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Employee Salaries for different job roles

Exploring Employee Salaries and Job Roles Across Industries

About Dataset

Welcome to the Employee Salaries for Different Job Roles Dataset! This dataset provides valuable insights into the compensation and job roles of employees across various industries and regions. Whether you're an HR analyst, data scientist, or someone interested in understanding salary trends, this dataset offers a wealth of information to explore and analyze.

Content:

The dataset contains the following fields:

work_year: The year of employment. experience_level: The experience level of the employee (e.g., entry-level, mid-level, senior). employment_type: The type of employment (e.g., full-time, part-time, contract). job_title: The job title or position of the employee within the company. salary: The salary amount in the local currency. salary_currency: The currency in which the salary is denoted. salary_in_usd: The equivalent salary amount in USD (United States Dollars). employee_residence: The location of the employee's residence. remote_ratio: The percentage of remote work allowed for the position. company_location: The location of the company. company_size: The size of the company (e.g., small, medium, large).

Usage:

This dataset can be utilized for various purposes, including but not limited to:

Analyzing salary trends across different job titles and experience levels. Investigating the impact of remote work on compensation. Comparing salary levels between full-time and part-time employment. Understanding the correlation between company size and employee salaries. Predictive analysis for forecasting salaries based on experience and job roles.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
```

In [2]:
```
os.getcwd()
```

Out[2]:
```
'C:\\Users\\lokes\\Downloads'
```

In [3]:
```
os.chdir('C:\\Users\\lokes\\Dropbox\\PC\\Downloads')
```

In [4]:
```
os.getcwd()
```

Out[4]:
```
'C:\\Users\\lokes\\Dropbox\\PC\\Downloads'
```

Loading the data

In [5]:
```
df=pd.read_csv('ds_salaries.csv')
df
```

Out[5]:

	Unnamed: 0	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd
0	0	2020	MI	FT	Data Scientist	70000	EUR	7983
1	1	2020	SE	FT	Machine Learning Scientist	260000	USD	26000
2	2	2020	SE	FT	Big Data Engineer	85000	GBP	10902
3	3	2020	MI	FT	Product Data Analyst	20000	USD	2000
4	4	2020	SE	FT	Machine Learning Engineer	150000	USD	15000
...	...	...	...	...	...	...	...	..
602	602	2022	SE	FT	Data Engineer	154000	USD	15400
603	603	2022	SE	FT	Data Engineer	126000	USD	12600
604	604	2022	SE	FT	Data Analyst	129000	USD	12900
605	605	2022	SE	FT	Data Analyst	150000	USD	15000
606	606	2022	MI	FT	AI Scientist	200000	USD	20000

607 rows × 12 columns

Information about the DataFrame

In [6]:
```
df.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
```

Data Preprocessing

In [7]:
```
#checking for null/missing values
df.isnull().sum()*100/len(df)
```

Out[7]:
```
Unnamed: 0            0.0
work_year             0.0
experience_level      0.0
employment_type       0.0
job_title             0.0
salary                0.0
salary_currency       0.0
salary_in_usd         0.0
employee_residence    0.0
remote_ratio          0.0
company_location      0.0
company_size          0.0
dtype: float64
```

In [8]:
```
#Descriptive statistics
df.describe()
```

Out[8]:

	Unnamed: 0	work_year	salary	salary_in_usd	remote_ratio
count	607.000000	607.000000	6.070000e+02	607.000000	607.00000
mean	303.000000	2021.405272	3.240001e+05	112297.869852	70.92257
std	175.370085	0.692133	1.544357e+06	70957.259411	40.70913
min	0.000000	2020.000000	4.000000e+03	2859.000000	0.00000
25%	151.500000	2021.000000	7.000000e+04	62726.000000	50.00000
50%	303.000000	2022.000000	1.150000e+05	101570.000000	100.00000
75%	454.500000	2022.000000	1.650000e+05	150000.000000	100.00000
max	606.000000	2022.000000	3.040000e+07	600000.000000	100.00000

In [9]:
```
df.columns
```

Out[9]:
```
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')
```

In [10]:
```
#Making a copy of the original data in case of errors and if we need it again later
df_original = df.copy()
#Droping the first column Unnamed:0 and checking for duplicate rows
df.drop(columns=['Unnamed: 0'], inplace=True)
duplicate_rows = df.duplicated()
df[duplicate_rows].head(10)
```

Out[10]:

	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd	employe
217	2021	MI	FT	Data Scientist	76760	EUR	90734	
256	2021	MI	FT	Data Engineer	200000	USD	200000	
331	2022	SE	FT	Data Analyst	90320	USD	90320	
332	2022	SE	FT	Data Analyst	112900	USD	112900	
333	2022	SE	FT	Data Analyst	90320	USD	90320	
353	2022	SE	FT	Data Scientist	123000	USD	123000	
362	2022	SE	FT	Data Analyst	130000	USD	130000	
363	2022	SE	FT	Data Analyst	61300	USD	61300	
370	2022	SE	FT	Data Scientist	123000	USD	123000	
374	2022	MI	FT	ETL Developer	50000	EUR	54957	

Drop the duplicate rows

As well as the columns Salary and Salary_Currency as we will be using Salary_in_usd for our Analysis

In [11]:
```
df.drop_duplicates(inplace=True)
df.drop(columns=['salary','salary_currency'], inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 565 entries, 0 to 606
Data columns (total 9 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   work_year           565 non-null    int64 
 1   experience_level    565 non-null    object
 2   employment_type     565 non-null    object
 3   job_title           565 non-null    object
 4   salary_in_usd       565 non-null    int64 
 5   employee_residence  565 non-null    object
 6   remote_ratio        565 non-null    int64 
 7   company_location    565 non-null    object
 8   company_size        565 non-null    object
dtypes: int64(3), object(6)
memory usage: 44.1+ KB
```

Exploratory Data Analysis

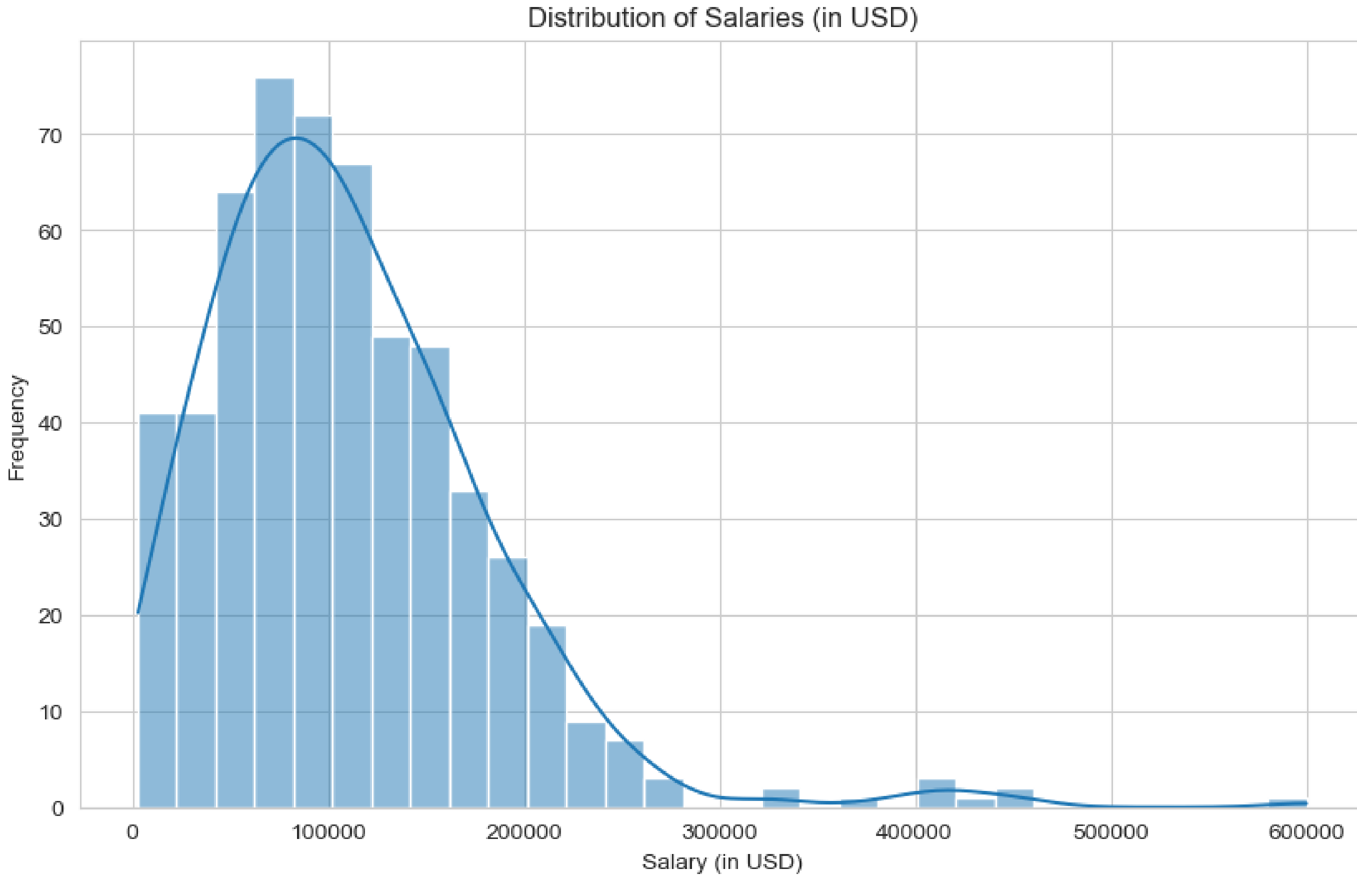
In the EDA,we will be looking at the data and try to understandthe data. Looking at the distribution of data across the dataset,followed by visualizing the data to understand the relationship between the feature and the target variable

Salary in USD

Highest frequency above 70 with range of 8000-9000 salary in USD,which denotes most people working under 8k-9k range with least of 60000 salary

In [12]:

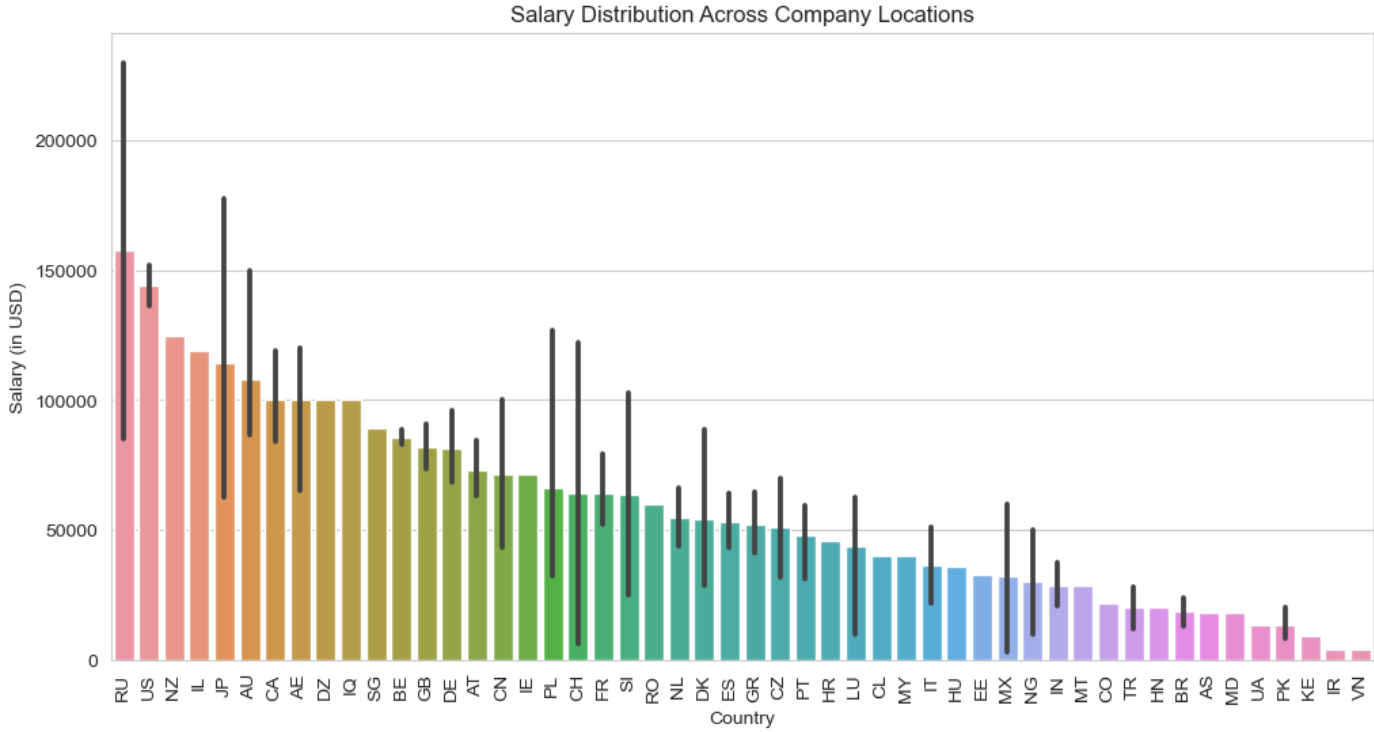
```
sns.set_style("whitegrid")

# Distribution of salaries in USD
plt.figure(figsize=(10, 6))
sns.histplot(df['salary_in_usd'], bins=30, kde=True)
plt.title('Distribution of Salaries (in USD)')
plt.xlabel('Salary (in USD)')
plt.ylabel('Frequency')
plt.show()
```



Plotting Salary vs Company Location (Country)

This graph help to breakdown that Russia providing more salary in USD than any other country followed by US.

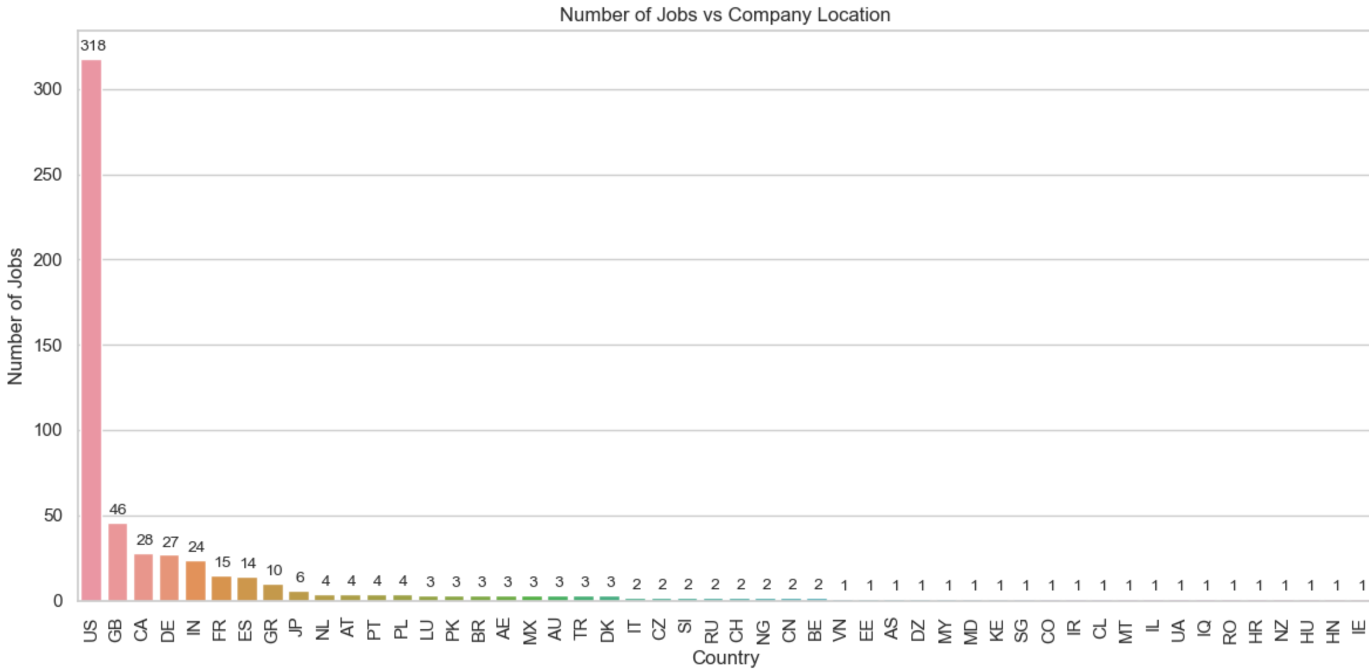
In [13]:
```
sorted_countries = df.groupby('company_location')['salary_in_usd'].mean().sort_values(as
plt.figure(figsize=(12, 6))
sns.barplot(x='company_location', y='salary_in_usd', data=df, order=sorted_countries)
plt.title('Salary Distribution Across Company Locations')
plt.xlabel('Country')
plt.ylabel('Salary (in USD)')
plt.xticks(rotation=90)
plt.show()
```



Number of Jobs by Company Location:

We observe that a significant number of Jobs in our Data (>50%) are from the United States. However, companies located in Russia only account for 2 Jobs in our data Because of fewer jobs, but much higher salaries, we are getting an incomplete picture, and this may skew our analysis or modeling.¶

In [14]:
```
sorted_country_counts = df['company_location'].value_counts().index #Sort in descending
plt.figure(figsize=(12, 6))
sns.set(style="whitegrid")
ax = sns.countplot(x='company_location', data=df, order=sorted_country_counts)

# Add Labels
for p in ax.patches:
    ax.annotate(format(p.get_height(), '.0f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha = 'center', va = 'center',
                xytext = (1, 7),
                textcoords = 'offset points',
               fontsize=10)

plt.xlabel('Country')
plt.ylabel('Number of Jobs')
plt.xticks(rotation=90)
plt.title('Number of Jobs vs Company Location')

# Show the plot
plt.tight_layout()
plt.show()
```

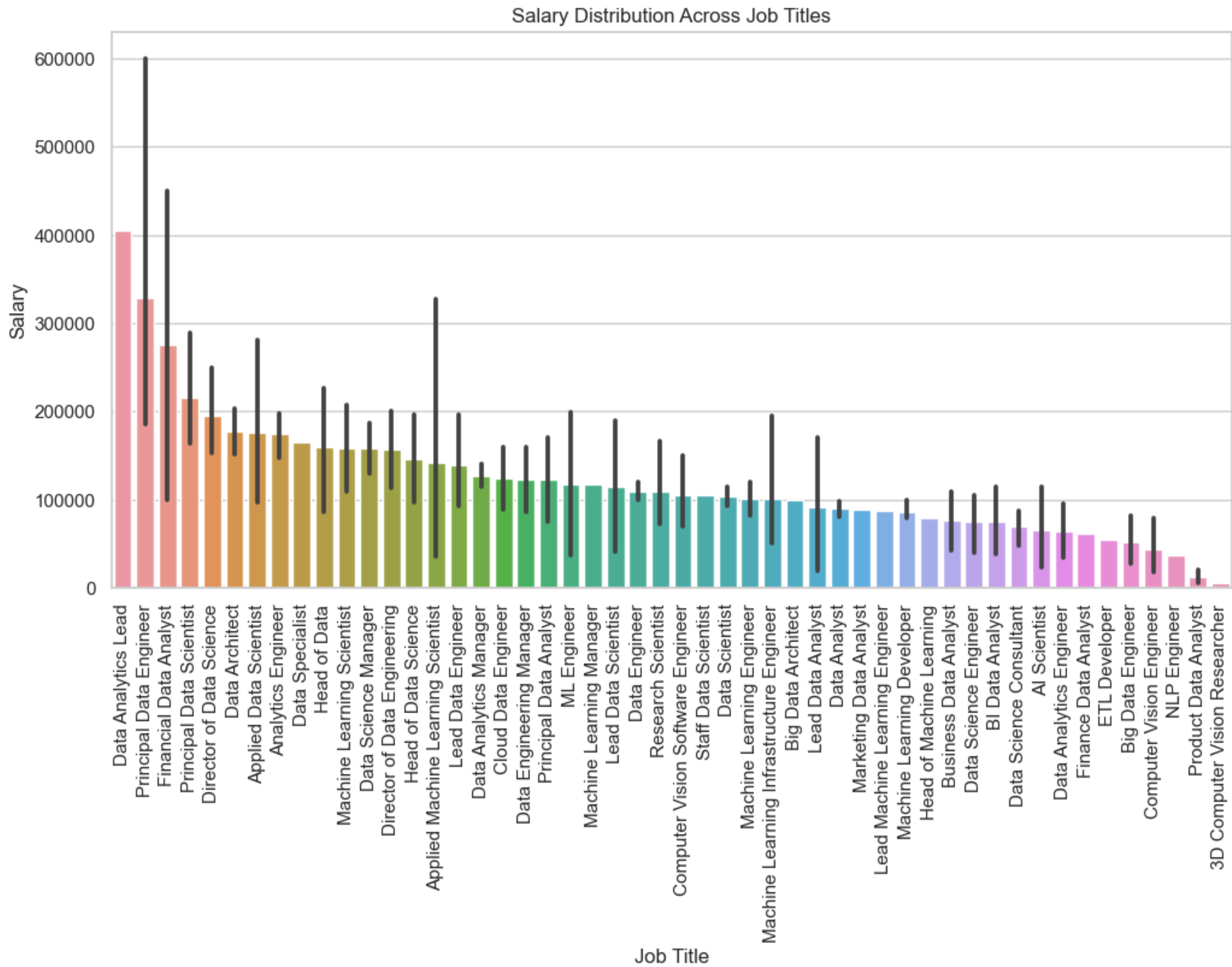


Job Salaries based on Job Title:

Data Analytics Lead, Principal Data Engineer, Financial Data Analyst, Principal Data Scientist, and Director of Data Science are the 5 highest paying Jobs in our Data. This could be due to these being leadership positions, or being in high-paying sectors like Finance. However, as we go along the X-axis on the graph, we can observe a few Jobs that sound similar but seem to have a big discrepancy in salaries. There is also a lot of variance in a few Job titles. This could be due to which countries these Jobs are located, whether they're remote or on-site, as well as other factors

In [15]:

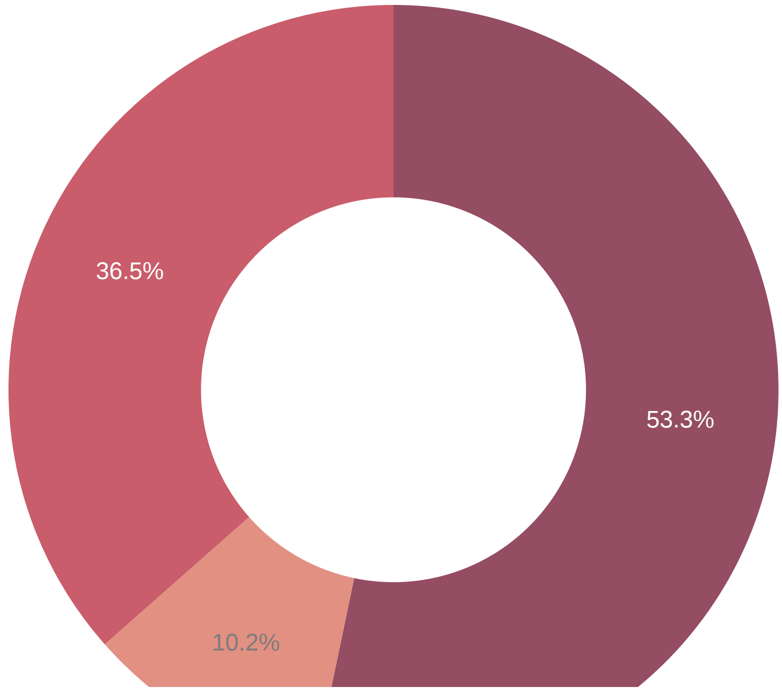
```
sorted_roles = df.groupby('job_title')['salary_in_usd'].mean().sort_values(ascending=Fal
plt.figure(figsize=(12, 6))
sns.barplot(x='job_title', y='salary_in_usd', data=df, order=sorted_roles)
plt.title('Salary Distribution Across Job Titles')
plt.xlabel('Job Title')
plt.ylabel('Salary')
plt.xticks(rotation=90)
plt.show()
```



Salary as per company size

This pie chart shows that majority of the Medium Size company providing more salary than Large and small with 53.3% on the dataset.

In [16]:
```
import plotly.express as px
fig = px.pie(df, values="salary_in_usd", names="company_size",
             color_discrete_sequence=px.colors.sequential.RdBu,
             opacity=0.7, hole=0.5)
fig.show()
```



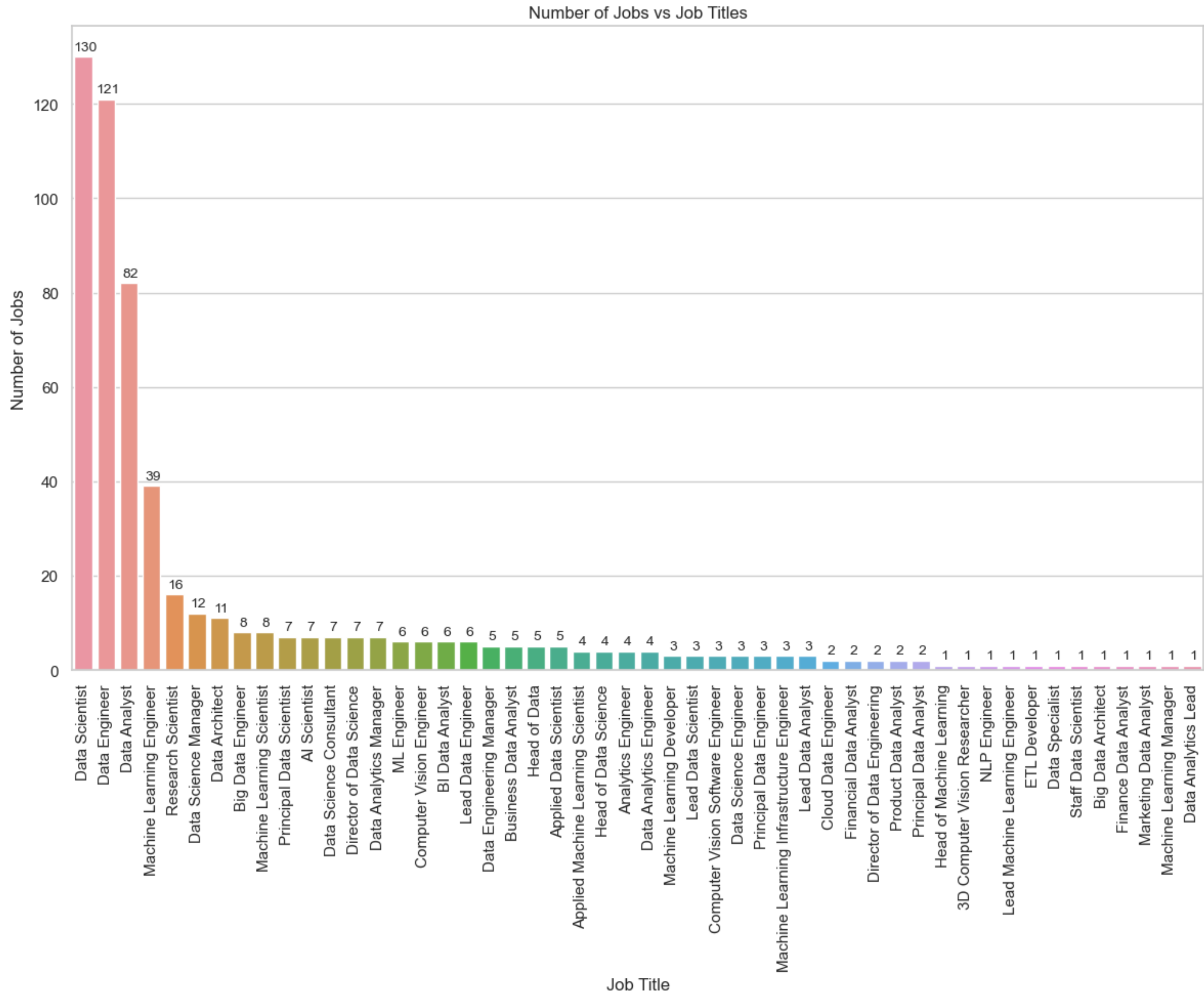
Number of Jobs based on Job Title:

Data Scientist, Data Engineer, and Data Analyst are the most common Job titles, followed by more specialized job titles. This could be because most companies only need Data Scientists, Engineers and Analysts for their Data-related needs, but companies that specialize in Data-related activities or Companies that are more mature in their adoption of Data-driven practices, seek out more specialized roles. However, this is only an assumption that cannot be proven by the current dataset. To support this assumption we would require additional data and need to perform deeper analysis.

In [17]:

```
sorted_jobtype_counts = df['job_title'].value_counts().index
plt.figure(figsize=(12, 10))
sns.set(style="whitegrid")
ax = sns.countplot(x='job_title', data=df, order=sorted_jobtype_counts)

for p in ax.patches:
    ax.annotate(format(p.get_height(), '.0f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha = 'center', va = 'center',
                xytext = (1, 7),
                textcoords = 'offset points',
               fontsize=10)

plt.xlabel('Job Title')
plt.ylabel('Number of Jobs')
plt.xticks(rotation=90)
plt.title('Number of Jobs vs Job Titles')
```

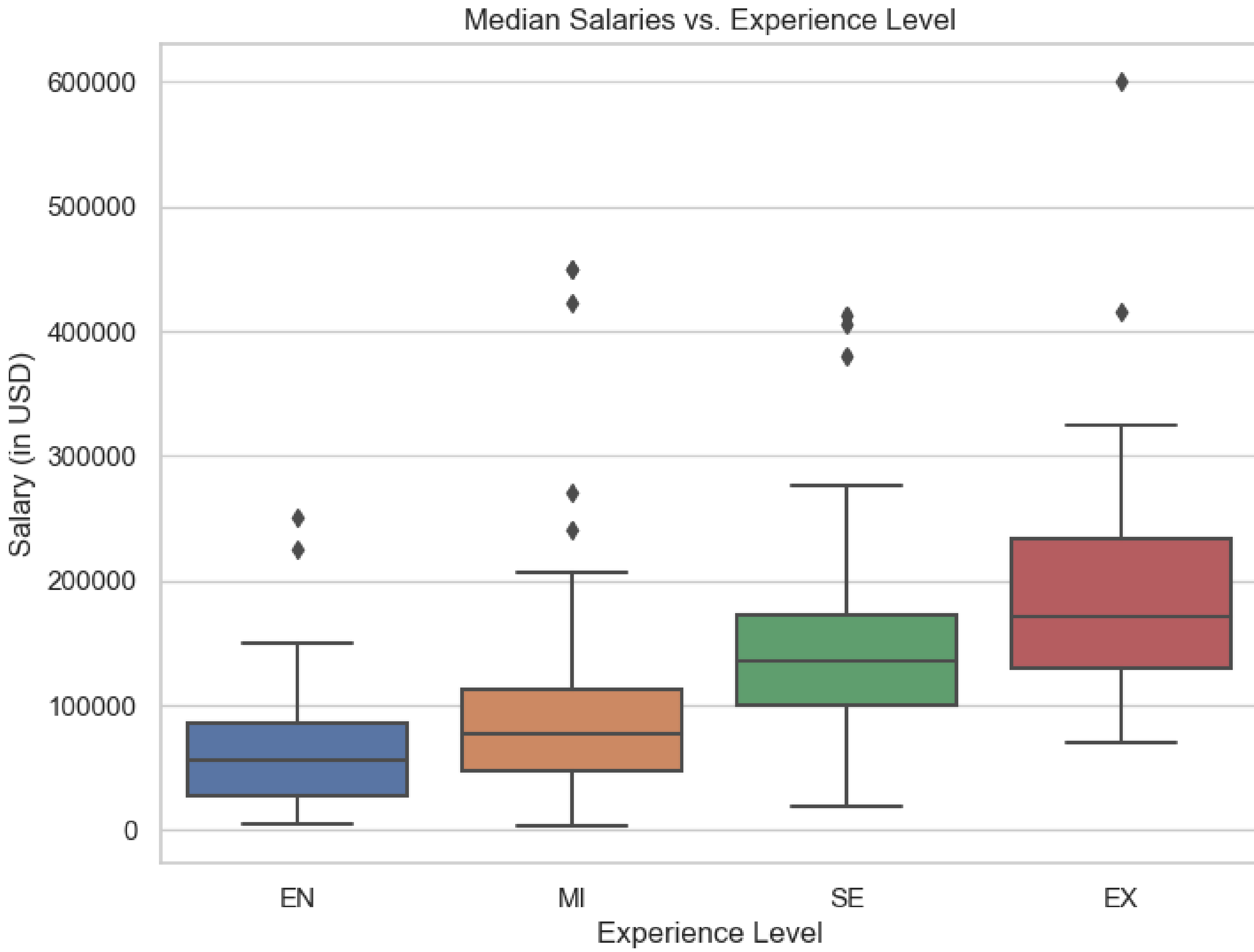
```
plt.tight_layout()
plt.show()
```



Median Salaries based on Experience Level.

Not surprisingly, Entry level jobs have the lowest salaries, followed by Mid Level jobs and Senior Level jobs, and Executive Level jobs have the highest salaries

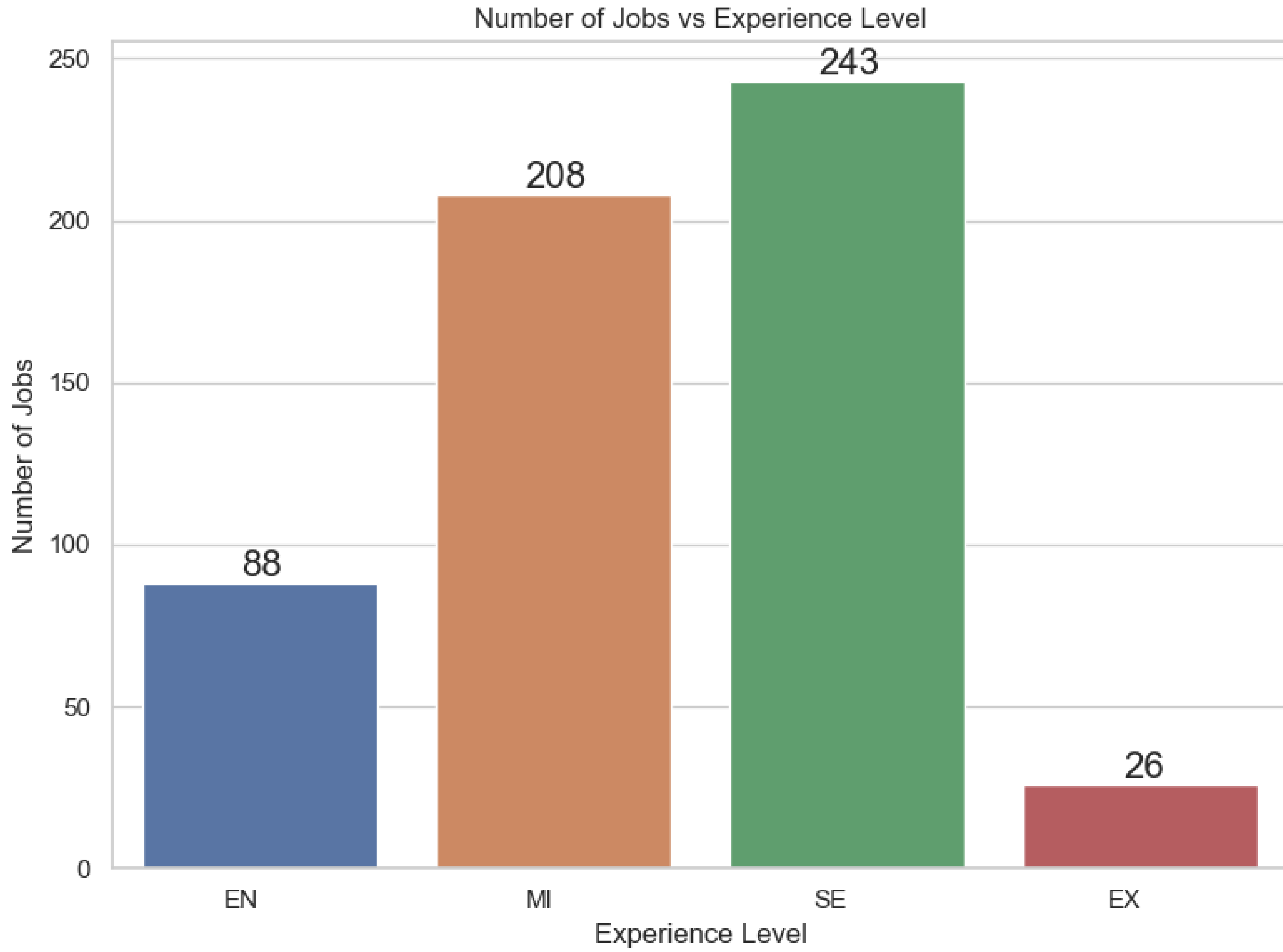
In [18]:
```
sorted_exp = ['EN', 'MI', 'SE', 'EX'] #Order by Seniority
plt.figure(figsize=(8, 6))
sns.boxplot(data=df, x='experience_level', y='salary_in_usd', order=sorted_exp)
plt.title('Median Salaries vs. Experience Level')
plt.xlabel('Experience Level')
plt.ylabel('Salary (in USD)')
plt.show()
```



Number of Jobs based on Experience level

From the graph it is clear that most of the jobs have a Senior level of Experience followed by Middle level and Entry level.

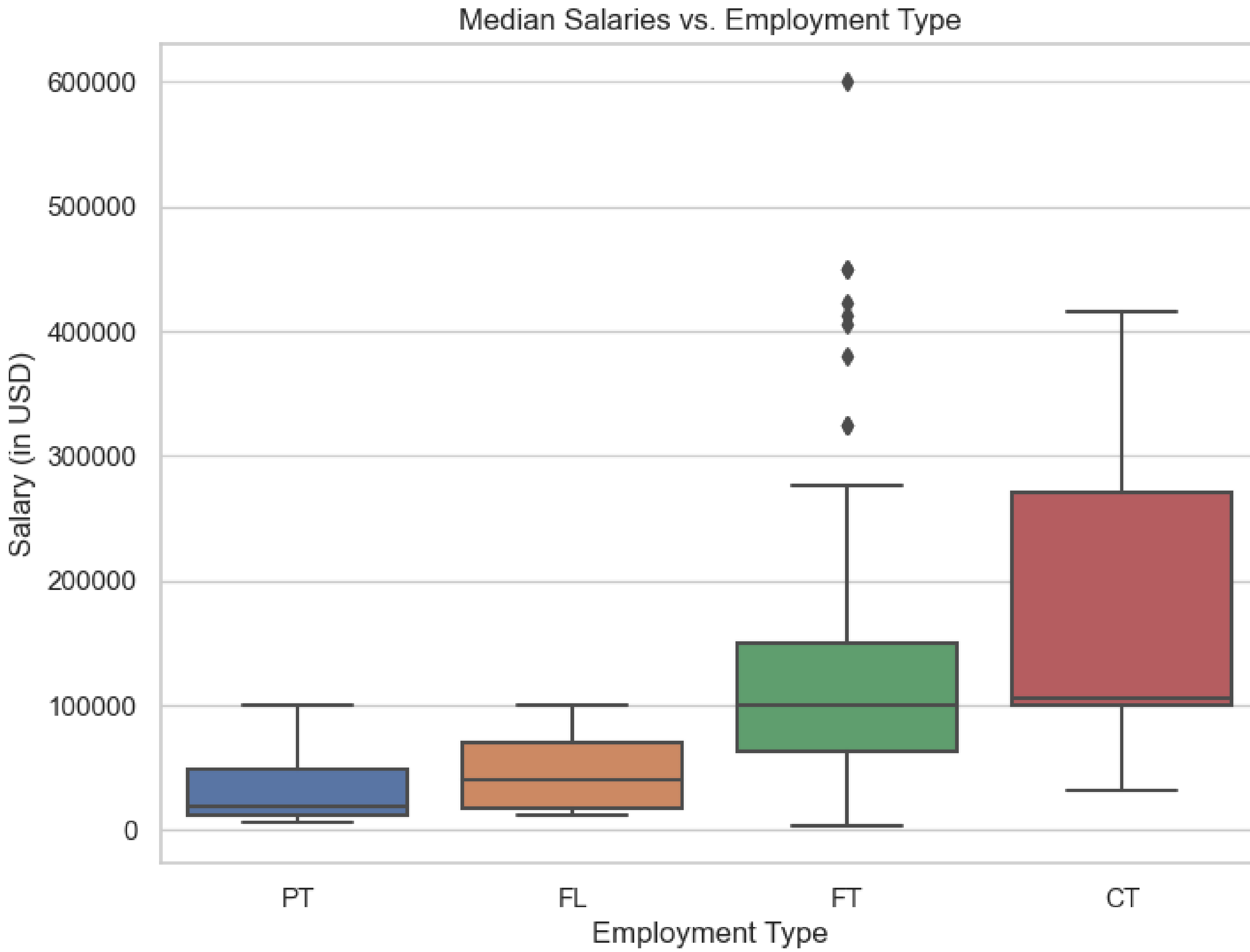
In [19]:
```
plt.figure(figsize=(8, 6))
sns.set(style="whitegrid")
ax = sns.countplot(x='experience_level', data=df, order=sorted_exp)

for p in ax.patches:
    ax.annotate(format(p.get_height(), '.0f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha = 'center', va = 'center',
                xytext = (1, 7),
                textcoords = 'offset points',
               fontsize=16)

plt.xlabel('Experience Level')
plt.ylabel('Number of Jobs')
plt.xticks(rotation=0, ha="right")
plt.title('Number of Jobs vs Experience Level')

plt.tight_layout()
plt.show()
```



Median salaries vs. employment_type

Number of Jobs based on Experience Level Executive level jobs are the least common, followed by Entry Level jobs. Mid-Level and Senior-Level Jobs account for about 80% of the Jobs in our data.

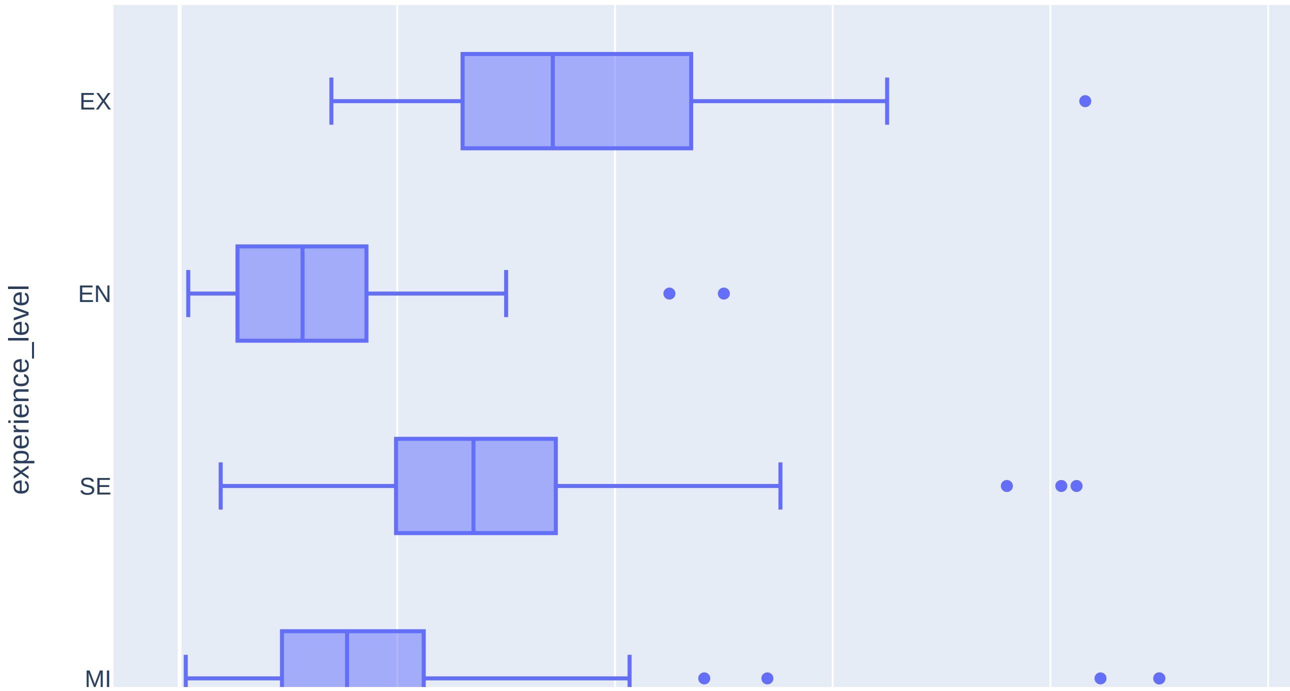
In [20]:
```
sorted_emp = df.groupby('employment_type')['salary_in_usd'].mean().sort_values(ascending

plt.figure(figsize=(8, 6))
sns.boxplot(data=df, x='employment_type', y='salary_in_usd', order=sorted_emp)
plt.title('Median Salaries vs. Employment Type')
plt.xlabel('Employment Type')
plt.ylabel('Salary (in USD)')
plt.show()
```



Salary in USD based on experience level

Inthe box plot helps us to shows that Experience level of employee has the highest salary range of 200k-250k followed by Senior level employee.

In [21]:
```
import plotly.express as px
fig = px.box(df, x="salary_in_usd", y="experience_level")
fig.show()
```



Number of Jobs vs Employment Type

When we break down the number of jobs in the data against the Employment Type, we observe that the vast majority (~95%) of the jobs listed are Full Time jobs.

In [22]:
```
plt.figure(figsize=(8, 6))
sns.set(style="whitegrid")
ax = sns.countplot(x='employment_type', data=df, order=sorted_emp)

for p in ax.patches:
    ax.annotate(format(p.get_height(), '.0f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha = 'center', va = 'center',
                xytext = (1, 7),
                textcoords = 'offset points',
               fontsize=16)

plt.xlabel('Employment Type')
plt.ylabel('Number of Jobs')
plt.xticks(rotation=0, ha="right")
plt.title('Number of Jobs vs Employment Type')


plt.tight_layout()
plt.show()
```

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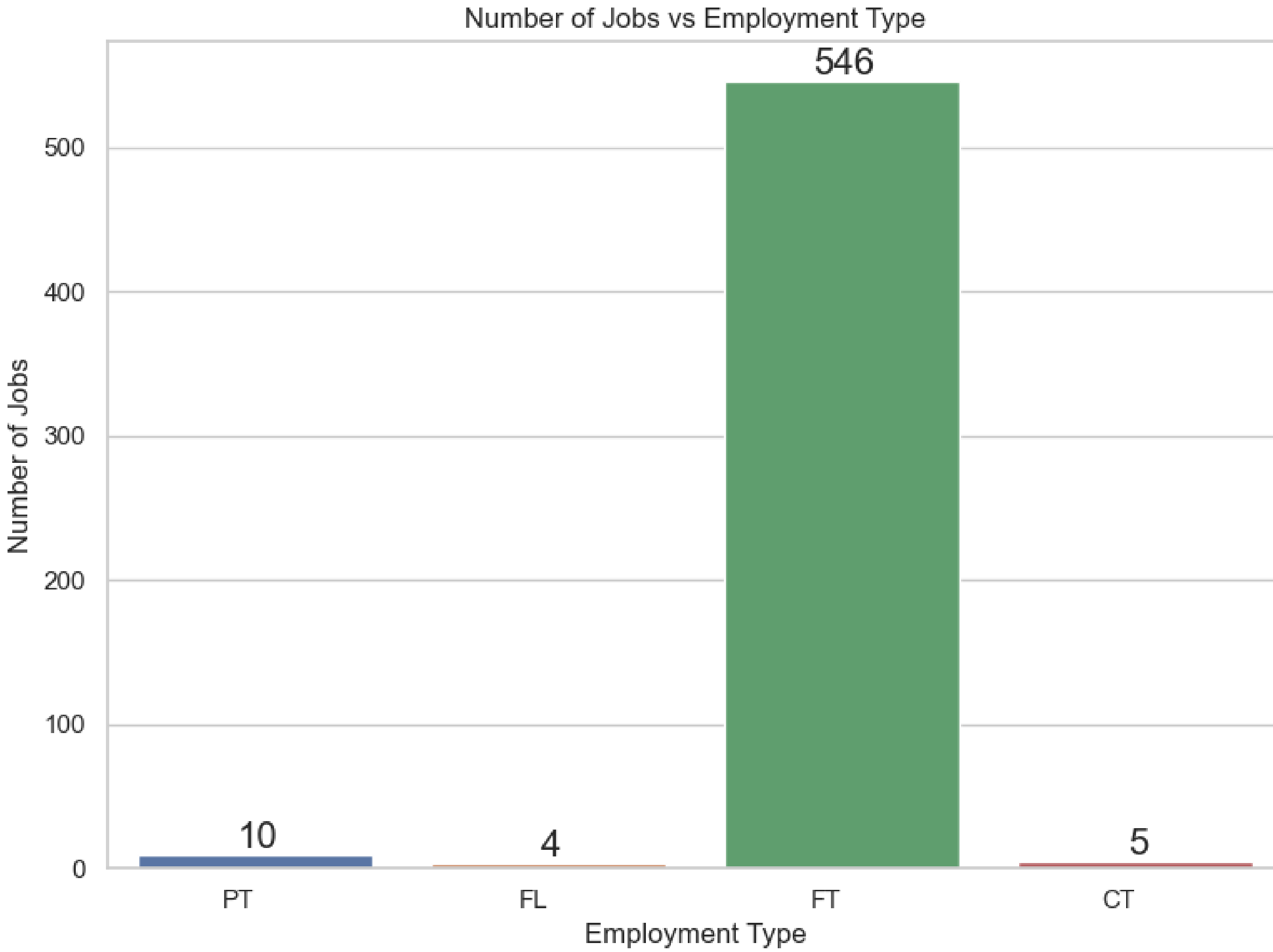
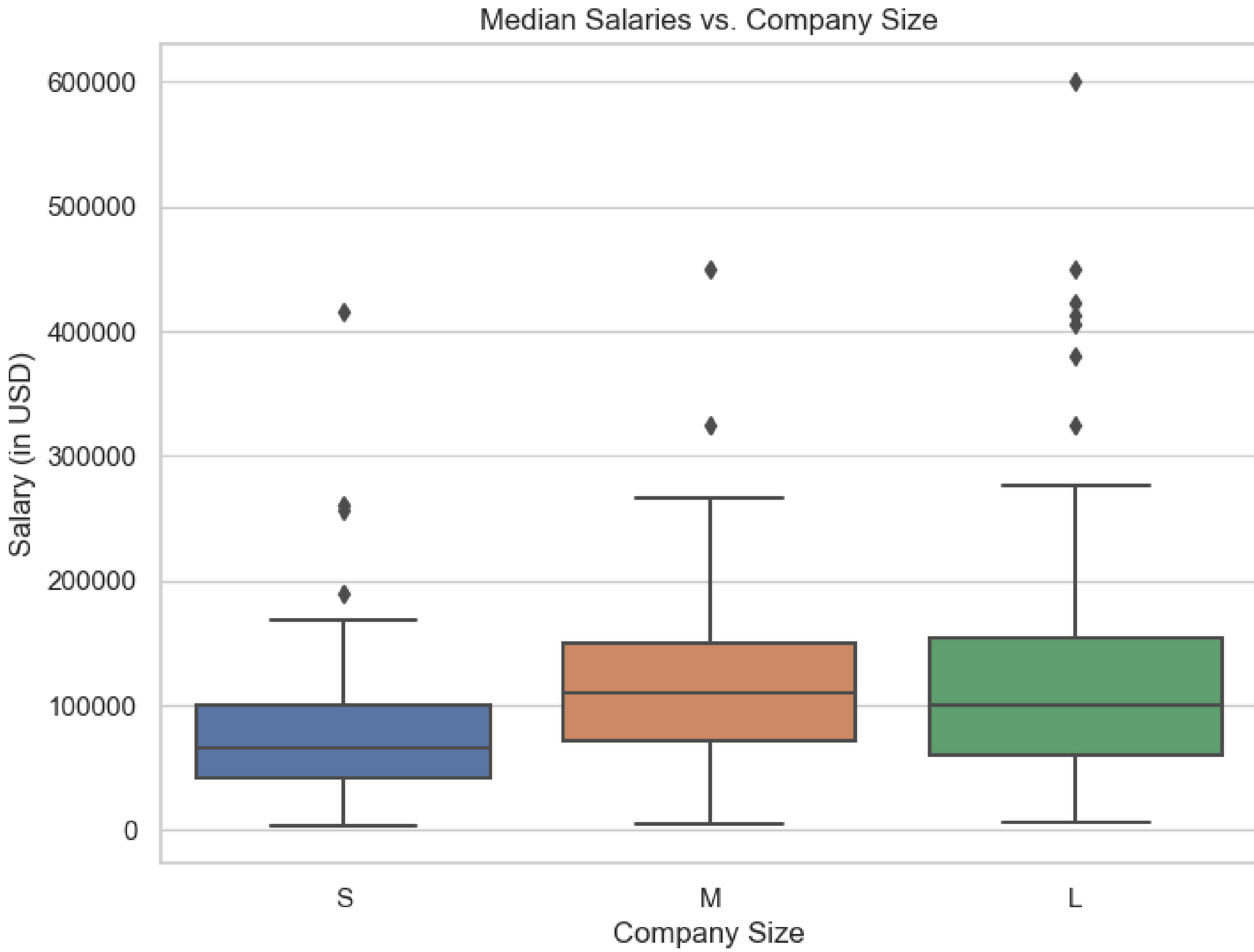


Median Salaries vs Company Size

We observe that Small companies (Small businesses or startups) pay the least, while Medium and Large organizations pay on the higher end.

This may be due to larger companies having better resources to pay their employees. There are big outliers for Large companies, and also a wider distribution in salaries as Large organizations may have a lot of employees, and compensation may depend on geographical location of the company, standard of living, etc.

In [23]:
```
sorted_size = ['S','M','L']
plt.figure(figsize=(8, 6))
sns.boxplot(data=df, x='company_size', y='salary_in_usd', order=sorted_size)
plt.title('Median Salaries vs. Company Size')
plt.xlabel('Company Size')
plt.ylabel('Salary (in USD)')
plt.show()
```



Number of Jobs vs Company Size

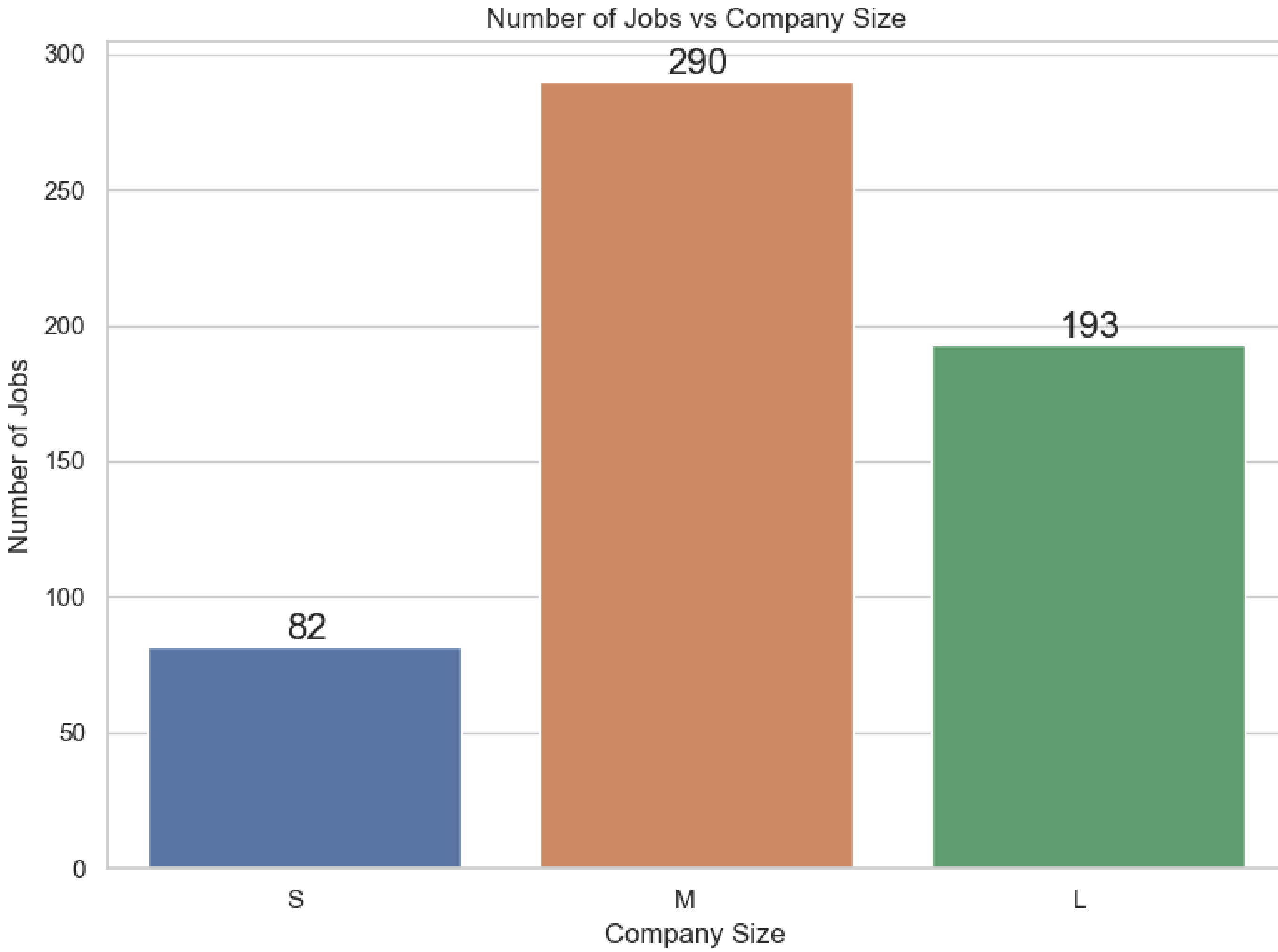
51% of the jobs in the data are employed at Medium sized companies. Out of the remaining 50%, Large corporations amount for more than double the jobs than Small businesses.

In [24]:
```
plt.figure(figsize=(8, 6))
sns.set(style="whitegrid")
ax = sns.countplot(x='company_size', data=df, order=sorted_size)

for p in ax.patches:
    ax.annotate(format(p.get_height(), '.0f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha = 'center', va = 'center',
                xytext = (1, 7),
                textcoords = 'offset points',
               fontsize=16)

plt.xlabel('Company Size')
plt.ylabel('Number of Jobs')
plt.xticks(rotation=0, ha="right")
plt.title('Number of Jobs vs Company Size')

plt.tight_layout()
plt.show()
```



Data preprocessing (2)

i)OneHotEncoding to categorical features.

ii)Normalization

In [25]:
```
threshold = 10

residence_counts = df['employee_residence'].value_counts()
residence_others = residence_counts[residence_counts < threshold].index
df['employee_residence'] = df['employee_residence'].replace(residence_others, 'Other')

location_counts = df['company_location'].value_counts()
location_others = location_counts[location_counts < threshold].index
df['company_location'] = df['company_location'].replace(location_others, 'Other')

job_title_counts = df['job_title'].value_counts()
job_title_others = job_title_counts[job_title_counts < threshold].index
df['job_title'] = df['job_title'].replace(job_title_others, 'Other')

# One-hot Encoding
df_encoded = pd.get_dummies(df, columns=['experience_level', 'employment_type', 'employe

# Feature Scaling
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df_encoded[['salary_in_usd', 'remote_ratio']] = scaler.fit_transform(df_encoded[['salary
```

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```
df_encoded.head()
```

Out[25]:

	work_year	salary_in_usd	remote_ratio	experience_level_EX	experience_level_MI	experience_level_SE	emplo
0	2020	-0.426180	-1.710815	0	1	0	
1	2020	2.068630	-1.710815	0	0	1	
2	2020	-0.021966	-0.487257	0	0	1	
3	2020	-1.254701	-1.710815	0	1	0	
4	2020	0.545437	-0.487257	0	0	1	

5 rows × 34 columns

Correlation Matrix Heatmap

In this correlation matrix,the major correlation are

*Work year and Job title

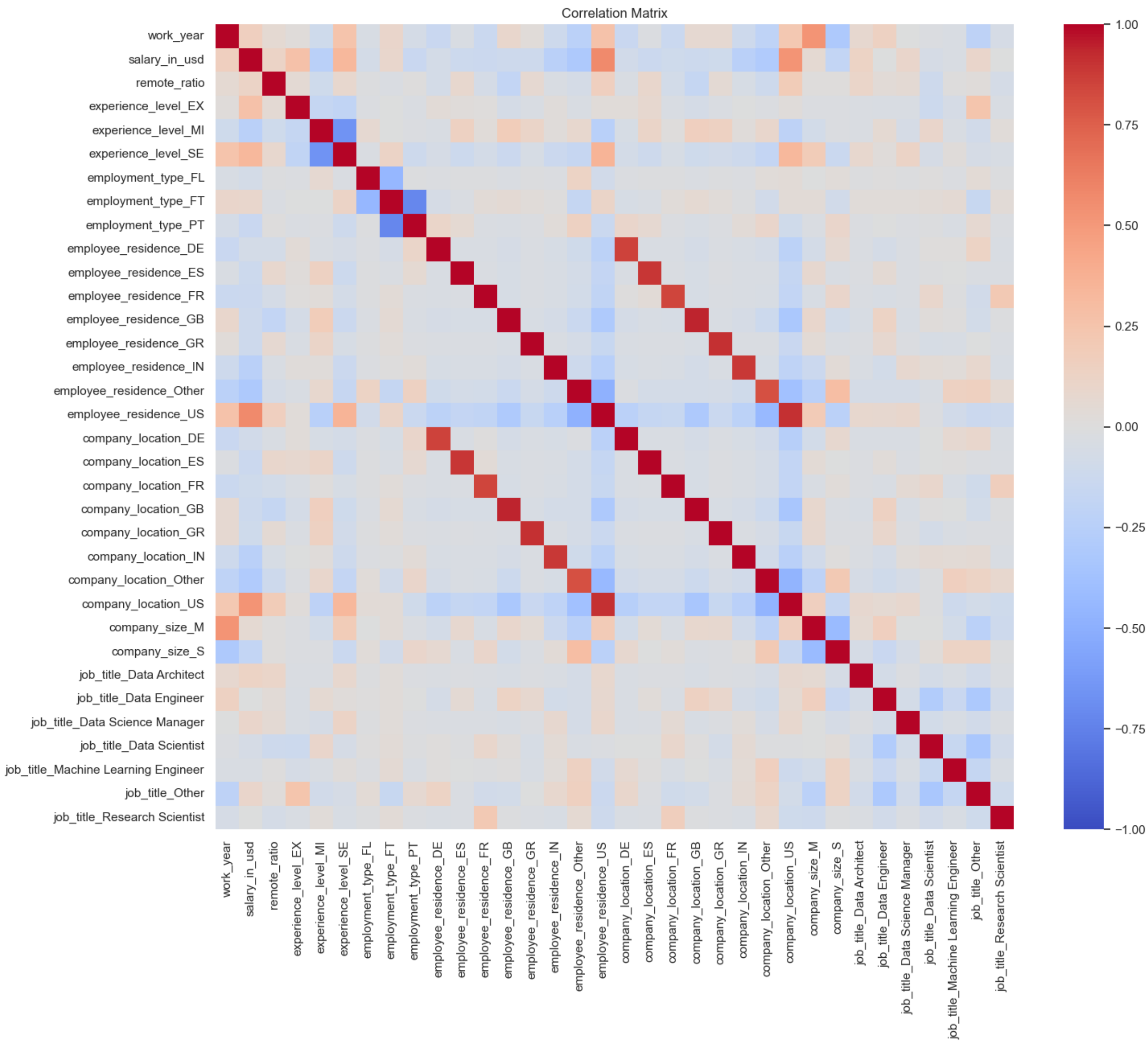
*Employee residence and company location

*salary in USD and Experience level

In [26]:

```
corr_matrix = df_encoded.corr()

plt.figure(figsize=(16, 13))
sns.heatmap(corr_matrix, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Matrix')
plt.show()
```



Data Model Building

i)Train test split

ii)LinearRegression Model

iii)Prediction

iv)Evaluation model.

In [27]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score,mean_squared_error, mean_absolute_error

# Splitting the data
X = df_encoded.drop('salary_in_usd', axis=1)
y = df_encoded['salary_in_usd']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42

# Model Training
Regression()
```

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```
lr.fit(X_train, y_train)

# Predictions
y_pred_train = lr.predict(X_train)
y_pred_test = lr.predict(X_test)

# Model Evaluation
train_rmse = mean_squared_error(y_train, y_pred_train, squared=False)
test_rmse = mean_squared_error(y_test, y_pred_test, squared=False)
train_mae = mean_absolute_error(y_train, y_pred_train)
test_mae = mean_absolute_error(y_test, y_pred_test)

train_rmse, test_rmse, train_mae, test_mae
```

Out[27]:
```
(0.6776595752484057,
 0.7314717029420559,
 0.46272119765325703,
 0.46151208953100364)
```

Using the following model :

```
i)RandomForestRegressor
ii)GradientBoostingRegressor
```

In both these models, the Test RMSE is significantly higher than Train RMSE, which indicates severe overfitting. These models need to be tweaked to get better performance. For now, we are discarding these models for the simpler, but better performing Linear Regression mode

In [28]:
```
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor

rf = RandomForestRegressor(n_estimators=100, random_state=42)
gb = GradientBoostingRegressor(n_estimators=100, random_state=42)

#Model Training
rf.fit(X_train, y_train)
gb.fit(X_train, y_train)

# Predictions
y_pred_rf_train = rf.predict(X_train)
y_pred_rf_test = rf.predict(X_test)
y_pred_gb_train = gb.predict(X_train)
y_pred_gb_test = gb.predict(X_test)

# Model Evaluation
rf_train_rmse = mean_squared_error(y_train, y_pred_rf_train, squared=False)
rf_test_rmse = mean_squared_error(y_test, y_pred_rf_test, squared=False)
rf_train_mae = mean_absolute_error(y_train, y_pred_rf_train)
rf_test_mae = mean_absolute_error(y_test, y_pred_rf_test)

gb_train_rmse = mean_squared_error(y_train, y_pred_gb_train, squared=False)
gb_test_rmse = mean_squared_error(y_test, y_pred_gb_test, squared=False)
gb_train_mae = mean_absolute_error(y_train, y_pred_gb_train)
gb_test_mae = mean_absolute_error(y_test, y_pred_gb_test)

print('rf_train_rmse:',rf_train_rmse)

(rf_train_rmse, rf_test_rmse, rf_train_mae, rf_test_mae), (gb_train_rmse, gb_test_rmse,
```

```
rf_train_rmse: 0.46384700602265205
```

Loading [MathJax]/extensions/Safe.js

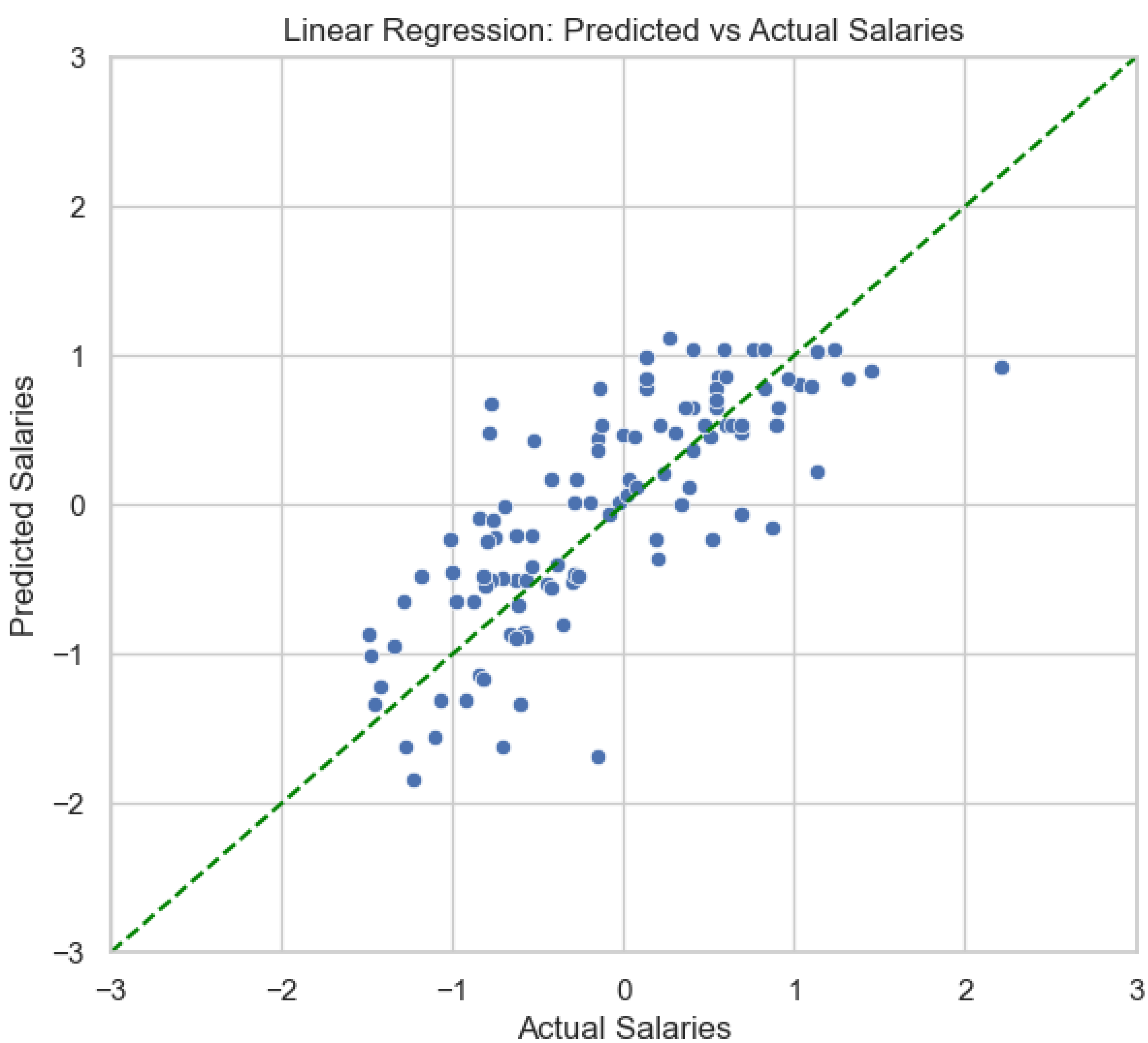
Out[28]:
```
((0.46384700602265205,
  0.7419236191072428,
  0.29347773038337793,
  0.43777438278303915),
 (0.5941441887234992,
  0.7237079289364042,
  0.4021992184392206,
  0.440993843656205))
```

Linear Regression: Predicted vs Actual Salaries

In [29]:
```
plt.figure(figsize=(15, 6))

# Plotting Predicted vs Actual Linear Regression
plt.subplot(1, 2, 1)
sns.scatterplot(x=y_test, y=y_pred_test)
plt.plot([-3, 3], [-3, 3], color='green', linestyle='--')
plt.xlabel('Actual Salaries')
plt.ylabel('Predicted Salaries')
plt.title('Linear Regression: Predicted vs Actual Salaries')
plt.xlim([-3, 3])
plt.ylim([-3, 3])
```

Out[29]:
```
(-3.0, 3.0)
```



Conclusion:

From the Exploratory Data Analysis, I have concluded that Salary in USD of the employees is dependent upon the following factors:

```
1.Job title
2.Experience level
3.Work year
```

Employees with greater year of experience ,having job title such as Data architect,Data science manager,Data engineer,Research scientist,Data Scientist, Machine Learning Engineer and Data Analyst are likely to have a higher salary.

With Machine Learning model, I have used regressor models-From the scatterplot of (Linear Regression: Predicted vs Actual Salaries). The Blue dots closest to the green line which clearly indicates that the most accurate predictions, while the dots furthest away from the green line shows the least accurate predictions.