

Chapter 5 Exercises

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Chapter 5

5.1 Basic usage of tigris

```
#install.packages("patchwork")
library(tigris)
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
```

```
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## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
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```

```
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## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
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```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
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```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
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```

```
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```

```
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```
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## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
## 126: The specified module could not be found.
```

```
## To enable  
## caching of data, set `options(tigris_use_cache = TRUE)` in your R script or .Rprofile.
```

```
library(tidyverse)
```

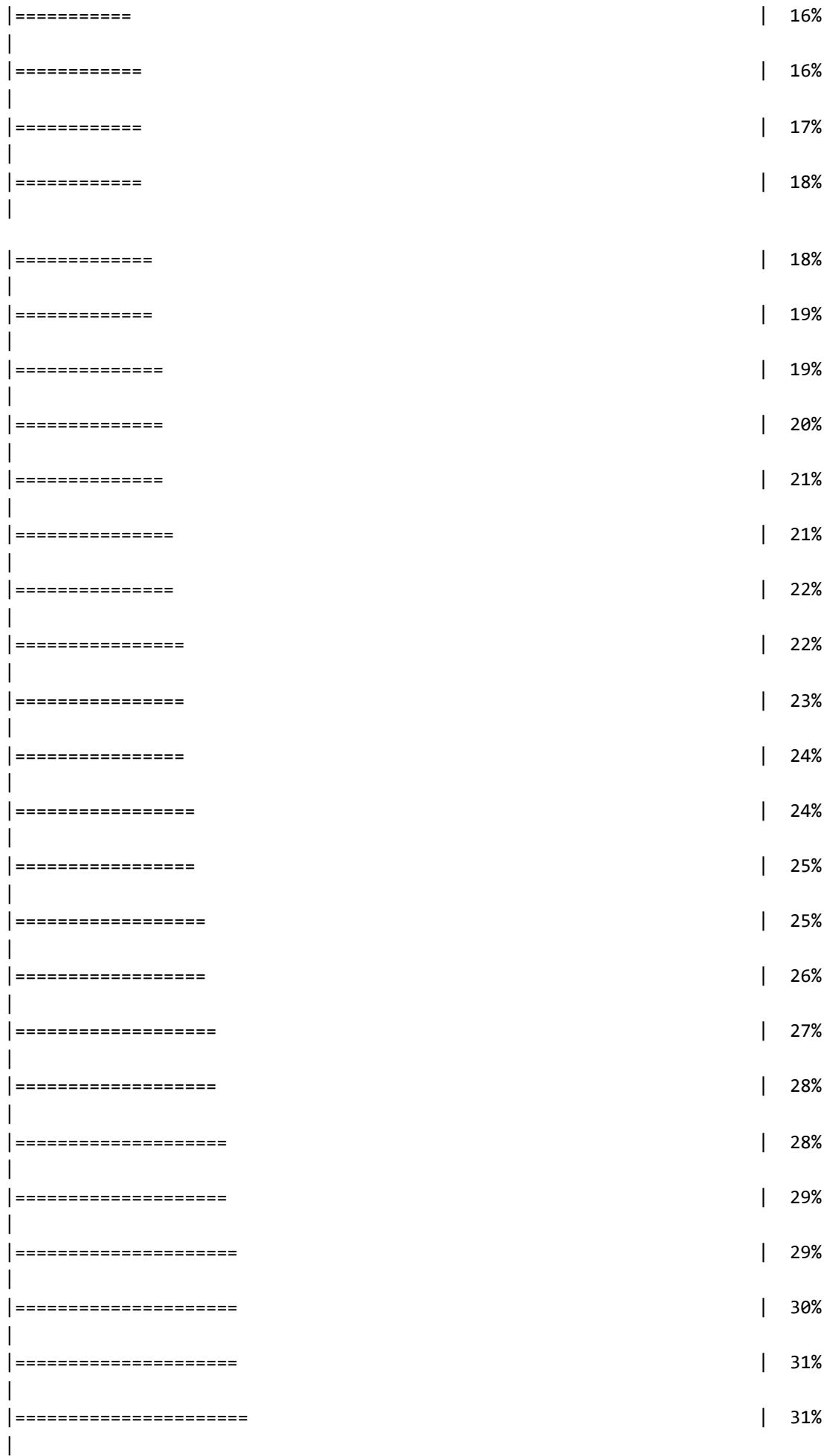
```
## -- Attaching packages ----- tidyverse 1.3.1 --
```

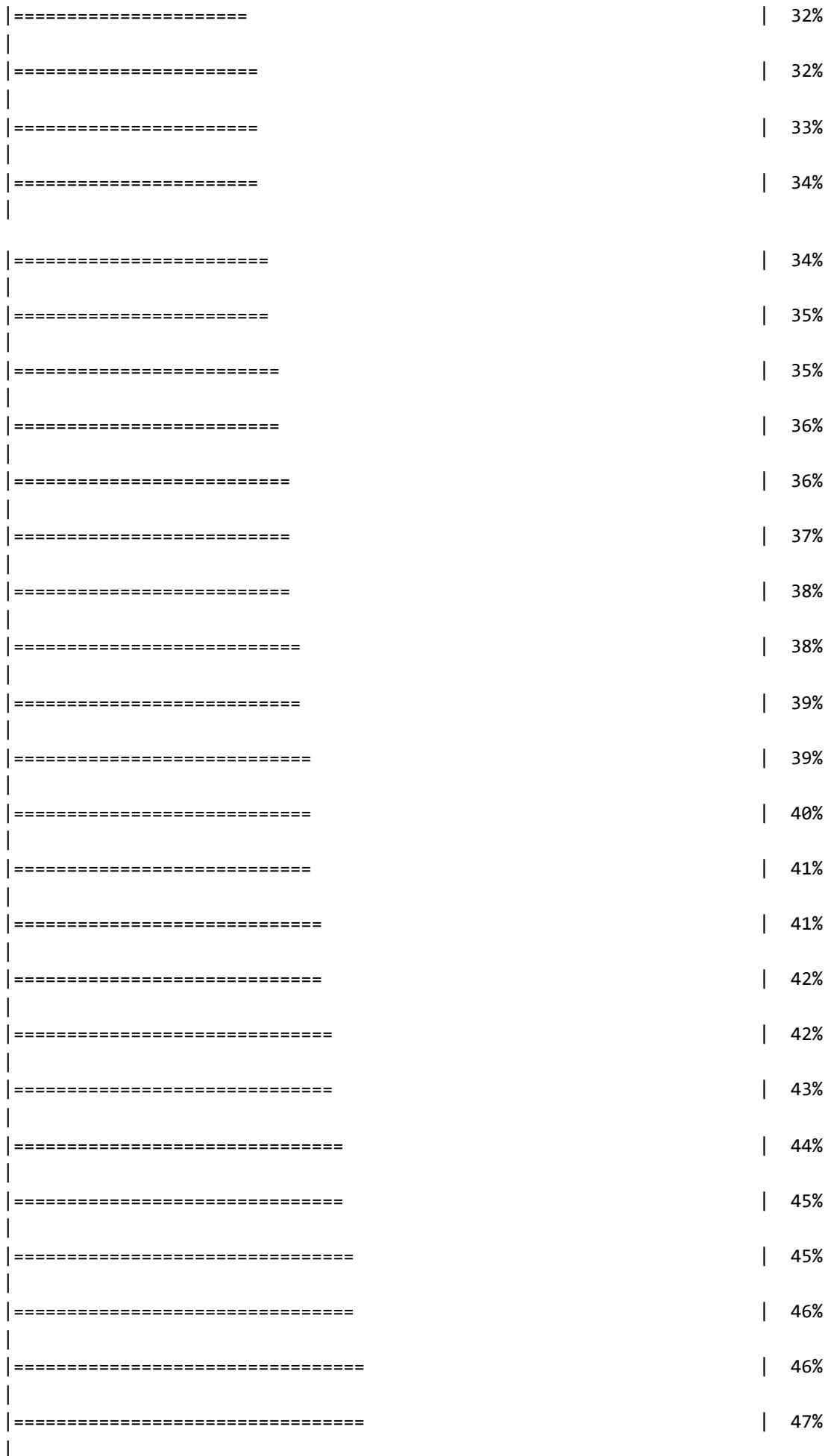
```
## v ggplot2 3.3.5     v purrr   0.3.4  
## v tibble  3.1.6     v dplyr    1.0.8  
## v tidyr   1.2.0     v stringr  1.4.0  
## v readr   2.1.2     vforcats  0.5.1
```

```
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

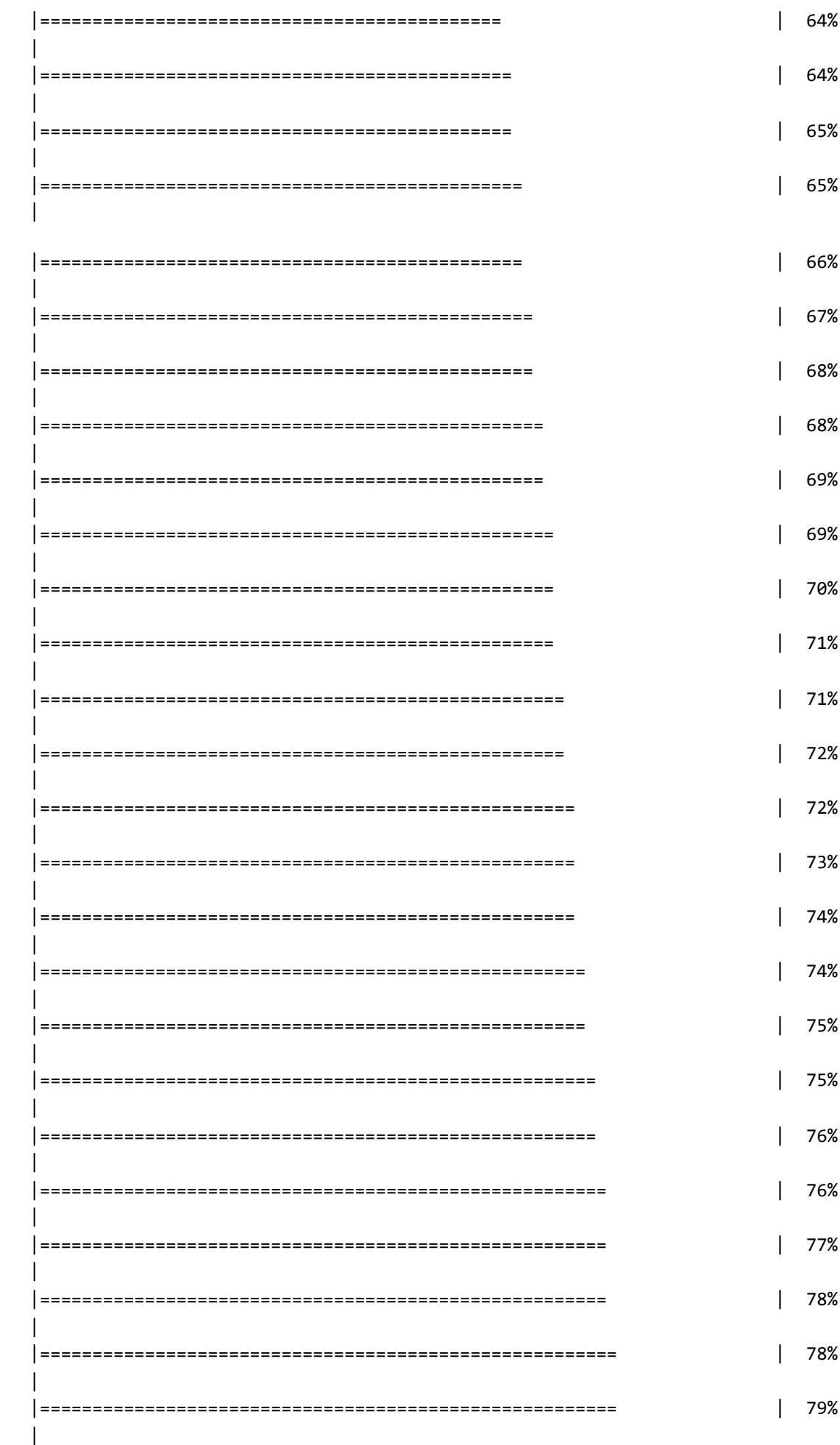
```
st <- states()
```

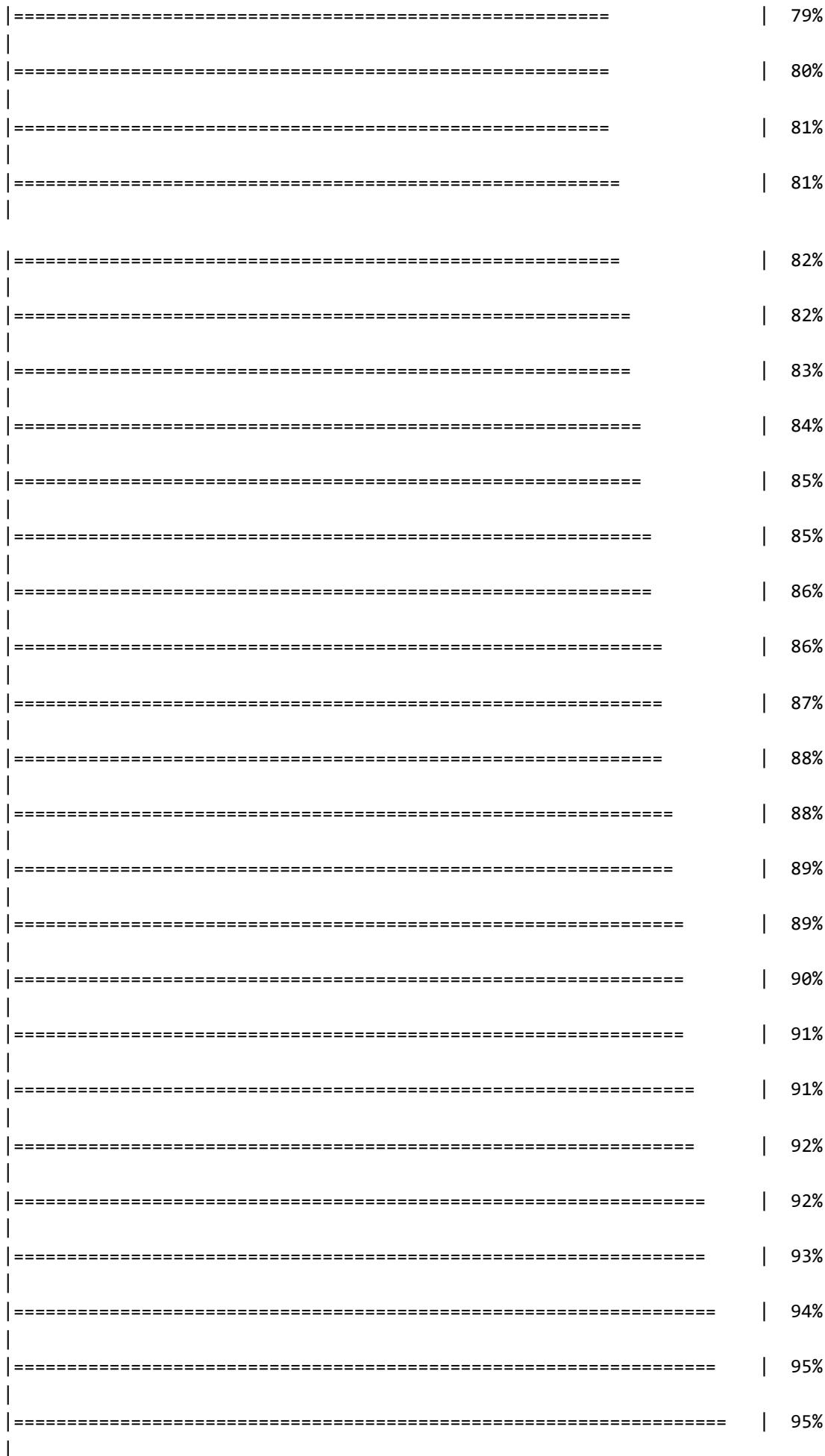
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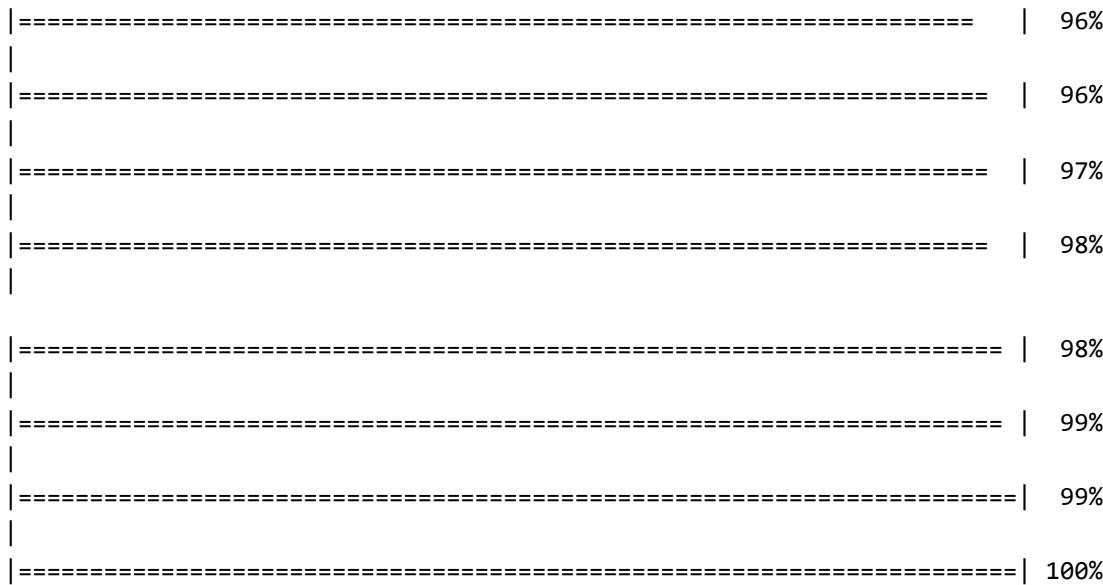




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```
class(st)
```

```
## [1] "sf"      "data.frame"
```

```
st
```

```

## Simple feature collection with 56 features and 14 fields
## Geometry type: MULTIPOLYGON
## Dimension: XY
## Bounding box: xmin: -179.2311 ymin: -14.60181 xmax: 179.8597 ymax: 71.43979
## Geodetic CRS: NAD83
## First 10 features:
##   REGION DIVISION STATEFP STATENS GEOID STUSPS           NAME LSAD MTFCC
## 1      3      5    54 01779805    54    WV West Virginia  00 G4000
## 2      3      5    12 00294478    12    FL     Florida  00 G4000
## 3      2      3    17 01779784    17    IL    Illinois  00 G4000
## 4      2      4    27 00662849    27    MN   Minnesota  00 G4000
## 5      3      5    24 01714934    24    MD    Maryland  00 G4000
## 6      1      1    44 01219835    44    RI Rhode Island 00 G4000
## 7      4      8    16 01779783    16    ID      Idaho  00 G4000
## 8      1      1    33 01779794    33    NH New Hampshire 00 G4000
## 9      3      5    37 01027616    37    NC North Carolina 00 G4000
## 10     1      1    50 01779802    50    VT    Vermont  00 G4000
##   FUNCSTAT        ALAND       AWATER      INTPTLAT      INTPTLON
## 1          A 62266231560 489271086 +38.6472854 -080.6183274
## 2          A 138947364717 31362872853 +28.4574302 -082.4091477
## 3          A 143779863817 6215723896 +40.1028754 -089.1526108
## 4          A 206230065476 18942261495 +46.3159573 -094.1996043
## 5          A 25151726296 6979340970 +38.9466584 -076.6744939
## 6          A 2677787140 1323663210 +41.5974187 -071.5272723
## 7          A 214049897859 2391604238 +44.3484222 -114.5588538
## 8          A 23189198255 1026903434 +43.6726907 -071.5843145
## 9          A 125925929633 13463401534 +35.5397100 -079.1308636
## 10         A 23874197924 1030383955 +44.0685773 -072.6691839
##   geometry
## 1 MULTIPOLYGON (((-81.74725 3...
## 2 MULTIPOLYGON (((-86.38865 3...
## 3 MULTIPOLYGON (((-91.18529 4...
## 4 MULTIPOLYGON (((-96.78438 4...
## 5 MULTIPOLYGON (((-77.45881 3...
## 6 MULTIPOLYGON (((-71.7897 41...
## 7 MULTIPOLYGON (((-116.8997 4...
## 8 MULTIPOLYGON (((-72.3299 43...
## 9 MULTIPOLYGON (((-82.41674 3...
## 10 MULTIPOLYGON (((-73.31328 4...

```

```

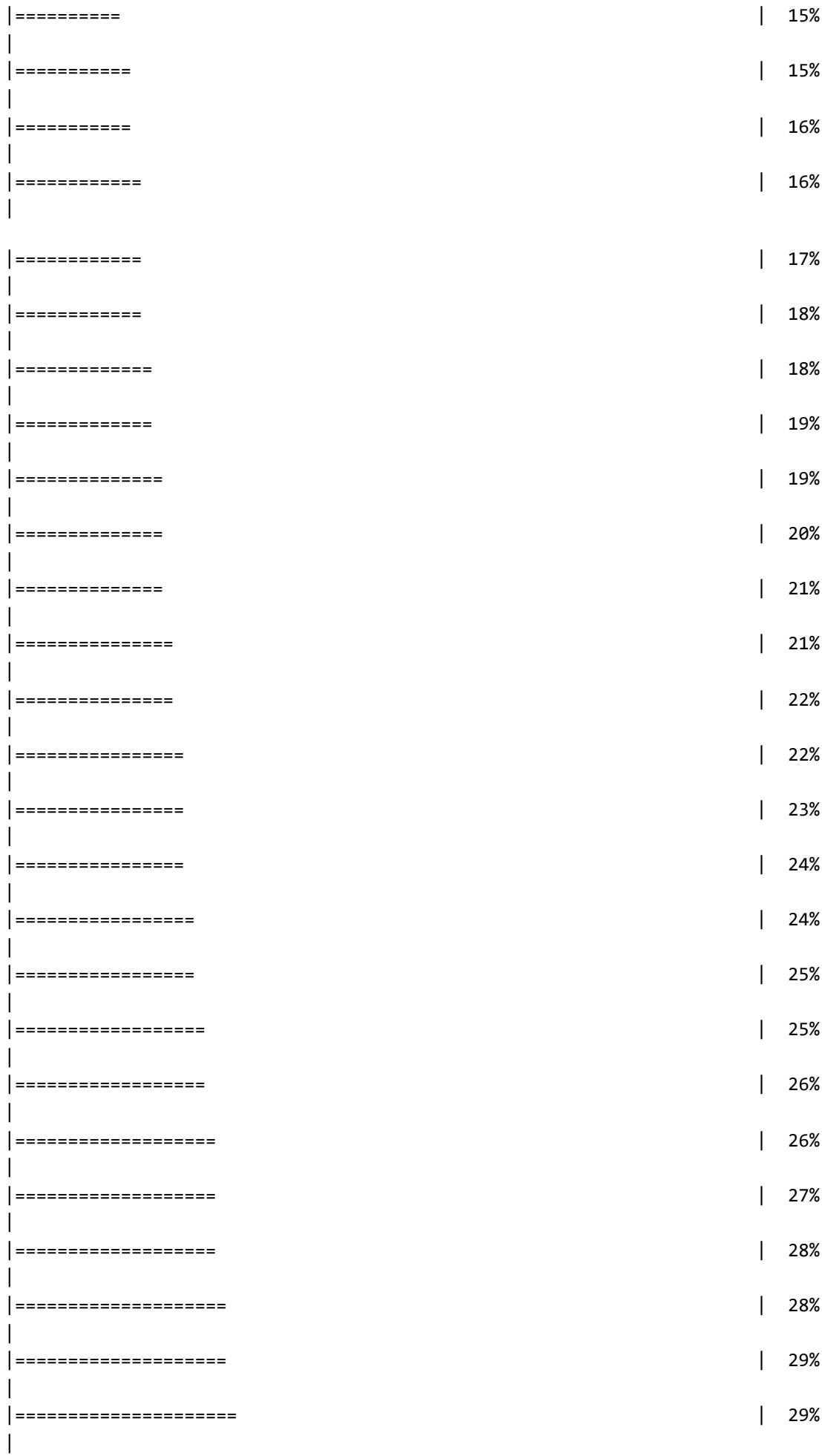
# plot(st$geometry)
## This takes a long time so for times sake I have commented it out

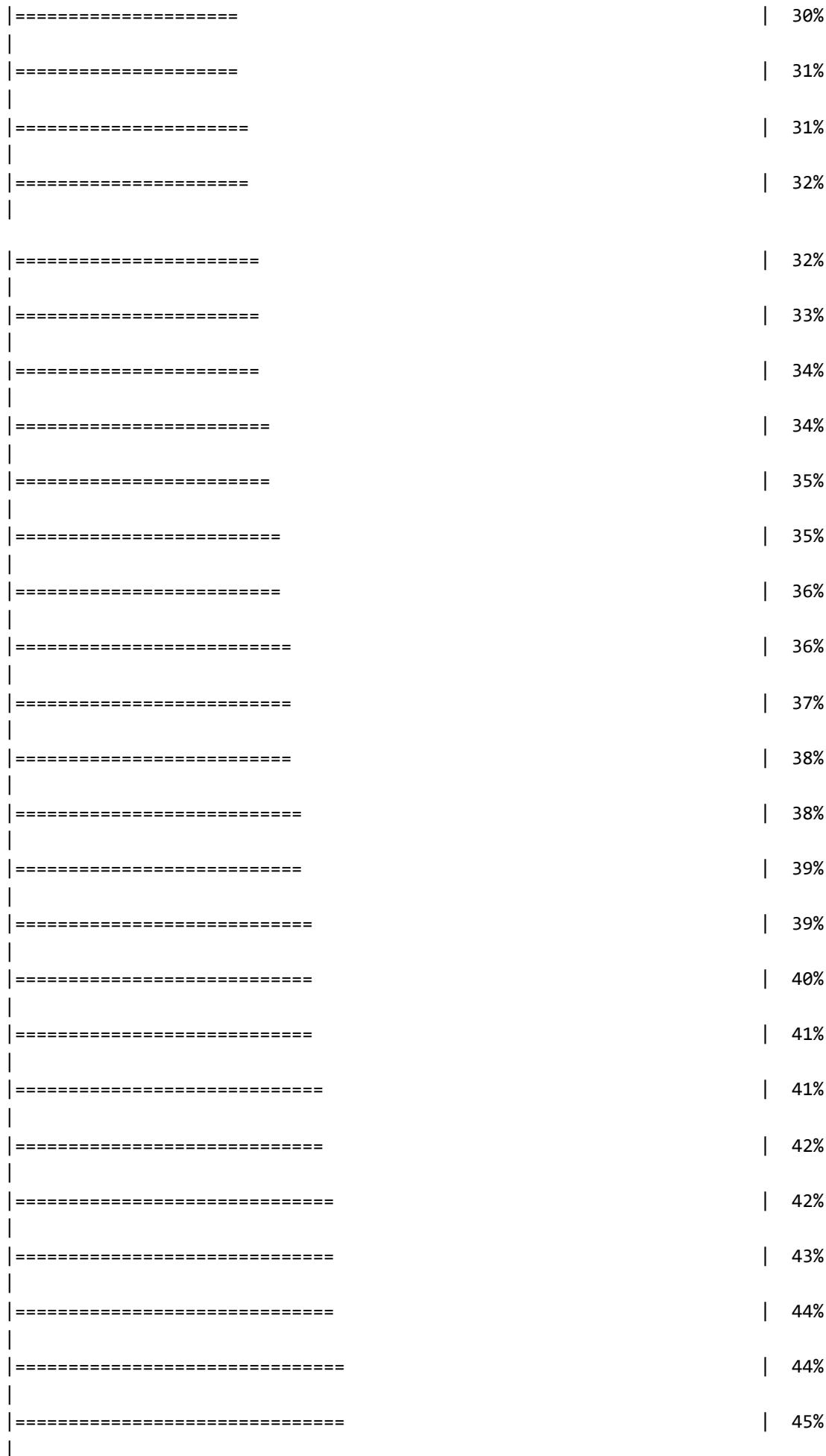
```

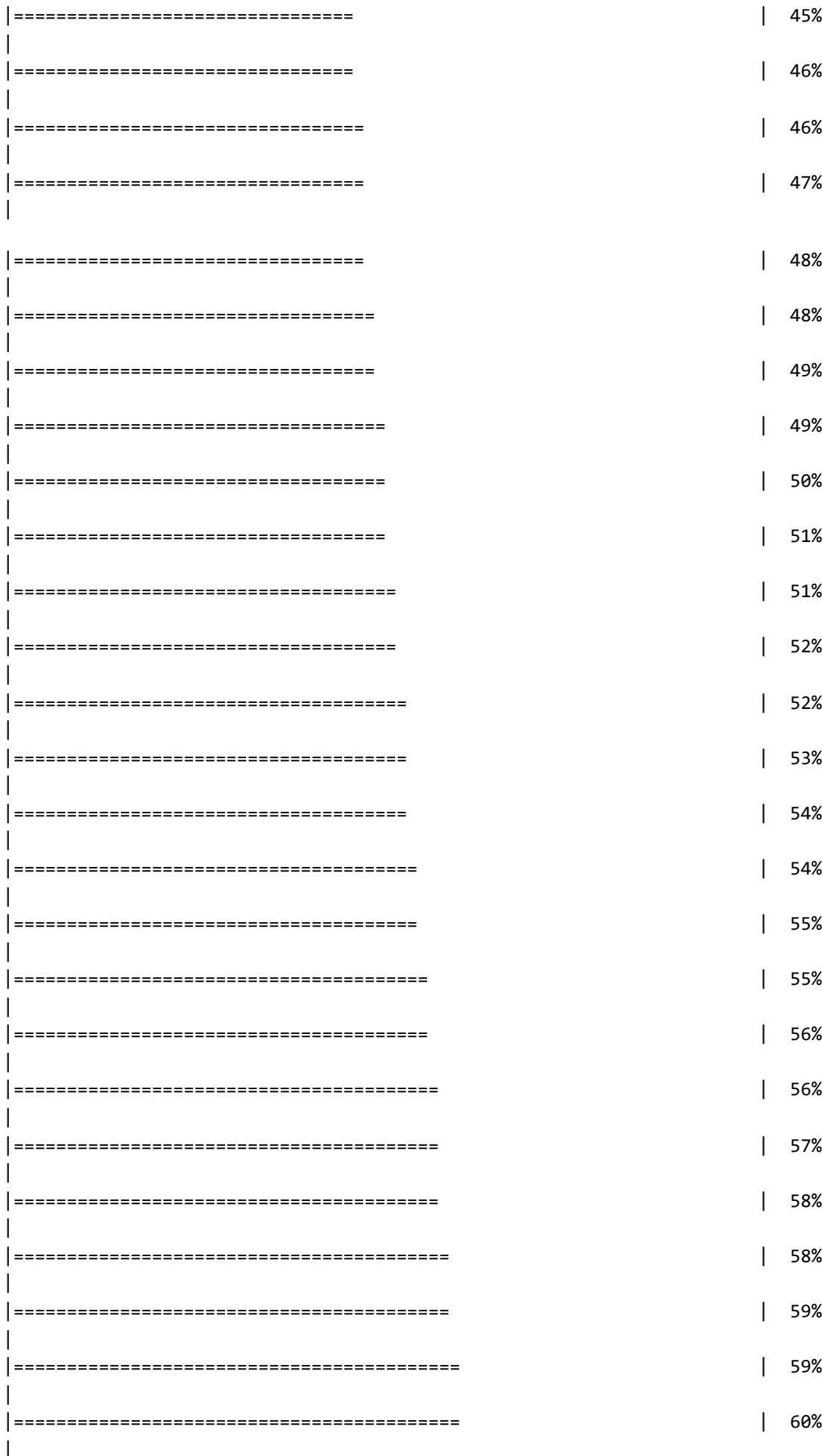
Plots States and makes a map of the United States

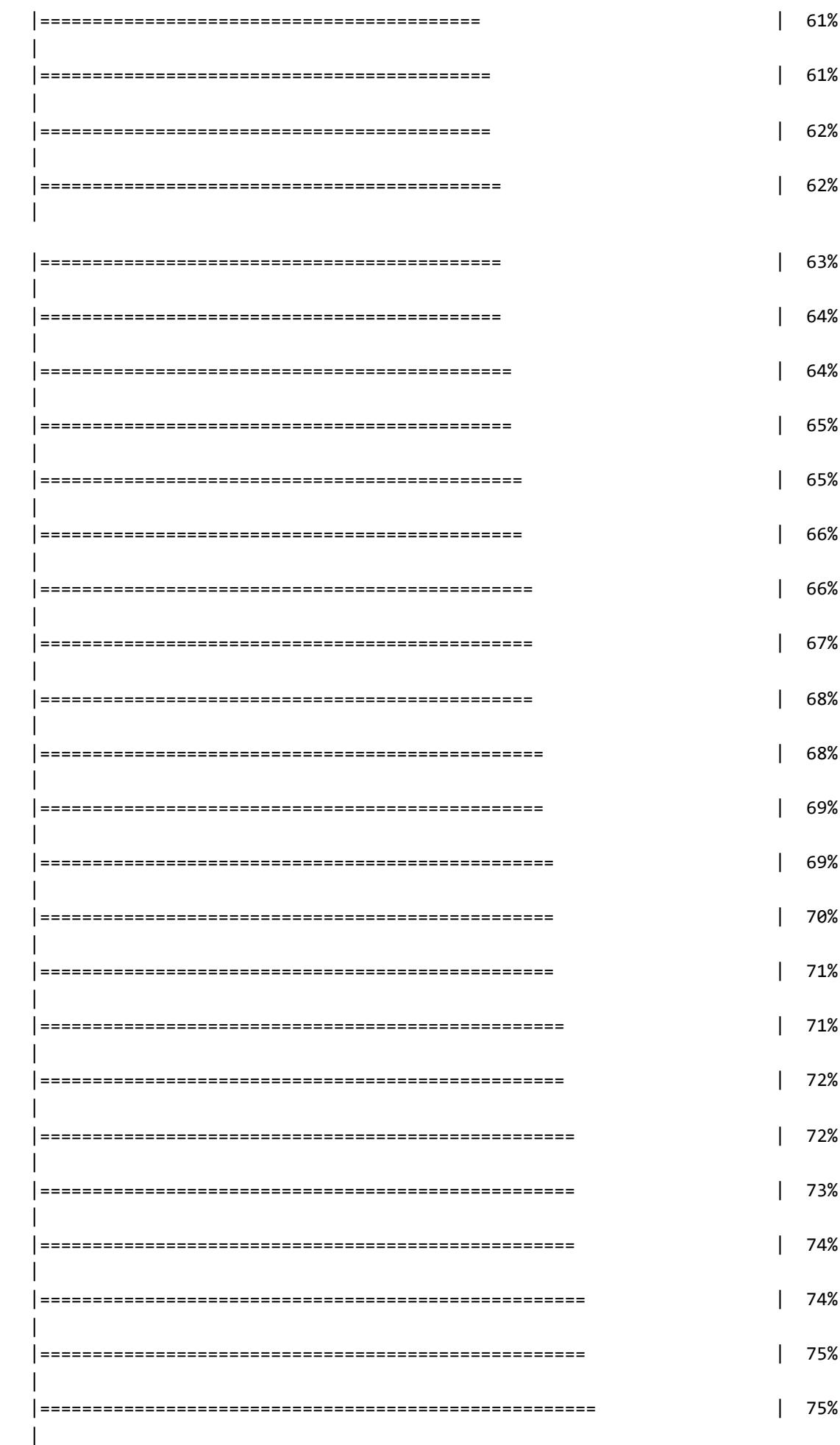
```
nm_counties <- counties("NM")
```

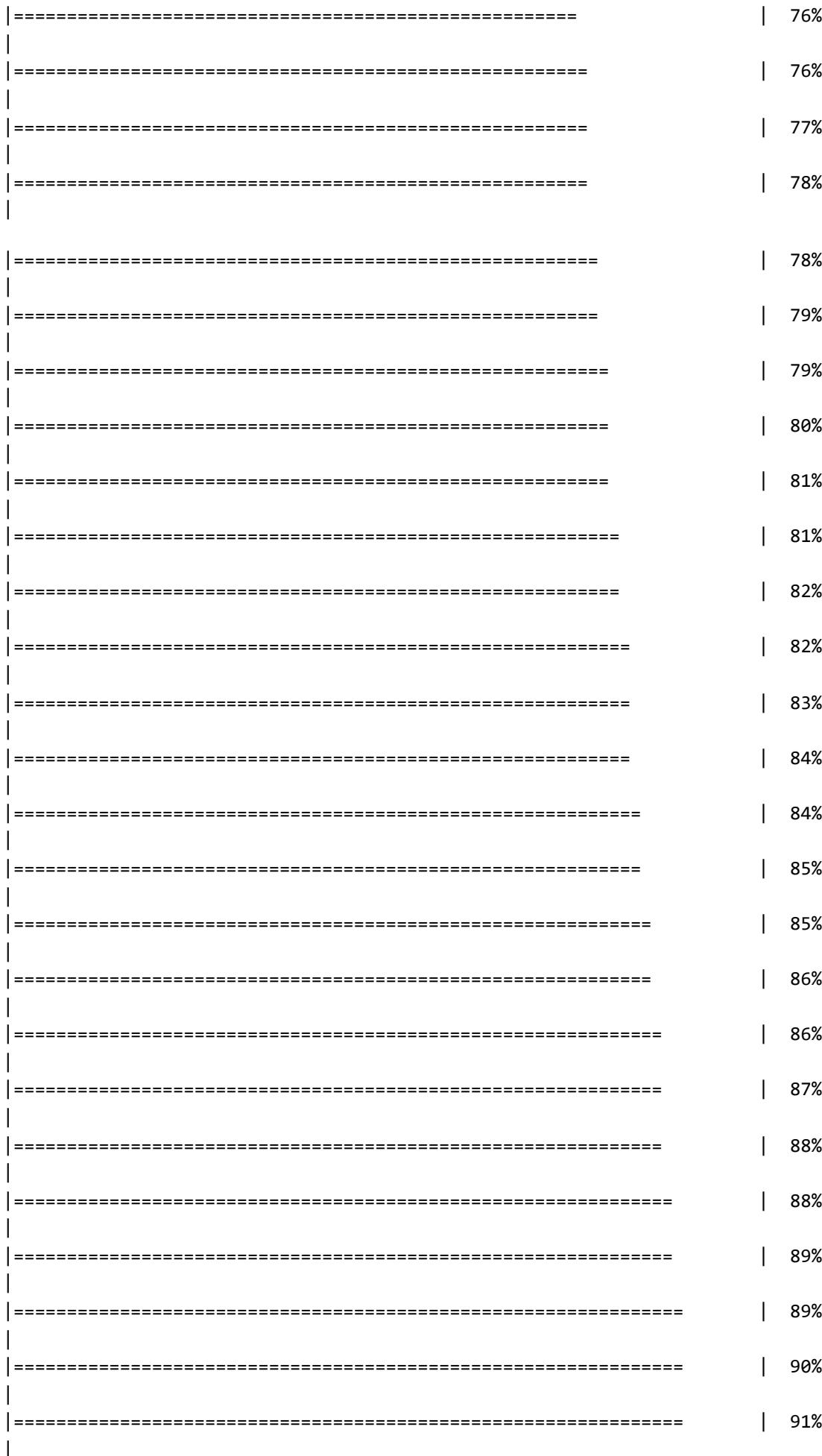
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```

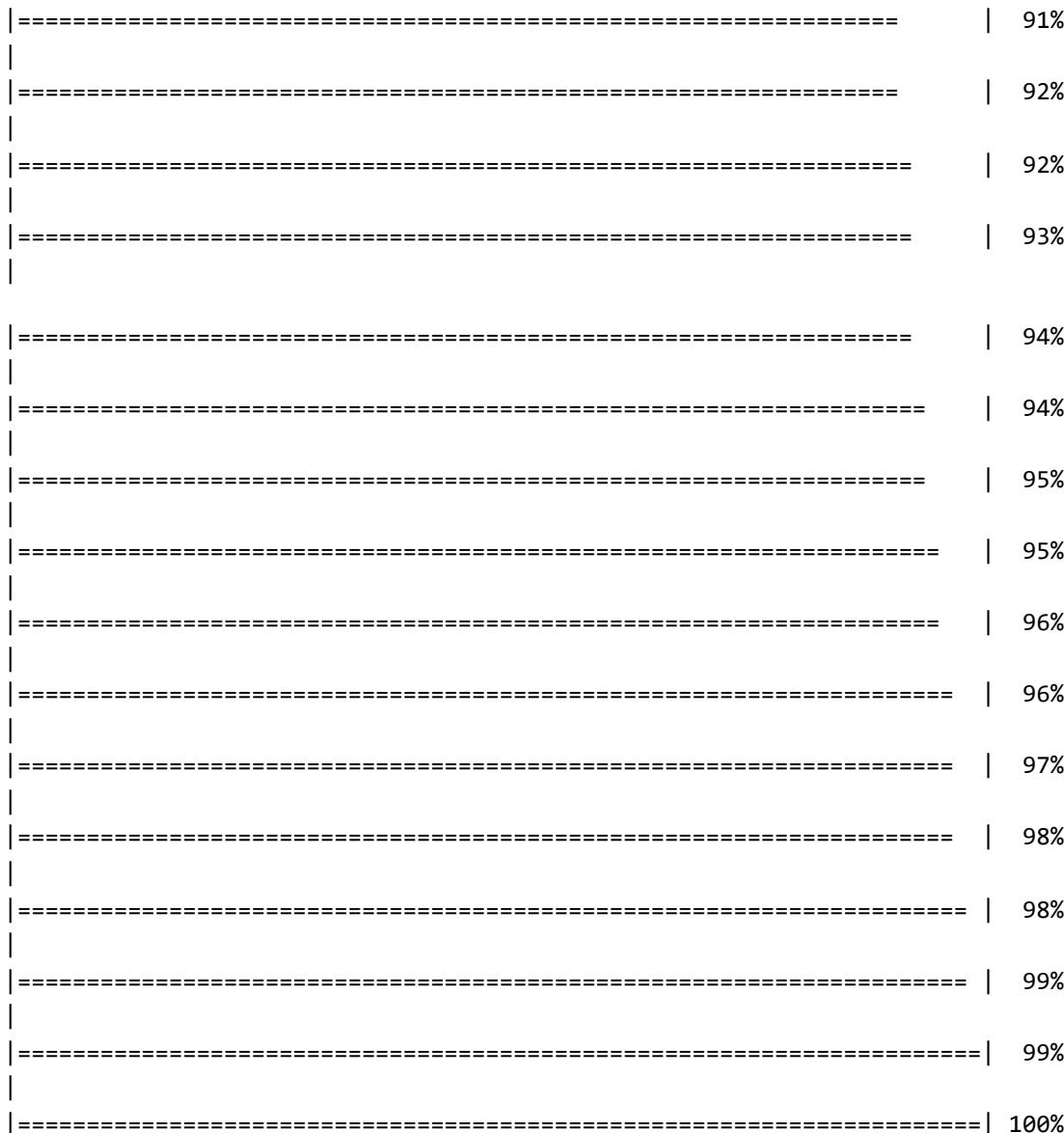




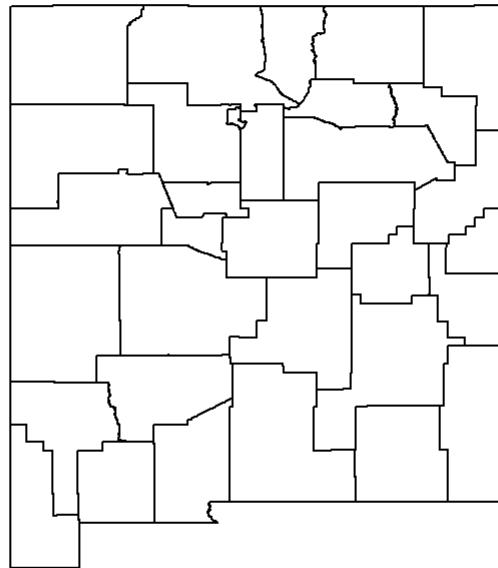








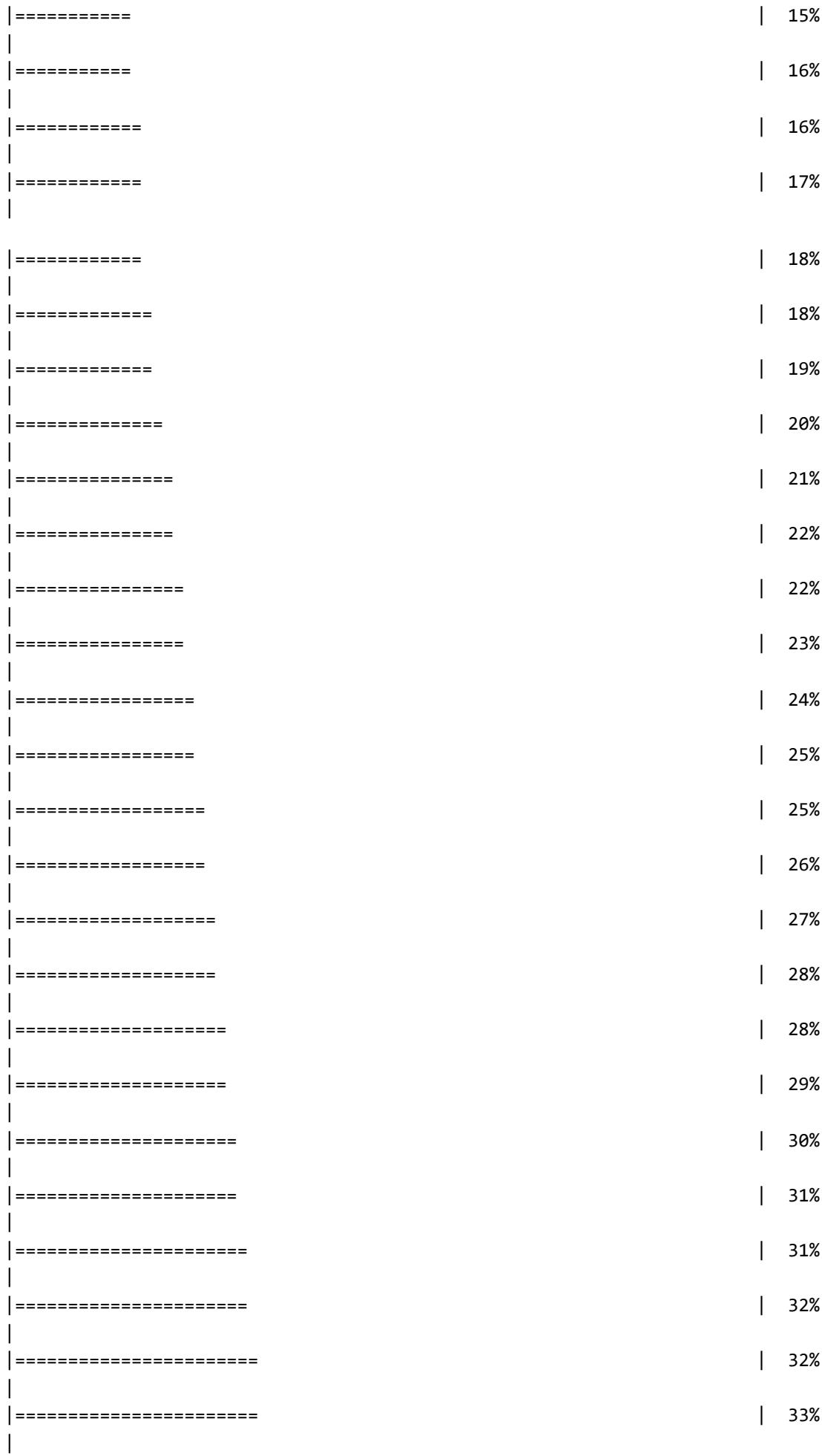
```
plot(nm_counties$geometry)
```

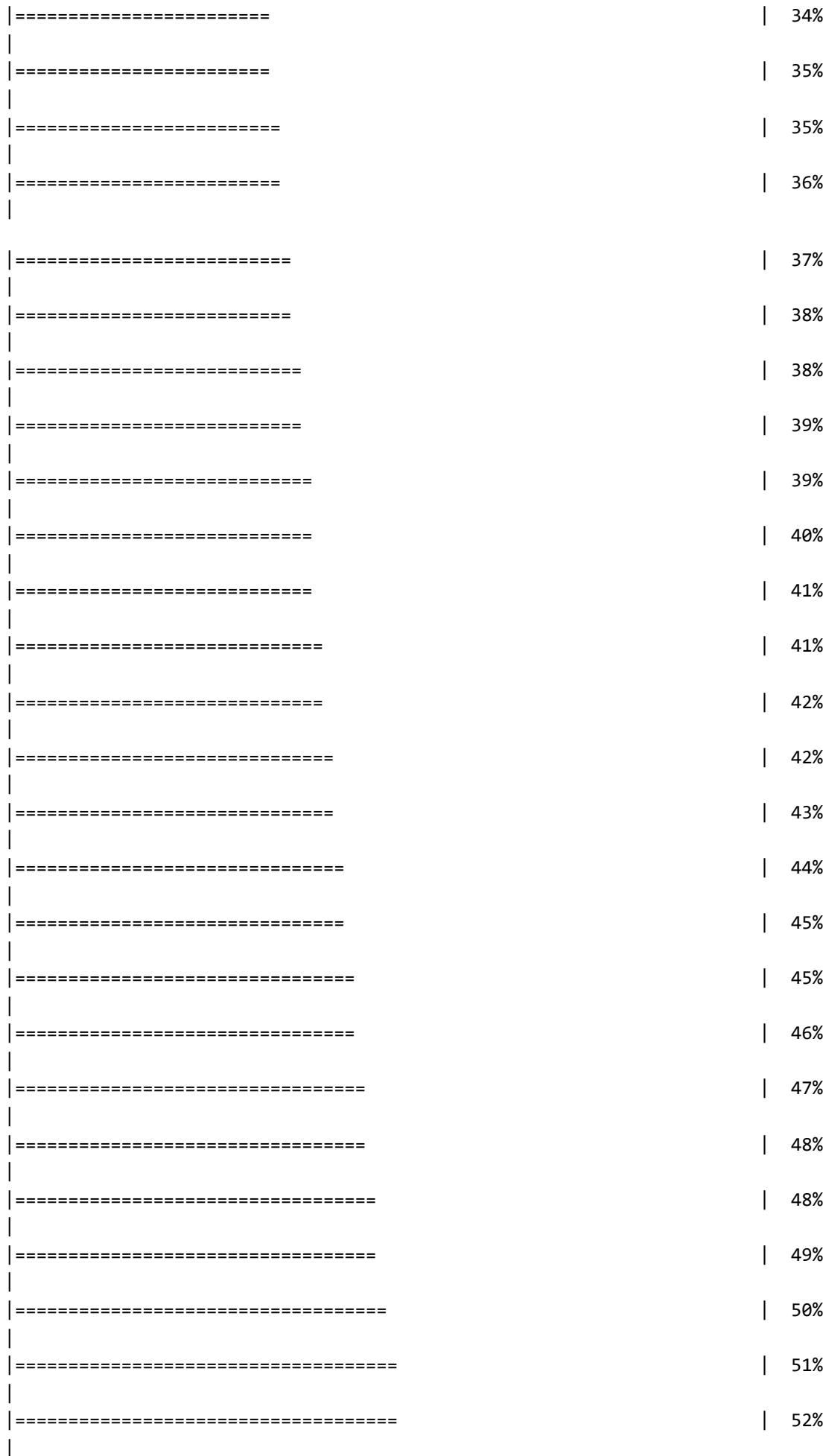


Specify counties in a given state, then plot geometry of states counties

```
la_tracts <- tracts("NM","Los Alamos")
```

```
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```



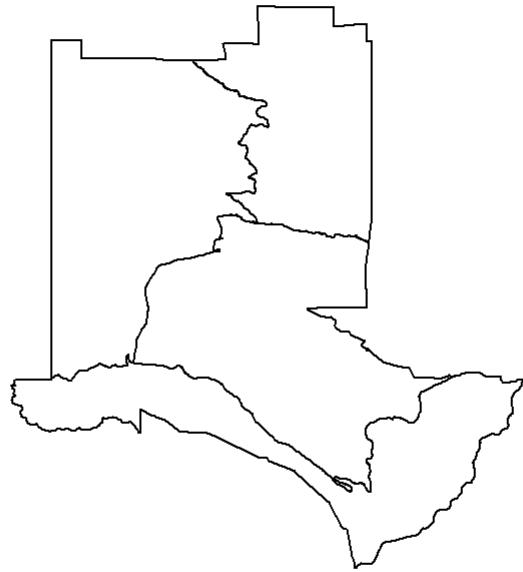






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```
plot(la_tracts$geometry)
```



Plots census tract boundaries in Los Alamos county NM

```
la_water <- area_water("NM", "Los Alamos")
```

```
##  
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|=====  
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|=====-----| 6%  
|=====-----| 72%  
|=====-----| 100%
```

```
plot(la_water$geometry)
```



Plots water area in Los Alamos County, NM

5.1.1 Understanding tigris and simple features

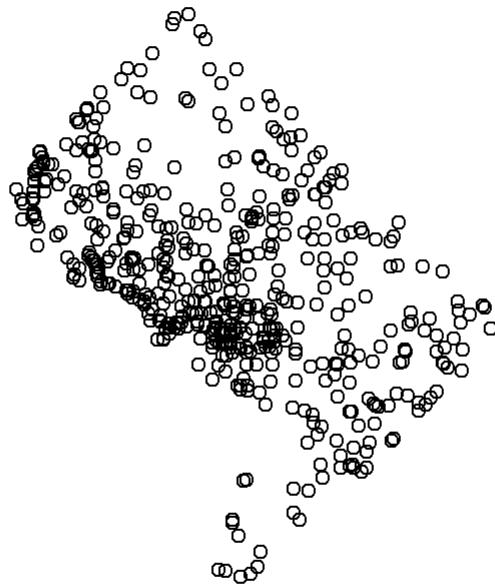
Data returned by the `tigris` package is *vector spatial data* which represents geographic features as points, lines, and polygons. Vector data in R is represented with the `sf` package.

5.1.1.1 Points

```
dc_landmarks <- landmarks("DC", type = "point")
```

```
##  
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|=====| 71%  
|=====| 100%
```

```
plot(dc_landmarks$geometry)
```



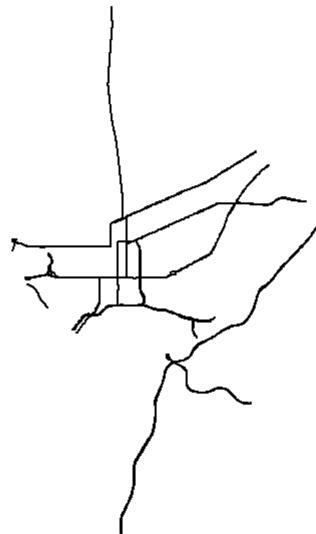
Plots census landmarks inside a specified geometry

5.1.1.2 Lines

```
dc_roads <- primary_secondary_roads("DC")
```

```
##  
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===== 31%  
===== 50%  
===== 59%  
===== 79%  
===== 88%  
===== 100%
```

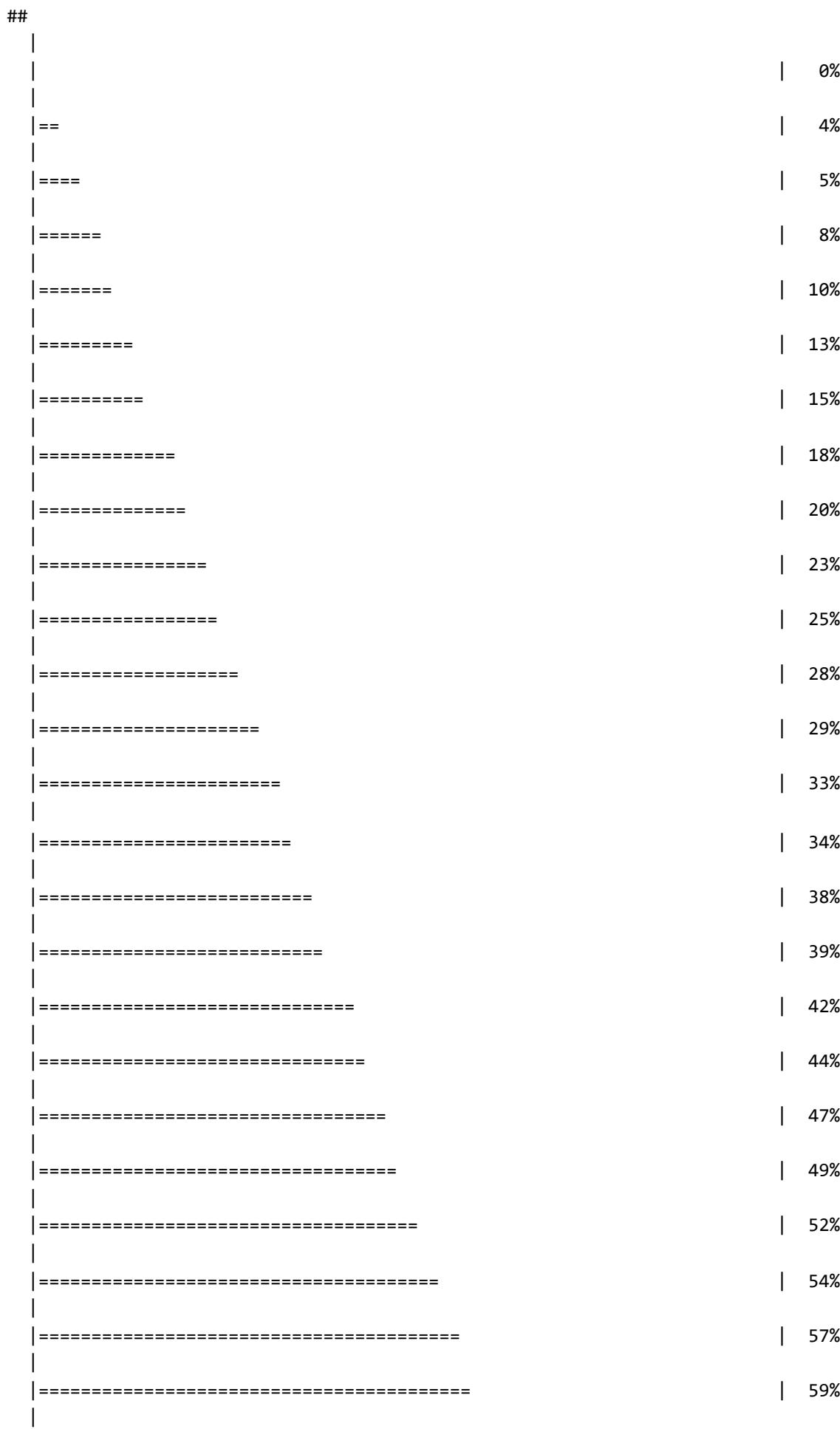
```
plot(dc_roads$geometry)
```



Plots primary and secondary roads within a geometry

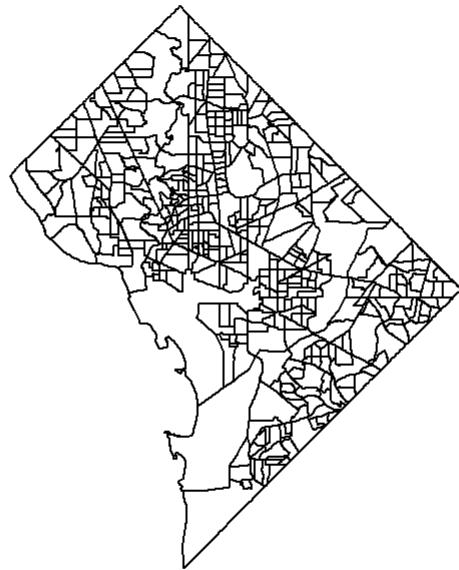
Polygons

```
dc_block_groups <- block_groups("DC")
```





```
plot(dc_block_groups$geometry)
```



Plots block groups in DC

5.1.2 Data availability in tigris

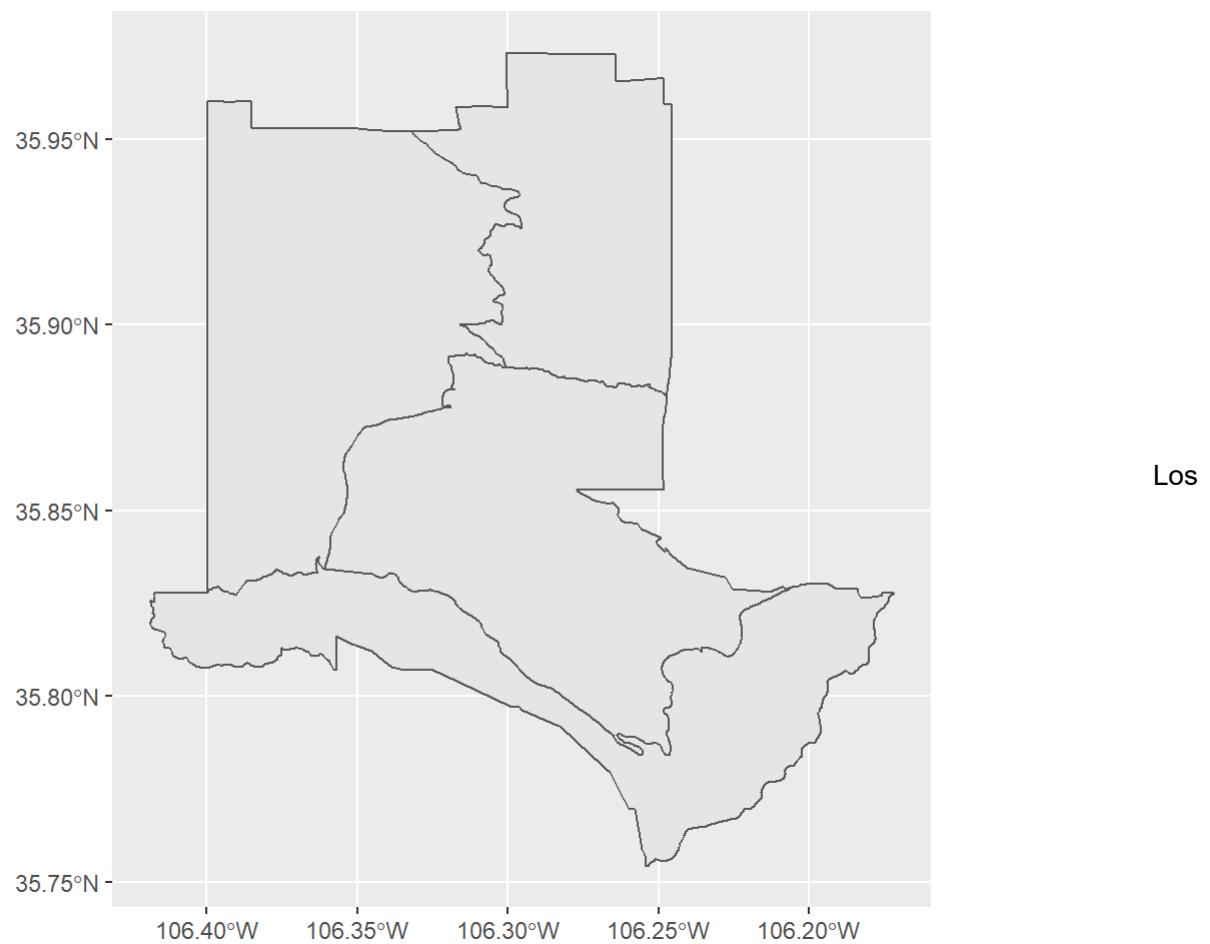
Lots of data and geometries available in TIGER/Line files for many different years.

5.2 Plotting Geographic data

In R geographic data will be first and foremost represented as a tabular data frame

5.2.1 ggplot2 and geom_sf()

```
library(ggplot2)  
  
ggplot(la_tracts) +  
  geom_sf()
```



Alamos County Census tracts plotted with `geom_sf`. This adds a grid and labels to the plot or map. The grid and labels can be removed with the function `theme_void()`

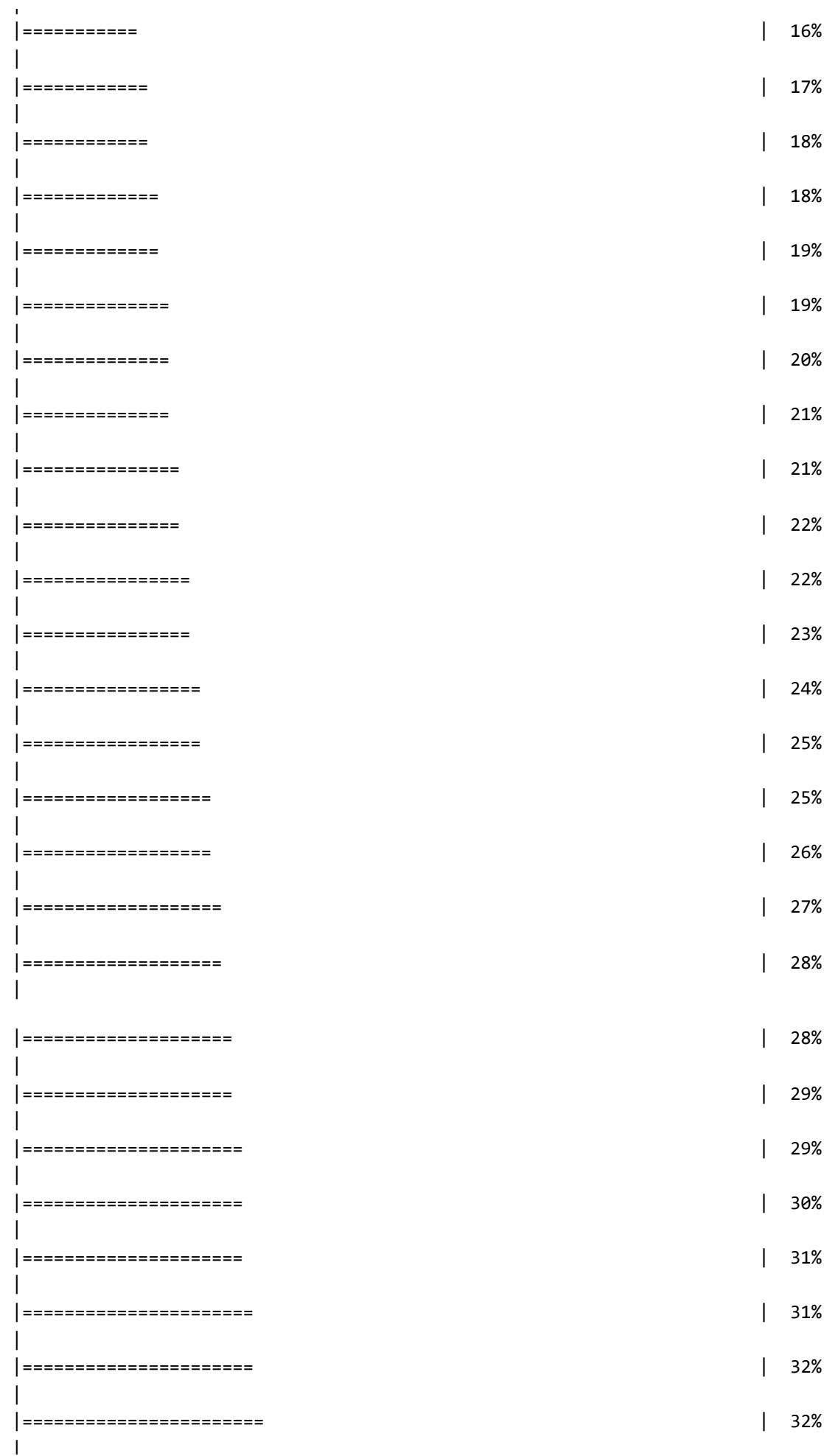
```
ggplot(la_tracts) +  
  geom_sf() +  
  theme_void()
```

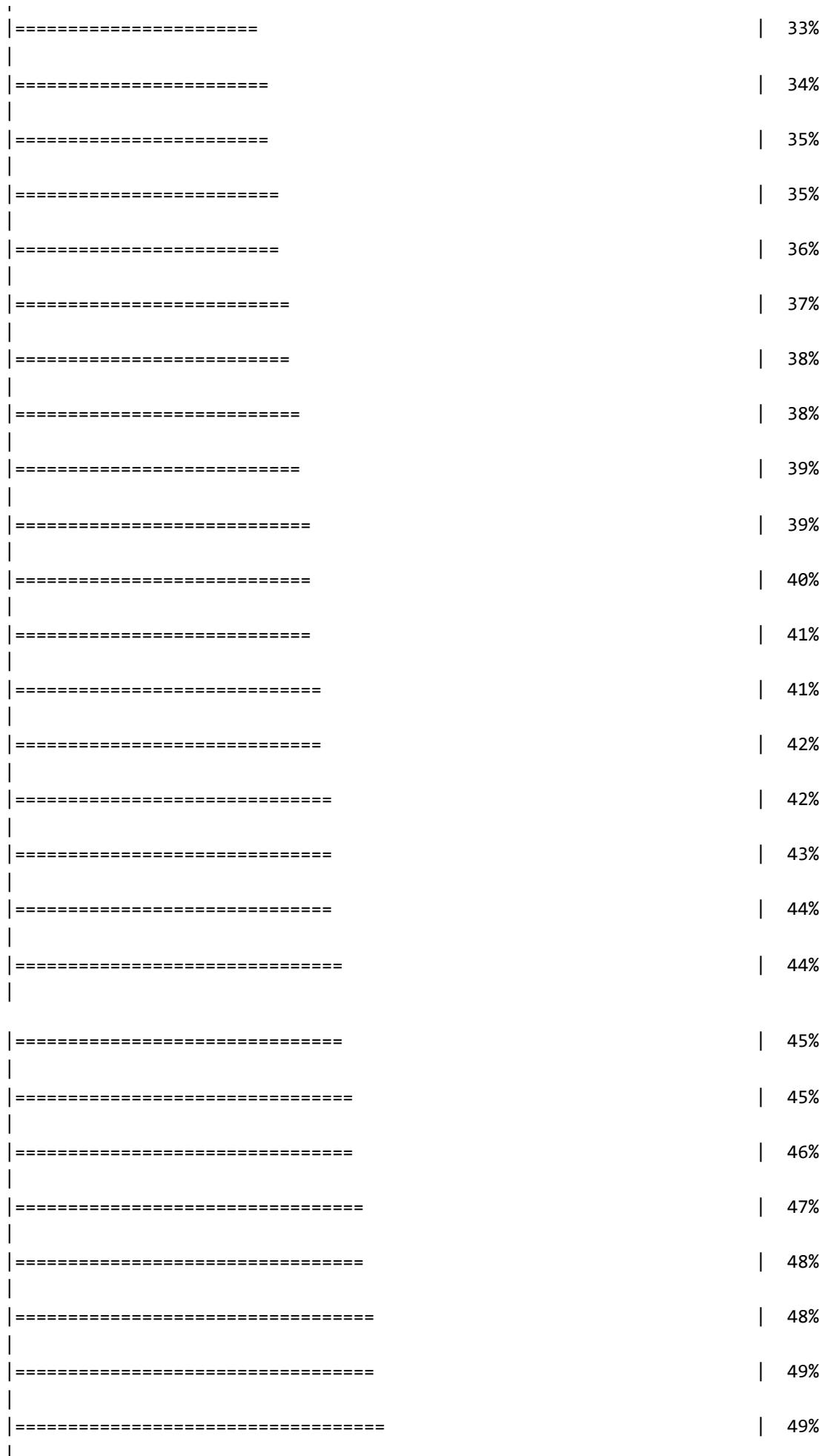


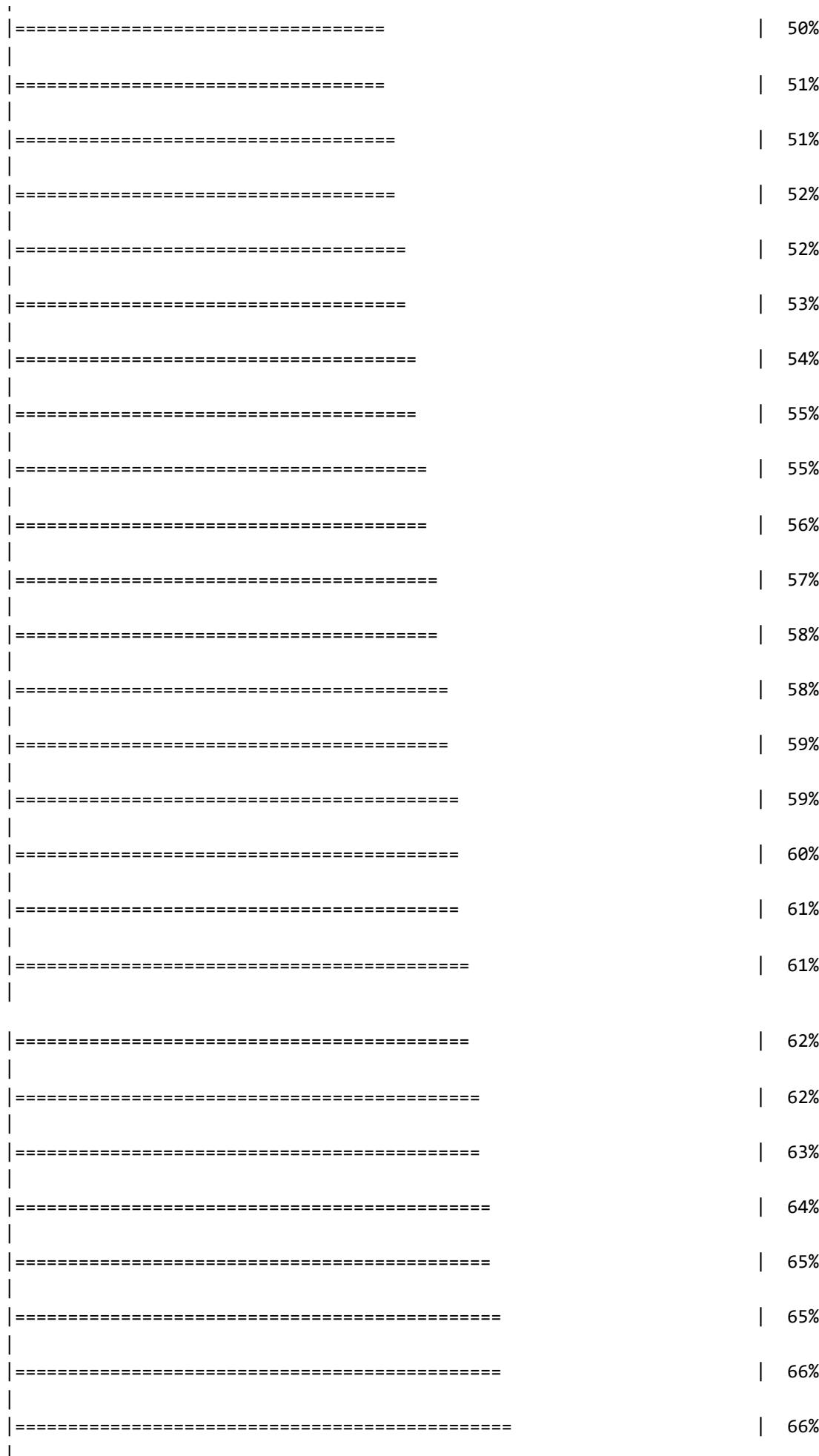
For comparative spatial plots, the patchwork package is used. This is used for arranging a multi- plot layout

```
library(patchwork)  
  
la_block_groups <- block_groups("NM", "Los Alamos")
```

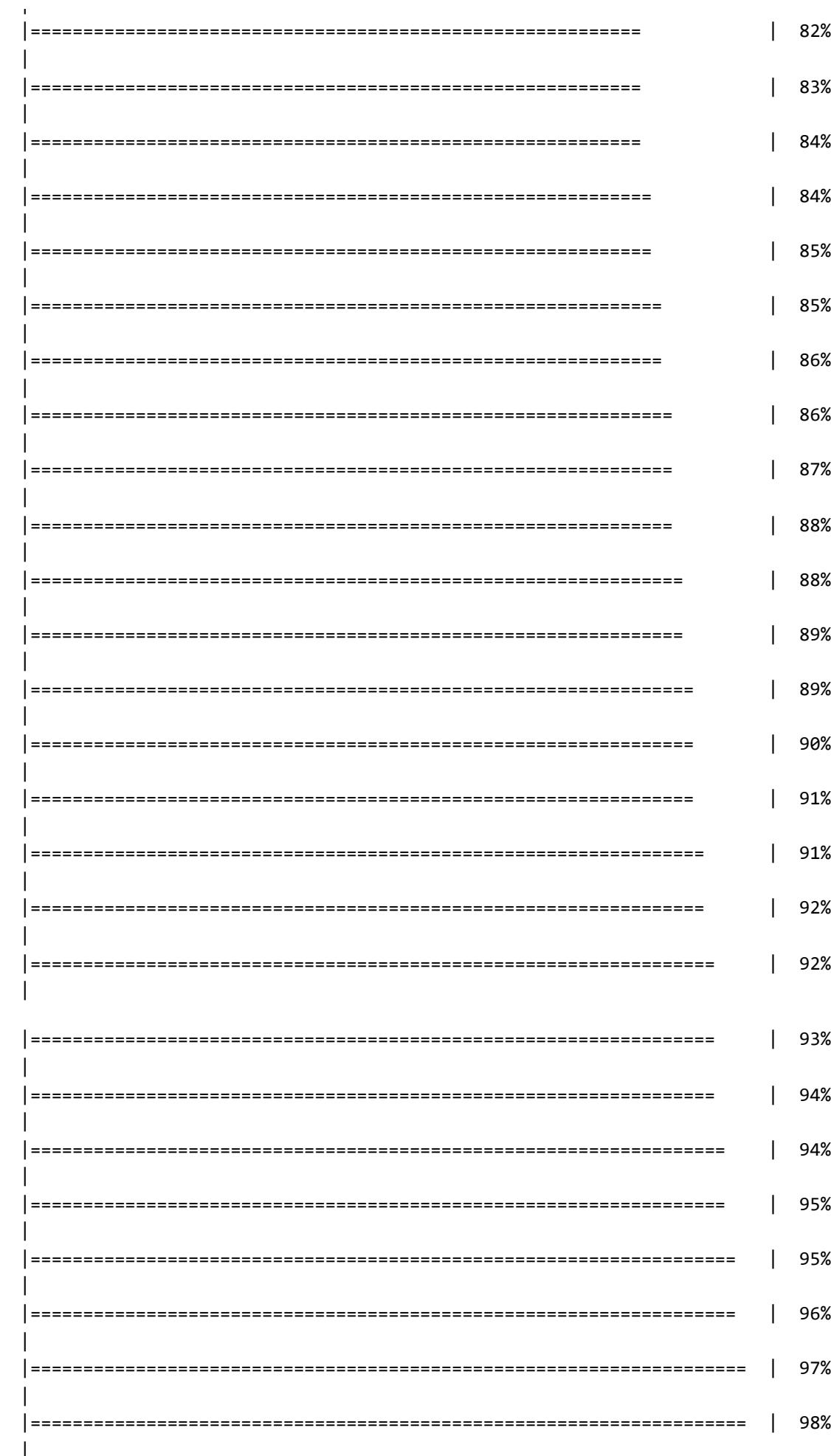
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```

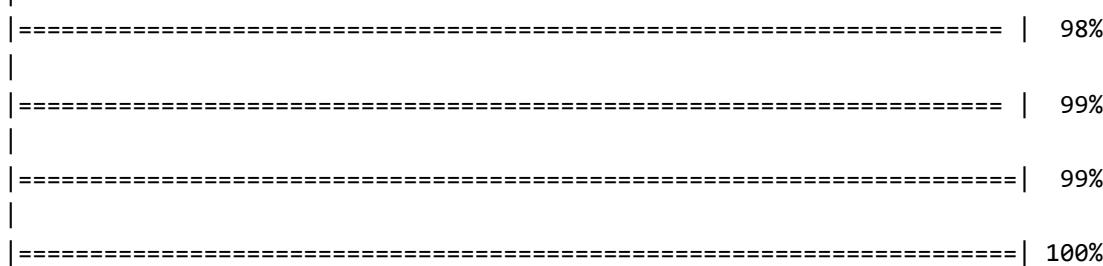












```
gg1 <- ggplot(la_tracts) +  
  geom_sf() +  
  theme_void() +  
  labs(title = "Census tracts")  
  
gg2 <- ggplot(la_block_groups) +  
  geom_sf() +  
  theme_void() +  
  labs(title = "Block groups")  
  
gg1 + gg2
```

Census tracts



Block groups



5.2.2 Interactive viewing with mapview

The mapview R package visualizes geographic data on an interactive zoomable map much like a desktop mapping software would.

```
library(mapview)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
## 126: The specified module could not be found.  
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

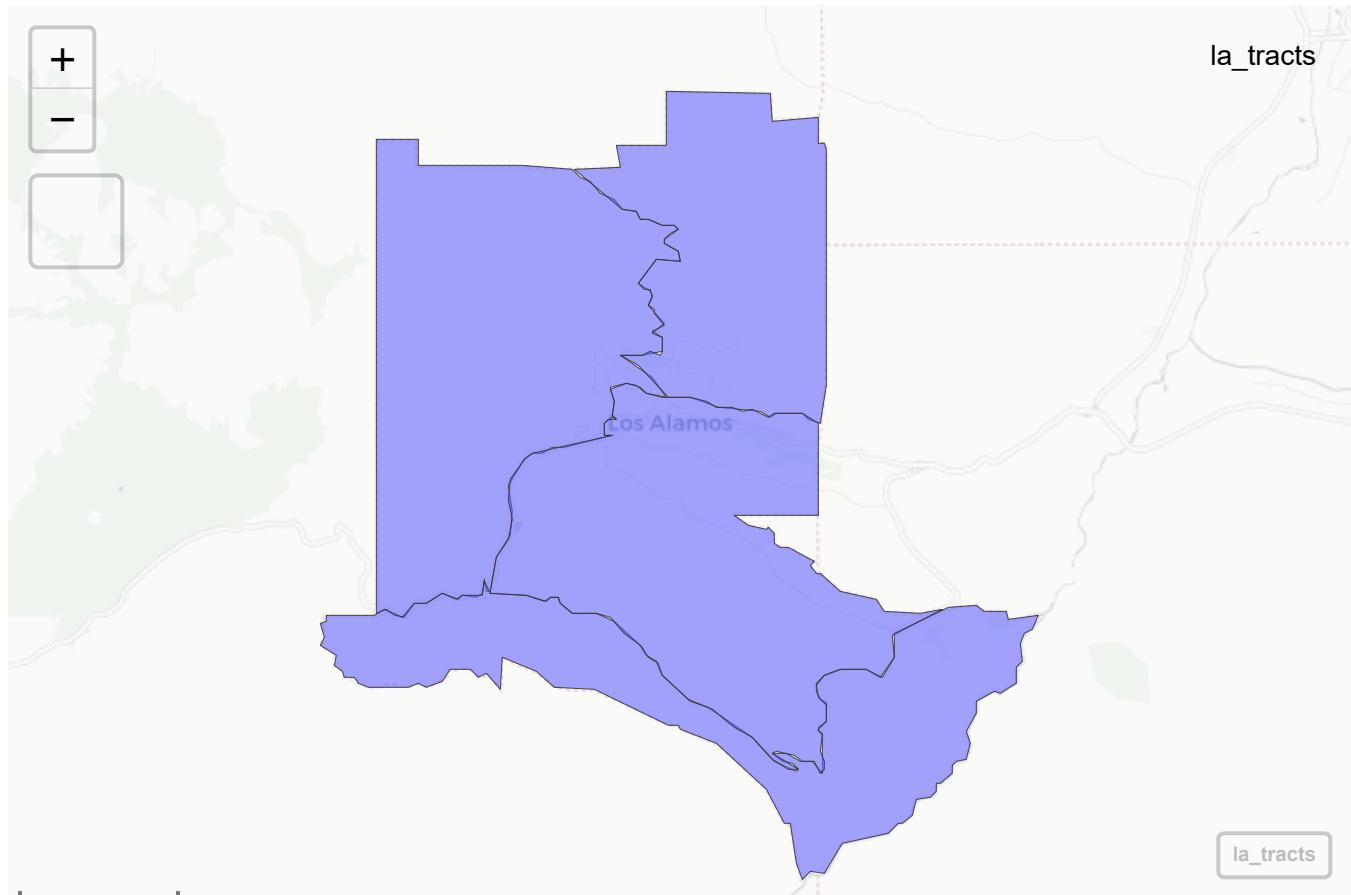
```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
mapview(la_tracts)
```



Interactive Map View of Los Alamos County census tracts

5.3 Tigris workflows

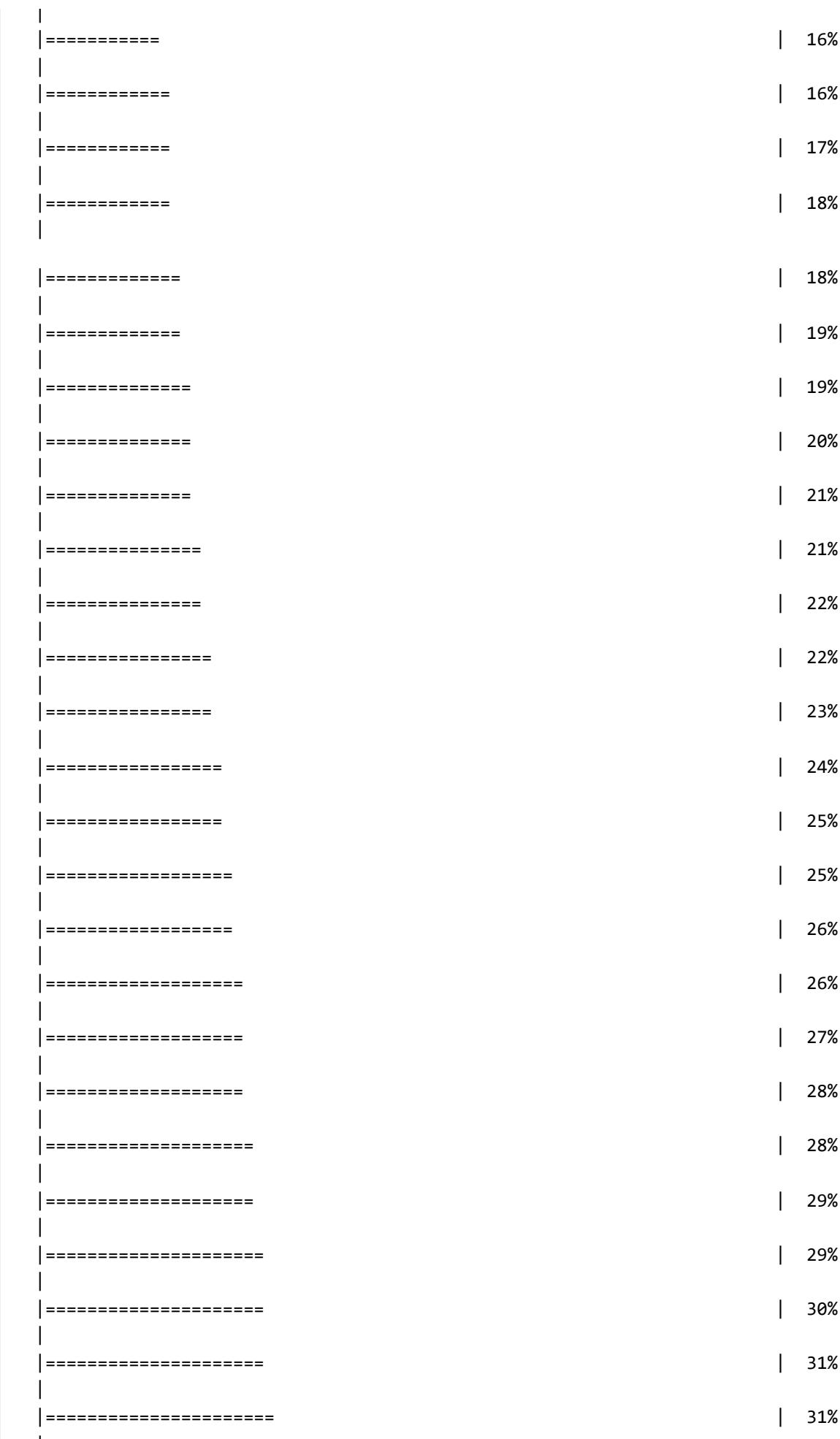
In this section additional functions of the Tigris package are demonstrated

5.3.1 TIGER/Line and cartographic boundary shapefiles

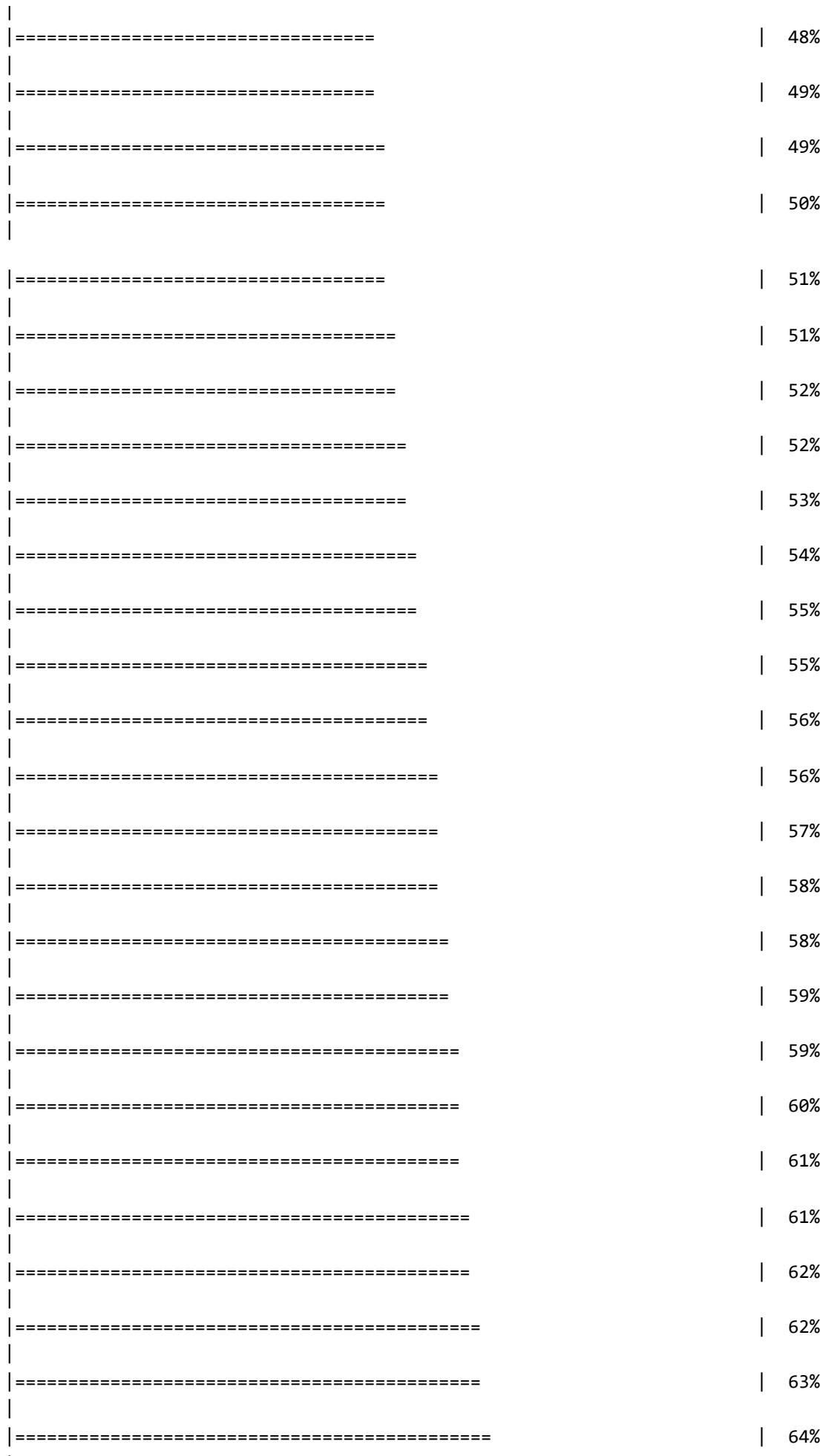
Most polygon data sets in tigris are cartographic boundary files and can be accessed with the argument: cb = TRUE Cartographic boundary files resolves the issue of TIGER/Line files containing water when representing geographic features which causes them to have an irregular or unfamiliar representation. Below patchwork is used to compare the TIGER/Line shape files to the Cartographic boundary shape files for counties in Michigan.

```
mi_counties <- counties("MI")
mi_counties_cb <- counties("MI", cb = TRUE)
```

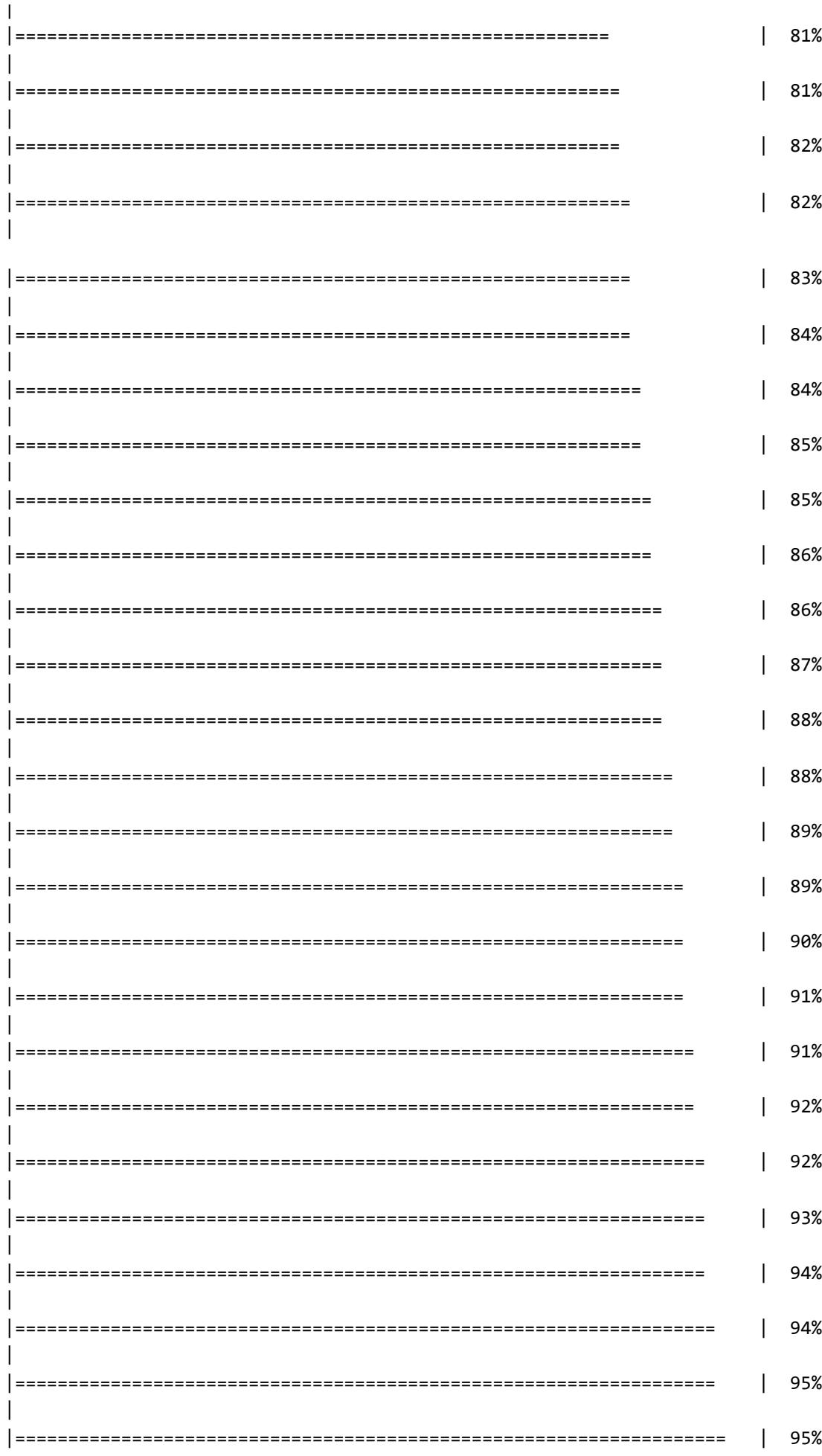
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```

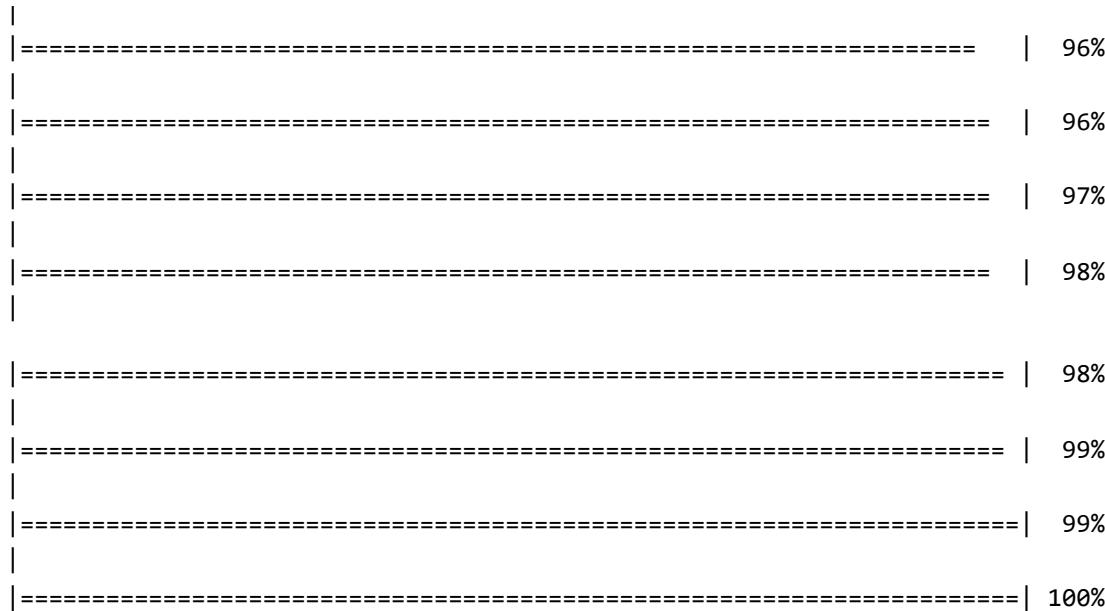






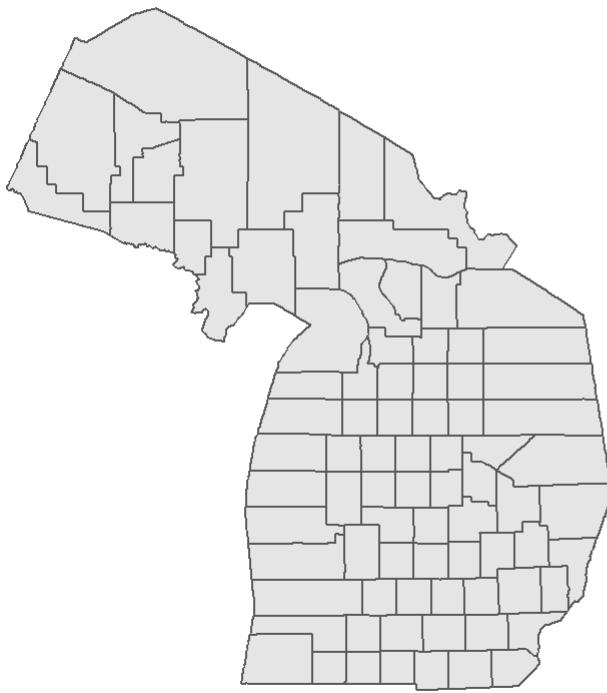






```
mi_tiger_gg <- ggplot(mi_counties) +  
  geom_sf() +  
  theme_void() +  
  labs(title = "TIGER/Line")  
  
mi_cb_gg <- ggplot(mi_counties_cb) +  
  geom_sf() +  
  theme_void() +  
  labs(title = "Cartographic boundary")  
  
mi_tiger_gg + mi_cb_gg
```

TIGER/Line



Cartographic boundary



5.3.2 Caching tigris data

Caches data and files to designated directory on your machine. This allows for quicker retrieval for large files and helps when internet connection is poor.

```
options(tigris_use_cache = TRUE)  
  
rappdirs::user_cache_dir("tigris")  
  
## [1] "C:\\\\Users\\\\tphil\\\\AppData\\\\Local/tigris/tigris/Cache"
```

5.3.3 Understanding yearly differences in TIGER/Line files

Some geographies will change year by year such as census tracts. This section demonstrates that for Texas

```

library(tidyverse)
library(patchwork)
library(glue)

yearly_plots <- map(seq(1990, 2020, 10), ~{
  year_tracts <- tracts("TX", "Tarrant", year = .x,
    cb = TRUE)

  ggplot(year_tracts) +
    geom_sf() +
    theme_void() +
    labs(title = glue("{.x}: {nrow(year_tracts)} tracts"))

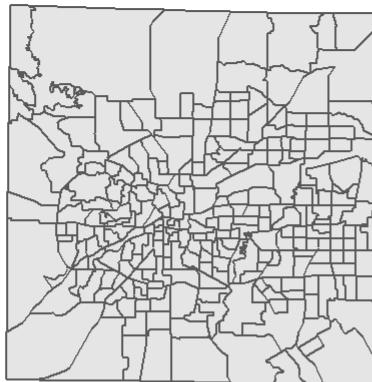
})

```

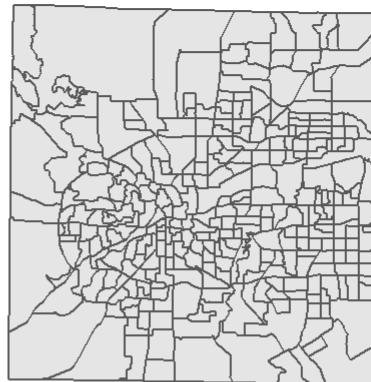
Now patchwork is used to facet the plots. The division operator allows for organization of plots in a grid.

```
(yearly_plots[[1]] + yearly_plots[[2]]) /
  (yearly_plots[[3]] + yearly_plots[[4]])
```

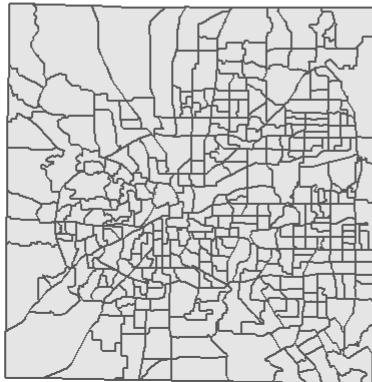
1990: 269 tracts



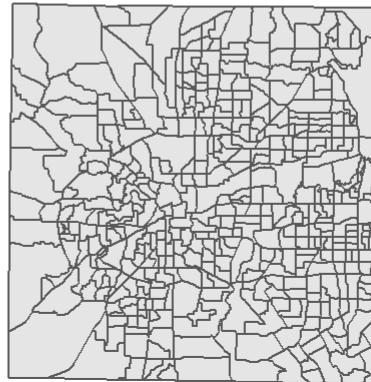
2000: 310 tracts



2010: 357 tracts



2020: 449 tracts



The differences between census tracts throughout time is now visualized.

Remember that the default year of shape files aligns with the most recent 5 year ACS data.

5.3.4 Combining tigris datasets

For smaller geographies the census bureau stores shape files by state and does not have a national file. Therefore tigris users must specify a state and county when requesting data.

```
state_codes <- c(state.abb, "DC", "PR")

us_bgs <- map_dfr(
  state_codes,
  ~block_groups(
    state = .x,
    cb = TRUE,
    year = 2020
  )
)

nrow(us_bgs)
```

```
## [1] 241898
```

The code above produces a national block group data set as shown for the year 2020. Notice how DC and PR were added to the state.abb function in order to retrieve postal codes for DC and PR. The map_dfr() function uses row bind data sets to produce its output.

5.4 Coordinate reference systems

This section overviews working with coordinate reference systems in relation to tigris. The default for tigris is to store its datasets in a geographic coordinate system (lat/long, relative to 3d model of earth). The coordinate system can be checked using the st_crs() function in the sf package.

```
library(sf)
```

```
## Linking to GEOS 3.9.1, GDAL 3.2.1, PROJ 7.2.1; sf_use_s2() is TRUE
```

```
fl_counties <- counties("FL", cb = TRUE)

st_crs(fl_counties)
```

```
## 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]]
```

The code above checks the Coordinate reference system for counties in Florida. The CRS for this data set is NAD 1983. All Census Bureau data sets are stored in the NAD 1983 geographic coordinate system.

5.4.1 Using the crssuggest package

This function returns possible choices for a suitable projected CRS for your data. This works by comparing geometry of your data set to a built in data set of CRS extents. The chosen data set minimizes the Hausdorff distance between your data set and those extents.

```
library(crsuggest)
```

```
## Using the EPSG Dataset v10.019, a product of the International Association of Oil & Gas Producers.
## Please view the terms of use at https://epsg.org/terms-of-use.html.
```

```
f1_crs <- suggest_crs(f1_counties)
```

After running the suggest function, the recommended CRS is the Florida GDL Albers. To transform the CRS of this dataset the `st_transform()` function will be used to transform it to “NAD83(HARN)/ Florida GDL Albers”.

```
f1_projected <- st_transform(f1_counties, crs = 3087)

head(f1_projected)
```

```
## Simple feature collection with 6 features and 9 fields
## Geometry type: MULTIPOLYGON
## Dimension: XY
## Bounding box: xmin: 83061.87 ymin: 130373.8 xmax: 788415.5 ymax: 780618.1
## Projected CRS: NAD83(HARN) / Florida GDL Albers
##   STATEFP COUNTYFP COUNTYNS      AFFGEOID GEOID          NAME LSAD     ALAND
## 24        12      075 00295724 0500000US12075 12075      Levy    06 2896183010
## 96        12      086 00295755 0500000US12086 12086  Miami-Dade    06 4920565755
## 97        12      073 00306916 0500000US12073 12073      Leon    06 1727237331
## 98        12      057 00295757 0500000US12057 12057 Hillsborough    06 2646772012
## 99        12      083 00306922 0500000US12083 12083      Marion    06 4113978836
## 100       12      113 00306914 0500000US12113 12113 Santa Rosa    06 2622050628
##   AWATER           geometry
## 24  762935040 MULTIPOLYGON (((493790.5 56...
## 96  1376144237 MULTIPOLYGON (((783767.5 17...
## 97  90397079 MULTIPOLYGON (((331309.7 70...
## 98  631505816 MULTIPOLYGON (((555139.4 42...
## 99  192297049 MULTIPOLYGON (((542215.5 56...
## 100 418020790 MULTIPOLYGON (((83268.36 76...
```

The features have changed to much larger numbers as they are in Meters as opposed to decimal degrees now.

```
st_crs(f1_projected)
```

```

## Coordinate Reference System:
##   User input: EPSG:3087
##   wkt:
## PROJCRS["NAD83(HARN) / Florida GDL Albers",
##   BASEGEOGCRS["NAD83(HARN)",
##     DATUM["NAD83 (High Accuracy Reference Network)",
##       ELLIPSOID["GRS 1980",6378137,298.257222101,
##         LENGTHUNIT["metre",1]]],
##     PRIMEM["Greenwich",0,
##       ANGLEUNIT["degree",0.0174532925199433]],
##     ID["EPSG",4152]],
##   CONVERSION["Florida GDL Albers (meters)",
##     METHOD["Albers Equal Area",
##       ID["EPSG",9822]],
##     PARAMETER["Latitude of false origin",24,
##       ANGLEUNIT["degree",0.0174532925199433],
##       ID["EPSG",8821]],
##     PARAMETER["Longitude of false origin",-84,
##       ANGLEUNIT["degree",0.0174532925199433],
##       ID["EPSG",8822]],
##     PARAMETER["Latitude of 1st standard parallel",24,
##       ANGLEUNIT["degree",0.0174532925199433],
##       ID["EPSG",8823]],
##     PARAMETER["Latitude of 2nd standard parallel",31.5,
##       ANGLEUNIT["degree",0.0174532925199433],
##       ID["EPSG",8824]],
##     PARAMETER["Easting at false origin",400000,
##       LENGTHUNIT["metre",1],
##       ID["EPSG",8826]],
##     PARAMETER["Northing at false origin",0,
##       LENGTHUNIT["metre",1],
##       ID["EPSG",8827]]],
##   CS[Cartesian,2],
##     AXIS["easting (X)",east,
##       ORDER[1],
##       LENGTHUNIT["metre",1]],
##     AXIS["northing (Y)",north,
##       ORDER[2],
##       LENGTHUNIT["metre",1]],
##   USAGE[
##     SCOPE["State-wide spatial data management."],
##     AREA["United States (USA) - Florida."],
##     BBOX[24.41,-87.63,31.01,-79.97]],
##     ID["EPSG",3087]]

```

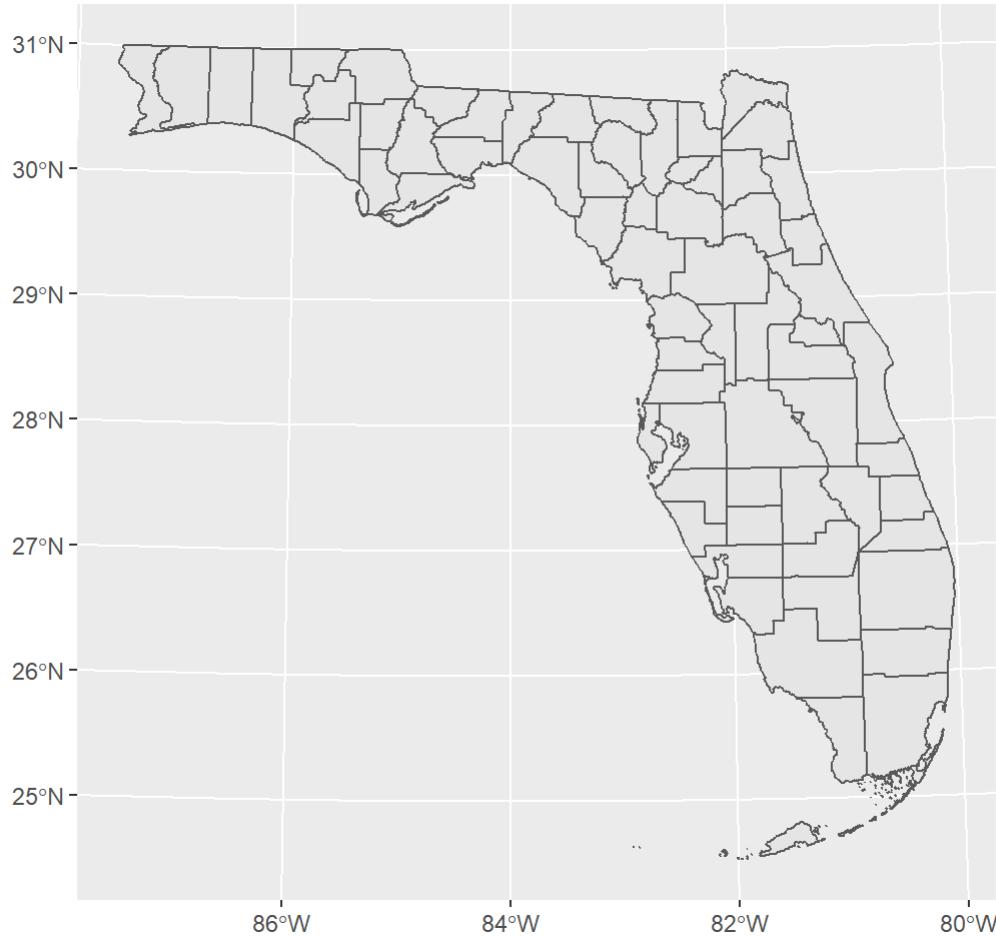
This code above just brings up information on the current CRS.

5.4.2 Plotting with {r eval = FALSE} coord_sf()

The `coord_sf` function allows you to specify a CRS transformation to be used for the visualization. The `coord_sf` will inherit the CRS of the spatial object plotted with the `geom_sf()` function. However it can also change the displayed CRS for an object without performing the CRS transformation with the `st_transform()` function.

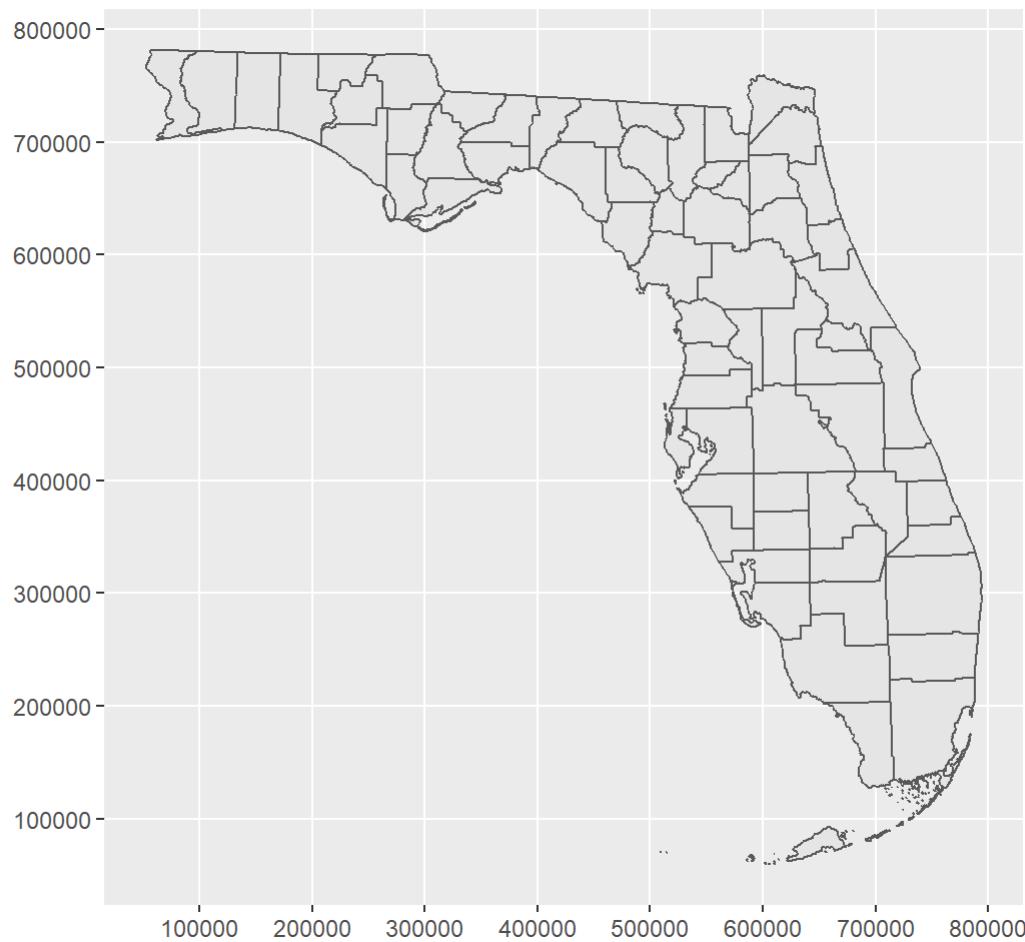
```
options(scipen = 999)

ggplot(f1_counties) +
  geom_sf() +
  coord_sf(crs = 3087)
```



To show the coordinates of the projected coordinate system, the `datum` argument can be used to control the gridlines

```
ggplot(f1_counties) +
  geom_sf() +
  coord_sf(crs = 3087, datum = 3087)
```



5.5 Working with geometries

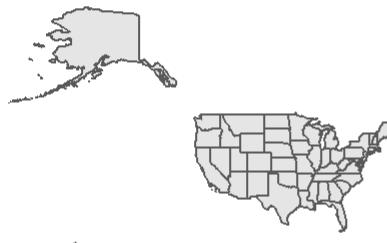
This section details how to manipulate geometries in various ways such as shifting them to different positions, changing the geometry type, and “exploding” multi part geometries into separate units.

5.5.1 Shifting and rescaling geometry for national US mapping

In this example the problem of the United States plotted geometry being very spaced out (islands/territories) is solved.

```
us_states <- states(cb = TRUE, resolution = "20m")

ggplot(us_states) +
  geom_sf() +
  theme_void()
```



The above code plots the default CRS for the United States. This doesn't work too well because of the Aleutian islands in the far west are instead being plotted on the east side of the map. To remedy this a projected coordinate system more appropriate for the United States could be used, in this case I will use the Albers Equal Area projection.

```
ggplot(us_states) +  
  geom_sf() +  
  coord_sf(crs = 'ESRI:102003') +  
  theme_void()
```



projection puts everything in its correct place, however it distorts Alaska, Hawaii, and Puerto Rico. This can be remedied by using the `shift_geometry()` function in `tigris`. This works by projecting geometries in these distorted areas to corrected CRS and then re sizing the geometries and moving them to an alternative layout in relationship to the rest of the United States which is using a different CRS.

```
us_states_shifted <- shift_geometry(us_states)

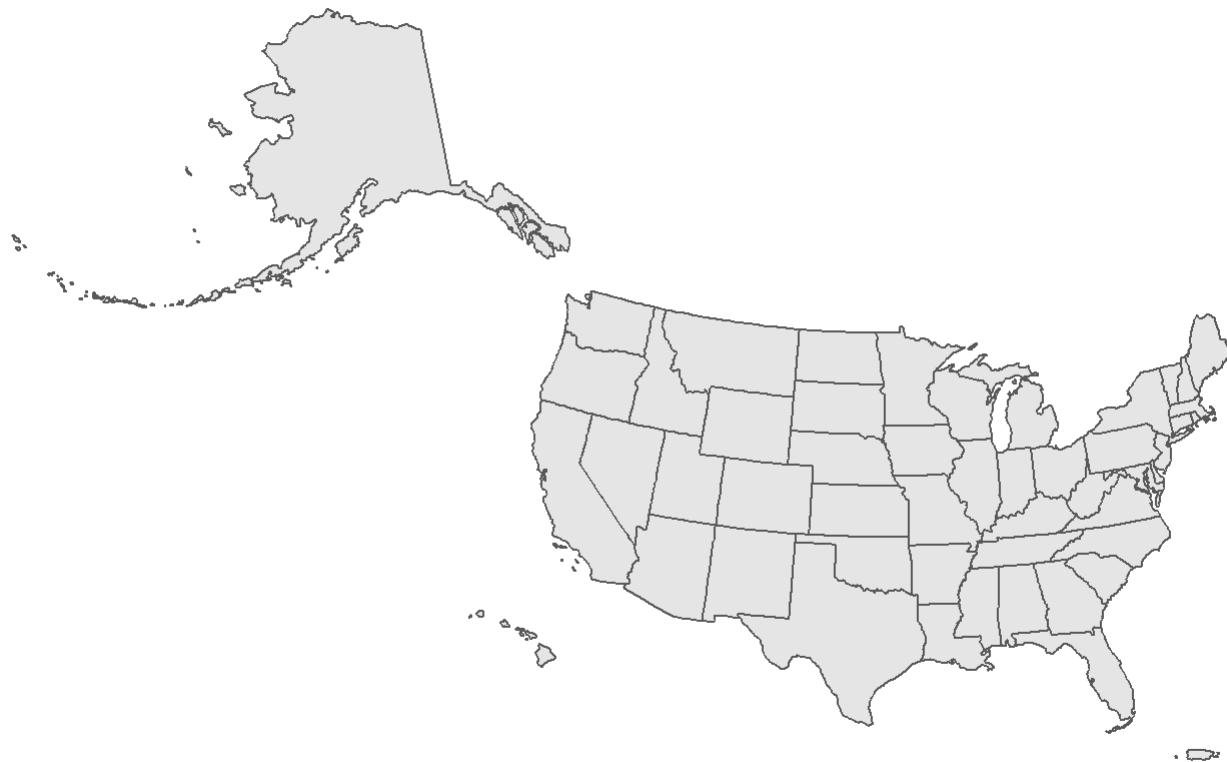
ggplot(us_states_shifted) +
  geom_sf() +
  theme_void()
```



This view uses two default arguments: `preserve_area = FALSE`, which shrinks Alaska and displays Hawaii and PR as bigger. And `position = "below"`, which places them below the continental United States.

```
us_states_outside <- shift_geometry(us_states,
                                      preserve_area = TRUE,
                                      position = "outside")

ggplot(us_states_outside) +
  geom_sf() +
  theme_void()
```



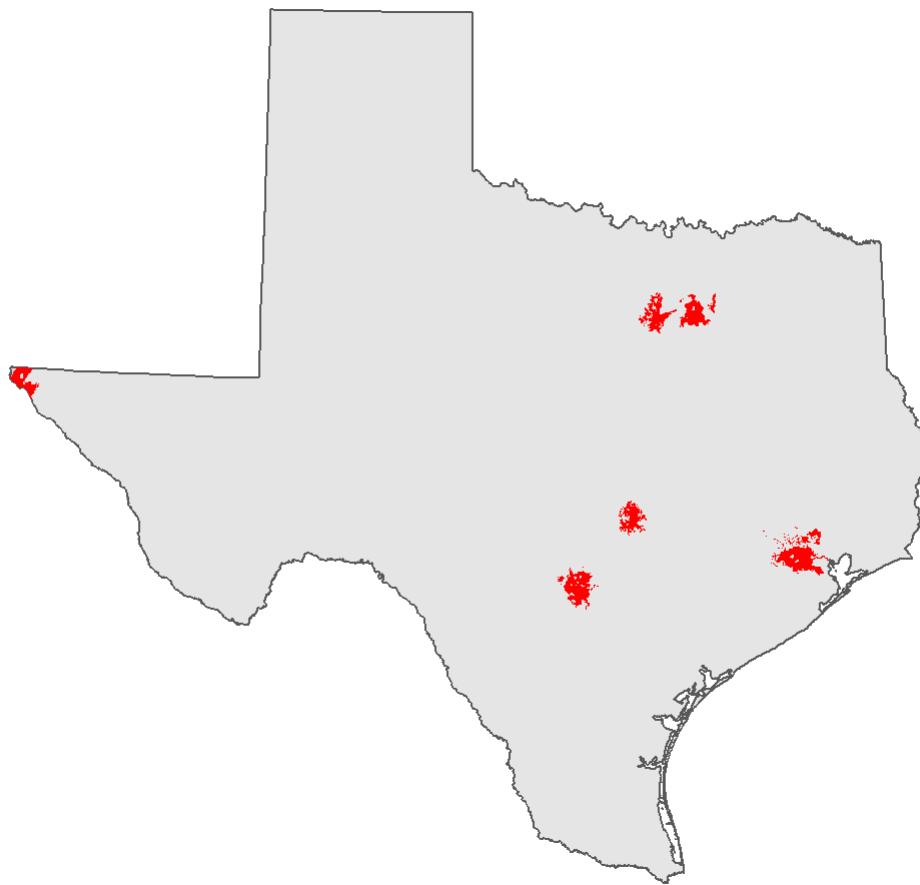
This code just changes the arguments position and preserve_area so that the map is displayed differently. shift_geometry can shift and rescale other geographic data sets for display in this way. It is important to remember however that the same arguments must be used for all layers or they will end up misaligned.

5.5.2 Converting polygons to points

```
tx_places <- places("TX", cb = TRUE) %>%
  filter(NAME %in% c("Dallas", "Fort Worth", "Houston",
                     "Austin", "San Antonio", "El Paso")) %>%
  st_transform(6580)

tx_outline <- states(cb = TRUE) %>%
  filter(NAME == "Texas") %>%
  st_transform(6580)

ggplot() +
  geom_sf(data = tx_outline) +
  geom_sf(data = tx_places, fill = "red", color = NA) +
  theme_void()
```



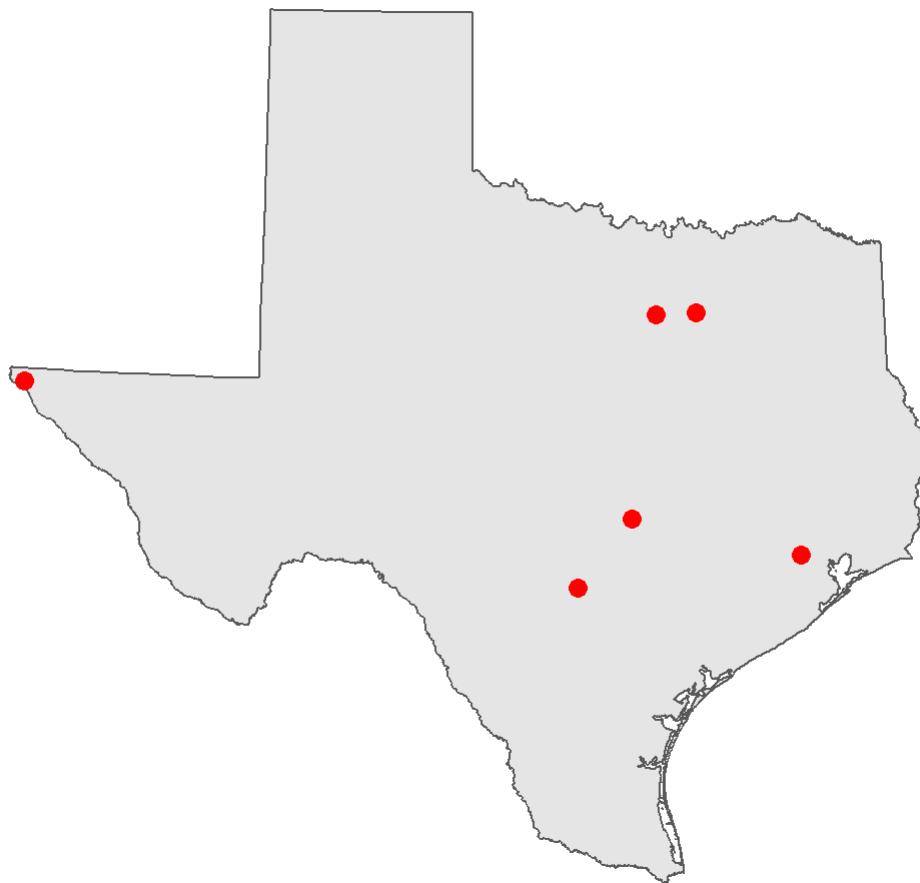
The above code plots the largest cities in Texas as polygons instead of points

This is a problem because cities are irregularly shaped, to fix this the `st_centroid` function is used to convert those polygons to central points.

```
tx_centroids <- st_centroid(tx_places)
```

```
## Warning in st_centroid.sf(tx_places): st_centroid assumes attributes are  
## constant over geometries of x
```

```
ggplot() +  
  geom_sf(data = tx_outline) +  
  geom_sf(data = tx_centroids, color = "red", size = 3) +  
  theme_void()
```

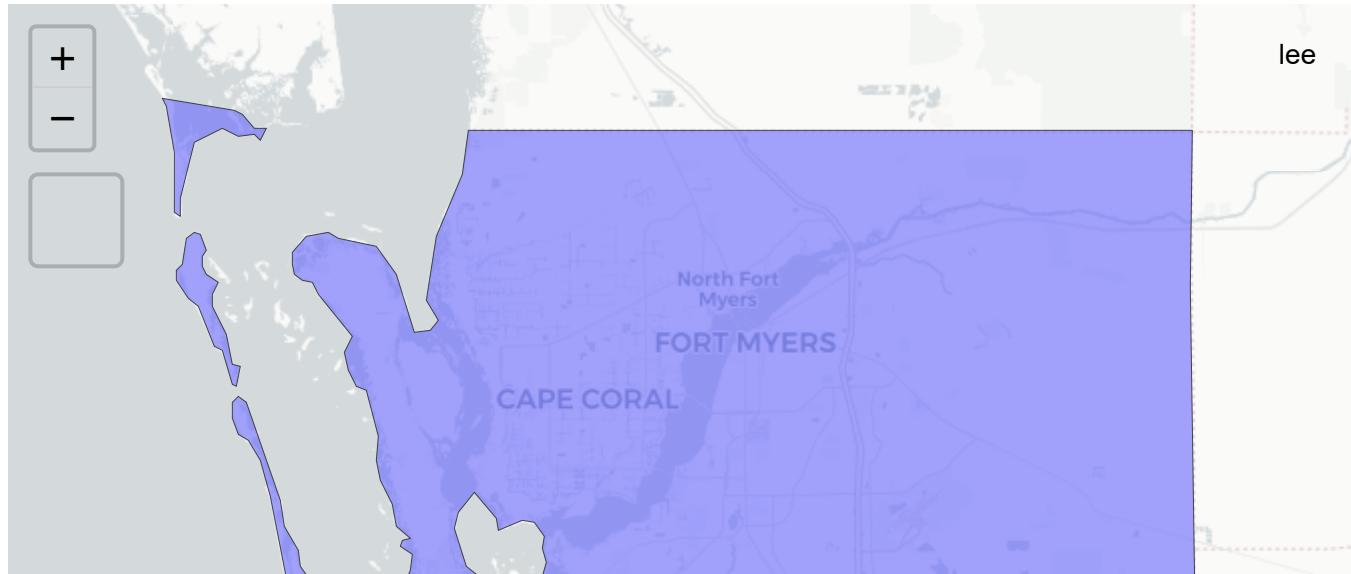


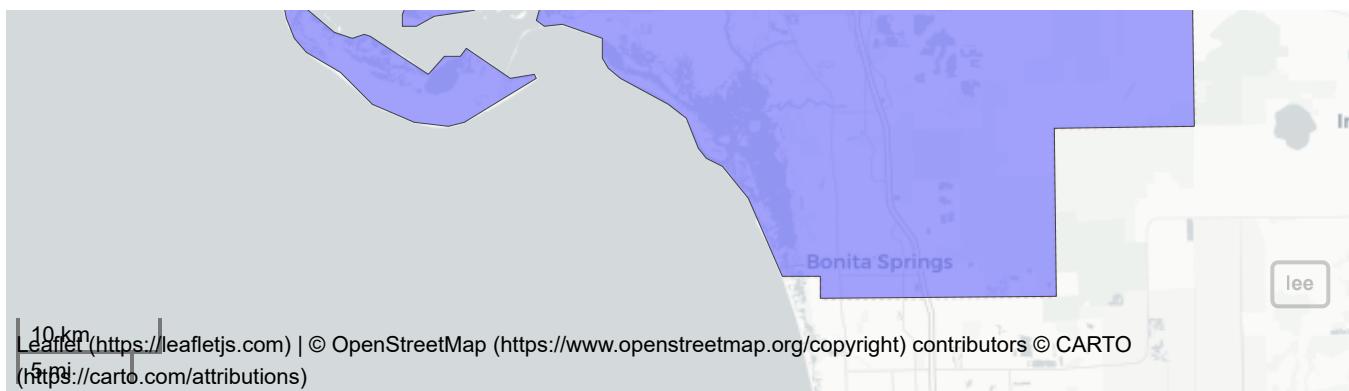
5.5.3 Exploding multipolygon geometries to single parts

In general, census features are returned with the MULTIPOLYGON geometry. This causes census features to include disconnected areas such as islands. This is particularly evident in Florida.

```
lee <- fl_projected %>%
  filter(NAME == "Lee")

mapview(lee)
```





The four distinct polygons can be seen here. R interprets these as one single feature.

Specific parts of the polygon can be extracted by exploding the multipart geometry into individual parts. This is done with the `st_cast` function as shown below.

```
lee_singlepart <- st_cast(lee, "POLYGON")
```

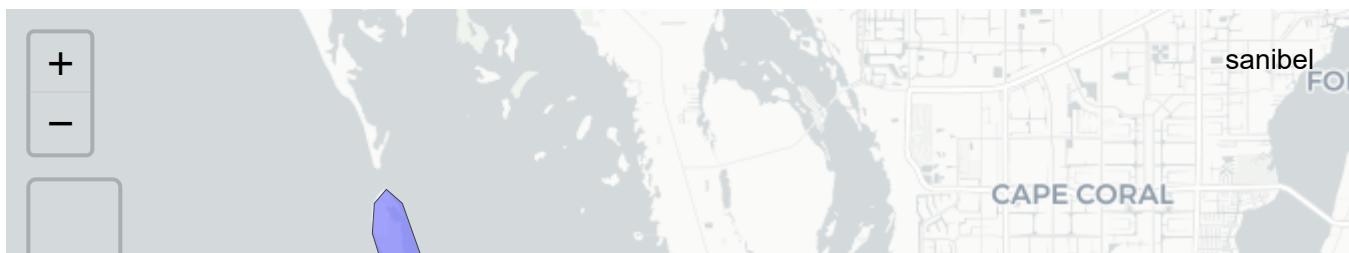
```
## Warning in st_cast.sf(lee, "POLYGON"): repeating attributes for all sub-
## geometries for which they may not be constant
```

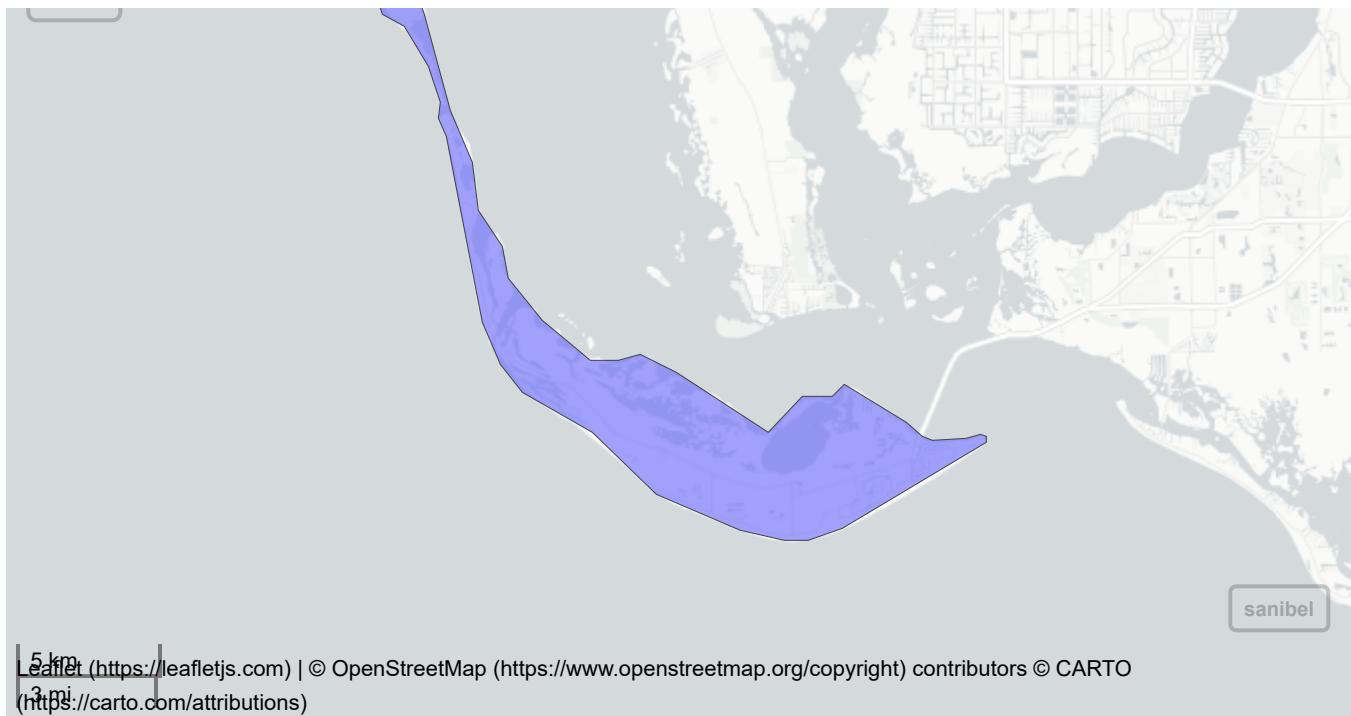
```
lee_singlepart
```

```
## Simple feature collection with 4 features and 9 fields
## Geometry type: POLYGON
## Dimension: XY
## Bounding box: xmin: 571477.3 ymin: 258767.6 xmax: 642721.2 ymax: 310583.5
## Projected CRS: NAD83(HARN) / Florida GDL Albers
##   STATEFP COUNTYFP COUNTYNS      AFFGEOID GEOID NAME LSAD      ALAND
## 1       12     071 00295758 0500000US12071 12071  Lee    06 2023963480
## 1.1     12     071 00295758 0500000US12071 12071  Lee    06 2023963480
## 1.2     12     071 00295758 0500000US12071 12071  Lee    06 2023963480
## 1.3     12     071 00295758 0500000US12071 12071  Lee    06 2023963480
##   AWATER           geometry
## 1 1116067200 POLYGON ((580415.6 300219.1...
## 1.1 1116067200 POLYGON ((576540.7 289935.2...
## 1.2 1116067200 POLYGON ((572595.7 298880.5...
## 1.3 1116067200 POLYGON ((571477.3 310583, ...
```

```
sanibel <- lee_singlepart[2,]
```

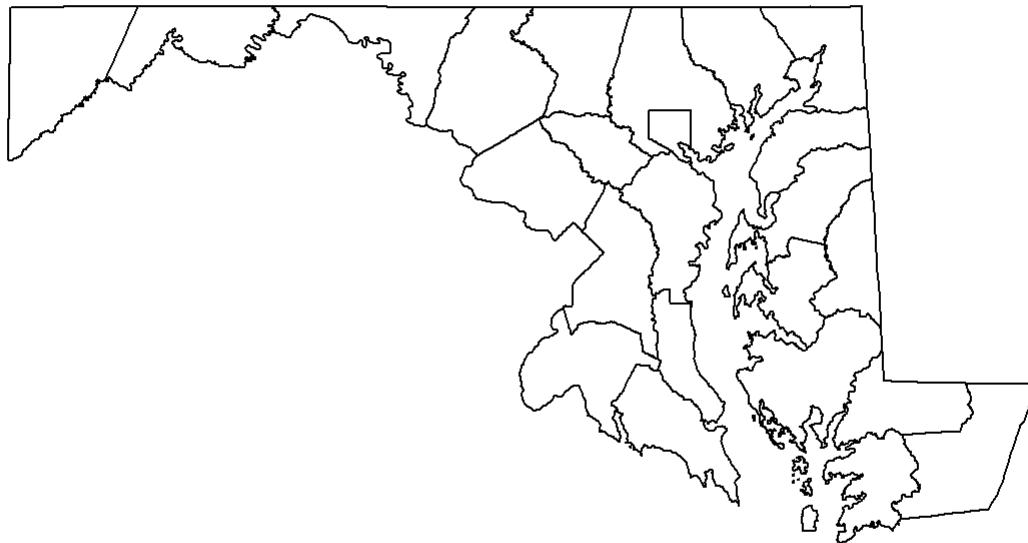
```
mapview(sanibel)
```





5.6 Exercises

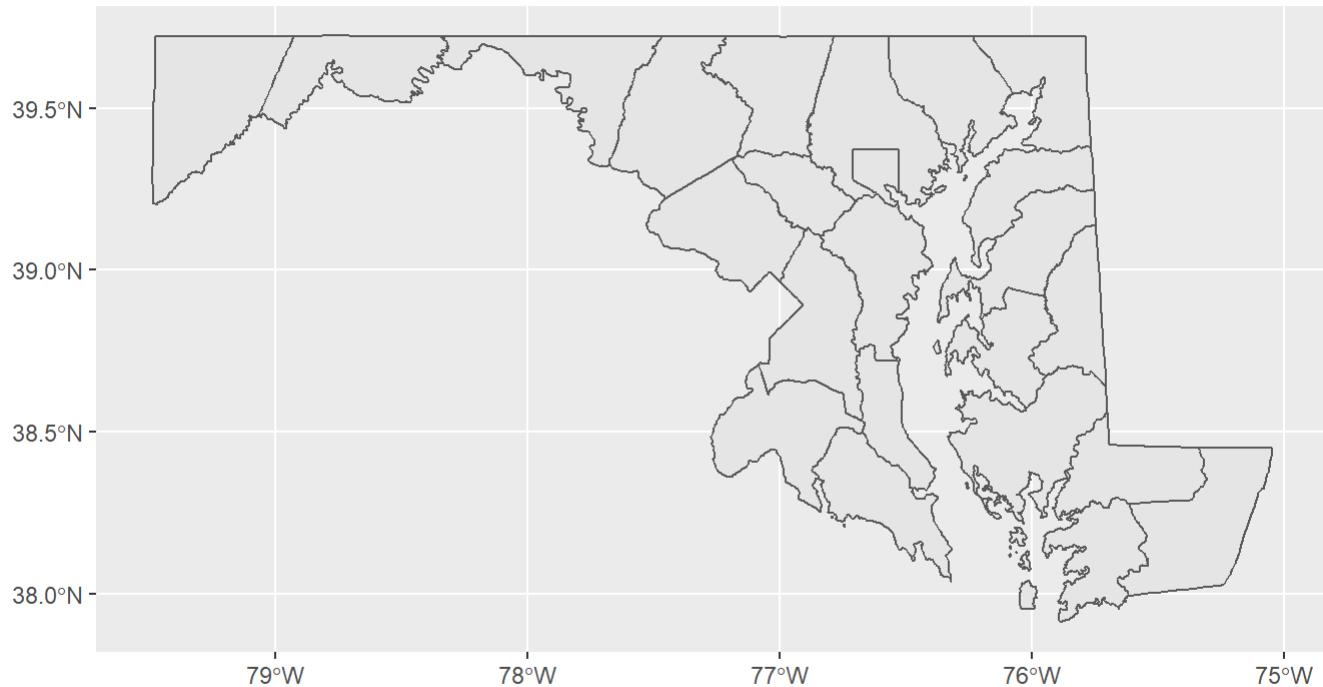
```
MD_counties <- counties(state = "MD", cb = TRUE, year = 2019)
plot(MD_counties$geometry)
```



This code is used to retrieve the tiger/line files for MD counties. Then does a basic plot of them.

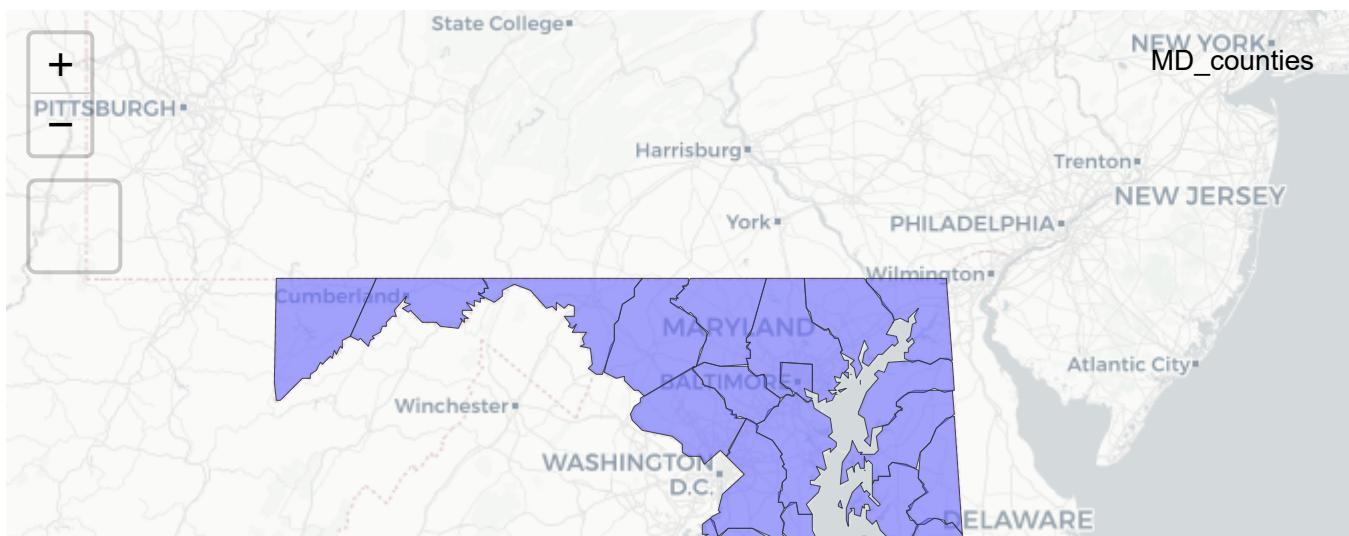
The next chunk of code plots MD_counties with the geom_sf option

```
ggplot(MD_counties) +  
  geom_sf()
```



This chunk of code shows MD counties with mapview

```
mapview(MD_counties)
```





The chunk(s) of code below uses `suggest_crs` to id a coordinate reference system for the data. Then `st_transform` is used to apply the CRS transformation to the data.

```
MD_crs <- suggest_crs(MD_counties)
```

The top suggestion is MD state plane in feet, and its CRS code is 6488

```
MD_projected <- st_transform(MD_counties, crs = 6488)

head(MD_projected)
```

```
## Simple feature collection with 6 features and 9 fields
## Geometry type: MULTIPOLYGON
## Dimension: XY
## Bounding box: xmin: 1120766 ymin: 91210.64 xmax: 1732542 ymax: 748562.5
## Projected CRS: NAD83(2011) / Maryland (ftUS)
##   STATEFP COUNTYFP COUNTYNS      AFFGEOID GEOOID      NAME LSAD     ALAND
## 268      24    035 00596089 05000000US24035 24035 Queen Anne's  06 962673216
## 294      24    005 01695314 05000000US24005 24005 Baltimore  06 1549745106
## 295      24    003 01710958 05000000US24003 24003 Anne Arundel  06 1074353655
## 296      24    013 01696228 05000000US24013 24013 Carroll    06 1159352918
## 297      24    021 01711211 05000000US24021 24021 Frederick  06 1710755614
## 298      24    039 00596907 05000000US24039 24039 Somerset  06 828145299
##   AWATER           geometry
## 268 360020725 MULTIPOLYGON (((1525983 453...
## 294 215959023 MULTIPOLYGON (((1503117 600...
## 295 448033072 MULTIPOLYGON (((1357636 523...
## 296 13112465 MULTIPOLYGON (((1224599 718...
## 297 17840723 MULTIPOLYGON (((1120766 604...
## 298 752652868 MULTIPOLYGON (((1611578 173...
```

Chapter 6

Tommy Phipps

6 Mapping Census data with R

Topics covered in this chapter:

Downloading geographic data with `tidycensus` ‘geometry’ parameter

Static maps with `ggplot2` and `tmap` packages

Interactive maps with `mapview` and `leaflet` packages

6.1 Using geometry in `tidycensus`

```
readRenviron("~/Renviron")
library(tidycensus)
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
```

```
## Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
```

```
options(tigris_use_cache = TRUE)

dc_income <- get_acs(
  geography = "tract",
  variables = "B19013_001",
  state = "DC",
  geometry = TRUE
)
```

```
## Getting data from the 2015-2019 5-year ACS
```

```
dc_income
```

```

## Simple feature collection with 179 features and 5 fields
## Geometry type: POLYGON
## Dimension: XY
## Bounding box: xmin: -77.11976 ymin: 38.79164 xmax: -76.9094 ymax: 38.99511
## Geodetic CRS: NAD83
## First 10 features:
##           GEOID          NAME
## 1 11001009509 Census Tract 95.09, District of Columbia, District of Columbia
## 2 11001010100 Census Tract 101, District of Columbia, District of Columbia
## 3 11001008301 Census Tract 83.01, District of Columbia, District of Columbia
## 4 11001002101 Census Tract 21.01, District of Columbia, District of Columbia
## 5 11001004100 Census Tract 41, District of Columbia, District of Columbia
## 6 11001008001 Census Tract 80.01, District of Columbia, District of Columbia
## 7 11001002900 Census Tract 29, District of Columbia, District of Columbia
## 8 11001005600 Census Tract 56, District of Columbia, District of Columbia
## 9 11001007605 Census Tract 76.05, District of Columbia, District of Columbia
## 10 11001005900 Census Tract 59, District of Columbia, District of Columbia
##           variable estimate    moe      geometry
## 1 B19013_001    75515 19621 POLYGON (((-77.00201 38.9510...
## 2 B19013_001    94861 16089 POLYGON (((-77.03653 38.9056...
## 3 B19013_001   138487 30838 POLYGON (((-77.00352 38.9000...
## 4 B19013_001    67984 11327 POLYGON (((-77.02803 38.9610...
## 5 B19013_001   156625 27218 POLYGON (((-77.05832 38.9177...
## 6 B19013_001   154423 28910 POLYGON (((-76.99025 38.8973...
## 7 B19013_001   116875 20769 POLYGON (((-77.03273 38.9341...
## 8 B19013_001    79357 16304 POLYGON (((-77.05779 38.9025...
## 9 B19013_001    38659  7543 POLYGON (((-76.98436 38.8666...
## 10 B19013_001   98750 21107 POLYGON (((-77.01901 38.8946...

```

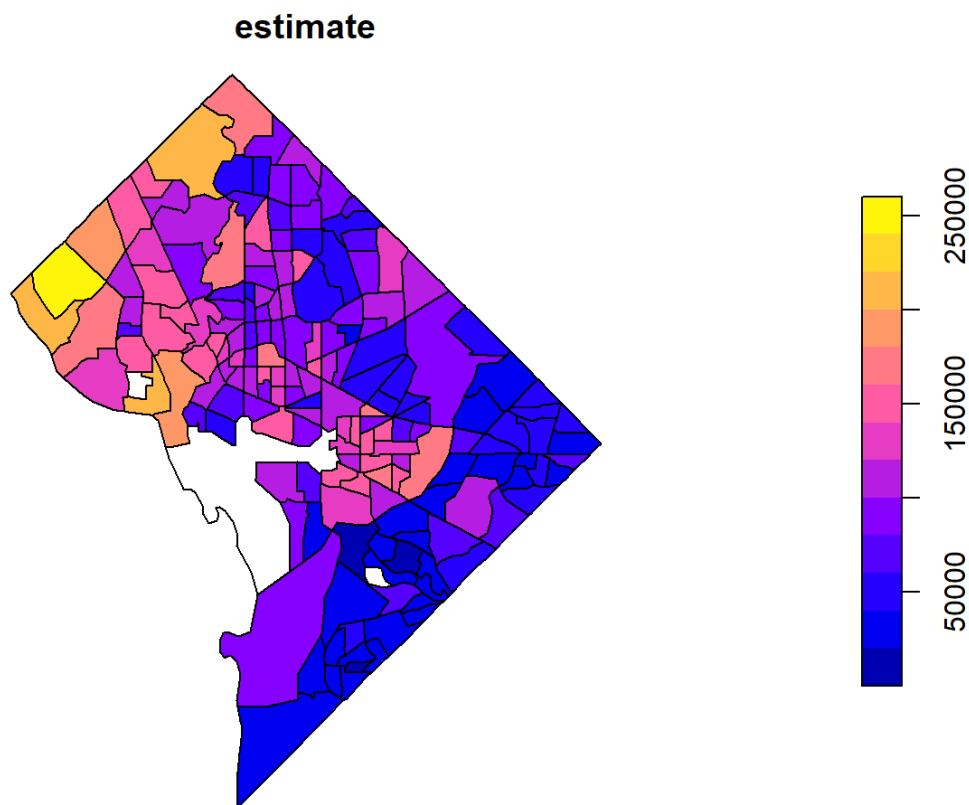
This retrieves median household income by census tract for DC and simple geographic data then caches it with tigris_use_cache function

6.1.1 Basic mapping of sf objects with plot()

visualize geographies attributes with plot by specifying column in brackets

ex. here is DC income

```
plot(dc_income["estimate"])
```



6.2 Map-making with ggplot2 and geom_sf

making custom maps with ggplot2

6.2.1 Choropleth mapping

Making choropleth maps with tidy census and ggplot2

```
library(tidycensus)
library(tidyverse)

## -- Attaching packages ----- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.8
## v tidyrr   1.2.0     v stringr 1.4.0
## v readr    2.1.2     vforcats 0.5.1

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()   masks stats::lag()

library(tigris)

## To enable
## caching of data, set `options(tigris_use_cache = TRUE)` in your R script or .Rprofile.
```

```
##  
## Attaching package: 'tigris'
```

```
## The following object is masked from 'package:tidycensus':  
##  
##     fips_codes
```

```
us_median_age <- get_acs(  
  geography = "state",  
  variables = "B01002_001",  
  year = 2019,  
  survey = "acs1",  
  geometry = TRUE,  
  resolution = "20m"  
) %>%  
  shift_geometry()
```

```
## The 1-year ACS provides data for geographies with populations of 65,000 and greater.
```

```
## Getting data from the 2019 1-year ACS
```

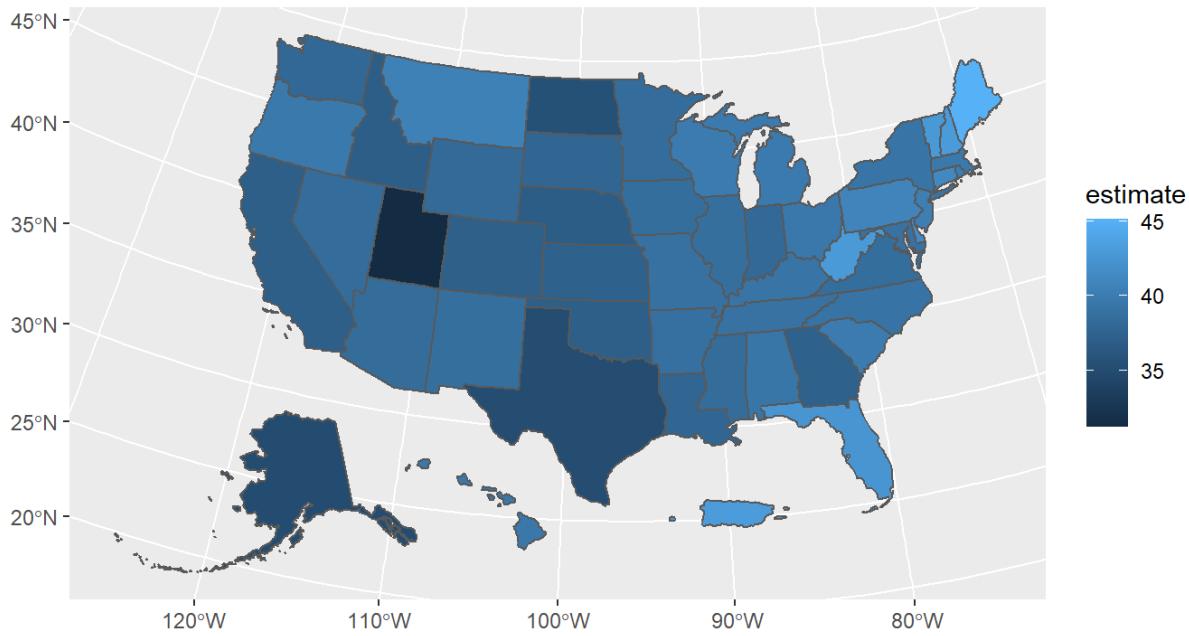
```
plot(us_median_age$geometry)
```



Retrieves median age by state then plots geomerty with tigris

Then styled with ggplot:

```
ggplot(data = us_median_age, aes(fill = estimate)) +  
  geom_sf()
```

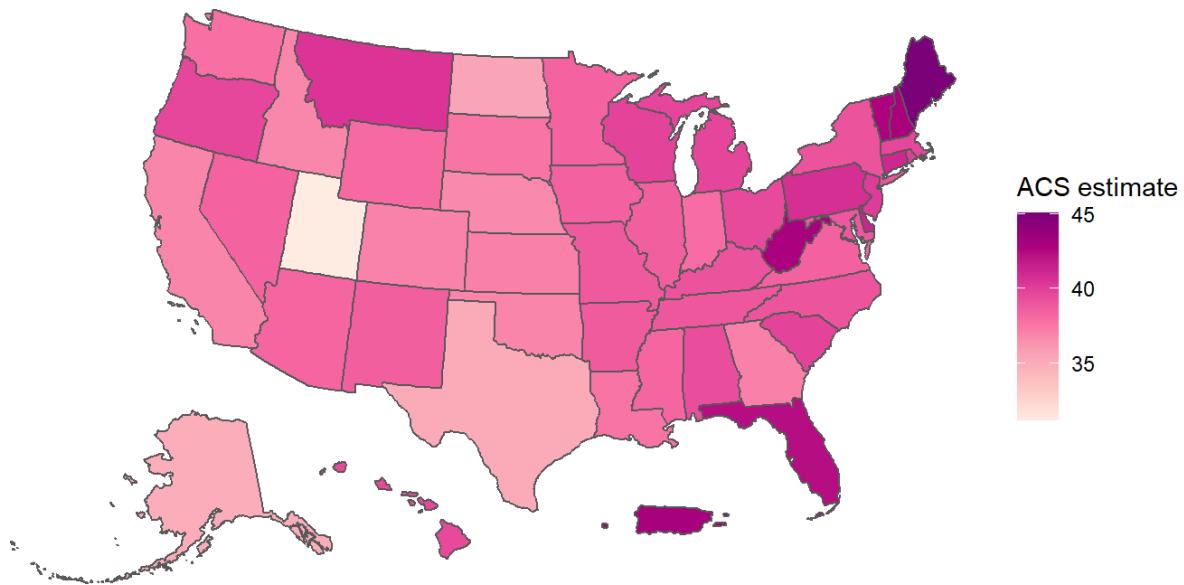


6.2.2 Customizing ggplot2 maps

Styling the map with ggplot2, changing the color palette, adjusting color ramp, adding legend, title, caption

```
ggplot(data = us_median_age, aes(fill = estimate)) +  
  geom_sf() +  
  scale_fill_distiller(palette = "RdPu",  
                      direction = 1) +  
  labs(title = " Median Age by State, 2019",  
       caption = "Data source: 2019 1-year ACS, US Census Bureau",  
       fill = "ACS estimate") +  
  theme_void()
```

Median Age by State, 2019



Data source: 2019 1-year ACS, US Census Bureau

6.3 Map-making with tmap

Visualizing data with tmap

Get ACS data on race and ethnicity for non-Hispanic white, non-Hispanic Black, Asian, and Hispanic populations for Census tracts in Hennepin County, Minnesota.

```
hennepin_race <- get_acs(
  geography = "tract",
  state = "MN",
  county = "Hennepin",
  variables = c(White = "B03002_003",
              Black = "B03002_004",
              Native = "B03002_005",
              Asian = "B03002_006",
              Hispanic = "B03002_012"),
  summary_var = "B03002_001",
  geometry = TRUE
) %>%
  mutate(percent = 100 * (estimate / summary_est))
```

```
## Getting data from the 2015-2019 5-year ACS
```

6.3.1 Choropleth maps with tmap

```
library(tmap)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
## (GDAL error 1)

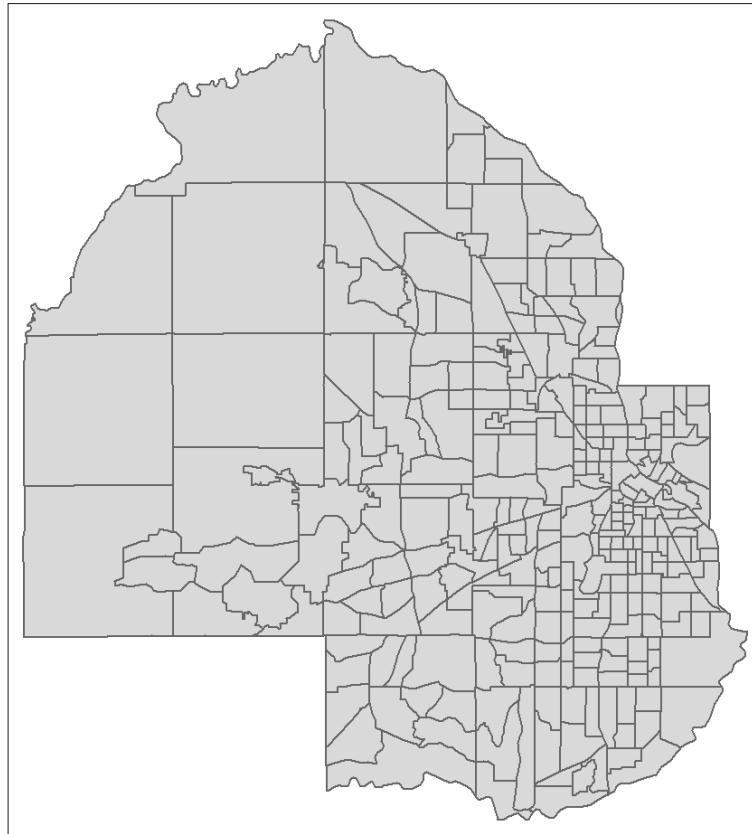
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

```
## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
## (GDAL error 1)

## Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll
## 126: The specified module could not be found.
## (GDAL error 1)
```

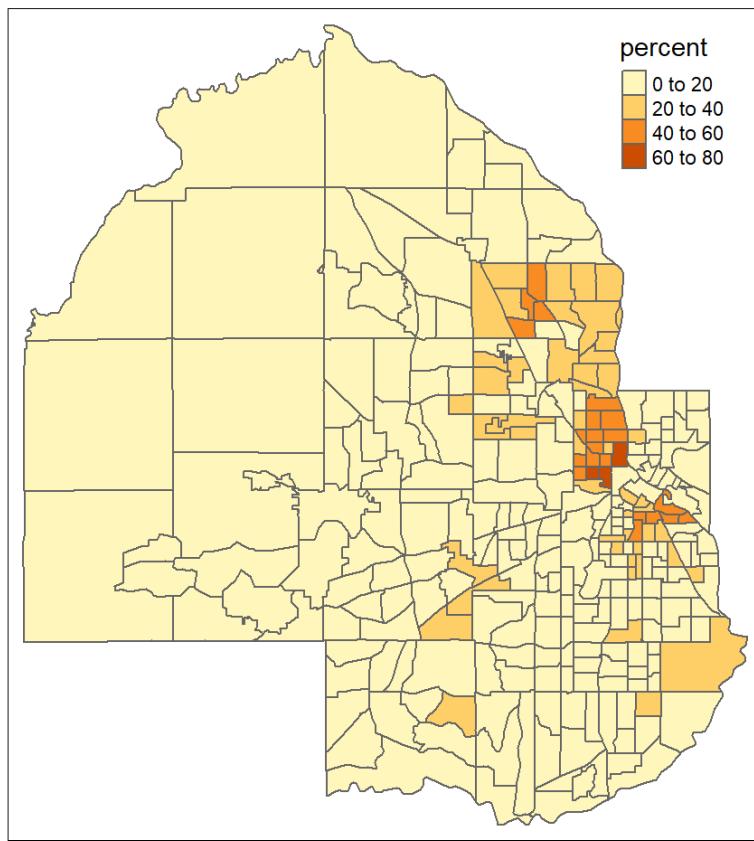
```
hennepin_black <- filter(hennepin_race,
                           variable == "Black")

tm_shape(hennepin_black) +
  tm_polygons()
```



This syntax initializes the map with `tm_shape` then allows us to view Census tracts with `tm_polygons`. The result is a map of census tracks in Hennepin county Minnesota

```
tm_shape(hennepin_black) +
  tm_polygons(col = "percent")
```

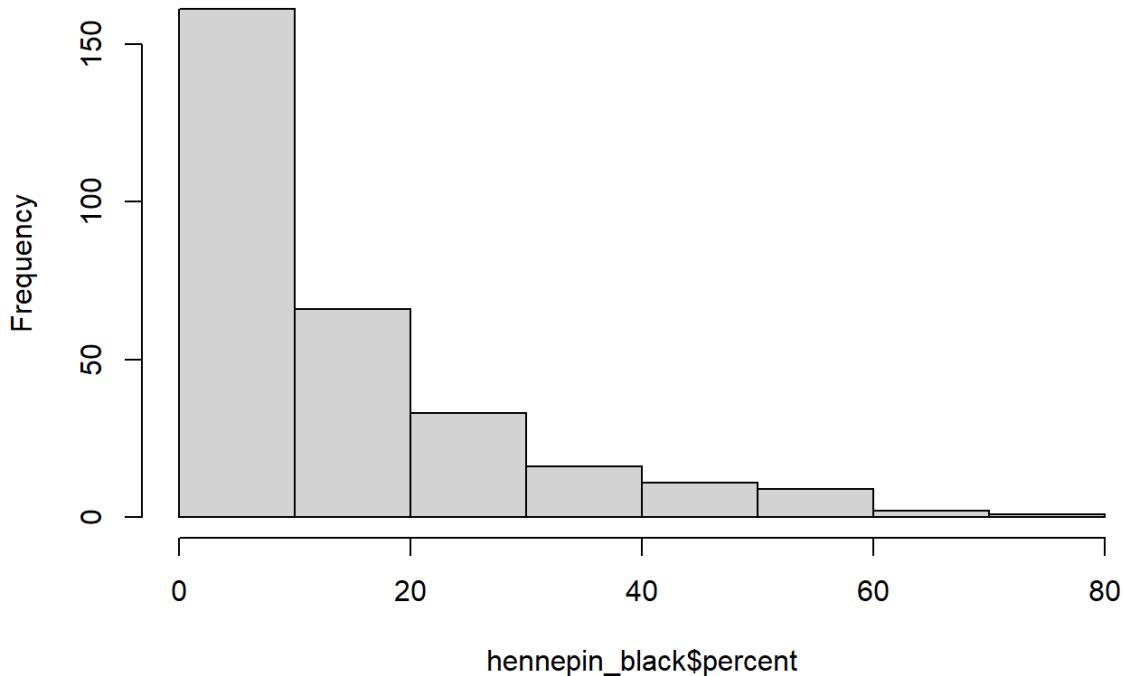


the tmn_fill function is used to produce the choropleth map notice how a class color system is used instead of a continuous palette used like in ggplot2 by default tmn_fill uses “pretty” as the default classification scheme which is clean looking intervals in the data

this can be seen in the data distribution below

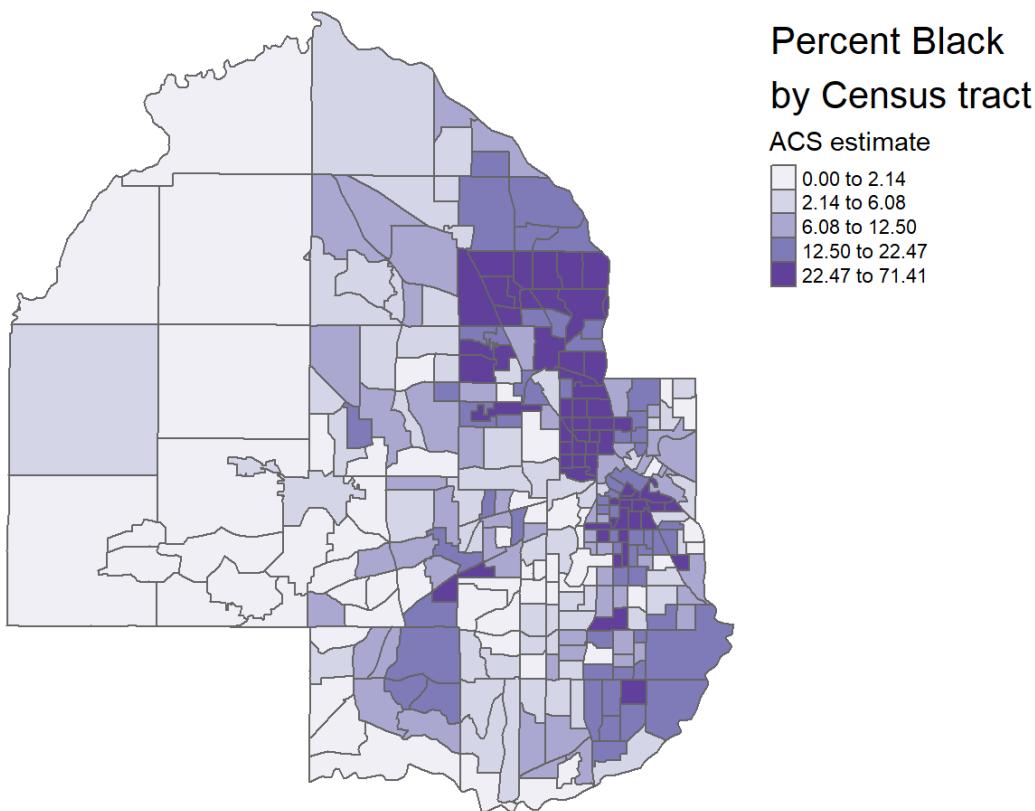
```
hist(hennepin_black$percent)
```

Histogram of hennepin_black\$percent



The code below changes the color palette and adds some supporting text to the map

```
tm_shape(hennepin_black,
         projection = sf::st_crs(26915)) +
  tm_polygons(col = "percent",
              style = "quantile",
              n = 5,
              palette = "Purples",
              title = "ACS estimate") +
  tm_layout(title = "Percent Black\nby Census tract",
            frame = FALSE,
            legend.outside = TRUE)
```



This also changes the classification scheme to quantile

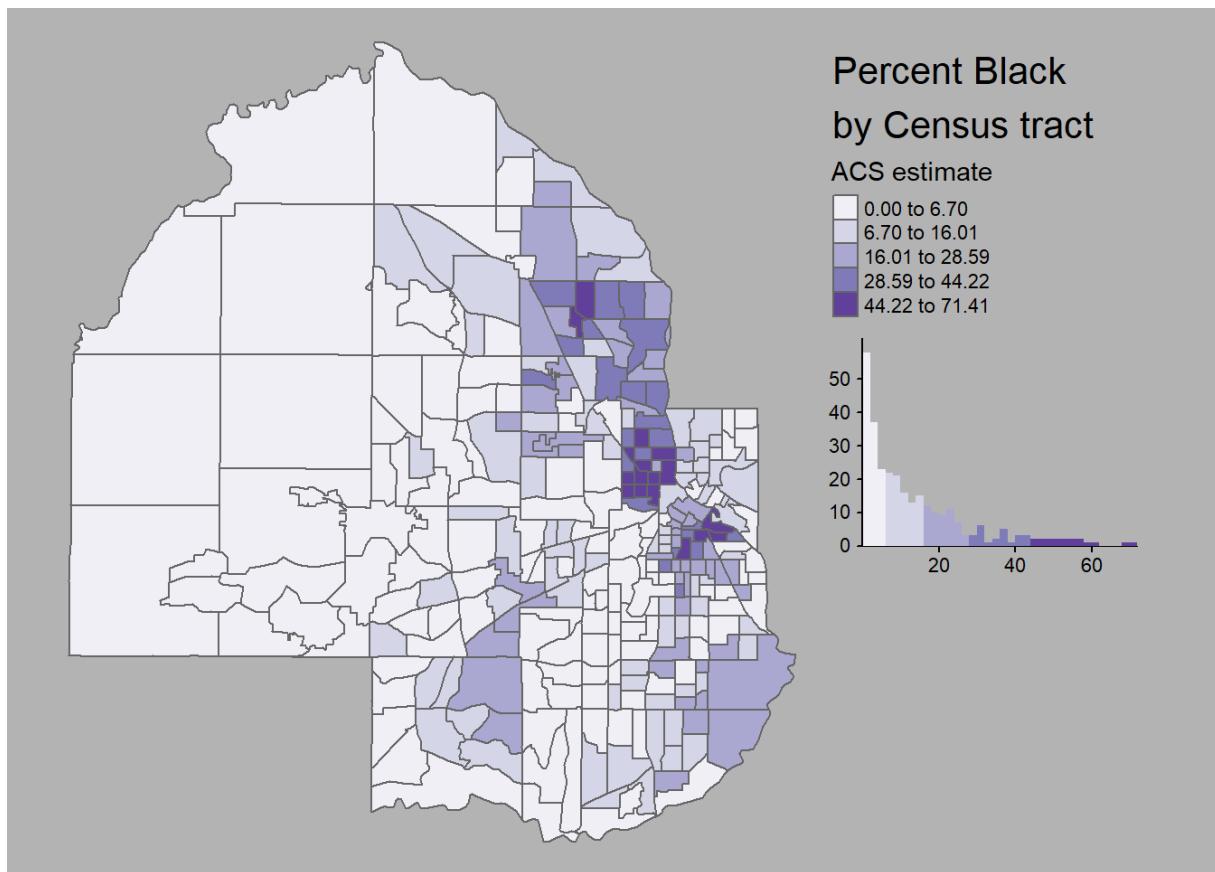
Now the code below will change it to the jenks-natural break method

```
tm_shape(hennepin_black,
  projection = sf::st_crs(26915)) +
tm_polygons(col = "percent",
  style = "jenks",
  n = 5,
  palette = "Purples",
  title = "ACS estimate",
  legend.hist = TRUE) +
tm_layout(title = "Percent Black\nby Census tract",
  frame = FALSE,
  legend.outside = TRUE,
  bg.color = "grey70",
  legend.hist.width = 5,
  fontfamily = "Verdana")
```

```
## Warning in grid.Call.graphics(C_text, as.graphicsAnnot(x$label), x$x, x$y, :
## font family not found in Windows font database

## Warning in grid.Call.graphics(C_text, as.graphicsAnnot(x$label), x$x, x$y, :
## font family not found in Windows font database

## Warning in grid.Call.graphics(C_text, as.graphicsAnnot(x$label), x$x, x$y, :
## font family not found in Windows font database
```



6.3.2 Adding reference elements to a map

This section goes over adding various reference elements to a map with tmap package tmap includes a read function to acquire basemap tiles from Openstreet Map read-osm

the example below uses the mapboxapi r package

```
install.packages("tmap") install.packages("mapboxapi") library(mapboxapi) # Replace with your token below
mb_access_token("pk.eyJ1IjoicGhpcHAyliwiYSI6ImNrend6dWJ4MzhjZXQybnBoOTloNTVmbG0ifQ.ewQp3Evgkg__j90jLXMbpQ")
install = TRUE

hennepin_tiles <- get_static_tiles( location = hennepin_black, zoom = 10, style_id = "light-v9", username = "mapbox" )
```

6.4 Cartographic workflows with non-Census data

6.4.1 National election mapping with tigris shapes

```
getwd()

## [1] "G:/My Drive/GES_486/Lab_3"

# Library(tidyverse)
# library(tigris)

# Data source: https://cookpolitical.com/2020-national-popular-vote-tracker
#vote2020 <- read_csv("/Volumes/GoogleDrive/My Drive/GES_486/Lab_3/us_vote_2020.csv")

#names(vote2020)
```

this code retrieves data for 2020 election results

```
#us_states <- states(cb = TRUE, resolution = "20m") %>%
# filter(NAME != "Puerto Rico") %>%
#shift_geometry()

#us_states_joined <- us_states %>%
#left_join(vote2020, by = c("NAME" = "state"))
```

this code brings geography in from tigris, then rescaling and merging political data to the map

```
#table(is.na(us_states_joined$state))
```

code to check that name and state geography are matched correctly

```
# ggplot(us_states_joined, aes(fill = called)) +
#   geom_sf(color = "white", Lwd = 0.2) +
#   scale_fill_manual(values = c("blue", "red")) +
#   theme_void() +
#   Labs(fill = "Party",
#        title = " 2020 US presidential election results by state",
#        caption = "Note: Nebraska and Maine split electoral college votes by congressional district")
```

use ggplot to format the map and add color values

6.4.2 Understanding and working with ZCTAs

```
irs_data <- read_csv("https://www.irs.gov/pub/irs-soi/18zpallnoagi.csv")
```

```
## Rows: 27658 Columns: 153
## -- Column specification -----
## Delimiter: ","
## chr  (3): STATEFIPS, STATE, ZIPCODE
## dbl (150): AGI_STUB, N1, MARS1, MARS2, MARS4, ELF, CPREP, PREP, DIR_DEP, N2, ...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
ncol(irs_data)
```

```
## [1] 153
```

read data from IRS income data

```
self_employment <- irs_data %>%
  select(ZIPCODE, self_emp = N09400, total = N1)
```

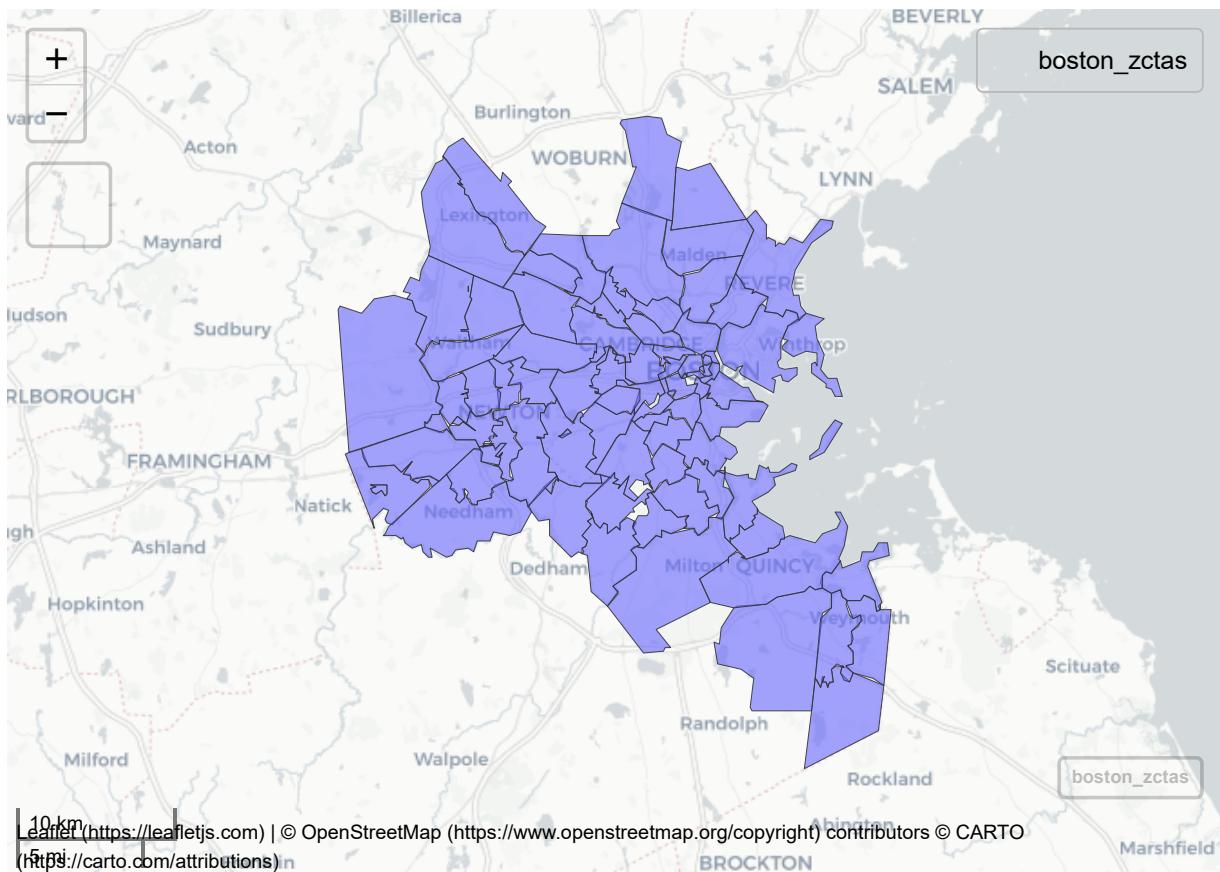
retreive irs data for self empolyment tax returns by zipcode

```
library(mapview)
library(tigris)
options(tigris_use_cache = TRUE)

boston_zctas <- zctas(
  cb = TRUE,
  starts_with = c("021", "022", "024"),
  year = 2018
)
```

Fetch zip code tabulation areas near boston with zctas then examine with mapview

```
mapview(boston_zctas)
```



```
names(boston_zctas)
```

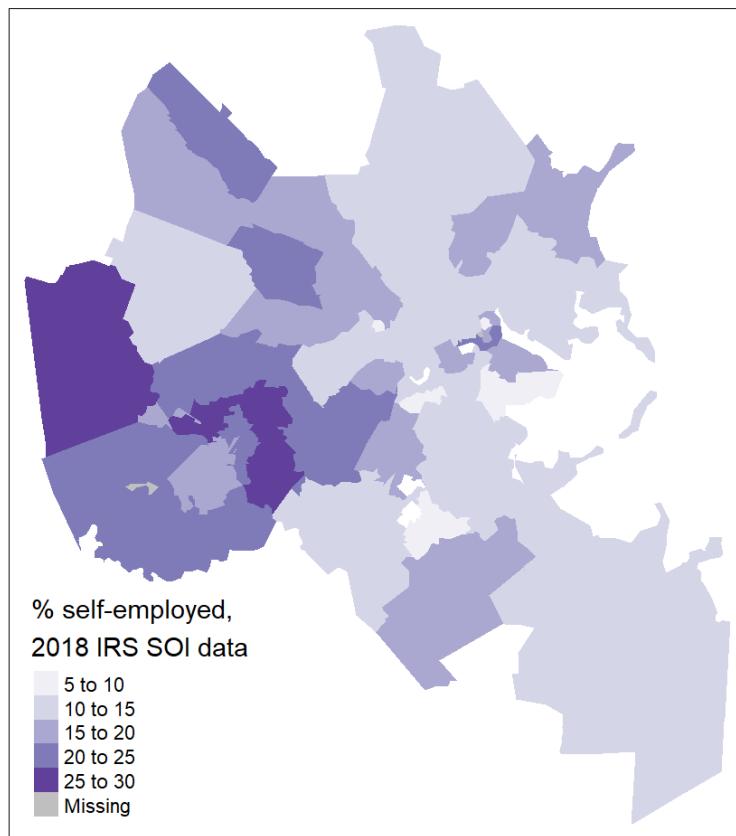
```
## [1] "ZCTA5CE10"   "AFFGEOID10"  "GEOID10"      "ALAND10"      "AWATER10"
## [6] "geometry"
```

code above examine attributes

```
boston_se_data <- boston_zctas %>%
  left_join(self_employment, by = c("GEOID10" = "ZIPCODE")) %>%
  mutate(pct_self_emp = 100 * (self_emp / total)) %>%
  select(GEOID10, self_emp, pct_self_emp)
```

the code above joins the IRS data to the spatial dataset and creates a new column representing the percentage of returns with self-employment income

```
library(tmap)
tm_shape(boston_se_data, projection = 26918) +
  tm_fill(col = "pct_self_emp",
          palette = "Purples",
          title = "% self-employed,\n2018 IRS SOI data")
```

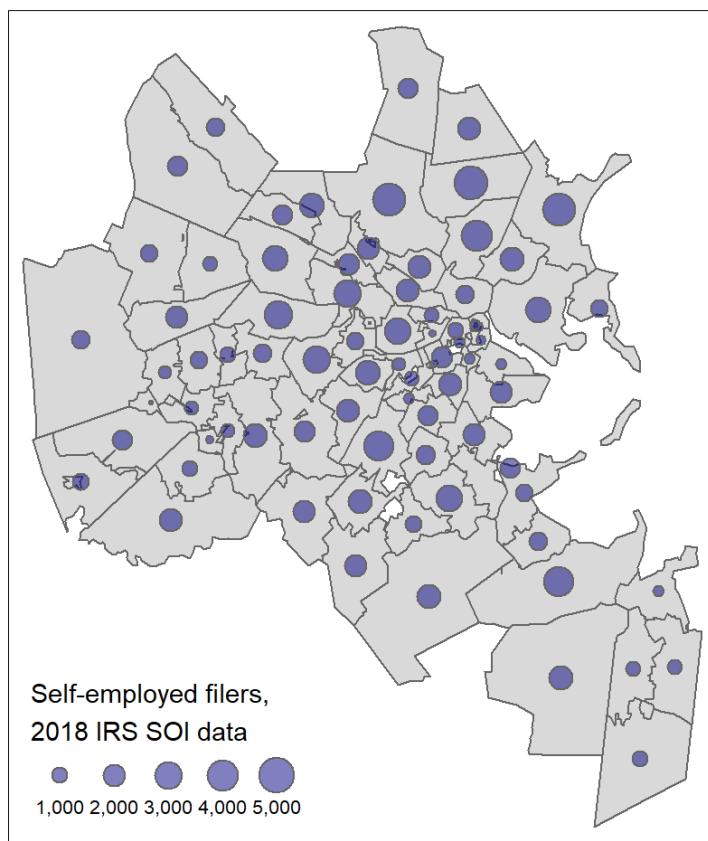


now this data can be visualized into a choropleth map

the code below changes it to a graduated symbol map

```
tm_shape(boston_se_data) +
  tm_polygons() +
  tm_bubbles(size = "self_emp",
             alpha = 0.5,
             col = "navy",
             title.size = "Self-employed filers,\n2018 IRS SOI data")
```

Legend labels were too wide. Therefore, legend.text.size has been set to 0.66. Increase legend.width (argument of tm_layout) to make the legend wider and therefore the labels larger.



6.5 Interactive mapping

making interactive maps with census data

6.5.1 Interactive mapping with Leaflet

visualize census data in an interactive leaflet map using mapview, tmap, leaflet

```
library(tidycensus)
dallas_bachelors <- get_acs(
  geography = "tract",
  variables = "DP02_0068P",
  year = 2019,
  state = "TX",
  county = "Dallas",
  geometry = TRUE
)
```

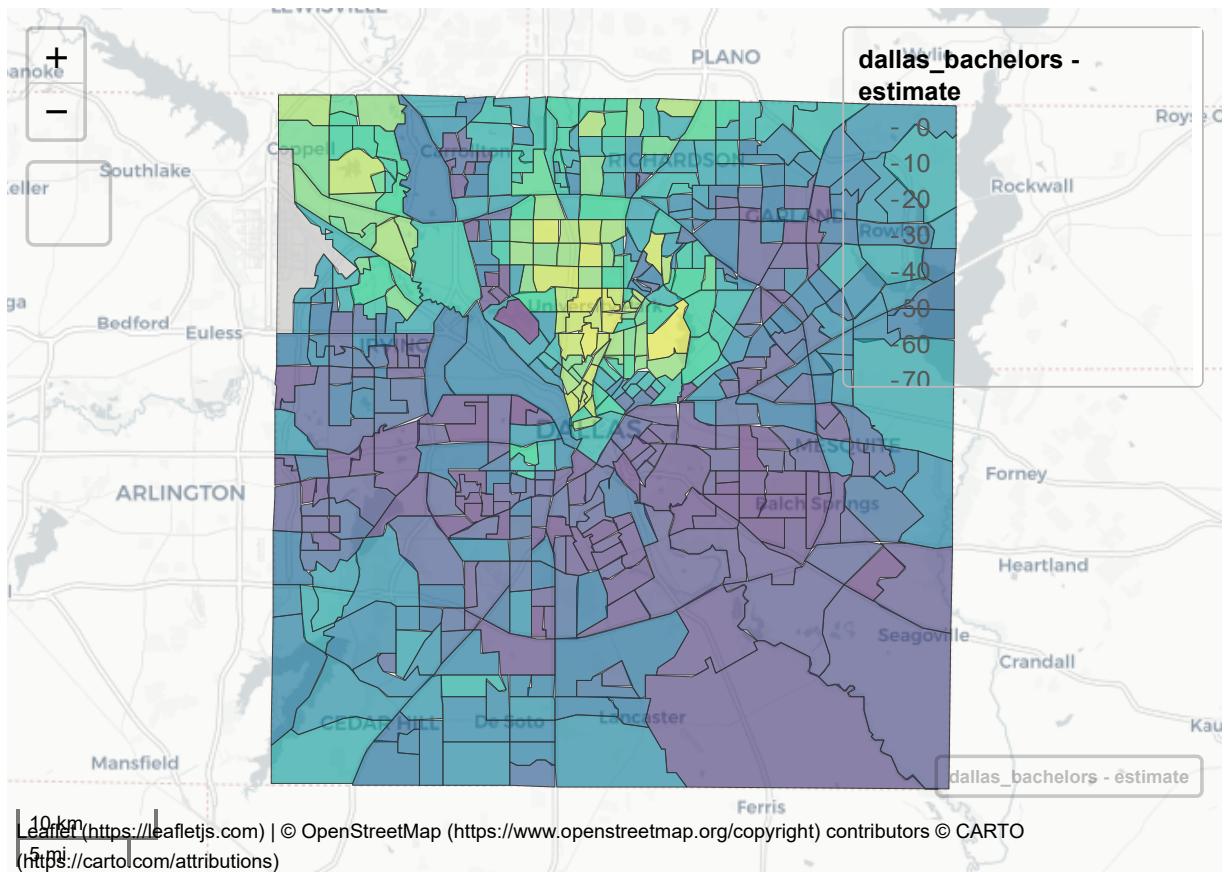
```
## Getting data from the 2015-2019 5-year ACS
```

```
## Using the ACS Data Profile
```

Get data for the percentage of the population aged 25 and up with a bachelor's degree or higher from the 2015-2019 ACS in Dallas TX

visualzie data below with mapview

```
library(mapview)
mapview(dallas_bachelors, zcol = "estimate")
```

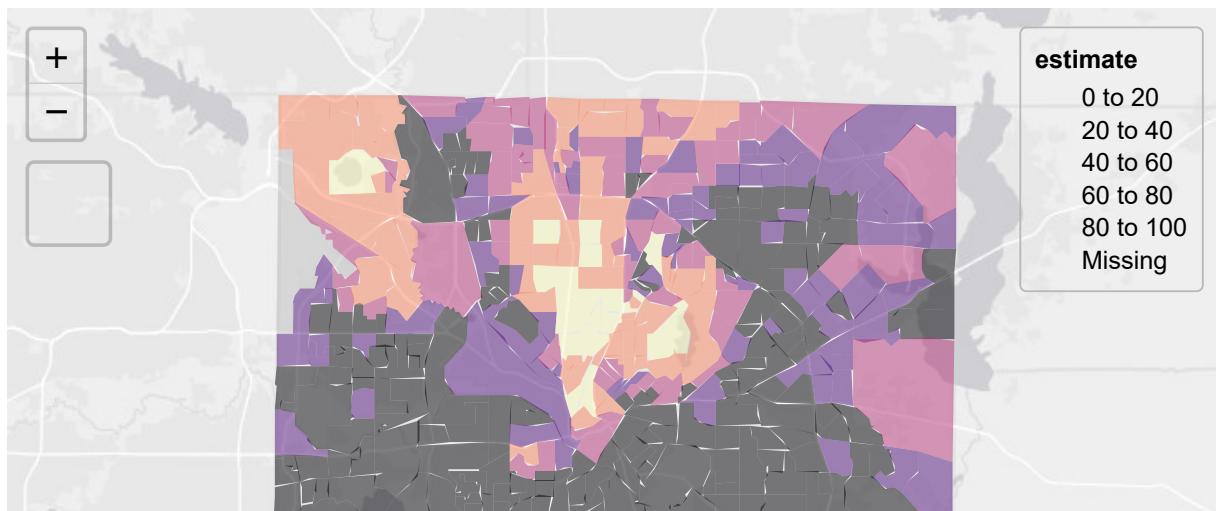


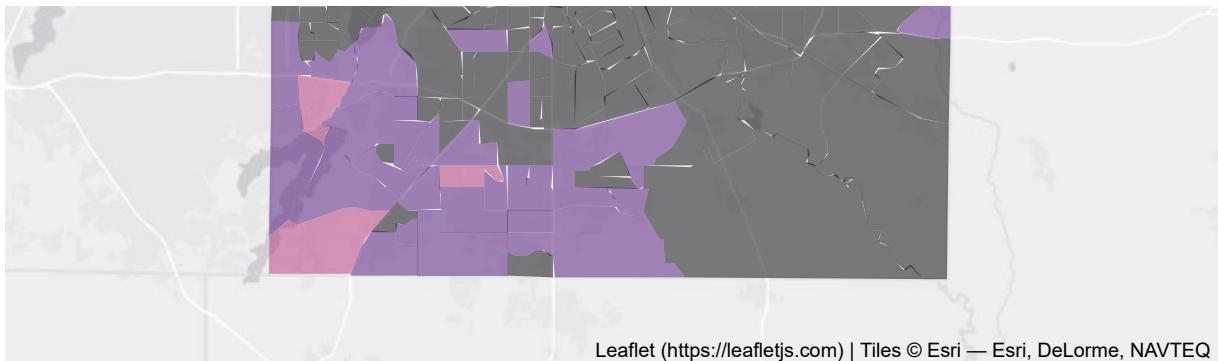
This code below now converts all subsequent maps in this session to leaflet interactive maps

```
library(tmap)
tmap_mode("view")
```

```
## tmap mode set to interactive viewing
```

```
tm_shape(dallas_bachelors) +
  tm_fill(col = "estimate", palette = "magma",
         alpha = 0.5)
```





Next this code below is run to format the map further. This code below changes the color palette

```
library(leaflet)

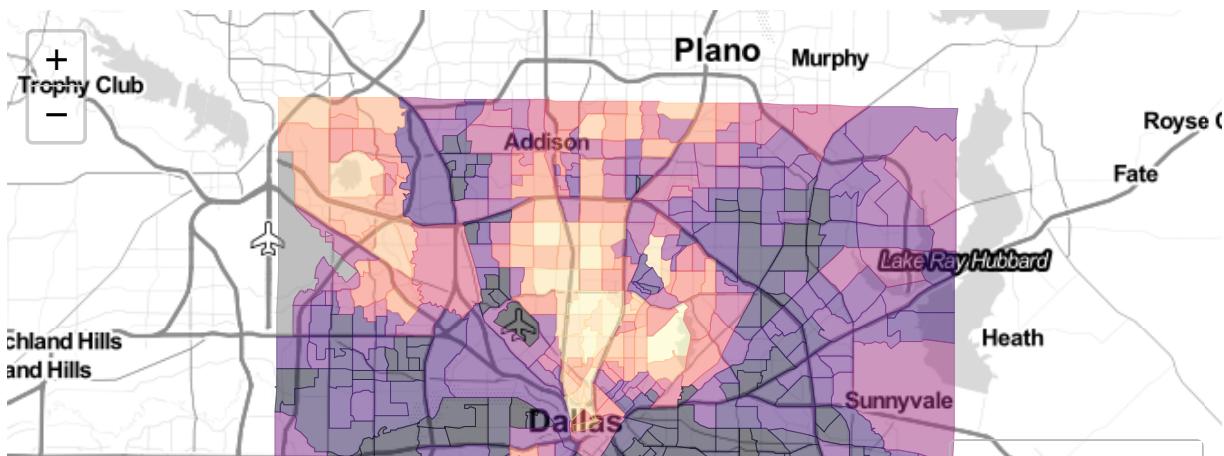
pal <- colorNumeric(
  palette = "magma",
  domain = dallas_bachelors$estimate
)

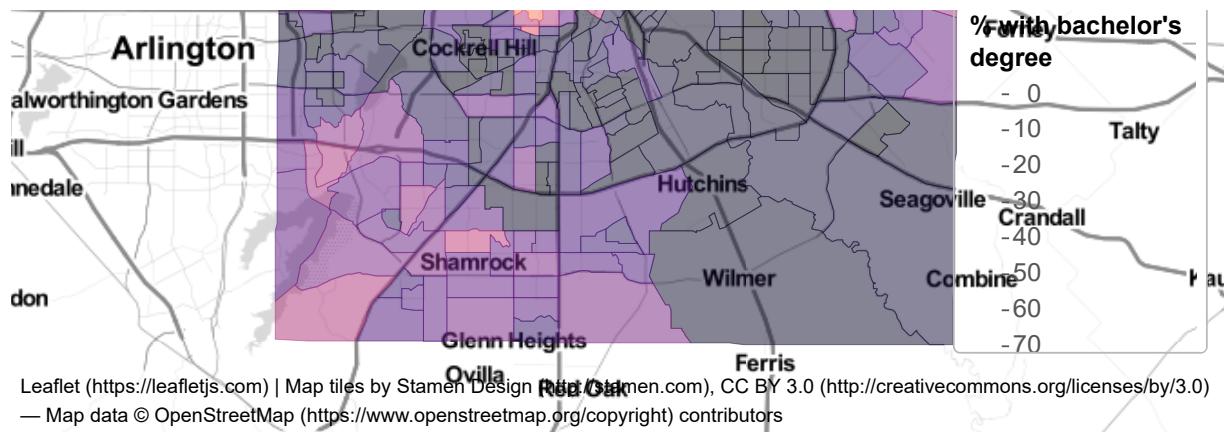
pal(c(10, 20, 30, 40, 50))

## [1] "#170F3C" "#430F75" "#6E1E81" "#9B2E7F" "#C83E73"

leaflet() %>%
  addProviderTiles(providers$Stamen.TonerLite) %>%
  addPolygons(data = dallas_bachelors,
    color = ~pal(estimate),
    weight = 0.5,
    smoothFactor = 0.2,
    fillOpacity = 0.5,
    label = ~estimate) %>%
  addLegend(
    position = "bottomright",
    pal = pal,
    values = dallas_bachelors$estimate,
    title = "% with bachelor's<br/>degree"
  )

## Warning: sf layer has inconsistent datum (+proj=longlat +datum=NAD83 +no_defs).
## Need '+proj=longlat +datum=WGS84'
```





This code above further formats the map adding labels, legend, and styles the census tracts

6.5.2 Alternative approaches to interactive mapping

```
us_value <- get_acs(
  geography = "state",
  variables = "B25077_001",
  year = 2019,
  survey = "acs1",
  geometry = TRUE,
  resolution = "20m"
)
```

```
## The 1-year ACS provides data for geographies with populations of 65,000 and greater.
```

```
## Getting data from the 2019 1-year ACS
```

This code retrieves median home value by state. In this example the problem of small scale mapping using the web mercator projection

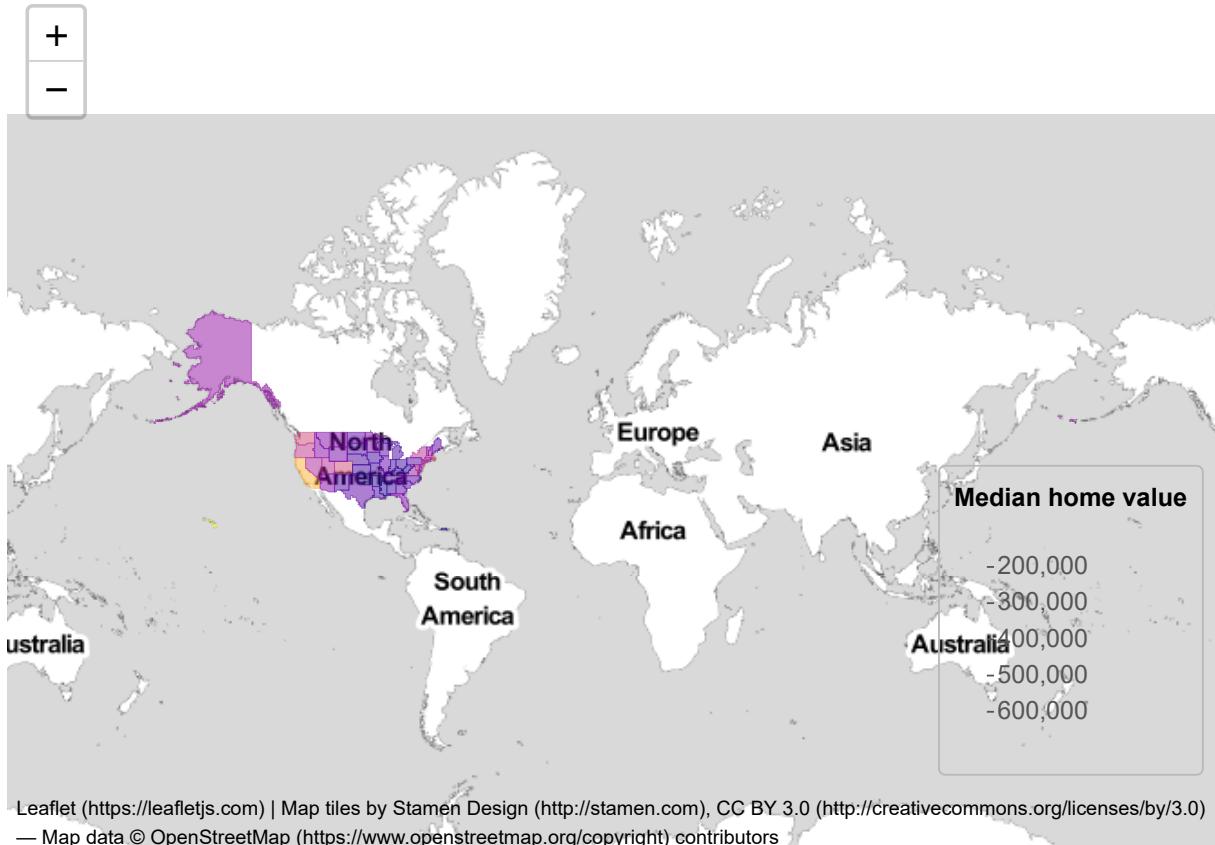
Map data using same techniques as done for the Dallas map

```
library(leaflet)

us_pal <- colorNumeric(
  palette = "plasma",
  domain = us_value$estimate
)

leaflet() %>%
  addProviderTiles(providers$Stamen.TonerLite) %>%
  addPolygons(data = us_value,
    color = ~us_pal(estimate),
    weight = 0.5,
    smoothFactor = 0.2,
    fillOpacity = 0.5,
    label = ~estimate) %>%
  addLegend(
    position = "bottomright",
    pal = us_pal,
    values = us_value$estimate,
    title = "Median home value"
)
```

```
## Warning: sf layer has inconsistent datum (+proj=longlat +datum=NAD83 +no_defs).
## Need '+proj=longlat +datum=WGS84'
```



Leaflet (<https://leafletjs.com>) | Map tiles by Stamen Design (<http://stamen.com>), CC BY 3.0 (<http://creativecommons.org/licenses/by/3.0>)
— Map data © OpenStreetMap (<https://www.openstreetmap.org/copyright>) contributors

As you can tell, Alaska is very distorted and Hawaii is hard to see.

The code below adds the ggiraph package to add interactivity to the map

```

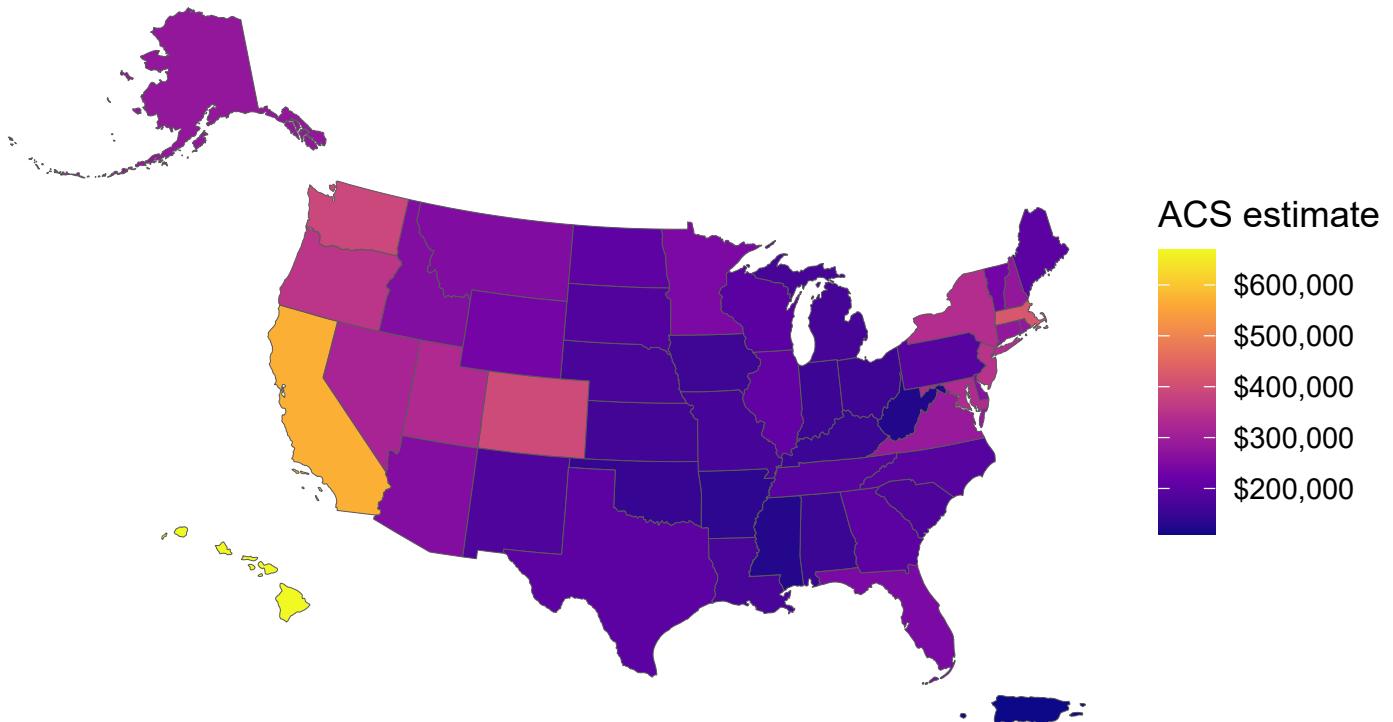
library(ggiraph)
library(ggplot2)
library(dplyr)
library(tigris)
us_value_shifted <- us_value %>%
  shift_geometry(position = "outside") %>%
  mutate(tooltip = paste(NAME, estimate, sep = ": "))

gg <- ggplot(us_value_shifted, aes(fill = estimate)) +
  geom_sf_interactive(aes(tooltip = tooltip, data_id = NAME),
                      size = 0.1) +
  scale_fill_viridis_c(option = "plasma", labels = scales::dollar) +
  labs(title = "Median housing value by State, 2019",
       caption = "Data source: 2019 1-year ACS, US Census Bureau",
       fill = "ACS estimate") +
  theme_void()

girafe(ggobj = gg) %>%
  girafe_options(opts_hover(css = "fill:cyan;"),
                 opts_zoom(max = 10))

```

Median housing value by State, 2019



Data source: 2019 1-year ACS, US Census Bureau

6.6 Advanced examples

more advanced visualization options from tidyCensus

6.6.1 Mapping migration flows

```
travis_inflow <- get_flows(
  geography = "county",
  state = "TX",
  county = "Travis",
  geometry = TRUE
) %>%
  filter(variable == "MOVEDIN") %>%
  na.omit() %>%
  arrange(desc(estimate))
```

obtaining flow data for migrants into travis county TX

once obtained run the code below to create the map

```
library(mapdeck)
```

```
##  
## Attaching package: 'mapdeck'
```

```
## The following object is masked from 'package:tibble':  
##  
##     add_column
```

```
#mapbox not working which is why background is missing  
token <- "YOUR TOKEN HERE"
```

```
travis_inflow %>%
  slice_max(estimate, n = 30) %>%
  mutate(weight = estimate / 500) %>%
  mapdeck(token = token) %>%
  add_arc(origin = "centroid2",
          destination = "centroid1",
          stroke_width = "weight",
          update_view = FALSE)
```

```
## Registered S3 method overwritten by 'jsonify':  
##   method      from  
##   print.json jsonlite
```



6.6.2 Linking maps and charts

```
library(tidycensus)
library(ggiraph)
library(tidyverse)
library(patchwork)

vt_income <- get_acs(
  geography = "county",
  variables = "B19013_001",
  state = "VT",
  year = 2019,
  geometry = TRUE
) %>%
  mutate(NAME = str_remove(NAME, " County, Vermont"))
```

```
## Getting data from the 2015-2019 5-year ACS
```

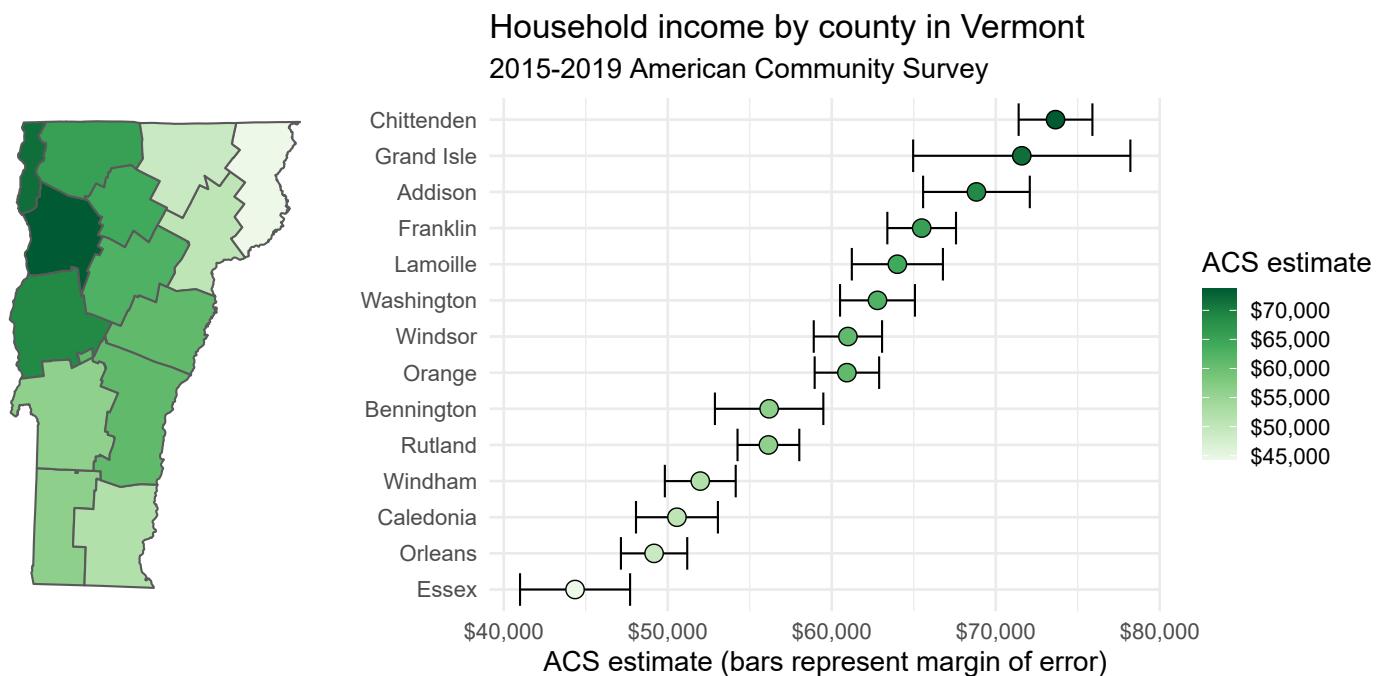
```

vt_map <- ggplot(vt_income, aes(fill = estimate)) +
  geom_sf_interactive(aes(data_id = GEOID)) +
  scale_fill_distiller(palette = "Greens",
    direction = 1,
    guide = "none") +
  theme_void()

vt_plot <- ggplot(vt_income, aes(x = estimate, y = reorder(NAME, estimate),
    fill = estimate)) +
  geom_errorbarh(aes(xmin = estimate - moe, xmax = estimate + moe)) +
  geom_point_interactive(color = "black", size = 4, shape = 21,
    aes(data_id = GEOID)) +
  scale_fill_distiller(palette = "Greens", direction = 1,
    labels = scales::dollar) +
  scale_x_continuous(labels = scales::dollar) +
  labs(title = "Household income by county in Vermont",
    subtitle = "2015-2019 American Community Survey",
    y = "",
    x = "ACS estimate (bars represent margin of error)",
    fill = "ACS estimate") +
  theme_minimal(base_size = 14)

girafe(ggobj = vt_map + vt_plot, width_svg = 10, height_svg = 5) %>%
  girafe_options(opts_hover(css = "fill:cyan;"))

```



6.6.3 Reactive mapping with Shiny

```
# app.R
library(tidycensus)
library(shiny)
library(leaflet)
library(tidyverse)

twin_cities_race <- get_acs(
  geography = "tract",
  variables = c(
    hispanic = "DP05_0071P",
    white = "DP05_0077P",
    black = "DP05_0078P",
    native = "DP05_0079P",
    asian = "DP05_0080P"
  ),
  state = "MN",
  county = c("Hennepin", "Ramsey", "Anoka", "Washington",
            "Dakota", "Carver", "Scott"),
  geometry = TRUE
)
```

```
## Getting data from the 2015-2019 5-year ACS
```

```
## Using the ACS Data Profile
```

```

groups <- c("Hispanic" = "hispanic",
          "White" = "white",
          "Black" = "black",
          "Native American" = "native",
          "Asian" = "asian")

ui <- fluidPage(
  sidebarLayout(
    sidebarPanel(
      selectInput(
        inputId = "group",
        label = "Select a group to map",
        choices = groups
      )
    ),
    mainPanel(
      leafletOutput("map", height = "600")
    )
  )
)

server <- function(input, output) {

  # Reactive function that filters for the selected group in the drop-down menu
  group_to_map <- reactive({
    filter(twin_cities_race, variable == input$group)
  })

  # Initialize the map object, centered on the Minneapolis-St. Paul area
  output$map <- renderLeaflet({

    leaflet(options = leafletOptions(zoomControl = FALSE)) %>%
      addProviderTiles(providers$Stamen.TonerLite) %>%
      setView(lng = -93.21,
             lat = 44.98,
             zoom = 8.5)

  })
}

observeEvent(input$group, {

  pal <- colorNumeric("viridis", group_to_map()$estimate)

  leafletProxy("map") %>%
    clearShapes() %>%
    clearControls() %>%
    addPolygons(data = group_to_map(),
                color = ~pal(estimate),
                weight = 0.5,
                fillOpacity = 0.5,
                smoothFactor = 0.2,
                label = ~estimate) %>%

    addLegend(
      position = "bottomright",
      pal = pal,
      values = group_to_map()$estimate,
      title = "% of population"
})
}

```

```
)  
}  
  
shinyApp(ui = ui, server = server)
```

```
## PhantomJS not found. You can install it with webshot::install_phantomjs(). If it is installed, please make sure the phantomjs executable can be found via the PATH variable.
```

Shiny applications not supported in static R Markdown documents

6.7 Working with software outside of R for cartographic projects

6.7.1 Exporting maps from R

```
library(tmap)  
hennepin_map <- tm_shape(hennepin_black,  
    projection = sf::st_crs(26915)) +  
    tm_polygons(col = "percent",  
        style = "jenks",  
        n = 5,  
        palette = "Purples",  
        title = "ACS estimate",  
        legend.hist = TRUE) +  
    tm_layout(title = "Percent Black\\nby Census tract",  
        frame = FALSE,  
        legend.outside = TRUE,  
        bg.color = "grey70",  
        legend.hist.width = 5,  
        fontfamily = "Verdana")
```

```
# tmap_save(
#   tm = hennepin_map,
#   filename = "~/images/hennepin_black_map.png",
#   height = 5.5,
#   width = 8,
#   dpi = 300
# )
```

6.8 Exercises

First I will make a race/ethnicity map for Howard County MD using the sample code:

```
howard_race <- get_acs(
  geography = "tract",
  state = "MD",
  county = "Howard",
  variables = c(White = "B03002_003",
               Black = "B03002_004",
               Native = "B03002_005",
               Asian = "B03002_006",
               Hispanic = "B03002_012"),
  summary_var = "B03002_001",
  geometry = TRUE
) %>%
  mutate(percent = 100 * (estimate / summary_est))
```

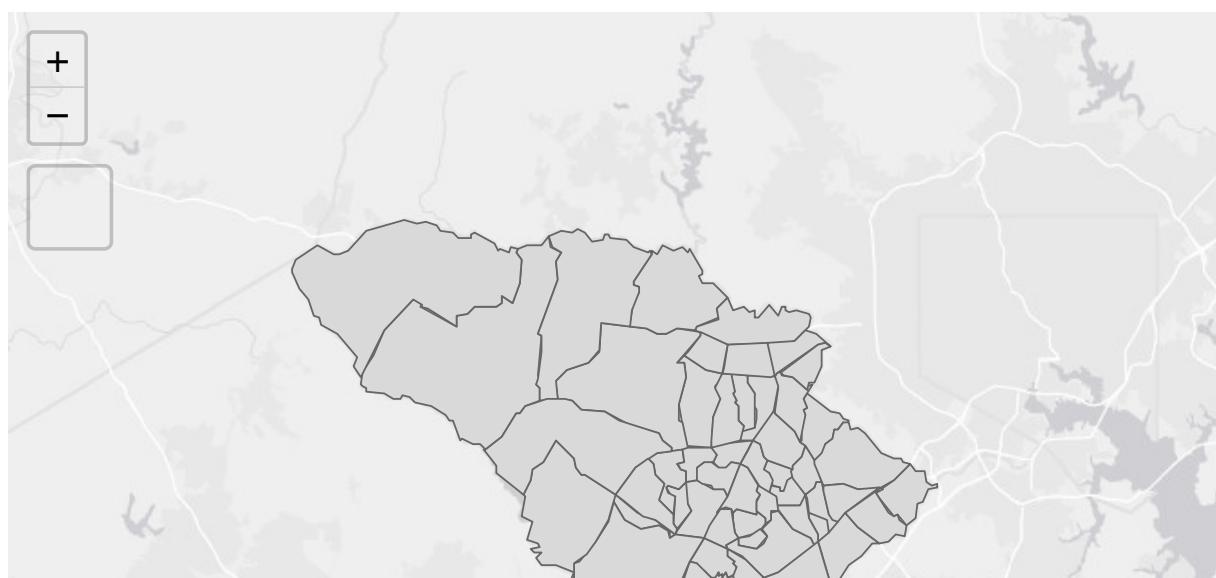
```
## Getting data from the 2015-2019 5-year ACS
```

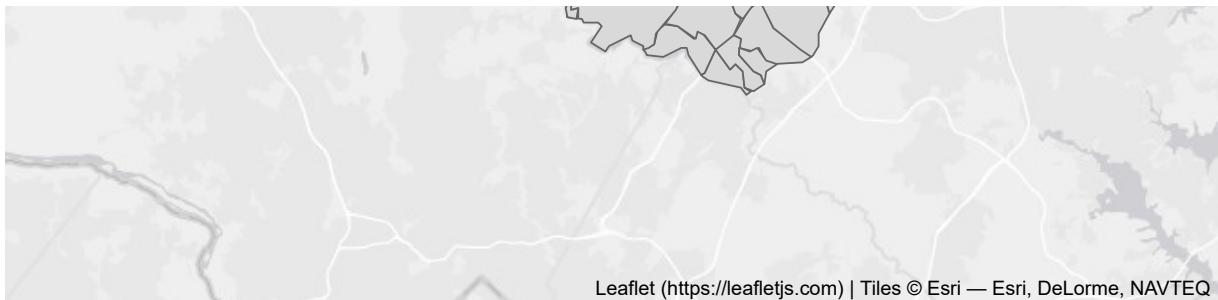
The code above is the first step, it retrieves the acs data for race and ethnicity in Howard County.

The next code below creates a view of census tracts in Howard County

```
library(tmap)
howard_asian <- filter(howard_race,
                        variable == "Asian")

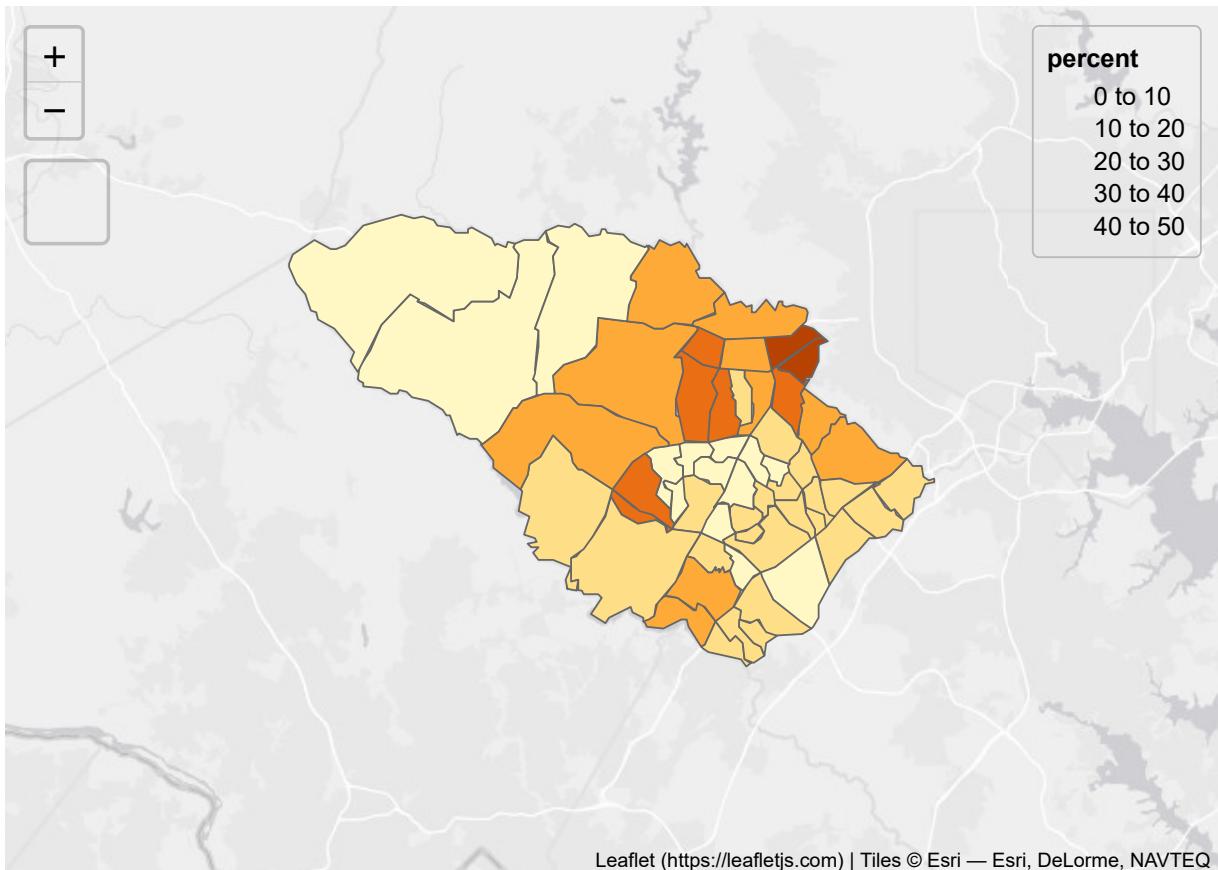
tm_shape(howard_asian) +
  tm_polygons()
```





Now it is time to use the tm_fill function to produce a choropleth map showing % Asian by census tract in Howard County

```
tm_shape(howard_asian) +  
  tm_polygons(col = "percent")
```



The map makes sense as you can see the highest % Asian is located in Ellicott City where “Korean Way” is located.

```
varsMD<- load_variables(2015, "acs5", cache = TRUE)  
  
view(varsMD)
```

Code above lists variables for the 5 year acs. I chose to make a map on German ancestry by MD county

```
md_germ <- get_acs(
  geography = "county",
  state = "MD",
  variables = "B04006_042",
  summary_var = "B04006_001",
  geometry = TRUE
) %>%
  mutate(percent = 100 * (estimate / summary_est))
```

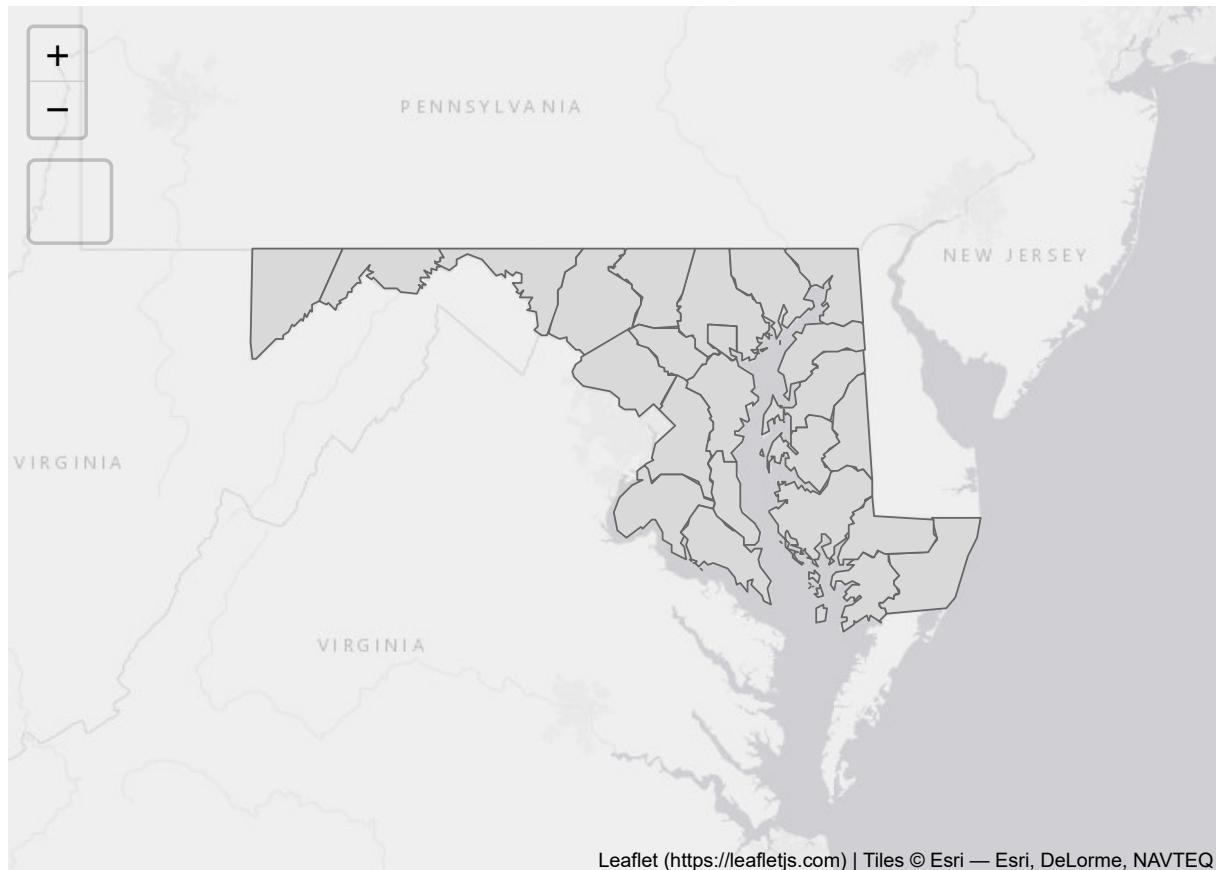
```
## Getting data from the 2015-2019 5-year ACS
```

The code above retrieves data for people reporting German ancestry by county in MD. The variable used is B04006_042. The summary variable is total pop est which is B04006_001

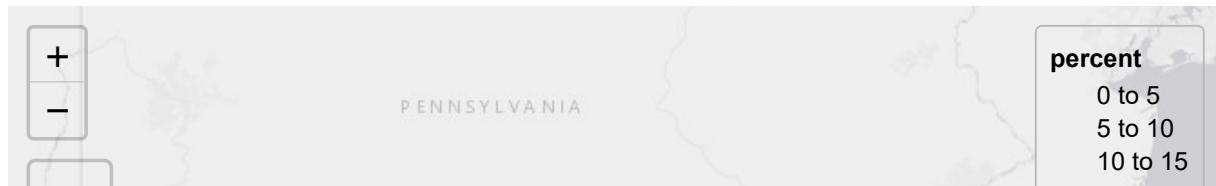
The code below creates a choropleth map showing % reporting german ancestry by MD county

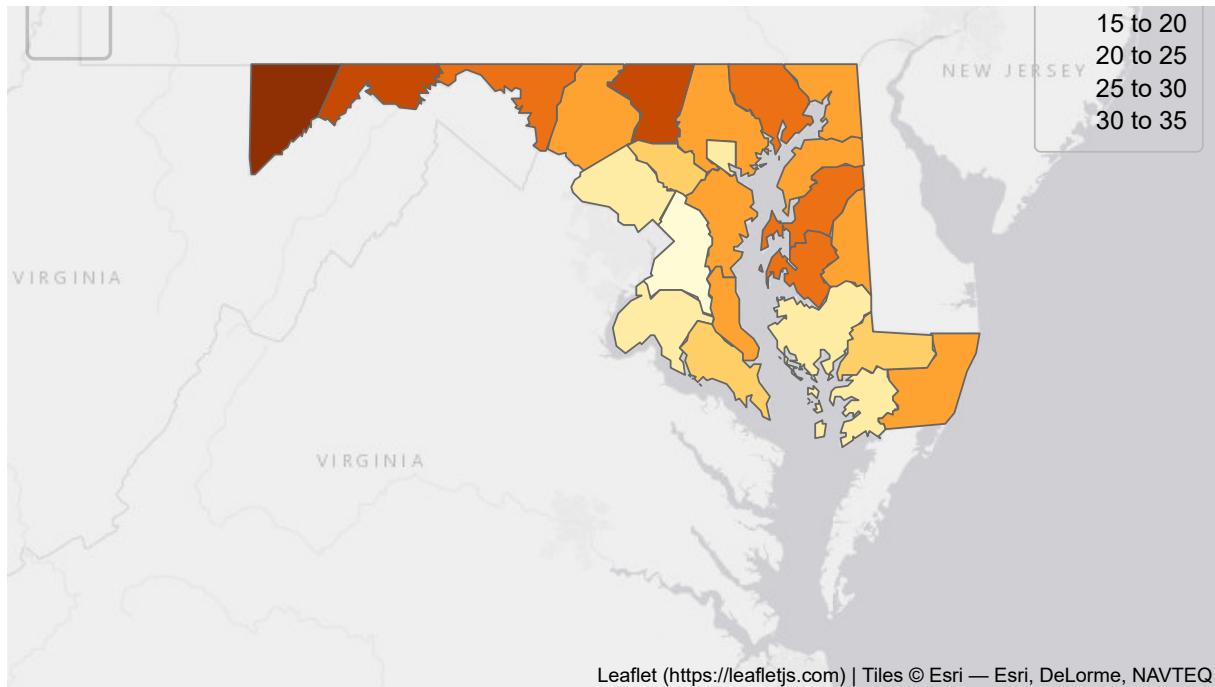
```
library(tmap)

tm_shape(md_germ) +
  tm_polygons()
```



```
tm_shape(md_germ) +
  tm_polygons(col = "percent")
```





R Notebook

tommy phipps

7 Spatial analysis with US Census data

7.1 Spatial overlay

7.1.1 Note: aligning coordinate reference systems

1. Download the datasets you plan to use in your spatial analysis;
2. Use suggest_crs() in the crssuggest package to identify an appropriate projected CRS for your layers;
3. Transform your data to the projected CRS using st_transform();
4. Compute the spatial overlay operation.

To avoid redundancy, step 2 is implied in the examples in this chapter and an appropriate projected coordinate reference system has been pre-selected for all sections.

7.1.2 Identifying geometries within a metropolitan area

Hide

```
library(tigris)
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
126: The specified module could not be found.
```

```
Warning in CPL_gdal_init(): GDAL Error 1: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
126: The specified module could not be found.
```

To enable caching of data, set `options(tigris_use_cache = TRUE)` in your R script or .Rprofile.

[Hide](#)

```
library(tidyverse)
```

```
-- Attaching packages ----- tidyverse 1.3.1 --
```

```
v ggplot2 3.3.5      v purrr   0.3.4
v tibble  3.1.6      v dplyr    1.0.8
v tidyrr   1.2.0     v stringr  1.4.0
v readr    2.1.2     vforcats  0.5.1
```

```
-- Conflicts ----- tidyverse_conflicts() --
```

```
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
```

[Hide](#)

```
library(sf)
```

```
Linking to GEOS 3.9.1, GDAL 3.2.1, PROJ 7.2.1; sf_use_s2() is TRUE
```

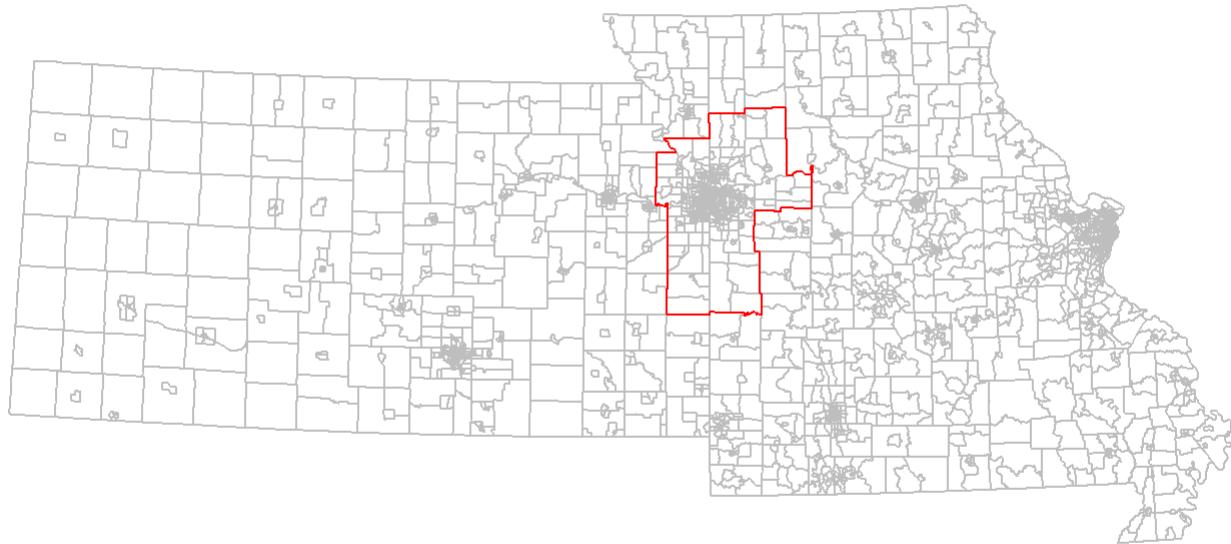
[Hide](#)

```
options(tigris_use_cache = TRUE)
```

```
# CRS used: NAD83(2011) Kansas Regional Coordinate System
# Zone 11 (for Kansas City)
ks_mo_tracts <- map_dfr(c("KS", "MO"), ~{
  tracts(.x, cb = TRUE, year = 2020)
}) %>%
  st_transform(8528)

kc_metro <- core_based_statistical_areas(cb = TRUE, year = 2020) %>%
  filter(str_detect(NAME, "Kansas City")) %>%
  st_transform(8528)

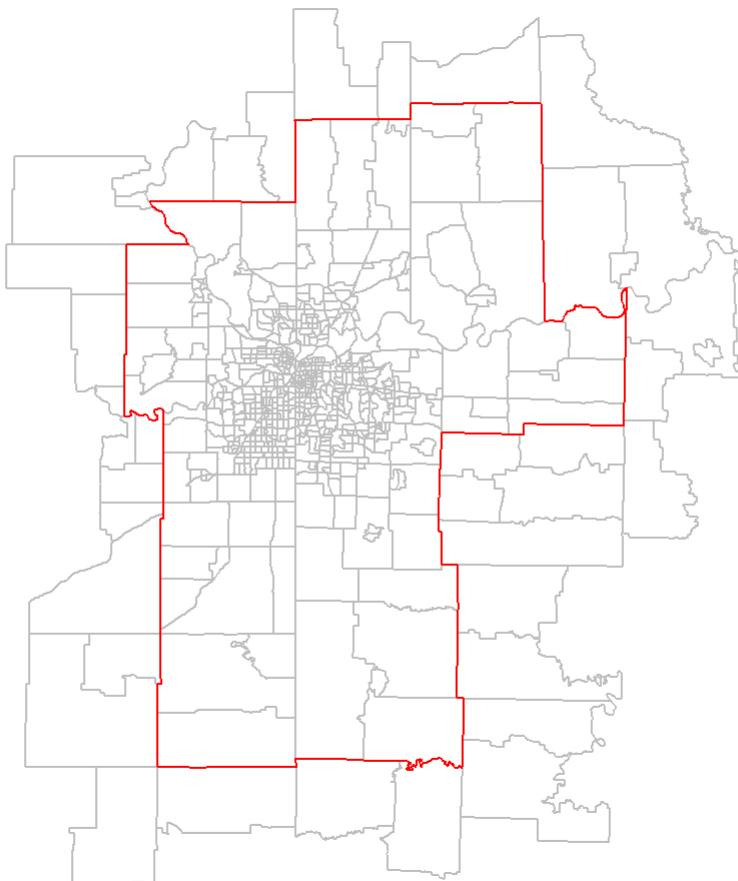
ggplot() +
  geom_sf(data = ks_mo_tracts, fill = "white", color = "grey") +
  geom_sf(data = kc_metro, fill = NA, color = "red") +
  theme_void()
```



7.1.3 Spatial subsets and spatial predicates

[Hide](#)

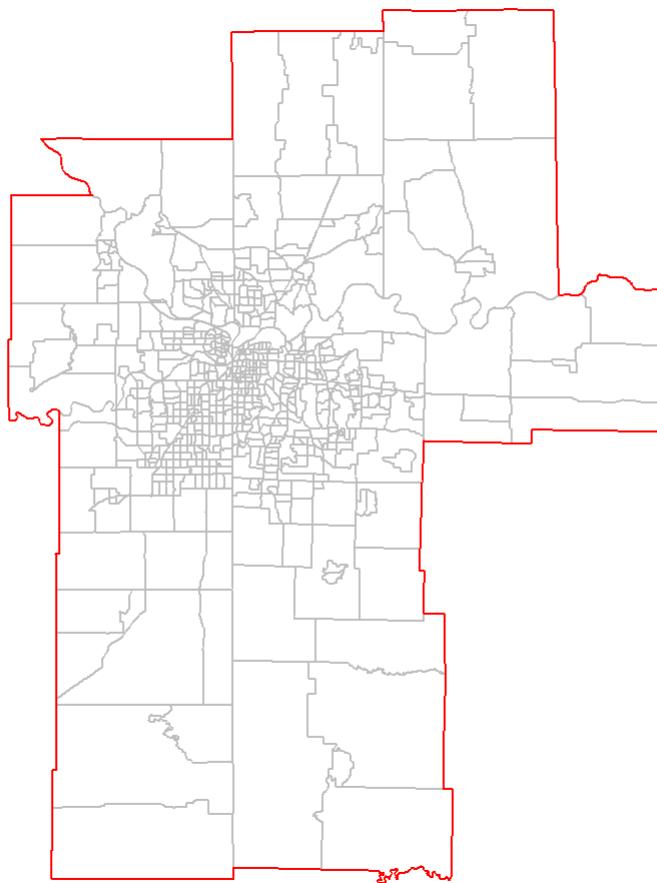
```
kc_tracts <- ks_mo_tracts[kc_metro, ]  
  
ggplot() +  
  geom_sf(data = kc_tracts, fill = "white", color = "grey") +  
  geom_sf(data = kc_metro, fill = NA, color = "red") +  
  theme_void()
```

[Hide](#)

```
kc_tracts_within <- ks_mo_tracts %>%
  st_filter(kc_metro, .predicate = st_within)

# Equivalent syntax:
# kc.metro2 <- kc.tracts[kc.metro, op = st_within]

ggplot() +
  geom_sf(data = kc_tracts_within, fill = "white", color = "grey") +
  geom_sf(data = kc_metro, fill = NA, color = "red") +
  theme_void()
```



7.2 Spatial joins

7.2.1 Point-in-polygon spatial joins

[Hide](#)

```
library(tidyverse)
library(sf)
library(tidycensus)
```

Attaching package: 'tidycensus'

The following object is masked from 'package:tigris':

fips_codes

[Hide](#)

```
library(mapview)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_FileGDB.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_MSSQLSpatial.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_OCI.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

```
Warning: Can't load requested DLL: C:\Program Files\GeoDa Software\ogr_PG.dll  
126: The specified module could not be found.  
(GDAL error 1)
```

[Hide](#)

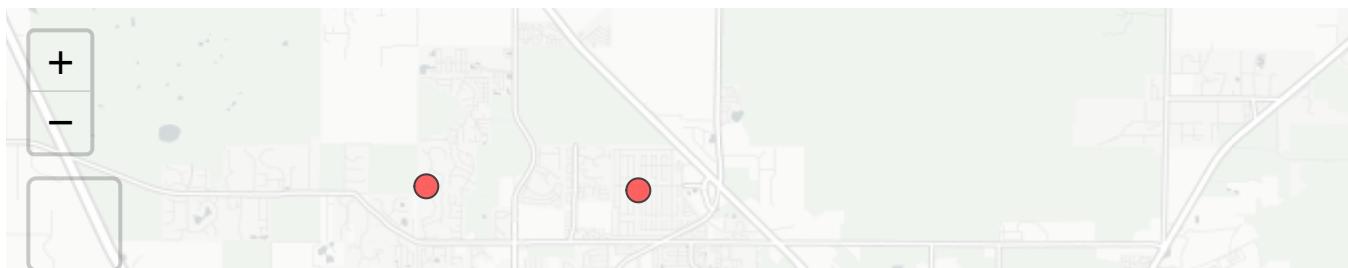
```
gainesville_patients <- tibble(  
  patient_id = 1:10,  
  longitude = c(-82.308131, -82.311972, -82.361748, -82.374377,  
    -82.38177, -82.259461, -82.367436, -82.404031,  
    -82.43289, -82.461844),  
  latitude = c(29.645933, 29.655195, 29.621759, 29.653576,  
    29.677201, 29.674923, 29.71099, 29.711587,  
    29.648227, 29.624037)  
)
```

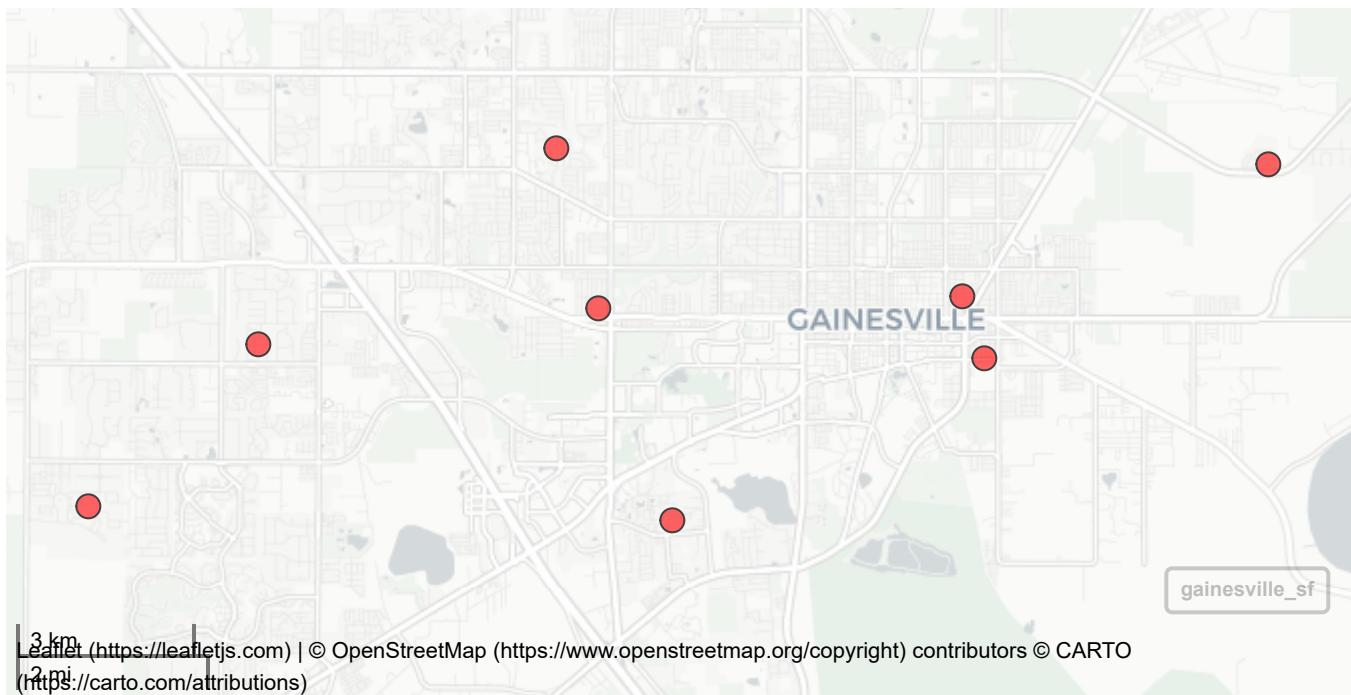
[Hide](#)

```
# CRS: NAD83(2011) / Florida North  
gainesville_sf <- gainesville_patients %>%  
  st_as_sf(coords = c("longitude", "latitude"),  
    crs = 4326) %>%  
  st_transform(6440)
```

[Hide](#)

```
mapview(  
  gainesville_sf,  
  col.regions = "red",  
  legend = FALSE  
)
```



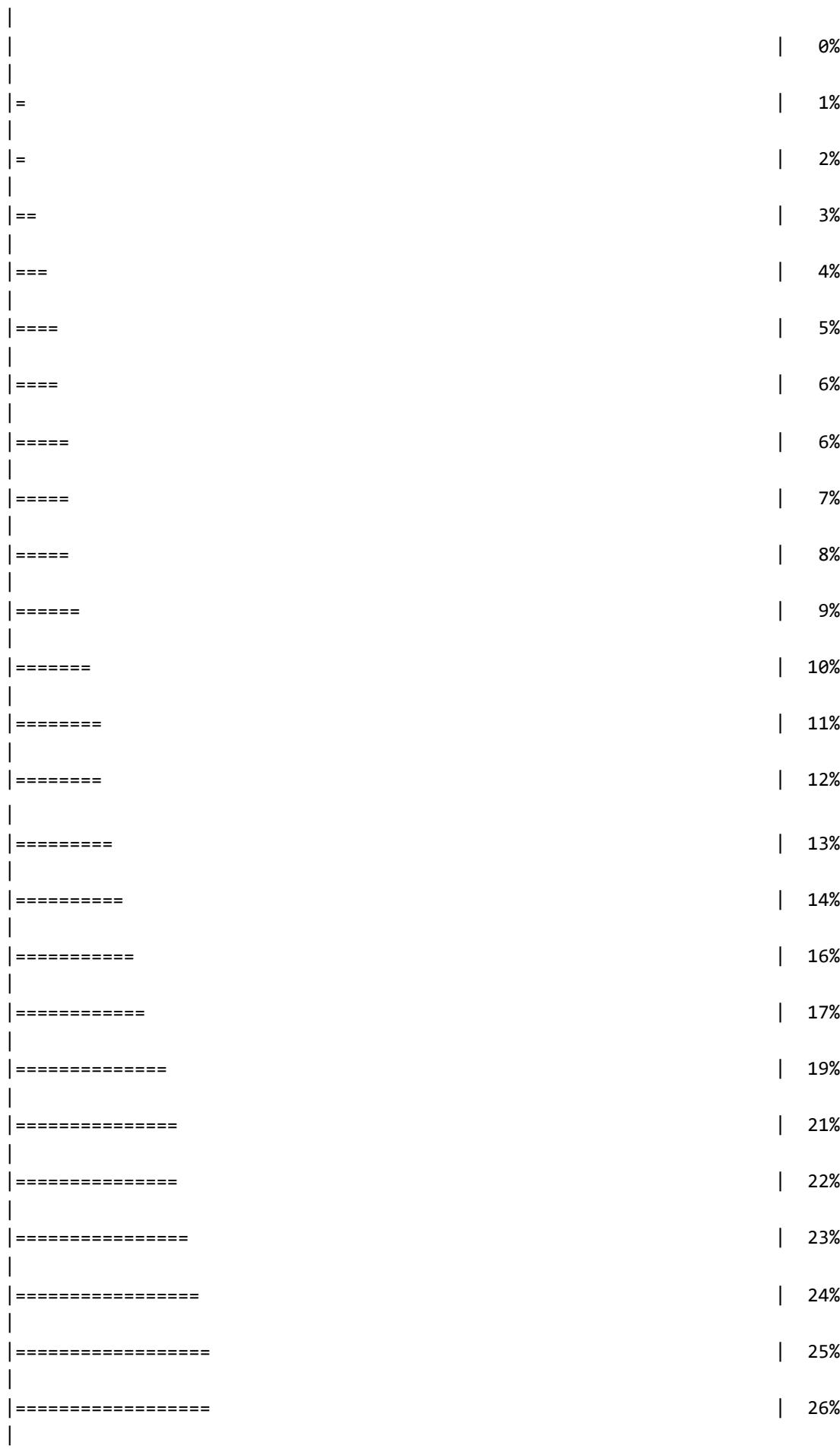


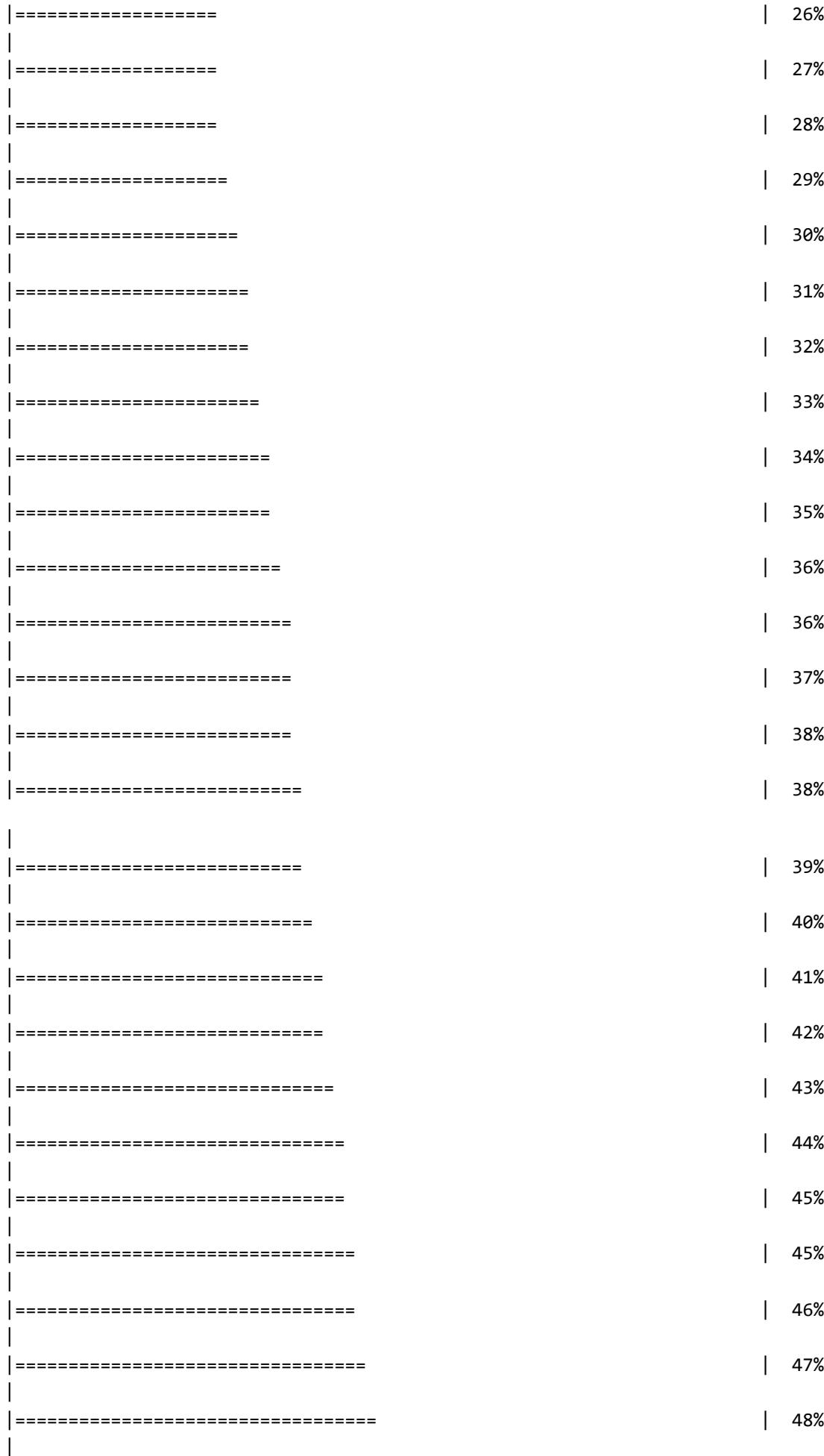
[Hide](#)

```
alachua_insurance <- get_acs(  
  geography = "tract",  
  variables = "DP03_0096P",  
  state = "FL",  
  county = "Alachua",  
  year = 2019,  
  geometry = TRUE  
) %>%  
  select(GEOID, pct_insured = estimate,  
         pct_insured_moe = moe) %>%  
  st_transform(6440)
```

Getting data from the 2015-2019 5-year ACS

Using the ACS Data Profile





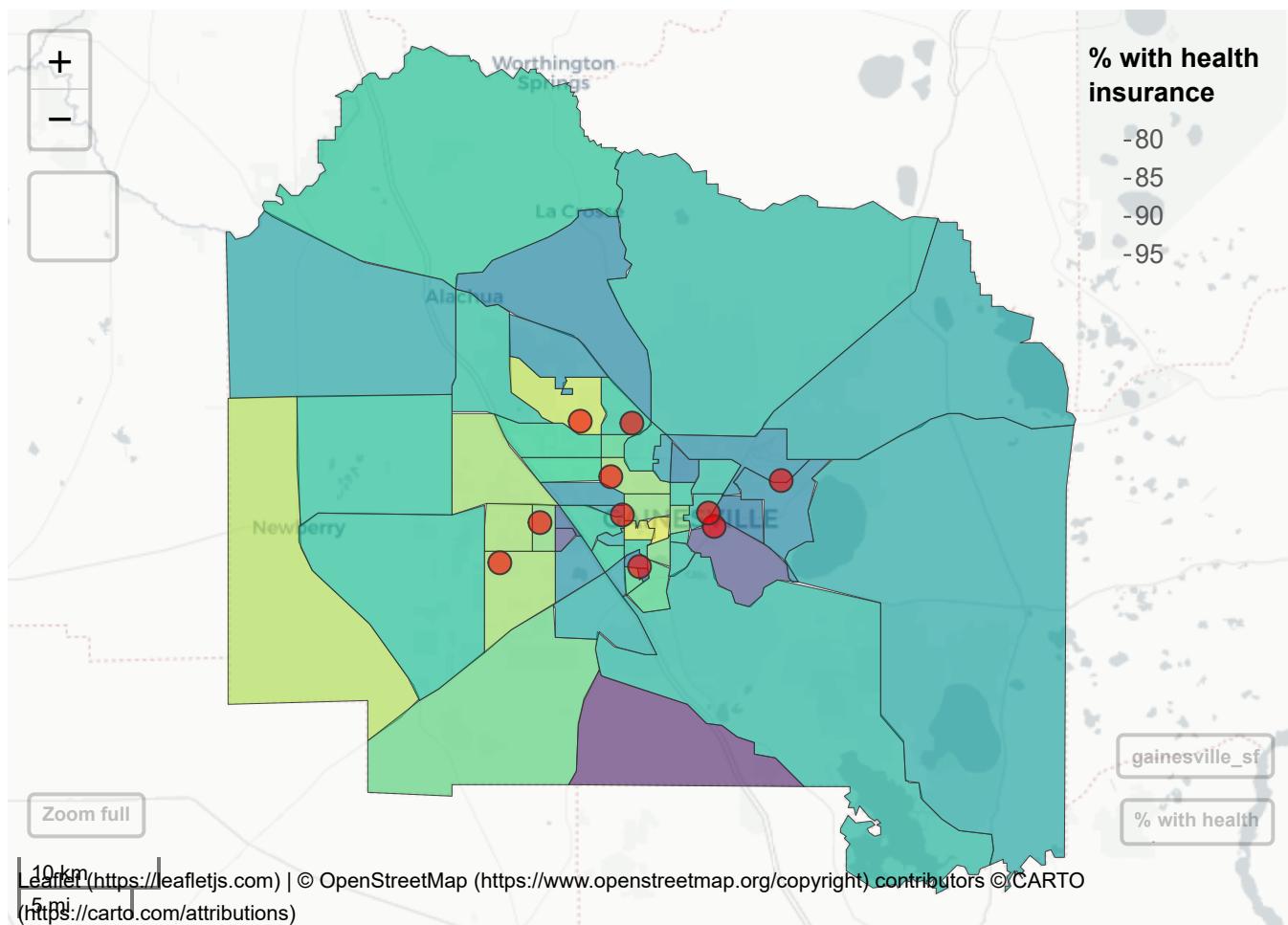




```
[===== | 96%
[===== | 97%
[===== | 98%
[===== | 99%
[===== | 100%
```

Hide

```
mapview(
  alachua_insurance,
  zcol = "pct_insured",
  layer.name = "% with health<br/>insurance"
) +
  mapview(
    gainesville_sf,
    col.regions = "red",
    legend = FALSE
)
```



Hide

```
patients_joined <- st_join(
  gainesville_sf,
  alachua_insurance
)
```

7.2.2 Spatial joins and group-wise spatial analysis

7.2.2.1 Spatial join data setup

[Hide](#)

```
library(tidycensus)
library(tidyverse)
library(sf)

# CRS: NAD83(2011) / Texas Centric Albers Equal Area
tx_cbsa <- get_acs(
  geography = "cbsa",
  variables = "B01003_001",
  year = 2019,
  survey = "acs1",
  geometry = TRUE
) %>%
  filter(str_detect(NAME, "TX")) %>%
  slice_max(estimate, n = 4) %>%
  st_transform(6579)
```

The 1-year ACS provides data for geographies with populations of 65,000 and greater.

Getting data from the 2019 1-year ACS

[Hide](#)

```
pct_hispanic <- get_acs(
  geography = "tract",
  variables = "DP05_0071P",
  state = "TX",
  year = 2019,
  geometry = TRUE
) %>%
  st_transform(6579)
```

Getting data from the 2015-2019 5-year ACS

Using the ACS Data Profile

7.2.2.2 Computing and visualizing the spatial join

[Hide](#)

```
hispanic_by_metro <- st_join(
  pct_hispanic,
  tx_cbsa,
  join = st_within,
  suffix = c("_tracts", "_metro"),
  left = FALSE
)
```

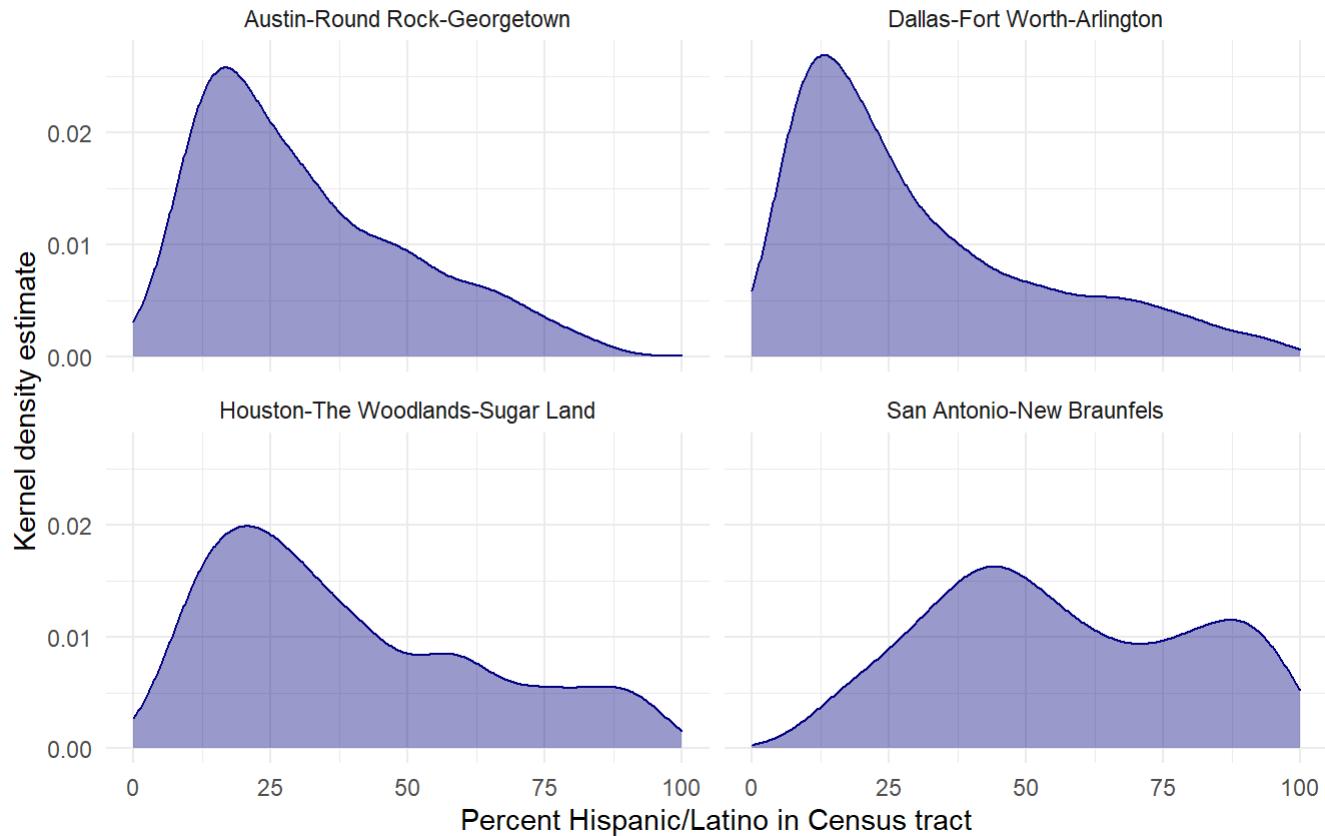
[Hide](#)

```
hispanic_by_metro %>%
  mutate(NAME_metro = str_replace(NAME_metro, " ", " TX Metro Area", "")) %>%
  ggplot() +
  geom_density(aes(x = estimate_tracts), color = "navy", fill = "navy",
               alpha = 0.4) +
  theme_minimal() +
  facet_wrap(~NAME_metro) +
  labs(title = "Distribution of Hispanic/Latino population by Census tract",
       subtitle = "Largest metropolitan areas in Texas",
       y = "Kernel density estimate",
       x = "Percent Hispanic/Latino in Census tract")
```

Warning: Removed 9 rows containing non-finite values (stat_density).

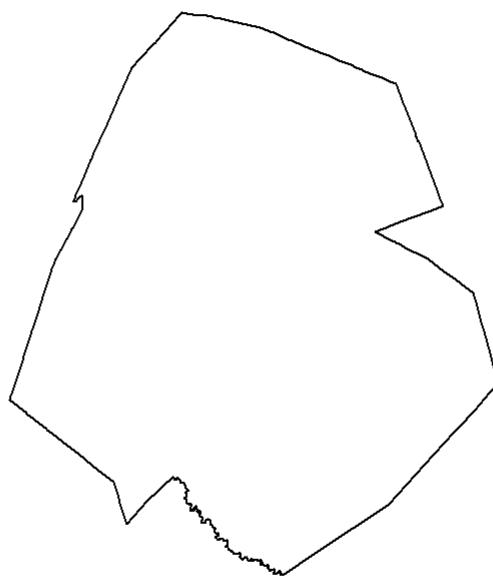
Distribution of Hispanic/Latino population by Census tract

Largest metropolitan areas in Texas



```
median_by_metro <- hispanic_by_metro %>%
  group_by(NAME_metro) %>%
  summarize(median_hispanic = median(estimate_tracts, na.rm = TRUE))
```

```
plot(median_by_metro[1, ]$geometry)
```



7.3 Distance and proximity analysis

```

library(tigris)
library(sf)
library(tidyverse)
options(tigris_use_cache = TRUE)

# CRS: NAD83 / Iowa North
ia_tracts <- tracts("IA", cb = TRUE, year = 2019) %>%
  st_transform(26975)

hospital_url <- "https://opendata.arcgis.com/api/v3/datasets/6ac5e325468c4cb9b905f1728d6fbf0f_0/
downloads/data?format=geojson&spatialRefId=4326"

trauma <- st_read(hospital_url) %>%
  filter(str_detect(TRAUMA, "LEVEL I\b|LEVEL II\b|RTH|RTC")) %>%
  st_transform(26975)

```

Reading layer `Hospitals' from data source
`https://opendata.arcgis.com/api/v3/datasets/6ac5e325468c4cb9b905f1728d6fbf0f_0/downloads/dat
a?format=geojson&spatialRefId=4326'
using driver `GeoJSON'
Simple feature collection with 7596 features and 32 fields
Geometry type: POINT
Dimension: XY
Bounding box: xmin: -176.6403 ymin: -14.29024 xmax: 145.7245 ymax: 71.29773
Geodetic CRS: WGS 84

[Hide](#)

```
names(trauma)
```

```

[1] "OBJECTID"      "ID"          "NAME"        "ADDRESS"      "CITY"
[6] "STATE"         "ZIP"         "ZIP4"        "TELEPHONE"   "TYPE"
[11] "STATUS"        "POPULATION"  "COUNTY"      "COUNTYFIPS"   "COUNTRY"
[16] "LATITUDE"      "LONGITUDE"   "NAICS_CODE"  "NAICS_DESC"  "SOURCE"
[21] "SOURCEDATE"    "VAL_METHOD"  "VAL_DATE"    "WEBSITE"     "STATE_ID"
[26] "ALT_NAME"      "ST_FIPS"     "OWNER"       "TTL_STAFF"   "BEDS"
[31] "TRAUMA"        "HELIPAD"     "geometry"

```

OBJECTID

ID

NAME

ADDRESS

CITY

STATE

ZIP

ZIP4

TELEPHONE

TYPE

STATUS

POPULATION

COUNTY

COUNTYFIPS

COUNTRY

LATITUDE

LONGITUDE

NAICS_CODE

NAICS_DESC

SOURCE

SOURCEDATE

VAL_METHOD

VAL_DATE

WEBSITE

STATE_ID

ALT_NAME

ST_FIPS

OWNER

TTL_STAFF

BEDS

TRAUMA

HELIPAD

geometry

7.3.1 Calculating distances

[Hide](#)

```
ia_trauma <- trauma %>%
  st_filter(ia_tracts,
            .predicate = st_is_within_distance,
            dist = 100000)

ggplot() +
  geom_sf(data = ia_tracts, color = "NA", fill = "grey50") +
  geom_sf(data = ia_trauma, color = "red") +
  theme_void()
```

[Hide](#)

```
dist <- ia_tracts %>%
  st_centroid() %>%
  st_distance(ia_trauma)
```

Warning in `st_centroid.sf(.)`: `st_centroid` assumes attributes are constant over geometries of x

[Hide](#)

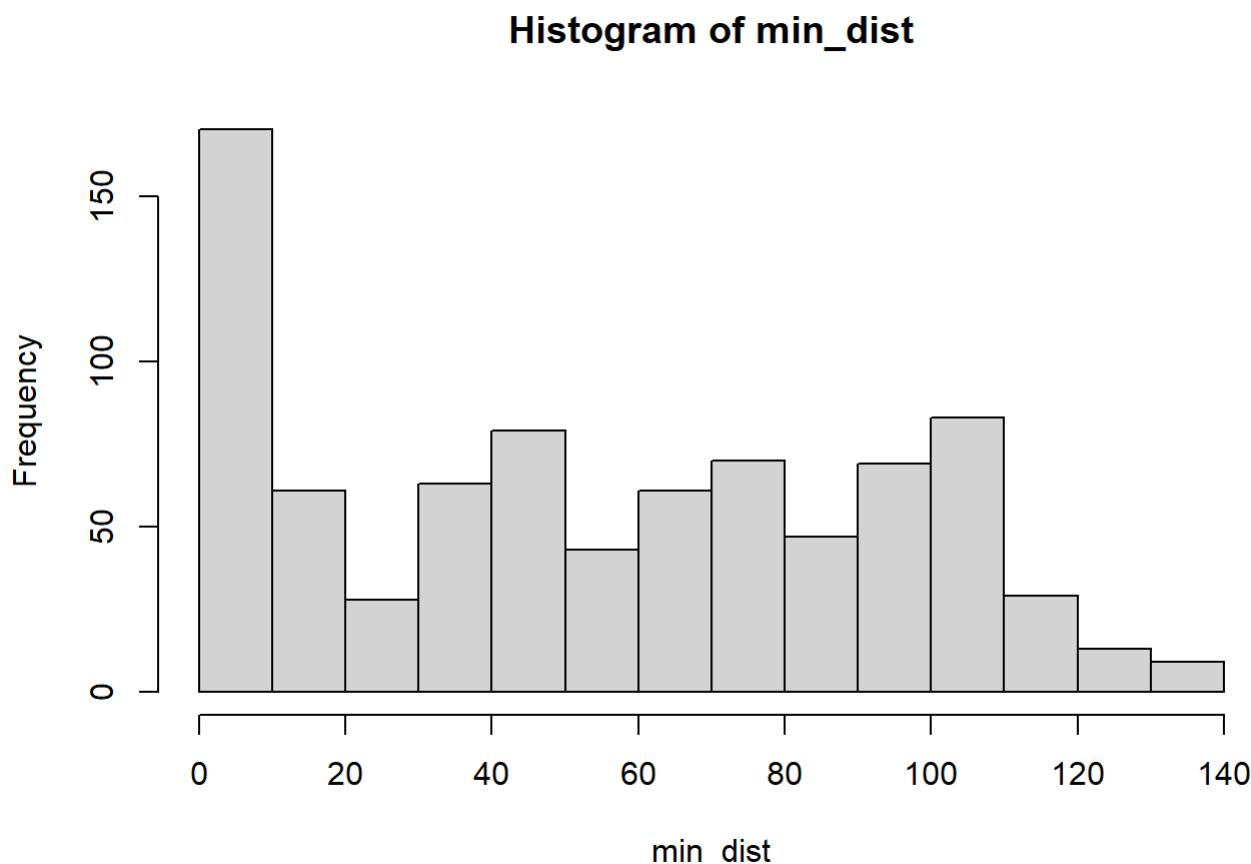
```
dist[1:5, 1:5]
```

Units: [m]

	[,1]	[,2]	[,3]	[,4]	[,5]
[1,]	279570.18	279188.81	385140.7	383863.7	257745.5
[2,]	298851.01	298409.46	400428.5	399022.9	276955.8
[3,]	350121.53	347800.57	353428.8	350263.3	404616.0
[4,]	361742.20	360450.59	421691.6	419364.9	369415.7
[5,]	66762.19	63479.67	143552.1	143935.5	194001.0

[Hide](#)

```
min_dist <- dist %>%  
  apply(1, min) %>%  
  as.vector() %>%  
  magrittr::divide_by(1000)  
  
hist(min_dist)
```



7.3.2 Calculating travel times

Not doing this section- mapbox api still having errors

7.3.3 Catchment areas with buffers and isochrones

Mapbox still having errors. Skipping this part for now

7.3.4 Computing demographic estimates for zones with areal interpolation

[Hide](#)

```
polk_poverty <- get_acs(
  geography = "block group",
  variables = c(poverty_denom = "B17010_001",
                poverty_num = "B17010_002"),
  state = "IA",
  county = "Polk",
  geometry = TRUE,
  output = "wide",
  year = 2019
) %>%
  select(poverty_denomE, poverty_numE) %>%
  st_transform(26975)
```

Getting data from the 2015-2019 5-year ACS

7.4 Better cartography with spatial overlay

[Hide](#)

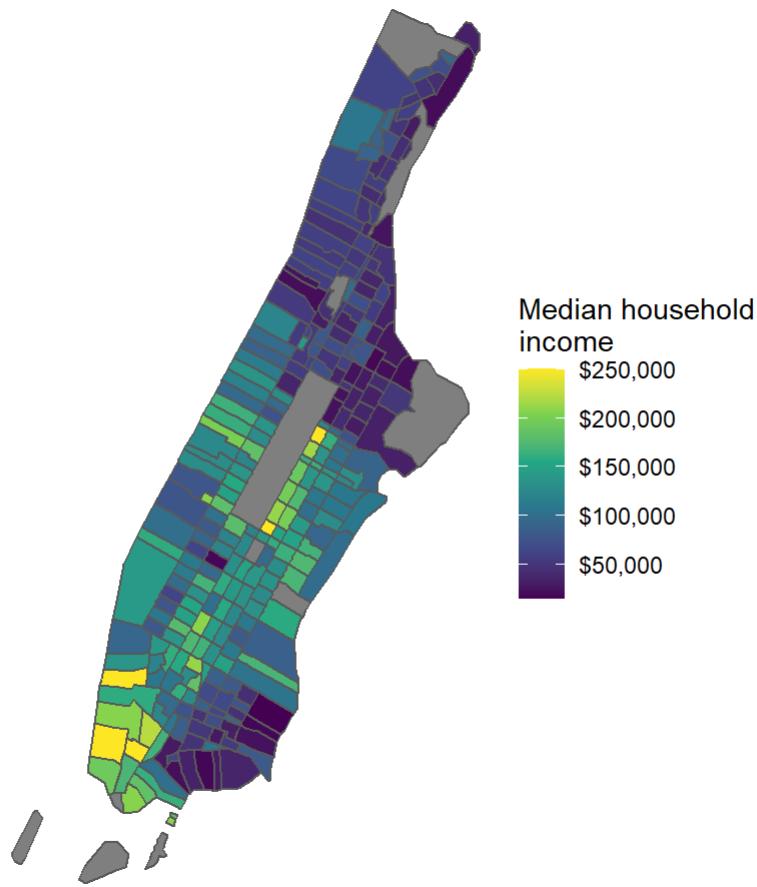
```
library(tidycensus)
library(tidyverse)
options(tigris_use_cache = TRUE)

ny <- get_acs(
  geography = "tract",
  variables = "B19013_001",
  state = "NY",
  county = "New York",
  year = 2019,
  geometry = TRUE
)
```

Getting data from the 2015-2019 5-year ACS

[Hide](#)

```
ggplot(ny) +
  geom_sf(aes(fill = estimate)) +
  scale_fill_viridis_c(labels = scales::dollar) +
  theme_void() +
  labs(fill = "Median household\nincome")
```



7.4.1 “Erasing” areas from Census polygons

[Hide](#)

```
# CRS: NAD83(2011) / New York Long Island
ny2 <- get_acs(
  geography = "tract",
  variables = "B19013_001",
  state = "NY",
  county = "New York",
  geometry = TRUE,
  year = 2019,
  cb = FALSE
) %>%
  st_transform(6538)
```

Getting data from the 2015-2019 5-year ACS

[Hide](#)

```
library(sf)
library(tigris)

st_erase <- function(x, y) {
  st_difference(x, st_union(y))
}

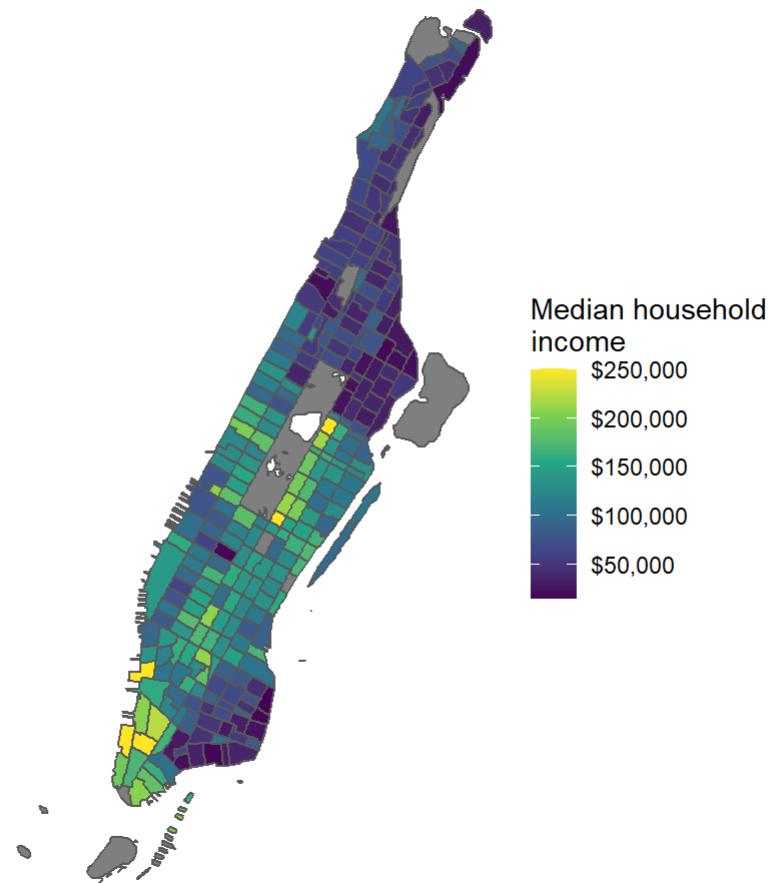
ny_water <- area_water("NY", "New York", year = 2019) %>%
  st_transform(6538)

ny_erase <- st_erase(ny2, ny_water)
```

Warning: attribute variables are assumed to be spatially constant throughout all geometries

Hide

```
ggplot(ny_erase) +
  geom_sf(aes(fill = estimate)) +
  scale_fill_viridis_c(labels = scales::dollar) +
  theme_void() +
  labs(fill = "Median household\nincome")
```



7.5 Spatial neighborhoods and spatial weights matrices

[Hide](#)

```
library(tidycensus)
library(tidyverse)
library(tigris)
library(sf)
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')`

[Hide](#)

```
options(tigris_use_cache = TRUE)

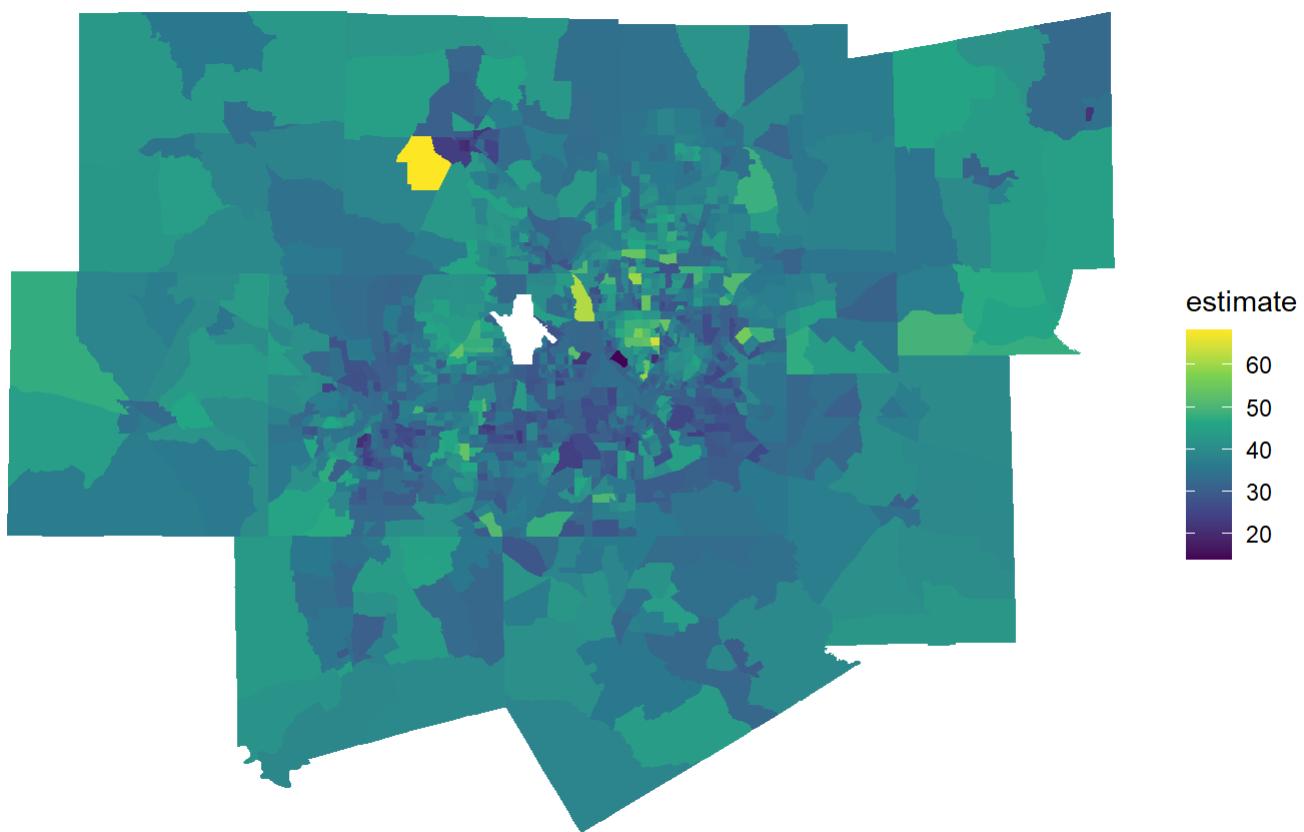
# CRS: NAD83 / Texas North Central
dfw <- core_based_statistical_areas(cb = TRUE, year = 2019) %>%
  filter(str_detect(NAME, "Dallas")) %>%
  st_transform(32138)

dfw_tracts <- get_acs(
  geography = "tract",
  variables = "B01002_001",
  state = "TX",
  year = 2019,
  geometry = TRUE
) %>%
  st_transform(32138) %>%
  st_filter(dfw, .predicate = st_within) %>%
  na.omit()
```

Getting data from the 2015-2019 5-year ACS

[Hide](#)

```
ggplot(dfw_tracts) +
  geom_sf(aes(fill = estimate), color = NA) +
  scale_fill_viridis_c() +
  theme_void()
```



7.5.1 Understanding spatial neighborhoods

[Hide](#)

```
neighbors <- poly2nb(dfw_tracts, queen = TRUE)  
  
summary(neighbors)
```

Neighbour list object:
Number of regions: 1310
Number of nonzero links: 8446
Percentage nonzero weights: 0.4921625
Average number of links: 6.447328
Link number distribution:

2	3	4	5	6	7	8	9	10	11	12	13	16
6	43	111	254	286	291	159	94	30	20	11	4	1

6 least connected regions:
15 626 663 768 823 824 with 2 links
1 most connected region:
924 with 16 links

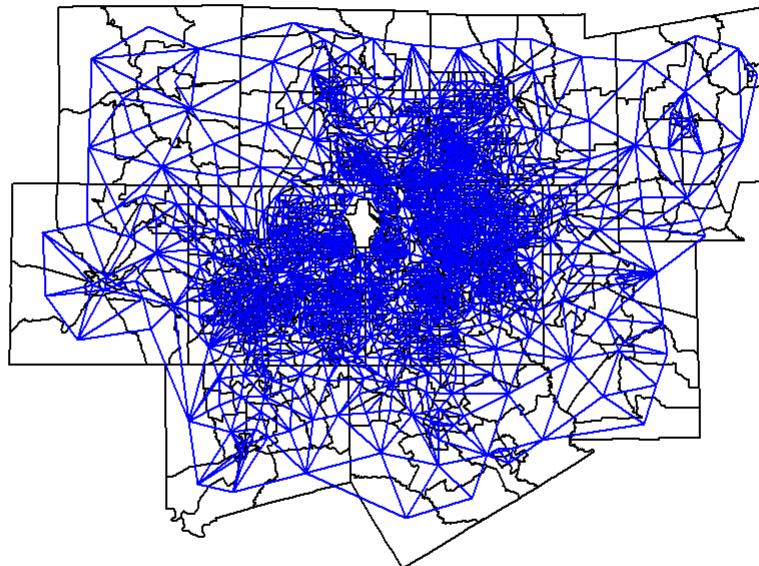
[Hide](#)

```
dfw_coords <- dfw_tracts %>%  
  st_centroid() %>%  
  st_coordinates()
```

Warning in st_centroid.sf(.): st_centroid assumes attributes are constant over
geometries of x

[Hide](#)

```
plot(dfw_tracts$geometry)  
plot(neighbors,  
  coords = dfw_coords,  
  add = TRUE,  
  col = "blue",  
  points = FALSE)
```



[Hide](#)

```
# Get the row indices of the neighbors of the Census tract at row index 1  
neighbors[[1]]
```

```
[1] 47 153 227 246 353 613 660 751 942 1025 1208
```

7.5.2 Generating the spatial weights matrix

[Hide](#)

```
weights <- nb2listw(neighbors, style = "W")
```

```
weights$weights[[1]]
```

```
[1] 0.09090909 0.09090909 0.09090909 0.09090909 0.09090909 0.09090909  
[7] 0.09090909 0.09090909 0.09090909 0.09090909 0.09090909
```

7.6 Global and local spatial autocorrelation

7.6.1 Spatial lags and Moran's I

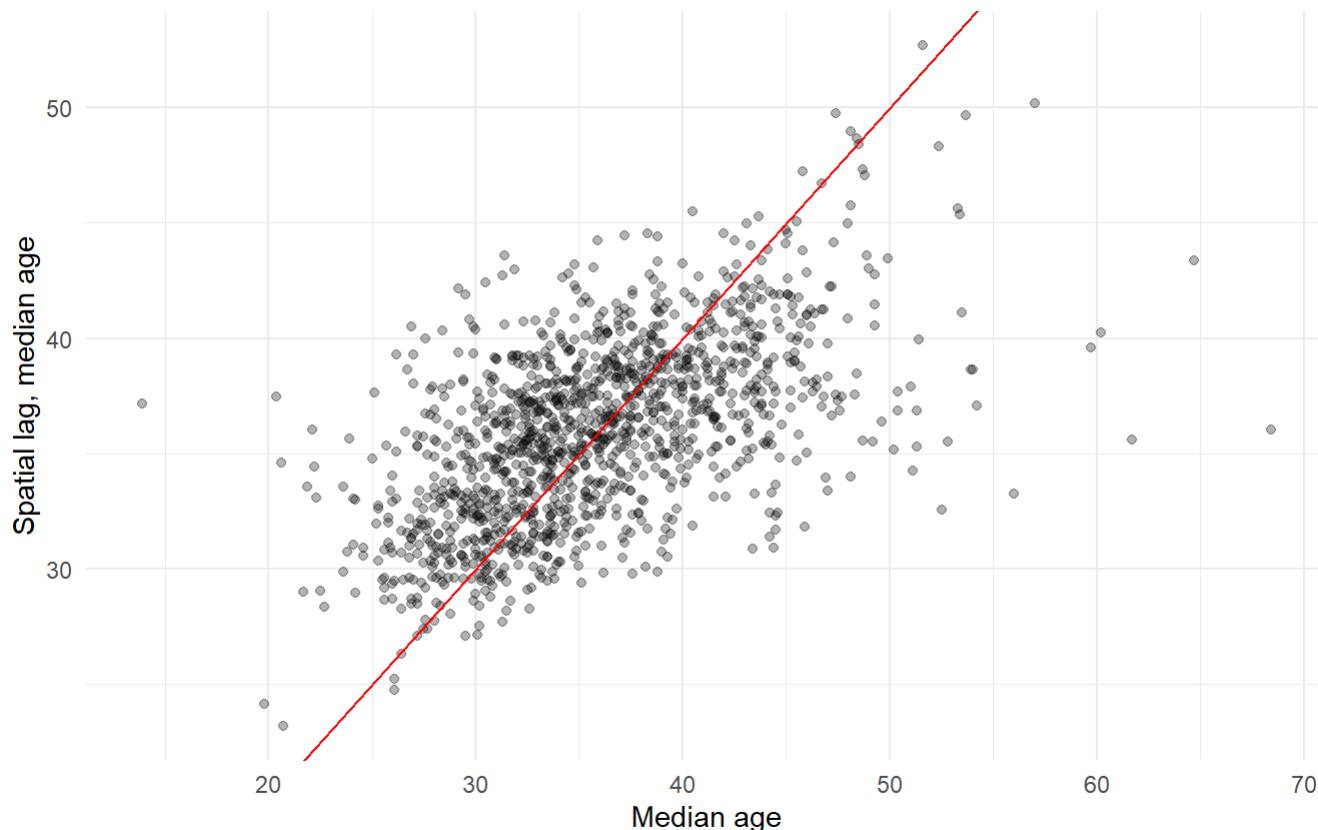
[Hide](#)

```
dfw_tracts$lag_estimate <- lag.listw(weights, dfw_tracts$estimate)
```

[Hide](#)

```
ggplot(dfw_tracts, aes(x = estimate, y = lag_estimate)) +  
  geom_point(alpha = 0.3) +  
  geom_abline(color = "red") +  
  theme_minimal() +  
  labs(title = "Median age by Census tract, Dallas-Fort Worth TX",  
       x = "Median age",  
       y = "Spatial lag, median age",  
       caption = "Data source: 2015-2019 ACS via the tidycensus R package.\nSpatial relationships based on queens-case polygon contiguity.")
```

Median age by Census tract, Dallas-Fort Worth TX



Data source: 2015-2019 ACS via the `tidycensus` R package.
Spatial relationships based on queens-case polygon contiguity.

[Hide](#)

```
moran.test(dfw_tracts$estimate, weights)
```

Moran I test under randomisation

```
data: dfw_tracts$estimate
weights: weights

Moran I statistic standard deviate = 22.979, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic      Expectation      Variance
0.3593580070     -0.0007639419     0.0002456130
```

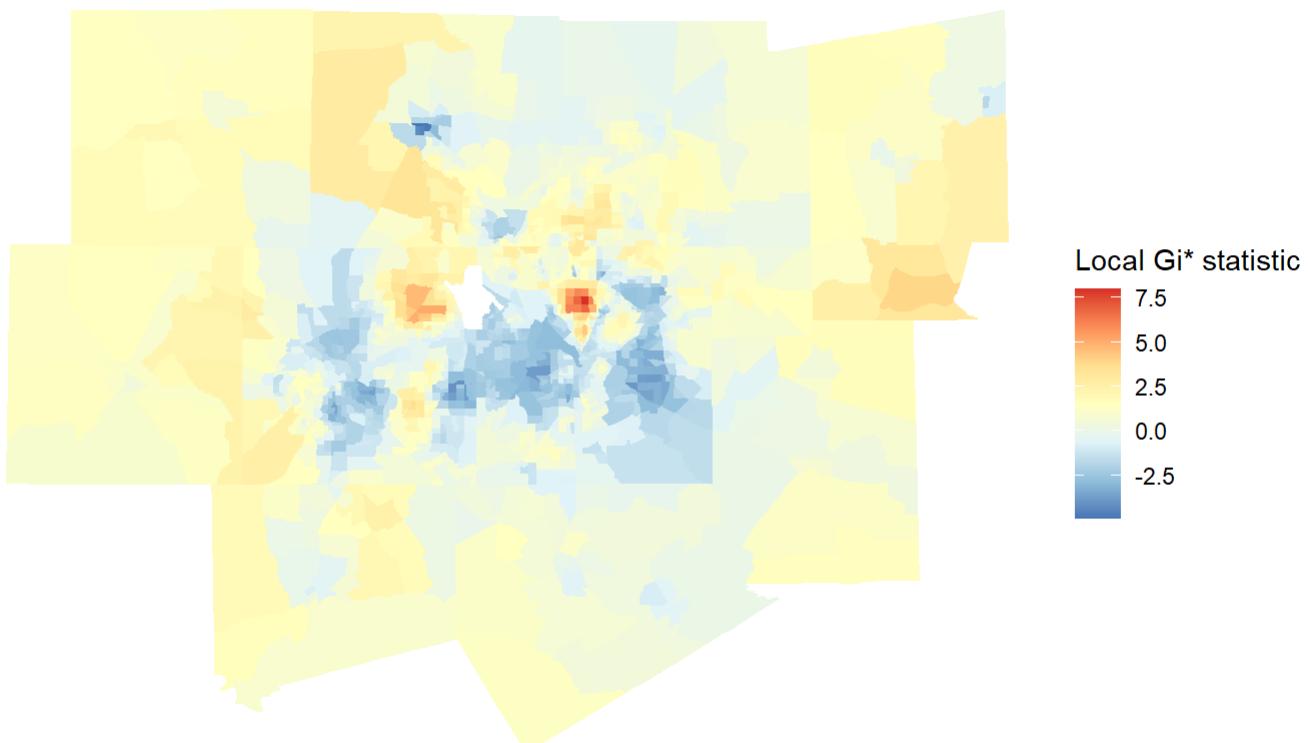
[Hide](#)

7.6.2 Local spatial autocorrelation

```
# For Gi*, re-compute the weights with `include.self()`
localg_weights <- nb2listw(include.self(neighbors))

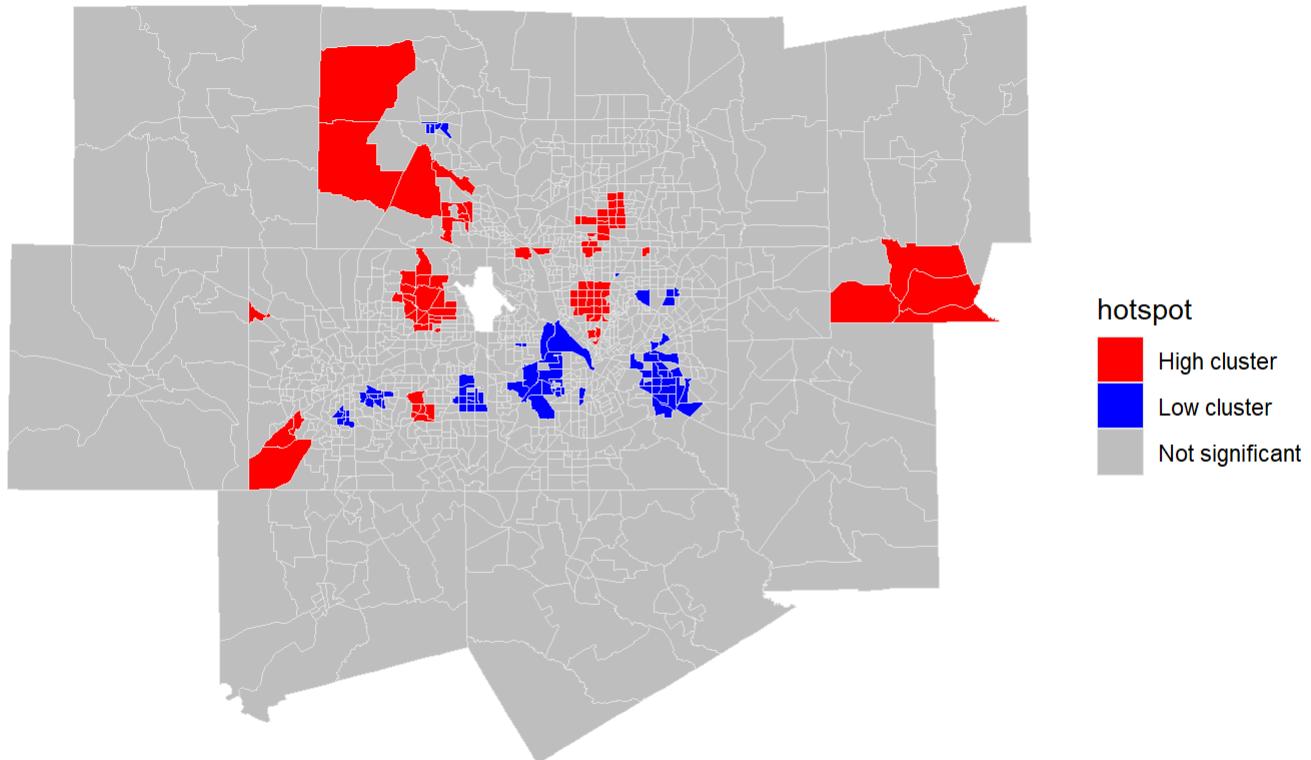
dfw_tracts$localG <- localG(dfw_tracts$estimate, localg_weights)

ggplot(dfw_tracts) +
  geom_sf(aes(fill = localG), color = NA) +
  scale_fill_distiller(palette = "RdYlBu") +
  theme_void() +
  labs(fill = "Local Gi* statistic")
```



Hide

```
dfw_tracts <- dfw_tracts %>%
  mutate(hotspot = case_when(
    localG >= 2.56 ~ "High cluster",
    localG <= -2.56 ~ "Low cluster",
    TRUE ~ "Not significant"
  ))
  ggplot(dfw_tracts) +
  geom_sf(aes(fill = hotspot), color = "grey90", size = 0.1) +
  scale_fill_manual(values = c("red", "blue", "grey")) +
  theme_void()
```



7.6.3 Identifying clusters and spatial outliers with local indicators of spatial association (LISA)

```
set.seed(1983)

dfw_tracts$scaled_estimate <- as.numeric(scale(dfw_tracts$estimate))

dfw_lisa <- localmoran_perm(
  dfw_tracts$scaled_estimate,
  weights,
  nsim = 999L,
  alternative = "two.sided"
) %>%
  as_tibble() %>%
  set_names(c("local_i", "exp_i", "var_i", "z_i", "p_i",
            "p_i_sim", "pi_sim_folded", "skewness", "kurtosis"))

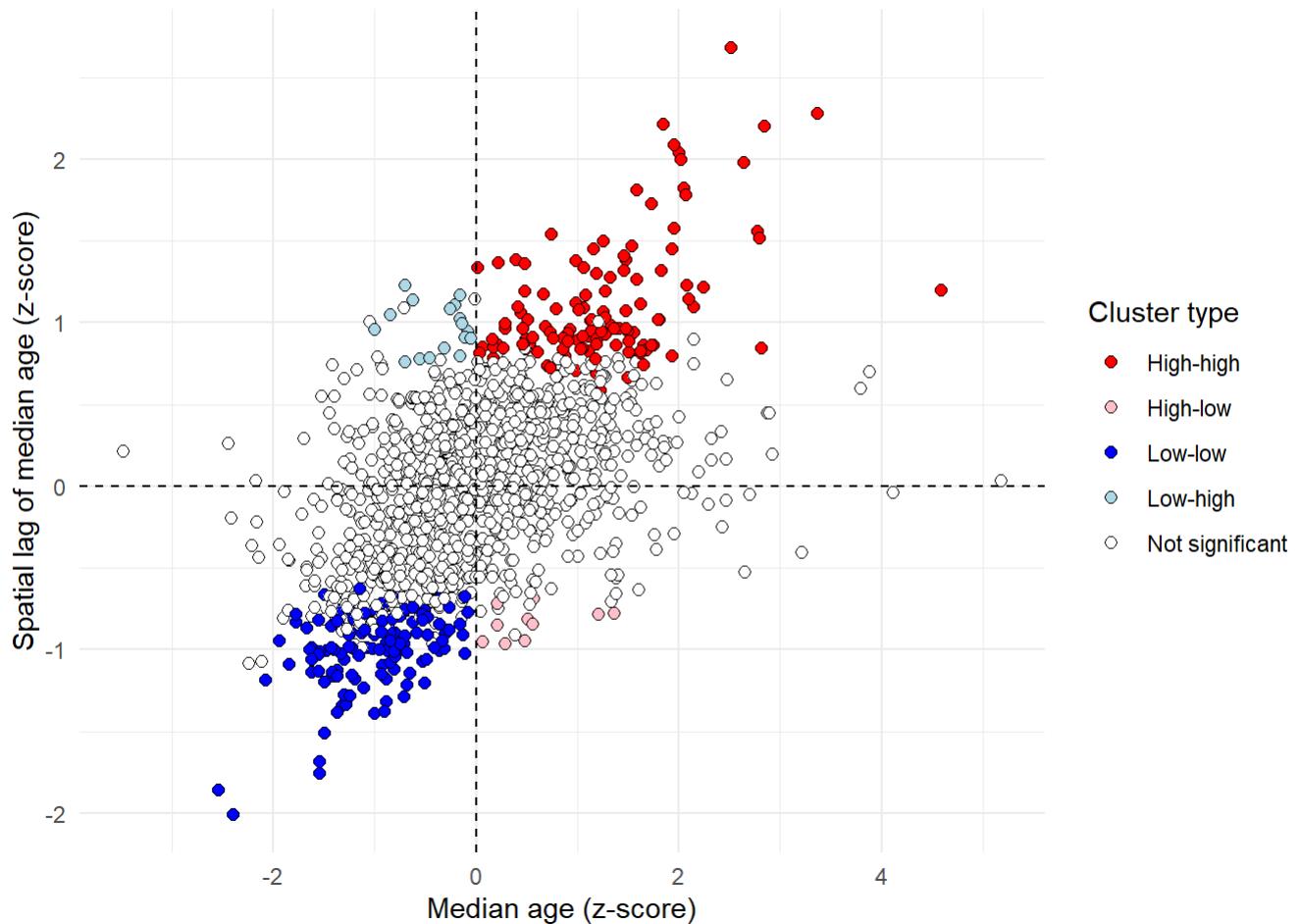
dfw_lisa_df <- dfw_tracts %>%
  select(GEOID, scaled_estimate) %>%
  mutate(lagged_estimate = lag.listw(weights, scaled_estimate)) %>%
  bind_cols(dfw_lisa)
```

```
dfw_lisa_clusters <- dfw_lisa_df %>%
  mutate(lisa_cluster = case_when(
    p_i >= 0.05 ~ "Not significant",
    scaled_estimate > 0 & local_i > 0 ~ "High-high",
    scaled_estimate > 0 & local_i < 0 ~ "High-low",
    scaled_estimate < 0 & local_i > 0 ~ "Low-low",
    scaled_estimate < 0 & local_i < 0 ~ "Low-high"
  ))
```

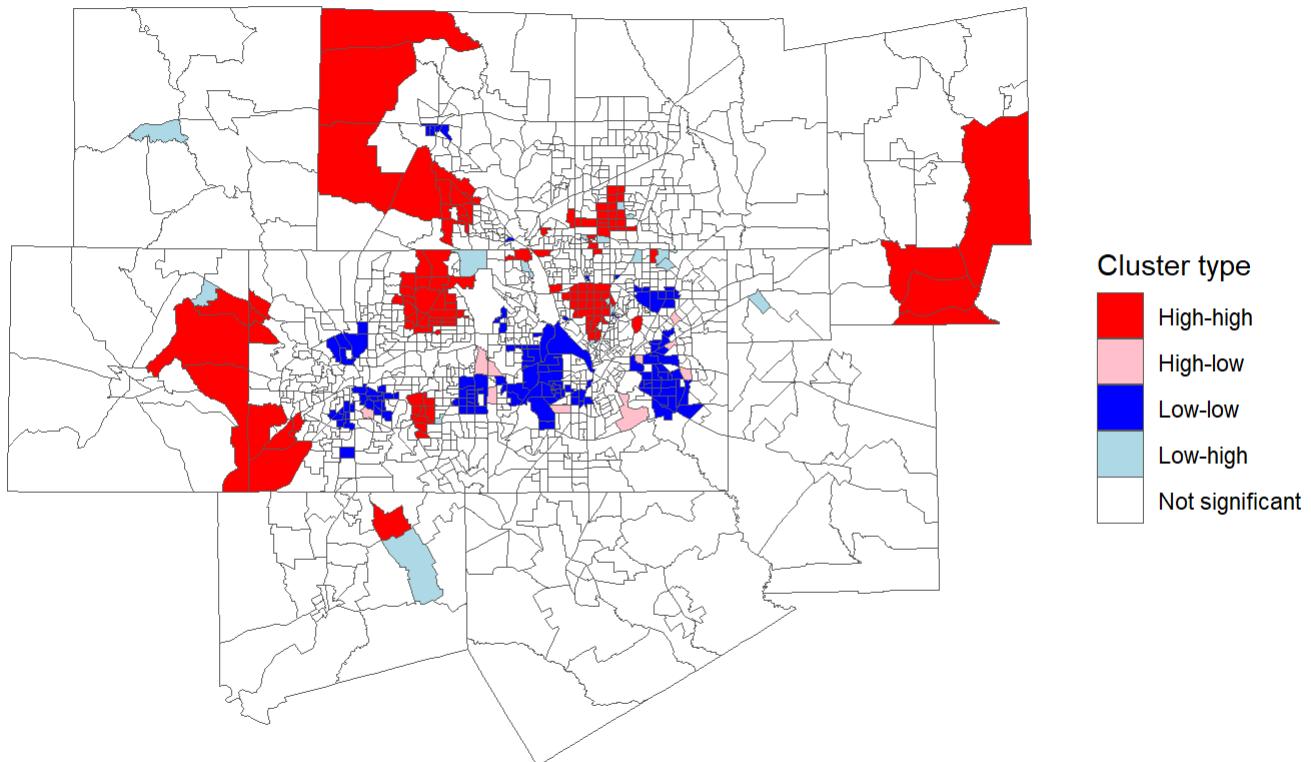
[Hide](#)

```
color_values <- c(`High-high` = "red",
  `High-low` = "pink",
  `Low-low` = "blue",
  `Low-high` = "lightblue",
  `Not significant` = "white")

ggplot(dfw_lisa_clusters, aes(x = scaled_estimate,
  y = lagged_estimate,
  fill = lisa_cluster)) +
  geom_point(color = "black", shape = 21, size = 2) +
  theme_minimal() +
  geom_hline(yintercept = 0, linetype = "dashed") +
  geom_vline(xintercept = 0, linetype = "dashed") +
  scale_fill_manual(values = color_values) +
  labs(x = "Median age (z-score)",
  y = "Spatial lag of median age (z-score)",
  fill = "Cluster type")
```

[Hide](#)

```
ggplot(dfw_lisa_clusters, aes(fill = lisa_cluster)) +  
  geom_sf(size = 0.1) +  
  theme_void() +  
  scale_fill_manual(values = color_values) +  
  labs(fill = "Cluster type")
```



7.7 Exercises

Identify a different core-based statistical area of interest and use the methods introduced in this chapter to extract Census tracts or block groups for that CBSA:

[Hide](#)

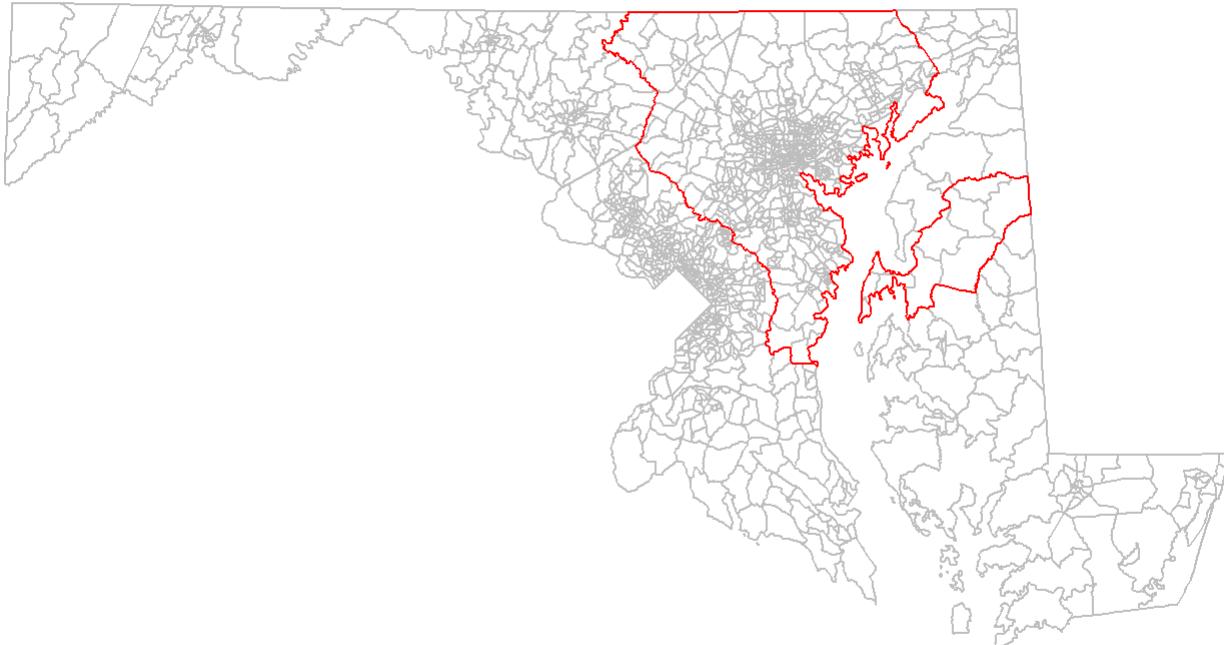
```
library(tigris)
library(tidyverse)
library(sf)
options(tigris_use_cache = TRUE)

# CRS used: NAD83(2011) / Maryland

Balt_MD_tracts <- map_dfr(c("MD"), ~{
  tracts(.x, cb = TRUE, year = 2020)
}) %>%
  st_transform(6488)

Balt_metro <- core_based_statistical_areas(cb = TRUE, year = 2020) %>%
  filter(str_detect(NAME, "Baltimore-Columbia-Towson")) %>%
  st_transform(6488)

ggplot() +
  geom_sf(data = Balt_MD_tracts, fill = "white", color = "grey") +
  geom_sf(data = Balt_metro, fill = NA, color = "red") +
  theme_void()
```



This code above first changes the projection to MD state plane, then outlines the Baltimore Metropolitan area in red. I am unsure as to why Queen Anne's County is included as well.

[Hide](#)

```
Balt_tracts <- Balt_MD_tracts[Balt_metro, ]  
  
ggplot() +  
  geom_sf(data = Balt_tracts, fill = "white", color = "grey") +  
  geom_sf(data = Balt_metro, fill = NA, color = "red") +  
  theme_void()
```



This code returns all of the census tracts that intersect the Baltimore Metropolitan area, and removes those that do not.

The code below will now return only the tracts that are within the Baltimore Metropolitan area.

[Hide](#)

```
Balt_tracts_within <- Balt_MD_tracts %>%  
  st_filter(Balt_metro, .predicate = st_within)  
  
ggplot() +  
  geom_sf(data = Balt_tracts_within, fill = "white", color = "grey") +  
  geom_sf(data = Balt_metro, fill = NA, color = "red") +  
  theme_void()
```



Next exercise: Replicate the `st_erase()` cartographic workflow for a different county with significant water area; a good choice is King County, Washington. Be sure to transform your data to an appropriate projected coordinate system (selected with `suggest_crs()`) first. If the operation creates too many “holes” for water areas, try filtering down the water dataset by its AWATER column and retaining only the largest water areas, then re-run and see what you get.

First grab data for King County Washington. Then find the best CRS and apply it.

[Hide](#)

```
library(tidycensus)
library(tidyverse)
library(crsuggest)
```

Using the EPSG Dataset v10.019, a product of the International Association of Oil & Gas Producers.

Please view the terms of use at <https://epsg.org/terms-of-use.html>.

[Hide](#)

```
options(tigris_use_cache = TRUE)

WA <- get_acs(
  geography = "tract",
  variables = "B19013_001",
  state = "WA",
  county = "King County",
  year = 2019,
  geometry = TRUE
)
```

Getting data from the 2015-2019 5-year ACS

[Hide](#)

```
WA_crs <- suggest_crs(WA)
```

Suggested CRS is Washington state plane in ft for the North region. The code to transform is: 6597

[Hide](#)

```
WA_projected <- st_transform(WA, crs = 6597)

head(WA_projected)
```

GEOID <chr>	NAME	variable <chr>	estimate <dbl>	mo <dbl>
153033011300	Census Tract 113, King County, Washington	B19013_001	56402	666
253033004900	Census Tract 49, King County, Washington	B19013_001	101203	1504
353033026801	Census Tract 268.01, King County, Washington	B19013_001	55761	1006
453033006400	Census Tract 64, King County, Washington	B19013_001	166125	1824
553033005100	Census Tract 51, King County, Washington	B19013_001	119625	2453
653033002000	Census Tract 20, King County, Washington	B19013_001	121184	1523

6 rows

The code below will combine my previous steps but will remove the cb = TRUE argument so that TIGER/Line files will be used.

[Hide](#)

```
# CRS: NAD83(2011) / Washington North (ftUS)
wa2 <- get_acs(
  geography = "tract",
  variables = "B19013_001",
  state = "WA",
  county = "King County",
  geometry = TRUE,
  year = 2019,
  cb = FALSE
) %>%
  st_transform(6597)
```

Getting data from the 2015-2019 5-year ACS

Next I will run the code below to identify water and then erase it from the polygons.

[Hide](#)

```
library(sf)
library(tigris)

wa_erase <- function(x, y) {
  st_difference(x, st_union(y))
}

wa_water <- area_water("WA", "King County", year = 2019) %>%
  st_transform(6597)

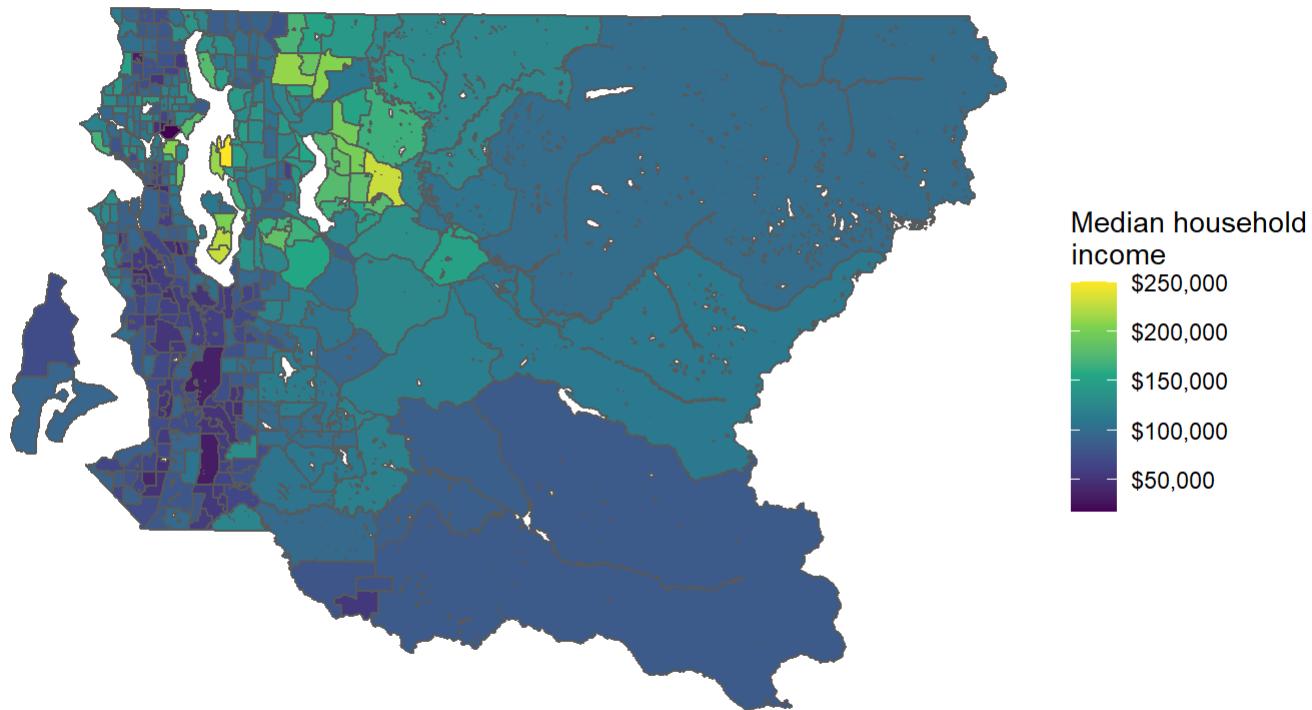
wa_erase <- wa_erase(wa2, wa_water)
```

Warning: attribute variables are assumed to be spatially constant throughout all geometries

Now I will map the result with the code below:

[Hide](#)

```
ggplot(wa_erase) +
  geom_sf(aes(fill = estimate)) +
  scale_fill_viridis_c(labels = scales::dollar) +
  theme_void() +
  labs(fill = "Median household\nincome")
```



As you can see, areas with water are removed from King County Washington.

Next exercise is to: Acquire a spatial dataset with `tidycensus` for a region of interest and a variable of interest to you. Follow the instructions in this chapter to generate a spatial weights matrix, then compute a hot-spot analysis with `localG()`.

First step is to find data for a region of interest. I am going to do median household income for Maryland Counties

[Hide](#)

```
library(tidycensus)
library(tidyverse)
library(tigris)
library(sf)
library(spdep)
options(tigris_use_cache = TRUE)

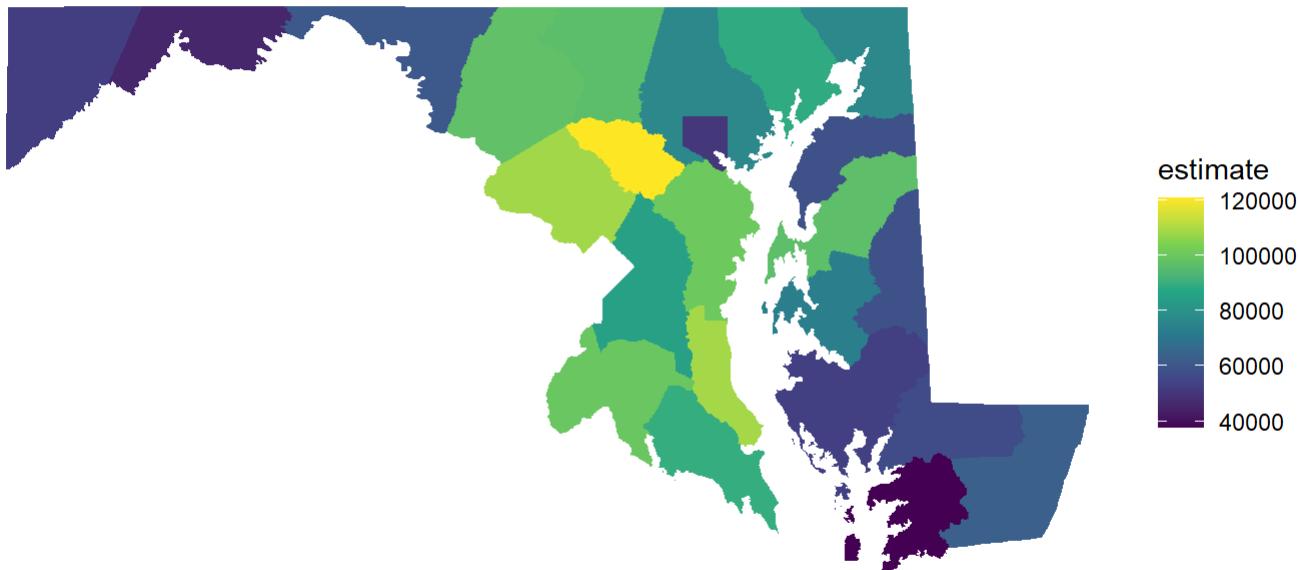
# CRS: NAD83 / Maryland State Plane

md_counties <- get_acs(
  geography = "county",
  variables = "B19013_001",
  state = "MD",
  year = 2019,
  geometry = TRUE
)
```

Getting data from the 2015-2019 5-year ACS

[Hide](#)

```
ggplot(md_counties) +  
  geom_sf(aes(fill = estimate), color = NA) +  
  scale_fill_viridis_c() +  
  theme_void()
```



Now lets produce the spatial weights matrix: I am going to use a Queens case neighbors since the geographic features (counties) are polygons.

[Hide](#)

```
neighbors <- poly2nb(md_counties, queen = TRUE)  
  
summary(neighbors)
```

Neighbour list object:

Number of regions: 24

Number of nonzero links: 72

Percentage nonzero weights: 12.5

Average number of links: 3

Link number distribution:

1 2 3 4 5 6

1 9 8 2 3 1

1 least connected region:

14 with 1 link

1 most connected region:

9 with 6 links

Now I will generate the matrix with the neighbors list.

[Hide](#)

```
weights <- nb2listw(neighbors, style = "W")
```

```
weights$weights[[1]]
```

```
[1] 0.3333333 0.3333333 0.3333333
```

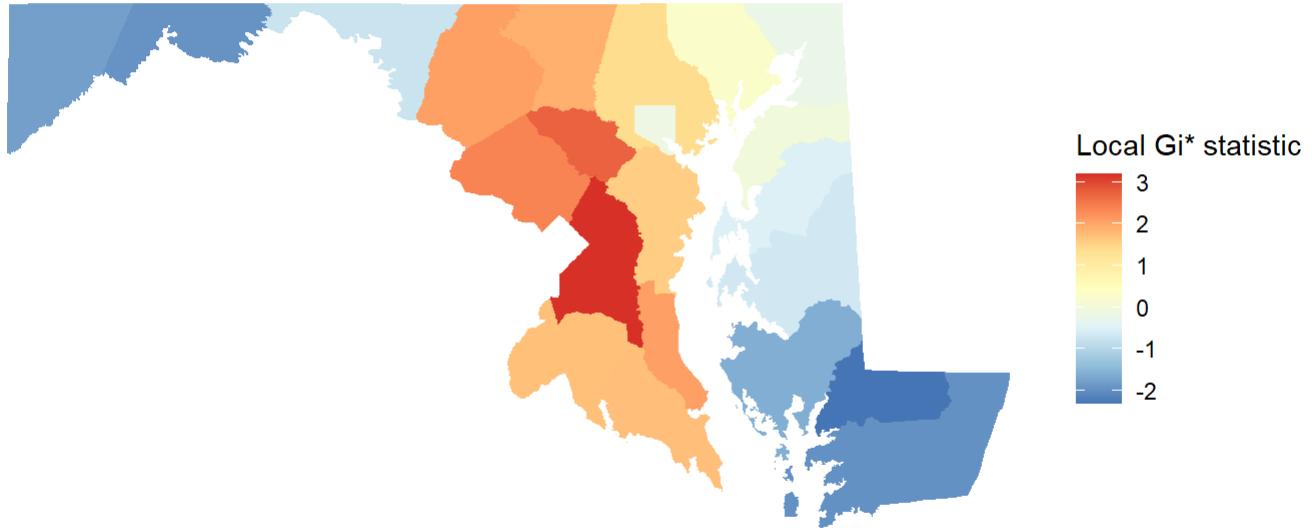
Now a hot spot analysis will be done using the localg function.

[Hide](#)

```
# For Gi*, re-compute the weights with `include.self()`
localg_weights <- nb2listw(include.self(neighbors))

md_counties$localG <- localG(md_counties$estimate, localg_weights)

ggplot(md_counties) +
  geom_sf(aes(fill = localG), color = NA) +
  scale_fill_distiller(palette = "RdYlBu") +
  theme_void() +
  labs(fill = "Local Gi* statistic")
```



The code below performs an analysis for plotting hotspot thresholds

[Hide](#)

```
md_counties <- md_counties %>%
  mutate(hotspot = case_when(
    localG >= 2.56 ~ "High cluster",
    localG <= -2.56 ~ "Low cluster",
    TRUE ~ "Not significant"
  ))

ggplot(md_counties) +
  geom_sf(aes(fill = hotspot), color = "grey90", size = 0.1) +
  scale_fill_manual(values = c("red", "blue", "grey")) +
  theme_void()
```

