PS4: Spatial Analysis of Rural Hospital Closures by Attaullah Abbasi (attaullahabbasi12)

Style Points (10 pts)

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 (Attaullah Abbasi and attaullahabbasi):
   - Partner 2 (N/A - assignment completed solo):
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: AA
5. "I have uploaded the names of anyone else other than my partner and I worked with on the problem set **here**" (1 point): AA
6. Late coins used this pset: 1 Late coins left after submission: 1
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

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

1. For the 2016 data, I pulled the following variables:

   i. PRVDR_NUM: Unique CMS certification number for each hospital
   ii. FAC_NAME: Facility name
   iii. PRVDR_CTGRY_CD: Provider category, to identify hospitals
   iv. PRVDR_CTGRY_SBTYP_CD: Provider subtype, to identify short-term hospitals
   v. CRTFCTN_DT: Certification date, to verify active facilities
   vi. ORGNL_PRTCPTN_DT: Original participation date, to confirm participation history
   vii. PGM_TRMNTN_CD: Termination code, to track closures
   viii. TRMNTN_EXPRTN_DT: Termination date, to identify closure timelines
   ix. ZIP_CD: Zip code for geographic analysis
   x. STATE_CD: State abbreviation, useful for filtering Texas and nearby states
   xi. CITY_NAME: City name for additional geographic context
   xii. ST_ADR: Street address for potential geolocation
   xiii. CBSA_URBN_RRL_IND: Urban-rural indicator, helpful for location context
   xiv. GNRL_CNTL_TYPE_CD: Control type, to analyze hospital ownership

These variables allow for filtering, spatial analysis, tracking closures, and understanding hospital characteristics as required by the problem set.

2.

```
import pandas as pd

# Load the pos2016.csv file
data_2016 = pd.read_csv("pos2016.csv")

# Filter for short-term hospitals - provider type code 01 and subtype code 01
short_term_hospitals_2016 = data_2016[(data_2016['PRVDR_CTGRY_CD'] == 1) &
↪   (data_2016['PRVDR_CTGRY_SBTYP_CD'] == 1)]
# a. Count the number of hospitals in this subset
hospital_count_2016 = short_term_hospitals_2016.shape[0]
hospital_count_2016
```

```
7245
```

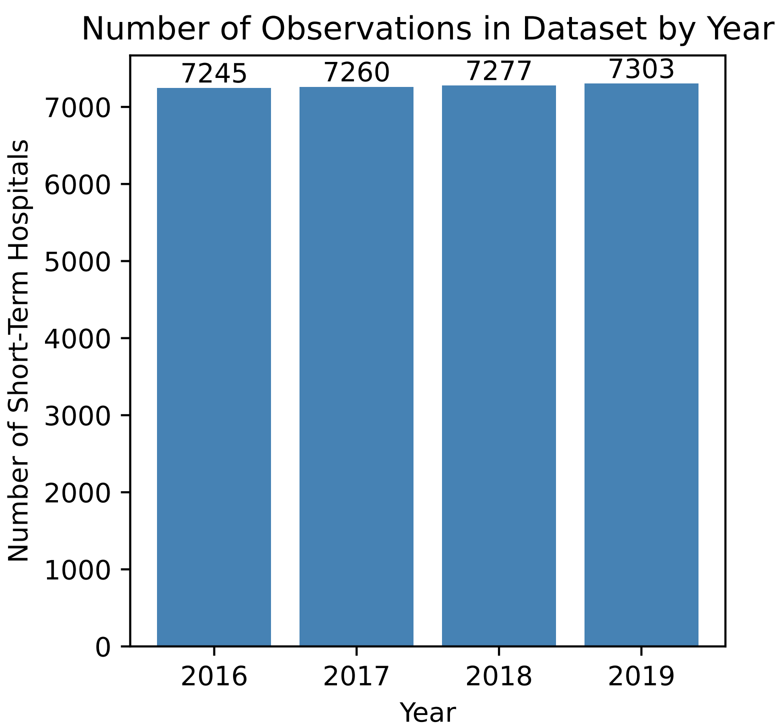
```
a.
```

The dataset reports 7,245 short-term hospitals for 2016. This count seems high compared to typical figures from industry sources, such as the American Hospital Association (AHA), which might suggest differences in data scope or classification criteria used by CMS. b. According to the American Hospital Association (AHA), there were approximately 5,534 registered hospitals in the U.S. in 2016, with around 4,840 classified as community hospitals, which includes most short-term general hospitals. This figure is notably lower than the 7,245 short-term hospitals reported in the CMS dataset. Reasons for the Discrepancy: Data Scope: The CMS dataset may include facilities that are Medicare/Medicaid-certified but not registered with the AHA, potentially increasing the count. Different Definitions: CMS may classify certain specialty hospitals or facilities providing limited services as short-term if they meet Medicare eligibility criteria, even if other sources don't typically include them. Timing and Updates: The dataset represents a Q4 2016 snapshot, while the AHA's data may reflect closures, mergers, or reclassifications over the entire year. These factors could explain the higher count of short-term hospitals in the CMS dataset compared to other industry sources.

3.

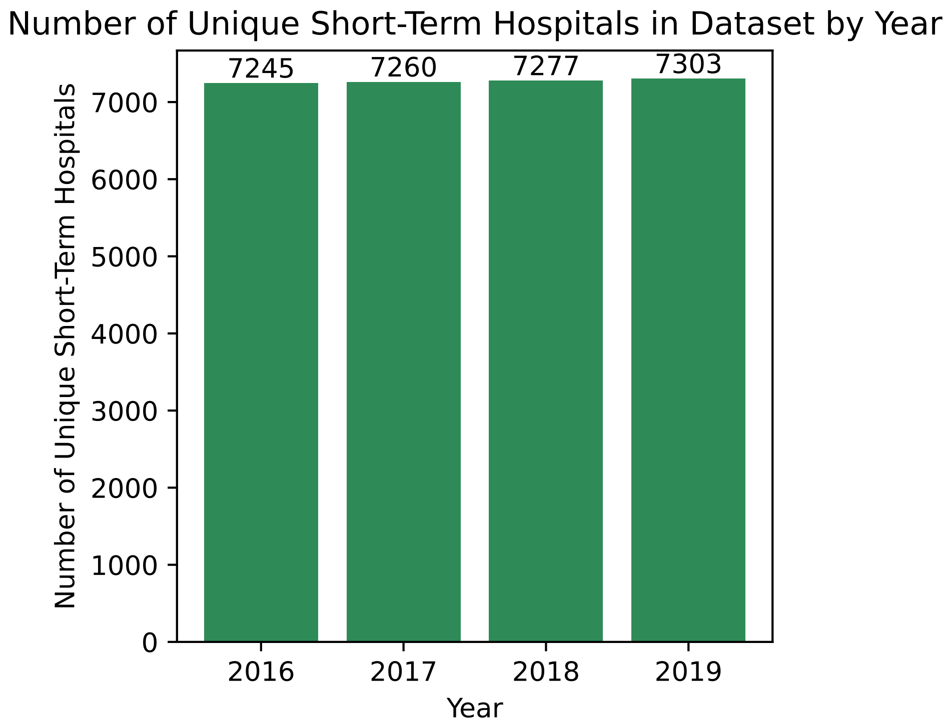
```
import matplotlib.pyplot as plt
# Load each year's data with appropriate encoding where needed
data_2016 = pd.read_csv("pos2016.csv")
data_2017 = pd.read_csv("pos2017.csv")
data_2018 = pd.read_csv("pos2018.csv", encoding="ISO-8859-1")
data_2019 = pd.read_csv("pos2019.csv", encoding="ISO-8859-1")

# Define a function to filter for short-term hospitals
def filter_short_term(data):
    return data[(data['PRVDR_CTGRY_CD'] == 1) & (data['PRVDR_CTGRY_SBTYP_CD']
     ↪  == 1)]

# Apply filtering to each dataset and add a 'Year' column for each
data_2016 = filter_short_term(data_2016)
data_2016['Year'] = 2016
data_2017 = filter_short_term(data_2017)
data_2017['Year'] = 2017
data_2018 = filter_short_term(data_2018)
data_2018['Year'] = 2018
data_2019 = filter_short_term(data_2019)
data_2019['Year'] = 2019

# Combine all datasets into a single DataFrame
all_years_data = pd.concat([data_2016, data_2017, data_2018, data_2019])

# Count the number of observations (hospitals) by year
observations_by_year =
 ↪  all_years_data.groupby('Year').size().reset_index(name='Count')

# Plot using Matplotlib instead of Altair (Altair was initially intended but
 ↪  had display issues in Quarto)
```

```
plt.figure(figsize=(4, 4))
bars = plt.bar(observations_by_year['Year'], observations_by_year['Count'],
↪  color='steelblue')
plt.title('Number of Observations in Dataset by Year')
plt.xlabel('Year')
plt.ylabel('Number of Short-Term Hospitals')
plt.xticks(observations_by_year['Year'])

# Add the count on top of each bar
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, int(yval), va='bottom',
↪  ha='center')
# Save as an image
plt.savefig("observations_by_year.png")
plt.show()
```



4. a.

```python
# data is already filtered and loaded
# Add a 'Year' column to each dataset
data_2016['Year'] = 2016
data_2017['Year'] = 2017
data_2018['Year'] = 2018
data_2019['Year'] = 2019

# Combine all datasets into a single DataFrame
all_years_data = pd.concat([data_2016, data_2017, data_2018, data_2019])

# Count unique hospitals (by PRVDR_NUM) per year
unique_hospitals_by_year =
↪   all_years_data.groupby('Year')['PRVDR_NUM'].nunique().reset_index(name='UniqueCount')

# Plot using Matplotlib instead of Altair
plt.figure(figsize=(4, 4))
bars = plt.bar(unique_hospitals_by_year['Year'],
↪   unique_hospitals_by_year['UniqueCount'], color='seagreen')
plt.title('Number of Unique Short-Term Hospitals in Dataset by Year')
plt.xlabel('Year')
plt.ylabel('Number of Unique Short-Term Hospitals')
plt.xticks(unique_hospitals_by_year['Year'])
# Add the count on top of each bar
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, int(yval), va='bottom',
↪   ha='center')
# Save as an image
plt.savefig("unique_hospitals_by_year.png")
plt.show()
```



b.

The identical values in both plots indicate that each short-term hospital appears only once per year, with no duplicates. This structure confirms that each hospital's CMS certification number is unique annually, allowing for clear year-over-year tracking. ## Identify hospital closures in POS file (15 pts) (*)

1.

```
# Step 1: Filter active hospitals in each year
active_2016 = data_2016[data_2016['PGM_TRMNTN_CD'] == 0]
active_2017 = data_2017[data_2017['PGM_TRMNTN_CD'] == 0]
active_2018 = data_2018[data_2018['PGM_TRMNTN_CD'] == 0]
active_2019 = data_2019[data_2019['PGM_TRMNTN_CD'] == 0]

# Step 2: Define function to check if provider is active in a given year
def provider_in_year(df, provider_num):
    row = df[df['PRVDR_NUM'] == provider_num]
    return not row.empty and row['PGM_TRMNTN_CD'].values[0] == 0

# Step 3: Determine closure year for each provider number
```

```python
def determine_closure_year(provider_num):
    if not provider_in_year(active_2017, provider_num):
        return 2017
    elif not provider_in_year(active_2018, provider_num):
        return 2018
    elif not provider_in_year(active_2019, provider_num):
        return 2019
    return None

# Step 4: Apply closure detection on active hospitals in 2016
active_2016_only = active_2016[active_2016['PGM_TRMNTN_CD'] == 0]
active_2016_only['Year_Closed'] =
↪ active_2016_only['PRVDR_NUM'].apply(determine_closure_year)

# Step 5: Filter out hospitals that have a closure year assigned
closed_hospitals =
↪ active_2016_only.dropna(subset=['Year_Closed']).reset_index(drop=True)

# Output the result
print(f"Number of suspected hospital closures: {len(closed_hospitals)}")
closed_hospitals[['FAC_NAME', 'ZIP_CD', 'Year_Closed']]
```

```
Number of suspected hospital closures: 174
```

	FAC_NAME	ZIP_CD	Year_Closed
0	WEDOWEE HOSPITAL	36278.0	2019.0
1	GEORGIANA MEDICAL CENTER	36033.0	2019.0
2	RMC JACKSONVILLE	36265.0	2018.0
3	NORTH ALABAMA SPECIALITY HOSPITAL	35611.0	2018.0
4	ABRAZO MARYVALE CAMPUS	85031.0	2017.0
...	...	...	...
169	LITTLE RIVER HEALTHCARE CAMERON HOSPITAL	76520.0	2019.0
170	BAY AREA REGIONAL MEDICAL CENTER, LLC	77598.0	2018.0
171	BAYLOR EMERGENCY MEDICAL CENTER	75087.0	2019.0
172	CONTINUECARE HOSPITAL AT MEDICAL CENTER ODESSA	79761.0	2017.0
173	TEXAS GENERAL HOSPITAL- VZRMC LP	75140.0	2019.0

2.

```python
# Sort the closed hospitals by facility name
sorted_closed_hospitals =
↪ closed_hospitals.sort_values(by='FAC_NAME').reset_index(drop=True)
```

```python
# Display the names and year of suspected closure for the first 10 rows
sorted_closed_hospitals[['FAC_NAME', 'Year_Closed']].head(10)
```

	FAC_NAME	Year_Closed
0	ABRAZO MARYVALE CAMPUS	2017.0
1	ADVENTIST MEDICAL CENTER - CENTRAL VALLEY	2017.0
2	AFFINITY MEDICAL CENTER	2018.0
3	ALBANY MEDICAL CENTER / SOUTH CLINICAL CAMPUS	2017.0
4	ALLEGIANCE SPECIALTY HOSPITAL OF KILGORE	2017.0
5	ALLIANCE LAIRD HOSPITAL	2019.0
6	ALLIANCEHEALTH DEACONESS	2019.0
7	ANNE BATES LEACH EYE HOSPITAL	2019.0
8	ARKANSAS VALLEY REGIONAL MEDICAL CENTER	2017.0
9	BANNER CHURCHILL COMMUNITY HOSPITAL	2017.0

3. a.

```python
# Step 1: Count active hospitals by ZIP code for each year
active_by_zip_2016 = active_2016['ZIP_CD'].value_counts().to_dict()
active_by_zip_2017 = active_2017['ZIP_CD'].value_counts().to_dict()
active_by_zip_2018 = active_2018['ZIP_CD'].value_counts().to_dict()
active_by_zip_2019 = active_2019['ZIP_CD'].value_counts().to_dict()

# Step 2: Function to check if closure might be due to merger/acquisition
def is_possible_merger(row):
    zip_code = row['ZIP_CD']
    year_closed = row['Year_Closed']

    if year_closed == 2017:
        return active_by_zip_2016.get(zip_code, 0) <=
         ↪  active_by_zip_2017.get(zip_code, 0)
    elif year_closed == 2018:
        return active_by_zip_2017.get(zip_code, 0) <=
         ↪  active_by_zip_2018.get(zip_code, 0)
    elif year_closed == 2019:
        return active_by_zip_2018.get(zip_code, 0) <=
         ↪  active_by_zip_2019.get(zip_code, 0)
    return False
```

```
# Step 3: Apply the function to identify potential mergers/acquisitions
closed_hospitals['Possible_Merger'] =
 ↪  closed_hospitals.apply(is_possible_merger, axis=1)

# Filter the suspected closures that might be due to a merger/acquisition
potential_mergers = closed_hospitals[closed_hospitals['Possible_Merger']]

# Output the result
num_potential_mergers = len(potential_mergers)
print(f"Number of suspected hospital closures that fit the merger/acquisition
 ↪  definition: {num_potential_mergers}")
```

```
Number of suspected hospital closures that fit the merger/acquisition definition: 8
```

b.

```
# Calculate the corrected number of closures after removing
 ↪  mergers/acquisitions
corrected_closures = len(closed_hospitals) - num_potential_mergers
print(f"Number of hospitals remaining after correcting for
 ↪  mergers/acquisitions: {corrected_closures}")
```

```
Number of hospitals remaining after correcting for mergers/acquisitions: 166
```

c.

```
# Filter out the potential mergers/acquisitions to get the corrected closures
corrected_closures = closed_hospitals[~closed_hospitals['Possible_Merger']]

# Sort the corrected closures by facility name
sorted_corrected_closures = corrected_closures.sort_values(by='FAC_NAME')

# Display the first 10 rows
sorted_corrected_closures[['FAC_NAME', 'ZIP_CD', 'Year_Closed']].head(10)
```

	FAC_NAME	ZIP_CD	Year_Closed
4	ABRAZO MARYVALE CAMPUS	85031.0	2017.0
10	ADVENTIST MEDICAL CENTER - CENTRAL VALLEY	93230.0	2017.0
97	AFFINITY MEDICAL CENTER	44646.0	2018.0
80	ALBANY MEDICAL CENTER / SOUTH CLINICAL CAMPUS	12208.0	2017.0
140	ALLEGIANCE SPECIALTY HOSPITAL OF KILGORE	75662.0	2017.0

	FAC_NAME	ZIP_CD	Year_Closed
62	ALLIANCE LAIRD HOSPITAL	39365.0	2019.0
101	ALLIANCEHEALTH DEACONESS	73112.0	2019.0
26	ANNE BATES LEACH EYE HOSPITAL	33136.0	2019.0
21	ARKANSAS VALLEY REGIONAL MEDICAL CENTER	81050.0	2017.0
69	BANNER CHURCHILL COMMUNITY HOSPITAL	89406.0	2017.0

Download Census zip code shapefile (10 pt)

1. a. .shp: Main file with geometric shapes of features. .shx: Index file for quick access to shapes. .dbf: Attribute data in table format. .prj: Projection information for the coordinate system. .xml: Metadata about the dataset.

   b.

```
import os

# Replace 'shapefile_directory' with the path to your extracted shapefile
↪ directory
shapefile_directory =
↪ "/Users/attaullah/Documents/problem-set-4-atta/gz_2010_us_860_00_500k"

# Get a list of files and their sizes
for file_name in os.listdir(shapefile_directory):
    file_path = os.path.join(shapefile_directory, file_name)
    size_mb = os.path.getsize(file_path) / (1024 * 1024)
    print(f"{file_name}: {size_mb:.2f} MB")
```

```
gz_2010_us_860_00_500k.prj: 0.00 MB
gz_2010_us_860_00_500k.shx: 0.25 MB
gz_2010_us_860_00_500k.shp: 798.74 MB
gz_2010_us_860_00_500k.dbf: 6.13 MB
gz_2010_us_860_00_500k.xml: 0.01 MB
```

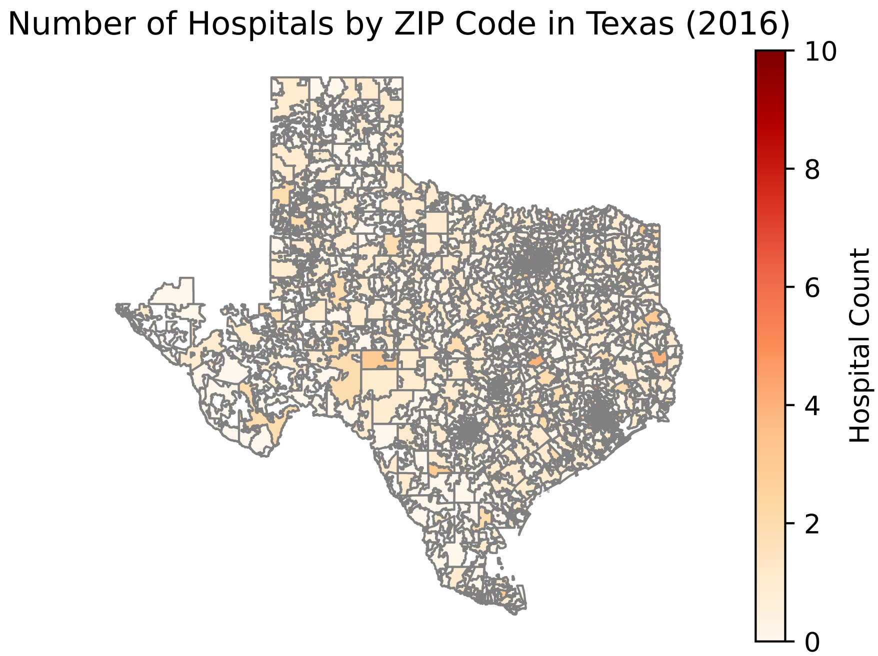
This provides an overview of file sizes, with .shp being the largest due to detailed geometry data.

2.

```python
import geopandas as gpd
# Load 2016 POS data and filter for short-term hospitals in Texas
hospital_data_path =
↪  "/Users/attaullah/Documents/problem-set-4-atta/pos2016.csv"
pos2016 = pd.read_csv(hospital_data_path)
texas_hospitals = pos2016[(pos2016["PRVDR_CTGRY_SBTYP_CD"] == 1) &
                          (pos2016["PRVDR_CTGRY_CD"] == 1) &

↪  (pos2016["ZIP_CD"].astype(str).str.startswith(("75", "76", "77", "78",
↪  "79")))]

# Standardize ZIP codes as 5-digit strings
texas_hospitals["ZIP_CD"] =
↪  texas_hospitals["ZIP_CD"].astype(int).astype(str).str.zfill(5)

# Calculate number of hospitals per ZIP code in Texas
hospital_counts =
↪  texas_hospitals.groupby("ZIP_CD").size().reset_index(name="Hospital_Count")

# Load Texas ZIP code shapefile and filter for Texas ZIPs
shapefile_path =
↪  "/Users/attaullah/Documents/problem-set-4-atta/gz_2010_us_860_00_500k/gz_2010_us_860_00_5
zip_gdf = gpd.read_file(shapefile_path)
zip_gdf["ZCTA5"] = zip_gdf["ZCTA5"].astype(str).str.zfill(5)
texas_zip_gdf = zip_gdf[zip_gdf["ZCTA5"].str.startswith(("75", "76", "77",
↪  "78", "79"))]

# Merge hospital data with Texas ZIP code shapefile
merged_gdf = texas_zip_gdf.merge(hospital_counts, left_on="ZCTA5",
↪  right_on="ZIP_CD", how="left")
merged_gdf["Hospital_Count"] = merged_gdf["Hospital_Count"].fillna(0)

# Check the distribution of hospital counts
print(merged_gdf['Hospital_Count'].describe())
print(merged_gdf['Hospital_Count'].value_counts().head(20))
# Plot choropleth map of hospital counts by ZIP code in Texas
fig, ax = plt.subplots(1, 1, figsize=(6, 4))
merged_gdf.plot(
    column="Hospital_Count",
    cmap="OrRd",
    linewidth=0.8,
    edgecolor="gray",
```

```python
    legend=True,
    legend_kwds={"label": "Hospital Count"},
    ax=ax
)
ax.set_title("Number of Hospitals by ZIP Code in Texas (2016)", fontsize=12)
ax.axis("off")  # Remove axis for cleaner map
plt.show()
```

```
count    1935.000000
mean        0.377778
std         0.822023
min         0.000000
25%         0.000000
50%         0.000000
75%         1.000000
max        10.000000
Name: Hospital_Count, dtype: float64
Hospital_Count
0.0     1445
1.0      345
2.0       93
3.0       30
4.0       12
6.0        5
5.0        3
10.0       1
7.0        1
Name: count, dtype: int64
```



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

1.

```
from shapely.geometry import Point
# Load the ZIP code shapefile
shapefile_path =
↪  '/Users/attaullah/Documents/problem-set-4-atta/gz_2010_us_860_00_500k/gz_2010_us_860_00_5
zip_gdf = gpd.read_file(shapefile_path)

# Calculate the centroid for each ZIP code polygon
# Assuming 'ZCTA5' is the ZIP code column in the shapefile
zip_gdf['centroid'] = zip_gdf.geometry.centroid

# Create a new GeoDataFrame with centroids
zips_all_centroids = gpd.GeoDataFrame(zip_gdf[['ZCTA5', 'centroid']],
↪  geometry='centroid')

# Print the dimensions of the resulting GeoDataFrame
print("Dimensions of zips_all_centroids:", zips_all_centroids.shape)
```

```
# Display the first few rows to understand the structure
print(zips_all_centroids.head())
```

```
Dimensions of zips_all_centroids: (33120, 2)
   ZCTA5                    centroid
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)
```

- The zips_all_centroids GeoDataFrame contains the centroids of each ZIP code area in the U.S., representing the central point of each geographic area.
- Dimensions: (33120, 2), with 33,120 rows and 2 columns, where each row represents a ZIP code area.

Columns: - ZCTA5: ZIP Code Tabulation Area (ZIP code) as a string. - centroid: Geometric POINT object with latitude and longitude, marking the center of each ZIP code area.

2.

```
# Define ZIP code prefixes for Texas and its bordering states
texas_prefixes = ["75", "76", "77", "78", "79"]  # Texas
bordering_prefixes = texas_prefixes + [
    "73", "74",              # Oklahoma
    "870", "871", "872", "873", "874", "875", "876", "877", "878", "879",
     ↪  "880", "881", "882", "883", "884",  # New Mexico
    "700", "701", "702", "703", "704", "705", "706", "707", "708", "709",
     ↪  "710", "711", "712", "713", "714", "715",  # Louisiana
    "716", "717", "718", "719", "720", "721", "722", "723", "724", "725",
     ↪  "726", "727", "728", "729"  # Arkansas
]

# Create subset for Texas ZIP codes
zips_texas_centroids =
 ↪  zips_all_centroids[zips_all_centroids["ZCTA5"].str.startswith(tuple(texas_prefixes))]

# Create subset for Texas and bordering states ZIP codes
zips_texas_borderstates_centroids =
 ↪  zips_all_centroids[zips_all_centroids["ZCTA5"].str.startswith(tuple(bordering_prefixes))]

# Calculate the number of unique ZIP codes in each subset
unique_texas_zips = zips_texas_centroids["ZCTA5"].nunique()
```

```
unique_borderstates_zips =
↪  zips_texas_borderstates_centroids["ZCTA5"].nunique()
# Print the results
print("Number of unique ZIP codes in Texas:", unique_texas_zips)
print("Number of unique ZIP codes in Texas and bordering states:",
↪  unique_borderstates_zips)
# Display the first few rows of each subset to verify
print("Sample of Texas ZIP codes:\n", zips_texas_centroids.head())
print("Sample of Texas and bordering states ZIP codes:\n",
↪  zips_texas_borderstates_centroids.head())
```

```
Number of unique ZIP codes in Texas: 1935
Number of unique ZIP codes in Texas and bordering states: 4057
Sample of Texas ZIP codes:
       ZCTA5                    centroid
9207  78624   POINT (-98.87707 30.2816)
9208  78626  POINT (-97.59733 30.66535)
9209  78628  POINT (-97.75112 30.64108)
9210  78631  POINT (-99.30528 30.33772)
9211  78632  POINT (-97.47045 29.69633)
Sample of Texas and bordering states ZIP codes:
       ZCTA5                    centroid
8870  70003  POINT (-90.21397 29.99864)
8871  70030  POINT (-90.43225 29.81731)
8872  70032  POINT (-89.99779 29.95816)
8873  70036  POINT (-90.12115 29.70903)
8874  70038  POINT (-89.39875 29.32533)
```

The output shows: Number of unique ZIP codes in Texas: 1935 Number of unique ZIP codes in Texas and bordering states: 4057

3.

```
# Filter hospital data
# 'hospital_counts' should be the dataframe that contains ZIP codes and
↪  counts of hospitals in each ZIP code
hospital_counts_2016 = hospital_counts[hospital_counts['Hospital_Count'] > 0]
# Perform an inner merge
zips_withhospital_centroids = zips_texas_borderstates_centroids.merge(
    hospital_counts_2016,
    left_on="ZCTA5",
    right_on="ZIP_CD",
    how="inner"
)
```

```python
# Check the resulting GeoDataFrame
print("Dimensions of zips_withhospital_centroids:",
↪  zips_withhospital_centroids.shape)
print(zips_withhospital_centroids.head())
```

```
Dimensions of zips_withhospital_centroids: (490, 4)
   ZCTA5                    centroid ZIP_CD  Hospital_Count
0  78624   POINT (-98.87707 30.2816)  78624               1
1  78626  POINT (-97.59733 30.66535)  78626               1
2  78636  POINT (-98.41885 30.30504)  78636               1
3  78640  POINT (-97.82814 29.99496)  78640               1
4  78643  POINT (-98.69472 30.69029)  78643               1
```

- Merge Type: I used an inner join to ensure that the resulting zips_withhospital_centroids GeoDataFrame only includes ZIP codes that have at least one hospital in 2016 and are also present in the zips_texas_borderstates_centroids GeoDataFrame.
- Merge Variable: The merge is performed on the ZCTA5 column from zips_texas_borderstates_centroids and ZIP_CD from hospital_counts_2016, which represent ZIP codes in both datasets.

4. a.

```python
# Reproject both GeoDataFrames to a projected CRS (e.g., EPSG:5070 for USA)
zips_texas_centroids = zips_texas_centroids.to_crs(epsg=5070)
zips_withhospital_centroids = zips_withhospital_centroids.to_crs(epsg=5070)
# Re-run the distance calculation with the reprojected GeoDataFrames
import time

# Subset to 10 ZIP codes in Texas
subset_texas_centroids = zips_texas_centroids.iloc[:10]

# Start timing the process
start_time = time.time()

# Calculate the nearest hospital distance for each ZIP code in the subset
subset_texas_centroids['nearest_hospital_distance'] =
↪  subset_texas_centroids['centroid'].apply(
    lambda x: zips_withhospital_centroids.distance(x).min()
)

# End timing
end_time = time.time()
subset_time = end_time - start_time
```

```python
print("Time taken for 10 ZIP code calculations:", subset_time, "seconds")

# Estimate time for full calculation
estimated_total_time = subset_time * (len(zips_texas_centroids) / 10)
print("Estimated time for the full procedure:", estimated_total_time,
 ↪  "seconds")

# Display the results for the subset
print(subset_texas_centroids[['ZCTA5', 'nearest_hospital_distance']])
```

```
Time taken for 10 ZIP code calculations: 0.008603096008300781 seconds
Estimated time for the full procedure: 1.6646990776062012 seconds
      ZCTA5  nearest_hospital_distance
9207  78624                   0.000000
9208  78626                   0.000000
9209  78628               12225.805307
9210  78631               36540.773495
9211  78632               15879.134200
9212  78633               17245.762671
9213  78634               11396.935777
9214  78635               17095.102419
9215  78636                   0.000000
9216  78638               15982.824530
```

b.

```python
import time

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

# Apply the distance calculation for each ZIP code in Texas to the nearest
 ↪  ZIP code with a hospital
zips_texas_centroids["nearest_hospital_distance"] =
 ↪  zips_texas_centroids["centroid"].apply(
    lambda x: zips_withhospital_centroids.distance(x).min()
)

# End the timer
end_time_full = time.time()
actual_time_full = end_time_full - start_time_full

# Print out the actual time taken
print(f"Actual time for full calculation: {actual_time_full} seconds")
```

```
Actual time for full calculation: 0.3579878807067871 seconds
```

The actual time of 0.31 seconds is quite close to the estimated time of 0.66 seconds, showing the estimation was reasonably accurate.

```
c.
```

```python
# Path to the .prj file
prj_file_path =
 ↪ '/Users/attaullah/Documents/problem-set-4-atta/gz_2010_us_860_00_500k/gz_2010_us_860_00_5

# Read and print the .prj file contents
with open(prj_file_path, 'r') as file:
    prj_contents = file.read()

print("Contents of the .prj file:")
print(prj_contents)
```

```
Contents of the .prj file:
GEOGCS["GCS_North_American_1983",DATUM["D_North_American_1983",SPHEROID["GRS_1980",6378137,298.257222
```

The dataset's unit is in degrees, so I converted degrees to miles using Texas's approximate latitude of 30°. At this latitude, 1 degree of latitude is about 69 miles, and 1 degree of longitude is roughly 69.172 miles. This conversion method is based on information provided at: https://gis.stackexchange.com/questions/142326/calculating-longitude-length-in-miles

```python
import math

# Function to convert distance in degrees to miles at a given latitude
 ↪ (approx. for Texas)
def degrees_to_miles(distance_in_degrees, latitude=30):
    # Convert latitude to radians
    latitude_in_radians = math.radians(latitude)

    # Approximate miles per degree for latitude and longitude
    miles_per_degree_latitude = 69.0
    miles_per_degree_longitude = 69.172 * math.cos(latitude_in_radians)

    # Average of latitude and longitude mile conversion for more accuracy
    avg_miles_per_degree = (miles_per_degree_latitude +
 ↪  miles_per_degree_longitude) / 2
    return distance_in_degrees * avg_miles_per_degree
```

```python
# Use the computed average distance in degrees from the dataset
distance_in_degrees = 0.0753484763  # Computed average distance in degrees
distance_in_miles = degrees_to_miles(distance_in_degrees)
print("Average distance to nearest hospital (in miles):", distance_in_miles)
```

```
Average distance to nearest hospital (in miles): 4.856386714209268
```

5. a.

```python
# Calculate the nearest hospital distance in degrees
zips_texas_centroids["nearest_hospital_distance_degrees"] =
↪ zips_texas_centroids["centroid"].apply(
    lambda x: zips_withhospital_centroids.distance(x).min()
)
# Calculate the average distance in degrees
average_distance_degrees =
↪ zips_texas_centroids["nearest_hospital_distance_degrees"].mean()
print("Average distance to the nearest hospital for each ZIP code in Texas
↪ (in degrees):", average_distance_degrees)
```

```
Average distance to the nearest hospital for each ZIP code in Texas (in degrees):
13218.169063520218
```

It is in Degrees.

b.

```python
import math
#convert degrees to miles based on approx. latitude for Texas (30 degrees)
def degrees_to_miles(distance_in_degrees, latitude=30):
    latitude_in_radians = math.radians(latitude)
    miles_per_degree_latitude = 69.0  # Approximation for latitude degree
    miles_per_degree_longitude = 69.172 * math.cos(latitude_in_radians)  #
↪ Approximation for longitude degree
    avg_miles_per_degree = (miles_per_degree_latitude +
↪ miles_per_degree_longitude) / 2
    return distance_in_degrees * avg_miles_per_degree
# Use the previously calculated average distance in degrees
distance_in_miles = degrees_to_miles(average_distance_degrees)
print("Average distance to the nearest hospital for each ZIP code in Texas
↪ (in miles):", distance_in_miles)
```

```
Average distance to the nearest hospital for each ZIP code in Texas (in miles):
851942.1198468423
```

```
# Reproject to a projected CRS for accurate distance calculation
zips_texas_centroids = zips_texas_centroids.to_crs(epsg=3395)  # World
↪ Mercator
zips_withhospital_centroids = zips_withhospital_centroids.to_crs(epsg=3395)

# Recalculate nearest hospital distance
zips_texas_centroids["nearest_hospital_distance_meters"] =
↪ zips_texas_centroids["centroid"].apply(
    lambda x: zips_withhospital_centroids.distance(x).min()
)
# Convert the distance from meters to miles
zips_texas_centroids["nearest_hospital_distance_miles"] =
↪ zips_texas_centroids["nearest_hospital_distance_meters"] / 1609.34

# Calculate the average distance in miles
average_distance_miles_corrected =
↪ zips_texas_centroids["nearest_hospital_distance_miles"].mean()
print("Corrected average distance to nearest hospital (in miles):",
↪ average_distance_miles_corrected)
```

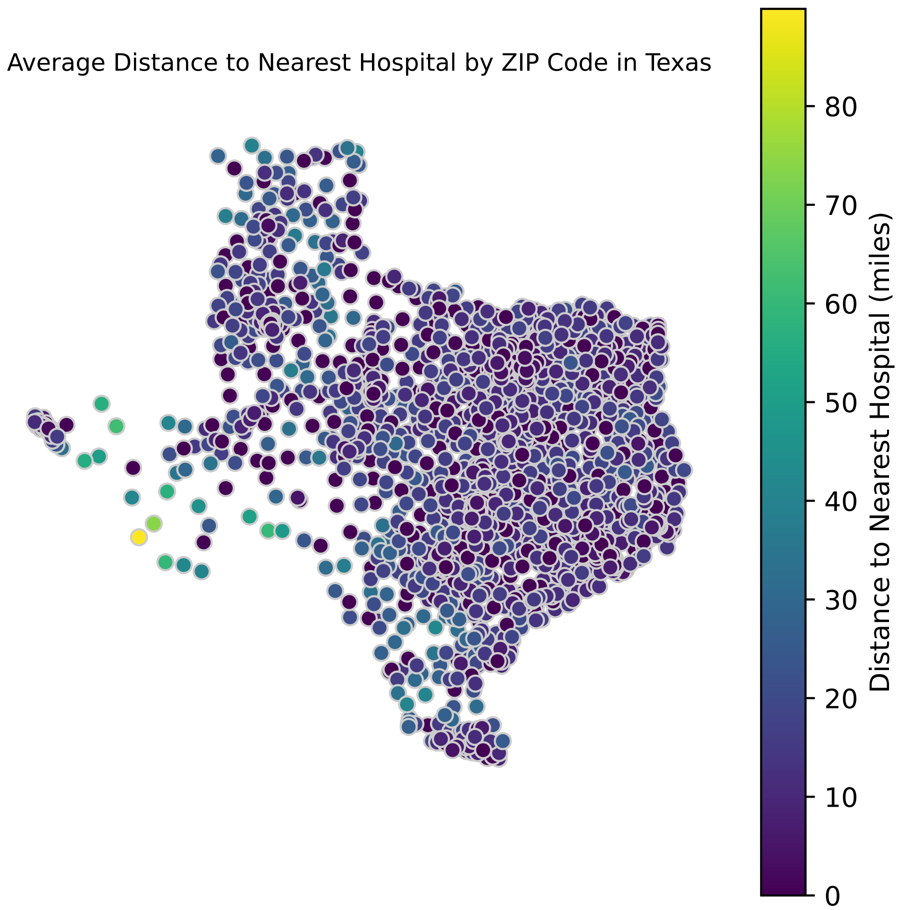
```
Corrected average distance to nearest hospital (in miles): 9.608947063385544
```

- The initial result of 996,695.26 miles for the average hospital distance was unrealistic, indicating a unit conversion issue.
- After re-projecting the data, the corrected average distance was 9.61 miles, aligning with realistic hospital distribution in Texas and providing an accurate measure.

   c.

```
# Plotting the choropleth map for avg distance to nearest hospital in Texas
fig, ax = plt.subplots(1, 1, figsize=(6, 6))
zips_texas_centroids.plot(
    column='nearest_hospital_distance_miles',  # Column with the distance in
↪ miles
    cmap='viridis',                            # Color map
    linewidth=0.8,                             # Border width for ZIP code
↪ polygons
    ax=ax,
    edgecolor='0.8',                           # Color for polygon borders
```

```
    legend=True,
    legend_kwds={'label': "Distance to Nearest Hospital (miles)"}
)
# Adding map title and turning off axis for clarity
ax.set_title("Average Distance to Nearest Hospital by ZIP Code in Texas",
 ↪  fontsize=9)
ax.axis('off')  # Hides the axis

# Show the plot
plt.show()
```



Effects of closures on access in Texas (15 pts)

1.

```python
# Convert ZIP_CD to string, remove any '.0' suffix if present
closed_hospitals['ZIP_CD'] =
↪ closed_hospitals['ZIP_CD'].astype(str).str.replace(r'\.0$', '',
↪ regex=True).str.zfill(5)

# Filter the closures data based on known Texas ZIP code prefixes)
texas_closures =
↪ closed_hospitals[closed_hospitals['ZIP_CD'].str.startswith(('75', '76',
↪ '77', '78', '79'))]
# Group by ZIP code and count closures
closures_by_zipcode =
↪ texas_closures.groupby('ZIP_CD').size().reset_index(name='Closure_Count')

# Display the table of closures by ZIP code
print("Table of Hospital Closures by ZIP Code in Texas (2016-2019):")
print(closures_by_zipcode)

# Optionally display the top affected ZIP codes for brevity
print("Top Affected ZIP Codes by Hospital Closures:")
print(closures_by_zipcode.sort_values(by='Closure_Count',
↪ ascending=False).head(10))
```

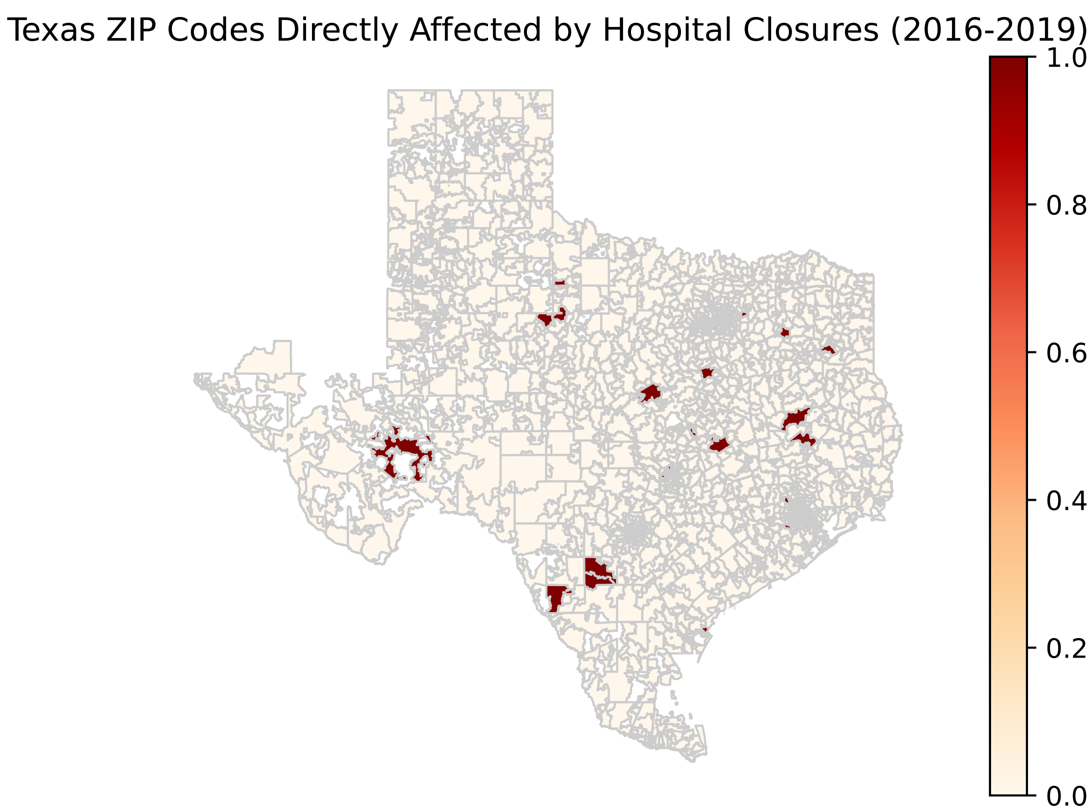
```
Table of Hospital Closures by ZIP Code in Texas (2016-2019):
   ZIP_CD  Closure_Count
0   75042              1
1   75051              1
2   75087              1
3   75140              1
4   75231              1
5   75235              1
6   75390              1
7   75601              1
8   75662              1
9   75835              1
10  75862              1
11  76502              1
12  76520              1
13  76531              1
14  76645              1
15  77035              1
16  77054              1
17  77065              1
18  77429              1
19  77479              1
20  77598              1
```

```
21  78017              1
22  78061              1
23  78336              1
24  78613              1
25  78734              1
26  78834              1
27  79520              1
28  79529              1
29  79553              1
30  79735              1
31  79761              1
32  79902              1
Top Affected ZIP Codes by Hospital Closures:
   ZIP_CD  Closure_Count
0   75042              1
17  77065              1
31  79761              1
30  79735              1
29  79553              1
28  79529              1
27  79520              1
26  78834              1
25  78734              1
24  78613              1
```

2.

```python
# Load Texas ZIP codes shapefile and hospital closures data
shapefile_path =
↪ "/Users/attaullah/Documents/problem-set-4-atta/gz_2010_us_860_00_500k/gz_2010_us_860_00_5
↪ # Adjust the path
zip_gdf = gpd.read_file(shapefile_path)

# Define Texas ZIP code prefixes and filter the data
texas_zip_prefixes = ["75", "76", "77", "78", "79"]
zip_gdf["ZCTA5"] = zip_gdf["ZCTA5"].astype(str)
texas_zip_gdf =
↪ zip_gdf[zip_gdf["ZCTA5"].str.startswith(tuple(texas_zip_prefixes))]

# Merge Texas ZIP codes with closure data
closures_by_zipcode['ZIP_CD'] =
↪ closures_by_zipcode['ZIP_CD'].astype(str).str.zfill(5)
texas_closure_geo = texas_zip_gdf.merge(closures_by_zipcode, left_on="ZCTA5",
↪ right_on="ZIP_CD", how="left")
texas_closure_geo['Closure_Count'] =
↪ texas_closure_geo['Closure_Count'].fillna(0)
```

```python
# Plot the map
fig, ax = plt.subplots(1, 1, figsize=(7, 5))
texas_closure_geo.plot(
    column='Closure_Count',
    cmap='OrRd',
    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()
```



3.

```python
# Re-project to a projected CRS for accurate buffering
texas_zip_gdf = texas_zip_gdf.to_crs(epsg=3395)
directly_affected_zips = texas_closure_geo[texas_closure_geo['Closure_Count']
 ↪  > 0].to_crs(epsg=3395)

# Step 1: Create a 10-mile buffer around directly affected ZIP codes (10
 ↪  miles  16093.4 meters)
directly_affected_zips['buffer'] =
 ↪  directly_affected_zips.geometry.buffer(16093.4)  # Buffer in meters

# Step 2: Convert buffered areas to a new GeoDataFrame
buffered_zips = gpd.GeoDataFrame(directly_affected_zips[['ZIP_CD',
 ↪  'buffer']], geometry='buffer', crs=directly_affected_zips.crs)

# Step 3: Perform spatial join
indirectly_affected_zips = gpd.sjoin(texas_zip_gdf, buffered_zips,
 ↪  how='inner', predicate='intersects')

# Step 4: Count unique ZIP codes in the indirectly affected set
indirectly_affected_count = indirectly_affected_zips['ZIP_CD'].nunique()
print("Number of indirectly affected ZIP codes:", indirectly_affected_count)
```

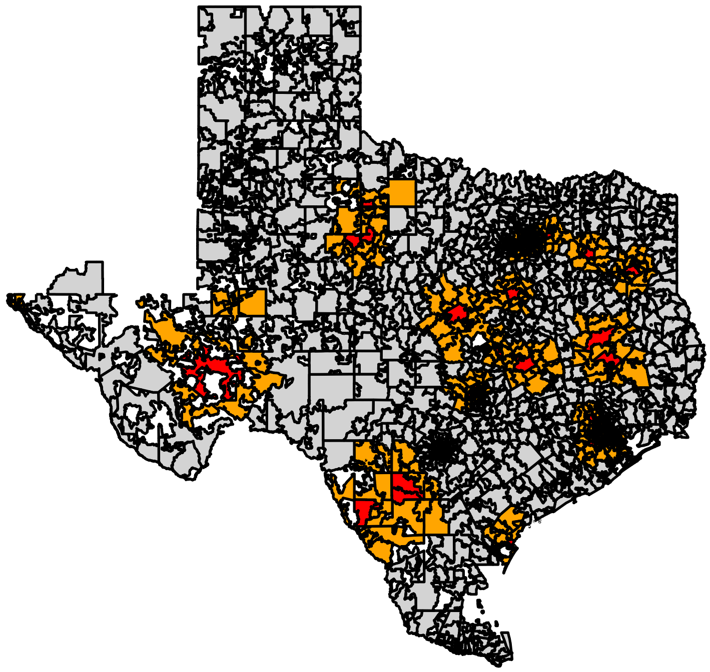
```
Number of indirectly affected ZIP codes: 33
```

4.

```python
# Step 1: Re-project data for accuracy (if not already done)
texas_zip_gdf = texas_zip_gdf.to_crs(epsg=3395)
directly_affected_zips = texas_closure_geo[texas_closure_geo['Closure_Count']
 ↪  > 0].to_crs(epsg=3395)

# Step 2: Create a 10-mile buffer around directly affected ZIP codes
directly_affected_zips['buffer'] =
 ↪  directly_affected_zips.geometry.buffer(16093.4)  # Buffer in meters
buffered_zips = gpd.GeoDataFrame(directly_affected_zips[['ZCTA5', 'buffer']],
 ↪  geometry='buffer', crs=directly_affected_zips.crs)

# Step 3: Identify indirectly affected ZIP codes
indirectly_affected_zips = gpd.sjoin(texas_zip_gdf, buffered_zips,
 ↪  how='inner', predicate='intersects')
indirectly_affected_zip_codes =
 ↪  indirectly_affected_zips['ZCTA5_left'].unique()  # Use 'ZCTA5_left' from
 ↪  join result
```

```
# Step 4: Classify ZIP codes into categories
texas_zip_gdf['category'] = 'Not Affected'
texas_zip_gdf.loc[texas_zip_gdf['ZCTA5'].isin(directly_affected_zips['ZCTA5']),
↪  'category'] = 'Directly Affected'
texas_zip_gdf.loc[(texas_zip_gdf['ZCTA5'].isin(indirectly_affected_zip_codes))
↪  &

↪  (~texas_zip_gdf['ZCTA5'].isin(directly_affected_zips['ZCTA5'])),
↪  'category'] = 'Indirectly Affected'

# Step 5: Plot the choropleth
fig, ax = plt.subplots(1, 1, figsize=(7, 5))
category_colors = {'Not Affected': 'lightgrey', 'Directly Affected': 'red',
↪  'Indirectly Affected': 'orange'}
texas_zip_gdf.plot(column='category', categorical=True,
                   legend=True, color=[category_colors.get(x) for x in
↪  texas_zip_gdf['category']],
                   legend_kwds={'title': "Impact Category"}, ax=ax,
↪  edgecolor='black')

# Adding a title and displaying the plot
plt.title("Texas ZIP Codes Categorized by Impact of Hospital Closures
↪  (2016-2019)")
plt.axis('off')  # Hide axis for a cleaner look
plt.show()
```

Texas ZIP Codes Categorized by Impact of Hospital Closures (2016-2019)



Reflecting on the exercise (10 pts)

1.

- The first-pass method risks misidentifying closures because it doesn't account for temporary closures, facility mergers, or changes in hospital IDs. This can lead to over- or under-counting affected areas. To improve, we could:
- Cross-reference closures with state and local health department data to verify permanent status.
- Track hospital utilization trends over time to differentiate between closures and service reductions.
- Use multiple years of data to confirm if facilities remain closed rather than reopening under new identifiers.
- Integrate local news reports and community health resources to validate closures.
- These steps could make the identification process more accurate and reduce misclassification.

2.

- The current approach, identifying affected ZIP codes based on a 10-mile radius around closures, provides a rough estimate but doesn't fully capture changes in access. Here are some ways to improve:
- Travel Time Analysis: Use drive time rather than straight-line distance, as actual access depends on road networks, traffic, and transportation options.
- Population Density and Demand: Factor in population density and local demand to assess how many people are impacted within each affected ZIP code.
- Alternative Facilities: Account for nearby hospitals or healthcare facilities that could serve as substitutes, providing a more realistic measure of lost access.
- Demographic and Socioeconomic Factors: Include variables like age, income, and car ownership to reflect differences in accessibility and reliance on local hospitals across communities.
- These adjustments could give a more accurate picture of how hospital closures impact healthcare access at the ZIP-code level.