

# Data Visualization - 7.

## Make Maps (2)

Kieran Healy

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
```



# 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                         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

```
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
```

# Let's make a summary table

```
1 nyc_license %>  
2   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            2017
```

# 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...       11278
```

# 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
```

# 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

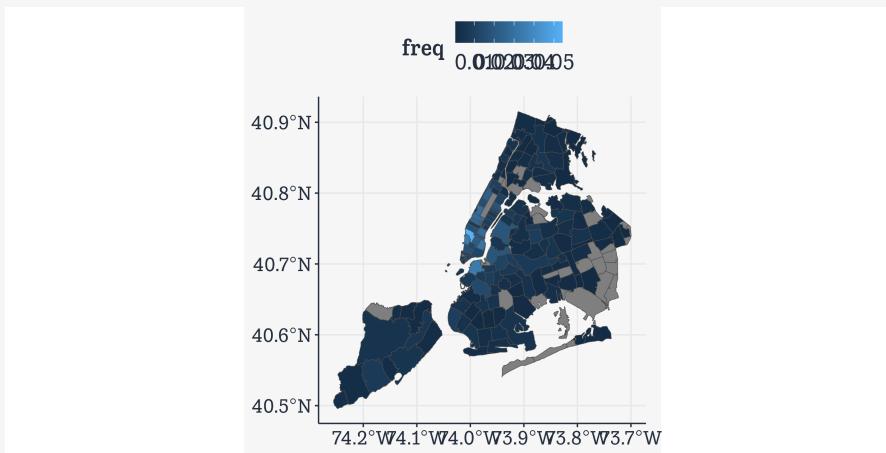
Just moving the legend, really.

```
theme_nympa <- 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"  
    )  
}
```



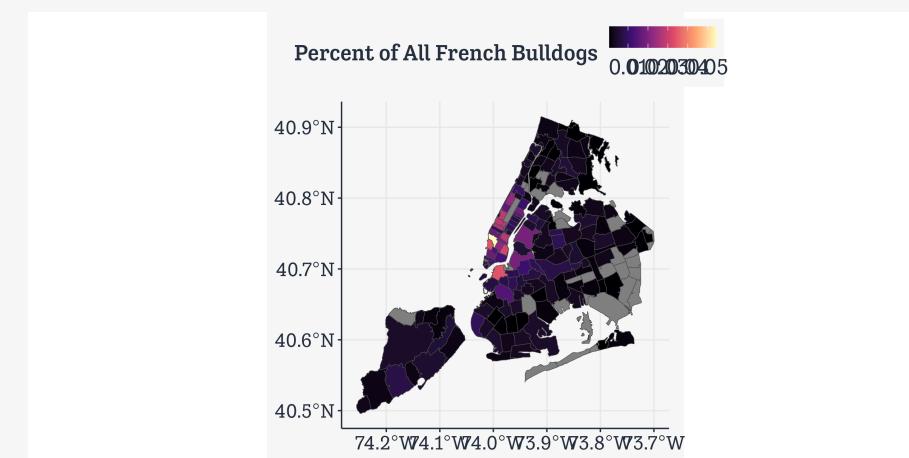
# First cut at a map

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



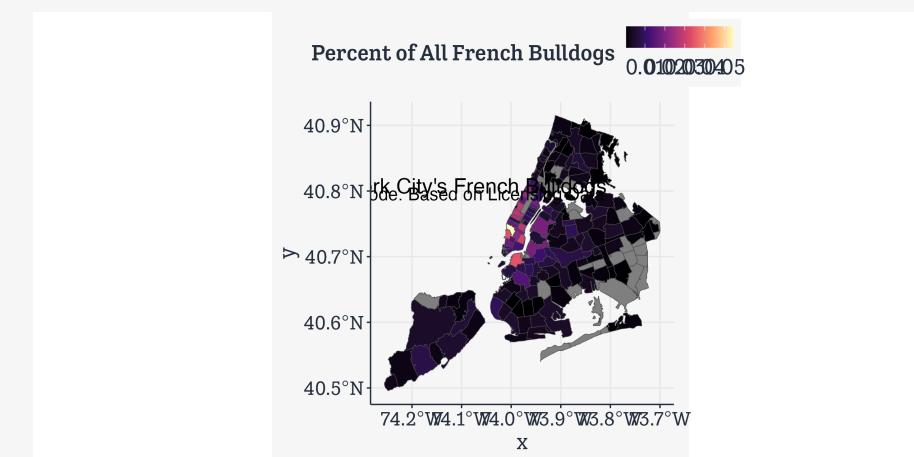
# First cut at a map

```
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")
```



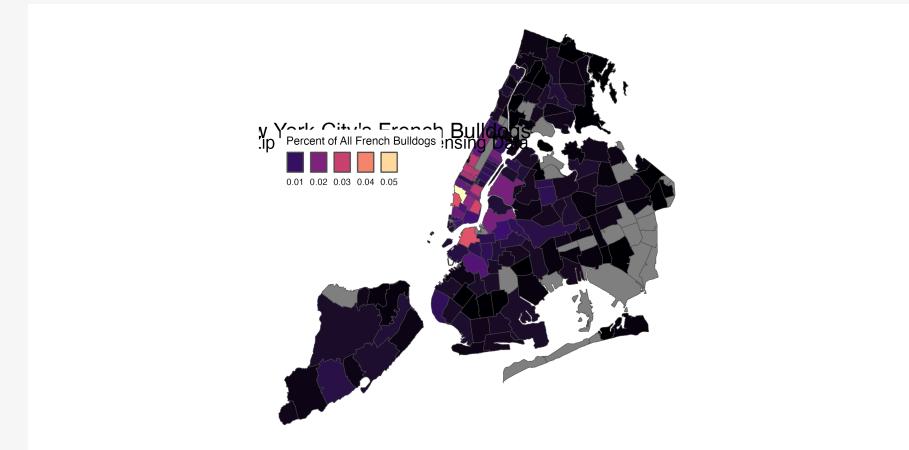
# First cut at a map

```
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

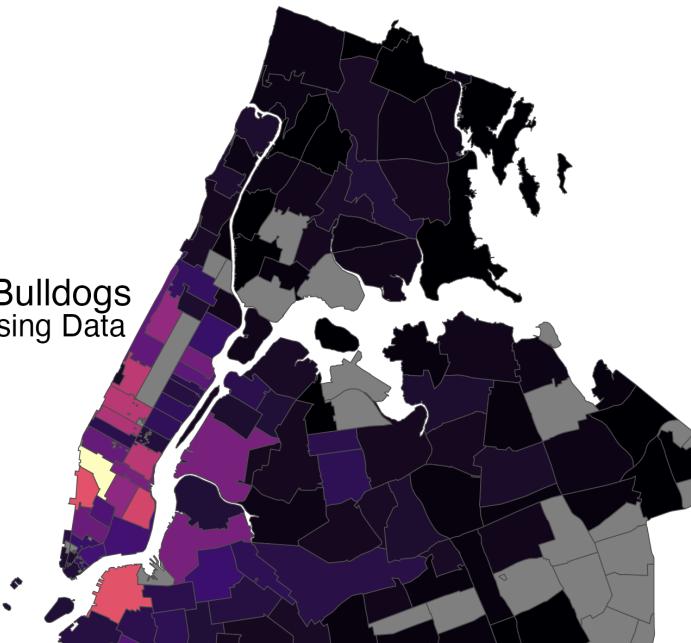
```
fb_map >
  ggplot(mapping = aes(fill = freq)) +
  geom_sf(color = "gray30", size = 0.1) + #<<
  scale_fill_viridis_c(option = "A") +
  labs(fill = "Percent of All French Bulldogs")
  annotate(geom = "text",
           x = -74.145 + 0.029,
           y = 40.82-0.012,
           label = "New York City's French 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) +
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

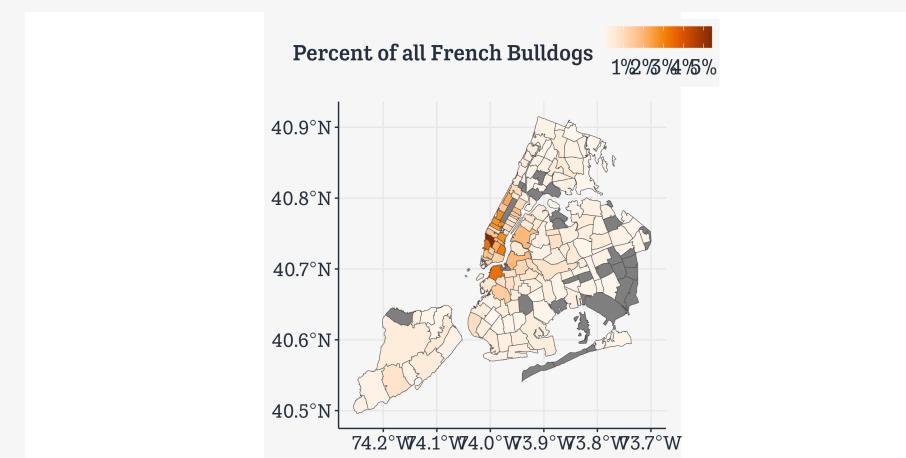
0.01	0.02	0.03	0.04	0.05
------	------	------	------	------



# Use a different palette

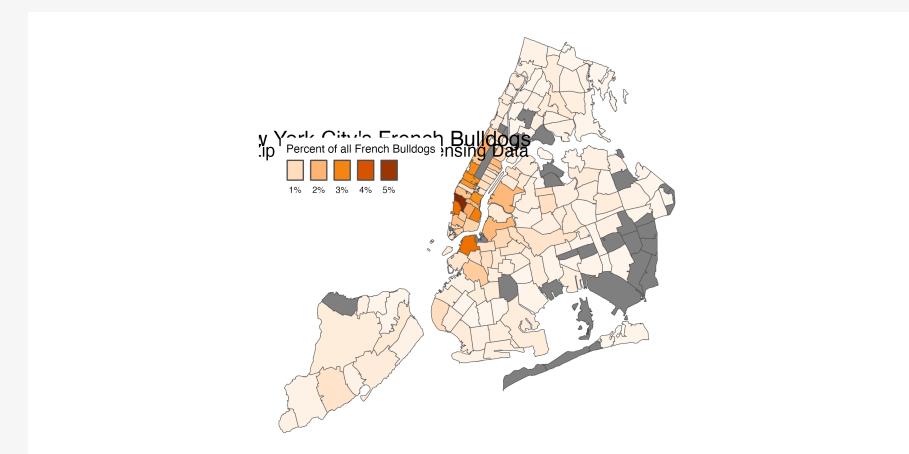
```
library(colorspace)

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")
```



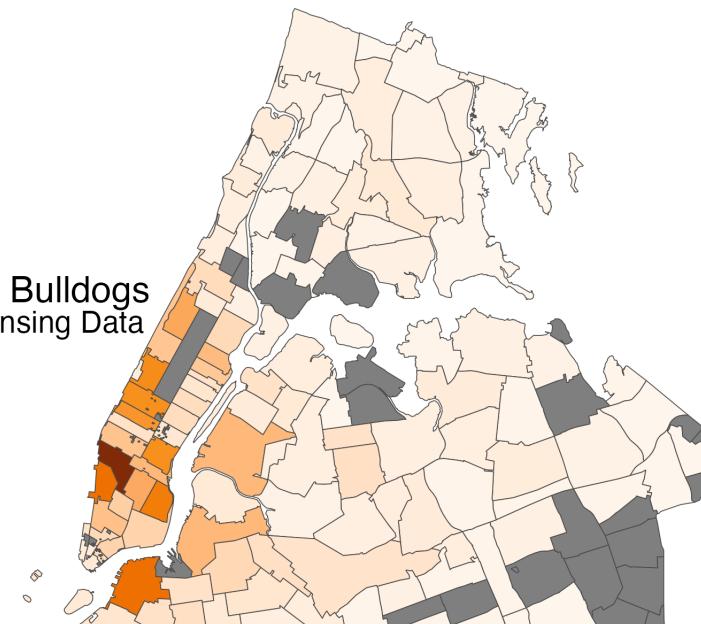
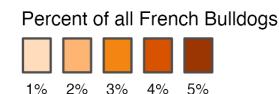
# Use a different palette

```
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 Bulldog Licensing Data",
    size = 6) +
  annotate(geom = "text",
    x = -74.1468 + 0.029,
    y = 40.7955,
    label = "By Zip Code. Based on License Data",
    size = 5) +
  kjhslides::kjh_theme_nymap() +
  guides(fill =
    guide_legend(title.position = "top",
      label.position = "bottom",
      keywidth = 1
```



NYC Dogs Map mark 2

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



# 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)
```

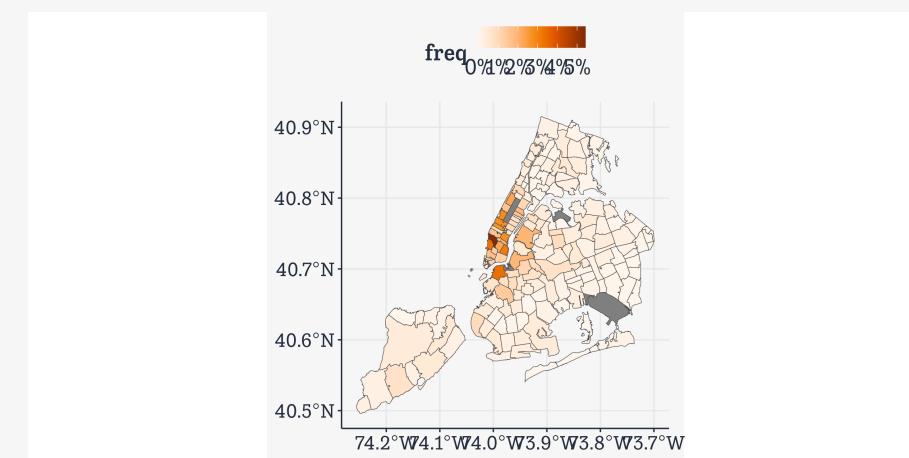
```
Simple feature collection with 262 features and 6 fields
Geometry type: POLYGON
Dimension: XY
Bounding box: xmin: -74.25576 ymin: 40.49584 xmax: -73.6996 ymax: 40.91517
Geodetic CRS: WGS 84
# A tibble: 262 × 7
  zip_code po_name     borough breed_rc      n    freq
  <int> <chr>       <chr>   <chr> <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.



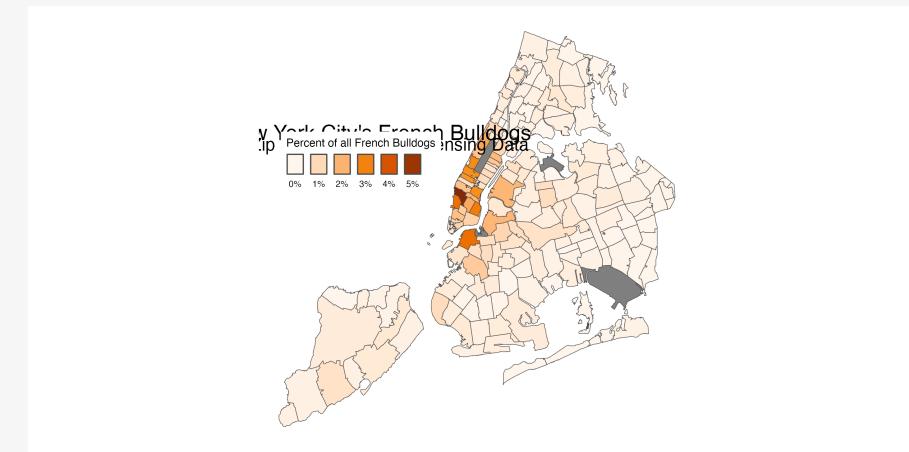
# Keep the Zero-count Zips

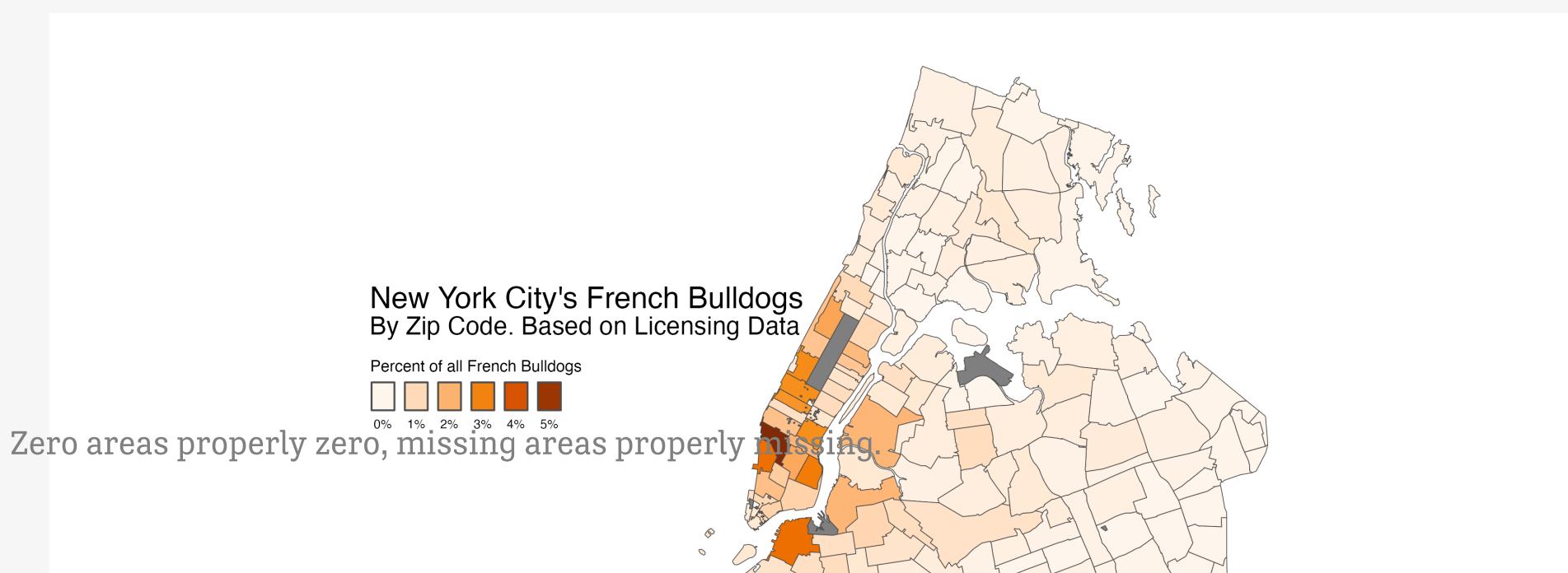
```
fb_map2 >  
  ggplot(mapping = aes(fill = freq)) +  
  geom_sf(color = "gray30", size = 0.1) +  
  scale_fill_continuous_sequential(  
    palette = "Oranges",  
    labels = scales::label_percent())
```



# 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 License Data",
    size = 5) +
  kjhslides::kjh_theme_nymap() +
  guides(fill =
    guide_legend(title.position = "top",
      label.position = "bottom",
      keywidth = 1
```





# 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"))
```

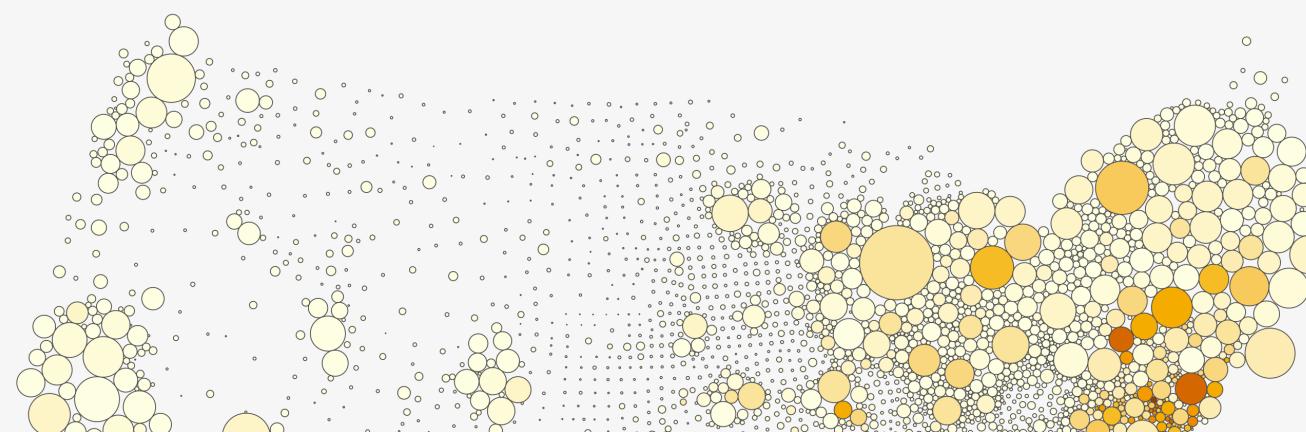
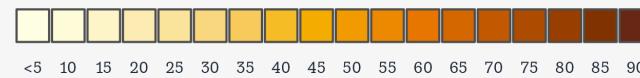
# Dorling Cartograms



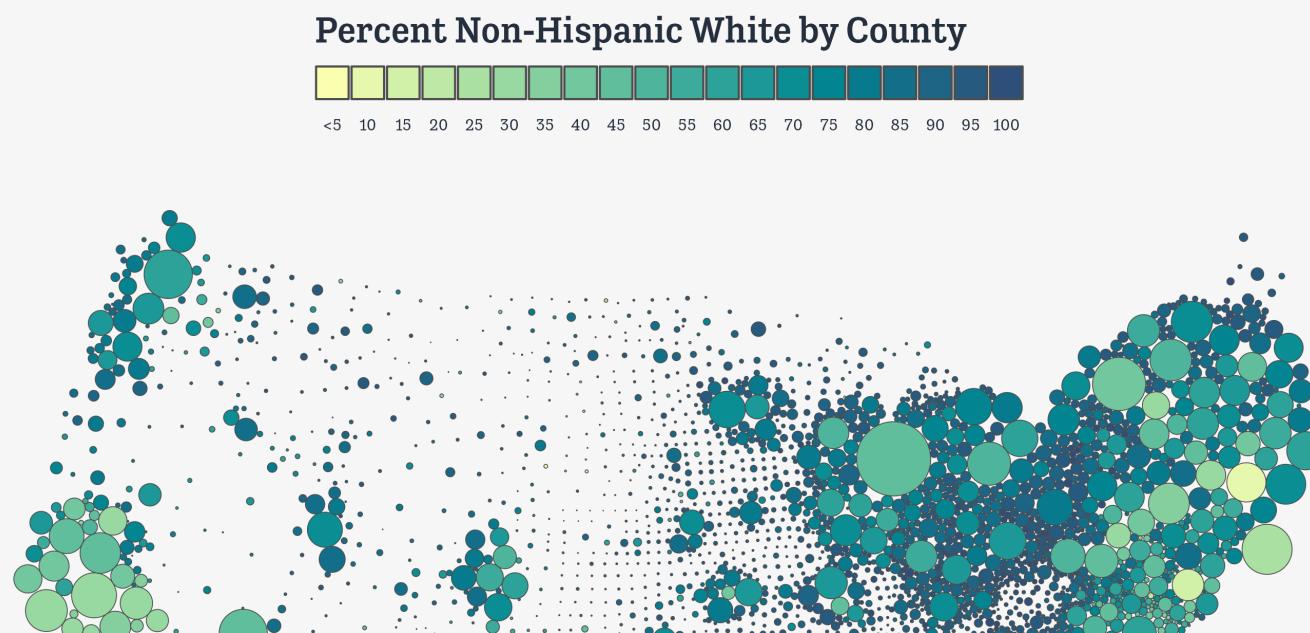
```
print(out_black)
```

Bubble size corresponds to County Population

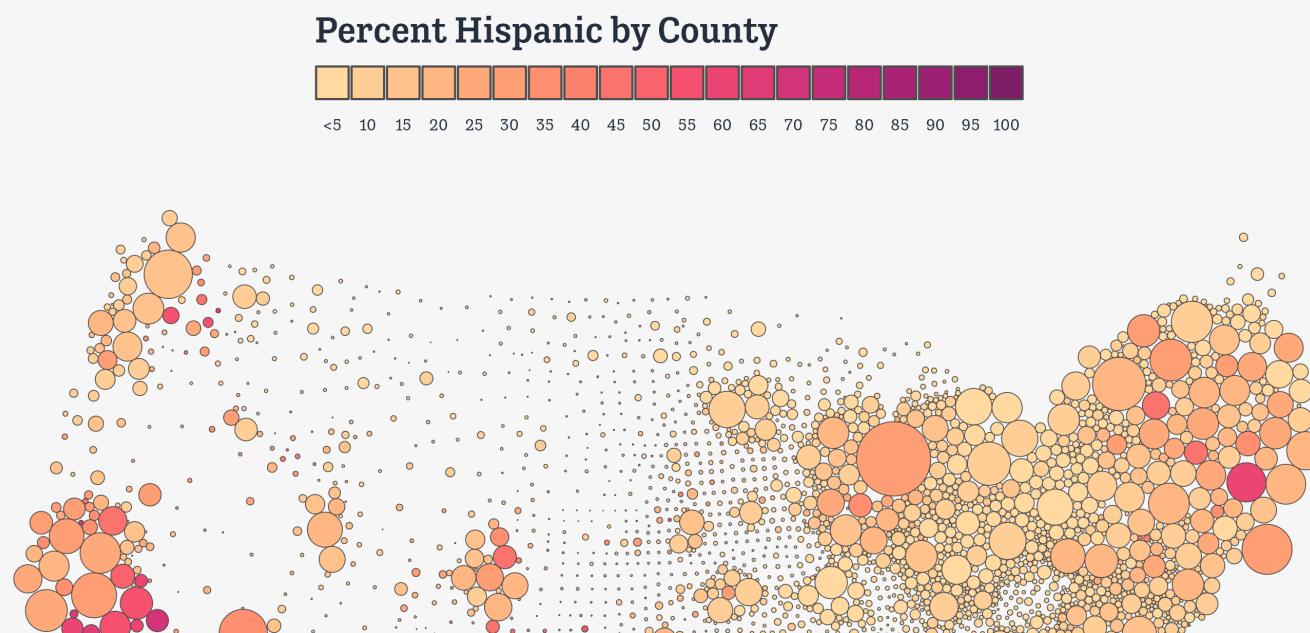
### Percent Black by County



```
print(out_white)
```



```
print(out_hispanic)
```



```
print(out_asian)
```

