Programming with Data

Session 4: Forecasting with Linear Regressions

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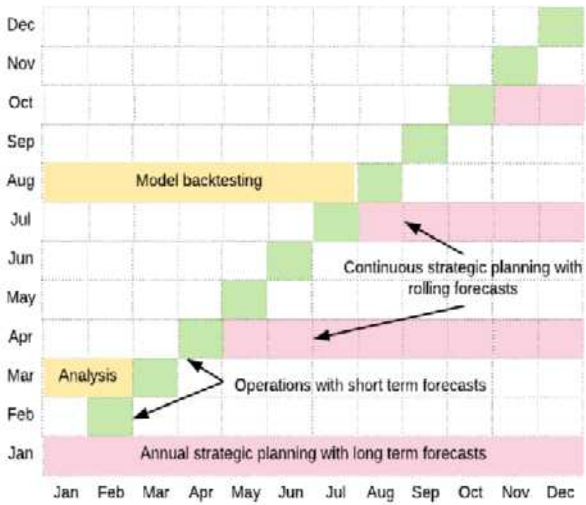
Application: Revenue prediction

The question

> What factors can help us to forecast revenue of a company for budgeting, reporting, valuation, and other purposes?

- Case: Uber's financial forecasting with DS and ML



- Other interesting readings from Uber
  - Finance Computation Platform
  - Fraud Detection
  - Internal Audit

Weather data? Satellite images?

- Case: Weather as a Commodity

- "Hedge Funds now employ a variety of techniques to track weather fluctuation in order to get a cutting edge over competitors and to increase their profit margins."
- "A legacy has been created by RS Metrics LLC., a provider of satellite imagery and quantitative analysis, ever since they forecasted Walmart’s second quarter customer traffic in 2011 using satellite images of parking lot traffic measurements."
- **What other creative data might there be?**

Forecasting application

- Forecast sales of a real estate company in Singapore
- using financial and non-financial data:
  - company's own data
  - other companies' data
  - macro economic data

Linear models

What is a linear model?

- Revist the following model

$$\hat{y} = \alpha + \beta\hat{x} + \varepsilon$$

- This simplest model is trying to predict some outcome $\hat{y}$ as a function of an input $\hat{x}$
  - $\hat{y}$ in our case is a firm's revenue in a given year
  - $\hat{x}$ could be a firm's assets in a given year or any other factors we can identify
  - α and β are coefficients solved for
  - ε is the error in the measurement

> This is an *OLS* model -- **O**rdinary **L**east **S**quare regression

Example

> Let's predict UOL's revenue

- **COMPUSTAT** has data for UOL since 1989 (till 2019 for this example)
  - more missing data before 1994
  - numbers in Millions

```r
# revt: Revenue, at: Assets
summary(uol[ , c("revt", "at")])
```

```
##       revt               at       
##  Min.   :  94.78   Min.   : 1218  
##  1st Qu.: 213.05   1st Qu.: 3052  
##  Median : 464.99   Median : 3520  
##  Mean   : 774.38   Mean   : 6510  
##  3rd Qu.:1212.26   3rd Qu.: 9044  
##  Max.   :2397.34   Max.   :20664  
```

Linear models in R

- To run a linear model, use `lm()`
  - The first argument is a formula for your model, where tilde `~` is used in place of an equals sign
    - The left side is what you want to predict
    - The right side is inputs for prediction, separated by `+`
    - `y ~ x1 + x2 + x3`
  - The second argument is the data to use
- Additional variations for the formula:
  - Functions transforming inputs (as vectors), such as `log()`
  - Fully interacting variables using asterisk/star `*`
    - i.e., `A*B` includes, A, B, and A times B in the model
  - Interactions using colon `:`
    - i.e., `A:B` just includes A times B in the model

```
# Example:
lm(revt ~ at, data = uol)
```

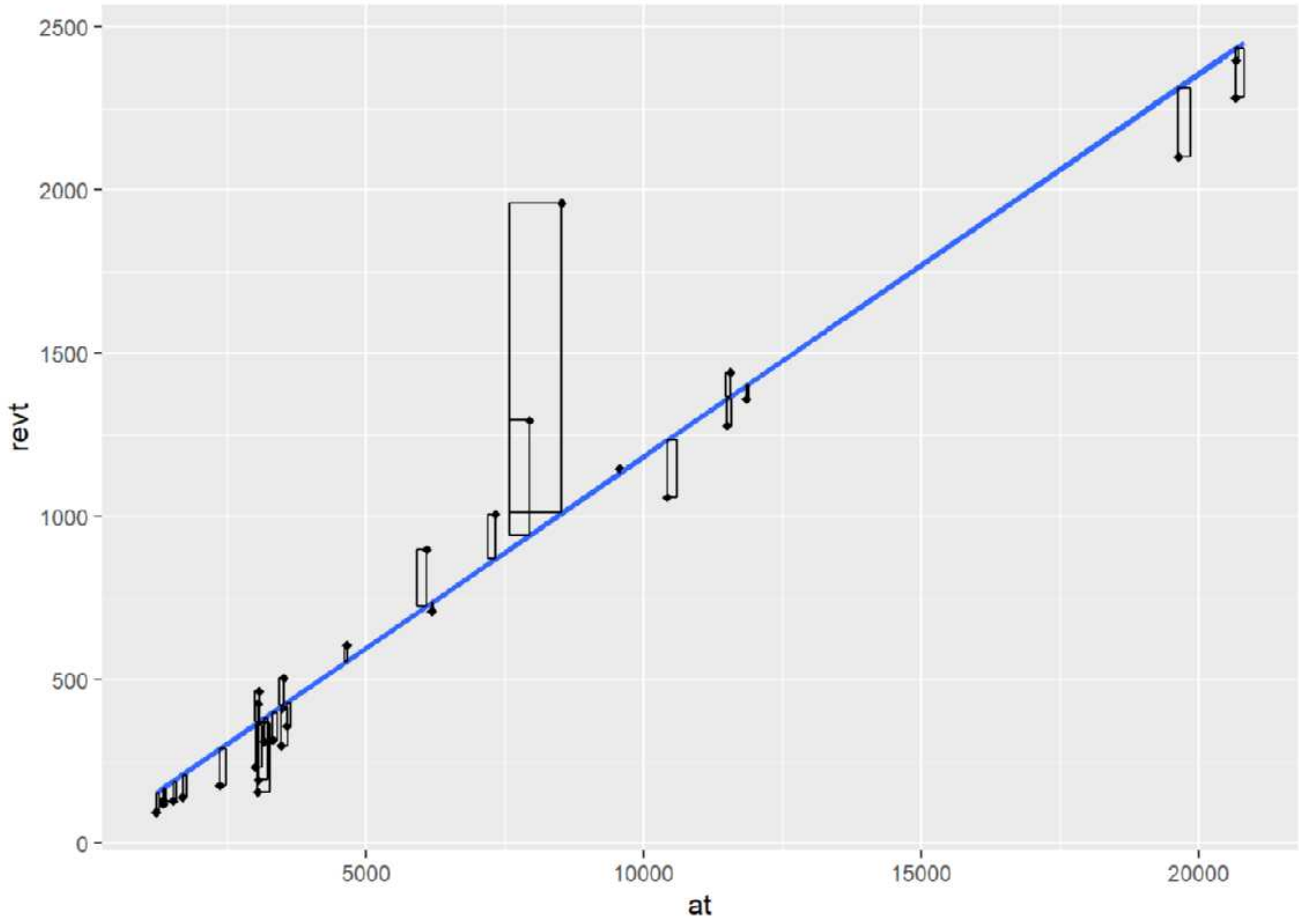
Example: UOL

```
mod1 <- lm(revt ~ at, data = uol)
summary(mod1)
```

```
##
## Call:
## lm(formula = revt ~ at, data = uol)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -212.45  -98.13  -48.29   53.50  949.34
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.101598  60.085716   0.168    0.868
## at           0.117403   0.007031  16.698   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 216.7 on 29 degrees of freedom
## Multiple R-squared:  0.9058,	Adjusted R-squared:  0.9025
## F-statistic: 278.8 on 1 and 29 DF,  p-value: < 2.2e-16
```

> $1 more in assets leads to $0.12 more in revenue

What's Ordinary Least Squares?



Zoom in on OLS output

- **Residuals**: actual value of y minus what the model predicted

```
summary(uol$revt - mod1$fitted.values)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -212.45  -98.13  -48.29    0.00   53.50  949.34
```

- **Estimate**: estimated coefficients that minimize the sum of the square of the errors/residuals
- **Std. Error**: Residual Standard Error (see below) divided by the square root of the sum of the square of that particular x variable.
- **t value**: Estimate divided by Std. Error
- **Pr(>|t|)**: the probability of estimated coefficient = 0 (H0), a.k.a `p-value`
- **Residual standard error**: a tweaked standard deviation of the residual/error

```
#Residual Standard error (Like Standard Deviation)
k = length(mod1$coefficients) - 1 #number of x excluding intercept
n = length(mod1$residuals) #number of data
SSE = sum(mod1$residuals**2) #sum of squared error
sqrt(SSE/(n - (1 + k))) #Residual Standard Error
```

```
## [1] 216.7404
```

Zoom in on OLS output

- **Multiple R-squared**: how much variance of Y is explained by X

```
#Multiple R-Squared
SSY = sum((uol$revt - mean(uol$revt))**2) # sum of variance of Y
(SSY - SSE)/SSY
```

```
## [1] 0.905791
```

- **Adjusted R-Squared**: R-squared controlled for number of X and data

```
#Adjusted R-Squared
1-(SSE/SSY)*(n-1)/(n-(k+1))
```

```
## [1] 0.9025424
```

- **F-Statistic**: a "global" test that checks if at least one coefficient is nonzero

```
#F-Statistic
#Ho: All coefficients are zero
#Ha: At least one coefficient is nonzero
((SSY-SSE)/k) / (SSE/(n - (k + 1)))
```

```
## [1] 278.8262
```

Example: UOL

- This model wasn't so interesting...
  - Bigger firms have more revenue -- this is a given
- How about... revenue *growth*?
- And *change* in assets
  - i.e., Asset growth

$$\Delta x_t = \frac{x_t}{x_{t-1}} - 1$$

Calculating changes in R

- The easiest way is using `package:tidyverse`'s `package:dplyr`
  - `lag()` function along with `mutate()`
  - `package:data.table` is also popular but I prefer `package:dplyr`
- The default way to do it is to create a vector manually

```
# tidyverse with pipe %>%
uol <- uol %>%
  mutate(revt_growth1 = revt / lag(revt, order_by = fyear) - 1)

# which is equivalent to
uol <- mutate(uol, revt_growth2 = revt / lag(revt, order_by = fyear) - 1)

# Base R way, [-n] to remove the nth element from a vector
uol$revt_growth3 = uol$revt / c(NA, uol$revt[-length(uol$revt)]) - 1
identical(uol$revt_growth1, uol$revt_growth3)
```

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

```
# magrittr %<>% to combine <- and %>%
library(magrittr)
uol %<>% mutate(revt_growth4 = revt / lag(revt) - 1)
identical(uol$revt_growth1, uol$revt_growth4)
```

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

A note on lag() and lead()

- `lag()` or `lead()` finds the "previous" or "next" values in a vector.
- Very useful for comparing values ahead of or behind the current values.
- The dataset must be sorted by the key (eg, time for time series data)

```
# Use order_by if data not already ordered
dff <- data.frame(year = 2001:2003, value = (1:3) ^ 2)
scrambled <- dff[sample(nrow(dff)), ]

wrong <- mutate(scrambled, prev = lag(value))
arrange(wrong, year)
```

```
##   year value prev
## 1 2001     1    9
## 2 2002     4   NA
## 3 2003     9    4
```

```
right <- mutate(scrambled, prev = lag(value, order_by = year))
arrange(right, year)
```

```
##   year value prev
## 1 2001     1   NA
## 2 2002     4    1
## 3 2003     9    4
```

A note on mutate()

- `mutate()` adds variables to an existing data frame
  - Also mutate multiple columns
    - `mutate_all()` applies a transformation to all values in a data frame and adds these to the data frame
    - `mutate_at()` does this for a set of specified variables
    - `mutate_if()` transforms all variables matching a condition
      - Such as `is.numeric`
- Mutate can be very powerful when making more complex variables
  - For instance: Calculating growth within company in a multi-company data frame (cross-sectional with time series data, ie, panel data)
- Do Exercise 1 in the R Practice

Example: UOL with changes

```r
# Make the other needed change
uol <- uol %>%
  mutate(at_growth = at / lag(at) - 1)  # From dplyr
# Rename our revenue growth variable
uol <- rename(uol, revt_growth = revt_growth1)  # From dplyr
# Run the OLS model
mod2 <- lm(revt_growth ~ at_growth, data = uol)
summary(mod2)
```

```
##
## Call:
## lm(formula = revt_growth ~ at_growth, data = uol)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.56897 -0.12016 -0.01099  0.15012  0.42991
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.08443    0.05215   1.619   0.1167
## at_growth    0.55576    0.26591   2.090   0.0458 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.237 on 28 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.135,    Adjusted R-squared:  0.1041
## F-statistic: 4.368 on 1 and 28 DF,  p-value: 0.04582
```

Example: UOL with changes

- ΔAssets doesn't capture ΔRevenue so well
- Perhaps change in total assets is a bad choice?
- Or perhaps we need to expand our model?

Scaling up!

$$\hat{y} = \alpha + \beta_1 \hat{x}_1 + \beta_2 \hat{x}_2 + \ldots + \varepsilon$$

- OLS doesn't need to be restricted to just 1 input!
  - Not unlimited though (yet)
    - Number of inputs must be less than the number of observations minus 1
- Each $\hat{x}_i$ is an input in our model
- Each β_i is something we will solve for
- $\hat{y}$, α, and ε are the same as before

> We have... 823 variables from Compustat Global alone!

- Let's just add them all?
  - This is a very machine-learning mindset
- We only have 31 observations...
  - 31 << 823...

> Now what?

Scaling up our model

> Building a model requires careful thought!

- What makes sense to add to our model?

> This is where having accounting and business knowledge comes in!

- Some potential sources to consider:
  - Direct accounting relations
    - Financing? Capex? R&D? Other expenditures?
  - Business management and corporate structure
    - Some management characteristics may matter
    - Corporate governance may also matter
  - Economics
    - Macro econ: trade, economic growth, population, weather
    - Micro econ: Other related firms like suppliers and customers
  - Legal factors
    - Any changes in law? Favorable or not?
  - Market factors
    - Interest rates, cost of capital, foreign exchange?

> Any other factors?

Scaling up our model

- One possible improvement:

```r
# lct: short term liabilities, che: cash and equivalents, ebit: EBIT
# list(name = ~f(.)) for repeated functions/formula
# broom::tidy(): to report a more concised summary using the broom package
uol <- uol %>%
  mutate_at(vars(lct, che, ebit), list(growth = ~(. / lag(.) - 1)))
mod3 <- lm(revt_growth ~ lct_growth + che_growth +
             ebit_growth, data = uol)
broom::tidy(mod3)
```

```
## # A tibble: 4 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)   0.0685    0.0457      1.50 0.146
## 2 lct_growth    0.237     0.0699      3.39 0.00222
## 3 che_growth   -0.114     0.0882     -1.29 0.209
## 4 ebit_growth   0.0386    0.0213      1.81 0.0812
```

```r
broom::glance(mod3)
```

```
## # 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     0.338         0.261 0.215      4.42  0.0122     3   5.67 -1.34  5.66
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

Formalizing testing

Why formalize?

- Our current approach has been ad hoc
  - What is our goal?
  - How will we know if we have achieved it?
- Formalization provides more rigor

Scientific method

1. Question
   - What are we trying to determine?
   - Fundamentally, the question is asked/answered to solve your business problems
2. Hypothesis
   - What do we think will happen? Make a statement
     - "If X, then Y"
     - e.g., "If capital expenditures increase, revenue will increase."
     - A good hypothesis based on information in prior research, ie, hypothesis typically follows a thorough *literature review*
   - Null hypothesis, a.k.a. H_0
     - Typically: The statement *doesn't* work
   - Alternative hypothesis, a.k.a. H_1 or H_A
     - The statement *does* work (and perhaps how it works)
3. Research design
   - What exactly will we test? How to measure X and Y?
   - Formalize a statistical model
4. Testing
   - Test the model
5. Analysis
   - Did it work?

Test statistics

- Testing a coefficient:
  - Use a t (less assumption on normality, unknown population s.d., more commonly used) or z test (known population s.d.)
- Testing a model as a whole
  - F-test, check *adjusted* R squared as well
- Testing across models
  - Chi squared (χ^2) test
  - Vuong test (comparing R^2)
  - Akaike Information Criterion (AIC) (Comparing MLEs, lower is better)

> All of these have p-values, except for AIC

Revisiting the previous problem

Formalizing our last test

1. Question
   -
2. Hypotheses
   - H_0:
   - H_1:
3. Research design
   - Individual variables:
   - Model:
4. Testing:
   -

Formalizing our last test

1. Question
    - Can we predict changes in revenue using a firm's accounting information?
2. Hypotheses
    - H_0: Our variables do not predict UOL's change in revenue
    - H_1: Our variables are help to predict UOL's change in revenue
3. Research design
    - Individual variables
        - Growth in current liabilities (+)
        - Growth in cash and cash equivalent (+)
        - Growth in EBIT (+)
    - Model: OLS
4. Testing:
    - t-test for coefficients and F-test for model

Is this model better?

```r
anova(mod2, mod3, test = "Chisq")
```

```
## Analysis of Variance Table
##
## Model 1: revt_growth ~ at_growth
## Model 2: revt_growth ~ lct_growth + che_growth + ebit_growth
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     28 1.5721
## 2     26 1.2035  2   0.36861  0.01865 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

> A bit better at $p < 0.05$

- This means our model with change in current liabilities, cash, and EBIT appears to be better than the model with change in assets.

> Note: p-value tells the prob that the two models are the same (in terms of variance explained). If the first model is better, the Sum of Sq number will be significantly negative. RSS also speaks.

Panel data

Expanding our methodology

- Why should we limit ourselves to 1 firm's data?
- The nature of data analysis is such:

> Adding more data usually helps improve predictions

- Assuming:
  - The data isn't of low quality (too noisy)
  - The data is relevant
  - Any differences can be reasonably controlled for

Expanding our question

- Previously: Can we predict revenue using a firm's accounting information?
    - This is simultaneous, and thus is not forecasting
- Now: Can we predict *future* revenue using a firm's accounting information?
    - By trying to predict ahead, we are now in the realm of forecasting
    - What do we need to change?
        - $\hat{y}$ will need to be 1 year in the future

First things first

- When using a lot of data, it is important to make sure the data is clean
- In our case, we may want to remove any very small firms

```
# Ensure firms have at least $1M (local currency), and have revenue
# df contains all real estate companies excluding North America
df_clean <- filter(df, df$at > 1, df$revt > 0)

# We cleaned out 2,177 observations!
print(c(nrow(df), nrow(df_clean)))
```

```
## [1] 34156 31979
```

```
# Another useful cleaning function:
# Replaces NaN, Inf, and -Inf with NA for all numeric variables!
df_clean <- df_clean %>%
  mutate_if(is.numeric, list(~replace(., !is.finite(.), NA)))
```

- `is.finite()` returns a vector of the same length as x the jth element of which is TRUE if x[j] is finite (i.e., it is not one of the values NA, NaN, Inf or -Inf) and FALSE otherwise.

Looking back at the prior models

```r
uol <- uol %>% mutate(revt_lead = lead(revt))  # From dplyr
forecast1 <-
  lm(revt_lead ~ lct + che + ebit, data = uol)
library(broom)  # To display regression outputs in a tidy fashion
tidy(forecast1)  # present regression output
```

```
## # A tibble: 4 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)   64.0     127.        0.505  0.618
## 2 lct            0.392     0.237     1.65   0.111
## 3 che            0.141     0.330     0.425  0.674
## 4 ebit           2.03      1.04      1.96   0.0613
```

```r
glance(forecast1)  # present regression statistics
```

```
## # 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     0.746         0.717  369.      25.5 0.0000000663     3  -218.  446.  453.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

> The model is significant but not the coefficients. We can do better.

Expanding the prior model

```
forecast2 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit , data = uol)
tidy(forecast2)
```

```
## # A tibble: 7 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)   75.2      97.1       0.775 0.446
## 2 revt           1.63      0.318     5.11  0.0000356
## 3 act            0.212     0.168     1.26  0.219
## 4 che            0.264     0.290     0.912 0.371
## 5 lct           -0.238     0.190    -1.25  0.223
## 6 dp            -1.45      4.42     -0.328 0.746
## 7 ebit          -3.28      1.12     -2.91  0.00780
```

- Revenue (revt) to capture stickiness of revenue
- Current assest (act) & Cash (che) to capture asset base
- Current liabilities (lct) to capture payments due
- Depreciation (dp) to capture decrease in real estate asset values
- EBIT to capture operational performance

Expanding the prior model

```r
glance(forecast2)
```

```
## # 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     0.923         0.903  216.      46.1 1.11e-11     6  -200.  416.  427.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```r
anova(forecast1, forecast2, test = "Chisq")
```

```
## Analysis of Variance Table
##
## Model 1: revt_lead ~ lct + che + ebit
## Model 2: revt_lead ~ revt + act + che + lct + dp + ebit
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     26 3548955
## 2     23 1074135  3   2474820 1.84e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

> This is better (Adj. R^2, χ^2, AIC).

Panel data

- Panel data refers to data with the following characteristics:
  - There is a time dimension
  - There is at least 1 other dimension to the data (firm, country, etc.)
- Special cases:
  - A panel where all dimensions have the same number of observations is called *balanced*
    - Otherwise we call it *unbalanced*
  - A panel missing the time dimension is *cross-sectional*
  - A panel missing the other dimension(s) is a *time series*
- Format:
  - Long: Indexed by all dimensions (e.g., country-year)
  - Wide: Indexed only by other dimensions (e.g., country only)

dplyr makes transpose easy

- Depending on data source, you may need to transform the data format from wide to long (or long to wide).
- The `package::dplyr` has a `gather()` function is to do so.

Gather() gather(year, growth, q1_2017:q4_2018)

Messy

country	q1_2017	q2_2017	q3_2017	q4_2017
A	0.03	0.05	0.04	0.03
B	0.05	0.07	0.05	0.02
C	0.01	0.02	0.01	0.04

tidier

country	time	growth
A	q1_2017	0.03
B	q1_2017	0.05
C	q1_2017	0.01
A	q2_2017	0.05
B	q2_2017	0.07
C	q2_2017	0.02
A	q3_2017	0.04
B	q3_2017	0.05
C	q3_2017	0.01
A	q4_2017	0.03

Wide versus long data

```r
university_wide # randomly generated numbers
```

```
##   university rand.2016 rand.2017 rand.2018
## 1        SMU        59        27        69
## 2        NTU        59        27        69
## 3        NUS        59        27        69
```

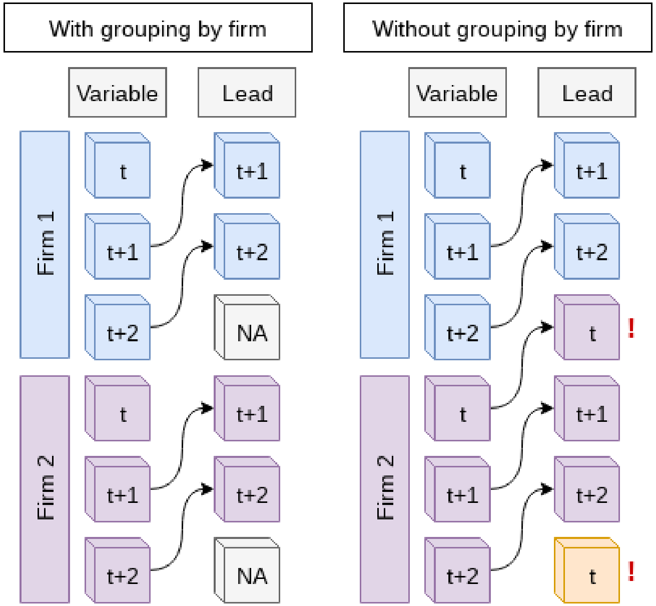
```r
# convert wide to long dataset
library("tidyr", "dplyr")
university_long <- university_wide %>%
    gather(year, rand, rand.2016:rand.2018) %>%
    mutate(year = as.numeric(gsub("rand.", "", year))) %>%
    arrange(desc(year))
university_long
```

```
##   university year rand
## 1        SMU 2018   69
## 2        NTU 2018   69
## 3        NUS 2018   69
## 4        SMU 2017   27
## 5        NTU 2017   27
## 6        NUS 2017   27
## 7        SMU 2016   59
## 8        NTU 2016   59
## 9        NUS 2016   59
```

All SG real estate companies

```r
# group_by - without it, lead() will pull from the subsequent firm!
# ungroup() tells R that we finished grouping
df_clean <- df_clean %>%
  group_by(isin) %>%
  mutate(revt_lead = lead(revt)) %>%
  ungroup()
```

- Do Exercises 2 and 3 of the R Practice



All SG real estate companies

```
forecast3 <- lm(revt_lead ~ revt + act + che + lct + dp + ebit,
                data = df_clean[df_clean$fic == "SGP", ])
tidy(forecast3)
```

```
## # A tibble: 7 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept) 21.5       11.6         1.86  6.39e- 2
## 2 revt         0.537      0.0579      9.26  1.07e-18
## 3 act          0.00999    0.0405      0.247 8.05e- 1
## 4 che          0.480      0.118       4.07  5.59e- 5
## 5 lct          0.218      0.0612      3.56  4.20e- 4
## 6 dp           4.38       0.960       4.56  6.67e- 6
## 7 ebit        -1.13       0.238      -4.72  3.17e- 6
```

All SG real estate companies

```
glance(forecast3)
```

```
## # 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     0.836         0.833  206.      352. 1.30e-159     6 -2850. 5717. 5749.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

> Lower adjusted R^2 -- This is worse? Why?

- Note: χ^2 can only be used for models on the same data
  - Same for AIC

Worldwide real estate companies

```
forecast4 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit , data = df_clean)
tidy(forecast4)
```

```
## # A tibble: 7 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept) 220.     579.          0.379 7.04e- 1
## 2 revt          1.05     0.00634   165.    0
## 3 act          -0.0234   0.00539    -4.33  1.50e- 5
## 4 che           0.0203   0.0269      0.756 4.49e- 1
## 5 lct           0.0553   0.00866     6.39  1.82e-10
## 6 dp            0.172    0.186       0.927 3.54e- 1
## 7 ebit          0.126    0.0652      1.94  5.29e- 2
```

Worldwide real estate companies

```
glance(forecast4)
```

```
## # 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     0.947         0.947 40818.    15138.       0     6 -61343. 122702. 122754.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

> Higher adjusted R^2 -- better!

- Note: χ^2 can only be used for models on the same data
  - Same for AIC

Model accuracy

> Why is 1 model better while the other model is worse?

- Ranking:
  1. Worldwide real estate model
  2. UOL model
  3. Singapore real estate model

> Different sources of noise, amounts of data

Dealing with noise

Noise

> Statistical noise is random error in the data

- Many sources of noise:
  - Other factors not included in
  - Error in measurement
    - Accounting measurement!
  - Unexpected events / shocks

> Noise is OK, but the more we remove, the better!

Removing noise: Singapore model

- Different companies may behave slightly differently (but time-invariant)
    - Control for this using a *Fixed Effect* of companies
    - Note: ISIN uniquely identifies companies
    - factor(isin): (n-1) dummy variables
    - FE equivalent to unique intercept for each company

```r
forecast3.1 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit + factor(isin),
     data = df_clean[df_clean$fic == "SGP", ])
# n=7 to prevent outputting every fixed effect
print(tidy(forecast3.1), n = 7)
```

```
## # A tibble: 30 x 5
##   term        estimate std.error statistic      p.value
##   <chr>          <dbl>     <dbl>     <dbl>        <dbl>
## 1 (Intercept) -0.00946   36.8    -0.000257 1.00
## 2 revt         0.403      0.0712  5.66     0.0000000293
## 3 act          0.0486     0.0453  1.07     0.284
## 4 che          0.276      0.139   1.99     0.0472
## 5 lct          0.239      0.0656  3.65     0.000300
## 6 dp           4.86       1.05    4.63     0.00000487
## 7 ebit        -1.07       0.269  -3.98     0.0000825
## # ... with 23 more rows
```

Removing noise: Singapore model

```r
glance(forecast3.1)
```

```
## # 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     0.852         0.841  201.      77.9 8.39e-144    29 -2828. 5719. 5844.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```r
anova(forecast3, forecast3.1, 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 + factor(isin)
##   Res.Df      RSS Df Sum of Sq Pr(>Chi)
## 1    416 17663454
## 2    393 15915304 23   1748150 0.006616 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

> The model 3.1 is better

Another way to do fixed effects

- The library `package:lfe` has `felm()`: **f**ixed **e**ffects **l**inear **m**odel
  - Better for 2 or more factors with thousands of levels, otherwise `lm` should be better
  - `lfe` is designed to produce the same results as `lm` will do if run with the full set of dummies
  - We will see a future example which cannot be handled by `lm()`

```r
library(lfe)
forecast3.2 <-
  felm(revt_lead ~ revt + act + che + lct + dp + ebit | factor(isin),
       data = df_clean[df_clean$fic == "SGP", ])
tidy(forecast3.2)
```

```
## # A tibble: 6 x 5
##   term  estimate std.error statistic      p.value
##   <chr>    <dbl>     <dbl>     <dbl>        <dbl>
## 1 revt    0.403     0.0712      5.66 0.0000000293
## 2 act     0.0486    0.0453      1.07 0.284
## 3 che     0.276     0.139       1.99 0.0472
## 4 lct     0.239     0.0656      3.65 0.000300
## 5 dp      4.86      1.05        4.63 0.00000487
## 6 ebit   -1.07      0.269      -3.98 0.0000825
```

A faster way to do fixed effects

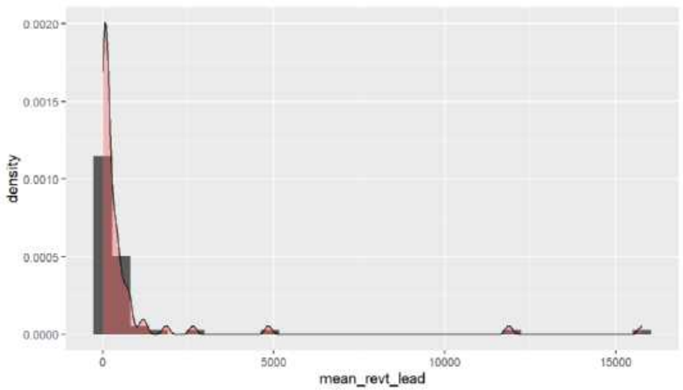
- The library `package:fixest` has `feols()`: **f**ixed **e**ffects **ols**
  - similar to `lfe` but claim to be much faster
  - `lfe` and `fixest` produce the same results for OLS

```
library(fixest)
forecast3.3 <-
  feols(revt_lead ~ revt + act + che + lct + dp + ebit | factor(isin),
        data = df_clean[df_clean$fic == "SGP", ])
summary(forecast3.3)
```

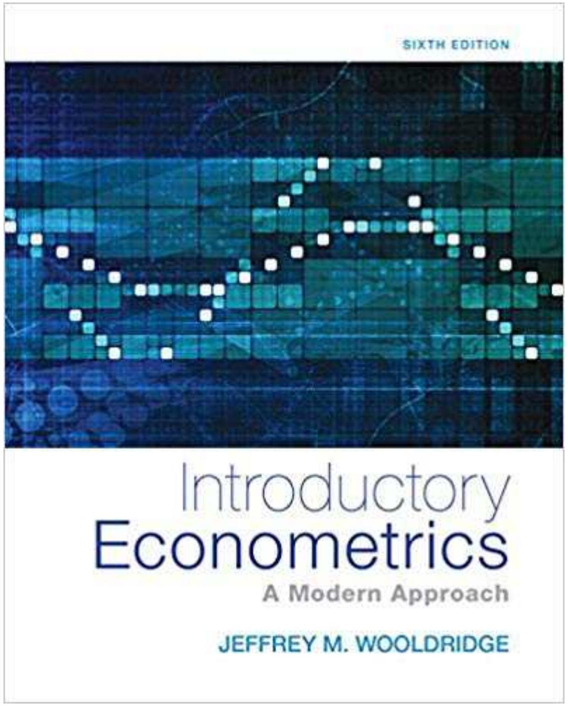
```
## OLS estimation, Dep. Var.: revt_lead
## Observations: 423
## Fixed-effects: factor(isin): 24
## Standard-errors: Clustered (factor(isin))
##       Estimate Std. Error   t value Pr(>|t|))
## revt  0.403058   0.189383  2.128300  0.044248 *
## act   0.048569   0.088568  0.548387  0.588710
## che   0.276009   0.174173  1.584700  0.126693
## lct   0.239423   0.162586  1.472600  0.154416
## dp    4.857000   1.494900  3.248900  0.003539 **
## ebit -1.070700   0.662245 -1.616800  0.119564
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 193.1     Adj. R2: 0.840904
##               Within R2: 0.771772
```

Why exactly would we use FE?

- Fixed effects are used when the average of $\hat{y}$ varies by some group in our data
    - In our problem, the average revenue of each firm is different, see histogram below
- Fixed effects absorb this difference



- Further reading:
    - Introductory Econometrics by Jeffrey M. Wooldridge



What else can we do?

- What else could we do to improve our prediction model?

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)

```
expectations %>%
  arrange(level_2, level_3, desc(year)) %>%  # sort the data
  select(year, quarter, level_2, level_3, value) %>%
  datatable(options = list(pageLength = 3), rownames=FALSE)
```

Show 3 entries Search:

year	quarter	level_2	level_3	value
2019	1	Accommodation & Food Services	Accommodation	-2
2019	2	Accommodation & Food Services	Accommodation	25
2019	3	Accommodation & Food Services	Accommodation	22

Showing 1 to 3 of 891 entries

Previous 1 2 3 4 5 … 297 Next

Transforming macro data

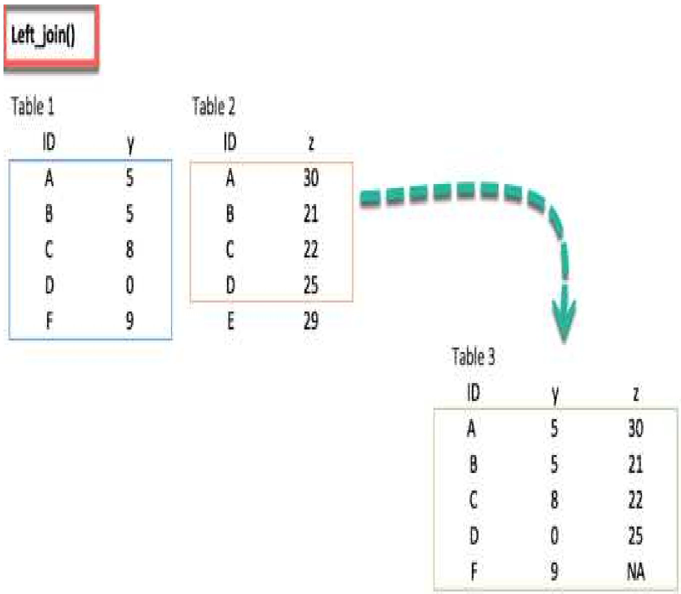
```r
# extract out F&I only, calculate annual average value
expectations_avg <- expectations %>%
  filter(level_2 == "Financial & Insurance") %>%     # Keep F&I sector
  group_by(year) %>%                                 # Group data by year
  mutate(fin_sentiment=mean(value, na.rm=TRUE)) %>%  # Calculate yearly average
  slice(1)                                           # Take only 1 row per group
head(expectations_avg)
```

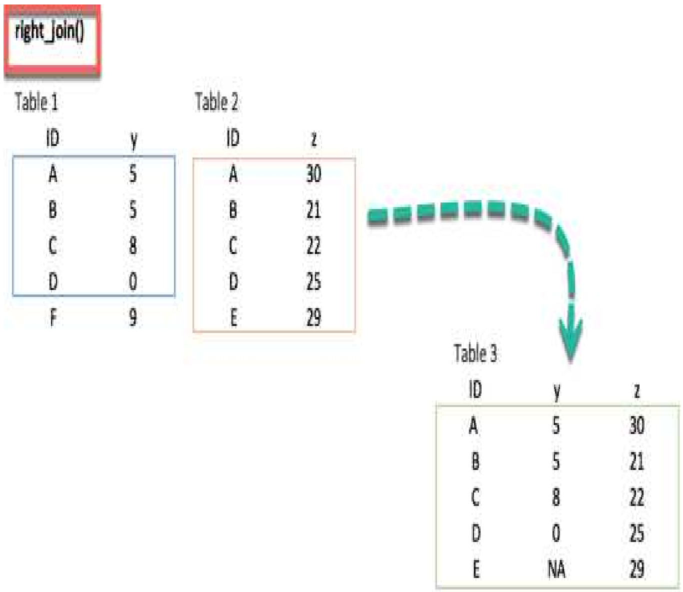
```
## # A tibble: 6 x 7
## # Groups:   year [6]
##   quarter level_1               level_2     level_3    value  year fin_sentiment
##     <dbl> <chr>                 <chr>       <chr>      <dbl> <dbl>         <dbl>
## 1       1 Total Services Sector Financial ~ Banks & F~    22  1995         23.8
## 2       1 Total Services Sector Financial ~ Banks & F~    23  1996         17
## 3       1 Total Services Sector Financial ~ Banks & F~    24  1997         -0.25
## 4       1 Total Services Sector Financial ~ Banks & F~   -30  1998        -38
## 5       1 Total Services Sector Financial ~ Banks & F~   -24  1999         15.8
## 6       1 Total Services Sector Financial ~ Banks & F~    64  2000         18.6
```

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

dplyr makes merging easy

- For merging, use `package:dplyr`'s `*_join()` commands
    - `left_join()` and `right_join()` for merging a dataset into another
    - `inner_join()` for keeping only matched observations
    - `full_join()` for making all possible combinations





dplyr makes merging easy

- `inner_join()` vs. `full_join()`

inner_join()

Table 1

ID	y
A	5
B	5
C	8
D	0
F	9

Table 2

ID	z
A	30
B	21
C	22
D	25
E	29

Table 3

ID	y	z
A	5	30
B	5	21
C	8	22
D	0	25

full_join()

Table 1

ID	y
A	5
B	5
C	8
D	0
F	9

Table 2

ID	z
A	30
B	21
C	22
D	25
E	29

Table 3

ID	y	z
A	5	30
B	5	21
C	8	22
D	0	25
E	NA	29
F	9	NA

Merging example

- Merge in the finance sentiment data to our accounting data

```r
# subset out our 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)
tidy(macro1)
```

```
## # A tibble: 8 x 5
##   term          estimate std.error statistic  p.value
##   <chr>            <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)    19.1      13.8        1.39  1.66e- 1
## 2 revt            0.532     0.0599     8.88  2.47e-17
## 3 act             0.0119    0.0421     0.283 7.78e- 1
## 4 che             0.483     0.124      3.89  1.16e- 4
## 5 lct             0.216     0.0635     3.41  7.19e- 4
## 6 dp              4.42      0.992      4.46  1.08e- 5
## 7 ebit           -1.12      0.247     -4.55  7.10e- 6
## 8 fin_sentiment   0.302     0.561      0.538 5.91e- 1
```

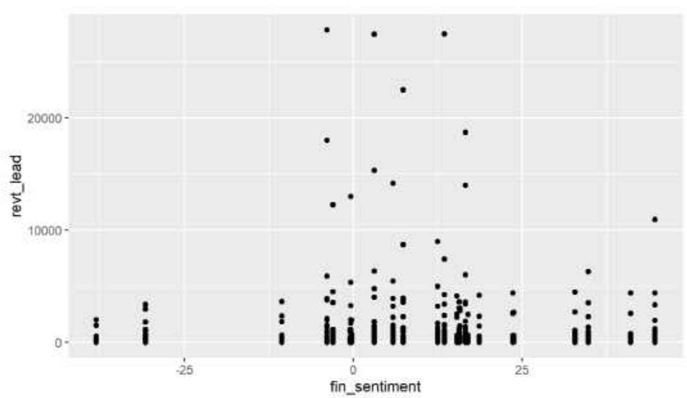
> It isn't significant. Why is this?

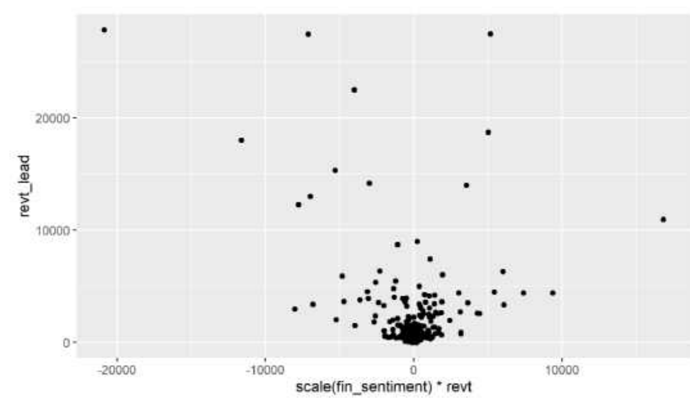
Scale matters

- All of our firm data is on the same scale as revenue: dollars within a given firm
- But `fin_sentiment` has much smaller range of constant scale (-38 to 44.65)
  - one sentiment value is corresponding to many revenue points, as depicted in the left chart below
  - Need to scale (standardize or normalize) this to fit the problem
- Do Exercise 4 of the R Practice on visualization using ggplot2

```
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()
```





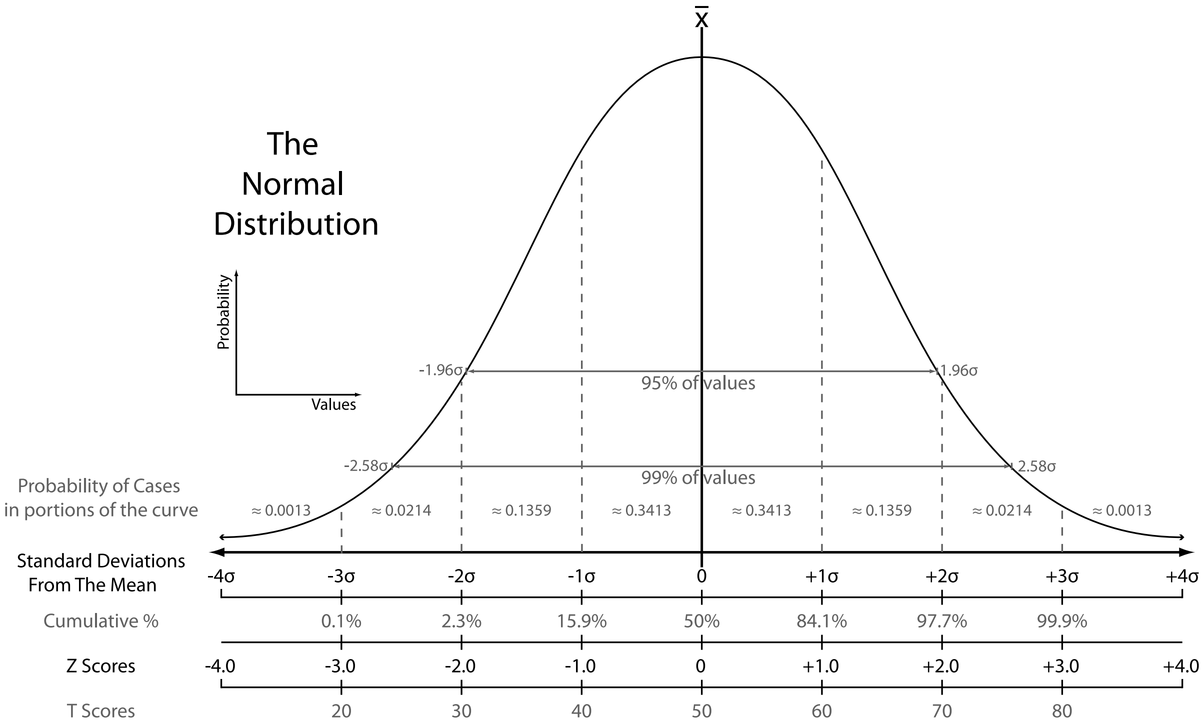
Feature scaling

- There are various ways to scale variables/features. In general, one way is to scale to a standard normal distribution ("standardization") and the other is to scale to range [0, 1] ("normalization")
- Standardization (or Z-score normalization): features will be rescaled so that they'll have the properties of a standard normal distribution with zero mean ($\mu = 0$) and one standard deviation ($\sigma = 1$).
- Standard scores (also called z scores) are calculated as follows:

$$z = \frac{x - \mu}{\sigma}$$

- z score measures how many S.D. below or above the variable mean, thus the unit of z score is S.D. of the variable

The normal distribution

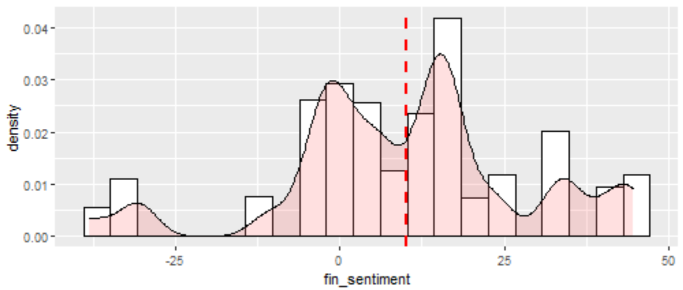


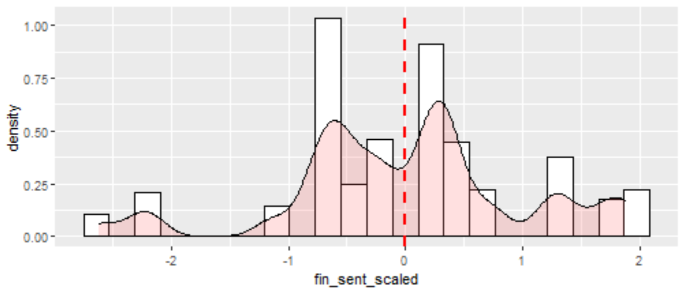
The scale() function in Base R

- scale() function centers/scales the columns of a numeric matrix.
- package:standardize is another option.

```
# Scale creates z-scores with 0 mean and 1 sd
df_SG_macro$fin_sent_scaled <- scale(df_SG_macro$fin_sentiment)
summary(df_SG_macro[ , c("fin_sentiment", "fin_sent_scaled")])
```

```
##  fin_sentiment      fin_sent_scaled.V1
##  Min.   :-38.0000   Min.   :-2.61441
##  1st Qu.: -0.4667   1st Qu.:-0.57333
##  Median : 12.4500   Median : 0.12909
##  Mean   : 10.0762   Mean   : 0.00000
##  3rd Qu.: 17.0000   3rd Qu.: 0.37652
##  Max.   : 44.6500   Max.   : 1.88014
##  NA's   :68         NA's   :68
```





Scaled macro data

- z-score normalization and scale by revenue

```
# Scale creates z-scores
df_SG_macro$fin_sent_scaled <- scale(df_SG_macro$fin_sentiment)
macro3 <-
  lm(revt_lead ~ revt + act + che + lct + dp + ebit + fin_sent_scaled:revt,
     data=df_SG_macro)  # fin_sent_scaled:revt = fin_sent_scaled x revt
tidy(macro3)
```

```
## # A tibble: 8 x 5
##   term                estimate std.error statistic  p.value
##   <chr>                  <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)          21.8      12.0        1.81  7.09e- 2
## 2 revt                  0.533     0.0593     8.99  1.04e-17
## 3 act                   0.0220    0.0417     0.527 5.98e- 1
## 4 che                   0.419     0.125      3.35  8.74e- 4
## 5 lct                   0.227     0.0628     3.62  3.39e- 4
## 6 dp                    3.89      0.999      3.90  1.14e- 4
## 7 ebit                 -0.949     0.252     -3.77  1.86e- 4
## 8 revt:fin_sent_scaled  0.0907    0.0315     2.88  4.25e- 3
```

Model comparisons

```r
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     0.835         0.833  211.      333. 6.69e-151     6 -2712. 5441. 5473.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```r
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     0.839         0.836  210.      292. 2.15e-151     7 -2708. 5434. 5470.
## # ... 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    394 17617000
## 2    393 17253888  1    363112 0.004029 **
## ---
## 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` (18.4 points)
  - Revenue stickiness increases by ~9%
- Over the range of data (-38 to 44.65)...
  - Revenue stickiness change ranges from -23.7% to 17%

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*
- Sometimes acceptable:
  - Withhold a random sample of data when building the model
  - Check performance on *hold out sample*

> This is the basic idea of machine learning, we will cover more formally in future topics

Estimation

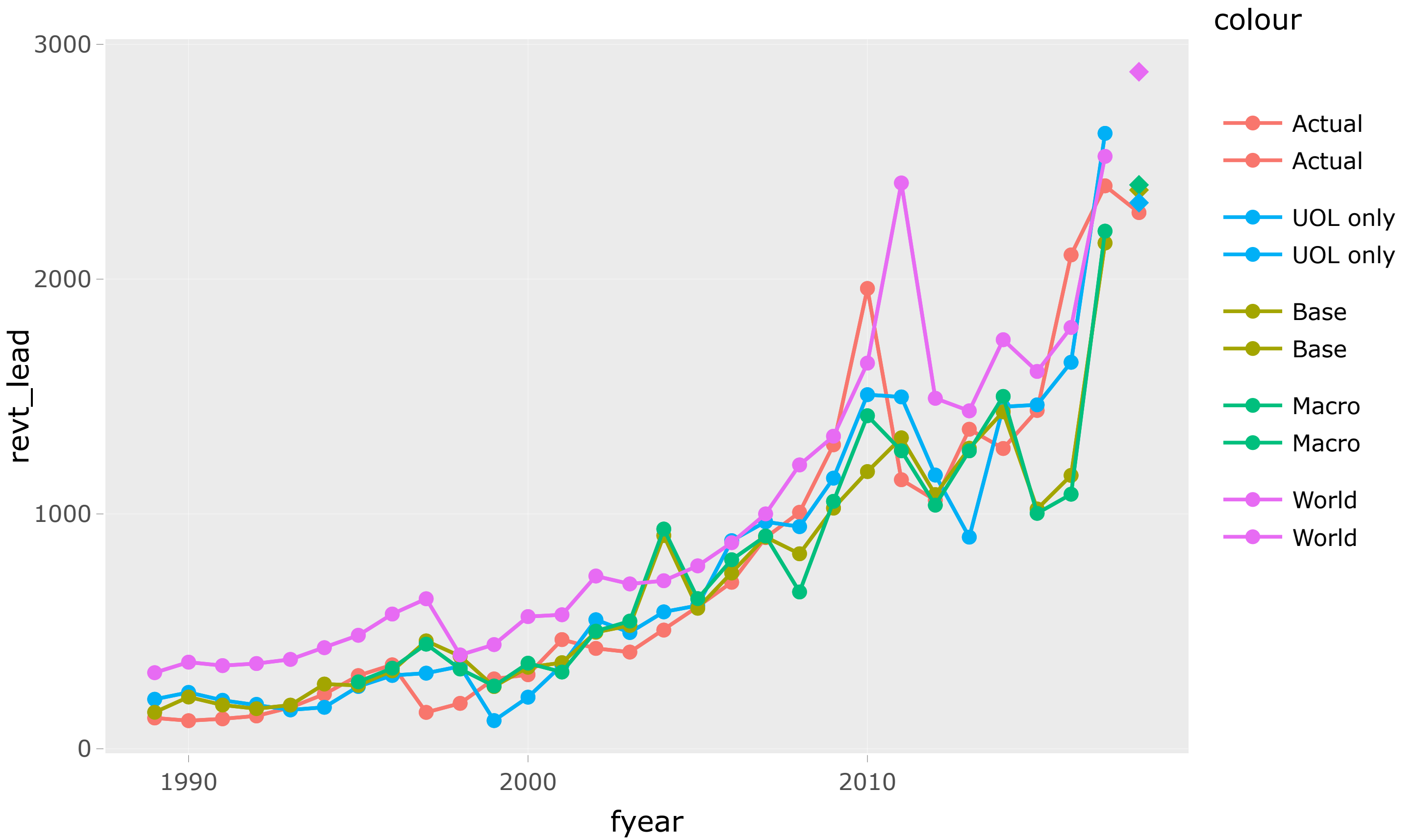
- As we never constructed a hold out sample, let's end by estimating UOL's *2019* year revenue
- It is lead prediction, so fyear = 2018 for the 2019 forecast

```
p_uol <- predict(forecast2, uol[uol$fyear == 2018, ])
p_base <- predict(baseline,
  df_SG_macro[df_SG_macro$isin == "SG1S83002349" & df_SG_macro$fyear == 2018,])
p_macro <- predict(macro3,
  df_SG_macro[df_SG_macro$isin == "SG1S83002349" & df_SG_macro$fyear == 2018,])
p_world <- predict(forecast4,
  df_clean[df_clean$isin == "SG1S83002349" & df_clean$fyear == 2018,])
preds <- c(p_uol, p_base, p_macro, p_world)
names(preds) <- c("UOL 2019 UOL", "UOL 2019 Base", "UOL 2019 Macro",
                  "UOL 2019 World")
preds
```

```
##   UOL 2019 UOL  UOL 2019 Base UOL 2019 Macro UOL 2019 World 
##       2325.326       2379.430       2401.298       2882.955
```

Visualizing our prediction

- I plot 2019 forecast separately from other years' forecast
- I also plot the actual revenue for comparison
- Click the legend to mute it



In Sample Accuracy

```r
# series data is calculated, see the R code file
# Root Mean Square Error (RMSE)
# the st. deviation of the residuals (prediction errors).
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 2019 UOL", "UOL 2019 Base",
                 "UOL 2019 Macro", "UOL 2019 World")
rmse
```

```
##   UOL 2019 UOL  UOL 2019 Base UOL 2019 Macro UOL 2019 World
##       189.2207       273.6917       300.6274       349.6541
```

> Why is UOL the best for in sample?
>
> UOL is trained to minimize variation only in that context. It is potentially overfitted, meaning it won't predict well *out of sample*. Out of sample prediction is much more useful than in sample, however.

Summary of Session 4

For next week

- Try to replicate the code
- Start to explore your group project data
- Continue your Datacamp career track
- Second individual assignment
  - Do this one individually!
  - Submission and feedback on eLearn

R Coding Style Guide

Style is subjective and arbitrary but it is important to follow a generally accepted style if you want to share code with others. I suggest the The tidyverse style guide which is also adopted by Google with some modification

- Highlights of **the tidyverse style guide**:
  - *File names*: end with .R
  - *Identifiers*: variable_name, function_name, try not to use "." as it is reserved by Base R's S3 objects
  - *Line length*: 80 characters
  - *Indentation*: two spaces, no tabs (RStudio by default converts tabs to spaces and you may change under global options)
  - *Spacing*: x = 0, not x=0, no space before a comma, but always place one after a comma
  - *Curly braces {}*: first on same line, last on own line
  - *Assignment*: use `<-`, not = nor `->`
  - *Semicolon(;)*: don't use, I used once for the interest of space
  - *return()*: Use explicit returns in functions: default function return is the last evaluated expression
  - *File paths*: use relative file path "../../filename.csv" rather than absolute path "C:/mydata/filename.csv". Backslash needs `\\`

R packages used in this slide

This slide was prepared on 2021-09-05 from Session_4s.Rmd with R version 4.1.1 (2021-08-10) Kick Things on Windows 10 x64 build 18362 😃.

The attached packages used in this slide are:

```
##     plotly         DT      fixest        lfe     Matrix      broom   magrittr 
##  "4.9.4.1"     "0.18"     "0.9.0"    "2.8-7"    "1.3-4"    "0.7.9"    "2.0.1" 
##    forcats    stringr       dplyr      purrr      readr      tidyr     tibble 
##    "0.5.1"    "1.4.0"     "1.0.7"    "0.3.4"    "2.0.1"    "1.1.3"    "3.1.3" 
##    ggplot2  tidyverse kableExtra      knitr 
##    "3.3.5"    "1.3.1"     "1.3.4"     "1.33"
```