MSD 2019 Final Project

A replication and extension of Ethnicity, Insurgency, and Civil War by James D. Fearon & David D. Laitin, American Political Science Review

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Paper Overview

Fearon and Laitin analyzed post-WWII global civil wars to see if they could create a model to predict the likelihood of civil war onset. They investigated unique characteristics of the countries at hand to see if they could hypothesize which variable played the biggest role in the making of the civil war. Such as poverty, political instability, ethnic and religious diversity.

They defined civil war as conflicts that meet three criteria: involved fighting between agents of a state and organized nonstate groups who sought to take control of a government policicies, the conflict killed at least 1,000 over its course with at least an average of 100 yearly deaths, and at least 100 were killed on both sides, including civilians attacked by rebels

Eleven hypotheses were were investigated. For example one was: "measures of country's ethnic or religious diversity should be associated with a higher risk of civil war." And most of the other followed suit but with different parameters in the hypothesis.

The paper concluded that there was not enough evidence to conclude that any of the hypothesis were on target and finished with saying that civil wars are incredible hard to predict, but it is easier to predict insurgencies. It includes a cast of doubt on three wide-held notions concerning political conflict findings: prevalence of civil war in the 1990s was not due to the end of the Cold War, greater religious and/or ethnic diversity, on its own does not make a country more prone to civil war, and cannot predict where a civil war will break out - based off of strong ethnic or political grievances.

FIGURE 2. Probability of Civil War Onset per Five-Year Period

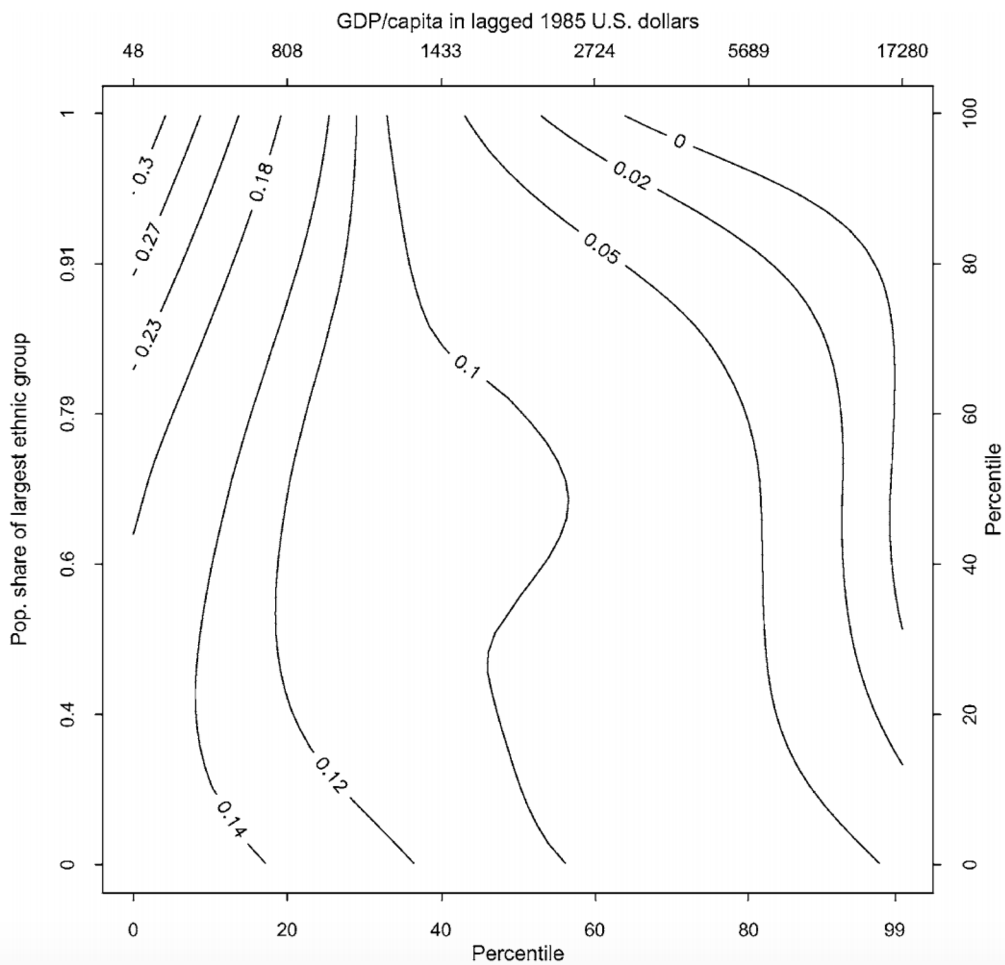


Figure 1: Figure 1

Figures

We seek to replicate the following two figures from the paper. Figure 1 plots the number of countries with ongoing civil wars by year, from 1945 to 1999 (solid line). The paper also shows the proportion of countries with at least one ongoing war in each year (dashed line). What is interesting is that this graph indicates that post-1990s civil wars were not due to the effects of the fall of the Berlin Wall (which signified the end of the Cold War). However, conflicts associated with the fall of the Soviet Union were partly responsible for the sharp increase we witness in the early 1990s.

Overview of Data

Their dataset uses data across the world from the period of 1945-1999 on 161 countries that had a population of at least hal a million in 1990.

It includes information on the contries: economy, location, population, employment, minerals/resources, civil war information (time frame, deaths, leader, etc.), ethnic onset, oil, GDP, Colonial country, religion percentage, and more. It allows us to explore various parameteres.

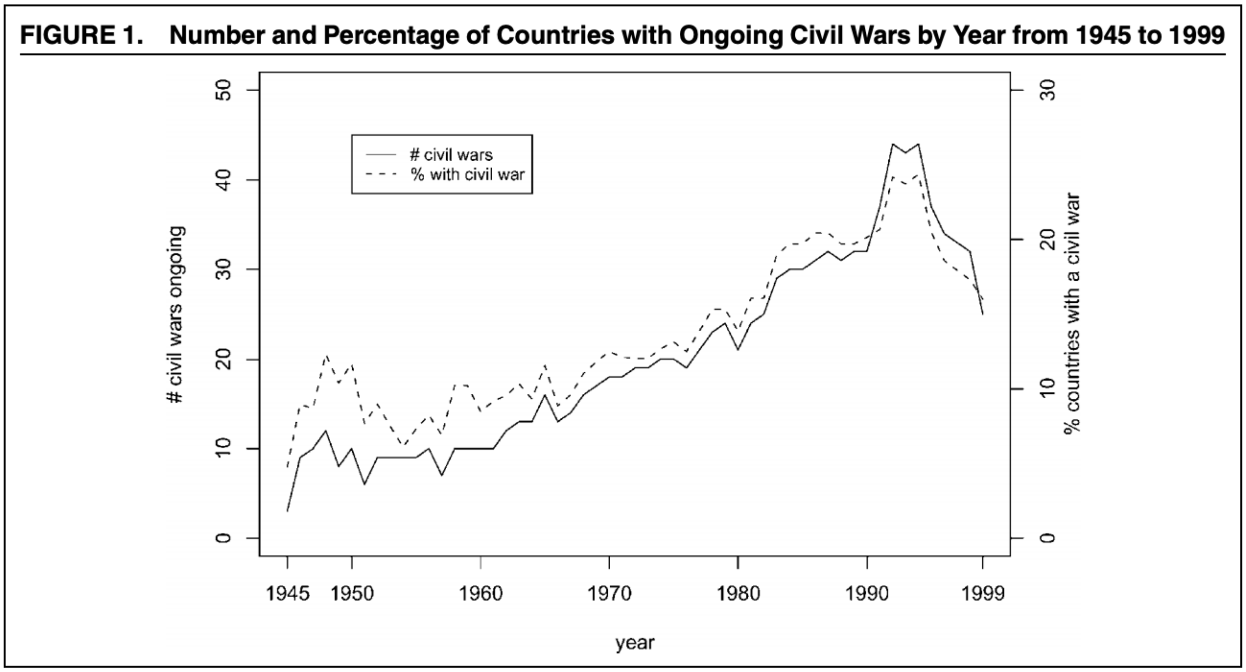


Figure 2: Figure 2

Conclusions

Our conclusion for the replication of Figures 1&2 (AYSHA)

Our conclusion for the replication of first column of table 1 (CHAIM)

Our conclusion for the extensions

By Continent:

The reason we wanted to see how the civil wars broke down by continent is that we could more accurately use a historical events timeline. So we know that the end of a Cold War was not a as important event as people originally claims. The Cold War ended in 1991, ans you can see from the figure it was in fact South Africa region that has a increase along with Asia, but eastern European actually saw a decrease after that time period. Before 1960 the civil wars was dominated by Asia and Eastern Europe (which historically is accurate). Then the colonial civil wars started to take place (North Africa and Middle East/ South Africa), and consistently played a key rile in the overall average of the civil wars in the world.

Predictability of model

Thoughts on the papers conclusions.

The authors of the paper conclude that "…the civil wars of the period have structural roots, in the combination of a simple, robust military technology and decolonization, which created an international system numerically dominated by fragile states with limited administrative control of their peripheries." Having a poor economy with a bleak future can make joining an insurgency an appealing option for someone who feels they will not have a successful future. So an environment with a weak government that doesn't back up a robust economic system is a good breeding ground for an insurgency. Ethnic diversity on it's own may not necessarily preclude a civil war becuase as long as there are jobs available and the potential to succeed in life, younger people will not see joining a war as an appealing option.

Figure 1 Replication

```r
repdata <- read.dta("./data/repdata.dta")

glance(repdata)
```

```
## Warning: 'glance.data.frame' is deprecated.
## See help("Deprecated")
```

```
## # A tibble: 1 x 4
##    nrow  ncol complete.obs na.fraction
##   <int> <int>        <int>       <dbl>
## 1  6610    69           69      0.0765
```

```r
# View(repdata)

sumwars_per_year <- repdata %>%
  group_by(year) %>%
  filter(war == 1) %>%
  summarize(
    count_wars_total = sum(wars)
  )

wars_per_year <- repdata %>%
  group_by(year) %>%
  filter(war == 1) %>%
  summarize(
    count_wars = sum(war)
  )

raw_num_countries <- repdata %>%
  group_by(year) %>%
  summarize(
    count_countries = sum(n())
  ) %>%
  ungroup(year)

perc_civil_war <- merge(wars_per_year, raw_num_countries, by = "year")
perc_civil_war <- merge(perc_civil_war, sumwars_per_year, by = "year")

# View(perc_civil_war)

perc_civil_war$perc <- (perc_civil_war$count_wars/perc_civil_war$count_countries)*100

plot(perc_civil_war$year, perc_civil_war$count_wars_total, axes = FALSE,
     ylim = c(0, 50), xlab = "", ylab = "", type = "l",
     col = "blue", main = "# and % of Countries with Ongoing Civil Wars (1945-1999)")
axis(2, ylim = c(0, 50), col = "black", las = 1)
mtext("# Ongoing Wars", side = 2, col = "black", line = 2.5)

# Plot the second plot and draw the axis on the right
par(new = TRUE)
plot(perc_civil_war$year, perc_civil_war$perc, pch = "solid", xlab = "", ylab = "", ylim = c(0, 30), axe
mtext("% Countries with a Civil War", side = 4, col = "black", line = 2.5)
axis(4, ylim = c(0, 30), col = "black", col.axis = "black")
```

```
# Draw the time axis
axis(1, pretty(range(perc_civil_war$year), 4))
mtext("Year", side = 1, col = "black", line = 2.5)

# Draw the legend
legend("topleft", legend = c("# civil wars", "% with civil war"),
       text.col = c("blue", "red"), col = c("blue", "red"), lty = 1:2, cex = 0.7)
```

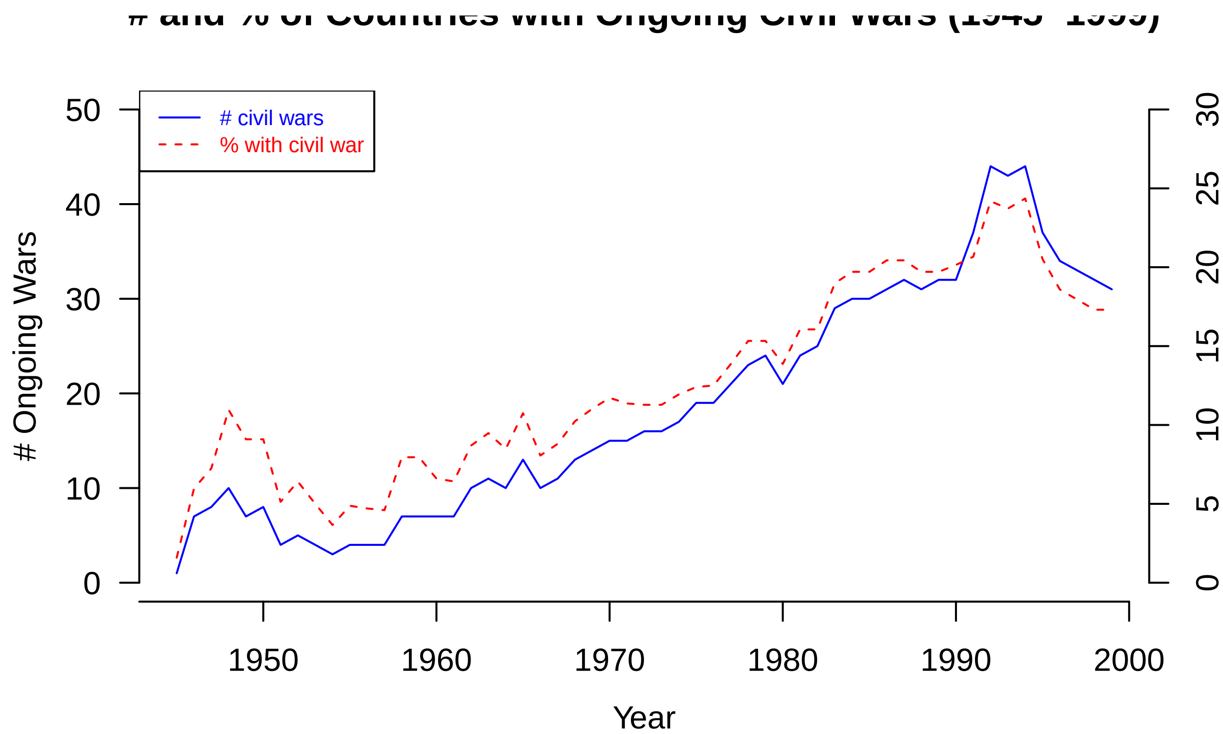


Figure 2 Replication: Part A

```
gdp_per_year <- repdata %>%
  drop_na(gdpen) %>%
  drop_na(pop) %>%
  group_by(year) %>%
  summarize(
    gdp_sum = sum(gdpen),
    pop_sum = sum(pop)
  )

gdp_per_year$gdp_pc <- gdp_per_year$gdp_sum / gdp_per_year$pop_sum * 10000

gdp_per_year_perc <- merge(gdp_per_year, perc_civil_war, by = "year")
gdp_per_year_perc$cv_percentile <- round(gdp_per_year_perc$perc / max(gdp_per_year_perc$perc), digits =

# View(gdp_per_year_perc)

gdp_per_year_perc %>%
  ggplot(aes(x = perc, y = gdp_pc)) +
```

```
  geom_line(color = "red")
```

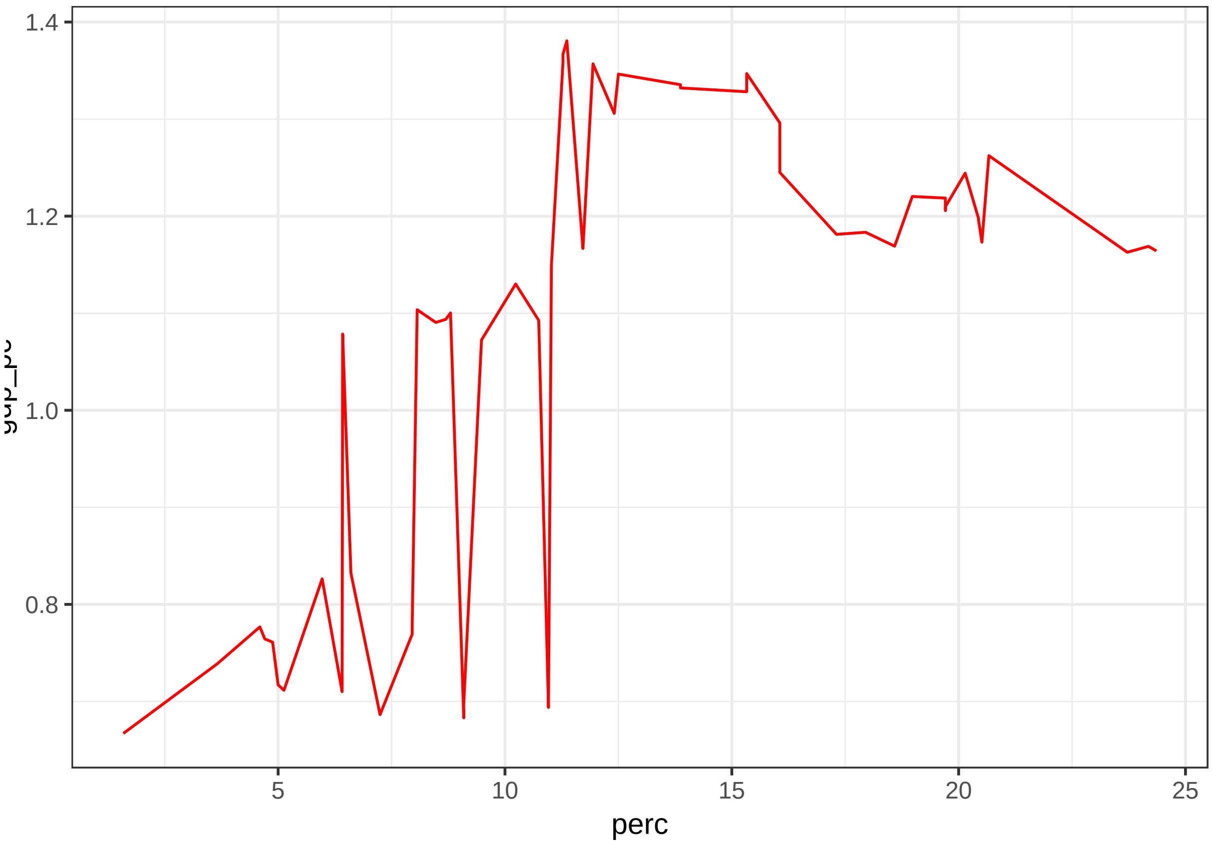
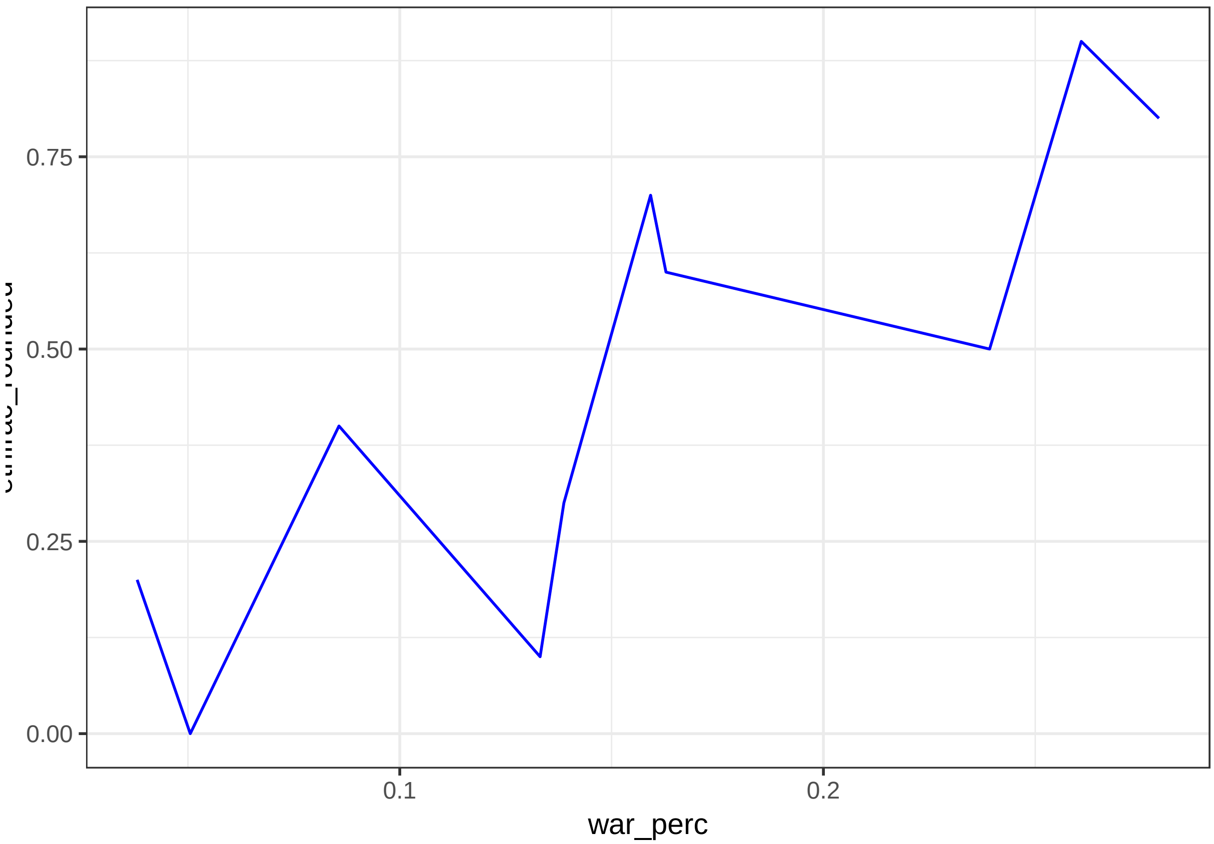


Figure 2 Replication: Part B

```
rep_data_eth <- repdata %>%
  select(ethfrac, war) %>%
  mutate(ethfrac_rounded = round(ethfrac, digits = 1)) %>%
  group_by(ethfrac_rounded) %>%
  summarize(
    sum_countries = sum(n()),
    sumwars_per_eth = sum(war)
  )

rep_data_eth$war_perc = rep_data_eth$sumwars_per_eth/rep_data_eth$sum_countries

# View(rep_data_eth)

rep_data_eth %>%
  ggplot(aes(x = war_perc, y = ethfrac_rounded)) +
  geom_line(color = "blue")
```




```r
# using everything the paper does for table 1
mylogit1 <- glm(as.factor(onset) ~ warl + gdpenl + lpopl1 + lmtnest
+ ncontig + Oil + nwstate + instab + polity2l + ethfrac + relfrac,  data =repdata, family = "binomial")
summary(mylogit1)
```

```
##
## Call:
## glm(formula = as.factor(onset) ~ warl + gdpenl + lpopl1 + lmtnest +
##     ncontig + Oil + nwstate + instab + polity2l + ethfrac + relfrac,
##     family = "binomial", data = repdata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1412  -0.2001  -0.1446  -0.1011   3.4209
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -6.73134    0.73577  -9.149  < 2e-16 ***
## warl        -0.95437    0.31439  -3.036 0.002400 **
## gdpenl      -0.34386    0.07179  -4.790 1.67e-06 ***
## lpopl1       0.26294    0.07271   3.616 0.000299 ***
## lmtnest      0.21880    0.08475   2.582 0.009830 **
## ncontig      0.44333    0.27399   1.618 0.105646
## Oil          0.85764    0.27919   3.072 0.002127 **
## nwstate      1.70946    0.33859   5.049 4.45e-07 ***
## instab       0.61754    0.23510   2.627 0.008621 **
## polity2l     0.02086    0.01677   1.244 0.213536
```

```
## ethfrac      0.16641    0.37310   0.446 0.655581
## relfrac      0.28505    0.50874   0.560 0.575273
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1077.1  on 6326  degrees of freedom
## Residual deviance:  960.8  on 6315  degrees of freedom
##   (283 observations deleted due to missingness)
## AIC: 984.8
##
## Number of Fisher Scoring iterations: 8
```

```r
# removing gdp
mylogit2 <- glm(as.factor(onset) ~ warl  + lpopl1 + lmtnest
+ ncontig + Oil + nwstate + instab + polity2l + ethfrac + relfrac,  data =repdata, family = "binomial")
summary(mylogit2)
```

```
##
## Call:
## glm(formula = as.factor(onset) ~ warl + lpopl1 + lmtnest + ncontig +
##     Oil + nwstate + instab + polity2l + ethfrac + relfrac, family = "binomial",
##     data = repdata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8162  -0.1932  -0.1491  -0.1163   3.3182
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -7.67571    0.72234 -10.626  < 2e-16 ***
## warl        -0.68283    0.30477  -2.240  0.02506 *
## lpopl1       0.22684    0.07548   3.005  0.00265 **
## lmtnest      0.26306    0.08308   3.166  0.00154 **
## ncontig      0.32127    0.26854   1.196  0.23155
## Oil          0.44160    0.26035   1.696  0.08985 .
## nwstate      2.13690    0.31199   6.849 7.43e-12 ***
## instab       0.90637    0.22928   3.953 7.72e-05 ***
## polity2l    -0.02102    0.01525  -1.379  0.16802
## ethfrac      0.88025    0.37415   2.353  0.01864 *
## relfrac      0.22592    0.48826   0.463  0.64357
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1116.4  on 6525  degrees of freedom
## Residual deviance: 1029.4  on 6515  degrees of freedom
##   (84 observations deleted due to missingness)
## AIC: 1051.4
##
## Number of Fisher Scoring iterations: 7
```

```r
set.seed(42)
ndx <- sample(nrow(repdata), floor(nrow(repdata) * 0.9))
train <- repdata[ndx,]
test <- repdata[-ndx,]
logit_train <- glm(as.factor(onset) ~ warl + gdpenl + lpopl1 + lmtnest
+ ncontig + Oil + nwstate + instab + polity2l + ethfrac + relfrac,  data = train, family = "binomial")
summary(logit_train)
```

```
##
## Call:
## glm(formula = as.factor(onset) ~ warl + gdpenl + lpopl1 + lmtnest +
##     ncontig + Oil + nwstate + instab + polity2l + ethfrac + relfrac,
##     family = "binomial", data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1437  -0.2014  -0.1451  -0.1008   3.3906
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -6.62714    0.76593  -8.652  < 2e-16 ***
## warl        -0.87960    0.31970  -2.751  0.00594 **
## gdpenl      -0.34254    0.07488  -4.574 4.77e-06 ***
## lpopl1       0.25003    0.07611   3.285  0.00102 **
## lmtnest      0.24011    0.08961   2.680  0.00737 **
## ncontig      0.47678    0.28514   1.672  0.09451 .
## Oil          0.87021    0.29461   2.954  0.00314 **
## nwstate      1.75250    0.36410   4.813 1.49e-06 ***
## instab       0.73598    0.23917   3.077  0.00209 **
## polity2l     0.01970    0.01756   1.122  0.26198
## ethfrac      0.06207    0.39135   0.159  0.87399
## relfrac      0.23315    0.52908   0.441  0.65946
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 982.53  on 5697  degrees of freedom
## Residual deviance: 876.39  on 5686  degrees of freedom
##   (251 observations deleted due to missingness)
## AIC: 900.39
##
## Number of Fisher Scoring iterations: 8
```

```r
pred <- predict(logit_train, test, type="response")
summary(pred)
```

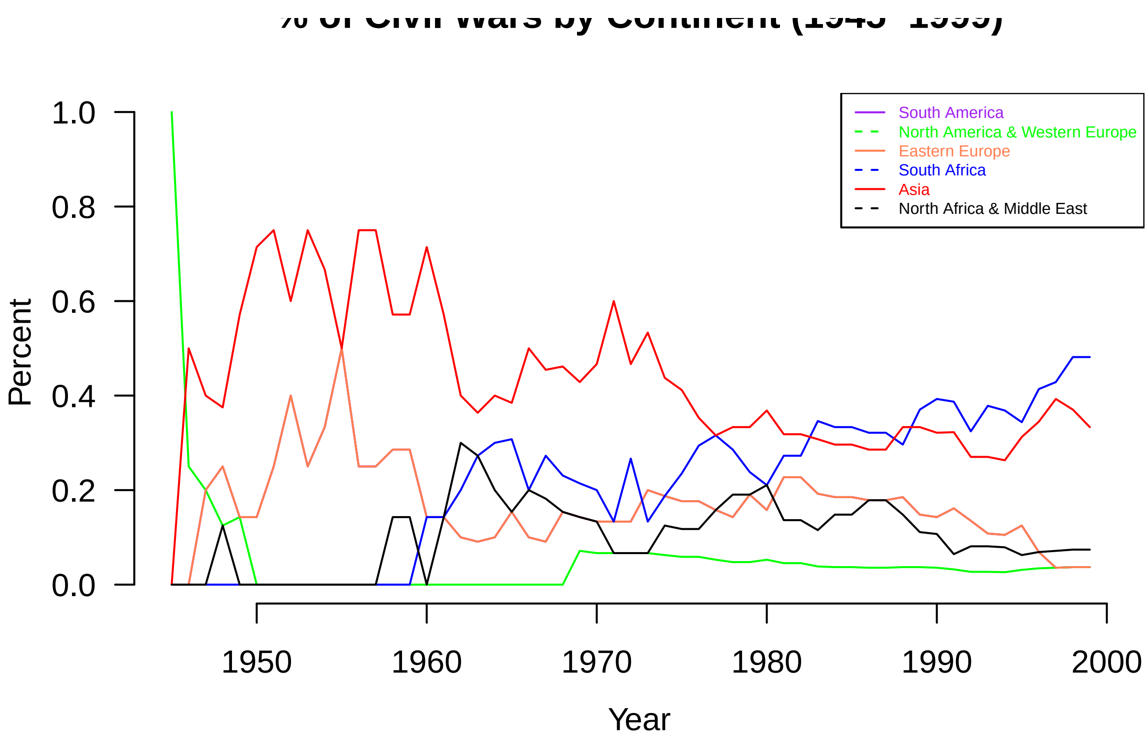
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## 0.00000 0.00569 0.01092 0.01919 0.02140 0.48006      32
```

```r
#(as.factor(test$onset))
yTest <- as.factor(test$onset)
```

Extensions

```
sumwars_per_year <- repdata %>% group_by(year) %>% filter(war == 1) %>%summarize(count_wars_total = sum

wars_per_year <- repdata %>% group_by(year) %>%filter(war == 1) %>%summarize(count_wars = sum(war))

raw_num_countries <- repdata %>% group_by(year) %>% summarize(count_countries = sum(n())) %>%ungroup(yea

perc_civil_war <- merge(wars_per_year, raw_num_countries, by = "year")
perc_civil_war <- merge(perc_civil_war, sumwars_per_year, by = "year")
#perc_civil_war$perc <- (perc_civil_war$count_wars/perc_civil_war$count_countries)*100

southamerica <- repdata  %>%
  filter (lamerica == 1)

wars_per_year_SA <- southamerica %>% group_by(year) %>%
  summarize(count_wars = sum(war))

percent_SA <- (wars_per_year_SA$count_wars/perc_civil_war$count_wars)
plot(wars_per_year_SA$year, percent_SA, axes = FALSE,
     ylim = c(0, 1), xlim = c(1945, 2000), xlab = "" , ylab = "", type = "l",
     col = "purple", main = "% of Civil Wars by Continent (1945-1999)")

western <- repdata %>% filter (western == 1)
wars_per_year_WS <- western %>% group_by(year)  %>% summarize(count_wars = sum(war))
percent_WS <- (wars_per_year_WS$count_wars/perc_civil_war$count_wars)
lines(wars_per_year_WS$year, percent_WS, col = "green")

easteurope <- repdata  %>% filter (eeurop == 1)
wars_per_year_EE <- easteurope %>% group_by(year)  %>% summarize(count_wars = sum(war))
percent_EE <- (wars_per_year_SA$count_wars/perc_civil_war$count_wars)
lines(wars_per_year_EE$year, percent_EE, col = "coral")

southafrica <- repdata  %>% filter (ssafrica == 1)
wars_per_year_SAF <- southafrica%>% group_by(year)  %>% summarize(count_wars = sum(war))
percent_SAF <- (wars_per_year_SAF$count_wars/perc_civil_war$count_wars)
lines(wars_per_year_SAF$year, percent_SAF, col = "blue")

asia <- repdata  %>% filter (asia == 1)
wars_per_year_AS <- asia %>% group_by(year)  %>% summarize(count_wars = sum(war))
percent_AS <- (wars_per_year_AS$count_wars/perc_civil_war$count_wars)
lines(wars_per_year_AS$year, percent_AS, col = "red")

northafricamiddleeast <- repdata %>% filter (nafrme == 1)
wars_per_year_NAM <- northafricamiddleeast %>% group_by(year)  %>% summarize(count_wars = sum(war))
percent_NAM <- (wars_per_year_NAM$count_wars/perc_civil_war$count_wars)
lines(wars_per_year_NAM$year, percent_NAM, col = "black")

#sumwars_per_year <- repdata %>% group_by(year) %>% filter(war == 1) %>% summarize(count_wars = sum(war
#lines(sumwars_per_year$year, sumwars_per_year$count_wars, col = "darkgreen")

axis(2, ylim = c(0, 1), col = "black", las = 1)
axis(1, xlim = c(1945, 1999), col = "black", las = 1)
```

```r
mtext("Percent ", side = 2, col = "black", line = 2.5)
mtext("Year", side = 1, col = "black", line = 2.5)
#legend("topleft", legend = c("South America", "North America & Western Europe", "Eastern Europe","Sout
#text.col = c("purple", "green", "coral", "blue", "red", "orange", "darkgreen"), col = c("purple", "gre
legend("topright", legend = c("South America", "North America & Western Europe", "Eastern Europe","Sout
       text.col = c("purple", "green", "coral", "blue", "red", "black"), col = c("purple", "green", "co
```




```r
repdata <- repdata %>% group_by(war) %>% mutate(outcome = ifelse(war == 1 ,'civil_war','no_war'))
repdata$outcome <- as.factor(repdata$outcome)
# View(repdata)

set.seed(42)
ndx <- sample(nrow(repdata), floor(nrow(repdata) * 0.9))
train <- repdata[ndx,]
test <- repdata[-ndx,]

xTrain <- train[,-70]
yTrain <- train$outcome

xTest <- test[,-70]
yTest <- test$outcome

# model <- naiveBayes(xTrain, yTrain)
# summary(model)

model <- naiveBayes(outcome ~ warl + gdpenl + lpopl1 + lmtnest
+ ncontig + Oil + nwstate + instab + polity2l + ethfrac + relfrac,  data = train, family = "binomial")
summary(model)
```

```
##           Length Class  Mode
```

```
## apriori    2     table  numeric
## tables    11     -none- list
## levels     2     -none- character
## isnumeric 11     -none- logical
## call       5     -none- call
```

```r
df <- data.frame(actual = yTest, pred = predict(model, test))
```

```
## Warning in data.matrix(newdata): NAs introduced by coercion

## Warning in data.matrix(newdata): NAs introduced by coercion

## Warning in data.matrix(newdata): NAs introduced by coercion

## Warning in data.matrix(newdata): NAs introduced by coercion
```

```r
head(df)
```

```
##   actual   pred
## 1 no_war no_war
## 2 no_war no_war
## 3 no_war no_war
## 4 no_war no_war
## 5 no_war no_war
## 6 no_war no_war
```

```r
table(df)
```

```
##            pred
## actual      civil_war no_war
##   civil_war        90      9
##   no_war            5    557
```

```r
# accuracy: fraction of correct classifications
df %>%
  summarize(acc = mean(pred == actual))
```

```
##       acc
## 1 0.97882
```

```r
# precision: fraction of positive predictions that are actually true
df %>%
  filter(pred == 'civil_war') %>%
  summarize(prec = mean(actual == 'civil_war'))
```

```
##        prec
## 1 0.9473684
```

```r
# recall: fraction of true examples that we predicted to be positive
# aka true positive rate, sensitivity
df %>%
  filter(actual == 'civil_war') %>%
  summarize(recall = mean(pred == 'civil_war'))
```

```
##      recall
## 1 0.9090909
```

```r
# false positive rate: fraction of false examples that we predicted to be positive
df %>%
```

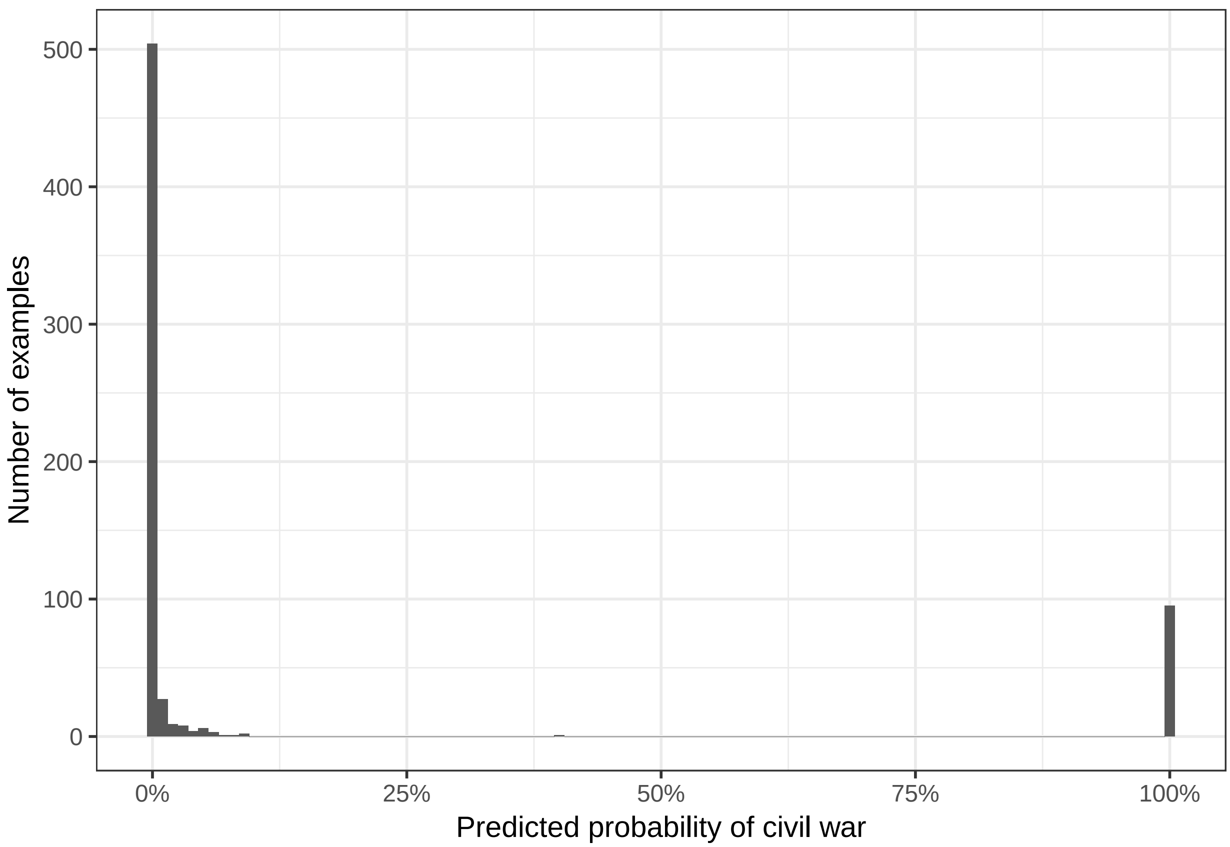
```r
  filter(actual == 'no_war') %>%
  summarize(fpr = mean(pred == 'civil_war'))
```

```
##           fpr
## 1 0.008896797
```

```r
# plot histogram of predicted probabilities
# note overconfident predictions
probs <- data.frame(predict(model, test, type="raw"))
```

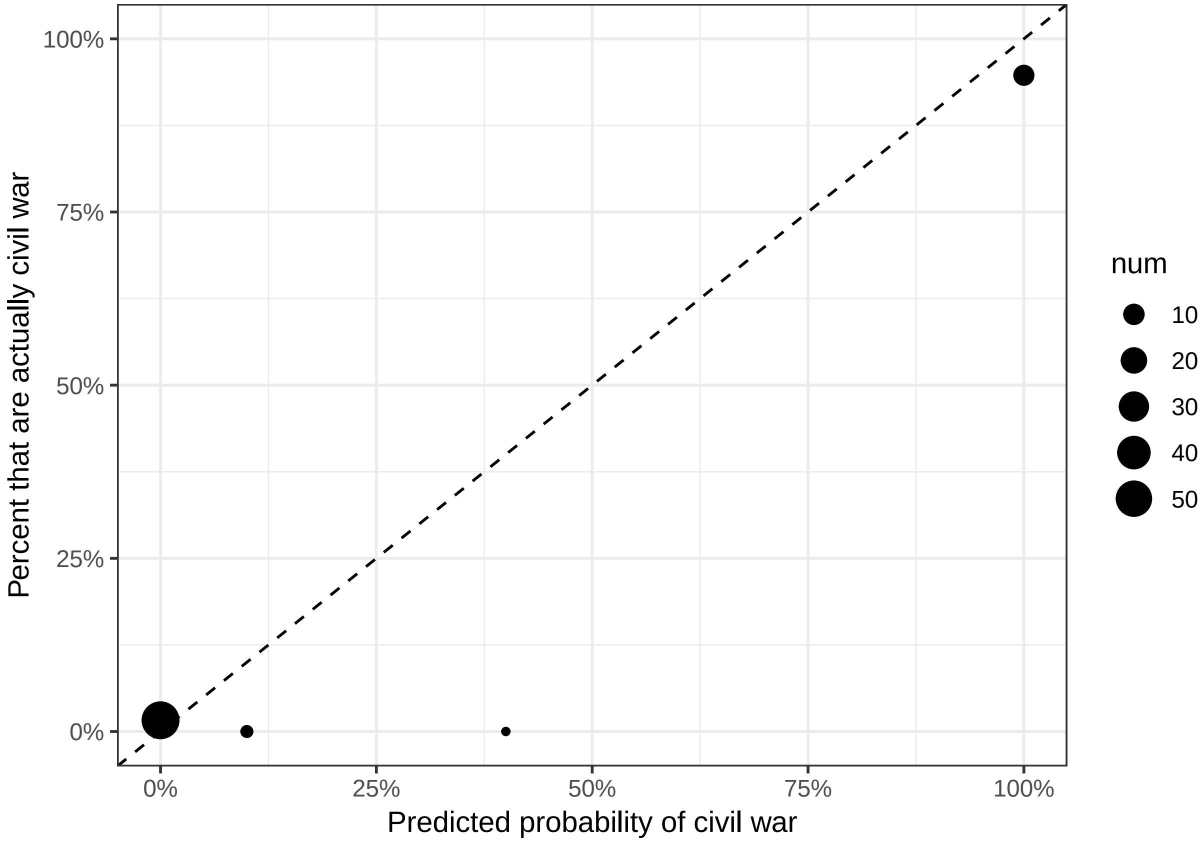
```
## Warning in data.matrix(newdata): NAs introduced by coercion

## Warning in data.matrix(newdata): NAs introduced by coercion

## Warning in data.matrix(newdata): NAs introduced by coercion

## Warning in data.matrix(newdata): NAs introduced by coercion
```

```r
ggplot(probs, aes(x = civil_war)) +
  geom_histogram(binwidth = 0.01) +
  scale_x_continuous(label = percent) +
  xlab('Predicted probability of civil war') +
  ylab('Number of examples')
```

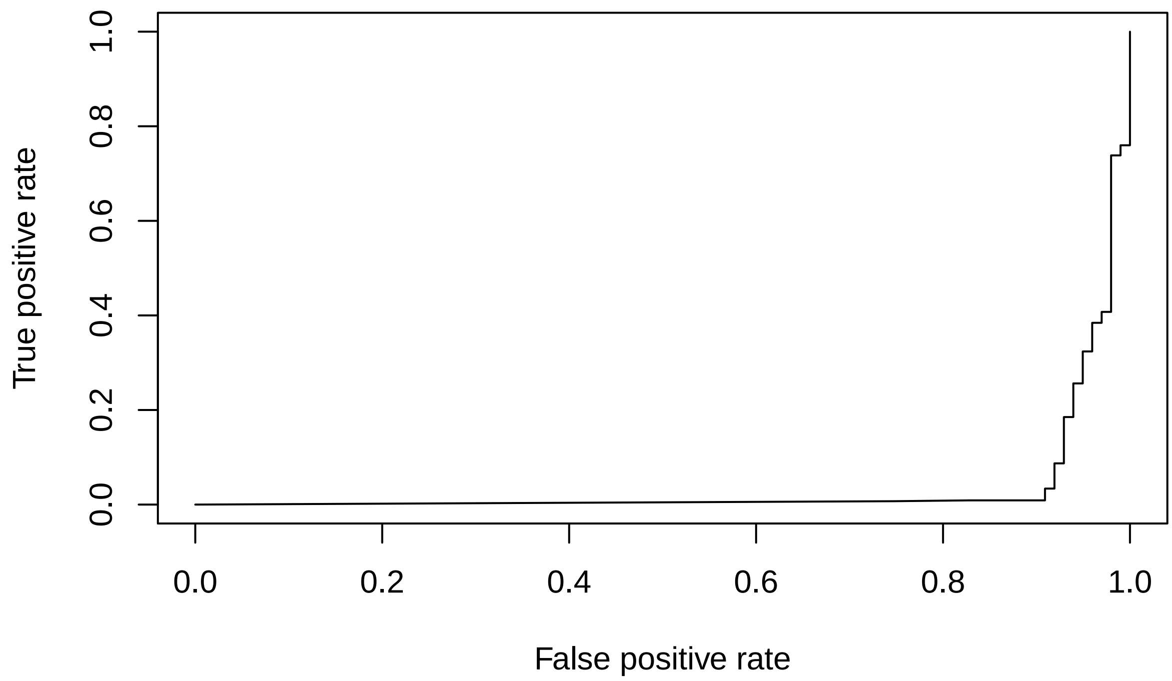



```r
data.frame(predicted=probs[, "civil_war"], actual=yTest) %>%
  group_by(predicted=round(predicted*10)/10) %>%
  summarize(num=n(), actual=mean(actual == "civil_war")) %>%
  ggplot(data=., aes(x=predicted, y=actual, size=num)) +
```

```
  geom_point() +
  geom_abline(linetype=2) +
  scale_x_continuous(labels=percent, lim=c(0,1)) +
  scale_y_continuous(labels=percent, lim=c(0,1)) +
  xlab('Predicted probability of civil war') +
  ylab('Percent that are actually civil war')
```




```
# create a ROCR object
pred <- prediction(probs[, "civil_war"], yTest)

# create a ROCR object
pred <- prediction(probs[, "civil_war"], yTest)

# plot ROC curve
perf_nb <- performance(pred, measure='tpr', x.measure='fpr')
plot(perf_nb)
```




```r
performance(pred, 'auc')
```

```
## An object of class "performance"
## Slot "x.name":
## [1] "None"
##
## Slot "y.name":
## [1] "Area under the ROC curve"
##
## Slot "alpha.name":
## [1] "none"
##
## Slot "x.values":
## list()
##
## Slot "y.values":
## [[1]]
## [1] 0.03610842
##
##
## Slot "alpha.values":
## list()
```

```r
sessionInfo()
```

```
## R version 3.5.1 (2018-07-02)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS  10.14.4
##
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRlapack.dylib
##
```

```
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] grid      stats     graphics  grDevices utils     datasets  methods
## [8] base
##
## other attached packages:
##  [1] e1071_1.7-1     pROC_1.14.0     ROCR_1.0-7      gplots_3.0.1.1
##  [5] scales_1.0.0    broom_0.5.2     lubridate_1.7.4 forcats_0.4.0
##  [9] stringr_1.4.0   dplyr_0.8.0.1   purrr_0.3.2     readr_1.3.1
## [13] tidyr_0.8.3     tibble_2.1.1    ggplot2_3.1.1   tidyverse_1.2.1
## [17] foreign_0.8-70
##
## loaded via a namespace (and not attached):
##  [1] gtools_3.8.1       tidyselect_0.2.5   xfun_0.6
##  [4] haven_2.1.0        lattice_0.20-35    colorspace_1.4-1
##  [7] generics_0.0.2     htmltools_0.3.6    yaml_2.2.0
## [10] utf8_1.1.4         rlang_0.3.4        pillar_1.3.1
## [13] glue_1.3.1         withr_2.1.2        modelr_0.1.4
## [16] readxl_1.3.1       plyr_1.8.4         munsell_0.5.0
## [19] gtable_0.3.0       cellranger_1.1.0   rvest_0.3.3
## [22] caTools_1.17.1.2   evaluate_0.13      labeling_0.3
## [25] knitr_1.22         class_7.3-14       fansi_0.4.0
## [28] Rcpp_1.0.1         KernSmooth_2.23-15 backports_1.1.4
## [31] gdata_2.18.0       jsonlite_1.6       hms_0.4.2
## [34] digest_0.6.18      stringi_1.4.3      cli_1.1.0
## [37] tools_3.5.1        bitops_1.0-6       magrittr_1.5
## [40] lazyeval_0.2.2     crayon_1.3.4       pkgconfig_2.0.2
## [43] xml2_1.2.0         assertthat_0.2.1   rmarkdown_1.12
## [46] httr_1.4.0         rstudioapi_0.10    R6_2.4.0
## [49] nlme_3.1-137       compiler_3.5.1
```