

HW 3

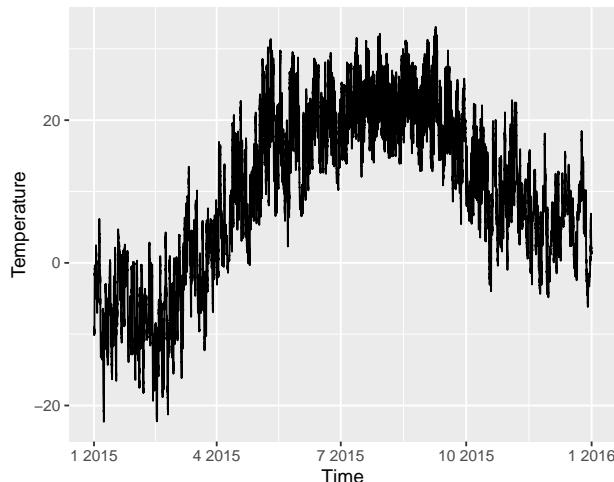
2019150432 임효진

October 31, 2020

1

```
library(macleish)
library(ggplot2)
library(dplyr)
head(whately_2015)

## # A tibble: 6 x 8
##   when           temperature wind_speed wind_dir rel_humidity pressure
##   <dttm>          <dbl>      <dbl>      <dbl>      <dbl>      <int>
## 1 2015-01-01 00:00:00     -9.32      1.40     225.      54.6      985
## 2 2015-01-01 00:10:00     -9.46      1.51     248.      55.4      985
## 3 2015-01-01 00:20:00     -9.44      1.62     258.      56.2      985
## 4 2015-01-01 00:30:00     -9.3       1.14     244.      56.4      985
## 5 2015-01-01 00:40:00     -9.32      1.22     238.      56.9      984
## 6 2015-01-01 00:50:00     -9.34      1.09     242.      57.2      984
## # ... with 2 more variables: solar_radiation <dbl>, rainfall <int>
whately_2015 %>% ggplot(aes(x=when, y=temperature)) +
  geom_line() +
  xlab("Time") +
  ylab("Temperature")
```



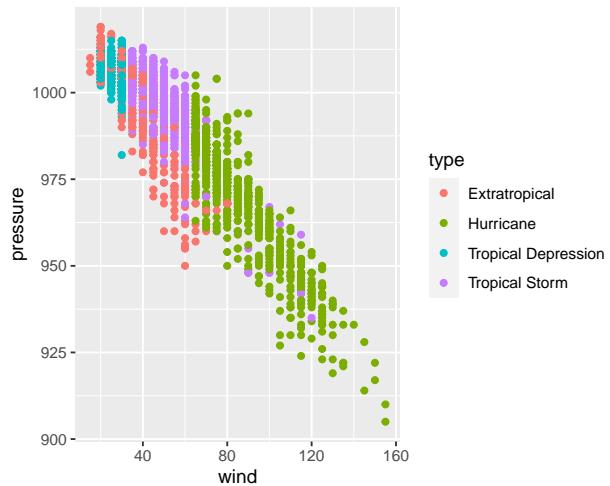
2

(a)

```
library(nasaweather)
head(storms)

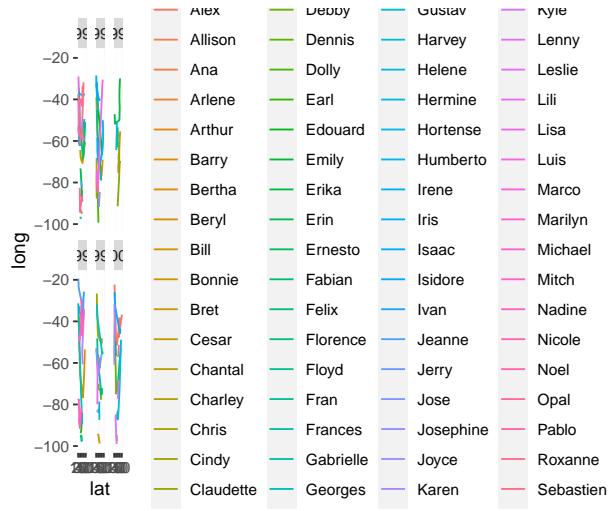
## # A tibble: 6 x 11
##   name      year month   day hour   lat   long pressure wind type      seasday
##   <chr>     <int> <int> <int> <dbl> <dbl>    <int> <int> <chr>      <int>
## 1 Allis~  1995     6     3     0  17.4 -84.3     1005     30 Tropical De~      3
## 2 Allis~  1995     6     3     6  18.3 -84.9     1004     30 Tropical De~      3
## 3 Allis~  1995     6     3    12  19.3 -85.7     1003     35 Tropical St~      3
## 4 Allis~  1995     6     3    18  20.6 -85.8     1001     40 Tropical St~      3
## 5 Allis~  1995     6     4     0  22.0 -86.0      997     50 Tropical St~      4
## 6 Allis~  1995     6     4     6  23.3 -86.3      995     60 Tropical St~      4

storms %>% ggplot(aes(wind, pressure)) +
  geom_point(aes(col=type))
```



(b)

```
storms %>% filter(type=="Tropical Storm") %>%
  ggplot(aes(lat, long)) +
  geom_path(aes(col=name)) +
  facet_wrap(~year)
```

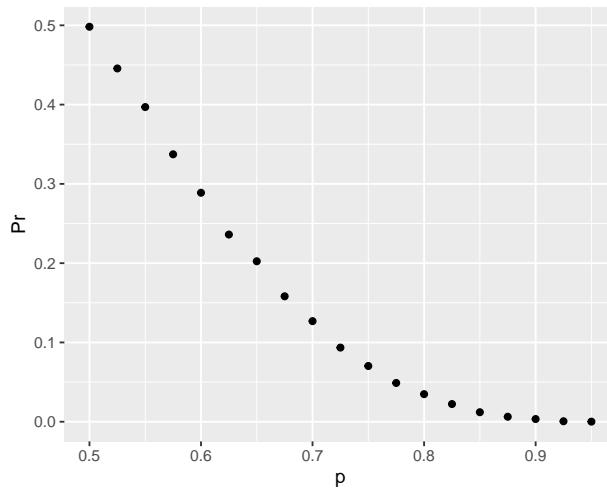


3

(a)

```
prob_win <- function(p){
B <- 10000
result <- replicate(B, {
b_win <- sample(c(1,0), 7, replace = TRUE, prob = c(1-p, p))
sum(b_win)>=4
})
mean(result)
}

Pr=sapply(seq(0.5, 0.95, 0.025), prob_win)
df=data.frame(p=seq(0.5, 0.95, 0.025), Pr)
df %>% ggplot(aes(p, Pr))+
  geom_point()
```



(b)

```
prob_win <- function(N, p=0.75){  
  B <- 10000  
  result <- replicate(B, {  
    b_win <- sample(c(1,0), N, replace = TRUE, prob = c(1-p, p))  
    sum(b_win)>=(N+1)/2  
  })  
  mean(result)  
}  
  
sapply(seq(1, 25, 2), prob_win)  
  
## [1] 0.2476 0.1585 0.1052 0.0735 0.0491 0.0348 0.0231 0.0175 0.0121 0.0086  
## [11] 0.0055 0.0038 0.0038
```

4

(1)

```
library(dslabs)  
data("polls_us_election_2016")  
polls <- polls_us_election_2016 %>%  
  filter(enddate >= "2016-10-31" & state == "U.S.")  
N <- polls$samplesize[1]  
x_hat=polls$rawpoll_clinton[1]/100  
se_hat=sqrt(x_hat*(1-x_hat)/N)  
x_hat+c(-1, 1)*qnorm(1-0.025)*se_hat  
  
## [1] 0.4492385 0.4907615
```

(2)

```
polls %>% mutate(x_hat=polls$rawpoll_clinton/100,  
                   se_hat=sqrt(x_hat*(1-x_hat)/N),  
                   lower=x_hat-qnorm(1-0.025)*se_hat,  
                   upper=x_hat+qnorm(1-0.025)*se_hat)%>%  
  select(pollster, enddate, x_hat, lower, upper)  
  
##                                     pollster      enddate   x_hat  
## 1 ABC News/Washington Post 2016-11-06 0.4700  
## 2 Google Consumer Surveys 2016-11-07 0.3803  
## 3 Ipsos 2016-11-06 0.4200  
## 4 YouGov 2016-11-07 0.4500  
## 5 Gravis Marketing 2016-11-06 0.4700  
## 6 Fox News/Anderson Robbins Research/Shaw & Company Research 2016-11-06 0.4800  
## 7 CBS News/New York Times 2016-11-06 0.4500
```

## 8	NBC News/Wall Street Journal	2016-11-05	0.4400
## 9	IBD/TIPP	2016-11-07	0.4120
## 10	Selzer & Company	2016-11-06	0.4400
## 11	Angus Reid Global	2016-11-04	0.4800
## 12	Monmouth University	2016-11-06	0.5000
## 13	Marist College	2016-11-03	0.4400
## 14	The Times-Picayune/Lucid	2016-11-07	0.4500
## 15	USC Dornsife/LA Times	2016-11-07	0.4361
## 16	RKM Research and Communications, Inc.	2016-11-05	0.4760
## 17	CVOTER International	2016-11-06	0.4891
## 18	Morning Consult	2016-11-05	0.4500
## 19	SurveyMonkey	2016-11-06	0.4700
## 20	Rasmussen Reports/Pulse Opinion Research	2016-11-06	0.4500
## 21	Insights West	2016-11-07	0.4900
## 22	RAND (American Life Panel)	2016-11-01	0.4370
## 23	Fox News/Anderson Robbins Research/Shaw & Company Research	2016-11-03	0.4550
## 24	CBS News/New York Times	2016-11-01	0.4500
## 25	ABC News/Washington Post	2016-11-05	0.4700
## 26	Ipsos	2016-11-04	0.4300
## 27	ABC News/Washington Post	2016-11-04	0.4800
## 28	YouGov	2016-11-06	0.4290
## 29	IBD/TIPP	2016-11-06	0.4070
## 30	ABC News/Washington Post	2016-11-03	0.4700
## 31	IBD/TIPP	2016-11-03	0.4440
## 32	IBD/TIPP	2016-11-05	0.4300
## 33	ABC News/Washington Post	2016-11-02	0.4700
## 34	ABC News/Washington Post	2016-11-01	0.4700
## 35	ABC News/Washington Post	2016-10-31	0.4600
## 36	Ipsos	2016-11-03	0.4320
## 37	IBD/TIPP	2016-11-04	0.4420
## 38	YouGov	2016-11-01	0.4600
## 39	IBD/TIPP	2016-10-31	0.4460
## 40	Ipsos	2016-11-02	0.4550
## 41	Rasmussen Reports/Pulse Opinion Research	2016-11-03	0.4400
## 42	The Times-Picayune/Lucid	2016-11-06	0.4500
## 43	Ipsos	2016-11-01	0.4470
## 44	IBD/TIPP	2016-11-02	0.4400
## 45	IBD/TIPP	2016-11-01	0.4400
## 46	Rasmussen Reports/Pulse Opinion Research	2016-11-02	0.4200
## 47	Ipsos	2016-10-31	0.4400
## 48	The Times-Picayune/Lucid	2016-11-05	0.4500
## 49	Rasmussen Reports/Pulse Opinion Research	2016-10-31	0.4400
## 50	Google Consumer Surveys	2016-10-31	0.3769
## 51	CVOTER International	2016-11-05	0.4925
## 52	Rasmussen Reports/Pulse Opinion Research	2016-11-01	0.4400
## 53	CVOTER International	2016-11-04	0.4906
## 54	The Times-Picayune/Lucid	2016-11-04	0.4500
## 55	USC Dornsife/LA Times	2016-11-06	0.4323

```

## 56 CVOTER International 2016-11-03 0.4853
## 57 The Times-Picayune/Lucid 2016-11-03 0.4400
## 58 USC Dornsife/LA Times 2016-11-05 0.4263
## 59 CVOTER International 2016-11-02 0.4878
## 60 USC Dornsife/LA Times 2016-11-04 0.4256
## 61 CVOTER International 2016-11-01 0.4881
## 62 The Times-Picayune/Lucid 2016-11-02 0.4400
## 63 Gravis Marketing 2016-10-31 0.4600
## 64 USC Dornsife/LA Times 2016-11-03 0.4338
## 65 The Times-Picayune/Lucid 2016-11-01 0.4300
## 66 USC Dornsife/LA Times 2016-11-02 0.4247
## 67 Gravis Marketing 2016-11-02 0.4700
## 68 USC Dornsife/LA Times 2016-11-01 0.4236
## 69 The Times-Picayune/Lucid 2016-10-31 0.4200
## 70 USC Dornsife/LA Times 2016-10-31 0.4328

##      lower      upper
## 1  0.4492385 0.4907615
## 2  0.3601059 0.4004941
## 3  0.3994690 0.4405310
## 4  0.4293053 0.4706947
## 5  0.4492385 0.4907615
## 6  0.4592177 0.5007823
## 7  0.4293053 0.4706947
## 8  0.4193513 0.4606487
## 9  0.3915257 0.4324743
## 10 0.4193513 0.4606487
## 11 0.4592177 0.5007823
## 12 0.4792010 0.5207990
## 13 0.4193513 0.4606487
## 14 0.4293053 0.4706947
## 15 0.4154716 0.4567284
## 16 0.4552250 0.4967750
## 17 0.4683060 0.5098940
## 18 0.4293053 0.4706947
## 19 0.4492385 0.4907615
## 20 0.4293053 0.4706947
## 21 0.4692052 0.5107948
## 22 0.4163668 0.4576332
## 23 0.4342854 0.4757146
## 24 0.4293053 0.4706947
## 25 0.4492385 0.4907615
## 26 0.4094059 0.4505941
## 27 0.4592177 0.5007823
## 28 0.4084118 0.4495882
## 29 0.3865640 0.4274360
## 30 0.4492385 0.4907615
## 31 0.4233319 0.4646681
## 32 0.4094059 0.4505941

```

```

## 33 0.4492385 0.4907615
## 34 0.4492385 0.4907615
## 35 0.4392677 0.4807323
## 36 0.4113943 0.4526057
## 37 0.4213414 0.4626586
## 38 0.4392677 0.4807323
## 39 0.4253227 0.4666773
## 40 0.4342854 0.4757146
## 41 0.4193513 0.4606487
## 42 0.4293053 0.4706947
## 43 0.4263182 0.4676818
## 44 0.4193513 0.4606487
## 45 0.4193513 0.4606487
## 46 0.3994690 0.4405310
## 47 0.4193513 0.4606487
## 48 0.4293053 0.4706947
## 49 0.4193513 0.4606487
## 50 0.3567413 0.3970587
## 51 0.4717034 0.5132966
## 52 0.4193513 0.4606487
## 53 0.4698047 0.5113953
## 54 0.4293053 0.4706947
## 55 0.4116926 0.4529074
## 56 0.4645100 0.5060900
## 57 0.4193513 0.4606487
## 58 0.4057282 0.4468718
## 59 0.4670072 0.5085928
## 60 0.4050326 0.4461674
## 61 0.4673069 0.5088931
## 62 0.4193513 0.4606487
## 63 0.4392677 0.4807323
## 64 0.4131841 0.4544159
## 65 0.4094059 0.4505941
## 66 0.4041383 0.4452617
## 67 0.4492385 0.4907615
## 68 0.4030453 0.4441547
## 69 0.3994690 0.4405310
## 70 0.4121897 0.4534103

```

(3)

```

polls %>% mutate(x_hat=polls$rawpoll_clinton/100,
                     se_hat=sqrt(x_hat*(1-x_hat)/N),
                     lower=x_hat-qnorm(1-0.025)*se_hat,
                     upper=x_hat+qnorm(1-0.025)*se_hat,
                     hit=0.482>=lower&0.482<=upper)%>%
  select(pollster, enddate, x_hat, lower, upper, hit)

```

```

##                                     pollster   enddate x_hat
## 1                               ABC News/Washington Post 2016-11-06 0.4700
## 2                               Google Consumer Surveys 2016-11-07 0.3803
## 3                               Ipsos 2016-11-06 0.4200
## 4                               YouGov 2016-11-07 0.4500
## 5                               Gravis Marketing 2016-11-06 0.4700
## 6 Fox News/Anderson Robbins Research/Shaw & Company Research 2016-11-06 0.4800
## 7                               CBS News/New York Times 2016-11-06 0.4500
## 8                               NBC News/Wall Street Journal 2016-11-05 0.4400
## 9                               IBD/TIPP 2016-11-07 0.4120
## 10                             Selzer & Company 2016-11-06 0.4400
## 11                             Angus Reid Global 2016-11-04 0.4800
## 12                             Monmouth University 2016-11-06 0.5000
## 13                             Marist College 2016-11-03 0.4400
## 14 The Times-Picayune/Lucid 2016-11-07 0.4500
## 15                             USC Dornsife/LA Times 2016-11-07 0.4361
## 16 RKM Research and Communications, Inc. 2016-11-05 0.4760
## 17                             CVOTER International 2016-11-06 0.4891
## 18                             Morning Consult 2016-11-05 0.4500
## 19                             SurveyMonkey 2016-11-06 0.4700
## 20 Rasmussen Reports/Pulse Opinion Research 2016-11-06 0.4500
## 21                             Insights West 2016-11-07 0.4900
## 22 RAND (American Life Panel) 2016-11-01 0.4370
## 23 Fox News/Anderson Robbins Research/Shaw & Company Research 2016-11-03 0.4550
## 24                             CBS News/New York Times 2016-11-01 0.4500
## 25                             ABC News/Washington Post 2016-11-05 0.4700
## 26                             Ipsos 2016-11-04 0.4300
## 27                             ABC News/Washington Post 2016-11-04 0.4800
## 28                             YouGov 2016-11-06 0.4290
## 29                             IBD/TIPP 2016-11-06 0.4070
## 30                             ABC News/Washington Post 2016-11-03 0.4700
## 31                             IBD/TIPP 2016-11-03 0.4440
## 32                             IBD/TIPP 2016-11-05 0.4300
## 33                             ABC News/Washington Post 2016-11-02 0.4700
## 34                             ABC News/Washington Post 2016-11-01 0.4700
## 35                             ABC News/Washington Post 2016-10-31 0.4600
## 36                             Ipsos 2016-11-03 0.4320
## 37                             IBD/TIPP 2016-11-04 0.4420
## 38                             YouGov 2016-11-01 0.4600
## 39                             IBD/TIPP 2016-10-31 0.4460
## 40                             Ipsos 2016-11-02 0.4550
## 41 Rasmussen Reports/Pulse Opinion Research 2016-11-03 0.4400
## 42 The Times-Picayune/Lucid 2016-11-06 0.4500
## 43                             Ipsos 2016-11-01 0.4470
## 44                             IBD/TIPP 2016-11-02 0.4400
## 45                             IBD/TIPP 2016-11-01 0.4400
## 46 Rasmussen Reports/Pulse Opinion Research 2016-11-02 0.4200
## 47                             Ipsos 2016-10-31 0.4400

```

```

## 48           The Times-Picayune/Lucid 2016-11-05 0.4500
## 49           Rasmussen Reports/Pulse Opinion Research 2016-10-31 0.4400
## 50           Google Consumer Surveys 2016-10-31 0.3769
## 51           CVOTER International 2016-11-05 0.4925
## 52           Rasmussen Reports/Pulse Opinion Research 2016-11-01 0.4400
## 53           CVOTER International 2016-11-04 0.4906
## 54           The Times-Picayune/Lucid 2016-11-04 0.4500
## 55           USC Dornsife/LA Times 2016-11-06 0.4323
## 56           CVOTER International 2016-11-03 0.4853
## 57           The Times-Picayune/Lucid 2016-11-03 0.4400
## 58           USC Dornsife/LA Times 2016-11-05 0.4263
## 59           CVOTER International 2016-11-02 0.4878
## 60           USC Dornsife/LA Times 2016-11-04 0.4256
## 61           CVOTER International 2016-11-01 0.4881
## 62           The Times-Picayune/Lucid 2016-11-02 0.4400
## 63           Gravis Marketing 2016-10-31 0.4600
## 64           USC Dornsife/LA Times 2016-11-03 0.4338
## 65           The Times-Picayune/Lucid 2016-11-01 0.4300
## 66           USC Dornsife/LA Times 2016-11-02 0.4247
## 67           Gravis Marketing 2016-11-02 0.4700
## 68           USC Dornsife/LA Times 2016-11-01 0.4236
## 69           The Times-Picayune/Lucid 2016-10-31 0.4200
## 70           USC Dornsife/LA Times 2016-10-31 0.4328

##      lower      upper     hit
## 1  0.4492385 0.4907615 TRUE
## 2  0.3601059 0.4004941 FALSE
## 3  0.3994690 0.4405310 FALSE
## 4  0.4293053 0.4706947 FALSE
## 5  0.4492385 0.4907615 TRUE
## 6  0.4592177 0.5007823 TRUE
## 7  0.4293053 0.4706947 FALSE
## 8  0.4193513 0.4606487 FALSE
## 9  0.3915257 0.4324743 FALSE
## 10 0.4193513 0.4606487 FALSE
## 11 0.4592177 0.5007823 TRUE
## 12 0.4792010 0.5207990 TRUE
## 13 0.4193513 0.4606487 FALSE
## 14 0.4293053 0.4706947 FALSE
## 15 0.4154716 0.4567284 FALSE
## 16 0.4552250 0.4967750 TRUE
## 17 0.4683060 0.5098940 TRUE
## 18 0.4293053 0.4706947 FALSE
## 19 0.4492385 0.4907615 TRUE
## 20 0.4293053 0.4706947 FALSE
## 21 0.4692052 0.5107948 TRUE
## 22 0.4163668 0.4576332 FALSE
## 23 0.4342854 0.4757146 FALSE
## 24 0.4293053 0.4706947 FALSE

```

```
## 25 0.4492385 0.4907615 TRUE
## 26 0.4094059 0.4505941 FALSE
## 27 0.4592177 0.5007823 TRUE
## 28 0.4084118 0.4495882 FALSE
## 29 0.3865640 0.4274360 FALSE
## 30 0.4492385 0.4907615 TRUE
## 31 0.4233319 0.4646681 FALSE
## 32 0.4094059 0.4505941 FALSE
## 33 0.4492385 0.4907615 TRUE
## 34 0.4492385 0.4907615 TRUE
## 35 0.4392677 0.4807323 FALSE
## 36 0.4113943 0.4526057 FALSE
## 37 0.4213414 0.4626586 FALSE
## 38 0.4392677 0.4807323 FALSE
## 39 0.4253227 0.4666773 FALSE
## 40 0.4342854 0.4757146 FALSE
## 41 0.4193513 0.4606487 FALSE
## 42 0.4293053 0.4706947 FALSE
## 43 0.4263182 0.4676818 FALSE
## 44 0.4193513 0.4606487 FALSE
## 45 0.4193513 0.4606487 FALSE
## 46 0.3994690 0.4405310 FALSE
## 47 0.4193513 0.4606487 FALSE
## 48 0.4293053 0.4706947 FALSE
## 49 0.4193513 0.4606487 FALSE
## 50 0.3567413 0.3970587 FALSE
## 51 0.4717034 0.5132966 TRUE
## 52 0.4193513 0.4606487 FALSE
## 53 0.4698047 0.5113953 TRUE
## 54 0.4293053 0.4706947 FALSE
## 55 0.4116926 0.4529074 FALSE
## 56 0.4645100 0.5060900 TRUE
## 57 0.4193513 0.4606487 FALSE
## 58 0.4057282 0.4468718 FALSE
## 59 0.4670072 0.5085928 TRUE
## 60 0.4050326 0.4461674 FALSE
## 61 0.4673069 0.5088931 TRUE
## 62 0.4193513 0.4606487 FALSE
## 63 0.4392677 0.4807323 FALSE
## 64 0.4131841 0.4544159 FALSE
## 65 0.4094059 0.4505941 FALSE
## 66 0.4041383 0.4452617 FALSE
## 67 0.4492385 0.4907615 TRUE
## 68 0.4030453 0.4441547 FALSE
## 69 0.3994690 0.4405310 FALSE
## 70 0.4121897 0.4534103 FALSE
```

(4)

```
polls1=polls %>% mutate(x_hat=polls$rawpoll_clinton/100,
                         se_hat=sqrt(x_hat*(1-x_hat)/N),
                         lower=x_hat-qnorm(1-0.025)*se_hat,
                         upper=x_hat+qnorm(1-0.025)*se_hat,
                         hit=0.482>=lower&0.482<=upper)%>%
  select(pollster, enddate, x_hat, lower, upper, hit)

polls1%>%summarise(mean(hit))

##   mean(hit)
## 1 0.2857143
```

(5)

```
# 0.95
```

(6)

```
polls <- polls_us_election_2016 %>%
  filter(enddate >= "2016-10-31" & state == "U.S.") %>%
  mutate(d_hat = rawpoll_clinton / 100 - rawpoll_trump / 100)

N <- polls$samplesize[1]
d_hat <- polls$d_hat[1]
x_hat <- (d_hat+1)/2
se_hat <- 2*sqrt(x_hat*(1-x_hat)/N)
d_hat + c(-1,1)*qnorm(0.975)*se_hat

## [1] -0.001564627  0.081564627
```

5

(1)

```
library(HistData)
library(tidyr)
library(broom)
data("GaltonFamilies")
set.seed(1)
galton_heights <- GaltonFamilies %>%
  group_by(family, gender) %>%
  sample_n(1) %>%
  ungroup()
galton_heights%>%
```

```

gather(parent, parentHeight, 'father':'mother') %>%
  mutate(child = ifelse(gender == "female", "daughter", "son"))%>%
  group_by(parent, child)%>%
  do(tidy(lm(childHeight~parentHeight, data=.)))

```

A tibble: 8 x 7

Groups: parent, child [4]

parent	child	term	estimate	std.error	statistic	p.value
<chr>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
## 1 father	daughter	(Intercept)	40.2	4.34	9.26	7.76e-17
## 2 father	daughter	parentHeight	0.345	0.0625	5.52	1.21e- 7
## 3 father	son	(Intercept)	39.8	4.47	8.91	5.96e-16
## 4 father	son	parentHeight	0.426	0.0646	6.59	4.74e-10
## 5 mother	daughter	(Intercept)	37.6	4.78	7.87	3.61e-13
## 6 mother	daughter	parentHeight	0.413	0.0745	5.55	1.07e- 7
## 7 mother	son	(Intercept)	49.3	4.73	10.4	4.36e-20
## 8 mother	son	parentHeight	0.312	0.0739	4.22	3.84e- 5

(2)

```

galton_heights%>%
  gather(parent, parentHeight, 'father':'mother') %>%
  mutate(child = ifelse(gender == "female", "daughter", "son"))%>%
  group_by(parent, child)%>%
  do(tidy(lm(childHeight~parentHeight, data=.), conf.int=T))

```

A tibble: 8 x 9

Groups: parent, child [4]

parent	child	term	estimate	std.error	statistic	p.value	conf.low	conf.high
<chr>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
## 1 father	daugh~	(Inter~	40.2	4.34	9.26	7.76e-17	31.6	48.7
## 2 father	daugh~	parent~	0.345	0.0625	5.52	1.21e- 7	0.222	0.468
## 3 father	son	(Inter~	39.8	4.47	8.91	5.96e-16	31.0	48.6
## 4 father	son	parent~	0.426	0.0646	6.59	4.74e-10	0.299	0.553
## 5 mother	daugh~	(Inter~	37.6	4.78	7.87	3.61e-13	28.2	47.0
## 6 mother	daugh~	parent~	0.413	0.0745	5.55	1.07e- 7	0.266	0.560
## 7 mother	son	(Inter~	49.3	4.73	10.4	4.36e-20	39.9	58.6
## 8 mother	son	parent~	0.312	0.0739	4.22	3.84e- 5	0.166	0.458

(3)

```

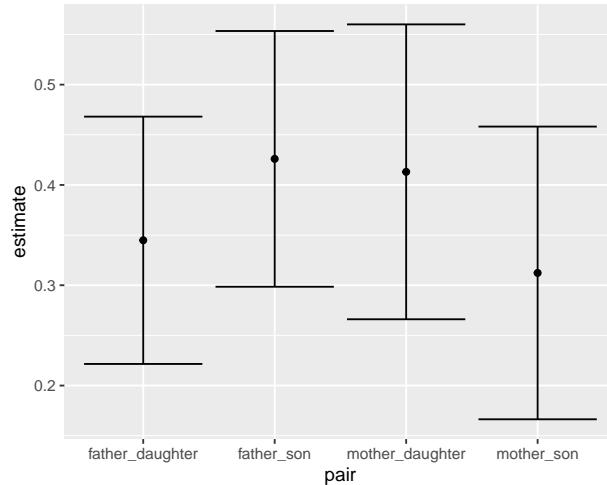
galton_heights%>%
  gather(parent, parentHeight, 'father':'mother') %>%
  mutate(child = ifelse(gender == "female", "daughter", "son"))%>%
  unite(pair, c("parent", "child")) %>%
  group_by(pair) %>%
  do(tidy(lm(childHeight~parentHeight, data=.), conf.int=T))%>%

```

```

filter(term=="parentHeight")%>%
ggplot(aes(x=pair, y=estimate, ymin=conf.low,
           ymax=conf.high))+ 
geom_errorbar()+
geom_point()

```



6

(1)

```

dat=research_funding_rates%>%
  rename(success_total=success_rates_total,
         success_men=success_rates_men,
         success_women=success_rates_women)%>%
  gather(key, value, -discipline)%>%
  separate(key, into = c("status", "gender"))%>%
  spread(status, value)%>%
  filter(gender!="total")
dat%>%group_by(gender) %>%
  summarise(total_award=sum(awards),
            not_award=sum(applications)-sum(total_award))

```

```

## # A tibble: 2 x 3
##   gender total_award not_award
##   <chr>      <dbl>     <dbl>
## 1 men          290      1345
## 2 women        177      1011

```

(2)

```

dat2=dat%>%group_by(gender) %>%
  summarise(total_award=sum(awards),
            not_award=sum(applications)-sum(total_award))
dat2%>%group_by(gender)%>%
  summarise(diff=total_award/(total_award+not_award))

## # A tibble: 2 x 2
##   gender   diff
##   <chr>   <dbl>
## 1 men     0.177
## 2 women   0.149

```

(3)

```

dat2%>%select(-gender) %>%
  do(tidy(chisq.test(.)))

## # A tibble: 1 x 4
##   statistic p.value parameter method
##       <dbl>    <dbl>      <int> <chr>
## 1      3.81  0.0509          1 Pearson's Chi-squared test with Yates' continuity

```

(4)

```

research_funding_rates%>%
  mutate(discipline=reorder(discipline, success_rates_total))%>%
  rename(success_total=success_rates_total,
        success_men=success_rates_men,
        success_women=success_rates_women)%>%
  gather(key, value, -discipline)%>%
  separate(key, into = c("status", "gender"))%>%
  spread(status, value)%>%
  filter(gender!="total")

```

	discipline	gender	applications	awards	success
## 1	Social sciences	men	425	65	15.3
## 2	Social sciences	women	409	47	11.5
## 3	Medical sciences	men	245	46	18.8
## 4	Medical sciences	women	260	29	11.2
## 5	Interdisciplinary	men	105	12	11.4
## 6	Interdisciplinary	women	78	17	21.8
## 7	Humanities	men	230	33	14.3
## 8	Humanities	women	166	32	19.3
## 9	Technical sciences	men	189	30	15.9
## 10	Technical sciences	women	62	13	21.0
## 11	Earth/life sciences	men	156	38	24.4
## 12	Earth/life sciences	women	126	18	14.3

```

## 13 Physical sciences men 135 26 19.3
## 14 Physical sciences women 39 9 23.1
## 15 Chemical sciences men 83 22 26.5
## 16 Chemical sciences women 39 10 25.6
## 17 Physics men 67 18 26.9
## 18 Physics women 9 2 22.2

```

(5)

```

research_funding_rates %>%
  mutate(discipline=reorder(discipline, success_rates_total)) %>%
  rename(success_total=success_rates_total,
         success_men=success_rates_men,
         success_women=success_rates_women) %>%
  gather(key, value, -discipline) %>%
  separate(key, into = c("status", "gender")) %>%
  spread(status, value) %>%
  filter(gender!="total") %>%
  ggplot(aes(discipline, success,
             size=applications, color=gender)) +
  geom_point() +
  theme(axis.text.x = element_text(angle=90, vjust = 1))

```

