Part_I_exploration_template

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1 Part I - (Dataset Exploration for a Salary Survey)

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1.2 Introduction

In this project we will explore a dataset related to a salary survey. It contains salary amounts in US dollar for 27147 persons from different origins, ethnicities, age ranges, industries and so forth who filled the survey form for the purpose.

1.3 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
```

1.3.1 Collecting data

```
In [2]: # Loading data
        df_salary = pd.read_csv('salary_survey_data.csv')

In [3]: df_salary.shape

Out[3]: (27147, 23)
```

Dataset description Our dataset has 27147 rows and 23 columns that are described as follows: 1. **Unnamed: 0** which is an id column 2. **Timestamp** this is the date and time the person information were saved 3. **Age** this is the person's age range 4. **Industrie** this is specifies in which Indrustry the responding person works in 5. **Occupation** this is the job position of tha person in their work industry 6. **Salaire** this the salary amount in local currency for the responding person 7. **Monnaie_salaire** this specifies the local currency of the above-mentioned salary 8. **Pays** this is the home country of the person 9. **Ville** this is the home city of the person 10. **Annee_exp_totale** this is the range of the person's total number of years of experience in working 11. **Annee_exp_present** this is the range of the person's number of years of experience in the actual position 12. **Niveau_edu**

this is the highest study levelof the person 13. **Sexe** this is the sex of the person 14. **Race** this shows all ethnicities the rresponding person belongs to

Race and ethnicity columns 15. **Anotheroptionnotlistedhereorprefernottoanswer** 16. **AsianorAsianAmerican** 17. **BlackorAfricanAmerican** 18. **Hispanic_Latino_or_Spanish origin** 19. **MiddleEasternorNorthernAfrican** 20. **NativeAmericanorAlaskaNative** 21. **White**

These columns contain 1 (Yes) if the person belongs to that ethnicity, and 0 (No) if not

22. **coef_monnaie** this gives the coefficient by which local salary shall be multiplied in order to convert it into US dollar
23. **Salaire_USD** this is the salary amount in US dollar corresponding to local salary of the person.

1.3.2 Assessing data

```
In [4]: df_salary.head()
```

```
Out[4]:    Unnamed: 0            Timestamp    Age                        Indrustrie  \
        0           0  2021-04-27 11:02:10  25-34   Education (Higher Education)
        1           1  2021-04-27 11:02:22  25-34               Computing or Tech
        2           2  2021-04-27 11:02:38  25-34  Accounting, Banking & Finance
        3           3  2021-04-27 11:02:41  25-34                     Nonprofits
        4           4  2021-04-27 11:02:42  25-34  Accounting, Banking & Finance

                                        Occupation  Salaire Monnaie_salaire  \
        0       Research and Instruction Librarian  55000.0             USD
        1  Change & Internal Communications Manager  54600.0             GBP
        2                     Marketing Specialist  34000.0             USD
        3                          Program Manager  62000.0             USD
        4                       Accounting Manager  60000.0             USD

                    Pays        Ville Annee_exp_totale     ...        Race  \
        0            usa       Boston        5-7 years     ...       White
        1  united kingdom    Cambridge     8 - 10 years     ...       White
        2             us  Chattanooga      2 - 4 years     ...       White
        3            usa    Milwaukee     8 - 10 years     ...       White
        4             us   Greenville     8 - 10 years     ...       White

          Anotheroptionnotlistedhereorprefernottoanswer AsianorAsianAmerican  \
        0                                             0                    0
        1                                             0                    0
        2                                             0                    0
        3                                             0                    0
        4                                             0                    0

          BlackorAfricanAmerican  Hispanic_Latino_or_Spanish origin  \
        0                      0                                  0
```

```
1                   0                              0
2                   0                              0
3                   0                              0
4                   0                              0

   MiddleEasternorNorthernAfrican  NativeAmericanorAlaskaNative  White  \
0                               0                             0      1
1                               0                             0      1
2                               0                             0      1
3                               0                             0      1
4                               0                             0      1

   coef_monnaie  Salaire_USD
0          1.00      55000.0
1          1.15      62790.0
2          1.00      34000.0
3          1.00      62000.0
4          1.00      60000.0

[5 rows x 23 columns]
```

In [5]:
```
# dataset description
df_salary.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27147 entries, 0 to 27146
Data columns (total 23 columns):
Unnamed: 0                                      27147 non-null int64
Timestamp                                       27147 non-null object
Age                                             27147 non-null object
Indrustrie                                      27147 non-null object
Occupation                                      27147 non-null object
Salaire                                         27147 non-null float64
Monnaie_salaire                                 27147 non-null object
Pays                                            27147 non-null object
Ville                                           27147 non-null object
Annee_exp_totale                                27147 non-null object
Annee_exp_present                               27147 non-null object
Niveau_edu                                      27147 non-null object
Sexe                                            27147 non-null object
Race                                            27147 non-null object
Anotheroptionnotlistedhereorprefernottoanswer    27147 non-null int64
AsianorAsianAmerican                            27147 non-null int64
BlackorAfricanAmerican                          27147 non-null int64
Hispanic_Latino_or_Spanish origin               27147 non-null int64
MiddleEasternorNorthernAfrican                  27147 non-null int64
NativeAmericanorAlaskaNative                    27147 non-null int64
White                                           27147 non-null int64
```

```
coef_monnaie                                      27147 non-null float64
Salaire_USD                                       27147 non-null float64
dtypes: float64(3), int64(8), object(12)
memory usage: 4.8+ MB
```

```
In [3]: # Let's make all columns names be in lower case
        df_salary.rename(str.lower, axis= 'columns', inplace = True)

In [7]: df_salary.race.value_counts()[:10]

Out[7]: White                                                  22723
        AsianorAsianAmerican                                    1315
        BlackorAfricanAmerican                                   645
        Anotheroptionnotlistedhereorprefernottoanswer            583
        Hispanic,Latino,orSpanishorigin                          568
        Hispanic,Latino,orSpanishorigin,White                    374
        AsianorAsianAmerican,White                               336
        BlackorAfricanAmerican,White                             121
        MiddleEasternorNorthernAfrican,White                      79
        NativeAmericanorAlaskaNative,White                        65
        Name: race, dtype: int64
```

Issue **race** column should be dropped for there are columns related to ethnicity in the same dataset instead of having both **race** and ethnicity values columns

```
In [4]: # To make them easy to address, we'll replace each of them by a descriptive string

        list_ = ['unnamed: 0', 'timestamp', 'age', 'industrie', 'occupation', 'salaire',
               'monnaie_salaire', 'pays', 'ville', 'annee_exp_totale',
               'annee_exp_present', 'niveau_edu', 'sexe', 'race',
                 'other_no_say', 'asian_a_american',
               'black_af_american', 'hispanic_latino_spanish',
               'mid_east_north_african', 'nat_american_alaska_native',
               'white', 'coef_monnaie', 'salaire_usd']

        df_salary.rename(columns =  lambda x: str(list_[list(df_salary.columns).index(x)]) if (x

In [5]: # Let's drop unuseful columns
        df_salary.drop(['unnamed: 0', 'timestamp', 'race', 'salaire', 'monnaie_salaire', 'coef_m

In [10]: df_salary.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27147 entries, 0 to 27146
Data columns (total 17 columns):
age                            27147 non-null object
industrie                      27147 non-null object
occupation                     27147 non-null object
```

```
pays                            27147 non-null object
ville                           27147 non-null object
annee_exp_totale                27147 non-null object
annee_exp_present               27147 non-null object
niveau_edu                      27147 non-null object
sexe                            27147 non-null object
other_no_say                    27147 non-null int64
asian_a_american                27147 non-null int64
black_af_american               27147 non-null int64
hispanic_latino_spanish         27147 non-null int64
mid_east_north_african          27147 non-null int64
nat_american_alaska_native      27147 non-null int64
white                           27147 non-null int64
salaire_usd                     27147 non-null float64
dtypes: float64(1), int64(7), object(9)
memory usage: 3.5+ MB
```

In [72]:
```
df_salary.annee_exp_totale.value_counts()
```

Out[72]:
```
11 - 20 years       9345
8 - 10 years        5225
5-7 years           4719
21 - 30 years       3540
2 - 4 years         2875
31 - 40 years        840
1 year or less       483
41 years or more     120
Name: annee_exp_totale, dtype: int64
```

In [73]:
```
df_salary.annee_exp_present.value_counts()
```

Out[73]:
```
11 - 20 years       6352
5-7 years           6323
2 - 4 years         6022
8 - 10 years        4821
21 - 30 years       1828
1 year or less      1396
31 - 40 years        367
41 years or more      38
Name: annee_exp_present, dtype: int64
```

In [6]:
```
# convert annee_exp_totale and annee_exp_present into ordered categorical types
exp_order = ['1 year or less',
             '2 - 4 years',
             '5-7 years',
             '8 - 10 years',
             '11 - 20 years',
             '21 - 30 years',
```

```
                '31 - 40 years',
                '41 years or more']
ordered_var = pd.api.types.CategoricalDtype(ordered = True, categories = exp_order)
df_salary.annee_exp_totale = df_salary.annee_exp_totale.astype(ordered_var)
df_salary.annee_exp_present = df_salary.annee_exp_present.astype(ordered_var)
df_salary.dtypes
```

Out[6]:
```
age                                object
industrie                          object
occupation                         object
pays                               object
ville                              object
annee_exp_totale                 category
annee_exp_present                category
niveau_edu                         object
sexe                               object
other_no_say                        int64
asian_a_american                    int64
black_af_american                   int64
hispanic_latino_spanish             int64
mid_east_north_african              int64
nat_american_alaska_native          int64
white                               int64
salaire_usd                       float64
dtype: object
```

In [7]:
```
# Getting persons with salary >= 2000 USD
df_salary = df_salary[df_salary.salaire_usd >= 2000]
df_salary.shape
```

Out[7]:
```
(27054, 17)
```

1.3.3 What is the structure of your dataset?

After a bit of cleaning, our dataset contains 27054 persons and 17 features retained for exploration. We have got rid of unuseful columns and all persons whose annual salary is lesser than 2000 USD in order to approach a realistic situation.

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

Through this exploration we are interested in figuring out what features impact the **salary** of a person in our dataset.

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

We expect that **industry**, **job position** and **years of experience** will strongly determine salary level. Moreover, we think **education level** may have at leat a minor effect when compared to that of these three main features.

1.4 Univariate Exploration

In this section, investigate distributions of individual variables. If you see unusual points or outliers, take a deeper look to clean things up and prepare yourself to look at relationships between variables.

1.4.1 Question 1: What is the distribution of our feature of interest (salary)?

In [75]:
```
# Let's see the max salary
df_salary['salaire_usd'].max()
```

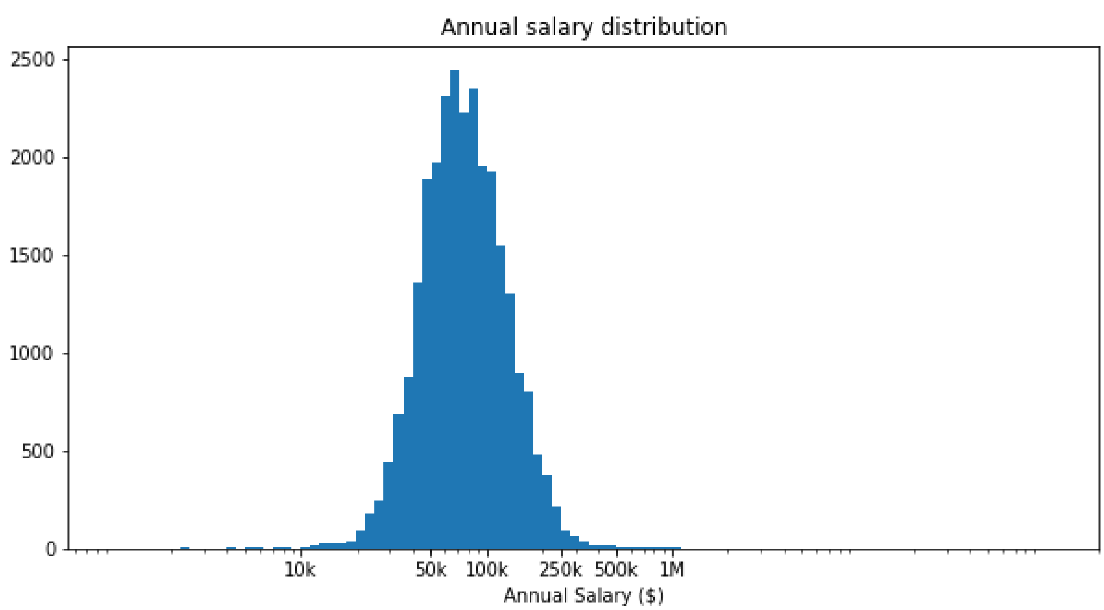
Out[75]: 102000000.0

In [14]:
```
# Let's see the min salary
df_salary['salaire_usd'].min()
```

Out[14]: 2350.0

1.4.2 Visualization

In [76]:
```
# The standard-scaled plot is computationally expensive and trickier.
# Because of high values therein let's directly reduce values using log10
binsize = 0.05
bins = 10 ** np.arange(3, np.log10(df_salary['salaire_usd'].max())+binsize, binsize)
plt.figure(figsize=[10, 5])
plt.hist(data = df_salary, x = 'salaire_usd', bins = bins)
plt.xscale('log')
plt.xticks([1e4, 5e4, 1e5, 25e4, 5e5, 1e6], ['10k', '50k', '100k', '250k', '500k', '1M'
plt.xlabel('Annual Salary ($)')
plt.title('Annual salary distribution')
plt.show()
```



```
In [9]: # Statistics to confirm the visual
        df_salary[(df_salary.salaire_usd >= 50000) & (df_salary.salaire_usd <= 100000)].shape
```

```
Out[9]: (14037, 17)
```

```
In [78]: df_salary.shape
```

```
Out[78]: (27054, 17)
```

1.4.3 Observation

From this visual we notice the salary has almost a normal distribution with the peak between 50000 and 100000. In fact, statistics prove that more than 50% of persons actually in our dataset are paid between 50000 and 100000 USD.

1.4.4 Question 2 : How are indutries distributed in the data ?

Let's now take industry feature

```
In [18]: # Let's see how many industries are here
         len(df_salary.industrie.value_counts())
```

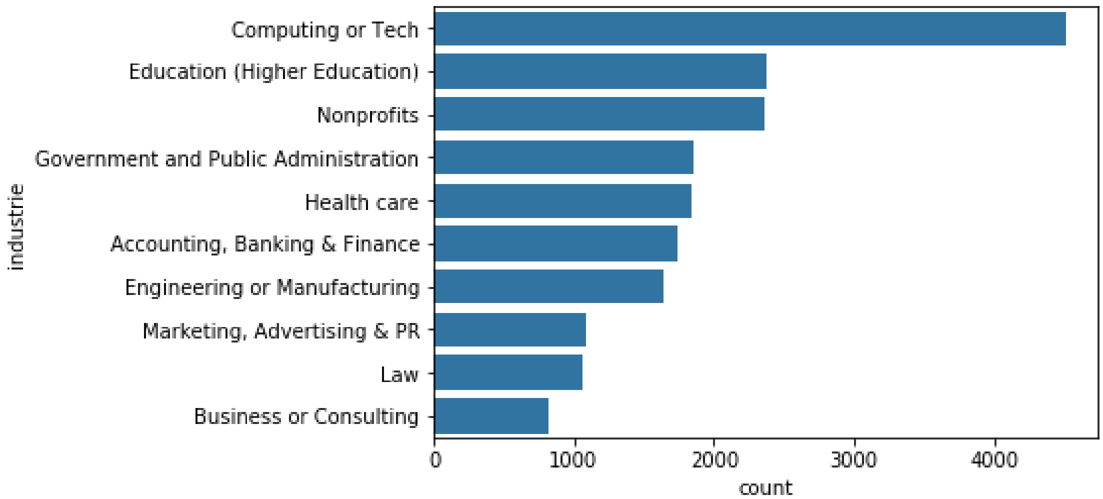
```
Out[18]: 1185
```

```
In [81]: # Since a plot for all these 1185 values is hardly ever readable, let's take the first
         df_salary.industrie.value_counts()[:10]
```

```
Out[81]: Computing or Tech                          4510
         Education (Higher Education)               2375
         Nonprofits                                 2362
         Government and Public Administration       1846
         Health care                                1835
         Accounting, Banking & Finance              1742
         Engineering or Manufacturing               1640
         Marketing, Advertising & PR                1090
         Law                                        1063
         Business or Consulting                      820
         Name: industrie, dtype: int64
```

1.4.5 Visualization

```
In [20]: # Plotting the top 10 industries
         ind_order = df_salary.industrie.value_counts()[:10].index
         base_color = sb.color_palette()[0]
         sb.countplot(data = df_salary, y = 'industrie', color = base_color, order = ind_order);
```



1.4.6 Observation

From this visual we understand that among the top 10 industries picked up *Computing or Tech* is the first with more than 4000 persons, *Higher education* and *Nonprofits* are respectively the second and the third with more than 2000 persons each, the rest of them have less than 2000 persons and we noted *Business or Consulting* which is the last with less than 1000 persons.

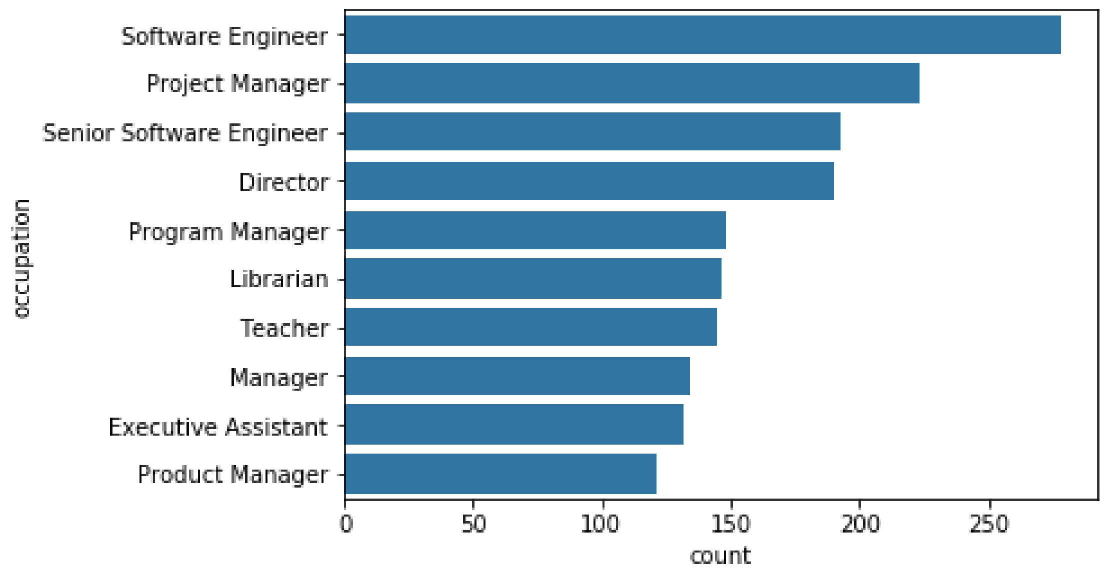
1.4.7 Question 3: How are occupations distributed in data ?

Let's take occupation (job position)

```
In [82]: # Let's see how many occupations are here
         len(df_salary.occupation.value_counts())

Out[82]: 13932

In [22]: # Since it impossible to plot all these values, let's take the first 10
         df_salary.occupation.value_counts()[:10]

Out[22]: Software Engineer            278
         Project Manager              223
         Senior Software Engineer     193
         Director                     190
         Program Manager              148
         Librarian                    146
         Teacher                      145
         Manager                      134
         Executive Assistant          132
         Product Manager              121
         Name: occupation, dtype: int64
```

1.4.8 Visualization

```
In [23]: # Plotting the top 10 occupations
         ind_order = df_salary.occupation.value_counts()[:10].index
         base_color = sb.color_palette()[0]
         sb.countplot(data = df_salary, y = 'occupation', color = base_color, order = ind_order)
```



1.4.9 Observation

Software engineer and *Project Manager* are highly occupied positions respectively the first with 278 persons and the second with 223. All the rest have less than 200 persons and among them *Product Manager* is the last with 121 persons.

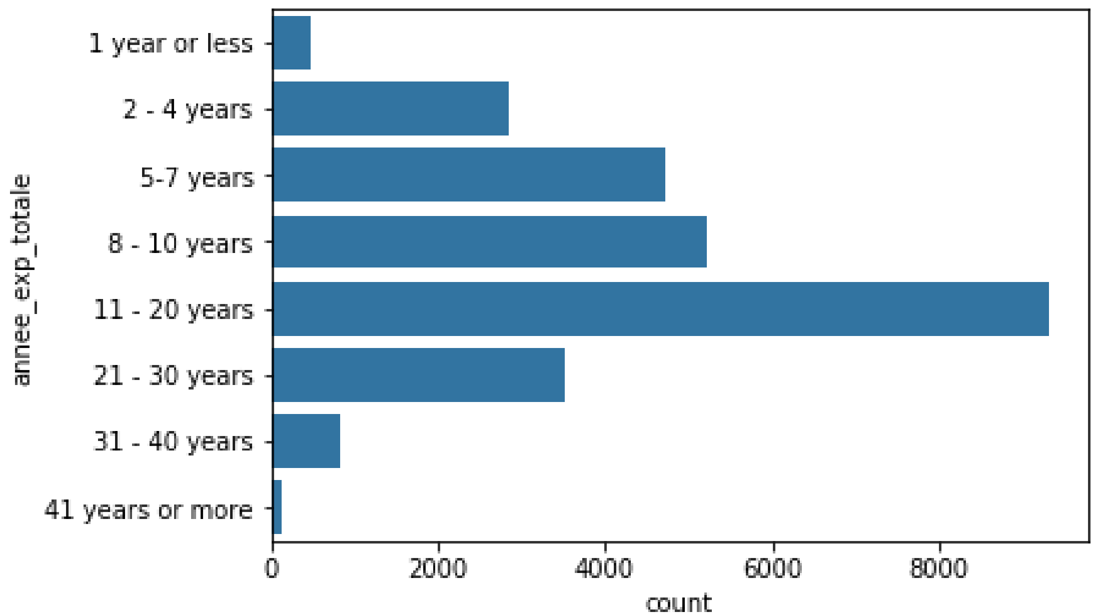
1.4.10 Question 4 : How are experiences ranges distributed in data ?

Let's take experience columns (annee_exp_totale and annee_exp_present) to see it clearer

```
In [11]: df_salary.annee_exp_totale.value_counts()

Out[11]: 11 - 20 years       9323
         8 - 10 years        5215
         5-7 years           4708
         21 - 30 years       3520
         2 - 4 years         2857
         31 - 40 years        833
         1 year or less       478
         41 years or more     120
         Name: annee_exp_totale, dtype: int64
```

1.4.11 Visualization

```
In [13]: # Plotting the ranges
         base_color = sb.color_palette()[0]
         sb.countplot(data = df_salary, y = 'annee_exp_totale', color = base_color);
```



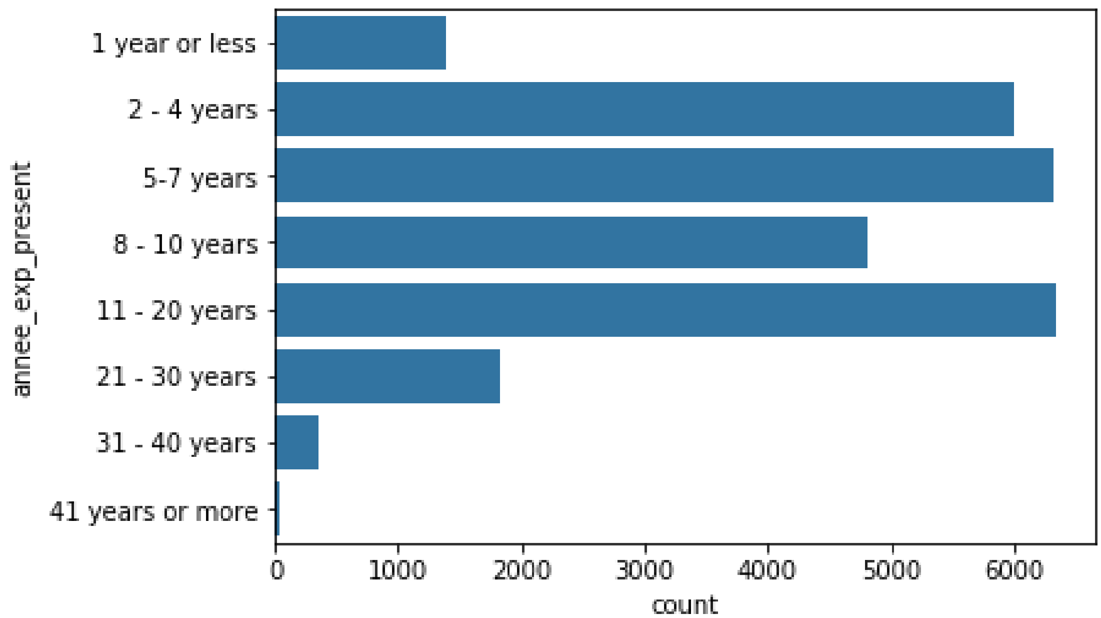
1.4.12 Observation

Hre we notice that 19246 (more than 70%) persons have their total years of experience between 5 and 20, among these 9323 persons have between 11 and 20 years, 5215 persons have between 8 and 10 years, 4708 have between 5 and 7 years. Among the rest of persons 3520 have between 21 and 30 years, 2857 between 2 and 4 years, 833 between 31 and 40 years, 478 have 1 year or less and finally 120 have 41 or more years.

```
In [12]: df_salary.annee_exp_present.value_counts()

Out[12]: 11 - 20 years       6335
         5-7 years           6312
         2 - 4 years         5999
         8 - 10 years        4802
         21 - 30 years       1818
         1 year or less      1386
         31 - 40 years        364
         41 years or more      38
         Name: annee_exp_present, dtype: int64
```

1.4.13 Visualization

```
In [86]: # Plotting the ranges
         base_color = sb.color_palette()[0]
         sb.countplot(data = df_salary, y = 'annee_exp_present', color = base_color);
```



1.4.14 Observation

We notice that more than 17000 persons have years of experience between 5 and 20 in their actual jobs. Among these we find three ranges : *11 - 20 years* with 6335 persons, *5-7 years* with 6312, and *8 - 10 years* with 4802. The rest of persons are shared between other ranges among which *2 - 4 years* is mentioned with 5999 persons and *41 years or more* which is the last one.

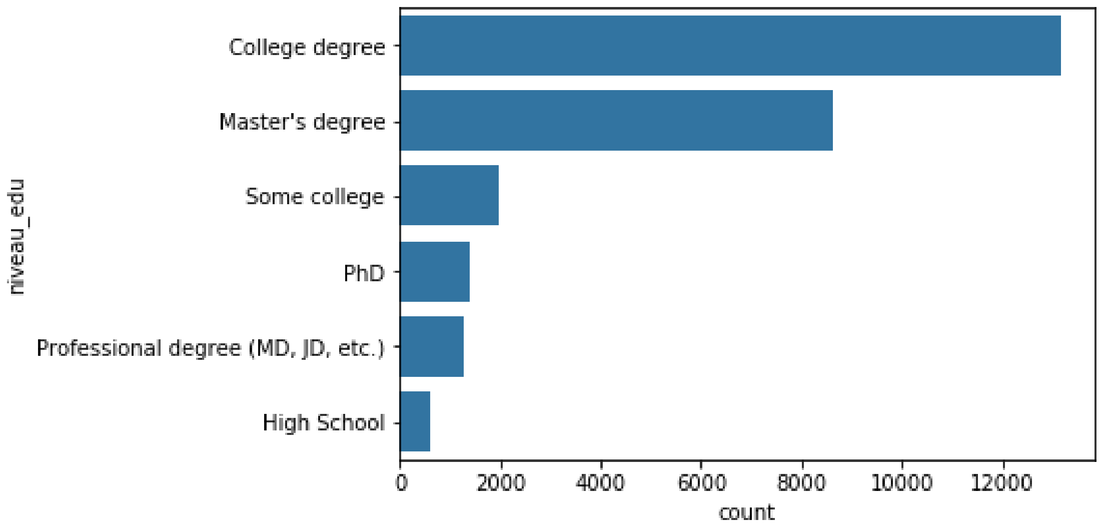
1.4.15 Question 5 : How are study levels distributed in data ?

Let's take niveau_edu feature to see that

```
In [14]: df_salary.niveau_edu.value_counts()

Out[14]: College degree                          13176
         Master's degree                          8614
         Some college                             1992
         PhD                                      1380
         Professional degree (MD, JD, etc.)       1285
         High School                               607
         Name: niveau_edu, dtype: int64
```

1.4.16 Visualization

```
In [15]: # Plotting the education levels
         base_color = sb.color_palette()[0]
         educ_index = df_salary.niveau_edu.value_counts().index
         sb.countplot(data = df_salary, y = 'niveau_edu', color = base_color, order = educ_index
```



1.4.17 Observation

More than 21000 persons have either a college degree or a master's degree. *College degree* is the highest education level for 13176 persons. 8614 have a *master's degree*, 1992 persons have followed *some college* education. Only 2600 persons or so have either PhD or a Professional degree. And 607 persons have got High School degree.

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

From the visual we notice the salary has almost a normal distribution the peak of which is between 50000 and 100000. In fact, that is reinforced by statistics proof showing that more than 50% of persons actually in our dataset are paid between 50000 and 100000 USD, which expalins why the peak is between those values. Looking at the plot basis, just 28 persons have less than 10000 USD and 57 persons more than 500000 USD. We have considered salary values lesser than 2000 as outliers and got rid of them. Because of high values found, we have used log 10 transformation to adapt the plot and make it easily readable.

1.4.19 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?

Form the above-mentioned important features, we have taken the top 10 industries and occupations with high number of persons. *Computing or Tech* industry and related positions stood out to have more persons. We have noticed that the two experience columns were prone to be ordinal categorical variables as the ranges of values therein are ordered in ascending order. So we converted them that way.

1.5 Bivariate Exploration

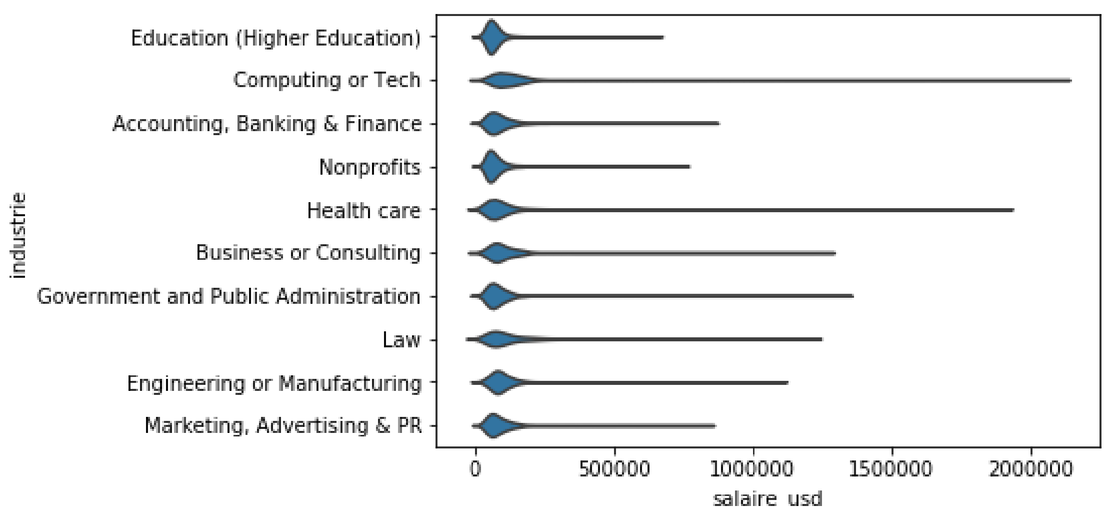
In this section, we'll investigate relationships between pairs of variables in our data using the variables that we introduced in some the previous section (univariate exploration).

1.5.1 Question 1 : How are salaries distributed through the top 10 industries ?

Here we will plot relationship between industry and salary.

In [28]:
```
# Data for top 10 industies
industries = df_salary.industrie.value_counts()[:10].index
df_top10_ind = df_salary[df_salary.industrie.isin(industries)]
```

In [96]:
```
# Let's plot for all salaries first
base_color = sb.color_palette()[0]
sb.violinplot(data = df_top10_ind, y = 'industrie', x = 'salaire_usd', color = base_col
```

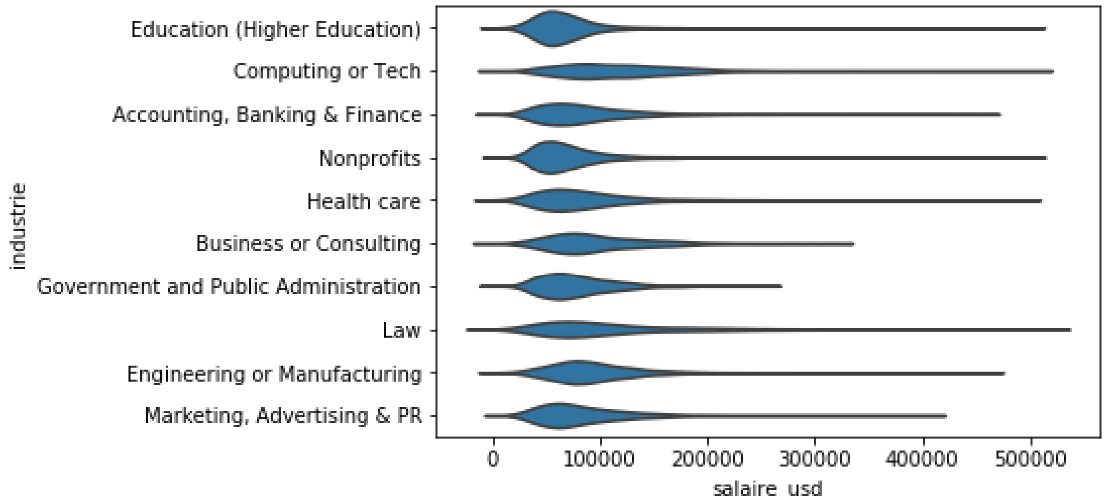


1.5.2 Observation

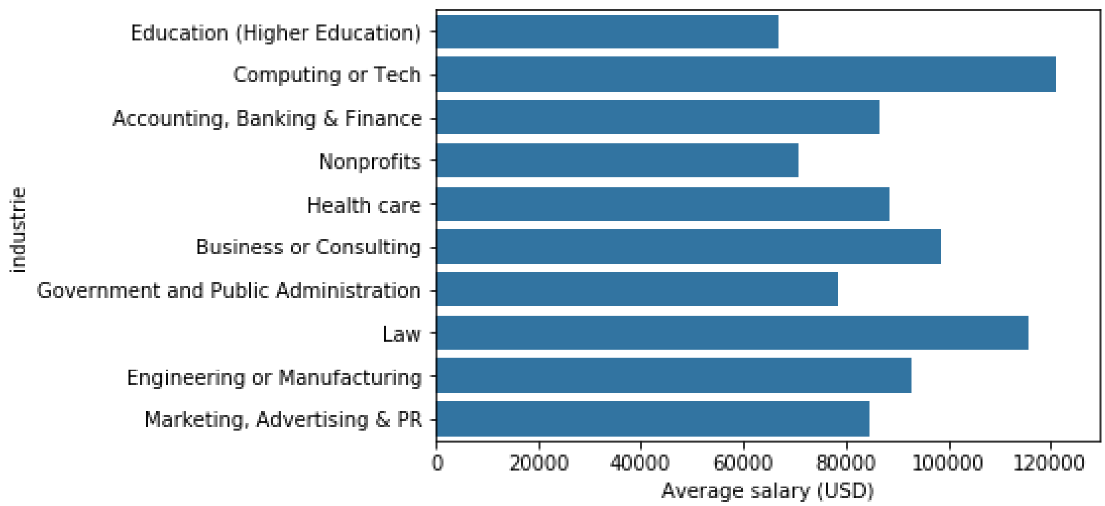
We observe that for all top 10 industries high density is shown before 500000 USD. So we have decided to split the data and get jut salaries from the minimum up to 500000 USD ensuring the plotting order does not change for the top 10 industries.

```
In [123]: # splitting to get salaries from minimum up to 500000 USD
          # this helped get rid of more outliers
          df_top10_ind = df_top10_ind[(df_top10_ind.salaire_usd <= 500000)]
```

```
In [124]: base_color = sb.color_palette()[0]
          sb.violinplot(data = df_top10_ind, y = 'industrie', x = 'salaire_usd', color = base_co
```




```
In [14]: # To make things clearer let's these top 10 industries against salary average
         base_color = sb.color_palette()[0]
         sb.barplot(data= df_top10_ind, x= 'salaire_usd', y= 'industrie', color = base_color, er
         plt.xlabel('Average salary (USD)');
```



1.5.3 Observation

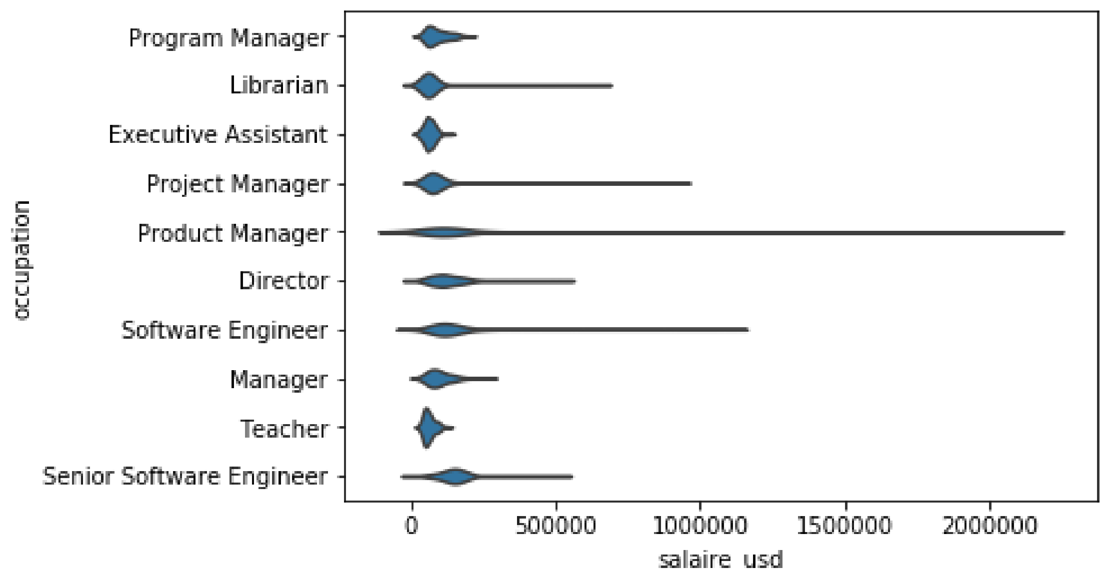
Now we clearly see that *Computing or Tech* industry has the best distribution of salaries with an average greater than 120000 USD. The next is *Law* with about 110000 USD average followed by *Business or Consulting*. The rest of industies have less than 100000 USD average, among them *Higher Education* is the last with generally low salaries.

1.5.4 Question 2 : How are salaries distributed through the top 10 occupations ?

Here we will plot relationship between occupation and salary.

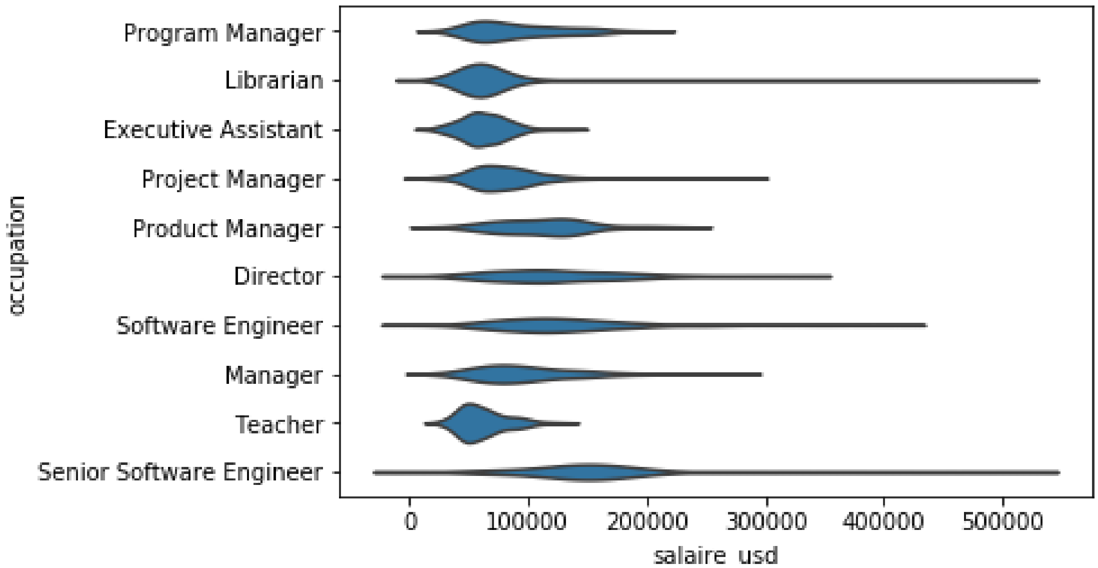
In [15]:
```
# Data for top 10 occupations
occupations = df_salary.occupation.value_counts()[:10].index
df_top10_occ = df_salary[df_salary.occupation.isin(occupations)]
```

In [114]:
```
# Let's plot for all occupations first
base_color = sb.color_palette()[0]
sb.violinplot(data = df_top10_occ, y = 'occupation', x = 'salaire_usd', color = base_c
```

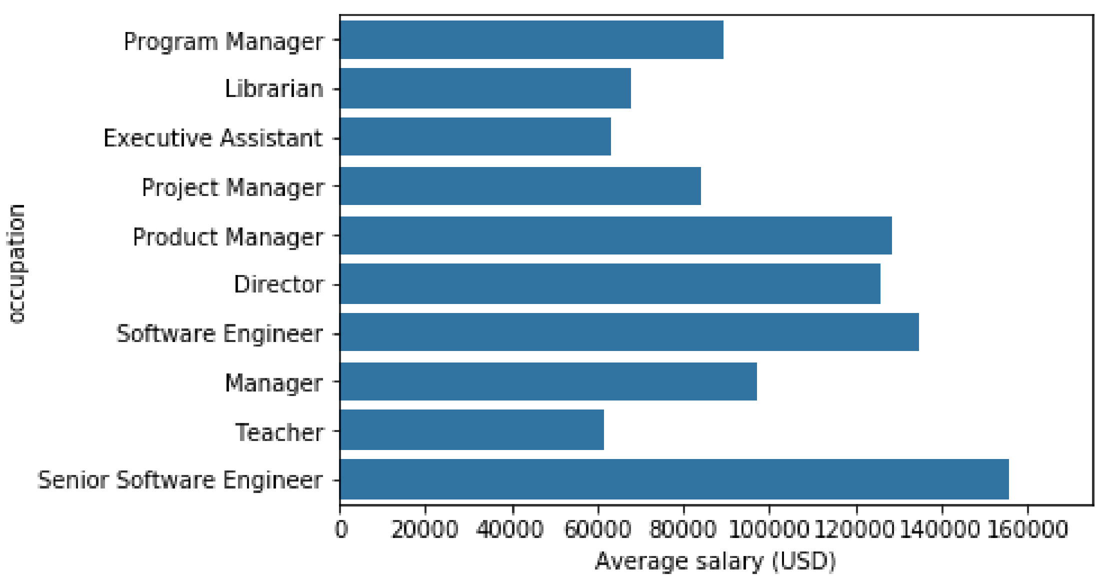


In [127]:
```
# splitting to get salaries from minimum up to 500000 USD
# this helped get rid of more outliers
df_top10_occ = df_top10_occ[(df_top10_occ.salaire_usd <= 500000)]
```

In [128]:
```
base_color = sb.color_palette()[0]
sb.violinplot(data = df_top10_occ, y = 'occupation', x = 'salaire_usd', color = base_c
```




```
In [16]: # To make things clearer let's these top 10 occupations against salary average
         base_color = sb.color_palette()[0]
         sb.barplot(data= df_top10_occ, x= 'salaire_usd', y= 'occupation', color = base_color, e
         plt.xlabel('Average salary (USD)');
```



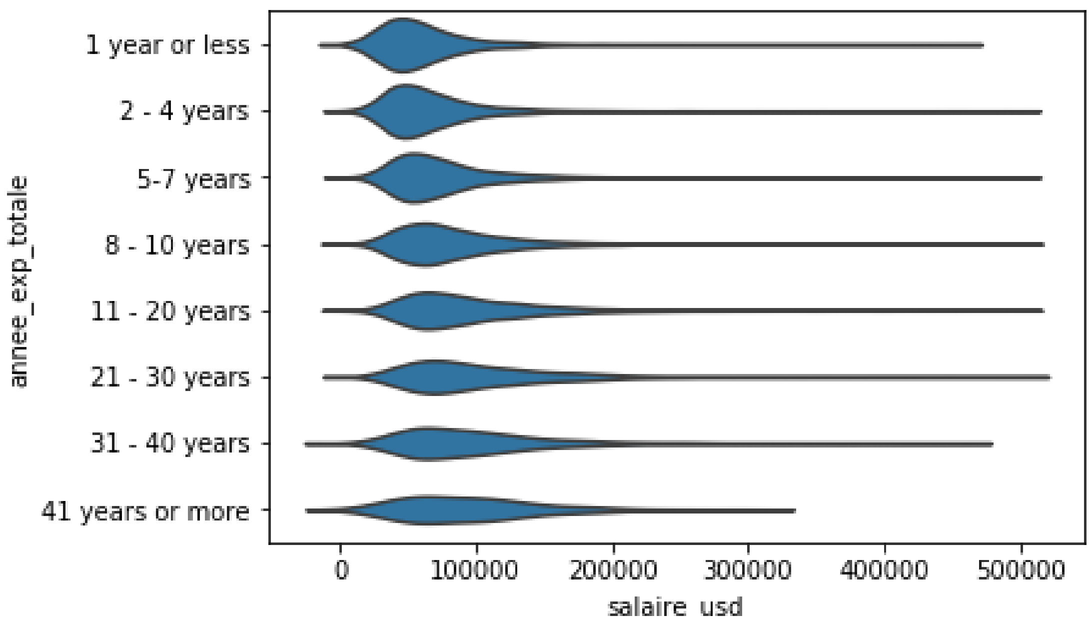
1.5.5 Observation

The position of *Senior Software Engineer* has generally the highest average salary, more than 150000 USD, followed by *Software engineer* with about an average of 140000 USD, *Product Manager* and *Director* with an average between 120000 and 140000 USD. The rest of occupations have an average of less than 100000 USD, among them *Teacher* is the last with generally low salaries.

1.5.6 Question 3 : How are salaries distributed through the experience ranges ?

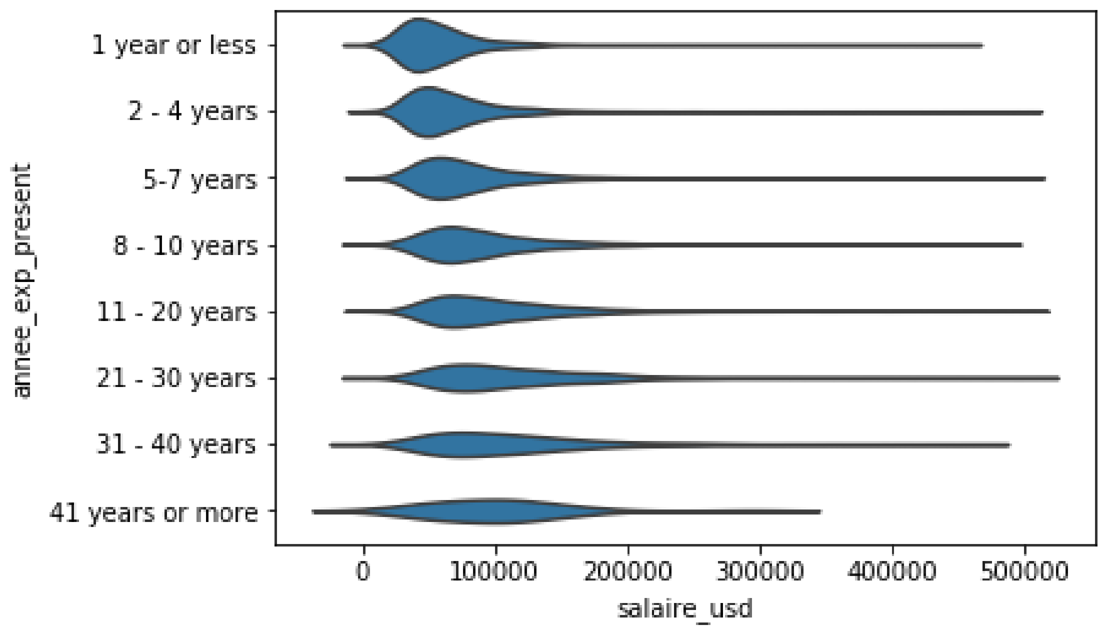
Here we will plot relationship between annee_exp_totale and salary.

```
In [17]: # Get salaries <= 500000 and plot
         df_salary_500 = df_salary[df_salary.salaire_usd <= 500000]
         base_color = sb.color_palette()[0]
         sb.violinplot(data = df_salary_500, y = 'annee_exp_totale', x = 'salaire_usd', color =
```

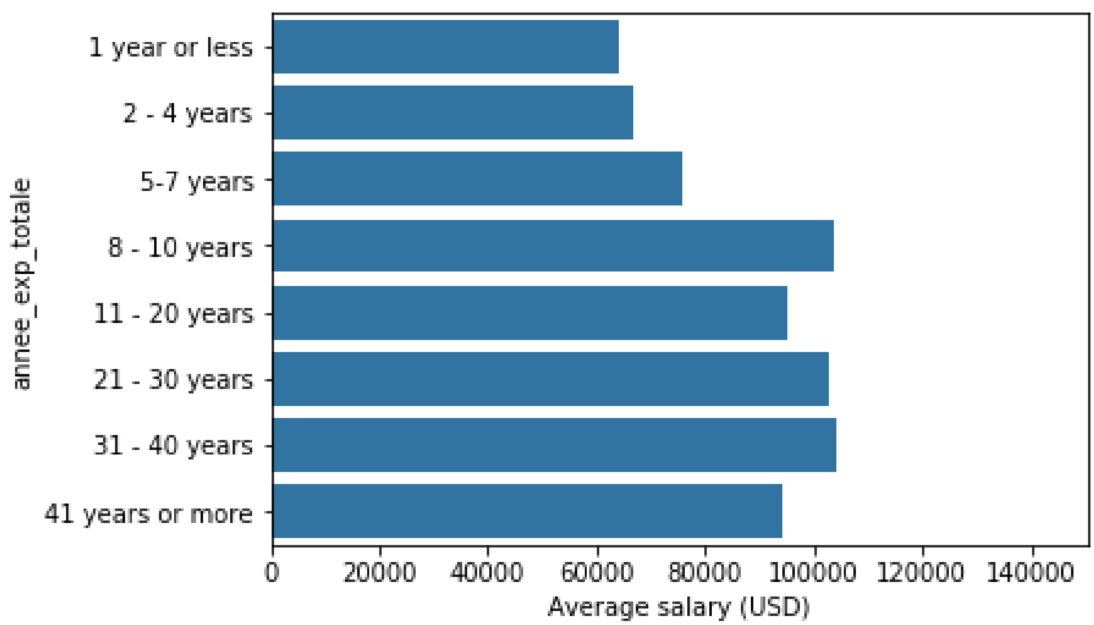


Here we will plot relationship between annee_exp_present and salary.

```
In [18]: # Get salaries <= 500000 and plot
         base_color = sb.color_palette()[0]
         sb.violinplot(data = df_salary_500, y = 'annee_exp_present', x = 'salaire_usd', color =
```



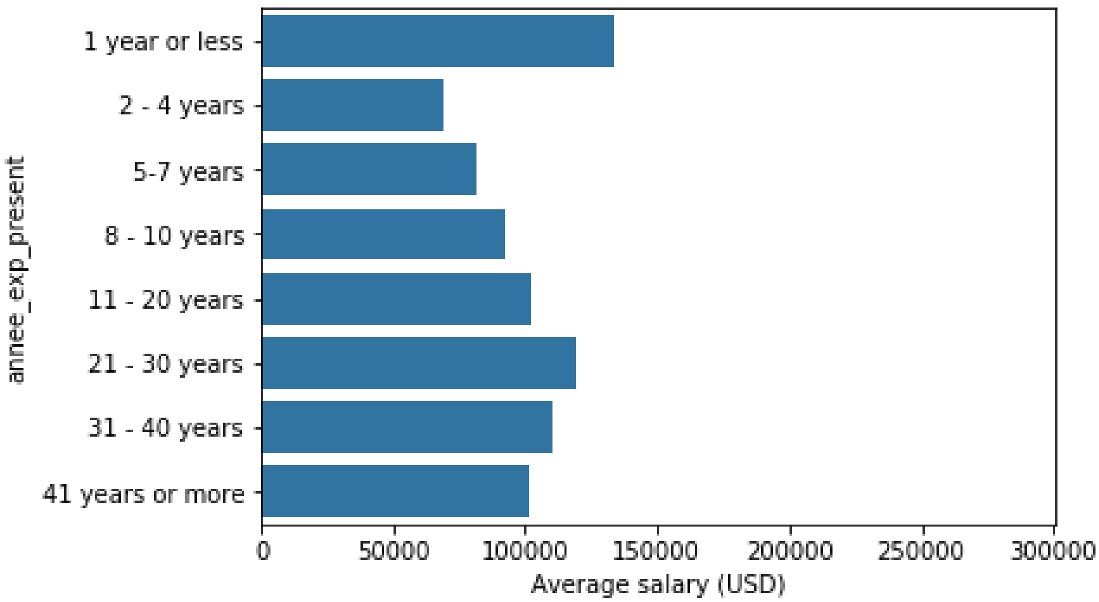

```
In [19]: # Let's plot these against average salary

         # For annee_exp_totale
         base_color = sb.color_palette()[0]
         sb.barplot(data= df_salary, x= 'salaire_usd', y= 'annee_exp_totale', color = base_color
         plt.xlabel('Average salary (USD)');
```



In [22]:
```
df_salary_500.shape
```

Out[22]:
```
(26997, 17)
```

In [23]:
```
# annee_exp_present
base_color = sb.color_palette()[0]
sb.barplot(data= df_salary, x= 'salaire_usd', y= 'annee_exp_present', color = base_colo
plt.xlabel('Average salary (USD)');
```



1.5.7 Observation

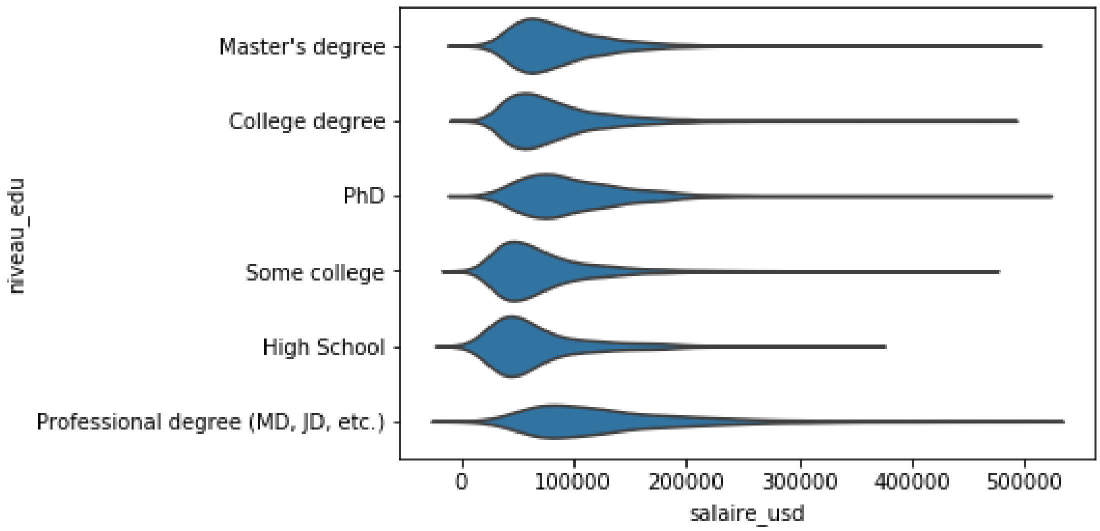
The Best distribution belongs to *11-20 years*, *21-30 years* and *31-40 years* ranges. *41 years or more* and *8-10 years* ranges have the next best distribution. The rest of ranges have low density.

Considering average salary, persons with total years between 31 and 40 have the highest average salary followed by those having from 8 to 10 years and those having from 21 to 30 years. On the other side, the average salary of persons starting their job or with 1 year of present experience is the highest.

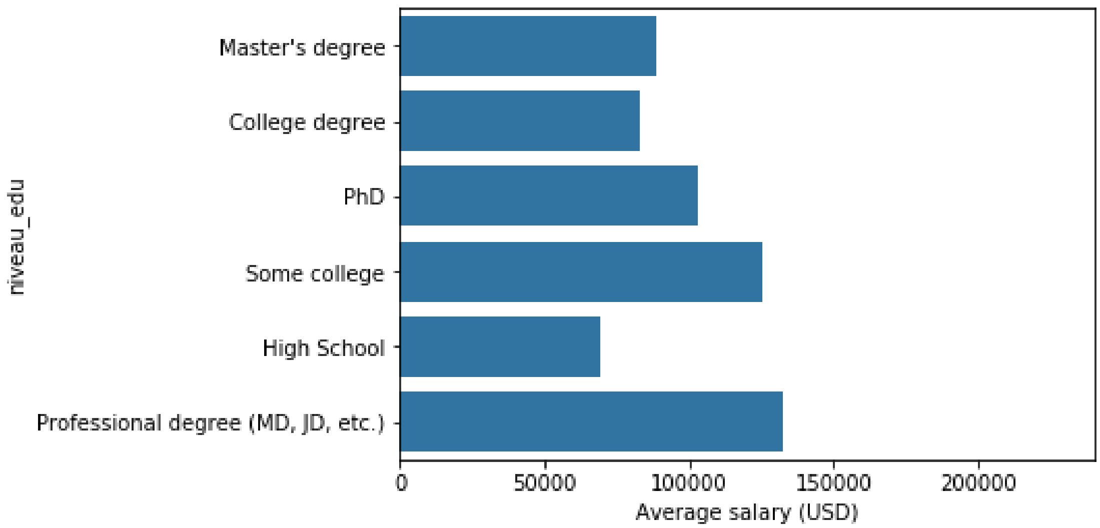
1.5.8 Question 4 : How are salaries distributed through study levels ?

Here we will plot relationship between niveau_edu and salary.

In [24]:
```
# Get salaries <= 500000 and plot
base_color = sb.color_palette()[0]
sb.violinplot(data = df_salary_500, y = 'niveau_edu', x = 'salaire_usd', color = base_c
```




```
In [25]: # niveau_edu
         base_color = sb.color_palette()[0]
         sb.barplot(data= df_salary, x= 'salaire_usd', y= 'niveau_edu', color = base_color, errw
         plt.xlabel('Average salary (USD)');
```



1.5.9 Observation

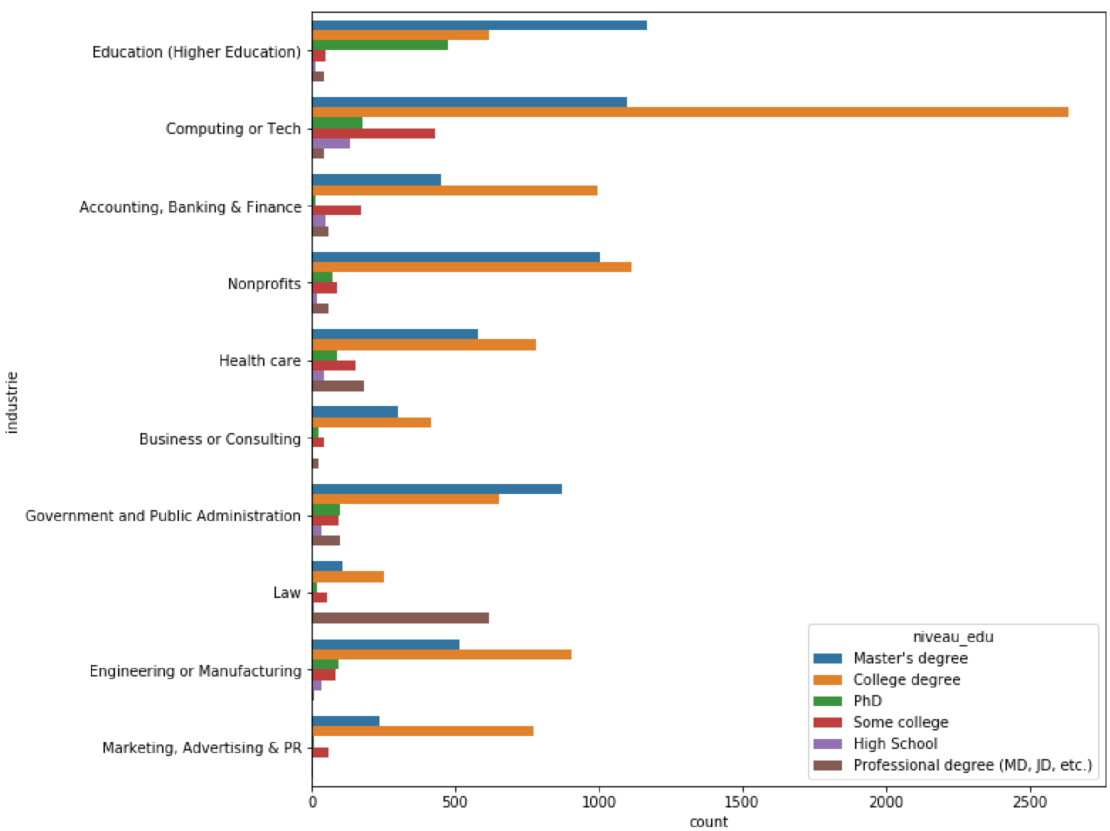
The *Professional degree* has the best distribution, followed by PhD. The rest of levels seem to have the lowest salaries, with *Some college* and *High School* levels having peaker distributions. *High school* is level has generally the lowest salaries.

1.5.10 Ralationship between industry and study level features

In [55]:
```
df_top10_ind.industrie.value_counts()
```

Out[55]:
```
Computing or Tech                        4510
Education (Higher Education)             2375
Nonprofits                               2362
Government and Public Administration     1846
Health care                              1835
Accounting, Banking & Finance            1742
Engineering or Manufacturing             1640
Marketing, Advertising & PR              1090
Law                                      1063
Business or Consulting                    820
Name: industrie, dtype: int64
```

In [54]:
```
plt.figure(figsize= (10, 10))
sb.countplot(data = df_top10_ind, y = 'industrie', hue = 'niveau_edu');
```

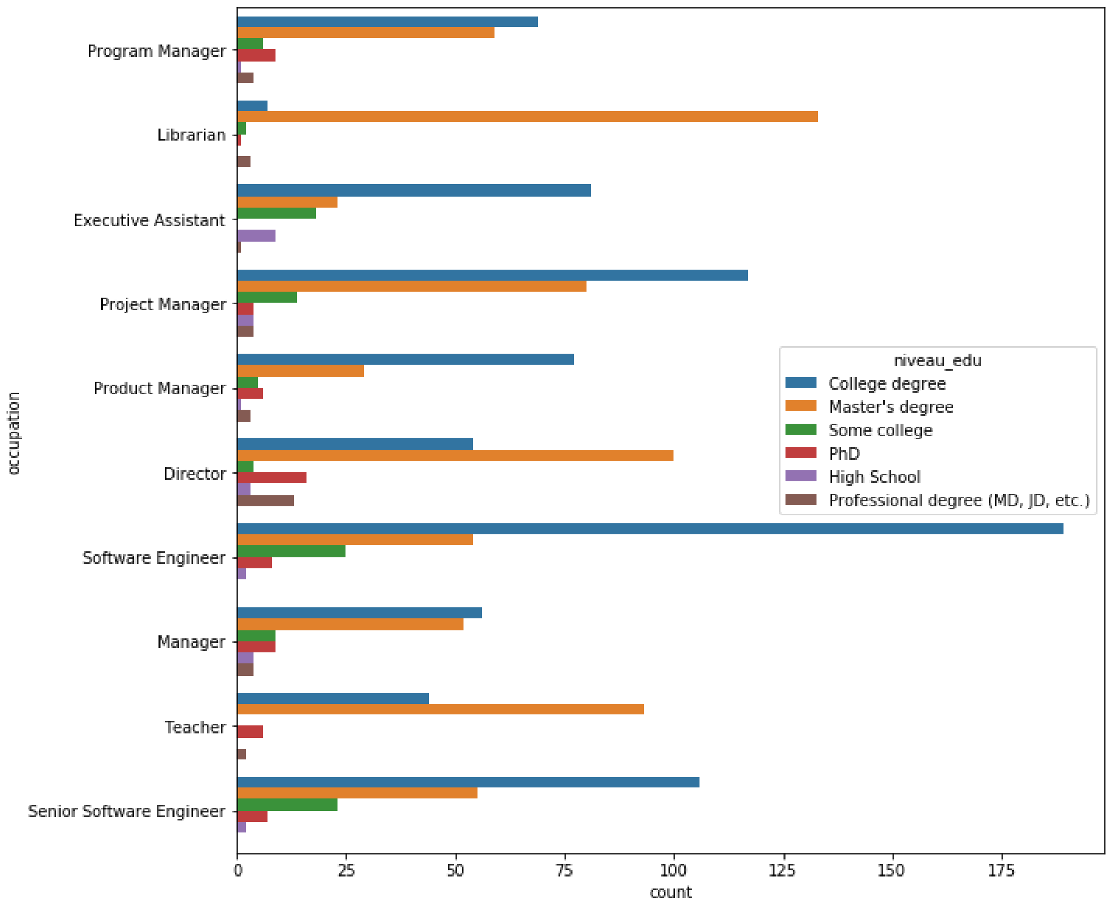


1.5.11 Relationship between occupation and study level

In [57]:
```
df_top10_occ.occupation.value_counts()
```

```
Out[57]: Software Engineer          278
         Project Manager            223
         Senior Software Engineer   193
         Director                   190
         Program Manager            148
         Librarian                  146
         Teacher                    145
         Manager                    134
         Executive Assistant        132
         Product Manager            121
         Name: occupation, dtype: int64
```

```
In [56]: plt.figure(figsize= (10, 10))
         sb.countplot(data = df_top10_occ, y = 'occupation', hue = 'niveau_edu');
```



1.5.12 Observation

Under univariate exploration section, we stated that *Computing or Tech* industry count is the highest among top 10 industries picked in the dataset, also *master* and *College* degrees were the most found among persons. From this plot we understand that those industries with higher counts generally have higher numbers of *master* and *College* degrees, which explain a relationship between industry and study level. The same observation is valid for the top 10 occupations picked too.

1.5.13 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?

Now we clearly see that *Computing or Tech* industry has the best distribution of salaries with an average greater than 120000 USD. The next is *Law* with about 110000 USD average followed by *Business or Consulting*. The rest of industies have less than 100000 USD average, among them *Higher Education* is the last with generally low salaries.

The position of *Director* has the best density followed by *Software engineer*, *Program Manager*, *Manager*, *Product Manager* and *Senior Software Engineer* have the next best density. *Teacher*, *Librarian*, *Executive Assistant* have low density. The position of *Senior Software Engineer* has generally the highest average salary, more than 150000 USD, followed by *Software engineer* with about an average of 140000 USD, *Product Manager* and *Director* with an average between 120000 and 140000 USD. The rest of occupations have an average of less than 100000 USD, among them *Teacher* is the last with generally low salaries.

For experience ranges of years, the Best distribution belongs to *11-20 years*, *21-30 years* and *31-40 years* ranges. *41 years or more* and *8-10 years* ranges have the next best distribution. The rest of ranges have low density. Considering average salary, persons with total years between 31 and 40 have the highest average salary followed by those having from 8 to 10 years and those having from 21 to 30 years. On the other side, the average salary of persons starting their job or with 1 year of present experience is the highest.

The *Professional degree* has the best distribution, followed by PhD. The rest of levels seem to have the lowest salaries, with *Some college* and *High School* levels having peaker distributions. *High school* is level has generally the lowest salaries.

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

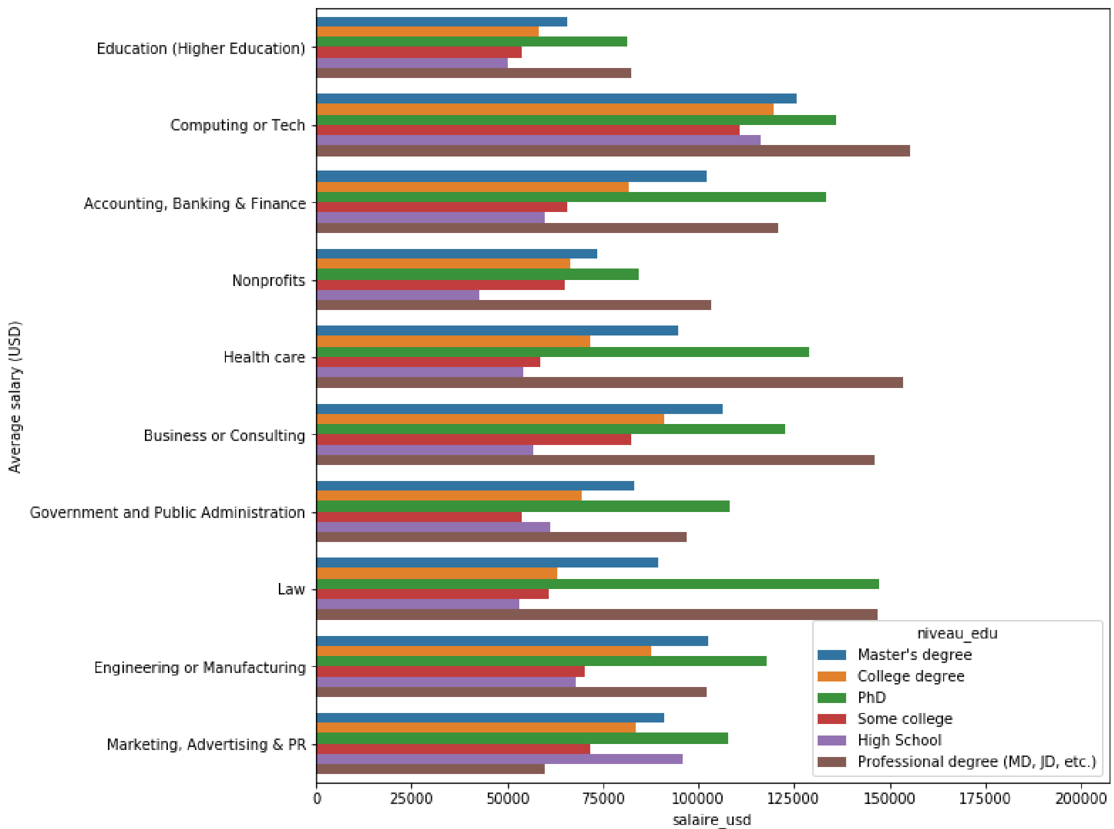
Under univariate exploration section, we stated that *Computing or Tech* industry count is the highest among top 10 industries picked in the dataset, also *master* and *College* degrees were the most found among persons. From these plots we understand that those industries with higher counts generally have higher numbers of *master* and *College* degrees, which explain a relationship between industry and study level. The same observation is valid for the top 10 occupations picked too.

1.6 Multivariate Exploration

Create plots of three or more variables to investigate your data even further. Make sure that your investigations are justified, and follow from your work in the previous sections.

For bivariate exploration we plotted industry against average salary. Here, we'll add study level feature to turn that plot into multivariate plot.

```
In [58]: plt.figure(figsize= (10, 10))
         sb.barplot(data= df_top10_ind, x = 'salaire_usd', y= 'industrie', hue= 'niveau_edu', er
         plt.ylabel('Average salary (USD)');
```



1.6.1 Observation

Previously we noticed that *Computing or Tech* industry has the highest count among the top 10 industries. We also remarked that *Professional degree* has the highest average salary under bivariate exploration. Here we can see that for the first industry *Computing or Tech* the average salary for Professional degree is the highest too, but that relationship is not the same for the rest of industries. For instance, the second industry is *Higher education* but the average salary of *Professional degree* in that industry is not the second highest average for this study level. This means that the relationship between industry and study level in view of average salary is not monotonic.

1.6.2 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?

During univariate exploration we noticed that *Computing or Tech* industry has the highest count among the top 10 industries. We also remarked that *Professional degree* has the highest average salary under bivariate exploration. We also showed a relationship between industry and study level previously. Combining industry, study level and average salary we can see that for the first industry *Computing or Tech* the average salary for Professional degree is the highest.

1.6.3 Were there any interesting or surprising interactions between features?

By examining the relationship between industry, study level and average salary we notice that relationship is not the same for the rest of industries. For instance, the second industry is *Higher education* but the average salary of *Professional degree* in that industry is not the second highest average for this study level through all 10 industries. In fact, the second highest average salary for Professional degree belong to Health care industry which is neither the second industry with the highest count nor the industry with the second highest average salary. This means that the relationship between industry and study level in view of average salary is not monotonic.

1.7 Conclusions

During the data exploration process, we covered univariate, bivariate and multivariatte explorations respectively to understand our dataset through one, two and three variables.

Under univariate exploration, we visualized our feature of interest using a histogram to see salary distribution. Looking at it we understood salary is almost normally distributed. Consequently we visualized other retained features : industry, job position and experience features using barplots since they are all categorical variables (two nominal and two ordinal). From plots under univariate exploration we noticed that:

1. *Computer or Tech* industry is the first of top 10 industries picked and *Business or Consulting* is the last one.
2. *Software Engineer* is the first of top 10 occupations picked and *Porduct Manager* the last one
3. The group of persons with total years of experience *between 11 and 20* has the highest count and that of persons having 41 years or more has the lowest count. This is the same observation even for years of experience in current jobs.
4. *College degree* has the highest count and *High school* has the lowest one.

From plots under bivariate exploration we noticed that:

1. *Computer or Tech* has the best distribution of salary with the highest average salary and *Higher education* the lowest salaries.
2. *Senior Software Engineer* has the highest average salary among the top 10 occupations and *Teacher* occupation has the lowest one.
3. Persons with total years of experience between 31 and 40 have the highest average salary. On the other side, the average salary of persons starting their job or with 1 year of present experience is the highest.
4. Average salary for *Professional degree* is the highest while that of *High school* is the lowest.
5. There seems to be a relationship between industry and study level according to which as the industry count grows greater generally the number of persons for each study levels grows almost accordingly. This observation is the same even for occupations

From plots under multivariate exploration, we understand that even though there is a relationship between industry and study level as stated before, that relationship changes its behaviour when plotted against average salary. This led to conclude that it not a monotonic relationship.

```
In [ ]:
```