Data Science Job Salaries *(Exploratory data analysis)* :-

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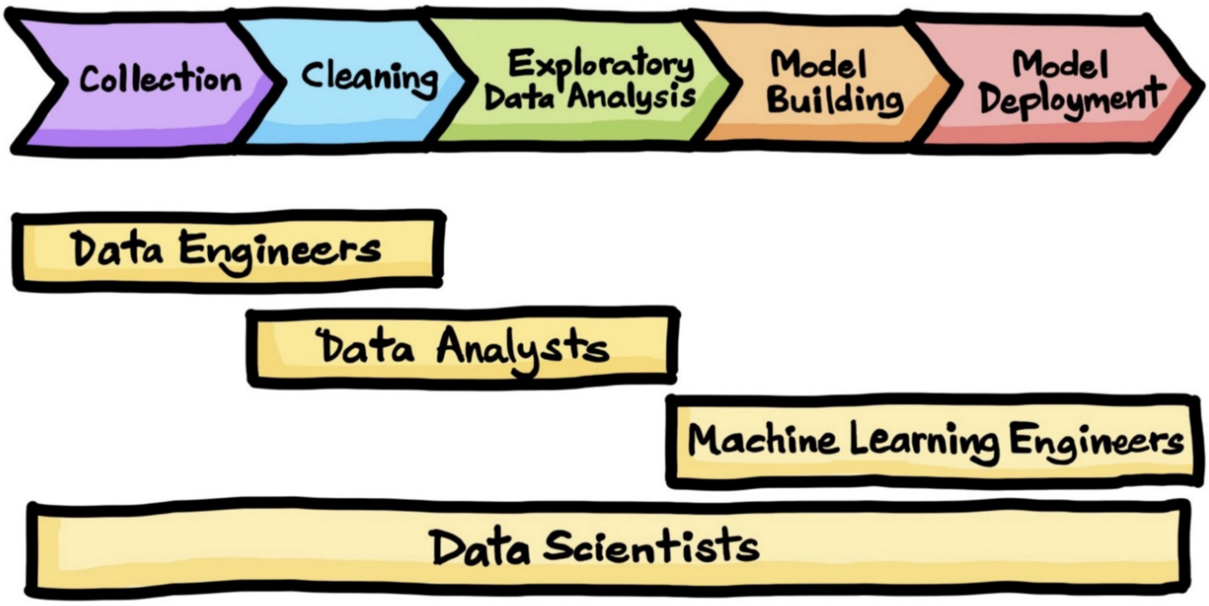

What is Data Science?

Data Science can be explained as the entire process of gathering actionable insights from raw data that involves various concepts that include statistical analysis, data analysis, machine learning algorithms, data modeling, preprocessing of data, etc.

Who is a Data Scientist?

Data scientists are IT professionals whose main role in an organization is to perform data wrangling on a large volume of data—structured and unstructured—after gathering and analyzing it. Data scientists need this voluminous data for multiple reasons including building hypotheses, analyzing market and customer patterns, and making inferences.

Data Information :-

Column Description :-

- work_year The year the salary was paid.
- experience_level The experience level in the job during the year with the following possible values: EN Entry-level / Junior MI Mid-level / Intermediate SE Senior-level / Expert EX Executive-level / Director
- employment_type The type of employement for the role: PT Part-time FT Full-time CT Contract FL Freelance
- job_title The role worked in during the year.
- salary The total gross salary amount paid.
- salary_currency The currency of the salary paid as an ISO 4217 currency code.

- salary_in_usd The salary in USD (FX rate divided by avg. USD rate for the respective year via fxdata.foorilla.com).
- employee_residence Employee's primary country of residence in during the work year as an ISO 3166 country code.
- remote_ratio The overall amount of work done remotely, possible values are as follows: 0 No remote work (less than 20%) 50 Partially remote 100 Fully remote (more than 80%)
- company_location The country of the employer's main office or contracting branch as an ISO 3166 country code.
- company_size The average number of people that worked for the company during the year: S less than 50 employees (small) M 50 to 250 employees (medium) L more than 250 employees (large)

Importing Required Libraries :-

In [2]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter("ignore")
```

Loading Date-Set :-

In [3]:

```
data=pd.read_csv("/kaggle/input/data-science-job-salaries/ds_salaries.csv")
data.head()
```

Out[3]:

	Unnamed: 0	work_year	experience_level	employment_type	job_title	salary	salary_currer
0	0	2020	MI	FT	Data Scientist	70000	E
1	1	2020	SE	FT	Machine Learning Scientist	260000	U
2	2	2020	SE	FT	Big Data Engineer	85000	G
3	3	2020	MI	FT	Product Data Analyst	20000	U
4	4	2020	SE	FT	Machine Learning Engineer	150000	U

Basic Information Regarding Dataset :-

In [4]:

```
data.shape
```

Out[4]:

```
(607, 12)
```

In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 607 entries, 0 to 606
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Unnamed: 0          607 non-null    int64 
 1   work_year           607 non-null    int64 
 2   experience_level    607 non-null    object
 3   employment_type     607 non-null    object
 4   job_title           607 non-null    object
 5   salary              607 non-null    int64 
 6   salary_currency     607 non-null    object
 7   salary_in_usd       607 non-null    int64 
 8   employee_residence  607 non-null    object
 9   remote_ratio        607 non-null    int64 
 10  company_location    607 non-null    object
 11  company_size        607 non-null    object
dtypes: int64(5), object(7)
memory usage: 57.0+ KB
```

In [6]:

```
data.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	
Unnamed: 0	607.0	303.000000	1.753701e+02	0.0	151.5	303.0	454.5	
work_year	607.0	2021.405272	6.921330e-01	2020.0	2021.0	2022.0	2022.0	
salary	607.0	324000.062603	1.544357e+06	4000.0	70000.0	115000.0	165000.0	304
salary_in_usd	607.0	112297.869852	7.095726e+04	2859.0	62726.0	101570.0	150000.0	6
remote_ratio	607.0	70.922570	4.070913e+01	0.0	50.0	100.0	100.0	

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In [7]:

```
data.describe(exclude="object").T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	
Unnamed: 0	607.0	303.000000	1.753701e+02	0.0	151.5	303.0	454.5	
work_year	607.0	2021.405272	6.921330e-01	2020.0	2021.0	2022.0	2022.0	
salary	607.0	324000.062603	1.544357e+06	4000.0	70000.0	115000.0	165000.0	304
salary_in_usd	607.0	112297.869852	7.095726e+04	2859.0	62726.0	101570.0	150000.0	6
remote_ratio	607.0	70.922570	4.070913e+01	0.0	50.0	100.0	100.0	

In [8]:

```
data.columns
```

Out[8]:

```
Index(['Unnamed: 0', 'work_year', 'experience_level', 'employment_type',
       'job_title', 'salary', 'salary_currency', 'salary_in_usd',
       'employee_residence', 'remote_ratio', 'company_location',
       'company_size'],
      dtype='object')
```

Detection Of Missing Values :-

In [9]:

```
data.isnull().sum()
```

Out[9]:

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

Dropping Irrelevant Columns :-

In [10]:

```
data.drop(columns="Unnamed: 0",inplace=True)
data.drop(columns=["salary_currency"],inplace=True)
```

Data Preparation/ Data Mapping :-

In [11]:

```
data["experience_level"].unique()
```

Out[11]:

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

In [12]:

```
data["experience_level"]=data["experience_level"].map({"MI":"Mid-level","SE":"Senior
```

In [13]:

```
data["experience_level"]
```

Out[13]:

```
0         Mid-level
1      Senior-level
2      Senior-level
3         Mid-level
4      Senior-level
           ...
602    Senior-level
603    Senior-level
604    Senior-level
605    Senior-level
606       Mid-level
Name: experience_level, Length: 607, dtype: object
```

In [14]:

```
data["employment_type"].unique()
```

Out[14]:

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

In [15]:

```
data["employment_type"]=data["employment_type"].map({"FT":"Full-Time","CT":"Contract
```

In [16]:

```
data["employment_type"]
```

Out[16]:

```
0      Full-Time
1      Full-Time
2      Full-Time
3      Full-Time
4      Full-Time
         ...
602    Full-Time
603    Full-Time
604    Full-Time
605    Full-Time
606    Full-Time
Name: employment_type, Length: 607, dtype: object
```

In [17]:

```
data["company_size"].unique()
```

Out[17]:

```
array(['L', 'S', 'M'], dtype=object)
```

In [18]:

```
data["company_size"]=data["company_size"].map({"L":"Large-cap","S":"Small-cap","M":"
data["company_size"]
```

Out[18]:

```
0      Large-cap
1      Small-cap
2        Mid-Cap
3      Small-cap
4      Large-cap
         ...
602      Mid-Cap
603      Mid-Cap
604      Mid-Cap
605      Mid-Cap
606    Large-cap
Name: company_size, Length: 607, dtype: object
```

In [19]:

```
data["remote_ratio"].value_counts()
```

Out[19]:

```
100    381
0      127
50      99
Name: remote_ratio, dtype: int64
```

In [20]:

```
data["remote_ratio"]=data["remote_ratio"].map({0:"No Remote",50:"Partially Remote",1
```

- remote_ratio The overall amount of work done remotely, possible values are as follows: 0 No remote work (less than 20%) 50 Partially remote 100 Fully remote (more than 80%)

INSIGHTS :-

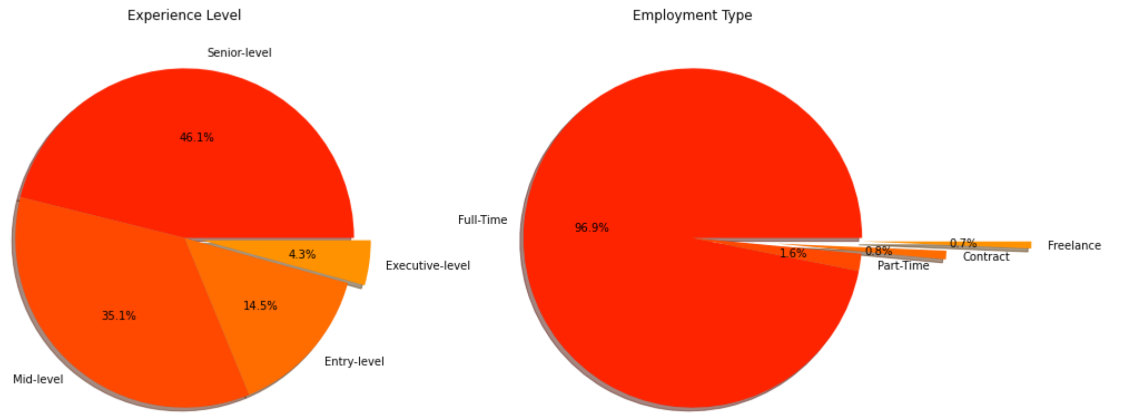
Step1 :- [Univariate Analysis]

Experience Analysis :-

In [21]:

```
plt.figure(figsize=(15,7))
color=sns.set_palette("autumn")
plt.subplot(1,2,1)
k=data["experience_level"].value_counts()
plt.pie(k,labels=k.index,autopct="%0.01f%%",shadow=True,explode=[0,0,0,0.1],)
plt.title("Experience Level")

plt.subplot(1,2,2)
k1=data["employment_type"].value_counts()
plt.pie(k1,labels=k1.index,autopct="%0.01f%%",shadow=True,explode=[0,0,0.5,1])
plt.title("Employment Type")
plt.show()
```



- **Senior Level** Data Scientist Are In Majority Whereas **Executive-Level** are the least.
- **Full-Time** Jobs For Data Scientist Are Far More As Compared to Part-time, Contract, Freelance Jobs In Market.

Most Popular Job Profile In Data-Domain :-

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In [22]:

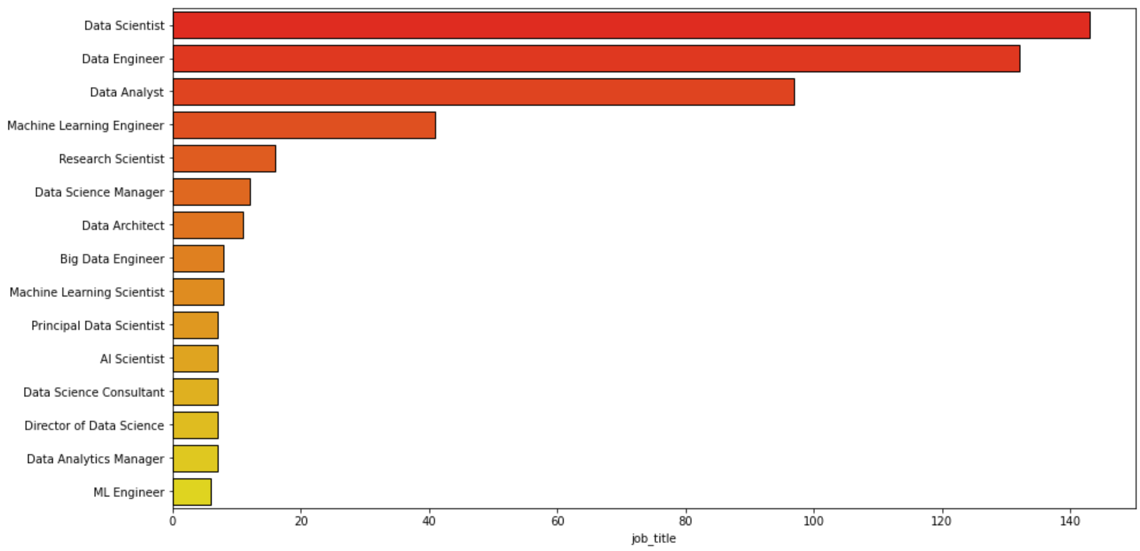
```
kk=data["job_title"].value_counts()[:15]
kk=kk.to_frame()
kk
```

Out[22]:

	job_title
Data Scientist	143
Data Engineer	132
Data Analyst	97
Machine Learning Engineer	41
Research Scientist	16
Data Science Manager	12
Data Architect	11
Big Data Engineer	8
Machine Learning Scientist	8
Principal Data Scientist	7
AI Scientist	7
Data Science Consultant	7
Director of Data Science	7
Data Analytics Manager	7
ML Engineer	6

In [23]:

```
#job_title
plt.figure(figsize=(15,8))
sns.barplot(y=kk.index,x=kk["job_title"],data=kk,palette="autumn",edgecolor="black")
plt.show()
```



- **Data Scientist** is Most Popular Job Profile Amongest Data-Domain.
- **Data Scientist, Data Engigneer & Data Analyst** Are Top-3 job Profiles in Data Domain.

Most No. Of Data Employee Residence & Countries with Most No. Of Companies.

In [24]:

```
ee=data["employee_residence"].value_counts()[:15].to_frame()
ee
```

Out[24]:

	employee_residence
US	332
GB	44
IN	30
CA	29
DE	25
FR	18
ES	15
GR	13
JP	7
PT	6
BR	6
PK	6
NL	5
PL	4
IT	4

In [25]:

```
ee1=data["company_location"].value_counts()[:15].to_frame()
ee1
```

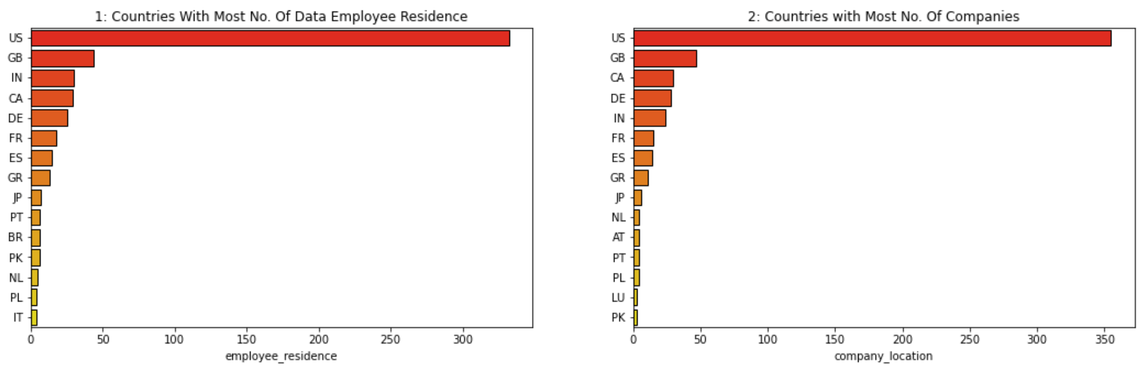
Out[25]:

	company_location
US	355
GB	47
CA	30
DE	28
IN	24
FR	15
ES	14
GR	11
JP	6
NL	4
AT	4
PT	4
PL	4
LU	3
PK	3

In [26]:

```
#employee_residence
plt.figure(figsize=(18,5))
plt.subplot(1,2,1)
sns.barplot(y=ee.index,x=ee["employee_residence"],data=ee,palette="autumn",edgecolor
plt.title("1: Countries With Most No. Of Data Employee Residence")

plt.subplot(1,2,2)
sns.barplot(y=ee1.index,x=ee1["company_location"],data=ee1,palette="autumn",edgecolc
plt.title("2: Countries with Most No. Of Companies");
```



- **In Chart 1:** The **United States (US)** Residence Employee more work in the **Data Related Field** as Compared to Other Countries Residence.

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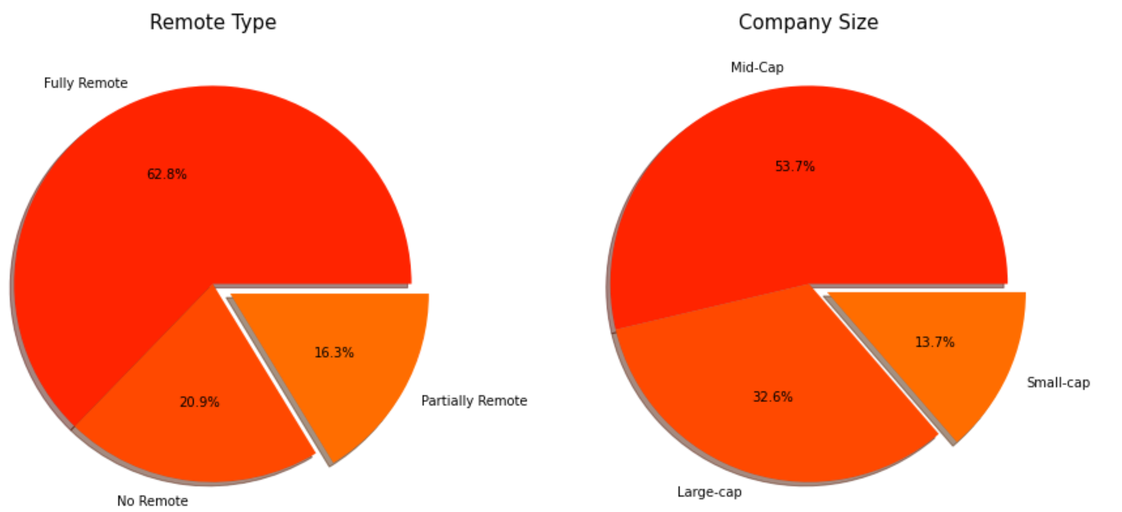
In [27]:

```python
#remote_ratio & company_size
plt.figure(figsize=(15,7))
plt.subplot(1,2,1)
ss=data["remote_ratio"].value_counts()
plt.pie(ss,labels=ss.index,autopct="%0.01f%%",shadow=True,explode=[0,0,0.1],colors=c
plt.title("Remote Type",fontsize=15)

plt.subplot(1,2,2)
vv=data["company_size"].value_counts()
plt.pie(vv,labels=vv.index,autopct="%0.01f%%",shadow=True,explode=[0,0,0.1],colors=c
plt.title("Company Size",fontsize=15)
plt.show()
```



- Majority of the employees work **Fully remotely** (60% remote work).
- **Mid-Cap** Companies Has Most No. Data Professional Employess As Compared To Large-cap ANd Small-cap Companiees.

Step 2 :- [Bivariate Analysis]

What The Average Salaries ($) Based On Their Experience Level ?

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In [28]:

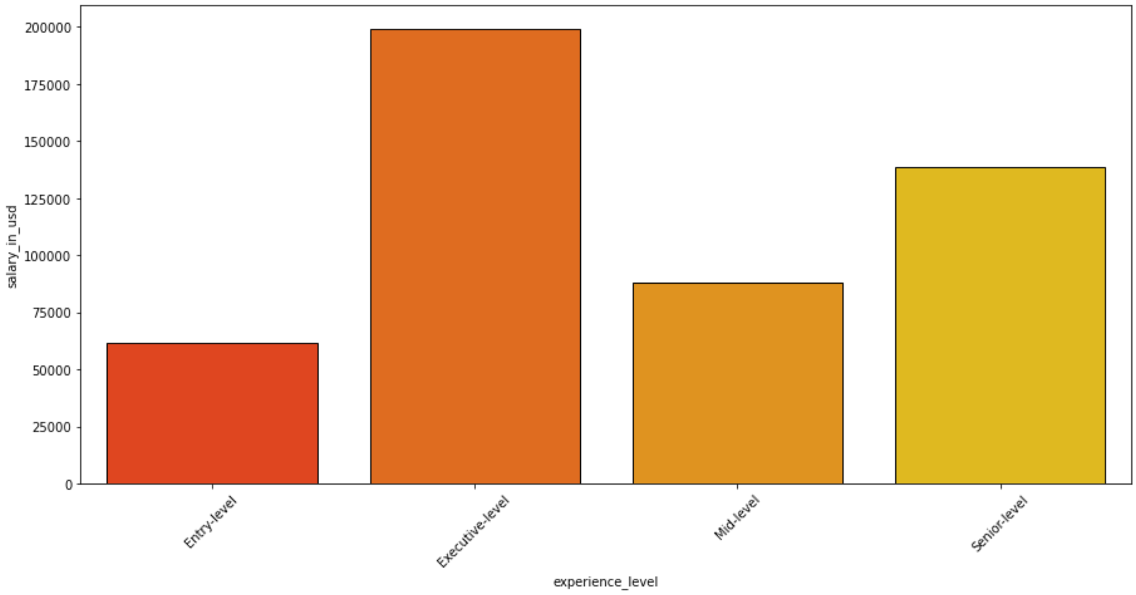
```
salaries=data.groupby(["experience_level"])["salary_in_usd"].mean().to_frame()
salaries
```

Out[28]:

experience_level	salary_in_usd
Entry-level	61643.318182
Executive-level	199392.038462
Mid-level	87996.056338
Senior-level	138617.292857

In [29]:

```
plt.figure(figsize=(15,7))
sns.barplot(x=salaries.index,y=salaries["salary_in_usd"],data=salaries,palette="autu
plt.xticks(rotation=45)
plt.show()
```



- Salary of **Exceutive-Level** Employee has Much Higher As Compared to Senior-Level & Mid-Level Employee.

What The Average Salaries($) Based On Their Employment Types ?

In [30]:

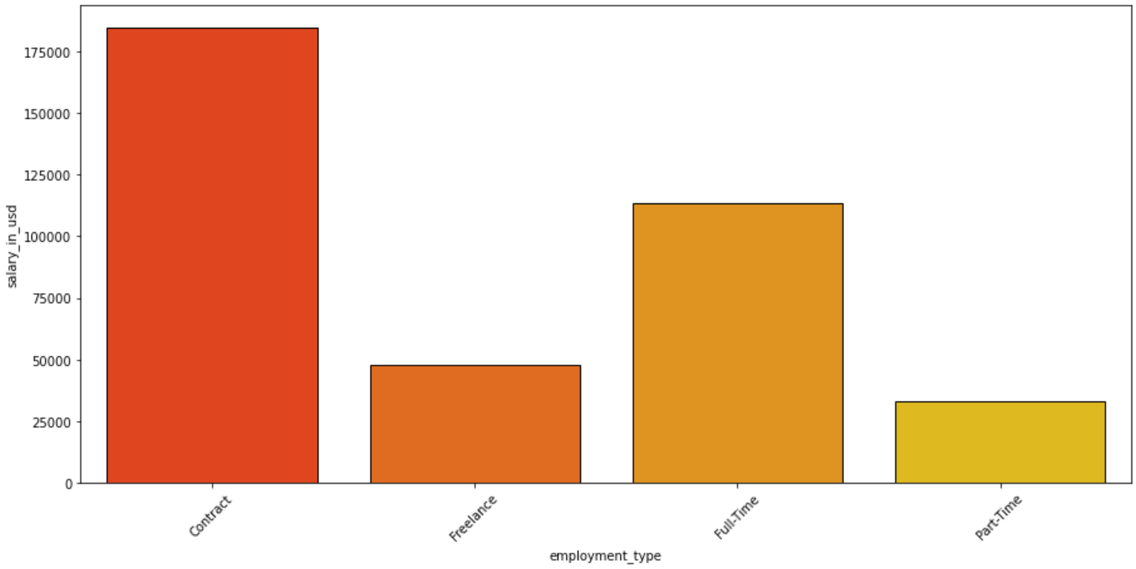
```
e_type=data.groupby(["employment_type"])["salary_in_usd"].mean().to_frame()
e_type
```

Out[30]:

employment_type	salary_in_usd
Contract	184575.000000
Freelance	48000.000000
Full-Time	113468.073129
Part-Time	33070.500000

In [31]:

```
plt.figure(figsize=(15,7))
sns.barplot(x=e_type.index,y=e_type["salary_in_usd"],data=e_type,palette="autumn",ec
plt.xticks(rotation=45)
plt.show()
```



- Those Employees Who Work's On **Contract** Based Agreement Got Higher **Salaries** As Compared To **Full-Time Worker's Or Freelance Worker's** .

Which Are The Top 10 Highest Paying Job Profile ?

In [32]:

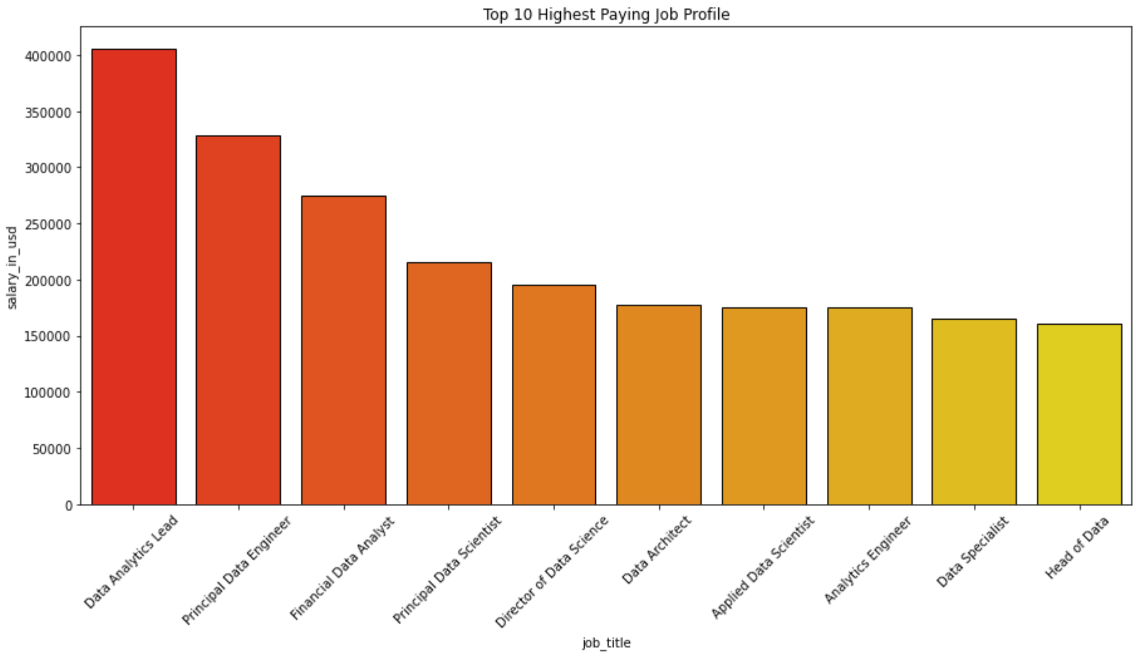
```
title=data.groupby(["job_title"])["salary_in_usd"].mean().sort_values(ascending=Fals
title=title.to_frame()
title
```

Out[32]:

job_title	salary_in_usd
Data Analytics Lead	405000.000000
Principal Data Engineer	328333.333333
Financial Data Analyst	275000.000000
Principal Data Scientist	215242.428571
Director of Data Science	195074.000000
Data Architect	177873.909091
Applied Data Scientist	175655.000000
Analytics Engineer	175000.000000
Data Specialist	165000.000000
Head of Data	160162.600000

In [33]:

```
plt.figure(figsize=(15,7))
sns.barplot(x=title.index,y=title["salary_in_usd"],data=title,palette="autumn",edgec
plt.xticks(rotation=45)
plt.title("Top 10 Highest Paying Job Profile")
plt.show()
```



- Above Chart Tells About The Top 10 Highest Paying Jobs In This Field.
- **Data Analytics Lead** Job Profile Got Higher Salaries Packages From The Companies.

Which Company Type Are More Flexibile Towards Remote Jobs?

In [34]:

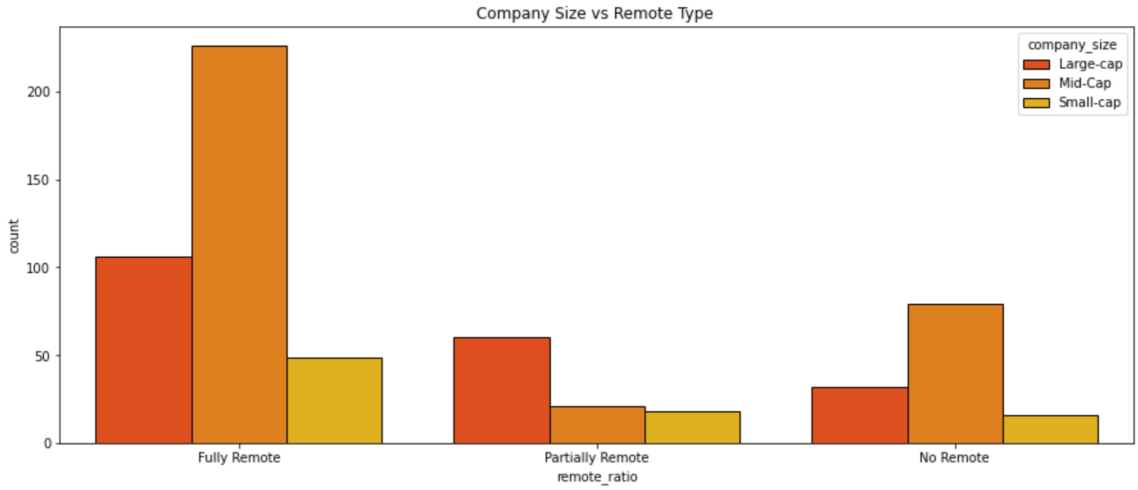
```
data1=data.groupby(["company_size"])["remote_ratio"].value_counts().to_frame().renam
data1=data1.reset_index()
data1
```

Out[34]:

	company_size	remote_ratio	count
0	Large-cap	Fully Remote	106
1	Large-cap	Partially Remote	60
2	Large-cap	No Remote	32
3	Mid-Cap	Fully Remote	226
4	Mid-Cap	No Remote	79
5	Mid-Cap	Partially Remote	21
6	Small-cap	Fully Remote	49
7	Small-cap	Partially Remote	18
8	Small-cap	No Remote	16

In [35]:

```
plt.figure(figsize=(15,6))
sns.barplot(x="remote_ratio",y="count",data=data1,hue="company_size",palette="autumr
plt.title("Company Size vs Remote Type ");
```



- **Fully-Remote Jobs** are Higher In Mid-cap Company as Compared To Large-cap & Small-cap Companies.
- **Partially Remote Jobs** are Higher In Large-cap Companies as Compared To Others.
- **No-Remote Jobs** are Higher In Mid-cap Companies as Comapred to Large-cap & Small-cap Companies.

Which Companies Location Which Give Higher Average Salaries to Their Data Professionals?

In [36]:

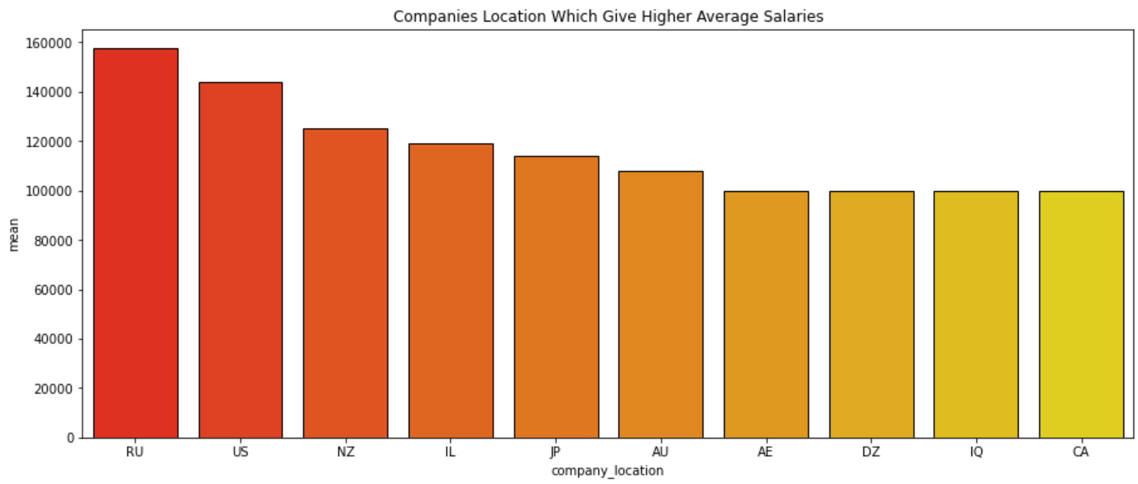
```
comp_sal=data.groupby(["company_location"])["salary_in_usd"].agg(["mean"]).sort_valu
comp_sal
```

Out[36]:

	mean
company_location	
RU	157500.000000
US	144055.261972
NZ	125000.000000
IL	119059.000000
JP	114127.333333
AU	108042.666667
AE	100000.000000
DZ	100000.000000
IQ	100000.000000
CA	99823.733333

In [37]:

```
plt.figure(figsize=(15,6))
sns.barplot(x=comp_sal.index,y="mean",data=comp_sal,palette="autumn",edgecolor="blac
plt.title("Companies Location Which Give Higher Average Salaries");
```



- Companies Located In **Russia (RU)** Gives Higher Average Salaries To Their Data Professionals Employees Than **United States (US)** And Than **NewZealand (NZ).**

How Remote Type Jobs & Company Size Affect The

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In [38]:

```
remote=data.groupby(["remote_ratio"])["salary_in_usd"].mean().to_frame()
remote
```

Out[38]:

remote_ratio	salary_in_usd
Fully Remote	122457.454068
No Remote	106354.622047
Partially Remote	80823.030303

In [39]:

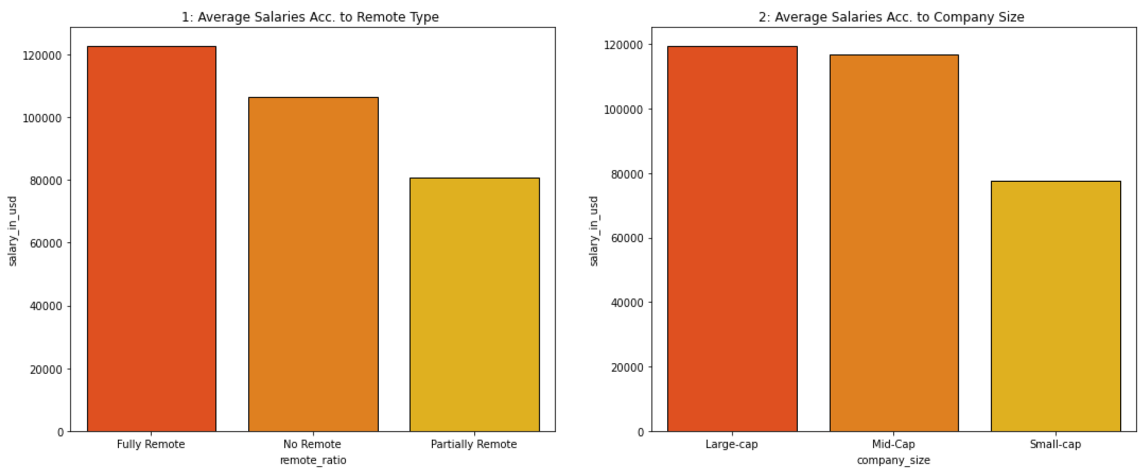
```
size=data.groupby(["company_size"])["salary_in_usd"].mean().to_frame()
size
```

Out[39]:

company_size	salary_in_usd
Large-cap	119242.994949
Mid-Cap	116905.466258
Small-cap	77632.674699

In [40]:

```
plt.figure(figsize=(18,7))
plt.subplot(1,2,1)
sns.barplot(x=remote.index,y=remote["salary_in_usd"],data=remote,palette="autumn",ec
plt.title("1: Average Salaries Acc. to Remote Type ")

plt.subplot(1,2,2)
sns.barplot(x=size.index,y=size["salary_in_usd"],data=size,palette="autumn",edgecolc
plt.title("2: Average Salaries Acc. to Company Size ")

plt.show()
```



- **Chart 1:** The Average Salaries of **Fully Remote** Employees Is Much Higher Than The **Partially Remote And Non Remote Employees**.

- **Chart 2:** The **Large-Cap & Mid-Cap** Companies Almost Give Equivalent Salaries to Their Employees.

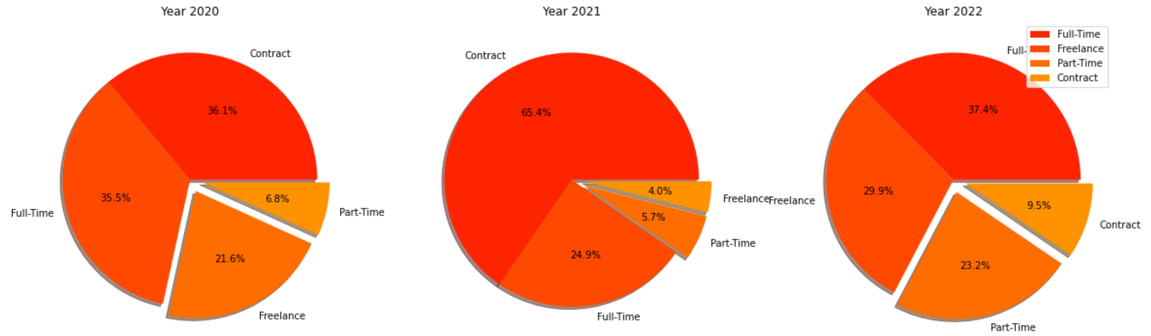
Step 3 :- [Multi-Variate Analysis]

Over Years Salaries Trend With Employment Type :-

(*Full-Time, Part-Time, Freelance, Contract*)

In [41]:

```
year1=data[data["work_year"]==2020]
yr1=year1.groupby("employment_type")["salary_in_usd"].mean().sort_values(ascending=F

year2=data[data["work_year"]==2021]
yr2=year2.groupby("employment_type")["salary_in_usd"].mean().sort_values(ascending=F

year3=data[data["work_year"]==2022]
yr3=year3.groupby("employment_type")["salary_in_usd"].mean().sort_values(ascending=F

plt.figure(figsize=(20,10))
plt.subplot(1, 3, 1)
plt.pie(yr1,labels=yr1.index,autopct="%0.01f%%",explode=[0,0,0.1,0.1],shadow=True)
plt.title("Year 2020")


plt.subplot(1, 3, 2)
plt.pie(yr2,labels=yr2.index,autopct="%0.01f%%",explode=[0,0,0.1,0.1],shadow=True)
plt.title("Year 2021")


plt.subplot(1,3, 3)
plt.pie(yr3,labels=yr3.index,autopct="%0.01f%%",explode=[0,0,0.1,0.1],shadow=True)
plt.title("Year 2022")

plt.legend()

plt.show()

```



- In **Year-2020** The Salaries are Approx. Similar For **Contract Based & Full-Time Employment.** (36.1% & 35.5% Respectively)
- But, In **Year-2021 Contract-Based** Got Higher Salaries (65.4%) as Compared Other Types.

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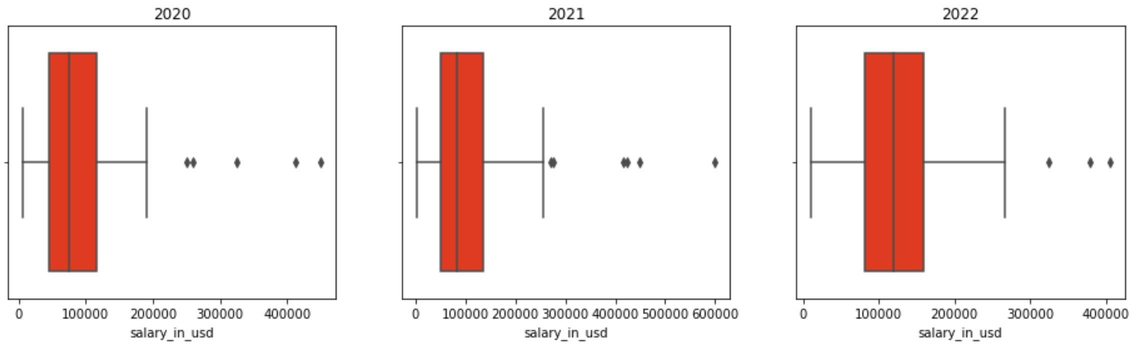
- In **Year-2022 Full-Time And Freelance** Got Higher Salaries As Compared to **Contract based and Part-Time Jobs**

Over Years Salaries Distributions Of Data Professionals :-

In [42]:

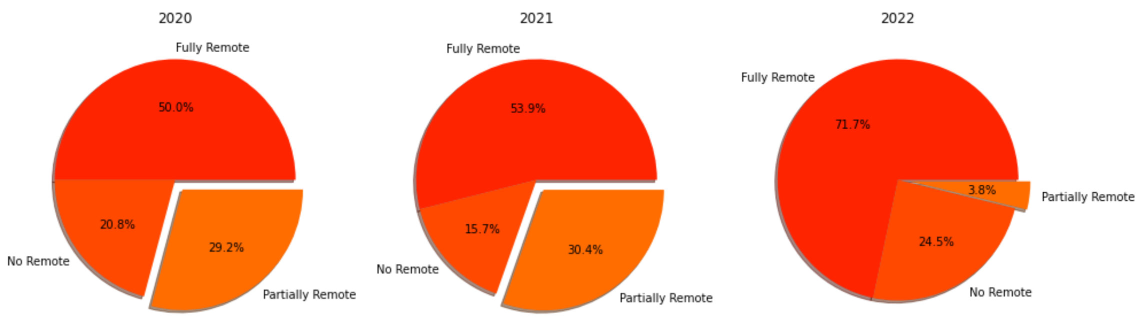
```
plt.figure(figsize=(16,4))
plt.subplot(1,3,1)
sns.boxplot(year1["salary_in_usd"],)
plt.title("2020")

plt.subplot(1,3,2)
sns.boxplot(year2["salary_in_usd"],)
plt.title("2021")

plt.subplot(1,3,3)
sns.boxplot(year3["salary_in_usd"],)
plt.title("2022")

plt.show()
```



Over Years Ratio of Remote Trends In Data Jobs:-

In [43]:

```
remote1=year1.groupby(["remote_ratio"])["remote_ratio"].count()

remote2=year2.groupby(["remote_ratio"])["remote_ratio"].count()

remote3=year3.groupby(["remote_ratio"])["remote_ratio"].count()

plt.figure(figsize=(16,8))
plt.subplot(1,3,1)
plt.pie(remote1,labels=remote1.index,autopct="%0.01f%%",explode=[0,0,0.1],shadow=Tru
plt.title("2020")

plt.subplot(1,3,2)
plt.pie(remote2,labels=remote2.index,autopct="%0.01f%%",explode=[0,0,0.1],shadow=Tru
plt.title("2021")

plt.subplot(1,3,3)
plt.pie(remote3,labels=remote3.index,autopct="%0.01f%%",explode=[0,0,0.1],shadow=Tru
plt.title("2022")

plt.show()
```

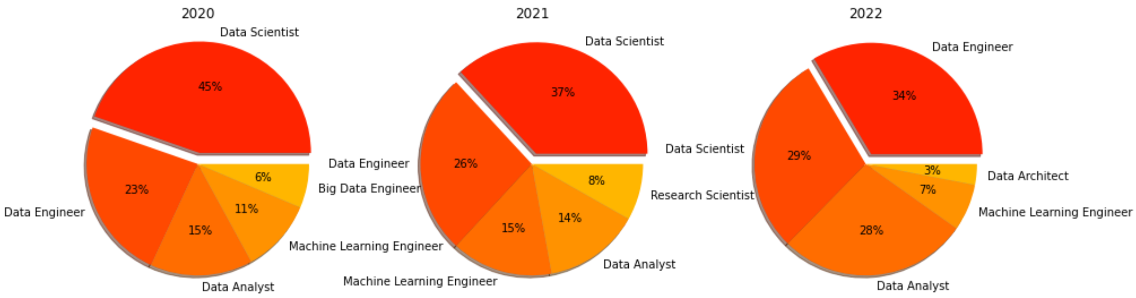


- In **Year-2020** Their is **Fully remote** Jobs With (50.0%) & **No Remote** Jobs (20.8%) and **Partially Remote** Jobs (29.2%).
- In **Year-2021 Fully remote and Partially Remote** Jobs Are Increased Whereas **Non remote** Jobs Are Decreased by the Time.
- In **Year-2022 Fully remote** Jobs Increased Massively with (71.7%) and **Partially remote** Jobs Are Decreased to (3.8%)

Top-5 Jobs Over The Years In Data Domian:-

In [44]:

```
top1=year1["job_title"].value_counts()[:5]
top2=year2["job_title"].value_counts()[:5]
top3=year3["job_title"].value_counts()[:5]

plt.figure(figsize=(15,15))
plt.subplot(1,3,1)
plt.pie(top1,labels=top1.index,autopct="%0.0f%%",explode=[0.1,0,0,0,0],shadow=True)
plt.title("2020")

plt.subplot(1,3,2)
plt.pie(top2,labels=top2.index,autopct="%0.0f%%",explode=[0.1,0,0,0,0],shadow=True)
plt.title("2021")

plt.subplot(1,3,3)
plt.pie(top3,labels=top3.index,autopct="%0.0f%%",explode=[0.1,0,0,0,0],shadow=True)
plt.title("2022")

plt.show()
```



- Above Pie Chart Indicate's Top-5 Jobs Over The Years in Data World.
- In **Year- (2020 & 2021)** :- **DATA SCIENTIST** Is The Most Popuplar Job In Data Domain,
- But In **Year- (2022)** :- **DATA ENGINEER** Is The Most Popular Job In Data Domain.

How Many Employees Who Are Employeed in Their Own Native Country ?

In [45]:

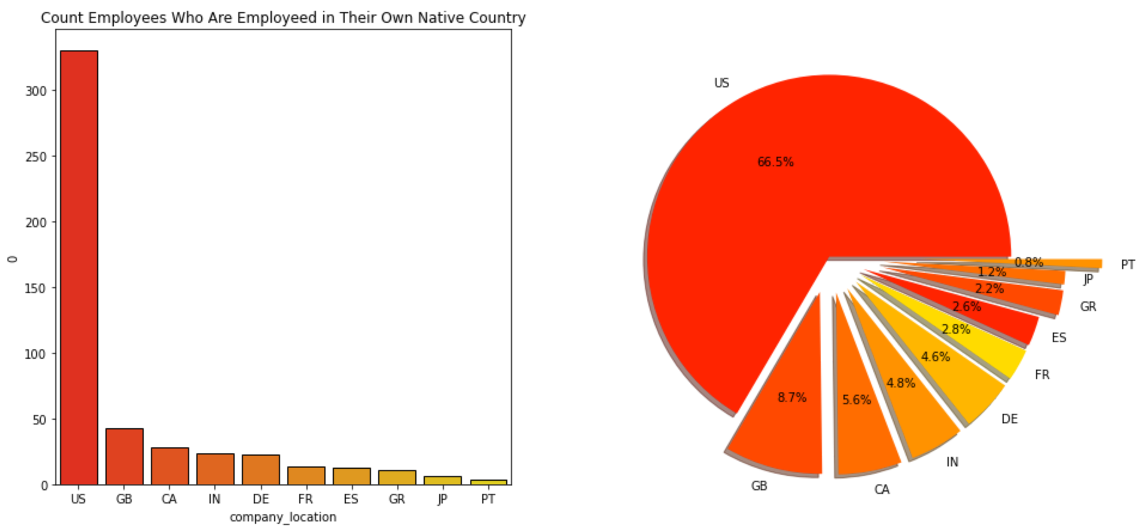
```
location=data[data["employee_residence"]==data["company_location"]]
location1=data[data["employee_residence"]!=data["company_location"]]
k=location[["employee_residence","company_location"]].value_counts().reset_index()[:
k
```

Out[45]:

	employee_residence	company_location	0
0	US	US	330
1	GB	GB	43
2	CA	CA	28
3	IN	IN	24
4	DE	DE	23
5	FR	FR	14
6	ES	ES	13
7	GR	GR	11
8	JP	JP	6
9	PT	PT	4

In [46]:

```
plt.figure(figsize=(15,7))
plt.subplot(1,2,1)
sns.barplot(x=k["company_location"],y=k[0],data=k1,palette="autumn",edgecolor="black
plt.title("Count Employees Who Are Employeed in Their Own Native Country")

plt.subplot(1,2,2)
plt.pie(k[0],labels=k["employee_residence"],autopct="%0.01f%%",explode=[0,0.2,0.2,0.
plt.show()
```



- Above Chart Indicate's The Count Employees Who Are Employeed in Their Own Native Country.
- **United States(US)** residence has massive majority in being Employed in Their Own Country.

How Many Employees Are Employeed In Some Other Countries ?

In [47]:

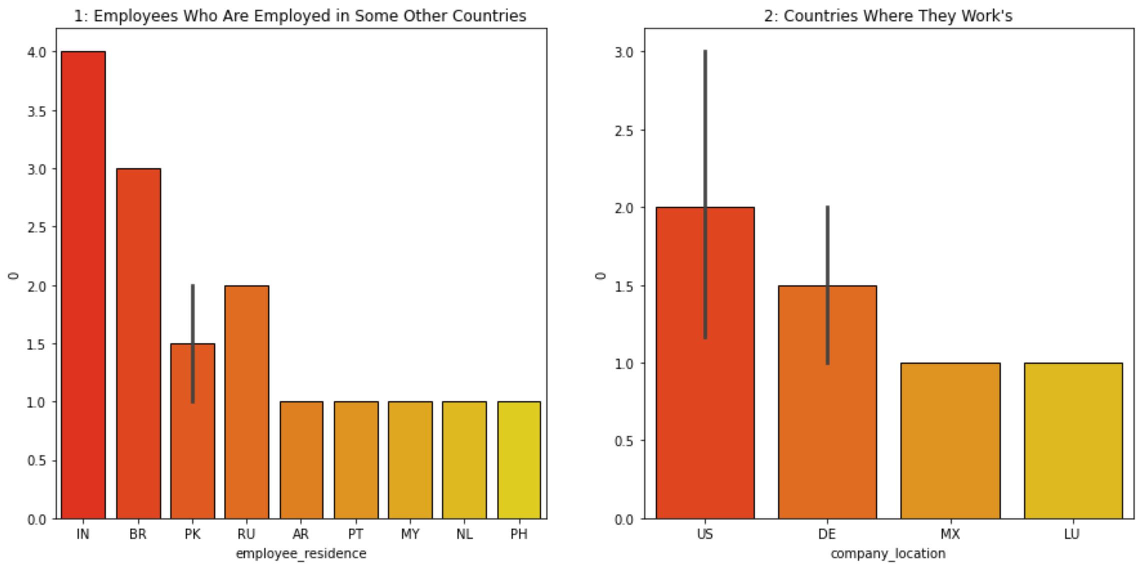
```
location1=data[data["employee_residence"]!=data["company_location"]]
k1=location1[["employee_residence","company_location"]].value_counts().reset_index()
k1
```

Out[47]:

	employee_residence	company_location	0
0	IN	US	4
1	BR	US	3
2	PK	DE	2
3	RU	US	2
4	AR	MX	1
5	PT	LU	1
6	MY	US	1
7	NL	DE	1
8	PH	US	1
9	PK	US	1

In [48]:

```
plt.figure(figsize=(15,7))
plt.subplot(1,2,1)
sns.barplot(x=k1["employee_residence"],y=k1[0],data=k1,palette="autumn",edgecolor="b
plt.title("1: Employees Who Are Employed in Some Other Countries")

plt.subplot(1,2,2)
sns.barplot(x=k1["company_location"],y=k1[0],data=k1,palette="autumn",edgecolor="bla
plt.title("2: Countries Where They Work's")
plt.show()
```



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- In **Charts-1** Indicate's Employees Who Are Employed in Some Other Countries,
- **India** Has Highest No. Peoples Who Employed In Some Diffirent Countries.
- In **Charts-2** Indicate's Countries Where They Work's.

Which are the Highest Paying Jobs Profile In India ?

In [49]:

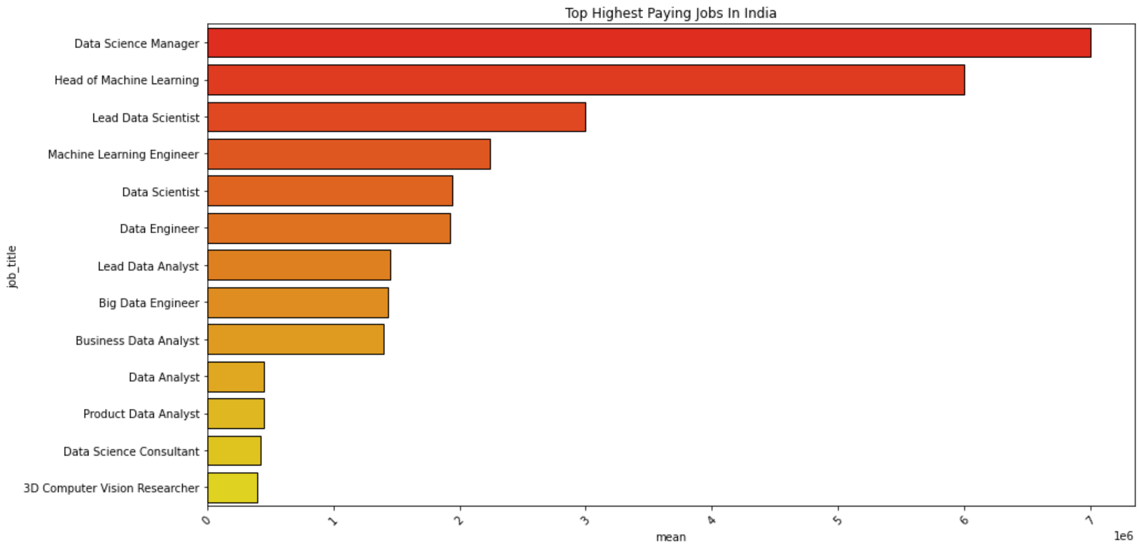
```
india=data[data["company_location"]=="IN"]
job1=india.groupby("job_title")["salary"].agg(["mean"]).sort_values(by="mean",ascenc
job1
```

Out[49]:

	mean
job_title	
Data Science Manager	7000000.0
Head of Machine Learning	6000000.0
Lead Data Scientist	3000000.0
Machine Learning Engineer	2239999.0
Data Scientist	1943750.0
Data Engineer	1925000.0
Lead Data Analyst	1450000.0
Big Data Engineer	1436000.0
Business Data Analyst	1400000.0
Data Analyst	450000.0
Product Data Analyst	450000.0
Data Science Consultant	423000.0
3D Computer Vision Researcher	400000.0

In [50]:

```
plt.figure(figsize=(15,8))
sns.barplot(x=job1["mean"],y=job1.index,data=job1,palette="autumn",edgecolor="black"
plt.title("Top Highest Paying Jobs In India")
plt.xticks(rotation=45)
plt.show()
```



- **DATA SCIENCE MANAGER & HEAD OF MACHINE LEARNING** job Profile's is Most High Paying jobs In India.

Analysis Finished.

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In [ ]:

```
 
```