notebook

January 19, 2026

[64]:
```
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.colors as mcolors
```

[65]:
```
df = pd.read_csv("data/Canadian_Health_Survey_Sample_cleaned.csv")
```

0.0.1 Analyzing dataset

[66]:
```
df.head()
```

[66]:
```
                    Province  Gender  Age    Income   BMI  PhysicalActivity  \
0                    Ontario  Female   59   80572.0  25.7               3.8
1              New Brunswick    Male   38  125739.0  24.2               3.4
2               Saskatchewan    Male   30   75947.0  28.3               3.9
3               Saskatchewan  Female   79  113966.0  31.2               1.6
4  Newfoundland and Labrador  Female   24  101828.0  27.8               4.5

  Smoking SelfRatedHealth  StressLevel BMI_Category IncomeBracket  \
0     Yes            Good            6   Overweight       80-110k
1      No            Good            9       Normal         >110k
2      No       Excellent           10   Overweight        50-80k
3      No            Fair            6        Obese         >110k
4     Yes            Good            5   Overweight       80-110k

   SelfRatedHealth_Num
0                    3
1                    3
2                    5
3                    2
4                    3
```

[67]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 825 entries, 0 to 824
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
```

```
 0   Province            825 non-null    object
 1   Gender              825 non-null    object
 2   Age                 825 non-null    int64
 3   Income              825 non-null    float64
 4   BMI                 825 non-null    float64
 5   PhysicalActivity    825 non-null    float64
 6   Smoking             825 non-null    object
 7   SelfRatedHealth     825 non-null    object
 8   StressLevel         825 non-null    int64
 9   BMI_Category        825 non-null    object
 10  IncomeBracket       825 non-null    object
 11  SelfRatedHealth_Num  825 non-null    int64
dtypes: float64(3), int64(3), object(6)
memory usage: 77.5+ KB
```

[68]:
```
df.describe(include='all')
```

[68]:
```
       Province Gender         Age         Income         BMI  \
count       825    825  825.000000     825.000000  825.000000
unique       10      2         NaN            NaN         NaN
top      Quebec   Male         NaN            NaN         NaN
freq         97    426         NaN            NaN         NaN
mean        NaN    NaN   49.408485   77545.210909   27.472039
std         NaN    NaN   18.187646   22145.238035    4.953750
min         NaN    NaN   18.000000    5000.000000   13.500000
25%         NaN    NaN   33.000000   64115.000000   24.200000
50%         NaN    NaN   49.000000   78130.000000   27.488861
75%         NaN    NaN   66.000000   90100.000000   30.700000
max         NaN    NaN   80.000000  250000.000000   60.000000

        PhysicalActivity Smoking SelfRatedHealth  StressLevel BMI_Category  \
count         825.000000     825             825   825.000000          825
unique               NaN       2               5          NaN            4
top                  NaN      No            Good          NaN   Overweight
freq                 NaN     640             254          NaN          333
mean            3.503246     NaN             NaN     5.294545          NaN
std             1.899122     NaN             NaN     2.121156          NaN
min             0.000000     NaN             NaN     1.000000          NaN
25%             2.100000     NaN             NaN     4.000000          NaN
50%             3.500000     NaN             NaN     5.000000          NaN
75%             4.700000     NaN             NaN     7.000000          NaN
max            10.400000     NaN             NaN    10.000000          NaN

       IncomeBracket  SelfRatedHealth_Num
count            825           825.000000
unique             4                  NaN
top           50-80k                  NaN
```

```
freq              394                NaN
mean              NaN           3.208485
std               NaN           1.147042
min               NaN           1.000000
25%               NaN           2.000000
50%               NaN           3.000000
75%               NaN           4.000000
max               NaN           5.000000
```

0.0.2 Cleaning & Standardizing Categories

- Normalizing gender values and smoking values

[69]:
```python
# normalizing gender values to Male or Female
df['Gender'] = df['Gender'].str.lower()
df['Gender'] = df['Gender'].replace({
    'male': 'Male',
    'm': 'Male',
    'female': 'Female',
    'f': 'Female'
})

# normalizing smoking to Yes or No
df['Smoking'] = df['Smoking'].str.lower()
df['Smoking'] = df['Smoking'].replace({
    'yes': 'Yes',
    'y': 'Yes',
    'no': 'No',
    'n': 'No'
})
```

0.0.3 Data Cleaning

- Filled missing BMI and Income values using averages (mean/median) to preserve dataset size without distorting quantitative distributions.
- Dropped rows with missing StressLevel because it is ordinal, and imputing an ordered scale would distort the meaning of the categories.
- Filled missing PhysicalActivity values using the mean, since it is a discrete numeric variable and will not affect categorical encodings in later visualizations.

[70]:
```python
df['BMI'] = df['BMI'].fillna(df['BMI'].mean())
df['Income'] = df['Income'].fillna(df['Income'].median())
df = df.dropna(subset=['StressLevel'])
df['PhysicalActivity'] = df['PhysicalActivity'].fillna(df['PhysicalActivity'].
 ↪mean())
```

0.1 Enforcing Correct Data Types

[71]:
```
df['Age'] = df['Age'].astype(int)
df['Income'] = df['Income'].astype(float)
df['BMI'] = df['BMI'].astype(float)
df['StressLevel'] = df['StressLevel'].astype(int)
```

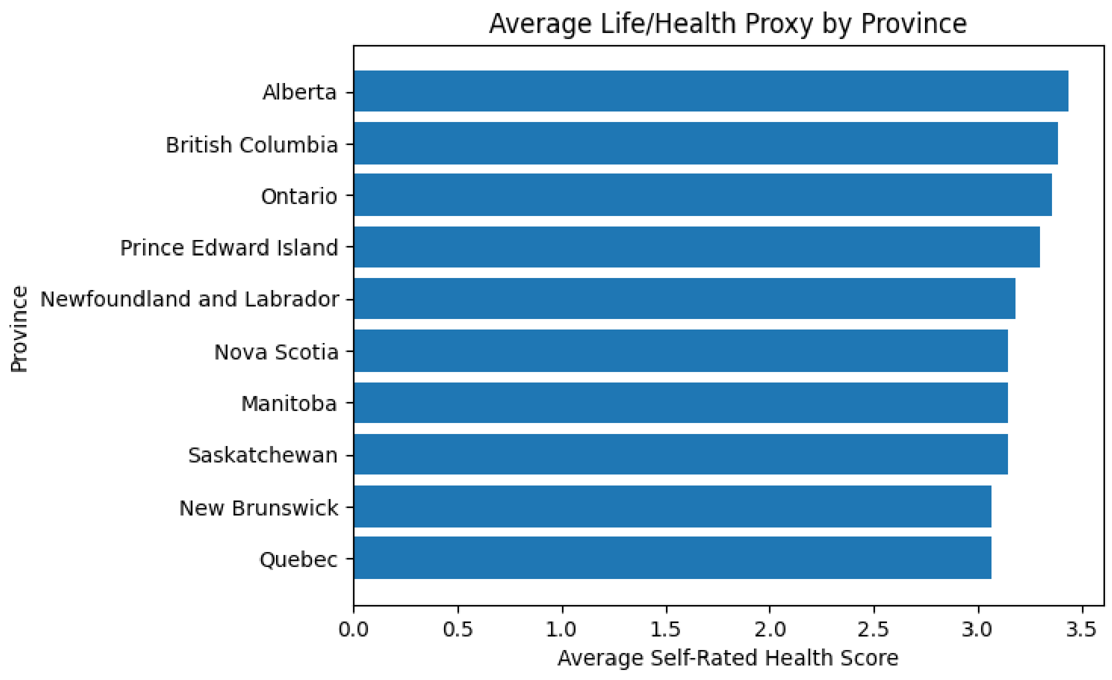
0.1.1 Enhancing the Dataset with Derived Features

[72]:
```
# create new column
df['BMI_Category'] = None

# create column values based on constraints
df.loc[df['BMI'] < 18.5, 'BMI_Category'] = 'Underweight'
df.loc[(df['BMI'] >= 18.5) & (df['BMI'] <= 24.9), 'BMI_Category'] = 'Normal'
df.loc[(df['BMI'] >= 25) & (df['BMI'] <= 29.9), 'BMI_Category'] = 'Overweight'
df.loc[df['BMI'] >= 30, 'BMI_Category'] = 'Obese'

# create new column
df['IncomeBracket'] = None

# create column values based on constraints
df.loc[df['Income'] < 50000, 'IncomeBracket'] = '<50k'
df.loc[(df['Income'] >= 50000) & (df['Income'] < 80000), 'IncomeBracket'] =␣
  ↪'50-80k'
df.loc[(df['Income'] >= 80000) & (df['Income'] < 110000), 'IncomeBracket'] =␣
  ↪'80-110k'
df.loc[df['Income'] >= 110000, 'IncomeBracket'] = '>110k'
```

0.1.2 Bar Chart - Average Life/Health Proxy by Province Analysis

- This bar chart is created to compare the average self-rated health score across provinces.

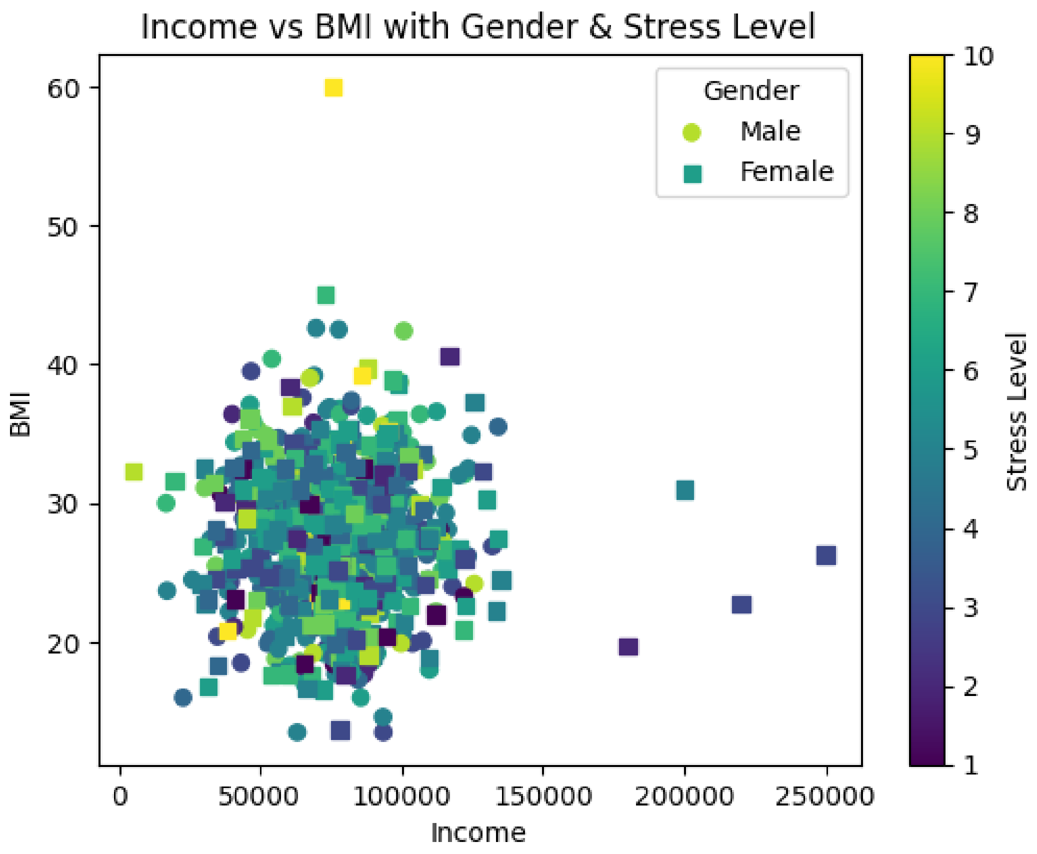
[73]:
```
# create new column
df['SelfRatedHealth_Num'] = None

# create column values based on constraints
df.loc[df['SelfRatedHealth'] == 'Poor', 'SelfRatedHealth_Num'] = 1
df.loc[df['SelfRatedHealth'] == 'Fair', 'SelfRatedHealth_Num'] = 2
df.loc[df['SelfRatedHealth'] == 'Good', 'SelfRatedHealth_Num'] = 3
df.loc[df['SelfRatedHealth'] == 'Very Good', 'SelfRatedHealth_Num'] = 4
df.loc[df['SelfRatedHealth'] == 'Excellent', 'SelfRatedHealth_Num'] = 5

# group each province
groups = df.groupby('Province')

# get the average score for each province
avg_score = groups['SelfRatedHealth_Num'].mean()
avg_score = avg_score.sort_values() # better visualization

# plot
plt.barh(avg_score.index, avg_score.values)

plt.xlabel('Average Self-Rated Health Score')
plt.ylabel('Province')
plt.title('Average Life/Health Proxy by Province')

plt.show()
```



0.1.3 Scatter Plot - Income vs BMI Analysis

- This scatter plot is created to examine the relationship between Income and BMI while also showing how StressLevel and Gender influence the pattern.

[74]:
```
# create two new dataframes only containing the gender column where one is only␣
↪males and the other is only females
male_df = df[df['Gender'] == 'Male']
female_df = df[df['Gender'] == 'Female']

# for males
plt.scatter(
    male_df['Income'],
    male_df['BMI'],
    c = male_df['StressLevel'], # colormap with stress level
    cmap = 'viridis',
    marker = 'o', # circle for males
    label = 'Male' # for legend
)

# for females
plt.scatter(
    female_df['Income'],
    female_df['BMI'],
    c = female_df['StressLevel'], # colormap with stress level
    cmap = 'viridis',
    marker = 's', # squares for females
    label = 'Female' # for legend
)

# Colorbar for StessLevel
colorbar = plt.colorbar()
colorbar.set_label('Stress Level')

plt.xlabel('Income')
plt.ylabel('BMI')
plt.title('Income vs BMI with Gender & Stress Level')

plt.legend(title='Gender')
plt.show()
```

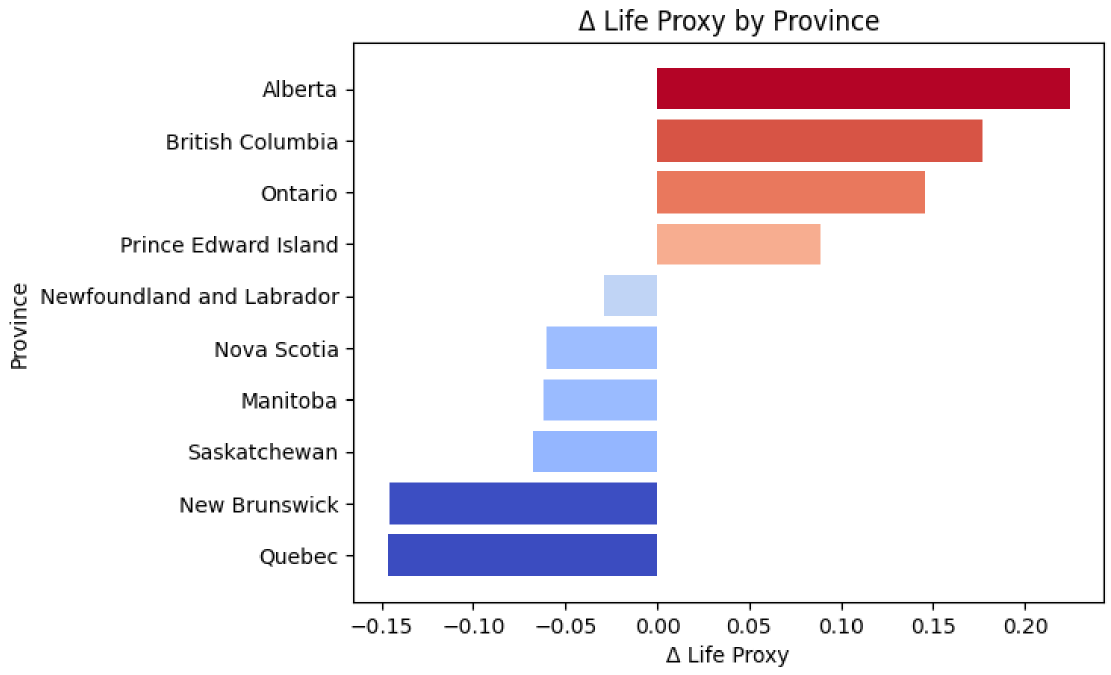


0.1.4 Diverging Bar Chart - Life Proxy Difference by Province Analysis

- This diverging bar chart is used to show how each province's average self-rated health score differs from the overall national average.
- The values can be both above and below zero, a diverging visualization is the correct choice as it highlights positive vs. negative deviation around a meaningful midpoint.

[75]:
```python
groups = df.groupby('Province')

# get the average score for each province
province_avg = groups['SelfRatedHealth_Num'].mean()

# get the overall average
ovr_avg = df['SelfRatedHealth_Num'].mean()

life_proxy = province_avg - ovr_avg
life_proxy = life_proxy.sort_values()
life_proxy = life_proxy.astype(float)

# color map
```

```
cmap = plt.cm.coolwarm # choose coolwarm color map

low = life_proxy.min()
high = life_proxy.max()
center = 0

color_map = mcolors.TwoSlopeNorm(vmin = low, vcenter = center, vmax = high)
colors = cmap(color_map(life_proxy.values)) # mapping each value to a color


plt.barh(life_proxy.index, life_proxy.values, color = colors)

plt.xlabel('Δ Life Proxy')
plt.ylabel('Province')
plt.title('Δ Life Proxy by Province')

plt.show()
```


Δ Life Proxy by Province
Alberta
British Columbia
Ontario
Prince Edward Island
Newfoundland and Labrador
Nova Scotia
Manitoba
Saskatchewan
New Brunswick
Quebec
Province
Δ Life Proxy