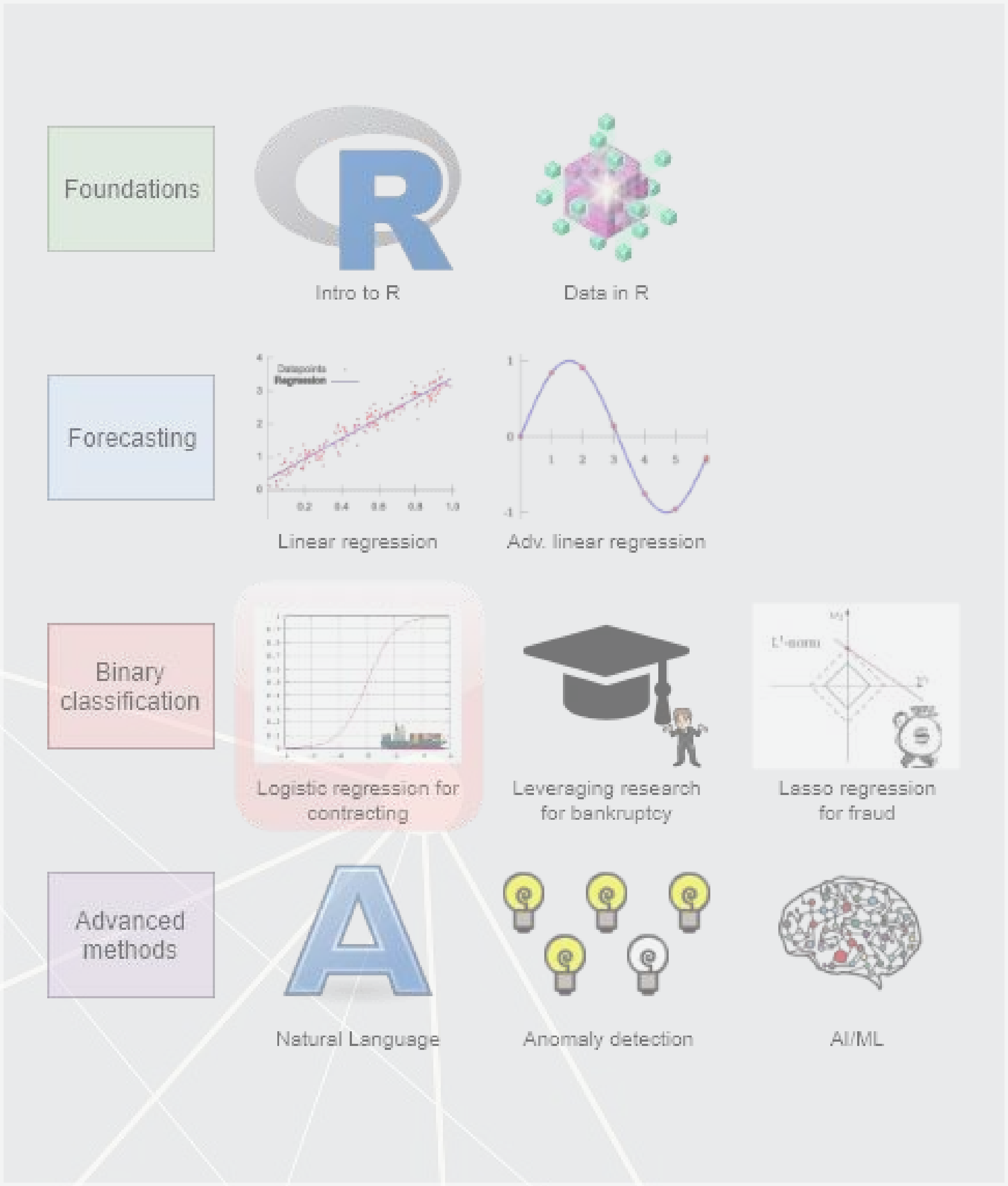
ACCT 420: Logistic Regression

Session 5

Dr. Richard M. Crowley

Front matter

Learning objectives



- **Theory:**
  - Further understand:
    - Binary problems
- **Application:**
  - Detecting shipping delays caused by typhoons
- **Methodology:**
  - Logistic regression

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:
  - You can work in *pairs* on the homework.
    - If you choose to do this, please only make 1 submission and include both your names on the submission

Weekly revenue prediction

Shifted from week 4

The question

> How can we weekly departmental revenue for Walmart, leveraging our knowledge of Walmart, its business, and some limited historical information

- Predict weekly for 115,064 (Store, Department, Week) tuples
  - From 2012-11-02 to 2013-07-26
- Using [incomplete] weekly revenue data from 2010-02-015 to 2012-10-26
  - By department (some weeks missing for some departments)

More specifically…

- Consider time dimensions
  - What matters:
    - Time of the year?
    - Holidays?
    - Do different stores or departments behave differently?
- Wrinkles:
  - Walmart won’t give us testing data
    - But they’ll tell us how well the algorithm performs
  - We can’t use past week sales for prediction because we won’t have it for most of the prediction…

The data

- Revenue by week for each department of each of 45 stores
  - Department is just a number between 1 and 99
  - Date of that week
  - If the week is considered a holiday for sales purposes
    - Super Bowl, Labor Day, Black Friday, Christmas
- Store data:
  - Which store the data is for, 1 to 45
  - Store type (A, B, or C)
  - Store size
- Other data, by week and location:
  - Temperature, gas price, sales (by department), CPI, Unemployment, Holidays

Walmart’s evaluation metric

- Walmart uses MAE (mean absolute error), but with a twist:
  - They care more about holidays, so any error on holidays has **5 times** the penalty
  - They call this WMAE, for *weighted* mean absolute error

$$WMAE = \frac{1}{\sum w_i} \sum_{i=1}^{n} w_i \left| y_i - \hat{y}_i \right|$$

- n is the number of test data points
- $\hat{y}_i$ is your prediction
- y_i is the actual sales
- w_i is 5 on holidays and 1 otherwise

```
wmae <- function(actual, predicted, holidays) {
  sum(abs(actual-predicted)*(holidays*4+1)) / (length(actual) + 4*sum(holidays))
}
```

Before we get started…

- The data isn't very clean:
  - Markdowns are given by 5 separate variables instead of 1
  - Date is text format instead of a date
  - CPI and unemployment data are missing in around a third of the testing data
  - There are some (week, store, department) groups missing from our training data!

> We'll have to fix these

Also…

- Some features to add:
  - Year
  - Week
  - A unique ID for tracking (week, firm, department) tuples
  - The ID Walmart requests we use for submissions
  - Average sales by (store, department)
  - Average sales by (week, store, department)

Load data and packages

```r
library(tidyverse)  # we'll extensively use dplyr here
library(lubridate)  # Great for simple date functions
library(broom)
weekly <- read.csv("../../Data/WMT_train.csv", stringsAsFactors=FALSE)
weekly.test <- read.csv("../../Data/WMT_test.csv", stringsAsFactors=FALSE)
weekly.features <- read.csv("../../Data/WMT_features.csv", stringsAsFactors=FALSE)
weekly.stores <- read.csv("../../Data/WMT_stores.csv", stringsAsFactors=FALSE)
```

- `weekly` is our training data
- `weekly.test` is our testing data – no `Weekly_Sales` column
- `weekly.features` is general information about (week, store) pairs
  - Temperature, pricing, etc.
- `weekly.stores` is general information about each store

Cleaning

```
preprocess_data <- function(df) {
  # Merge the data together (Pulled from outside of function -- "scoping")
  df <- inner_join(df, weekly.stores)
  df <- inner_join(df, weekly.features[,1:11])

  # Compress the weird markdown information to 1 variable
  df$markdown <- 0
  df[!is.na(df$MarkDown1),]$markdown <- df[!is.na(df$MarkDown1),]$MarkDown1
  df[!is.na(df$MarkDown2),]$markdown <- df[!is.na(df$MarkDown2),]$MarkDown2
  df[!is.na(df$MarkDown3),]$markdown <- df[!is.na(df$MarkDown3),]$MarkDown3
  df[!is.na(df$MarkDown4),]$markdown <- df[!is.na(df$MarkDown4),]$MarkDown4
  df[!is.na(df$MarkDown5),]$markdown <- df[!is.na(df$MarkDown5),]$MarkDown5

  # Fix dates and add useful time variables
  df$date <- as.Date(df$Date)
  df$week <- week(df$date)
  df$year <- year(df$date)

  df
}
```

```
df <- preprocess_data(weekly)
df_test <- preprocess_data(weekly.test)
```

> Merge data, fix markdown, build time data

What this looks like

```
df[91:94,] %>%
  select(Store, date, markdown, MarkDown3, MarkDown4, MarkDown5) %>%
  html_df()
```

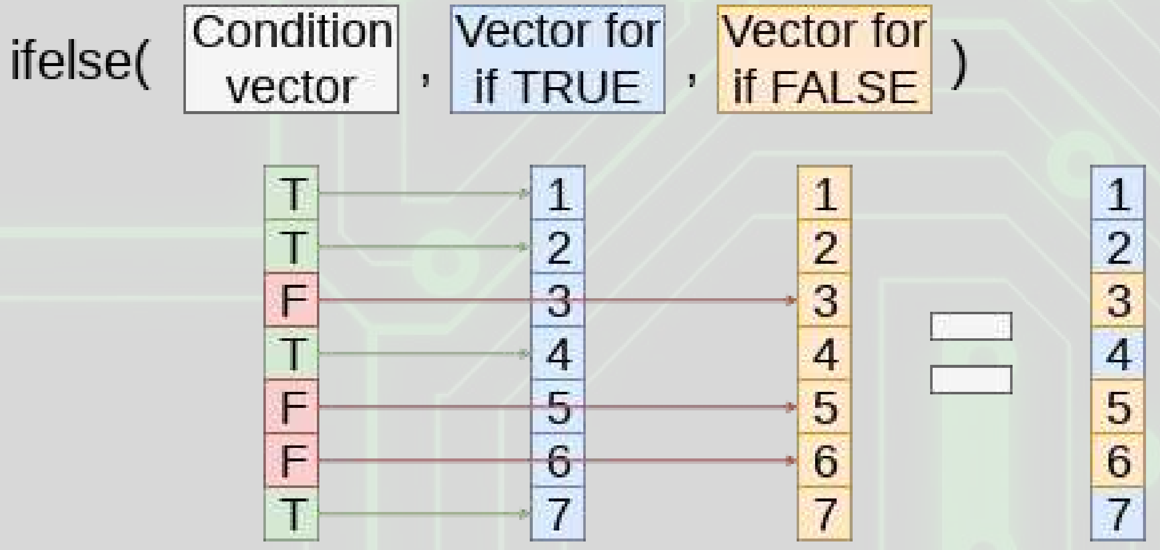
	Store	date	markdown	MarkDown3	MarkDown4	MarkDown5
91	1	2011-10-28	0.00	NA	NA	NA
92	1	2011-11-04	0.00	NA	NA	NA
93	1	2011-11-11	6551.42	215.07	2406.62	6551.42
94	1	2011-11-18	5988.57	51.98	427.39	5988.57

```
df[1:2,] %>% select(date, week, year) %>% html_df()
```

date	week	year
2010-02-05	6	2010
2010-02-12	7	2010

Cleaning: Missing CPI and Unemployment

```
# Fill in missing CPI and Unemployment data
df_test <- df_test %>%
  group_by(Store, year) %>%
  mutate(CPI=ifelse(is.na(CPI), mean(CPI,na.rm=T), CPI),
         Unemployment=ifelse(is.na(Unemployment),
                             mean(Unemployment,na.rm=T),
                             Unemployment)) %>%
  ungroup()
```



> Apply the (year, Store)'s CPI and Unemployment to missing data

Cleaning: Adding IDs

- Build a unique ID
  - Since Store, week, and department are all 2 digits, make a 6 digit number with 2 digits for each
    - `sswwdd`
- Build Walmart's requested ID for submissions
  - `ss_dd_YYYY-MM-DD`

```r
# Unique IDs in the data
df$id <- df$Store *10000 + df$week * 100 + df$Dept
df_test$id <- df_test$Store *10000 + df_test$week * 100 + df_test$Dept

# Unique ID and factor building
swd <- c(df$id, df_test$id)  # Pool all IDs
swd <- unique(swd)  # Only keep unique elements
swd <- data.frame(id=swd)  # Make a data frame
swd$swd <- factor(swd$id)  # Extract factors for using later

# Add unique factors to data -- ensures same factors for both data sets
df <- left_join(df,swd)
df_test <- left_join(df_test,swd)
```

```r
df_test$Id <- paste0(df_test$Store,'_',df_test$Dept,"_",df_test$date)
```

What the IDs look like

```
html_df(df_test[c(20000,40000,60000),c("Store","week","Dept","id","swd","Id")])
```

Store	week	Dept	id	swd	Id
8	27	33	82733	82733	8_33_2013-07-05
15	46	91	154691	154691	15_91_2012-11-16
23	52	25	235225	235225	23_25_2012-12-28

Add in (store, department) average sales

```
# Calculate average by store-dept and distribute to df_test
df <- df %>%
  group_by(Store, Dept) %>%
  mutate(store_avg=mean(Weekly_Sales, rm.na=T)) %>%
  ungroup()
df_sa <- df %>%
  group_by(Store, Dept) %>%
  slice(1) %>%
  select(Store, Dept, store_avg) %>%
  ungroup()
df_test <- left_join(df_test, df_sa)
```

```
## Joining, by = c("Store", "Dept")
```

```
# 36 observations have messed up department codes -- ignore (set to 0)
df_test[is.na(df_test$store_avg),]$store_avg  <- 0

# Calculate multipliers based on store_avg (and removing NaN and Inf)
df$Weekly_mult <- df$Weekly_Sales / df$store_avg
df[!is.finite(df$Weekly_mult),]$Weekly_mult <- NA
```

Add in (week, store, dept) average sales

```
# Calculate mean by week-store-dept and distribute to df_test
df <- df %>%
  group_by(Store, Dept, week) %>%
  mutate(naive_mean=mean(Weekly_Sales, rm.na=T)) %>%
  ungroup()
df_wm <- df %>%
  group_by(Store, Dept, week) %>%
  slice(1) %>%
  ungroup() %>%
  select(Store, Dept, week, naive_mean)
df_test <- df_test %>% arrange(Store, Dept, week)
df_test <- left_join(df_test, df_wm)
```

```
## Joining, by = c("Store", "Dept", "week")
```

ISSUE: New (week, store, dept) groups

- This is in our testing data!
  - So we'll need to predict out groups we haven't observed at all

```
table(is.na(df_test$naive_mean))
```

```
##
##  FALSE   TRUE
## 113827   1237
```

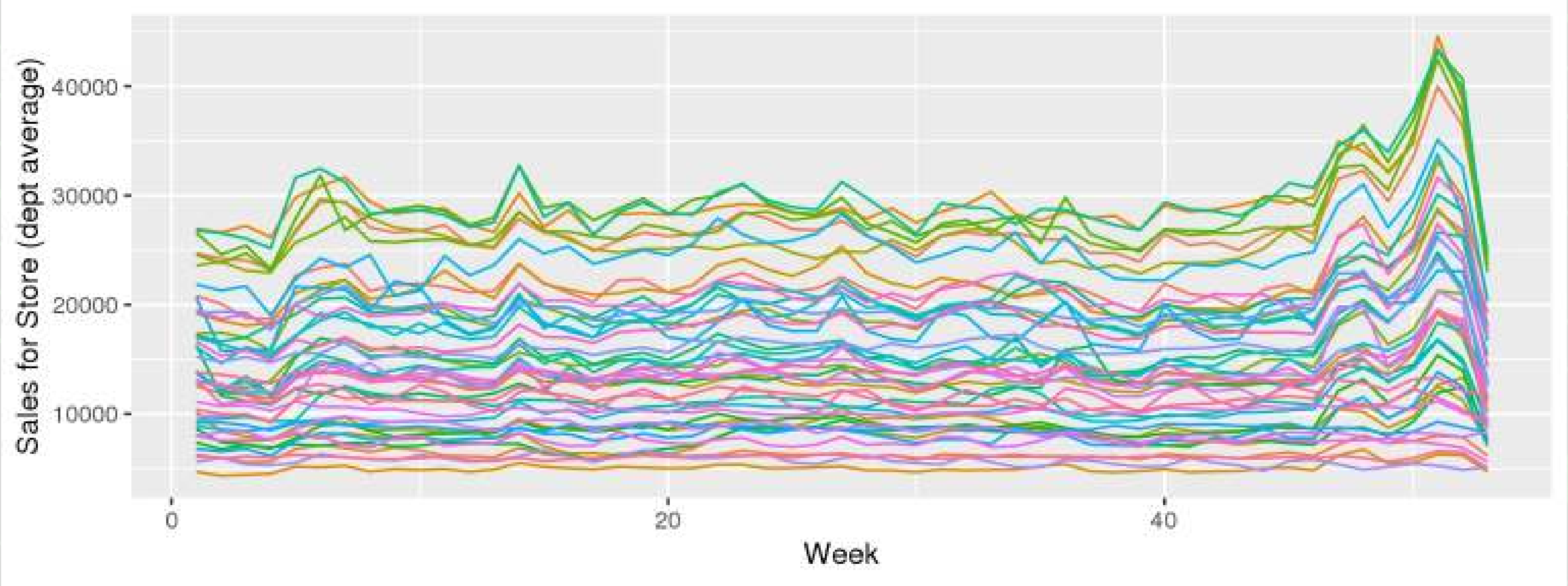
- Fix: Fill with 1 or 2 lags where possible using `ifelse()` and `lag()`
- Fix: Fill with 1 or 2 leads where possible using `ifelse()` and `lag()`
- Fill with `store_avg` when the above fail
- Code is available in the code file – a bunch of code like:

```
df_test <- df_test %>%
  arrange(Store, Dept, date) %>%
  group_by(Store, Dept) %>%
  mutate(naive_mean=ifelse(is.na(naive_mean), lag(naive_mean),naive_mean)) %>%
  ungroup()
```

Cleaning is done

- Data is in order
  - No missing values where data is needed
  - Needed values created

```
df %>%
  group_by(week, Store) %>%
  mutate(sales=mean(Weekly_Sales)) %>%
  slice(1) %>%
  ungroup() %>%
  ggplot(aes(y=sales, x=week, color=factor(Store))) +
  geom_line() + xlab("Week") + ylab("Sales for Store (dept average)") +
  theme(legend.position="none")
```



Tackling the problem

First try

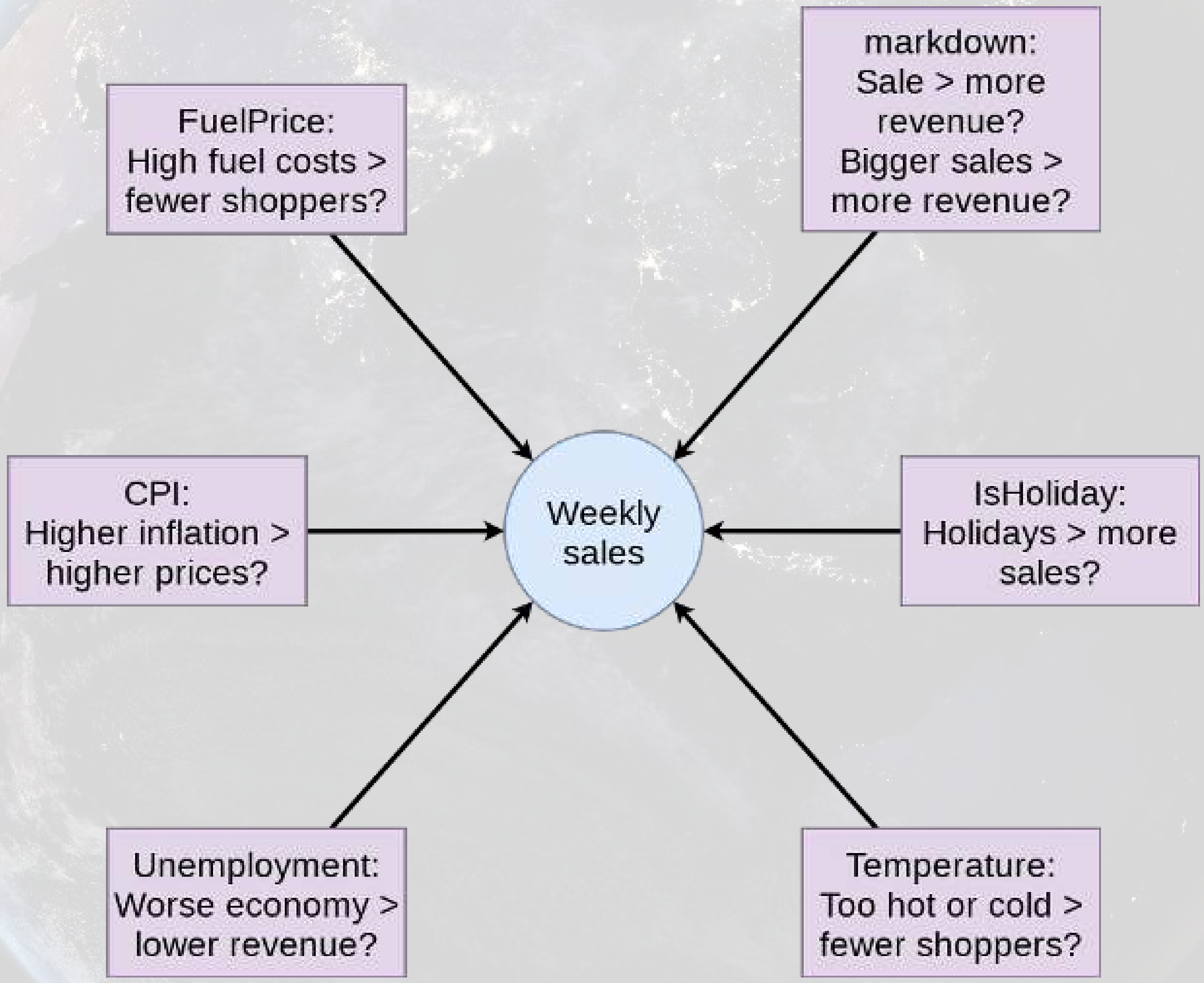
- Ideal: Use last week top predict next week!
  - Like week 3

> No data for testing…

- First instinct: try to use a linear regression to solve this
  - Like from week 3

> We have this

What to put in the model?



First model

```
mod1 <- lm(Weekly_mult ~ factor(IsHoliday) + factor(markdown>0) +
                        markdown + Temperature +
                        Fuel_Price + CPI + Unemployment,
           data=df)
tidy(mod1)
```

```
## # A tibble: 8 x 5
##   term                      estimate   std.error statistic   p.value
##   <chr>                        <dbl>       <dbl>     <dbl>     <dbl>
## 1 (Intercept)              1.24        0.0370        33.5   4.10e-245
## 2 factor(IsHoliday)TRUE     0.0868      0.0124         6.99  2.67e- 12
## 3 factor(markdown > 0)TRUE  0.0531      0.00885        6.00  2.00e-  9
## 4 markdown                 0.000000741 0.000000875     0.847 3.97e-  1
## 5 Temperature             -0.000763    0.000181       -4.23  2.38e-  5
## 6 Fuel_Price              -0.0706      0.00823        -8.58  9.90e- 18
## 7 CPI                     -0.0000837   0.0000887      -0.944 3.45e-  1
## 8 Unemployment             0.00410     0.00182         2.25  2.45e-  2
```

```
glance(mod1)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic  p.value    df  logLik    AIC
## *     <dbl>         <dbl> <dbl>     <dbl>    <dbl> <int>   <dbl>  <dbl>
## 1  0.000481      0.000464  2.03      29.0 2.96e-40     8 -8.96e5 1.79e6
## # ... with 3 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>
```

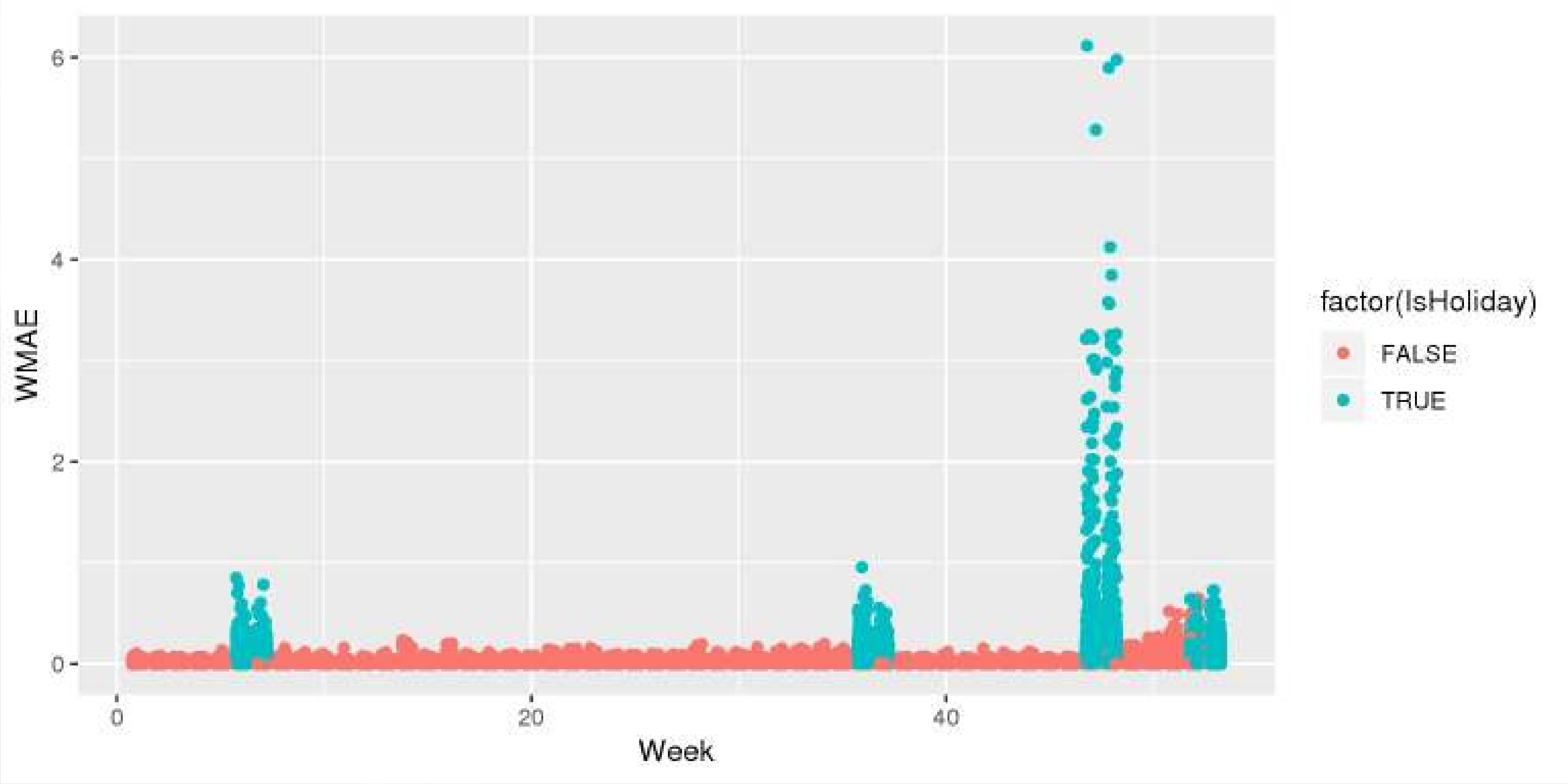
Prep submission and check in sample WMAE

```
# Out of sample result
df_test$Weekly_mult <- predict(mod1, df_test)
df_test$Weekly_Sales <- df_test$Weekly_mult * df_test$store_avg

# Required to submit a csv of Id and Weekly_Sales
write.csv(df_test[,c("Id","Weekly_Sales")],
          "WMT_linear.csv",
          row.names=FALSE)

# track
df_test$WS_linear <- df_test$Weekly_Sales

# Check in sample WMAE
df$WS_linear <- predict(mod1, df) * df$store_avg
w <- wmae(actual=df$Weekly_Sales, predicted=df$WS_linear, holidays=df$IsHoliday)
names(w) <- "Linear"
wmaes <- c(w)
wmaes
```

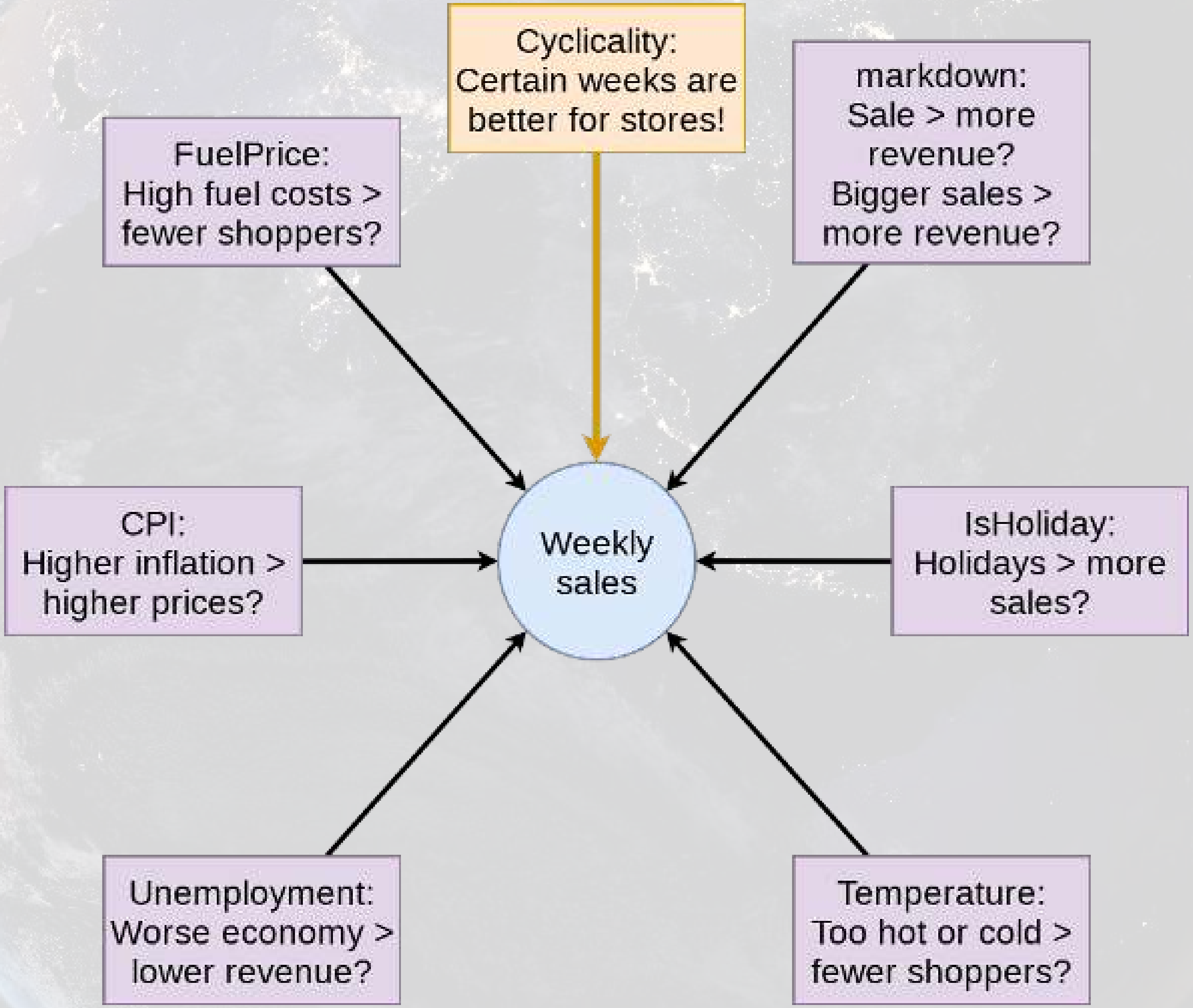
```
##  Linear
## 3073.57
```

Visualizing in sample WMAE

```
wmae_obs <- function(actual, predicted, holidays) {
  abs(actual-predicted)*(holidays*5+1) / (length(actual) + 4*sum(holidays))
}
df$wmaes  <- wmae_obs(actual=df$Weekly_Sales, predicted=df$WS_linear,
                      holidays=df$IsHoliday)
ggplot(data=df, aes(y=wmaes, x=week, color=factor(IsHoliday))) +
  geom_jitter(width=0.25) + xlab("Week") + ylab("WMAE")
```



Back to the drawing board…



Second model: Including week

```
mod2 <- lm(Weekly_mult ~ factor(week) + factor(IsHoliday) + factor(markdown>0) +
                       markdown + Temperature +
                       Fuel_Price + CPI + Unemployment,
           data=df)
tidy(mod2)
```

```
## # A tibble: 60 x 5
##    term            estimate std.error statistic   p.value
##    <chr>              <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)       1.000     0.0452     22.1  3.11e-108
##  2 factor(week)2   -0.0648    0.0372     -1.74 8.19e-  2
##  3 factor(week)3   -0.169     0.0373     -4.54 5.75e-  6
##  4 factor(week)4   -0.0716    0.0373     -1.92 5.47e-  2
##  5 factor(week)5    0.0544    0.0372      1.46 1.44e-  1
##  6 factor(week)6    0.161     0.0361      4.45 8.79e-  6
##  7 factor(week)7    0.265     0.0345      7.67 1.72e- 14
##  8 factor(week)8    0.109     0.0340      3.21 1.32e-  3
##  9 factor(week)9    0.0823    0.0340      2.42 1.55e-  2
## 10 factor(week)10   0.101     0.0341      2.96 3.04e-  3
## # ... with 50 more rows
```

```
glance(mod2)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic p.value    df  logLik     AIC
## *     <dbl>         <dbl> <dbl>     <dbl>   <dbl> <int>   <dbl>   <dbl>
## 1   0.00501       0.00487  2.02      35.9       0    60 -8.95e5 1.79e6
## # ... with 3 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>
```

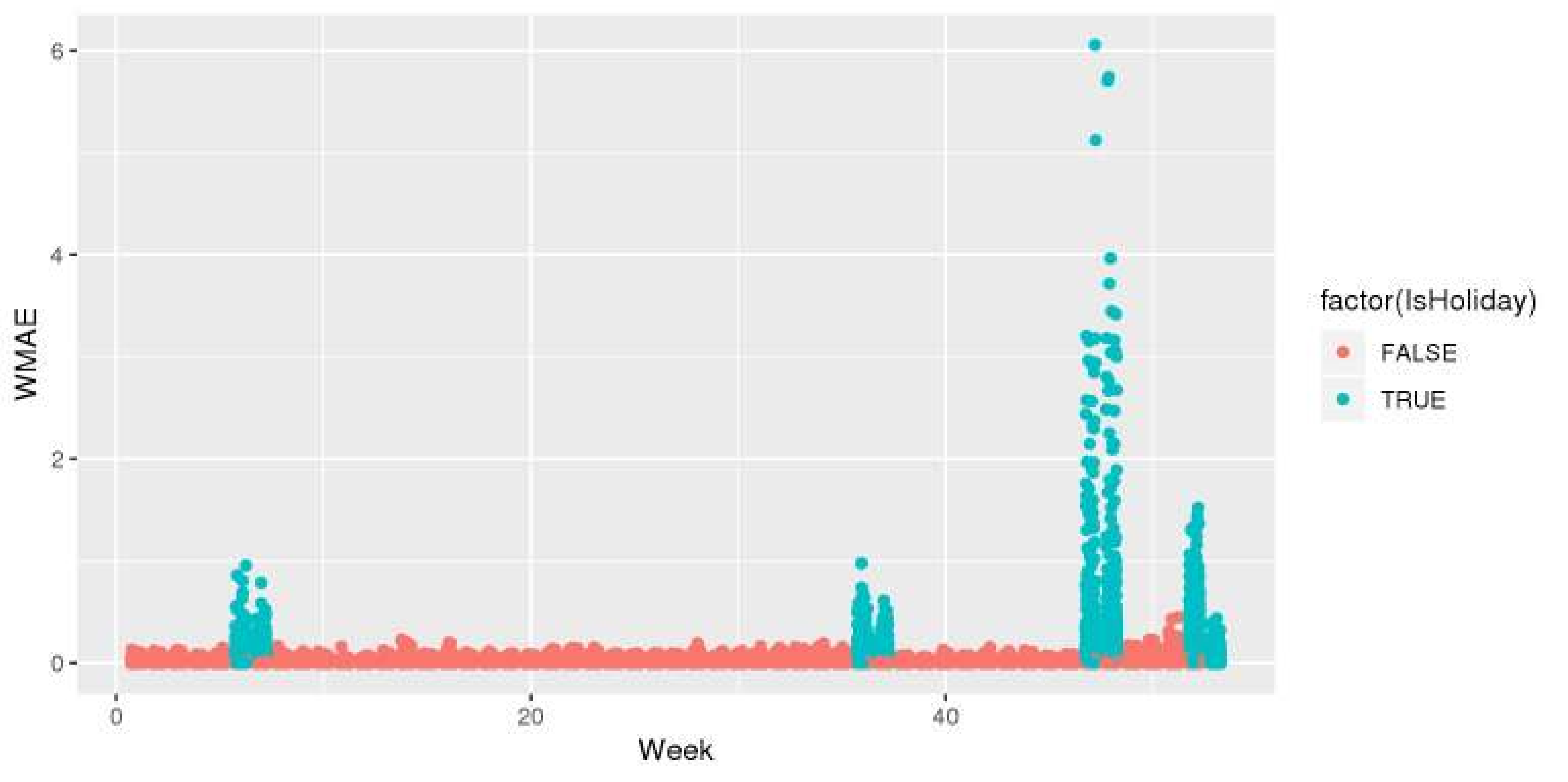
Prep submission and check in sample WMAE

```r
# Out of sample result
df_test$Weekly_mult <- predict(mod2, df_test)
df_test$Weekly_Sales <- df_test$Weekly_mult * df_test$store_avg

# Required to submit a csv of Id and Weekly_Sales
write.csv(df_test[,c("Id","Weekly_Sales")],
          "WMT_linear2.csv",
          row.names=FALSE)

# track
df_test$WS_linear2 <- df_test$Weekly_Sales

# Check in sample WMAE
df$WS_linear2 <- predict(mod2, df) * df$store_avg
w <- wmae(actual=df$Weekly_Sales, predicted=df$WS_linear2, holidays=df$IsHoliday)
names(w) <- "Linear 2"
wmaes <- c(wmaes, w)
wmaes
```

```
##   Linear Linear 2
## 3073.570 3230.643
```

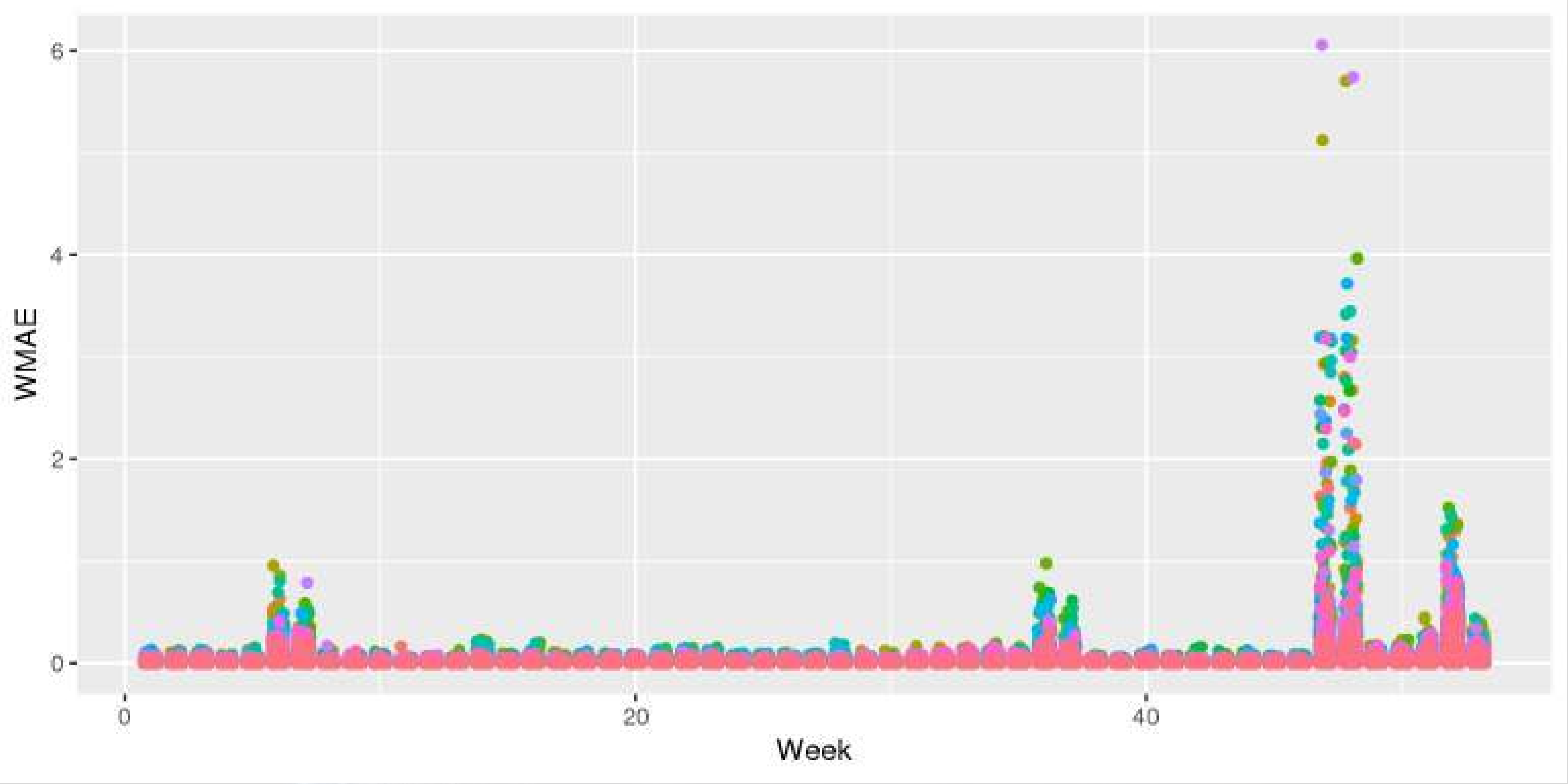
Visualizing in sample WMAE

```r
df$wmaes  <- wmae_obs(actual=df$Weekly_Sales, predicted=df$WS_linear2,
                      holidays=df$IsHoliday)
ggplot(data=df, aes(y=wmaes,
                    x=week,
                    color=factor(IsHoliday))) +
  geom_jitter(width=0.25) + xlab("Week") + ylab("WMAE")
```



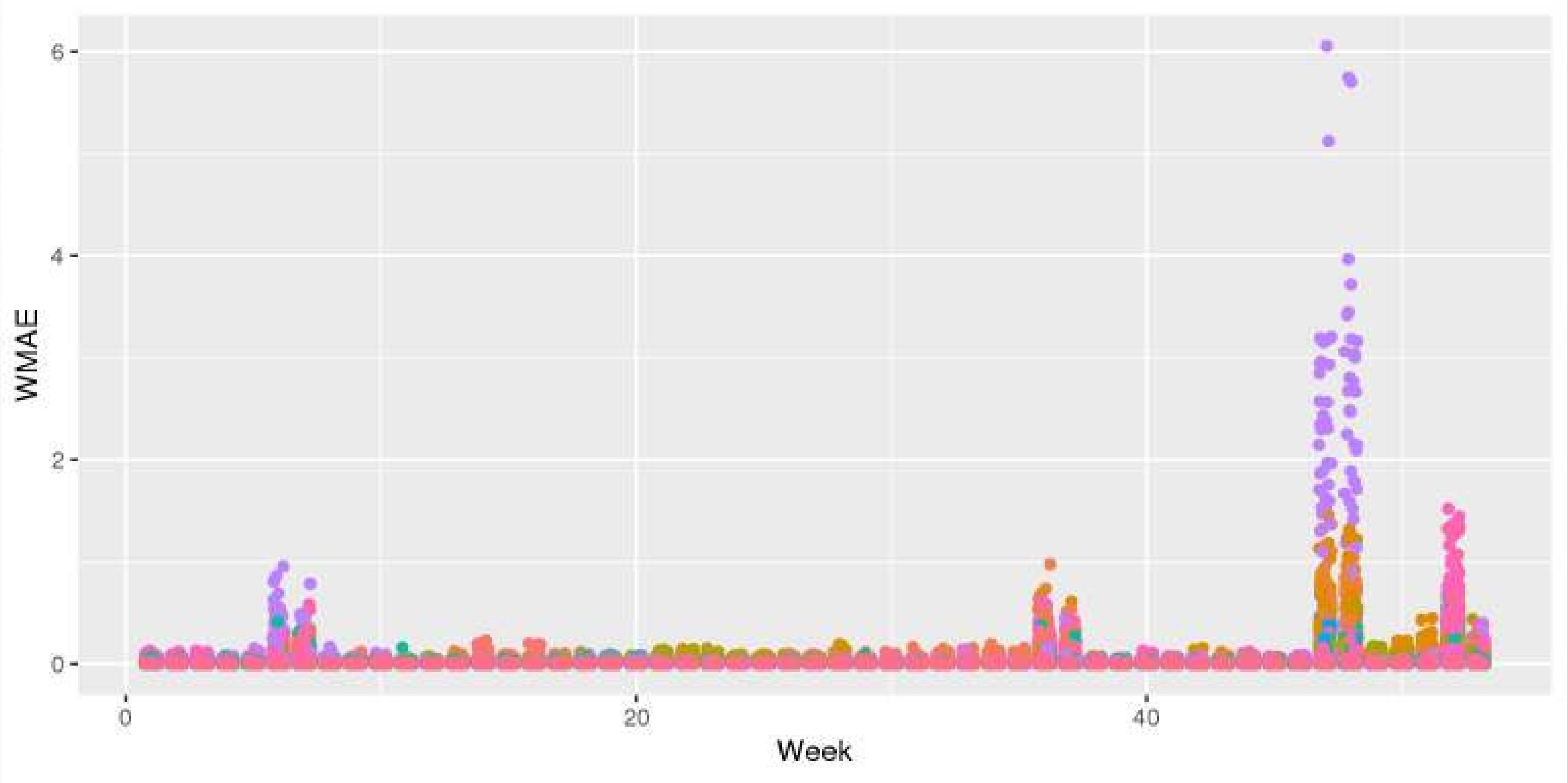
Visualizing in sample WMAE by Store

```
ggplot(data=df, aes(y=wmae_obs(actual=df$Weekly_Sales, predicted=df$WS_linear2,
                               holidays=df$IsHoliday),
                    x=week,
                    color=factor(Store))) +
  geom_jitter(width=0.25) + xlab("Week") + ylab("WMAE") +
  theme(legend.position="none")
```

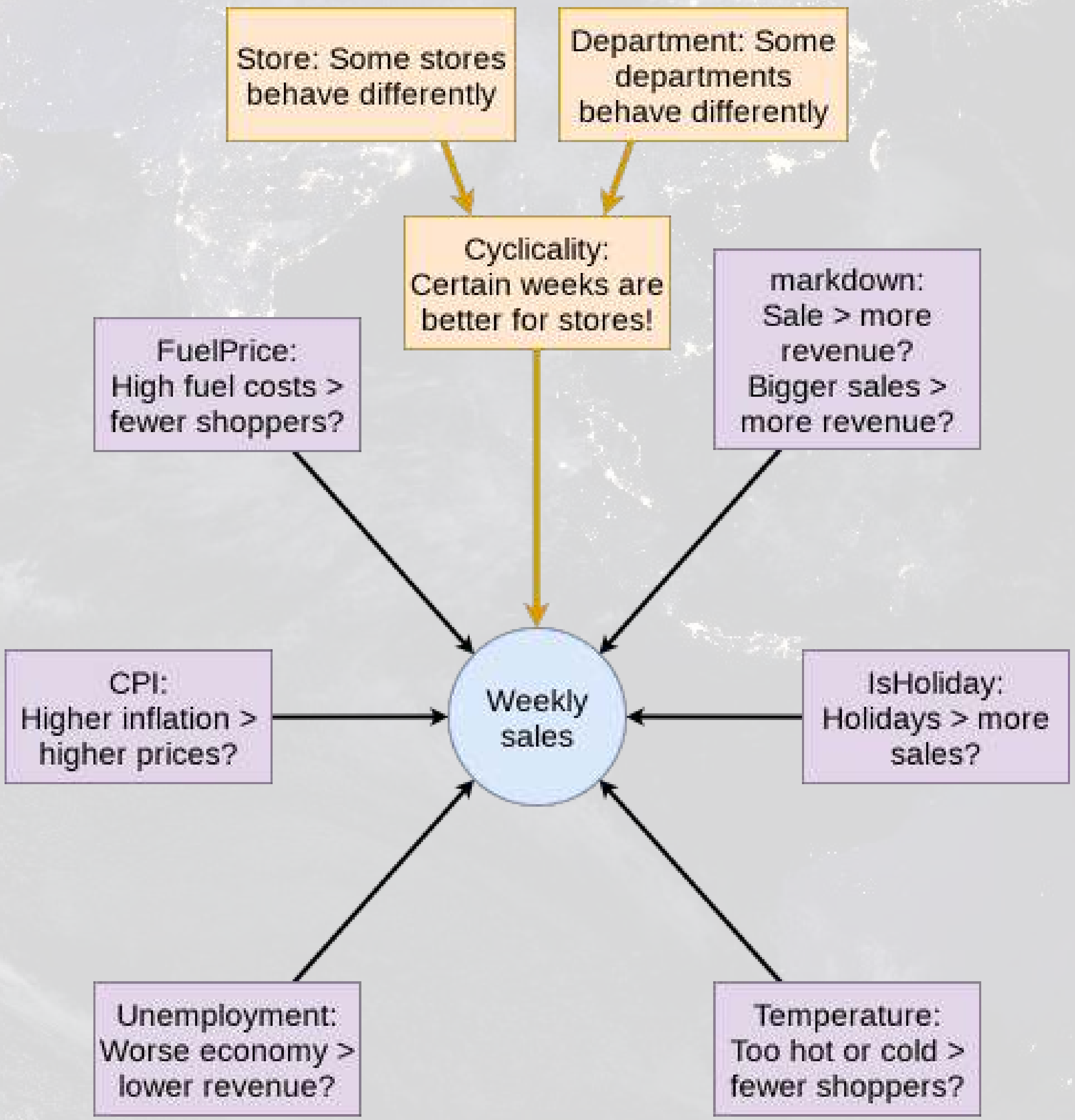


Visualizing in sample WMAE by Dept

```r
ggplot(data=df, aes(y=wmae_obs(actual=df$Weekly_Sales, predicted=df$WS_linear2,
                               holidays=df$IsHoliday),
                    x=week,
                    color=factor(Dept))) +
  geom_jitter(width=0.25) + xlab("Week") + ylab("WMAE") +
  theme(legend.position="none")
```



Back to the drawing board…



Third model: Including week x Store x Dept

```
mod3 <- lm(Weekly_mult ~ factor(week):factor(Store):factor(Dept) + factor(IsHoliday) + factor(markdown>
                        markdown + Temperature +
                        Fuel_Price + CPI + Unemployment,
           data=df)
## Error: cannot allocate vector of size 606.8Gb
```

> . . .

Third model: Including week x Store x Dept

- Use lfe's felm() – it really is more efficient!

```
library(lfe)
mod3 <- felm(Weekly_mult ~ markdown +
          Temperature +
          Fuel_Price +
          CPI +
          Unemployment | swd, data=df)
tidy(mod3)
```

```
## # A tibble: 5 x 5
##   term            estimate   std.error statistic  p.value
##   <chr>              <dbl>       <dbl>     <dbl>    <dbl>
## 1 markdown     -0.00000139 0.000000581     -2.40 1.65e- 2
## 2 Temperature   0.00135    0.000442         3.05 2.28e- 3
## 3 Fuel_Price   -0.0637     0.00695         -9.17 4.89e-20
## 4 CPI           0.00150    0.00102          1.46 1.43e- 1
## 5 Unemployment -0.0303     0.00393         -7.70 1.32e-14
```

```
glance(mod3)
```

```
## # A tibble: 1 x 7
##   r.squared adj.r.squared sigma statistic p.value     df df.residual
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl>  <dbl>       <dbl>
## 1     0.823         0.712  1.09      7.43       0 259457      259457
```

PROBLEM

- We need to be able to predict out of sample to make our submission

> `felm()` models don't support predict

- So build it:

```
predict.felm <- function(object, newdata, use.fe=T, ...) {
  # compatible with tibbles
  newdata <- as.data.frame(newdata)
  co <- coef(object)

  y.pred <- t(as.matrix(unname(co))) %*% t(as.matrix(newdata[,names(co)]))

  fe.vars <- names(object$fe)

  all.fe <- getfe(object)
  for (fe.var in fe.vars) {
    level <- all.fe[all.fe$fe == fe.var,]
    frows <- match(newdata[[fe.var]],level$idx)
    myfe <- level$effect[frows]
    myfe[is.na(myfe)] = 0

    y.pred <- y.pred + myfe
  }
  as.vector(y.pred)
}
```

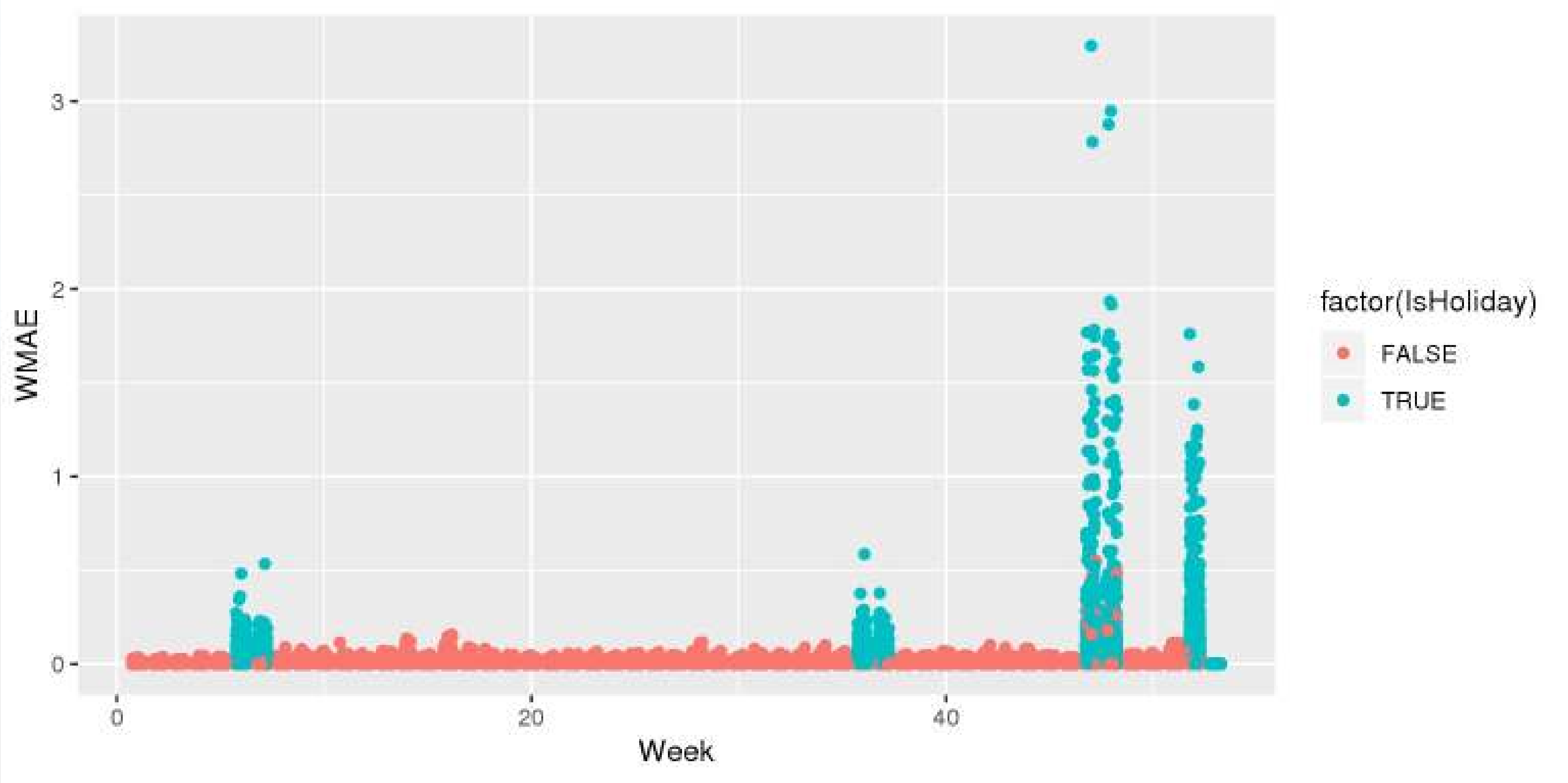
Prep submission and check in sample WMAE

```
# Out of sample result
df_test$Weekly_mult <- predict(mod3, df_test)
df_test$Weekly_Sales <- df_test$Weekly_mult * df_test$store_avg

# Required to submit a csv of Id and Weekly_Sales
write.csv(df_test[,c("Id","Weekly_Sales")],
          "WMT_FE.csv",
          row.names=FALSE)

# track
df_test$WS_FE <- df_test$Weekly_Sales

# Check in sample WMAE
df$WS_FE <- predict(mod3, df) * df$store_avg
w <- wmae(actual=df$Weekly_Sales, predicted=df$WS_FE, holidays=df$IsHoliday)
names(w) <- "FE"
wmaes <- c(wmaes, w)
wmaes
```

```
##   Linear Linear 2       FE
## 3073.570 3230.643 1552.173
```

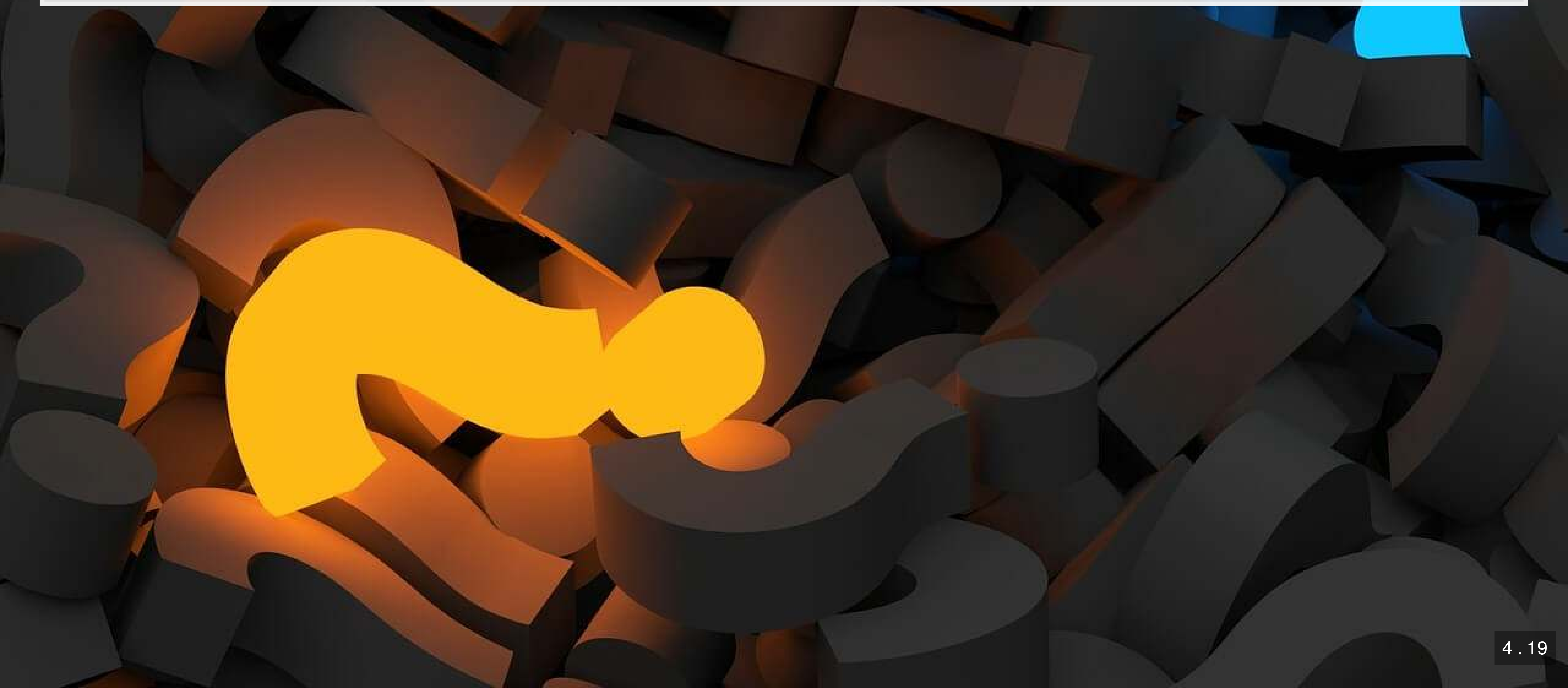
Visualizing in sample WMAE

```r
df$wmaes  <- wmae_obs(actual=df$Weekly_Sales, predicted=df$WS_FE,
                      holidays=df$IsHoliday)
ggplot(data=df, aes(y=wmaes,
                    x=week,
                    color=factor(IsHoliday))) +
  geom_jitter(width=0.25) + xlab("Week") + ylab("WMAE")
```



Maybe the data is part of the problem?

- What problems might there be for our testing sample?
  - What is different from testing to training?
- Can we fix them?
  - If so, how?



This was a real problem!

- Walmart provided this data back in 2014 as part of a recruiting exercise
  - Details here
  - Discussion of first place entry
    - Code for first place entry
  - Discussion of second place entry
- This is what the group project will be like
  - 4 to 5 group members tackling a real life data problem
  - You will have training data but testing data will be withheld
  - Submit on Kaggle

Project deliverables

1. Kaggle submission
2. Your code for your submission, walking through what you did
3. A 15 minute presentation on the last day of class describing:
    - Your approach
4. A report discussing
    - Main points and findings
    - Exploratory analysis of the data used
    - Your model development, selection, implementation, evaluation, and refinement
    - A conclusion on how well your group did and what you learned in the process

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

> We can assign a probability to any of these

Regression approach: Logistic regression

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

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

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)

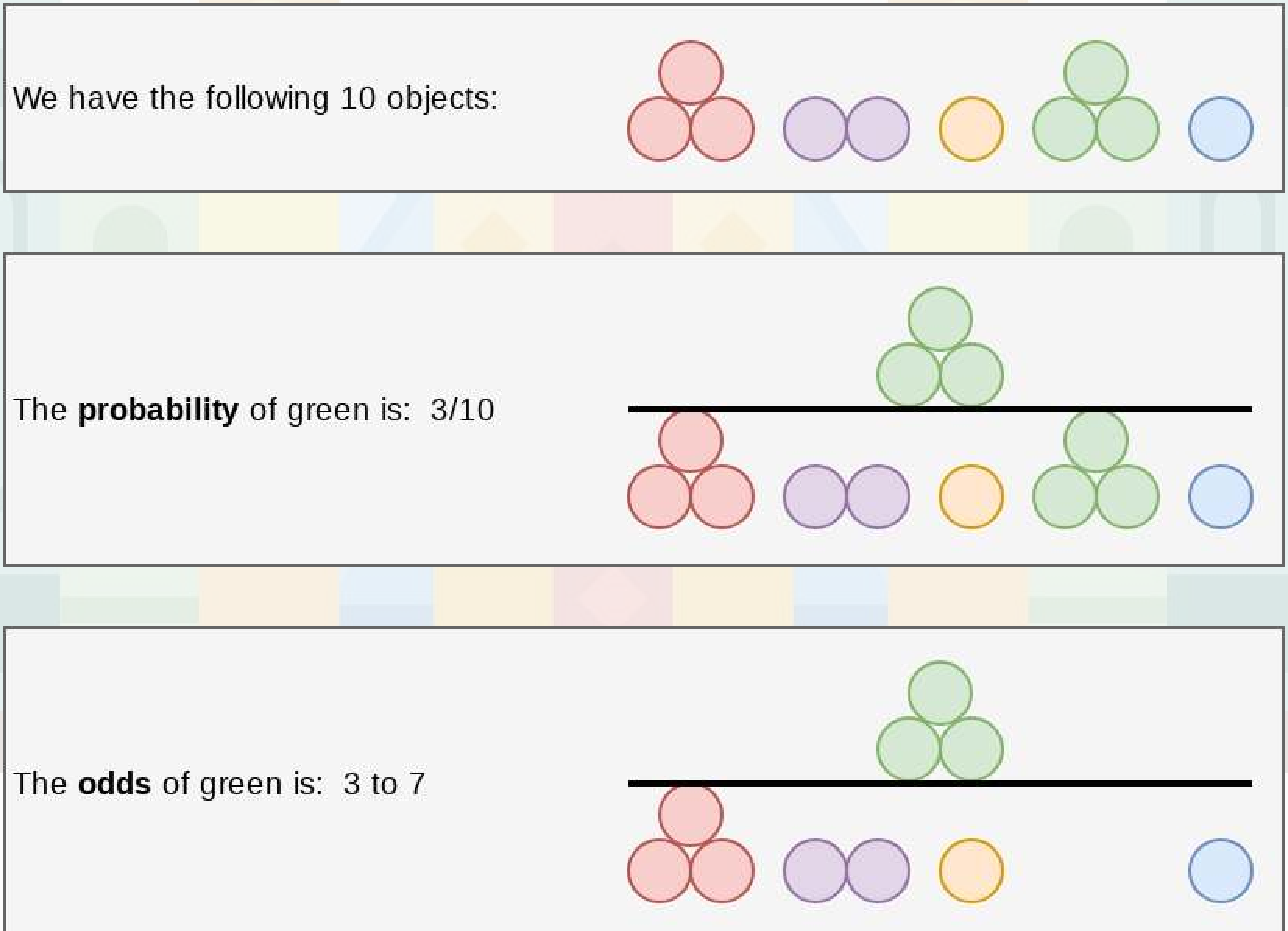
- To regress a GLM, we use the `glm()` command.
  - In fact, the `lm()` command we have been using is actually `glm()` when you specify the option `family=gaussian`
- To run a Logit regression:

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

summary(mod)
```

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 the coefficient is different
  - The relationship isn't linear between x_i and y now
  - Instead, coefficient is in log odds
    - Thus, e^{β_i} gives you the *odds*, o
    - To get probability, p, we can calculate $p = \frac{o}{1+o}$
- You can directly interpret the log odds for a coefficient (increased by $\beta\%$)
- You can directly interpret the odds for a coefficient (increased by $(o-1)\%$)
- You need to sum all relevant log odds before converting to probability!

Odds vs probability



Example logit regression

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

```r
# Create the binary variable
df$double <- ifelse(df$Weekly_Sales > df$store_avg*2,1,0)
```

```r
fit <- glm(double ~ IsHoliday, data=df, family=binomial)
summary(fit)
```

```
##
## Call:
## glm(formula = double ~ IsHoliday, family = binomial, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.3260  -0.2504  -0.2504  -0.2504   2.6375
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -3.446804   0.009236 -373.19   <2e-16 ***
## IsHolidayTRUE  0.538640   0.027791   19.38   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

Converting logit coefficients

- coef() extracts model coefficients from regression models
- exp() is exponentiation: exp(x) is e^x

```
odds <- exp(coef(fit))
odds
```

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

```
probability <- odds / (1 + odds)
probability
```

```
##   (Intercept) IsHolidayTRUE
##    0.03086431    0.63149603
```

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/420r5

Today's Application: Shipping delays

The question

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

A bit about shipping data

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

- 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

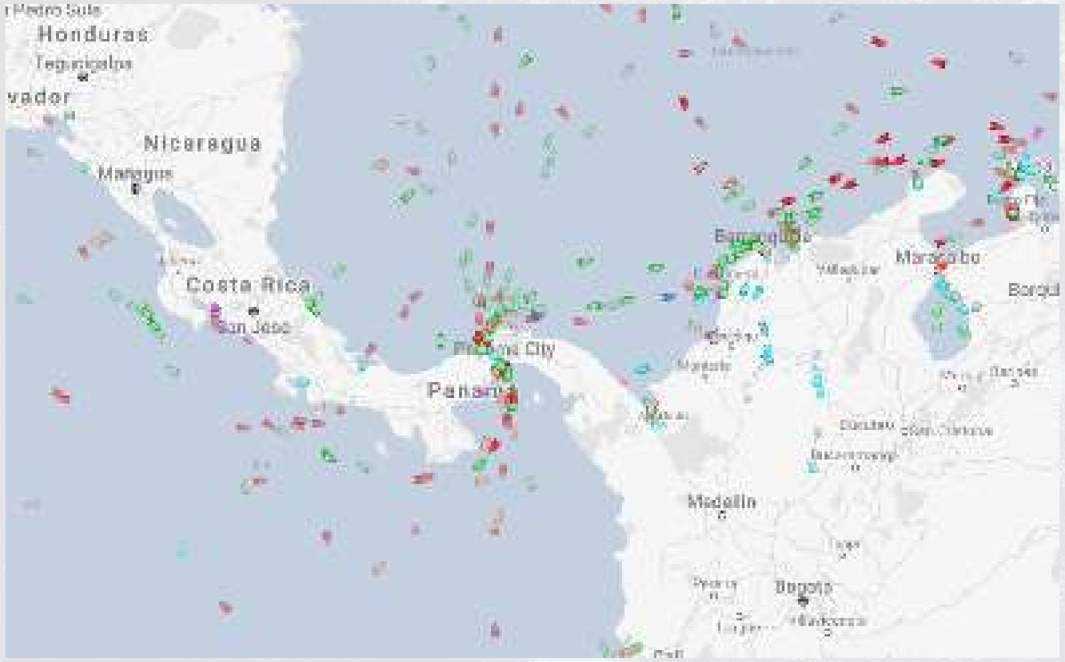
What can we see from naval data?

Yachts in the Mediterranean

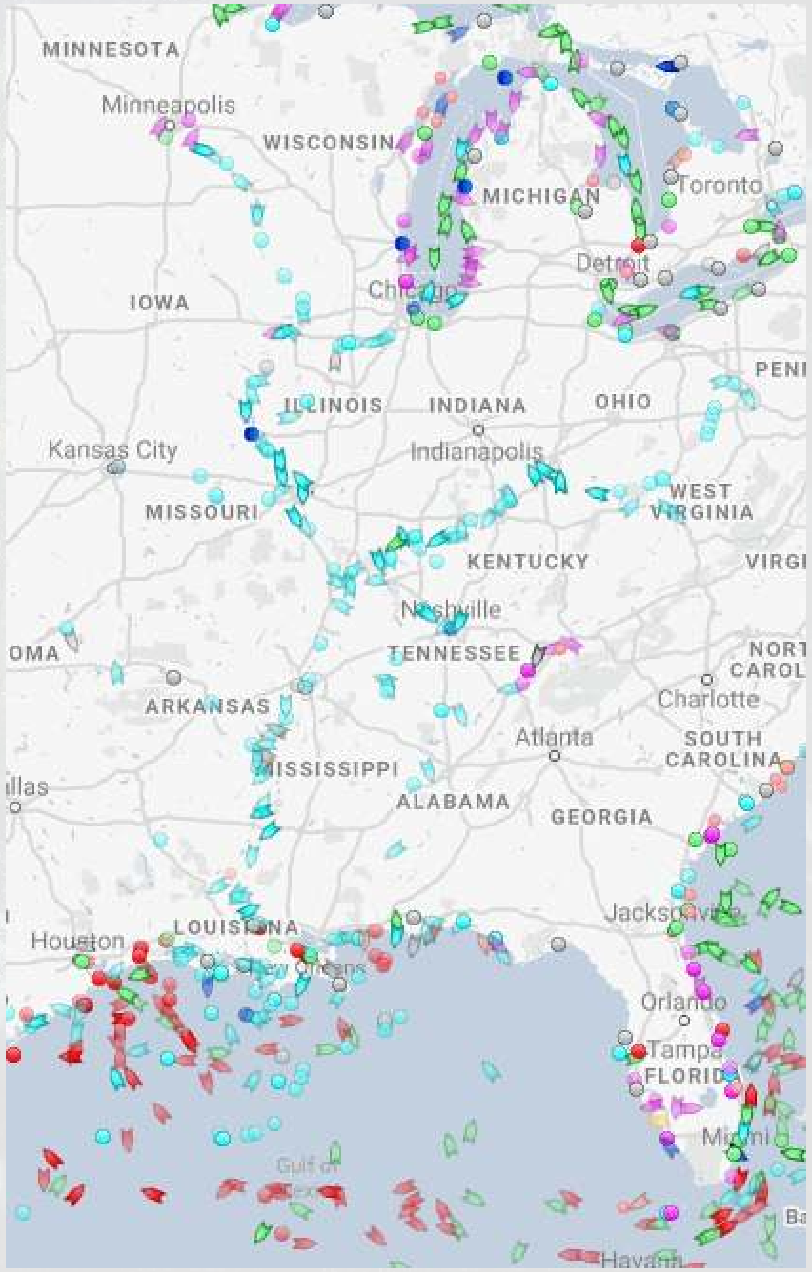
Oil tankers in the Persian gulf

What can we see from naval data?

Shipping route via the Panama canal

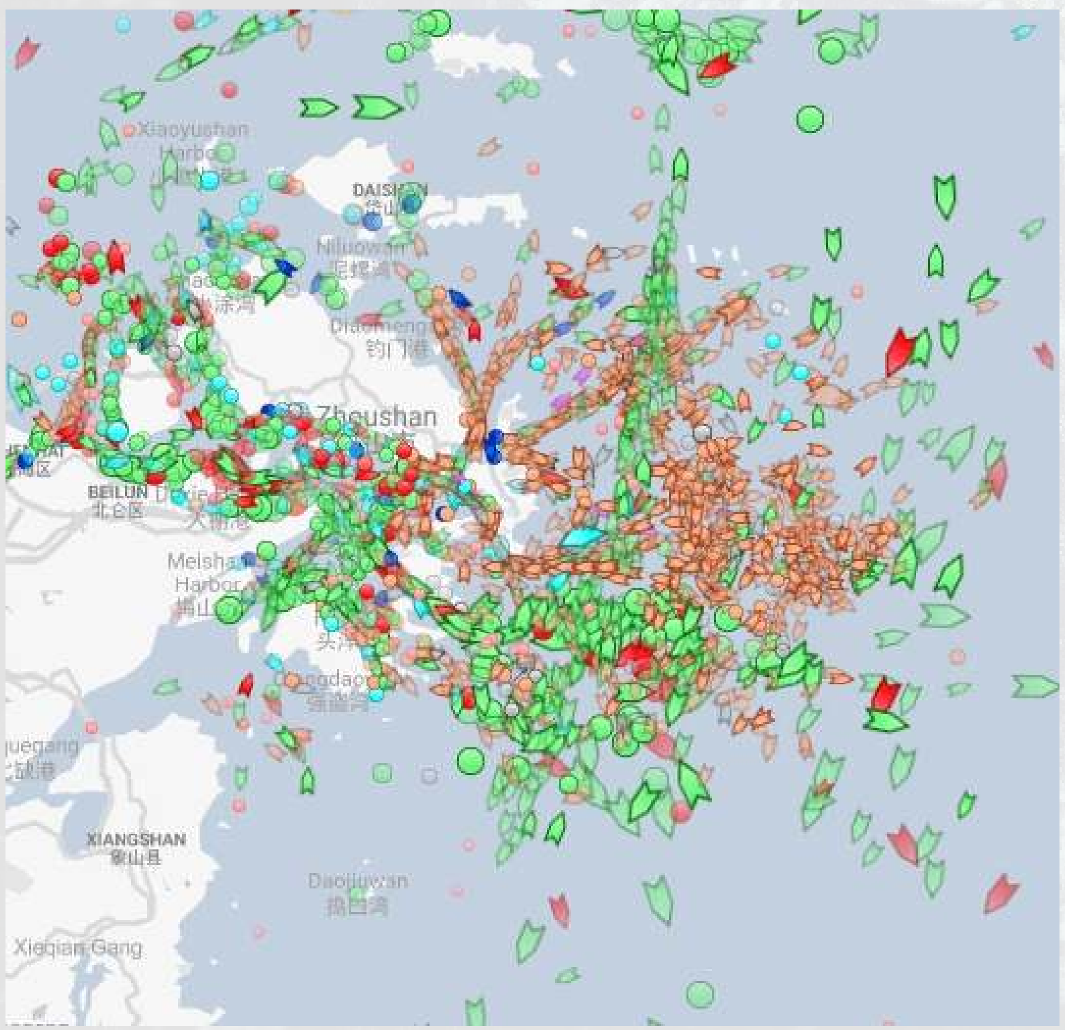


River shipping on the Mississippi river, USA

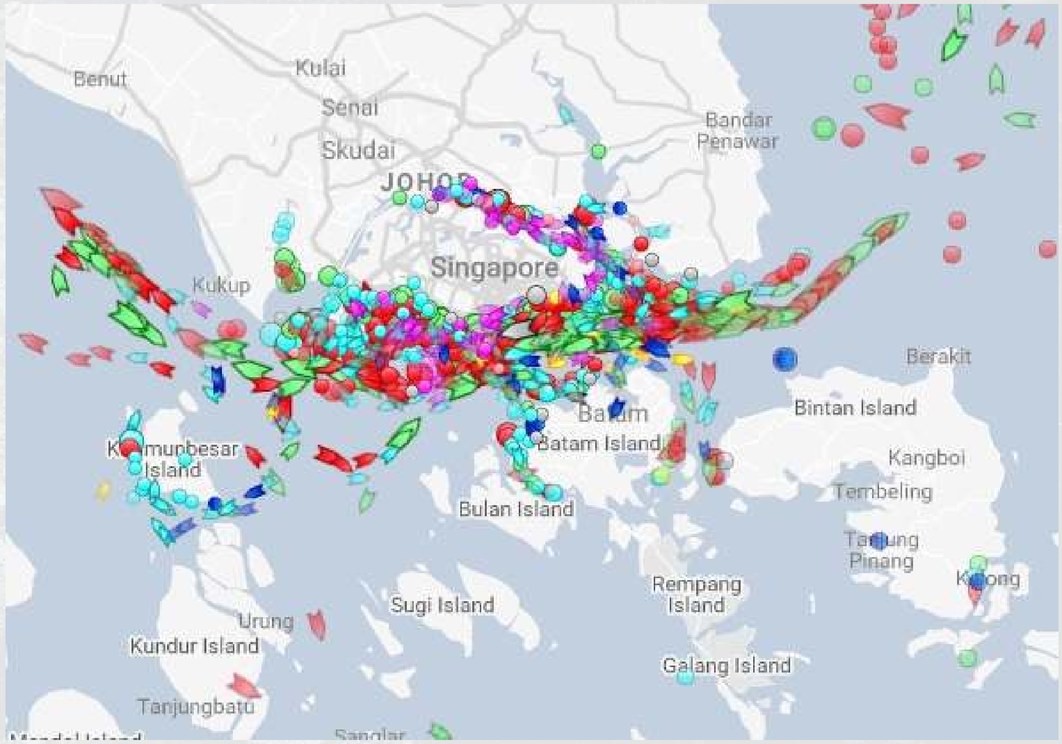


What can we see from naval data?

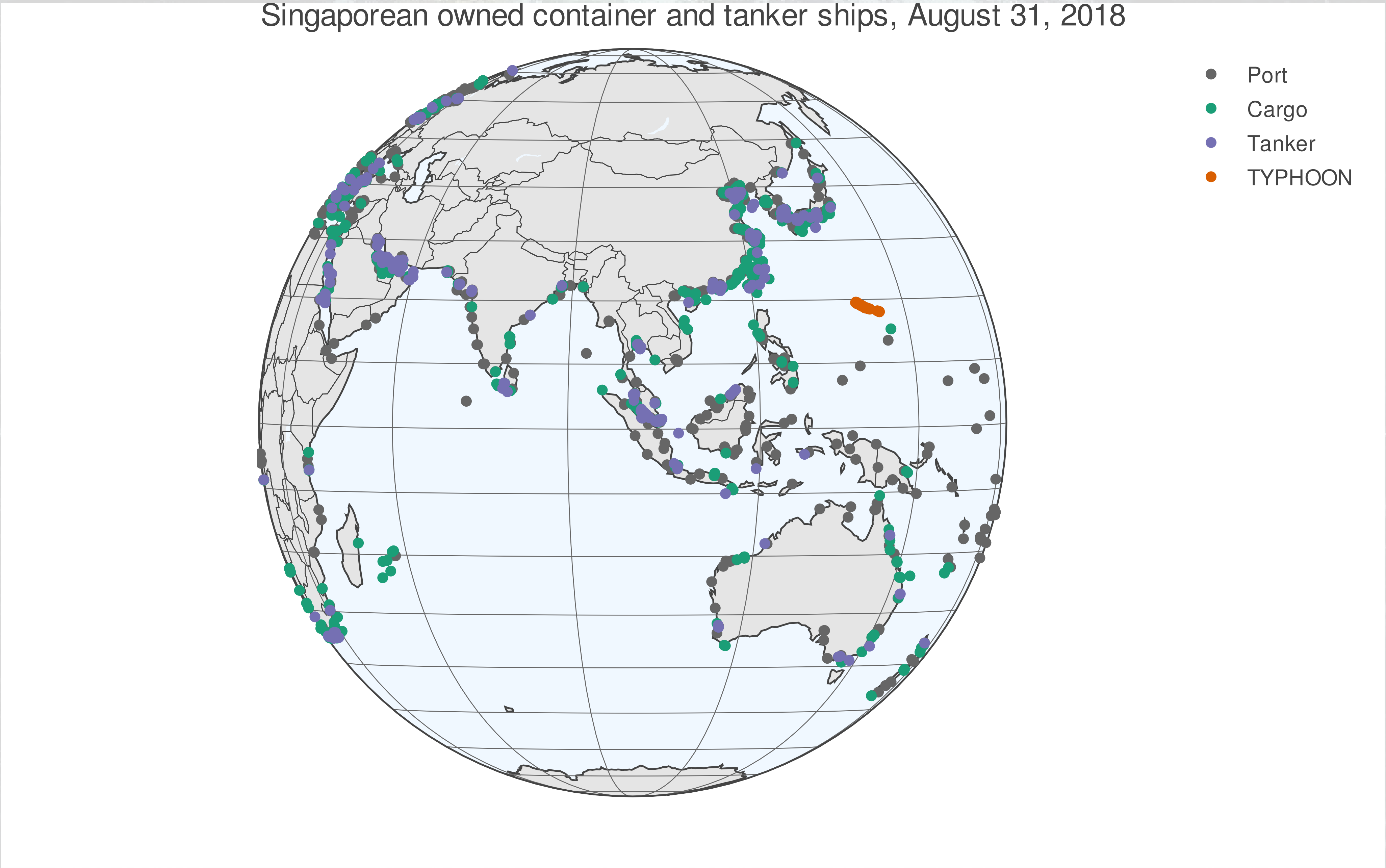
Busiest ports by containers and tons (Shanghai & Ningbo-Zhoushan, China)



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")

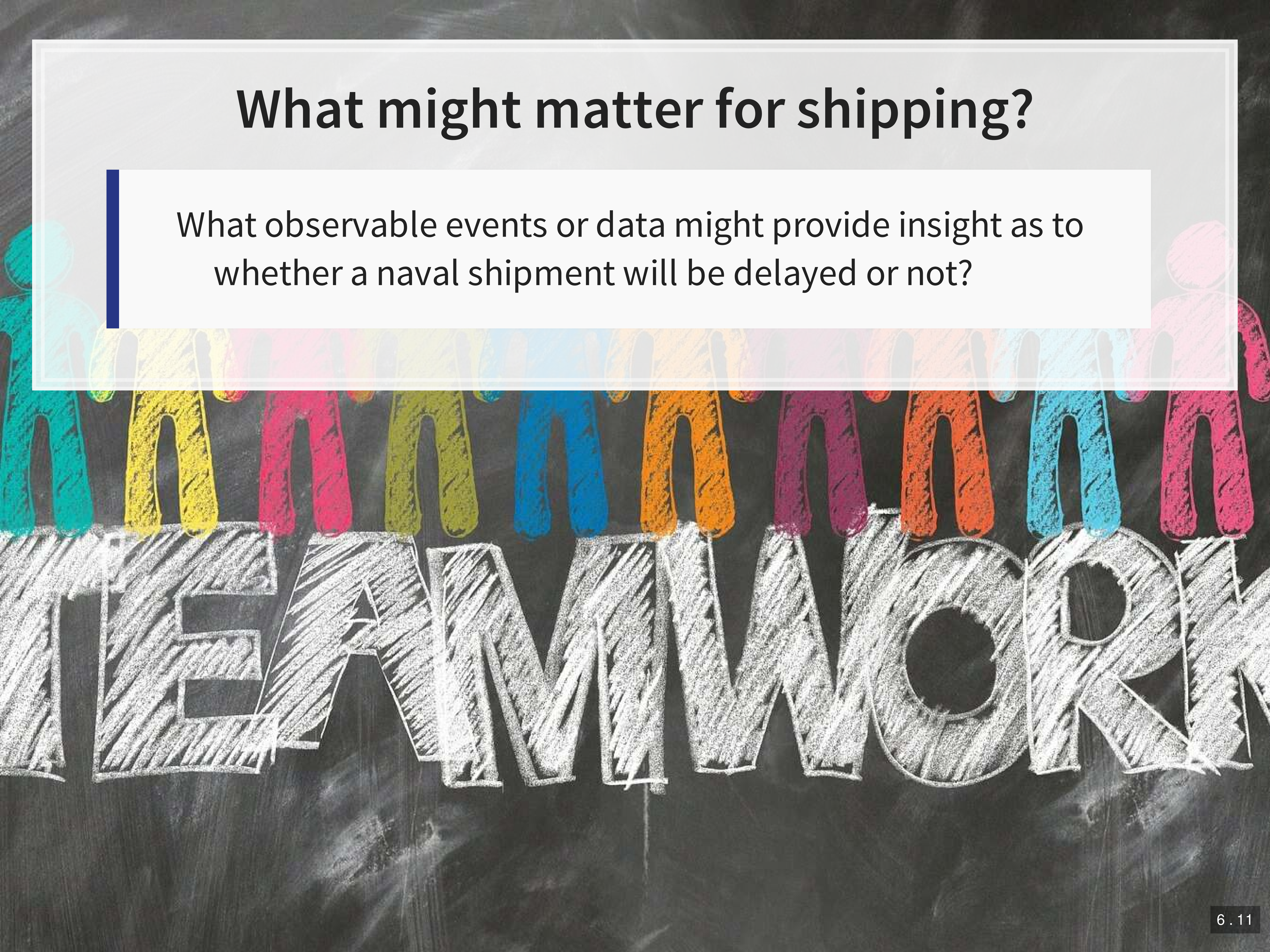
Singaporean ship movement

Link to ship movement animation

Code for last slide’s map

```r
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)
```

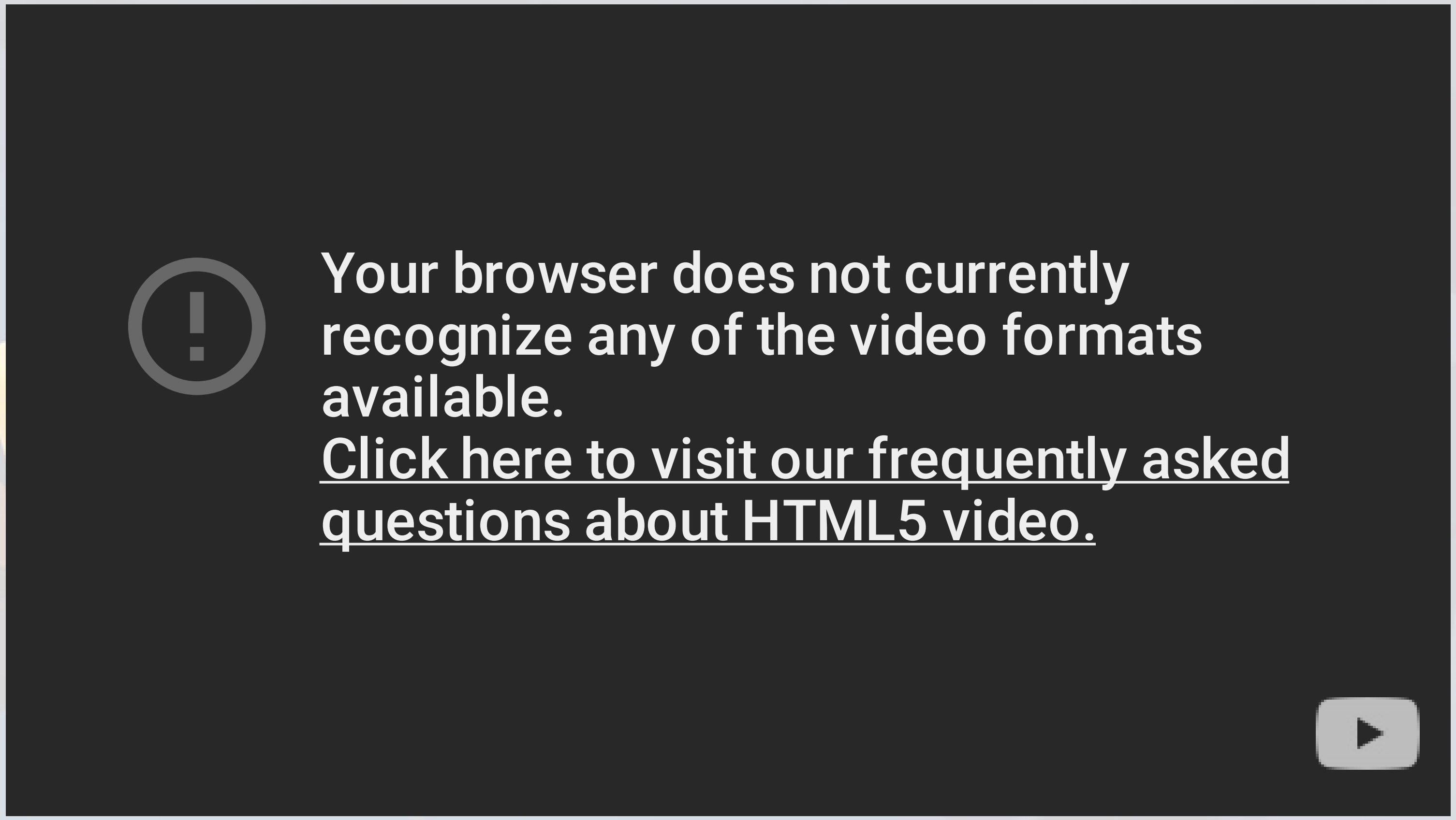
- world1 contains the map data
- geom_sf() plots map data passed to ggplot()
- geom_point() plots ship locations as longitude and latitude
- ggplotly() converts the graph to html and animates it
  - Animation follows the frame aesthetic



What might matter for shipping?

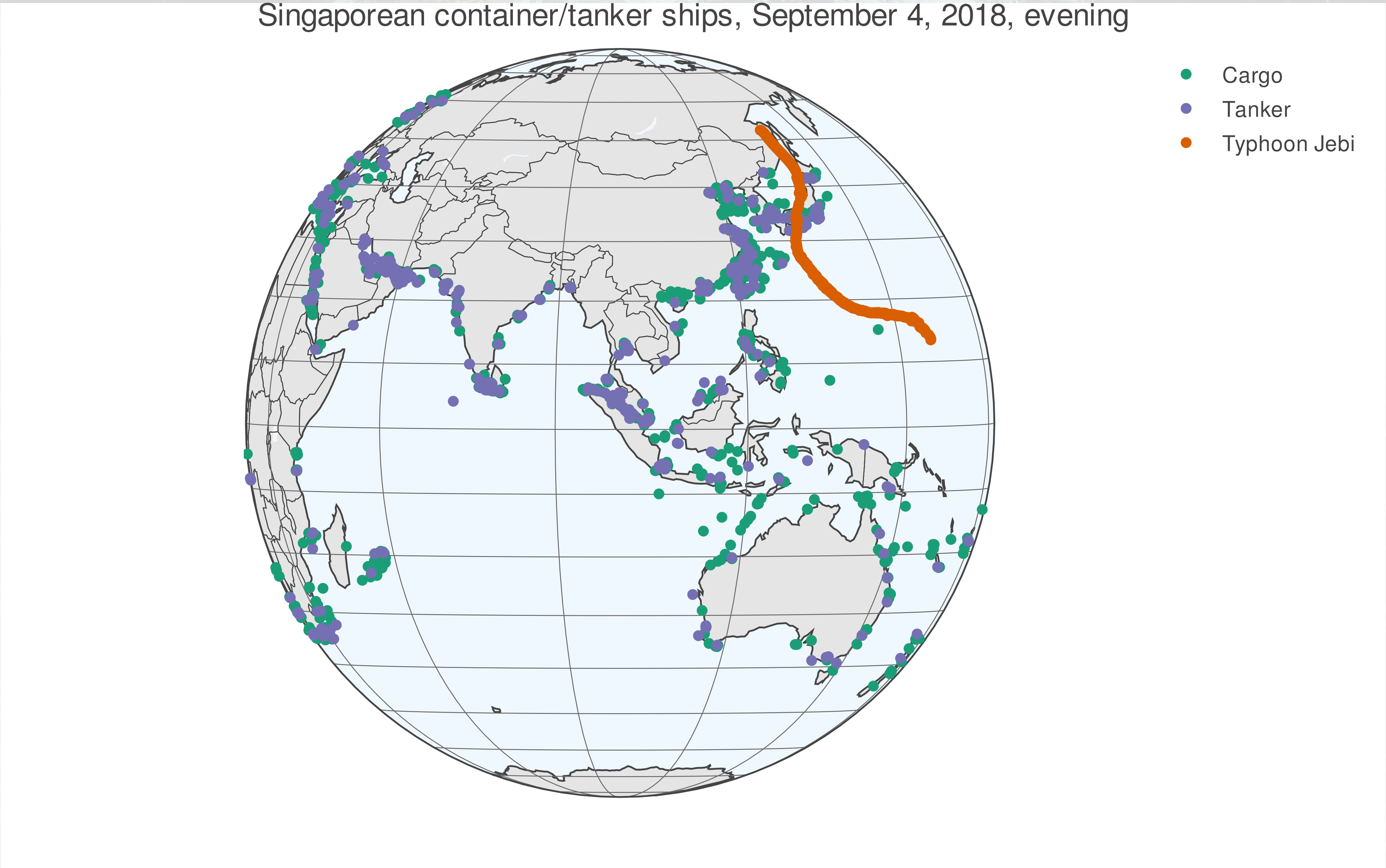
> What observable events or data might provide insight as to whether a naval shipment will be delayed or not?

Typhoon Jebi



- link

Typhoons in the data

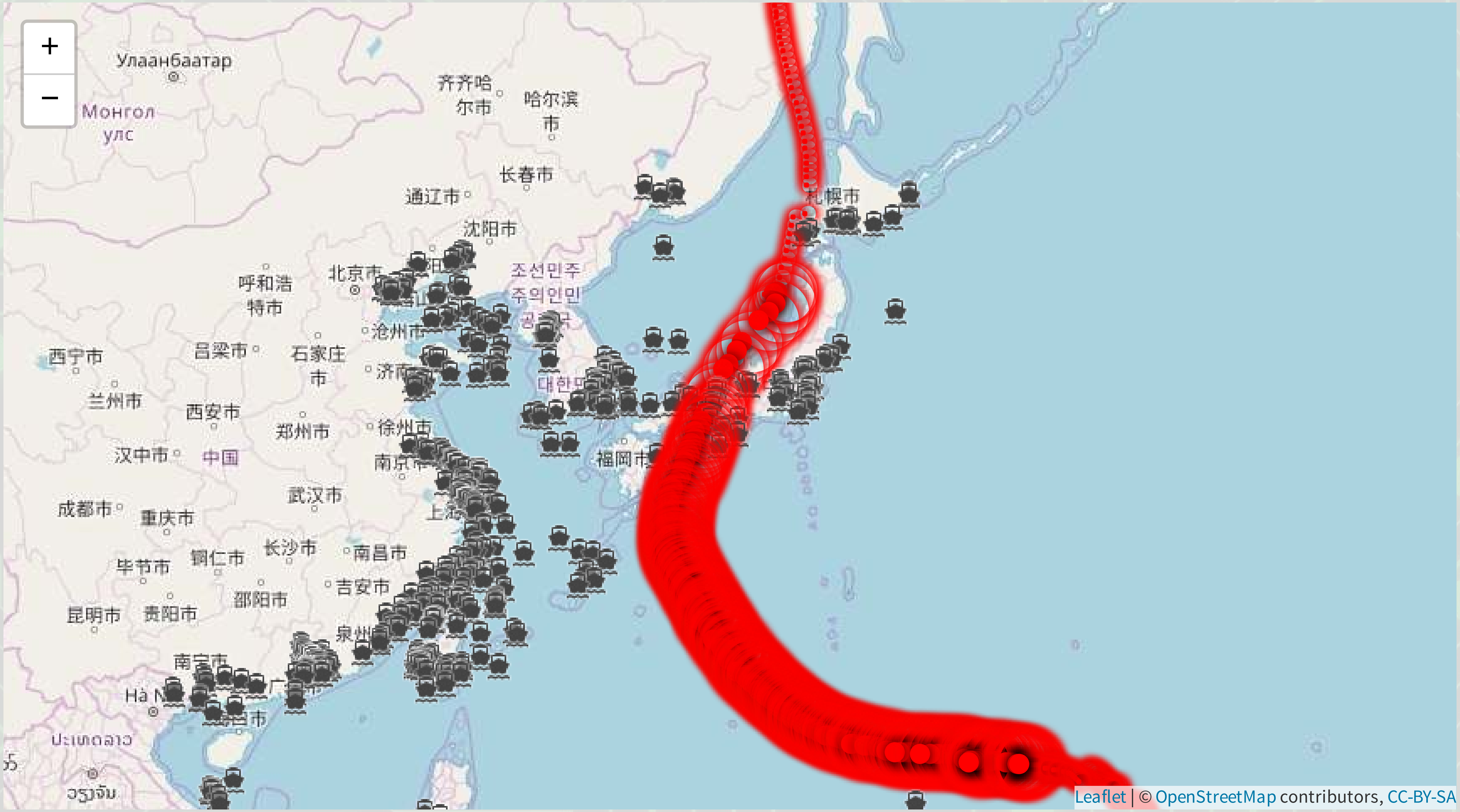


Code for last slide's map

```
# 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)
# icons
typhoonicons <- pulseIcons(color='red',
  heartbeat = ifelse(typhoon_Jebi$intensity_vmax > 150/1.852, 0.8,
    ifelse(typhoon$intensity_vmax < 118, 1.6, 1.2)),
  iconSize=ifelse(typhoon_Jebi$intensity_vmax > 150/1.852, 12,
    ifelse(typhoon_Jebi$intensity_vmax < 118, 3, 8)))
shipicons <- iconList(
  ship = makeIcon("../Figures/ship.png", NULL, 18, 18))
# plot
leaflet() %>%
  addTiles() %>%
  setView(lng = 136, lat = 34, zoom=4) %>%
  addPulseMarkers(data=typhoon_Jebi, lng=~lon, lat=~lat, label=~date,
                icon=typhoonicons) %>%
  addMarkers(data=df_all[df_all$frame == 14,], lng=~lon, lat=~lat,
           label=~shipname, icon=shipicons)
```

- pulseIcons(): pulsing icons from leaflet.extras
- iconList(): pulls icons stored on your computer
- leaflet(): start the map; addTiles() pulls from OpenStreetMap
- setView(): sets the frame for the map
- addPulseMarkers(): adds pulsing markers
- addMarkers(): adds normal markers

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
- Do exercises 3 and 4 in today's practice file
  - R Practice
  - Shortlink: rmc.link/420r5

Predicting delays due to typhoons

Data

- If the ship will report a delay of at least 3 hours in the next 12-24 hours
- Ship location
- Typhoon location
- Typhoon wind speed

> We need to calculate distance between ships and typhoons

Distance for geo

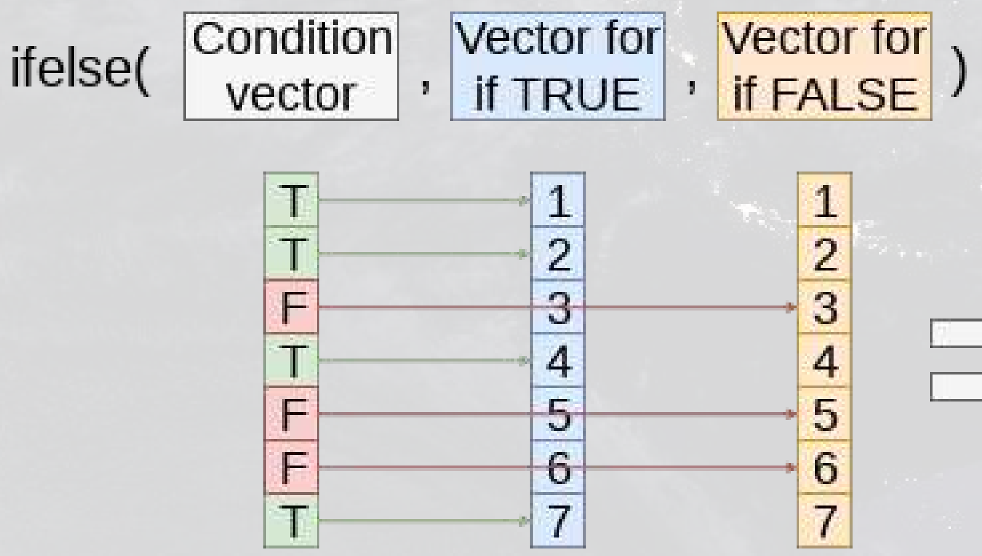
- There are a number of formulas for this
  - *Haversine* for a simple calculation
  - *Vincenty's formulae* for a complex, incredibly accurate calculation
    - Accurate within **0.5mm**
- Use `distVincentyEllipsoid()` from `geosphere` to get a reasonably quick and accurate calculation
  - Calculates 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

```r
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)
##
```

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 17% higher odds of having a delay

```
prob_odds1 <- c(exp(coef(fit1)[1]),
                exp(coef(fit1)[c(2, 3, 4)] + coef(fit1)[c(1, 1, 1)]))
probability1 <- prob_odds1 / (1 + prob_odds1)
probability1
```

```
## (Intercept)  typhoon_500 typhoon_1000 typhoon_2000
##   0.02523980   0.02894356   0.03081733   0.02950702
```

- Ships 1,000 to 2,000 km from a typhoon have a 3% chance of having a delay (baseline of 2.5%)

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 bins
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 ,c(41, 63, 88, 118, 150, 1000)/1.852)
table(df3$HK_intensity)
```

```
##
##   (22.1,34]   (34,47.5] (47.5,63.7]   (63.7,81]    (81,540]
##       13715       13228        9238        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

```
odds2 <- exp(coef(fit2))
odds2[c(1, 3, 10)]
```

```
##         (Intercept) typhoon_500:Moderate   typhoon_2000:Super
##          0.02589637           2.04505487           1.36507575
```

- Ships within 500km of a moderately strong storm have 104% higher odds of being delayed
- Ships 1,000 to 2,000km from a super typhoon have 36% higher odds

```
prob_odds2 <- c(exp(coef(fit2)[1]),
                exp(coef(fit2)[c(3, 10)] + coef(fit2)[c(1, 1)]))
probability2 <- prob_odds2 / (1 + prob_odds2)
probability2
```

```
##         (Intercept) typhoon_500:Moderate   typhoon_2000:Super
##          0.02524268           0.05029586           0.03414352
```

- Ships within 500km of a moderately strong storm have a 5% chance of being delayed (baseline: 2.5%)
- Ships 1,000 to 2,000km from a super typhoon have a 3.4% chance

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 the end of *next* Thursday
    - 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
- 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
  )
)
```