Lab 03: Spatial autocorrelation, globally and locally

Read the instructions COMPLETELY before starting the lab

This lab builds on many of the discussions and exercises from class, including previous labs.

Attribution

 $This \ lab \ uses \ some \ code \ examples \ and \ directions \ from \ https://mgimond.github.io/Spatial/spatial-autocorrelation-in-r. \ html$

Formatting your submission

This lab must be placed into a public repository on GitHub (www.github.com). Before the due date, submit on Canvas a link to the repository. I will then download your repositories and run your code. The code must be contained in either a .R script or a .Rmd markdown document. As I need to run your code, any data you use in the lab must be referenced using relative path names. Finally, answers to questions I pose in this document must also be in the repository at the time you submit your link to Canvas. They can be in a separate text file, or if you decide to use an RMarkdown document, you can answer them directly in the doc.

Data

The data for this lab can be found on the US Census website.

- 1. First, go here: https://www.census.gov/geographies/mapping-files/2010/geo/tiger-data.html
- 2. Second, scroll to the "Demographic Profile 1 ShapeFile Format" section
- 3. Click on "Counties" to download the county data for all of the US (the direct link is also here: http://www2.census.gov/geo/tiger/TIGER2010DP1/County_2010Census_DP1.zip)

Introduction

In this lab, we will be calculating the spatial autocorrelation of various Census variables across a subset of the US. Please note, the dataset you downloaded above is larger than the current 100MB limit GitHub imposes on single files. This means you'll be unable to push that dataset to GitHub. Accordingly, I strongly suggest you subset the data such that your files are under this limit. This will be vital when I grade your submissions. If you're not certain how to save a subset of the file to disk, look at ?sf::write_sf for help. We will also be using a new package called spdep in this assignment.

We begin by loading the relevant packages and data

library(spdep)

```
## Loading required package: sp
```

Loading required package: spData

```
## To access larger datasets in this package, install the spDataLarge
## package with: 'install.packages('spDataLarge',
## repos='https://nowosad.github.io/drat/', type='source')'
## Loading required package: sf
## Linking to GEOS 3.8.1, GDAL 3.2.1, PROJ 7.2.1
library(sf)
library(tidyverse)
## -- Attaching packages ------ tidyverse 1.3.1 --
## v ggplot2 3.3.5
                    v purrr
                               0.3.4
## v tibble 3.1.2
                     v dplyr
                               1.0.7
          1.1.3
## v tidyr
                     v stringr 1.4.0
          1.4.0
## v readr
                     v forcats 0.5.1
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                   masks stats::lag()
library(tmap)
Next, we load our data, look at it, then maybe plot it (the plot might take some time)
d.all <- sf::read_sf("../data/County_2010Census_DP1.shp")</pre>
glimpse(d.all)
## Rows: 3,221
## Columns: 196
               <chr> "02013", "02016", "28107", "28101", "28027", "22065", "5154~
## $ GEOID10
## $ NAMELSAD10 <chr> "Aleutians East Borough", "Aleutians West Census Area"
<dbl> 18083148800, 11370762625, 1774515519, 1497282694, 143081823~
## $ ALAND10
## $ AWATER10
               <dbl> 20792209033, 25190643524, 51767046, 3879399, 79539470, 6853~
## $ INTPTLAT10 <chr> "+55.2437223", "+51.9594469", "+34.3652052", "+32.4019702",~
## $ INTPTLON10 <chr> "-161.9507485", "+178.3388130", "-089.9630654", "-089.11841~
## $ DP0010001 <int> 3141, 5561, 34707, 21720, 26151, 12093, 43475, 139966, 6650~
## $ DP0010002 <int> 123, 205, 2552, 1528, 2115, 808, 2305, 9964, 413, 1279, 192~
## $ DP0010003 <int> 105, 227, 2485, 1609, 2015, 838, 1665, 6354, 375, 1253, 183~
## $ DP0010004 <int> 88, 226, 2626, 1510, 2156, 820, 1485, 4630, 403, 1294, 1734~
## $ DP0010005 <int> 104, 249, 2733, 1867, 2327, 863, 2702, 4953, 558, 1221, 169~
## $ DP0010006 <int> 249, 334, 2200, 1275, 1905, 850, 10545, 8142, 623, 1810, 17~
## $ DP0010007 <int> 301, 517, 2094, 1218, 1651, 1021, 4981, 17762, 387, 1726, 1~
## $ DP0010008 <int> 213, 455, 2062, 1282, 1493, 904, 3162, 16419, 389, 1540, 18~
## $ DP0010009 <int> 242, 477, 2168, 1400, 1473, 742, 2186, 13569, 344, 1483, 17~
## $ DP0010010 <int> 355, 660, 2163, 1368, 1454, 720, 2238, 11224, 407, 1626, 16~
## $ DP0010011 <int> 431, 627, 2558, 1397, 1705, 879, 2208, 9706, 409, 1744, 164~
## $ DP0010012 <int> 340, 605, 2531, 1475, 1785, 844, 2145, 8987, 427, 1696, 152~
## $ DP0010013 <int> 264, 458, 2203, 1315, 1582, 775, 2100, 8282, 415, 1410, 124~
```

\$ DP0010014 <int> 171, 328, 1921, 1243, 1304, 595, 1736, 7168, 432, 1395, 991~ <int> 75, 110, 1419, 958, 955, 457, 1224, 4587, 332, 921, 68641, ~ ## \$ DP0010015 <int> 33, 47, 1139, 754, 761, 307, 896, 2758, 269, 695, 48095, 10~ ## \$ DP0010016 <int> 25, 17, 803, 612, 617, 262, 726, 1935, 196, 529, 37439, 964~ ## \$ DP0010017 ## \$ DP0010018 <int> 15, 14, 564, 486, 428, 227, 614, 1605, 123, 483, 27990, 659~ ## \$ DP0010019 <int> 7, 5, 486, 423, 425, 181, 557, 1921, 148, 460, 25807, 548, ~ <int> 2093, 3723, 16683, 10412, 12003, 5986, 20754, 67262, 3093, ~ ## \$ DP0010020 <int> 68, 106, 1333, 742, 1084, 381, 1166, 5094, 200, 661, 98699,~ ## \$ DP0010021 ## \$ DP0010022 <int> 55, 113, 1263, 820, 989, 435, 856, 3178, 185, 651, 93807, 1~ ## \$ DP0010023 <int> 40, 129, 1353, 808, 1094, 422, 748, 2361, 209, 629, 88229, ~ ## \$ DP0010024 <int> 63, 149, 1398, 948, 1134, 440, 1264, 2535, 253, 646, 86936,~ <int> 187, 233, 1067, 627, 957, 475, 4816, 3691, 300, 962, 87243,~ ## \$ DP0010025 ## \$ DP0010026 <int> 208, 375, 987, 538, 708, 546, 2621, 8233, 196, 916, 99270, ~ ## \$ DP0010027 <int> 144, 319, 941, 615, 612, 514, 1615, 7980, 186, 796, 93937, ~ ## \$ DP0010028 <int> 182, 344, 1047, 665, 653, 359, 1090, 6782, 163, 752, 88930,~ ## \$ DP0010029 <int> 251, 464, 998, 672, 633, 318, 1111, 5699, 202, 801, 83056, ~ <int> 299, 432, 1228, 706, 752, 445, 1086, 4957, 200, 865, 82530,~ ## \$ DP0010030 ## \$ DP0010031 <int> 223, 420, 1251, 688, 783, 390, 998, 4313, 199, 822, 75445, ~ <int> 174, 299, 1048, 623, 746, 380, 1007, 3710, 178, 681, 59632,~ ## \$ DP0010032 ## \$ DP0010033 <int> 104, 222, 917, 593, 636, 267, 793, 3352, 194, 674, 46472, 8~ ## \$ DP0010034 <int> 46, 70, 635, 459, 395, 219, 522, 2164, 151, 418, 31365, 719~ ## \$ DP0010035 <int> 18, 34, 523, 333, 307, 142, 367, 1225, 124, 311, 21287, 477~ <int> 14, 8, 338, 262, 247, 110, 294, 809, 73, 223, 15468, 443, 2~ ## \$ DP0010036 ## \$ DP0010037 <int> 12, 6, 220, 188, 138, 80, 231, 622, 38, 185, 10681, 286, 17~ ## \$ DP0010038 <int> 5, 0, 136, 125, 135, 63, 169, 557, 42, 130, 8015, 214, 15, ~ ## \$ DP0010039 <int> 1048, 1838, 18024, 11308, 14148, 6107, 22721, 72704, 3557, ~ ## \$ DP0010040 <int> 55, 99, 1219, 786, 1031, 427, 1139, 4870, 213, 618, 94139, ## \$ DP0010041 <int> 50, 114, 1222, 789, 1026, 403, 809, 3176, 190, 602, 89704, ~ ## \$ DP0010042 <int> 48, 97, 1273, 702, 1062, 398, 737, 2269, 194, 665, 85174, 1~ ## \$ DP0010043 <int> 41, 100, 1335, 919, 1193, 423, 1438, 2418, 305, 575, 82257,~ ## \$ DP0010044 <int> 62, 101, 1133, 648, 948, 375, 5729, 4451, 323, 848, 84338, ~ ## \$ DP0010045 <int> 93, 142, 1107, 680, 943, 475, 2360, 9529, 191, 810, 98561, ~ ## \$ DP0010046 <int> 69, 136, 1121, 667, 881, 390, 1547, 8439, 203, 744, 93273, ~ <int> 60, 133, 1121, 735, 820, 383, 1096, 6787, 181, 731, 89206, ~ ## \$ DP0010047 <int> 104, 196, 1165, 696, 821, 402, 1127, 5525, 205, 825, 81795,~ ## \$ DP0010048 ## \$ DP0010049 <int> 132, 195, 1330, 691, 953, 434, 1122, 4749, 209, 879, 82445,~ ## \$ DP0010050 <int> 117, 185, 1280, 787, 1002, 454, 1147, 4674, 228, 874, 77463~ ## \$ DP0010051 <int> 90, 159, 1155, 692, 836, 395, 1093, 4572, 237, 729, 64982, ~ ## \$ DP0010052 <int> 67, 106, 1004, 650, 668, 328, 943, 3816, 238, 721, 52644, 8~ ## \$ DP0010053 <int> 29, 40, 784, 499, 560, 238, 702, 2423, 181, 503, 37276, 676~ ## \$ DP0010054 <int> 15, 13, 616, 421, 454, 165, 529, 1533, 145, 384, 26808, 572~ ## \$ DP0010055 <int> 11, 9, 465, 350, 370, 152, 432, 1126, 123, 306, 21971, 521,~ ## \$ DP0010056 <int> 3, 8, 344, 298, 290, 147, 383, 983, 85, 298, 17309, 373, 32~ ## \$ DP0010057 <int> 2, 5, 350, 298, 290, 118, 388, 1364, 106, 330, 17792, 334, ~ ## \$ DP0020001 <dbl> 42.1, 40.7, 36.5, 37.1, 32.8, 34.6, 27.8, 35.6, 37.6, 39.1,~ <dbl> 42.1, 41.1, 35.0, 35.7, 30.3, 32.5, 27.7, 35.4, 35.5, 37.2,~ ## \$ DP0020002 ## \$ DP0020003 <dbl> 42.3, 39.9, 37.9, 38.3, 34.9, 37.1, 28.0, 35.8, 39.5, 40.7,~ ## \$ DP0030001 <int> 2811, 4853, 26512, 16739, 19438, 9463, 37697, 118159, 5393,~ ## \$ DP0030002 <int> 1922, 3350, 12464, 7859, 8620, 4659, 17802, 56202, 2459, 90~ <int> 889, 1503, 14048, 8880, 10818, 4804, 19895, 61957, 2934, 94~ ## \$ DP0030003 <int> 2770, 4746, 25363, 16067, 18487, 9071, 37001, 115996, 5226,~ ## \$ DP0040001 ## \$ DP0040002 <int> 1898, 3294, 11858, 7518, 8159, 4465, 17439, 55111, 2385, 87~ ## \$ DP0040003 <int> 872, 1452, 13505, 8549, 10328, 4606, 19562, 60885, 2841, 91~ ## \$ DP0050001 <int> 2684, 4600, 23849, 14821, 17077, 8587, 32740, 113243, 4764,~

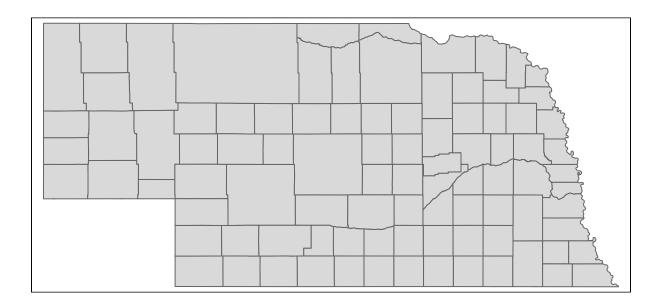
\$ DP0050002 <int> 1844, 3190, 11095, 6914, 7454, 4200, 15587, 53655, 2197, 83~ <int> 840, 1410, 12754, 7907, 9623, 4387, 17153, 59588, 2567, 882~ ## \$ DP0050003 ## \$ DP0060001 <int> 247, 366, 5526, 3926, 3907, 1765, 4979, 16876, 1331, 3856, ~ <int> 149, 235, 2401, 1704, 1576, 774, 2050, 7290, 547, 1644, 113~ ## \$ DP0060002 ## \$ DP0060003 <int> 98, 131, 3125, 2222, 2331, 991, 2929, 9586, 784, 2212, 1511~ ## \$ DP0070001 <int> 155, 193, 4411, 3233, 3186, 1434, 4017, 12806, 1068, 3088, ~ <int> 95, 118, 1852, 1367, 1222, 614, 1583, 5377, 428, 1267, 8681~ ## \$ DP0070002 <int> 60, 75, 2559, 1866, 1964, 820, 2434, 7429, 640, 1821, 12115~ ## \$ DP0070003 ## \$ DP0080001 <int> 3141, 5561, 34707, 21720, 26151, 12093, 43475, 139966, 6650~ ## \$ DP0080002 <int> 2988, 5250, 34402, 21531, 26019, 11982, 42166, 134741, 6539~ ## \$ DP0080003 <int> 660, 2004, 17161, 13734, 5989, 4498, 30031, 85186, 6050, 15~ <int> 219, 332, 16875, 6567, 19752, 7381, 8437, 30491, 347, 1071,~ ## \$ DP0080004 ## \$ DP0080005 <int> 876, 857, 76, 1092, 23, 24, 116, 589, 73, 111, 17133, 317, ~ ## \$ DP0080006 <int> 1130, 1606, 68, 52, 123, 27, 2771, 8432, 29, 3432, 119250, ~ ## \$ DP0080007 <int> 4, 9, 15, 5, 21, 1, 506, 1761, 4, 615, 37659, 39, 1, 0, 16,~ ## \$ DP0080008 <int> 3, 8, 21, 12, 65, 7, 884, 1304, 9, 497, 12612, 50, 2, 0, 18~ ## \$ DP0080009 <int> 1041, 1395, 7, 18, 15, 3, 167, 1379, 0, 321, 8873, 48, 0, 1~ ## \$ DP0080010 <int> 15, 26, 2, 1, 0, 0, 73, 280, 6, 50, 1897, 4, 0, 0, 3, 4, 24~ <int> 2, 17, 7, 5, 2, 2, 403, 1143, 4, 764, 9825, 9, 0, 0, 1, 3, ~ ## \$ DP0080011 ## \$ DP0080012 <int> 28, 123, 3, 11, 7, 11, 143, 485, 1, 544, 26276, 18, 2, 0, 7~ ## \$ DP0080013 <int> 37, 28, 13, 0, 13, 3, 595, 2080, 5, 641, 22108, 99, 0, 0, 1~ ## \$ DP0080014 <int> 19, 103, 0, 0, 4, 0, 17, 141, 12, 14, 1222, 15, 0, 1, 5, 2,~ <int> 3, 10, 0, 0, 2, 0, 8, 35, 0, 4, 339, 1, 0, 0, 4, 0, 23, 0, ~ ## \$ DP0080015 ## \$ DP0080016 <int> 0, 1, 0, 0, 0, 0, 3, 53, 0, 1, 345, 0, 0, 1, 0, 2, 8, 0, 0,~ ## \$ DP0080017 <int> 5, 70, 0, 0, 2, 0, 1, 19, 5, 0, 154, 0, 0, 0, 0, 0, 6, 0, 0~ <int> 11, 22, 0, 0, 0, 0, 5, 34, 7, 9, 384, 14, 0, 0, 1, 0, 110, ~ ## \$ DP0080018 ## \$ DP0080019 <int> 84, 348, 222, 86, 128, 52, 794, 9902, 28, 1323, 367610, 558~ ## \$ DP0080020 <int> 153, 311, 305, 189, 132, 111, 1309, 5225, 111, 908, 66863, ~ ## \$ DP0080021 <int> 59, 90, 79, 59, 4, 29, 132, 372, 40, 86, 6773, 136, 3, 6, 7~ ## \$ DP0080022 <int> 19, 58, 28, 14, 10, 6, 457, 1423, 14, 334, 7454, 43, 0, 2, ~ <int> 1, 5, 98, 66, 39, 29, 394, 1012, 35, 120, 10195, 155, 1, 15~ ## \$ DP0080023 ## \$ DP0080024 <int> 25, 27, 16, 14, 12, 3, 84, 1021, 3, 187, 26207, 231, 6, 45,~ ## \$ DP0090001 <int> 780, 2221, 17403, 13895, 6065, 4576, 31197, 89445, 6148, 16~ ## \$ DP0090002 <int> 235, 362, 17048, 6660, 19851, 7452, 9010, 32378, 393, 1278,~ ## \$ DP0090003 <int> 964, 1000, 211, 1181, 54, 84, 379, 1508, 119, 257, 30403, 5~ ## \$ DP0090004 <int> 1179, 1743, 109, 72, 160, 41, 3330, 10441, 49, 3874, 132393~ ## \$ DP0090005 <int> 28, 148, 15, 3, 15, 2, 55, 363, 22, 51, 3458, 56, 0, 1, 10,~ ## \$ DP0090006 <int> 125, 425, 244, 105, 157, 62, 921, 11504, 37, 1589, 402416, ~ ## \$ DP0100001 <int> 3141, 5561, 34707, 21720, 26151, 12093, 43475, 139966, 6650~ <int> 385, 726, 494, 287, 293, 188, 2223, 22524, 103, 3556, 90594~ ## \$ DP0100002 ## \$ DP0100003 <int> 305, 605, 378, 196, 165, 118, 954, 2352, 49, 348, 762168, 9~ ## \$ DP0100004 <int> 6, 8, 10, 18, 36, 10, 200, 1603, 8, 164, 8883, 73, 0, 4, 62~ ## \$ DP0100005 <int> 10, 8, 13, 8, 9, 8, 119, 399, 10, 60, 4279, 22, 0, 0, 4, 9,~ ## \$ DP0100006 <int> 64, 105, 93, 65, 83, 52, 950, 18170, 36, 2984, 130610, 3541~ <int> 2756, 4835, 34213, 21433, 25858, 11905, 41252, 117442, 6547~ ## \$ DP0100007 <int> 3141, 5561, 34707, 21720, 26151, 12093, 43475, 139966, 6650~ ## \$ DP0110001 <int> 385, 726, 494, 287, 293, 188, 2223, 22524, 103, 3556, 90594~ ## \$ DP0110002 <int> 235, 259, 180, 135, 71, 102, 1204, 10308, 68, 1857, 483168,~ ## \$ DP0110003 ## \$ DP0110004 <int> 7, 14, 74, 31, 54, 24, 93, 713, 2, 41, 9468, 102, 0, 21, 25~ <int> 7, 16, 6, 20, 3, 1, 51, 262, 2, 49, 9803, 97, 2, 31, 65, 7,~ ## \$ DP0110005 ## \$ DP0110006 <int> 17, 31, 7, 1, 9, 1, 13, 81, 0, 29, 1453, 11, 1, 0, 8, 1, 19~ ## \$ DP0110007 <int> 0, 1, 0, 0, 0, 0, 4, 32, 0, 3, 348, 2, 0, 0, 0, 2, 17, 0, 0~ ## \$ DP0110008 <int> 83, 343, 208, 77, 121, 44, 705, 9417, 28, 1275, 364264, 550~ ## \$ DP0110009 <int> 36, 62, 19, 23, 35, 16, 153, 1711, 3, 302, 37436, 409, 6, 5~

\$ DP0110010 <int> 2756, 4835, 34213, 21433, 25858, 11905, 41252, 117442, 6547~ <int> 425, 1745, 16981, 13599, 5918, 4396, 28827, 74878, 5982, 13~ ## \$ DP0110011 ## \$ DP0110012 <int> 212, 318, 16801, 6536, 19698, 7357, 8344, 29778, 345, 1030,~ <int> 869, 841, 70, 1072, 20, 23, 65, 327, 71, 62, 7330, 220, 1, ~ ## \$ DP0110013 ## \$ DP0110014 <int> 1113, 1575, 61, 51, 114, 26, 2758, 8351, 29, 3403, 117797, ~ ## \$ DP0110015 <int> 19, 102, 0, 0, 4, 0, 13, 109, 12, 11, 874, 13, 0, 1, 5, 0, ~ <int> 1, 5, 14, 9, 7, 8, 89, 485, 0, 48, 3346, 76, 0, 1, 11, 9, 5~ ## \$ DP0110016 <int> 117, 249, 286, 166, 97, 95, 1156, 3514, 108, 606, 29427, 31~ ## \$ DP0110017 ## \$ DP0120001 <int> 3141, 5561, 34707, 21720, 26151, 12093, 43475, 139966, 6650~ ## \$ DP0120002 <int> 1415, 3018, 34392, 21120, 25484, 10502, 41037, 138139, 6250~ ## \$ DP0120003 <int> 553, 1212, 12839, 8214, 9461, 4025, 17778, 68082, 2603, 834~ <int> 235, 508, 5592, 4017, 3004, 1500, 4996, 22819, 1227, 4431, ~ ## \$ DP0120004 ## \$ DP0120005 <int> 440, 887, 10790, 6580, 8740, 3378, 7490, 26785, 1732, 5802,~ <int> 335, 729, 7036, 4761, 5812, 2336, 5586, 21259, 1248, 4156, ~ ## \$ DP0120006 ## \$ DP0120007 <int> 66, 156, 3765, 1560, 3117, 1132, 1858, 7577, 358, 1483, 229~ ## \$ DP0120008 <int> 26, 64, 2135, 813, 1718, 644, 716, 1860, 147, 349, 91091, 1~ ## \$ DP0120009 <int> 5, 6, 262, 146, 197, 59, 181, 831, 45, 265, 21935, 210, 7, ~ ## \$ DP0120010 <int> 121, 255, 1406, 749, 1162, 467, 8915, 12876, 330, 1981, 133~ ## \$ DP0120011 <int> 7, 12, 142, 77, 94, 41, 101, 378, 26, 72, 8400, 133, 2, 18,~ ## \$ DP0120012 <int> 2, 3, 57, 50, 58, 29, 101, 310, 17, 51, 3854, 51, 2, 15, 31~ ## \$ DP0120013 <int> 68, 109, 774, 404, 651, 296, 1205, 4691, 148, 369, 56766, 8~ ## \$ DP0120014 <int> 1726, 2543, 315, 600, 667, 1591, 2438, 1827, 400, 521, 3039~ <int> 0, 4, 139, 159, 256, 1544, 228, 974, 74, 313, 20998, 5768, ~ ## \$ DP0120015 ## \$ DP0120016 <int> 0, 1, 97, 79, 147, 995, 96, 594, 18, 95, 14078, 5440, 7, 10~ <int> 0, 3, 42, 80, 109, 549, 132, 380, 56, 218, 6920, 328, 23, 2~ ## \$ DP0120017 ## \$ DP0120018 <int> 1726, 2539, 176, 441, 411, 47, 2210, 853, 326, 208, 9400, 3~ ## \$ DP0120019 <int> 1319, 2047, 66, 219, 248, 32, 1071, 481, 139, 123, 5312, 17~ ## \$ DP0120020 <int> 407, 492, 110, 222, 163, 15, 1139, 372, 187, 85, 4088, 133,~ ## \$ DP0130001 <int> 553, 1212, 12839, 8214, 9461, 4025, 17778, 68082, 2603, 834~ <int> 363, 711, 9086, 5802, 6393, 2778, 7518, 30978, 1726, 5545, ~ ## \$ DP0130002 <int> 198, 408, 3706, 2500, 2882, 1208, 3182, 12919, 703, 2358, 2~ ## \$ DP0130003 ## \$ DP0130004 <int> 235, 508, 5592, 4017, 3004, 1500, 4996, 22819, 1227, 4431, ~ ## \$ DP0130005 <int> 114, 277, 1984, 1557, 1079, 523, 1907, 8972, 448, 1899, 184~ ## \$ DP0130006 <int> 54, 87, 768, 417, 531, 217, 512, 2306, 123, 310, 49205, 725~ ## \$ DP0130007 <int> 36, 56, 327, 191, 223, 89, 209, 907, 58, 99, 22276, 367, 12~ ## \$ DP0130008 <int> 74, 116, 2726, 1368, 2858, 1061, 2010, 5853, 376, 804, 1369~ ## \$ DP0130009 <int> 48, 75, 1395, 752, 1580, 596, 1066, 3040, 197, 360, 77791, ~ ## \$ DP0130010 <int> 190, 501, 3753, 2412, 3068, 1247, 10260, 37104, 877, 2802, ^ ## \$ DP0130011 <int> 147, 393, 3306, 2156, 2691, 1099, 6063, 29564, 753, 2002, 2~ ## \$ DP0130012 <int> 109, 288, 1548, 942, 1166, 508, 2713, 12626, 268, 812, 1115~ ## \$ DP0130013 <int> 20, 14, 366, 264, 286, 138, 350, 1426, 95, 179, 15817, 401,~ ## \$ DP0130014 <int> 38, 105, 1758, 1214, 1525, 591, 3350, 16938, 485, 1190, 128~ <int> 13, 22, 895, 684, 749, 289, 969, 3456, 251, 528, 39941, 863~ ## \$ DP0130015 ## \$ DP0140001 <int> 214, 437, 4719, 2934, 3661, 1534, 3587, 14048, 797, 2552, 3~ <int> 90, 95, 3370, 2369, 2439, 1047, 2991, 10061, 777, 2085, 155~ ## \$ DP0150001 <dbl> 2.56, 2.49, 2.68, 2.57, 2.69, 2.61, 2.31, 2.03, 2.40, 2.64,~ ## \$ DP0160001 ## \$ DP0170001 <dbl> 3.04, 3.18, 3.22, 3.10, 3.32, 3.16, 2.91, 2.85, 2.92, 3.11,~ ## \$ DP0180001 <int> 747, 1929, 14697, 9373, 10792, 4804, 19189, 72376, 2936, 86~ ## \$ DP0180002 <int> 553, 1212, 12839, 8214, 9461, 4025, 17778, 68082, 2603, 834~ <int> 194, 717, 1858, 1159, 1331, 779, 1411, 4294, 333, 333, 8729~ ## \$ DP0180003 <int> 45, 85, 384, 205, 488, 177, 671, 2200, 127, 115, 54347, 482~ ## \$ DP0180004 ## \$ DP0180005 <int> 1, 34, 9, 18, 20, 6, 59, 143, 5, 9, 1668, 21, 1, 8, 18, 4, ~ ## \$ DP0180006 <int> 0, 45, 173, 89, 112, 22, 205, 449, 74, 79, 10575, 145, 16, ~ ## \$ DP0180007 <int> 5, 187, 51, 29, 35, 10, 58, 124, 3, 19, 1937, 56, 8, 94, 22~

```
#tmap::tm_shape(d.all) + tm_polygons() # commented out because
#it's a large dataset that takes a long time to plot
```

Again, the data are too large, so we need to creat a subset we can work with later. Let's use the GEOID10 to create a dataset with only those counties in Nebraska. Be sure to check the data type of GEOID.

```
# get just nebraska
neb <- d.all %>% dplyr::filter(stringr::str_starts(GEOID10, "31"))
# map it to verify
tmap::tm_shape(neb) + tm_polygons()
```

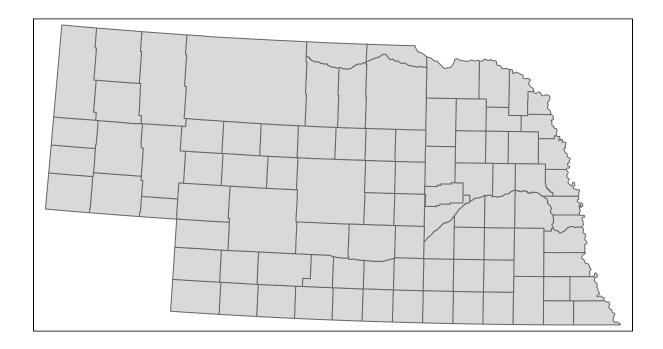


Next, we'll formalize our space by creating neighbors, and thus, W

- First we'll project
- Next, we'll use Queen contiguity to define W

plot it again to make sure nothing broke
tmap::tm_shape(neb.projected) + tm_polygons()

```
# Check it first
sf::st_crs(neb)
## Coordinate Reference System:
     User input: NAD83
##
##
     wkt:
## GEOGCRS["NAD83",
##
       DATUM["North American Datum 1983",
           ELLIPSOID["GRS 1980",6378137,298.257222101,
##
               LENGTHUNIT["metre",1]]],
##
##
       PRIMEM["Greenwich",0,
           ANGLEUNIT["degree",0.0174532925199433]],
##
##
       CS[ellipsoidal,2],
##
           AXIS["latitude", north,
##
               ORDER[1],
               ANGLEUNIT["degree", 0.0174532925199433]],
##
##
           AXIS["longitude", east,
##
               ORDER[2],
##
               ANGLEUNIT["degree", 0.0174532925199433]],
##
       ID["EPSG",4269]]
# then reproject to north american equidistant conic
neb.projected <- neb %>% sf::st_transform(., "ESRI:102010")
```



```
# make the neighborhood
nb <- spdep::poly2nb(neb.projected, queen = TRUE)</pre>
```

For each polygon in our polygon object, nb lists all neighboring polygons. For example, to see the neighbors for the first polygon in the object, type:

```
nb[[1]]
```

[1] 24 27 43 47

Polygon 1 has 4 neighbors. The numbers represent the polygon IDs as stored in the spatial object neb.projected. Polygon 1 is associated with the County attribute name "Burt County" and its four neighboring polygons are associated with the counties:

```
neb.projected$NAMELSAD10[1] # county in index 1
```

[1] "Burt County"

nb[[1]] %>% neb.projected\$NAMELSAD10[.] # and it's neighbors.

- ## [1] "Cuming County" "Thurston County" "Dodge County"
- ## [4] "Washington County"

Note we're doing this programmatically step-by-step

Next, we need to assign weights to each neighboring polygon. In our case, each neighboring polygon will be assigned equal weight (style="W"). This is accomplished by assigning the fraction: 1 / (# of neighbors) to each neighboring county then summing the weighted values. While this is the most intuitive way to summaries the neighbors' values it has one drawback in that polygons along the edges of the study area will base their lagged values on fewer polygons thus potentially over- or under-estimating the true nature of the spatial autocorrelation in the data. For this example, we'll stick with the style="W" option for simplicity's sake but note that other more robust options are available, notably style="B".

```
lw <- nb2listw(nb, style="W", zero.policy=TRUE)</pre>
```

The zero.policy=TRUE option allows for lists of non-neighbors. This should be used with caution since the user may not be aware of missing neighbors in their dataset. However, a zero.policy of FALSE would return an error if you have a dataset where a polygon does not have a neighbor.

To see the weight of the first polygon's four neighbors type:

lw\$weights[1]

```
## [[1]]
## [1] 0.25 0.25 0.25 0.25
```

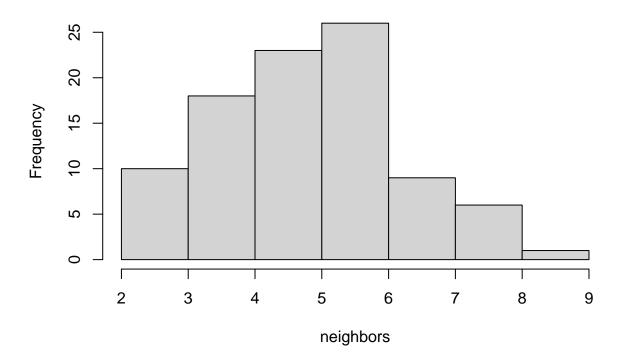
This row-normalized our weights!

We can also plot the distribution of neighbors across the dataset.

```
# use attr to get the count of neighbors in W
neighbors <- attr(lw$weights,"comp")$d

# plot it
hist(neighbors)</pre>
```

Histogram of neighbors



Finally, we'll compute the average neighbor population of Females > 65 years of age for each polygon. These values are often referred to as spatially lagged values. The following table shows the average neighboring F > 65 values (stored in the F65.lag object) for each county.

```
F65.lag <- lag.listw(lw, neb.projected$DP0070003)
F65.lag
```

##	[1]	1741.7500	1542.6667	10628.1667	185.8000	1135.5000	640.6000
##	[7]	1819.6667	622.2500	1208.5000	670.2500	884.5000	456.0000
##	[13]	1386.7500	624.0000	1170.8333	1600.0000	214.8000	1802.2000
##	[19]	547.0000	289.2000	566.6667	3766.3333	1050.2857	1203.5000
##	[25]	490.0000	701.3333	932.8000	1183.8333	587.0000	3648.5714
##	[31]	1199.2000	310.0000	1501.0000	326.8000	1168.4000	641.3333
##	[37]	1294.0000	4698.8000	618.1250	176.0000	432.0000	362.2000
##	[43]	5543.2857	235.0000	11847.3333	440.0000	12176.6667	458.1667
##	[49]	1039.4000	3680.0000	7188.2500	216.4286	1216.0000	4621.4000
##	[55]	614.0000	1094.1429	672.2500	1403.3333	890.5000	1595.5000
##	[61]	563.4000	932.4000	804.5000	579.0000	1349.0000	428.6667
##	[67]	491.5000	960.2500	690.5000	1075.1429	1777.6667	3792.3750
##	[73]	817.2000	930.5000	1098.0000	1658.6000	481.6000	1018.8333
##	[79]	658.2500	1025.0000	822.8333	3754.0000	901.4286	743.8333
##	[85]	992.6000	428.2000	1494.2500	1719.6667	377.1250	948.1250
##	Γα17	1004 4286	1089 4444	1630 3750			

Computing Moran's I

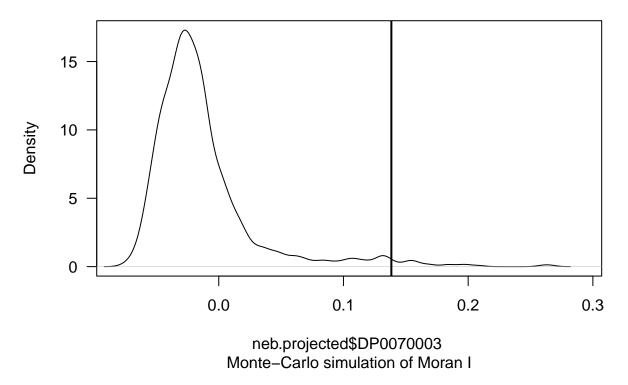
To get the Moran's I value, simply use the moran.test function.

```
moran.test(neb.projected$DP0070003, 1w)
```

```
##
##
   Moran I test under randomisation
##
## data: neb.projected$DP0070003
## weights: lw
##
## Moran I statistic standard deviate = 3.3554, p-value = 0.0003963
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic
                           Expectation
                                                 Variance
##
         0.138417655
                          -0.010869565
                                              0.001979517
```

Note that the p-value computed from the moran.test function is not computed from an MC simulation but analytically instead. This may not always prove to be the most accurate measure of significance. To test for significance using the MC simulation method instead, use the moran.mc function.

```
MC<- moran.mc(neb.projected$DP0070003, lw, nsim=999)
# View results (including p-value)
MC
##
   Monte-Carlo simulation of Moran I
##
##
## data: neb.projected$DP0070003
## weights: lw
## number of simulations + 1: 1000
##
## statistic = 0.13842, observed rank = 981, p-value = 0.019
## alternative hypothesis: greater
# Plot the distribution
# Plot the distribution (note that this is a density plot instead of a histogram)
plot(MC, main="", las=1)
```



What is being plotted in this density plot?

Defining W using a distance band

Next, we will explore spatial autocorrelation as a function of distance bands.

Instead of defining neighbors as contiguous polygons, we will define neighbors based on distances to **polygon centers**. We therefore need to extract the center of each polygon. The object coords stores all pairs of coordinate values corresponding to polygon centroids. Note, we need to convert from an sf object to a spatial one for the coordinates() function to work.

```
coords <- neb.projected %>% as_Spatial() %>% coordinates()
```

Next, we will define the search radius to include all neighboring polygon centers within 50 km (or 50,000 meters)

```
s.dist <- dnearneigh(coords, 0, 50000)
```

The dnearneigh function takes on three parameters:

- 1. the coordinate values coords
- 2. the radius for the inner radius of the annulus band
- 3. and the radius for the outer annulus band.

In our example, the inner annulus radius is 0 which implies that all polygon centers up to 50km are considered neighbors.

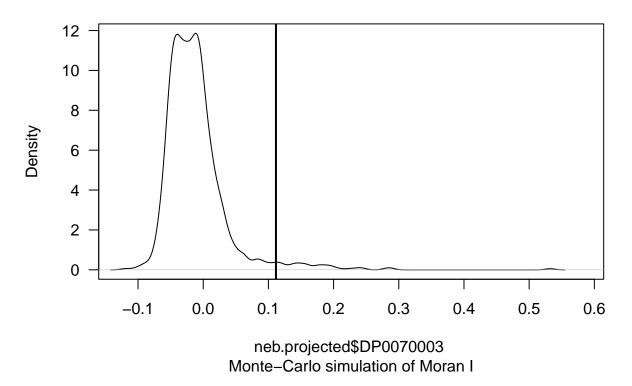
Note that if we chose to restrict the neighbors to all polygon centers between 50 km and 100 km, for example, then we would define a search annulus (instead of a circle) as dnearneigh(coords, 50000, 100000)

Now that we defined our search circle, we need to identify all neighboring polygons for each polygon in the dataset.

```
lw <- nb2listw(s.dist, style="W",zero.policy=T)

#Run the MC simulation.
MI <- moran.mc(neb.projected$DP0070003, lw, nsim=999, zero.policy=T)

#Plot the results.
plot(MI, main="", las=1)</pre>
```



```
#Display p-value and other summary statistics.
MI
```

```
##
## Monte-Carlo simulation of Moran I
##
## data: neb.projected$DP0070003
## weights: lw
```

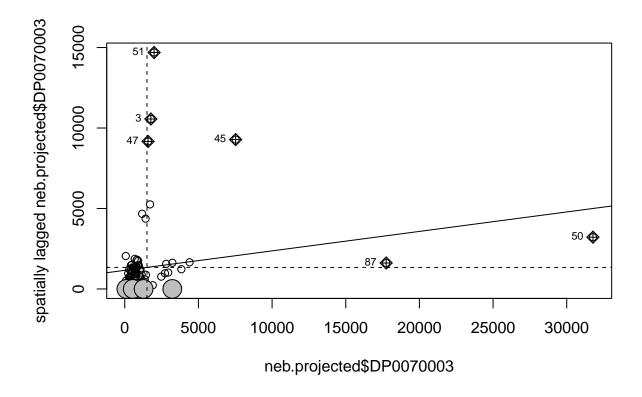
```
## number of simulations + 1: 1000
##
## statistic = 0.11161, observed rank = 967, p-value = 0.033
## alternative hypothesis: greater
```

Moran's plots

Thus far, our analysis has been a global investigation of spatial autocorrelation. We can also use local indicators of spatial autocorrelation (LISA) to analyze our dataset. One way of doing so is through the use of a Moran plot.

The process to make a plot is relatively simple:

```
# use zero.policy = T because some polygons don't have neighbors
moran.plot(neb.projected$DP0070003, lw, zero.policy=TRUE, plot=TRUE)
```



Your tasks

- 1. Create a spatial subset of the US, with at AT MINIMUM 4 states, MAXIMUM 7 states. States must be contiguous. Save this subset as a shapefile such that it's sufficiently small in size that GitHub will accept the git-push
- 2. Choose a variable. If it's a raw count, you should normalize the variable in an appropriate manner (e.g., by total population, percent, by area)
- 3. Make a histogram of your chosen variable

4. Make a choropleth map of your chosen variable. Choose an appropriate data classification scheme

- 5. Develop a contiguity-based spatial weights matrix of your choosing (i.e., rook or queen)
- 6. Row-standardize the W
- 7. Plot a histogram of the number of neighbors
- 8. Calculate the average number of neighbors
- 9. Make a Moran Plot
- 10. Repeat #5 (and 5.1 5.4) above with a W developed using the IDW method. You will need to investigate the spdep documentation to find the correct method/function.

Questions:

- 1. Describe in your own words how Moran's I is calculated
- 2. Describe in your own words: what is a spatially-lagged variable?
- 3. How does your analysis in this lab (as simple as it is) diffr by how you have formalized W (e.g., space, neighbors) in two different methods? How might it affect analysis?
- 4. What does it mean if an observation falls in the "H-L" quadrant? Why might it be useful to detect such occurances?

Bonus (+50 points)

B1. make another Moran plot, this time do so manually (use geom_point from ggplot). You must label each quadrant with HH, HL, LL, and LH, respectively. You should also use color and/or shape to denote whether an observation is statistically significant. Tip, you can find the data you want using the moran.plot function, but you'll have to alter the function call and read some documentation.

B2. plot a choropleth map of your dataset with a categorical color scheme, where the shading corresponds to the Moran plot (really, "LISA") quadrants. Thus, your map will have four shades of color.