HW4

高嘉妤、柯堯珹、吳承恩、趙友誠

2024-10-30

Table of contents


```r
library(rio)            #read sav file
library(labelled)       #remove attribute of sav data
library(Hmisc)          #describe
library(sf)             #render map
#remotes::install_github("shihjyun/twmap")
library(twmap)          #map data
library(showtext)       #show zw-tw in ggplot2
library(dplyr);library(ggplot2);library(MASS)
pollsav <- import("poll.sav")
```

0. 資料簡介

Dimension of the Data : ***1671 samples*** × ***15 columns***

Table 1: 變數解釋

Variables	Explanation	remark
V1	District	1: 北區, 2: 中西區
V2、V3	Li	v2: 33 個里, v3: 20 個里
V4_1~V4_8	Candidate known	1~10 號
V5	Candidate supported	1~10 號
V6	Age	1:20 到 29 歲,2:30 到 39 歲,3:40 到 49 歲,4:50 到 59 歲,5:60 歲以上
V7	Education level	1: 小學, 2: 國中, 3: 高中, 4: 專科, 5: 大學以上
V8	Sex	1:male, 2:female

1. 資料整理、資料清洗、missing values 診斷、資料視覺化

```r
pollcsv <- data.frame(
  apply(pollsav,2,
        function(col){
          as.factor(remove_attributes(col,
                                      attributes = c("label","format.spss","display_width","labels")))
})) #sav 格式的" 屬性" 會造成 describe 的 bug，因此將標籤移除
pollcsv <- remove_attributes(pollcsv, "dimnames")
n <- dim(pollcsv)[1]
latex(describe(pollcsv), file="")
```

pollcsv
15 Variables 1671 Observations

---

v1

n	missing	distinct
1671	0	2

Value	1	2
Frequency	1107	564
Proportion	0.662	0.338

---

v2

n	missing	distinct
1671	0	36

lowest : 1 10 11 12 13, highest: 7 8 9 98 99

---

v3

n	missing	distinct
1671	0	23

lowest : 1 10 11 12 13, highest: 7 8 9 98 99

---

v4_1

n	missing	distinct
1671	0	12

Value	1	10	2	3	4	5	6	7	8	9	91	98
Frequency	328	11	5	214	43	27	38	47	4	1	14	939
Proportion	0.196	0.007	0.003	0.128	0.026	0.016	0.023	0.028	0.002	0.001	0.008	0.562

---

v4_2

n	missing	distinct
1671	0	10

Value	10	2	3	4	5	6	7	8	9	99
Frequency	15	6	189	59	32	75	99	2	4	1190
Proportion	0.009	0.004	0.113	0.035	0.019	0.045	0.059	0.001	0.002	0.712

---

v4_3

n	missing	distinct
1671	0	9

Value	10	3	4	5	6	7	8	9	99
Frequency	19	6	60	36	61	91	1	2	1395
Proportion	0.011	0.004	0.036	0.022	0.037	0.054	0.001	0.001	0.835

---

v4_4

n	missing	distinct
1671	0	8

Value	10	4	5	6	7	8	9	99
Frequency	20	4	28	41	52	3	4	1519
Proportion	0.012	0.002	0.017	0.025	0.031	0.002	0.002	0.909

---

v4_5

n	missing	distinct
1671	0	7

Value	10	5	6	7	8	9	99
Frequency	15	3	14	38	4	3	1594
Proportion	0.009	0.002	0.008	0.023	0.002	0.002	0.954

v4_6

n	missing	distinct
1671	0	6

Value	10	6	7	8	9	99
Frequency	20	3	12	6	7	1623
Proportion	0.012	0.002	0.007	0.004	0.004	0.971

v4_7

n	missing	distinct
1671	0	5

Value	10	7	8	9	99
Frequency	12	3	2	3	1651
Proportion	0.007	0.002	0.001	0.002	0.988

v4_8

n	missing	distinct
1671	0	3

Value	10	8	99
Frequency	4	1	1666
Proportion	0.002	0.001	0.997

v5

n	missing	distinct
1671	0	13

Value	1	10	2	3	4	5	6	7	8	9	91	98	99
Frequency	158	53	9	205	79	33	98	195	6	8	10	269	548
Proportion	0.095	0.032	0.005	0.123	0.047	0.020	0.059	0.117	0.004	0.005	0.006	0.161	0.328

v6

n	missing	distinct
1671	0	6

Value	1	2	3	4	5	6
Frequency	52	94	201	336	946	42
Proportion	0.031	0.056	0.120	0.201	0.566	0.025

v7

n	missing	distinct
1671	0	6

Value	1	2	3	4	5	95
Frequency	292	165	431	198	520	65
Proportion	0.175	0.099	0.258	0.118	0.311	0.039

v8

n	missing	distinct
1671	0	2

Value	1	2
Frequency	682	989
Proportion	0.408	0.592

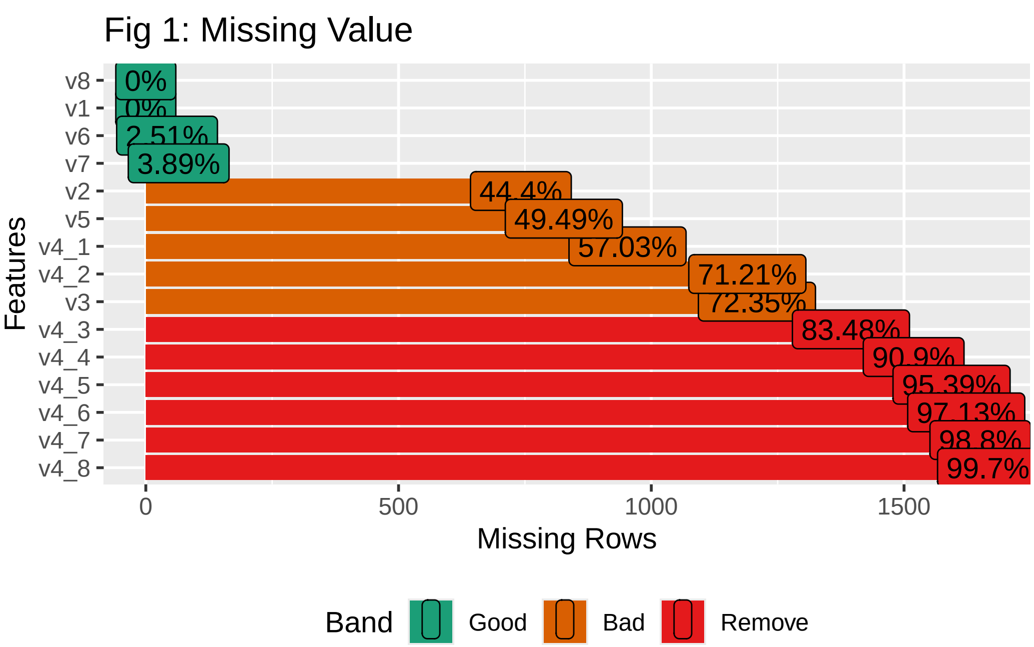
Table 2: 遺失值定義

Variables	Missing
V1	98,99
V2、V3	44,98,99
V4_1~V4_8	91,98,99
V5	91,98,99
V6	6,99
V7	95,99
V8	99

遺失值比例圖

將定義的遺失值轉換成 NA 並以遺失值比例圖 (by variable) 的方式呈現。考量到遺失值的性質，我們並未刪除任何資料，決定後續對不同變數分析時再移除。

```
pollcsv <- data.frame(
  t(apply(pollcsv,MARGIN = 1, FUN = function(row){
    row[row==99 | row==98 | row==95 | row==91 | row==44] <- NA
    return(row)
  }))
)
pollcsv$v6[pollcsv$v6==6] <- NA
DataExplorer::plot_missing(pollcsv, title = "Fig 1: Missing Value",)
```



2. 分析所有候選人的支持率

支持度定義: 支持度 $= \frac{\text{第五題出現次數}}{\text{樣本數}}$

```
# 計算總體支持度
count5.total <- sapply(1:11,function(x){
  if(x==11) return(sum(is.na(pollcsv$v5))/n)
  else return(sum(pollcsv$v5[!is.na(pollcsv$v5)]==x)/n)
} )
# 計算分區支持度（北區中西區）v1
support.district <- do.call(rbind, lapply(1:2,function(i){
  tempdata <- pollcsv[pollcsv$v1==i,]
  n.temp <- dim(tempdata)[1]
  return(sapply(1:11, function(x){
    if(x==11) return(sum(is.na(tempdata$v5))/n.temp)
    else return(sum(tempdata$v5[!is.na(tempdata$v5)]==x)/n.temp)
    }))
}))
# 計算性別支持度 v8
support.sex <- do.call(rbind, lapply(1:2,function(i){
```

```r
  tempdata <- pollcsv[pollcsv$v8==i,]
  n.temp <- dim(tempdata)[1]
  return(sapply(1:11, function(x){
    if(x==11) return(sum(is.na(tempdata$v5))/n.temp)
    else return(sum(tempdata$v5[!is.na(tempdata$v5)]==x)/n.temp)
    }))
}))
# 計算年齡支持度 v6
support.age <- do.call(rbind, lapply(1:5,function(i){
  tempdata <- pollcsv[pollcsv$v6==i,]
  n.temp <- dim(tempdata)[1]
  return(sapply(1:11, function(x){
    if(x==11) return(sum(is.na(tempdata$v5))/n.temp)
    else return(sum(tempdata$v5[!is.na(tempdata$v5)]==x)/n.temp)
    }))
}))
# 計算教育程度支持度 v7
support.edu <- do.call(rbind, lapply(1:5,function(i){
  tempdata <- pollcsv[pollcsv$v7==i,]
  n.temp <- dim(tempdata)[1]
  return(sapply(1:11, function(x){
    if(x==11) return(sum(is.na(tempdata$v5))/n.temp)
    else return(sum(tempdata$v5[!is.na(tempdata$v5)]==x)/n.temp)
    }))
}))
table.support <- rbind(
  count5.total,
  support.district,
  support.sex,
  support.age,
  support.edu
)
table.support <- data.frame(
  apply(table.support, 2, function(col) paste0(round(col,3)*100,"%"))
)
rownames(table.support) <- c(
  "",
  "北區","中西區",
  "男性","女性",
  "20 到 29 歲","30 到 39 歲","40 到 49 歲","50 到 59 歲","60 歲以上",
  "小學","國中","高中","專科","大學以上")
colnames(table.support) <- c(1:10,"沒決定")
latex(table.support, file = "",title="",
      rgroup = c("總計","分區","性別","年齡","學歷"),
      n.rgroup = c(1,2,2,5,5),
      caption = "候選人支持度整理表"
)
```

3. 3 號候選人的競選策略 (需在何地、對何人進行拉票)

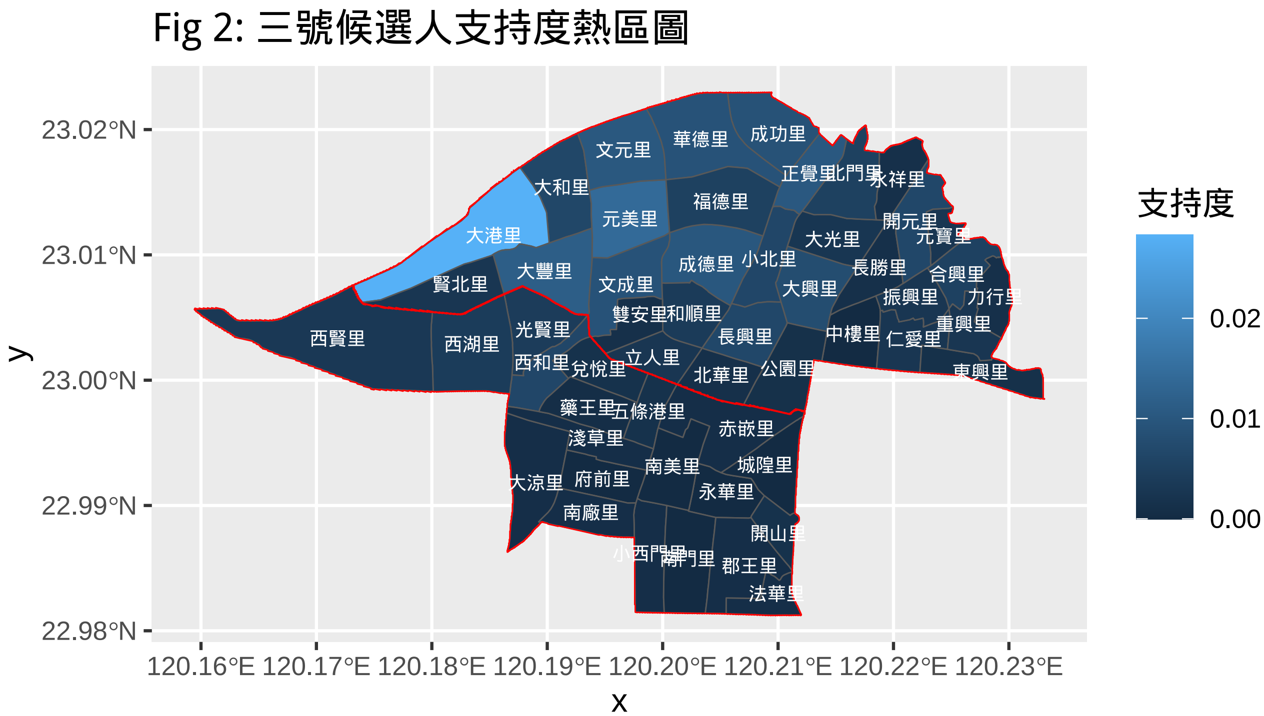
```r
# 計算三號候選人對於里的支持度
support.li_north <- data.frame(
```

Table 3: 候選人支持度整理表

	1	2	3	4	5	6	7	8	9	10	沒決定
總計											
	9.5%	0.5%	12.3%	4.7%	2%	5.9%	11.7%	0.4%	0.5%	3.2%	49.5%
分區											
北區	5.1%	0.6%	14.7%	2.9%	2.6%	7.5%	12.9%	0.3%	0.4%	2.7%	50.3%
中西區	18.1%	0.4%	7.4%	8.3%	0.7%	2.7%	9.2%	0.5%	0.7%	4.1%	47.9%
性別											
男性	9.8%	0.9%	12.9%	5.6%	2.5%	7.3%	11.6%	0.7%	0.3%	4%	44.4%
女性	9.2%	0.3%	11.8%	4.1%	1.6%	4.9%	11.7%	0.1%	0.6%	2.6%	53%
年齡											
20 到 29 歲	3.2%	1.1%	5.3%	3.2%	0%	1.1%	11.7%	1.1%	0%	1.1%	72.3%
30 到 39 歲	5.9%	1.5%	8.8%	1.5%	2.2%	4.4%	11.8%	1.5%	0.7%	2.9%	58.8%
40 到 49 歲	4.5%	1.2%	12.8%	4.5%	3.3%	5.3%	16%	0%	0.8%	1.2%	50.2%
50 到 59 歲	10.6%	0.8%	13.8%	5%	2.6%	5.8%	11.4%	0.3%	0.5%	1.9%	47.4%
60 歲以上	9.6%	0%	10.6%	4.5%	1.2%	5.7%	8.6%	0.2%	0.3%	3.8%	55.5%
學歷											
小學	8.7%	0%	7.6%	1.4%	0.6%	3.4%	5%	0.3%	0%	1.1%	72%
國中	7.8%	0%	11.3%	2.6%	1.3%	2.2%	7.4%	0%	0%	3%	64.3%
高中	9.1%	0%	12.9%	5%	2.6%	6.5%	9.5%	0.4%	0.8%	3.2%	50%
專科	7.2%	0.4%	11.8%	3.8%	2.3%	6.1%	7.6%	0%	0%	2.3%	58.6%
大學以上	7.2%	1.4%	9.7%	5.3%	1.5%	5.6%	15.4%	0.5%	0.7%	3.4%	49.2%

```
  support = sapply(1:33, function(i){
    tempdata <- pollcsv[pollcsv$v2==i,]
    n.temp <- dim(tempdata)[1]
    return(sum(tempdata$v5[!is.na(tempdata$v5)]==3)/n.temp)}
  ),
  VILLNAME = names(attr(pollsav$v2,"labels"))[1:33]
)
support.li_midwest <- data.frame(
  support = sapply(1:20, function(i){
    tempdata <- pollcsv[pollcsv$v3==i,]
    n.temp <- dim(tempdata)[1]
    return(sum(tempdata$v5[!is.na(tempdata$v5)]==3)/n.temp)
  }),
  VILLNAME = names(attr(pollsav$v3,"labels"))[1:20]
)
# 從台灣地圖選取中西區與北區里層級的地圖資料
myMap <- tw_village[
  tw_village$COUNTYNAME == " 臺南市" &
  (tw_village$TOWNNAME==" 中西區"| tw_village$TOWNNAME==" 北區") ,]
myMap <- merge(x = myMap, y = rbind(support.li_midwest, support.li_north), by = "VILLNAME")
showtext_auto()
ggplot(data = myMap) +
  geom_sf(aes(fill = support)) +  # 填充區域
  geom_sf(
    data = summarize(
      group_by(myMap,TOWNNAME),
      geometry = st_union(st_buffer(geometry,dist = 0.01))) , fill = NA, color = 'red') +
      #st_buffer 是為了解決 union 之後內部還有線條的問題 (地圖資料有問題)
  geom_sf_text(aes(label=VILLNAME), size = 2, color = "white")+
```

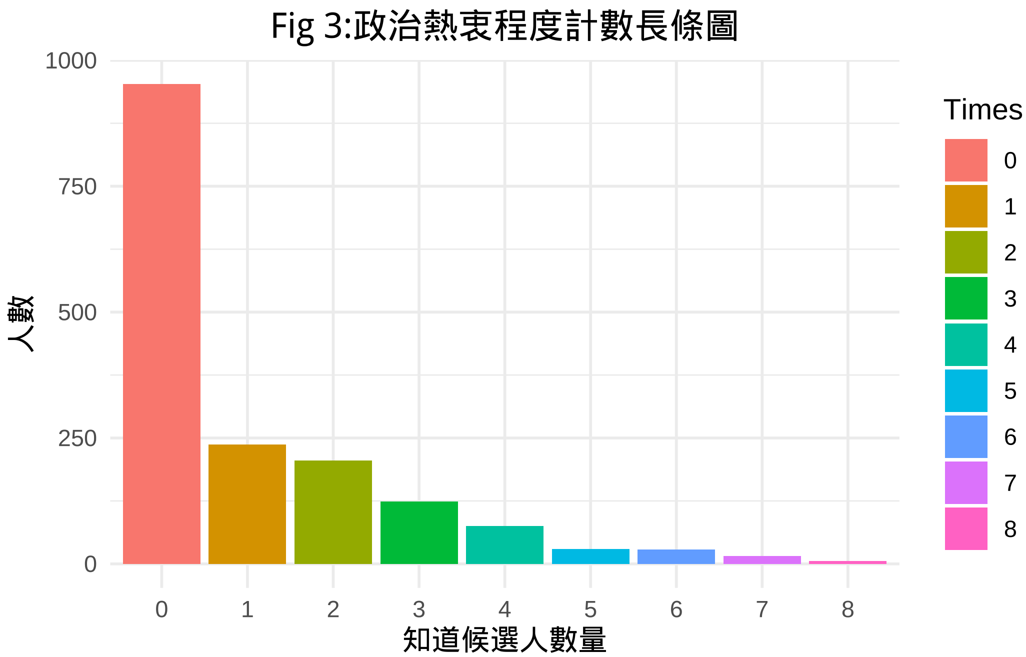
```
  ggtitle("Fig 2: 三號候選人支持度熱區圖")+
  labs(fill = " 支持度")+
  theme_gray(base_family ="Arial", base_size = 10)
```



4. 以 V4 回答出候選人人數來評估受訪者「政治熱衷程度」，建立合適統計模型分析該變數並說明使用該方法的原因

```
pollcsv$known_count <- rowSums(!is.na(pollcsv[,c("v4_1", "v4_2", "v4_3", "v4_4", "v4_5", "v4_6", "v4_7",
pollcsv$sup3 <- ifelse(pollcsv$v5=="3",1,0)
count_data <- data.frame(
  Times = factor(0:8),
  Values = sapply(0:8,function(x){
    sum(pollcsv$known_count==x)
  })
)

# 建立次數圖
ggplot(count_data, aes(x = Times, y = Values , fill = Times ))+
  geom_bar(stat = 'identity')+
  scale_x_discrete(breaks = 0:8)+
  labs(title='Fig 3: 政治熱衷程度計數長條圖', x = '知道候選人數量', y = '人數')+
  theme_minimal()+
  theme(plot.title = element_text(hjust = 0.5))
```




```r
poiv4<-glm(known_count~v1+v6+v7+v8, data = pollcsv, family = poisson())
AER::dispersiontest(poiv4)
```

```
    Overdispersion test

data:  poiv4
z = 12.524, p-value < 2.2e-16
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  2.321796
```

```r
nbv4 <- glm.nb(known_count~v1+v6+v7+v8, data = pollcsv)
lmtest::lrtest(poiv4,nbv4) # 決定要用 Poisson 還是 Negative binomial
```

```
Likelihood ratio test

Model 1: known_count ~ v1 + v6 + v7 + v8
Model 2: known_count ~ v1 + v6 + v7 + v8
  #Df  LogLik Df  Chisq Pr(>Chisq)
1  11 -2635.0
2  12 -2280.5  1 709.13  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(nbv4)
```

```
Call:
glm.nb(formula = known_count ~ v1 + v6 + v7 + v8, data = pollcsv,
    init.theta = 0.6258750942, link = log)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
```

```
(Intercept) -1.07825    0.30518  -3.533 0.000411 ***
v12         -0.14018    0.08591  -1.632 0.102753
v62          0.77007    0.31503   2.444 0.014506 *
v63          0.89173    0.29142   3.060 0.002213 **
v64          1.01004    0.28303   3.569 0.000359 ***
v65          0.93793    0.27922   3.359 0.000782 ***
v72          0.25893    0.16467   1.572 0.115855
v73          0.50668    0.13195   3.840 0.000123 ***
v74          0.51789    0.15992   3.239 0.001201 **
v75          0.50471    0.14010   3.603 0.000315 ***
v82         -0.19371    0.08241  -2.350 0.018749 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(0.6259) family taken to be 1)

    Null deviance: 1531.0  on 1600  degrees of freedom
Residual deviance: 1485.5  on 1590  degrees of freedom
  (因為不存在，70 個觀察量被刪除了)
AIC: 4584.9

Number of Fisher Scoring iterations: 1

              Theta:  0.6259
          Std. Err.:  0.0473

 2 x log-likelihood:  -4560.9200
```

```r
library(pscl)     # 建立 zero-inflated negative model
zinb_model <- zeroinfl(known_count ~ v1 +v6+v7+v8, data = pollcsv, dist = "negbin")
lmtest::lrtest(nbv4,zinb_model) # 決定要用 Negative 或 zero-inflated
```

```
Likelihood ratio test

Model 1: known_count ~ v1 + v6 + v7 + v8
Model 2: known_count ~ v1 + v6 + v7 + v8
  #Df  LogLik Df  Chisq Pr(>Chisq)
1  12 -2280.5
2  23 -2238.9 11 83.162  3.599e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(zinb_model)
```

```

Call:
zeroinfl(formula = known_count ~ v1 + v6 + v7 + v8, data = pollcsv, dist = "negbin")

Pearson residuals:
    Min      1Q  Median      3Q     Max
-0.8393 -0.7052 -0.5357  0.4613  4.6745

Count model coefficients (negbin with log link):
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.587285   0.399595  -1.470  0.14164
v12         -0.094520   0.079076  -1.195  0.23196
```

```
v62          1.043282   0.398262   2.620  0.00880 **
v63          1.081087   0.384695   2.810  0.00495 **
v64          1.185464   0.382191   3.102  0.00192 **
v65          1.240723   0.383341   3.237  0.00121 **
v72         -0.008993   0.158309  -0.057  0.95470
v73          0.162114   0.124789   1.299  0.19391
v74          0.201598   0.146656   1.375  0.16925
v75          0.254145   0.131547   1.932  0.05336 .
v82         -0.058140   0.072576  -0.801  0.42308
Log(theta)   1.476716   0.266200   5.547  2.9e-08 ***

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.7381     1.2734  -0.580  0.56219
v12           0.1319     0.1521   0.867  0.38574
v62           0.7652     1.2615   0.607  0.54415
v63           0.5669     1.2510   0.453  0.65042
v64           0.5615     1.2538   0.448  0.65428
v65           0.8606     1.2597   0.683  0.49447
v72          -0.4869     0.2819  -1.727  0.08408 .
v73          -0.6751     0.2189  -3.084  0.00204 **
v74          -0.6209     0.2714  -2.288  0.02215 *
v75          -0.4509     0.2308  -1.954  0.05070 .
v82           0.2961     0.1477   2.005  0.04496 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Theta = 4.3785
Number of iterations in BFGS optimization: 69
Log-likelihood: -2239 on 23 Df
```

先將每位受訪者知道的候選人用計數的方式去呈現出政治熱忠程度，而這些資料就轉變成 count data，也因此先使用 Poisson model 去做模型。然而在使用 Poisson model 之後並且去做 Dispersion test 時，可以發現這個模型有 Overdispersion 的情形產生，並且 Likelihood ratio test 的結果也建議我們使用 Negative binomial 的模型。在做出資料的分布圖後，可以發現受訪者完全不知道候選人的比例偏高，也就是 0 的資料，也因此想要使用 Zero-inflated negative binomial model 去解決 0 所帶來的問題。由 ZINB 的報表可以得知，在 count model 底下，也就是有講出候選人的受訪者中，30~39 歲，40~49 歲，50~59 歲以及 60 歲以上，他們相較於 20~29 歲是顯著的，並且他們的係數是逐步提高的，因此我們可以認為隨著年齡提高，政治熱忠程度也會隨之提高。而在零膨脹模型，教育程度的變數當中，高中及專科相較於國小是顯著的，也代表著高中及專科的受訪者更可能出現非零值，也就是說他們相較於教育程度只有國小的受訪者是更可能回答出候選人的。而在性別的部分，可以發現女性相較於男性是顯著的，藉由係數我們可以解釋成女性相較於男性較可能回答不出候選人，也就是說女性提高了結構性零的機率。

5. 3 號候選人支持率 (具資料不平衡特性) 的預測模式與資料不平衡的處理

```r
set.seed(123)  # For reproducibility
library(smotefamily)
library(dplyr)
new_poll <- pollcsv[,c(1,13,14,15,16,17)]
new_poll_wei <- pollcsv[,c(1,13,14,15,16,17)]
# 由於在 V1 V6 V7 V8 當中，缺失值並不多，因此我選擇刪除缺失值
new_poll <- na.omit(new_poll)
new_poll_wei <- na.omit(new_poll_wei)
```

```r
new_poll_wei$sup3 <- as.numeric(new_poll_wei$sup3)
# 轉換為數值才能使用 smote
new_poll <- new_poll %>%
  mutate_if(is.character, as.factor) %>%
  mutate_if(is.factor, as.numeric)

poll_balanced <- SMOTE(X = new_poll[, -which(names(new_poll) == "sup3")],
                       target = new_poll$sup3,
                       K = 5)
table(poll_balanced$data$class)
```

```

  0   1
631 615
```

```r
poll_balanced <- poll_balanced$data
# 由於 smote 過後他新增的資料可能會有不是整數的狀況，然而在這筆資料當中應該要為整數，也因此我選擇將那些有小數點
poll_balanced[] <- lapply(poll_balanced, function(x) if(is.numeric(x)) round(x) else x)
poll_balanced$class <- as.numeric(poll_balanced$class)
# 轉換為 factor
poll_balanced[c("v1", "v6", "v7", "v8")] <- lapply(poll_balanced[c("v1", "v6", "v7", "v8")], as.factor)
describe(poll_balanced)
```

```
poll_balanced

 6  Variables      1246  Observations
--------------------------------------------------------------------------------
v1
       n  missing distinct
    1246        0        2

Value          1     2
Frequency    888   358
Proportion 0.713 0.287
--------------------------------------------------------------------------------
v6
       n  missing distinct
    1246        0        5

Value          1     2     3     4     5
Frequency     34    79   173   294   666
Proportion 0.027 0.063 0.139 0.236 0.535
--------------------------------------------------------------------------------
v7
       n  missing distinct
    1246        0        5

Value          1     2     3     4     5
Frequency    154   128   382   163   419
Proportion 0.124 0.103 0.307 0.131 0.336
--------------------------------------------------------------------------------
v8
       n  missing distinct
    1246        0        2
```

```
Value          1     2
Frequency    551   695
Proportion 0.442 0.558
--------------------------------------------------------------------------------
known_count
       n  missing distinct     Info     Mean      Gmd
    1246        0        9    0.928    1.508    1.761

Value          0     1     2     3     4     5     6     7     8
Frequency    476   258   213   149    78    19    35    13     5
Proportion 0.382 0.207 0.171 0.120 0.063 0.015 0.028 0.010 0.004

For the frequency table, variable is rounded to the nearest 0
--------------------------------------------------------------------------------
class
       n  missing distinct     Info      Sum     Mean      Gmd
    1246        0        2     0.75      615   0.4936   0.5003

--------------------------------------------------------------------------------
```

```
train_nrow <- floor(0.7 * nrow(poll_balanced))
train_idx <- sample(seq_len(nrow(poll_balanced)), size=train_nrow)

poll_training <- poll_balanced[train_idx, ]
cat("Training set size:", nrow(poll_training))
```

```
Training set size: 872
```

```
poll_testing <- poll_balanced[-train_idx, ]
cat("Test set size:", nrow(poll_testing))
```

```
Test set size: 374
```

```
sup3_log <- glm(class ~ ., data = poll_training, family = binomial)
summary(sup3_log)
```

```

Call:
glm(formula = class ~ ., family = binomial, data = poll_training)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.34263    0.55502   0.617   0.5370
v12         -1.10782    0.16331  -6.783 1.17e-11 ***
v62         -0.01088    0.55815  -0.019   0.9844
v63          0.42888    0.51779   0.828   0.4075
v64         -0.04804    0.50527  -0.095   0.9243
v65          0.26147    0.50358   0.519   0.6036
v72          0.29462    0.30658   0.961   0.3366
v73         -0.18501    0.23864  -0.775   0.4382
v74         -0.15635    0.29413  -0.532   0.5950
v75         -0.44837    0.26660  -1.682   0.0926 .
v82          0.16870    0.14496   1.164   0.2445
known_count -0.04571    0.04178  -1.094   0.2739
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1208.3  on 871  degrees of freedom
Residual deviance: 1142.6  on 860  degrees of freedom
AIC: 1166.6

Number of Fisher Scoring iterations: 4
```

```r
pred_prob <- predict(sup3_log, poll_testing, type = "response")

pred_class <- ifelse(pred_prob > 0.5, 1, 0)

library(caret)
```

```
載入需要的套件：lattice
```

```r
confusionMatrix(factor(pred_class), factor(poll_testing$class))
```

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 104  43
         1 102 125

               Accuracy : 0.6123
                 95% CI : (0.5609, 0.662)
    No Information Rate : 0.5508
    P-Value [Acc > NIR] : 0.009403

                  Kappa : 0.2411

 Mcnemar's Test P-Value : 1.46e-06

            Sensitivity : 0.5049
            Specificity : 0.7440
         Pos Pred Value : 0.7075
         Neg Pred Value : 0.5507
             Prevalence : 0.5508
         Detection Rate : 0.2781
   Detection Prevalence : 0.3930
      Balanced Accuracy : 0.6245

       'Positive' Class : 0
```

```r
#Weighted logistic regression

class_counts <- table(new_poll_wei$sup3)
class_counts
```

```

  0   1 
631 205 
```

```r
train_nrow_wei <- floor(0.7 * nrow(new_poll_wei))
train_idx_wei <- sample(seq_len(nrow(new_poll_wei)), size=train_nrow_wei)

poll_training_wei <- new_poll_wei[train_idx_wei, ]

weights <- ifelse(poll_training_wei$sup3 == 1,
                  class_counts[1] / (class_counts[1]+class_counts[2]),
                  class_counts[2] / (class_counts[1]+class_counts[2]))
poll_testing_wei <- new_poll_wei[-train_idx_wei, ]

weighted_logit_model <- glm(sup3 ~ v1 + v6 + v7 + v8,
                            data = poll_training_wei,
                            family = binomial,
                            weights = weights)
```

```
Warning in eval(family$initialize): non-integer #successes in a binomial glm!
```

```r
summary(weighted_logit_model)
```

```

Call:
glm(formula = sup3 ~ v1 + v6 + v7 + v8, family = binomial, data = poll_training_wei,
    weights = weights)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.93891    1.40858  -0.667  0.50505
v12         -1.02284    0.31675  -3.229  0.00124 **
v62          1.58573    1.40773   1.126  0.25998
v63          1.66866    1.34324   1.242  0.21414
v64          1.49261    1.33179   1.121  0.26239
v65          1.30923    1.33008   0.984  0.32496
v72          0.27427    0.58442   0.469  0.63885
v73         -0.10286    0.48808  -0.211  0.83309
v74         -0.03042    0.60068  -0.051  0.95962
v75         -0.68075    0.54459  -1.250  0.21129
v82          0.12031    0.29466   0.408  0.68306
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 301.28  on 584  degrees of freedom
Residual deviance: 282.76  on 574  degrees of freedom
AIC: 207.54

Number of Fisher Scoring iterations: 4
```

```r
pred_prob_wei <- predict(weighted_logit_model, poll_testing_wei, type = "response")

library(pROC)
```

```
Type 'citation("pROC")' for a citation.


載入套件：'pROC'
```

```
下列物件被遮斷自 'package:stats':

    cov, smooth, var
```

```r
# 使用 roc curve 找出最佳的閥值
roc_curve <- roc(poll_testing_wei$sup3, pred_prob_wei)
```

```
Setting levels: control = 0, case = 1

Setting direction: controls < cases
```

```r
best_coords <- coords(roc_curve, "best", best.method = "youden")
pred_class_wei <- ifelse(pred_prob_wei > best_coords$threshold, 1, 0)

confusionMatrix(factor(pred_class_wei), factor(poll_testing_wei$sup3))
```

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 125  27
         1  66  33

               Accuracy : 0.6295
                 95% CI : (0.5665, 0.6894)
    No Information Rate : 0.761
    P-Value [Acc > NIR] : 1

                  Kappa : 0.1672

 Mcnemar's Test P-Value : 8.134e-05

            Sensitivity : 0.6545
            Specificity : 0.5500
         Pos Pred Value : 0.8224
         Neg Pred Value : 0.3333
             Prevalence : 0.7610
         Detection Rate : 0.4980
   Detection Prevalence : 0.6056
      Balanced Accuracy : 0.6022

       'Positive' Class : 0
```

在處理不平衡資料的時候，我選擇使用 smote 以及 weighted logistic regression 來處理。我分別將他們都切成訓練集以及測試集，並且對他們做 confusion matrics 以此來判斷哪個模型較佳。在這過程當中，weighted logistic regression 在最後分類的 accuracy rate 高達 0.7214，而 smote 的 accuracy rate 則僅有 0.5825，因此我認為使用 weighted logistic regression 在這裡是較佳的。此外，weighted 權重的部分我是以比例去決定的，以此減少資料的不平衡。