PROJECT 3 GROUP 6

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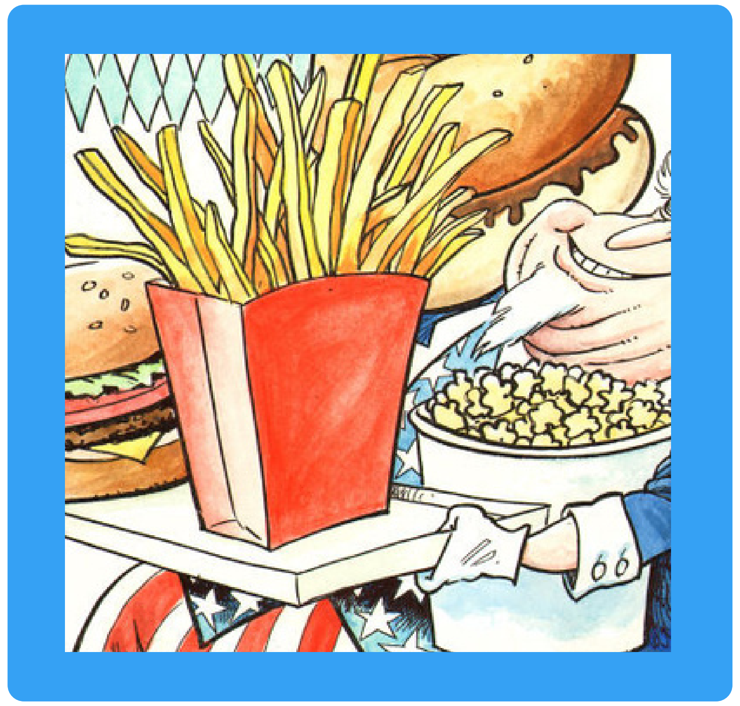
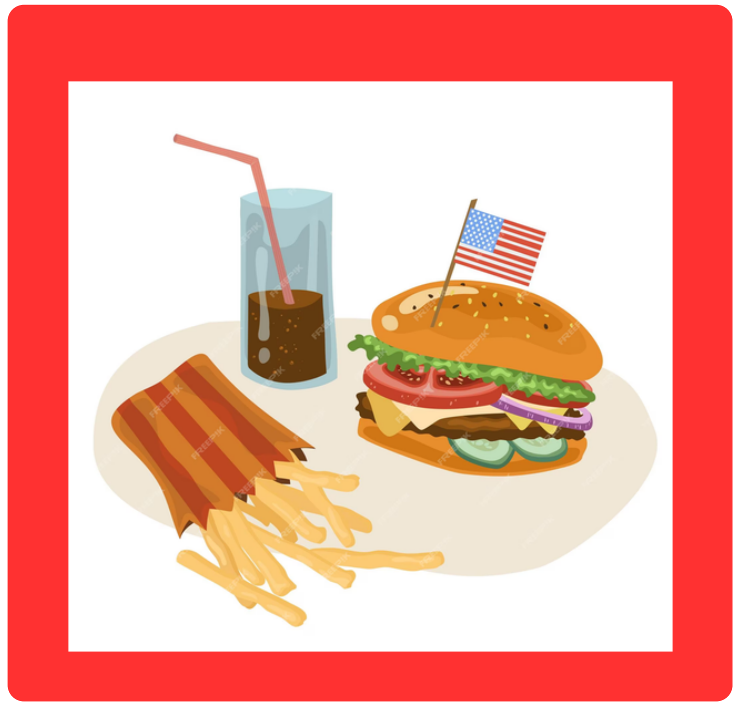
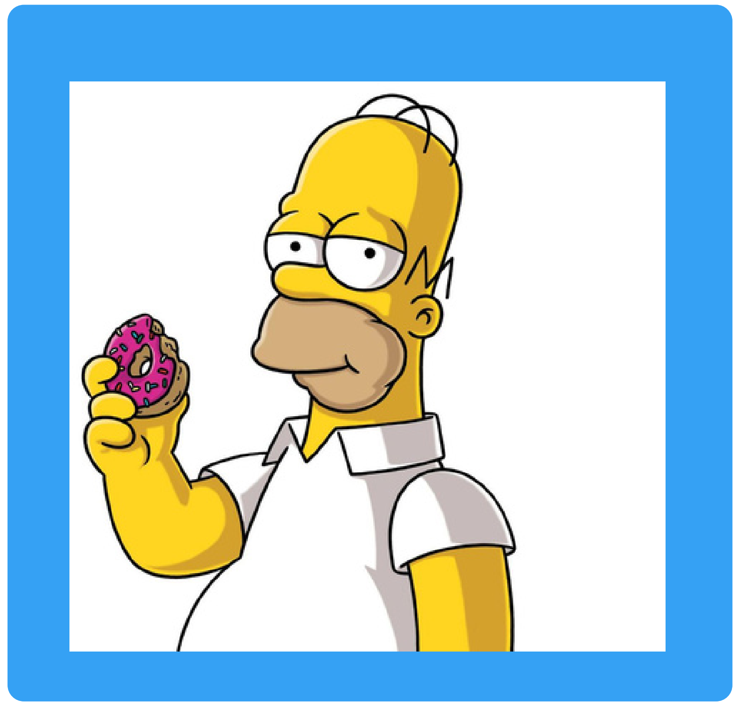
USA ANALYSIS







Obesity Trends Vs. The Number of Fast Food Restaurants

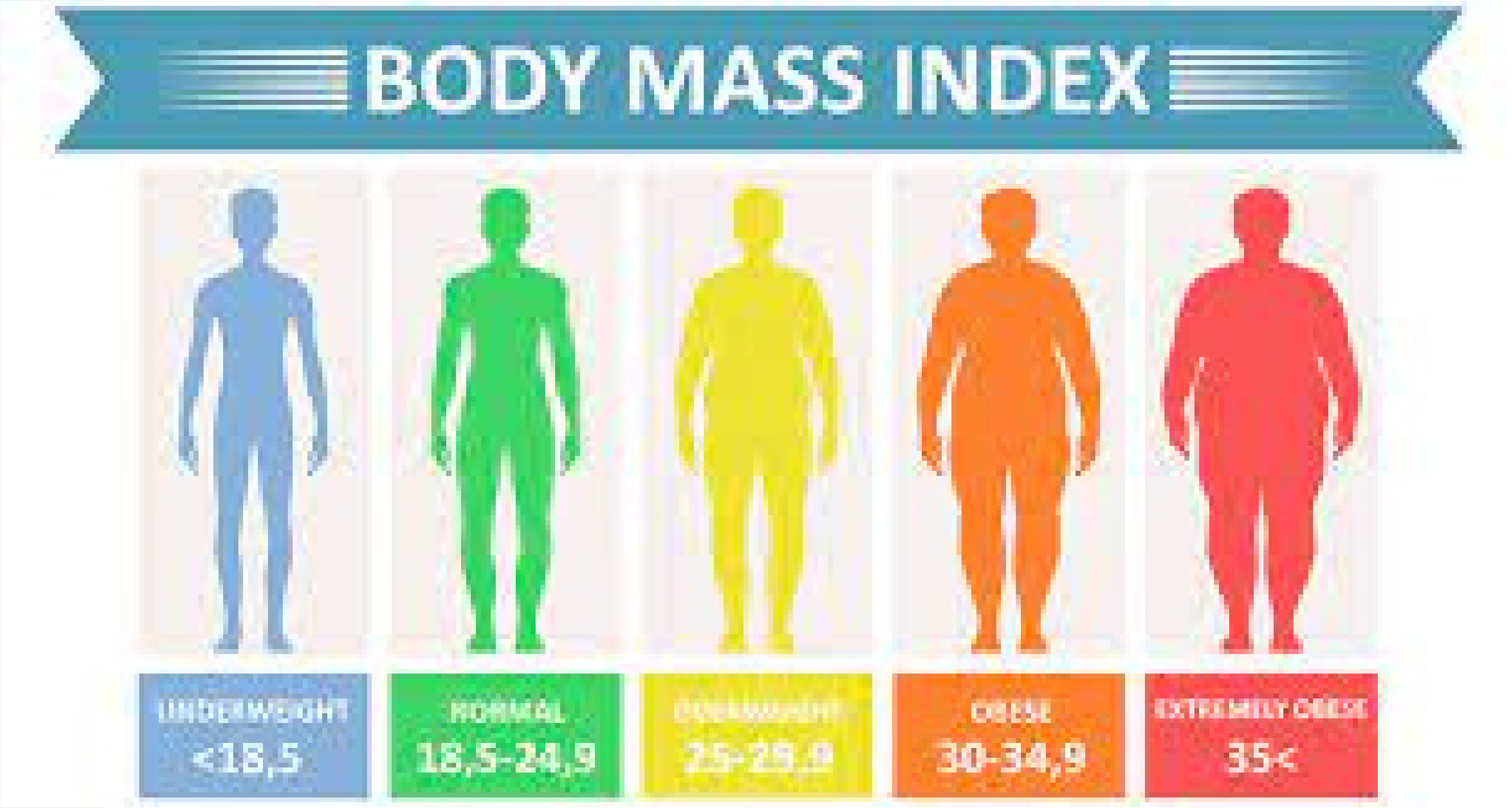
2014-2019

DATA ANALYSIS

1. U.S OBESITY RATES BETWEEN 2014-2019
2. NUMBER OF FAST FOOD RESTAURANTS IN THE U.S BETWEEN 2014-2019
3. U.S GDP BETWEEN 2014-2019
4. U.S OBESITY MORTALITY RATE DURING 2014-2019

OBESITY SNAPSHOT

- Obesity: BMI of 30 or higher.
- Multitude of health risks,
- Prevalence is increasing



BACK TO AGENDA PAGE

TECHNICAL SKILLS

1. JUPYTER NOTEBOOK
2. SQLITE
3. JAVASCRIPT
4. PYTHON FLASK API

DATA CLEANING

```
[2]: # Store filepath in a variable
     file_one = Path("Resources/BRFSS__Table_of_Overweight_and_Obesity__BMI__20231102.csv")
```

```
[3]: # Read our Data file with the pandas library
     # Not every CSV requires an encoding, but be aware this can come up
     file_one_df = pd.read_csv(file_one, encoding="ISO-8859-1")
```

```
[4]: # Show just the header
     file_one_df.head()
```

[4]:

	Year	Locationabbr	Locationdesc	Class	Topic	Question	Response	Break_Out	Break_Out_Category	Sam
0	2020	AK	Alaska	Overweight and Obesity (BMI)	BMI Categories	Weight classification by Body Mass Index (BMI)...	Underweight (BMI 12.0-18.4)	45-54	Age Group	
1	2019	AL	Alabama	Overweight and Obesity (BMI)	BMI Categories	Weight classification by Body Mass Index (BMI)...	Underweight (BMI 12.0-18.4)	35-44	Age Group	
2	2019	AL	Alabama	Overweight and Obesity (BMI)	BMI Categories	Weight classification by Body Mass Index (BMI)...	Underweight (BMI 12.0-18.4)	Other, non-Hispanic	Race/Ethnicity	
3	2019	AL	Alabama	Overweight and Obesity (BMI)	BMI Categories	Weight classification by Body Mass Index (BMI)...	Underweight (BMI 12.0-18.4)	Multiracial, non-Hispanic	Race/Ethnicity	

```
# Export file as a CSV, without the Pandas index, but with the header
cleaned_columns_df.to_csv("clean_data/BRFSS__Table_of_Overweight_and_Obesity__BMI__20231102_cleaned.csv
```

```
# Filter Response to "Obese" only to filter out the Data_value with entries
cleaned_columns_df['Response'] = cleaned_columns_df['Response'].astype(str)
print(cleaned_columns_df.dtypes)
cleaned_columns_df = cleaned_columns_df.loc[(cleaned_columns_df["Response"].str.contains("Obese")) | (c
print(cleaned_columns_df.count())
cleaned_columns_df

unique_years = cleaned_columns_df['Year'].unique()
count = len(unique_years)
print(f"Number of unique_years: {count}")
```

	A	B	C	D	E	F	G	H	I	J
1	address	city	country	keys	latitude	longitude	name	postalCod	province	websites
2	324 Main S	Massena	US	us/ny/ma	44.9213	-74.8902	McDonald	13662	NY	http://mcd
3	530 Clinto	Washingto	US	us/oh/wa	39.53255	-83.4453	Wendy's	43160	OH	http://www
4	408 Marke	Maysville	US	us/ky/ma	38.62736	-83.7914	Frisch's Bi	41056	KY	http://www
5	6098 State	Massena	US	us/ny/ma	44.95008	-74.8455	McDonald	13662	NY	http://mcd
6	139 Colum	Athens	US	us/oh/ath	39.35155	-82.0973	OMG! Rot	45701	OH	http://www
7	4182 Tony	Hamilton	US	us/oh/har	39.4176	-84.4764	Domino's	45011	OH	https://ww
8	590 S Mair	Englewoo	US	us/oh/eng	39.86969	-84.2936	Domino's	45322	OH	https://ww
9	401 N Jenr	Saluda	US	us/sc/salu	34.00598	-81.7704	McDonald	29138	SC	http://www
10	205 W Chu	Batesburg	US	us/sc/bate	33.91335	-81.5333	Wendy's	29006	SC	http://www

```
restaurants_count_df = restaurants_count_df.rename(columns={'State': 'state_code'})
restaurants_count_df.head()
```

	state_code	counts
0	CA	1201
1	TX	811
2	FL	621
3	OH	522
4	GA	420

SQLITE DATA RETRIVING & MERGING

```
# Python SQL toolkit and Object Relational Mapper
import sqlalchemy
from sqlalchemy.ext.automap import automap_base
from sqlalchemy.orm import Session
from sqlalchemy import create_engine, inspect
import sqlite3
import pandas as pd
```

```
# Create engine using the sqlite database file
engine = create_engine("sqlite:///./database/project3_group6.sqlite")
```

```
# Reflect Database into ORM classes
Base = automap_base()
Base.prepare(autoload_with=engine)
Base.classes.keys()
```

['death_rates', 'fast_food', 'us_states', 'gdp_state', 'overweight_obesity']

```
merged_df_with_avg_obesity_2019 = pd.merge(final_merged_df, overall_average_da
merged_df_with_avg_obesity_2019
```

	ID	state_code	counts	state_name	latitude	longitude	data_value
0	1	CA	1201	California	37.638640	-121.000000	30.958333
1	2	TX	811	Texas	31.827240	-99.426770	34.583333
2	3	FL	621	Florida	28.932040	-81.928961	31.441667
3	4	OH	522	Ohio	40.060210	-82.404260	34.141667
4	5	GA	420	Georgia	32.839681	-83.627580	33.091667
5	6	IL	405	Illinois	40.485010	-88.997710	32.275000

```
# Round columns to the specified number of decimals
location_gdp_df['amount_2014'] = location_gdp_df['amount_2014'].round(decimals)
location_gdp_df['amount_2015'] = location_gdp_df['amount_2015'].round(decimals)
location_gdp_df['amount_2016'] = location_gdp_df['amount_2016'].round(decimals)
location_gdp_df['amount_2017'] = location_gdp_df['amount_2017'].round(decimals)
location_gdp_df['amount_2018'] = location_gdp_df['amount_2018'].round(decimals)
location_gdp_df['amount_2019'] = location_gdp_df['amount_2019'].round(decimals)
location_gdp_df
```

	ID	state_name	description	amount_2014	amount_2015	amount_2016	amount_2017	amount_2018	amount_2019	state_code	latitude	longitude
0	2	Alabama	GDP (Billions of Dollars)	189.89	191.34	194.28	196.97	200.37	203.43	AL	32.840571	-86.631861
1	3	Alaska	GDP (Billions of Dollars)	54.19	54.74	54.25	54.28	53.33	53.43	AK	64.845080	-147.722059
2	4	Arizona	GDP (Billions of Dollars)	276.95	282.58	291.28	303.61	314.83	325.40	AZ	34.865970	-111.763811
3	5	Arkansas	GDP (Billions of Dollars)	111.73	112.35	112.80	113.85	115.89	117.13	AR	34.748650	-92.274491
4	6	California	GDP (Billions of Dollars)	2256.05	2357.45	2427.89	2538.20	2644.06	2729.23	CA	37.638640	-121.000000
5	7	Colorado	GDP (Billions of Dollars)	298.66	312.41	318.95	329.91	342.73	358.44	CO	38.843841	-106.133611

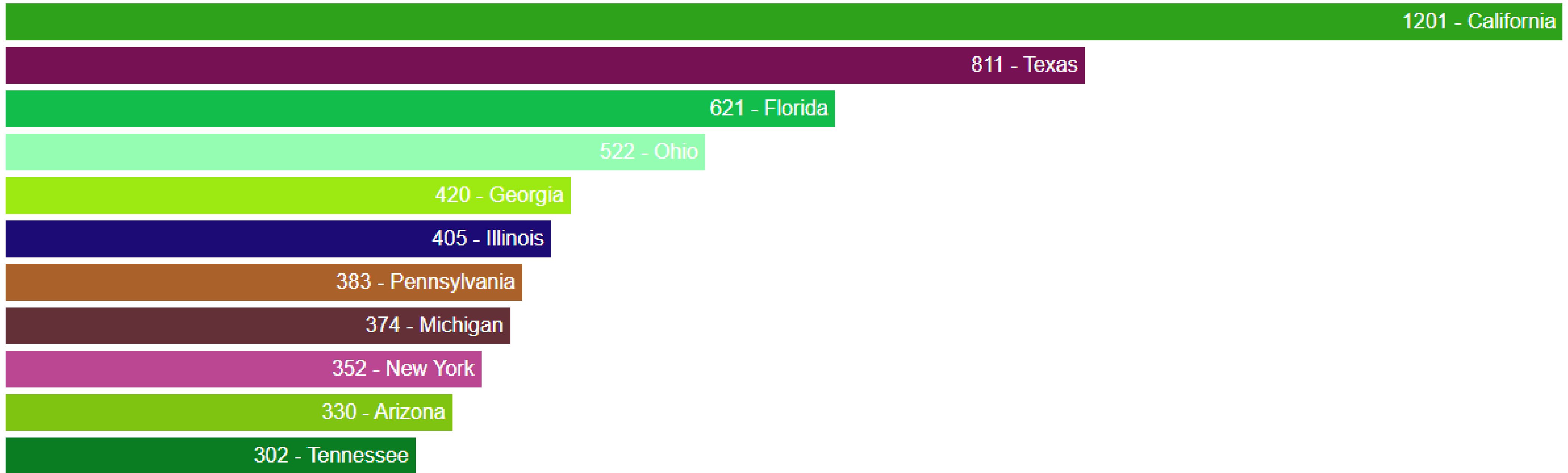
JSON

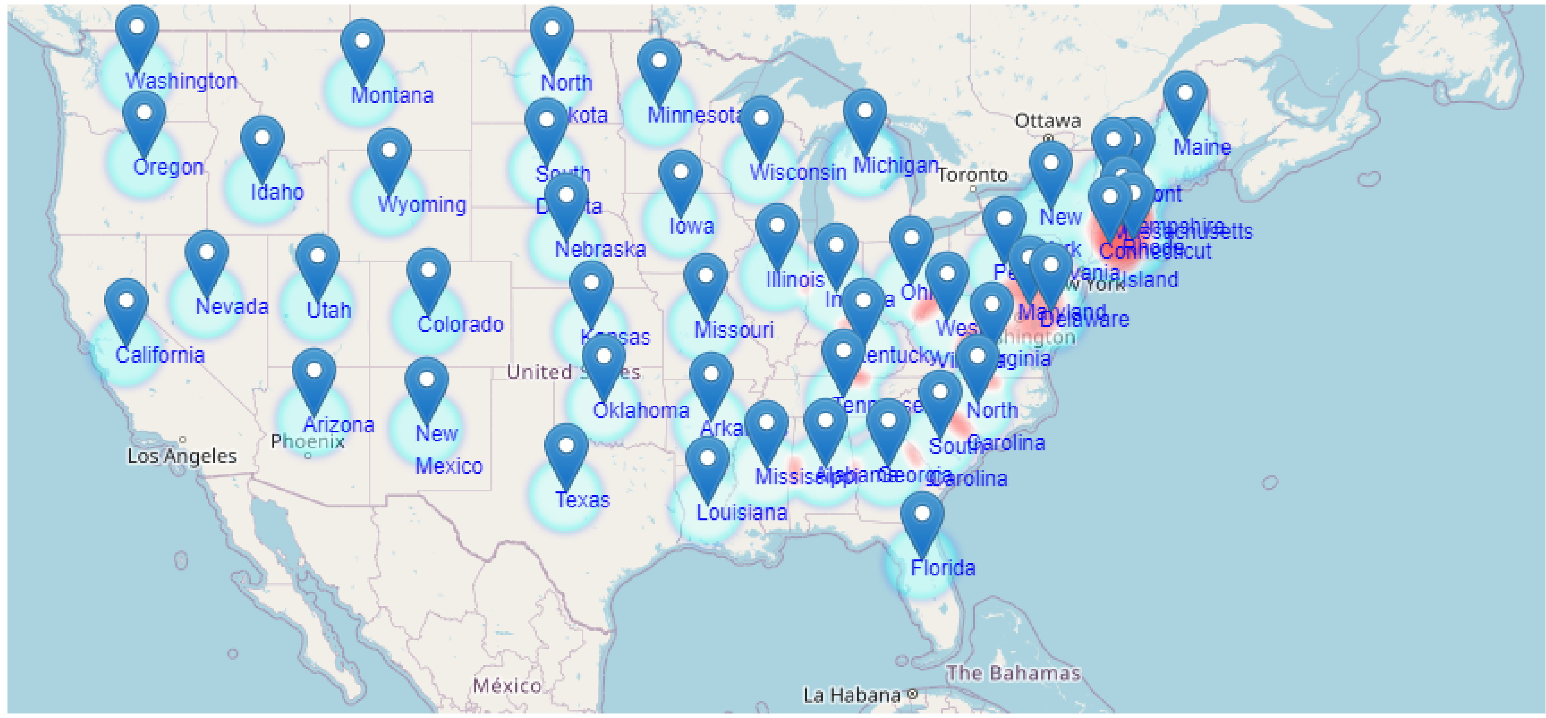
VISUALISATIONS USING HTML AND JAVASCRIPT

visualisation > JS script_for_restaurant_barchart.js > ...

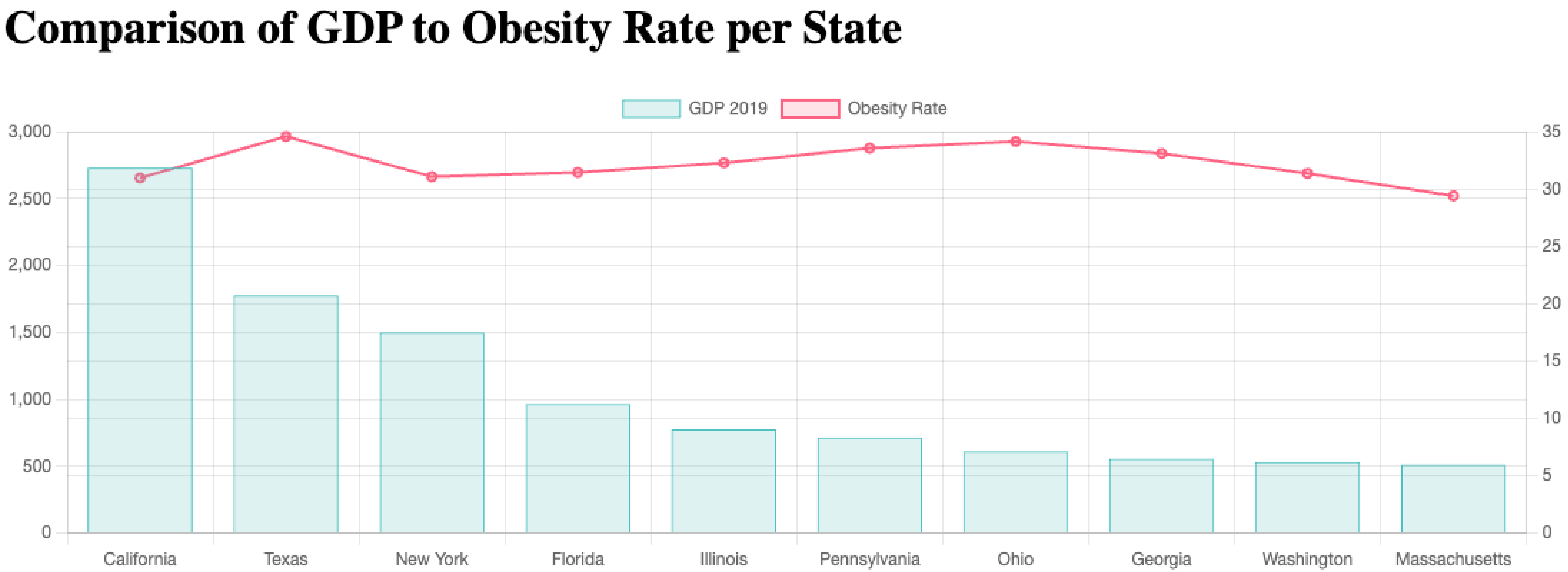
```javascript
// Function to create a bar chart using D3.js
function createBarChart(data) {
    const chartContainer = d3.select("#chartContainer");

    chartContainer
        .selectAll(".bar")
        .data(data)
        .enter()
        .append("div")
        .attr("class", "bar")
        .style("height", d => d.counts + "px")
        .attr("title", d => `${d.state_name}: ${d.counts} counts`)
        .text(d => d.counts);
}

// Use d3.json to load the data from the JSON file
d3.json("savedata_records.json").then(data => {
    // Call the function with the loaded data
    createBarChart(data);
});
```

```html
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Fastfood Restaurant Counts Horizontal Bar Chart</title>
    <style>
        body {
            font-family: Arial, sans-serif;
        }
        .chart-container {
            width: 80%;
            margin: 50px auto;
        }
        .bar-container {
            display: flex;
            align-items: center;
            margin-bottom: 5px;
```



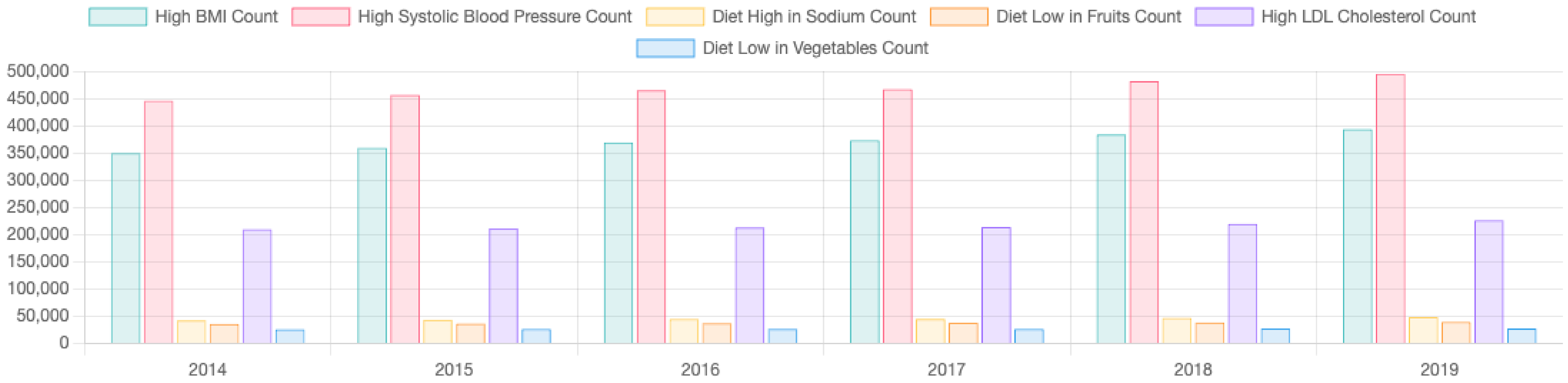


GDP VS. OBESITY RATES



DEATH RATES RELATED to OBESITY

Death Rates related to Obesity



CONCLUSION

Limitations

- In the analysis, we only covered the United States. If we covered other countries, we would be able to investigate other factors that affect obesity rates worldwide i.e physical activity.
- Another limitation was that our number of fast-food restaurants, we were only able to find data for 2019.

Conclusions

- Our analysis concluded that there was no strong correlation between GDP and obesity.
- There was also no direct link between the number of fast-food restaurants and obesity and overweight.
- We did find that there was a higher rate of obesity and overweight rate in the eastern state of the USA rate.

DEMONSTRATION

THANK YOU!

ANY QUESTION?