

Assignment 2

Task 1

The dataset assigned to me is 'Alzheimer's Disease and Healthy Aging Data. Alzheimer's is a type of dementia that affects large number of people all around the world. A part of brain that has control over memory and thoughts gets affected in case of getting diagnosed with this disease. A person with Alzheimer's finds it very difficult to carry on routine tasks. Simple tasks that involve talking, thinking and taking appropriate actions gets affected and the ability to do these gets taken away from the person diagnosed with this disease.

This assignment involves analyzing data about Alzheimer's and healthy aging.

1: Data Cleaning and Transformation

Handling missing data

The dataset looks like a survey that consists information about health data. It consists of 250937 records and 39 columns.

The significance of this dataset is that it has health related questions like 'Percentage of older adults ever told they have arthritis', 'Percentage of older adults getting sufficient sleep (>6)' or 'Percentage of older adults with a lifetime diagnosis of depression'. The response to this is in the column 'Data_Value' in percentages.

Dataset also comprises of columns like years, location, geolocation

```
In [51]: # Importing dependencies
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from scipy.stats import gaussian_kde

from sklearn.preprocessing import LabelEncoder

from mpl_toolkits.mplot3d import Axes3D
import matplotlib as mpl
```

```
In [2]: # Loading data
df_health_data = pd.read_csv("C:\\Users\\Sayal\\OneDrive\\Desktop\\6600_NU\\Assignment 2\\Task 1\\Alzheimer_s_Disease_and_Healthy_Aging_Data.csv")

C:\\Users\\Sayal\\AppData\\Local\\Temp\\ipykernel_35792\\1878087459.py:2: DtypeWarning: Columns (17,18) have mixed types. Specify dtype option on import or set low_memory=False.
df_health_data = pd.read_csv("C:\\Users\\Sayal\\OneDrive\\Desktop\\6600_NU\\Assignment 2\\Task 1\\Alzheimer_s_Disease_and_Healthy_Aging_Data.csv")
```

```
In [3]: # Inspecting dataframe  
df_health_data
```

Out[3]:

	RowId	YearStart	YearEnd	LocationAbbr	Location
0	BRFSS~2021~2021~9004~Q43~TOC11~AGE~RACE	2021	2021	WEST	
1	BRFSS~2017~2017~9001~Q43~TOC11~AGE~OVERALL	2017	2017	NRE	Nor
2	BRFSS~2019~2019~9002~Q02~TNC02~AGE~OVERALL	2019	2019	MDW	Mi
3	BRFSS~2020~2020~59~Q43~TOC11~AGE~GENDER	2020	2020	US	United S Terr
4	BRFSS~2020~2020~33~Q03~TMC01~AGE~GENDER	2020	2020	NH	Ham
...	
250932	BRFSS~2015~2015~54~Q30~TCC01~AGE~RACE	2015	2015	WV	West Vi
250933	BRFSS~2015~2015~40~Q35~TOC03~AGE~RACE	2015	2015	OK	Okla
250934	BRFSS~2017~2017~33~Q44~TOC12~AGE~OVERALL	2017	2017	NH	Ham
250935	BRFSS~2015~2015~51~Q39~TGC04~AGE~RACE	2015	2015	VA	Vi
250936	BRFSS~2015~2015~49~Q02~TNC02~AGE~RACE	2015	2015	UT	

RowId	YearStart	YearEnd	LocationAbbr	Location
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350000 30 1

```
In [4]: # Selecting top 10 rows
df_health_data.head(10)
```

Out[4]:

	RowId	YearStart	YearEnd	LocationAbbr	LocationDesc
0	BRFSS~2021~2021~9004~Q43~TOC11~AGE~RACE	2021	2021	WEST	West
1	BRFSS~2017~2017~9001~Q43~TOC11~AGE~OVERALL	2017	2017	NRE	Northeast
2	BRFSS~2019~2019~9002~Q02~TNC02~AGE~OVERALL	2019	2019	MDW	Midwest
3	BRFSS~2020~2020~59~Q43~TOC11~AGE~GENDER	2020	2020	US	United States, DC & Territories
4	BRFSS~2020~2020~33~Q03~TMC01~AGE~GENDER	2020	2020	NH	New Hampshire
5	BRFSS~2015~2015~9002~Q43~TOC11~AGE~RACE	2015	2015	MDW	Midwest
6	BRFSS~2020~2020~59~Q35~TOC03~AGE~GENDER	2020	2020	US	United States, DC & Territories
7	BRFSS~2021~2021~9001~Q18~TSC08~AGE~OVERALL	2021	2021	NRE	Northeast
8	BRFSS~2021~2021~17~Q08~TOC01~AGE~GENDER	2021	2021	IL	Illinois
9	BRFSS~2020~2020~50~Q34~TOC09~AGE~OVERALL	2020	2020	VT	Vermont

10 rows x 20 columns

```
In [5]: # Selecting bottom rows  
df_health_data.tail(10)
```

Out[5]:

	RowId	YearStart	YearEnd	LocationAbbr	LocationD
250927	BRFSS~2016~2016~39~Q07~TOC05~AGE~RACE	2016	2016	OH	O
250928	BRFSS~2015~2015~9004~Q19~TSC04~AGE~RACE	2015	2015	WEST	W
250929	BRFSS~2018~2018~44~Q13~TNC04~AGE~RACE	2018	2018	RI	Rhode Isl
250930	BRFSS~2016~2016~34~Q03~TMC01~AGE~GENDER	2016	2016	NJ	New Jer
250931	BRFSS~2019~2019~40~Q35~TOC03~AGE~GENDER	2019	2019	OK	Oklahc
250932	BRFSS~2015~2015~54~Q30~TCC01~AGE~RACE	2015	2015	WV	West Virg
250933	BRFSS~2015~2015~40~Q35~TOC03~AGE~RACE	2015	2015	OK	Oklahc
250934	BRFSS~2017~2017~33~Q44~TOC12~AGE~OVERALL	2017	2017	NH	N Hampsl
250935	BRFSS~2015~2015~51~Q39~TGC04~AGE~RACE	2015	2015	VA	Virg
250936	BRFSS~2015~2015~49~Q02~TNC02~AGE~RACE	2015	2015	UT	U

RowId	YearStart	YearEnd	LocationAbbr	LocationD
-------	-----------	---------	--------------	-----------

10	2000	2001		
----	------	------	--	--

```
In [6]: # Inspecting dimensions: retrieveing the number of rows and columns
df_health_data.shape
```

```
Out[6]: (250937, 39)
```

```
In [7]: # Checking columns names
list(df_health_data)
```

```
Out[7]: ['RowId',
'YearStart',
'YearEnd',
'LocationAbbr',
'LocationDesc',
'Datasource',
'Class',
'Topic',
'Question',
'Response',
'Data_Value_Unit',
'DataValueTypeID',
'Data_Value_Type',
'Data_Value',
'Data_Value_Alt',
'Data_Value_Footnote_Symbol',
'Data_Value_Footnote',
'Low_Confidence_Limit',
'High_Confidence_Limit',
'Sample_Size',
'StratificationCategory1',
'Stratification1',
'StratificationCategory2',
'Stratification2',
'StratificationCategory3',
'Stratification3',
'Geolocation',
'ClassID',
'TopicID',
'QuestionID',
'ResponseID',
'LocationID',
'StratificationCategoryID1',
'StratificationID1',
'StratificationCategoryID2',
'StratificationID2',
'StratificationCategoryID3',
'StratificationID3',
'Report']
```

```
In [8]: # Checking datatypes for all the columns
column_datatypes = df_health_data.dtypes
print(column_datatypes)
```


RowId	object
YearStart	int64
YearEnd	int64
LocationAbbr	object
LocationDesc	object
Datasource	object
Class	object
Topic	object
Question	object
Response	float64
Data_Value_Unit	object
DataValueTypeID	object
Data_Value_Type	object
Data_Value	float64
Data_Value_Alt	float64
Data_Value_Footnote_Symbol	object
Data_Value_Footnote	object
Low_Confidence_Limit	object
High_Confidence_Limit	object
Sample_Size	float64
StratificationCategory1	object
Stratification1	object
StratificationCategory2	object
Stratification2	object
StratificationCategory3	float64
Stratification3	float64
Geolocation	object
ClassID	object
TopicID	object
QuestionID	object
ResponseID	float64
LocationID	int64
StratificationCategoryID1	object
StratificationID1	object
StratificationCategoryID2	object
StratificationID2	object
StratificationCategoryID3	float64
StratificationID3	float64
Report	float64
dtype:	object

```
In [9]: # Below is the summary of the dataset
df_health_data.describe()
```

Out[9]:

	YearStart	YearEnd	Response	Data_Value	Data_Value_Alt	Sample_Size	Stratifica
count	250937.000000	250937.000000	0.0	169302.000000	169302.000000	0.0	
mean	2017.940933	2018.169716	NaN	37.328349	37.328349	NaN	
std	2.031564	2.081039	NaN	25.213181	25.213181	NaN	
min	2015.000000	2015.000000	NaN	0.000000	0.000000	NaN	
25%	2016.000000	2016.000000	NaN	15.700000	15.700000	NaN	
50%	2018.000000	2018.000000	NaN	32.300000	32.300000	NaN	
75%	2020.000000	2020.000000	NaN	56.000000	56.000000	NaN	
max	2021.000000	2021.000000	NaN	100.000000	100.000000	NaN	

In [10]:

```
# Counting the number of missing values for all the columns  
df_health_data.isnull().sum()
```

```
Out[10]: RowId          0
YearStart        0
YearEnd          0
LocationAbbr     0
LocationDesc     0
Datasource       0
Class            0
Topic            0
Question         0
Response         250937
Data_Value_Unit  0
DataValueTypeID  0
Data_Value_Type  0
Data_Value       81635
Data_Value_Alt   81635
Data_Value_Footnote_Symbol 151823
Data_Value_Footnote 151823
Low_Confidence_Limit 81785
High_Confidence_Limit 81785
Sample_Size      250937
StratificationCategory1 0
Stratification1   0
StratificationCategory2 32376
Stratification2   32376
StratificationCategory3 250937
Stratification3   250937
Geolocation      26709
ClassID          0
TopicID          0
QuestionID       0
ResponseID       250937
LocationID       0
StratificationCategoryID1 0
StratificationID1 0
StratificationCategoryID2 0
StratificationID2 0
StratificationCategoryID3 250937
StratificationID3 250937
Report           250937
dtype: int64
```

```
In [11]: # Dropping the columns that does not have a single record

df_health_data.drop('Response', axis=1, inplace=True)
df_health_data.drop('Sample_Size', axis=1, inplace=True)
df_health_data.drop('StratificationCategory3', axis=1, inplace=True)
df_health_data.drop('Stratification3', axis=1, inplace=True)
df_health_data.drop('ResponseID', axis=1, inplace=True)
df_health_data.drop('StratificationCategoryID3', axis=1, inplace=True)
df_health_data.drop('StratificationID3', axis=1, inplace=True)
df_health_data.drop('Report', axis=1, inplace=True)
```

```
In [12]: # Inspecting dimensions after columns have been dropped
df_health_data.shape
```

```
Out[12]: (250937, 31)
```

```
In [13]: # Filling missing values in columns 'Data_Value' & 'Data_Value_Alt' with zero
```

```
df_health_data['Data_Value'] = df_health_data['Data_Value'].fillna(0)
df_health_data['Data_Value_Alt'] = df_health_data['Data_Value_Alt'].fillna(0)
```

```
In [14]: # Filling missing values in columns 'Data_Value_Footnote_Symbol' & 'Data_Value_Footnote'

df_health_data['Data_Value_Footnote_Symbol'] = df_health_data['Data_Value_Footnote_Symbol'].fillna(0)
df_health_data['Data_Value_Footnote'] = df_health_data['Data_Value_Footnote'].fillna(0)
```

```
In [15]: datatype = df_health_data.dtypes['Low_Confidence_Limit']
print(datatype)
```

object

Column 'Low_Confidence_Limit' is an object type having values ranging between -0.7 to 99.6 and column 'High_Confidence_Limit' too is an object type having values ranging between 1.4 to 100. Filling missing values in both these columns with "Unknown"

```
In [73]: # Filling missing values in columns 'Low_Confidence_Limit' & 'High_Confidence_Limit' with 'Unknown'

df_health_data['Low_Confidence_Limit'] = df_health_data['Low_Confidence_Limit'].fillna('Unknown')
df_health_data['High_Confidence_Limit'] = df_health_data['High_Confidence_Limit'].fillna('Unknown')
```

```
In [17]: # Filling missing values in columns 'StratificationCategory2', 'Geolocation' & 'StratificationCategory1'

df_health_data['StratificationCategory2'] = df_health_data['StratificationCategory2'].fillna('Unknown')
df_health_data['StratificationCategory1'] = df_health_data['StratificationCategory1'].fillna('Unknown')
df_health_data['Geolocation'] = df_health_data['Geolocation'].fillna('Unknown')
```

```
In [18]: # Checking number of missing values again after filling it with appropriate values

df_health_data.isnull().sum()
```

```
Out[18]: RowId          0
YearStart        0
YearEnd          0
LocationAbbr     0
LocationDesc     0
Datasource       0
Class            0
Topic            0
Question         0
Data_Value_Unit  0
DataValueTypeID  0
Data_Value_Type  0
Data_Value       0
Data_Value_Alt   0
Data_Value_Footnote_Symbol 0
Data_Value_Footnote 0
Low_Confidence_Limit 0
High_Confidence_Limit 0
StratificationCategory1 0
Stratification1 0
StratificationCategory2 0
Stratification2 0
Geolocation      0
ClassID          0
TopicID          0
QuestionID       0
LocationID       0
StratificationCategoryID1 0
StratificationID1 0
StratificationCategoryID2 0
StratificationID2 0
dtype: int64
```

Duplicate Records

The file does not contain any duplicate records as seen below

```
In [19]: # checking for duplicate values

duplicate_values = df_health_data.duplicated()
print(duplicate_values)
```

```
0      False
1      False
2      False
3      False
4      False
...
250932  False
250933  False
250934  False
250935  False
250936  False
Length: 250937, dtype: bool
```

Checking for inaccuracies and inconsistencies in the data

Columns 'Low_Confidence_Limit' & 'High_Confidence_Limit' contains '.'. Replacig it with "Unknown" value

```
In [20]: # Replacing '.' with 'Unknown' values

df_health_data['Low_Confidence_Limit'].replace('.', 0, inplace=True)
df_health_data['High_Confidence_Limit'].replace('.', 0, inplace=True)
```

Data Normalization or scaling

Dataset mostly consists of categorical data. The few numeric columns that are present do not require normalization or scaling for the kind of analysis that would be done on it.

Below are the numeric columns:

- 'YearStart' & 'YearEnd' do not require normalization as I would be directly analyzing it with various categorical features and the range of values for these two features isn't large
- 'Data_Value' & 'Data_Value_Alt' too would not require normalization as I am analyzing it individually to show the distribution of the values in it
- 'StratificationCategory3' & 'Stratification3' does not require normalization because there are no mathematical operations being performed on it for analysis purpose. Additionally, keeping their original values is necessary for meaningful visualizations
- 'LocationID' too does not require normalization as I am analyzing it with categorical features and require their original values for appropriate and meaningful visualizations

Encoding Categorical Data - Not required for the analysis that would be done

Feature Engineering

Creating two columns: YearStart_catergorical & YearEnd_catergorical from existing features 'YearStart' and 'YearEnd' to create meaningful visualizations.

```
In [74]: df_health_data['YearStart_catergorical'] = df_health_data['YearStart'].astype('category')
df_health_data['YearEnd_catergorical'] = df_health_data['YearEnd'].astype('category')

print(df_health_data['YearStart_catergorical'].dtype)
print(df_health_data['YearEnd_catergorical'].dtype)

category
category
```

```
In [75]: df_health_data
```

Out[75]:

	RowId	YearStart	YearEnd	LocationAbbr	Location
	0	BRFSS~2021~2021~9004~Q43~TOC11~AGE~RACE	2021	2021	WEST
	1	BRFSS~2017~2017~9001~Q43~TOC11~AGE~OVERALL	2017	2017	NRE Nor
	2	BRFSS~2019~2019~9002~Q02~TNC02~AGE~OVERALL	2019	2019	MDW Mi
	3	BRFSS~2020~2020~59~Q43~TOC11~AGE~GENDER	2020	2020	US United S Terr
	4	BRFSS~2020~2020~33~Q03~TMC01~AGE~GENDER	2020	2020	NH Ham

	250932	BRFSS~2015~2015~54~Q30~TCC01~AGE~RACE	2015	2015	WV West Vi
	250933	BRFSS~2015~2015~40~Q35~TOC03~AGE~RACE	2015	2015	OK Okla
	250934	BRFSS~2017~2017~33~Q44~TOC12~AGE~OVERALL	2017	2017	NH Ham
	250935	BRFSS~2015~2015~51~Q39~TGC04~AGE~RACE	2015	2015	VA Vi
	250936	BRFSS~2015~2015~49~Q02~TNC02~AGE~RACE	2015	2015	UT

	RowId	YearStart	YearEnd	LocationAbbr	Location
0500007	007	1	2	1	1

Newly generated dataframe includes two new features 'YearStart_categorical' and 'YearEnd_categorical'

Date and time extration feature extraction - not relevant

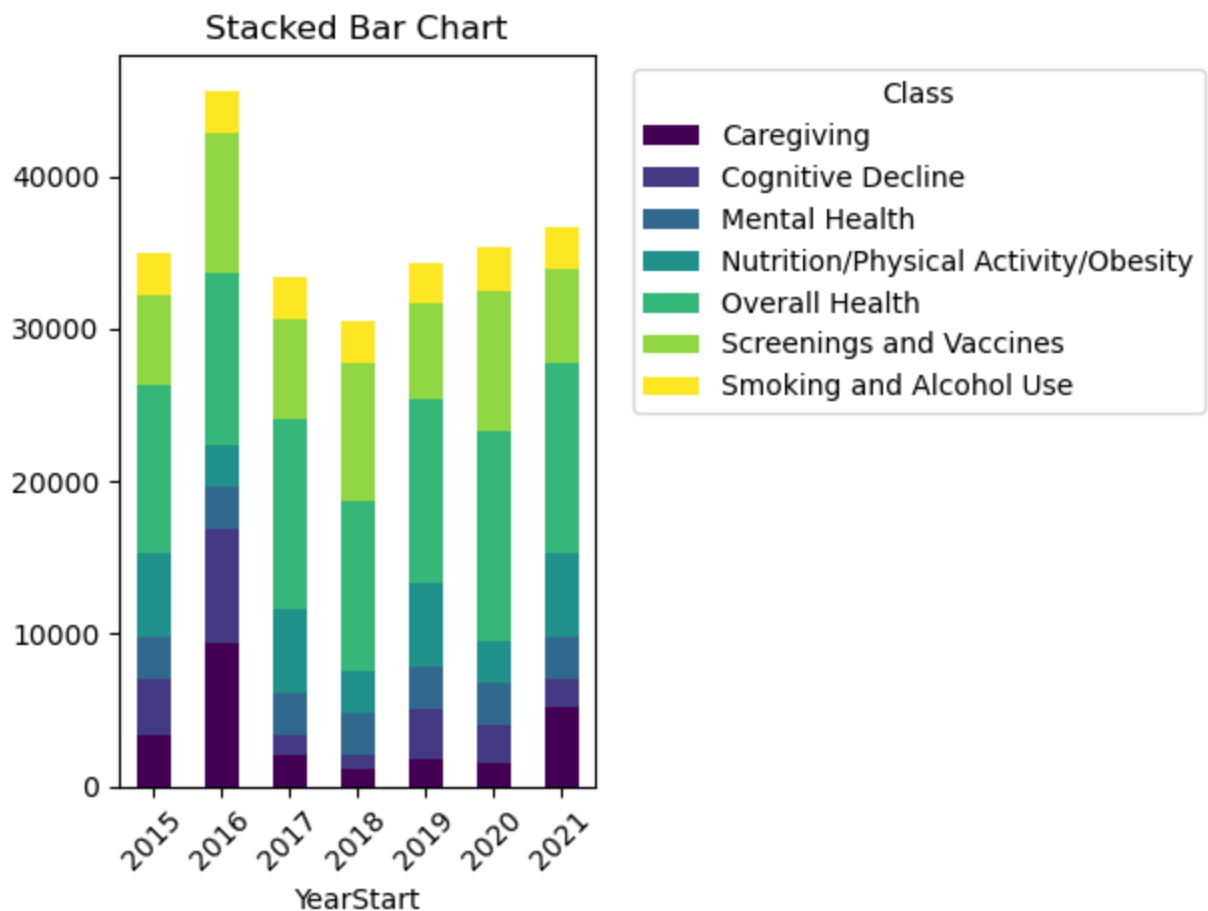
2. Create 15 distinct visualizations using matplotlib, each representing various features, columns, or attributes. Employ different types of charts for each visualization, ensuring none are repeated. Utilize a wide range of attributes in the dataset. None of the charts should be same. Provide insights for each visualization, incorporating at least 8 to 10 different types of charts.

Visualization 1

Stacked Bar Chart: Comparing number of classes by year

```
In [76]: class_by_year = df_health_data.groupby('YearStart')['Class'].value_counts().unstack(fill_value=0)
plt.figure(figsize=(10,6))
class_by_year.plot(kind='bar', stacked=True, cmap='viridis')
plt.xticks(rotation=45)
plt.title('Stacked Bar Chart')
plt.legend(title='Class', bbox_to_anchor=(1.05,1), loc='upper left')
plt.tight_layout()
plt.show()
```

<Figure size 1000x600 with 0 Axes>



Insights with conclusion for Stacked Bar Chart:

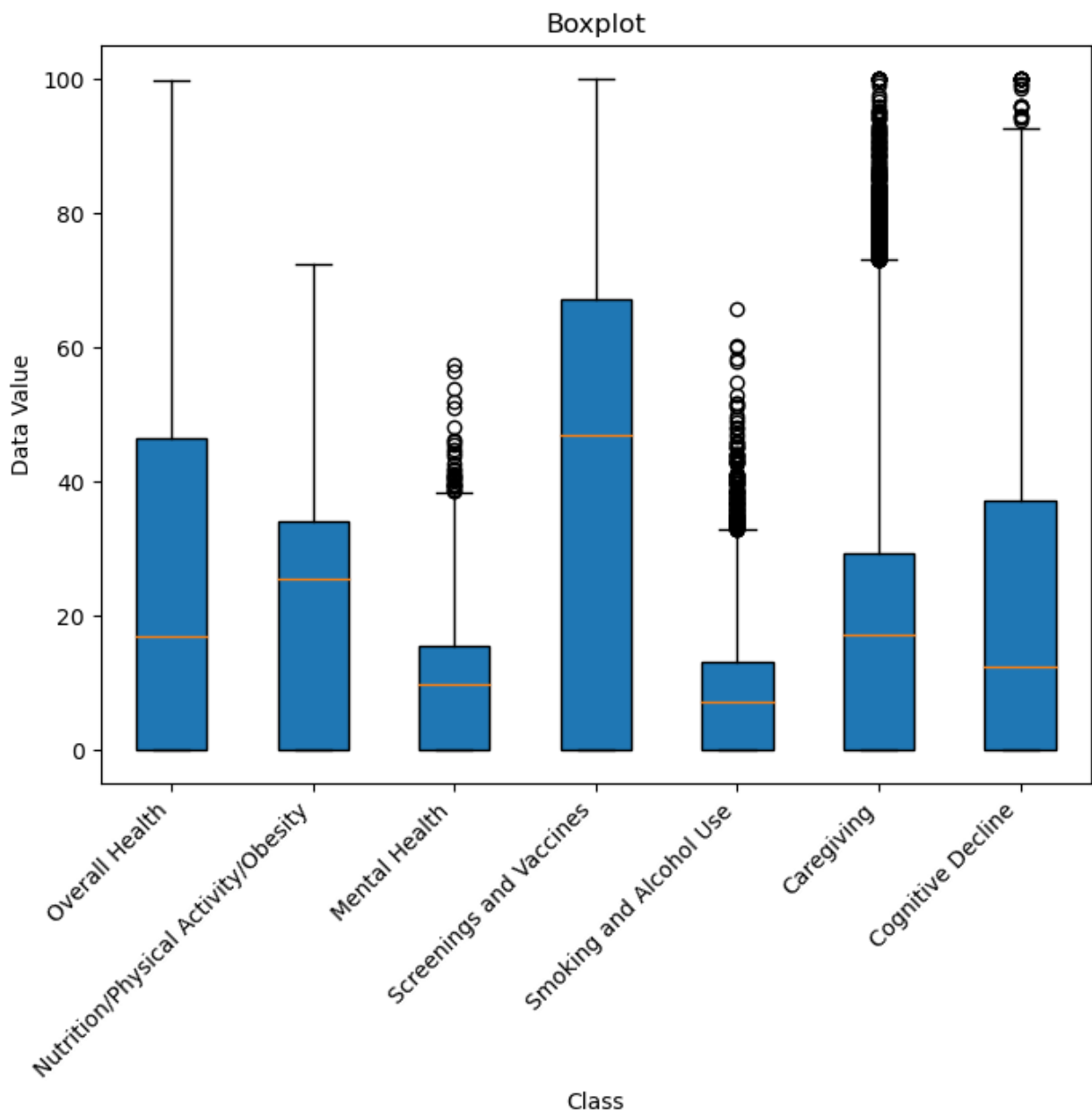
The visualization shows comparison of different classes across various years. Classes comprise of various health related categories as seen in the plot. There seems to have been a lot of survey done in the year 2016 with main focus on topics like 'Caregiving', 'Overall Health' and 'Screenings and Vaccines'. This means that people would have gone through screenings for various health related tests and greater percentage would have been diagnosed with some health issue due to which the Caregiving Class seems to have a greater percentage.

Visualization 2

Box plot: Distribution of data values in various categories of class

```
In [36]: data_grouped = [df_health_data[df_health_data['Class'] == category]['Data_Value'].tolist()
          for category in df_health_data['Class'].unique()]

plt.figure(figsize=(8,6))
plt.boxplot(data_grouped, labels=df_health_data['Class'].unique(), patch_artist=True)
plt.xticks(rotation=45, ha='right') #adjusting rotation and alignment
plt.title('Boxplot')
plt.xlabel('Class')
plt.ylabel('Data Value')
plt.grid(False)
plt.show()
```



Insights & conclusion for boxplot:

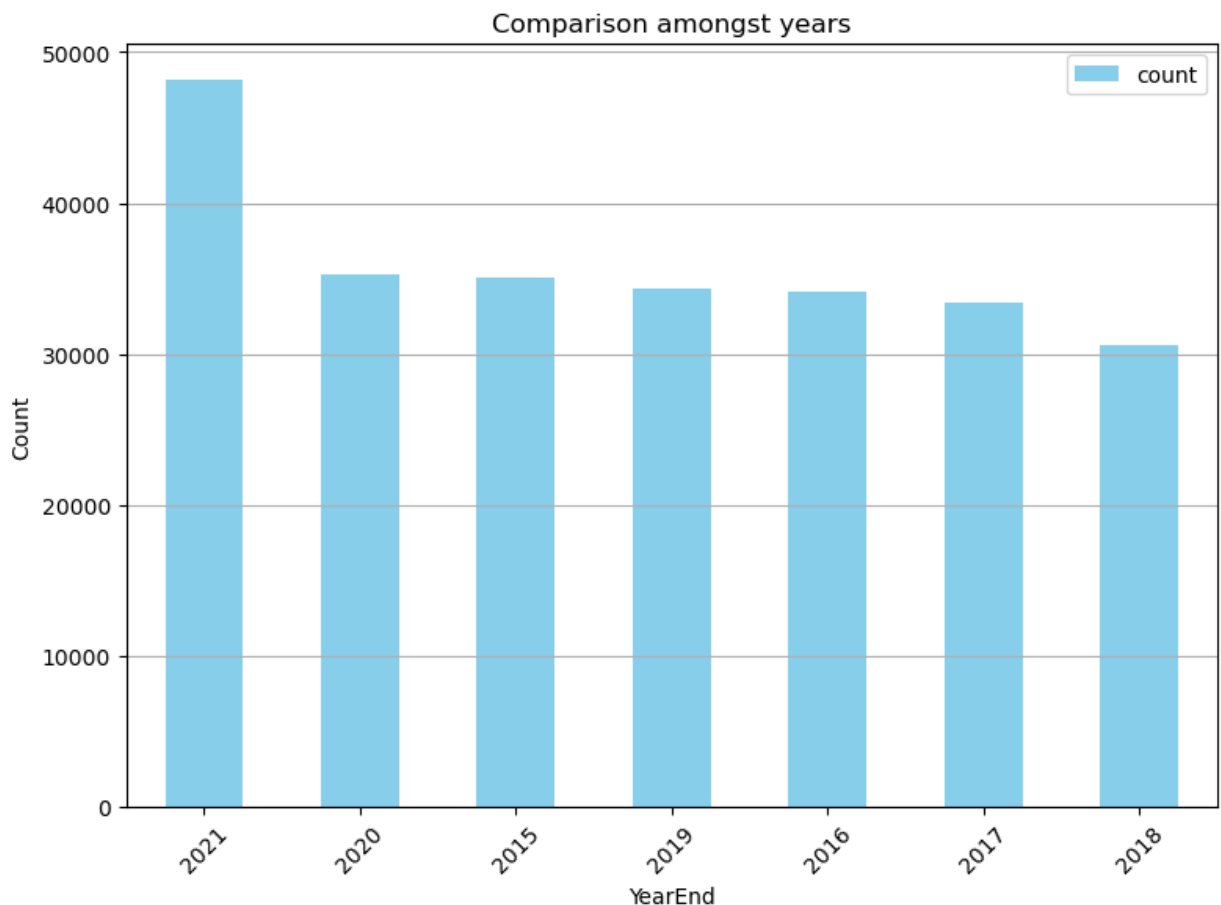
Plot shows distribution of data values(response to the questions in percentages) to categories of class. It can be seen that there is a lot of difference in central tendencies of all the categories. The plot depicts that people are aware of the importance of getting their health checked due to which the spread across 'Screenings and Vaccines' is more. There is not lot many people having mental health issues as compared to nutrition, ohysical activity, obesity. By having an active lifestyle, this percentage could be reduced. Addiitonally, eventhough the percentage of mental health issues and issues realted to smoking and alcohol are relatively less, it would be better to have no issues with it. TO do so, people would have to reduce smoking and alcohol intake and instead get engaged in extra-curricular activites which would eventually help with mental health problems as well.

Visualization 3

Simple Bar Chart

```
In [82]: count_of_survey_yearwise = df_health_data['YearEnd'].value_counts()

plt.figure(figsize=(8,6))
count_of_survey_yearwise.plot(kind='bar', color='skyblue')
plt.title('Comparison amongst years')
plt.xlabel('YearEnd')
plt.ylabel('Count')
plt.xticks(ticks=range(len(count_of_survey_yearwise)), labels=[label for label in count_of_survey_yearwise.index])
plt.grid(axis='y')
plt.tight_layout()
plt.legend()
plt.show()
```



Insights & conclusion for simple bar chart:

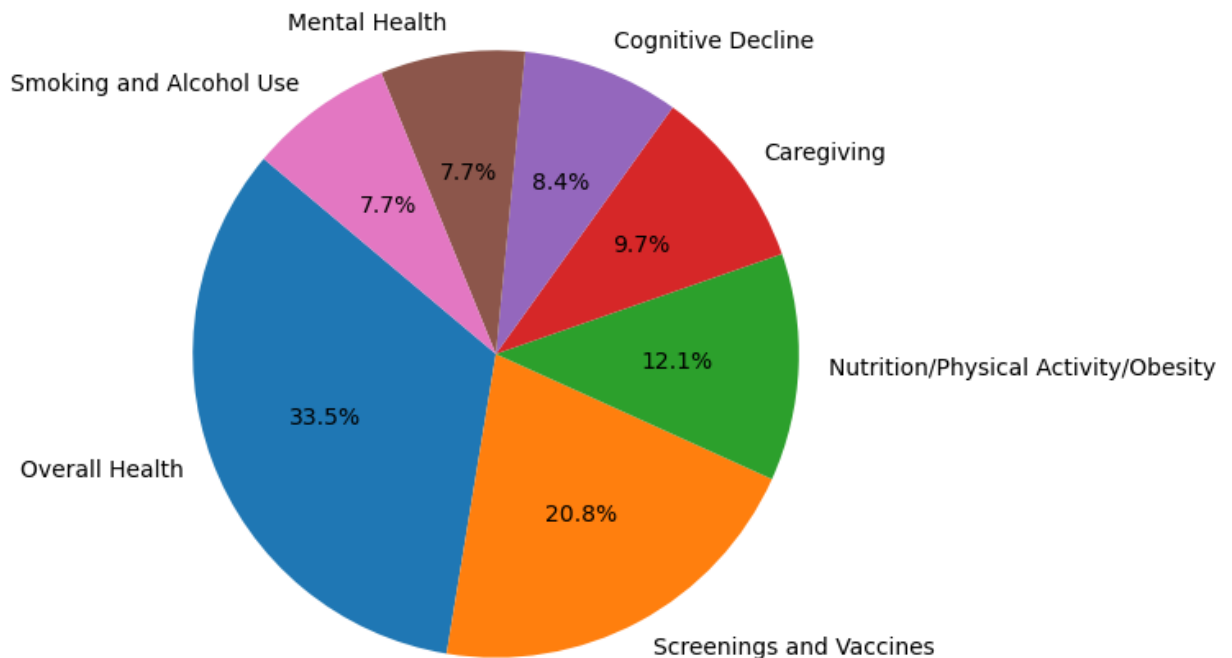
Visualization shows comparison of the count of survey being done each year. As seen above, maximum survey was completed in the year 2021 and the least was completed in 2018. This could have been due to various reasons like administrative difficulties, people being surveyed in the year 2018 were not very responsive or the resources needed to complete the survey were insufficient. The good part is that after 2018, the number of surveys being completed kept on increasing so the problem that arised in 2018 seems to have been resolved thus helping more number of people get aware of their health. This ultimately helps in improving the overall health too, which was a result of survey being done and appropriate advise being taken by individuals.

Visualization 4

Pie Chart

```
In [44]: count = df_health_data['Class'].value_counts()

plt.figure(figsize=(8,6))
plt.pie(count, labels=count.index, autopct='%1.1f%%', startangle=140)
plt.show()
```



Insights & conclusion for Pie Chart:

In this, I counted the unique values of feature 'Class' which ultimately shows the distribution of it. The size of each slice is representing the proportion of one category with respect to the remaining Class categories. It can be seen that the most amount of survey was done related to overall health and the least was conducted on topics related to mental health, smoking and alcohol use. It is clear that not much survey has been done on important topics like nutrition, physical activity and obesity. There is a direct link to less physical activity being a major cause of increase in stress levels affecting an individual's mental health. It is important to give more focus on nutrition and physical health to be able to increase awareness amongst people and improve overall mental health.

Visualization 5

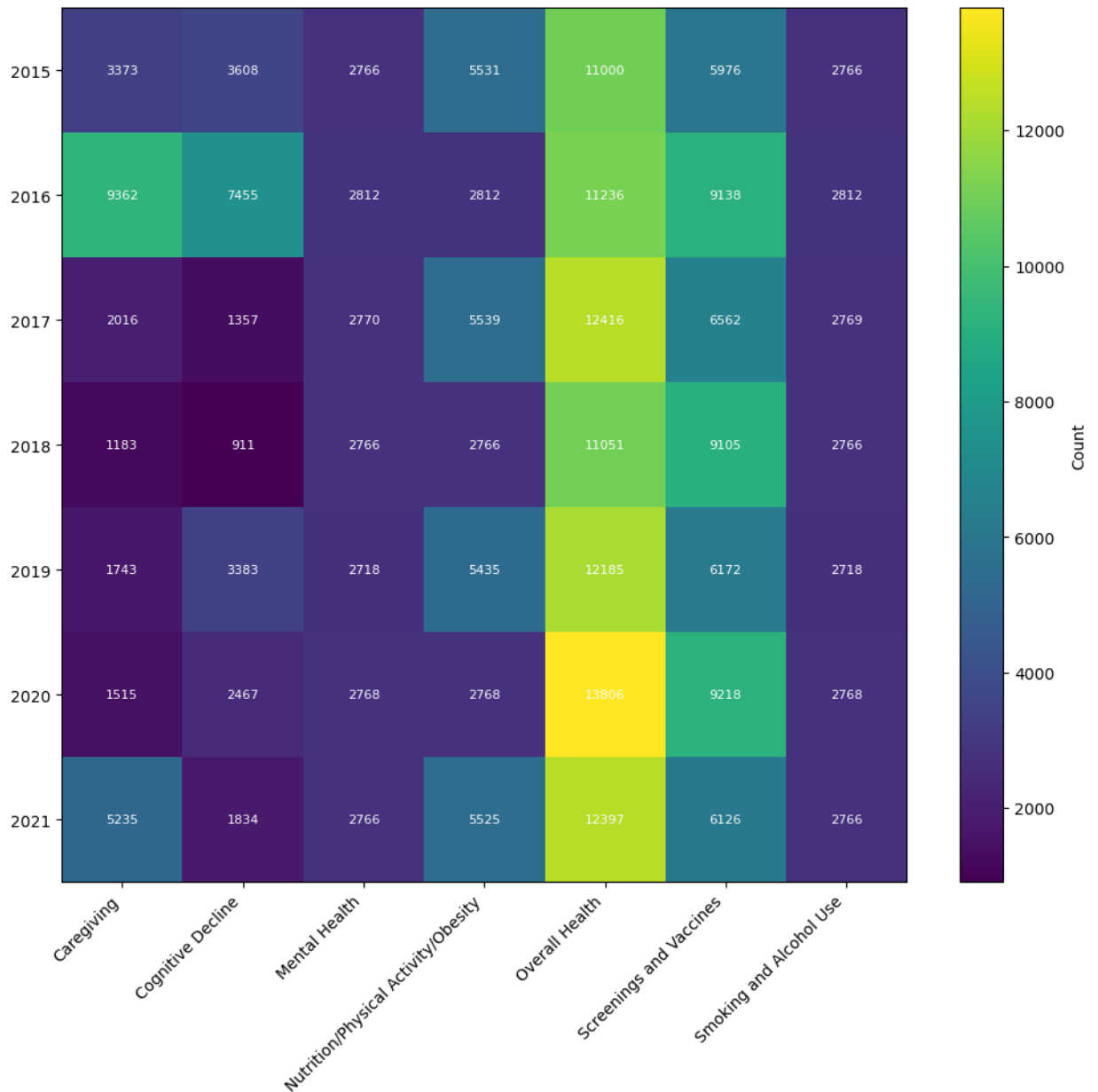
Heatmap

```
In [83]: count_of_class = df_health_data.groupby(['YearStart_catergorical', 'Class']).size().unstack()

plt.figure(figsize=(12,10))
plt.imshow(count_of_class, cmap='viridis', aspect='auto')

for a in range(len(count_of_class)):
    for b in range(len(count_of_class.columns)):
        plt.text(b,a, count_of_class.values[a,b], ha='center', va='center', color='white')

plt.xticks(np.arange(len(count_of_class.columns)), count_of_class.columns, rotation=45)
plt.yticks(np.arange(len(count_of_class)), count_of_class.index)
plt.colorbar(label='Count')
plt.show()
```



Insights & conclusion: Heatmap:

The plot depicts distribution and the relationship between categorical values present in Year with Class categories. Here, each cell is representing the number of times a combination of specific combination of 'year' and 'class' has occurred. It is clear that the

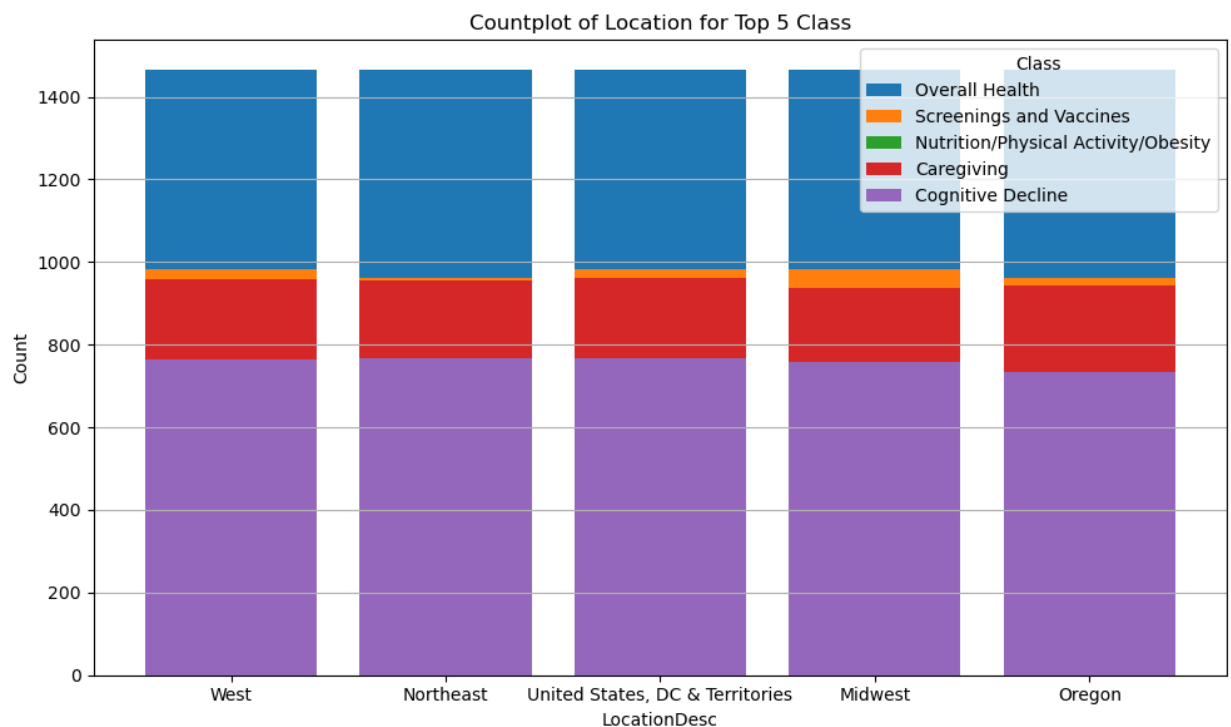
dark colored cell combinations have occurred less as compared to the lighter ones. The survey conducted in the year 2020 on overall health is maximum. This could have been a result of year 2020 being in the middle of pandemic. Naturally, people were falling sick often which can be seen in the response of this survey. After becoming aware of overall health, people would have definitely taken appropriate actions thus leading to a good overall health as well.

Visualization 6

Countplot

```
In [53]: top_five_loc = df_health_data['LocationDesc'].value_counts().nlargest(5).index
top_five_class = df_health_data['Class'].value_counts().nlargest(5).index

df_health_data_top = df_health_data[df_health_data['LocationDesc'].isin(top_five_loc)]
plt.figure(figsize=(10,6))
for cl in top_five_class:
    plt.bar(df_health_data_top[df_health_data_top['Class'] == cl]['LocationDesc'].value_counts(),
            df_health_data_top[df_health_data_top['Class'] == cl]['LocationDesc'].value_counts(),
            label=cl)
plt.xlabel('LocationDesc')
plt.ylabel('Count')
plt.title('Countplot of Location for Top 5 Class')
plt.legend(title='Class')
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```



Insights & conclusion:

The plot above shows the distribution of the count of occurrences of values in top 5 Locations for top 5 class categories. It is clear that the least amount of survey being done

on screenings and vaccine was at the location northeast. The cognitive decline survey seems to be in equal quantities across all 5 locations. It is important to increase the content of survey on the northeast to improve the overall health. This could have been a result of insufficient good quality equipments that are needed for conducting screenings. By increasing the good quality equipments, this issue could be resolved.

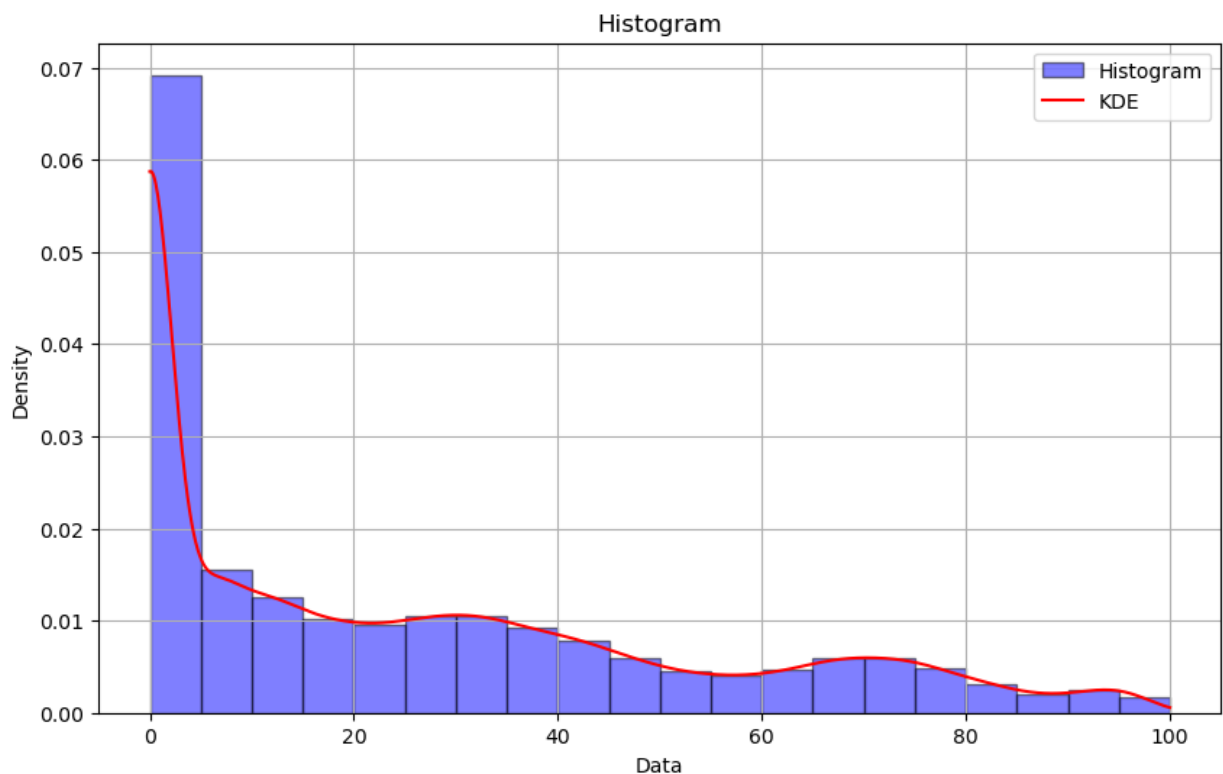
Visualization 7

Histogram

```
In [85]: plt.figure(figsize=(10,6))
plt.hist(df_health_data['Data_Value'], bins=20, alpha=0.5, color='blue', edgecolor='b)

kde=gaussian_kde(df_health_data['Data_Value'])
x_vals=np.linspace(min(df_health_data['Data_Value']), max(df_health_data['Data_Value'])
plt.plot(x_vals, kde(x_vals), color='red', label='KDE')

plt.xlabel('Data')
plt.ylabel('Density')
plt.title('Histogram')
plt.legend()
plt.grid(True)
plt.show()
```



Insights & conclusion for histogram:

This plot visualizes the distribution of data values. Data values are the responses to the health related questions in the form of percentage. It is clear that there is very less percentage of health related questions that are above 80%. This also means that responses to questions like 'Percentage of older adults ever told they have arthritis' or

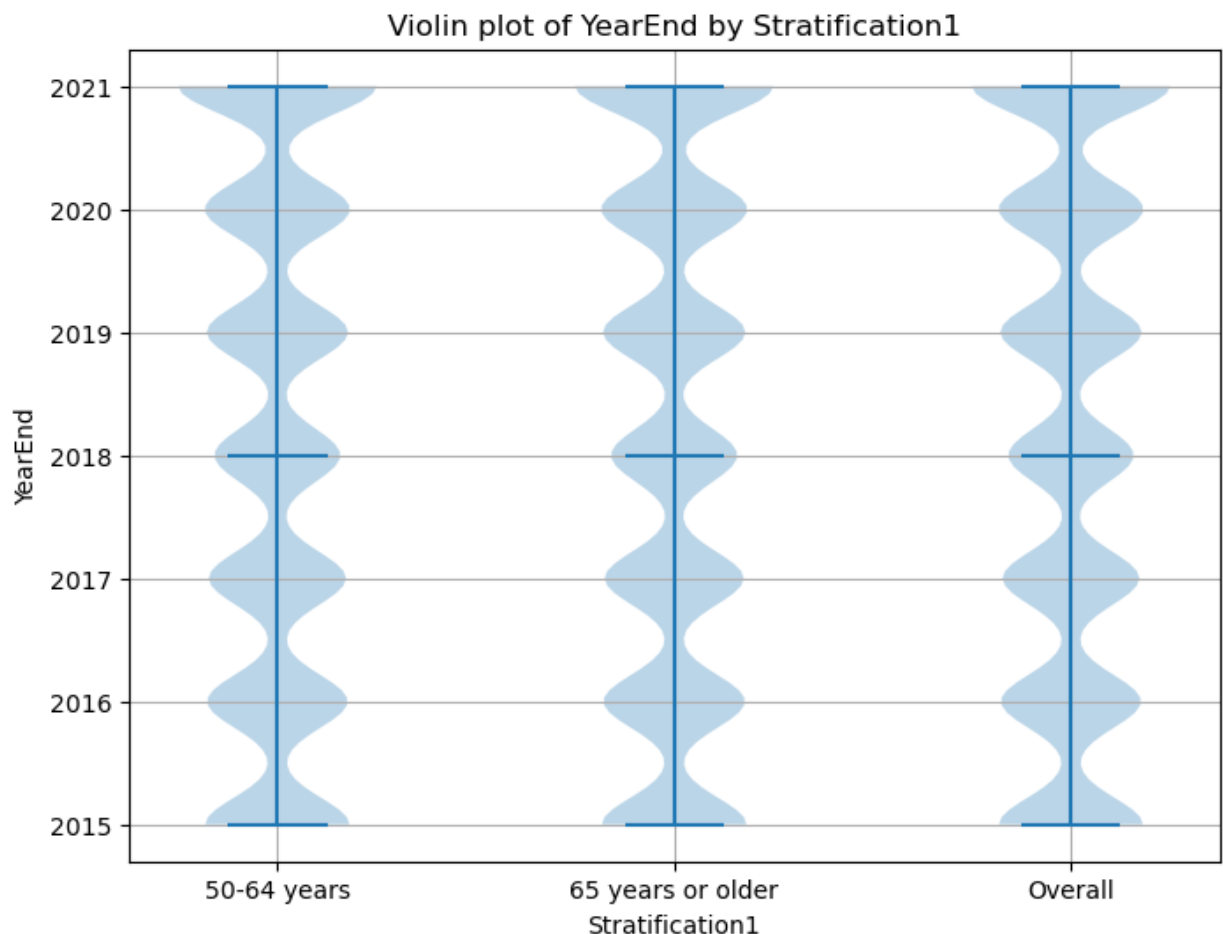
'Percentage of older adults with a lifetime diagnosis of depression' is quite less which can be a good thing. This also means that if effective measures are taken for every health related problem, overall health amongst individuals can improve.

Visualization 8

Violin Plot

```
In [25]: data_grouped = df_health_data.groupby('Stratification1')['YearEnd'].apply(list)

plt.figure(figsize=(8,6))
plt.violinplot(data_grouped, showmeans=False, showextrema=True, showmedians=True)
plt.xticks(np.arange(1, len(data_grouped) + 1), data_grouped.index)
plt.title('Violin plot of YearEnd by Stratification1')
plt.xlabel('Stratification1')
plt.ylabel('YearEnd')
plt.grid(True)
plt.show()
```



Insights & conclusion for violin plot:

This plot depicts that there is uniform distribution amongst older age groups across all the years. This shows that even old people do keep a check on their health making it possible for them to take preventive action in case of any diagnosis. This helps in reducing the workload on the healthcare industry. Problem can arise when older generation is not

aware of their health condidiotns ultimatley putting a lot of pressure on the resources of the healthcare system.

Visualization 9

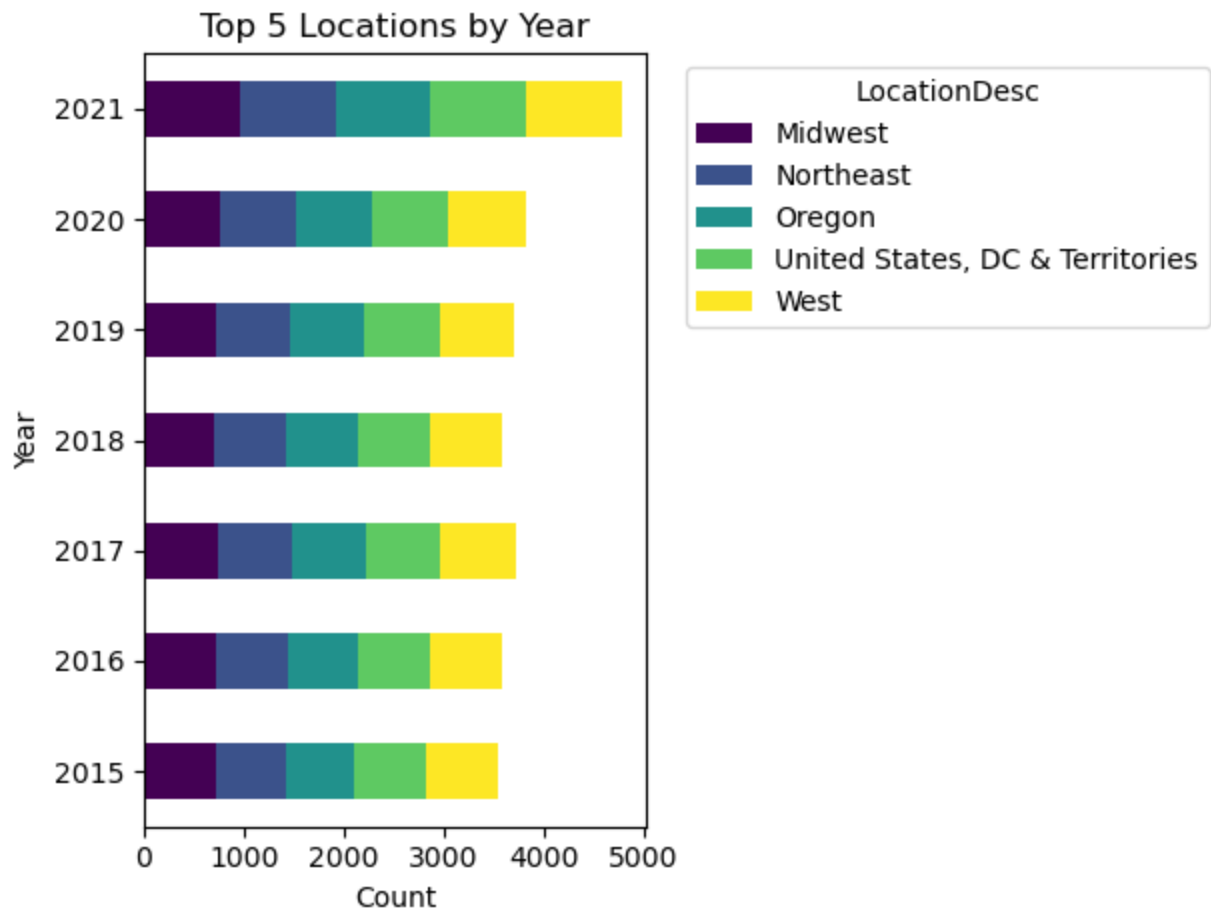
Horizontal Stacked Bar Chart

```
In [86]: top_five_loc = df_health_data['LocationDesc'].value_counts().nlargest(5).index
df_new = df_health_data[df_health_data['LocationDesc'].isin(top_five_loc)]

year = df_new.groupby('YearEnd')['LocationDesc'].value_counts().unstack(fill_value=0)

plt.figure(figsize=(10,6))
year.plot(kind='barh', stacked=True, cmap='viridis')
plt.xlabel('Count')
plt.ylabel('Year')
plt.title('Top 5 Locations by Year')
plt.legend(title='LocationDesc', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

<Figure size 1000x600 with 0 Axes>



Insights & conclusion:

From the plot above, it is clear that number of surveys being held increased alot in the year 2021 across all top 5 locations. This can be a result of COVID-19. Post pandemic,

every individual tried best to become aware of overall health. There is a probability that the healthcare industry too would have encouraged everyone to keep a check on their health to be able to improve overall immunity after becoming aware of their health conditions. This definitely helps in improving the health globally.

Visualization 10

Scatter Plot

```
In [34]: df_health_data['latitude'] = df_health_data['Geolocation'].str.split().str[1]
df_health_data['longitude'] = df_health_data['Geolocation'].str.split().str[2]

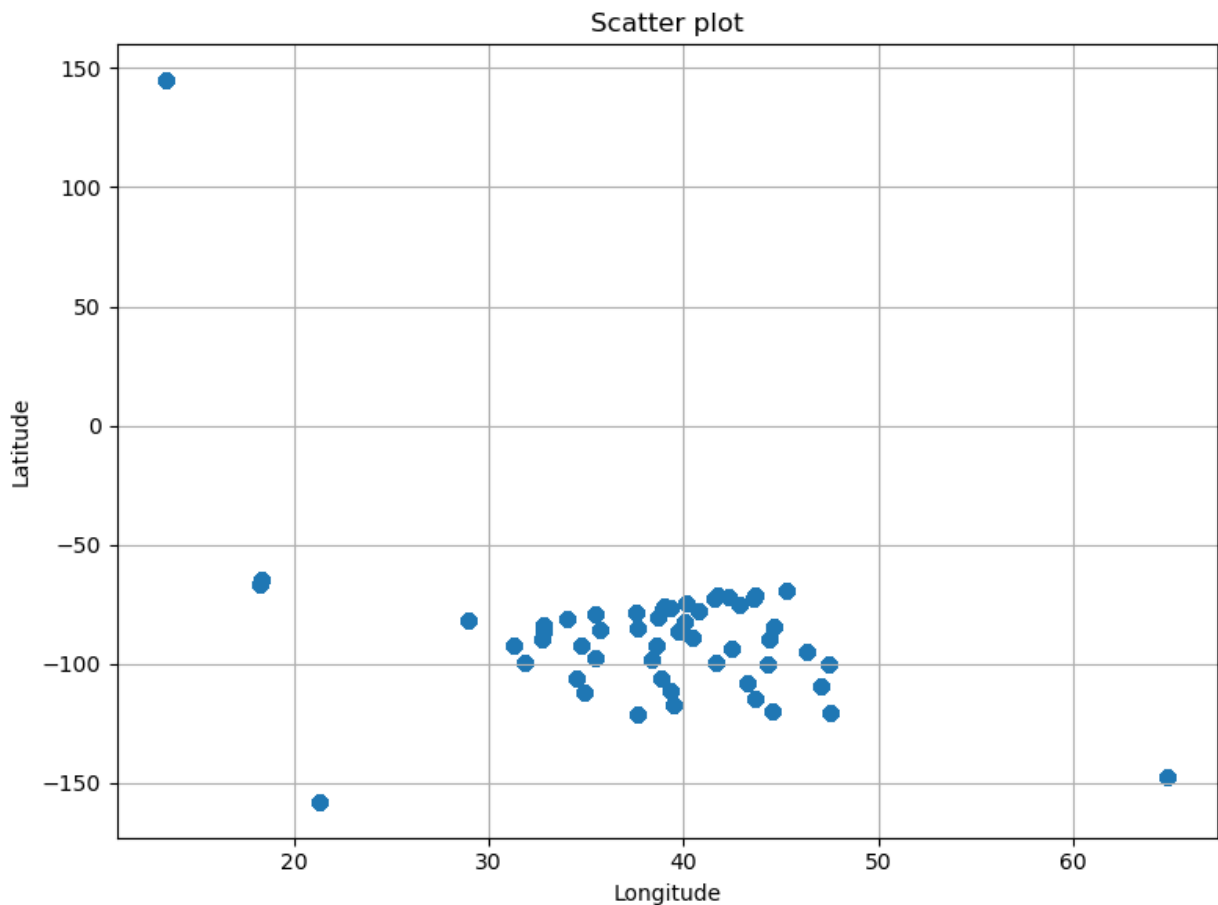
df_health_data['latitude'] = df_health_data['latitude'].str.strip('(').astype(float)
df_health_data['longitude'] = df_health_data['longitude'].str.strip('(').astype(float)

print(df_health_data['latitude'])
print(df_health_data['longitude'])
```

```
0          NaN
1          NaN
2          NaN
3          NaN
4      -71.500361
...
250932    -80.712640
250933    -97.521070
250934    -71.500361
250935    -78.457890
250936   -111.587131
Name: latitude, Length: 250937, dtype: float64
0          NaN
1          NaN
2          NaN
3          NaN
4      43.655950
...
250932     38.665510
250933     35.472031
250934     43.655950
250935     37.542681
250936     39.360700
Name: longitude, Length: 250937, dtype: float64
```

```
In [36]: df_health_data_geo = df_health_data.dropna(subset=['latitude', 'longitude'])

plt.figure(figsize=(8,6))
plt.scatter(df_health_data_geo['longitude'],df_health_data_geo['latitude'] )
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Scatter plot')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Insights & conclusion:

It can be seen from the scatter plot above that there is a lot of concentration at the lower middle of the plot. This tells us that the survey being held was concentrated at a particular location (USA, in this case). Few outliers can also be seen indicating that there were few places far away from USA where the survey was held.

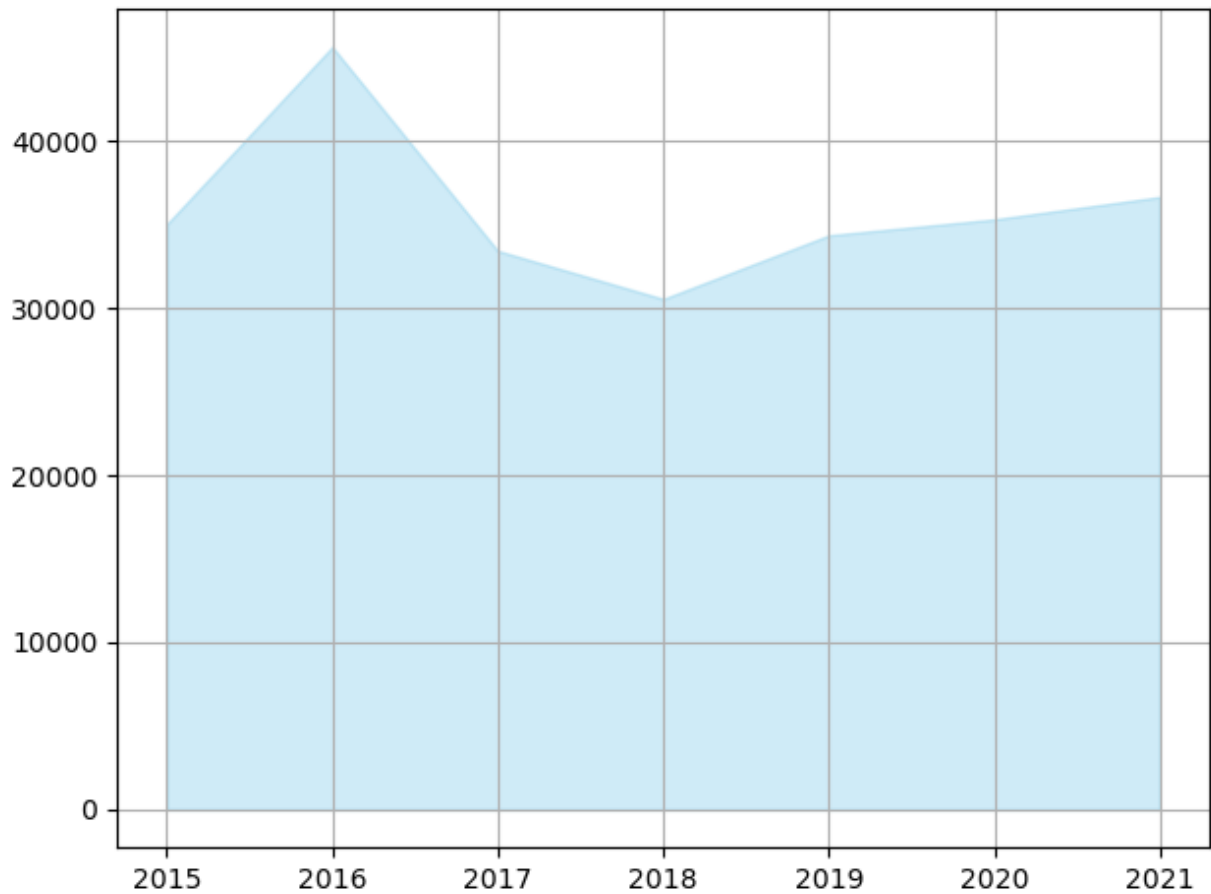
Visualization 11

Area Plot

```
In [53]: count_of_year = df_health_data['YearStart'].value_counts().sort_index()
plt.fill_between(count_of_year.index, count_of_year.values, color='skyblue', alpha=0.4)

plt.xlabel('Years')
plt.ylabel('Number of Occurrences')
plt.title('Area Plot of Year Occurrences')
plt.xticks(count_of_year.index)
plt.grid(True)
plt.tight_layout()

plt.show()
```



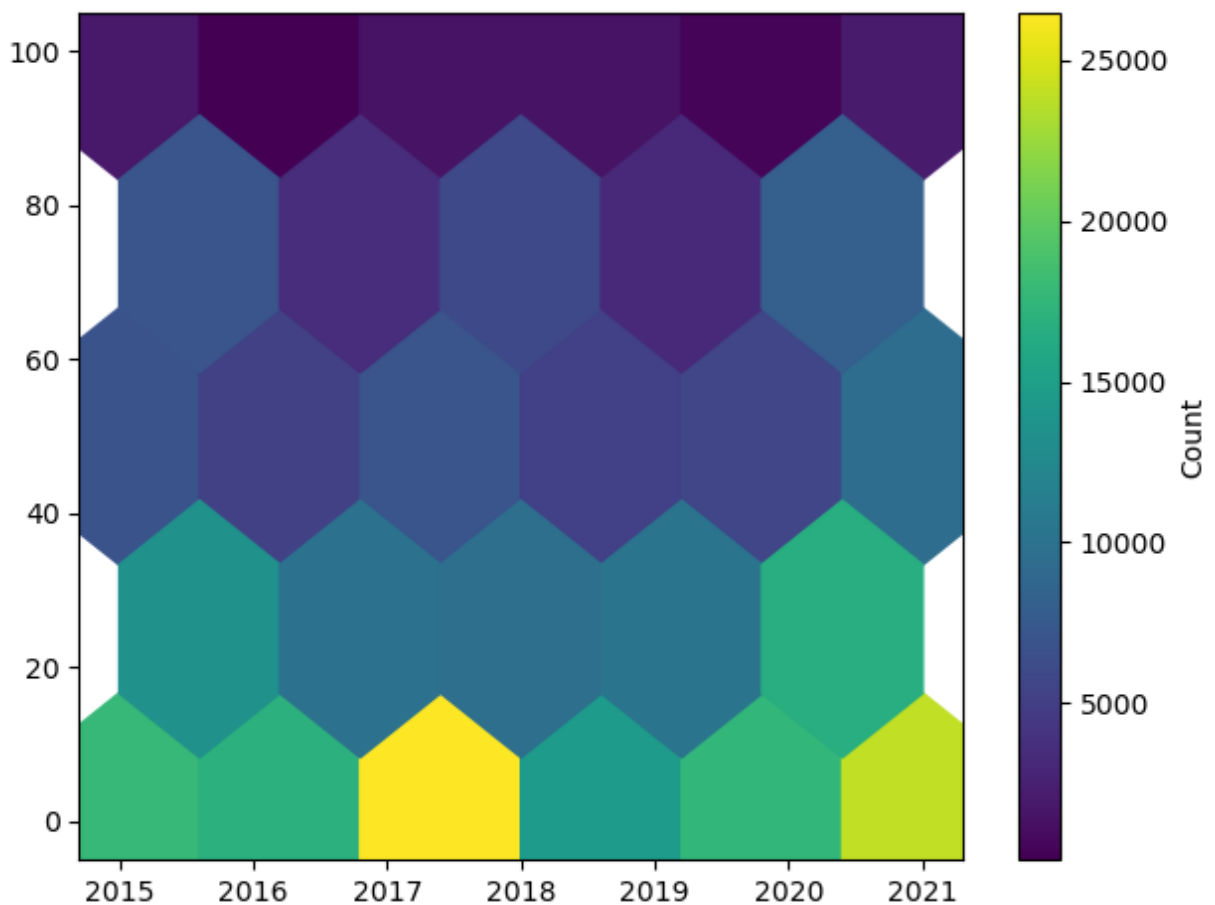
Insights & conclusion:

The plot shows the number of surveys that were held in the specified years. There seems to be a drop in it in the year 2018. This could have been a result of either having limited resources or some difficulty in getting the responses for health related questions.

Visualization 12

Hexagonal Bin Plot

```
In [58]: plt.hexbin(df_health_data['YearEnd'], df_health_data['Data_Value'], gridsize=5, cmap='
plt.colorbar(label='Count')
plt.tight_layout()
plt.show()
```



Insights & conclusions:

The plot above shows the distribution of data values for the years in the form in a scatter plot. It is clear that there were many responses in the year 2017 indicating that conducting the survey in that year was successful. Again, in the year 2021, the survey seems to have been a success as there seems to be a concentration of data points in that year. This could be a result of COVID-19.

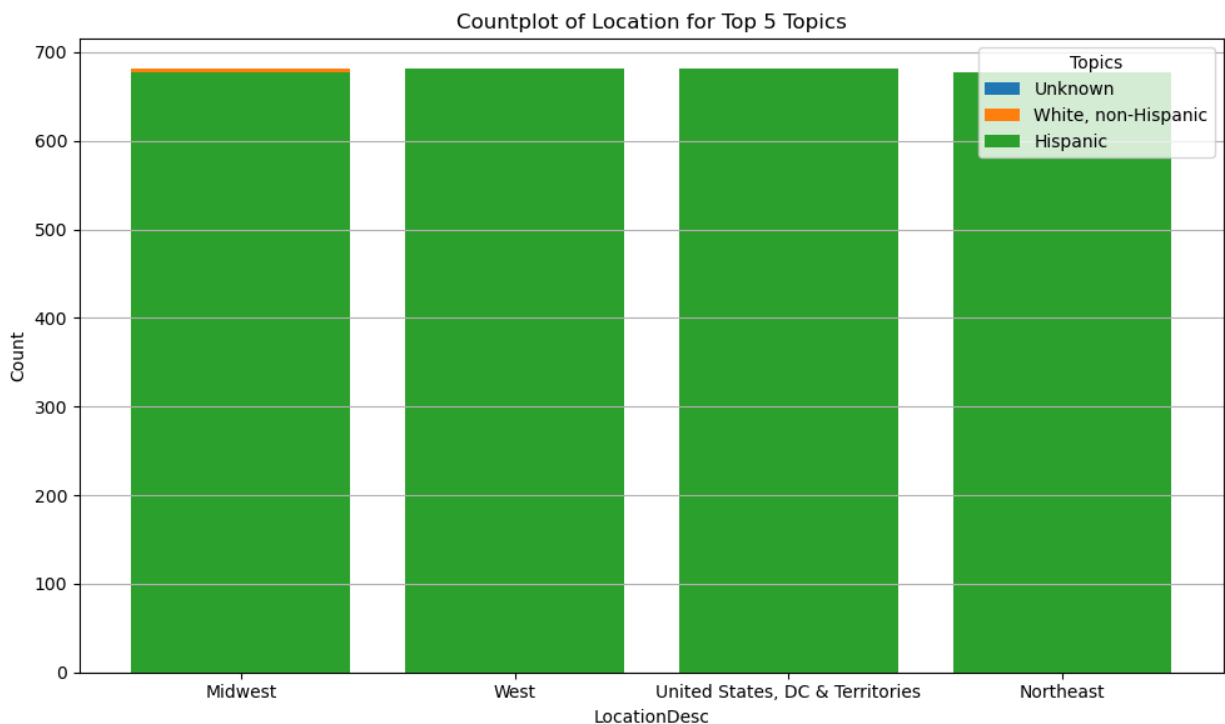
Visualization 13

Countplot

```
In [87]: top_four_loc = df_health_data['LocationDesc'].value_counts().nlargest(4).index
top_three_strat = df_health_data['Stratification2'].value_counts().nlargest(3).index

df_health_data_top = df_health_data[df_health_data['LocationDesc'].isin(top_four_loc)]
plt.figure(figsize=(10,6))
for t in top_three_strat:
    plt.bar(df_health_data_top[df_health_data_top['Stratification2'] == t]['LocationDesc'],
            df_health_data_top[df_health_data_top['Stratification2'] == t].value_counts(),
            label=t)
plt.xlabel('LocationDesc')
plt.ylabel('Count')
plt.title('Countplot of Location for Top 5 Topics')
plt.legend(title='Topics')
plt.grid(axis='y')
```

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



Insights & conclusion:

From the countplot plotted above, it can be seen that there seems to very less amount of 'White, non-Hispanic' group of people at the location Midwest. This means that not many people belonging to this group were part of the survey that lived in the Midwest area. This could be a result of that particular area not having many residents belonging to this group. It is important to make sure to include as many people from diverse backgrounds while conducting this survey. This helps in analyzing it properly after all information collection and drawing conclusions to be able to take appropriate steps in the medical field.

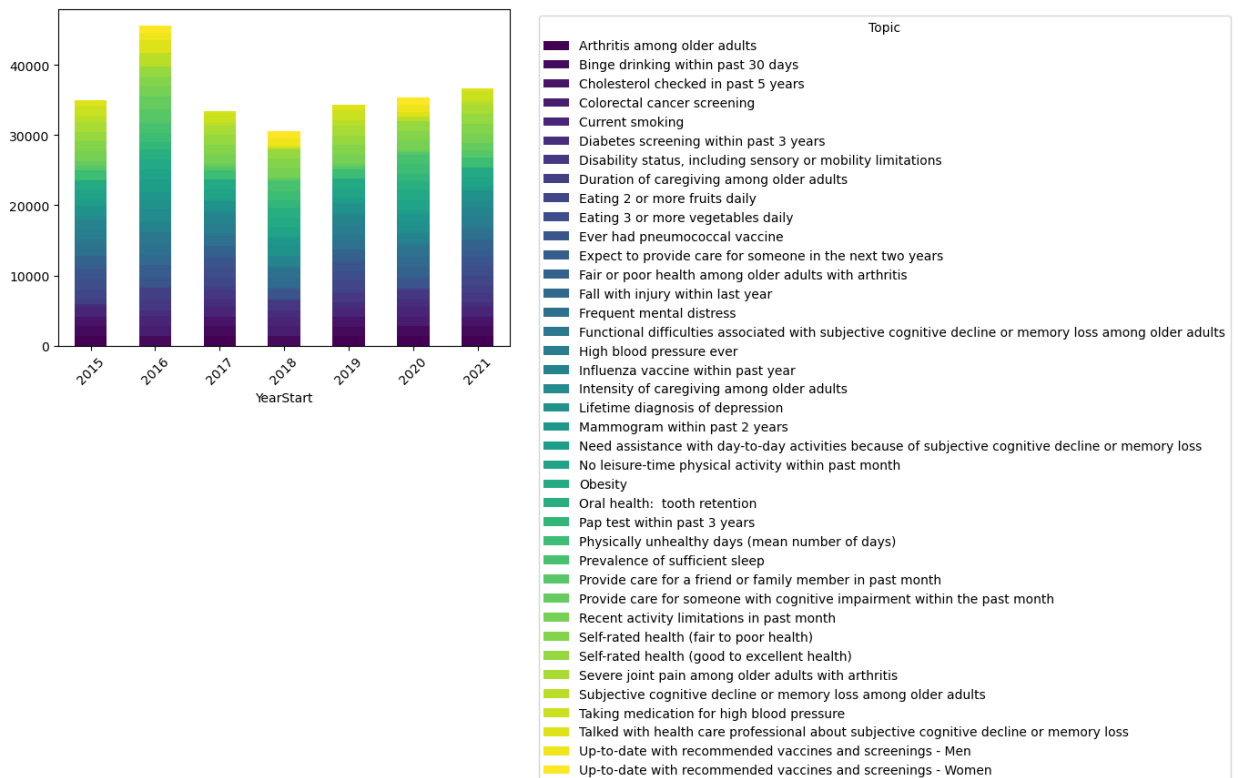
Visualization 14

Bar Plot

```
In [68]: class_by_year = df_health_data.groupby('YearStart')['Topic'].value_counts().unstack(fill_value=0)
plt.figure(figsize=(10,6))
class_by_year.plot(kind='bar', stacked=True, cmap='viridis')
plt.xticks(rotation=45)
plt.legend(title='Topic', bbox_to_anchor=(1.05,1), loc='upper left')
plt.tight_layout()
plt.show()
```

C:\Users\Sayal\AppData\Local\Temp\ipykernel_35792\2798462604.py:6: UserWarning: Tight layout not applied. The left and right margins cannot be made large enough to accommodate all axes decorations.

```
plt.tight_layout()
<Figure size 1000x600 with 0 Axes>
```



Insights & conclusion:

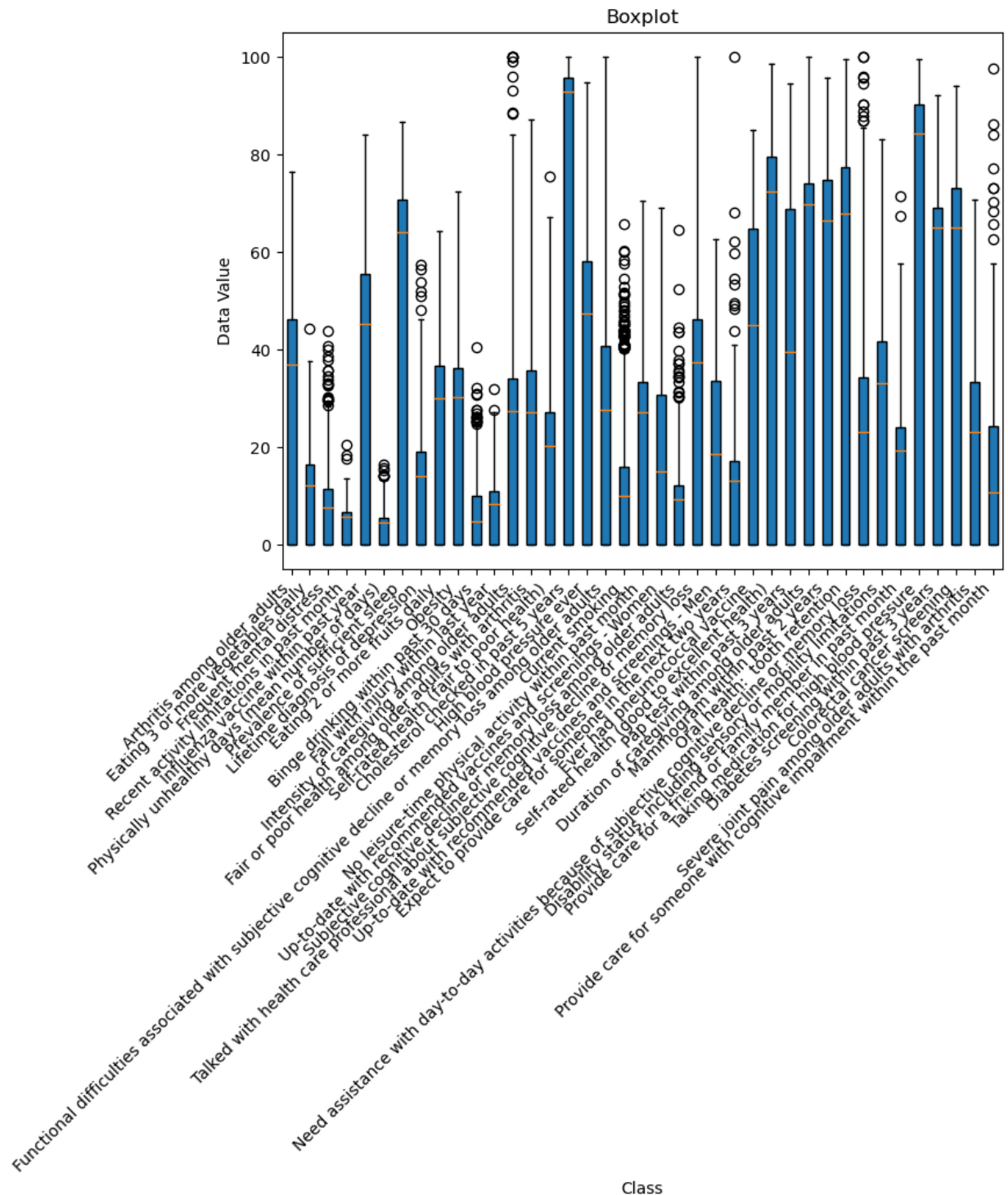
The bar plot compares the survey help on various health related topics amongst various years. It is clear that every topic was euqually focussed and was not preferred over other. This shows that the survey is conducted by keeping in mind all the important factors in an individual's health

Visualization 15

Box Plot

```
In [70]: data_grouped = [df_health_data[df_health_data['Topic'] == category]['Data_Value'].tolist()
          for category in df_health_data['Topic'].unique()]

plt.figure(figsize=(8,6))
plt.boxplot(data_grouped, labels=df_health_data['Topic'].unique(), patch_artist=True)
plt.xticks(rotation=45, ha='right') #adjusting rotation and alignment
plt.title('Boxplot')
plt.xlabel('Class')
plt.ylabel('Data Value')
plt.grid(False)
plt.show()
```



Insights & conclusion:

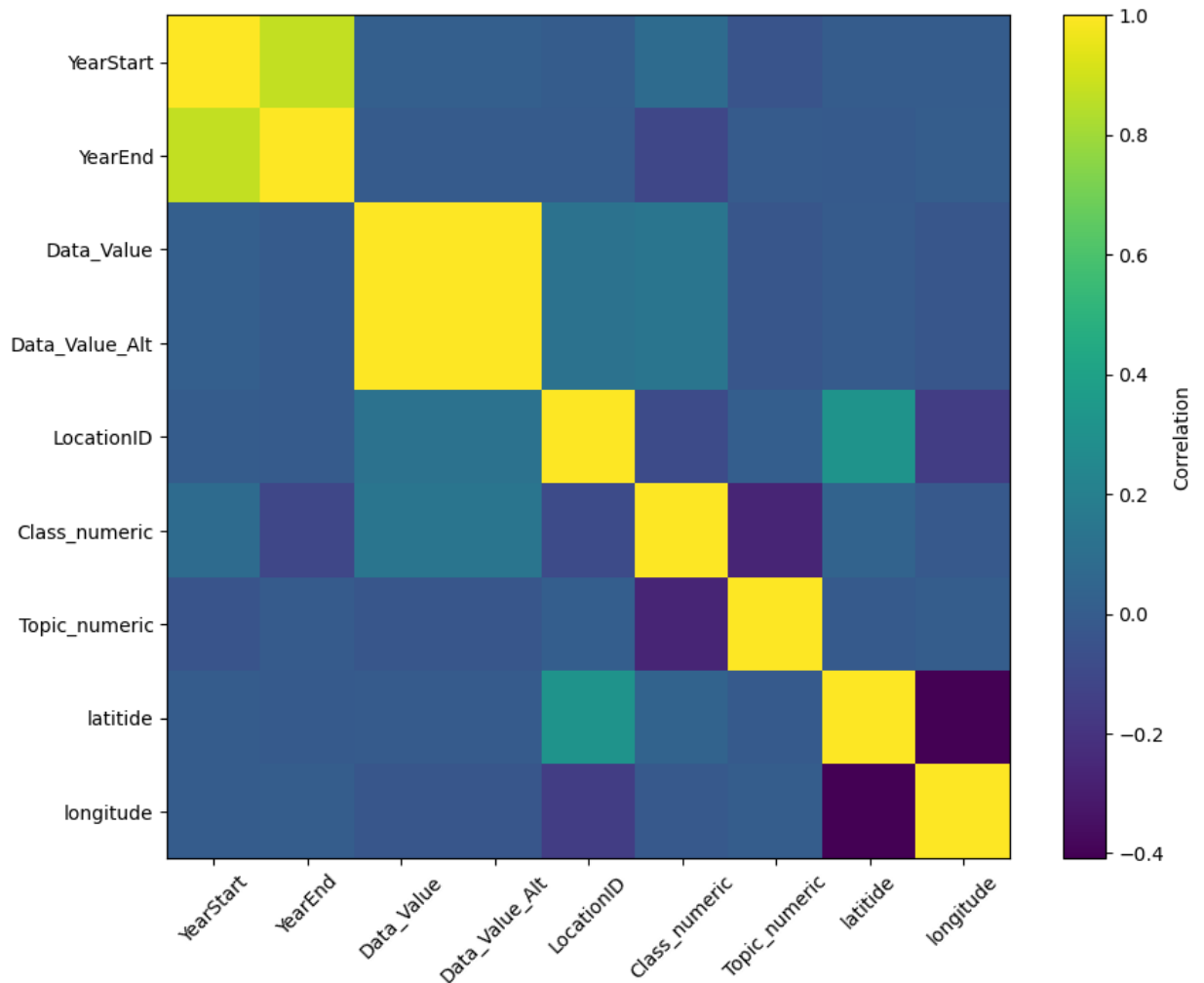
The boxplot shows the distribution of data values in health related topics. It can be seen from the plot that the least one is for the topic 'Physically unhealthy days'. This also tells us that most of the days, individuals are having physically healthy days thus, showcasing that the overall health of most people is good. Few of the reasons why some people might be having physically unhealthy days could be 'flu' or 'physical injury' making them unfit to carry on their usual routine.

Question 3: Correlation matrix of numerical features


```
In [72]: numeric_df = df_health_data.select_dtypes(include=[np.number])

corr_matrix = numeric_df.corr()

plt.figure(figsize=(10,8))
plt.imshow(corr_matrix, cmap='viridis', interpolation='nearest')
plt.colorbar(label='Correlation')
plt.xticks(range(len(corr_matrix.columns)), corr_matrix.columns, rotation=45)
plt.yticks(range(len(corr_matrix.columns)), corr_matrix.columns)
plt.show()
```



Insights & conclusion:

This plot showcases the relationship between the numerical features of this dataset. It is clear that the features that have high correlation amongst themselves are 'latitude and longitude' and 'data value & data_value_alt'. This tells us that change in one value of latitude would impact the value of longitude greatly. Similarly, data value has a lot of impact on the feature data_value_int.

In []: