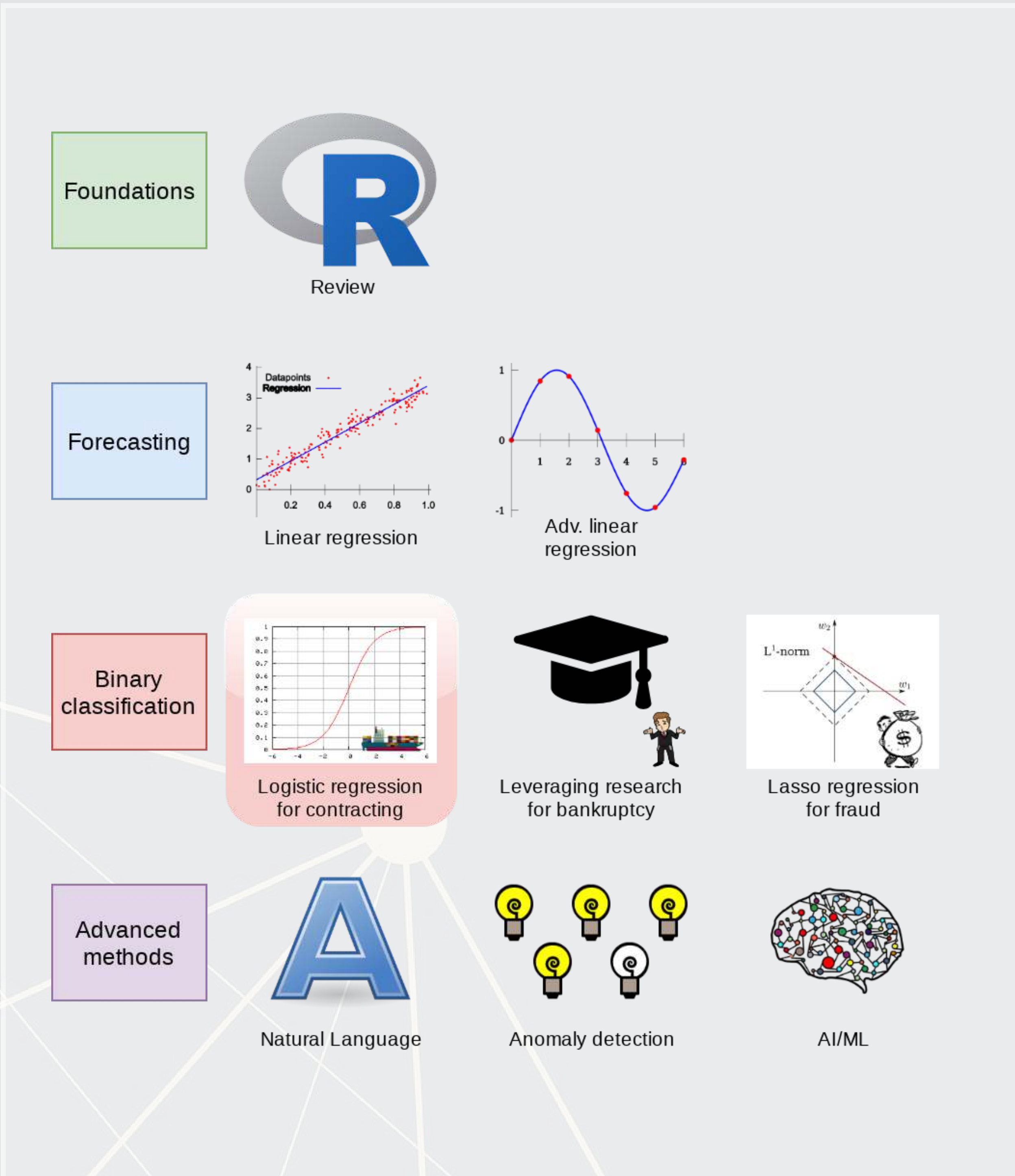
ACCT 420: Logistic Regression

Session 4

Dr. Richard M. Crowley

Front matter

Learning objectives



- **Theory:**
  - Understanding binary problems
- **Application:**
  - Detecting shipping delays caused by typhoons
- **Methodology:**
  - Logistic regression
  - Spatial visualization

Datacamp

- Explore on your own
- No specific required class this week

Assignment 2

- Looking at Singaporean retail firms
  - Mostly focused on time and cyclicality
  - Some visualization
  - A little of what we cover today
- Optional (but encouraged):
  - You can work in *pairs* on this assignment
    - If you choose to do this, please only make 1 submission and include both your names on the submission

Binary outcomes

What are binary outcomes?

- Thus far we have talked about events with continuous outcomes
  - Revenue: Some positive number
  - Earnings: Some number
  - ROA: Some percentage
- Binary outcomes only have two possible outcomes
  - Did something happen, *yes* or *no*?
  - Is a statement *true* or *false*?

Accounting examples of binary outcomes

- Financial accounting:
  - Will the company’s earnings meet analysts’ expectations?
  - Will the company have positive earnings?
- Managerial accounting:
  - Will we have ___ problem with our supply chain?
  - Will our customer go bankrupt?
- Audit:
  - Is the company committing fraud?
- Taxation:
  - Is the company too aggressive in their tax positions?

> We can assign a probability to any of these

Regression approach: Logistic regression

- When modeling a binary outcome, we use logistic regression
  - A.k.a. logit model
- The *logit* function is $logit(x) = \log\left(\frac{x}{1-x}\right)$
  - Also called *log odds*

$$\log\left(\frac{\text{Prob}(y=1|X)}{1-\text{Prob}(y=1|X)}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots + \varepsilon$$

> There are other ways to model this though, such as probit

Implementation: Logistic regression

- The logistic model is related to our previous linear models as such:

> Both linear and logit models are under the class of General Linear Models (GLMs)

- To regress a GLM, we use the `glm()` command.
  - In fact, the `lm()` command we have been using is actually `glm()` when you specify the option `family=gaussian`
- To run a logit regression:

```
mod <- glm(y ~ x1 + x2 + x3 + ..., data=df, family=binomial)

summary(mod)
```

> `family=binomial` is what sets the model to be a logit

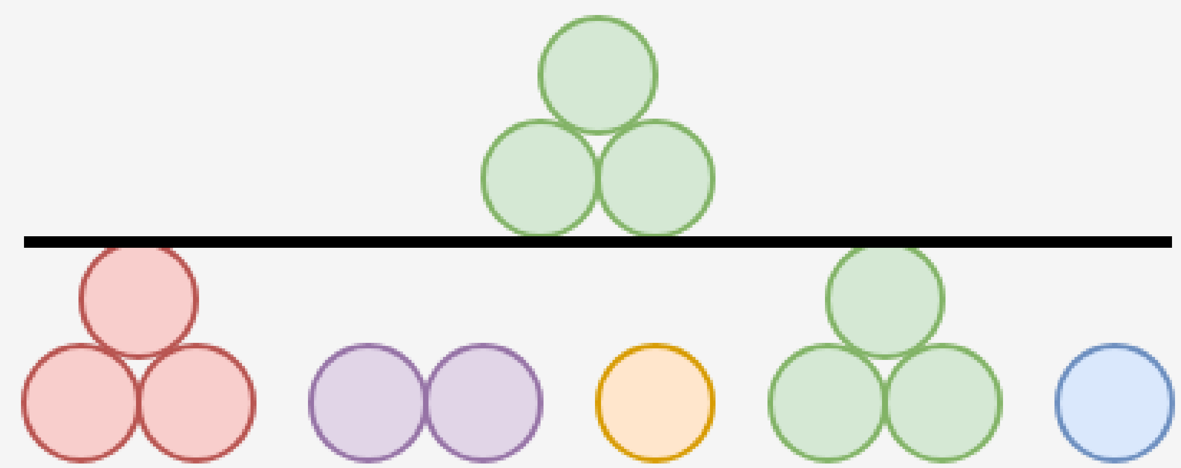
Interpreting logit values

- The **sign** of the coefficients means the same as before
  - +: *increases* the likelihood of y occurring
  - -: *decreases* the likelihood of y occurring
- The level of a coefficient is different
  - The relationship isn't linear between x_i and y now
  - Instead, coefficients are in log odds
    - Thus, e^{β_i} gives you the *odds*, o
- You can interpret the odds for a coefficient
  - Increased by $[o-1]\%$
- You need to sum all relevant log odds before converting to a probability!

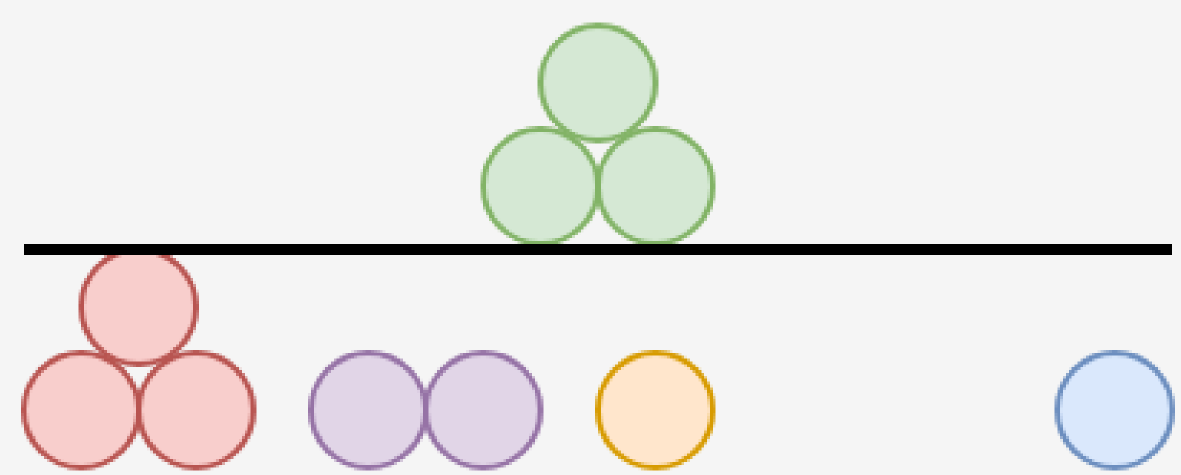
Odds vs probability

We have the following 10 objects:

The **probability** of green is: 3/10



The **odds** of green is: 3 to 7



Example logit regression

Do holidays increase the likelihood that a department more than doubles its store's average weekly sales across departments?

```
# Create the binary variable from Walmart sales data
df$double <- ifelse(df$Weekly_Sales > df$store_avg*2,1,0)
fit <- glm(double ~ IsHoliday, data=df, family=binomial)
tidy(fit)
```

```
## # A tibble: 2 x 5
##   term          estimate std.error statistic  p.value
##   <chr>            <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)     -3.45    0.00924    -373.  0.
## 2 IsHolidayTRUE    0.539   0.0278       19.4 1.09e-83
```

Holidays increase the odds… but by how much?

Logistic regression interpretation

A simple interpretation

- The model we just saw the following model:

$$logodds(Double\ sales) = -3.45 + 0.54IsHoliday$$

- There are two ways to interpret this:
  1. Coefficient by coefficient
  2. In total

Interpretting specific coefficients

$$logodds(Double\ sales) = -3.45 + 0.54 IsHoliday$$

- Interpreting specific coefficients is easiest done manually
- Odds for the $IsHoliday$ coefficient are `exp(0.54) = 1.72`
  - This means that having a holiday modifies the baseline (i.e., non-Holiday) odds by 1.72 to 1
    - Where 1 to 1 is considered no change
  - Baseline is 0.032 to 1

```r
# Automating the above:
exp(coef(fit))
```

```
##   (Intercept) IsHolidayTRUE
##    0.03184725    1.71367497
```

Interpretting in total

- It is important to note that log odds are additive
  - So, calculate a new log odd by plugging in values for variables and adding it all up
    - Holiday: $-3.45 + 0.54 * 1 = -2.89$
    - No holiday: $-3.45 + 0.54 * 0 = -3.45$
- Then calculate odds and log odds like before
  - With holiday: `exp(-2.89) = 0.056`
  - Without holiday: `exp(-3.45) = 0.032`
  - Ratio of holiday to without: 1.72!
    - This is the individual log odds for holiday

> We need to specify values to calculate log odds in total

Converting to probabilities

- We can calculate a probability at any given point using the log odds

$$Probability = \frac{odds}{odds + 1}$$

  - Probability of double sales…
    - With a holiday: `0.056 / (0.056 + 1) = 0.052`
    - Without a holiday: `0.032 / (0.032 + 1) = 0.031`

> These are easier to interpret, but require specifying values for each model input to calculate

Using predict() to simplify it

- `predict()` can calculate log odds and probabilities for us with minimal effort
  - Specify `type="response"` to get probabilities

```
test_data <- as.data.frame(IsHoliday = c(0,1))
predict(model, test_data)   # log odds
```

```
## [1] -3.44 -2.90
```

```
predict(model, test_data, type="response")   #probabilities
```

```
## [1] 0.03106848 0.05215356
```

  - Here, we see the baseline probability is 3.1%
  - The probability of doubling sales on a holiday is higher, at 5.2%

R practice: Logit

- A continuation of last week's practices answering:
  - Is Walmart more likely to see a year over year decrease in quarterly revenue during a recession?
- Practice using `mutate()` and `glm()`
- Do exercises 1 and 2 in today's practice file
  - R Practice
  - Shortlink: rmc.link/420r4

Logistic regression interpretation redux

What about more complex models?

- Continuous inputs in the model
  - What values do we pick to determine probabilities?
- Multiple inputs?
  - We can scale up what we did, but things get messy
    - Mathematically, the inputs get interacted within the inner workings of logit…
      - So the impact of each input depends on the values of the others!

Consider this model

```r
model2 <- glm(double ~ IsHoliday + Temperature + Fuel_Price, data=df, family=binom
summary(model2)
```

```
##
## Call:
## glm(formula = double ~ IsHoliday + Temperature + Fuel_Price,
##     family = binomial, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.4113  -0.2738  -0.2464  -0.2213   2.8562
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -1.7764917  0.0673246  -26.39   <2e-16 ***
## IsHolidayTRUE  0.3704298  0.0284395   13.03   <2e-16 ***
## Temperature   -0.0108268  0.0004698  -23.04   <2e-16 ***
## Fuel_Price    -0.3091950  0.0196234  -15.76   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 120370  on 421569  degrees of freedom
```

Odds and probabilities

```
# Odds
exp(coef(model2))
```

```
##   (Intercept) IsHolidayTRUE   Temperature    Fuel_Price
##     0.1692308     1.4483570     0.9892316     0.7340376
```

```
# Typical September days
hday_sep    <- mean(predict(model2, filter(df, IsHoliday, month==9), type="respons
no_hday_sep <-  mean(predict(model2, filter(df, !IsHoliday, month==9), type="respo
# Typical December days
hday_dec    <- mean(predict(model2, filter(df, IsHoliday, month==12), type="respon
no_hday_dec <-  mean(predict(model2, filter(df, !IsHoliday, month==12), type="resp

html_df(data.frame(Month=c(9,9,12,12),
                   IsHoliday=c(FALSE,TRUE,FALSE,TRUE),
                   Probability=c(no_hday_sep, hday_sep, no_hday_dec, hday_dec)))
```

Month	IsHoliday	Probability
9	FALSE	0.0266789
9	TRUE	0.0374761
12	FALSE	0.0398377
12	TRUE	0.0586483

A bit easier: Marginal effects

> Marginal effects tell us the *average* change in our output for a change of 1 to an input

- The above definition is very similar to how we interpret linear regression coefficients
  - The only difference is the word *average* – the effect changes a bit depending on the input data
- Using `margins`, we can calculate marginal effects
- There are a few types that we could calculate:
  - An *Average Marginal Effect* tells us what the average effect of an input is across all values in our data
    - This is the default method in the package
  - We can also specify a specific value to calculate marginal effects at (like with our probabilities last slides)

Marginal effects in action

```
# Calculate AME marginal effects
library(margins)
m <- margins(model2)
m
```

```
##  Temperature Fuel_Price IsHoliday
##   -0.0003377  -0.009644   0.01334
```

- A holiday increase the probability of doubling by a flat 1.33%
  - Not too bad when you consider that the probability of doubling is 3.23%
- If the temperature goes up by 1°F (0.55°C), the probability of doubling changes by -0.03%
- If the fuel price increases by 1 USD for 1 gallon of gas, the probability of doubling changes by -0.96%

`margins` niceties

- We can get some extra information about our marginal effects through `summary()`:

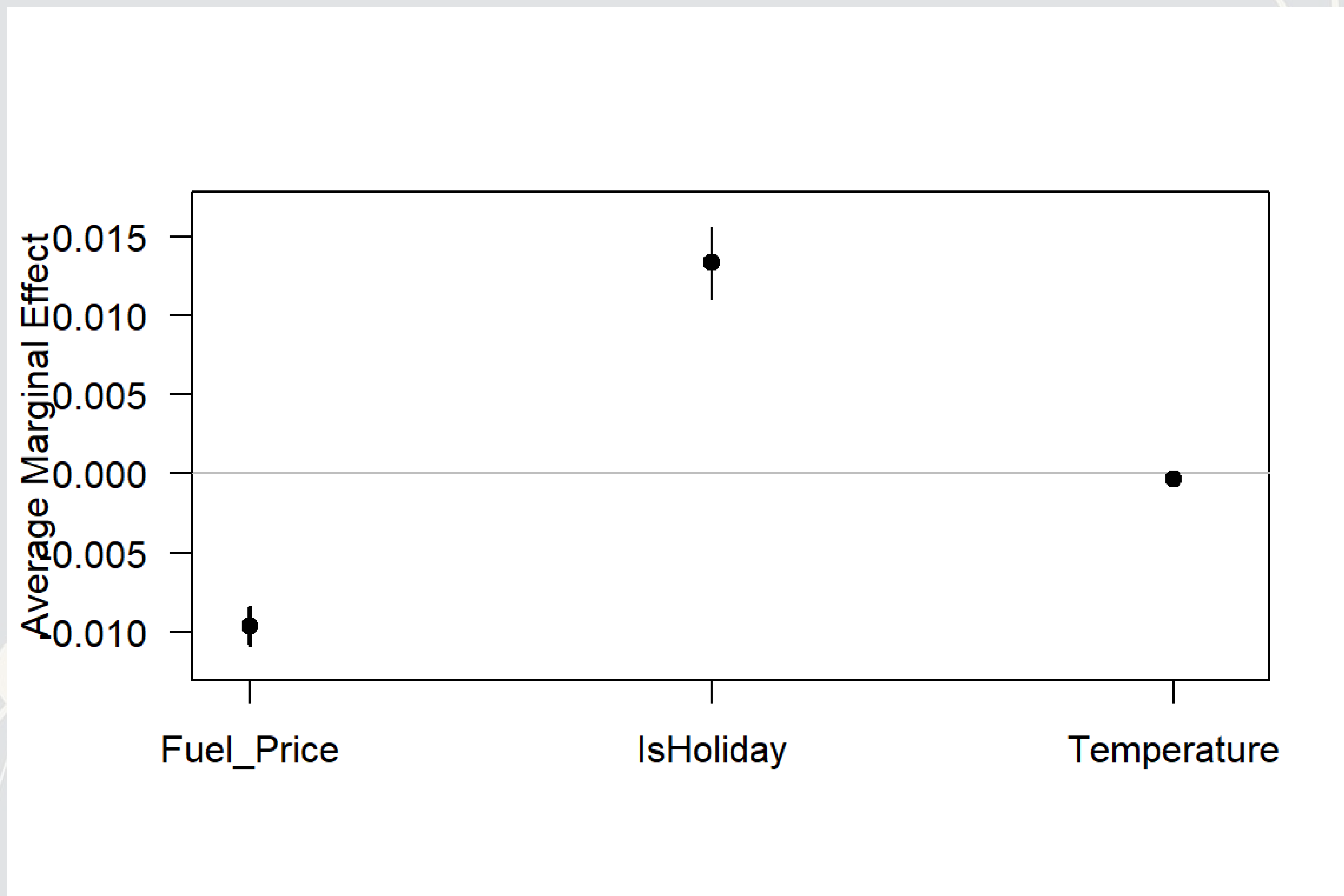
```
summary(m) %>%
  html_df()
```

factor	AME	SE	z	p	lower	upper
Fuel_Price	-0.0096438	0.0006163	-15.64800	0	-0.0108517	-0.0084359
IsHoliday	0.0133450	0.0011754	11.35372	0	0.0110413	0.0156487
Temperature	-0.0003377	0.0000149	-22.71255	0	-0.0003668	-0.0003085

  - Those p-values work just like with our linear models
  - We also get a confidence interval
    - Which we can plot!

Plotting marginal effects

```
plot(m, which=summary(m)$factor)
```



> Note: The `which...` part is absolutely necessary at the moment due to a bug in the package

Marginal effects at a specified value

```r
margins(model2, at = list(IsHoliday = c(TRUE, FALSE)),
        variables = c("Temperature", "Fuel_Price")) %>%
  summary() %>%
  html_df()
```

factor	IsHoliday	AME	SE	z	p	lower	upper
Fuel_Price	FALSE	-0.0093401	0.0005989	-15.59617	0	-0.0105139	-0.0081664
Fuel_Price	TRUE	-0.0131335	0.0008717	-15.06650	0	-0.0148420	-0.0114250
Temperature	FALSE	-0.0003271	0.0000146	-22.46024	0	-0.0003556	-0.0002985
Temperature	TRUE	-0.0004599	0.0000210	-21.92927	0	-0.0005010	-0.0004188

```r
margins(model2, at = list(Temperature = c(0, 20, 40, 60, 80, 100)),
        variables = c("IsHoliday")) %>%
  summary() %>%
  html_df()
```

factor	Temperature	AME	SE	z	p	lower	upper
IsHoliday	0	0.0234484	0.0020168	11.62643	0	0.0194955	0.0274012
IsHoliday	20	0.0194072	0.0016710	11.61387	0	0.0161320	0.0226824
IsHoliday	40	0.0159819	0.0013885	11.51001	0	0.0132604	0.0187033
IsHoliday	60	0.0131066	0.0011592	11.30623	0	0.0108345	0.0153786
IsHoliday	80	0.0107120	0.0009732	11.00749	0	0.0088046	0.0126193
IsHoliday	100	0.0087305	0.0008213	10.62977	0	0.0071207	0.0103402

Today’s Application: Shipping delays

The question

> Can we leverage global weather data to predict shipping delays?

Formalization

1. Question
   - How can predict naval shipping delays?
2. Hypothesis (just the alternative ones)
   1. Global weather data helps to predict shipping delays
3. Prediction
   - Use Logistic regression and z-tests for coefficients
   - No hold out sample this week – too little data

A bit about shipping data

- WRDS doesn’t have shipping data
- There are, however, vendors for shipping data, such as:

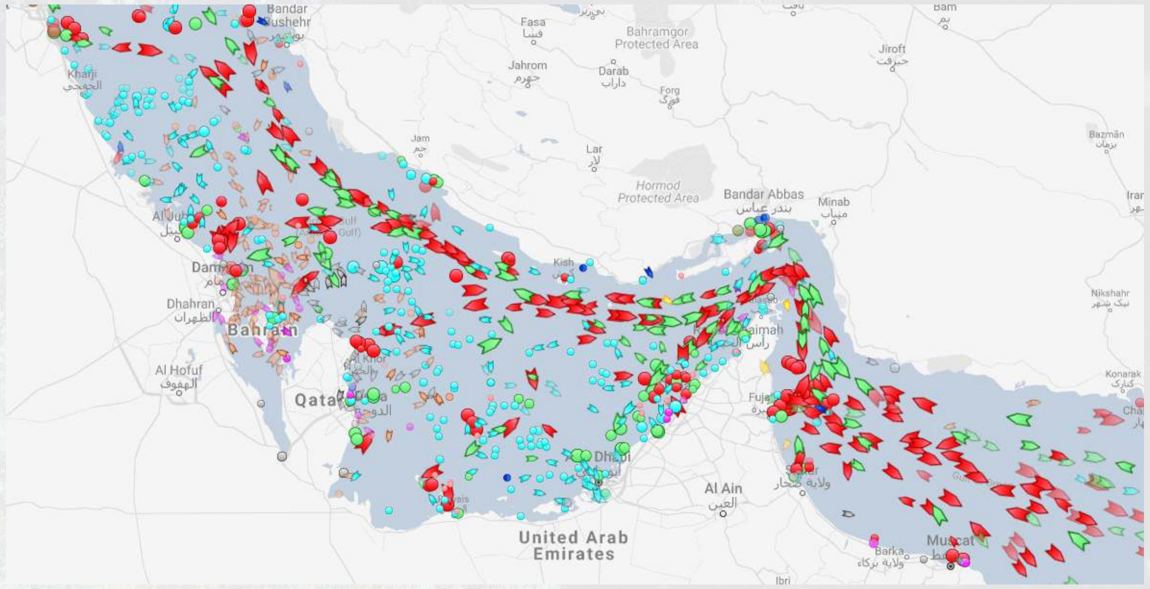
MarineTraffic

- They pretty much have any data you could need:
  - Over 650,000 ships tracked using ground and satellite based AIS
    - AIS: Automatic Identification System
  - Live mapping
  - Weather data
  - Fleet tracking
  - Port congestion
  - Inmarsat support for ship operators

What can we see from naval data?

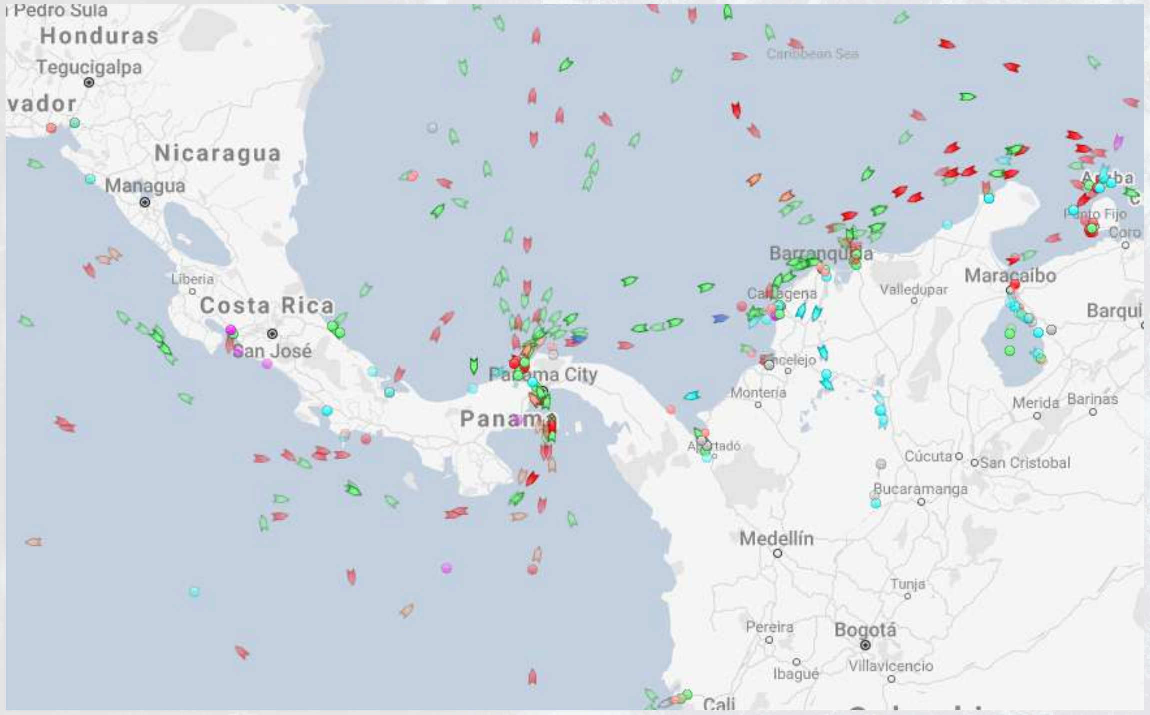
Yachts in the Mediterranean

Oil tankers in the Persian gulf

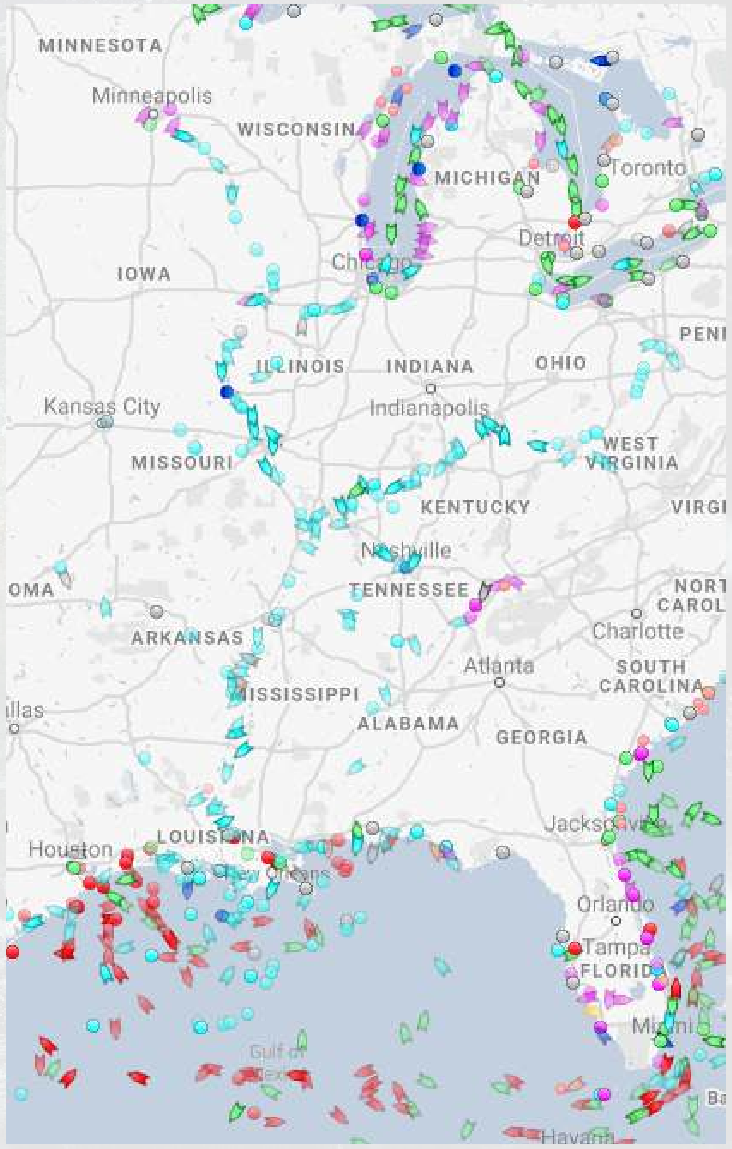


What can we see from naval data?

Shipping route via the Panama canal

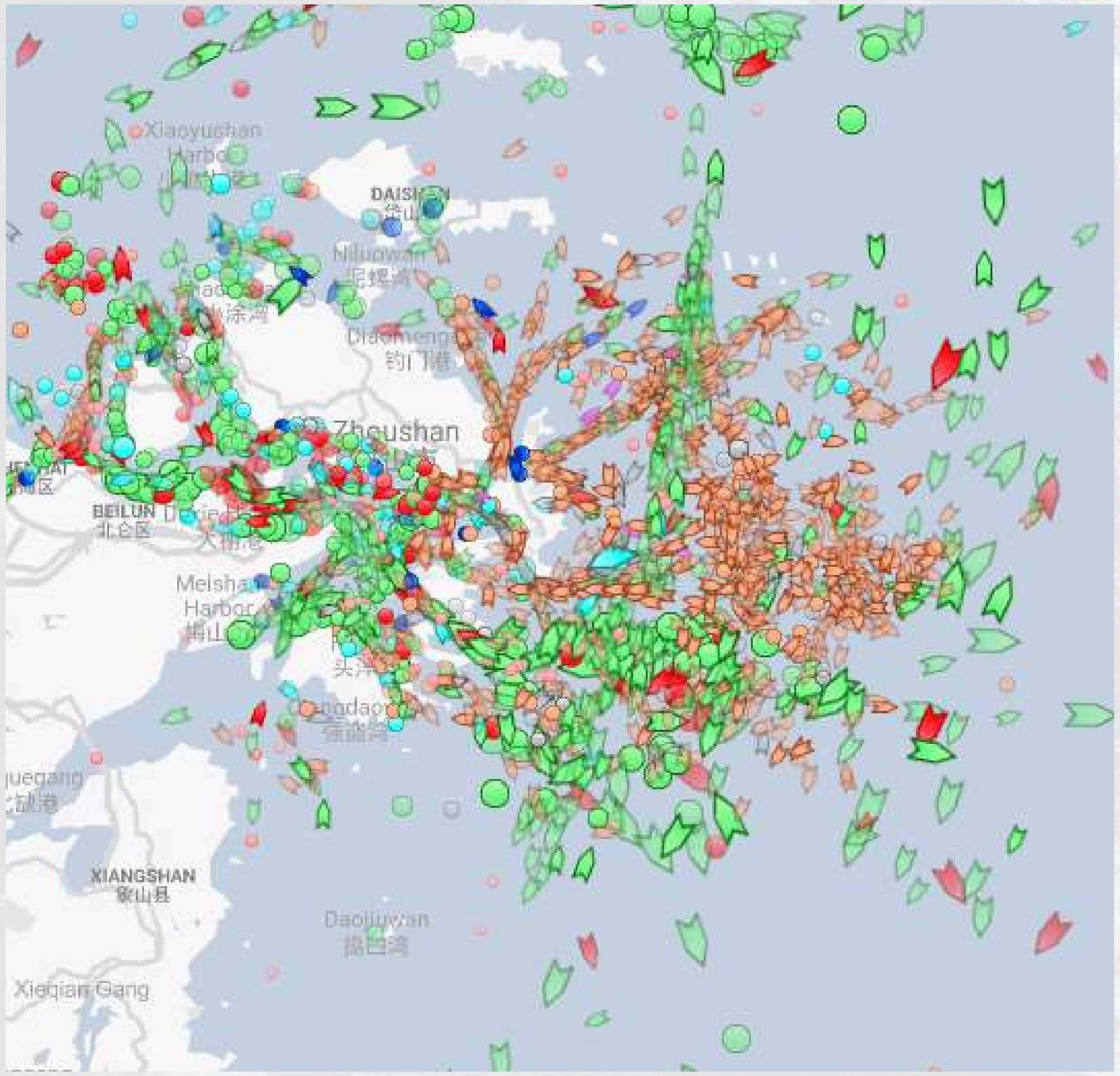


River shipping on the Mississippi river, USA

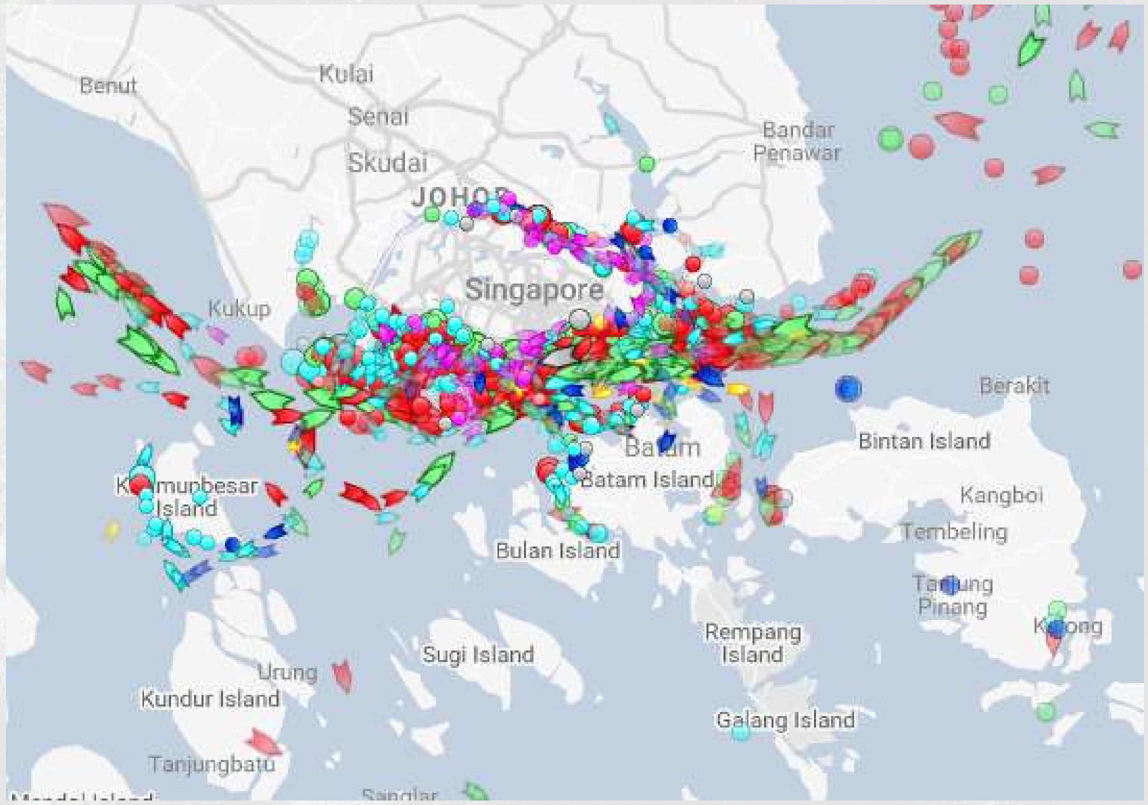


What can we see from naval data?

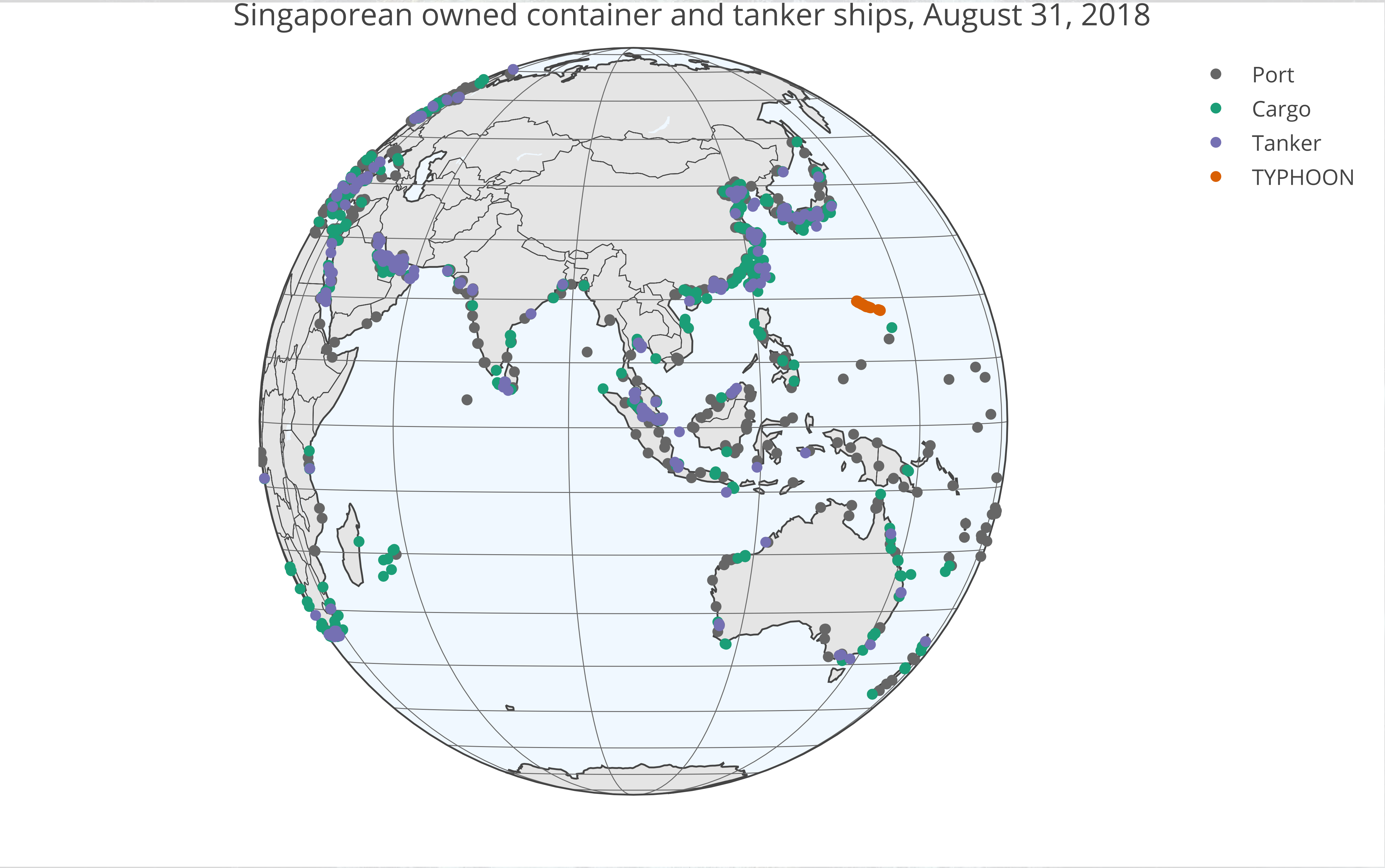
Busiest ports by containers and tons (Shanghai & Ningbo-Zhoushan, China)



Busiest port for transshipment (Singapore)



Examining Singaporean owned ships



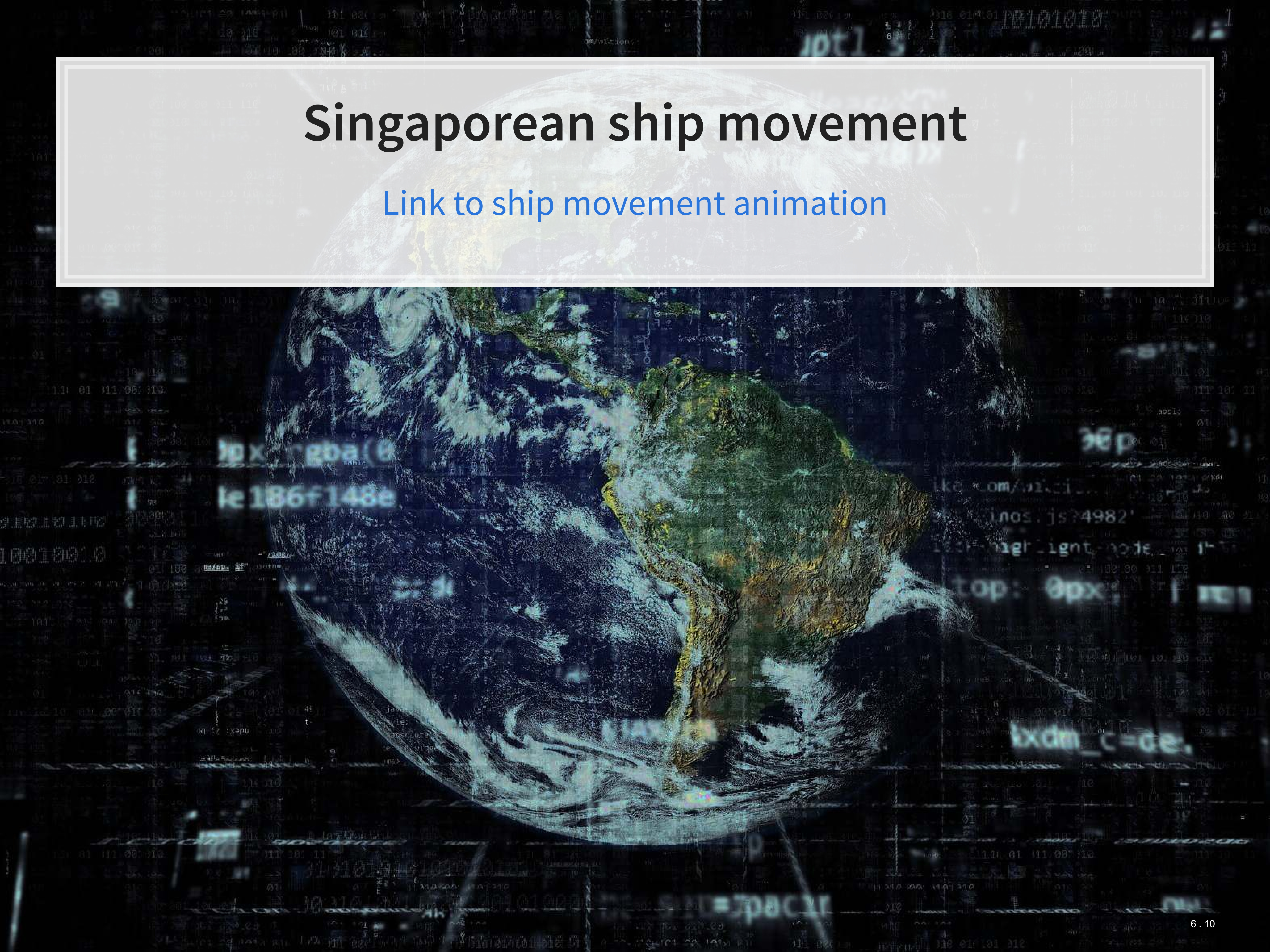
Code for last slide's map

```
library(plotly)  # for plotting
library(RColorBrewer)  # for colors
# plot with boats, ports, and typhoons
# Note: geo is defined in the appendix -- it controls layout
palette = brewer.pal(8, "Dark2")[c(1,8,3,2)]
p <- plot_geo(colors=palette) %>%
  add_markers(data=df_ports, x = ~port_lon, y = ~port_lat, color = "Port") %>%
  add_markers(data=df_Aug31, x = ~lon, y = ~lat, color = ~ship_type,
              text=~paste('Ship name',shipname)) %>%
  add_markers(data=typhoon_Aug31, x = ~lon, y = ~lat, color="TYPHOON",
              text=~paste("Name", typhoon_name)) %>%
   layout(showlegend = TRUE, geo = geo,
    title = 'Singaporean owned container and tanker ships, August 31, 2018')
p
```

- `plot_geo()` is from `plotly`
- `add_markers()` adds points to the map
- `layout()` adjusts the layout
- Within geo, a list, the following makes the map a globe
  - `projection=list(type="orthographic")`

Singaporean ship movement

Link to ship movement animation



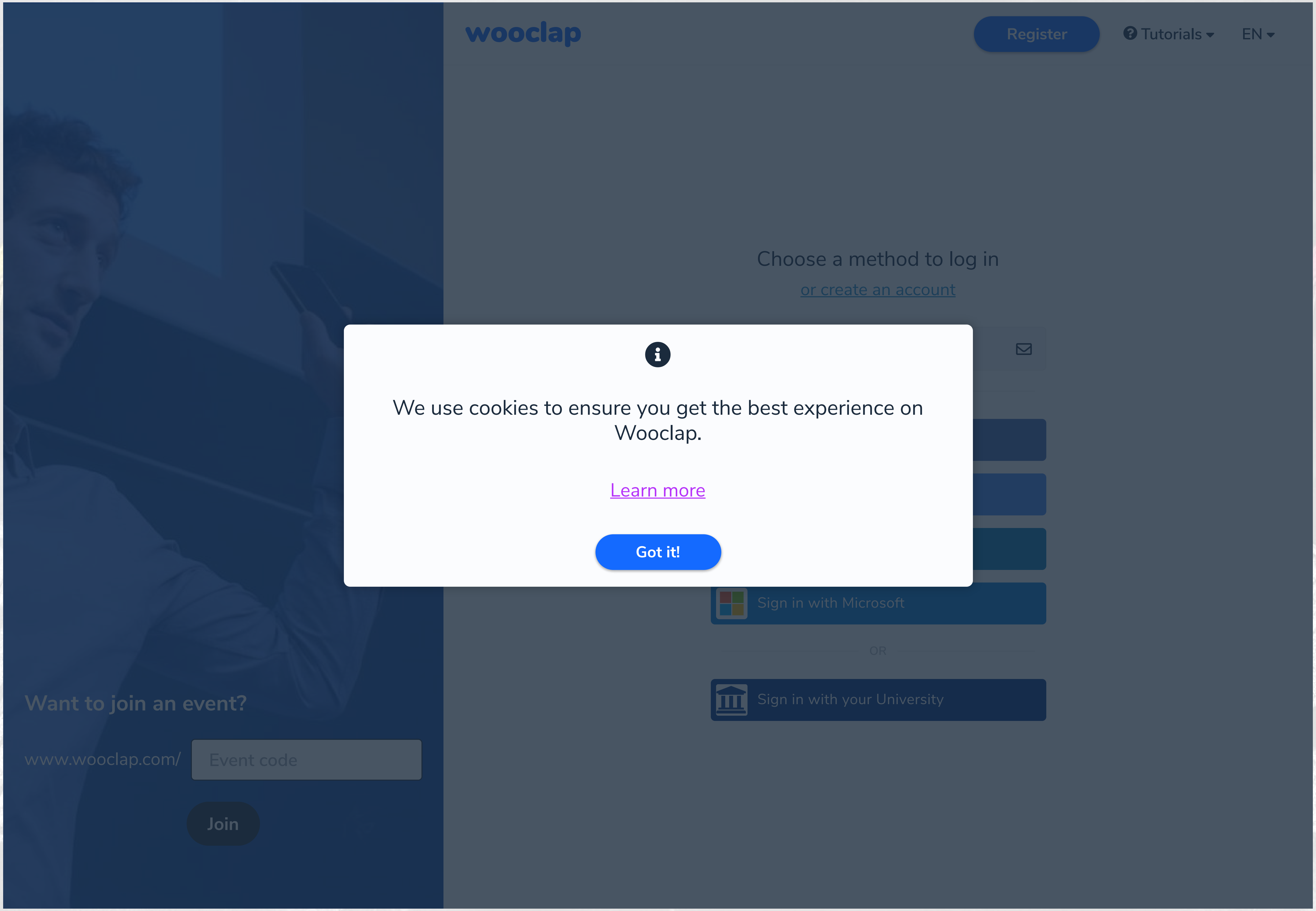
Code for last slide’s map

```
library(sf)  # Note: very difficult to install except on Windows
library(maps)
# Requires separately installing "maptools" and "rgeos" as well
# This graph requires ~7GB of RAM to render
world1 <- sf::st_as_sf(map('world', plot = FALSE, fill = TRUE))

df_all <- df_all %>% arrange(run, imo)

p <- ggplot(data = world1) +
  geom_sf() +
  geom_point(data = df_all, aes(x = lon, y = lat, frame=frame,
                                text=paste("name:",shipname)))
ggplotly(p) %>%
   animation_opts(
    1000, easing = "linear", redraw = FALSE)
```

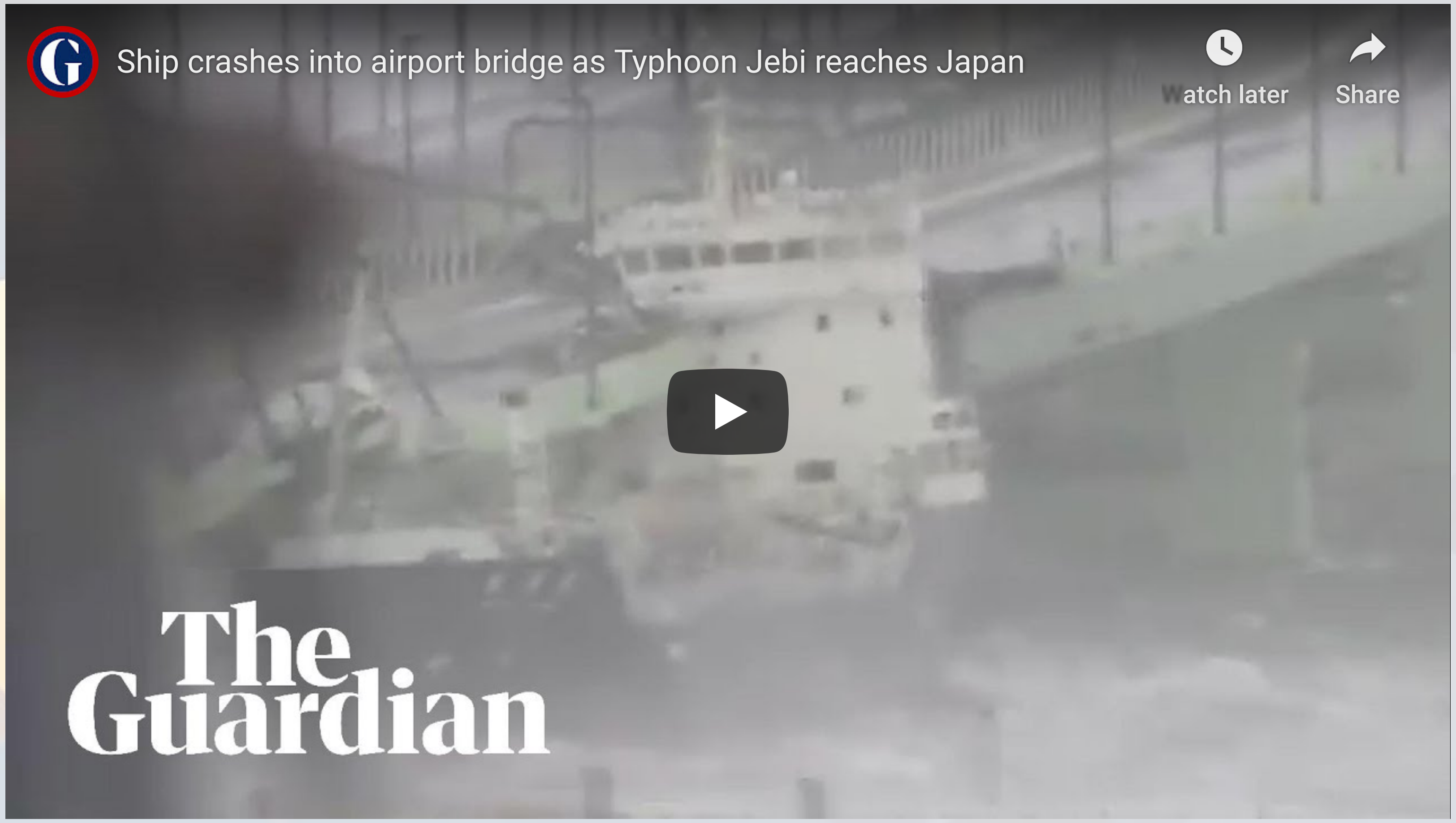
- `world1` contains the map data
- `geom_sf()` plots map data passed to `ggplot()`
- `geom_point()` plots ship locations as longitude and latitude
- `ggplotly()` converts the graph to html and animates it
  - Animation follows the `frame` aesthetic

What might matter for shipping?

> What observable events or data might provide insight as to whether a naval shipment will be delayed or not?

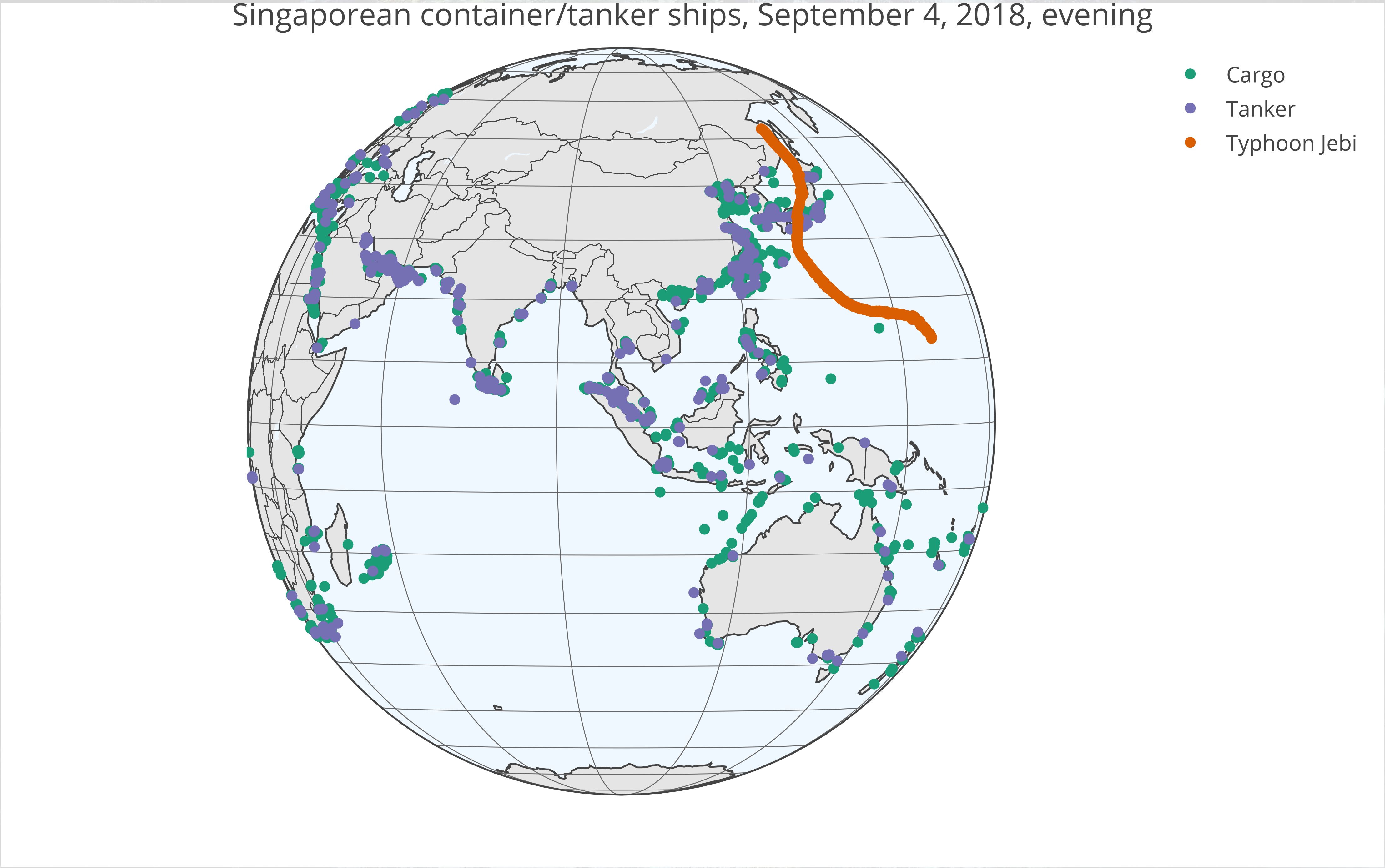

wooclap
Register
Tutorials
EN
Choose a method to log in
or create an account
We use cookies to ensure you get the best experience on Wooclap.
Learn more
Got it!
Sign in with Microsoft
OR
Sign in with your University
Want to join an event?
www.wooclap.com/
Event code
Join

Typhoon Jebi



- link
- Nullschool plot

Typhoons in the data

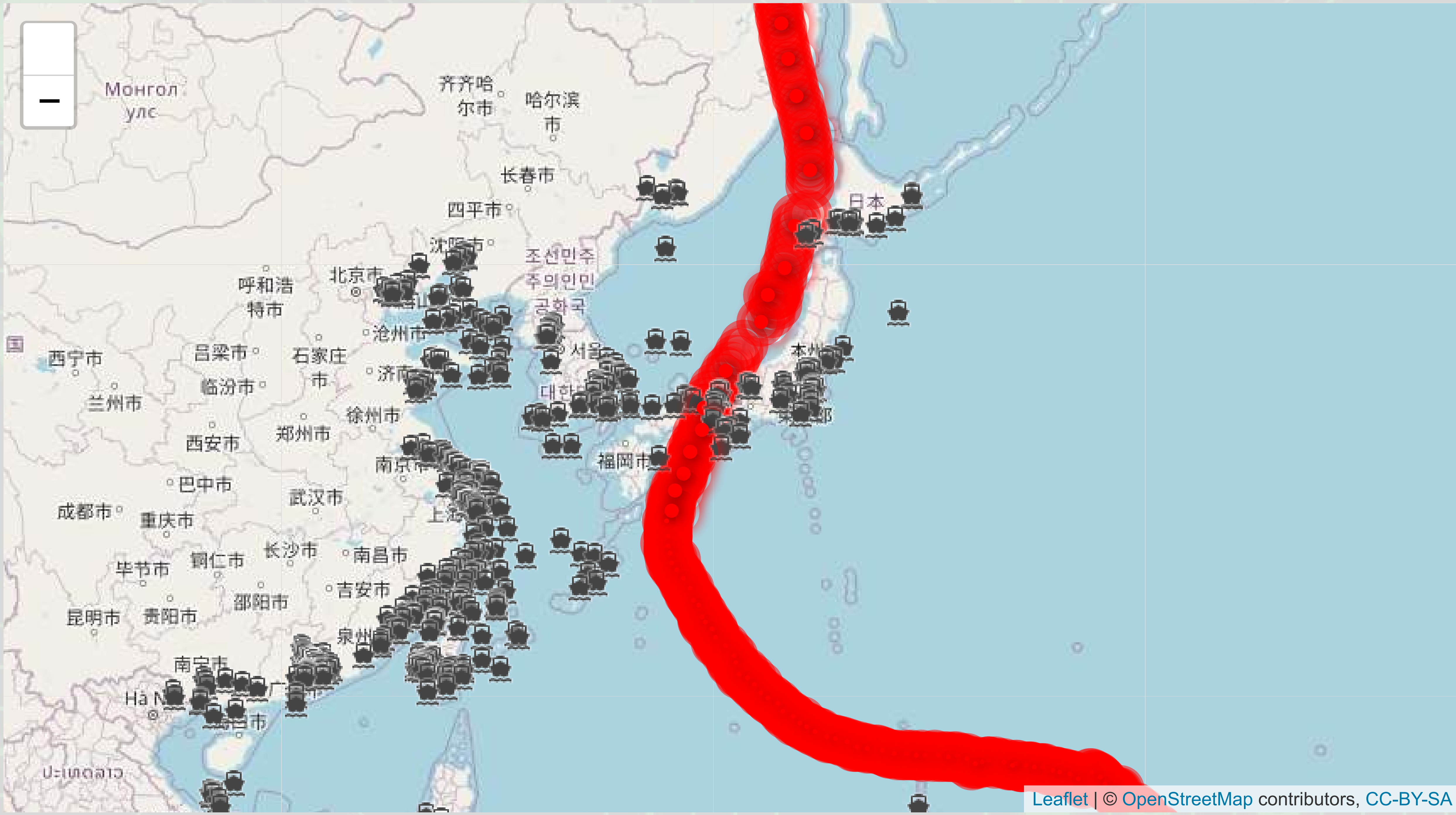


Code for last slide’s map

```
# plot with boats and typhoons
palette = brewer.pal(8, "Dark2")[c(1,3,2)]
p <- plot_geo(colors=palette) %>%
  add_markers(data=df_all[df_all$frame == 14,], x = ~lon, y = ~lat,
              color = ~ship_type, text=~paste('Ship name',shipname)) %>%
  add_markers(data=typhoon_Jebi, x = ~lon,
              y = ~lat, color="Typhoon Jebi",
              text=~paste("Name", typhoon_name, "</br>Time: ", date)) %>%
   layout(showlegend = TRUE, geo = geo,
    title = 'Singaporean container/tanker ships, September 4, 2018, evening')
p
```

- This map is made the same way as the first map

Typhoons in the data using leaflet



Code for last slide's map

```
library(leaflet)
library(leaflet.extras)

# typhoon icons
icons <- pulseIcons(color='red',
  heartbeat = ifelse(typhoon_Jebi$intensity_vmax > 150/1.852, 0.8,
    ifelse(typhoon$intensity_vmax < 118/1.852, 1.6, 1.2)),
  iconSize=ifelse(typhoon_Jebi$intensity_vmax > 150/1.852, 5,
    ifelse(typhoon_Jebi$intensity_vmax < 118/1.852, 2, 3)))

# ship icons
shipicons <- iconList(
  ship = makeIcon("../Figures/ship.png", NULL, 18, 18)
)
leaflet() %>%
  addTiles() %>%
  setView(lng = 136, lat = 34, zoom=4) %>%
  addPulseMarkers(data=typhoon_Jebi[seq(1,nrow(typhoon_Jebi),5),], lng=~lon,
                  lat=~lat, label=~date, icon=icons) %>%
  addCircleMarkers(data=typhoon_Jebi[typhoon_Jebi$intensity_vmax > 150/1.852,],
```

R Practice on mapping

- Practice mapping typhoon data
  - 1 map using `plotly`
  - 1 map using `leaflet`
- Practice using `plotly` and `leaflet`
  - No practice using `ggplot2` as `sf` is missing on DataCamp light
    - And `sf` can be tough to install for anyone on a Mac
- Do exercises 3 and 4 in today's practice file
  - R Practice
  - Shortlink: rmc.link/420r4

Predicting delays due to typhoons

Data

- If the ship will report a delay of at least 3 hours some time in the next 12-24 hours
- What we have:
  - Ship location
  - Typhoon location
  - Typhoon wind speed

> We need to calculate distance between ships and typhoons

Distance for geo

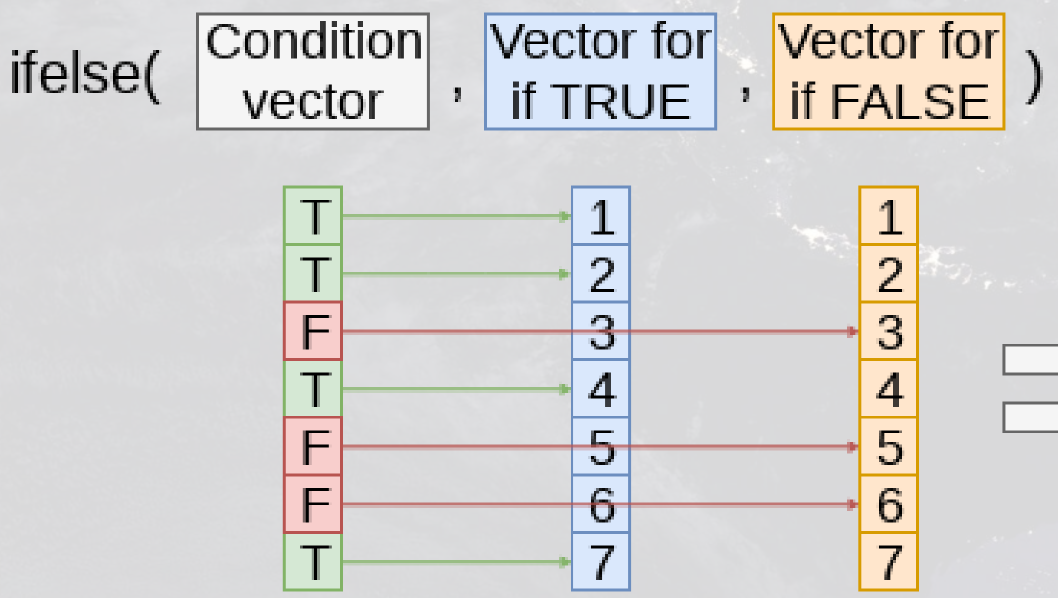
- There are a number of formulas for this
  - *Haversine* for a simple calculation
  - *Vincenty's formulae* for a complex, incredibly accurate calculation
    - Accurate within **0.5mm**
- Use `distVincentyEllipsoid()` from `geosphere` to get a reasonably quick and accurate calculation
  - Calculates distance between two sets of points, x and y, structured as matrices
  - Matrices must have longitude in the first column and latitude in the second column
  - Provides distance in meters by default

```
library(geosphere)
x <- as.matrix(df3[,c("lon","lat")])  # ship location
y <- as.matrix(df3[,c("ty_lon","ty_lat")]) # typhoon location

df3$dist_typhoon <- distVincentyEllipsoid(x, y) / 1000
```

Clean up

- Some indicators to cleanly capture how far away the typhoon is

```
df3$typhoon_500 = ifelse(df3$dist_typhoon < 500 &
                         df3$dist_typhoon >= 0, 1, 0)
df3$typhoon_1000 = ifelse(df3$dist_typhoon < 1000 &
                          df3$dist_typhoon >= 500, 1, 0)
df3$typhoon_2000 = ifelse(df3$dist_typhoon < 2000 &
                          df3$dist_typhoon >= 1000, 1, 0)
```



Do typhoons delay shipments?

```r
fit1 <- glm(delayed ~ typhoon_500 + typhoon_1000 + typhoon_2000, data=df3,
            family=binomial)
summary(fit1)
```

```
##
## Call:
## glm(formula = delayed ~ typhoon_500 + typhoon_1000 + typhoon_2000,
##     family = binomial, data = df3)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.2502  -0.2261  -0.2261  -0.2261   2.7127
##
## Coefficients:
##              Estimate Std. Error  z value Pr(>|z|)
## (Intercept)  -3.65377    0.02934 -124.547   <2e-16 ***
## typhoon_500   0.14073    0.16311    0.863   0.3883
## typhoon_1000  0.20539    0.12575    1.633   0.1024
## typhoon_2000  0.16059    0.07106    2.260   0.0238 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 14329  on 59184  degrees of freedom
```

It appears so!

Interpretation of coefficients

```
odds1 <- exp(coef(fit1))
odds1
```

```
##   (Intercept)   typhoon_500 typhoon_1000 typhoon_2000
##    0.02589334    1.15111673   1.22800815   1.17420736
```

- Ships 1,000 to 2,000 km from a typhoon have a 17% increased odds of having a delay

```
m1 <- margins(fit1)
summary(m1)
```

```
##        factor    AME     SE      z      p   lower  upper
##  typhoon_1000 0.0052 0.0032 1.6322 0.1026 -0.0010 0.0115
##  typhoon_2000 0.0041 0.0018 2.2570 0.0240  0.0005 0.0076
##   typhoon_500 0.0036 0.0042 0.8626 0.3883 -0.0046 0.0117
```

- Ships 1,000 to 2,000 km from a typhoon have an extra 0.41% chance of having a delay (baseline of 2.61%)

What about typhoon intensity?

- Hong Kong's typhoon classification: Official source
  1. 41-62 km/h: Tropical depression
  2. 63-87 km/h: Tropical storm
  3. 88-117 km/h: Severe tropical storm
  4. 118-149 km/h: **Typhoon**
  5. 150-184 km/h: **Severe typhoon**
  6. 185+km/h: **Super typhoon**

```
# Cut makes a categorical variable out of a numerical variable using specified bin
df3$Super <- ifelse(df3$intensity_vmax * 1.852 > 185, 1, 0)
df3$Moderate <- ifelse(df3$intensity_vmax * 1.852 >= 88 &
                         df3$intensity_vmax * 1.852 < 185, 1, 0)
df3$Weak <- ifelse(df3$intensity_vmax * 1.852 >= 41 &
                     df3$intensity_vmax * 1.852 < 88, 1, 0)
df3$HK_intensity <- cut(df3$intensity_vmax * 1.852 ,c(-1,41, 62, 87, 117, 149, 999
table(df3$HK_intensity)
```

```
##
##   (-1,41]   (41,62]   (62,87]  (87,117] (117,149] (149,999]
##      3398     12039     12615     11527      2255     21141
```

Typhoon intensity and delays

```r
fit2 <- glm(delayed ~ (typhoon_500 + typhoon_1000 + typhoon_2000) :
              (Weak + Moderate + Super), data=df3,
            family=binomial)
tidy(fit2)
```

```
## # A tibble: 10 x 5
##    term                  estimate std.error statistic p.value
##    <chr>                    <dbl>     <dbl>     <dbl>   <dbl>
##  1 (Intercept)           -3.65       0.0290 -126.     0
##  2 typhoon_500:Weak      -0.00879    0.213    -0.0413 0.967
##  3 typhoon_500:Moderate   0.715      0.251     2.86   0.00430
##  4 typhoon_500:Super     -8.91     123.       -0.0726 0.942
##  5 typhoon_1000:Weak      0.250      0.161     1.55   0.121
##  6 typhoon_1000:Moderate  0.123      0.273     0.451  0.652
##  7 typhoon_1000:Super    -0.0269     0.414    -0.0648 0.948
##  8 typhoon_2000:Weak      0.182      0.101     1.80   0.0723
##  9 typhoon_2000:Moderate  0.0253     0.134     0.189  0.850
## 10 typhoon_2000:Super     0.311      0.136     2.29   0.0217
```

Moderate storms predict delays when within 500km

Super typhoons predict delays when 1,000 to 2,000km away

Interpretation of coefficients

```r
m2 <- margins(fit2)
summary(m2) %>%
  html_df()
```

factor	AME	SE	z	p	lower	upper
Moderate	0.0007378	0.0006713	1.0990530	0.2717449	-0.0005779	0.0020535
Super	-0.0050241	0.0860163	-0.0584087	0.9534231	-0.1736129	0.1635647
typhoon_1000	0.0035473	0.0036186	0.9802921	0.3269420	-0.0035450	0.0106396
typhoon_2000	0.0039224	0.0017841	2.1985908	0.0279070	0.0004257	0.0074191
typhoon_500	-0.0440484	0.6803640	-0.0647424	0.9483791	-1.3775373	1.2894405
Weak	0.0009975	0.0005154	1.9353011	0.0529534	-0.0000127	0.0020077

- Delays appear to be driven mostly by 2 factors:
  1. A typhoon 1,000 to 2,000 km away from the ship
  2. Weak typhoons

Interpretating interactions

factor	Weak	AME	SE	z	p	lower	upper
typhoon_1000	1	0.0073057	0.0053682	1.360938	0.1735332	-0.0032157	0.0178271
typhoon_2000	1	0.0067051	0.0031225	2.147328	0.0317671	0.0005850	0.0128251
typhoon_500	1	-0.0458116	0.7052501	-0.064958	0.9482075	-1.4280764	1.3364531

factor	Moderate	AME	SE	z	p	lower	upp
typhoon_1000	1	0.0059332	0.0078245	0.7582856	0.4482800	-0.0094025	0.021
typhoon_2000	1	0.0044871	0.0039453	1.1373050	0.2554108	-0.0032457	0.012
typhoon_500	1	-0.0311946	0.6847130	-0.0455586	0.9636620	-1.3732074	1.310

factor	Super	AME	SE	z	p	lower	upper
typhoon_1000	1	0.0030638	0.0111295	0.2752891	0.7830941	-0.0187495	0.024877
typhoon_2000	1	0.0102513	0.0041568	2.4661549	0.0136572	0.0021041	0.018398
typhoon_500	1	-0.2241250	3.1608062	-0.0709076	0.9434713	-6.4191913	5.970941

What might matter for shipping?

> What other observable events or data might provide insight as to whether a naval shipment will be delayed or not?

- What is the reason that this event or data would be useful in predicting delays?
  - I.e., how does it fit into your mental model?

End matter

For next week

- For next week:
  - Second individual assignment
    - Finish by 2 classes from now
    - Submit on eLearn
  - Think about who you want to work with for the project

Packages used for these slides

- `broom`
- `geosphere`
- `kableExtra`
- `knitr`
- `leaflet`
- `leaflet.extras`
- `lubridate`
- `magrittr`
- `margins`
- `maps`
- `maptools`
- `plotly`
- `revealjs`
- `rgeos`
- `sf`
- `tidyverse`

Custom code

```r
# styling for plotly maps
geo <- list(
  showland = TRUE,
  showlakes = TRUE,
  showcountries = TRUE,
  showocean = TRUE,
  countrywidth = 0.5,
  landcolor = toRGB("grey90"),
  lakecolor = toRGB("aliceblue"),
  oceancolor = toRGB("aliceblue"),
  projection = list(
    type = 'orthographic',  # detailed at https://plot.ly/r/reference/#layout-geo-projection
    rotation = list(
      lon = 100,
      lat = 1,
      roll = 0
    )
  ),
  lonaxis = list(
    showgrid = TRUE,
    gridcolor = toRGB("gray40"),
    gridwidth = 0.5
  ),
  lataxis = list(
    showgrid = TRUE,
    gridcolor = toRGB("gray40"),
    gridwidth = 0.5
  )
)
```