Bush 631-603: Quantitative Methods

Lecture 6 (02.22.2022): Prediction vol. I

Rotem Dvir

The Bush school of Government and Public Policy

Texas A&M University

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What is today's plan?

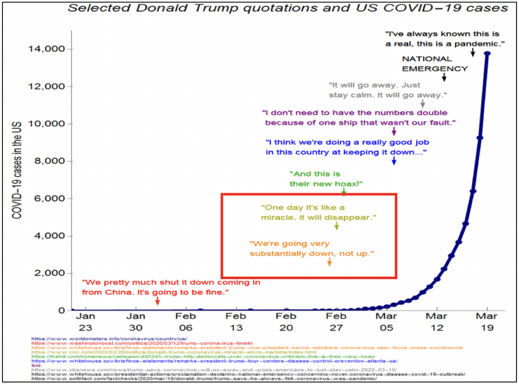
- Why predictions?
- Tech basics - loops, conditional statements.
- Making predictions with data: elections, FP expenses, military aid.
- Using dates data.
- R work: loops, if{}, if{}else{}, as.date(), line plots.
- Task II: Working with R

Predicting with data

- Social science research:
  - Establish causality.
  - The role of measurement.
- Predictions:
  - Support for causal statements.
  - Generate accurate predictions about potential outcomes.

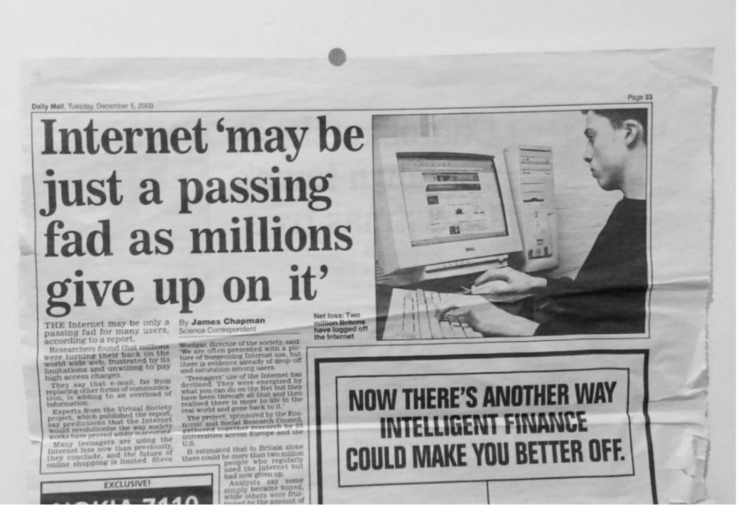
Not the best. . . predictions!

Oh no. . .



Some more gems

Daily Mail - December 5, 2000



Daily Mail, Tuesday, December 5, 2000 Page 33

Internet 'may be just a passing fad as millions give up on it'

By **James Chapman**
Science Correspondent

THE Internet may be only a passing fad for many users, according to a report.

Researchers found that millions were turning their back on the world wide web, frustrated by its limitations and unwilling to pay high access charges.

They say that e-mail, far from replacing other forms of communication, is adding to an overload of information.

Experts from the Virtual Society project, which published the report, say predictions that the Internet would revolutionise the way society works have proved wildly inaccurate.

Many teenagers are using the Internet less now than previously, they conclude, and the future of online shopping is limited. Steve Woolgar, director of the society, said: 'We are often presented with a picture of burgeoning Internet use, but there is evidence already of drop-off and saturation among users.

'Teenagers' use of the Internet has declined. They were energised by what you can do on the Net but they have been through all that and then realised there is more to life in the real world and gone back to it.'

The project, sponsored by the Economic and Social Research Council, gathered together research by 25 universities across Europe and the U.S.

It estimated that in Britain alone there could be more than two million people who regularly used the Internet but had now given up.

Analysts say some simply became bored, while others were frustrated by the amount of

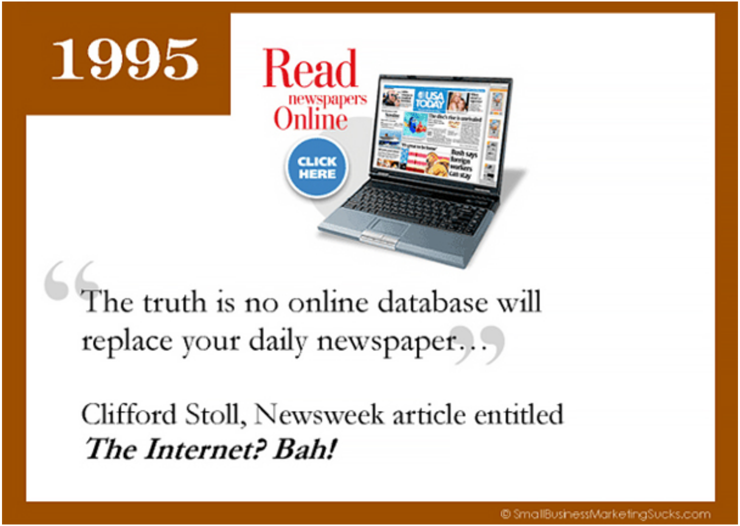
Net loss: Two million Britons have logged off the Internet

EXCLUSIVE!

NOW THERE'S ANOTHER WAY INTELLIGENT FINANCE COULD MAKE YOU BETTER OFF.

Some more gems

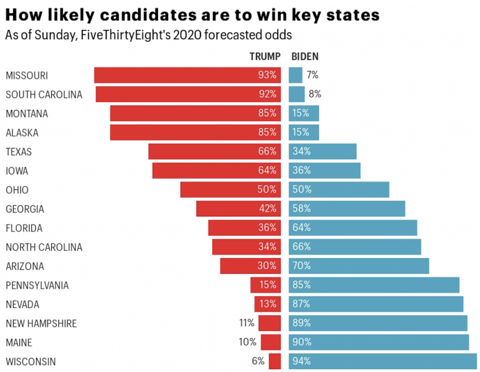
Well. . .



Some groundwork

Loops

- Useful to repeat the same operation multiple times.
- Efficient analysis tool.



Loops in R

- Run similar code chunk repeatedly.

```
for (i in X) {
  expression1
  expression2
  ...
  expression3
}
```

- Elements of loop:
  - i: counter (change as you like).
  - X: Vector of ordered values for the counter.
  - expression: set of expressions to run repeatedly.
  - {}: curly braces define the beginning and end of a loop.

Loops in R

```
weeks <- c(1,2,3,4,5)
n <- length(weeks)
t <- rep(NA,n)

# loop counter
for (i in 1:n){
  t[i] <- weeks[i] * 2
  cat("I completed Swirl HW number", weeks[i], "in",
      t[i], "minutes", "\n")
}
```

```
## I completed Swirl HW number 1 in 2 minutes
## I completed Swirl HW number 2 in 4 minutes
## I completed Swirl HW number 3 in 6 minutes
## I completed Swirl HW number 4 in 8 minutes
## I completed Swirl HW number 5 in 10 minutes
```

Debugging a loop

- Check code for errors (prevalent in loops).
- Run loop (code) with simple example.
- Use Google to identify problem.
- More information and ideas $\rightarrow$ Link

Conditional statements

- General form - implement code chunks based on logical expressions.

If statements

Syntax: if(x = a condition){set of commands}

Run command(s) only if value if X is TRUE

```
weather <- "rain"
if (weather == "rain"){
  cat("I should take my umbrella")
}
```

```
## I should take my umbrella
```

Flexible if statements

Using if(){} else {}

```
weather <- "sunny"
if (weather == "rain"){
  cat("I should take my umbrella")
} else {
  cat("I should wear my Aggie hat")
}
```

```
## I should wear my Aggie hat
```

Complex conditional statements

Join conditional statements into a loop.

```r
days <- 1:7
n <- length(days)

for (i in 1:n){
  x <- days[i]
  r <- x %% 2

  if (r == 0){
    cat("Day", x, "is even and I need my umbrella \n")
  } else {
    cat("Day", x, "is odd and I need my Aggie cap \n")
  }
}
```

```
## Day 1 is odd and I need my Aggie cap
## Day 2 is even and I need my umbrella
## Day 3 is odd and I need my Aggie cap
## Day 4 is even and I need my umbrella
## Day 5 is odd and I need my Aggie cap
## Day 6 is even and I need my umbrella
## Day 7 is odd and I need my Aggie cap
```

Conditional statements

Integrate conditional statements within a conditional statement.

```r
  output$tab <- function(){

## Season 2016: Tables
    if(input$year == 2016){
      data2016 <- mydata %>%
        filter(season == 2016)

    if (input$data == "QBR") {
      dat_tab <- data2016 %>%
        filter(QBR_rank < 16) %>%
        select(First, Last, QBR)

      dat_tab %>%
        knitr::kable("html") %>%
        kable_styling(font_size = 15, "striped", full_width = F, position = "center") %>%
        add_header_above(c("QBR: Top 15" = 3)) %>%
        scroll_box(height = "250px", width = "450px")
    } else
     if (input$data == "EPA") {
        dat_tab <- data2016 %>%
          filter(EPA_rank < 16) %>%
          select(First, Last, EPA_play) %>%
          arrange(-EPA_play)
```

Conditional statements

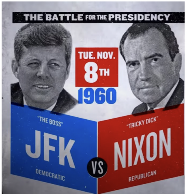
Caution:

- if(){} else{} are complex.
- Double check the curly braces for each statement.
- Use the automatic indentation.
- 'Space-out' your code.
- Add comments (using #) to clearly mark each step.

Predictions

- Awesome research tool. . . with the right design.
- Predict: elections, economic trends, behavior, Superbowl winners, etc.

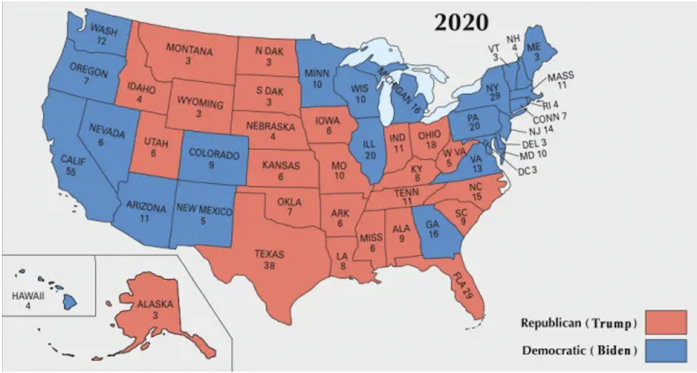
Elections winner



US electoral system

Electoral college

Plurality of votes in a state: “Winner-take-all”



Election predictions

Measurement problem:

- National vote vs. electoral votes.
- Bush - Gore (2000).
- Clinton - Trump (2016).

Electoral vote:

- Number of electors does not align with number of voters per state.
- Votes are "unaccounted".

A Prediction problem:

- Accurate forecast of **each state** winner.

Polls and election predictions

Data: 2016 elections (polls)

```r
head(polls16)
```

```
##   state  middate daysleft                   pollster
## 1    AK  8/11/16       89  Lake Research Partners
## 2    AK  8/20/16       80              SurveyMonkey
## 3    AK 10/20/16       19                    YouGov
## 4    AK 10/26/16       13 Google Consumer Surveys
## 5    AK  9/30/16       39 Google Consumer Surveys
## 6    AK 10/12/16       27 Google Consumer Surveys
##   clinton trump margin
## 1    30.0  38.0   8.00
## 2    31.0  38.0   7.00
## 3    37.4  37.7   0.30
## 4    38.0  39.0   1.00
## 5    47.5  36.7 -10.76
## 6    34.6  30.0  -4.62
```

Poll prediction by states (using R loop)

```r
poll.pred <- rep(NA, 51) # place holder

# get list of unique state names to iterate over
st.names <- unique(polls16$state)

# add labels to holder
names(poll.pred) <- st.names

for (i in 1:51) {
  state.data <- subset(polls16, subset = (state == st.names[i]))

  latest <- state.data$daysleft == min(state.data$daysleft)

  poll.pred[i] <- mean(state.data$margin[latest])
}

head(poll.pred)
```

```
##     AK     AL     AR     AZ     CA     CO
##  14.73  29.72  20.02   2.50 -23.00  -7.05
```

Errors in polling

Prediction error = actual outcome - predicted outcome

```
errors <- pres16$margin - poll.pred
names(errors) <- st.names
```

```
mean(errors)
```

```
## [1] 3.81
```

Root mean-square-error (RMSE): average magnitude of prediction error

```
sqrt(mean(errors^2))
```

```
## [1] 9.6
```

Prediction challenges

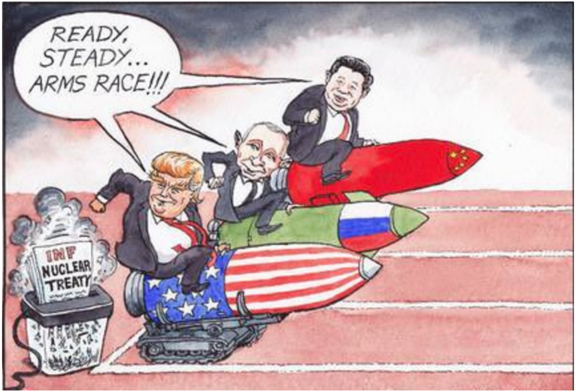
Prediction of binary outcome variable $\rightarrow$ classification problem

Wrong prediction $\rightarrow$ misclassification:

1. true positive: predict Trump wins when he actually wins.
2. **false positive**: predict Trump wins when he actually loses.
3. true negative: predict Trump loses when he actually loses.
4. **false negative**: predict Trump loses when he actually wins.

2016 elections: misclassification rate was high: 9.8% (5/51 states).

Predictions in INTA



Military expenditures:

- Increase arms? The security dilemma.
- Risky environment (Israel in Middle-east).

Study military expenses

Research questions:

1. How increase in expenditures drive conflicts?
2. Arms expansion and the probability of war?
3. Arms expenditure and preventive strike?

Does increase in spending (arms race) leads to conflict?

Arms and war??

Early findings (1960 study) → not too promising

1. HAVE MOST WARS BEEN PRECEDED BY ARMS RACES? ARE ARMS RACES A RECENT INNOVATION?

HISTORIANS mention arms races only for 10 out of 84 wars that ended between 1820 and 1929. Those 10 wars are listed in Table 4.

TABLE 4

Dates of Beginnings and Sites of Wars
1914, World
1865, La Plata
1892, Armenia
1829, Caucasus; 1845, Punjab; 1859, Italy; 1878, Tekke Turkomans; 1892, Central Africa; 1894, Madagascar; 1926, China

Arms and war??

Improved measurements; study dyads (1979)

war.[5] This polynomial function shall be used to estimate the time rate of change (delta) for each nation for the year prior to the dispute. The existence of an arms race prior to the dispute or war shall be determined by obtaining the *product* of the national rates of change for each side, with higher values representing "arms-race" dyads. By calculating national

TABLE 2

	Arms Race	*No Arms Race*
War	23	3
No War	5	68

Arms and war??

Problems - case selection (remove world wars).

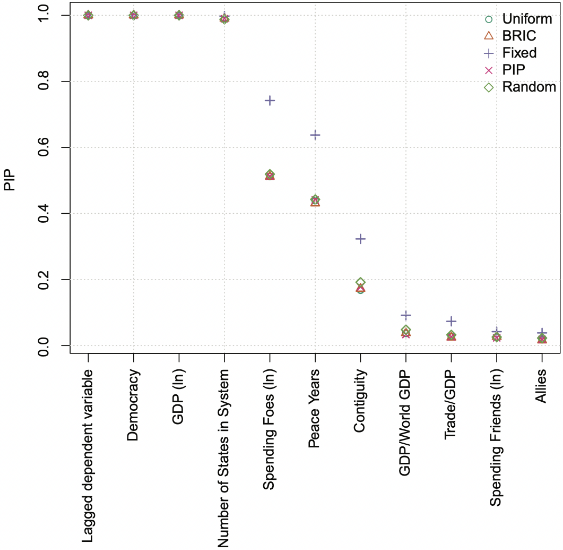
Improved methods and data (Sample 1998):

Probabilities of Escalation to War, 1816-1993,
Based on the Estimated Coefficients in Table 2

	p
Baseline; all independent variables at 0	.08
Mutual military buildup; all other independent variables at 0	.21
High defense burden; all other independent variables at 0	.18
Military buildup and defense burden; all other independent variables at 0	.40
Dispute over issue of territory; all other independent variables at 0	.16
Military buildup, defense burden, and territorial dispute; all other independent variables at 0	.59
Military buildup, defense burden, territorial dispute, parity, transition, and rapid approach; nuclear at zero	.69
Nuclear; all other independent variables at 0	.02
Military buildup and nuclear; all other independent variables at 0	.05
All variables at 1	.25

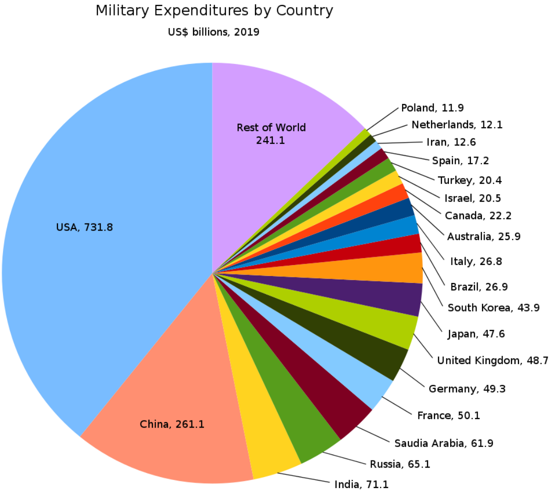
Related research question

What drives the decision to increase military expenditures?

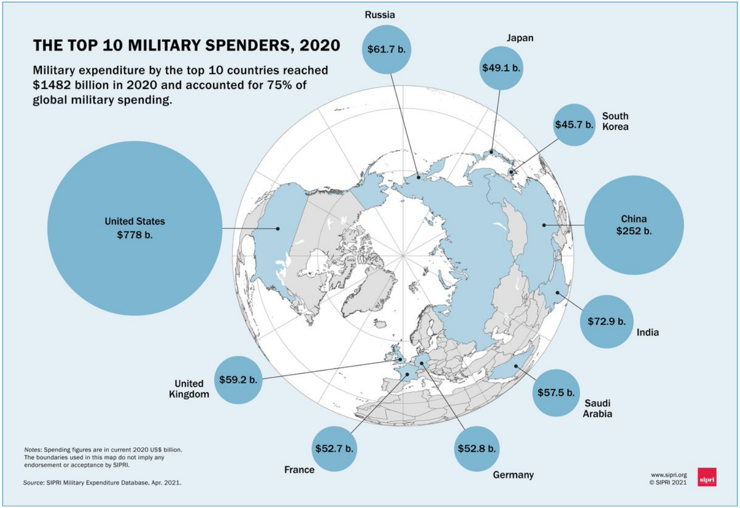


Arms race

Measure $\rightarrow$ military expenditures



Military spending across the globe



Predicting military spending

Our data:

- 157 Countries
- Time frame: 1999-2019
- Measure: military spending as proportion of total gov't spending.

Why this measure?

- Reflect state's preferences.
- Trade-off: *Guns vs. Butter*.

Our predictions:

- Using 1999-2019 data to predict 2020 levels.
- Test predictions with actual data.

Military spending data

```
dim(mil_exp)
```

```
## [1] 157  25
```

```
head(mil_exp, n=8)
```

```
## # A tibble: 8 x 25
##   Country      Group1 Subgroup1 `1999` `2000` `2001` `2002` `2003` `2004` `2
##   <chr>        <chr>  <chr>      <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <
## 1 Algeria      Africa North Af~ 0.118  0.120  0.122  0.108  0.101  0.107  0.
## 2 Libya        Africa North Af~ 0.115  0.103  0.0630 0.0524 0.0484 0.0490 0.
## 3 Morocco      Africa North Af~ 0.145  0.0898 0.145  0.125  0.134  0.123  0.
## 4 Tunisia      Africa North Af~ 0.0618 0.0614 0.0605 0.0590 0.0603 0.0591 0.
## 5 Angola       Africa Sub-Saha~ 0.274  0.129  0.108  0.0919 0.109  0.116  0.
## 6 Benin        Africa Sub-Saha~ 0.0452 0.0264 0.0232 0.0407 0.0473 0.0506 0.
## 7 Botswana     Africa Sub-Saha~ 0.0759 0.0817 0.0899 0.0900 0.0915 0.0848 0.
## 8 Burkina Faso Africa Sub-Saha~ 0.0576 0.0624 0.0588 0.0605 0.0610 0.0596 0.
## # ... with 15 more variables: 2006 <dbl>, 2007 <dbl>, 2008 <dbl>, 2009 <dbl>
## #   2010 <dbl>, 2011 <dbl>, 2012 <dbl>, 2013 <dbl>, 2014 <dbl>, 2015 <dbl>,
## #   2016 <dbl>, 2017 <dbl>, 2018 <dbl>, 2019 <dbl>, 2020 <dbl>
```

Reshaping the data

- Use the gather() function
- Increase the data size.
- Each case (country for us) has multiple observations (rows).

countries	population_in_million	gdp_percapita
A	100	2000
B	200	7000
C	120	15000

wide

TO

Long

countries	time	value
A	population_in_million	100
B	population_in_million	200
C	population_in_million	120
A	gdp_percapita	2000
B	gdp_percapita	7000
C	gdp_percapita	15000

Reshaping the data

gather() function: long-form data.

```
spend_long <- mil_exp2 %>%
  gather(year, exp, '1999':'2019',-Country, -Group1, -Subgroup1) %>%
  arrange(Country)

head(spend_long, n=9)
```

```
## # A tibble: 9 x 5
##   Country     Group1          Subgroup1  year    exp
##   <chr>       <chr>           <chr>      <chr> <dbl>
## 1 Afghanistan Asia & Oceania South Asia 1999  NA
## 2 Afghanistan Asia & Oceania South Asia 2000  NA
## 3 Afghanistan Asia & Oceania South Asia 2001  NA
## 4 Afghanistan Asia & Oceania South Asia 2002  NA
## 5 Afghanistan Asia & Oceania South Asia 2003  NA
## 6 Afghanistan Asia & Oceania South Asia 2004   0.161
## 7 Afghanistan Asia & Oceania South Asia 2005   0.127
## 8 Afghanistan Asia & Oceania South Asia 2006   0.104
## 9 Afghanistan Asia & Oceania South Asia 2007   0.119
```

Predicting spending

Predict 2020 $\rightarrow$ mean of spending (1999-2019)

Use loop to calculate means for all countries

```
## loop
pred.mean <- rep(NA,157)
c.names <- unique(spend_long$Country)
names(pred.mean) <- as.character(c.names)

for (i in 1:157){
  c.dat <- subset(spend_long, subset = (Country == c.names[i]))
  pred.mean[i] <- mean(c.dat$exp, na.rm = T)
}
```

Predicting spending for 2020

```
pred.mean
         Afghanistan              Albania              Algeria               Angola            Argentina              Armenia
        7.693784e-02         4.803755e-02         1.167886e-01         1.142081e-01         2.865062e-02         1.572688e-01
           Australia              Austria           Azerbaijan              Bahrain           Bangladesh              Belarus
        5.117444e-02         1.621721e-02         1.159260e-01         1.365441e-01         1.024893e-01         3.055717e-01
             Belgium               Belize                Benin              Bolivia   Bosnia-Herzegovina             Botswana
        2.104063e-02         3.481603e-02         4.312747e-02         5.311684e-02         3.023730e-02         7.708387e-02
              Brazil               Brunei             Bulgaria         Burkina Faso              Burundi             Cambodia
        3.954679e-02         8.537055e-02         5.727167e-02         6.086991e-02         1.238733e-01         9.068995e-02
            Cameroon               Canada           Cape Verde Central African Rep.                 Chad                Chile
        7.432152e-02         2.898024e-02         1.845547e-02         1.090412e-01         1.641743e-01         1.010081e-01
               China             Colombia    Congo, Dem. Rep.   Congo, Republic of           Costa Rica        Côte d'Ivoire
        8.147621e-02         1.133810e-01         9.082535e-02         8.326183e-02         0.000000e+00         7.179591e-02
             Croatia               Cyprus              Czechia              Denmark             Djibouti       Dominican Rep.
        4.203798e-02         4.971926e-02         3.230034e-02         2.517054e-02         1.513522e-01         4.516247e-02
             Ecuador                Egypt          El Salvador    Equatorial Guinea              Estonia             eSwatini
        7.900969e-02         6.539493e-02         4.407673e-02         5.624585e-02         4.613709e-02         6.040772e-02
            Ethiopia                 Fiji              Finland               France                Gabon               Gambia
        1.032980e-01         5.669500e-02         2.704904e-02         3.599000e-02         7.089440e-02         3.735918e-02
             Georgia              Germany                Ghana               Greece            Guatemala               Guinea
        1.093521e-01         2.686035e-02         2.040455e-02         5.686649e-02         3.739819e-02         1.172825e-01
       Guinea-Bissau               Guyana                Haiti             Honduras              Hungary              Iceland
        9.553127e-02         4.376836e-02         6.134272e-06         4.366182e-02         2.511546e-02         0.000000e+00
               India            Indonesia                 Iran                 Iraq              Ireland               Israel
        9.692641e-02         4.121770e-02         1.431855e-01         6.366464e-02         1.471538e-02         1.420280e-01
               Italy              Jamaica                Japan               Jordan           Kazakhstan                Kenya
        3.099443e-02         2.671973e-02         2.559871e-02         1.535606e-01         4.722987e-02         6.172174e-02
        Korea, South               Kuwait           Kyrgyzstan                 Laos               Latvia              Lebanon
        1.276501e-01         1.222232e-01         4.838694e-02         2.179216e-02         3.728258e-02         1.416378e-01
             Lesotho              Liberia                Libya            Lithuania           Luxembourg           Madagascar
        4.794950e-02         2.041134e-02         6.558880e-02         3.439832e-02         1.313624e-02         5.316299e-02
              Malawi             Malaysia                 Mali                Malta           Mauritania            Mauritius
        2.908423e-02         6.375313e-02         8.162525e-02         1.457119e-02         1.070985e-01         7.006463e-03
```

Good prediction?

Checking for errors:

```
# Calculate errors & assign country names
errors <- mil_exp$`2020` - pred.mean
names(errors) <- c.names

# Average error
mean(errors, na.rm = T)
```

```
## [1] -0.01210775
```

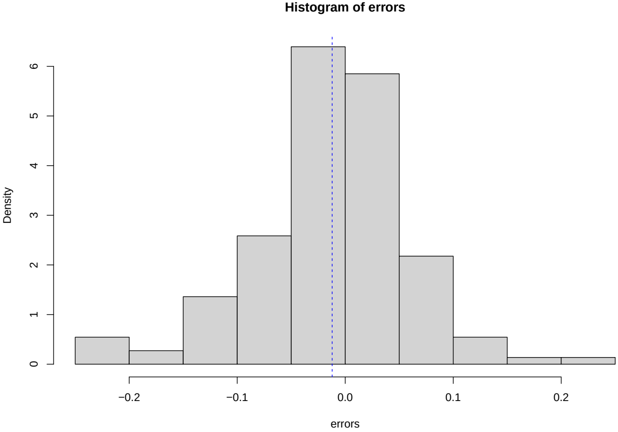
```
# RMSE
sqrt(mean(errors^2, na.rm = T))
```

```
## [1] 0.07380063
```

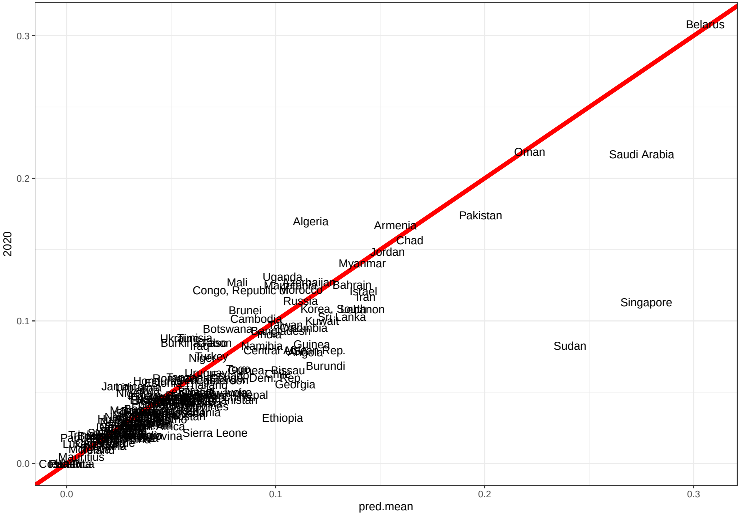
Prediction errors

How far off are we?

```
hist(errors, freq = FALSE)
abline(v = mean(errors, na.rm = T), lty = "dashed", col = "blue")
```



Accuracy of predictions



Find outlier predictions

Identify where we were off. . .

```
# Errors distribution
summary(n.dat$error)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.      NA's 
## -0.164364 -0.017092 -0.004715 -0.008734  0.000374  0.053107        10
```

```
# Create variable for large outliers
n.dat$large.inc <- NA
n.dat$large.inc[n.dat$error > 0.01] <- "Much More"
n.dat$large.inc[n.dat$error < -0.01] <- "Much Less"

# Create subset of outliers: less than average
n.dat2 <- n.dat %>%
  filter(large.inc == "Much Less") %>%
  mutate(error = error * 100) %>%
  select(Group1, error) %>% arrange(desc(error))

tail(n.dat2, n=9)
```

```
##                      Group1      error
## Chile              Americas  -3.785553
## Nepal        Asia & Oceania  -4.102959
## Sierra Leone         Africa  -4.945523
## Georgia              Europe  -5.375066
## Burundi              Africa  -5.521676
## Saudi Arabia    Middle East  -5.806989
## Ethiopia             Africa  -7.119952
## Sudan                Africa -15.832405
## Singapore    Asia & Oceania -16.436356
```

Time series and predicted value

Focus on big-5 spenders

Format data to long-form

```
dat3 <- n.dat %>%
  filter(Country == "Russia" | Country == "USA" |
           Country == "China" | Country == "Iran" | Country == "Israel") %>%
  select(-Subgroup1, -error, -large.inc)

dat3.l <- dat3 %>%
  gather(year, exp, '1999':'2020',-Country, -Group1, -pred.mean) %>%
  arrange(Country) %>%
  mutate(exp = round(exp*100,2))
```

Working with dates

Working with dates:

- Package $\rightarrow$ library(lubridate)
- Define variables as dates and choose format
- We can calculate number of days between date variables

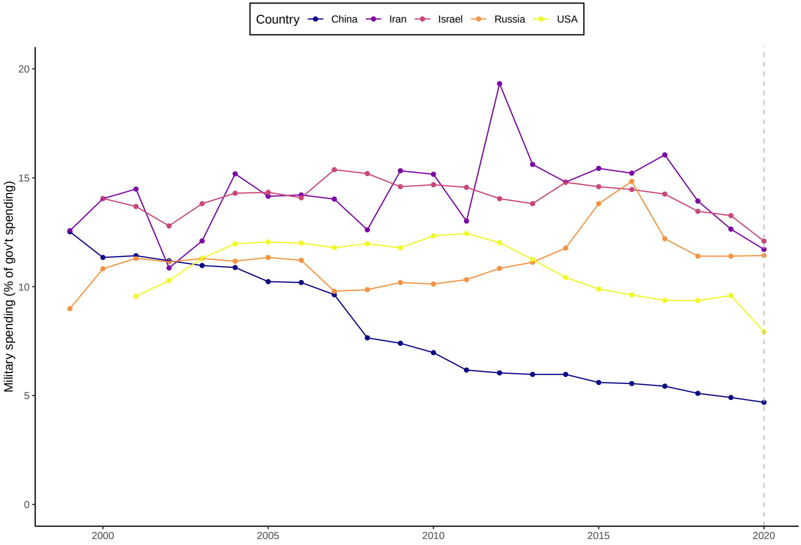
```
# Working with dates
arrive <- as.Date("2015-07-01")
today <- as.Date("2022-02-22")

# How long have I been in the US?
today - arrive
```

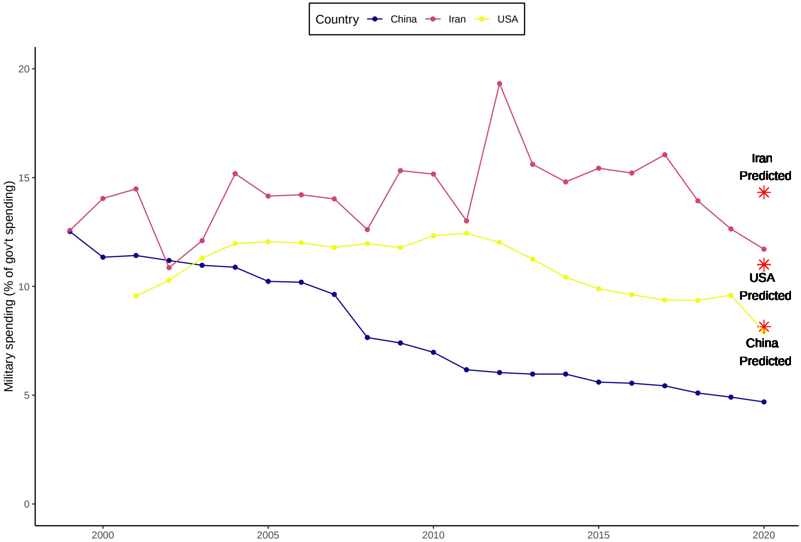
```
## Time difference of 2428 days
```

```
# Define dates in our expenditures data
dat3.l$year.f <- as.Date(dat3.l$year, format = "%Y")
dat3.l$year.f2 <- year(dat3.l$year.f)
```

Spending over time



Spending over time (and predicted 2020 - the ‘big 3’)



US Military Aid

- Approximately $11-12 Billion per year.
- FP tool with various goals:
  - *quid-pro-quo* compliance with target government.
  - Augment US national security.
  - Require aid target cooperation.
- Outcomes? Not too promising...
  - Reduce cooperation (2011).
  - Reduce terrorism under certain conditions (2014).
  - Limited in lowering civil conflict (2018).
- Great data resource: *ForeignAssistance.gov* (Link)

Aid data

- US Aid (1990-2006)

```
# Explore Military aid data
dim(mil_aid2)
```

```
## [1] 2643   34
```

```
summary(mil_aid2$militaryaid)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.00    0.00    0.20   34.49    1.30 3365.70       3
```

Predicting US Military Aid

- Predict 2006 levels → mean of aid (1990-2005)
- Use loop to calculate means for all countries

```
## Loop procedure
pred.aid <- rep(NA,168)
c.names <- unique(mil_aid2$country)
names(pred.aid) <- as.character(c.names)

for (i in 1:168){
  c.dat <- subset(mil_aid2, subset = (country == c.names[i]))
  pred.aid[i] <- mean(c.dat$militaryaid, na.rm = T)
}

pred.aid[pred.aid > 80]
```

```
##      Greece      Turkey        Iraq       Egypt      Jordan      Israel
##   196.29375   309.69375   179.95625  1595.04999   154.68125  2516.30624
## Afghanistan    Pakistan
##   115.82500    81.24375
```

Predicting Aid

- Check our predictions

```r
# Error vectors and plot
aid.error <- mil_aid3$militaryaid - pred.aid
names(aid.error) <- c.names
mean(aid.error, na.rm = T)
```

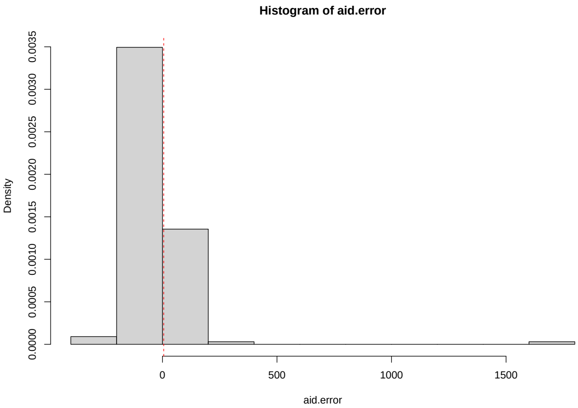
```
## [1] 5.719636
```

```r
sqrt(mean(aid.error^2, na.rm = T))
```

```
## [1] 139.2933
```

Plot errors (outliers?)

```
hist(aid.error, freq = FALSE)
abline(v = mean(aid.error, na.rm = T), lty = "dashed", col = "red")
```



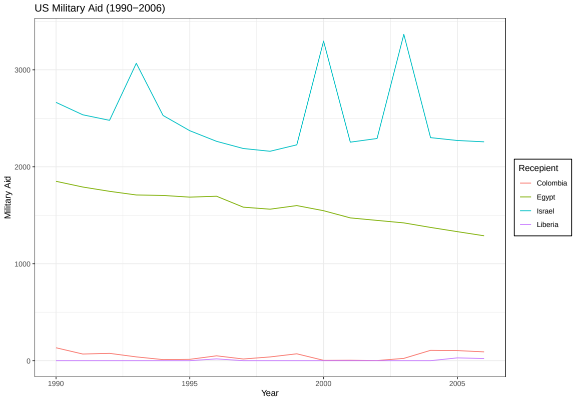

```
aid.error[aid.error > 1000]
```

```
##          <NA>        <NA> Afghanistan
##            NA          NA    1691.175
```

US Military aid: Time trends

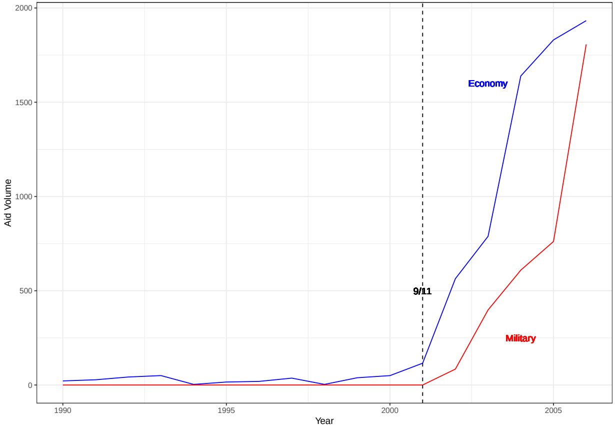
```
mil_aid4 <- mil_aid %>%
  filter(country == "Colombia" | country == "Egypt" | country == "Israel" | country == "Liberia")

ggplot(mil_aid4, aes(x = year, y = militaryaid)) +
  geom_line(aes(color = country)) +
  scale_color_discrete(name = "Recepient") +
  theme_bw() + xlab("Year") + ylab("Military Aid") + ggtitle("US Military Aid (1990-2006)") +
  theme(legend.position = "right",
        legend.background = element_rect(size = 0.5, linetype = "solid", colour = "black"))
```



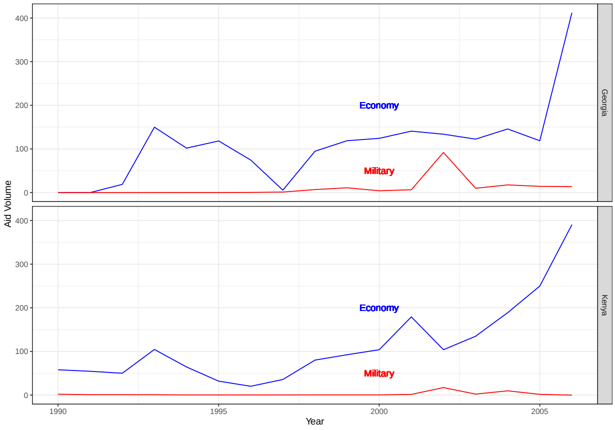
Military and Economic aid: Afghanistan (1990-2006)

```
mil_aid %>%
  filter(country == "Afghanistan") %>%
  ggplot() +
  geom_line(aes(year,economicaid), color = "blue") + xlab("Year") +
  geom_line(aes(year,militaryaid), color = "red") + ylab("Aid Volume") +
  geom_text(aes(x = 2003, y = 1600, label = "Economy"), color = "blue") +
  geom_text(aes(x = 2004, y = 250, label = "Military"), color = "red") +
  geom_vline(aes(xintercept = 2001), linetype = "dashed", color = "black") +
  geom_text(aes(x = 2001, y = 500, label = "9/11"), color = "black") + theme_bw()
```



Military and Econ aid: Always tracking??

```
mil_aid %>%
  filter(country == "Georgia" | country == "Kenya") %>%
  ggplot(aes(group = country)) +
  geom_line(aes(year,economicaid), color = "blue") + xlab("Year") +
  geom_line(aes(year,militaryaid), color = "red") + ylab("Aid Volume") +
  geom_text(aes(x = 2000, y = 200, label = "Economy"), color = "blue") +
  geom_text(aes(x = 2000, y = 50, label = "Military"), color = "red") +
  facet_grid(country~.) + theme_bw()
```



Military and Economic aid (1990-2006)

- Checking for correlations

```
# Build data frame for means of aid types
type <- c("Military","Economic")
value <- c(mean(mil_aid$militaryaid,na.rm = T),
           mean(mil_aid$economicaid,na.rm = T))
aid_types <- data.frame(type,value)
aid_types
```

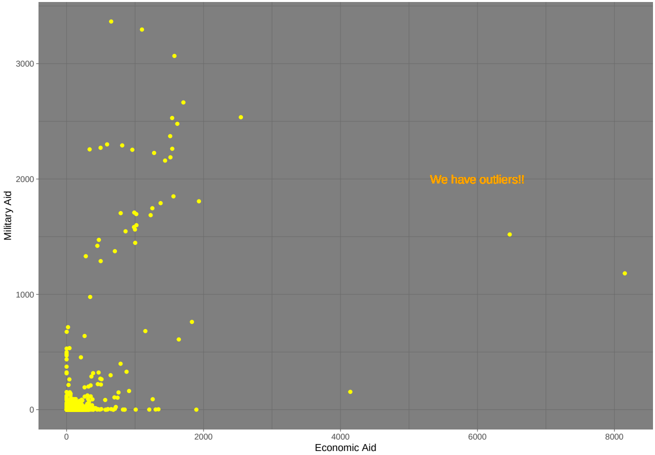
```
##       type    value
## 1 Military 33.08976
## 2 Economic 66.11048
```

```
# Correlation
cor(mil_aid$militaryaid, mil_aid$economicaid, use = "complete.obs")
```

```
## [1] 0.5559843
```

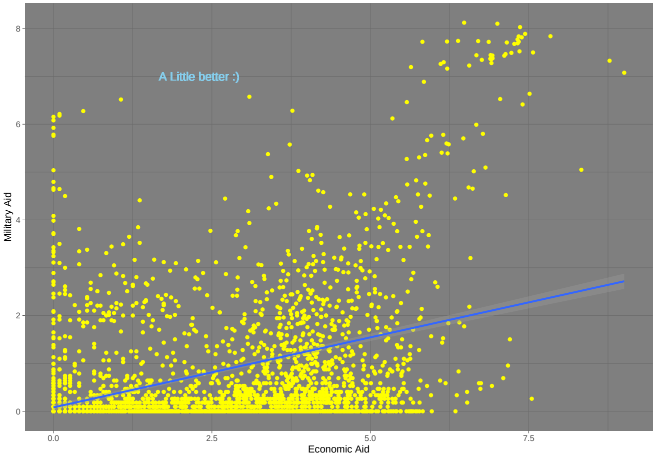
Plotting corrleation

```
ggplot(mil_aid, aes(x=economicaid, y=militaryaid)) +
  geom_point(color = "yellow") +
  xlab("Economic Aid") + ylab("Military Aid") +
  geom_text(aes(x =6000, y = 2000, label = "We have outliers!!"), color = "orange", size = 4.5) +
  theme_dark()
```



Plotting correlations: "Remove" outliers

```
ggplot(mil_aid, aes(x=logeconomicaid, y=logmilitaryaid)) +
  geom_point(color = "yellow") +
  geom_smooth(method = "lm") +
  xlab("Economic Aid") + ylab("Military Aid") +
  geom_text(aes(x =2.3, y = 7, label = "A Little better :)"), color = "skyblue", size = 4.5) +
  theme_dark()
```



Wrapping up week 6

Summary:

- Predictions. . .
- Using data to 'best- guess' some quantity.
- Repeated computations? Use Loops.
- Always check for prediction errors.
- Classification errors: false positive and false negative.
- Data over time
- US military aid data: predictions, errors and some insights

Almost done ↓

Task 2: R

- Explore INTA data.
- Answer all questions with R Markdown.
- Use revised template:
  - Be organized.
  - Add comments to your work (using #).
  - Add spaces using \vspace{1em}
  - When plotting - remember your reader!