

Rmd File

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November 14, 2018

Instructions

Attempt to implement at least 3 versions of your team's highest priority method as outlined in the revised proposal. This could look like:

If you are focusing on regression, you could: Run a few bivariate regression models Try a few subset selection methods Experiment with ridge regression and lasso

If you are prioritizing classification, you could try kNN, QDA, LDA, and Logistic regression (and comparing the assumptions violated in each) If your plan was to do classification and then regression, could the class on November 12 provide inspiration? Leverage cross-validation with different number of folds to tune various hyper-parameters (such as penalties or the k in kNN).

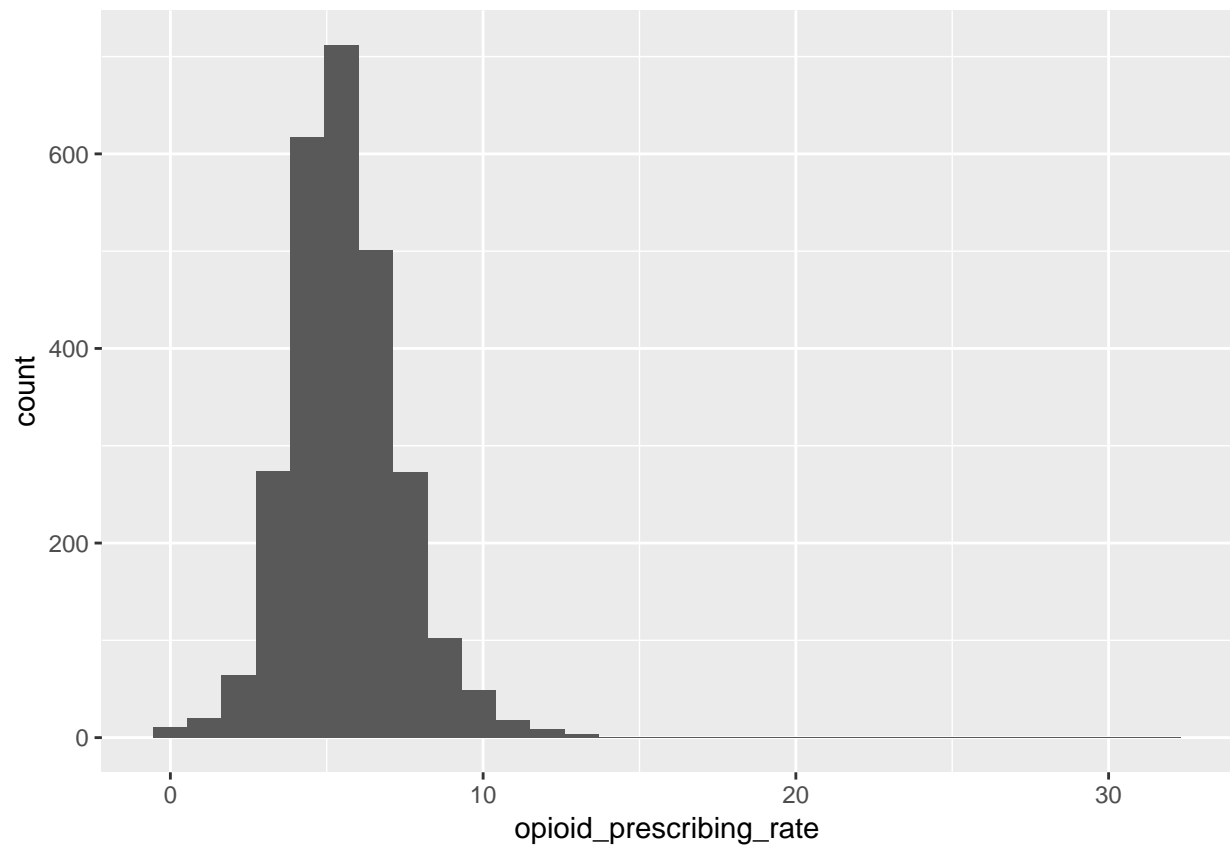
```
## reading in data files, joining to access prescribing behavior (response vars)
library(tidyverse)
library(corrplot)
County_Drug <- read_csv("County_Drug.csv")
prescribing_behavior <- read_csv("293 COUNTY DATA/prescribing_behavior.csv") %>%
  mutate(county_id = paste0("05000US", FIPS)) %>%
  subset(select = -c(`State Name`, `State Abbreviation`, `County Name`, `FIPS`))
colnames(prescribing_behavior) <- c("part_d_prescribers", "part_d_opioid_prescribers", "opioid_claims",

## joining data sets
working_data <- County_Drug %>%
  inner_join(prescribing_behavior, by = "county_id") %>%
  na.omit() %>%
  subset(select = -c(X1))

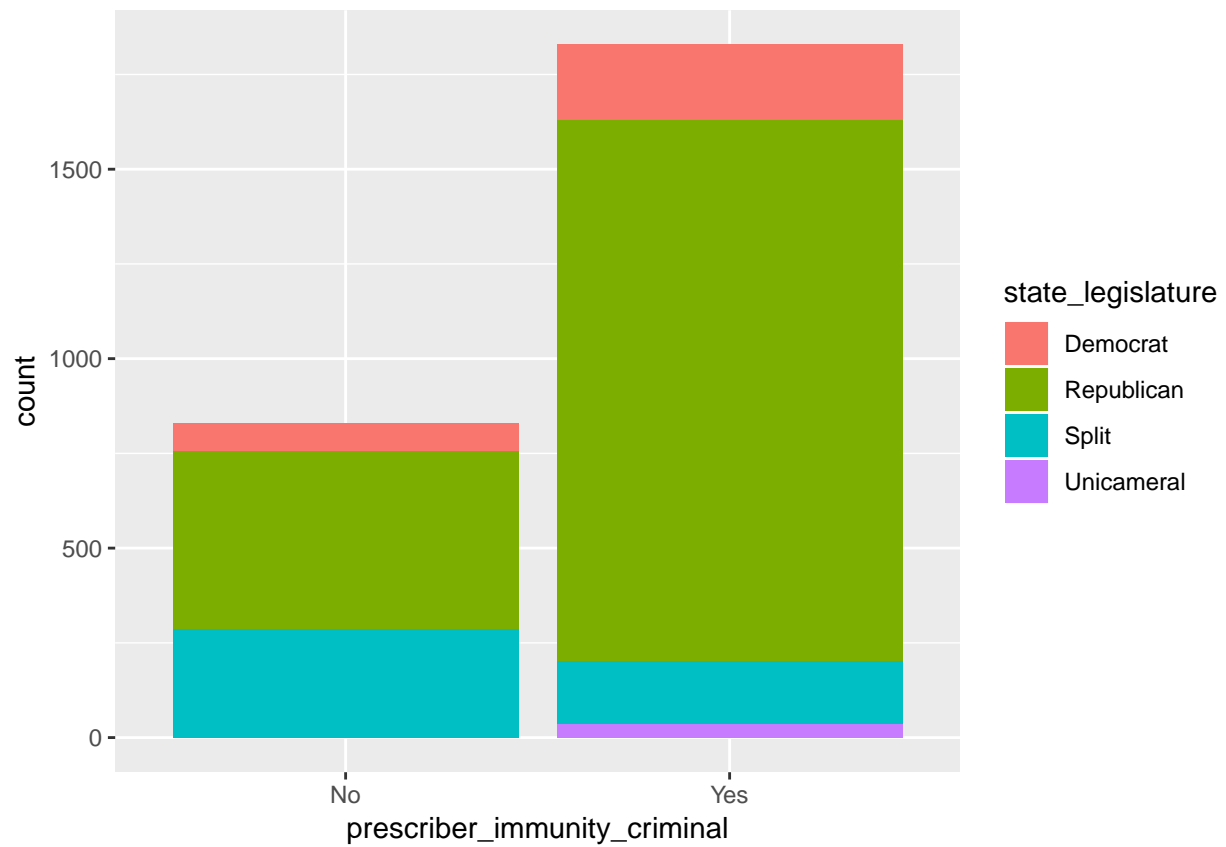
## some visualizations

ggplot(working_data, aes(x = opioid_prescribing_rate)) +
  geom_histogram()

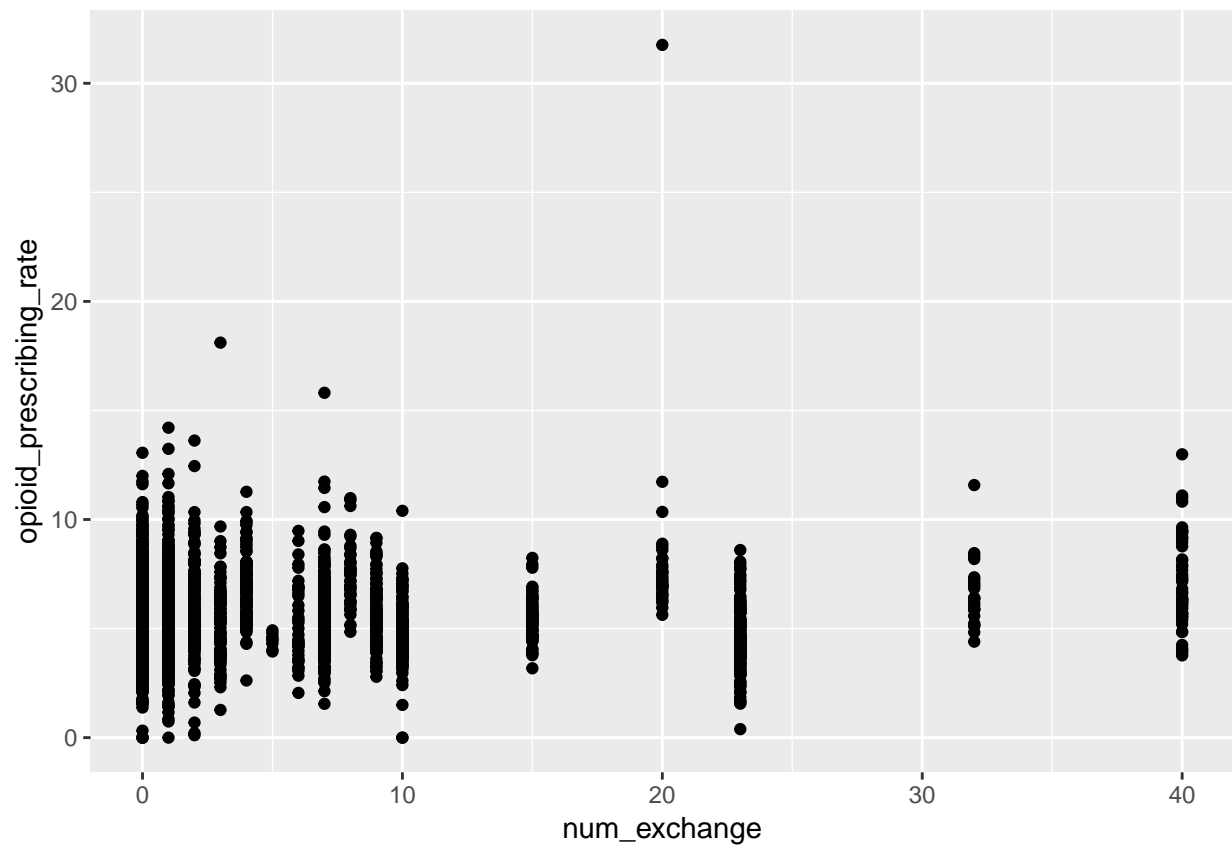
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



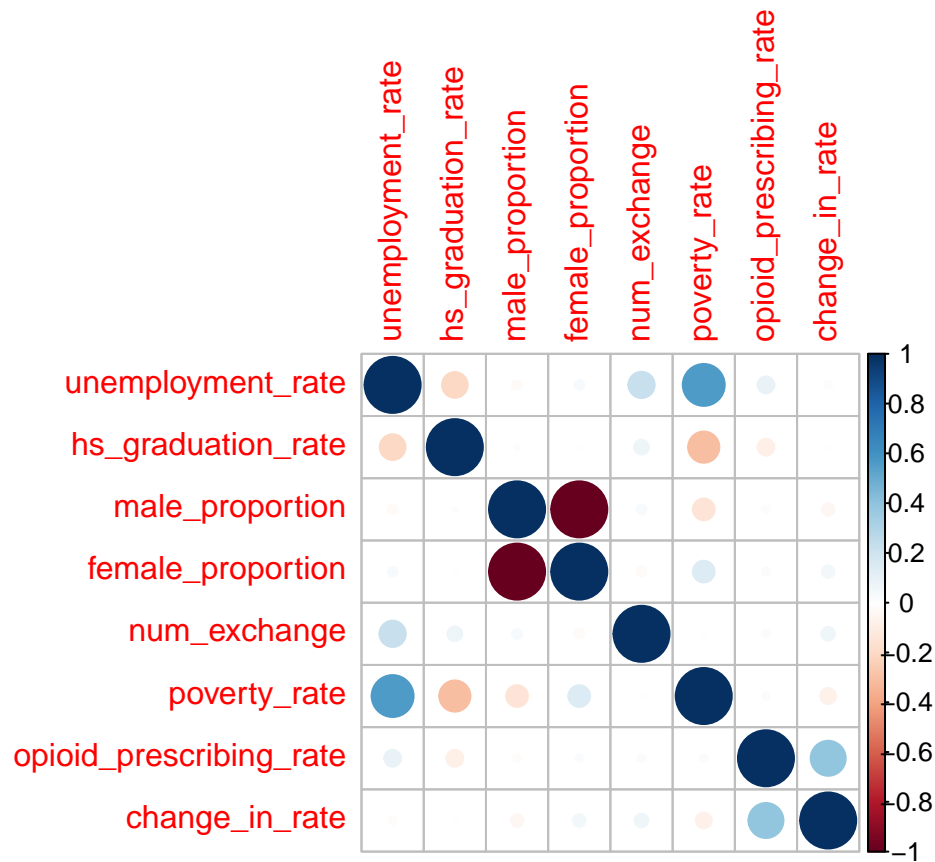
```
ggplot(working_data, aes(x = prescriber_immunity_criminal, fill = state_legislature)) +  
  geom_bar()
```



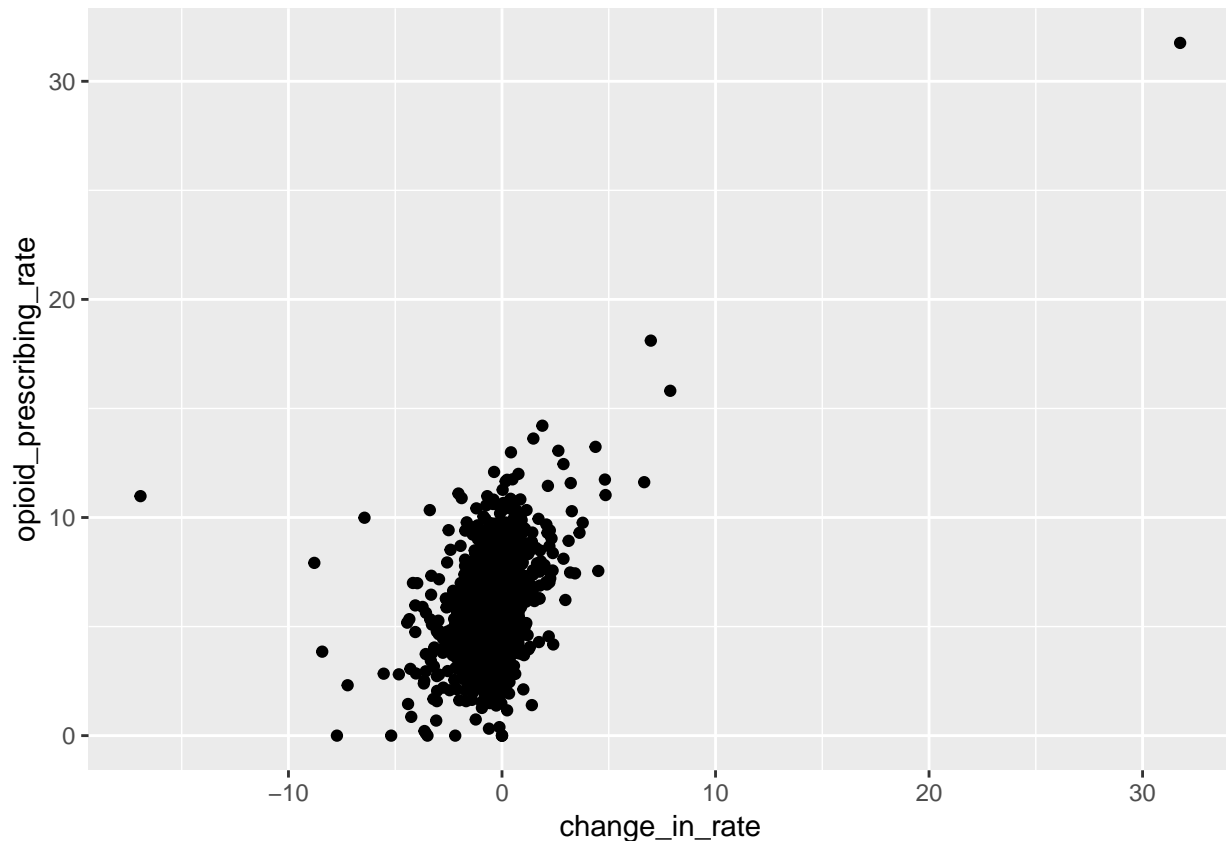
```
ggplot(working_data, aes(x = num_exchange, y = opioid_prescribing_rate)) +  
  geom_point()
```



```
numeric_only <- working_data[, sapply(working_data, is.numeric)] %>%
  select(unemployment_rate, hs_graduation_rate, male_proportion, female_proportion, num_exchange, pover
cor_data <- cor(numeric_only) %>%
  round(2)
corrplot(cor_data, method = "circle")
```



```
ggplot(working_data, aes(x = change_in_rate, y = opioid_prescribing_rate)) +
  geom_point()
```



Plot 1: Checking normality of response variable (opioid prescription rate)

The first graph in this series of initial visualizations is meant to help determine if the values of our response variable are distributed normally among the many counties ($n > 2,000$) that we will be using for analysis. We observe from this graph that the values are centered between 5% and 6%, and that they do not show any notable skew towards higher or lower values. If we decide to pursue regression, this is a huge positive.

Plot 2: Examining makeup of state legislatures versus state harm reduction policies

We wanted to get a look at whether our initial intuition—that democrat-leaning states would represent a greater proportion of the states with comprehensive harm reduction policies—holds up within this data set. Actually, we note that in general, republican-leaning counties make up a larger proportion of our sample, and while they do make up the largest proportion of states without comprehensive HR policies, they also make up the largest proportion of states that do have these measures in place. This leads us to consider the results we might observe in our future analysis, which is based around the intuition that more conservative states/counties will be less progressive in their harm reduction policy and have higher opioid prescription rates.

Plot 3: Comparing harm reduction policy with opioid-prescription rate (state-level)

With this plot, we wanted to get a sense of whether basic harm reduction initiatives, like needle exchanges, showed any obvious relationship with opioid prescribing rate (the intuition being that states implementing

HR policies may also be taking steps to curb their opioid prescribing rate). We actually saw that there is a slight positive association between the number of needle exchanges and the prescribing rate, which in a way also makes a certain amount of sense. However, this association is relatively weak.

Plot 4: Correlation of variables of interest (numeric)

As we are limited to calculating a correlation matrix for numeric variables, this is what we decided to do. We omitted variables associated with race because they would have made the table too large, and this is only a preliminary look. We observed that high correlation ($0.5 < |\text{cor}|$) is only really occurring where it is to be expected, between the proportions of male and female residents, as well as between the poverty rate and the unemployment rate. We might consider evaluating this second set of variables for relevance; perhaps one should be removed to lessen the potential for multicollinearity to interfere with model fitting.

Plot 5: Scatterplot of opioid prescription rate versus change in that rate (since 2013)

This final scatterplot was created in order to investigate the relationship between prescription rate and the change in this rate since 2013. We wanted to evaluate whether high prescribing rates were coupled with significant decreases or increases in those rates over the temporal span between 2013 and 2015; we observed that the changes in rates are primarily clustered in the range $[-5, 5]$ and that these changes guide prescription rates to within $[1, 10]$, primarily. There is a single highly unusual county indicated as having both a prescribing rate and change in rate of 31.76; after looking specifically at this county, we have determined that perhaps prescription rate data was not available for this area in 2013, and so the “change in rate” simply jumped when data were eventually added. We will consider whether to include this case if change in prescription rate becomes a variable we’d like to explore further.

```
## numerical summaries
library(mosaic)
library(Hmisc)

favstats(working_data$population)

##      min      Q1  median    Q3      max      mean      sd      n missing
##  1084 16461.25 33573.5 85146 10150558 120263.3 357044.8 2658      0

describe(working_data$opioid_prescribing_rate)

## working_data$opioid_prescribing_rate
##      n missing distinct    Info    Mean     Gmd     .05     .10
##   2658      0        734      1    5.593    1.974    3.015    3.590
##    .25     .50     .75     .90     .95
##   4.393    5.430    6.600    7.833    8.682
##
## lowest :  0.00  0.11  0.21  0.32  0.39, highest: 13.62 14.21 15.81 18.11 31.76

working_data %>%
  group_by(state_legislature) %>%
  summarise(mean = mean(opioid_prescribing_rate))

## # A tibble: 4 x 2
##   state_legislature mean
##   <chr>           <dbl>
## 1 Democrat        5.65
## 2 Republican      5.69
```

```
## 3 Split          5.22
## 4 Unicameral     4.86
```

```
working_data %>%
  group_by(state) %>%
  summarise(avg_rate = mean(opioid_prescribing_rate)) %>%
  arrange(avg_rate) %>%
  tail(5)
```

```
## # A tibble: 5 x 2
##   state      avg_rate
##   <chr>      <dbl>
## 1 Oregon      7.27
## 2 Colorado    7.38
## 3 Utah        8.10
## 4 Washington  8.10
## 5 Nevada      8.29
```

```
working_data %>%
  group_by(state) %>%
  summarise(avg_rate = mean(opioid_prescribing_rate)) %>%
  arrange(avg_rate) %>%
  head(5)
```

```
## # A tibble: 5 x 2
##   state      avg_rate
##   <chr>      <dbl>
## 1 Rhode Island  3.66
## 2 New York      4.02
## 3 North Dakota  4.08
## 4 Massachusetts 4.37
## 5 New Jersey    4.42
```

Summary 1: Quartile distribution of county population sizes

We thought it might be pertinent to our investigation to have some sense of the range of population sizes represented in our sample. We see that the median size is 33573 while the mean is 120263, indicating that this distribution is likely skewed towards higher populations.

Summary 2: Highest and lowest opioid prescription rates

In order to get a better sense of what “normal” versus “extreme” might look like in the sense of opioid prescription rate, we took a look at the five lowest and five highest prescription rates. We wanted to see, first and foremost, if the highest rates were clustered closely together, or if there were some notable standouts. We were also interested in determining what these values tend to look like. We were able to observe that all but the highest prescribing rate fall below 19% (the highest is >30%). We were also able to determine that the lowest values do not share similar variation.

Summary 3: Mean opioid prescription rate by state legislature composition

We wanted to determine whether there might be a significant association between political party and prescribing rates. After running these numbers, we observed that Republican and Democratic legislatures have nearly identical mean rates of prescription, and split legislatures are only slightly lower. Nebraska is

a unicameral legislature and has an even lower mean, though we are chalking this up to it's status as the singular unicameral legislative body in the nation.

Summary 4: Highest prescribing states

As we began to wind down our preliminary visualizations, we decided to determine which 5 states had the highest average (mean) prescribing rates and which had the lowest. The highest states included Nevada, Washington, Utah, Colorado, and Oregon, while the lowest were Rhode Island, New York, North Dakota, Massachusetts, and New Jersey (both lists in descending order). This summary has helped us to better observe the presence of a regional divide in prescribing practices (east vs. west), and it presents some interesting ideas as we think about ways in which we may want to expand on our data (i.e. categorizing states by region to perform more aggregate analyses).

```
## methods set up
library(class)

working_data$over_avg_rx_rate = 0
working_data$over_avg_rx_rate[working_data$opioid_prescribing_rate > median(working_data$opioid_prescribing_rate)] = 0

## setting up testing & training datasets
working_data$id <- 1:nrow(working_data)
train = working_data %>% dplyr::sample_frac(.75)
test = dplyr::anti_join(working_data, train, by = 'id')

set.seed(1)

## logistic regression
glm_fit = glm(over_avg_rx_rate ~ unemployment_rate +
              hs_graduation_rate +
              average_age +
              population +
              male_proportion +
              num_exchange +
              poverty_rate,
              data=working_data,
              family = binomial)
summary(glm_fit)

##
## Call:
## glm(formula = over_avg_rx_rate ~ unemployment_rate + hs_graduation_rate +
##      average_age + population + male_proportion + num_exchange +
##      poverty_rate, family = binomial, data = working_data)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.7687  -1.1398  -0.9326   1.1737   1.4788
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   3.657e+00  1.222e+00   2.993  0.00276 **
## unemployment_rate  6.205e+00  2.082e+00   2.981  0.00288 **
## hs_graduation_rate -1.986e+00  4.556e-01  -4.359  1.31e-05 ***
## average_age      -1.950e-02  8.705e-03  -2.240  0.02506 *
```

```
## population      1.312e-08  1.167e-07   0.112  0.91047
## male_proportion -3.144e-02  2.033e-02  -1.546  0.12200
## num_exchange    -3.582e-03  4.871e-03  -0.735  0.46211
## poverty_rate    -6.677e-01  8.415e-01  -0.793  0.42752
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 3684.7 on 2657 degrees of freedom
## Residual deviance: 3638.2 on 2650 degrees of freedom
## AIC: 3654.2
##
## Number of Fisher Scoring iterations: 4
```

Method 1: Logistic Regression

For this first attempt, we considered unemployment rate, high school graduation rate, average age, population, male proportion, number of needle exchange programs, and poverty rate as predictors of opioid prescribing rate (above or below average, when looking at the country as a whole). Based on p-values, it looks like population, male proportion, number of needle exchanges, and poverty rate are unlikely to be strongly related to over-average prescription of opioids. The smallest p-value here is for high school graduation rate, and the negative coefficient suggests that as high school graduation rate in a county rises, the rate of opioid prescription is less likely to be greater than average. The p-values for both high school graduation rate and unemployment rate are very small, less than 0.01, so there's evidence that there is an association between them and prescribing rate. One concern for this step is it assumes the predictors are independent, and we actually found some correlation between high school graduation rate and unemployment rate in plot 4.

```
## knn
knn_train = train %>%
  select(unemployment_rate, hs_graduation_rate)
knn_test = test %>%
  select(unemployment_rate, hs_graduation_rate)
knn_train_rx_rate = train %>%
  select(over_avg_rx_rate) %>%
  .$over_avg_rx_rate
knn_test_rx_rate = test %>%
  select(over_avg_rx_rate) %>%
  .$over_avg_rx_rate

knn_pred_1 = knn(knn_train,
                 knn_test,
                 knn_train_rx_rate,
                 k = 1)

table(knn_pred_1, knn_test_rx_rate)
```

```
##           knn_test_rx_rate
## knn_pred_1  0    1
##           0 166 178
##           1 143 177

mean(knn_pred_1 == knn_test_rx_rate)

## [1] 0.5165663
```

```

knn_pred_3 = knn(knn_train,
                 knn_test,
                 knn_train_rx_rate,
                 k = 3)

table(knn_pred_3, knn_test_rx_rate)

##           knn_test_rx_rate
## knn_pred_3    0    1
##           0 182 175
##           1 127 180

mean(knn_pred_3 == knn_test_rx_rate)

## [1] 0.5451807

knn_pred_5 = knn(knn_train,
                 knn_test,
                 knn_train_rx_rate,
                 k = 5)

table(knn_pred_5, knn_test_rx_rate)

##           knn_test_rx_rate
## knn_pred_5    0    1
##           0 179 167
##           1 130 188

mean(knn_pred_5 == knn_test_rx_rate)

## [1] 0.5527108

knn_pred_10 = knn(knn_train,
                  knn_test,
                  knn_train_rx_rate,
                  k = 10)

table(knn_pred_10, knn_test_rx_rate)

##           knn_test_rx_rate
## knn_pred_10    0    1
##           0 179 171
##           1 130 184

mean(knn_pred_10 == knn_test_rx_rate)

## [1] 0.5466867

```

Method 2: KNN

In this attempt, we used KNN with high school graduation rate and unemployment rate. In this case, after trying with several different values of k (1, 3, 5, 10), we found that we were predicting with around 50% accuracy, and that there wasn't a significant change in accuracy when we changed k , indicating that perhaps KNN isn't the right method here.

Method 3: ??? to classify states as over- or under-prescribing (relative to country-wide average)

Probably not KNN because KNN requires numeric predictors, and we would need to figure out how to make evenly spaced numeric representations of each state.