Part I - Exploratory Analytics: Data related job salaries

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Introduction

> Introduce the dataset

The salaries dataset we will work with is from ai-jobs. Ai-jobs collects salary information anonymously from professionals all over the world in the AI/ML and Big Data space and makes it publicly available for anyone to use, share and play around with. The data is being updated regularly with new data coming in, usually on a weekly basis. The primary goal is to have data that can provide better guidance in regards to what's being paid globally. So newbies, experienced pros, hiring managers, recruiters and also startup founders or people wanting to make a career switch can make better informed decisions.

The dataset contains one table structured as follow:

- **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)

Preliminary Wrangling

In [1]:
```
# import all packages and set plots to be embedded inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

%matplotlib inline
```

> Load in your dataset and describe its properties through the questions below. Try and motivate your exploration goals through this section.

In [2]:
```
# load data from csv file
salaries_df = pd.read_csv('datasets/salaries.csv')
# write the shape of thte dataset
print( "There are {} enteries and {} variables".format(salaries_df.shape[0], salaries_df
# output random samples
salaries_df.sample(5)
```

```
There are 1332 enteries and 11 variables
```

Out[2]:

	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd	employee_re
305	2022	SE	FT	Analytics Engineer	110000	USD	110000	
489	2022	MI	FT	Data Scientist	90000	GBP	111469	
553	2022	MI	FT	Data Scientist	85000	EUR	89494	
67	2022	EN	PT	Data Analyst	125404	USD	125404	
727	2022	MI	FT	Machine Learning Engineer	75000	GBP	92891	

What is the structure of your dataset?

> The dataset contains 1332 employees' salaries for data related jobs from 2020 to 2022. 11 variables are used to record the salaries. Most variables are qualitative with both ordered and un ordered factor variables.

What is/are the main feature(s) of interest in your dataset?

> The primary goal of the data is to provide better guidance in regards to what's being paid globally. We are interested in finding which factors accounts for higher salaries and salary trends within the years.

What features in the dataset do you think will help support your investigation into your feature(s) of interest?

> We think that the most factor that influence salary is employee experience. Job title, job type, year of work and company size also affect salary but at a lower extend. But since we are not certain, we will test the correlation of salaries with the other variables (employee residence and company location).

Assessment & Cleaning

Assessment

In [3]:
```python
# Let's start by having a summary view of our table
salaries_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1332 entries, 0 to 1331
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   work_year           1332 non-null   int64 
 1   experience_level    1332 non-null   object
 2   employment_type     1332 non-null   object
 3   job_title           1332 non-null   object
 4   salary              1332 non-null   int64 
 5   salary_currency     1332 non-null   object
 6   salary_in_usd       1332 non-null   int64 
 7   employee_residence  1332 non-null   object
 8   remote_ratio        1332 non-null   int64 
 9   company_location    1332 non-null   object
 10  company_size        1332 non-null   object
dtypes: int64(4), object(7)
memory usage: 114.6+ KB
```

> We notice there is no null value in our table and columns' name contain no space. Even though we can work with the data types as they are, we will do some modifications: change experience level, company size and remote ratio to ordered-category and employment type to unordered category.

In [4]:
```python
# Verify if there are duplicates and how many they are.
# False = unique entries
# True = duplicate entries
salaries_df.duplicated().value_counts()
```

Out[4]:
```
False    1069
True      263
dtype: int64
```

In [5]:
```python
# Display the of entries for each year for both the whole dataset and the duplicates

duplicates = salaries_df[salaries_df.duplicated()]
print(salaries_df.work_year.value_counts())
duplicates.work_year.value_counts()
```

```
2022    1029
2021     228
2020      75
Name: work_year, dtype: int64
```

Out[5]:
```
2022    260
2021      2
2020      1
Name: work_year, dtype: int64
```

> Regarding the variables in our table, it is logically possible to have two or more people having the same entries. So we can't confirm if they are duplicates or distinc entries. Fortunately, most of the duplicates are found in 2022 and 2022 has the largest number of entries. We can delete the duplicates.

In [6]:
```
# Display summary statistics for numeric columns
salaries_df.describe()
```

Out[6]:

	work_year	salary	salary_in_usd	remote_ratio
count	1332.000000	1.332000e+03	1332.000000	1332.000000
mean	2021.716216	2.377124e+05	123374.658408	63.851351
std	0.562228	1.077369e+06	65945.872172	45.263587
min	2020.000000	2.324000e+03	2324.000000	0.000000
25%	2022.000000	8.000000e+04	75593.000000	0.000000
50%	2022.000000	1.300000e+05	120000.000000	100.000000
75%	2022.000000	1.751000e+05	164997.000000	100.000000
max	2022.000000	3.040000e+07	600000.000000	100.000000

Cleaning

In [7]:
```
# Copy the dataframe before working on
salaries_clean = salaries_df.copy()
```

In [8]:
```
# Function to convert datatype to categorical (ordinal and nominal)
def to_category(var: str, ordered: bool, df: pd.DataFrame, categories: list):
    """ Converts type to category
            parameters:
            var: string, the name of the column to convert type
            ordered: boolean, If false, then the categorical is treated as unordered
            df: dataframe,
            categories: the ordered list of the category

            return: the converted series

    """
    # Note: based on the pandas version, you need to code differently
    pd_ver = pd.__version__.split(".")
    if (int(pd_ver[0]) > 0) or (int(pd_ver[1]) >= 21): # v0.21 or later
        classes = pd.api.types.CategoricalDtype(ordered = ordered, categories = categori
        df[var] = df[var].astype(classes)
    else: # pre-v0.21
        df[var] = df[var].astype('category', ordered = ordered,categories = categories)
    return df[var]
```

In [9]:
```
# Create category type
experience = ['EN', 'MI', 'SE', 'EX']
company = ['S', 'M', 'L']
employment_type = ['PT', 'FT', 'CT', 'FL']
remote = [0, 50, 100]
year = [2020, 2021, 2022]

salaries_clean['experience_level'] = to_category('experience_level', True, salaries_clea
salaries_clean['company_size'] = to_category('company_size', True, salaries_clean, compa
salaries_clean['employment_type'] = to_category('employment_type', False, salaries_clean
```

```
salaries_clean['remote_ratio'] = to_category('remote_ratio', True, salaries_clean, remot
salaries_clean['work_year'] = to_category('work_year', True, salaries_clean, year)

# Test types were converted. Dtype should be category
salaries_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1332 entries, 0 to 1331
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype   
---  ------              --------------  -----   
 0   work_year           1332 non-null   category
 1   experience_level    1332 non-null   category
 2   employment_type     1332 non-null   category
 3   job_title           1332 non-null   object  
 4   salary              1332 non-null   int64   
 5   salary_currency     1332 non-null   object  
 6   salary_in_usd       1332 non-null   int64   
 7   employee_residence  1332 non-null   object  
 8   remote_ratio        1332 non-null   category
 9   company_location    1332 non-null   object  
 10  company_size        1332 non-null   category
dtypes: category(5), int64(2), object(4)
memory usage: 69.9+ KB
```

In [10]:

```
# Delete duplicates and reset index
salaries_clean.drop_duplicates(inplace= True, ignore_index=True)
```

In [11]:

```
# Test duplicates were deleted. result should be 0
salaries_clean.duplicated().sum()
```

Out[11]:

```
0
```

In [12]:

```
salaries_clean.shape
```

Out[12]:

```
(1069, 11)
```

In [13]:

```
# Save the cleaned data in a csv file
salaries_clean.to_csv('datasets/salaries_master.csv', index=False)
```

We are done with the assessment and cleaning. Next, we will start ploting our visualizations

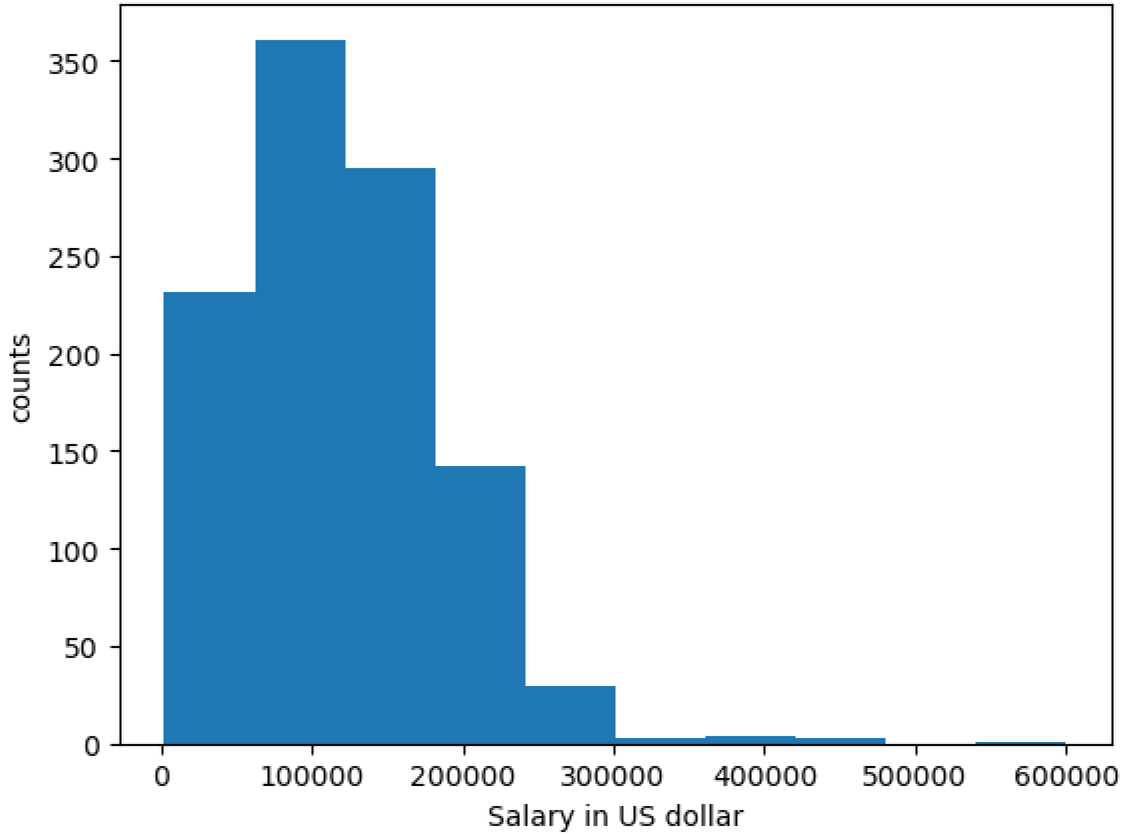
Univariate Exploration

Question: What is the distribution of salaries?

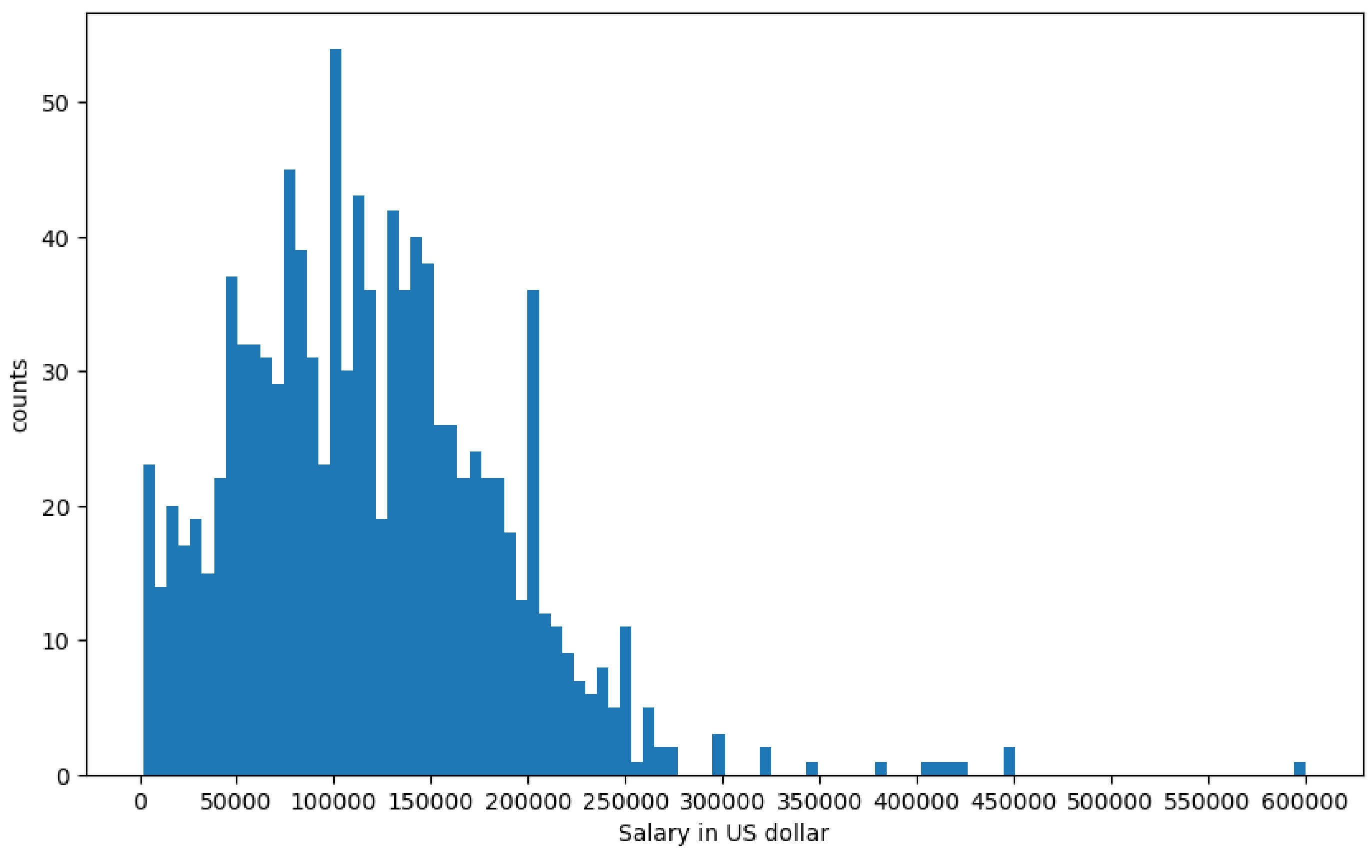
We will start with our main variabble of interest; salary. For uniformity in currency, we will exclusively work only with salaries in US dollar.

In [14]:

```
plt.hist(data=salaries_clean, x='salary_in_usd')
plt.xlabel('Salary in US dollar')
plt.ylabel('counts')
plt.show()
```



In [15]:
```
plt.figure(figsize = [10, 6])
xticks = [0, 50000, 100000, 150000, 200000, 250000, 300000, 350000, 400000, 450000, 5000
plt.hist(data=salaries_clean, x='salary_in_usd', bins = 100)
plt.xticks(xticks)
plt.xlabel('Salary in US dollar')
plt.ylabel('counts');
```



Observation: As we could predict, salary has a right-skewed distribution. When the number of bins are increased, the distribution is made up of peaks with the highest around 100000 dollars and steep jumps. The discontinuity above 285000 dollars on the graph emphasizes the gap or difference between top salaries and others in the data science industry.

Let's have a closer look at these top salaries which create discontinuity in the distribution.

In [16]:
```
# collect rows with salaries on the right of the graph
discontinous_salaries = salaries_clean[salaries_clean.salary_in_usd > 275000]
print(discontinous_salaries.shape)
discontinous_salaries.sort_values(by='salary_in_usd', ascending=False)
```

```
(15, 11)
```

Out[16]:

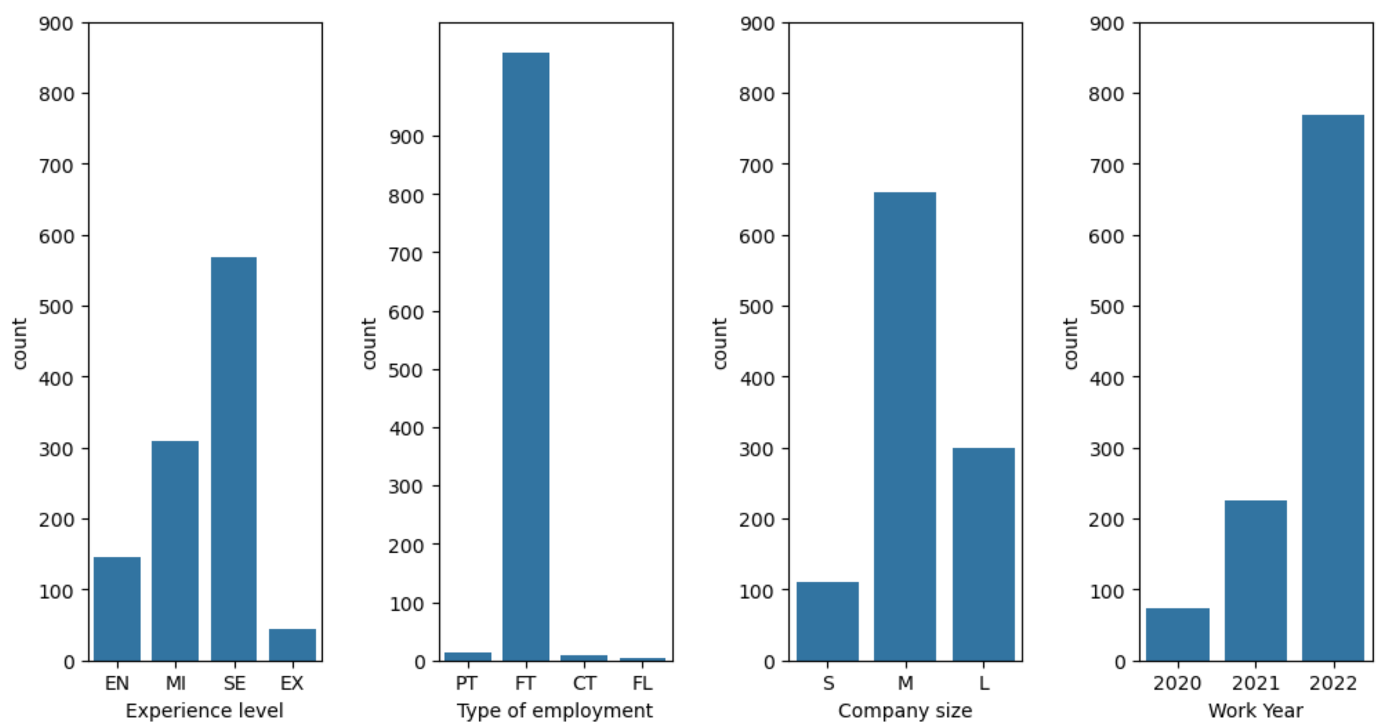
	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd	employee_r
1016	2021	EX	FT	Principal Data Engineer	600000	USD	600000	
832	2020	MI	FT	Research Scientist	450000	USD	450000	
889	2021	MI	FT	Financial Data Analyst	450000	USD	450000	
1061	2021	MI	FT	Applied Machine Learning Scientist	423000	USD	423000	
987	2021	EX	CT	Principal Data Scientist	416000	USD	416000	
1064	2020	SE	FT	Data Scientist	412000	USD	412000	
773	2022	SE	FT	Data Analytics Lead	405000	USD	405000	
778	2022	SE	FT	Applied Data Scientist	380000	USD	380000	
112	2022	SE	FT	Data Architect	345600	USD	345600	
1010	2020	EX	FT	Director of Data Science	325000	USD	325000	
726	2022	EX	FT	Data Engineer	324000	USD	324000	
68	2022	SE	FT	Data Engineer	300000	USD	300000	
544	2022	SE	FT	Data Science Manager	300000	USD	300000	
305	2022	EX	FT	Data Engineer	297500	USD	297500	
893	2021	SE	FT	Lead Data Engineer	276000	USD	276000	

The entries are pretty similar. These data should be correct.

Question: What is the distribution of employee's experience, type of employment and company size?

All two (2) variables are qualitative, ordinal values. We will use bar chart to visualize their distribution.

In [17]:
```
# let's plot all three together to get an idea of each categorical variable's distributi

fig, ax = plt.subplots(ncols=4, figsize = [12,6])
yticks = [0, 100, 200, 300, 400, 500, 600, 700, 800, 900]
default_color = sb.color_palette()[0]
sb.countplot(data = salaries_clean, x = 'experience_level', color = default_color, ax =
ax[0].set_yticks(yticks)
sb.countplot(data = salaries_clean, x = 'employment_type', color = default_color, ax = a
ax[1].set_yticks(yticks)
sb.countplot(data = salaries_clean, x = 'company_size', color = default_color, ax = ax[2
ax[2].set_yticks(yticks)
sb.countplot(data = salaries_clean, x = 'work_year', color = default_color, ax = ax[3]).
ax[3].set_yticks(yticks)
plt.subplots_adjust(wspace=0.5)
plt.show()
```



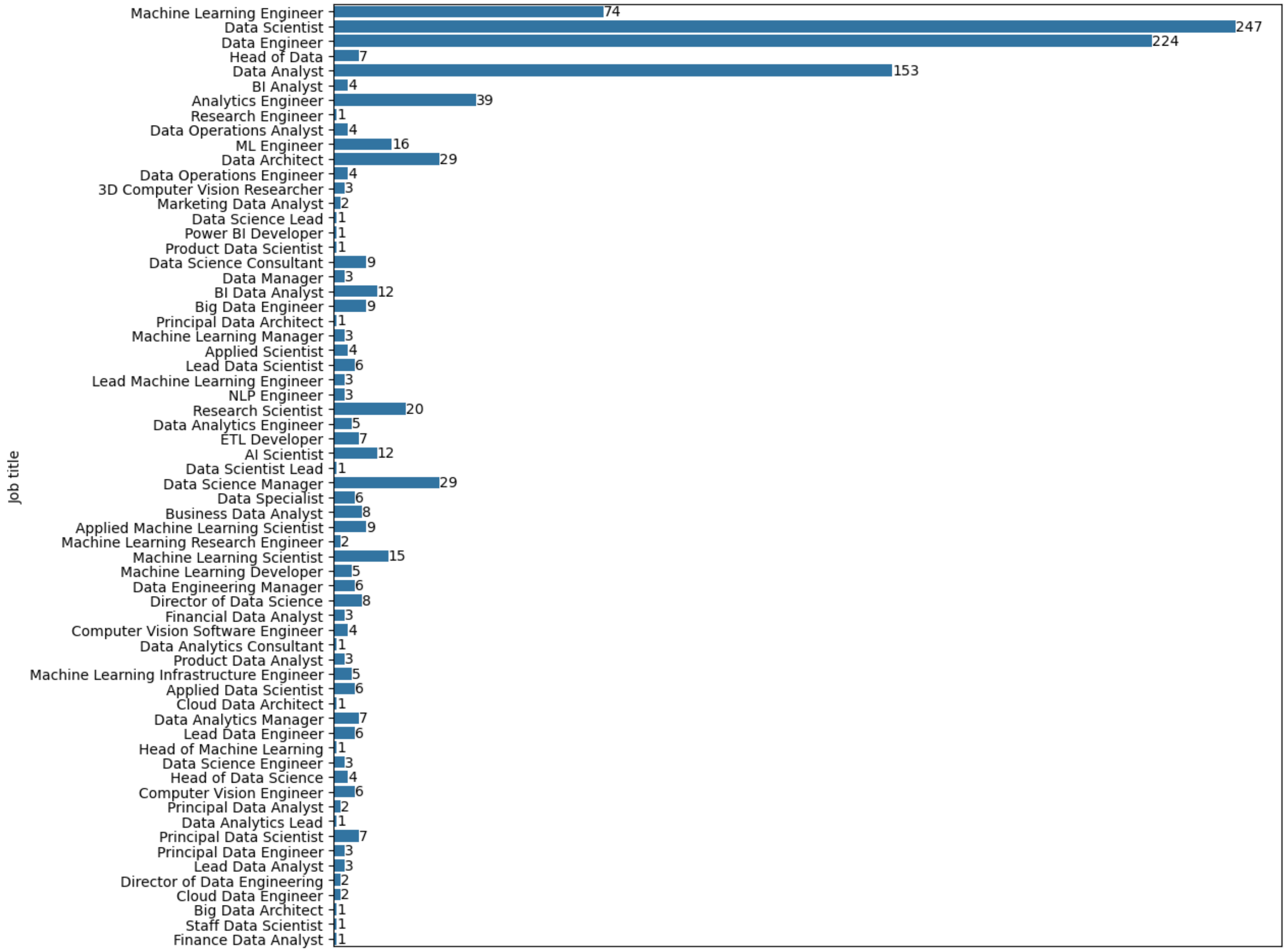
Observation: The dataset contains mostly employees with senior-level/expert experience level. Almost all the employees have a full time job. Most employees work in a medium-size company. The majority of the salaries were paid on 2022.

Question: What is the distribution of Job title?

Finally, let's look at the distribution of job title over our dataset.

In [18]:
```
plt.figure(figsize=[12,12])
ax_job = sb.countplot(data=salaries_clean,color=default_color, y='job_title')
ax_job.axes.get_xaxis().set_visible(False)
ax_job.bar_label(ax_job.containers[0])
```

```
plt.ylabel('Job title')
plt.show()
```

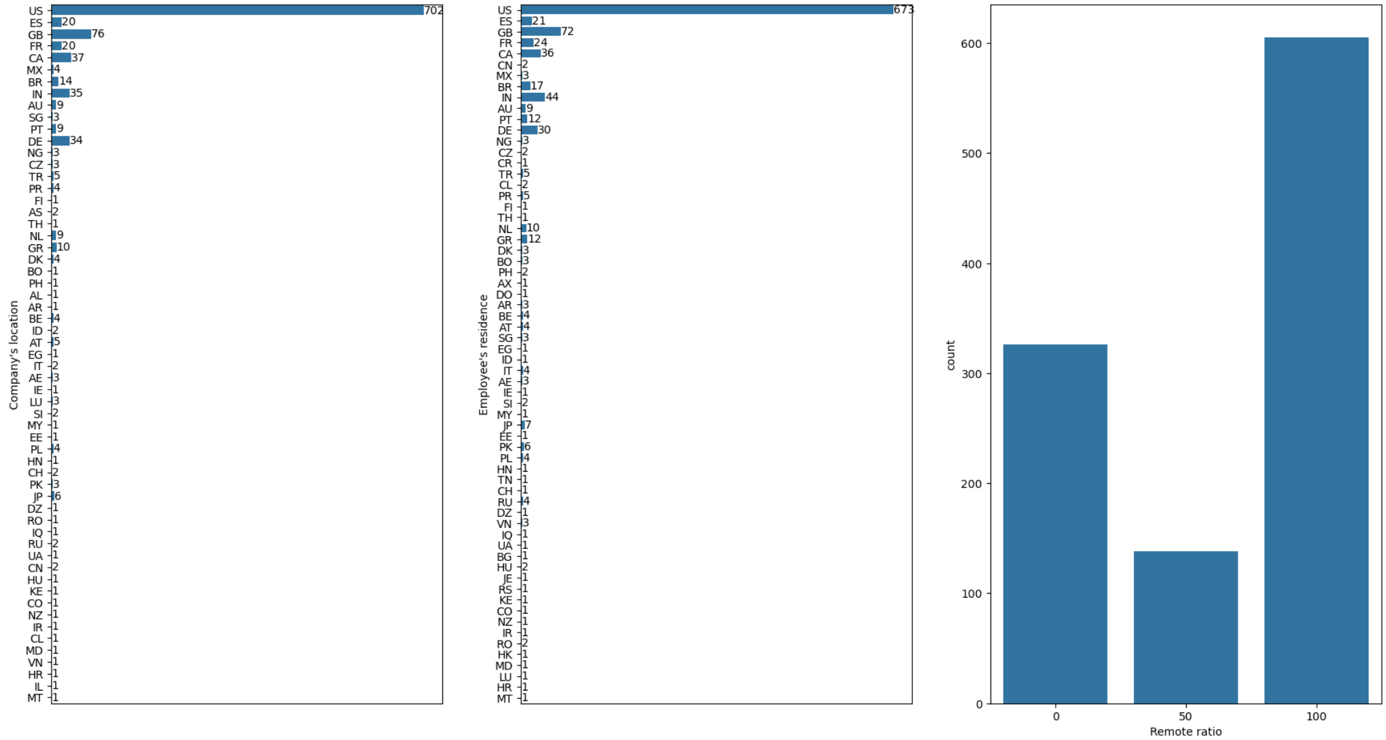


Observation: The top five roles in descending order are:

1. Data Scientist - 247
2. Data Engineer - 224
3. Data Analyst - 153
4. Machine Learning Engineer - 74
5. Analytics Engineer - 39

Before moving to the next section let's have a look on the distribution of the other variables (company location, employee residence and remote ration)

In [19]:
```
# let's plot all three together to get an idea of each ordinal variable's distribution.

fig, ax = plt.subplots(ncols=3, figsize = [8,8])
default_color = sb.color_palette()[0]
sb.countplot(data = salaries_clean, y = 'company_location', color = default_color, ax =
ax[0].axes.get_xaxis().set_visible(False)
ax[0].bar_label(ax[0].containers[0])
sb.countplot(data = salaries_clean, y = 'employee_residence', color = default_color, ax
    ylabel="Employee's residence")
ax[1].axes.get_xaxis().set_visible(False)
ax[1].bar_label(ax[1].containers[0])
sb.countplot(data = salaries_clean, x = 'remote_ratio', color = default_color, ax = ax[2
plt.subplots_adjust(right=2.2, top=1.2)
plt.show()
```



Observation: Companies and employees have the same top five countries: USA, Great Britain, India, Canada and Germany. Most of the jobs are remote

Discuss the distribution(s) of your variable(s) of interest. Were there any unusual points? Did you need to perform any transformations?

> The salary variable has a right-skewed distribution. Salaries concentrate on the low end of the graph as there are more jobs with low wages than higher wages. After increasing the number of bins, the distribution is made up of peaks with the highest around 100000 dollars and steep jumps. The discontinuity above 285000 dollars on the graph emphasizes the gap or difference between top salaries and others in the data science industry. We were concerned about discontinuous points on the graph, but after a deeper look, we concluded that they were correct.

Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

> All features under investigation had usual distributions. We changed the data type of some features for data quality reason and make sure only desired operations can be performed on the data. We changed experience level, company size and remote ratio to ordered-category variables and employment type to an unordered category variable.

Bivariate Exploration

In this section, we investigate relationships between pairs of variables we used in the previous section.

Question: What is the correlation between salary and categorical variables?

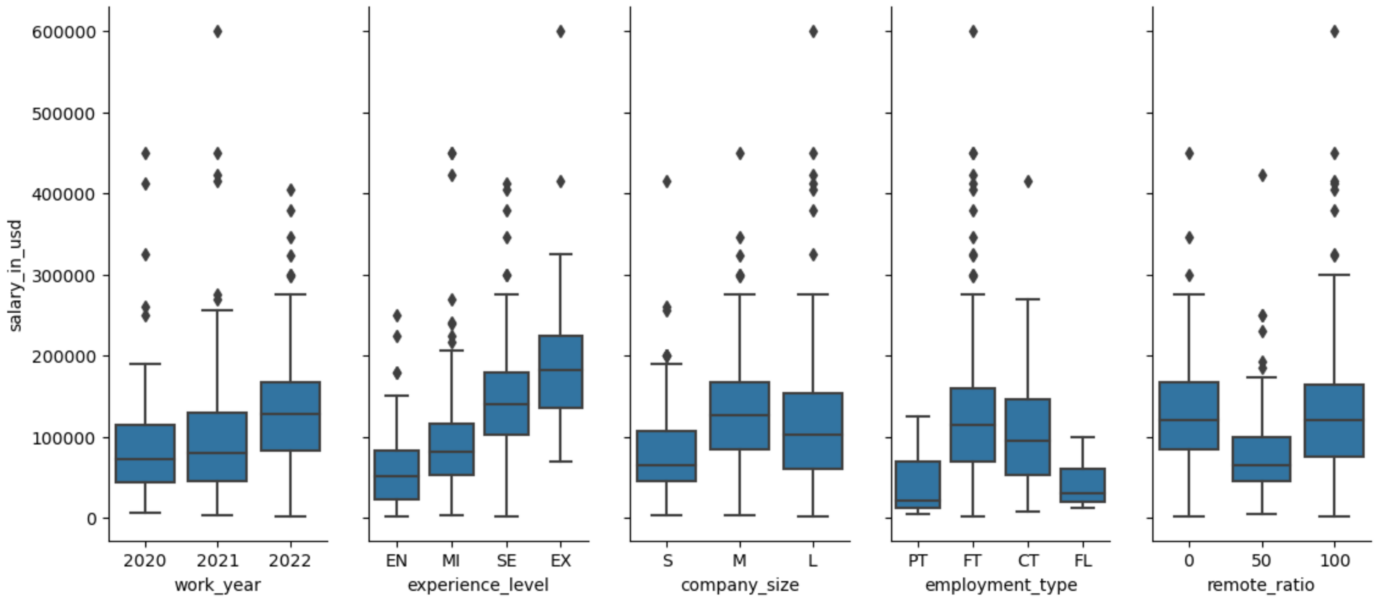
The categorical variables here are variables with a very limited number of possible values they can take. These variables are: experience_level, company_size, employment_type, remote_ratio.

In [20]:
```
# List of categorical variable
lim_categoric_vars = ['work_year', 'experience_level', 'company_size', 'employment_type'
categoric_vars = ['company_location', 'employee_residence', 'job_title']
```

In [21]:
```
def boxgrid(x, y, **kwargs):
    """ Creating box plots with seaborn's PairGrid. """
    default_color = sb.color_palette()[0]
    sb.boxplot(x=x, y=y, color = default_color)
```

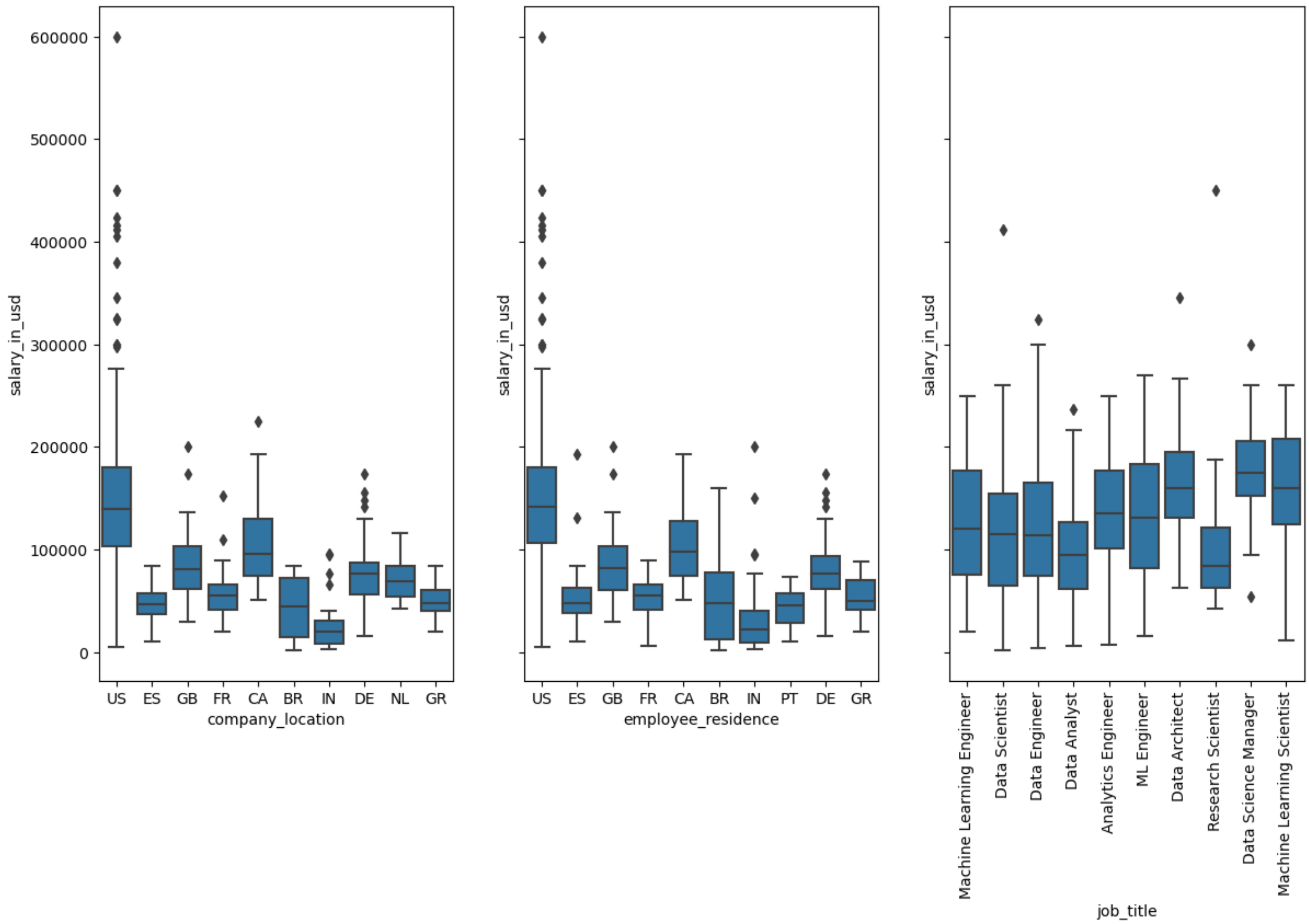
In [22]:
```
# plot matrix of salary in US dollar against categorical features.
plt.figure(figsize = [10, 10])
g = sb.PairGrid(data = salaries_clean, y_vars = ['salary_in_usd'], x_vars = lim_categori
g.map(boxgrid)
g.fig.set_size_inches(8,6)
plt.subplots_adjust(right=1.35)
plt.show();
```

```
<Figure size 1000x1000 with 0 Axes>
```



Observation: Salaries have globally increasing through years. As expected salaries increases with an increase in experience. Medium companies turn to pay higher average wages than any other company but large companies have more outliers with high wages. Complete remote and onsite jobs turn to have higher wages than patial remote jobs. Among the three categorical variables, experience level has the strongest correlation with salary.

In [23]:
```
fig, ax = plt.subplots(ncols=3, figsize = [8,8], sharey=True)
count = 0
# loop through qualittive values with too many values to select top 10 and plot a box pl
for var in categoric_vars:
    z = salaries_clean[var].value_counts().head(10)
    #print(salaries_clean[salaries_clean[var].apply(lambda x: x in z.index)])
    sb.boxplot(data = salaries_clean[salaries_clean[var].apply(lambda x: x in z.index)],
               x = var, y = "salary_in_usd", ax = ax[count])
    count+= 1

ax[count-1].tick_params(axis='x', rotation=90)
plt.subplots_adjust(right=1.5)
```



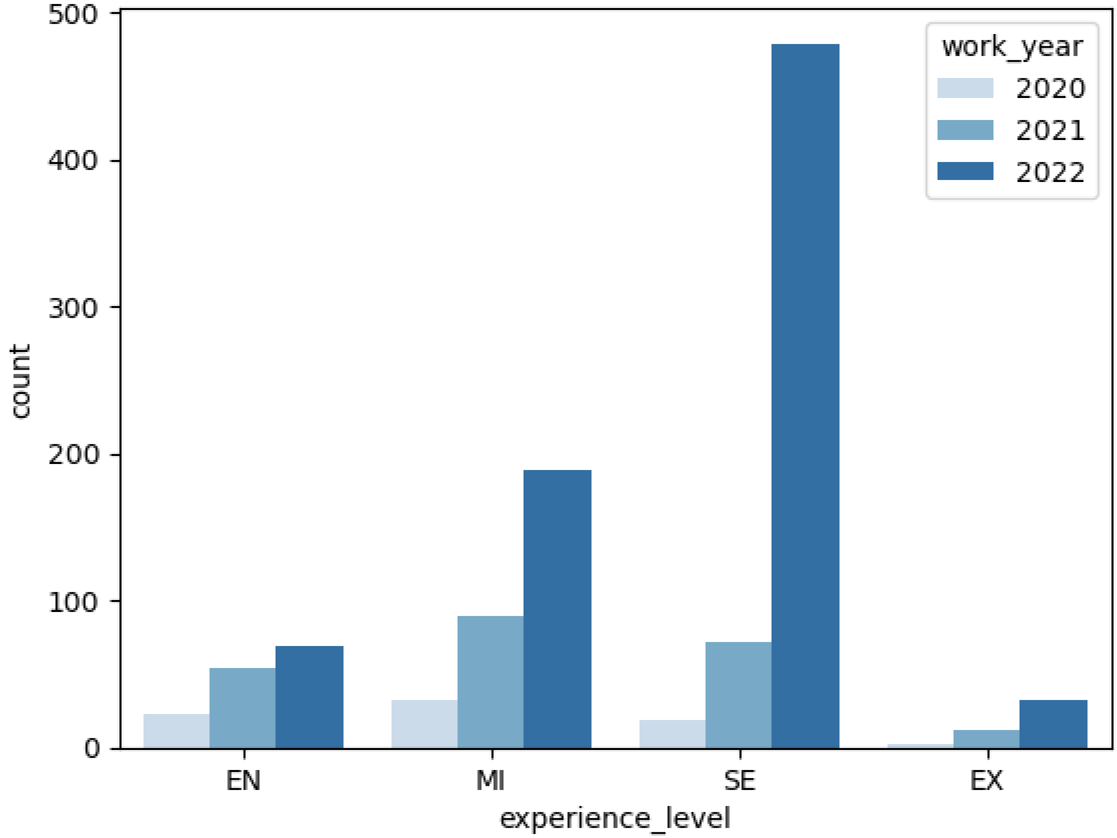
Observation: Companies in the united states of America (USA) offer the highest wages. Employees living in USA are better paid than those in any other country. The correlation between the job role and the salary is weak.

Question: What are the relationships between categorical variables?

It will be cumbersome to plot the relationships between all the 8 variables. I will choose relationships we beleive important for our initial question; which factor greatly influence the salary of a worker and the trend with the years.

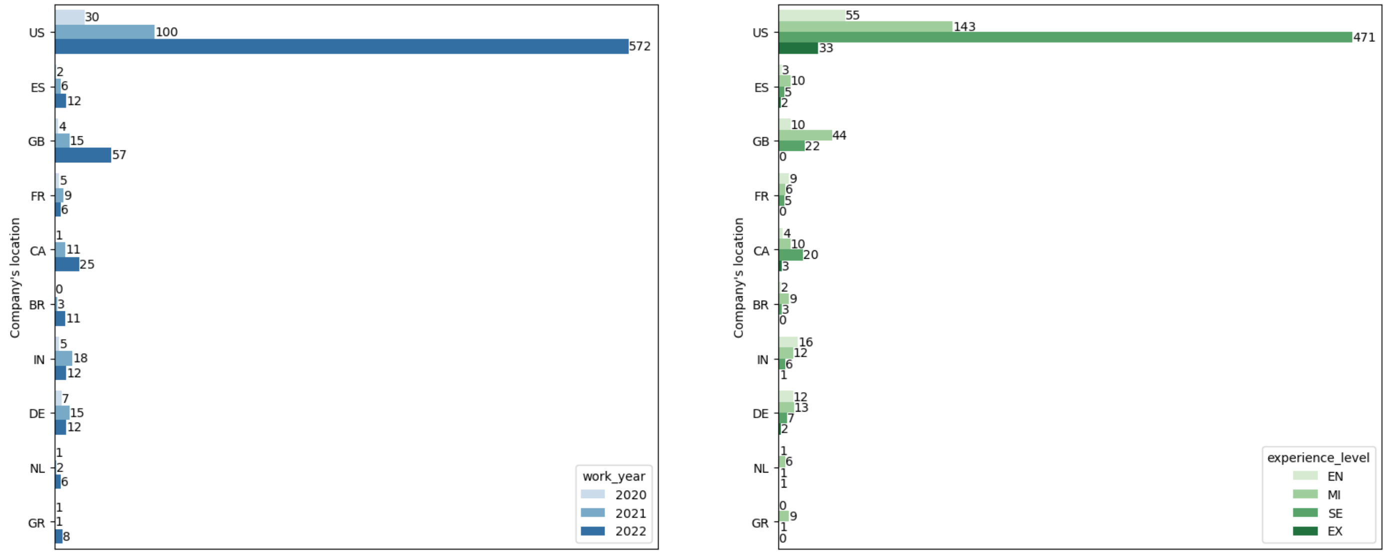
From the above relations with salary, experience level, company location, work year have a faily strong relationship with salary.

In [24]:
```
# since there's only three subplots to create, using the full data should be fine.
#plt.figure(figsize = [8,8])
# work year vs experience level
sb.countplot(data = salaries_clean, x = 'experience_level', hue = 'work_year', palette =
plt.show()
```



In [25]:

```
# We will consider the top 10 because above the number companies are too small
z = salaries_clean['company_location'].value_counts().head(10)
company_10 = salaries_clean[salaries_clean['company_location'].apply(lambda x: x in z.in
fig, ax = plt.subplots(ncols=2, figsize = [8,8])

# subplot 1: company location vs work year
sb.countplot(data = company_10, y = 'company_location', hue = 'work_year', palette = 'Bl
             ax = ax[0]).set(ylabel="Company's location")
ax[0].axes.get_xaxis().set_visible(False)
for x in range(len(ax[0].containers)):
    ax[0].bar_label(ax[0].containers[x])

# subplot 2: company location vs experience level
sb.countplot(data = company_10, y = 'company_location', hue = 'experience_level', palett
             ax = ax[1]).set(ylabel="Company's location")
ax[1].axes.get_xaxis().set_visible(False)

for x in range(len(ax[1].containers)):
    ax[1].bar_label(ax[1].containers[x])

plt.subplots_adjust(right=2)


plt.show()
```



Observation: There is an increase in the experience level over years with a boom on senio-level/expert. Globally, there is an increase in the number of companies in every country over years with a peak in US. Companies employ mostly senior-level/expert and mid-level/intermediate.

Talk about some of the relationships you observed in this part of the investigation. How did the feature(s) of interest vary with other features in the dataset?

> As expected, there is a strong correlation between salary and the experience level of the employee. The box plot of salary against the experience level looks like linear relationship. It was interestly surprising to see that medium companies turn to pay better salaries than large companies

Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

> The company's location have insignificant correlation with the expeience level. So no further exploration. A positive corrolation between experience level and work year. The experience level that seems to have much influence on salary turns to be influence by the work year. In the section below we will have a deeper look on the relation between this three variables.

Multivariate Exploration

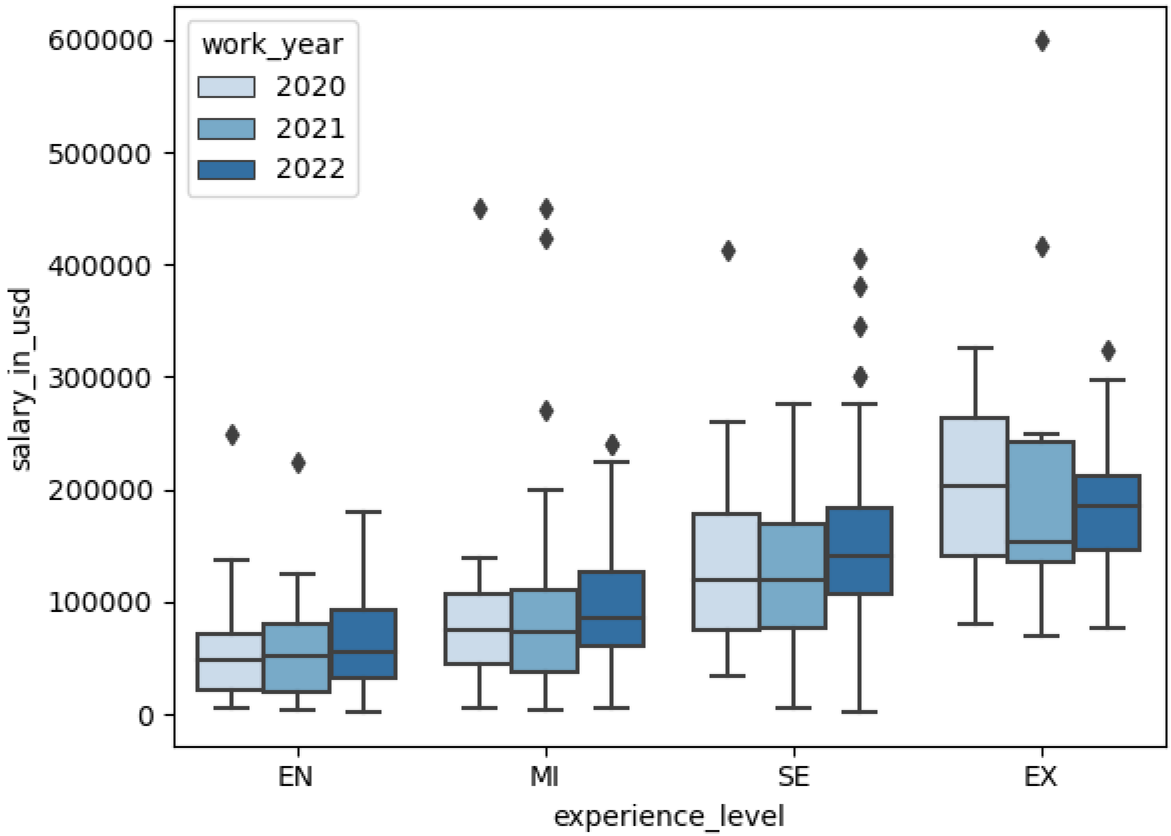
> Salary, experience level and work year have an interesting relationship that we want to explore further.

Question: What is the relationship between salary, experience and work year?

Let's look at how Salary, experience and work year are related.

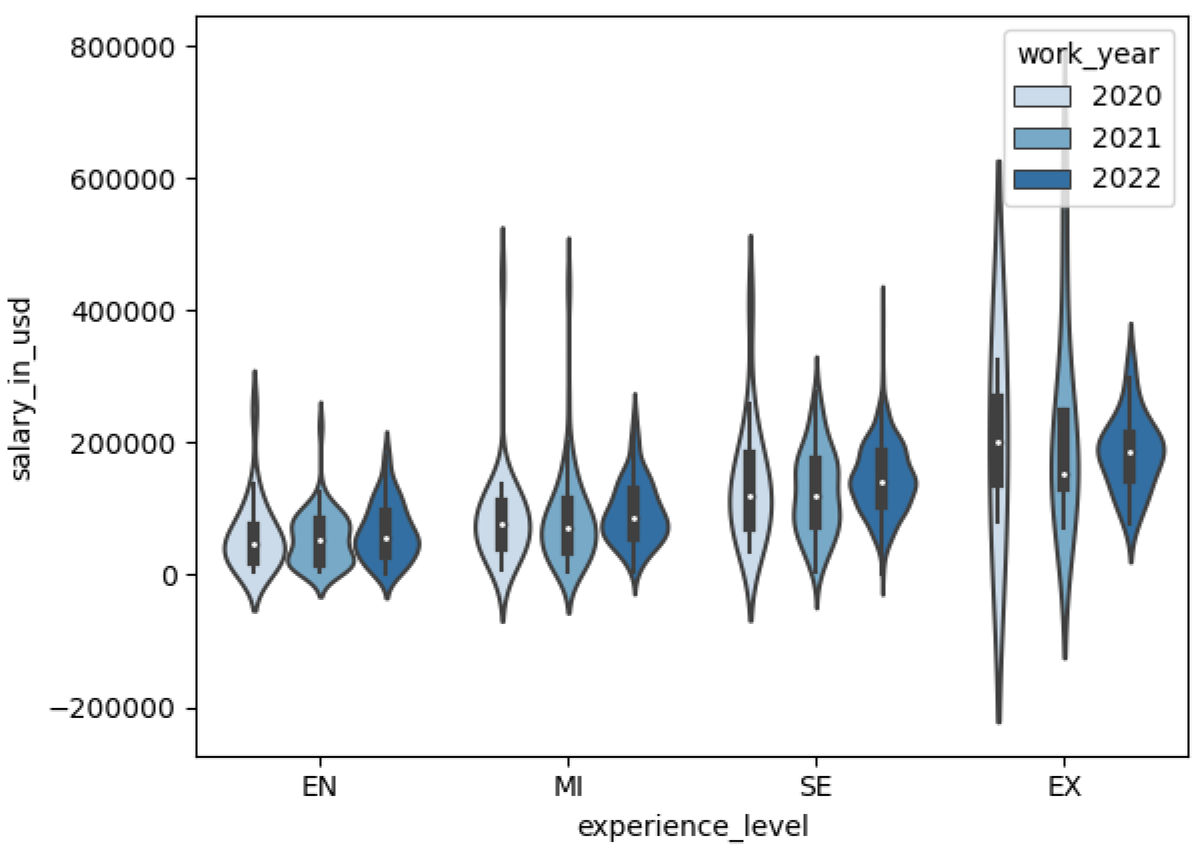
In [26]:

```
# plot matrix of salary in US dollar against categorical features.
sb.boxplot(data = salaries_clean, y = 'salary_in_usd', x = 'experience_level', hue='work
plt.show();
```



In [27]:

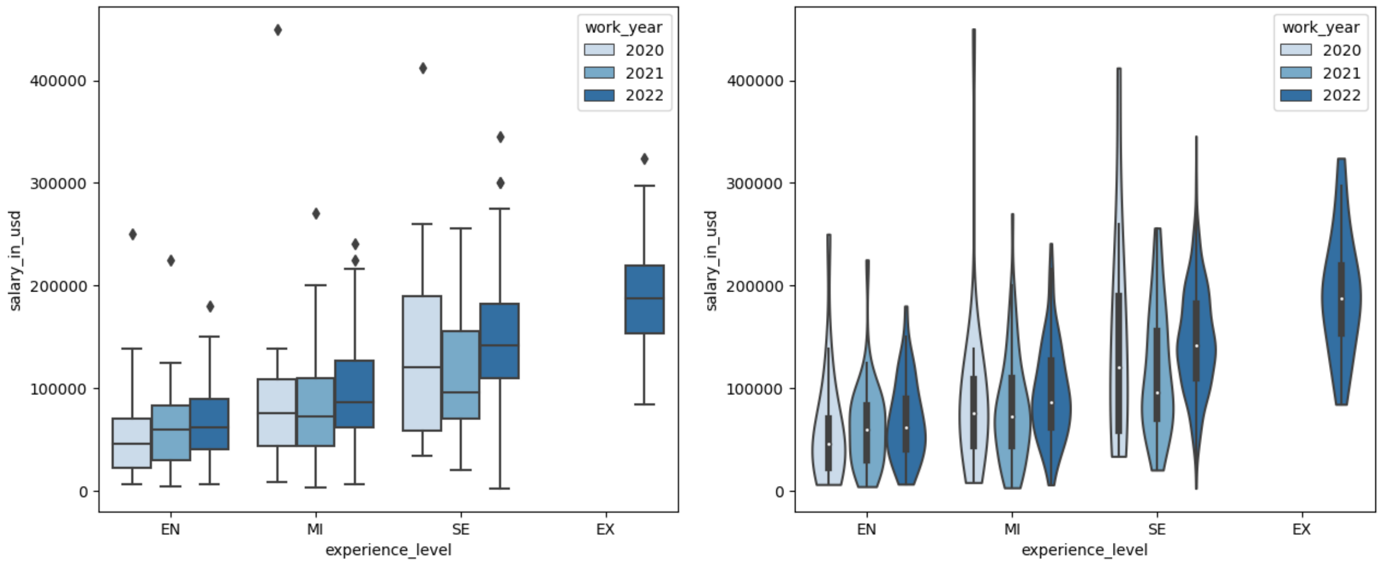
```
# plot matrix of salary in US dollar against categorical features.
sb.violinplot(data = salaries_clean, y = 'salary_in_usd', x = 'experience_level', hue='w
plt.show();
```



Observation: From the box plot it is difficult to clearly see the changes between salary and experience level over year, especially for 2020 and 2021. With the propability density on the violin plot, we notice that for each experience level, the probability density increases over years.

Let's consider only the top 10 jobs which make 79.14% of our cleaned data. This will held reduce the noice on the plots.

In [28]:
```
z = salaries_clean['job_title'].value_counts().head(10)
job_10 = salaries_clean[salaries_clean['job_title'].apply(lambda x: x in z.index)]


fig, ax = plt.subplots(ncols = 2, figsize = [12,6])
sb.boxplot(data = job_10, y = 'salary_in_usd', x = 'experience_level', hue='work_year',
sb.violinplot(data = job_10, y = 'salary_in_usd', x = 'experience_level', hue='work_year
plt.subplots_adjust(right=1.1)
plt.show();
```



Outliners have reduce and we have a better perception on changes over years. For the top job titles in the data set, Executive-level / Director exist only for 2022.

Let's have a look on the Executive-level / Director jobs

In [29]:
```
Ex_exp = job_10[job_10['experience_level'].str.contains('EX')]
Ex_exp.job_title.value_counts()
```

Out[29]:
```
Data Engineer                8
Analytics Engineer           6
Data Science Manager         4
Machine Learning Scientist   2
Data Analyst                 2
Research Scientist           1
Name: job_title, dtype: int64
```

Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest?

> Among all the features only experience level and work year turn to have a pretty strong relationship with salaries. When we looked at the correlation bewteen the experience level and the work year, we found that the count of each experience level value increases over year with a boom in 2022 for senior-level.

Were there any interesting or surprising interactions between features?

> Regarding the strong correlation between work year and experience level, and experience level with salary, we thought when placing the three features on a single plot we will have an easy-to-read strong relationship.

Conclusions

> We found that among our features, experience has the strongest positive relationship with salary. Experience itself is influence by the work year. When the three features are plotted on a single graph, it is difficult to percieve the relationship. Maybe with a larger dataset the