Employee Data (US)

> this dataset is downloaded from kaggle

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Reading Data from file and testing

In [49]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [17]:
```
emp_df = pd.read_csv('project/employee/employee_data.csv', index_col = 'ID')
```

In [19]:
```
emp_df.head(5)
```

Out[19]:

ID	Gender	Experience (Years)	Position	Salary
1	F	4	DevOps Engineer	109976
2	M	6	DevOps Engineer	120088
3	M	17	Web Developer	181301
4	M	7	Systems Administrator	77530
5	F	13	Systems Administrator	152397

Success: This box indicates a successful action.

Getting overview of Data

In [752…
```
emp_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 400 entries, 1 to 400
Data columns (total 4 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Gender              400 non-null    object
 1   Experience (Years)  400 non-null    int64 
 2   Position            400 non-null    object
 3   Salary              400 non-null    int64 
dtypes: int64(2), object(2)
memory usage: 31.8+ KB
```

In [35]:
```
emp_df.describe()
```

Out[35]:

	Experience (Years)	Salary
count	400.000000	400.00000
mean	9.670000	131701.19750
std	6.101571	43351.50899
min	0.000000	43643.00000
25%	4.000000	100484.75000
50%	10.000000	128561.50000
75%	15.000000	157735.00000
max	20.000000	269950.00000

In [39]:
```
131701.19750+43351.50899
```
Out[39]:
```
175052.70649
```

From info() we can see there is no missing data in our dataset and describe tell about basicality of Data.

> **Experience:**
>
> mean is **9.5** and by std we can conclude we have emp of mostly **3 years to 15 year exp**.
>
> **Salary:**
>
> mean **131701** and by std we can conclude we have emp of mostly **88349 to 175052 salaries emp**

Indentifying Outliers

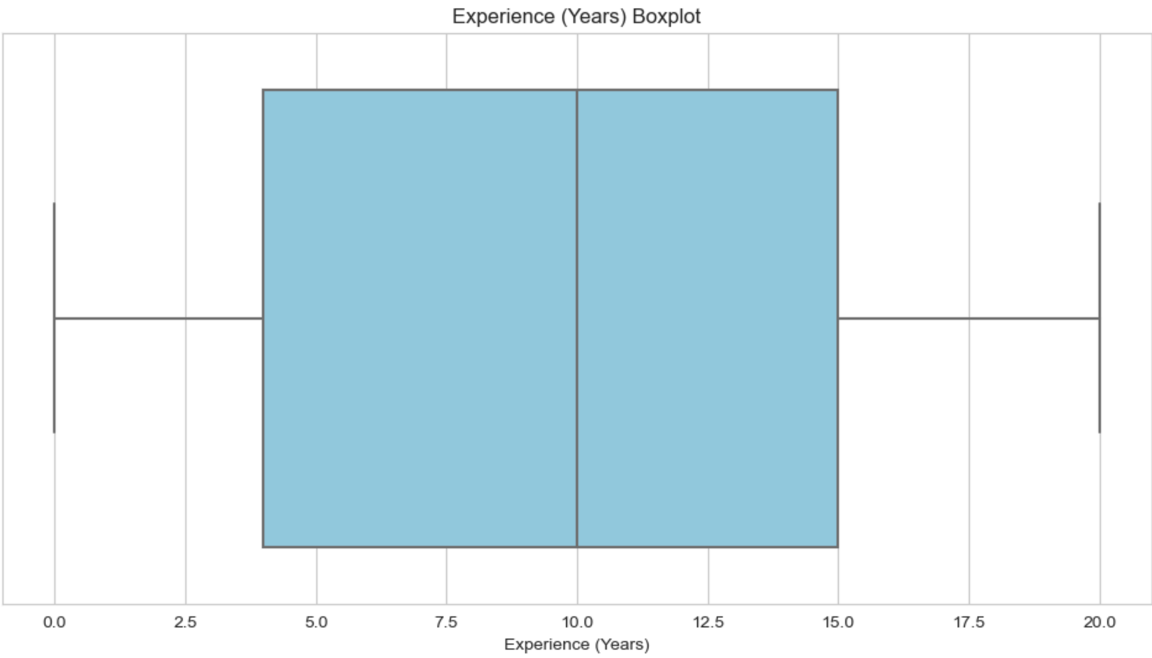
we removes the outliers, as mean really affected by outlieaars for further calculations

In [70]:
```
print(emp_df.columns)
```
```
Index(['Gender', 'Experience (Years)', 'Position', 'Salary'], dtype='objec
t')
```

In [66]:
```
emp_df.columns = emp_df.columns.str.strip()
```

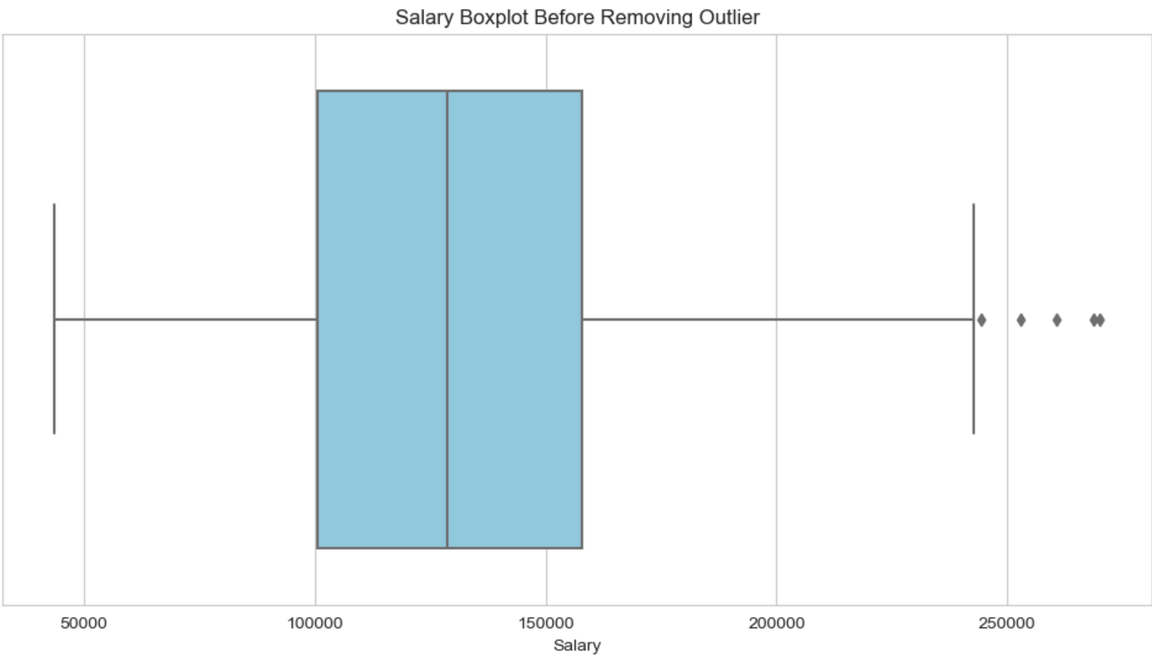
In [153…
```
sns.set_style('whitegrid')
```

In [610…
```
plt.figure(figsize=(12,6))
sns.boxplot(x = emp_df['Experience (Years)'], color ='skyblue').set_title(
```
Out[610]:
```
Text(0.5, 1.0, 'Experience (Years) Boxplot')
```



In [608…
```
plt.figure(figsize=(12,6))
sns.boxplot(x = emp_df['Salary'],color ='skyblue').set_title('Salary Boxpl
```

Out[608]:
```
Text(0.5, 1.0, 'Salary Boxplot Before Removing Outlier')
```



from the boxplot we conclude that,

> **Experience:** have no outliers
>
> **Salary:** have apperently **5 outliers**

Data Cleaning

Extracting Outliers

In [197…

```
# Calculate Q1 (25th percentile) and Q3 (75th percentile)
Q1 = emp_df['Salary'].quantile(0.25)
Q3 = emp_df['Salary'].quantile(0.75)

# Calculate IQR
IQR = Q3 - Q1


upper_bound = Q3 + 1.4 * IQR
```

> The commonly use multiplier is 1.5, but as analyzing our need i adjust the multiplier to 1.4 for removing outliers

In [702…

```
emp_df[emp_df['Salary'] >= upper_bound].sort_values(by = 'Salary')
```

Out[702]:

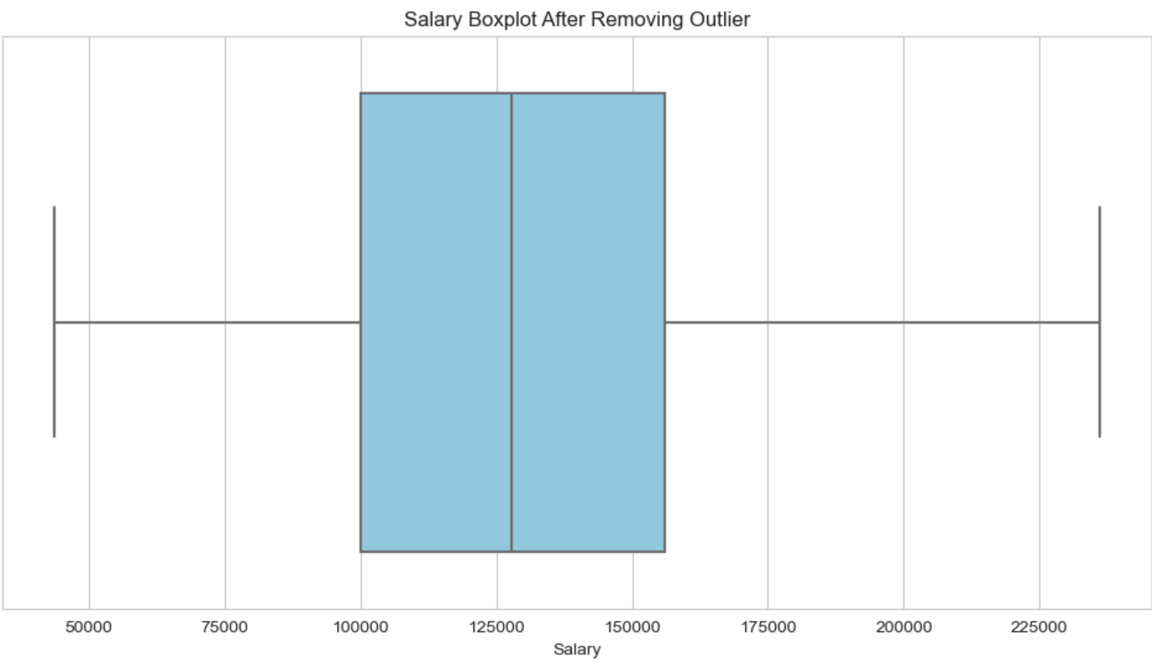
ID	Gender	Experience (Years)	Position	Salary
318	M	18	Cloud Solutions Architect	242808
348	F	19	DevOps Engineer	242819
162	M	17	IT Manager	244446
260	M	14	Cloud Solutions Architect	252949
62	M	17	IT Manager	260594
121	F	18	IT Manager	268774
116	M	18	IT Manager	269950

In [850…

```
filtered_emp_df = emp_df[emp_df['Salary'] <= upper_bound]
```

In [606…

```
plt.figure(figsize=(12,6))
plot = sns.boxplot(x = filtered_emp_df['Salary'], color ='skyblue').set_ti
```



Extracting EMP base on salaries

Employees that have higher salaries

In [350…
```
higher_pay_emp = filtered_emp_df[filtered_emp_df['Salary'] >= 200000]
```

In [352…
```
higher_pay_emp
```

Out[352]:

ID	Gender	Experience (Years)	Position	Salary
22	F	19	IT Security Analyst	232972
24	F	13	IT Manager	235235
71	F	19	Cloud Solutions Architect	226461
97	F	12	IT Manager	207518
108	M	14	IT Manager	205579
117	M	16	DevOps Engineer	214282
120	F	17	DevOps Engineer	230965
124	M	18	Software Engineer	215034
145	M	12	Cloud Solutions Architect	217422
151	M	16	IT Security Analyst	207529
197	F	18	IT Security Analyst	224671
227	M	20	DevOps Engineer	218258
232	M	14	IT Manager	204549
304	F	10	IT Manager	200409
317	F	20	Systems Analyst	206324
327	F	15	DevOps Engineer	211620
332	M	20	Database Administrator (DBA)	214420
333	M	20	DevOps Engineer	205418
351	M	19	Cloud Solutions Architect	229450
362	F	18	DevOps Engineer	211696
364	F	12	DevOps Engineer	200228
396	F	19	Cloud Solutions Architect	236045

Highest Male Salary

In [329…
```
filtered_male_df = filtered_emp_df[[ 'Gender', 'Salary']][filtered_emp_df[

# Find the highest salary among males
highest_male_sal = filtered_male_df['Salary'].max()

print("Highest salary among males:", highest_male_sal)
```

```
Highest salary among males: 229450
```

Lowest Male Salary

In [377…
```
filtered_male_df = filtered_emp_df[[ 'Gender', 'Salary']][filtered_emp_df[

lowest_male_sal = filtered_male_df['Salary'].min()

print("Lowest salary among males:", lowest_male_sal)
```

```
Lowest salary among males: 48710
```

Highest Female Salary

In [333…
```
filtered_female_df = filtered_emp_df[[ 'Gender', 'Salary']][filtered_emp_d

# Find the highest salary among females
highest_female_sal = filtered_female_df['Salary'].max()

print("Highest salary among males:", highest_female_sal)
```

```
Highest salary among males: 236045
```

Lowest Female Salary

In [380…
```
filtered_female_df = filtered_emp_df[[ 'Gender', 'Salary']][filtered_emp_d

lowest_female_sal = filtered_female_df['Salary'].min()

print("Lowest salary among males:", lowest_female_sal)
```

```
Lowest salary among males: 43643
```

Dependency Salary increment on Experience

In [365…
```
filtered_emp_df['Experience (Years)'].corr( filtered_emp_df['Salary'])
```

Out[365]:
```
0.6093419374642316
```

In [566…
```
df_sorted = filtered_emp_df.sort_values(by='Experience (Years)')

# Plotting
plt.figure(figsize=(10, 6))
sns.lineplot(data=df_sorted, x='Experience (Years)', y='Salary', marker='o
plt.xlabel('Experience (Years)')
plt.ylabel('Salary')
plt.title('Salary vs. Experience (Years)')
plt.grid(True)
plt.show()
```

it shows salary increases by as experience increase

Grouping Data for Position Analysis

In [273…

```
salary_distribution = filtered_emp_df.groupby('Position')['Salary'].descri
```

In [275…

```
salary_distribution
```

Out[275]:

Position	count	mean	std	min	25%	50%	
Cloud Solutions Architect	28.0	154624.714286	40511.614561	92288.0	127063.75	147967.0	1778
Database Administrator (DBA)	38.0	132864.552632	32989.308937	67396.0	108245.00	131083.5	1535
DevOps Engineer	36.0	159610.194444	35984.341332	103940.0	131318.25	155968.5	1849
IT Manager	36.0	160686.055556	34198.249200	87871.0	145854.00	159398.5	1872
IT Security Analyst	39.0	134440.820513	38863.676876	70591.0	110864.50	129205.0	1535
IT Support Specialist	31.0	87683.806452	24455.386067	43643.0	69931.50	90049.0	1022
Network Administrator	31.0	116865.064516	30385.225368	61605.0	93233.00	116964.0	1385
Software Engineer	36.0	131357.416667	38248.092780	66956.0	99886.75	132678.5	1624
Systems Administrator	38.0	113117.447368	32081.497420	55964.0	94392.00	112383.5	1314
Systems Analyst	37.0	127658.189189	37746.843766	72006.0	93558.00	126171.0	1537
Web Developer	43.0	108238.116279	34902.475399	57567.0	81649.50	102394.0	1298

by this we can conclude man things

> **the most employees are web developers.**
>
> **the most salary varies in Cloud Solutions Architect**
>
> **IT Managers have highest it concludes that as we removed outliers so IT managers gettting paid more we will check it below**

In [586…

```
salary_max_position = round(filtered_emp_df.groupby('Position')['Salary'].
salary_max_position_df = salary_max_position.reset_index()
salary_max_position_df.sort_values(by='Salary')
```

Out[586]:

	Position	Salary
5	IT Support Specialist	87684.0
10	Web Developer	108238.0
8	Systems Administrator	113117.0
6	Network Administrator	116865.0
9	Systems Analyst	127658.0
7	Software Engineer	131357.0
1	Database Administrator (DBA)	132865.0
4	IT Security Analyst	134441.0
0	Cloud Solutions Architect	154625.0
2	DevOps Engineer	159610.0
3	IT Manager	160686.0

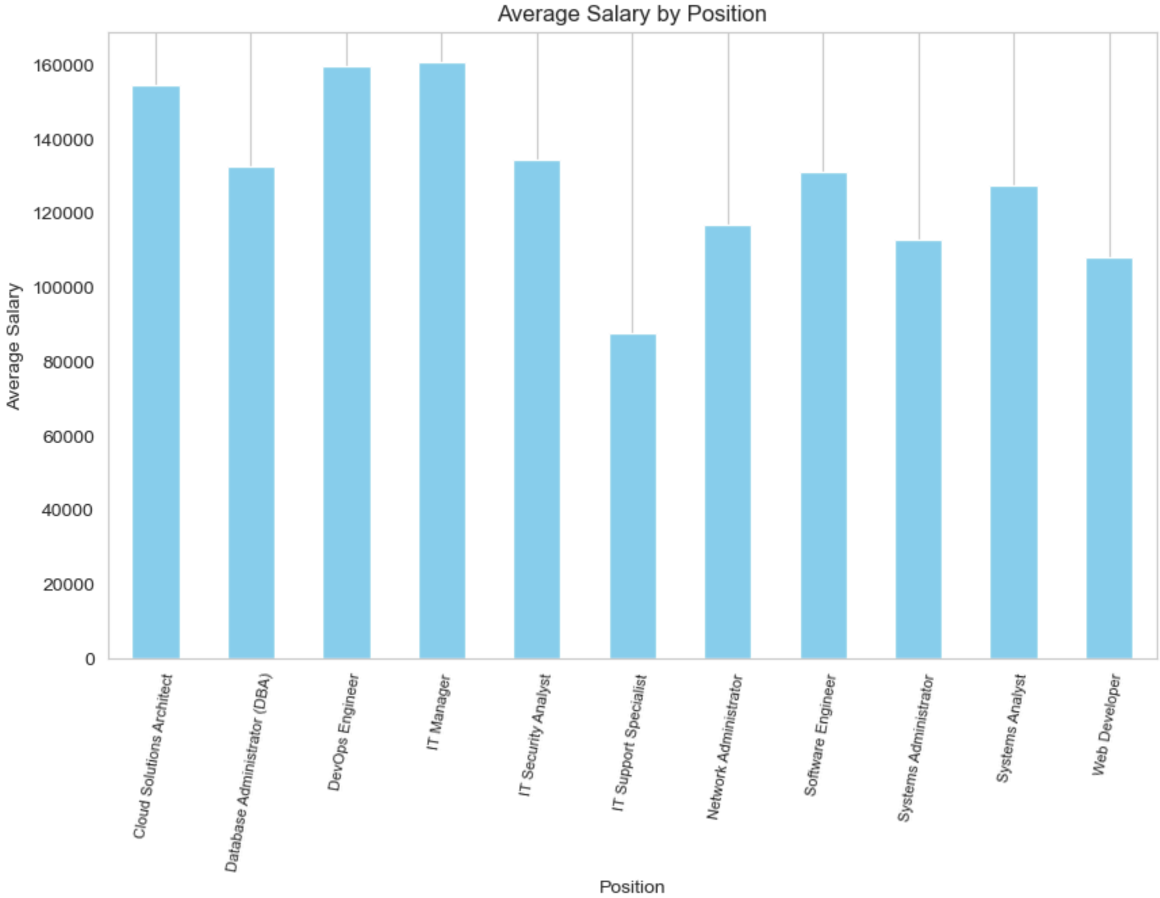
by this we are sure that the max salary is taken IT managers

In [477…

```
Avg_Sal_byPosition = filtered_emp_df.groupby('Position')['Salary'].mean()
```

In [511…

```
plt.figure(figsize=(10, 6))
Avg_Sal_byPosition.plot(kind='bar', color='skyblue')
plt.xlabel('Position')
plt.ylabel('Average Salary')
plt.title('Average Salary by Position')
plt.xticks(rotation=80)
plt.xticks(fontsize=8)
plt.grid(axis='y')
plt.show()
```



In [706…

```
Avg_Sal_byGender = filtered_emp_df.groupby('Gender')['Salary'].mean()
Avg_Sal_byGender_df = Avg_Sal_byGender.reset_index()
Avg_Sal_byGender_df
```

Out[706]:

	Gender	Salary
0	F	131373.173469
1	M	127659.883249

In [712…

```
Avg_Exp_worker = filtered_emp_df.groupby('Gender')['Experience (Years)'].m
```

In [714…

```
Avg_Exp_worker
```

Out[714]:

```
Gender
F    9.678571
M    9.390863
Name: Experience (Years), dtype: float64
```

It is good that both Man and Women almost getting same pay

Seperating Employees by Experience

In [794…

```
total_empployees = filtered_emp_df['Salary'].count()
# filtered_emp_df['Experience (Years)'].count()
total_empployees
```

Out[794]:

```
393
```

In [798…
```
experienced_emps = filtered_emp_df[filtered_emp_df['Experience (Years)'] >
experienced_emps
```

Out[798]:

ID	Gender	Experience (Years)	Position	Salary
3	M	17	Web Developer	181301
11	F	19	Network Administrator	158856
13	F	16	Database Administrator (DBA)	137662
18	F	16	Database Administrator (DBA)	188681
21	F	20	Network Administrator	139766
...	...	...	...	...
379	M	20	IT Manager	190956
380	F	16	Systems Analyst	149281
396	F	19	Cloud Solutions Architect	236045
397	F	20	Web Developer	182770
399	M	18	Database Administrator (DBA)	129996

98 rows × 4 columns

so we have 98 employer out of 393 employeer who have more experience than 15 year

In [801…
```
unexperienced_emps = filtered_emp_df[filtered_emp_df['Experience (Years)']
unexperienced_emps
```

Out[801]:

ID	Gender	Experience (Years)	Position	Salary
1	F	4	DevOps Engineer	109976
8	M	2	DevOps Engineer	111494
12	M	2	DevOps Engineer	103940
17	M	4	IT Security Analyst	111156
19	F	5	IT Security Analyst	129205
...	...	...	...	...
389	F	4	Systems Administrator	102856
392	F	3	Cloud Solutions Architect	159870
393	F	1	Network Administrator	79333
394	M	2	Software Engineer	91029
395	M	3	IT Support Specialist	54938

126 rows × 4 columns

126 employeer have less than 5 year of experience

In [805…

```
midExp_emps = filtered_emp_df[(filtered_emp_df['Experience (Years)'] > 5)
midExp_emps
```

Out[805]:

ID	Gender	Experience (Years)	Position	Salary
2	M	6	DevOps Engineer	120088
4	M	7	Systems Administrator	77530
5	F	13	Systems Administrator	152397
6	F	13	Web Developer	114998
7	F	11	Systems Administrator	82328
...	...	...	...	...
385	F	14	Systems Administrator	108497
390	F	9	IT Security Analyst	107445
391	M	11	IT Support Specialist	66076
398	F	9	Network Administrator	85550
400	F	11	IT Security Analyst	169058

169 rows × 4 columns

169 employees have more than 5 year of experiance and less than 15 year of experience

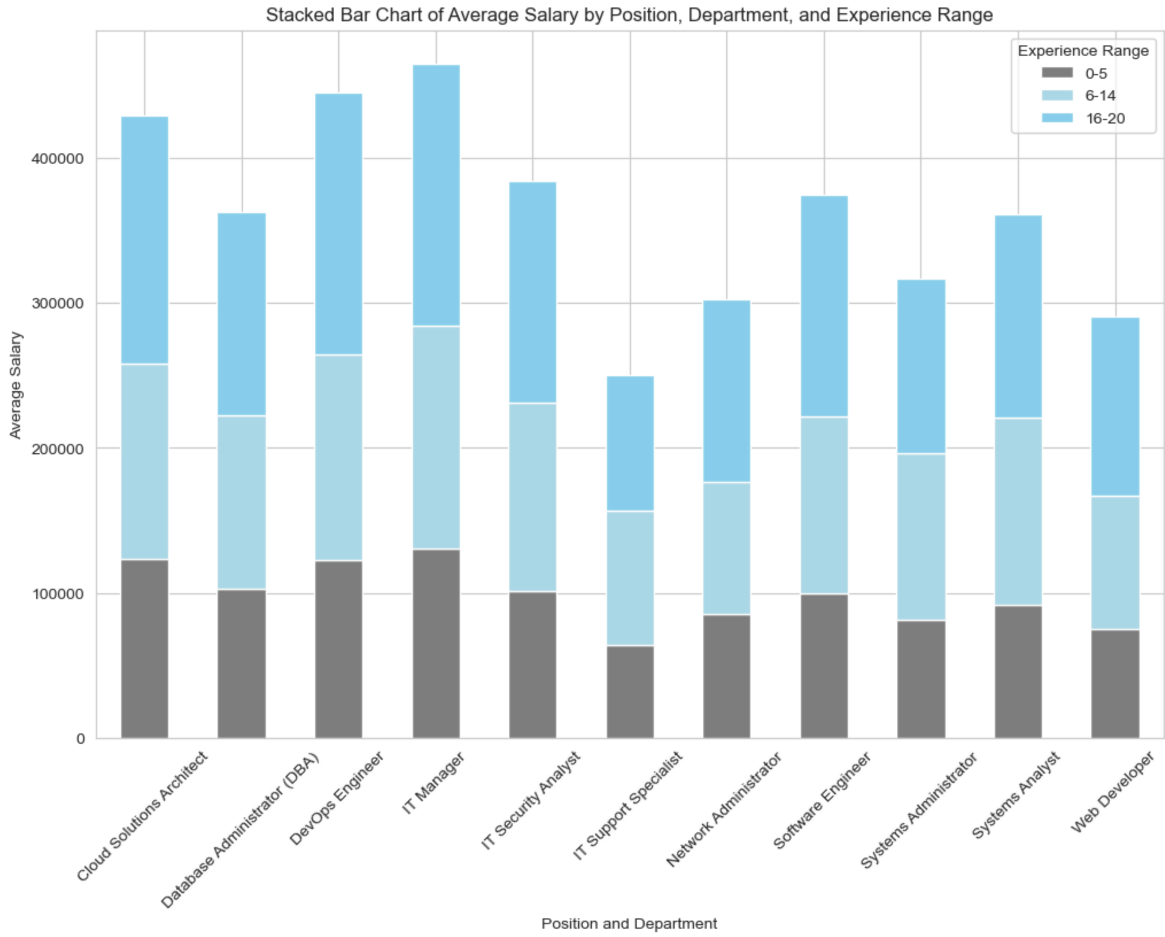
In [820…

```
print('Total employees is', experienced_emps['Experience (Years)'].count()
unexperienced_emps['Experience (Years)'].count())
```

```
Total employees is 393
```

In [895…

```
# Define bins for experience ranges
bins = [0, 5, 10, 15]
labels = ['0-5', '6-14', '16-20']

# Make a copy of the DataFrame to avoid SettingWithCopyWarning
df_copy = filtered_emp_df.copy()

# Assign experience ranges
df_copy['Experience Range'] = pd.cut(df_copy['Experience (Years)'], bins=b

# Calculate average salary for each combination of Position, Department, a
avg_salary_df = df_copy.groupby(['Position', 'Experience Range'])['Salary'

# Plot stacked bar chart
avg_salary_df.plot(kind='bar', stacked=True, figsize=(12, 8),
                   color=['grey', 'lightblue','skyblue'])


plt.xlabel('Position and Department')
plt.ylabel('Average Salary')
plt.title('Stacked Bar Chart of Average Salary by Position, Department, an
plt.xticks(rotation=45)
plt.legend(title='Experience Range')
plt.show()
```



so it shows more experience employees have more higher mean salaries that show salaries increased by experiences

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Conclusion

> IT managers and Dev OPs Engineers are taking more salaries, or as we have more web developer in less salaries so it show web developers are less expensive to company, and we have almost equal ratios of men and women who are working here, and with expereince employees salaries are increasing, **for further decision we need revenues of postions to judge where we have to do focuds more**