Importing Required Modules

In [1]:
```
# Import Neccessary libraries
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

In [2]:
```
# Import Visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [3]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [4]:
```
df=pd.read_csv('ds_salaries.csv')
df.head()
```

Out[4]:

	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd	employee_residence	remote_ratio	compa
0	2023	SE	FT	Principal Data Scientist	80000	EUR	85847	ES	100	
1	2023	MI	CT	ML Engineer	30000	USD	30000	US	100	
2	2023	MI	CT	ML Engineer	25500	USD	25500	US	100	
3	2023	SE	FT	Data Scientist	175000	USD	175000	CA	100	
4	2023	SE	FT	Data Scientist	120000	USD	120000	CA	100	

Domain Knowledge

- `work_year [categorical]` : This represents the specific year in which the salary was disbursed. Different years may have different economic conditions which can impact the salary level.
- `experience_level [categorical]` : The level of experience a person holds in a particular job. This is a key determinant in salary calculation as typically, more experienced individuals receive higher pay due to their advanced skills and knowledge.
- `employment_type [categorical]` : The nature of the employment contract such as full-time, part-time, or contractual can greatly influence the salary. Full-time employees often have higher annual salaries compared to their part-time or contractual counterparts.
- `job_title [categorical]` : The role an individual holds within a company. Different roles have different salary scales based on the responsibilities and skills required. For example, managerial roles typically pay more than entry-level positions.
- `salary [numerical]` : The total gross salary paid to the individual. This is directly influenced by factors such as experience level, job title, and employment type.
- `salary_currency [categorical]` : The specific currency in which the salary is paid, denoted by an ISO 4217 code. Exchange rates could affect the value of the salary when converted into different currencies.
- `salary_in_usd [numerical]` : The total gross salary amount converted to US dollars. This allows for a uniform comparison of salaries across different countries and currencies.
- `employee_residence [categorical]` : The primary country of residence of the employee, denoted by an ISO 3166 code. The cost of living and prevailing wage rates in the employee's country of residence can impact salary levels.
- `remote_ratio [ratio]` : The proportion of work done remotely. With the rise of remote work, companies may adjust salaries based on the cost of living in the employee's location and the proportion of remote work.
- `company_location [categorical]` : The location of the employer's main office or the branch that holds the contract. Companies in different locations may offer different salary scales due to varying economic conditions and cost of living.
- `company_size [categorical]` : The median number of employees in the company during the work year. Larger companies often have structured salary scales and may offer higher salaries due to economies of scale and larger revenue streams.

In [5]:
```
#removing unneccssary columns
df.drop(['salary','salary_currency'],axis=1,inplace=True)
```

In [6]:
```
df.head()
```

Out[6]:

	work_year	experience_level	employment_type	job_title	salary_in_usd	employee_residence	remote_ratio	company_location	company_size
0	2023	SE	FT	Principal Data Scientist	85847	ES	100	ES	L
1	2023	MI	CT	ML Engineer	30000	US	100	US	S
2	2023	MI	CT	ML Engineer	25500	US	100	US	S
3	2023	SE	FT	Data Scientist	175000	CA	100	CA	M
4	2023	SE	FT	Data Scientist	120000	CA	100	CA	M

In [7]:
```
# Check Duplicates
duplicates = df.duplicated()

if duplicates.any():
    print("Duplicates found!")
    duplicate_rows = df[duplicates]
    print(duplicate_rows)
else:
    print("No duplicates found.")
```

```
Duplicates found!
      work_year experience_level employment_type           job_title  \
115        2023               SE              FT      Data Scientist
123        2023               SE              FT  Analytics Engineer
153        2023               MI              FT       Data Engineer
154        2023               MI              FT       Data Engineer
160        2023               SE              FT       Data Engineer
...         ...              ...             ...                 ...
3439       2022               MI              FT      Data Scientist
3440       2022               SE              FT       Data Engineer
3441       2022               SE              FT       Data Engineer
3586       2021               MI              FT       Data Engineer
3709       2021               MI              FT      Data Scientist

      salary_in_usd employee_residence  remote_ratio company_location  \
115          150000                 US             0                US
123          289800                 US             0                US
153          100000                 US           100                US
154           70000                 US           100                US
160          115000                 US             0                US
...             ...                ...           ...               ...
3439          78000                 US           100                US
3440         135000                 US           100                US
3441         115000                 US           100                US
3586         200000                 US           100                US
3709          90734                 DE            50                DE

     company_size
115             M
123             M
153             M
154             M
160             M
...           ...
3439            M
3440            M
3441            M
3586            L
3709            L

[1171 rows x 9 columns]
```

In [8]:
```
def des_analysis(dataframe):
    methods = {
```

```
        "shape": lambda: print(dataframe.shape),
        "columns": lambda: print(dataframe.columns),
        "info": lambda: print(dataframe.info()),
        "Descriptive": lambda: print(dataframe.describe()),
        "Null_values": lambda: print(dataframe.isnull().sum()),
        "Unique_Values": lambda: print(dataframe.nunique())
    }

    for method in methods:
        print(f"---------------------------- {method} -----------------------------------------\n")
        if method in methods:
            methods[method]()
            print("\n\n")
```

In [9]:
```
des_analysis(df)
```

```
---------------------------- shape -------------------------------------------

(3755, 9)



---------------------------- columns -----------------------------------------

Index(['work_year', 'experience_level', 'employment_type', 'job_title',
       'salary_in_usd', 'employee_residence', 'remote_ratio',
       'company_location', 'company_size'],
      dtype='object')



---------------------------- info --------------------------------------------

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3755 entries, 0 to 3754
Data columns (total 9 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   work_year           3755 non-null   int64 
 1   experience_level    3755 non-null   object
 2   employment_type     3755 non-null   object
 3   job_title           3755 non-null   object
 4   salary_in_usd       3755 non-null   int64 
 5   employee_residence  3755 non-null   object
 6   remote_ratio        3755 non-null   int64 
 7   company_location    3755 non-null   object
 8   company_size        3755 non-null   object
dtypes: int64(3), object(6)
memory usage: 264.1+ KB
None



---------------------------- Descriptive -------------------------------------

         work_year  salary_in_usd  remote_ratio
count  3755.000000    3755.000000   3755.000000
mean   2022.373635  137570.389880     46.271638
std       0.691448   63055.625278     48.589050
min    2020.000000    5132.000000      0.000000
```

```
25%    2022.000000   95000.000000      0.000000
50%    2022.000000  135000.000000      0.000000
75%    2023.000000  175000.000000    100.000000
max    2023.000000  450000.000000    100.000000
```

```
---------------------------- Null_values ----------------------------------------
```

```
work_year             0
experience_level      0
employment_type       0
job_title             0
salary_in_usd         0
employee_residence    0
remote_ratio          0
company_location      0
company_size          0
dtype: int64
```

```
---------------------------- Unique_Values --------------------------------------
```

```
work_year               4
experience_level        4
employment_type         4
job_title              93
salary_in_usd        1035
employee_residence     78
remote_ratio            3
company_location       72
company_size            3
dtype: int64
```

EDA(Exploratory Data Analysis)

In [11]:
```
df['experience_level'].unique()
```

Out[11]:
```
array(['SE', 'MI', 'EN', 'EX'], dtype=object)
```

Here We can see there are 4 unique values which are:

- SE - Senior level/Expert
- MI - Medium level/Intermediate
- EN - Entry level
- EX - Executive level

Let's rename the values

In [12]:
```
df['experience_level']=df['experience_level'].replace('SE','Senior level')
df['experience_level']=df['experience_level'].replace('MI','Intermediate level')
df['experience_level']=df['experience_level'].replace('EN','Entry level')
df['experience_level']=df['experience_level'].replace('EX','Executive level')
```

In [13]:
```
df.head()
```

Out[13]:

	work_year	experience_level	employment_type	job_title	salary_in_usd	employee_residence	remote_ratio	company_location	company_size
0	2023	Senior level	FT	Principal Data Scientist	85847	ES	100	ES	L
1	2023	Intermediate level	CT	ML Engineer	30000	US	100	US	S
2	2023	Intermediate level	CT	ML Engineer	25500	US	100	US	S
3	2023	Senior level	FT	Data Scientist	175000	CA	100	CA	M
4	2023	Senior level	FT	Data Scientist	120000	CA	100	CA	M

In [14]:
```
df['employment_type'].unique()
```

Out[14]:
```
array(['FT', 'CT', 'FL', 'PT'], dtype=object)
```

It has 4 unique values which are :

- FT - Full Time
- CT - Contract
- FL - Freelance
- PT - Part Time

So Let's convert them

In [15]:
```
df['employment_type']=df['employment_type'].replace('FT','Full Time')
df['employment_type']=df['employment_type'].replace('CT','Contract')
df['employment_type']=df['employment_type'].replace('FL','Freelance')
df['employment_type']=df['employment_type'].replace('PT','Part Time')
```

In [16]:
```
df.head()
```

Out[16]:

	work_year	experience_level	employment_type	job_title	salary_in_usd	employee_residence	remote_ratio	company_location	company_size
0	2023	Senior level	Full Time	Principal Data Scientist	85847	ES	100	ES	L
1	2023	Intermediate level	Contract	ML Engineer	30000	US	100	US	S
2	2023	Intermediate level	Contract	ML Engineer	25500	US	100	US	S
3	2023	Senior level	Full Time	Data Scientist	175000	CA	100	CA	M
4	2023	Senior level	Full Time	Data Scientist	120000	CA	100	CA	M

In [17]:
```
jobs=df['job_title'].value_counts()
jobs
```

Out[17]:
```
Data Engineer                            1040
Data Scientist                            840
Data Analyst                              612
Machine Learning Engineer                 289
Analytics Engineer                        103
                                         ...
Principal Machine Learning Engineer         1
Azure Data Engineer                         1
Manager Data Management                     1
Marketing Data Engineer                     1
Finance Data Analyst                        1
Name: job_title, Length: 93, dtype: int64
```

Here if We See above the most jobs equipped by professionals are Data Scientist,Data Engineer followed by Data Analyst and Machine Learning Engineer

Let's Check top 15 Jobs

In [18]:
```
top15_jobs=jobs[:15]
top15_jobs
```

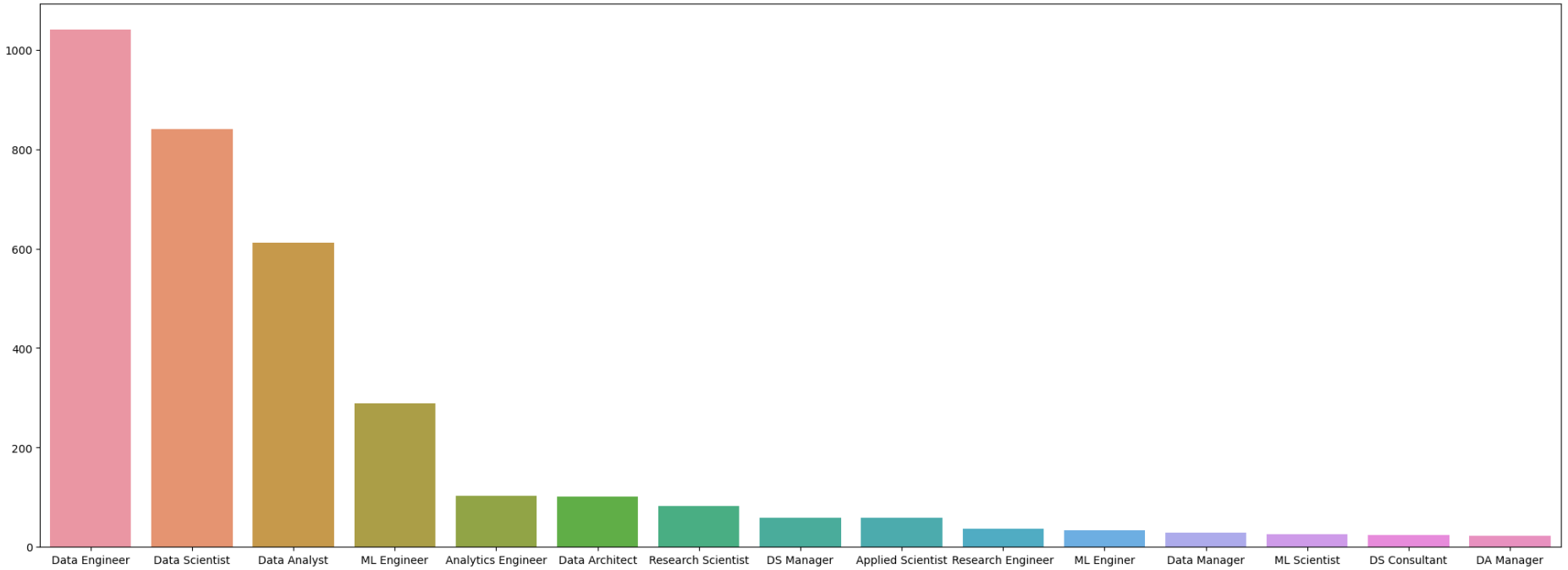
Out[18]:
```
Data Engineer                 1040
Data Scientist                 840
Data Analyst                   612
Machine Learning Engineer      289
Analytics Engineer             103
Data Architect                 101
Research Scientist              82
Data Science Manager            58
Applied Scientist               58
Research Engineer               37
ML Engineer                     34
Data Manager                    29
Machine Learning Scientist      26
Data Science Consultant         24
Data Analytics Manager          22
Name: job_title, dtype: int64
```

In [19]:
```
job_title=['Data Engineer','Data Scientist', 'Data Analyst','ML Engineer', 'Analytics Engineer','Data Architect','Rese
counts=np.array(top15_jobs)
```

In [20]:
```
counts
```

Out[20]:
```
array([1040,  840,  612,  289,  103,  101,   82,   58,   58,   37,   34,
         29,   26,   24,   22])
```

In [21]:
```
plt.figure(figsize=(25,9))
sns.barplot(x=job_title,y=counts)
plt.show()
```



This Graph gives us insight that most people are having Data Engineer Job Role

Let's Explore Salaries based on other features

Average Salaries Based On Job Titles

In [22]:
```
df['salary_in_usd'].groupby(df['job_title']).mean()
```

Out[22]:
```
job_title
3D Computer Vision Researcher     21352.250000
AI Developer                     136666.090909
AI Programmer                     55000.000000
AI Scientist                     110120.875000
Analytics Engineer               152368.631068
                                         ...
Research Engineer                163108.378378
Research Scientist               161214.195122
Software Data Engineer            62510.000000
Staff Data Analyst                15000.000000
Staff Data Scientist             105000.000000
Name: salary_in_usd, Length: 93, dtype: float64
```

Maximum Salary Getting Job Role

In [23]:
```
average_salary_by_job = df['salary_in_usd'].groupby(df['job_title']).mean()
max_avg_salary_job = average_salary_by_job.idxmax()
```

In [24]:
```
print("The Maxmimum Average sallary is of \"",max_avg_salary_job,"\" Which is ",average_salary_by_job["Data Science Te
```

```
The Maxmimum Average sallary is of " Data Science Tech Lead " Which is  375000.0
```

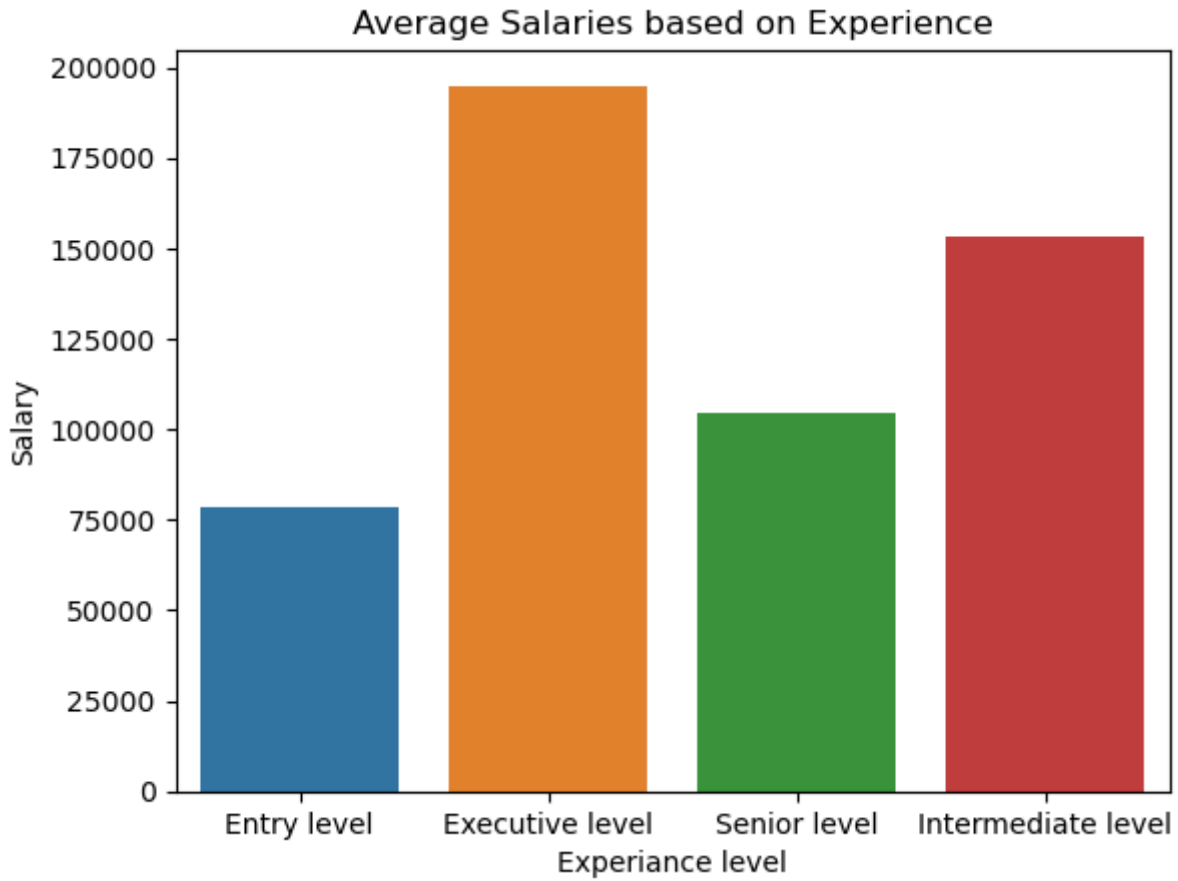
Salaries based on Experiance level

In [25]:
```
exp_wise_salary=np.array(df['salary_in_usd'].groupby(df['experience_level']).mean())
```

In [26]:
```
exp_wise_salary
```

Out[26]:
```
array([ 78546.284375  , 194930.92982456, 104525.93913043, 153051.07154213])
```

In [27]:
```
plt.title("Average Salaries based on Experience")
plt.xlabel('Experiance level')
plt.ylabel('Salary')
sns.barplot(x=['Entry level', 'Executive level', 'Senior level', 'Intermediate level'],y=exp_wise_salary)
plt.show()
```



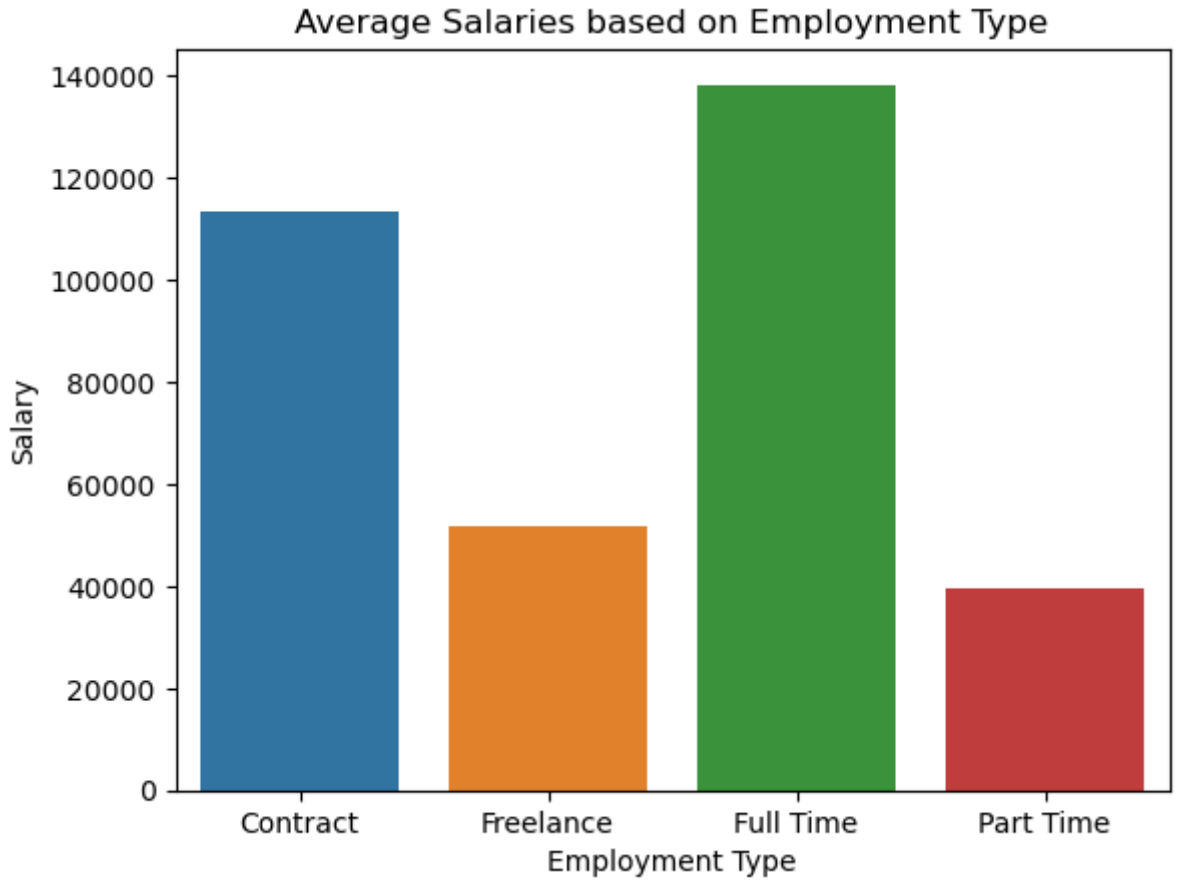
We Can Conclude here that Executive Level People get maximum salaries

Salaries based on Employment Type

In [28]:
```
df['salary_in_usd'].groupby(df['employment_type']).mean()
```

Out[28]:
```
employment_type
Contract     113446.900000
Freelance     51807.800000
Full Time    138314.199570
Part Time     39533.705882
Name: salary_in_usd, dtype: float64
```

In [29]:
```
employ_wise_salary=np.array(df['salary_in_usd'].groupby(df['employment_type']).mean())
plt.title("Average Salaries based on Employment Type")
plt.xlabel('Employment Type')
plt.ylabel('Salary')
sns.barplot(x=['Contract', 'Freelance', 'Full Time', 'Part Time'],y=employ_wise_salary)
plt.show()
```



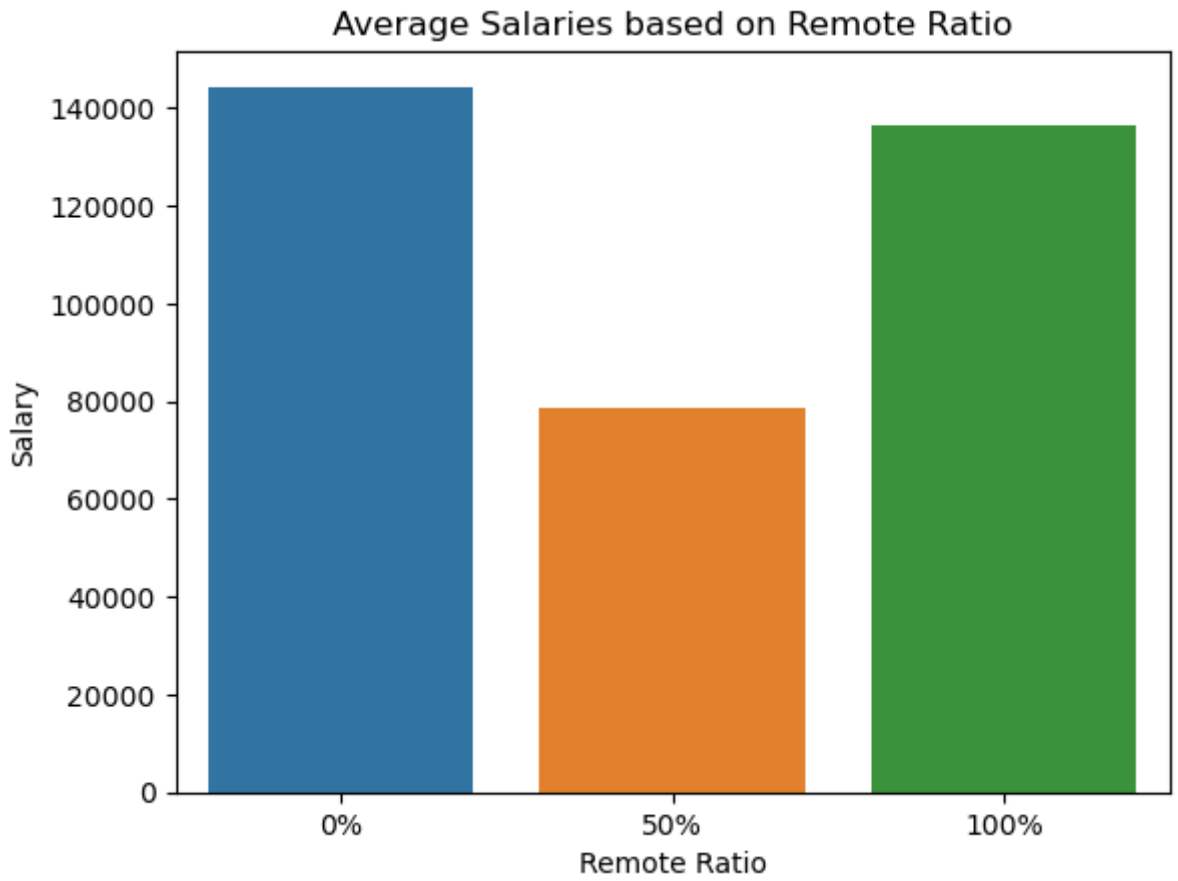
Full Time Employees get more salary as compared to others

Salaries based on Remote ratio

In [30]:
```
df['salary_in_usd'].groupby(df['remote_ratio']).mean()
```

Out[30]:
```
remote_ratio
0       144316.202288
50       78400.687831
100     136481.452830
Name: salary_in_usd, dtype: float64
```

In [31]:
```
remote_wise_salary=np.array(df['salary_in_usd'].groupby(df['remote_ratio']).mean())
plt.title("Average Salaries based on Remote Ratio")
plt.xlabel('Remote Ratio')
plt.ylabel('Salary')
sns.barplot(x=['0%', '50%', '100%'],y=remote_wise_salary)
plt.show()
```



We can see that those who doesn't do inoffice Jobs gets More Salary

Salaries based on Company Location

In [32]:
```
df['salary_in_usd'].groupby(df['company_location']).mean()
```

Out[32]:
```
company_location
AE    100000.000000
AL     10000.000000
AM     50000.000000
AR     25000.000000
AS     29351.000000
          ...
TH     23064.333333
TR     19058.000000
UA     57850.000000
US    151822.009539
VN     12000.000000
Name: salary_in_usd, Length: 72, dtype: float64
```

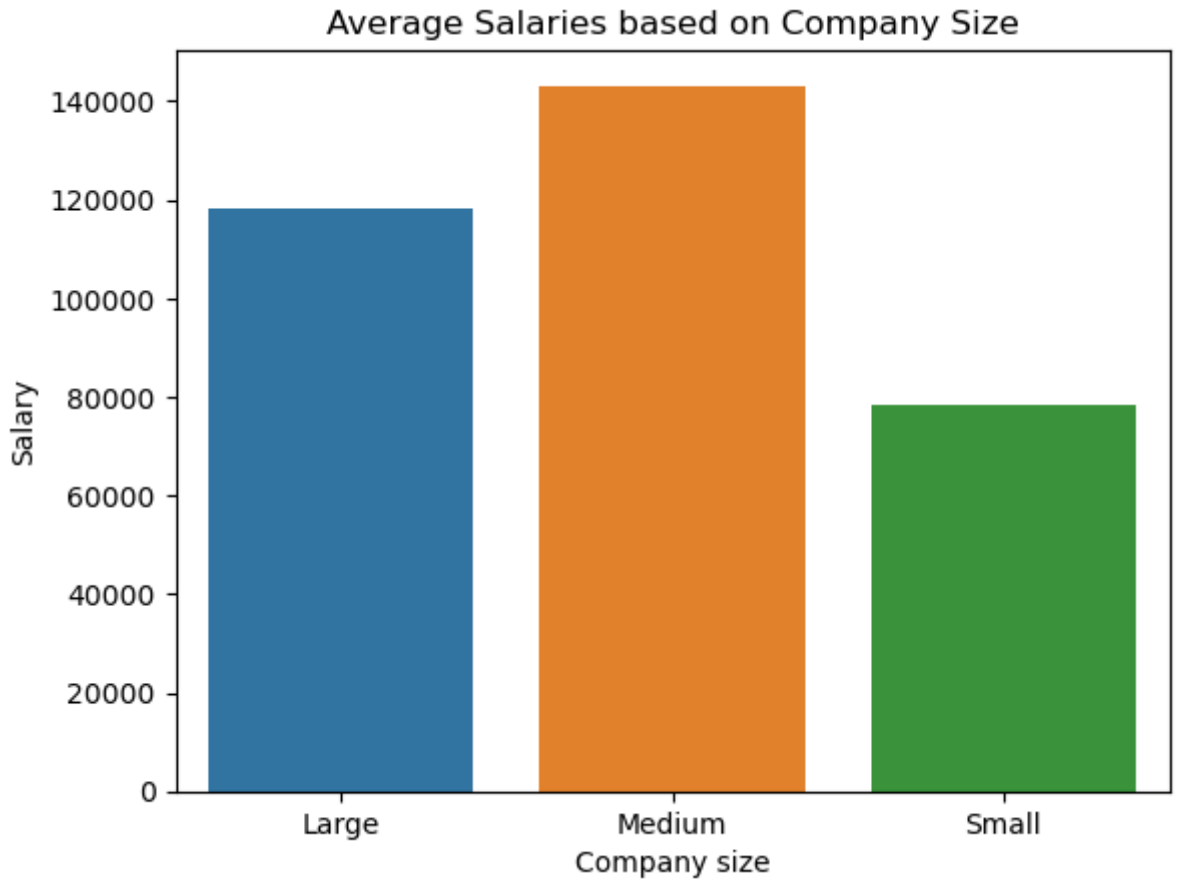
These are the Average salaries people get based on location

Salaries based on Company Size

In [33]:
```
df['salary_in_usd'].groupby(df['company_size']).mean()
```

Out[33]:
```
company_size
L    118300.982379
M    143130.548367
S     78226.682432
Name: salary_in_usd, dtype: float64
```

In [34]:
```
compsize_based_salary=np.array(df['salary_in_usd'].groupby(df['company_size']) .mean())
compsize_based_title=['Large', 'Medium', 'Small']
plt.title("Average Salaries based on Company Size")
plt.xlabel('Company size')
plt.ylabel('Salary')
sns.barplot(x=compsize_based_title,y=compsize_based_salary)
plt.show()
```



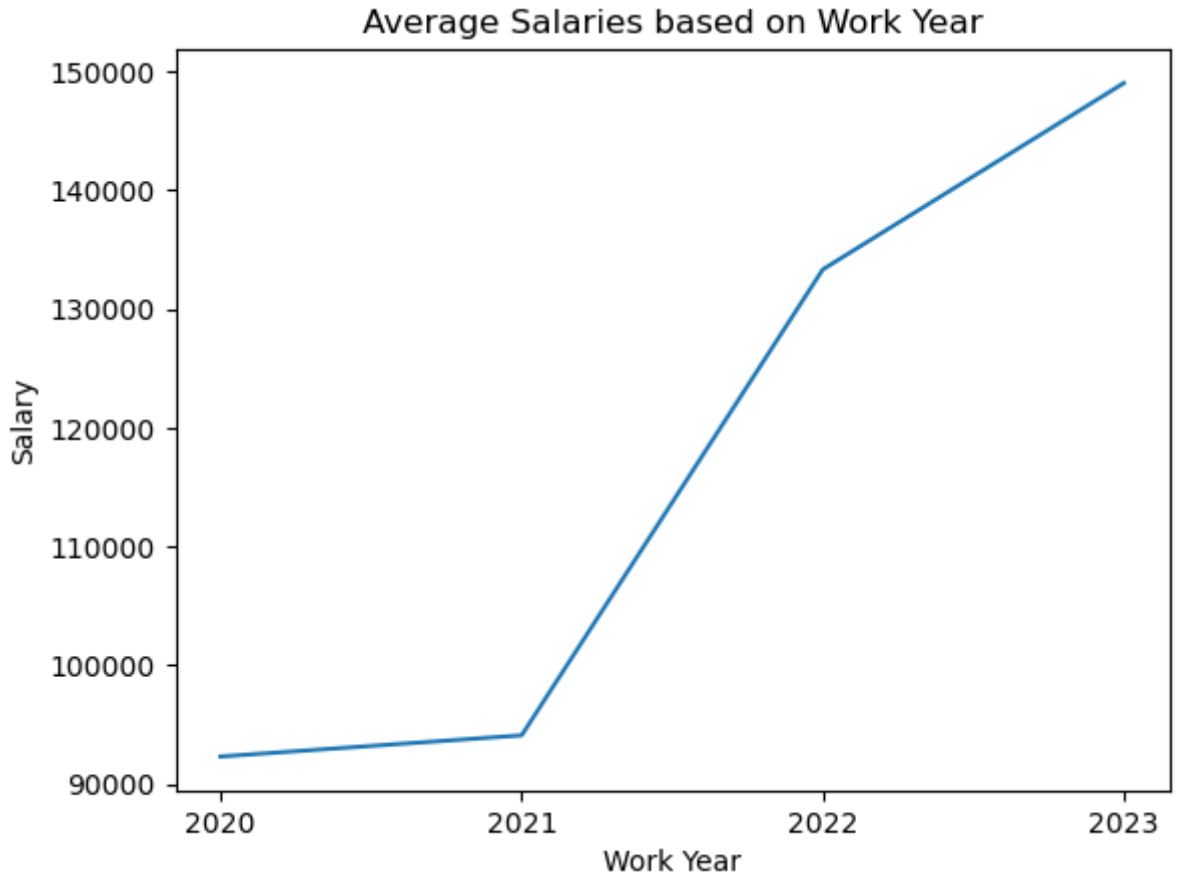
We Can see that Medium size companies gives more salary

Salaries based on work years

In [35]:
```
df['salary_in_usd'].groupby(df['work_year']).mean()
```

Out[35]:
```
work_year
2020     92302.631579
2021     94087.208696
2022    133338.620793
2023    149045.541176
Name: salary_in_usd, dtype: float64
```

In [36]:
```
year_based_salary=np.array(df['salary_in_usd'].groupby(df['work_year']).mean())
plt.title("Average Salaries based on Work Year")
plt.xlabel('Work Year')
plt.ylabel('Salary')
sns.lineplot(x=['2020', '2021', '2022','2023'],y=year_based_salary)
plt.show()
```



The salaries of data science fields goes on increasing with time as the amount of data generated by community is increasing rapidly

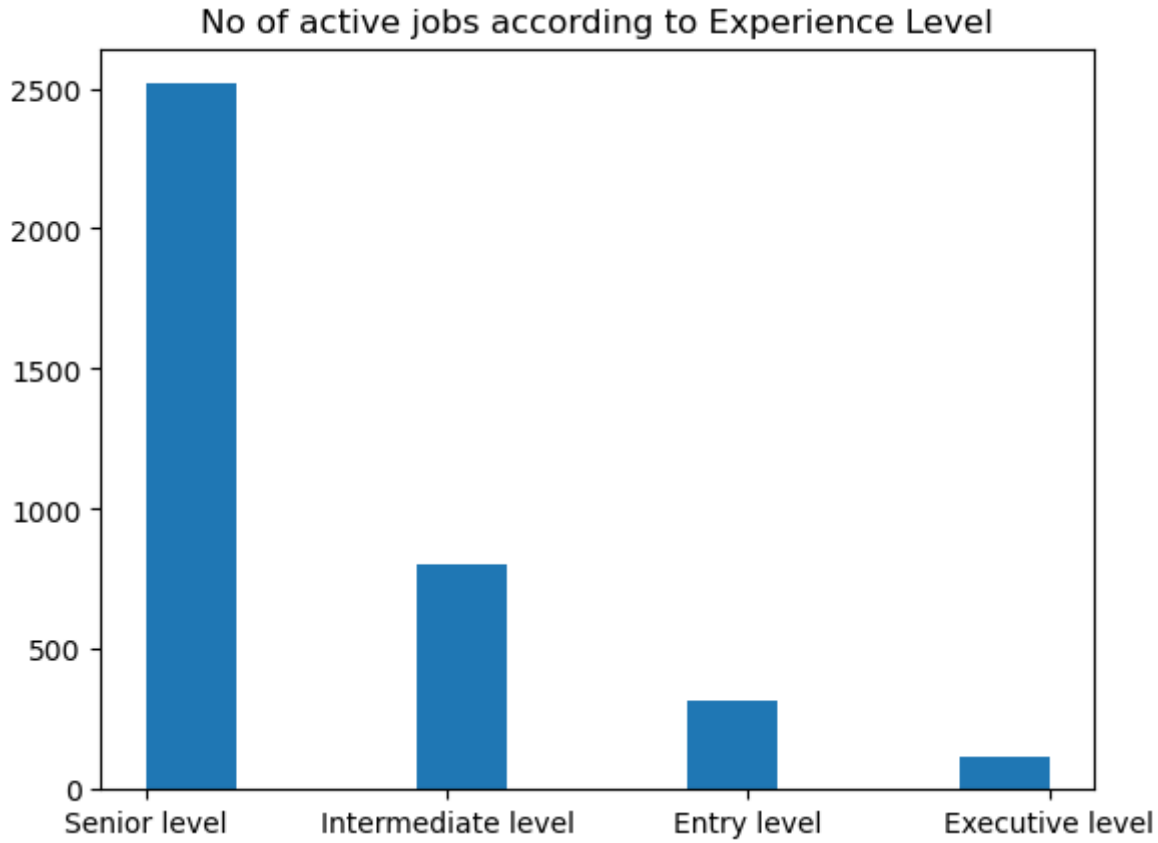
No of Jobs based on other features

No of jobs based on Experiance level

In [37]:
```
df['experience_level'].value_counts()
```

Out[37]:
```
Senior level          2516
Intermediate level     805
Entry level            320
Executive level        114
Name: experience_level, dtype: int64
```

In [38]:
```
plt.title('No of active jobs according to Experience Level')
df['experience_level'].hist(grid=False)
plt.show()
```



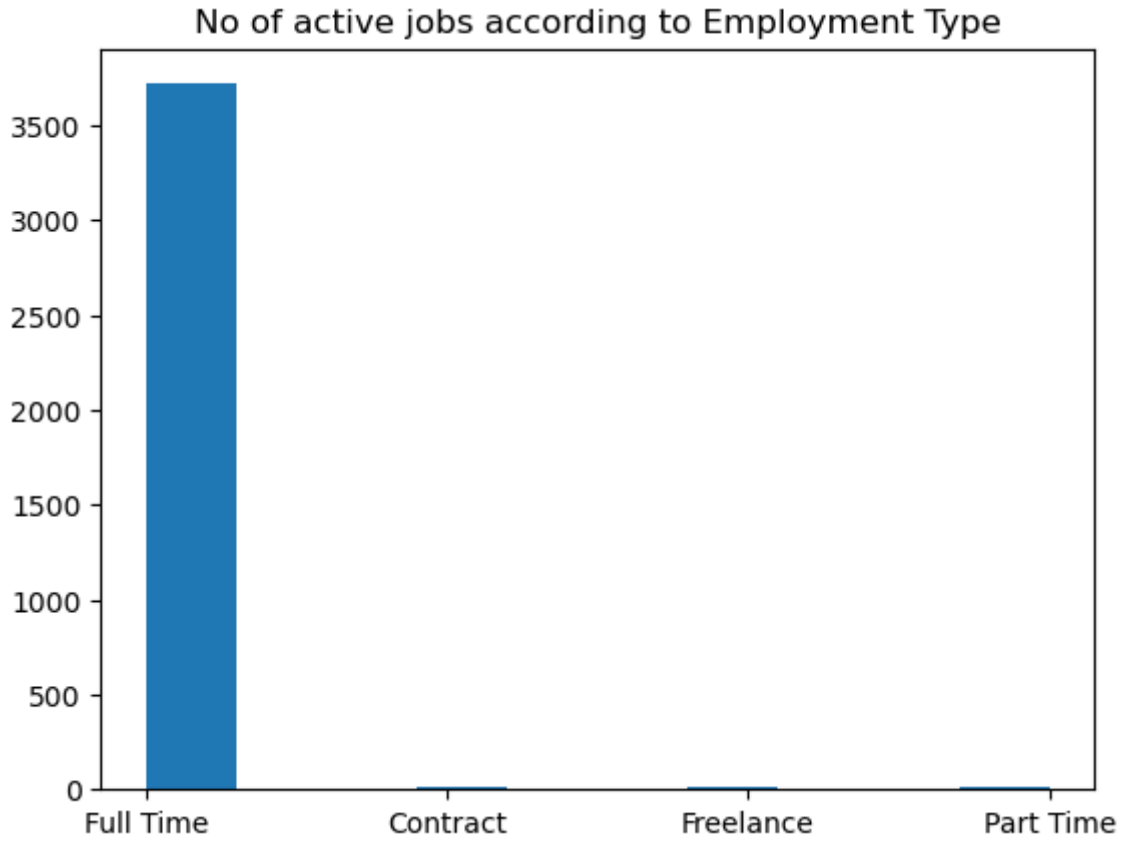
Here we Conclude that Senior Level Experience people likely to have more jobs

No of jobs based on Employment type

In [39]:
```
df['employment_type'].value_counts()
```

Out[39]:
```
Full Time    3718
Part Time      17
Contract       10
Freelance      10
Name: employment_type, dtype: int64
```

In [40]:
```
plt.title('No of active jobs according to Employment Type')
df['employment_type'].hist(grid=False)
plt.show()
```

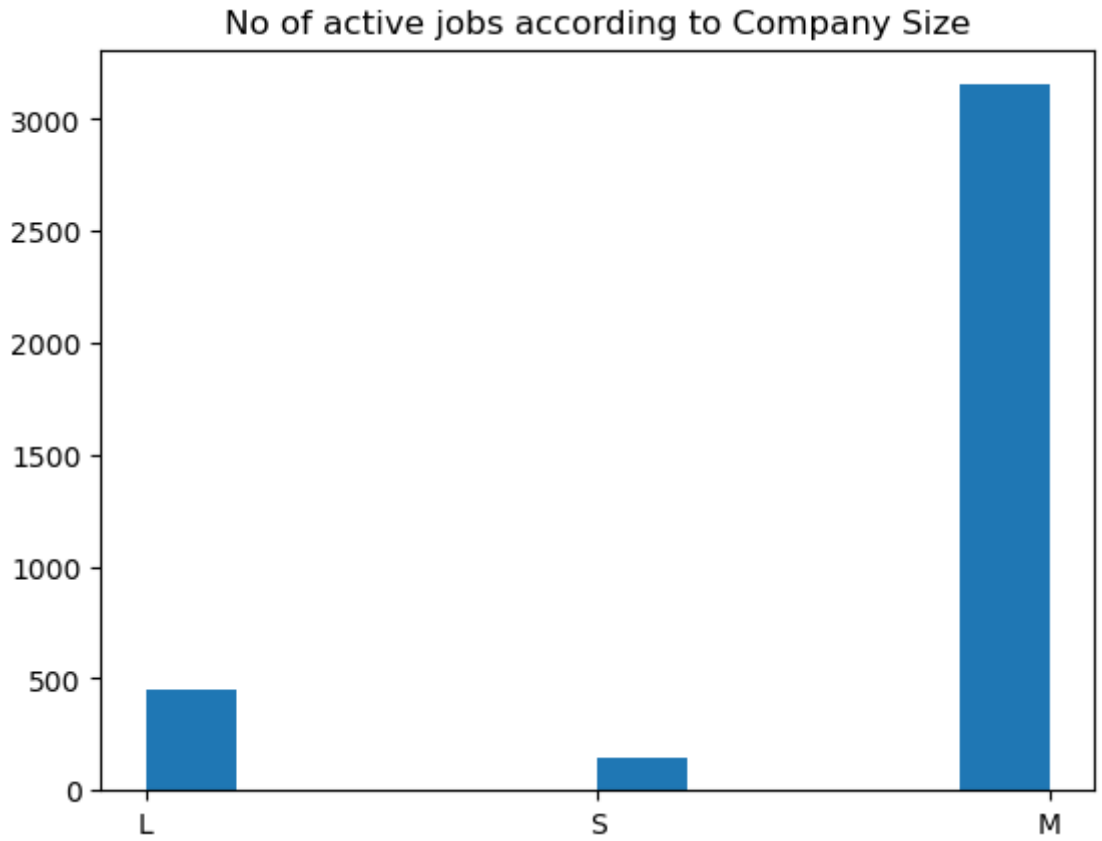


No of jobs based on Company Size

In [41]:
```
df['company_size'].value_counts()
```

Out[41]:
```
M    3153
L     454
S     148
Name: company_size, dtype: int64
```

In [42]:
```
plt.title('No of active jobs according to Company Size')
df['company_size'].hist(grid=False)
plt.show()
```



No of jobs based on Company Location

In [43]:
```
df['company_location'].value_counts()
```

Out[43]:
```
US    3040
GB     172
CA      87
ES      77
IN      58
      ...
MK       1
BS       1
IR       1
CR       1
MT       1
Name: company_location, Length: 72, dtype: int64
```

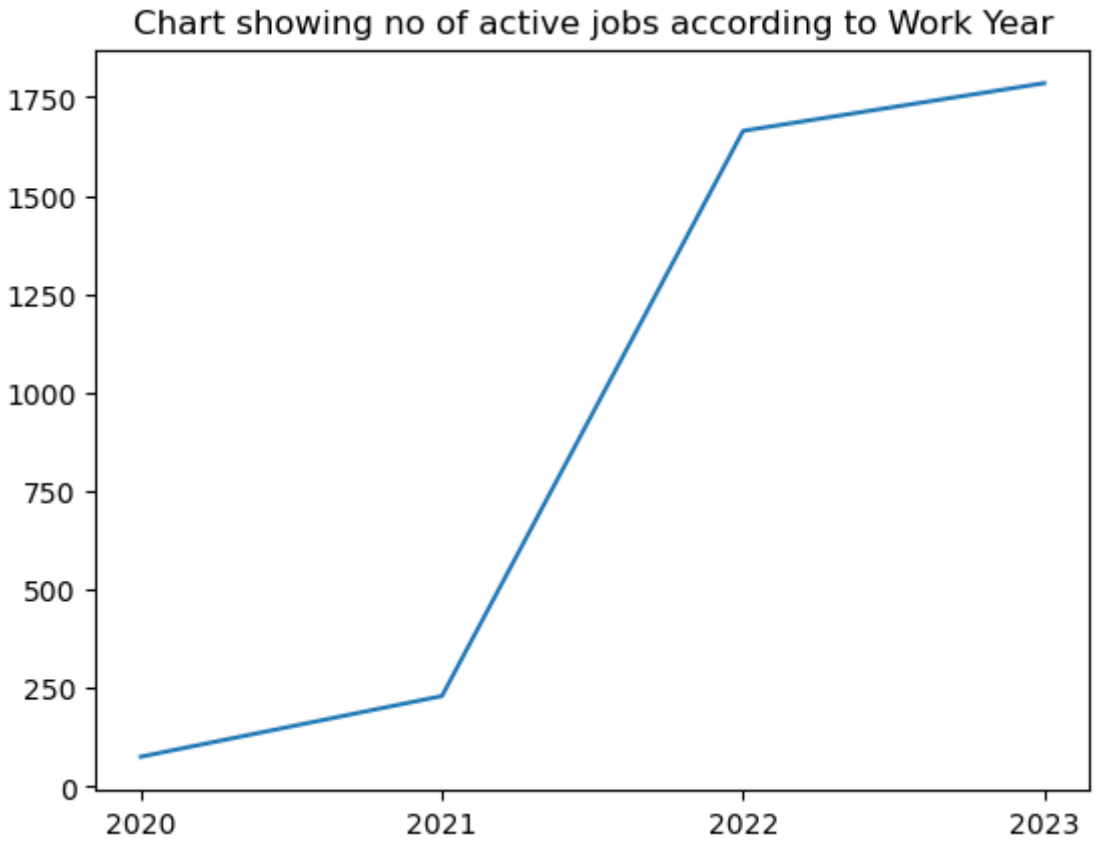
No of jobs based on Work Year

In [44]:
```
df['work_year'].value_counts()
```

Out[44]:
```
2023    1785
2022    1664
2021     230
2020      76
Name: work_year, dtype: int64
```

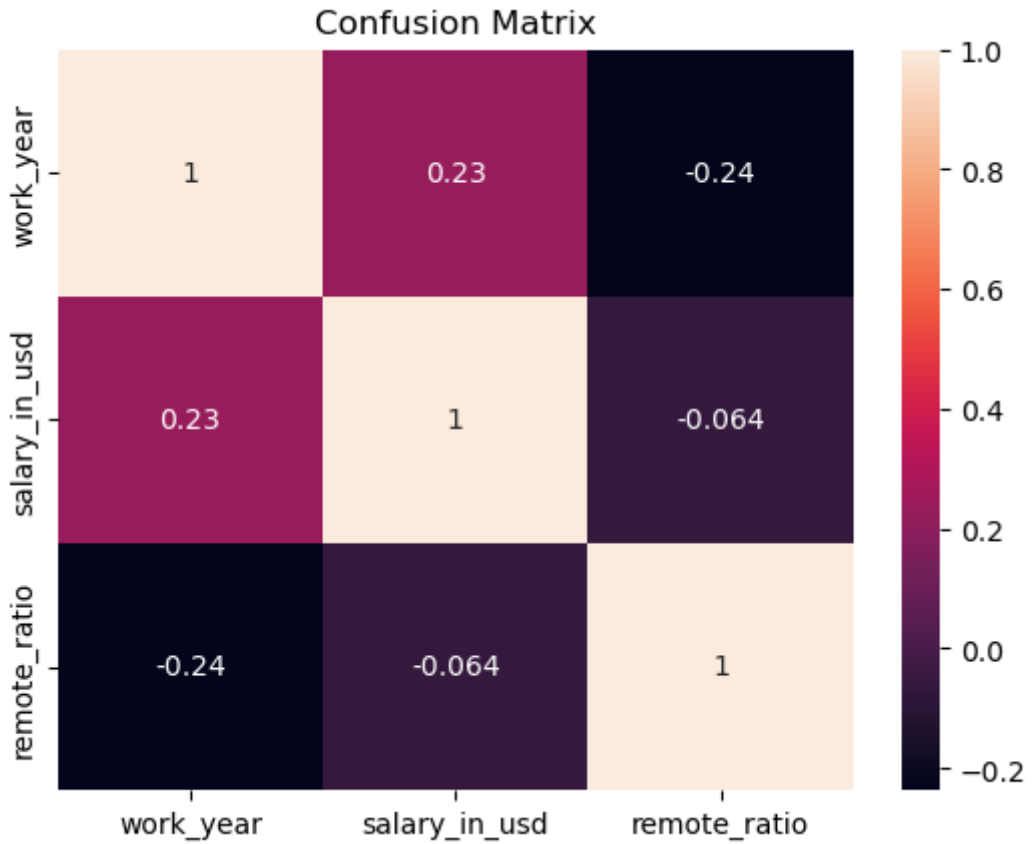
In [45]:
```
work_year_count=list(df['work_year'].value_counts())
work_year_count.reverse()
```

In [46]:
```
plt.title('Chart showing no of active jobs according to Work Year')
sns.lineplot(x=['2020', '2021', '2022','2023'],y=work_year_count)
plt.show()
```



No of jobs related to data science field goes on increasing with time to time

In [47]:
```
plt.title("Confusion Matrix")
sns.heatmap(df.corr(),annot=True)
plt.show()
```



This Confusion Matrix shows that as year passes the salaries are increasing

Thank You

*project by **Rishu Raj Gautam***

In [ ]: