Technical Report

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Data

The GSS dataset

The general social survey (GSS) is a massive survey conducted of people within the United States since 1972. The GSS aims to get a representative sample of people in the United States and to understand information about them and how they feel about social and political issues. We have chosen some key variables collected from this survey, along with participants from 2000 or more recent, in order for us to attempt to classify political affiliation of participants. Our subset of the GSS dataset contains 5,800 rows, 16 columns, and 0 NA's.

Filtering

Most of this filtering was done for the `infer` package `gss` dataset and can be attributed to authors of that package. We have included more rows and columns than that package, however, much initial tidying and subsetting can be attributed to them (Bray et al. 2020). Below is the code adapted from the `infer` package to attain our dataset, `gss_subset`:

```
load("gss/gss_orig.rda")
gss_subset <- gss_orig %>%
  filter(!stringr::str_detect(sample, "blk oversamp")) %>% # this is for weighting
  select(year, age, sex, college = degree, partyid, hompop, hours = hrs1, income,
         class, finrela, wrkgovt, marital, educ, race, incom16, weight = wtssall) %>%
  mutate_if(is.factor, ~ fct_collapse(., NULL = c("IAP", "NA", "iap", "na"))) %>%
  mutate(
    age = age %>%
      fct_recode("89" = "89 or older",
                 NULL = "DK") %>%
      as.character() %>%
      as.numeric(),
    hompop = hompop %>%
      fct_collapse(NULL = c("DK")) %>%
      as.character() %>%
      as.numeric(),
    hours = hours %>%
      fct_recode("89" = "89+ hrs",
                 NULL = "DK") %>%
      as.character() %>%
      as.numeric(),
    weight = weight %>%
      as.character() %>%
      as.numeric(),
```

```r
    partyid = fct_collapse(
      partyid,
      dem = c("strong democrat", "not str democrat"),
      rep = c("strong republican", "not str republican"),
      ind = c("ind,near dem", "independent", "ind,near rep"),
      other = "other party"
    ),
    income = factor(income, ordered = TRUE),
    college = fct_collapse(
      college,
      degree = c("junior college", "bachelor", "graduate"),
      "no degree"  = c("lt high school", "high school"),
      NULL = "dk"
    )
  ) %>%
  filter(year >= 2000) %>%
  filter(partyid %in% c("dem", "rep")) %>%
  drop_na()
```

Given our goal to understand which factors influence party affiliation in the US, we selected `year` (year of the election), `age` (age of time of survey), `college` (degree or no degree), `partyid` (democrat or republican), `hompop` (number of people in the respondent's household), `hours` (number of hours worked in the last week), `income` (total family income, categorical), `class` (socioeconomic class as described by respondent), `finrela` (respondent's opinion on family's income level), `wrkgovt` (whether or not the respondent works for the government), `marital` (respondent's martial status), `educ` (highest year of school completed), `race` (race of respondent), `income16` (respondent's family income at the age of 16), and `weight` (survey weight).

We made some choices while filtering the dataset which will effect the final results of our models. First of all, we have filtered all observations which do not state that their political affiliation was either democrat or republican. We are most interested in answering the question of whether or not we can classify between these parties rather than considering much smaller third parties. Also, we have filtered all observations with any NA's. We chose to do this for ease of analysis and because many of the models we use will not consider a row that includes NA's in any of the columns being used for the model.

Exploratory Data Analysis

Before we dig too deeply in to the dataset, it is important to understand its structure:

```r
# Number of rows
nrow(gss_subset)
```

```
## [1] 5800
```

```r
# Number of columns
ncol(gss_subset)
```

```
## [1] 16
```

```r
# Response variable summary
summary(gss_subset$partyid)
```

```
##   dem   ind   rep other    DK
##  3316     0  2484     0     0
```

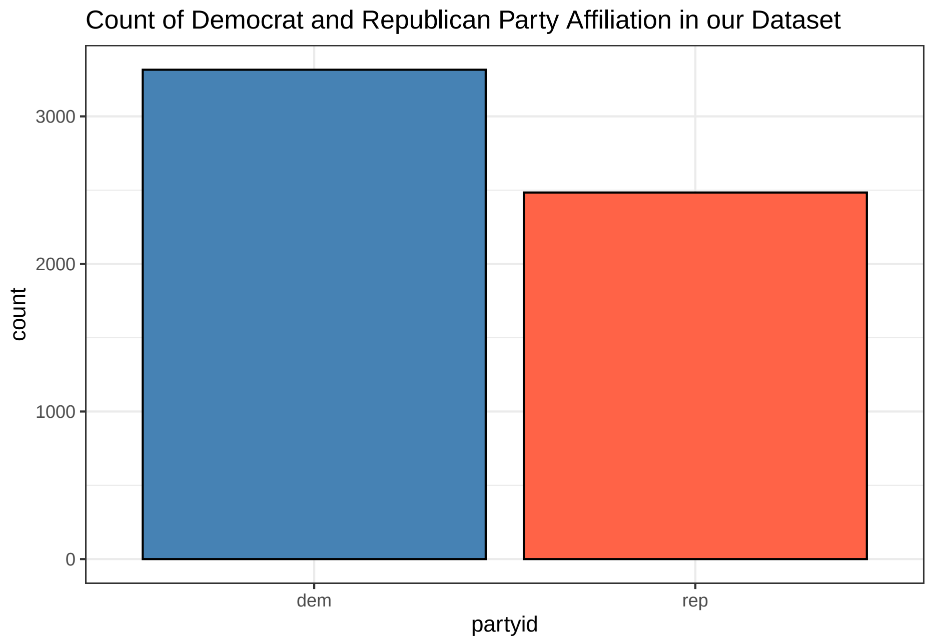
```r
# Data Structure
str(gss_subset)
```

```
## tibble [5,800 x 16] (S3: tbl_df/tbl/data.frame)
##  $ year   : num [1:5800] 2002 2002 2002 2002 2002 ...
##   ..- attr(*, "label")= chr "gss year for this respondent "
##   ..- attr(*, "format.stata")= chr "%8.0g"
##  $ age    : num [1:5800] 25 43 46 71 37 23 33 57 42 63 ...
##  $ sex    : Factor w/ 2 levels "male","female": 2 1 1 2 1 1 1 1 2 1 ...
##  $ college: Factor w/ 2 levels "no degree","degree": 1 2 1 1 1 1 2 2 2 2 ...
##  $ partyid: Factor w/ 5 levels "dem","ind","rep",..: 3 3 3 3 3 1 1 1 1 1 ...
##  $ hompop : num [1:5800] 1 1 2 1 1 3 4 2 1 1 ...
##  $ hours  : num [1:5800] 40 72 40 24 50 60 70 40 65 44 ...
##  $ income : Ord.factor w/ 12 levels "lt $1000"<"$1000 to 2999"<..: 12 12 12 11 12 12 12 12 12 12 ...
##  $ class  : Factor w/ 6 levels "lower class",..: 3 3 3 2 3 2 2 3 2 3 ...
##  $ finrela: Factor w/ 6 levels "far below average",..: 3 4 4 3 3 3 3 3 4 4 ...
##  $ wrkgovt: Factor w/ 3 levels "government","private",..: 2 2 2 2 2 2 2 2 2 1 ...
##  $ marital: Factor w/ 5 levels "married","widowed",..: 3 1 3 3 5 4 1 1 5 5 ...
##  $ educ   : Factor w/ 22 levels "0","1","2","3",..: 15 17 15 13 16 13 17 17 17 18 ...
##  $ race   : Factor w/ 3 levels "white","black",..: 1 1 1 1 1 2 3 1 1 1 ...
##  $ incom16: Factor w/ 7 levels "far below average",..: 3 4 4 3 2 3 3 4 2 4 ...
##  $ weight : num [1:5800] 0.558 0.558 1.116 0.558 0.558 ...
```

```r
# Glimpse of dataset
gss_subset %>%
  select(-weight) %>%
  rename(home = hompop, party = partyid) %>%
  head() %>%
  knitr::kable()
```

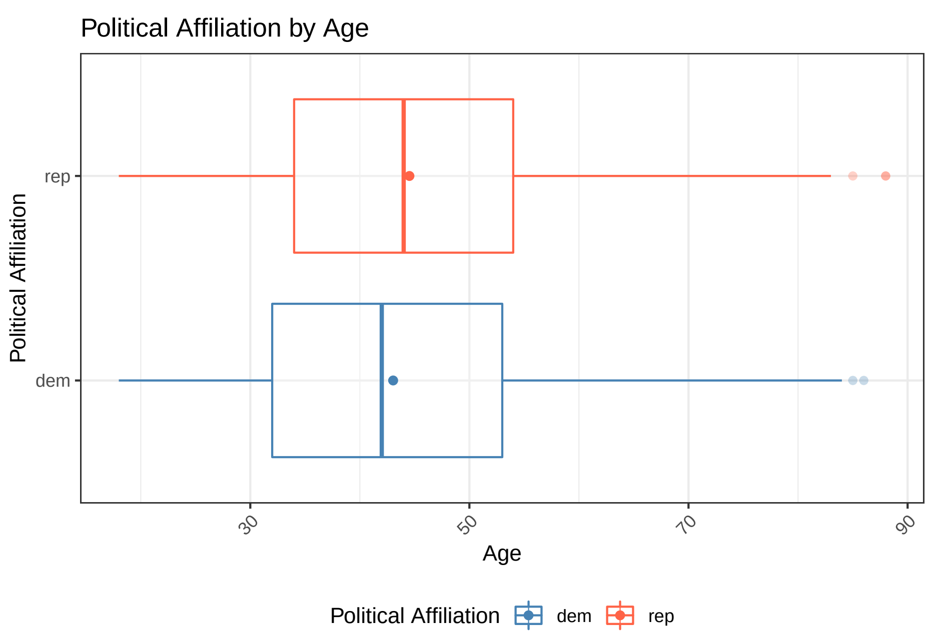
year	age	sex	college	party	home	hours	income	class	finrela	wrkgovt	marital	educ	race	incom16
2002	25	female	no degree	rep	1	40	$25000 or more	middle class	average	private	divorced	14	white	average
2002	43	male	degree	rep	1	72	$25000 or more	middle class	above average	private	married	16	white	above average
2002	46	male	no degree	rep	2	40	$25000 or more	middle class	above average	private	divorced	14	white	above average
2002	71	female	no degree	rep	1	24	$20000 - 24999	working class	average	private	divorced	12	white	average
2002	37	male	no degree	rep	1	50	$25000 or more	middle class	average	private	never married	15	white	below average
2002	23	male	no degree	dem	3	60	$25000 or more	working class	average	private	separated	12	black	average

As we first explore the dataset, we can look at the distribution of democrats and republications in our dataset in counts:

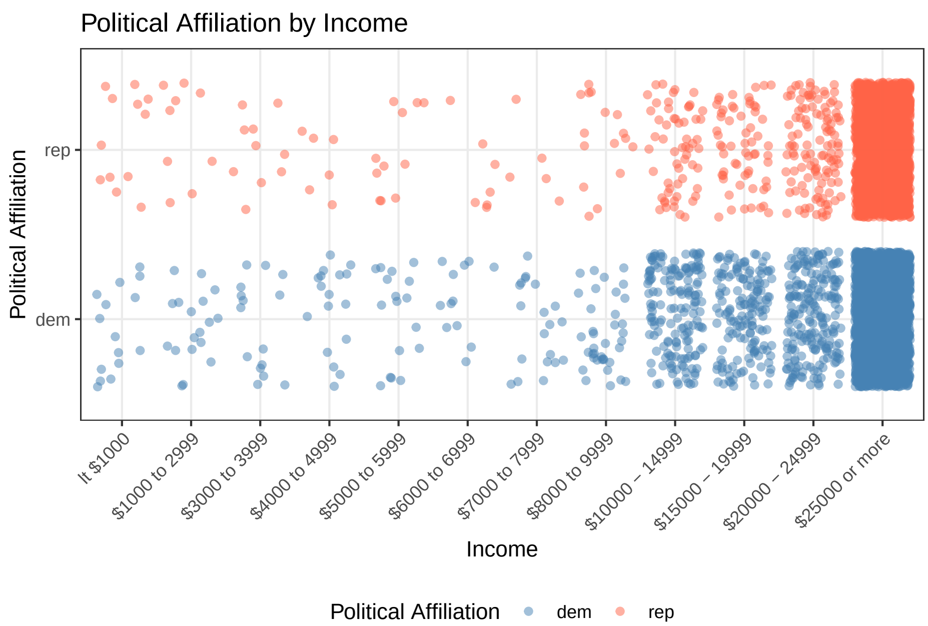


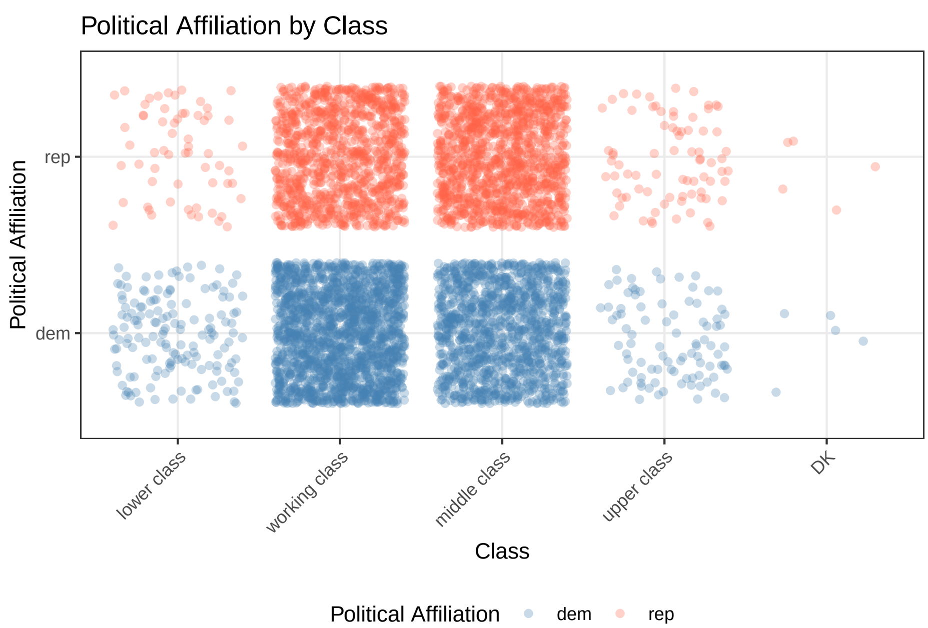
There appears to me more democrats than republicans represented in this dataset, which could be because democrats are more likely to participate in this survey, or it could be that the way we selected our data systemically oversampled democrats. Notably from this, it is the case that our the weights associated with our sample of the GSS dataset would not be the same as the weights that the GSS uses for the dataset, so the `weight` variable should be ignored entirely.

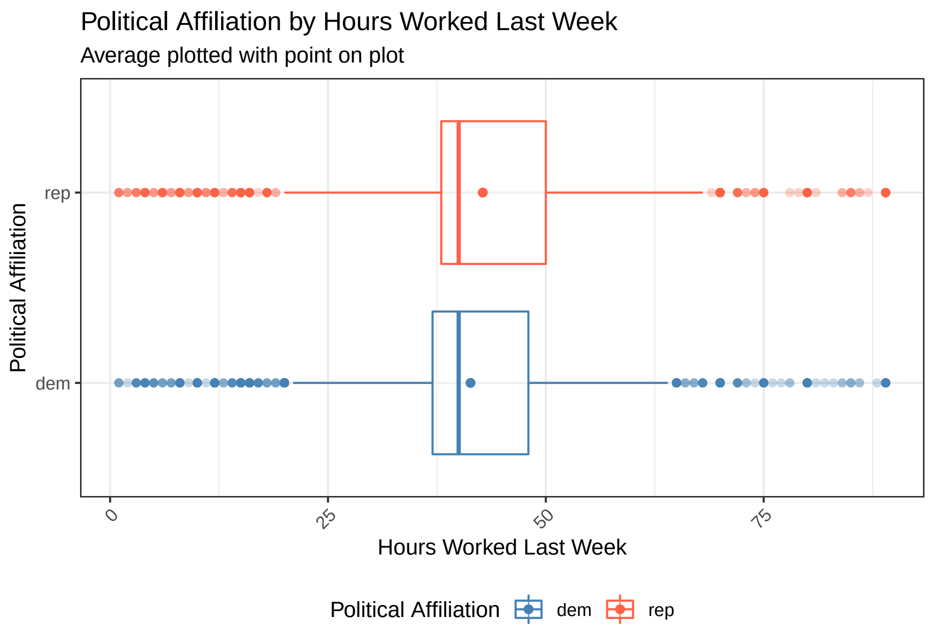
Now, we can examine some of our predictor variables with our response, `partyid`, to see the relationships there are between variables. First, we see in this side-by-side boxplot with the means plotted on top that republicans tend to be older on average:



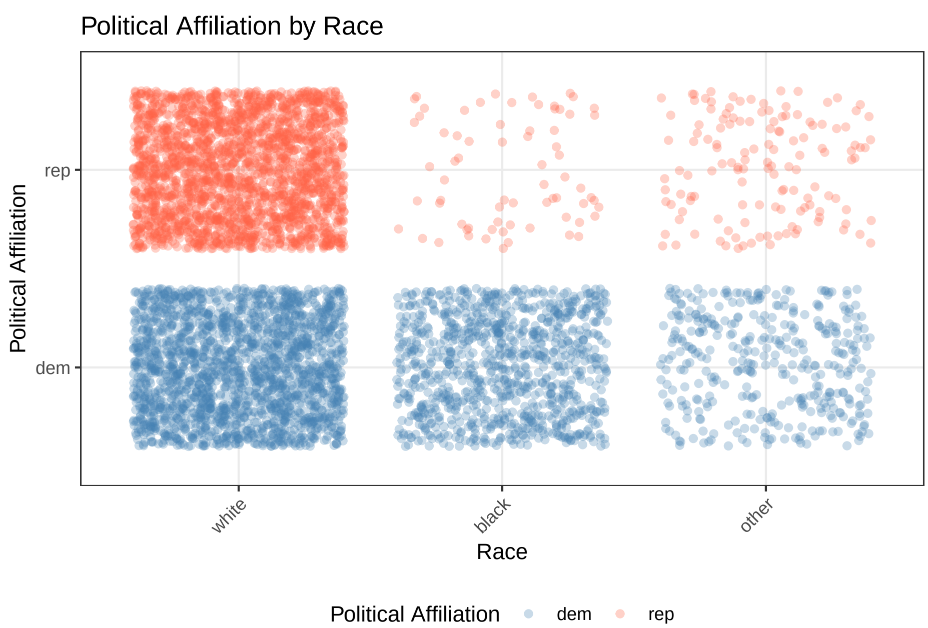
Next, it is interesting to consider economic status across political affiliations. By comparing political affiliation to income, class, and hours worked in the last week we can see small relationships between political affiliation and economic status:

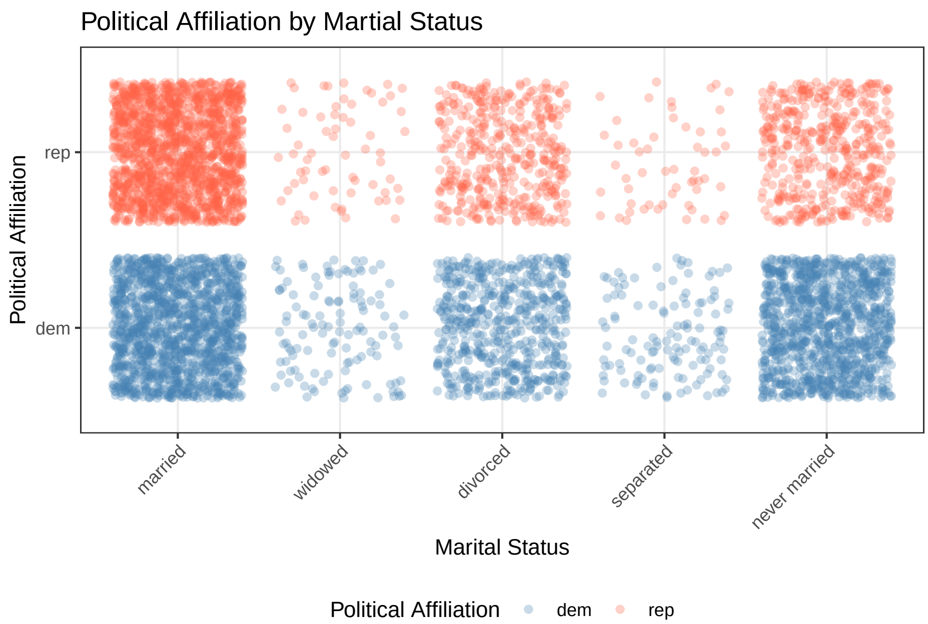


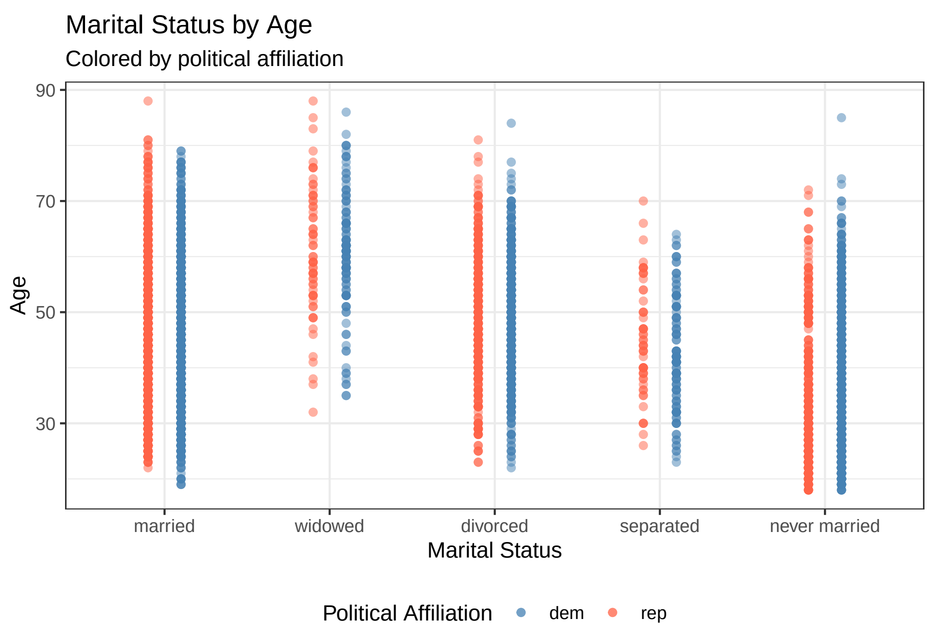


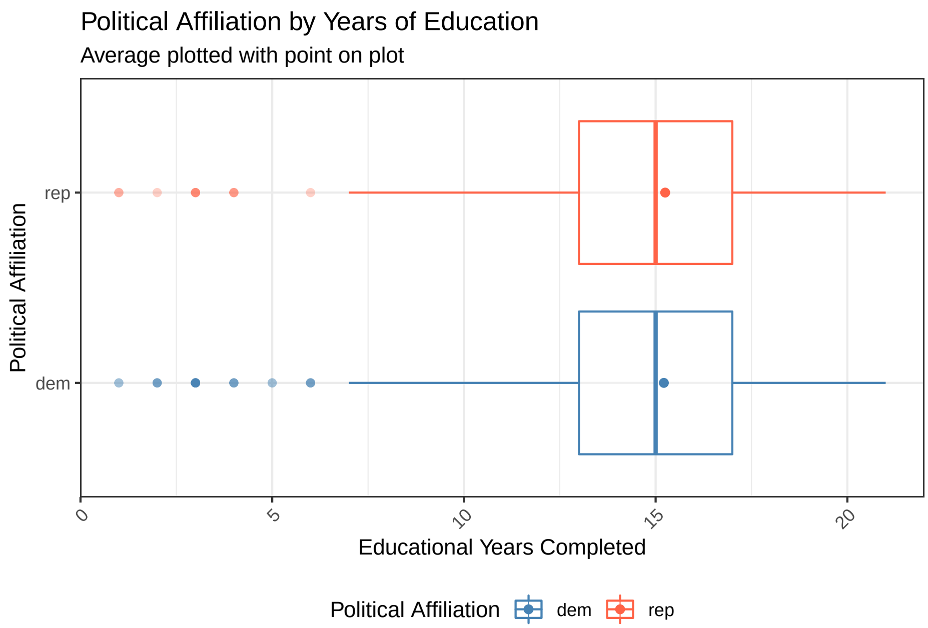


It is also relevant to look at other variables such as race, marital status, and education as factors related to political party affiliation. Most notably, there is a much larger proportion of white republicans than democrats. We can see this in the first plot in the following plots:




Political Affiliation by Martial Status
Political Affiliation
rep
dem
married
widowed
divorced
separated
never married
Marital Status
Political Affiliation
dem
rep


Marital Status by Age
Colored by political affiliation
Age
90
70
50
30
married
widowed
divorced
separated
never married
Marital Status
Political Affiliation
dem
rep



After completing these exploratory analyses, it is clear that while there are some weak relationships within many variables, we will likely need all of these variables to make models which have good predictive power. None of the predictors appear to have an extremely strong relationship with political party affiliation, and so we will need to use many of them for our models to perform well.

We also examined two classification model methods for accuracy in predicting partyid based on some of our 16 predictors. Linear disriminany analysis (LDA) appeare to perform better job correctly classifying Democrats than Republicans based on these 6 predictors, as there was an equal amount of Republicans incorrectly predicted to those correctly predicted. Our logistic regression model with all 16 predictors also appears to better classify Democrats than Republicans, but not by much, with an overall training error rate of about 18%. These results suggest that the current classification models we have used throughout this course may not be successful in predicting partyid with high accuracy on their own. We hope to leverage these methods through model stacking in our Methods and Results section.

```
#taking a look at how LDA could perform on our dataset with just a couple of variables
library(MASS)
```

```
##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select
```

```
set.seed(2020)
mlda <- lda(partyid ~ race + age + year + hompop + income + wrkgovt, data = gss_subset)
```

```
## Warning in lda.default(x, grouping, ...): groups ind other DK are empty
```

```r
mlda_pred <- predict(mlda)
conf_mlda <- table(mlda_pred$class,gss_subset$partyid)
conf_mlda
```

```
##
##          dem  ind  rep other   DK
##   dem   1651    0  464     0    0
##   ind      0    0    0     0    0
##   rep   1665    0 2020     0    0
##   other    0    0    0     0    0
##   DK       0    0    0     0    0
```

```r
#taking a look at how logistic regression could perform on our dataset with just a couple of variables
simple_logreg<-glm(partyid ~ race + age + year + hompop + income + wrkgovt, data = gss_subset, family=
summary(simple_logreg)
```

```
##
## Call:
## glm(formula = partyid ~ race + age + year + hompop + income +
##     wrkgovt, family = "binomial", data = gss_subset)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6308  -1.1936  -0.3684   1.1004   2.6449
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)    19.645497  11.633733   1.689   0.0913 .
## raceblack      -2.726179   0.128901 -21.149  < 2e-16 ***
## raceother      -1.149020   0.107074 -10.731  < 2e-16 ***
## age             0.005456   0.002224   2.453   0.0142 *
## year           -0.009976   0.005788  -1.724   0.0848 .
## hompop          0.089863   0.022250   4.039 5.37e-05 ***
## income.L       -0.764534   0.344701  -2.218   0.0266 *
## income.Q        0.592449   0.389611   1.521   0.1284
## income.C        0.294515   0.366015   0.805   0.4210
## income^4        0.103443   0.390148   0.265   0.7909
## income^5       -0.363236   0.366427  -0.991   0.3215
## income^6        0.259640   0.394253   0.659   0.5102
## income^7       -0.088836   0.383146  -0.232   0.8166
## income^8        0.025585   0.398678   0.064   0.9488
## income^9       -0.752271   0.421740  -1.784   0.0745 .
## income^10       0.567971   0.408693   1.390   0.1646
## income^11       0.627012   0.481088   1.303   0.1925
## wrkgovtprivate  0.081194   0.073943   1.098   0.2722
## wrkgovtDK      -0.122282   0.280065  -0.437   0.6624
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 7920.7  on 5799  degrees of freedom
## Residual deviance: 6939.2  on 5781  degrees of freedom
```

```
## AIC: 6977.2
##
## Number of Fisher Scoring iterations: 5
```

```r
full_logreg<-glm(partyid ~ ., data = gss_subset, family= "binomial")
summary(full_logreg)
```

```
##
## Call:
## glm(formula = partyid ~ ., family = "binomial", data = gss_subset)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8081  -1.0644  -0.3376   1.0318   2.7773
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)               9.934e+00  1.208e+01   0.823  0.41076
## year                     -4.422e-03  5.979e-03  -0.740  0.45952
## age                      -7.696e-04  2.665e-03  -0.289  0.77276
## sexfemale                -3.593e-01  6.220e-02  -5.777 7.62e-09 ***
## collegedegree             9.412e-02  1.191e-01   0.790  0.42930
## hompop                   -4.604e-03  2.723e-02  -0.169  0.86576
## hours                     2.927e-03  2.150e-03   1.361  0.17347
## income.L                 -7.907e-01  3.574e-01  -2.212  0.02695 *
## income.Q                  4.297e-01  4.032e-01   1.066  0.28649
## income.C                  7.981e-02  3.755e-01   0.213  0.83167
## income^4                  6.986e-02  3.996e-01   0.175  0.86120
## income^5                 -4.738e-01  3.753e-01  -1.263  0.20669
## income^6                  2.337e-01  4.002e-01   0.584  0.55930
## income^7                 -1.640e-01  3.927e-01  -0.418  0.67619
## income^8                  4.602e-02  4.068e-01   0.113  0.90993
## income^9                 -8.015e-01  4.272e-01  -1.876  0.06064 .
## income^10                 5.947e-01  4.161e-01   1.429  0.15291
## income^11                 7.482e-01  4.893e-01   1.529  0.12623
## classworking class       -1.070e-01  1.901e-01  -0.563  0.57349
## classmiddle class         1.601e-01  1.975e-01   0.811  0.41762
## classupper class         -1.058e-01  2.650e-01  -0.399  0.68984
## classDK                   2.152e-01  7.134e-01   0.302  0.76295
## finrelabelow average     -6.919e-02  1.816e-01  -0.381  0.70317
## finrelaaverage           -2.840e-02  1.818e-01  -0.156  0.87582
## finrelaabove average      1.231e-01  1.899e-01   0.648  0.51679
## finrelafar above average  1.670e-01  2.650e-01   0.630  0.52869
## finrelaDK                 6.747e-02  5.946e-01   0.113  0.90965
## wrkgovtprivate           -3.290e-02  7.750e-02  -0.425  0.67115
## wrkgovtDK                -2.093e-01  2.892e-01  -0.724  0.46937
## maritalwidowed           -3.838e-01  1.827e-01  -2.101  0.03563 *
## maritaldivorced          -2.530e-01  8.915e-02  -2.838  0.00454 **
## maritalseparated         -3.928e-01  1.896e-01  -2.072  0.03826 *
## maritalnever married     -7.027e-01  8.675e-02  -8.100 5.50e-16 ***
## educ1                    -2.062e+00  1.625e+00  -1.269  0.20445
## educ2                    -1.405e+00  1.313e+00  -1.070  0.28460
## educ3                    -6.373e-01  1.426e+00  -0.447  0.65488
## educ4                    -1.326e+01  2.235e+02  -0.059  0.95268
```

```
## educ5                       -1.386e+00  1.610e+00  -0.861  0.38939
## educ6                       -1.733e+00  1.234e+00  -1.404  0.16042
## educ7                       -1.908e+00  1.415e+00  -1.349  0.17744
## educ8                       -5.753e-01  1.192e+00  -0.483  0.62942
## educ9                       -1.161e+00  1.181e+00  -0.982  0.32588
## educ10                      -5.666e-01  1.173e+00  -0.483  0.62911
## educ11                      -6.585e-01  1.164e+00  -0.566  0.57151
## educ12                      -6.432e-01  1.151e+00  -0.559  0.57636
## educ13                      -4.646e-01  1.154e+00  -0.402  0.68732
## educ14                      -7.047e-01  1.154e+00  -0.611  0.54125
## educ15                      -7.206e-01  1.157e+00  -0.623  0.53359
## educ16                      -7.899e-01  1.157e+00  -0.682  0.49497
## educ17                      -1.173e+00  1.164e+00  -1.008  0.31363
## educ18                      -1.231e+00  1.162e+00  -1.060  0.28912
## educ19                      -1.532e+00  1.171e+00  -1.307  0.19110
## educ20                      -1.647e+00  1.166e+00  -1.413  0.15779
## raceblack                   -2.621e+00  1.313e-01 -19.957  < 2e-16 ***
## raceother                   -1.070e+00  1.110e-01  -9.637  < 2e-16 ***
## incom16below average         1.976e-01  1.251e-01   1.581  0.11398
## incom16average               2.729e-01  1.204e-01   2.267  0.02337 *
## incom16above average         2.685e-01  1.324e-01   2.028  0.04255 *
## incom16far above average     1.607e-01  2.191e-01   0.733  0.46344
## weight                       1.421e-01  6.028e-02   2.357  0.01843 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 7920.7  on 5799  degrees of freedom
## Residual deviance: 6701.7  on 5740  degrees of freedom
## AIC: 6821.7
##
## Number of Fisher Scoring iterations: 11
```

```r
probs<-predict(full_logreg, gss_subset, type = "response")
preds<-ifelse(probs >=.5, 1, 0)
conf_log <- table(preds, gss_subset$partyid)
conf_log
```

```
##
## preds  dem  ind  rep other   DK
##     0 2255    0  808     0    0
##     1 1061    0 1676     0    0
```

```r
n <- length(gss_subset$partyid)
false_pos <- conf_log[1,2]
false_neg <- conf_log[2,1]
error <- 1/n *(false_pos + false_neg)
error
```

```
## [1] 0.182931
```

References

Bray, Andrew, Chester Ismay, Evgeni Chasnovski, Ben Baumer, and Mine Cetinkaya-Rundel. 2020. *Infer: Tidy Statistical Inference*. https://CRAN.R-project.org/package=infer.