Adding to the story: Annotations, maps and interactions

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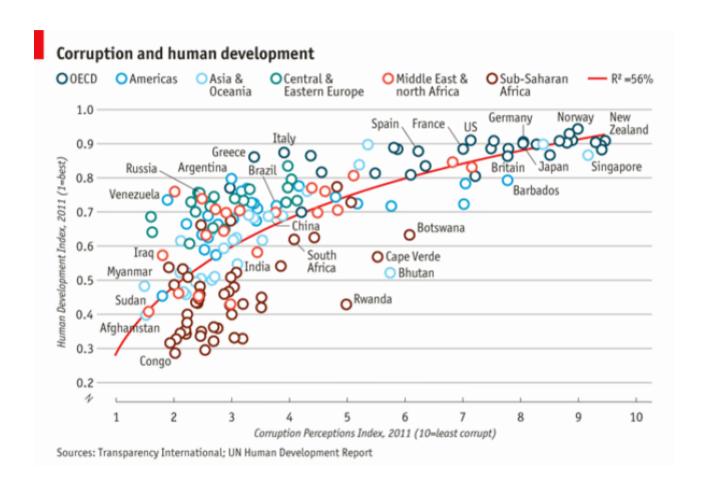
Spring 2019

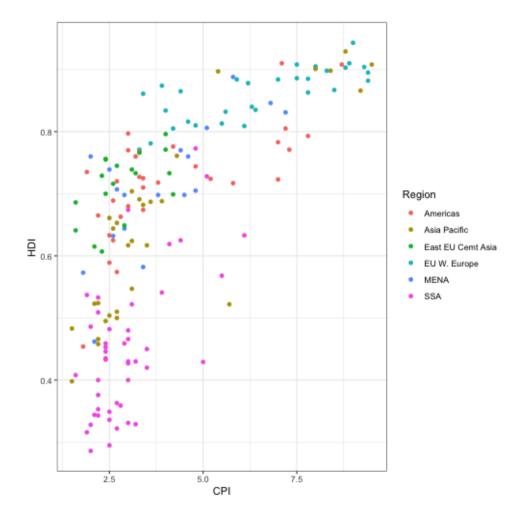
Annotations

Stand-alone stories

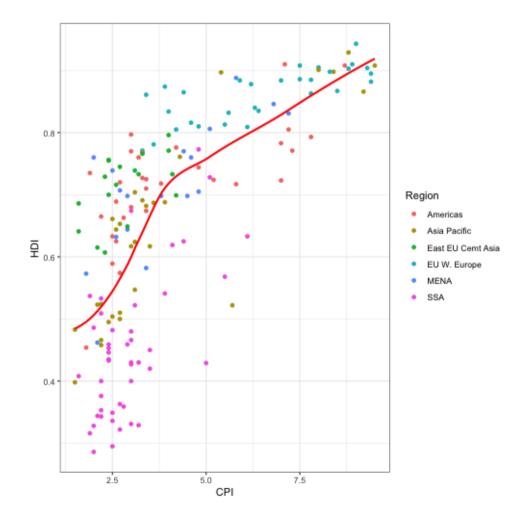
- You would like a data visualization to stand on its own
- Relevant information should be placed on the graph
- However, you need to balance the information content with real estate
 - Don't clutter the graph and make it not readable

An example

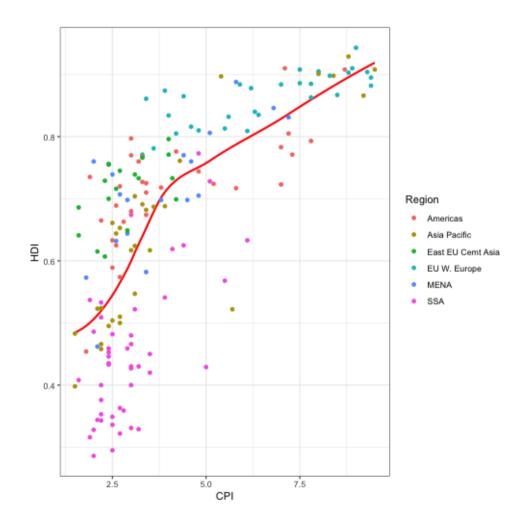




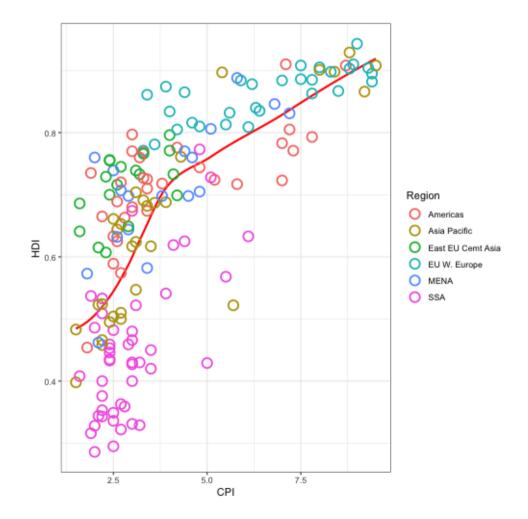
Add a trend line



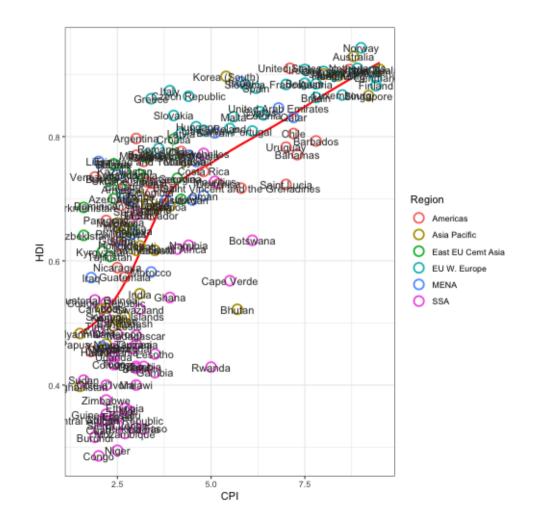
Reverse order so points are above line



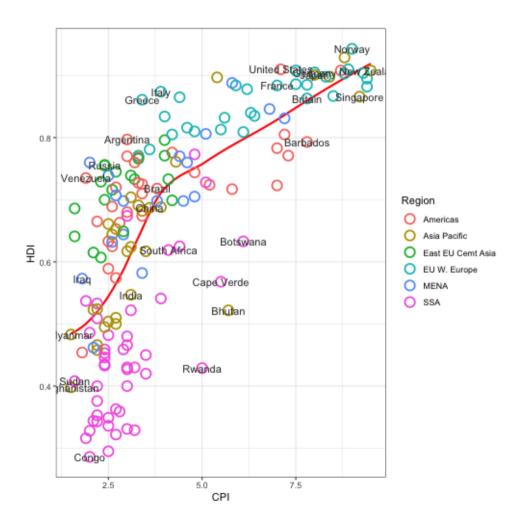
Different shape for points



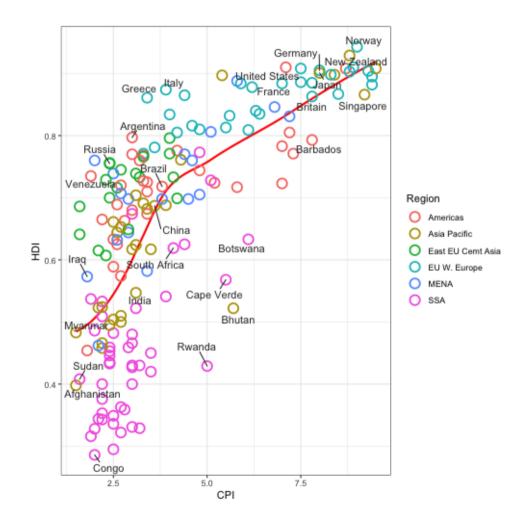
Label countries



Better, but labels are overlayed on points

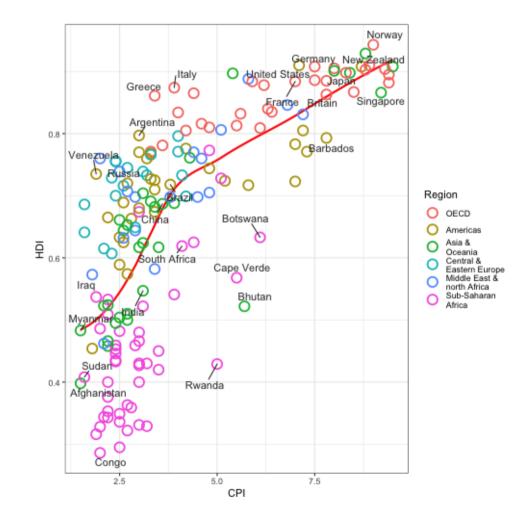


```
library(ggrepel)
pointsToLabel <- c("Russia", "Venezuela", "Iraq", "My</pre>
                    "Afghanistan", "Congo", "Greece",
                    "India", "Italy", "China", "South
                    "Botswana", "Cape Verde", "Bhutan"
                    "United States", "Germany", "Brita
                   "New Zealand", "Singapore")
(plt <- ggplot(econ_data,</pre>
       aes(x = CPI, y = HDI, color=Region))+
 geom_smooth(color='red', se=F) +
  geom_point(shape = 1, size = 4, stroke=1.25) +
  geom_text_repel(aes(label=Country),
            color = 'gray20',
            force=20.
            data = econ data %>%
              filter(Country %in% pointsToLabel)))
```



Let's re-order the regions

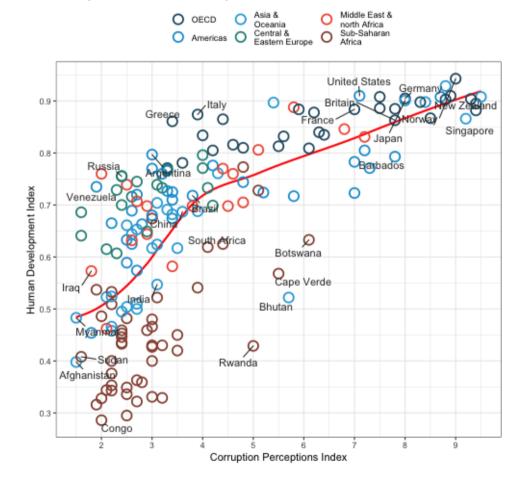
```
econ_data$Region <-
 factor(econ_data$Region,
         levels = c("EU W. Europe",
                     "Americas",
                     "Asia Pacific",
                     "East EU Cemt Asia",
                     "MENA",
                     "SSA"),
         labels = c("OECD",
                     "Americas",
                     "Asia &\nOceania",
                     "Central &\nEastern Europe",
                     "Middle East &\nnorth Africa",
                     "Sub-Saharan\nAfrica"))
plt$data = econ_data
plt
```



Clean up the graphic

```
(plt_corrupt <-</pre>
   plt +
  scale_x_continuous(name = 'Corruption Perceptions I
                     breaks = 1:10) +
  scale_y_continuous(name="Human Development Index",
                     breaks = seg(0.2, 1, by = 0.1))+
 scale_color_manual(name = ''
                     values = c("#24576D",
                                 "#099DD7".
                                 "#28AADC"
                                 "#248E84"
                                 "#F2583F"
                                 "#96503F")) +
  ggtitle("Corruption and Human development")+
 theme_bw()+
 theme(legend.position='top',
        legend.direction='horizontal')
```

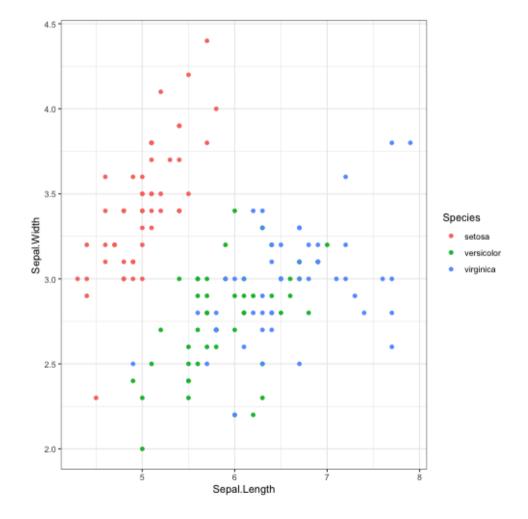
Corruption and Human development



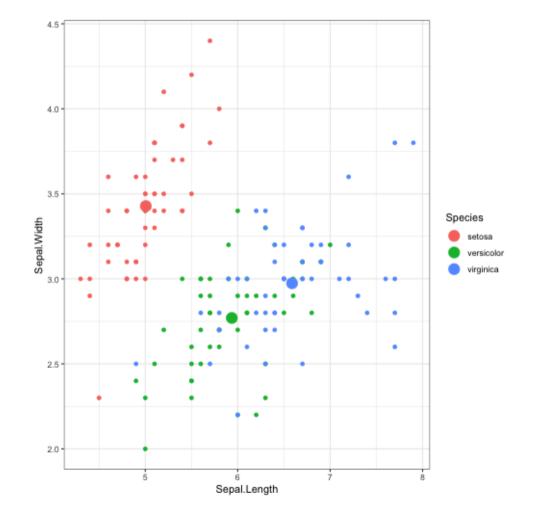
Adding derived statistics to a plot

Adding group means

```
ggplot(iris,
    aes(x = Sepal.Length,
        y = Sepal.Width,
        color = Species))+
geom_point()+
theme_bw()
```

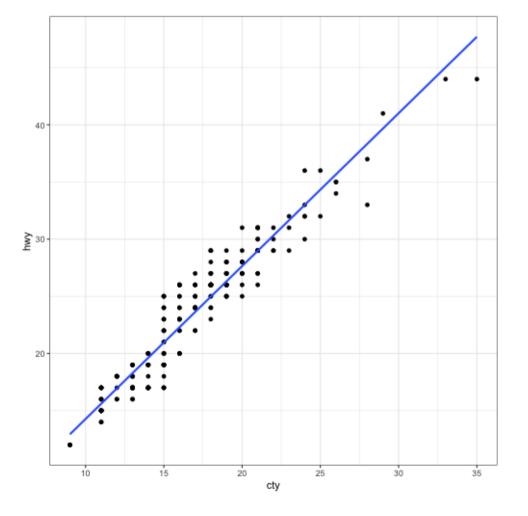


Adding group means



Adding regression metrics

Regress highway mileage on city mileage (data: mpg)

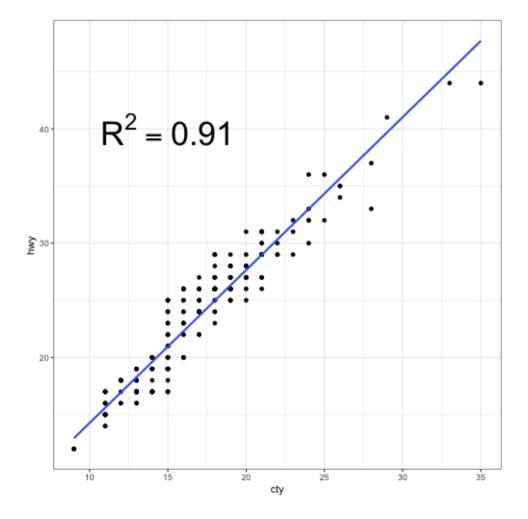


Adding regression metrics

Regress highway mileage on city mileage (data: mpg)

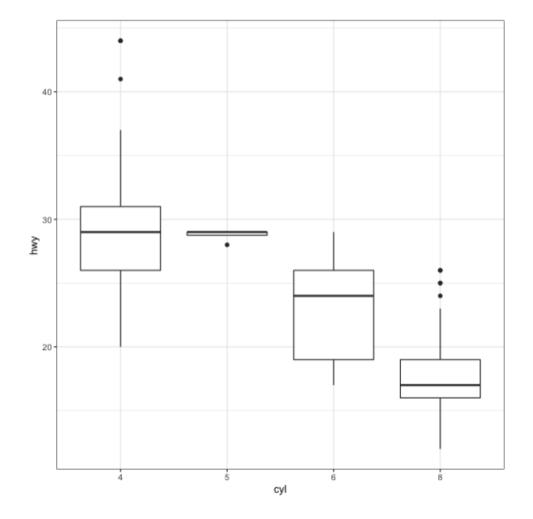
```
mod1 <- lm(hwy ~ cty, data = mpg)
r2 <- broom::glance(mod1) %>% pull(r.squared) %>%
  round(., 2)

ggplot(mpg,
        aes(x = cty, y = hwy))+
  geom_point() +
  geom_smooth(method = 'lm', se=F)+
  annotate(geom='text',
        x = 15, y = 40,
        label=glue::glue("R^2 == {r}",r=r2),
        size=12,
        parse=T) +
  theme_bw()
```



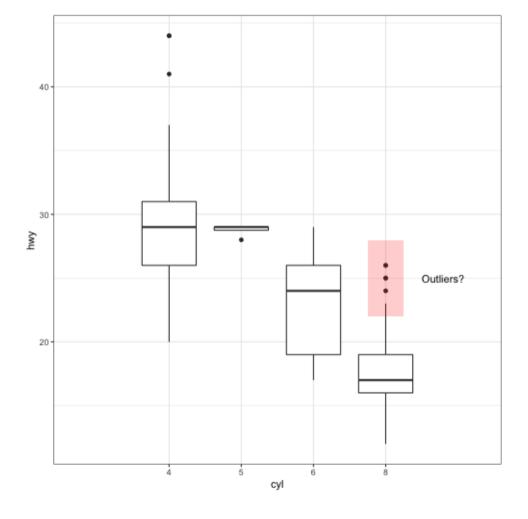
Highlighting regions

```
mpg %>%
  mutate(cyl = as.factor(cyl)) %>%
  ggplot(aes(x = cyl, y = hwy)) +
  geom_boxplot() +
  theme_bw()
```



Highlighting regions

```
mpg %>%
  mutate(cyl = as.factor(cyl)) %>%
  ggplot(aes(x = cyl, y = hwy)) +
  geom_boxplot() +
  theme_bw()+
  annotate(geom = 'rect',
           xmin=3.75, xmax=4.25,
           ymin = 22, ymax = 28,
           fill = 'red',
           alpha = 0.2) +
  annotate('text',
           x = 4.5, y = 25,
           label = 'Outliers?',
           hjust = 0)+
  coord_cartesian(xlim = c(0,5))+
  theme_bw()
```



Maps

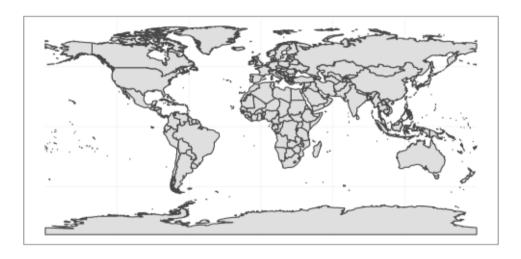
For maps, we need a couple of new packages.

- sf: Simple features in R
- rnaturalearth & rnaturalearthdata: map data

BIOF 439, Spring 2019

```
library(sf)
library(rnaturalearth)
library(rnaturalearthdata)

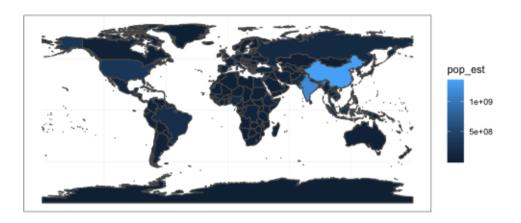
world <- ne_countries(scale='medium', returnclass='sf
ggplot(data = world) +
   geom_sf()</pre>
```



BIOF 439, Spring 2019

```
library(sf)
library(rnaturalearth)
library(rnaturalearthdata)

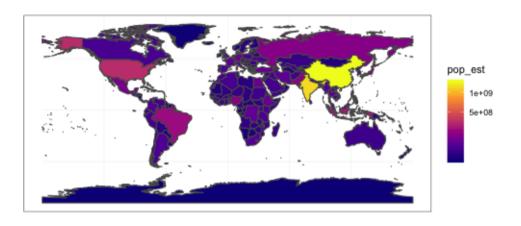
world <- ne_countries(scale='medium', returnclass='sf
ggplot(data = world) +
   geom_sf(aes(fill = pop_est))</pre>
```



BIOF 439, Spring 2019

```
library(sf)
library(rnaturalearth)
library(rnaturalearthdata)

world <- ne_countries(scale='medium', returnclass='sf
ggplot(data = world) +
   geom_sf(aes(fill = pop_est))+
   scale_fill_viridis_c(option = 'plasma', trans='sqrt</pre>
```



Looking at Florida



Looking at Florida



```
#> # A tibble: 6 x 14
     County Bush Bush_perc
                               Gore Gore_perc Nader
     <chr>
             <db1> <chr>
                              <db1> <chr>
                                              <db1>
#> 1 Alach...
            34135 39.80%
                              47380 55.25%
                                               3228
   2 Baker
            5611 68.80%
                               2392 29.33%
                                                53
   3 Bav
             38682 65.70%
                              18873 32.06%
                                               830
   4 Bradf... 5416 62.43%
                           3075 35.45%
                                               84
   5 Breva... 115253 52.75%
                           97341 44.55%
                                               4471
   6 Browa... 177939 30.93%
                             387760 67.41%
                                              7105
   # ... with 6 more variables: Buchanan_perc <chr>, C
       Other_perc <chr>, Margin <dbl>, Margin_perc <
```

Now we need the map information

```
library(maps)
counties <- st_as_sf(maps::map('county', plot = F, fi
head(counties)
counties <- counties %>% filter(str_detect(ID, 'flori
counties <- counties %>% separate(ID, c('State','Coun
    mutate_at(vars(State:County), str_to_title)
```

```
Simple feature collection with 6 features and 1 t
   geometry type: MULTIPOLYGON
                   XY
   dimension:
   bbox:
                   xmin: -88.01778 ymin: 30.24071 xm
  epsg (SRID):
                   4326
   proj4string: +proj=longlat +datum=WGS84 +no_de
#>
                           geometry
                                                ID
   1 MULTIPOLYGON (((-86.50517 3... alabama, autauga
   2 MULTIPOLYGON (((-87.93757 3... alabama, baldwin
   3 MULTIPOLYGON (((-85.42801 3... alabama, barbour
   4 MULTIPOLYGON (((-87.02083 3... alabama,bibb
   5 MULTIPOLYGON (((-86.9578 33... alabama,blount
   6 MULTIPOLYGON (((-85.66866 3... alabama.bullock
```

The nice thing about the sf package is that it renders all the data into a data frame, so adding to it, or merging new data becomes easy.

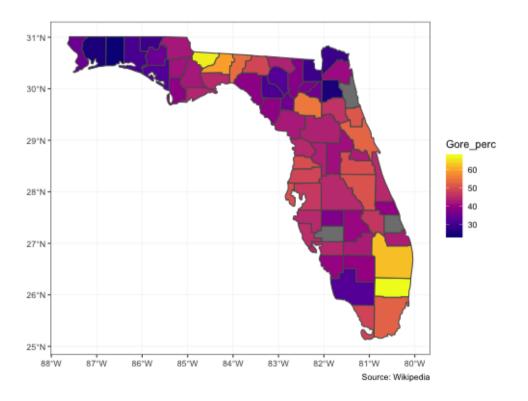
We will now merge the election data with the map data

```
election_by_county <- counties %>% left_join(florida_
head(election_by_county)
```

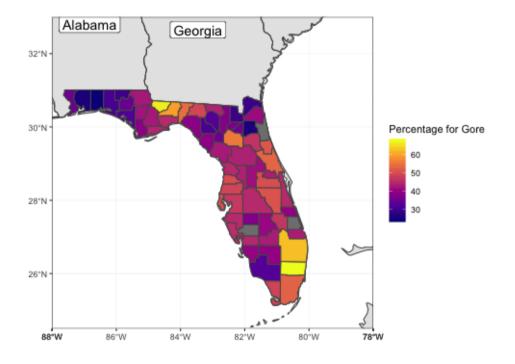
```
Simple feature collection with 6 features and 15
   geometry type: MULTIPOLYGON
                   XY
   dimension:
   bbox:
                   xmin: -85.98951 ymin: 25.94926 xm
   epsg (SRID):
                   4326
   proi4string:
                   +proj=longlat +datum=WGS84 +no_de
                        Bush Bush_perc
                                          Gore Gore_p
       State
                County
    1 Florida Alachua
                       34135
                                  39.80
                                         47380
   2 Florida
                Baker
                        5611
                                  68.80
                                          2392
   3 Florida
                        38682
                                  65.70
                                         18873
                                                   32
                   Bay
   4 Florida Bradford
                        5416
                                  62.43
                                          3075
   5 Florida Brevard 115253
                                  52.75
                                         97341
   6 Florida Broward 177939
                                  30.93 387760
                                                   67
     Buchanan Buchanan_perc Other Other_perc
                                               Margin
           263
                               751
                        0.31
                                         0.88
                                               -13245
          7.3
                        0.90
                                26
                                         0.32
                                                 3219
          248
                        0.42
                               243
                                         0.41
                                                19809
         65
                        0.75
                                35
                                                 2341
                                         0.40
           571
                               852
                                         0.39
                                                17912
                             1640
                                         0.29 - 209821
#>
                            geometry
    1 MULTIPOLYGON (((-82.66062 2...
   2 MULTIPOLYGON (((-82.04182 3...
   3 MULTIPOLYGON (((-85.40509 3...
   4 MULTIPOLYGON (((-82.4257 29...
   5 MULTIPOLYGON (((-80.94747 2...
   6 MULTIPOLYGON (((-80.89018 2...
```

Now we're ready to plot

```
ggplot(election_by_county) +
  geom_sf(aes(fill = Gore_perc)) +
  scale_fill_viridis_c(option = 'plasma') +
  labs(caption = 'Source: Wikipedia')
```



We can clean this up a bit, and add surrounding states



Genomic data

Visualizing a proteomic network

We read a dataset that contains the network relationships between different proteins

```
library(ggnetwork)
datf <- rio::import('data/string_graph.txt')
head(datf)</pre>
```

```
node2 node1_string_id node2_string_id
#>
        node1
        CXCR3
                CCR7
#>
                              1855969
                                               1843829
        ITGA4
                 EED
                              1858446
                                              1845338
#>
         SMC.3
               CFNPK
                              1854200
                                              1843648
    4 HNRNPA1 LUC7L3
                              1852510
                                              1843556
         SMC2
                 RB1
                              1847012
                                              1845924
        RBBP4 CENPK
                              1855919
                                              1843648
      node2_external_id neighborhood fusion cooccuren
#>
        ENSP00000246657
#>
        ENSP00000263360
#>
        ENSP00000242872
        ENSP00000240304
        ENSP00000267163
        ENSP00000242872
      experimental knowledge textmining combined_scor
#>
             0.000
                          0.9
                                   0.878
                                                   0.91
             0.566
                                   0.312
                                                   0.68
             0.000
                                   0.081
                                                   0.96
             0.309
                                   0.394
                                                   0.56
             0.000
                                   0.097
                                                   0.91
             0.000
                                   0.046
                                                   0.96
```

Visualizing a proteomic network

The igraph package allows the creation of network graphs.

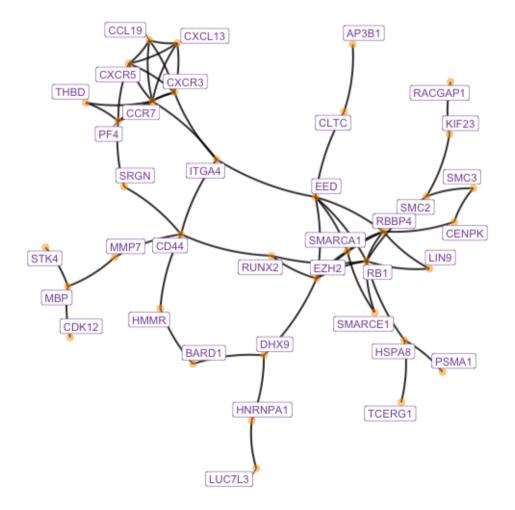
However, here, we're only using it for data ingestion

We see that this object holds the different connections.

```
IGRAPH 879a27d UN-- 37 58 --
+ attr: name (v/c)
+ edges from 879a27d (vertex names):
            --CCR7
                      ITGA4
                                        SMC3
 Γ57 SMC2
            --RB1
                      RBBP4 --CFNPK
                                        CXCR5
 Г97 CXCR5
            --PF4
                      PF4
                              --THBD
                                        SMARCA1--E
Γ137 MBP
            --MMP7
                      CCL 19
                             --CCR7
            --HSPA8
                      DHX9
                              --BARD1
Γ177 RB1
                                        CXCL13
     CD44
            --HMMR
                      ITGA4
                             --CD44
Γ257 MBP
            --STK4
                      RBBP4
                             --L TN9
Γ297 PSMA1
            --HSPA8
                             --SMARCA1 CXCR3
                      RBBP4
+ ... omitted several edges
```

Visualizing a proteomic network

We can then transform this data into ggplotfriendly data, to use ggplot for the plotting



Composing different genomic data into tracks

The ggbio package

The ggbio package has several functions that allow graphical representations of different genomic entities.

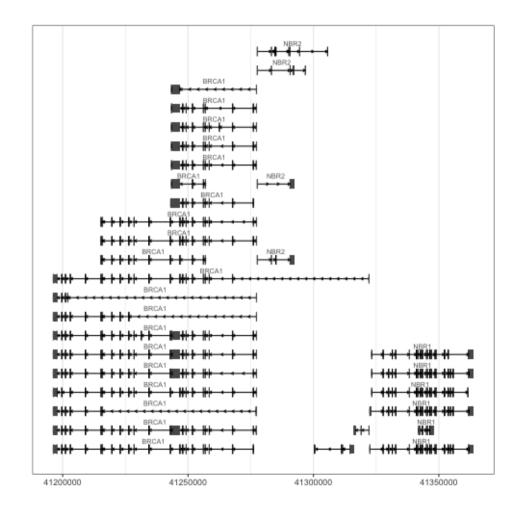
An ideogram

```
library(ggbio)
p.ideo <- Ideogram(genome = 'hg19')
p.ideo</pre>
```

The ggbio package

Visualizing the gene model

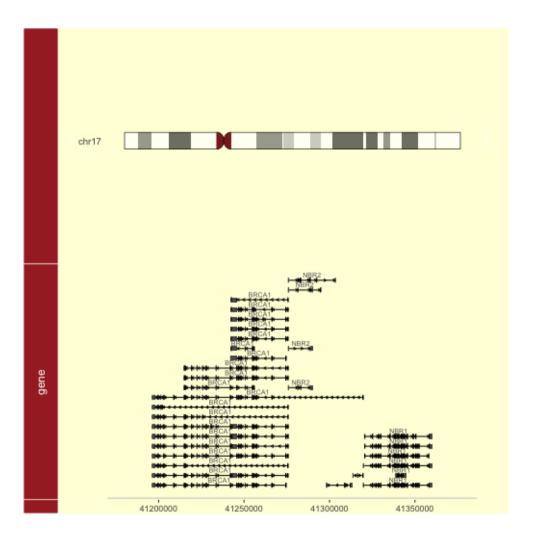
```
library(Homo.sapiens)
data(genesymbol, package='biovizBase')
wh <- genesymbol[c('BRCA1','NBR1')]
wh <- range(wh, ignore.strand=T)
p.txdb <- autoplot(Homo.sapiens, which = wh)
p.txdb</pre>
```



The ggbio package

Putting it into tracks

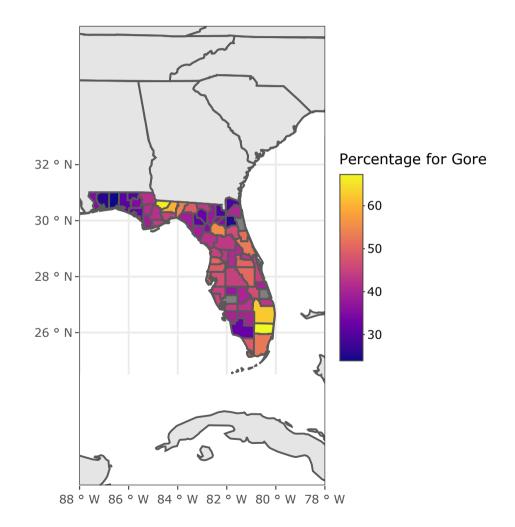
```
library(GenomicRanges)
gr17 <- GRanges("chr17", IRanges(41234415, 41234569))
tks <- tracks(p.ideo, gene = p.txdb) + xlim(gr17)
tks + theme_tracks_sunset()</pre>
```



Interactive maps

Using plotly

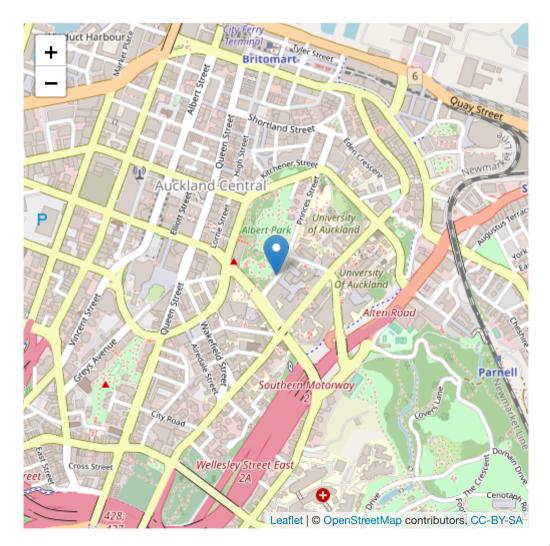
```
library(plotly)
ggplotly(plt_map)
```



Using real maps

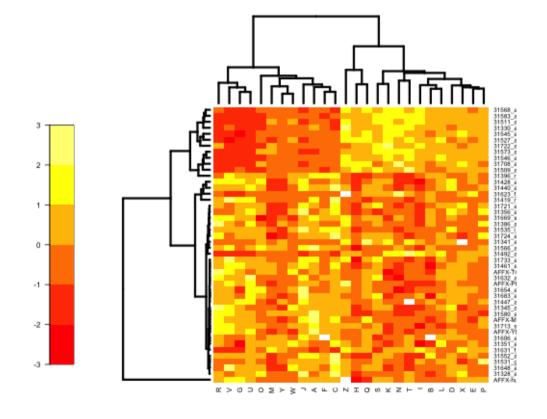
```
library(leaflet)

m <- leaflet() %>%
   addTiles() %>% # Add default OpenStreetMap map til
   addMarkers(lng=174.768, lat=-36.852, popup="The bir
m
```



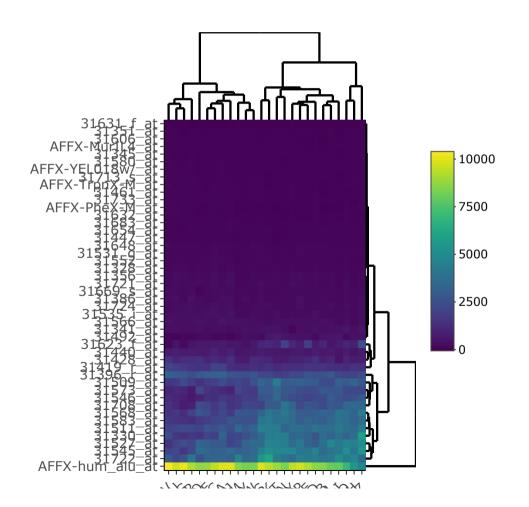
Heatmaps

Recall our heatmap



Using heatmaply

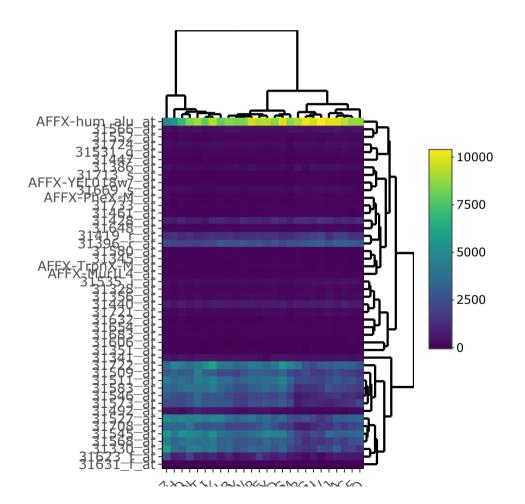
```
library(heatmaply)
heatmaply(exprs(exdat2))
```



Using heatmaply

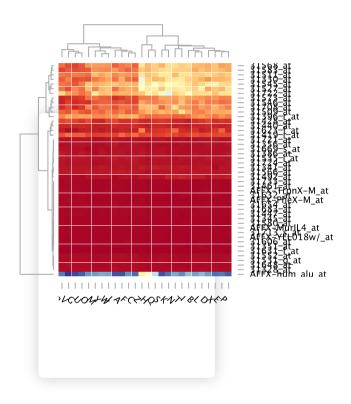
You can also easily use the correlation metric

```
heatmaply(exprs(exdat2), distfun = 'pearson')
```



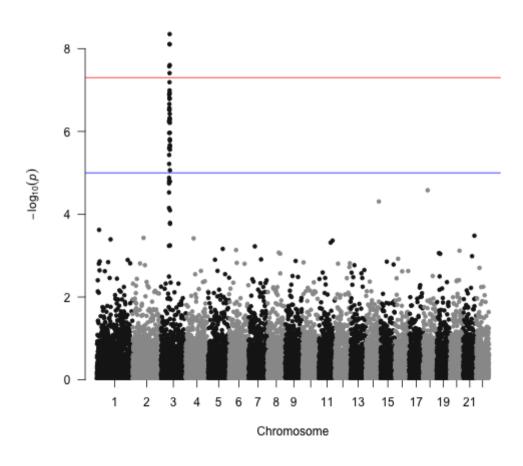
Using d3heatmap

library(d3heatmap)
d3heatmap(exprs(exdat2))

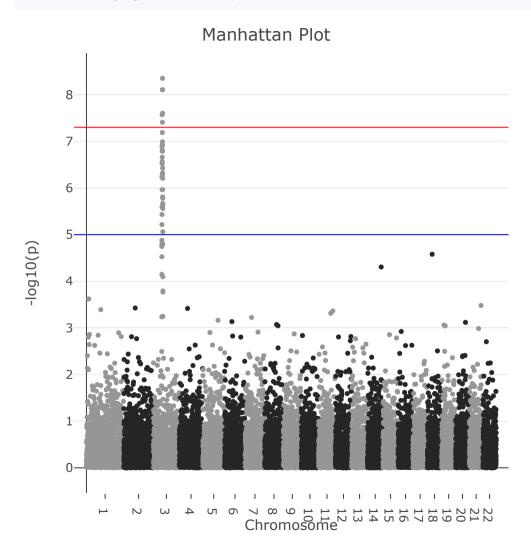


Manhattan plots

library(qqman)
manhattan(gwasResults)



library(manhattanly)
manhattanly(gwasResults)



Interactions using plotly

- Plot.ly is a web service that produces interactive graphics from data
- They made their backend open-source
- In R, you can interact with plot.ly using the package plotly.

Interactions using plotly

• Plotly makes it very easy to create interactive plots based on ggplot

plt_corrupt

Interactions using plotly

• Plotly makes it very easy to create interactive plots based on ggplot

```
library(plotly)
ggplotly(plt_corrupt)
```

Corruption and Human development

