Data Science Job Market EDA

About Dataset

Data Science Job Salaries Dataset contains 11 columns, each are:

- **1. work_year**: The year the salary was paid.
- **2. experience_level**: The experience level in the job during the year
- **3. employment_type**: The type of employment for the role
- **4. job_title**: The role worked in during the year.
- **5. salary**: The total gross salary amount paid.
- **6. salary_currency**: The currency of the salary paid as an ISO 4217 currency code.
- **7. salaryinusd**: The salary in USD
- **8. employee_residence**: Employee's primary country of residence in during the work year as an ISO 3166 country code.
- **9. remote_ratio**: The overall amount of work done remotely
- **10. company_location**: The country of the employer's main office or contracting branch
- **11. company_size**: The median number of people that worked for the company during the year

Notebook Objectives🔎

Goal of the notebook is to:

1. 📊 Explore **every feature** in the dataset;
2. 📅 **Work Year Analysis**(with **Salary, Remote Ratio**);
3. 📝 **Experience Level Analysis** (with **Employment Type, Top 3 Job Title, Company Size**);
4. 🗺 **Company Location Analysis** (with **Experience Level**)
5. 💰 💵 **Salary Analysis** (with **Work Year, Experience Level, Company Size, Job Title, Remote Ratio**)

1. Import Necessary Libraries

First, import necessary libraries below:

```
#install
!pip install country_converter

# data
import pandas as pd
import numpy as np
import country_converter as coco

# visualization
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
import plotly.express as px
import plotly.figure_factory as ff
import plotly.graph_objects as go
from wordcloud import WordCloud

# nltk
import nltk

# styling
%matplotlib inline
sns.set_theme(style="dark")
mpl.rcParams['axes.unicode_minus'] = False
pd.set_option('display.max_columns',None)
plt.style.use('seaborn-dark-palette')
plt.style.use('dark_background')

# read dataframe (drop 3 columns)
df = pd.read_csv('/content/ds_salaries.csv')
df.drop(df[['salary','salary_currency','Unnamed: 0']],axis=1, inplace=True)
```

```
Collecting country_converter
  Downloading country_converter-1.1.1-py3-none-any.whl (45 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 45.1/45.1 kB 1.3 MB/s eta 0:00:00
Requirement already satisfied: pandas>=1.0 in /usr/local/lib/python3.10/dist-packages (from country_converter) (1.5.3)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0->coun
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0->country_conver
Requirement already satisfied: numpy>=1.21.0 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0->country_conve
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1->pandas>
Installing collected packages: country_converter
Successfully installed country_converter-1.1.1
<ipython-input-1-65202ab7b069>:27: MatplotlibDeprecationWarning: The seaborn styles shipped by Matplotlib are deprecated
  plt.style.use('seaborn-dark-palette')
```

```
print(df.shape)
df.head(20)
```

```
(607, 9)
```

	work_year	experience_level	employment_type	job_title	salary_in_usd	employee_residence	remote_ratio	company_loca
0	2020	MI	FT	Data Scientist	79833	DE	0	
1	2020	SE	FT	Machine Learning Scientist	260000	JP	0	
2	2020	SE	FT	Big Data Engineer	109024	GB	50	
3	2020	MI	FT	Product Data Analyst	20000	HN	0	
4	2020	SE	FT	Machine Learning Engineer	150000	US	50	
5	2020	EN	FT	Data Analyst	72000	US	100	
6	2020	SE	FT	Lead Data Scientist	190000	US	100	
7	2020	MI	FT	Data Scientist	35735	HU	50	
				Business				

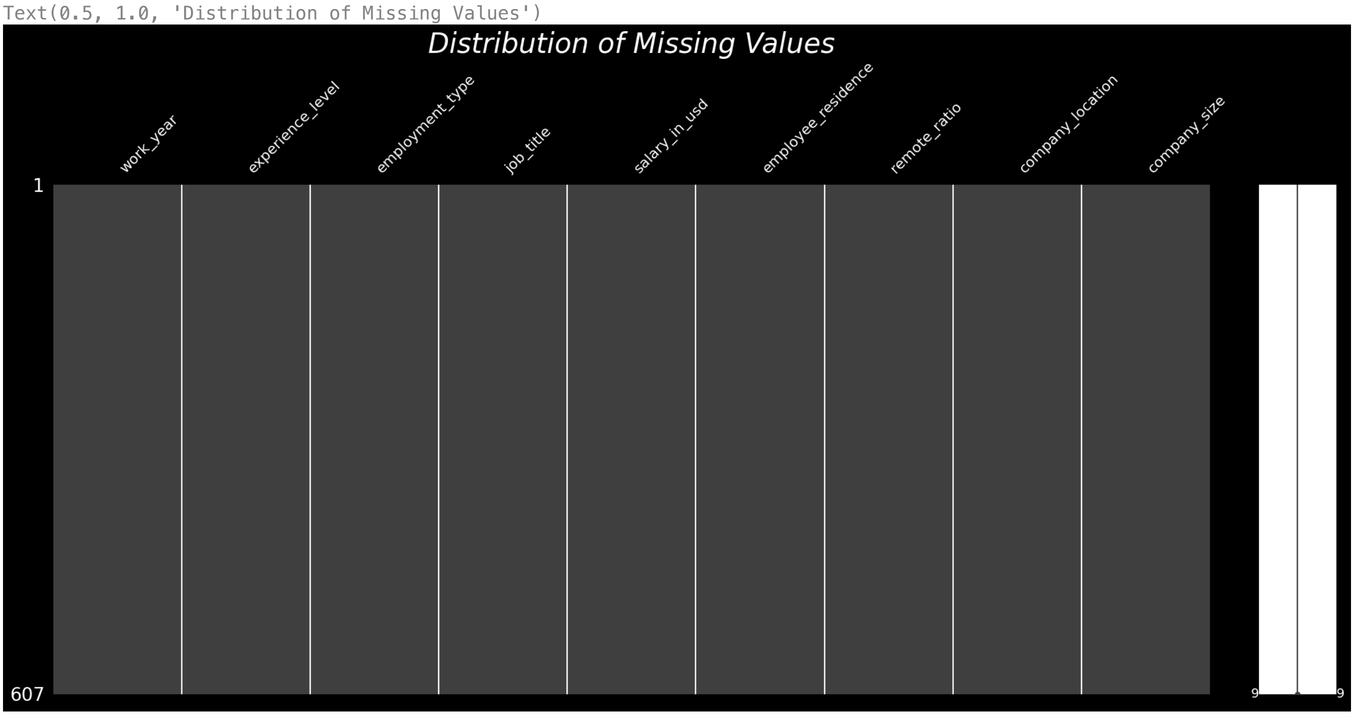
Finally, we got 9 columns with 607 rows:

3 numeric columns: (1)work_year, (2)salary_in_usd, (3)remote_ratio

6 categorical columns: (1)experience_level, (2)employment_type, (3)job_title, (4)employee_residense, (5)company_location, (6)company_size

```
msno.matrix(df)
plt.title('Distribution of Missing Values',fontsize=30, fontstyle= 'oblique')
```

```
Text(0.5, 1.0, 'Distribution of Missing Values')
```



And it is clear that there's **no missing value** on the dataset.

2. Univariate Analysis 📊 (explore each columns)

In this section, we'll explore each columns in the dataset to see the distributions of features, and to get some useful informations.

Mainly two parts in the section: Analysis on categorical columns; Analysis on numeric columns.

2.1. Categorical Columns

6 categorical columns in the dataset:

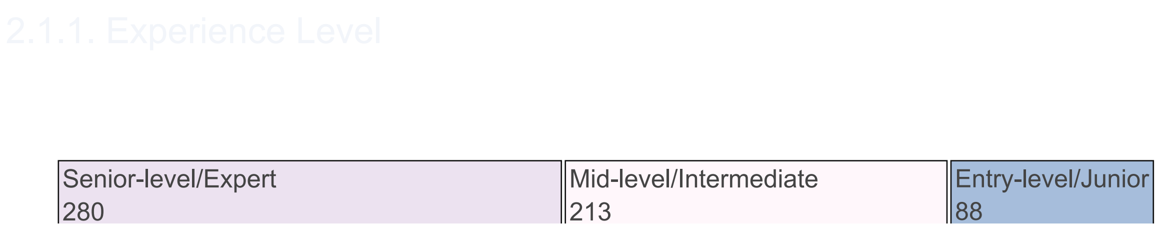
- Experiece Level
- Job Titles
- Employment Type
- Employee Resdience
- Company Location
- Company Size.

2.1.1. Experience Level

There's 4 categorical values in column 'Experience Level', each are:

EN, which refers to **Entry-level / Junior**
MI, which refers to **Mid-level / Intermediate**
SE, which refers to **Senior-level / Expert**
EX, which refers to **Executive-level / Director**

```
df['experience_level'] = df['experience_level'].replace('EN','Entry-level/Junior')
df['experience_level'] = df['experience_level'].replace('MI','Mid-level/Intermediate')
df['experience_level'] = df['experience_level'].replace('SE','Senior-level/Expert')
df['experience_level'] = df['experience_level'].replace('EX','Executive-level/Director')

ex_level = df['experience_level'].value_counts()
fig = px.treemap(ex_level,
                 path=[ex_level.index],
                 values=ex_level.values,
                 title = '2.1.1. Experience Level',
                 color=ex_level.index,
                 color_discrete_sequence=px.colors.sequential.PuBuGn,
                 template='plotly_dark',

                 width=1000, height=500)

percents = np.round((100*ex_level.values / sum(ex_level.values)).tolist(),2)
fig.data[0].customdata = [35.09, 46.13, 4.28 , 14.5]
fig.data[0].texttemplate = '%{label}<br>%{value}<br>%{customdata}%'

fig.update_layout(
    font=dict(size=19,family="Franklin Gothic"))

fig.show()
```



From treemap above, we can notice that Senior-level/Expert accounts for 46%, and Mid-level/Intermediate ranked the next. There's only 4.28% of Executive-level/Directior.

2.1.2. Job Titles

In this section, We'll answer two questions below:

1. **How many** job titles in the dataset?
2. Which are **top 10 frequent** job titles?

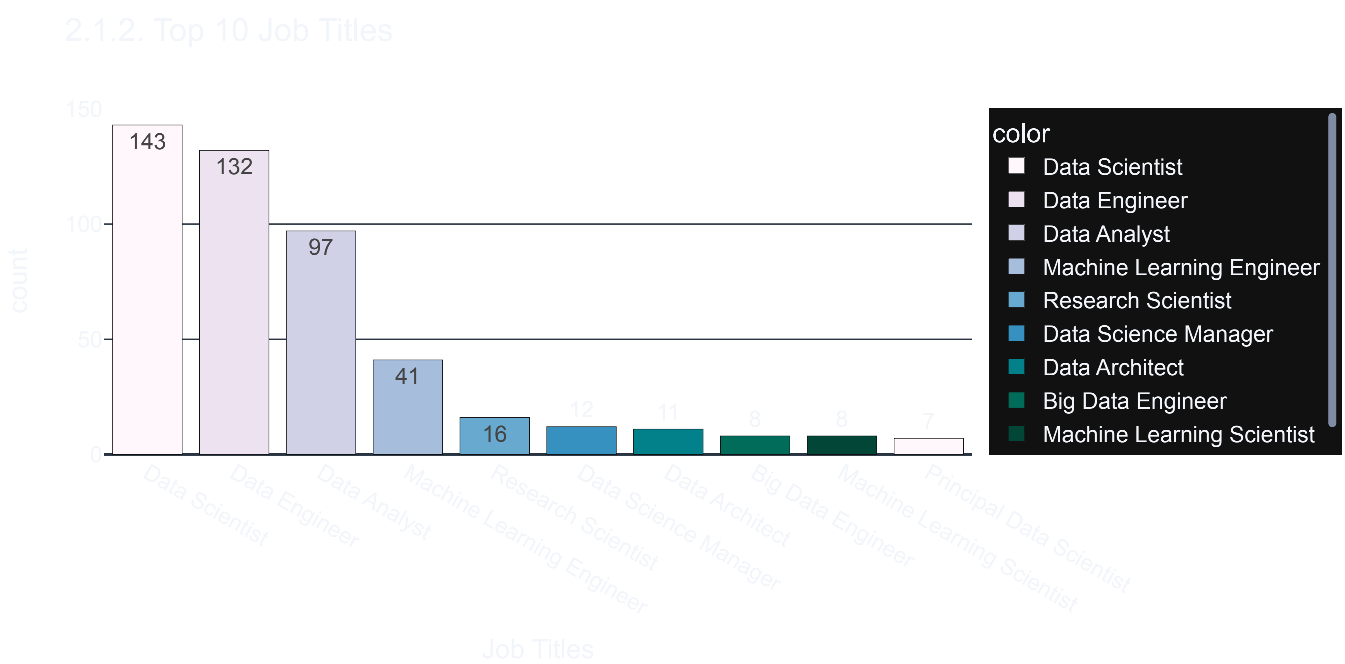
```
print('how many job titles in the dataset: ',df['job_title'].value_counts().size)
```

```
how many job titles in the dataset:  50
```

Shown as above, there are 50 job titles in the dataset.

plot a bar chart to see top 10 job titles below:

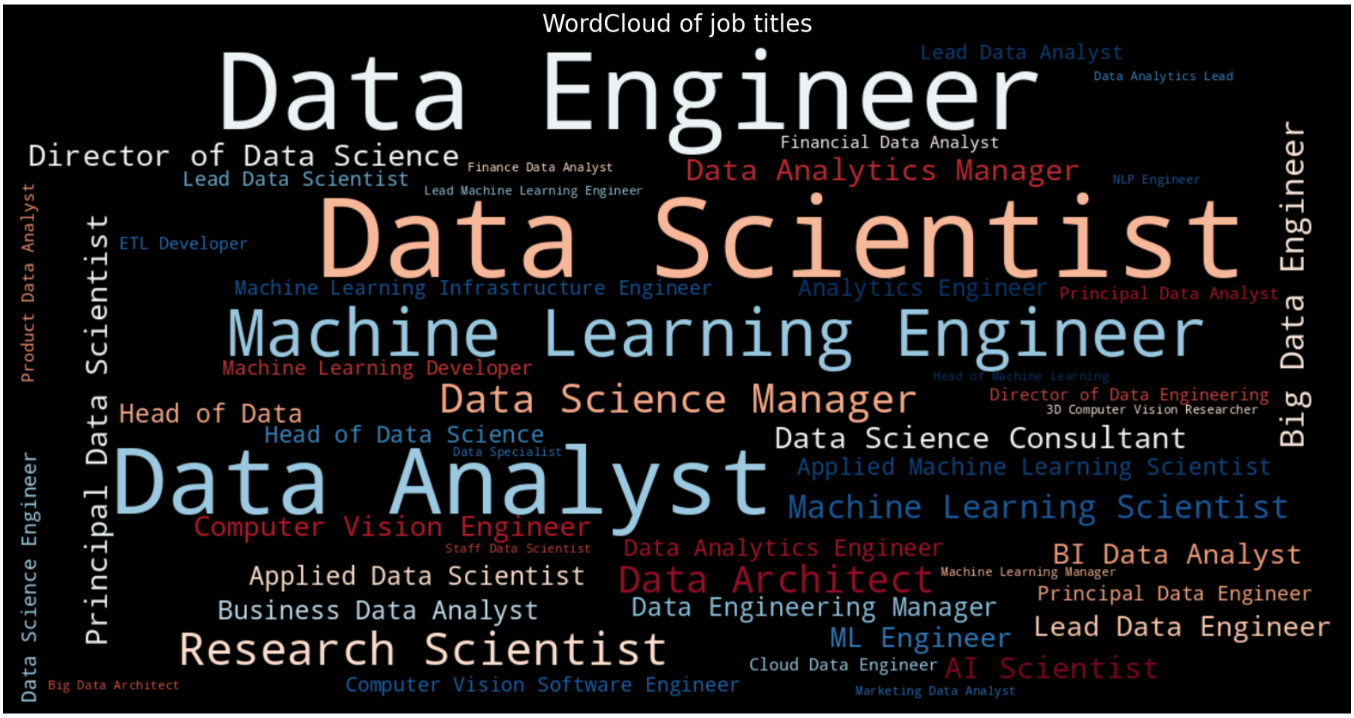
```
top10_job_title = df['job_title'].value_counts()[:10]
fig = px.bar(y=top10_job_title.values,
             x=top10_job_title.index,
             color = top10_job_title.index,
             color_discrete_sequence=px.colors.sequential.PuBuGn,
             text=top10_job_title.values,
             title= '2.1.2. Top 10 Job Titles',
             template= 'plotly_dark')
fig.update_layout(
    xaxis_title="Job Titles",
    yaxis_title="count",
    font = dict(size=17,family="Franklin Gothic"))
fig.show()
```



Data scientist, data engineer and data analyst ranked top 3 frequent job titles, but it can be easily seen that others are also related to those top 3 job titles.

and **WordCloud of job title** shown as below:

```
def Freq_df(cleanwordlist):
    Freq_dist_nltk = nltk.FreqDist(cleanwordlist)
    df_freq = pd.DataFrame.from_dict(Freq_dist_nltk, orient='index')
    df_freq.columns = ['Frequency']
    df_freq.index.name = 'Term'
    df_freq = df_freq.sort_values(by=['Frequency'],ascending=False)
    df_freq = df_freq.reset_index()
    return df_freq

def Word_Cloud(data, color_background, colormap, title):
    plt.figure(figsize = (20,15))
    wc = WordCloud(width=1200,
                   height=600,
                   max_words=50,
                   colormap= colormap,
                   max_font_size = 100,
                   random_state=88,
                   background_color=color_background).generate_from_frequencies(data)
    plt.imshow(wc, interpolation='bilinear')
    plt.title(title, fontsize=20)
    plt.axis('off')
    plt.show()


freq_df = Freq_df(df['job_title'].values.tolist())
data = dict(zip(freq_df['Term'].tolist(), freq_df['Frequency'].tolist()))
data = freq_df.set_index('Term').to_dict()['Frequency']

Word_Cloud(data ,'black','RdBu', 'WordCloud of job titles')
```



2.1.3. Employment Type

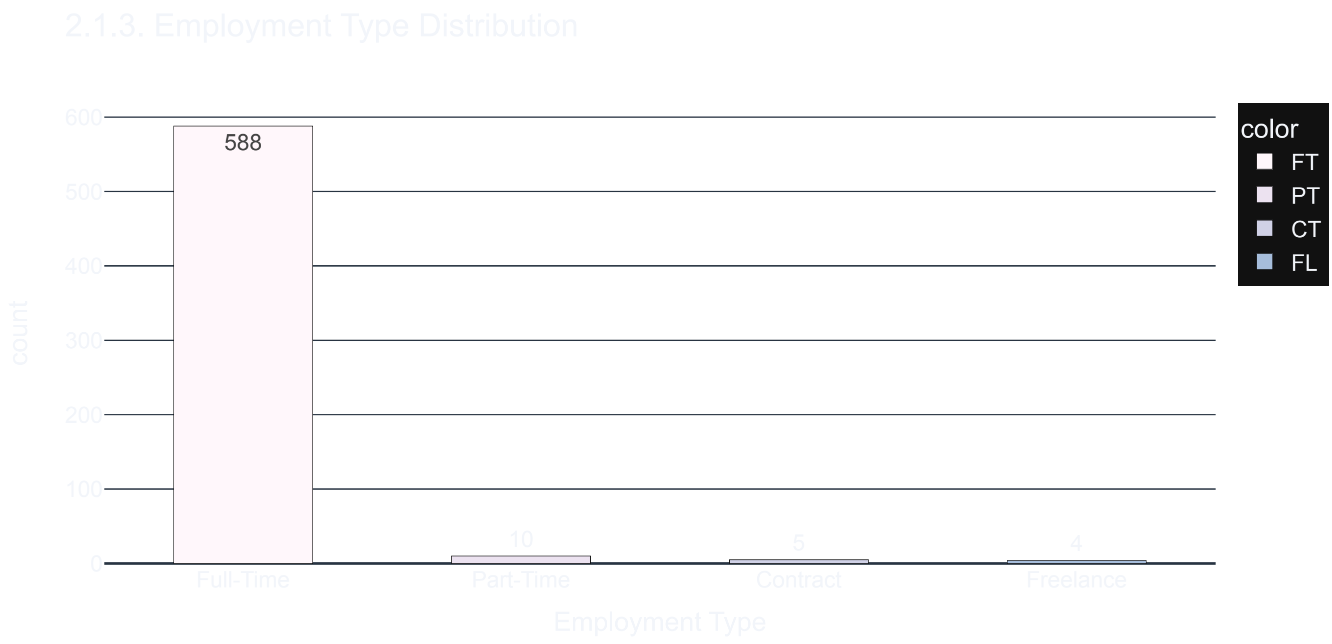
4 employment type here, each are:

PT: Part-time
FT: Full-time

CT: Contract

FL: Freelance

```
type_grouped = df['employment_type'].value_counts()
e_type = ['Full-Time','Part-Time','Contract','Freelance']
fig = px.bar(x = e_type, y = type_grouped.values,
       color = type_grouped.index,
       color_discrete_sequence=px.colors.sequential.PuBuGn,
       template = 'plotly_dark',
       text = type_grouped.values, title = '2.1.3. Employment Type Distribution')
fig.update_layout(
    xaxis_title="Employment Type",
    yaxis_title="count",
    font = dict(size=17,family="Franklin Gothic"))
fig.update_traces(width=0.5)
fig.show()
```



Most of employee types are full-time.

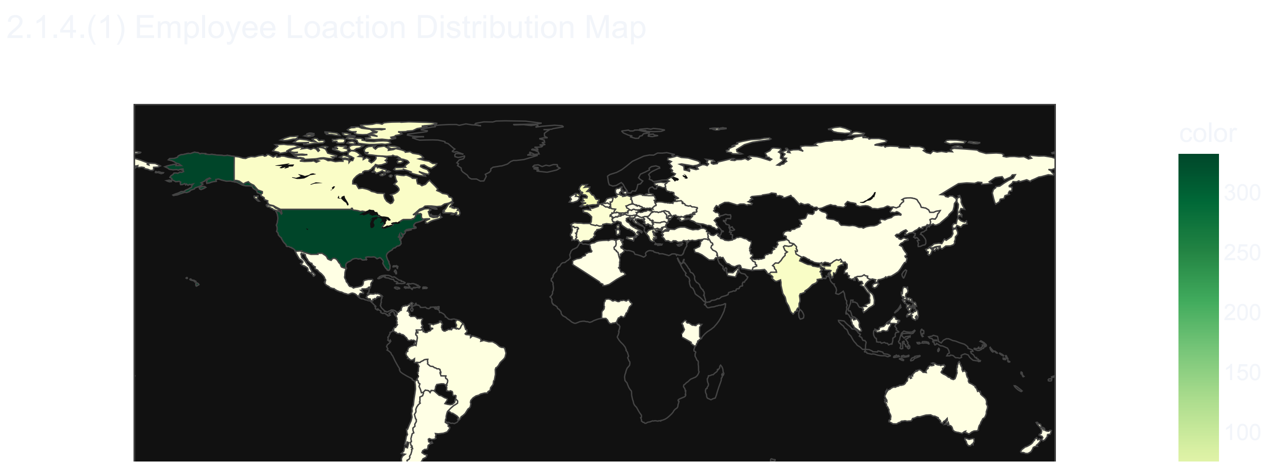
2.1.4. Employee Residence & Company Location

We'll explore employee's residence and company location by plotting map & bar charts in this section.

convert country into choropleth readable type:

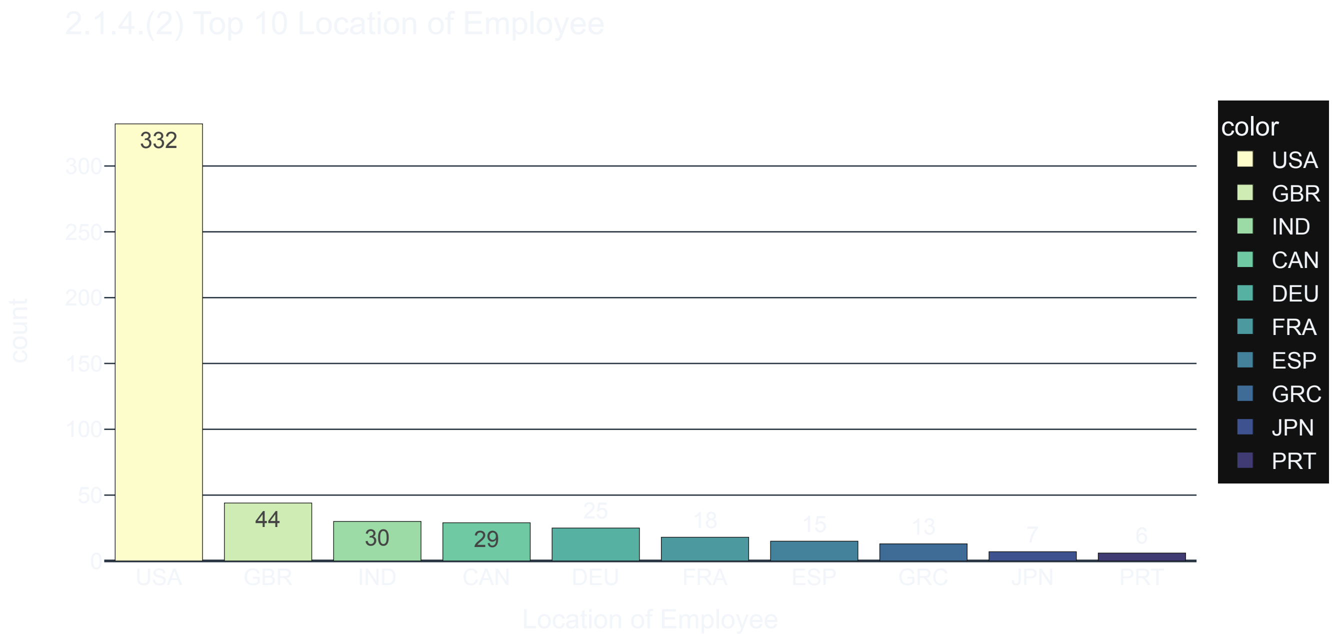
```
converted_country = coco.convert(names=df['employee_residence'], to="ISO3")
df['employee_residence'] = converted_country
```

```
residence = df['employee_residence'].value_counts()
fig = px.choropleth(locations=residence.index,
                    color=residence.values,
                    color_continuous_scale=px.colors.sequential.YlGn,
                    template='plotly_dark',
                    title = '2.1.4.(1) Employee Loaction Distribution Map')

fig.update_layout(font = dict(size= 17, family="Franklin Gothic"))
fig.show()
```



Most of the employees are from USA, and bar plot below:

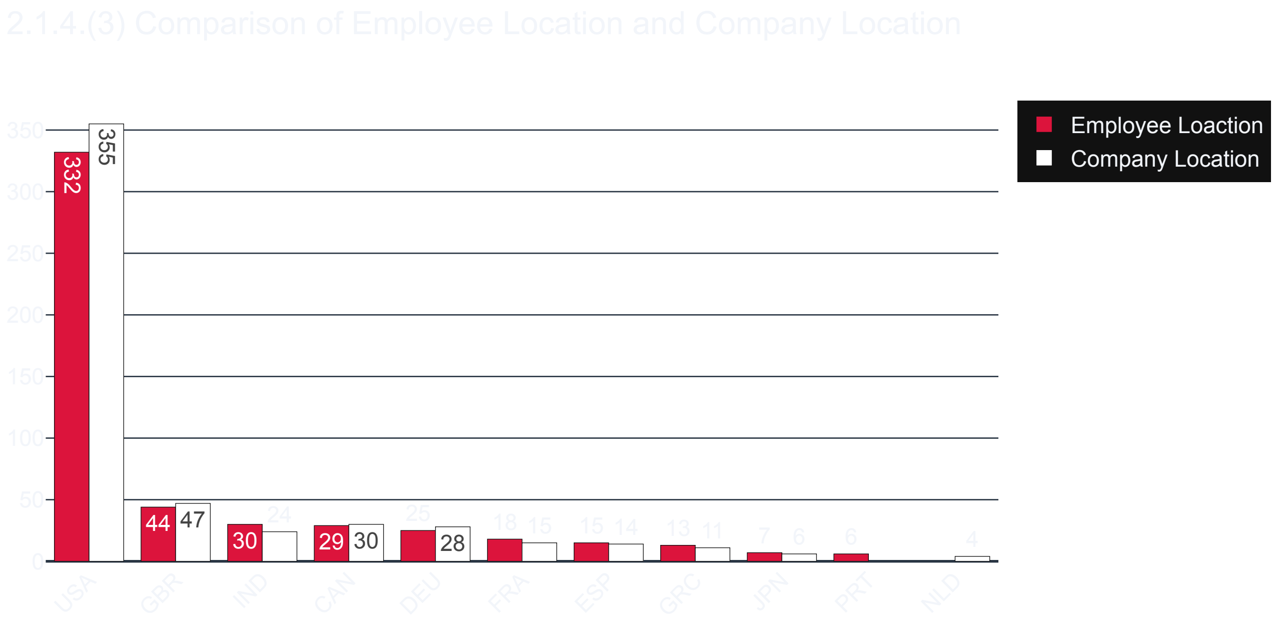
```
top10_employee_location = residence[:10]
fig = px.bar(y=top10_employee_location.values,
             x=top10_employee_location.index,
             color = top10_employee_location.index,
             color_discrete_sequence=px.colors.sequential.deep,
             text=top10_employee_location.values,
             title= '2.1.4.(2) Top 10 Location of Employee',
             template= 'plotly_dark')
fig.update_layout(
    xaxis_title="Location of Employee",
    yaxis_title="count",
    font = dict(size=17,family="Franklin Gothic"))
fig.show()
```



Now we found that the USA contains about 332 accounts, and GBR, IND ranked the next.

Let's compare employee residence and company location below:

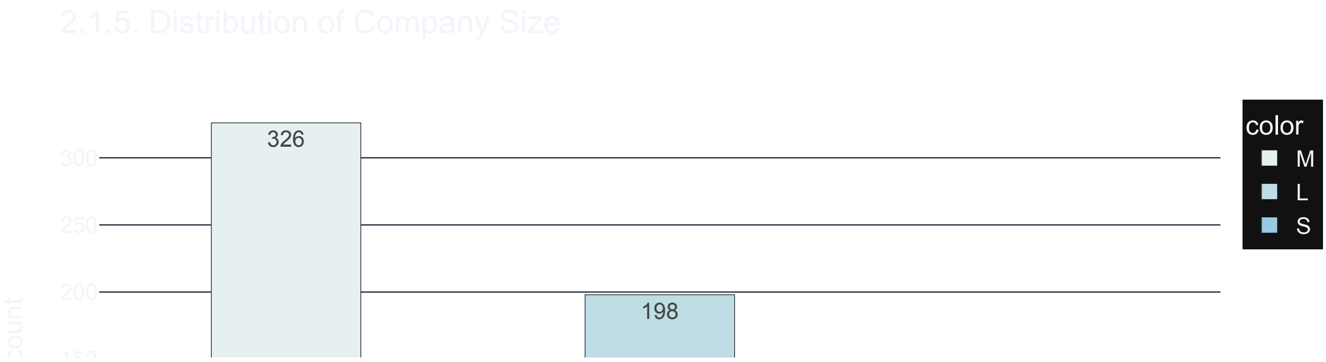
```
converted_country = coco.convert(names=df['company_location'], to="ISO3")
df['company_location'] = converted_country
c_location = df['company_location'].value_counts()
top_10_company_location = c_location[:10]
fig = go.Figure(data=[
    go.Bar(name='Employee Loaction',
           x=top10_employee_location.index, y=top10_employee_location.values,
           text=top10_employee_location.values,marker_color='crimson'),
    go.Bar(name='Company Location', x=top_10_company_location.index,
           y=top_10_company_location.values,text=top_10_company_location.values,marker_color='white')
])
fig.update_layout(barmode='group', xaxis_tickangle=-45,
                  title='2.1.4.(3) Comparison of Employee Location and Company Location',template='plotly_dark',
                  font = dict(size=17,family="Franklin Gothic"))

fig.show()
```



USA, GBR, CAN and DEU have higher count of company location then employee location as shown above.

2.1.5. Company Size

```
grouped_size = df['company_size'].value_counts()

fig = px.bar(y=grouped_size.values,
             x=grouped_size.index,
             color = grouped_size.index,
             color_discrete_sequence=px.colors.sequential.dense,
             text=grouped_size.values,
             title= '2.1.5. Distribution of Company Size',
             template= 'plotly_dark')

fig.update_traces(width=0.4)
fig.update_layout(
    xaxis_title="Company Size",
    yaxis_title="count",
    font = dict(size=17,family="Franklin Gothic"))
fig.show()
```



Company size mostly consists of **medium size**, and the **large size** ranked the next.

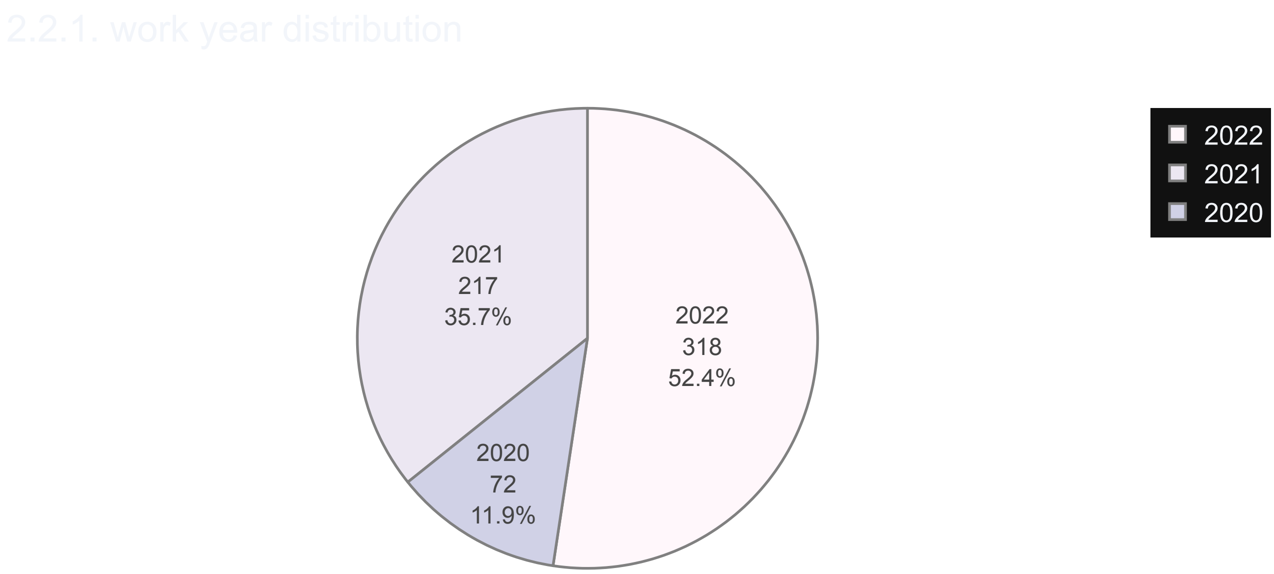
2.2. Explore Numeric Columns

We'll explore 3 numeric columns in this section, each are:

- **work_year**: The year the salary was paid
- **salary_in_usd**: The salary in USD
- **remote_ratio**: The overall amount of work done remotely,

2.2.1. Work Year

```
wkyear = df['work_year'].value_counts()
fig = px.pie(values=wkyear.values,
             names=wkyear.index,
             color_discrete_sequence=px.colors.sequential.PuBu,
             title= '2.2.1. work year distribution',template='plotly_dark')
fig.update_traces(textinfo='label+percent+value', textfont_size=18,
                  marker=dict(line=dict(color='#100000', width=0.2)))

fig.data[0].marker.line.width = 2
fig.data[0].marker.line.color='gray'
fig.update_layout(
    font=dict(size=20,family="Franklin Gothic"))
fig.show()
```

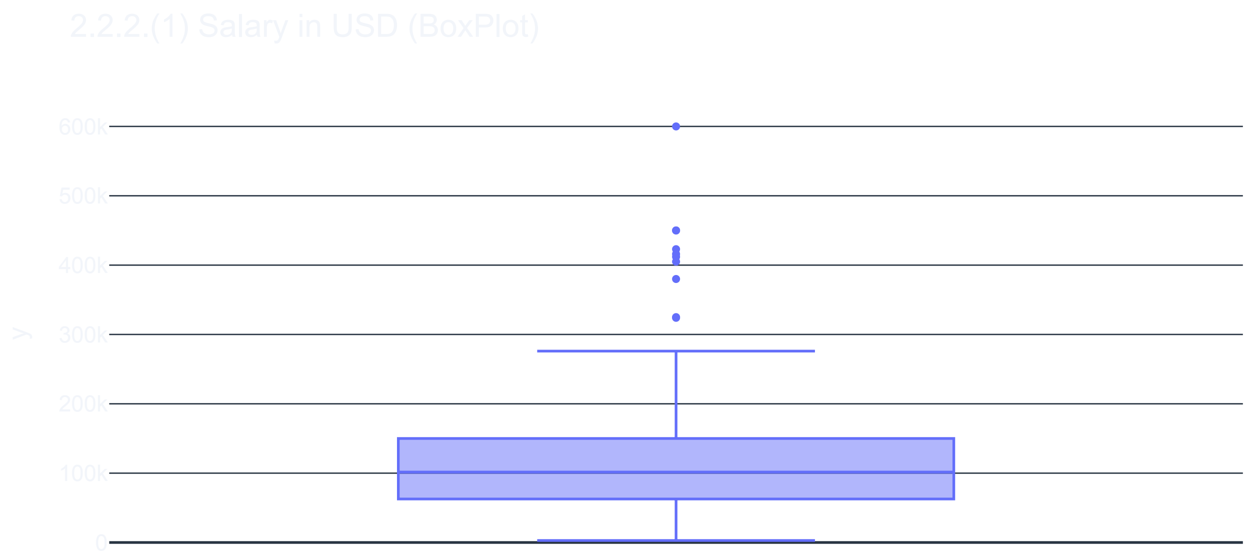


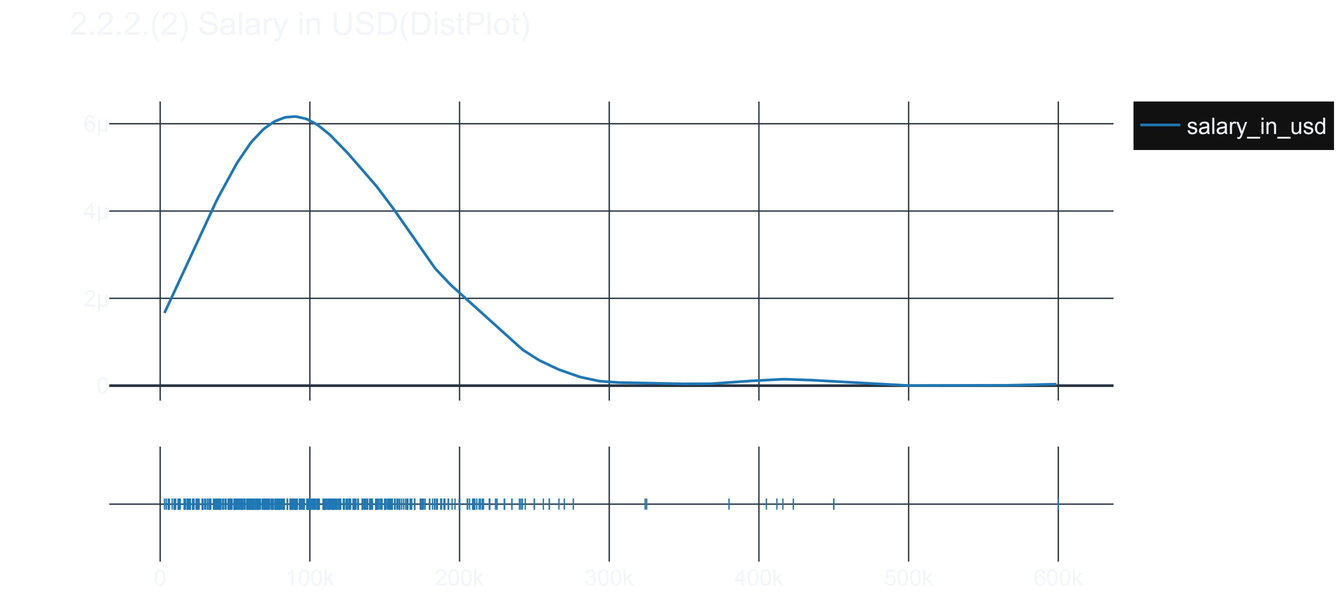
2022 year data accounts for 52.4% in the dataset, the next is 2021, which accounts for 35.7%.

2.2.2. Salary in USD

Used box plot & distplot to see the distribution of Salary in USD

```
hist_data = [df['salary_in_usd']]
group_labels = ['salary_in_usd']
fig1 = px.box(y=df['salary_in_usd'],template= 'plotly_dark', title = '2.2.2.(1) Salary in USD (BoxPlot)')
fig2 = ff.create_distplot(hist_data, group_labels, show_hist=False)
fig2.layout.template = 'plotly_dark'
fig1.update_layout(font = dict(size=17,family="Franklin Gothic"))
fig2.update_layout(title='2.2.2.(2) Salary in USD(DistPlot)', font = dict(size=17, family="Franklin Gothic"))
fig1.show()
fig2.show()
```





Salary in USD is shown as above, we can see that salary mostly distributed between 100k and 150k.

2.2.3. Remote Ratio

Remote Ratio consists of 3 values: 100, 50, 0.

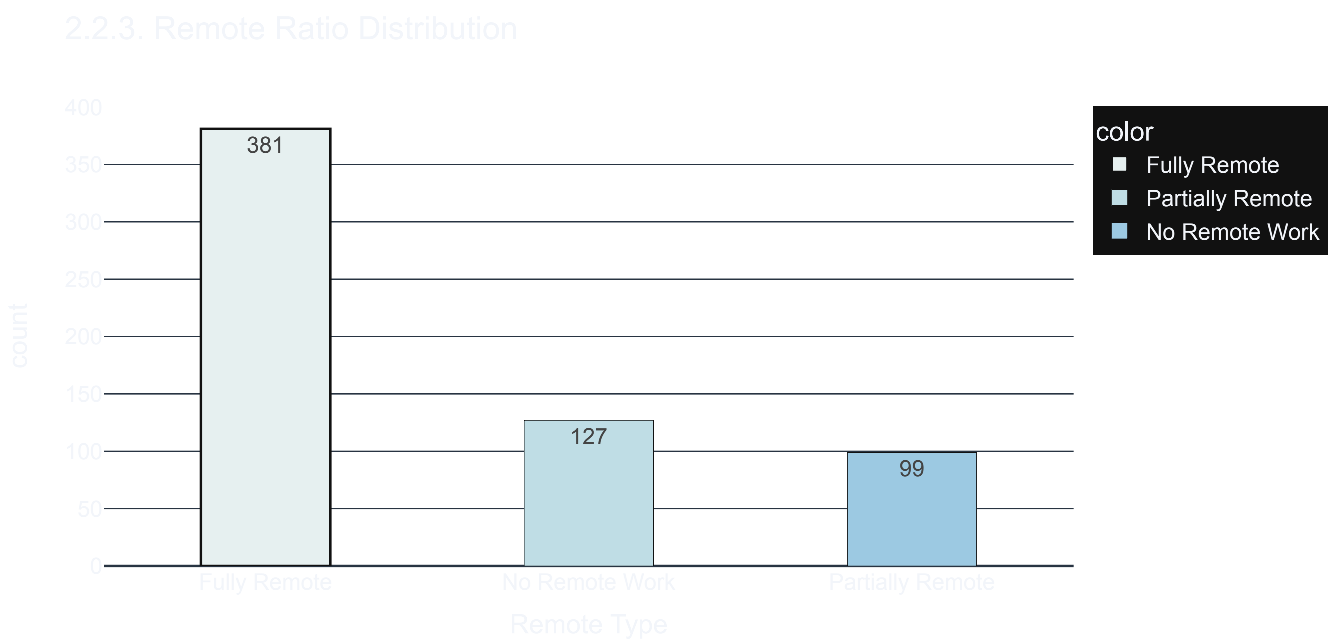
possible values are as follows:

0 No remote work (less than 20%)

50 Partially remote

100 Fully remote(more than 80%)

```
remote_type = ['Fully Remote','Partially Remote','No Remote Work']

plt.figure(figsize=(20,5))
fig = px.bar(x = ['Fully Remote','No Remote Work','Partially Remote'],
       y = df['remote_ratio'].value_counts().values,
       color = remote_type,
       color_discrete_sequence=px.colors.sequential.dense,
       text=df['remote_ratio'].value_counts().values,
       title = '2.2.3. Remote Ratio Distribution',
       template='plotly_dark')

fig.update_traces(width=0.4)

fig.data[0].marker.line.width = 2


fig.update_layout(
    xaxis_title="Remote Type",
    yaxis_title="count",
    font = dict(size=17,family="Franklin Gothic"))
fig.show()
```




```
<Figure size 2000x500 with 0 Axes>
```

381 of works are fully remoted, and no remote work ranked the next, with count of 127.

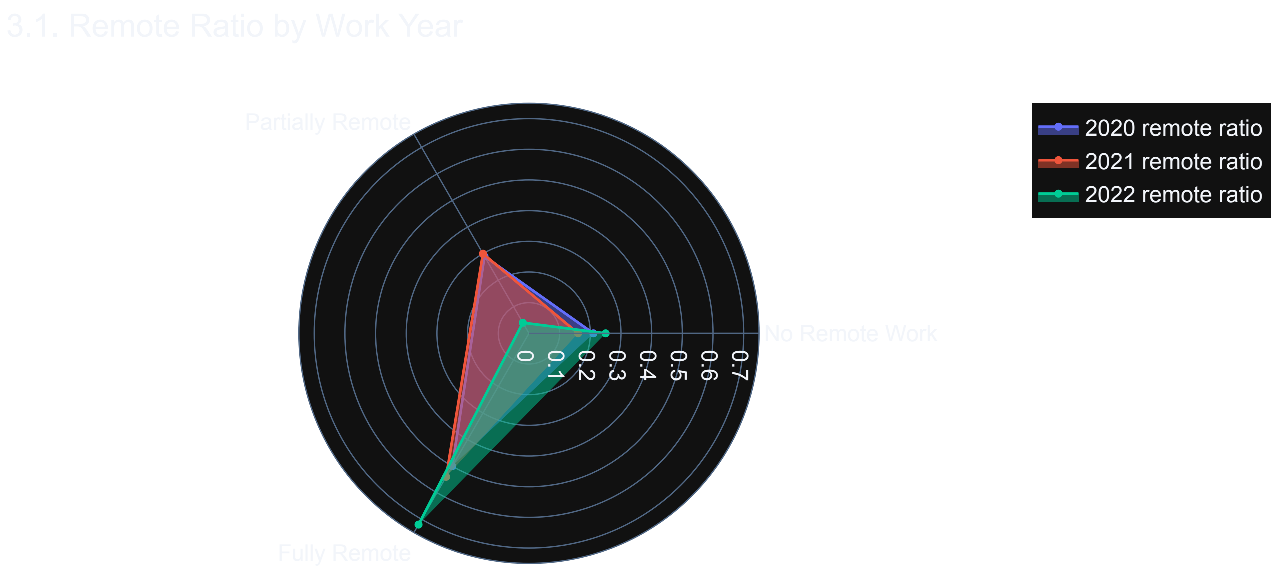
3. Work Year Analysis📆

We'll do analysis on Remote Ratio by Work Year in this section to explore whether remote ratio affected by work year.

3.1. Remote Ratio by Work Year

Plot Rader plot to observe relations between Remoto Ratio and Work Year below:

```
remote_year = df.groupby(['work_year','remote_ratio']).size()
ratio_2020 = np.round(remote_year[2020].values/remote_year[2020].values.sum(),2)
ratio_2021 = np.round(remote_year[2021].values/remote_year[2021].values.sum(),2)
ratio_2022 = np.round(remote_year[2022].values/remote_year[2022].values.sum(),2)
fig = go.Figure()
categories = ['No Remote Work', 'Partially Remote', 'Fully Remote']
fig.add_trace(go.Scatterpolar(
             r = ratio_2020,
             theta = categories,
             fill = 'toself',
             name = '2020 remote ratio'
             ))
fig.add_trace(go.Scatterpolar(
             r = ratio_2021,
             theta = categories,
             fill = 'toself',
             name = '2021 remote ratio'
#              fillcolor = 'lightred'
             ))
fig.add_trace(go.Scatterpolar(
             r = ratio_2022,
             theta = categories,
             fill = 'toself',
             name = '2022 remote ratio'
#              fillcolor = 'lightblue'
             ))

fig.update_layout(
  polar=dict(
    radialaxis=dict(
#       visible=True,
      range=[0, 0.75]
    )),
  font = dict(family="Franklin Gothic", size=17),
  showlegend=True,
  title = '3.1. Remote Ratio by Work Year'
)
fig.layout.template = 'plotly_dark'
fig.show()
```



72% of companies adopt **fully remote work** in **2022 year**, which is the largest ratio among 2021 year & 2020 year.

We can guess that it is due to **pandemic.**

4. Experience Level Analysis

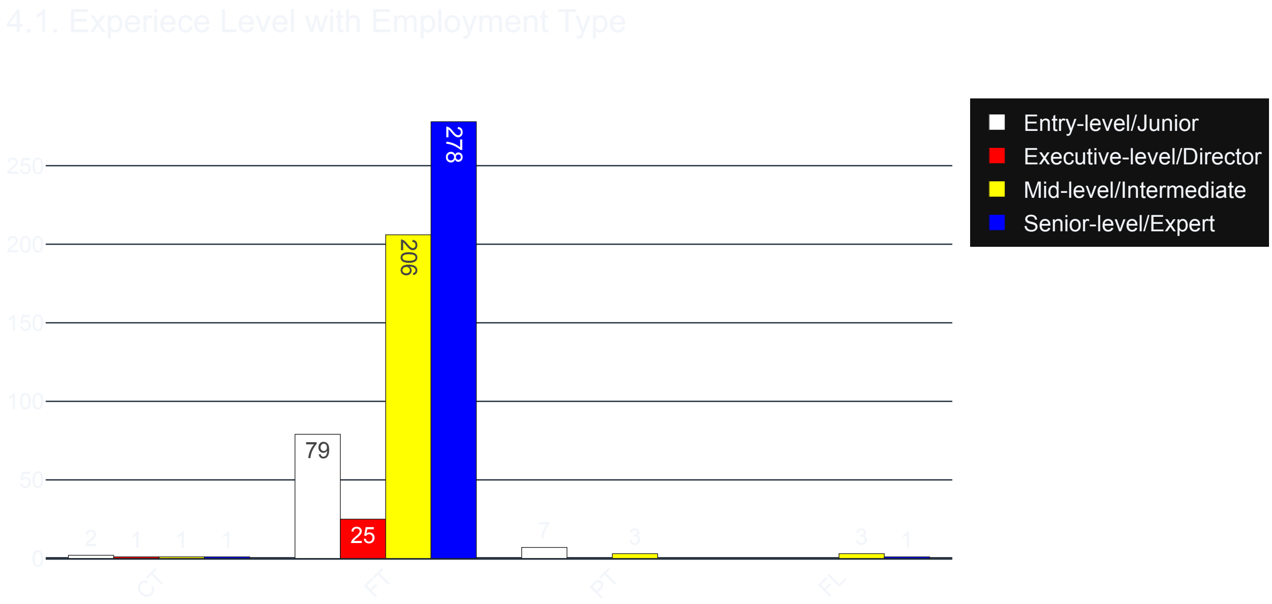
3 main parts in section 4, each are:

- 1. **Employment Type** by Experience Level

- 2. **Top 3 Job Title** by Experience Level
- 3. **Company Size** by Experience Level

4.1. Employment Type by Experience Level

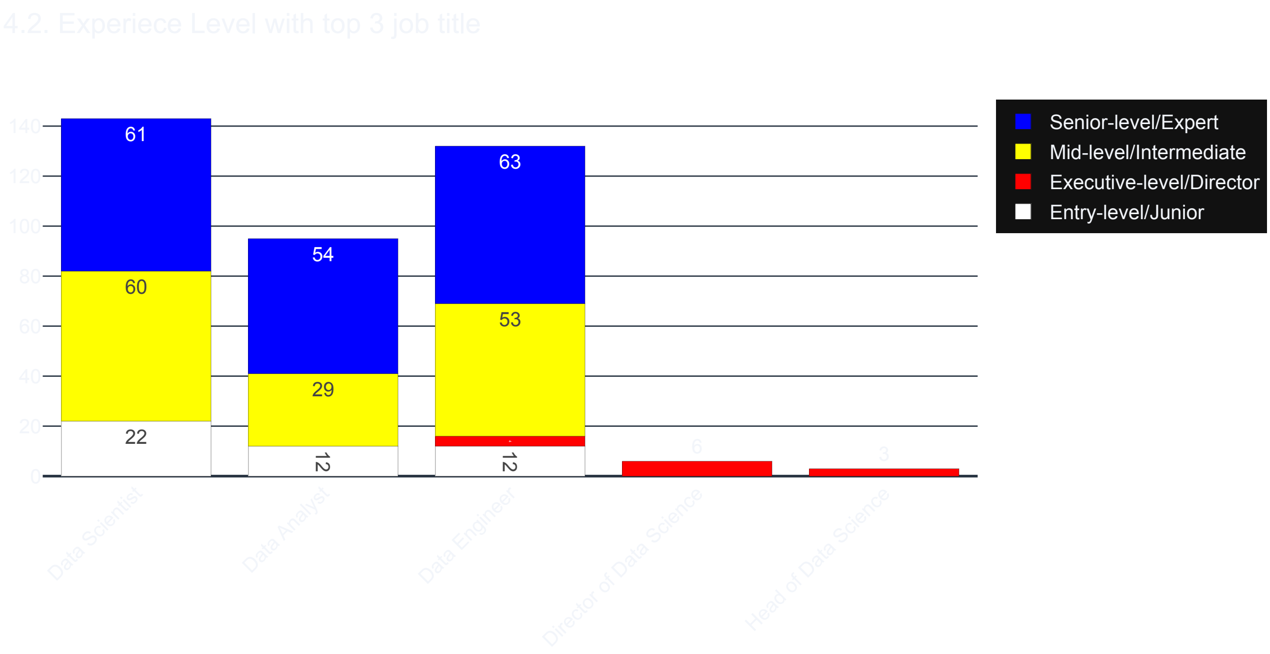
```
exlevel_type = df.groupby(['experience_level','employment_type']).size()
fig = go.Figure(data=[
    go.Bar(name='Entry-level/Junior', x=exlevel_type['Entry-level/Junior'].index, y=exlevel_type['Entry-level/Junior'].value
           text=exlevel_type['Entry-level/Junior'].values, marker_color='white'),
    go.Bar(name='Executive-level/Director', x=exlevel_type['Executive-level/Director'].index, y=exlevel_type['Executive-leve
           text=exlevel_type['Executive-level/Director'].values, marker_color='red'),
    go.Bar(name='Mid-level/Intermediate', x=exlevel_type['Mid-level/Intermediate'].index, y=exlevel_type['Mid-level/Intermec
           text=exlevel_type['Mid-level/Intermediate'].values, marker_color='yellow'),
    go.Bar(name='Senior-level/Expert', x=exlevel_type['Senior-level/Expert'].index, y=exlevel_type['Senior-level/Expert'].va
           text=exlevel_type['Senior-level/Expert'].values, marker_color='blue'),
])
fig.update_layout(xaxis_tickangle=-45, title='4.1. Experiece Level with Employment Type', font = dict(family="Franklin Gothi

fig.show()
```



Type of Part-Time consists of Entry-level and Mid-level.
Additionally, type of Freelance consists of Mid-level and Senior-level.

4.2. Top 3 Job Title by Experience Level

```
exlevel_job = df.groupby(['experience_level','job_title']).size()

entry_top3 = exlevel_job['Entry-level/Junior'].sort_values(ascending=False)[:3]
executive_top3 = exlevel_job['Executive-level/Director'].sort_values(ascending=False)[:3]
mid_top3 = exlevel_job['Mid-level/Intermediate'].sort_values(ascending=False)[:3]
senior_top3 = exlevel_job['Senior-level/Expert'].sort_values(ascending=False)[:3]

exlevel_type = df.groupby(['experience_level','employment_type']).size()
fig = go.Figure(data=[
    go.Bar(name='Entry-level/Junior', x=entry_top3.index, y=entry_top3.values,
           text=entry_top3.values, marker_color='white'),
    go.Bar(name='Executive-level/Director', x=executive_top3.index, y=executive_top3.values,
           text=executive_top3.values, marker_color='red'),
    go.Bar(name='Mid-level/Intermediate', x=mid_top3.index, y=mid_top3.values,
           text=mid_top3.values, marker_color='yellow'),
    go.Bar(name='Senior-level/Expert', x=senior_top3.index, y=senior_top3.values,
           text=senior_top3.values, marker_color='blue'),
])
fig.update_layout(barmode = 'stack', xaxis_tickangle=-45, title='4.2. Experiece Level with top 3 job title', font = dict(fam

fig.show()
```



- 1. **Entry-level/Junior** tends to have **data scientist position** rather than data analyst and data engineer;
- 2. **Mid-level/Intermediate** tends to have **data sceintist** and **data engineer position** rather then analyst;
- 3. Obviously, there's no data scientist and analyst job with **Executive-level/Director**, but tends to have **data engineer** and **director position**.

4.3. Company Size by Experience Level

```
exlevel_size = df.groupby(['experience_level','company_size']).size()
fig = go.Figure(data=[
    go.Bar(name='Entry-level/Junior', x=exlevel_size['Entry-level/Junior'].index, y=exlevel_size['Entry-level/Junior'].value
           text=exlevel_size['Entry-level/Junior'].values, marker_color='white'),
    go.Bar(name='Executive-level/Director', x=exlevel_size['Executive-level/Director'].index, y=exlevel_size['Executive-leve
           text=exlevel_size['Executive-level/Director'].values, marker_color='red'),
    go.Bar(name='Mid-level/Intermediate', x=exlevel_size['Mid-level/Intermediate'].index, y=exlevel_size['Mid-level/Intermec
           text=exlevel_size['Mid-level/Intermediate'].values, marker_color='yellow'),
    go.Bar(name='Senior-level/Expert', x=exlevel_size['Senior-level/Expert'].index, y=exlevel_size['Senior-level/Expert'].va
           text=exlevel_size['Senior-level/Expert'].values, marker_color='blue'),
])
fig.update_layout(xaxis_tickangle=-45, title='4.3. Experience Level with Company Size', font=dict(family="Franklin Gothic",

fig.show()
```

We can notice that most of **Senior-level/Expert** works in medium size of company.

5. Company Location Analysis🗺️

Here, we'll explore company location by experience level using map plot

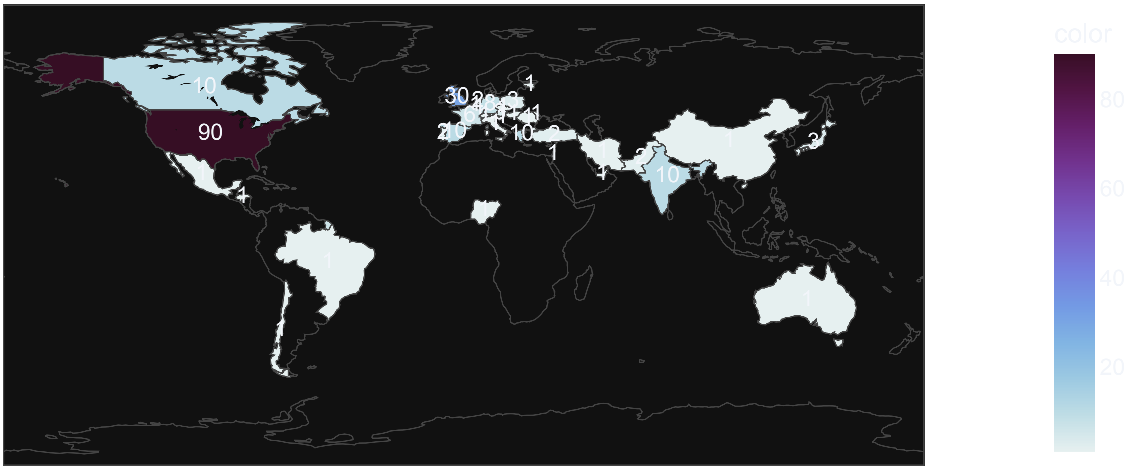
5.1. Experience Level

plot choropleth for each experience levels:

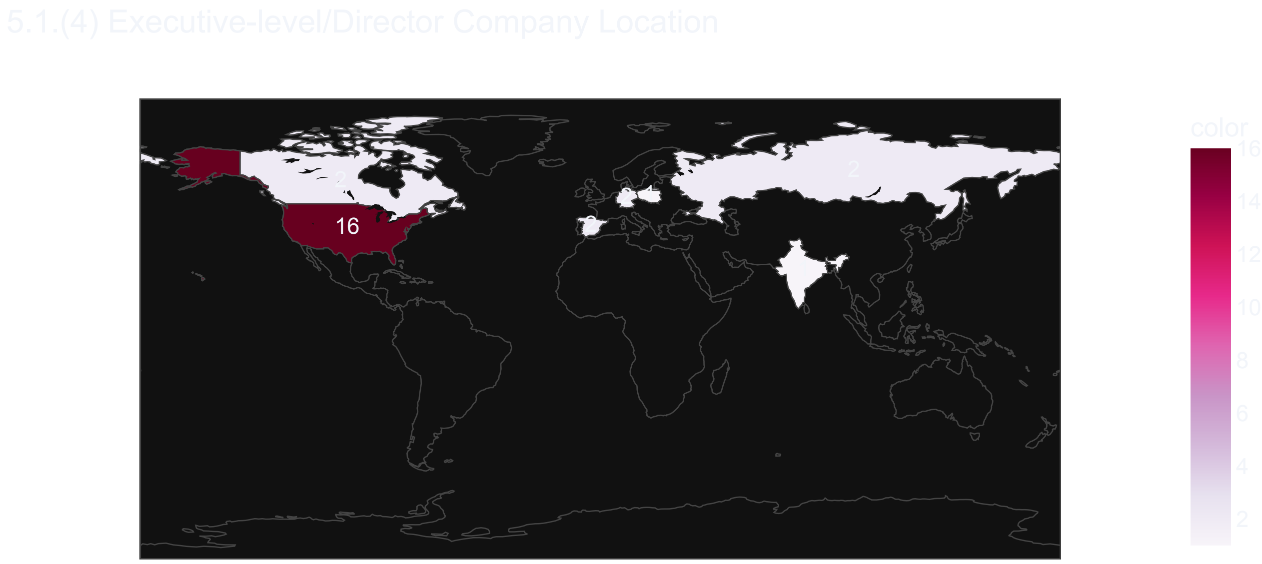
```
exlevel_location = df.groupby(['experience_level','company_location']).size()

entry_location = exlevel_location['Entry-level/Junior']
executive_location = exlevel_location['Executive-level/Director']
mid_location = exlevel_location['Mid-level/Intermediate']
senior_location = exlevel_location['Senior-level/Expert']

fig1 = px.choropleth(locations=entry_location.index,
                    color=entry_location.values,
                    color_continuous_scale=px.colors.sequential.Peach,
                    template='plotly_dark',
                    title = '5.1.(1) Entry-level/Junior Company Location')

fig2 = px.choropleth(locations=mid_location.index,
                    color=mid_location.values,
                    color_continuous_scale=px.colors.sequential.dense,
                    template='plotly_dark',
                    title = '5.1.(2) Mid-level/Intermediate Company Location')
fig3 = px.choropleth(locations=senior_location.index,
                    color=senior_location.values,
                    color_continuous_scale=px.colors.sequential.GnBu,
                    template='plotly_dark',
                    title = '5.1.(3) Senior-level/Expert Company Location')
fig4 = px.choropleth(locations=executive_location.index,
                    color=executive_location.values,
                    color_continuous_scale=px.colors.sequential.PuRd,
                    template='plotly_dark',
                    title = '5.1.(4) Executive-level/Director Company Location')

fig1.add_scattergeo(
    locations=entry_location.index,
    text= entry_location.values,
    mode='text')

fig2.add_scattergeo(
    locations=mid_location.index,
    text= mid_location.values,
    mode='text')

fig3.add_scattergeo(
    locations=senior_location.index,
    text= senior_location.values,
    mode='text')


fig4.add_scattergeo(
    locations=executive_location.index,
    text= executive_location.values,
    mode='text')

fig1.update_layout(font = dict(size = 17, family="Franklin Gothic"))
fig2.update_layout(font = dict(size = 17, family="Franklin Gothic"))
fig3.update_layout(font = dict(size = 17, family="Franklin Gothic"))
fig4.update_layout(font = dict(size = 17, family="Franklin Gothic"))

fig1.show()
fig2.show()
fig3.show()
fig4.show()
```

5.1.(1) Entry-level/Junior Company Location

5.1.(2) Mid-level/Intermediate Company Location



5.1.(3) Senior-level/Expert Company Location



A higher level means tends to go to the United States,
while lower levels often mean staying in one's own country.

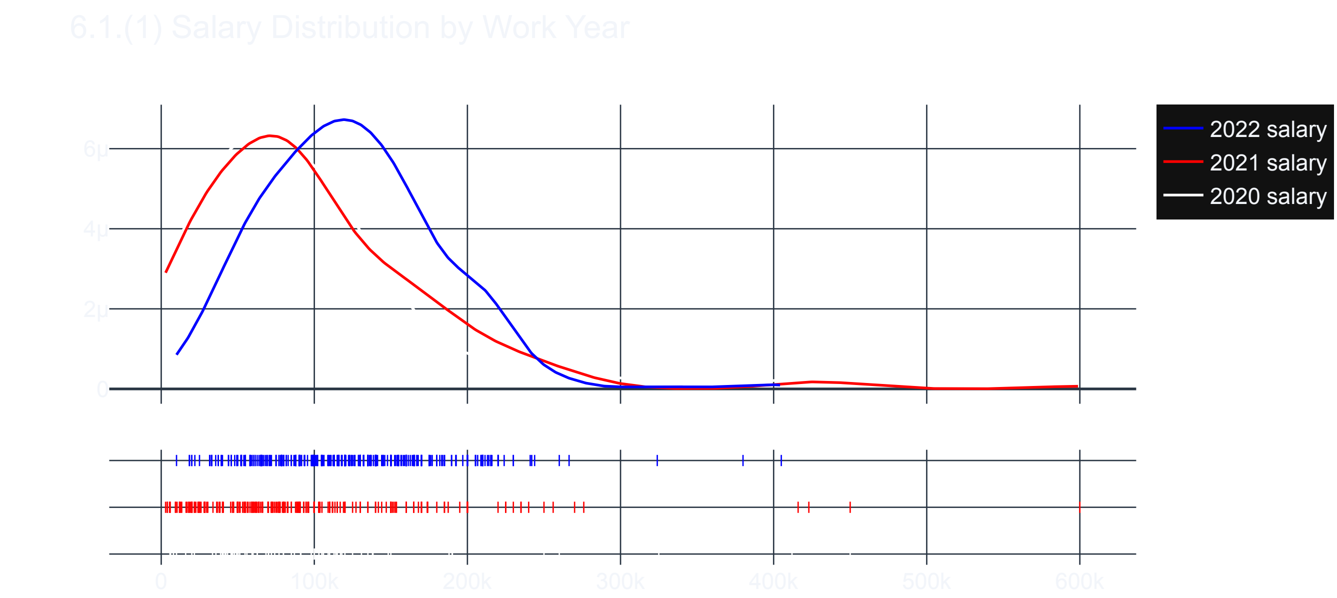
6. Salary Analysis 💰💵

The part 'Salary Analysis' consists of 5 parts, each are:

1. **Salary** by Work Year
2. **Salary** by Experience Level
3. **Salary** by Company Size
4. **Higest salaries** by Job Titles
5. **Average Salary** by Company Location

6.1. Salary by work year

```
w2020 = df.loc[(df['work_year'] == 2020)]
w2021 = df.loc[(df['work_year'] == 2021)]
w2022 = df.loc[(df['work_year'] == 2022)]
hist_data = [w2020['salary_in_usd'],w2021['salary_in_usd'],w2022['salary_in_usd']]
group_labels = ['2020 salary','2021 salary','2022 salary']
colors = ['white','red','blue']

year_salary = pd.DataFrame(columns=['2020','2021','2022'])
year_salary['2020'] = w2020.groupby('work_year').mean('salary_in_usd')['salary_in_usd'].values
year_salary['2021'] = w2021.groupby('work_year').mean('salary_in_usd')['salary_in_usd'].values
year_salary['2022'] = w2022.groupby('work_year').mean('salary_in_usd')['salary_in_usd'].values

fig1 = ff.create_distplot(hist_data, group_labels, show_hist=False,colors=colors)
fig2 = go.Figure(data=px.bar(x= year_salary.columns,
                             y=year_salary.values.tolist()[0],
                             color = year_salary.columns,
                             color_discrete_sequence= colors,
                             title='6.1.(2) Mean Salary by Work Year',
                             text = np.round([num/1000 for num in year_salary.values.tolist()[0]],2),
#                              width = [year_salary.values.tolist()[0]],
                             template = 'plotly_dark',
                             height=500))
fig1.layout.template = 'plotly_dark'
fig1.update_layout(title='6.1.(1) Salary Distribution by Work Year', font = dict(size=17,family="Franklin Gothic"))
fig2.update_traces(width=0.3)
fig2.update_layout(
    xaxis_title="Work Year",
    yaxis_title="Mean Salary (k)",
    font = dict(size=17,family="Franklin Gothic"))
fig1.show()
fig2.show()
```



There are higher salary amounts in 2022 than the levels in 2021 and 2020.
The levels in 2021 and 2020 are about the same.

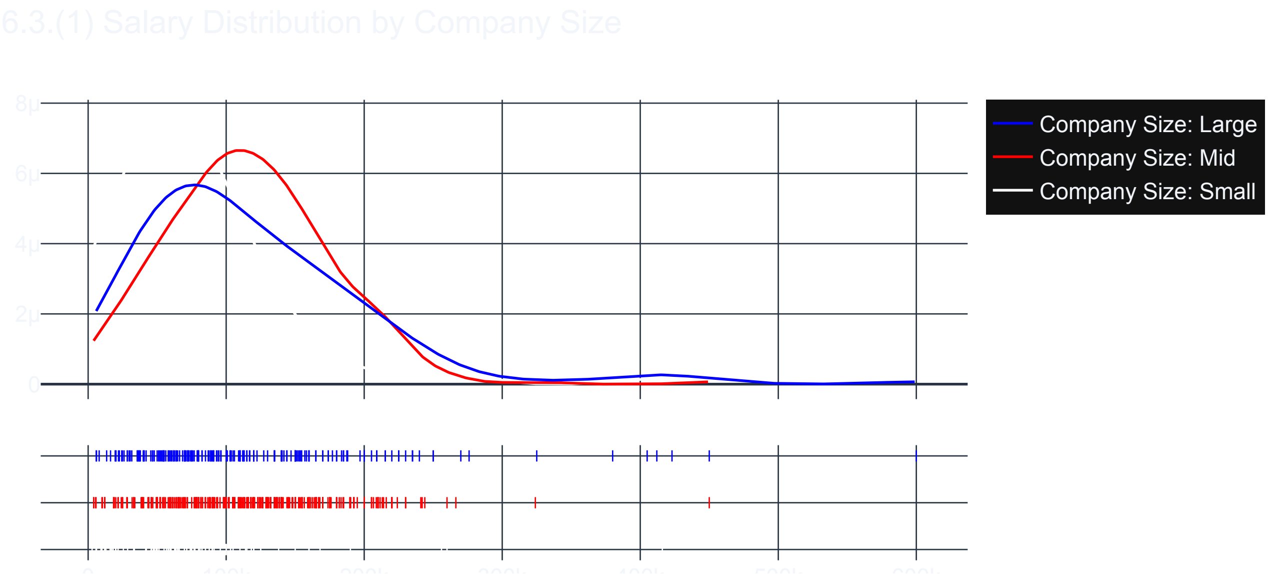
6.2. Salary by Experience Level

```
exlevel_salary = df[['experience_level','salary_in_usd']]

entry_salary = exlevel_salary.loc[exlevel_salary['experience_level']=='Entry-level/Junior']
executive_salary = exlevel_salary.loc[exlevel_salary['experience_level']=='Executive-level/Director']
mid_salary = exlevel_salary.loc[exlevel_salary['experience_level']=='Mid-level/Intermediate']
senior_salary = exlevel_salary.loc[exlevel_salary['experience_level']=='Senior-level/Expert']

hist_data = [entry_salary['salary_in_usd'],mid_salary['salary_in_usd'],senior_salary['salary_in_usd'],executive_salary['sala
group_labels = ['Entry-level/Junior','Mid-level/Intermediate','Senior-level/Expert','Executive-level/Director']
colors = ['white','yellow','blue','red']

lst = [entry_salary['salary_in_usd'].mean(),
       mid_salary['salary_in_usd'].mean(),
       senior_salary['salary_in_usd'].mean(),
       executive_salary['salary_in_usd'].mean(),]

fig1 = ff.create_distplot(hist_data, group_labels, show_hist=False, colors=colors)
fig2 = go.Figure(data=px.bar(x= group_labels,
                             y=lst,
                             color = group_labels,
                             color_discrete_sequence= colors,
                             title='6.2.(2) Mean Salary by Experience Level',
                             text = np.round([num/1000 for num in lst],2),
                             template = 'plotly_dark',
                             height=500))

fig1.layout.template = 'plotly_dark'
fig1.update_layout(title='6.2.(1) Salary Distribution by Experience Level',font = dict(size=17,family="Franklin Gothic"))
fig2.update_traces(width=0.4)
fig2.update_layout(
    xaxis_title="Experience Level",
    yaxis_title="Mean Salary (k) ",
    font = dict(size=17,family="Franklin Gothic"))
fig1.show()
fig2.show()
```

One can see that entry-level is distributed along with lower salaries, while the executive-level is plotted along higher salaries.

6.3. Salary by Company Size

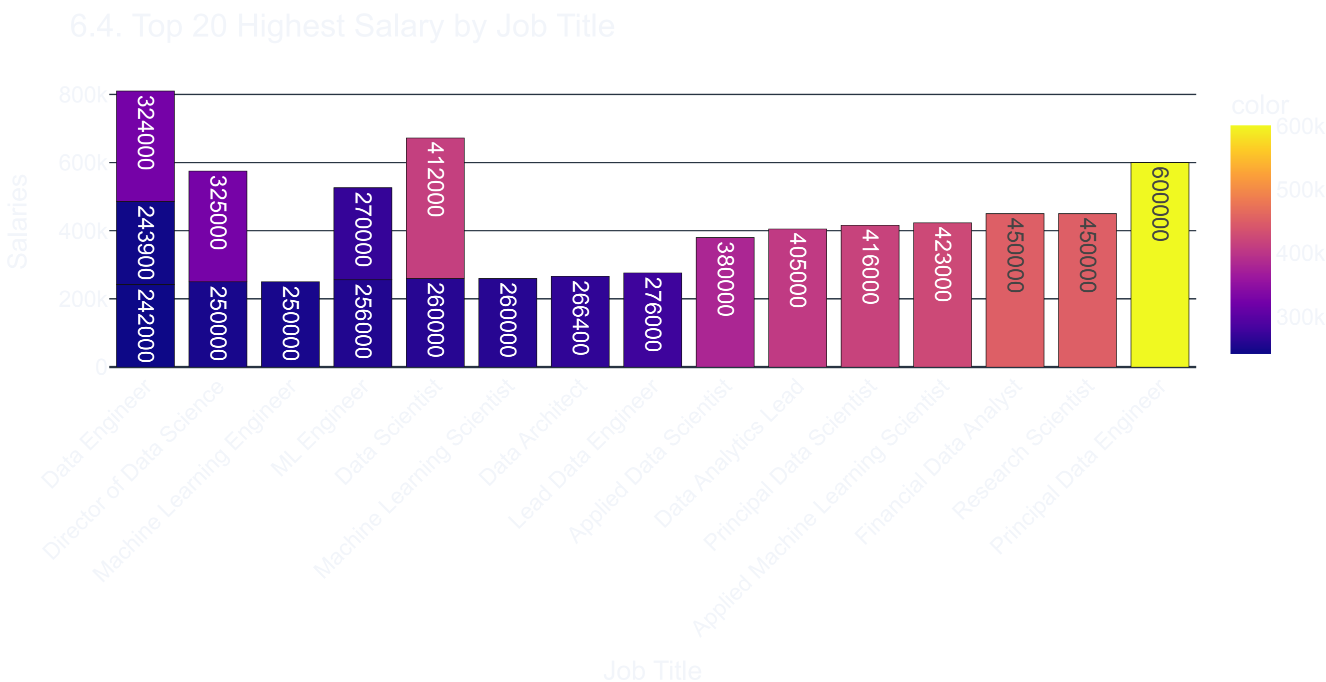
```
c_size = df[['company_size','salary_in_usd']]
small = exlevel_salary.loc[c_size['company_size']=='S']
mid = exlevel_salary.loc[c_size['company_size']=='M']
large = exlevel_salary.loc[c_size['company_size']=='L']
hist_data = [small['salary_in_usd'],mid['salary_in_usd'],large['salary_in_usd']]
group_labels = ['Company Size: Small','Company Size: Mid','Company Size: Large']
colors = ['white','red','blue']

lst = [small['salary_in_usd'].mean(),
       mid['salary_in_usd'].mean(),
       large['salary_in_usd'].mean()]

plt.figure(figsize=(20,5))
fig1 = ff.create_distplot(hist_data, group_labels, show_hist=False, colors=colors)

fig2 = go.Figure(data=px.bar(x= group_labels,
                            y=lst,
                            color = group_labels,
                            color_discrete_sequence= colors,
                            title='6.3.(2) Mean Salary by Company Size',
                            text = np.round([num/1000 for num in lst],2),
                            template = 'plotly_dark',
                            height=500))

fig1.layout.template = 'plotly_dark'
fig1.update_layout(title='6.3.(1) Salary Distribution by Company Size',font = dict(size=17,family="Franklin Gothic"))
fig2.update_traces(width=0.3)
fig2.update_layout(
    xaxis_title="Company Size",
    yaxis_title="Mean Salary (k)",
    font = dict(size=17,family="Franklin Gothic"))
fig1.show()
fig2.show()
```



White, yellow and **blue** lines each stand for **Small**, Mid, **Large size** of company.
It is obvious that **Mid size of company** distributed along with **higher salaries**, and **Large size company** has **higher salaries** than **Small size company**.
Thus, we can get a conclusion as **large size company** not necessarily has **higher salaries** than **mid size company**.

6.4. Highest salaries by job title

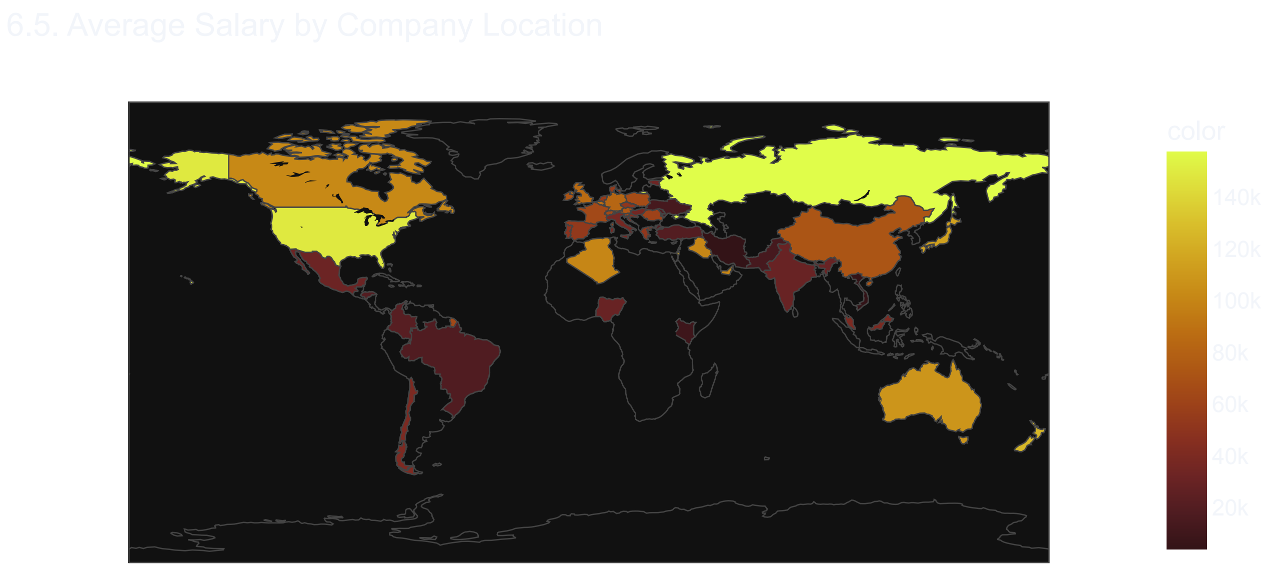
```
salary_job = df.groupby(['salary_in_usd','job_title']).size().reset_index()
salary_job = salary_job[-20:]
fig = px.bar(x=salary_job['job_title'],y=salary_job['salary_in_usd'],text = salary_job['salary_in_usd'],
                   color = salary_job['salary_in_usd'], color_discrete_sequence=px.colors.sequential.PuBu)

fig.update_layout(
    xaxis_title="Job Title",
    yaxis_title="Salaries ")
# fig.update_traces(width=0.9)
fig.update_layout(barmode = 'relative',xaxis_tickangle=-45,
                  title='6.4. Top 20 Highest Salary by Job Title', template='plotly_dark',font = dict(size=17,family="Frankl
```



Collected here are the 20 highest salaries listed through job title.

6.5. Average Salary by Company Location

```
salary_location = df.groupby(['salary_in_usd','company_location']).size().reset_index()
average = salary_location.groupby('company_location').mean().reset_index()

fig = px.choropleth(locations=average['company_location'],
                    color=average['salary_in_usd'],
                    color_continuous_scale=px.colors.sequential.solar,
                    template='plotly_dark',
                    title = '6.5. Average Salary by Company Location')
fig.update_layout(font = dict(size=17,family="Franklin Gothic"))
fig.show()
```



Higher average salaries have brighter colours, while lower average salaries have darker colours.
Here, we can see that USA and Russia have higher average salaries and brighter colours.

```
fig, ax = plt.subplots()
fig.set_size_inches(20,15)
sns.heatmap(df.corr(), vmax =.8, square = True, annot = True)
plt.title('Confusion Matrix',fontsize=20,fontstyle= 'oblique')
```