ACCT 420: Advanced linear regression

Session 3

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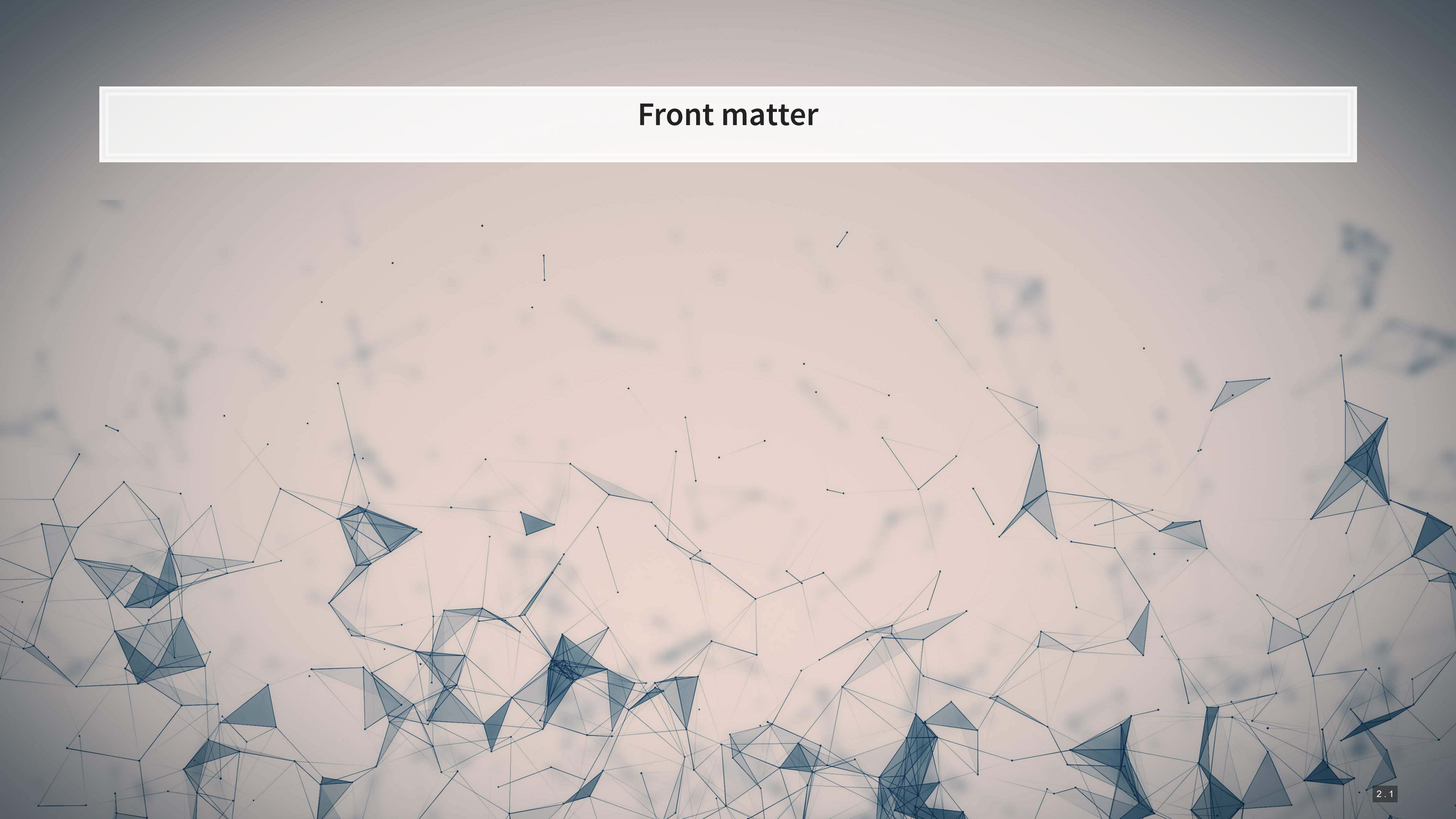
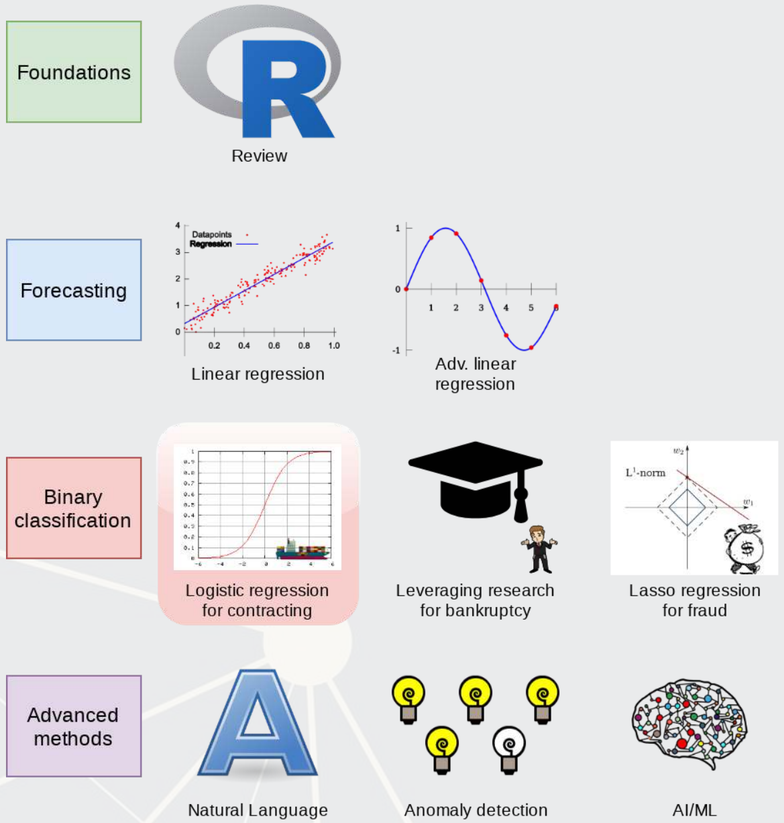
Front matter



Learning objectives



- **Theory:**
  - Further understand stats treatments
    - Panel data
    - Time (seasonality)
- **Application:**
  - Using international data for our UOL problem
  - Predicting revenue quarterly and weekly
- **Methodology:**
  - Univariate
  - Linear regression (OLS)
  - Visualization

Datacamp

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

Revisiting UOL with macro data

Macro data sources

- For Singapore: Data.gov.sg
  - Covers: Economy, education, environment, finance, health, infrastructure, society, technology, transport
- For real estate in Singapore: URA's REALIS system
  - Access through the library
- WRDS has some as well
- For US: data.gov, as well as many agency websites
  - Like BLS or the Federal Reserve

Loading macro data

- Singapore business expectations data (from data.gov.sg)

```r
# extract out Q1, finance only
expectations_avg <- expectations %>%
  filter(quarter == 1,                                  # Keep only the first quarter
         level_2 == "Financial & Insurance") %>%        # Keep only financial responses
  group_by(year) %>%                                    # Group data by year
  mutate(fin_sentiment=mean(value, na.rm=TRUE)) %>%     # Calculate average
  slice(1) %>%                                          # Take only 1 row per group
  ungroup()
```

- At this point, we can merge with our accounting data

What was in the macro data?

```r
expectations %>%
  arrange(level_2, level_3, desc(year)) %>%  # sort the data
  select(year, quarter, level_2, level_3, value) %>%  # keep only these variables
  datatable(options = list(pageLength = 5), rownames=FALSE)  # display using DT
```

Show ▾ entries

Search:

year	quarter	level_2	level_3	value
2018	1	Accommodation & Food Services	Accommodation	-7
2018	2	Accommodation & Food Services	Accommodation	38
2017	1	Accommodation & Food Services	Accommodation	-15
2017	2	Accommodation & Food Services	Accommodation	27
2017	3	Accommodation & Food Services	Accommodation	11

Showing 1 to 5 of 846 entries

Previous 1 2 3 4 5 … 170 Next

dplyr makes merging easy

- For merging, use `dplyr`'s `*_join()` commands
  - `left_join()` for merging a dataset into another
  - `inner_join()` for keeping only matched observations
  - `outer_join()` for making all possible combinations
- For sorting, `dplyr`'s `arrange()` command is easy to use
  - For sorting in reverse, combine `arrange()` with `desc()`
    - Or you can just put a – in front of the column name

Merging example

Merge in the finance sentiment data to our accounting data

```
# subset out our Singaporean data, since our macro data is Singapore-specific
df_SG <- df_clean %>% filter(fic == "SGP")

# Create year in df_SG (date is given by datadate as YYYYMMDD)
df_SG$year = round(df_SG$datadate / 10000, digits=0)

# Combine datasets
# Notice how it automatically figures out to join by "year"
df_SG_macro <- left_join(df_SG, expectations_avg[,c("year","fin_sentiment")])
```

```
## Joining, by = "year"
```

Predicting with macro data

Building in macro data

- First try: Just add it in

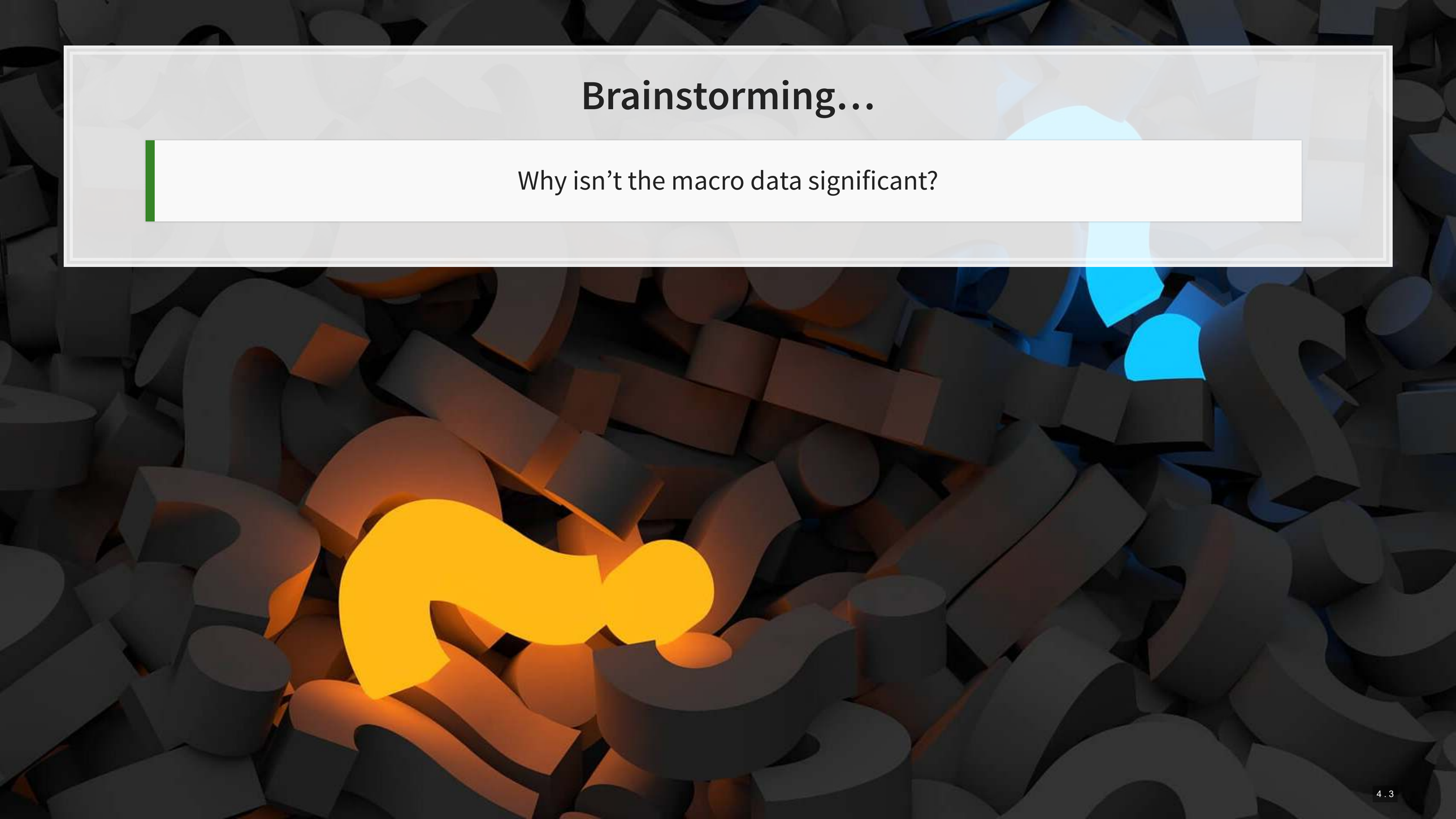
```
macro1 <- lm(revt_lead ~ revt + act + che + lct + dp + ebit + fin_sentiment,
             data=df_SG_macro)
library(broom)
tidy(macro1)
```

```
## # A tibble: 8 x 5
##   term          estimate std.error statistic       p.value
##   <chr>            <dbl>     <dbl>     <dbl>         <dbl>
## 1 (Intercept)     24.0     15.9         1.50  0.134
## 2 revt             0.497    0.0798      6.22  0.00000000162
## 3 act             -0.102    0.0569     -1.79  0.0739
## 4 che              0.495    0.167       2.96  0.00329
## 5 lct              0.403    0.0903      4.46  0.0000114
## 6 dp               4.54     1.63        2.79  0.00559
## 7 ebit            -0.930    0.284      -3.28  0.00117
## 8 fin_sentiment    0.122    0.472       0.259 0.796
```

It isn’t significant. Why is this?

Brainstorming…

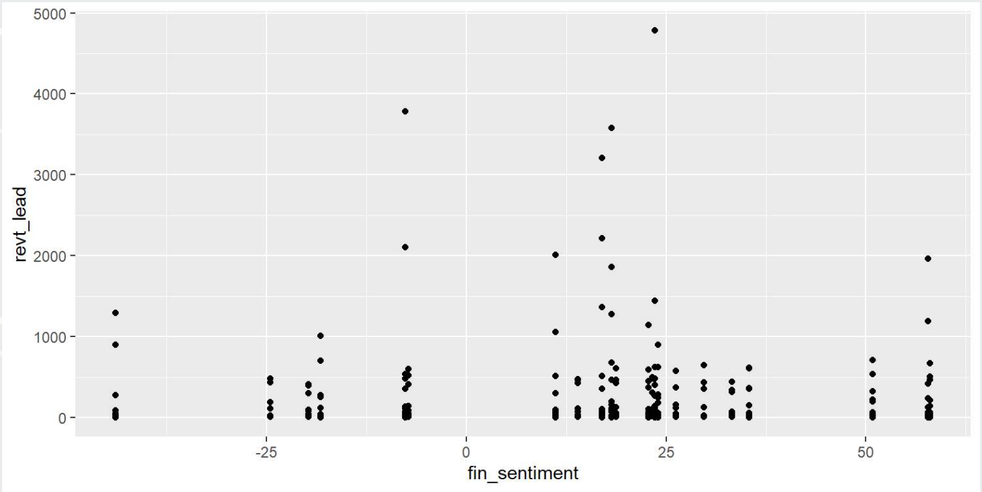
Why isn’t the macro data significant?



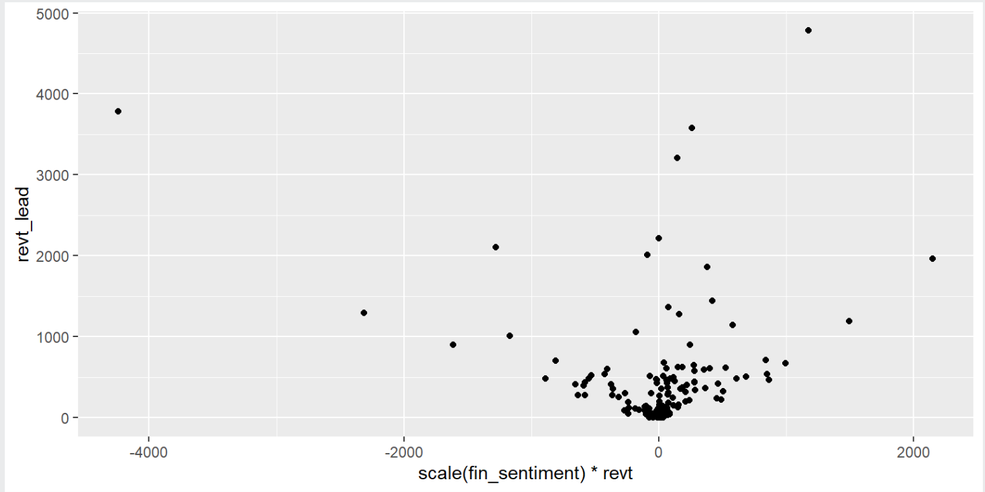
Scaling matters

- All of our firm data is on the same terms as revenue: dollars within a given firm
- But `fin_sentiment` is a constant scale…
  - Need to scale this to fit the problem
    - The current scale would work for revenue growth

```
df_SG_macro %>%
  ggplot(aes(y=revt_lead,
             x=fin_sentiment)) +
  geom_point()
```




```
df_SG_macro %>%
  ggplot(aes(y=revt_lead,
    x=scale(fin_sentiment) * revt)) +
  geom_point()
```



Scaled macro data

- Normalize and scale by revenue

```
# Scale creates z-scores, but returns a matrix by default.  [,1] gives a vector
df_SG_macro$fin_sent_scaled <- scale(df_SG_macro$fin_sentiment)[,1]
macro3 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit + fin_sent_scaled:revt,
     data=df_SG_macro)
tidy(macro3)
```

```
## # A tibble: 8 x 5
##   term                 estimate std.error statistic       p.value
##   <chr>                   <dbl>     <dbl>     <dbl>         <dbl>
## 1 (Intercept)            25.5      13.8         1.84 0.0663
## 2 revt                    0.490     0.0789      6.21 0.00000000170
## 3 act                    -0.0677    0.0576     -1.18 0.241
## 4 che                     0.439     0.166       2.64 0.00875
## 5 lct                     0.373     0.0898      4.15 0.0000428
## 6 dp                      4.10      1.61        2.54 0.0116
## 7 ebit                   -0.793     0.285      -2.78 0.00576
## 8 revt:fin_sent_scaled    0.0897    0.0332      2.70 0.00726
```

```
glance(macro3)
```

```
## # 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     0.847         0.844  215.      240. 1.48e-119     7 -2107. 4232. 4265.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

Model comparisons

```
baseline <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit,
     data=df_SG_macro[!is.na(df_SG_macro$fin_sentiment),])
glance(baseline)
```

```
## # 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     0.843         0.840  217.      273. 3.13e-119     6 -2111. 4237. 4267.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
glance(macro3)
```

```
## # 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     0.847         0.844  215.      240. 1.48e-119     7 -2107. 4232. 4265.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

Adjusted R^2 and AIC are slightly better with macro data

Model comparisons

```
anova(baseline, macro3, test="Chisq")
```

```
## Analysis of Variance Table
##
## Model 1: revt_lead ~ revt + act + che + lct + dp + ebit
## Model 2: revt_lead ~ revt + act + che + lct + dp + ebit + fin_sent_scaled:revt
##   Res.Df      RSS Df Sum of Sq Pr(>Chi)
## 1    304 14285622
## 2    303 13949301  1    336321 0.006875 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Macro model definitely fits better than the baseline model!

Takeaway

1. Adding macro data can help explain some exogenous variation in a model
   - Exogenous meaning outside of the firms, in this case
2. Scaling is very important
   - Not scaling properly can suppress some effects from being visible

> Interpretating the macro variable

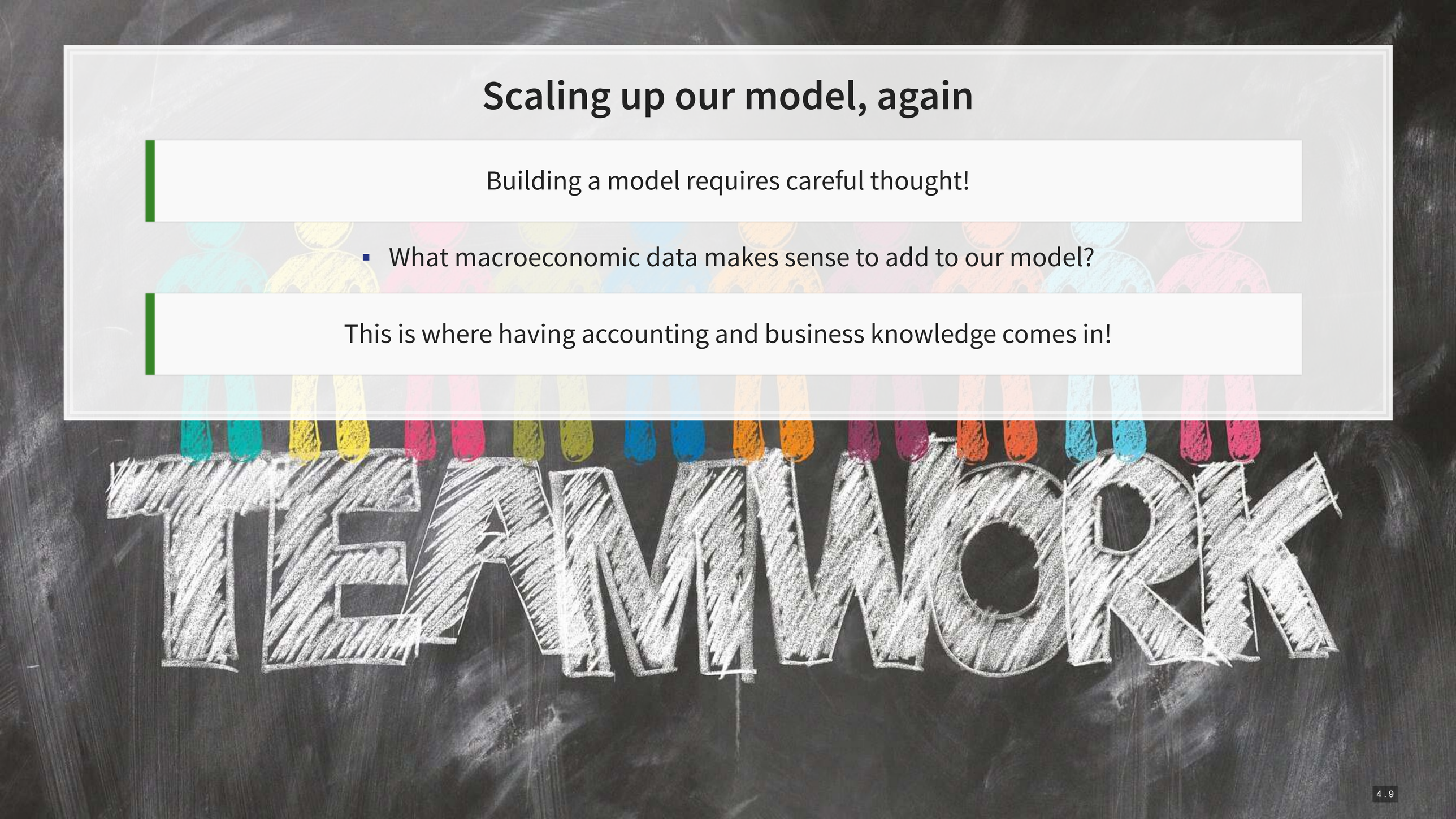
- For every 1 S.D. increase in `fin_sentiment` (25.7 points)
  - Revenue stickiness increases by ~1.1%
- Over the range of data (-43.8 to 58)…
  - Revenue stickiness ranges from -1.8% to 2.4%

Scaling up our model, again

Building a model requires careful thought!

- What macroeconomic data makes sense to add to our model?

This is where having accounting and business knowledge comes in!



Brainstorming...

What other macro data would you like to add to this model?

Validation: Is it better?

Validation

- Ideal:
  - Withhold the last year (or a few) of data when building the model
  - Check performance on *hold out sample*
  - This is *out of sample* testing
- Sometimes acceptable:
  - Withhold a random sample of data when building the model
  - Check performance on *hold out sample*

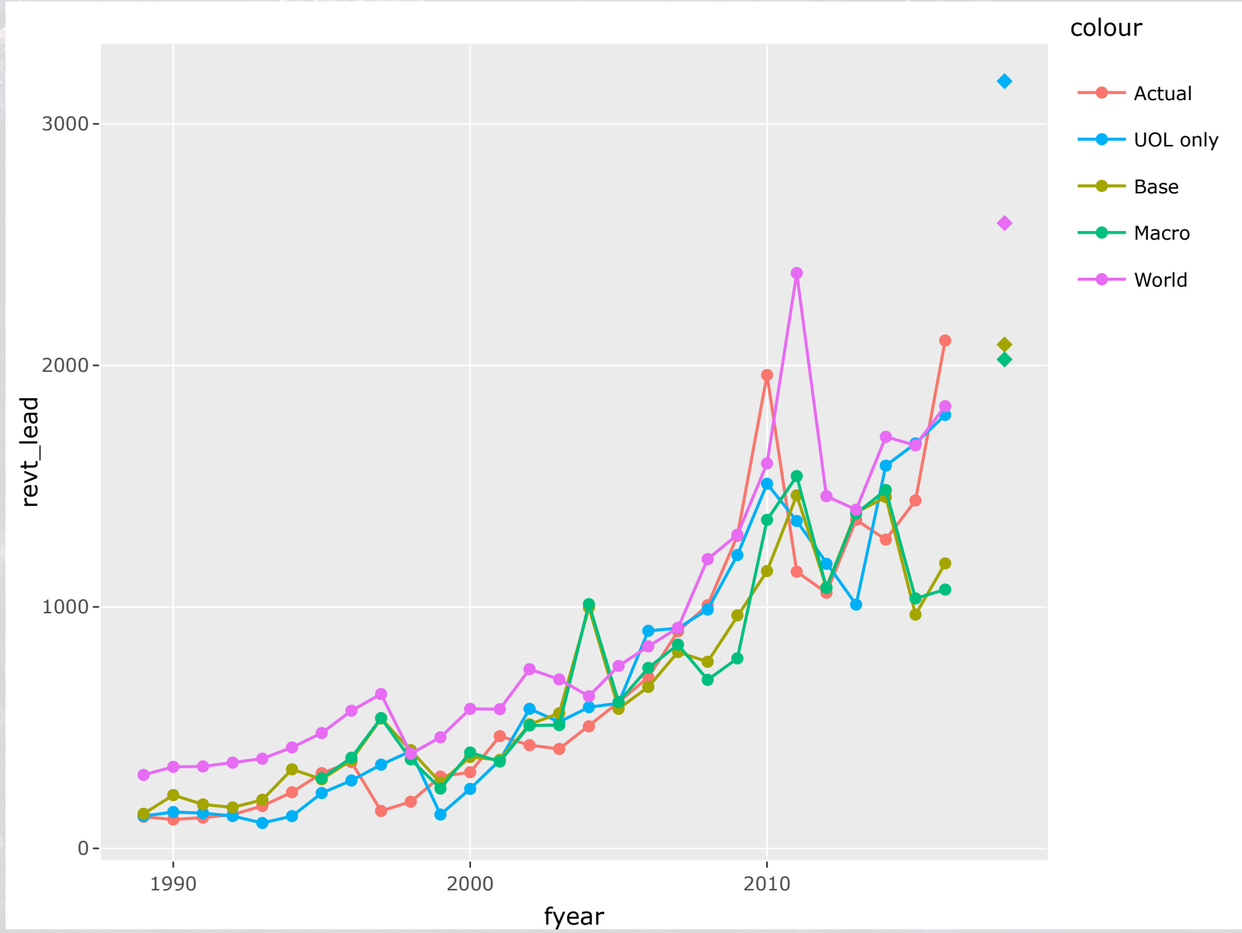
Estimation

- As we never constructed a hold out sample, let's end by estimating UOL's *2018* year revenue
  - Announced in 2019

```
p_uol <- predict(forecast2, uol[uol$fyear==2017,])
p_base <- predict(baseline,
  df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear==2017,])
p_macro <- predict(macro3,
  df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear==2017,])
p_world <- predict(forecast4,
  df_clean[df_clean$isin=="SG1S83002349" & df_clean$fyear==2017,])
preds <- c(p_uol, p_base, p_macro, p_world)
names(preds) <- c("UOL 2018 UOL", "UOL 2018 Base", "UOL 2018 Macro",
                  "UOL 2018 World")
preds
```

```
##   UOL 2018 UOL  UOL 2018 Base UOL 2018 Macro UOL 2018 World
##       3177.073       2086.437       2024.842       2589.636
```

Visualizing our prediction



In Sample Accuracy

```r
# series vectors calculated here -- See appendix
rmse <- function(v1, v2) {
  sqrt(mean((v1 - v2)^2, na.rm=T))
}

rmse <- c(rmse(actual_series, uol_series), rmse(actual_series, base_series),
          rmse(actual_series, macro_series), rmse(actual_series, world_series))
names(rmse) <- c("UOL 2018 UOL", "UOL 2018 Base", "UOL 2018 Macro", "UOL 2018 World")
rmse
```

```
##    UOL 2018 UOL  UOL 2018 Base UOL 2018 Macro UOL 2018 World
##        175.5609       301.3161       344.9681       332.8101
```

Why is UOL the best for *in sample*?

Actual Accuracy

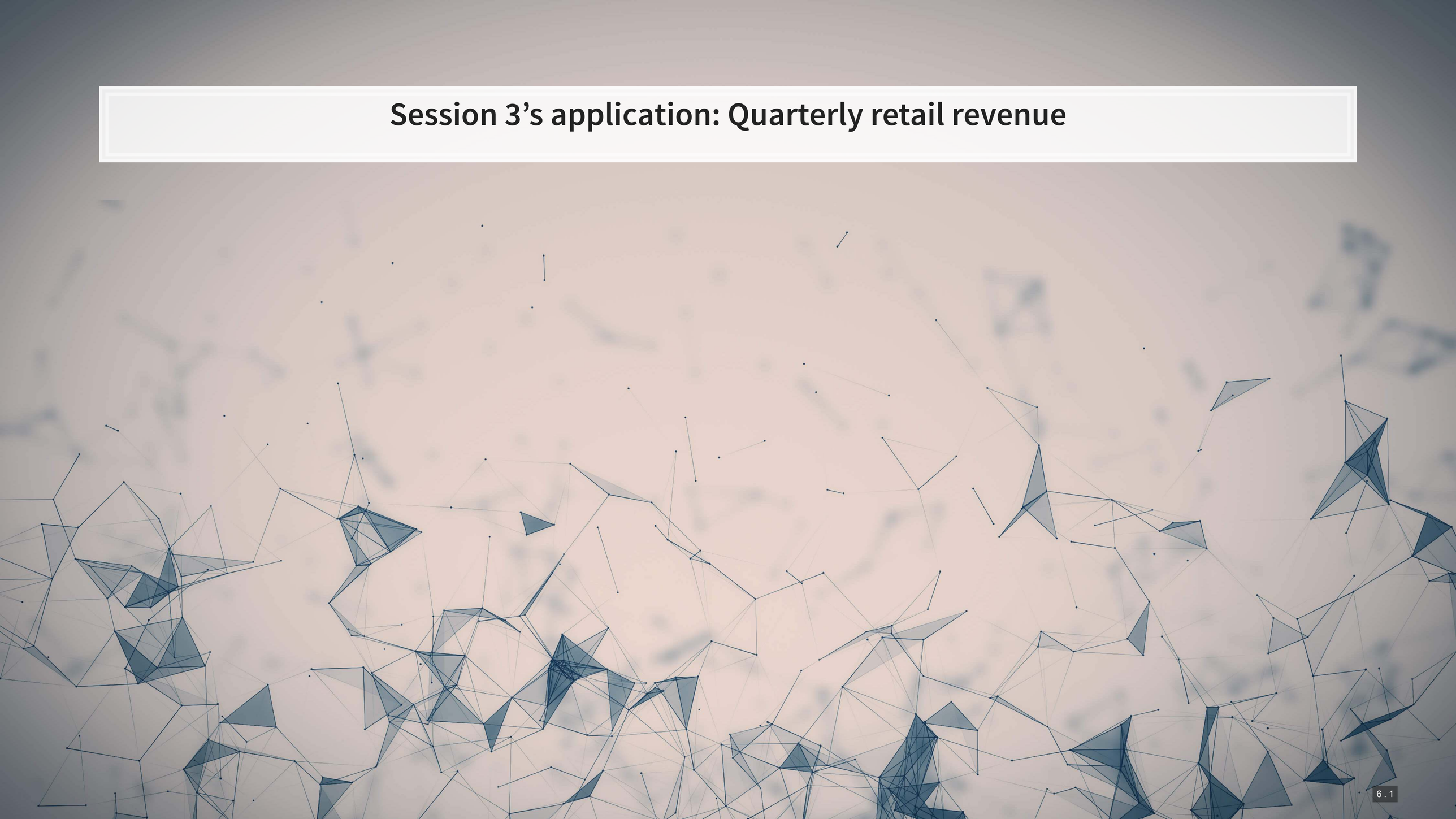
UOL posted a $2.40B in revenue in 2018.

```
preds
```

```
##   UOL 2018 UOL  UOL 2018 Base UOL 2018 Macro UOL 2018 World
##       3177.073       2086.437       2024.842       2589.636
```

Why is the global model better? Consider UOL's business model (2018 annual report)

Session 3’s application: Quarterly retail revenue



The question

> How can we predict quarterly revenue for retail companies, leveraging our knowledge of such companies?

- In aggregate
- By Store
- By department

More specifically…

- Consider time dimensions
  - What matters:
    - Last quarter?
    - Last year?
    - Other time frames?
  - Cyclicality

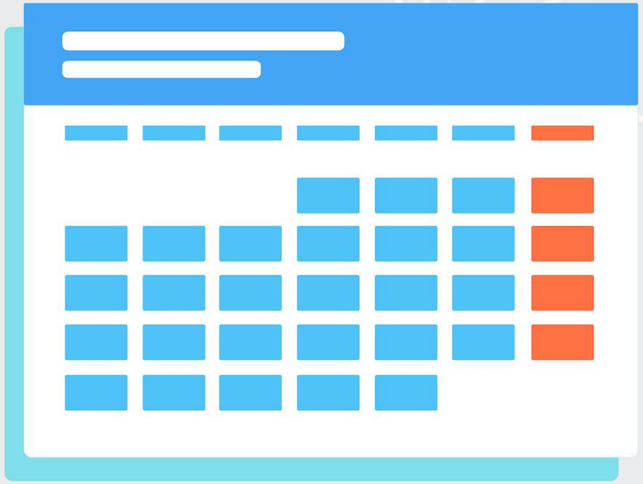
Time and OLS

Time matters a lot for retail

Great Singapore Sale

How to capture time effects?

- Autoregression
  - Regress y_t on earlier value(s) of itself
    - Last quarter, last year, etc.
- Controlling for time directly in the model
  - Essentially the same as fixed effects last week



Quarterly revenue prediction

The data

- From quarterly reports
- Two sets of firms:
  - US “Hypermarkets & Super Centers” (GICS: 30101040)
  - US “Multiline Retail” (GICS: 255030)
- Data from Compustat - Capital IQ > North America - Daily > Fundamentals Quarterly

Formalization

1. Question
   - How can we predict quarterly revenue for large retail companies?
2. Hypothesis (just the alternative ones)
   1. Current quarter revenue helps predict next quarter revenue
   2. 3 quarters ago revenue helps predict next quarter revenue (Year-over-year)
   3. Different quarters exhibit different patterns (seasonality)
   4. A long-run autoregressive model helps predict next quarter revenue
3. Prediction
   - Use OLS for all the above – t-tests for coefficients
   - Hold out sample: 2015-2017

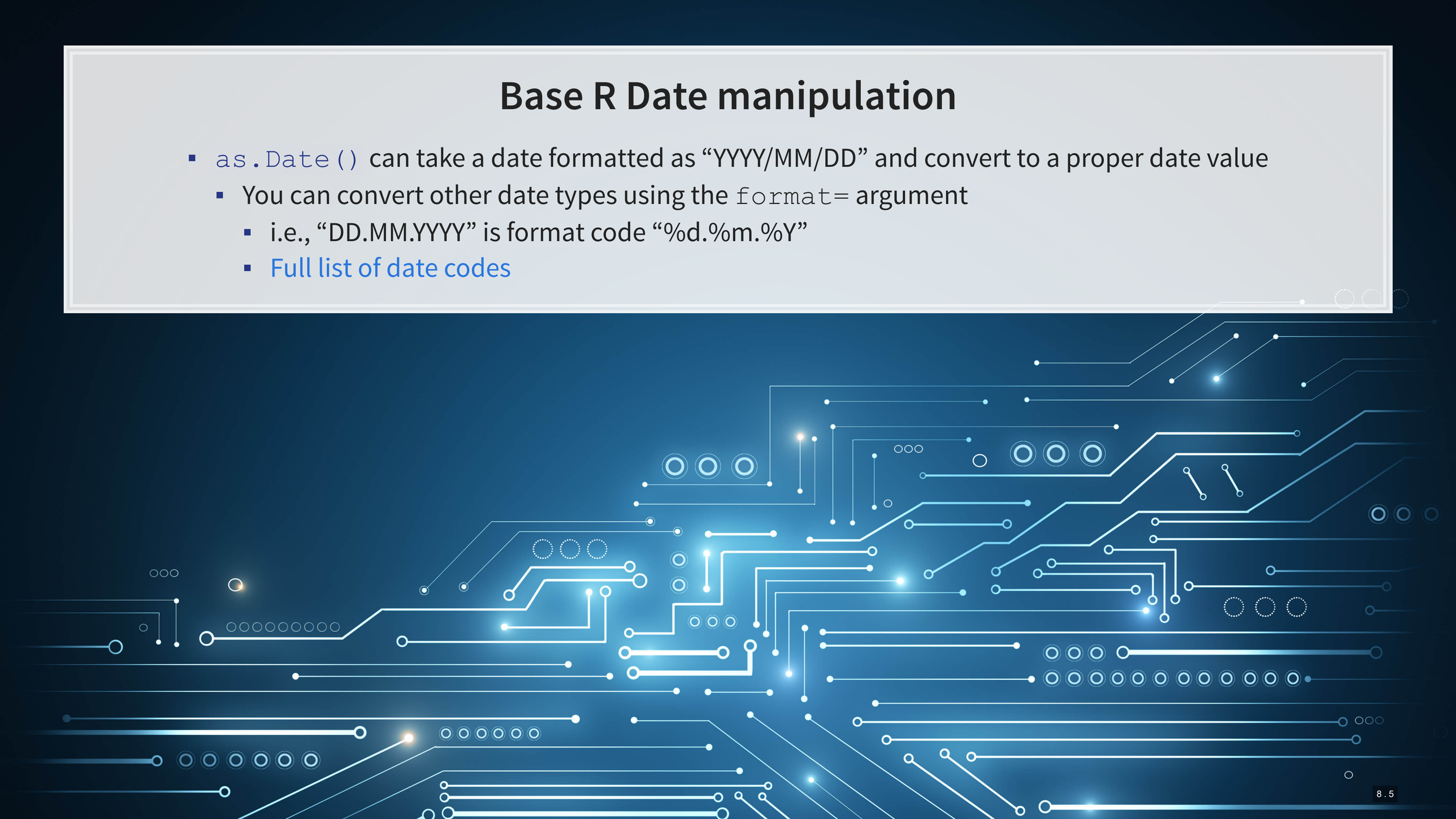
Variable generation

```r
library(tidyverse)  # As always
library(plotly)  # interactive graphs
library(lubridate)  # import some sensible date functions

# Generate quarter over quarter growth "revtq_gr"
df <- df %>% group_by(gvkey) %>% mutate(revtq_gr=revtq / lag(revtq) - 1) %>% ungroup()

# Generate year-over-year growth "revtq_yoy"
df <- df %>% group_by(gvkey) %>% mutate(revtq_yoy=revtq / lag(revtq, 4) - 1) %>% ungroup()

# Generate first difference "revtq_d"
df <- df %>% group_by(gvkey) %>% mutate(revtq_d=revtq - lag(revtq)) %>% ungroup()

# Generate a proper date
# Date was YYMMDDs10: YYYY/MM/DD, can be converted from text to date easily
df$date <- ymd(df$datadate)  # From lubridate
df$qtr <- quarter(df$date)   # From lubridate
```

- Use mutate for variables using lags
- `ymd()` from `lubridate` is a handy way of converting any date listing year, then month, than day.
  - It also has `ydm()`, `mdy()`, `myd()`, `dmy()` and `dym()`
  - It can handle quarters, times, and date-times as well
  - Cheat sheet

Base R Date manipulation

- `as.Date()` can take a date formatted as “YYYY/MM/DD” and convert to a proper date value
  - You can convert other date types using the `format=` argument
    - i.e., “DD.MM.YYYY” is format code “%d.%m.%Y”
    - Full list of date codes



Example output

conm	date	revtq	revtq_gr	revtq_yoy	revtq_d
ALLIED STORES	1962-04-30	156.5	NA	NA	NA
ALLIED STORES	1962-07-31	161.9	0.0345048	NA	5.4
ALLIED STORES	1962-10-31	176.9	0.0926498	NA	15.0
ALLIED STORES	1963-01-31	275.5	0.5573770	NA	98.6
ALLIED STORES	1963-04-30	171.1	-0.3789474	0.0932907	-104.4
ALLIED STORES	1963-07-31	182.2	0.0648743	0.1253860	11.1

```
## # A tibble: 6 x 3
##   conm          date       datadate
##   <chr>         <date>     <chr>
## 1 ALLIED STORES 1962-04-30 1962/04/30
## 2 ALLIED STORES 1962-07-31 1962/07/31
## 3 ALLIED STORES 1962-10-31 1962/10/31
## 4 ALLIED STORES 1963-01-31 1963/01/31
## 5 ALLIED STORES 1963-04-30 1963/04/30
## 6 ALLIED STORES 1963-07-31 1963/07/31
```

Create 8 quarters (2 years) of lags

- 8 is easy to do by copying and pasting code, but it is nice to have something more flexible
  - What if we wanted 100 lags?
    - That would be a lot of copying
      - The for this is in the appendix
- Three solutions, though none is straightforward
  - Use sapply and a function to reassemble output into a data frame (omitted)
  - Use advanced dplyr programming with quosures
  - Use `purrr` to loop into a data frame
- To compare the methods, we'll make a copy of the data frame

```
# Make a copy of our data frame to compare later
df_purrr <- df
```

The methods

```r
# Approach #1: Advanced programming using quosures...
library(rlang)
multi_lag <- function(df, lags, var, postfix="") {
  var <- enquo(var)
  quosures <- map(lags, ~quo(lag(!!var, !!.x))) %>%
    set_names(paste0(quo_text(var), postfix, lags))
  return(ungroup(mutate(group_by(df, gvkey), !!!quosures)))
}
```

```r
# Approach #2: Mixing purrr with dplyr across()
library(purrr)
multi_lag_purrr <- function(df, lags, var, postfix="") {
  new_columns <-
    map_dfc(lags,
      function(x) df %>%
        group_by(gvkey) %>%
        transmute(across(all_of(var),
                         .fns = list(~ lag(., x)),
                         .names = paste0('{col}', postfix, x) ) ) %>%
        ungroup() %>%
        select(-gvkey))
  cbind(df, new_columns)
}
```

- `paste0()`: creates a string vector by concatenating all inputs
- `setNames()`: allows for storing a value and name simultaneously
- `transmute()`: like mutate except it extracts the column it makes automatically

Comparing the methods

1. Using advanced programming techniques

```r
df <- multi_lag(df, 1:8, revtq, "_l")   # Generate lags "revtq_l#"
df <- multi_lag(df, 1:8, revtq_gr)      # Generate changes "revtq_gr#"
df <- multi_lag(df, 1:8, revtq_yoy)     # Generate year-over-year changes "revtq_yoy#"
df <- multi_lag(df, 1:8, revtq_d)       # Generate first differences "revtq_d#"
```

2. Using `purrr` + `dplyr`

```r
df_purrr <- multi_lag_purrr(df_purrr, 1:8, 'revtq', "_l")   # Generate lags "revtq_l#"
df_purrr <- multi_lag_purrr(df_purrr, 1:8, 'revtq_gr')      # Generate changes "revtq_gr#"
df_purrr <- multi_lag_purrr(df_purrr, 1:8, 'revtq_yoy')     # Generate year-over-year changes "revtq_yoy#"
df_purrr <- multi_lag_purrr(df_purrr, 1:8, 'revtq_d')       # Generate first differences "revtq_d#"
```

- Verify that the output is the same

```r
all(df==df_purrr, na.rm=T)
```

```
## [1] TRUE
```

Example output

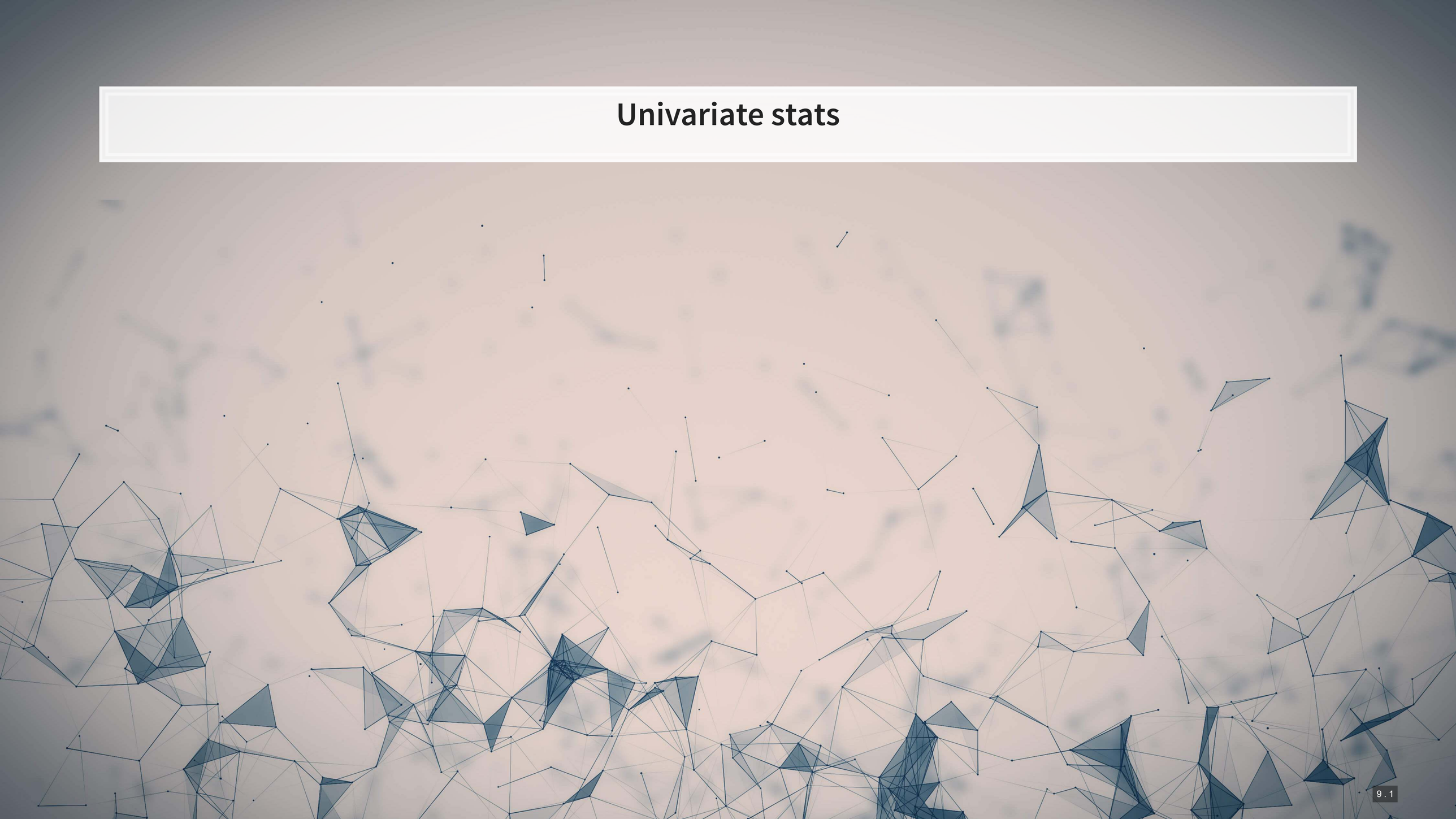
conm	date	revtq	revtq_l1	revtq_l2	revtq_l3	revtq_l4
ALLIED STORES	1962-04-30	156.5	NA	NA	NA	NA
ALLIED STORES	1962-07-31	161.9	156.5	NA	NA	NA
ALLIED STORES	1962-10-31	176.9	161.9	156.5	NA	NA
ALLIED STORES	1963-01-31	275.5	176.9	161.9	156.5	NA
ALLIED STORES	1963-04-30	171.1	275.5	176.9	161.9	156.5
ALLIED STORES	1963-07-31	182.2	171.1	275.5	176.9	161.9

Clean and split into training and testing

```r
# Clean the data: Replace NaN, Inf, and -Inf with NA
df <- df %>%
  mutate(across(where(is.numeric), ~replace(., !is.finite(.), NA)))

# Split into training and testing data
# Training data: We'll use data released before 2015
train <- filter(df, year(date) < 2015)

# Testing data: We'll use data released 2015 through 2018
test <- filter(df, year(date) >= 2015)
```

- Same cleaning function as last week:
  - Replaces all `NaN`, `Inf`, and `-Inf` with `NA`
- `year()` comes from `lubridate`

Univariate stats



Univariate stats

- To get a better grasp on the problem, looking at univariate stats can help
  - Summary stats (using `summary()`)
  - Correlations using `cor()`
  - Plots using your preferred package such as `ggplot2`

```
summary(df[,c("revtq","revtq_gr","revtq_yoy", "revtq_d","qtr")])
```

```
##      revtq              revtq_gr          revtq_yoy          revtq_d
##  Min.   :     0.00   Min.   :-1.0000   Min.   :-1.0000   Min.   :-24325.21
##  1st Qu.:    64.46   1st Qu.:-0.1112   1st Qu.: 0.0077   1st Qu.:   -19.33
##  Median :   273.95   Median : 0.0505   Median : 0.0740   Median :     4.30
##  Mean   :  2439.38   Mean   : 0.0650   Mean   : 0.1273   Mean   :    22.66
##  3rd Qu.:  1254.21   3rd Qu.: 0.2054   3rd Qu.: 0.1534   3rd Qu.:    55.02
##  Max.   :136267.00   Max.   :14.3333   Max.   :47.6600   Max.   : 15495.00
##  NA's   :367         NA's   :690       NA's   :940       NA's   :663
##       qtr
##  Min.   :1.000
##  1st Qu.:2.000
##  Median :3.000
##  Mean   :2.503
##  3rd Qu.:3.000
##  Max.   :4.000
##
```

ggplot2 for visualization

- The next slides will use some custom functions using `ggplot2`
- `ggplot2` has an odd syntax:
  - It doesn't use pipes (`%>%`), but instead adds everything together (+)

```
library(ggplot2)  # or tidyverse -- it's part of tidyverse
df %>%
  ggplot(aes(y=var_for_y_axis, x=var_for_x_axis)) +
  geom_point()  # scatterplot
```

- `aes()` is for aesthetics – how the chart is set up
- Other useful aesthetics:
  - `group=` to set groups to list in the legend. Not needed if using the below though
  - `color=` to set color by some grouping variable. Put `factor()` around the variable if you want discrete groups, otherwise it will do a color scale (light to dark)
  - `shape=` to set shapes for points – see here for a list

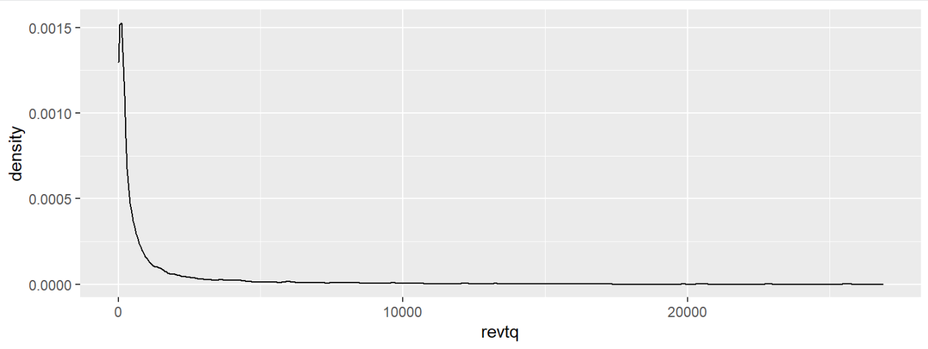
ggplot2 for visualization

```
library(ggplot2)   # or tidyverse -- it's part of tidyverse
df %>%
  ggplot(aes(y=var_for_y_axis, x=var_for_x_axis)) +
  geom_point()   # scatterplot
```

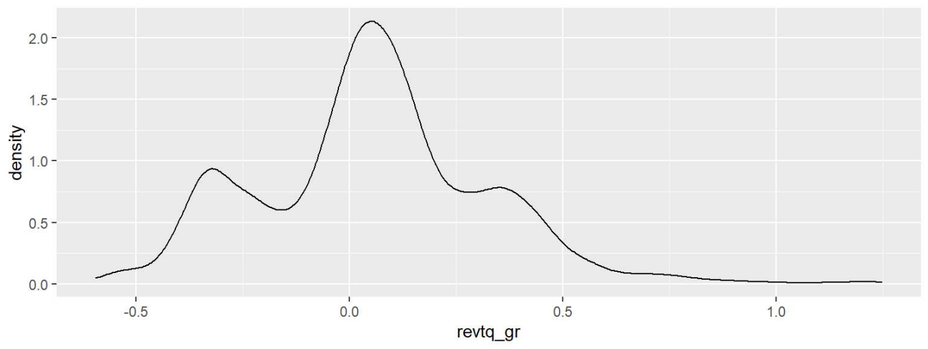
- `geom` stands for geometry – any shapes, lines, etc. start with `geom`
- Other useful geoms:
  - `geom_line()`: makes a line chart
  - `geom_bar()`: makes a bar chart – y is the height, x is the category
  - `geom_smooth(method="lm")`: Adds a linear regression into the chart
  - `geom_abline(slope=1)`: Adds a 45° line
- Add `xlab("Label text here")` to change the x-axis label
- Add `ylab("Label text here")` to change the y-axis label
- Add `ggtitle("Title text here")` to add a title
- Plenty more details in the 'Data Visualization Cheat Sheet' on eLearn

Plotting: Distribution of revenue

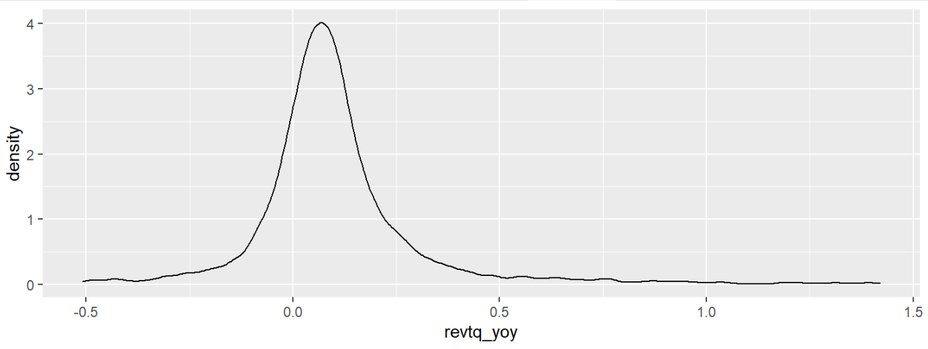
1. Revenue



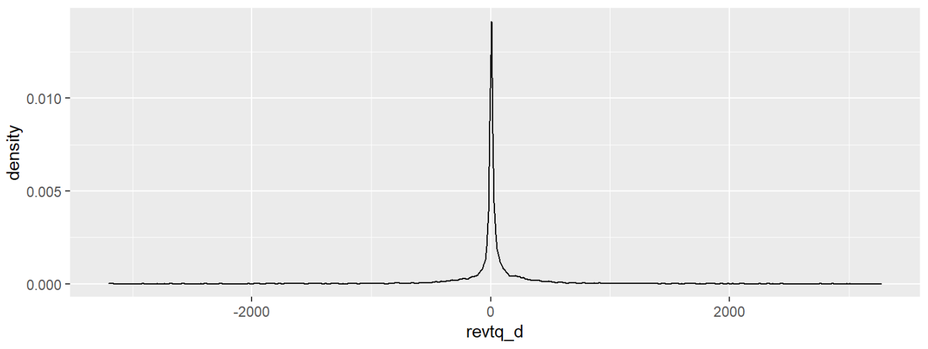
2. Quarterly growth



3. Year-over-year growth



4. First difference

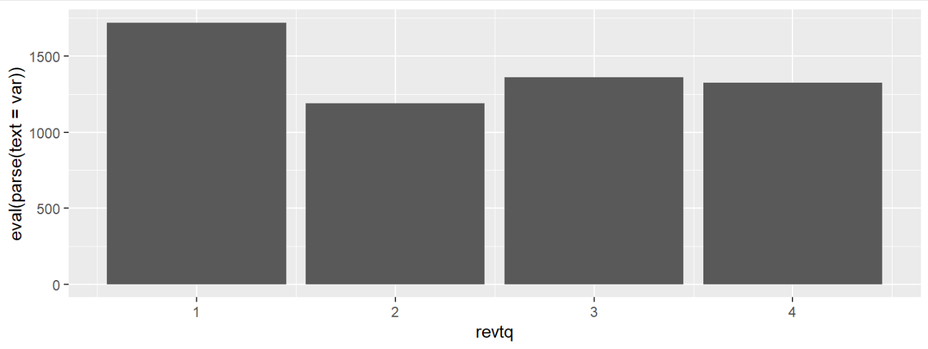


What do we learn from these graphs?

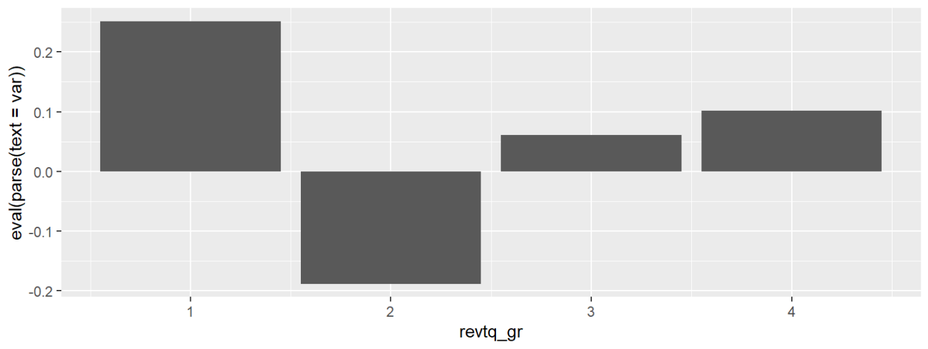
1. Revenue
   -
2. Quarterly growth
   -
3. Year-over-year growth
   -
4. First difference
   -

Plotting: Mean revenue by quarter

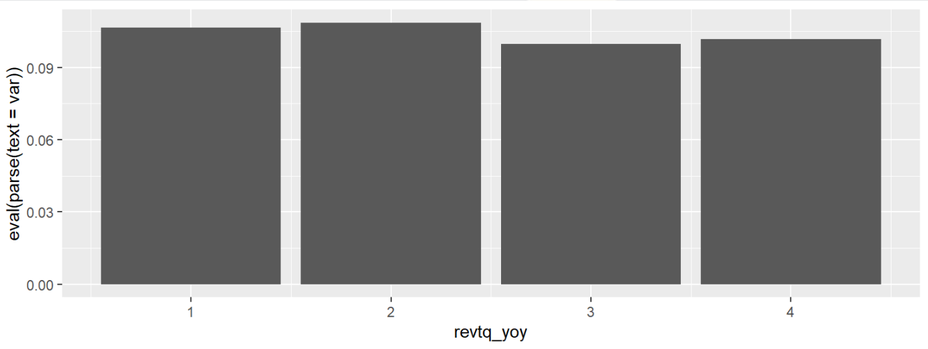
1. Revenue



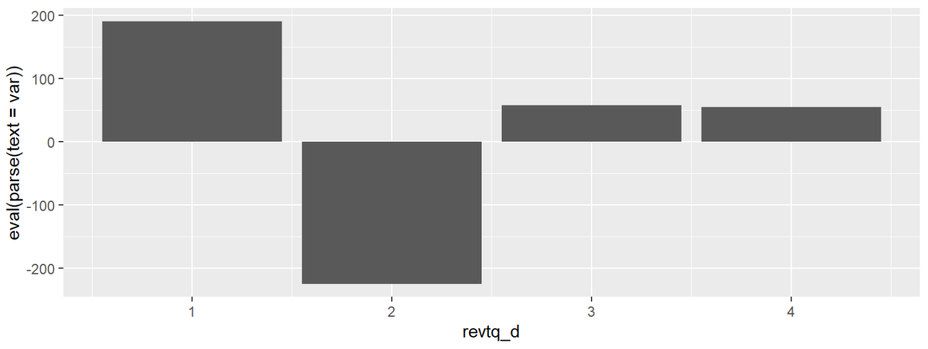
2. Quarterly growth



3. Year-over-year growth



4. First difference

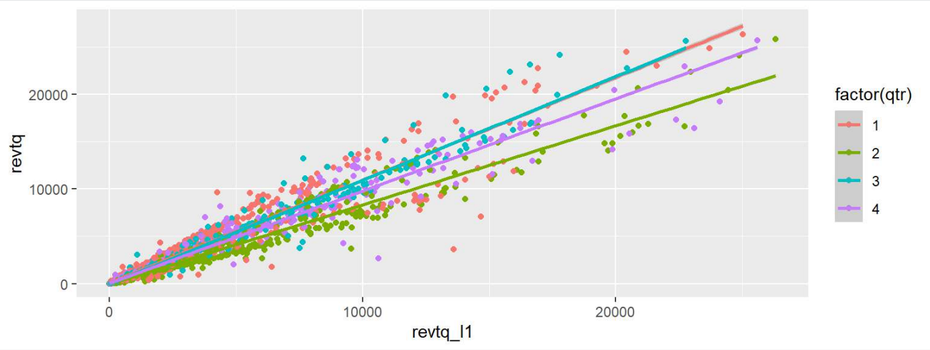


What do we learn from these graphs?

1. Revenue
   -
2. Quarterly growth
   -
3. Year-over-year growth
   -
4. First difference
   -

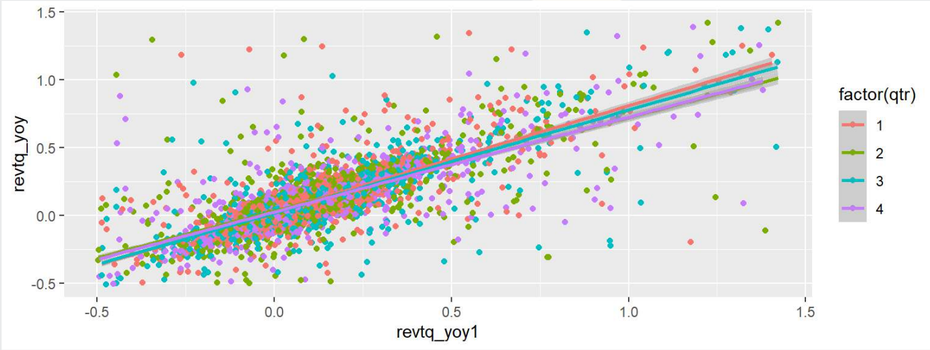
Plotting: Revenue vs lag by quarter

1. Revenue

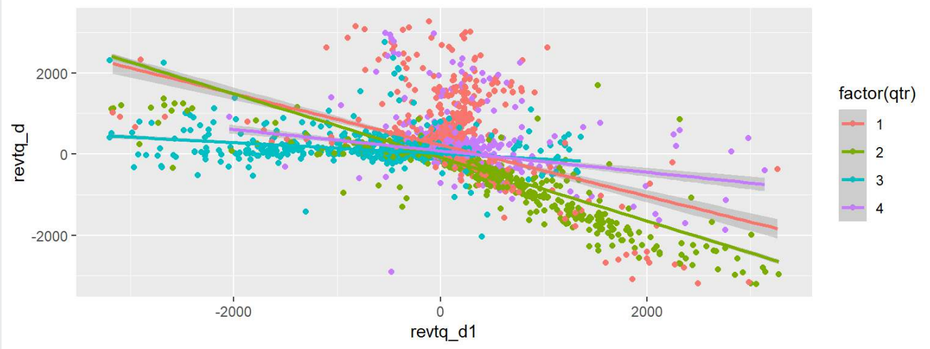


2. Quarterly growth

3. Year-over-year growth



4. First difference



What do we learn from these graphs?

1. Revenue
   - Revenue is really linear! But each quarter has a distinct linear relation.
2. Quarterly growth
   - All over the place. Each quarter appears to have a different pattern though. Quarters will matter.
3. Year-over-year growth
   - Linear but noisy.
4. First difference
   - Again, all over the place. Each quarter appears to have a different pattern though. Quarters will matter.

Correlation matrices

```
cor(train[,c("revtq","revtq_l1","revtq_l2","revtq_l3", "revtq_l4")],
    use="complete.obs")
```

```
##              revtq  revtq_l1  revtq_l2  revtq_l3  revtq_l4
## revtq    1.0000000 0.9916167 0.9938489 0.9905522 0.9972735
## revtq_l1 0.9916167 1.0000000 0.9914767 0.9936977 0.9898184
## revtq_l2 0.9938489 0.9914767 1.0000000 0.9913489 0.9930152
## revtq_l3 0.9905522 0.9936977 0.9913489 1.0000000 0.9906006
## revtq_l4 0.9972735 0.9898184 0.9930152 0.9906006 1.0000000
```

```
cor(train[,c("revtq_gr","revtq_gr1","revtq_gr2","revtq_gr3", "revtq_gr4")],
    use="complete.obs")
```

```
##              revtq_gr   revtq_gr1   revtq_gr2   revtq_gr3   revtq_gr4
## revtq_gr   1.00000000 -0.32291329  0.06299605 -0.22769442  0.64570015
## revtq_gr1 -0.32291329  1.00000000 -0.31885020  0.06146805 -0.21923630
## revtq_gr2  0.06299605 -0.31885020  1.00000000 -0.32795121  0.06775742
## revtq_gr3 -0.22769442  0.06146805 -0.32795121  1.00000000 -0.31831023
## revtq_gr4  0.64570015 -0.21923630  0.06775742 -0.31831023  1.00000000
```

Retail revenue has really high autocorrelation! Concern for multicolinearity. Revenue growth is less autocorrelated and oscillates.

Correlation matrices

```
cor(train[,c("revtq_yoy","revtq_yoy1","revtq_yoy2","revtq_yoy3", "revtq_yoy4")],
    use="complete.obs")
```

```
##            revtq_yoy revtq_yoy1 revtq_yoy2 revtq_yoy3 revtq_yoy4
## revtq_yoy  1.0000000  0.6554179  0.4127263  0.4196003  0.1760055
## revtq_yoy1 0.6554179  1.0000000  0.5751128  0.3665961  0.3515105
## revtq_yoy2 0.4127263  0.5751128  1.0000000  0.5875643  0.3683539
## revtq_yoy3 0.4196003  0.3665961  0.5875643  1.0000000  0.5668211
## revtq_yoy4 0.1760055  0.3515105  0.3683539  0.5668211  1.0000000
```

```
cor(train[,c("revtq_d","revtq_d1","revtq_d2","revtq_d3", "revtq_d4")],
    use="complete.obs")
```

```
##             revtq_d   revtq_d1   revtq_d2   revtq_d3   revtq_d4
## revtq_d   1.0000000 -0.6181516  0.3309349 -0.6046998  0.9119911
## revtq_d1 -0.6181516  1.0000000 -0.6155259  0.3343317 -0.5849841
## revtq_d2  0.3309349 -0.6155259  1.0000000 -0.6191366  0.3165450
## revtq_d3 -0.6046998  0.3343317 -0.6191366  1.0000000 -0.5864285
## revtq_d4  0.9119911 -0.5849841  0.3165450 -0.5864285  1.0000000
```

Year over year change fixes the multicollinearity issue. First difference oscillates like quarter over quarter growth.

R Practice

- This practice will look at predicting Walmart's quarterly revenue using:
  - 1 lag
  - Cyclicality
- Practice using:
  - `lm()`
  - `ggplot2`
- Do the exercises in today's practice file
  - R Practice
  - Short link: rmc.link/420r3

Forecasting

1 period models

1. 1 Quarter lag: We saw a very strong linear pattern here earlier

```
mod1 <- lm(revtq ~ revtq_l1, data=train)
```

2. Quarter and year lag: Year-over-year seemed pretty constant

```
mod2 <- lm(revtq ~ revtq_l1 + revtq_l4, data=train)
```

3. 2 years of lags: Other lags could also help us predict

```
mod3 <- lm(revtq ~ revtq_l1 + revtq_l2 + revtq_l3 + revtq_l4 + revtq_l5 +
           revtq_l6 + revtq_l7 + revtq_l8, data=train)
```

4. 2 years of lags, by observation quarter: Take into account cyclicality observed in bar charts

```
mod4 <- lm(revtq ~ (revtq_l1 + revtq_l2 + revtq_l3 + revtq_l4 + revtq_l5 +
                    revtq_l6 + revtq_l7 + revtq_l8):factor(qtr), data=train)
```

Quarter lag

```
summary(mod1)
```

```
##
## Call:
## lm(formula = revtq ~ revtq_l1, data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -24438.7    -34.0    -11.7     34.6  15200.5
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 15.639975  13.514877   1.157    0.247
## revtq_l1     1.003038   0.001556 644.462   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1152 on 7676 degrees of freedom
##   (662 observations deleted due to missingness)
## Multiple R-squared:  0.9819, Adjusted R-squared:  0.9819
## F-statistic: 4.153e+05 on 1 and 7676 DF,  p-value: < 2.2e-16
```

Quarter and year lag

```
summary(mod2)
```

```
##
## Call:
## lm(formula = revtq ~ revtq_l1 + revtq_l4, data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20245.7    -18.4     -4.4     19.1   9120.8
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.444986   7.145633   0.762    0.446
## revtq_l1    0.231759   0.005610  41.312   <2e-16 ***
## revtq_l4    0.815570   0.005858 139.227   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 592.1 on 7274 degrees of freedom
##   (1063 observations deleted due to missingness)
## Multiple R-squared:  0.9954, Adjusted R-squared:  0.9954
## F-statistic: 7.94e+05 on 2 and 7274 DF,  p-value: < 2.2e-16
```

2 years of lags

```
summary(mod3)
```

```
##
## Call:
## lm(formula = revtq ~ revtq_l1 + revtq_l2 + revtq_l3 + revtq_l4 +
##     revtq_l5 + revtq_l6 + revtq_l7 + revtq_l8, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5005.6   -12.9    -3.7     9.3  5876.3
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.02478    4.37003   0.921   0.3571
## revtq_l1     0.77379    0.01229  62.972  < 2e-16 ***
## revtq_l2     0.10497    0.01565   6.707 2.16e-11 ***
## revtq_l3    -0.03091    0.01538  -2.010   0.0445 *
## revtq_l4     0.91982    0.01213  75.800  < 2e-16 ***
## revtq_l5    -0.76459    0.01324 -57.749  < 2e-16 ***
## revtq_l6    -0.08080    0.01634  -4.945 7.80e-07 ***
## revtq_l7     0.01146    0.01594   0.719   0.4721
## revtq_l8     0.07924    0.01209   6.554 6.03e-11 ***
## ---
```

2 years of lags, by observation quarter

```
summary(mod4)
```

```
##
## Call:
## lm(formula = revtq ~ (revtq_l1 + revtq_l2 + revtq_l3 + revtq_l4 +
##     revtq_l5 + revtq_l6 + revtq_l7 + revtq_l8):factor(qtr), data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5316.5   -12.2     0.9    15.7  5283.2
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -0.45240    4.32484  -0.105 0.916692
## revtq_l1:factor(qtr)1    0.91094    0.02610  34.896  < 2e-16 ***
## revtq_l1:factor(qtr)2    0.67361    0.02376  28.355  < 2e-16 ***
## revtq_l1:factor(qtr)3    0.97588    0.02747  35.525  < 2e-16 ***
## revtq_l1:factor(qtr)4    0.65106    0.02216  29.377  < 2e-16 ***
## revtq_l2:factor(qtr)1    0.05733    0.02872   1.996 0.045997 *
## revtq_l2:factor(qtr)2    0.14708    0.03410   4.313 1.64e-05 ***
## revtq_l2:factor(qtr)3    0.02910    0.02976   0.978 0.328253
## revtq_l2:factor(qtr)4    0.36807    0.03468  10.614  < 2e-16 ***
## revtq_l3:factor(qtr)1   -0.09063    0.03717  -2.438 0.014788 *
```

Testing out of sample

- RMSE: Root mean square Error
- RMSE is very affected by outliers, and a bad choice for noisy data where you are OK with missing a few outliers here and there
  - Doubling error *quadruples* the penalty

```r
rmse <- function(v1, v2) {
  sqrt(mean((v1 - v2)^2, na.rm=T))
}
```

- MAE: Mean absolute error
- MAE is measures average accuracy with no weighting
  - Doubling error *doubles* the penalty

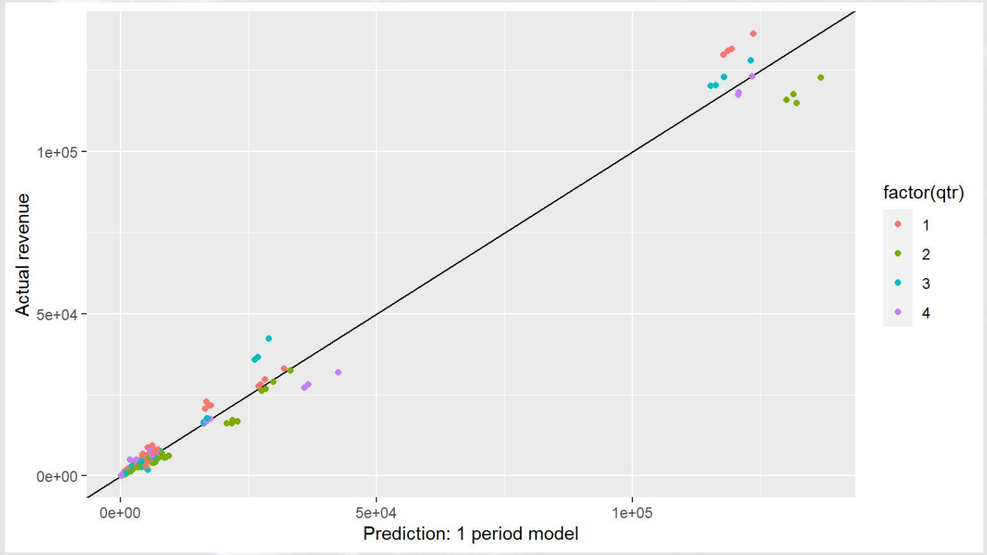
```r
mae <- function(v1, v2) {
  mean(abs(v1-v2), na.rm=T)
}
```

Both are commonly used for evaluating OLS out of sample

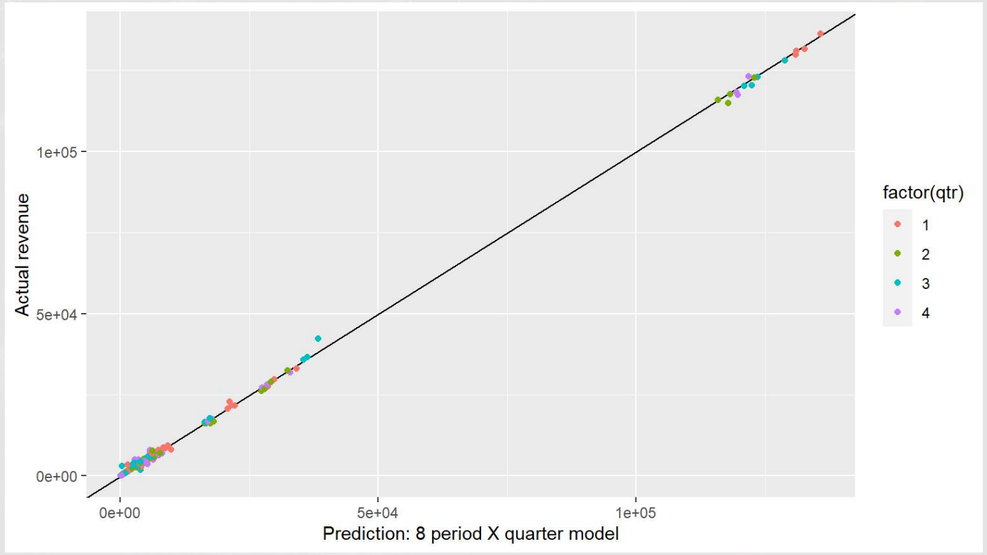
Testing out of sample

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.9818514	1151.3535	322.73819	2947.3619	1252.5196
1 and 4 periods	0.9954393	591.9500	156.20811	1400.3841	643.9823
8 periods	0.9985643	345.8053	94.91083	677.6218	340.8236
8 periods w/ quarters	0.9987376	323.6768	94.07378	633.8951	332.0945

1 quarter model



8 period model, by quarter



What about for revenue growth?

$$revt_t = (1 + growth_t) \times revt_{t-1}$$

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.0910390	1106.3730	308.4833	3374.728	1397.6541
1 and 4 periods	0.4398456	530.6444	154.1509	1447.035	679.3536
8 periods	0.6761666	456.2551	123.3407	1254.201	584.9709
8 periods w/ quarters	0.7547897	423.7594	113.6537	1169.282	537.2325

What about for YoY revenue growth?

$$revt_t = (1 + yoy\_growth_t) \times revt_{t-4}$$

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.4370372	513.3264	129.2309	1867.4957	798.0327
1 and 4 periods	0.5392281	487.6441	126.6012	1677.4003	731.2841
8 periods	0.5398870	384.2923	101.0104	822.0065	403.5445
8 periods w/ quarters	0.1040702	679.9093	187.4486	1330.7890	658.4296

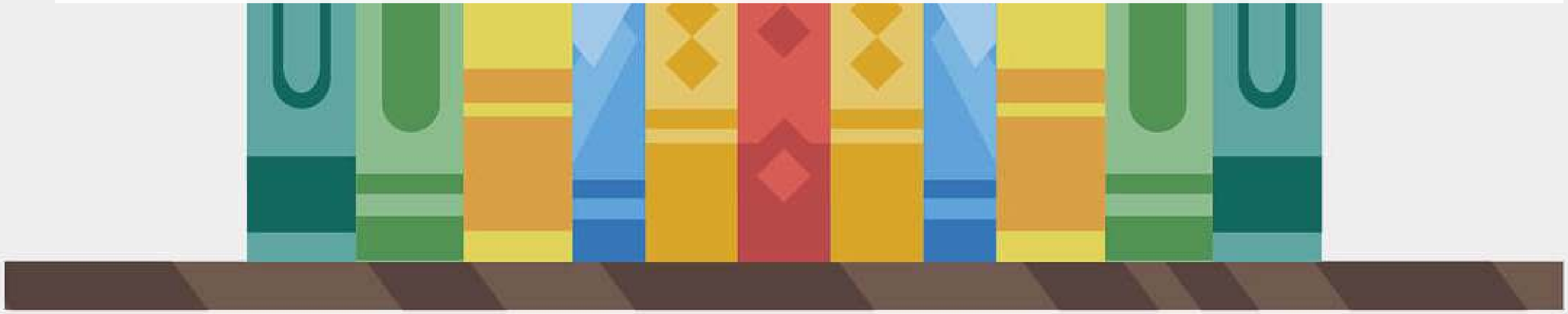
What about for first difference?

$$revt_t = change_t + revt_{t-1}$$

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.3532044	896.7969	287.77940	2252.7605	1022.0960
1 and 4 periods	0.8425348	454.8651	115.52694	734.8120	377.5281
8 periods	0.9220849	333.0054	95.95924	651.4967	320.0567
8 periods w/ quarters	0.9312580	312.2140	88.24559	661.4063	331.0617

Takeaways

1. The first difference model works a bit better than the revenue model at predicting next quarter revenue
    - It also doesn’t suffer (as much) from multicollinearity
        - This is why time series analysis is often done on first differences
            - Or second differences (difference in differences)
2. The other models perform pretty well as well
3. Extra lags generally seems helpful when accounting for cyclicality
4. Regressing by quarter helps a bit, particularly with revenue growth



What about for revenue growth?

Predicting quarter over quarter revenue growth itself

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.0910390	0.3509269	0.2105219	0.2257396	0.1750580
1 and 4 periods	0.4398456	0.2681899	0.1132003	0.1597771	0.0998087
8 periods	0.6761666	0.1761825	0.0867347	0.1545298	0.0845826
8 periods w/ quarters	0.7547897	0.1530278	0.0816612	0.1433094	0.0745658

What about for YoY revenue growth?

Predicting YoY revenue growth itself

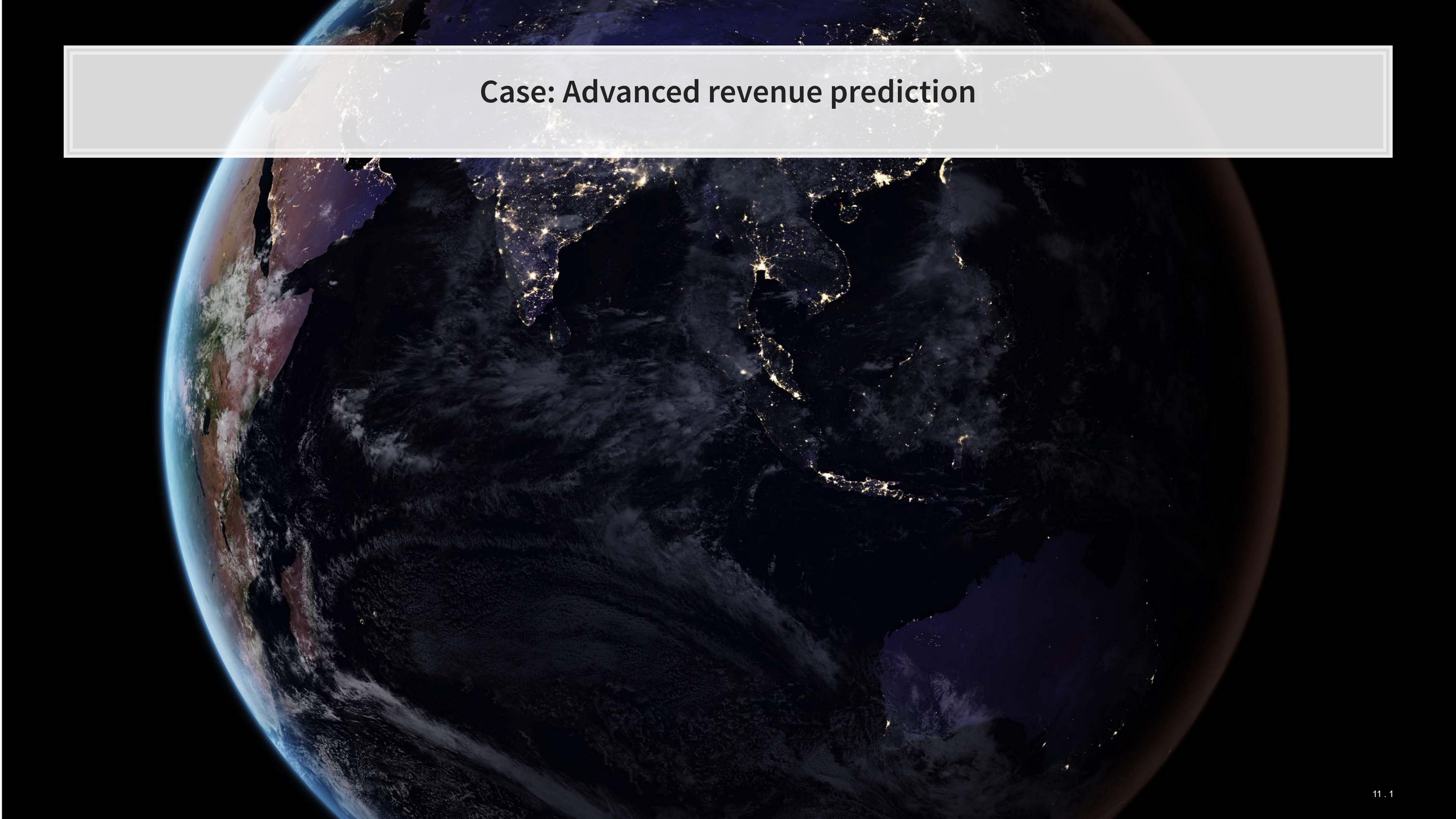
	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.4370372	0.3116645	0.1114610	0.1515638	0.0942544
1 and 4 periods	0.5392281	0.2451749	0.1015699	0.1498755	0.0896079
8 periods	0.5398870	0.1928940	0.0764447	0.1346238	0.0658011
8 periods w/ quarters	0.1040702	0.2986735	0.1380062	0.1960325	0.1020124

What about for first difference?

Predicting first difference in revenue itself

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.3532044	896.7969	287.77940	2252.7605	1022.0960
1 and 4 periods	0.8425348	454.8651	115.52694	734.8120	377.5281
8 periods	0.9220849	333.0054	95.95924	651.4967	320.0567
8 periods w/ quarters	0.9312580	312.2140	88.24559	661.4063	331.0617

Case: Advanced revenue prediction



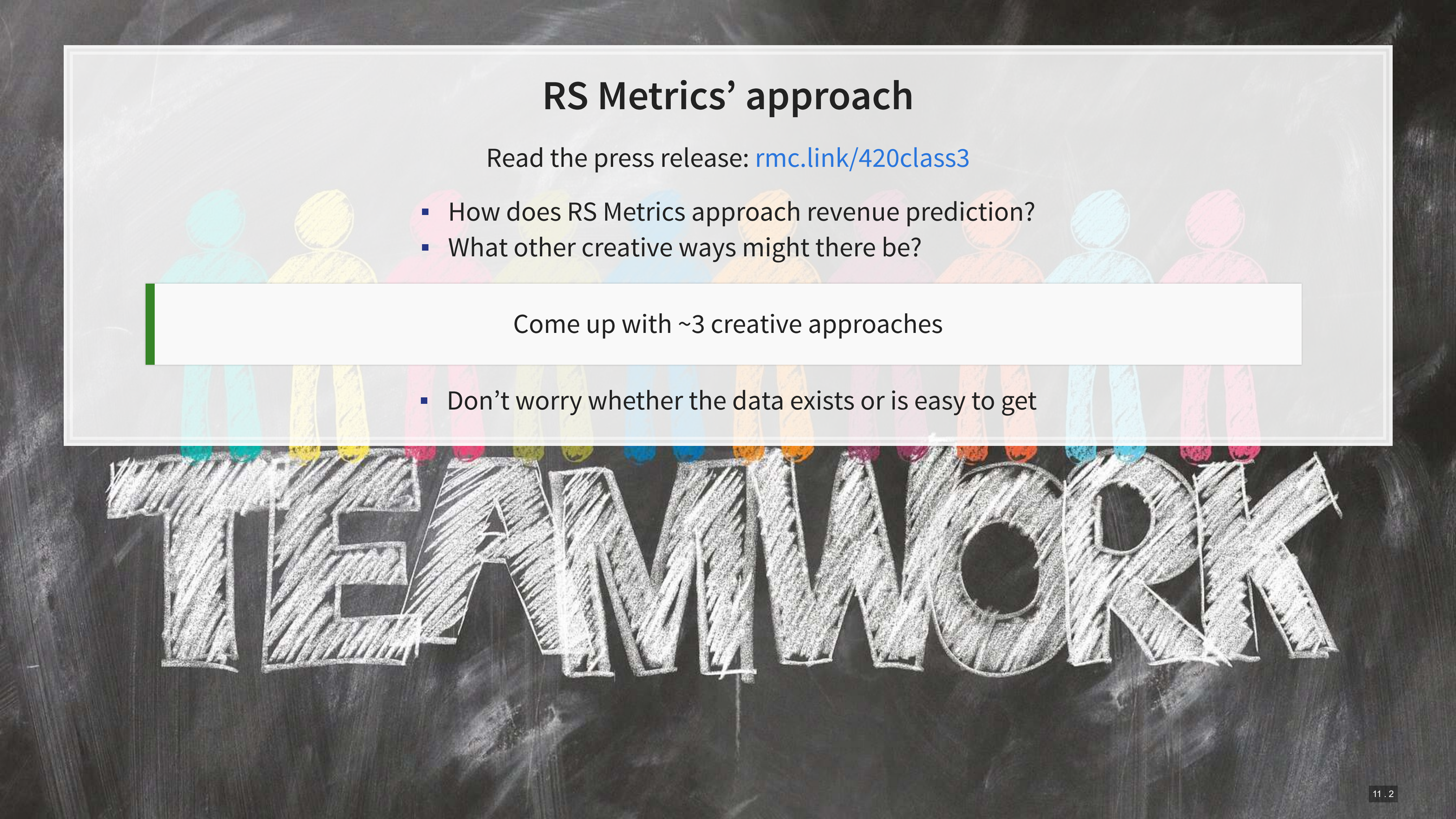
RS Metrics' approach

Read the press release: rmc.link/420class3

- How does RS Metrics approach revenue prediction?
- What other creative ways might there be?

> Come up with ~3 creative approaches

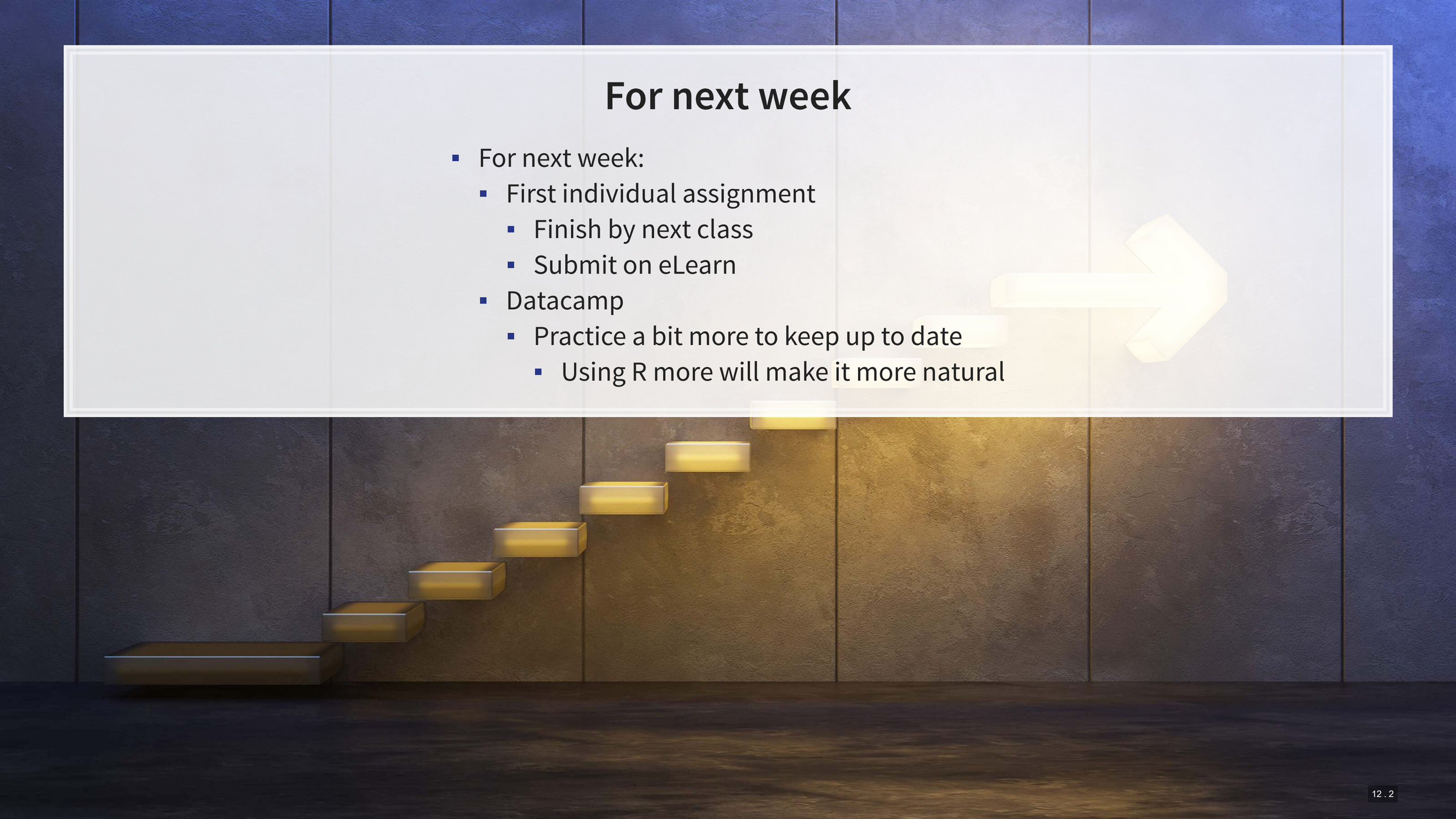
- Don't worry whether the data exists or is easy to get



End matter

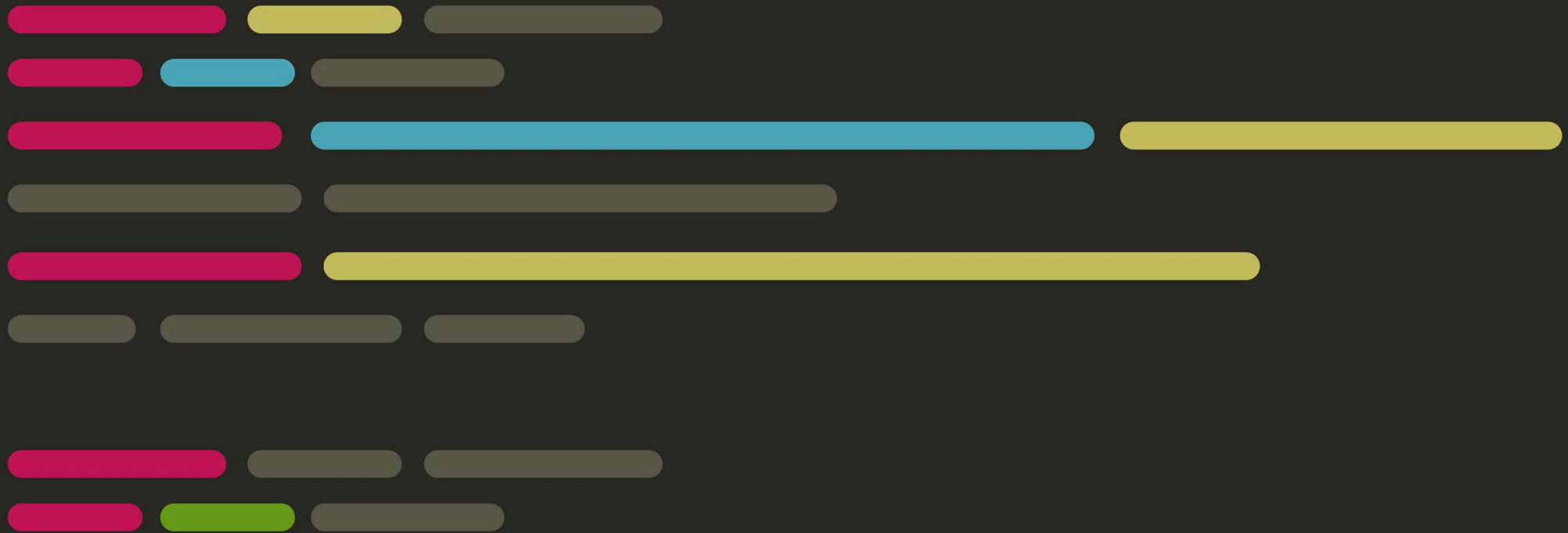
For next week

- For next week:
  - First individual assignment
    - Finish by next class
    - Submit on eLearn
  - Datacamp
    - Practice a bit more to keep up to date
      - Using R more will make it more natural



Packages used for these slides

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



Custom code

```r
# Brute force code for variable generation of quarterly data lags
df <- df %>%
  group_by(gvkey) %>%
  mutate(revtq_lag1=lag(revtq), revtq_lag2=lag(revtq, 2),
         revtq_lag3=lag(revtq, 3), revtq_lag4=lag(revtq, 4),
         revtq_lag5=lag(revtq, 5), revtq_lag6=lag(revtq, 6),
         revtq_lag7=lag(revtq, 7), revtq_lag8=lag(revtq, 8),
         revtq_lag9=lag(revtq, 9), revtq_gr=revtq / revtq_lag1 - 1,
         revtq_gr1=lag(revtq_gr), revtq_gr2=lag(revtq_gr, 2),
         revtq_gr3=lag(revtq_gr, 3), revtq_gr4=lag(revtq_gr, 4),
         revtq_gr5=lag(revtq_gr, 5), revtq_gr6=lag(revtq_gr, 6),
         revtq_gr7=lag(revtq_gr, 7), revtq_gr8=lag(revtq_gr, 8),
         revtq_yoy=revtq / revtq_lag4 - 1, revtq_yoy1=lag(revtq_yoy),
         revtq_yoy2=lag(revtq_yoy, 2), revtq_yoy3=lag(revtq_yoy, 3),
         revtq_yoy4=lag(revtq_yoy, 4), revtq_yoy5=lag(revtq_yoy, 5),
         revtq_yoy6=lag(revtq_yoy, 6), revtq_yoy7=lag(revtq_yoy, 7),
         revtq_yoy8=lag(revtq_yoy, 8), revtq_d=revtq - revtq_l1,
         revtq_d1=lag(revtq_d), revtq_d2=lag(revtq_d, 2),
         revtq_d3=lag(revtq_d, 3), revtq_d4=lag(revtq_d, 4),
         revtq_d5=lag(revtq_d, 5), revtq_d6=lag(revtq_d, 6),
         revtq_d7=lag(revtq_d, 7), revtq_d8=lag(revtq_d, 8)) %>%
  ungroup()
```

```r
# Custom html table for small data frames
library(knitr)
library(kableExtra)
html_df <- function(text, cols=NULL, col1=FALSE, full=F) {
  if(!length(cols)) {
    cols=colnames(text)
  }
  if(!col1) {
    kable(text,"html", col.names = cols, align = c("l",rep('c',length(cols)-1))) %>%
      kable_styling(bootstrap_options = c("striped","hover"), full_width=full)
  } else {
    kable(text,"html", col.names = cols, align = c("l",rep('c',length(cols)-1))) %>%
      kable_styling(bootstrap_options = c("striped","hover"), full_width=full) %>%
      column_spec(1,bold=T)
  }
}
```

Custom code

```r
# Calculating Root Mean Squared Error (Slide 11.5)
actual_series <- df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,]$revt_lead
uol_series <- uol[uol$fyear < 2017,]$pred_uol
base_series <- df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,]$pred_base
macro_series <- df_SG_macro[df_SG_macro$isin=="SG1S83002349" & df_SG_macro$fyear < 2017,]$pred_macro
world_series <- df_clean[df_clean$isin=="SG1S83002349" & df_clean$fyear < 2017,]$pred_world

rmse <- function(v1, v2) {
  sqrt(mean((v1 - v2)^2, na.rm=T))
}

rmse <- c(rmse(actual_series, uol_series),
          rmse(actual_series, base_series),
          rmse(actual_series, macro_series),
          rmse(actual_series, world_series))
names(rmse) <- c("UOL 2018, UOL only", "UOL 2018 Baseline", "UOL 2018 w/ macro", "UOL 2018 w/ world")
rmse
```

```r
# These functions are a bit ugly, but can construct many charts quickly
# eval(parse(text=var)) is just a way to convert the string name to a variable reference
# Density plot for 1st to 99th percentile of data
plt_dist <- function(df,var) {
  df %>%
    filter(eval(parse(text=var)) < quantile(eval(parse(text=var)),0.99, na.rm=TRUE),
           eval(parse(text=var)) > quantile(eval(parse(text=var)),0.01, na.rm=TRUE)) %>%
    ggplot(aes(x=eval(parse(text=var)))) +
    geom_density() + xlab(var)
}
```

Custom code

```r
# Density plot for 1st to 99th percentile of both columns
plt_bar <- function(df,var) {
  df %>%
    filter(eval(parse(text=var)) < quantile(eval(parse(text=var)),0.99, na.rm=TRUE),
           eval(parse(text=var)) > quantile(eval(parse(text=var)),0.01, na.rm=TRUE)) %>%
    ggplot(aes(y=eval(parse(text=var)), x=qtr)) +
    geom_bar(stat = "summary", fun.y = "mean") + xlab(var)
}
```

```r
# Scatter plot with lag for 1st to 99th percentile of data
plt_sct <- function(df,var1, var2) {
  df %>%
    filter(eval(parse(text=var1)) < quantile(eval(parse(text=var1)),0.99, na.rm=TRUE),
           eval(parse(text=var2)) < quantile(eval(parse(text=var2)),0.99, na.rm=TRUE),
           eval(parse(text=var1)) > quantile(eval(parse(text=var1)),0.01, na.rm=TRUE),
           eval(parse(text=var2)) > quantile(eval(parse(text=var2)),0.01, na.rm=TRUE)) %>%
    ggplot(aes(y=eval(parse(text=var1)), x=eval(parse(text=var2)), color=factor(qtr))) +
    geom_point() + geom_smooth(method = "lm") + ylab(var1) + xlab(var2)
}
```

```r
# Calculating various in and out of sample statistics
models <- list(mod1,mod2,mod3,mod4)
model_names <- c("1 period", "1 and 4 period", "8 periods", "8 periods w/ quarters")

df_test <- data.frame(adj_r_sq=sapply(models, function(x)summary(x)[["adj.r.squared"]]),
                      rmse_in=sapply(models, function(x)rmse(train$revtq, predict(x,train))),
                      mae_in=sapply(models, function(x)mae(train$revtq, predict(x,train))),
                      rmse_out=sapply(models, function(x)rmse(test$revtq, predict(x,test))),
                      mae_out=sapply(models, function(x)mae(test$revtq, predict(x,test))))
rownames(df_test) <- model_names
html_df(df_test)  # Custom function using knitr and kableExtra
```