lab7_2024_v1

April 3, 2024

1 Lab 7: Predicting Social Mobility using Cross Validation and Random Forests

1.1 Methods/concepts: loops, steady states, random forests, cross validation

Name: Shreya Chaturvedi

Email: shreyachaturvedi@hks.harvard.edu

HUID: 31575036

Lab: Thursday 3pm at HKS

Date: April 4th, 2024

LAB DESCRIPTION

This is the second lab on prediction policy questions. In this lab, you will predict upward mobility using *decision trees* and *random forests*. The measure of upward mobility that we will focus on is **Statistic 1: Absolute Mobility at the 25th Percentile** in each county (**kfr_pooled_pooled_p25**). For more details on the variables included in these data, see Table 1.

The "training" dataset is a 50% random sample of all counties with at least 10,000 residents available from the Opportunity Atlas. You will use 121 community characteristics to predict the variable **kfr_pooled_pooled_p25**. The other half of these data has been set aside as a "lock box" data set that you will use to evaluate your models. The training data set contains predictors for both the test and training sets to avoid data snooping, but only outcomes for the training set. The lock box data set contains only the outcomes for the test set.

In the R labs, we will start from starter scripts that can either be run on your computer or the Ec 50 Jupyter Hub.

1.2 QUESTIONS

1. Primer on for loops in the context of steady states. We will start with a review of the calculation from the Lecture where Professor Chetty introduced the concept of a steady state (Becker and Tomes 1979). This review will also give us an opportunity to walk through loops step by step. Chetty et al. (2020) report the following rank-rank regression pooling all races and genders:

$$\text{Rank}_{\text{kids}} = 33.31 \ + \ 0.351\text{Rank}_{\text{parents}}$$

Using the sample code, show that this model predicts convergence in incomes across racial groups. This result is unrealistic because racial disparities have persisted for many generations in the U.S. However, the model is incorrect: we know from Lab 2 and Lecture that children of different races experience very different rates of upward mobility across generations. In particular, Chetty et al. (2020) report the following rank-rank regression for Black children:

$$\text{Rank}_{\text{kids}} = 25.4 \; + \; 0.28\text{Rank}_{\text{parents}}$$

and for Hispanic children:

$$\text{Rank}_{\text{kids}} = 36.14 \; + \; 0.26\text{Rank}_{\text{parents}}$$

Use a for loop to find the **steady state prediction** of the model for Black and Hispanic children.

[1]:
```
#  The following program starts with a primer on loops in the context of steady
#  states.  You'll modify the example loop to study how differences in intergen-
#  erational mobility by race and ethnicity affects inequality in the long run.
#
#  The next part of the program shows how to implement cross validation and
#  random forests using data from the Opportunity Atlas.  The example code␣
↪illustrates
#  10-fold cross validation.  You have to modify the code to instead implement␣
↪5 fold
#  cross validation.  You also have to choose your own predictors. After␣
↪running the
#  loop for cross validation, the example code shows how to plot the cross␣
↪validation
#  RMSPE as a function of the tree depth.
#
#  The next step is to use the cross validation graph to choose the optimal␣
↪tree depth
#  and implement a decision tree with that chosen depth.
#
#  Then the code illustrates how to estimate two random forests (one with
#  hand picked predictors and the other using all the predictors), generate
#  predictions, and make variable importance plot for the large random forest.
#
#  The last part of the code calculates the RMSPE for the three models using
#  the training data (atlas_training.dta) and the "lock box data"␣
↪(atlas_lockbox.dta)
#
#  The code may have some typos -- please be on the look out for them -- and to
#  receive credit for the lab you have to make edits to estimate your own
#  decision tree and random forests.  These are simply examples of what you␣
↪might
#  what to  do in your analysis, but you are expected to make an effort to
```

```r
#  understand what you are doing with the code.
#
#  Inputs:  atlas_training.dta and atlas_lockbox.dta (download from canvas)
#           randomForest to estimate random forest models
#           rpart library to estimate decision trees
#           tidyverse library for data manipulations
#           haven library to load stata data sets into R
#
#  Outputs: figure1.png, figure2.png, figure3.png

# Question 1 example code
rm(list=ls()) # removes all objects from the environment

# Install packages (if necessary) and load required libraries
if (!require(haven)) install.packages("haven"); library(haven)
if (!require(randomForest)) install.packages("randomForest");␣
 ↪library(randomForest)
if (!require(rpart)) install.packages("rpart"); library(rpart)
if (!require(tidyverse)) install.packages("tidyverse"); library(tidyverse)

#Set seed for cross validation and random forests
HUID <- 50505050 #Replace with your HUID
set.seed(HUID)

#--------------------------------------------------------------------------------
# Primer on loops in the context of steady states
#--------------------------------------------------------------------------------

# Chetty et al. (2020) report the following rank-rank regression pooling all
# races and genders: Rank_{kids} =  33.31 + 0.351 *  Rank_{parents}
#
# The average income rank for white parents today is the $57.9$th percentile.
# We predict that the average white child will reach the following percentile
# when they are adults:

parents_rank <- 57.9
kids_rank <- 33.31 + 0.351 * parents_rank
kids_rank

# For the next generation, the predicted rank for the (average) white grandchild
# is:

parents_rank = kids_rank
kids_rank = 33.31 + 0.351 * parents_rank
kids_rank

# Now we may want to study the predictions from this model across many
```

```
# generations: the grandchilden, the great grandchildren, and the
# great great grand children, and so on.  We can do this using a loop

generations <- seq(1,7,1) #This is for generations 1 through 7

parents_rank = 57.9 #This is the starting value for the parent's generation

# use a for loop to run the experiment
for(j in generations){
  #Calculate kid's predicted rank
  kids_rank <- 33.31 + 0.351 * parents_rank

  #Print the output to the console
  print(paste0("In generation ", j, ", parent_rank = ", parents_rank, ",␣
 ↪child_rank = ", kids_rank))

  #Set parent's rank equal to kids' rank so we are ready for the next iteration
  parents_rank <- kids_rank
}

# Notice that the model predicts that the average white child will reach the
# 51.3rd percentile in generation 7, which is lower than where the first
# generation started from (which you will recall was the $57.9$th percentile).
# This is a reduction of around 6 percentiles.
#
# Meanwhile, the average income rank for Black parents is the 32.7th percentile.
# If we apply the same rank-rank relationship between Black parents and Black
# children that we did above, our model predicts that the average Black child
# will reach the 44.9th percentile when they grow up, with further gains for
# future generations.

generations <- seq(1,7,1) #This is for generations 1 through 7
parents_rank = 32.7 #This is the starting value for the parent's generation
for(j in generations){
  kids_rank <- 33.31 + 0.351 * parents_rank
  print(paste0("In generation ", j, ", parent_rank = ", parents_rank, ",␣
 ↪child_rank = ", kids_rank))
  parents_rank <- kids_rank
}

# As you can see, this model predicts substantial improvements in outcomes for
# Black children across generations, with average gains of 12 percentiles in a
# single generation.  The model makes the unrealistic prediction of convergence
# in outcomes across racial groups: By generation 7, both white and Black␣
 ↪children
# are at the 51.3 percentile.  This result is unrealistic because racial␣
 ↪disparities
```

```r
# have persisted for many generations in the United States.
#
# However, the model is incorrect: we know from Lab 2 and Lecture that Black
# children and white children experience very different rates of upward␣
↪mobility
# across generations. In particular, Chetty et al. (2020) report the following
# rank-rank regression for Black children:
#
# Rank_{kids} =  25.4 + 0.28 *  Rank_{parents}
#
# The prediction implied by this rank-rank graph is very different than the
# previous calculations suggested.  To see this, in the first generation this
# model predicts:

parents_rank = 32.7
kids_rank = 25.4 + 0.28 * parents_rank
kids_rank

# In stark contrast to the predictions from the calculations earlier, here
# there is hardly any predicted improvement in the income rank for Black␣
↪children
# in generation 1.  To see what happens across generations, we can update our
# loop:

generations <- seq(1,7,1) #This is for generations 1 through 7
parents_rank = 32.7 #This is the starting value for the parent's generation
for(j in generations){
  kids_rank = 25.4 + 0.28 * parents_rank
  print(paste0("In generation ", j, ", parent_rank = ", parents_rank, ",␣
↪child_rank = ", kids_rank))
  parents_rank <- kids_rank
}
```

```
Loading required package: haven

Loading required package: randomForest

randomForest 4.7-1.1

Type rfNews() to see new features/changes/bug fixes.

Loading required package: rpart

Loading required package: tidyverse

  Attaching core tidyverse packages                tidyverse
2.0.0
```

```
  dplyr     1.1.3      readr     2.1.4
  forcats   1.0.0      stringr   1.5.0
  ggplot2   3.4.4      tibble    3.2.1
  lubridate 1.9.3      tidyr     1.3.0
  purrr     1.0.2
   Conflicts
tidyverse_conflicts()
  dplyr::combine()  masks
randomForest::combine()
  dplyr::filter()   masks
stats::filter()
  dplyr::lag()      masks stats::lag()
  ggplot2::margin() masks
randomForest::margin()
  Use the conflicted package
(<http://conflicted.r-lib.org/>) to force all conflicts to
become errors
```

53.6329

52.1351479

```
[1] "In generation 1, parent_rank = 57.9, child_rank = 53.6329"
[1] "In generation 2, parent_rank = 53.6329, child_rank = 52.1351479"
[1] "In generation 3, parent_rank = 52.1351479, child_rank = 51.6094369129"
[1] "In generation 4, parent_rank = 51.6094369129, child_rank =
51.4249123564279"
[1] "In generation 5, parent_rank = 51.4249123564279, child_rank =
51.3601442371062"
[1] "In generation 6, parent_rank = 51.3601442371062, child_rank =
51.3374106272243"
[1] "In generation 7, parent_rank = 51.3374106272243, child_rank =
51.3294311301557"
[1] "In generation 1, parent_rank = 32.7, child_rank = 44.7877"
[1] "In generation 2, parent_rank = 44.7877, child_rank = 49.0304827"
[1] "In generation 3, parent_rank = 49.0304827, child_rank = 50.5196994277"
[1] "In generation 4, parent_rank = 50.5196994277, child_rank =
51.0424144991227"
[1] "In generation 5, parent_rank = 51.0424144991227, child_rank =
51.2258874891921"
[1] "In generation 6, parent_rank = 51.2258874891921, child_rank =
51.2902865087064"
[1] "In generation 7, parent_rank = 51.2902865087064, child_rank =
51.312890564556"
```

34.556

```
[1] "In generation 1, parent_rank = 32.7, child_rank = 34.556"
[1] "In generation 2, parent_rank = 34.556, child_rank = 35.07568"
[1] "In generation 3, parent_rank = 35.07568, child_rank = 35.2211904"
```

```
[1] "In generation 4, parent_rank = 35.2211904, child_rank = 35.261933312"
[1] "In generation 5, parent_rank = 35.261933312, child_rank = 35.27334132736"
[1] "In generation 6, parent_rank = 35.27334132736, child_rank =
35.2765355716608"
[1] "In generation 7, parent_rank = 35.2765355716608, child_rank =
35.277429960065"
```

[2]:
```
# As you can see, the income rank hardly improves at all for the second and
# third generation, and eventually stabilizes after four generations at the
# 35.3rd percentile. The 35.3rd percentile is the steady state (or fixed point)
# prediction for Black children, because the model predicts no further
# improvement once average income reaches this level.
#
# In contrast, similar calculations would show that the 54.2nd percentile
# is the steady state (or fixed point) of the model for white children.
# These stark steady state gaps show that addressing racial disparities in
# upward mobility is crucial for lessening racial disparities in the United␣
↪States.
#
# ## Trying it on your own
#
# Chetty, Hendren, Jones, and Porter (2020) report the following estimates
# for Hispanic children:
#
# Rank_{kids} =  36.14 + 0.26 *  Rank_{parents}
#
# The average income rank for Hispanic parents is the 36.17th percentile.
#
# Write your own for loop to study the predictions from the model for Hispanic
# children over the next 7 generations.
#
# Using the output from your for loop, what is the steady state prediction for
# Hispanic children?

## YOUR QUESTION 1 CODE GOES HERE
parents_rank = 36.14 #This is the starting value for the parent's generation
for(j in generations){
  kids_rank = 36.14 + 0.26 * parents_rank
  print(paste0("In generation ", j, ", parent_rank = ", parents_rank, ",␣
↪child_rank = ", kids_rank))
  parents_rank <- kids_rank
}
```

```
[1] "In generation 1, parent_rank = 36.14, child_rank = 45.5364"
[1] "In generation 2, parent_rank = 45.5364, child_rank = 47.979464"
[1] "In generation 3, parent_rank = 47.979464, child_rank = 48.61466064"
[1] "In generation 4, parent_rank = 48.61466064, child_rank = 48.7798117664"
[1] "In generation 5, parent_rank = 48.7798117664, child_rank = 48.822751059264"
```

```
[1] "In generation 6, parent_rank = 48.822751059264, child_rank =
48.8339152754086"
[1] "In generation 7, parent_rank = 48.8339152754086, child_rank =
48.8368179716063"
```

Question 1 Answer

From this loop, we can see that the steady state prediction for Hispanic children is 48.8 percentile rank as this is the approximate value that the rank converges to after the 4th or 5th iteration of the loop.

2. Explain briefly how cross-validation helps us avoid the overfit problem.

[3]:
```
# QUESTION 2 Code
```

Question 2 Answer

Cross-validation is a statistical method used to evaluate the generalizability of a model by dividing the data into multiple parts, training the model on some parts and validating it on the others. This process helps in avoiding the overfitting problem by ensuring that the model performs well not just on the data it was trained on, but also on unseen data. By repeatedly training and testing the model on different subsets of data, cross-validation provides a more accurate measure of a model's predictive power and robustness, reducing the risk of it capturing noise as if it were a true pattern.

3. Modify the example code to implement **five-fold cross validation** to choose the depth of a decision tree that uses just two predictors. It is your choice of which two predictors, but they should not be the same as my two! Pick your own! The predictors are the variables P_1 through P_121 in the data, but their real names are included in the data dictionary available in Table 3 below.

    1. Plot the cross-validation pseudo out-of-sample root mean squared prediction error (CV RMSE) versus the depth of the tree.
    2. Using the graph that you produced, what tree depth is optimal?
    3. Now use the full training data set to estimate a tree of the depth you selected in the previous question. Visualize the tree. Which predictors are being used in the first several splits of the tree?
    4. Obtain predictions in the training sample.

[4]:
```
#------------------------------------------------------------------------------
# Data set up
#------------------------------------------------------------------------------

#Open stata data set
download.file("https://raw.githubusercontent.com/ekassos/ec50_s24/main/
↪atlas_training.dta", "atlas_training.dta", mode = "wb")
atlas_training <- read_dta("atlas_training.dta")
head(atlas_training)

#Store predictor variables which all start with P_*
vars <- colnames(atlas_training[,grep("^[P_]", names(atlas_training))])
```

```
vars

#Create a training data frame with just predictors P_* and kfr_pooled_pooled_p25
training <- subset(atlas_training, training==1, vars)
training$kfr_pooled_pooled_p25 <-
 ↪atlas_training[atlas_training$training==1,]$kfr_pooled_pooled_p25
```

A tibble: 6 × 128

geoid <dbl>	place <chr>	pop <dbl>	housing <dbl>	kfr_pooled_pooled_p25 <dbl>	test <dbl>	training <dbl>
1003	Baldwin County	187114	104061	38.88471	0	1
1005	Barbour County	27321	11829	34.93856	0	1
1007	Bibb County	22754	8981	36.33907	0	1
1013	Butler County	20624	9964	35.72486	0	1
1015	Calhoun County	117714	53289	36.18467	0	1
1017	Chambers County	34145	17004	34.05749	0	1

1. 'P_1' 2. 'P_2' 3. 'P_3' 4. 'P_4' 5. 'P_5' 6. 'P_6' 7. 'P_7' 8. 'P_8' 9. 'P_9' 10. 'P_10' 11. 'P_11' 12. 'P_12' 13. 'P_13' 14. 'P_14' 15. 'P_15' 16. 'P_16' 17. 'P_17' 18. 'P_18' 19. 'P_19' 20. 'P_20' 21. 'P_21' 22. 'P_22' 23. 'P_23' 24. 'P_24' 25. 'P_25' 26. 'P_26' 27. 'P_27' 28. 'P_28' 29. 'P_29' 30. 'P_30' 31. 'P_31' 32. 'P_32' 33. 'P_33' 34. 'P_34' 35. 'P_35' 36. 'P_36' 37. 'P_37' 38. 'P_38' 39. 'P_39' 40. 'P_40' 41. 'P_41' 42. 'P_42' 43. 'P_43' 44. 'P_44' 45. 'P_45' 46. 'P_46' 47. 'P_47' 48. 'P_48' 49. 'P_49' 50. 'P_50' 51. 'P_51' 52. 'P_52' 53. 'P_53' 54. 'P_54' 55. 'P_55' 56. 'P_56' 57. 'P_57' 58. 'P_58' 59. 'P_59' 60. 'P_60' 61. 'P_61' 62. 'P_62' 63. 'P_63' 64. 'P_64' 65. 'P_65' 66. 'P_66' 67. 'P_67' 68. 'P_68' 69. 'P_69' 70. 'P_70' 71. 'P_71' 72. 'P_72' 73. 'P_73' 74. 'P_74' 75. 'P_75' 76. 'P_76' 77. 'P_77' 78. 'P_78' 79. 'P_79' 80. 'P_80' 81. 'P_81' 82. 'P_82' 83. 'P_83' 84. 'P_84' 85. 'P_85' 86. 'P_86' 87. 'P_87' 88. 'P_88' 89. 'P_89' 90. 'P_90' 91. 'P_91' 92. 'P_92' 93. 'P_93' 94. 'P_94' 95. 'P_95' 96. 'P_96' 97. 'P_97' 98. 'P_98' 99. 'P_99' 100. 'P_100' 101. 'P_101' 102. 'P_102' 103. 'P_103' 104. 'P_104' 105. 'P_105' 106. 'P_106' 107. 'P_107' 108. 'P_108' 109. 'P_109' 110. 'P_110' 111. 'P_111' 112. 'P_112' 113. 'P_113' 114. 'P_114' 115. 'P_115' 116. 'P_116' 117. 'P_117' 118. 'P_118' 119. 'P_119' 120. 'P_120' 121. 'P_121'

[5]:
```
# Question 3a example code

#-----------------------------------------------------------------------------
# Decision tree with cross validation and two hand picked predictors
#-----------------------------------------------------------------------------

# Implement five-fold cross validation to choose the depth of a decision tree
# that uses two of the predictors (your choice which predictors). Plot the
# cross-validation out of sample root mean squared prediction error (CV RMSE)
# versus the depth of the tree.

# Modify the code to change from 10 fold cross validation to 5
# and change the predictors that I use to two others
# (Don't use my predictors! Pick your own!)

##Illustrate cross validation##
#K-fold Cross validation to select tree depth
```

```r
# First we need to set a few objects that will be used in the loop below
n <- nrow(training) # the number of observations
K <- 5 # the number of `folds'
B <- seq(1,20,1) #This is for tree depths for 1 to 20

# We'll create a copy of the training data that we'll use inside the loop
cv <- training

# Now we define the folds: create a vector of fold memberships (random order)
cv$foldid <- rep(1:K,each=ceiling(n/K))[sample(1:n)]

# Now we create an empty data frame of results
# In each iteration of the loop, we fill it in row by row
OOS <- data.frame(fold=rep(NA,K*length(B) ),
                  squarederror=rep(NA,K*length(B) ),
                  maxdepth=rep(NA,K*length(B) ))

# Start an object row = 0, that will be increased by 1 in each iteration of the
  ↪loop
# We'll use that to fill in each row in the data frame
row <- 0

#Now we run a "double" loop: loop over tree depths 1 through B, loop over folds
  ↪1 through K

#This part loops over tree depths
for(j in B){

  #This part loops over the folds
  for(k in 1:K){

    #This part increases the "row" by 1 in each iteration of the loop
    row <- row + 1

    #This part divides the data into all the folds but one for training
    #This part uses the k from the inner loop (looping over folds)
    cvtrain <- subset(cv, foldid != k) # train on all but fold `k'

    #This part sets the left out fold aside as a separate data frame
    #We'll use that to calculate the RMSPE
    #This part uses the k from the inner loop (looping over folds)
    cvfold <- subset(cv, foldid == k) # fold `k'

    # Now we fit a decision tree on all but fold `k'
    # You'll want to change the predictors from P_37 and P_56 to two others
    cvtree <- rpart(kfr_pooled_pooled_p25 ~ P_32 + P_64,
                    data=cvtrain, #Train data using all the folds but 1
```

```
                    maxdepth = c(j), #set the max depth equal to j from outer␣
↪loop
                    cp=0)


    #Get predictions for the left out fold
    predfull <- predict(cvtree, newdata=cvfold) # Get predictions for fold `k'

    #Store the sum of squared errors using data in left out fold
    #It will be put in row 1 in the first iteration, row 2 in the next␣
↪iteration, etc
    OOS$squarederror[row] <- sum((cvfold$kfr_pooled_pooled_p25 - predfull)^2) #␣
↪Calculate prediction errors for fold `k'

    #Store the depth that was used in the tree in this row of the data frame
    OOS$maxdepth[row] <- j # store the maxdepth

    #Store which fold was left out in this row of the data frame
    OOS$fold[row] <- k # store the fold

    #This bracket ends the inner loop (looping over folds)
  }

  #This bracket ends the outer loop (looping over tree depths)
}

#Summarize the results
OOS
summary(OOS)

#Calculate the combined error across folds
ssr <- tapply(OOS$squarederror, OOS$maxdepth, sum)
ssr <- as.data.frame(ssr)
ssr$maxdepth <- seq(1,20,1)
ssr

#Calculate the CV RMSPE as a new variable inside the SSR data frame
ssr$rmse <- sqrt(ssr$ssr / nrow(training))
min_rmse_row <- ssr[which.min(ssr$rmse),]

#Draw a graph of the cross validation error rate versus the depth of the tree
ggplot(ssr, aes(x=maxdepth, y=rmse)) +
  geom_point() +
  geom_line() +
  labs(y = "Cross Validation RMSPE", x = "Tree Depth") +
  geom_vline(xintercept = min_rmse_row$maxdepth, linetype="dashed", color =␣
↪"red") +
```

```
  geom_text(aes(x=min_rmse_row$maxdepth, y=min_rmse_row$rmse, label=paste("Min␣
↪RMSPE: ", round(min_rmse_row$rmse, 2), "\nDepth: ", min_rmse_row$maxdepth)),
            vjust = -1, color = "red")

ggsave("figure1.png")
```

A data.frame: 100 × 3

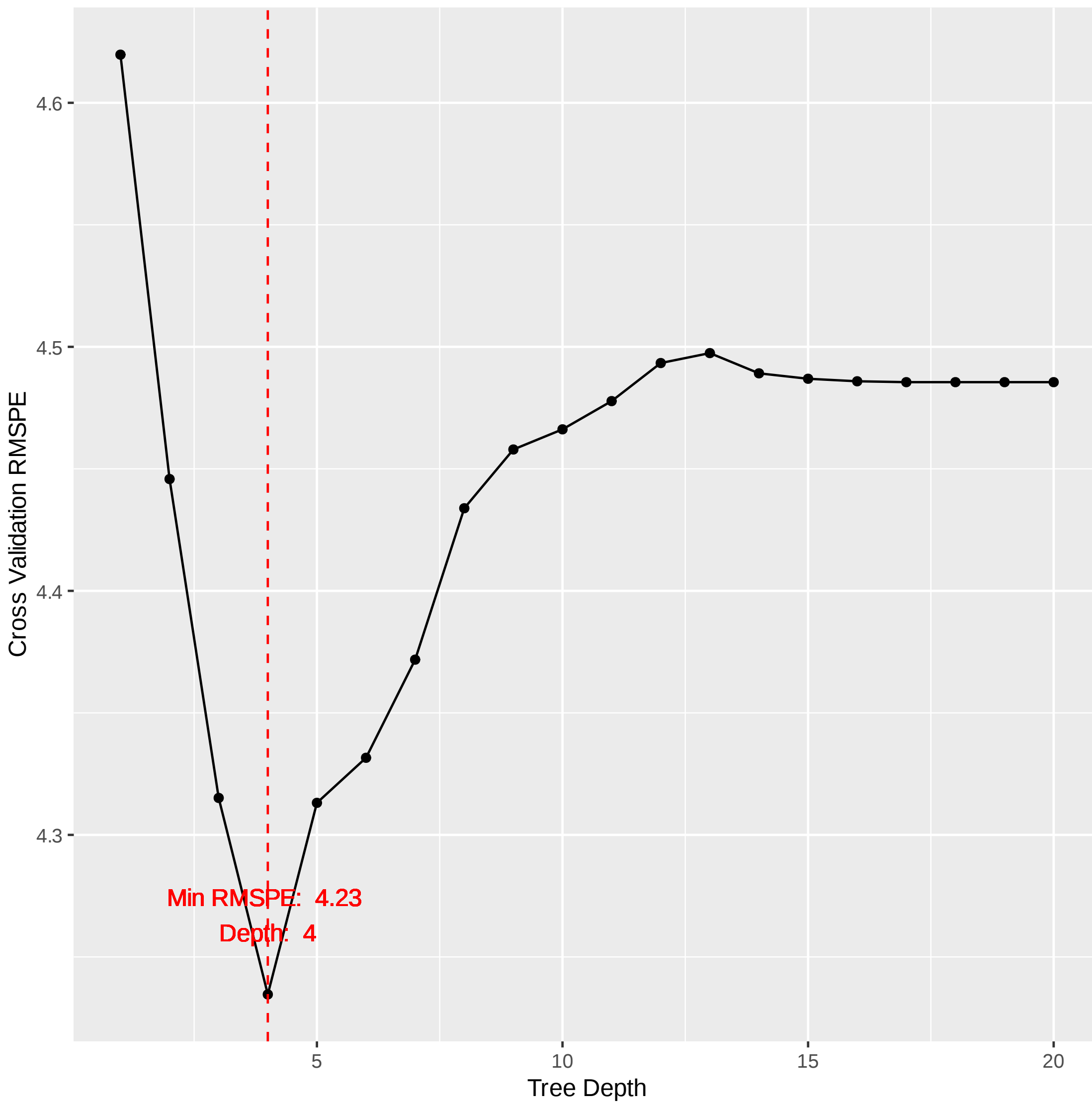
fold	squarederror	maxdepth
<int>	<dbl>	<dbl>
1	5624.321	1
2	5274.516	1
3	6071.866	1
4	5211.319	1
5	4687.461	1
1	5296.612	2
2	4679.135	2
3	5198.713	2
4	4865.258	2
5	4844.859	2
1	4728.110	3
2	4494.082	3
3	5012.969	3
4	4994.098	3
5	4213.951	3
1	4645.238	4
2	4248.671	4
3	4571.043	4
4	4928.785	4
5	4182.845	4
1	4800.046	5
2	4447.456	5
3	4841.319	5
4	4947.661	5
5	4384.826	5
1	4572.002	6
2	4640.863	6
3	5116.752	6
4	4999.903	6
5	4292.807	6
1	5046.447	15
2	5143.821	15
3	5603.986	15
4	5070.132	15
5	4482.382	15
1	5046.956	16
2	5143.821	16
3	5603.986	16
4	5070.132	16
5	4470.193	16
1	5046.956	17
2	5143.821	17
3	5603.986	17
4	5070.132	17
5	4466.146	17
1	5046.956	18
2	5143.821	18
3	5603.986	18
4	5070.132	18
5	4466.146	18

```
      fold    squarederror       maxdepth
 Min.   :1   Min.   :4183   Min.   : 1.00
 1st Qu.:2   1st Qu.:4645   1st Qu.: 5.75
 Median :3   Median :5047   Median :10.50
 Mean   :3   Mean   :4973   Mean   :10.50
 3rd Qu.:4   3rd Qu.:5150   3rd Qu.:15.25
 Max.   :5   Max.   :6072   Max.   :20.00
```

A data.frame: 20 × 2

	ssr	maxdepth
	<dbl>	<dbl>
1	26869.48	1
2	24884.58	2
3	23443.21	3
4	22576.58	4
5	23421.31	5
6	23622.33	6
7	24062.95	7
8	24750.76	8
9	25020.36	9
10	25113.11	10
11	25243.42	11
12	25419.55	12
13	25465.71	13
14	25371.89	14
15	25346.77	15
16	25335.09	16
17	25331.04	17
18	25331.04	18
19	25331.04	19
20	25331.04	20

```
Saving 6.67 x 6.67 in image
```



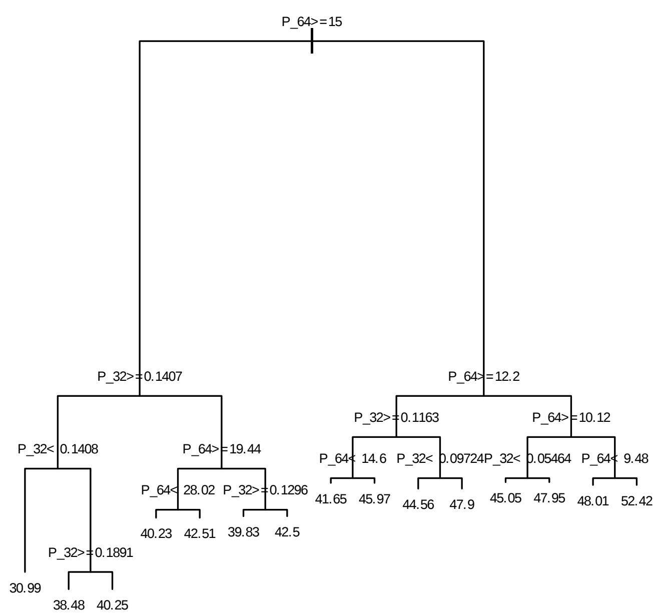
[6]:
```
# Question 3b sample code

### What is the optimal tree depth based on this graph?
cv_optimal_depth = 4
```

[7]:
```
# Question 3c sample code

### Modify this example code to estimate tree using the depth you chose above
### using the full training data.  Remember to change the predictors!
tree <- rpart(kfr_pooled_pooled_p25 ~ P_32 + P_64,
                        data=training,
                        maxdepth = cv_optimal_depth,
                        cp=0)
```

```r
#Visualize the fitted decision tree
plot(tree, margin = 0.2)
text(tree, cex = 0.5)

#Save figure
dev.copy(png,'figure2.png')
dev.off()
```

png: 3

png: 2



[8]:
```
# Question 3d sample code

#Calculate predictions for all rows in training sample
y_train_predictions_tree <- predict(tree, newdata=training)
```

Question 3 Answer

A. As seen in the plot, the out of sample RMSPE goes down with depth upto a certain point, after which the tree starts overfitting and the error for out of sample predictions shoots up again. B. Accordingly, the optimal depth is the point with the lowest out of sample RMSPE or 4, as labelled in the graph. C. The tree above is created from the full training data. In the first split of the tree, the decision is made based on the value of P_64 (share of 18-64 persons without insurance). Visually, it seems that both P_64 and P_32 are used in roughly the same number of splits. D. Code to obtain predictions in training sample above.

4. Explain briefly how random forests improve upon decision trees using (i) bagging and (ii) input randomization.

[9]:
```
# QUESTION 4 Code
```

Question 4 Answer

Bagging, or Bootstrap Aggregating, involves creating multiple decision trees on different subsets of the data (drawn with replacement), and then averaging their predictions. This reduces the variance and avoids overfitting, making the model more generalizable. Input randomization introduces further diversity by selecting a random subset of features for splitting at each node of a tree, thereby increasing the model's ability to capture complex patterns and interactions among features without being overly sensitive to noise. Together, these techniques make random forests a powerful and reliable predictive model.

5. Now implement a random forest with at least 1000 trees (bootstrap samples) using the same two predictors you selected for the decision tree. Obtain predictions in the training sample.

[10]:
```
# QUESTION 5 Code

#------------------------------------------------------------------------------
# Random Forest using same two predictors as the tree
#------------------------------------------------------------------------------

#Two R libraries implement random forests: randomForest() and ranger()
#ranger() is quicker, but randomForests() alows nicer importance plots

#Random Forest from 1000 Bootstrapped Samples (ntree=100)
#Random Forests may take a while to run!  Be patient!

## Modify the code to change the predictors that I use to two others
# (Don't use my predictors! Pick your own!)

smallforest <- randomForest(kfr_pooled_pooled_p25 ~ P_32 + P_64,
                            ntree=1000,
```

```
                              mtry=2,
                              data=training)

#Tuning parameters are ntree and mtry
#ntree is number of trees in your forest
#mtry is the number of predictors considered at each split (default is number␣
↪of predictors divided by 3)

smallforest #Review the Random Forest Results

#Generate predictions for training data
y_train_predictions_smallforest <- predict(smallforest, newdata=training,␣
↪type="response")
```

```
Call:
 randomForest(formula = kfr_pooled_pooled_p25 ~ P_32 + P_64, data = training,    ␣
↪  ntree = 1000, mtry = 2)
               Type of random forest: regression
                     Number of trees: 1000
No. of variables tried at each split: 2

          Mean of squared residuals: 18.50375
                    % Var explained: 30.74
```

Question 5 Answer

Modified code above.

6. Next, implement a random forest with at least 1000 trees (bootstrap samples) using the full predictor set (consisting of the 121 predictors corresponding to variables P_1 through P_121 included in the training data). Obtain predictions in the training sample.

[11]:
```
# QUESTION 6 Code

#-------------------------------------------------------------------------------
# Random Forest with the full set of predictors
#-------------------------------------------------------------------------------

#Two commands to implement random forests: randomForest() and ranger()
#ranger() is quicker

#Random Forest from 1000 Bootstrapped Samples (ntree=100)
#Random Forests may take a while to run!  Be patient!
mobilityforest <- randomForest(kfr_pooled_pooled_p25 ~ .,
                              ntree=1000,
                              mtry=60,
                              importance=TRUE, ## add importance=TRUE so that␣
↪we store the variable importance information
```

```
                                         data=training)

#Tuning parameters are ntree and mtry
#ntree is number of trees in your forest
#mtry is the number of predictors considered at each split (default is number␣
 ↪of predictors divided by 3)
#Setting mtry<121 can help in small samples like this one.

mobilityforest #Review the Random Forest Results

#Generate predictions for training data
y_train_predictions_forest  <- predict(mobilityforest, newdata=training,␣
 ↪type="response")

### Try changing mtry to 20 (16.5% of predictors), 60 (50% of predictors), or␣
 ↪121 (all predictors)
```

```
Call:
 randomForest(formula = kfr_pooled_pooled_p25 ~ ., data = training,      ntree =␣
 ↪1000, mtry = 60, importance = TRUE)
               Type of random forest: regression
                     Number of trees: 1000
No. of variables tried at each split: 60

          Mean of squared residuals: 4.747495
                    % Var explained: 82.23
```

Question 6 Answer

Random Forest with mtry = 60 (50% of predictors) shown above.

7. Random forests typically result in improved accuracy over prediction using a single tree. Unfortunately, however, it can be difficult to interpret the resulting model. Recall from Lab 6 that one of the advantages of decision trees is the attractive and easily interpreted diagram that results.

   One can obtain an overall summary of the importance of each predictor in a random forest by measuring how the mean squared error decreases when the predictor is used define tree splits. A large value indicates an important predictor.

   Using the random forest from the previous question, which variables are the most important predictors using this metric? Refer to the data dictionary in Table 3 below to determine what these variables measure.

[12]:
```
# QUESTION 7 Code

#--------------------------------------------------------------------------------
# What variables are the most important predictors?
#--------------------------------------------------------------------------------
```

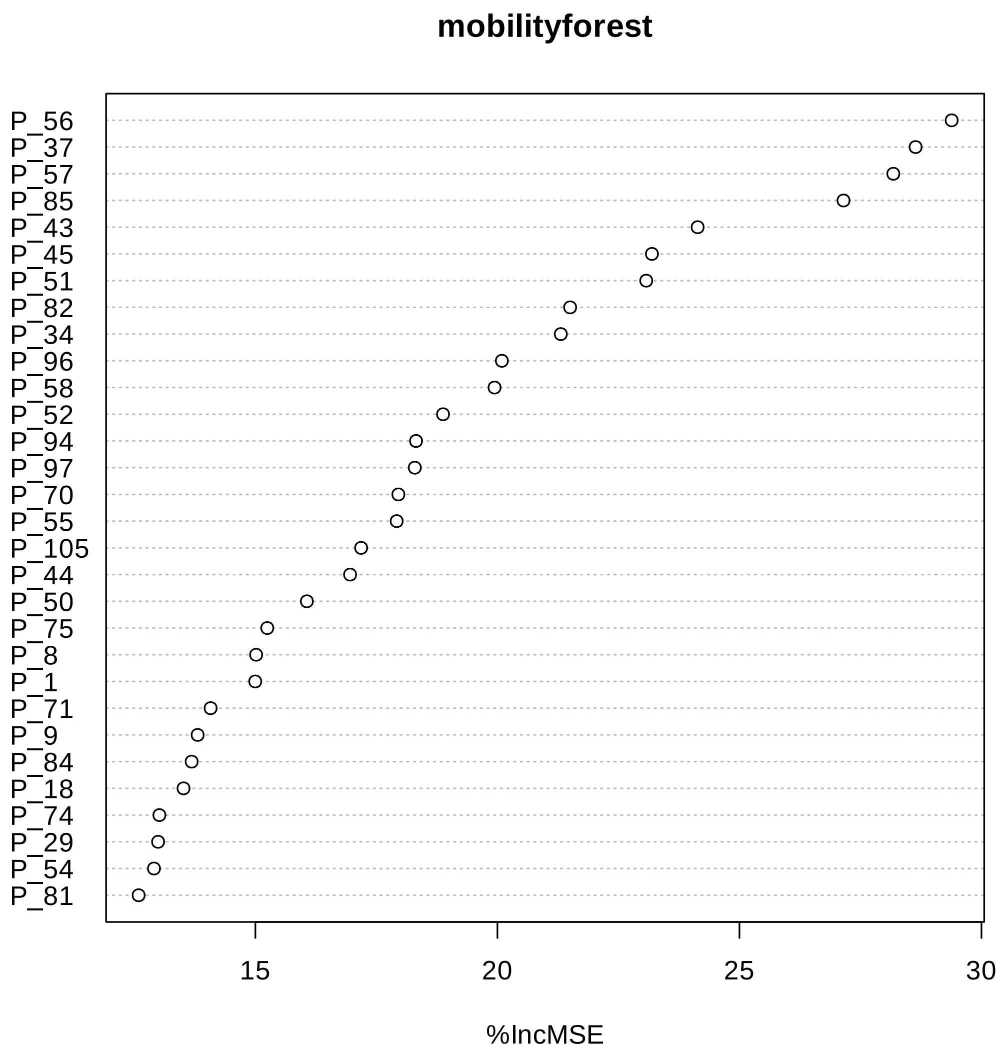
```
importance(mobilityforest)
varImpPlot(mobilityforest, type=1) #Plot the Random Forest Results

#type        is either 1 or 2, specifying the type of importance measure
#(1=mean decrease in accuracy, 2=mean decrease in node impurity)

#Save figure
dev.copy(png,'figure3.png')
dev.off()
```

A matrix: 121 × 2 of type dbl

	%IncMSE	IncNodePurity
P_1	14.996716	197.33550
P_2	11.731866	89.10111
P_3	10.649786	105.86876
P_4	10.871882	106.48611
P_5	11.891062	187.91943
P_6	11.533372	131.07387
P_7	11.937764	161.48765
P_8	15.015651	215.45977
P_9	13.807028	182.19695
P_10	10.129496	110.21672
P_11	7.069986	45.09324
P_12	9.248953	69.45720
P_13	3.024961	33.63679
P_14	6.962237	71.57946
P_15	9.864219	70.26290
P_16	2.755587	47.55528
P_17	9.809135	86.88104
P_18	13.515204	114.72705
P_19	7.292563	67.64377
P_20	5.585463	48.94728
P_21	4.939702	57.35775
P_22	2.509362	43.88483
P_23	6.231628	64.46041
P_24	9.972091	83.87208
P_25	8.630618	99.41561
P_26	4.600764	38.26911
P_27	2.796103	60.03872
P_28	6.996938	52.18413
P_29	12.989977	507.06177
P_30	11.998202	149.69852
P_92	3.0260163	40.719620
P_93	7.7861138	100.800474
P_94	18.3189091	274.813780
P_95	10.2073310	106.898849
P_96	20.0921848	1784.413342
P_97	18.2935647	197.527935
P_98	3.6940300	7.403184
P_99	5.4872325	27.393566
P_100	-0.6146927	3.982722
P_101	-0.1544891	2.151949
P_102	-0.1076852	2.070993
P_103	1.0032107	10.035314
P_104	2.0820152	37.618459
P_105	17.1845041	470.911115
P_106	0.8553893	4.338622
P_107	-1.2237806	1.490381
P_108	2.1860349	9.584670
P_109	4.9066970	35.035898
P_110	0.9151437	1.228150
P_111	5.6019019	20.654596
P_112	0.5472770	10.741587

png: 3

png: 2



Question 7 Answer

According to this plot, the most important predictors are (in order) P_56, P_37, P_57 and P_85 (followed by a gap). The interpretation of these variables as from the table below is:

P_56 - Mentally Unhealthy Days per Month (Persons 18 Years and Over)

P_37 - Share black 2000

P_57 - Percent of Adults That Report Fair or Poor Health (Persons 18 Years and Over)

P_85 - % Total: Roman Catholic

8. Calculate and compare the root mean squared prediction error for your three models in the **training sample**. Which model does the best?

[13]:
```
# QUESTION 8 Code

#-------------------------------------------------------------------------------
# Calculate and compare the mean squared error in the training sample.
#-------------------------------------------------------------------------------

## Root mean squared prediction error in  the training sample.
p <- 3
RMSPE <- matrix(0, p, 1)
RMSPE[1] <- sqrt(mean((training$kfr_pooled_pooled_p25 -␣
↪y_train_predictions_tree)^2, na.rm=TRUE))
RMSPE[2] <- sqrt(mean((training$kfr_pooled_pooled_p25 -␣
↪y_train_predictions_smallforest)^2, na.rm=TRUE))
RMSPE[3] <- sqrt(mean((training$kfr_pooled_pooled_p25 -␣
↪y_train_predictions_forest)^2, na.rm=TRUE))

#Display a table of the results
data.frame(RMSPE, method = c("Tree", "Small RF", "Large RF"))
```

A data.frame: 3 × 2

RMSPE <dbl>	method <chr>
3.9710639	Tree
2.1104591	Small RF
0.8673262	Large RF

Question 8 Answer

As seen below, a large RF has the lowest RMSPE and therefore performs the best, with a significant improvement over tree and small RF.

9. Now turn to the lock box data set **atlas_lockbox.dta**. These data contain a variable called **kfr_actual** which is the “truth:” the actual value of **kfr_pooled_pooled_p25** for all the counties in the sample, including the 50% of the data in the lock box sample. Calculate predictions from your models and use **kfr_actual** to calculate the root mean squared prediction error for the test sample. Which model did the best?

[14]:
```
# QUESTION 9 Code

#-------------------------------------------------------------------------------
# Part 6 Calculate and compare the mean squared error in  the lock box data
#-------------------------------------------------------------------------------

#Read in data with truth. Truth is kfr_actual in these data
download.file("https://raw.githubusercontent.com/ekassos/ec50_s24/main/
↪atlas_lockbox.dta", "atlas_lockbox.dta", mode = "wb")
atlas_test <- read_dta("atlas_lockbox.dta")
```

```r
#Merge with truth to evaluate predictions.
atlas <- left_join(atlas_test, atlas_training , by="geoid")

#Separate test data set as a separate data frame
test <- subset(atlas, training==0)

#Get predictions for test data
y_test_predictions_tree <- predict(tree, newdata=test)
y_test_predictions_smallforest <- predict(smallforest, newdata=test, type="response")
y_test_predictions_forest  <- predict(mobilityforest, newdata=test, type="response")

#Calculate RMSPE for test data
p <- 3
OOS_RMSPE <- matrix(0, p, 1)
OOS_RMSPE[1] <- sqrt(mean((test$kfr_actual - y_test_predictions_tree)^2, na.rm=TRUE))
OOS_RMSPE[2] <- sqrt(mean((test$kfr_actual - y_test_predictions_smallforest)^2, na.rm=TRUE))
OOS_RMSPE[3] <- sqrt(mean((test$kfr_actual - y_test_predictions_forest)^2, na.rm=TRUE))

# Display table of results
data.frame(OOS_RMSPE, method = c("Tree", "Small RF", "Large RF"))
```

A data.frame: 3 × 2

OOS_RMSPE <dbl>	method <chr>
4.128169	Tree
4.277144	Small RF
2.209853	Large RF

Question 9 Answer

Here as well the large RF has the lowest RMSPE in the out of sample predictions, however the gap is somewhat smaller that in the case of training data.

10. Create an annotated/commented do-file, .ipynb Jupyter Notebook, or .R file that can replicate all your analyses above. This will be the final code that you submit on Gradescope. The motivation for using do-files and .R files is described on page 4, which has been adapted from training materials used by Innovations for Poverty Action (IPA) and the Abdul Latif Jameel Poverty Action Lab (J-PAL).

Final Submission Checklist for Lab 7

If you're working with R

If you're working with Stata

Lab 7 Write-Up:

PDF of your answers. For graphs, you must save them as images (e.g., .png files) and insert them into the document.

Lab 7 Code:

.R script file, well-annotated replicating all your analyses;OR

.ipynb file and a .PDF version of this file.

Lab 7 Write-Up:

PDF of your answers. For graphs, you must save them as images (e.g., .png files) and insert them into the document.

Lab 7 Code:

do-file, well-annotated replicating all your analyses;AND

log-file, not a .smcl file, with the log showing the output generated by your final do-file.

If you're working with an .ipynb notebook

It is likely that your .ipynb file will be greater than 1 MB in size. Therefore, for this assignment please submit both your *well-annotated* **.ipynb file** and **a .PDF version of this file**. The notebook should replicate all your analyses for Lab 5 (with enough comments that a principal investigator on a research project would be able to follow and understand what each step of the code is doing).

1.3 How to submit your assignment

Step 1	Access the lab assignment under the "Assignments" tab on Canvas
Step 2	Access Gradescope from Canvas
Step 3	Access the lab assignment on Gradescope
Step 4	Upload your files *Check What files to submit to confirm what files you need to submit.*
Step 5	What you'll see after submitting your lab assignment
Step 6	Check your submitted files
Step 7	You'll receive an email confirmation as well

1.4 What files to submit

If you're using Python Notebook to write your R code, and a document editor to write your answers
If you're using a Python Notebook to write your R code AND to write your answers

1.5 WHAT ARE DO-FILES AND .R FILES AND WHY DO WE NEED ONE?

Let's imagine the following situation - you just found out you have to present your results to a partner– all the averages you produced and comparisons you made. Suppose you also found out that the data you had used to produce all these results was not completely clean, and have only just fixed it. You now have incorrect numbers and need to re-do everything.

How would you go about it? Would you reproduce everything you did for Lab 1 from scratch? Can you do it? How long would it take you to do? Just re-typing all those commands into Stata or R in order and checking them would take an hour.

An important feature of any good research project is that the results should be reproducible. For Stata and R the easiest way to do this is to create a text file that lists all your commands in order, so anyone can re-run all your Stata or R work on a project anytime. Such text files that are produced within Stata or linked to Stata are called do-files, because they have an extension .do (like intro_exercise.do). Similarly, in R, these files are called .R files because they have an extension of .R. These files feed commands directly into Stata or R without you having to type or copy them into the command window.

An added bonus is that having do-files and .R files makes it very easy to fix your typos, re-order commands, and create more complicated chains of commands that wouldn't work otherwise. You can now quickly reproduce your work, correct it, adjust it, and build on it.

Finally, do-files and .R files make it possible for multiple people to work on a project, which is necessary for collaborating with others or when you hand off a project to someone else.

1.6 DATA DESCRIPTION, FILE: atlas_training.dta [training data]

The data consist of all 2,518 counties with at least 10,000 residents available from the Opportunity Atlas. For n = 1,259 counties in the "test" portion of the data, the outcome variable is set to missing. These observations are a 50% random sample of all counties with at least 10,000 residents available from the Opportunity Atlas. For more details on the construction of the variables included in this data set, please see Chetty, Raj, John Friedman, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter. 2018. "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility." NBER Working Paper No. 25147.

TABLE 1

Training Data

Variable

Definition

Obs.

(1)

(2)

(3)

geoid

County FIPS code

2,518

pop

County Population from DataCommons

2,518

housing

Total number of housing units from Census

2,518

kfr_pooled_pooled_p25

Statistic 1: Absolute Mobility at the 25th Percentile

(missing for n = 1,259 counties in the test data, non-missing for the other n = 1,259 counties)

1,259

test

1 = Observation is in test data set (outcome variable is missing)

0 = Observation is in training data (outcome variable is non-missing)

2,518

training

1 = Observation is in training data set (outcome variable is non-missing)

0 = Observation is in the test data (outcome variable is missing)

2,518

P_1 through P_121

Predictors taken from the Opportunity Insights' county characteristics file and various other sources

2,518

Note: Full list of definitions of *P_1* through *P_121* is in Table 3.

1.7 DATA DESCRIPTION, FILE: atlas_lockbox.dta [Lock box data]

The data consist of all 2,518 counties with at least 10,000 residents available from the Opportunity Atlas. For $n = 1{,}259$ counties in the "test" portion of the data, the outcome variable is set to missing. These observations are a 50% random sample of all counties with at least 10,000 residents available from the Opportunity Atlas. For more details on the construction of the variables included in this data set, please see Chetty, Raj, John Friedman, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter. 2018. "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility." NBER Working Paper No. 25147.

TABLE 2

Lock Box Data

Variable	Definition	Obs.
(1)	(2)	(3)
kfr_actual	Actual value for *kfr_pooled_pooled_p25* for all 2,518 counties with at least 10,000 residents	2,518
geoid	County FIPS code	2,518

1.8 DATA DESCRIPTION, FILE: atlas_training.dta [training data]

TABLE 3

Complete List of All Predictor Variables in Training Data

Variable

Description

Obs.

(1)

(2)

(3)

1

geoid

County FIPS code

2,518

2

pop

County Population from DataCommons

2,518

3

housing

Total number of housing units from Census

2,518

4

kfr_pooled_pooled_p25

Statistic 1 Absolute Mobility at the 25th Percentile

1,259

5

test

1 = Observation is in test data set (outcome variable is missing)

0 = Observation is in training data (outcome variable is non-missing)

2,518

6

training

1 = Observation is in training data set (outcome variable is non-missing)

0 = Observation is in the test data (outcome variable is missing)

2,518

7

P_1

Bankruptcies per 1000 adults in 2008

2,518

8

P_2

Bankruptcies per 1000 adults in 2009

2,518

9

P_3

Bankruptcies per 1000 adults in 2010

2,518

10

P_4

Bankruptcies per 1000 adults in 2011

2,518

11

P_5

Bankruptcies per 1000 adults in 2012

2,518

12

P_6

Bankruptcies per 1000 adults in 2013

2,518

13

P_7

Bankruptcies per 1000 adults in 2014

2,518

14

P_8

Bankruptcies per 1000 adults in 2015

2,518

15

P_9

Bankruptcies per 1000 adults in 2016

2,518

16

P_10

% of Individuals Earning < 138% of the FPL without Insurance in 2013

2,518

17

P_11

% of Individuals Earning 138%-400% of the FPL without Insurance in 2013

2,518

18

P_12

Total Violent and Property Crimes Rate

2,518

19

P_13

Total Violent Crimes Rate: Murder Rate

2,518

20

P_14

Total Violent Crimes Rate: Rape Rate

2,518

21

P_15

Total Violent Crimes Rate: Robbery Rate

2,518

22

P_16

Total Violent Crimes Rate: Aggravated Assault Rate

2,518

23

P_17

Total Property Crimes Rate

2,518

24

P_18

Total Property Crimes Rate: Burglary Rate

2,518

25

P_19

Total Property Crimes Rate: Larceny Rate

2,518

26

P_20

Total Property Crimes Rate: Motor Vehicle Theft Rate

2,518

27

P_21

Total Violent and Property Crime Arrests Rate

2,518

28

P_22

Total Violent and Property Crime Arrests Rate: Violent Crime Arrests Rate

2,518

29

P_23

Total Violent and Property Crime Arrests Rate: Property Crime Arrests Rate

2,518

30

P_24

Mean Household Income 2000

2,518

31

P_25

Average Commute Time of Working Adults in 2000

2,518

32

P_26

Fraction of Residents w/ a College Degree or More in 2000

2,518

33

P_27

Fraction of Residents w/ a College Degree or More in 2006-2010 ACS

2,518

33

P_28

Share of Population Born Outside the U.S. in 2006-2010 ACS

2,518

34

P_29

Median Household Income in 2016

2,518

35

P_30

Median Household Income in 1990

2,518

36

P_31

Share Below Poverty Line 2006-2010 ACS

2,518

37

P_32

Share Below Poverty Line 2000

2,518

38

P_33

Share Below Poverty Line 1990

2,518

39

P_34

Share black 2010

2,518

40

P_35

Share hisp 2010

2,518

41

P_36

Share asian 2010

2,518

42

P_37

Share black 2000

2,518

43

P_38

Share white 2000

2,518

44

P_39

Share hisp 2000

2,518

45

P_40

Share asian 2000

2,518

46

P_41

Average School District Level Standardized Test Scores in 3rd Grade in 2013

2,518

47

P_42

Average Rent for Two-Bedroom Apartment in 2015

2,518

48

P_43

Share of Single-Headed Households with Children 2006-2010 ACS

2,518

49

P_44

Share of Single-Headed Households with Children 1990

2,518

50

P_45

Share of Single-Headed Households with Children 2000

2,518

51

P_46

Share of Working Adults w/ Commute Time of 15 Minutes Or Less in 2006-2010 ACS

2,518

52

P_47

Employment Rate 2000

2,518

53

P_48

Census Form Rate Return Rate 2010

2,518

54

P_49

Log wage growth for HS Grad., 2005-2014

2,518

55

P_50

Share of People who are not white 2010

2,518

56

P_51

Population Density (per square mile) in 2010

2,518

57

P_52

Population Density (per square mile) in 2000

2,518

58

P_53

Average Annual Job Growth Rate 2004-2013

2,518

59

P_54

Job Density (in square miles) in 2013

2,518

60

P_55

Physically Unhealthy Days per Month (Persons 18 Years and Over)

2,518

61

P_56

Mentally Unhealthy Days per Month (Persons 18 Years and Over)

2,518

62

P_57

Percent of Adults That Report Fair or Poor Health (Persons 18 Years and Over)

2,518

63

P_58

Percent of Low Birthweight Births (<2.5kg)

2,518

64

P_59

Primary Care Physicians (PCP) Rate per 100,000 Population

2,518

65

P_60

Mental Health Providers (MHP) Rate per 100,000 Population

2,518

66

P_61

Dentists Rate per 100,000 Population

2,518

67

P_62

Health Care Costs Price-adjusted Medicare Reimbursements

2,518

68

P_63

Percent of Persons Without Insurance (Population Under 19 Years, 2013 est.)

2,518

69

P_64

Percent of Persons Without Insurance (Population 18 to 64 Years, 2013 est.)

2,518

70

P_65

Percent of Persons Without Insurance (Population Under 65 Years, 2013 est.)

2,518

71

P_66

Premature Age-adjusted Mortality Rate per 100,000 Population

2,518

72

P_67

Drug Poisoning Mortality Rate per 100,000 Population

2,518

73

P_68

Percent Diabetics (Adults)

2,518

74

P_69

Percent of Diabetic Medicare Enrollees Receiving Hba1c Test

2,518

75

P_70

Diabetic Medicare Enrollees (Out of Total Medicare Enrolles)

2,518

76

P_71

Teen Births Rate per 100,000 Population (Females 15 to 19 Years)

2,518

77

P_72

Chlamydia Cases Rate per 100,000 Population

2,518

78

P_73

HIV Prevalence Rate per 100,000 Population

2,518

79

P_74

Percent Current Smokers (Persons 18 Years and Over)

2,518

80

P_75

Percent Drinking Adults (Persons 18 Years and Over)

2,518

81

P_76

Percent of Persons with Limited Access to Healthy Foods

2,518

82

P_77

Percent of Persons with Access to Exercise Opportunities

2,518

83

P_78

Percent Obese Persons (20 Years and Over)

2,518

84

P_79

Percent Percent Physically Inactive Persons (20 Years and Over)

2,518

85

P_80

Percent of Children Eligible for Free Lunch (Persons < 18 Years)

2,518

86

P_81

Food Environment Index

2,518

87

P_82

% Total: Evangelical Protestant

2,518

88

P_83

% Total: Mainline Protestant

2,518

89

P_84

% Total: Historically Black Protestant

2,518

90

P_85

% Total: Roman Catholic

2,518

91

P_86

% Total: Jewish Congregations

2,518

92

P_87

% Total: Latter-day Saint (Mormon)

2,518

93

P_88

% Total: Islamic

2,518

94

P_89

% Total: Hindu

2,518

95

P_90

% Total: Buddhist

2,518

96

P_91

% Total: Orthodox Christian

2,518

97

P_92

% Total: Jehovah’s Witnesses

2,518

98

P_93

% Total: Other

2,518

99

P_94

% Total: Evangelical Protestant Member Count

2,518

100

P_95

% Total: Mainline Protestant Member Count

2,518

101

P_96

% Total: Historically Black Protestant Member Count

2,518

102

P_97

% Total: Roman Catholic Member Count

2,518

103

P_98

% Total: Jewish Member Count

2,518

104

P_99

% Total: Latter-day Saint (Mormon) Member Count

2,518

105

P_100

% Total: Islamic Member Count

2,518

106

P_101

% Total: Hindu Member Count

2,518

107

P_102

% Total: Buddhist Member Count

2,518

108

P_103

% Total: Orthodox Christian Member Count

2,518

109

P_104

% Total: Jehovah's Witnesses Member Count

2,518

110

P_105

% Total: Other Member Count

2,518

111

P_106

% Total Evangelical Protestant: Advent Christian Church

2,518

112

P_107

% Total Evangelical Protestant: Adventists - Other

2,518

113

P_108

% Total Evangelical Protestant: Church of God General Conference

2,518

114

P_109

% Total Evangelical Protestant: Seventh Day Adventists

2,518

115

P_110

% Total Evangelical Protestant: Seventh Day Church of God

2,518

116

P_111

% Total Evangelical Protestant: American Baptist Association

2,518

117

P_112

% Total Evangelical Protestant: Baptist General Conference

2,518

118

P_113

% Total Evangelical Protestant: Baptist - Other

2,518

119

P_114

% Total Evangelical Protestant: Baptist Bible Fellowship

2,518

120

P_115

% Total Evangelical Protestant: Baptist Missionary Association of America

2,518

121

P_116

% Total Evangelical Protestant: Cooperative Baptist Fellowship

2,518

122

P_117

% Total Evangelical Protestant: Independent Baptist Churches

2,518

123

P_118

% Total Evangelical Protestant: Conservative Baptist Association

2,518

124

P_119

% Total Evangelical Protestant: Free Will Baptists

2,518

125

P_120

% Total Evangelical Protestant: General Assoc. of Regular Baptists

2,518

126

P_121

% Total Evangelical Protestant: Assoc. of General Baptists

2,518

```
[ ]:
```