WileyWinters_Week6_Assignment

February 23, 2024

0.0.1 Week 6 Assignment

- Wiley Winters
- MSDS 670 — Data Visualization
- 25-FEB-2024

0.0.2 Dataset Information

Dataset: Jobs and Salaries in Data Science Metadata: - `work_year`: Year in which data was recorded. - `job_title`: Specific title of the job role. - `job_category`: Classification of the job role into broader categories for easier analysis - `salary_currency`: Currency in which the salary is paid - `salary`: Annual gross salary of the role in the local currency - `salary_in_usd`: Annual gross salary in USD - `employee_residence`: Country of residence - `experience_level`: Classifies the professional experience level of the employee - `employment_type`: Specifies the type of employment such as *full-time*, *part-time*, *contract*, *etc* - `work_setting`: Work setting or environment such as *remote*, *in-person*, or *hybrid* - `company_location`: Country where the company is located - `company_size`: Size of the employer company categorized as *small (S)*, *medium (M)*, and *large (L)*

Formal Reference to Dataset

Qaasim, H. (2023, December). Jobs and Salaries in Data Science. Version 6. Retrieved December 25, 2023 from https://www.kaggle.com/datasets/hummaamqaasim/jobs-in-data/data

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Import required packages and libraries. Set global configuration items.

[1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as mtick
from matplotlib import rcParams
import numpy as np

# Suppress Warnings
import warnings
warnings.filterwarnings('ignore')

# Set seaborn style and autoconfig
```

```
sns.set_style('whitegrid')
rcParams.update({'figure.autolayout': True})
```

Read dataset into a Pandas DataFrame

[2]:
```
jobs_df = pd.read_csv('../data/jobs_in_data.csv')
jobs_df.sample(5)
```

[2]:
```
      work_year                  job_title               job_category  \
3193       2023              Data Engineer           Data Engineering
5850       2023             Data Scientist  Data Science and Research
1981       2023             Data Scientist  Data Science and Research
3966       2023             Data Scientist  Data Science and Research
8825       2022  Machine Learning Engineer    Machine Learning and AI

     salary_currency  salary  salary_in_usd employee_residence  \
3193             USD  105700         105700      United States
5850             USD  160000         160000      United States
1981             USD  185000         185000      United States
3966             USD  143250         143250      United States
8825             USD  164996         164996      United States

     experience_level employment_type work_setting company_location  \
3193           Senior       Full-time    In-person    United States
5850           Senior       Full-time    In-person    United States
1981           Senior       Full-time    In-person    United States
3966           Senior       Full-time    In-person    United States
8825           Senior       Full-time    In-person    United States

     company_size
3193            L
5850            M
1981            M
3966            M
8825            M
```

[3]:
```
jobs_df.describe().T
```

[3]:
```
                count           mean           std      min       25%  \
work_year      9355.0    2022.760449      0.519470   2020.0    2023.0
salary         9355.0  149927.981293  63608.835387  14000.0  105200.0
salary_in_usd  9355.0  150299.495564  63177.372024  15000.0  105700.0

                    50%       75%       max
work_year        2023.0    2023.0    2023.0
salary         143860.0  187000.0  450000.0
salary_in_usd  143000.0  186723.0  450000.0
```

The dataset covers years from 2020 to 2023. In order to not double count some values. I will only work with 2023 data

Check some basic items to see if the dataset requires cleaning or not

[4]:
```
print(jobs_df.info())
print('\nNaN Values:\n', jobs_df.isna().sum())
print('\nDuplicates: ', jobs_df.duplicated().sum())
print('\nSize: ', jobs_df.size)
print('\nDistribution:\n', jobs_df.describe().T)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9355 entries, 0 to 9354
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   work_year           9355 non-null   int64 
 1   job_title           9355 non-null   object
 2   job_category        9355 non-null   object
 3   salary_currency     9355 non-null   object
 4   salary              9355 non-null   int64 
 5   salary_in_usd       9355 non-null   int64 
 6   employee_residence  9355 non-null   object
 7   experience_level    9355 non-null   object
 8   employment_type     9355 non-null   object
 9   work_setting        9355 non-null   object
 10  company_location    9355 non-null   object
 11  company_size        9355 non-null   object
dtypes: int64(3), object(9)
memory usage: 877.2+ KB
None

NaN Values:
 work_year             0
job_title              0
job_category           0
salary_currency        0
salary                 0
salary_in_usd          0
employee_residence     0
experience_level       0
employment_type        0
work_setting           0
company_location       0
company_size           0
dtype: int64

Duplicates:  4014
```

```
Size:  112260

Distribution:
                 count           mean           std      min       25%  \
work_year       9355.0    2022.760449      0.519470   2020.0    2023.0
salary          9355.0  149927.981293  63608.835387  14000.0  105200.0
salary_in_usd   9355.0  150299.495564  63177.372024  15000.0  105700.0

                    50%       75%       max
work_year        2023.0    2023.0    2023.0
salary         143860.0  187000.0  450000.0
salary_in_usd  143000.0  186723.0  450000.0
```

Looks like there is a lot of duplicates. I will remove them.

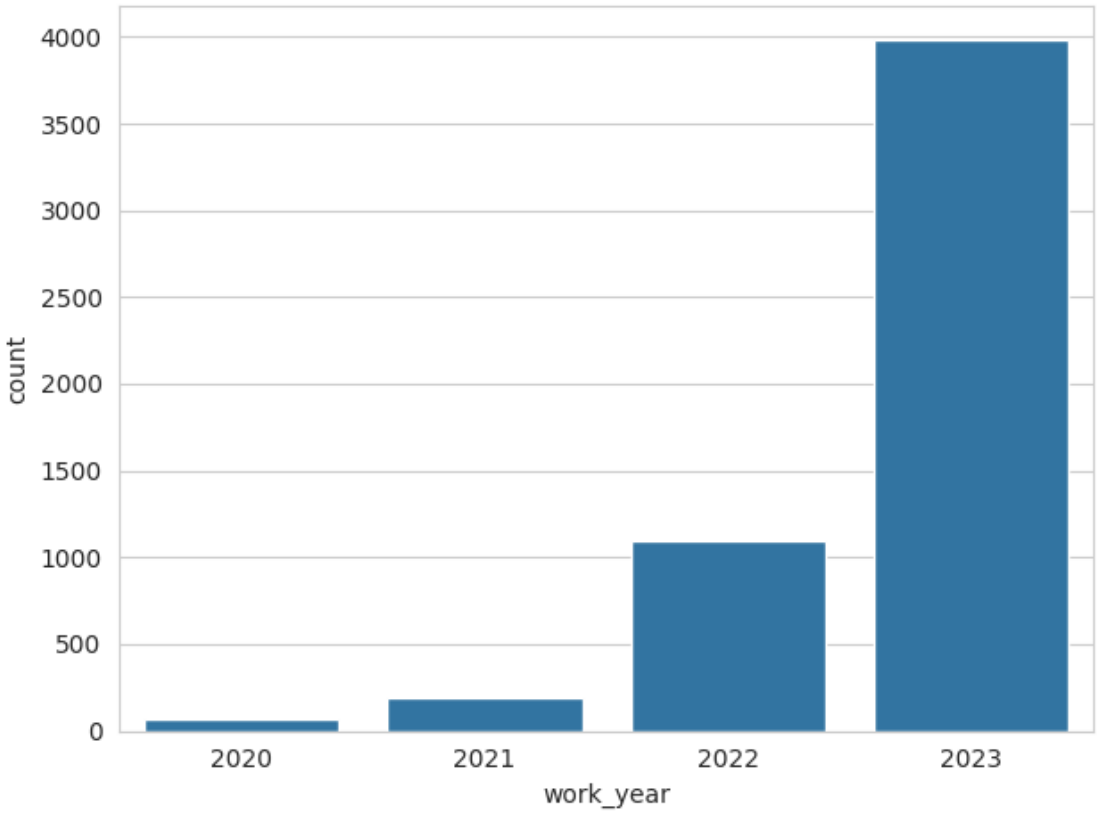
[5]:
```
jobs_df.drop_duplicates(keep='first', inplace=True)
jobs_df.duplicated().sum()
```

[5]:
```
0
```

0.0.3 Basic EDA

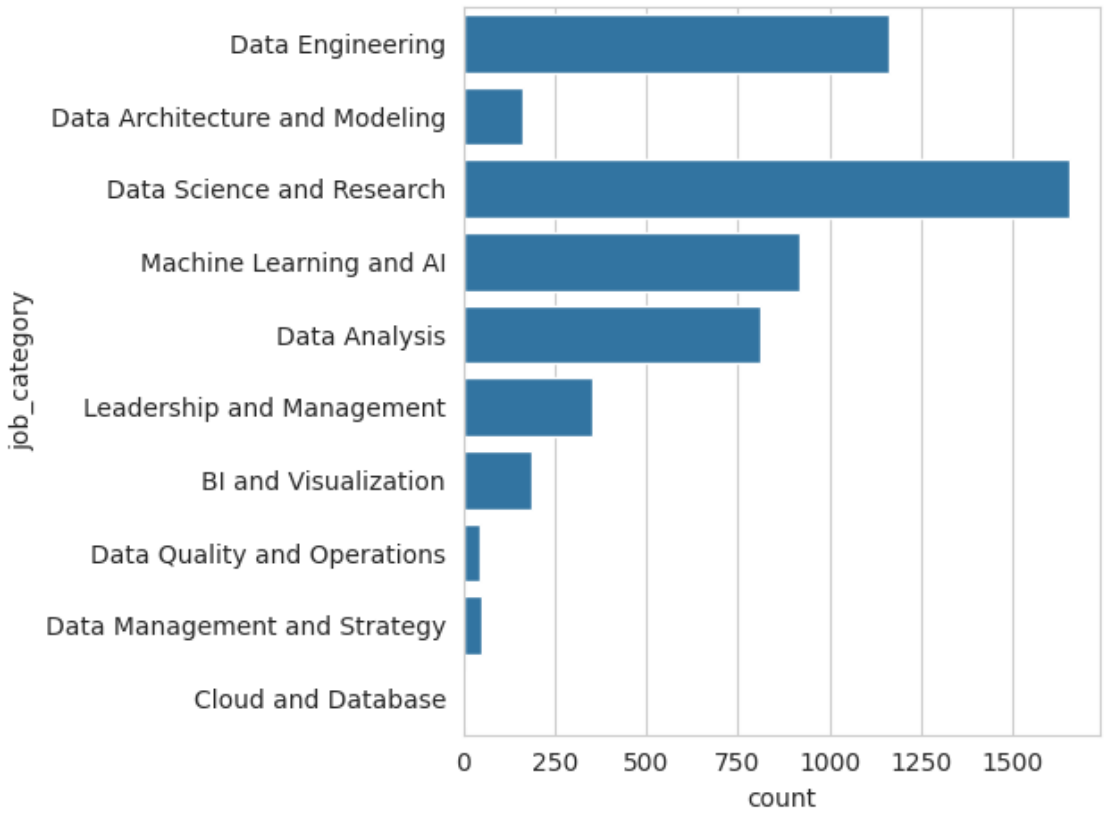
[6]:
```
sns.countplot(jobs_df, x='work_year')
```

[6]:
```
<Axes: xlabel='work_year', ylabel='count'>
```



[7]:
```
sns.countplot(jobs_df, y='job_category')
```

[7]:
```
<Axes: xlabel='count', ylabel='job_category'>
```

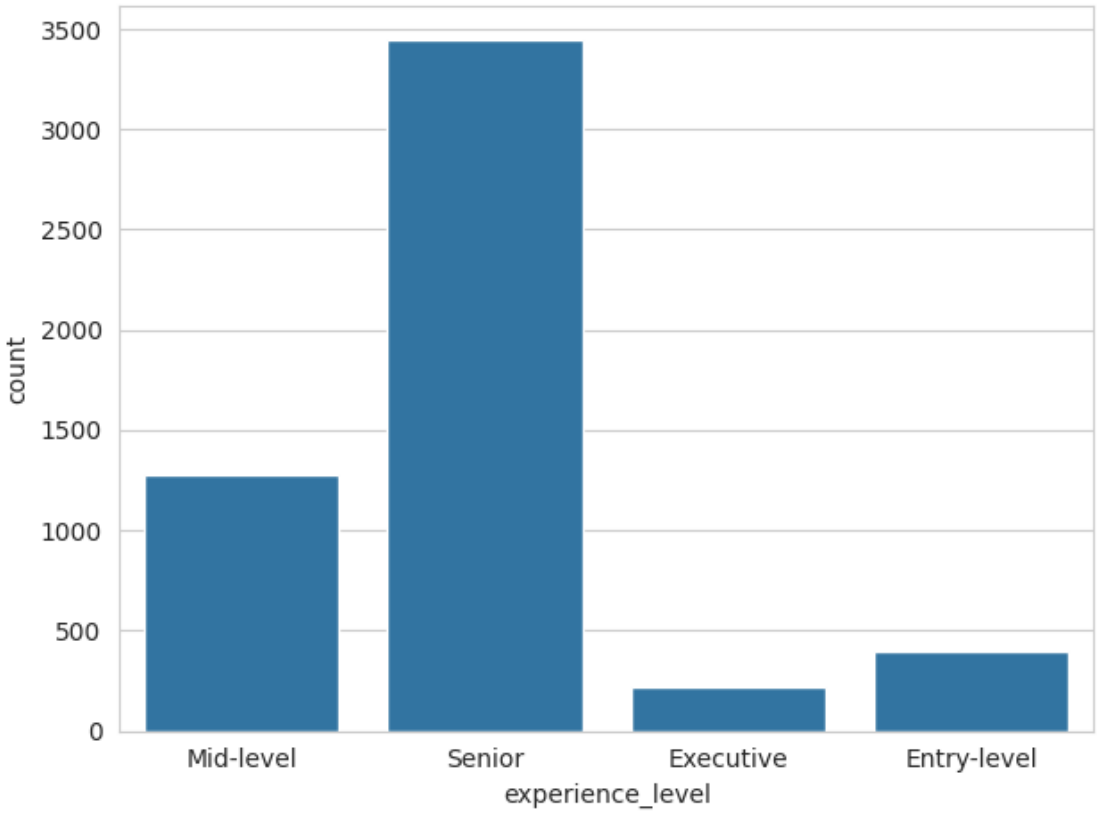


[8]:
```
jobs_df['employee_residence'].value_counts().head(10)
#sns.countplot(data=jobs_df, y='employee_residence')
```

[8]:
```
employee_residence
United States     4255
United Kingdom     351
Canada             196
Germany             65
Spain               63
France              53
Portugal            26
Netherlands         21
Italy               20
Brazil              19
Name: count, dtype: int64
```

[9]:
```
sns.countplot(data=jobs_df, x='experience_level')
```

[9]:
```
<Axes: xlabel='experience_level', ylabel='count'>
```

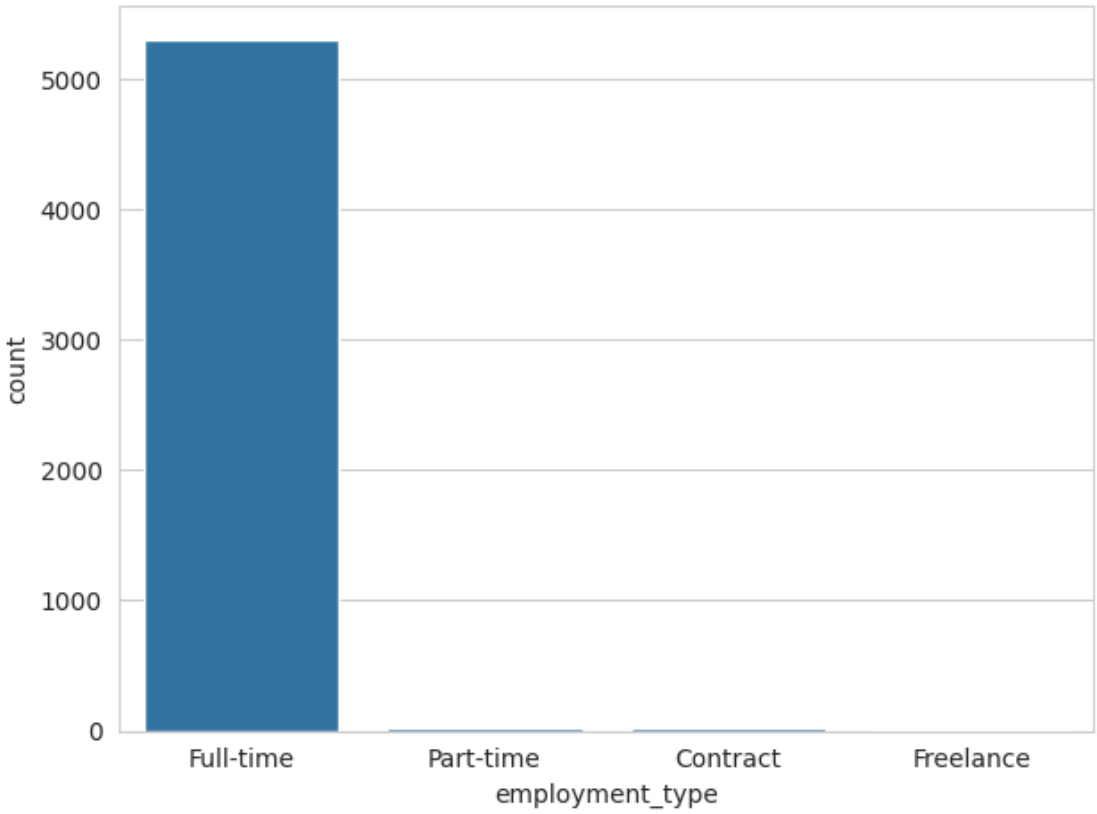


[10]:
```
jobs_df['experience_level'].value_counts()
```

[10]:
```
experience_level
Senior         3444
Mid-level      1274
Entry-level     400
Executive       223
Name: count, dtype: int64
```

[11]:
```
sns.countplot(data=jobs_df, x='employment_type')
```

[11]:
```
<Axes: xlabel='employment_type', ylabel='count'>
```

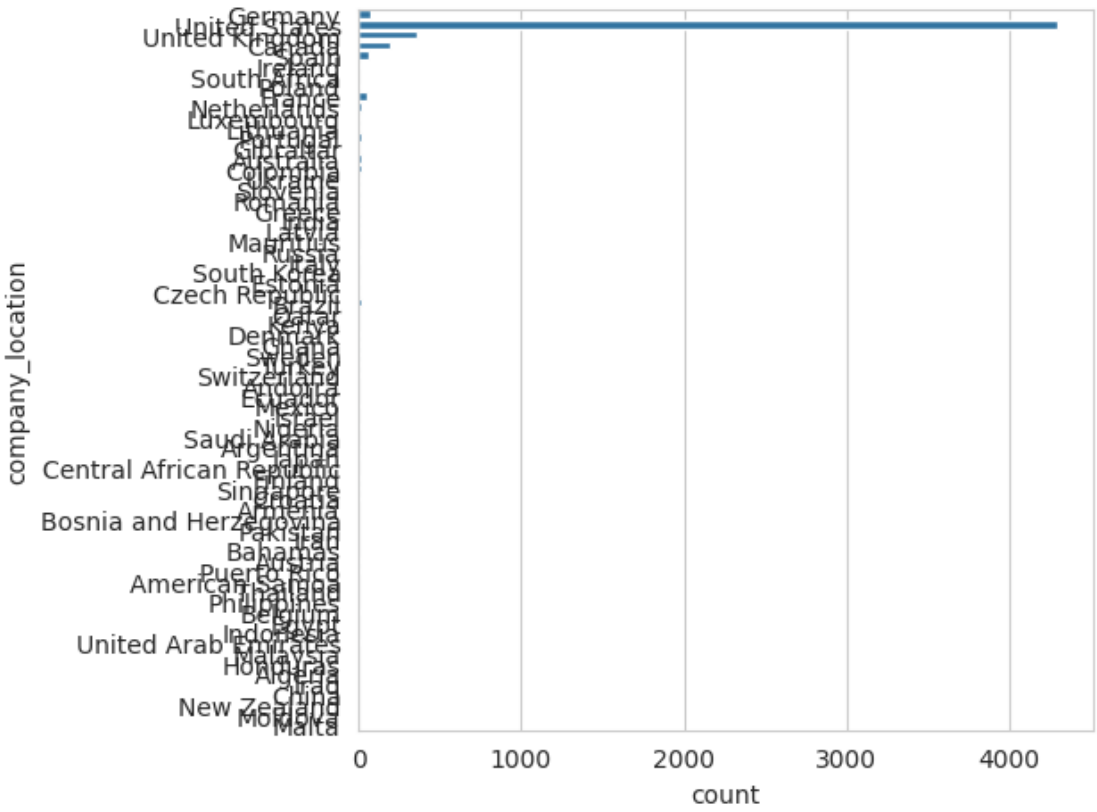


[12]:
```
jobs_df['employment_type'].value_counts()
```

[12]:
```
employment_type
Full-time    5296
Contract       19
Part-time      15
Freelance      11
Name: count, dtype: int64
```

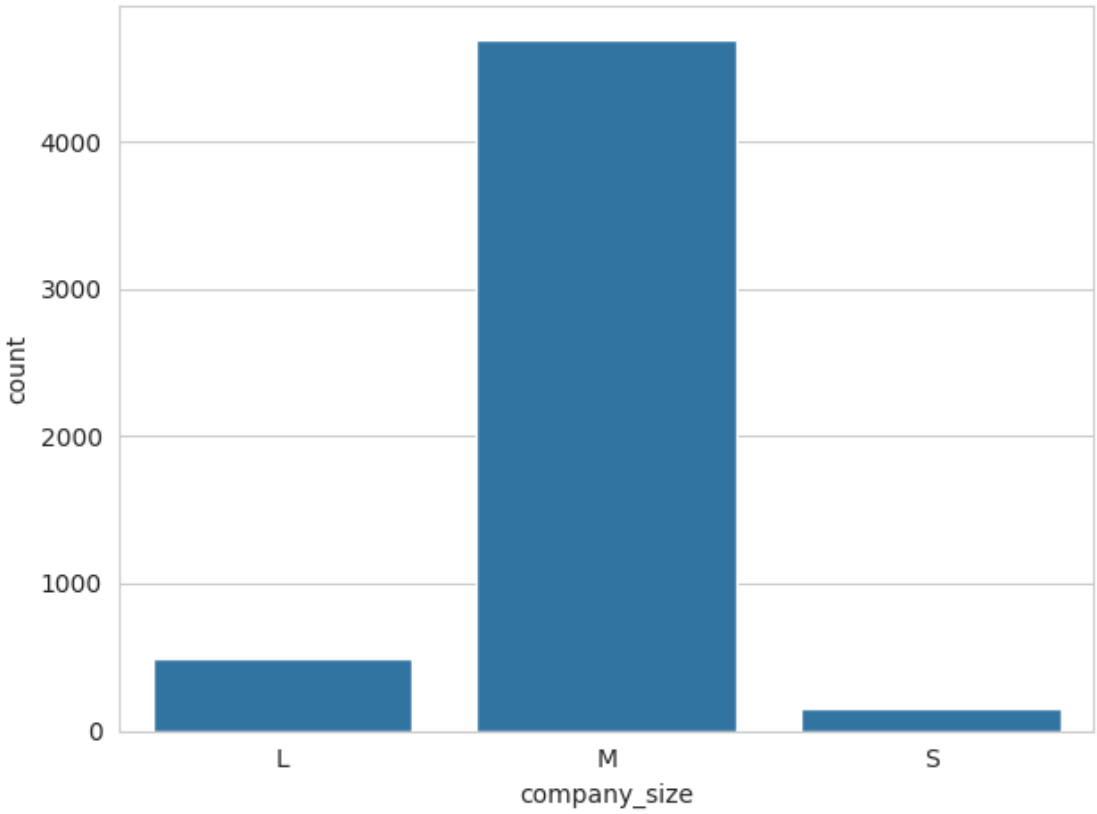
[13]:
```
sns.countplot(data=jobs_df, y='company_location')
```

[13]:
```
<Axes: xlabel='count', ylabel='company_location'>
```



[14]:
```
sns.countplot(data=jobs_df, x='company_size')
```

[14]: <Axes: xlabel='company_size', ylabel='count'>



Based on EDA performed, I will limit the number of `company_location` and `employee_residence` to 10 countries. I found that some of the countries are only listed a couple of time; therefore, are not well distributed.

[15]:
```
jobs_df.value_counts(['company_location', 'employee_residence']).head(15)
```

[15]:
```
company_location  employee_residence
United States     United States         4249
United Kingdom    United Kingdom         350
Canada            Canada                 192
Germany           Germany                 60
Spain             Spain                   57
France            France                  46
Portugal          Portugal                23
Netherlands       Netherlands             19
Brazil            Brazil                  17
Australia         Australia               17
Colombia          Colombia                14
Italy             Italy                   13
Greece            Greece                  11
Mexico            Mexico                   9
```

```
Ireland           Ireland                 8
Name: count, dtype: int64
```

[16]:
```
countries = ['United States', 'United Kingdom', 'Canada', 'Germany',
             'Spain', 'France', 'Portugal', 'Netherlands', 'Australia',
             'Brazil', 'Colombia', 'Italy', 'Greece']
jobs_df = jobs_df[jobs_df['company_location'].isin(countries)]
jobs_df = jobs_df[jobs_df['employee_residence'].isin(countries)]
jobs_df.sample(10)
```

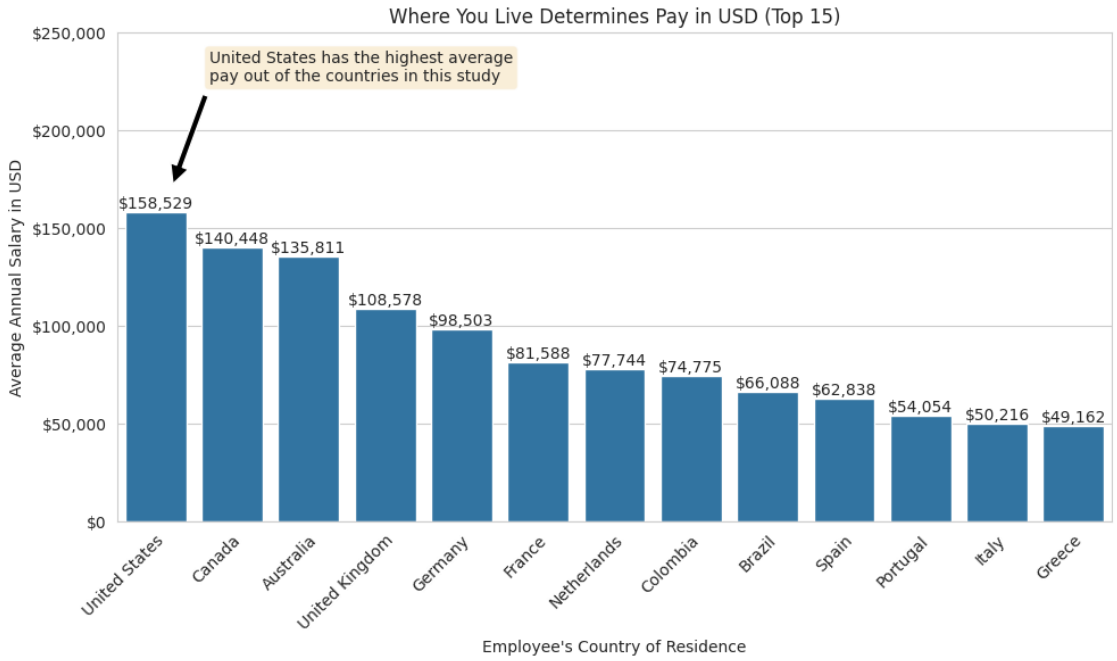
[16]:

	work_year	job_title	job_category	salary_currency	salary	salary_in_usd	employee_residence	experience_level	employment_type	work_setting	company_location	company_size
781	2023	Research Scientist	Data Science and Research	USD	166000	166000	United States	Senior	Full-time	In-person	United States	
5610	2023	Machine Learning Engineer	Machine Learning and AI	USD	170000	170000	United States	Mid-level	Full-time	Remote	United States	
9337	2021	Data Analyst	Data Analysis	USD	75000	75000	United States	Mid-level	Full-time	In-person	United States	
2271	2023	Data Science Lead	Data Science and Research	USD	142200	142200	United States	Senior	Full-time	In-person	United States	
6350	2023	Data Analyst	Data Analysis	USD	121600	121600	United States	Senior	Full-time	Remote	United States	
2254	2023	Data Engineer	Data Engineering	USD	134000	134000	United States	Senior	Full-time	Remote	United States	
4261	2023	Data Engineer	Data Engineering	USD	198900	198900	United States	Mid-level	Full-time	In-person	United States	
5633	2023	Machine Learning Engineer	Machine Learning and AI	USD	199000	199000	United States	Senior	Full-time	Remote	United States	
6329	2023	Data Scientist	Data Science and Research	USD	239748	239748	United States	Senior	Full-time	In-person	United States	
8086	2022	Data Manager	Leadership and Management	USD	45600	45600	United States	Entry-level	Full-time	Remote	United States	

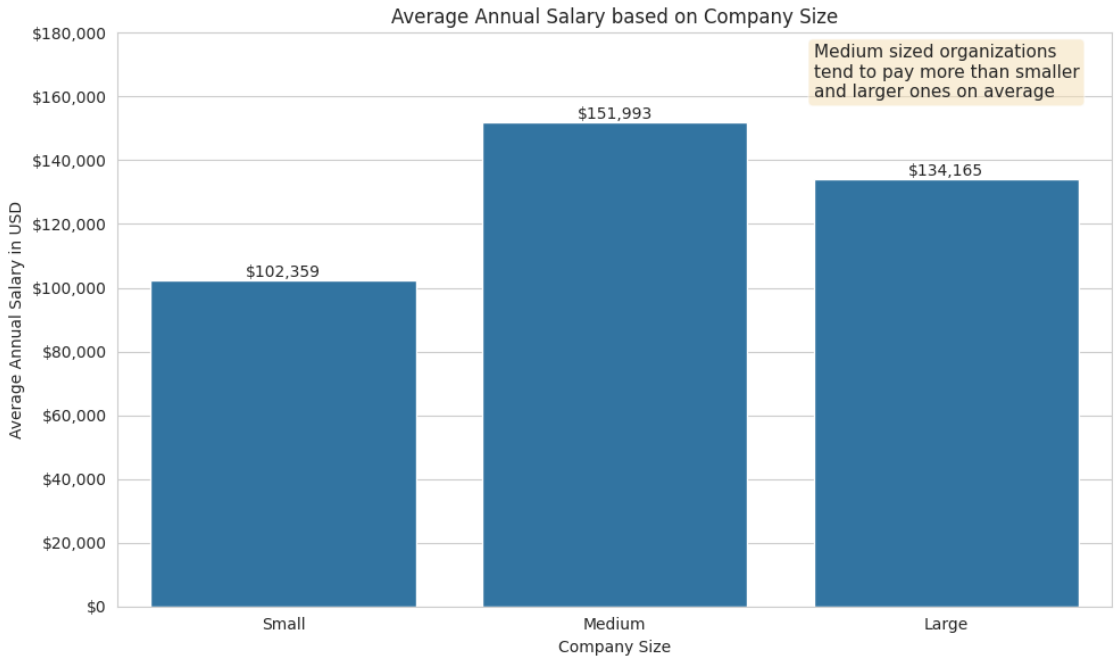
```
781             M
5610            M
9337            L
2271            M
6350            M
2254            M
4261            M
5633            M
6329            M
8086            M
```

0.0.4 Look for interesting items to plot

[17]:
```
# Highest pay by employee_residence in USD. Top 10
pay_residence = jobs_df.groupby('employee_residence').agg({'salary_in_usd':␣
 ↪'mean'}). \
                                sort_values('salary_in_usd', ascending=False).
 ↪head(15)
fig, ax = plt.subplots(figsize=(10,6))
props = dict(boxstyle='round', facecolor='wheat', alpha=0.5)
ax.yaxis.set_major_formatter(mtick.StrMethodFormatter('${x:,.0f}'))
ax.set(xlabel='Employee\'s Country of Residence', ylabel='Average Annual Salary␣
 ↪in USD', \
       title='Where You Live Determines Pay in USD (Top 15)', ylim=(0,250000))
sns.barplot(data=pay_residence, x='employee_residence', y='salary_in_usd')
plt.xticks(rotation=45, ha='right', rotation_mode='anchor')
textstr = '\n'.join(('United States has the highest average',
                     'pay out of the countries in this study'))
ax.annotate(textstr, xy=(0.2,170000), xytext=(0.7,225000), bbox=props,
            fontsize=10, arrowprops=dict(facecolor='black', shrink=0.05))
ax.bar_label(ax.containers[0], fmt='${:,.0f}')
fig.savefig('../images/highResidenceUSD.png', bbox_inches='tight', dpi=300)
```

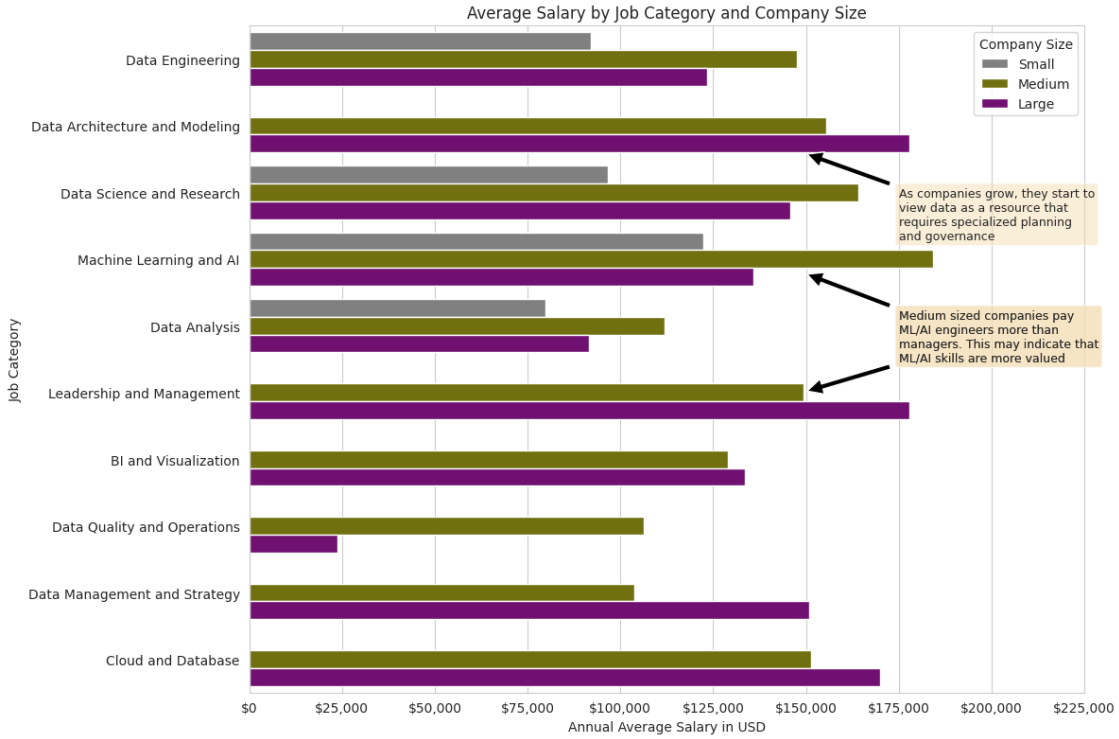


[18]:
```
# Isolate study to USA
sizes = ('Small','Medium','Large')
size = jobs_df.groupby('company_size').agg({'salary_in_usd': 'mean'}). \
                        sort_values('company_size', ascending=False)
fig, ax = plt.subplots(figsize=(10,6))
sns.barplot(data=size, x='company_size', y='salary_in_usd')
ax.yaxis.set_major_formatter(mtick.StrMethodFormatter('${x:,.0f}'))
x_pos = np.arange(len(sizes))
ax.set_xticks(x_pos, labels=sizes)
ax.set(xlabel='Company Size', ylabel='Average Annual Salary in USD',
       title='Average Annual Salary based on Company Size',
       ylim=(0,180000))
textstr = '\n'.join(('Medium sized organizations',
                     'tend to pay more than smaller',
                     'and larger ones on average'))
props = dict(boxstyle='round', facecolor='wheat', alpha=0.5)
ax.text(0.7, 0.98, textstr, transform=ax.transAxes, fontsize=11,
        verticalalignment='top', bbox=props)
ax.bar_label(ax.containers[0], fmt='${:,.0f}')
fig.savefig('../images/aveCompanySize.png', bbox_inches='tight', dpi=300)
```



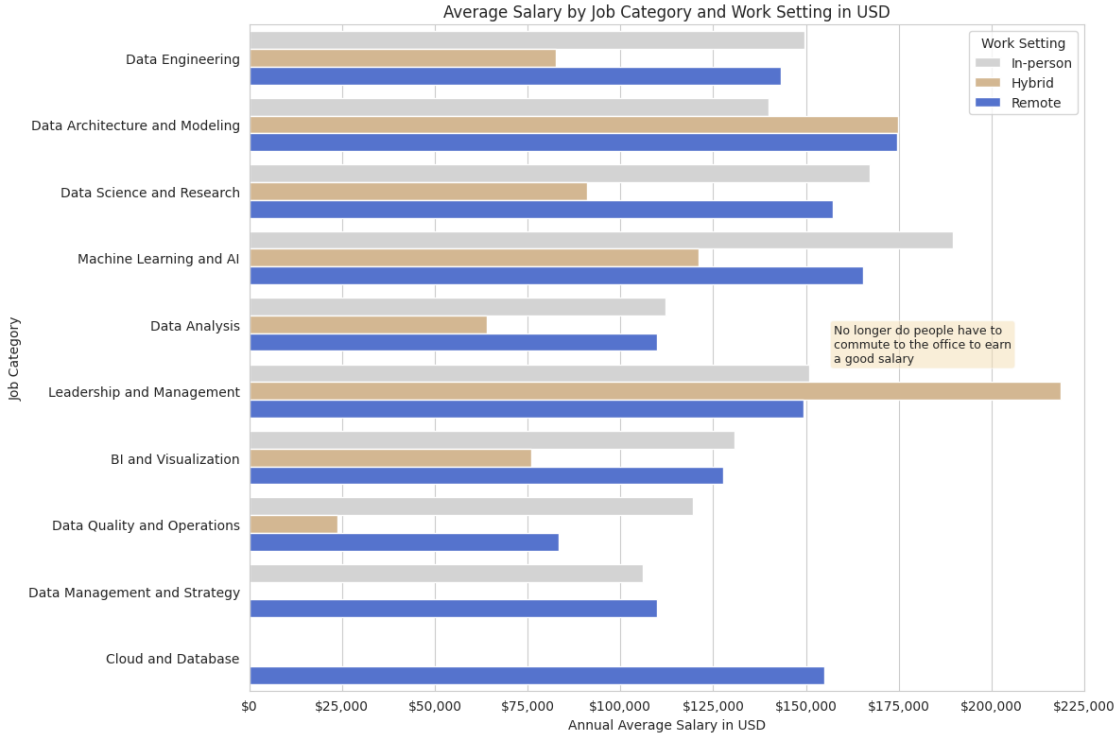
[19]:
```
fig, ax = plt.subplots(figsize=(12,8))
ax.xaxis.set_major_formatter(mtick.StrMethodFormatter('${x:,.0f}'))
ax.set(xlabel='Annual Average Salary in USD', ylabel='Job Category',
       title='Average Salary by Job Category and Company Size',
       xlim=(0,225000))
hue_order = ['S', 'M', 'L']
bar_colors = ['grey', 'olive', 'purple']
sns.barplot(data=jobs_df, x='salary_in_usd', y='job_category',␣
 ↪hue='company_size',
            hue_order=hue_order, palette=bar_colors, ci=None)
ax.legend(['Small','Medium', 'Large'], title='Company Size')
props = dict(boxstyle='round', facecolor='wheat', alpha=0.5)
text1 = '\n'.join(('As companies grow, they start to',
                   'view data as a resource that',
                   'requires specialized planning',
                   'and governance'))
text2 = '\n'.join(('Large companies pay well for',
                   'leadership, management, and',
                   'strategy.  Indicating this is a',
                   'priority for them.'))
text3 = '\n'.join(('Medium sized companies pay',
                   'ML/AI engineers more than',
                   'managers. This may indicate that',
                   'ML/AI skills are more valued'))
an1 = ax.annotate(text1, xytext=(175000,2.70), xy=(149000,1.4), bbox=props,
```

```
                  fontsize=9, arrowprops=dict(facecolor='black', shrink=0.05))
an2 = ax.annotate(text3, xytext=(175000,4.53), xy=(149000,3.2), bbox=props,
                  fontsize=9, arrowprops=dict(facecolor='black', shrink=0.05))
an3 = ax.annotate(text3, xytext=(175000,4.53), xy=(149000,5.0), bbox=props,
                  fontsize=9, arrowprops=dict(facecolor='black', shrink=0.05))
fig.savefig('../images/aveCatSize.png', bbox_inches='tight', dpi=300)
```



[20]:
```
# Average Salary by employee type
fig, ax = plt.subplots(figsize=(12,8))
ax.xaxis.set_major_formatter(mtick.StrMethodFormatter('${x:,.0f}'))
ax.set(xlabel='Annual Average Salary in USD', ylabel='Job Category',
       title='Average Salary by Job Category and Work Setting in USD',␣
 ↪xlim=(0,225000))
#hue_order = ['Remote', 'Hybrid', 'In-person']
hue_order = ['In-person', 'Hybrid', 'Remote']
bar_colors = ['lightgrey', 'burlywood', 'royalblue']
props = dict(boxstyle='round', facecolor='wheat', alpha=0.5)
sns.barplot(data=jobs_df, x='salary_in_usd', y='job_category',␣
 ↪hue='work_setting',
            hue_order=hue_order, palette=bar_colors, ci=None)
ax.legend(title='Work Setting')
text1 = '\n'.join(('No longer do people have to',
                   'commute to the office to earn',
```

```
                    'a good salary'))
ax.text(0.7, 0.55, text1, transform=ax.transAxes, fontsize=9,
        verticalalignment='top', bbox=props)
fig.savefig('../images/aveCatWork.png', bbox_inches='tight', dpi=300)
```



[ ]: