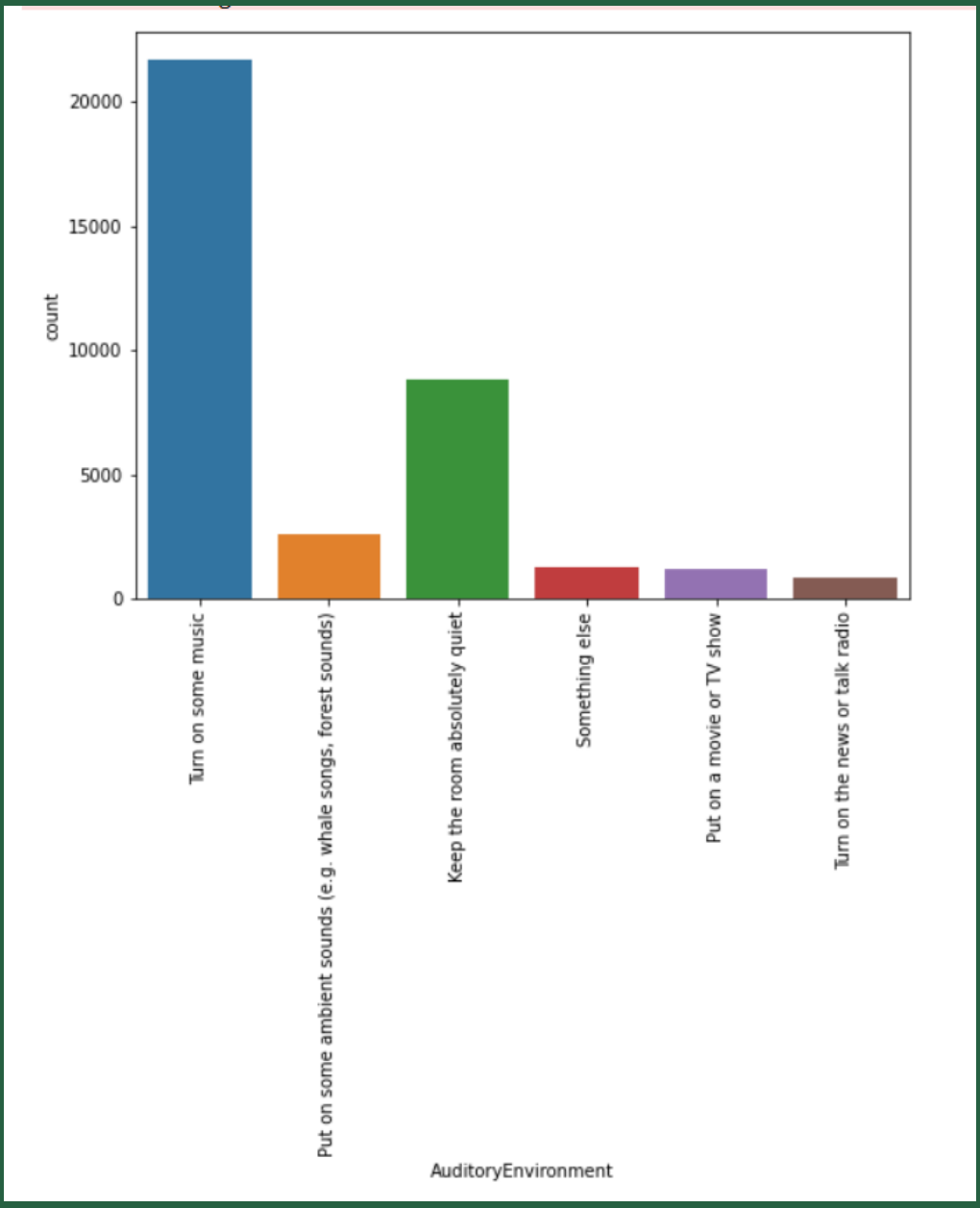
```
In [4]: df['AuditoryEnvironment'].nunique()
```

```
Out[4]: 6
```

```
In [5]: df['AuditoryEnvironment'].count()
```

```
Out[5]: 36457
```

```
In [6]: plt.figure(figsize = (8,6))
        sns.countplot(df['AuditoryEnvironment'] )
        plt.xticks(rotation=90)
        plt.show()
```



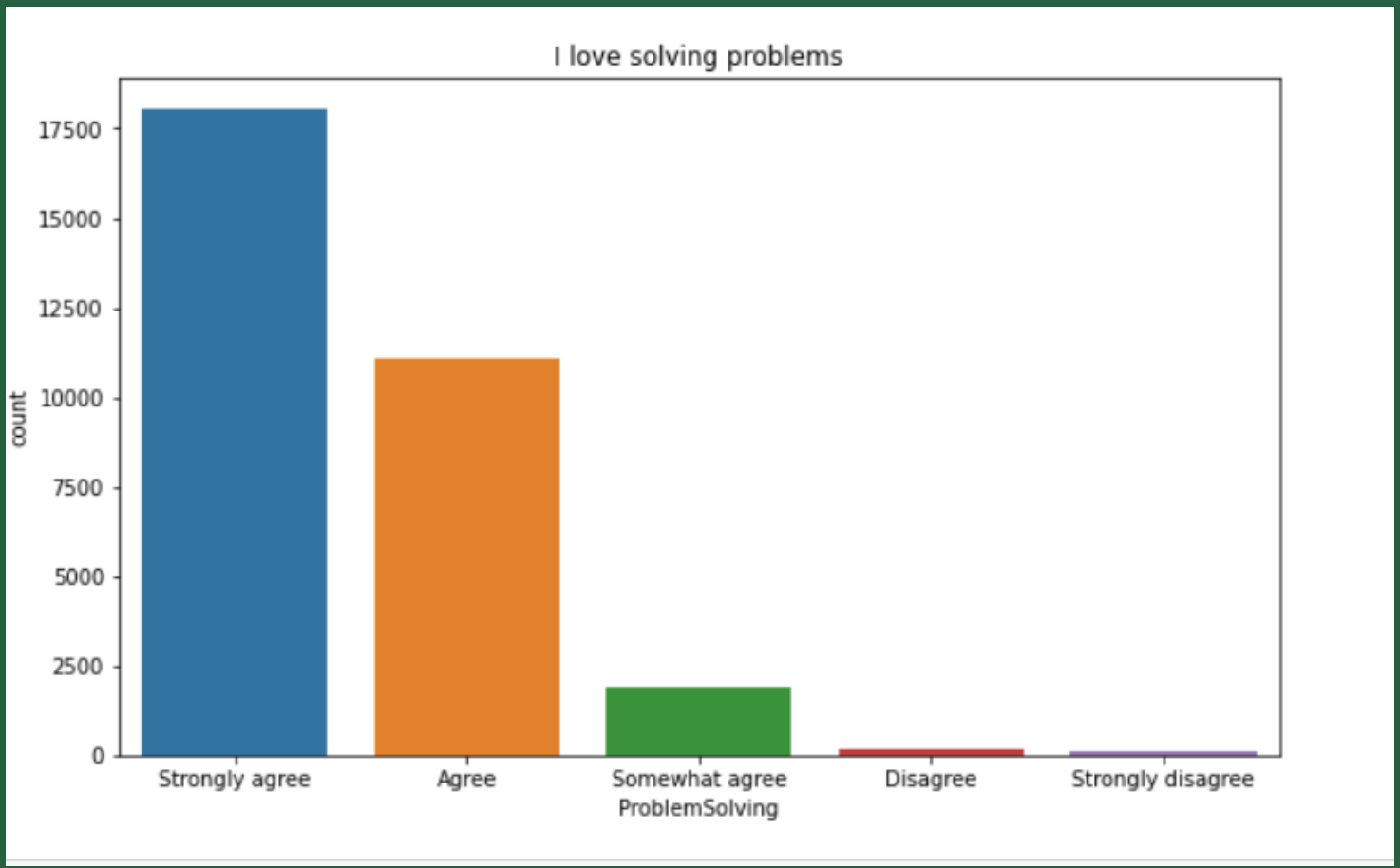
In [7]:
```
df.iloc[:,13:20].head()
```

Out[7]:

	ProblemSolving	LearningNewTech	JobSecurity	DiversityImportant	SeriousWork	WorkPayCare	ChallengeMyself
0	Strongly agree	Agree	Strongly agree	Agree	Strongly agree	Strongly disagree	Agree
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	Strongly agree	Strongly agree	Agree	Strongly agree	Agree	Disagree	Agree
3	Strongly agree	Strongly agree	Somewhat agree	Agree	Strongly agree	Disagree	Strongly agree
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN

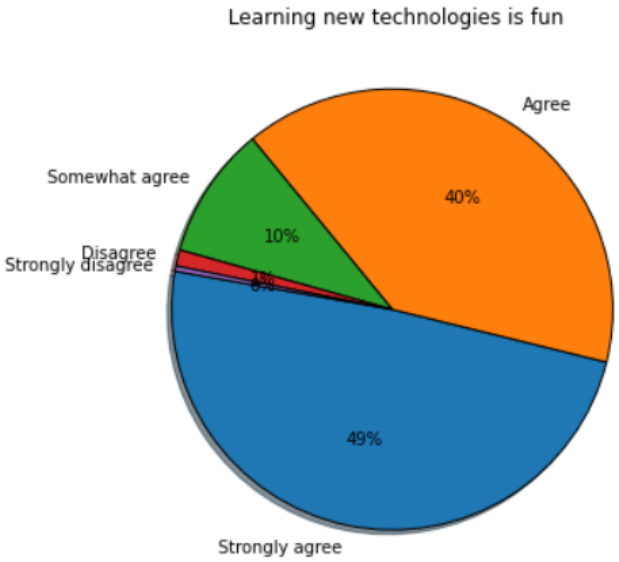
In [8]:
```
#ProblemSolving: I love solving problems
#LearningNewTech: Learning new technologies is fun
#JobSecurity: Job security is important to me
#DiversityImportant: Diversity in the workplace is important
#SeriousWork:I take my work very seriously
#WorkPayCare: I don't really care what I work on, so long as I'm paid well
#ChallengeMyself: I like to challenge myself
```

In [9]:
```
plt.figure(figsize=(10,6))
sns.countplot(x='ProblemSolving',data =df)
plt.title('I love solving problems')
```



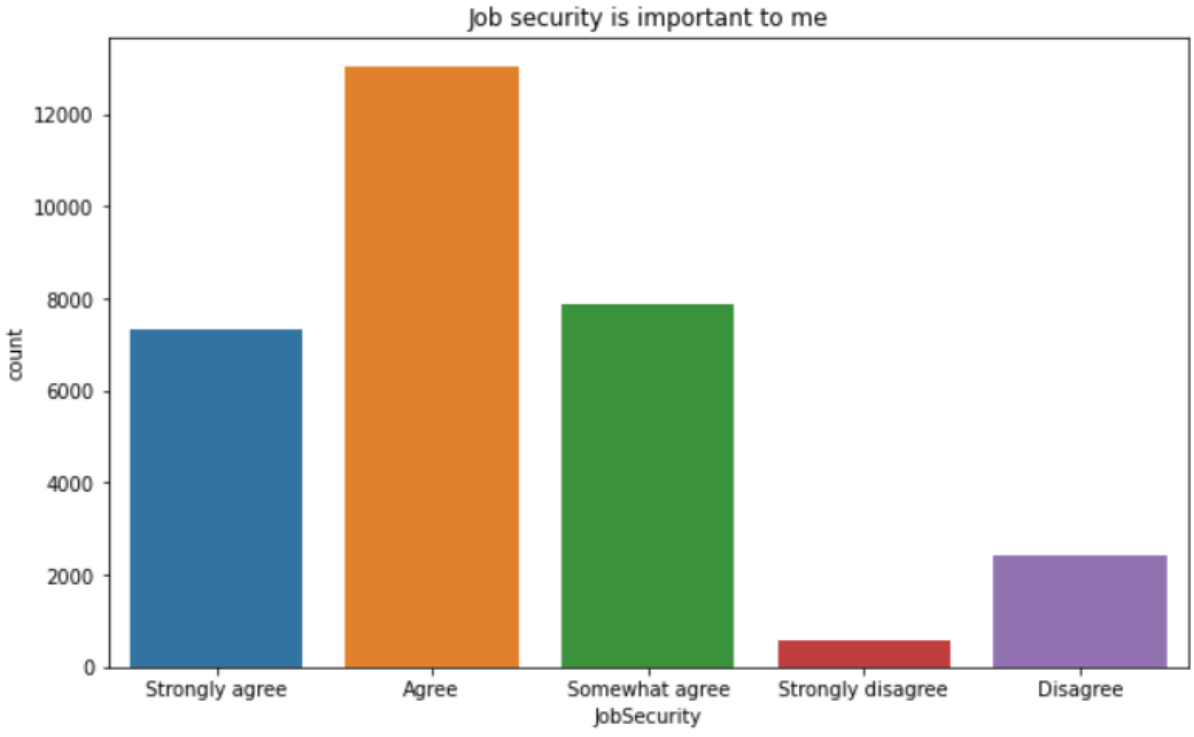
In [10]:
```
plt.figure(figsize=(10,6))
plt.pie(df['LearningNewTech'].value_counts(), labels= df['LearningNewTech'].value_counts().index,
           startangle=170, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title(" Learning new technologies is fun")
```

Out[10]: Text(0.5, 1.0, ' Learning new technologies is fun')



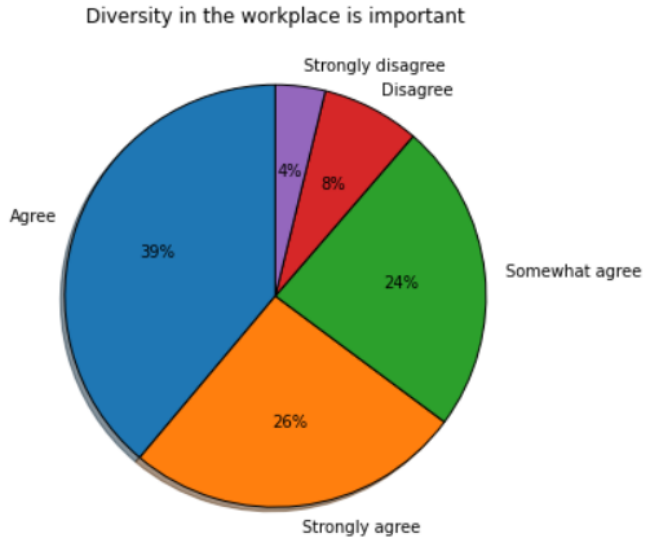
In [11]:
```
plt.figure(figsize=(10,6))
sns.countplot(x='JobSecurity',data =df)
plt.title('Job security is important to me')
```

Out[11]: Text(0.5, 1.0, 'Job security is important to me')



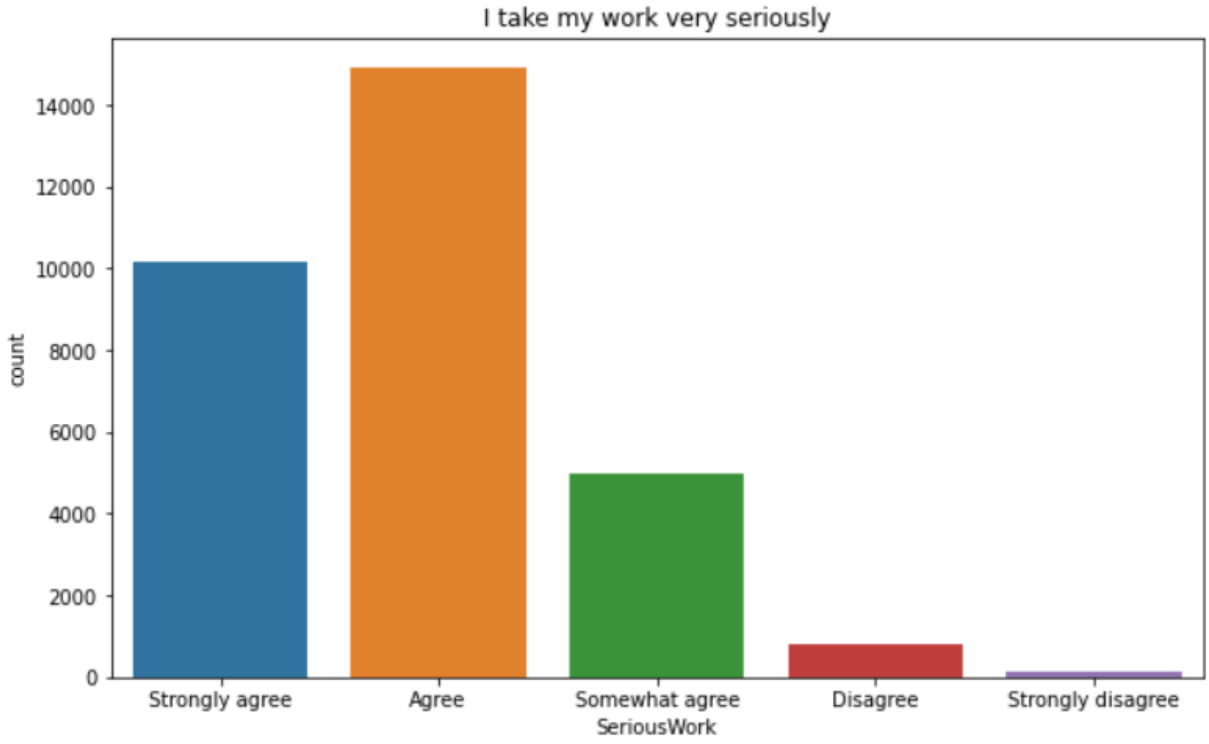
In [12]:
```
plt.figure(figsize=(10,6))
plt.pie(df['DiversityImportant'].value_counts(), labels= df['DiversityImportant'].value_counts().index,
          startangle=90, wedgeprops={'edgecolor': 'black'}, autopct='%1.f%%', shadow=True)
plt.title("Diversity in the workplace is important")
```

Out[12]: Text(0.5, 1.0, 'Diversity in the workplace is important')



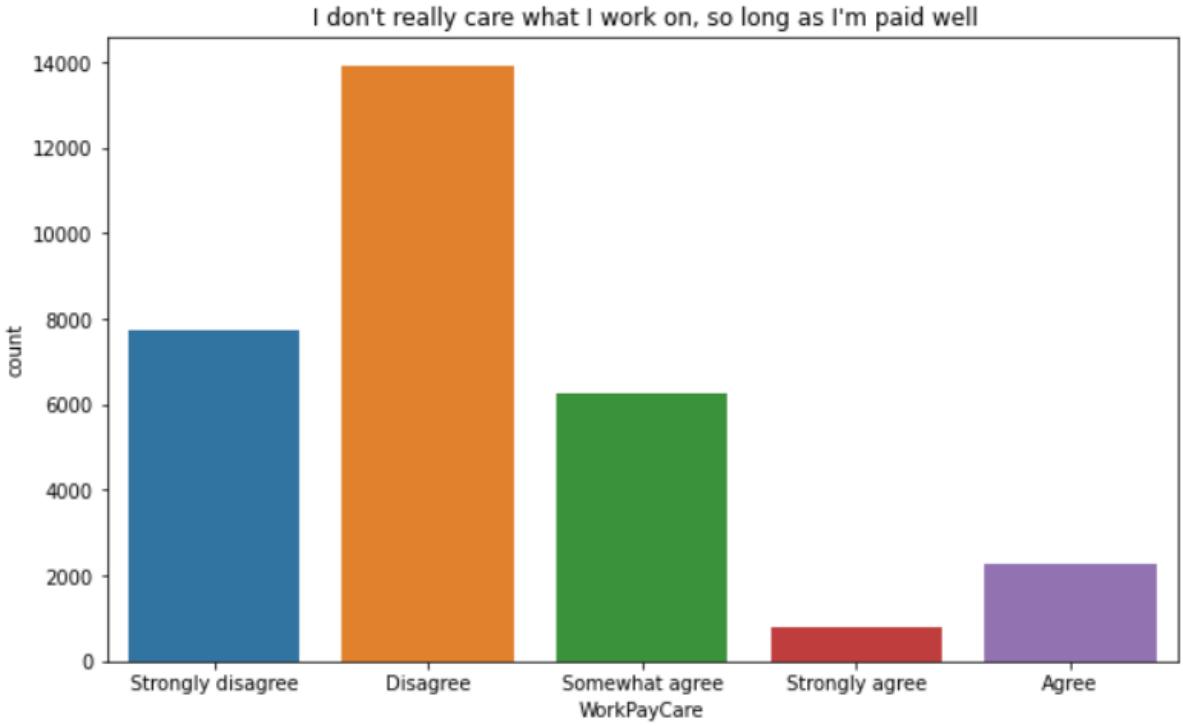
In [13]:
```
plt.figure(figsize=(10,6))
sns.countplot(x='SeriousWork',data =df)
plt.title('I take my work very seriously')
```

Out[13]: Text(0.5, 1.0, 'I take my work very seriously')



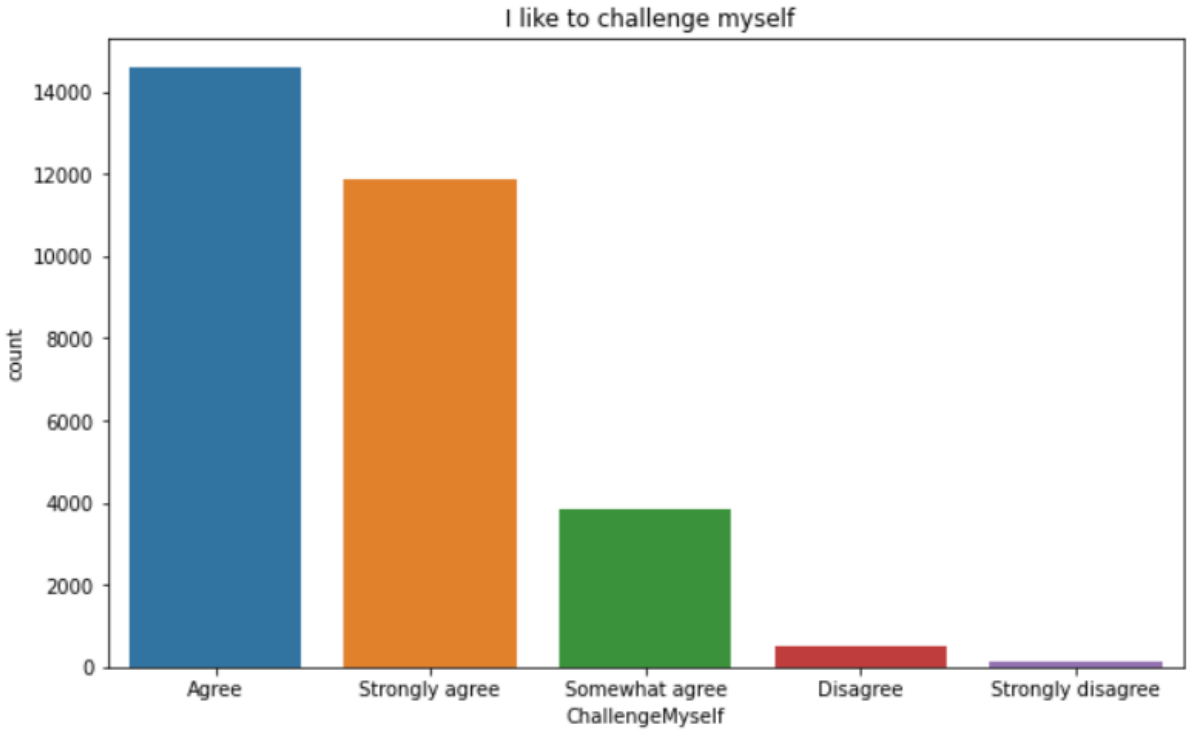
In [14]:
```
plt.figure(figsize=(10,6))
sns.countplot(x='WorkPayCare',data =df)
plt.title(" I don't really care what I work on, so long as I'm paid well")
```

Out[14]: Text(0.5, 1.0, " I don't really care what I work on, so long as I'm paid well")



In [15]:
```
#ChallengeMyself: I like to challenge myself
plt.figure(figsize=(10,6))
sns.countplot(x='ChallengeMyself',data =df)
plt.title(" I like to challenge myself")
```

Out[15]: Text(0.5, 1.0, ' I like to challenge myself')



Last New Job

```
In [16]: df['LastNewJob'].unique()
```

```
Out[16]: array(['Not applicable/ never', nan, 'Between 2 and 4 years ago',
                'More than 4 years ago', 'Less than a year ago',
                'Between 1 and 2 years ago'], dtype=object)
```

```
In [17]: df['LastNewJob'].nunique()
```

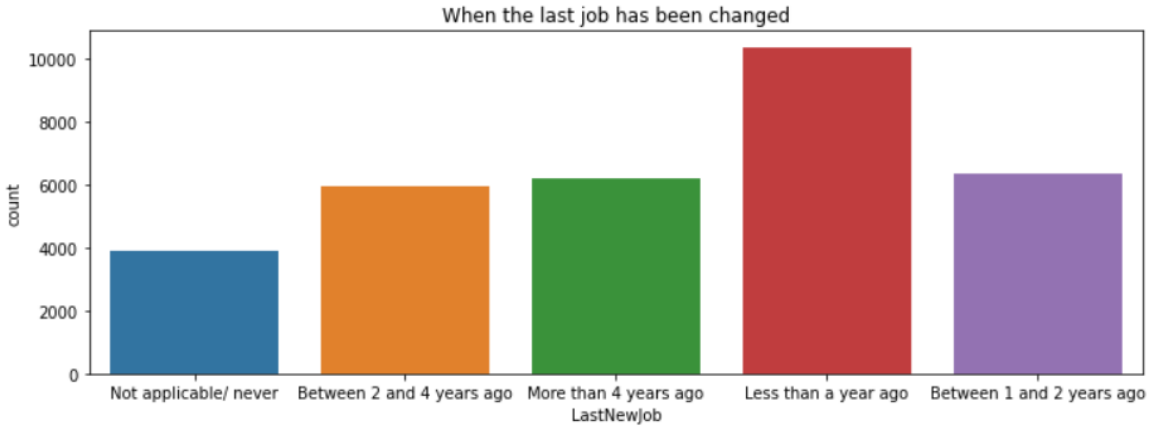
```
Out[17]: 5
```

```
In [18]: df['LastNewJob'].count()
```

```
Out[18]: 32710
```

```
In [19]: plt.figure(figsize = (12,4))
         sns.countplot(x='LastNewJob',data = df)
         plt.title('When the last job has been changed')
```

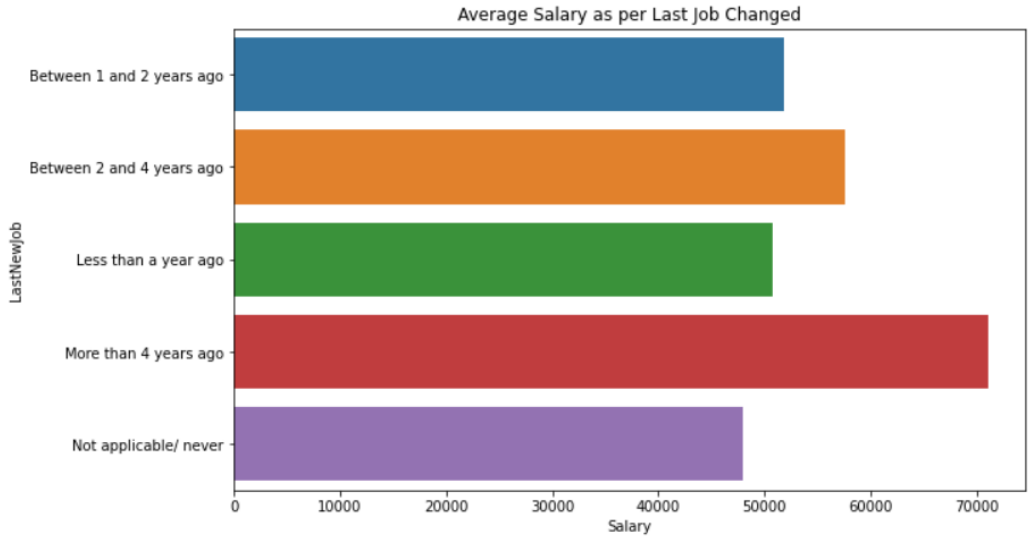
```
Out[19]: Text(0.5, 1.0, 'When the last job has been changed')
```




```
In [20]: df.groupby('LastNewJob')['Salary'].mean()
```

```
Out[20]: LastNewJob
         Between 1 and 2 years ago    51876.225155
         Between 2 and 4 years ago    57633.631064
         Less than a year ago         50825.185580
         More than 4 years ago        71009.633631
         Not applicable/ never        48016.855979
         Name: Salary, dtype: float64
```

```
In [21]: plt.figure(figsize=(10,6))
         sns.barplot(x=df.groupby('LastNewJob')['Salary'].mean(),y=df.groupby('LastNewJob')['Salary'].mean().index)
         plt.title('Average Salary as per Last Job Changed')
         plt.show()
```



CONCLUSIONS

- Imputing Salary as per the years coded job and finding out that job satisfaction and career satisfaction both are directly related to salary and years coded job.
- Cleaning Asses columns to make Assess score for further references in ML and Deep learning.
- Analyzing and cleaning gender gives a view that men are leading the count in the development field and also gender doesn't decide how much salary a developer would get.
- The average salary is maximum in Bermuda followed by Angilla, American Samoa and so on.
- Mostly Developers on StackOverFlow are residents of United States, India and United Kingdom.
- Visual Studio is most popular IDE followed by Notepad++, Sublime Text and Vim.
- JavaScript , SQL and Java are the most popular languages worldwide as well as in India.
- SmallTalk, TypeScirpt, Rust lead the race of average salary worldwide.
- Also MySql and Windows is the most used Database and Platform for Development respectively.
- Auditory Environment is somehow a plus for many developers.
- Most Information Technology companies have a start time of morning.
- We have much more analyses that is not mentioned here (for full and proper analysis report please refer the Jupyter Notebook file present in the GitHub repository whose link has been provided).

Github Repository Link :https://github.com/g-4-gagan/Developer-data-analysis

Future Works

- We have much more columns than we have analyzed in this project, our aim is to enhance our study on this dataset.

- We are having a look on some algorithms to provide us proper Languages, Platform, IDE and Database for better Job Opportunities.

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- <https://seaborn.pydata.org/>
- <https://www.kaggle.com/>