Cyber_Security_Salary_Analysis

November 10, 2022

1 Importing Necessary Libraries

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
```

2 Reading CSV File as pd df

[ ]:
```
df = pd.read_csv('salaries_cyber.csv')
```

3 Displaying df

The csv file used for the analysis contains 11 Columns and 1247 Rows.

[ ]:
```
df
```

[ ]:
```
      work_year experience_level employment_type  \
0          2022               EN              FT
1          2022               MI              FT
2          2022               MI              FT
3          2022               MI              FT
4          2022               EN              CT
…           …                …               …
1242       2020               MI              FT
1243       2021               SE              FT
1244       2021               SE              FT
1245       2021               MI              FT
1246       2021               MI              FT

                     job_title  salary salary_currency  salary_in_usd  \
0         Cyber Program Manager   63000             USD          63000
1              Security Analyst   95000             USD          95000
2              Security Analyst   70000             USD          70000
3           IT Security Analyst  250000             BRL          48853
4        Cyber Security Analyst  120000             USD         120000
```

```
…                                 …      …               …             …
1242        Cyber Security Analyst  140000             AUD          96422
1243  Information Security Manager   60000             GBP          82528
1244  Penetration Testing Engineer  126000             USD         126000
1245  Information Security Analyst   42000             GBP          57769
1246   Threat Intelligence Analyst   66310             USD          66310

     employee_residence  remote_ratio company_location company_size
0                    US            50               US            S
1                    US             0               US            M
2                    US             0               US            M
3                    BR            50               BR            L
4                    BW           100               BW            S
…                   …             …                …           …
1242                 AU            50               AU            M
1243                 GB            50               GB            L
1244                 US           100               US            L
1245                 GB           100               GB            L
1246                 US             0               US            L

[1247 rows x 11 columns]
```

4 Displaying df's info

df.info() function returns the basic information of the DataFrame including its columns, non-null count, DataType for each column, memory usage, and others.

```
[ ]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1247 entries, 0 to 1246
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   work_year           1247 non-null   int64
 1   experience_level    1247 non-null   object
 2   employment_type     1247 non-null   object
 3   job_title           1247 non-null   object
 4   salary              1247 non-null   int64
 5   salary_currency     1247 non-null   object
 6   salary_in_usd       1247 non-null   int64
 7   employee_residence  1247 non-null   object
 8   remote_ratio        1247 non-null   int64
 9   company_location    1247 non-null   object
 10  company_size        1247 non-null   object
dtypes: int64(4), object(7)
memory usage: 107.3+ KB
```

5 Data Descriptive Statistic

df.describe() function returns the descriptive statsistics (count, mean, std, min, max, and so on) of the columns of the DataFrame.

[ ]:
```
df.describe()
```

[ ]:

	work_year	salary	salary_in_usd	remote_ratio
count	1247.000000	1.247000e+03	1247.000000	1247.000000
mean	2021.316760	5.608525e+05	120278.218925	71.491580
std	0.715501	1.415944e+07	70291.394942	39.346851
min	2020.000000	1.740000e+03	2000.000000	0.000000
25%	2021.000000	7.975450e+04	74594.500000	50.000000
50%	2021.000000	1.200000e+05	110000.000000	100.000000
75%	2022.000000	1.600800e+05	150000.000000	100.000000
max	2022.000000	5.000000e+08	910991.000000	100.000000

6 Displaying unique value counts for each column

df.nunique() returns the count of unique values corresponding to each column.

[ ]:
```
df.nunique()
```

[ ]:
```
work_year               3
experience_level        4
employment_type         4
job_title              87
salary                384
salary_currency        21
salary_in_usd         579
employee_residence     58
remote_ratio            3
company_location       55
company_size            3
dtype: int64
```

7 Columns on which we will be working

df.columns returns the columns present in the DataFrame

[ ]:
```
df.columns
```

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

8 Max and Min Job Title in every Year

The main aim is to find the Job Title whose employee were max and min every Year.

[ ]:
```
grp_Wy=df.groupby('work_year')
print('Max Job Title in every year',grp_Wy['job_title'].max())
print('\nMin Job Title in every year',grp_Wy['job_title'].min())
```

```
Max Job Title in every year work_year
2020             Vulnerability Researcher
2021    Vulnerability Management Engineer
2022             Vulnerability Researcher
Name: job_title, dtype: object

Min Job Title in every year work_year
2020    Application Security Engineer
2021    Application Security Engineer
2022     Application Security Analyst
Name: job_title, dtype: object
```

This analysis has helped us to know the most popular and the least popular Job Title in the Cyber Security domain every year.

9 Average Salary and Remote Ratio of different Experience levels in each Year

The main ain is to find the average salary and remove ratio yearwise for each experience level.

[ ]:
```
pd.pivot_table(df,index=['work_year','experience_level'],aggfunc='mean')
```

```
/tmp/ipykernel_2992/2088990623.py:1: FutureWarning:

The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a
future version, numeric_only will default to False. Either specify numeric_only
or select only columns which should be valid for the function.
```

[ ]:

work_year	experience_level	remote_ratio	salary	salary_in_usd
2020	EN	53.225806	1.363616e+05	57538.193548
	EX	50.000000	2.335130e+05	238966.857143
	MI	53.623188	1.212405e+05	99386.637681
	SE	74.675325	1.407476e+05	126701.103896
2021	EN	61.607143	1.047068e+05	64864.633929
	EX	80.357143	3.291071e+05	190844.357143
	MI	66.666667	2.245488e+05	91925.771930
	SE	73.410405	1.561298e+05	129844.612717
2022	EN	73.611111	7.299861e+04	64181.444444
	EX	86.842105	2.127895e+05	200924.578947

MI	67.151163	1.304377e+05	116362.627907
SE	81.818182	1.859227e+06	157762.114478

The use of pivot table has helped us to do more than one grouping efficiently. The above Pivot Table can easily explain the average salary and remote ratio for each experience level yearwise.

10 Creating Word Cloud for most used words

Word Cloud is one of the most efficient ways to find the most popular keywords used in the dataset.

[ ]:
```
text_variable = " ".join(title for title in df.job_title)

word_cloud1 = WordCloud(collocations = False, background_color='white').
↪generate(text_variable)
word_cloud1.to_file('word_cloud.png')
```

[ ]:
```
<wordcloud.wordcloud.WordCloud at 0x7fe081e72b60>
```

Displaying Word Cloud

[ ]:
```
plt.imshow(word_cloud1, interpolation='bilinear')
plt.axis("off")
plt.show()
```

The above Word Cloud is explaining that the most popular keywords in the Cyber Security Salary Dataset are Security, Engineer, Analysi, Cyber, Information, and so on.

11 Median Salary Analysis WorldWide

Geo Analysis helps in analysing any data worldwide. Thus, the following World Map is providing the details of Median Salary for every country.

[ ]:
```
import country_converter as cc
import plotly.express as px
df['company_location'] = cc.convert(names=df['company_location'], to="ISO3")

grouped = df[['company_location', 'salary_in_usd']].groupby('company_location').
  ↪median().reset_index()

fig = px.choropleth(locations=grouped['company_location'],␣
  ↪color=grouped['salary_in_usd'], color_continuous_scale=px.colors.sequential.
  ↪Peach)
fig.show()
```

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The data of Greyed Out Countries are not available. For rest of the countries, darker the color, higher the median salary.

12 Experience v/s Salary Bar Plot

Visualization along with Analysis helps our mind to easily understand the stastistic. Thus, all queries from now are also visualized.

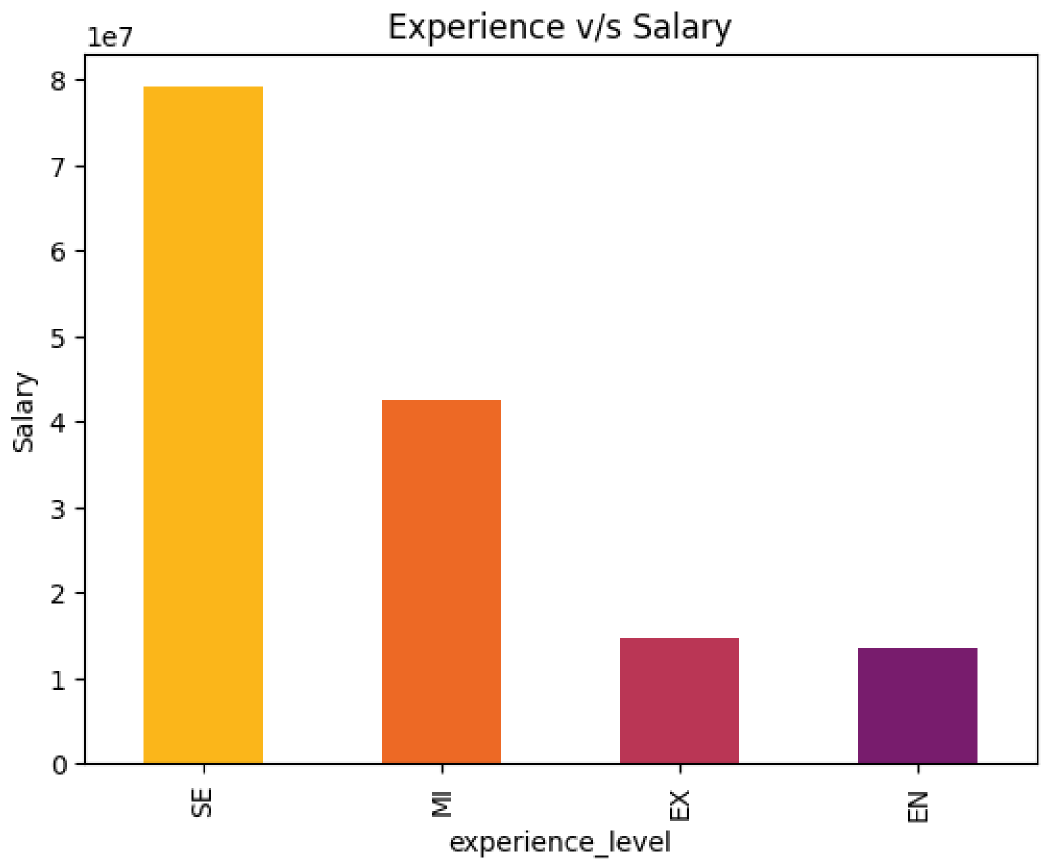
The following query explains the salary of employees according to their experience level.

[ ]:
```
df.groupby('experience_level')['salary_in_usd'].sum().
  ↪sort_values(ascending=False)
```

[ ]:
```
experience_level
SE    79074451
```

```
MI    42591357
EX    14651544
EN    13669587
Name: salary_in_usd, dtype: int64
```

[ ]:
```
plt.title('Experience v/s Salary')
plt.xlabel('Experience  Level')
plt.ylabel('Salary')
df.groupby('experience_level')['salary_in_usd'].sum().
 ↪sort_values(ascending=False).plot(kind='bar',color=sns.
 ↪color_palette("inferno_r", 5))
plt.show()
```



The above Bar Plot depicts that SE experience level earns the most while EN experience level earns the least.

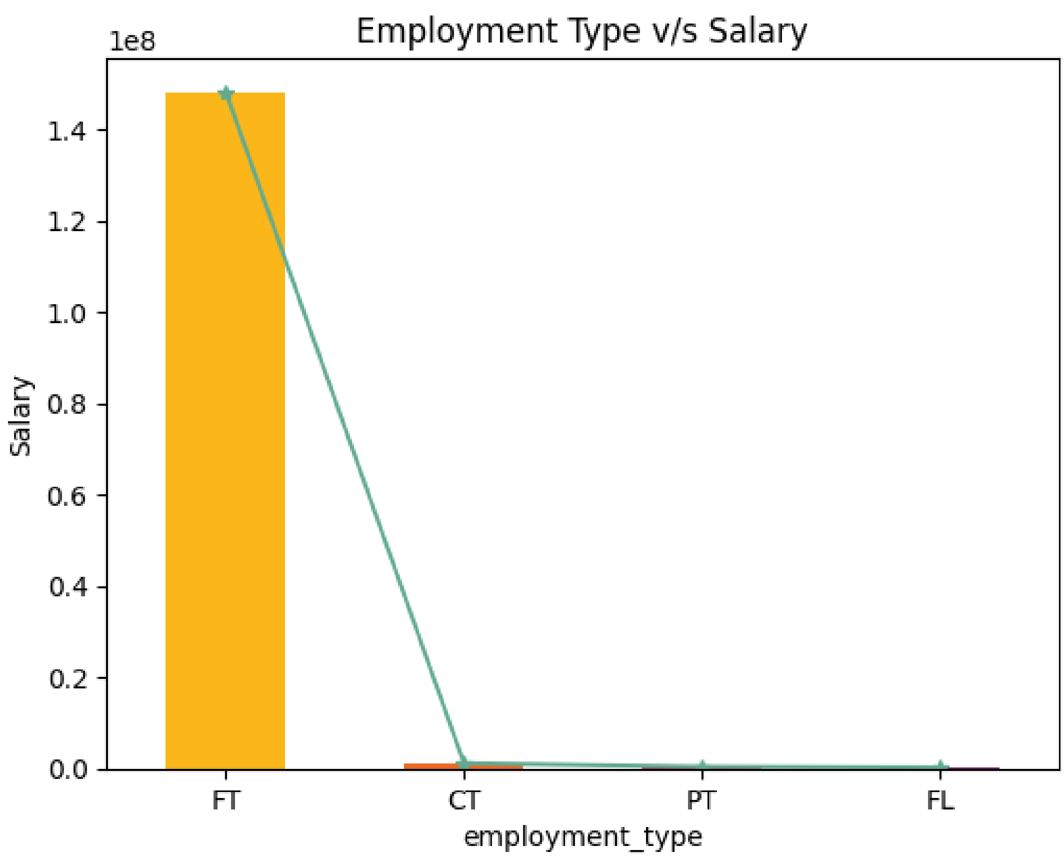
13 Employment Type v/s Salary Bar & Line Plot

It is important to know the Salary difference of Full Time, Part Time, and other Employment Type workers in the CyberSecurity domain.

[ ]:
```
df.groupby('employment_type')['salary_in_usd'].sum().
  ↪sort_values(ascending=False)
```

[ ]:
```
employment_type
FT    148180589
CT      1145631
PT       408886
FL       251833
Name: salary_in_usd, dtype: int64
```

[ ]:
```
plt.title('Employment Type v/s Salary')
plt.xlabel('Employment Type')
plt.ylabel('Salary')
df.groupby('employment_type')['salary_in_usd'].sum().
  ↪sort_values(ascending=False).plot(kind='bar',color=sns.
  ↪color_palette("inferno_r", 5))
df.groupby('employment_type')['salary_in_usd'].sum().
  ↪sort_values(ascending=False).plot(kind='line', marker='*', color=sns.
  ↪color_palette("crest", 3))
plt.show()
```



Full Time employees (FT) earns the most while the remaining job type employees earns too little in compare to FT.

14 Company Size v/s Salary Line Plot

One of the most important factors affecting Salary is Company Size. The following analysis and visualization will show the real comparision in the industry.

[ ]:
```
df.groupby('company_size')['salary_in_usd'].sum().sort_values(ascending=False)
```

[ ]:
```
company_size
L    93645628
M    48889816
S     7451495
Name: salary_in_usd, dtype: int64
```

[ ]:
```
plt.title('company_size v/s salary')
plt.ylabel('salary')
df.groupby('company_size')['salary_in_usd'].sum().sort_values(ascending=False).
 ↪plot(kind='line', marker='*', color=sns.color_palette('flare', 5))
plt.show()
```

The above Line Plot shows that there is no comparision in the Salary given by Large Companies with that of Small Companies.

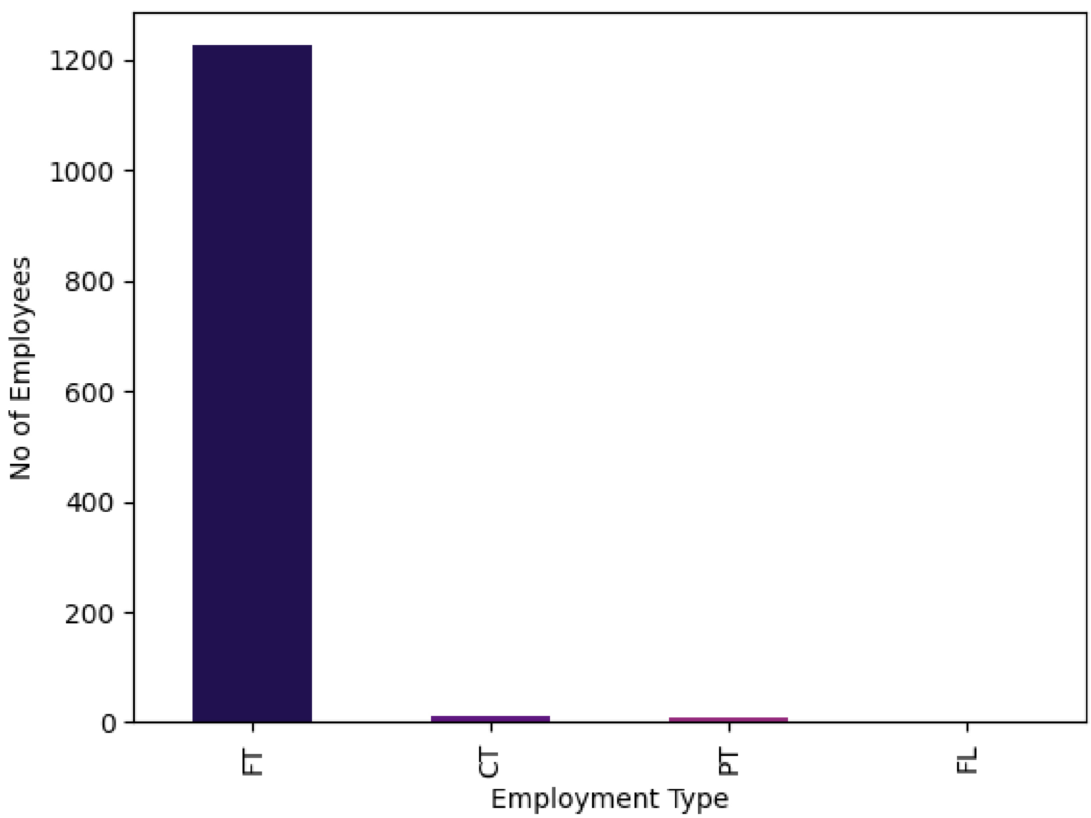
15 No of Employees for Each Employee Type

Some people prefer Full Time, while some prefer Part Time. So, this analysis brings out the statistical data for the same.

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

[ ]:
```
FT    1225
CT      11
PT       8
FL       3
Name: employment_type, dtype: int64
```

[ ]:
```
df['employment_type'].value_counts().plot(kind='bar',color=sns.
 ↪color_palette("magma"))
plt.xlabel("Employment Type")
plt.ylabel("No of Employees")
plt.show()
```



The above Analysis and Visualization tells that most of the CyberSecurity domain employees works Full Time.

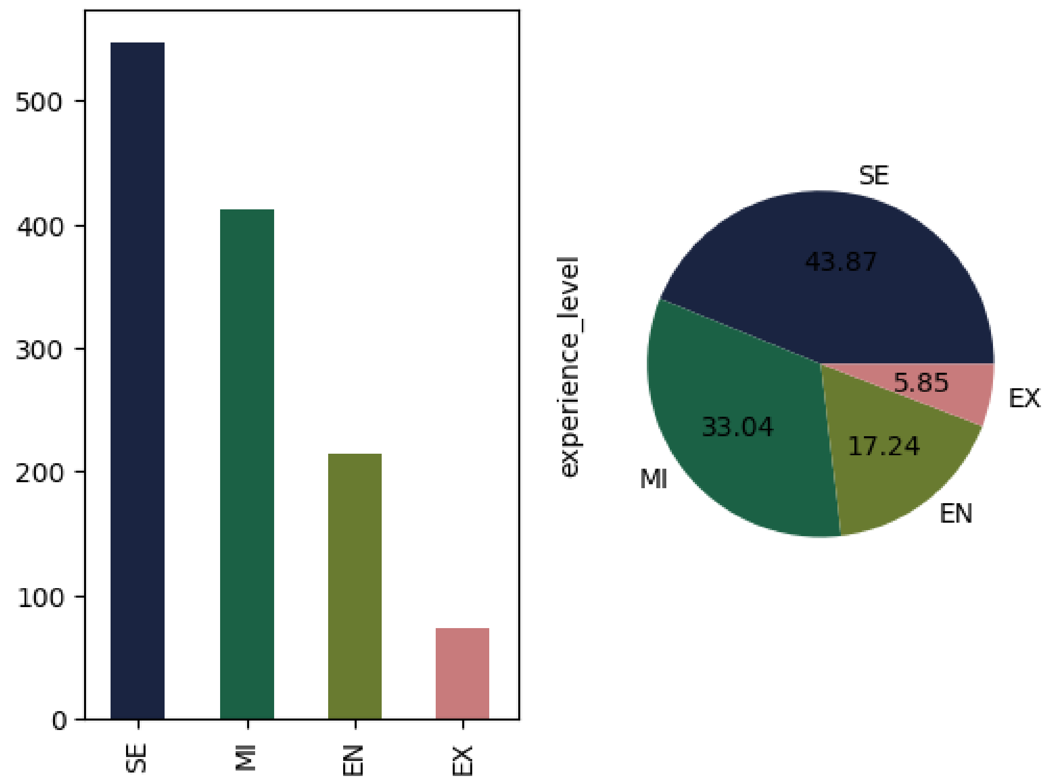
16 No of Employees for Each Experience Level

Different Experience levels have different numbers of employees. For example, the total number of Assistant Professors will differ from that of Associate Professors.

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

[ ]:
```
SE    547
MI    412
EN    215
EX     73
Name: experience_level, dtype: int64
```

[ ]:
```
plt.subplot(1,2,1)
df['experience_level'].value_counts().plot(kind='bar',color=sns.
 ↪color_palette("cubehelix"))
plt.subplot(1,2,2)
df['experience_level'].value_counts().plot(kind='pie',colors=sns.
 ↪color_palette("cubehelix"), autopct="%.2f")
plt.show()
```



Outcome: 43.87% (max) Employees are of SE experience level.

17 Remote Ratio Comparision

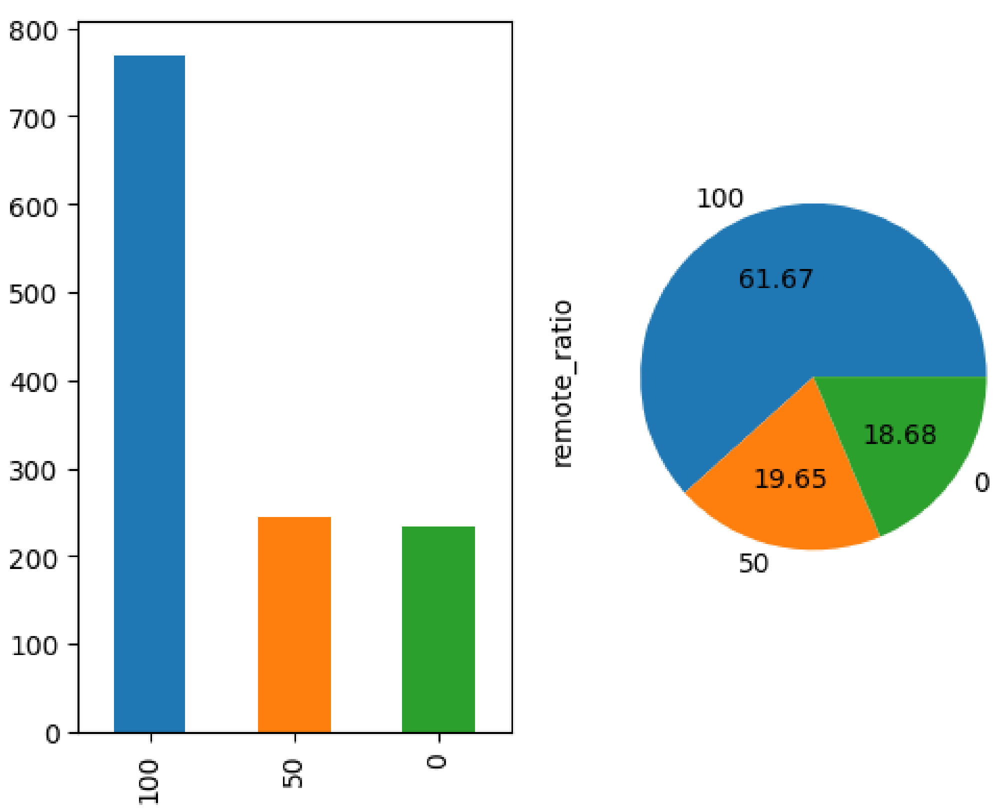
Some employees prefer work from office while some prefer work from home. But, there are some employees who also visit office occasionaly, thus maintaining 50-50 office and remote work ratio.

[ ]:
```
df['remote_ratio'].value_counts()
```

[ ]:
```
100    769
50     245
0      233
Name: remote_ratio, dtype: int64
```

[ ]:
```
plt.subplot(1,2,1)
df['remote_ratio'].value_counts().plot(kind='bar',color=sns.
 ↪color_palette("tab10"))
plt.subplot(1,2,2)
df['remote_ratio'].value_counts().plot(kind='pie',colors=sns.
 ↪color_palette('tab10'),autopct="%.2f")
```

[ ]:
```
<AxesSubplot: ylabel='remote_ratio'>
```



Most Employees work from office while the least Employees work remotely.

18 Employees with Different Salary Currency

Since the dataset covers global data, the Salary Currency of Employees will differ.

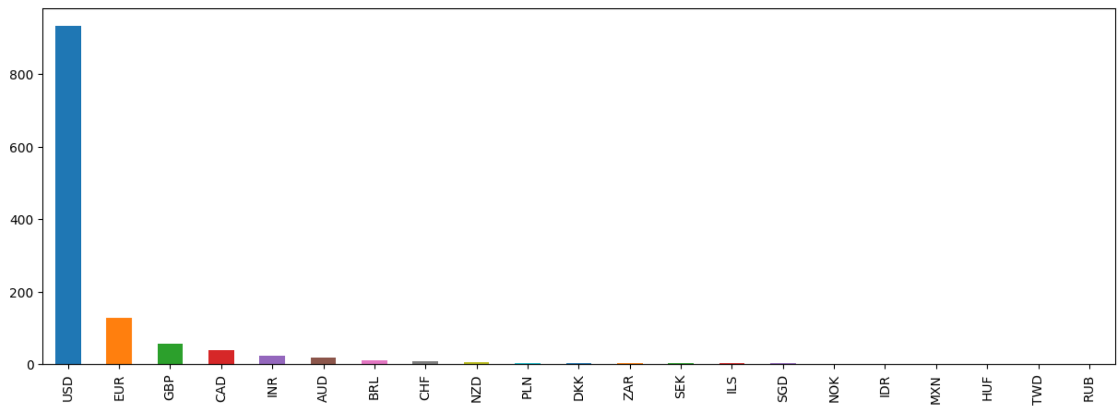
[ ]:
```
df['salary_currency'].value_counts()
```

[ ]:
```
USD    934
EUR    127
GBP     56
CAD     39
INR     23
AUD     18
BRL     12
CHF      9
NZD      5
PLN      4
DKK      4
ZAR      3
SEK      3
```

```
ILS       2
SGD       2
NOK       1
IDR       1
MXN       1
HUF       1
TWD       1
RUB       1
Name: salary_currency, dtype: int64
```

[ ]:
```
plt.figure(figsize=(15,5))
df['salary_currency'].value_counts().plot(kind='bar',color=sns.
 ↪color_palette("tab10"))
```

[ ]: <AxesSubplot: >



Most Employees earns in USD.

19 Employee Count on different Company Location

The number of Employees in every Country will differ according to the Company Location. This analysis is to find the Employee Count in each Country.

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

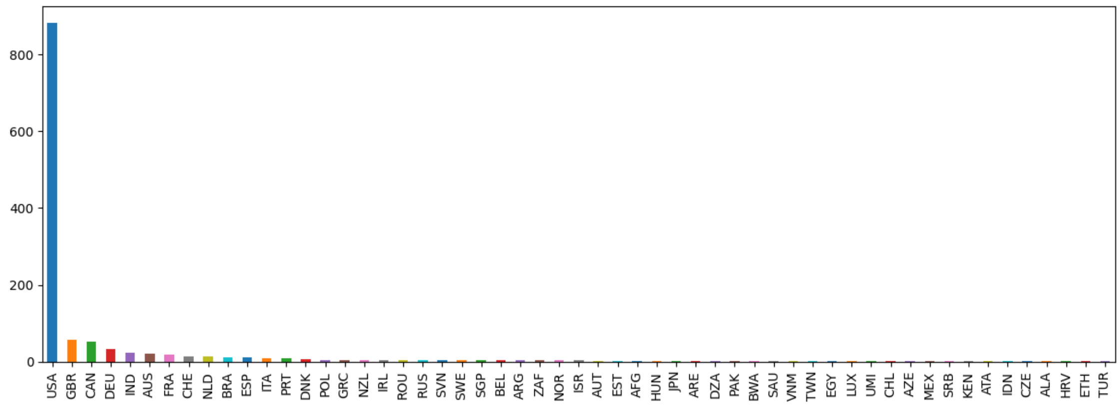
[ ]:
```
USA    882
GBR     57
CAN     51
DEU     33
IND     23
AUS     21
FRA     19
CHE     14
```

NLD	13
BRA	12
ESP	11
ITA	8
PRT	8
DNK	6
POL	5
GRC	5
NZL	5
IRL	5
ROU	4
RUS	4
SVN	4
SWE	4
SGP	4
BEL	3
ARG	3
ZAF	3
NOR	3
ISR	3
AUT	2
EST	2
AFG	2
HUN	2
JPN	2
ARE	2
DZA	2
PAK	1
BWA	1
SAU	1
VNM	1
TWN	1
EGY	1
LUX	1
UMI	1
CHL	1
AZE	1
MEX	1
SRB	1
KEN	1
ATA	1
IDN	1
CZE	1
ALA	1
HRV	1
ETH	1
TUR	1

```
Name: company_location, dtype: int64
```

[ ]:
```
plt.figure(figsize=(15,5))
df['company_location'].value_counts().plot(kind='bar',color=sns.
 ↪color_palette("tab10"))
```

[ ]:
```
<AxesSubplot: >
```



Most CyberSecurity employees are in USA.

20 No of Employess for each Job Title

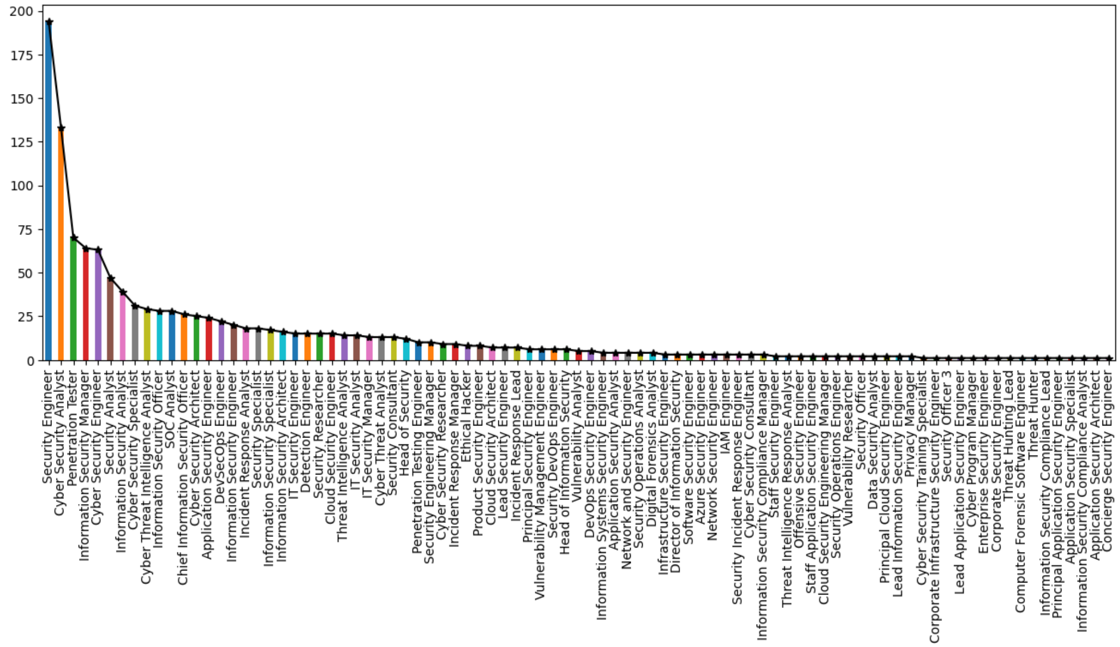
This analysis will help in finding the most and the least popular Job Title in the CyberSecurity domain.

[ ]:
```
df['job_title'].value_counts()
```

[ ]:
```
Security Engineer                             194
Cyber Security Analyst                        133
Penetration Tester                             70
Information Security Manager                   64
Cyber Security Engineer                        63
                                             …
Principal Application Security Engineer         1
Application Security Specialist                 1
Information Security Compliance Analyst         1
Application Security Architect                  1
Concierge Security Engineer                     1
Name: job_title, Length: 87, dtype: int64
```

[ ]:
```
plt.figure(figsize=(15,5))
df['job_title'].value_counts().plot(kind='line',color='black',marker="*")
df['job_title'].value_counts().plot(kind='bar',color=sns.color_palette("tab10"))
```

[ ]: <AxesSubplot: >

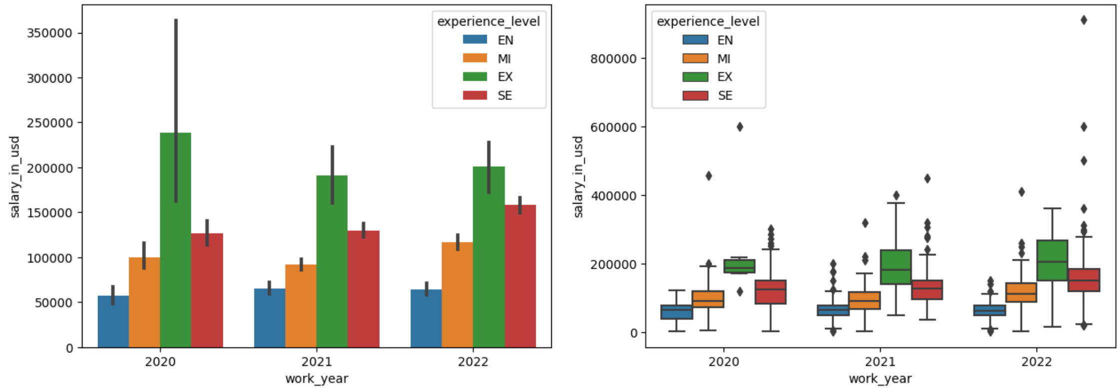


Most CyberSecurity domain Employees are Security Engineer.

21 Salary v/s Experience Level for each Year

The Salary of employees also vary according to their Experience level.

[ ]:
```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
sns.barplot(x=df['work_year'],y=df['salary_in_usd'],hue=df['experience_level'])
plt.subplot(1,2,2)
sns.boxplot(x=df['work_year'],y=df['salary_in_usd'],hue=df['experience_level'])
plt.show()
plt.show()
```

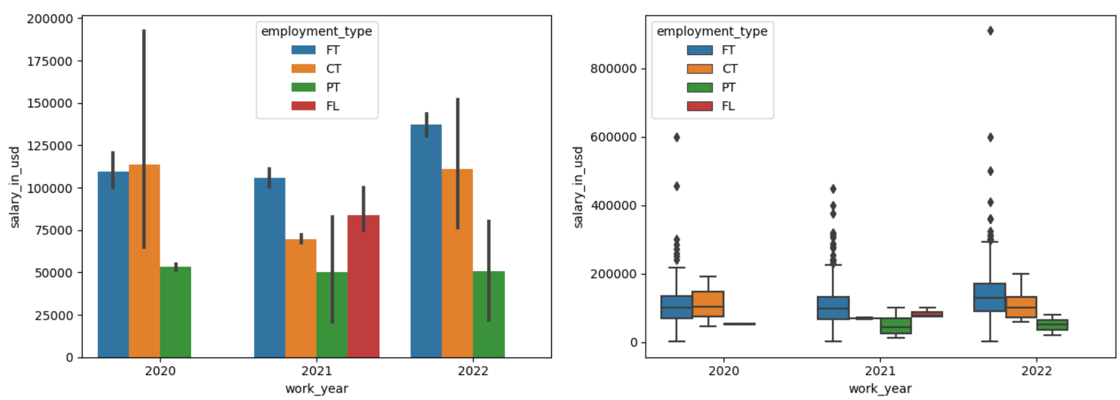


Box Plot has helped in analysing those employees (outliers) who earn more or less than the average of their Experience Level each year.

22 Salary v/s Employee Type for each Year

It is important to know whether the Salary varies if an employee is working Full Time, Part Time, or other Employment Type.

[ ]:
```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
sns.barplot(x=df['work_year'],y=df['salary_in_usd'],hue=df['employment_type'])
plt.subplot(1,2,2)
sns.boxplot(x=df['work_year'],y=df['salary_in_usd'],hue=df['employment_type'])
plt.show()
```

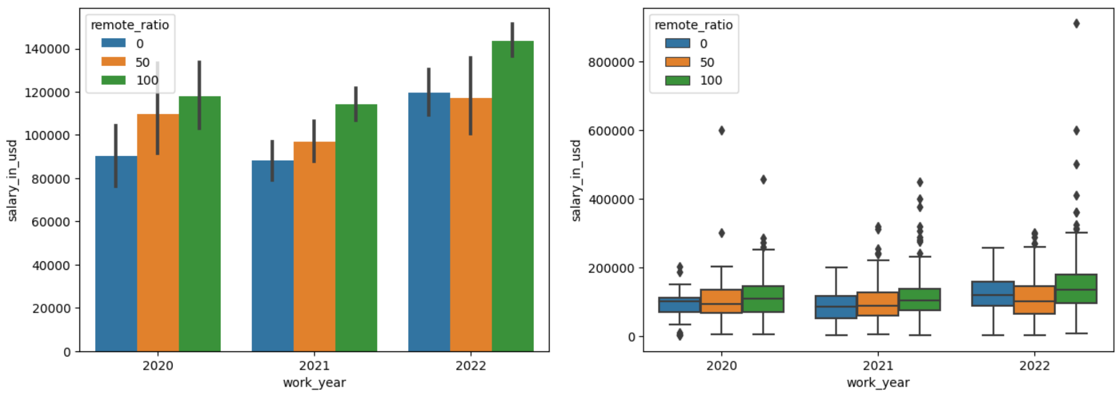


The Salary on the basis of Employment type is varying every year. Thus, the Salary doesn't depend on Employment Type in CyberSecurity domain.

23 Salary v/s Remote Ratio for each Year

Does Salary vary if an employee is working remotely or he/she gets the same salary as employee working from office?

[ ]:
```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
sns.barplot(x=df['work_year'],y=df['salary_in_usd'],hue=df['remote_ratio'])
plt.subplot(1,2,2)
sns.boxplot(x=df['work_year'],y=df['salary_in_usd'],hue=df['remote_ratio'])
plt.show()
```

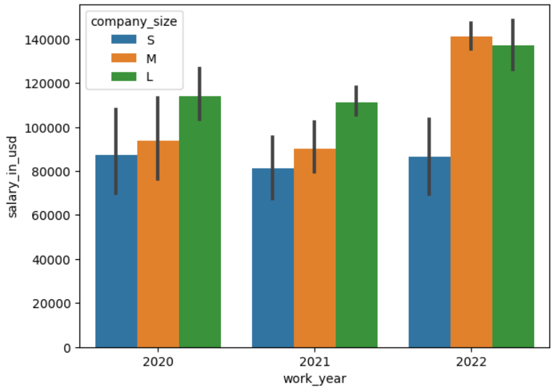


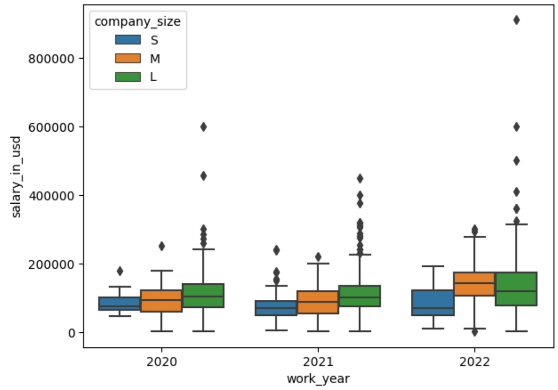
Employees working from office earns the most while Remote workers earns the least.

24 Salary v/s Company Size for each Year

We have already discussed that Large companies pay more than Small and Medium sized company. But, is it true for every year?

[ ]:
```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
sns.barplot(x=df['work_year'],y=df['salary_in_usd'],hue=df['company_size'])
plt.subplot(1,2,2)
sns.boxplot(x=df['work_year'],y=df['salary_in_usd'],hue=df['company_size'])
plt.show()
```





Medium size companies has paid more to their employees in 2022 than Large and Small sized companies. Thus, the trend of giving more salaries by Large companies is broken in 2022.

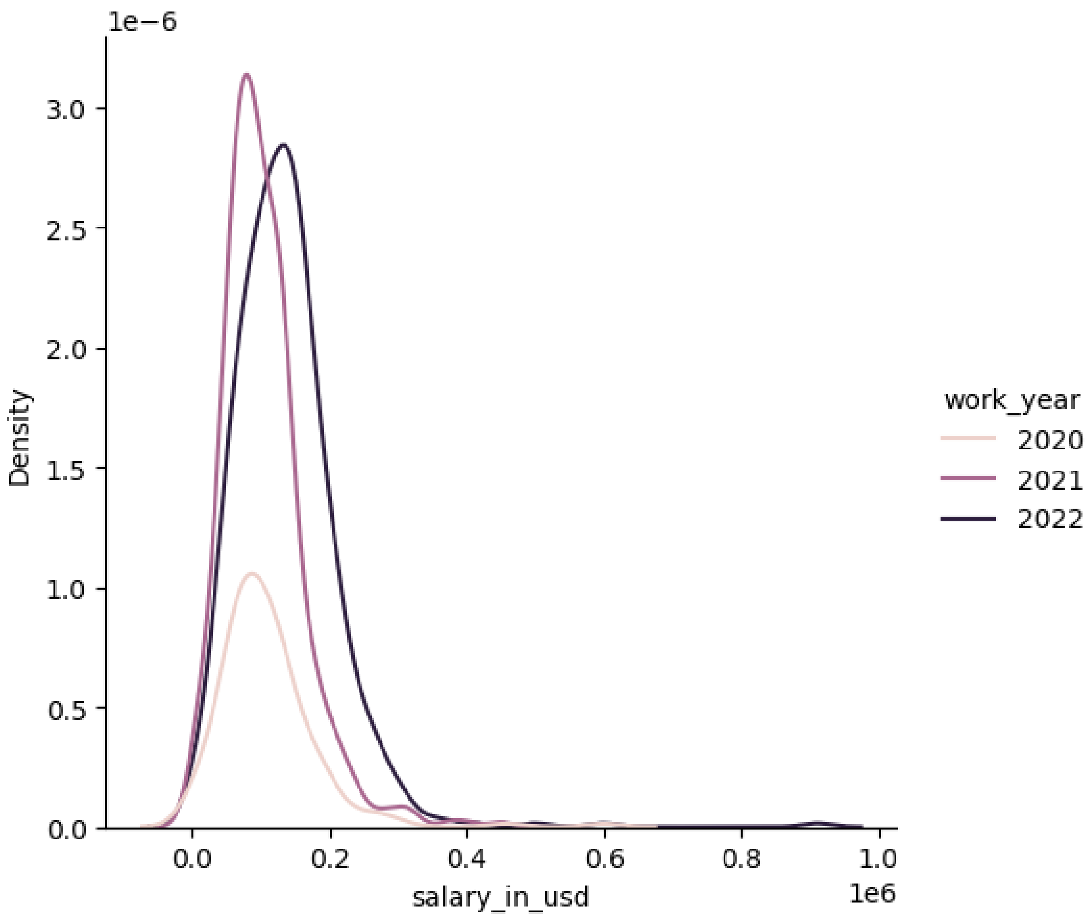
Even though, the maximum package offered every year is by Large size company and it is relatively higher in 2022. (Box Plot)

25 Salary (USD) Growth Analysis

The trend of salary growth every year.

[ ]:
```
sns.displot(data=df,x='salary_in_usd', hue='work_year', kind='kde')
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7fe07db42d70>



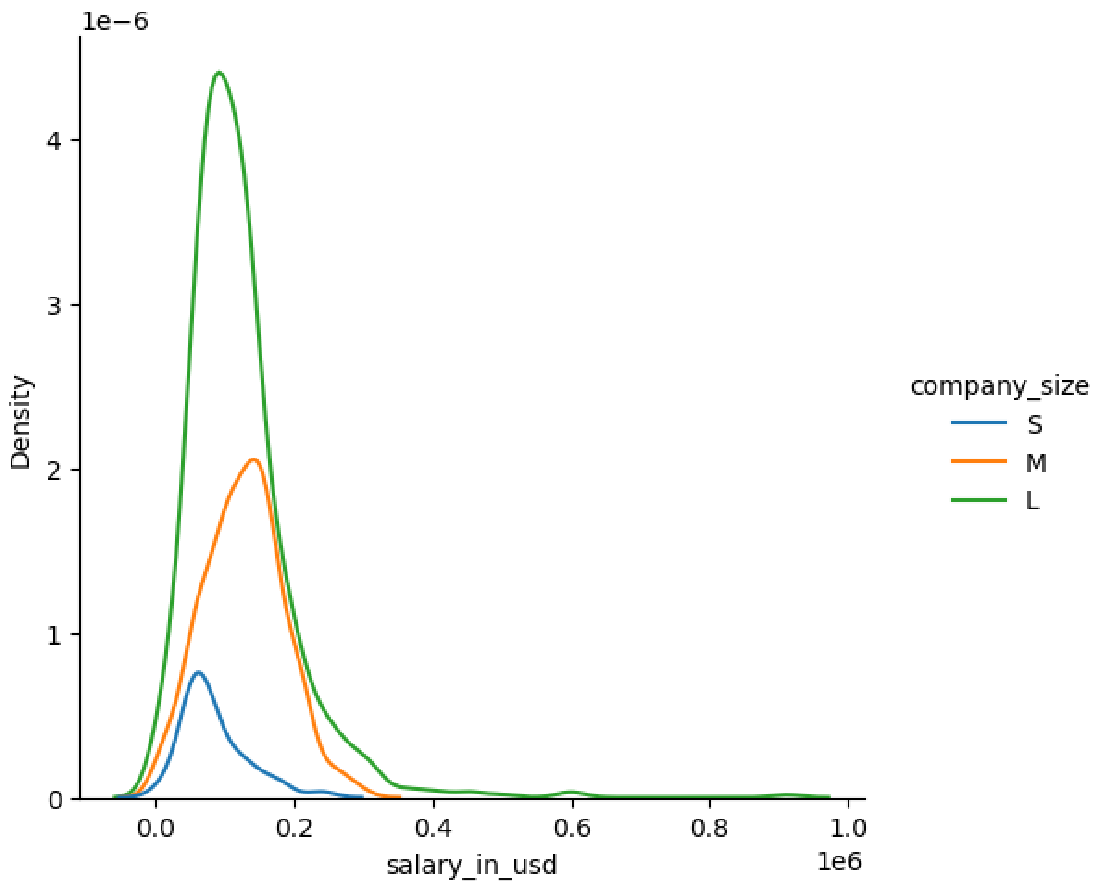
Salary for employees have increased every year.

26 Salary Trend a/c Company Size

Growth of Salary w.r.t. their company size.

[ ]:
```
sns.displot(data=df, x='salary_in_usd', hue='company_size', kind='kde')
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7fe07e0820b0>



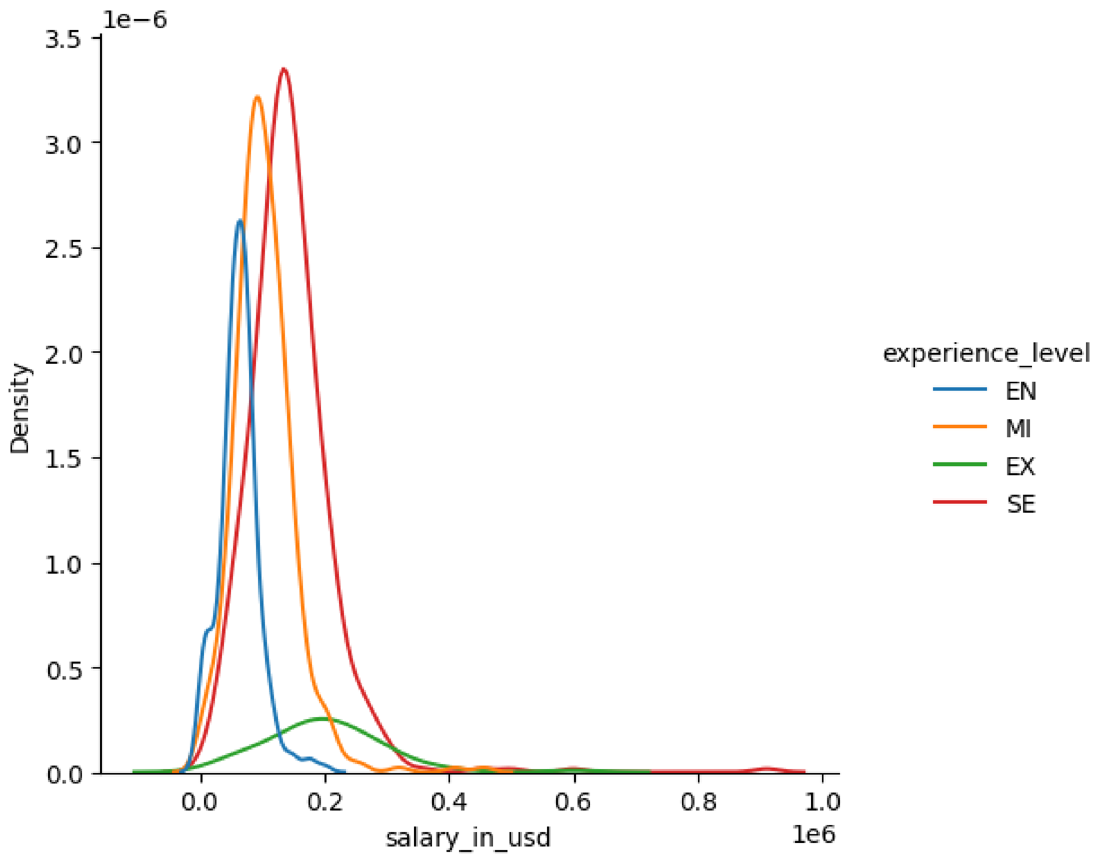
The average salary offered to the most employees of Large size companies is almost similar to the maximum offered salary to a few employees of Small size companies.

27 Salary v/s Experience Level Comparision

Salary also differs with Experience level. The following displot depicts the same.

[ ]:
```
sns.displot(data=df, x='salary_in_usd', hue='experience_level', kind='kde')
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7fe081ba8610>
```



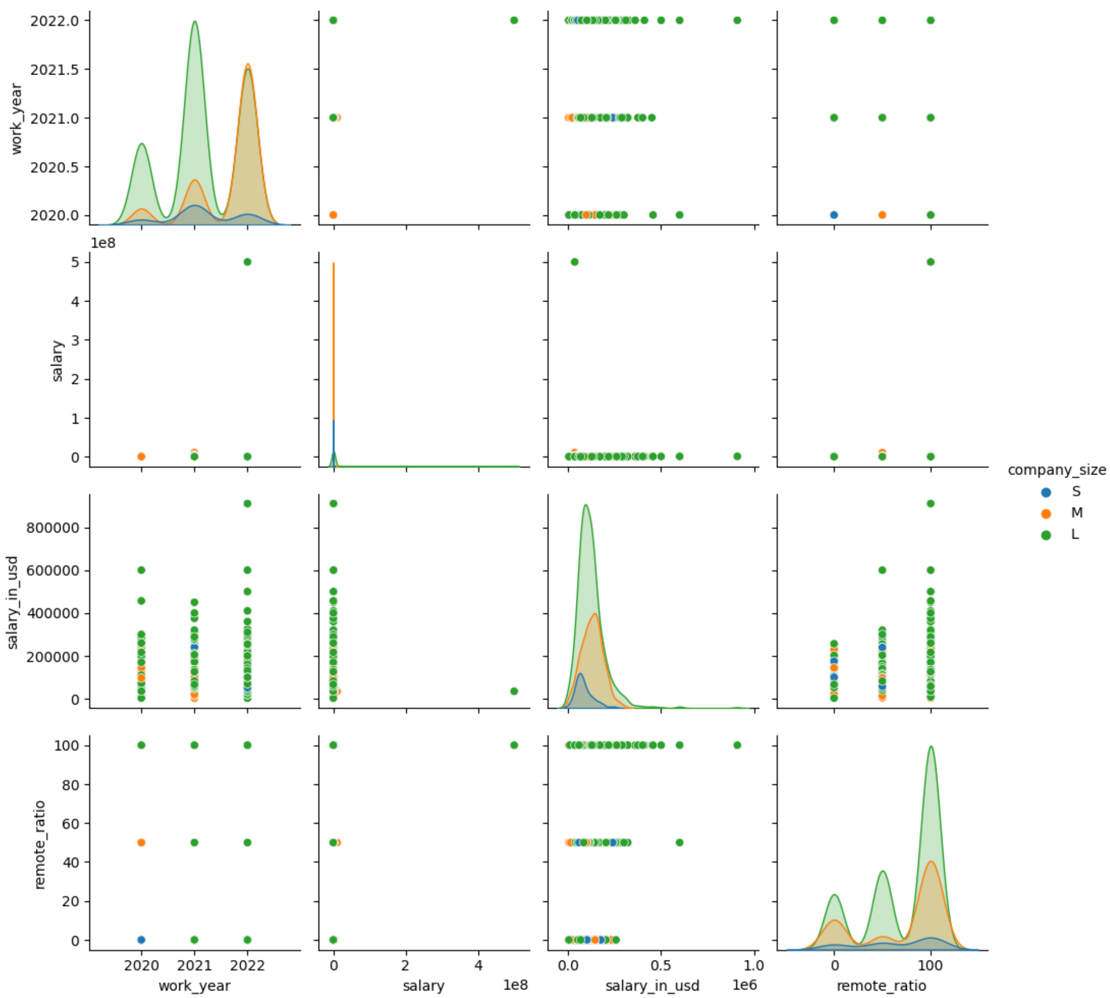
The average salary earned by most employees of SE experience is almost similar to the maximum salary earned by least employees of EN experience level.

28 Analysis of Entire Dataset through Pair Plot

The following Plot provides complete analysis of the Dataset.

[ ]:
```
sns.pairplot(df,hue='company_size')
```

[ ]:
```
<seaborn.axisgrid.PairGrid at 0x7fe081d4ed10>
```


work_year
salary
salary_in_usd
remote_ratio
1e8
1e6
company_size
S
M
L