# Chaper 5 Excercises

April 22, 2025

## 0.1 Hands-On Data Preprocessing in Python

Learn how to effectively prepare data for successful data analytics

`AUTHOR: Dr. Roy Jafari`

### 0.1.1 Chapter 5: Data Visualization

**Excercises**

```
[1]: import pandas as pd
     import matplotlib.pyplot as plt
     import numpy as np
     import seaborn as sns
     from ipywidgets import interact, widgets
```

# 1 Excercise 1

In this exercise, we will be using Universities_imputed_reduced.csv. Draw the following described visualizations.

```
a.  Use boxplots to compare the student to faculty ratio (stud./fac. ratio) for the two popula
b.  Use a histogram to compare the student to faculty ratio (stud./fac. ratio) for the two popu
c.  use subplots to put the results of a and b on top of one another to create a visual that co
```

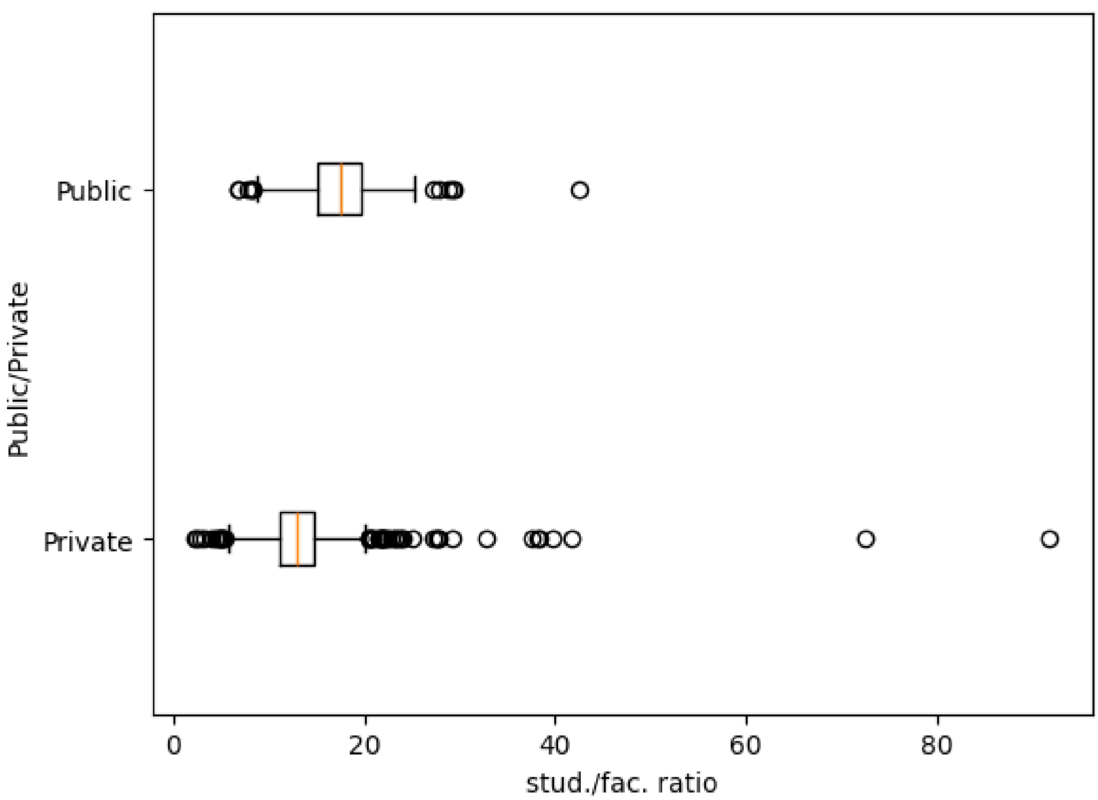
```
[2]: uni_df = pd.read_csv('Universities_imputed_reduced.csv')
     uni_df.head()
```

```
[2]:                          College Name State Public/Private  num_appli_rec  \
     0          Alaska Pacific University    AK        Private            193
     1  University of Alaska at Fairbanks    AK         Public           1852
     2     University of Alaska Southeast    AK         Public            146
     3  University of Alaska at Anchorage    AK         Public           2065
     4        Alabama Agri. & Mech. Univ.    AL         Public           2817

        num_appl_accepted  num_new_stud_enrolled  in-state tuition  \
     0                146                     55              7560
     1               1427                    928              1742
     2                117                     89              1742
     3               1598                   1162              1742
     4               1920                    984              1700
```

| | out-of-state tuition | % fac. w/PHD | stud./fac. ratio | Graduation rate |
|---|---|---|---|---|
| 0 | 7560 | 76 | 11.9 | 15 |
| 1 | 5226 | 67 | 10.0 | 60 |
| 2 | 5226 | 39 | 9.5 | 39 |
| 3 | 5226 | 48 | 13.7 | 60 |
| 4 | 3400 | 53 | 14.3 | 40 |

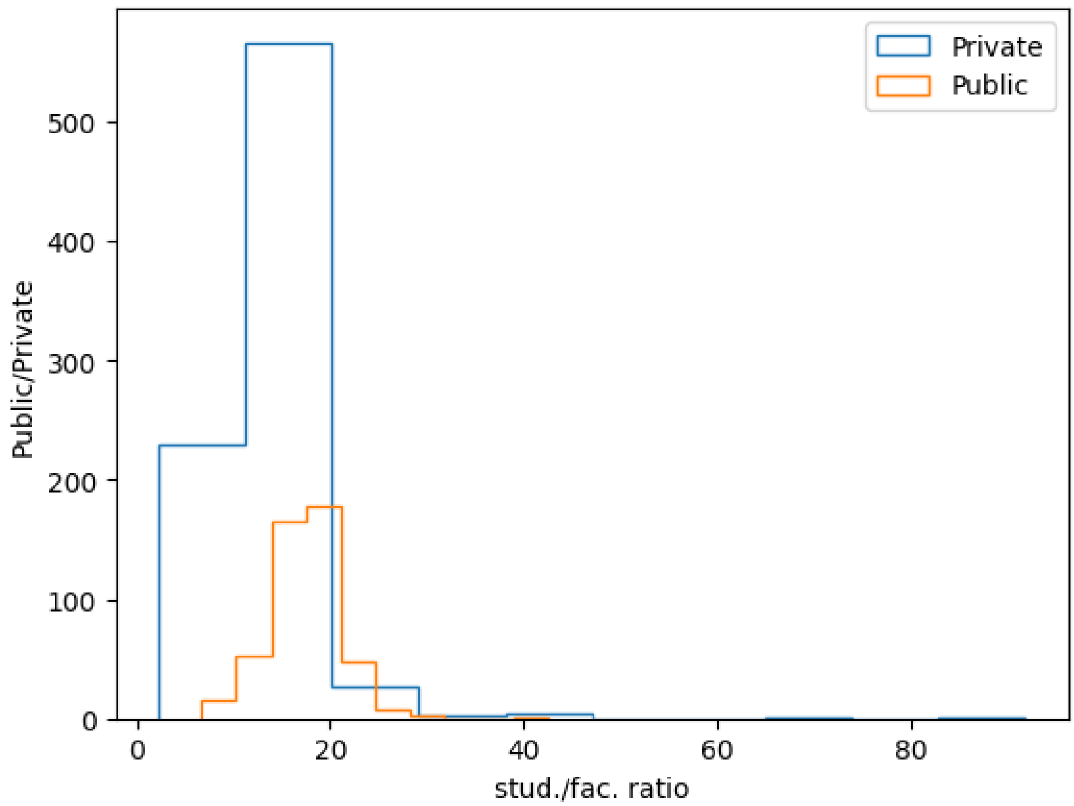
a.

[3]:
```
private_public_possiblilites = uni_df['Public/Private'].unique()

box_sr = pd.Series('', index=private_public_possiblilites)

for poss in private_public_possiblilites:
    BM = uni_df['Public/Private'] == poss
    box_sr[poss] = uni_df[BM]['stud./fac. ratio']

plt.boxplot(box_sr, vert=False)
plt.yticks([1, 2], private_public_possiblilites)
plt.xlabel('stud./fac. ratio')
plt.ylabel('Public/Private')
plt.show()
```



b.

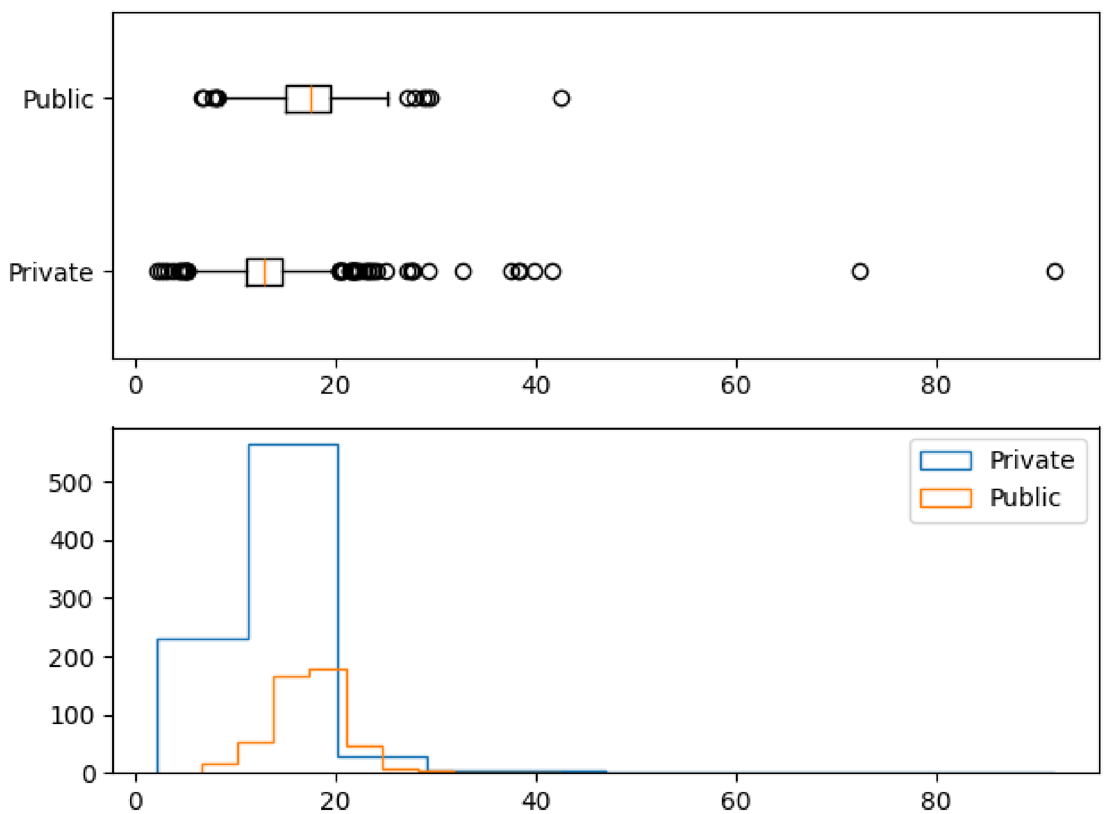
[4]:
```
private_public_possiblilites = uni_df['Public/Private'].unique()

for poss in private_public_possiblilites:
    BM = uni_df['Public/Private'] == poss
    plt.hist(uni_df[BM]['stud./fac. ratio'],
             histtype='step', label=poss)

plt.legend()
plt.xlabel('stud./fac. ratio')
plt.ylabel('Public/Private')
plt.show()
```




c.

[5]:
```
private_public_possiblilites = uni_df['Public/Private'].unique()

dataForBox_dic = {}
```

```
for poss in private_public_possiblilites:
    BM = uni_df['Public/Private'] == poss
    dataForBox_dic[poss] = uni_df[BM]['stud./fac. ratio']

plt.subplot(2, 1, 1)
plt.boxplot(dataForBox_dic.values(), vert=False)
plt.yticks([1, 2], private_public_possiblilites)

plt.subplot(2, 1, 2)
for poss in private_public_possiblilites:
    BM = uni_df['Public/Private'] == poss
    plt.hist(uni_df[BM]['stud./fac. ratio'],
            histtype='step', label=poss)
plt.legend()

plt.tight_layout()
plt.show()
```



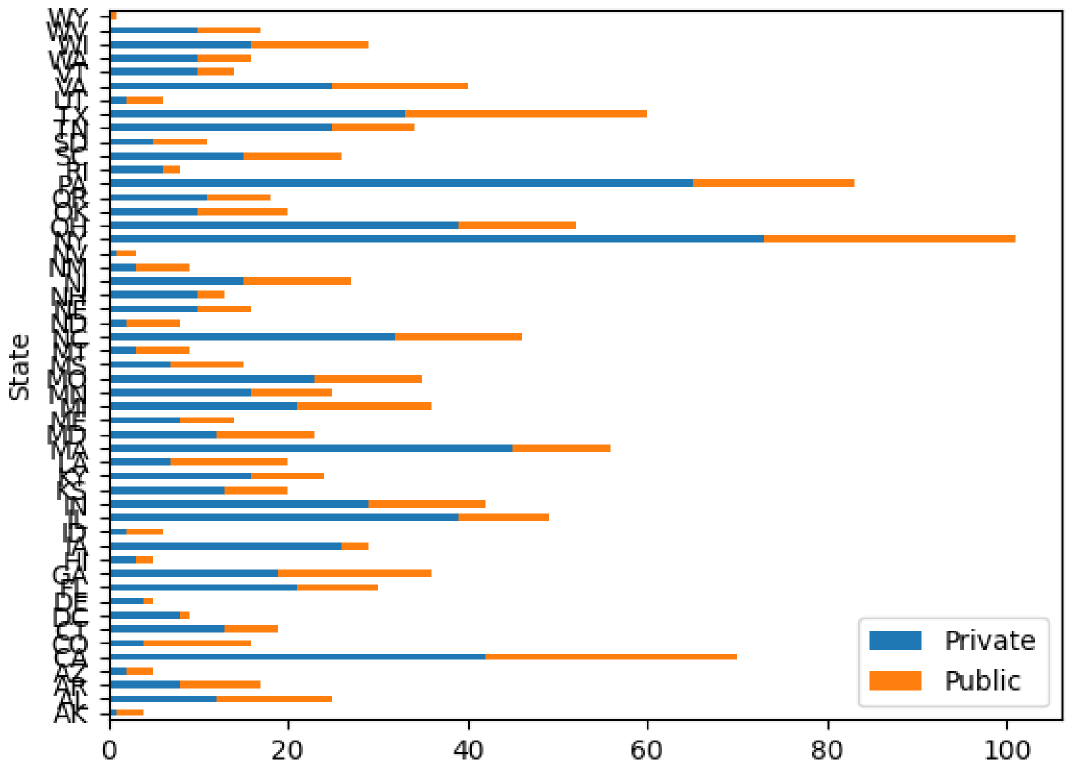
## 2 Excercise 2

In this exercise, we will continue using Universities_imputed_reduced.csv. Draw the following described visualizations.

```
a.  Use a bar chart to compare the private/public ratio of all the states in the dataset. In th
b.  Improve the visualizations by sorting the states on the visuals based on the total number o
c.  Create a stacked bar chart that shows the compare the percentages of public and private sch
```

a.

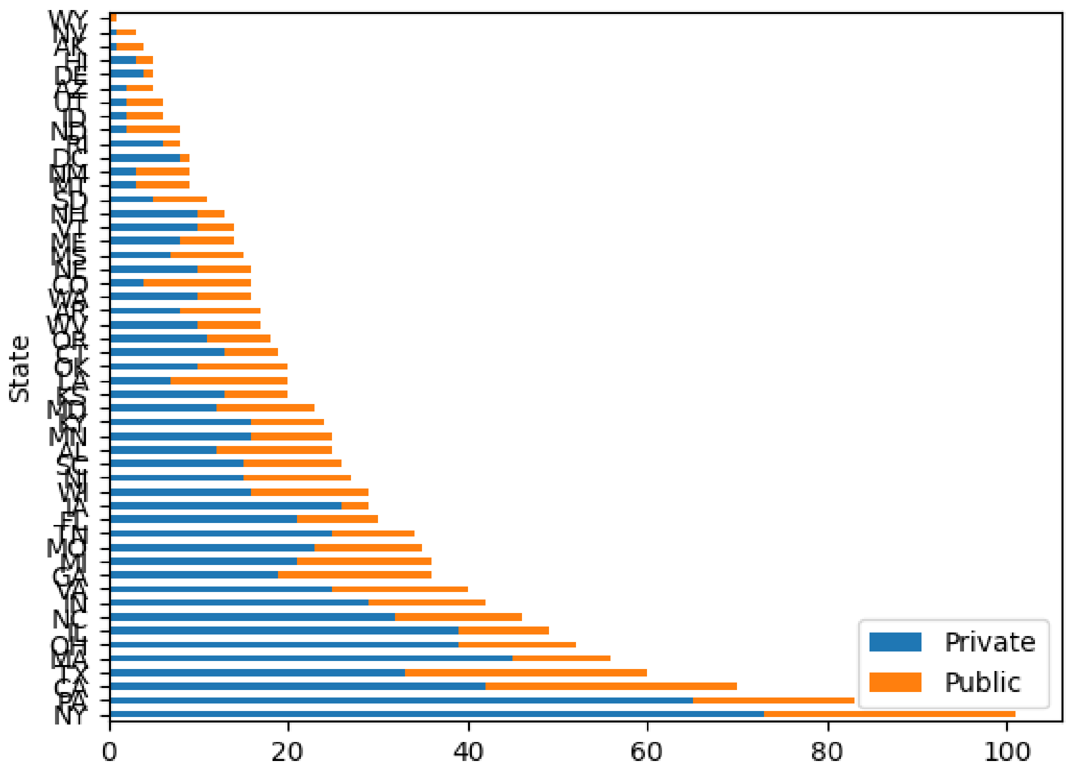
[6]:
```python
uni_df.groupby(['State', 'Public/Private']).size().unstack().plot.
  ↪barh(stacked=True)
plt.legend(loc=4)
plt.show()
```




b.

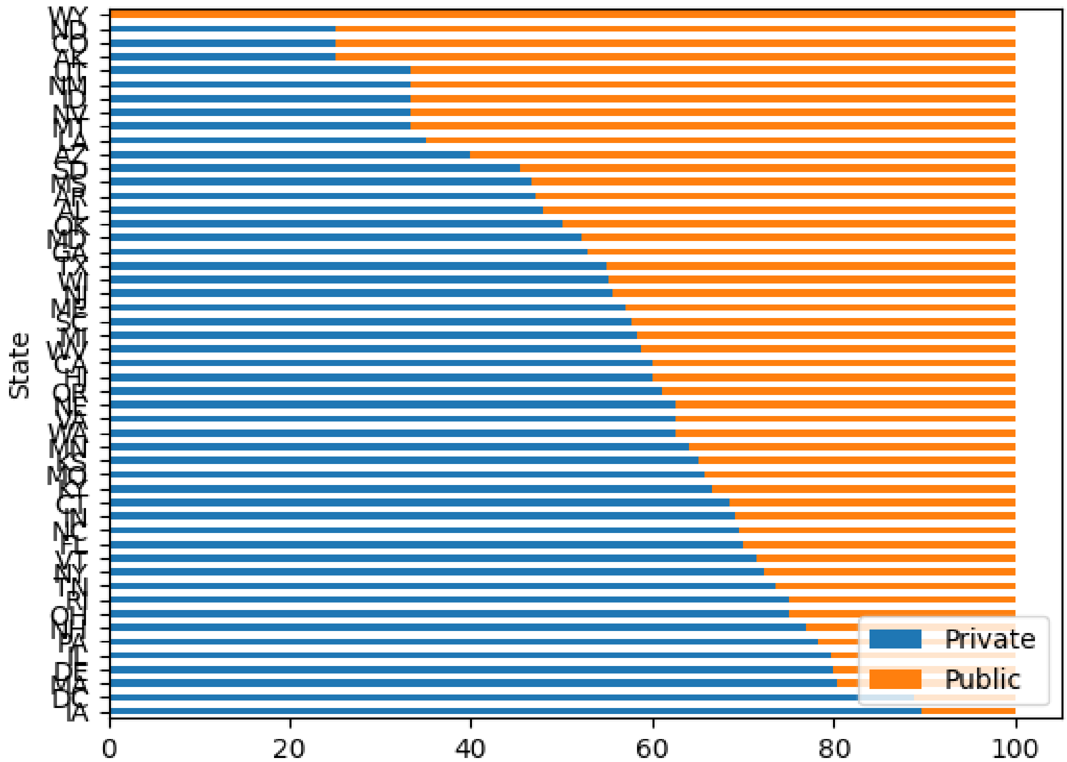
[7]:
```python
state_counts = uni_df.groupby(['State', 'Public/Private']).size().unstack()
state_counts['Total'] = state_counts.sum(axis=1)

state_counts.sort_values(by='Total', ascending=False).drop(columns='Total').
  ↪plot.barh(stacked=True)
plt.legend(loc=4)
```

```
plt.show()
```




c.

[8]:
```
state_counts = uni_df.groupby(['State', 'Public/Private']).size().unstack()
state_counts['Total'] = state_counts.sum(axis=1)
state_percentages = state_counts.div(state_counts['Total'], axis=0) * 100
state_percentages = state_percentages.drop(columns='Total')
state_percentages = state_percentages.sort_values(by='Private', ascending=False)

state_percentages.plot.barh(stacked=True)
plt.legend(loc=4)
plt.show()
```




## 3 Excercise 3

For this example, we will be using WH Report_preprocessed.csv. Draw the following described visualizations.

```
a.  Create a visual that compares the relationship between all the happiness indices.
b.  Use the visual you created in a) to report the happiness indices with strong relationships
c.  Confirm the relationship you found and described by calculating their correlation coeffici
```

[9]:
```
report_df = pd.read_csv('WH Report_preprocessed.csv')
report_df.head()
```

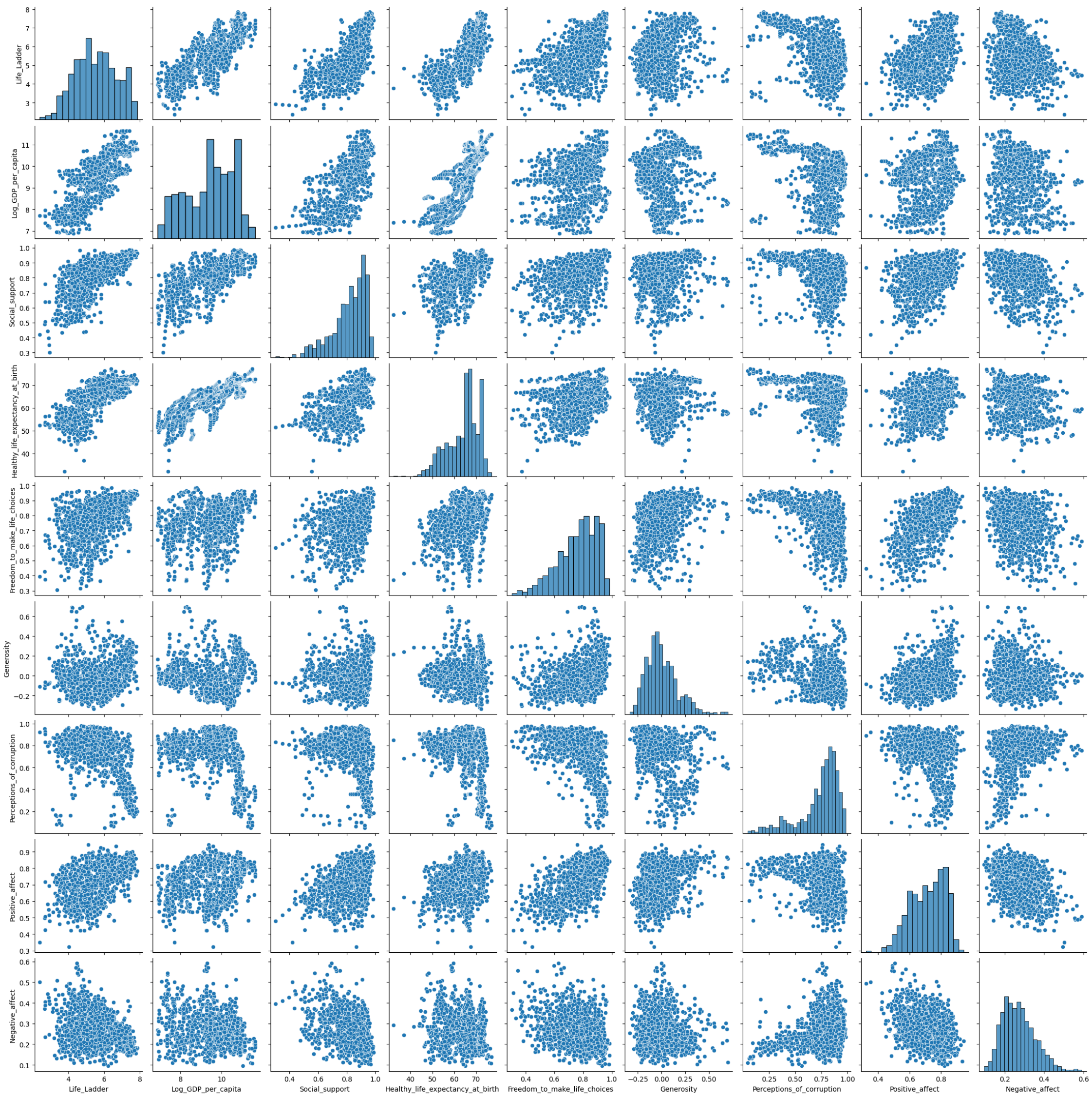
[9]:
```
          Name Continent  year  population  Life_Ladder  Log_GDP_per_capita  \
0  Afghanistan      Asia  2010  29185507.0        4.758               7.647
1  Afghanistan      Asia  2011  30117413.0        3.832               7.620
2  Afghanistan      Asia  2012  31161376.0        3.783               7.705
3  Afghanistan      Asia  2013  32269589.0        3.572               7.725
4  Afghanistan      Asia  2014  33370794.0        3.131               7.718

   Social_support  Healthy_life_expectancy_at_birth  \
0           0.539                             51.60
1           0.521                             51.92
```

```
2          0.521                             52.24
3          0.484                             52.56
4          0.526                             52.88

   Freedom_to_make_life_choices  Generosity  Perceptions_of_corruption  \
0                         0.600       0.121                      0.707
1                         0.496       0.162                      0.731
2                         0.531       0.236                      0.776
3                         0.578       0.061                      0.823
4                         0.509       0.104                      0.871

   Positive_affect  Negative_affect
0            0.618            0.275
1            0.611            0.267
2            0.710            0.268
3            0.621            0.273
4            0.532            0.375
```

a.

[10]:

```
happiness_indices = [
    'Life_Ladder',
    'Log_GDP_per_capita',
    'Social_support',
    'Healthy_life_expectancy_at_birth',
    'Freedom_to_make_life_choices',
    'Generosity',
    'Perceptions_of_corruption',
    'Positive_affect',
    'Negative_affect'
]
sns.pairplot(report_df[happiness_indices])
plt.show()
```




b.

[11]:
```
# base on a
```

c.

[12]:
```
corr_matrix = report_df[happiness_indices].corr()
corr_matrix
```

[12]:
```
                                  Life_Ladder  Log_GDP_per_capita  \
Life_Ladder                          1.000000            0.798912
Log_GDP_per_capita                   0.798912            1.000000
Social_support                       0.723686            0.718969
Healthy_life_expectancy_at_birth     0.758287            0.857981
```

```
Freedom_to_make_life_choices         0.518618            0.357799
Generosity                           0.198072            0.010562
Perceptions_of_corruption           -0.465268           -0.368602
Positive_affect                      0.518226            0.296845
Negative_affect                     -0.302013           -0.261958

                                  Social_support  \
Life_Ladder                             0.723686
Log_GDP_per_capita                      0.718969
Social_support                          1.000000
Healthy_life_expectancy_at_birth        0.629507
Freedom_to_make_life_choices            0.421854
Generosity                              0.099973
Perceptions_of_corruption              -0.258575
Positive_affect                         0.429687
Negative_affect                        -0.425569

                                  Healthy_life_expectancy_at_birth  \
Life_Ladder                                               0.758287
Log_GDP_per_capita                                        0.857981
Social_support                                            0.629507
Healthy_life_expectancy_at_birth                          1.000000
Freedom_to_make_life_choices                              0.393043
Generosity                                                0.018837
Perceptions_of_corruption                                -0.353142
Positive_affect                                           0.339499
Negative_affect                                          -0.209444

                                  Freedom_to_make_life_choices  Generosity  \
Life_Ladder                                           0.518618    0.198072
Log_GDP_per_capita                                    0.357799    0.010562
Social_support                                        0.421854    0.099973
Healthy_life_expectancy_at_birth                      0.393043    0.018837
Freedom_to_make_life_choices                          1.000000    0.325176
Generosity                                            0.325176    1.000000
Perceptions_of_corruption                            -0.504291   -0.296068
Positive_affect                                       0.635665    0.359233
Negative_affect                                      -0.313267   -0.121400

                                  Perceptions_of_corruption  Positive_affect  \
Life_Ladder                                       -0.465268         0.518226
Log_GDP_per_capita                                -0.368602         0.296845
Social_support                                    -0.258575         0.429687
Healthy_life_expectancy_at_birth                  -0.353142         0.339499
Freedom_to_make_life_choices                      -0.504291         0.635665
Generosity                                        -0.296068         0.359233
Perceptions_of_corruption                          1.000000        -0.320755
```

```
Positive_affect                                     -0.320755          1.000000
Negative_affect                                      0.345491         -0.372535

                                   Negative_affect
Life_Ladder                              -0.302013
Log_GDP_per_capita                       -0.261958
Social_support                           -0.425569
Healthy_life_expectancy_at_birth         -0.209444
Freedom_to_make_life_choices             -0.313267
Generosity                               -0.121400
Perceptions_of_corruption                 0.345491
Positive_affect                          -0.372535
Negative_affect                           1.000000
```

Strong & Notable Relationships Among Happiness Indices

1. Life Ladder & Log GDP per Capita Correlation coefficient: +0.80

Interpretation: A very strong positive relationship. Countries with higher income per person tend to report greater happiness. Economic stability clearly supports life satisfaction.

2. Life Ladder & Healthy Life Expectancy Correlation coefficient: +0.76

Interpretation: People in countries with longer, healthier lives tend to be happier. This emphasizes the impact of health systems and longevity on well-being.

3. Life Ladder & Social Support Correlation coefficient: +0.72

Interpretation: Strong social connections contribute significantly to happiness. Societies with tight-knit communities and supportive networks foster greater life satisfaction.

4. Log GDP per Capita & Healthy Life Expectancy Correlation coefficient: +0.86

Interpretation: The strongest correlation in your data. Countries with high economic wealth also have high life expectancy — likely due to better healthcare, nutrition, and living conditions.

5. Life Ladder & Freedom to Make Life Choices Correlation coefficient: +0.52

Interpretation: People who feel more in control of their lives tend to be happier. This moderate relationship highlights the importance of autonomy and civil liberties.

6. Life Ladder & Positive Affect Correlation coefficient: +0.52

Interpretation: Happier people tend to experience more positive emotions (joy, laughter, etc.). Though not a perfect match, the emotional tone of life plays a big role.

7. Life Ladder & Perceptions of Corruption Correlation coefficient: −0.47

Interpretation: A moderate negative relationship. Higher levels of perceived corruption are associated with lower happiness, likely due to mistrust and systemic dissatisfaction.

Weaker or Less Clear Relationships

1. Generosity & Life Ladder: +0.20

Suggests generosity doesn't directly track with happiness, or that it varies a lot by culture/context.

2. Negative Affect & Life Ladder: −0.30

A mild negative relationship: more negative emotions slightly predict lower happiness, as expected.

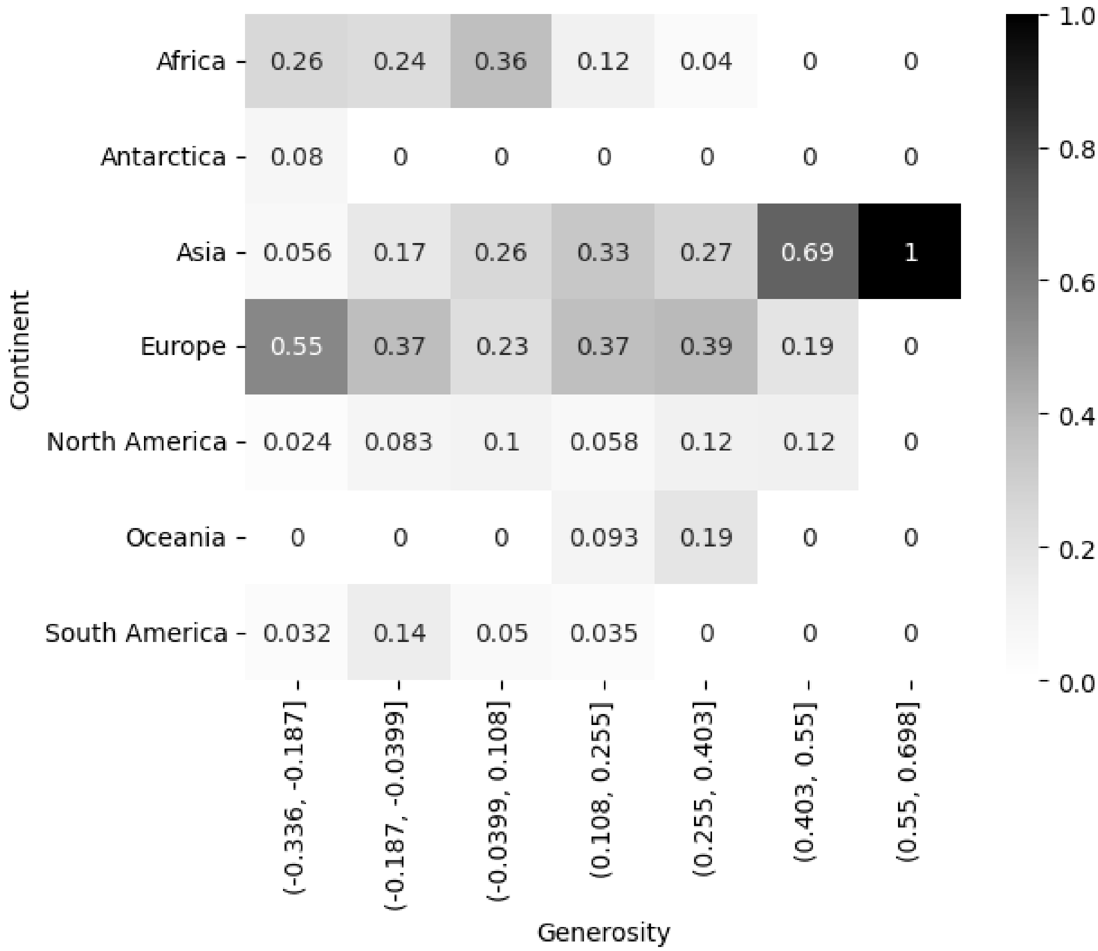
## 4 Excercise 4

For this exercise, we will continue using WH Report_preprocessed.csv. Draw the following described visualizations.

```
a.  Draw a visual that examine the relationship between the two attributes Continent and Genero
b.  Based on the visual, is there a relationship between the two attributes? Explain why.
```

a.

```
[13]: generosity_discretized = pd.cut(report_df['Generosity'], bins=7)
contingency_tbl = pd.crosstab(report_df['Continent'], generosity_discretized)
probability_tbl = contingency_tbl / contingency_tbl.sum()
sns.heatmap(probability_tbl, annot=True, center=0.5, cmap="Greys")
plt.show()
```



b.

Yes, there is a relationship between Continent and Generosity, as seen in the heatmap and table. Some continents have a higher likelihood of countries falling into specific generosity ranges than others — which indicates a non-random distribution

| Continent | Pattern in Generosity Distribution |
|---|---|
| **Africa** | Majority falls in lower bins (`-0.336` to `0.108`) – **high concentration in low generosity ranges**. |
| **Asia** | **Spread across the entire spectrum**, **only region with values in the highest bin `(0.55, 0.698]`**. Indicates diverse and high generosity levels. |
| **Europe** | Strong presence in low to moderate bins, but **absent from the top generosity bin**. |
| **North America** | Appears more in **lower-middle generosity ranges**, no countries in top bins. |
| **South America** | Heavily weighted toward **lower generosity**, barely any representation in higher bins. |
| **Oceania** | **Very limited data**, but slight mid-range generosity. |
| **Antarctica** | Likely an outlier or placeholder (ignore in analysis). |

## 5 Excercise 5

For this exercise, we will be using whickham.csv. Draw the following described visualizations.

```
a.  What is the numerical attribute in this dataset? Draw two different plots that summarize th
b.  What are the categorical attributes in this dataset? Draw a plot per attribute that summari
c.   Draw a visual that examine the relationship between outcome and smoker. Do you notice any
d.  To demystify the surprising relationship you observed on c) run the following code, and st
```

```
person_df = pd.read_csv('whickham.csv') person_df['age_discretized'] =
pd.cut(person_df.age, bins = 4, labels=False) person_df.groupby(['age_discretized','smoker']).
plt.show()
```

```
e.  Using the visual that was created under d) explain the surprising observation under c).
f.  How many dimensions the visual that was created under d) has? How did we manage to add dime
```

[14]:
```
person_df = pd.read_csv('whickham.csv')
person_df.head()
```

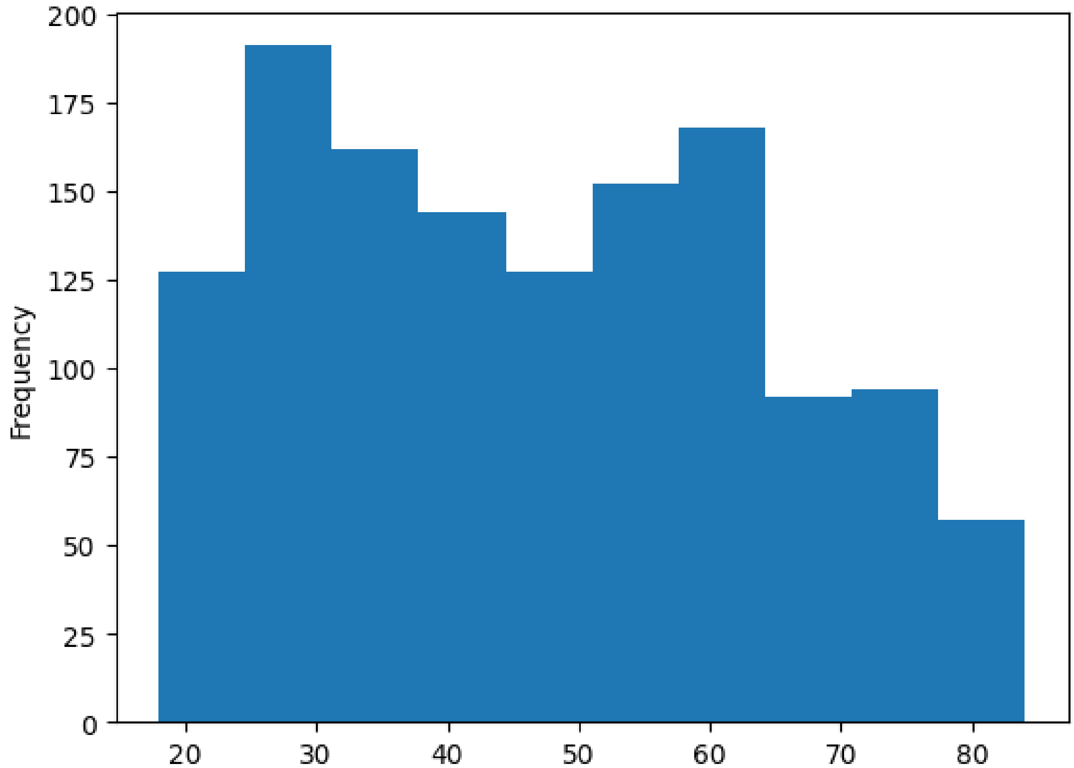
[14]:

| | outcome | smoker | age |
|---|---|---|---|
| 0 | Alive | Yes | 23 |
| 1 | Alive | Yes | 18 |
| 2 | Dead | Yes | 71 |
| 3 | Alive | No | 67 |
| 4 | Alive | No | 64 |

a.

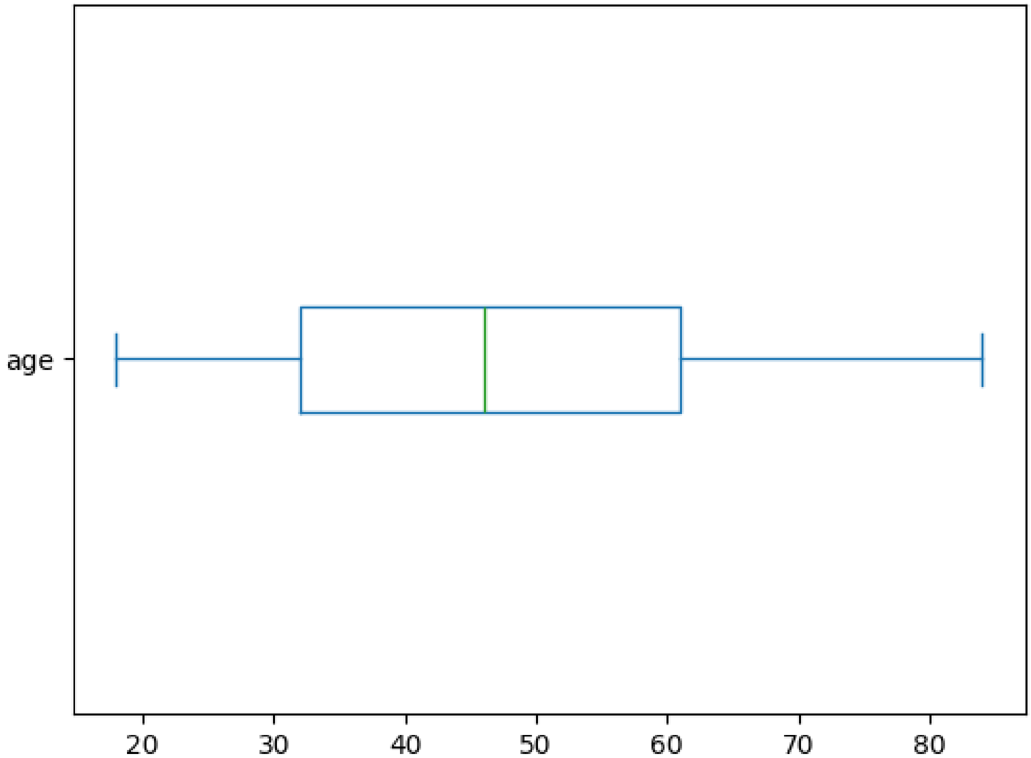
[15]:
```
numerical_att = 'age'
person_df[numerical_att].plot.hist()
```

[15]: <Axes: ylabel='Frequency'>



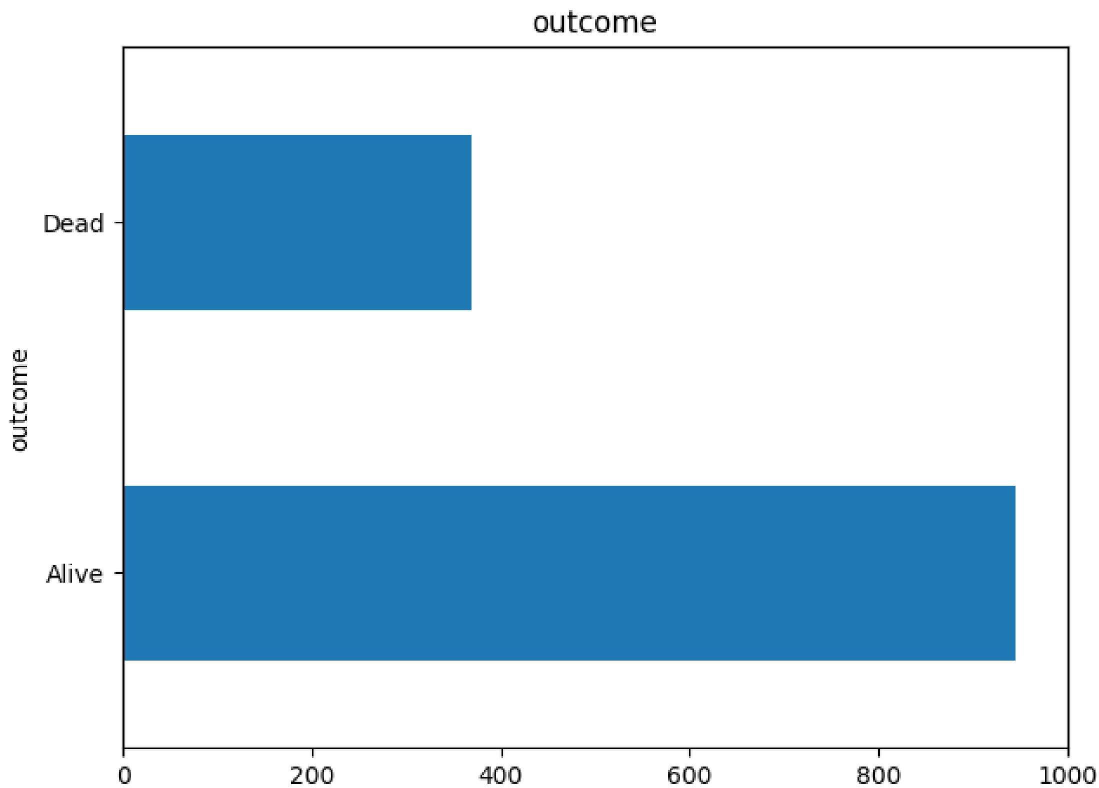

[16]:
```
person_df[numerical_att].plot.box(vert=False)
```

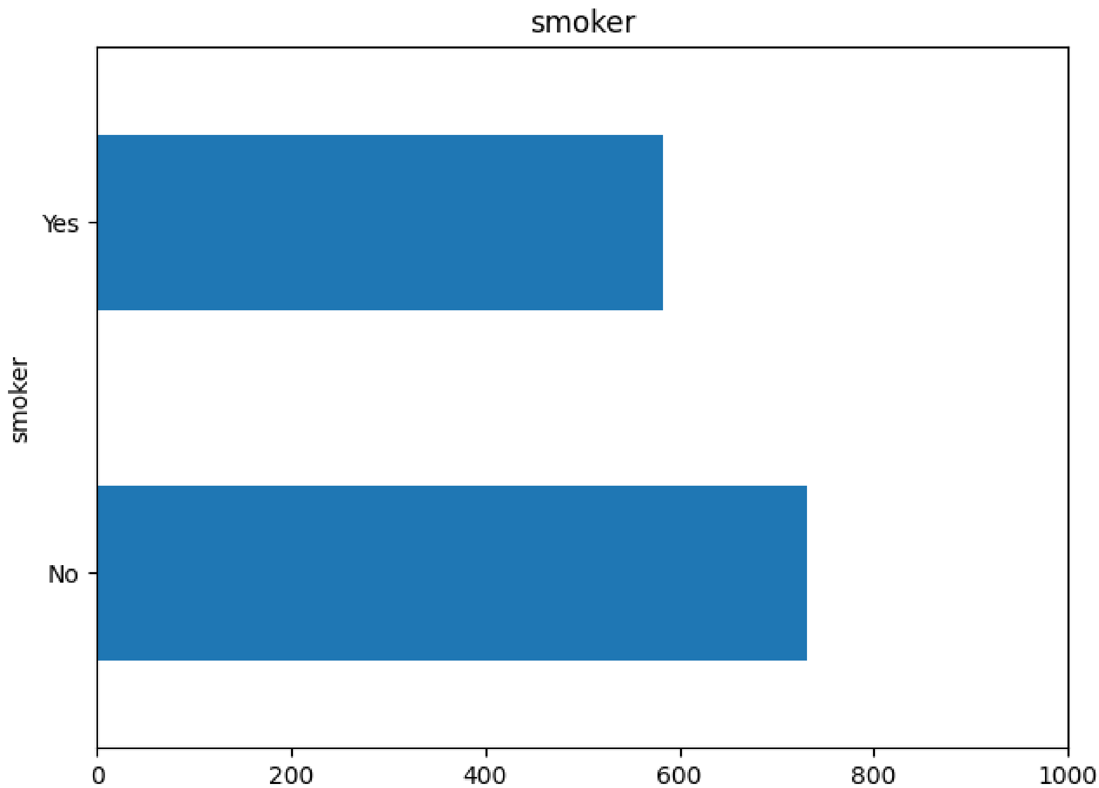
[16]: <Axes: >




b.

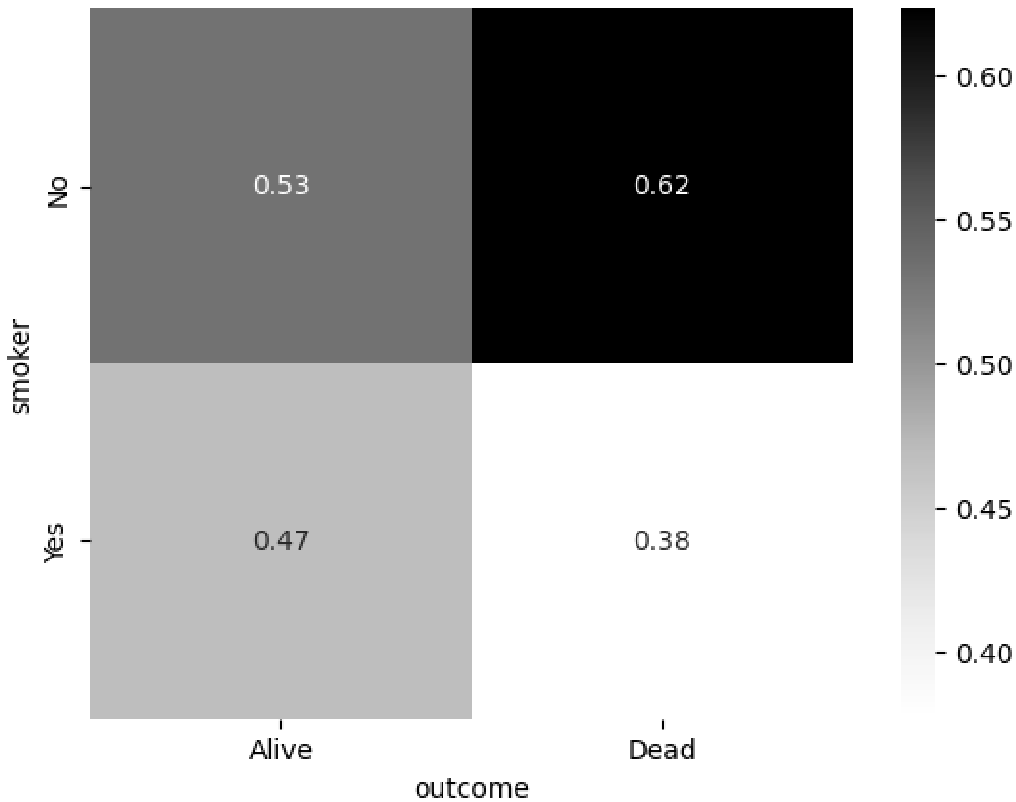
[17]:
```
categorical_attributes = ['outcome', 'smoker']

for att in categorical_attributes:
    person_df[att].value_counts().plot.barh()
    plt.title(att)
    plt.tight_layout()
    plt.xlim(0, 1000)
    plt.show()
```


outcome
Dead
Alive
outcome
0
200
400
600
800
1000




c.

[18]:
```
contingency_tbl = pd.crosstab(person_df['smoker'], person_df['outcome'])
probability_tbl = contingency_tbl / contingency_tbl.sum()
sns.heatmap(probability_tbl, annot=True, center=0.5, cmap="Greys")
plt.show()
```

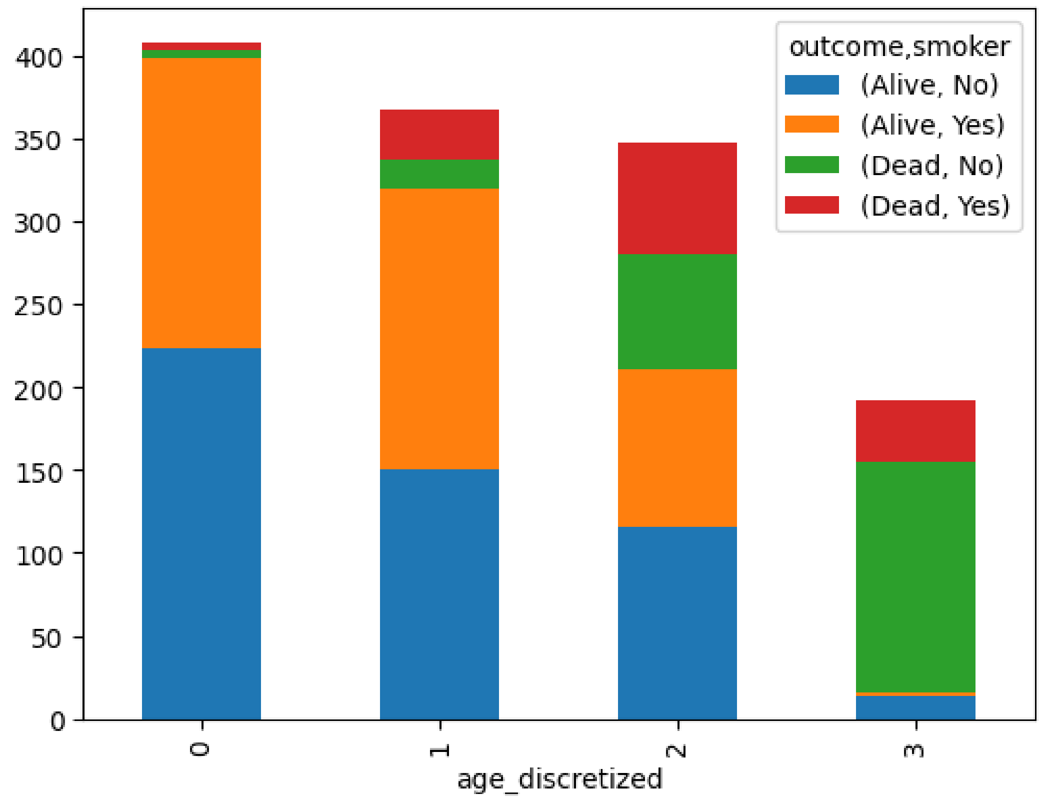



More non-smokers died than smokers (contrary to expectations).

But this is misleading because it doesn't account for age distribution (smokers might be younger).

d.

[19]:
```
person_df = pd.read_csv('whickham.csv')
person_df['age_discretized'] = pd.cut(person_df.age, bins = 4, labels=False)
person_df.groupby(['age_discretized','smoker']).outcome.value_counts().
    ↪unstack().unstack().plot.bar(stacked=True)
plt.show()
```




e.

The surprising observation (smokers appearing to survive more) is due to:

1. Age Confounding:
   - Smokers are younger (mean age = 45) vs. non-smokers (mean age = 50).
   - Younger people naturally survive longer, regardless of smoking.
2. Simpson's Paradox:
   - Aggregating data hides subgroup trends.
   - When stratified by age, smoking reduces survival in every age group.

Example:

Age Group 0 (youngest): Smokers have 90% survival vs. non-smokers' 95%.

Age Group 3 (oldest): Smokers have 20% survival vs. non-smokers' 30%.

f.

Number of Dimensions: 3

1. Primary Dimension (x-axis): age_discretized (4 age groups).
2. Secondary Dimension (color stacks): smoker (Yes/No).

3. Tertiary Dimension (stack height): outcome (Alive/Dead).

How Dimensions Were Added:

- groupby(): Split data by age_discretized and smoker (2 dimensions).
- value_counts() + unstack(): Pivoted outcome into columns (3rd dimension).
- plot.bar(stacked=True): Visualized stacks for Alive/Dead within each smoker-age group.

# 6 Excercise 6

For this exercise, we will be using WH Report_preprocessed.csv.

```
a.  Use this dataset to create a 5-dimensional scatterplot to show the interactions between the
b.  Interact with and study the visual you created under a) and report your observations.
```

[20]:
```python
report_df = pd.read_csv('WH Report_preprocessed.csv')
report_df.head()
```

[20]:
```
          Name Continent  year  population  Life_Ladder  Log_GDP_per_capita  \
0  Afghanistan      Asia  2010  29185507.0        4.758               7.647
1  Afghanistan      Asia  2011  30117413.0        3.832               7.620
2  Afghanistan      Asia  2012  31161376.0        3.783               7.705
3  Afghanistan      Asia  2013  32269589.0        3.572               7.725
4  Afghanistan      Asia  2014  33370794.0        3.131               7.718

   Social_support  Healthy_life_expectancy_at_birth  \
0           0.539                             51.60
1           0.521                             51.92
2           0.521                             52.24
3           0.484                             52.56
4           0.526                             52.88

   Freedom_to_make_life_choices  Generosity  Perceptions_of_corruption  \
0                         0.600       0.121                      0.707
1                         0.496       0.162                      0.731
2                         0.531       0.236                      0.776
3                         0.578       0.061                      0.823
4                         0.509       0.104                      0.871

   Positive_affect  Negative_affect
0            0.618            0.275
1            0.611            0.267
2            0.710            0.268
3            0.621            0.273
4            0.532            0.375
```

a.

[39]:
```
import pandas as pd
import matplotlib.pyplot as plt
from ipywidgets import interact, IntSlider

# Define continent colors
continent_poss = report_df['Continent'].unique()
colors_dic = {
    'Asia': 'blue',
    'Europe': 'green',
    'Africa': 'red',
    'South America': 'cyan',
    'Oceania': 'magenta',
    'North America': 'yellow',
    'Antarctica': 'black'
}

# Sort by population for better visualization
report_df = report_df.sort_values('population', ascending=False)

def plot_year(year):
    plt.figure(figsize=(12, 8))

    for continent in continent_poss:
        # Filter data for year and continent
        mask = (report_df['year'] == year) & (report_df['Continent'] ==␣
↪continent)
        df_filtered = report_df[mask]

        # Skip if no data for this continent-year combination
        if len(df_filtered) == 0:
            continue

        # Create scatter plot with multiple dimensions
        plt.scatter(
            x=df_filtered['Healthy_life_expectancy_at_birth'],  # x-axis
            y=df_filtered['Life_Ladder'],                       # y-axis
            s=df_filtered['population']/500000,                 # marker size␣
↪(scaled)
            c=df_filtered['Social_support'],                    # marker color
            cmap='viridis',                                     # color map
            vmin=0, vmax=1,                                     # color scale␣
↪limits
            alpha=0.7,                                          # transparency
            edgecolors='w',                                     # white borders
            linewidths=0.5,                                     # border width
            label=continent
        )
```

```python
    # Formatting
    plt.title(f'World Happiness Report - {year}')
    plt.xlabel('Healthy Life Expectancy at Birth')
    plt.ylabel('Life Ladder (Happiness Score)')
    plt.xlim(40, 85)
    plt.ylim(2, 8)
    plt.grid(alpha=0.2)

    # Add colorbar for Social_support
    plt.colorbar(label='Social Support')

    # Add legend for continents
    plt.legend(title='Continent', markerscale=0.7, loc=2)

    plt.show()

# Create interactive widget
interact(
    plot_year,
    year=IntSlider(min=report_df['year'].min(),
                   max=report_df['year'].max(),
                   step=1,
                   value=report_df['year'].median())
)
```

```
interactive(children=(IntSlider(value=2014, description='year', max=2019,␣
↪min=2010), Output()), _dom_classes=(…
```

[39]:
```
<function __main__.plot_year(year)>
```

b.

[35]:
```python
# based on a
```

## 7 Excercise 7

For this exercise, we will continue using WH Report_preprocessed.csv.

```
a.  Create a visual that shows the trend of change for the attribute Generosity for all the co
b.  Add three more line plots to the previous visual using the color blue and a thicker line (
```

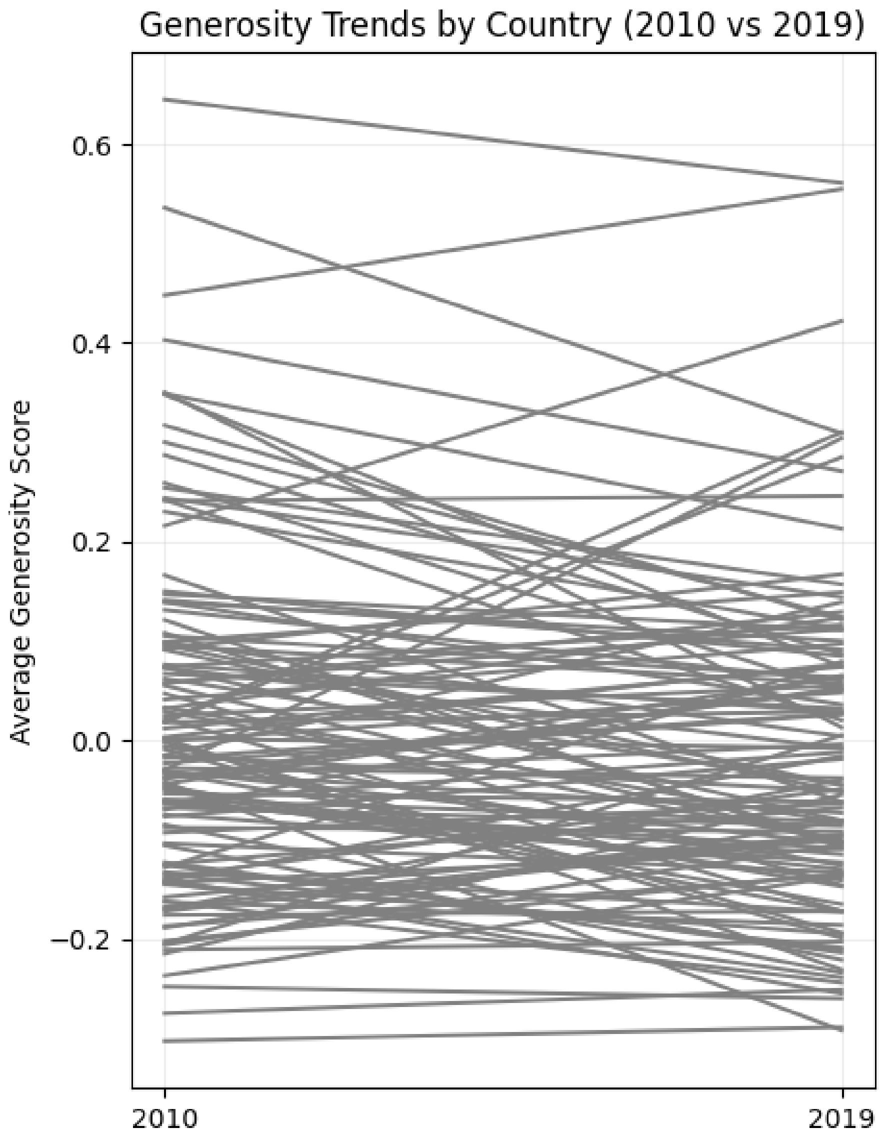
Figure 5. 23. Line plot comparing Generosity across all countries in 2010 and 2019 with emphasis on the United States, India, and China

```
c.  Report your observations from the visual. Make sure to employ all of the line plots (grey a
```

a.

[71]:

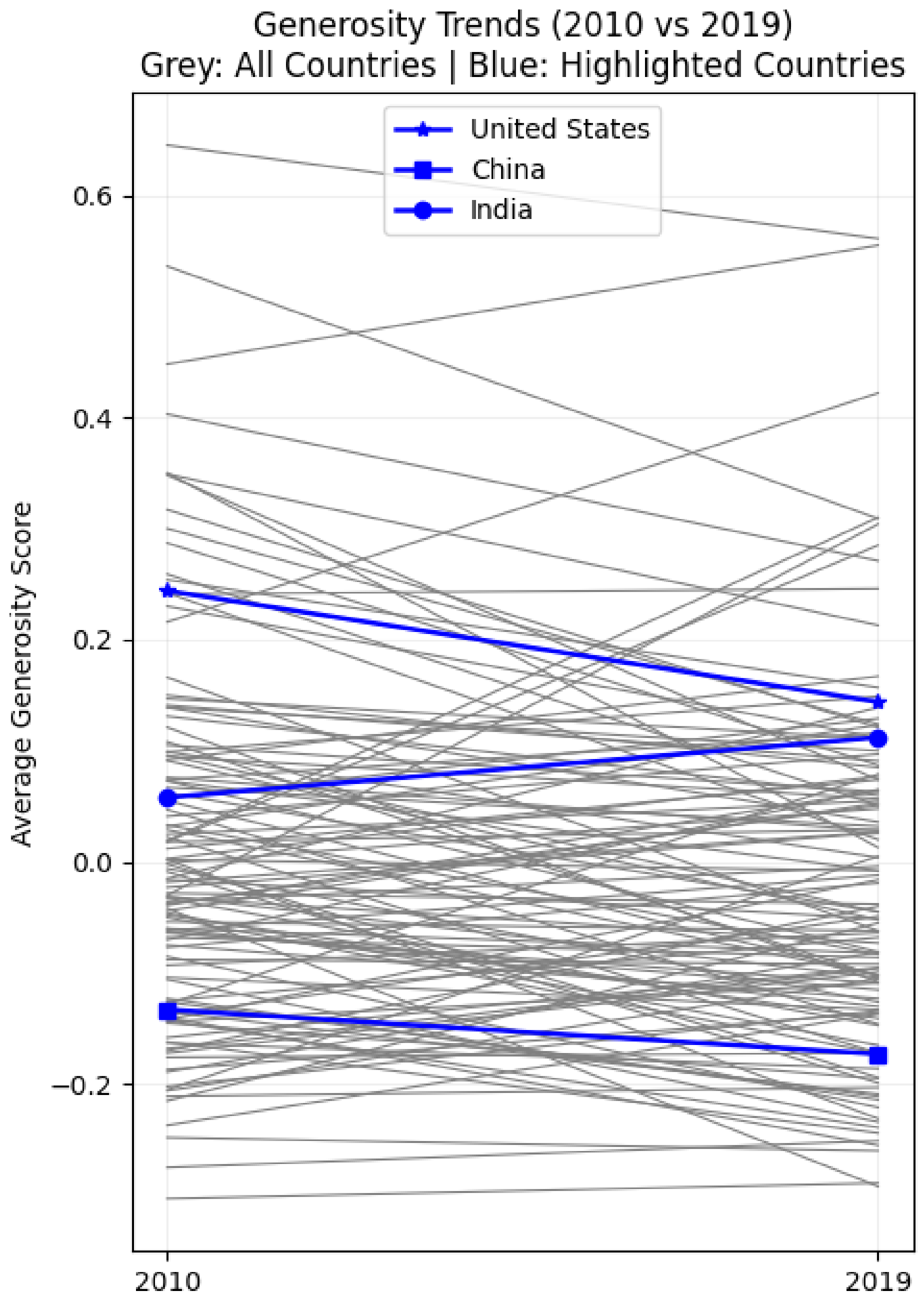
```
import pandas as pd
import matplotlib.pyplot as plt

# Load data
country_df = pd.read_csv('WH Report_preprocessed.csv')

# Aggregate Generosity by Continent and Year
byCountryYear_df = country_df.groupby(['Name','year'])['Generosity'].mean()

# Plot setup
plt.figure(figsize=(5, 7))

# Plot lines connecting 2010-2019 for each continent
for i, continent in enumerate(byCountryYear_df.index.get_level_values(0).
 ↪unique()):
    plt.plot([2010, 2019],
            byCountryYear_df.loc[continent, [2010, 2019]],
            color='grey',  # Using grey for all lines
            )

# Formatting
plt.xticks([2010, 2019])
plt.title('Generosity Trends by Country (2010 vs 2019)')
plt.ylabel('Average Generosity Score')
plt.grid(alpha=0.2)
```




b.

```
[72]: import pandas as pd
import matplotlib.pyplot as plt

# Load data
country_df = pd.read_csv('WH Report_preprocessed.csv')

# Aggregate Generosity by Country and Year
byCountryYear_df = country_df.groupby(['Name','year'])['Generosity'].mean()

# Plot setup
```

```python
plt.figure(figsize=(5, 7))

# Plot grey lines for all countries
for country in byCountryYear_df.index.get_level_values(0).unique():
    plt.plot([2010, 2019],
             byCountryYear_df.loc[country, [2010, 2019]],
             color='grey',
             linewidth=0.8)

highlight_markers = {
    'United States': '*',  # Star
    'China': 's',          # Square
    'India': 'o'         # Circle
}

# Highlight specific countries in blue
for country, marker in highlight_markers.items():
    plt.plot([2010, 2019],
             byCountryYear_df.loc[country, [2010, 2019]],
             color='blue',
             marker=marker,
             linewidth=1.8,
             label=country)

# Formatting
plt.xticks([2010, 2019])
plt.title('Generosity Trends (2010 vs 2019)\nGrey: All Countries | Blue:␣
 ↪Highlighted Countries')
plt.ylabel('Average Generosity Score')
plt.grid(alpha=0.2)

# Add legend only for highlighted countries
plt.legend(loc=9)

plt.tight_layout()
plt.show()
```




c.

[57]:
```
# refer to b
```