Bush 631-600: Quantitative Methods

Lecture 6 (10.04.2022): Prediction vol. II

Rotem Dvir

The Bush school of Government and Public Policy

Texas A&M University

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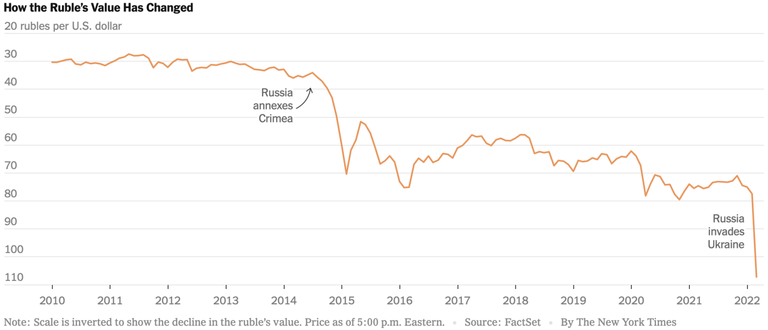
What is today's plan?

- Predictions: Improved (and more accurate) methods.
- Identify correlations in data with plots.
- The linear model: correlations, predictions, fit.
- Final project prep: Formulate your research question.
- R work: scatterplot(), lm(), cor().

Framing a messege with a plot

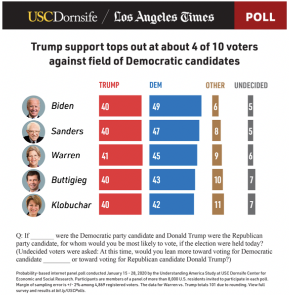


How the Ruble’s Value Has Changed

Note: Scale is inverted to show the decline in the ruble’s value. Price as of 5:00 p.m. Eastern. • Source: FactSet • By The New York Times

Predicting with data

Elections forecasting

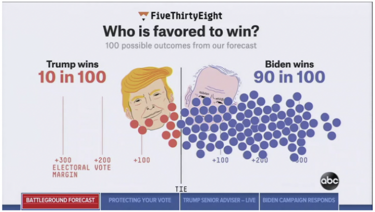


Trump support tops out at about 4 of 10 voters against field of Democratic candidates

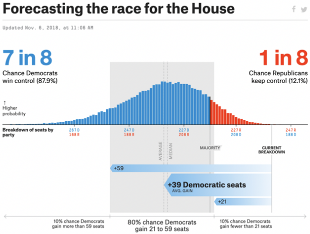
	TRUMP	DEM	OTHER	UNDECIDED
Biden	40	49	6	5
Sanders	40	47	8	5
Warren	41	45	9	6
Buttigieg	40	43	10	7
Klobuchar	40	42	11	7

Q: If _______ were the Democratic party candidate and Donald Trump were the Republican party candidate, for whom would you be most likely to vote, if the election were held today? (Undecided voters were asked: At this time, would you lean more toward voting for Democratic candidate ________ or toward voting for Republican candidate Donald Trump?)

Probability-based internet panel poll conducted January 15 - 28, 2020 by the Understanding America Study at USC Dornsife Center for Economic and Social Research. Participants are members of a panel of more than 8,000 U.S. residents invited to participate in each poll. Margin of sampling error is +/- 2% among 4,869 registered voters. The data for Warren vs. Trump totals 101 due to rounding. View full survey and results at *bit.ly/USCPolls*.

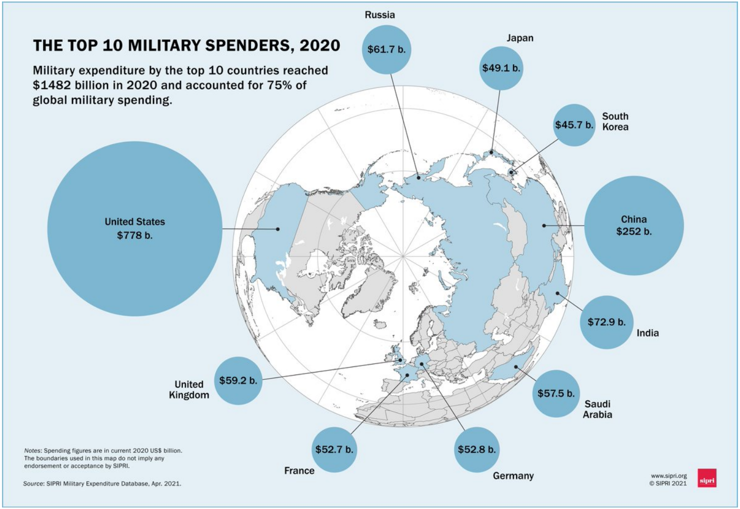


Predicting with Polls



Predicting with data

Military spending → arms race



THE TOP 10 MILITARY SPENDERS, 2020

Military expenditure by the top 10 countries reached $1482 billion in 2020 and accounted for 75% of global military spending.

Notes: Spending figures are in current 2020 US$ billion. The boundaries used in this map do not imply any endorsement or acceptance by SIPRI.

Source: SIPRI Military Expenditure Database, Apr. 2021.

Predicting with data

Method:

- Calculate values per group.
- Prediction = mean value.
- Elections: 51 US states (2016).
- Arms: 157 countries (1999-2019).
- Main benefit: simple and consistent.
- Foundation for customer outreach: Purchasing (Amazon); Content (Netflix).

However,

- Mean → sensitive to outliers/extreme values.
- Median?
- 'Ignore' context of special circumstances.

Better predicting with data

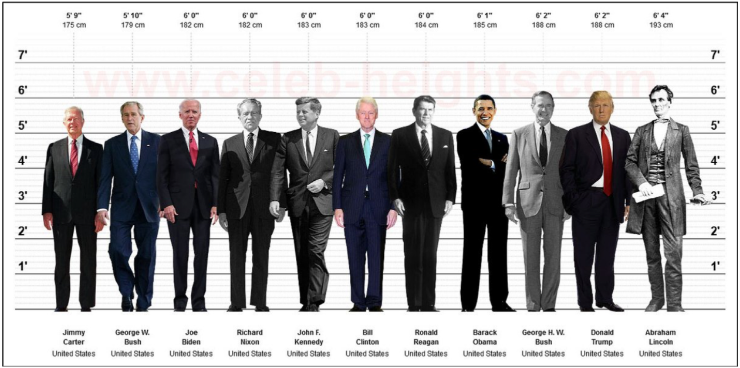
Explore linear relationship between factors

Advanced statistical methods to explore causality:

- Account for average and extreme values.
- Account for confounders.
- Integrate uncertainty in nature.

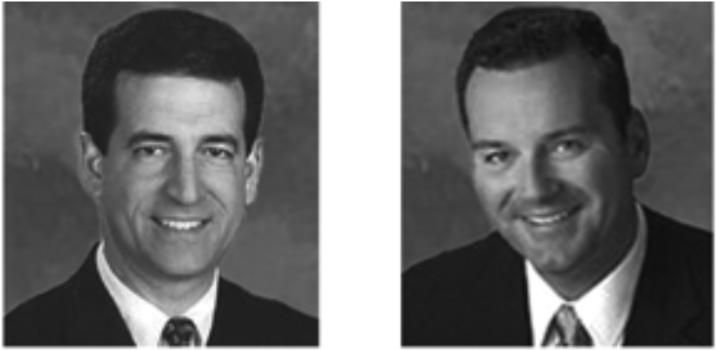
Data and linear relationship

Physical appearance and electoral victory



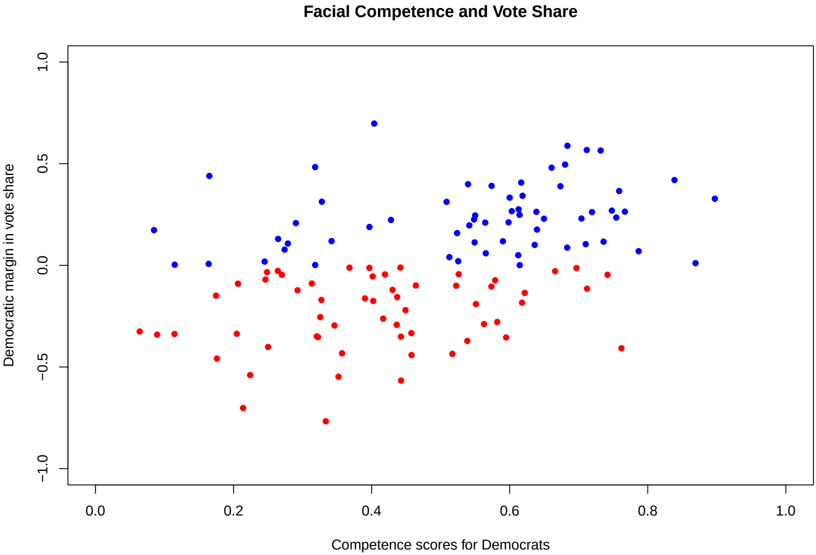
Data and linear relationship

Facial appearance too?



Which person is the more competent?

Data and linear relationship



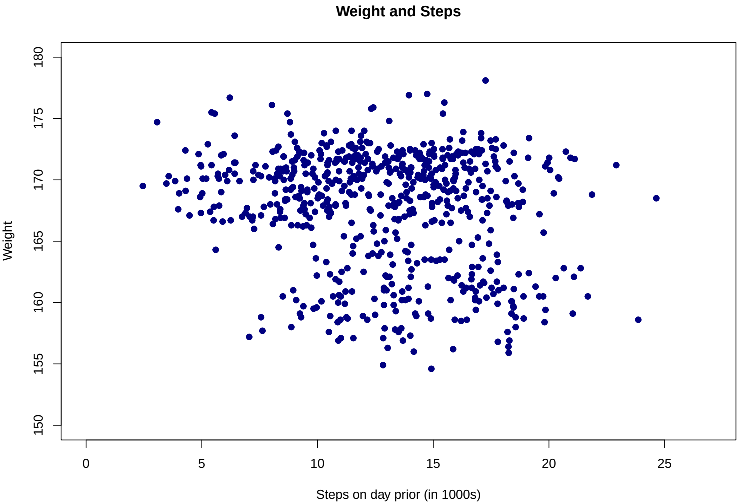
Checking correlation

- Upward trend linking competence score and winning.
- Facial appearance can help winning...
- Is it?

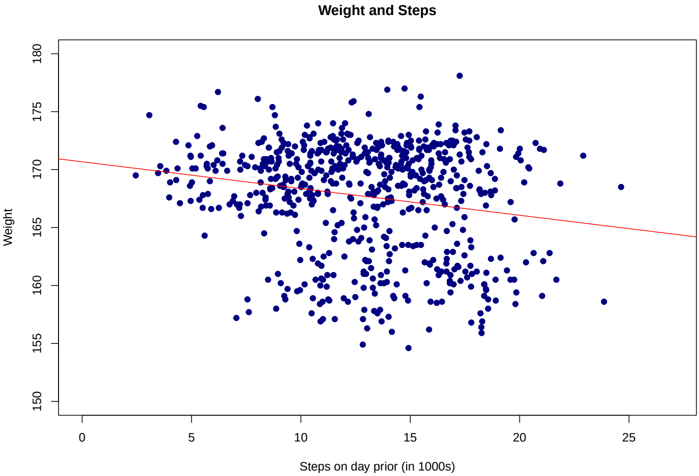
```
# Correlation
cor(face$d.comp, face$diff.share)
```

```
## [1] 0.4327743
```

More examples



Should I walk to work??



```
cor(health$steps.lag, health$weight)
```

```
## [1] -0.1907032
```

Identify correlation in data

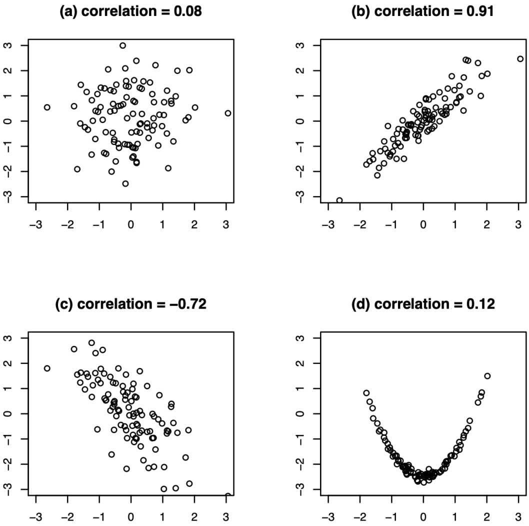
Correlation and scatter plots:

- Positive correlation $\rightarrow$ upward slope
- Negative correlation $\rightarrow$ downward slope
- High correlation $\rightarrow$ tighter, closer to a line
- Correlation cannot capture nonlinear relationship.

Can we see it?

Identify correlation in data

Scatter plots and correlations:



(a) correlation = 0.08

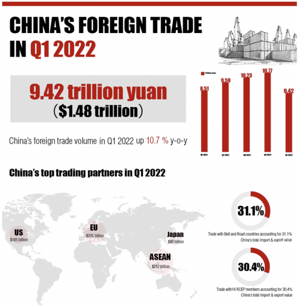
(b) correlation = 0.91

(c) correlation = −0.72

(d) correlation = 0.12

Correlations and predictions: INTA style

Global Trade Flows



CHINA'S FOREIGN TRADE IN Q1 2022

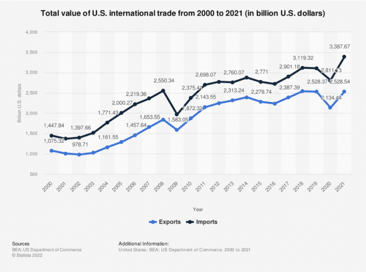
9.42 trillion yuan ($1.48 trillion)

China's foreign trade volume in Q1 2022 up 10.7 % y-o-y

China's top trading partners in Q1 2022

Trade with Belt and Road countries accounting for 31.1% China's total import & export value

Trade with14 RCEP members accounting for 30.4% China's total import & export value



Total value of U.S. international trade from 2000 to 2021 (in billion U.S. dollars)

Sources
BEA; US Department of Commerce
© Statista 2022

Additional Information:
United States; BEA; US Department of Commerce; 2000 to 2021

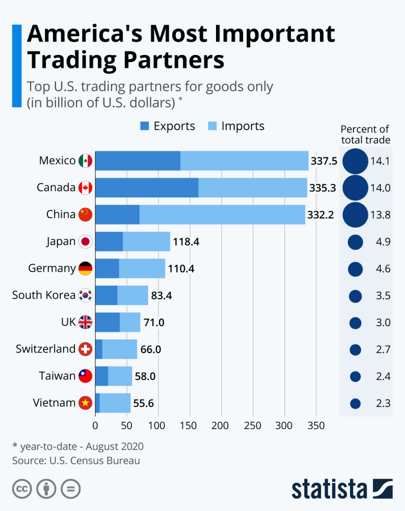
- Volume (Q1 - 2022): $7.7 trillion.
- Increases in goods and services (20-25% higher than Q1 2021)

Explaining international trade

The Gravity Model

- "Workhorse of int'l trade"
- Trade volume b-w countries:

1. Size of economies.
2. Distance.



America's Most Important Trading Partners

Top U.S. trading partners for goods only (in billion of U.S. dollars) *

* year-to-date - August 2020

Source: U.S. Census Bureau

Measuring Gravity and Trade

- Distance, land area, population size, borders, etc.

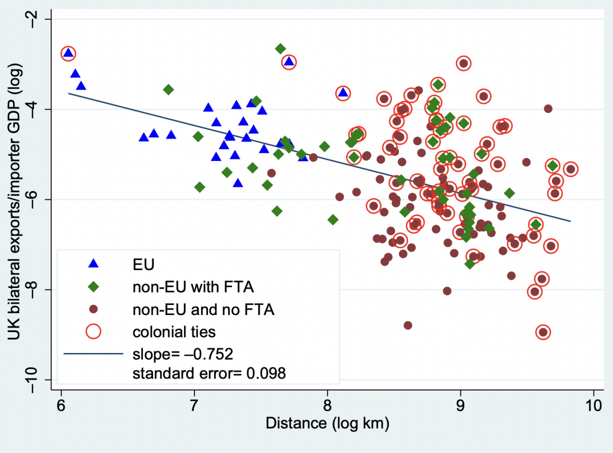


Fig. 2. *UK Bilateral Exports/Importer GDP and Distance, 2017.*

The Gravity Model

Trade and global processes

- International conflict / global alliances:
  - Trade persist b-w strong economies.
  - Weak and strong economy: trade increases with defense pact.
  - Weak and strong economy: trade decays with military conflict.
- Move towards Democratization:
  - Increased trade → consolidate democracy.
  - Openness (free trade) increase democratization.

International Trade and democracy promotion

Doces and Magee (2015)

- Benefits of globalization:
  - Abundant labor → trade helps workers (and harms capital).
  - Abundant capital → trade helps capital (and harms workers).
- Trade → strengthen democracy (labor abundant).
- Trade → weaken democracy (capital abundant).

Trade and Democracy

- Data: democracy and econ (1960-2007)

```
dim(a)
```

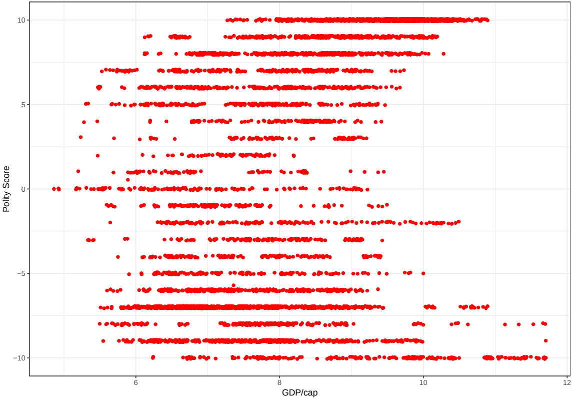
```
## [1] 10421    33
```

```
head(a, n=5)
```

```
## # A tibble: 5 x 33
##    year my_code open_hat1 wb_code country  pwt_c~1 polity2 America Europe Af
##   <dbl>   <dbl>     <dbl> <chr>   <chr>      <dbl>   <dbl>   <dbl>  <dbl> <
## 1  1960       1      15.8 AFG     Afghani~      NA     -10       0      0
## 2  1961       1      15.7 AFG     Afghani~      NA     -10       0      0
## 3  1962       1      15.5 AFG     Afghani~      NA     -10       0      0
## 4  1963       1      16.1 AFG     Afghani~      NA     -10       0      0
## 5  1964       1      17.5 AFG     Afghani~      NA      -7       0      0
## # ... with 23 more variables: Pacific <dbl>, oil <dbl>,
## #   female_percent_pop <dbl>, pop_15_64 <dbl>, pop_15_under <dbl>, urban <db
## #   region_polity_20 <dbl>, region_polity_10 <dbl>, region_open_20 <dbl>,
## #   region_open_10 <dbl>, lang_num2 <dbl>, ethnic_num2 <dbl>,
## #   religion_num2 <dbl>, colony_1945 <dbl>, yrs_indep <dbl>, time <dbl>,
## #   open3 <dbl>, ln_gdppc8 <dbl>, ln_pop8 <dbl>, kl8 <dbl>, median_kl8 <dbl>
## #   above_median_kl8 <dbl>, above_avg_kl8 <dbl>, and abbreviated variable ..
## # i Use `colnames()` to see all variable names
```

Gravity model - Trade data

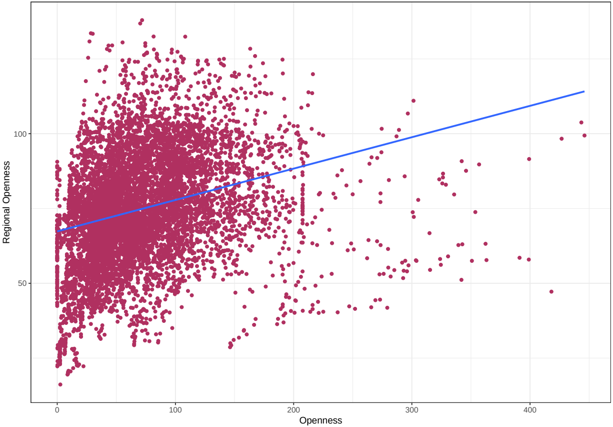
```
ggplot(a, aes(ln_gdppc8,polity2)) +
  geom_jitter(color = "red") + xlab("GDP/cap") + ylab("Polity Score") +
  theme_bw()
```



```
cor(a$polity2,a$ln_gdppc8, use = "complete")
```

```
## [1] 0.4396297
```

Gravity model - Trade data



```
## [1] 0.2756198
```

Trade and democracy - with a caveat

Labor abundant → more workers: Trade boost democracy

```r
# Only labor abundant countries
aa <- a %>%
  filter(above_median_kl8 == 0)

# Trade and religious diversity
cor(aa$open3, aa$religion_num2, use = "complete")
```

```
## [1] -0.210249
```

```r
# Trade and working population
cor(aa$open3, aa$pop_15_64, use = "complete")
```

```
## [1] 0.1137331
```

```r
# Trade and Democracy
cor(aa$open_hat1, aa$polity2, use = "complete")
```

```
## [1] 0.1928551
```

Trade and democracy - with a caveat

Capital abundant → less workers: Trade harms democracy

```r
# Only capital abundant countries
aaa <- a %>%
  filter(above_median_kl8 == 1)

# Trade and religious diversity
cor(aaa$open3, aaa$religion_num2, use = "complete")
```

```
## [1] 0.3193981
```

```r
# Trade and linguistic diversity
cor(aaa$open3, aaa$lang_num2, use = "complete")
```

```
## [1] 0.2963194
```

```r
# Trade and Democracy
cor(aaa$open_hat1, aaa$polity2, use = "complete")
```

```
## [1] -0.09662274
```

Least squared

A Linear model

$$Y = \alpha + \beta * X_i + \epsilon$$

Elements of model:

- *Intercept* (α): the average value of Y when X is zero.
- *Slope* (β): the average increase in Y when X increases by 1 unit.
- *Error/disturbance term* (ϵ): the deviation of an observation from a perfect linear relationship.

Our model:

- **Y** → Democracy score (polity).
- **X** → Extent of int'l trade (openness).

Least squared

- Assumption: model $\rightsquigarrow$ Data generation process (DGS)
- **Parameters/coefficients** (α, β): true values unknown.
- Use data to estimate $\alpha, \beta \Longrightarrow \hat{\alpha}, \hat{\beta}$
- Predicting (finally!):
  - Use the *regression line*.
  - Calculate *fitted value* ($\neq$ observed value)

$$\hat{Y} = \hat{\alpha} + \hat{\beta} * x$$

Linear model elements

- *Residual/prediction error*: the difference b-w fitted and observed values.
- Real error is unknown $\Rightarrow \hat{\epsilon}$

$$\hat{\epsilon} = Y - \hat{Y}$$

Linear model estimation

Least squared:

- A method to estimate the regression line.
- Use data (values of Y & X_i).
- 'select' $\hat{\alpha}, \hat{\beta}$ to minimize SSR.
- Calculate RMSE: average magnitude of prediction error (magnitude of least squared).

$$SSR = \sum_{i=1}^{n} \hat{\epsilon}^2 = \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 = \sum_{i=1}^{n} (Y_i - \hat{\alpha} - \hat{\beta} * X_i)^2$$

Few more points:

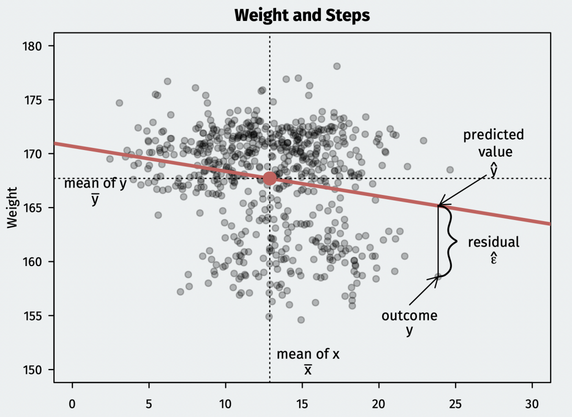
- Mean of residuals ($\hat{\epsilon}$) $==0$.
- Regression line goes through center of data ($\bar{X}$, $\bar{Y}$).
- $\bar{X}$, $\bar{Y}$: Sample means of X & Y.

Linear regression in R

Fit the model

- Syntax: lm(Y ∼ x, data = mydata)
- Y = dependent variable; x = independent variable(s).

How does it look like?



Trade and democracy - fitting the model

```
# Fit the model
fit <- lm(polity2 ~ open3, data = a)
fit
```

```
##
## Call:
## lm(formula = polity2 ~ open3, data = a)
##
## Coefficients:
## (Intercept)        open3
##    0.711664    -0.006503
```

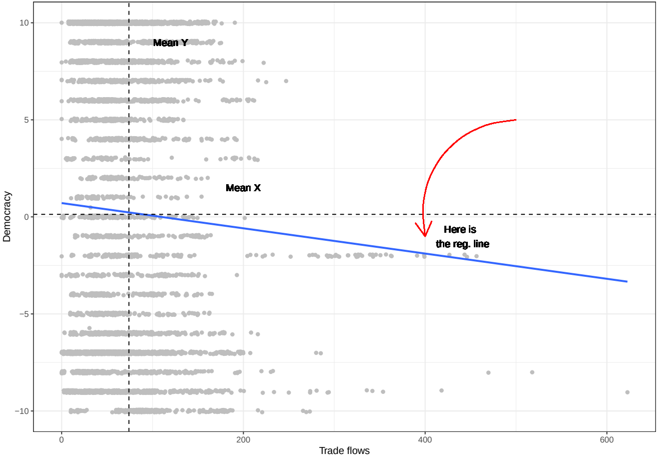
```
# Directly obtain coefficients
coef(fit)
```

```
##  (Intercept)        open3
##  0.711663968 -0.006502699
```

```
# Directly pull fitted values
head(fitted(fit))
```

```
##         1         2         3         4         5         6
## 0.6452021 0.6453733 0.6452360 0.6022816 0.5264752 0.5652951
```

Trade and democracy - visualize the model



Trade and democracy - labor vs. capital

```r
# Labor abundant
fit2 <- lm(polity2 ~ open3, data = aa)
fit2
```

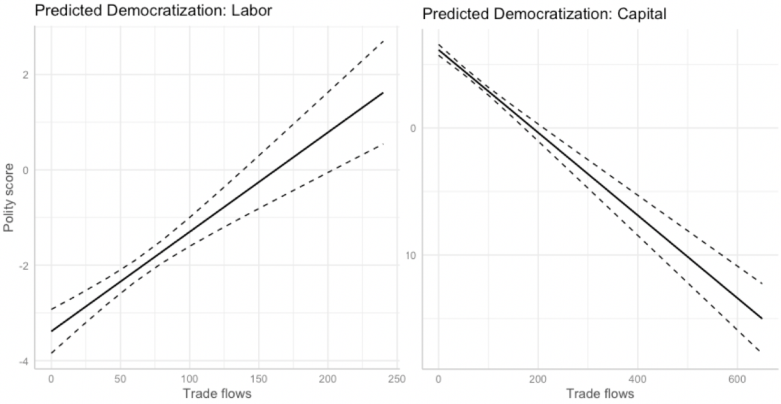
```
##
## Call:
## lm(formula = polity2 ~ open3, data = aa)
##
## Coefficients:
## (Intercept)        open3
##    -3.38618      0.02086
```

```r
# Capital abundant
fit3 <- lm(polity2 ~ open3, data = aaa)
fit3
```

```
##
## Call:
## lm(formula = polity2 ~ open3, data = aaa)
##
## Coefficients:
## (Intercept)        open3
##     6.14921     -0.03257
```

Trade and democracy - labor vs. capital

Predicted Polity score ← Trade volume



Least square

- Regression line → “line of best fit”
- Minimize prediction error
- Predictions of fitted line are accurate. How come?
- $\bar{\hat{\epsilon}} = 0$.
- Linear model: not necessarily represent DGS (assumption).

Errors/Curses/Anomalies

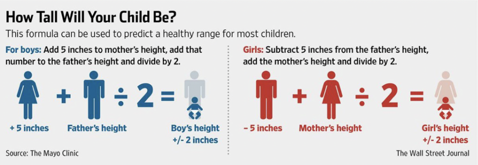
Riddell
BROWNS
EA SPORTS
MADDEN NFL 12

Cursed??

Roger Federer
WHAT THE MASTER CAN TEACH US
BY L. JON WERTHEIM
Sports Illustrated
MAYWEATHER-MCGREGOR FIGHT CIRCUS OF THE CENTURY
BY GREG BISHOP
The Dodgers Have Their Eyes On History.
(But Mostly the World Series)
BY STEPHANIE APSTEIN
It's been a season-long party for Justin Turner (10) and the Dodgers but it won't matter if they're not dousing each other in October.
BEST. TEAM. EVER?

Errors/Curses/Anomalies

Fighter pilots performance?



How Tall Will Your Child Be?

This formula can be used to predict a healthy range for most children.

For boys: Add 5 inches to mother's height, add that number to the father's height and divide by 2.

+ 5 inches + Father's height ÷ 2 = Boy's height +/- 2 inches

Girls: Subtract 5 inches from the father's height, add the mother's height and divide by 2.

– 5 inches + Mother's height ÷ 2 = Girl's height +/- 2 inches

Source: The Mayo Clinic

The Wall Street Journal

My kids height?

Actually

Regression to the mean

- Empirical - data driven.
- Explained by (random) chance.
- High (low) observations are followed by low (high) observations.
- Observations ‘regress’ towards the average value of the data.

Merging data sets

- Combine data with shared variables.
- Expand data available: more years, same information.
- Technical: use columns / rows.
- Multiple approaches.

Merging

(1) merge function:

- Join two datasets.
- Merge based on common variable (*by* argument).
- 2008-2012 voting data: state Abb. name (QSS pp. 150-151).
- Common variable: matching of rows and columns.
- Other common columns? Appended with .x or .y after name.

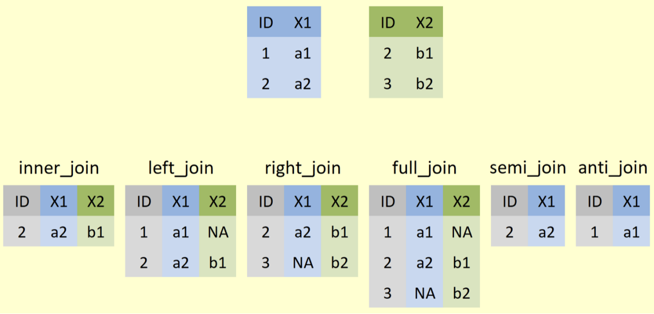
(2) cbind function:

- Column binding of multiple datasets.
- Main drawback: assumes similar sorting.
- Keeps duplicates.
- rbind(): join data by rows (add observations to data).

Merging

(3) Join (tidyverse):

- More flexible: multiple options.
- Keep one data, join by common variable.
- Keep all data, join by common variable.



ID	X1
1	a1
2	a2

ID	X2
2	b1
3	b2

inner_join

ID	X1	X2
2	a2	b1

left_join

ID	X1	X2
1	a1	NA
2	a2	b1

right_join

ID	X1	X2
2	a2	b1
3	NA	b2

full_join

ID	X1	X2
1	a1	NA
2	a2	b1
3	NA	b2

semi_join

ID	X1
2	a2

anti_join

ID	X1
1	a1

Apply prediction with regression

- Linear model → predict Y using X_i
- Using linear predictions - policy:
  - Predict crime waves - deploy police resources.
  - Predict students performance - target interventions.
- Using linear predictions - business:
  - Predict preferred products based on previous purchases.
  - Predict Netflix/Spotify content based on what I saw/heard?

Model fit

Our well does a linear model predict the data (outcome)?

Model fit:

- Measures to assess model predictive accuracy.

Coefficient of determination (R^2):

- The proportion of total variation in outcome explained by model.
- How much variation in Y explained by our model.
- Values from 0 (no correlation) to 1 (perfect correlation).

Model fit: R-squared

$$R^2 = \frac{TSS - SSR}{TSS}$$

TSS (Total sum of squares): prediction error with mean Y only

$$TSS = \sum_{i=1}^{n} (Y_i - \bar{Y})^2$$

SSR (Sum of squared residuals): prediction error with model

$$SSR = \sum_{i=1}^{n} \hat{\epsilon}^2$$

Model fit with data: Florida (1996-2000)

Independent candidates 'inertia'?

```
# Use summary function
summary(fit3 <- lm(Buchanan00 ~ Perot96, data = florida))
```

```
##
## Call:
## lm(formula = Buchanan00 ~ Perot96, data = florida)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -612.74  -65.96    1.94   32.88 2301.66
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.34575   49.75931   0.027    0.979
## Perot96      0.03592    0.00434   8.275 9.47e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 316.4 on 65 degrees of freedom
## Multiple R-squared:  0.513,  Adjusted R-squared:  0.5055
## F-statistic: 68.48 on 1 and 65 DF,  p-value: 9.474e-12
```

- 51% of Buchanan (2000) explained by Perot (1996) voters.

Model fit with data: Florida (1996-2000)

‘Conventional’ candidates: Clinton - Gore

```
summary(lm(Gore00 ~ Clinton96, data = florida))
```

```
##
## Call:
## lm(formula = Gore00 ~ Clinton96, data = florida)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -30689.3  -1161.5   -622.4   1040.3  23309.1
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 434.49448  921.26520   0.472    0.639
## Clinton96     1.13120    0.01216  92.997   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6523 on 65 degrees of freedom
## Multiple R-squared:  0.9925, Adjusted R-squared:  0.9924
## F-statistic:  8648 on 1 and 65 DF,  p-value: < 2.2e-16
```

Model fit with data: Florida (1996-2000)

‘Conventional’ candidates: Dole - Bush

```
summary(lm(Bush00 ~ Dole96, data = florida))
```

```
##
## Call:
## lm(formula = Bush00 ~ Dole96, data = florida)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -18276.9   -781.9   -105.3   1599.5  21759.1
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 799.82813  701.76481    1.14    0.259
## Dole96        1.27333    0.01262  100.91   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4587 on 65 degrees of freedom
## Multiple R-squared:  0.9937, Adjusted R-squared:  0.9936
## F-statistic: 1.018e+04 on 1 and 65 DF,  p-value: < 2.2e-16
```

Model fit with data: Florida (1996-2000)

Where did the independents go for the millennium?

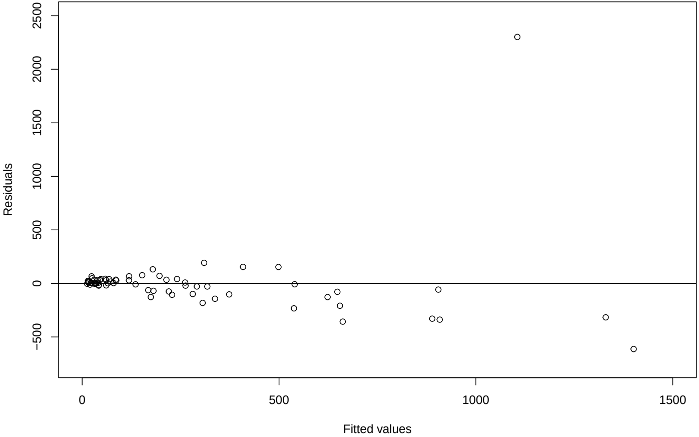
```
summary(lm(Bush00 ~ Perot96, data = florida))
```

```
##
## Call:
## lm(formula = Bush00 ~ Perot96, data = florida)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -49100  -5003  -2951   -582 145169
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1810.4147  3853.0142    0.47     0.64
## Perot96        5.7646     0.3361   17.15   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 24500 on 65 degrees of freedom
## Multiple R-squared:  0.8191, Adjusted R-squared:  0.8163
## F-statistic: 294.2 on 1 and 65 DF,  p-value: < 2.2e-16
```

Model fit with data: Florida (1996-2000)

Maybe not all of them? *Palm beach county*

```
plot(fitted(fit3), resid(fit3), xlim = c(0,1500), ylim = c(-750,2500),
     xlab = "Fitted values", ylab = "Residuals")
abline(h=0)
```



Model fit with data: Florida (1996-2000)

Remove outlier - better prediction

```
summary(lm(Buchanan00 ~ Perot96, data = florida_cut))
```

```
##
## Call:
## lm(formula = Buchanan00 ~ Perot96, data = florida_cut)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -206.70  -43.51  -16.02   26.92  269.03
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 45.841933  13.892746    3.30  0.00158 **
## Perot96      0.024352   0.001273   19.13  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 87.75 on 64 degrees of freedom
## Multiple R-squared:  0.8512, Adjusted R-squared:  0.8488
## F-statistic:   366 on 1 and 64 DF,  p-value: < 2.2e-16
```

Model fit

- R^2: measure of *in-sample* fit.
- *Out-of-sample-fit*: how model predicts outcomes ‘outside’ the sample.

Overfitting:

- OLS $\rightarrow$ good for in-sample.
- Poor performance for out-of-sample.
- Example: use gender to predict 2016 democratic primaries winner.

Wrapping up week 6

Summary:

- Prediction: beyond sample means.
- Using plots to find correlations/trends in data.
- Least squared method.
- Linear model and estimating coefficients.
- Predictions based on linear model.
- Merging data.
- Model fit.

Looking ahead

- **Final Project**:
  - Objective.
  - Technical aspects.
- Next task - research proposal:
  - What is the topic / area?
  - Why important?
  - How will you study it?
  - Sources: substance and data.
  - Final visual product outline.

Proposal due November 1, 2022