PhD Salaries - Data Cleaning and Analysis

[32]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

[33]:
```
data = pd.read_csv('data_raw.csv')
data_original = data.copy()
```

[34]:
```
# Print number of rows and columns
data_original.shape
```

[34]:
```
(8707, 11)
```

[35]:
```
# first of all, let's remove duplicates (people with the same pay from the same␣
 ↪department)
data = data.drop_duplicates()
# we are then left with 8526 rows
data.shape
```

[35]:
```
(8526, 11)
```

[ ]:
```
# let's have a look at the first 5 entries
data.head()
```

[36]:
```
# it looks like the 'Overall Pay' already takes into account the sum of the␣
 ↪12M, 9M, 3M values minus the fees. Let's check the sum:
data[['12 M Gross Pay',        '9 M Gross Pay', '3 M Gross Pay']].sum()
```

[36]:
```
Series([], dtype: float64)
```

[37]:
```
# That didn't work because the Gross Pay columns are not formatted as floats
data.dtypes
```

[37]:
```
University         object
Department         object
Overall Pay        object
LW Ratio          float64
Academic Year      object
```

```
Program Year       object
12 M Gross Pay     object
9 M Gross Pay      object
3 M Gross Pay      object
Fees               object
Comments           object
dtype: object
```

[38]:
```
# In order to format them as floats, let's first remove the dollar sign
data['Overall Pay'] = data['Overall Pay'].str.replace('$', '')
data['12 M Gross Pay'] = data['12 M Gross Pay'].str.replace('$', '')
data['9 M Gross Pay'] = data['9 M Gross Pay'].str.replace('$', '')
data['3 M Gross Pay'] = data['3 M Gross Pay'].str.replace('$', '')
data['Fees'] = data['Fees'].str.replace('$', '')

# and also remove the commas
data['Overall Pay'] = data['Overall Pay'].str.replace(',', '')
data['12 M Gross Pay'] = data['12 M Gross Pay'].str.replace(',', '')
data['9 M Gross Pay'] = data['9 M Gross Pay'].str.replace(',', '')
data['3 M Gross Pay'] = data['3 M Gross Pay'].str.replace(',', '')
data['Fees'] = data['Fees'].str.replace(',', '')

# while we are doing these string replacements, let's also clean up the␣
 ↪university names
data['University'] = data['University'].str.replace('-',',').str.replace(';
 ↪','').str.replace('&amp','&').str.replace('&#39','\'')
```

[ ]:
```
data.head()
```

[39]:
```
# And finally convert the relevant columns to float
data[['Overall Pay', '12 M Gross Pay',        '9 M Gross Pay', '3 M Gross Pay',␣
 ↪'Fees']] = data[['Overall Pay', '12 M Gross Pay', '9 M Gross Pay', '3 M␣
 ↪Gross Pay', 'Fees']].astype(float)
data.dtypes
```

[39]:
```
University         object
Department         object
Overall Pay       float64
LW Ratio          float64
Academic Year      object
Program Year       object
12 M Gross Pay    float64
9 M Gross Pay     float64
3 M Gross Pay     float64
Fees              float64
Comments           object
dtype: object
```

[40]:
```
# Now we can confirm that the 'Overall Pay' is equal to the sum of the 12M, 9M,␣
↪3M values minus the fees
data['Overall Pay'].sum() == data[['12 M Gross Pay', '9 M Gross Pay', '3 M␣
↪Gross Pay']].sum().sum() - data['Fees'].sum()
```

[40]:
```
True
```

[41]:
```
# so we can remove the 12M, 9M, 3M and fees columns and simplify the DataFrame
data = data.drop(['12 M Gross Pay', '9 M Gross Pay', '3 M Gross Pay', 'Fees'],␣
↪axis=1)
data.head()
```

[41]:

	University	Department	Overall Pay	LW Ratio	Academic Year	Program Year	Comments
0	University of Tennessee , Knoxville	Economics	1850.0	0.09	2020-2021	1st	NaN
1	University of Arizona (U of A)	Economics	21000.0	1.01	2020-2021	1st	$10500 per semester. RA/TA required. Need to p…
2	University of Arizona (U of A)	Economics	19800.0	0.96	2020-2021	1st	NaN
3	University of Florida	ECE	22600.0	NaN	2020-2021	1st	NaN
4	University of Virginia (UVA)	ECE	26000.0	1.14	2020-2021	1st	NaN

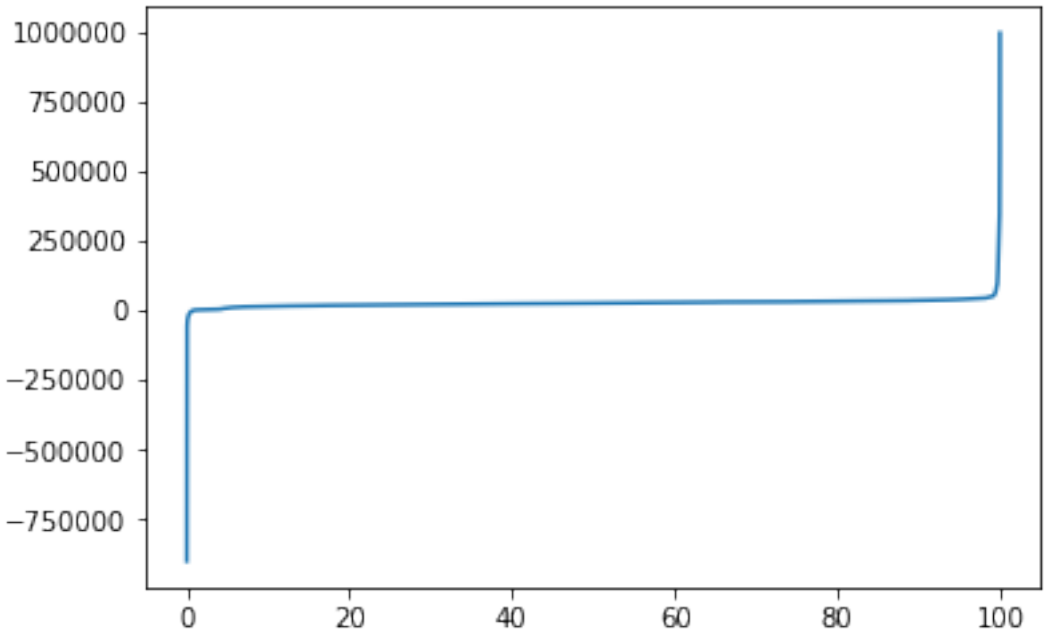
[42]:
```
# use pandas 'describe' function to get basic statistics of the numerical␣
↪columns
data.describe()
```

[42]:

	Overall Pay	LW Ratio
count	8505.000000	7651.000000
mean	25153.337331	1.075993
std	21805.844892	0.834647
min	-900000.000000	-34.010000
25%	19007.000000	0.850000
50%	25000.000000	1.100000
75%	30445.000000	1.300000
max	994000.000000	40.970000

[43]:
```
# the max and min values are very far from the median (50% percentile) and from␣
 ↪the 25-75% percentiles, which suggests there are ouliers. To confirm that,␣
 ↪the plot of the inverse CDF (cumulative distribution) has very sharp jumps␣
 ↪at the start and end:
def plot_inverse_CDF(data, min_perc=0, max_perc=100, step=0.01, vlines=[]):
    percentiles = np.arange(min_perc, max_perc+step, step)
    inv_CDF = [np.nanpercentile(data, p) for p in percentiles]
    print('{0} percentile: {1:.2f}'.format(min_perc, inv_CDF[0]))
    print('{0} percentile: {1:.2f}'.format(max_perc, inv_CDF[-1]))
    plt.plot(percentiles, inv_CDF)
    for x in vlines:
        plt.axvline(x=x, linestyle='--', color='r')
    plt.show()
plot_inverse_CDF(data=data['Overall Pay'].values)
```

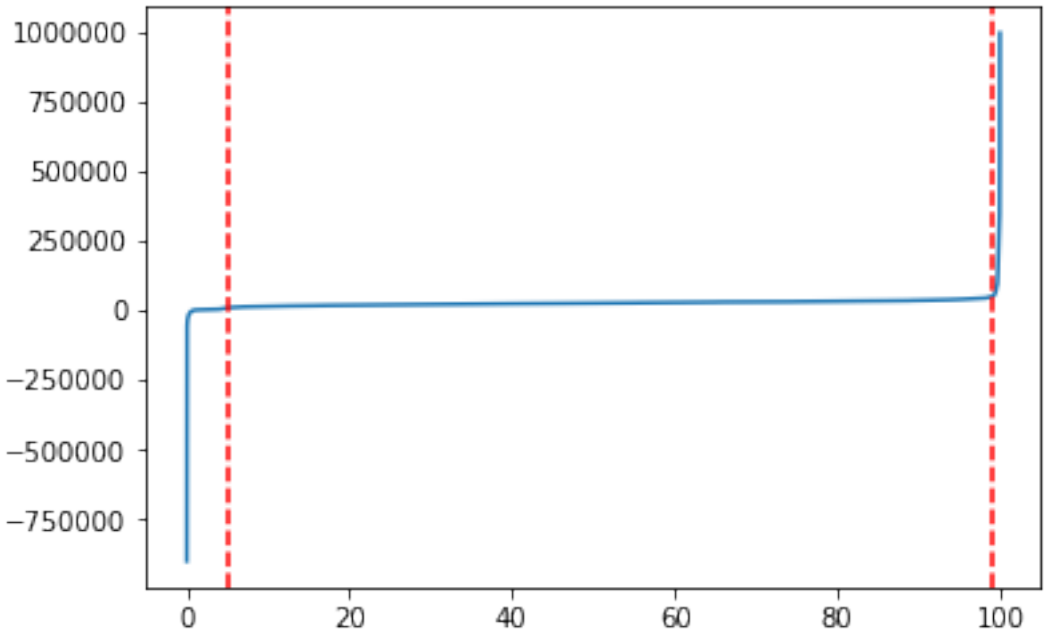
```
0 percentile: -900000.00
100 percentile: 994000.00
```



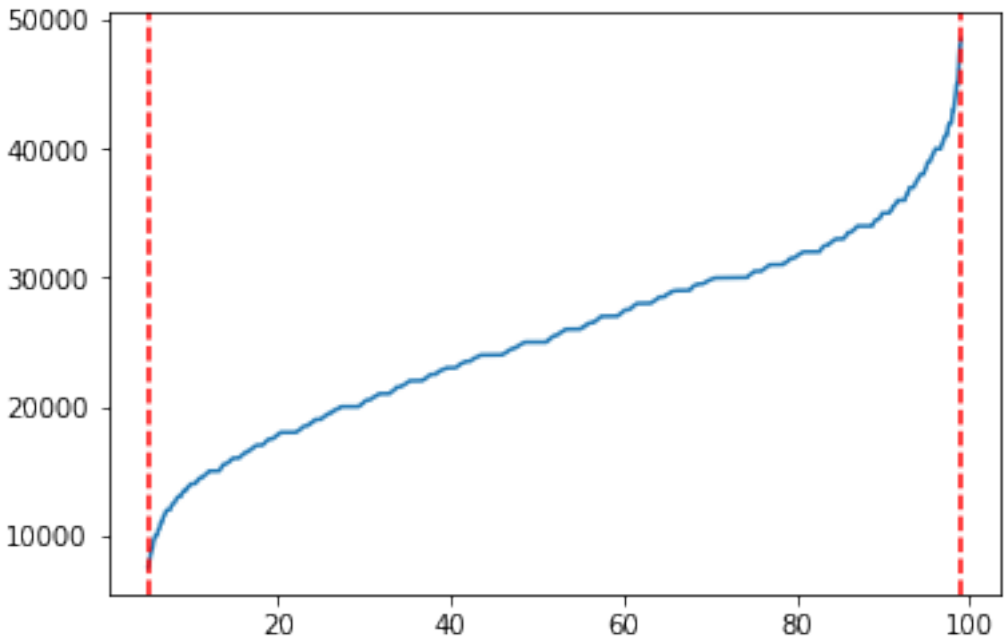
[44]:
```
# Let's then excude the bottom 5% and top 1% of the values, in order to ignore␣
 ↪the extreme cases (in particular the negative values, where the fees are␣
 ↪higher than the pay). The remaining pay values are between $7500.00 and␣
 ↪$48498.96
min_perc_threshold = 5
max_perc_threshold = 99
```

```
plot_inverse_CDF(data=data['Overall Pay'].values, vlines=[min_perc_threshold,␣
 ↪max_perc_threshold])
plot_inverse_CDF(data=data['Overall Pay'].values, min_perc=min_perc_threshold,␣
 ↪max_perc=max_perc_threshold, vlines=[min_perc_threshold, max_perc_threshold])
min_pay_threshold, max_pay_threshold = np.nanpercentile(data['Overall Pay'].
 ↪values, [min_perc_threshold, max_perc_threshold])
print('min_pay_threshold = {0}'.format(min_pay_threshold))
print('max_pay_threshold = {0}'.format(max_pay_threshold))
data = data[(data['Overall Pay']>=min_pay_threshold) & (data['Overall␣
 ↪Pay']<=max_pay_threshold)]
```

```
0 percentile: -900000.00
100 percentile: 994000.00
```




```
5 percentile: 7500.00
99 percentile: 48498.96
```




```
min_pay_threshold = 7500.0
max_pay_threshold = 48498.95999999998
```

[45]:
```
# after cleaning, we are left with 7996 rows
data.shape
```

[45]:
```
(7996, 7)
```

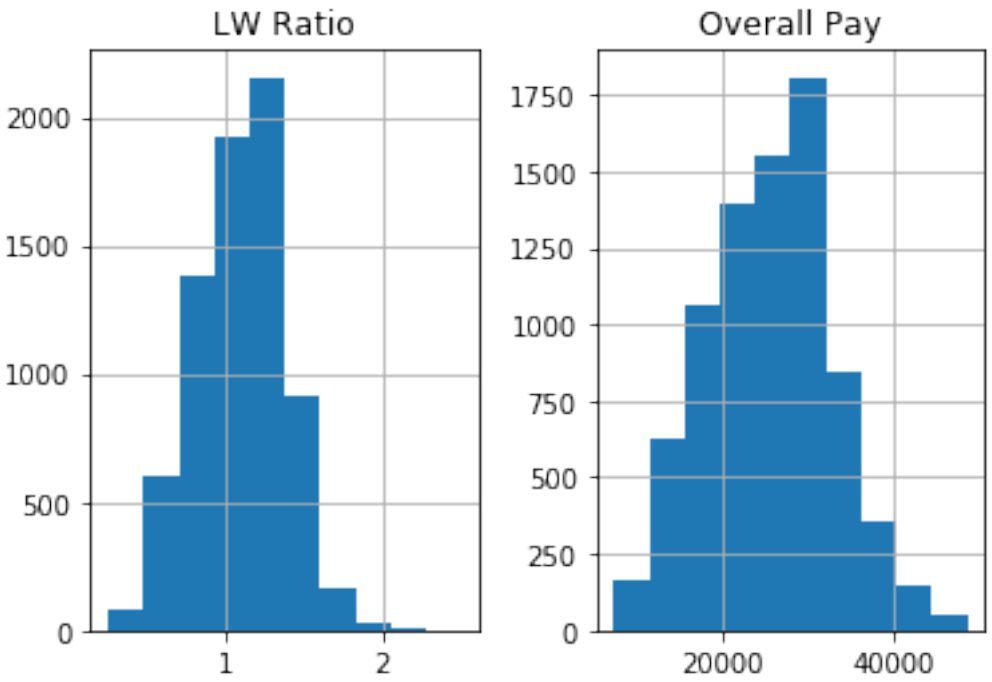
[46]:
```
# the median didn't change (still $25500), but now the STD is more reasonable
↪($7355 instead of $21805)
data.describe()
```

[46]:

	Overall Pay	LW Ratio
count	7996.000000	7262.000000
mean	25523.989370	1.097447
std	7355.036001	0.285997
min	7500.000000	0.250000
25%	20000.000000	0.880000
50%	25500.000000	1.115000
75%	30500.000000	1.300000
max	48474.000000	2.510000

[47]:
```
# The histograms of the LW Ratio and Overall Pay
data.hist()
```

[47]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000201CE91ECF8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000201CE914860>]],
      dtype=object)
```

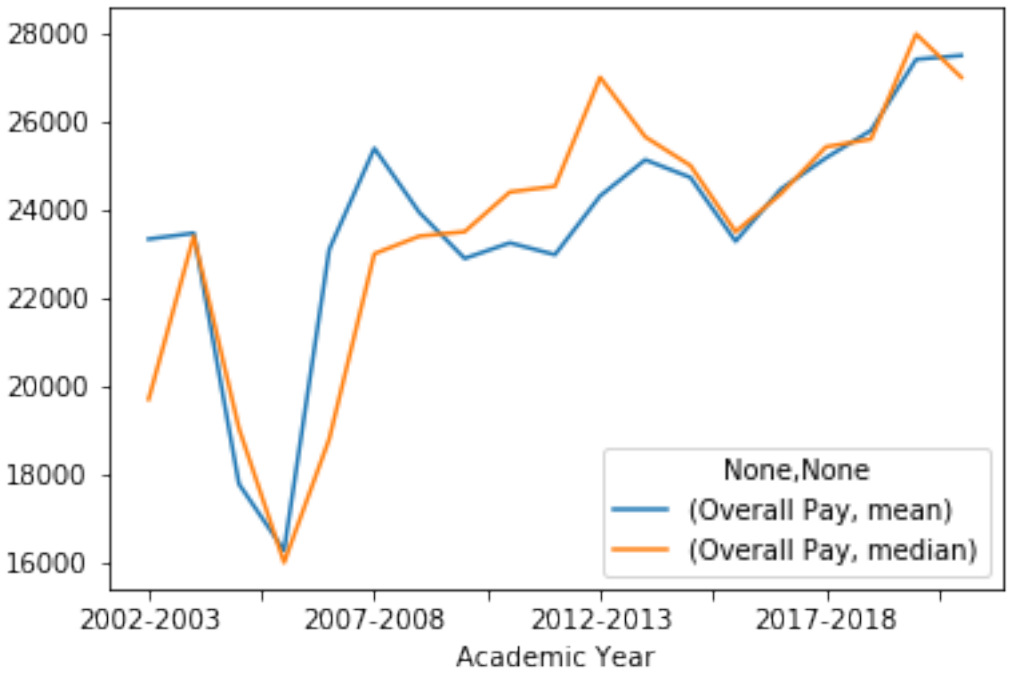


[48]:
```
# 36% of the remaining PhD salaries after cleaning are still below the living␣
↪wage
(data['LW Ratio']<=1).sum() / len(data['LW Ratio'].dropna())
```

[48]:
```
0.3646378408152024
```

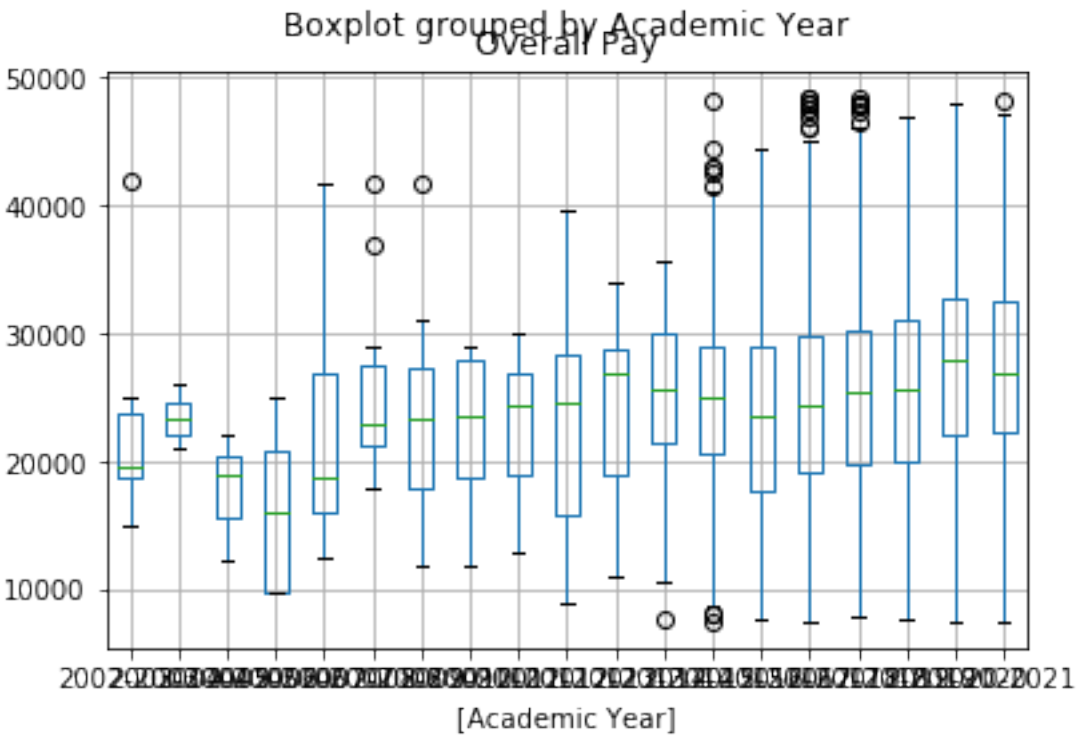
[49]:
```
# the mean and median pay fluctuate over the years, with a small upward trend
data[['Overall Pay', 'Academic Year']].groupby('Academic Year').agg(['mean',␣
↪'median']).plot()
```

[49]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x201ce9d5ba8>
```



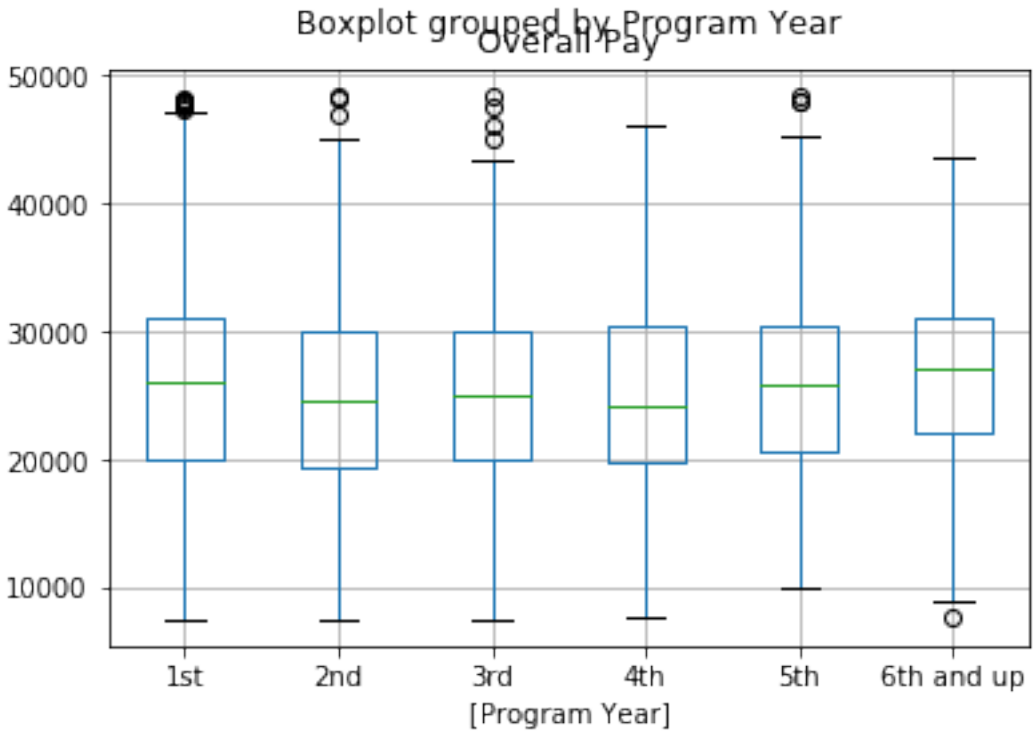
[50]:
```
# however, we should take into account the high variance around the mean
data[['Overall Pay', 'Academic Year']].boxplot(by='Academic Year')
```

[50]: <matplotlib.axes._subplots.AxesSubplot at 0x201cfa22c50>



[51]:
```
# on the other hand, there is no significant variation of pay over the course␣
 ↪of the PhD program
data[['Overall Pay', 'Program Year']].boxplot(by='Program Year')
```

[51]: <matplotlib.axes._subplots.AxesSubplot at 0x201cfc5f710>



[ ]:
```
# get locations from Mapbox and add them to the DataFrame (https://github.com/
 ↪mapbox/mapbox-sdk-py/blob/master/docs/geocoding.md#geocoding)
# If you don't want to set up Mapbox, you can skip to the next cell to load the␣
 ↪geo-tagged data
from mapbox import Geocoder
with open('mapbox_tkn.txt', 'r') as f:
    mapbox_key = f.read().strip()
geocoder = Geocoder(access_token=mapbox_key)
data.assign(lon=np.NaN)
data.assign(lat=np.NaN)
uni_names = data['University'].dropna().unique()
for i, uni in enumerate(uni_names[174:]):
    print(uni)
    response = geocoder.forward(uni, limit=1)
    if response.geojson()['features']:
        lon, lat = response.geojson()['features'][0]['center']
        print(lon, lat)
        mask = data['University'] == uni
        data.loc[mask, 'lon'] = lon
        data.loc[mask, 'lat'] = lat
        print('\n')
# save geo-tagged data
data.to_csv('data_cleaned_geoloc.csv')
```

```
data.head()
```

[52]:
```
# load geo-tagged data
data = pd.read_csv('data_cleaned_geoloc.csv')
```

[ ]:
```
# Aggregate nearby universities and compute average pay.
# This takes a long time to run!!! You can skip to the next cell to load the␣
 ↪final aggregated and geo-tagged data.
# adapted from: https://www.jphwang.com/
 ↪interactive-maps-with-python-pandas-and-plotly/
data = data.assign(merged=False)
data = data.assign(counts=1)
data = data.assign(pay_sum=data['Overall Pay'])
dist_thresh = 0.0001
for i in range(len(data)):
    src_ind = data.iloc[i].name
    if not data.loc[src_ind]['merged']:
        print(src_ind)
        for j in range(i+1, len(data)):
            tgt_ind = data.iloc[j].name
            if not data.loc[tgt_ind]['merged']:
                lat_dist = data.loc[src_ind]['lat'] - data.loc[tgt_ind]['lat']
                lon_dist = data.loc[src_ind]['lon'] - data.loc[tgt_ind]['lon']
                tot_dist = (lat_dist ** 2 + lon_dist ** 2) ** 0.5
                if tot_dist < dist_thresh:
                    print(f'Found duplicate item "{data.
 ↪loc[tgt_ind]["University"]}", index {tgt_ind}')
                    data.loc[src_ind, 'counts'] += 1
                    data.loc[src_ind, 'pay_sum'] += data.loc[tgt_ind, 'Overall␣
 ↪Pay']
                    if data.loc[tgt_ind, 'University'] not in data.loc[src_ind,␣
 ↪'University']:
                        data.loc[src_ind, 'University'] = data.loc[src_ind,␣
 ↪'University'] + ' | ' + data.loc[tgt_ind, 'University']
                    data.loc[tgt_ind, 'merged'] = True

# Update counts
data = data[data.merged == False]
data = data.assign(pay_average=data['pay_sum']/data['counts'])
# save final aggregated and geo-tagged data
data.to_csv('data_cleaned_geoloc_aggregated.csv')
```

[53]:
```
# load final aggregated and geo-tagged data
data = pd.read_csv('data_cleaned_geoloc_aggregated.csv')
with open('mapbox_tkn.txt', 'r') as f:
    mapbox_key = f.read().strip()
```

[57]:
```
# display interactive and zoomable world map, with colour and size of␣
↪universities proportional to the average pay (tooltip shows university name␣
↪and average pay)
import plotly.express as px
fig = px.scatter_mapbox(
    data, lat="lat" , lon="lon", color="pay_average", size="pay_average",
    hover_name='University', hover_data=['pay_average'], zoom=0.2, size_max=15)
fig.update_layout(mapbox_style="light", mapbox_accesstoken=mapbox_key)
fig.update_layout(margin={"r": 0, "t": 0, "l": 0, "b": 0})
fig.show(config={'displayModeBar': False, 'editable': False})
```

[58]:
```
# display the non-interactive version of the map
from IPython.display import Image
Image(filename='world_map.png')
```

[58]: