Forecasting and Forensic Analytics

Session 3: Advanced Linear Regression and Simulation

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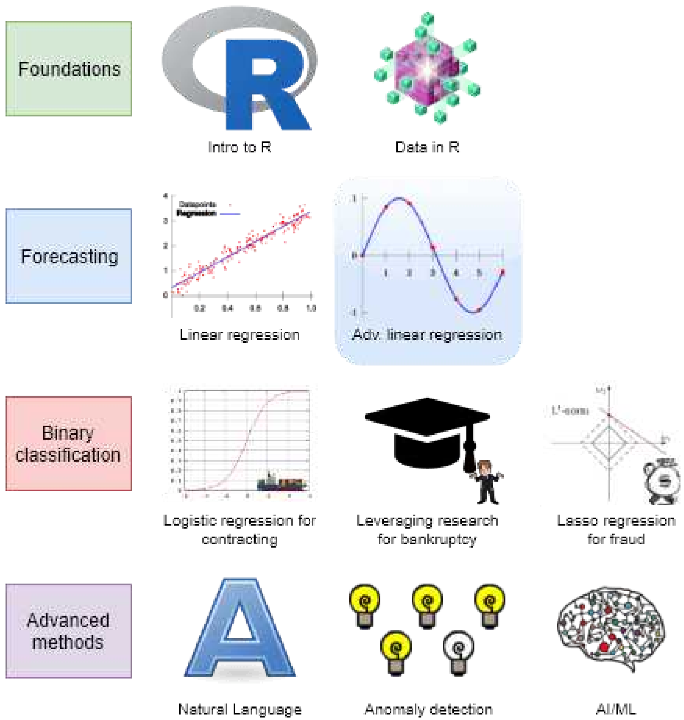
Preface

Learning objectives



- **Theory:**
  - Further understand:
    - Statistics/Causation
    - Data/Time
- **Application:**
  - Predicting quarterly revenue
  - Managing uncertainties by simulation
- **Methodology:**
  - Univariate
  - Linear regression (OLS)
  - Visualization
  - Monte Carlo simulation

Quarterly retail revenue

The question

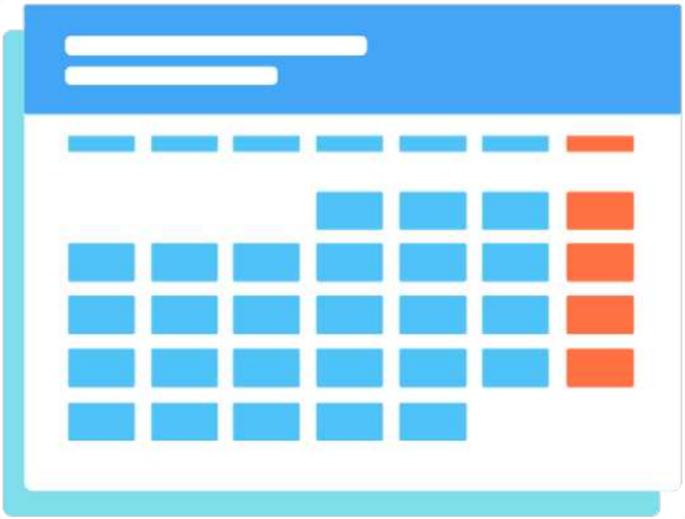
> How can we predict quarterly revenue for retail companies, leveraging our knowledge of such companies

- In aggregate
- By Store
- By department
- Consider time dimensions
    - What matters:
        - Last quarter?
        - Last year?
        - Other timeframes?
    - Cyclicality

Time and OLS

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 of US retail companies
- Two sets of firms:
  - US "Hypermarkets & Super Centers" [GICS(gsubind): 30101040]
  - US "Multiline Retail" [GICS(gind): 255030]
- Data from Compustat - Capital IQ > North America - Daily > Fundamentals Quarterly
  - datadate: all available (1962 to 2020 for this case)

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. Research design
   - Use OLS for all the above -- t-tests for coefficients
   - Hold out sample (testing data): 2016-2020

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 in R
# datadate (end of reporting period) is YYMMDDn8. (int 20200630)
# quarter() is to generate the calendar quarter based on date
# which may be different from company's fiscal quarter
df$date <- ymd(df$datadate)  # From lubridate
df$cqtr <- quarter(df$date)   # From lubridate
```

Date manipulation in R

- `ymd()` from `package:lubridate` is a handy way of converting date.
    - It also has `ydm()`, `mdy()`, `myd()`, `dmy()` and `dym()`
    - It can handle quarters, times, and date-times as well
    - Cheat sheet
    - It will convert the date format to the ISO 8601 international standard which expresses a day as "2001-02-03".
- `as.Date()` from the Base R 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
        - e.g., "DD.MM.YYYY" is format code "%d.%m.%Y"
        - Full list of date codes
    - The default date format also follows ISO 8601.
    - The following code can do the same as `ymd()`

```
# Generate a proper date in R
# Datadate is YYMMDDn8. (integer 20200630)
df$date <- as.Date(as.character(df$datadate), format = "%Y%m%d")
```

Example output

- The following shows some selective columns

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 5
##   conm          date       datadate  fqtr  cqtr
##   <chr>         <date>        <int> <int> <int>
## 1 ALLIED STORES 1962-04-30 19620430     1     2
## 2 ALLIED STORES 1962-07-31 19620731     2     3
## 3 ALLIED STORES 1962-10-31 19621031     3     4
## 4 ALLIED STORES 1963-01-31 19630131     4     1
## 5 ALLIED STORES 1963-04-30 19630430     1     2
## 6 ALLIED STORES 1963-07-31 19630731     2     3
```

Create 8 quarters (2 years) of lags

```r
# Brute force code for variable generation of quarterly data lags
df <- df %>%
  group_by(gvkey) %>%
  mutate(revtq_l1 = lag(revtq), revtq_l2 = lag(revtq, 2),
         revtq_l3 = lag(revtq, 3), revtq_l4 = lag(revtq, 4),
         revtq_l5 = lag(revtq, 5), revtq_l6 = lag(revtq, 6),
         revtq_l7 = lag(revtq, 7), revtq_l8 = lag(revtq, 8),
         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_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_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()
```

Create 8 quarters (2 years) of lags

```
# Custom function to generate a series of lags
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)))
}
# Generate lags "revtq_l#"
df <- multi_lag(df, 1:8, revtq, "_l")

# Generate changes "revtq_gr#"
df <- multi_lag(df, 1:8, revtq_gr)

# Generate year-over-year changes "revtq_yoy#"
df <- multi_lag(df, 1:8, revtq_yoy)

# Generate first differences "revtq_d#"
df <- multi_lag(df, 1:8, revtq_d)
```

- require more advanced understanding of `metaprogramming`, `advanced R`, `tidy evaluation`, and `quosure` concepts.
- `paste0()`: creates a string vector by concatenating all inputs
- `paste()`: same as `paste0()`, but with spaces added in between

Example output

conm	date	revtq	revtq_l1	revtq_gr1	revtq_yoy1	revtq_d1
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	0.0345048	NA	5.4
ALLIED STORES	1963-01-31	275.5	176.9	0.0926498	NA	15.0
ALLIED STORES	1963-04-30	171.1	275.5	0.5573770	NA	98.6
ALLIED STORES	1963-07-31	182.2	171.1	-0.3789474	0.0932907	-104.4

Clean and holdout sample

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

# Split into training and test datasets
# Training dataset: We'll use data released before 2015
train <- filter(df, year(date) < 2016)

# Test dataset: We'll use data released 2016 through 2019 (till 3Q2019)
test <- filter(df, year(date) >= 2016)
```

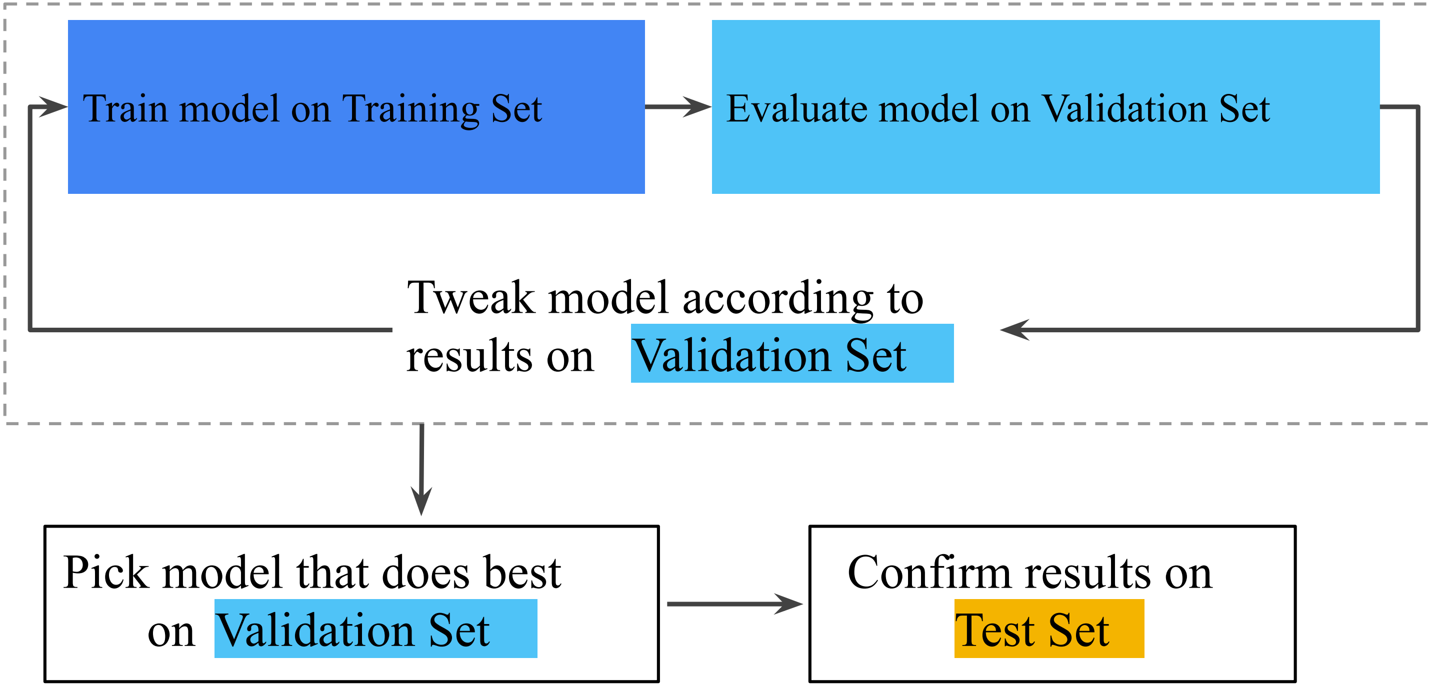
- Same cleaning function as last week:
  - Replaces all `NaN`, `Inf`, and `-Inf` with `NA`
- `year()` comes from `package:lubridate`

Training vs. test datasets

> train a model and test/validate it using the same set of data?

- We build analytics models for forecasting and other predictive purposes
- The key question: **could the model be generalized to new dataset?**
  - We need to have a new dataset to test how well the model performs
  - Existing data will be divided into training data and test data
- Training data will be used to train/build the model
  - It can be further divided into training set and validation set.
  - The validation set can be used to further tune the model (eg, detect overfitting problem), which helps get the most optimized model.
  - We will cover (cross) validation in a future topic
- Testing data will be used to test how well the model performs

Workflow with training/test sets



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 `package:ggplot2`

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

```
##      revtq              revtq_gr          revtq_yoy           revtq_d
##  Min.   :     0.00   Min.   :-1.0000   Min.   :-1.0000   Min.   :-24325.206
##  1st Qu.:    66.01   1st Qu.:-0.1091   1st Qu.: 0.0024   1st Qu.:   -20.260
##  Median :   312.59   Median : 0.0501   Median : 0.0704   Median :     4.548
##  Mean   :  2545.48   Mean   : 0.0625   Mean   : 0.1185   Mean   :    23.730
##  3rd Qu.:  1386.50   3rd Qu.: 0.2032   3rd Qu.: 0.1476   3rd Qu.:    60.146
##  Max.   :141671.00   Max.   :14.3333   Max.   :47.6600   Max.   : 16117.000
##  NA's   :394         NA's   :731       NA's   :1020      NA's   :704
##       fqtr
##  Min.   :1.000
##  1st Qu.:1.000
##  Median :2.000
##  Mean   :2.479
##  3rd Qu.:3.000
##  Max.   :4.000
##
```

ggplot2 for visualization

- The following slides will use some custom functions using `package:ggplot2`
- `package: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_y_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

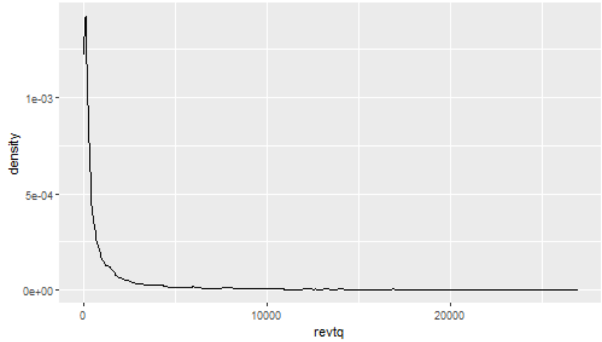
ggplot2 for visualization

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

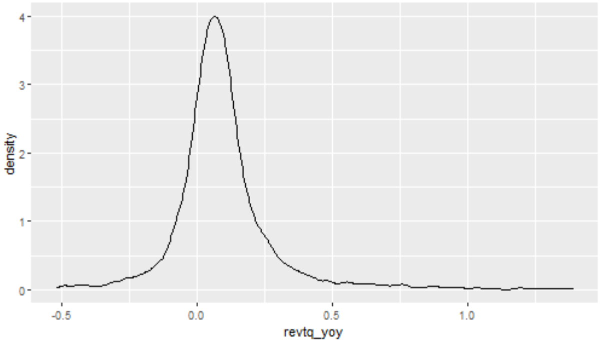
- `geom` stands for geometry -- any shapes, lines, etc. start with `geom`
- Other useful geoms:
  - `geom_line()`: makes a line chart
  - `geom_bar()`: makes a bar chart -- y is the height, x is the category
  - `geom_smooth(method="lm")`: Adds a linear regression into the chart
  - `geom_abline(slope=1)`: 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'

Plotting: Distribution of revenue

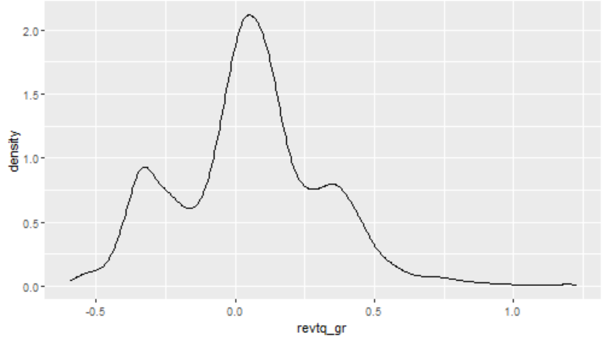
- Revenue



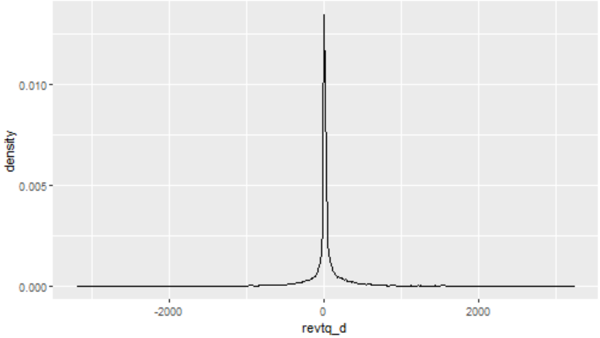
- Year-over-year growth



- Quarterly growth



- First difference



What we learn from the graphs?

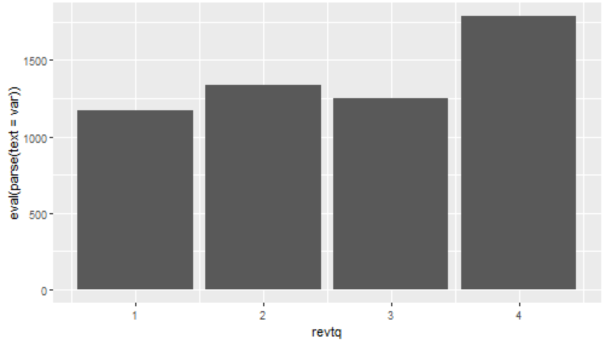
1. Revenue
   -
2. Quarterly growth
   -
3. Year-over-year growth
   -
4. First difference
   -

What we learn from the graphs?

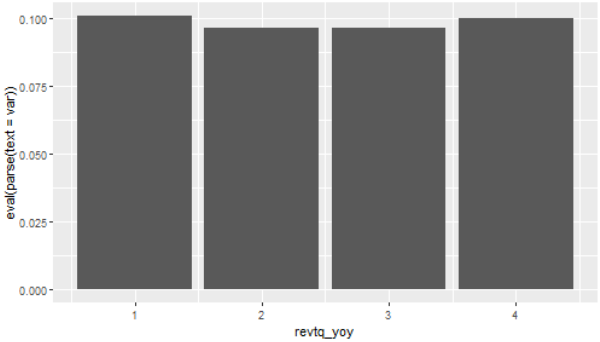
1. Revenue
    - This is really skewed data -- a lot of small revenue quarters, but a significant amount of large revenue quarters in the tail
        - Potential fix: use `log(revtq)`?
2. Quarterly growth
    - Quarterly growth is reasonably close to normally distributed
        - Good for OLS
3. Year-over-year growth
    - Year over year growth is reasonably close to normally distributed
        - Good for OLS
4. First difference
    - Reasonably close to normally distributed, with really long tails
        - Good enough for OLS

Plotting: Mean revenue by quarter

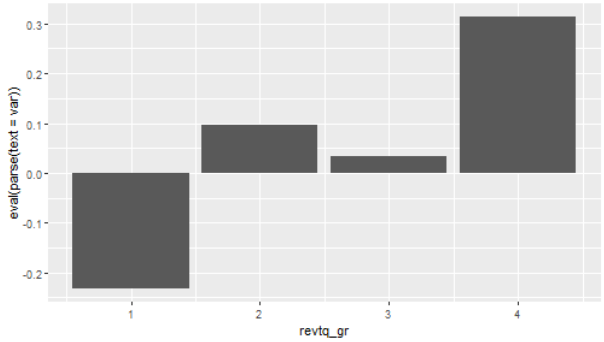
- Revenue



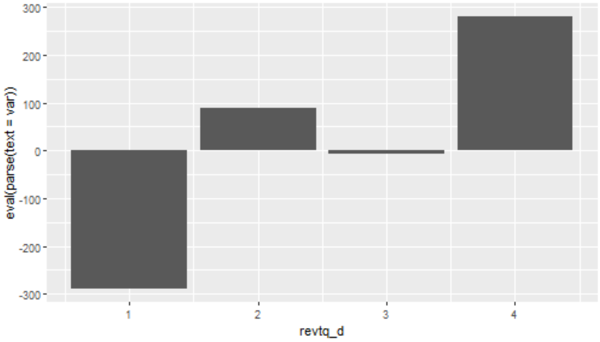
- Year-over-year growth



- Quarterly growth



- First difference



What we learn from the graphs?

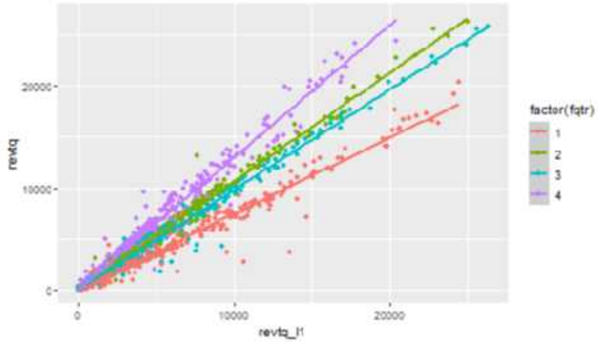
1. Revenue
   -
2. Quarterly growth
   -
3. Year-over-year growth
   -
4. First difference
   -

What we learn from the graphs?

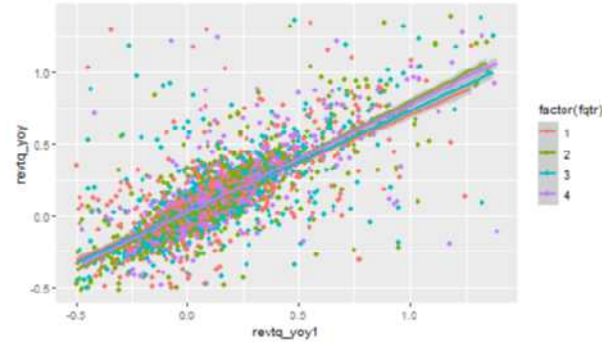
1. Revenue
   - Revenue seems cyclical!
2. Quarterly growth
   - Definitely cyclical!
3. Year-over-year growth
   - Year over year difference is less cyclical -- more constant
4. First difference
   - Definitely cyclical!

Plotting: Revenue vs lag by quarter

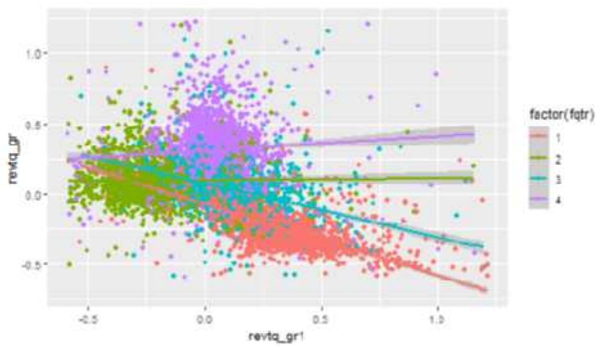
- Revenue



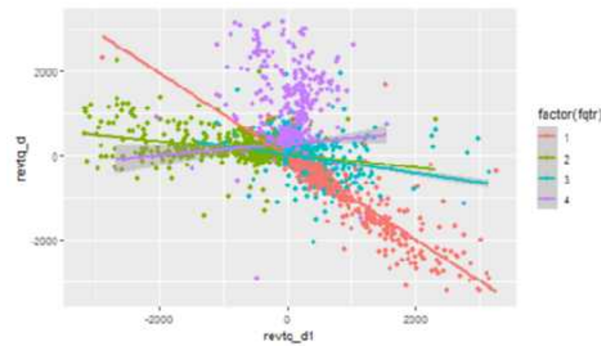
- Year-over-year growth



- Quarterly growth



- First difference



What we learn from the 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

```r
cor(train[,c("revtq","revtq_l1","revtq_l2","revtq_l3","revtq_l4")],
    use = "complete.obs") # delete row if with NA
```

```
##              revtq  revtq_l1  revtq_l2  revtq_l3  revtq_l4
## revtq    1.0000000 0.9917996 0.9939751 0.9907381 0.9973540
## revtq_l1 0.9917996 1.0000000 0.9917016 0.9938476 0.9901821
## revtq_l2 0.9939751 0.9917016 1.0000000 0.9916042 0.9932811
## revtq_l3 0.9907381 0.9938476 0.9916042 1.0000000 0.9910049
## revtq_l4 0.9973540 0.9901821 0.9932811 0.9910049 1.0000000
```

```r
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 -0.33021570  0.06675942 -0.23736085  0.65335232
## revtq_gr1 -0.33021570  1.00000000 -0.32597810  0.06581984 -0.22955824
## revtq_gr2  0.06675942 -0.32597810  1.00000000 -0.33452265  0.07215056
## revtq_gr3 -0.23736085  0.06581984 -0.33452265  1.00000000 -0.32429873
## revtq_gr4  0.65335232 -0.22955824  0.07215056 -0.32429873  1.00000000
```

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

Correlation matrices

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

```
##             revtq_yoy revtq_yoy1 revtq_yoy2 revtq_yoy3 revtq_yoy4
## revtq_yoy  1.0000000  0.6588642  0.4183968  0.4216933  0.1805950
## revtq_yoy1 0.6588642  1.0000000  0.5802585  0.3731204  0.3546604
## revtq_yoy2 0.4183968  0.5802585  1.0000000  0.5921796  0.3738081
## revtq_yoy3 0.4216933  0.3731204  0.5921796  1.0000000  0.5710053
## revtq_yoy4 0.1805950  0.3546604  0.3738081  0.5710053  1.0000000
```

```r
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 -0.6203336  0.3300007 -0.6075689  0.9165429
## revtq_d1   -0.6203336  1.0000000 -0.6171063  0.3311438 -0.5872559
## revtq_d2    0.3300007 -0.6171063  1.0000000 -0.6209104  0.3152248
## revtq_d3   -0.6075689  0.3311438 -0.6209104  1.0000000 -0.5908631
## revtq_d4    0.9165429 -0.5872559  0.3152248 -0.5908631  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:
  - `mutate()`
  - `lm()`
  - `package:ggplot2`
- Do the exercises in today's practice file
  - R Practice

Forecasting

1 period models

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

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

- Quarter and year lag
  - Year-over-year seemed pretty constant

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

- 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)
```

- 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(fqtr),
           data = train)
```

Quarter lag

```r
summary(mod1)
```

```
##
## Call:
## lm(formula = revtq ~ revtq_l1, data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -24399.7    -35.8    -13.0     36.3  15314.7
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 17.299837  12.991379   1.332    0.183
## revtq_l1     1.001776   0.001474 679.753   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1151 on 8294 degrees of freedom
##   (702 observations deleted due to missingness)
## Multiple R-squared:  0.9824,	Adjusted R-squared:  0.9824
## F-statistic: 4.621e+05 on 1 and 8294 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
## -20224.4    -21.6     -7.4     17.8   9320.8
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 8.740416   6.900972   1.267    0.205
## revtq_l1    0.225726   0.005434  41.540   <2e-16 ***
## revtq_l4    0.816635   0.005650 144.532   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 594.5 on 7855 degrees of freedom
##   (1140 observations deleted due to missingness)
## Multiple R-squared:  0.9955,    Adjusted R-squared:  0.9955
## F-statistic: 8.753e+05 on 2 and 7855 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
## -4854.9   -14.8    -5.7     8.0  5868.9
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.173259   4.176286   1.478   0.1394
## revtq_l1     0.785242   0.011881  66.095  < 2e-16 ***
## revtq_l2     0.106283   0.015152   7.015 2.52e-12 ***
## revtq_l3    -0.026460   0.014771  -1.791   0.0733 .
## revtq_l4     0.931266   0.011653  79.915  < 2e-16 ***
## revtq_l5    -0.779892   0.012756 -61.141  < 2e-16 ***
## revtq_l6    -0.079794   0.015819  -5.044 4.67e-07 ***
## revtq_l7     0.006604   0.015313   0.431   0.6663
## revtq_l8     0.065782   0.011621   5.660 1.57e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

2 years of lags, by observation quarter

```r
summary(mod4)
```

```
##
## Call:
## lm(formula = revtq ~ (revtq_l1 + revtq_l2 + revtq_l3 + revtq_l4 +
##     revtq_l5 + revtq_l6 + revtq_l7 + revtq_l8):factor(fqtr),
##     data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6141.4   -14.6     0.3    15.7  4980.3
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)              -0.42798    3.89557  -0.110 0.912521
## revtq_l1:factor(fqtr)1  0.50358    0.02104  23.934  < 2e-16 ***
## revtq_l1:factor(fqtr)2  1.11831    0.02231  50.121  < 2e-16 ***
## revtq_l1:factor(fqtr)3  0.81435    0.02848  28.591  < 2e-16 ***
## revtq_l1:factor(fqtr)4  0.89057    0.02585  34.456  < 2e-16 ***
## revtq_l2:factor(fqtr)1  0.25042    0.03399   7.367 1.94e-13 ***
## revtq_l2:factor(fqtr)2 -0.09685    0.02387  -4.057 5.02e-05 ***
## revtq_l2:factor(fqtr)3  0.21067    0.03883   5.425 5.97e-08 ***
## revtq_l2:factor(fqtr)4  0.27270    0.03498   7.797 7.25e-15 ***
```

Testing out of sample

- RMSE: Root Mean Square Error
- RMSE is very affected by outliers, and a bad choice for noisy data that you are OK with missing a few outliers here and there
  - Doubling error *quadruples* that part of the error

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

- MAE: Mean Absolute Error
- MAE is measures average accuracy with no weighting
  - Doubling error *doubles* that part of the error

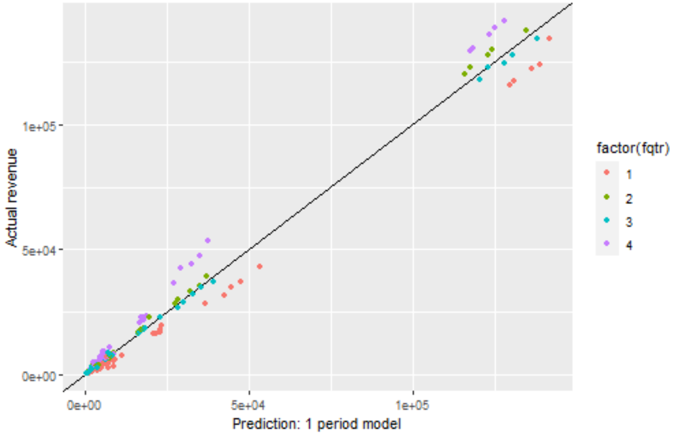
```
mae <- function(v1, v2) {
  mean(abs(v1-v2), na.rm = TRUE)
}
```

> Both are commonly used for evaluating OLS out of sample

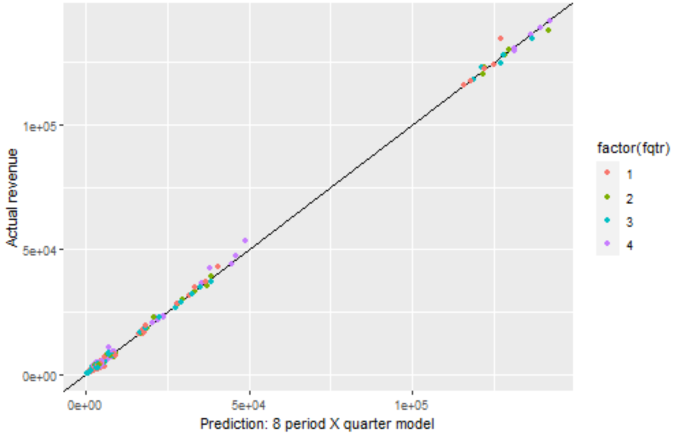
Testing out of sample

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.9823645	1151.0560	323.82144	2916.3430	1223.4301
1 and 4 periods	0.9955321	594.4151	157.48397	1143.8276	553.5204
8 periods	0.9986241	343.5646	94.98273	764.7114	362.1292
8 periods w/ quarters	0.9989338	301.9370	92.26997	757.4591	354.6585

1 quarter model



8 period model, by quarter

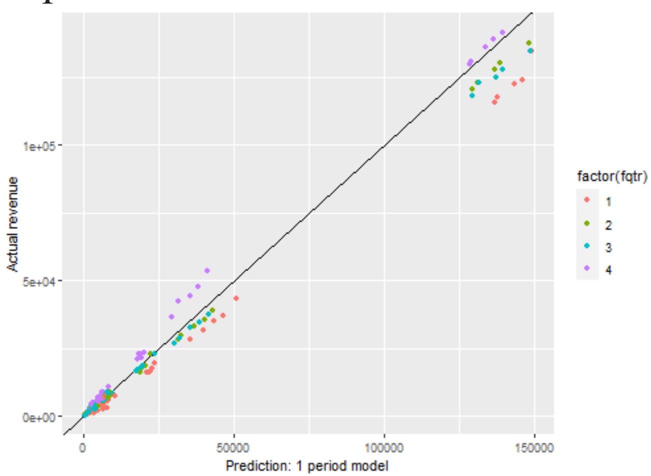


What about for revenue growth?

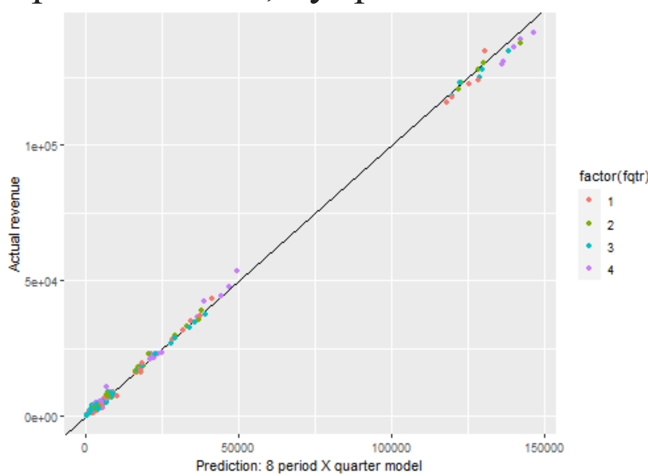
Backing out a revenue prediction, $revt_t = (1 + growth_t) \times revt_{t-1}$

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.0955220	1110.5010	307.8361	3202.2234	1338.9696
1 and 4 periods	0.4497703	530.0174	152.8021	1355.5009	631.5524
8 periods	0.6788386	463.3719	123.3965	1165.7280	530.6755
8 periods w/ quarters	0.7720057	381.7661	99.5676	986.1408	452.1947

1 quarter model



8 period model, by quarter

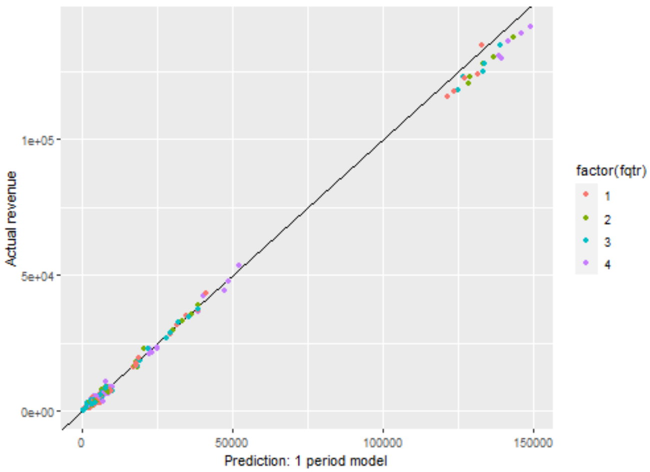


What about for YoY growth?

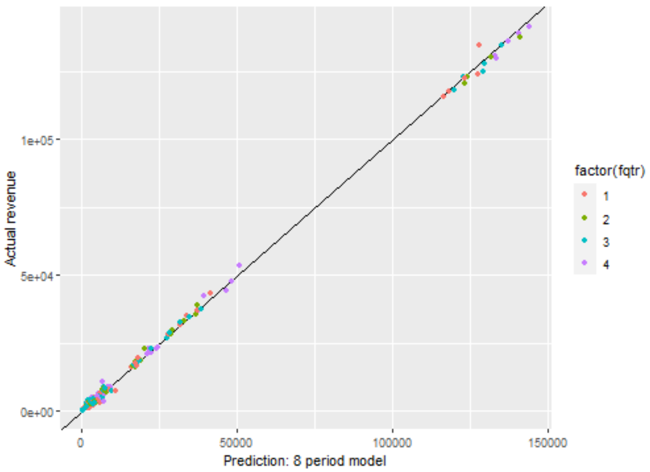
Backing out a revenue prediction, $revt_t = (1 + yoy\_growth_t) \times revt_{t-4}$

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.4376253	520.7532	129.1364	1570.5401	695.8093
1 and 4 periods	0.5378241	495.5506	127.3290	1400.2662	642.0383
8 periods	0.5430590	383.6760	101.1748	863.9954	425.6484
8 periods w/ quarters	0.1462837	705.8313	193.7847	1214.8656	620.3688

1 quarter model



8 period model

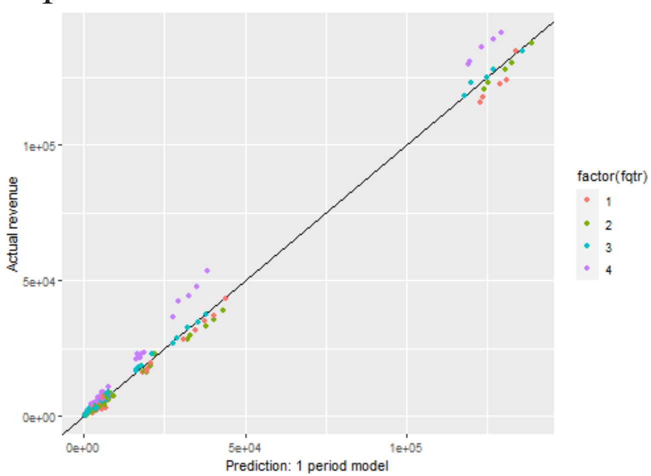


What about for first difference?

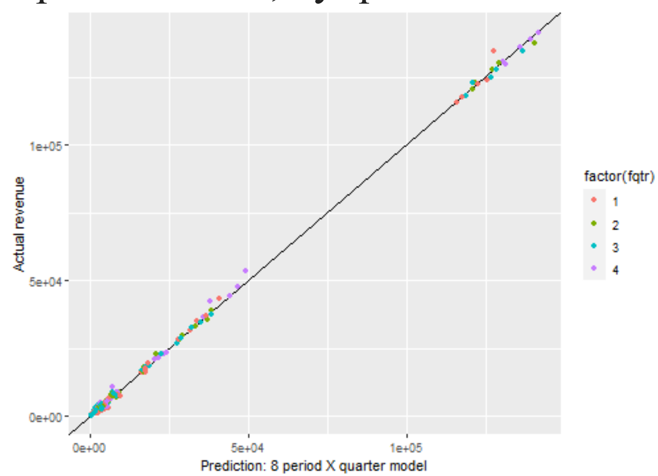
Backing out a revenue prediction, $revt_t = change_t + revt_{t-1}$

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.3578089	896.1441	286.47866	2247.2158	986.9519
1 and 4 periods	0.8502591	444.9570	113.00284	860.6968	411.8824
8 periods	0.9242547	329.4611	95.17826	764.8854	348.4883
8 periods w/ quarters	0.9383434	296.7399	88.32380	731.1697	343.4773

1 quarter model



8 period model, by quarter



Takeaways

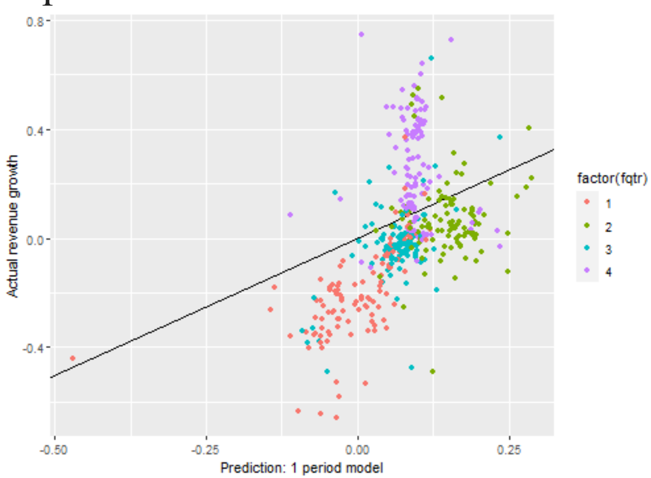
1. The first difference model works about as well as the revenue model at predicting next quarter revenue
   - From earlier, it doesn't suffer (as much) from multicollinearity either
     - This is why time series analysis is often done on first differences
       - Or second differences (difference 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?

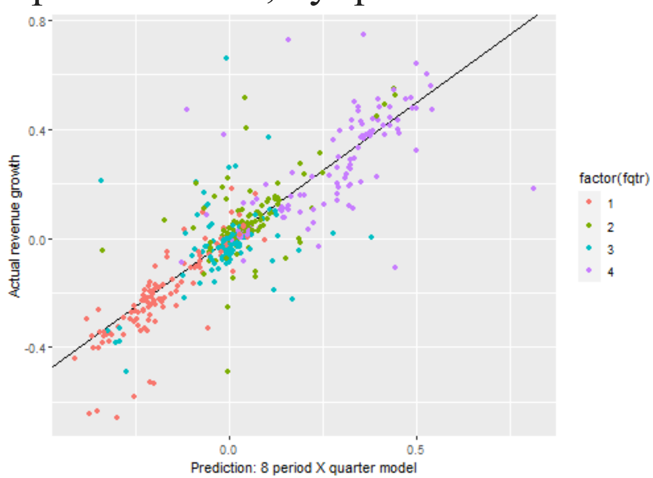
Predicting quarter over quarter revenue growth itself

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.0955220	0.3436252	0.2073042	0.2087555	0.1663210
1 and 4 periods	0.4497703	0.2611941	0.1103827	0.1373419	0.0947553
8 periods	0.6788386	0.1737244	0.0848606	0.1269428	0.0801675
8 periods w/ quarters	0.7720057	0.1461233	0.0762027	0.1267874	0.0758181

1 quarter model



8 period model, by quarter

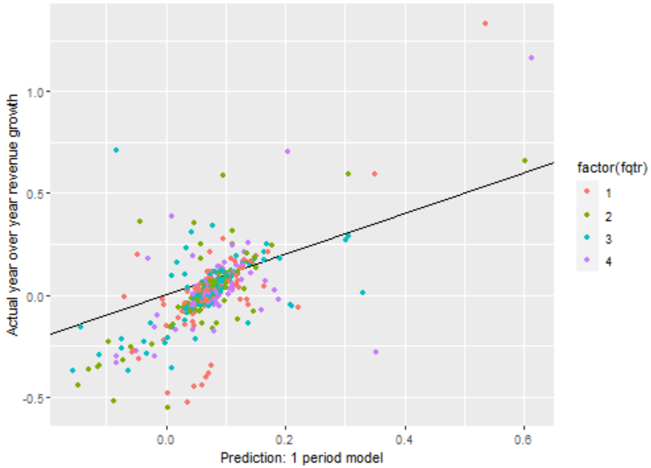


What about for YoY growth?

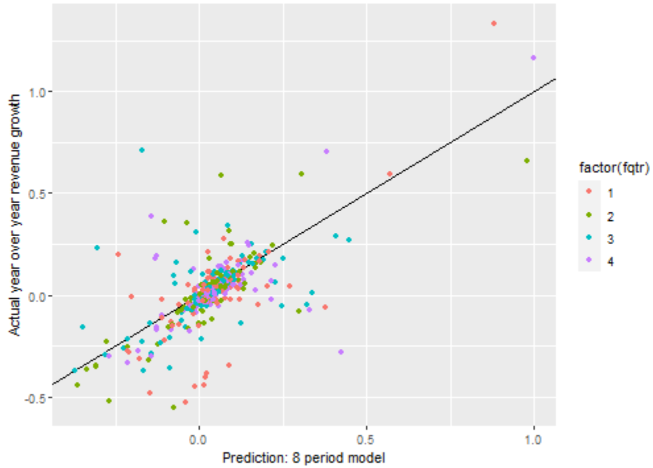
Predicting YoY revenue growth itself

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.4376253	0.3022800	0.1085684	0.1511589	0.1006249
1 and 4 periods	0.5378241	0.2389085	0.0993933	0.1493757	0.0967341
8 periods	0.5430590	0.1881716	0.0750616	0.1358365	0.0753768
8 periods w/ quarters	0.1462837	0.2935877	0.1373069	0.1866005	0.1137764

1 quarter model



8 period model

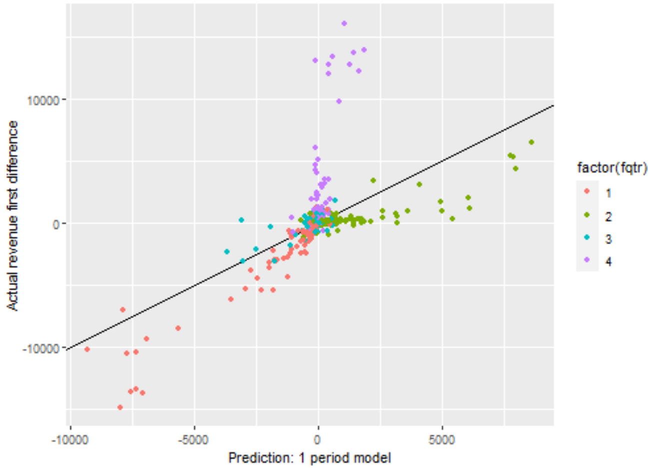


What about for first difference?

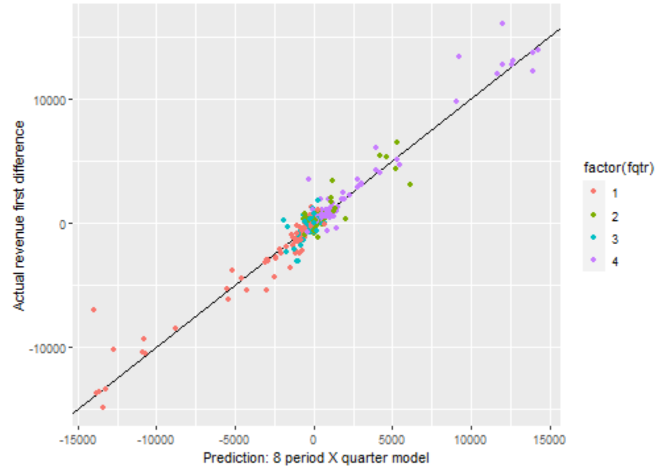
Predicting first difference in revenue itself

	adj_r_sq	rmse_in	mae_in	rmse_out	mae_out
1 period	0.3578089	896.1441	286.47866	2247.2158	986.9519
1 and 4 periods	0.8502591	444.9570	113.00284	860.6968	411.8824
8 periods	0.9242547	329.4611	95.17826	764.8854	348.4883
8 periods w/ quarters	0.9383434	296.7399	88.32380	731.1697	343.4773

1 quarter model



8 period model, by quarter



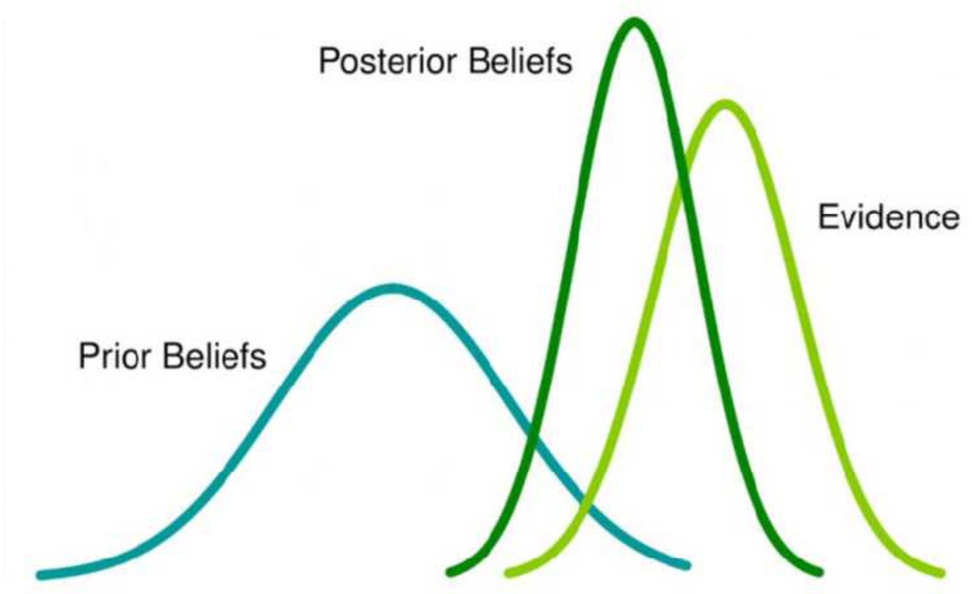
Monte Carlo Simulation

Business question

- “What’s the likelihood your organization will reach the target/goal?”

Bayesian statistics

- What is the Bayesian Statistics?



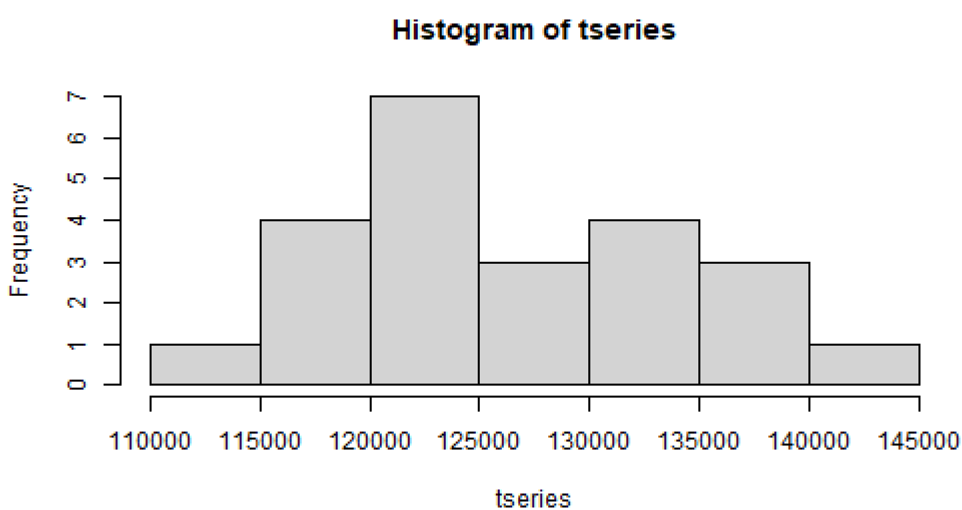
As we learn more, our beliefs should change

Monte Carlo Simulation

- Monte Carlo simulation is named after the gambling hot spot in Monaco. It was first developed by Stanislaw Ulam, a mathematician who worked on the Manhattan Project (nuclear weapons). He played countless games of solitaire and became interested in plotting the outcome in order to observe their distribution and determine the probability of winning. He shared the idea with John Von Neumann and the duo collaborated to develop the Monte Carlo simulation.

Step 1: Prepare Data

```r
# We use Walmart's qsales 2015Q4~2020Q3 (20Q) to predict 2020Q4
set.seed(8) # to produce the same random generated data
wmt <- df %>% filter(tic=="WMT", fyearq >= 2015) %>% select("revtq")
# Create time series
tseries <- ts(wmt$revtq, frequency = 4, start = c(2015, 4))
hist(tseries) # Check the distribution
```




```r
tseries_df = as.data.frame(tseries) # create dataframe
```

Step 2a: fit various prior distributions

```r
# fit some distribution
library(fitdistrplus)
fit.norm <- fitdist(as.numeric(tseries_df$x), "norm")
fit.weibull <- fitdist(as.numeric(tseries_df$x), "weibull")
fit.lnorm <- fitdist(as.numeric(tseries_df$x), "lnorm")
fit.gamma <- fitdist(as.numeric(tseries_df$x), "gamma")
fit.logistic <- fitdist(as.numeric(tseries_df$x), "logis")
fit.cauchy <- fitdist(as.numeric(tseries_df$x), "cauchy")
# Compare Goodness-of-fit statistics
gofstat(list(fit.norm, fit.weibull, fit.lnorm, fit.gamma,
             fit.logistic, fit.cauchy),
        fitnames = c("fit.norm", "fit.weibull", "fit.lnorm",
                     "fit.gamma", "fit.logistic", "fit.cauchy"))
```

```
## Goodness-of-fit statistics
##                                fit.norm fit.weibull  fit.lnorm  fit.gamma
## Kolmogorov-Smirnov statistic 0.11508001  0.14269208 0.10955650 0.10921256
## Cramer-von Mises statistic   0.05803522  0.08249682 0.05316731 0.05453097
## Anderson-Darling statistic   0.37663151  0.51919298 0.34923725 0.35690682
##                              fit.logistic fit.cauchy
## Kolmogorov-Smirnov statistic   0.11509395 0.15603017
## Cramer-von Mises statistic     0.05485176 0.09252265
## Anderson-Darling statistic     0.38550884 0.74514994
```

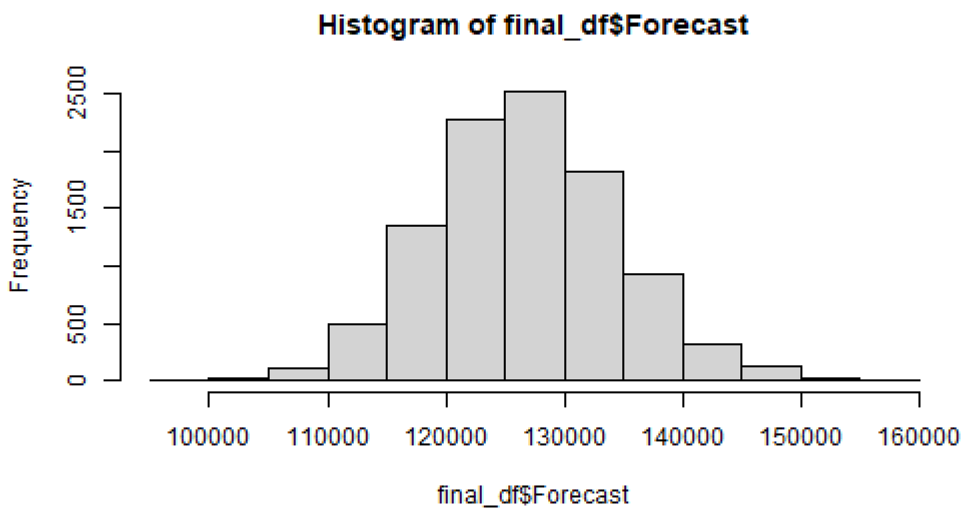
Step 2b: choose the best-fit distribution

```
# the best Goodness-of-fit statistics is for the log normal distributic
summary(fit.lnorm)
```

```
## Fitting of the distribution ' lnorm ' by maximum likelihood
## Parameters :
##            estimate  Std. Error
## meanlog 11.74728263 0.012732243
## sdlog    0.06106169 0.008992192
## Loglikelihood:  -238.5181   AIC:  481.0361   BIC:  483.3071
## Correlation matrix:
##              meanlog        sdlog
## meanlog 1.000000e+00 4.067529e-13
## sdlog   4.067529e-13 1.000000e+00
```

Step 3a: generate forecast

```r
# rlnorm() is the log normal distribution generator
fit.coef <- coef(fit.lnorm)
final_df <- as.data.frame(rlnorm(n=10^4,
                                 meanlog = fit.coef["meanlog"],
                                 sdlog = fit.coef["sdlog"]))
colnames(final_df) <- 'Forecast'
hist(final_df$Forecast) #plot histogram of forecasted quantities
```



Step 3b: calculate probability to meet the target

- Assume 2020Q4 sales target is $120 bil
- Probability to meet the target is as follows (note that the numbers in millions USD):

```
myproba_lnorm <- sum(final_df$Forecast >= 120000) / 100
myproba_lnorm
```

```
## [1] 80.27
```

Try the normal distribution instead

- Instead of using computer, you may determine the distribution
- The probability to meet the target based on normal distribution is as follows:

```r
# normal distribution generator
library(truncnorm)
fit.coef <- coef(fit.norm)
final_df <- as.data.frame(rtruncnorm(n = 10^4,
                                      a = min(tseries_df$x),
                                      b = max(tseries_df$x),
                                      mean = fit.coef["mean"],
                                      sd = fit.coef["sd"]))
colnames(final_df) <- 'Forecast'
myproba_norm <- sum(final_df$Forecast >= 120000) / 100
myproba_norm
```

```
## [1] 85.83
```

Summary of Session 3

For next week

- First individual assignment
    - Finish by tonight 1159pm
    - Submit on eLearn
    - .rmd, .html and .pdf files only, no data file, no zip please
- Supplementary practice
    - One more assignment on eLearn
    - Focus on Exploratory Data Analysis (EDA)
    - No need to submit, for your own practice only
- Try to replicate the code for this session
- Datacamp
    - Practice a bit more to keep up to date
        - Using R more will make it more natural
- Case: Walmart Store Sales Forecasting