From Cambodia to the Soviet Union: What Factors Influence the Probability of Death for Members of Authoritarian Regimes?

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Contents

1 Introduction

Dictatorships and totalitarian regimes differ highly with respect to their propagandistic strategies, economic policy, foreign policy, their rhetoric or their treatment of opponents. While some seize power via the corruption of democratic mechanisms like the NSDAP did in 1933, others – like the Military Junta in Argentina or the Libyan dictator Muammar al Gaddafi – do so by using pure military force. Some are even set into power by foreign nations. Once in charge patterns of legitimization need to be constructed. May it be political ideas like communism, religious dogma or a believed racist superiority – totalitarian regimes are manifold.

Despite all differences: What unifies them is the exertion of violence to stay in power, may it be against their own citizens or their neighbors or both. Every authoritarian, dictatorial regime uses collective violence as a tool to exercise control. Hereby dictators throughout history turned out to be very inventive. German concentration camps and Soviet gulags are known worldwide and gained questionable fame. In the last decades newspapers were full of reports about torture chambers in Libya or Syria, China's suppression of their Uyghur minority isn't a secret, too. In Argentina the stories of dissidents being thrown into the sea out of flying helicopters are commonly known. Of course, not every authoritarian regime commits thousandfold mass murder – sometimes locking up journalists and political opponents is enough to remain in power. Nevertheless, very often violence falls back on those who exert it. As long as the existence of totalitarian regimes and dictatorships their members fell victim to violence themselves. An internal fight for power, a lost war or a revolution – there are many situations to think of. Also, there are many circumstances that can be thought of that influence violent death of members of such regimes.

2 Model Specification

In this section, we give a short overview on how the model was constructed, as well as brief justifications as to why some variables are included. The variable selection is based on variables of interest, rather than trying to maximize the predictive power of the model. The dummy for the country in which the regime is, or was, located. There might be cultural reasons why countries in Latin America or Asia might differ from countries in Europe. Furthermore, the duration of the regime is included, as it might be the case that regimes that have been in power for longer have an increasing effect on the probability of death for its members, simply due to being longer in power giving more chances to die, either natural or not. Related to this, the demeaned end year of the regime is included, as the possibility of time trends seems plausible. E.g. when regimes were overturned 100 years ago, the population might have been less averse to peaceful transitions. An earlier version of this model included the start year, however, the variance inflation factor (VIF) on the coefficient was relatively large, compared to the others, so it was excluded from the model. End-of-regime two-year average GDP growth is included, as a worse economic situation might lead to a more desperate population, which in turn might lead to increased propensity of a more violent approach to overturning the current regime. Lastly, all other variables are included simply out of interest, not due to an assumption on the sign and size of the partial correlations with the outcome variable.

3 Results and Interpretation

As Table 1 shows, quite a lot of coefficients are not statistically significant. Ignoring this for a moment, there is a positive relationship between death during, or at the end of the regime and tenure in regime. The same is observed for regime end: with higher deviation from the mean end year of regime, the log-odds of death increases. The opposite effects are observed for female and GDP growth. Being female decreases the log-odds of death during, or at the end of the regime. Higher GDP growth in the country also decreases the log-odds of death. Even though other variables are insignificant, we can still look at their coefficient signs. Being part of the regime in a European country decreases the log-odds of death. The same applies for economists or individuals who were previously military members. The insignificance may stem from the small sample size.

Log-odds can show us relationships between the dependent and independent variables, whereas it is preferable to also use odds and marginal effects to understand the coefficients better. The odds for death are 1,036 times higher when tenure increases by one unit, keeping other variables constant. In other words, the odds for death increase by 3.6% with one year increase. For a one unit increase in the GDP growth in the last 2 years of the regime we expect to see almost 19% decrease in the odds of dying during the regime, i.e. the chance of NOT dying is higher for members whose countries experienced a GDP growth (odds are 0.814; not sure if I should include intercept). The later the regime ended, the higher are the odds of dying during/at the end of the regime (1,058 maybe because many of them ended later?). Even though it is insignificant, being part of a regime in Europe decreases the average probability of death by 10.7 percentage points.

Ill look through the second paragraph later.

- insignificant coefficient on economists due to only 3% of the sample being economists, and approx. 10% are military members. Economists appear to have a *clearer* effect compared to military, but still neither effect is significant
- 2Y growth, tenure, regime end (deviation from the mean end-year) seem like the largest drivers, all three have larger variations (not binary variables)
- Changes from regular estimation to bootstrap:

  highly significant effect of being a woman now (SE's changed from 723 to 0.376)! stronger effect for Economists (twice as large, but much larger standard errors), otherwise no major differences (usually only changes in the second or third decimal point)
- for the presentation: significance can be checked approximately by $coefficient/standard\ error \geq 2$, maybe some finance guys don't know that and I don't include stars for the significance level
- $\mathbb{P}\mathrm{r}(\mathrm{death}_{Hitler} = 1 \mid \mathbf{x}_{Hitler}) = 11.76\%$, so if we observe an infinite amount of Hitlers across identical universes, then only 11.76% of them would be predicted to die during/at the end of their regimes (maybe keep this part for the presentation rather than the handout)

  predicted probabilities based on regular estimation, not bootstrap
- $\mathbb{P}\mathrm{r}(\mathrm{death}_{Goebbles} = 1 \mid \mathbf{x}_{Goebbles}) = 10.86\%$
- still need to find 2-3 suitable candidates for calculating the predicted probabilites (maybe Pol Pot?)

(Katrin and Dominik)

4 Model Diagnostics and Issues

None of the coefficients exhibit a VIF value that seems to lead to any larger concerns, using a critical value of 10 on the determination for problematic imperfect multicollinearity. Some of the standards appear quite large, this is, at least partly, due to the VIFs, as indicated in Table 2 of Appendix A. As is denoted in Table 1, the McFadden R^2 is 0.091, so the model appears to have some explanatory power. To put this in further context, the hit-rate of the model, using a cutoff value of 0.5, is 88.07%, compared to a hit-rate of 87.66% when simply guessing the most likely outcome of not dying. One issue with such a model is, per definition, that external validity is not given, as we pre-select for being part of an authoritarian regime. Furthermore, the inclusion of variables specific for the regime, such as the duration, don't allow for out-of-sample validation methods, only allowing for validation and calibration based on random sub-samples of this particular dataset.

5 Conclusion

The model cannot capture a lot of the country-specific and time-specific factors which drive the unobserved dependent variable, at least given the data available. Thus, we are somewhat limited in the conclusions we are able to draw from this model. However, within this model, the first of four main drivers of the variation of the death probability, the economic growth rates immediately before the regime falls, which negatively influences the unobserved outcome variable. Secondly, the year in which the regime fell, which has a positive sign on the coefficient, additionally, the tenure of the individual member in their respective regime, which also has a positive coefficient. Lastly, female members of totalitarian regimes would have a significantly smaller probability of death, compared to their c.p. male counterparts.

Appendix A: Tables

Table 1: Logistic Regression Results (Bootstrapped Coefficients and Standard Errors)

	Dependent variable: Death Dummy		*Dependent variable:* Death Dummy
Europe Dummy	−1.052 (0.626)	Regime Duration	−0.001 (0.012)
Female Dummy	−15.502 (0.376)	Age at Regime Entrance	0.010 (0.018)
Tenure in Regime	0.036 (0.015)	2Y GDP Growth[1]	−0.208 (0.061)
Economist Dummy	−2.675 (5.511)	Military Dummy	−0.186 (0.560)
Regime End	0.059 (0.024)	Constant	−2.150 (1.025)
Observations	721	Log Likelihood	−245.020
McFadden R^2	0.091		

Note: Bootstrap standard errors of coefficients in round brackets.
[1]Two-year GDP growth measured in the last two years of the respective regimes.

Table 2: Variance Inflation Factors

Europe Dummy	3.54	Regime Duration	3.97	Female Dummy	1.00
Age at Regime Entrance	1.22	Tenure in Regime	1.15	2Y GDP Growth	4.19
Economist Dummy	1.01	Military Dummy	1.39	Regime End	8.01

Appendix B: Project Code

```r
# clear workspace
rm(list = ls())

# load needed libraries
library(readr)
library(pscl)
library(car)
library(pROC)
library(margins)

# read dataset
data <- read_csv("C:/Users/samue/Downloads/Studium/Economics (Master - Vienna)/1. Semester/Microeconome

# check if import worked
head(data)
```

```
## # A tibble: 6 x 22
##   COWCODE STATE REG_START REG_END REG_PARTY REG_REINST ELITE_NAME ELITE_PARTY
##     <dbl> <chr> <chr>     <chr>   <chr>     <chr>      <chr>      <chr>
## 1     255 Germ~ 30/1/1933 23/5/1~ National~ Cabinet    Backe, He~ NSDAP
## 2     255 Germ~ 30/1/1933 23/5/1~ National~ Cabinet    Blomberg,~ Independent
## 3     255 Germ~ 30/1/1933 23/5/1~ National~ Cabinet    Bormann, ~ NSDAP
## 4     255 Germ~ 30/1/1933 23/5/1~ National~ Cabinet    Darré, Ri~ NSDAP
## 5     255 Germ~ 30/1/1933 23/5/1~ National~ Cabinet    Dönitz, K~ NSDAP
## 6     255 Germ~ 30/1/1933 23/5/1~ National~ Cabinet    Dorpmülle~ NSDAP
## # ... with 14 more variables: ELITE_BIRTHDATE <chr>, ELITE_DEATHDATE <chr>,
## #   ELITE_FEMALE <dbl>, ELITE_REENTER <chr>, ELITE_REEXIT <chr>,
## #   ELITE_ENTERAGE <chr>, ELITE_EXITAGE <chr>, ELITE_RETENURE <chr>,
## #   ELITE_EXITTYPE <chr>, ELITE_EXITFATE <chr>, ELITE_EXITLEADER <chr>,
## #   ELITE_REPOSITION <chr>, ELITE_OCCUPATION <chr>, EC_GR_2Y <dbl>
```

```r
head(data$ELITE_NAME)
```

```
## [1] "Backe, Herbert"              "Blomberg, Werner von"
## [3] "Bormann, Martin"             "Darré, Richard Walther"
## [5] "Dönitz, Karl"                "Dorpmüller, Julius Heinrich"
```

```r
table(data$ELITE_EXITFATE)
```

```
##
##             .     Execution         Exile  Incarcerated Incarceration
##            19            13             4             1            23
##           N/A No punishment No Punishment            OK
##             6             2           480            10
```

```r
table(data$ELITE_EXITTYPE)
```

```
##
##              Assassination                       Death
##                          1                          67
##              Death- natural           Death - accidental
##                          1                           1
##        Death - Assassination Death - Automobile accident
##                          1                           1
```

```
##               Death - combat              Death - natural
##                            1                            2
##              Death - Natural              Death - suicide
##                            8                            4
##                     Demotion                    Execution
##                          253                            2
##                    Expulsion                Regime Change
##                           87                          178
##                  Resignation   Ruling Institution Change
##                          185                           10
```

```r
# create dummy for death during regime or at end
dim(data); n <- dim(data)[1]
```

```
## [1] 827  22
```

```r
death1 <- rep(1,n)

# dummy for first type of death
for(i in 1:n){
  death1[i] <- ifelse(data$ELITE_EXITTYPE[i] != 'Demotion'
                      && data$ELITE_EXITTYPE[i] != 'Expulsion'
                      && data$ELITE_EXITTYPE[i] != 'Death- natural'
                      && data$ELITE_EXITTYPE[i] != 'Regime Change'
                      && data$ELITE_EXITTYPE[i] != 'Resignation',1,0)}
table(death1)
```

```
## death1
##   0   1
## 704  98
```

```r
# dummy for second type of death
death2 <- rep(1,n)
for(i in 1:n){
  death2[i] <- ifelse(data$ELITE_EXITFATE[i] == 'Execution',1,0)
}
table(death2)
```

```
## death2
##   0   1
## 545  13
```

```r
# merge dummies
a <- which(death2==1)
b <- which(death1==1)
c <- c(a,b)
death <- rep(0,n)
death[c] <- 1
table(death)
```

```
## death
##   0   1
## 716 111
```

```r
# dummy for country being in europe
EUROPE <- rep(0,n)
for(i in 1:n){
  EUROPE[i] <- ifelse(data$STATE[i] == 'Germany' || data$STATE[i] == 'Poland'
```

```
                   || data$STATE[i] == 'East Germany' || data$STATE[i] == 'Hungary'
                   || data$STATE[i] == 'Norway' || data$STATE[i] == 'Romania'
                   || data$STATE[i] == 'Soviet Union',1,0)
}
table(EUROPE)
```

```
## EUROPE
##   0   1
## 209 618
```

```
# dummy for military as occupation outside of regime
MIL <- rep(0,n)
for(i in 1:n){
  MIL[i] <- ifelse(data$ELITE_OCCUPATION[i] == 'Soldier'
                   || data$ELITE_OCCUPATION[i] == 'State Security'
                   || data$ELITE_OCCUPATION[i] == 'Army officer'
                   || data$ELITE_OCCUPATION[i] == 'Naval officer'
                   || data$ELITE_OCCUPATION[i] == 'Military Police officer'
                   || data$ELITE_OCCUPATION[i] == 'Police officer'
                   || data$ELITE_OCCUPATION[i] == 'Air Force Officer'
                   || data$ELITE_OCCUPATION[i] == 'Air Force officer',1,0)
}
table(MIL)
```

```
## MIL
##   0   1
## 714  95
```

```
# dummy for economists
ECON <- rep(0,n)
for(i in 1:n){
  ECON[i] <- ifelse(data$ELITE_OCCUPATION[i] == 'Economist'
                    || data$ELITE_OCCUPATION[i] == 'economist',1,0)
}
table(ECON)
```

```
## ECON
##   0   1
## 784  25
```

```
# create function to extract date from string
substrRight <- function(x, n){
  substr(x, nchar(x)-n+1, nchar(x))
}

# get regime end year
END <- data$REG_END
END <- substrRight(END, 4)
END <- as.numeric(END)
table(END)
```

```
## END
## 1945 1949 1958 1966 1968 1973 1977 1979 1983 1989 1990 1991 2011 2019
##   71   10    5    4    9    5   12   10   22  223  176  160    4    6
```

```
# get regime start year
START <- as.numeric(substrRight(data$REG_START, 4))
```

```r
table(START)
```

```
## START
## 1922 1933 1942 1944 1945 1947 1948 1949 1955 1957 1963 1966 1969 1971 1973 1975
##  160   51   20  106  117   95   10  129    9    5    4    5   12   16   12   44
## 1976 1979 1992 2010
##   13    9    6    4
```

```r
# take care of regimes that have not ended
END <- ifelse(is.na(END),2020,END)
table(END)
```

```
## END
## 1945 1949 1958 1966 1968 1973 1977 1979 1983 1989 1990 1991 2011 2019 2020
##   71   10    5    4    9    5   12   10   22  223  176  160    4    6  110
```

```r
# variable for regime duration
DURATION <- END-START
table(DURATION)
```

```
## DURATION
##   1   3   4   7   8  12  13  17  27  41  43  44  45  49  69  71
##  19  24  19  18  12  51   9  12   6  69  95 117 140  16 160  60
```

```r
# standardize regime start year
mean(START)
```

```
## [1] 1945.261
```

```r
START <- START-mean(START)

mean(END)
```

```
## [1] 1988.707
```

```r
END <- END - mean(END)

#View(data)



# make data numeric for the model
death <- as.numeric(death)
ELITE_FEMALE <- as.numeric(data$ELITE_FEMALE)
ELITE_ENTERAGE <- as.numeric(data$ELITE_ENTERAGE)
ELITE_RETENURE <- as.numeric(data$ELITE_RETENURE)
EC_GR_2Y <- as.numeric(data$EC_GR_2Y)

# create dataset only based on relevant variables
data0 <- cbind(data$ELITE_NAME,death,EUROPE,START,DURATION,ELITE_FEMALE,
               ELITE_ENTERAGE,ELITE_RETENURE,EC_GR_2Y,ECON,MIL,END)
data <- cbind(death,EUROPE,START,DURATION,ELITE_FEMALE,ELITE_ENTERAGE,
              ELITE_RETENURE,EC_GR_2Y,ECON,MIL,END)

# get vectors for specific people:
hitler <- c(1,data[21,-c(1,3)])
# check if person is correct
data0[21,8] == data[21,7]
```

```
## ELITE_RETENURE
##           TRUE
```

```r
goebbles <- c(1,data[13,-c(1,3)])

# check dimenstion for later calculations
length(hitler)
```

```
## [1] 10
```

```r
t(rep(1,length(hitler)))%*%hitler
```

```
##          [,1]
## [1,] 12.99564
```

```r
data <- as.data.frame(data)
data0 <- as.data.frame(data0)
data0 <- na.exclude(data0)
#View(data0)

# remove NAs
data <- na.exclude(data)

#View(data)


# logit model
model1 <- glm(death ~ EUROPE+START+DURATION+ELITE_FEMALE+ELITE_ENTERAGE
              +ELITE_RETENURE+EC_GR_2Y+ECON+MIL,
    family = binomial(link = 'logit'), data=data)
summary(model1)
```

```
##
## Call:
## glm(formula = death ~ EUROPE + START + DURATION + ELITE_FEMALE +
##     ELITE_ENTERAGE + ELITE_RETENURE + EC_GR_2Y + ECON + MIL,
##     family = binomial(link = "logit"), data = data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1440  -0.5687  -0.4116  -0.3107   2.9320
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -4.54890    1.12984  -4.026 5.67e-05 ***
## EUROPE          -1.06026    0.57492  -1.844 0.065157 .
## START            0.05698    0.02149   2.652 0.007998 **
## DURATION         0.05515    0.01421   3.882 0.000104 ***
## ELITE_FEMALE   -15.55979  723.00312  -0.022 0.982830
## ELITE_ENTERAGE   0.01017    0.01389   0.732 0.464133
## ELITE_RETENURE   0.03543    0.01424   2.488 0.012839 *
## EC_GR_2Y        -0.20591    0.05481  -3.756 0.000172 ***
## ECON            -0.43318    0.75572  -0.573 0.566505
## MIL             -0.15738    0.46691  -0.337 0.736062
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 538.91  on 720  degrees of freedom
## Residual deviance: 490.04  on 711  degrees of freedom
## AIC: 510.04
##
## Number of Fisher Scoring iterations: 16
```

```
# pseudo R2s
pR2(model1)
```

```
## fitting null model for pseudo-r2
```

```
##           llh       llhNull            G2      McFadden          r2ML
## -245.01964860 -269.45408398   48.86887076    0.09068126    0.06553331
##          r2CU
##    0.12448740
```

```
# variance inflation factors
vif(model1)
```

```
##         EUROPE          START       DURATION   ELITE_FEMALE ELITE_ENTERAGE
##       3.543817      11.733995       5.790912       1.000000       1.219254
## ELITE_RETENURE        EC_GR_2Y           ECON            MIL
##       1.151339       4.189975       1.011020       1.394974
```

```
# cor(data) shows correlations across all variables
cor(EUROPE,START)
```

```
## [1] -0.7091193
```

```
# model without START
model2 <- glm(death ~ EUROPE+DURATION+ELITE_FEMALE+ELITE_ENTERAGE+ELITE_RETENURE
              +EC_GR_2Y+ECON+MIL+END,
    family = binomial(link = 'logit'), data = data)
summary(model2)
```

```
##
## Call:
## glm(formula = death ~ EUROPE + DURATION + ELITE_FEMALE + ELITE_ENTERAGE +
##     ELITE_RETENURE + EC_GR_2Y + ECON + MIL + END, family = binomial(link = "logit"),
##     data = data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1440  -0.5687  -0.4116  -0.3107   2.9320
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -2.073215   0.841672  -2.463 0.013770 *
## EUROPE          -1.060259   0.574921  -1.844 0.065157 .
## DURATION        -0.001833   0.011757  -0.156 0.876084
## ELITE_FEMALE   -15.559791 723.003116  -0.022 0.982830
## ELITE_ENTERAGE   0.010169   0.013891   0.732 0.464133
## ELITE_RETENURE   0.035427   0.014238   2.488 0.012839 *
## EC_GR_2Y        -0.205906   0.054814  -3.756 0.000172 ***
## ECON            -0.433185   0.755722  -0.573 0.566505
```

```
## MIL              -0.157384   0.466913  -0.337 0.736062
## END               0.056983   0.021486   2.652 0.007998 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 538.91  on 720  degrees of freedom
## Residual deviance: 490.04  on 711  degrees of freedom
## AIC: 510.04
##
## Number of Fisher Scoring iterations: 16
```

```r
pR2(model2)
```

```
## fitting null model for pseudo-r2
```

```
##          llh      llhNull           G2     McFadden         r2ML
## -245.01964860 -269.45408398   48.86887076    0.09068126    0.06553331
##         r2CU
##   0.12448740
```

```r
# Variance Inflation Factors
vif(model2)
```

```
##         EUROPE       DURATION   ELITE_FEMALE ELITE_ENTERAGE ELITE_RETENURE
##       3.543817       3.966153       1.000000       1.219254       1.151339
##       EC_GR_2Y           ECON            MIL            END
##       4.189975       1.011020       1.394974       8.011559
```

```r
############################################
######### BOOTSTRAP ETIMATION ##############
############################################

set.seed(1234); N <- 500
Coeff_boot <- matrix(rep(0,N*10),ncol = 10, nrow = 500)
for(i in 1:N){
  boot_sample <- sample(1:n,size = n,replace = TRUE)
  mod_boot <- glm(death ~ EUROPE+DURATION+ELITE_FEMALE+ELITE_ENTERAGE+ELITE_RETENURE
             +EC_GR_2Y+ECON+MIL+END,
    family = binomial(link = 'logit'), data = data[boot_sample,])
  Coeff_boot[i,] <- mod_boot$coefficients
}
coeff_boot <- apply(Coeff_boot,2,mean)
se_boot <- rep(0,10)
for(i in 1:10){
  se_boot[i] <- sqrt(var(Coeff_boot[,i]))
}
txt <- c('Intercept','EUROPE','DURATION','FEMALE','AGE','TENURE',
         '2YGR','ECON','MIL','END')
rbind(txt,round(coeff_boot,3),round(se_boot,3))
```

```
##     [,1]        [,2]     [,3]       [,4]      [,5]    [,6]     [,7]
## txt "Intercept" "EUROPE" "DURATION" "FEMALE"  "AGE"   "TENURE" "2YGR"
##     "-2.15"     "-1.052" "-0.001"   "-15.502" "0.01"  "0.036"  "-0.208"
##     "1.025"     "0.626"  "0.012"    "0.376"   "0.018" "0.015"  "0.061"
##     [,8]     [,9]     [,10]
```

```
## txt "ECON"   "MIL"    "END"
##     "-2.675" "-0.186" "0.059"
##     "5.511"  "0.56"   "0.024"
```

```r
# get hit rate of the model with a 0.5 cutoff (based on original model)
cutoff <- 0.5
# get predicted probabilities
latent_pred <- predict.glm(model2,type = 'response')
# get binary result from the cutoff
latent_bin <- ifelse(latent_pred >= cutoff,1,0)
# hitrate
mean(latent_bin==data$death)
```

```
## [1] 0.8807212
```

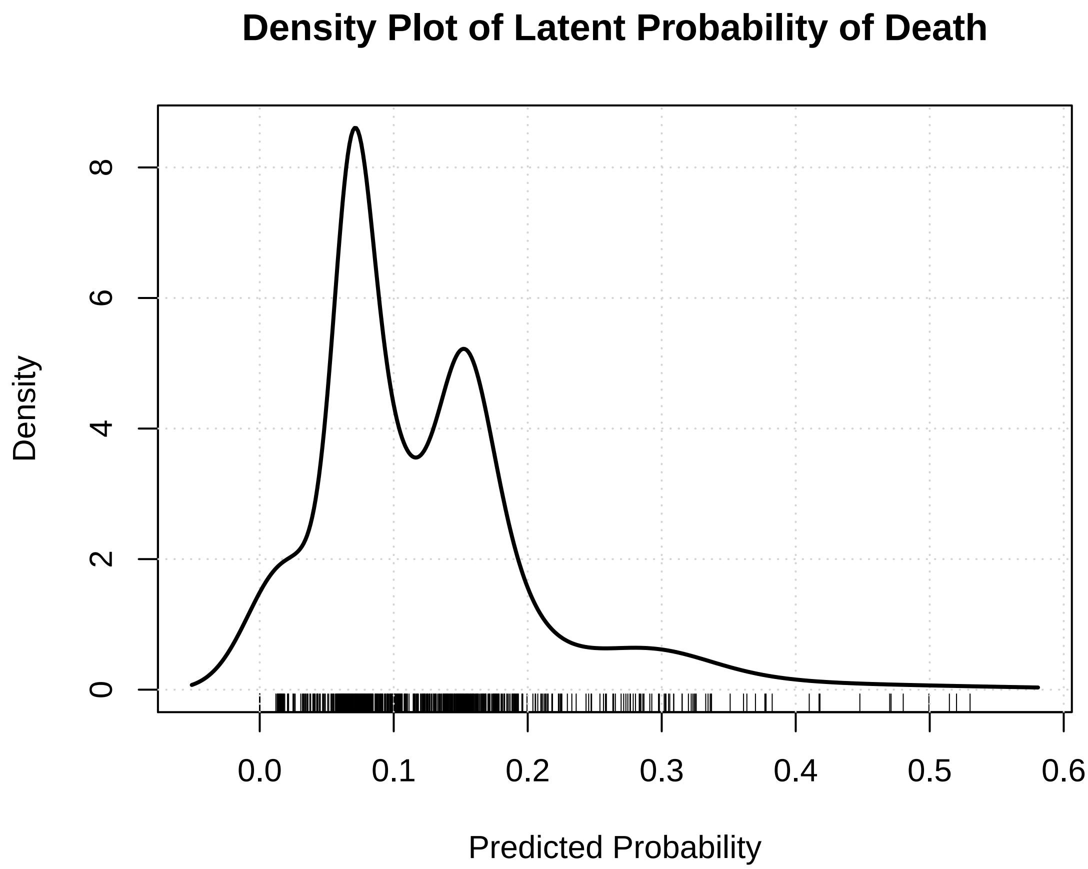
```r
# percentage by just guessing more likely outcome
1-mean(data$death)
```

```
## [1] 0.8765603
```

```r
# maximal predicted probability
max(latent_pred)
```

```
## [1] 0.5301167
```

```r
densityPlot(latent_pred, ylab = 'Density',
            xlab = 'Predicted Probability',
            main = 'Density Plot of Latent Probability of Death')
```




```
# check coefficient vector lengths
length(model2$coefficients);length(hitler)
```

```
## [1] 10
```

```
## [1] 10
```

```
# check vectors for matching variables
hitler
```

```
##                      EUROPE      DURATION  ELITE_FEMALE ELITE_ENTERAGE
##         1.00000     1.00000     12.00000      0.00000      43.80822
## ELITE_RETENURE    EC_GR_2Y         ECON          MIL           END
##        12.25479   -13.36000      0.00000      0.00000     -43.70738
```

```
model2$coefficients
```

```
##     (Intercept)        EUROPE      DURATION  ELITE_FEMALE ELITE_ENTERAGE
##    -2.073214543  -1.060258788  -0.001833297 -15.559790990   0.010168763
## ELITE_RETENURE      EC_GR_2Y          ECON           MIL           END
##     0.035427232  -0.205906013  -0.433184552  -0.157384010   0.056982796
```

```
# get probabilities
Pr_hitler <- 1/(1+exp(-t(model2$coefficients)%*%(hitler)))
Pr_hitler
```

```
##           [,1]
```

```
## [1,] 0.1175843
```

```r
Pr_goebbles <- 1/(1+exp(-t(model2$coefficients)%*%(goebbles)))
Pr_goebbles
```

```
##           [,1]
## [1,] 0.1086048
```

```r
# verify that the model would predict wrongly
latent_bin[21]==data$death[21]
```

```
##    21
## FALSE
```

```r
latent_bin[13]==data$death[13]
```

```
##    13
## FALSE
```

```r
# Get the predicted probabilities for Hitler, Goebbels, someone from
# SE Asia (no external war), Stalin (communist).

# check for percentage of economists and military
mean(na.omit(data$ECON)); mean(na.omit(data$MIL))
```

```
## [1] 0.03467406
```

```
## [1] 0.1054092
```

```r
mean(na.omit(data$death))
```

```
## [1] 0.1234397
```

```r
# average marginal effects
mar <- margins(model2)
summary(mar)
```

```
##          factor     AME      SE       z      p     lower    upper
##        DURATION -0.0002  0.0012 -0.1559 0.8761   -0.0025   0.0021
##        EC_GR_2Y -0.0207  0.0055 -3.7574 0.0002   -0.0315  -0.0099
##            ECON -0.0436  0.0760 -0.5732 0.5665   -0.1925   0.1054
##  ELITE_ENTERAGE  0.0010  0.0014  0.7323 0.4640   -0.0017   0.0038
##    ELITE_FEMALE -1.5644 72.6939 -0.0215 0.9828 -144.0418 140.9129
##  ELITE_RETENURE  0.0036  0.0014  2.4976 0.0125    0.0008   0.0064
##             END  0.0057  0.0022  2.6537 0.0080    0.0015   0.0100
##          EUROPE -0.1066  0.0575 -1.8527 0.0639   -0.2194   0.0062
##             MIL -0.0158  0.0469 -0.3372 0.7360   -0.1078   0.0762
```

```r
mean(na.omit(data$ELITE_FEMALE))
```

```
## [1] 0.04022191
```

```r
mean(na.omit(data$death[na.omit(data$ELITE_FEMALE) == 1]))
```

```
## [1] 0
```

```r
# turns out no women died
```

References

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