Data Visualization - 7. Make Maps (2)

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Code Horizons

December 10, 2023

Making Maps

Load our packages

```r
library(here)      # manage file paths
library(socviz)    # data and some useful functions
library(tidyverse) # your friend and mine
library(maps)      # Some basic maps
library(sf)        # Simple Features Geometries and geom_sf()
library(ggforce)   # Useful enhancements to ggplot
```

Maps using Simple Features

`geom_polygon()` is limiting

It's very useful to have the intuition that, when drawing maps, we're just working with tables of `x` and `y` coordinates, and shapes represent quantities in our data, in a way that's essentially the same as any other geom. This makes it worth getting comfortable with what `geom_polygon()` and `coord_map()` are doing. But the business of having very large map tables and manually specifying projections is inefficient.

In addition, sometimes our data *really is* properly spatial, at which point we need a more rigorous and consistent way of specifying those elements. There's a whole world of Geodesic standards and methods devoted to specifying these things for GIS applications. R is not a dedicated GIS, but we can take advantage of these tools.

Enter simple features, the `sf` package, and `geom_sf()`

The Simple Features package

When we load `sf` it creates a way to use several standard GIS concepts and tools, such as the GEOS library for computational geometry, the PROJ software that transforms spatial coordinates from one reference system to another, as in map projections, and the Simple Features standard for specifying the elements of spatial attributes.

```
library(sf)
```

```
Linking to GEOS 3.11.0, GDAL 3.5.3, PROJ 9.1.0; sf_use_s2() is TRUE
```

Let's see the main upshot for us.

The nycdogs package

```r
library(nycdogs)
nyc_license
```

```
# A tibble: 493,072 × 9
   animal_name animal_gender animal_birth_year breed_rc         borough zip_code
   <chr>       <chr>                     <dbl> <chr>            <chr>      <int>
 1 Paige       F                          2014 Pit Bull (or Mi… Manhat…    10035
 2 Yogi        M                          2010 Boxer            Bronx      10465
 3 Ali         M                          2014 Basenji          Manhat…    10013
 4 Queen       F                          2013 Akita Crossbreed Manhat…    10013
 5 Lola        F                          2009 Maltese          Manhat…    10028
 6 Ian         M                          2006 Unknown          Manhat…    10013
 7 Buddy       M                          2008 Unknown          Manhat…    10025
 8 Chewbacca   F                          2012 Labrador (or Cr… Manhat…    10013
 9 Heidi-Bo    F                          2007 Dachshund Smoot… Brookl…    11215
10 Massimo     M                          2009 Bull Dog, French Brookl…    11201
# ℹ 493,062 more rows
# ℹ 3 more variables: license_issued_date <date>, license_expired_date <date>,
#   extract_year <dbl>
```

The nycdogs package

The metadata tells you this is not a regular tibble.

```
nyc_zips
```

```
Simple feature collection with 262 features and 11 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: -74.25576 ymin: 40.49584 xmax: -73.6996 ymax: 40.91517
Geodetic CRS:  WGS 84
# A tibble: 262 × 12
   objectid zip_code po_name     state borough st_fips cty_fips bld_gpostal_code
      <int>    <int> <chr>       <chr> <chr>   <chr>   <chr>               <int>
 1        1    11372 Jackson He… NY    Queens  36      081                     0
 2        2    11004 Glen Oaks   NY    Queens  36      081                     0
 3        3    11040 New Hyde P… NY    Queens  36      081                     0
 4        4    11426 Bellerose   NY    Queens  36      081                     0
 5        5    11365 Fresh Mead… NY    Queens  36      081                     0
 6        6    11373 Elmhurst    NY    Queens  36      081                     0
 7        7    11001 Floral Park NY    Queens  36      081                     0
 8        8    11375 Forest Hil… NY    Queens  36      081                     0
 9        9    11427 Queens Vil… NY    Queens  36      081                     0
10       10    11374 Rego Park   NY    Queens  36      081                     0
# ℹ 252 more rows
```

The nycdogs package

```r
nyc_zips ▷
  select(objectid:borough)
```

```
Simple feature collection with 262 features and 5 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: -74.25576 ymin: 40.49584 xmax: -73.6996 ymax: 40.91517
Geodetic CRS:  WGS 84
# A tibble: 262 × 6
   objectid zip_code po_name          state borough                     geometry
      <int>    <int> <chr>            <chr> <chr>                  <POLYGON [°]>
 1        1    11372 Jackson Heights NY    Queens  ((-73.86942 40.74916, -73.89…
 2        2    11004 Glen Oaks       NY    Queens  ((-73.71068 40.75004, -73.70…
 3        3    11040 New Hyde Park   NY    Queens  ((-73.70098 40.7389, -73.703…
 4        4    11426 Bellerose       NY    Queens  ((-73.7227 40.75373, -73.722…
 5        5    11365 Fresh Meadows   NY    Queens  ((-73.81089 40.72717, -73.81…
 6        6    11373 Elmhurst        NY    Queens  ((-73.88722 40.72753, -73.88…
 7        7    11001 Floral Park     NY    Queens  ((-73.70098 40.7389, -73.699…
 8        8    11375 Forest Hills    NY    Queens  ((-73.85625 40.73672, -73.85…
 9        9    11427 Queens Village  NY    Queens  ((-73.74169 40.73682, -73.73…
10       10    11374 Rego Park       NY    Queens  ((-73.86451 40.73407, -73.85…
# ℹ 252 more rows
```

The `polygon` column is a list of lat/lon points that, when joined, draw the outline of the zip code area. This is *much* more compact than a big table where every row is a single point.

Let’s make a summary table

```r
nyc_license
```

```
# A tibble: 493,072 × 9
   animal_name animal_gender animal_birth_year
breed_rc         borough zip_code
   <chr>       <chr>                     <dbl>
<chr>            <chr>      <int>
 1 Paige       F                          2014
Pit Bull (or Mi… Manhat…    10035
 2 Yogi        M                          2010
Boxer            Bronx      10465
 3 Ali         M                          2014
Basenji          Manhat…    10013
 4 Queen       F                          2013
Akita Crossbreed Manhat…    10013
 5 Lola        F                          2009
Maltese          Manhat…    10028
 6 Ian         M                          2006
Unknown          Manhat…    10013
 7 Buddy       M                          2008
Unknown          Manhat…    10025
```

Let’s make a summary table

```r
nyc_license |>
  filter(extract_year == 2018)
```

```
# A tibble: 117,371 × 9
   animal_name animal_gender animal_birth_year
breed_rc          borough zip_code
   <chr>       <chr>                     <dbl>
<chr>             <chr>      <int>
 1 Ali         M                          2014
Basenji           Manhat…    10013
 2 Ian         M                          2006
Unknown           Manhat…    10013
 3 Chewbacca   F                          2012
Labrador (or Cr… Manhat…    10013
 4 Lola        F                          2006
Miniature Pinsc… Manhat…    10022
 5 Lucy        F                          2014
Dachshund Smoot… Brookl…    11215
 6 June        F                          2010
Cavalier King C… Brookl…    11238
 7 Apple       M                          2013
Havanese          Manhat…    10025
```

Let's make a summary table

```r
nyc_license |>
  filter(extract_year == 2018) |>
  group_by(breed_rc, zip_code)
```

```
# A tibble: 117,371 × 9
# Groups:   breed_rc, zip_code [18,945]
   animal_name animal_gender animal_birth_year
breed_rc          borough zip_code
   <chr>       <chr>                     <dbl>
<chr>             <chr>      <int>
 1 Ali         M                          2014
Basenji           Manhat…    10013
 2 Ian         M                          2006
Unknown           Manhat…    10013
 3 Chewbacca   F                          2012
Labrador (or Cr… Manhat…    10013
 4 Lola        F                          2006
Miniature Pinsc… Manhat…    10022
 5 Lucy        F                          2014
Dachshund Smoot… Brookl…    11215
 6 June        F                          2010
Cavalier King C… Brookl…    11238
 7 Apple       M                          2013
```

Let’s make a summary table

```r
nyc_license |>
  filter(extract_year == 2018) |>
  group_by(breed_rc, zip_code) |>
  tally()
```

```
# A tibble: 18,945 × 3
# Groups:   breed_rc [311]
   breed_rc      zip_code     n
   <chr>            <int> <int>
 1 Affenpinscher    10005     1
 2 Affenpinscher    10011     1
 3 Affenpinscher    10013     1
 4 Affenpinscher    10014     1
 5 Affenpinscher    10016     1
 6 Affenpinscher    10017     1
 7 Affenpinscher    10018     1
 8 Affenpinscher    10019     1
 9 Affenpinscher    10021     1
10 Affenpinscher    10023     1
# ℹ 18,935 more rows
```

Let’s make a summary table

```r
nyc_license |>
  filter(extract_year == 2018) |>
  group_by(breed_rc, zip_code) |>
  tally() |>
  mutate(freq = n / sum(n))
```

```
# A tibble: 18,945 × 4
# Groups:   breed_rc [311]
   breed_rc      zip_code     n   freq
   <chr>            <int> <int>  <dbl>
 1 Affenpinscher    10005     1 0.0303
 2 Affenpinscher    10011     1 0.0303
 3 Affenpinscher    10013     1 0.0303
 4 Affenpinscher    10014     1 0.0303
 5 Affenpinscher    10016     1 0.0303
 6 Affenpinscher    10017     1 0.0303
 7 Affenpinscher    10018     1 0.0303
 8 Affenpinscher    10019     1 0.0303
 9 Affenpinscher    10021     1 0.0303
10 Affenpinscher    10023     1 0.0303
# ℹ 18,935 more rows
```

Let's make a summary table

```r
nyc_license |>
  filter(extract_year == 2018) |>
  group_by(breed_rc, zip_code) |>
  tally() |>
  mutate(freq = n / sum(n)) |>
  filter(breed_rc == "French Bulldog")
```

```
# A tibble: 161 × 4
# Groups:   breed_rc [1]
   breed_rc       zip_code     n    freq
   <chr>             <int> <int>   <dbl>
 1 French Bulldog    10001    27 0.0167
 2 French Bulldog    10002    20 0.0123
 3 French Bulldog    10003    36 0.0222
 4 French Bulldog    10004     9 0.00555
 5 French Bulldog    10005    15 0.00925
 6 French Bulldog    10006     8 0.00494
 7 French Bulldog    10007    17 0.0105
 8 French Bulldog    10009    51 0.0315
 9 French Bulldog    10010    31 0.0191
10 French Bulldog    10011    88 0.0543
# ℹ 151 more rows
```

Let’s make a summary table

```
nyc_license |>
  filter(extract_year == 2018) |>
  group_by(breed_rc, zip_code) |>
  tally() |>
  mutate(freq = n / sum(n)) |>
  filter(breed_rc == "French Bulldog") ->
  nyc_fb
```

Let’s make a summary table

```
nyc_license  |>
  filter(extract_year == 2018) |>
  group_by(breed_rc, zip_code) |>
  tally() |>
  mutate(freq = n / sum(n)) |>
  filter(breed_rc == "French Bulldog") ->
  nyc_fb
```

Now we have two tables again

```r
nyc_zips |> select(objectid:st_fips)
```

```
Simple feature collection with 262 features and 6 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: -74.25576 ymin: 40.49584 xmax: -73.6996 ymax: 40.91517
Geodetic CRS:  WGS 84
# A tibble: 262 × 7
   objectid zip_code po_name     state borough st_fips                  geometry
      <int>    <int> <chr>       <chr> <chr>   <chr>               <POLYGON [°]>
 1        1    11372 Jackson He… NY    Queens  36      ((-73.86942 40.74916, -7…
 2        2    11004 Glen Oaks   NY    Queens  36      ((-73.71068 40.75004, -7…
 3        3    11040 New Hyde P… NY    Queens  36      ((-73.70098 40.7389, -73…
 4        4    11426 Bellerose   NY    Queens  36      ((-73.7227 40.75373, -73…
 5        5    11365 Fresh Mead… NY    Queens  36      ((-73.81089 40.72717, -7…
 6        6    11373 Elmhurst    NY    Queens  36      ((-73.88722 40.72753, -7…
 7        7    11001 Floral Park NY    Queens  36      ((-73.70098 40.7389, -73…
 8        8    11375 Forest Hil… NY    Queens  36      ((-73.85625 40.73672, -7…
 9        9    11427 Queens Vil… NY    Queens  36      ((-73.74169 40.73682, -7…
10       10    11374 Rego Park   NY    Queens  36      ((-73.86451 40.73407, -7…
# ℹ 252 more rows
```

```r
nyc_fb |> select(breed_rc:n)
```

```
# A tibble: 161 × 3
# Groups:   breed_rc [1]
   breed_rc       zip_code     n
   <chr>             <int> <int>
 1 French Bulldog    10001    27
 2 French Bulldog    10002    20
 3 French Bulldog    10003    36
 4 French Bulldog    10004     9
 5 French Bulldog    10005    15
 6 French Bulldog    10006     8
 7 French Bulldog    10007    17
 8 French Bulldog    10009    51
 9 French Bulldog    10010    31
10 French Bulldog    10011    88
# ℹ 151 more rows
```

Join them:

```r
fb_map <- left_join(nyc_zips, nyc_fb, by = "zip_code")
```

Ready to map

```r
fb_map |> select(zip_code, po_name, borough, breed_rc:freq, geometry)
```

```
Simple feature collection with 262 features and 6 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: -74.25576 ymin: 40.49584 xmax: -73.6996 ymax: 40.91517
Geodetic CRS:  WGS 84
# A tibble: 262 × 7
   zip_code po_name    borough breed_rc      n     freq                  geometry
      <int> <chr>      <chr>   <chr>     <int>    <dbl>             <POLYGON [°]>
 1    11372 Jackson H… Queens  French …     13  8.02e-3 ((-73.86942 40.74916, -7…
 2    11004 Glen Oaks  Queens  French …      1  6.17e-4 ((-73.71068 40.75004, -7…
 3    11040 New Hyde … Queens  <NA>         NA NA       ((-73.70098 40.7389, -73…
 4    11426 Bellerose  Queens  French …      1  6.17e-4 ((-73.7227 40.75373, -73…
 5    11365 Fresh Mea… Queens  French …      7  4.32e-3 ((-73.81089 40.72717, -7…
 6    11373 Elmhurst   Queens  French …     14  8.64e-3 ((-73.88722 40.72753, -7…
 7    11001 Floral Pa… Queens  <NA>         NA NA       ((-73.70098 40.7389, -73…
 8    11375 Forest Hi… Queens  French …      8  4.94e-3 ((-73.85625 40.73672, -7…
 9    11427 Queens Vi… Queens  French …      2  1.23e-3 ((-73.74169 40.73682, -7…
10    11374 Rego Park  Queens  French …      6  3.70e-3 ((-73.86451 40.73407, -7…
# ℹ 252 more rows
```

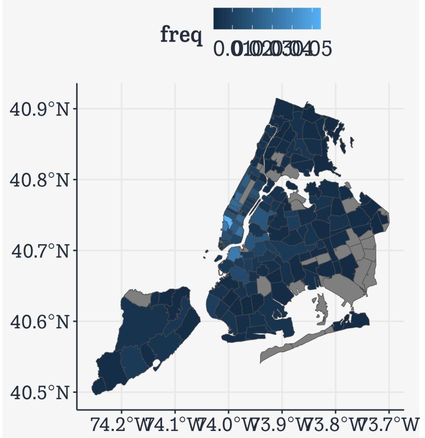
A NYC map theme

Just moving the legend, really.

```r
theme_nymap <- function(base_size=9, base_family="") {
    require(grid)
    theme_bw(base_size=base_size, base_family=base_family) %+replace%
        theme(axis.line=element_blank(),
              axis.text=element_blank(),
              axis.ticks=element_blank(),
              axis.title=element_blank(),
              panel.background=element_blank(),
              panel.border=element_blank(),
              panel.grid=element_blank(),
              panel.spacing=unit(0, "lines"),
              plot.background=element_blank(),
              legend.justification = c(0,0),
              legend.position = c(0.05, 0.58),
              legend.direction = "horizontal"
        )
}
```

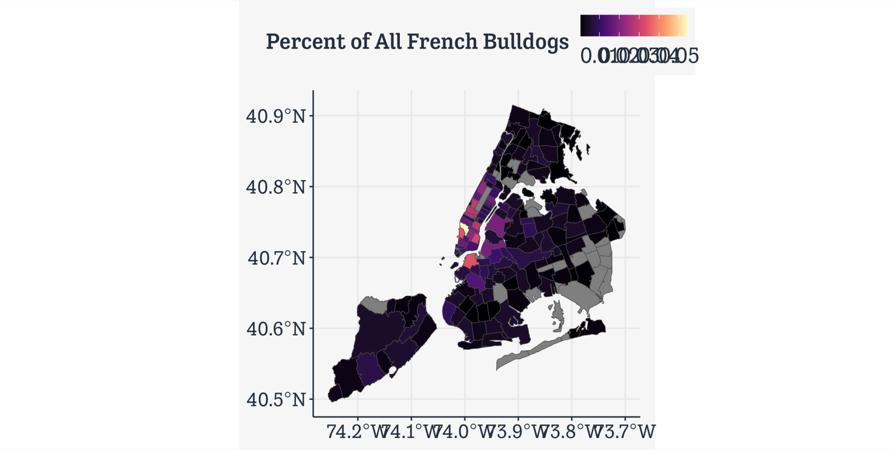
First cut at a map

```
fb_map ▷
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1)
```



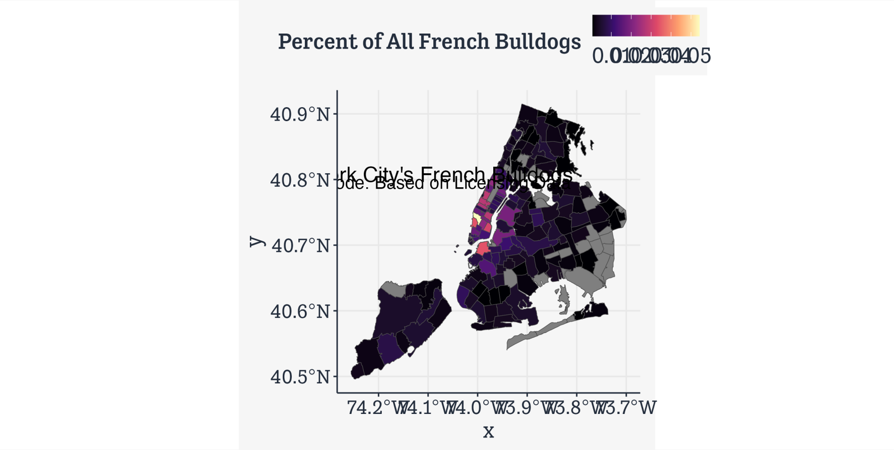
First cut at a map

```
fb_map |>
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) + #<<
  scale_fill_viridis_c(option = "A") +
  labs(fill = "Percent of All French Bulldogs")
```



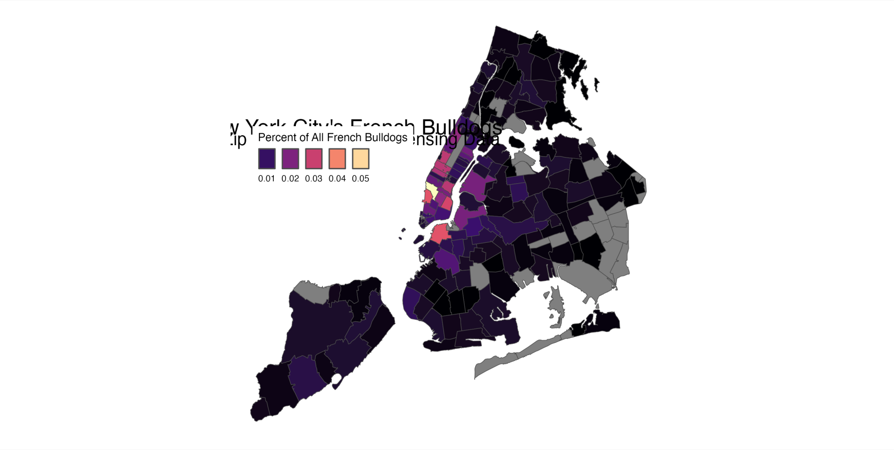
First cut at a map

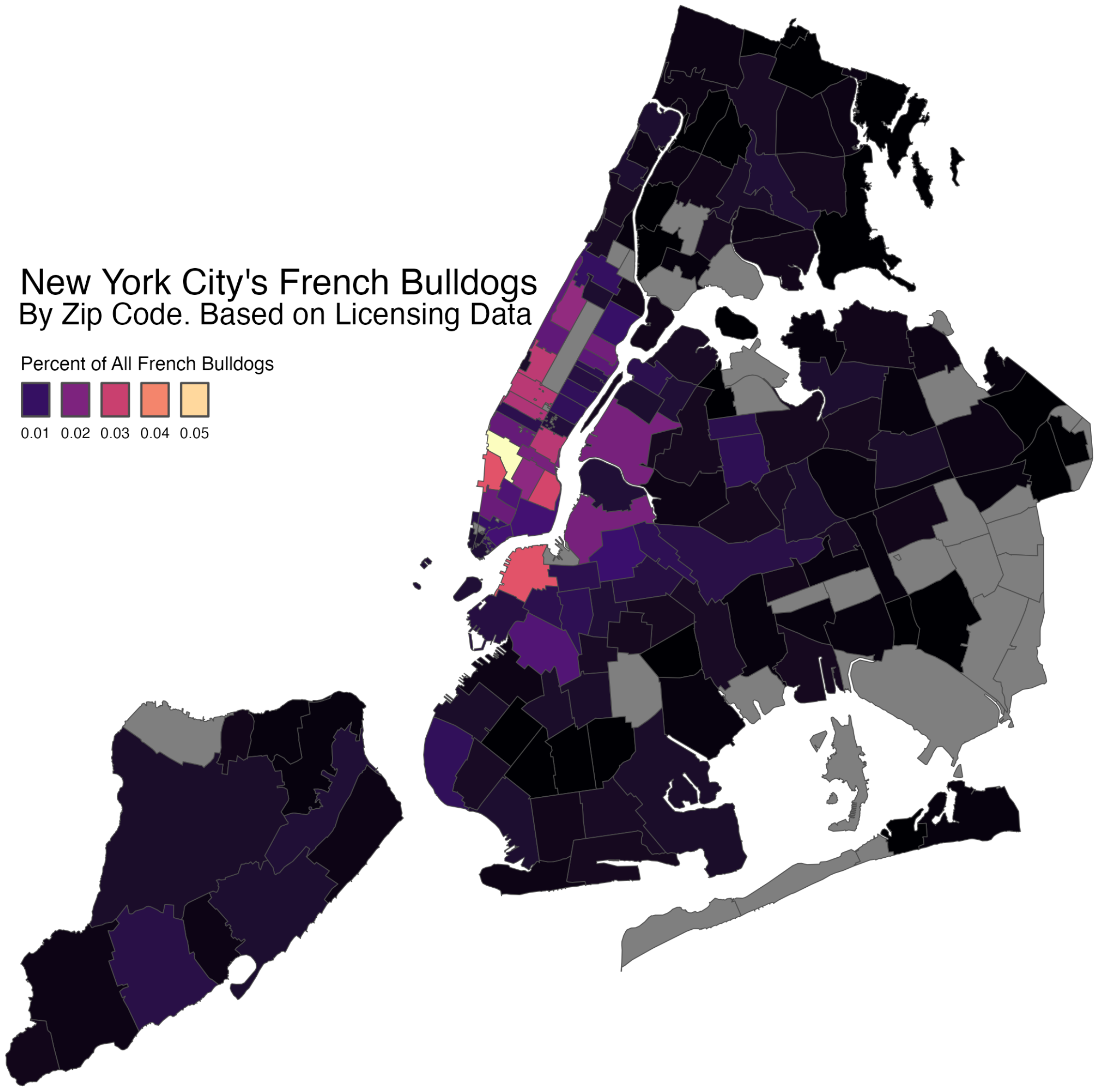
```
fb_map |>
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) + #<<
  scale_fill_viridis_c(option = "A") +
  labs(fill = "Percent of All French Bulldogs")
  annotate(geom = "text",
           x = -74.145 + 0.029,
           y = 40.82-0.012,
         label = "New York City's French Bull
         size = 6) +
    annotate(geom = "text",
           x = -74.1468 + 0.029,
           y = 40.8075-0.012,
         label = "By Zip Code. Based on Licen
         size = 5)
```



First cut at a map

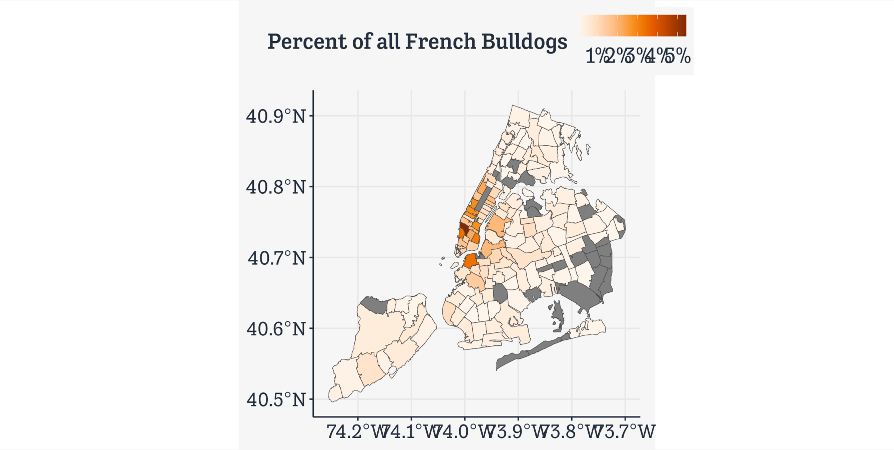
```r
fb_map |>
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) + #<<
  scale_fill_viridis_c(option = "A") +
  labs(fill = "Percent of All French Bulldogs")
  annotate(geom = "text",
           x = -74.145 + 0.029,
           y = 40.82-0.012,
         label = "New York City's French Bull
         size = 6) +
  annotate(geom = "text",
           x = -74.1468 + 0.029,
           y = 40.8075-0.012,
         label = "By Zip Code. Based on Licen
         size = 5) +
  kjhslides::kjh_theme_nymap() +
  guides(fill =
         guide_legend(title.position = "top",
              label.position = "bottom",
              keywidth = 1,
              nrow = 1))
```




New York City's French Bulldogs
By Zip Code. Based on Licensing Data
Percent of All French Bulldogs
0.01
0.02
0.03
0.04
0.05

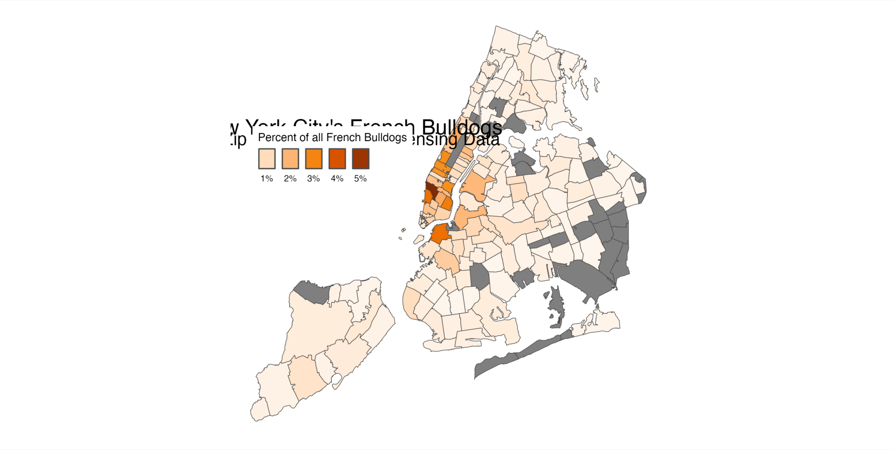
Use a different palette

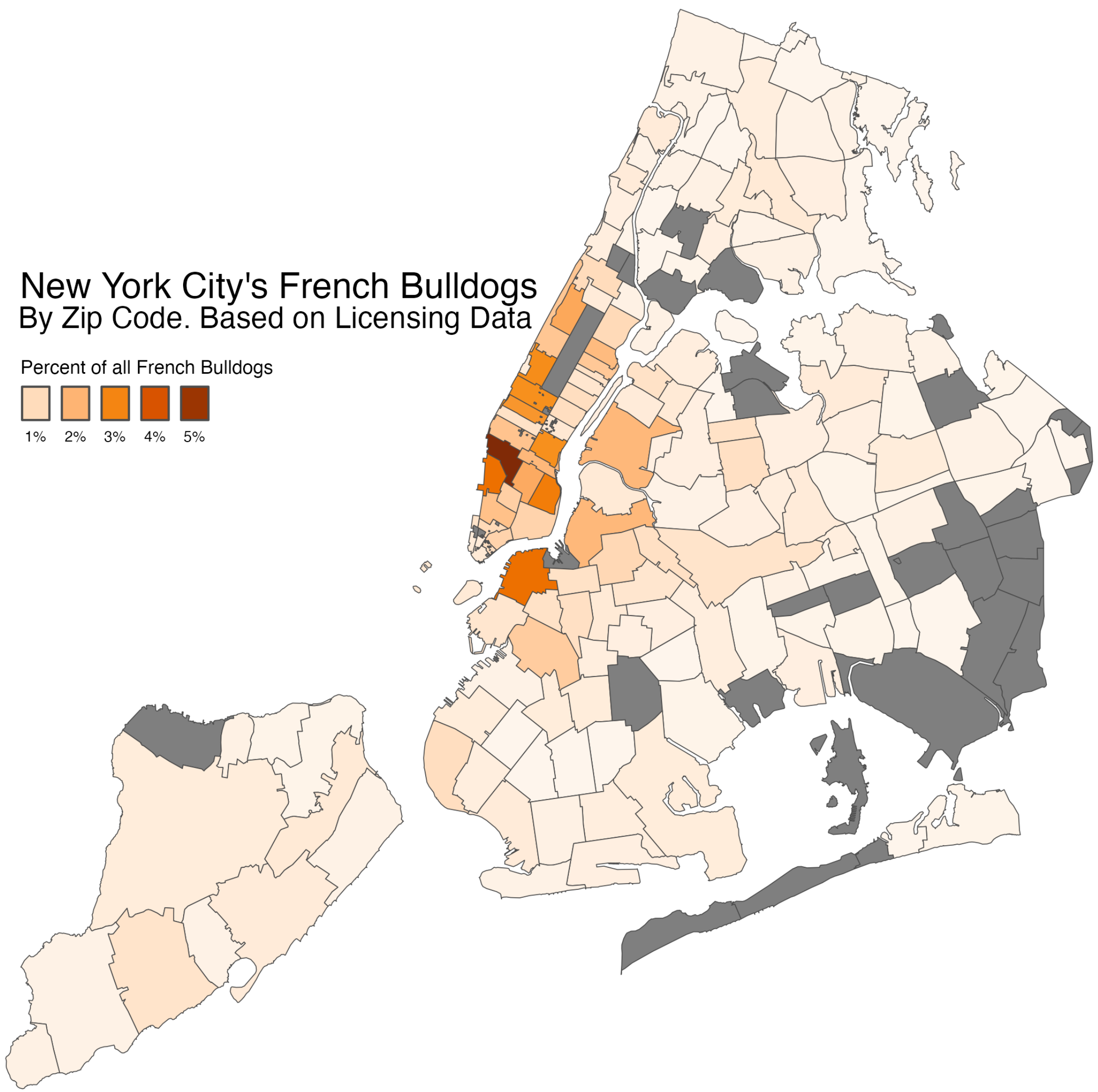
```
library(colorspace)

fb_map |>
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) +
  scale_fill_continuous_sequential(
    palette = "Oranges",
    labels = scales::label_percent()) +
  labs(fill = "Percent of all French Bulldogs")
```



Use a different palette

```r
fb_map |>
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) +
  scale_fill_continuous_sequential(
    palette = "Oranges",
    labels = scales::label_percent()) +
  labs(fill = "Percent of all French Bulldogs")
  annotate(geom = "text",
           x = -74.145 + 0.029,
           y = 40.82-0.012,
           label = "New York City's French Bull
           size = 6) +
  annotate(geom = "text",
           x = -74.1468 + 0.029,
           y = 40.7955,
           label = "By Zip Code. Based on Licen
           size = 5) +
  kjhslides::kjh_theme_nymap() +
  guides(fill =
           guide_legend(title.position = "top",
                label.position = "bottom",
                keywidth = 1,
```





NYC Dogs Map mark 2

Keep the Zero-count Zips

```r
nyc_license |>
  filter(extract_year == 2018) |>
  group_by(breed_rc, zip_code) |>
  tally() |>
  ungroup() |>
  complete(zip_code, breed_rc,
           fill = list(n = 0)) |>
  # Regroup to get the right denominator
  group_by(breed_rc) |>
  mutate(freq = n / sum(n)) |>
  filter(breed_rc == "French Bulldog") ->
  nyc_fb2

fb_map2 <- left_join(nyc_zips,
                     nyc_fb2,
                     by = "zip_code")
```

Keep the Zero-count Zips

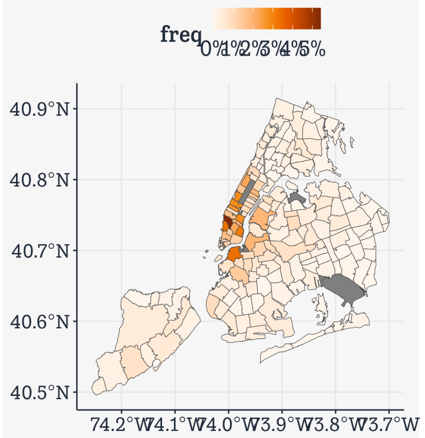
```r
fb_map2 |> select(zip_code, po_name, borough, breed_rc:freq, geometry)
```

```
Simple feature collection with 262 features and 6 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: -74.25576 ymin: 40.49584 xmax: -73.6996 ymax: 40.91517
Geodetic CRS:  WGS 84
# A tibble: 262 × 7
   zip_code po_name     borough breed_rc      n    freq                  geometry
      <int> <chr>       <chr>   <chr>     <int>   <dbl>             <POLYGON [°]>
 1    11372 Jackson He… Queens  French …     13 8.02e-3 ((-73.86942 40.74916, -7…
 2    11004 Glen Oaks   Queens  French …      1 6.17e-4 ((-73.71068 40.75004, -7…
 3    11040 New Hyde P… Queens  French …      0 0       ((-73.70098 40.7389, -73…
 4    11426 Bellerose   Queens  French …      1 6.17e-4 ((-73.7227 40.75373, -73…
 5    11365 Fresh Mead… Queens  French …      7 4.32e-3 ((-73.81089 40.72717, -7…
 6    11373 Elmhurst    Queens  French …     14 8.64e-3 ((-73.88722 40.72753, -7…
 7    11001 Floral Park Queens  French …      0 0       ((-73.70098 40.7389, -73…
 8    11375 Forest Hil… Queens  French …      8 4.94e-3 ((-73.85625 40.73672, -7…
 9    11427 Queens Vil… Queens  French …      2 1.23e-3 ((-73.74169 40.73682, -7…
10    11374 Rego Park   Queens  French …      6 3.70e-3 ((-73.86451 40.73407, -7…
# ℹ 252 more rows
```

This time, a number of previous NA rows are now zeroes instead.

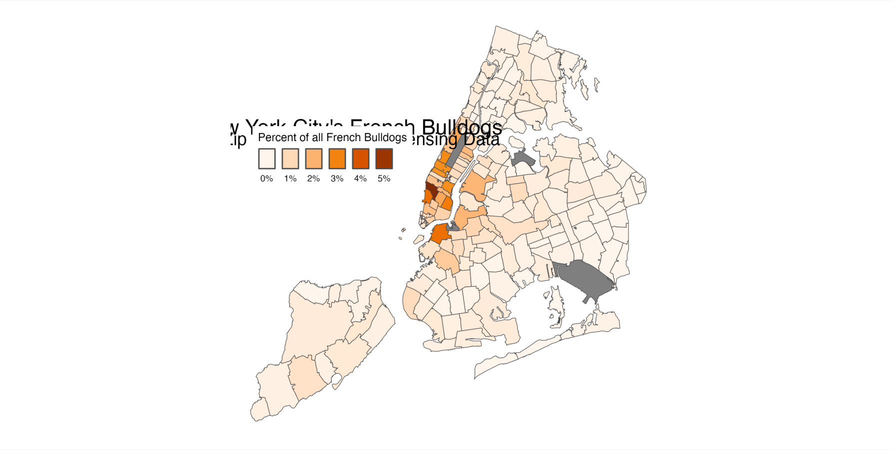
Keep the Zero-count Zips

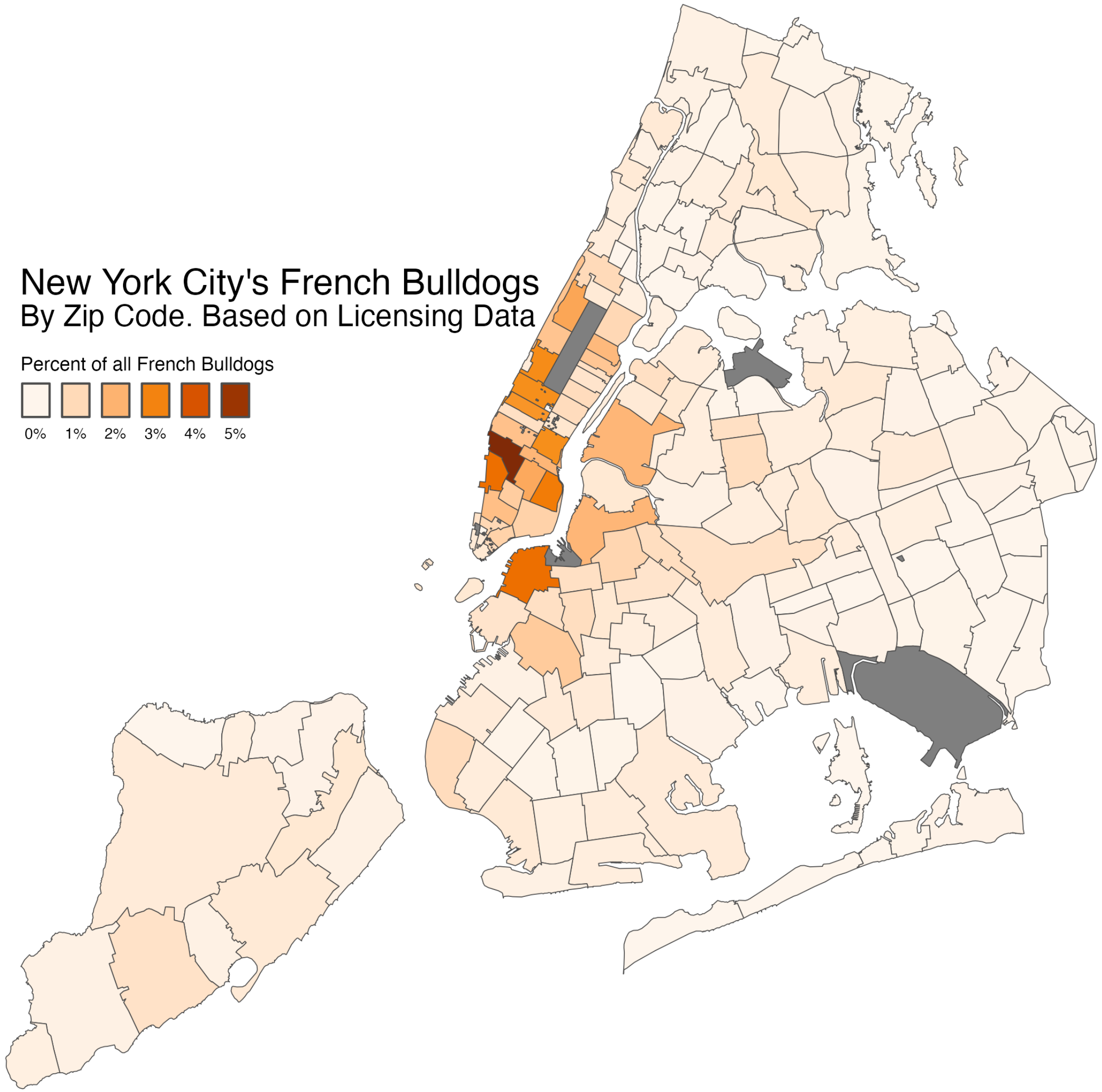
```r
fb_map2 ▷
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) +
  scale_fill_continuous_sequential(
    palette = "Oranges",
    labels = scales::label_percent())
```



Keep the Zero-count Zips

```r
fb_map2 |>
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) +
  scale_fill_continuous_sequential(
    palette = "Oranges",
    labels = scales::label_percent()) +
  labs(fill = "Percent of all French Bulldogs")
  annotate(geom = "text",
           x = -74.145 + 0.029,
           y = 40.82-0.012,
           label = "New York City's French Bull
           size = 6) +
  annotate(geom = "text",
           x = -74.1468 + 0.029,
           y = 40.7955,
           label = "By Zip Code. Based on Licen
           size = 5) +
  kjhslides::kjh_theme_nymap() +
  guides(fill =
           guide_legend(title.position = "top",
                        label.position = "botto
                        keywidth = 1,
```





Zero areas properly zero, missing areas properly missing.

Care with Spatial Distribution

A random point-process

Care with Spatial Distribution

A heatmap derived from the random process

Care with Spatial Distribution

A formal test of significant hotspots

Example: Dorling Cartograms

Dorling Cartograms

```r
# install.packages("cartogram")
library(cartogram)
options(tigris_use_cache = TRUE)
```

Dorling Cartograms

```r
pop_names <- tribble(
    ~varname, ~clean,
    "B01003_001", "pop",
    "B01001B_001", "black",
    "B01001A_001", "white",
    "B01001H_001", "nh_white",
    "B01001I_001", "hispanic",
    "B01001D_001", "asian"
  )

pop_names
```

```
# A tibble: 6 × 2
  varname     clean
  <chr>       <chr>
1 B01003_001  pop
2 B01001B_001 black
3 B01001A_001 white
4 B01001H_001 nh_white
5 B01001I_001 hispanic
6 B01001D_001 asian
```

Dorling Cartograms

```r
library(tidycensus)
fips_pop <- get_acs(geography = "county",
                    variables = pop_names$varname,
                    cache_table = TRUE) |>
  left_join(pop_names, join_by(variable == varname)) |>
  mutate(variable = clean) |>
  select(-clean, -moe) |>
  pivot_wider(names_from = variable, values_from = estimate) |>
  rename(fips = GEOID, name = NAME) |>
  mutate(prop_pop = pop/sum(pop),
         prop_black = black/pop,
         prop_hisp = hispanic/pop,
         prop_white = white/pop,
         prop_nhwhite = nh_white/pop,
         prop_asian = asian/pop)

fips_map <- get_acs(geography = "county",
                    variables = "B01001_001",
                    geometry = TRUE,
                    shift_geo = FALSE,
                    cache_table = TRUE) |>
  select(GEOID, NAME, geometry) |>
```

Dorling Cartograms

```r
pop_cat_labels <- c("<5", as.character(seq(10, 95, 5)), "100")

counties_sf <- fips_map |>
  left_join(fips_pop, by = c("fips", "name")) |>
  mutate(black_disc = cut(prop_black*100,
                          breaks = seq(0, 100, 5),
                          labels = pop_cat_labels,
                          ordered_result = TRUE),
         hisp_disc = cut(prop_hisp*100,
                          breaks = seq(0, 100, 5),
                          labels = pop_cat_labels,
                          ordered_result = TRUE),
         nhwhite_disc = cut(prop_nhwhite*100,
                          breaks = seq(0, 100, 5),
                          labels = pop_cat_labels,
                          ordered_result = TRUE),
        asian_disc = cut(prop_asian*100,
                          breaks = seq(0, 100, 5),
                          labels = pop_cat_labels,
                          ordered_result = TRUE)) |>
  sf::st_transform(crs = 2163)
```

Dorling Cartograms

```
counties_sf
```

```
Simple feature collection with 3221 features and 18 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -6433624 ymin: -2354609 xmax: 3668029 ymax: 3912355
Projected CRS: NAD27 / US National Atlas Equal Area
First 10 features:
    fips                              name  white black asian nh_white hispanic
1  20161              Riley County, Kansas  58797  4509  3414    55420     6125
2  19159             Ringgold County, Iowa   4525     4     9     4494      128
3  30009            Carbon County, Montana  10013    77    44     9773      284
4  16007             Bear Lake County, Idaho   5945    14    18     5839      283
5  55011         Buffalo County, Wisconsin  12789    98     5    12643      335
6  31185             York County, Nebraska  13234   206    32    12780      743
7  08037            Eagle County, Colorado  45327   504   807    36122    16400
8  42129 Westmoreland County, Pennsylvania 332528  8233  3590   330055     4640
9  40079          Le Flore County, Oklahoma  35333   873   386    33833     3560
10 48053              Burnet County, Texas  41346   708   331    35042    10987
      pop     prop_pop   prop_black  prop_hisp prop_white prop_nhwhite
1   72602 2.180000e-04 0.0621057271 0.08436407  0.8098537    0.7633399
```

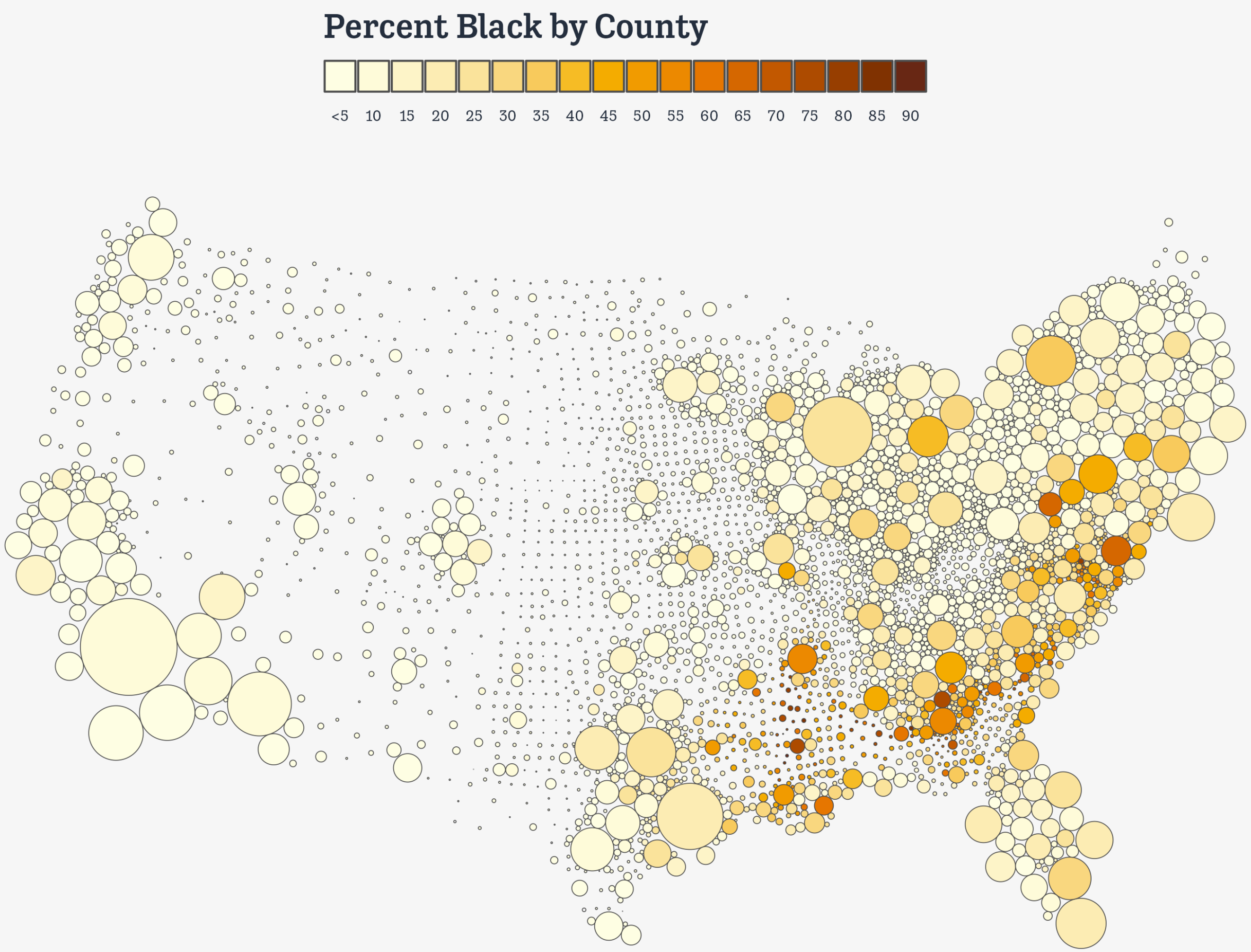
Dorling Cartograms

```
## Be patient
county_dorling <- cartogram_dorling(x = counties_sf,
    weight = "prop_pop",
    k = 0.2, itermax = 100)

out_black <- county_dorling |>
  filter(!str_detect(name, "Alaska|Hawaii|Puerto|Guam")) |>
  ggplot(aes(fill = black_disc)) +
  geom_sf(color = "grey30", size = 0.1) +
  coord_sf(crs = 2163, datum = NA) +
  scale_fill_discrete_sequential(palette = "YlOrBr",
                                 na.translate=FALSE) +
  guides(fill = guide_legend(title.position = "top",
                             label.position = "bottom",
                             nrow = 1)) +
  labs(
     subtitle = "Bubble size corresponds to County Population",
     caption = "Graph: @kjhealy. Source: Census Bureau / American Community Survey",
       fill = "Percent Black by County") +
  theme(legend.position = "top",
        legend.spacing.x = unit(0, "cm"),
        legend.title = element_text(size = rel(1.5), face = "bold"),
```

Dorling Cartograms

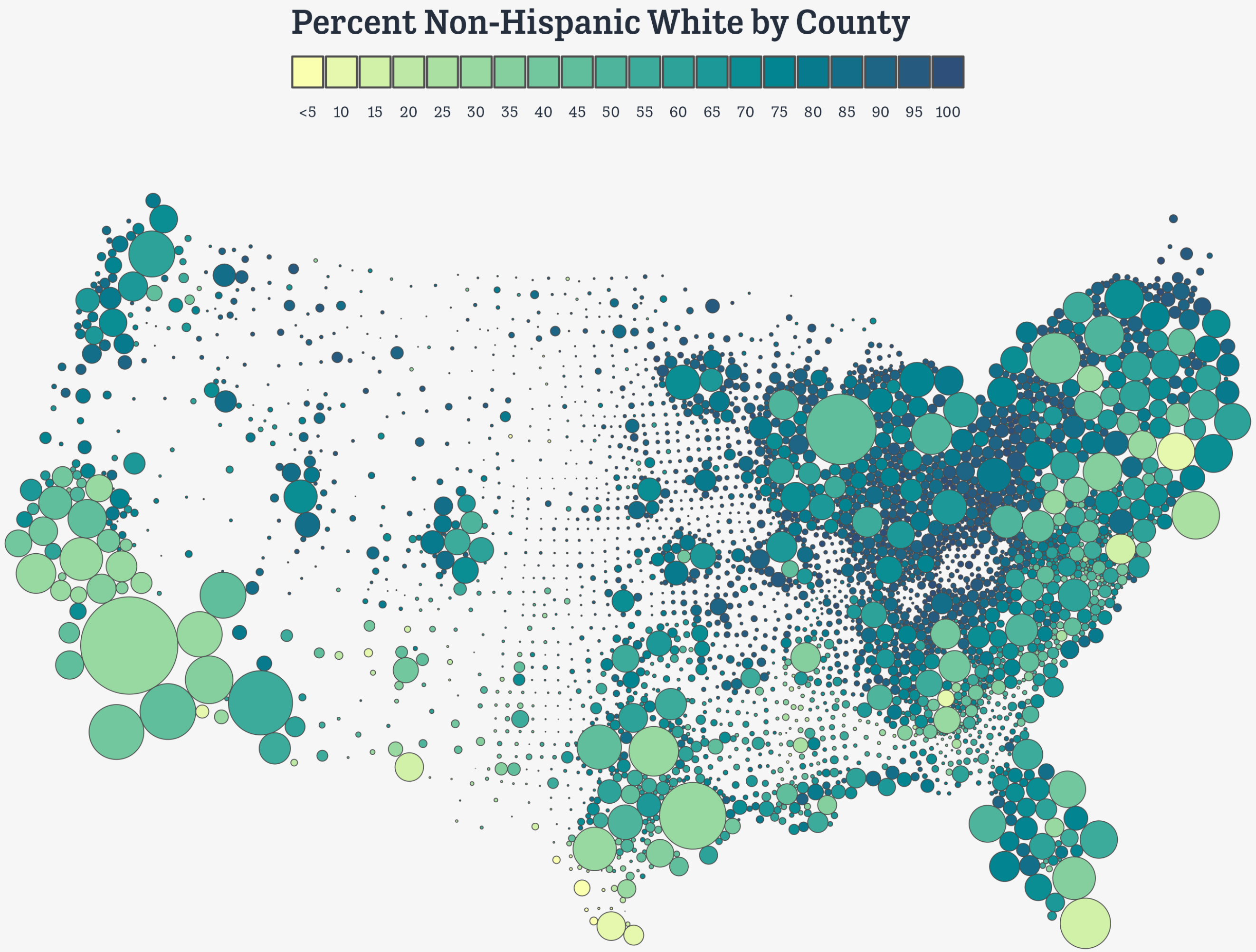
```
print(out_black)
```

Bubble size corresponds to County Population

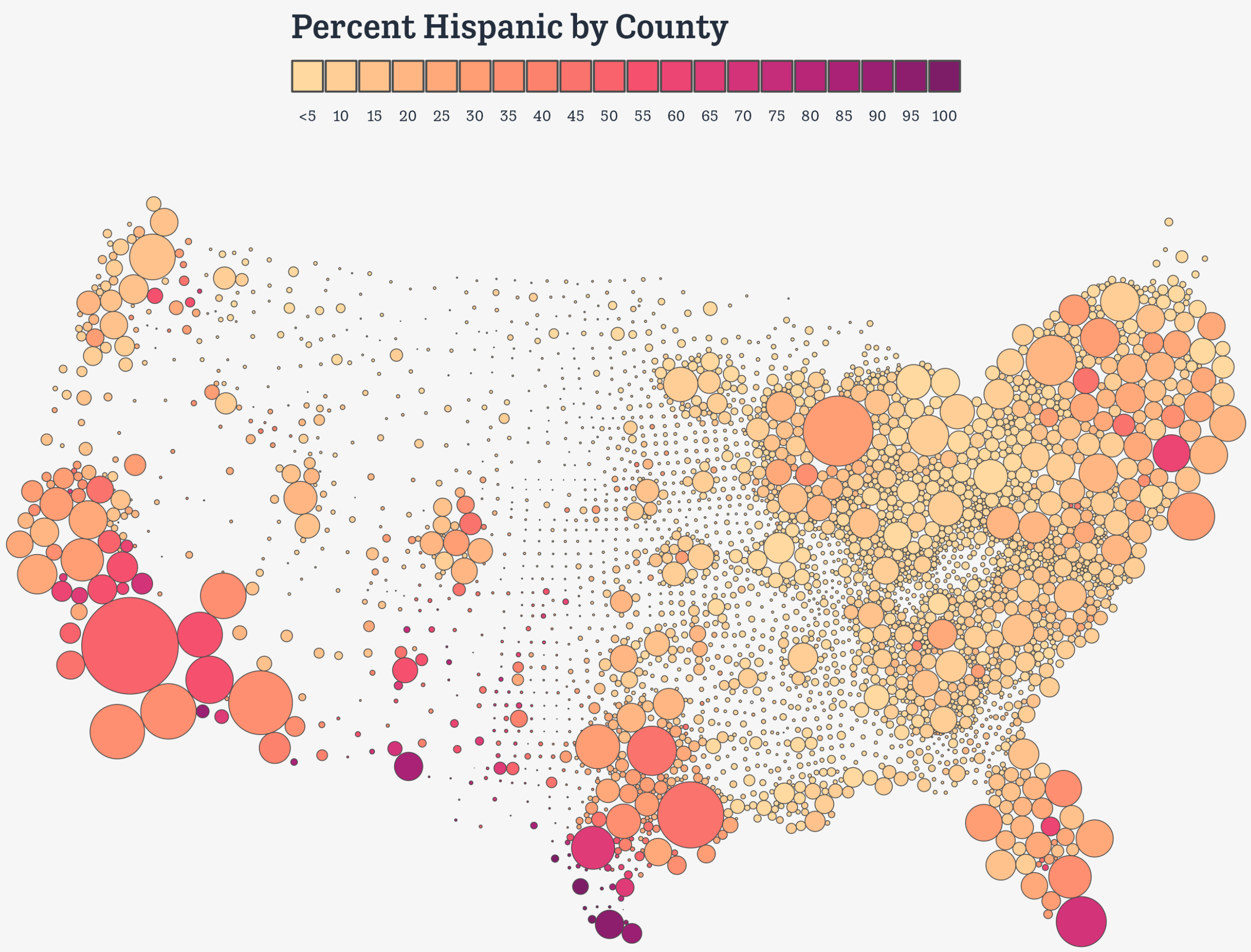


Graph: @kjhealy. Source: Census Bureau / American Community Survey

```
print(out_white)
```



```python
print(out_hispanic)
```



```
print(out_asian)
```