Salary_transforming

February 21, 2023

[423]:
```
# import necessary libraries - (CELL 1)
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
plt.rcParams['figure.figsize'] = [10, 6]
```

[424]:
```
# read in the dataset - (CELL 2)
data = pd.read_csv("Surveys_cleaned.csv", sep=',')
```

[425]:
```
# see what the data looks like - (CELL 3)
display(data.head())
print(data.shape)
```

```
              datetime age_band                         industry  \
0  2021-04-27 11:02:10    25-34   Education (Higher Education)
1  2021-04-27 11:02:22    25-34              Computing or Tech
2  2021-04-27 11:02:38    25-34  Accounting, Banking & Finance
3  2021-04-27 11:02:41    25-34                     Nonprofits
4  2021-04-27 11:02:42    25-34  Accounting, Banking & Finance

                                  job_title  salary  compensation currency  \
0        research and instruction librarian   55000             0      USD
1  change & internal communications manager   54600          4000      GBP
2                      marketing specialist   34000             0      USD
3                           program manager   62000          3000      USD
4                        accounting manager   60000          7000      USD

                    country           state overall_experience_band  \
0  united states of america   Massachusetts               5-7 years
1            united kingdom    Not American              8-10 years
2  united states of america       Tennessee               2-4 years
3  united states of america       Wisconsin              8-10 years
4  united states of america  South Carolina              8-10 years

  field_experience_band        education      gender
0             5-7 years  Master's degree       Woman
1             5-7 years   College degree  Non-binary
```

```
2             2-4 years   College degree       Woman
3             5-7 years   College degree       Woman
4             5-7 years   College degree       Woman
```

```
(27090, 13)
```

[ ]:
```
# CELL 4
```

1 Data cleansing and preparation

[426]:
```
# get currency types - (CELL 5)
currencies = list(data['currency'].unique())
print(currencies)
```

```
['USD', 'GBP', 'CAD', 'EUR', 'AUD/NZD', 'CHF', 'ZAR', 'SEK', 'JPY']
```

[427]:
```
# conversion rate of currencies to USD on 2023 january 25 13:00 UTC - (CELL 6)
currency_to_USD = {
    'USD': 1.0000,
    'GBP': 1.2300,
    'CAD': 0.7500,
    'EUR': 1.0900,
    'AUD/NZD': 0.6800,
    'CHF': 1.0900,
    'ZAR': 0.0580,
    'SEK': 0.9800,
    'JPY': 0.0077
}

# replace currency with the conversion rates
data['currency'] = data['currency'].replace(currency_to_USD)

# check if replacement worked
print(data['currency'].value_counts())
```

```
1.0000    22763
0.7500     1641
1.2300     1552
1.0900      608
0.6800      489
0.0077       22
0.0580       13
0.9800        2
Name: currency, dtype: int64
```

[428]:
```python
# calculate salary and compensation to USD - (CELL 7)
data['salary'] = (data['salary'] * data['currency']).round(0).astype(int)
data['compensation'] = (data['compensation'] * data['currency']).round(0).
 ↪astype(int)
```

[429]:
```python
# drop unnecessary columns for further transformation - (CELL 8)
data = data.drop('currency', axis='columns')
data = data.drop('datetime', axis='columns')
data = data.drop('job_title', axis='columns')
data = data.drop('state', axis='columns')
```

[430]:
```python
# assign correct dtypes - (CELL 9)
data['age_band'] = data['age_band'].astype('category')
data['industry'] = data['industry'].astype('category')
data['country'] = data['country'].astype('category')
data['overall_experience_band'] = data['overall_experience_band'].
 ↪astype('category')
data['field_experience_band'] = data['field_experience_band'].astype('category')
data['education'] = data['education'].astype('category')
data['gender'] = data['gender'].astype('category')

# check dtypes
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27090 entries, 0 to 27089
Data columns (total 9 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   age_band                 27090 non-null  category
 1   industry                 27090 non-null  category
 2   salary                   27090 non-null  int64
 3   compensation             27090 non-null  int64
 4   country                  27090 non-null  category
 5   overall_experience_band  27090 non-null  category
 6   field_experience_band    27090 non-null  category
 7   education                27090 non-null  category
 8   gender                   27090 non-null  category
dtypes: category(7), int64(2)
memory usage: 612.0 KB
None
```

[431]:
```python
# CELL 10
display(data.head())
```

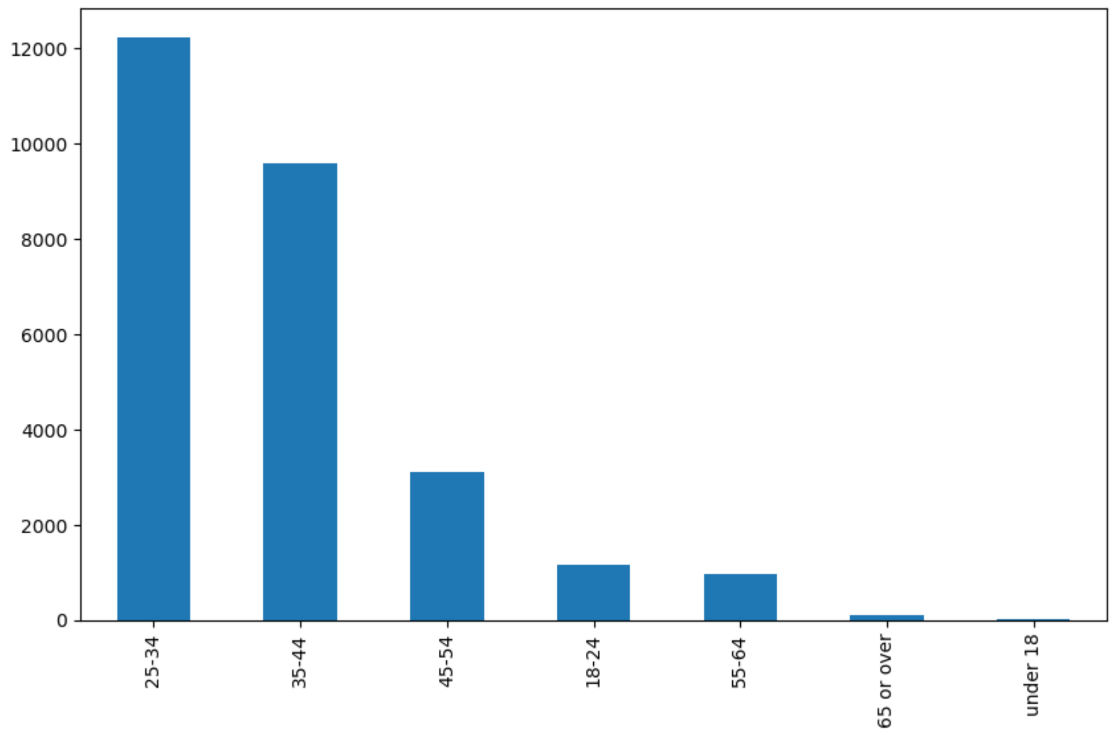
```
  age_band                    industry  salary  compensation  \
0    25-34   Education (Higher Education)   55000             0
```

```
1    25-34             Computing or Tech   67158          4920
2    25-34  Accounting, Banking & Finance   34000             0
3    25-34                    Nonprofits   62000          3000
4    25-34  Accounting, Banking & Finance   60000          7000

                    country overall_experience_band field_experience_band  \
0  united states of america               5-7 years             5-7 years
1            united kingdom              8-10 years             5-7 years
2  united states of america               2-4 years             2-4 years
3  united states of america              8-10 years             5-7 years
4  united states of america              8-10 years             5-7 years

         education      gender
0  Master's degree       Woman
1   College degree  Non-binary
2   College degree       Woman
3   College degree       Woman
4   College degree       Woman
```

[ ]:
```
# CELL 11
```

2 Data exploration an visualization

[432]:
```
# show distribution of age band - (CELL 12)
data['age_band'].value_counts().plot(kind='bar')
plt.show()
```



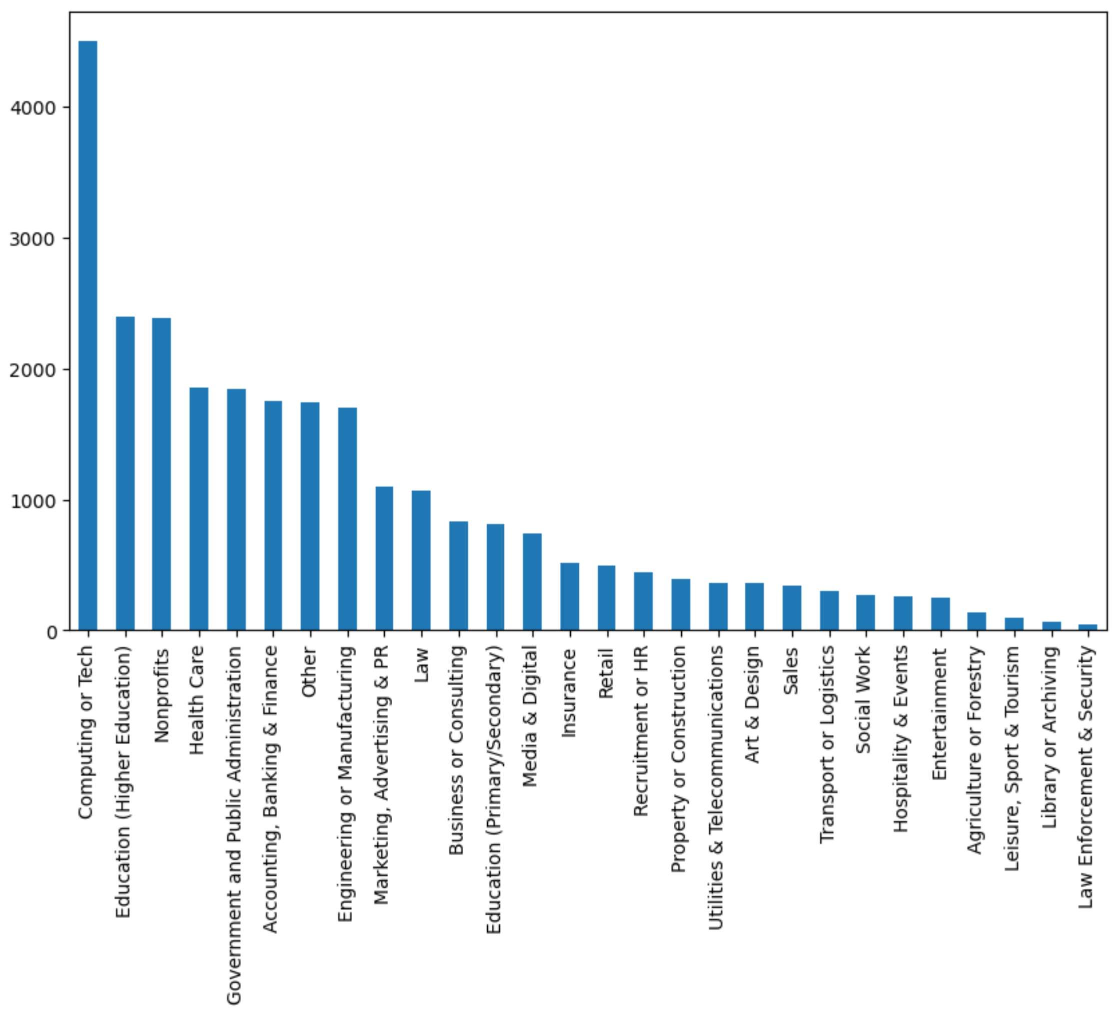
[433]:
```
# labelencode mapping - (CELL 13)
encoded_age_band = {
    'under 18': 0,
    '18-24': 1,
    '25-34': 2,
    '35-44': 3,
    '45-54': 4,
    '55-64': 5,
    '65 or over': 6,
}
```

[434]:
```
# labelencode age band (ordinal variable) - (CELL 14)
data['age_band_le'] = data['age_band']
data['age_band_le'] = data['age_band_le'].replace(encoded_age_band)
display(data.head())
```

```
  age_band                        industry  salary  compensation  \
0    25-34   Education (Higher Education)   55000             0
1    25-34              Computing or Tech   67158          4920
2    25-34  Accounting, Banking & Finance   34000             0
3    25-34                     Nonprofits   62000          3000
4    25-34  Accounting, Banking & Finance   60000          7000

                    country overall_experience_band field_experience_band  \
```

```
0  united states of america               5-7 years              5-7 years
1            united kingdom              8-10 years              5-7 years
2  united states of america               2-4 years              2-4 years
3  united states of america              8-10 years              5-7 years
4  united states of america              8-10 years              5-7 years

         education      gender age_band_le
0  Master's degree       Woman           2
1   College degree  Non-binary           2
2   College degree       Woman           2
3   College degree       Woman           2
4   College degree       Woman           2
```

[435]:
```
# show distribution of industry - (CELL 15)
data['industry'].value_counts().plot(kind='bar')
plt.show()
```



[436]:
```python
# create dummies for industry (nominal variable) - (CELL 16)
industry_dummies = pd.get_dummies(data['industry'] )
```

[437]:
```python
# drop 1 dummy variable to prevent dummy variable trap (https://www.
↪learndatasci.com/glossary/dummy-variable-trap/) - (CELL 17)
industry_dummies = industry_dummies.drop('Media & Digital', axis='columns')
```

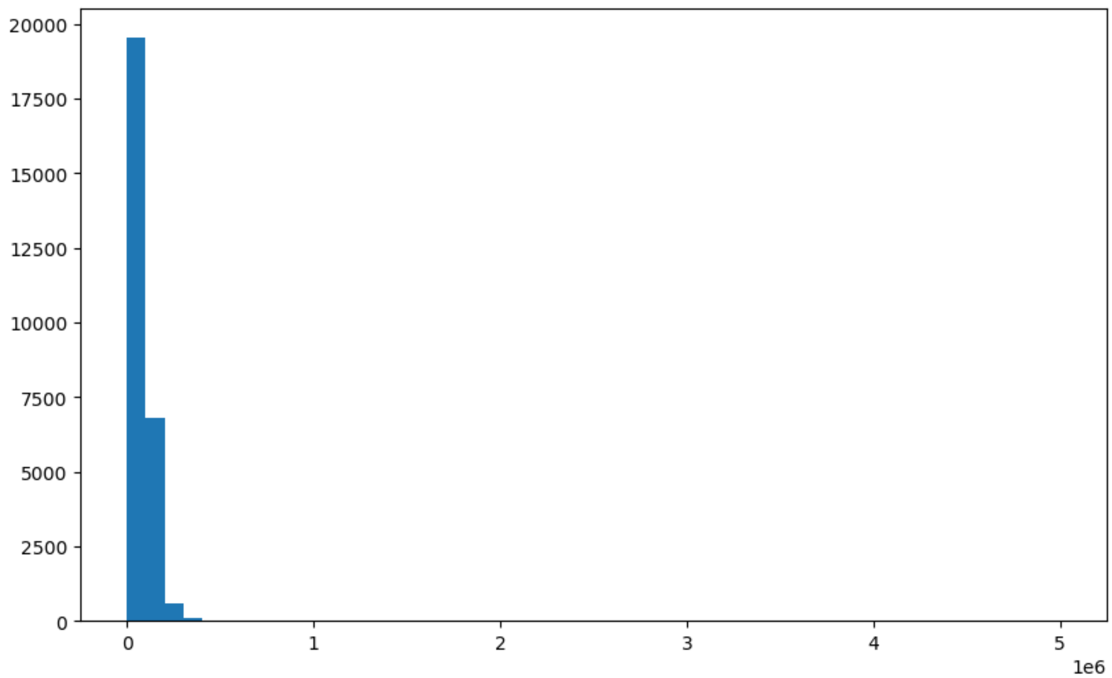
[438]:
```python
# show dummies - (CELL 18)
display(industry_dummies.head())
```

```
   Accounting, Banking & Finance  Agriculture or Forestry  Art & Design  \
0                              0                        0             0
1                              0                        0             0
2                              1                        0             0
3                              0                        0             0
4                              1                        0             0

   Business or Consulting  Computing or Tech  Education (Higher Education)  \
0                       0                  0                             1
1                       0                  1                             0
2                       0                  0                             0
3                       0                  0                             0
4                       0                  0                             0

   Education (Primary/Secondary)  Engineering or Manufacturing  Entertainment  \
0                              0                             0              0
1                              0                             0              0
2                              0                             0              0
3                              0                             0              0
4                              0                             0              0

   Government and Public Administration  …  Marketing, Advertising & PR  \
0                                     0  …                            0
1                                     0  …                            0
2                                     0  …                            0
3                                     0  …                            0
4                                     0  …                            0

   Nonprofits  Other  Property or Construction  Recruitment or HR  Retail  \
0           0      0                         0                  0       0
1           0      0                         0                  0       0
2           0      0                         0                  0       0
3           1      0                         0                  0       0
4           0      0                         0                  0       0

   Sales  Social Work  Transport or Logistics  Utilities & Telecommunications
0      0            0                       0                               0
```

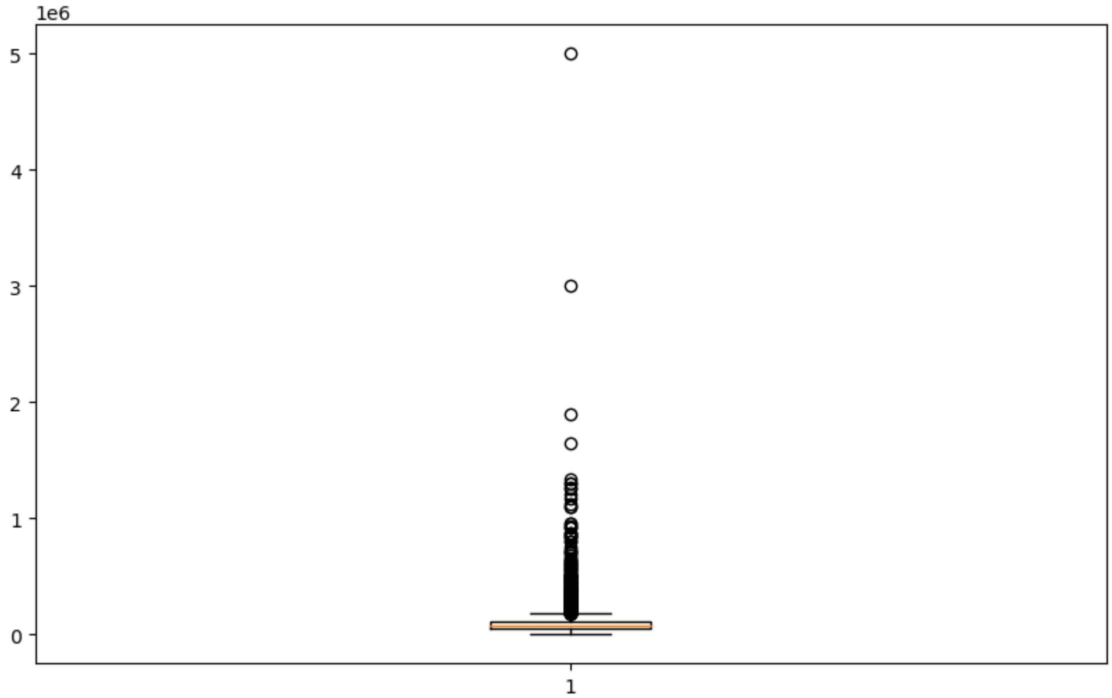
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

[5 rows x 27 columns]

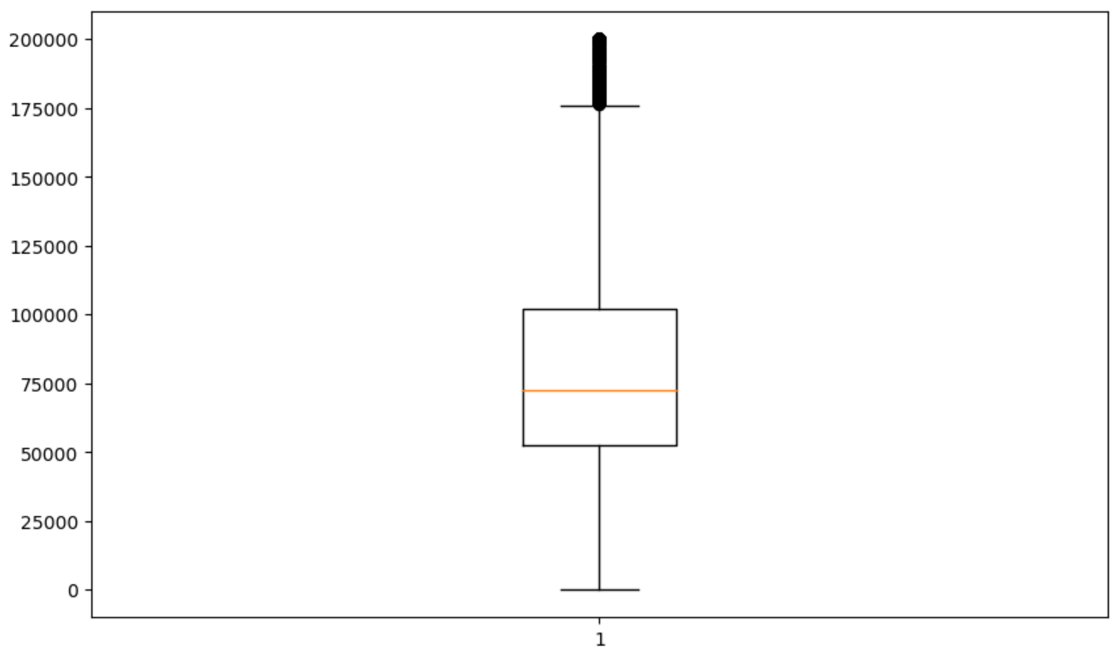
[439]:
```
# show salary distribution - (CELL 19)
salaries = np.array(data['salary'])
plt.hist(salaries, bins=50)
plt.show()
```



[440]:
```
# visualize salary outliers - (CELL 20)
plt.boxplot(salaries)
plt.show()
```



[441]:
```
# visualize with outlier salaries below certain amount - (CELL 21)
salary_threshold = 200000
plt.boxplot(salaries[salaries <= salary_threshold])
plt.show()
```

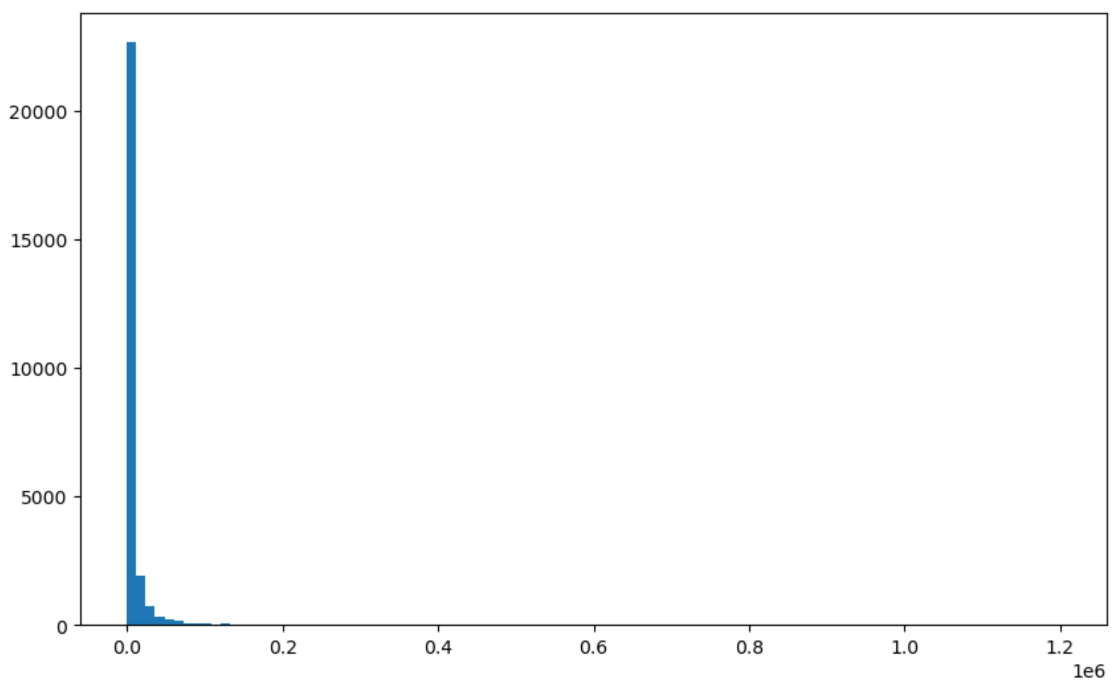


[442]:
```python
# projection of how many rows will be lost - (CELL 22)
current_rows = data.shape[0]
new_rows = data[data['salary'] <= salary_threshold].shape[0]
lost_perc = abs(round(((new_rows - current_rows) / current_rows) * 100, 1))

print(f"current row amount: {current_rows}")
print(f"remaining row amount after removal: {new_rows}")
print(f"rows percentage lost: {lost_perc}%")
```

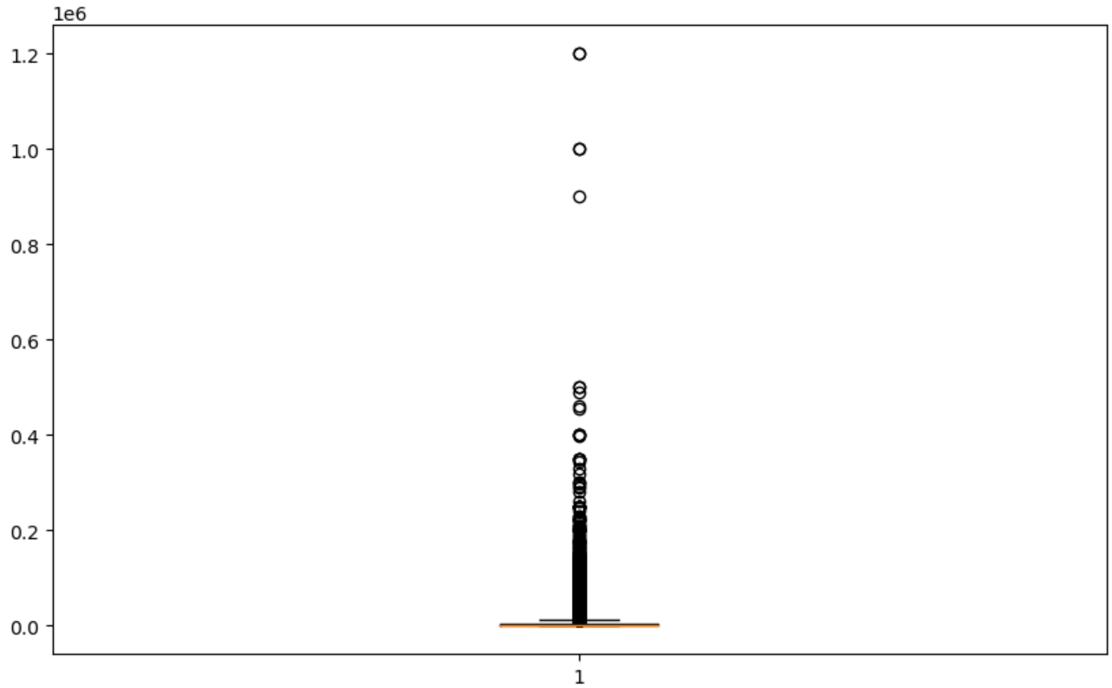
```
current row amount: 27090
remaining row amount after removal: 26327
rows percentage lost: 2.8%
```

[443]:
```python
# remove outliers with salary above threshold - (CELL 23)
salary_outlier_filter = data['salary'] > salary_threshold
data = data[~salary_outlier_filter]
```

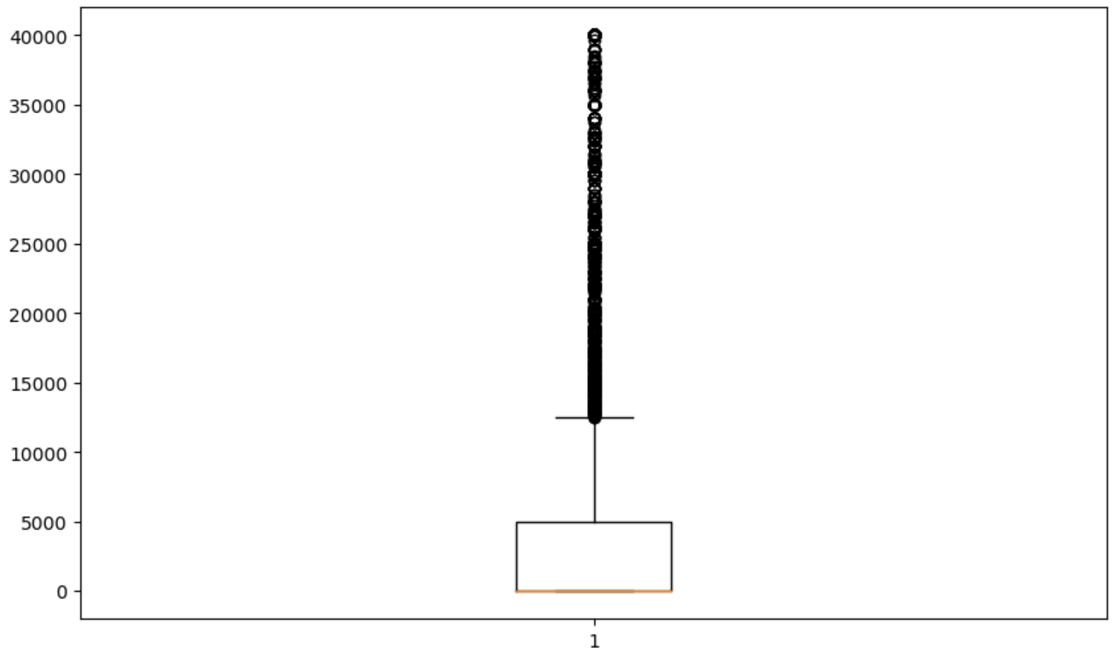
[444]:
```python
# show compensation distribution - (CELL 24)
compensations = np.array(data['compensation'])
plt.hist(compensations, bins=100)
plt.show()
```



[445]:
```
# visualize compensation outliers - (CELL 25)
plt.boxplot(compensations)
plt.show()
```



[446]:
```
# visualize with outlier compensations below certain amount - (CELL 26)
compensation_threshold = 40000
plt.boxplot(compensations[compensations <= compensation_threshold])
plt.show()
```

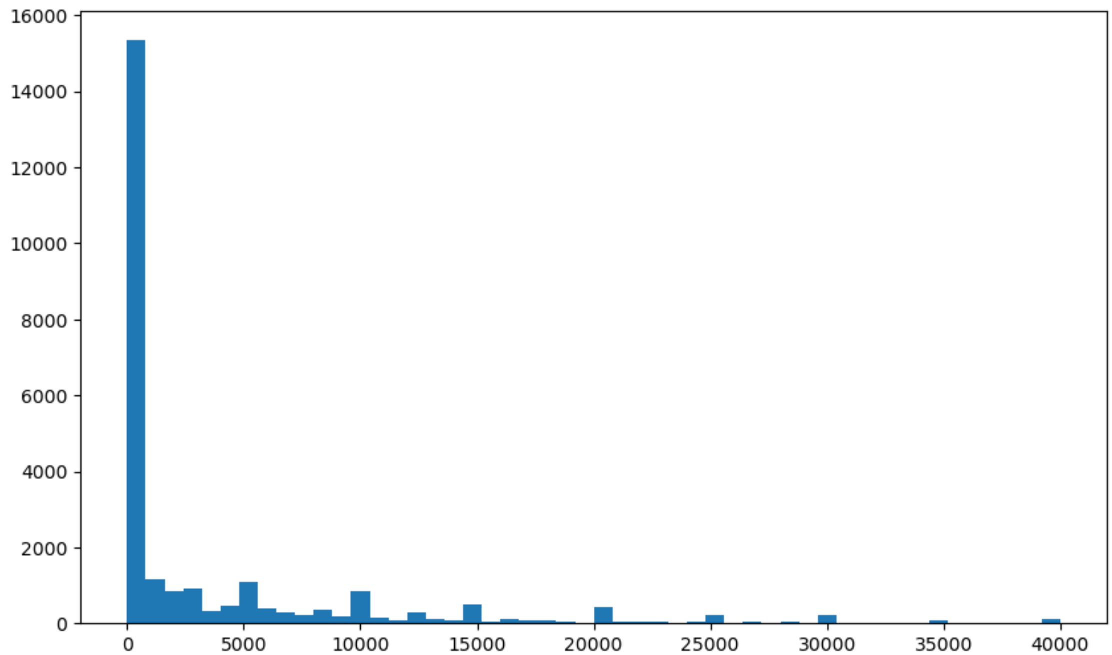


[447]:
```
# projection of how many rows will be lost - (CELL 27)
current_rows = data.shape[0]
new_rows = data[data['compensation'] <= compensation_threshold].shape[0]
lost_perc = abs(round(((new_rows - current_rows) / current_rows) * 100, 1))

print(f"current row amount: {current_rows}")
print(f"remaining row amount after removal: {new_rows}")
print(f"rows percentage lost: {lost_perc}%")
```

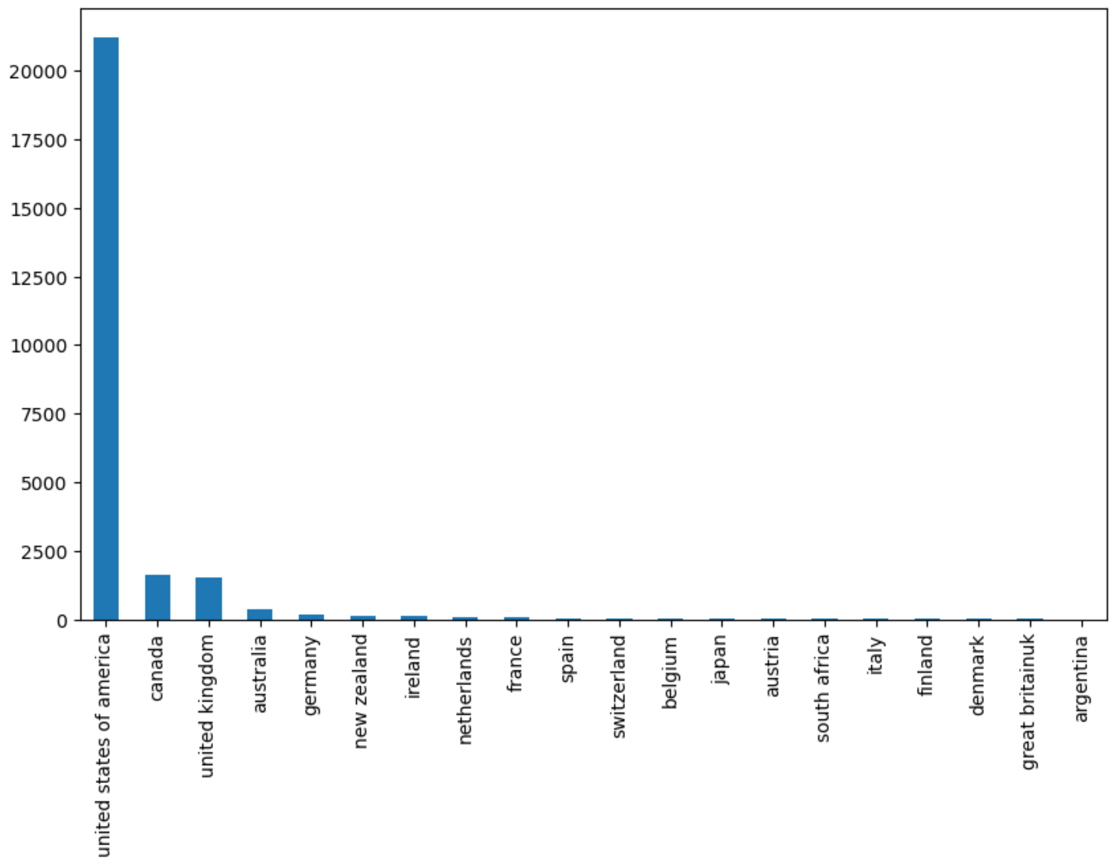
```
current row amount: 26327
remaining row amount after removal: 25508
rows percentage lost: 3.1%
```

[448]:
```
# remove outliers with compensation above threshold - (CELL 28)
comp_outlier_filter = data['compensation'] > compensation_threshold
data = data[~comp_outlier_filter]
```

[449]:
```
# show compensation distribution again - (CELL 29)
compensations = np.array(data['compensation'])
plt.hist(compensations, bins=50)
plt.show()
```



[450]:
```python
# show distribution of country - (CELL 30)
data['country'].value_counts().plot(kind='bar')
plt.show()
```



[451]:
```
# create dummies for country (nominal variable) - (CELL 31)
country_dummies = pd.get_dummies(data['country'] )
```

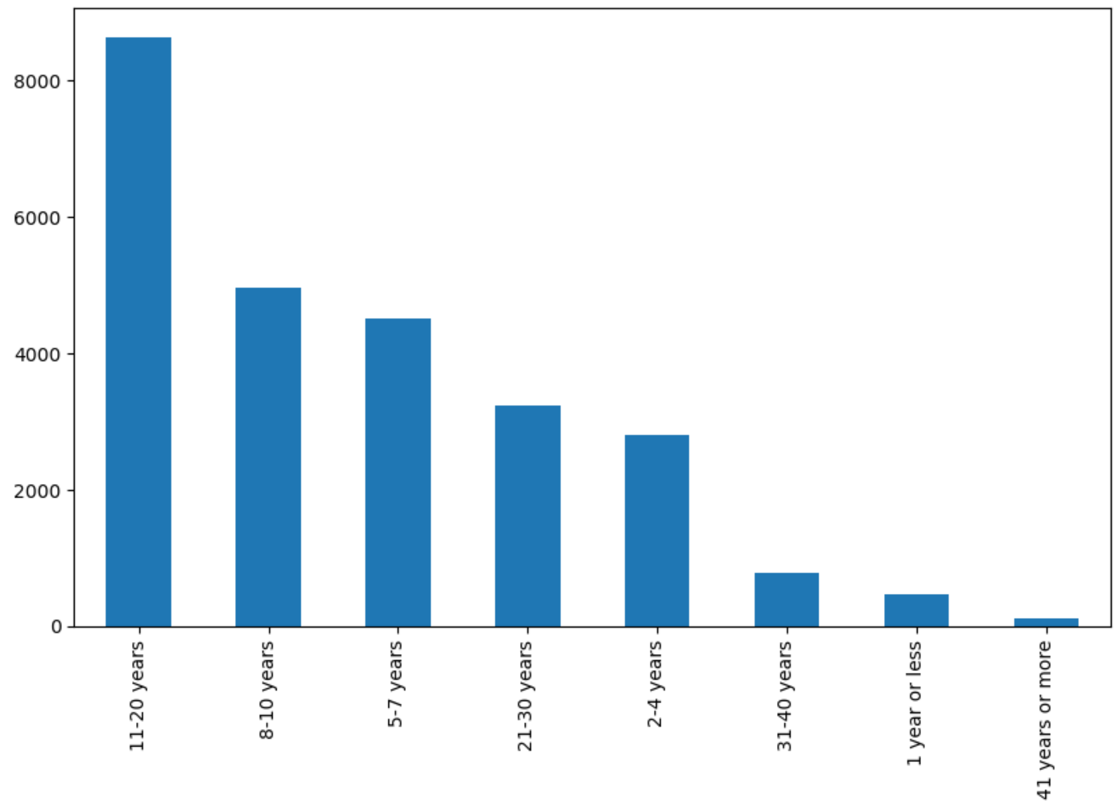
[452]:
```
# drop 1 dummy variable to prevent dummy variable trap (https://www.
↪learndatasci.com/glossary/dummy-variable-trap/) - (CELL 32)
country_dummies = country_dummies.drop('germany', axis='columns')
```

[453]:
```
# show dummies - (CELL 33)
display(country_dummies.head())
```

```
   argentina  australia  austria  belgium  canada  denmark  finland  france  \
0          0          0        0        0       0        0        0       0
1          0          0        0        0       0        0        0       0
2          0          0        0        0       0        0        0       0
3          0          0        0        0       0        0        0       0
4          0          0        0        0       0        0        0       0

   great britainuk  ireland  italy  japan  netherlands  new zealand  \
0                0        0      0      0            0            0
1                0        0      0      0            0            0
```

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

   south africa  spain  switzerland  united kingdom  united states of america
0             0      0            0               0                         1
1             0      0            0               1                         0
2             0      0            0               0                         1
3             0      0            0               0                         1
4             0      0            0               0                         1
```

[454]:
```python
# show distribution of overall experience band - (CELL 34)
data['overall_experience_band'].value_counts().plot(kind='bar')
plt.show()
```



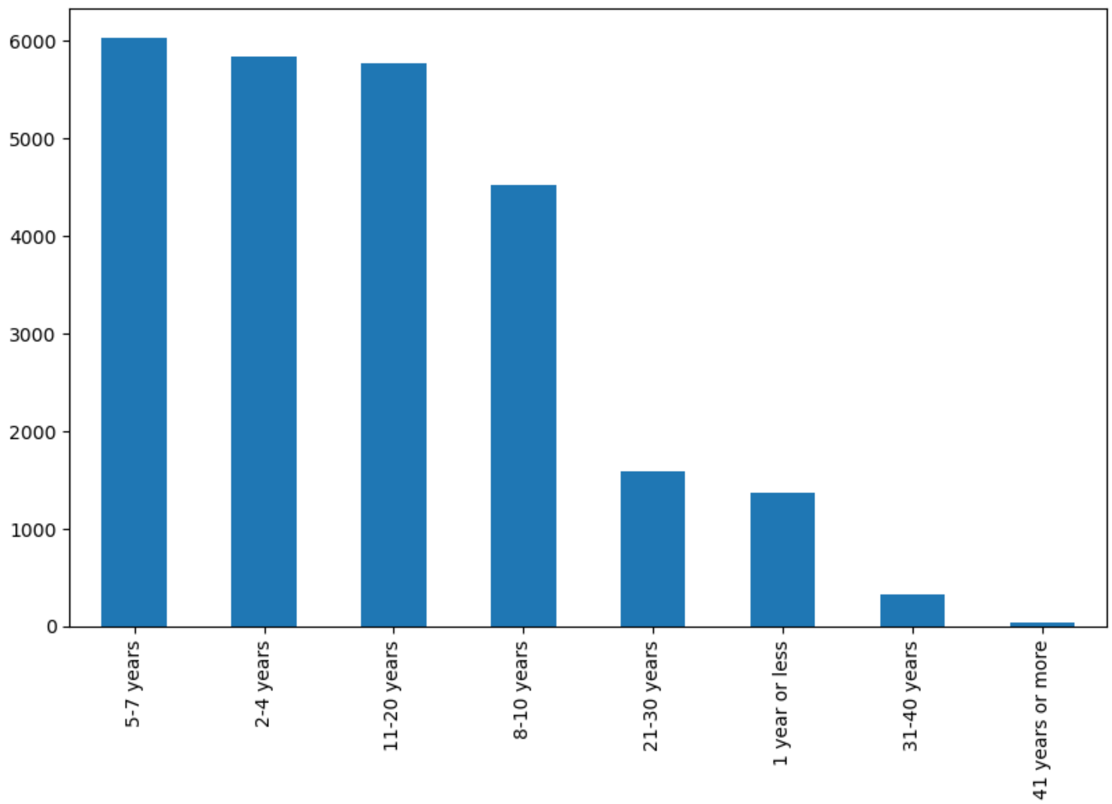
[455]:
```python
# labelencode mapping - (CELL 35)
encoded_overall_experience_band = {
    '1 year or less': 0,
    '2-4 years': 1,
    '5-7 years': 2,
    '8-10 years': 3,
    '11-20 years': 4,
```

```
    '21-30 years': 5,
    '31-40 years': 6,
    '41 years or more': 7
}
```

[456]:
```
# labelencode overall experience band (ordinal variable) - (CELL 36)
data['overall_experience_band_le'] = data['overall_experience_band']
data['overall_experience_band_le'] = data['overall_experience_band_le'].
↪replace(encoded_overall_experience_band)
display(data.head())
```

```
  age_band                        industry  salary  compensation  \
0    25-34   Education (Higher Education)   55000             0
1    25-34               Computing or Tech   67158          4920
2    25-34  Accounting, Banking & Finance   34000             0
3    25-34                      Nonprofits   62000          3000
4    25-34  Accounting, Banking & Finance   60000          7000

                    country overall_experience_band field_experience_band  \
0  united states of america               5-7 years             5-7 years
1            united kingdom              8-10 years             5-7 years
2  united states of america               2-4 years             2-4 years
3  united states of america              8-10 years             5-7 years
4  united states of america              8-10 years             5-7 years

         education      gender age_band_le overall_experience_band_le
0  Master's degree       Woman           2                          2
1   College degree  Non-binary           2                          3
2   College degree       Woman           2                          1
3   College degree       Woman           2                          3
4   College degree       Woman           2                          3
```

[457]:
```
# show distribution of field experience band - (CELL 37)
data['field_experience_band'].value_counts().plot(kind='bar')
plt.show()
```



[458]:
```
# labelencode mapping - (CELL 38)
encoded_field_experience_band = {
    '1 year or less': 0,
    '2-4 years': 1,
    '5-7 years': 2,
    '8-10 years': 3,
    '11-20 years': 4,
    '21-30 years': 5,
    '31-40 years': 6,
    '41 years or more': 7
}
```

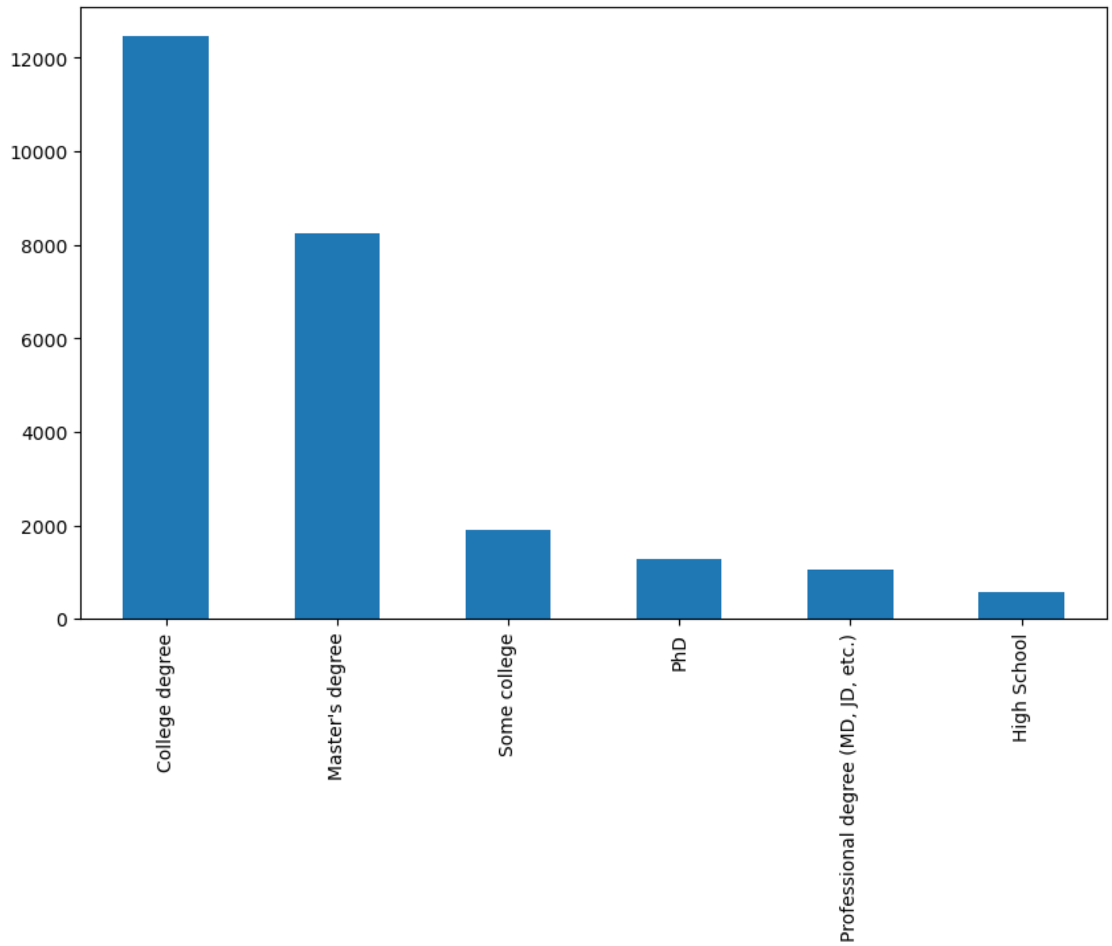
[459]:
```
# labelencode field experience band (ordinal variable) - (CELL 39)
data['field_experience_band_le'] = data['field_experience_band']
data['field_experience_band_le'] = data['field_experience_band_le'].
 ↪replace(encoded_field_experience_band)
display(data.head())
```

```
  age_band                     industry  salary  compensation  \
0    25-34  Education (Higher Education)   55000             0
1    25-34             Computing or Tech   67158          4920
2    25-34  Accounting, Banking & Finance   34000             0
```

```
3    25-34                       Nonprofits   62000          3000
4    25-34  Accounting, Banking & Finance   60000          7000

                    country overall_experience_band field_experience_band  \
0  united states of america               5-7 years             5-7 years
1            united kingdom              8-10 years             5-7 years
2  united states of america               2-4 years             2-4 years
3  united states of america              8-10 years             5-7 years
4  united states of america              8-10 years             5-7 years

         education      gender age_band_le overall_experience_band_le  \
0  Master's degree       Woman           2                          2
1   College degree  Non-binary           2                          3
2   College degree       Woman           2                          1
3   College degree       Woman           2                          3
4   College degree       Woman           2                          3

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

[460]:

```
# show distribution of education - (CELL 40)
data['education'].value_counts().plot(kind='bar')
plt.show()
```



[461]:
```
# labelencode mapping - (CELL 41)
encoded_education = {
    'High School': 0,
    'Some college': 1,
    'College degree': 2,
    'Professional degree (MD, JD, etc.)': 3,
    "Master's degree": 4,
    'PhD': 5,
}
```

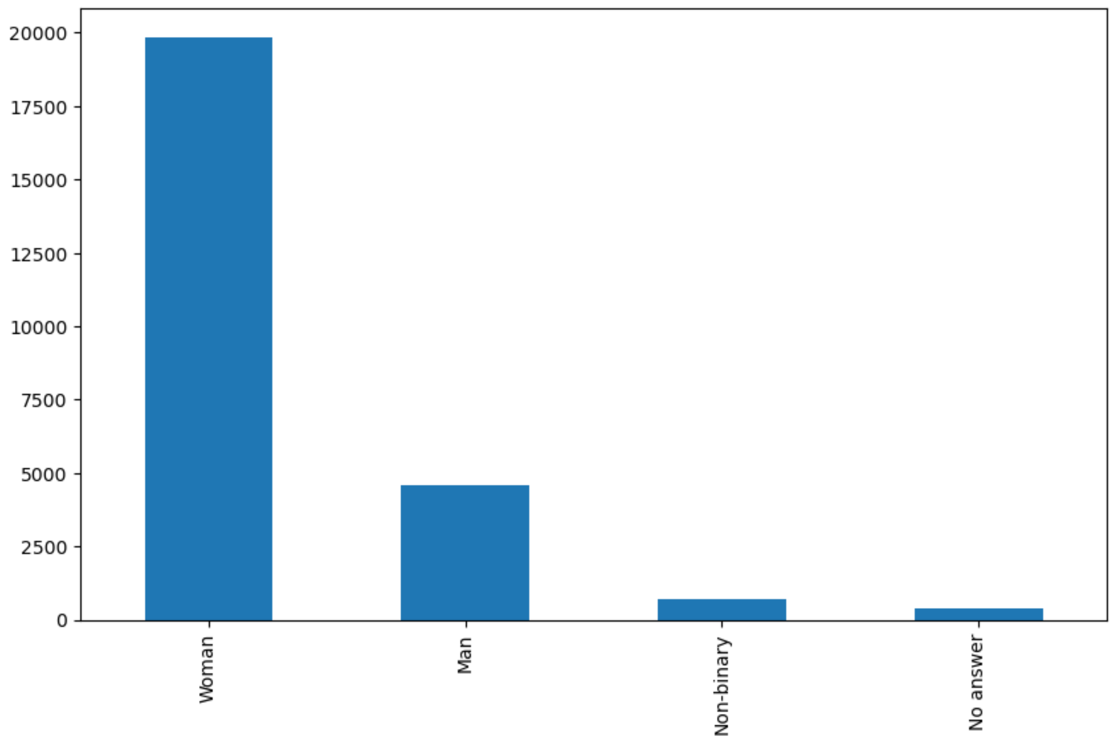
[462]:
```
# labelencode education (ordinal variable) - (CELL 42)
data['education_le'] = data['education']
data['education_le'] = data['education_le'].replace(encoded_education)
display(data.head())
```

```
  age_band                       industry  salary  compensation  \
0    25-34  Education (Higher Education)   55000             0
1    25-34              Computing or Tech   67158          4920
```

```
2    25-34  Accounting, Banking & Finance   34000            0
3    25-34                     Nonprofits   62000         3000
4    25-34  Accounting, Banking & Finance   60000         7000

                    country overall_experience_band field_experience_band  \
0  united states of america               5-7 years             5-7 years
1            united kingdom              8-10 years             5-7 years
2  united states of america               2-4 years             2-4 years
3  united states of america              8-10 years             5-7 years
4  united states of america              8-10 years             5-7 years

         education      gender age_band_le overall_experience_band_le  \
0  Master's degree       Woman           2                          2
1   College degree  Non-binary           2                          3
2   College degree       Woman           2                          1
3   College degree       Woman           2                          3
4   College degree       Woman           2                          3

  field_experience_band_le education_le
0                        2            4
1                        2            2
2                        1            2
3                        2            2
4                        2            2
```

[463]:

```
# show distribution of gender - (CELL 43)
data['gender'].value_counts().plot(kind='bar')
plt.show()
```



[464]:
```
# create dummies for gender (nominal variable) - (CELL 44)
gender_dummies = pd.get_dummies(data['gender'] )
```

[465]:
```
# drop 1 dummy variable to prevent dummy variable trap (https://www.
 ↪learndatasci.com/glossary/dummy-variable-trap/) - (CELL 45)
gender_dummies = gender_dummies.drop('Man', axis='columns')
```

[466]:
```
# show dummies - (CELL 46)
display(gender_dummies.head())
```

	No answer	Non-binary	Woman
0	0	0	1
1	0	1	0
2	0	0	1
3	0	0	1
4	0	0	1

[467]:
```
# merge all dummies on the dataframe - (CELL 47)
data_joined = data.join(industry_dummies).join(country_dummies).
 ↪join(gender_dummies)
print(data_joined.shape)
```

```
(25508, 62)
```

[468]:
```
# show joined dataframe - (CELL 48)
display(data_joined.head())
```

```
  age_band                      industry  salary  compensation  \
0    25-34   Education (Higher Education)   55000             0
1    25-34              Computing or Tech   67158          4920
2    25-34  Accounting, Banking & Finance   34000             0
3    25-34                     Nonprofits   62000          3000
4    25-34  Accounting, Banking & Finance   60000          7000

                    country overall_experience_band field_experience_band  \
0  united states of america               5-7 years             5-7 years
1            united kingdom              8-10 years             5-7 years
2  united states of america               2-4 years             2-4 years
3  united states of america              8-10 years             5-7 years
4  united states of america              8-10 years             5-7 years

        education      gender age_band_le  … netherlands new zealand  \
0  Master's degree       Woman           2  …           0           0
1   College degree  Non-binary           2  …           0           0
2   College degree       Woman           2  …           0           0
3   College degree       Woman           2  …           0           0
4   College degree       Woman           2  …           0           0

  south africa  spain  switzerland  united kingdom  united states of america  \
0            0      0            0               0                         1
1            0      0            0               1                         0
2            0      0            0               0                         1
3            0      0            0               0                         1
4            0      0            0               0                         1

   No answer  Non-binary  Woman
0          0           0      1
1          0           1      0
2          0           0      1
3          0           0      1
4          0           0      1

[5 rows x 62 columns]
```

[469]:
```
# drop text columns which have been converted to dummies or labelencoding -
↪(CELL 49)
drop_cols = ['age_band', 'industry', 'country', 'overall_experience_band',
↪'field_experience_band', 'education', 'gender']
data_final = data_joined.drop(drop_cols, axis='columns')
print(data_final.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25508 entries, 0 to 27089
Data columns (total 55 columns):
 #   Column                              Non-Null Count  Dtype   
---  ------                              --------------  -----   
 0   salary                              25508 non-null  int64   
 1   compensation                        25508 non-null  int64   
 2   age_band_le                         25508 non-null  category
 3   overall_experience_band_le          25508 non-null  category
 4   field_experience_band_le            25508 non-null  category
 5   education_le                        25508 non-null  category
 6   Accounting, Banking & Finance       25508 non-null  uint8   
 7   Agriculture or Forestry             25508 non-null  uint8   
 8   Art & Design                        25508 non-null  uint8   
 9   Business or Consulting              25508 non-null  uint8   
 10  Computing or Tech                   25508 non-null  uint8   
 11  Education (Higher Education)        25508 non-null  uint8   
 12  Education (Primary/Secondary)       25508 non-null  uint8   
 13  Engineering or Manufacturing        25508 non-null  uint8   
 14  Entertainment                       25508 non-null  uint8   
 15  Government and Public Administration 25508 non-null  uint8   
 16  Health Care                         25508 non-null  uint8   
 17  Hospitality & Events                25508 non-null  uint8   
 18  Insurance                           25508 non-null  uint8   
 19  Law                                 25508 non-null  uint8   
 20  Law Enforcement & Security          25508 non-null  uint8   
 21  Leisure, Sport & Tourism            25508 non-null  uint8   
 22  Library or Archiving                25508 non-null  uint8   
 23  Marketing, Advertising & PR         25508 non-null  uint8   
 24  Nonprofits                          25508 non-null  uint8   
 25  Other                               25508 non-null  uint8   
 26  Property or Construction            25508 non-null  uint8   
 27  Recruitment or HR                   25508 non-null  uint8   
 28  Retail                              25508 non-null  uint8   
 29  Sales                               25508 non-null  uint8   
 30  Social Work                         25508 non-null  uint8   
 31  Transport or Logistics              25508 non-null  uint8   
 32  Utilities & Telecommunications      25508 non-null  uint8   
 33  argentina                           25508 non-null  uint8   
 34  australia                           25508 non-null  uint8   
 35  austria                             25508 non-null  uint8   
 36  belgium                             25508 non-null  uint8   
 37  canada                              25508 non-null  uint8   
 38  denmark                             25508 non-null  uint8   
 39  finland                             25508 non-null  uint8   
 40  france                              25508 non-null  uint8   
 41  great britainuk                     25508 non-null  uint8   
 42  ireland                             25508 non-null  uint8   
```

```
 43  italy                                 25508 non-null  uint8
 44  japan                                 25508 non-null  uint8
 45  netherlands                           25508 non-null  uint8
 46  new zealand                           25508 non-null  uint8
 47  south africa                          25508 non-null  uint8
 48  spain                                 25508 non-null  uint8
 49  switzerland                           25508 non-null  uint8
 50  united kingdom                        25508 non-null  uint8
 51  united states of america              25508 non-null  uint8
 52  No answer                             25508 non-null  uint8
 53  Non-binary                            25508 non-null  uint8
 54  Woman                                 25508 non-null  uint8
dtypes: category(4), int64(2), uint8(49)
memory usage: 2.9 MB
None
```

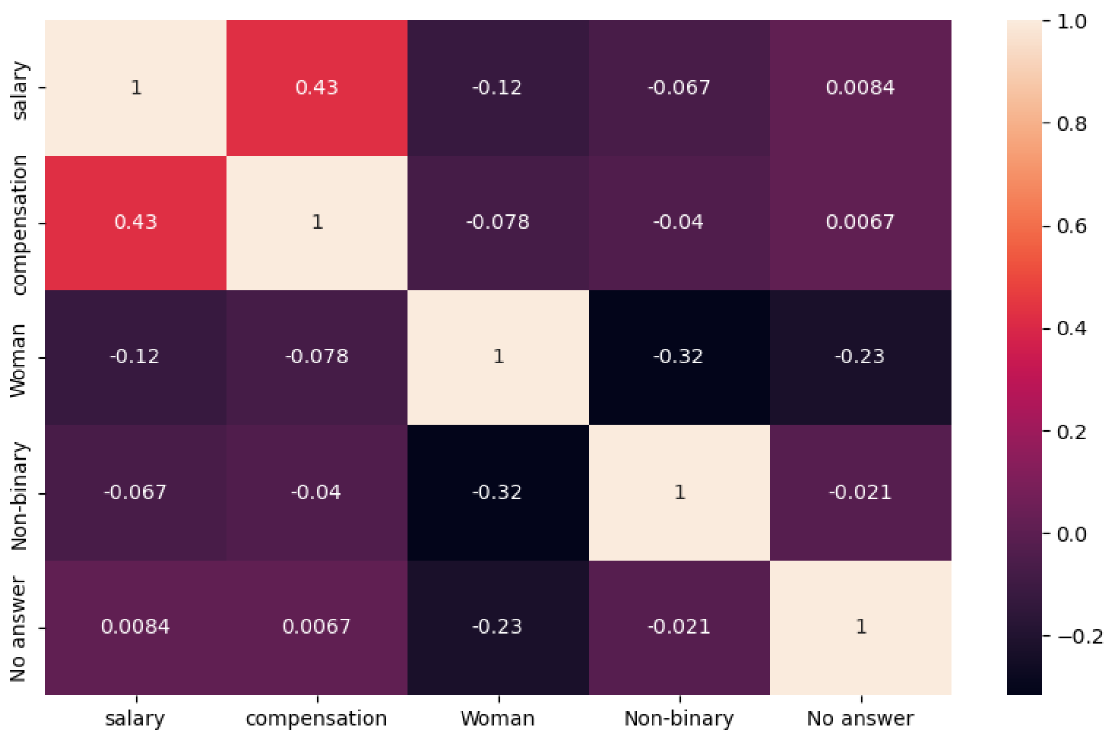
[474]:
```python
# show finalized transformend dataframe - (CELL 50)
display(data_final.head())
print(data_final.shape)
```

```
   salary  compensation age_band_le overall_experience_band_le  \
0   55000             0           2                          2
1   67158          4920           2                          3
2   34000             0           2                          1
3   62000          3000           2                          3
4   60000          7000           2                          3

  field_experience_band_le education_le  Accounting, Banking & Finance  \
0                        2            4                              0
1                        2            2                              0
2                        1            2                              1
3                        2            2                              0
4                        2            2                              1

   Agriculture or Forestry  Art & Design  Business or Consulting  …  \
0                        0             0                       0  …
1                        0             0                       0  …
2                        0             0                       0  …
3                        0             0                       0  …
4                        0             0                       0  …

   netherlands  new zealand  south africa  spain  switzerland  united kingdom  \
0            0            0             0      0            0               0
1            0            0             0      0            0               1
2            0            0             0      0            0               0
3            0            0             0      0            0               0
4            0            0             0      0            0               0
```

```
   united states of america  No answer  Non-binary  Woman
0                        1          0           0      1
1                        0          0           1      0
2                        1          0           0      1
3                        1          0           0      1
4                        1          0           0      1

[5 rows x 55 columns]

(25508, 55)
```

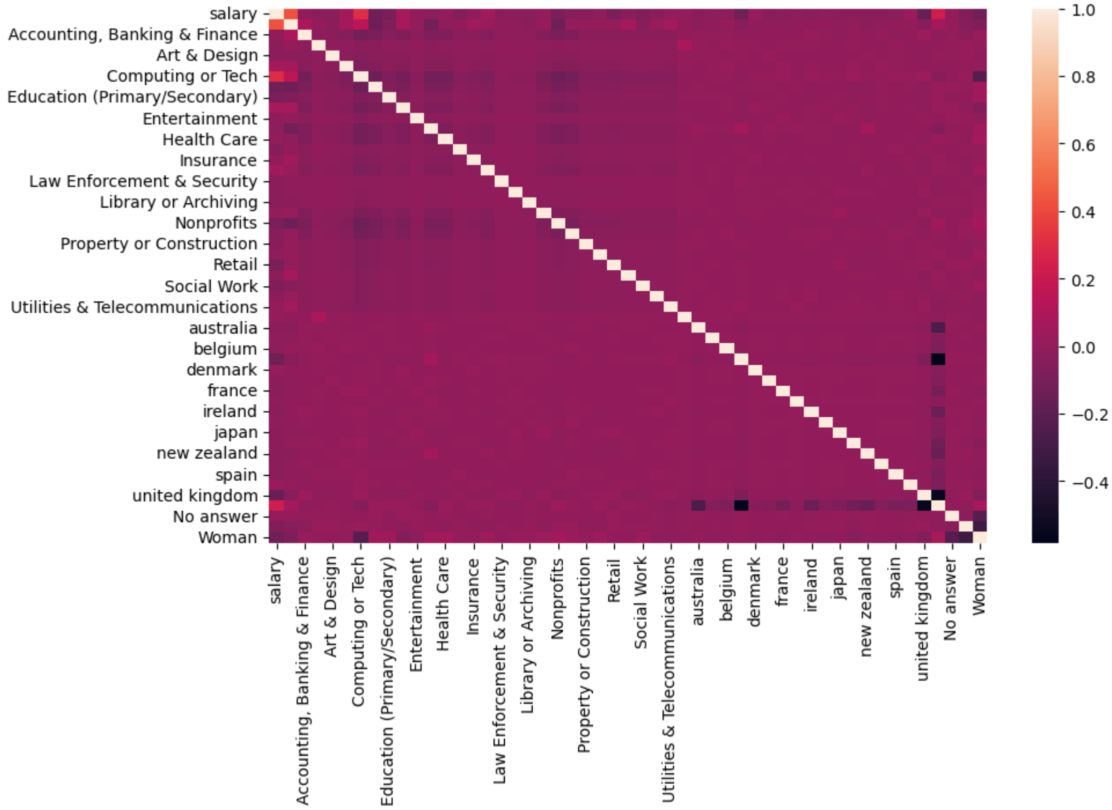
[475]:
```python
# save transformend data - (CELL 51)
data_final.to_csv('Surveys_transformed.csv', index=False)
```

[472]:
```python
# check correlation between all non-labelencoded columns - (CELL 52)
corr_cols = ['salary', 'compensation', 'age_band_le',␣
↪'overall_experience_band_le', 'field_experience_band_le', \
             'Woman', 'Non-binary', 'No answer']
corr_matrix = data_final.loc[:, corr_cols].corr()
sns.heatmap(corr_matrix, annot=True)
plt.show()
```



[473]:
```python
# check correlation between all columns - (CELL 53)
corr_matrix = data_final.corr()
```

```
sns.heatmap(corr_matrix)
plt.show()
```



[ ]:
```
# CELL 54
```

3 Early hypothesis

looking at the correlations. Any predictive modeling is going to be very difficult. There are barely any strong linear correlations between salary and the other variables. A few strong ones, such as salary & compensation, but the overall majority are too weak. It is expected that the machine learning models trained with this data will not deliver accurate results.