GoDaddy - Microbusiness Density Forecasting

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1. Introduction

1.1. Goal of the Competition

The challenge in this competition is to forecast microbusiness activity across the United States, as measured by the density of microbusinesses in US counties. Microbusinesses are often too small or too new to show up in traditional economic data sources, but microbusiness activity may be correlated with other economic indicators of general interest.

This work will help policymakers gain visibility into microbusinesses, a growing trend of very small entities. Additional information will enable new policies and programs to improve the success and impact of these smallest of businesses.

GoDaddy's Venture Forward team has gathered data on over 20 million microbusinesses in the United States, defined as businesses with an online presence and ten or fewer employees, to help policymakers understand the factors associated with these small businesses. While traditional economic data sources often miss these businesses, GoDaddy's survey data can provide insights into this sector of the economy. The data can be used to improve predictions and inform decision-making to create more inclusive and resilient economies. The competition hosted by GoDaddy aims to empower entrepreneurs by giving them the tools they need to grow online and make a substantial impact on communities across the country.

Model accuracy will be evaluated on SMAPE (Symmetric mean absolute percentage error) between forecasts and actual values. We define SMAPE = 0 when the actual and predicted values are both 0.

SMAPE formula is usually defined as follows:

$$\mathrm{SMAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\frac{|F_t - A_t|}{(|F_t| + |A_t|)/2}$$

where:

- n is the number of observations in the time series
- $\mathrm{F_t}$ is the forecasted value at time t
- $\mathrm{A_t}$ is the actual value at time t
- $|\mathrm{x}|$ denotes the absolute value of x.

1.2. Datasets

A great deal of data is publicly available about counties and we have not attempted to gather it all here. You are strongly encouraged to use external data sources for features.

train.csv

- `row_id` An ID code for the row.
- `cfips` A unique identifier for each county using the Federal Information Processing System. The first two digits correspond to the state FIPS code, while the following 3 represent the county.
- `county_name` The written name of the county.
- `state_name` The name of the state.
- `first_day_of_month` The date of the first day of the month.
- `microbusiness_density` Microbusinesses per 100 people over the age of 18 in the given county. This is the target variable. The population figures used to calculate the density are on a two-year lag due to the pace of update provided by the U.S. Census Bureau, which provides the underlying population data annually. 2021 density figures are calculated using 2019 population figures, etc.
- `active` The raw count of microbusinesses in the county. Not provided for the test set.

test.csv Metadata for the submission rows. This file will remain unchanged throughout the competition.

- `row_id` An ID code for the row.
- `cfips` A unique identifier for each county using the Federal Information Processing System. The first two digits correspond to the state FIPS code, while the following 3 represent the county.
- `first_day_of_month` The date of the first day of the month.

census_starter.csv Examples of useful columns from the Census Bureau's American Community Survey (ACS) at data.census.gov. The percentage fields were derived from the raw counts provided by the ACS. All fields have a two year lag to match what information was avaiable at the time a given microbusiness data update was published.

- `pct_bb_[year]` The percentage of households in the county with access to broadband of any type. Derived from ACS table B28002: PRESENCE AND TYPES OF INTERNET SUBSCRIPTIONS IN HOUSEHOLD.
- `cfips` The CFIPS code.
- `pct_college_[year]` The percent of the population in the county over age 25 with a 4-year college degree. Derived from ACS table S1501: EDUCATIONAL ATTAINMENT.
- `pct_foreign_born_[year]` The percent of the population in the county born outside of the United States. Derived from ACS table DP02: SELECTED SOCIAL CHARACTERISTICS IN THE UNITED STATES.
- `pct_it_workers_[year]` The percent of the workforce in the county employed in information related industries. Derived from ACS table S2405: INDUSTRY BY OCCUPATION FOR THE CIVILIAN EMPLOYED POPULATION 16 YEARS AND OVER.

- `median_hh_inc_[year]` The median household income in the county. Derived from ACS table S1901: INCOME IN THE PAST 12 MONTHS (IN 2021 INFLATION-ADJUSTED DOLLARS).

2. Setup the Environment

First, we'll set the working directory using **`setwd()`**, and then import the required libraries. As we proceed through the report the list of libraries might change.

```
# Set the working directory
setwd("/Users/dreamer/Downloads/Godaddy/godaddy_microbusiness_forecasting")
# Importing the libraries

# Recognize package conflicts
library(conflicted)

# Multi-purpose package for data import, tidying, manipulation, visualisation, and
programming
# Most common packages include: ggplot2, purrr, tibble, dplyr, tidyr, stringr, read
r, forcats
library(tidyverse)

# Deal with missing data
library(mice)

# Related to plots
library(maps)
#library(ggmap)
library(gridExtra)
library(mapdata)
library(ggcorrplot)
library(corrplot)

# Training
library(caret)
library(gbm)

# Color palette
library(viridis)

# Future Selection
#library(KernSmooth)
```

```
library(glmnet)
library(randomForest)

# libraries required for calculating SMAPE
library(forecast)
library(Metrics)
```

3. Exploratory Data Analysis

3.1. Exploring the datasets

Explore the datasets to get a better understanding of the data.
Load the **train**, **test**, and **census_starter** datasets into R dataframes.

```
# Load train.csv into a dataframe
train_df <- read.csv("./datasets/train.csv")

# Load test.csv into a dataframe
test_df <- read.csv("./datasets/test.csv")

# Load census_starter.csv into a dataframe
census_df <- read.csv("./datasets/census_starter.csv")
```

After reading the CSV files into dataframes, we should check whether the data is loaded correctly or not. We can use the `head()` function of R to display the first few rows of the dataframes and `tail()` function to display the last rows. This will display the first and last six rows of the **train**, **test** and **census** dataframes. We can also use other R functions such as `str()` and `summary()` to get more information about the dataframes, such as column names, data types, and summary statistics.

```
# Display the first 6 rows of the dataframes
head(train_df)
##            row_id cfips         county   state first_day_of_month
## 1 1001_2019-08-01  1001 Autauga County Alabama         2019-08-01
## 2 1001_2019-09-01  1001 Autauga County Alabama         2019-09-01
## 3 1001_2019-10-01  1001 Autauga County Alabama         2019-10-01
## 4 1001_2019-11-01  1001 Autauga County Alabama         2019-11-01
## 5 1001_2019-12-01  1001 Autauga County Alabama         2019-12-01
## 6 1001_2020-01-01  1001 Autauga County Alabama         2020-01-01
##   microbusiness_density active
## 1              3.007682   1249
## 2              2.884870   1198
```

```
## 3              3.055843   1269
## 4              2.993233   1243
## 5              2.993233   1243
## 6              2.969090   1242
head(test_df)
##            row_id cfips first_day_of_month
## 1 1001_2022-11-01  1001         2022-11-01
## 2 1003_2022-11-01  1003         2022-11-01
## 3 1005_2022-11-01  1005         2022-11-01
## 4 1007_2022-11-01  1007         2022-11-01
## 5 1009_2022-11-01  1009         2022-11-01
## 6 1011_2022-11-01  1011         2022-11-01
head(census_df)
##   pct_bb_2017 pct_bb_2018 pct_bb_2019 pct_bb_2020 pct_bb_2021 cfips
## 1        76.6        78.9        80.6        82.7        85.5  1001
## 2        74.5        78.1        81.8        85.1        87.9  1003
## 3        57.2        60.4        60.5        64.6        64.6  1005
## 4        62.0        66.1        69.2        76.1        74.6  1007
## 5        65.8        68.5        73.0        79.6        81.0  1009
## 6        49.4        58.9        60.1        60.6        59.4  1011
##   pct_college_2017 pct_college_2018 pct_college_2019 pct_college_2020
## 1             14.5             15.9             16.1             16.7
## 2             20.4             20.7             21.0             20.2
## 3              7.6              7.8              7.6              7.3
## 4              8.1              7.6              6.5              7.4
## 5              8.7              8.1              8.6              8.9
## 6              6.6              7.4              7.4              6.1
##   pct_college_2021 pct_foreign_born_2017 pct_foreign_born_2018
## 1             16.4                   2.1                   2.0
## 2             20.6                   3.2                   3.4
## 3              6.7                   2.7                   2.5
## 4              7.9                   1.0                   1.4
## 5              9.3                   4.5                   4.4
## 6              8.1                   1.8                   0.9
##   pct_foreign_born_2019 pct_foreign_born_2020 pct_foreign_born_2021
## 1                   2.3                   2.3                   2.1
## 2                   3.7                   3.4                   3.5
## 3                   2.7                   2.6                   2.6
## 4                   1.5                   1.6                   1.1
```

```
## 5                   4.5                    4.4                    4.5
## 6                   0.7                    1.5                    1.2
##   pct_it_workers_2017 pct_it_workers_2018 pct_it_workers_2019
## 1                 1.3                 1.1                 0.7
## 2                 1.4                 1.3                 1.4
## 3                 0.5                 0.3                 0.8
## 4                 1.2                 1.4                 1.6
## 5                 1.3                 1.4                 0.9
## 6                 0.4                 0.3                 0.5
##   pct_it_workers_2020 pct_it_workers_2021 median_hh_inc_2017 median_hh_inc_2018
## 1                 0.6                 1.1              55317              58786
## 2                 1.0                 1.3              52562              55962
## 3                 1.1                 0.8              33368              34186
## 4                 1.7                 2.1              43404              45340
## 5                 1.1                 0.9              47412              48695
## 6                 0.3                 0.2              29655              32152
##   median_hh_inc_2019 median_hh_inc_2020 median_hh_inc_2021
## 1              58731              57982              62660
## 2              58320              61756              64346
## 3              32525              34990              36422
## 4              47542              51721              54277
## 5              49358              48922              52830
## 6              37785              33866              29063
# Display the last 6 rows of the dataframes
tail(train_df)
##                  row_id cfips        county   state first_day_of_month
## 122260 56045_2022-05-01 56045 Weston County Wyoming         2022-05-01
## 122261 56045_2022-06-01 56045 Weston County Wyoming         2022-06-01
## 122262 56045_2022-07-01 56045 Weston County Wyoming         2022-07-01
## 122263 56045_2022-08-01 56045 Weston County Wyoming         2022-08-01
## 122264 56045_2022-09-01 56045 Weston County Wyoming         2022-09-01
## 122265 56045_2022-10-01 56045 Weston County Wyoming         2022-10-01
##        microbusiness_density active
## 122260              1.803249    101
## 122261              1.803249    101
## 122262              1.803249    101
## 122263              1.785395    100
## 122264              1.785395    100
## 122265              1.785395    100
```

```
tail(test_df)
##                  row_id cfips first_day_of_month
## 25075 56035_2023-06-01 56035         2023-06-01
## 25076 56037_2023-06-01 56037         2023-06-01
## 25077 56039_2023-06-01 56039         2023-06-01
## 25078 56041_2023-06-01 56041         2023-06-01
## 25079 56043_2023-06-01 56043         2023-06-01
## 25080 56045_2023-06-01 56045         2023-06-01
tail(census_df)
##      pct_bb_2017 pct_bb_2018 pct_bb_2019 pct_bb_2020 pct_bb_2021 cfips
## 3137        82.9        81.7        85.6        88.1        89.8 56035
## 3138        82.2        82.4        84.0        86.7        88.4 56037
## 3139        83.5        85.9        87.1        89.1        90.5 56039
## 3140        83.8        88.2        89.5        91.4        90.6 56041
## 3141        76.4        78.3        78.2        82.8        85.4 56043
## 3142        71.1        73.3        76.8        79.7        81.3 56045
##      pct_college_2017 pct_college_2018 pct_college_2019 pct_college_2020
## 3137             19.2             19.0             16.7             21.7
## 3138             15.3             15.2             14.8             13.7
## 3139             37.7             37.8             38.9             37.2
## 3140             11.9             10.5             11.1             12.6
## 3141             15.4             15.0             15.4             15.0
## 3142             14.1             13.5             13.4             12.7
##      pct_college_2021 pct_foreign_born_2017 pct_foreign_born_2018
## 3137             20.9                   3.9                   3.1
## 3138             12.4                   5.0                   5.3
## 3139             38.3                  10.8                  11.2
## 3140             12.3                   2.9                   3.1
## 3141             17.2                   2.3                   1.4
## 3142             13.9                   3.8                   4.1
##      pct_foreign_born_2019 pct_foreign_born_2020 pct_foreign_born_2021
## 3137                   4.4                   5.1                   5.1
## 3138                   4.7                   5.2                   5.5
## 3139                  11.8                  11.4                  11.1
## 3140                   2.9                   2.9                   2.9
## 3141                   1.6                   2.2                   1.0
## 3142                   1.7                   2.3                   1.6
##      pct_it_workers_2017 pct_it_workers_2018 pct_it_workers_2019
## 3137                 0.1                 0.0                 0.0
```

```
## 3138                  0.6                 0.6                 1.0
## 3139                  0.7                 1.2                 1.4
## 3140                  1.2                 1.2                 1.4
## 3141                  1.3                 1.0                 0.9
## 3142                  0.6                 0.6                 0.0
##      pct_it_workers_2020 pct_it_workers_2021 median_hh_inc_2017
## 3137                  0.0                 0.0               84911
## 3138                  0.9                 1.0               71083
## 3139                  1.5                 2.0               80049
## 3140                  1.7                 0.9               54672
## 3141                  0.9                 1.1               51362
## 3142                  0.0                 0.0               59605
##      median_hh_inc_2018 median_hh_inc_2019 median_hh_inc_2020
## 3137              78680              77403              78655
## 3138              73008              74843              73384
## 3139              83831              84678              87053
## 3140              58235              63403              72458
## 3141              53426              54158              57306
## 3142              52867              57031              53333
##      median_hh_inc_2021
## 3137              82342
## 3138              76668
## 3139              94498
## 3140              75106
## 3141              62271
## 3142              65566
# Display information about the train dataframe
str(train_df)
## 'data.frame':    122265 obs. of  7 variables:
##  $ row_id               : chr  "1001_2019-08-01" "1001_2019-09-01" "1001_2019-10
-01" "1001_2019-11-01" ...
##  $ cfips                : int  1001 1001 1001 1001 1001 1001 1001 1001 1001 1001
...
##  $ county               : chr  "Autauga County" "Autauga County" "Autauga County
" "Autauga County" ...
##  $ state                : chr  "Alabama" "Alabama" "Alabama" "Alabama" ...
##  $ first_day_of_month   : chr  "2019-08-01" "2019-09-01" "2019-10-01" "2019-11-0
1" ...
##  $ microbusiness_density: num  3.01 2.88 3.06 2.99 2.99 ...
##  $ active               : int  1249 1198 1269 1243 1243 1242 1217 1227 1255 1257
...
```

```
#cat(rep("=", 40), "\n") # Print a line of 40 equal signs
summary(train_df)
##     row_id              cfips          county             state
##  Length:122265      Min.   : 1001   Length:122265      Length:122265
##  Class :character   1st Qu.:18177   Class :character   Class :character
##  Mode  :character   Median :29173   Mode  :character   Mode  :character
##                     Mean   :30376
##                     3rd Qu.:45077
##                     Max.   :56045
##  first_day_of_month microbusiness_density     active
##  Length:122265      Min.   :  0.000       Min.   :      0
##  Class :character   1st Qu.:  1.639       1st Qu.:    145
##  Mode  :character   Median :  2.587       Median :    488
##                     Mean   :  3.818       Mean   :   6443
##                     3rd Qu.:  4.519       3rd Qu.:   2124
##                     Max.   :284.340       Max.   :1167744
# Display information about the test dataframe
str(test_df)
## 'data.frame':    25080 obs. of  3 variables:
##  $ row_id            : chr  "1001_2022-11-01" "1003_2022-11-01" "1005_2022-11-01
" "1007_2022-11-01" ...
##  $ cfips             : int  1001 1003 1005 1007 1009 1011 1013 1015 1017 1019 ..
.
##  $ first_day_of_month: chr  "2022-11-01" "2022-11-01" "2022-11-01" "2022-11-01"
...
#cat(rep("=", 40), "\n") # Print a line of 40 equal signs
summary(test_df)
##     row_id              cfips       first_day_of_month
##  Length:25080       Min.   : 1001   Length:25080
##  Class :character   1st Qu.:18177   Class :character
##  Mode  :character   Median :29173   Mode  :character
##                     Mean   :30376
##                     3rd Qu.:45077
##                     Max.   :56045
# Display information about the census dataframe
str(census_df)
## 'data.frame':    3142 obs. of  26 variables:
##  $ pct_bb_2017          : num  76.6 74.5 57.2 62 65.8 49.4 58.2 71 62.8 67.5 ...
##  $ pct_bb_2018          : num  78.9 78.1 60.4 66.1 68.5 58.9 62.1 73 66.5 68.6 .
..
```

```
##  $ pct_bb_2019         : num  80.6 81.8 60.5 69.2 73 60.1 64.6 75.1 69.4 70.7 .
..
##  $ pct_bb_2020         : num  82.7 85.1 64.6 76.1 79.6 60.6 73.6 79.8 74.5 75 .
..
##  $ pct_bb_2021         : num  85.5 87.9 64.6 74.6 81 59.4 76.3 81.6 77.1 76.7 .
..
##  $ cfips               : int  1001 1003 1005 1007 1009 1011 1013 1015 1017 1019
...
##  $ pct_college_2017     : num  14.5 20.4 7.6 8.1 8.7 6.6 9.6 10.2 9 6.6 ...
##  $ pct_college_2018     : num  15.9 20.7 7.8 7.6 8.1 7.4 9.7 10.2 9.3 6.8 ...
##  $ pct_college_2019     : num  16.1 21 7.6 6.5 8.6 7.4 9.7 10.5 9.5 6.6 ...
##  $ pct_college_2020     : num  16.7 20.2 7.3 7.4 8.9 6.1 10.1 10.5 10.5 6.3 ...
##  $ pct_college_2021     : num  16.4 20.6 6.7 7.9 9.3 8.1 8.1 11.4 9.6 6.2 ...
##  $ pct_foreign_born_2017: num  2.1 3.2 2.7 1 4.5 1.8 1 2.6 1.3 0.7 ...
##  $ pct_foreign_born_2018: num  2 3.4 2.5 1.4 4.4 0.9 1.4 2.7 1.4 0.8 ...
##  $ pct_foreign_born_2019: num  2.3 3.7 2.7 1.5 4.5 0.7 0.8 2.7 1.8 0.9 ...
##  $ pct_foreign_born_2020: num  2.3 3.4 2.6 1.6 4.4 1.5 1.9 2.5 1.9 1.9 ...
##  $ pct_foreign_born_2021: num  2.1 3.5 2.6 1.1 4.5 1.2 1.7 2.5 2 2 ...
##  $ pct_it_workers_2017  : num  1.3 1.4 0.5 1.2 1.3 0.4 1.1 1.4 2.4 1.4 ...
##  $ pct_it_workers_2018  : num  1.1 1.3 0.3 1.4 1.4 0.3 1.4 1.4 2.1 1.3 ...
##  $ pct_it_workers_2019  : num  0.7 1.4 0.8 1.6 0.9 0.5 1.7 1.2 2.1 1.2 ...
##  $ pct_it_workers_2020  : num  0.6 1 1.1 1.7 1.1 0.3 1.3 1 2.3 0.9 ...
##  $ pct_it_workers_2021  : num  1.1 1.3 0.8 2.1 0.9 0.2 1.4 1 1.8 0.4 ...
##  $ median_hh_inc_2017   : int  55317 52562 33368 43404 47412 29655 36326 43686 3
7342 40041 ...
##  $ median_hh_inc_2018   : num  58786 55962 34186 45340 48695 ...
##  $ median_hh_inc_2019   : int  58731 58320 32525 47542 49358 37785 40688 47255 4
2289 41919 ...
##  $ median_hh_inc_2020   : num  57982 61756 34990 51721 48922 ...
##  $ median_hh_inc_2021   : num  62660 64346 36422 54277 52830 ...
#cat(rep("=", 40), "\n") # Print a line of 40 equal signs
summary(census_df)
##   pct_bb_2017     pct_bb_2018     pct_bb_2019     pct_bb_2020
##  Min.   :24.50   Min.   :25.70   Min.   :34.80   Min.   :33.30
##  1st Qu.:64.20   1st Qu.:67.42   1st Qu.:70.50   1st Qu.:74.10
##  Median :70.70   Median :73.60   Median :76.45   Median :79.60
##  Mean   :69.92   Mean   :72.69   Mean   :75.40   Mean   :78.54
##  3rd Qu.:76.40   3rd Qu.:78.80   3rd Qu.:81.40   3rd Qu.:84.10
##  Max.   :94.60   Max.   :95.50   Max.   :96.00   Max.   :97.10
##                                                  NA's   :1
##   pct_bb_2021         cfips       pct_college_2017 pct_college_2018
##  Min.   :37.00   Min.   : 1001   Min.   : 2.40    Min.   : 0.00
```

```
##  1st Qu.:76.40   1st Qu.:18178   1st Qu.: 9.70    1st Qu.: 9.90  
##  Median :81.70   Median :29176   Median :12.80    Median :13.00  
##  Mean   :80.54   Mean   :30384   Mean   :13.81    Mean   :14.01  
##  3rd Qu.:85.90   3rd Qu.:45080   3rd Qu.:16.80    3rd Qu.:17.10  
##  Max.   :97.60   Max.   :56045   Max.   :43.70    Max.   :48.00  
##  NA's   :1                                                       
##  pct_college_2019 pct_college_2020 pct_college_2021 pct_foreign_born_2017
##  Min.   : 0.00    Min.   : 0.00    Min.   : 0.00    Min.   : 0.000       
##  1st Qu.:10.10    1st Qu.:10.50    1st Qu.:10.60    1st Qu.: 1.400       
##  Median :13.25    Median :13.60    Median :13.80    Median : 2.700       
##  Mean   :14.24    Mean   :14.63    Mean   :14.85    Mean   : 4.702       
##  3rd Qu.:17.30    3rd Qu.:17.90    3rd Qu.:18.00    3rd Qu.: 5.700       
##  Max.   :45.40    Max.   :43.00    Max.   :43.70    Max.   :52.900       
##                   NA's   :1        NA's   :1                             
##  pct_foreign_born_2018 pct_foreign_born_2019 pct_foreign_born_2020
##  Min.   : 0.000        Min.   : 0.000        Min.   : 0.000       
##  1st Qu.: 1.400        1st Qu.: 1.400        1st Qu.: 1.400       
##  Median : 2.700        Median : 2.700        Median : 2.800       
##  Mean   : 4.725        Mean   : 4.769        Mean   : 4.749       
##  3rd Qu.: 5.700        3rd Qu.: 5.700        3rd Qu.: 5.700       
##  Max.   :53.300        Max.   :53.700        Max.   :54.000       
##                                              NA's   :1            
##  pct_foreign_born_2021 pct_it_workers_2017 pct_it_workers_2018
##  Min.   : 0.000        Min.   : 0.000      Min.   : 0.000     
##  1st Qu.: 1.400        1st Qu.: 0.800      1st Qu.: 0.800     
##  Median : 2.700        Median : 1.300      Median : 1.300     
##  Mean   : 4.744        Mean   : 1.427      Mean   : 1.382     
##  3rd Qu.: 5.700        3rd Qu.: 1.900      3rd Qu.: 1.800     
##  Max.   :54.000        Max.   :17.400      Max.   :11.700     
##  NA's   :1                                 NA's   :1          
##  pct_it_workers_2019 pct_it_workers_2020 pct_it_workers_2021 median_hh_inc_2017
##  Min.   : 0.000      Min.   : 0.000      Min.   : 0.000      Min.   : 19264    
##  1st Qu.: 0.700      1st Qu.: 0.700      1st Qu.: 0.600      1st Qu.: 41123    
##  Median : 1.200      Median : 1.200      Median : 1.100      Median : 48066    
##  Mean   : 1.339      Mean   : 1.309      Mean   : 1.273      Mean   : 49754    
##  3rd Qu.: 1.800      3rd Qu.: 1.800      3rd Qu.: 1.700      3rd Qu.: 55764    
##  Max.   :10.500      Max.   :15.200      Max.   :15.200      Max.   :129588    
##                      NA's   :1           NA's   :1                            
##  median_hh_inc_2018 median_hh_inc_2019 median_hh_inc_2020 median_hh_inc_2021
```

```
##  Min.   : 20188     Min.   : 21504     Min.   : 22292     Min.   : 17109
##  1st Qu.: 42480     1st Qu.: 44155     1st Qu.: 45653     1st Qu.: 48180
##  Median : 49888     Median : 51758     Median : 52842     Median : 55907
##  Mean   : 51583     Mean   : 53476     Mean   : 55012     Mean   : 58223
##  3rd Qu.: 57611     3rd Qu.: 59867     3rd Qu.: 61501     3rd Qu.: 64930
##  Max.   :136268     Max.   :142299     Max.   :147111     Max.   :156821
##  NA's   :1                             NA's   :2          NA's   :2
```

The data type of `first_day_of_month` column in **train_df** and **test_df** is *character*. We will convert the character to *Date* format.

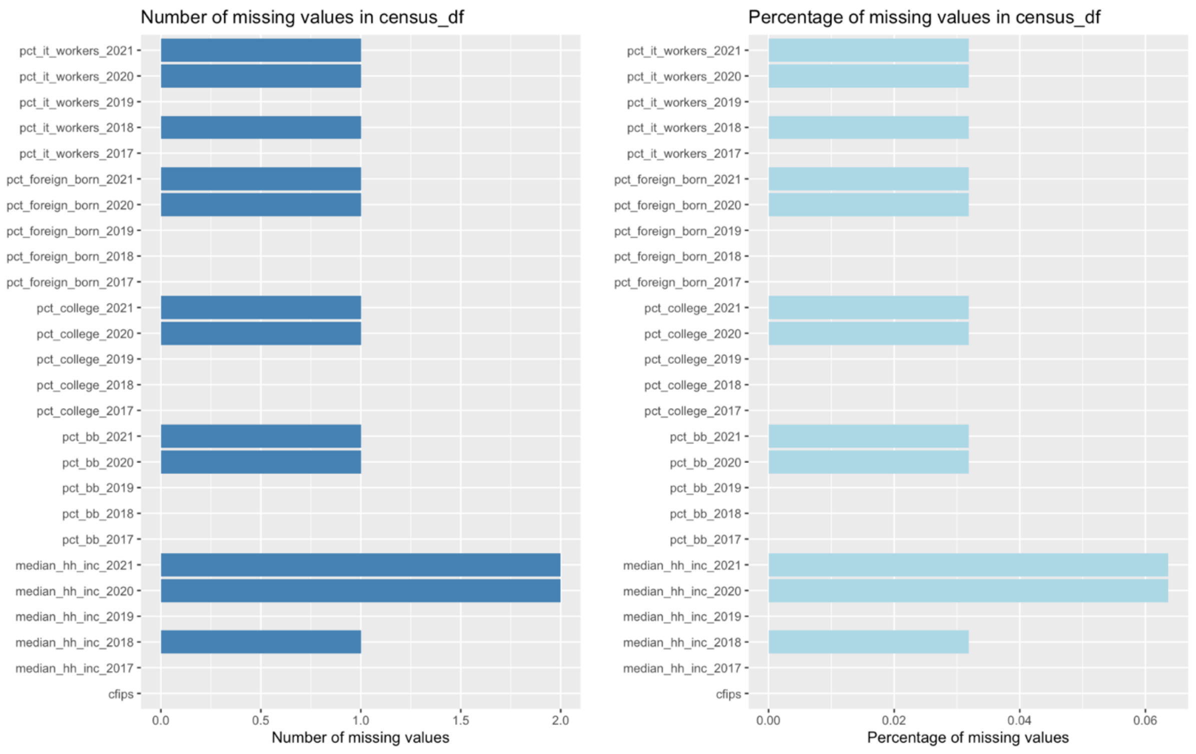
```
# Change first_day_of_month data type to Date
train_df$first_day_of_month <- as.Date(train_df$first_day_of_month)
test_df$first_day_of_month <- as.Date(test_df$first_day_of_month)
str(train_df$first_day_of_month)
##  Date[1:122265], format: "2019-08-01" "2019-09-01" "2019-10-01" "2019-11-01" "20
19-12-01" ...
```

3.2. Checking the Dataframes for Missing Values

The `is.na()` function is used to create a logical matrix where *TRUE* represents a missing value and *FALSE* represents a non-missing value. The `colSums()` function is then used to count the number of missing values in each column of the data frame. If the sum of a column is greater than 0, it means that there is at least one missing value in that column.

```
# Check for missing values in the train data frame
colSums(is.na(train_df))
##                row_id                 cfips                county
##                     0                     0                     0
##                 state    first_day_of_month microbusiness_density
##                     0                     0                     0
##                active
##                     0
# Check for missing values in the test data frame
colSums(is.na(test_df))
##             row_id              cfips first_day_of_month
##                  0                  0                  0
# Check for missing values in the census data frame
colSums(is.na(census_df))
##           pct_bb_2017           pct_bb_2018           pct_bb_2019
##                     0                     0                     0
```

```
##           pct_bb_2020           pct_bb_2021                 cfips
##                     1                     1                     0
##      pct_college_2017      pct_college_2018      pct_college_2019
##                     0                     0                     0
##      pct_college_2020      pct_college_2021 pct_foreign_born_2017
##                     1                     1                     0
## pct_foreign_born_2018 pct_foreign_born_2019 pct_foreign_born_2020
##                     0                     0                     1
## pct_foreign_born_2021   pct_it_workers_2017   pct_it_workers_2018
##                     1                     0                     1
##   pct_it_workers_2019   pct_it_workers_2020   pct_it_workers_2021
##                     0                     1                     1
##    median_hh_inc_2017    median_hh_inc_2018    median_hh_inc_2019
##                     0                     1                     0
##    median_hh_inc_2020    median_hh_inc_2021
##                     2                     2
#{r fig.width=7, fig.align='center', fig.height=4, out.width='100%'}
# Calculate the number and percentage of missing values for each column
missing_data <- census_df %>%
  summarise_all(~ sum(is.na(.))) %>%
  gather(variable, missing_count) %>%
  mutate(missing_percent = missing_count/nrow(census_df)*100)

# Create two plots side by side
plot1 <- ggplot(missing_data, aes(x = missing_count, y = variable)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  labs(x = "Number of missing values", y = "") +
  ggtitle("Number of missing values in census_df") +
  theme_gray()

plot2 <- ggplot(missing_data, aes(x = missing_percent, y = variable)) +
  geom_bar(stat = "identity", fill = "lightblue") +
  labs(x = "Percentage of missing values", y = "") +
  ggtitle("Percentage of missing values in census_df") +
  theme_gray()

# Arrange the two plots side by side
grid.arrange(plot1, plot2, ncol = 2)
```



We use the `complete.cases()` function to determine which rows have complete data and which rows have missing values. This function returns a logical vector indicating which rows have no missing values. Therefore, to identify the rows with missing values, we use the `!` operator to negate the logical vector returned by `complete.cases()`. Then, we use the `is.na()` function to identify which columns have missing values for each missing row:

```
# Identify rows with missing values in census_df
missing_rows <- which(!complete.cases(census_df))


# Identify columns with missing values for each missing row
for (i in missing_rows) {
  cat("Row", i, "has missing values in columns:",
      paste(names(census_df)[is.na(census_df[i,])], collapse = ", "), "\n")
}
## Row 93 has missing values in columns: pct_bb_2020, pct_bb_2021, pct_college_2020
, pct_college_2021, pct_foreign_born_2020, pct_foreign_born_2021, pct_it_workers_20
20, pct_it_workers_2021, median_hh_inc_2020, median_hh_inc_2021
## Row 1817 has missing values in columns: pct_it_workers_2018, median_hh_inc_2018
## Row 2645 has missing values in columns: median_hh_inc_2020
## Row 2674 has missing values in columns: median_hh_inc_2021
print(census_df[missing_rows,])
##      pct_bb_2017 pct_bb_2018 pct_bb_2019 pct_bb_2020 pct_bb_2021 cfips
## 93          80.5        79.1        80.4          NA          NA  2261
## 1817        49.1        52.1        57.6        60.7        63.5 35039
```

```
## 2645        66.3        66.6        61.2        63.2        70.1 48243
## 2674        64.5        72.7        73.3        96.8        97.0 48301
##      pct_college_2017 pct_college_2018 pct_college_2019 pct_college_2020
## 93               23.1             19.0             16.5               NA
## 1817             12.0             12.5             12.6             10.6
## 2645             18.4             16.0             10.8             14.3
## 2674              4.7              0.0              0.0              0.0
##      pct_college_2021 pct_foreign_born_2017 pct_foreign_born_2018
## 93                 NA                   4.9                   6.3
## 1817             10.1                   4.5                   3.7
## 2645             10.9                  22.4                  14.9
## 2674              0.0                  10.8                  15.7
##      pct_foreign_born_2019 pct_foreign_born_2020 pct_foreign_born_2021
## 93                     6.6                    NA                    NA
## 1817                   4.2                   4.5                   4.8
## 2645                  20.9                  10.1                  12.7
## 2674                  12.2                   0.0                   1.2
##      pct_it_workers_2017 pct_it_workers_2018 pct_it_workers_2019
## 93                   3.3                 3.9                 5.3
## 1817                 0.8                  NA                 0.8
## 2645                 0.0                 0.0                 0.0
## 2674                 0.0                 0.0                 0.0
##      pct_it_workers_2020 pct_it_workers_2021 median_hh_inc_2017
## 93                    NA                  NA              86019
## 1817                 0.4                 0.7              33422
## 2645                 0.0                 0.0              46534
## 2674                 0.0                 0.0              80938
##      median_hh_inc_2018 median_hh_inc_2019 median_hh_inc_2020
## 93                82306              79867                 NA
## 1817                 NA              39952              42264
## 2645              53194              53088                 NA
## 2674              81875              83750              44076
##      median_hh_inc_2021
## 93                   NA
## 1817              46994
## 2645              38659
## 2674                 NA
```

3.3. Dealing with Missing Values

The `mice` package implements a method to deal with missing data. The package creates multiple imputations (replacement values) for multivariate missing data.

We'll use the `mice` package to impute missing values in the **census_df** dataframe with below arguments:

- *m*: The number of imputations to generate was set to 5, because, generally, *m* should be set to at least 5 for good imputation performance. Creating too many datasets will increase the computational load and may not necessarily lead to better results.
- *maxit*: The *maxit* value was set to 50 to allow for a larger number of iterations to ensure that the imputation algorithm converges and fills in missing values as accurately as possible.
- *method*: In this case, we are using *"pmm"* which stands for *Predictive Mean Matching*, because it is a flexible and widely used imputation method that works well with continuous variables. The method estimates the missing values by drawing from a set of observed values that have similar characteristics to the missing values.
- *print*: The print value is set to *FALSE* because this function prints a huge log output to console.

```
# Impute missing data using mice
imputed_data <- mice(census_df, m = 5, maxit = 50, method = "pmm", print = FALSE)
# Extract imputed data
imputed_data <- complete(imputed_data)
# Check for missing values in imputed data
colSums(is.na(imputed_data))
##            pct_bb_2017            pct_bb_2018            pct_bb_2019
##                      0                      0                      0
##            pct_bb_2020            pct_bb_2021                  cfips
##                      0                      0                      0
##       pct_college_2017       pct_college_2018       pct_college_2019
##                      0                      0                      0
##       pct_college_2020       pct_college_2021 pct_foreign_born_2017
##                      0                      0                      0
## pct_foreign_born_2018 pct_foreign_born_2019 pct_foreign_born_2020
##                      0                      0                      0
## pct_foreign_born_2021    pct_it_workers_2017    pct_it_workers_2018
##                      0                      0                      0
##    pct_it_workers_2019    pct_it_workers_2020    pct_it_workers_2021
##                      0                      0                      0
##     median_hh_inc_2017     median_hh_inc_2018     median_hh_inc_2019
##                      0                      0                      0
##     median_hh_inc_2020     median_hh_inc_2021
```

```
##                     0                      0
# Check the filled missing values
print(imputed_data[missing_rows,])
##      pct_bb_2017 pct_bb_2018 pct_bb_2019 pct_bb_2020 pct_bb_2021 cfips
## 93          80.5        79.1        80.4        81.0        83.5  2261
## 1817        49.1        52.1        57.6        60.7        63.5 35039
## 2645        66.3        66.6        61.2        63.2        70.1 48243
## 2674        64.5        72.7        73.3        96.8        97.0 48301
##      pct_college_2017 pct_college_2018 pct_college_2019 pct_college_2020
## 93               23.1             19.0             16.5             15.1
## 1817             12.0             12.5             12.6             10.6
## 2645             18.4             16.0             10.8             14.3
## 2674              4.7              0.0              0.0              0.0
##      pct_college_2021 pct_foreign_born_2017 pct_foreign_born_2018
## 93               15.1                   4.9                   6.3
## 1817             10.1                   4.5                   3.7
## 2645             10.9                  22.4                  14.9
## 2674              0.0                  10.8                  15.7
##      pct_foreign_born_2019 pct_foreign_born_2020 pct_foreign_born_2021
## 93                     6.6                   6.0                   7.6
## 1817                   4.2                   4.5                   4.8
## 2645                  20.9                  10.1                  12.7
## 2674                  12.2                   0.0                   1.2
##      pct_it_workers_2017 pct_it_workers_2018 pct_it_workers_2019
## 93                   3.3                 3.9                 5.3
## 1817                 0.8                 0.5                 0.8
## 2645                 0.0                 0.0                 0.0
## 2674                 0.0                 0.0                 0.0
##      pct_it_workers_2020 pct_it_workers_2021 median_hh_inc_2017
## 93                   5.6                 1.0              86019
## 1817                 0.4                 0.7              33422
## 2645                 0.0                 0.0              46534
## 2674                 0.0                 0.0              80938
##      median_hh_inc_2018 median_hh_inc_2019 median_hh_inc_2020
## 93                82306              79867              78889
## 1817              36148              39952              42264
## 2645              53194              53088              42285
## 2674              81875              83750              44076
##      median_hh_inc_2021
```

```
## 93                 81817
## 1817               46994
## 2645               38659
## 2674               52842
```

3.4. Checking the Time Frame of *train* and *test* Dataframes

After dealing with the missing values, we have to check the time frame provided in the **train** and **test** datasets.

```
index <- unique(train_df$first_day_of_month)
print(index)
##  [1] "2019-08-01" "2019-09-01" "2019-10-01" "2019-11-01" "2019-12-01"
##  [6] "2020-01-01" "2020-02-01" "2020-03-01" "2020-04-01" "2020-05-01"
## [11] "2020-06-01" "2020-07-01" "2020-08-01" "2020-09-01" "2020-10-01"
## [16] "2020-11-01" "2020-12-01" "2021-01-01" "2021-02-01" "2021-03-01"
## [21] "2021-04-01" "2021-05-01" "2021-06-01" "2021-07-01" "2021-08-01"
## [26] "2021-09-01" "2021-10-01" "2021-11-01" "2021-12-01" "2022-01-01"
## [31] "2022-02-01" "2022-03-01" "2022-04-01" "2022-05-01" "2022-06-01"
## [36] "2022-07-01" "2022-08-01" "2022-09-01" "2022-10-01"
```

The training data time frame includes 08/2019 to 10/2022

```
index <- unique(test_df$first_day_of_month)
print(index)
## [1] "2022-11-01" "2022-12-01" "2023-01-01" "2023-02-01" "2023-03-01"
## [6] "2023-04-01" "2023-05-01" "2023-06-01"
```

The prediction dates provided include 11/2022 to 06/2023

3.5. Adding New Columns to *train* and *test*

To make analysis easier and be able to group the data by year and month, we will use `substr()` function to extract the relevant characters of the `first_day_of_month` column, which is a string that contains the date in the format "YYYY-MM-DD". Then, `as.integer()` function is used to convert the extracted year and month values from character strings to integers.

```
# Add year, month and year_month columns to train_df
train_df$year <- as.integer(substr(train_df$first_day_of_month, 1, 4))
train_df$month <- as.integer(substr(train_df$first_day_of_month, 6, 7))
train_df$year_month <- substr(train_df$first_day_of_month, 1, 7)
str(train_df)
```

```
## 'data.frame':    122265 obs. of  10 variables:
##  $ row_id               : chr  "1001_2019-08-01" "1001_2019-09-01" "1001_2019-10
-01" "1001_2019-11-01" ...
##  $ cfips                : int  1001 1001 1001 1001 1001 1001 1001 1001 1001 1001
...
##  $ county               : chr  "Autauga County" "Autauga County" "Autauga County
" "Autauga County" ...
##  $ state                : chr  "Alabama" "Alabama" "Alabama" "Alabama" ...
##  $ first_day_of_month   : Date, format: "2019-08-01" "2019-09-01" ...
##  $ microbusiness_density: num  3.01 2.88 3.06 2.99 2.99 ...
##  $ active               : int  1249 1198 1269 1243 1243 1242 1217 1227 1255 1257
...
##  $ year                 : int  2019 2019 2019 2019 2019 2020 2020 2020 2020 2020
...
##  $ month                : int  8 9 10 11 12 1 2 3 4 5 ...
##  $ year_month           : chr  "2019-08" "2019-09" "2019-10" "2019-11" ...
# Add year, month and year_month columns to test_df
test_df$year <- as.integer(substr(test_df$first_day_of_month, 1, 4))
test_df$month <- as.integer(substr(test_df$first_day_of_month, 6, 7))
test_df$year_month <- substr(test_df$first_day_of_month, 1, 7)
```

3.6. Merging the *train* and *imputed_data* datasets

The merging process is challenging because all data fields provided in the **imputed_data** (formerly **census_df)** dataframe have a two-year lag to match the data in the **train_df** dataframe. Also, the data provided in the **imputed_data** is on a yearly basis, but the data in the **train_df** dataframe is on a monthly basis. To merge these two dataframes, it is assumed that the yearly data provided is valid for all the months of the corresponding year. For example, data provided in the `pct_bb_2017` is valid for all the months of *2019* in the **train_df**.

```
# Set variables of interest
vars <- c("pct_bb", "pct_college", "pct_foreign_born", "pct_it_workers", "median_hh
_inc")


# Loop through variables and merge with train_df
merged_df <- train_df


for (var in vars) {
  # Select columns and pivot longer
  merged_df <- imputed_data %>%
    select(cfips, paste0(var, "_2017"):paste0(var, "_2020")) %>%
    pivot_longer(cols = starts_with(var),
```

```
                 names_to = "year",
                 values_to = var) %>%
    # Modify year and month columns
    mutate(year = as.integer(str_sub(year, -4)) + 2) %>%
    uncount(12, .id = "month") %>%
    mutate(month = month) %>%
    # Merge with merged_df
    merge(merged_df, by = c("cfips", "year", "month"), all.x = TRUE) %>%
    arrange(cfips, row_id)
}
merged_df <- merged_df %>%
  select(row_id, cfips, county, state, first_day_of_month, microbusiness_density, a
ctive, year_month, year, month, pct_bb, pct_college, pct_foreign_born, pct_it_worke
rs, median_hh_inc)


merged_test <- test_df
for (var in vars) {
  # Select columns and pivot longer
  merged_test <- imputed_data %>%
    select(cfips, paste0(var, "_2020"):paste0(var, "_2021")) %>%
    pivot_longer(cols = starts_with(var),
                 names_to = "year",
                 values_to = var) %>%
    # Modify year and month columns
    mutate(year = as.integer(str_sub(year, -4)) + 2) %>%
    uncount(12, .id = "month") %>%
    mutate(month = month) %>%
    # Merge with merged_df
    merge(merged_test, by = c("cfips", "year", "month"), all.x = TRUE) %>%
    arrange(cfips, row_id)
}
merged_test <- merged_test %>%
  select(row_id, cfips, first_day_of_month, year_month, year, month, pct_bb, pct_co
llege, pct_foreign_born, pct_it_workers, median_hh_inc)
colSums(is.na(merged_df))
##                row_id                 cfips                county
##                 28551                     0                 28551
##                 state    first_day_of_month microbusiness_density
##                 28551                 28551                 28551
##                active            year_month                  year
##                 28551                 28551                     0
```

```
##                 month                pct_bb            pct_college
##                     0                     0                      0
##       pct_foreign_born        pct_it_workers          median_hh_inc
##                     0                     0                      0
colSums(is.na(merged_test))
##            row_id              cfips  first_day_of_month          year_month
##             50328                  0               50328               50328
##              year              month               pct_bb         pct_college
##                 0                  0                    0                   0
##   pct_foreign_born     pct_it_workers       median_hh_inc
##                 0                  0                    0
```

Since the data from 1/2019 to 7/2019 and 11/2022 to 12/2022 is not available in **train_df** merging the data has created NA values in **merged_df** for those months. Now we have to remove the rows with missing values.

```
# remove NA values created in merged_df
merged_df <- merged_df %>%
  na.omit(merged_df)

merged_test <- merged_test %>%
  na.omit(merged_test)
colSums(is.na(merged_df))
##                row_id                 cfips                county
##                     0                     0                     0
##                 state    first_day_of_month microbusiness_density
##                     0                     0                     0
##                active            year_month                  year
##                     0                     0                     0
##                 month                pct_bb            pct_college
##                     0                     0                     0
##       pct_foreign_born        pct_it_workers          median_hh_inc
##                     0                     0                     0
colSums(is.na(merged_test))
##            row_id              cfips  first_day_of_month          year_month
##                 0                  0                    0                   0
##              year              month               pct_bb         pct_college
##                 0                  0                    0                   0
##   pct_foreign_born     pct_it_workers       median_hh_inc
##                 0                  0                    0
summary(merged_df)
```

```
##     row_id              cfips           county             state          
##  Length:122265      Min.   : 1001   Length:122265      Length:122265     
##  Class :character   1st Qu.:18177   Class :character   Class :character  
##  Mode  :character   Median :29173   Mode  :character   Mode  :character  
##                     Mean   :30376                                        
##                     3rd Qu.:45077                                        
##                     Max.   :56045                                        
##  first_day_of_month  microbusiness_density     active       
##  Min.   :2019-08-01  Min.   :  0.000       Min.   :      0  
##  1st Qu.:2020-05-01  1st Qu.:  1.639       1st Qu.:    145  
##  Median :2021-03-01  Median :  2.587       Median :    488  
##  Mean   :2021-03-01  Mean   :  3.818       Mean   :   6443  
##  3rd Qu.:2022-01-01  3rd Qu.:  4.519       3rd Qu.:   2124  
##  Max.   :2022-10-01  Max.   :284.340       Max.   :1167744  
##   year_month             year          month            pct_bb     
##  Length:122265      Min.   :2019   Min.   : 1.000   Min.   :24.50  
##  Class :character   1st Qu.:2020   1st Qu.: 4.000   1st Qu.:69.30  
##  Mode  :character   Median :2021   Median : 7.000   Median :75.80  
##                     Mean   :2021   Mean   : 6.692   Mean   :74.69  
##                     3rd Qu.:2022   3rd Qu.:10.000   3rd Qu.:81.20  
##                     Max.   :2022   Max.   :12.000   Max.   :97.10  
##   pct_college    pct_foreign_born pct_it_workers   median_hh_inc   
##  Min.   : 0.00   Min.   : 0.000   Min.   : 0.000   Min.   : 19264  
##  1st Qu.:10.10   1st Qu.: 1.400   1st Qu.: 0.700   1st Qu.: 43505  
##  Median :13.20   Median : 2.700   Median : 1.200   Median : 51094  
##  Mean   :14.22   Mean   : 4.745   Mean   : 1.356   Mean   : 52830  
##  3rd Qu.:17.30   3rd Qu.: 5.700   3rd Qu.: 1.800   3rd Qu.: 59230  
##  Max.   :48.00   Max.   :54.000   Max.   :17.400   Max.   :147111  
```

3.7. Data Visualization

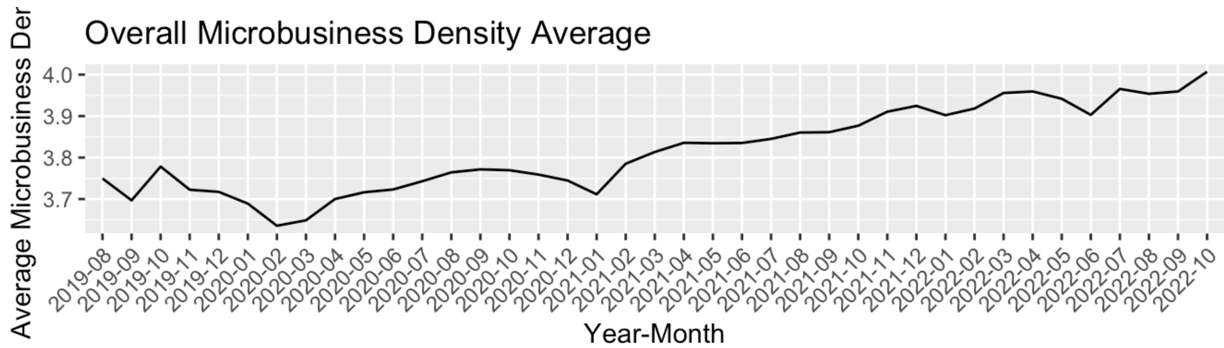
The main feature in this project is `microbusiness_density` provided in the **merged_df.** Also, the number of active microbusinesses is provided in the `active` column.

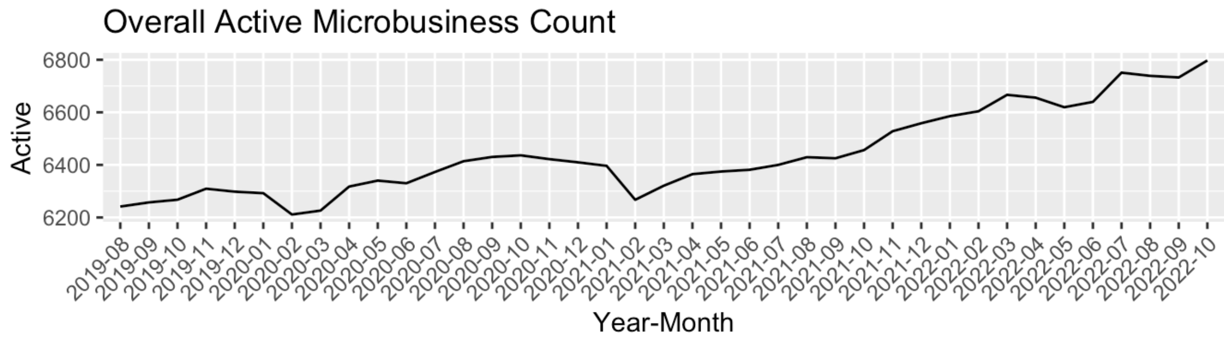
3.7.1. Overall Microbusiness Density and Count

First, we will plot overall microbusiness density and count of active microbusiness in the United States:

```
# Create plots
p1 <- merged_df %>%
```

```
  # Group merged_df by year_month
  group_by(year_month) %>%
  # calculate the mean value of microbusiness_density for each group
  summarise(mean_microbusiness_density = mean(microbusiness_density)) %>%
  ggplot(aes(x = year_month, y = mean_microbusiness_density, group = 1)) +
  geom_line() +
  labs(title = "Overall Microbusiness Density Average",
       x = "Year-Month",
       y = "Average Microbusiness Density") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

p2 <- merged_df %>%
  group_by(year_month) %>%
  summarize(avg_active = mean(active)) %>%
  ggplot(aes(x = year_month, y = avg_active)) +
  geom_line(group = 1) +
  labs(title = "Overall Active Microbusiness Count",
       x = "Year-Month",
       y = "Active") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))



# Display the plots
grid.arrange(p1, p2, nrow = 2)
```

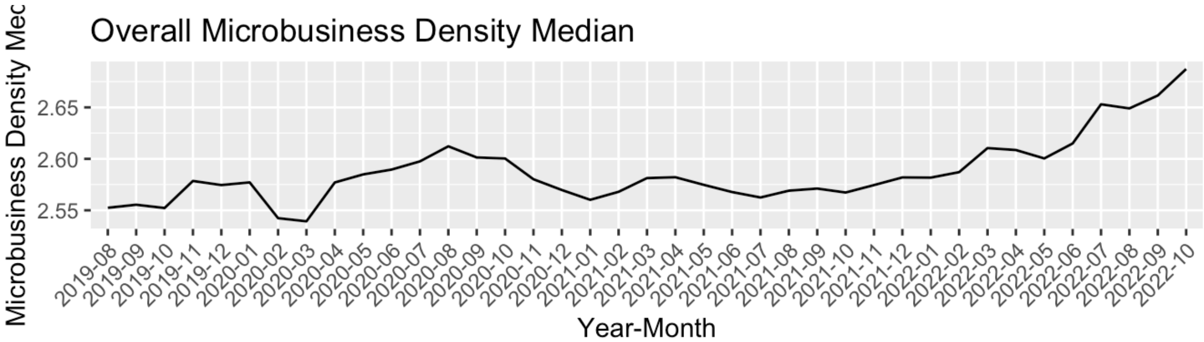


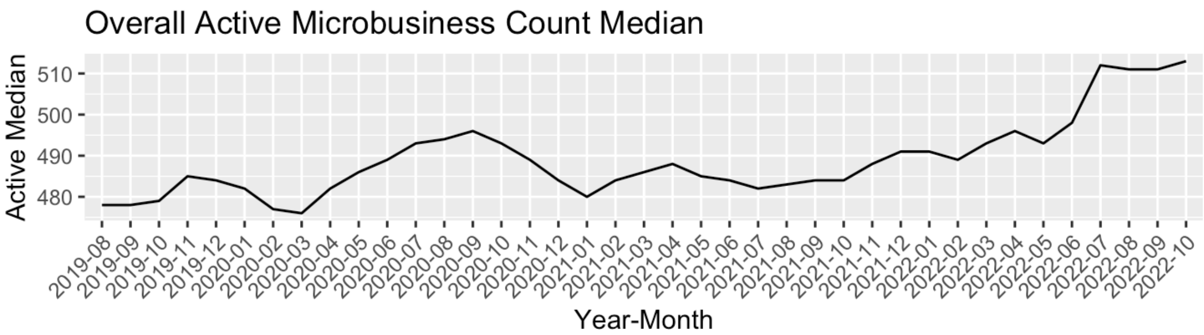


As expected, these two graphs show almost similar behavior. If we ignore the slight fluctuations of the two graphs, the general microbusiness density and count are growing over the whole time frame.

```
# Create plots
p1 <- merged_df %>%
  # Group merged_df by year_month
  group_by(year_month) %>%
  # calculate the median value of microbusiness_density for each group
  summarise(median_microbusiness_density = median(microbusiness_density)) %>%
  ggplot(aes(x = year_month, y = median_microbusiness_density, group = 1)) +
  geom_line() +
  labs(title = "Overall Microbusiness Density Median",
       x = "Year-Month",
       y = "Microbusiness Density Median") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

p2 <- merged_df %>%
  group_by(year_month) %>%
  summarize(median_active = median(active)) %>%
  ggplot(aes(x = year_month, y = median_active)) +
  geom_line(group = 1) +
  labs(title = "Overall Active Microbusiness Count Median",
       x = "Year-Month",
       y = "Active Median") +
```

```
  theme(axis.text.x = element_text(angle = 45, hjust = 1))



# Display the plots
grid.arrange(p1, p2, nrow = 2)
```

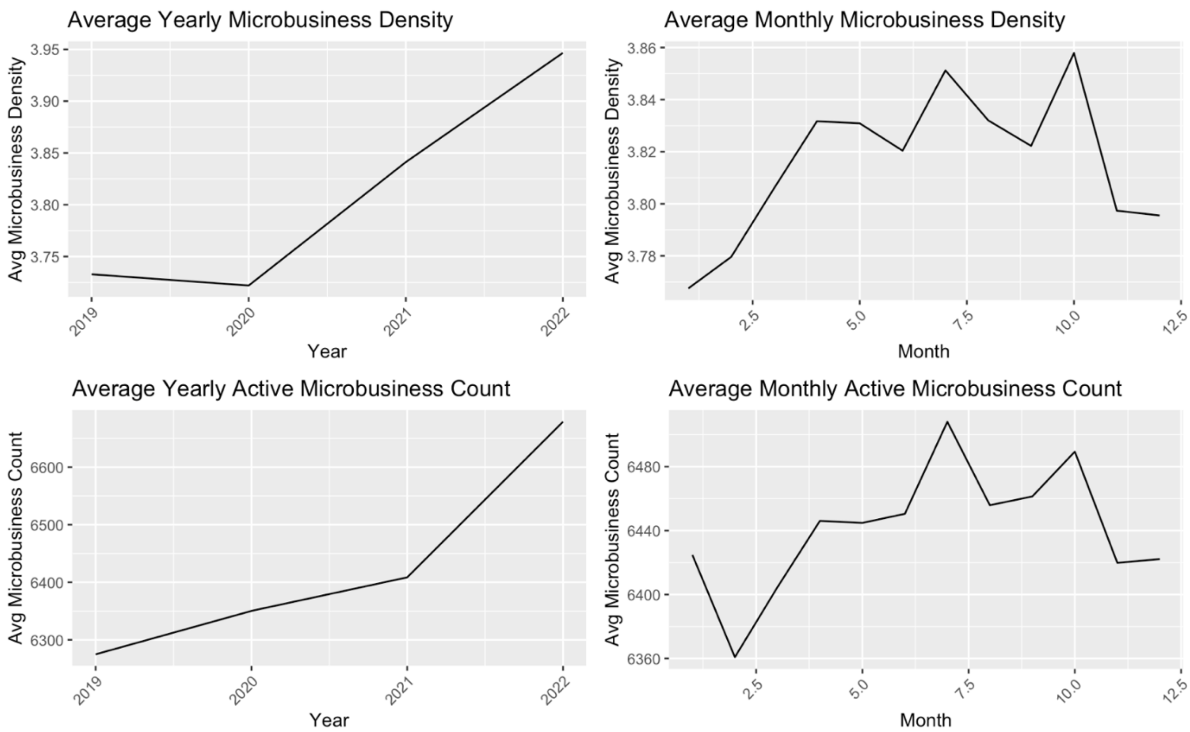




Then, we will examine the behavior of these two variables (*microbusiness density* and *active*) while grouping the data by month and year:

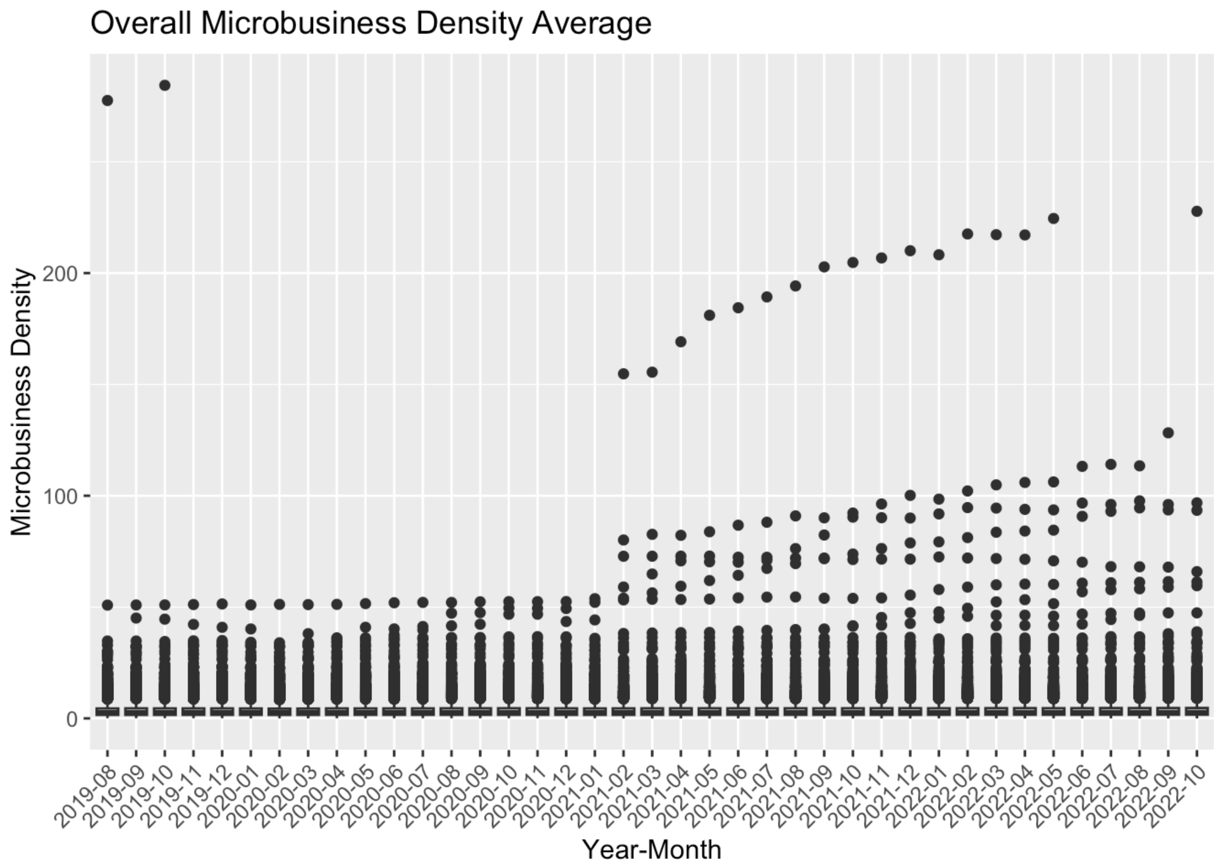
```
# Group merged_df by year and calculate the mean value of microbusiness_density and
active for each group
merged_df_mean_year <- merged_df %>%
  group_by(year) %>%
  summarize(avg_microbusiness_density = mean(microbusiness_density),
            avg_active = mean(active))


# Group merged_df by month and calculate the mean value of the microbusiness_densit
y for each group
merged_df_mean_month <- merged_df %>%
  group_by(month) %>%
  summarize(avg_microbusiness_density = mean(microbusiness_density),
            avg_active = mean(active))


# Plot the monthly mean values for microbusiness density
p1 <-
  ggplot(merged_df_mean_month, aes(x = month, y = avg_microbusiness_density)) +
```

```
  geom_line() +
  ggtitle("Average Monthly Microbusiness Density") +
  xlab("Month") +
  ylab("Avg Microbusiness Density") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

# Plot the yearly mean values for microbusiness density
p2 <-
  ggplot(merged_df_mean_year, aes(x = year, y = avg_microbusiness_density)) +
  geom_line() +
  ggtitle("Average Yearly Microbusiness Density") +
  xlab("Year") +
  ylab("Avg Microbusiness Density") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

# Plot the monthly mean values for active
p3 <-
  ggplot(merged_df_mean_month, aes(x = month, y = avg_active)) +
  geom_line() +
  ggtitle("Average Monthly Active Microbusiness Count") +
  xlab("Month") +
  ylab("Avg Microbusiness Count") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

# Plot the yearly mean values for active
p4 <-
  ggplot(merged_df_mean_year, aes(x = year, y = avg_active)) +
  geom_line() +
  ggtitle("Average Yearly Active Microbusiness Count") +
  xlab("Year") +
  ylab("Avg Microbusiness Count") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

# Display the plots side by side
grid.arrange(p2, p1, p4, p3, nrow = 2, ncol = 2)
```



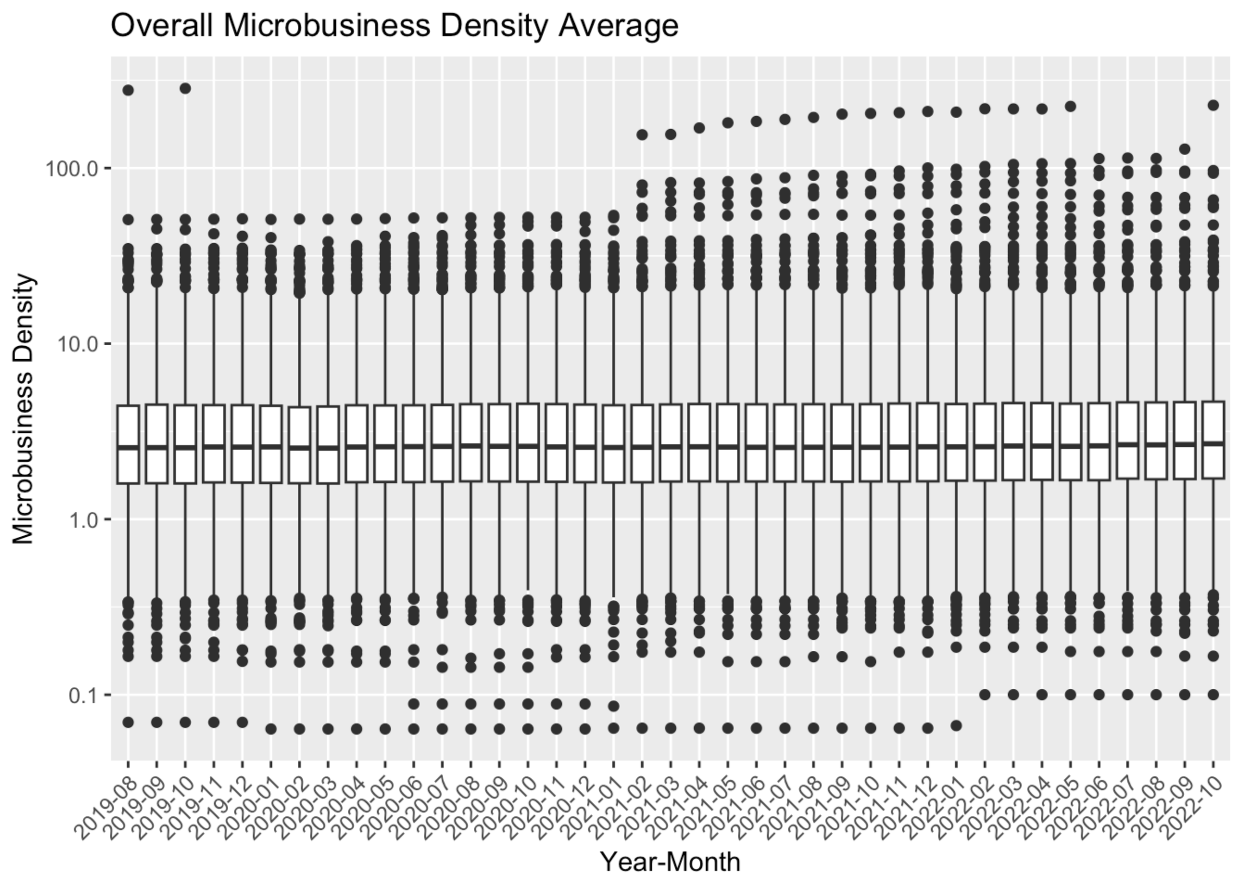
The left plots show that the average microbusiness density has increased slightly over the years, starting at approximately 3.73 in 2019 and reaching 3.94 in 2022. On the other hand, the average active count has also increased, starting at approximately 6274 in 2019 and reaching 6679 in 2022. In comparison, the right plots show fluctuations in the monthly averages for both variables. Generally, it follows a slightly upward trend over the year, with some peak values observed in July and October for the microbusiness density and active count, respectively. These peak values may represent seasonal variations, indicating that microbusinesses are more active during certain months. Overall, the plot shows some correlation between the monthly average values of microbusiness_density and active count, indicating that common factors may influence both variables.

```
# Create a grid of box plots
ggplot(merged_df, aes(x=year_month, y=microbusiness_density)) +
  geom_boxplot() +
  labs(x="Year-Month", y="Microbusiness Density") +
  ggtitle("Overall Microbusiness Density Average") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Above plot is not very informative because the small values are obscured by the larger ones. Therefore, using a logarithmic scale on the Y-axis can help to reduce this distortion and provide a more informative visualization of the data.

```
# Create a grid of box plots
ggplot(merged_df, aes(x=year_month, y=microbusiness_density)) +
  geom_boxplot() +
  scale_y_log10() +
  labs(x="Year-Month", y="Microbusiness Density") +
  ggtitle("Overall Microbusiness Density Average") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



3.7.2. Economic Regional Divisions

The Bureau of Economic Analysis (BEA) divides the United States into eight distinct economic regions[1].

These regions are based on similarities in economic characteristics such as industry composition, income levels, and employment patterns. The eight regions are:

1. **New England**: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont.

   The economy in this region is largely based on manufacturing, healthcare, education, and finance.

2. **Mideast**: Delaware, Maryland, New Jersey, New York, Pennsylvania, and the District of Columbia.

   The region has a diverse economy, with a mix of manufacturing, finance, healthcare, and professional services.

3. **Great Lakes**: Illinois, Indiana, Michigan, Ohio, and Wisconsin.

   The region has a strong manufacturing base, particularly in the automotive industry, and also has a significant healthcare sector.

4. **Plains**: Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota.

[1] https://doi.org/10.1371/journal.pone.0256407.g001

Agriculture and energy production are major industries in this region, along with manufacturing and healthcare.

5. **Southeast**: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia.

   The Southeast has a diverse economy, with significant industries in healthcare, finance, and manufacturing, as well as tourism and agriculture.

6. **Southwest**: Arizona, New Mexico, Oklahoma, and Texas.

   The region has a strong energy sector, particularly in oil and gas production, and also has significant industries in manufacturing, healthcare, and finance.

7. **Rocky Mountain**: Colorado, Idaho, Montana, Utah, and Wyoming.

   The region is known for its natural resources, particularly in mining and energy production, as well as tourism, healthcare, and manufacturing.

8. **Far West**: Alaska, California, Hawaii, Nevada, Oregon, and Washington.

   This region has a diverse economy, with significant industries in technology, finance, healthcare, and manufacturing, as well as tourism and agriculture.

To draw the map for the BEA regions, first, we need to convert state and county columns in **merged_df** to lowercase letters. Merging two dataframes will cause problems because the data from `map_data()` will be in lowercase letters.

```
# Convert state and county columns in merged_df to lowercase

merged_df <- merged_df %>%

  mutate(state = tolower(state)) %>%

  mutate(county = tolower(county))
```

Then, we'll create a new column in **merged_df** named `region` and assign region values based on `state` column:

```
# Create a new column named region and initialize all values as NA

merged_df$region <- NA


# Assign region values based on state column

for (i in 1:nrow(merged_df)) {

  if (merged_df$state[i] %in% c("connecticut", "maine", "massachusetts", "new hamps
hire", "rhode island", "vermont")) {

    merged_df$region[i] <- "new england"

  } else if (merged_df$state[i] %in% c("delaware", "maryland", "new jersey", "new y
ork", "pennsylvania", "district of columbia")) {

    merged_df$region[i] <- "mideast"

  } else if (merged_df$state[i] %in% c("illinois", "indiana", "michigan", "ohio", "
wisconsin")) {

    merged_df$region[i] <- "great lakes"

  } else if (merged_df$state[i] %in% c("iowa", "kansas", "minnesota", "missouri", "
nebraska", "north dakota", "south dakota")) {

    merged_df$region[i] <- "plains"
```

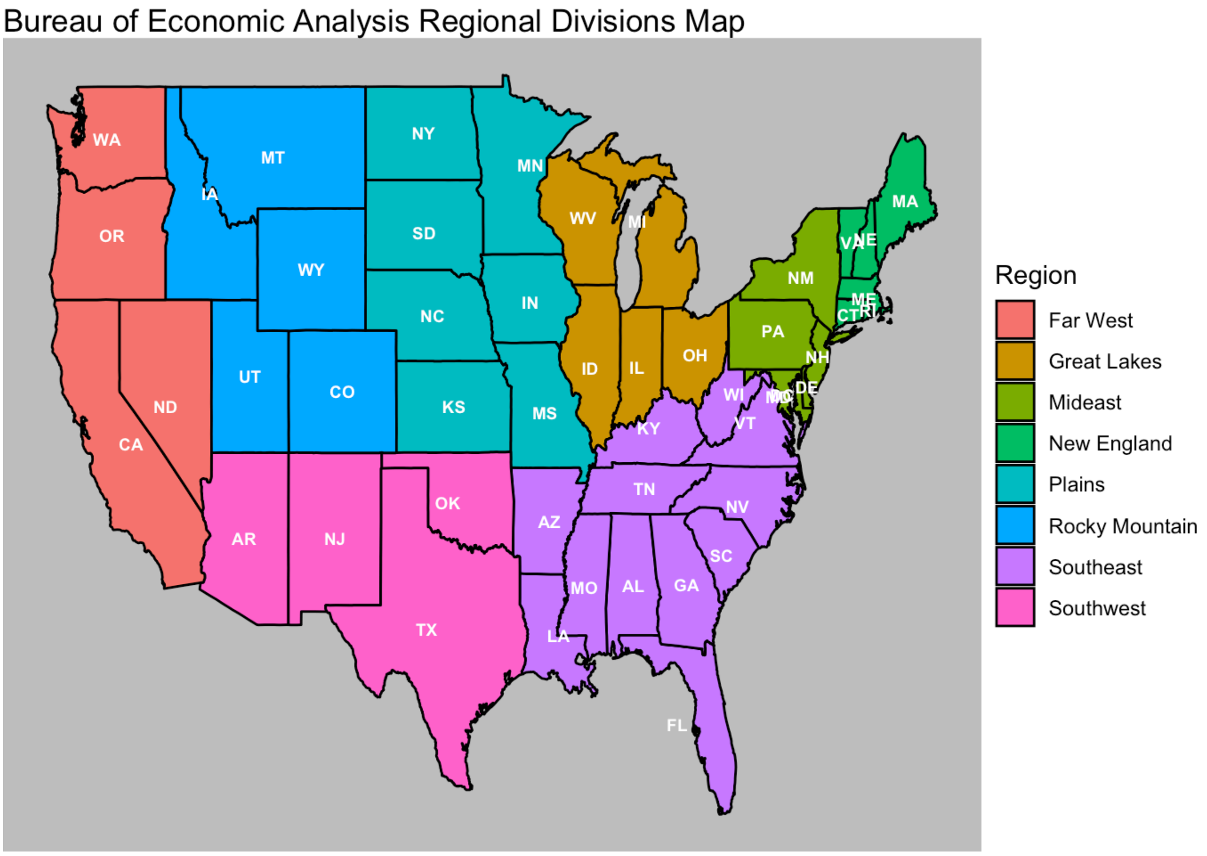
```
  } else if (merged_df$state[i] %in% c("alabama", "arkansas", "florida", "georgia", "kentucky", "louisiana", "mississippi", "north carolina", "south carolina", "tennessee", "virginia", "west virginia")) {
    merged_df$region[i] <- "southeast"
  } else if (merged_df$state[i] %in% c("arizona", "new mexico", "oklahoma", "texas")) {
    merged_df$region[i] <- "southwest"
  } else if (merged_df$state[i] %in% c("colorado", "idaho", "montana", "utah", "wyoming")) {
    merged_df$region[i] <- "rocky mountain"
  } else if (merged_df$state[i] %in% c("alaska", "california", "hawaii", "nevada", "oregon", "washington")) {
    merged_df$region[i] <- "far west"
  } else {
    merged_df$region[i] <- "other"
  }
}
# Print all the unique values in the region column
unique(merged_df$region)
## [1] "southeast"      "far west"       "southwest"      "rocky mountain"
## [5] "new england"    "mideast"        "great lakes"    "plains"
```

Now that the data in the dataframe matches the `map_data()` output, we appoint each state to the region it belongs to and then use `ggplot()` to draw the map:

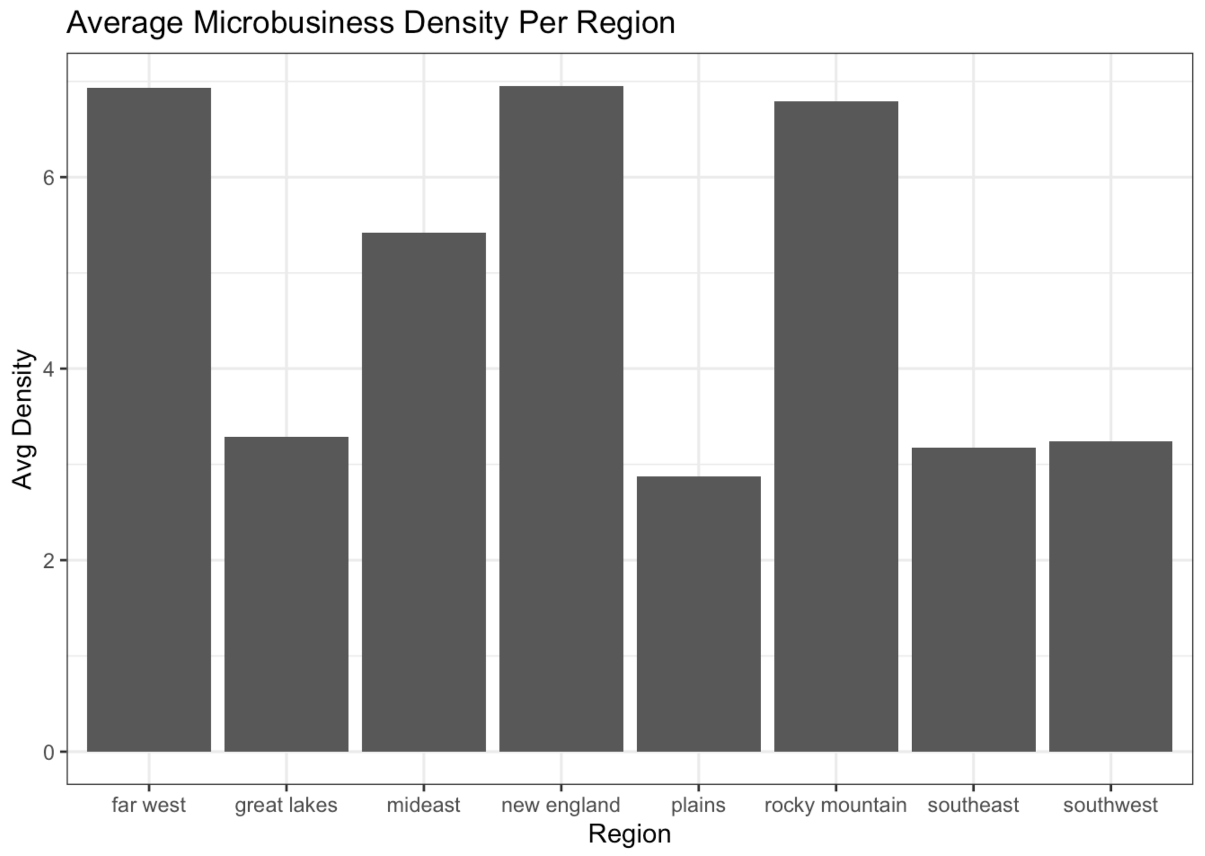
```
# Get the map of the United States
us_map <- map_data("state")


# Create a lookup table for state abbreviations and their corresponding full names
state_names <- data.frame(state = state.abb, name = tolower(state.name))


# Map the regions to the states
region_map <- us_map %>%
#left_join(state_names, by = c("region" = "state")) %>%
  left_join(state_names, by = c("region" = "name")) %>%
# merge(us_map, state_names, by.x=c("region"), by.y=c("name")) %>%
  mutate(region =
           ifelse(region %in% c("connecticut", "maine", "massachusetts", "new hampshire", "rhode island", "vermont"), "New England",
                        ifelse(region %in% c("delaware", "maryland", "new jersey", "new york", "pennsylvania", "district of columbia"), "Mideast",
                                ifelse(region %in% c("illinois", "indiana", "michigan", "ohio", "wisconsin"), "Great Lakes",
```

```
                                       ifelse(region %in% c("iowa", "kansas", "minn
esota", "missouri", "nebraska", "north dakota", "south dakota"), "Plains",
                                              ifelse(region %in% c("alabama", "arka
nsas", "florida", "georgia", "kentucky", "louisiana", "mississippi", "north carolin
a", "south carolina", "tennessee", "virginia", "west virginia"), "Southeast",
                                                     ifelse(region %in% c("arizona"
, "new mexico", "oklahoma", "texas"), "Southwest",
                                                            ifelse(region %in% c("c
olorado", "idaho", "montana", "utah", "wyoming"), "Rocky Mountain",
                                                                   ifelse(region %i
n% c("alaska", "california", "hawaii", "nevada", "oregon", "washington"), "Far West
", NA
                                                                   )))))))))



# Summarize the data to get the center coordinates of each state
#state_centers <- region_map %>%
#  group_by(state) %>%
#  summarise(long = mean(long), lat = mean(lat))
# add labels
states <- aggregate(cbind(long, lat) ~ region, data=us_map,
                FUN=function(x)mean(range(x)))
states$group <- c("AL", "AR", "AZ", "CA", "CO", "CT", "DE", "DC", "FL", "GA", "IA",
              "ID", "IL", "IN", "KS", "KY", "LA", "MA", "MD", "ME", "MI", "MN",
              "MO", "MS", "MT", "NC", "ND", "NE", "NH", "NJ", "NM", "NV", "NY",
              "OH", "OK", "OR", "PA", "RI", "SC", "SD", "TN", "TX", "UT", "VA",
              "VT", "WA", "WI", "WV", "WY")

# names(states)[names(states) == "region"] <- "group"



#Plot the map
ggplot(region_map, aes(x = long, y = lat, group = group, fill = region)) +
  geom_polygon(color = "black", show.legend = TRUE) +
#  geom_text(aes(label = state), data = region_map, size = 3, vjust = 2, hjust = 2)
+
#  geom_text(aes(label = state), data = state_centers, size = 2, vjust = 2, hjust =
2) +
  geom_text(data = states, aes(long, lat, label = group), size = 2.5, inherit.aes =
FALSE, color = "white", fontface = "bold") +
#  scale_fill_gradient(low = "white", high = "darkred") +
#  scale_fill_manual(values = viridis(n = 60), na.value = "gray") +
  labs(title = "Bureau of Economic Analysis Regional Divisions Map", fill = "Region
") +
```

```
#   geom_text(aes(x = long, y = lat, label = state), data = state_centers, size = 3,
color = "white") +

  theme_void() +

  theme(panel.background = element_rect(fill = "gray75", color = NA))
```



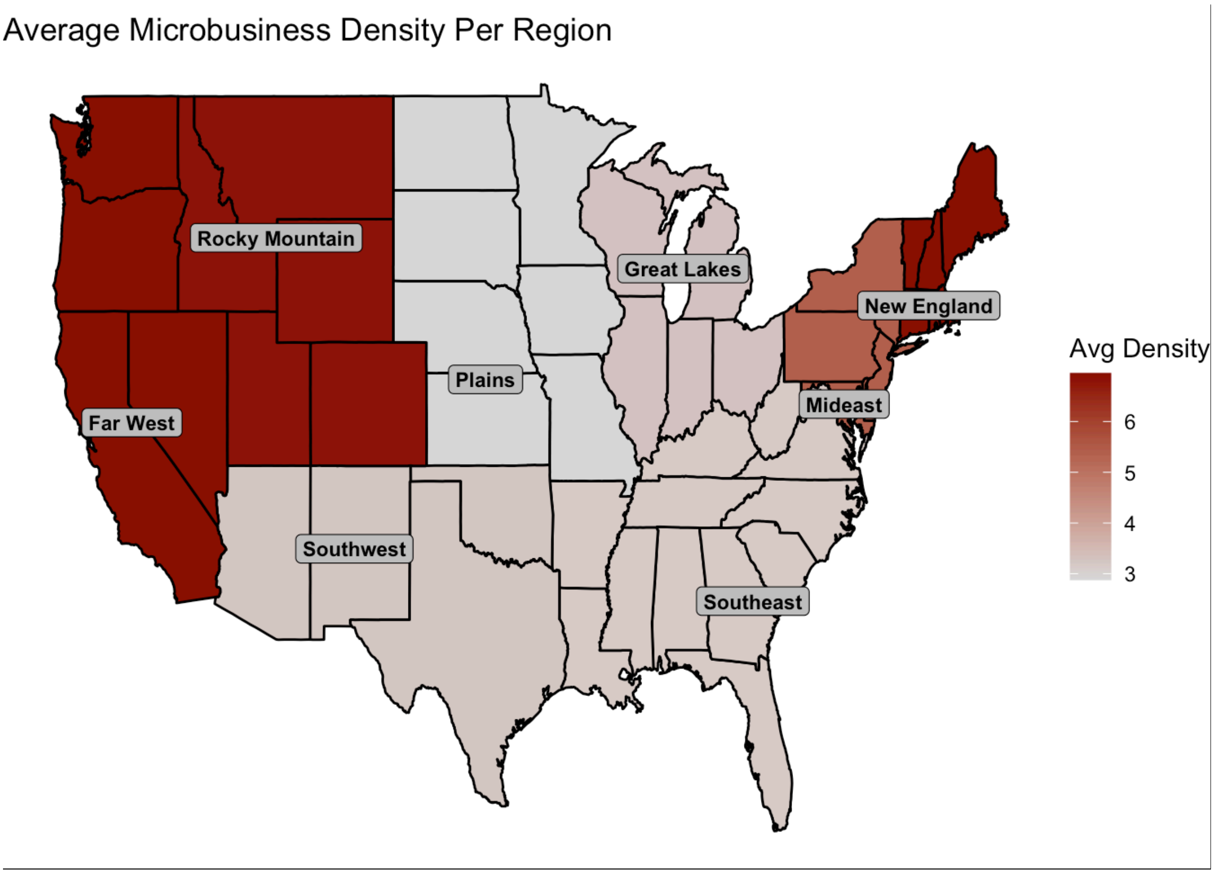

```
# Group merged_df by region and calculate average microbusiness density
merged_df %>%
  group_by(region) %>%
  summarize(avg_density = mean(microbusiness_density)) %>%

  # Create bar plot of average density by region
  ggplot(aes(x = region, y = avg_density)) +
  geom_bar(stat = "identity") +

  # Add plot title and axis labels
  labs(title = "Average Microbusiness Density Per Region",
       x = "Region", y = "Avg Density") +

  # Apply a black and white theme to the plot
  theme_bw()
```



According to the above plot *New England* has the highest average microbusiness density, followed by *Farwest* and *Rocky Mountain* respectively, with a tiny difference, valuing more than 6.75. In contrast, *plains* has the lowest average microbusiness density, followed by *Southeast* and *Southwest*, all valued under 3.25. We can use a choropleth map to get a better view on the above information.

```
# choropleth map
# Group merged_df by region and calculate average microbusiness density
avg_density <- merged_df %>%
  group_by(region) %>%
  summarize(avg_density = mean(microbusiness_density))

# Create a lookup table for state abbreviations and their corresponding full names
state_names <- data.frame(state = state.abb, name = tolower(state.name))

# Lowercase region column of region_map
region_map <- region_map %>%
  mutate(region = tolower(region))

# Merge the average density data with the region_map data
plot_data <- merge(region_map, avg_density, by = "region") %>%
  arrange(order)
```

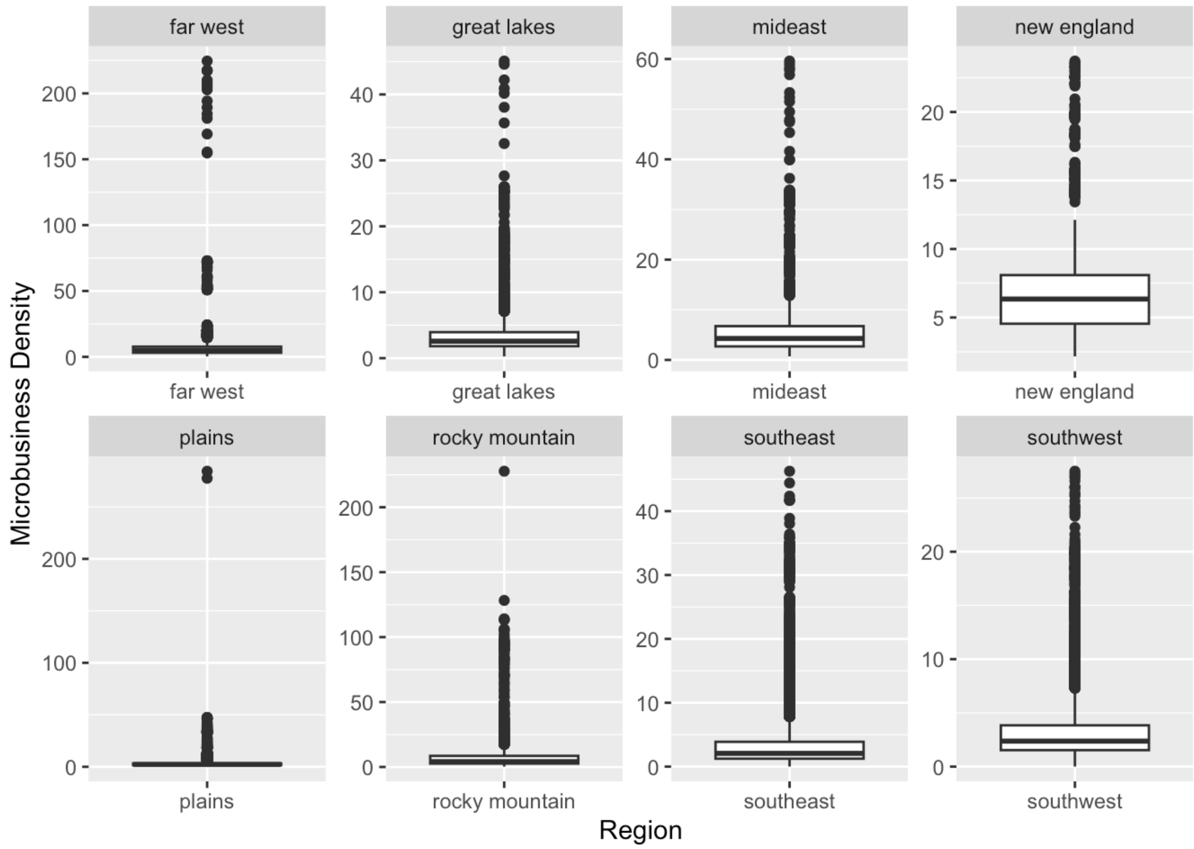
```r
# Coordinates of the center of regions
bea_regions <- data.frame(
  group = c("New England", "Mideast", "Great Lakes", "Plains",
              "Southeast", "Southwest", "Rocky Mountain", "Far West"),
  x = c(-71.8, -76.9, -86.6, -98.5, -82.4, -106.4, -111.1, -119.8),
  y = c(42.2, 39, 43.4, 39.8, 32.6, 34.3, 44.4, 38.4)
)

# Create the plot
ggplot(plot_data, aes(x = long, y = lat, group = group, fill = avg_density)) +
  geom_polygon(color = "black") +
  geom_label(data = bea_regions,
              aes(x = x, y = y, label = group),
              size = 3, fontface = "bold",
              label.padding = unit(0.2, "lines"),
              label.size = 0.2,
              fill = "gray75", color = "black") +

  scale_fill_gradient(low = "gray85", high = "darkred") +
  # scale_fill_viridis(name = "Avg Density", na.value = "gray") +
  labs(title = "Average Microbusiness Density Per Region", fill = "Avg Density") +
  theme_void()
```




```
#  theme(panel.background = element_rect(fill = "gray90", color = NA))
```

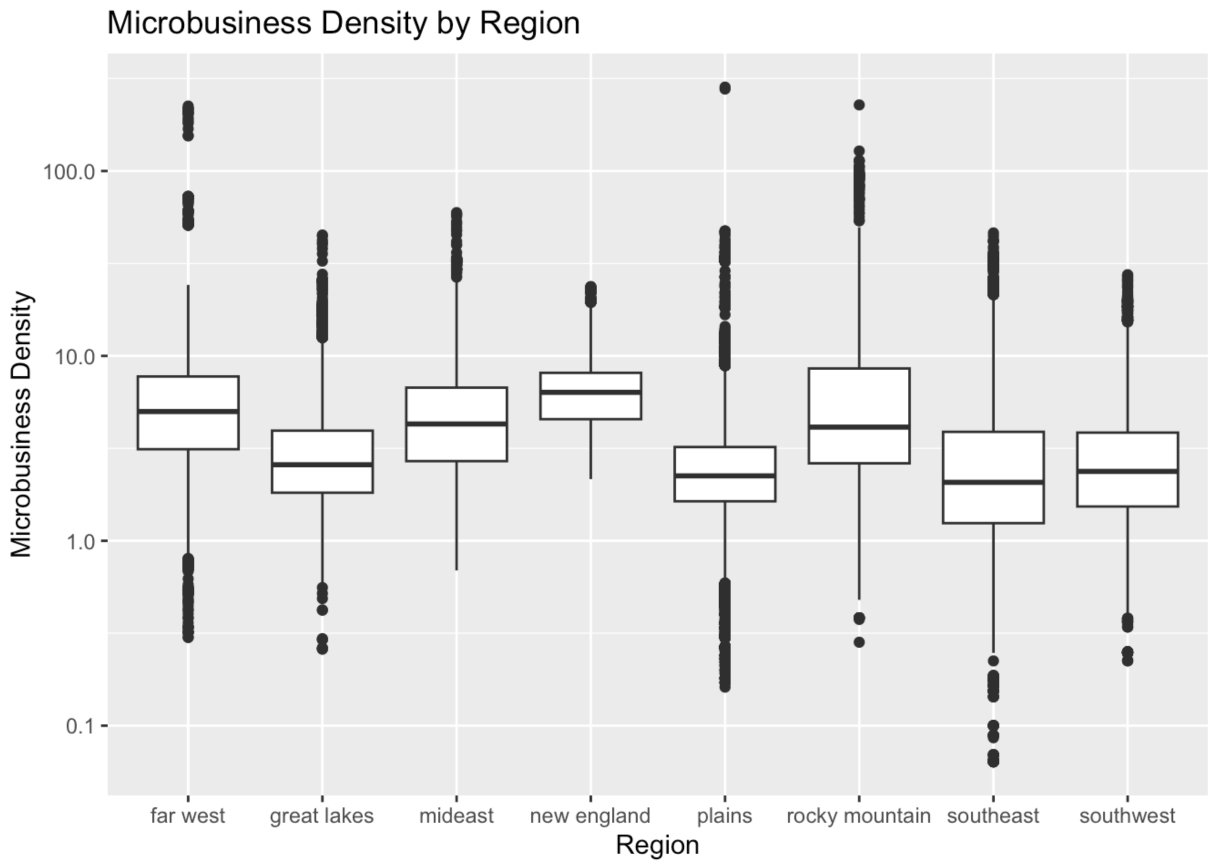
Although, we can only see only one parameter on above map. To have a better look on the distribution, central tendency, spread, and variability of the `microbusiness_density` variable, we can use boxplots.

```
# Aggregate data by region
df_by_region <- aggregate(microbusiness_density ~ region, merged_df, median)


# Create boxplot
ggplot(merged_df, aes(x = region, y = microbusiness_density)) +
  geom_boxplot() +
  labs(x = "Region", y = "Microbusiness Density") +
  # Arrange plots in grid
  facet_wrap(~ region, scales = "free", nrow = 2)
```



Above plots are not very informative because the small values are obscured by the larger ones. Therefore, using a logarithmic scale on the Y-axis can help to reduce this distortion and provide a more informative visualization of the data.

```
# Create a grid of box plots
ggplot(merged_df, aes(x=region, y=microbusiness_density)) +
  geom_boxplot() +
  scale_y_log10() +
  labs(x="Region", y="Microbusiness Density") +
  ggtitle("Microbusiness Density by Region")
```

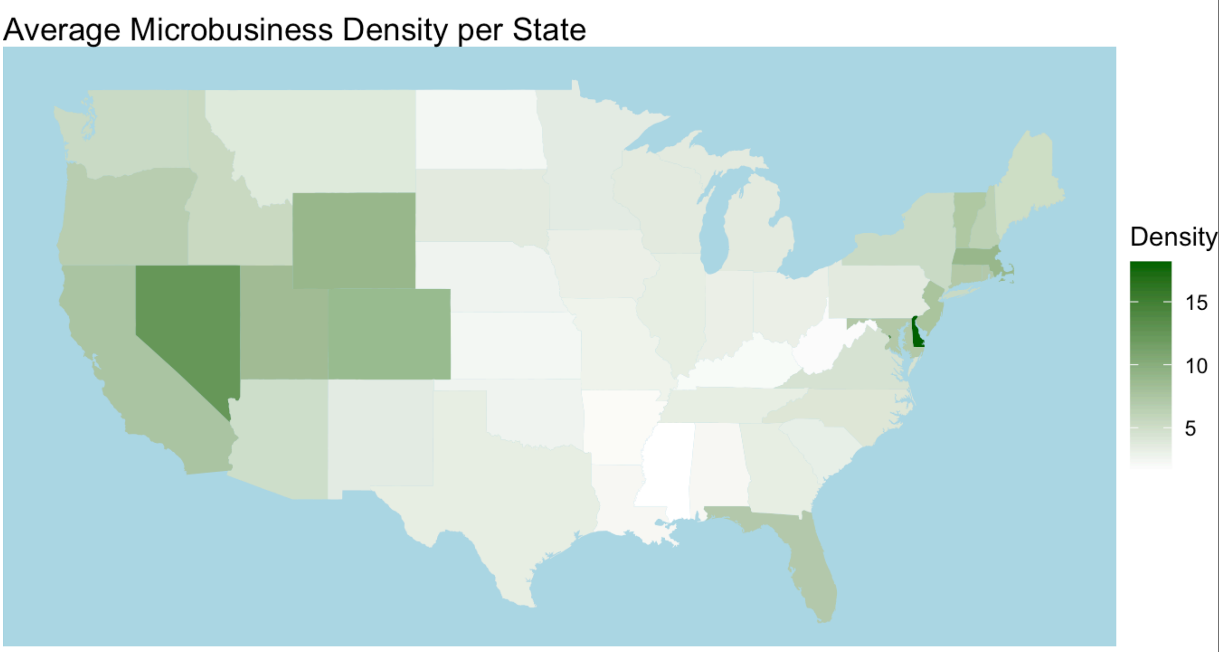


These boxplots are more informative, because using a logarithmic scale on the Y-axis helps to better reveal the differences and similarities between regions that helps to highlight any potential patterns or trends in the data. Some of the points that can be inferred from this boxplot include:

- All regions have at least some microbusiness activity. Because minimum microbusiness density is greater than 0 in all regions.
- The median microbusiness density is highest in the *New England* region, followed by the *Far West* and the *Mideast* regions.
- The 3rd quartile microbusiness density is highest in the *Rocky Mountain* region, followed by the *New England* and the *Far West* regions.
- The maximum microbusiness density is highest in the *Plains* region, followed by the *Rocky Mountain* and the *Far West* regions.
- The mean microbusiness density is highest in the *New England* region, followed by the *Far West* and the *Rocky Mountain* regions.
- The interquartile range (IQR = the difference between the 1st and 3rd quartiles) of microbusiness density is widest in the *Rocky Mountain* region, indicating that there is a greater range of microbusiness density in that region. In contrast, the IQR is narrowest in the *Plains* region.

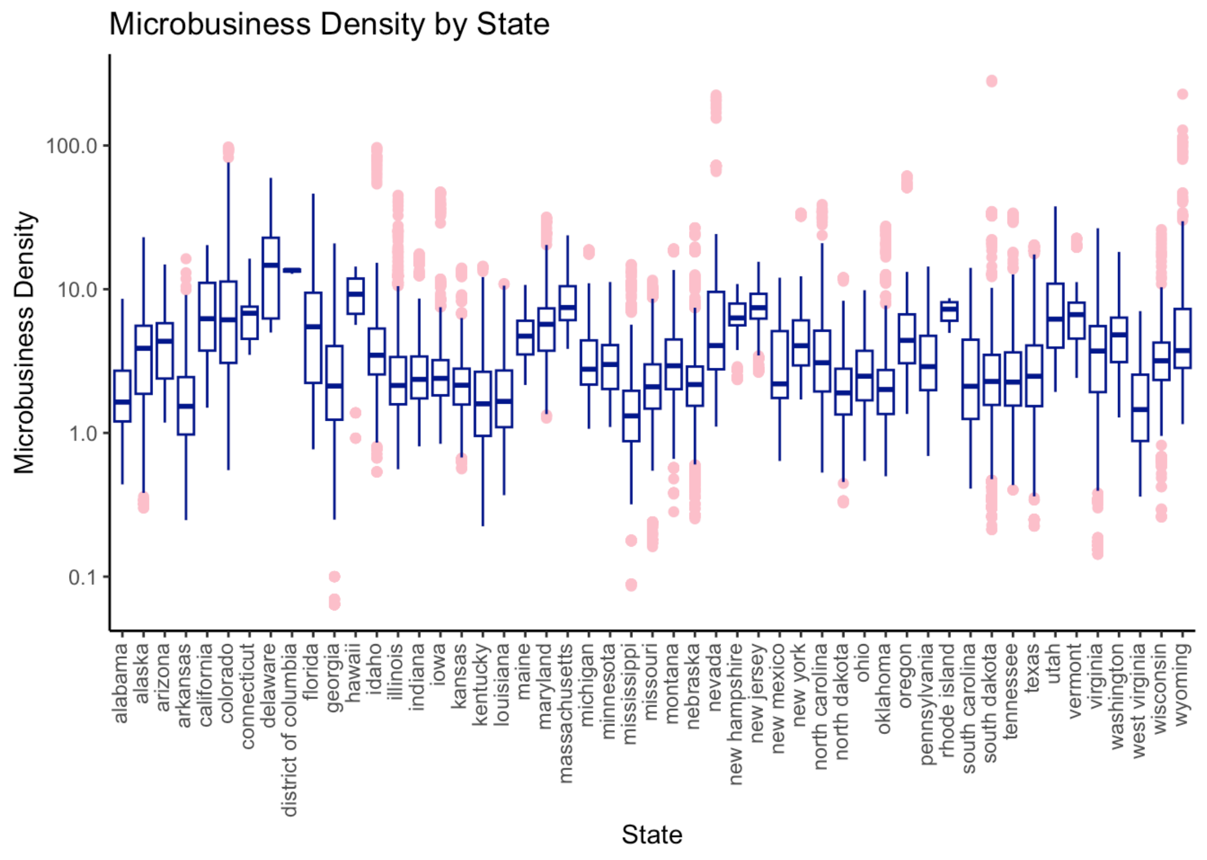
```
# by(merged_df$microbusiness_density, merged_df$region, summary)
# Aggregate microbusiness density by state
state_avg <- aggregate(microbusiness_density ~ state, data = merged_df, FUN = mean)
```

```
# Load US map data
us_map <- map_data("state")

# Merge state_avg with us_map based on region and state
map_data <- merge(us_map, state_avg, by.x = "region", by.y = "state")

# Create a heatmap of microbusiness density by state
ggplot(map_data, aes(x = long, y = lat, group = group, fill = microbusiness_density
)) +
  geom_polygon() +
  scale_fill_gradient(low = "white", high = "darkgreen") +
  coord_map() +
  labs(title = "Average Microbusiness Density per State", fill = "Density") +
  theme_void() +
  theme(panel.background = element_rect(fill = "lightblue", color = NA))
```



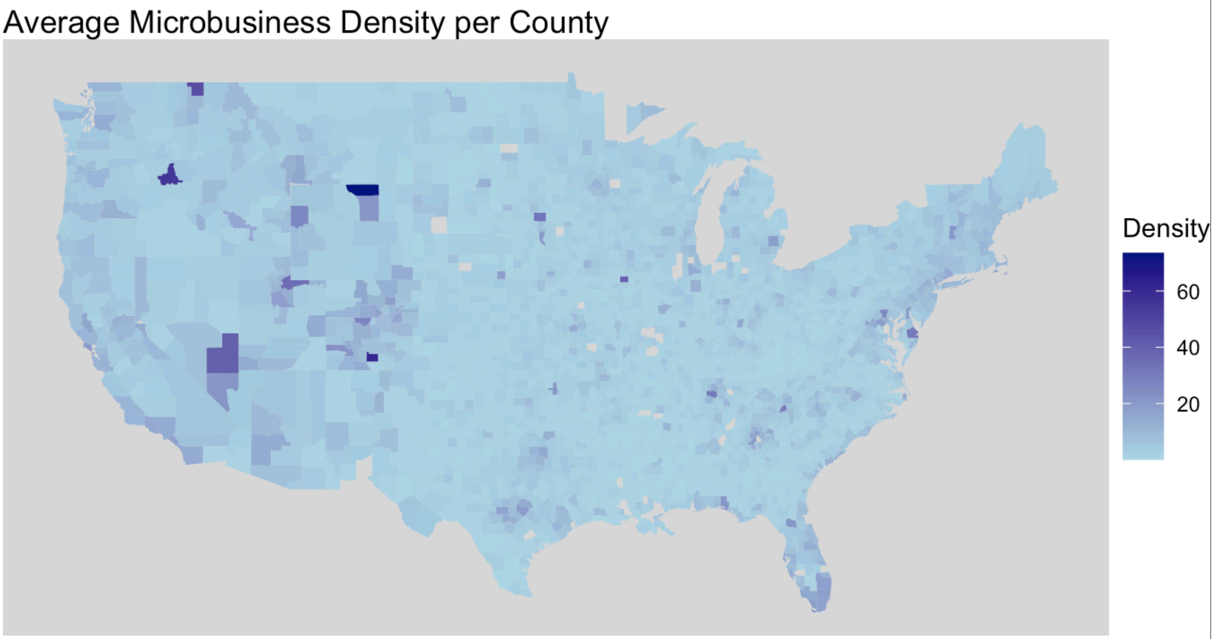

```
# Create a grid of box plots
ggplot(merged_df, aes(x=state, y=microbusiness_density)) +
  geom_boxplot(colour = "darkblue", outlier.colour = "pink") +
  scale_y_log10() +
  labs(x="State", y="Microbusiness Density") +
```

```
  ggtitle("Microbusiness Density by State") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.3))
```




```
# {r fig.width = 10 ,fig.height = 12, out.width='100%', fig.align='center'}
# Aggregate microbusiness density by county

#county_avg <- merged_df %>%
#  group_by(cfips, county) %>%
#  summarise(microbusiness_density = mean(microbusiness_density))

county_avg <- aggregate(microbusiness_density ~ county + state, data = merged_df, F
UN = mean)

# Get rid of county, city, and parish in the end of county names
county_avg$county <- gsub(" county", "", county_avg$county)
county_avg$county <- gsub(" city", "", county_avg$county)
county_avg$county <- gsub(" parish", "", county_avg$county)



# Load US county map data
```

```r
us_map <- map_data("county")


# Merge county_avg with us_map based on region and county
map_data <- merge(us_map, county_avg, by.x = c("subregion", "region"), by.y = c("county", "state")) %>%
  arrange(order)


# Create a heatmap of microbusiness density by county using ggplot2
ggplot(map_data, aes(x = long, y = lat, group = group, fill = microbusiness_density)) +
  geom_polygon() +
  scale_fill_gradient(low = "lightblue", high = "navyblue") +
  coord_map() +
  labs(title = "Average Microbusiness Density per County", fill = "Density") +
  theme_void() +
  theme(panel.background = element_rect(fill = "gray85", color = NA))
```

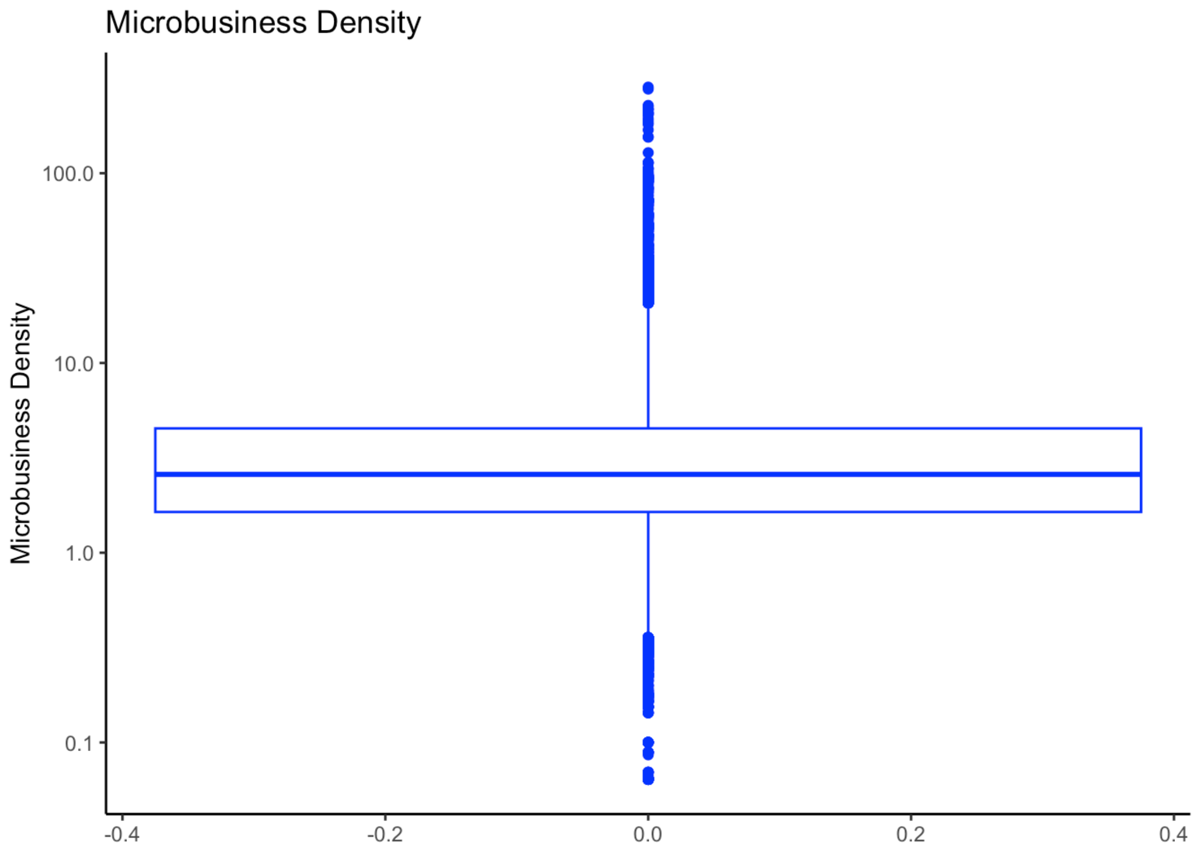



```r
str(merged_df)
## 'data.frame':    122265 obs. of  16 variables:
##  $ row_id                  : chr  "1001_2019-08-01" "1001_2019-09-01" "1001_2019-10-01" "1001_2019-11-01" ...
```

```
##  $ cfips                 : int  1001 1001 1001 1001 1001 1001 1001 1001 1001 1001
...
##  $ county                : chr  "autauga county" "autauga county" "autauga county
" "autauga county" ...
##  $ state                 : chr  "alabama" "alabama" "alabama" "alabama" ...
##  $ first_day_of_month    : Date, format: "2019-08-01" "2019-09-01" ...
##  $ microbusiness_density: num  3.01 2.88 3.06 2.99 2.99 ...
##  $ active                : int  1249 1198 1269 1243 1243 1242 1217 1227 1255 1257
...
##  $ year_month            : chr  "2019-08" "2019-09" "2019-10" "2019-11" ...
##  $ year                  : num  2019 2019 2019 2019 2019 ...
##  $ month                 : int  8 9 10 11 12 1 2 3 4 5 ...
##  $ pct_bb                : num  76.6 76.6 76.6 76.6 76.6 78.9 78.9 78.9 78.9 78.9
...
##  $ pct_college           : num  14.5 14.5 14.5 14.5 14.5 15.9 15.9 15.9 15.9 15.9
...
##  $ pct_foreign_born      : num  2.1 2.1 2.1 2.1 2.1 2 2 2 2 2 ...
##  $ pct_it_workers        : num  1.3 1.3 1.3 1.3 1.3 1.1 1.1 1.1 1.1 1.1 ...
##  $ median_hh_inc         : num  55317 55317 55317 55317 55317 ...
##  $ region                : chr  "southeast" "southeast" "southeast" "southeast" .
..
##  - attr(*, "na.action")= 'omit' Named int [1:28551] 40 41 42 43 44 45 46 47 48 8
8 ...
##   ..- attr(*, "names")= chr [1:28551] "40" "41" "42" "43" ...
```

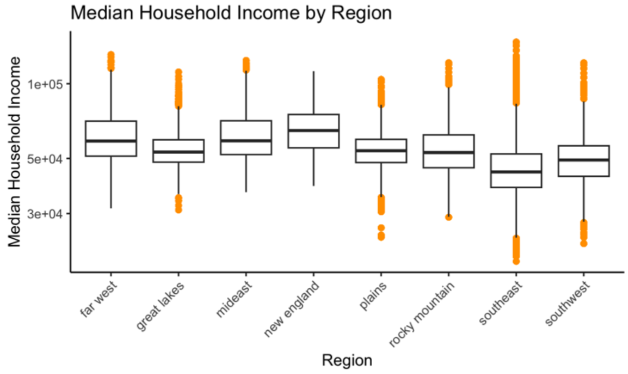
Boxplots are a visualization tool that provide insights into the central tendency and spread of a dataset, as well as identify outliers and skewness. They are useful for detecting anomalies and comparing variable distributions in a dataset, providing valuable insights into data distribution for exploratory data analysis.

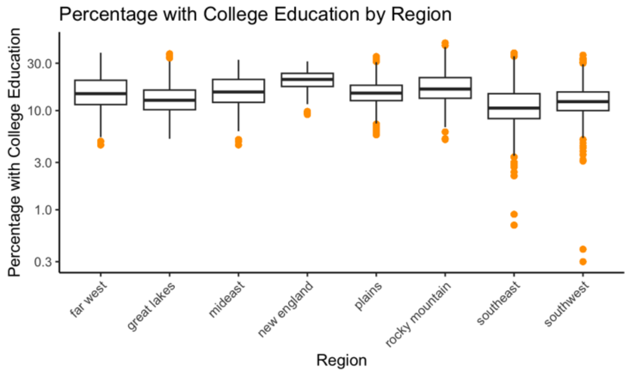
```
ggplot(merged_df, aes(y = microbusiness_density)) +
#  ggplot(merged_df, aes(x=region, y=microbusiness_density)) +
  geom_boxplot(colour = "blue") +
  scale_y_log10() +
  labs(y="Microbusiness Density") +
  ggtitle("Microbusiness Density") +
  theme_classic()
```

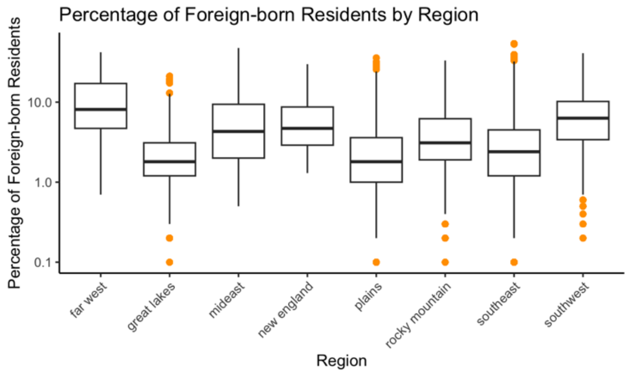


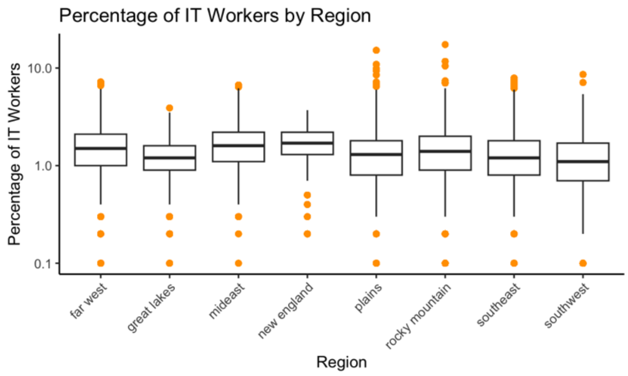

```
# Create a grid of box plots
par(mfrow=c(3,2))
p1 <- ggplot(merged_df, aes(x=region, y=median_hh_inc)) +
  geom_boxplot(outlier.colour = "orange") +
  scale_y_log10() +
  labs(x="Region", y="Median Household Income") +
  ggtitle("Median Household Income by Region") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

p2 <- ggplot(merged_df, aes(x=region, y=pct_college)) +
  geom_boxplot(outlier.colour = "orange") +
  scale_y_log10() +
  labs(x="Region", y="Percentage with College Education") +
  ggtitle("Percentage with College Education by Region") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

p3 <- ggplot(merged_df, aes(x=region, y=pct_foreign_born)) +
  geom_boxplot(outlier.colour = "orange") +
```

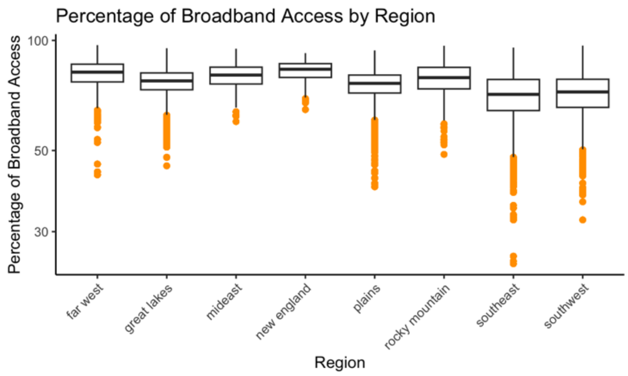
```
  scale_y_log10() +
  labs(x="Region", y="Percentage of Foreign-born Residents") +
  ggtitle("Percentage of Foreign-born Residents by Region") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

p4 <- ggplot(merged_df, aes(x=region, y=pct_it_workers)) +
  geom_boxplot(outlier.colour = "orange") +
  scale_y_log10() +
  labs(x="Region", y="Percentage of IT Workers") +
  ggtitle("Percentage of IT Workers by Region") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

p5 <- ggplot(merged_df, aes(x=region, y=pct_bb)) +
  geom_boxplot(outlier.colour = "orange") +
  scale_y_log10() +
  labs(x="Region", y="Percentage of Broadband Access") +
  ggtitle("Percentage of Broadband Access by Region") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))



grid.arrange(p1, p2, p3, p4, p5, nrow = 5)
```


Median Household Income by Region
Median Household Income
1e+05
5e+04
3e+04
far west
great lakes
mideast
new england
plains
rocky mountain
southeast
southwest
Region


Percentage with College Education by Region
Percentage with College Education
30.0
10.0
3.0
1.0
0.3
far west
great lakes
mideast
new england
plains
rocky mountain
southeast
southwest
Region

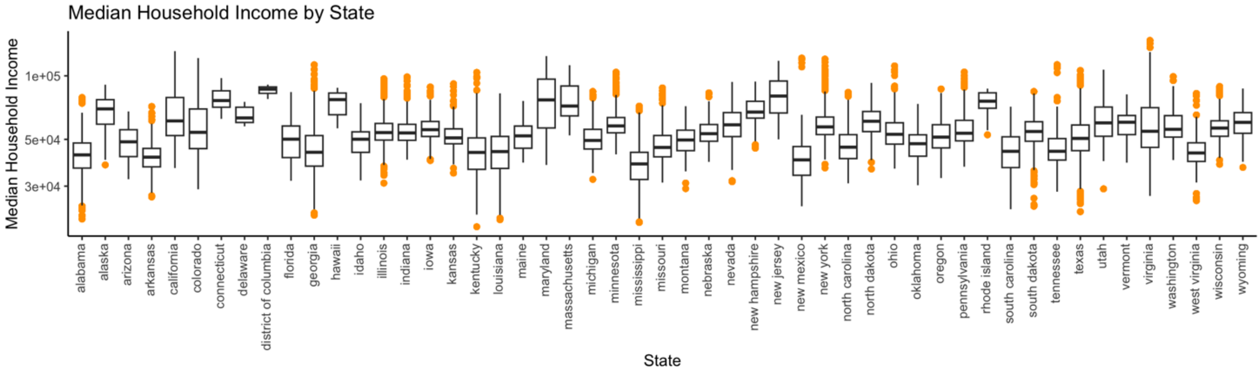

Percentage of Foreign-born Residents by Region
Percentage of Foreign-born Residents
10.0
1.0
0.1
far west
great lakes
mideast
new england
plains
rocky mountain
southeast
southwest
Region

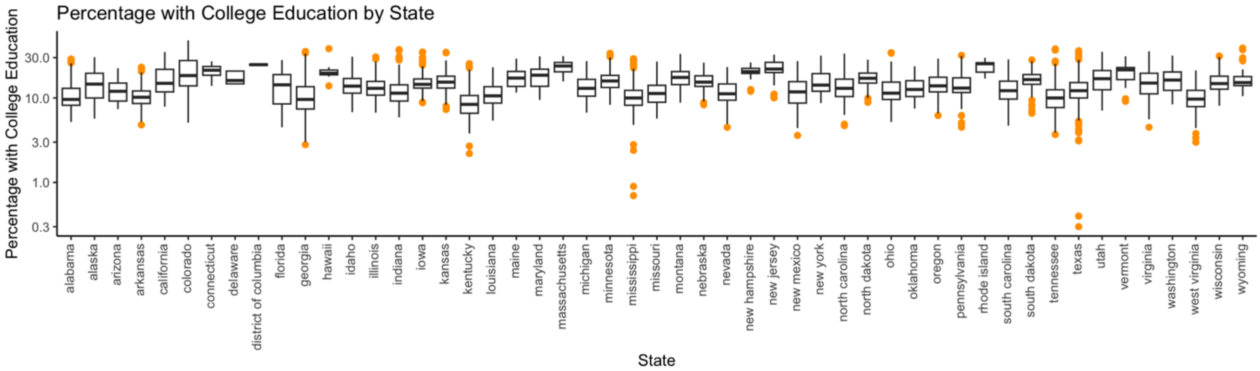

Percentage of IT Workers by Region
Percentage of IT Workers
10.0
1.0
0.1
far west
great lakes
mideast
new england
plains
rocky mountain
southeast
southwest
Region

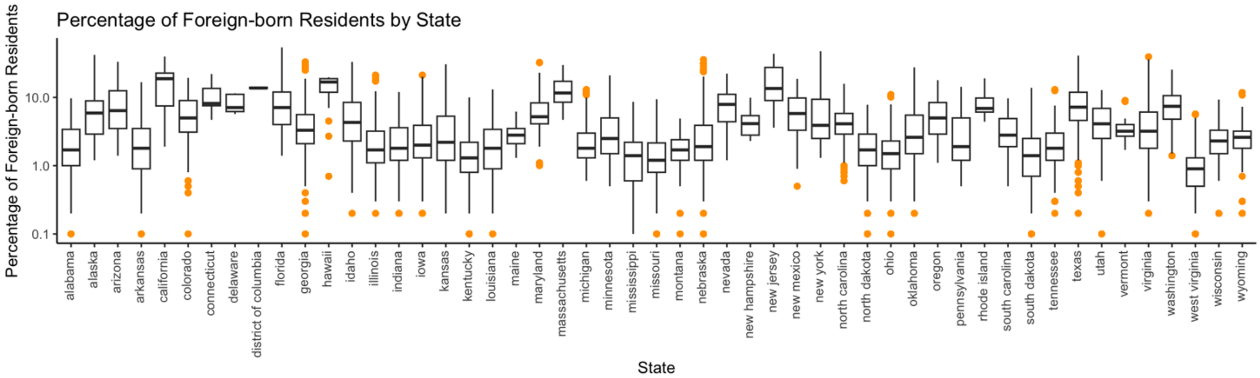

Percentage of Broadband Access by Region
Percentage of Broadband Access
100
50
30
far west
great lakes
mideast
new england
plains
rocky mountain
southeast
southwest
Region

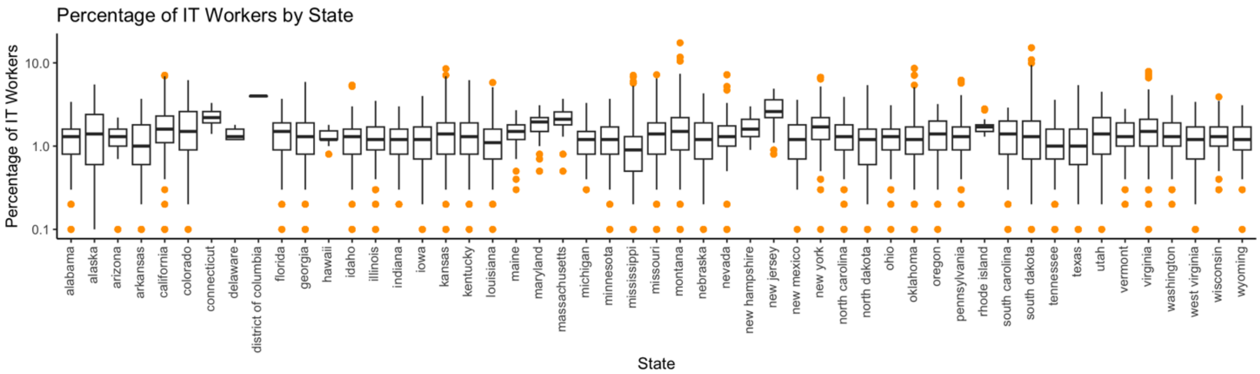
```
# Create a grid of box plots

p1 <- ggplot(merged_df, aes(x=state, y=median_hh_inc)) +
  geom_boxplot(outlier.colour = "orange") +
  scale_y_log10() +
  labs(x="State", y="Median Household Income") +
  ggtitle("Median Household Income by State") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.3))

p2 <- ggplot(merged_df, aes(x=state, y=pct_college)) +
  geom_boxplot(outlier.colour = "orange") +
  scale_y_log10() +
  labs(x="State", y="Percentage with College Education") +
  ggtitle("Percentage with College Education by State") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.3))

p3 <- ggplot(merged_df, aes(x=state, y=pct_foreign_born)) +
  geom_boxplot(outlier.colour = "orange") +
  scale_y_log10() +
  labs(x="State", y="Percentage of Foreign-born Residents") +
  ggtitle("Percentage of Foreign-born Residents by State") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.3))

p4 <- ggplot(merged_df, aes(x=state, y=pct_it_workers)) +
  geom_boxplot(outlier.colour = "orange") +
  scale_y_log10() +
  labs(x="State", y="Percentage of IT Workers") +
  ggtitle("Percentage of IT Workers by State") +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.3))

p5 <- ggplot(merged_df, aes(x=state, y=pct_bb)) +
  geom_boxplot(outlier.colour = "orange") +
  scale_y_log10() +
  labs(x="State", y="Percentage of Broadband Access") +
  ggtitle("Percentage of Broadband Access by State") +
```

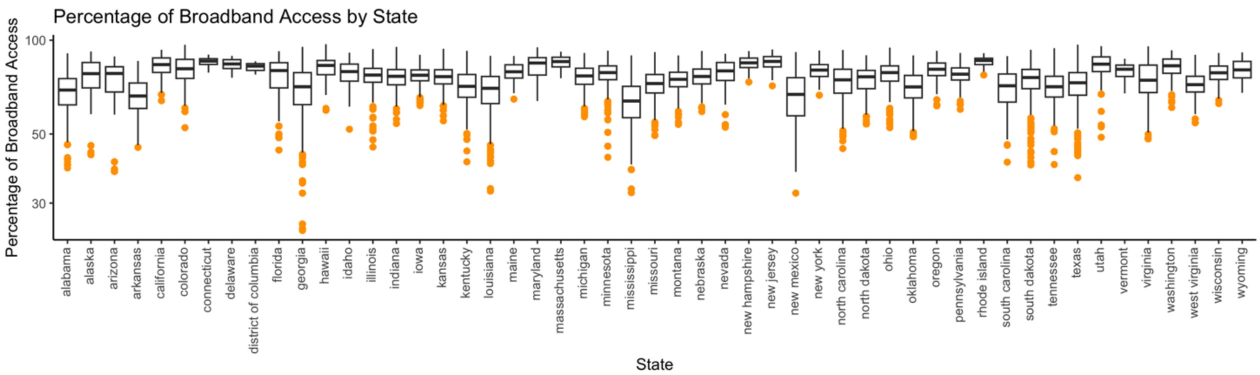
```
  theme_classic() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.3))

grid.arrange(p1, p2, p3, p4, p5, nrow = 5)
```


Median Household Income by State
Median Household Income
1e+05
5e+04
3e+04
State


Percentage with College Education by State
Percentage with College Education
30.0
10.0
3.0
1.0
0.3
State


Percentage of Foreign-born Residents by State
Percentage of Foreign-born Residents
10.0
1.0
0.1
State


Percentage of IT Workers by State
Percentage of IT Workers
10.0
1.0
0.1
State

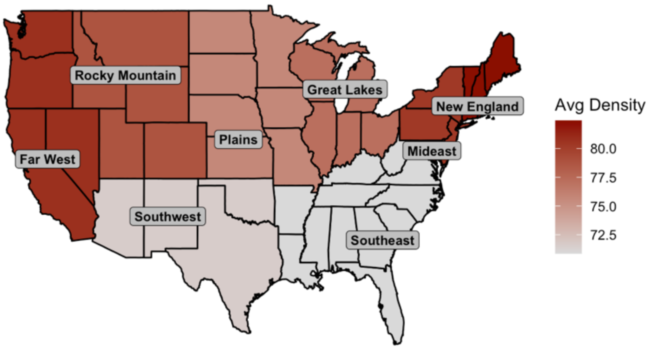

Percentage of Broadband Access by State
Percentage of Broadband Access
100
50
30
State

```
# choropleth map with 5 variables
# Group merged_df by region and calculate average variables
avg_variables <- merged_df %>%
group_by(region) %>%
summarize(avg_pct_bb = mean(pct_bb),
avg_pct_college = mean(pct_college),
avg_pct_foreign_born = mean(pct_foreign_born),
avg_pct_it_workers = mean(pct_it_workers),
avg_median_hh_inc = mean(median_hh_inc))

# Create a lookup table for state abbreviations and their corresponding full names
state_names <- data.frame(state = state.abb, name = tolower(state.name))

# Lowercase region column of region_map
region_map <- region_map %>%
mutate(region = tolower(region))

# Merge the average density data with the region_map data
plot_data <- merge(region_map, avg_variables, by = "region") %>%
arrange(order)

# Coordinates of the center of regions
bea_regions <- data.frame(
group = c("New England", "Mideast", "Great Lakes", "Plains",
"Southeast", "Southwest", "Rocky Mountain", "Far West"),
x = c(-71.8, -76.9, -86.6, -98.5, -82.4, -106.4, -111.1, -119.8),
y = c(42.2, 39, 43.4, 39.8, 32.6, 34.3, 44.4, 38.4)
)

# Create the plot with a grid of 5 rows and 1 column
p1 <- ggplot(plot_data, aes(x = long, y = lat, group = group, fill = avg_pct_bb)) +
geom_polygon(color = "black") +
  geom_label(data = bea_regions,
             aes(x = x, y = y, label = group),
             size = 3, fontface = "bold",
             label.padding = unit(0.2, "lines"),
             label.size = 0.2,
             fill = "gray75", color = "black") +
scale_fill_gradient(low = "gray85", high = "darkred") +
```

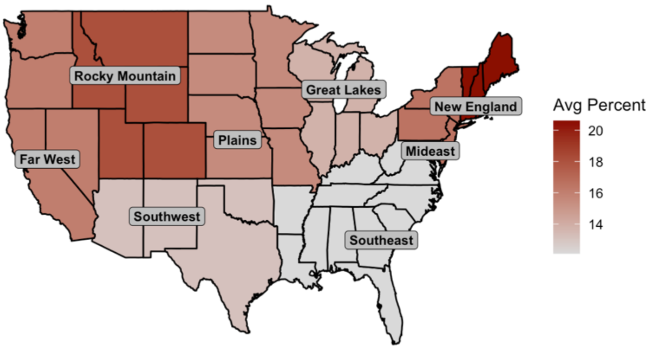
```
labs(title = "Average Percent of Broadband Access Per Region", fill = "Avg Density"
) +
theme_void()


p2 <- ggplot(plot_data, aes(x = long, y = lat, group = group, fill = avg_pct_colleg
e)) +
geom_polygon(color = "black") +
  geom_label(data = bea_regions,
             aes(x = x, y = y, label = group),
             size = 3, fontface = "bold",
             label.padding = unit(0.2, "lines"),
             label.size = 0.2,
             fill = "gray75", color = "black") +
scale_fill_gradient(low = "gray85", high = "darkred") +
labs(title = "Average Percent of College Graduates Per Region", fill = "Avg Percent
") +
theme_void()


p3 <- ggplot(plot_data, aes(x = long, y = lat, group = group, fill = avg_pct_foreig
n_born)) +
geom_polygon(color = "black") +
  geom_label(data = bea_regions,
             aes(x = x, y = y, label = group),
             size = 3, fontface = "bold",
             label.padding = unit(0.2, "lines"),
             label.size = 0.2,
             fill = "gray75", color = "black") +
scale_fill_gradient(low = "gray85", high = "darkred") +
labs(title = "Average Percent of Foreign-Born Population Per Region", fill = "Avg P
ercent") +
theme_void()


p4 <- ggplot(plot_data, aes(x = long, y = lat, group = group, fill = avg_pct_it_wor
kers)) +
geom_polygon(color = "black") +
  geom_label(data = bea_regions,
             aes(x = x, y = y, label = group),
             size = 3, fontface = "bold",
             label.padding = unit(0.2, "lines"),
             label.size = 0.2,
             fill = "gray75", color = "black") +
scale_fill_gradient(low = "gray85", high = "darkred") +
```

```
labs(title = "Average Percent of IT Workers Per Region", fill = "Avg Percent") +
theme_void()


p5 <- ggplot(plot_data, aes(x = long, y = lat, group = group, fill = avg_median_hh_
inc)) +
geom_polygon(color = "black") +
  geom_label(data = bea_regions,
             aes(x = x, y = y, label = group),
             size = 3, fontface = "bold",
             label.padding = unit(0.2, "lines"),
             label.size = 0.2,
             fill = "gray75", color = "black") +
scale_fill_gradient(low = "gray85", high = "darkred") +
labs(title = "Average Median Household inc Per Region", fill = "Avg inc") +
theme_void()


grid.arrange(p1, p2, p3, p4, p5, nrow = 5)
```

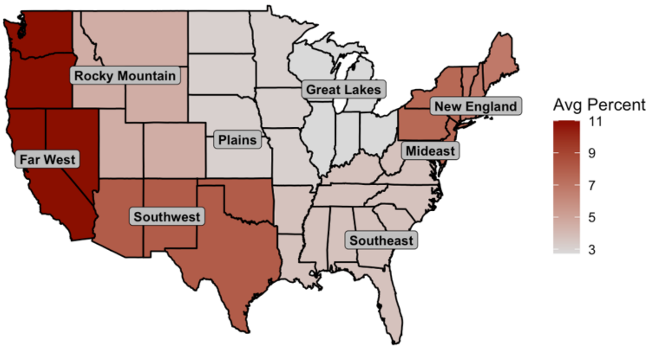
Average Percent of Broadband Access Per Region



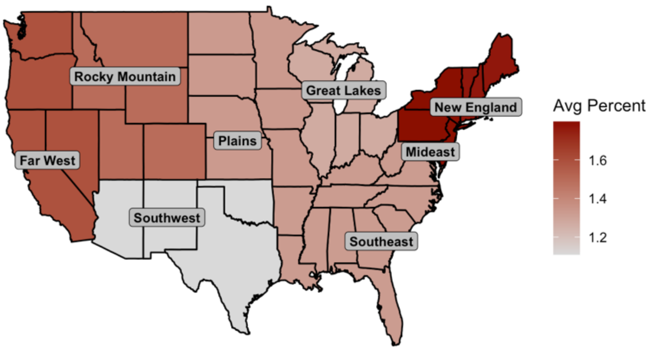
Average Percent of College Graduates Per Region



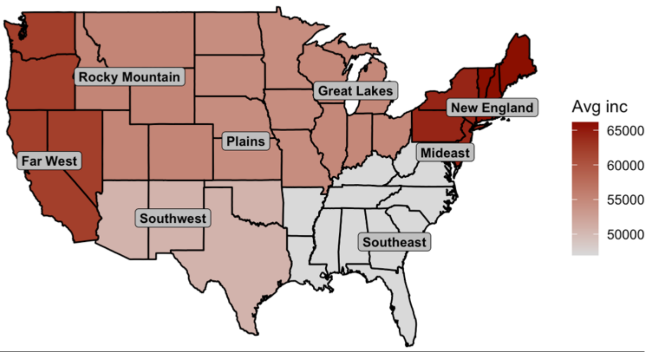
Average Percent of Foreign-Born Population Per Region



Average Percent of IT Workers Per Region



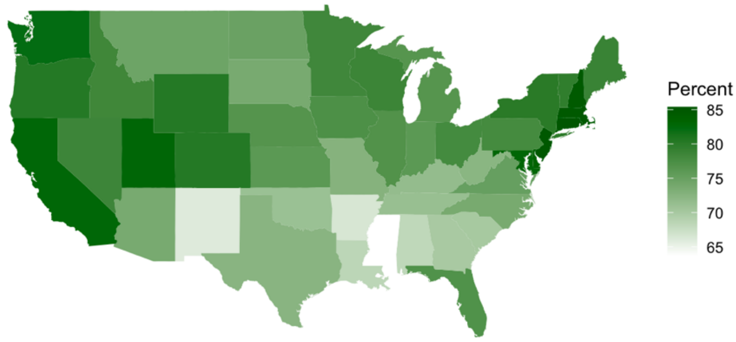
Average Median Household inc Per Region



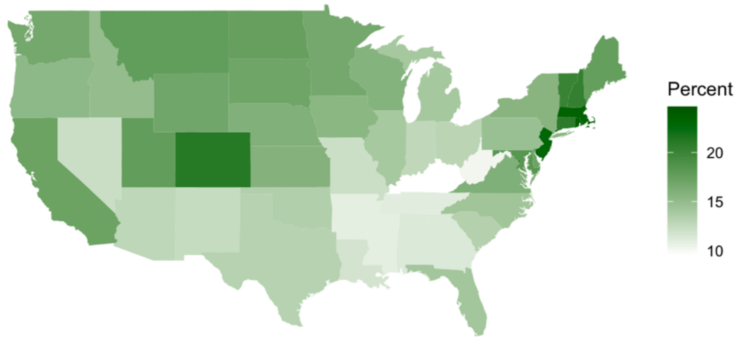
```
state_avg <- aggregate(cbind(pct_bb, pct_college, pct_foreign_born, pct_it_workers, median_hh_inc) ~ state, data = merged_df, FUN = mean)



#Load US state map data

us_map <- map_data("state")


#Merge state_avg with us_map based on region and state

map_data <- merge(us_map, state_avg, by.x = c("region"), by.y = c("state")) %>%

arrange(order)


#Create a grid of heatmaps for each variable

grid_arrange_shared_legend <- function(...) {

plots <- list(...)

g <- ggplotGrob(plots[[1]] + theme(legend.position="bottom"))$grobs

legend <- g[[which(sapply(g, function(x) x$name) == "guide-box")]]

lheight <- sum(legend$height)

grid.arrange(

do.call(arrangeGrob, lapply(plots, function(x)

x + theme(legend.position="none") + theme(panel.background = element_rect(fill = "gray85", color = NA))

),

bottom = legend,

ncol = 5,

heights = rep((unit(1, "npc") - lheight) / length(plots), length(plots))

)

}


heatmap_bb <- ggplot(map_data, aes(x = long, y = lat, group = group, fill = pct_bb)) +

  geom_polygon() +

  scale_fill_gradient(low = "white", high = "darkgreen") +

  coord_map() +

  labs(title = "Percent of Broadband Access per State", fill = "Percent") +

  theme_void()


heatmap_college <-

  ggplot(map_data, aes(x = long, y = lat, group = group, fill = pct_college)) +

  geom_polygon() +

  scale_fill_gradient(low = "white", high = "darkgreen") +
```

```
  coord_map() +
  labs(title = "Percent of Population with College Education per State", fill = "Pe
rcent") +
  theme_void()


heatmap_foreign_born <-
  ggplot(map_data, aes(x = long, y = lat, group = group, fill = pct_foreign_born))
+
  geom_polygon() +
  scale_fill_gradient(low = "white", high = "darkgreen") +
  coord_map() +
  labs(title = "Percent of Foreign-born Population per State", fill = "Percent") +
  theme_void()


heatmap_it_workers <-
  ggplot(map_data, aes(x = long, y = lat, group = group, fill = pct_it_workers)) +
  geom_polygon() +
  scale_fill_gradient(low = "white", high = "darkgreen") +
  coord_map() +
  labs(title = "Percent of IT Workers per State", fill = "Percent") +
  theme_void()
heatmap_inc <-
  ggplot(map_data, aes(x = long, y = lat, group = group, fill = median_hh_inc)) +
  geom_polygon() +
  scale_fill_gradient(low = "white", high = "darkgreen") +
  coord_map() +
  labs(title = "Median Household Income per State", fill = "Dollars") +
  theme_void()


#Plot the grid of heatmaps
#grid_arrange_shared_legend(heatmap_bb, heatmap_college, heatmap_foreign_born, heat
map_it_workers, heatmap_inc)
grid.arrange(heatmap_bb, heatmap_college, heatmap_foreign_born, heatmap_it_workers,
heatmap_inc, nrow = 5)
```

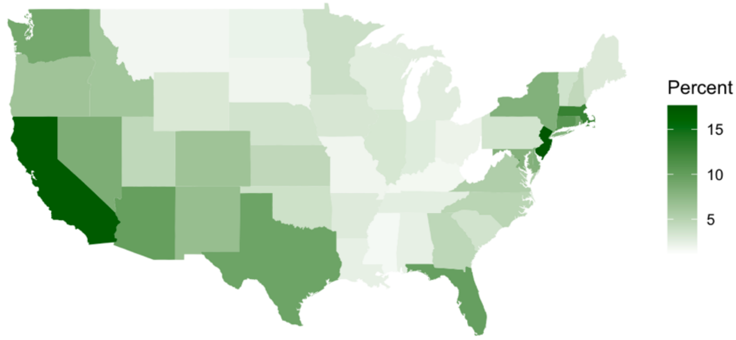
Percent of Broadband Access per State



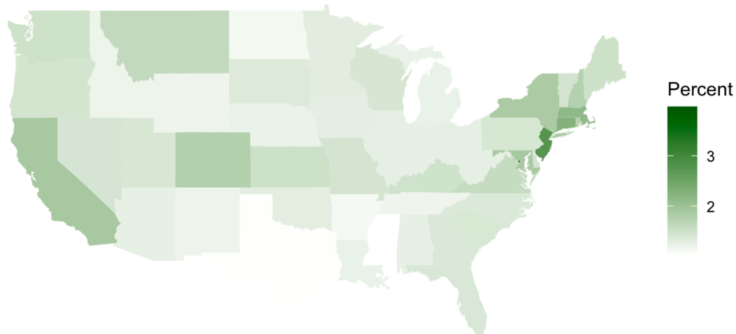
Percent of Population with College Education per State



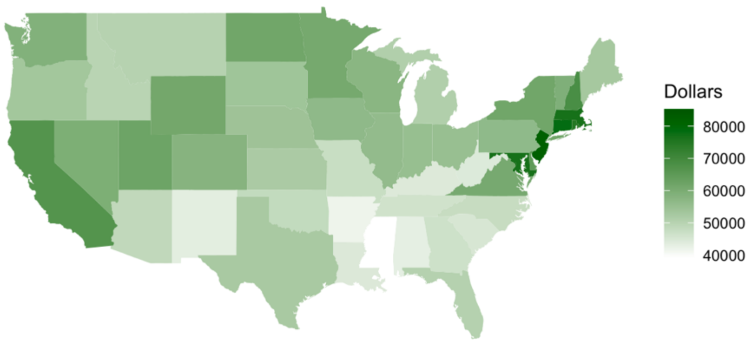
Percent of Foreign-born Population per State



Percent of IT Workers per State



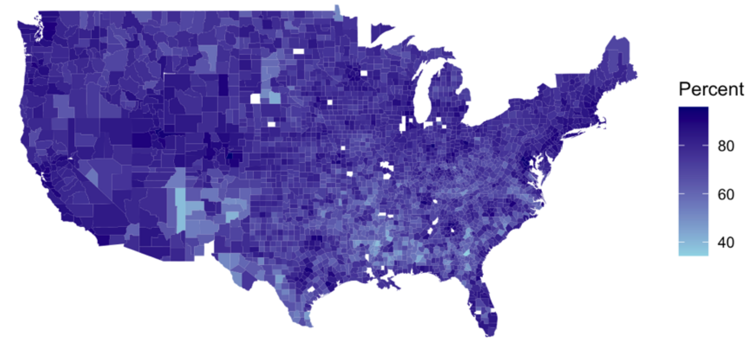
Median Household Income per State



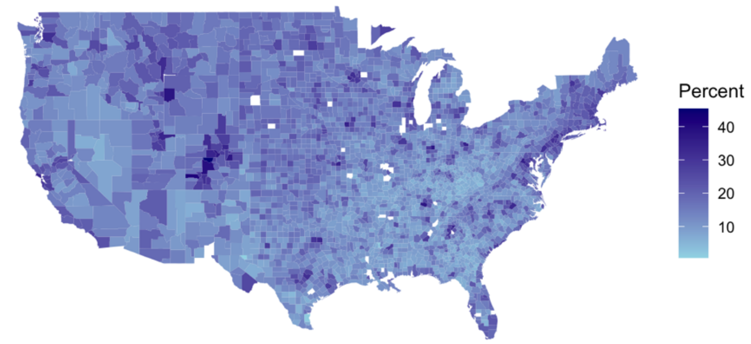
```
county_avg <- aggregate(cbind(pct_bb, pct_college, pct_foreign_born, pct_it_workers
, median_hh_inc) ~ county + state, data = merged_df, FUN = mean)


#Get rid of county, city, and parish in the end of county names

county_avg$county <- gsub(" county", "", county_avg$county)

county_avg$county <- gsub(" city", "", county_avg$county)

county_avg$county <- gsub(" parish", "", county_avg$county)


#Load US county map data

us_map <- map_data("county")


#Merge county_avg with us_map based on region and county

map_data <- merge(us_map, county_avg, by.x = c("subregion", "region"), by.y = c("co
unty", "state")) %>%

arrange(order)


#Create a grid of heatmaps for each variable

grid_arrange_shared_legend <- function(...) {

plots <- list(...)

g <- ggplotGrob(plots[[1]] + theme(legend.position="bottom"))$grobs

legend <- g[[which(sapply(g, function(x) x$name) == "guide-box")]]

lheight <- sum(legend$height)

grid.arrange(

do.call(arrangeGrob, lapply(plots, function(x)

x + theme(legend.position="none") + theme(panel.background = element_rect(fill = "g
ray85", color = NA)))

),

bottom = legend,

ncol = 5,

heights = rep((unit(1, "npc") - lheight) / length(plots), length(plots))

)

}


heatmap_bb <- ggplot(map_data, aes(x = long, y = lat, group = group, fill = pct_bb)
) +

  geom_polygon() +

  scale_fill_gradient(low = "lightblue", high = "navyblue") +

  coord_map() +

  labs(title = "Percent of Broadband Access per County", fill = "Percent") +

  theme_void()
```

```
heatmap_college <-
  ggplot(map_data, aes(x = long, y = lat, group = group, fill = pct_college)) +
  geom_polygon() +
  scale_fill_gradient(low = "lightblue", high = "navyblue") +
  coord_map() +
  labs(title = "Percent of Population with College Education per County", fill = "P
ercent") +
  theme_void()


heatmap_foreign_born <-
  ggplot(map_data, aes(x = long, y = lat, group = group, fill = pct_foreign_born))
+
  geom_polygon() +
  scale_fill_gradient(low = "lightblue", high = "navyblue") +
  coord_map() +
  labs(title = "Percent of Foreign-born Population per County", fill = "Percent") +
  theme_void()


heatmap_it_workers <-
  ggplot(map_data, aes(x = long, y = lat, group = group, fill = pct_it_workers)) +
  geom_polygon() +
  scale_fill_gradient(low = "lightblue", high = "navyblue") +
  coord_map() +
  labs(title = "Percent of IT Workers per County", fill = "Percent") +
  theme_void()
heatmap_inc <-
  ggplot(map_data, aes(x = long, y = lat, group = group, fill = median_hh_inc)) +
  geom_polygon() +
  scale_fill_gradient(low = "lightblue", high = "navyblue") +
  coord_map() +
  labs(title = "Median Household Income per County", fill = "Dollars") +
  theme_void()


#Plot the grid of heatmaps
#grid_arrange_shared_legend(heatmap_bb, heatmap_college, heatmap_foreign_born, heat
map_it_workers, heatmap_inc)
grid.arrange(heatmap_bb, heatmap_college, heatmap_foreign_born, heatmap_it_workers,
heatmap_inc, nrow = 5)
```

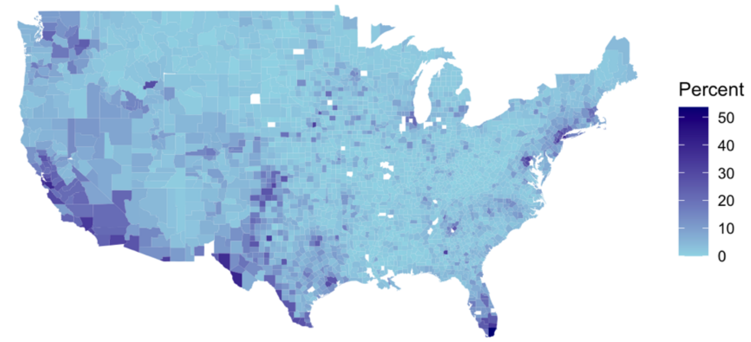
Percent of Broadband Access per County



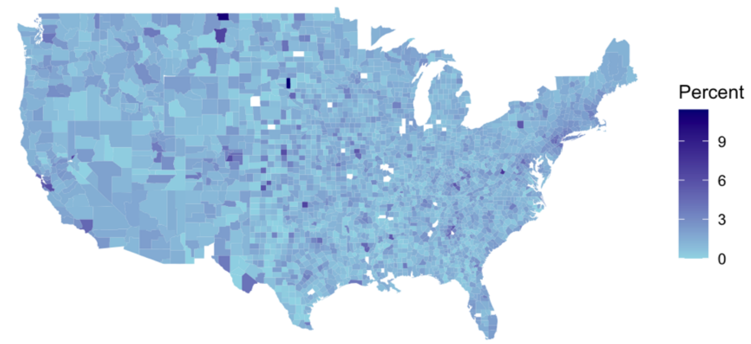
Percent of Population with College Education per County



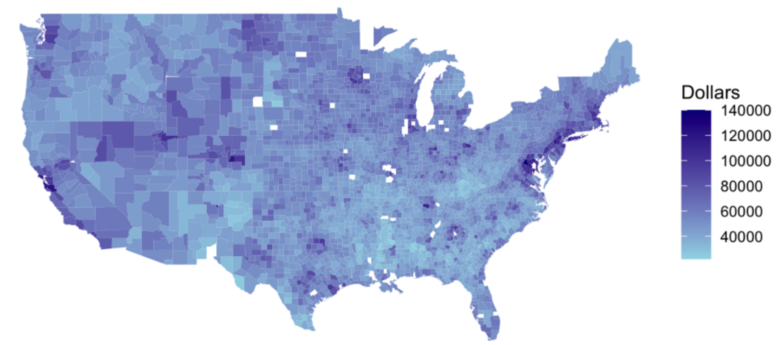
Percent of Foreign-born Population per County



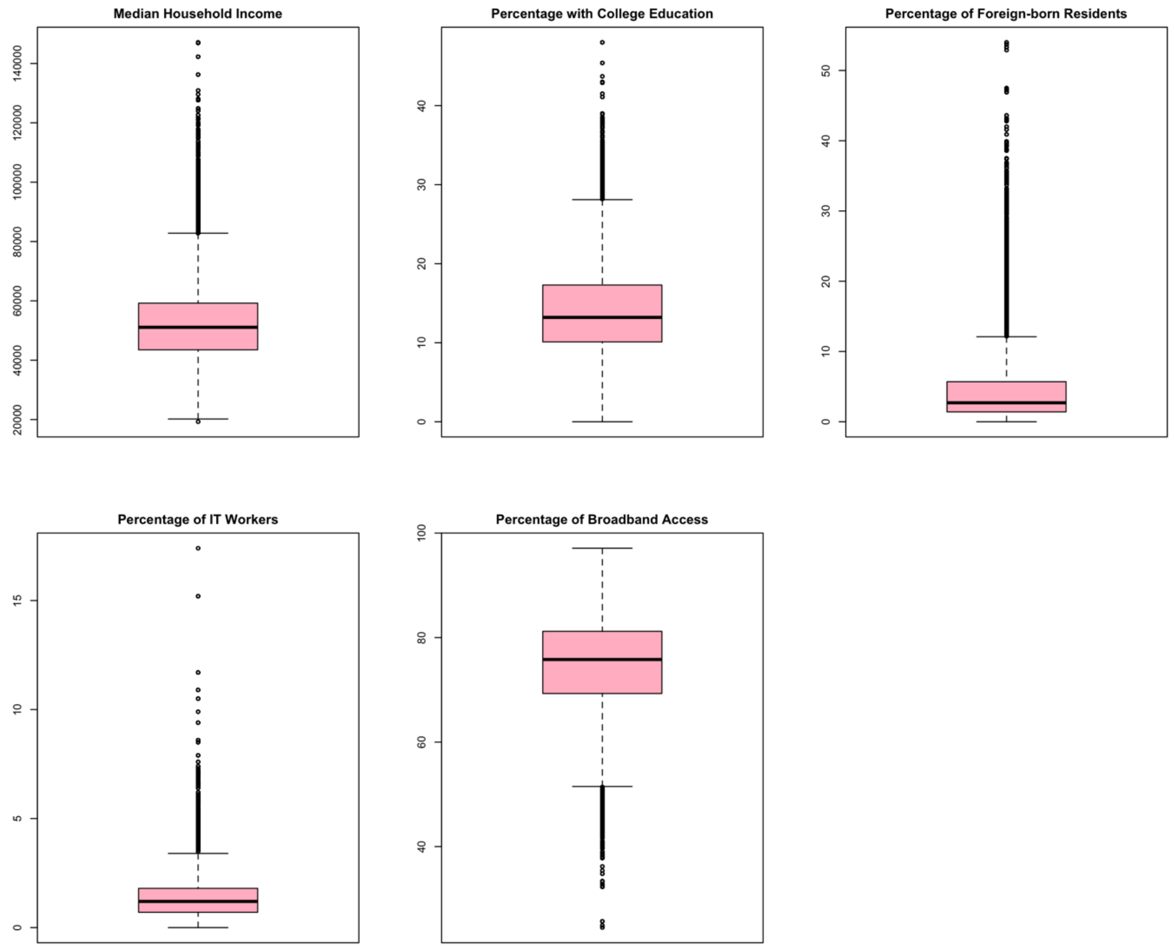
Percent of IT Workers per County



Median Household Income per County



```
par(mfrow=c(3,2)) # set plot layout to 3 rows and 2 columns
boxplot(merged_df$median_hh_inc, col = "pink", main = "Median Household Income")
boxplot(merged_df$pct_college, col = "pink", main = "Percentage with College Educat
ion")
boxplot(merged_df$pct_foreign_born, col = "pink", main = "Percentage of Foreign-bor
n Residents")
boxplot(merged_df$pct_it_workers, col = "pink", main = "Percentage of IT Workers")
boxplot(merged_df$pct_bb, col = "pink", main = "Percentage of Broadband Access")
#boxplot(merged_df$active, col = "pink", main = "Active Microbusiness Count")
```



3.8. Outlier Detection

Outlier detection is an important step in data analysis, as outliers can significantly affect the results of statistical analyses. There are several methods to detect outliers depending on the distribution of the data.

The Shapiro-Wilk normality test is a statistical test used to determine if a given dataset follows a normal distribution. We will perform a Shapiro-Wilk normality test on a random sample of 5000 observations from the `microbusiness_density` column of **merged_df** dataframe. To run this test we first set the seed value using **`set.seed()`** function to a specific random seed to ensure that the results are reproducible if the code is run again. Then, we weill use the **`shapiro.test()`** function to perform the Shapiro-Wilk normality test on the **sample_data** object. The function returns the test statistic (W) and the p-value. A W value closer to 1 indicates that the data is more normally distributed, while a W value closer to 0 indicates greater deviation from normality. If the p-value is less than the significance level (typically 0.05), then the null hypothesis (that the sample data is normally distributed) is rejected in favor of the alternative hypothesis (that the sample data is not normally distributed).

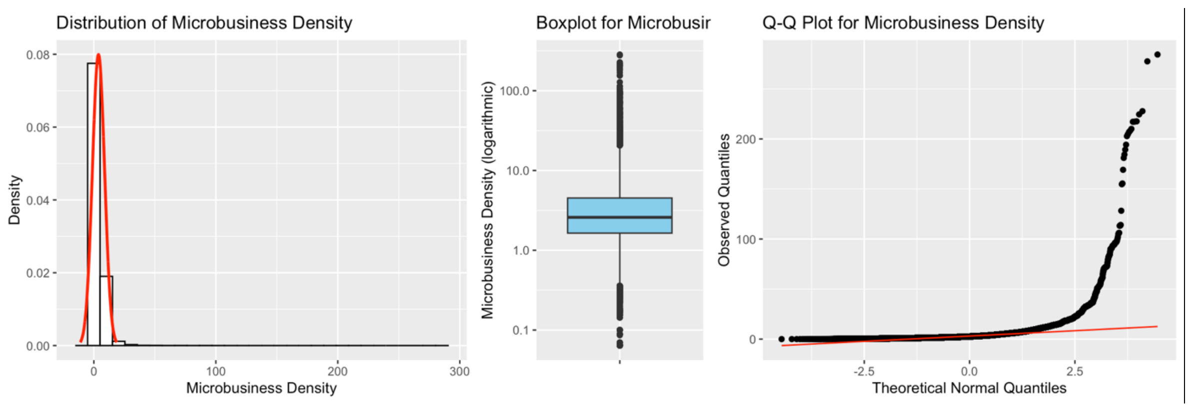
```
# Sample 5000 observations from microbusiness_density column
set.seed(92) # Set seed for reproducibility
sample_data <- sample(merged_df$microbusiness_density, 5000)


# Perform Shapiro-Wilk test on sample_data
shapiro.test(sample_data)
##
##  Shapiro-Wilk normality test
##
## data:  sample_data
## W = 0.55179, p-value < 2.2e-16
```

The test resulted in a W statistic of 0.55179 and a p-value of less than 2.2e-16. Based on the results of the Shapiro-Wilk normality test, it can be concluded that the **sample_data** is not normally distributed.

To have a better visual on distribution of the data we will use a bell curve, a boxplot, and a Q-Q plot on `microbusiness_density`.

```
# Calculate the mean and standard deviation of 'microbusiness_density'
mean_density <- mean(merged_df$microbusiness_density)
sd_density <- sd(merged_df$microbusiness_density)


# Create a range of values for the x-axis
x_values <- seq(mean_density - 3*sd_density, mean_density + 3*sd_density, length.ou
t = 1000)


# Create a bell curve with mean and standard deviation calculated above
y_values <- dnorm(x_values, mean = mean_density, sd = sd_density)
```

```r
# Combine the 'x_values' and 'y_values' into a data frame
density_df <- data.frame(x = x_values, y = y_values)

# Create a boxplot
boxplot <- ggplot(data = merged_df, aes(x = "", y = merged_df$microbusiness_density
)) +
  geom_boxplot(fill = "skyblue") +
  scale_y_log10() +
  labs(x = "", y = "Microbusiness Density (logarithmic)") +
  ggtitle("Boxplot for Microbusiness Density")

# Create a Q-Q plot and add a diagonal line
qqplot <- ggplot(data = merged_df, aes(sample = microbusiness_density)) +
  stat_qq() +
  stat_qq_line(colour = "red") +
  labs(x = "Theoretical Normal Quantiles", y = "Observed Quantiles") +
  ggtitle("Q-Q Plot for Microbusiness Density")

# Create a histogram and add the bell curve
densityplot <- ggplot(data = merged_df, aes(x = microbusiness_density)) +
  geom_histogram(aes(y = after_stat(density)), bins = 30, colour = "black", fill =
"white") +
  geom_line(data = density_df, aes(x = x, y = y), colour = "red", linewidth = 1) +
  labs(x = "Microbusiness Density", y = "Density") +
  ggtitle("Distribution of Microbusiness Density")

# Arrange the plots in one row using the 'grid.arrange' function from the 'gridExtr
a' package
grid.arrange(densityplot, boxplot, qqplot, ncol = 3, widths = c(2, 1, 2))
```



The above distribution plot explains that the dataset is right-skewed. The boxplot shows some data points away from the upper whisker; hence outliers are present in `microbusiness_density`. Q-Q plot's alignment is away from the 45-degree angle depicting outliers in the dataset.

Since the data is right-skewed and not normally distributed, a common approach to detecting outliers is to use the interquartile range (IQR) method. Now, we have to find the boundary of minimum and maximum values, out of which data would be considered an outlier.

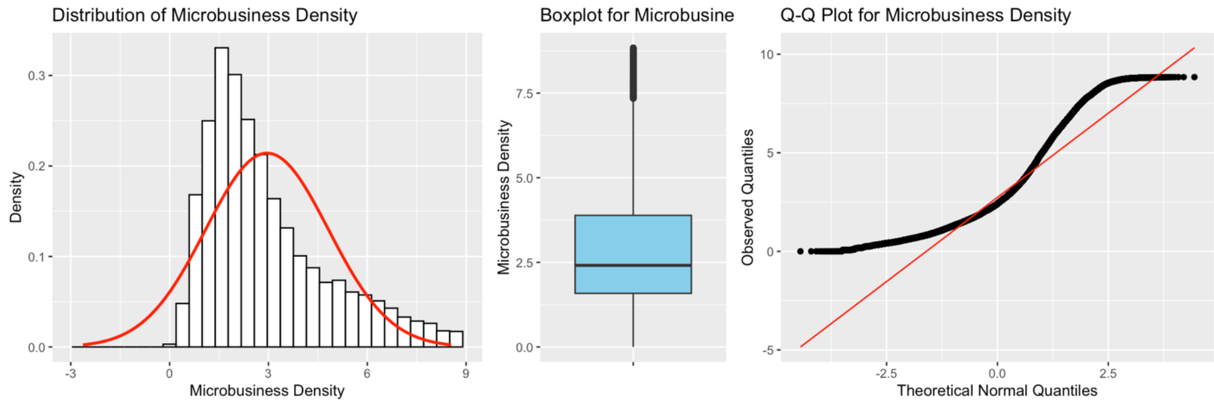
The decision range approach involves setting a range of values outside of which any observations are considered outliers. One common approach is to use the interquartile range (IQR) to define the decision range. The IQR is calculated as the difference between the third quartile (Q3) and the first quartile (Q1) of the data.

The decision range is then defined as the range from \(Q1 - 1.5 * IQR\) to \(Q3 + 1.5 * IQR\). Any observations that fall outside of this range are considered outliers. This method is useful for identifying potential outliers in a dataset and can help to ensure that statistical analyses are robust and accurate.

```
quartiles <- quantile(merged_df$microbusiness_density, probs = seq(0, 1, 0.25), na.
rm = FALSE,

         names = TRUE, type = 7, digits = 6)

quartiles

##          0%        25%        50%        75%       100%

##    0.000000   1.639344   2.586543   4.519231 284.340030

# Calculate IQR of microbusiness_density column

q <- quantile(merged_df$microbusiness_density, c(0.25, 0.75))

iqr <- q[2] - q[1]


# Calculate lower and upper bounds for outliers

lower_bound <- q[1] - 1.5*iqr

upper_bound <- q[2] + 1.5*iqr


# Count number of outliers

num_outliers <- sum(merged_df$microbusiness_density < lower_bound | merged_df$micro
business_density > upper_bound)


# Calculate percent of outliers

percent_outliers <- num_outliers / length(merged_df$microbusiness_density) * 100


# Print results

cat("Number of outliers:", num_outliers, "\n")

## Number of outliers: 8746

cat("Percent of outliers:", percent_outliers, "%\n")

## Percent of outliers: 7.153315 %

# Create new dataframe without outliers

merged_df_new <- merged_df[merged_df$microbusiness_density >= lower_bound & merged_
df$microbusiness_density <= upper_bound,]
```

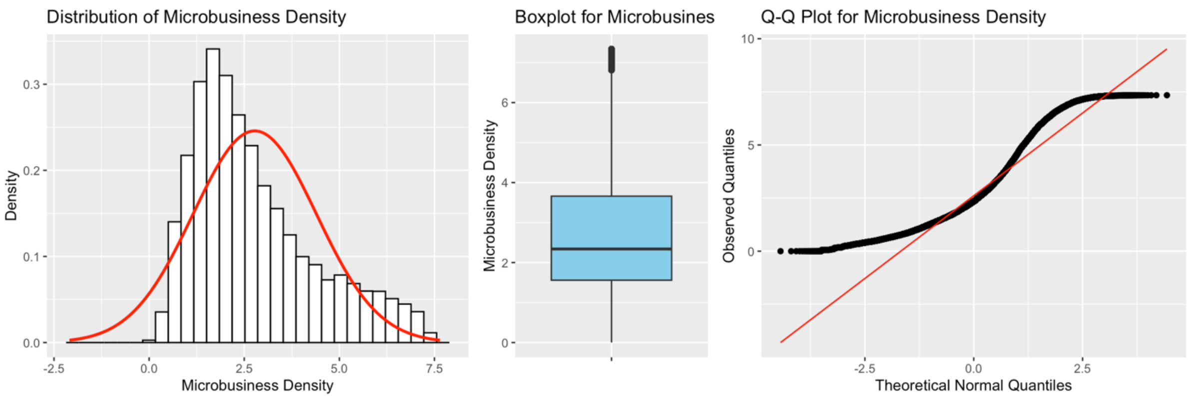
```
# Print number of rows removed
cat("Number of rows removed:", nrow(merged_df) - nrow(merged_df_new), "\n")
## Number of rows removed: 8746
# Calculate the mean and standard deviation of 'microbusiness_density'
mean_density <- mean(merged_df_new$microbusiness_density)
sd_density <- sd(merged_df_new$microbusiness_density)

# Create a range of values for the x-axis
x_values <- seq(mean_density - 3*sd_density, mean_density + 3*sd_density, length.ou
t = 1000)

# Create a bell curve with mean and standard deviation calculated above
y_values <- dnorm(x_values, mean = mean_density, sd = sd_density)

# Combine the 'x_values' and 'y_values' into a data frame
density_df <- data.frame(x = x_values, y = y_values)

# Create a boxplot
boxplot <- ggplot(data = merged_df_new, aes(x = "", y = merged_df_new$microbusiness
_density)) +
  geom_boxplot(fill = "skyblue") +
#  scale_y_log10() +
  labs(x = "", y = "Microbusiness Density") +
  ggtitle("Boxplot for Microbusiness Density")

# Create a Q-Q plot and add a diagonal line
qqplot <- ggplot(data = merged_df_new, aes(sample = microbusiness_density)) +
  stat_qq() +
  stat_qq_line(colour = "red") +
  labs(x = "Theoretical Normal Quantiles", y = "Observed Quantiles") +
  ggtitle("Q-Q Plot for Microbusiness Density")

# Create a bell curve and add the bell curve
densityplot <- ggplot(data = merged_df_new, aes(x = microbusiness_density)) +
  geom_histogram(aes(y = after_stat(density)), bins = 30, colour = "black", fill =
"white") +
  geom_line(data = density_df, aes(x = x, y = y), colour = "red", linewidth = 1) +
  labs(x = "Microbusiness Density", y = "Density") +
  ggtitle("Distribution of Microbusiness Density")
```

```
# Arrange the plots in one row
grid.arrange(densityplot, boxplot, qqplot, ncol = 3, widths = c(2, 1, 2))
```



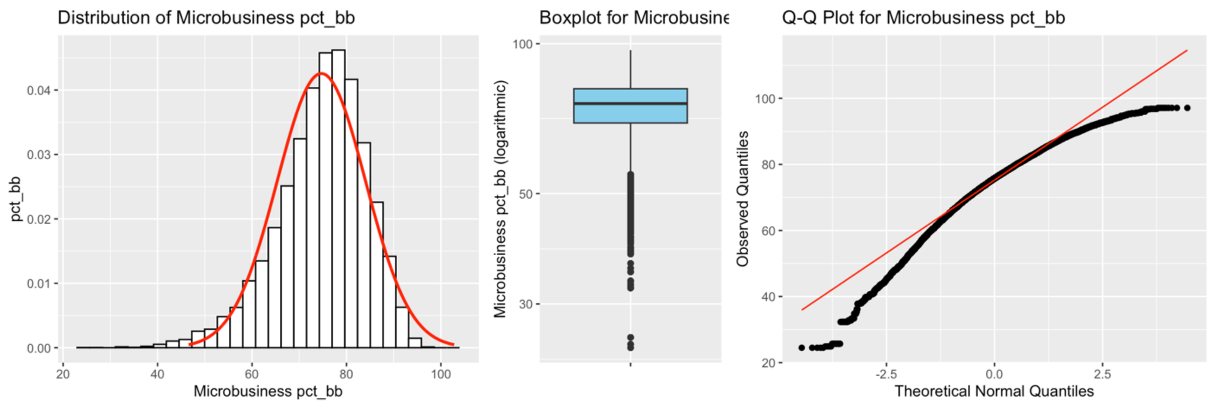

```
# Calculate IQR of microbusiness_density column
q <- quantile(merged_df_new$microbusiness_density, c(0.25, 0.75))
iqr <- q[2] - q[1]

# Calculate lower and upper bounds for outliers
lower_bound <- q[1] - 1.5*iqr
upper_bound <- q[2] + 1.5*iqr

# Count number of outliers
num_outliers <- sum(merged_df_new$microbusiness_density < lower_bound | merged_df_n
ew$microbusiness_density > upper_bound)

# Calculate percent of outliers
percent_outliers <- num_outliers / length(merged_df_new$microbusiness_density) * 10
0

# Print results
cat("Number of outliers:", num_outliers, "\n")
## Number of outliers: 3946
cat("Percent of outliers:", percent_outliers, "%\n")
## Percent of outliers: 3.47607 %
# Create new dataframe without outliers
merged_df_clean <- merged_df_new[merged_df_new$microbusiness_density >= lower_bound
& merged_df_new$microbusiness_density <= upper_bound,]

# Print number of rows removed
cat("Number of rows removed:", nrow(merged_df_new) - nrow(merged_df_clean), "\n")
## Number of rows removed: 3946
cat("Total rows removed:", nrow(merged_df) - nrow(merged_df_clean))
```

```
## Total rows removed: 12692

# Calculate the mean and standard deviation of 'microbusiness_density'
mean_density <- mean(merged_df_clean$microbusiness_density)
sd_density <- sd(merged_df_clean$microbusiness_density)

# Create a range of values for the x-axis
x_values <- seq(mean_density - 3*sd_density, mean_density + 3*sd_density, length.ou
t = 1000)

# Create a bell curve with mean and standard deviation calculated above
y_values <- dnorm(x_values, mean = mean_density, sd = sd_density)

# Combine the 'x_values' and 'y_values' into a data frame
density_df <- data.frame(x = x_values, y = y_values)

# Create a boxplot
boxplot <- ggplot(data = merged_df_clean, aes(x = "", y = merged_df_clean$microbusi
ness_density)) +
  geom_boxplot(fill = "skyblue") +
#  scale_y_log10() +
  labs(x = "", y = "Microbusiness Density") +
  ggtitle("Boxplot for Microbusiness Density")

# Create a Q-Q plot and add a diagonal line
qqplot <- ggplot(data = merged_df_clean, aes(sample = microbusiness_density)) +
  stat_qq() +
  stat_qq_line(colour = "red") +
  labs(x = "Theoretical Normal Quantiles", y = "Observed Quantiles") +
  ggtitle("Q-Q Plot for Microbusiness Density")

# Create a histogram and add the bell curve
densityplot <- ggplot(data = merged_df_clean, aes(x = microbusiness_density)) +
  geom_histogram(aes(y = after_stat(density)), bins = 30, colour = "black", fill =
"white") +
  geom_line(data = density_df, aes(x = x, y = y), colour = "red", linewidth = 1) +
  labs(x = "Microbusiness Density", y = "Density") +
  ggtitle("Distribution of Microbusiness Density")

# Arrange the plots in one row using the 'grid.arrange' function from the 'gridExtr
a' package
grid.arrange(densityplot, boxplot, qqplot, ncol = 3, widths = c(2, 1, 2))
```




```
# Calculate the mean and standard deviation of 'pct_bb'
mean_pct_bb <- mean(merged_df$pct_bb)
sd_pct_bb <- sd(merged_df$pct_bb)

# Create a range of values for the x-axis
x_values <- seq(mean_pct_bb - 3*sd_pct_bb, mean_pct_bb + 3*sd_pct_bb, length.out =
1000)

# Create a bell curve with mean and standard deviation calculated above
y_values <- dnorm(x_values, mean = mean_pct_bb, sd = sd_pct_bb)

# Combine the 'x_values' and 'y_values' into a data frame
pct_bb_df <- data.frame(x = x_values, y = y_values)

# Create a boxplot
boxplot <- ggplot(data = merged_df, aes(x = "", y = merged_df$pct_bb)) +
  geom_boxplot(fill = "skyblue") +
  scale_y_log10() +
  labs(x = "", y = "Microbusiness pct_bb (logarithmic)") +
  ggtitle("Boxplot for Microbusiness pct_bb")

# Create a Q-Q plot and add a diagonal line
qqplot <- ggplot(data = merged_df, aes(sample = pct_bb)) +
  stat_qq() +
  stat_qq_line(colour = "red") +
  labs(x = "Theoretical Normal Quantiles", y = "Observed Quantiles") +
  ggtitle("Q-Q Plot for Microbusiness pct_bb")

# Create a histogram and add the bell curve
densityplot <- ggplot(data = merged_df, aes(x = pct_bb)) +
```

```
  geom_histogram(aes(y = after_stat(density)), bins = 30, colour = "black", fill =
"white") +

  geom_line(data = pct_bb_df, aes(x = x, y = y), colour = "red", linewidth = 1) +

  labs(x = "Microbusiness pct_bb", y = "pct_bb") +

  ggtitle("Distribution of Microbusiness pct_bb")


# Arrange the plots in one row using the 'grid.arrange' function from the 'gridExtr
a' package

grid.arrange(densityplot, boxplot, qqplot, ncol = 3, widths = c(2, 1, 2))
```




```
# Specify the columns to analyze

cols_to_analyze <- c("pct_bb", "pct_college", "pct_it_workers", "pct_foreign_born",
"median_hh_inc")


# Loop through each column and detect outliers using the IQR method

for (col in cols_to_analyze) {

  # Calculate the interquartile range (IQR) of the column

  q1 <- quantile(merged_df_new[[col]], 0.25)

  q3 <- quantile(merged_df_new[[col]], 0.75)

  iqr <- q3 - q1


  # Calculate the upper and lower bounds for outliers

  upper_bound <- q3 + (1.5 * iqr)

  lower_bound <- q1 - (1.5 * iqr)


  # Identify the outliers in the column

  outliers <- merged_df_new[[col]][merged_df_new[[col]] > upper_bound | merged_df_n
ew[[col]] < lower_bound]


  # Print the results

#  cat(paste("Outliers in", col, ":", toString(outliers), "\n"))

  # Count number of outliers
```

```
  num_outliers <- sum(merged_df_new[[col]] < lower_bound | merged_df_new[[col]] > u
pper_bound)

  # Calculate percent of outliers

  percent_outliers <- num_outliers / length(merged_df_new[[col]]) * 100


# Print results

cat("Number of outliers in", col,":", num_outliers, "\n")

cat("Percent of outliers in", col,":", percent_outliers, "%\n")

}

## Number of outliers in pct_bb : 2507

## Percent of outliers in pct_bb : 2.208441 %

## Number of outliers in pct_college : 1428

## Percent of outliers in pct_college : 1.257939 %

## Number of outliers in pct_it_workers : 2556

## Percent of outliers in pct_it_workers : 2.251605 %

## Number of outliers in pct_foreign_born : 8329

## Percent of outliers in pct_foreign_born : 7.337098 %

## Number of outliers in median_hh_inc : 3410

## Percent of outliers in median_hh_inc : 3.003902 %

# Create a copy of the original dataframe

merged_df_clean <- merged_df_new


# Loop through each column and detect outliers using the IQR method

for (col in cols_to_analyze) {

  # Calculate the interquartile range (IQR) of the column

  q1 <- quantile(merged_df_clean[[col]], 0.25)

  q3 <- quantile(merged_df_clean[[col]], 0.75)

  iqr <- q3 - q1


  # Calculate the upper and lower bounds for outliers

  upper_bound <- q3 + (1.5 * iqr)

  lower_bound <- q1 - (1.5 * iqr)


  # Identify the outliers in the column

  outliers <- merged_df_clean[[col]][merged_df_clean[[col]] > upper_bound | merged_
df_clean[[col]] < lower_bound]


  # Remove the outliers from the dataframe

  merged_df_clean <- merged_df_clean[!(merged_df_clean[[col]] %in% outliers), ]

}
```

```
# Print the dimensions of the original and cleaned dataframes
cat("Original dataframe dimensions:", nrow(merged_df_new), "\n")
## Original dataframe dimensions: 113519
cat("Cleaned dataframe dimensions:", nrow(merged_df_clean), "\n")
## Cleaned dataframe dimensions: 97098
cat("Total rows removed:", nrow(merged_df) - nrow(merged_df_clean), "\n")
## Total rows removed: 25167
cat("Total percent removed:", 100 * (nrow(merged_df) - nrow(merged_df_clean)) / nro
w(merged_df),"%", "\n")
## Total percent removed: 20.58398 %
```

3.9. Non-Parametric Test

```
# Specify a list of column pairs to compare
col_pairs <- list(c("microbusiness_density", "pct_bb"), c("microbusiness_density",
"pct_college"), c("microbusiness_density", "pct_foreign_born"), c("microbusiness_de
nsity", "pct_it_workers"), c("microbusiness_density", "median_hh_inc"))


# Loop through each column pair and perform the Wilcoxon signed-rank test
for (pair in col_pairs) {
  test_result <- wilcox.test(merged_df_new[[pair[1]]], merged_df_new[[pair[2]]], pa
ired = TRUE)
  cat(paste("Wilcoxon signed-rank test results for", pair[1], "and", pair[2], ":\n"
))
  print(test_result)
  cat("\n")
}
## Wilcoxon signed-rank test results for microbusiness_density and pct_bb :
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## V = 0, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
##
##
## Wilcoxon signed-rank test results for microbusiness_density and pct_college :
##
##  Wilcoxon signed rank test with continuity correction
##
```

```
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## V = 6780, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
##
##
## Wilcoxon signed-rank test results for microbusiness_density and pct_foreign_born
:
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## V = 2843324130, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
##
##
## Wilcoxon signed-rank test results for microbusiness_density and pct_it_workers :
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## V = 5996103713, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
##
##
## Wilcoxon signed-rank test results for microbusiness_density and median_hh_inc :
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## V = 0, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
# Specify a list of column pairs to compare
col_pairs <- list(c("microbusiness_density", "pct_bb"), c("microbusiness_density",
"pct_college"), c("microbusiness_density", "pct_foreign_born"), c("microbusiness_de
nsity", "pct_it_workers"), c("microbusiness_density", "median_hh_inc"))


# Loop through each column pair and perform the Wilcoxon rank sum test
for (pair in col_pairs) {
  test_result <- wilcox.test(merged_df_new[[pair[1]]], merged_df_new[[pair[2]]], pa
ired = FALSE)
  cat(paste("Wilcoxon rank-sum test results for", pair[1], "and", pair[2], ":\n"))
```

```
  print(test_result)
  cat("\n")
}
## Wilcoxon rank-sum test results for microbusiness_density and pct_bb :
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## W = 0, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
##
##
## Wilcoxon rank-sum test results for microbusiness_density and pct_college :
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## W = 112644499, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
##
##
## Wilcoxon rank-sum test results for microbusiness_density and pct_foreign_born :
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## W = 6244818672, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
##
##
## Wilcoxon rank-sum test results for microbusiness_density and pct_it_workers :
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## W = 1.0468e+10, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
##
##
```

```
## Wilcoxon rank-sum test results for microbusiness_density and median_hh_inc :
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  merged_df_new[[pair[1]]] and merged_df_new[[pair[2]]]
## W = 0, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
```

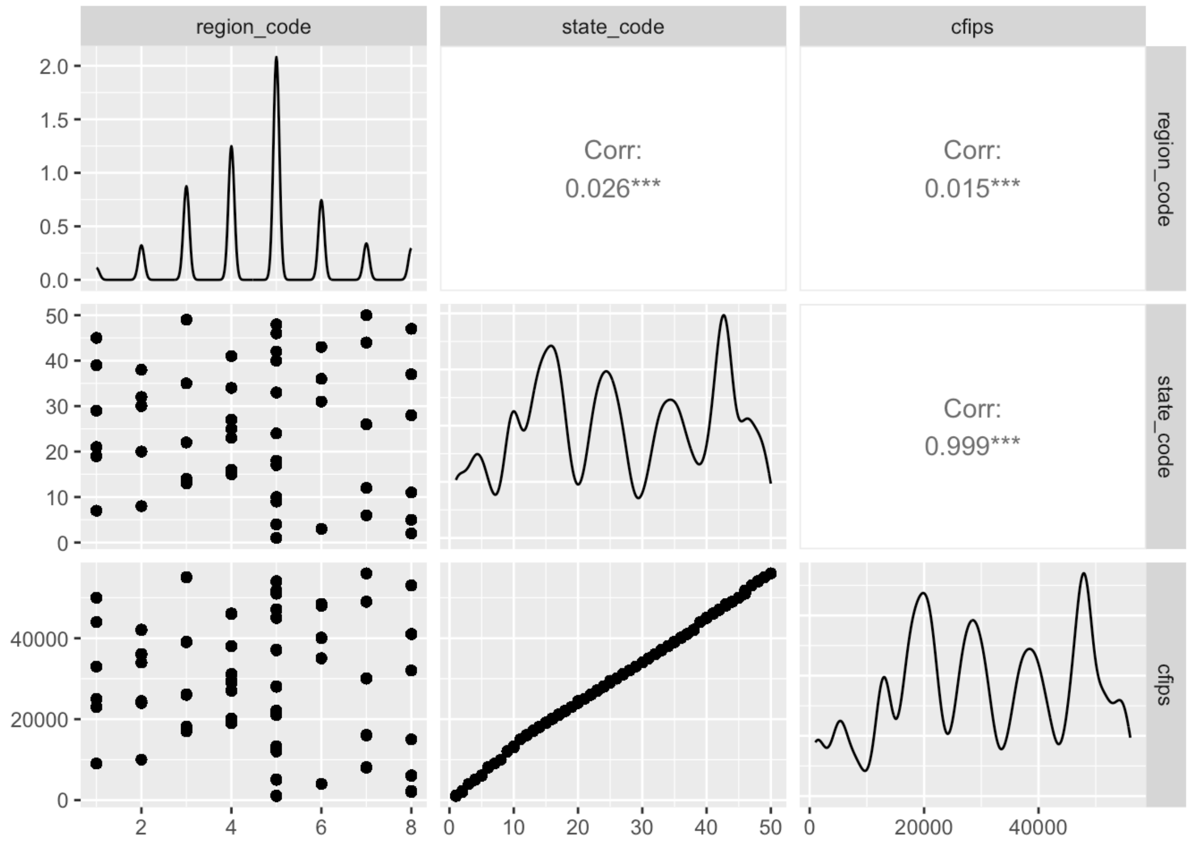
The results show that for each pair of columns, the p-value is less than the significance level of 0.05, which means that we reject the null hypothesis that the median difference between the two columns is zero. Instead, we conclude that there is a statistically significant difference between the two columns.

The results suggest that there is evidence to support the hypothesis that the population median of each column is different from the population median of microbusiness_density.

kernel regression

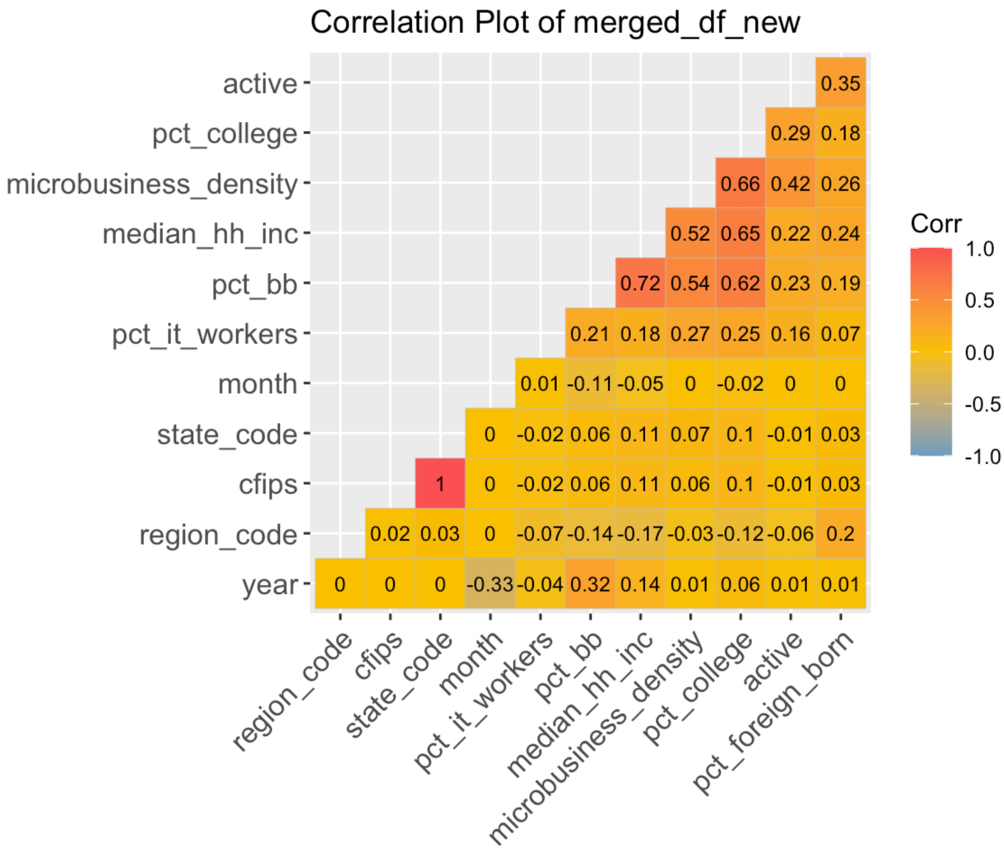
```
# create a vector of region names and their corresponding codes
region_codes <- c("new england" = 1,
                  "mideast" = 2,
                  "great lakes" = 3,
                  "plains" = 4,
                  "southeast" = 5,
                  "southwest" = 6,
                  "rocky mountain" = 7,
                  "far west" = 8)

# use the `match()` function to find the region code for each row in `merged_df_new
$region`
merged_df_new$region_code <- match(merged_df_new$region, names(region_codes))
merged_df_clean$region_code <- match(merged_df_clean$region, names(region_codes))



# create a vector of state names and their corresponding codes
state_codes <- sort(unique(merged_df_new$state))
state_codes <- setNames(1:length(state_codes), state_codes)

# use the `match()` function to find the state code for each row in `merged_df_new$
state`
merged_df_new$state_code <- match(merged_df_new$state, names(state_codes))

state_codes <- sort(unique(merged_df_clean$state))
state_codes <- setNames(1:length(state_codes), state_codes)
```

```
merged_df_clean$state_code <- match(merged_df_clean$state, names(state_codes))

# print head of the updated dataframe
head(merged_df_new)
##            row_id cfips         county   state first_day_of_month
## 1 1001_2019-08-01  1001 autauga county alabama         2019-08-01
## 2 1001_2019-09-01  1001 autauga county alabama         2019-09-01
## 3 1001_2019-10-01  1001 autauga county alabama         2019-10-01
## 4 1001_2019-11-01  1001 autauga county alabama         2019-11-01
## 5 1001_2019-12-01  1001 autauga county alabama         2019-12-01
## 6 1001_2020-01-01  1001 autauga county alabama         2020-01-01
##   microbusiness_density active year_month year month pct_bb pct_college
## 1              3.007682   1249    2019-08 2019     8   76.6        14.5
## 2              2.884870   1198    2019-09 2019     9   76.6        14.5
## 3              3.055843   1269    2019-10 2019    10   76.6        14.5
## 4              2.993233   1243    2019-11 2019    11   76.6        14.5
## 5              2.993233   1243    2019-12 2019    12   76.6        14.5
## 6              2.969090   1242    2020-01 2020     1   78.9        15.9
##   pct_foreign_born pct_it_workers median_hh_inc    region region_code
## 1              2.1            1.3         55317 southeast           5
## 2              2.1            1.3         55317 southeast           5
## 3              2.1            1.3         55317 southeast           5
## 4              2.1            1.3         55317 southeast           5
## 5              2.1            1.3         55317 southeast           5
## 6              2.0            1.1         58786 southeast           5
##   state_code
## 1          1
## 2          1
## 3          1
## 4          1
## 5          1
## 6          1
merged_df_new |>
  GGally::ggpairs(columns = c(17,18,2))
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
```



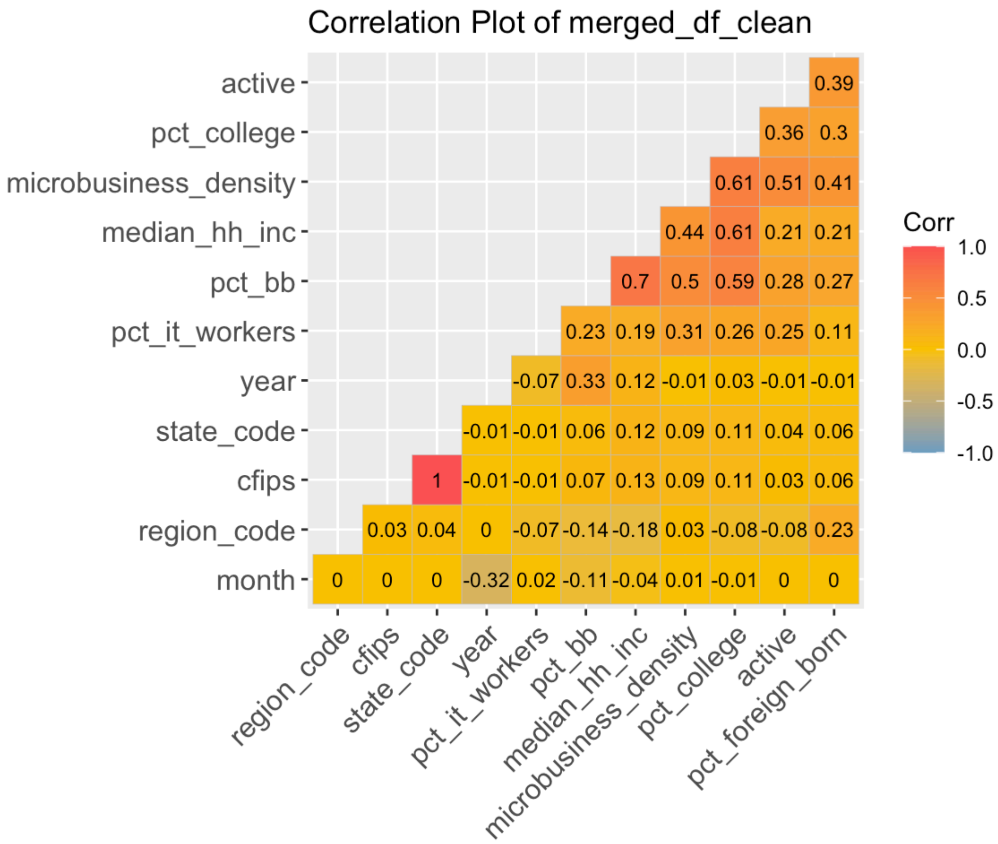

```
# Select the columns with numeric data
numeric_cols <- c("cfips", "state_code", "region_code", "microbusiness_density", "active", "year", "month", "pct_bb", "pct_college", "pct_foreign_born", "pct_it_workers", "median_hh_inc")


# Subset the dataframe with the selected columns
merged_df_numeric <- merged_df_new[, numeric_cols]


# Calculate the correlation matrix
cor_matrix <- cor(merged_df_numeric, use="pairwise.complete.obs")


# Plot the correlation matrix using ggcorrplot
ggcorrplot(cor_matrix,
           hc.order = TRUE,
           type = "lower",
           method = "square",
           lab = TRUE,
           lab_size = 3,
           title = "Correlation Plot of merged_df_new",
           colors = c("#6D9EC1", "#FAC200", "#FA5252"),
           ggtheme = ggplot2::theme_gray,
```

```
           show.legend = TRUE)
```




```
# Select the columns with numeric data

numeric_cols <- c("cfips", "state_code", "region_code", "microbusiness_density", "active", "year", "month", "pct_bb", "pct_college", "pct_foreign_born", "pct_it_workers", "median_hh_inc")


# Subset the dataframe with the selected columns

merged_df_numeric <- merged_df_clean[, numeric_cols]


# Calculate the correlation matrix

cor_matrix <- cor(merged_df_numeric, use="pairwise.complete.obs")


# Plot the correlation matrix using ggcorrplot

ggcorrplot(cor_matrix,

           hc.order = TRUE,

           type = "lower",

           method = "square",

           lab = TRUE,

           lab_size = 3,

           title = "Correlation Plot of merged_df_clean",

           colors = c("#6D9EC1", "#FAC200", "#FA5252"),
```

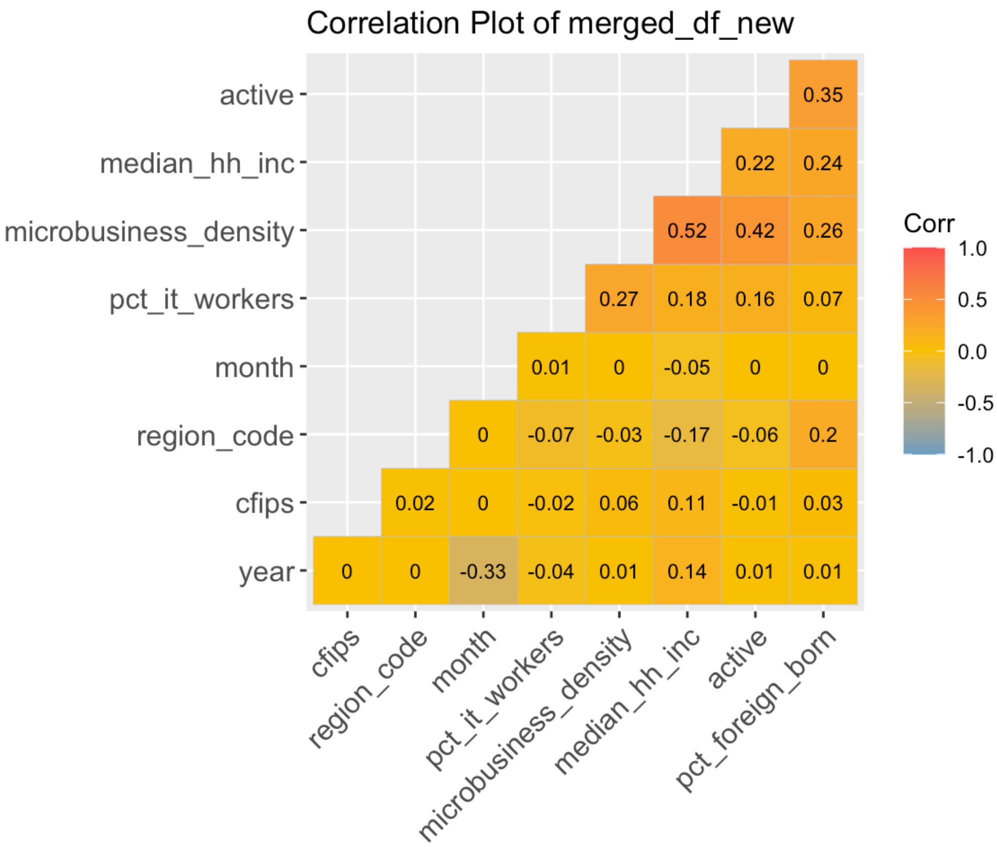
```
          ggtheme = ggplot2::theme_gray,
          show.legend = TRUE)
```



The `cfips` column and `state_code` have a completely positive correlation. So, we will remove the redundant feature `state_code`. Also, `pct_bb` strongly correlates with `median_hh_inc` and `pct_college`. Also, `pct_college` strongly correlates with `microbusiness_density`, `median_hh_inc` and `pct_bb`. As features with moderate strong and strong correlation are redundant, we will remove these features (`pct_bb` and `pct_college`) before further analysis. Now, we draw the new correlation plot.

```
# Select the columns with numeric data (not including "state_code", "pct_bb", "pct_
college")

numeric_cols <- c("cfips",  "region_code", "microbusiness_density", "active", "year
", "month", "pct_foreign_born", "pct_it_workers", "median_hh_inc")


# Subset the dataframe with the selected columns

merged_df_numeric <- merged_df_new[, numeric_cols]


# Calculate the correlation matrix

cor_matrix <- cor(merged_df_numeric, use="pairwise.complete.obs")


# Plot the correlation matrix using ggcorrplot

ggcorrplot(cor_matrix,
          hc.order = TRUE,
```

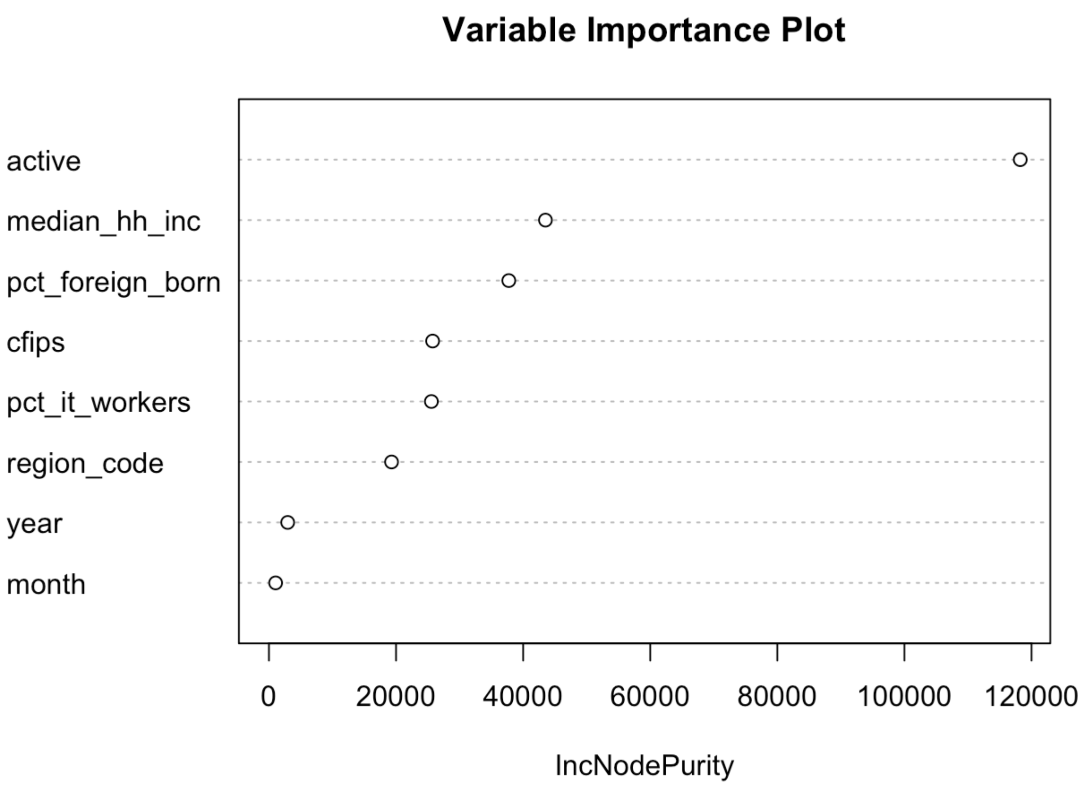
```
           type = "lower",
           method = "square",
           lab = TRUE,
           lab_size = 3,
           title = "Correlation Plot of merged_df_new",
           colors = c("#6D9EC1", "#FAC200", "#FA5252"),
           ggtheme = ggplot2::theme_gray,
           show.legend = TRUE)
```



3.10. Feature Importance Using Random Forest

```
# Split the dataset into training and testing sets
set.seed(92) # for reproducibility
train_index <- sample(nrow(merged_df_new), 0.7 * nrow(merged_df_new))
train_data <- merged_df_new[train_index, ]
test_data <- merged_df_new[-train_index, ]

# Build the random forest model
```

```
model <- randomForest(microbusiness_density ~ cfips + region_code + active + year +
month + pct_foreign_born + pct_it_workers + median_hh_inc,
                      data = train_data)

# Make predictions on the test set
predictions <- predict(model, test_data)

# Check the accuracy of the model
# accuracy <- sum(predictions == test_data$microbusiness_density) / nrow(test_data)
# cat("Accuracy:", accuracy, "\n")

# Plot the variable importance
varImpPlot(model, main = "Variable Importance Plot")
```



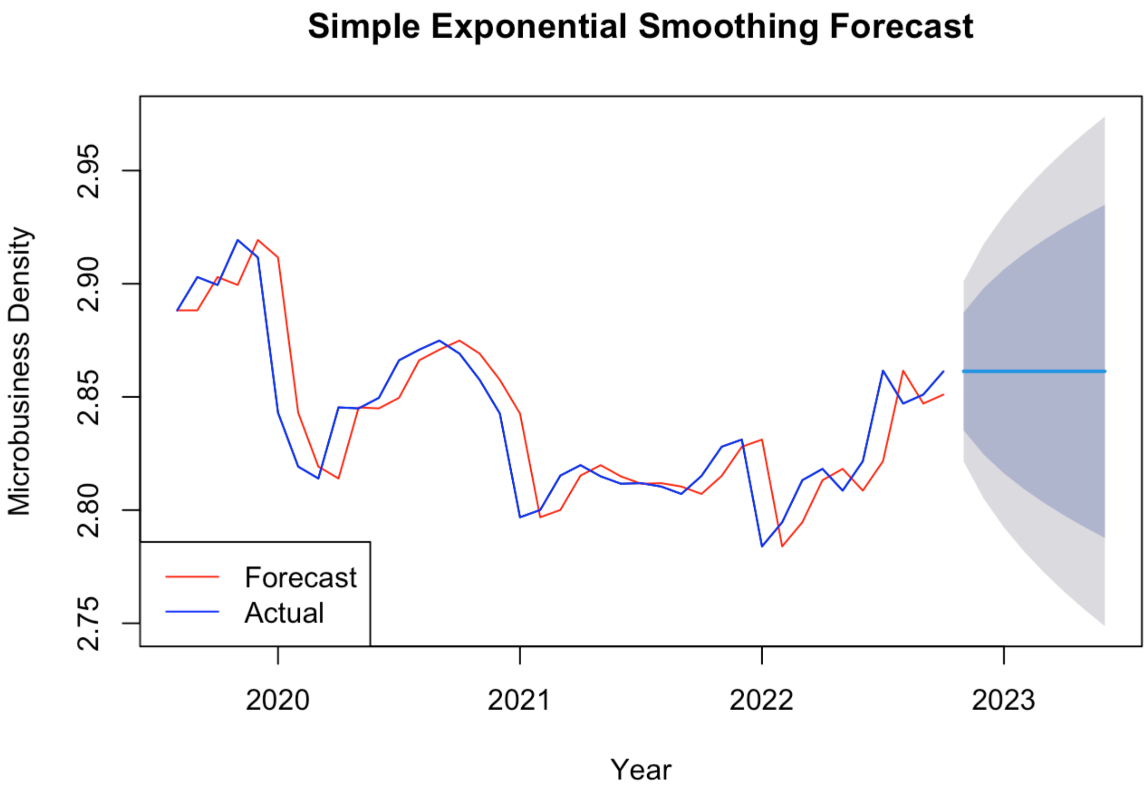
```
# Load revealed_test.csv into a dataframe
revealed_test_df <- read.csv("./datasets/revealed_test.csv")

# Change first_day_of_month format in "revealed_test_df" to Date
revealed_test_df$first_day_of_month <- as.Date(revealed_test_df$first_day_of_month)
```

4. Time Series Forecasting

4.1 Exponential Forecasting

Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. In other words, the more recent the observation the higher the associated weight. This framework generates reliable forecasts quickly and for a wide range of time series, which is a great advantage and of major importance to applications in industry. ### 4.1.1. Simple Exponential Smoothing Forecast Exponential smoothing is a general technique for smoothing time series data by giving more weight to recent observations. The simplest of the exponentially smoothing methods is naturally called simple exponential smoothing (SES). This method is suitable for forecasting data with no clear trend or seasonal pattern. (There is a grow in the last few years, which might suggest a trend. We will consider whether a trended method would be better for this series later.)

```
# Select relevant predictor columns
# predictors <- merged_df_new[, c("microbusiness_density", "cfips")]

merged_df_ts <- merged_df_clean %>%
  group_by(first_day_of_month) %>%
  summarise(microbusiness_density = mean(microbusiness_density))

# Convert data to time series format
ts_data <- ts(merged_df_ts$microbusiness_density, start = c(2019, 8), frequency = 1
2)
# fit a simple exponential smoothing model to the time series data
fit <- ets(ts_data, model = "ANN")



# generate forecasts for the time series data using the fitted model
forecast_values <- forecast::forecast(fit, h = 8)
plot(forecast_values, main = "Simple Exponential Smoothing Forecast", xlab = "Year"
, ylab = "Microbusiness Density")
lines(forecast_values$fitted, col = "red")
lines(ts_data, col = "blue")
legend("bottomleft", legend = c("Forecast", "Actual"), col = c("red", "blue"), lty
= 1)
```



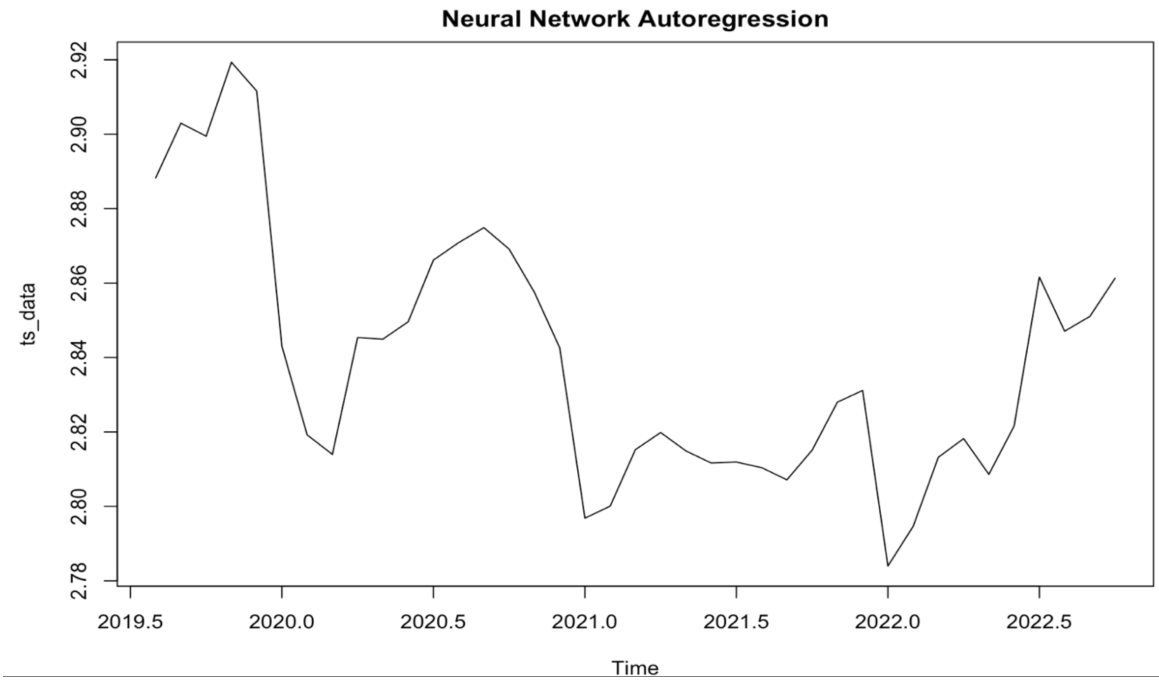
The forecasts for the period 11/2022 to 06/2023 are plotted in above. Also, plotted are one-step-ahead fitted values alongside the data over the period 08/2019 to 10/2022.

```
# Split data into training and testing sets
train_data <- window(ts_data, end = c(2022, 2))
test_data <- window(ts_data, start = c(2022, 3))


# Train neural network autoregression model
nnetar_model <- nnetar(ts_data)


# Make forecasts using the trained model
forecast_data <- forecast::forecast(nnetar_model, h = length(test_data))
# Convert data to time series format
ts_data <- ts(merged_df_ts$microbusiness_density, start = c(2019, 8), frequency = 1
2)


# Split data into training and testing sets
train_data <- window(ts_data, end = c(2022, 2))
test_data <- window(ts_data, start = c(2022, 3))


# Fit a neural network autoregression model with error("A"), trend("N"), season("N"
) preferences
```

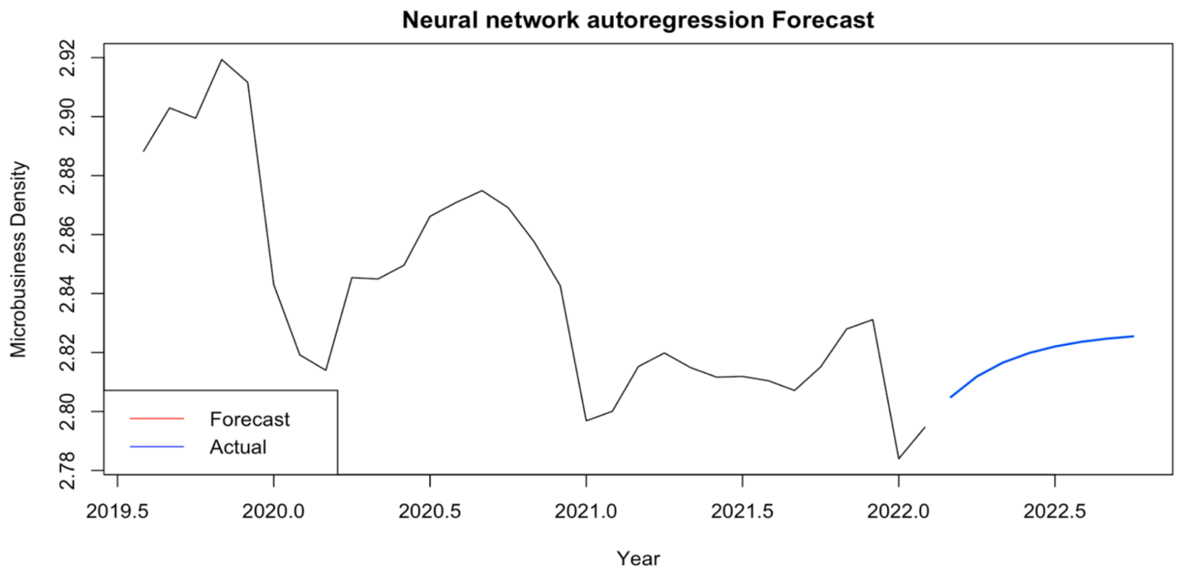
```
nnetar_model <- nnetar(train_data, lambda = 0, P = 12, size = 10, repeats = 10,
                       decay = 0.5, maxit = 1000, trace = TRUE,
                       entropy = FALSE, parallel = FALSE, xreg = NULL)
## # weights:  41
## initial  value 21.283645
## iter  10 value 11.004232
## iter  20 value 10.950528
## iter  30 value 10.940432
## iter  40 value 10.939499
## final  value 10.939493
## converged
## # weights:  41
## initial  value 59.692453
## iter  10 value 11.964849
## iter  20 value 10.974613
## iter  30 value 10.949670
## iter  40 value 10.945596
## iter  50 value 10.941198
## iter  60 value 10.939534
## final  value 10.939493
## converged
## # weights:  41
## initial  value 70.392818
## iter  10 value 11.771520
## iter  20 value 10.980551
## iter  30 value 10.943868
## iter  40 value 10.939699
## iter  50 value 10.939518
## final  value 10.939493
## converged
## # weights:  41
## initial  value 26.849765
## iter  10 value 10.989322
## iter  20 value 10.955714
## iter  30 value 10.951777
## iter  40 value 10.951562
## final  value 10.951541
## converged
## # weights:  41
```

```
## initial  value 32.025911
## iter  10 value 11.050677
## iter  20 value 10.979900
## iter  30 value 10.942657
## iter  40 value 10.939626
## iter  50 value 10.939493
## final  value 10.939493
## converged
## # weights:  41
## initial  value 42.111868
## iter  10 value 11.083042
## iter  20 value 10.953153
## iter  30 value 10.951628
## iter  40 value 10.951561
## iter  50 value 10.951540
## iter  50 value 10.951540
## iter  50 value 10.951540
## final  value 10.951540
## converged
## # weights:  41
## initial  value 51.452718
## iter  10 value 13.681090
## iter  20 value 10.979947
## iter  30 value 10.958008
## iter  40 value 10.954194
## iter  50 value 10.952654
## iter  60 value 10.951666
## iter  70 value 10.951540
## iter  70 value 10.951540
## iter  70 value 10.951540
## final  value 10.951540
## converged
## # weights:  41
## initial  value 38.123377
## iter  10 value 11.066611
## iter  20 value 10.957299
## iter  30 value 10.951926
## iter  40 value 10.951545
## final  value 10.951540
```

```
## converged
## # weights:  41
## initial  value 33.945638
## iter  10 value 11.005029
## iter  20 value 10.957049
## iter  30 value 10.951637
## iter  40 value 10.951559
## iter  50 value 10.951540
## final  value 10.951540
## converged
## # weights:  41
## initial  value 53.766483
## iter  10 value 12.197989
## iter  20 value 10.958533
## iter  30 value 10.943320
## iter  40 value 10.941039
## iter  50 value 10.939557
## iter  60 value 10.939496
## final  value 10.939493
## converged
# Make predictions using the fitted model
nnetar_fc <- forecast::forecast(nnetar_model, h = length(test_data))

# Print the forecasted values
print(nnetar_fc$mean)
##           Mar      Apr      May      Jun      Jul      Aug      Sep      Oct
## 2022 2.804899 2.811903 2.816620 2.819850 2.822088 2.823652 2.824751 2.825525
# Plot actual and predicted values for comparison
plot(ts_data, type = "l", main = "Neural Network Autoregression")
#lines(nnetar_fc$mean, col = "blue")
legend("topleft", legend = c("Actual", "Predicted"), col = c("black", "blue"), lty
= 1)
```




```
# Calculate accuracy measures
forecast::accuracy(nnetar_fc$mean, test_data)
##                   ME       RMSE       MAE       MPE      MAPE      ACF1
## Test set 0.01666848 0.02306722 0.0186722 0.5839484 0.6552904 0.3798398
##          Theil's U
## Test set  1.367118
# Calculate forecast errors
nnetar_errors <- test_data - nnetar_fc$mean
mean(nnetar_errors)
## [1] 0.01666848
sd(nnetar_errors)
## [1] 0.01704644
plot(nnetar_fc, main = "Neural network autoregression Forecast", xlab = "Year", yla
b = "Microbusiness Density")
lines(nnetar_fc$mean, col = "red")
#lines(ts_data, col = "blue")
legend("bottomleft", legend = c("Forecast", "Actual"), col = c("red", "blue"), lty
= 1)
```




```
# Plot forecasts and actual values
plot(forecast_data, main = "Neural Network Autoregression Forecasts")
lines(test_data, col = "blue")
```