POLI 271 Problem set 4

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Problem 1

a

```
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becor
```

```
library(gt)
```

```
Warning: package 'gt' was built under R version 4.4.2
```

```
library(modelsummary)
```

```
Warning: package 'modelsummary' was built under R version 4.4.2
```

```
`modelsummary` 2.0.0 now uses `tinytable` as its default table-drawing
  backend. Learn more at: https://vincentarelbundock.github.io/tinytable/

Revert to `kableExtra` for one session:

  options(modelsummary_factory_default = 'kableExtra')
  options(modelsummary_factory_latex = 'kableExtra')
  options(modelsummary_factory_html = 'kableExtra')

Silence this message forever:

  config_modelsummary(startup_message = FALSE)
```

```
library(stargazer)
```

```
Please cite as:

 Hlavac, Marek (2022). stargazer: Well-Formatted Regression and Summary Statistics Tables.
 R package version 5.2.3. https://CRAN.R-project.org/package=stargazer
```

```
library(ROCR)
```

```
Warning: package 'ROCR' was built under R version 4.4.2
```

```
library(caret)
```

```
Warning: package 'caret' was built under R version 4.4.2

Loading required package: lattice

Attaching package: 'caret'

The following object is masked from 'package:purrr':

    lift
```

```
library(cvTools)
```

```
Warning: package 'cvTools' was built under R version 4.4.2

Loading required package: robustbase

Warning: package 'robustbase' was built under R version 4.4.2
```

```r
library(MASS)
```

```
Attaching package: 'MASS'

The following object is masked from 'package:dplyr':

    select
```

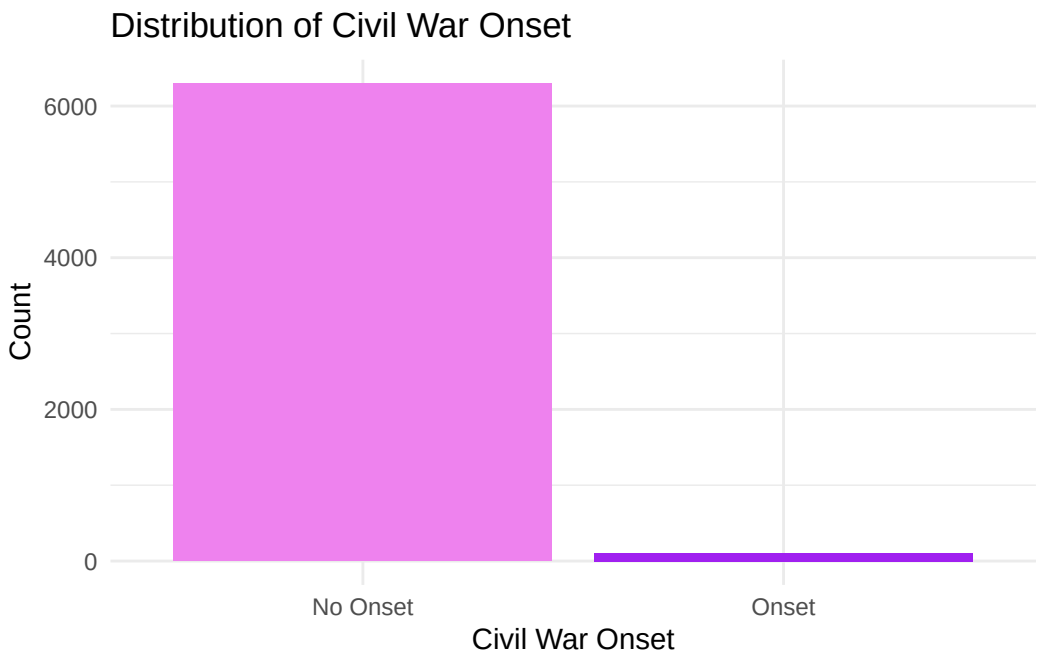
```r
options(warn = -1)
options(message = -1)
```

```r
flmdw <- read.csv("flmdw-1.csv")
head(flmdw, 20)
```

```
    X country year onset instab warl gdpenl   lpopl1  lmtnest ncontig Oil
1   1     USA 1945     0      0    0  7.626 11.85630 3.214868       1   0
2   2     USA 1946     0      0    0  7.626 11.85630 3.214868       1   0
3   3     USA 1947     0      0    0  7.654 11.86313 3.214868       1   0
4   4     USA 1948     0      0    0  8.025 11.86859 3.214868       1   0
5   5     USA 1949     0      0    0  8.270 11.88673 3.214868       1   0
6   6     USA 1950     0      0    0  8.040 11.90488 3.214868       1   0
7   7     USA 1951     0      0    0  8.772 11.93343 3.214868       1   0
8   8     USA 1952     0      0    0  9.109 11.95118 3.214868       1   0
9   9     USA 1953     0      0    0  9.074 11.96862 3.214868       1   0
10 10     USA 1954     0      0    0  9.300 11.98589 3.214868       1   0
11 11     USA 1955     0      0    0  9.089 12.00274 3.214868       1   0
12 12     USA 1956     0      0    0  9.723 12.01932 3.214868       1   0
13 13     USA 1957     0      0    0  9.712 12.03696 3.214868       1   0
14 14     USA 1958     0      0    0  9.643 12.05429 3.214868       1   0
15 15     USA 1959     0      0    0  9.370 12.07121 3.214868       1   0
16 16     USA 1960     0      0    0  9.839 12.08797 3.214868       1   0
17 17     USA 1961     0      0    0  9.895 12.10444 3.214868       1   0
18 18     USA 1962     0      0    0  9.946 12.12099 3.214868       1   0
```

```
19 19     USA 1963     0      0    0 10.358 12.13638 3.214868       1   0
20 20     USA 1964     0      0    0 10.642 12.15079 3.214868       1   0
   nwstate polity2l   ethfrac relfrac
1        0       10 0.3569501   0.596
2        0       10 0.3569501   0.596
3        0       10 0.3569501   0.596
4        0       10 0.3569501   0.596
5        0       10 0.3569501   0.596
6        0       10 0.3569501   0.596
7        0       10 0.3569501   0.596
8        0       10 0.3569501   0.596
9        0       10 0.3569501   0.596
10       0       10 0.3569501   0.596
11       0       10 0.3569501   0.596
12       0       10 0.3569501   0.596
13       0       10 0.3569501   0.596
14       0       10 0.3569501   0.596
15       0       10 0.3569501   0.596
16       0       10 0.3569501   0.596
17       0       10 0.3569501   0.596
18       0       10 0.3569501   0.596
19       0       10 0.3569501   0.596
20       0       10 0.3569501   0.596
```

```r
library(ggplot2)
ggplot(flmdw, aes(x = factor(onset))) +
  geom_bar(fill = c("violet", "purple")) +
  labs(title = "Distribution of Civil War Onset",
       x = "Civil War Onset",
       y = "Count") +
  scale_x_discrete(labels = c("No Onset", "Onset")) +
  theme_minimal()
```



This is a rare event. Bayesian Logistic Regression; LASSO

b

```
library(dplyr)
colnames(flmdw)
```

```
 [1] "X"         "country"   "year"      "onset"     "instab"    "warl"
 [7] "gdpenl"    "lpopl1"    "lmtnest"   "ncontig"   "Oil"       "nwstate"
[13] "polity2l" "ethfrac"   "relfrac"
```

```
flmdw_complete <- flmdw %>%
  dplyr::select(onset, gdpenl, lpopl1, lmtnest, Oil, polity2l, relfrac) %>%
  na.omit()

model1 <- glm(onset ~ gdpenl + lpopl1 + lmtnest,
              data = flmdw_complete, family = binomial)
model2 <- glm(onset ~ gdpenl + lpopl1 + lmtnest,
              data = flmdw_complete, family = binomial(link = "probit"))
model3 <- glm(onset ~ gdpenl + lpopl1 + lmtnest + Oil + polity2l + relfrac,
              data = flmdw_complete, family = binomial(link = "probit"))
```

```r
model4 <- glm(onset ~ gdpenl + lpopl1 + lmtnest + Oil + polity2l * relfrac,
              data = flmdw_complete, family = binomial(link = "probit"))

summary(model1)
```

```
Call:
glm(formula = onset ~ gdpenl + lpopl1 + lmtnest, family = binomial,
    data = flmdw_complete)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -6.04197    0.61198  -9.873  < 2e-16 ***
gdpenl      -0.29518    0.06235  -4.734  2.2e-06 ***
lpopl1       0.23632    0.06169   3.831 0.000128 ***
lmtnest      0.17810    0.07996   2.227 0.025923 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1079.6  on 6401  degrees of freedom
Residual deviance: 1013.1  on 6398  degrees of freedom
AIC: 1021.1

Number of Fisher Scoring iterations: 8
```

```r
summary(model2)
```

```
Call:
glm(formula = onset ~ gdpenl + lpopl1 + lmtnest, family = binomial(link = "probit"),
    data = flmdw_complete)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.96613    0.25589 -11.591  < 2e-16 ***
gdpenl      -0.11373    0.02314  -4.914 8.92e-07 ***
lpopl1       0.09964    0.02664   3.740 0.000184 ***
lmtnest      0.07451    0.03199   2.329 0.019843 *
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1079.6  on 6401  degrees of freedom
Residual deviance: 1012.4  on 6398  degrees of freedom
AIC: 1020.4

Number of Fisher Scoring iterations: 8
```

```
summary(model3)
```

```
Call:
glm(formula = onset ~ gdpenl + lpopl1 + lmtnest + Oil + polity2l +
    relfrac, family = binomial(link = "probit"), data = flmdw_complete)

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.950436   0.273591 -10.784  < 2e-16 ***
gdpenl      -0.139777   0.026540  -5.267 1.39e-07 ***
lpopl1       0.088005   0.026775   3.287 0.001013 **
lmtnest      0.085062   0.033273   2.556 0.010574 *
Oil          0.404288   0.116519   3.470 0.000521 ***
polity2l     0.013098   0.006503   2.014 0.043981 *
relfrac      0.222227   0.198665   1.119 0.263311
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1079.63  on 6401  degrees of freedom
Residual deviance:  999.01  on 6395  degrees of freedom
AIC: 1013

Number of Fisher Scoring iterations: 8
```

```
summary(model4)
```

```
Call:
```

```
glm(formula = onset ~ gdpenl + lpopl1 + lmtnest + Oil + polity2l *
    relfrac, family = binomial(link = "probit"), data = flmdw_complete)

Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)      -3.037835   0.279631 -10.864  < 2e-16 ***
gdpenl           -0.147410   0.026829  -5.494 3.92e-08 ***
lpopl1            0.093681   0.026971   3.473 0.000514 ***
lmtnest           0.089834   0.033466   2.684 0.007267 **
Oil               0.402871   0.117037   3.442 0.000577 ***
polity2l         -0.006433   0.012563  -0.512 0.608617
relfrac           0.318370   0.202051   1.576 0.115097
polity2l:relfrac  0.053889   0.029070   1.854 0.063767 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1079.63  on 6401  degrees of freedom
Residual deviance:  995.66  on 6394  degrees of freedom
AIC: 1011.7

Number of Fisher Scoring iterations: 8
```

```
library(broom)
glance(model1)
```

```
# A tibble: 1 x 8
  null.deviance df.null logLik   AIC   BIC deviance df.residual  nobs
          <dbl>   <int>  <dbl> <dbl> <dbl>    <dbl>       <int> <int>
1         1080.    6401  -507. 1021. 1048.    1013.        6398  6402
```

```
glance(model2)
```

```
# A tibble: 1 x 8
  null.deviance df.null logLik   AIC   BIC deviance df.residual  nobs
          <dbl>   <int>  <dbl> <dbl> <dbl>    <dbl>       <int> <int>
1         1080.    6401  -506. 1020. 1047.    1012.        6398  6402
```

```r
glance(model3)
```

```
# A tibble: 1 x 8
  null.deviance df.null logLik   AIC   BIC deviance df.residual  nobs
          <dbl>   <int>  <dbl> <dbl> <dbl>    <dbl>       <int> <int>
1         1080.    6401  -500. 1013. 1060.     999.        6395  6402
```

```r
glance(model4)
```

```
# A tibble: 1 x 8
  null.deviance df.null logLik   AIC   BIC deviance df.residual  nobs
          <dbl>   <int>  <dbl> <dbl> <dbl>    <dbl>       <int> <int>
1         1080.    6401  -498. 1012. 1066.     996.        6394  6402
```

Based on the results and AIC values, Model 4 is the most promising due to its lower AIC and inclusion of interaction effects, which likely capture more nuanced relationships between variables.

```r
library(broom)
library(gt)

model_summaries <- bind_rows(
  tidy(model1, conf.int = TRUE) %>% mutate(model = "Model 1"),
  tidy(model2, conf.int = TRUE) %>% mutate(model = "Model 2"),
  tidy(model3, conf.int = TRUE) %>% mutate(model = "Model 3"),
  tidy(model4, conf.int = TRUE) %>% mutate(model = "Model 4")
)

gt_table <- gt(model_summaries) %>%
  tab_header(
    title = "Results of Logistic and Probit Regression Models"
  ) %>%
  fmt_number(
    columns = vars(estimate, std.error, statistic, p.value, conf.low, conf.high),
    decimals = 3
  ) %>%
  cols_label(
    estimate = "Estimate",
    std.error = "Std. Error",
    statistic = "z value",
```

```
    p.value = "P Value",
    conf.low = "CI Low",
    conf.high = "CI High",
    term = "Term"
  ) %>%
  tab_spanner(
    label = "Confidence Interval",
    columns = vars(conf.low, conf.high)
  )

gtsave(gt_table, filename = "gt_table.pdf")
```

c

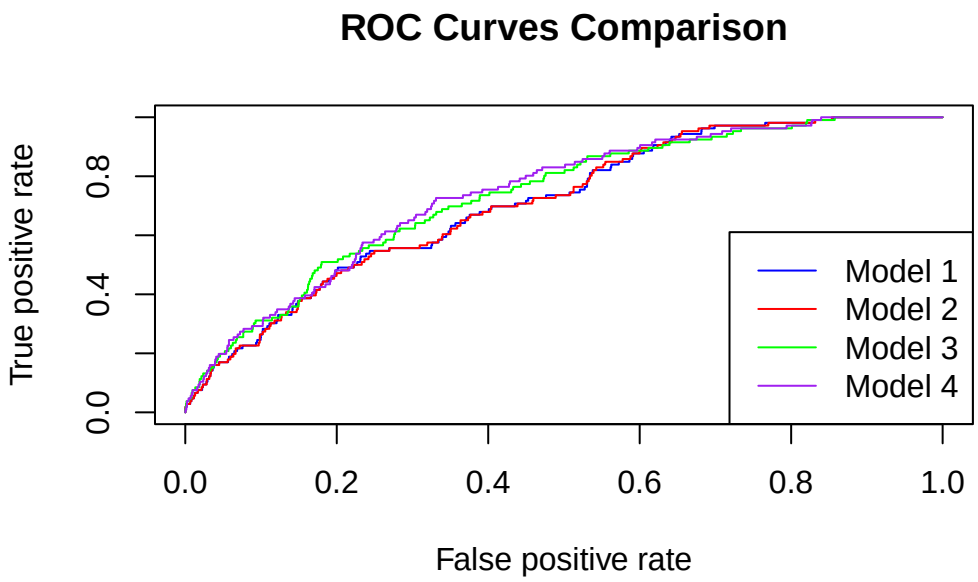
```
pred1 <- prediction(predict(model1, type = "response"), flmdw_complete$onset)
roc1 <- performance(pred1, "tpr", "fpr")

pred2 <- prediction(predict(model2, type = "response"), flmdw_complete$onset)
roc2 <- performance(pred2, "tpr", "fpr")

pred3 <- prediction(predict(model3, type = "response"), flmdw_complete$onset)
roc3 <- performance(pred3, "tpr", "fpr")

pred4 <- prediction(predict(model4, type = "response"), flmdw_complete$onset)
roc4 <- performance(pred4, "tpr", "fpr")

plot(roc1, col = "blue", main = "ROC Curves Comparison", xlim = c(0, 1), ylim = c(0, 1))
plot(roc2, col = "red", add = TRUE)
plot(roc3, col = "green", add = TRUE)
plot(roc4, col = "purple", add = TRUE)
legend("bottomright", legend = c("Model 1", "Model 2", "Model 3", "Model 4"),
       col = c("blue", "red", "green", "purple"), lty = 1)
```



d

```
model_restricted <- glm(onset ~ gdpenl + lpopl1 + lmtnest + Oil + relfrac,
                        data = flmdw_complete, family = binomial(link = "probit"))

lr_test <- anova(model_restricted, model4, test = "Chisq")

print(lr_test)
```

```
Analysis of Deviance Table

Model 1: onset ~ gdpenl + lpopl1 + lmtnest + Oil + relfrac
Model 2: onset ~ gdpenl + lpopl1 + lmtnest + Oil + polity2l * relfrac
  Resid. Df Resid. Dev Df Deviance Pr(>Chi)
1      6396    1003.01
2      6394     995.66  2   7.3558  0.02528 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The p-value (0.02528) is less than 0.05, meaning we reject the null hypothesis that $\beta_{dem} = \beta_{demfrac} = 0$

e

```
library(caret)
library(pROC)
```

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

```

Attaching package: 'pROC'
```

```
The following objects are masked from 'package:stats':

    cov, smooth, var
```

```
set.seed(3407) # 3407 is all you need

flmdw_complete$onset <- factor(flmdw_complete$onset, levels = c(0,1), labels = c("No", "Yes")

cv_control <- trainControl(method = "cv", number = 10, classProbs = TRUE, summaryFunction = t

cv_model1 <- train(onset ~ gdpenl + lpopl1 + lmtnest,
                   data = flmdw_complete, method = "glm", family = binomial(),
                   trControl = cv_control, metric = "ROC")

cv_model2 <- train(onset ~ gdpenl + lpopl1 + lmtnest + Oil,
                   data = flmdw_complete, method = "glm", family = binomial(),
                   trControl = cv_control, metric = "ROC")

cv_model3 <- train(onset ~ gdpenl + lpopl1 + lmtnest + Oil + polity2l + relfrac,
                   data = flmdw_complete, method = "glm", family = binomial(link = "probit")
                   trControl = cv_control, metric = "ROC")

cv_model4 <- train(onset ~ gdpenl + lpopl1 + lmtnest + Oil + polity2l * relfrac,
                   data = flmdw_complete, method = "glm", family = binomial(link = "probit")
                   trControl = cv_control, metric = "ROC")

prob1 <- predict(cv_model1, flmdw_complete, type = "prob")[,"Yes"]
prob2 <- predict(cv_model2, flmdw_complete, type = "prob")[,"Yes"]
prob3 <- predict(cv_model3, flmdw_complete, type = "prob")[,"Yes"]
prob4 <- predict(cv_model4, flmdw_complete, type = "prob")[,"Yes"]
```

```
roc1 <- roc(flmdw_complete$onset, prob1)
```

```
Setting levels: control = No, case = Yes
```

```
Setting direction: controls < cases
```

```
roc2 <- roc(flmdw_complete$onset, prob2)
```

```
Setting levels: control = No, case = Yes
Setting direction: controls < cases
```

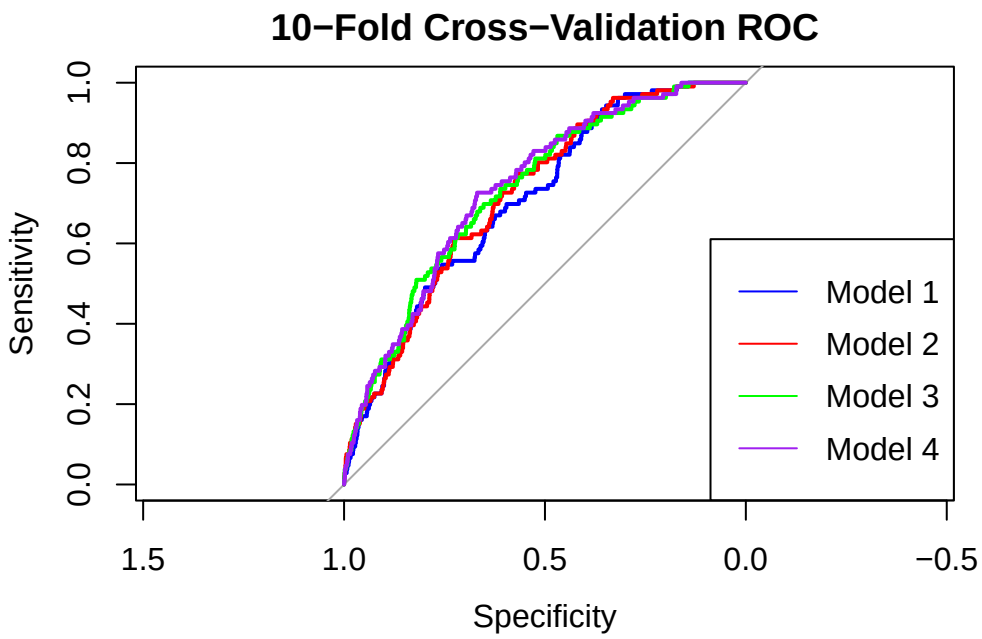
```
roc3 <- roc(flmdw_complete$onset, prob3)
```

```
Setting levels: control = No, case = Yes
Setting direction: controls < cases
```

```
roc4 <- roc(flmdw_complete$onset, prob4)
```

```
Setting levels: control = No, case = Yes
Setting direction: controls < cases
```

```
plot(roc1, col = "blue", main = "10-Fold Cross-Validation ROC")
lines(roc2, col = "red")
lines(roc3, col = "green")
lines(roc4, col = "purple")
legend("bottomright", legend = c("Model 1", "Model 2", "Model 3", "Model 4"),
       col = c("blue", "red", "green", "purple"), lty = 1)
```




```
auc(roc1)
```

```
Area under the curve: 0.7091
```

```
auc(roc2)
```

```
Area under the curve: 0.7229
```

```
auc(roc3)
```

```
Area under the curve: 0.7339
```

```
auc(roc4)
```

```
Area under the curve: 0.7405
```

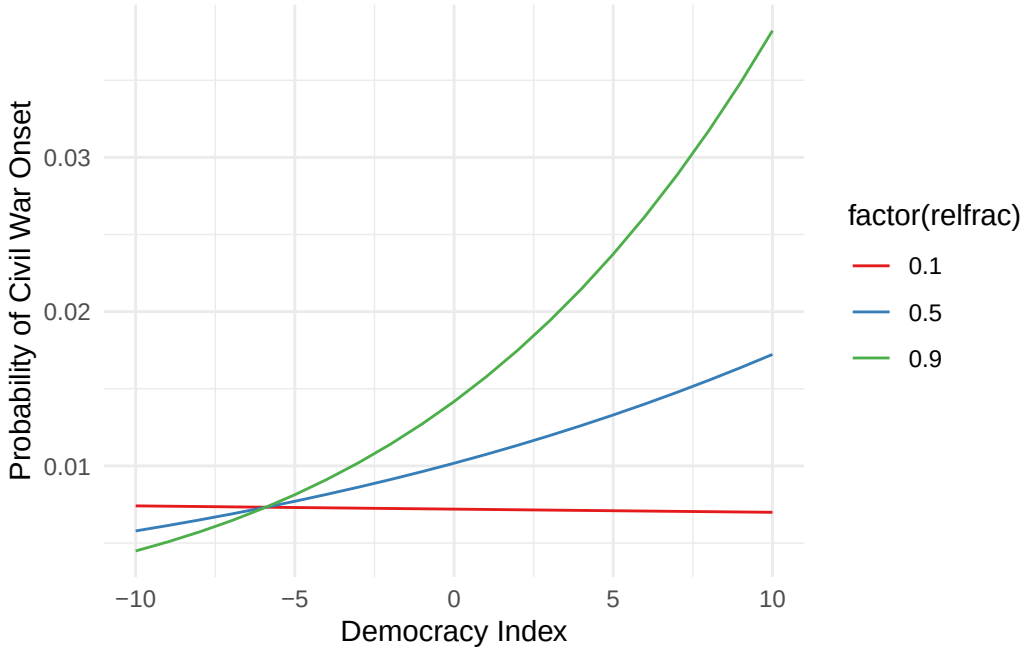
Clearly model4 has the highest AUC. Hard to reject this one.

f

```r
# Prepare data for predictions
prediction_data <- expand.grid(
  polity2l = seq(min(flmdw_complete$polity2l), max(flmdw_complete$polity2l), by = 1),
  relfrac = c(0.1, 0.5, 0.9),
  gdpenl = mean(flmdw_complete$gdpenl),
  lpopl1 = mean(flmdw_complete$lpopl1),
  lmtnest = mean(flmdw_complete$lmtnest),
  Oil = mean(flmdw_complete$Oil)
)

# Predict probabilities
prediction_data$predicted_prob <- predict(cv_model4, newdata = prediction_data, type = "prob"

# Plotting
ggplot(prediction_data, aes(x = polity2l, y = predicted_prob, color = factor(relfrac))) +
  geom_line() +
  labs(x = "Democracy Index", y = "Probability of Civil War Onset") +
  scale_color_brewer(palette = "Set1") +
  theme_minimal()
```



The data suggest that while democracy is generally promoted as a means to prevent conflict, its effectiveness can vary significantly depending on the religious composition of a society. In

highly diverse societies, the introduction of democracy should be handled with care, potentially supplemented by measures that promote intergroup dialogue and reconciliation to mitigate the risks of increased conflict.