WEEKLY DATA ANALYSIS CHALLANGE 21

Extracting the dataset

In [1]:

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

In [2]:

```
ds = pd.read_csv('ds_salaries.csv')
ds
```

Out[2]:

	Unnamed: 0	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd	employee_re
0	0	2020	MI	FT	Data Scientist	70000	EUR	79833	
1	1	2020	SE	FT	Machine Learning Scientist	260000	USD	260000	
2	2	2020	SE	FT	Big Data Engineer	85000	GBP	109024	
3	3	2020	MI	FT	Product Data Analyst	20000	USD	20000	
4	4	2020	SE	FT	Machine Learning Engineer	150000	USD	150000	
...	...	...	...	...	...	...	...	...	
602	602	2022	SE	FT	Data Engineer	154000	USD	154000	
603	603	2022	SE	FT	Data Engineer	126000	USD	126000	
604	604	2022	SE	FT	Data Analyst	129000	USD	129000	
605	605	2022	SE	FT	Data Analyst	150000	USD	150000	
606	606	2022	MI	FT	AI Scientist	200000	USD	200000	

607 rows × 12 columns

CLEANING AND TRANSFORMATION

1. **Is there any missing values?**

In [3]:

```
ds.isnull().sum()
```

Out[3]:

```
Unnamed: 0          0
```

```
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
```

In [4]:

```
count_nan = ds.isna().sum().sum()
print(f'Number of missing values: {count_nan}')
```

```
Number of missing values: 0
```

1. **Are the data types in each columns correct?**

In [5]:

```
ds.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
```

1. **Remove and rename unnecessary columns**

In [6]:

```
rename = {
    'Unnamed: 0':'employee_id'
}

ds = ds.rename(columns=rename)
```

In [7]:

```
ds = ds.drop(['salary_currency', 'salary'], axis=1)
ds.head()
```

Out[7]:

	employee_id	work_year	experience_level	employment_type	job_title	salary_in_usd	employee_residence	remote_ratio	co
0	0	2020	MI	FT	Data Scientist	79833	DE	0	
					Machine				

	employee_id	work_year	experience_level	employment_type	job_title	salary_in_usd	employee_residence	remote_ratio	co
1	1	2020	SE	FT	Learning Scientist	260000	JP	0	
2	2	2020	SE	FT	Big Data Engineer	109024	GB	50	
3	3	2020	MI	FT	Product Data Analyst	20000	HN	0	
4	4	2020	SE	FT	Machine Learning Engineer	150000	US	50	

VISUALISATION

1. **Which role has the highest salary employment wise?**

In [8]:

```
salary_pivot = ds.pivot_table(index='job_title', values='salary_in_usd', aggfunc='mean')
sorted_salary = salary_pivot.sort_values(by='salary_in_usd', ascending=False).round(0).a
stype(int)
sorted_salary
```

Out[8]:

	salary_in_usd
job_title	
Data Analytics Lead	405000
Principal Data Engineer	328333
Financial Data Analyst	275000
Principal Data Scientist	215242
Director of Data Science	195074
Data Architect	177874
Applied Data Scientist	175655
Analytics Engineer	175000
Data Specialist	165000
Head of Data	160163
Machine Learning Scientist	158412
Data Science Manager	158328
Director of Data Engineering	156738
Head of Data Science	146719
Applied Machine Learning Scientist	142069
Lead Data Engineer	139724
Data Analytics Manager	127134
Cloud Data Engineer	124647
Data Engineering Manager	123227
Principal Data Analyst	122500
ML Engineer	117504
Machine Learning Manager	117104
Lead Data Scientist	115190
Data Engineer	112725
Research Scientist	109020

job_title	salary_in_usd
Data Scientist	108187
Computer Vision Software Engineer	105249
Staff Data Scientist	105000
Machine Learning Engineer	104880
Machine Learning Infrastructure Engineer	101145
Big Data Architect	99703
Data Analyst	92893
Lead Data Analyst	92203
Marketing Data Analyst	88654
Lead Machine Learning Engineer	87932
Machine Learning Developer	85861
Head of Machine Learning	79039
Business Data Analyst	76691
Data Science Engineer	75803
BI Data Analyst	74755
Data Science Consultant	69421
AI Scientist	66136
Data Analytics Engineer	64799
Finance Data Analyst	61896
ETL Developer	54957
Big Data Engineer	51974
Computer Vision Engineer	44419
NLP Engineer	37236
Product Data Analyst	13036
3D Computer Vision Researcher	5409

1. **Which employment types do employers prefer to hire**

In [9]:

```
ep_type = ds.pivot_table(index='employment_type', values='employee_id', aggfunc='count')
sorted_epType = ep_type.sort_values(by='employee_id', ascending=False)
sorted_epType
```

Out[9]:

employment_type	employee_id
FT	588
PT	10
CT	5
FL	4

1. **Which role are entry leveled generally hired for?**

In [10]:

```
entry_level = ds[ds['experience_level'] == 'EN']
count = entry_level['job_title'].value_counts()
count
```

Out[10]:

```
Data Scientist                          22
Data Analyst                            12
Data Engineer                           12
Machine Learning Engineer                9
Data Science Consultant                  5
AI Scientist                             4
Research Scientist                       4
Big Data Engineer                        3
Computer Vision Engineer                 3
Business Data Analyst                    2
ML Engineer                              2
Computer Vision Software Engineer        2
BI Data Analyst                          2
Machine Learning Scientist               1
Applied Data Scientist                   1
Machine Learning Developer               1
Financial Data Analyst                   1
Applied Machine Learning Scientist       1
Data Analytics Engineer                  1
Name: job_title, dtype: int64
```

1. **Which countries pay the highest for which role?**

In [11]:

```python
grouped = ds.groupby('job_title')['salary_in_usd'].max()
result = ds.groupby(['job_title', 'salary_in_usd'])['company_location'].first().reset_in
dex()
result = result.sort_values('salary_in_usd', ascending=False)
result
```

Out[11]:

	job_title	salary_in_usd	company_location
472	Principal Data Engineer	600000	US
387	Financial Data Analyst	450000	US
497	Research Scientist	450000	US
19	Applied Machine Learning Scientist	423000	US
479	Principal Data Scientist	416000	US
...	...	...	...
268	Data Scientist	5679	US
0	3D Computer Vision Researcher	5409	IN
267	Data Scientist	4000	VN
138	Data Engineer	4000	IR
266	Data Scientist	2859	MX

499 rows × 3 columns

1. **what insight can you find regaurding employees demographic?**

In [12]:

```python
# employees location count

location_count = ds['employee_residence'].value_counts()
location_count
```

Out[12]:

```
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
RU       4
AE       3
AT       3
VN       3
TR       3
AU       3
RO       2
BE       2
SG       2
SI       2
DK       2
HU       2
NG       2
MX       2
BO       1
MY       1
TN       1
IE       1
DZ       1
AR       1
CZ       1
JE       1
LU       1
PR       1
RS       1
EE       1
CL       1
HK       1
KE       1
MD       1
CO       1
IR       1
CN       1
MT       1
UA       1
IQ       1
HN       1
BG       1
HR       1
PH       1
NZ       1
CH       1
Name: employee_residence, dtype: int64
```

In [13]:

```python
# employees remote ratio count

ratio_count = ds['remote_ratio'].value_counts()
ratio_count
```

Out[13]:

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

1. Which experinece level has the highest hiring?

In [14]:

```
experience_count = ds['experience_level'].value_counts()
experience_count
```

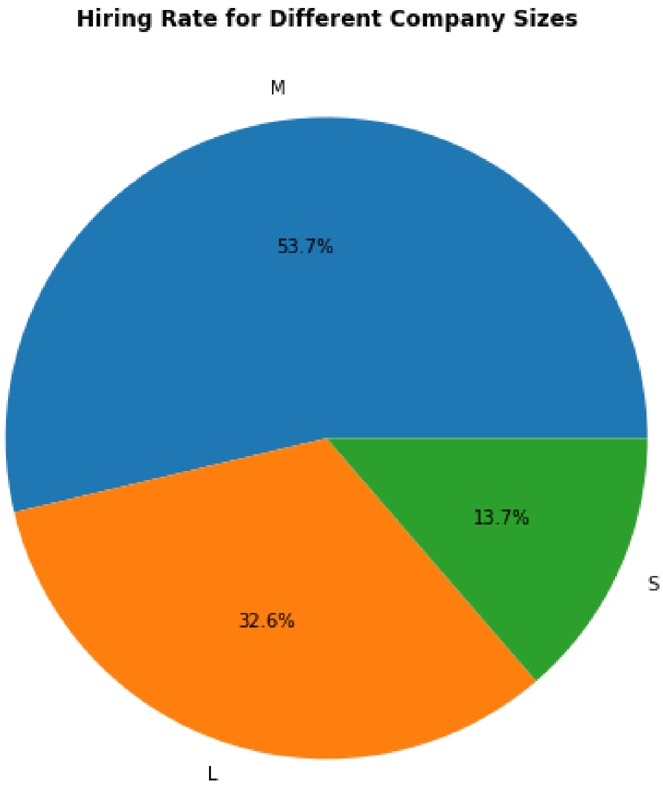
Out[14]:

```
SE    280
MI    213
EN     88
EX     26
Name: experience_level, dtype: int64
```

1. **Does company size affect the rate of hiring and pay scale**

In [15]:

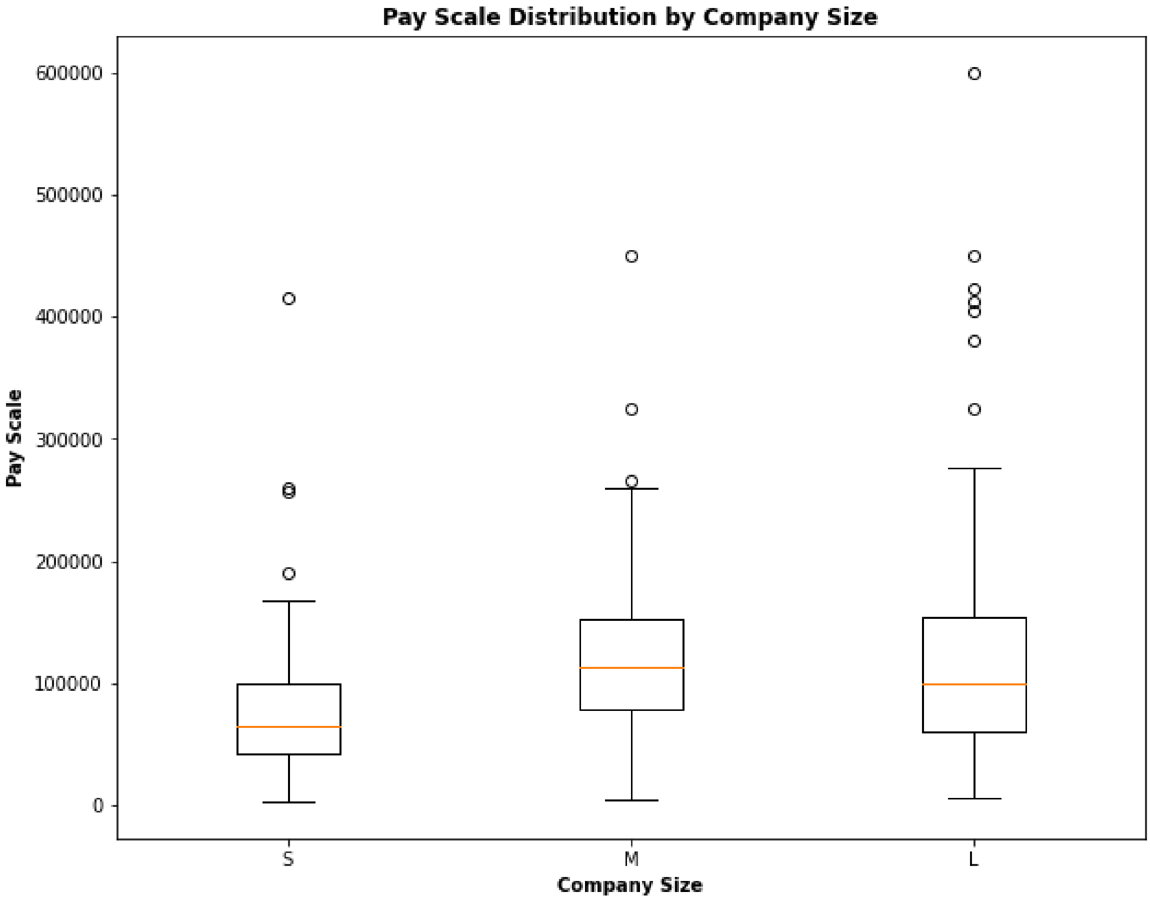
```
# hiring rate distribution by company size

company_size = ds['company_size'].value_counts()
company_size

fig = plt.figure(figsize=(10, 8))
plt.pie(company_size, labels=company_size.index, autopct='%1.1f%%')
plt.title('Hiring Rate for Different Company Sizes', weight='bold')
plt.show()
```



In [16]:

```
# Pay scale in different company sizes

data = {
    'Comapny Size' : ds['company_size'],
    'Salary' : ds['salary_in_usd']
}
pay_scale = pd.DataFrame(data)

fig = plt.figure(figsize=(10,8))
box_plot = plt.boxplot(
```

```
    [
    pay_scale[pay_scale['Comapny Size'] == 'S']['Salary'],
    pay_scale[pay_scale['Comapny Size'] == 'M']['Salary'],
    pay_scale[pay_scale['Comapny Size'] == 'L']['Salary']
    ],
    labels=['S', 'M', 'L'],
)

plt.title('Pay Scale Distribution by Company Size', weight='bold')
plt.xlabel('Company Size', weight='bold')
plt.ylabel('Pay Scale', weight='bold')
plt.show()
```

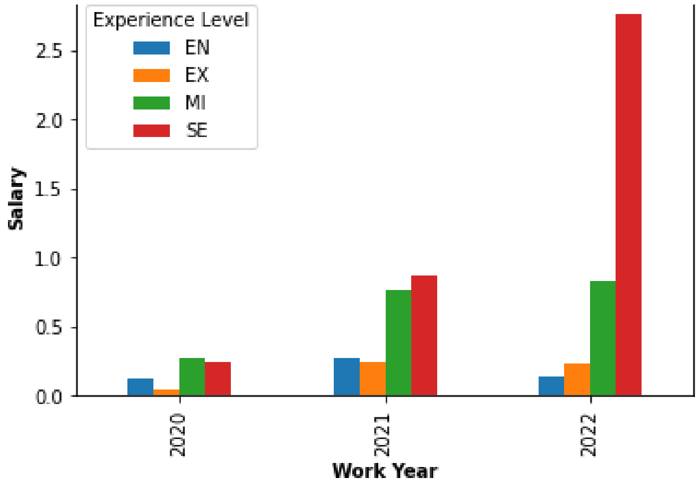


1. **What is the Year over Year salary growth at different levels?**

In [20]:

```
data = {
    'Work Year': ds['work_year'],
    'Experience Level': ds['experience_level'],
    'Salary': ds['salary_in_usd']
}
YoY = pd.DataFrame(data)

grouped_data = YoY.groupby(['Work Year', 'Experience Level']).sum().reset_index()
pivoted_data = grouped_data.pivot(index='Work Year', columns='Experience Level', values=
'Salary')

plt.figure(figsize=(10,8))
pivoted_data.plot(kind='bar')

plt.xlabel('Work Year', weight='bold')
plt.ylabel('Salary', weight='bold')
plt.title('Year-on-Year Salary Growth at Different Experience Levels', weight='bold')

plt.show()
```

```
<Figure size 720x576 with 0 Axes>
```


Experience Level
EN
EX
MI
SE
Salary
2.5
2.0
1.5
1.0
0.5
0.0
2020
2021
2022
Work Year