

# Group Assignment 4

March 12, 2021

## 1 Assignment # 5

In this notebook I conduct a spatial Autocorrelation on my data set of industries. Here I want to look at the Accommodation industry that has experienced the most job loss during the COVID-19 Pandemic. When I first ran this code the areas were a bit scattered, so I'm hoping to narrow down the area that held these positions in 2019.

### 1.1 Bringing in the libraries

```
[1]: import geopandas as gpd
import matplotlib.pyplot as plt
import pandas as pd
import contextily as ctx
from sodapy import Socrata
import seaborn as sns
from pointpats import centrography
from matplotlib.patches import Ellipse
import numpy
import urllib.request, json
import plotly.express as px
import esda
from esda.moran import Moran, Moran_Local
import splot
from splot.esda import moran_scatterplot, plot_moran,
    lisa_cluster, plot_moran_simulation
import libpysal as lps
import matplotlib.pyplot as plt
import plotly.express as px
```

```
/opt/conda/lib/python3.8/site-packages/geopandas/_compat.py:106: UserWarning:
The Shapely GEOS version (3.8.1-CAPI-1.13.3) is incompatible with the GEOS
version PyGEOS was compiled with (3.9.0-CAPI-1.16.2). Conversions between both
will be slow.
```

```
warnings.warn(
```

## 1.2 Uploading the Data set and cleaning it up.

The previous industry dataset that I investigated was an overall industry employment during 2020 and the income in each industry based within each census tract. Unfortunately that data is not yet available during for 2020, so I will be looking at the 2019 dataset from CensusExplorer to get idea of the industries by census tract. Previously, I also look at occupations in the areas, but in order to make comparisons I opted to look at the industries moving forward. I was having a hard time looking up occupation data for 2020.

```
[2]: industry = gpd.read_file('acs2019_5yr_B24031_14000US06037432102.geojson')
```

### 1.2.1 In the following cells, I'll clean the data

First I look at what's in this data frame. I drop the first row, and unnecessary columns. I think relabel the columns and check the data by looking at the top rows.

```
[3]: industry.head ()
```

```
[3]:
```

	geoid		name	B24031001	\
0	05000US06037		Los Angeles County, CA	36039.0	
1	14000US06037101110	Census Tract	1011.10, Los Angeles, CA	39444.0	
2	14000US06037101122	Census Tract	1011.22, Los Angeles, CA	43300.0	
3	14000US06037101210	Census Tract	1012.10, Los Angeles, CA	24579.0	
4	14000US06037101220	Census Tract	1012.20, Los Angeles, CA	31139.0	

	B24031001, Error	B24031002	B24031002, Error	B24031003	B24031003, Error	\
0	148.0	24925.0	1218.0	22153.0	724.0	
1	10750.0	NaN	NaN	NaN	NaN	
2	7628.0	NaN	NaN	NaN	NaN	
3	4419.0	155000.0	238813.0	155000.0	238813.0	
4	3738.0	NaN	NaN	NaN	NaN	

	B24031004	B24031004, Error	...	B24031023, Error	B24031024	\
0	65732.0	9358.0	...	233.0	31705.0	
1	NaN	NaN	...	10705.0	25714.0	
2	NaN	NaN	...	14945.0	47273.0	
3	NaN	NaN	...	8991.0	NaN	
4	NaN	NaN	...	1835.0	NaN	

	B24031024, Error	B24031025	B24031025, Error	B24031026	B24031026, Error	\
0	379.0	20905.0	182.0	24115.0	381.0	
1	44930.0	19952.0	11180.0	32379.0	14273.0	
2	14945.0	NaN	NaN	22708.0	31090.0	
3	NaN	25739.0	3717.0	19071.0	5736.0	
4	NaN	9356.0	1809.0	24000.0	8491.0	

	B24031027	B24031027, Error	\
--	-----------	------------------	---

0	61372.0	971.0
1	62938.0	26179.0
2	33750.0	39781.0
3	10881.0	2462.0
4	86154.0	62406.0

		geometry
0	MULTIPOLYGON	(((-118.70339 34.16859, -118.7033...
1	MULTIPOLYGON	(((-118.30229 34.25870, -118.3009...
2	MULTIPOLYGON	(((-118.30334 34.27371, -118.3033...
3	MULTIPOLYGON	(((-118.29945 34.25598, -118.2979...
4	MULTIPOLYGON	(((-118.28593 34.25227, -118.2859...

[5 rows x 57 columns]

```
[4]: industry = industry.drop ([0])
```

```
[5]: columns_to_keep = ['geoid',
                        'name',
                        'B24031001',
                        'B24031003',
                        'B24031004',
                        'B24031005',
                        'B24031006',
                        'B24031007',
                        'B24031008',
                        'B24031010',
                        'B24031011',
                        'B24031012',
                        'B24031014',
                        'B24031015',
                        'B24031017',
                        'B24031018',
                        'B24031019',
                        'B24031021',
                        'B24031022',
                        'B24031024',
                        'B24031025',
                        'B24031026',
                        'B24031027',
                        'geometry']
```

```
[6]: industry = industry[columns_to_keep]
```

```
[7]: industry.columns = ['geoid',
                        'name',
                        'total',
```

```
'Agriculture, forestry, fishing and hunting',
'Mining, quarrying, and oil and gas extraction',
'Construction',
'Manufacturing',
'Wholesale trade',
'Retail trade',
'Transportation and warehousing',
'Utilities',
'Information',
'Finance and insurance',
'Real estate and rental and leasing',
'Professional, scientific, and technical services',
'Management of companies and enterprises',
'Administrative and support and waste management services',
'Educational services',
'Health care and social assistance',
'Arts, entertainment, and recreation',
'Accommodation and food services',
'Other services',
'Public administration',
'geometry']
```

```
[8]: industry.head ()
```

```
[8]:
```

	geoid	name	total	\
1	14000US06037101110	Census Tract 1011.10, Los Angeles, CA	39444.0	
2	14000US06037101122	Census Tract 1011.22, Los Angeles, CA	43300.0	
3	14000US06037101210	Census Tract 1012.10, Los Angeles, CA	24579.0	
4	14000US06037101220	Census Tract 1012.20, Los Angeles, CA	31139.0	
5	14000US06037101300	Census Tract 1013, Los Angeles, CA	50993.0	

	Agriculture, forestry, fishing and hunting	\
1	NaN	
2	NaN	
3	155000.0	
4	NaN	
5	NaN	

	Mining, quarrying, and oil and gas extraction	Construction	Manufacturing	\
1	NaN	72813.0	24901.0	
2	NaN	44375.0	68646.0	
3	NaN	17697.0	29301.0	
4	NaN	22000.0	32292.0	
5	NaN	44167.0	71202.0	

	Wholesale trade	Retail trade	Transportation and warehousing	...	\
1	43304.0	19038.0	61607.0	...	

2	50938.0	29531.0	19009.0	...
3	45223.0	16818.0	50903.0	...
4	66250.0	27625.0	60125.0	...
5	36776.0	23646.0	63281.0	...

Professional, scientific, and technical services \

1	94167.0
2	96818.0
3	75106.0
4	100156.0
5	67548.0

Management of companies and enterprises \

1	NaN
2	NaN
3	NaN
4	NaN
5	NaN

Administrative and support and waste management services \

1	14853.0
2	22083.0
3	12320.0
4	32386.0
5	19659.0

Educational services Health care and social assistance \

1	31314.0	43750.0
2	34583.0	41288.0
3	15675.0	31452.0
4	28162.0	35156.0
5	47083.0	61632.0

Arts, entertainment, and recreation Accommodation and food services \

1	25714.0	19952.0
2	47273.0	NaN
3	NaN	25739.0
4	NaN	9356.0
5	43750.0	40833.0

Other services Public administration \

1	32379.0	62938.0
2	22708.0	33750.0
3	19071.0	10881.0
4	24000.0	86154.0
5	70694.0	16700.0

```

                                geometry
1  MULTIPOLYGON (((-118.30229 34.25870, -118.3009...
2  MULTIPOLYGON (((-118.30334 34.27371, -118.3033...
3  MULTIPOLYGON (((-118.29945 34.25598, -118.2979...
4  MULTIPOLYGON (((-118.28593 34.25227, -118.2859...
5  MULTIPOLYGON (((-118.27822 34.25068, -118.2782...

```

[5 rows x 24 columns]

```
[9]: industry['geoid'] = industry['geoid'].str.replace('14000US','')
      industry.tail()
```

```
[9]:
      geoid                                name    total  \
2342  06037980031  Census Tract 9800.31, Los Angeles, CA  64500.0
2343  06037980033  Census Tract 9800.33, Los Angeles, CA      NaN
2344  06037990100    Census Tract 9901, Los Angeles, CA      NaN
2345  06037990200    Census Tract 9902, Los Angeles, CA      NaN
2346  06037990300    Census Tract 9903, Los Angeles, CA      NaN

      Agriculture, forestry, fishing and hunting  \
2342                                           NaN
2343                                           NaN
2344                                           NaN
2345                                           NaN
2346                                           NaN

      Mining, quarrying, and oil and gas extraction  Construction  \
2342                                           NaN      NaN
2343                                           NaN      NaN
2344                                           NaN      NaN
2345                                           NaN      NaN
2346                                           NaN      NaN

      Manufacturing  Wholesale trade  Retail trade  \
2342           NaN           NaN           NaN
2343           NaN           NaN           NaN
2344           NaN           NaN           NaN
2345           NaN           NaN           NaN
2346           NaN           NaN           NaN

      Transportation and warehousing  ...  \
2342           NaN  ...
2343           NaN  ...
2344           NaN  ...
2345           NaN  ...
2346           NaN  ...

```

	Professional, scientific, and technical services	\
2342		NaN
2343		NaN
2344		NaN
2345		NaN
2346		NaN

	Management of companies and enterprises	\
2342		NaN
2343		NaN
2344		NaN
2345		NaN
2346		NaN

	Administrative and support and waste management services	\
2342		NaN
2343		NaN
2344		NaN
2345		NaN
2346		NaN

	Educational services	Health care and social assistance	\
2342	NaN		NaN
2343	NaN		NaN
2344	NaN		NaN
2345	NaN		NaN
2346	NaN		NaN

	Arts, entertainment, and recreation	Accommodation and food services	\
2342	NaN		NaN
2343	NaN		NaN
2344	NaN		NaN
2345	NaN		NaN
2346	NaN		NaN

	Other services	Public administration	\
2342	NaN		NaN
2343	NaN		NaN
2344	NaN		NaN
2345	NaN		NaN
2346	NaN		NaN

		geometry
2342	MULTIPOLYGON (((-118.29105 33.75378, -118.2905...	
2343	MULTIPOLYGON (((-118.24897 33.75590, -118.2470...	
2344	MULTIPOLYGON (((-118.95114 33.99643, -118.9505...	
2345	MULTIPOLYGON (((-118.63598 34.03255, -118.6325...	

```
2346 MULTIPOLYGON (((-118.47656 33.75038, -118.4661...
```

```
[5 rows x 24 columns]
```

I start narrowing down on which data I plan on running stat by sorting the values by Accommodation and food services

```
[10]: industry.sort_values(by='Accommodation and food services', ascending = True).  
      ↪tail(50)
```

```
[10]:
```

	geoid	name	total	\
2120	06037701201	Census Tract 7012.01, Los Angeles, CA	91500.0	
2149	06037703002	Census Tract 7030.02, Los Angeles, CA	63896.0	
2154	06037800202	Census Tract 8002.02, Los Angeles, CA	79925.0	
2156	06037800204	Census Tract 8002.04, Los Angeles, CA	68375.0	
2170	06037800506	Census Tract 8005.06, Los Angeles, CA	107619.0	
2174	06037900201	Census Tract 9002.01, Los Angeles, CA	36471.0	
2184	06037900606	Census Tract 9006.06, Los Angeles, CA	33623.0	
2197	06037901003	Census Tract 9010.03, Los Angeles, CA	NaN	
2208	06037901210	Census Tract 9012.10, Los Angeles, CA	43585.0	
2209	06037901213	Census Tract 9012.13, Los Angeles, CA	59549.0	
2220	06037910210	Census Tract 9102.10, Los Angeles, CA	55556.0	
2252	06037910811	Census Tract 9108.11, Los Angeles, CA	30750.0	
2253	06037910812	Census Tract 9108.12, Los Angeles, CA	54338.0	
2256	06037920011	Census Tract 9200.11, Los Angeles, CA	51000.0	
2257	06037920012	Census Tract 9200.12, Los Angeles, CA	47661.0	
2265	06037920026	Census Tract 9200.26, Los Angeles, CA	32375.0	
2271	06037920033	Census Tract 9200.33, Los Angeles, CA	32375.0	
2298	06037920200	Census Tract 9202, Los Angeles, CA	NaN	
2315	06037930101	Census Tract 9301.01, Los Angeles, CA	51136.0	
2316	06037930200	Census Tract 9302, Los Angeles, CA	52218.0	
2317	06037930301	Census Tract 9303.01, Los Angeles, CA	50893.0	
2318	06037980001	Census Tract 9800.01, Los Angeles, CA	NaN	
2319	06037980002	Census Tract 9800.02, Los Angeles, CA	NaN	
2320	06037980003	Census Tract 9800.03, Los Angeles, CA	NaN	
2321	06037980004	Census Tract 9800.04, Los Angeles, CA	NaN	
2322	06037980005	Census Tract 9800.05, Los Angeles, CA	NaN	
2323	06037980006	Census Tract 9800.06, Los Angeles, CA	NaN	
2324	06037980007	Census Tract 9800.07, Los Angeles, CA	NaN	
2325	06037980008	Census Tract 9800.08, Los Angeles, CA	NaN	
2326	06037980009	Census Tract 9800.09, Los Angeles, CA	5833.0	
2327	06037980010	Census Tract 9800.10, Los Angeles, CA	50000.0	
2328	06037980013	Census Tract 9800.13, Los Angeles, CA	NaN	
2329	06037980014	Census Tract 9800.14, Los Angeles, CA	NaN	
2330	06037980015	Census Tract 9800.15, Los Angeles, CA	53843.0	
2331	06037980018	Census Tract 9800.18, Los Angeles, CA	NaN	
2332	06037980019	Census Tract 9800.19, Los Angeles, CA	105750.0	



2333	06037980020	Census Tract 9800.20, Los Angeles, CA	NaN
2334	06037980021	Census Tract 9800.21, Los Angeles, CA	70417.0
2335	06037980022	Census Tract 9800.22, Los Angeles, CA	NaN
2336	06037980023	Census Tract 9800.23, Los Angeles, CA	NaN
2337	06037980024	Census Tract 9800.24, Los Angeles, CA	51250.0
2338	06037980025	Census Tract 9800.25, Los Angeles, CA	NaN
2339	06037980026	Census Tract 9800.26, Los Angeles, CA	NaN
2340	06037980028	Census Tract 9800.28, Los Angeles, CA	NaN
2341	06037980030	Census Tract 9800.30, Los Angeles, CA	NaN
2342	06037980031	Census Tract 9800.31, Los Angeles, CA	64500.0
2343	06037980033	Census Tract 9800.33, Los Angeles, CA	NaN
2344	06037990100	Census Tract 9901, Los Angeles, CA	NaN
2345	06037990200	Census Tract 9902, Los Angeles, CA	NaN
2346	06037990300	Census Tract 9903, Los Angeles, CA	NaN

Agriculture, forestry, fishing and hunting \

2120	NaN
2149	NaN
2154	NaN
2156	NaN
2170	NaN
2174	33977.0
2184	NaN
2197	NaN
2208	NaN
2209	14808.0
2220	NaN
2252	NaN
2253	NaN
2256	NaN
2257	29000.0
2265	NaN
2271	NaN
2298	NaN
2315	NaN
2316	NaN
2317	NaN
2318	NaN
2319	NaN
2320	NaN
2321	NaN
2322	NaN
2323	NaN
2324	NaN
2325	NaN
2326	NaN
2327	NaN

2328	NaN
2329	NaN
2330	NaN
2331	NaN
2332	NaN
2333	NaN
2334	NaN
2335	NaN
2336	NaN
2337	NaN
2338	NaN
2339	NaN
2340	NaN
2341	NaN
2342	NaN
2343	NaN
2344	NaN
2345	NaN
2346	NaN

	Mining, quarrying, and oil and gas extraction	Construction \
2120	NaN	NaN
2149	NaN	101635.0
2154	NaN	NaN
2156	NaN	18036.0
2170	NaN	241250.0
2174	NaN	40833.0
2184	NaN	41845.0
2197	NaN	NaN
2208	NaN	52083.0
2209	NaN	47727.0
2220	NaN	76546.0
2252	NaN	NaN
2253	NaN	76818.0
2256	NaN	NaN
2257	NaN	50000.0
2265	NaN	NaN
2271	NaN	26750.0
2298	NaN	NaN
2315	NaN	NaN
2316	NaN	NaN
2317	NaN	NaN
2318	NaN	NaN
2319	NaN	NaN
2320	NaN	NaN
2321	NaN	NaN
2322	NaN	NaN

2323		NaN	NaN
2324		NaN	NaN
2325		NaN	NaN
2326		NaN	NaN
2327		NaN	NaN
2328		NaN	NaN
2329		NaN	NaN
2330		NaN	32969.0
2331		NaN	NaN
2332		NaN	NaN
2333		NaN	NaN
2334		NaN	NaN
2335		NaN	NaN
2336		NaN	NaN
2337		NaN	NaN
2338		NaN	NaN
2339		NaN	NaN
2340		NaN	NaN
2341		NaN	NaN
2342		NaN	NaN
2343		NaN	NaN
2344		NaN	NaN
2345		NaN	NaN
2346		NaN	NaN

	Manufacturing	Wholesale trade	Retail trade \
2120	131750.0	33000.0	32500.0
2149	141417.0	85333.0	21250.0
2154	104826.0	250001.0	52642.0
2156	158108.0	128482.0	44939.0
2170	141913.0	NaN	NaN
2174	26250.0	NaN	NaN
2184	37750.0	NaN	21250.0
2197	NaN	NaN	NaN
2208	43654.0	NaN	43839.0
2209	136375.0	NaN	48958.0
2220	86775.0	NaN	60682.0
2252	NaN	NaN	9423.0
2253	226563.0	NaN	NaN
2256	NaN	NaN	NaN
2257	71932.0	NaN	16250.0
2265	NaN	NaN	NaN
2271	29063.0	NaN	21563.0
2298	NaN	NaN	NaN
2315	NaN	NaN	43750.0
2316	52019.0	NaN	NaN
2317	188750.0	6467.0	31328.0

2318	NaN	NaN	NaN
2319	NaN	NaN	NaN
2320	NaN	NaN	NaN
2321	NaN	NaN	NaN
2322	NaN	NaN	NaN
2323	NaN	NaN	NaN
2324	NaN	NaN	NaN
2325	NaN	NaN	NaN
2326	NaN	NaN	NaN
2327	NaN	NaN	NaN
2328	NaN	NaN	NaN
2329	NaN	NaN	NaN
2330	67031.0	NaN	30688.0
2331	NaN	NaN	NaN
2332	NaN	NaN	NaN
2333	NaN	NaN	NaN
2334	NaN	NaN	NaN
2335	NaN	NaN	NaN
2336	NaN	NaN	NaN
2337	NaN	NaN	47708.0
2338	NaN	NaN	NaN
2339	NaN	NaN	NaN
2340	NaN	NaN	NaN
2341	NaN	NaN	NaN
2342	NaN	NaN	NaN
2343	NaN	NaN	NaN
2344	NaN	NaN	NaN
2345	NaN	NaN	NaN
2346	NaN	NaN	NaN

	Transportation and warehousing ... \	
2120	NaN ...	
2149	28681.0 ...	
2154	NaN ...	
2156	NaN ...	
2170	NaN ...	
2174	NaN ...	
2184	NaN ...	
2197	NaN ...	
2208	18542.0 ...	
2209	170278.0 ...	
2220	67000.0 ...	
2252	NaN ...	
2253	NaN ...	
2256	NaN ...	
2257	NaN ...	
2265	NaN ...	

2271	NaN	...
2298	NaN	...
2315	NaN	...
2316	NaN	...
2317	NaN	...
2318	NaN	...
2319	NaN	...
2320	NaN	...
2321	NaN	...
2322	NaN	...
2323	NaN	...
2324	NaN	...
2325	NaN	...
2326	NaN	...
2327	NaN	...
2328	NaN	...
2329	NaN	...
2330	NaN	...
2331	NaN	...
2332	NaN	...
2333	NaN	...
2334	NaN	...
2335	NaN	...
2336	NaN	...
2337	NaN	...
2338	NaN	...
2339	NaN	...
2340	NaN	...
2341	NaN	...
2342	NaN	...
2343	NaN	...
2344	NaN	...
2345	NaN	...
2346	NaN	...

Professional, scientific, and technical services \

2120	100625.0
2149	70871.0
2154	75978.0
2156	176518.0
2170	132946.0
2174	68026.0
2184	NaN
2197	NaN
2208	81667.0
2209	48938.0
2220	41563.0

2252	NaN
2253	53750.0
2256	NaN
2257	83631.0
2265	NaN
2271	25208.0
2298	NaN
2315	190313.0
2316	52778.0
2317	NaN
2318	NaN
2319	NaN
2320	NaN
2321	NaN
2322	NaN
2323	NaN
2324	NaN
2325	NaN
2326	NaN
2327	NaN
2328	NaN
2329	NaN
2330	100125.0
2331	NaN
2332	77250.0
2333	NaN
2334	NaN
2335	NaN
2336	NaN
2337	NaN
2338	NaN
2339	NaN
2340	NaN
2341	NaN
2342	NaN
2343	NaN
2344	NaN
2345	NaN
2346	NaN

Management of companies and enterprises \

2120	NaN
2149	NaN
2154	NaN
2156	NaN
2170	NaN
2174	NaN

2184	NaN
2197	NaN
2208	NaN
2209	NaN
2220	NaN
2252	NaN
2253	NaN
2256	NaN
2257	NaN
2265	NaN
2271	NaN
2298	NaN
2315	NaN
2316	NaN
2317	NaN
2318	NaN
2319	NaN
2320	NaN
2321	NaN
2322	NaN
2323	NaN
2324	NaN
2325	NaN
2326	NaN
2327	NaN
2328	NaN
2329	NaN
2330	NaN
2331	NaN
2332	NaN
2333	NaN
2334	NaN
2335	NaN
2336	NaN
2337	NaN
2338	NaN
2339	NaN
2340	NaN
2341	NaN
2342	NaN
2343	NaN
2344	NaN
2345	NaN
2346	NaN

	Administrative and support and waste management services \
2120	41667.0

2149	53421.0
2154	53409.0
2156	250001.0
2170	NaN
2174	NaN
2184	30538.0
2197	NaN
2208	42000.0
2209	38250.0
2220	42196.0
2252	NaN
2253	NaN
2256	51250.0
2257	NaN
2265	NaN
2271	NaN
2298	NaN
2315	NaN
2316	NaN
2317	NaN
2318	NaN
2319	NaN
2320	NaN
2321	NaN
2322	NaN
2323	NaN
2324	NaN
2325	NaN
2326	NaN
2327	NaN
2328	NaN
2329	NaN
2330	NaN
2331	NaN
2332	NaN
2333	NaN
2334	NaN
2335	NaN
2336	NaN
2337	NaN
2338	NaN
2339	NaN
2340	NaN
2341	NaN
2342	NaN
2343	NaN
2344	NaN



2345	NaN
2346	NaN

	Educational services	Health care and social assistance \
2120	69844.0	44219.0
2149	72569.0	80208.0
2154	26574.0	51944.0
2156	71902.0	44953.0
2170	51860.0	92115.0
2174	33281.0	32938.0
2184	33973.0	34893.0
2197	NaN	NaN
2208	27083.0	41625.0
2209	53250.0	54519.0
2220	48824.0	44507.0
2252	NaN	NaN
2253	NaN	50250.0
2256	NaN	NaN
2257	61442.0	48417.0
2265	123750.0	18365.0
2271	12917.0	73750.0
2298	NaN	NaN
2315	NaN	NaN
2316	NaN	NaN
2317	45781.0	29861.0
2318	NaN	NaN
2319	NaN	NaN
2320	NaN	NaN
2321	NaN	NaN
2322	NaN	NaN
2323	NaN	NaN
2324	NaN	NaN
2325	NaN	NaN
2326	5625.0	NaN
2327	NaN	NaN
2328	NaN	NaN
2329	NaN	NaN
2330	NaN	53603.0
2331	NaN	NaN
2332	103750.0	126250.0
2333	NaN	NaN
2334	NaN	NaN
2335	NaN	NaN
2336	NaN	NaN
2337	80313.0	NaN
2338	NaN	NaN
2339	NaN	NaN

2340	NaN	NaN
2341	NaN	NaN
2342	NaN	NaN
2343	NaN	NaN
2344	NaN	NaN
2345	NaN	NaN
2346	NaN	NaN

	Arts, entertainment, and recreation	Accommodation and food services	\
2120	37143.0	NaN	
2149	14975.0	NaN	
2154	88488.0	NaN	
2156	153125.0	NaN	
2170	250001.0	NaN	
2174	NaN	NaN	
2184	NaN	NaN	
2197	NaN	NaN	
2208	NaN	NaN	
2209	10729.0	NaN	
2220	11395.0	NaN	
2252	NaN	NaN	
2253	NaN	NaN	
2256	NaN	NaN	
2257	NaN	NaN	
2265	NaN	NaN	
2271	NaN	NaN	
2298	NaN	NaN	
2315	NaN	NaN	
2316	NaN	NaN	
2317	NaN	NaN	
2318	NaN	NaN	
2319	NaN	NaN	
2320	NaN	NaN	
2321	NaN	NaN	
2322	NaN	NaN	
2323	NaN	NaN	
2324	NaN	NaN	
2325	NaN	NaN	
2326	NaN	NaN	
2327	NaN	NaN	
2328	NaN	NaN	
2329	NaN	NaN	
2330	NaN	NaN	
2331	NaN	NaN	
2332	NaN	NaN	
2333	NaN	NaN	
2334	NaN	NaN	

2335	NaN	NaN
2336	NaN	NaN
2337	NaN	NaN
2338	NaN	NaN
2339	NaN	NaN
2340	NaN	NaN
2341	NaN	NaN
2342	NaN	NaN
2343	NaN	NaN
2344	NaN	NaN
2345	NaN	NaN
2346	NaN	NaN

	Other services	Public administration \
2120	43125.0	NaN
2149	11184.0	61680.0
2154	NaN	NaN
2156	NaN	NaN
2170	45833.0	104038.0
2174	36000.0	97321.0
2184	15625.0	53375.0
2197	NaN	NaN
2208	25868.0	112656.0
2209	54196.0	103472.0
2220	17440.0	90238.0
2252	NaN	NaN
2253	NaN	NaN
2256	NaN	NaN
2257	11875.0	118750.0
2265	23750.0	NaN
2271	NaN	NaN
2298	NaN	NaN
2315	NaN	NaN
2316	NaN	NaN
2317	NaN	NaN
2318	NaN	NaN
2319	NaN	NaN
2320	NaN	NaN
2321	NaN	NaN
2322	NaN	NaN
2323	NaN	NaN
2324	NaN	NaN
2325	NaN	NaN
2326	NaN	NaN
2327	NaN	NaN
2328	NaN	NaN
2329	NaN	NaN

2330	NaN	82813.0
2331	NaN	NaN
2332	NaN	NaN
2333	NaN	NaN
2334	NaN	NaN
2335	NaN	NaN
2336	NaN	NaN
2337	NaN	NaN
2338	NaN	NaN
2339	NaN	NaN
2340	NaN	NaN
2341	NaN	NaN
2342	NaN	NaN
2343	NaN	NaN
2344	NaN	NaN
2345	NaN	NaN
2346	NaN	NaN

		geometry
2120	MULTIPOLYGON (((-118.50440 34.04017, -118.5040...	
2149	MULTIPOLYGON (((-118.38655 33.97716, -118.3862...	
2154	MULTIPOLYGON (((-118.71177 34.10542, -118.7117...	
2156	MULTIPOLYGON (((-118.69824 34.14388, -118.6981...	
2170	MULTIPOLYGON (((-118.65342 34.07002, -118.6531...	
2174	MULTIPOLYGON (((-118.05924 34.68994, -118.0584...	
2184	MULTIPOLYGON (((-118.13709 34.70395, -118.1369...	
2197	MULTIPOLYGON (((-118.23669 34.70207, -118.2366...	
2208	MULTIPOLYGON (((-118.43776 34.69477, -118.4377...	
2209	MULTIPOLYGON (((-118.37804 34.64508, -118.3778...	
2220	MULTIPOLYGON (((-118.21032 34.61809, -118.2098...	
2252	MULTIPOLYGON (((-118.40529 34.38096, -118.3972...	
2253	MULTIPOLYGON (((-118.11829 34.47830, -118.1182...	
2256	MULTIPOLYGON (((-118.54254 34.48617, -118.5424...	
2257	MULTIPOLYGON (((-118.45431 34.59261, -118.4541...	
2265	MULTIPOLYGON (((-118.46752 34.47406, -118.4675...	
2271	MULTIPOLYGON (((-118.44536 34.45159, -118.4430...	
2298	MULTIPOLYGON (((-118.61830 34.48921, -118.6182...	
2315	MULTIPOLYGON (((-118.28661 34.28156, -118.2865...	
2316	MULTIPOLYGON (((-118.51028 34.34504, -118.5102...	
2317	MULTIPOLYGON (((-118.18075 34.28729, -118.1806...	
2318	MULTIPOLYGON (((-118.37031 34.20120, -118.3658...	
2319	MULTIPOLYGON (((-118.25753 33.80197, -118.2571...	
2320	MULTIPOLYGON (((-118.14019 34.78468, -118.1401...	
2321	MULTIPOLYGON (((-118.12795 34.64591, -118.1274...	
2322	MULTIPOLYGON (((-118.35210 33.85818, -118.3517...	
2323	MULTIPOLYGON (((-118.09420 33.78670, -118.0941...	
2324	MULTIPOLYGON (((-118.11512 33.76305, -118.1135...	

```

2325 MULTIPOLYGON (((-118.50267 34.22121, -118.5015...
2326 MULTIPOLYGON (((-118.33707 34.14160, -118.3361...
2327 MULTIPOLYGON (((-118.25165 34.08038, -118.2515...
2328 MULTIPOLYGON (((-118.39627 33.92804, -118.3962...
2329 MULTIPOLYGON (((-118.26088 33.76850, -118.2602...
2330 MULTIPOLYGON (((-118.31048 33.76685, -118.3102...
2331 MULTIPOLYGON (((-118.18066 33.80597, -118.1806...
2332 MULTIPOLYGON (((-118.59919 34.07436, -118.5991...
2333 MULTIPOLYGON (((-118.34412 34.21700, -118.3438...
2334 MULTIPOLYGON (((-118.40183 34.26509, -118.4017...
2335 MULTIPOLYGON (((-118.50266 34.30809, -118.5026...
2336 MULTIPOLYGON (((-118.64870 34.23120, -118.6480...
2337 MULTIPOLYGON (((-118.51849 34.18389, -118.5184...
2338 MULTIPOLYGON (((-118.25712 33.83927, -118.2571...
2339 MULTIPOLYGON (((-118.35173 34.28034, -118.3517...
2340 MULTIPOLYGON (((-118.45246 33.94315, -118.4464...
2341 MULTIPOLYGON (((-118.43712 33.91639, -118.4299...
2342 MULTIPOLYGON (((-118.29105 33.75378, -118.2905...
2343 MULTIPOLYGON (((-118.24897 33.75590, -118.2470...
2344 MULTIPOLYGON (((-118.95114 33.99643, -118.9505...
2345 MULTIPOLYGON (((-118.63598 34.03255, -118.6325...
2346 MULTIPOLYGON (((-118.47656 33.75038, -118.4661...

```

[50 rows x 24 columns]

```
[11]: industry = industry[industry['Accommodation and food services'] >= 1]
```

```
[12]: industry.shape
```

```
[12]: (2208, 24)
```

```
[13]: industry.sort_values(by='Accommodation and food services').tail(20)
```

```

[13]:
      geoid      name      total  \
924  06037275603  Census Tract 2756.03, Los Angeles, CA  60598.0
998  06037300901  Census Tract 3009.01, Los Angeles, CA  86203.0
2038 06037620602  Census Tract 6206.02, Los Angeles, CA  75128.0
1375 06037462900      Census Tract 4629, Los Angeles, CA  54575.0
1076 06037401002  Census Tract 4010.02, Los Angeles, CA  58197.0
837  06037262704  Census Tract 2627.04, Los Angeles, CA  77159.0
1802 06037554519  Census Tract 5545.19, Los Angeles, CA  66923.0
875  06037269500      Census Tract 2695, Los Angeles, CA 101830.0
1061 06037400205  Census Tract 4002.05, Los Angeles, CA  90560.0
1988 06037602302  Census Tract 6023.02, Los Angeles, CA  78164.0
828  06037262100      Census Tract 2621, Los Angeles, CA 100408.0
2161 06037800328  Census Tract 8003.28, Los Angeles, CA  49184.0
2117 06037700902  Census Tract 7009.02, Los Angeles, CA  69914.0

```

1935	06037577501	Census Tract 5775.01, Los Angeles, CA	66250.0
330	06037139802	Census Tract 1398.02, Los Angeles, CA	82670.0
2169	06037800504	Census Tract 8005.04, Los Angeles, CA	77679.0
1385	06037463700	Census Tract 4637, Los Angeles, CA	85360.0
2113	06037700700	Census Tract 7007, Los Angeles, CA	149205.0
1006	06037301300	Census Tract 3013, Los Angeles, CA	79875.0
2030	06037620301	Census Tract 6203.01, Los Angeles, CA	109152.0

Agriculture, forestry, fishing and hunting \

924	NaN
998	NaN
2038	NaN
1375	NaN
1076	NaN
837	NaN
1802	NaN
875	NaN
1061	NaN
1988	NaN
828	NaN
2161	NaN
2117	NaN
1935	NaN
330	NaN
2169	NaN
1385	NaN
2113	NaN
1006	NaN
2030	NaN

Mining, quarrying, and oil and gas extraction Construction \

924	NaN	59063.0
998	NaN	NaN
2038	NaN	63171.0
1375	NaN	44615.0
1076	NaN	63182.0
837	NaN	NaN
1802	NaN	NaN
875	NaN	NaN
1061	NaN	128906.0
1988	NaN	73269.0
828	NaN	NaN
2161	NaN	46705.0
2117	NaN	40446.0
1935	NaN	105474.0
330	NaN	81000.0
2169	NaN	250001.0

1385	NaN	103245.0
2113	NaN	NaN
1006	NaN	NaN
2030	NaN	53571.0

	Manufacturing	Wholesale trade	Retail trade \
924	102391.0	64688.0	61083.0
998	119333.0	30114.0	40855.0
2038	92414.0	52188.0	34917.0
1375	54837.0	NaN	33750.0
1076	73750.0	57813.0	34375.0
837	72232.0	91250.0	26023.0
1802	74792.0	71827.0	24135.0
875	106474.0	25988.0	76250.0
1061	66705.0	119318.0	36500.0
1988	122232.0	63523.0	22614.0
828	NaN	100272.0	44432.0
2161	149722.0	83393.0	14786.0
2117	63277.0	77609.0	71628.0
1935	101667.0	128750.0	38450.0
330	114853.0	NaN	23155.0
2169	NaN	NaN	44816.0
1385	131953.0	NaN	40250.0
2113	NaN	107308.0	25208.0
1006	17222.0	69464.0	26563.0
2030	250001.0	125313.0	38750.0

	Transportation and warehousing ... \
924	72059.0 ...
998	NaN ...
2038	50284.0 ...
1375	48333.0 ...
1076	NaN ...
837	NaN ...
1802	32019.0 ...
875	NaN ...
1061	NaN ...
1988	56283.0 ...
828	161042.0 ...
2161	15357.0 ...
2117	62600.0 ...
1935	51128.0 ...
330	NaN ...
2169	NaN ...
1385	NaN ...
2113	NaN ...
1006	68750.0 ...

2030 26058.0 ...

	Professional, scientific, and technical services \
924	62216.0
998	140254.0
2038	140568.0
1375	103875.0
1076	115139.0
837	142273.0
1802	59712.0
875	191250.0
1061	129167.0
1988	102065.0
828	125357.0
2161	86364.0
2117	86429.0
1935	93929.0
330	91250.0
2169	118750.0
1385	131845.0
2113	213712.0
1006	86000.0
2030	162188.0

	Management of companies and enterprises \
924	NaN
998	NaN
2038	NaN
1375	NaN
1076	NaN
837	NaN
1802	NaN
875	NaN
1061	NaN
1988	NaN
828	NaN
2161	NaN
2117	NaN
1935	NaN
330	NaN
2169	NaN
1385	NaN
2113	NaN
1006	NaN
2030	NaN

Administrative and support and waste management services \



924	24205.0
998	103776.0
2038	40988.0
1375	4234.0
1076	26406.0
837	NaN
1802	38125.0
875	NaN
1061	NaN
1988	NaN
828	NaN
2161	NaN
2117	NaN
1935	26216.0
330	70909.0
2169	24615.0
1385	49688.0
2113	NaN
1006	48750.0
2030	49500.0

	Educational services	Health care and social assistance \
924	42571.0	62639.0
998	75950.0	81066.0
2038	46159.0	46796.0
1375	42857.0	46351.0
1076	59539.0	57647.0
837	91023.0	14375.0
1802	63594.0	79286.0
875	58269.0	62708.0
1061	78750.0	126786.0
1988	77045.0	75500.0
828	35208.0	250001.0
2161	46944.0	64625.0
2117	61475.0	62891.0
1935	76172.0	93594.0
330	43365.0	86979.0
2169	84345.0	92738.0
1385	61433.0	80455.0
2113	18000.0	250001.0
1006	43500.0	82292.0
2030	22321.0	128966.0

	Arts, entertainment, and recreation	Accommodation and food services \
924	101618.0	72880.0
998	51602.0	73895.0
2038	160972.0	75125.0

1375	90560.0	75192.0
1076	27500.0	81295.0
837	21944.0	81591.0
1802	NaN	82159.0
875	250001.0	85298.0
1061	NaN	85563.0
1988	40536.0	97206.0
828	42273.0	98958.0
2161	13625.0	100239.0
2117	42714.0	105813.0
1935	NaN	106250.0
330	NaN	107667.0
2169	7344.0	109063.0
1385	60000.0	112904.0
2113	NaN	125705.0
1006	250001.0	135104.0
2030	15694.0	250001.0

	Other services	Public administration \
924	24091.0	141250.0
998	11250.0	44657.0
2038	21667.0	101293.0
1375	17917.0	89125.0
1076	20515.0	148056.0
837	20909.0	NaN
1802	52813.0	104375.0
875	103393.0	175139.0
1061	47045.0	76667.0
1988	16765.0	70469.0
828	30875.0	NaN
2161	32946.0	88889.0
2117	11875.0	NaN
1935	148594.0	3629.0
330	23482.0	72500.0
2169	7442.0	NaN
1385	NaN	72772.0
2113	21853.0	70500.0
1006	NaN	61250.0
2030	5893.0	NaN

	geometry
924	MULTIPOLYGON (((-118.41555 33.98671, -118.4148...
998	MULTIPOLYGON (((-118.22547 34.16131, -118.2254...
2038	MULTIPOLYGON (((-118.37280 33.85916, -118.3728...
1375	MULTIPOLYGON (((-118.09867 34.14625, -118.0986...
1076	MULTIPOLYGON (((-117.87252 34.13665, -117.8725...
837	MULTIPOLYGON (((-118.55638 34.03798, -118.5561...

```

1802 MULTIPOLYGON (((-118.06361 33.85858, -118.0622...
875  MULTIPOLYGON (((-118.40065 34.04654, -118.4005...
1061 MULTIPOLYGON (((-117.75680 34.14402, -117.7567...
1988 MULTIPOLYGON (((-118.37874 33.89872, -118.3787...
828  MULTIPOLYGON (((-118.46823 34.12921, -118.4681...
2161 MULTIPOLYGON (((-118.73706 34.15444, -118.7367...
2117 MULTIPOLYGON (((-118.39914 34.06029, -118.3990...
1935 MULTIPOLYGON (((-118.13066 33.75524, -118.1294...
330  MULTIPOLYGON (((-118.56889 34.13847, -118.5687...
2169 MULTIPOLYGON (((-118.71425 34.03070, -118.7141...
1385 MULTIPOLYGON (((-118.16776 34.14147, -118.1676...
2113 MULTIPOLYGON (((-118.42704 34.09063, -118.4263...
1006 MULTIPOLYGON (((-118.27918 34.17249, -118.2790...
2030 MULTIPOLYGON (((-118.41250 33.90190, -118.4096...

```

[20 rows x 24 columns]

```

[14]: minx, miny, maxx, maxy = industry.geometry.total_bounds
print(minx)
print(maxx)
print(miny)
print(maxy)

```

```

-118.94518
-117.655235
32.75004
34.823301

```

Once I sort the values and get an ideal of what the visual might look like. Next steps I take are to normalize the data, specifically just the Accommodation and food service.

```

[15]: industry_web = industry.to_crs('EPSG:4326')

```

```

[16]: industry['Accommodation_and_food_services_per_1000'] = industry['Accommodation_
      ↪and food services']/industry['total']*1000

```

```

[17]: industry.sort_values(by="Accommodation_and_food_services_per_1000").head()

```

```

[17]:      geoid      name      total  \
825  06037261101  Census Tract 2611.01, Los Angeles, CA  103651.0
2096 06037670406  Census Tract 6704.06, Los Angeles, CA  115625.0
2121 06037701202  Census Tract 7012.02, Los Angeles, CA   81904.0
2027 06037620101  Census Tract 6201.01, Los Angeles, CA   76725.0
1387 06037463900    Census Tract 4639, Los Angeles, CA   74063.0

      Agriculture, forestry, fishing and hunting  \
825                                             NaN
2096                                             NaN

```

2121	NaN
2027	NaN
1387	NaN

	Mining, quarrying, and oil and gas extraction	Construction	\
825	NaN	64500.0	
2096	NaN	NaN	
2121	NaN	57813.0	
2027	NaN	70885.0	
1387	NaN	90150.0	

	Manufacturing	Wholesale trade	Retail trade	\
825	123750.0	NaN	41161.0	
2096	160795.0	119250.0	99500.0	
2121	31250.0	NaN	78417.0	
2027	121096.0	200533.0	44271.0	
1387	100086.0	31607.0	50208.0	

	Transportation and warehousing	...	\
825	28490.0	...	
2096	231250.0	...	
2121	57000.0	...	
2027	38750.0	...	
1387	127000.0	...	

	Management of companies and enterprises	\
825	NaN	
2096	NaN	
2121	NaN	
2027	NaN	
1387	NaN	

	Administrative and support and waste management services	\
825	68106.0	
2096	NaN	
2121	76250.0	
2027	21667.0	
1387	15809.0	

	Educational services	Health care and social assistance	\
825	78681.0	64449.0	
2096	78250.0	117981.0	
2121	82763.0	71875.0	
2027	60313.0	77575.0	
1387	72250.0	80117.0	

	Arts, entertainment, and recreation	Accommodation and food services	\
--	-------------------------------------	---------------------------------	---

825	87159.0	2499.0
2096	8636.0	3000.0
2121	41389.0	2499.0
2027	20795.0	2499.0
1387	36354.0	2499.0

	Other services	Public administration \
825	35781.0	NaN
2096	63000.0	NaN
2121	53571.0	79531.0
2027	36607.0	130804.0
1387	71750.0	53750.0

	geometry \
825	MULTIPOLYGON (((-118.41760 34.10724, -118.4175...
2096	MULTIPOLYGON (((-118.39328 33.76111, -118.3928...
2121	MULTIPOLYGON (((-118.49502 34.03232, -118.4946...
2027	MULTIPOLYGON (((-118.42878 33.93097, -118.4272...
1387	MULTIPOLYGON (((-118.16805 34.12392, -118.1677...

	Accommodation_and_food_services_per_1000
825	24.109753
2096	25.945946
2121	30.511330
2027	32.570870
1387	33.741544

[5 rows x 25 columns]

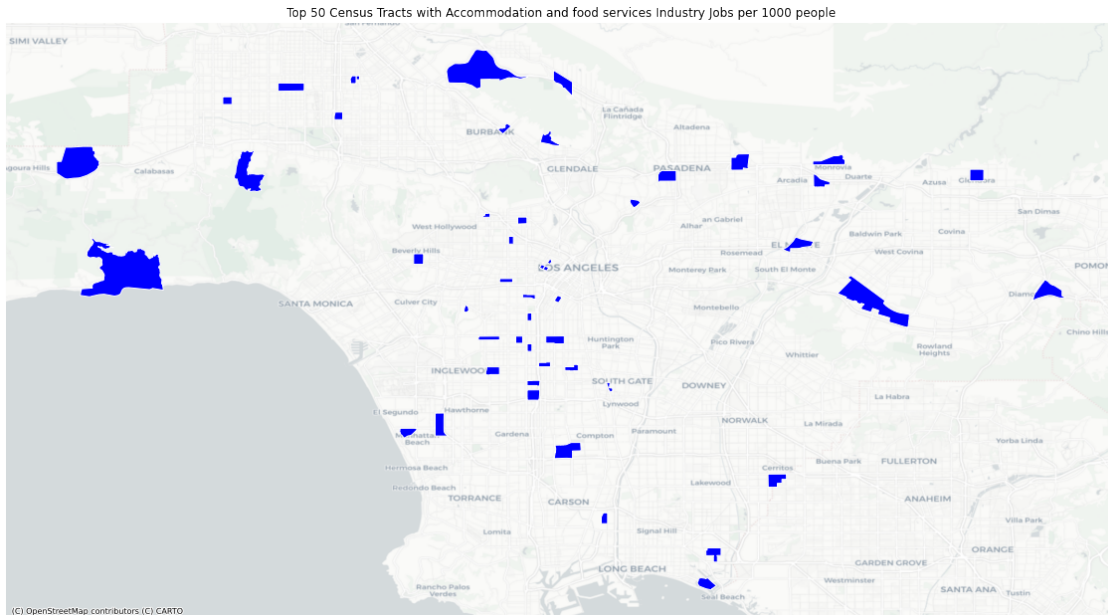
I map out what the top 50 census tracts. I choose 50 to show because I am curious to refine this to specific areas. From the comments I received from my midterm, I found that the historical comparisons from 2008 recession and 2020 would be interested to see what improvements occurred and where to help determine long term strategies to economic recovery.

```
[48]: fig,ax = plt.subplots(figsize=(20,20))
industry.
    ↪sort_values(by='Accommodation_and_food_services_per_1000',ascending=False)[:
    ↪50].plot(ax=ax,
                                                    color='blue',
                                                    ↪
    ↪edgecolor='white')

ax.set_title('Top 50 Census Tracts with Accommodation and food services
    ↪Industry Jobs per 1000 people')

ax.axis('off')
```

```
ctx.add_basemap(ax,
                crs='epsg:4326',
                source=ctx.providers.CartoDB.Positron)
```



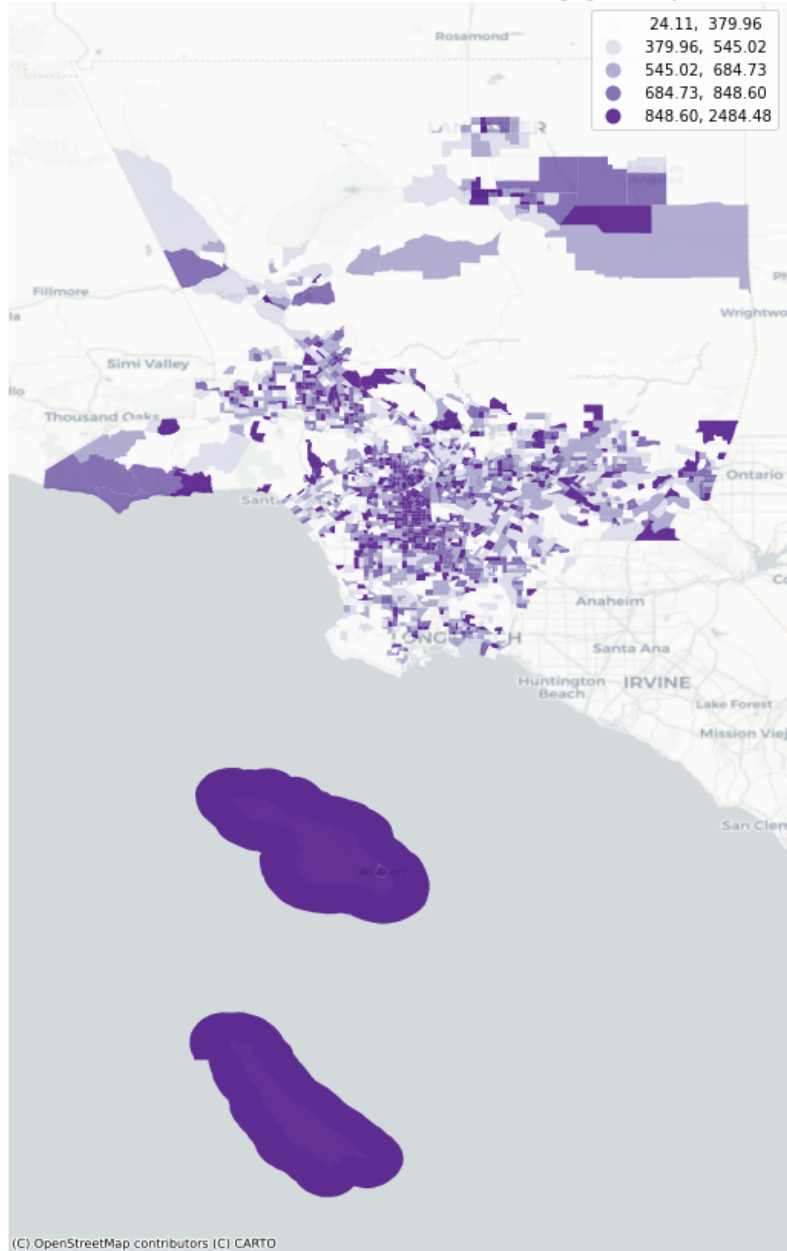
in the following map, I produce a choropleth map in quartiles of people per the 1000 that held a job in the Accommodation and food services industry. This map looks a bit scattered, but South LA looks like the area with a concentration of census tracts

```
[19]: fig,ax = plt.subplots(figsize=(15,15))

industry.plot(ax=ax,
              column='Accommodation_and_food_services_per_1000',
              legend=True,
              alpha=0.8,
              cmap='Purples',
              scheme='quantiles')

ax.axis('off')
ax.set_title('Accommodation and food services Industry Jobs per 1000_
↳people',fontsize=22)
ctx.add_basemap(ax,
                crs='epsg:4326', # surprise! You can change the crs here!
                source=ctx.providers.CartoDB.Positron)
```

## Accommodation and food services Industry Jobs per 1000 people



In the next cells I start the spatial autocorrelation to refine the data so that the areas are narrowed.

I calculate the spatial weight to create a lag.

```
[20]: wq = lps.weights.KNN.from_dataframe(industry,k=8)

wq.transform = 'r'
```

```
[21]: industry['Accommodation_and_food_services_per_1000_lag'] = lps.weights.  
      ↪lag_spatial(wq, industry['Accommodation_and_food_services_per_1000'])
```

```
[22]: industry.sample(10)[['total', 'Accommodation and food_  
      ↪services', 'Accommodation_and_food_services_per_1000', 'Accommodation_and_food_services_per_1  
      ↪geometry']]
```

```
[22]:
```

	total	Accommodation and food services \
76	40198.0	20673.0
1932	62453.0	29407.0
1960	24881.0	16875.0
476	56991.0	45781.0
525	23304.0	14083.0
1893	49667.0	6333.0
1844	50352.0	19018.0
1922	46521.0	26553.0
770	28846.0	18596.0
2221	67188.0	16923.0

	Accommodation_and_food_services_per_1000 \
76	514.279317
1932	470.866091
1960	678.228367
476	803.302276
525	604.316855
1893	127.509211
1844	377.700985
1922	570.774489
770	644.664772
2221	251.875335

	Accommodation_and_food_services_per_1000_lag \
76	647.231799
1932	515.895598
1960	648.345676
476	650.650469
525	699.049741
1893	573.548081
1844	259.082011
1922	683.178128
770	735.205568
2221	333.195746

	geometry
76	MULTIPOLYGON (((-118.49151 34.25024, -118.4915...
1932	MULTIPOLYGON (((-118.16264 33.73965, -118.1625...
1960	MULTIPOLYGON (((-118.34784 33.97174, -118.3472...



```

476 MULTIPOLYGON (((-118.28355 34.08389, -118.2815...
525 MULTIPOLYGON (((-118.20956 34.02717, -118.2095...
1893 MULTIPOLYGON (((-118.13405 33.78446, -118.1340...
1844 MULTIPOLYGON (((-118.14247 33.83481, -118.1424...
1922 MULTIPOLYGON (((-118.18443 33.76261, -118.1837...
770 MULTIPOLYGON (((-118.31775 33.97502, -118.3177...
2221 MULTIPOLYGON (((-118.23629 34.63307, -118.2362...

```

```

[23]: industry['Accommodation_and_food_services_per_1000_lag_diff'] =_
      ↪industry['Accommodation_and_food_services_per_1000'] -_
      ↪industry['Accommodation_and_food_services_per_1000_lag']

```

After I create the Spatial Lag, I look for the donut and diamond.

```

[24]: industry_donut = industry.
      ↪sort_values(by='Accommodation_and_food_services_per_1000_lag_diff').head(1)
industry_donut

```

```

[24]:      geoid      name      total \
2213  06037910201  Census Tract 9102.01, Los Angeles, CA  48054.0

      Agriculture, forestry, fishing and hunting \
2213      NaN

      Mining, quarrying, and oil and gas extraction  Construction \
2213      NaN      48902.0

      Manufacturing  Wholesale trade  Retail trade \
2213      71523.0      37305.0      38021.0

      Transportation and warehousing ...  Educational services \
2213      49750.0 ...      51125.0

      Health care and social assistance  Arts, entertainment, and recreation \
2213      85556.0      NaN

      Accommodation and food services  Other services  Public administration \
2213      2499.0      9500.0      66207.0

      geometry \
2213  MULTIPOLYGON (((-118.14777 34.61262, -118.1477...

      Accommodation_and_food_services_per_1000 \
2213      52.003996

      Accommodation_and_food_services_per_1000_lag \
2213      758.333805

```

```

Accommodation_and_food_services_per_1000_lag_diff
2213 -706.32981

```

```
[1 rows x 27 columns]
```

The donut is in palmdale, people are making less in the Accomodation and food services industry.

```
[25]: industry_diamond = industry.
      ↪sort_values(by='Accommodation_and_food_services_per_1000_lag_diff').tail(1)
      industry_diamond

```

```
[25]:
      geoid                                name    total \
1699  06037543100  Census Tract 5431, Los Angeles, CA  26261.0

      Agriculture, forestry, fishing and hunting \
1699                                19514.0

      Mining, quarrying, and oil and gas extraction  Construction \
1699                                NaN          35938.0

      Manufacturing  Wholesale trade  Retail trade \
1699          27040.0          53224.0          23077.0

      Transportation and warehousing ...  Educational services \
1699          31696.0 ...          54375.0

      Health care and social assistance  Arts, entertainment, and recreation \
1699          15735.0          23897.0

      Accommodation and food services  Other services  Public administration \
1699          65245.0          22679.0          65372.0

      geometry \
1699  MULTIPOLYGON (((-118.26600 33.87342, -118.2659...

      Accommodation_and_food_services_per_1000 \
1699          2484.482693

      Accommodation_and_food_services_per_1000_lag \
1699          426.426381

      Accommodation_and_food_services_per_1000_lag_diff
1699          2058.056312

```

```
[1 rows x 27 columns]
```

The diamond is in downtown LA, the Arts District. This tells me that the area has high income for people who are in the accommodation and food services industry. Given the gentrification of the area, this might be due to the different types of businesses that cater to specific clientele and different level of services.

In the following map I look at the difference between the Accommodation and food services per 1000 and the spatial lag

```
[39]: fig, ax = plt.subplots(1, 2, figsize=(15, 8))
industry.plot(ax=ax[0],
              column='Accommodation_and_food_services_per_1000',
              cmap='Reds',
              scheme='quantiles',
              k=5,
              edgecolor='grey',
              linewidth=0,
              alpha=0.75,
              )

ax[0].axis("off")
ax[0].set_title("Accommodation and food services Industry Jobs per 1000")

industry.plot(ax=ax[1],
              column='Accommodation_and_food_services_per_1000_lag',
              cmap='Reds',
              scheme='quantiles',
              k=5,
              edgecolor='grey',
              linewidth=0,
              alpha=0.75,
              )

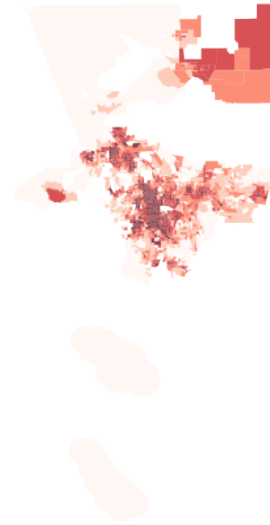
ax[1].axis("off")
ax[1].set_title("Accommodation and food services Industry Jobs per 1000 -  
→ Spatial Lag")

plt.show()
```

Accommodation and food services Industry Jobs per 1000



Accommodation and food services Industry Jobs per 1000 - Spatial Lag

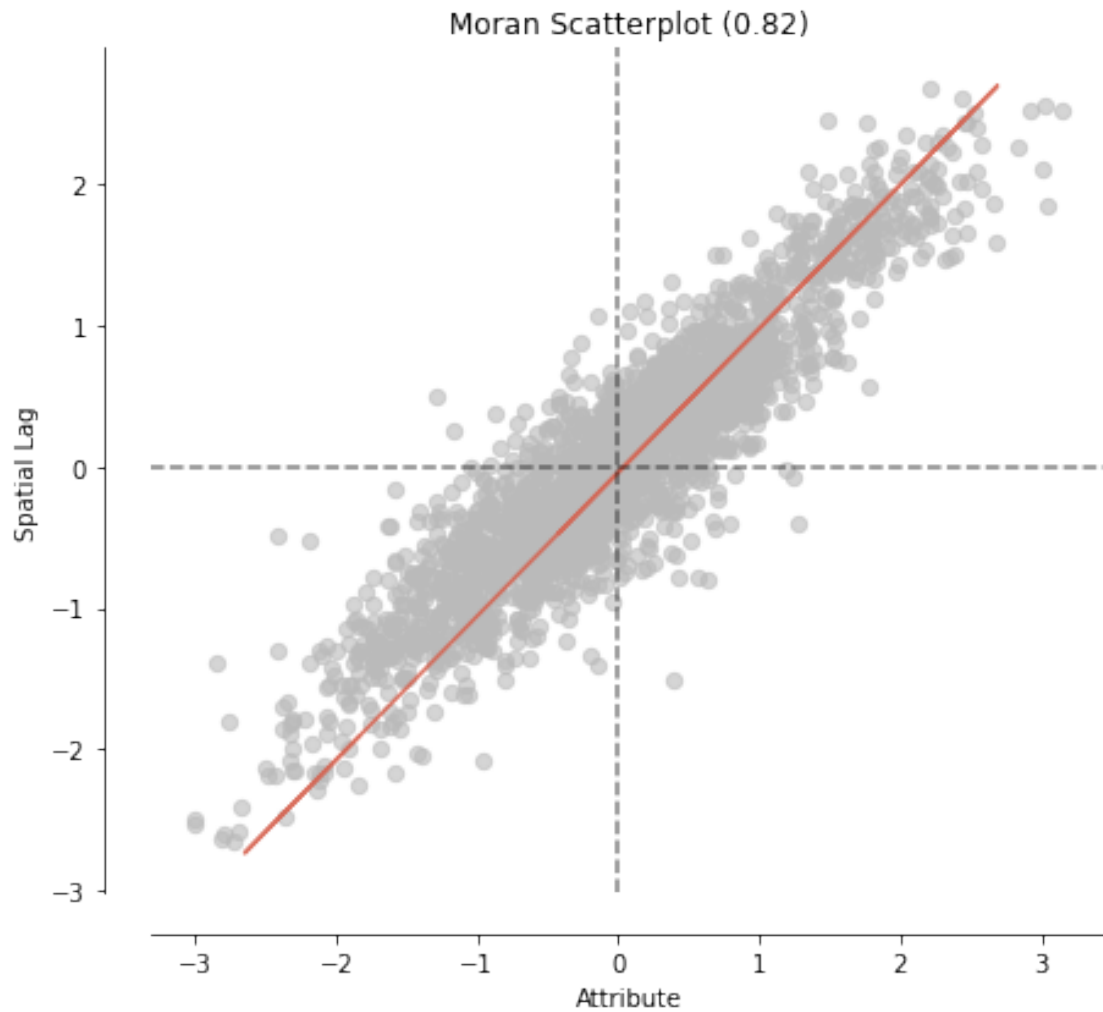


the Spatial Lag really makes a difference, its clearer to see where the concentration lies in the spatial lag map. This map helps isolate specific regions that hold individuals with incomes in the the accomodation industry. People in the darkest red areas rely more on an income and have lower incomes in the accomodation industry.

### 1.3 Below I map out the Moran Local ScatterPlot

I'll calcualte the moran values and then plot them to see if there is autocorrelation

```
[68]: fig, ax = moran_scatterplot(moran, aspect_equal=True)
      plt.show()
```



```
[27]: industry_web = industry.to_crs('EPSG:4326')
```

```
[28]: minx, miny, maxx, maxy = industry_web.geometry.total_bounds
      center_lat_gdf_web = (maxy-miny)/2+miny
      center_lon_gdf_web = (maxx-minx)/2+minx
```

```
[29]: industry_web.Accommodation_and_food_services_per_1000_lag.describe()
```

```
[29]: count    2208.000000
      mean      633.203414
      std      160.159239
      min      153.012219
      25%      529.589370
      50%      630.862927
      75%      738.860074
```

```
max      1137.532668
Name: Accommodation_and_food_services_per_1000_lag, dtype: float64
```

```
[30]: median = industry_web.Accommodation_and_food_services_per_1000_lag.median()
```

```
[31]: y = industry.Accommodation_and_food_services_per_1000_lag
      moran = Moran(y, wq)
      moran.I
```

```
[31]: 0.8246451518525661
```

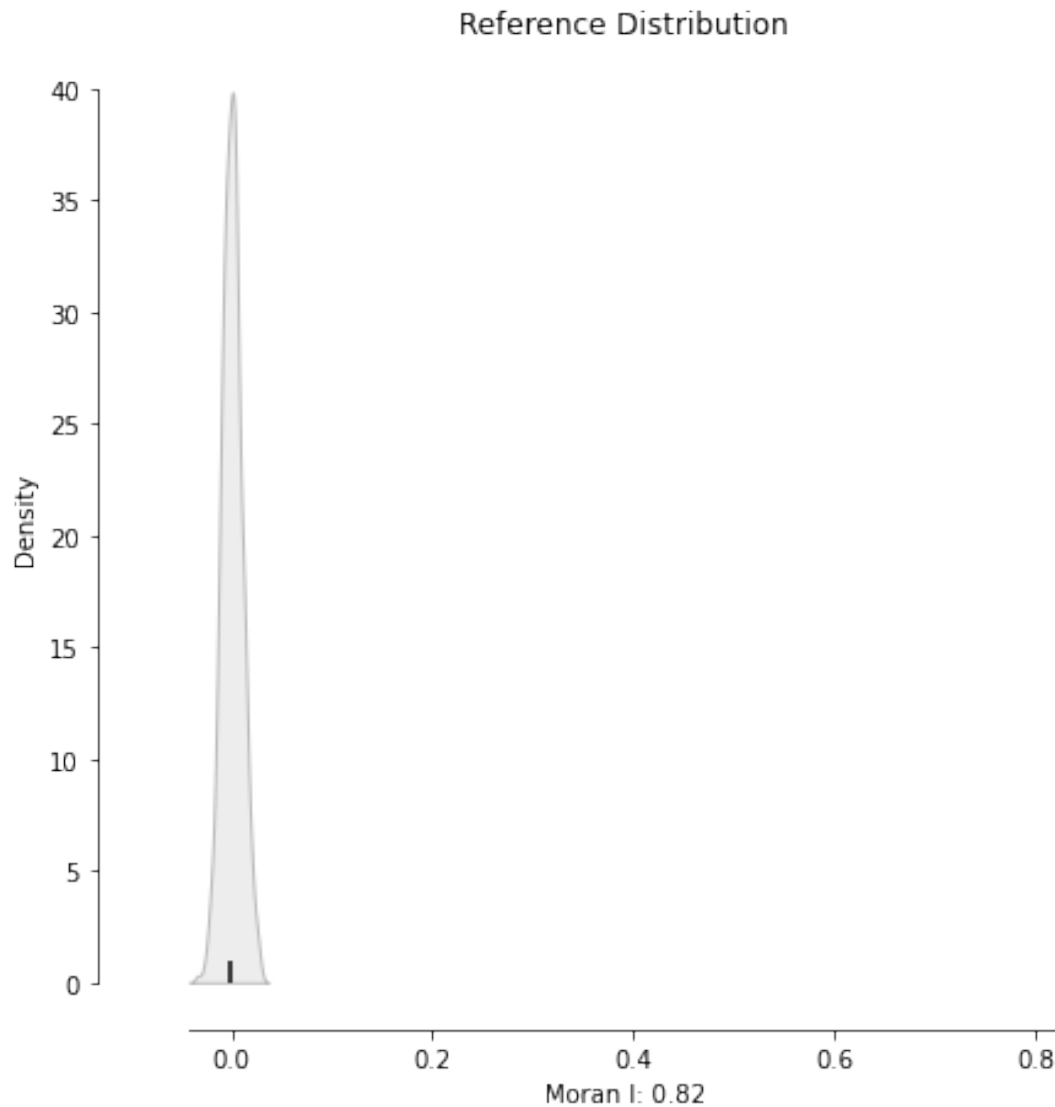
```
[32]: moran.p_sim
```

```
[32]: 0.001
```

```
[69]: plot_moran_simulation(moran,aspect_equal=False)
```

```
/opt/conda/lib/python3.8/site-packages/splot/_viz_esda_mpl.py:47:
MatplotlibDeprecationWarning:
The set_smart_bounds function was deprecated in Matplotlib 3.2 and will be
removed two minor releases later.
    ax.spines['left'].set_smart_bounds(True)
/opt/conda/lib/python3.8/site-packages/splot/_viz_esda_mpl.py:48:
MatplotlibDeprecationWarning:
The set_smart_bounds function was deprecated in Matplotlib 3.2 and will be
removed two minor releases later.
    ax.spines['bottom'].set_smart_bounds(True)
```

```
[69]: (<Figure size 504x504 with 1 Axes>,
      <matplotlib.axes._subplots.AxesSubplot at 0x7fbcf3b100a0>)
```

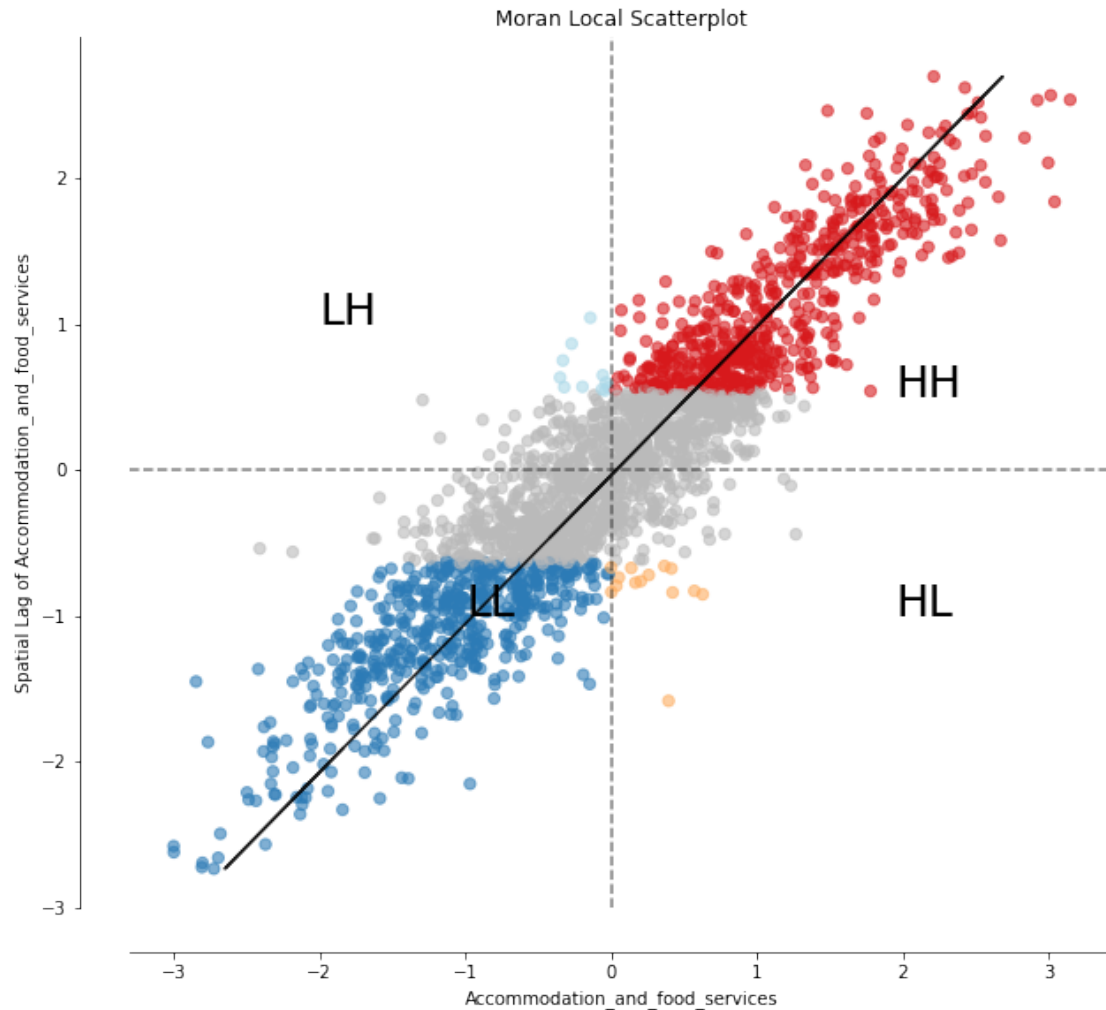


```
[33]: lisa = esda.moran.Moran_Local(y, wq)
```

```
[34]: fig,ax = plt.subplots(figsize=(10,15))

moran_scatterplot(lisa, ax=ax, p=0.05)
ax.set_xlabel("Accommodation_and_food_services")
ax.set_ylabel('Spatial Lag of Accommodation_and_food_services')

plt.text(1.95, 0.5, "HH", fontsize=25)
plt.text(1.95, -1, "HL", fontsize=25)
plt.text(-2, 1, "LH", fontsize=25)
plt.text(-1, -1, "LL", fontsize=25)
plt.show()
```



I added: HH areas with individuals high working in the Accomodation industry with low incomes. HL areas with individuals high working in the Accomodation industry with mid low incomes. LH areas with individuals high working in the Accomodation industry with mid high incomes. LL areas with individuals high working in the Accomodation industry with high incomes.

The distribution looks like there is even distribution, but I would argue that there are more areas that might fall under the HH category or more people who work in the Accomodation and food services that also have low incomes.

Below I map the moran scatter plot data, so we can visually see these statistically significant clusters.

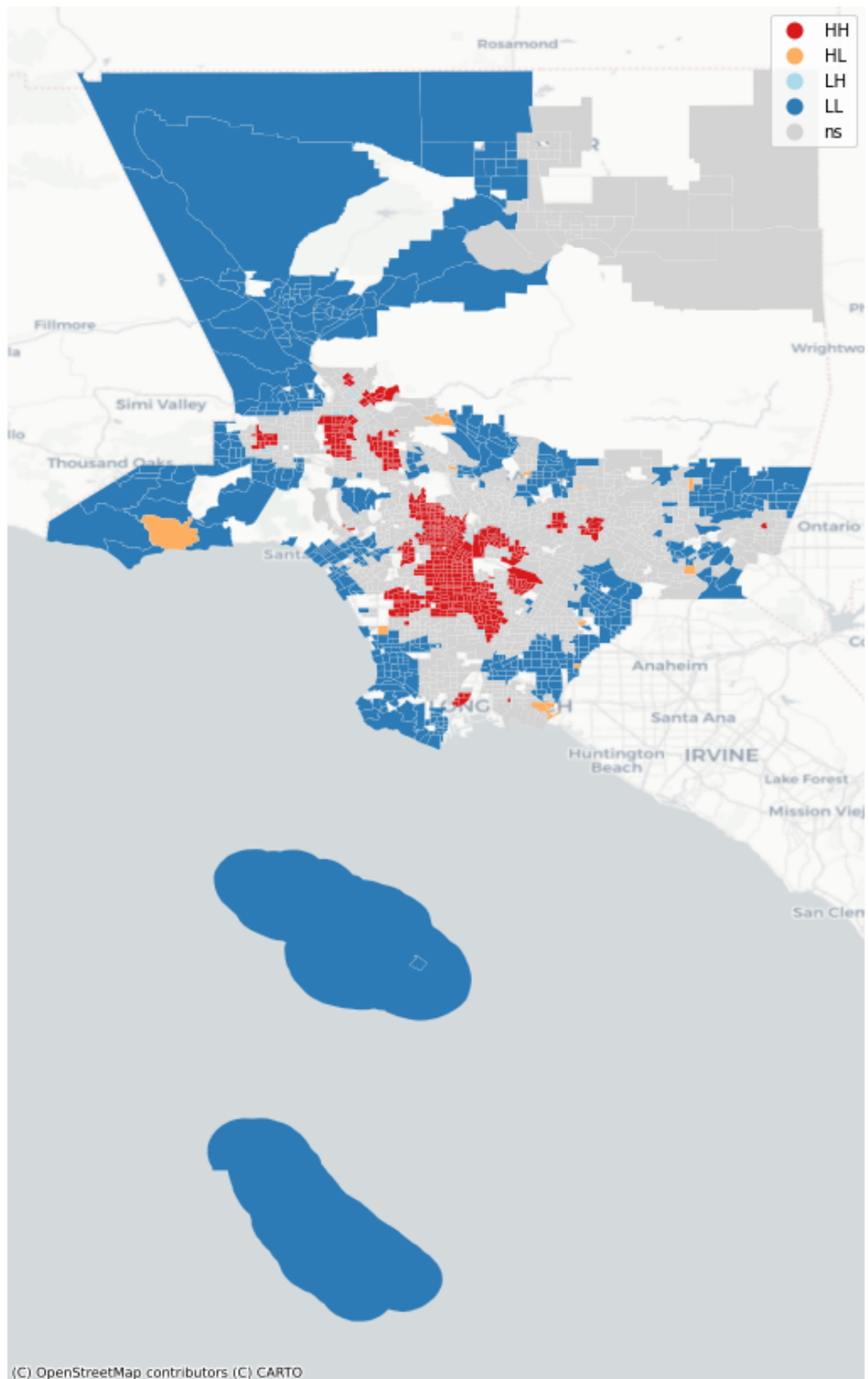
```
[35]: fig, ax = plt.subplots(figsize=(15,15))
      lisa_cluster(lisa, industry, p=0.05, ax=ax)

      ctx.add_basemap(ax,
```



```
crs='epsg:4326', # surprise! You can change the crs here!  
source=ctx.providers.CartoDB.Positron)
```

```
plt.show()
```



Similar map that I mapped earlier, but this map shows the stat significant areas. So this is more evidence to show that there are areas that can statically see high unemployment because of the pandemic.

Below I compare the P-values at .01 and .001. Because I did want to zoom in on specific areas, I when with a higher accomodation and food service jobs and low incomes, so I want to look at the areas most concentrated with most likly low incomes.

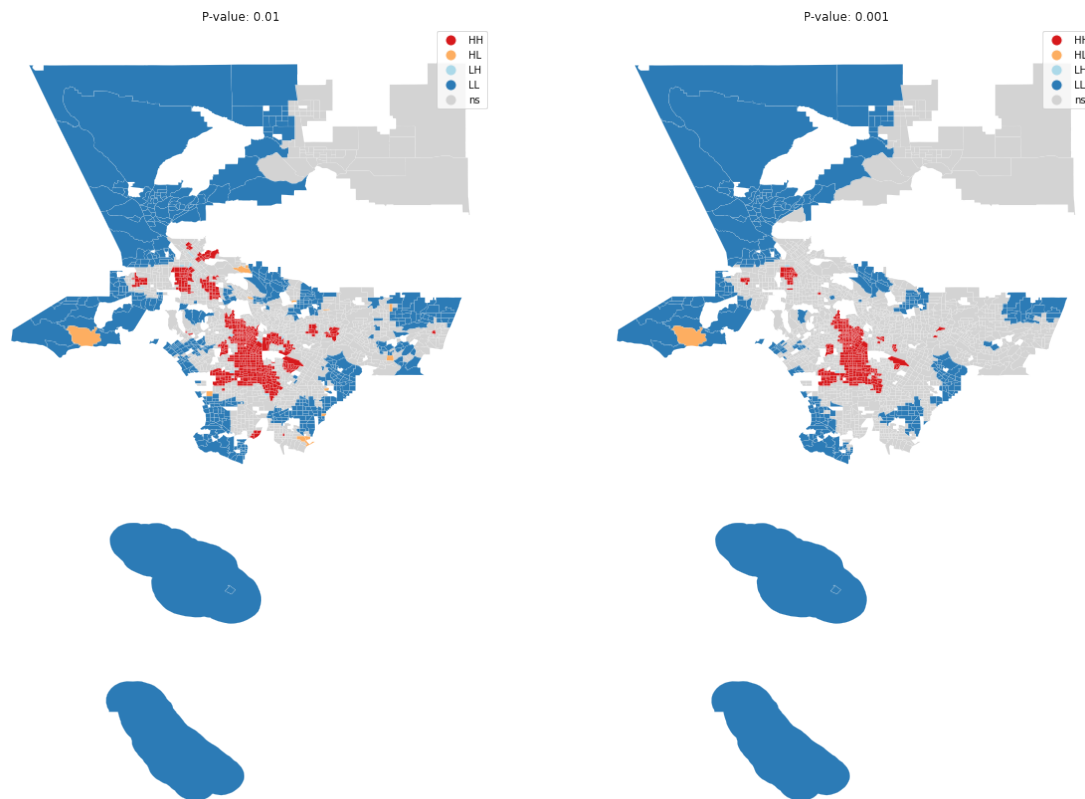
```
[36]: # create the 1x2 subplots
fig, ax = plt.subplots(1, 2, figsize=(20, 20))

# regular count map on the left
lisa_cluster(lisa, industry, p=0.05, ax=ax[0])

ax[0].axis("off")
ax[0].set_title("P-value: 0.01")

# spatial lag map on the right
lisa_cluster(lisa, industry, p=0.01, ax=ax[1])
ax[1].axis("off")
ax[1].set_title("P-value: 0.001")

plt.show()
```



The p-value of .001, shows a narrow area in South LA, district 9, that has a high concentration of individuals with low incomes in the accomodation and food service industry. I will want to take a close look at what's happening in this area.

Below I wanted to see if I could look at the make up of Accomodation and food services jobs by district. Still needs somework, but I'm curious at how can all indicators be represented on on map. Is this possible? I would want to see the distribution of industry incomes by council district, especial the ones that overlap with areas impacted.

```
[49]: gdf_cd = gpd.read_file('http://boundaries.latimes.com/1.0/boundary-set/
→la-city-council-districts-2012/?format=geojson')
```

```
[50]: indicators = ['Agriculture, forestry, fishing and hunting',
                    'Mining, quarrying, and oil and gas extraction',
                    'Construction',
                    'Manufacturing',
                    'Wholesale trade',
                    'Retail trade',
                    'Transportation and warehousing',
                    'Utilities',
                    'Information',
```

```

'Finance and insurance',
'Real estate and rental and leasing',
'Professional, scientific, and technical services',
'Management of companies and enterprises',
'Administrative and support and waste management services',
'Educational services',
'Health care and social assistance',
'Arts, entertainment, and recreation',
'Accommodation and food services',
'Other services',
'Public administration']

```

```

[52]: for indicator in indicators:
      print ('mean for ' + indicator + ' is ' + str(industry[indicator].mean()))

```

```

mean for Agriculture, forestry, fishing and hunting is 25922.434343434343
mean for Mining, quarrying, and oil and gas extraction is 59982.25
mean for Construction is 42366.87367357251
mean for Manufacturing is 49788.20947515095
mean for Wholesale trade is 47544.251041047
mean for Retail trade is 29009.10409090909
mean for Transportation and warehousing is 40218.94689378757
mean for Utilities is 91461.61373390559
mean for Information is 68037.93617021276
mean for Finance and insurance is 66210.66373239437
mean for Real estate and rental and leasing is 52722.36931380108
mean for Professional, scientific, and technical services is 60021.23940149626
mean for Management of companies and enterprises is 100663.0
mean for Administrative and support and waste management services is
33040.53336653386
mean for Educational services is 41798.397222222222
mean for Health care and social assistance is 43141.15660463005
mean for Arts, entertainment, and recreation is 36429.68241965974
mean for Accommodation and food services is 22524.48822463768
mean for Other services is 27975.448130841123
mean for Public administration is 62534.72802850356

```

```

[66]: for indicator in indicators:
      print(indicator)
      print (industry.sort_values(by = indicator, ascending=False)[indicator].
      ↪head(10))

```

```

Agriculture, forestry, fishing and hunting
3      155000.0
38     117661.0
1081    100132.0
74      55694.0

```

1086	55000.0
1621	51528.0
16	49886.0
1110	46250.0
1246	42563.0
19	41544.0

Name: Agriculture, forestry, fishing and hunting, dtype: float64

Mining, quarrying, and oil and gas extraction

2200	83500.0
2177	67143.0
1070	52619.0
1685	36667.0
1	NaN
3	NaN
4	NaN
5	NaN
6	NaN
7	NaN

Name: Mining, quarrying, and oil and gas extraction, dtype: float64

Construction

1072	250001.0
841	250001.0
2157	250001.0
2169	250001.0
247	243719.0
2155	215536.0
1402	192031.0
1396	177833.0
2163	177708.0
826	170529.0

Name: Construction, dtype: float64

Manufacturing

2030	250001.0
2168	250001.0
827	250001.0
458	216094.0
546	194306.0
456	194091.0
1397	180750.0
2098	175313.0
911	174375.0
2051	172431.0

Name: Manufacturing, dtype: float64

Wholesale trade

67	250001.0
1738	250001.0
2166	250001.0
2159	250001.0

874	250001.0
1456	250001.0
624	240417.0
2158	225375.0
915	216065.0
368	215446.0

Name: Wholesale trade, dtype: float64

Retail trade

872	250001.0
830	188676.0
847	177500.0
2124	161574.0
1348	161389.0
2046	135027.0
921	127955.0
2125	125769.0
1079	116184.0
2099	114338.0

Name: Retail trade, dtype: float64

Transportation and warehousing

1357	250001.0
2163	250001.0
2042	250001.0
2096	231250.0
308	176250.0
302	172650.0
828	161042.0
2050	160238.0
2094	139028.0
62	137500.0

Name: Transportation and warehousing, dtype: float64

Utilities

1798	250001.0
1069	215500.0
2313	161429.0
1749	153324.0
2076	151071.0
1386	149167.0
1396	146563.0
1044	146222.0
1842	145250.0
1011	143125.0

Name: Utilities, dtype: float64

Information

2180	250001.0
1349	250001.0
845	250001.0
875	250001.0

1891	250001.0
2032	250001.0
1456	250001.0
1402	250001.0
2090	250001.0
2091	250001.0

Name: Information, dtype: float64

Finance and insurance

2125	250001.0
2087	250001.0
317	250001.0
874	250001.0
872	250001.0
2030	250001.0
999	250001.0
828	250001.0
2113	250001.0
2046	250001.0

Name: Finance and insurance, dtype: float64

Real estate and rental and leasing

2030	250001.0
831	250001.0
830	250001.0
1367	250001.0
1288	250001.0
458	250001.0
828	215208.0
1341	215111.0
340	215000.0
1349	205588.0

Name: Real estate and rental and leasing, dtype: float64

Professional, scientific, and technical services

2113	213712.0
875	191250.0
2042	189688.0
1380	174063.0
2101	170000.0
2030	162188.0
2168	162159.0
825	161667.0
249	161563.0
344	160117.0

Name: Professional, scientific, and technical services, dtype: float64

Management of companies and enterprises

923	250001.0
1383	96429.0
2107	78988.0
2157	66786.0



830	11111.0
1	NaN
3	NaN
4	NaN
5	NaN
6	NaN

Name: Management of companies and enterprises, dtype: float64

Administrative and support and waste management services

846	250001.0
1277	202594.0
977	182813.0
201	171655.0
643	170781.0
461	162865.0
1346	156250.0
2314	151471.0
1843	150938.0
1884	150568.0

Name: Administrative and support and waste management services, dtype: float64

Educational services

311	171576.0
593	137830.0
2123	135640.0
2127	126528.0
1390	125563.0
827	121250.0
402	108125.0
1956	106250.0
1704	104453.0
1848	103229.0

Name: Educational services, dtype: float64

Health care and social assistance

2091	250001.0
2113	250001.0
828	250001.0
404	250001.0
2101	201250.0
642	180833.0
996	161000.0
2163	161000.0
919	160333.0
831	155169.0

Name: Health care and social assistance, dtype: float64

Arts, entertainment, and recreation

1006	250001.0
875	250001.0
321	250001.0
2155	250001.0

```

1346    250001.0
2033    220688.0
313     205833.0
1676    205104.0
301     186607.0
307     174091.0
Name: Arts, entertainment, and recreation, dtype: float64
Accommodation and food services
2030    250001.0
1006    135104.0
2113    125705.0
1385    112904.0
2169    109063.0
330     107667.0
1935    106250.0
2117    105813.0
2161    100239.0
828     98958.0
Name: Accommodation and food services, dtype: float64
Other services
2101    193125.0
2094    170781.0
869     160250.0
1935    148594.0
2246    148221.0
1939    140197.0
1140    111250.0
1999    108235.0
2114    106042.0
875     103393.0
Name: Other services, dtype: float64
Public administration
1120    248200.0
406     202768.0
2146    200625.0
1462    199167.0
2163    177969.0
910     177734.0
874     175227.0
875     175139.0
2215    169167.0
347     168250.0
Name: Public administration, dtype: float64

```

```

[63]: # function to create a council district map
def cd_map(name = '1', column = 'Accommodation and food services'):
    # this cd

```

```

this_cd = gdf_cd[gdf_cd['name']==name]

# spatial join to get tracts
tracts = gpd.sjoin(industry,this_cd)

# plot it
fig,ax = plt.subplots()

# map
tracts.plot(ax=ax,
            column=column,
            vmin=0,
            vmax=100,
            legend=True)

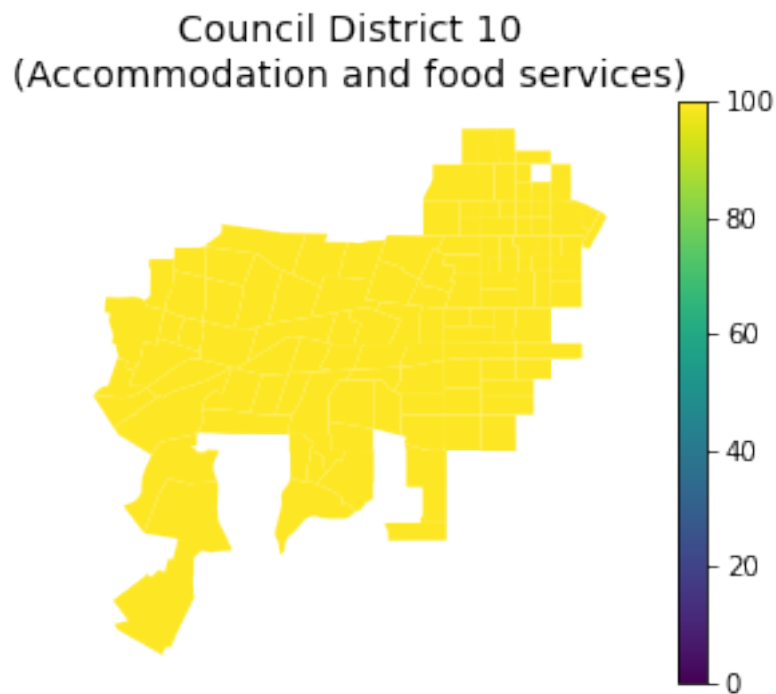
ax.axis('off')
ax.set_title('Council District ' + name + '\n(' + column + ')', fontsize=14)

```

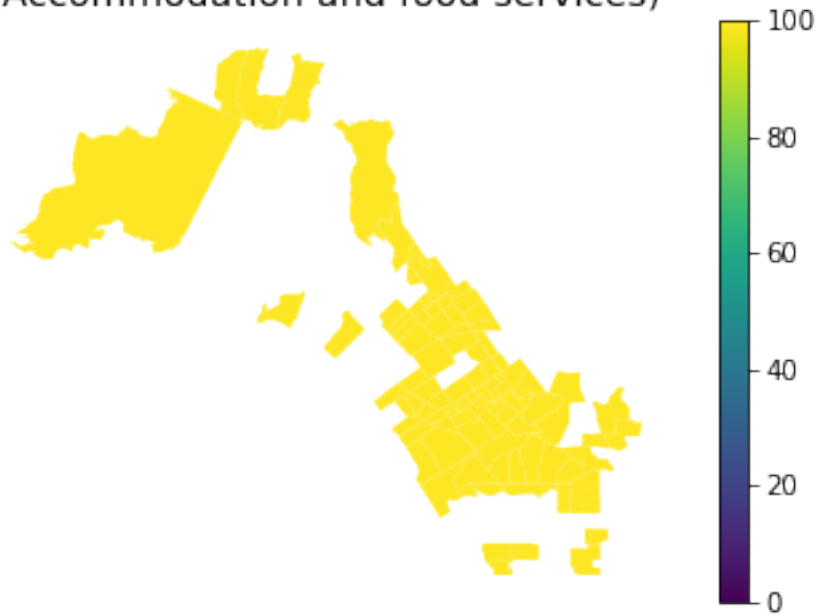
```

[64]: for index, row in gdf_cd.iterrows():
      cd_map(name = row['name'])

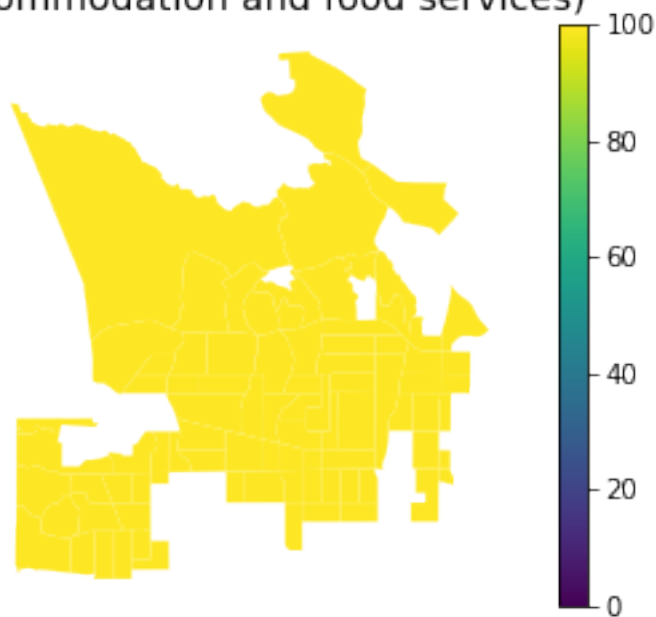
```



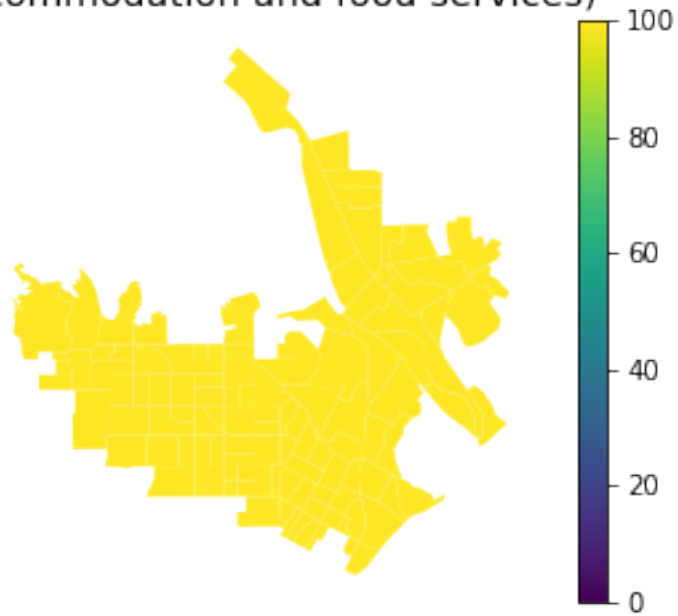
Council District 11  
(Accommodation and food services)



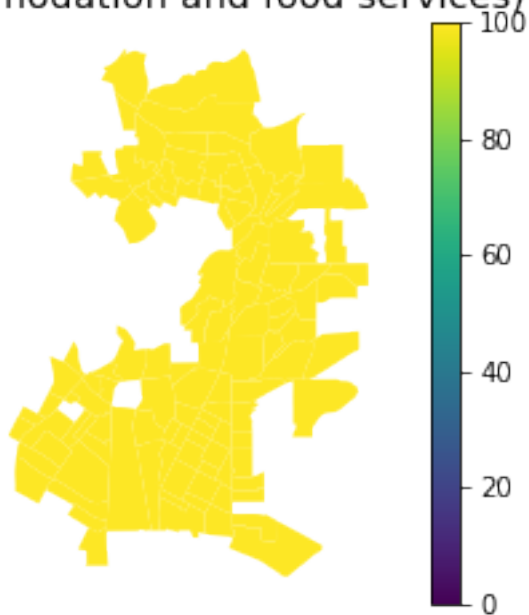
Council District 12  
(Accommodation and food services)



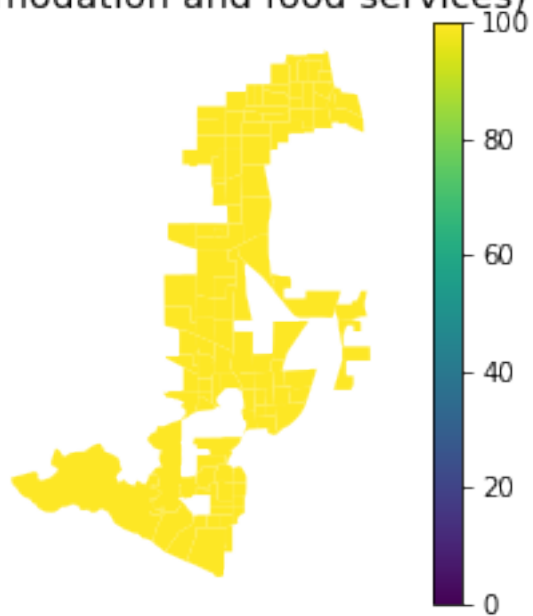
Council District 13  
(Accommodation and food services)



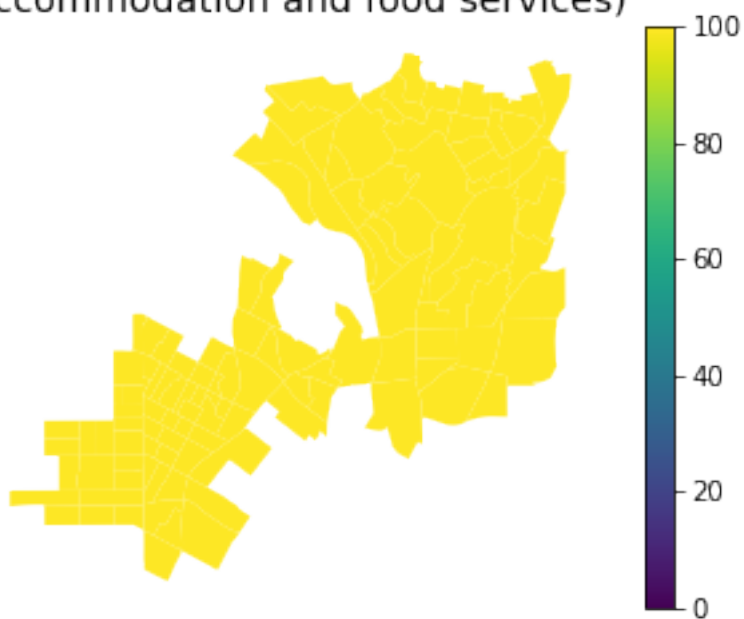
Council District 14  
(Accommodation and food services)



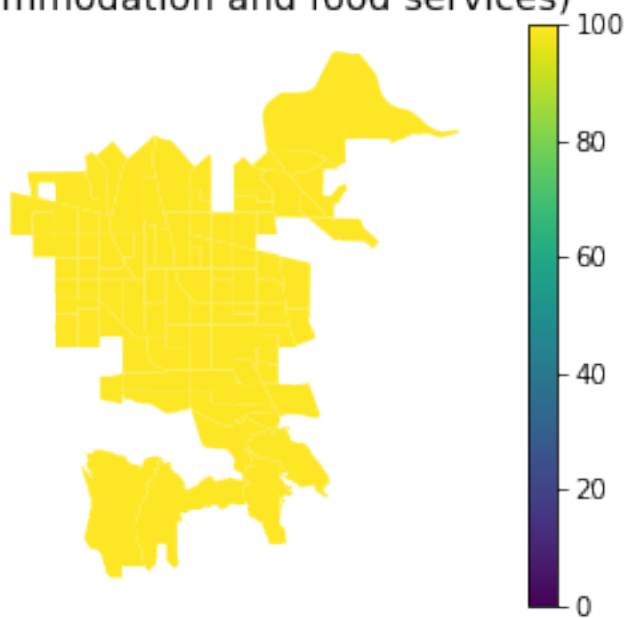
Council District 15  
(Accommodation and food services)



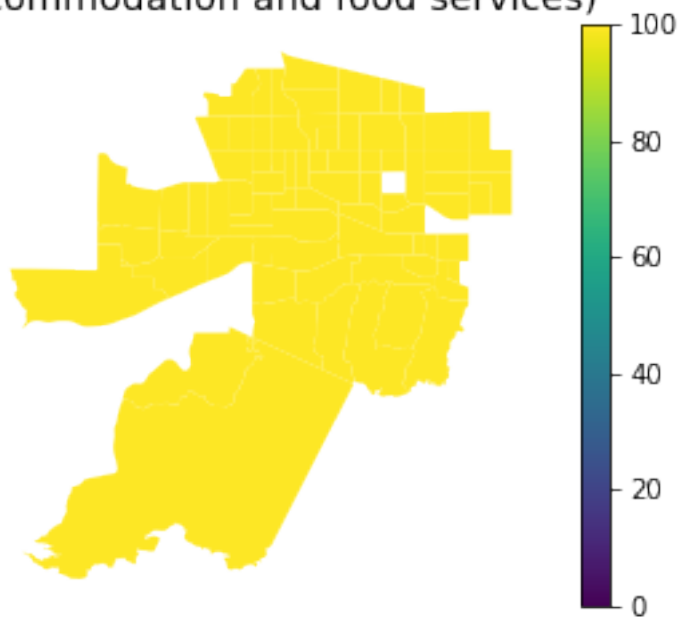
Council District 1  
(Accommodation and food services)



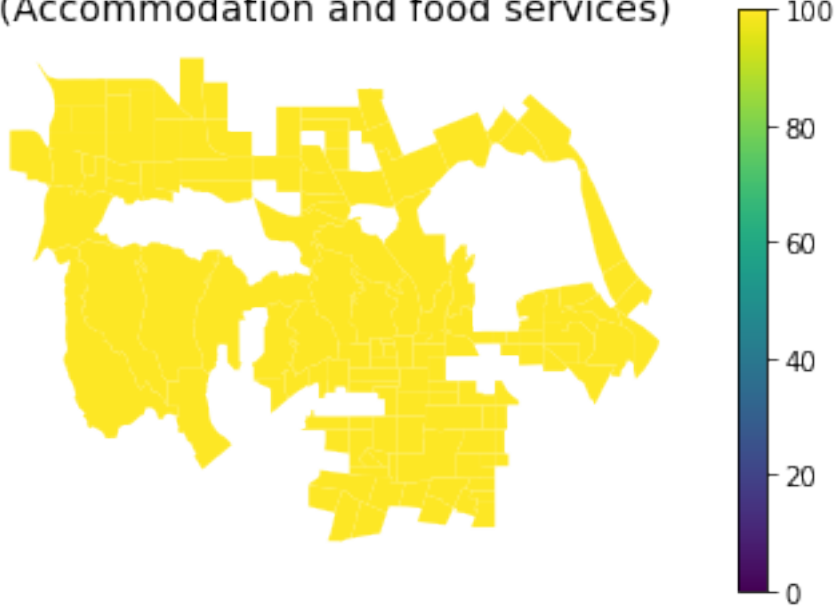
Council District 2  
(Accommodation and food services)



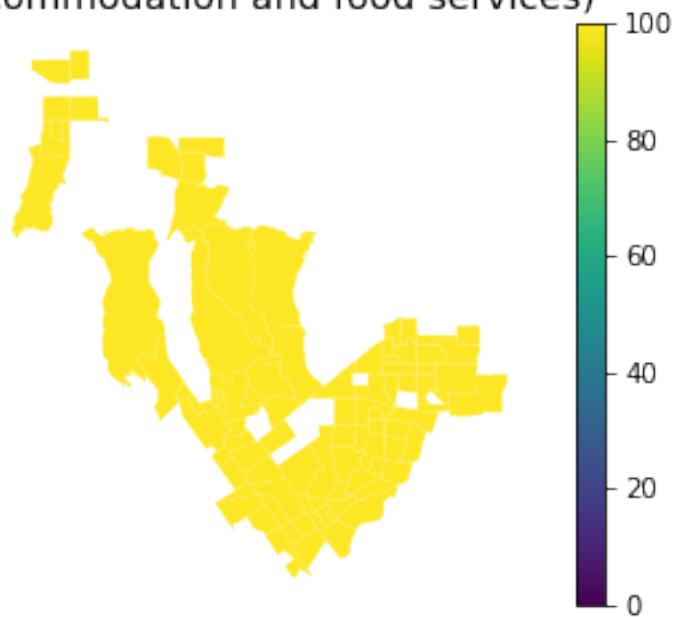
Council District 3  
(Accommodation and food services)



Council District 4  
(Accommodation and food services)

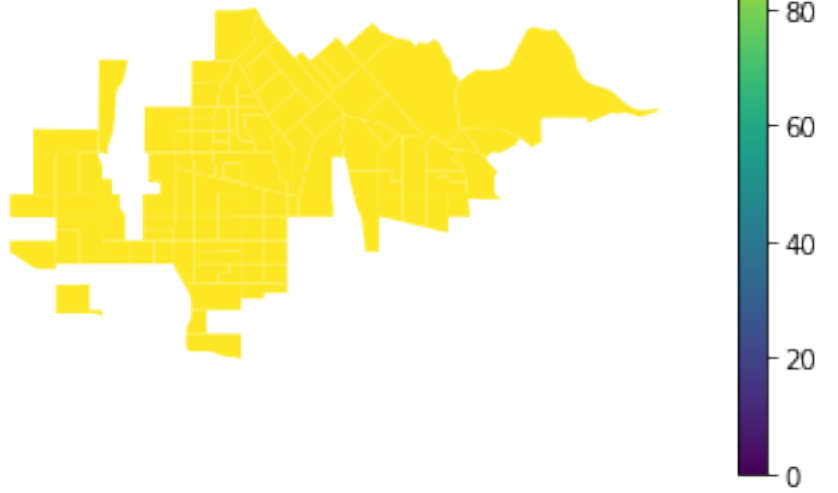


Council District 5  
(Accommodation and food services)





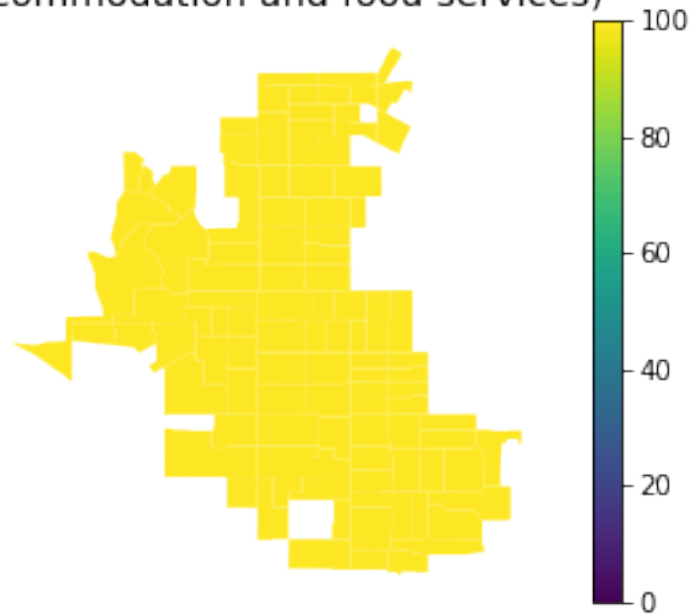
Council District 6  
(Accommodation and food services)



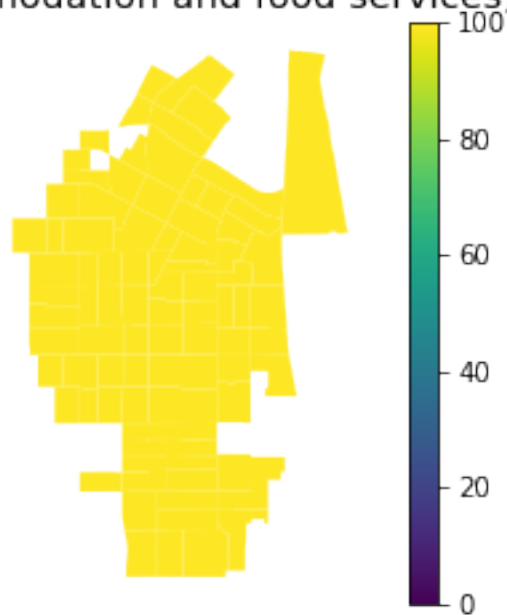
Council District 7  
(Accommodation and food services)



Council District 8  
(Accommodation and food services)

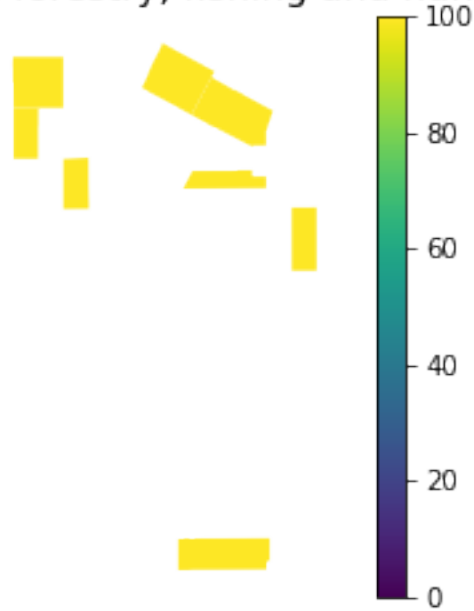


Council District 9  
(Accommodation and food services)

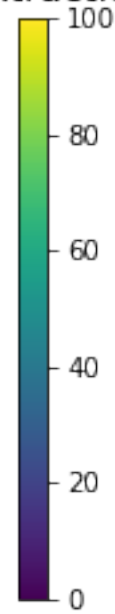


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[67]: for indicator in indicators:  
       cd_map(name='9',column=indicator)
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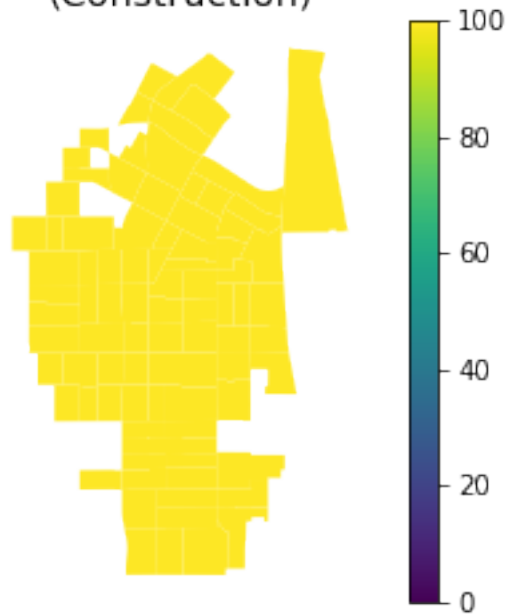
Council District 9  
(Agriculture, forestry, fishing and hunting)



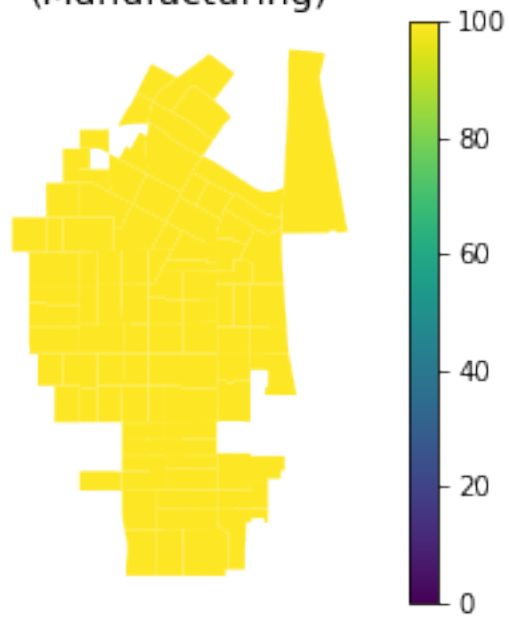
Council District 9  
(Mining, quarrying, and oil and gas extraction)



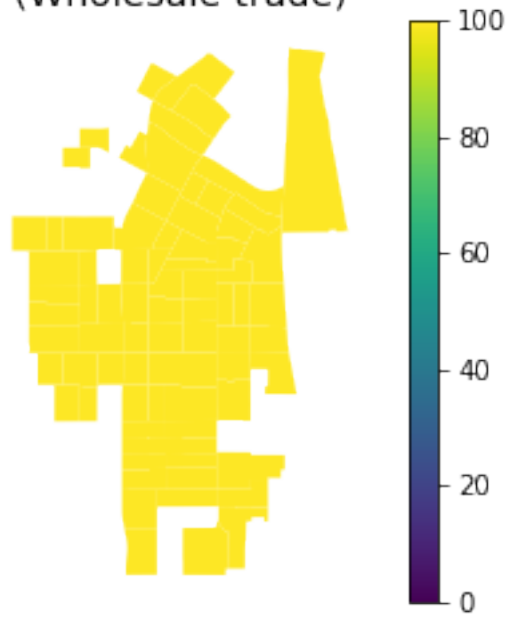
Council District 9  
(Construction)



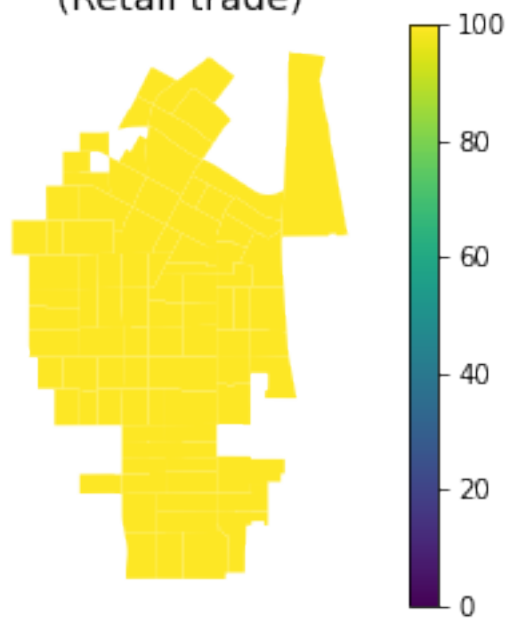
Council District 9  
(Manufacturing)



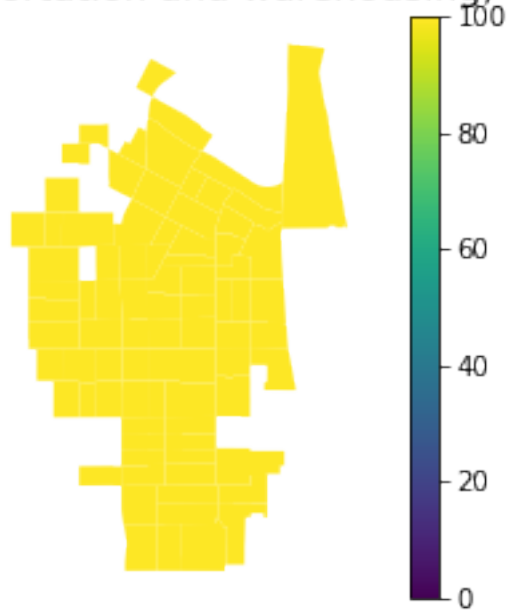
Council District 9  
(Wholesale trade)



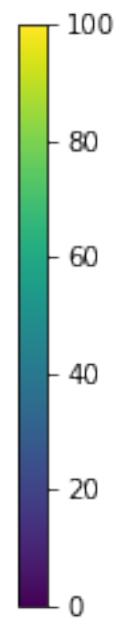
Council District 9  
(Retail trade)



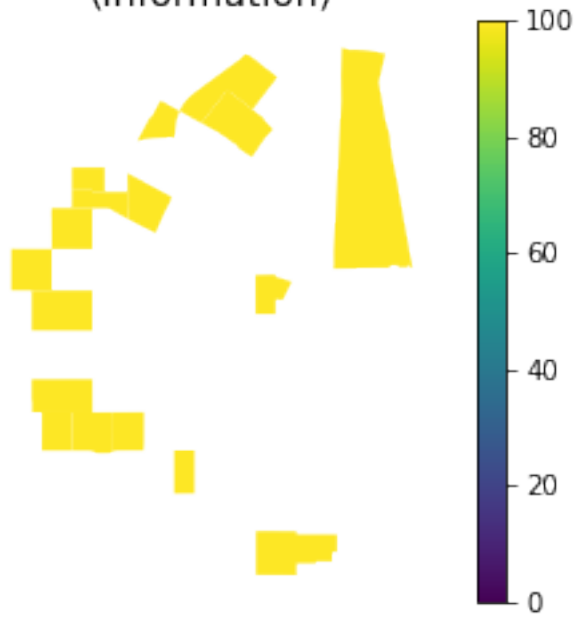
Council District 9  
(Transportation and warehousing)



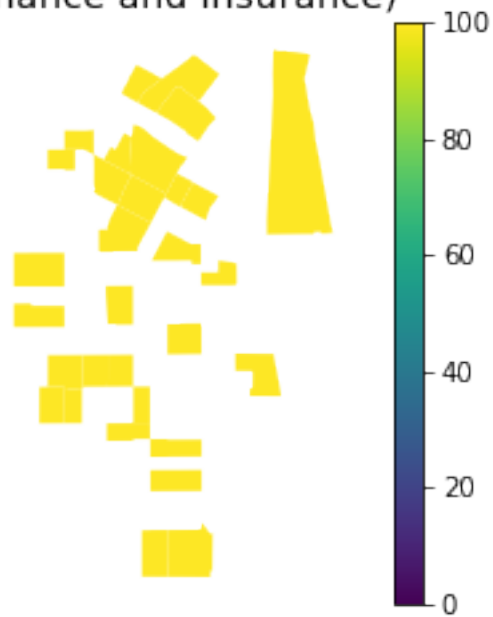
Council District 9  
(Utilities)



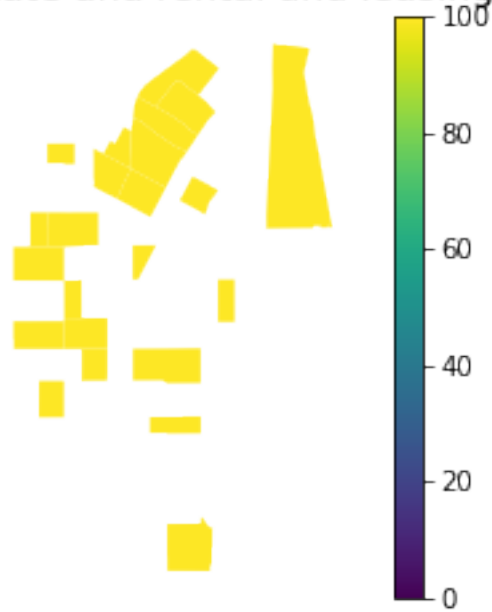
Council District 9  
(Information)



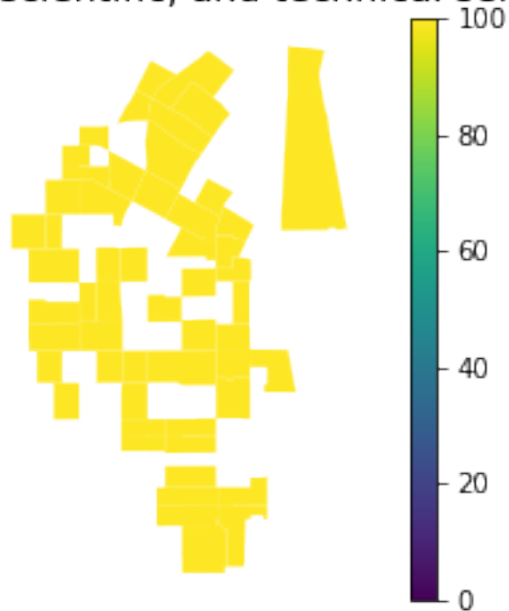
Council District 9  
(Finance and insurance)



Council District 9  
(Real estate and rental and leasing)

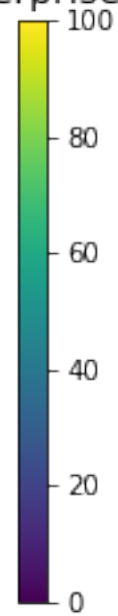


Council District 9  
(Professional, scientific, and technical services)

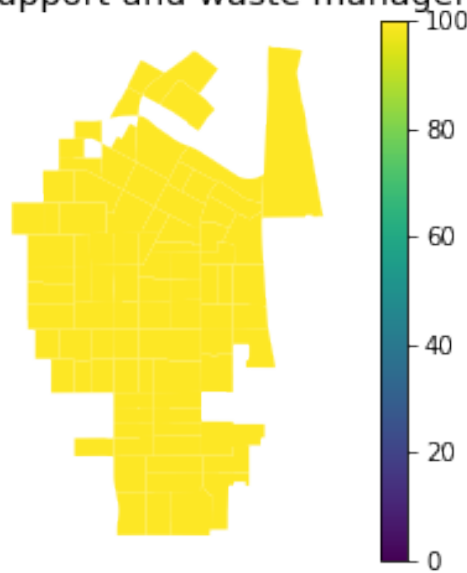




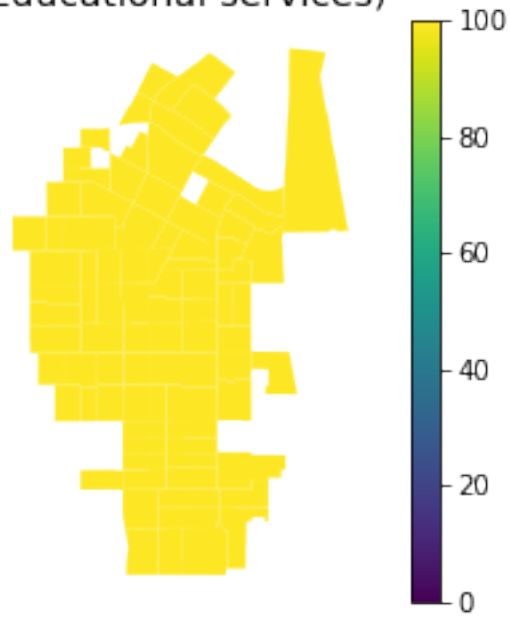
Council District 9  
(Management of companies and enterprises)



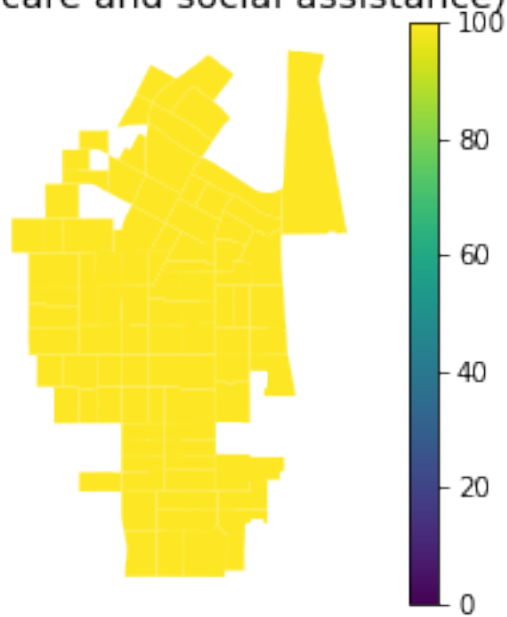
Council District 9  
(Administrative and support and waste management services)



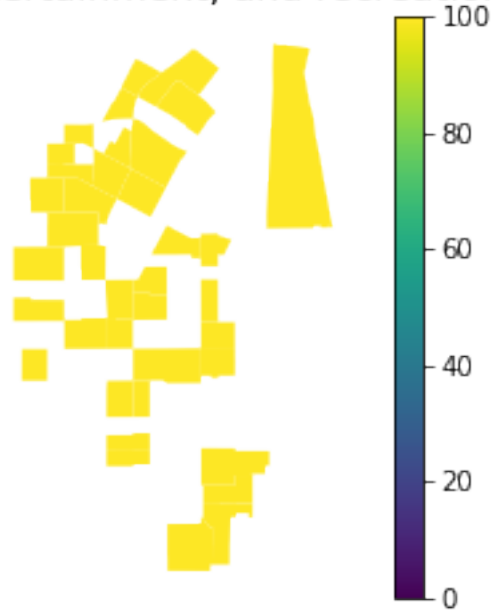
Council District 9  
(Educational services)



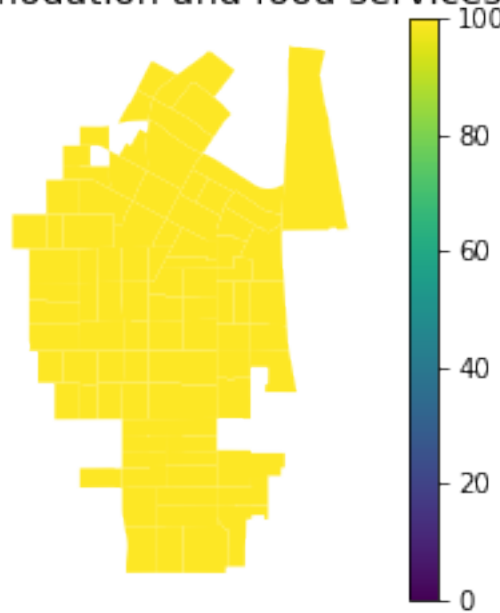
Council District 9  
(Health care and social assistance)

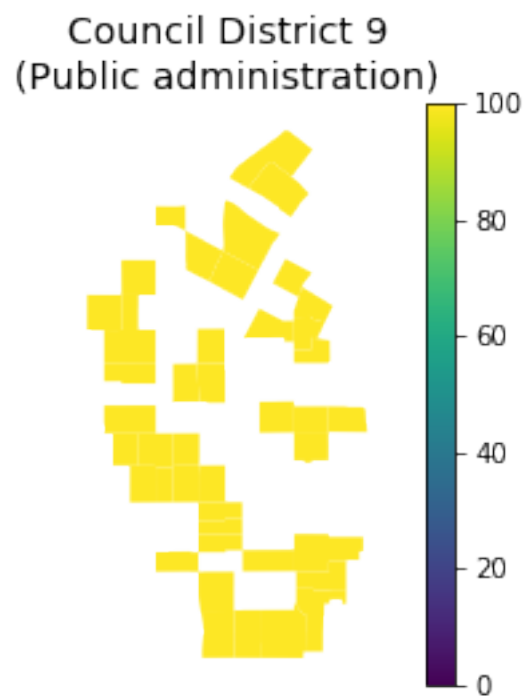
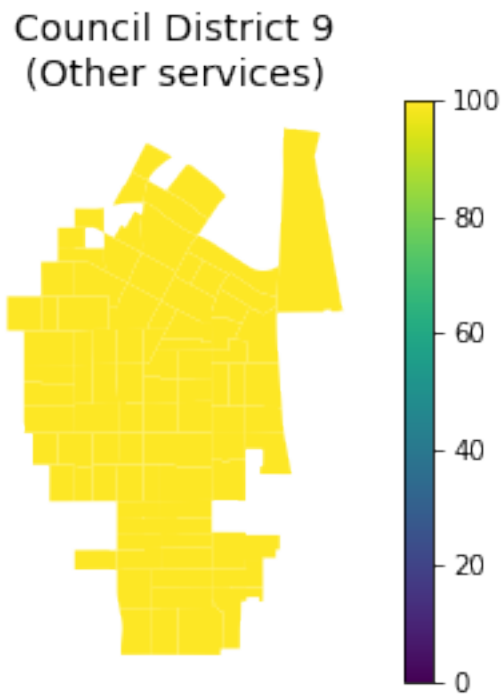


Council District 9  
(Arts, entertainment, and recreation)



Council District 9  
(Accommodation and food services)





I choose to only look at council district 9 because this is the area that overlaps. I will

look at historical data from the 2008 recession to see what the changes have occurred, if any.