MelodyRios_module08PythonProject

December 15, 2023

1 Python Project

1.1 Melody Rios

1.1.1 December 11, 2023

1.2 Instructions

You are a data scientist and would like to know where the top 5 places in the world (country or city) where your salary will go the farthest with respect to each individual index within the cost_of_living.csv file. Provide a simple statistical analysis in a Jupyter Notebook file and provide visualizations to support your analysis (I am looking for data wrangling more than anything).

[12]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

1.2.1 Import Data

I will be importing data for cost of living and salary data. I will then clean the data as needed.

[13]:
```
# Import Cost of Living Data
cost_of_living_df = pd.read_csv('cost_of_living.csv')
cost_of_living_df.head()
```

[13]:
```
   Rank                 City  Cost of Living Index  Rent Index  \
0   NaN    Hamilton, Bermuda                149.02       96.10
1   NaN  Zurich, Switzerland                131.24       69.26
2   NaN   Basel, Switzerland                130.93       49.38
3   NaN     Zug, Switzerland                128.13       72.12
4   NaN  Lugano, Switzerland                123.99       44.99

   Cost of Living Plus Rent Index  Groceries Index  Restaurant Price Index  \
0                          124.22           157.89                  155.22
1                          102.19           136.14                  132.52
2                           92.70           137.07                  130.95
3                          101.87           132.61                  130.93
4                           86.96           129.17                  119.80
```

```
   Local Purchasing Power Index
0                         79.43
1                        129.79
2                        111.53
3                        143.40
4                        111.96
```

[3]:
```
clean_cost_of_living_df = cost_of_living_df.drop(columns = ['Rank'])
clean_cost_of_living_df.head()
```

[3]:
```
                  City  Cost of Living Index  Rent Index  \
0    Hamilton, Bermuda                149.02       96.10
1  Zurich, Switzerland                131.24       69.26
2   Basel, Switzerland                130.93       49.38
3     Zug, Switzerland                128.13       72.12
4  Lugano, Switzerland                123.99       44.99

   Cost of Living Plus Rent Index  Groceries Index  Restaurant Price Index  \
0                          124.22           157.89                  155.22
1                          102.19           136.14                  132.52
2                           92.70           137.07                  130.95
3                          101.87           132.61                  130.93
4                           86.96           129.17                  119.80

   Local Purchasing Power Index
0                         79.43
1                        129.79
2                        111.53
3                        143.40
4                        111.96
```

[4]:
```
# Import Salaries
ds_salaries_df = pd.read_csv('Levels_Fyi_Salary_Data.csv')
ds_salaries_df.head()
```

[4]:
```
            timestamp    company level                        title  \
0   6/7/2017 11:33:27     Oracle    L3              Product Manager
1  6/10/2017 17:11:29       eBay  SE 2            Software Engineer
2  6/11/2017 14:53:57     Amazon    L7              Product Manager
3   6/17/2017 0:23:14      Apple    M1  Software Engineering Manager
4  6/20/2017 10:58:51  Microsoft    60            Software Engineer

   totalyearlycompensation           location  yearsofexperience  \
0                   127000   Redwood City, CA                1.5
1                   100000  San Francisco, CA                5.0
2                   310000        Seattle, WA                8.0
```

```
3                   372000      Sunnyvale, CA                7.0
4                   157000  Mountain View, CA                5.0

   yearsatcompany  tag  basesalary  …  Doctorate_Degree  Highschool  \
0             1.5  NaN    107000.0  …                 0           0
1             3.0  NaN         0.0  …                 0           0
2             0.0  NaN    155000.0  …                 0           0
3             5.0  NaN    157000.0  …                 0           0
4             3.0  NaN         0.0  …                 0           0

  Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
0            0          0           0                 0           0
1            0          0           0                 0           0
2            0          0           0                 0           0
3            0          0           0                 0           0
4            0          0           0                 0           0

   Race_Hispanic  Race  Education
0              0   NaN        NaN
1              0   NaN        NaN
2              0   NaN        NaN
3              0   NaN        NaN
4              0   NaN        NaN

[5 rows x 29 columns]
```

I will be selecting certain columns from the DS Salaries Data Frame to work with.

[5]:
```
select_ds_salary_columns = ds_salaries_df[['title', 'basesalary']]
select_ds_salary_columns.head()
```

[5]:
```
                        title  basesalary
0             Product Manager    107000.0
1           Software Engineer         0.0
2             Product Manager    155000.0
3  Software Engineering Manager    157000.0
4           Software Engineer         0.0
```

I will narrow down to only work with data that involves the job titles of Data Scientist and Business Analyst.

[6]:
```
selected_titles = select_ds_salary_columns[
    (select_ds_salary_columns['title'].isin(['Data Scientist', 'Business␣
 ↪Analyst']))
]
selected_titles.head()
```

[6]:

	title	basesalary
419	Data Scientist	162000.0
440	Data Scientist	165000.0
444	Data Scientist	0.0
454	Data Scientist	200000.0
495	Data Scientist	190000.0

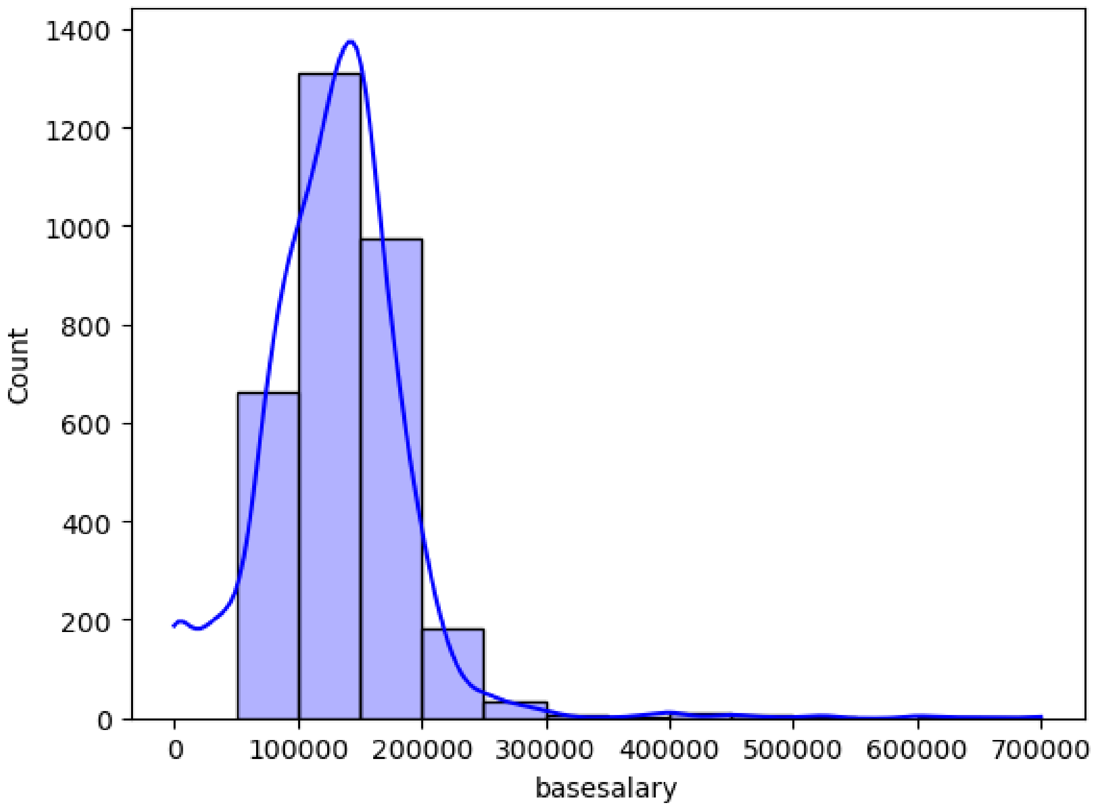
Now, I want to find the average salary based on the job titles selected.

[16]:
```
avg_selected_titles = selected_titles['basesalary'].mean()
print('The average salary for either a Data Scientist or Business Analyst role␣
 ↪is:',
      round(avg_selected_titles, 2))
```

```
The average salary for either a Data Scientist or Business Analyst role is:
129225.24
```

Below, we can see the average distribution of Base Salaries for the chosen roles.

[15]:
```
hist_chart = sns.histplot(selected_titles['basesalary'],
                        color = 'blue',
                        alpha = 0.30,
                        bins = [50000, 100000, 150000, 200000, 250000, 300000,␣
 ↪350000, 400000, 450000, 500000, 550000,
                        600000, 650000, 700000],
                        kde = True)
plt.show()
```



Based on the data from where it was retrieved, https://www.numbeo.com/cost-of-living/cpi_explained.jsp, New York City is the baseline at 100%. I will use the average salary of $129,225.24 USD as my baseline moving forward and assume an index of 100% as well.

I chose this and the roles because it's the most realistic to my situation once I graduate.

Next, I will compare the following indexes across global locations:

1. **Cost of Living**

2. **Rent**

3. **Cost of Living Plus Rent**

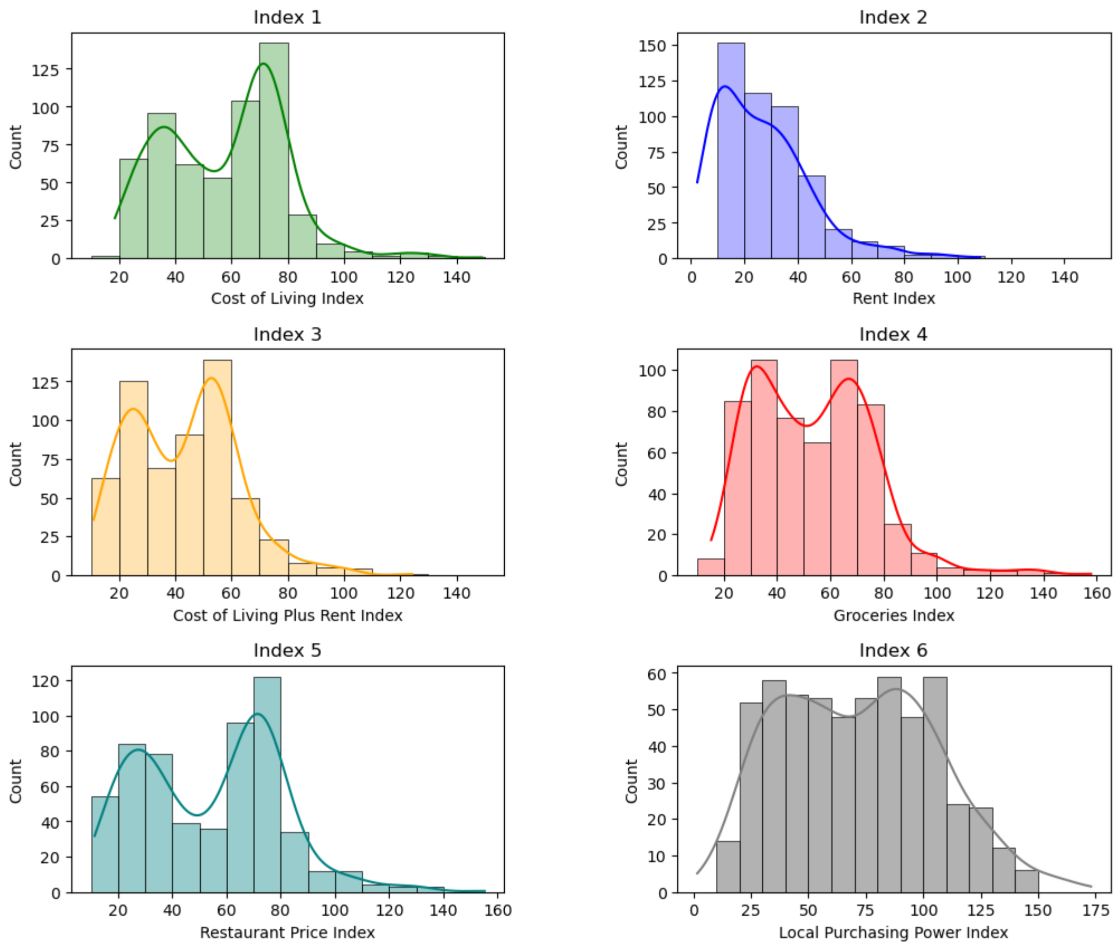
4. **Groceries**

5. **Restaurant Price**

6. **Local Purchasing Power**

[9]:
```
fig = plt.figure(figsize=(12, 10))
fig.subplots_adjust(hspace=0.4, wspace=0.4)

# histogram bins
bins = [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150]

# first subplot (top-left)
plt.subplot(3, 2, 1)
sns.histplot(clean_cost_of_living_df['Cost of Living Index'], bins = bins,␣
 ↪color = 'green', alpha = 0.3, edgecolor = 'black', linewidth = 0.5, kde =␣
 ↪True)
plt.title('Index 1')

# second subplot (top-right)
plt.subplot(3, 2, 2)
# Repeat the process for the other subplots
sns.histplot(clean_cost_of_living_df['Rent Index'], bins = bins, color =␣
 ↪'blue', alpha = 0.3, edgecolor = 'black', linewidth = 0.5, kde = True)
plt.title('Index 2')

# third subplot (middle-left)
plt.subplot(3, 2, 3)
sns.histplot(clean_cost_of_living_df['Cost of Living Plus Rent Index'], bins =␣
 ↪bins, color = 'orange', alpha = 0.3, edgecolor = 'black', linewidth = 0.5,␣
 ↪kde = True)
plt.title('Index 3')

# fourth subplot (middle-right)
plt.subplot(3, 2, 4)
sns.histplot(clean_cost_of_living_df['Groceries Index'], bins = bins, color =␣
 ↪'red', alpha = 0.3, edgecolor = 'black', linewidth = 0.5, kde = True)
plt.title('Index 4')

# fifth subplot (bottom-left)
plt.subplot(3, 2, 5)
sns.histplot(clean_cost_of_living_df['Restaurant Price Index'], bins = bins,␣
 ↪color = 'teal', alpha = 0.4, edgecolor = 'black', linewidth = 0.5, kde =␣
 ↪True)
plt.title('Index 5')

# sixth subplot (bottom-right)
plt.subplot(3, 2, 6)
sns.histplot(clean_cost_of_living_df['Local Purchasing Power Index'], bins =␣
 ↪bins, color = 'grey', alpha = 0.6, edgecolor = 'black', linewidth = 0.5, kde␣
 ↪= True)
plt.title('Index 6')
```

```
plt.show()
```



First, I wanted to show the various distributions for each index. I'll be taking the median of each index and using that to compare the base salary.

1.3 Cost of Living Index

[17]:
```
median_col = clean_cost_of_living_df['Cost of Living Index'].median()
print('The median for the Cost of Living Index is:', round(median_col, 1))
```

```
The median for the Cost of Living Index is: 62.4
```

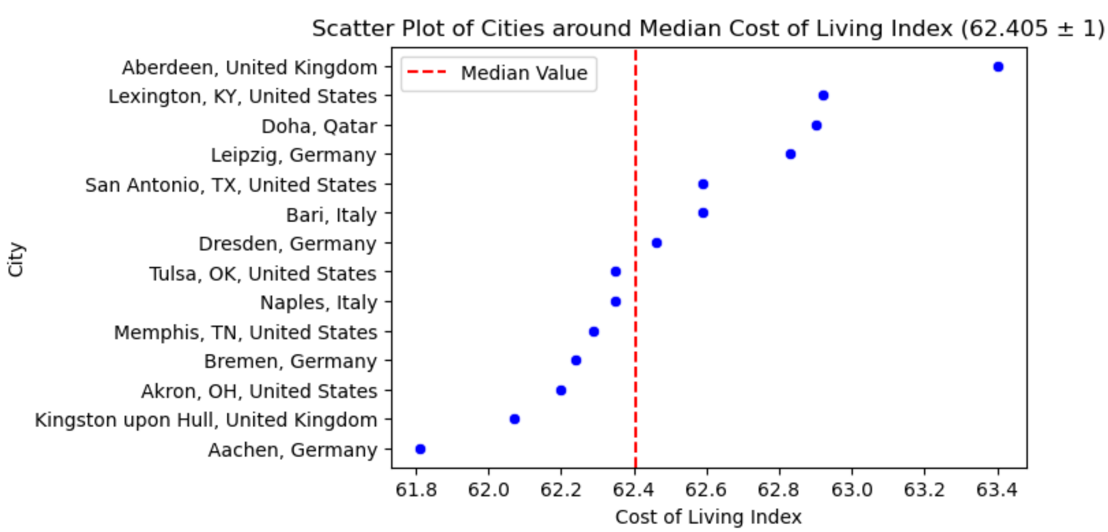
We will use the median to convert the percentage to USD based on my base salary of $129,225.25.

[18]:
```
#convert salary to USD based on our 129,225.25 salary
base_amount = 129225.24
percentage = 62.4
```

```
amount = (percentage / 100) * base_amount
print('The salary required for a comfortable standard of living, determined by␣
↪the median cost of living:', round(amount, 2))
```

```
The salary required for a comfortable standard of living, determined by the
median cost of living: 80636.55
```

[27]:
```
median_value = clean_cost_of_living_df['Cost of Living Index'].median()
tolerance = 1

median_city_df = clean_cost_of_living_df.loc[
    (clean_cost_of_living_df['Cost of Living Index'] >= median_value -␣
↪tolerance) &
    (clean_cost_of_living_df['Cost of Living Index'] <= median_value +␣
↪tolerance),
    ['City', 'Cost of Living Index']]

# scatter plot - Median Cost of Living Index
plt.figure(figsize=(6, 4))
sns.scatterplot(x='Cost of Living Index', y='City', data=median_city_df,␣
↪color='blue')

# vertical line at the median value
plt.axvline(x=median_value, color='red', linestyle='--', label='Median Value')

plt.title(f'Scatter Plot of Cities around Median Cost of Living Index␣
↪({median_value} ± {tolerance})')
plt.legend()
plt.show()
```



Above, we can see several cities aligning with our median value. As we approach this benchmark, Tulsa, Oklahoma, is the most fitting choice based on the Cost of Living Index.

1.4 Rent Index

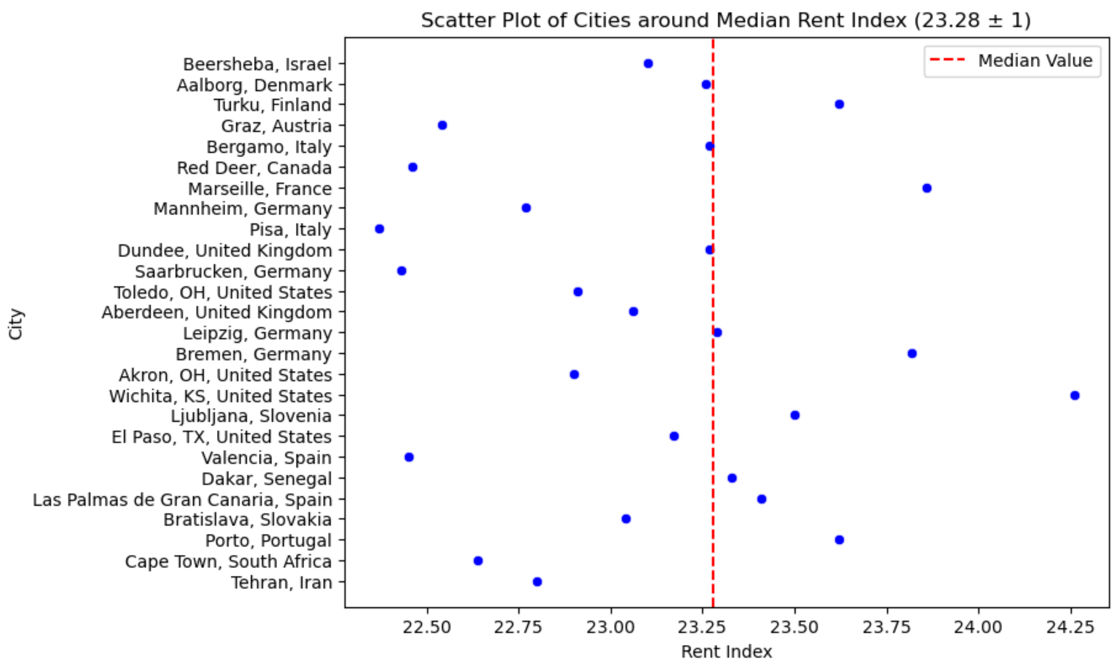
[20]:
```
median_rent = clean_cost_of_living_df['Rent Index'].median()
print('The median for the Rent Index is:', round(median_rent, 1))
```

```
The median for the Rent Index is: 23.3
```

[21]:
```
#convert salary to USD based on our 129,225.25 salary
base_amount = 129225.24
percentage = 23.3

amount = (percentage / 100) * base_amount
print('The salary required for a comfortable standard of living, determined by␣
↪the median Rent Index:', round(amount, 2))
```

```
The salary required for a comfortable standard of living, determined by the
median Rent Index: 30109.48
```

[26]:
```
tolerance = 1

median_rent_df = clean_cost_of_living_df.loc[
    (clean_cost_of_living_df['Rent Index'] >= median_rent - tolerance) &
    (clean_cost_of_living_df['Rent Index'] <= median_rent + tolerance),
    ['City', 'Rent Index']]

# scatter plot - Median Rent Index
plt.figure(figsize = (8, 6))
sns.scatterplot(x = 'Rent Index', y = 'City', data = median_rent_df, color␣
↪='blue')

# vertical line at the median value
plt.axvline(x = median_rent, color = 'red', linestyle = '--', label = 'Median␣
↪Value')

plt.title(f'Scatter Plot of Cities around Median Rent Index ({median_rent} ±␣
↪{tolerance})')
plt.legend()
plt.show()
```



More cities align with our median value for the Rent Index. As we approach this benchmark, Dundee, United Kingdom is the most fitting choice based on the Rent Index.

1.5 Cost of Living Plust Rent

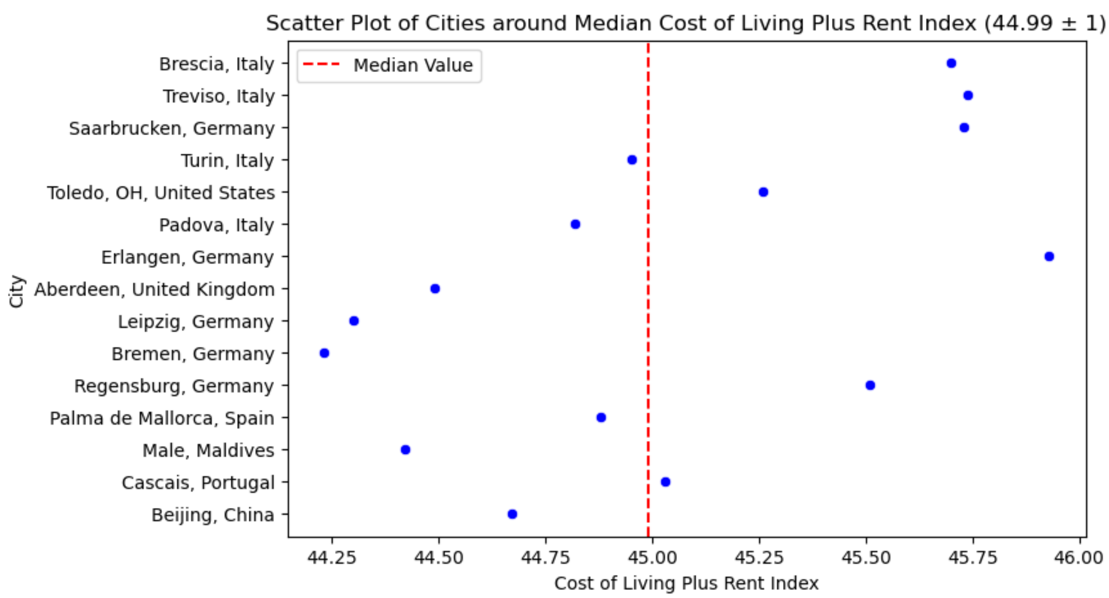
[23]:
```python
median_col_rent = clean_cost_of_living_df['Cost of Living Plus Rent Index'].median()
print('The median for the Cost of Living Plus Rent Index is:', round(median_col_rent, 1))
```

```
The median for the Cost of Living Plus Rent Index is: 45.0
```

[24]:
```python
#convert salary to USD based on our 129,225.25 salary
base_amount = 129225.24
percentage = 45.0

amount = (percentage / 100) * base_amount
print("The salary required for a comfortable standard of living in various cities, determined by the median \n cost of living plus rent:", round(amount, 2))
```

```
The salary required for a comfortable standard of living in various cities,
determined by the median
 cost of living plus rent: 58151.36
```

[28]:
```python
tolerance = 1

median_col_rent_df = clean_cost_of_living_df.loc[
    (clean_cost_of_living_df['Cost of Living Plus Rent Index'] >=␣
 ↪median_col_rent - tolerance) &
    (clean_cost_of_living_df['Cost of Living Plus Rent Index'] <=␣
 ↪median_col_rent + tolerance),
    ['City', 'Cost of Living Plus Rent Index']]

# scatter plot - Median Cost of Living plus Rent Index
plt.figure(figsize = (8, 5))
sns.scatterplot(x = 'Cost of Living Plus Rent Index', y = 'City', data =␣
 ↪median_col_rent_df, color ='blue')

# vertical line at the median value
plt.axvline(x = median_col_rent, color = 'red', linestyle = '--', label =␣
 ↪'Median Value')

plt.title(f'Scatter Plot of Cities around Median Cost of Living Plus Rent Index␣
 ↪({median_col_rent} ± {tolerance})')
plt.legend()
plt.show()
```



The best choice for city based on the Median Cost of Living Plus Rent is Turin, Italy.

1.6 Groceries Index

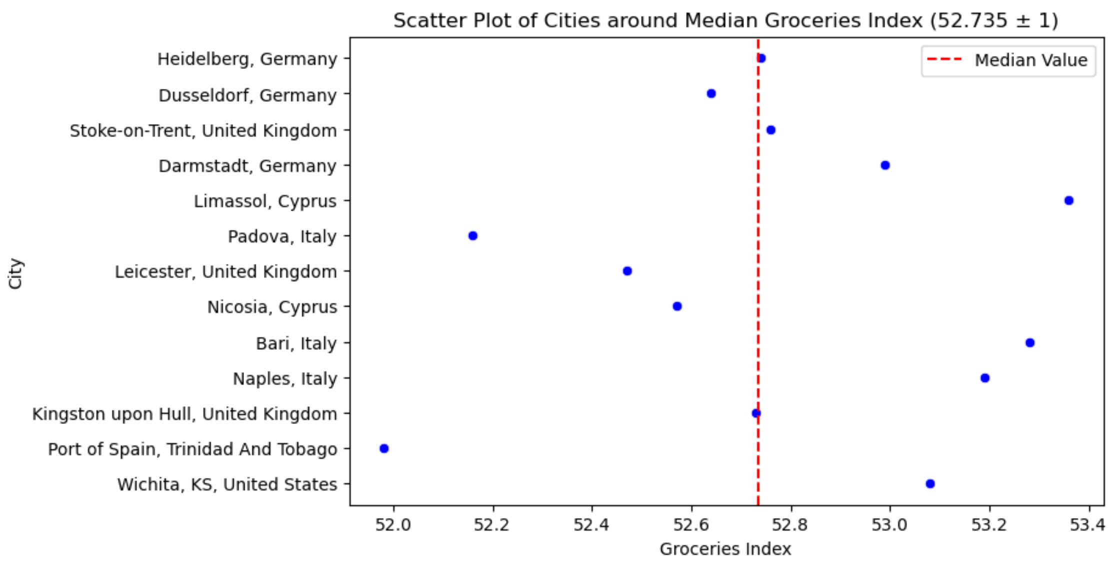
[29]:
```
median_groceries = clean_cost_of_living_df['Groceries Index'].median()
print('The median for Groceries Index is:', round(median_groceries, 1))
```

```
The median for Groceries Index is: 52.7
```

[30]:
```
#convert salary to USD based on our 129,225.25 salary
base_amount = 129225.24
percentage = 52.7

amount = (percentage / 100) * base_amount
print("The salary required for a comfortable standard of living in various␣
↪cities, determined by the median \n Groceries Index:", round(amount, 2))
```

```
The salary required for a comfortable standard of living in various cities,
determined by the median
 Groceries Index: 68101.7
```

[32]:
```
tolerance = 1

median_groceries_df = clean_cost_of_living_df.loc[
    (clean_cost_of_living_df['Groceries Index'] >= median_groceries -␣
↪tolerance) &
    (clean_cost_of_living_df['Groceries Index'] <= median_groceries +␣
↪tolerance),
    ['City', 'Groceries Index']]

# scatter plot - Median Groceries Index
plt.figure(figsize = (8, 5))
sns.scatterplot(x = 'Groceries Index', y = 'City', data = median_groceries_df,␣
↪color ='blue')

# vertical line at the median value
plt.axvline(x = median_groceries, color = 'red', linestyle = '--', label =␣
↪'Median Value')

plt.title(f'Scatter Plot of Cities around Median Groceries Index␣
↪({median_groceries} ± {tolerance})')
plt.legend()
plt.show()
```



The best choice for city based on the median Groceries Index is Kingston upon Hull, United Kingdom.

1.7 Restaurant Price Index

[33]:
```
median_restaurant = clean_cost_of_living_df['Restaurant Price Index'].median()
print('The median for Restaurant Price Index is:', round(median_restaurant, 1))
```

```
The median for Restaurant Price Index is: 59.1
```

[34]:
```
#convert salary to USD based on our 129,225.25 salary
base_amount = 129225.24
percentage = 59.1

amount = (percentage / 100) * base_amount
print("The salary required for a comfortable standard of living in various␣
↪cities, determined by the median \n of the Restaurant Price Index:",␣
↪round(amount, 2))
```

```
The salary required for a comfortable standard of living in various cities,
determined by the median
 of the Restaurant Price Index: 76372.12
```

[35]:
```
tolerance = 1

median_restaurant_df = clean_cost_of_living_df.loc[
    (clean_cost_of_living_df['Restaurant Price Index'] >= median_restaurant -␣
↪tolerance) &
```

```
    (clean_cost_of_living_df['Restaurant Price Index'] <= median_restaurant +␣
↪tolerance),
    ['City', 'Restaurant Price Index']]

# scatter plot - Restaurant Price Index
plt.figure(figsize = (7, 4))
sns.scatterplot(x = 'Restaurant Price Index', y = 'City', data =␣
↪median_restaurant_df, color ='blue')

# vertical line at the median value
plt.axvline(x = median_restaurant, color = 'red', linestyle = '--', label =␣
↪'Median Value')

plt.title(f'Scatter Plot of Cities around Median Restaurant Price Index␣
↪({median_restaurant} ± {tolerance})')
plt.legend()
plt.show()
```

This visual certainly surprised me in that there are not that many cities close to the Median Value. Though the closest city based on our Median Restaurant Price Index is Dayton, Ohio.

1.8 Local Purchasing Power Index

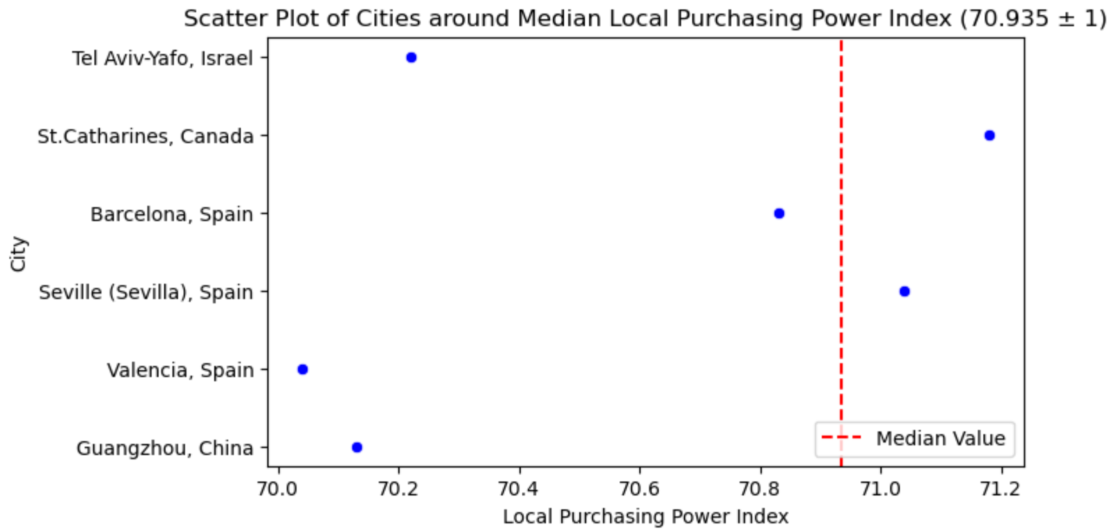
[36]:
```
median_purchase = clean_cost_of_living_df['Local Purchasing Power Index'].
↪median()
print('The median for Local Purchasing Power Index is:', round(median_purchase,␣
↪1))
```

```
The median for Local Purchasing Power Index is: 70.9
```

[37]:
```python
#convert salary to USD based on our 129,225.25 salary
base_amount = 129225.24
percentage = 70.9

amount = (percentage / 100) * base_amount
print("The salary required for a comfortable standard of living in various␣
↪cities, determined by the median \n of the Local Purchasing Power Index:",␣
↪round(amount, 2))
```

```
The salary required for a comfortable standard of living in various cities,
determined by the median
 of the Local Purchasing Power Index: 91620.7
```

[53]:
```python
# median_restaurant = clean_cost_of_living_df['Restaurant Price Index'].median()
tolerance = 1

median_purchase_df = clean_cost_of_living_df.loc[
    (clean_cost_of_living_df['Local Purchasing Power Index'] >= median_purchase␣
↪- tolerance) &
    (clean_cost_of_living_df['Local Purchasing Power Index'] <= median_purchase␣
↪+ tolerance),
    ['City', 'Local Purchasing Power Index']]

# scatter plot - Local Purchasing Power Index
plt.figure(figsize = (7, 4))
sns.scatterplot(x = 'Local Purchasing Power Index', y = 'City', data =␣
↪median_purchase_df, color ='blue')

# vertical line at the median value
plt.axvline(x = median_purchase, color = 'red', linestyle = '--', label =␣
↪'Median Value')

plt.title(f'Scatter Plot of Cities around Median Local Purchasing Power Index␣
↪({median_purchase} ± {tolerance})')
plt.legend(loc = 'lower right')
plt.show()
```



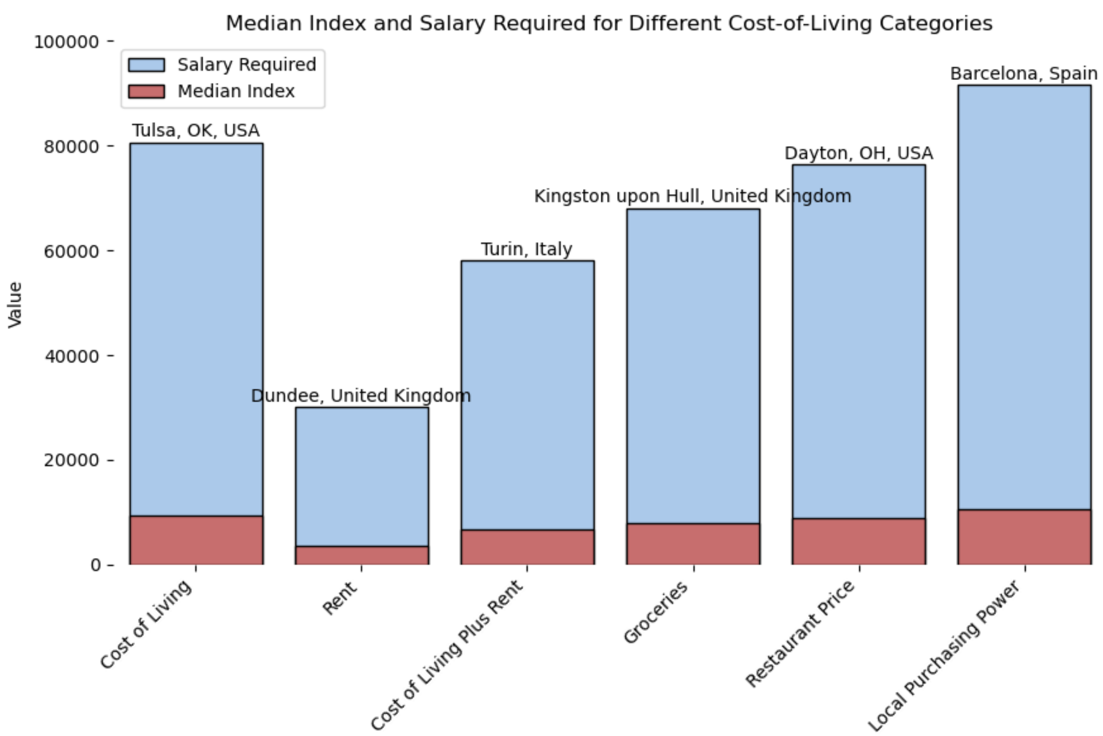
While not many cities offer substantial purchasing power based on the median value, Barcelona, Spain, stands out as the top choice in this regard.

1.9 Summary

To summarize, I chose 6 cities where my base salary could go a long way based on the median of the selected indexes.

[42]:
```
# create df for data to summarize
best_cities_df = {
    'Category': ['Cost of Living', 'Rent', 'Cost of Living Plus Rent',␣
 ↪'Groceries', 'Restaurant Price', 'Local Purchasing Power'],
    'Median Index': [62.4, 23.3, 45.0, 52.7, 59.1, 70.9],
    'Salary Required': [80636.55, 30109.48, 58151.36, 68101.7, 76372.12, 91620.
 ↪7],
    'Best City': ['Tulsa, OK, USA', 'Dundee, United Kingdom', 'Turin, Italy',␣
 ↪'Kingston upon Hull, United Kingdom', 'Dayton, OH, USA', 'Barcelona, Spain']
}

median_data_df = pd.DataFrame(best_cities_df)
# print(median_data_df)

scaling_factor = 150
median_data_df['Median Index'] = median_data_df['Median Index'] * scaling_factor

# size of chart
f, ax = plt.subplots(figsize = (9, 6))

# salary chart
sns.set_color_codes("pastel")
```

```
sns.barplot(x = "Category", y = "Salary Required", data = median_data_df,
            label = "Salary Required", color = "b", edgecolor = "black")

# median index chart
sns.set_color_codes("muted")
sns.barplot(x = "Category", y = "Median Index", data = median_data_df,
            label = "Median Index", color = "r", edgecolor = "black")

# labels, titles
ax.set_ylabel('Value')
ax.set_title('Median Index and Salary Required for Different Cost-of-Living␣
 ↪Categories')
ax.legend(ncol = 1, loc = "best", frameon = True)
ax.set(ylim = (0, 100000), xlabel = "")
sns.despine(left = True, bottom = True)

for index, row in median_data_df.iterrows():
    ax.text(index, row['Salary Required'] + 1000, row['Best City'], ha='center')

plt.xticks(rotation = 45, ha = 'right')
plt.tight_layout()
plt.show()
```



We can see that the Median Index exhibits relatively minor variations across the different indexes, with the most significant fluctuation occurring in the Rent Index. If I were to select a single city based on the presented data, Dundee, United Kingdom, would be my preferred choice.