Bush 631-607: Quantitative Methods

Lecture 6 (10.12.2021): Prediction vol. II

Rotem Dvir

The Bush school of Government and Public Policy

Texas A&M University

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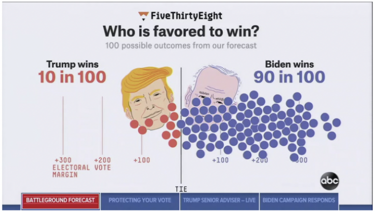
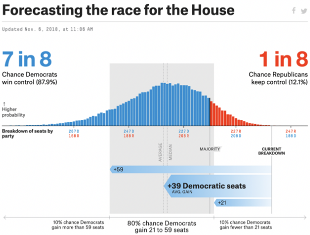
What is today's plan?

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

Predicting with data

Elections forecast.

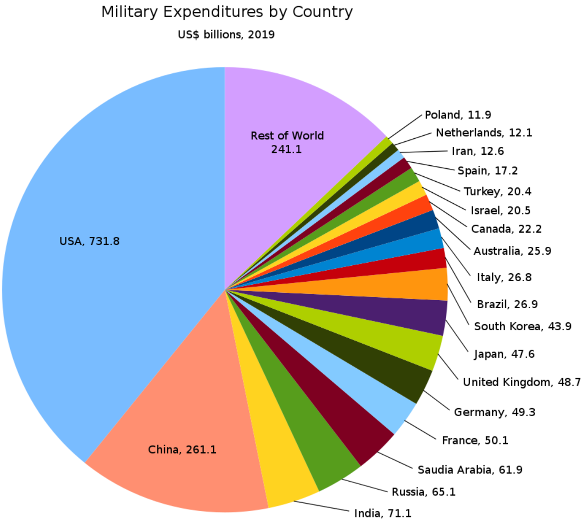




Predicting with Polls

Predicting with data

Military spending $\rightarrow$ arms race



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.

However,

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

Better predicting with data

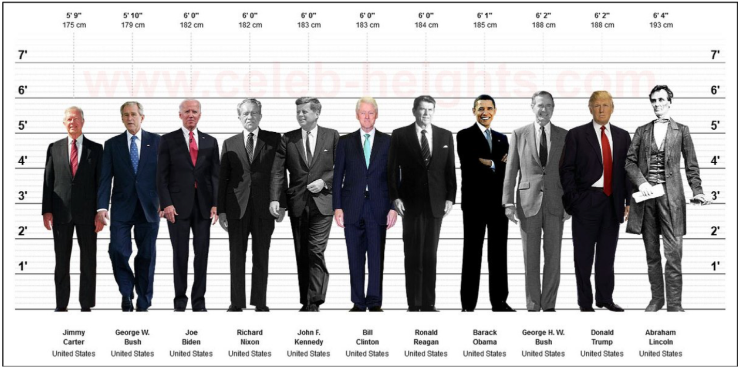
Advanced statistical methods to explore causality:

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

Explore linear relationship between factors

Data and linear relationship

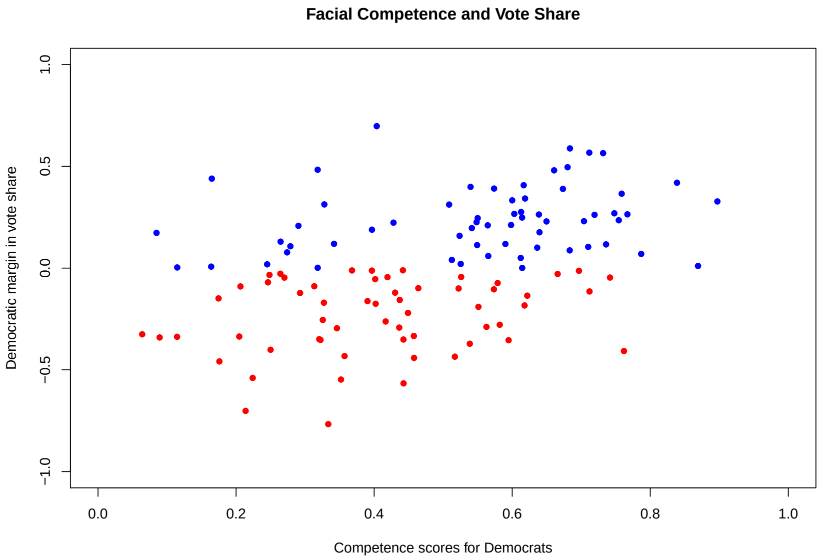
Physical appearance and electoral victory



Data and linear relationship

Facial appearance too?

Data and linear relationship



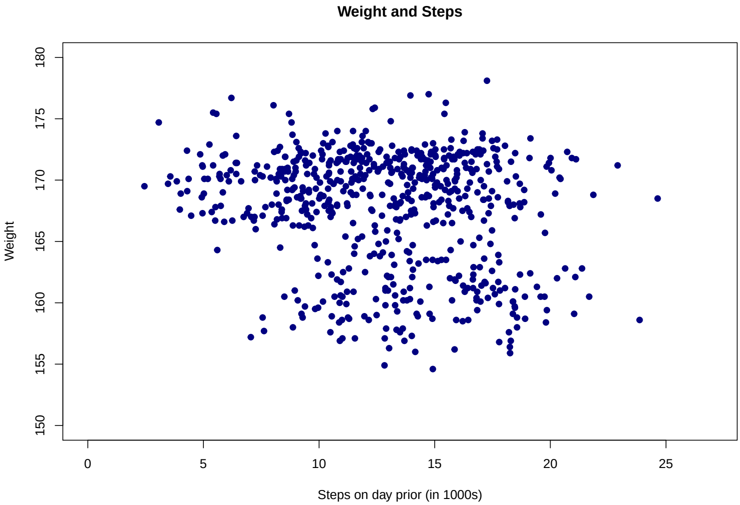
Checking correlation

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

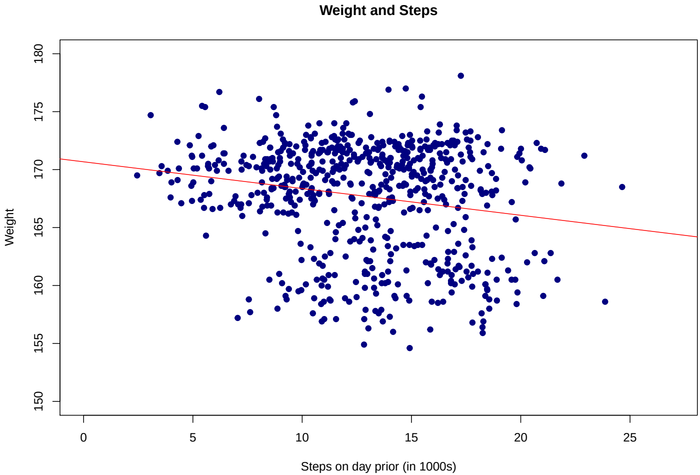
```r
# Correlation
cor(face$d.comp, face$diff.share)
```

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

More examples



Should I walk to work??




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

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

Identify correlation in data

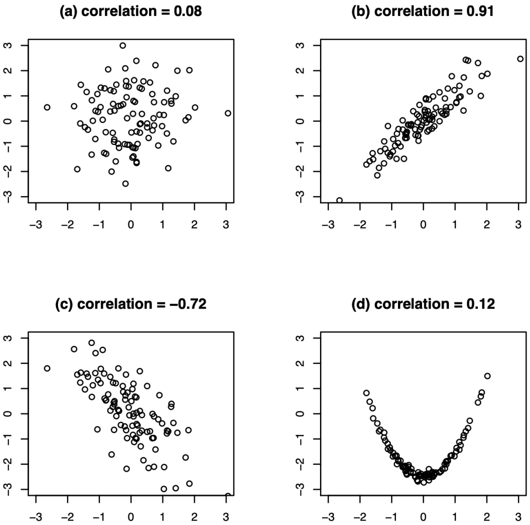
Correlation and scatter plots:

- 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?

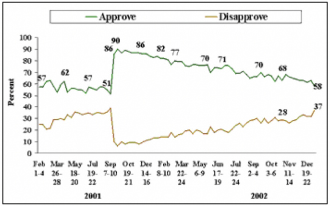
Identify correlation in data

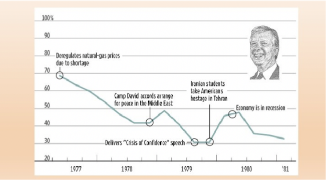
Scatter plots and correlations:



Correlations and predictions: INTA style

Crisis behavior and public approval





Crisis and public approval

Lin-Greenberg (2019):

- Conflict/crisis scenario.
- Actions mitigate public criticism.
- Method: experimental design
- Topic $\rightarrow$ *audience costs*

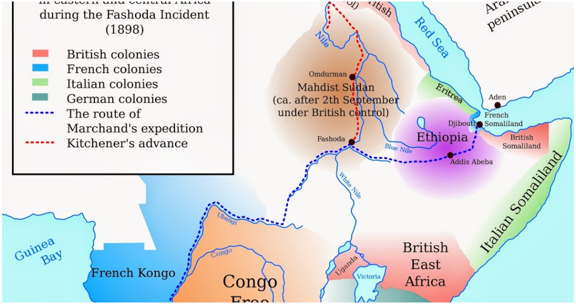
Audience costs

Fearon (1994)

- International crisis $\rightarrow$ “war of nerves”
- Public events, actions (threats, troop movements)
- The role of honor, credibility, and reputation
- Leaders’ actions shaped by domestic audience
- The cost of *backing down*
- The strategic implications of audience costs

Audience costs

- Main problem? Observability.
- Can we ‘see’ audience costs?



Measuring audience costs

The solution: experimental research designs

- Conflict scenario
- Leader issues a public threat
- Main treatment: follow-through or back-down
- Compare public approval $\rightarrow$ measure for AC

Are there audience costs?

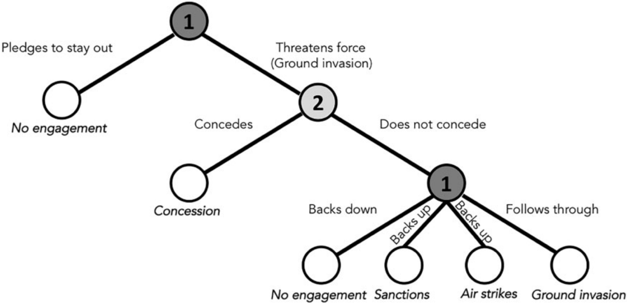
Tomz (2007): experimental design

	Public reaction to empty threat (%)	−	*Public reaction to staying out (%)*	=	*Difference in opinion (%)*	*Summary of differences (%)*
Disapprove						
Disapprove very strongly	31 (27 to 35)		20 (17 to 23)		11 (6 to 17)	16 (10 to 22)
Disapprove somewhat	18 (14 to 21)		13 (10 to 16)		5 (0 to 9)	
Neither						
Lean toward disapproving	8 (6 to 11)		9 (7 to 11)		0 (−3 to 3)	−4 (−9 to 2)
Don't lean either way	21 (17 to 24)		21 (18 to 24)		0 (−5 to 4)	
Lean toward approving	8 (6 to 11)		11 (9 to 14)		−3 (−6 to 0)	
Approve						
Approve somewhat	8 (5 to 10)		13 (11 to 16)		−6 (−9 to −2)	−12 (−17 to −8)
Approve very strongly	6 (4 to 9)		13 (10 to 16)		−7 (−10 to −3)	

Backing-up, not down...

Lin-Greenberg (2019):

- Employ less risky action → reduce audience costs



Measuring audience costs

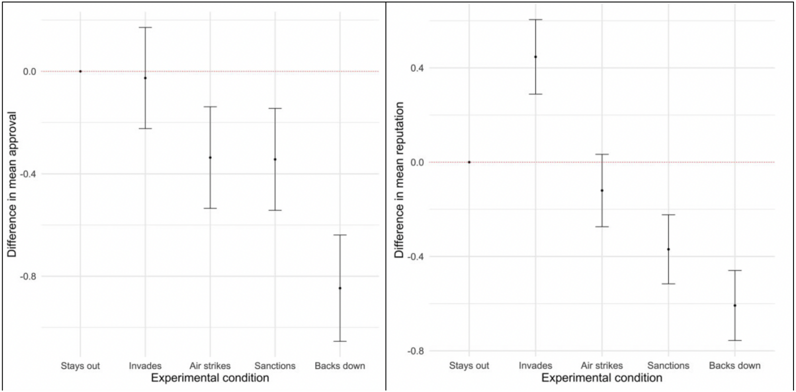
Compare:

- Does policy action matter?
- Approval
- Reputation

Our goal?

- Explore approval & reputation ratings.

Some results



The data

```
dim(mydata)
```

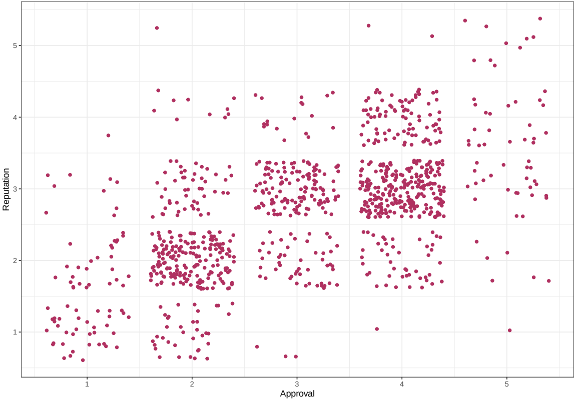
```
## [1] 1006   23
```

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

```
##   None Invades Airstrikes Sanctions Backs.Down Intro.Q Approval Justification_2
## 1    0       0          1         0          0       1        4               1
## 2    0       0          1         0          0       1        1               2
## 3    0       0          1         0          0       1        2               9
## 4    0       0          1         0          0       1        5               5
## 5    0       0          1         0          0       1        2               2
##   Justification Criticize.Sitting.Out Consistence Reputation Future.Threats
## 1             1                    NA           3          3              3
## 2             2                    NA           4          2              4
## 3             2                    NA           2          2              3
## 4             1                    NA           4          5              4
## 5             2                    NA           2          2              3
##   Competence FPView Gender Age Education Ideology PolActive Mil Income
## 1          4      3      2  27         6        3         1   1      3
## 2          3      1      2  29         5        4         2   1      1
## 3          3      5      1  36         3        3         2   1      3
## 4          5      5      1  31         5        4         1   1      1
## 5          3      2      1  58         7        2         2   1      2
##   treatment
## 1         3
## 2         3
## 3         3
## 4         3
## 5         3
```

Detecting correlations

```
# Scatter plot: tidyverse approach
ggplot(mydata, aes(Approval,Reputation)) +
  geom_jitter(color = "maroon") + theme_bw()
```

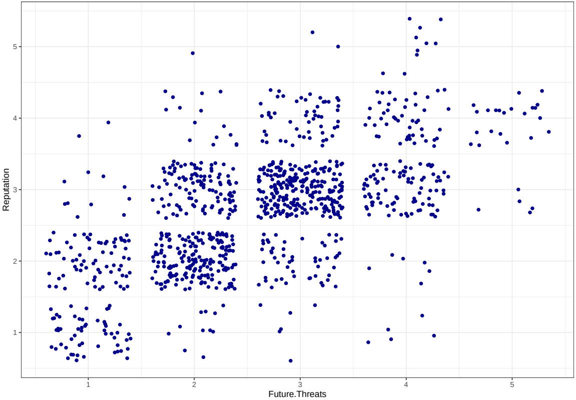



```
cor(mydata$Approval,mydata$Reputation)
```

```
## [1] 0.6221307
```

Detecting correlations

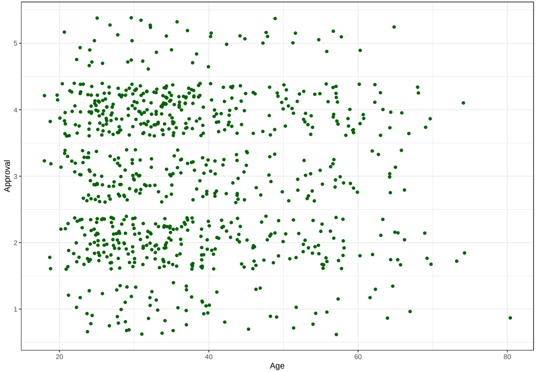
```
# Scatter plot: tidyverse approach
ggplot(mydata, aes(Future.Threats,Reputation)) +
  geom_jitter(color = "darkblue") + theme_bw()
```




```
cor(mydata$Future.Threats,mydata$Reputation)
```

```
## [1] 0.6230729
```

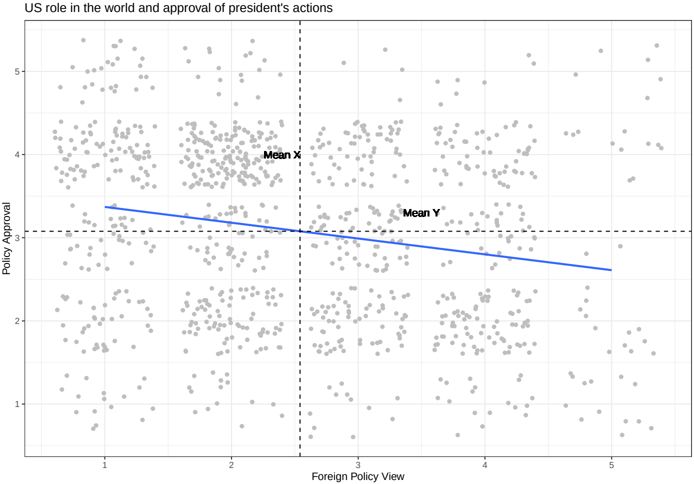
Detecting correlations




```
cor(mydata$Approval,mydata$Age)
```

```
## [1] -0.1106591
```

What about negative correlations?



Negative association

Increase in global involvement & decrease in approval

```
cor(mydata$FPView, mydata$Approval)
```

```
## [1] -0.2001058
```

```
cor(mydata$FPView, mydata$Ideology)
```

```
## [1] 0.1514648
```

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** $\rightarrow$ approval for leader's actions.
- **X** $\rightarrow$ leader's actions (back-down or back-up).

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($Y \sim x$, data = mydata)
- Y = dependent variable; x = independent variable(s).

How does it look like?

Leaders' Audience costs: fitting the model

```r
# Fit the model
fit <- lm(Approval ~ FPView, data = mydata)
fit
```

```
##
## Call:
## lm(formula = Approval ~ FPView, data = mydata)
##
## Coefficients:
## (Intercept)       FPView
##      3.5605      -0.1901
```

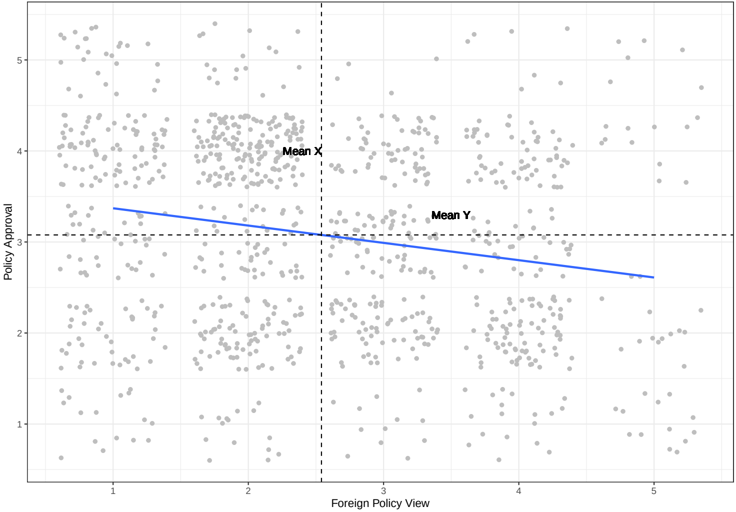
```r
# Directly obtain coefficients
coef(fit)
```

```
## (Intercept)      FPView
##   3.5605290  -0.1900987
```

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

```
##        1        2        3        4        5        6
## 2.990233 3.370430 2.610036 2.610036 3.180332 3.180332
```

Fitted model on plot



Approval & Reputation: regression models

Back-up (Airstrikes) or Back-down

```r
# Fit model
fit2 <- lm(Approval ~ Reputation, data = mydata2)
fit2
```

```
##
## Call:
## lm(formula = Approval ~ Reputation, data = mydata2)
##
## Coefficients:
## (Intercept)   Reputation
##      0.7181       0.8382
```

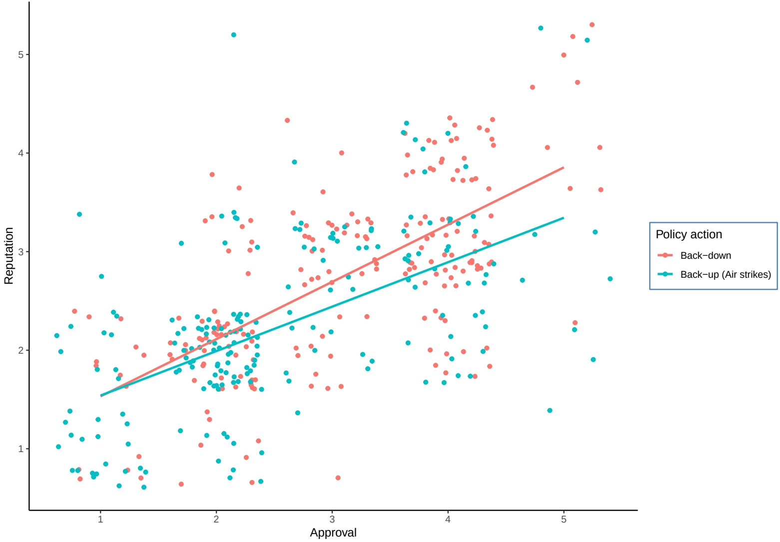
```r
# Fitted (predicted) values
head(fitted(fit2))
```

```
##        1        2        3        4        5        6
## 3.232531 2.394373 2.394373 4.908849 2.394373 3.232531
```

```r
# Errors
head(resid(fit2))
```

```
##          1          2          3          4          5          6
##  0.7674687 -1.3943726 -0.3943726  0.0911513 -0.3943726  0.7674687
```

Plotting both conditions



Approval & Reputation: different actions

How do leaders' FP actions matter for Approval - Reputation link?

```
# Subset of Air strike action
mydata3 <- subset(mydata, subset = (treatment == 5))
cor(mydata3$Approval,mydata3$Reputation)
```

```
## [1] 0.6116879
```

```
# subset of Backing down
mydata4 <- subset(mydata, subset = (treatment == 3))
cor(mydata4$Approval,mydata4$Reputation)
```

```
## [1] 0.688027
```

Least square

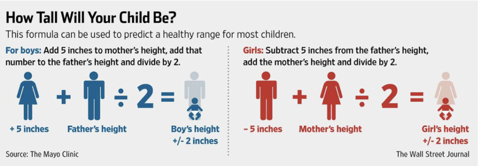
- Regression line $\rightarrow$ "line of best fit"
- Minimize prediction error
- Predictions of fitted line are accurate. How come?
- $\bar{\hat{\epsilon}} = 0$.
- Linear model: not necessarily represent DGS (assumption).

Errors/Curses/Anomalies

Cursed??

Errors/Curses/Anomalies

Fighter pilots performance?



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 $\rightarrow$ 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’?

```r
# 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?

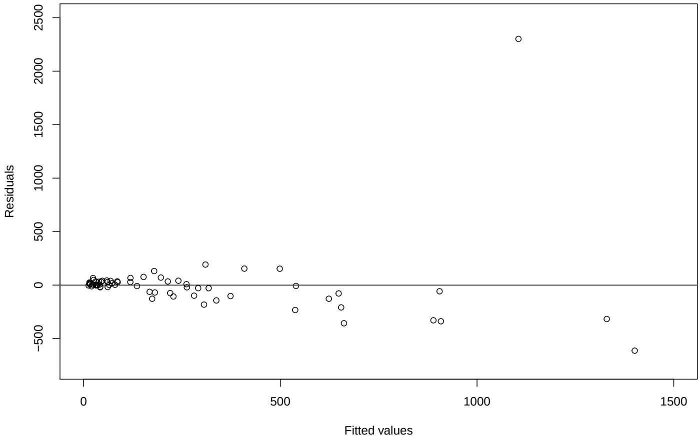
```r
summary(lm(Bush00 ~ Perot96, data = florida))
```

```
##
## 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.

Avoid overfitting

- Multiple mitigating procedures.
- **Cross validation**:
  - Test set: select randomly.
  - Training set: estimate coefficients.
  - Asses model fit with test set.
  - Repeat test with training set.
  - Average results.

You know machine learning 101!

Wrapping up week 7

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.