ACCT 420: Project Example

Project Example

Dr. Richard M. Crowley
rcrowley@smu.edu.sg
http://rmc.link/

Weekly revenue prediction at Walmart

The question

> How can we predict 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
    - We don't know what these numbers mean
  - 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)
    - We don't know what these letters mean
  - Store size
- Other data, by week and location:
  - Temperature, gas price, sales (by department), CPI, Unemployment rate, 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

```r
wmae <- function(actual, predicted, holidays) {
  ids <- !is.na(actual) & !is.na(predicted) & !is.na(holidays)
          sum(abs(actual[ids]-predicted[ids])*(holidays[ids]*4+1)) / (length(actual[ids]) + 4*sum(holidays[ids]))
}
```

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

```r
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
}
```

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

Merge data, fix `markdown`, build time data

What this looks like

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

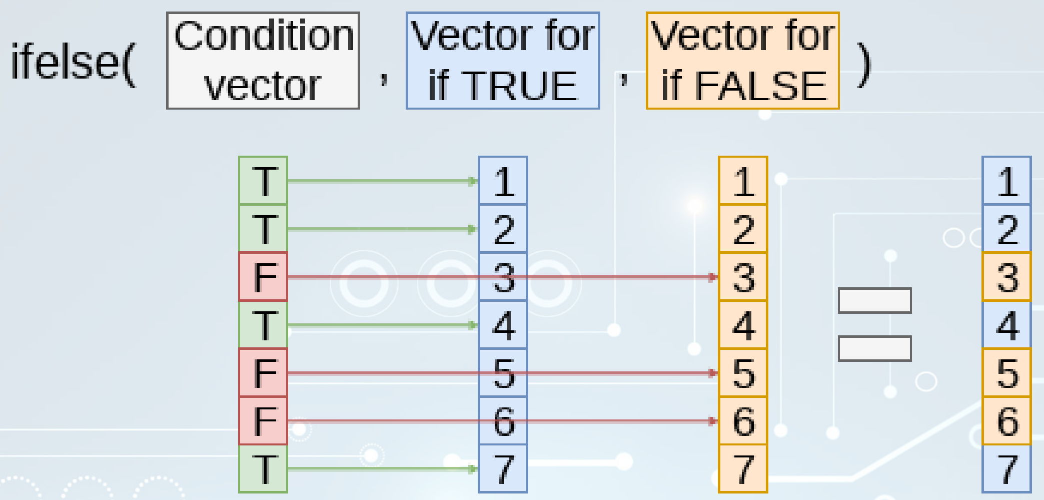
	Store	date	markdown	MarkDown3	MarkDown4	MarkDown5
91	1	2011-10-28	0.00	NA	NA	NA
92	1	2011-11-04	0.00	NA	NA	NA
93	1	2011-11-11	6551.42	215.07	2406.62	6551.42
94	1	2011-11-18	5988.57	51.98	427.39	5988.57

```r
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

```r
# 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(swd=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

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

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

Add in (store, department) average sales

```r
# 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")
```

```r
# 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

```r
# 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
```

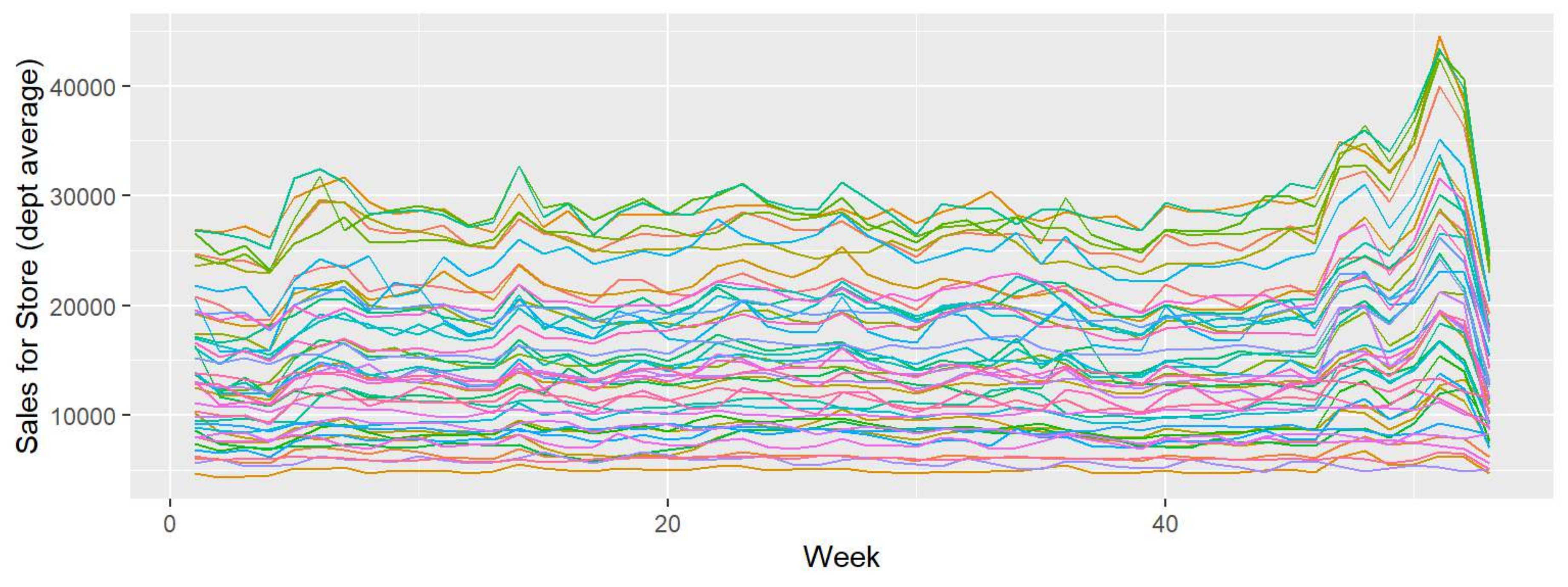
- Fix: Fill with 1 or 2 lags where possible using `ifelse()` and `lag()`
- Fix: Fill with 1 or 2 leads where possible using `ifelse()` and `lag()`
- Fill with `store_avg` when the above fail
- Code is available in the code file – a bunch of code like:

```
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

```r
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

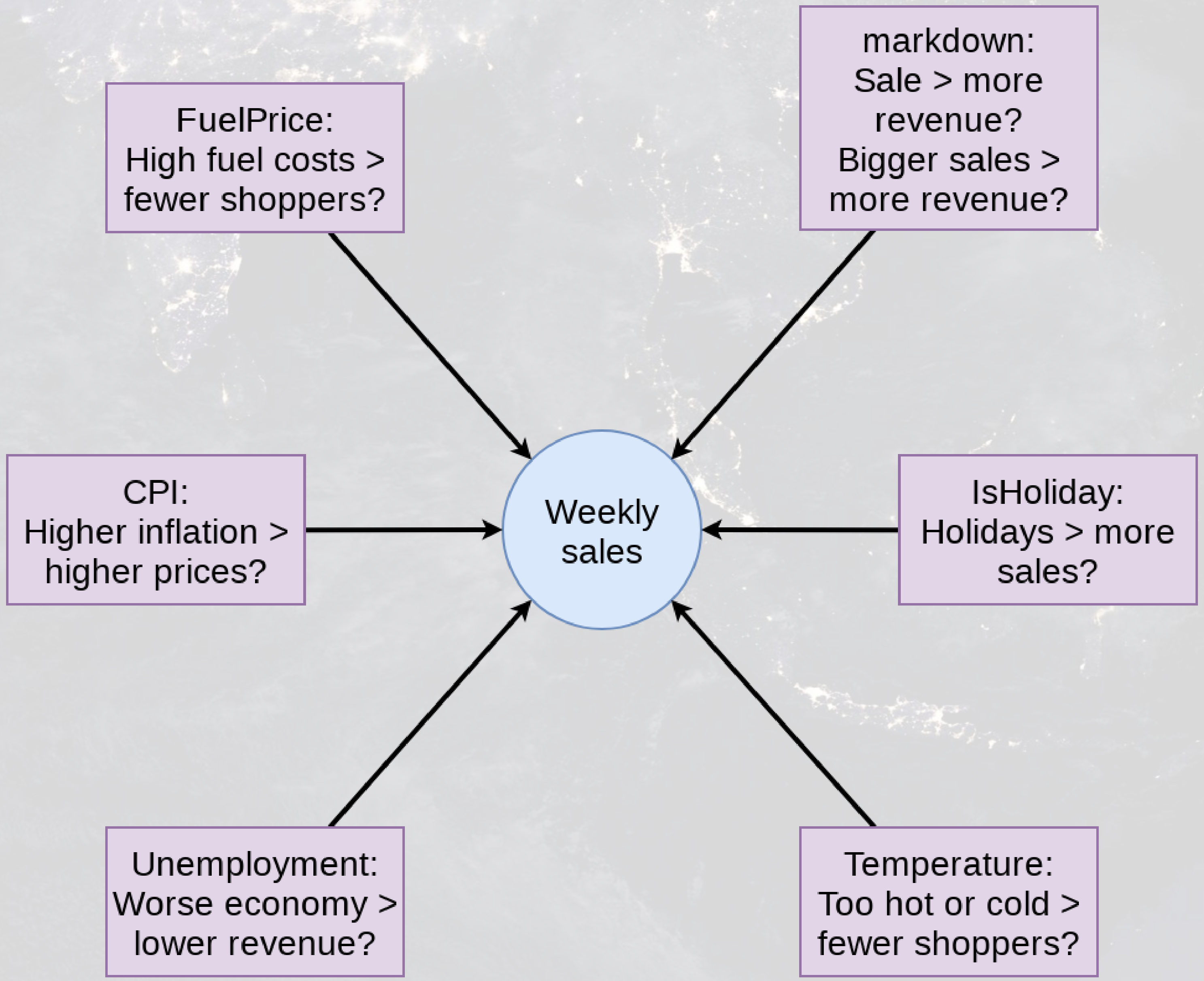
- Ideal: Use last week to predict next week!

No data for testing…

- First instinct: try to use a linear regression to solve this

We have this

What to put in the model?



First model

```r
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
```

```r
glance(mod1)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df   logLik     AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>    <dbl>   <dbl>  <dbl>
## 1  0.000481      0.000464  2.03      29.0 2.96e-40     7 -895684.  1.79e6 1.79e6
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

Prep submission and check in sample WMAE

```r
# 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
```

Performance for linear model

Your most recent submission

Name	Submitted	Wait time	Execution time	Score
WMT_linear.csv	just now	1 seconds	1 seconds	4993.42375

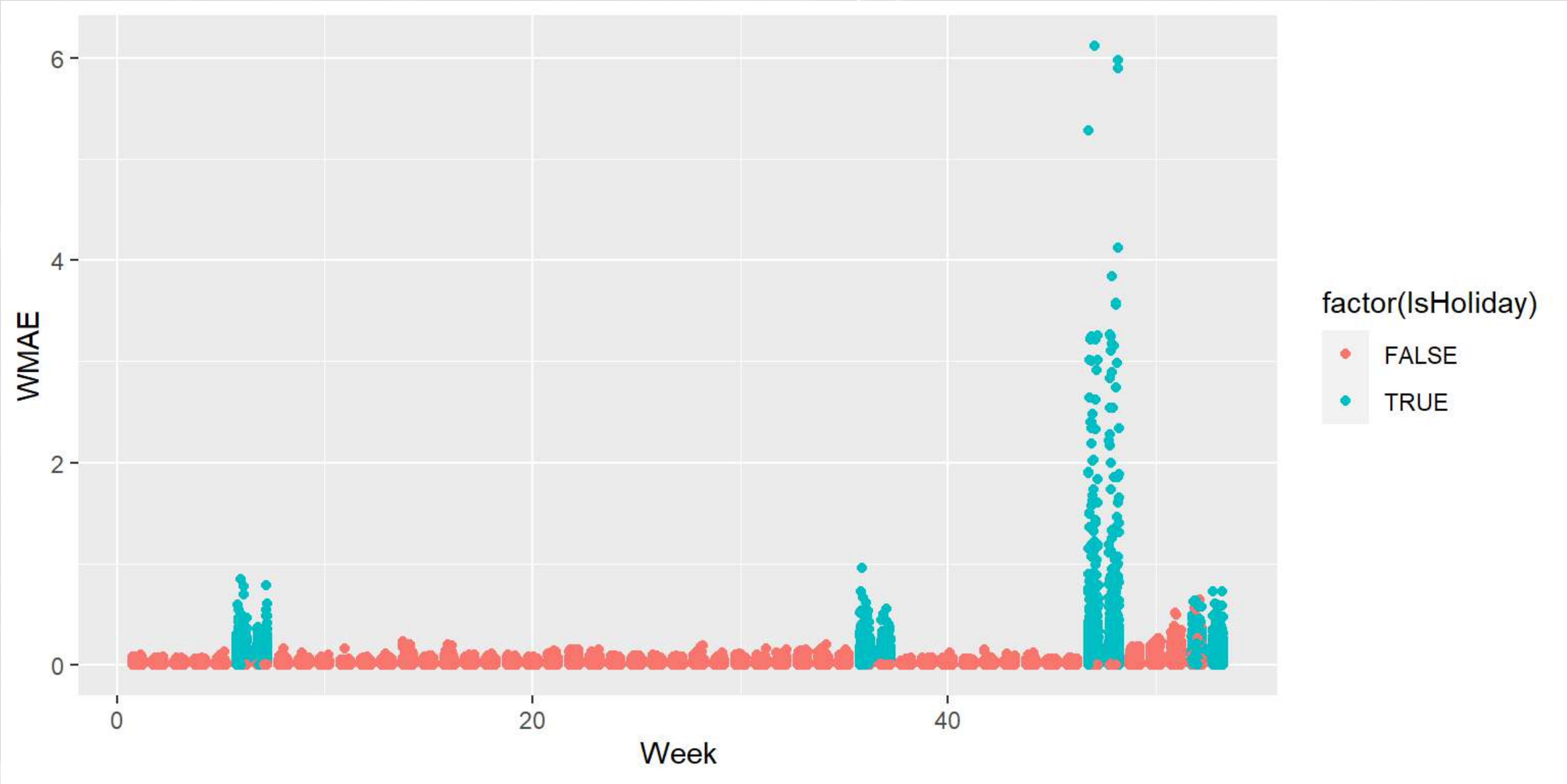
Complete

Jump to your position on the leaderboard ▾

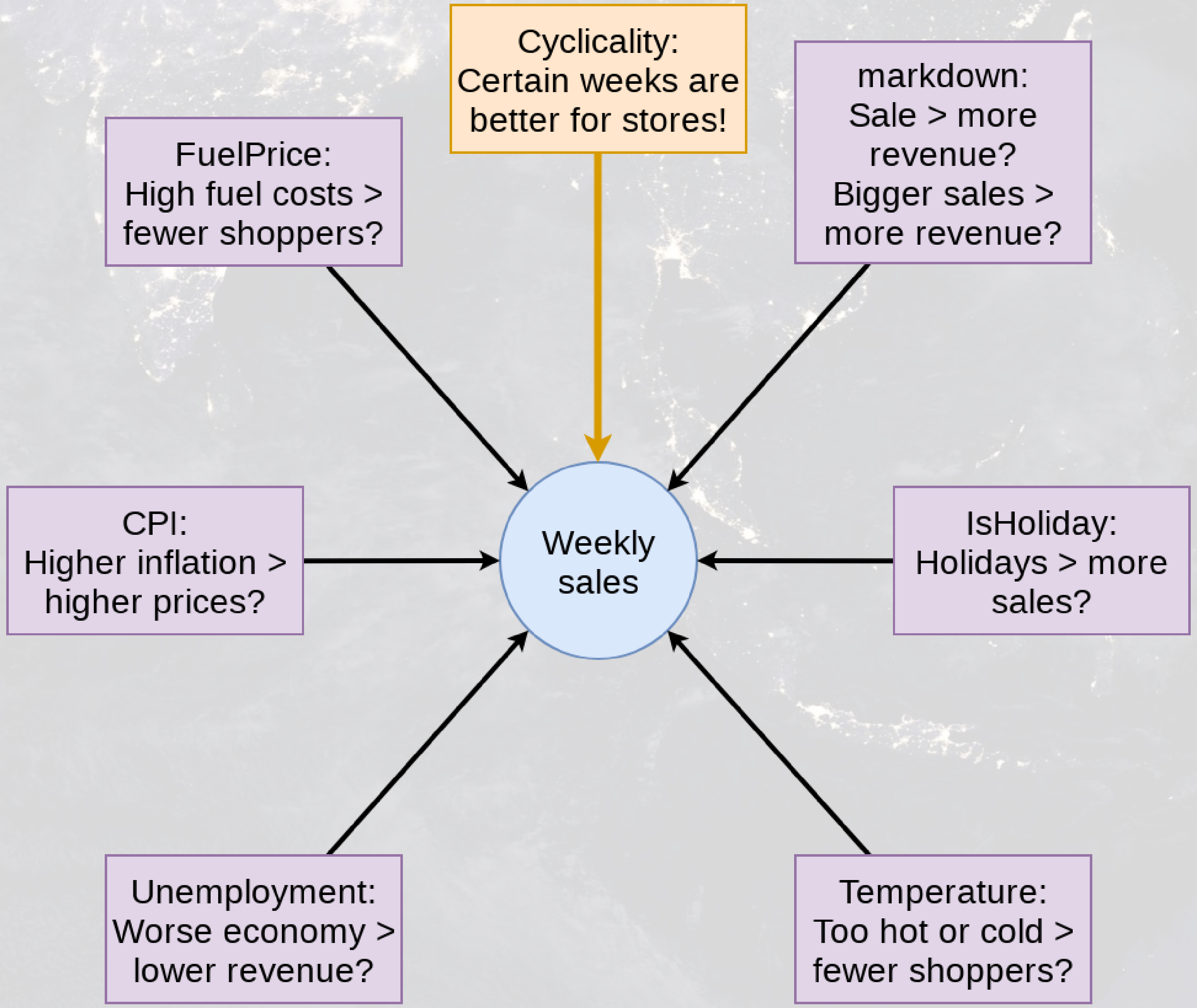
431	▾ 3	**Yogesh Bhalerao**	4972.22957	1	4y
432	▾ 1	**HQ**	4992.62853	10	4y
433	▴ 12	**Liam**	5030.06478	13	5y
434	▾ 2	**PopRocks**	5038.53020	7	4y

Visualizing in sample WMAE

```r
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

```r
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)       1.00      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
```

```r
glance(mod2)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df    logLik     AIC     BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>     <dbl>   <dbl>   <dbl>
## 1   0.00501       0.00487  2.02      35.9       0    59 -894728.  1.79e6  1.79e6
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <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
```

Performance for linear model 2

Your most recent submission

Name	Submitted	Wait time	Execution time	Score
WMT_linear2.csv	just now	1 seconds	1 seconds	5618.38979

Complete

Jump to your position on the leaderboard ▾

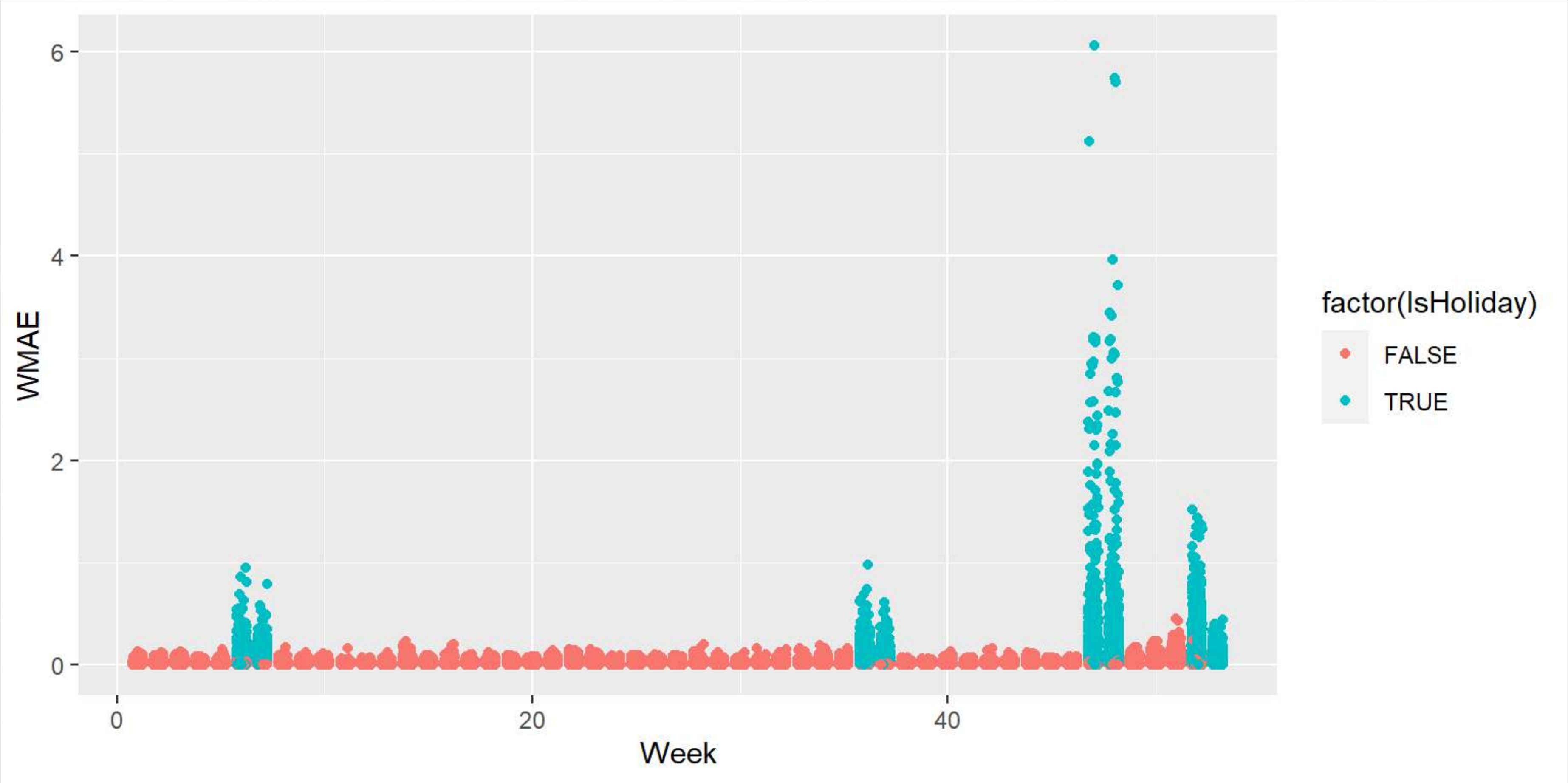
466	—	Jesus Fernandez-Bes	5547.45068	12	4y
467	▾ 3	Carmine Genovese	5553.17509	8	4y
468	▴ 4	27685	5694.66116	5	4y
469	—	nini	5705.89035	12	4y

```r
wmaes_out
```

```
##   Linear Linear 2
##   4993.4   5618.4
```

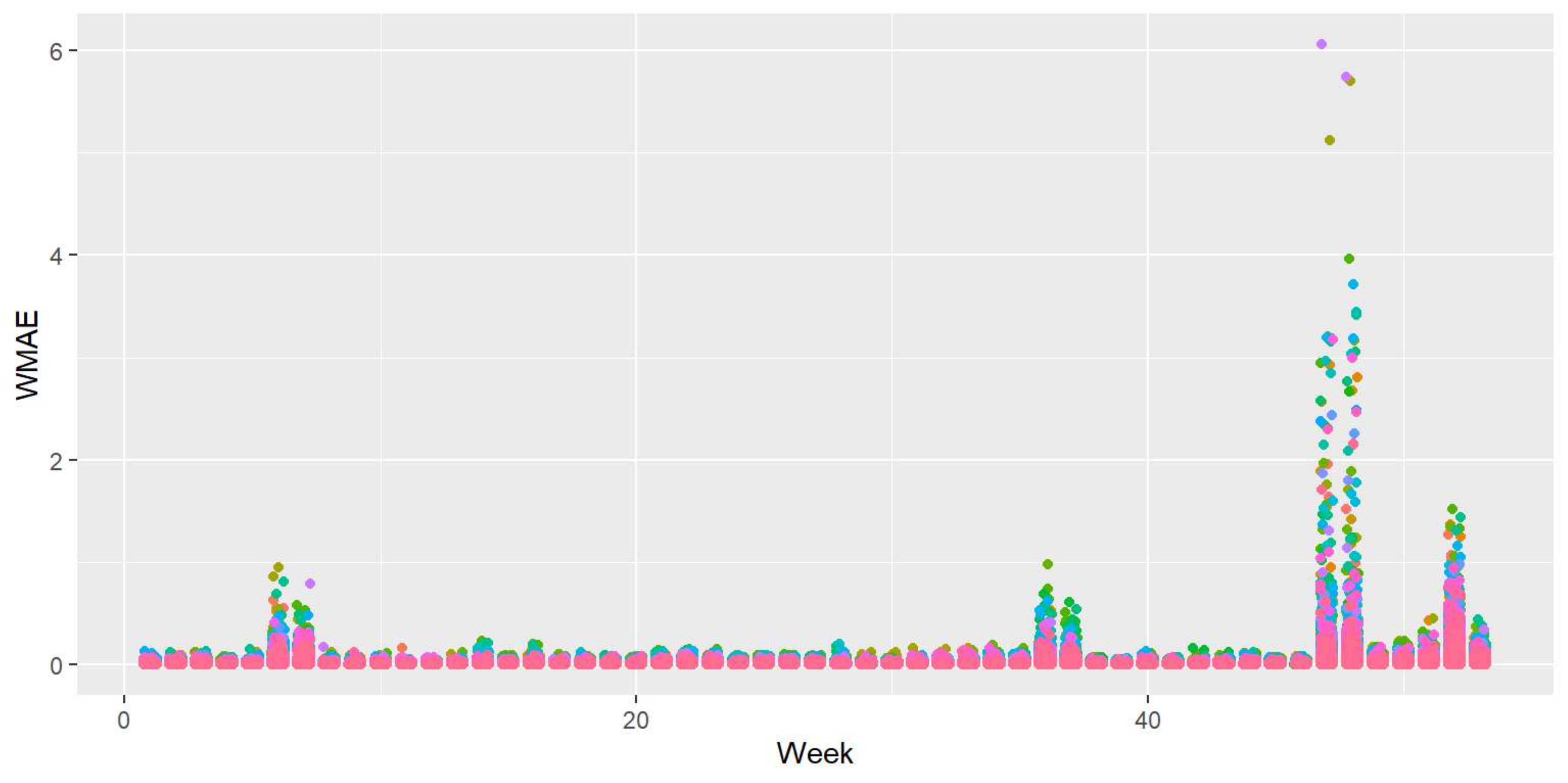
Visualizing in sample WMAE

```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")
```



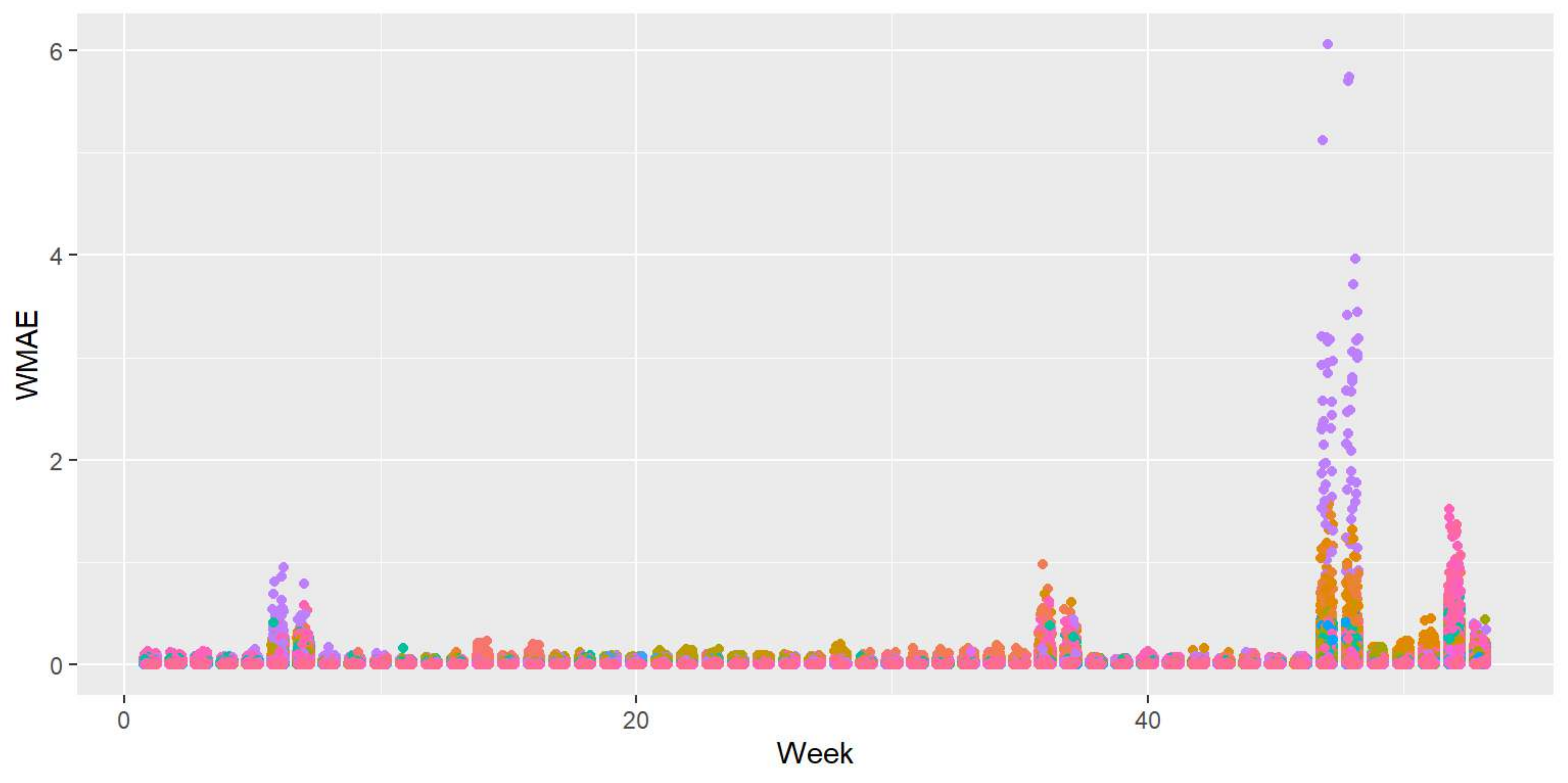
Visualizing in sample WMAE by Store

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

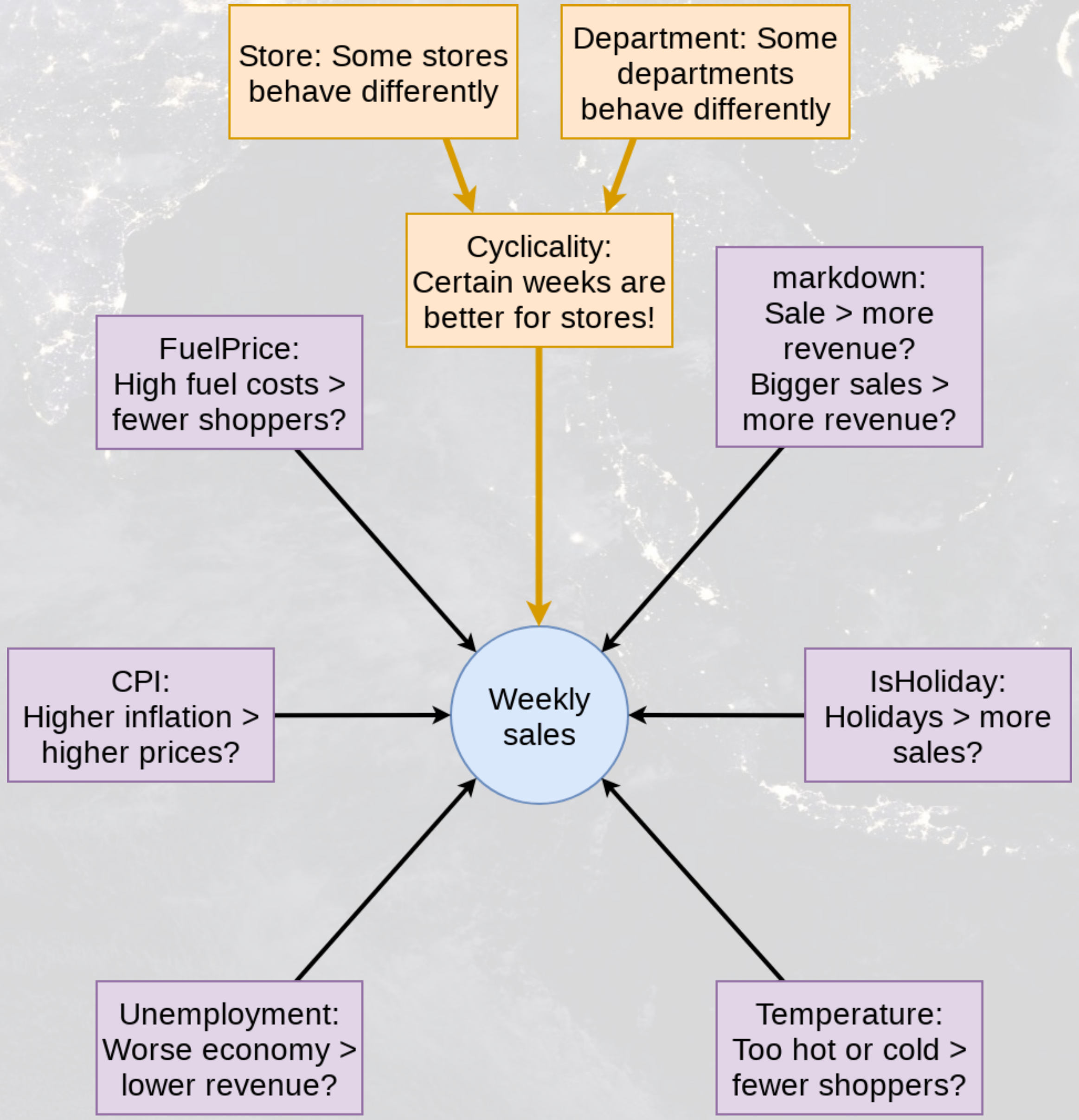


Visualizing in sample WMAE by Dept

```r
ggplot(data=df, aes(y=wmae_obs(actual=Weekly_Sales, predicted=WS_linear2,
                               holidays=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>0) +
                         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 `fixest`'s `feols()` – it really is more efficient!

```r
library(fixest)
mod3 <- feols(Weekly_mult ~ markdown +
            Temperature +
            Fuel_Price +
            CPI +
            Unemployment | id, 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 0.000000295     -4.73 2.24e- 6
## 2 Temperature   0.00135    0.000243         5.55 2.83e- 8
## 3 Fuel_Price   -0.0637     0.00905         -7.04 1.92e-12
## 4 CPI           0.00150    0.000800         1.87 6.13e- 2
## 5 Unemployment -0.0303     0.00386         -7.85 4.14e-15
```

```r
glance(mod3)
```

```
## # A tibble: 1 x 9
##   r.squared adj.r.squared within.r.squared pseudo.r.squared sigma   nobs     AIC
##       <dbl>         <dbl>            <dbl>            <dbl> <dbl>  <int>   <dbl>
## 1     0.823         0.712         0.000540               NA  1.09 421564  1.39e6
## # ... with 2 more variables: BIC <dbl>, logLik <dbl>
```

Prep submission and check in sample WMAE

```r
# Out of sample result
df_test$Weekly_mult <- predict(mod3, df_test)
df_test$Weekly_Sales <- df_test$Weekly_mult * df_test$store_avg
# Replace NA values with store average
df_test <- df_test %>%
  mutate(Weekly_Sales = ifelse(is.na(Weekly_Sales), naive_mean, Weekly_Sales))


# 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"
```

```
##   Linear Linear 2       FE
## 3073.570 3230.643 1552.190
```

Performance for FE model

Your most recent submission

Name	Submitted	Wait time	Execution time	Score
WMT_FE.csv	just now	1 seconds	1 seconds	3379.33623

Complete

Jump to your position on the leaderboard ▾

266	▾10	Gautam Gogoi	3370.85784	38	7y
267	▴2	JunkyardTornado	3371.93323	25	7y
268	▾1	ChandraAbha singh	3386.35229	5	7y
269	▾3	유훈 김	3404.50484	3	7y

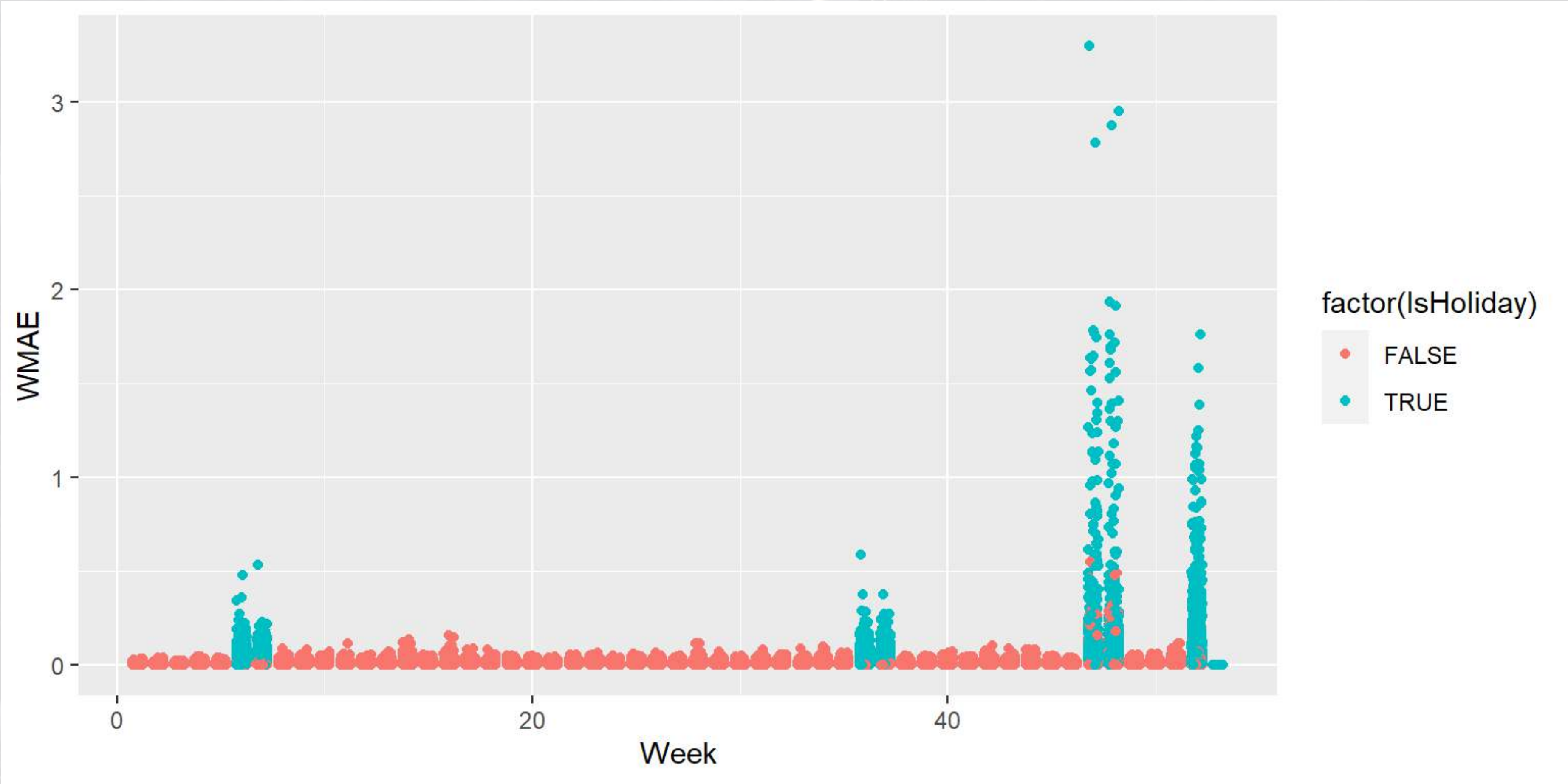
```r
wmaes_out
```

```
##   Linear Linear 2       FE
##   4993.4   5618.4   3379.3
```

Visualizing in sample WMAE

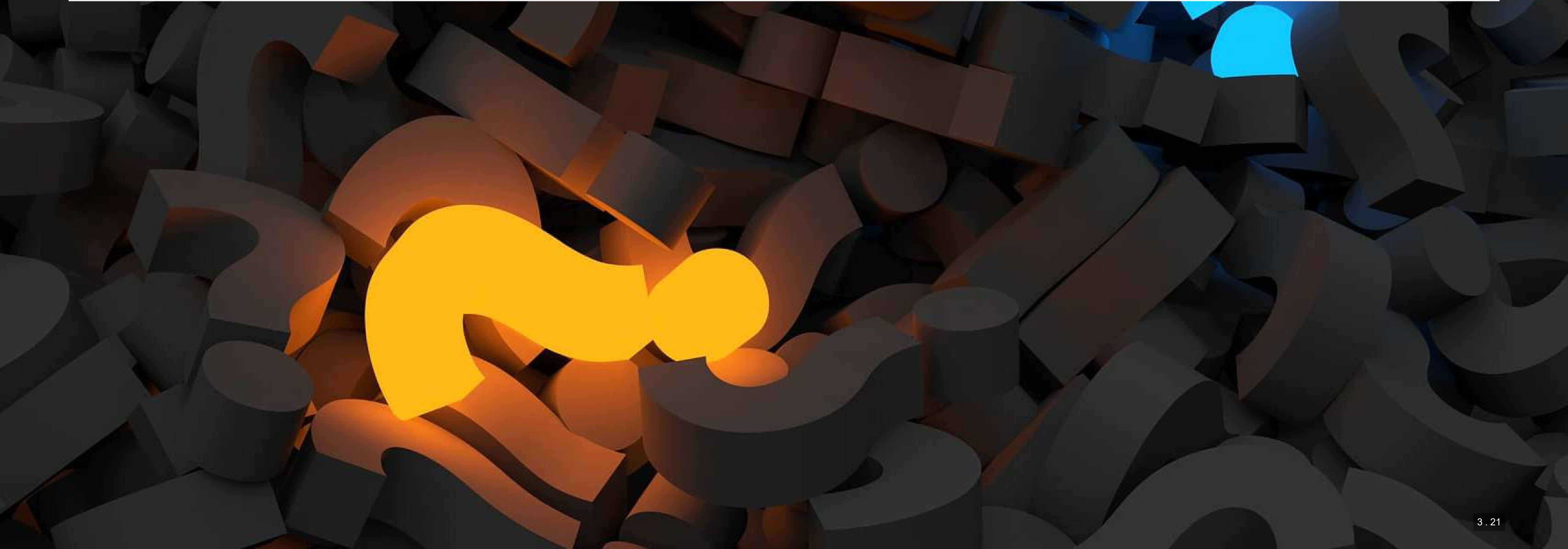
```r
df$wmaes  <- wmae_obs(actual=df$Weekly_Sales, predicted=df$WS_FE,
                      holidays=df$IsHoliday)
ggplot(data=df, aes(y=wmaes,
                    x=week,
                    color=factor(IsHoliday))) +
  geom_jitter(width=0.25) + xlab("Week") + ylab("WMAE")
```

```
## Warning: Removed 6 rows containing missing values (geom_point).
```



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?



Problems with the data

1. The holidays are not always on the same week
   - The Super Bowl is in weeks 6, 6, 7, *6*
   - Labor day isn't in our testing data at all!
   - Black Friday is in weeks 48, 47, and *47*
   - Christmas is in weeks 53, 52, and *52*
   - Manually adjust the data for these differences
2. Yearly growth – we aren't capturing it, since we have such a small time span
   - We can manually adjust the data for this

> Code is in the code file – a lot of `dplyr`

Performance overall

Your most recent submission

Name	Submitted	Wait time	Execution time	Score
WMT_FE_shift.csv	24 minutes ago	1 seconds	1 seconds	3274.80011

Complete

Jump to your position on the leaderboard ▾

241	▾2	Ugly Duckling	3264.66376	19	7y
242	▾2	Chiranjeev	3266.39474	3	7y
243	▴1	DataGeek	3277.58024	64	7y
244	▴5	Andrey Belyaev	3280.48211	1	7y

```r
wmaes_out
```

```
##      Linear   Linear 2         FE Shifted FE
##      4993.4     5618.4     3378.8     3274.8
```

End Matter

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

Packages used for these slides

- `broom`
- `fixest`
- `kableExtra`
- `knitr`
- `lubridate`
- `magrittr`
- `revealjs`
- `tidyverse`