CSSS508, Week 9

Mapping

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UW CS&SS

Today

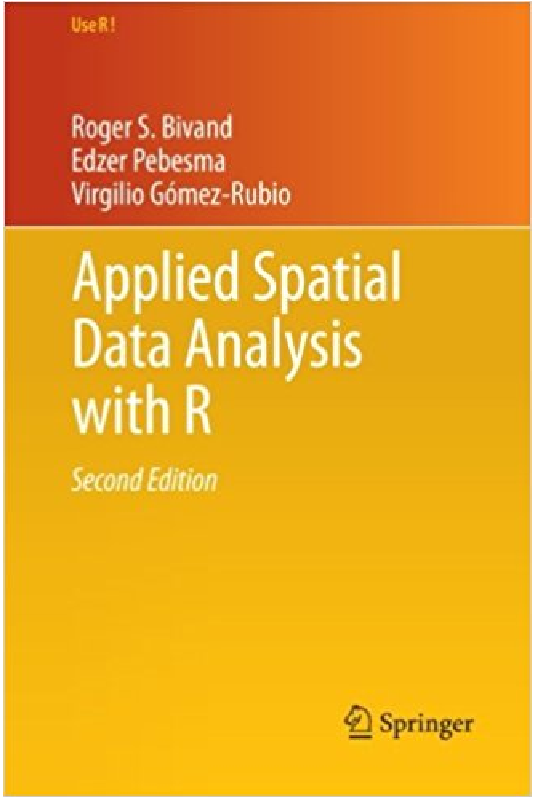
Basic Mapping in `ggplot2`

- Mapping with raw `ggplot2` using coordinates
- `ggmap` for mashing up maps with `ggplot2`
- Labeling points and using `ggrepel` to avoid overlaps

Advanced Mapping

- `sf`: Simple Features geometry for R
- `tidycensus` and `tigris` for obtaining Census Bureau data and shapefiles

Mapping in R: A quick plug



This is great if you are interested in mapping, GIS, and geospatial analysis in R--but new things are on the way!.

RSpatial.org is also great.

You may also consider taking Jon Wakefield's **CSSS 554: Statistical Methods for Spatial Data**, however it is challenging and focuses more heavily on statistics than mapping.

CSDE offers workshops using QGIS and/or ArcGIS. I recommend QGIS because it is free software with an extensive feature set.

Basic Mapping

`ggplot2` and `ggmap`

One Day of SPD Incidents

In Week 5, we looked at types of incidents the Seattle Police Department responded to in a single day. Now, we'll look at where those were.

```
library(tidyverse)
```

```
spd_raw <- read_csv("https://clanfear.github.io/CSSS508/Seattle_Polic
```

Taking a `glimpse()`

```r
glimpse(spd_raw)
```

```
## Rows: 706
## Columns: 19
## $ `CAD CDW ID`                    <dbl> 1701856, 1701857, 1701853, 170~
## $ `CAD Event Number`              <dbl> 16000104006, 16000103970, 1600~
## $ `General Offense Number`        <dbl> 2016104006, 2016103970, 201610~
## $ `Event Clearance Code`          <chr> "063", "064", "161", "245", "2~
## $ `Event Clearance Description`   <chr> "THEFT - CAR PROWL", "SHOPLIFT~
## $ `Event Clearance SubGroup`      <chr> "CAR PROWL", "THEFT", "TRESPAS~
## $ `Event Clearance Group`         <chr> "CAR PROWL", "SHOPLIFTING", "T~
## $ `Event Clearance Date`          <chr> "03/25/2016 11:58:30 PM", "03/~
## $ `Hundred Block Location`        <chr> "S KING ST / 8 AV S", "92XX BL~
## $ `District/Sector`               <chr> "K", "S", "D", "M", "M", "B", ~
## $ `Zone/Beat`                     <chr> "K3", "S3", "D2", "M1", "M3", ~
## $ `Census Tract`                  <dbl> 9100.102, 11800.602, 7200.106,~
## $ Longitude                       <dbl> -122.3225, -122.2680, -122.342~
## $ Latitude                        <dbl> 47.59835, 47.51985, 47.61422, ~
## $ `Incident Location`             <chr> "(47.598347, -122.32245)", "(4~
## $ `Initial Type Description`      <chr> "THEFT (DOES NOT INCLUDE SHOPL~
## $ `Initial Type Subgroup`         <chr> "OTHER PROPERTY", "SHOPLIFTING~
## $ `Initial Type Group`            <chr> "THEFT", "THEFT", "TRESPASS", ~
## $ `At Scene Time`                 <chr> "03/25/2016 10:25:51 PM", "03/~
```

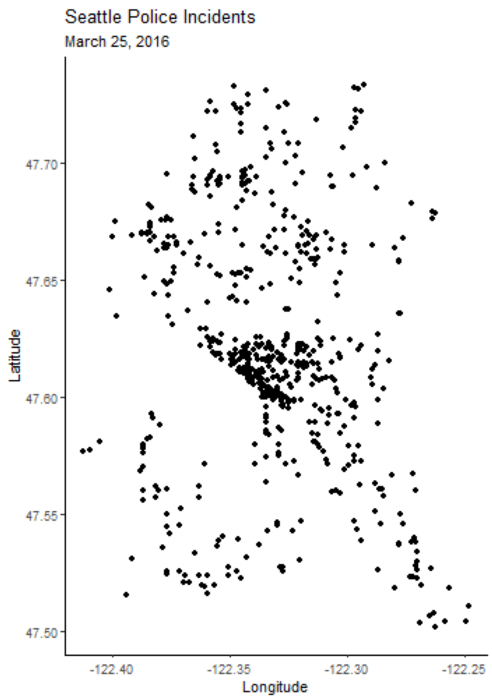
`x`, `y` as Coordinates

Coordinates, such as longitude and latitude, can be provided in `aes()` as `x` and `y` values.

This is ideal when you don't need to place points over some map for reference.

```
ggplot(spd_raw,
       aes(Longitude, Latitude)) +
  geom_point() +
  coord_fixed() + # evenly spaces x and y
  ggtitle("Seattle Police Incidents",
          subtitle="March 25, 2016") +
  theme_classic()
```

Sometimes, however, we want to plot these points over existing maps.



`ggmap`

`ggmap`

`ggmap` is a package that works with `ggplot2` to plot spatial data directly on map images downloaded from Google Maps[1] and Stamen Maps (good artistic/minimal options).

What this package does for you:

1. Queries servers for a map (`get_map()`) at the location and scale you want
2. Plots the **raster** (bitmap) image as a `ggplot` object
3. Lets you add more `ggplot` layers like points, 2D density plots, text annotations
4. Additional functions for interacting with Google Maps (e.g. getting distances by bike)

[1] Requires a Google API Key.

Installation

We can install `ggmap` like other packages:

```
install.packages("ggmap")
```

Because the map APIs it uses change frequently, sometimes you may need to get a newer development version of `ggmap` from the author's GitHub. This can be done using the `remotes` package.

```
if(!requireNamespace("remotes")) install.packages("remotes")
remotes::install_github("dkahle/ggmap")
```

Note, this may require compilation on your computer.

```
library(ggmap)
```

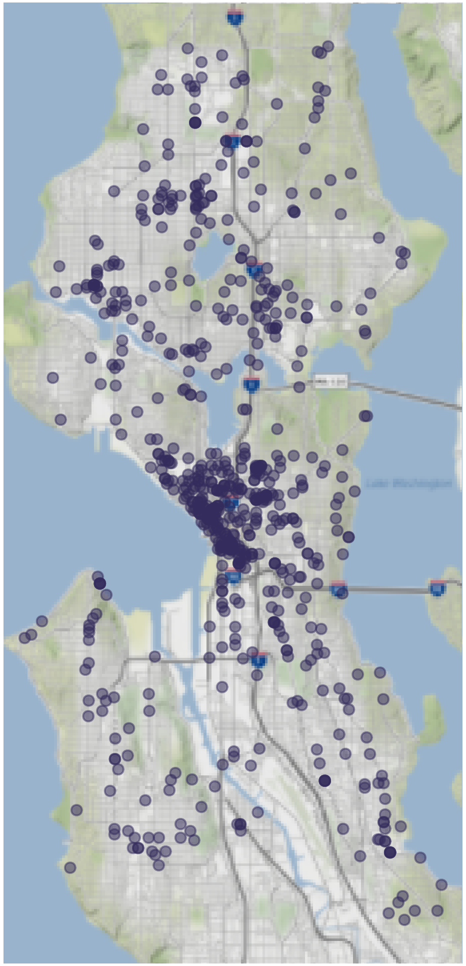
Quick Maps with `qmplot()`

`qmplot` will automatically set the map region based on your data:

```
qmplot(data = spd_raw,
       x = Longitude,
       y = Latitude,
       color = I("#342c5c"),
       alpha = I(0.5))
```

All I provided was numeric latitude and longitude, and it placed the data points correctly on a raster map of Seattle.

`I()` is used here to specify *set* (constant) rather than *mapped* values.



`get_map()`

Both `qmplot()` and `qmap()` are wrappers for a function called `get_map()` that retrieves a base map layer. Some options:

- `location=` search query or numeric vector of longitude and latitude
- `zoom=` a zoom level (3 = continent, 10 = city, 21 = building)
- `source=`
  - `"google"`: Google Maps for general purpose maps[1]
  - `"stamen"`: Aesthetically pleasing alternatives based on OpenStreetMaps
- `maptype=`
  - Google types: `"terrain"`, `"terrain-background"`, `"satellite"`, `"roadmap"`, `"hybrid"`
  - Stamen types: `"watercolor"`, `"toner"`, `"toner-background"`, `"toner-lite"`
- `color=` `"color"` or `"bw"`

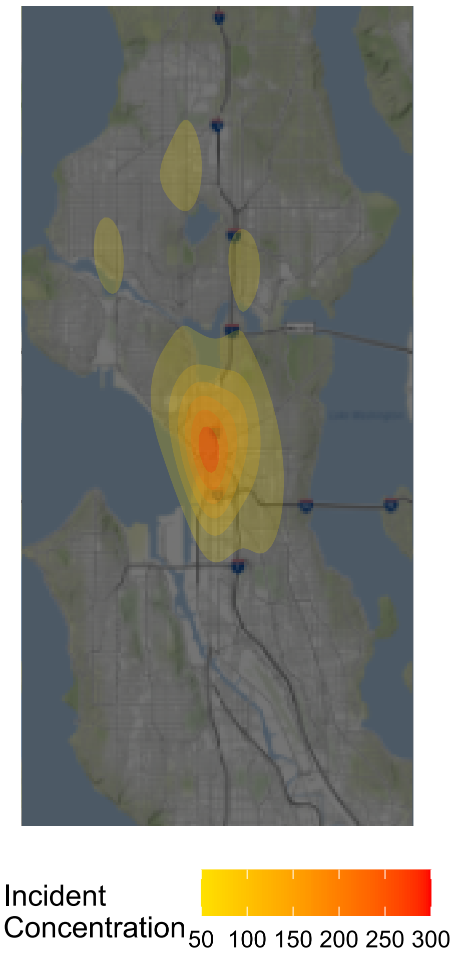
[1] Requires API key!

Adding Density Layers

Call `qmplot()` with no `geom()`, and then add density layers:

```
qmplot(data = spd_raw, geom = "blank",
  x = Longitude, y = Latitude,
  maptype = "toner-lite",
  darken = 0.5) +
  stat_density_2d(
    aes(fill = stat(level)),
      geom = "polygon",
      alpha = .2, color = NA) +
  scale_fill_gradient2(
      "Incident\nConcentration",
      low = "white",
      mid = "yellow",
      high = "red") +
  theme(legend.position = "bottom")
```

`stat(level)` indicates we want `fill=` to be based on `level` values calculated by the layer.



Labeling Points

Let's label the assaults and robberies specifically in downtown:

First filter to downtown based on values "eyeballed" from our earlier map:

```
downtown <- spd_raw %>%
  filter(Latitude  >   47.58, Latitude  <   47.64,
         Longitude > -122.36, Longitude < -122.31)
```

Then make a dataframe of just assaults and robberies:

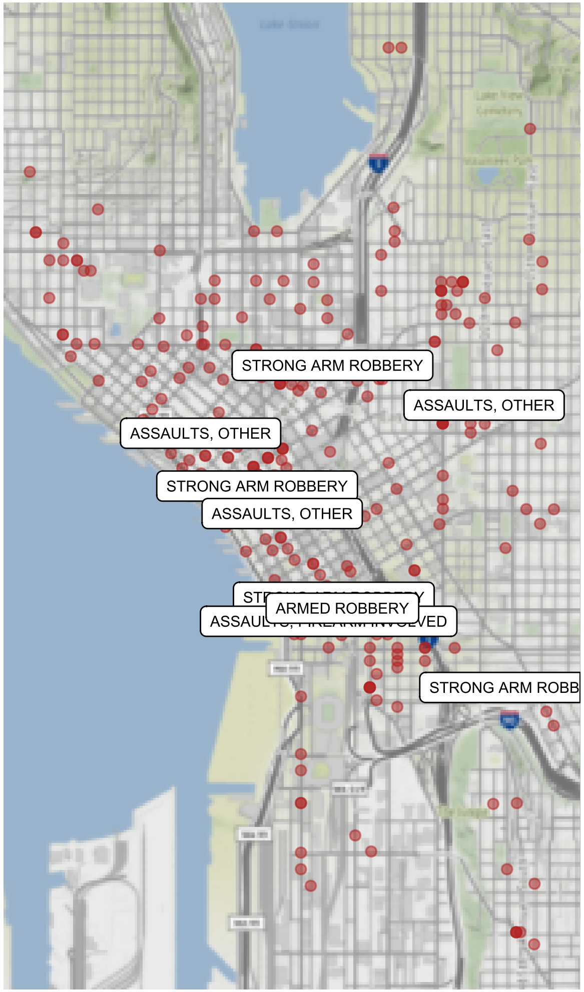
```
assaults <- downtown %>%
  filter(`Event Clearance Group` %in%
                  c("ASSAULTS", "ROBBERY")) %>%
  rename(assault_label = `Event Clearance Description`)
```

Labels

Now let's plot the events and label them with `geom_label()` (`geom_text()` without background or border):

```
qmplot(data = downtown,
       x = Longitude,
       y = Latitude,
       maptype = "toner-lite",
       color = I("firebrick"),
       alpha = I(0.5)) +
  geom_label(data = assaults,
       aes(label = assault_label),
       size=2)
```

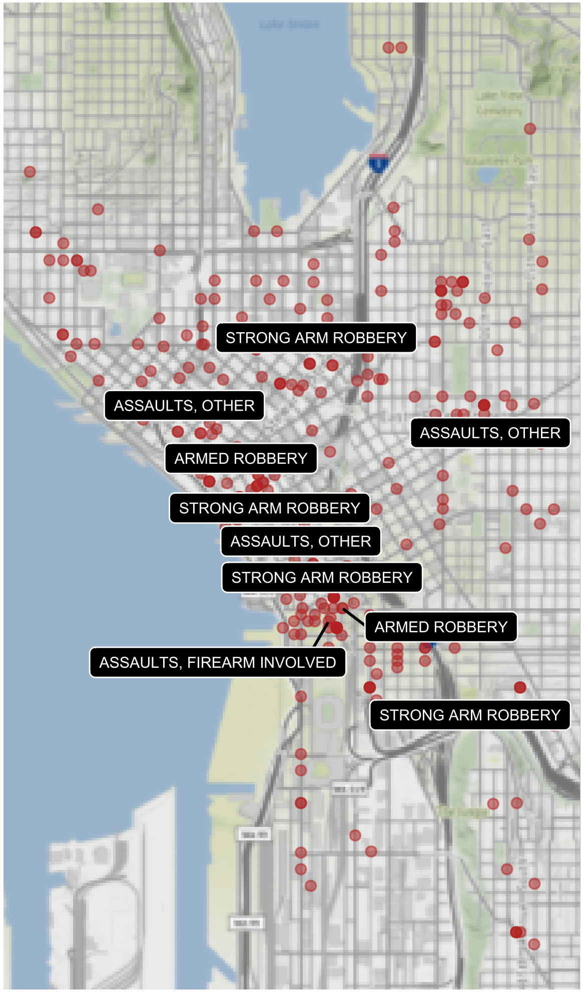
Placing the arguments for `color=` and `alpha=` inside `I()` prevents them from also applying to the labels. We would get transparent red labels otherwise!



ggrepel

You can also try `geom_label_repel()` or `geom_text_repel()` in the `ggrepel` package to fix or reduce overlaps (total space is limited here):

```
library(ggrepel)
qmplot(data =
    downtown,
    x = Longitude,
    y = Latitude,
    maptype = "toner-lite",
    color = I("firebrick"),
    alpha = I(0.5)) +
  geom_label_repel(
    data = assaults,
    aes(label = assault_label),
    fill = "black",
    color = "white",
    segment.color = "black",
    size=2)
```



Advanced Mapping

GIS and R with `sf`

Terminology

- Simple Features (`sf`)
- Coordinate Reference System (CRS)
- Shapefile

`sf`

Until recently, the main way to work with geospatial data in R was through the `sp` package. `sp` works well but does not store data the same way as most GIS packages and can be bulky and complicated.

The more recent `sf` package implements the GIS standard of **Simple Features** in R.

`sf` is also integrated into the `tidyverse`: e.g. `geom_sf()` in `ggplot2`.

The package is somewhat new but is expected to *replace* `sp` eventually. The principle authors and contributors to `sf` are the same authors as `sp` but with new developers from the `tidyverse` as well.

Because `sf` is the new standard, we will focus on it today.

```
library(sf)
```

Simple Features

A **Simple Feature** is a single observation with some defined geospatial location(s). Features are stored in special data frames (class `sf`) with two properties:

- **Geometry**: Properties describing a location (usually on Earth).
    - Usually 2 dimensions, but support for up to 4.
    - Stored in a single reserved *list-column* (`geom`, of class `sfc`).[1]
    - Contain a defined coordinate reference system.

- **Attributes**: Characteristics of the location (such as population).
    - These are non-spatial measures that describe a feature.
    - Standard data frame columns.

[1] A list-column is the same length as all other columns in the data, but each element contains *sub-elements* (class `sfg`) with all the geometrical components.

List-columns require special functions to manipulate, *including removing them*.

Coordinate Reference Systems

Coordinate reference systems (**CRS**) specify what location on Earth geometry coordinates are *relative to* (e.g. what location is (0,0) when plotting).

The most commonly used is **WGS84**, the standard for Google Earth, the Department of Defense, and GPS satellites.

There are two common ways to define a CRS in `sf`:

- **EPSG codes** (`epsg` in R)
  - Numeric codes which *refer to a predefined CRS*
  - Example: WGS84 is `4326`
- **PROJ.4 strings** (`proj4string` in R)
  - Text strings of parameters that *define a CRS*
  - Example: NAD83(NSRS2007) / Washington North

```
+proj=lcc +lat_1=48.73333333333333 +lat_2=47.5 +lat_0=47
+lon_0=-120.8333333333333 +x_0=500000 +y_0=0 +ellps=GRS80
+towgs84=0,0,0,0,0,0,0 +units=m +no_defs
```

Shapefiles

Geospatial data is typically stored in **shapefiles** which store geometric data as **vectors** with associated attributes (variables)

Shapefiles actually consist of multiple individual files. There are usually at least three (but up to 10+):

- `.shp`: The feature geometries
- `.shx`: Shape positional index
- `.dbf`: Attributes describing features[1]

Often there will also be a `.prj` file defining the coordinate system.

[2] This is just a dBase IV file which is an ancient and common database storage file format.

Using `sf`

Selected `sf` Functions

`sf` is a huge, feature-rich package. Here is a sample of useful functions:

- `st_read()`, `st_write()`: Read and write shapefiles.
- `geom_sf()`: `ggplot()` layer for `sf` objects.
- `st_as_sf()`: Convert a data frame into an `sf` object.
- `st_join()`: Join data by spatial relationship.
- `st_transform()`: Convert between CRS.
- `st_drop_geometry()`: Remove geometry from a `sf` data frame.
- `st_relate()`: Compute relationships between geometries (like neighbor matrices).
- `st_interpolate_aw()`: Areal-weighted interpolation of polygons.[1]

[1] I recommend the dedicated `areal` package for this though!

Loading Data

We will work with the voting data from Homework 5. You can obtain a shape file of King County voting precincts from the [county GIS data portal](#).

We can load the file using `st_read()`.

```
precinct_shape <- st_read("./data/district/votdst.shp") %>%
  select(Precinct=NAME, geometry)
```

```
## Reading layer `votdst' from data source `C:\Users\cclan\OneDrive\GitHub\CS
## Simple feature collection with 2592 features and 5 fields
## Geometry type: MULTIPOLYGON
## Dimension:     XY
## Bounding box:  xmin: 1220179 ymin: 31555.16 xmax: 1583562 ymax: 287678
## Projected CRS: NAD83(HARN) / Washington North (ftUS)
```

[If following along, click here to download a zip of the shapefile.](#)

Voting Data: Processing

```r
precincts_votes_sf <-
  read_csv("./data/king_county_elections_2016.txt") %>%
  filter(Race == "US President & Vice President" &
         str_detect(Precinct, "SEA ")) %>%
  select(Precinct, CounterType, SumOfCount) %>%
  group_by(Precinct) %>%
  filter(CounterType %in%
           c("Donald J. Trump & Michael R. Pence",
             "Hillary Clinton & Tim Kaine",
             "Registered Voters",
             "Times Counted")) %>%
  mutate(CounterType =
           recode(CounterType,
                  `Donald J. Trump & Michael R. Pence` = "Trump",
                  `Hillary Clinton & Tim Kaine` = "Clinton",
                  `Registered Voters`= "RegisteredVoters",
                  `Times Counted` = "TotalVotes")) %>%
  pivot_wider(names_from = CounterType,
              values_from = SumOfCount) %>%
  mutate(P_Dem = Clinton / TotalVotes,
         P_Rep = Trump / TotalVotes,
         Turnout = TotalVotes / RegisteredVoters) %>%
  select(Precinct, P_Dem, P_Rep, Turnout) %>%
  filter(!is.na(P_Dem)) %>%
  left_join(precinct_shape) %>%
  st_as_sf() # Makes sure resulting object is an sf dataframe
```

Taking a `glimpse()`

```
glimpse(precincts_votes_sf)
```

```
## Rows: 960
## Columns: 5
## Groups: Precinct [960]
## $ Precinct <chr> "SEA 11-1256", "SEA 11-1550", "SEA 11-1552", "SEA 1~
## $ P_Dem    <dbl> 0.7707510, 0.8168421, 0.7507987, 0.8376328, 0.83259~
## $ P_Rep    <dbl> 0.15612648, 0.07789474, 0.13418530, 0.08649469, 0.0~
## $ Turnout  <dbl> 0.6931507, 0.7274119, 0.7347418, 0.7522831, 0.75792~
## $ geometry <MULTIPOLYGON [US_survey_foot]> MULTIPOLYGON (((1273698 1~
```

Notice the `geometry` column and its unusual class: `MULTIPOLYGON`

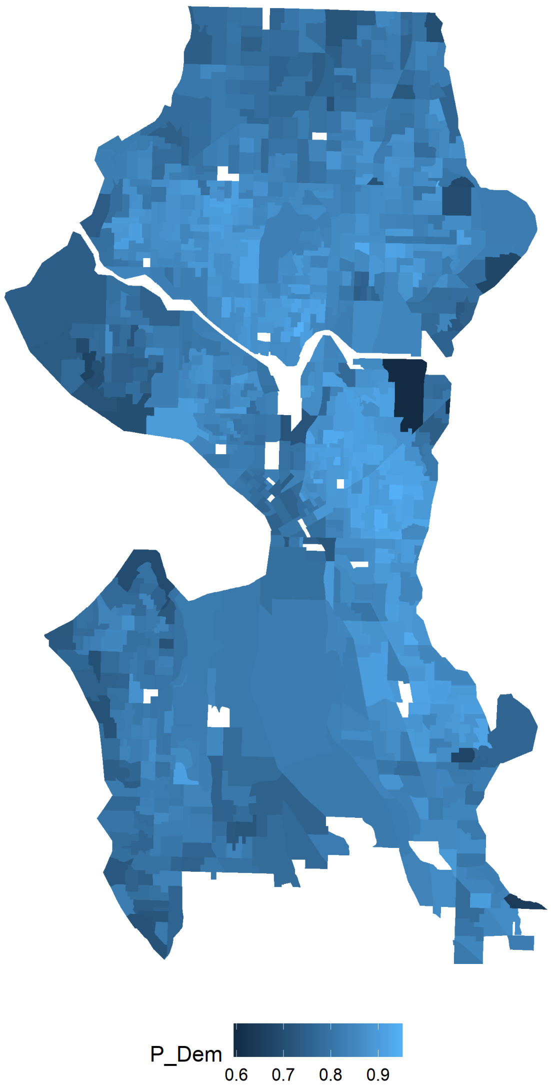
A single observation (row) has a geometry which may consist of multiple polygons.

Voting Map

We can plot `sf` geometry using `geom_sf()`.

```
ggplot(precincts_votes_sf,
       aes(fill = P_Dem)) +
  geom_sf(size = NA) +
  theme_void() +
  theme(legend.position =
          "bottom")
```

- `fill=P_Dem` maps color inside precincts to `P_Dem`.
- `size=NA` removes precinct outlines.
- `theme_void()` removes axes and background.



`tidycensus`

`tidycensus`

`tidycensus` can be used to search the American Community Survey (ACS) and Dicennial Census for variables, then download them and automatically format them as tidy dataframes.

These dataframes include geographical boundaries such as tracts!

This package utilizes the Census API, so you will need to obtain a [Census API key](#).

Application Program Interface (API): A type of computer interface that exists as the "native" method of communication between computers, often via http (usable via `httr` package).

- R packages that interface with websites and databases typically use APIs.
- APIs make accessing data easy while allowing websites to control access.

See [the developer's GitHub page](#) for detailed instructions.

Key `tidycensus` Functions

- `census_api_key()` - Install a census api key.
  - Note you will need to run this prior to using any `tidycensus` functions.
- `load_variables()` - Load searchable variable lists.
  - `year =`: Sets census year or endyear of 5-year ACS
  - `dataset =`: Sets dataset (see `?load_variables`)
- `get_decennial()` - Load Census variables and geographical boundaries.
  - `variables =`: Provide vector of variable IDs
  - `geography =`: Sets unit of analysis (e.g. `state`, `tract`, `block`)
  - `year =`: Census year (`1990`, `2000`, or `2010`)
  - `geometry = TRUE`: Returns `sf` geometry
- `get_acs()` - Load ACS variables and boundaries.

Searching for Variables

```r
library(tidycensus)
# census_api_key("PUT YOUR KEY HERE", install=TRUE)
acs_2015_vars <- load_variables(2015, "acs5")
acs_2015_vars[10:18,] %>% print()
```

```
## # A tibble: 9 x 3
##   name       label                                  concept
##   <chr>      <chr>                                  <chr>
## 1 B01001_008 Estimate!!Total!!Male!!20 years        SEX BY AGE
## 2 B01001_009 Estimate!!Total!!Male!!21 years        SEX BY AGE
## 3 B01001_010 Estimate!!Total!!Male!!22 to 24 years SEX BY AGE
## 4 B01001_011 Estimate!!Total!!Male!!25 to 29 years SEX BY AGE
## 5 B01001_012 Estimate!!Total!!Male!!30 to 34 years SEX BY AGE
## 6 B01001_013 Estimate!!Total!!Male!!35 to 39 years SEX BY AGE
## 7 B01001_014 Estimate!!Total!!Male!!40 to 44 years SEX BY AGE
## 8 B01001_015 Estimate!!Total!!Male!!45 to 49 years SEX BY AGE
## 9 B01001_016 Estimate!!Total!!Male!!50 to 54 years SEX BY AGE
```

Getting Data

```
king_county <- get_acs(geography = "tract",   state = "WA",
                       county    = "King", geometry = TRUE,
                       variables = c("B02001_001E",
                                     "B02009_001E"),
                       output    = "wide")
```

What do these look like?

```
glimpse(king_county)
```

```
## Rows: 398
## Columns: 7
## $ GEOID       <chr> "53033011300", "53033004900", "53033026801", "53~
## $ NAME        <chr> "Census Tract 113, King County, Washington", "Ce~
## $ B02001_001E <dbl> 6656, 7489, 6056, 3739, 3687, 3854, 4362, 3991, ~
## $ B02001_001M <dbl> 447, 605, 642, 192, 236, 271, 388, 430, 442, 286~
## $ B02009_001E <dbl> 951, 66, 571, 189, 141, 54, 757, 302, 1058, 163,~
## $ B02009_001M <dbl> 370, 61, 432, 123, 141, 76, 449, 266, 384, 170, ~
## $ geometry    <MULTIPOLYGON [°]> MULTIPOLYGON (((-122.3551 4..., MUL~
```

With `output="wide"`, **estimates** end in `E` and *error margins* in `M`.

Processing Data

We can drop the margins of error, rename the estimates then, `mutate()` into a proportion `Any Black` measure.

```
king_county <-  king_county %>%
  select(-ends_with("M")) %>%
  rename(`Total Population`= B02001_001E,
         `Any Black`       = B02009_001E) %>%
  mutate(`Any Black` = `Any Black` / `Total Population`)
glimpse(king_county)
```

```
## Rows: 398
## Columns: 5
## $ GEOID              <chr> "53033011300", "53033004900", "5303302680~
## $ NAME               <chr> "Census Tract 113, King County, Washingto~
## $ `Total Population` <dbl> 6656, 7489, 6056, 3739, 3687, 3854, 4362,~
## $ `Any Black`        <dbl> 0.142878606, 0.008812926, 0.094286658, 0.~
## $ geometry           <MULTIPOLYGON [°]> MULTIPOLYGON (((-122.3551 4.~
```

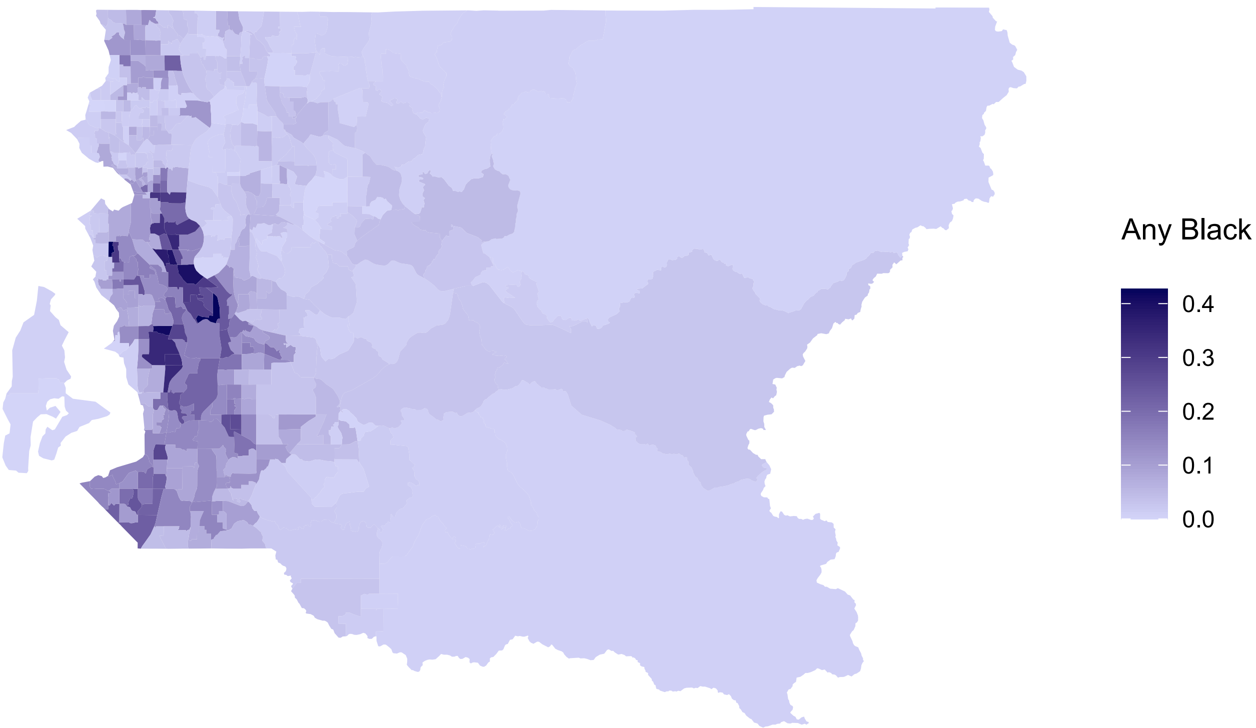
Mapping Code

```
king_county %>%
  ggplot(aes(fill = `Any Black`)) +
  geom_sf(size = NA) +
  coord_sf(crs = "+proj=longlat +datum=WGS84", datum = NA) +
  scale_fill_continuous(name = "Any Black\n",
                        low  = "#d4d5f9",
                        high = "#00025b") +
  theme_minimal() + ggtitle("Proportion Any Black")
```

New functions:

- `geom_sf()` draws Simple Features coordinate data.
    - `size = NA` removes outlines
- `coord_sf()` is used here with these arguments:
    - `crs`: Modifies the coordinate reference system (CRS); WGS84 is possibly the most commonly used CRS.
    - `datum=NA`: Removes graticule lines, which are geographical lines such as meridians and parallels.

Proportion Any Black



Removing Water

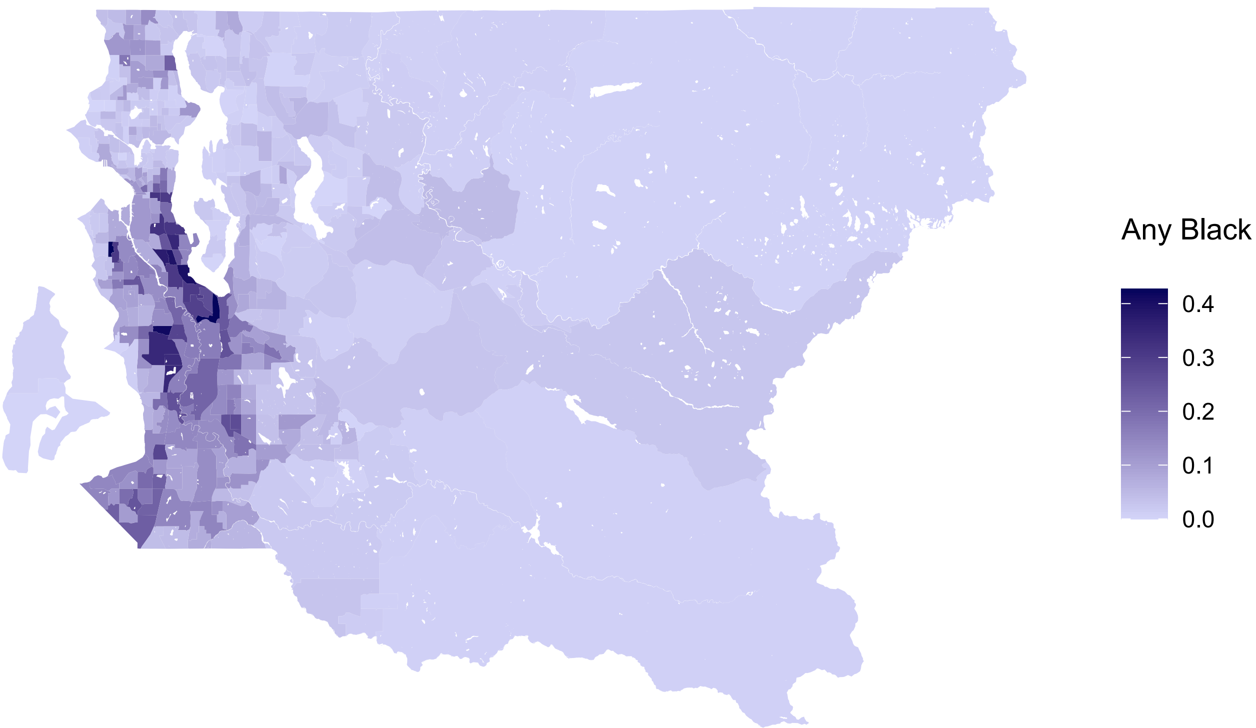
With a simple function and boundaries of water bodies in King County, we can replace water with empty space.

```
st_erase <- function(x, y) {
  st_difference(x, st_make_valid(st_union(st_combine(y))))
}
kc_water <- tigris::area_water("WA", "King", class = "sf")
kc_nowater <- king_county %>%
  st_erase(kc_water)
```

- `st_combine()` merges all geometries into one
- `st_union()` resolves internal boundaries
- `st_difference()` subtracts `y` geometry from `x`
- `st_make_valid()` fixes geometry errors from subtraction
- `area_water()` obtains `sf` geometry of water bodies

Then we can reproduce the same plot using `kc_nowater`...

Proportion Any Black



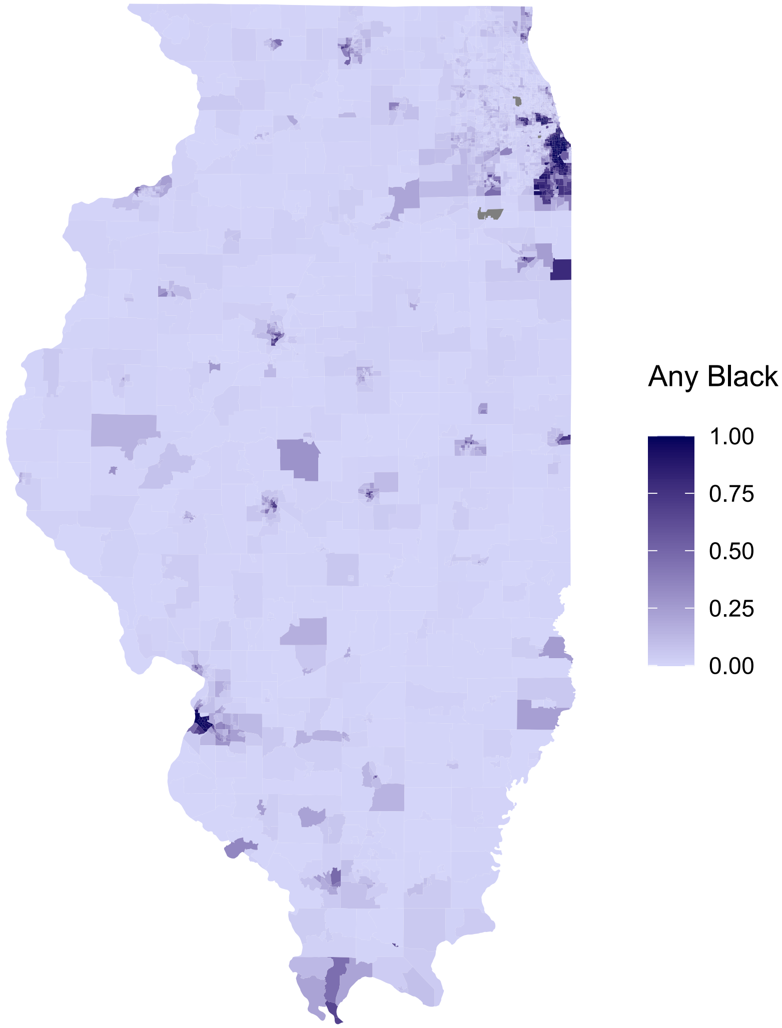
State Example Data

Let's do this again, but for the entire state of Illinois.

```
pb_state <-
  get_acs(geography = "tract", state = "IL",
          geometry  = TRUE,
          variables = c("B02001_001E",
                        "B02009_001E"),
          output = "wide") %>%
  select(-ends_with("M")) %>%
  rename(`Total Population`=B02001_001E,
         `Any Black`=B02009_001E) %>%
  mutate(`Any Black` = `Any Black` / `Total Population`)
```

State Example Plot

```
pb_state %>%
  ggplot(aes(fill = `Any Black`)) +
  geom_sf(size = NA) +
  coord_sf(crs = "+proj=longlat +datum=WGS84", datum=NA) +
  scale_fill_continuous(name = "Any Black\n",
                        low  = "#d4d5f9",
                        high = "#00025b") +
  theme_minimal()
```


Any Black
1.00
0.75
0.50
0.25
0.00

Multiple `geom_sf` Layers

As with other `ggplot2` layers, we can add additional `geom_sf()` layers using new data.

This is useful for…

- Adding points
  - Cities in states
  - Crimes in police beats
- Adding lines
  - Street grids over tracts
- Adding outlines or highlights
  - Elevation contours
  - *Showing urban boundaries*

Add Urban Outlines

We can use `tigris` to download urban boundaries and add them to our prior map.

```
urbans <- tigris::urban_areas(cb = TRUE, class = "sf")
glimpse(urbans)
```

```
## Rows: 3,601
## Columns: 9
## $ UACE10     <chr> "18856", "83116", "79363", "96670", "97750", "574~
## $ AFFGEOID10 <chr> "400C100US18856", "400C100US83116", "400C100US793~
## $ GEOID10    <chr> "18856", "83116", "79363", "96670", "97750", "574~
## $ NAME10     <chr> "Colorado Springs, CO", "South Bend, IN--MI", "Sa~
## $ LSAD10     <chr> "75", "75", "75", "75", "75", "76", "75", "75", "~
## $ UATYP10    <chr> "U", "U", "U", "U", "U", "C", "U", "U", "U", "C",~
## $ ALAND10    <dbl> 486995256, 417310226, 137815683, 835565506, 34223~
## $ AWATER10   <dbl> 962957, 8281569, 141396, 6442279, 1377397, 151536~
## $ geometry   <MULTIPOLYGON [°]> MULTIPOLYGON (((-104.6051 3..., MULT~
```

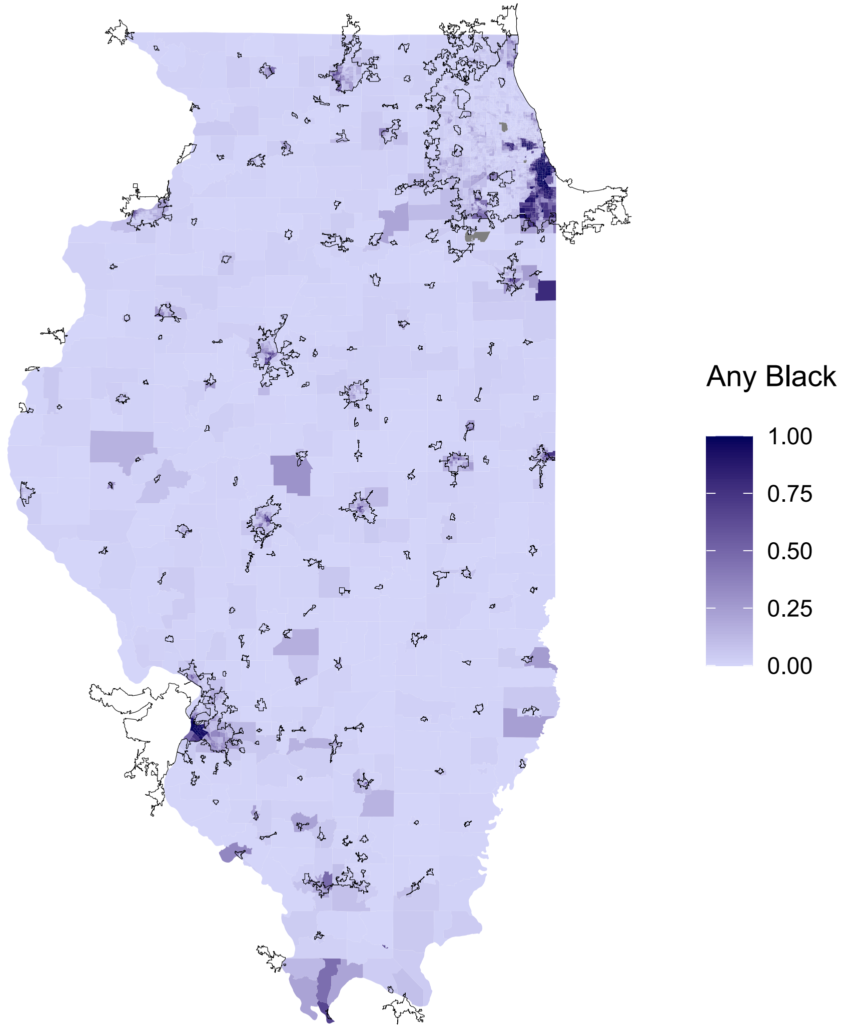
```
urban_il <- urbans %>% filter(str_detect(NAME10, "IL"))
```

With Urban Outlines

```
pb_state %>%
  ggplot(aes(fill=`Any Black`)) +
  geom_sf(size = NA) +
  geom_sf(data = urban_il, color = "black",
          fill = NA, size = 0.1, inherit.aes=FALSE) +
  coord_sf(crs = "+proj=longlat +datum=WGS84", datum=NA) +
  scale_fill_continuous(name = "Any Black\n",
                        low  = "#d4d5f9",
                        high = "#00025b") +
  theme_minimal()
```

We add the `urban_il` data as a new layer:

- `fill=NA` removes the polygon fill
- `size=0.1` and `color="black"` give a thin outline


Any Black
1.00
0.75
0.50
0.25
0.00

Optional Exercise

Use the HW 7 template to practice making maps of the restaurant inspection data.

If you wish to submit it for bonus points, turn it in via Canvas by 11:59 PM next Tuesday.