

Data Visualization - 7.

Make Maps (2)

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Code Horizons

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Making Maps

Load our packages

```
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

```
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

```
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
    <int>    <int> <chr>        <chr> <chr>
1       1     11372 Jackson Heights NY   Queens
2       2     11004 Glen Oaks       NY   Queens
3       3     11040 New Hyde Park  NY   Queens
4       4     11426 Bellerose      NY   Queens
5       5     11365 Fresh Meadows  NY   Queens
6       6     11373 Elmhurst       NY   Queens
7       7     11001 Floral Park    NY   Queens
8       8     11375 Forest Hills   NY   Queens
9       9     11427 Queens Village NY   Queens
10      10    11374 Rego Park      NY   Queens
# i 252 more rows
# 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

```
1 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

```
1 nyc_license %>%  
2   filter(extract_year == 2018)
```

```
# A tibble: 117,371 x 9  
#>   animal_name animal_gender animal_birth_year  
#>   <chr>        <chr>        <dbl>  
#>   breed_rc    borough      zip_code  
#>   <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

```
1 nyc_license %>  
2   filter(extract_year == 2018) %>  
3   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

```
1 nyc_license %>  
2   filter(extract_year == 2018) %>  
3   group_by(breed_rc, zip_code) %>  
4   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

```
1 nyc_license %>  
2   filter(extract_year == 2018) %>  
3   group_by(breed_rc, zip_code) %>  
4   tally() %>  
5   mutate(freq = n / sum(n))
```

```
# A tibble: 18,945 x 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

```
1 nyc_license >
2   filter(extract_year == 2018) >
3   group_by(breed_rc, zip_code) >
4   tally() >
5   mutate(freq = n / sum(n)) >
6   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

```
1 nyc_license >
2   filter(extract_year == 2018) >
3   group_by(breed_rc, zip_code) >
4   tally() >
5   mutate(freq = n / sum(n)) >
6   filter(breed_rc == "French Bulldog") ->
7   nyc_fb
```

Let's make a summary table

```
1 nyc_license >
2   filter(extract_year == 2018) >
3   group_by(breed_rc, zip_code) >
4   tally() >
5   mutate(freq = n / sum(n)) >
6   filter(breed_rc == "French Bulldog") ->
7   nyc_fb
```

Now we have two tables again

```
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 Belleroose   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
```

```
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:

```
fb_map ← left_join(nyc_zips, nyc_fb, by = "zip_code")
```

Ready to map

```
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
  <int> <chr>      <chr>   <chr>    <int>   <dbl>
1 11372 Jackson H... Queens French ...     13 8.02e-3
2 11004 Glen Oaks  Queens French ...      1 6.17e-4
3 11040 New Hyde ... Queens <NA>        NA NA
4 11426 Bellerose   Queens French ...      1 6.17e-4
5 11365 Fresh Mea... Queens French ...      7 4.32e-3
6 11373 Elmhurst    Queens French ...     14 8.64e-3
7 11001 Floral Pa... Queens <NA>        NA NA
8 11375 Forest Hi... Queens French ...      8 4.94e-3
9 11427 Queens Vi... Queens French ...      2 1.23e-3
10 11374 Rego Park  Queens French ...     6 3.70e-3
# i 252 more rows
```

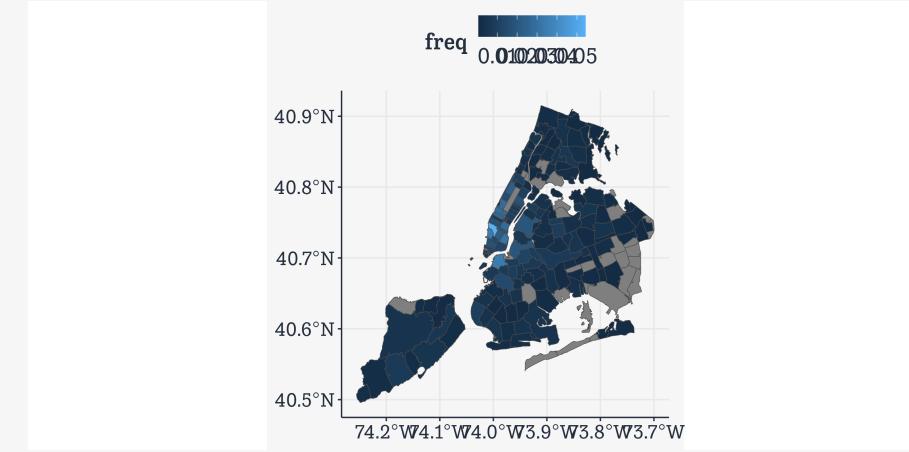
A NYC map theme

Just moving the legend, really.

```
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"  
    )  
}
```

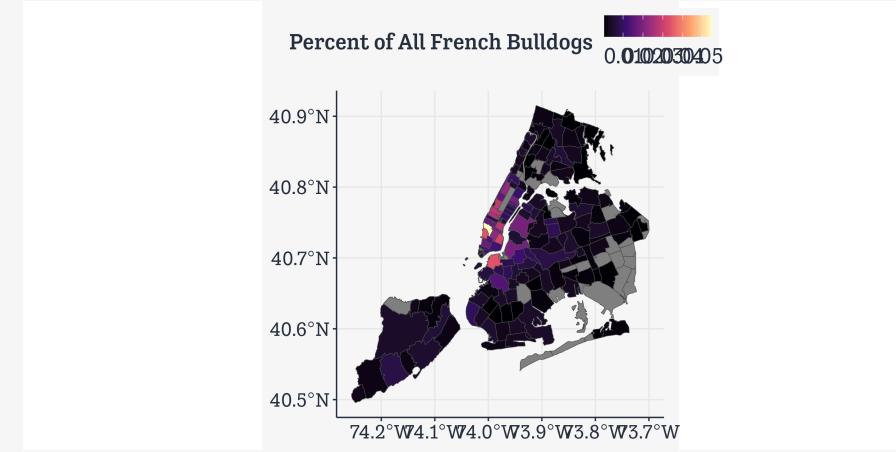
First cut at a map

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



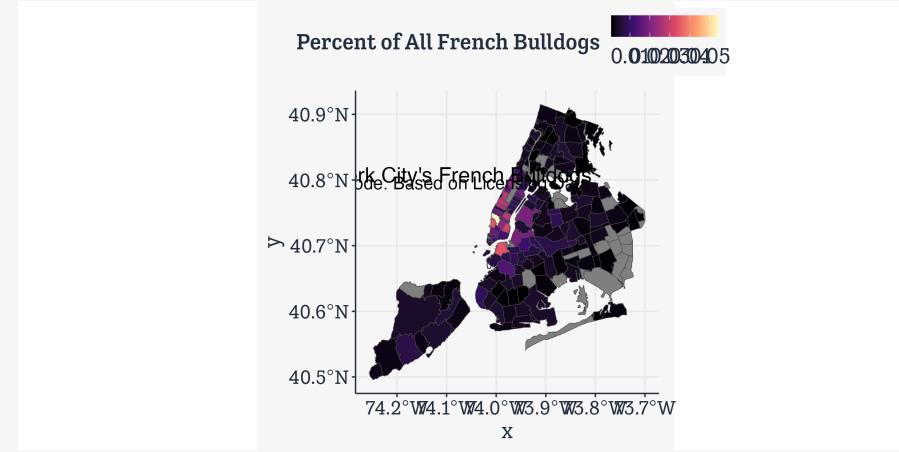
First cut at a map

```
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")
```



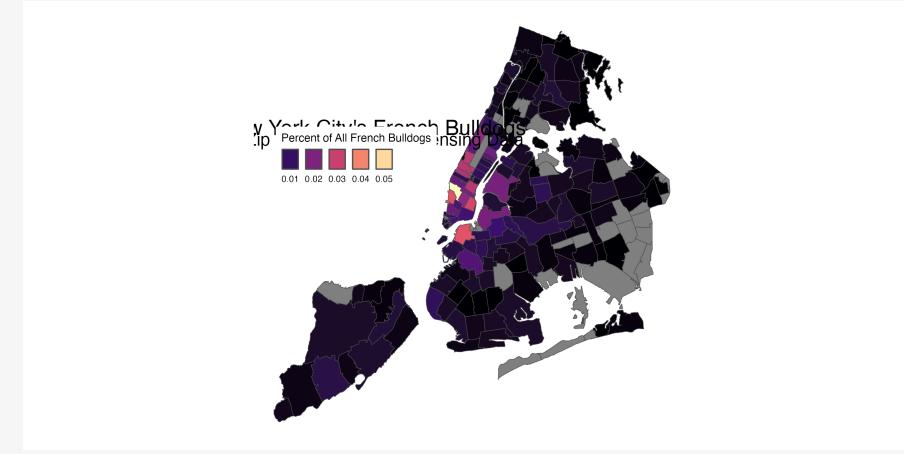
First cut at a map

```
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 Licens  
size = 5)
```



First cut at a map

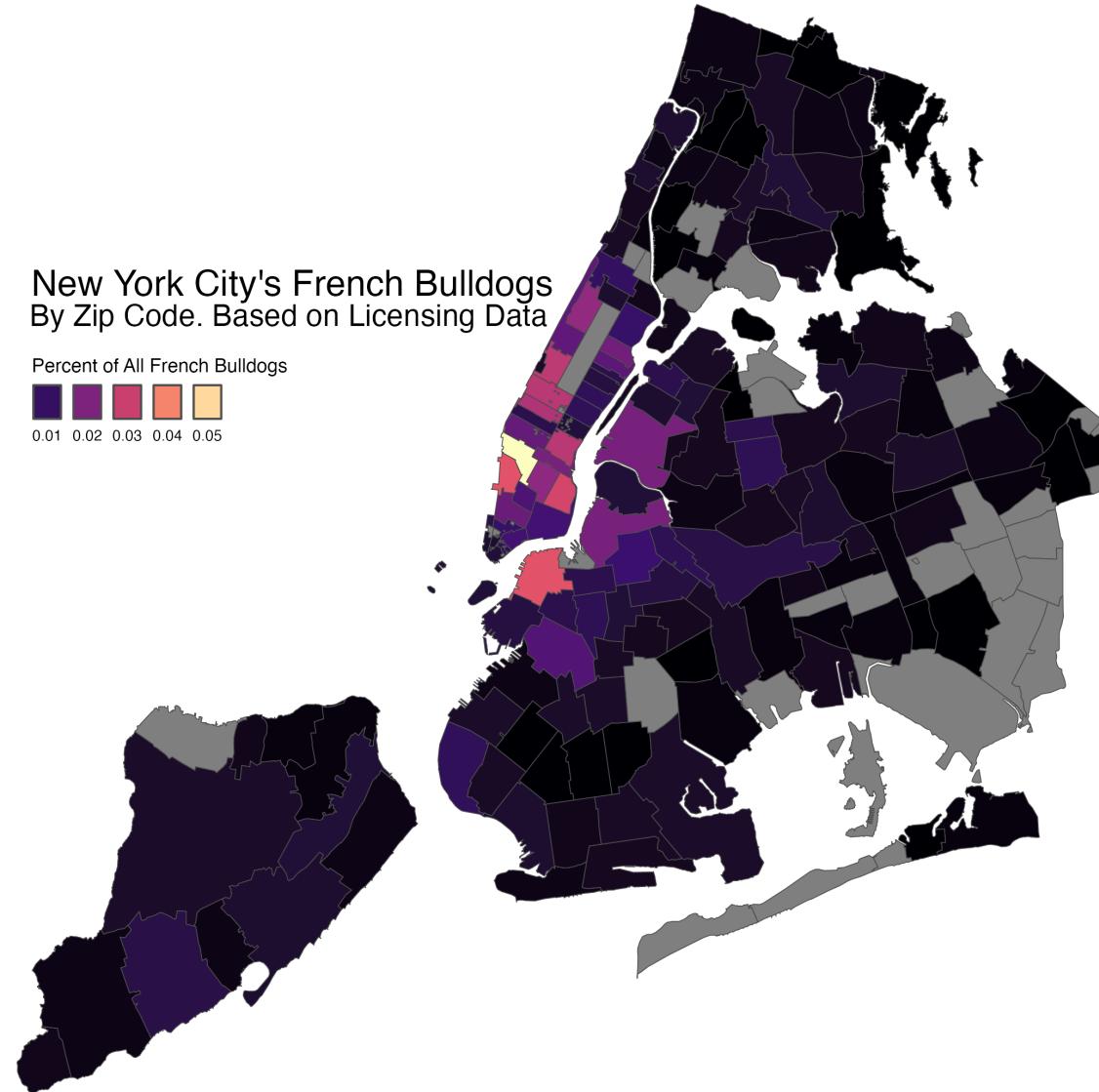
```
fb_map >
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) + #<<
  scale_fill_viridis_c(option = "A") +
  labs(fill = "Percent of All French Bulldogs")
  annotate(geom = "text",
    x = -74.145 + 0.029,
    y = 40.82-0.012,
    label = "New York City's French Bulldog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

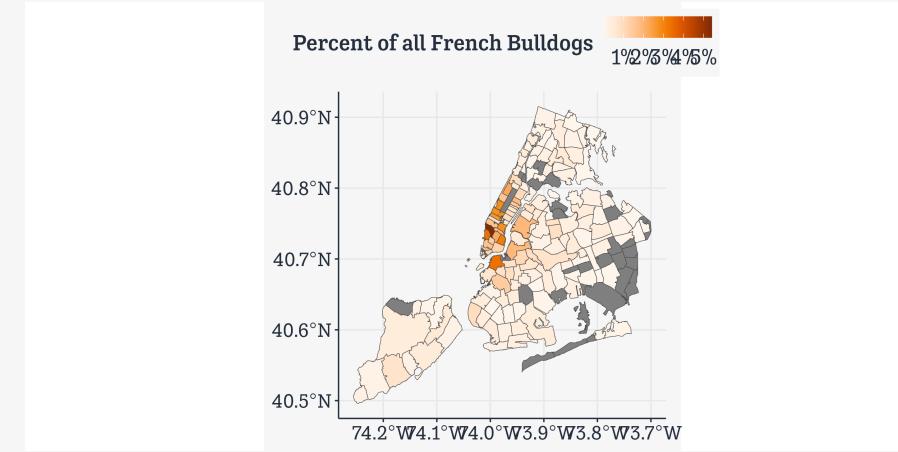
0.01 0.02 0.03 0.04 0.05



Use a different palette

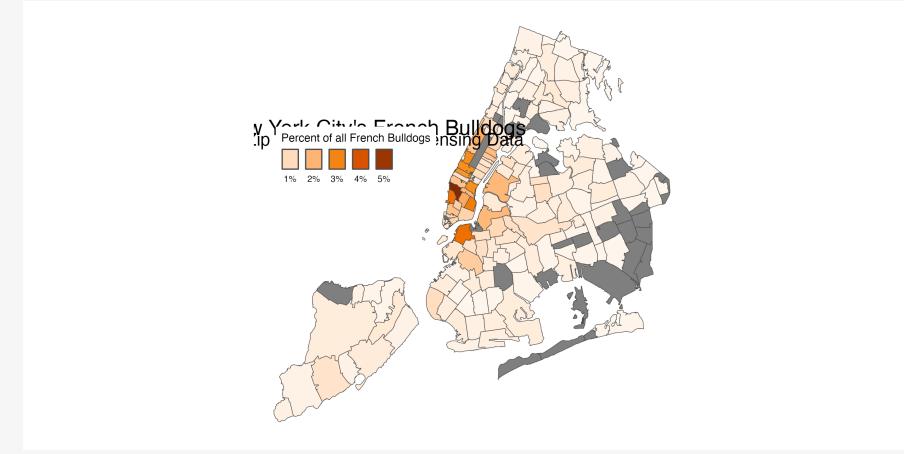
```
library(colorspace)

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

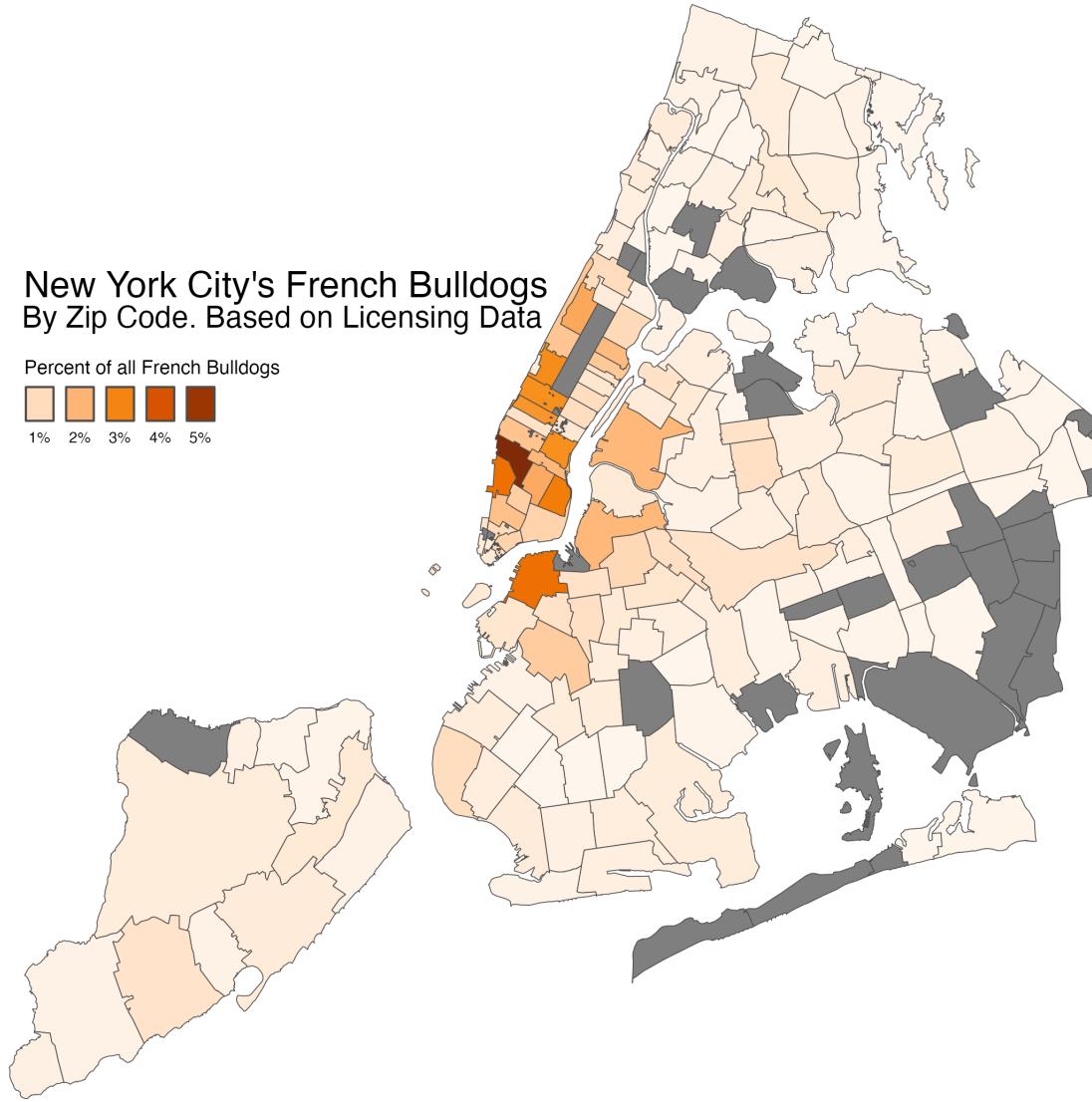
```
fb_map >  
  ggplot(mapping = aes(fill = freq)) +  
  geom_sf(color = "gray30", size = 0.1) +  
  scale_fill_continuous_sequential(  
    palette = "Oranges",  
    labels = scales::label_percent()) +  
  labs(fill = "Percent of all French Bulldogs")  
  annotate(geom = "text",  
    x = -74.145 + 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 Licens  
    size = 5) +  
  kjhslides::kjh_theme_nymap() +  
  guides(fill =  
    guide_legend(title.position = "top",  
      label.position = "bottom",  
      keywidth = 1,
```



New York City's French Bulldogs By Zip Code. Based on Licensing Data

Percent of all French Bulldogs

1% 2% 3% 4% 5%



NYC Dogs Map mark 2

Keep the Zero-count Zips

```
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

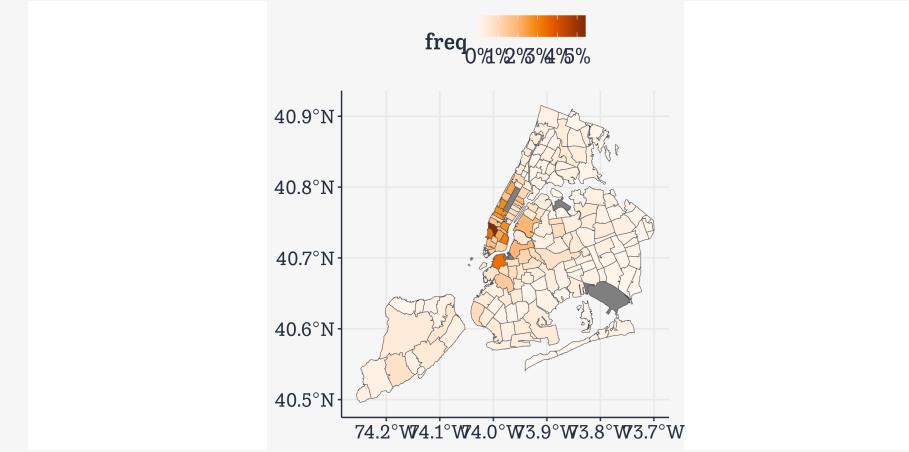
```
fb_map2 ▷ select(zip_code, po_name, borough, breed_rc:freq, geometry)
```

```
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
  <int> <chr>      <chr>   <chr> <int>   <dbl>
1 11372 Jackson He... Queens French ... 13 8.02e-3
2 11004 Glen Oaks   Queens French ... 1 6.17e-4
3 11040 New Hyde P... Queens French ... 0 0
4 11426 Bellerose   Queens French ... 1 6.17e-4
5 11365 Fresh Mead... Queens French ... 7 4.32e-3
6 11373 Elmhurst    Queens French ... 14 8.64e-3
7 11001 Floral Park Queens French ... 0 0
8 11375 Forest Hil... Queens French ... 8 4.94e-3
9 11427 Queens Vil... Queens French ... 2 1.23e-3
10 11374 Rego Park   Queens French ... 6 3.70e-3
# i 252 more rows
```

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

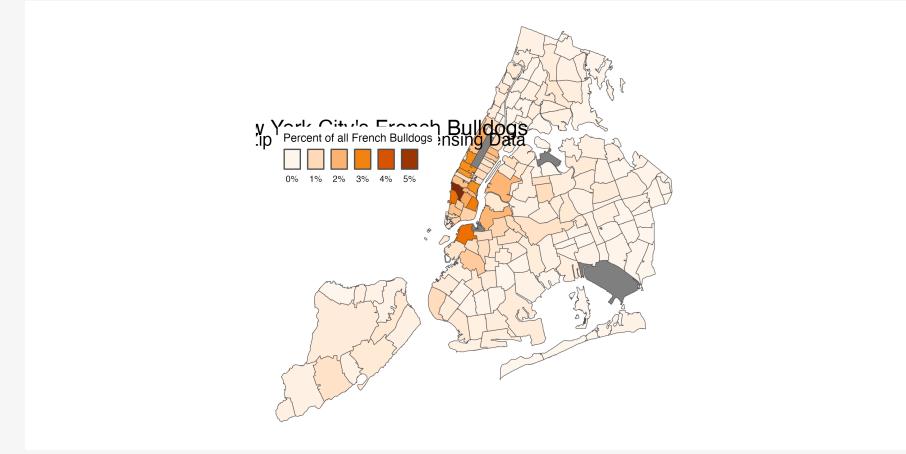
Keep the Zero-count Zips

```
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

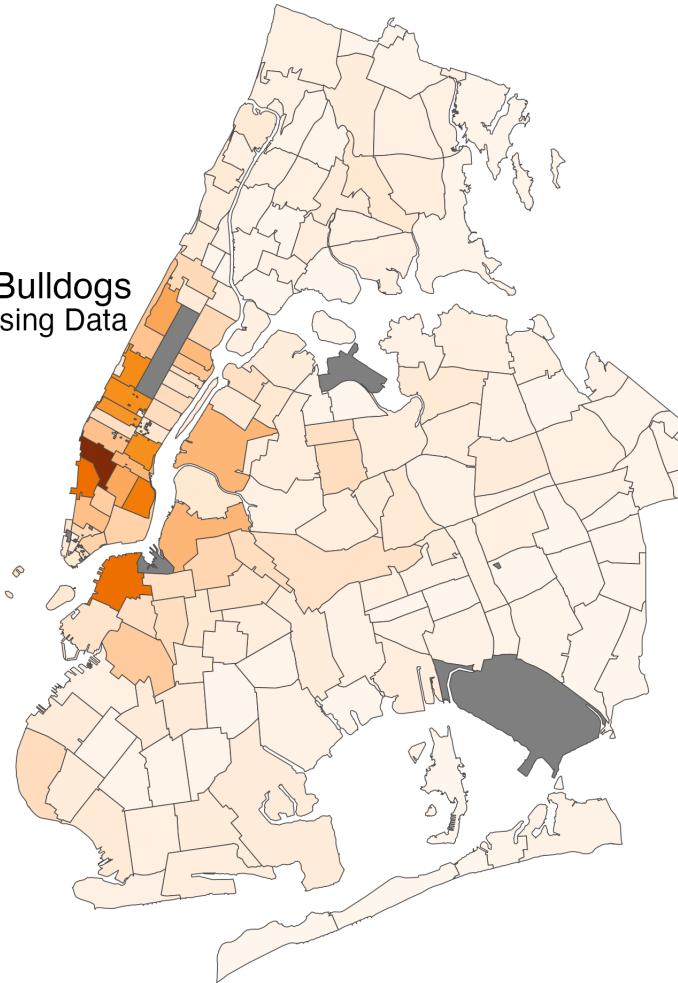
```
fb_map2 >
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) +
  scale_fill_continuous_sequential(
    palette = "Oranges",
    labels = scales::label_percent()) +
  labs(fill = "Percent of all French Bulldogs")
  annotate(geom = "text",
    x = -74.145 + 0.029,
    y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



New York City's French Bulldogs By Zip Code. Based on Licensing Data

Percent of all French Bulldogs

0% 1% 2% 3% 4% 5%



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

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

Dorling Cartograms

```
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

```
library(tidy census)
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

```
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)

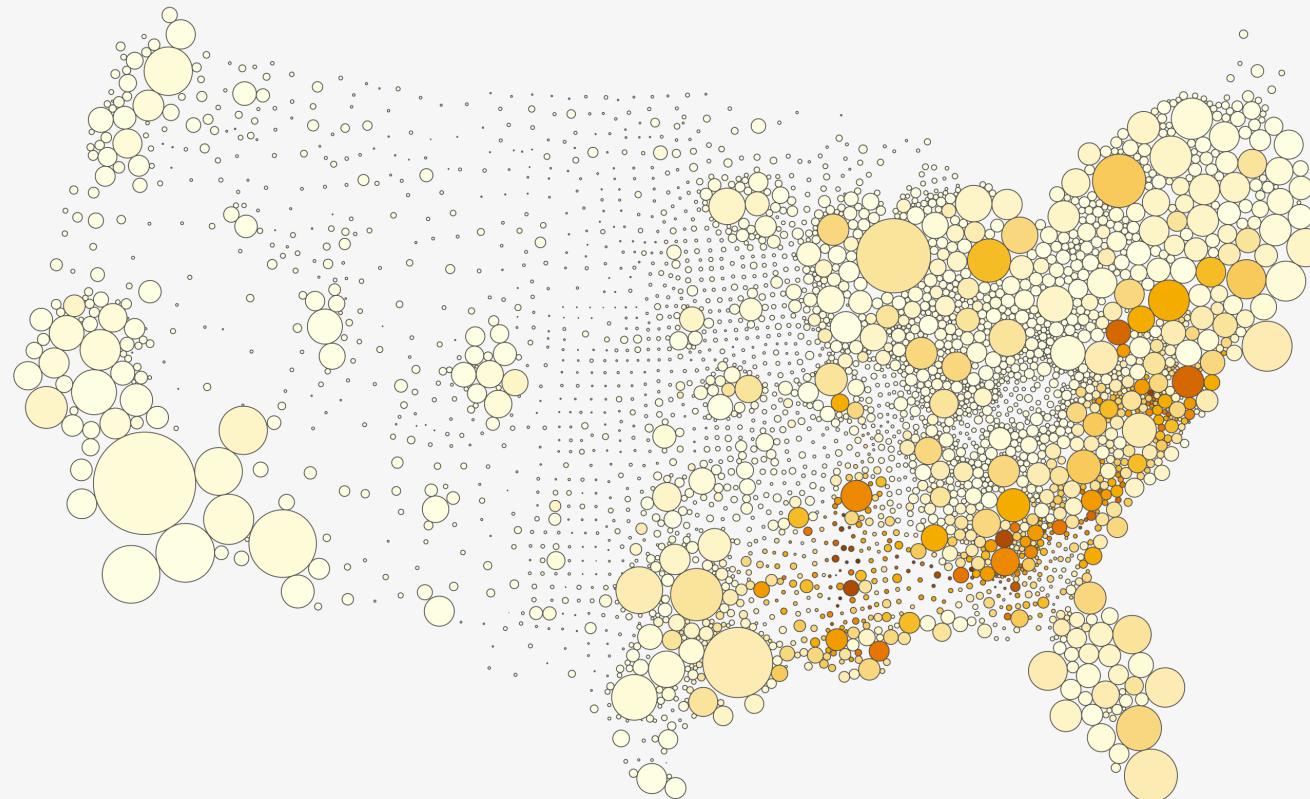
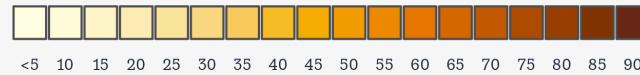
out_black ← county_dorling %>
  filter(!str_detect(name, "Alaska|Hawaii|Puerto|Guam")) %>
  ggplot(aes(fill = black_disc)) +
  geom_sf(color = "grey30", size = 0.1) +
  coord_sf(crs = 2163, datum = NA) +
  scale_fill_discrete_sequential(palette = "YlOrBr",
                                  na.translate=FALSE) +
  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)
```

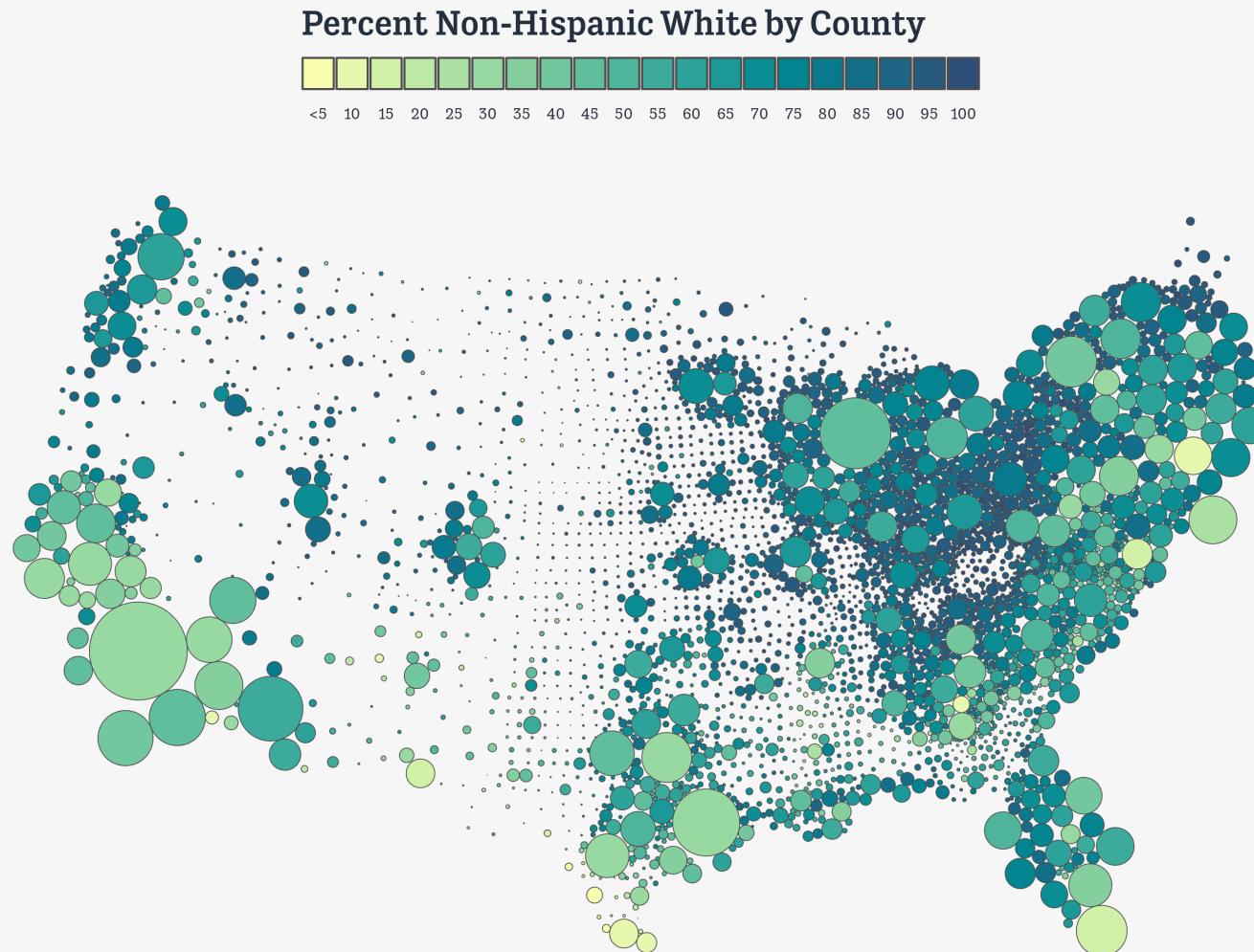
Bubble size corresponds to County Population

Percent Black by County

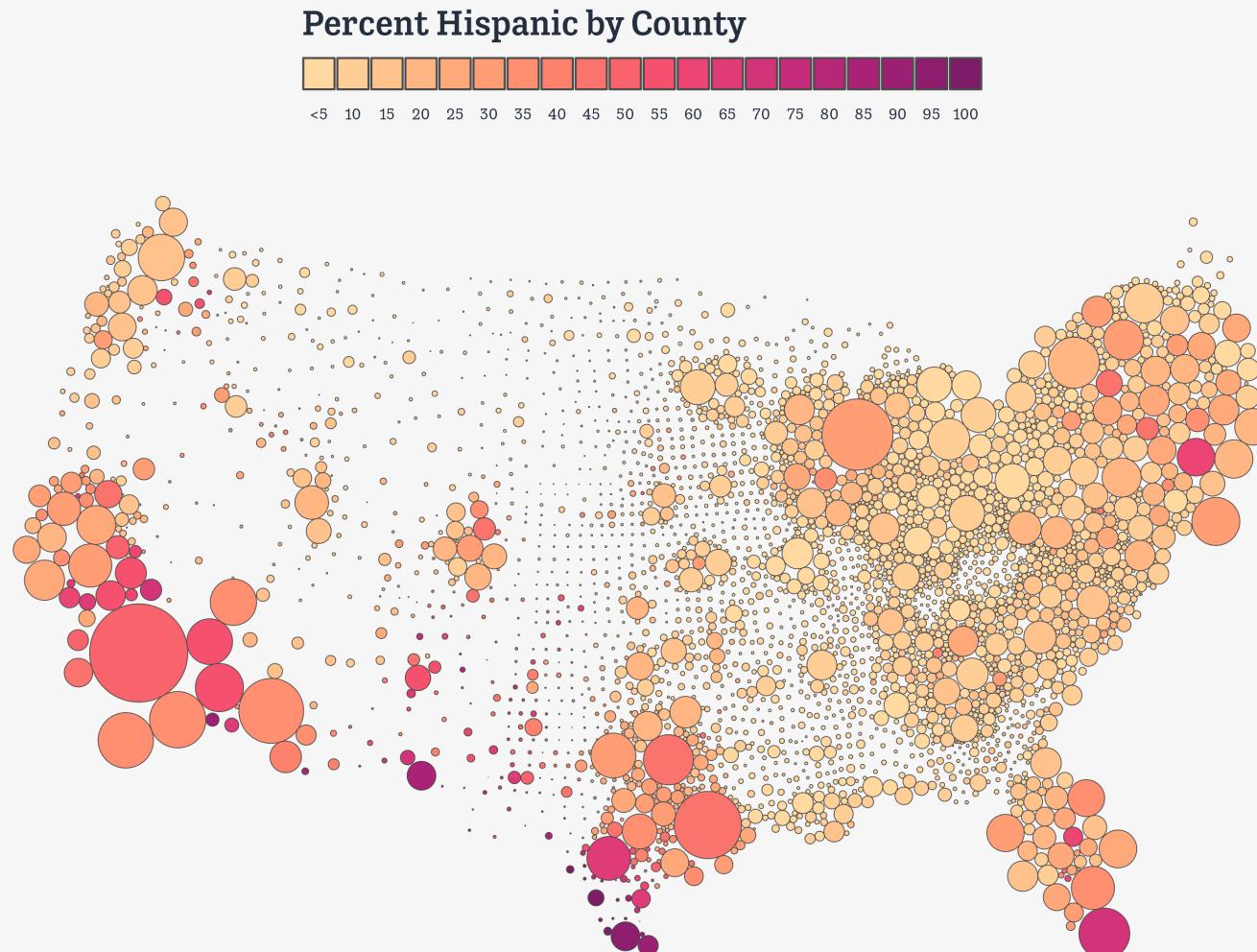


Graph: @kjhealy. Source: Census Bureau / American Community Survey

```
print(out_white)
```



```
print(out_hispanic)
```



```
print(out_asian)
```

