Aim: Introduction to Data science and Data preparation using Pandas steps.

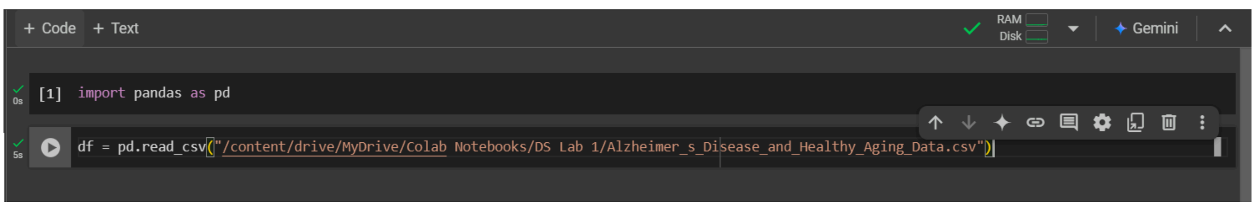
- Load data in Pandas.
- Description of the dataset.
- Drop columns that aren't useful.
- Drop rows with maximum missing values.
- Take care of missing data.
- Create dummy variables.
- Find out outliers (manually)
- standardization and normalization of columns

Steps:

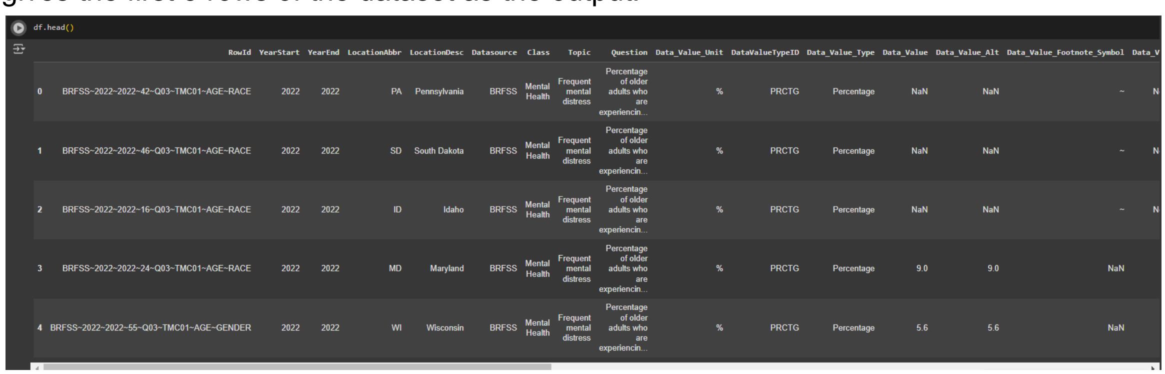
1) Load the file.

To load a file onto python for analysis, we need to make use of the pandas library. It gives us functionalities to read a CSV (Comma Separated Values) file and perform various functions on it.

Commands: **import pandas as pd** (Importing the pandas library onto Google Colab Notebook)
df = pd.read_csv(<Path_of_csv_file>) (Mounts and reads the file in Python and assigns it to variable df for ease of use further)
(Note: Replace <Path_of_csv_file> with the actual path of the file in "")



To check whether the file is loaded or not, we will run the command **df.head().** This command gives the first 5 rows of the dataset as the output.



```
df.head()
```

	RowId	YearStart	YearEnd	LocationAbbr	LocationDesc	Datasource	Class	Topic	Question	Data_Value_Unit	DataValueTypeID	Data_Value_Type	Data_Value	Data_Value_Alt	Data_Value_Footnote_Symbol	Data_V
0	BRFSS~2022~2022~42~Q03~TMC01~AGE~RACE	2022	2022	PA	Pennsylvania	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	NaN	NaN	~	N
1	BRFSS~2022~2022~46~Q03~TMC01~AGE~RACE	2022	2022	SD	South Dakota	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	NaN	NaN	~	N
2	BRFSS~2022~2022~16~Q03~TMC01~AGE~RACE	2022	2022	ID	Idaho	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	NaN	NaN	~	N
3	BRFSS~2022~2022~24~Q03~TMC01~AGE~RACE	2022	2022	MD	Maryland	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	9.0	9.0	NaN	
4	BRFSS~2022~2022~55~Q03~TMC01~AGE~GENDER	2022	2022	WI	Wisconsin	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	5.6	5.6	NaN	

2) Description of the dataset

The description of the dataset gives the user an idea on what are the features, what is the count of rows and columns, etc. To achieve this, we can use the following commands.

Command 1: df.head()

As mentioned before, **head** function give us the first 5 rows of the dataset. This allows for the user to get an overview on what values are being listed in the dataset.

```
df.head()
```

	RowId	YearStart	YearEnd	LocationAbbr	LocationDesc	Datasource	Class	Topic	Question	Data_Value_Unit	DataValueTypeID	Data_Value_Type	Data_Value	Data_Value_Alt	Data_Value_Footnote_Symbol	Data_V
0	BRFSS~2022~2022~42~Q03~TMC01~AGE~RACE	2022	2022	PA	Pennsylvania	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	NaN	NaN	~	N
1	BRFSS~2022~2022~46~Q03~TMC01~AGE~RACE	2022	2022	SD	South Dakota	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	NaN	NaN	~	N
2	BRFSS~2022~2022~16~Q03~TMC01~AGE~RACE	2022	2022	ID	Idaho	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	NaN	NaN	~	N
3	BRFSS~2022~2022~24~Q03~TMC01~AGE~RACE	2022	2022	MD	Maryland	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	9.0	9.0	NaN	
4	BRFSS~2022~2022~55~Q03~TMC01~AGE~GENDER	2022	2022	WI	Wisconsin	BRFSS	Mental Health	Frequent mental distress	Percentage of older adults who are experiencin...	%	PRCTG	Percentage	5.6	5.6	NaN	

Command 2: df.info()

This command gives all the information about the features (columns) of the dataset and the data type of each of these columns. It also gives a summary of all the values in the dataset.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284142 entries, 0 to 284141
Data columns (total 31 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   RowId                       284142 non-null  object
 1   YearStart                   284142 non-null  int64
 2   YearEnd                     284142 non-null  int64
 3   LocationAbbr                284142 non-null  object
 4   LocationDesc                284142 non-null  object
 5   Datasource                  284142 non-null  object
 6   Class                       284142 non-null  object
 7   Topic                       284142 non-null  object
 8   Question                    284142 non-null  object
 9   Data_Value_Unit             284142 non-null  object
 10  DataValueTypeID             284142 non-null  object
 11  Data_Value_Type             284142 non-null  object
 12  Data_Value                  192808 non-null  float64
 13  Data_Value_Alt              192808 non-null  float64
 14  Data_Value_Footnote_Symbol  109976 non-null  object
```

```
 15  Data_Value_Footnote         109976 non-null  object
 16  Low_Confidence_Limit        192597 non-null  float64
 17  High_Confidence_Limit       192597 non-null  float64
 18  StratificationCategory1     284142 non-null  object
 19  Stratification1             284142 non-null  object
 20  StratificationCategory2     247269 non-null  object
 21  Stratification2             247269 non-null  object
 22  Geolocation                 253653 non-null  object
 23  ClassID                     284142 non-null  object
 24  TopicID                     284142 non-null  object
 25  QuestionID                  284142 non-null  object
 26  LocationID                  284142 non-null  int64
 27  StratificationCategoryID1   284142 non-null  object
 28  StratificationID1           284142 non-null  object
 29  StratificationCategoryID2   284142 non-null  object
 30  StratificationID2           284142 non-null  object
dtypes: float64(4), int64(3), object(24)
memory usage: 67.2+ MB
```

Command 3: df.describe()
This command gives the details of all the values under all the features of the dataset. The command having no parameters gives information about count, max, min, standard deviation, top 25%ile, 50%ile, 75%ile and max value of the dataset.

```
df.describe()
```

	YearStart	YearEnd	Data_Value	Data_Value_Alt	Low_Confidence_Limit	High_Confidence_Limit	LocationID
count	284142.000000	284142.000000	192808.000000	192808.000000	192597.000000	192597.000000	284142.000000
mean	2018.596065	2018.657735	37.676757	37.676757	33.027824	42.595333	800.322677
std	2.302815	2.360105	25.213484	25.213484	24.290016	26.156408	2511.564977
min	2015.000000	2015.000000	0.000000	0.000000	-0.700000	1.300000	1.000000
25%	2017.000000	2017.000000	15.900000	15.900000	12.600000	19.700000	19.000000
50%	2019.000000	2019.000000	32.800000	32.800000	27.000000	38.900000	34.000000
75%	2021.000000	2021.000000	56.900000	56.900000	49.400000	64.600000	49.000000
max	2022.000000	2022.000000	100.000000	100.000000	99.600000	100.000000	9004.000000

If the parameter of include="all" is included { df.describe(include="all")}, this includes even the non numeric values and gives some more information on fields such as count of unique values, top value, etc.

```
df.describe(include = "all")
```

	RowId	YearStart	YearEnd	LocationAbbr	LocationDesc	Datasource	Class	Topic	Ques
count	284142	284142.000000	284142.000000	284142	284142	284142	284142	284142	28
unique	36046	NaN	NaN	59	59	1	7	39	
top	BRFSS~2022~2022~42~Q03~TMC01~AGE~RACE	NaN	NaN	US	United States, DC & Territories	BRFSS	Overall Health	Frequent mental distress	Percei of adults experier
freq	15	NaN	NaN	6132	6132	284142	96753	11092	1
mean	NaN	2018.596065	2018.657735	NaN	NaN	NaN	NaN	NaN	
std	NaN	2.302815	2.360105	NaN	NaN	NaN	NaN	NaN	
min	NaN	2015.000000	2015.000000	NaN	NaN	NaN	NaN	NaN	
25%	NaN	2017.000000	2017.000000	NaN	NaN	NaN	NaN	NaN	
50%	NaN	2019.000000	2019.000000	NaN	NaN	NaN	NaN	NaN	
75%	NaN	2021.000000	2021.000000	NaN	NaN	NaN	NaN	NaN	
max	NaN	2022.000000	2022.000000	NaN	NaN	NaN	NaN	NaN	

11 rows × 31 columns

3) Drop columns that are not useful

In data science, it is important to drop the columns that would not help the user while working on the dataset as it would make it cleaner to work with.

Here, we will first check the columns that are present using **df.columns** command

```
[79] df.columns

Index(['RowId', 'YearStart', 'YearEnd', 'LocationAbbr', 'LocationDesc',
       'Datasource', 'Class', 'Topic', 'Question', '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',
       'StratificationCategory1', 'Stratification1', 'StratificationCategory2',
       'Stratification2', 'Geolocation', 'ClassID', 'TopicID', 'QuestionID',
       'LocationID', 'StratificationCategoryID1', 'StratificationID1',
       'StratificationCategoryID2', 'StratificationID2'],
      dtype='object')
```

Now, we will list down the columns that are to be dropped and then pass it on to the command **df.drop(<column_names>, axis=1, inplace=True)**
Replace column names with either the list created previously, or with the column names itself. The inplace attribute takes care that the dataset will stay updated for the rest of the analysis.

```
[80] columns_to_drop = ["RowId", "LocationDesc", "Data_Value_Footnote_Symbol", "Data_Value_Footnote", "Geolocation"]

df.drop(columns_to_drop, axis = 1, inplace = True)
```

After running these commands, we run the **df.columns** command once again to check with the list of columns.

```
[82] df.columns

Index(['YearStart', 'YearEnd', 'LocationAbbr', 'Datasource', 'Class', 'Topic',
       'Question', 'Data_Value_Unit', 'DataValueTypeID', 'Data_Value_Type',
       'Data_Value', 'Data_Value_Alt', 'Low_Confidence_Limit',
       'High_Confidence_Limit', 'StratificationCategory1', 'Stratification1',
       'StratificationCategory2', 'Stratification2', 'ClassID', 'TopicID',
       'QuestionID', 'LocationID', 'StratificationCategoryID1',
       'StratificationID1', 'StratificationCategoryID2', 'StratificationID2'],
      dtype='object')
```

As observed here, the columns of RowId, LocationDesc, Data_Value_Footnote_Symbol, Data_Value_Footnote and Geolocation have been dropped.

4) Drop rows with maximum missing columns

It is important to drop the rows with maximum missing values as they would hinder the performance of the analysis and can lead to inaccuracies in the dataset. To perform this, follow these steps:

df.describe(): This command will give the count of rows present in the dataset.

```
df.describe()
```

	YearStart	YearEnd	Data_Value	Data_Value_Alt	Low_Confidence_Limit	High_Confidence_Limit	LocationID
count	284142.000000	284142.000000	192808.000000	192808.000000	192597.000000	192597.000000	284142.000000
mean	2018.596065	2018.657735	37.676757	37.676757	33.027824	42.595333	800.322677
std	2.302815	2.360105	25.213484	25.213484	24.290016	26.156408	2511.564977
min	2015.000000	2015.000000	0.000000	0.000000	-0.700000	1.300000	1.000000
25%	2017.000000	2017.000000	15.900000	15.900000	12.600000	19.700000	19.000000
50%	2019.000000	2019.000000	32.800000	32.800000	27.000000	38.900000	34.000000
75%	2021.000000	2021.000000	56.900000	56.900000	49.400000	64.600000	49.000000
max	2022.000000	2022.000000	100.000000	100.000000	99.600000	100.000000	9004.000000

df["missing_count"] = df.isnull().sum(axis=1)
max_missing = df["missing_count"].max()

Here the maximum missing count is 6. So to clean up some of the data, we will remove the rows with 4 or more missing values.

df = df[df["missing_count"] < 4]

The above set of commands do the following function:
i) Create a column called missing_count where the sum of all the cells having null values is stored.
ii) The maximum value from this missing_count column is considered for deletion
iii) Finally, we update the dataset by keeping the rows which have missing values less than a particular value.

```
df.describe()
```

	YearStart	YearEnd	Data_Value	Data_Value_Alt	Low_Confidence_Limit	High_Confidence_Limit	LocationID	missing_count
count	192808.000000	192808.000000	192808.000000	192808.000000	192597.000000	192597.000000	192808.000000	192808.000000
mean	2018.595224	2018.655372	37.676757	37.676757	33.027824	42.595333	1145.457766	0.383573
std	2.301531	2.357772	25.213484	25.213484	24.290016	26.156408	2959.026567	0.787414
min	2015.000000	2015.000000	0.000000	0.000000	-0.700000	1.300000	1.000000	0.000000
25%	2017.000000	2017.000000	15.900000	15.900000	12.600000	19.700000	19.000000	0.000000
50%	2019.000000	2019.000000	32.800000	32.800000	27.000000	38.900000	35.000000	0.000000
75%	2021.000000	2021.000000	56.900000	56.900000	49.400000	64.600000	51.000000	0.000000
max	2022.000000	2022.000000	100.000000	100.000000	99.600000	100.000000	9004.000000	2.000000

After running these sets of commands, we run the command **df.describe()** once again. Using this, we can see that the number of rows dropped from 284142 to 192808. (~32.14%)

5) Take care of missing data

To take care of the missing data that has not been removed, one of the 2 methods can be used:
→ If the feature is of a numeric data type, we can use either mean, median or mode of the feature. If the data is normally distributed, use mean, if it is skewed, use median, and if many

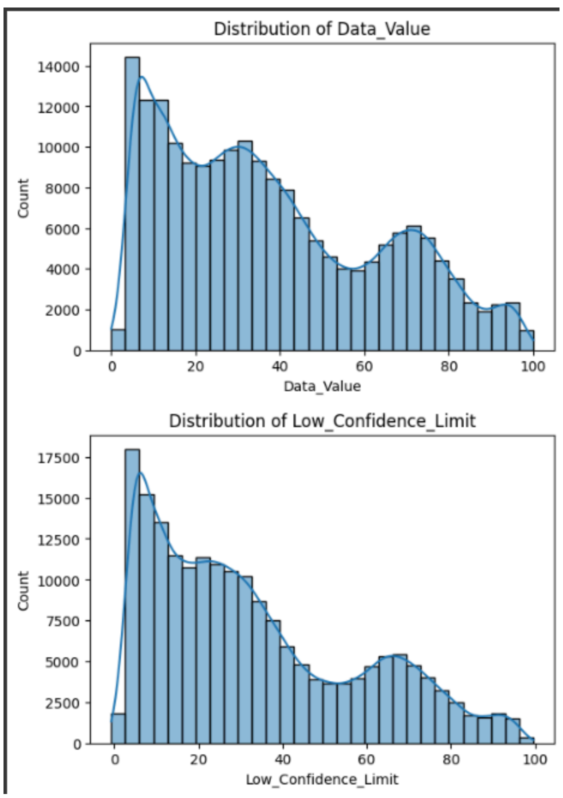
values are repeated, use mode.
→ If the feature contains different categories, there are 2 ways. Either fill it with the mode of the column, or add a custom value such as “Data Unavailable”.
Here, we would be filling the missing data for columns of Data_Value, Low_Confidence_Limit and High_Confidence_Limit
To check how to fill the missing data, follow the steps below.

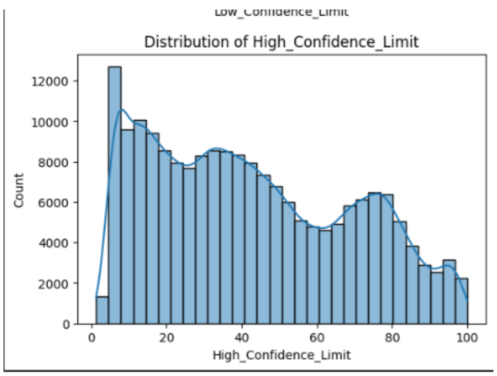
i) **Check for skewness**

```
import seaborn as sns
import matplotlib.pyplot as plt

num_cols = ["Data_Value", "Low_Confidence_Limit", "High_Confidence_Limit"]

for col in num_cols:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[col], kde=True, bins=30)
    plt.title(f"Distribution of {col}")
    plt.show()
```





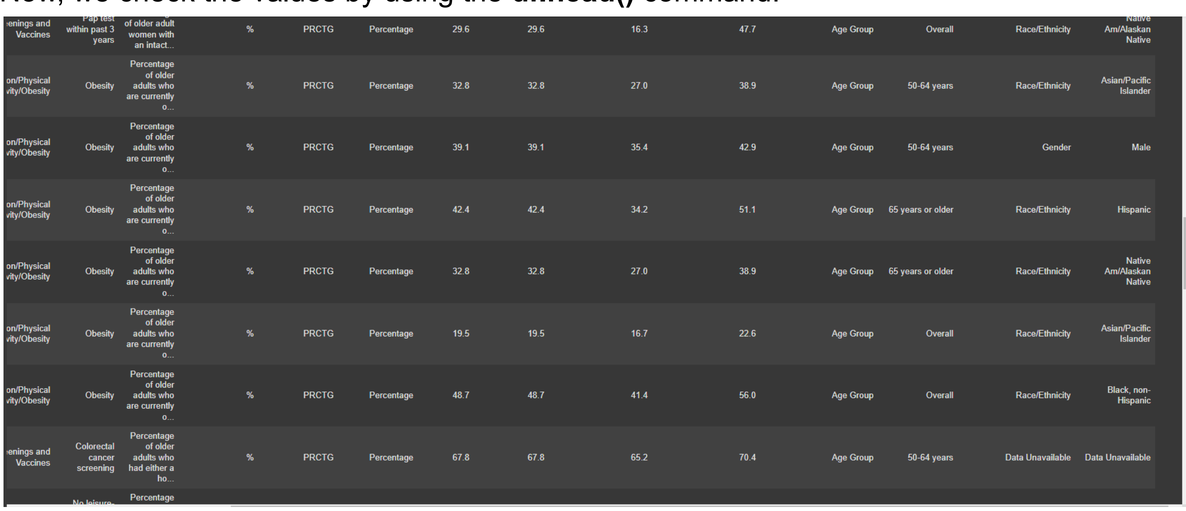
As we can see here, there is a skewness to the left of the graph for each parameter, which means the data is not evenly distributed. Hence we use median.

Commands:
df[“Data_Value”].fillna(df[“Data_Value”].median(), inplace=True)
df[“Low_Confidence_Limit”].fillna(df[“Low_Confidence_Limit”].median(), inplace=True)
df[“High_Confidence_Limit”].fillna(df[“High_Confidence_Limit”].median(), inplace=True)

For columns StratificationCategory2 and Stratification2, as sufficient data is not available, we would fill the missing values with a placeholder “Data Unavailable”

Commands:
df["StratificationCategory2"].fillna("Data Unavailable", inplace=True)
df["Stratification2"].fillna("Data Unavailable", inplace=True)

Now, we check the values by using the **df.head()** command.



enings and Vaccines	Pap test within past 3 years	of older adult women with an intact...	%	PRCTG	Percentage	29.6	29.6	16.3	47.7	Age Group	Overall	Race/Ethnicity	Native Am/Alaskan Native
on/Physical vity/Obesity	Obesity	Percentage of older adults who are currently o...	%	PRCTG	Percentage	32.8	32.8	27.0	38.9	Age Group	50-64 years	Race/Ethnicity	Asian/Pacific Islander
on/Physical vity/Obesity	Obesity	Percentage of older adults who are currently o...	%	PRCTG	Percentage	39.1	39.1	35.4	42.9	Age Group	50-64 years	Gender	Male
on/Physical vity/Obesity	Obesity	Percentage of older adults who are currently o...	%	PRCTG	Percentage	42.4	42.4	34.2	51.1	Age Group	65 years or older	Race/Ethnicity	Hispanic
on/Physical vity/Obesity	Obesity	Percentage of older adults who are currently o...	%	PRCTG	Percentage	32.8	32.8	27.0	38.9	Age Group	65 years or older	Race/Ethnicity	Native Am/Alaskan Native
on/Physical vity/Obesity	Obesity	Percentage of older adults who are currently o...	%	PRCTG	Percentage	19.5	19.5	16.7	22.6	Age Group	Overall	Race/Ethnicity	Asian/Pacific Islander
on/Physical vity/Obesity	Obesity	Percentage of older adults who are currently o...	%	PRCTG	Percentage	48.7	48.7	41.4	56.0	Age Group	Overall	Race/Ethnicity	Black, non-Hispanic
enings and Vaccines	Colorectal cancer screening	Percentage of older adults who had either a ho...	%	PRCTG	Percentage	67.8	67.8	65.2	70.4	Age Group	50-64 years	Data Unavailable	Data Unavailable
	No leisure-	Percentage											

6) Create Dummy Variables

It is essential to create dummy variables to the columns that contain categorical data as most of the algorithms cannot understand the data directly. So they are classified as True and False or 0 and 1 which makes it easier.

To create the dummy variables, we will list the columns that fall under categorical columns and then create another variable as pd_dummies to get the output of this. Pandas library provides a inbuilt function called as get_dummies which takes the data from the columns and create all the required dummy variables

Command:
categorial_columns = ["LocationAbbr", "Question", "StratificationCategory1", "Stratification1"]
df_dummies = pd.get_dummies(df, columns=categorial_columns, drop_first=True)

To check these new columns, we use the command **df_dummies.columns.** As we see in the output, each Question is being treated as a new column.

```
df_dummies.columns

Index(['YearStart', 'YearEnd', 'Datasource', 'Class', 'Topic',
       'Data_Value_Unit', 'DataValueTypeID', 'Data_Value_Type', 'Data_Value',
       'Data_Value_Alt',
       ...
       'Question_Percentage of older adults who reported that as a result of subjective cognitive decline or memory loss that they need assistance with day-to-day activities',
       'Question_Percentage of older adults who self-reported that their health is "fair" or "poor"',
       'Question_Percentage of older adults who self-reported that their health is "good", "very good", or "excellent"',
       'Question_Percentage of older adults with a lifetime diagnosis of depression',
       'Question_Percentage of older adults with subjective cognitive decline or memory loss who reported talking with a health care professional about it',
       'Question_Percentage of older adults without diabetes who reported a blood sugar or diabetes test within 3 years',
       'Question_Physically unhealthy days (mean number of days in past month)',
       'Question_Severe joint pain due to arthritis among older adults with doctor-diagnosed arthritis',
       'Stratification1_65 years or older', 'Stratification1_Overall'],
      dtype='object', length=112)
```

7) Find out Outliers

Outliers are those data values that vary vastly from the other dataset values. It is important to detect these values as they affect the analysis result.

To find the outliers, there are 2 ways:

Method 1: Box-Plot

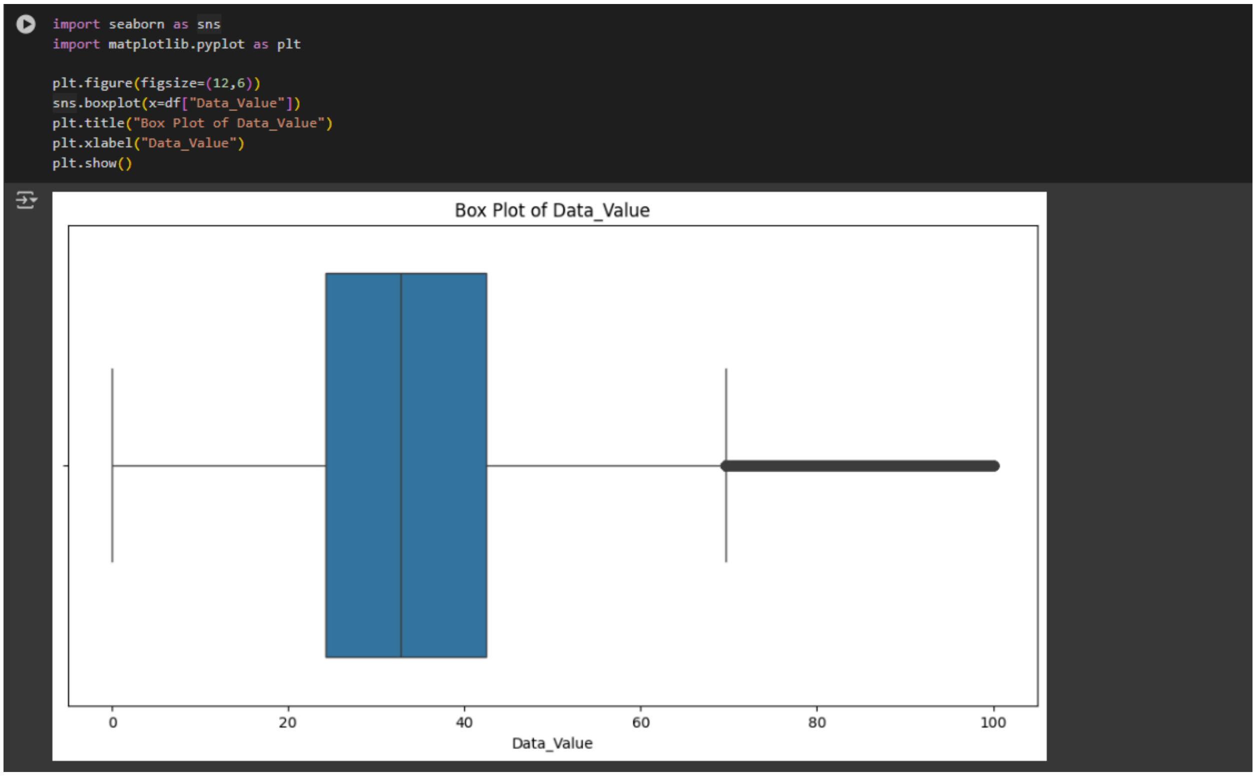
In this method, we use the column values to plot a box-plot graph. The values are usually in a box having lower and higher limit. If any outliers present, the come out of the box of the graph.

Command:

```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(12,6))
sns.boxplot(x=df["Data_Value"])
plt.title("Box Plot of Data_Value")
plt.xlabel("Data_Value")
```

plt.show()



Method 2: Using IQR Value.

In this method, we find the IQR value fo the column; which is the difference between Q1 - 1.5 * IQR and Q3 + 1.5 * IQR. This is a standard that is followed, the factor 1.5 can be modified between 1 to 3 based on the requirement.

Command:

```
Q1 = df['Data_Value'].quantile(0.25)
Q3 = df['Data_Value'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
outliers = df[(df['Data_Value'] < lower_bound) | (df['Data_Value'] > upper_bound)]
print("Number of Outliers in Data Value:", len(outliers))
print(outliers.head())
```

```python
Q1 = df['Data_Value'].quantile(0.25)
Q3 = df['Data_Value'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
outliers = df[(df['Data_Value'] < lower_bound) | (df['Data_Value'] > upper_bound)]
print("Number of Outliers in Data Value:", len(outliers))
print(outliers.head())
```

```
Number of Outliers in Data Value: 29810
    YearStart  YearEnd LocationAbbr Datasource                  Class  \
10       2022     2022           MD      BRFSS         Overall Health
11       2022     2022           NY      BRFSS         Overall Health
33       2022     2022           WA      BRFSS  Screenings and Vaccines
34       2022     2022           HI      BRFSS  Screenings and Vaccines
35       2022     2022           HI      BRFSS  Screenings and Vaccines

                        Topic  \
10 Oral health:  tooth retention
11 Oral health:  tooth retention
33 Mammogram within past 2 years
34 Mammogram within past 2 years
35 Mammogram within past 2 years

                                             Question Data_Value_Unit  \
10 Percentage of older adults who report having l...               %
11 Percentage of older adults who report having l...               %
33 Percentage of older adult women who have recei...               %
34 Percentage of older adult women who have recei...               %
35 Percentage of older adult women who have recei...               %

   DataValueTypeID Data_Value_Type  Data_Value  Data_Value_Alt  \
10           PRCTG      Percentage        71.5            71.5
11           PRCTG      Percentage        73.9            73.9
33           PRCTG      Percentage        73.2            73.2
34           PRCTG      Percentage        75.0            75.0
35           PRCTG      Percentage        84.4            84.4

    Low_Confidence_Limit  High_Confidence_Limit StratificationCategory1  \
10                  50.0                   86.3               Age Group
11                  60.4                   84.0               Age Group
33                  71.0                   75.3               Age Group
34                  67.9                   80.9               Age Group
35                  66.1                   93.7               Age Group

      Stratification1 StratificationCategory2        Stratification2
10  65 years or older          Race/Ethnicity  Asian/Pacific Islander
11  65 years or older          Race/Ethnicity  Asian/Pacific Islander
```

From both the outputs, we get to know that there are some outliers present in the dataset. We can analyse the dataset manually to get the outliers, or use IQR score which gives us how many outliers are present based on our conditions.

8) Standardization and Normalization of columns

We can standardize and normalize columns using 1 of 2 methods. Either by their formulae, or by the SKLearn Library.

Standardize Column:
Using formula:

mean_value = df["Data_Value"].mean()
std_value = df["Data_Value"].std()
df["Standardized_Data_Value"] = (df["Data_Value"] - mean_value) / std_value

Using Library:

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df['Standardized Data Value Scalar'] = scaler.fit_transform(df[['Data_Value']])

```
[68] df[["Data_Value", "Standardized_Data_Value", "Standardized Data Value Scalar"]].head()
```

	Data_Value	Standardized_Data_Value	Standardized Data Value Scalar
0	32.8	-0.158409	-0.158410
1	32.8	-0.158409	-0.158410
2	32.8	-0.158409	-0.158410
3	9.0	-1.297282	-1.297284
4	5.6	-1.459978	-1.459980

Normalize column:

Method 1: Formula

min_val = df['Data_Value'].min()
max_val = df['Data_Value'].max()

df['Data_Value_Normalized'] = (df['Data_Value'] - min_val) / (max_val - min_val)

Method 2: Scaler library

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df['Normalized Data Value Scalar'] = scaler.fit_transform(df[['Data_Value']])

```
[73] df[['Data_Value', 'Data_Value_Normalized', 'Normalized Data Value Scalar']].head()
```

	Data_Value	Data_Value_Normalized	Normalized Data Value Scalar
0	32.8	0.328	0.328
1	32.8	0.328	0.328
2	32.8	0.328	0.328
3	9.0	0.090	0.090
4	5.6	0.056	0.056

Conclusion:

Thus we have performed pre-processing on the dataset of Alzhiemers diseases and Healthy Aging data.

To load the data into pandas, we used the read_csv() function of the pandas library to load it. To verify this, we used the head() function to show the 1st 5 entries of the dataset.

For a description, we used various methods such as head(), info(), describe() which gave information such as data types, mean, max, min, count, etc.

Using drop() command, we dropped the columns off the dataset that would not have had much impact on the analysis. In this dataset, we dropped columns such as RowId, LocationDesc, Data_Value_Footnote_Symbol, Data_Value_Footnote and Geolocation.

For dropping rows with maximum missing values, we implemented a series of commands on our dataset that checked each entry for missing values, selected the max from amongst them and then deleted those rows with maximum missing values. This is done so that it does not bring up the skewness of the dataset. In our dataset, the data is reduced from 284142 to 192808. (~32.14%)

Now, to take care of the missing data, we analysed the data which is available by taking graphs of it, and used the apt method (mean, median, mode) to fill up the missing values of the database.

Columns such as Questions, LoactionAbbr would have caused an error while performing analysis on the dataset. To reduce this, such columns are being converted to dummy variables where their entries are 0 or 1.

To find the outliers, we first plotted the boxplot. From this graph, we got to know about the outliers present outside the box graph. After manual analysis, we decided to use the IQR index technique to check out the outliers of the dataset.

Now, while analysis, data with higher values can tend to affect the analysis. To reduce this anomaly, we normalize and standardize the graph based on minmax/standard deviation methods to get the values to a reasonable range for the analysis to take place smoothly.