Final Code

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```
library(tidyverse)
library(RColorBrewer)
library(randomForest)
library(gam)
library(knitr)
library(caret)
library(leaps)
library(LogisticDx)
library(ResourceSelection)
library(MASS)
library(car)
library(caret)
library(pROC)
```

```
url <- "https://meps.ahrq.gov/mepsweb/data_files/pufs/h209dat.zip"
download.file(url, temp <- tempfile())
meps_path <- unzip(temp, exdir = tempdir())
source("https://meps.ahrq.gov/mepsweb/data_stats/download_data/pufs/h209/h209ru.txt")
unlink(temp)
```

```
# creating a reduced data frame including only the variables that we'll be considering
h209red <- data.frame("pap" = h209$ADPAP42,
                      "region" = h209$REGION18,
                      "race" = h209$RACETHX,
                      "age" = h209$AGE18X,
                      "marital_stat" = h209$MARRY18X,
                      "educ" = h209$EDUCYR,
                      "smoke_freq" = h209$OFTSMK53,
                      "income_indiv" = h209$TTLP18X,
                      "income_fam" = h209$FAMINC18,
                      "income_percpov" = h209$POVLEV18,
                      "hrsworked_rd1" = h209$HOUR31H,
                      "hrsworked_rd2" = h209$HOUR42H,
                      "hrsworked_rd3" = h209$HOUR53H,
                      "limitation" = h209$ACTLIM31,
                      "menhlth_rd1" = h209$MNHLTH31,
                      "menhlth_rd2" = h209$MNHLTH42,
                      "menhlth_rd3" = h209$MNHLTH53,
                      "genhlth_rd1" = h209$RTHLTH31,
                      "genhlth_rd2" = h209$RTHLTH42,
                      "genhlth_rd3" = h209$RTHLTH53,
                      "totexp" = h209$TOTEXP18,
                      "outofpocket_exp" = h209$TOTSLF18,
```

```r
                      "afford_care" = h209$AFRDCA42,
                      "have_usc" = h209$HAVEUS42,
                      "dist_from_usc" = h209$TMTKUS42,
                      "rch_usc_byphn" = h209$PHNREG42,
                      "usc_offhrs_nw" = h209$OFFHOU42,
                      "usc_asks_abt_trts" = h209$TREATM42,
                      "usc_asks_hlp_dec" = h209$DECIDE42,
                      "usc_expln_options" = h209$EXPLOP42,
                      "inscov_gen_2018" = h209$INSCOV18)

rm(h209) # remove original data set from environment

h209red <- h209red %>%
  as_tibble() %>%
  filter(pap != -1) %>% # filtering out the people who were not asked pap smear question
  filter(age >= 21 & age <= 65) # filtering to women ages 21-65
```

```r
## inputting NAs into hours worked variables
h209red$hrsworked_rd1[h209red$hrsworked_rd1 == -1] <- NA
h209red$hrsworked_rd2[h209red$hrsworked_rd2 == -1] <- NA
h209red$hrsworked_rd3[h209red$hrsworked_rd3 == -1] <- NA

# hours worked (rounded average)
h209red <- h209red %>% rowwise() %>%
  mutate(hrs_worked_avg = round(mean(c(hrsworked_rd1, hrsworked_rd2, hrsworked_rd3), na.rm = TRUE)))

h209red$hrs_worked_avg[is.nan(as.numeric(h209red$hrs_worked_avg))] <- NA

summary(h209red$hrs_worked_avg) # too many missing variables to use
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    1.00   30.00   40.00   36.36   40.00  168.00    1654
```

```r
# re-calculating the mental and general health variables

# perceived mental heath adding NA
h209red$menhlth_rd1[h209red$menhlth_rd1 == -8 ]<- NA
h209red$menhlth_rd1[h209red$menhlth_rd1 == -1 ]<- NA

h209red$menhlth_rd2[h209red$menhlth_rd2 == -7 ]<- NA
h209red$menhlth_rd2[h209red$menhlth_rd2 == -8 ]<- NA

h209red$menhlth_rd3[h209red$menhlth_rd3 == -7 ]<- NA
h209red$menhlth_rd3[h209red$menhlth_rd3 == -8 ]<- NA
h209red$menhlth_rd3[h209red$menhlth_rd3 == -1 ]<- NA

# perceived mental health, rounded average for each group
h209red <- h209red %>% rowwise() %>%
  mutate(menhlth_avg = round(mean(c(menhlth_rd1, menhlth_rd2, menhlth_rd3), na.rm=TRUE)))

summary(h209red$menhlth_avg)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   2.115   3.000   5.000
```

```r
# perceived mental health converted to factor
h209red <- h209red %>%
  mutate(menhlth_avg_f = factor(menhlth_avg,
                                levels = c("5", "4", "3", "2", "1"))) %>%
  mutate(menhlth_avg_f = fct_recode(menhlth_avg_f,
                                    "poor" = "5",
                                    "fair" = "4",
                                    "good" = "3",
                                    "very good" = "2",
                                    "excellent" = "1"))


# re-calculating the general health variables

# perceived general heath NA
h209red$genhlth_rd1[h209red$genhlth_rd1 == -8 ] <- NA
h209red$genhlth_rd1[h209red$genhlth_rd1 == -1 ] <- NA

h209red$genhlth_rd2[h209red$genhlth_rd2 == -8 ] <- NA

h209red$genhlth_rd3[h209red$genhlth_rd3 == -7 ] <- NA
h209red$genhlth_rd3[h209red$genhlth_rd3 == -8 ] <- NA
h209red$genhlth_rd3[h209red$genhlth_rd3 == -1 ] <- NA

# perceived mental health, rounded average of each group
h209red <- h209red %>% rowwise() %>%
  mutate(genhlth_avg = round(mean(c(genhlth_rd1, genhlth_rd2, genhlth_rd3), na.rm=TRUE)))

summary(h209red$genhlth_avg)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   2.000   2.351   3.000   5.000
```

```r
# perceived general health converted to factor
h209red <- h209red %>%
  mutate(genhlth_avg_f = factor(genhlth_avg,
                                levels = c("5", "4", "3", "2", "1"))) %>%
  mutate(genhlth_avg_f = fct_recode(genhlth_avg_f,
                                   "poor" = "5",
                                   "fair" = "4",
                                   "good" = "3",
                                   "very good" = "2",
                                   "excellent" = "1"))
```

```r
# creating factor versions of other categorical variables

# pap status
h209red <- h209red %>%
  mutate(pap_f = factor(pap,
                        levels = c("1", "2", "-15"))) %>%
  mutate(pap_f = fct_recode(pap_f,
                            "yes" = "1",
                            "no" = "2",
                            NULL = "-15"))
```

```r
# region
h209red <- h209red %>%
  mutate(region_f = factor(region,
                           levels = c("1", "2", "3", "4"))) %>%
  mutate(region_f = fct_recode(region_f,
                               "northeast" = "1",
                               "midwest" = "2",
                               "south" = "3",
                               "west" = "4"))

# race
h209red <- h209red %>%
  mutate(race_f = factor(race,
                         levels = c("2", "1", "3", "4", "5"))) %>%
  mutate(race_f = fct_recode(race_f,
                             "white" = "2",
                             "hispanic" = "1",
                             "black" = "3",
                             "asian" = "4",
                             "other or multiple races" = "5"))

# marital status
h209red <- h209red %>%
  mutate(marital_stat_f = factor(marital_stat,
                                 levels = c("5", "1", "2", "3", "4"))) %>%
  mutate(marital_stat_f = fct_recode(marital_stat_f,
                                     "never married" = "5",
                                     "married" = "1",
                                     "widowed" = "2",
                                     "divorced" = "3",
                                     "seperated" = "4"))
# education
h209red <- h209red %>%
  mutate(educ_f = factor(educ)) %>%
  mutate(educ_f = fct_collapse(educ_f,
                               "none or any elementary" = c("0", "1", "2", "3", "4", "5", "6", "7", "8"
                               "any high school" = c("9", "10", "11", "12"),
                               "any college" = c("13", "14", "15", "16", "17"),
                               NULL = "-15",
                               NULL = c("-8", "-7")))

# smoking frequency
h209red <- h209red %>%
  mutate(smoke_freq_f = factor(smoke_freq,
                               levels = c("3", "2", "1", "-8", "-7", "-1"))) %>%
  mutate(smoke_freq_f = fct_recode(smoke_freq_f,
                                   "never" = "3",
                                   "some days" = "2",
                                   "every day" = "1",
                                   NULL = "-8",
                                   NULL = "-7",
                                   NULL = "-1"))
```

```r
# limitation
h209red <- h209red %>%
  mutate(limitation_f = factor(limitation,
                               levels = c("2", "1", "-8", "-7", "-1"))) %>%
  mutate(limitation_f = fct_recode(limitation_f,
                                   "no" = "2",
                                   "yes" = "1",
                                   NULL = "-8",
                                   NULL = "-7",
                                   NULL = "-1"))


# ability to afford care
h209red <- h209red %>%
  mutate(afford_care_f = factor(afford_care,
                                levels = c("2", "1", "-8", "-7"))) %>%
  mutate(afford_care_f = fct_recode(afford_care_f,
                                    "no" = "2",
                                    "yes" = "1",
                                    NULL = "-8",
                                    NULL = "-7"))

# usual source of care status
h209red <- h209red %>%
  mutate(have_usc_f = factor(have_usc,
                             levels = c("2", "1", "-8", "-7"))) %>%
  mutate(have_usc_f = fct_recode(have_usc_f,
                                 "no" = "2",
                                 "yes" = "1",
                                 NULL = "-8",
                                 NULL = "-7"))

# distance from provider
h209red <- h209red %>%
  mutate(dist_from_usc = ifelse(have_usc_f == "no",
                                -100,
                                dist_from_usc)) %>% # creating level for not having a provider
  mutate(dist_from_usc_f = factor(dist_from_usc,
                                  levels = c("1", "2", "3", "4", "5", "6", "-100", "-8", "-7", "-1")))
  mutate(dist_from_usc_f = fct_recode(dist_from_usc_f,
                                      "<15" = "1",
                                      "15 to 30" = "2",
                                      "31 to 60" = "3",
                                      "61 to 90" = "4",
                                      "91 to 120" = "5",
                                      ">120" = "6",
                                      "no usc" = "-100",
                                      NULL = "-8",
                                      NULL = "-7",
                                      NULL = "-1"))

# ability to reach provider by phone
h209red <- h209red %>%
```

```
  mutate(rch_usc_byphn = ifelse(have_usc_f == "no",
                                -100,
                                rch_usc_byphn)) %>% # creating level for not having a provider
  mutate(rch_usc_byphn_f = factor(rch_usc_byphn,
                                  levels = c("4", "3", "2", "1", "-100", "-8", "-7", "-1"))) %>%
  mutate(rch_usc_byphn_f = fct_recode(rch_usc_byphn_f,
                                      "not at all difficult" = "4",
                                      "not too difficult" = "3",
                                      "somewhat difficult" = "2",
                                      "very difficult" = "1",
                                      "no usc" = "-100",
                                      NULL = "-8",
                                      NULL = "-7",
                                      NULL = "-1"))

# provider offers office hours during nights/weekends
h209red <- h209red %>%
  mutate(usc_offhrs_nw = ifelse(have_usc_f == "no",
                                -100,
                                usc_offhrs_nw)) %>% # creating level for not having a provider
  mutate(usc_offhrs_nw_f = factor(usc_offhrs_nw,
                                  levels = c("-100", "2", "1", "-8", "-7", "-1"))) %>%
  mutate(usc_offhrs_nw_f = fct_recode(usc_offhrs_nw_f,
                                      "no usc" = "-100",
                                      "no" = "2",
                                      "yes" = "1",
                                      NULL = "-8",
                                      NULL = "-7",
                                      NULL = "-1"))
# provider asks about treatments
h209red <- h209red %>%
  mutate(usc_asks_abt_trts = ifelse(have_usc_f == "no",
                                    -100,
                                    usc_asks_abt_trts)) %>% # creating level for not having a provider
  mutate(usc_asks_abt_trts_f = factor(usc_asks_abt_trts,
                                      levels = c("-100", "2", "1", "-8", "-7", "-1"))) %>%
  mutate(usc_asks_abt_trts_f = fct_recode(usc_asks_abt_trts_f,
                                          "no usc" = "-100",
                                          "no" = "2",
                                          "yes" = "1",
                                          NULL = "-8",
                                          NULL = "-7",
                                          NULL = "-1"))

# provider asks person to help make decisions
h209red <- h209red %>%
   mutate(usc_asks_hlp_dec = ifelse(have_usc_f == "no",
                                    -100,
                                    usc_asks_hlp_dec)) %>% # creating level for not having a provider
  mutate(usc_asks_hlp_dec_f = factor(usc_asks_hlp_dec,
                                     levels = c("-100", "1", "2", "3", "4", "-8", "-7", "-1"))) %>%
  mutate(usc_asks_hlp_dec_f = fct_recode(usc_asks_hlp_dec_f,
                                         "no usc" = "-100",
```

```r
                                        "never" = "1",
                                        "sometimes" = "2",
                                        "usually" = "3",
                                        "always" = "4",
                                        NULL = "-8",
                                        NULL = "-7",
                                        NULL = "-1"))

# provider presents and explains all options
h209red <- h209red %>%
  mutate(usc_expln_options = ifelse(have_usc_f == "no",
                                    -100,
                                    usc_expln_options)) %>% # creating level for not having a provider
  mutate(usc_expln_options_f = factor(usc_expln_options,
                                      levels = c("-100", "2", "1", "-8", "-7", "-1"))) %>%
  mutate(usc_expln_options_f = fct_recode(usc_expln_options_f,
                                          "no usc" = "-100",
                                          "no" = "2",
                                          "yes" = "1",
                                          NULL = "-8",
                                          NULL = "-7",
                                          NULL = "-1"))

# insurance indicator in 2018
h209red <- h209red %>%
  mutate(inscov_gen_2018_f = factor(inscov_gen_2018,
                                    levels = c("1", "2", "3"))) %>%
  mutate(inscov_gen_2018_f = fct_recode(inscov_gen_2018_f,
                                        "any private" = "1",
                                        "public only" = "2",
                                        "uninsured" = "3"))
```

```r
# creating combined provider availability variable using 1) distance 2) ability to reach by phone 3) of
h209red <- h209red %>%
  mutate(dist_from_usc = ifelse(have_usc_f == "no", 0, dist_from_usc))
h209red$dist_from_usc[h209red$dist_from_usc == -8] <- NA
h209red$dist_from_usc[h209red$dist_from_usc == -7] <- NA

h209red <- h209red %>%
  mutate(rch_usc_byphn = ifelse(have_usc_f == "no", 0, rch_usc_byphn))
h209red$rch_usc_byphn[h209red$rch_usc_byphn == -8] <- NA
h209red$rch_usc_byphn[h209red$rch_usc_byphn == -7] <- NA

h209red <- h209red %>%
  mutate(usc_offhrs_nw = ifelse(have_usc_f == "no", 0, usc_offhrs_nw))
h209red$usc_offhrs_nw[h209red$usc_offhrs_nw == -8] <- NA
h209red$usc_offhrs_nw[h209red$usc_offhrs_nw == -7] <- NA
h209red$usc_offhrs_nw[h209red$usc_offhrs_nw == -1] <- NA

# creating binary access variables to use for making combined score
# give 0 to those w/o provider
# give 1 to people who have to travel 30+ minutes
# and give 2 to people who are within 30 min
h209red <- h209red %>% mutate(dist_from_usc_bin = ifelse(dist_from_usc %in% c(1, 2), 2,
```

```
                                                         ifelse(dist_from_usc %in% c(3, 4, 5, 6), 1,
                                                                dist_from_usc)))

# give 0 to those w/o provider
# and give 1 to people who answer somewhat difficult or very difficult
# give 2 to people who answer not at all difficult or not too difficult
h209red <- h209red %>% mutate(rch_usc_byphn_bin = ifelse(rch_usc_byphn %in% c(1, 2), 1,
                                                         ifelse(rch_usc_byphn %in% c(3, 4, 5, 6), 2,
                                                                rch_usc_byphn)))

# give 0 to those w/o provider
# and give 1 to people whose provider does not offer office hours during night/weekend
# give 2 to people whose provider does offer
h209red <- h209red %>% mutate(usc_offhrs_nw_bin = ifelse(usc_offhrs_nw == 1, 2,
                                                         ifelse(usc_offhrs_nw == 2, 1,
                                                                usc_offhrs_nw)))

# finally creating combined availability score from binary variables
h209red <- h209red %>%
  mutate(usc_access_score = dist_from_usc_bin + rch_usc_byphn_bin + usc_offhrs_nw_bin)
```

```
# creating combined provider satisfaction variable using 1) asking about treatments 2) asks person to h
h209red <- h209red %>%
  mutate(usc_asks_abt_trts = ifelse(have_usc_f == "no", 0, usc_asks_abt_trts))
h209red$usc_asks_abt_trts[h209red$usc_asks_abt_trts == -8] <- NA
h209red$usc_asks_abt_trts[h209red$usc_asks_abt_trts == -7] <- NA

h209red <- h209red %>%
   mutate(usc_asks_hlp_dec = ifelse(have_usc_f == "no", 0, usc_asks_hlp_dec))
h209red$usc_asks_hlp_dec[h209red$usc_asks_hlp_dec == -8] <- NA
h209red$usc_asks_hlp_dec[h209red$usc_asks_hlp_dec == -7] <- NA

h209red <- h209red %>%
  mutate(usc_expln_options = ifelse(have_usc_f == "no", 0, usc_expln_options))
h209red$usc_expln_options[h209red$usc_expln_options == -8] <- NA
h209red$usc_expln_options[h209red$usc_expln_options == -7] <- NA


# creating binary access variables to use for making combined score
# give 0 to those w/o provider
# give 1 to those who answered no
# and give 2 to those who answered yes
h209red <- h209red %>% mutate(usc_asks_abt_trts_bin = ifelse(usc_asks_abt_trts == 1, 2,
                                                             ifelse(usc_asks_abt_trts == 2, 1,
                                                                    usc_asks_abt_trts)))

# give 0 to those w/o provider
# and give 1 to those who answered never or sometimes
# give 2 to those who answered usually or always
h209red <- h209red %>% mutate(usc_asks_hlp_dec_bin = ifelse(usc_asks_hlp_dec %in% c(1, 2), 1,
                                                            ifelse(usc_asks_hlp_dec %in% c(3, 4), 2,
                                                                   usc_asks_hlp_dec)))

# give 0 to those w/o provider
```

```r
# and give 1 to people who answer no
# give 2 to those who answered yes
h209red <- h209red %>% mutate(usc_expln_options_bin = ifelse(usc_expln_options == 1, 2,
                                                      ifelse(usc_expln_options == 2, 1,
                                                             usc_expln_options)))

# finally creating combined satisfaction score from binary variables
h209red <- h209red %>%
  mutate(usc_satisf_score = usc_asks_abt_trts_bin + usc_asks_hlp_dec_bin + usc_expln_options_bin)
```

```r
# creating our data set of variables we'll use in our modeling
df <- h209red %>% dplyr::select(pap_f, age, income_indiv, income_fam, totexp,
                                outofpocket_exp, genhlth_avg_f, region_f,
                                race_f, marital_stat_f, educ_f, smoke_freq_f,
                                limitation_f, afford_care_f, have_usc_f,
                                inscov_gen_2018_f)  %>%
  mutate(pap_num = as.numeric(pap_f) - 1) # create numeric pap variable

# identify number of missing values in entire df
sum(is.na(df %>% dplyr::select(-pap_num)))
```

```
## [1] 815
```

```r
# identify number of missing values in outcome
sum(is.na(df$pap_num))
```

```
## [1] 595
```

```r
summary(df)
```

```
##   pap_f           age         income_indiv      income_fam
##  yes :4480   Min.   :21.00   Min.   :-24696   Min.   :-47834
##  no  :1561   1st Qu.:32.00   1st Qu.:  9000   1st Qu.: 27000
##  NA's: 595   Median :41.00   Median : 25000   Median : 56405
##              Mean   :42.44   Mean   : 35224   Mean   : 75645
##              3rd Qu.:54.00   3rd Qu.: 50000   3rd Qu.:103400
##              Max.   :65.00   Max.   :312462   Max.   :583219
##
##      totexp          outofpocket_exp      genhlth_avg_f       region_f
##  Min.   :     0.0   Min.   :    0.00   poor     : 108   northeast:1023
##  1st Qu.:   343.8   1st Qu.:    8.75   fair     : 621   midwest  :1356
##  Median :  1572.0   Median :  201.50   good     :1993   south    :2612
##  Mean   :  6117.1   Mean   :  760.12   very good:2682   west     :1645
##  3rd Qu.:  5430.0   3rd Qu.:  739.25   excellent:1232
##  Max.   :807611.0   Max.   :36425.00
##
##                        race_f           marital_stat_f
##  white                    :3293   never married:1972
##  hispanic                 :1680   married      :3440
##  black                    :1048   widowed      : 194
##  asian                    : 395   divorced     : 805
##  other or multiple races: 220   seperated    : 225
##
##
##                      educ_f        smoke_freq_f  limitation_f afford_care_f
##  any college           :3896   never    :5642   no  :6075    no  :6080
```

```
##  any high school       :2379   some days: 293   yes : 545    yes : 542
##  none or any elementary: 314   every day: 676   NA's:  16    NA's:  14
##  NA's                  :  47   NA's     :  25
##
##
##
##  have_usc_f    inscov_gen_2018_f    pap_num
##  no  :1823   any private:4437    Min.   :0.0000
##  yes :4695   public only:1498    1st Qu.:0.0000
##  NA's: 118   uninsured  : 701    Median :0.0000
##                                  Mean   :0.2584
##                                  3rd Qu.:1.0000
##                                  Max.   :1.0000
##                                  NA's   :595
```

```r
# create complete cases data set for modeling
cc_df <- df %>% drop_na()
```

```r
# check for high correlation between variables
cc_df_num <- data.frame(cc_df$pap_num, cc_df$age, cc_df$income_indiv,
                        cc_df$income_fam, cc_df$totexp, cc_df$outofpocket_exp,
                        as.numeric(cc_df$genhlth_avg_f) - 1,
                        as.numeric(cc_df$region_f) - 1,
                        as.numeric(cc_df$race_f) - 1,
                        as.numeric(cc_df$marital_stat_f) - 1,
                        as.numeric(cc_df$educ_f) - 1,
                        as.numeric(cc_df$smoke_freq_f) - 1,
                        as.numeric(cc_df$limitation_f) - 1,
                        as.numeric(cc_df$afford_care_f) - 1,
                        as.numeric(cc_df$have_usc_f) - 1,
                        as.numeric(cc_df$inscov_gen_2018_f) - 1)
names <- colnames(cc_df)[2:16]
colnames(cc_df_num) <- c("pap_num", names)
correlation_matrix <- round(cor(cc_df_num), digits = 2)
kable(correlation_matrix)
```

	pap_num	age	income_indiv	income_fam	totexp	outofpocket_exp	genhlth_avg_f	region_f	race_f	marital_stat_f	educ_f	smoke_freq_f	limitation_f	afford_care_f	have_usc_f	inscov_gen_2018_f
pap_num	1.00	-0.01	-0.18	-0.15	-0.07	-0.08	-0.06	0.03	0.13	-0.06	0.17	0.08	0.05	0.01	-0.16	0.20
age	-0.01	1.00	0.14	0.09	0.12	0.15	-0.13	-0.05	-0.06	0.36	0.07	0.04	0.16	0.03	0.19	-0.08
income_indiv	-0.18	0.14	1.00	0.66	0.03	0.14	0.21	-0.02	-0.11	0.08	-0.32	-0.13	-0.16	-0.09	0.09	-0.34
income_fam	-0.15	0.09	0.66	1.00	0.02	0.14	0.26	0.00	-0.11	-0.04	-0.31	-0.18	-0.16	-0.14	0.10	-0.37
totexp	-0.07	0.12	0.03	0.02	1.00	0.34	-0.21	-0.06	-0.05	0.05	-0.02	0.03	0.25	0.01	0.13	-0.06
outofpocket_exp	-0.08	0.15	0.14	0.14	0.34	1.00	-0.04	-0.03	-0.12	0.06	-0.10	-0.02	0.05	0.04	0.12	-0.13
genhlth_avg_f	-0.06	-0.13	0.21	0.26	-0.21	-0.04	1.00	0.02	-0.07	-0.09	-0.21	-0.18	-0.38	-0.21	-0.09	-0.17
region_f	0.03	-0.05	-0.02	0.00	-0.06	-0.03	0.02	1.00	0.11	0.00	0.06	-0.07	-0.03	0.01	-0.07	0.06
race_f	0.13	-0.06	-0.11	-0.11	-0.05	-0.12	-0.07	0.11	1.00	-0.07	0.10	-0.04	0.04	-0.01	-0.08	0.12

	pap_num	age	income_indiv	[illegible]	totexp	outofpocket	[illegible]	region_f	race_f	marital_stat_f	educ_f	smoke_freq_f	limitation_f	afford_care_f	have_usc_f	inscov_gen_2018_f
marital_stat_f	-0.06	0.36	0.08	-0.04	0.05	0.06	-0.09	0.00	-0.07	1.00	0.05	0.04	0.09	0.08	0.09	0.02
educ_f	0.17	0.07	-0.32	-0.31	-0.02	-0.10	-0.21	0.06	0.10	0.05	1.00	0.12	0.09	0.05	-0.06	0.32
smoke_freq_f	0.08	0.04	-0.13	-0.18	0.03	-0.02	-0.18	-0.07	-0.04	0.04	0.12	1.00	0.15	0.07	0.00	0.12
limitation_f	0.05	0.16	-0.16	-0.16	0.25	0.05	-0.38	-0.03	0.04	0.09	0.09	0.15	1.00	0.08	0.11	0.14
afford_care_f	0.01	0.03	-0.09	-0.14	0.01	0.04	-0.21	0.01	-0.01	0.08	0.05	0.07	0.08	1.00	-0.06	0.15
have_usc_f	-0.16	0.19	0.09	0.10	0.13	0.12	-0.09	-0.07	-0.08	0.09	-0.06	0.00	0.11	-0.06	1.00	-0.18
inscov_gen_2018_f	0.20	-0.08	-0.34	-0.37	-0.06	-0.13	-0.17	0.06	0.12	0.02	0.32	0.12	0.14	0.15	-0.18	1.00

```r
# looks pretty good
# we shouldn't expect much multicollinearity in our models based on these results but we'll check just
```

Nonlinearity exploration

```r
lin_age <- glm(pap_num ~ age, family = binomial(), data = cc_df)
quad_age <- glm(pap_num ~ age + I(age^2), family = binomial(), data = cc_df)
summary(quad_age)  # quad term has p-value <0.05
```

```
##
## Call:
## glm(formula = pap_num ~ age + I(age^2), family = binomial(),
##     data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0117  -0.7762  -0.6944   1.3526   1.8039
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  2.3403556  0.3521514   6.646 3.01e-11 ***
## age         -0.1721247  0.0175370  -9.815  < 2e-16 ***
## I(age^2)     0.0019756  0.0002021   9.775  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 6568.3  on 5860  degrees of freedom
## AIC: 6574.3
##
## Number of Fisher Scoring iterations: 4
```

```r
lin_income_indiv <- glm(pap_num ~ income_indiv, family = binomial(), data = cc_df)
quad_income_indiv <- glm(pap_num ~ income_indiv + I(income_indiv^2), family = binomial(), data = cc_df)
summary(quad_income_indiv)  # quad term has p-value <0.05
```

```
##
## Call:
## glm(formula = pap_num ~ income_indiv + I(income_indiv^2), family = binomial(),
##     data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1936  -0.8340  -0.6697   1.4082   2.2974
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -5.278e-01  4.743e-02 -11.129  < 2e-16 ***
## income_indiv      -2.151e-05  2.017e-06 -10.666  < 2e-16 ***
## I(income_indiv^2)  5.679e-11  1.409e-11   4.031 5.55e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 6422.3  on 5860  degrees of freedom
## AIC: 6428.3
##
## Number of Fisher Scoring iterations: 5
```

```r
lin_income_fam <- glm(pap_num ~ income_fam, family = binomial(), data = cc_df)
quad_income_fam <- glm(pap_num ~ income_fam + I(income_fam^2), family = binomial(), data = cc_df)
summary(quad_income_fam)  # quad term has p-value <0.05
```

```
##
## Call:
## glm(formula = pap_num ~ income_fam + I(income_fam^2), family = binomial(),
##     data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0686  -0.8239  -0.6845   1.3946   2.0632
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -4.973e-01  5.475e-02  -9.083  < 2e-16 ***
## income_fam      -1.071e-05  1.072e-06  -9.987  < 2e-16 ***
## I(income_fam^2)  1.905e-11  3.532e-12   5.395 6.86e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 6496.2  on 5860  degrees of freedom
## AIC: 6502.2
##
## Number of Fisher Scoring iterations: 4
```

```r
lin_totexp <- glm(pap_num ~ totexp, family = binomial(), data = cc_df)
quad_totexp <- glm(pap_num ~ totexp + I(totexp^2), family = binomial(), data = cc_df)
summary(quad_totexp)  # quad term has p-value <0.05
```

```
##
## Call:
## glm(formula = pap_num ~ totexp + I(totexp^2), family = binomial(),
##     data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3927  -0.7985  -0.7726   1.6010   2.3857
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -9.563e-01  3.433e-02 -27.855  < 2e-16 ***
## totexp      -2.400e-05  4.009e-06  -5.986 2.15e-09 ***
## I(totexp^2)  7.859e-11  2.048e-11   3.838 0.000124 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 6619.4  on 5860  degrees of freedom
## AIC: 6625.4
##
## Number of Fisher Scoring iterations: 4
```

```r
lin_outofpocket_exp <- glm(pap_num ~ outofpocket_exp, family = binomial(), data = cc_df)
quad_outofpocket_exp <- glm(pap_num ~ outofpocket_exp + I(outofpocket_exp^2), family = binomial(), data
summary(quad_outofpocket_exp) # quad term has p-value <0.05
```

```
##
## Call:
## glm(formula = pap_num ~ outofpocket_exp + I(outofpocket_exp^2),
##     family = binomial(), data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.7806  -0.8229  -0.7591   1.5649   2.5019
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -8.765e-01  3.508e-02 -24.984  < 2e-16 ***
## outofpocket_exp      -3.609e-04  3.979e-05  -9.071  < 2e-16 ***
## I(outofpocket_exp^2)  1.475e-08  2.327e-09   6.337 2.35e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 6553.0  on 5860  degrees of freedom
```

```
## AIC: 6559
##
## Number of Fisher Scoring iterations: 4
```

```r
# potential nonlinearity in all these continuous covariates
```

Associational modeling

Now we will create associational models on the full complete cases data set.

```r
# full model
mod_full <- glm(pap_num ~ age + income_indiv + income_fam + totexp + outofpocket_exp + genhlth_avg_f + r
summary(mod_full)
```

```
##
## Call:
## glm(formula = pap_num ~ age + income_indiv + income_fam + totexp +
##     outofpocket_exp + genhlth_avg_f + region_f + race_f + marital_stat_f +
##     educ_f + smoke_freq_f + limitation_f + afford_care_f + have_usc_f +
##     inscov_gen_2018_f, family = binomial(), data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7407  -0.7688  -0.5571   0.8748   2.8002
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    -1.101e+00  3.174e-01  -3.470 0.000521 ***
## age                             1.618e-02  3.008e-03   5.379 7.49e-08 ***
## income_indiv                   -1.105e-05  1.458e-06  -7.576 3.57e-14 ***
## income_fam                      1.289e-06  7.304e-07   1.764 0.077680 .
## totexp                         -1.008e-05  3.369e-06  -2.991 0.002780 **
## outofpocket_exp                -2.265e-05  2.415e-05  -0.938 0.348393
## genhlth_avg_ffair               2.811e-01  2.742e-01   1.025 0.305198
## genhlth_avg_fgood               1.103e-01  2.715e-01   0.406 0.684451
## genhlth_avg_fvery good          2.502e-02  2.756e-01   0.091 0.927670
## genhlth_avg_fexcellent          1.305e-01  2.839e-01   0.460 0.645778
## region_fmidwest                -1.476e-01  1.125e-01  -1.312 0.189669
## region_fsouth                   6.767e-02  1.000e-01   0.677 0.498702
## region_fwest                   -3.938e-02  1.072e-01  -0.367 0.713478
## race_fhispanic                  1.957e-01  8.820e-02   2.219 0.026505 *
## race_fblack                     1.177e-01  9.878e-02   1.192 0.233339
## race_fasian                     1.173e+00  1.309e-01   8.958  < 2e-16 ***
## race_fother or multiple races   1.424e-01  1.744e-01   0.816 0.414267
## marital_stat_fmarried          -7.907e-01  8.532e-02  -9.268  < 2e-16 ***
## marital_stat_fwidowed          -3.374e-01  1.885e-01  -1.791 0.073365 .
## marital_stat_fdivorced         -5.092e-01  1.186e-01  -4.292 1.77e-05 ***
## marital_stat_fseperated        -5.457e-01  1.761e-01  -3.100 0.001938 **
## educ_fany high school           4.639e-01  7.220e-02   6.426 1.31e-10 ***
## educ_fnone or any elementary    3.160e-01  1.517e-01   2.083 0.037241 *
## smoke_freq_fsome days           2.536e-01  1.474e-01   1.721 0.085279 .
## smoke_freq_fevery day           3.218e-01  1.021e-01   3.152 0.001621 **
## limitation_fyes                 2.347e-01  1.297e-01   1.809 0.070477 .
## afford_care_fyes               -3.208e-01  1.186e-01  -2.705 0.006826 **
## have_usc_fyes                  -6.090e-01  7.143e-02  -8.525  < 2e-16 ***
```

```
## inscov_gen_2018_fpublic only   1.124e-02  8.882e-02   0.127 0.899331
## inscov_gen_2018_funinsured     5.956e-01  1.077e-01   5.529 3.22e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 5970.1  on 5833  degrees of freedom
## AIC: 6030.1
##
## Number of Fisher Scoring iterations: 5
```

```
vif(mod_full) # correlation looks good
```

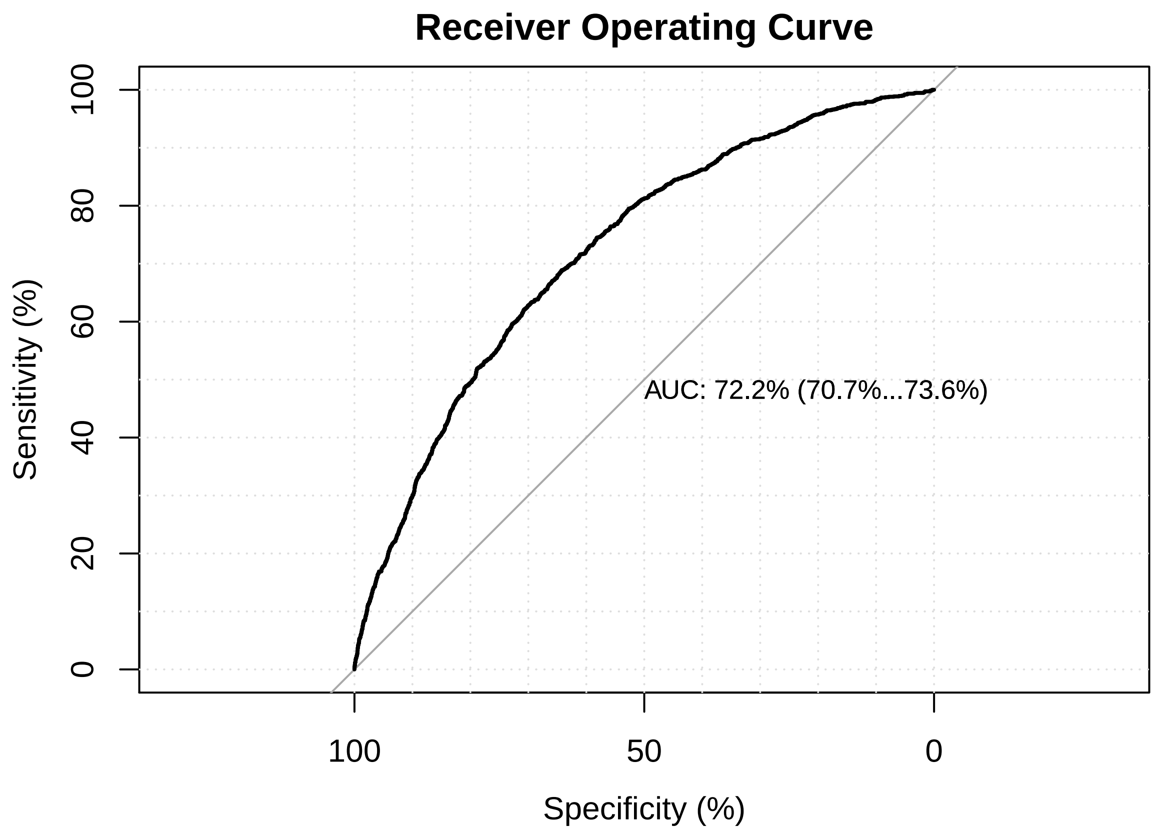
```
##                       GVIF Df GVIF^(1/(2*Df))
## age               1.495309  1        1.222828
## income_indiv      1.691205  1        1.300463
## income_fam        1.932126  1        1.390009
## totexp            1.325187  1        1.151168
## outofpocket_exp   1.211220  1        1.100554
## genhlth_avg_f     1.531871  4        1.054758
## region_f          1.253373  3        1.038357
## race_f            1.677527  4        1.066802
## marital_stat_f    1.818178  4        1.077592
## educ_f            1.343687  2        1.076650
## smoke_freq_f      1.156677  2        1.037058
## limitation_f      1.450423  1        1.204335
## afford_care_f     1.097856  1        1.047786
## have_usc_f        1.126836  1        1.061525
## inscov_gen_2018_f 1.739732  2        1.148472
```

```
hoslem.test(cc_df$pap_num, fitted(mod_full), g = 10) # good fit for full model!
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  cc_df$pap_num, fitted(mod_full)
## X-squared = 7.3206, df = 8, p-value = 0.5025
```

```
gof(mod_full, g = 10)
```

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

## Setting direction: controls < cases
```




```
##       chiSq df pVal
## PrI       1  2    4
## drI       2  2    2
## PrG       1  1    3
## drG       2  1    1
## PrCT      1  1    3
## drCT      2  1    1
##                    val df pVal
## HL chiSq             9  3    4
## mHL F                8  4    9
## OsRo Z               7  5    1
## SstPgeq0.5 Z         2  5    7
## SstPl0.5 Z           3  5    3
## SstBoth chiSq        6  2    5
## SllPgeq0.5 chiSq     1  1    8
## SllPl0.5 chiSq       4  1    2
## SllBoth chiSq        5  2    6
```

```
# forward/backward selection model

# forward model selection
mod_forw <- step(glm(pap_num ~ 1, data = cc_df, family = binomial()), ~ age + income_indiv + income_fam
```

```
## Start:  AIC=6665.86
## pap_num ~ 1
##
##                       Df Deviance    AIC
## + income_indiv         1   6434.5 6438.5
```

```
## + inscov_gen_2018_f  2   6454.4 6460.4
## + educ_f            2   6483.7 6489.7
## + race_f            4   6512.6 6522.6
## + income_fam        1   6519.3 6523.3
## + have_usc_f        1   6521.3 6525.3
## + marital_stat_f    4   6524.0 6534.0
## + outofpocket_exp   1   6609.8 6613.8
## + totexp            1   6629.5 6633.5
## + smoke_freq_f      2   6628.1 6634.1
## + region_f          3   6631.3 6639.3
## + genhlth_avg_f     4   6633.1 6643.1
## + limitation_f      1   6651.8 6655.8
## <none>                  6663.9 6665.9
## + age               1   6663.0 6667.0
## + afford_care_f     1   6663.6 6667.6
##
## Step:  AIC=6438.55
## pap_num ~ income_indiv
##
##                     Df Deviance    AIC
## + have_usc_f        1   6322.8 6328.8
## + race_f            4   6322.5 6334.5
## + inscov_gen_2018_f  2   6338.3 6346.3
## + marital_stat_f    4   6335.6 6347.6
## + educ_f            2   6356.0 6364.0
## + totexp            1   6404.6 6410.6
## + outofpocket_exp   1   6409.8 6415.8
## + region_f          3   6410.0 6420.0
## + smoke_freq_f      2   6417.0 6425.0
## + income_fam        1   6423.0 6429.0
## + genhlth_avg_f     4   6425.7 6437.7
## <none>                  6434.5 6438.5
## + age               1   6433.2 6439.2
## + limitation_f      1   6433.8 6439.8
## + afford_care_f     1   6434.0 6440.0
##
## Step:  AIC=6328.77
## pap_num ~ income_indiv + have_usc_f
##
##                     Df Deviance    AIC
## + race_f            4   6229.6 6243.6
## + marital_stat_f    4   6238.0 6252.0
## + educ_f            2   6245.5 6255.5
## + inscov_gen_2018_f  2   6256.5 6266.5
## + smoke_freq_f      2   6303.7 6313.7
## + totexp            1   6307.5 6315.5
## + outofpocket_exp   1   6309.6 6317.6
## + age               1   6312.6 6320.6
## + region_f          3   6309.0 6321.0
## + genhlth_avg_f     4   6307.3 6321.3
## + income_fam        1   6314.9 6322.9
## + limitation_f      1   6316.3 6324.3
## <none>                  6322.8 6328.8
## + afford_care_f     1   6321.0 6329.0
```

```
##
## Step:  AIC=6243.58
## pap_num ~ income_indiv + have_usc_f + race_f
##
##                    Df Deviance    AIC
## + marital_stat_f     4   6151.0 6173.0
## + educ_f             2   6159.5 6177.5
## + inscov_gen_2018_f  2   6172.9 6190.9
## + smoke_freq_f       2   6195.6 6213.6
## + age                1   6217.1 6233.1
## + limitation_f       1   6220.4 6236.4
## + totexp             1   6220.5 6236.5
## + income_fam         1   6220.5 6236.5
## + genhlth_avg_f      4   6216.5 6238.5
## + outofpocket_exp    1   6223.7 6239.7
## + region_f           3   6222.5 6242.5
## <none>                   6229.6 6243.6
## + afford_care_f      1   6228.7 6244.7
##
## Step:  AIC=6172.96
## pap_num ~ income_indiv + have_usc_f + race_f + marital_stat_f
##
##                    Df Deviance    AIC
## + educ_f             2   6083.3 6109.3
## + inscov_gen_2018_f  2   6107.3 6133.3
## + age                1   6111.4 6135.4
## + smoke_freq_f       2   6127.5 6153.5
## + totexp             1   6141.3 6165.3
## + region_f           3   6141.1 6169.1
## + limitation_f       1   6145.2 6169.2
## + genhlth_avg_f      4   6141.1 6171.1
## + outofpocket_exp    1   6147.7 6171.7
## <none>                   6151.0 6173.0
## + afford_care_f      1   6149.1 6173.1
## + income_fam         1   6151.0 6175.0
##
## Step:  AIC=6109.32
## pap_num ~ income_indiv + have_usc_f + race_f + marital_stat_f +
##     educ_f
##
##                    Df Deviance    AIC
## + inscov_gen_2018_f  2   6049.8 6079.8
## + age                1   6053.3 6081.3
## + smoke_freq_f       2   6069.8 6099.8
## + totexp             1   6074.1 6102.1
## + region_f           3   6074.1 6106.1
## + limitation_f       1   6078.9 6106.9
## + outofpocket_exp    1   6081.2 6109.2
## + afford_care_f      1   6081.2 6109.2
## <none>                   6083.3 6109.3
## + income_fam         1   6082.0 6110.0
## + genhlth_avg_f      4   6077.3 6111.3
##
## Step:  AIC=6079.78
```

```
## pap_num ~ income_indiv + have_usc_f + race_f + marital_stat_f +
##     educ_f + inscov_gen_2018_f
##
##                   Df Deviance    AIC
## + age              1   6019.1 6051.1
## + smoke_freq_f     2   6036.5 6070.5
## + totexp           1   6043.3 6075.3
## + limitation_f     1   6043.9 6075.9
## + afford_care_f    1   6044.6 6076.6
## + outofpocket_exp  1   6047.4 6079.4
## + income_fam       1   6047.5 6079.5
## <none>                 6049.8 6079.8
## + region_f         3   6044.0 6080.0
## + genhlth_avg_f    4   6043.4 6081.4
##
## Step:  AIC=6051.05
## pap_num ~ income_indiv + have_usc_f + race_f + marital_stat_f +
##     educ_f + inscov_gen_2018_f + age
##
##                   Df Deviance    AIC
## + totexp           1   6008.7 6042.7
## + smoke_freq_f     2   6007.4 6043.4
## + afford_care_f    1   6012.7 6046.7
## + outofpocket_exp  1   6014.6 6048.6
## + income_fam       1   6016.2 6050.2
## + limitation_f     1   6016.9 6050.9
## <none>                 6019.1 6051.1
## + region_f         3   6013.4 6051.4
## + genhlth_avg_f    4   6014.4 6054.4
##
## Step:  AIC=6042.73
## pap_num ~ income_indiv + have_usc_f + race_f + marital_stat_f +
##     educ_f + inscov_gen_2018_f + age + totexp
##
##                   Df Deviance    AIC
## + smoke_freq_f     2   5996.8 6034.8
## + afford_care_f    1   6002.7 6038.7
## + limitation_f     1   6003.2 6039.2
## + income_fam       1   6005.7 6041.7
## <none>                 6008.7 6042.7
## + region_f         3   6003.2 6043.2
## + outofpocket_exp  1   6007.5 6043.5
## + genhlth_avg_f    4   6002.7 6044.7
##
## Step:  AIC=6034.84
## pap_num ~ income_indiv + have_usc_f + race_f + marital_stat_f +
##     educ_f + inscov_gen_2018_f + age + totexp + smoke_freq_f
##
##                   Df Deviance    AIC
## + afford_care_f    1   5990.0 6030.0
## + limitation_f     1   5992.1 6032.1
## + income_fam       1   5993.1 6033.1
## <none>                 5996.8 6034.8
## + region_f         3   5991.4 6035.4
```

```
## + outofpocket_exp  1   5995.7 6035.7
## + genhlth_avg_f    4   5991.4 6037.4
##
## Step:  AIC=6030.02
## pap_num ~ income_indiv + have_usc_f + race_f + marital_stat_f +
##     educ_f + inscov_gen_2018_f + age + totexp + smoke_freq_f +
##     afford_care_f
##
##                   Df Deviance    AIC
## + limitation_f     1   5984.7 6026.7
## + income_fam       1   5986.9 6028.9
## <none>                 5990.0 6030.0
## + region_f         3   5984.4 6030.4
## + outofpocket_exp  1   5989.2 6031.2
## + genhlth_avg_f    4   5983.3 6031.3
##
## Step:  AIC=6026.67
## pap_num ~ income_indiv + have_usc_f + race_f + marital_stat_f +
##     educ_f + inscov_gen_2018_f + age + totexp + smoke_freq_f +
##     afford_care_f + limitation_f
##
##                   Df Deviance    AIC
## + income_fam       1   5981.7 6025.7
## <none>                 5984.7 6026.7
## + region_f         3   5979.2 6027.2
## + outofpocket_exp  1   5983.9 6027.9
## + genhlth_avg_f    4   5979.5 6029.5
##
## Step:  AIC=6025.7
## pap_num ~ income_indiv + have_usc_f + race_f + marital_stat_f +
##     educ_f + inscov_gen_2018_f + age + totexp + smoke_freq_f +
##     afford_care_f + limitation_f + income_fam
##
##                   Df Deviance    AIC
## <none>                 5981.7 6025.7
## + region_f         3   5976.2 6026.2
## + outofpocket_exp  1   5980.9 6026.9
## + genhlth_avg_f    4   5976.6 6028.6
```

```r
summary(mod_forw)
```

```
##
## Call:
## glm(formula = pap_num ~ income_indiv + have_usc_f + race_f +
##     marital_stat_f + educ_f + inscov_gen_2018_f + age + totexp +
##     smoke_freq_f + afford_care_f + limitation_f + income_fam,
##     family = binomial(), data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7658  -0.7686  -0.5623   0.8736   2.8036
##
## Coefficients:
##                                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   -1.063e+00  1.395e-01  -7.622 2.50e-14 ***
```

```
## income_indiv                    -1.121e-05  1.457e-06  -7.695 1.42e-14 ***
## have_usc_fyes                   -6.204e-01  7.081e-02  -8.761  < 2e-16 ***
## race_fhispanic                   2.372e-01  8.541e-02   2.777 0.005487 **
## race_fblack                      1.890e-01  9.494e-02   1.991 0.046494 *
## race_fasian                      1.189e+00  1.292e-01   9.203  < 2e-16 ***
## race_fother or multiple races  1.586e-01  1.741e-01   0.911 0.362171
## marital_stat_fmarried           -7.847e-01  8.498e-02  -9.234  < 2e-16 ***
## marital_stat_fwidowed           -3.148e-01  1.878e-01  -1.677 0.093569 .
## marital_stat_fdivorced          -4.984e-01  1.182e-01  -4.217 2.48e-05 ***
## marital_stat_fseperated         -5.203e-01  1.751e-01  -2.971 0.002966 **
## educ_fany high school            4.722e-01  7.177e-02   6.579 4.73e-11 ***
## educ_fnone or any elementary     3.401e-01  1.509e-01   2.254 0.024204 *
## inscov_gen_2018_fpublic only     1.703e-02  8.750e-02   0.195 0.845693
## inscov_gen_2018_funinsured       6.130e-01  1.067e-01   5.744 9.25e-09 ***
## age                              1.628e-02  2.980e-03   5.461 4.72e-08 ***
## totexp                          -1.069e-05  3.135e-06  -3.409 0.000652 ***
## smoke_freq_fsome days            2.531e-01  1.471e-01   1.720 0.085410 .
## smoke_freq_fevery day            3.331e-01  1.014e-01   3.286 0.001016 **
## afford_care_fyes                -2.981e-01  1.161e-01  -2.567 0.010269 *
## limitation_fyes                  2.812e-01  1.223e-01   2.299 0.021526 *
## income_fam                       1.260e-06  7.246e-07   1.739 0.082110 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 5981.7  on 5841  degrees of freedom
## AIC: 6025.7
##
## Number of Fisher Scoring iterations: 5
```

```
vif(mod_forw) # correlation looks good
```

```
##                      GVIF Df GVIF^(1/(2*Df))
## income_indiv      1.680824  1        1.296466
## have_usc_f        1.109049  1        1.053114
## race_f            1.434313  4        1.046118
## marital_stat_f    1.791701  4        1.075618
## educ_f            1.323530  2        1.072589
## inscov_gen_2018_f 1.640730  2        1.131773
## age               1.473158  1        1.213737
## totexp            1.153797  1        1.074150
## smoke_freq_f      1.142073  2        1.033769
## afford_care_f     1.058842  1        1.029000
## limitation_f      1.294997  1        1.137979
## income_fam        1.897364  1        1.377448
```

```
# no values above >2 so it doesn't seem we have much multicollinearity in the model so we will not be u

# backward model selection
mod_back <- step(mod_full, direction = "backward")
```

```
## Start:  AIC=6030.07
## pap_num ~ age + income_indiv + income_fam + totexp + outofpocket_exp +
```

```
##     genhlth_avg_f + region_f + race_f + marital_stat_f + educ_f +
##     smoke_freq_f + limitation_f + afford_care_f + have_usc_f +
##     inscov_gen_2018_f
##
##                     Df Deviance    AIC
## - genhlth_avg_f      4   5975.3 6027.3
## - outofpocket_exp    1   5971.0 6029.0
## - region_f           3   5975.7 6029.7
## <none>                   5970.1 6030.1
## - income_fam         1   5973.1 6031.1
## - limitation_f       1   5973.3 6031.3
## - afford_care_f      1   5977.6 6035.6
## - smoke_freq_f       2   5981.6 6037.6
## - totexp             1   5980.5 6038.5
## - age                1   5999.1 6057.1
## - inscov_gen_2018_f  2   6003.1 6059.1
## - educ_f             2   6011.3 6067.3
## - income_indiv       1   6030.9 6088.9
## - race_f             4   6046.6 6098.6
## - have_usc_f         1   6041.8 6099.8
## - marital_stat_f     4   6059.2 6111.2
##
## Step:  AIC=6027.34
## pap_num ~ age + income_indiv + income_fam + totexp + outofpocket_exp +
##     region_f + race_f + marital_stat_f + educ_f + smoke_freq_f +
##     limitation_f + afford_care_f + have_usc_f + inscov_gen_2018_f
##
##                     Df Deviance    AIC
## - outofpocket_exp    1   5976.2 6026.2
## - region_f           3   5980.9 6026.9
## <none>                   5975.3 6027.3
## - income_fam         1   5978.5 6028.5
## - limitation_f       1   5980.2 6030.2
## - afford_care_f      1   5982.0 6032.0
## - totexp             1   5985.4 6035.4
## - smoke_freq_f       2   5987.6 6035.6
## - age                1   6005.7 6055.7
## - inscov_gen_2018_f  2   6007.9 6055.9
## - educ_f             2   6018.0 6066.0
## - income_indiv       1   6037.4 6087.4
## - have_usc_f         1   6046.1 6096.1
## - race_f             4   6052.9 6096.9
## - marital_stat_f     4   6065.2 6109.2
##
## Step:  AIC=6026.18
## pap_num ~ age + income_indiv + income_fam + totexp + region_f +
##     race_f + marital_stat_f + educ_f + smoke_freq_f + limitation_f +
##     afford_care_f + have_usc_f + inscov_gen_2018_f
##
##                     Df Deviance    AIC
## - region_f           3   5981.7 6025.7
## <none>                   5976.2 6026.2
## - income_fam         1   5979.2 6027.2
## - limitation_f       1   5981.1 6029.1
```

```
## - afford_care_f      1   5983.2 6031.2
## - smoke_freq_f       2   5988.5 6034.5
## - totexp             1   5989.7 6037.7
## - age                1   6006.1 6054.1
## - inscov_gen_2018_f  2   6008.3 6054.3
## - educ_f             2   6019.2 6065.2
## - income_indiv       1   6038.9 6086.9
## - have_usc_f         1   6048.1 6096.1
## - race_f             4   6054.5 6096.5
## - marital_stat_f     4   6066.4 6108.4
##
## Step:  AIC=6025.7
## pap_num ~ age + income_indiv + income_fam + totexp + race_f +
##     marital_stat_f + educ_f + smoke_freq_f + limitation_f + afford_care_f +
##     have_usc_f + inscov_gen_2018_f
##
##                     Df Deviance    AIC
## <none>                   5981.7 6025.7
## - income_fam         1   5984.7 6026.7
## - limitation_f       1   5986.9 6028.9
## - afford_care_f      1   5988.5 6030.5
## - smoke_freq_f       2   5994.1 6034.1
## - totexp             1   5995.5 6037.5
## - age                1   6011.6 6053.6
## - inscov_gen_2018_f  2   6017.6 6057.6
## - educ_f             2   6025.0 6065.0
## - income_indiv       1   6044.6 6086.6
## - race_f             4   6062.7 6098.7
## - have_usc_f         1   6057.4 6099.4
## - marital_stat_f     4   6070.1 6106.1
```

```r
summary(mod_back) # forward and backward selection produce the same model here
```

```
##
## Call:
## glm(formula = pap_num ~ age + income_indiv + income_fam + totexp +
##     race_f + marital_stat_f + educ_f + smoke_freq_f + limitation_f +
##     afford_care_f + have_usc_f + inscov_gen_2018_f, family = binomial(),
##     data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7658  -0.7686  -0.5623   0.8736   2.8036
##
## Coefficients:
##                                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   -1.063e+00  1.395e-01  -7.622 2.50e-14 ***
## age                            1.628e-02  2.980e-03   5.461 4.72e-08 ***
## income_indiv                  -1.121e-05  1.457e-06  -7.695 1.42e-14 ***
## income_fam                     1.260e-06  7.246e-07   1.739 0.082110 .
## totexp                        -1.069e-05  3.135e-06  -3.409 0.000652 ***
## race_fhispanic                 2.372e-01  8.541e-02   2.777 0.005487 **
## race_fblack                    1.890e-01  9.494e-02   1.991 0.046494 *
## race_fasian                    1.189e+00  1.292e-01   9.203  < 2e-16 ***
## race_fother or multiple races  1.586e-01  1.741e-01   0.911 0.362171
```

```
## marital_stat_fmarried         -7.847e-01  8.498e-02  -9.234  < 2e-16 ***
## marital_stat_fwidowed         -3.148e-01  1.878e-01  -1.677 0.093569 .
## marital_stat_fdivorced        -4.984e-01  1.182e-01  -4.217 2.48e-05 ***
## marital_stat_fseperated       -5.203e-01  1.751e-01  -2.971 0.002966 **
## educ_fany high school          4.722e-01  7.177e-02   6.579 4.73e-11 ***
## educ_fnone or any elementary   3.401e-01  1.509e-01   2.254 0.024204 *
## smoke_freq_fsome days          2.531e-01  1.471e-01   1.720 0.085410 .
## smoke_freq_fevery day          3.331e-01  1.014e-01   3.286 0.001016 **
## limitation_fyes                2.812e-01  1.223e-01   2.299 0.021526 *
## afford_care_fyes              -2.981e-01  1.161e-01  -2.567 0.010269 *
## have_usc_fyes                 -6.204e-01  7.081e-02  -8.761  < 2e-16 ***
## inscov_gen_2018_fpublic only   1.703e-02  8.750e-02   0.195 0.845693
## inscov_gen_2018_funinsured     6.130e-01  1.067e-01   5.744 9.25e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 5981.7  on 5841  degrees of freedom
## AIC: 6025.7
##
## Number of Fisher Scoring iterations: 5
```

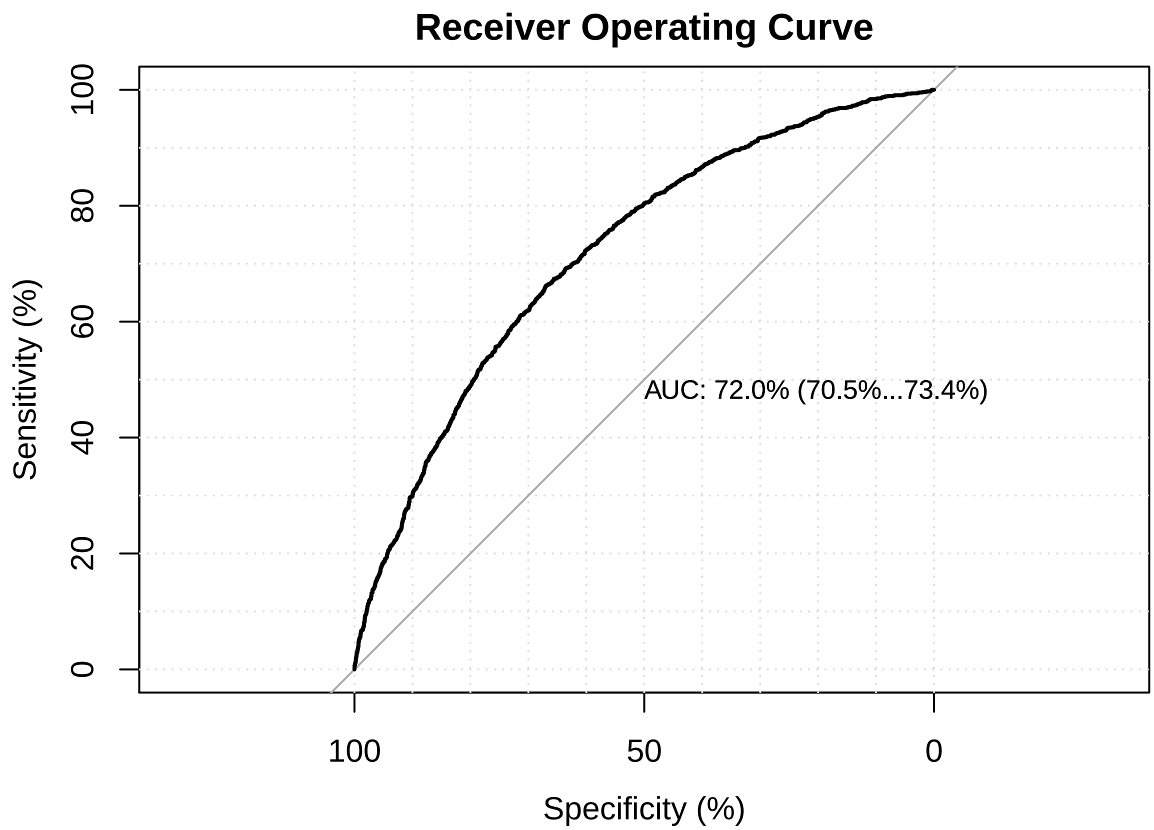
```
hoslem.test(cc_df$pap_num, fitted(mod_back), g = 10) # good fit for forward/backward model!
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  cc_df$pap_num, fitted(mod_back)
## X-squared = 7.1074, df = 8, p-value = 0.5251
```

```
gof(mod_back, g = 10)
```

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

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




```
##      chiSq df pVal
## PrI      1  2    2
## drI      2  2    4
## PrG      1  1    1
## drG      2  1    3
## PrCT     1  1    1
## drCT     2  1    3
##                    val df pVal
## HL chiSq             9  3    4
## mHL F                8  4    9
## OsRo Z               7  5    1
## SstPgeq0.5 Z         2  5    7
## SstPl0.5 Z           4  5    3
## SstBoth chiSq        6  2    5
## SllPgeq0.5 chiSq     1  1    8
## SllPl0.5 chiSq       3  1    2
## SllBoth chiSq        5  2    6
```

```r
# testing if nonlinear terms are needed for age

# trying quadratic
mod_age_quad <- glm(pap_num ~ age + I(age^2) + income_indiv + income_fam + totexp + race_f + marital_sta
summary(mod_age_quad)
```

```
##
## Call:
## glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam +
##     totexp + race_f + marital_stat_f + educ_f + smoke_freq_f +
```

```
##     limitation_f + afford_care_f + have_usc_f + inscov_gen_2018_f,
##     family = binomial(), data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7595  -0.7668  -0.5506   0.8249   2.8077
##
## Coefficients:
##                                Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   1.405e+00  3.889e-01   3.612 0.000304 ***
## age                          -1.168e-01  1.988e-02  -5.873 4.28e-09 ***
## I(age^2)                      1.532e-03  2.265e-04   6.766 1.32e-11 ***
## income_indiv                 -9.778e-06  1.470e-06  -6.653 2.87e-11 ***
## income_fam                    9.854e-07  7.273e-07   1.355 0.175460
## totexp                       -1.148e-05  3.199e-06  -3.590 0.000330 ***
## race_fhispanic                2.843e-01  8.611e-02   3.302 0.000961 ***
## race_fblack                   2.400e-01  9.560e-02   2.510 0.012071 *
## race_fasian                   1.234e+00  1.307e-01   9.442  < 2e-16 ***
## race_fother or multiple races 1.970e-01  1.751e-01   1.125 0.260655
## marital_stat_fmarried        -6.293e-01  8.805e-02  -7.146 8.90e-13 ***
## marital_stat_fwidowed        -3.378e-01  1.891e-01  -1.786 0.074049 .
## marital_stat_fdivorced       -4.005e-01  1.203e-01  -3.329 0.000870 ***
## marital_stat_fseperated      -3.933e-01  1.770e-01  -2.222 0.026268 *
## educ_fany high school         4.502e-01  7.211e-02   6.244 4.27e-10 ***
## educ_fnone or any elementary  3.292e-01  1.515e-01   2.173 0.029789 *
## smoke_freq_fsome days         2.760e-01  1.480e-01   1.865 0.062233 .
## smoke_freq_fevery day         3.865e-01  1.022e-01   3.782 0.000156 ***
## limitation_fyes               2.869e-01  1.230e-01   2.333 0.019641 *
## afford_care_fyes             -2.760e-01  1.167e-01  -2.366 0.017999 *
## have_usc_fyes                -6.220e-01  7.115e-02  -8.742  < 2e-16 ***
## inscov_gen_2018_fpublic only  6.290e-02  8.800e-02   0.715 0.474717
## inscov_gen_2018_funinsured    6.776e-01  1.077e-01   6.290 3.18e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 5936.1  on 5840  degrees of freedom
## AIC: 5982.1
##
## Number of Fisher Scoring iterations: 5
```

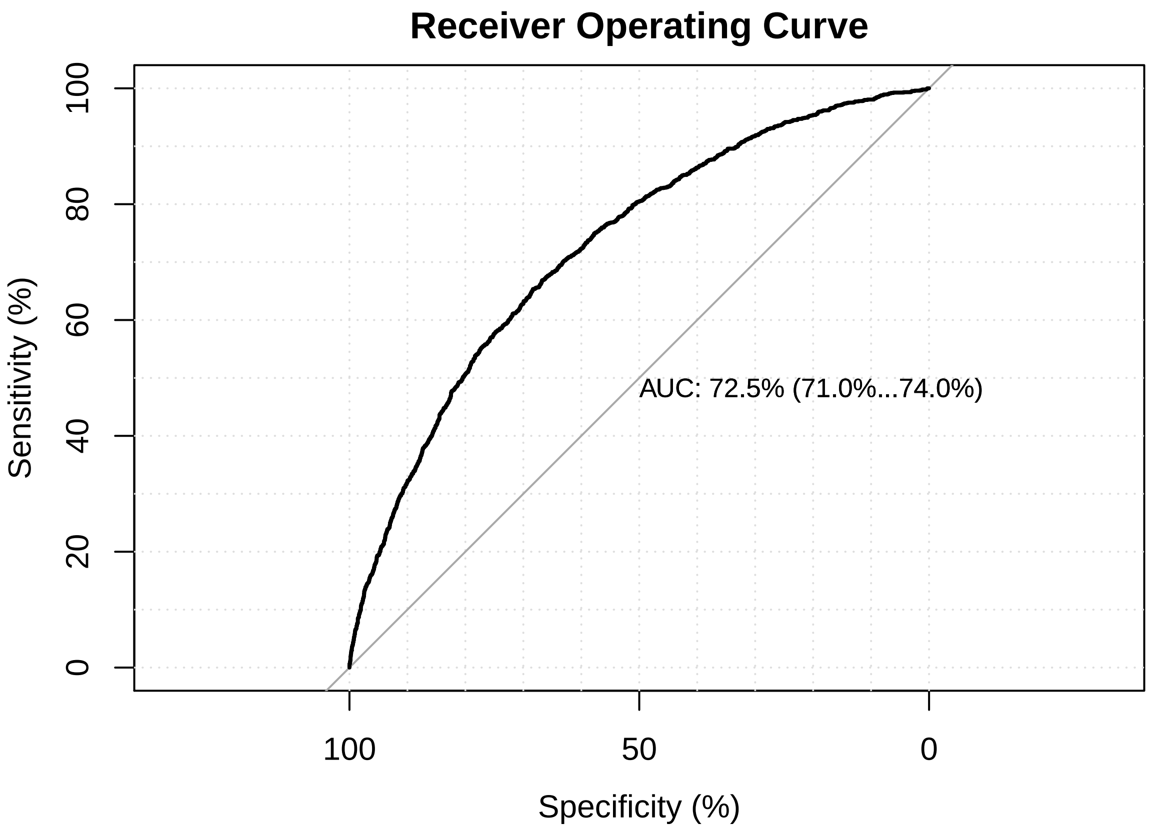
```r
# p < 0.05 for age^2 term so makes sense to keep quadratic term

hoslem.test(cc_df$pap_num, fitted(mod_age_quad), g = 10) # good fit
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  cc_df$pap_num, fitted(mod_age_quad)
## X-squared = 6.3499, df = 8, p-value = 0.6081
```

```r
gof(mod_age_quad, g = 10)
```

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

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




```
##       chiSq df pVal
## PrI       1  2    4
## drI       2  2    2
## PrG       1  1    3
## drG       2  1    1
## PrCT      1  1    3
## drCT      2  1    1
##                  val df pVal
## HL chiSq           9  3    2
## mHL F              8  4    9
## OsRo Z             7  5    1
## SstPgeq0.5 Z       6  5    3
## SstPl0.5 Z         5  5    6
## SstBoth chiSq      4  2    7
## SllPgeq0.5 chiSq   2  1    4
## SllPl0.5 chiSq     1  1    5
## SllBoth chiSq      3  2    8
```

```r
# trying cubic spline
library(splines)
library(splines2)

# fit cubic spline with 3 knots
```

```r
mod_age_cubic_spline <- glm(pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income_fam + to
summary(mod_age_cubic_spline)
```

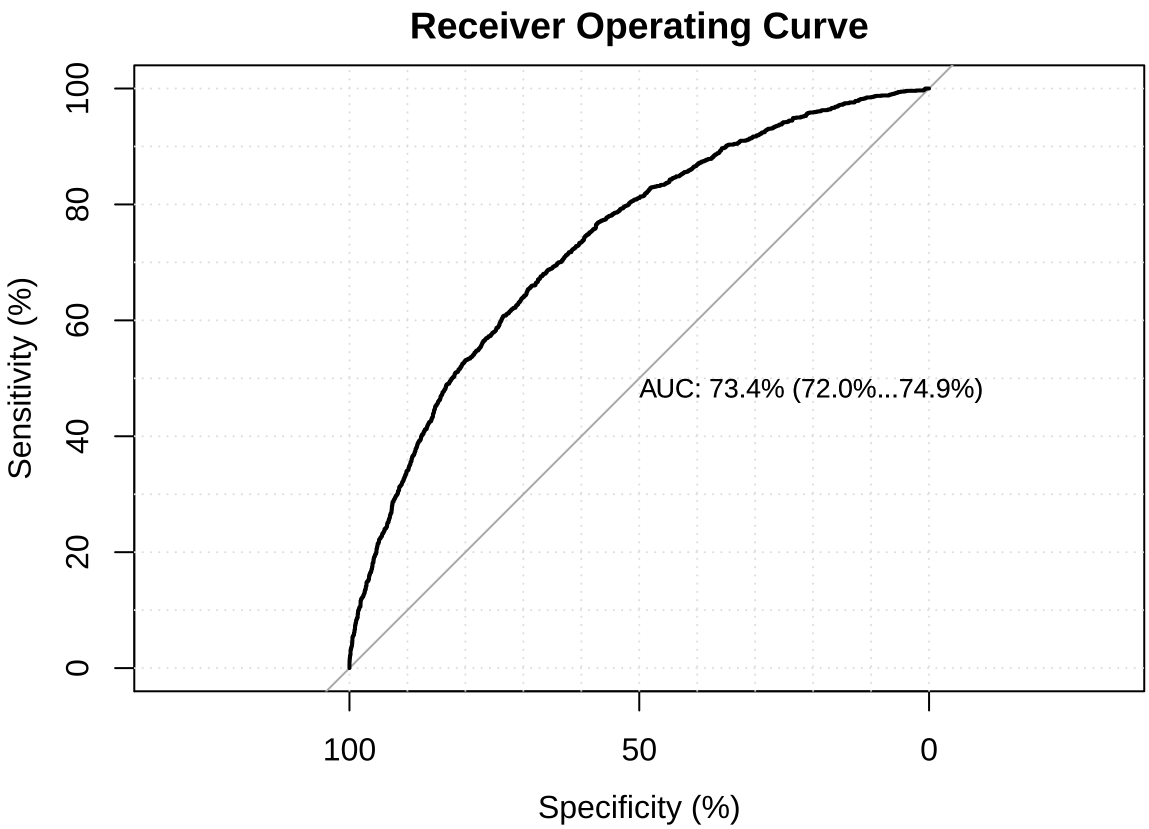
```
##
## Call:
## glm(formula = pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv +
##     income_fam + totexp + race_f + marital_stat_f + educ_f +
##     smoke_freq_f + limitation_f + afford_care_f + have_usc_f +
##     inscov_gen_2018_f, family = binomial(), data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8377  -0.7559  -0.5417   0.7198   2.6854
##
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)                         5.786e-01  1.914e-01   3.023 0.002500 **
## bSpline(age, df = 6, degree = 3)1 -1.700e+00  3.390e-01  -5.014 5.33e-07 ***
## bSpline(age, df = 6, degree = 3)2 -1.641e+00  2.356e-01  -6.965 3.27e-12 ***
## bSpline(age, df = 6, degree = 3)3 -1.514e+00  2.817e-01  -5.374 7.69e-08 ***
## bSpline(age, df = 6, degree = 3)4 -2.980e-01  2.750e-01  -1.084 0.278463
## bSpline(age, df = 6, degree = 3)5 -1.316e+00  2.909e-01  -4.522 6.14e-06 ***
## bSpline(age, df = 6, degree = 3)6 -2.807e-01  2.507e-01  -1.120 0.262750
## income_indiv                       -8.352e-06  1.479e-06  -5.647 1.63e-08 ***
## income_fam                          2.542e-07  7.449e-07   0.341 0.732902
## totexp                             -1.054e-05  3.154e-06  -3.340 0.000837 ***
## race_fhispanic                      2.572e-01  8.689e-02   2.960 0.003079 **
## race_fblack                         2.337e-01  9.640e-02   2.424 0.015332 *
## race_fasian                         1.211e+00  1.315e-01   9.209  < 2e-16 ***
## race_fother or multiple races       1.780e-01  1.782e-01   0.999 0.317934
## marital_stat_fmarried              -5.600e-01  8.997e-02  -6.224 4.83e-10 ***
## marital_stat_fwidowed              -3.099e-01  1.895e-01  -1.635 0.102051
## marital_stat_fdivorced             -3.945e-01  1.210e-01  -3.259 0.001117 **
## marital_stat_fseperated            -3.801e-01  1.781e-01  -2.134 0.032839 *
## educ_fany high school               4.460e-01  7.278e-02   6.128 8.91e-10 ***
## educ_fnone or any elementary        3.137e-01  1.515e-01   2.070 0.038430 *
## smoke_freq_fsome days               3.204e-01  1.489e-01   2.152 0.031379 *
## smoke_freq_fevery day               3.951e-01  1.028e-01   3.842 0.000122 ***
## limitation_fyes                     2.657e-01  1.236e-01   2.149 0.031659 *
## afford_care_fyes                   -2.930e-01  1.176e-01  -2.492 0.012688 *
## have_usc_fyes                      -6.562e-01  7.211e-02  -9.100  < 2e-16 ***
## inscov_gen_2018_fpublic only        1.016e-01  8.891e-02   1.143 0.253172
## inscov_gen_2018_funinsured          6.916e-01  1.085e-01   6.377 1.80e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 5859.6  on 5836  degrees of freedom
## AIC: 5913.6
##
## Number of Fisher Scoring iterations: 5
```

```r
hoslem.test(cc_df$pap_num, fitted(mod_age_cubic_spline), g = 10) # good fit
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  cc_df$pap_num, fitted(mod_age_cubic_spline)
## X-squared = 3.1256, df = 8, p-value = 0.9262
```

```r
gof(mod_age_cubic_spline, g = 10)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```




```
##       chiSq df  pVal
## PrI       1  2     4
## drI       2  2     3
## PrG       1  1     2
## drG       2  1     1
## PrCT      1  1     2
## drCT      2  1     1
##                    val  df  pVal
## HL chiSq             8   3     8
## mHL F                9   4     9
## OsRo Z               5   5     3
## SstPgeq0.5 Z         2   5     6
## SstPl0.5 Z           6   5     2
## SstBoth chiSq        4   2     7
## SllPgeq0.5 chiSq     1   1     5
```

```
## S11P10.5 chiSq     3  1    1
## S11Both chiSq      7  2    4
```

```r
anova(mod_back, mod_age_cubic_spline, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: pap_num ~ age + income_indiv + income_fam + totexp + race_f +
##     marital_stat_f + educ_f + smoke_freq_f + limitation_f + afford_care_f +
##     have_usc_f + inscov_gen_2018_f
## Model 2: pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income_fam +
##     totexp + race_f + marital_stat_f + educ_f + smoke_freq_f +
##     limitation_f + afford_care_f + have_usc_f + inscov_gen_2018_f
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      5841     5981.7
## 2      5836     5859.6  5   122.14 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# LRT p-value < 0.05 so makes sense to have this spline term


# testing to see if quadratic age is sufficient or we need cubic spline
# we can do this since quad age model is nested within cubic spline model
anova(mod_age_quad, mod_age_cubic_spline, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: pap_num ~ age + I(age^2) + income_indiv + income_fam + totexp +
##     race_f + marital_stat_f + educ_f + smoke_freq_f + limitation_f +
##     afford_care_f + have_usc_f + inscov_gen_2018_f
## Model 2: pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income_fam +
##     totexp + race_f + marital_stat_f + educ_f + smoke_freq_f +
##     limitation_f + afford_care_f + have_usc_f + inscov_gen_2018_f
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      5840     5936.1
## 2      5836     5859.6  4   76.517 9.518e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# p-value < 0.05 so makes sense to use cubic spline term instead of quad term only
```

```r
# Building off the spline model to add interactions

# interaction model 1
mod_spline_interaction1 <- glm(pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income_fam +
summary(mod_spline_interaction1)
```

```
##
## Call:
## glm(formula = pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv +
##     income_fam + totexp + race_f + marital_stat_f + educ_f +
##     smoke_freq_f + limitation_f + afford_care_f + have_usc_f +
##     inscov_gen_2018_f + marital_stat_f * income_fam, family = binomial(),
##     data = cc_df)
##
## Deviance Residuals:
```

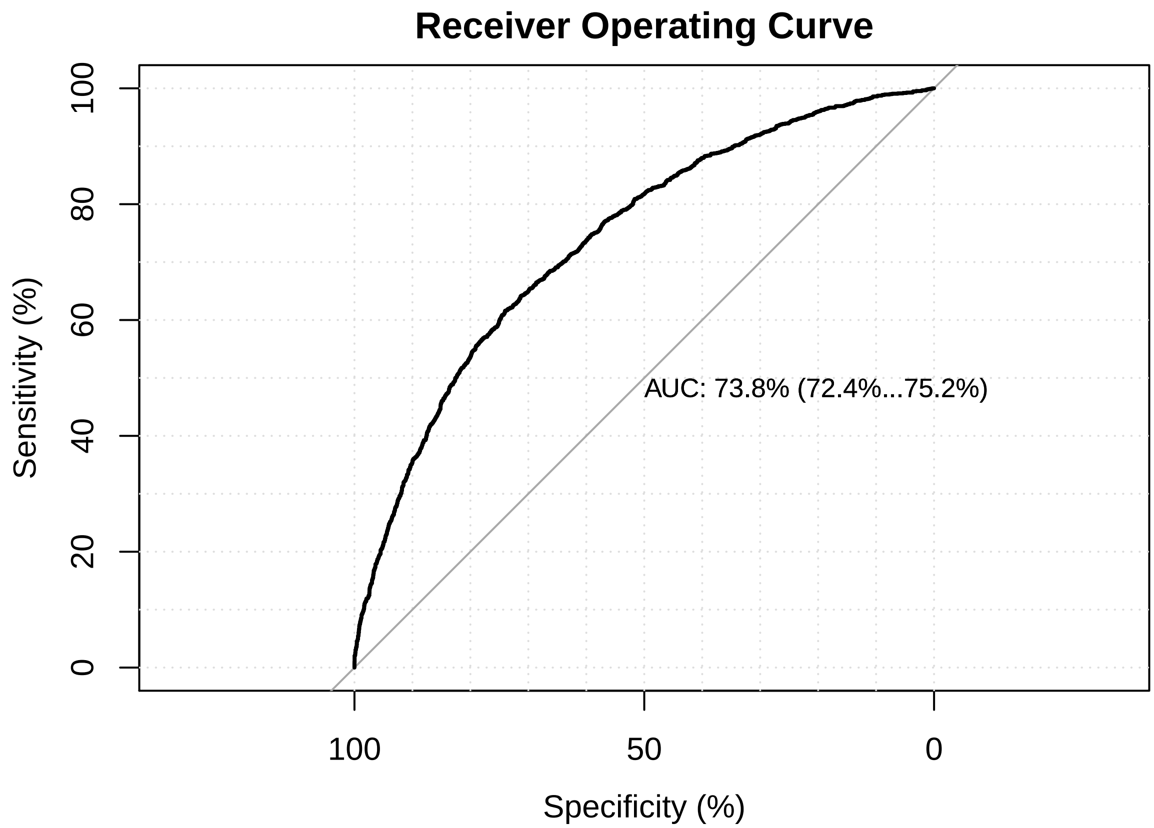
```
##      Min       1Q   Median       3Q      Max
## -1.9041  -0.7601  -0.5392   0.6994   2.9388
##
## Coefficients:
##                                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)                          3.062e-01  2.002e-01   1.529 0.126182
## bSpline(age, df = 6, degree = 3)1  -1.629e+00  3.398e-01  -4.794 1.64e-06 ***
## bSpline(age, df = 6, degree = 3)2  -1.562e+00  2.363e-01  -6.612 3.79e-11 ***
## bSpline(age, df = 6, degree = 3)3  -1.409e+00  2.829e-01  -4.982 6.30e-07 ***
## bSpline(age, df = 6, degree = 3)4  -1.764e-01  2.767e-01  -0.638 0.523626
## bSpline(age, df = 6, degree = 3)5  -1.211e+00  2.924e-01  -4.142 3.45e-05 ***
## bSpline(age, df = 6, degree = 3)6  -1.932e-01  2.516e-01  -0.768 0.442719
## income_indiv                       -7.718e-06  1.546e-06  -4.992 5.97e-07 ***
## income_fam                          4.182e-06  1.144e-06   3.655 0.000258 ***
## totexp                             -1.049e-05  3.146e-06  -3.334 0.000855 ***
## race_fhispanic                      2.448e-01  8.715e-02   2.809 0.004973 **
## race_fblack                         2.389e-01  9.635e-02   2.479 0.013160 *
## race_fasian                         1.197e+00  1.331e-01   8.997  < 2e-16 ***
## race_fother or multiple races       1.804e-01  1.784e-01   1.012 0.311713
## marital_stat_fmarried              -2.030e-01  1.173e-01  -1.730 0.083605 .
## marital_stat_fwidowed              -2.471e-01  2.611e-01  -0.946 0.343918
## marital_stat_fdivorced             -1.678e-01  1.751e-01  -0.958 0.338008
## marital_stat_fseperated            -5.044e-01  2.394e-01  -2.107 0.035101 *
## educ_fany high school               4.468e-01  7.281e-02   6.137 8.40e-10 ***
## educ_fnone or any elementary        2.863e-01  1.517e-01   1.887 0.059165 .
## smoke_freq_fsome days               3.280e-01  1.490e-01   2.202 0.027665 *
## smoke_freq_fevery day               3.992e-01  1.027e-01   3.887 0.000101 ***
## limitation_fyes                     2.594e-01  1.239e-01   2.095 0.036206 *
## afford_care_fyes                   -2.955e-01  1.173e-01  -2.520 0.011747 *
## have_usc_fyes                      -6.586e-01  7.224e-02  -9.117  < 2e-16 ***
## inscov_gen_2018_fpublic only        1.300e-01  8.898e-02   1.461 0.143962
## inscov_gen_2018_funinsured          7.012e-01  1.084e-01   6.470 9.80e-11 ***
## income_fam:marital_stat_fmarried   -6.252e-06  1.336e-06  -4.679 2.88e-06 ***
## income_fam:marital_stat_fwidowed   -1.844e-06  4.455e-06  -0.414 0.678883
## income_fam:marital_stat_fdivorced  -5.985e-06  3.179e-06  -1.883 0.059745 .
## income_fam:marital_stat_fseperated  4.274e-06  4.451e-06   0.960 0.336950
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 5832.9  on 5832  degrees of freedom
## AIC: 5894.9
##
## Number of Fisher Scoring iterations: 5
```

```r
hoslem.test(cc_df$pap_num, fitted(mod_spline_interaction1), g = 10) # good fit
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  cc_df$pap_num, fitted(mod_spline_interaction1)
## X-squared = 4.8074, df = 8, p-value = 0.7779
```

```r
gof(mod_spline_interaction1, g = 10)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```




```
##       chiSq df  pVal
## PrI       2  2     2
## drI       1  2     4
## PrG       2  1     1
## drG       1  1     3
## PrCT      2  1     1
## drCT      1  1     3
##                   val  df  pVal
## HL chiSq            8   3     6
## mHL F               9   4     9
## OsRo Z              7   5     1
## SstPgeq0.5 Z        4   5     5
## SstPl0.5 Z          6   5     2
## SstBoth chiSq       5   2     7
## SllPgeq0.5 chiSq    1   1     4
## SllPl0.5 chiSq      2   1     3
## SllBoth chiSq       3   2     8
```

```r
anova(mod_age_cubic_spline, mod_spline_interaction1, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income_fam +
```

```
##     totexp + race_f + marital_stat_f + educ_f + smoke_freq_f +
##     limitation_f + afford_care_f + have_usc_f + inscov_gen_2018_f
## Model 2: pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income_fam +
##     totexp + race_f + marital_stat_f + educ_f + smoke_freq_f +
##     limitation_f + afford_care_f + have_usc_f + inscov_gen_2018_f +
##     marital_stat_f * income_fam
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      5836     5859.6
## 2      5832     5832.9  4   26.639 2.351e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# LRT p-value < 0.05 so makes sense to keep this interaction

# interaction model 2
mod_spline_interaction2 <- glm(pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income_fam +
summary(mod_spline_interaction2)
```

```
##
## Call:
## glm(formula = pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv +
##     income_fam + totexp + race_f + marital_stat_f + educ_f +
##     smoke_freq_f + limitation_f + afford_care_f + have_usc_f +
##     inscov_gen_2018_f + marital_stat_f * income_fam + educ_f *
##     totexp, family = binomial(), data = cc_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9130  -0.7633  -0.5364   0.6918   3.1283
##
## Coefficients:
##                                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)                        3.507e-01  2.009e-01   1.746 0.080847 .
## bSpline(age, df = 6, degree = 3)1 -1.636e+00  3.396e-01  -4.816 1.47e-06 ***
## bSpline(age, df = 6, degree = 3)2 -1.549e+00  2.362e-01  -6.559 5.40e-11 ***
## bSpline(age, df = 6, degree = 3)3 -1.402e+00  2.828e-01  -4.957 7.15e-07 ***
## bSpline(age, df = 6, degree = 3)4 -1.770e-01  2.767e-01  -0.640 0.522448
## bSpline(age, df = 6, degree = 3)5 -1.206e+00  2.925e-01  -4.123 3.74e-05 ***
## bSpline(age, df = 6, degree = 3)6 -1.832e-01  2.519e-01  -0.727 0.467116
## income_indiv                      -7.694e-06  1.547e-06  -4.974 6.54e-07 ***
## income_fam                         4.141e-06  1.145e-06   3.616 0.000299 ***
## totexp                            -2.026e-05  5.670e-06  -3.574 0.000352 ***
## race_fhispanic                     2.400e-01  8.712e-02   2.754 0.005879 **
## race_fblack                        2.355e-01  9.637e-02   2.444 0.014515 *
## race_fasian                        1.181e+00  1.331e-01   8.877  < 2e-16 ***
## race_fother or multiple races      1.866e-01  1.789e-01   1.043 0.296751
## marital_stat_fmarried             -2.107e-01  1.173e-01  -1.796 0.072525 .
## marital_stat_fwidowed             -2.539e-01  2.621e-01  -0.969 0.332738
## marital_stat_fdivorced            -1.852e-01  1.757e-01  -1.054 0.292005
## marital_stat_fseperated           -5.084e-01  2.398e-01  -2.120 0.034003 *
## educ_fany high school              3.617e-01  7.927e-02   4.562 5.06e-06 ***
## educ_fnone or any elementary       3.022e-01  1.633e-01   1.850 0.064269 .
## smoke_freq_fsome days              3.326e-01  1.491e-01   2.230 0.025724 *
## smoke_freq_fevery day              3.941e-01  1.028e-01   3.833 0.000127 ***
## limitation_fyes                    2.574e-01  1.245e-01   2.067 0.038724 *
```

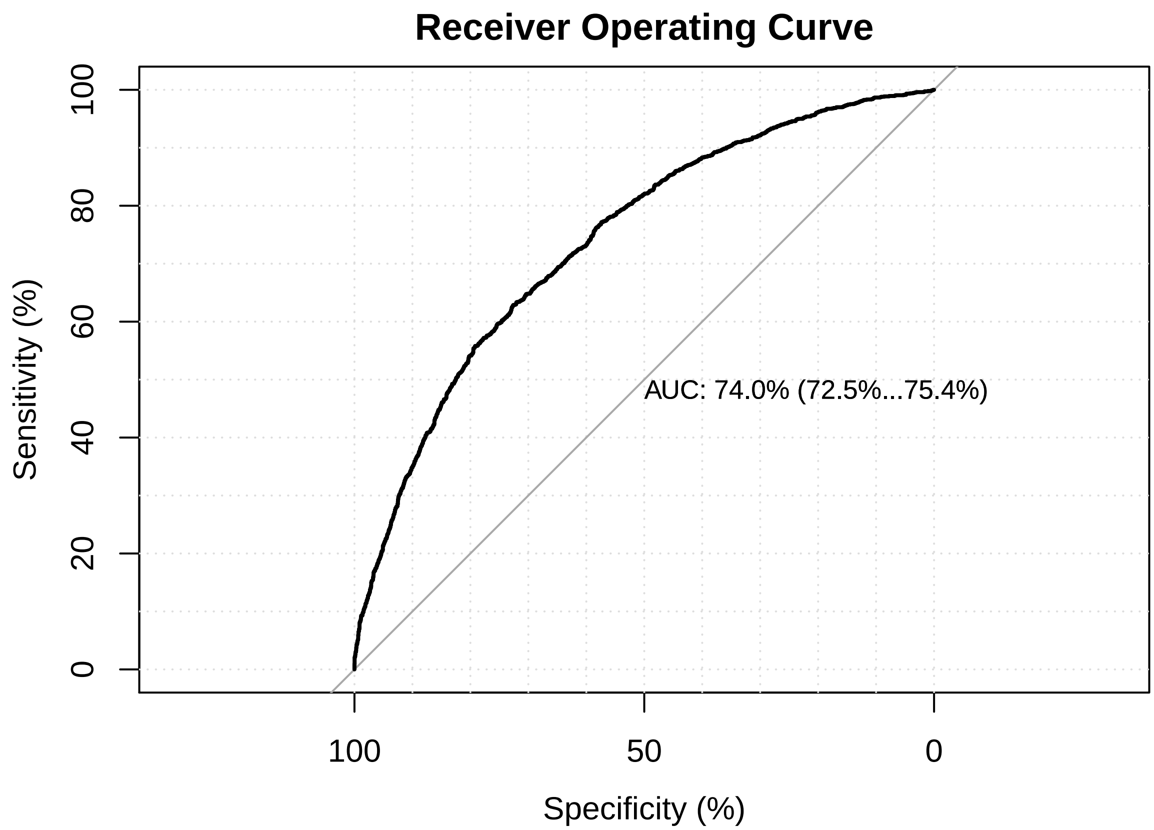
```
## afford_care_fyes                    -2.920e-01  1.174e-01  -2.487 0.012873 *
## have_usc_fyes                       -6.554e-01  7.228e-02  -9.068  < 2e-16 ***
## inscov_gen_2018_fpublic only         1.336e-01  8.902e-02   1.501 0.133343
## inscov_gen_2018_funinsured           6.999e-01  1.083e-01   6.462 1.03e-10 ***
## income_fam:marital_stat_fmarried    -6.187e-06  1.337e-06  -4.629 3.67e-06 ***
## income_fam:marital_stat_fwidowed    -1.756e-06  4.466e-06  -0.393 0.694160
## income_fam:marital_stat_fdivorced   -5.770e-06  3.195e-06  -1.806 0.070922 .
## income_fam:marital_stat_fseperated   3.972e-06  4.469e-06   0.889 0.374158
## totexp:educ_fany high school         1.754e-05  6.673e-06   2.628 0.008583 **
## totexp:educ_fnone or any elementary -3.469e-06  1.477e-05  -0.235 0.814280
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6663.9  on 5862  degrees of freedom
## Residual deviance: 5824.1  on 5830  degrees of freedom
## AIC: 5890.1
##
## Number of Fisher Scoring iterations: 5
```

```r
hoslem.test(cc_df$pap_num, fitted(mod_spline_interaction2), g = 10) # good fit
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  cc_df$pap_num, fitted(mod_spline_interaction2)
## X-squared = 7.2592, df = 8, p-value = 0.5089
```

```r
gof(mod_spline_interaction2, g = 10)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```




```
##       chiSq df pVal
## PrI       2  2    4
## drI       1  2    2
## PrG       2  1    3
## drG       1  1    1
## PrCT      2  1    3
## drCT      1  1    1
##                    val df pVal
## HL chiSq             9  3    6
## mHL F                8  4    9
## OsRo Z               7  5    1
## SstPgeq0.5 Z         2  5    8
## SstPl0.5 Z           3  5    2
## SstBoth chiSq        6  2    4
## SllPgeq0.5 chiSq     1  1    7
## SllPl0.5 chiSq       4  1    3
## SllBoth chiSq        5  2    5
```

```
anova(mod_spline_interaction1, mod_spline_interaction2, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income_fam +
##     totexp + race_f + marital_stat_f + educ_f + smoke_freq_f +
##     limitation_f + afford_care_f + have_usc_f + inscov_gen_2018_f +
##     marital_stat_f * income_fam
## Model 2: pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income_fam +
##     totexp + race_f + marital_stat_f + educ_f + smoke_freq_f +
```

```
##     limitation_f + afford_care_f + have_usc_f + inscov_gen_2018_f +
##     marital_stat_f * income_fam + educ_f * totexp
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      5832     5832.9
## 2      5830     5824.1  2    8.813   0.0122 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# LRT p-value < 0.05 so makes sense to keep this interaction
```

```r
# comparing AIC for all the association models we've built so far
AIC(mod_full,
    mod_back,
    mod_age_quad,
    mod_age_cubic_spline,
    mod_spline_interaction1,
    mod_spline_interaction2)
```

```
##                         df      AIC
## mod_full                30 6030.070
## mod_back                22 6025.698
## mod_age_quad            23 5982.076
## mod_age_cubic_spline    27 5913.560
## mod_spline_interaction1 31 5894.920
## mod_spline_interaction2 33 5890.107
```

```r
# final association model

kable(summary(mod_spline_interaction2)$coefficients)
```

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.3507453	0.2009087	1.7457943	0.0808467
bSpline(age, df = 6, degree = 3)1	-1.6356743	0.3396448	-4.8158378	0.0000015
bSpline(age, df = 6, degree = 3)2	-1.5490867	0.2361593	-6.5594989	0.0000000
bSpline(age, df = 6, degree = 3)3	-1.4020432	0.2828291	-4.9572090	0.0000007
bSpline(age, df = 6, degree = 3)4	-0.1769737	0.2767043	-0.6395771	0.5224476
bSpline(age, df = 6, degree = 3)5	-1.2060016	0.2925262	-4.1227126	0.0000374
bSpline(age, df = 6, degree = 3)6	-0.1832088	0.2519446	-0.7271790	0.4671163
income_indiv	-0.0000077	0.0000015	-4.9744563	0.0000007
income_fam	0.0000041	0.0000011	3.6164508	0.0002987
totexp	-0.0000203	0.0000057	-3.5740258	0.0003515
race_fhispanic	0.2399707	0.0871203	2.7544765	0.0058786
race_fblack	0.2355481	0.0963680	2.4442574	0.0145151
race_fasian	1.1813189	0.1330808	8.8767037	0.0000000
race_fother or multiple races	0.1866396	0.1788719	1.0434259	0.2967511
marital_stat_fmarried	-0.2107004	0.1173288	-1.7958108	0.0725246
marital_stat_fwidowed	-0.2538686	0.2620945	-0.9686146	0.3327375
marital_stat_fdivorced	-0.1851787	0.1757359	-1.0537329	0.2920052
marital_stat_fseperated	-0.5084346	0.2398230	-2.1200414	0.0340026
educ_fany high school	0.3616504	0.0792671	4.5624280	0.0000051
educ_fnone or any elementary	0.3021977	0.1633230	1.8503065	0.0642694
smoke_freq_fsome days	0.3325559	0.1491047	2.2303512	0.0257241
smoke_freq_fevery day	0.3941092	0.1028287	3.8326777	0.0001268
limitation_fyes	0.2574488	0.1245457	2.0671038	0.0387244
afford_care_fyes	-0.2920098	0.1174020	-2.4872641	0.0128730

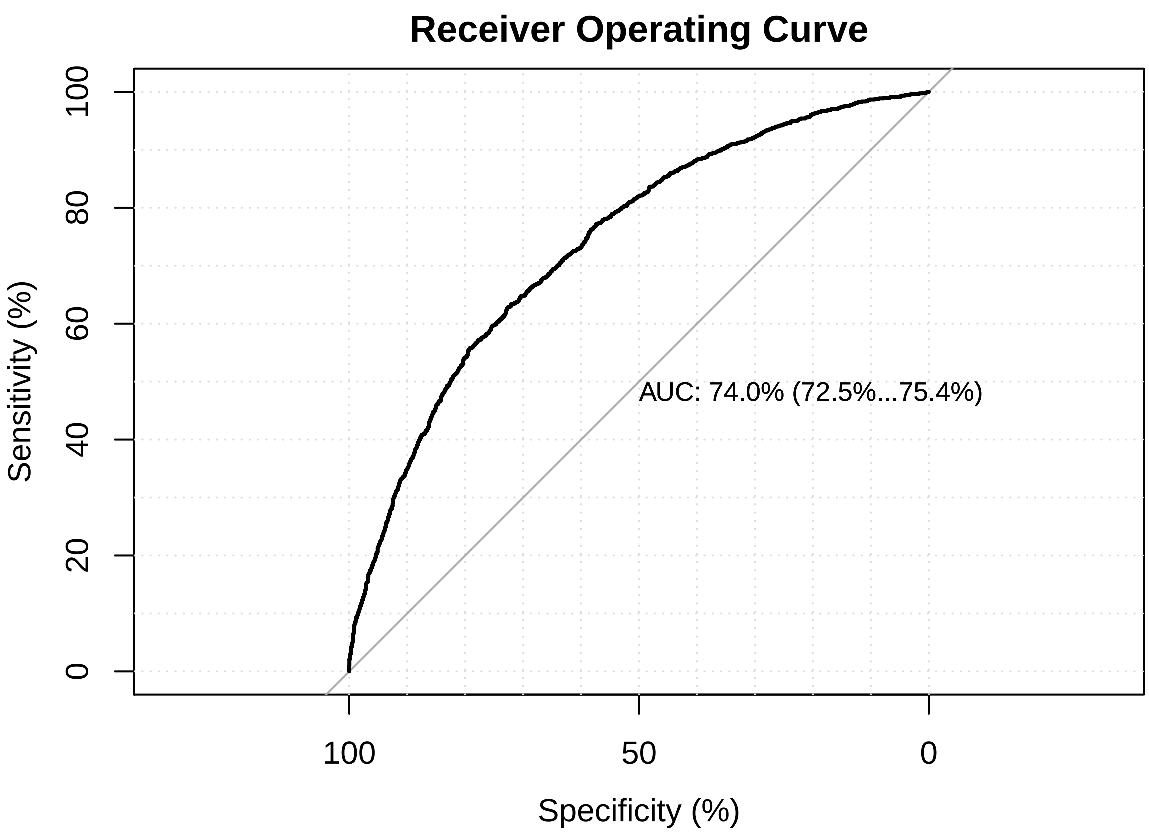
	Estimate	Std. Error	z value	Pr(>|z|)
have_usc_fyes	-0.6554217	0.0722767	-9.0682238	0.0000000
inscov_gen_2018_fpublic only	0.1336261	0.0890217	1.5010503	0.1333425
inscov_gen_2018_funinsured	0.6999469	0.1083155	6.4621121	0.0000000
income_fam:marital_stat_fmarried	-0.0000062	0.0000013	-4.6289919	0.0000037
income_fam:marital_stat_fwidowed	-0.0000018	0.0000045	-0.3932157	0.6941602
income_fam:marital_stat_fdivorced	-0.0000058	0.0000032	-1.8059737	0.0709225
income_fam:marital_stat_fseperated	0.0000040	0.0000045	0.8887114	0.3741582
totexp:educ_fany high school	0.0000175	0.0000067	2.6282367	0.0085829
totexp:educ_fnone or any elementary	-0.0000035	0.0000148	-0.2349077	0.8142804

```r
hoslem.test(cc_df$pap_num, fitted(mod_spline_interaction2), g = 10) # good fit
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  cc_df$pap_num, fitted(mod_spline_interaction2)
## X-squared = 7.2592, df = 8, p-value = 0.5089
```

```r
gof(mod_spline_interaction2, g = 10)
```

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

## Setting direction: controls < cases
```




```
##      chiSq df pVal
## PrI      2  2    4
## drI      1  2    2
```

```
## PrG      2  1    3
## drG      1  1    1
## PrCT     2  1    3
## drCT     1  1    1
##                  val df pVal
## HL chiSq           9  3    6
## mHL F              8  4    9
## OsRo Z             7  5    1
## SstPgeq0.5 Z       2  5    8
## SstPl0.5 Z         3  5    2
## SstBoth chiSq      6  2    4
## SllPgeq0.5 chiSq   1  1    7
## SllPl0.5 chiSq     4  1    3
## SllBoth chiSq      5  2    5
```

```r
# afford care
exp(coef(mod_spline_interaction2)["afford_care_fyes"])
```

```
## afford_care_fyes
##        0.7467612
```

```r
exp(coef(mod_spline_interaction2)["have_usc_fyes"])
```

```
## have_usc_fyes
##     0.5192231
```

```r
exp(coef(mod_spline_interaction2)["inscov_gen_2018_fpublic only"])
```

```
## inscov_gen_2018_fpublic only
##                     1.142965
```

```r
exp(coef(mod_spline_interaction2)["inscov_gen_2018_funinsured"])
```

```
## inscov_gen_2018_funinsured
##                   2.013646
```

```r
exp(confint(mod_spline_interaction2))
```

```
## Waiting for profiling to be done...

##                                       2.5 %    97.5 %
## (Intercept)                      0.95906456 2.1092730
## bSpline(age, df = 6, degree = 3)1   0.09967648 0.3777107
## bSpline(age, df = 6, degree = 3)2   0.13349694 0.3369838
## bSpline(age, df = 6, degree = 3)3   0.14100680 0.4274823
## bSpline(age, df = 6, degree = 3)4   0.48663797 1.4400445
## bSpline(age, df = 6, degree = 3)5   0.16840537 0.5302919
## bSpline(age, df = 6, degree = 3)6   0.50687164 1.3615580
## income_indiv                     0.99998925 0.9999953
## income_fam                       1.00000191 1.0000064
## totexp                           0.99996783 0.9999901
## race_fhispanic                   1.07124106 1.5074109
## race_fblack                      1.04698127 1.5277014
## race_fasian                      2.50849132 4.2277787
## race_fother or multiple races    0.84310937 1.7015648
## marital_stat_fmarried            0.64364036 1.0195814
## marital_stat_fwidowed            0.46195645 1.2930983
## marital_stat_fdivorced           0.58970962 1.1750373
```

```
## marital_stat_fseperated            0.37352866 0.9582774
## educ_fany high school              1.22902220 1.6769683
## educ_fnone or any elementary       0.98109409 1.8621214
## smoke_freq_fsome days              1.03724312 1.8620609
## smoke_freq_fevery day              1.21106956 1.8125521
## limitation_fyes                    1.01198734 1.6493303
## afford_care_fyes                   0.59153419 0.9375012
## have_usc_fyes                      0.45066011 0.5982933
## inscov_gen_2018_fpublic only       0.95961007 1.3604233
## inscov_gen_2018_funinsured         1.62811197 2.4896224
## income_fam:marital_stat_fmarried    0.99999118 0.9999964
## income_fam:marital_stat_fwidowed    0.99998930 1.0000069
## income_fam:marital_stat_fdivorced   0.99998768 1.0000002
## income_fam:marital_stat_fseperated  0.99999486 1.0000126
## totexp:educ_fany high school        1.00000486 1.0000311
## totexp:educ_fnone or any elementary 0.99996233 1.0000214
```

Prediction modeling

Now we're working on creating prediction models using the training set and then testing it on the testing set.

```
# build test and train set
set.seed(1)
train_index <- createDataPartition(cc_df$pap_num, times = 1, p = 0.7, list = FALSE)
train_set <- cc_df[train_index, ]
```

```
## Warning: The `i` argument of ``[`()` can't be a matrix as of tibble 3.0.0.
## Convert to a vector.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_warnings()` to see where this warning was generated.
```

```
test_set <- cc_df[-train_index, ]
```

```
# create function for looking at prediction metrics
pred_metrics <- function(model, cutoff) {
  p_hat <- predict(model, newdata = test_set, type = "response")
  y_hat <- ifelse(p_hat > cutoff, "no", "yes")
  confusion <- confusionMatrix(data = factor(y_hat, levels = c("yes", "no")),
                               reference = test_set$pap_f)

  roc <- roc(test_set$pap_num, p_hat)
  auc <- auc(roc)

  result <- list(p_hat = p_hat,
                 y_hat = y_hat,
                 confusion = confusion,
                 roc = roc,
                 auc = auc)
  result
}
```

```
# full model
fit_full <- glm(pap_num ~ age + income_indiv + income_fam + totexp + outofpocket_exp + genhlth_avg_f + i
summary(fit_full)
```

```
##
```

```
## Call:
## glm(formula = pap_num ~ age + income_indiv + income_fam + totexp +
##     outofpocket_exp + genhlth_avg_f + region_f + race_f + marital_stat_f +
##     educ_f + smoke_freq_f + limitation_f + afford_care_f + have_usc_f +
##     inscov_gen_2018_f, family = binomial(), data = train_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7444  -0.7754  -0.5649   0.9213   2.6450
##
## Coefficients:
##                                Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  -1.436e+00  4.027e-01  -3.565 0.000363 ***
## age                           1.696e-02  3.565e-03   4.758 1.96e-06 ***
## income_indiv                 -1.154e-05  1.729e-06  -6.670 2.56e-11 ***
## income_fam                    1.151e-06  8.581e-07   1.341 0.179775
## totexp                       -9.615e-06  4.128e-06  -2.329 0.019838 *
## outofpocket_exp              -1.455e-05  2.627e-05  -0.554 0.579752
## genhlth_avg_ffair             4.839e-01  3.539e-01   1.368 0.171462
## genhlth_avg_fgood             3.717e-01  3.506e-01   1.060 0.289032
## genhlth_avg_fvery good        2.836e-01  3.552e-01   0.799 0.424524
## genhlth_avg_fexcellent        4.035e-01  3.643e-01   1.108 0.268038
## region_fmidwest              -8.001e-02  1.344e-01  -0.595 0.551532
## region_fsouth                 1.143e-01  1.201e-01   0.952 0.341261
## region_fwest                  1.944e-03  1.281e-01   0.015 0.987891
## race_fhispanic                1.559e-01  1.057e-01   1.475 0.140344
## race_fblack                   1.613e-01  1.160e-01   1.390 0.164434
## race_fasian                   1.184e+00  1.558e-01   7.596 3.06e-14 ***
## race_fother or multiple races -1.448e-01  2.198e-01  -0.659 0.510096
## marital_stat_fmarried        -7.774e-01  1.012e-01  -7.685 1.53e-14 ***
## marital_stat_fwidowed        -2.791e-01  2.202e-01  -1.267 0.205014
## marital_stat_fdivorced       -3.905e-01  1.423e-01  -2.745 0.006059 **
## marital_stat_fseperated      -4.198e-01  2.054e-01  -2.043 0.041007 *
## educ_fany high school         4.512e-01  8.639e-02   5.222 1.77e-07 ***
## educ_fnone or any elementary  4.295e-01  1.775e-01   2.420 0.015513 *
## smoke_freq_fsome days         1.343e-01  1.804e-01   0.745 0.456526
## smoke_freq_fevery day         3.300e-01  1.217e-01   2.712 0.006688 **
## limitation_fyes               2.094e-01  1.547e-01   1.353 0.175921
## afford_care_fyes             -2.992e-01  1.390e-01  -2.152 0.031369 *
## have_usc_fyes                -5.510e-01  8.504e-02  -6.479 9.24e-11 ***
## inscov_gen_2018_fpublic only  4.978e-03  1.062e-01   0.047 0.962596
## inscov_gen_2018_funinsured    5.591e-01  1.279e-01   4.372 1.23e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 4695.8  on 4104  degrees of freedom
## Residual deviance: 4214.6  on 4075  degrees of freedom
## AIC: 4274.6
##
## Number of Fisher Scoring iterations: 5
```

```r
hoslem.test(train_set$pap_num, fitted(fit_full), g = 10) # good fit to training for full model
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_full)
## X-squared = 8.3656, df = 8, p-value = 0.3986
```

```r
# now we see how accurate full model is for future data

# testing to see what p cutoff balances sensitivity and specificity best
# so that we can use that cutoff when we run the prediction models at first
p_seq <- seq(0, 1, .01)
sensitivity <- rep(NA, length(p_seq))
specificity <- rep(NA, length(p_seq))
for (i in 1:length(p_seq)) {
  p_cutoff <- p_seq[i]
  prediction <- pred_metrics(fit_full, p_cutoff)
  confusion <- prediction$confusion
  sensitivity[i] <- confusion$byClass["Sensitivity"]
  specificity[i] <- confusion$byClass["Specificity"]
}
test_cutoff_df <- data.frame(p_seq, sensitivity, specificity)
# cutoff of 0.26 looks best

# get prediction metrics for full fit
fit_full_pred_metrics <- pred_metrics(fit_full, 0.26)
fit_full_pred_metrics$confusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction yes  no
##        yes 870 146
##        no  453 289
##
##                Accuracy : 0.6593
##                  95% CI : (0.6366, 0.6814)
##     No Information Rate : 0.7526
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.2603
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.6576
##             Specificity : 0.6644
##          Pos Pred Value : 0.8563
##          Neg Pred Value : 0.3895
##              Prevalence : 0.7526
##          Detection Rate : 0.4949
##    Detection Prevalence : 0.5779
##       Balanced Accuracy : 0.6610
##
```

```
##        'Positive' Class : yes
##
```

```
fit_full_pred_metrics$auc
```

```
## Area under the curve: 0.7214
```

```
# forward/backward selection

# forward model selection
fit_forw <- step(glm(pap_num ~ 1, data = train_set, family = binomial()), ~ age + income_indiv + income_
```

```
## Start:  AIC=4697.78
## pap_num ~ 1
##
##                     Df Deviance    AIC
## + income_indiv       1   4531.3 4535.3
## + inscov_gen_2018_f  2   4550.7 4556.7
## + educ_f             2   4566.4 4572.4
## + income_fam         1   4589.4 4593.4
## + race_f             4   4589.9 4599.9
## + marital_stat_f     4   4598.5 4608.5
## + have_usc_f         1   4607.4 4611.4
## + outofpocket_exp    1   4662.1 4666.1
## + totexp             1   4667.5 4671.5
## + smoke_freq_f       2   4672.2 4678.2
## + region_f           3   4673.6 4681.6
## + genhlth_avg_f      4   4672.7 4682.7
## + limitation_f       1   4688.1 4692.1
## <none>                   4695.8 4697.8
## + afford_care_f      1   4695.5 4699.5
## + age                1   4695.8 4699.8
##
## Step:  AIC=4535.3
## pap_num ~ income_indiv
##
##                     Df Deviance    AIC
## + race_f             4   4448.5 4460.5
## + have_usc_f         1   4463.8 4469.8
## + marital_stat_f     4   4460.8 4472.8
## + inscov_gen_2018_f  2   4468.6 4476.6
## + educ_f             2   4476.4 4484.4
## + totexp             1   4509.8 4515.8
## + outofpocket_exp    1   4518.2 4524.2
## + region_f           3   4516.1 4526.1
## + income_fam         1   4521.9 4527.9
## + smoke_freq_f       2   4520.4 4528.4
## + age                1   4527.9 4533.9
## + genhlth_avg_f      4   4523.2 4535.2
## <none>                   4531.3 4535.3
## + limitation_f       1   4530.9 4536.9
## + afford_care_f      1   4531.0 4537.0
##
## Step:  AIC=4460.49
## pap_num ~ income_indiv + race_f
```

```
##
##                    Df Deviance    AIC
## + marital_stat_f     4   4385.2 4405.2
## + have_usc_f         1   4394.4 4408.4
## + inscov_gen_2018_f  2   4395.5 4411.5
## + educ_f             2   4400.4 4416.4
## + smoke_freq_f       2   4426.6 4442.6
## + totexp             1   4436.5 4450.5
## + income_fam         1   4438.2 4452.2
## + outofpocket_exp    1   4443.2 4457.2
## + age                1   4443.3 4457.3
## + region_f           3   4440.7 4458.7
## <none>                   4448.5 4460.5
## + limitation_f       1   4446.8 4460.8
## + genhlth_avg_f      4   4441.7 4461.7
## + afford_care_f      1   4448.4 4462.4
##
## Step:  AIC=4405.24
## pap_num ~ income_indiv + race_f + marital_stat_f
##
##                    Df Deviance    AIC
## + have_usc_f         1   4337.9 4359.9
## + educ_f             2   4338.7 4362.7
## + inscov_gen_2018_f  2   4344.6 4368.6
## + age                1   4365.4 4387.4
## + totexp             1   4372.8 4394.8
## + smoke_freq_f       2   4370.9 4394.9
## + region_f           3   4375.1 4401.1
## + outofpocket_exp    1   4382.2 4404.2
## <none>                   4385.2 4405.2
## + afford_care_f      1   4384.7 4406.7
## + limitation_f       1   4384.8 4406.8
## + income_fam         1   4385.1 4407.1
## + genhlth_avg_f      4   4379.9 4407.9
##
## Step:  AIC=4359.87
## pap_num ~ income_indiv + race_f + marital_stat_f + have_usc_f
##
##                    Df Deviance    AIC
## + educ_f             2   4290.8 4316.8
## + age                1   4307.1 4331.1
## + inscov_gen_2018_f  2   4309.4 4335.4
## + smoke_freq_f       2   4323.4 4349.4
## + totexp             1   4330.6 4354.6
## + limitation_f       1   4335.1 4359.1
## <none>                   4337.9 4359.9
## + region_f           3   4331.9 4359.9
## + outofpocket_exp    1   4336.5 4360.5
## + afford_care_f      1   4336.6 4360.6
## + genhlth_avg_f      4   4330.7 4360.7
## + income_fam         1   4337.9 4361.9
##
## Step:  AIC=4316.81
## pap_num ~ income_indiv + race_f + marital_stat_f + have_usc_f +
```

```
##     educ_f
##
##                      Df Deviance    AIC
## + age                 1   4267.9 4295.9
## + inscov_gen_2018_f  2   4269.7 4299.7
## + totexp              1   4283.8 4311.8
## + smoke_freq_f       2   4282.4 4312.4
## <none>                    4290.8 4316.8
## + region_f           3   4284.9 4316.9
## + limitation_f       1   4289.0 4317.0
## + afford_care_f      1   4289.5 4317.5
## + outofpocket_exp    1   4290.0 4318.0
## + income_fam         1   4290.0 4318.0
## + genhlth_avg_f      4   4286.1 4320.1
##
## Step:  AIC=4295.86
## pap_num ~ income_indiv + race_f + marital_stat_f + have_usc_f +
##     educ_f + age
##
##                      Df Deviance    AIC
## + inscov_gen_2018_f  2   4245.7 4277.7
## + totexp              1   4257.9 4287.9
## + smoke_freq_f       2   4260.5 4292.5
## + region_f           3   4261.5 4295.5
## <none>                    4267.9 4295.9
## + outofpocket_exp    1   4266.0 4296.0
## + afford_care_f      1   4266.3 4296.3
## + income_fam         1   4266.8 4296.8
## + limitation_f       1   4267.6 4297.6
## + genhlth_avg_f      4   4263.3 4299.3
##
## Step:  AIC=4277.72
## pap_num ~ income_indiv + race_f + marital_stat_f + have_usc_f +
##     educ_f + age + inscov_gen_2018_f
##
##                    Df Deviance    AIC
## + totexp            1   4238.5 4272.5
## + smoke_freq_f     2   4238.3 4274.3
## + afford_care_f    1   4241.5 4275.5
## + outofpocket_exp  1   4243.6 4277.6
## <none>                  4245.7 4277.7
## + income_fam       1   4244.0 4278.0
## + limitation_f     1   4245.0 4279.0
## + region_f         3   4242.3 4280.3
## + genhlth_avg_f    4   4241.3 4281.3
##
## Step:  AIC=4272.48
## pap_num ~ income_indiv + race_f + marital_stat_f + have_usc_f +
##     educ_f + age + inscov_gen_2018_f + totexp
##
##                    Df Deviance    AIC
## + smoke_freq_f     2   4230.9 4268.9
## + afford_care_f    1   4234.5 4270.5
## + limitation_f     1   4236.1 4272.1
```

```
## <none>                 4238.5 4272.5
## + income_fam       1   4236.6 4272.6
## + outofpocket_exp  1   4238.2 4274.2
## + region_f         3   4235.1 4275.1
## + genhlth_avg_f    4   4234.4 4276.4
##
## Step:  AIC=4268.89
## pap_num ~ income_indiv + race_f + marital_stat_f + have_usc_f +
##     educ_f + age + inscov_gen_2018_f + totexp + smoke_freq_f
##
##                   Df Deviance    AIC
## + afford_care_f    1   4226.4 4266.4
## + income_fam       1   4228.7 4268.7
## <none>                 4230.9 4268.9
## + limitation_f     1   4229.0 4269.0
## + outofpocket_exp  1   4230.6 4270.6
## + region_f         3   4227.6 4271.6
## + genhlth_avg_f    4   4227.0 4273.0
##
## Step:  AIC=4266.44
## pap_num ~ income_indiv + race_f + marital_stat_f + have_usc_f +
##     educ_f + age + inscov_gen_2018_f + totexp + smoke_freq_f +
##     afford_care_f
##
##                   Df Deviance    AIC
## + limitation_f     1   4224.2 4266.2
## <none>                 4226.4 4266.4
## + income_fam       1   4224.6 4266.6
## + outofpocket_exp  1   4226.2 4268.2
## + region_f         3   4222.9 4268.9
## + genhlth_avg_f    4   4222.1 4270.1
##
## Step:  AIC=4266.19
## pap_num ~ income_indiv + race_f + marital_stat_f + have_usc_f +
##     educ_f + age + inscov_gen_2018_f + totexp + smoke_freq_f +
##     afford_care_f + limitation_f
##
##                   Df Deviance    AIC
## <none>                 4224.2 4266.2
## + income_fam       1   4222.4 4266.4
## + outofpocket_exp  1   4224.0 4268.0
## + region_f         3   4220.8 4268.8
## + genhlth_avg_f    4   4220.0 4270.0
```

```r
summary(fit_forw)
```

```
##
## Call:
## glm(formula = pap_num ~ income_indiv + race_f + marital_stat_f +
##     have_usc_f + educ_f + age + inscov_gen_2018_f + totexp +
##     smoke_freq_f + afford_care_f + limitation_f, family = binomial(),
##     data = train_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
```

```
## -1.7632  -0.7782  -0.5667   0.9275   2.6622
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -1.042e+00  1.635e-01  -6.370 1.89e-10 ***
## income_indiv                    -1.062e-05  1.543e-06  -6.883 5.84e-12 ***
## race_fhispanic                   1.922e-01  1.021e-01   1.882  0.05984 .
## race_fblack                      2.214e-01  1.106e-01   2.003  0.04521 *
## race_fasian                      1.213e+00  1.526e-01   7.950 1.87e-15 ***
## race_fother or multiple races -1.323e-01  2.191e-01  -0.604  0.54612
## marital_stat_fmarried           -7.305e-01  9.638e-02  -7.579 3.49e-14 ***
## marital_stat_fwidowed           -2.486e-01  2.187e-01  -1.137  0.25557
## marital_stat_fdivorced          -3.970e-01  1.413e-01  -2.810  0.00496 **
## marital_stat_fseperated         -4.134e-01  2.041e-01  -2.025  0.04286 *
## have_usc_fyes                   -5.566e-01  8.427e-02  -6.605 3.98e-11 ***
## educ_fany high school            4.446e-01  8.536e-02   5.209 1.90e-07 ***
## educ_fnone or any elementary     4.338e-01  1.760e-01   2.465  0.01371 *
## age                              1.682e-02  3.515e-03   4.783 1.72e-06 ***
## inscov_gen_2018_fpublic only    -1.415e-02  1.034e-01  -0.137  0.89110
## inscov_gen_2018_funinsured       5.652e-01  1.261e-01   4.481 7.45e-06 ***
## totexp                          -1.031e-05  3.778e-06  -2.728  0.00638 **
## smoke_freq_fsome days            1.413e-01  1.797e-01   0.786  0.43174
## smoke_freq_fevery day            3.271e-01  1.209e-01   2.706  0.00681 **
## afford_care_fyes                -2.926e-01  1.352e-01  -2.164  0.03047 *
## limitation_fyes                  2.229e-01  1.478e-01   1.508  0.13146
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 4695.8  on 4104  degrees of freedom
## Residual deviance: 4224.2  on 4084  degrees of freedom
## AIC: 4266.2
##
## Number of Fisher Scoring iterations: 5
```

```r
# backward model selection
fit_back <- step(fit_full, direction = "backward")
```

```
## Start:  AIC=4274.65
## pap_num ~ age + income_indiv + income_fam + totexp + outofpocket_exp +
##     genhlth_avg_f + region_f + race_f + marital_stat_f + educ_f +
##     smoke_freq_f + limitation_f + afford_care_f + have_usc_f +
##     inscov_gen_2018_f
##
##                     Df Deviance    AIC
## - genhlth_avg_f      4   4218.7 4270.7
## - region_f           3   4218.0 4272.0
## - outofpocket_exp    1   4215.0 4273.0
## - income_fam         1   4216.4 4274.4
## - limitation_f       1   4216.5 4274.5
## <none>                   4214.6 4274.6
## - afford_care_f      1   4219.4 4277.4
## - smoke_freq_f       2   4222.1 4278.1
## - totexp             1   4221.0 4279.0
```

```
## - inscov_gen_2018_f  2   4235.5 4291.5
## - age               1   4237.4 4295.4
## - educ_f            2   4242.6 4298.6
## - have_usc_f        1   4256.1 4314.1
## - income_indiv      1   4261.8 4319.8
## - race_f            4   4271.9 4323.9
## - marital_stat_f    4   4275.7 4327.7
##
## Step:  AIC=4270.71
## pap_num ~ age + income_indiv + income_fam + totexp + outofpocket_exp +
##     region_f + race_f + marital_stat_f + educ_f + smoke_freq_f +
##     limitation_f + afford_care_f + have_usc_f + inscov_gen_2018_f
##
##                    Df Deviance    AIC
## - region_f          3   4222.2 4268.2
## - outofpocket_exp   1   4219.0 4269.0
## - income_fam        1   4220.6 4270.6
## - limitation_f      1   4220.7 4270.7
## <none>                  4218.7 4270.7
## - afford_care_f     1   4223.3 4273.3
## - smoke_freq_f      2   4226.4 4274.4
## - totexp            1   4225.4 4275.4
## - inscov_gen_2018_f  2   4239.2 4287.2
## - age               1   4242.6 4292.6
## - educ_f            2   4247.5 4295.5
## - have_usc_f        1   4259.6 4309.6
## - income_indiv      1   4266.5 4316.5
## - race_f            4   4276.2 4320.2
## - marital_stat_f    4   4280.7 4324.7
##
## Step:  AIC=4268.22
## pap_num ~ age + income_indiv + income_fam + totexp + outofpocket_exp +
##     race_f + marital_stat_f + educ_f + smoke_freq_f + limitation_f +
##     afford_care_f + have_usc_f + inscov_gen_2018_f
##
##                    Df Deviance    AIC
## - outofpocket_exp   1   4222.4 4266.4
## - income_fam        1   4224.0 4268.0
## <none>                  4222.2 4268.2
## - limitation_f      1   4224.4 4268.4
## - afford_care_f     1   4226.6 4270.6
## - smoke_freq_f      2   4229.9 4271.9
## - totexp            1   4229.2 4273.2
## - inscov_gen_2018_f  2   4245.5 4287.5
## - age               1   4245.8 4289.8
## - educ_f            2   4251.1 4293.1
## - have_usc_f        1   4265.5 4309.5
## - income_indiv      1   4270.3 4314.3
## - race_f            4   4281.4 4319.4
## - marital_stat_f    4   4282.6 4320.6
##
## Step:  AIC=4266.44
## pap_num ~ age + income_indiv + income_fam + totexp + race_f +
##     marital_stat_f + educ_f + smoke_freq_f + limitation_f + afford_care_f +
```

```
##     have_usc_f + inscov_gen_2018_f
##
##                      Df Deviance    AIC
## - income_fam         1   4224.2 4266.2
## <none>                   4222.4 4266.4
## - limitation_f       1   4224.6 4266.6
## - afford_care_f      1   4226.9 4268.9
## - smoke_freq_f       2   4230.1 4270.1
## - totexp             1   4231.3 4273.3
## - inscov_gen_2018_f  2   4245.6 4285.6
## - age                1   4245.8 4287.8
## - educ_f             2   4251.4 4291.4
## - have_usc_f         1   4266.0 4308.0
## - income_indiv       1   4270.9 4312.9
## - race_f             4   4282.1 4318.1
## - marital_stat_f     4   4282.9 4318.9
##
## Step:  AIC=4266.19
## pap_num ~ age + income_indiv + totexp + race_f + marital_stat_f +
##     educ_f + smoke_freq_f + limitation_f + afford_care_f + have_usc_f +
##     inscov_gen_2018_f
##
##                      Df Deviance    AIC
## <none>                   4224.2 4266.2
## - limitation_f       1   4226.4 4266.4
## - afford_care_f      1   4229.0 4269.0
## - smoke_freq_f       2   4231.6 4269.6
## - totexp             1   4233.0 4273.0
## - inscov_gen_2018_f  2   4247.0 4285.0
## - age                1   4247.2 4287.2
## - educ_f             2   4252.1 4290.1
## - have_usc_f         1   4267.2 4307.2
## - marital_stat_f     4   4284.0 4318.0
## - income_indiv       1   4278.5 4318.5
## - race_f             4   4286.7 4320.7
```

```
summary(fit_back)
```

```
##
## Call:
## glm(formula = pap_num ~ age + income_indiv + totexp + race_f +
##     marital_stat_f + educ_f + smoke_freq_f + limitation_f + afford_care_f +
##     have_usc_f + inscov_gen_2018_f, family = binomial(), data = train_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7632  -0.7782  -0.5667   0.9275   2.6622
##
## Coefficients:
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -1.042e+00  1.635e-01  -6.370 1.89e-10 ***
## age                          1.682e-02  3.515e-03   4.783 1.72e-06 ***
## income_indiv                -1.062e-05  1.543e-06  -6.883 5.84e-12 ***
## totexp                      -1.031e-05  3.778e-06  -2.728  0.00638 **
## race_fhispanic               1.922e-01  1.021e-01   1.882  0.05984 .
```

```
## race_fblack                    2.214e-01  1.106e-01   2.003  0.04521 *
## race_fasian                    1.213e+00  1.526e-01   7.950 1.87e-15 ***
## race_fother or multiple races -1.323e-01  2.191e-01  -0.604  0.54612
## marital_stat_fmarried         -7.305e-01  9.638e-02  -7.579 3.49e-14 ***
## marital_stat_fwidowed         -2.486e-01  2.187e-01  -1.137  0.25557
## marital_stat_fdivorced        -3.970e-01  1.413e-01  -2.810  0.00496 **
## marital_stat_fseperated       -4.134e-01  2.041e-01  -2.025  0.04286 *
## educ_fany high school          4.446e-01  8.536e-02   5.209 1.90e-07 ***
## educ_fnone or any elementary   4.338e-01  1.760e-01   2.465  0.01371 *
## smoke_freq_fsome days          1.413e-01  1.797e-01   0.786  0.43174
## smoke_freq_fevery day          3.271e-01  1.209e-01   2.706  0.00681 **
## limitation_fyes                2.229e-01  1.478e-01   1.508  0.13146
## afford_care_fyes              -2.926e-01  1.352e-01  -2.164  0.03047 *
## have_usc_fyes                 -5.566e-01  8.427e-02  -6.605 3.98e-11 ***
## inscov_gen_2018_fpublic only  -1.415e-02  1.034e-01  -0.137  0.89110
## inscov_gen_2018_funinsured     5.652e-01  1.261e-01   4.481 7.45e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 4695.8  on 4104  degrees of freedom
## Residual deviance: 4224.2  on 4084  degrees of freedom
## AIC: 4266.2
##
## Number of Fisher Scoring iterations: 5
```

```r
# forward and backward selection produce the same model
hoslem.test(train_set$pap_num, fitted(fit_back), g = 10) # good fit to training for forward/backward mo
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_back)
## X-squared = 8.5181, df = 8, p-value = 0.3846
```

```r
# now we can see how forward/backward model performs on testing data
fit_back_pred_metrics <- pred_metrics(fit_back, 0.26)
```

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

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

```r
fit_back_pred_metrics$confusion # better accuracy than full fit
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction yes  no
##        yes 874 142
##        no  449 293
##
##                Accuracy : 0.6638
##                  95% CI : (0.6412, 0.6859)
##     No Information Rate : 0.7526
##     P-Value [Acc > NIR] : 1
##
```

```
##                   Kappa : 0.2702
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.6606
##             Specificity : 0.6736
##          Pos Pred Value : 0.8602
##          Neg Pred Value : 0.3949
##              Prevalence : 0.7526
##          Detection Rate : 0.4972
##    Detection Prevalence : 0.5779
##       Balanced Accuracy : 0.6671
##
##        'Positive' Class : yes
##
```

```
fit_back_pred_metrics$auc # slightly worse auc than full fit
```

```
## Area under the curve: 0.7205
```

```
# going to use auc as the main comparison metric for picking the best prediction model since it looks o
```

```
# going forward with building off of full model since it has better auc

# add nonlinear terms for age

# try quadratic first
fit_age_quad <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + totexp + outofpock
hoslem.test(train_set$pap_num, fitted(fit_age_quad), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_age_quad)
## X-squared = 3.6041, df = 8, p-value = 0.891
```

```
# now we can see how it performs on testing data
fit_age_quad_pred_metrics <- pred_metrics(fit_age_quad, 0.26)
```

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

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

```
fit_age_quad_pred_metrics$auc # 0.7266 (keep)
```

```
## Area under the curve: 0.7266
```

```
# try spline
fit_age_cubic_spline <- glm(formula = pap_num ~ bSpline(age, df = 6, degree = 3) + income_indiv + income
hoslem.test(train_set$pap_num, fitted(fit_age_cubic_spline), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_age_cubic_spline)
## X-squared = 7.8484, df = 8, p-value = 0.4484
```

```
# now we can see how it performs on testing data
fit_age_cubic_spline_pred_metrics <- pred_metrics(fit_age_cubic_spline, 0.26)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
fit_age_cubic_spline_pred_metrics$auc # 0.7265 (don't keep)
```

```
## Area under the curve: 0.7265
```

```
# try gam
fit_age_gam <- glm(formula = pap_num ~ s(age,4) + income_indiv + income_fam + totexp + outofpocket_exp +
hoslem.test(train_set$pap_num, fitted(fit_age_gam), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_age_gam)
## X-squared = 8.3656, df = 8, p-value = 0.3986
```

```
# now we can see how it performs on testing data
fit_age_gam_pred_metrics <- pred_metrics(fit_age_gam, 0.26)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
fit_age_gam_pred_metrics$auc # 0.7214 (don't keep)
```

```
## Area under the curve: 0.7214
```

```
# go with quad model
```

```
# building off of quad age model since it has the best auc so far

# add interaction terms

# interaction 1
fit_age_quad_interaction1 <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + totexp

hoslem.test(train_set$pap_num, fitted(fit_age_quad_interaction1), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_age_quad_interaction1)
## X-squared = 8.2218, df = 8, p-value = 0.4121
```

```
# now we can see how it performs on testing data
fit_age_quad_interaction1_pred_metrics <- pred_metrics(fit_age_quad_interaction1, 0.26)
```

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

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

```
fit_age_quad_interaction1_pred_metrics$auc # 0.7304 (keep)
```

```
## Area under the curve: 0.7304
```

```
# interaction 2
fit_age_quad_interaction2 <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + totexp

hoslem.test(train_set$pap_num, fitted(fit_age_quad_interaction2), g = 10) # good fit to training
```

```
##
```

```
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_age_quad_interaction2)
## X-squared = 5.6043, df = 8, p-value = 0.6915
```

```
# now we can see how it performs on testing data
fit_age_quad_interaction2_pred_metrics <- pred_metrics(fit_age_quad_interaction2, 0.26)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
fit_age_quad_interaction2_pred_metrics$auc # 0.7317 (keep)
```

```
## Area under the curve: 0.7317
```

```
# building off of the adjusted logistic model

# incorporating non-linear individual income

# quadratic individual income
fit_ii_quad <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + I(income_indiv^2) + income_fam +

hoslem.test(train_set$pap_num, fitted(fit_ii_quad), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_ii_quad)
## X-squared = 6.8567, df = 8, p-value = 0.5522
```

```
# now we can see how it performs on testing data
fit_ii_quad_pred_metrics <- pred_metrics(fit_ii_quad, 0.26)
```

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

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

```
fit_ii_quad_pred_metrics$auc # 0.7314 (don't keep)
```

```
## Area under the curve: 0.7314
```

```
# spline individual income
fit_ii_spline <- glm(formula = pap_num ~ age + I(age^2) + bSpline(income_indiv, df = 6, degree = 3) + in

hoslem.test(train_set$pap_num, fitted(fit_ii_spline), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_ii_spline)
## X-squared = 3.6219, df = 8, p-value = 0.8895
```

```
# now we can see how it performs on testing data
fit_ii_spline_pred_metrics <- pred_metrics(fit_ii_spline, 0.26)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
fit_ii_spline_pred_metrics$auc # 0.7289 (don't keep)
```

```
## Area under the curve: 0.7289
```

```r
# try gam
fit_ii_gam <- gam(formula = pap_num ~ age + I(age^2) + s(income_indiv, 4) + income_fam + totexp + outof

hoslem.test(train_set$pap_num, fitted(fit_ii_gam), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_ii_gam)
## X-squared = 7.4699, df = 8, p-value = 0.4869
```

```r
# now we can see how it performs on testing data
fit_ii_gam_pred_metrics <- pred_metrics(fit_ii_gam, 0.26)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
fit_ii_gam_pred_metrics$auc # 0.7308 (don't keep)
```

```
## Area under the curve: 0.7308
```

```r
# incorporating non-linear family income

# quadratic family income
fit_ifam_quad <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + I(income_fam^2) +

hoslem.test(train_set$pap_num, fitted(fit_ifam_quad), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_ifam_quad)
## X-squared = 5.5896, df = 8, p-value = 0.6931
```

```r
# now we can see how it performs on testing data
fit_ifam_quad_pred_metrics <- pred_metrics(fit_ifam_quad, 0.26)
```

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

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

```r
fit_ifam_quad_pred_metrics$auc # 0.7314  (don't keep)
```

```
## Area under the curve: 0.7314
```

```r
# spline family income
fit_ifam_spline <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + bSpline(income_fam, df = 6,

hoslem.test(train_set$pap_num, fitted(fit_ifam_spline), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_ifam_spline)
## X-squared = 2.0938, df = 8, p-value = 0.978
```

```r
# now we can see how it performs on testing data
fit_ifam_spline_pred_metrics <- pred_metrics(fit_ifam_spline, 0.26)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
```

```
## prediction from a rank-deficient fit may be misleading
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
fit_ifam_spline_pred_metrics$auc # 0.7302 (don't keep)
```

```
## Area under the curve: 0.7302
```

```
# try gam
fit_ifam_gam <- gam(formula = pap_num ~ age + I(age^2) + income_indiv + s(income_fam, 4) +  totexp + ou

hoslem.test(train_set$pap_num, fitted(fit_ifam_gam), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_ifam_gam)
## X-squared = 4.5853, df = 8, p-value = 0.8008
```

```
# now we can see how it performs on testing data
fit_ifam_gam_pred_metrics <- pred_metrics(fit_ifam_gam, 0.26)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
fit_ifam_gam_pred_metrics$auc # 0.7313 (don't keep)
```

```
## Area under the curve: 0.7313
```

```
# incorporating non-linear total expense
# quadratic total expense
fit_texp_quad <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + totexp + I(totexp

hoslem.test(train_set$pap_num, fitted(fit_texp_quad), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_texp_quad)
## X-squared = 5.9766, df = 8, p-value = 0.6498
```

```
# now we can see how it performs on testing data
fit_texp_quad_pred_metrics <- pred_metrics(fit_texp_quad, 0.26)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
fit_texp_quad_pred_metrics$auc # 0.7326 (don't keep)
```

```
## Area under the curve: 0.7326
```

```
# spline total expense
fit_texp_spline <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + bSpline(totexp,

hoslem.test(train_set$pap_num, fitted(fit_texp_spline), g = 10) # good fit to training
```

```
##
```

```
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_texp_spline)
## X-squared = 5.995, df = 8, p-value = 0.6478
```

```
# now we can see how it performs on testing data
fit_texp_spline_pred_metrics <- pred_metrics(fit_texp_spline, 0.26)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading

## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
fit_texp_spline_pred_metrics$auc # 0.7409 (keep)
```

```
## Area under the curve: 0.7409
```

```
# try gam
fit_texp_gam <- gam(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + s(totexp, 4) + out

hoslem.test(train_set$pap_num, fitted(fit_texp_gam), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_texp_gam)
## X-squared = 5.9825, df = 8, p-value = 0.6492
```

```
# now we can see how it performs on testing data
fit_texp_gam_pred_metrics <- pred_metrics(fit_texp_gam, 0.26)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading

## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
fit_texp_gam_pred_metrics$auc # 0.7369 (don't keep)
```

```
## Area under the curve: 0.7369
```

```
# spline term has best auc so let's keep that
```

```
# incorporating non-linear out of pocket expense
# quadratic out of pocket expense
fit_oop_quad <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + bSpline(totexp, df

hoslem.test(train_set$pap_num, fitted(fit_oop_quad), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_oop_quad)
## X-squared = 5.4791, df = 8, p-value = 0.7054
```

```
# now we can see how it performs on testing data
fit_oop_quad_pred_metrics <- pred_metrics(fit_oop_quad, 0.26)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
fit_oop_quad_pred_metrics$auc # 0.7409 (don't keep)
```

```
## Area under the curve: 0.7409
```

```r
# incorporating spline out of pocket expense
fit_oop_spline <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + bSpline(totexp, d

hoslem.test(train_set$pap_num, fitted(fit_oop_spline), g = 10) # good fit to training
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  train_set$pap_num, fitted(fit_oop_spline)
## X-squared = 7.4085, df = 8, p-value = 0.4933
```

```r
# now we can see how it performs on testing data
fit_oop_spline_pred_metrics <- pred_metrics(fit_oop_spline, 0.26)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
fit_oop_spline_pred_metrics$auc # 0.7404 (don't keep)
```

```
## Area under the curve: 0.7404
```

```r
# final model is fit_texp_spline

# spline total expense
fit_final <- glm(formula = pap_num ~ age + I(age^2) + income_indiv + income_fam + bSpline(totexp, df=6,
kable(summary(fit_final)$coefficients)
```

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	1.5992557	0.6365338	2.5124442	0.0119898
age	-0.1163195	0.0245117	-4.7454689	0.0000021
I(age^2)	0.0015846	0.0002781	5.6974811	0.0000000
income_indiv	-0.0000079	0.0000018	-4.2860707	0.0000182
income_fam	0.0000052	0.0000014	3.7004430	0.0002152
bSpline(totexp, df = 6, degrees = 3)1	-0.1855308	0.1918211	-0.9672079	0.3334401
bSpline(totexp, df = 6, degrees = 3)2	-1.1014068	0.1657245	-6.6460089	0.0000000
bSpline(totexp, df = 6, degrees = 3)3	-1.2363050	0.1542857	-8.0130911	0.0000000
bSpline(totexp, df = 6, degrees = 3)4	-1.9088076	1.1272849	-1.6932788	0.0904024
bSpline(totexp, df = 6, degrees = 3)5	-2.4926742	4.0449373	-0.6162454	0.5377325
bSpline(totexp, df = 6, degrees = 3)6	-7.5130246	8.0930300	-0.9283327	0.3532350
outofpocket_exp	0.0000131	0.0000241	0.5446767	0.5859759
genhlth_avg_ffair	0.5255282	0.3591940	1.4630762	0.1434465
genhlth_avg_fgood	0.3217651	0.3561637	0.9034191	0.3663035
genhlth_avg_fvery good	0.1467213	0.3611996	0.4062055	0.6845916
genhlth_avg_fexcellent	0.1554651	0.3712456	0.4187663	0.6753869
region_fmidwest	-0.0698802	0.1372735	-0.5090583	0.6107113
region_fsouth	0.0944786	0.1226282	0.7704473	0.4410346
region_fwest	-0.0640889	0.1312492	-0.4882993	0.6253378

	Estimate	Std. Error	z value	Pr(>|z|)
race_fhispanic	0.0427627	0.1100171	0.3886919	0.6975041
race_fblack	0.1855162	0.1183269	1.5678281	0.1169212
race_fasian	1.0750124	0.1637258	6.5659300	0.0000000
race_fother or multiple races	-0.1474384	0.2270754	-0.6492925	0.5161493
marital_stat_fmarried	-0.1817249	0.1400919	-1.2971830	0.1945682
marital_stat_fwidowed	-0.0542058	0.3066086	-0.1767914	0.8596723
marital_stat_fdivorced	-0.0670234	0.2087529	-0.3210658	0.7481605
marital_stat_fseperated	-0.2977082	0.2928810	-1.0164819	0.3094000
educ_fany high school	0.2762522	0.0958433	2.8823332	0.0039474
educ_fnone or any elementary	0.3363555	0.1955191	1.7203209	0.0853741
smoke_freq_fsome days	0.0722232	0.1854421	0.3894649	0.6969323
smoke_freq_fevery day	0.3833683	0.1243295	3.0834850	0.0020459
limitation_fyes	0.2593218	0.1587643	1.6333758	0.1023900
afford_care_fyes	-0.3023831	0.1418649	-2.1314870	0.0330490
have_usc_fyes	-0.4016763	0.0894287	-4.4915825	0.0000071
inscov_gen_2018_fpublic only	0.0827237	0.1084989	0.7624380	0.4457986
inscov_gen_2018_funinsured	0.3888730	0.1332907	2.9174811	0.0035287
income_fam:marital_stat_fmarried	-0.0000069	0.0000016	-4.2457175	0.0000218
income_fam:marital_stat_fwidowed	-0.0000045	0.0000053	-0.8397525	0.4010471
income_fam:marital_stat_fdivorced	-0.0000052	0.0000036	-1.4335945	0.1516880
income_fam:marital_stat_fseperated	0.0000019	0.0000059	0.3274364	0.7433379
educ_fany high school:totexp	0.0000145	0.0000073	1.9945394	0.0460931
educ_fnone or any elementary:totexp	-0.0000134	0.0000189	-0.7088432	0.4784218

```r
# find p cutoff that balances specifity and sensitivity best
p_seq <- seq(0, 1, .01)
sensitivity <- rep(NA, length(p_seq))
specificity <- rep(NA, length(p_seq))
for (i in 1:length(p_seq)) {
  p_cutoff <- p_seq[i]
  prediction <- pred_metrics(fit_final, p_cutoff)
  confusion <- prediction$confusion
  sensitivity[i] <- confusion$byClass["Sensitivity"]
  specificity[i] <- confusion$byClass["Specificity"]
}
test_cutoff_df_fit_final <- data.frame(p_seq, sensitivity, specificity)
# balance is at p = 0.26

# now we can see how it performs on testing data with that p = 0.26
fit_final_pred_metrics <- pred_metrics(fit_final, 0.26)
fit_final_pred_metrics$confusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction yes  no
##        yes 903 138
##        no  420 297
##
##                Accuracy : 0.6826
##                  95% CI : (0.6603, 0.7043)
##     No Information Rate : 0.7526
```

```
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.6825
##             Specificity : 0.6828
##          Pos Pred Value : 0.8674
##          Neg Pred Value : 0.4142
##              Prevalence : 0.7526
##          Detection Rate : 0.5137
##    Detection Prevalence : 0.5922
##       Balanced Accuracy : 0.6826
##
##        'Positive' Class : yes
##
```

```
fit_final_pred_metrics$auc
```

```
## Area under the curve: 0.7409
```

```
plot(fit_final_pred_metrics$roc)
```