Problem Set 4

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 : Sijie Wu, sijiewu
    - Partner 2 : Abu Bakar Siddique, abubakars
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: **___** **___**
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. `PRVDR_CTGRY_SBTYP_CD` for provider subtype code; `PRVDR_CTGRY_CD` for provider type code; `PRVDR_NUM` for CMS Certification Number; `PGM_TRMNTN_CD` for Termination Code; `ZIP_CD` for zip code; `TRMNTN_EXPRTN_DT` for Termination Date; `FAC_NAME` for facility name.
2.

```
import pandas as pd
filepath1 = "pos2016.csv"
pos2016 = pd.read_csv(filepath1)
pos2016.head()
pos2016["year"] = 2016
pos2016_short = pos2016[(pos2016["PRVDR_CTGRY_CD"] == 1) &
 ↪  (pos2016["PRVDR_CTGRY_SBTYP_CD"] == 1)]
```

```
unique_count1 = pos2016_short['FAC_NAME'].nunique()
unique_count2 = pos2016_short['PRVDR_NUM'].nunique()
print(f"Number of unique PRVDR_NUM values: {unique_count2}")
print(f"Number of unique FAC_NAME values: {unique_count1}")
```

```
Number of unique PRVDR_NUM values: 7245
Number of unique FAC_NAME values: 6770
```

```
a. I use `FAC_NAME` and `PRVDR_NUM` respectively to calculate the unique
value of the short-term hospitals. Under CMS Certification Number, there are
7245 unique hospitals in Q4 2016 data set. Under facility name, there are
6770 unique hospitals in Q4 2016 data set. I believe this number is a bit
large for short-term hospitals in Q4 2016.
```

b. I searched for number of hospitals in 2020 to 2024 on [this website] (https://www.aha.org/statistics/fast-facts-us-hospitals), and discovers that the total number of hospitals in the United States is a little bit more than 6000, with 6039 in 2022 and 6120 in 2024. Also, [Kaiser Family Foundation] (https://www.kff.org/report-section/a-look-at-rural-hospital-closures-and-implications-for-a
states that, there are nearly 5000 short-term hospitals in the US.

I believe the reason behind the difference is that, some hospitals change names over the time, and even though using the unique value of `facility name`, the hospitals are still not unique.

1.

```
filepath2 = "pos2017.csv"
pos2017 = pd.read_csv(filepath2)
pos2017["year"] = 2017
pos2017_short = pos2017[(pos2017["PRVDR_CTGRY_CD"] == 1) &
↪  (pos2017["PRVDR_CTGRY_SBTYP_CD"] == 1)]


filepath3 = "pos2018.csv"
pos2018 = pd.read_csv(filepath3, encoding='ISO-8859-1')
pos2018["year"] = 2018
pos2018_short = pos2018[(pos2018["PRVDR_CTGRY_CD"] == 1) &
↪  (pos2018["PRVDR_CTGRY_SBTYP_CD"] == 1)]

filepath4 = "pos2019.csv"
pos2019 = pd.read_csv(filepath4, encoding='ISO-8859-1')
pos2019["year"] = 2019
pos2019_short = pos2019[(pos2019["PRVDR_CTGRY_CD"] == 1) &
↪  (pos2019["PRVDR_CTGRY_SBTYP_CD"] == 1)]
```

```
pos_merge = pd.concat([pos2016_short, pos2017_short, pos2018_short,
↪  pos2019_short], ignore_index=True)
pos_merge.shape
pos_merge.to_csv("pos_merge.csv", index = False)
```

The plot of number of observations by year is as followed.

```
import altair as alt
from altair_saver import save
```

```
year_count = pos_merge["year"].value_counts().reset_index()
year_count.columns = ["year", "count"]

chart1 = alt.Chart(year_count).mark_bar().encode(
    x = alt.X("count:Q", title = "Number of Observations"),
    y = alt.Y("year:N", title = "year")
).properties(
    title = "Number of Observations by Year"
)

#save(chart1, 'chart1.png')
```

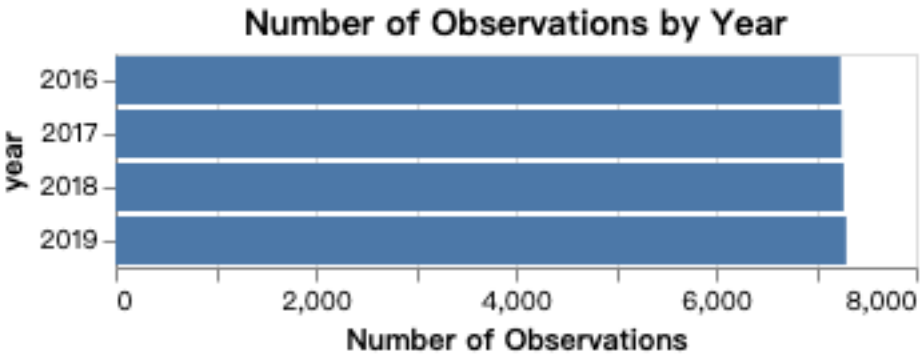


Figure 1: Number of Observations by Year

1. a.

```
year_count_unique = pos_merge.groupby(
    "year")["PRVDR_NUM"].nunique().reset_index()
year_count_unique.columns = ["year", "count"]

chart2 = alt.Chart(year_count_unique).mark_bar().encode(
    x=alt.X("count:Q", title="Number of Hospitals"),
    y=alt.Y("year:N", title="year")
).properties(
    title="Number of Unique Hospitals by Year"
)

#chart2
```

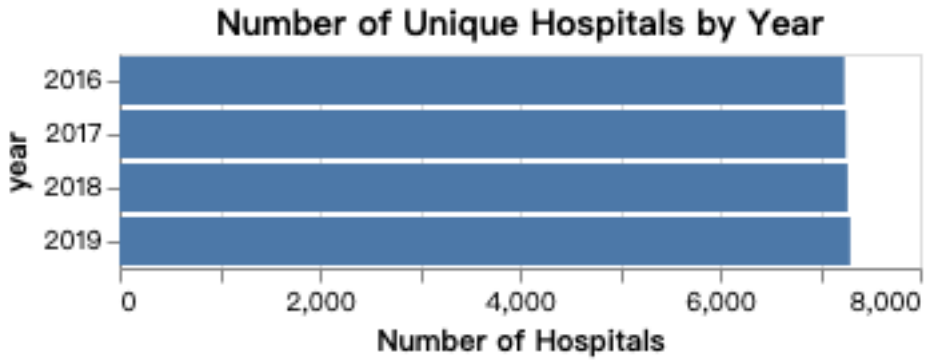


Figure 2: Number of Unique Hospitals by Year

b.

These two plots are the same. It means that the CMS certification number corresponds uniquely with the observations of hospitals.

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

1.

```
hospital_active2016 = pos2016_short[pos2016_short["PGM_TRMNTN_CD"] ==
 ↪  0]["PRVDR_NUM"].unique()
hospital_close_suspect = []
for hospital_id in hospital_active2016:
    hospital_data = pos_merge[pos_merge["PRVDR_NUM"] ==
 ↪  hospital_id].sort_values(by="year")
    closed = False
    for year in range(2017, 2020):  # 2017 to 2019
        year_data = hospital_data[hospital_data["year"] == year]
        if year_data.empty or (year_data["PGM_TRMNTN_CD"].iloc[0] != 0):
            # If hospital data is missing or not active in this year, record
             ↪  closure details
            facility_name = hospital_data["FAC_NAME"].iloc[0]
            zip_code = hospital_data["ZIP_CD"].iloc[0]
            hospital_close_suspect.append({
                "PRVDR_NUM": hospital_id,
                "FAC_NAME": facility_name,
                "ZIP_CD": zip_code,
                "year": year
            })
```

```
            closed = True
            break

hospital_close_suspect = pd.DataFrame(hospital_close_suspect)
```

There are 174 hospitals fit this definition.

2.

```
hospital_close_suspect = hospital_close_suspect.sort_values(by = "FAC_NAME")

hospital_close_top_10 = hospital_close_suspect[['FAC_NAME', 'year']].head(10)
print(hospital_close_top_10)
```

```
                                    FAC_NAME  year
0                        ABRAZO MARYVALE CAMPUS  2017
1      ADVENTIST MEDICAL CENTER - CENTRAL VALLEY  2017
2                        AFFINITY MEDICAL CENTER  2018
3  ALBANY MEDICAL CENTER / SOUTH CLINICAL CAMPUS  2017
4       ALLEGIANCE SPECIALTY HOSPITAL OF KILGORE  2017
5                        ALLIANCE LAIRD HOSPITAL  2019
6                       ALLIANCEHEALTH DEACONESS  2019
7                  ANNE BATES LEACH EYE HOSPITAL  2019
8        ARKANSAS VALLEY REGIONAL MEDICAL CENTER  2017
9            BANNER CHURCHILL COMMUNITY HOSPITAL  2017
```

3. I devide the question into two steps, and use GPT by asking 1) how to count the active hospitals by ZIP code for each year; and 2) how to identity the zip codes that the number of hospitals do not decrease in the next year.

```
# Step 1: Count active hospitals by ZIP code for each year (0 in
 ↪  PGM_TRMNTN_CD indicates "Active Provider")
active_hospitals_by_zip = pos_merge[pos_merge["PGM_TRMNTN_CD"] == 0].groupby(
    ["ZIP_CD", "year"])["PRVDR_NUM"].nunique().reset_index()
active_hospitals_by_zip.columns = ["ZIP_CD", "year", "active_hospitals"]

# Step 2: Identify ZIP codes to filter out
zip_codes_to_filter = []
for _, row in active_hospitals_by_zip.iterrows():
    zip_code = row["ZIP_CD"]
    current_year = row["year"]
```

```
    current_count = row["active_hospitals"]

    # Get count for the following year
    next_year_data =
↪   active_hospitals_by_zip[(active_hospitals_by_zip["ZIP_CD"] == zip_code) &
                                                (active_hospitals_by_zip["year"]
↪   == current_year + 1)]

    if not next_year_data.empty:
        next_year_count = next_year_data["active_hospitals"].values[0]

        # Check if the count does not decrease
        if next_year_count >= current_count:
            zip_codes_to_filter.append(zip_code)

# Step 3: Filter out suspected closures in these ZIP codes
corrected_closures =
↪   hospital_close_suspect[~hospital_close_suspect["ZIP_CD"].isin(
    zip_codes_to_filter)].reset_index()
```

a.

```
num_mergers = len(hospital_close_suspect) - len(corrected_closures)
print(f"{num_mergers} suspected hospital closures that fit the definition of
↪   a merger/acquisition.")
```

146 suspected hospital closures that fit the definition of a merger/acquisition.

b.

```
num_corrected = len(corrected_closures)
print(f"{num_corrected} corrected hospital closures is left after the
↪   filter.")
```

28 corrected hospital closures is left after the filter.

c.

```
corrected_closures = corrected_closures.sort_values(by = "FAC_NAME")

corrected_closures_top_10 = corrected_closures[['FAC_NAME', 'year']].head(10)
print(corrected_closures_top_10)
```

```
                                      FAC_NAME  year
0                          ABRAZO MARYVALE CAMPUS  2017
1        ALLEGIANCE SPECIALTY HOSPITAL OF KILGORE  2017
2         ARKANSAS VALLEY REGIONAL MEDICAL CENTER  2017
3             BANNER CHURCHILL COMMUNITY HOSPITAL  2017
4                    BAYSTATE MARY LANE HOSPITAL  2017
5  CAROLINAS  CONTINUECARE HOSPITAL AT UNIVERSITY  2017
6   CHILDREN'S HOSPITAL -SCOTT & WHITE HEALTHCARE  2017
7                        DIMMIT REGIONAL HOSPITAL  2017
8              EAST TEXAS MEDICAL CENTER TRINITY  2017
9                    FALLBROOK HOSPITAL DISTRICT  2017
```

Download Census zip code shapefile (10 pt)

1.

```
import geopandas as gpd
filepath1 = "gz_2010_us_860_00_500k/gz_2010_us_860_00_500k.dbf"
data1 = gpd.read_file(filepath1)
data1.head()
```

	GEO_ID	ZCTA5	NAME	LSAD	CENSUSAREA	geometry
0	8600000US01040	01040	01040	ZCTA5	21.281	POLYGON ((-72.62734 42.16203, -72.62
1	8600000US01050	01050	01050	ZCTA5	38.329	POLYGON ((-72.95393 42.34379, -72.95
2	8600000US01053	01053	01053	ZCTA5	5.131	POLYGON ((-72.68286 42.37002, -72.68
3	8600000US01056	01056	01056	ZCTA5	27.205	POLYGON ((-72.39529 42.18476, -72.39
4	8600000US01057	01057	01057	ZCTA5	44.907	MULTIPOLYGON (((-72.39191 42.0806

I don't know how to open and look up a .prj file, so I ask GPT "how to open the .prj file", and it offers me the `with open` code.

```
filepath2 = "gz_2010_us_860_00_500k/gz_2010_us_860_00_500k.prj"

with open(filepath2, 'r') as file:
    prj_content = file.read()
    print(prj_content)
```

```
GEOGCS["GCS_North_American_1983",DATUM["D_North_American_1983",SPHEROID["GRS_1980",6378137,29
```

```
filepath3 = "gz_2010_us_860_00_500k/gz_2010_us_860_00_500k.shp"
data3 = gpd.read_file(filepath3)
data3.head()
```

	GEO_ID	ZCTA5	NAME	LSAD	CENSUSAREA	geometry
0	8600000US01040	01040	01040	ZCTA5	21.281	POLYGON ((-72.62734 42.16203, -72.62
1	8600000US01050	01050	01050	ZCTA5	38.329	POLYGON ((-72.95393 42.34379, -72.95
2	8600000US01053	01053	01053	ZCTA5	5.131	POLYGON ((-72.68286 42.37002, -72.68
3	8600000US01056	01056	01056	ZCTA5	27.205	POLYGON ((-72.39529 42.18476, -72.39
4	8600000US01057	01057	01057	ZCTA5	44.907	MULTIPOLYGON (((-72.39191 42.0806

```
filepath4 = "gz_2010_us_860_00_500k/gz_2010_us_860_00_500k.shx"
data4 = gpd.read_file(filepath4)
data4.head()
```

	GEO_ID	ZCTA5	NAME	LSAD	CENSUSAREA	geometry
0	8600000US01040	01040	01040	ZCTA5	21.281	POLYGON ((-72.62734 42.16203, -72.62
1	8600000US01050	01050	01050	ZCTA5	38.329	POLYGON ((-72.95393 42.34379, -72.95
2	8600000US01053	01053	01053	ZCTA5	5.131	POLYGON ((-72.68286 42.37002, -72.68
3	8600000US01056	01056	01056	ZCTA5	27.205	POLYGON ((-72.39529 42.18476, -72.39
4	8600000US01057	01057	01057	ZCTA5	44.907	MULTIPOLYGON (((-72.39191 42.0806

I don't know how to read a .xml file either, so I asked GPT "how to open the .xml file", and it offers me the `tree` and `root` code.

```
import xml.etree.ElementTree as ET

# Replace with the path to your .xml file
filepath5 = "gz_2010_us_860_00_500k/gz_2010_us_860_00_500k.xml"
```

```
# Parse the XML file
tree = ET.parse(filepath5)
root = tree.getroot()
```

a.

The five types are .dbf, .prj, .shp, .shx, .xml, respectively. .dbf, .shp, and .shx looks like a DataFrame and have the same content, including variables `CEO_ID`, `ZCTA5`, `NAME`, `LSAD`, `CENSUSAREA`, and `geometry`. .prj only contains a string, with values of `GEOGCS`, `PRIMEM`, `UNIT`. .xml is an Element type file, contains metadata and many texts.

b.

```
import os

filepath_list = [
    filepath1,
    filepath2,
    filepath3,
    filepath4,
    filepath5
]

for filepath in filepath_list:
    file_name = os.path.basename(filepath)
    file_size = os.path.getsize(filepath)
    file_size_mb = file_size/(1024**2)
    print(f"{file_name} size: {file_size_mb:.2f} MB")
```

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

2.

```
zip = data3
zip.head()
zip.shape
```

```
(33120, 6)
```

```
zip_tx = zip[zip["NAME"].str[:3].isin(["733"]) | zip["NAME"].str[:2].isin([
    "75", "76", "77", "78", "79"])].copy()
zip_tx.loc[:, 'ZIP_CD'] = zip_tx['ZCTA5']
```

Below are all the hospitals counts in zip code nationwide.

```
count_zip2016 = pos2016_short.groupby("ZIP_CD").size().reset_index(name =
 ↪  "hospital_count")
count_zip2016
```

	ZIP_CD	hospital_count
0	603.0	1
1	613.0	1
2	614.0	1
3	618.0	1
4	625.0	1
...	...	...
5671	99801.0	1
5672	99833.0	1
5673	99835.0	2
5674	99901.0	1
5675	99929.0	1

```
pos2016_tx =
 ↪  pos2016_short[pos2016_short["ZIP_CD"].astype(str).str[:3].isin(["733"])|pos2016_short["Z
 ↪  "76", "77", "78", "79"])]

pos2016_tx_zipcount = pos2016_tx.groupby("ZIP_CD").size().reset_index(name =
 ↪  "hospital_count")
pos2016_tx_zipcount
```

	ZIP_CD	hospital_count
0	733.0	4
1	753.0	1
2	761.0	1
3	780.0	1

	ZIP_CD	hospital_count
4	785.0	2
...	...	...
527	79905.0	1
528	79915.0	1
529	79925.0	1
530	79936.0	1
531	79938.0	1

```
import warnings
with warnings.catch_warnings():
    warnings.simplefilter("ignore", FutureWarning)
    pos2016_tx_zipcount = pd.DataFrame(pos2016_tx_zipcount)
    pos2016_tx_zipcount['ZIP_CD'] = pos2016_tx_zipcount['ZIP_CD'].fillna(0)
    pos2016_tx_zipcount.loc[:, 'ZIP_CD'] =
↪   pos2016_tx_zipcount['ZIP_CD'].astype(int).astype(str).str.zfill(5)
```

```
zip_tx = gpd.GeoDataFrame(zip_tx)
zip_tx.loc[:, 'NAME'] = zip_tx['NAME'].astype(int).astype(str)
```

```
print(zip_tx.dtypes)
print(pos2016_tx.dtypes)
```

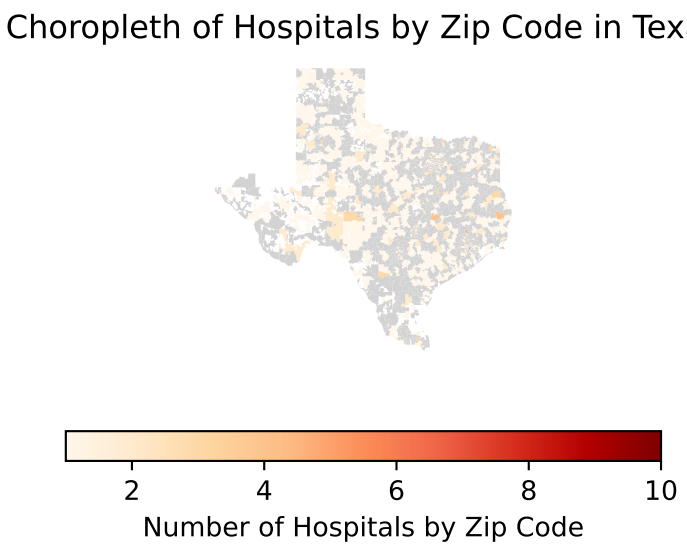
```
GEO_ID          object
ZCTA5           object
NAME            object
LSAD            object
CENSUSAREA     float64
geometry      geometry
ZIP_CD          object
dtype: object
PRVDR_CTGRY_SBTYP_CD    float64
PRVDR_CTGRY_CD            int64
FAC_NAME                 object
PRVDR_NUM                object
PGM_TRMNTN_CD             int64
TRMNTN_EXPRTN_DT        float64
ZIP_CD                  float64
year                      int64
dtype: object
```

```
import matplotlib.pyplot as plt
choropleth_data = zip_tx.merge(pos2016_tx_zipcount, on="ZIP_CD", how="left")
choropleth_data.head()
```

	GEO_ID	ZCTA5	NAME	LSAD	CENSUSAREA	geometry
0	8600000US78624	78624	78624	ZCTA5	708.041	POLYGON ((-98.96423 30.49848, -98.96
1	8600000US78626	78626	78626	ZCTA5	93.046	POLYGON ((-97.60944 30.57185, -97.61
2	8600000US78628	78628	78628	ZCTA5	73.382	POLYGON ((-97.69285 30.57122, -97.69
3	8600000US78631	78631	78631	ZCTA5	325.074	POLYGON ((-99.13053 30.36555, -99.13
4	8600000US78632	78632	78632	ZCTA5	96.278	POLYGON ((-97.40946 29.75929, -97.40

```
choropleth_data.to_csv("choropleth_data.csv", index = False)
```

```
fig, ax = plt.subplots(1, 1, figsize=(4, 3))
choropleth_data.plot(column='hospital_count', ax=ax, legend=True,
            legend_kwds={'label': "Number of Hospitals by Zip Code",
                         'orientation': "horizontal"},
            cmap='OrRd', missing_kwds={'color': 'lightgrey'})
ax.set_title('Choropleth of Hospitals by Zip Code in Texas')
ax.set_axis_off()

plt.show()
```



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

1.

```
zips_all_centroids = zip.copy().to_crs(epsg=32614)
zips_all_centroids["geometry"] = zips_all_centroids.centroid
dimensions = zips_all_centroids.shape
print(dimensions)
zips_all_centroids.head()
```

```
(33120, 6)
```

	GEO_ID	ZCTA5	NAME	LSAD	CENSUSAREA	geometry
0	8600000US01040	01040	01040	ZCTA5	21.281	POINT (2680901.614 5023480.354)
1	8600000US01050	01050	01050	ZCTA5	38.329	POINT (2659157.771 5025591.454)
2	8600000US01053	01053	01053	ZCTA5	5.131	POINT (2669825.294 5037254.622)
3	8600000US01056	01056	01056	ZCTA5	27.205	POINT (2696847.204 5026281.101)
4	8600000US01057	01057	01057	ZCTA5	44.907	POINT (2711728.101 5018798.677)

The dimension of this GeoDataFrame is (33120, 6). For each column, `GEO_ID` is the id, `ZCTA5` is the zip code, `NAME` is the zip code as well, `CENSUSAREA` is the area, `geometry` is the centroid of each zip code.

2.

```
texas_prefixes = ['75', '76', '77', '78', '79', '733']
bordering_states_prefixes = texas_prefixes + ['73', '74', '70', '71', '87',
↪  '88']

zips_texas_centroids =
↪  zips_all_centroids[zips_all_centroids['NAME'].str[:3].isin(['733']) |
↪  zips_all_centroids['NAME'].str[:2].isin(['75', '76', '77', '78',
↪  '79'])].copy()

zips_texas_centroids = zips_texas_centroids.to_crs(epsg=32614)

zips_texas_borderstates_centroids =
↪  zips_all_centroids[zips_all_centroids['NAME'].str[:2].isin(bordering_states_prefixes)].co

zips_texas_borderstates_centroids =
↪  zips_texas_borderstates_centroids.to_crs(epsg=32614)
```

```
texas_zip_count = zips_texas_centroids['NAME'].nunique()
texas_borderstates_zip_count =
 ↪  zips_texas_borderstates_centroids['NAME'].nunique()

print(f"There are {texas_zip_count} unique zip codes zips_texas_centroids
 ↪  subsets.")
print(f"There are {texas_borderstates_zip_count} unique zip codes
 ↪  zips_texas_borderstates_centroids subsets.")
```

```
There are 1935 unique zip codes zips_texas_centroids subsets.
There are 3596 unique zip codes zips_texas_borderstates_centroids subsets.
```

```
zips_texas_centroids.head()
```

	GEO_ID	ZCTA5	NAME	LSAD	CENSUSAREA	geometry
9207	8600000US78624	78624	78624	ZCTA5	708.041	POINT (511823.895 3349990.765)
9208	8600000US78626	78626	78626	ZCTA5	93.046	POINT (634378.798 3393352.86)
9209	8600000US78628	78628	78628	ZCTA5	73.382	POINT (619673.552 3390490.031)
9210	8600000US78631	78631	78631	ZCTA5	325.074	POINT (470662.193 3356245.449)
9211	8600000US78632	78632	78632	ZCTA5	96.278	POINT (647977.423 3286112.808)

3.

```
zips_texas_borderstates_centroids =
 ↪  zips_texas_borderstates_centroids.to_crs(epsg=32614)
count_zip2016 = pd.DataFrame(count_zip2016)
count_zip2016['ZIP_CD'] = count_zip2016['ZIP_CD'].fillna(0)
count_zip2016.loc[:, 'ZIP_CD'] =
 ↪  count_zip2016['ZIP_CD'].astype(int).astype(str).str.zfill(5)
zips_withhospital_centroids = zips_texas_borderstates_centroids.merge(
    count_zip2016,
    left_on='NAME',
    right_on='ZIP_CD',
    how='inner'
)
```

```
/var/folders/zc/d18v235x3mn0wtlnmmwm3_4c0000gn/T/ipykernel_13910/2177933344.py:4:
FutureWarning: Setting an item of incompatible dtype is deprecated and will
raise in a future error of pandas. Value '['00603' '00613' '00614' ...
'99835' '99901' '99929']' has dtype incompatible with float64, please
explicitly cast to a compatible dtype first.
  count_zip2016.loc[:, 'ZIP_CD'] =
  count_zip2016['ZIP_CD'].astype(int).astype(str).str.zfill(5)
```

I choose inner merge, with `NAME` variable for `zips_texas_borderstates_centroids` and `ZIP_CD` variable for `count_zip2016`. Both `NAME` and `ZIP_CD` represent the zip code.

4. a.

```
zips_texas_centroids_10 = zips_texas_centroids.head(10)
zips_texas_centroids_10 = zips_texas_centroids_10.to_crs(epsg=4326)
zips_texas_centroids_10
zips_withhospital_centroids = zips_withhospital_centroids.to_crs(epsg=4326)
```

```
# Convert both GeoDataFrames to a suitable projected CRS (NAD83 / Texas
 ↪ Central, EPSG:2272)
zips_texas_centroids_10 = zips_texas_centroids_10.to_crs(epsg=2272)
zips_withhospital_centroids = zips_withhospital_centroids.to_crs(epsg=2272)

import time
start_time = time.time()

nearest_distances = []

# Calculate the nearest distance for each zip code
for _, zip_row in zips_texas_centroids_10.iterrows():
    # Calculate distance to all hospitals
    distances =
 ↪ zips_withhospital_centroids.geometry.distance(zip_row.geometry)
    # Get the minimum distance
    nearest_distance = distances.min()
    nearest_distances.append(nearest_distance)

# Add the nearest distances to the GeoDataFrame
zips_texas_centroids_10['nearest_hospital_distance'] = nearest_distances

end_time = time.time()
print(f"Execution time: {end_time - start_time:.2f} seconds")
```

```
Execution time: 0.02 seconds
```

For 10 records, it takes 0.02 seconds. For there are 1935 records, I think the total calculation time is 0.02 * 193 = 4 seconds.

b.

```
start_time = time.time()

nearest_distances = []

# Calculate the nearest distance for each zip code
for _, zip_row in zips_texas_centroids.iterrows():
    # Calculate distance to all hospitals
    distances =
 ↪  zips_withhospital_centroids.geometry.distance(zip_row.geometry)
    # Get the minimum distance
    nearest_distance = distances.min()
    nearest_distances.append(nearest_distance)

# Add the nearest distances to the GeoDataFrame
zips_texas_centroids['nearest_hospital_distance'] = nearest_distances

end_time = time.time()
print(f"Execution time: {end_time - start_time:.2f} seconds")
```

```
Execution time: 2.06 seconds
```

The difference is close.

c.

```
with open(filepath2, 'r') as file:
    prj_content = file.read()
print(prj_content)
```

```
GEOGCS["GCS_North_American_1983",DATUM["D_North_American_1983",SPHEROID["GRS_1980",6378137,29
```

5. a. It is in feet now becasue I reprojected it to EPSG:2272

   b.

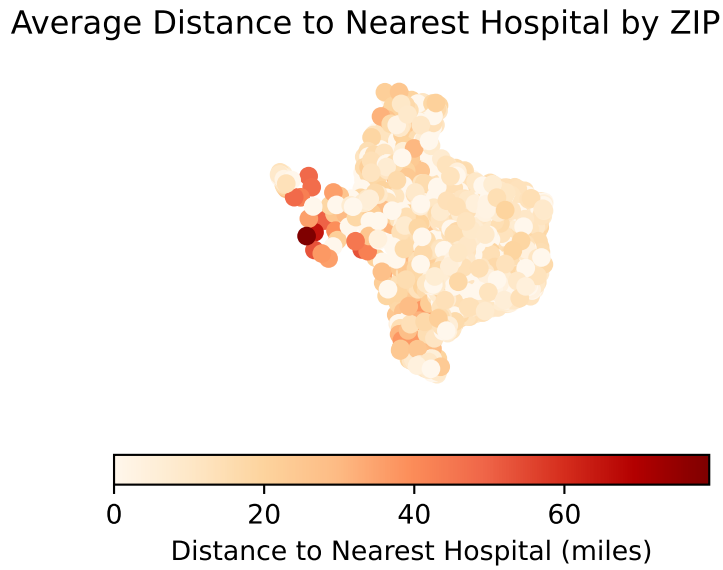
```
zips_texas_centroids = zips_texas_centroids.to_crs(epsg=2272)
zips_withhospital_centroids = zips_withhospital_centroids.to_crs(epsg=2272)

# Initialize a list to store nearest hospital distances for each ZIP centroid
nearest_distances = []

# Calculate the minimum distance for each ZIP centroid in Texas to the
 ↪  nearest hospital centroid
for _, zip_row in zips_texas_centroids.iterrows():
    distances =
 ↪  zips_withhospital_centroids.geometry.distance(zip_row.geometry)
    nearest_distance = distances.min()  # Minimum distance to the nearest
 ↪  hospital
    nearest_distances.append(nearest_distance)

# Add the calculated distances (in feet) to the GeoDataFrame and convert to
 ↪  miles
zips_texas_centroids['nearest_hospital_distance_feet'] = nearest_distances
zips_texas_centroids['nearest_hospital_distance_miles'] =
 ↪  zips_texas_centroids['nearest_hospital_distance_feet'] / 5280

# Calculate and display the average distance to the nearest hospital (in
 ↪  miles)
average_distance_miles =
 ↪  zips_texas_centroids['nearest_hospital_distance_miles'].mean()
print(f"Average distance to the nearest hospital in miles:
 ↪  {average_distance_miles:.2f}")
```

```
Average distance to the nearest hospital in miles: 8.29
```

c.

```
# Plot the map
fig, ax = plt.subplots(1, 1, figsize=(4, 3))
zips_texas_centroids.plot(column='nearest_hospital_distance_miles',
                          ax=ax,
                          legend=True,
                          legend_kwds={'label': "Distance to Nearest Hospital
 ↪  (miles)", 'orientation': "horizontal"},
                          cmap='OrRd',  # Choose an appropriate color map
                          missing_kwds={'color': 'lightgrey'})  # Color for
 ↪  missing values
```

```
# Customize the plot
ax.set_title('Average Distance to Nearest Hospital by ZIP Code')
ax.set_axis_off()  # Hide the axis for a cleaner map

plt.show()
```



Effects of closures on access in Texas (15 pts)

1.

```
corrected_closures

corrected_closures['ZIP_CD'] = corrected_closures['ZIP_CD'].astype(str)

# Filter the corrected closures dataset to include only ZIP codes in Texas
 ↪  and closures from 2016 to 2019
texas_closures = corrected_closures[
    (corrected_closures['ZIP_CD'].str.startswith('75') |  # Common Texas ZIP
 ↪  code prefixes
     corrected_closures['ZIP_CD'].str.startswith('76') |
     corrected_closures['ZIP_CD'].str.startswith('77') |
     corrected_closures['ZIP_CD'].str.startswith('78') |
```

```
    corrected_closures['ZIP_CD'].str.startswith('79') |
    corrected_closures['ZIP_CD'].str.startswith('733'))
]

# Count the number of closures by ZIP code
closures_by_zip =
 ↪  texas_closures.groupby('ZIP_CD').size().reset_index(name='closure_count')

import numpy as np
# Display the table of the number of closures by ZIP code
print("Table of the number of closures by ZIP code in Texas (2016-2019):")
closures_by_zip['ZIP_CD'] =
 ↪  closures_by_zip['ZIP_CD'].astype(float).astype(int).astype(str).str.zfill(5)
closures_by_zip
```

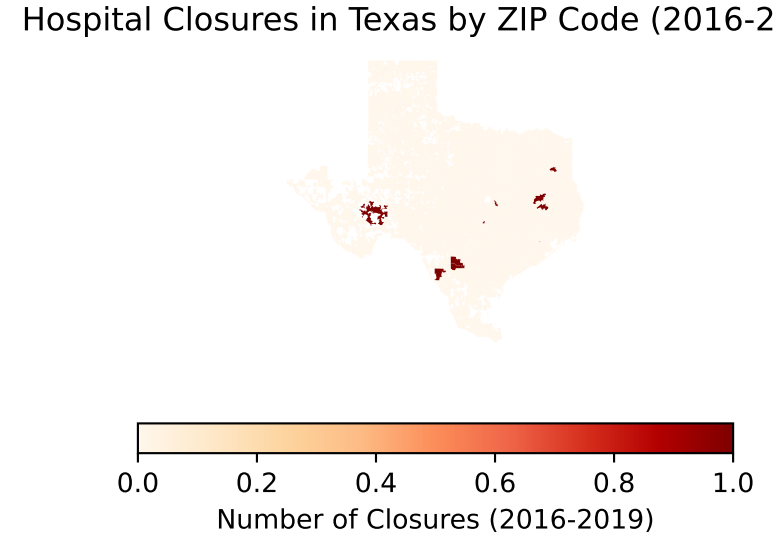
```
Table of the number of closures by ZIP code in Texas (2016-2019):
```

	ZIP_CD	closure_count
0	75662	1
1	75835	1
2	75862	1
3	76502	1
4	77035	1
5	78017	1
6	78061	1
7	78734	1
8	78834	1
9	79735	1

2.

```
# Ensure ZIP_CD in closures_by_zip and texas_zip_shapes are the same format
zip_tx['ZIP_CD'] = zip_tx['ZIP_CD'].astype(str).str.zfill(5)

# Merge the geographic data with the closure data
texas_closures_geo = zip_tx.merge(closures_by_zip, on='ZIP_CD',
 ↪  how='left').fillna(0)

# Plot the choropleth map
fig, ax = plt.subplots(1, 1, figsize=(4, 3))
texas_closures_geo.plot(column='closure_count', ax=ax, legend=True,
```

```
                        legend_kwds={'label': "Number of Closures
 ↪  (2016-2019)", 'orientation': "horizontal"},
                        cmap='OrRd',  # color map for the intensity of
 ↪  closures
                        missing_kwds={'color': 'lightgrey'})  # Color for
 ↪  areas with no data

# Customize the plot
ax.set_title('Hospital Closures in Texas by ZIP Code (2016-2019)')
ax.set_axis_off()  # Hide axis for a cleaner map

plt.show()

# Count the number of directly affected ZIP codes in Texas
num_affected_zip_codes = closures_by_zip['ZIP_CD'].nunique()
print(f"Number of directly affected ZIP codes in Texas:
 ↪  {num_affected_zip_codes}")
```




```
Number of directly affected ZIP codes in Texas: 10
```

3.

```
# Filter the directly affected ZIP codes from `closures_by_zip`
affected_zips = closures_by_zip[closures_by_zip['closure_count'] >
 ↪  0]['ZIP_CD'].unique()
```

```
# Convert `closures_by_zip` to a GeoDataFrame with directly affected ZIP
 ↪  codes only
directly_affected_geo = zip_tx[zip_tx['ZIP_CD'].isin(affected_zips)]

# Convert the GeoDataFrame to a projected coordinate system (e.g., EPSG:2272)
 ↪  for accurate distance-based operations
directly_affected_geo = directly_affected_geo.to_crs(epsg=2272)
texas_zip_shapes = zip_tx.to_crs(epsg=2272)

# Create a 10-mile buffer around each directly affected ZIP code
# 1 mile is approximately 1609.34 meters
buffer_distance = 10 * 1609.34  # 10 miles in meters
directly_affected_geo['geometry'] =
 ↪  directly_affected_geo.buffer(buffer_distance)

# Perform a spatial join to find ZIP codes within the 10-mile buffer of
 ↪  directly affected ZIP codes
indirectly_affected_geo = gpd.sjoin(texas_zip_shapes, directly_affected_geo,
 ↪  how='inner', predicate='intersects')

# Count unique indirectly affected ZIP codes
indirectly_affected_zip_count =
 ↪  indirectly_affected_geo['ZIP_CD_left'].nunique() - len(affected_zips)

# Display results
print(f"Number of indirectly affected ZIP codes in Texas:
 ↪  {indirectly_affected_zip_count}")
```

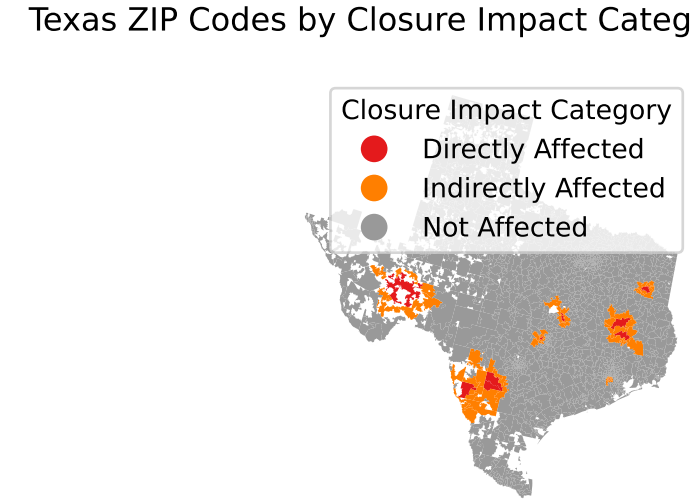
```
Number of indirectly affected ZIP codes in Texas: 95
```

4.

```
# Step 1: Prepare the Texas ZIP shapes and classify each ZIP code

# Step 1.1: Create a list of directly affected ZIP codes
directly_affected_zips = closures_by_zip[closures_by_zip['closure_count'] >
 ↪  0]['ZIP_CD'].unique()

# Step 1.2: Create the directly affected GeoDataFrame
directly_affected_geo = zip_tx[zip_tx['ZIP_CD'].isin(directly_affected_zips)]
```

```
# Convert to a projected CRS for distance calculation (e.g., EPSG:2272)
directly_affected_geo = directly_affected_geo.to_crs(epsg=2272)
texas_zip_shapes = texas_zip_shapes.to_crs(epsg=2272)

# Step 1.3: Create a 10-mile buffer around each directly affected ZIP code
buffer_distance = 10 * 1609.34  # 10 miles in meters
directly_affected_geo['geometry'] =
 ↪  directly_affected_geo.buffer(buffer_distance)

# Step 1.4: Perform a spatial join to identify indirectly affected ZIP codes
indirectly_affected_geo = gpd.sjoin(texas_zip_shapes, directly_affected_geo,
 ↪  how='inner', predicate='intersects')
indirectly_affected_zips = indirectly_affected_geo['ZIP_CD_left'].unique()

# Step 1.5: Classify ZIP codes
# Initialize a column to classify each ZIP code
texas_zip_shapes['closure_category'] = 'Not Affected'

# Mark directly affected ZIP codes
texas_zip_shapes.loc[texas_zip_shapes['ZIP_CD'].isin(directly_affected_zips),
 ↪  'closure_category'] = 'Directly Affected'

# Mark indirectly affected ZIP codes (exclude directly affected ones)
texas_zip_shapes.loc[
    (texas_zip_shapes['ZIP_CD'].isin(indirectly_affected_zips)) &
    (~texas_zip_shapes['ZIP_CD'].isin(directly_affected_zips)),
    'closure_category'
] = 'Indirectly Affected'

# Step 2: Plot the choropleth map

# Define a color map for the categories
category_colors = {
    'Not Affected': 'lightgrey',
    'Directly Affected': 'red',
    'Indirectly Affected': 'orange'
}

fig, ax = plt.subplots(1, 1, figsize=(4, 3))
texas_zip_shapes.plot(column='closure_category',
                      ax=ax,
                      legend=True,
```

```
                        categorical=True,
                        cmap='Set1',
                        legend_kwds={'title': "Closure Impact Category"})

# Customize the plot
ax.set_title('Texas ZIP Codes by Closure Impact Category (2016-2019)')
ax.set_axis_off()  # Hide axis for a cleaner map

plt.show()
```



Reflecting on the exercise (10 pts)

- **(Partner 1) The "first-pass" method we're using to address incorrectly identified closures in the data is imperfect. Can you think of some potential issues that could arise still and ways to do a better job at confirming hospital closures?**

The limitations and issues about current approach are: Delayed reopenings. If a hospital closes but reopens later under a different name or management, it may still be incorrectly counted as a closure. This problem is common in facilities that undergo temporary closures for renovations or changes in ownership.

The closure detection focuses only on the termination status without considering geographical factors. In rural areas, where hospital coverage is sparse, a closure has a more significant impact on access than it might be in an urban setting with multiple nearby hospitals.

Data completeness and consistency. Hospital data may not be consistently reported or may have gaps due to issues in data collection or reporting delays. This could lead to misidentification if a hospital simply fails to report data in one year but resumes the next year.

Mergers and new names– Hospitals might seem closed due to changes in their certification number or mergers. They may still be active under a different identity and potentially leading to incorrect closure identification.

Potential Improvements: Data collection procedures can be improved to ensure that mergers, rebranding and any type of changes are properly reflected. Track name and address changes by developing a more robust matching system that accounts for slight changes in hospital names or addresses. Using similarity metrics can help identify hospitals with minor name changes that might indicate the same facility under new management.

Consider factors which can indicate the impact of closures

Geographical impact of closures is also important. For example, the closure of the only hospital within a 20-mile radius has a different implication than a closure in a well-served urban area. Therefore, it could be interesting to analyze the geographical impact on surrounding ZIP codes or regions.

- **(Partner 2) Consider the way we are identifying zip codes affected by closures. How well does this reflect changes in zip-code-level access to hospitals? Can you think of some ways to improve this measure?**

The method assumes that if a zip code is in proximity of a hospital has acces to the hospital without consodering accessibility and accessibility infrastructure. To access a facility, the ZIP codes within a 10-mile radius might be impacted by factors like road quality and transportation. Every ZIP code area does not have a similar impact by a closure. It could be interesting to conisder the demographic factors such as age, income, and health impacted by a hospital closures.

Some ZIP codes may have access to alternative healthcare facilities, such as urgent care centers and outpatient clinics, which can partially mitigate the impact of hospital closures. However, areas without these alternatives are more significantly affected.

Adding population and demographics data, weighting the impact of closures by the population density and demographics of each affected ZIP code could be more valuable. Identifying areas that lack alternative healthcare facilities within a reasonable distance could be important. Calculating averag, min and max travel times to the nearest operational hospital can also be important.