\usepackage{fvextra} \DefineVerbatimEnvironment{Highlighting}{Verbatim}{breaklines,commandchars=\\\{\}}

\RecustomVerbatimEnvironment{verbatim}{Verbatim}{ showspaces = false, showtabs = false, breaksymbolleft={}, breaklines }

PSet 4

AUTHOR
Charisma Lambert and Prashanthi Subbiah

PUBLISHED
November 2, 2024

IMPORTANT NOTE 1: Our qmd was able to knit to show the code and output from Section 1 Q1 until Section 5 Q1. Section 5 Q2 onwards, the kernal kept crashing for on partners' systems. Thus, we wrote to Professor Maggie Shi, Professor Peter Ganong, and TA Ozzy Houck. We were instructed to comment out the codes of Section 5. They had also mentioned that while grading, the grader should run these codes on their system, and if it runs, we would get full credit, and if the output does not fully match the solutions, we would get partial credit. The codes for the following questions have been commented out as per these guidelines.

IMPORTANT NOTE 2: With reference to the following response from Professor Maggie Shi to our Ed Post, we have reduced the number of times we have read the file in our latest qmd so that running the code takes up less memory:

"Ozzy took a look at your submission this morning and had the following comment: I tried to run Charisma and Prashanthi's code and got an error in the sections they were having trouble in. I think their issue was partially that they kept re-reading in the data under different names and so I'm guessing the kernel was crashing because they ran out of memory.

If you can fix the code only to improve memory usage and can get it to knit, you can resubmit. Otherwise the graders will just grade based on your original submission. I'll have @Ozzy re-open the submission for you, which will close at 11:59."

Our kernels are still crashing when we run Section 5, but we are hoping that this updated code has a better chance at running on your system. We have replied in a post on Ed discussion on the initial thread. Thanks for the help!

PS4: Due Sat Nov 2 at 5:00PM Central. Worth 100 points. 1. This problem set is a paired problem set. 2. Play paper, scissors, rock to determine who goes first. Call that person Partner 1. • Partner 1 (name and cnet ID):Charisma Lambert, charisml • Partner 2 (name and cnet ID): Prashanthi Subbiah, prashanthis 3. Partner 1 will accept the ps4 and then share the link it creates with their partner. You can only share it with one partner so you will not be able to change it after your partner has accepted. 4. "This submission is our work alone and complies with the 30538 integrity policy." Add your initials to indicate your agreement: **CLPS**. 5. "I have uploaded the names of anyone else other than my partner and I worked with on the problem set here" (Ahona Roy) (1 point) 6. Late coins used this pset: **1** Late coins left after submission: **3** 7. Knit your ps4.qmd to an PDF file to make ps4.pdf, • The PDF should not be more than 25 pages. Use head() and re-size figures when appropriate. 8. (Partner 1): push ps4.qmd and ps4.pdf to your github repo. 9. (Partner 1): submit ps4.pdf via Gradescope. Add your partner on Gradescope. 10. (Partner 1): tag your submission in Gradescope

Section 1: Download and explore the Provider of Services (POS) file (10 pts) Partner 1

1.

```
import pandas as pd
import os
import csv
import warnings
warnings.filterwarnings("ignore")

base_path = r"/Users/charismalambert/Downloads"

health_path_16 = os.path.join(base_path, "pos2016.csv")
health_data_16 = pd.read_csv(health_path_16)
```

I pulled the following variables:
Provider code: PRVDR_CTGRY_CD and PRVDR_CTGRY_SBTYP_CD CMS certification number: PRVDR_NUM Termination code: PGM_TRMNTN_CD Facility Name: FAC_NAME Zipcode: ZIP_CD

2.

```
short_term_16 = health_data_16[(health_data_16["PRVDR_CTGRY_SBTYP_CD"] == 1) & (health_
short_term_16["year"] = 2016

short_term_len_16 = len(short_term_16)
print(f"There are {short_term_len_16} hospitals reported in the 2016 data.")
```

```
There are 7245 hospitals reported in the 2016 data.
```

a. There are 7,245 hospitals reported in the 2016 data.
b. I found a report from the American Hospital Association that there were 5,534 hospitals registered in the US in 2016. I think it differs because their data does not contain outliers or fuzz, such as a if a hospital closed at any point in 2016 they likely removed it from their dataset, whereas our dataset might have it for the full year.

3.

```
# Repeat 3 steps for 2017- 2019: 1) load data, 2) filter for short-term, and 3) find nu
health_path_17 = os.path.join(base_path, "pos2017.csv")
health_data_17 = pd.read_csv(health_path_17)
short_term_17 =  health_data_17[(health_data_17["PRVDR_CTGRY_SBTYP_CD"] == 1) & (health
short_term_17["year"] = 2017

health_path_18 = os.path.join(base_path, "pos2018.csv")
health_data_18 = pd.read_csv(health_path_18, encoding='latin1')
short_term_18 = health_data_18[(health_data_18["PRVDR_CTGRY_SBTYP_CD"] == 1) & (health_
short_term_18["year"] = 2018
```

```
health_path_19 = os.path.join(base_path, "pos2019.csv")
health_data_19 = pd.read_csv(health_path_19, encoding='latin1')
short_term_19 = health_data_19[(health_data_19["PRVDR_CTGRY_SBTYP_CD"] == 1) & (health_
short_term_19["year"] = 2019

short_term_len_17 = len(short_term_17)
short_term_len_18 = len(short_term_18)
short_term_len_19 = len(short_term_19)
```

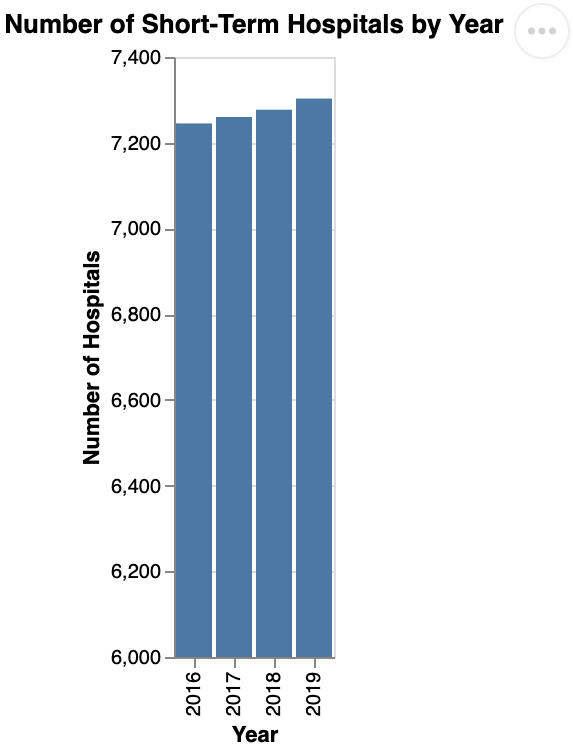
```
# Append the hospital data from 2016 - 2019 together
combined_df_final = pd.concat([short_term_16, short_term_17, short_term_18, short_term_19
combined_df_final
```

	PRVDR_CTGRY_SBTYP_CD	PRVDR_CTGRY_CD	CHOW_CNT	CHOW_DT	CITY_NAME	FAC_NAME
0	1.0	1	1	19730630.0	MULLENS	WYOMING COMM HOSP INC
1	1.0	1	1	19800401.0	STOCKTON	ST JOSEPHS PARKSIDE HOSPITAL
2	1.0	1	1	19800411.0	IRVING	PIONEER PARK MEDICAL CENTER
3	1.0	1	2	19800724.0	NEW ORLEANS	JO ELLEN SMITH MEMORIAL HOSPITAL
4	1.0	1	1	19800729.0	GORMAN	BLACKWELL HOSP S EASTLAND CO HOSP DIST
...	...	...	...	...	...	...
29080	1.0	1	0	NaN	CROCKETT	CROCKETT MEDICAL CENTER
29081	1.0	1	0	NaN	EL PASO	EL PASO LTA HOSPTIAL
29082	1.0	1	0	NaN	PFLUGERVILLE	BAYLOR SCOTT & WHITE MEDICAL

	PRVDR_CTGRY_SBTYP_CD	PRVDR_CTGRY_CD	CHOW_CNT	CHOW_DT	CITY_NAME	FAC_NAME
						CENTER ~ PFLUGERV...
29083	1.0	1	0	NaN	HOUSTON	THE HEIGHTS HOSPITAL
29084	1.0	1	0	NaN	SAN ANTONIO	SOUTHCROS HOSPITAL

29085 rows × 10 columns

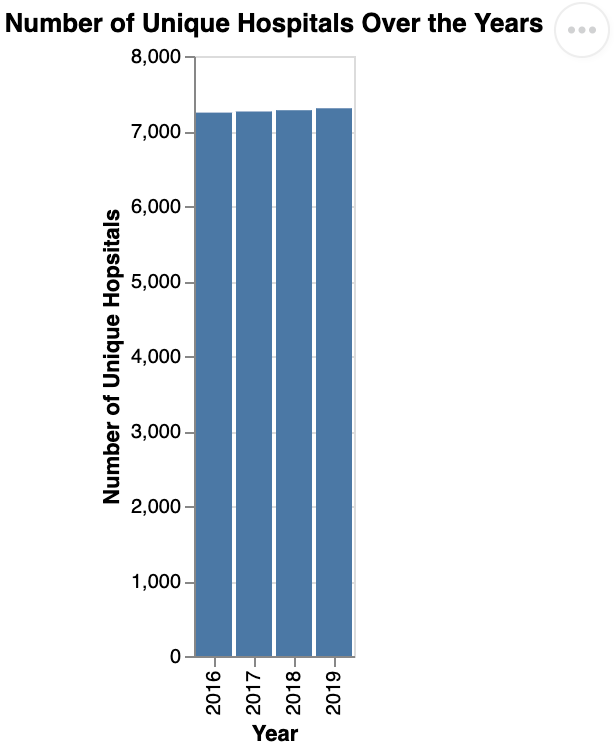
```
# Plot the number of observations by year
observations_by_year = combined_df_final.groupby("year").size().reset_index(name = "obs

import altair as alt
obs_by_year = alt.Chart(observations_by_year).mark_bar().encode(
  x = alt.X("year:O", title = "Year"),
  y = alt.Y("observations:Q", title = "Number of Hospitals", scale = alt.Scale(domain =
  ).properties(
  title = "Number of Short-Term Hospitals by Year")

obs_by_year
```



4. a.

```
# Plot the number of unique hospitals
unique_hospitals_yr = combined_df_final.groupby("year")["PRVDR_NUM"].nunique().reset_in
unique_hospitals_yr.columns = ["year", "unique_hospitals"]

unique_hospitals_chart = alt.Chart(unique_hospitals_yr).mark_bar().encode(
```

```
    x = alt.X("year:O", title = "Year"),
    y = alt.Y("unique_hospitals:Q", title = "Number of Unique Hopsitals")).properties(tit
unique_hospitals_chart
```



b. Comparing the two graphs, I am seeing that the data is pretty consistent over the years– that there is an increase over the years. There is long-term stability of hospitals, with a slight increase from year to year, so there are more unique hospitals (new or mergers) but less hospitals than the year total.

Section 2: Identify hospital closures in POS file (15 pts) (*) Partner 2

Q1

```
combined_df_final['ZIP_CD'] = combined_df_final['ZIP_CD'].astype(str)

# Creating dataframe for active hospitals in 2016
certified_2016 = combined_df_final[(combined_df_final["PGM_TRMNTN_CD"] == 00) & (combined

# Creating dataframe for active hospitals in 2017
certified_2017 = combined_df_final[(combined_df_final["PGM_TRMNTN_CD"] == 00) & (combined

# Creating dataframe for active hospitals in 2018
certified_2018 = combined_df_final[(combined_df_final["PGM_TRMNTN_CD"] == 00) & (combined

# Creating dataframe for active hospitals in 2019
certified_2019 = combined_df_final[(combined_df_final["PGM_TRMNTN_CD"] == 00) & (combined
```

```
# Finding out which hospitals were closed by 2019 that were active in 2016, by PRVDR_NUM
hospitals_closed = pd.merge(certified_2016, certified_2019, on='PRVDR_NUM', how='left', i
hospitals_closed = hospitals_closed[hospitals_closed['_merge'] == 'left_only'].drop(colum

# Filtering combined_df_final for entries of hospitals in hospitals_closed (by PGM_TRMNTN
filtered_hospitals_closed = combined_df_final[(combined_df_final['PGM_TRMNTN_CD'] != 00)
                            (combined_df_final['PRVDR_NUM'].isin(hospitals_closed['PRVDR_

# Grouping filtered_hospitals_closed by name of hospital and summarizing year of terminat
last_active_years = (filtered_hospitals_closed.groupby('FAC_NAME')
                     .agg(year_terminated_disappear =('year', 'min'),
                          zip=('ZIP_CD', lambda x: x.unique()[0]))
                     .reset_index())

# Print how many hospitals fit the description:
print("The number of hospitals active in 2016 that are suspected to have closed by 2019 i
```

```
The number of hospitals active in 2016 that are suspected to have closed by 2019 is 177
```

Q2

```
# Sorting by hospital name and printing first 10 hospitals
last_active_years.sort_values(by='FAC_NAME', ascending=True)
last_active_years_1 = last_active_years[["FAC_NAME", "year_terminated_disappear"]]
first_10 = last_active_years.head(10)
print(first_10)
```

```
                                      FAC_NAME  year_terminated_disappear  \
0  (CLOSED) HEALTHSOUTH CHATTANOOGA REHAB HOSPITAL                       2019
1                           ABRAZO MARYVALE CAMPUS                       2017
2        ADVENTIST MEDICAL CENTER - CENTRAL VALLEY                       2017
3                           AFFINITY MEDICAL CENTER                       2018
4    ALBANY MEDICAL CENTER / SOUTH CLINICAL CAMPUS                       2017
5         ALLEGIANCE SPECIALTY HOSPITAL OF KILGORE                       2017
6                           ALLIANCE LAIRD HOSPITAL                       2019
7                         ALLIANCEHEALTH DEACONESS                       2019
8          ARKANSAS VALLEY REGIONAL MEDICAL CENTER                       2017
9              ASCENSION NE WISCONSIN MERCY CAMPUS                       2018

       zip
0  37404.0
1  85031.0
2  93230.0
3  44646.0
4  12208.0
5  75662.0
6  39365.0
```

```
7  73112.0
8  81050.0
9  54904.0
```

Q3a

```
# Grouping by ZIP_CD and year, and summarizing number of active hospitals by filtering fo
active_hospitals_per_year = (combined_df_final[combined_df_final['PGM_TRMNTN_CD'] == 00]
                             .groupby(['ZIP_CD', 'year']).size().reset_index(name='active

active_hospitals_per_year = active_hospitals_per_year[active_hospitals_per_year["ZIP_CD"]

# Created pivot table with columns for ZIP_CD, 2016, 2017, 2018, 2019, each summarizing n
pivoted_df = active_hospitals_per_year.pivot(index='ZIP_CD', columns='year', values='acti

# To view entire dataframes
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
pd.set_option('display.max_colwidth', None)

# Filling 0 for NAs
pivoted_df = pivoted_df.fillna(0)

# Dataframe shows zipcodes that saw either an increase or steady number
increased_hospitals = pivoted_df[(pivoted_df[2017] >= pivoted_df[2016]) |
                                 (pivoted_df[2018] >= pivoted_df[2017]) |
                                 (pivoted_df[2019] >= pivoted_df[2018])]

# List of unique ZIP_CD in above dataframe
no_decrease_zips = increased_hospitals['ZIP_CD'].unique()

# Merges no_decrease_zips with last_active_years to filter out (exclude) zipcodes that sa
merged_df = last_active_years.merge(pivoted_df, how='left', left_on='zip', right_on='ZIP_
filtered_decreases_zips_df = merged_df[~((merged_df['year_terminated_disappear'] == 2016)
                          (merged_df['year_terminated_disappear'] == 2017) & (merged_df[2
                          (merged_df['year_terminated_disappear'] == 2018) & (merged_df[2

# Filtering master dataframe (combined_df_final) for only those hospitals that are in fil
merg_aq = combined_df_final[(combined_df_final['FAC_NAME'].isin(filtered_decreases_zips_d

# Dataframe with total number of hospitals in the corrected list of hospitals
provider_count = merg_aq.groupby('FAC_NAME') \
                        .agg(NUM_CMS=('PRVDR_NUM', 'count')) \
                        .reset_index()

# Dataframe with total number of hospitals that could be mergers of acquisitions
provider_count_1 = provider_count[(provider_count['NUM_CMS'] > 1)]
```

```
print("The number of hospitals that went through mergers or aquisitions is (Answer to 3a)

# Used BingChat with the following query "how do I create a pivot table that has a column
# Used BingChat with the following query "how do I check that the increase/no change in a
```

```
The number of hospitals that went through mergers or aquisitions is (Answer to 3a) 74
```

Q3b

```
# Dataframe with total number of hospitals that could be mergers of acquisitions
provider_count_1 = provider_count[(provider_count['NUM_CMS'] > 1)]

### b
print("The number of hospitals in the corrected list is (Answer to 3b)", len(provider_cou
```

```
The number of hospitals in the corrected list is (Answer to 3b) 81
```

Q3c

```
### c
provider_count.sort_values(by='FAC_NAME', ascending=True)
print("The answer to 3c is:")
print(provider_count.head(10))

# Used BingChat with the following query "how do I create a pivot table that has a column
# Used BingChat with the following query "how do I check that the increase/no change in a
```

```
The answer to 3c is:
                                          FAC_NAME  NUM_CMS
0     (CLOSED) HEALTHSOUTH CHATTANOOGA REHAB HOSPITAL        1
1                           ALLIANCE LAIRD HOSPITAL        4
2                         ALLIANCEHEALTH DEACONESS        4
3                      ATRIUM HEALTH KINGS MOUNTAIN        1
4                      BARIX CLINICS OF PENNSYLVANIA        4
5                    BAYLOR EMERGENCY MEDICAL CENTER       10
6  BAYLOR SCOTT & WHITE EMERGENCY MEDICAL CENTER AT C        4
7                         BELMONT COMMUNITY HOSPITAL        4
8                             BIG SKY MEDICAL CENTER        4
9               BLACK RIVER COMMUNITY MEDICAL CENTER        4
```

Section 3: Download Census zip code shapefile (10 pt) Partner 1

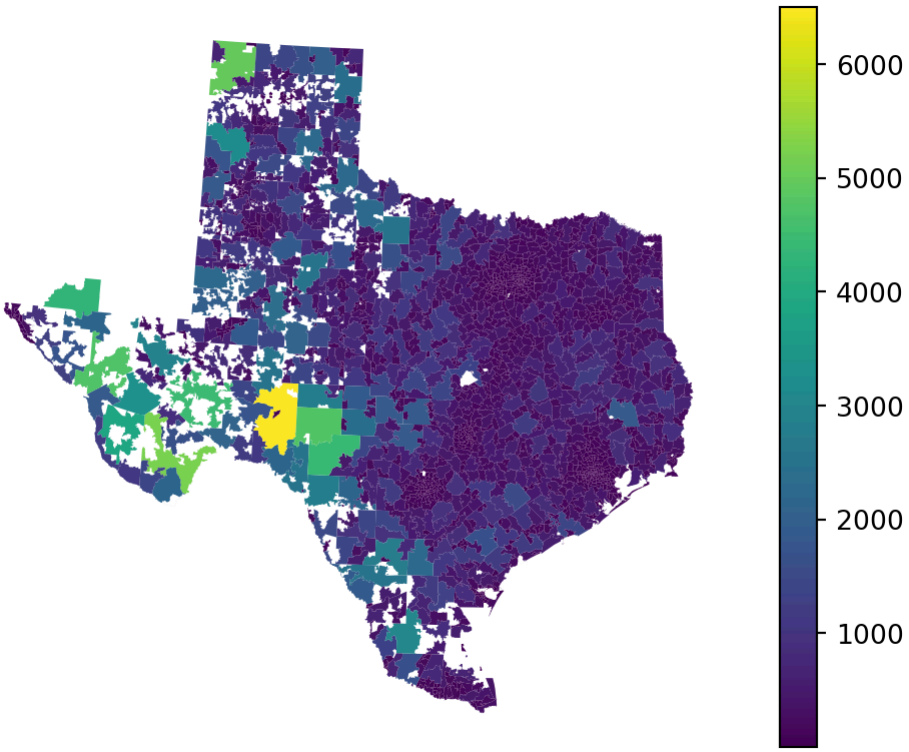
1.

```
import zipfile

zip_file_path = "/Users/charismalambert/Downloads/gz_2010_us_860_00_500k.zip"
extraction_path = "extracted_files"

with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
    zip_ref.extractall(extraction_path)

files = os.listdir(extraction_path)

file_info = []

for file in files:
    file_path = os.path.join(extraction_path, file)
    file_size = os.path.getsize(file_path)
    file_type = os.path.splitext(file)[1]

    file_info.append({
        "file_name": file,
        "file_type": file_type,
        "file_size_kb": file_size / 1024
    })

print("Answer to part b:")
for info in file_info:
    print(f" File: {info['file_name']}, Type: {info['file_type']}, Size: {info['file_size

# Citation:  Ran ChatGPT query on how to extract files from a zip file using Python and t
```

```
Answer to part b:
 File: gz_2010_us_860_00_500k.prj, Type: .prj, Size: 0.16 KB
 File: gz_2010_us_860_00_500k.shx, Type: .shx, Size: 258.85 KB
 File: gz_2010_us_860_00_500k.shp, Type: .shp, Size: 817914.63 KB
 File: gz_2010_us_860_00_500k.dbf, Type: .dbf, Size: 6274.88 KB
 File: gz_2010_us_860_00_500k.xml, Type: .xml, Size: 15.27 KB

a. The five file types are:
.xml: Metadata file describing the dataset.
.shx: An index file that provides quick access to the shapes within the .shp file.
.shp: Contains geographic shapes representing spatial data.
.prj: Contains coordinate system and projection information.
.dbf: Stores tabular attribute data associated with each spatial feature inn the .shp
file.

b. File: gz_2010_us_860_00_500k.prj, Type: .prj, Size: 0.16 KB
File: gz_2010_us_860_00_500k.shx, Type: .shx, Size: 258.85 KB
File: gz_2010_us_860_00_500k.shp, Type: .shp, Size: 817914.63 KB
File: gz_2010_us_860_00_500k.dbf, Type: .dbf, Size: 6274.88 KB
File: gz_2010_us_860_00_500k.xml, Type: .xml, Size: 15.27 KB
```

2.

```
# load zipcode shapefile
import geopandas as gdp

filepath = "/Users/charismalambert/Downloads/gz_2010_us_860_00_500k"
census_shp = gdp.read_file(filepath)

# restrict to Texas zip codes
census_shp["ZCTA5"] = census_shp["ZCTA5"].astype(str)
texas_zip = census_shp[census_shp["ZCTA5"].str.startswith(("75", "76", "77", "78", "79"))

short_term_16["ZIP_CD"] = short_term_16["ZIP_CD"].astype(str)
hospitals_by_zip = short_term_16["ZIP_CD"].value_counts().reset_index()
hospitals_by_zip.columns = ["zip_code", "total_hospitals"]
hospitals_by_zipTX = texas_zip.merge(hospitals_by_zip, left_on = "ZCTA5", right_on = "zip

# choropleth of hospitals by zp code in Texas
hospitals_by_zipTX = hospitals_by_zipTX.to_crs("EPSG:5070")
hospitals_by_zipTX["area_km2"] = hospitals_by_zipTX.area/1000000
hospitals_by_zipTX.plot(column = "area_km2", legend = True).set_axis_off()

#Citation: Ran ChatGPT query on .prj file to get the .to_crs conversion.
```



\usepackage{fvextra} \DefineVerbatimEnvironment{Highlighting}{Verbatim}{breaklines,commandchars=\\\{\}}

\RecustomVerbatimEnvironment{verbatim}{Verbatim}{ showspaces = false, showtabs = false, breaksymbolleft={}, breaklines }

PSet 4

AUTHOR
Charisma Lambert and Prashanthi Subbiah

PUBLISHED
November 2, 2024

Section 4: Calculate zip code's distance to the nearest hospital (20 pts) (*) Partner 2 ## Q1

```
import pandas as pd
import os
import csv
base_path = r"/Users/charismalambert/Downloads"

# Create the GeoDataFrame
import geopandas as gpd
import warnings
warnings.filterwarnings("ignore")

# Create the GeoDataFrame
zips_all_centroids = gpd.read_file("/Users/charismalambert/Downloads/gz_2010_us_860_00_50
print(zips_all_centroids.info())
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 33120 entries, 0 to 33119
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   GEO_ID      33120 non-null  object
 1   ZCTA5       33120 non-null  object
 2   NAME        33120 non-null  object
 3   LSAD        33120 non-null  object
 4   CENSUSAREA  33120 non-null  float64
 5   geometry    33120 non-null  geometry
dtypes: float64(1), geometry(1), object(4)
memory usage: 1.5+ MB
None
```

Dimensions of the GeoDataFrame: 33120 rows, 6 columns (variables)

Each column and what they capture:

1. GEO_ID: geographic identifier that uniquely identifies an area
2. ZCTA5: Zip Code (first 5 digits with leading 0)
3. NAME: the same as ZCTA5
4. LSAD: the way in which each area is named (all are ZCTA5)
5. CENSUSAREA: the area of region

6. geometry: the shape of region

Q2

```
# Filter Texas zip codes
zips_texas_centroids = zips_all_centroids[ (zips_all_centroids['GEO_ID'] >= "8600000US075

print("Number of unique ZipCodes for Texas = ", len(zips_texas_centroids.ZCTA5.unique()))

# Filter Texas and bordering states zipcodes
zips_texas_borderstates_centroids = zips_all_centroids[ (zips_all_centroids['GEO_ID'] >=

print("Number of unique ZipCodes for Texas and Neighboring states = ", len(zips_texas_bor
```

```
Number of unique ZipCodes for Texas =  164
Number of unique ZipCodes for Texas and Neighboring states =  303
```

EXTRA CREDIT - Section 4, Q2 with function attempt

```
# Filter Texas zip codes
zips_texas_centroids = zips_all_centroids[ (zips_all_centroids['GEO_ID'] >= "8600000US075

print("Number of unique ZipCodes for Texas and Neighboring states = ", len(zips_texas_cen

# Texas and bordering states
zips_texas_borderstates_centroids = zips_all_centroids[ (zips_all_centroids['GEO_ID'] >=

print("Number of unique ZipCodes for Texas and Neighboring states = ", len(zips_texas_bor

from shapely.geometry import Polygon
# Function to check if two polygons intersect
def polygons_intersect(poly1, poly2):
    return poly1.intersects(poly2)

# Creating Texas zipcodes dataframe
texas_combined = zips_texas_centroids.unary_union

# Creating Texas prefixes dataframe
texas_prefixes = zips_texas_centroids.GEO_ID

# Creating Texas and Bordering zipcodes dataframe
bordering_prefixes = zips_texas_borderstates_centroids.GEO_ID

# Creating Bordering zipcodes dataframe
bordering_states_only = zips_texas_borderstates_centroids[~zips_texas_borderstates_centro

# Creating Texas and Bordering zipcodes dataframe
bordering_states_only['intersects_texas'] = bordering_states_only['geometry'].apply(
```

```
    lambda x: polygons_intersect(texas_combined, x)
)

# Filter for those that intersect
intersecting_zips = bordering_states_only[bordering_states_only['intersects_texas']]

print(intersecting_zips)

print(f"Intersecting zip codes: {intersecting_zips.GEO_ID.nunique()}")

# USed BingChat to aid in creating the function
```

```
Number of unique ZipCodes for Texas and Neighboring states =  164
Number of unique ZipCodes for Texas and Neighboring states =  303
              GEO_ID  ZCTA5   NAME   LSAD  CENSUSAREA  \
816    8600000US07004  07004  07004  ZCTA5      10.286
817    8600000US07006  07006  07006  ZCTA5       9.247
824    8600000US07039  07039  07039  ZCTA5      13.803
826    8600000US07047  07047  07047  ZCTA5       5.134
827    8600000US07054  07054  07054  ZCTA5      13.724
828    8600000US07058  07058  07058  ZCTA5       2.931
829    8600000US07059  07059  07059  ZCTA5      19.567
832    8600000US07069  07069  07069  ZCTA5       6.333
834    8600000US07074  07074  07074  ZCTA5       1.255
835    8600000US07076  07076  07076  ZCTA5       8.998
836    8600000US07078  07078  07078  ZCTA5       6.470
919    8600000US07405  07405  07405  ZCTA5      19.687
925    8600000US07438  07438  07438  ZCTA5      27.438
927    8600000US07450  07450  07450  ZCTA5       5.760
930    8600000US07461  07461  07461  ZCTA5      84.158
932    8600000US07470  07470  07470  ZCTA5      23.779
1016   8600000US08736  08736  08736  ZCTA5       4.623
1246   8600000US08802  08802  08802  ZCTA5      23.990
1249   8600000US08807  08807  08807  ZCTA5      25.633
1250   8600000US08808  08808  08808  ZCTA5       0.040
1258   8600000US08826  08826  08826  ZCTA5      20.726
1259   8600000US08831  08831  08831  ZCTA5      50.398
1260   8600000US08836  08836  08836  ZCTA5       4.715
15092  8600000US07005  07005  07005  ZCTA5      18.816
15621  8600000US08801  08801  08801  ZCTA5      16.324
15903  8600000US07046  07046  07046  ZCTA5       2.631
15918  8600000US07407  07407  07407  ZCTA5       2.648
15954  8600000US07435  07435  07435  ZCTA5      14.943
15956  8600000US07439  07439  07439  ZCTA5       2.428
15965  8600000US07068  07068  07068  ZCTA5       3.539
15971  8600000US07452  07452  07452  ZCTA5       2.714
15972  8600000US07458  07458  07458  ZCTA5      10.185
15973  8600000US07460  07460  07460  ZCTA5      33.592
15977  8600000US07481  07481  07481  ZCTA5       6.554
15986  8600000US07072  07072  07072  ZCTA5       3.999
```

```
15988  8600000US07075  07075  07075  ZCTA5       1.097
16692  8600000US08827  08827  08827  ZCTA5      18.722
32986  8600000US08833  08833  08833  ZCTA5      33.360

                                                geometry  intersects_texas
816    POLYGON ((-74.32854 40.84467, -74.32881 40.845...              True
817    POLYGON ((-74.29835 40.83042, -74.29926 40.829...              True
824    POLYGON ((-74.36728 40.76107, -74.36753 40.761...              True
826    POLYGON ((-74.04586 40.75737, -74.04892 40.758...              True
827    POLYGON ((-74.38396 40.82499, -74.384 40.825, ...              True
828    POLYGON ((-74.32991 40.84916, -74.33034 40.849...              True
829    POLYGON ((-74.48243 40.62127, -74.48379 40.619...              True
832    POLYGON ((-74.44854 40.65542, -74.4479 40.6557...              True
834    POLYGON ((-74.07278 40.8474, -74.07305 40.8468...              True
835    POLYGON ((-74.38762 40.67823, -74.38493 40.674...              True
836    POLYGON ((-74.36307 40.7504, -74.36307 40.7504...              True
919    POLYGON ((-74.32841 41.00142, -74.32847 41.001...              True
925    POLYGON ((-74.54121 40.97056, -74.54528 40.972...              True
927    POLYGON ((-74.07965 40.98989, -74.07946 40.989...              True
930    POLYGON ((-74.64898 41.33638, -74.6416 41.3329...              True
932    POLYGON ((-74.20333 40.92446, -74.20436 40.924...              True
1016   POLYGON ((-74.02828 40.11742, -74.00718 40.097...              True
1246   POLYGON ((-74.99725 40.72785, -74.99744 40.727...              True
1249   MULTIPOLYGON (((-74.62967 40.64695, -74.62926 ...              True
1250   POLYGON ((-75.04737 40.73414, -75.04734 40.734...              True
1258   MULTIPOLYGON (((-74.91523 40.6707, -74.91508 4...              True
1259   POLYGON ((-74.40982 40.37944, -74.40976 40.379...              True
1260   POLYGON ((-74.5575 40.57948, -74.55767 40.5796...              True
15092  MULTIPOLYGON (((-74.39391 40.87765, -74.39337 ...              True
15621  POLYGON ((-74.89132 40.6565, -74.8906 40.65666...              True
15903  POLYGON ((-74.45026 40.87996, -74.45192 40.880...              True
15918  POLYGON ((-74.13355 40.90195, -74.13346 40.902...              True
15954  POLYGON ((-74.43018 41.01813, -74.43169 41.017...              True
15956  POLYGON ((-74.58576 41.08349, -74.57922 41.080...              True
15965  POLYGON ((-74.32917 40.8383, -74.32894 40.8382...              True
15971  POLYGON ((-74.14105 40.96635, -74.14096 40.966...              True
15972  POLYGON ((-74.10379 41.0869, -74.09821 41.0843...              True
15973  POLYGON ((-74.51699 41.15579, -74.51696 41.155...              True
15977  POLYGON ((-74.17099 40.977, -74.17706 40.97738...              True
15986  POLYGON ((-74.05307 40.83365, -74.04997 40.832...              True
15988  POLYGON ((-74.08761 40.86144, -74.08626 40.860...              True
16692  POLYGON ((-75.0151 40.60254, -75.01284 40.6093...              True
32986  MULTIPOLYGON (((-74.79082 40.62237, -74.78618 ...              True
Intersecting zip codes: 38
```

Q3

```
# Filter Texas Border States zip codes
zips_texas_borderstates_centroids = zips_all_centroids[ (zips_all_centroids['GEO_ID'] >=
```

```
# Filter Texas zip codes
zips_texas_centroids = zips_all_centroids[ (zips_all_centroids['GEO_ID'] >= "8600000US075

# Importing health data and filtering PRVDR_CTGRY_CD == 1 and PRVDR_CTGRY_SBTYP_CD == 1
base_path = r"/Users/charismalambert/Downloads"

health_path_16 = os.path.join(base_path, "pos2016.csv")
health_data_16 = pd.read_csv(health_path_16, dtype={'ZIP_CD': str})
short_term_16 = health_data_16[(health_data_16["PRVDR_CTGRY_SBTYP_CD"] == 1) & (health_da
short_term_16["year"] = 2016

base_path = r"/Users/charismalambert/Downloads"

health_path_17 = os.path.join(base_path, "pos2017.csv")
health_data_17 = pd.read_csv(health_path_17, dtype={'ZIP_CD': str})
short_term_17 =  health_data_17[(health_data_17["PRVDR_CTGRY_SBTYP_CD"] == 1) & (health_d
short_term_17["year"] = 2017

health_path_18 = os.path.join(base_path, "pos2018.csv")
health_data_18 = pd.read_csv(health_path_18, dtype={'ZIP_CD': str}, encoding='latin1')
short_term_18 = health_data_18[(health_data_18["PRVDR_CTGRY_SBTYP_CD"] == 1) & (health_da
short_term_18["year"] = 2018

health_path_19 = os.path.join(base_path, "pos2019.csv")
health_data_19 = pd.read_csv(health_path_19, dtype={'ZIP_CD': str}, encoding='latin1')
short_term_19 = health_data_19[(health_data_19["PRVDR_CTGRY_SBTYP_CD"] == 1) & (health_da
short_term_19["year"] = 2019

# Concatanating into combined_df_final and selecting required variables
combined_df = pd.concat([short_term_16, short_term_17, short_term_18, short_term_19], ign
combined_df_final = combined_df[["FAC_NAME", "PRVDR_CTGRY_CD", "PRVDR_CTGRY_SBTYP_CD", "P

# Adding leading 0's in combined_df_final['ZIP_CD']
combined_df_final['ZIP_CD'] = combined_df_final['ZIP_CD'].str.zfill(6)

# Dropping last digit from combined_df_final['ZIP_CD']
combined_df_final['ZIP_CD'] = combined_df_final['ZIP_CD'].str[:-1]
#print(combined_df_final[['ZIP_CD', 'PGM_TRMNTN_CD', 'year']])

# Creating dataframe that has only the zip codes in texas and bordering hospitals that ea
zips_tb_with_hosp = combined_df_final[
    combined_df_final['ZIP_CD'].isin(zips_texas_borderstates_centroids['ZCTA5']) &
    (combined_df_final["year"] == 2016)]

zips_tb_with_hosp = zips_tb_with_hosp.groupby('ZIP_CD').agg(number_of_hospitals =('PRVDR_
zips_tb_with_hosp = zips_tb_with_hosp[zips_tb_with_hosp['number_of_hospitals'] >= 1]

zips_tb_with_hosp_cent = zips_texas_borderstates_centroids[zips_texas_borderstates_centro

# Creating ZCTA5 in combined_df_final, which has all hospital data
```

```
combined_df_final['ZCTA5'] = combined_df_final['ZIP_CD']
combined_df_final_1 = combined_df_final

# Used an inner merge on ZCTA5
zips_withhospital_centroids = pd.merge(combined_df_final_1, zips_tb_with_hosp_cent, how='
print(zips_withhospital_centroids.head(5))
```

```
                              FAC_NAME  PRVDR_CTGRY_CD  \
0              PIONEER PARK MEDICAL CENTER               1
1                  WESTPARK MEDICAL CENTER               1
2               MEDICAL CENTER OF MCKINNEY               1
3          BAYLOR MEDICAL CENTER AT IRVING               1
4  BAYLOR SURGICAL HOSPITAL AT LAS COLINAS               1

   PRVDR_CTGRY_SBTYP_CD PRVDR_NUM ZIP_CD  PGM_TRMNTN_CD  year  ZCTA5  \
0                   1.0    450687  07506              1  2016  07506
1                   1.0    450394  07506              1  2016  07506
2                   1.0    450403  07506              0  2016  07506
3                   1.0    450079  07506              0  2016  07506
4                   1.0    450874  07506              0  2016  07506

           GEO_ID   NAME   LSAD  CENSUSAREA  \
0  8600000US07506  07506  ZCTA5       3.334
1  8600000US07506  07506  ZCTA5       3.334
2  8600000US07506  07506  ZCTA5       3.334
3  8600000US07506  07506  ZCTA5       3.334
4  8600000US07506  07506  ZCTA5       3.334

                                            geometry
0  POLYGON ((-74.16661 40.93433, -74.16683 40.934...
1  POLYGON ((-74.16661 40.93433, -74.16683 40.934...
2  POLYGON ((-74.16661 40.93433, -74.16683 40.934...
3  POLYGON ((-74.16661 40.93433, -74.16683 40.934...
4  POLYGON ((-74.16661 40.93433, -74.16683 40.934...
```

I did an inner merge, and merged on the variable 'ZCTA5', for zipcode.

Q4a

```
# Loading Libraries
from shapely.geometry import Point, Polygon
from shapely.ops import nearest_points
import time
import geopandas as gpd

# Making sure all are geodataframes
if not isinstance(zips_withhospital_centroids, gpd.GeoDataFrame):
    zips_withhospital_centroids = gpd.GeoDataFrame(zips_withhospital_centroids, geometry=

if 'geometry' not in zips_withhospital_centroids.columns:
```

```
    zips_withhospital_centroids['geometry'] = zips_withhospital_centroids.apply(
        lambda row: Point(row['longitude'], row['latitude']), axis=1)

# Ensure they use the same CRS
zips_texas_centroids = zips_texas_centroids.to_crs(epsg=4326)
zips_withhospital_centroids = gpd.GeoDataFrame(zips_withhospital_centroids, geometry='geo
zips_withhospital_centroids = zips_withhospital_centroids.to_crs(epsg=4326)

# Subset to 10 ZIP codes for testing
subset = zips_texas_centroids.head(10)
subset

# Calculating time for the join with the subset
def calculate_nearest(row, other_gdf, geom_col='geometry', src_col='ZCTA5'):
    if other_gdf.empty or row[geom_col] is None:
        return None, float('inf')
    other_geom_union = other_gdf.geometry.unary_union
    nearest_geom = nearest_points(row[geom_col], other_geom_union)[1]
    nearest_point = other_gdf.loc[other_gdf.geometry == nearest_geom]
    if nearest_point.empty:
        return None, float('inf')
    nearest_zip = nearest_point[src_col].values[0]
    distance = row[geom_col].distance(nearest_geom)
    return nearest_zip, distance

start_time = time.time()

subset['nearest_zip'], subset['distance_to_nearest'] = zip(
    *subset.apply(calculate_nearest, other_gdf=zips_withhospital_centroids, axis=1)
)

end_time = time.time()
time_taken = end_time - start_time

print(subset[['ZCTA5', 'nearest_zip', 'distance_to_nearest']])
print(f"Time taken for subset of 10 ZIP codes: {time_taken} seconds")

total_zip_codes = len(zips_texas_centroids)
estimated_time = (time_taken / 10) * total_zip_codes
print(f"Estimated time for the entire dataset: {estimated_time} seconds")

# Used BingChat with the following query: "how do I create a function that calculates the
# Used BingChat with the following query: "how do I measure the time for a spatial join?"
```

```
     ZCTA5 nearest_zip  distance_to_nearest
933  07501        None                  inf
934  07601        None                  inf
935  07624        None                  inf
936  07627        None                  inf
937  07642        None                  inf
```

```
938  07646        None                 inf
939  07660        None                 inf
940  07663        None                 inf
941  07675        None                 inf
942  07677        None                 inf
Time taken for subset of 10 ZIP codes: 23.054556131362915 seconds
Estimated time for the entire dataset: 378.0947205543518 seconds
```

Q4b

```
# Calculating time for join for all zipcodes
start_time = time.time()

zips_texas_centroids['nearest_zip'], zips_texas_centroids['distance_to_nearest'] = zip(
    *zips_texas_centroids.apply(calculate_nearest, other_gdf=zips_withhospital_centroids,
)

end_time = time.time()
time_taken = end_time - start_time

print(zips_texas_centroids[['ZCTA5', 'nearest_zip', 'distance_to_nearest']])
print(f"Time taken for all ZIP codes: {time_taken} seconds")
```

```
      ZCTA5 nearest_zip  distance_to_nearest
933    07501        None                 inf
934    07601        None                 inf
935    07624        None                 inf
936    07627        None                 inf
937    07642        None                 inf
...      ...         ...                 ...
32968  07652        None                 inf
32969  07726        None                 inf
32976  07801        None                 inf
32977  07869        None                 inf
32978  07974        None                 inf

[164 rows x 3 columns]
Time taken for all ZIP codes: 341.32185411453247 seconds
```

It takes longer to join all the zips than the estimated time.

Q4c

```
import geopandas as gpd
# Ensure they use the same CRS
zips_texas_centroids = zips_texas_centroids.to_crs(epsg=4326)
zips_withhospital_centroids = gpd.GeoDataFrame(zips_withhospital_centroids, geometry='geo
```

```
zips_withhospital_centroids = zips_withhospital_centroids.to_crs(epsg=4326)

# Q4c
# in degrees
distance = gpd.sjoin_nearest(zips_texas_centroids, zips_withhospital_centroids,
how = 'inner',
distance_col = 'distance')

# in miles and degrees
distance['distance_miles'] = distance['distance'] * 69
print(distance[['ZIP_CD', 'distance_miles', 'distance']].head(5))
print("Unique entries for distance_miles are",distance['distance_miles'].unique())

# Used BingChat with the following query: "how do I convert degrees in geopatial data to
```

```
    ZIP_CD  distance_miles  distance
933  07503            0.0       0.0
933  07503            0.0       0.0
933  07503            0.0       0.0
933  07503            0.0       0.0
933  07503            0.0       0.0
Unique entries for distance_miles are [0.         3.02911584 4.64296213 0.25841988
1.99839517]
```

The original unit of distance is degrees. I multiplied the distance given in degrees by 69 to convert to miles.

Q5a

```
# Creating dataframe with all Texas Zipcodes
zips_texas_centroids = zips_all_centroids[ (zips_all_centroids['GEO_ID'] >= "8600000US075

# Ensure both GeoDataFrames use the same coordinate reference system (CRS)
zips_texas_centroids = zips_texas_centroids.to_crs(epsg=4326)
zips_withhospital_centroids = zips_withhospital_centroids.to_crs(epsg=4326)

# Perform spatial join to find average distance to the nearest hospitals
joined = gpd.sjoin_nearest(zips_texas_centroids, zips_withhospital_centroids, how='inner'
joined_1 = joined.groupby('ZIP_CD').agg(average_distance_miles =('distance', 'first')).re

print(joined_1.head(5))

# Used BingChat with the following query: "how do I check if the dataframes are Geodatafr
```

```
  ZIP_CD  average_distance_miles
0  07004                    0.0
1  07005                    0.0
2  07006                    0.0
```

```
3  07039                    0.0
4  07046                    0.0
```

The original unit of distance is degrees.

Q5b

```
# Convert distance from degrees to miles (approximation: 1 degree = 69 miles)
joined['distance_miles'] = joined['distance'] * 69

# Calculate the average distance for each zip code
average_distance = joined.groupby('ZIP_CD')['distance_miles'].mean().reset_index()
average_distance.columns = ['ZIP_CD', 'average_distance_miles']

# Merge the average distances back to the original zip code GeoDataFrame
zips_texas_centroids['ZIP_CD'] = zips_texas_centroids['ZCTA5']
zips_texas_centroids = zips_texas_centroids.merge(average_distance, on='ZIP_CD', how='lef
zips_texas_centroids_1 = zips_texas_centroids.groupby('ZIP_CD').agg(average_distance_mile

print(zips_texas_centroids_1.head(10))

print("Unique entries for average_distance_miles are", zips_texas_centroids['average_dist

# Used BingChat with the following query: "how do I use something like this to calculate
```

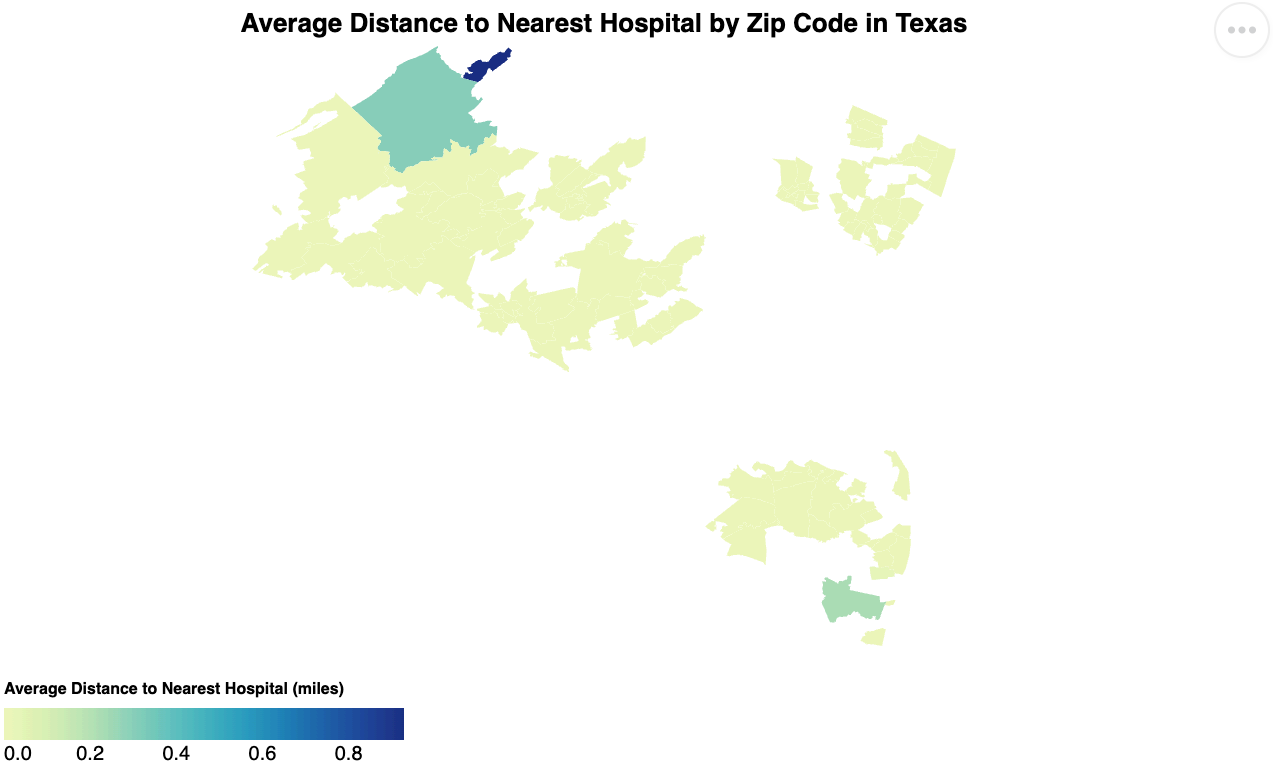
```
  ZIP_CD  average_distance_miles
0  07501                    0.0
1  07502                    0.0
2  07503                    0.0
3  07504                    0.0
4  07505                    0.0
5  07506                    0.0
6  07508                    0.0
7  07512                    NaN
8  07513                    NaN
9  07514                    0.0
Unique entries for average_distance_miles are [0.                nan 0.22204391
0.03691713 0.92859243 0.30291158]
```

Yes, this makes sense (for the NaNs, assuming that they do not have hospitals), as this table shows the average distance from the centroid of the zipcode to the nearest hospital, which can be used to analyze how accessible hospitals are in Texas zipcodes.

Q5c

```
import altair as alt
# Plot the results
chart = alt.Chart(zips_texas_centroids).mark_geoshape().encode(
```

```
    color=alt.Color('average_distance_miles:Q', legend=alt.Legend(title="Average Distance
    tooltip=['ZCTA5', 'average_distance_miles']
).project(
    type='identity', reflectY=True
).properties(
    title='Average Distance to Nearest Hospital by Zip Code in Texas',
    width=600,
    height=300
).configure_legend(
    orient='bottom'
)

chart.display()

# Used BingChat to aid in creating a plot that shows the average distance between hospita
# Used BingChat to aid in how to use something like this to calculate average distance: g
```



Section 5: Effects of closures on access in Texas (15 pts) Partner 1

1.

```
# closures_by_zip = merg_aq.groupby("ZIP_CD").agg(NUM_CMS = ("PRVDR_NUM", "count")).reset
# texas_closures_by_zip = closures_by_zip[closures_by_zip["ZIP_CD"].str.startswith(("75",
# print(texas_closures_by_zip)
```

2.

```
# import geopandas as gdp
# import matplotlib.pyplot as plt

# # load .shp file
# zip_gdf = census_shp
# zip_gdf = zip_gdf[["ZCTA5", "geometry"]]
# zip_gdf = zip_gdf.rename(columns= {"ZCTA5": "ZIP_CD"})
# print("ZIP_GDF:", zip_gdf)

# zip_gdf["ZIP_CD"] = zip_gdf["ZIP_CD"].astype(str)
# aggregated_closures = texas_closures_by_zip.groupby('ZIP_CD').agg({'NUM_CMS': 'sum'}).r

# # Merge the GeoDataFrame with the aggregated closures DataFrame
# zip_and_geo = zip_gdf.merge(aggregated_closures, on="ZIP_CD", how="inner")  # Query Cor

# # Create the choropleth map
# fig, ax = plt.subplots(figsize=(10, 10))
# zip_and_geo.plot(column='NUM_CMS', ax=ax, legend=True, cmap='Blues', edgecolor='black')
# plt.title('Choropleth Map of Closures by ZIP Code')

# plt.show()
#Citation: For Section 5, Q2-4 I was unable to run and edit because my kernel kept crashi
```

3.

```
# import geopandas as gpd
# import pandas as pd
# from shapely.geometry import Point

# # Load the Texas zip code shapefile
# all_zips = gpd.read_file("/Users/charismalambert/Downloads/gz_2010_us_860_00_500k")

# closures_gdf = gpd.GeoDataFrame(
#     texas_closures_by_zip,
#     geometry=gpd.points_from_xy(texas_closures_by_zip["ZIP_CD"].apply(lambda x: Point(x
#     crs='EPSG:4326'
# )  # Query Corrected

# # Create a 10-mile buffer around the affected zip codes
# texas_closures_by_zip['geometry'] = texas_closures_by_zipgeometry.buffer(10 * 1609.34)
# closures_buffered = texas_closures_by_zip.dissolve().reset_index()  # Query Corrected
# closures_buffered = gpd.GeoDataFrame(closures_buffered)  # Query Corrected

# indirectly_affected = gpd.sjoin(all_zips, closures_buffered, how="inner", op="intersect
# num_indirectly_affected_zips = indirectly_affected['ZCTA5'].nunique()

# print(f'The number of indirectly affected zip codes in Texas is: {num_indirectly_affect
#Citation: For Section 5, Q2-4 I was unable to run and edit because my kernel kept crashi
```

4.

```
# texas_zips = all_zips[all_zips["ZCTA5"].str.startswith(("75","76", "77", "78", "79"))]
# texas_zips = texas_zips.rename(columns = {"ZCTA5": "ZIP_CD"})

# texas_zips = texas_zips.to_crs(closures_buffered.crs)
# indirectly_affected = gpd.sjoin(texas_zips, closures_buffered, how="left", op="intersec

# texas_zips['category'] = 'Not Affected'

# texas_zips.loc[texas_zips['ZIP_CD'].isin(texas_closures_by_zip['ZIP_CD']), 'category']
# texas_zips.loc[indirectly_affected['index_right'].notna(), 'category'] = 'Indirectly Af

# color_map = {'Directly Affected': 'blue', 'Indirectly Affected': 'red', 'Not Affected':

# fig, ax = plt.subplots(1, 1, figsize=(10, 8))
# texas_zips.plot(column='category', color=texas_zips['category'].map(color_map), legend=

# ax.set_title('Texas Zip Codes Affected by Hospital Closures', fontsize=15)
# ax.set_axis_off()
# plt.show()

#Citation: For Section 5, Q2-4 I was unable to run and edit because my kernel kept crashi
```

Reflecting on the exercise (10 pts)

Section 6

Partner 1: The “first-pass” method might be misidentifying hospitals, for example a hospital with a temporary closure that is actually still open. One way to do a better job at confirming hospital closures is to cross-reference our findings to state licensing databases and the facility website, there may be a history tab that can help us identify when a change occured.

Partner 2: I believe that this reflects there has not been too much of a decrease in access to hospitals in Texas zipcodes. In this exercise, one manages to filter out the cases of mergers or aquisitions from the closures, which helps mitigate error. However, this could be further improved if we are given more accurate data on where in particular the hospitals are situated, with latitudinal and longitudinal data on the hospitals themselves alongside that of the zipcode.