Your Title

PS4: Due Sat Nov 2 at 5:00PM Central. Worth 100 points. We use (*) to indicate a problem that we think might be time consuming.

Style Points (10 pts)

Please refer to the minilesson on code style **here**.

Submission Steps (10 pts)

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): Alejandra Silva - aosilva
    - Partner 2 (name and cnet ID): Guillermina Marto - gmarto
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: **AS GM**
5. "I have uploaded the names of anyone else other than my partner and I worked with on the problem set **here**" (1 point)
6. Late coins used this pset: **___** Late coins left after submission: **___**
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

Important: Repositories are for tracking code. **Do not commit the data or shapefiles to your repo.** The best way to do this is with `.gitignore`, which we have covered in class. If you do accidentally commit the data, Github has a guide. The best course of action depends on whether you have pushed yet. This also means that both partners will have to download the initial raw data and any data cleaning code will need to be re-run on both partners' computers.

Download and explore the Provider of Services (POS) file (10 pts)

1.

```
import requests
import pandas as pd
import altair as alt

base_url = "https://data.cms.gov/data-api/v1/dataset/{uuid}/data"
uuid = "96ba2257-2080-49c1-9e5b-7726f9f83cad"

columns = [
    "PRVDR_CTGRY_CD",        # Provider Category Code
    "PRVDR_CTGRY_SBTYP_CD",  # Provider Subtype Code
    "PRVDR_NUM",             # CMS Certification Number
    "PGM_TRMNTN_CD",         # Termination Code
    "FAC_NAME",              # Facility Name
    "ZIP_CD",                # ZIP Code
    "STATE_CD"               # State Abbreviation
]

columns_param = ",".join(columns)

offset = 0
limit = 5000  #  API allows size to be set to 5000

all_data = []

while True:
    params = {

        "column": columns_param,
        "size": limit,
        "offset": offset
    }
```

```
    url = base_url.format(uuid=uuid)
    response = requests.get(url, params=params)

    if response.status_code != 200:
        print(f"Error: {response.status_code}, {response.text}")
        break

    data = response.json()

    if not data:
        print("No more data available.")
        break

    all_data.extend(data)

    offset += limit
    print(f"Fetched {len(data)} rows, moving to next batch...")

df = pd.DataFrame(all_data)


df.to_csv("pos2016.csv", index=False)
```

```
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
```

```
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 5000 rows, moving to next batch...
Fetched 1557 rows, moving to next batch...
No more data available.
```

2.

```
df = pd.read_csv("pos2016.csv")


df_st_hospitals = df[
    (df["PRVDR_CTGRY_CD"] == 1) &
    (df["PRVDR_CTGRY_SBTYP_CD"] == 1)
]

num_hospitals = df_st_hospitals.shape[0]
print(f"Number of short-term hospitals reported in the data:
 ↪  {num_hospitals}")

print(df_st_hospitals)
```

```
Number of short-term hospitals reported in the data: 7245
        PRVDR_CTGRY_CD  PRVDR_CTGRY_SBTYP_CD PRVDR_NUM  PGM_TRMNTN_CD  \
0                    1                   1.0    010001              0
1                    1                   1.0    010004              1
2                    1                   1.0    010005              0
3                    1                   1.0    010006              0
4                    1                   1.0    010007              0
...                ...                   ...       ...            ...
133526               1                   1.0    670114              0
133527               1                   1.0    670115              0
133528               1                   1.0    670116              0
133529               1                   1.0    670117              0
133530               1                   1.0    670118              0
```

```
                                FAC_NAME   ZIP_CD STATE_CD
0       SOUTHEAST ALABAMA MEDICAL CENTER  36301.0       AL
1                 NORTH JACKSON HOSPITAL  35740.0       AL
2          MARSHALL MEDICAL CENTER SOUTH  35957.0       AL
3         ELIZA COFFEE MEMORIAL HOSPITAL  35631.0       AL
4               MIZELL MEMORIAL HOSPITAL  36467.0       AL
...                                  ...      ...      ...
133526             WEIMAR MEDICAL CENTER  78962.0       TX
133527      CLEVELAND EMERGENCY HOSPTIAL  77327.0       TX
133528                WISE HEALTH SYSTEM  76177.0       TX
133529  TEXAS GENERAL HOSPITAL- VZRMC LP  75140.0       TX
133530              FIRST TEXAS HOSPITAL  77070.0       TX

[7245 rows x 7 columns]
```

The number of short-term hospitals reported in the dataset for Q4 2016 is 7,245.

According to the American Hospital Association (AHA) Annual Survey, the estimated number of short-term hospitals is 4,500–5,000. Similarly, the CMS Hospital Compare dataset indicates around 4,800 hospitals.

The discrepancy could be due to the narrower definition used in our dataset and the timing of data collection, which only includes hospitals in Q4 2016. Additionally, the CMS dataset might not include hospitals that do not participate in Medicare or Medicaid, which could lead to lower numbers.

3.

```python
uuid_dict = {
    "2016Q4": "96ba2257-2080-49c1-9e5b-7726f9f83cad",
    "2017Q4": "d338dc0d-641c-486a-b586-88a662f36963",
    "2018Q4": "4ff7fcfb-2a40-4f76-875d-a4ac2aec268e",
    "2019Q4": "03cca0cc-13a0-4b8d-82c4-57185b6bbfbd"
}

columns = [
    "PRVDR_CTGRY_CD",        # Provider Category Code
    "PRVDR_CTGRY_SBTYP_CD",  # Provider Subtype Code
    "PRVDR_NUM",             # CMS Certification Number
    "PGM_TRMNTN_CD",         # Termination Code
    "FAC_NAME",              # Facility Name
    "ZIP_CD",                # ZIP Code
    "STATE_CD"               # State Abbreviation
]
```

```
columns_param = ",".join(columns)

combined_data = []

for year_quarter, uuid in uuid_dict.items():
    offset = 0
    limit = 5000
    all_data = []

    print(f"Fetching data for {year_quarter}...")

    while True:
        params = {
            "column": columns_param,
            "size": limit,
            "offset": offset
        }

        url = f"https://data.cms.gov/data-api/v1/dataset/{uuid}/data"
        response = requests.get(url, params=params)

        if response.status_code != 200:
            print(f"Error: {response.status_code}, {response.text}")
            break

        data = response.json()

        if not data:
            print("No more data available.")
            break

        all_data.extend(data)

        offset += limit
        print(f"Fetched {len(data)} rows for {year_quarter}, moving to next
         ↪  batch...")

    year_data = pd.DataFrame(all_data)
    year_data["Year"] = year_quarter[:4]

    # filtro por las condiciones
```

```
    year_data = year_data[
    (year_data["PRVDR_CTGRY_CD"] == "01") &
    (year_data["PRVDR_CTGRY_SBTYP_CD"] == "01")
]

    combined_data.append(year_data)

combined_df = pd.concat(combined_data, axis=0)

combined_df.to_csv("combined_data.csv", index=False)

print(f"Total records retrieved across all years: {combined_df.shape[0]}")
```

```
Fetching data for 2016Q4...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
Fetched 5000 rows for 2016Q4, moving to next batch...
```

```
Fetched 1557 rows for 2016Q4, moving to next batch...
No more data available.
Fetching data for 2017Q4...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 5000 rows for 2017Q4, moving to next batch...
Fetched 4110 rows for 2017Q4, moving to next batch...
No more data available.
Fetching data for 2018Q4...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
```

```
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 5000 rows for 2018Q4, moving to next batch...
Fetched 1696 rows for 2018Q4, moving to next batch...
No more data available.
Fetching data for 2019Q4...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
```

```
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 5000 rows for 2019Q4, moving to next batch...
Fetched 4206 rows for 2019Q4, moving to next batch...
No more data available.
Total records retrieved across all years: 29085
```

```
import altair as alt

# Plotting Number of Observations Per Year

combined_year_df =
 ↪  combined_df.groupby("Year").size().reset_index(name="Number of
 ↪  Observations")

obs_chart = alt.Chart(combined_year_df).mark_bar().encode(
    x=alt.X("Year:O", title="Year"),
    y=alt.Y("Number of Observations:Q", title="Number of Observations"),
    tooltip=["Year", "Number of Observations"]
).properties(
    title="Number of Observations Per Year"
)

obs_chart.display()


# Plotting Number of Unique Hospitals Per Year
unique_hospitals =
 ↪  combined_df.groupby("Year")["PRVDR_NUM"].nunique().reset_index(name="Number
 ↪  of Unique Hospitals")

unique_hospitals_chart = alt.Chart(unique_hospitals).mark_bar().encode(
    x=alt.X("Year:O", title="Year"),
    y=alt.Y("Number of Unique Hospitals:Q", title="Number of Unique
 ↪  Hospitals"),
    tooltip=["Year", "Number of Unique Hospitals"]
```

```
).properties(
    title="Number of Unique Hospitals Per Year"
)

unique_hospitals_chart.display()


#print("Observations Per Year:")
#print(observations_per_year)
#print("\nUnique Hospitals Per Year:")
#print(unique_hospitals_per_year)

# Compare the two plots to understand the structure of the data.
# Observations per year may be higher due to multiple records for the same
 ↪  hospital.
# Unique hospitals per year give an idea of how many distinct hospitals are
 ↪  in the dataset for each year.
```

```
alt.Chart(...)
```

```
alt.Chart(...)
```

4. a.
   b.

Identify hospital closures in POS file (15 pts) (*)

1. Termination code equal to 00=ACTIVE PROVIDER. The data contain only up to the code 07. The other codes apply to CLIA.

```
combined_df["PGM_TRMNTN_CD"] = combined_df["PGM_TRMNTN_CD"].astype(str)

inactive_codes = ["01", "02", "03", "04", "05", "06", "07"]

active_2016 = combined_df[(combined_df["Year"] == "2016") &
 ↪  (combined_df["PGM_TRMNTN_CD"] == "00")]

print(active_2016.head())

suspected_closures = []
```

```
for idx, hospital in active_2016.iterrows():
    provider_num = hospital["PRVDR_NUM"]
    facility_name = hospital["FAC_NAME"]
    zip_code = hospital["ZIP_CD"]

    for year in ["2017", "2018", "2019"]:
        yearly_data = combined_df[(combined_df["PRVDR_NUM"] == provider_num)
 ↪  & (combined_df["Year"] == year)]

        if yearly_data.empty or
         ↪  yearly_data["PGM_TRMNTN_CD"].isin(inactive_codes).any():
            suspected_closures.append({
                "Provider Number": provider_num,
                "Facility Name": facility_name,
                "ZIP Code": zip_code,
                "Year Closed": year
            })
            break

suspected_closures_df = pd.DataFrame(suspected_closures)
num_closures = len(suspected_closures_df)

display(f"Total suspected hospital closures: {num_closures}")
display(suspected_closures_df.head())
```

```
  PRVDR_CTGRY_CD PRVDR_CTGRY_SBTYP_CD PRVDR_NUM PGM_TRMNTN_CD  \
0             01                   01    010001            00
2             01                   01    010005            00
3             01                   01    010006            00
4             01                   01    010007            00
5             01                   01    010008            00

                          FAC_NAME ZIP_CD STATE_CD  Year
0  SOUTHEAST ALABAMA MEDICAL CENTER  36301       AL  2016
2     MARSHALL MEDICAL CENTER SOUTH  35957       AL  2016
3    ELIZA COFFEE MEMORIAL HOSPITAL  35631       AL  2016
4          MIZELL MEMORIAL HOSPITAL  36467       AL  2016
5       CRENSHAW COMMUNITY HOSPITAL  36049       AL  2016

'Total suspected hospital closures: 174'
```

	Provider Number	Facility Name	ZIP Code	Year Closed
0	010032	WEDOWEE HOSPITAL	36278	2019
1	010047	GEORGIANA MEDICAL CENTER	36033	2019
2	010146	RMC JACKSONVILLE	36265	2018
3	010172	NORTH ALABAMA SPECIALITY HOSPITAL	35611	2018
4	030001	ABRAZO MARYVALE CAMPUS	85031	2017

2.

```
sorted_closures = suspected_closures_df.sort_values(by="Facility Name")

top_10_closures = sorted_closures[["Facility Name", "Year Closed"]].head(10)

display(top_10_closures)
```

	Facility Name	Year Closed
4	ABRAZO MARYVALE CAMPUS	2017
10	ADVENTIST MEDICAL CENTER - CENTRAL VALLEY	2017
97	AFFINITY MEDICAL CENTER	2018
80	ALBANY MEDICAL CENTER / SOUTH CLINICAL CAMPUS	2017
140	ALLEGIANCE SPECIALTY HOSPITAL OF KILGORE	2017
62	ALLIANCE LAIRD HOSPITAL	2019
101	ALLIANCEHEALTH DEACONESS	2019
26	ANNE BATES LEACH EYE HOSPITAL	2019
21	ARKANSAS VALLEY REGIONAL MEDICAL CENTER	2017
69	BANNER CHURCHILL COMMUNITY HOSPITAL	2017

3.

```
import pandas as pd
import numpy as np

# Step 1: Count the number of active hospitals (PGM_TRMNTN_CD == "00") by
 ↪  ZIP_CD (zip code) for each year
active_hospitals_by_year = (
    combined_df[combined_df['PGM_TRMNTN_CD'] == "00"]
    .groupby(['ZIP_CD', 'Year'])
    .size()
    .unstack(fill_value=0)
)
```

```
# Step 2: Create columns with differences between years for each ZIP_CD
# Calculate the differences between consecutive years
active_hospitals_by_year['diff_2017_2016'] = active_hospitals_by_year["2017"]
 ↪  - \
    active_hospitals_by_year["2016"]
active_hospitals_by_year['diff_2018_2017'] = active_hospitals_by_year["2018"]
 ↪  - \
    active_hospitals_by_year["2017"]
active_hospitals_by_year['diff_2019_2018'] = active_hospitals_by_year["2019"]
 ↪  - \
    active_hospitals_by_year["2018"]

# Reset index to prepare for merging
active_hospitals_by_year = active_hospitals_by_year.reset_index()

# Step 3: Merge the active_hospitals_by_year dataframe with
 ↪  suspected_closures by ZIP Code
merged_df = pd.merge(suspected_closures_df, active_hospitals_by_year,
                     left_on='ZIP Code', right_on='ZIP_CD', how='left')

# Initialize the closure_difference column with NaN
merged_df['closure_difference'] = np.nan

# Loop through each row and set closure_difference based on Year Closed
for index, row in merged_df.iterrows():
    if row['Year Closed'] == "2017":
        merged_df.at[index, 'closure_difference'] = row['diff_2018_2017']
    elif row['Year Closed'] == "2018":
        merged_df.at[index, 'closure_difference'] = row['diff_2019_2018']
    else:
        # Optionally set it to a specific value if Year Closed doesn't match
         ↪  any condition
        merged_df.at[index, 'closure_difference'] = None

# Step 5: Create a dummy variable that is 1 if the closure_difference is 0 or
 ↪  greater, else 0
merged_df['closure_dummy'] = merged_df['closure_difference'].apply(
    lambda x: 1 if pd.notna(x) and x > 0 else (0 if pd.notna(x) else np.nan)
)

# Count the number of rows where closure_dummy is 1
```

```
count_of_ones = merged_df['closure_dummy'].sum()
display(f"Number of rows with closure_dummy = 1: {count_of_ones}")

# Count the number of rows where closure_dummy is 0
count_of_zeros = (merged_df['closure_dummy'] == 0).sum()
display(f"Number of rows with closure_dummy = 0: {count_of_zeros}")
```

```
'Number of rows with closure_dummy = 1: 4.0'
```

```
'Number of rows with closure_dummy = 0: 94'
```

```
# Question a: Count hospitals that fit the definition of potentially being a
 ↪  merger/acquisition
count_of_ones = merged_df['closure_dummy'].sum()
display(f"Number of hospitals potentially being a merger/acquisition:
 ↪  {count_of_ones}")

# Question b: Count hospitals left after correcting for potential mergers
corrected_closures = merged_df[merged_df['closure_dummy'] == 0]
count_of_zeros = (merged_df['closure_dummy'] == 0).sum()
display(f"Number of hospitals left after correcting for potential mergers:
 ↪  {count_of_zeros}")

# Question c: Sort the corrected list of closures by hospital name and
 ↪  display the first 10 rows
sorted_corrected_closures = corrected_closures.sort_values(by='Facility
 ↪  Name').head(10)
display(sorted_corrected_closures[['Facility Name', 'ZIP Code', 'Year
 ↪  Closed', 'closure_difference']])
```

```
'Number of hospitals potentially being a merger/acquisition: 4.0'
```

```
'Number of hospitals left after correcting for potential mergers: 94'
```

	Facility Name	ZIP Code	Year Closed	closure_d
4	ABRAZO MARYVALE CAMPUS	85031	2017	0.0
10	ADVENTIST MEDICAL CENTER - CENTRAL VALLEY	93230	2017	0.0
97	AFFINITY MEDICAL CENTER	44646	2018	0.0
80	ALBANY MEDICAL CENTER / SOUTH CLINICAL CAMPUS	12208	2017	0.0
140	ALLEGIANCE SPECIALTY HOSPITAL OF KILGORE	75662	2017	0.0
21	ARKANSAS VALLEY REGIONAL MEDICAL CENTER	81050	2017	0.0

	Facility Name	ZIP Code	Year Closed	closure_d
69	BANNER CHURCHILL COMMUNITY HOSPITAL	89406	2017	0.0
5	BANNER PAYSON MEDICAL CENTER	85541	2018	0.0
170	BAY AREA REGIONAL MEDICAL CENTER, LLC	77598	2018	0.0
137	BAYLOR SCOTT & WHITE MEDICAL CENTER GARLAND	75042	2018	0.0

Download Census zip code shapefile (10 pt)

1. a. **Five File Types and Their Contents**

Based on the files provided, here is a summary of the five common shapefile-related formats and their typical contents:

1. **`.shp` (Shapefile)**: Stores the geometry of the feature, such as points, lines, or polygons representing geographic boundaries (e.g., ZIP code tabulation areas) (6.4 MB).
2. **`.shx` (Shape Index)**: Contains an index of the feature geometry, providing quick access to spatial data in the `.shp` file (165 bytes).
3. **`.dbf` (Database File)**: Stores attribute data associated with each shape, such as names, identifiers, and other relevant information (837.5 MB).
4. **`.prj` (Projection File)**: Contains projection information, specifying the coordinate system and projection details for the spatial data (265 KB).
5. **`.xml` (Metadata File)**: Provides metadata, including details about the data's origin, purpose, spatial extent, and additional descriptive information (16 KB).

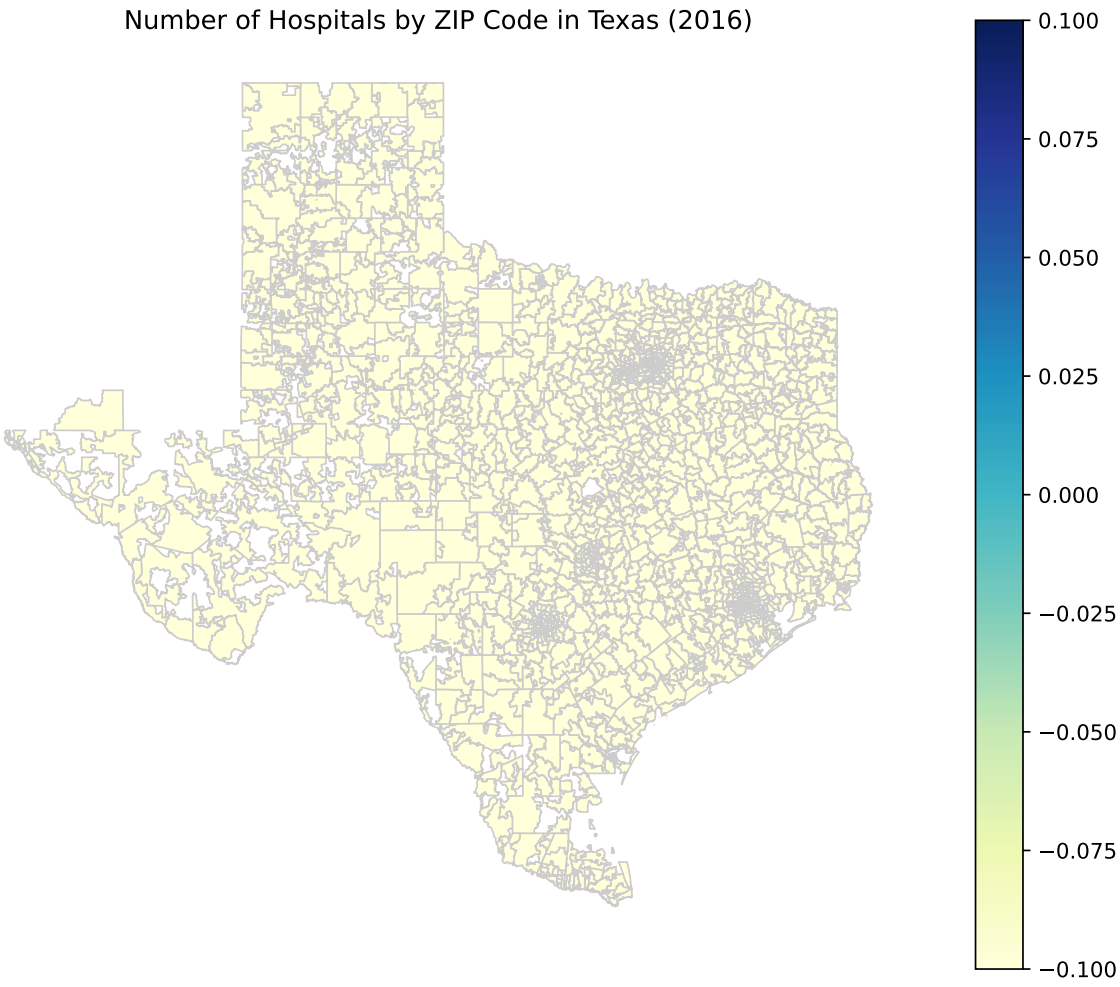
b. **File Sizes After Unzipping**

The sizes of the files were included above. However, to determine the size of each file after unzipping, use the following command in the terminal of the folder:

total 1648944 -rw-r–r–@ 1 aosilva staff 6.1M Sep 14 2011 gz_2010_us_860_00_500k.dbf -rw-r–r–@ 1 aosilva staff 165B Sep 14 2011 gz_2010_us_860_00_500k.prj -rw-r–r–@ 1 aosilva staff 799M Sep 14 2011 gz_2010_us_860_00_500k.shp -rw-r–r–@ 1 aosilva staff 259K Sep 14 2011 gz_2010_us_860_00_500k.shx -rw-rw-rw-@ 1 aosilva staff 15K Dec 9 2011 gz_2010_us_860_00_500k

2.

```
import geopandas as gpd

# Load the shapefile (replace 'path_to_shapefile' with the actual path)
zip_shapefile =
 ↪  gpd.read_file('gz_2010_us_860_00_500k/gz_2010_us_860_00_500k.shp')

# Filter for Texas ZIP codes (750-799)
texas_zip_shapefile =
 ↪  zip_shapefile[zip_shapefile['ZCTA5'].str.startswith(tuple(map(str,
 ↪  range(750, 800))))]

# Check the result
texas_zip_shapefile.head()

# Filter combined_df for 2016 and Texas ZIP codes
hospitals_2016 = combined_df[(combined_df['Year'] == 2016) &

 ↪  (combined_df['ZIP_CD'].str.startswith(tuple(map(str, range(750, 800)))))]

# Count hospitals per ZIP code
hospitals_per_zip =
 ↪  hospitals_2016.groupby('ZIP_CD').size().reset_index(name='hospital_count')

# Merge shapefile with hospital counts
texas_zip_map = texas_zip_shapefile.merge(hospitals_per_zip, left_on='ZCTA5',
 ↪  right_on='ZIP_CD', how='left')

# Fill NaN values with 0 for ZIP codes with no hospitals
texas_zip_map['hospital_count'] = texas_zip_map['hospital_count'].fillna(0)

import matplotlib.pyplot as plt

# Plot the choropleth
fig, ax = plt.subplots(1, 1, figsize=(10, 8))
texas_zip_map.plot(column='hospital_count', cmap='YlGnBu', linewidth=0.8,
 ↪  ax=ax, edgecolor='0.8', legend=True)
ax.set_title('Number of Hospitals by ZIP Code in Texas (2016)')
ax.axis('off')
plt.show()
```



Calculate zip code's distance to the nearest hospital (20 pts) (*)

1.

The GeoDataFrame, `zips_all_centroids`, has dimensions that correspond to the number of unique ZIP code areas, with two main columns: `ZIP Code` and `geometry`. The `ZIP Code` column holds the specific ZIP Code Tabulation Area (ZCTA) for each entry, representing each distinct postal region. The `geometry` column contains the centroid point of each ZIP code area, with each point indicating the latitude and longitude coordinates for the center of the ZIP code region. This structure allows for further geographic analysis, such as calculating distances to the nearest hospital.

```
import geopandas as gpd

# Calculate centroids for each ZIP code and create a new GeoDataFrame with
 ↪  these centroids
zip_shapefile['centroid'] = zip_shapefile.geometry.centroid  # Calculate
 ↪  centroids

# Convert this information into a new GeoDataFrame, focusing only on the
 ↪  centroids and ZIP code info
zips_all_centroids = gpd.GeoDataFrame(zip_shapefile[['ZCTA5', 'centroid']],
 ↪  geometry='centroid')

# Rename columns for clarity
zips_all_centroids.columns = ['ZIP Code', 'geometry']

# Display the dimensions and column descriptions
print("Dimensions of zips_all_centroids:", zips_all_centroids.shape)
print("Columns in zips_all_centroids:", zips_all_centroids.columns)

# Display the first few rows to verify the output
zips_all_centroids.head()
```

```
C:\Users\aosil\AppData\Local\Temp\ipykernel_32336\3876718460.py:4:
UserWarning: Geometry is in a geographic CRS. Results from 'centroid' are
likely incorrect. Use 'GeoSeries.to_crs()' to re-project geometries to a
projected CRS before this operation.

  zip_shapefile['centroid'] = zip_shapefile.geometry.centroid  # Calculate
  centroids

Dimensions of zips_all_centroids: (33120, 2)
Columns in zips_all_centroids: Index(['ZIP Code', 'geometry'],
dtype='object')
```

	ZIP Code	geometry
0	01040	POINT (-72.64107 42.21257)
1	01050	POINT (-72.86985 42.28786)
2	01053	POINT (-72.71162 42.35349)
3	01056	POINT (-72.45805 42.19215)
4	01057	POINT (-72.3243 42.09165)

2.

```
# Define ZIP code prefixes for Texas and its neighboring states
texas_prefixes = list(range(750, 799))
# Adding neighboring state prefixes
bordering_prefixes = texas_prefixes + [70, 71, 72, 73, 74, 87, 88]

# Convert prefixes to strings for matching with the 'ZIP Code' column
texas_prefixes_str = tuple(map(str, texas_prefixes))
bordering_prefixes_str = tuple(map(str, bordering_prefixes))

# Filter the zips_all_centroids GeoDataFrame for Texas ZIP codes
zips_texas_centroids = zips_all_centroids[
    zips_all_centroids['ZIP Code'].str.startswith(texas_prefixes_str)
]

# Filter the zips_all_centroids GeoDataFrame for Texas and bordering states
 ↪  ZIP codes
zips_texas_borderstates_centroids = zips_all_centroids[
    zips_all_centroids['ZIP Code'].str.startswith(bordering_prefixes_str)
]

# Print out the number of unique ZIP codes in each subset
num_texas_zips = zips_texas_centroids['ZIP Code'].nunique()
num_bordering_zips = zips_texas_borderstates_centroids['ZIP Code'].nunique()

print("Unique ZIP codes in Texas subset:", num_texas_zips)
print("Unique ZIP codes in Texas and bordering states subset:",
 ↪  num_bordering_zips)
```

```
Unique ZIP codes in Texas subset: 1910
Unique ZIP codes in Texas and bordering states subset: 4032
```

3.

We used an inner join to retain only the ZIP codes in Texas and neighboring states that have at least one hospital, ensuring that `zips_withhospital_centroids` includes only relevant ZIP codes. The join was conducted on the `ZIP Code` column from `zips_texas_borderstates_centroids` and `ZIP_CD` from `zips_with_hospital`, allowing us to filter specifically for ZIP codes that had at least one active hospital in 2016. The result is a GeoDataFrame, `zips_withhospital_centroids`, which contains only the ZIP codes in Texas or bordering states with at least one hospital in that year.

```
# Step 1: Filter hospitals active in 2016 and count by ZIP code

hospitals_per_zip = combined_df[(combined_df['Year'] == 2016) & (
    combined_df['PGM_TRMNTN_CD'] ==
 ↪  "00")].groupby('ZIP_CD').size().reset_index(name='hospital_count')


# Filter to keep only ZIP codes with at least one hospital
zips_with_hospital = hospitals_per_zip[hospitals_per_zip['hospital_count'] >
 ↪  0]

# Step 2: Merge this count data with zips_texas_borderstates_centroids on ZIP
 ↪  code
# Ensuring ZIP codes match data types between datasets
zips_texas_borderstates_centroids['ZIP Code'] =
 ↪  zips_texas_borderstates_centroids['ZIP Code'].astype(
    str)
zips_with_hospital['ZIP_CD'] = zips_with_hospital['ZIP_CD'].astype(str)

# Perform an inner join to keep only ZIP codes with hospitals in 2016
zips_withhospital_centroids = zips_texas_borderstates_centroids.merge(
    zips_with_hospital, left_on='ZIP Code', right_on='ZIP_CD', how='inner'
)

# Display
display(zips_withhospital_centroids.head())
```

```
C:\Users\aosil\AppData\Local\Programs\Python\Python312\Lib\site-packages\geopandas\geodatafra
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus
  super().__setitem__(key, value)
```

ZIP Code	geometry	ZIP_CD	hospital_count

4. a.

```
from shapely.ops import nearest_points
import time

# The geometry column is set as active in both GeoDataFrames
zips_texas_centroids = zips_texas_centroids.set_geometry('geometry')
zips_withhospital_centroids =
 ↪  zips_withhospital_centroids.set_geometry('geometry')

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

# Start timer
start_time = time.time()

# Calculate distances for each ZIP code in test subset
distances = []
for idx, row in test_zips_texas.iterrows():
    # Calculate the distance to the nearest hospital ZIP code
    nearest_hospital =
 ↪  zips_withhospital_centroids.distance(row.geometry).min()
    distances.append(nearest_hospital)

# End timer
end_time = time.time()
elapsed_time = end_time - start_time

# Output the time taken and estimated total time for the full dataset
print("Time taken for 10 ZIP codes:", elapsed_time, "seconds")

# Estimate total time
total_rows = len(zips_texas_centroids)
estimated_total_time = (elapsed_time / 10) * total_rows
print("Estimated time for entire dataset:", estimated_total_time, "seconds")
```

```
Time taken for 10 ZIP codes: 0.14083528518676758 seconds
Estimated time for entire dataset: 26.899539470672607 seconds
```

```
C:\Users\aosil\AppData\Local\Temp\ipykernel_32336\1307856507.py:18:
UserWarning: Geometry is in a geographic CRS. Results from 'distance' are
likely incorrect. Use 'GeoSeries.to_crs()' to re-project geometries to a
projected CRS before this operation.
```

```
  nearest_hospital = zips_withhospital_centroids.distance(row.geometry).min()
```

b.

The full dataset calculation completed significantly faster than initially estimated, suggesting that the small sample used for estimation might have over-predicted the time required. This difference could be due to optimizations in the spatial library that enhance performance with larger datasets, as well as variations in system performance between runs. Small sample estimates can sometimes lead to overestimations when the operation scales more efficiently across a larger volume of data.

```
import time

# Start timer for the full calculation
start_time_full = time.time()

# Calculate distances for each ZIP code in the entire Texas subset
full_distances = []
for idx, row in zips_texas_centroids.iterrows():
    # Calculate the distance to the nearest hospital ZIP code
    nearest_hospital_distance =
 ↪  zips_withhospital_centroids.distance(row.geometry).min()
    full_distances.append(nearest_hospital_distance)

# End timer
end_time_full = time.time()
elapsed_time_full = end_time_full - start_time_full

# Output the actual time taken
print("Actual time taken for full dataset:", elapsed_time_full, "seconds")

# Compare to estimated time from previous step
estimated_total_time = (elapsed_time / 10) * len(zips_texas_centroids)  #
 ↪  Using the previous subset estimate
print("Estimated time for entire dataset:", estimated_total_time, "seconds")
print("Difference between actual and estimated time:", abs(elapsed_time_full
 ↪  - estimated_total_time), "seconds")
```

```
C:\Users\aosil\AppData\Local\Temp\ipykernel_32336\3268991715.py:10:
UserWarning: Geometry is in a geographic CRS. Results from 'distance' are
likely incorrect. Use 'GeoSeries.to_crs()' to re-project geometries to a
projected CRS before this operation.
```

```
  nearest_hospital_distance =
  zips_withhospital_centroids.distance(row.geometry).min()

Actual time taken for full dataset: 19.329349279403687 seconds
Estimated time for entire dataset: 26.899539470672607 seconds
Difference between actual and estimated time: 7.570190191268921 seconds
```

c.

In the `.prj` file , the unit is degrees. This indicates that the geographic data is in a coordinate system based on latitude and longitude, with units in angular degrees rather than linear distance.

To convert degrees to miles, we can use an approximate conversion. Each degree of latitude corresponds to about 69 miles, a consistent value because latitude lines are parallel. For longitude, the conversion varies depending on latitude due to the Earth's curvature; at the equator, 1 degree of longitude equals approximately 69 miles, but this distance decreases as you move toward the poles. A common formula to estimate the distance per degree of longitude at a given latitude L is 69 x cos(L) .

5. a.

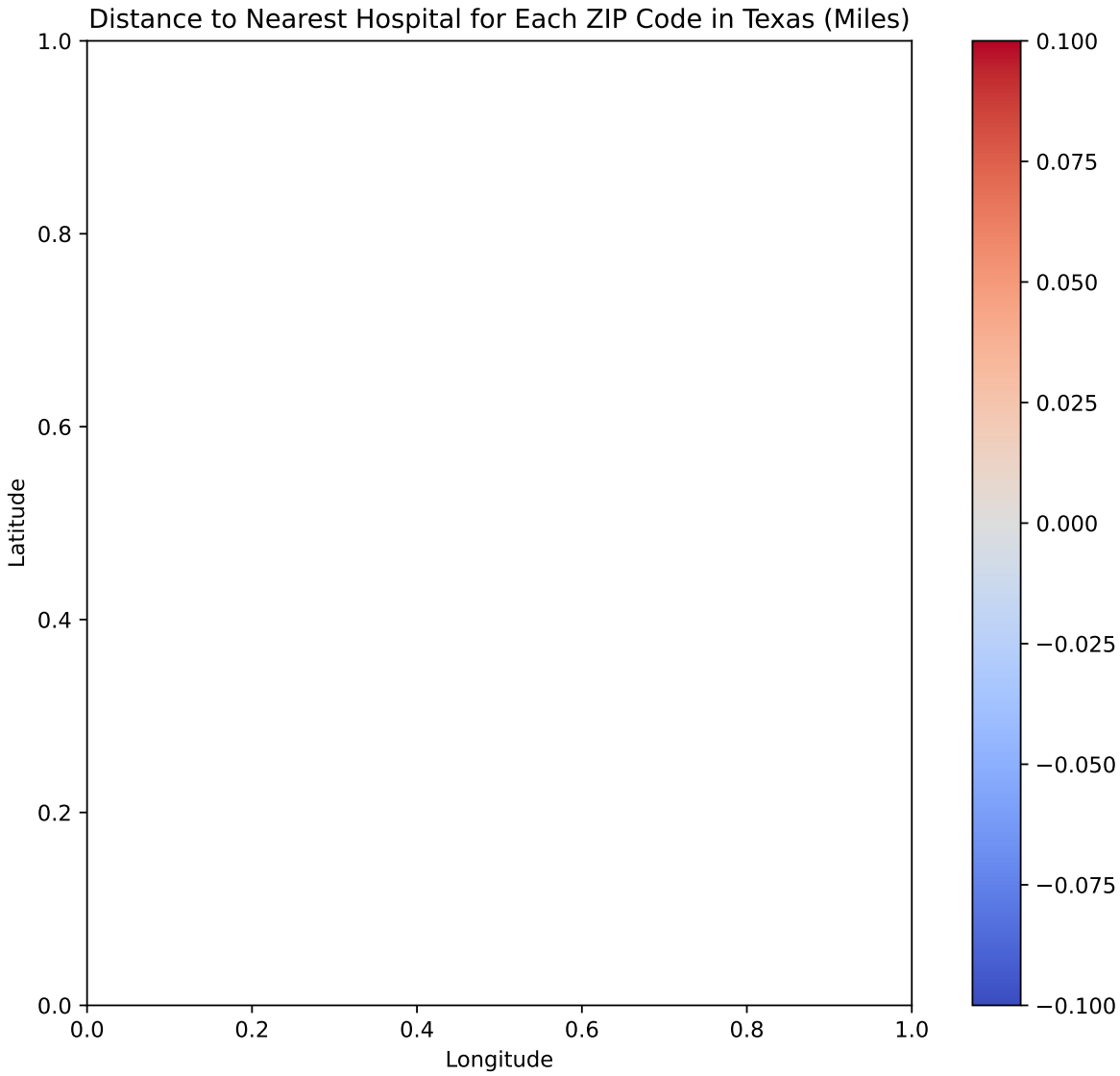
The distances are converted from degrees to miles.

```python
import geopandas as gpd
import matplotlib.pyplot as plt

# Calculate the distance to the nearest hospital for each ZIP code in Texas
zips_texas_centroids['nearest_hospital_distance'] =
 ↪  zips_texas_centroids.geometry.apply(
    lambda x: zips_withhospital_centroids.distance(x).min()
)

# Step 2: Calculate the average distance (in degrees)
avg_dist_degrees = zips_texas_centroids['nearest_hospital_distance'].mean()

# Step 3: Convert average distance from degrees to miles
avg_dist_miles = avg_dist_degrees * 69  # 1 degree  69 miles

print("Average distance to the nearest hospital (in degrees):",
 ↪  avg_dist_degrees)
print("Average distance to the nearest hospital (in miles):", avg_dist_miles)
```

```
C:\Users\aosil\AppData\Local\Temp\ipykernel_32336\3339965745.py:6:
UserWarning: Geometry is in a geographic CRS. Results from 'distance' are
likely incorrect. Use 'GeoSeries.to_crs()' to re-project geometries to a
projected CRS before this operation.

  lambda x: zips_withhospital_centroids.distance(x).min()

Average distance to the nearest hospital (in degrees): nan
Average distance to the nearest hospital (in miles): nan
```

b.

```
# Step 4: Map the value for each ZIP code in Texas
# Convert each ZIP code's distance to miles for mapping
zips_texas_centroids['nearest_hospital_distance_miles'] =
 ↪  zips_texas_centroids['nearest_hospital_distance'] * 69

fig, ax = plt.subplots(1, 1, figsize=(10, 8))
zips_texas_centroids.plot(column='nearest_hospital_distance_miles',
 ↪  cmap='coolwarm', legend=True, ax=ax)
ax.set_title("Distance to Nearest Hospital for Each ZIP Code in Texas
 ↪  (Miles)")
ax.set_xlabel("Longitude")
ax.set_ylabel("Latitude")
plt.show()
```



The choropleth map visually represents the distance to the nearest hospital for each ZIP code in Texas, showing regions with greater or lesser hospital access.

Effects of closures on access in Texas (15 pts)

1.

```
# Filter for Texas ZIP codes in the range 75000 to 79999 and for closures
 ↪  between 2016 and 2019
texas_closures = corrected_closures[
    (corrected_closures['ZIP Code'].astype(str).str.startswith(tuple(map(str,
 ↪  range(750, 799))))) &
    (corrected_closures['Year Closed'].between("2016", "2019"))
]

# Group by ZIP Code and count the number of closures for each ZIP code
closures_by_zipcode = texas_closures.groupby('ZIP
 ↪  Code').size().reset_index(name='Number of Closures')

# Display the result
closures_by_zipcode
```

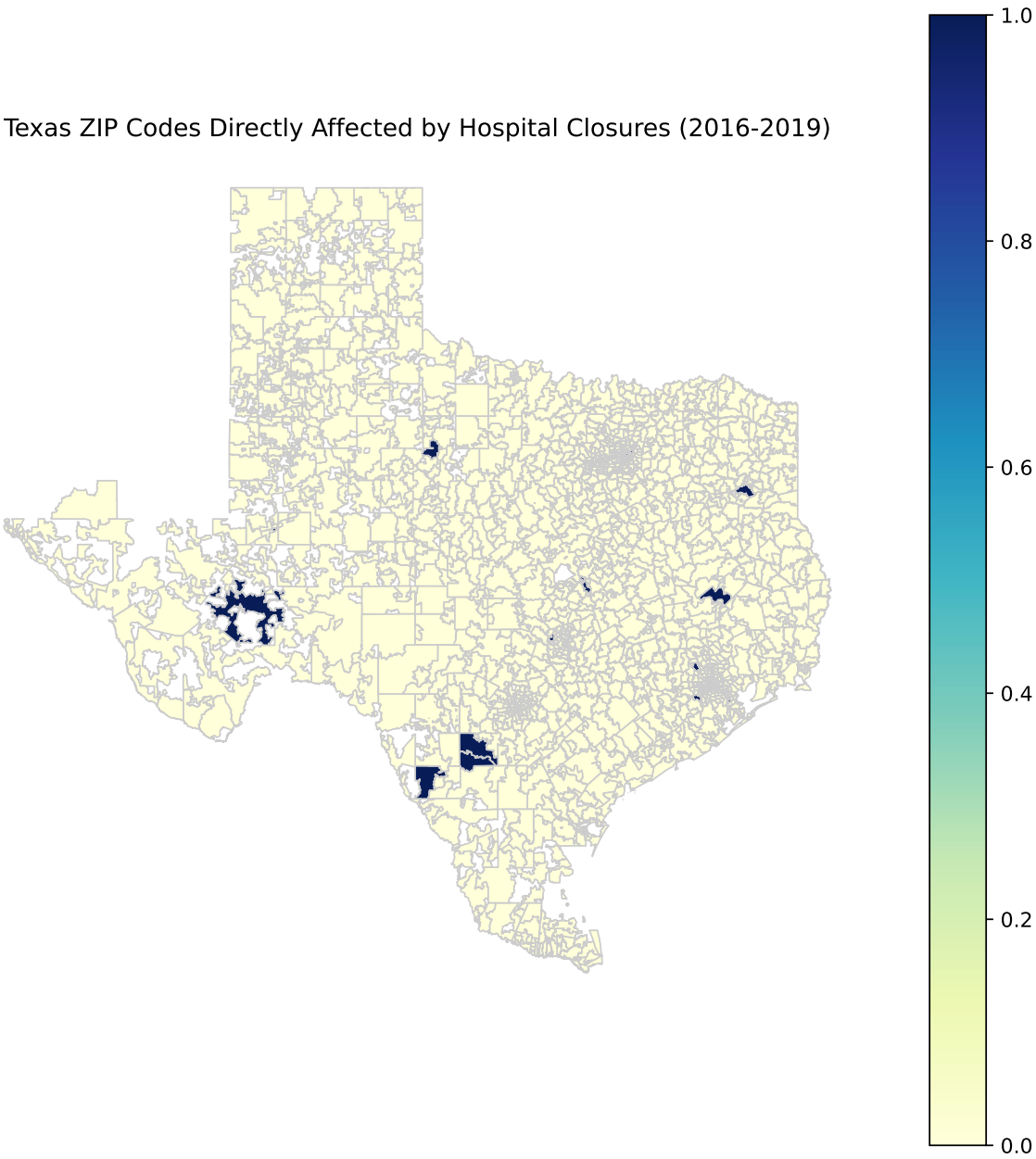
	ZIP Code	Number of Closures
0	75042	1
1	75231	1
2	75662	1
3	75862	1
4	76502	1
5	77035	1
6	77054	1
7	77429	1
8	77479	1
9	77598	1
10	78017	1
11	78061	1
12	785	1
13	78734	1
14	78834	1
15	79553	1
16	79735	1
17	79761	1

2.

```
import geopandas as gpd
import matplotlib.pyplot as plt
```

```
# Load the ZIP code shapefile
zip_shapefile =
 ↪  gpd.read_file('gz_2010_us_860_00_500k/gz_2010_us_860_00_500k.shp')

# Filter for Texas ZIP codes (ZIP codes starting with 750-799)
zip_shapefile =
 ↪  zip_shapefile[zip_shapefile['ZCTA5'].str.startswith(tuple(map(str,
 ↪  range(750, 800))))]

# Ensure ZIP code columns are strings for matching
zip_shapefile['ZCTA5'] = zip_shapefile['ZCTA5'].astype(str)
closures_by_zipcode['ZIP Code'] = closures_by_zipcode['ZIP Code'].astype(str)

# Merge the shapefile with closures data on ZIP code
texas_zip_closures = zip_shapefile.merge(closures_by_zipcode,
 ↪  left_on='ZCTA5', right_on='ZIP Code', how='left')

# Replace NaN values in 'Number of Closures' with 0 for ZIP codes without
 ↪  closures
texas_zip_closures['Number of Closures'] = texas_zip_closures['Number of
 ↪  Closures'].fillna(0)

# Count the number of directly affected ZIP codes (where Number of Closures >
 ↪  0)
affected_zip_count = texas_zip_closures[texas_zip_closures['Number of
 ↪  Closures'] > 0].shape[0]
print(f"Number of directly affected ZIP codes in Texas:
 ↪  {affected_zip_count}")

# Plot the choropleth map
fig, ax = plt.subplots(1, 1, figsize=(10, 10))
texas_zip_closures.plot(column='Number of Closures', cmap='YlGnBu',
 ↪  linewidth=0.8, ax=ax, edgecolor='0.8', legend=True)
ax.set_title('Texas ZIP Codes Directly Affected by Hospital Closures
 ↪  (2016-2019)')
ax.set_axis_off()
plt.show()
```

```
Number of directly affected ZIP codes in Texas: 17
```



3.
4.

Reflecting on the exercise (10 pts)