Wasserman_Project

April 22, 2024

[43]:
```
# import necessary packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
```

1 NYU Career Outcomes

1.1 Class of 2023

1.1.1 Introduction

This notebook will explore and visualize data on the career and life outcomes of 2023 NYU Graduates including both undergraduate and graduate students.

[44]:
```
# load csv as df
df = pd.read_csv('wasserman_data.csv')
```

1.1.2 Exploratory Data Analysis

[45]:
```
# fix typo in Student ID col
df.rename(columns={"StudnetID": "StudentID"}, inplace=True)
# df.head()
```

[46]:
```
# look at structure of df, number of rows and columns
df.shape
```

[46]:
```
(1000, 27)
```

[47]:
```
# look at list of all columns
df.columns
```

[47]:
```
Index(['StudentID', 'Degree Level', 'School', 'Major Group', 'Gender Identity',
       'Ethnicity', 'Domestic or International Status', 'Outcome',
       'Have Info?', 'Placement Status', 'Employer', 'Industry',
       'Full-time or Part-time', 'Position Type', 'Job Title', 'Job Level',
       'Promotion or Return Offer from an Internship',
```

```
 'Total post-graduation job offers', 'Employment Timing',
 'Annual Salary Amount', 'Used Wasserman Services',
 'Continuing Education School Name', 'Continuing Education Degree',
 'Continuning Education Field', 'City', 'State', 'Country'],
dtype='object')
```

[48]:
```
# look at data types: one numerical column, all others objects
# few cols with only 27 non-null values - continuing education
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 27 columns):
 #   Column                                    Non-Null Count  Dtype
---  ------                                    --------------  -----
 0   StudentID                                 1000 non-null   object
 1   Degree Level                              1000 non-null   object
 2   School                                    1000 non-null   object
 3   Major Group                               1000 non-null   object
 4   Gender Identity                           1000 non-null   object
 5   Ethnicity                                 1000 non-null   object
 6   Domestic or International Status          1000 non-null   object
 7   Outcome                                   1000 non-null   object
 8   Have Info?                                1000 non-null   object
 9   Placement Status                          1000 non-null   object
 10  Employer                                  967 non-null    object
 11  Industry                                  967 non-null    object
 12  Full-time or Part-time                    948 non-null    object
 13  Position Type                             967 non-null    object
 14  Job Title                                 967 non-null    object
 15  Job Level                                 742 non-null    object
 16  Promotion or Return Offer from an Internship  724 non-null    object
 17  Total post-graduation job offers          425 non-null    object
 18  Employment Timing                         349 non-null    object
 19  Annual Salary Amount                      302 non-null    float64
 20  Used Wasserman Services                   967 non-null    object
 21  Continuing Education School Name          27 non-null     object
 22  Continuing Education Degree               27 non-null     object
 23  Continuning Education Field               27 non-null     object
 24  City                                      923 non-null    object
 25  State                                     902 non-null    object
 26  Country                                   963 non-null    object
dtypes: float64(1), object(26)
memory usage: 211.1+ KB
```

[49]:
```
# will help in determining where nulls need to be removed/filled/included
# df.isnull().sum()
```

[50]:
```python
# get the number of unique values per column to see which cols might be less
↪standardized and need cleaning
df.nunique()
```

[50]:
```
StudentID                                          1000
Degree Level                                          4
School                                               12
Major Group                                          10
Gender Identity                                       4
Ethnicity                                             8
Domestic or International Status                      3
Outcome                                               5
Have Info?                                            1
Placement Status                                      3
Employer                                            649
Industry                                             31
Full-time or Part-time                                2
Position Type                                         8
Job Title                                           423
Job Level                                             4
Promotion or Return Offer from an Internship          3
Total post-graduation job offers                      5
Employment Timing                                     4
Annual Salary Amount                                 90
Used Wasserman Services                               2
Continuing Education School Name                      9
Continuing Education Degree                           3
Continuning Education Field                           8
City                                                139
State                                                29
Country                                              19
dtype: int64
```

[51]:
```python
# check cols with a lot of unique values for repeats - employers, job titles,
↪city
# based on unique values, there are some duplicate answers with different
↪format causing them to be counted as unique for example "Department of
↪Education" is in unique vals twice

# employer_unique =  df[df['Employer'].notnull()]['Employer'].unique()
# for x in sorted(employer_unique):
#     print(x)

# df['Employer'].value_counts()
# df['Job Title'].value_counts()
```

[52]:
```
# checking cities for repeat unique vals -- looks good
# cities_unique =  df[df['City'].notnull()]['City'].unique()
# for x in sorted(cities_unique):
#     print(x)
```

1.2 Demographics

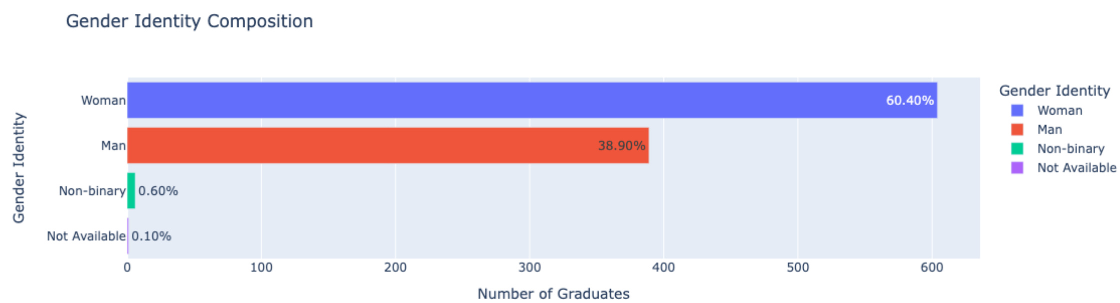
1.2.1 What demographics make up the data?

- Gender Identity
- Ethnicity
- Domestic or International Status
- Degree level
- Location: City, State, Country

[53]:
```
# create function that will return barchart and df containing demographic␣
↪percentages

def demographic_visual(col, df):
    # create demog df that groups data by demog and aggregates by count
    demog_df = df.groupby(col).count()[['StudentID']].reset_index().
↪rename(columns={'StudentID':'Count'})

    # create column that calculates percent of count
    demog_df['Percent'] = demog_df['Count']/demog_df['Count'].sum()

    # format column to percentage
    demog_df['Percent'] = demog_df['Percent'].map('{:,.2%}'.format)

    # sort df by Count
    demog_df.sort_values(by='Count', ascending=False, inplace=True)

    # create horizontal bar chart with plotly express
    demogFig = px.bar(demog_df, x='Count', y=col,
                orientation='h',
                title=col+' '+'Composition',
                hover_data=['Percent'],
                labels = {'Count':'Number of Graduates'},
                color=col,
                text=demog_df['Percent']
                )

    demogFig.show()
    return demog_df.reset_index(drop=True)
```

1.2.2 Gender Composition

[54]:
```
# create a bar chart visualization of genders and df with stats using function
demographic_visual('Gender Identity', df)
```



[54]:

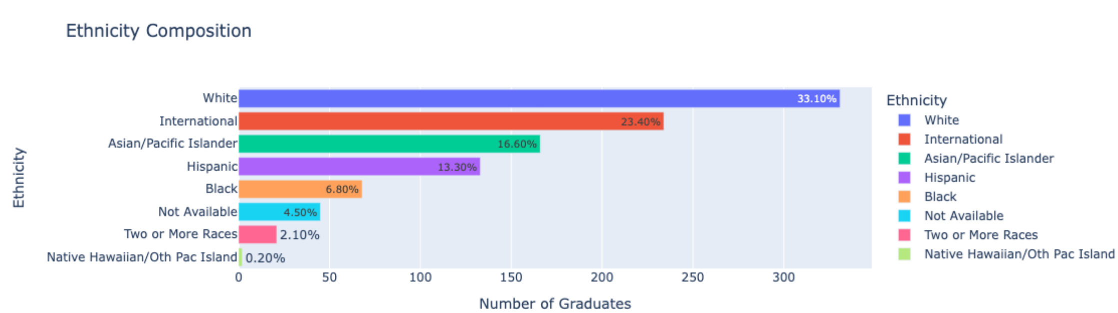
	Gender Identity	Count	Percent
0	Woman	604	60.40%
1	Man	389	38.90%
2	Non-binary	6	0.60%
3	Not Available	1	0.10%

Insights

1. Over half of the graduating class identify as women.
2. Male identifying graduates made up the second largest percentage of graduates.
3. Non-binary graduates are the least represented.

1.2.3 Ethnicity Composition

[55]:
```
# create a bar chart visualization of ethnicities and df with stats using␣
↪function
demographic_visual('Ethnicity', df)
```



[55]:

	Ethnicity	Count	Percent
0	White	331	33.10%
1	International	234	23.40%
2	Asian/Pacific Islander	166	16.60%
3	Hispanic	133	13.30%
4	Black	68	6.80%
5	Not Available	45	4.50%
6	Two or More Races	21	2.10%
7	Native Hawaiian/Oth Pac Island	2	0.20%

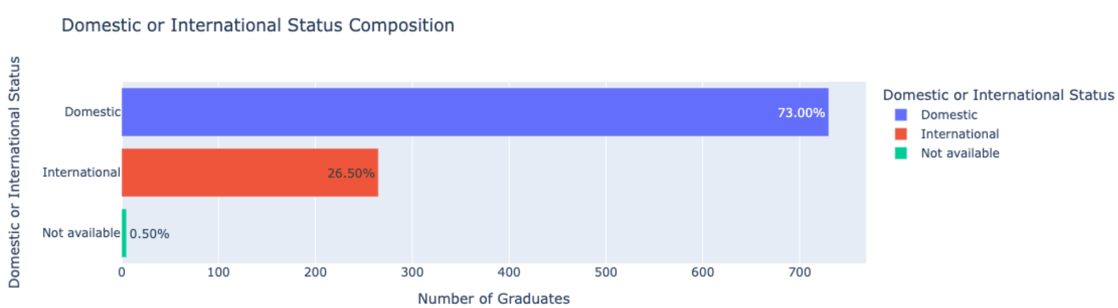
Insights

1. The largest portion of graduates were white.
2. The least represented demographic is Native Hawaiin/Other Pac Island.

1.2.4 Domestic or International Composition

[56]:

```python
# create a bar chart visualization of domestic/int status and df with stats␣
↪using function
demographic_visual('Domestic or International Status', df)
```



[56]:

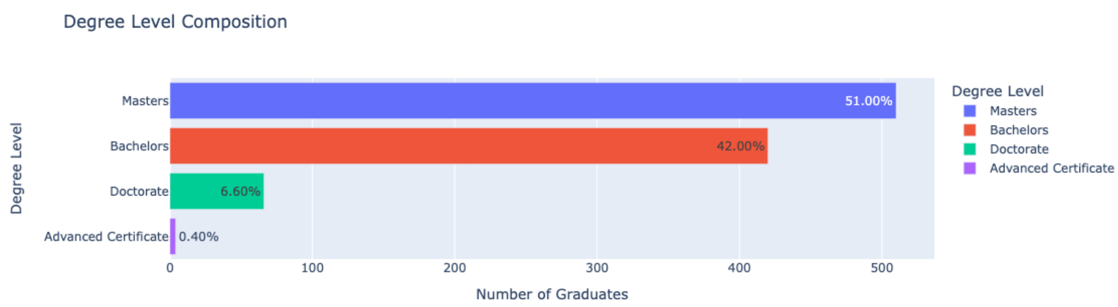
	Domestic or International Status	Count	Percent
0	Domestic	730	73.00%
1	International	265	26.50%
2	Not available	5	0.50%

Insights

1. A majority of the graduating class is domestic while a nearly 27% is international.

1.2.5 Degree Level Composition

[57]:
```
# create a bar chart visualization of degree level and df with stats using␣
↪function
demographic_visual('Degree Level', df)
```



[57]:

	Degree Level	Count	Percent
0	Masters	510	51.00%
1	Bachelors	420	42.00%
2	Doctorate	66	6.60%
3	Advanced Certificate	4	0.40%

Insights

1. Over half of the Class of 2023 graduated with a Masters degree.
2. Altogether, 58% of the graduating class obtained a graduate level degree.
3. There were only 4 Advanced Certifications received.

1.2.6 Location

Loading World Cities data In order to generate a map displaying cities populated by graduates, I had to load latitudinal and longitudinal data from Simple Maps World Cities Database, an accurate and up-to-date database of the world's cities and towns built from authoritative sources such as the NGIA, US Geological Survey, US Census Bureau, and NASA.

I will join the Wasserman location information with this data to get the latitude and longitude of the cities which I can use to create an interactive map with plotly express.

[58]:
```
# load worldcities csv
worldcities = pd.read_csv('worldcities.csv')

# create a location df from wasserman data that can be merged with worldcities␣
↪to find lat and long
location = df[['City', 'State', 'Country']]
# filter out null values
```

```
location = location[location['Country'].notnull()]
```

Joining Wasserman Location Data with World Cities In order to merge location data with world cities, use DataPrep library to add a country code column to Wasserman location data to standardize Country names.

The Data Prep Library includes functions for quickly and easily cleaning and validating location data. We will use the clean_country() function to clean the location country column and standardize it in the alpha-2 country code format.

The countries/regions supported and the regular expressions used can be found on GitHub.

[59]:
```
# install dataprep api to use clean_country() function - only run once
# conda install -c conda-forge dataprep
```

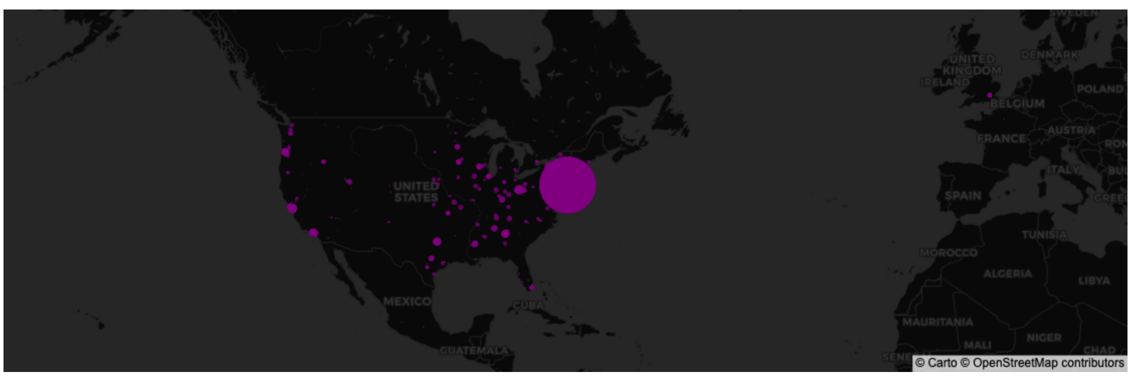
[60]:
```
from dataprep.clean import clean_country

# add a col of country code to locations to standardize country col so that can␣
↪merge with worldcities
# use clean_country function from data prep to get the alpha-2 codes for␣
↪country - only run once
location = clean_country(location, "Country", output_format='alpha-2')

# rename Country_clean column to alpha-2 for clarity
location.rename(columns={'Country_clean':'alpha-2'}, inplace=True)
```

```
/opt/anaconda3/lib/python3.11/site-packages/dask/dataframe/core.py:7234:
FutureWarning:

Meta is not valid, `map_partitions` and `map_overlap` expects output to be a
pandas object. Try passing a pandas object as meta or a dict or tuple
representing the (name, dtype) of the columns. In the future the meta you passed
will not work.


  0%|                                                     | 0/8 [00:00<?, ?it/s]

Country Cleaning Report:
        963 values cleaned (100.0%)
Result contains 963 (100.0%) values in the correct format and 0 null values
(0.0%)
```

[61]:
```
# check new location df containing alpha-2 codes that we can join with␣
↪worldcities
# location
```

[62]:
```
# join location df with worldcities df to get lat and long using left merge as␣
↪we only want to keep countries in wasserman location df
```

```python
merged = location.merge(worldcities, how='left', left_on=['City', 'alpha-2'], right_on=['city', 'iso2'])

# add col to df that has the value counts of cities to add as a label
# remove null values
merged['Number of Graduates'] = merged.groupby(['city']).city.transform('count')
merged = merged[merged['Number of Graduates'].notnull()]

# show map
px.scatter_mapbox(
    merged,
    lat="lat",
    lon="lng",
    hover_data=["Number of Graduates"],
    hover_name="City",
    color_discrete_sequence=['purple'],
    color_continuous_scale=px.colors.sequential.Rainbow,
    size='Number of Graduates',
    size_max=40,
).update_layout(mapbox={"style": "carto-darkmatter", "zoom": 2}, margin={"t":0,"b":0,"l":0,"r":0})
```



Insights

1. The highest concentration of graduates (677) reside in New York, New York.
2. Graduates are spread out across North America with a large portion remaining in the East.
3. A small spread of graduates live abroad across all continents expect Oceania and South America.

1.3 Outcomes

1.3.1 How is the data spread across the 5 outcomes per degree level?

1. Working
2. Working and In School

3. Seeking Employment
4. Seeking Continuing Education
5. Not Seeking Employment or Continuing Education

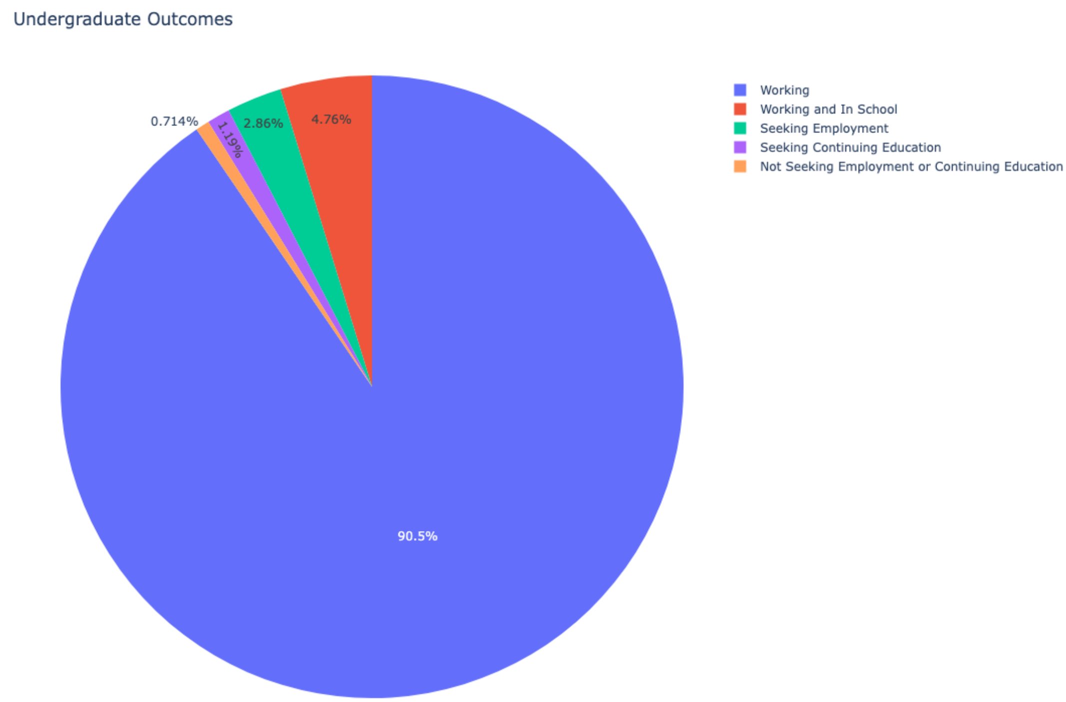
Since there is no data for "In School", we will not include this outcome in the charts

[89]:
```python
# define a function that returns stats and pie chart for outcomes filtered on␣
↪specified degree level

# assign degree type lists to variables for grad and undergrad
ug_degrees = ['Bachelors']
grad_degrees = ['Doctorate','Masters','Advanced Certificate']

def outcome_stats(degree, df):
    # filter df by degree level and groupby degree level aggregate on count
    filtered = df[df['Degree Level'].isin(degree)]
    outcomes = filtered.groupby('Outcome').count()[['StudentID']].reset_index().
↪rename(columns={'StudentID':'Count'})

    # create column that calculates percent of students per outcome
    outcomes['Percent'] = outcomes['Count']/outcomes['Count'].sum()

    # format column from int to percentage
    outcomes['Percent'] = outcomes['Percent'].map('{:,.2%}'.format)

    # sort df by Count
    outcomes.sort_values(by='Count', ascending=False, inplace=True)
    outcomes = outcomes.reset_index(drop=True)

    # create pie chart visualizing dist of outcomes with title corresponding to␣
↪specified degree level
    if degree == ['Bachelors']:
        fig = px.pie(outcomes,
                     values='Count',
                     names='Outcome',
                     title='Undergraduate Outcomes')
    elif "Bachelors" in ''.join(degree):
        fig = px.pie(outcomes,
                     values='Count',
                     names='Outcome',
                     title='Total Outcomes')
    else:
        fig = px.pie(outcomes,
                     values='Count',
                     names='Outcome',
                     title='Graduate Outcomes')

    fig.update_layout(width=950, height=800)
```

```python
    fig.show()

    return outcomes
```

1.3.2 Undergraduate Outcomes

[90]:
```python
outcome_stats(ug_degrees, df)
```



[90]:

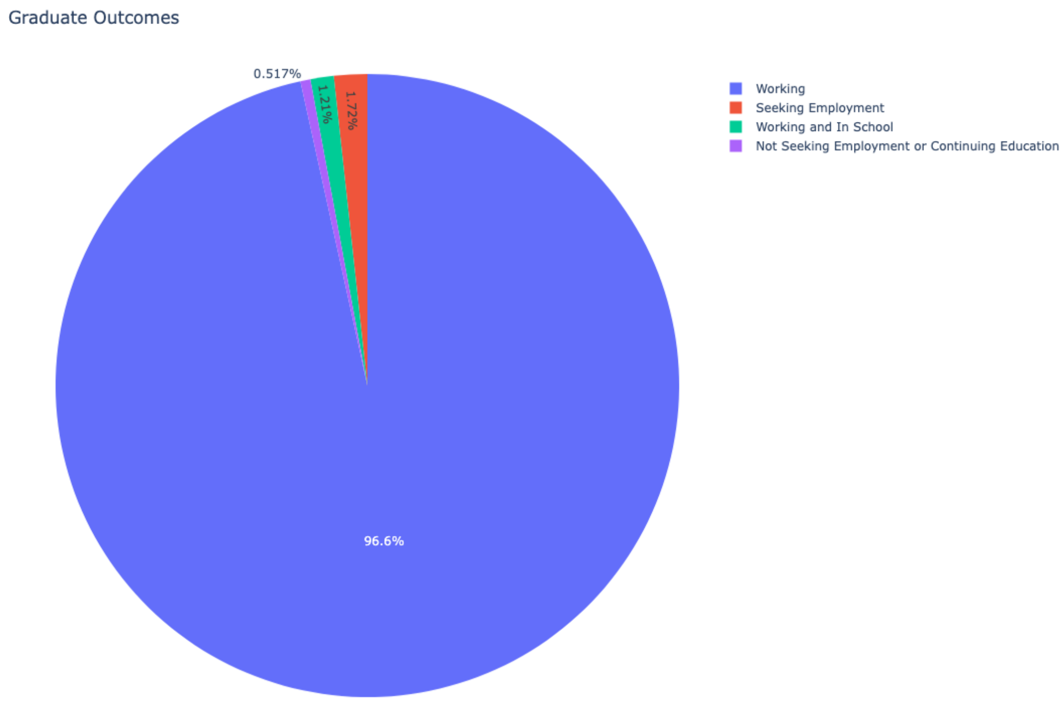
	Outcome	Count	Percent
0	Working	380	90.48%
1	Working and In School	20	4.76%
2	Seeking Employment	12	2.86%
3	Seeking Continuing Education	5	1.19%
4	Not Seeking Employment or Continuing Education	3	0.71%

Insights

1. The majority of undergraduate students started working after graduation.
2. The other 9.52% of undergraduate grads are spread across the other outcomes.

1.3.3 Graduate Outcomes

[91]:
```
outcome_stats(grad_degrees, df)
```



[91]:

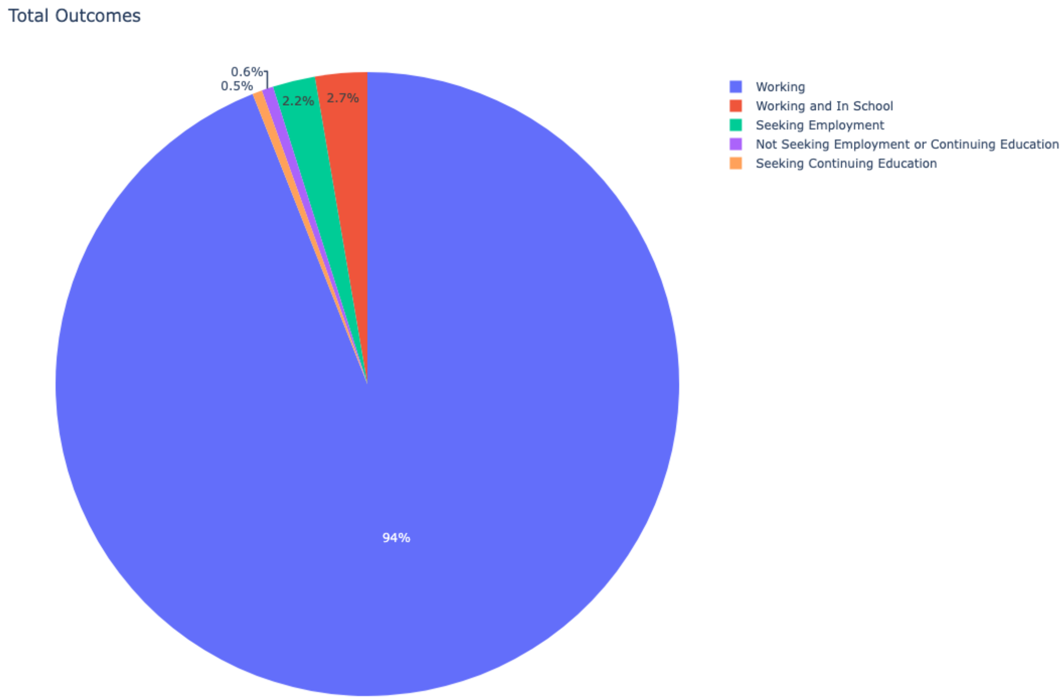
	Outcome	Count	Percent
0	Working	560	96.55%
1	Seeking Employment	10	1.72%
2	Working and In School	7	1.21%
3	Not Seeking Employment or Continuing Education	3	0.52%

Insights

1. The majority of graduate students started working after graduation.

1.3.4 Total Outcomes

[92]:
```
outcome_stats(['Doctorate','Masters','Advanced Certificate', 'Bachelors'], df)
```



[92]:

	Outcome	Count	Percent
0	Working	940	94.00%
1	Working and In School	27	2.70%
2	Seeking Employment	22	2.20%
3	Not Seeking Employment or Continuing Education	6	0.60%
4	Seeking Continuing Education	5	0.50%

Insights

1. As a majority of both graduate and undergraduate students started working post-grad, it makes sense that this majority is reflected in the total outcomes data.
2. No outcome category besides "Working" meets the minimum sample size of n=100 to be statistically meaningful. As a result, we will focus further analysis on employment. Recommend collecting more data.

1.4 Employment Statistics

What is the portion of grads working fulltime?

[67]:
```
ft_portion = len(df[df['Full-time or Part-time'].fillna('').str.
 ↪contains('Full-time')]['StudentID'])/(len(df['StudentID']))
ft_percent = '{:,.2%}'.format(ft_portion)
print(ft_percent+' of graduates working are employed fulltime.')
```

```
87.40% of graduates working are employed fulltime.
```

1.4.1 What are the following stats for grads working fulltime?

- Average salary by degree level
- Top industries
- Top employers
- Top job titles

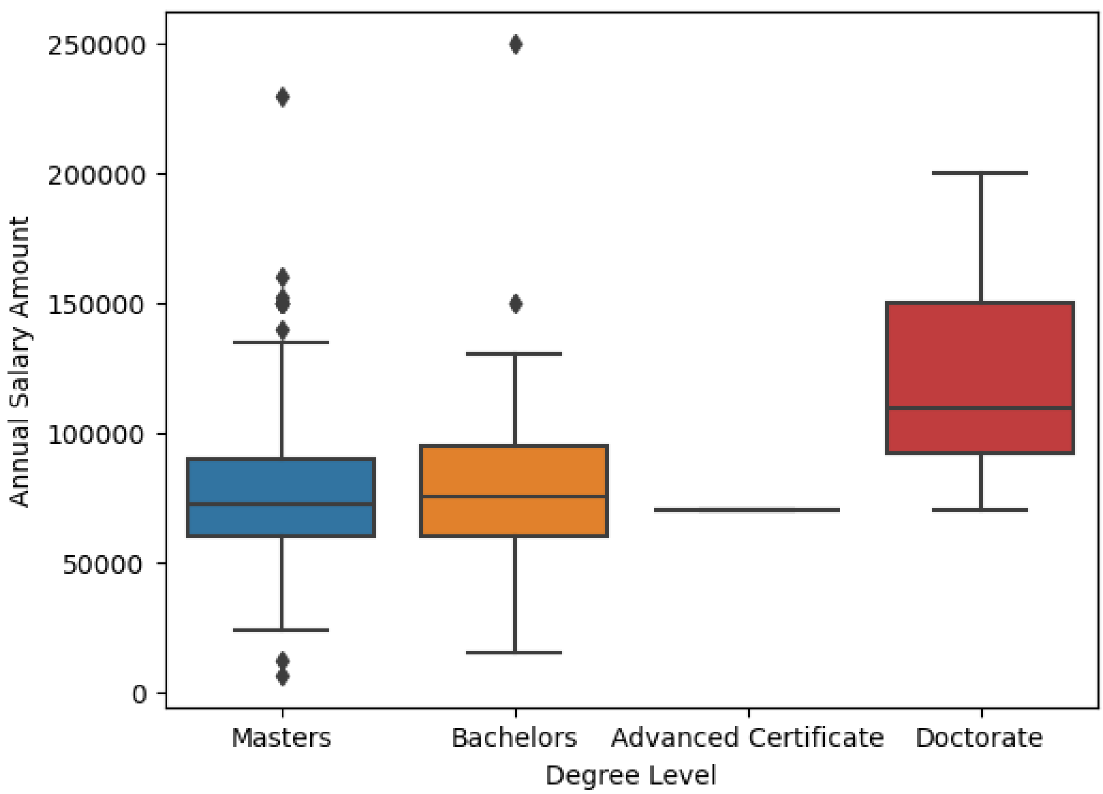
1.4.2 Average Fulltime Salary

Boxplot Check for outliers and compare distribution of salaries by degree level

[68]:
```python
# filter df by those working full time
ft_df = df[df['Full-time or Part-time'].fillna('').str.contains('Full-time')]
```

[69]:
```python
ft_salaries = ft_df[ft_df['Annual Salary Amount'].notnull()]
sns.boxplot(ft_salaries,y='Annual Salary Amount', x='Degree Level')
```

[69]:
```
<Axes: xlabel='Degree Level', ylabel='Annual Salary Amount'>
```



[70]:
```
print('There are '+str(ft_salaries[ft_salaries['Degree Level'] == 'Doctorate'].
 ↪shape[0]) + ' salary data points for Doctorate degree.')
print('There is '+str(ft_salaries[ft_salaries['Degree Level'] == 'Advanced␣
 ↪Certificate'].shape[0]) + ' salary data point for Advanced Certificate␣
 ↪degree.')
```

```
There are 13 salary data points for Doctorate degree.
There is 1 salary data point for Advanced Certificate degree.
```

Since there are few data points for salaries of Doctorate and Advanced Certificate grads, we will combine these with masters to look at salary on the graduate student level.

[71]:
```
# define function that finds average salary and allows degree level constraints
def avg_salary(degree: list, df):
    filtered = df[df['Degree Level'].isin(degree)]
    amt = round(filtered['Annual Salary Amount'].mean(),0)
    return amt
```

Undergraduate Fulltime Avg. Salary

[72]:
```
# pass undergrad list into function and format to dollar amount
ug_salary = avg_salary(ug_degrees, ft_df)
print('The average salary for 2023 grads with an undergraduate level degree is'␣
 ↪+ ' ' + '${:,.2f}'.format(ug_salary))
```

```
The average salary for 2023 grads with an undergraduate level degree is
$78,382.00
```

Graduate Fulltime Avg. Salary

[73]:
```
# pass graduate list into function and format to dollar amount
grad_salary = avg_salary(grad_degrees, ft_df)
print('The average salary for 2023 grads with a graduate level degree is' + ' '␣
 ↪+ '${:,.2f}'.format(grad_salary))
```

```
The average salary for 2023 grads with a graduate level degree is $82,145.00
```

Total Fulltime Avg. Salary

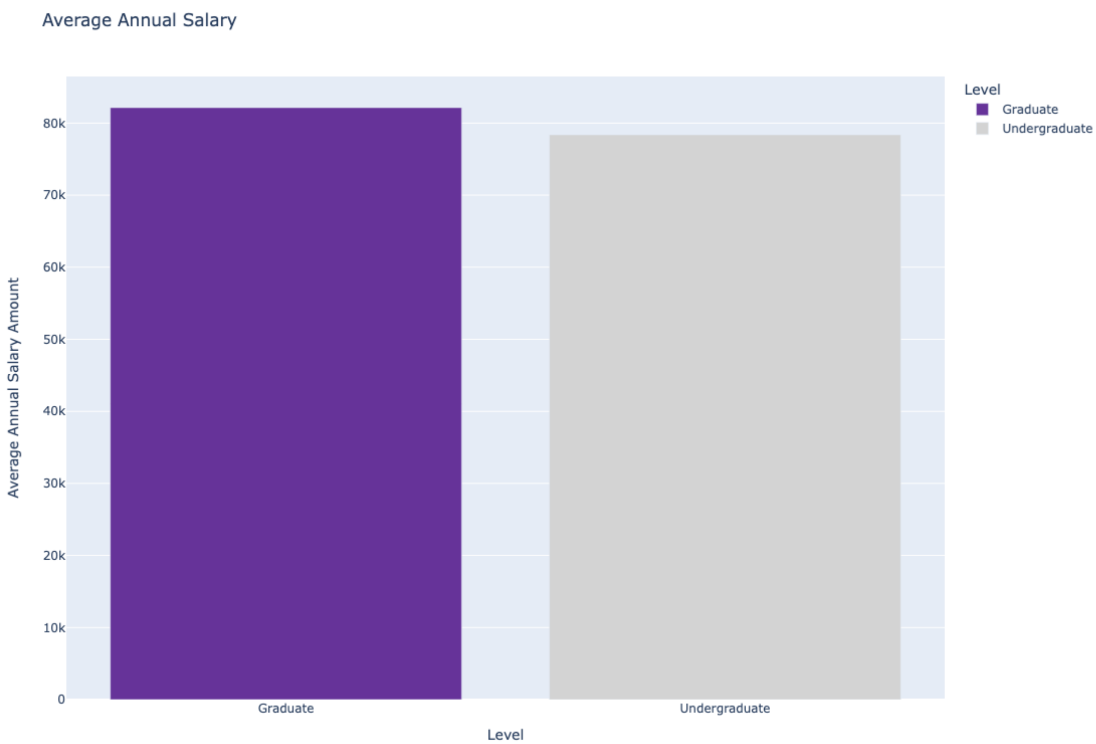
[74]:
```
# pass all degree types into function and format to dollar amount
total_salary = avg_salary(['Masters', 'Doctorate', 'Advanced Certificate',␣
 ↪'Bachelors'], ft_df)
print('The average salary for all 2023 grads regardless of degree type is' + '␣
 ↪' + '${:,.2f}'.format(total_salary))
```

```
The average salary for all 2023 grads regardless of degree type is $80,413.00
```

[83]:
```
# create table visualization of salaries
import plotly.graph_objects as go

tblFig = go.Figure(data=[go.Table(header=dict(values=['Undergraduate Average␣
 ↪Salary', 'Graduate Average Salary', 'Total Average Salary'],
```

```
                                                         align='left',
                                                         font=dict(color='white', size=14),
                                                         fill_color='rebeccapurple',
                                                        ),
                     cells=dict(values=['${:,.2f}'.format(ug_salary), '${:,.2f}'.
 ↪format(grad_salary),'${:,.2f}'.format(total_salary)],
                                height=35,
                                align='left',
                                font=dict(size=14),
                                fill_color='lavender'),)
                         ])
tblFig.update_layout(width=850, height=500)

tblFig.show()

# create barchart showing salaries for ug and grad
# create new col that signifies ug or grad
def grad_level(row):
    if row == 'Bachelors':
        return "Undergraduate"
    else:
        return "Graduate"

ft_salaries_copy = ft_salaries.copy()
ft_salaries_copy['Level'] = ft_salaries_copy['Degree Level'].apply(grad_level)

# group by grad level and calculate average salary
group_salaries = ft_salaries_copy[['Level', 'Annual Salary Amount']].
 ↪groupby('Level').mean().reset_index().rename(columns={'Annual Salary Amount':
 ↪'Average Annual Salary Amount'})
group_salaries['x'] = 0

barFig = px.bar(group_salaries, x='Level', y='Average Annual Salary Amount',
                color='Level',
                color_discrete_map = {
                    'Undergraduate' : 'lightgrey', 'Graduate':'rebeccapurple'},
                title='Average Annual Salary')
barFig.update_layout(width=800, height=800)

barFig.show()
```

Undergraduate Average Salary	Graduate Average Salary	Total Average Salary
$78,382.00	$82,145.00	$80,413.00



Difference in Avg. Fulltime Salary between Graduates and Undergraduates

[76]:
```
# calculate difference between two averages
percent_difference = (grad_salary-ug_salary)/((ug_salary+grad_salary)/2)
```

```
print('Graduate students have a'+' '+ '{:,.2%}'.format(percent_difference)+ '␣
↪higher average salary than Undergraduate students.')
```

```
Graduate students have a 4.69% higher average salary than Undergraduate
students.
```

1.4.3 Top Industries

[84]:
```
# define function that returns head of grouped data with value counts and␣
↪percentages

def top_table(df, col):
    # group df by industry and aggregate by count to find top industries
    res = df.groupby(col).count()[['StudentID']].rename(columns={'StudentID':
↪'Count'})
    res = res.sort_values(by='Count', ascending=False).reset_index()

    # create column that calculates percent of count
    res['Percent'] = res['Count']/res['Count'].sum()

    # format column to percentage
    res['Percent'] = res['Percent'].map('{:,.2%}'.format)

    # rename count col
    res = res.rename(columns={'Count':'Number of Graduates'})

    # format df to plotly table
    col_list = list(res.columns)
    fig = go.Figure(data=[go.Table(header=dict(values=col_list,
                                           align='left',
                                           font=dict(color='white', size=14),
                                           fill_color='rebeccapurple',
                                          ),
                 cells=dict(values=[res[col_list[0]], res[col_list[1]],␣
↪res[col_list[2]]],
                            height=35,
                            align='left',
                            font=dict(size=14),
                            fill_color='lavender'),
                                   columnwidth=[195,125,125])
                     ])
    fig.update_layout(width=900, height=600)

    fig.show()
```

[85]:
```
# Use function to find top 5 industries
top_industries = top_table(ft_df, 'Industry')
```

```
top_industries
```

Industry	Number of Graduates	Percent
Education/Teaching	218	24.94%
Financial Services/Banking	139	15.90%
Health Care	67	7.67%
Consulting	53	6.06%
Entertainment/Media	52	5.95%
Real Estate	46	5.26%
Computer Science/Technology	46	5.26%
Marketing/Advertising/PR	32	3.66%
Accounting	24	2.75%
Government/Military	22	2.52%
Non-Profit/Social Services	17	1.95%

1.4.4 Top Employers

[86]:
```
# Use function to find list of top employers
top_employers = top_table(ft_df, 'Employer')
top_employers
```

Employer	Number of Graduates	Percent
NYU	113	12.93%
Not Available	16	1.83%
PwC	15	1.72%
Self-employed	13	1.49%
NYU Langone Health	11	1.26%
Goldman Sachs	9	1.03%
JP Morgan Chase & Co.	9	1.03%
Morgan Stanley	8	0.92%
BlackRock	7	0.80%
The Soho Center for Mental Health Counseling	6	0.69%
Amazon	6	0.69%

1.4.5 Top Job Titles

[87]:
```
top_titles = top_table(ft_df, 'Job Title')
top_titles
```

Job Title	Number of Graduates	Percent
Analyst	111	12.70%
Associate	55	6.29%
Adjunct Instructor	33	3.78%
Assistant Project Manager	19	2.17%
Associate Consultant	17	1.95%
Assistant Research Scientist	16	1.83%
Assistant Professor	16	1.83%
Assistant Director	14	1.60%
Account Coordinator	12	1.37%
Associate Software Engineer	11	1.26%
Administrative Assistant	10	1.14%

Run tests to ensure data is grouped correct

[88]:
```
# test = ft_df.groupby('Industry').count()[['StudentID']].
↪rename(columns={'StudentID':'Count'}).sort_values(by='Count',␣
↪ascending=False).reset_index()
# test['Count'].sum() == len(ft_df['StudentID'])

# test = ft_df.groupby('Employer').count()[['StudentID']].
↪rename(columns={'StudentID':'Count'}).sort_values(by='Count',␣
↪ascending=False).reset_index()
# test['Count'].sum() == len(ft_df['StudentID'])

# test = ft_df.groupby('Job Title').count()[['StudentID']].
↪rename(columns={'StudentID':'Count'}).sort_values(by='Count',␣
↪ascending=False).reset_index()
# test['Count'].sum() == len(ft_df['StudentID'])
```

1.5 Conclusion

This analysis generated insight into the demographics of the graduating class and what they did after graduation. Given that a large majority of graduates ended up working full time, we examined the characteristics of their employment including average salary, top industries, employers, and job titles.

If I had more time, I would expand on the data filters and build functions that allow for more custom results such as school. I would also include student engagement metrics and additional employment analysis of time it took for grads to obtain their role and how many offers they received.