

Final Project EDA

Fall 2025

```
libraries <- read_csv("../data/libraries.csv")

## Rows: 6832 Columns: 28
## -- Column specification -----
## Delimiter: ","
## chr (2): state, Locale
## dbl (26): Service Area Population, Total Circulation, Percentage of Children...
##
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.

numeric_libraries <- libraries %>%
  select(where(is.numeric))
full_correlation_matrix <- cor(numeric_libraries)
```

Looking at the correlation plot, we see that there are many variables, with some of them having very little correlation to our variable of interest, Total Circulation. Let's drop some.

```
y_cor_matrix<- full_correlation_matrix[, "Total Circulation", drop = FALSE]
y_cor_matrix[order(abs(y_cor_matrix[, 1]), decreasing = TRUE), , drop = FALSE]
```

##	Total Circulation
## Total Circulation	1.00000000
## Physical Visits	0.89025206
## Local Revenue (\$)	0.85594139
## Hours/Year	0.83766165
## Service Area Population	0.81046353
## Registered Users	0.78177823
## Branch Library	0.77990997
## Internet Computers	0.71332256
## Children's Program Attendance	0.70207707
## Computer Uses	0.69813313
## Children's Programs	0.66688666
## Reference Transactions	0.62098179
## Young Adult Programs	0.56534446
## Adult Program Attendance	0.55176687
## Adult Programs	0.51878890
## State Revenue (\$)	0.49280567
## Federal Revenue (\$)	0.36914870
## Bookmobiles	0.36633538
## Other Revenue (\$)	0.32529456
## Central Library	-0.30214050
## General Interest Programs	0.28204319

## Inter-library Loans from Other Library	0.27570674
## General Interest Program Attendance	0.25989250
## Wireless Sessions	0.24455640
## Inter-library Loans to Other Library	0.24005347
## Percentage of Children's Material Circulation	0.04351038

There are too many variables for a simple correlation matrix, and looking at this list, it seems nearly all of the numeric variables have some correlation to Total Circulation.

However, this does not show us potential collinearity, for that we can fit a simple model and check the VIF:

```
model <- lm(`Total Circulation` ~ ., data = numeric_libraries)
vif(model)
```

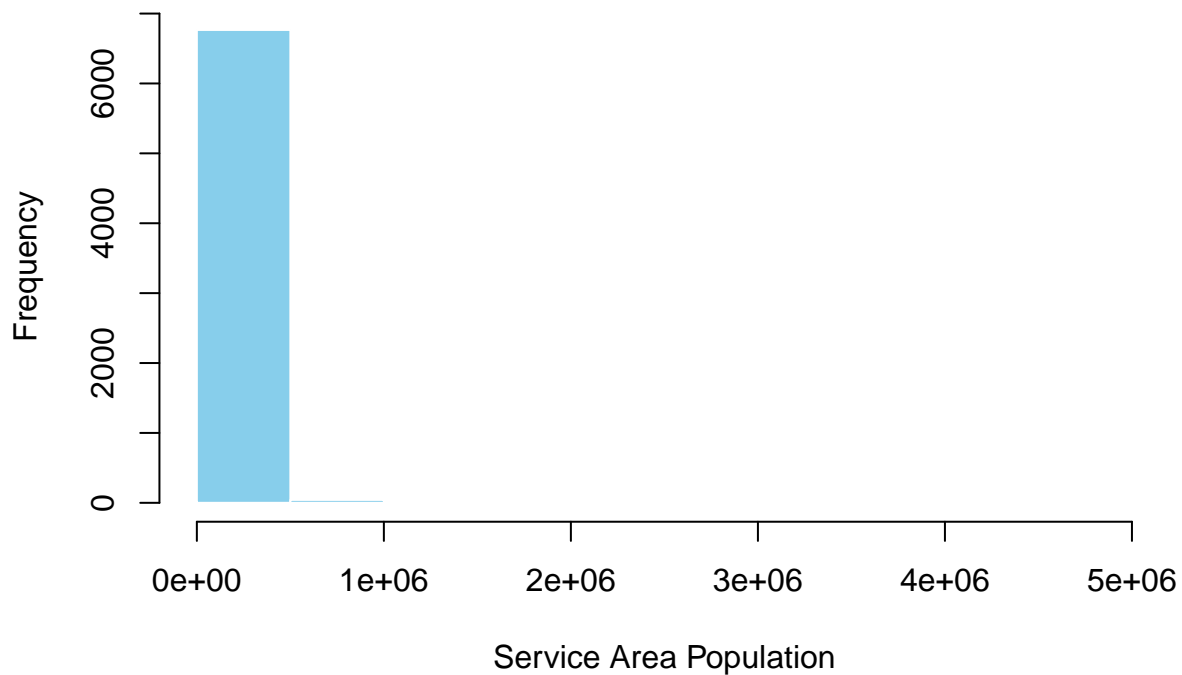
```
##           'Service Area Population'
##                6.594328
## 'Percentage of Children's Material Circulation'
##                1.034565
##           'Central Library'
##                1.183601
##           'Branch Library'
##                21.020578
##                Bookmobiles
##                1.278856
##           'Internet Computers'
##                4.810188
##           'Computer Uses'
##                2.862216
##           'Wireless Sessions'
##                1.088883
##           'Children's Programs'
##                11.928597
##           'Young Adult Programs'
##                6.529996
##           'Adult Programs'
##                11.766650
##           'Children's Program Attendance'
##                8.796485
##           'Adult Program Attendance'
##                6.874101
##           'General Interest Program Attendance'
##                1.681073
##           'General Interest Programs'
##                2.413284
##           'Local Revenue ($)'
##                7.826613
##           'State Revenue ($)'
##                1.711105
##           'Federal Revenue ($)'
##                1.745681
##           'Other Revenue ($)'
##                3.957116
##           'Hours/Year'
##                31.103517
```

```
##           'Physical Visits'
##           15.167099
##           'Reference Transactions'
##           4.545317
##           'Registered Users'
##           5.614272
##           'Inter-library Loans to Other Library'
##           5.856800
##           'Inter-library Loans from Other Library'
##           6.043276
```

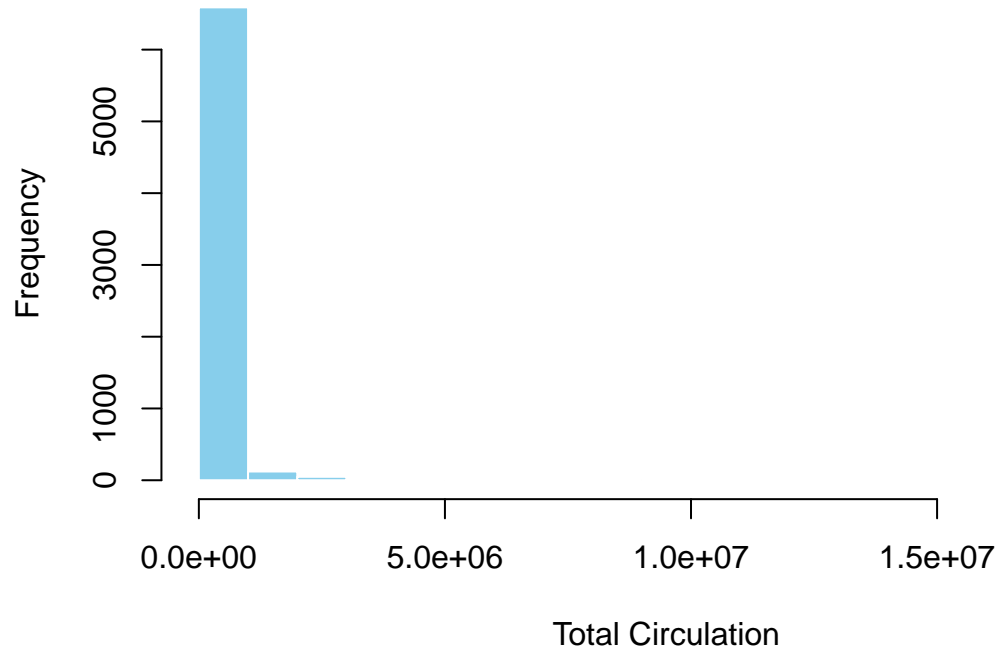
This shows that there is a generally high level of collinearity, and we should keep this in mind for the analysis.

```
for (col in names(numeric_libraries)) {
  hist(
    numeric_libraries[[col]],
    main = paste("Histogram of", col),
    xlab = col,
    col = "skyblue",
    border = "white"
  )
}
```

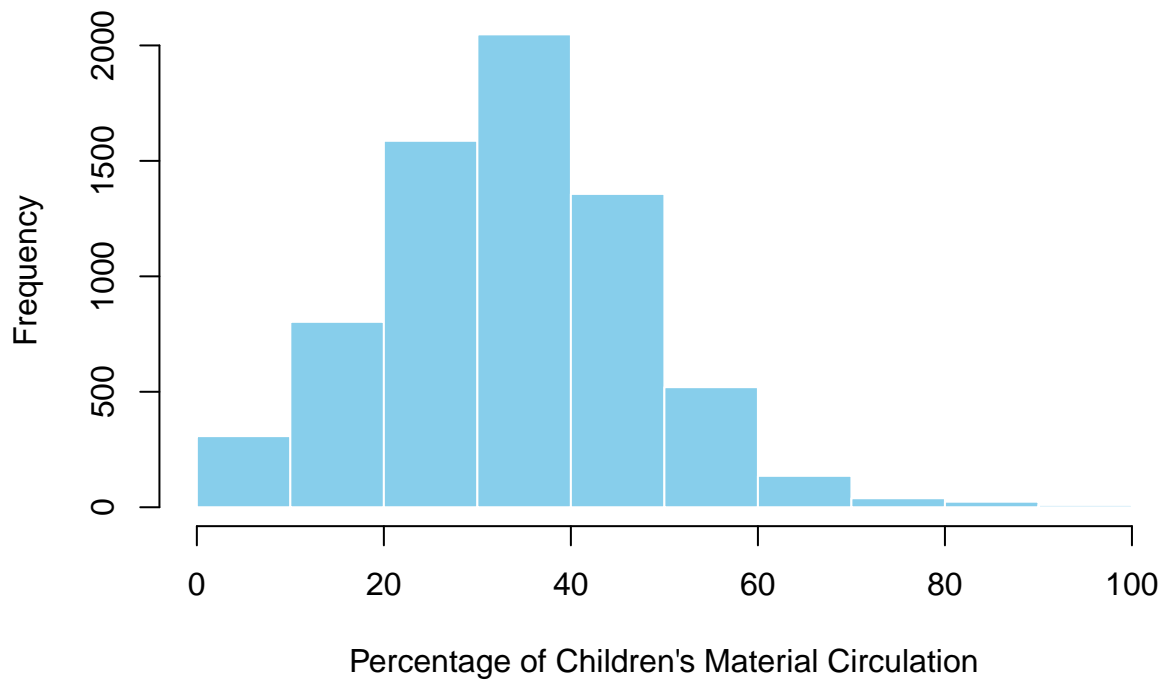
Histogram of Service Area Population



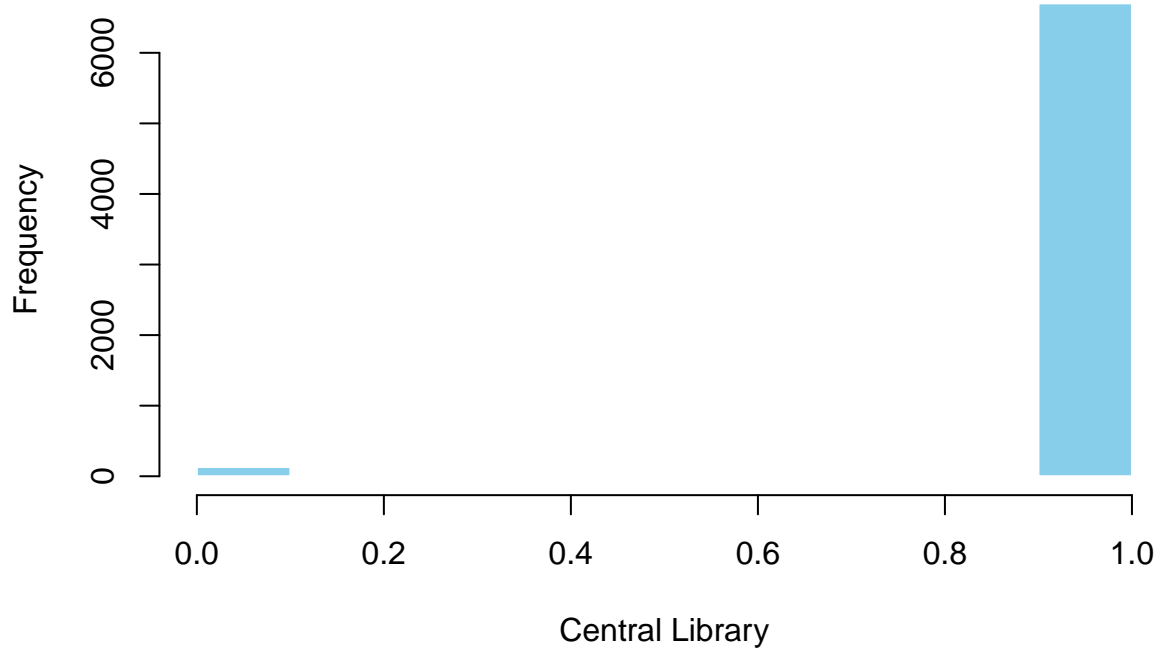
Histogram of Total Circulation



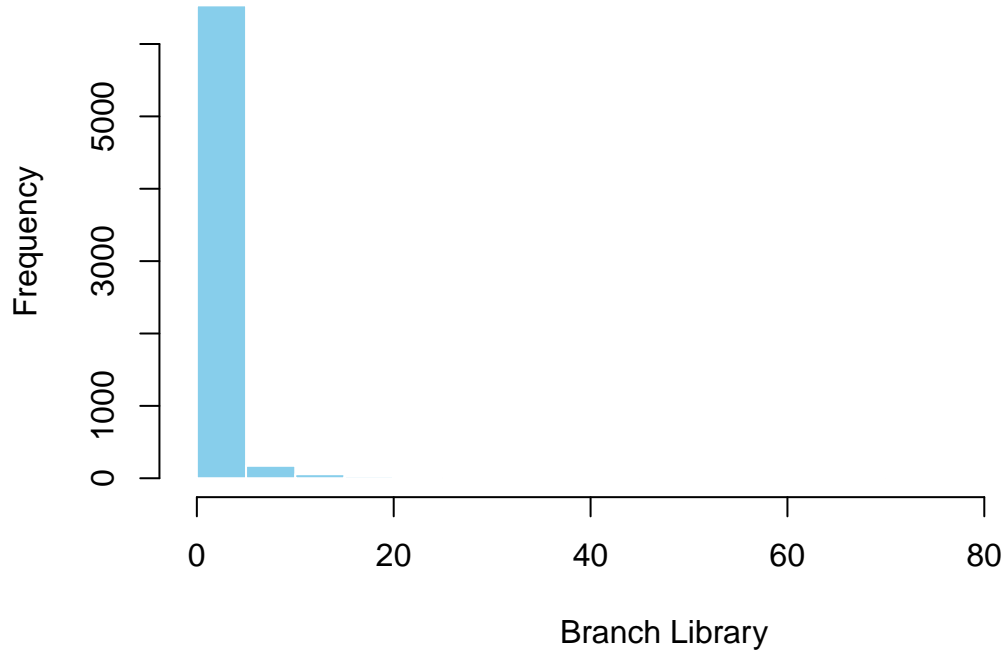
Histogram of Percentage of Children's Material Circulation



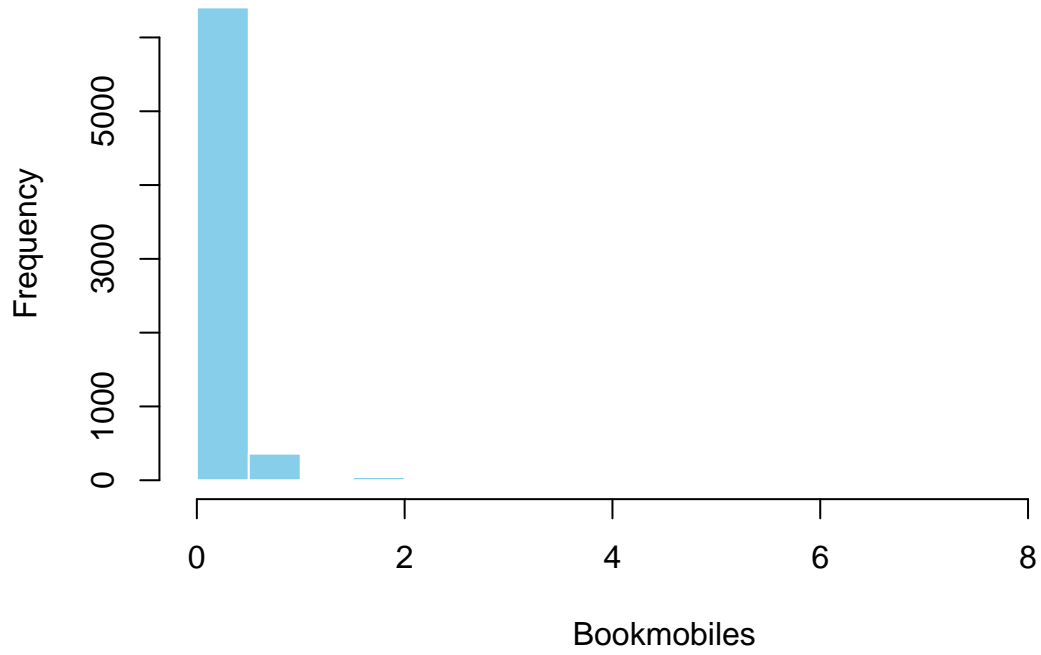
Histogram of Central Library



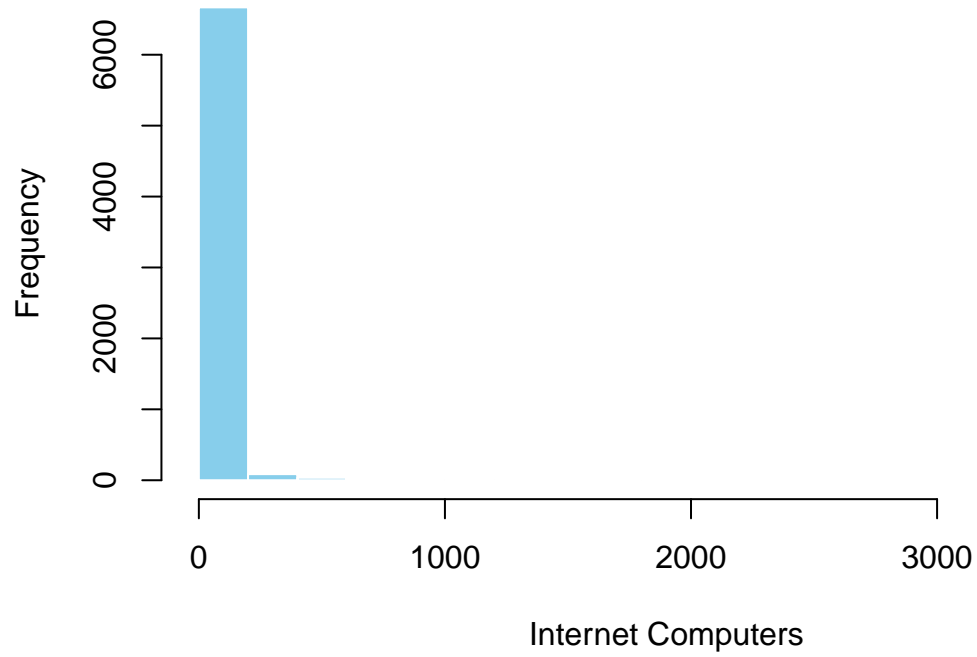
Histogram of Branch Library



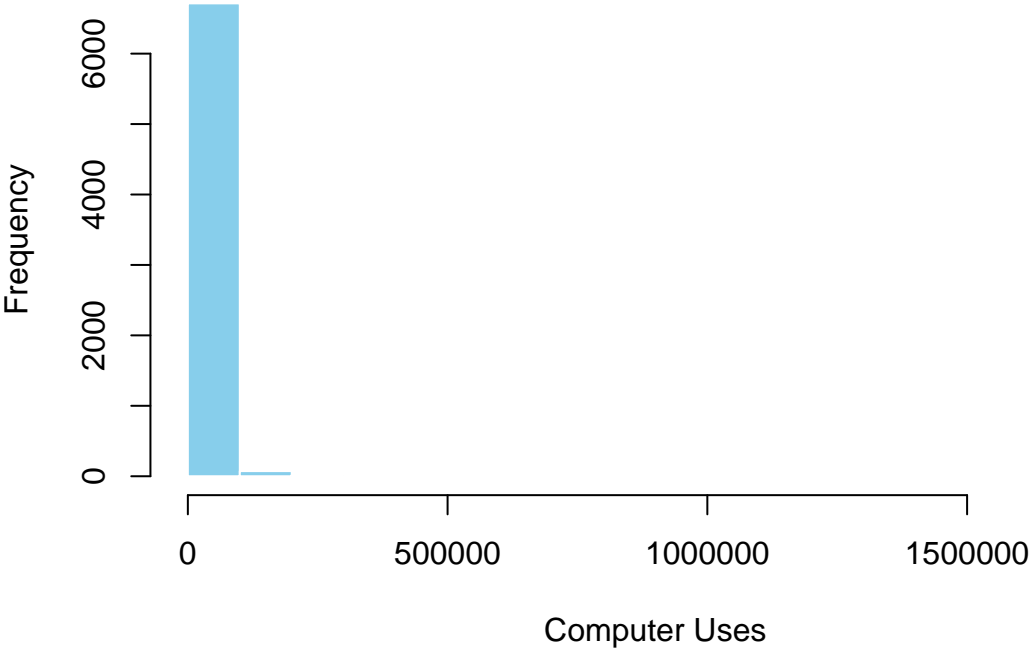
Histogram of Bookmobiles



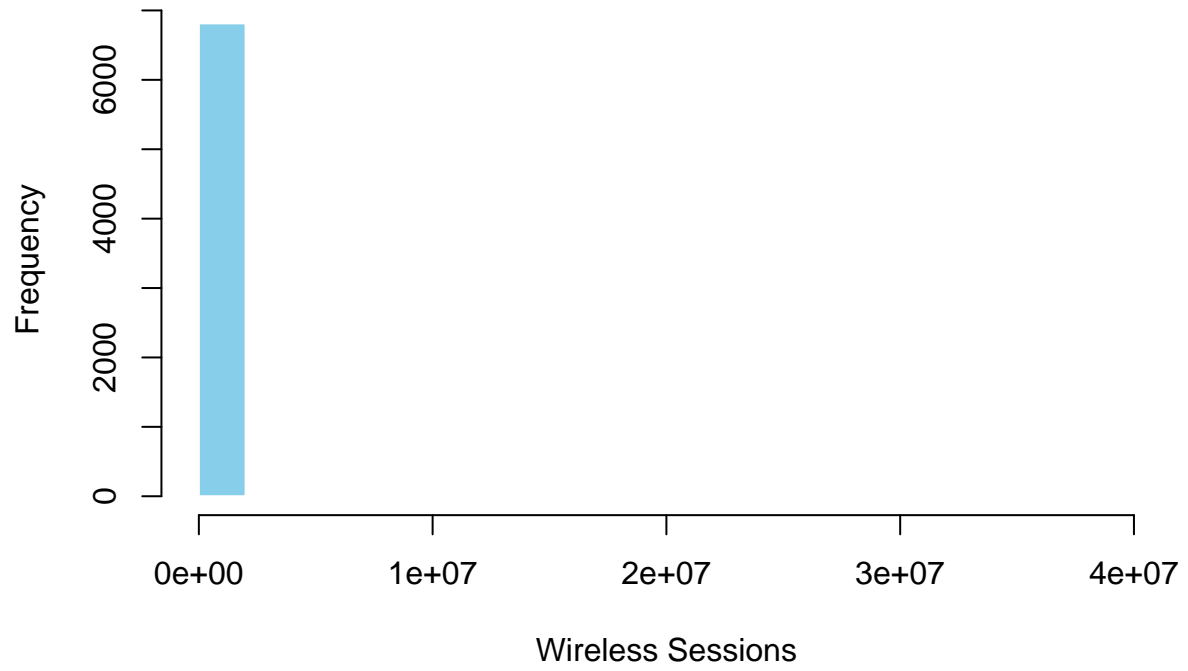
Histogram of Internet Computers



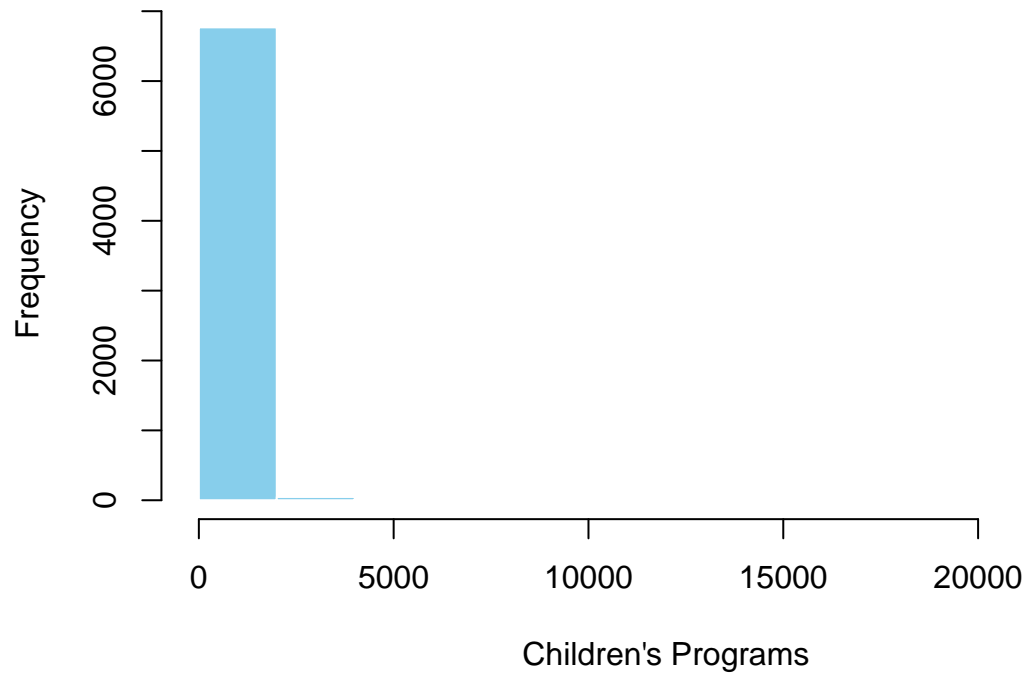
Histogram of Computer Uses



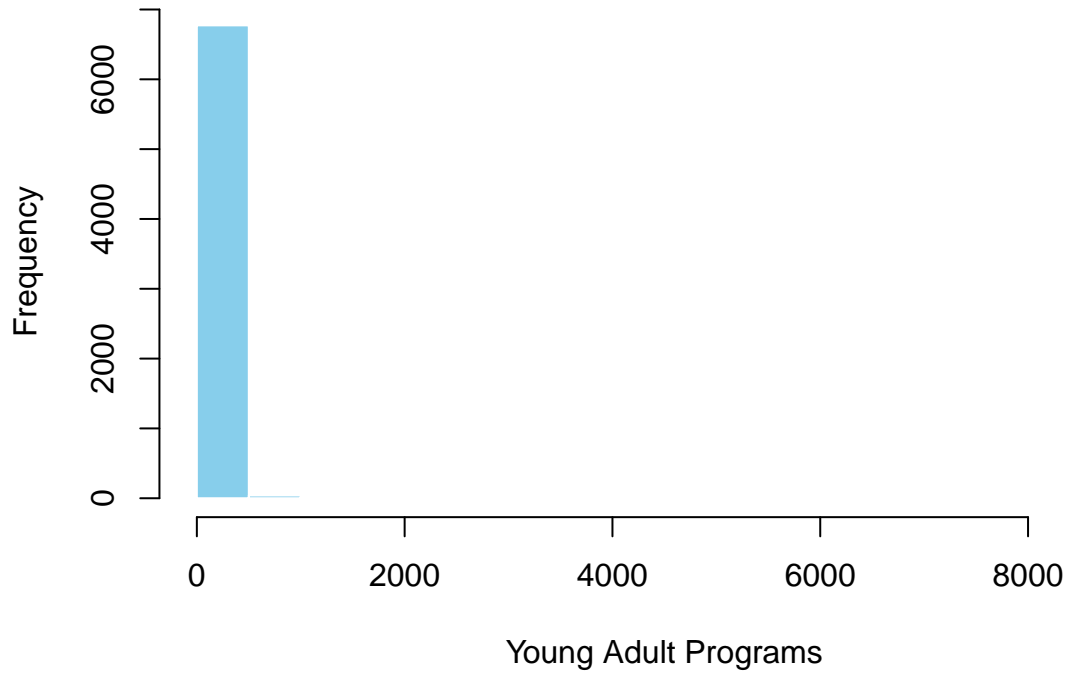
Histogram of Wireless Sessions



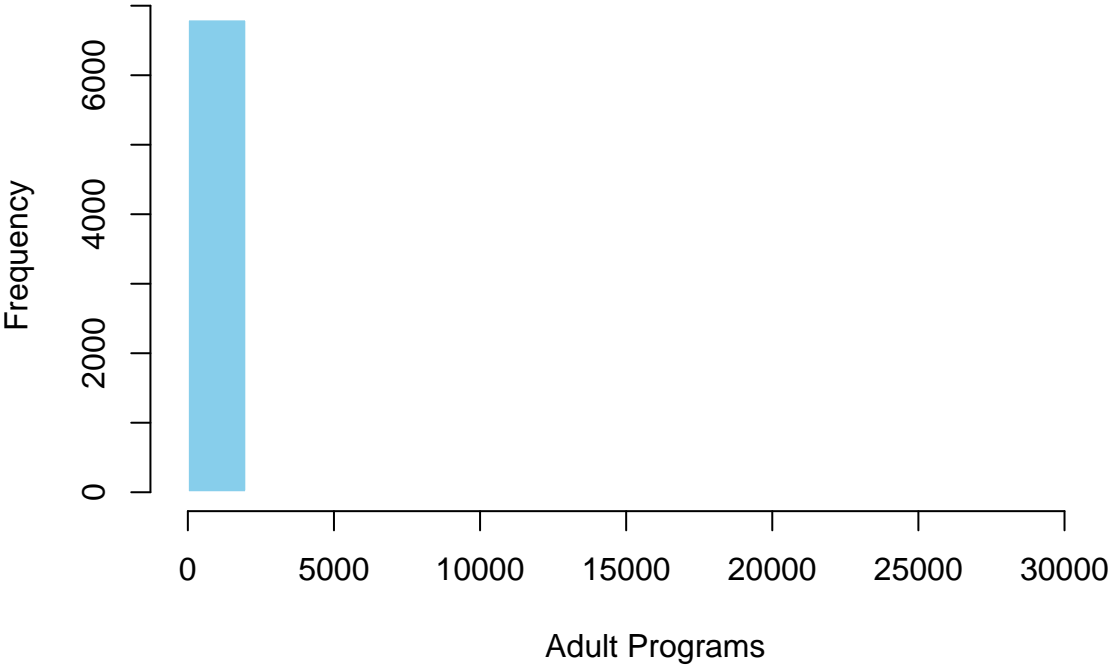
Histogram of Children's Programs



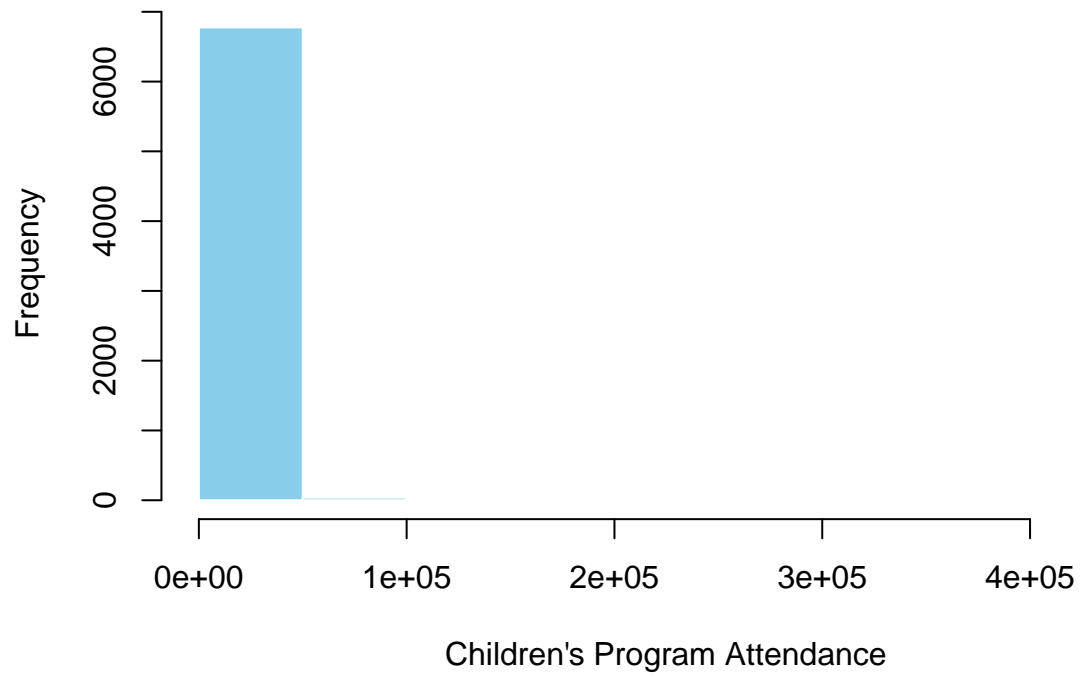
Histogram of Young Adult Programs

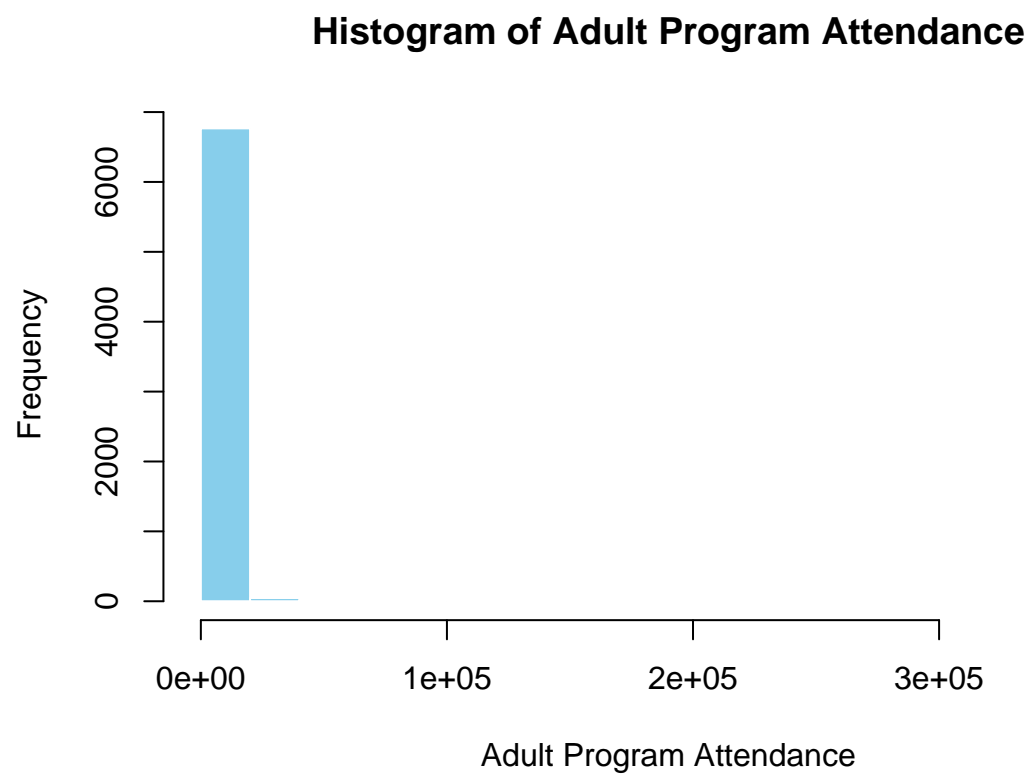


Histogram of Adult Programs

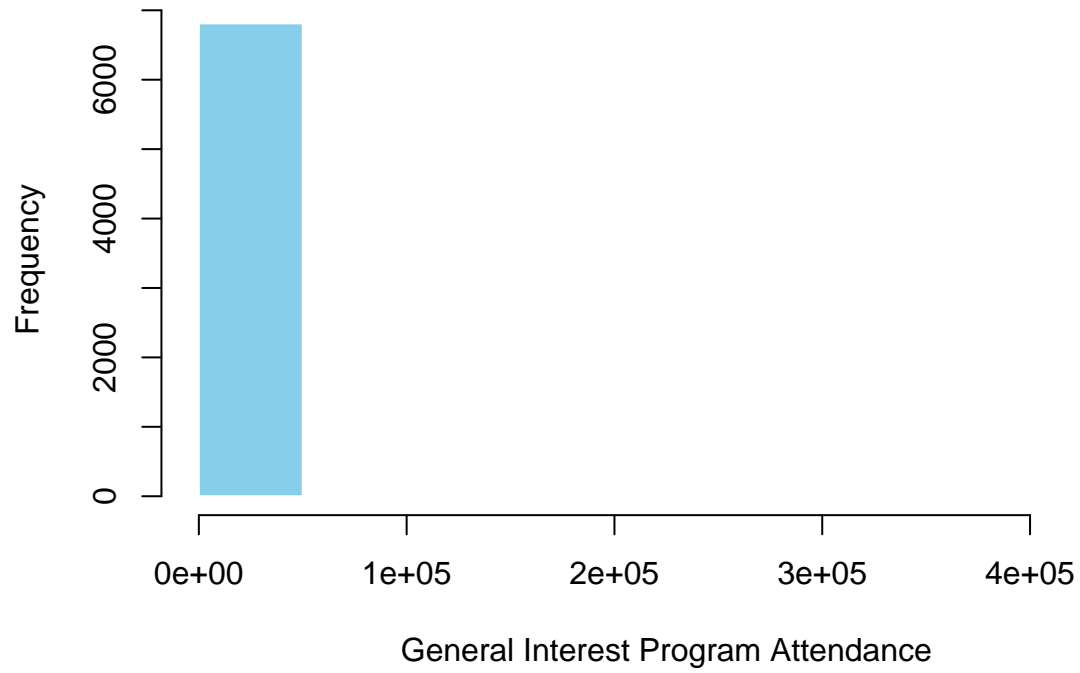


Histogram of Children's Program Attendance

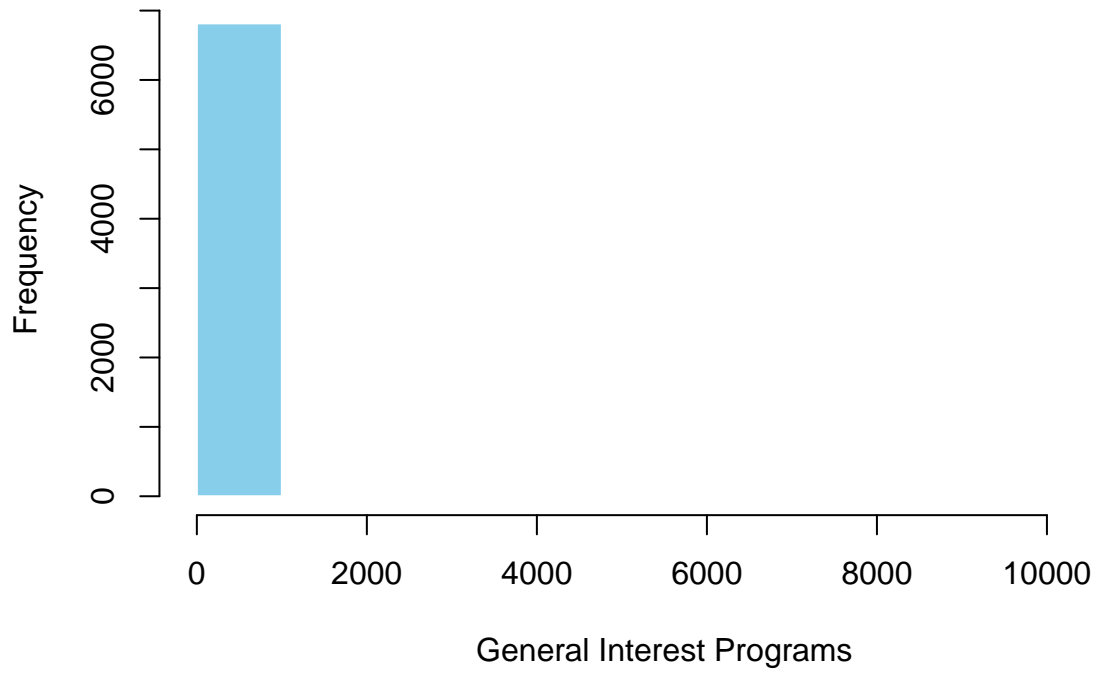




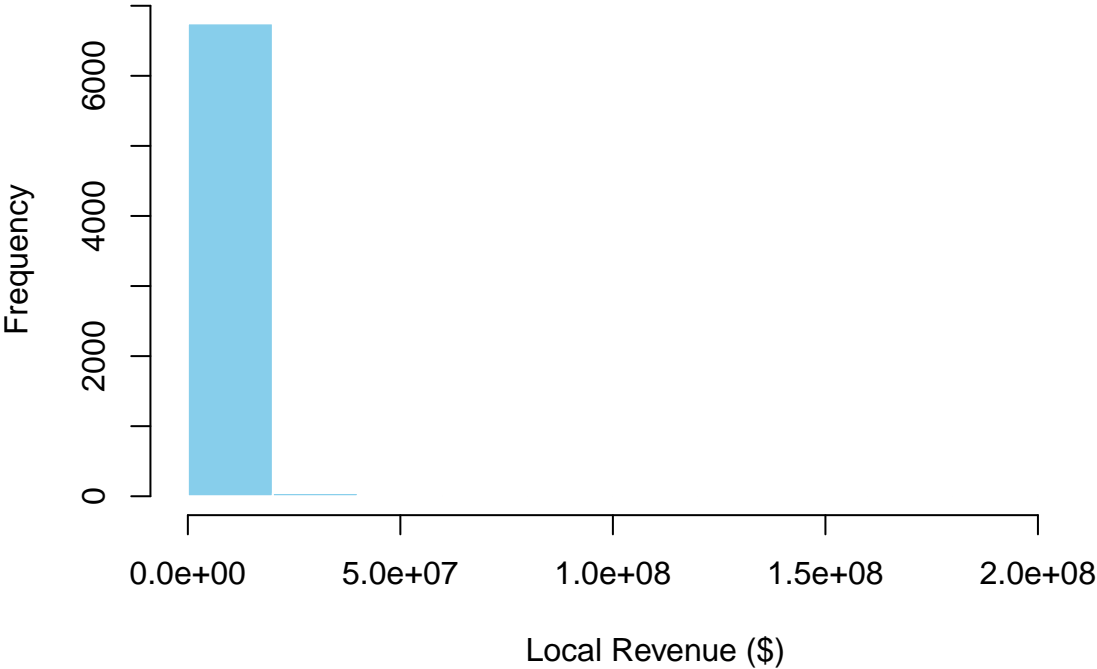
Histogram of General Interest Program Attendance



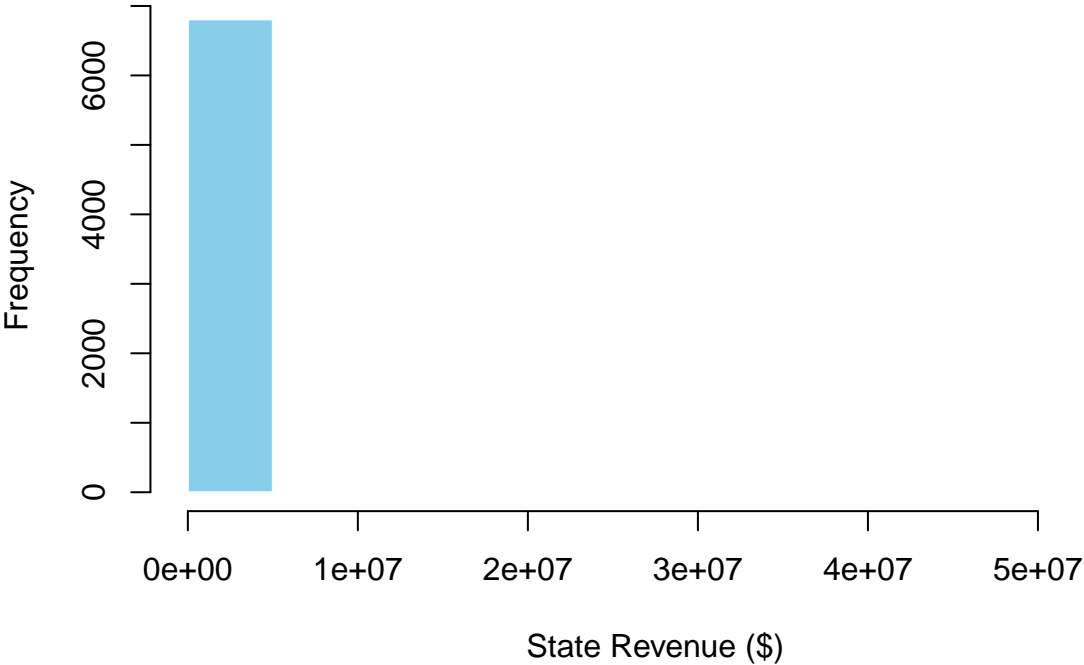
Histogram of General Interest Programs



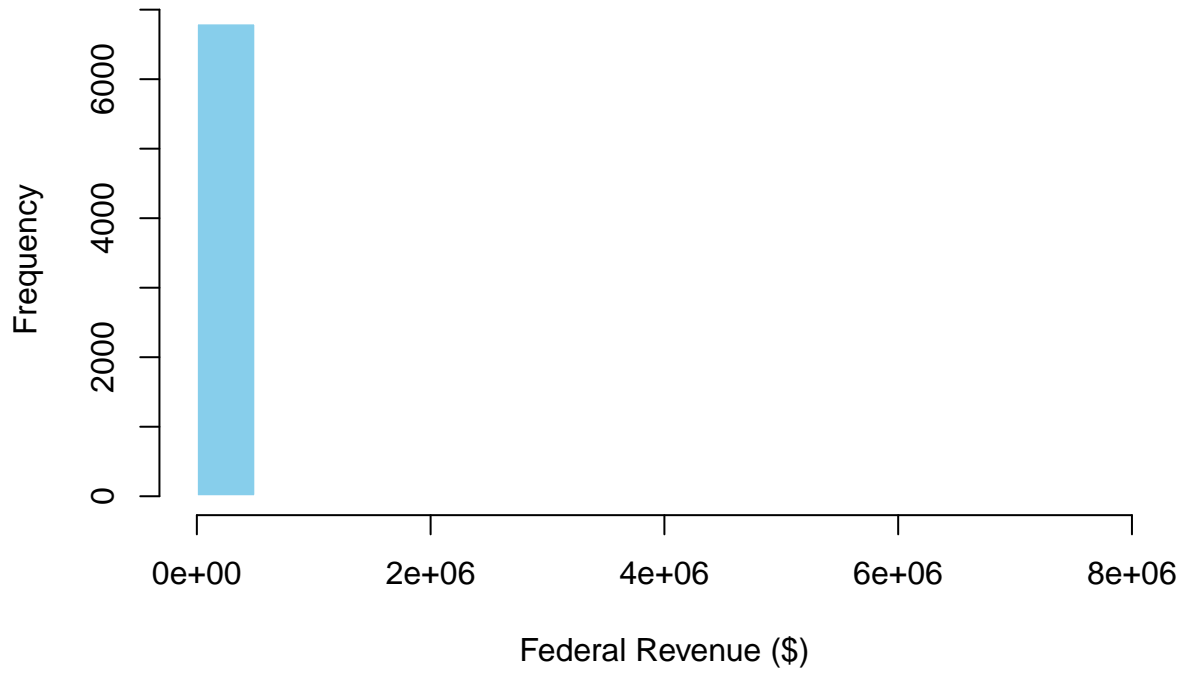
Histogram of Local Revenue (\$)



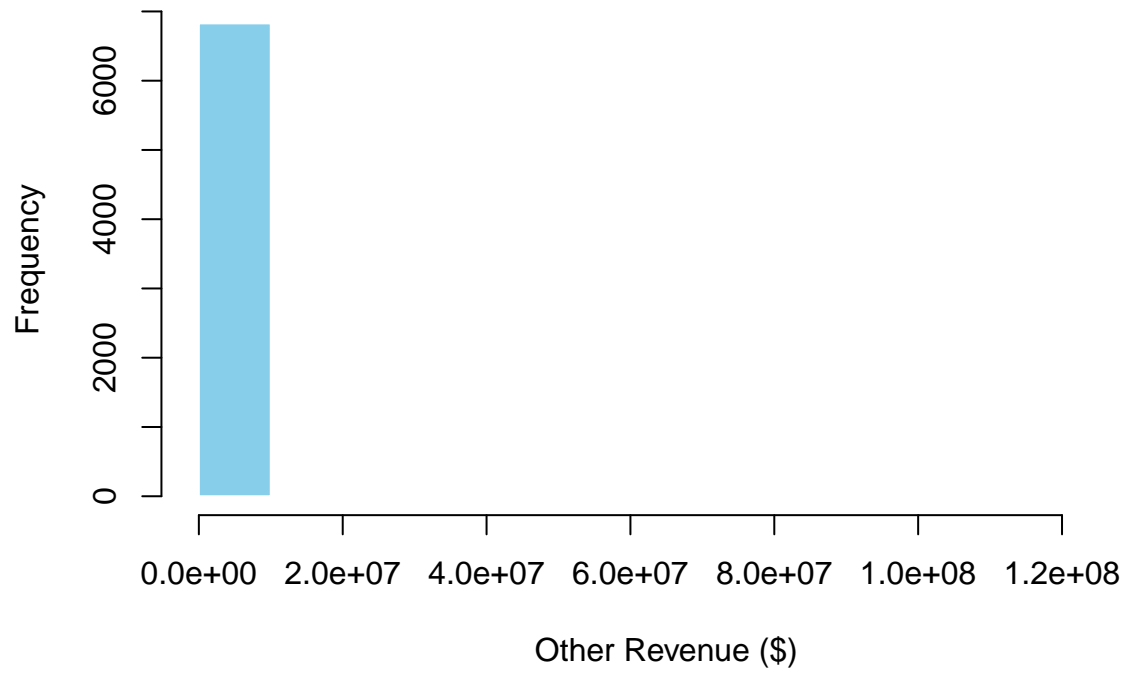
Histogram of State Revenue (\$)



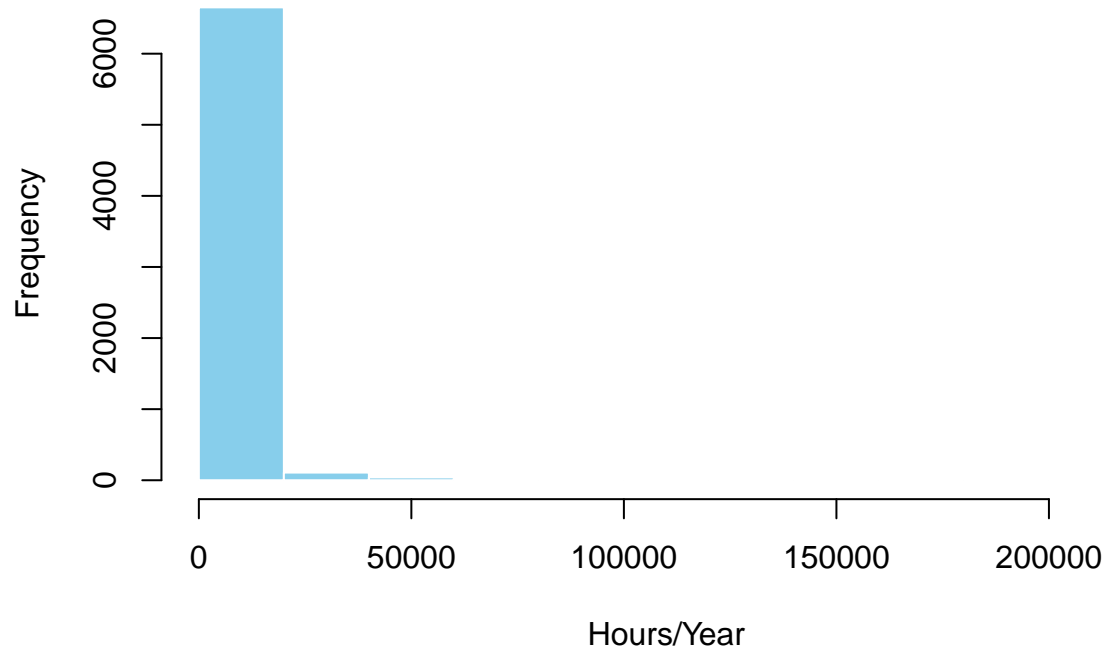
Histogram of Federal Revenue (\$)



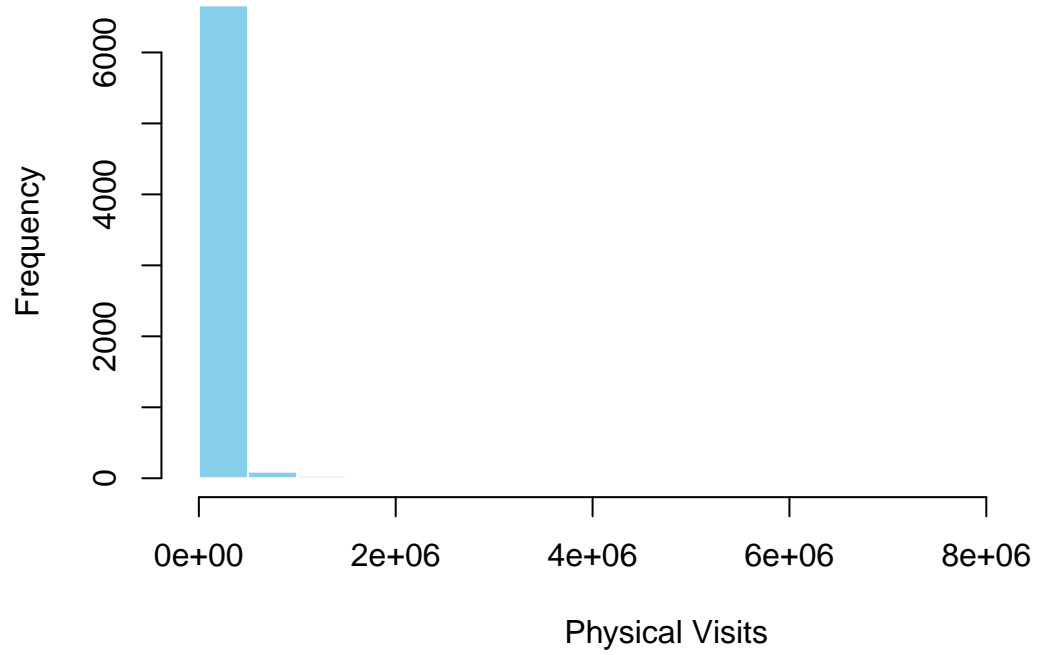
Histogram of Other Revenue (\$)



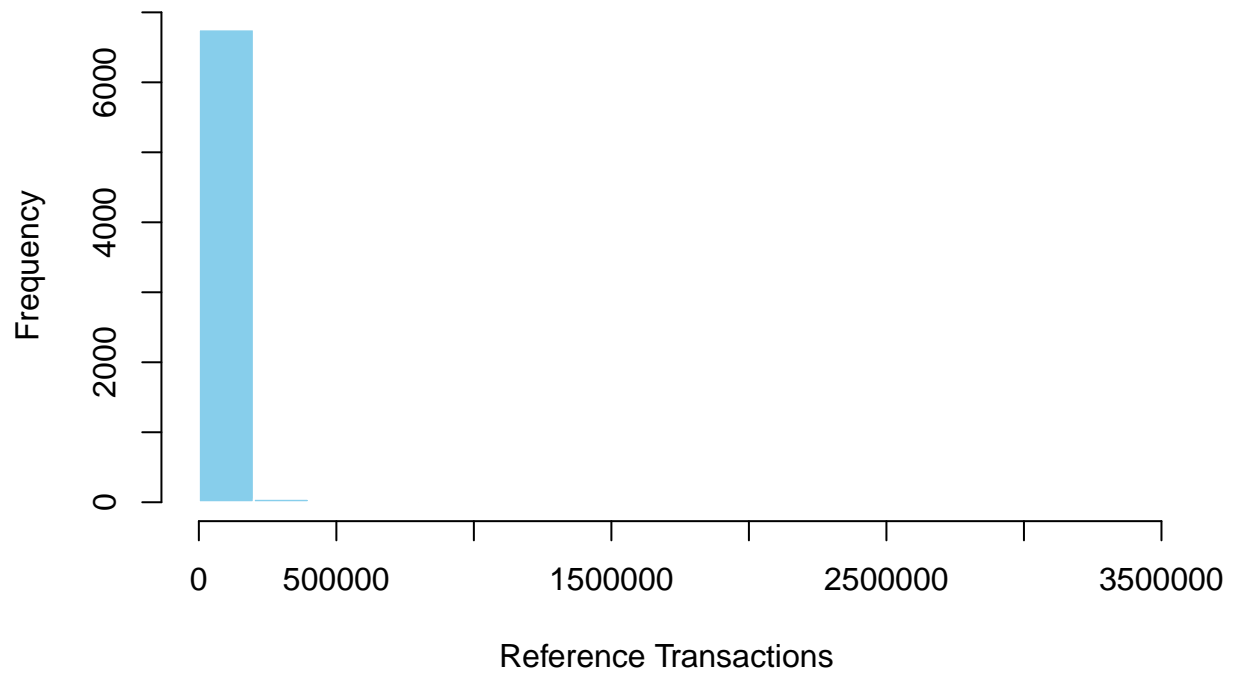
Histogram of Hours/Year



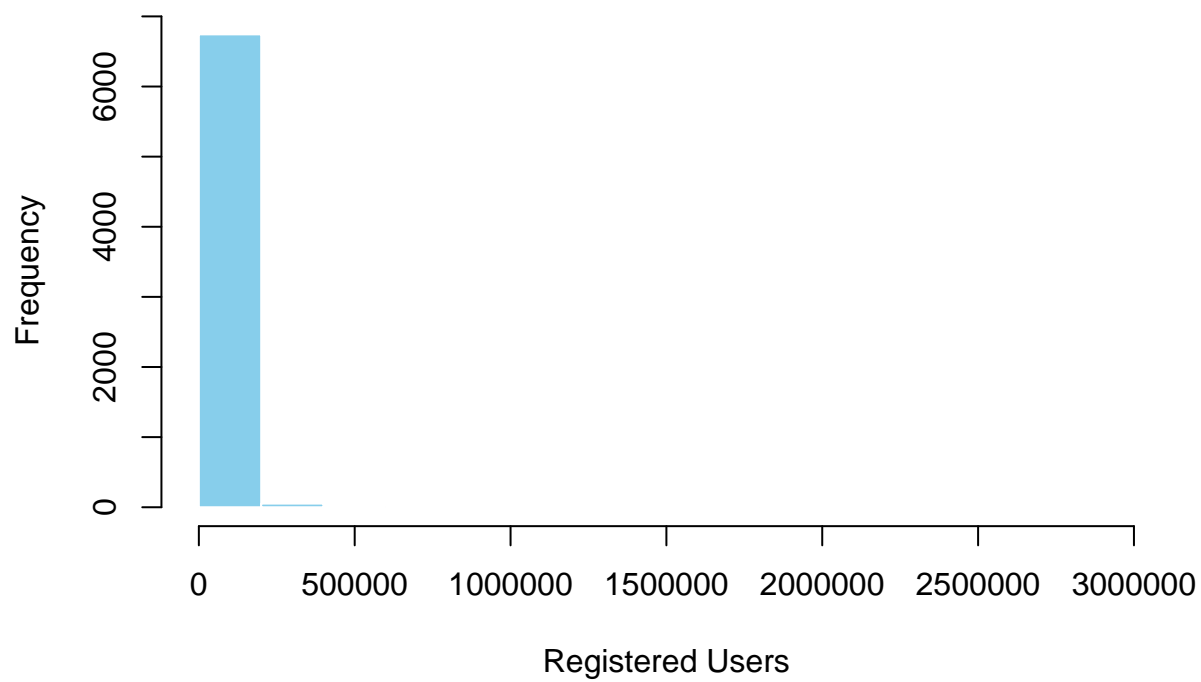
Histogram of Physical Visits



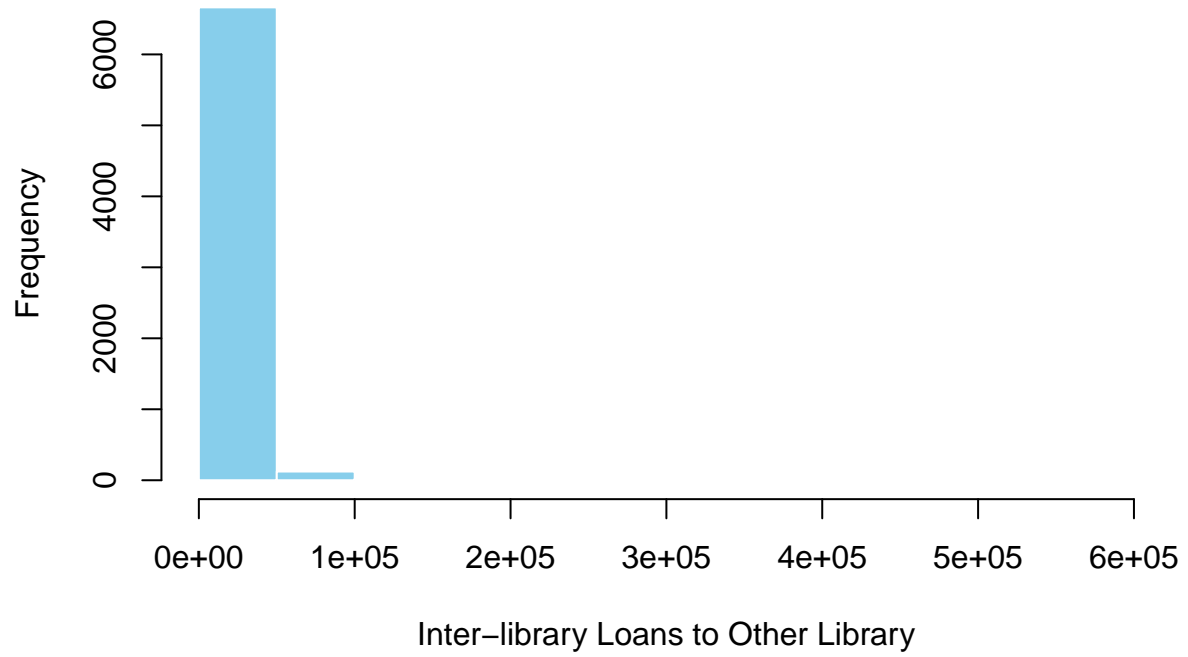
Histogram of Reference Transactions



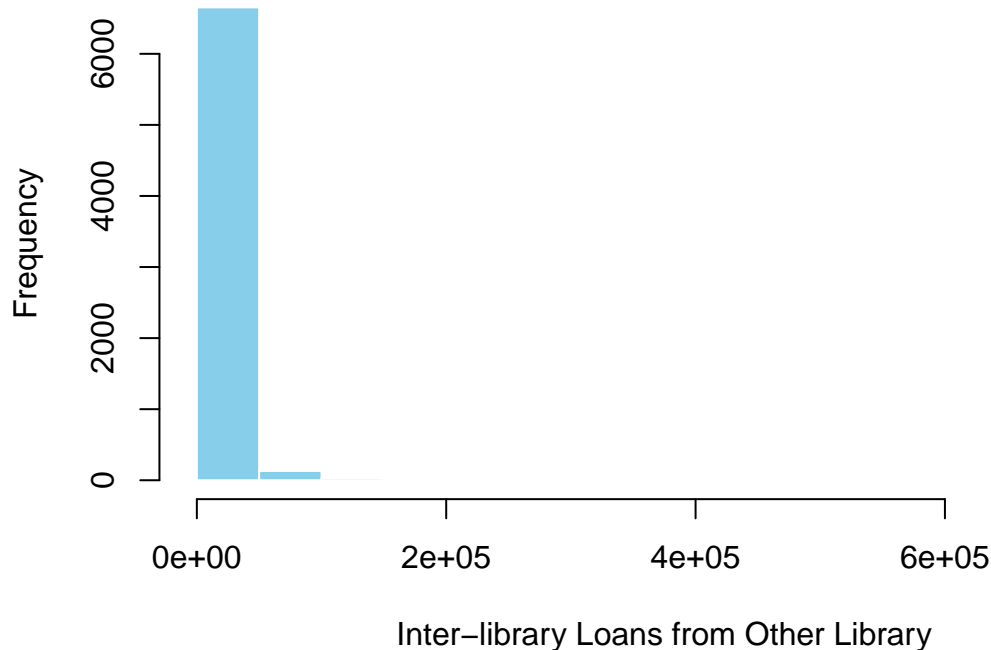
Histogram of Registered Users



Histogram of Inter-library Loans to Other Library



Histogram of Inter-library Loans from Other Library



The histograms of the numeric data show that many of these have extreme outliers, so let's remove them:

```
library(dplyr)
```

```
# Function to remove outliers using the IQR rule
remove_outliers <- function(x) {
  if (is.numeric(x) && length(unique(na.omit(x))) > 2) { # skip binary
    q1 <- quantile(x, 0.25, na.rm = TRUE)
    q3 <- quantile(x, 0.75, na.rm = TRUE)
    iqr <- q3 - q1
    lower <- q1 - 1.5 * iqr
    upper <- q3 + 1.5 * iqr
    x[x < lower | x > upper] <- NA # mark outliers
  }
  return(x)
}

# Columns to ignore
ignore_cols <- c("Bookmobiles", "Branch Library")

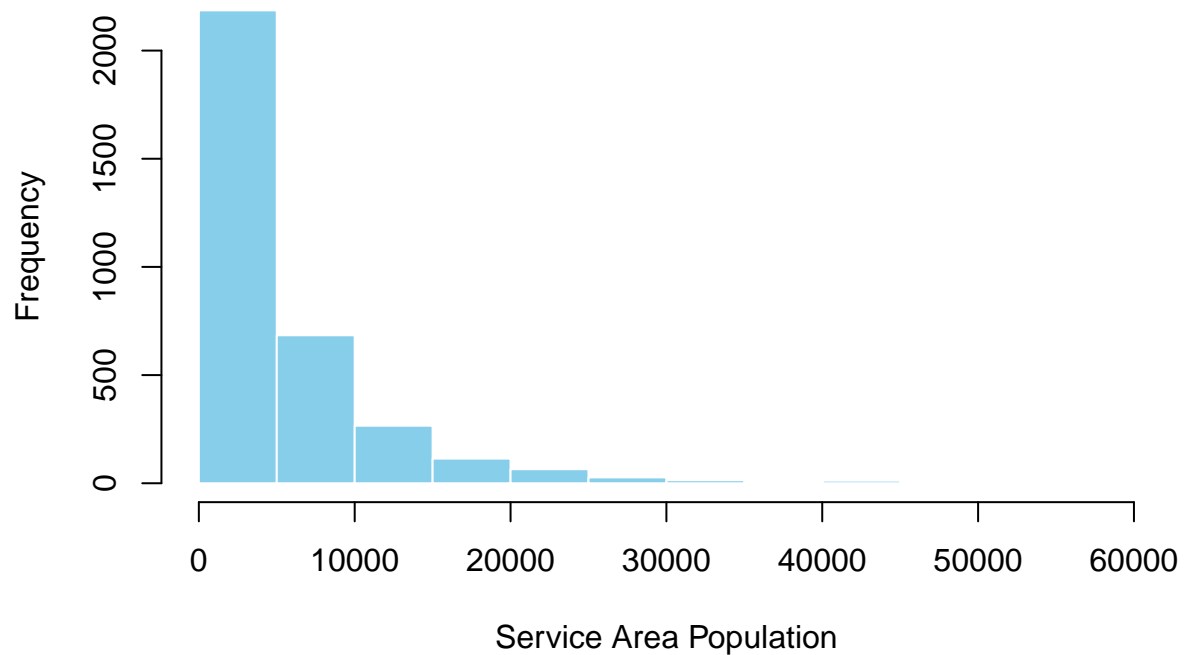
# Apply only to numeric, non-binary, and not ignored columns
libraries_no_outliers <- libraries %>%
  mutate(across(
    .cols = where(is.numeric) & !all_of(ignore_cols),
    .fns = remove_outliers
  )) %>%
  drop_na()
```

```

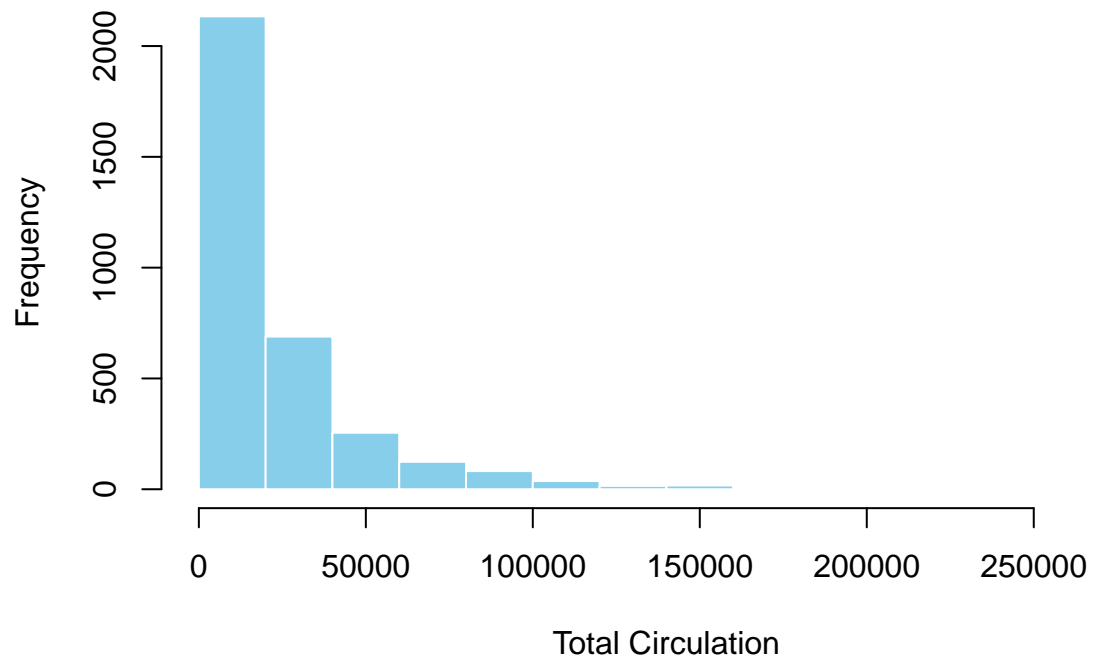
libraries_no_outliers_numeric <- libraries_no_outliers %>% select(where(is.numeric))
for (col in names(libraries_no_outliers_numeric)) {
  hist(
    libraries_no_outliers_numeric[[col]],
    main = paste("Histogram of", col),
    xlab = col,
    col = "skyblue",
    border = "white"
  )
}

```

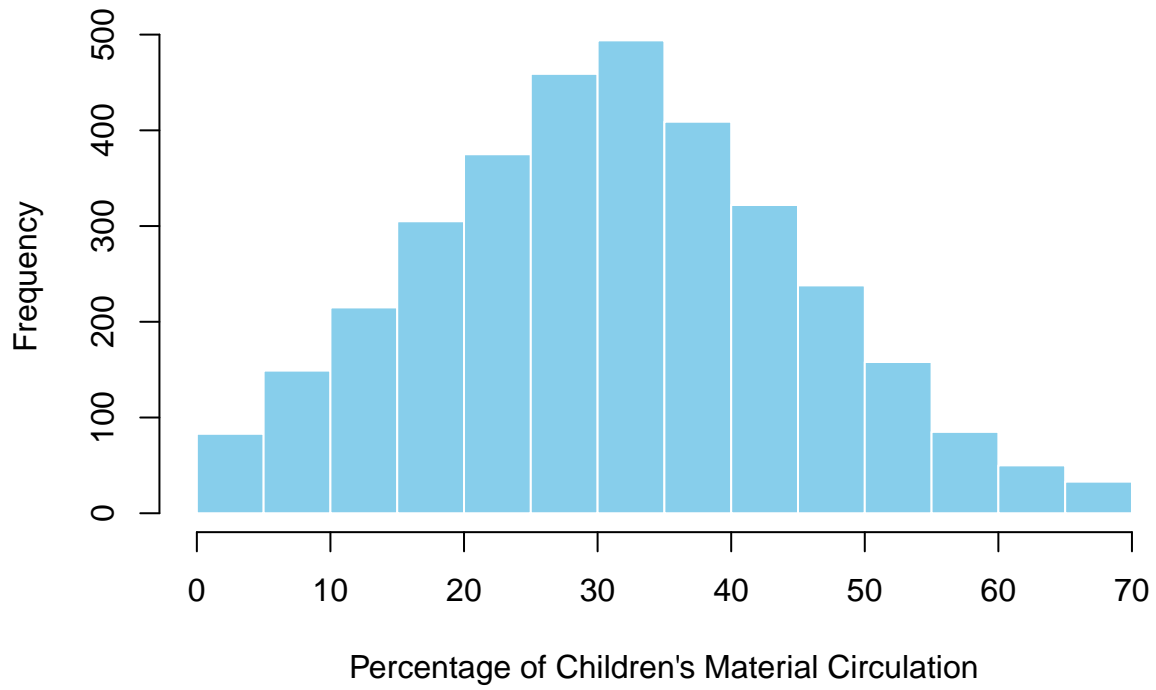
Histogram of Service Area Population

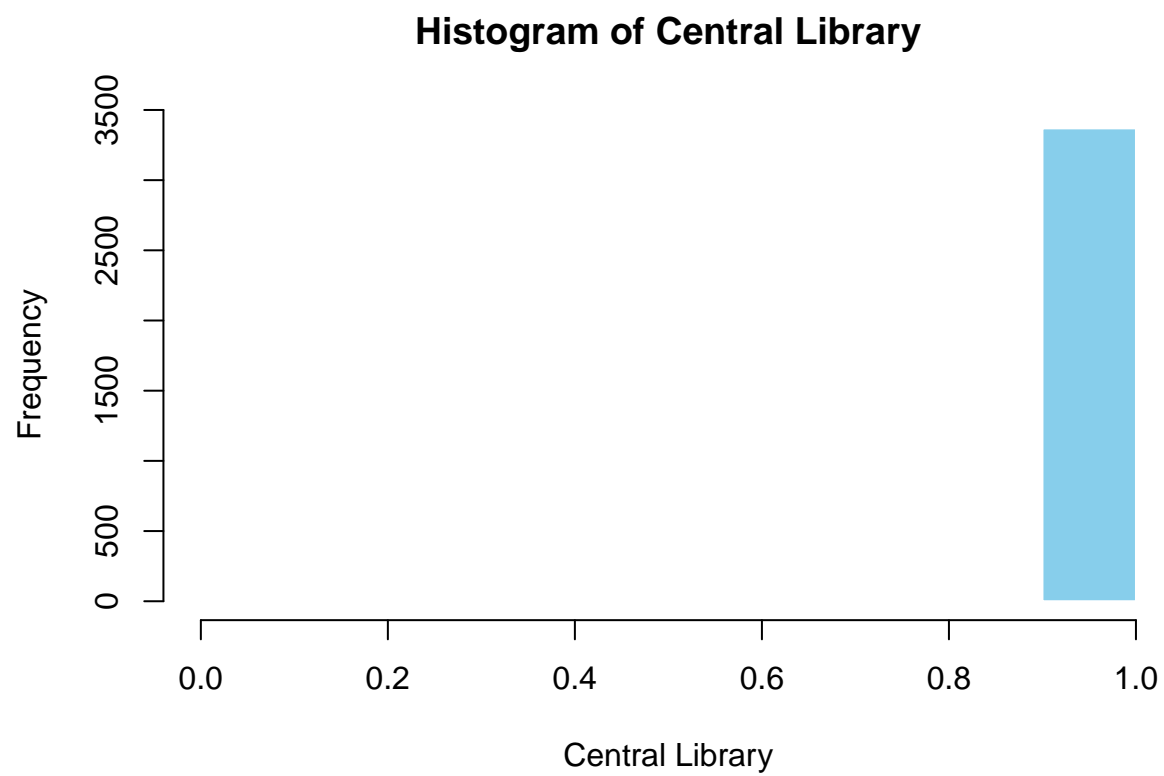


Histogram of Total Circulation

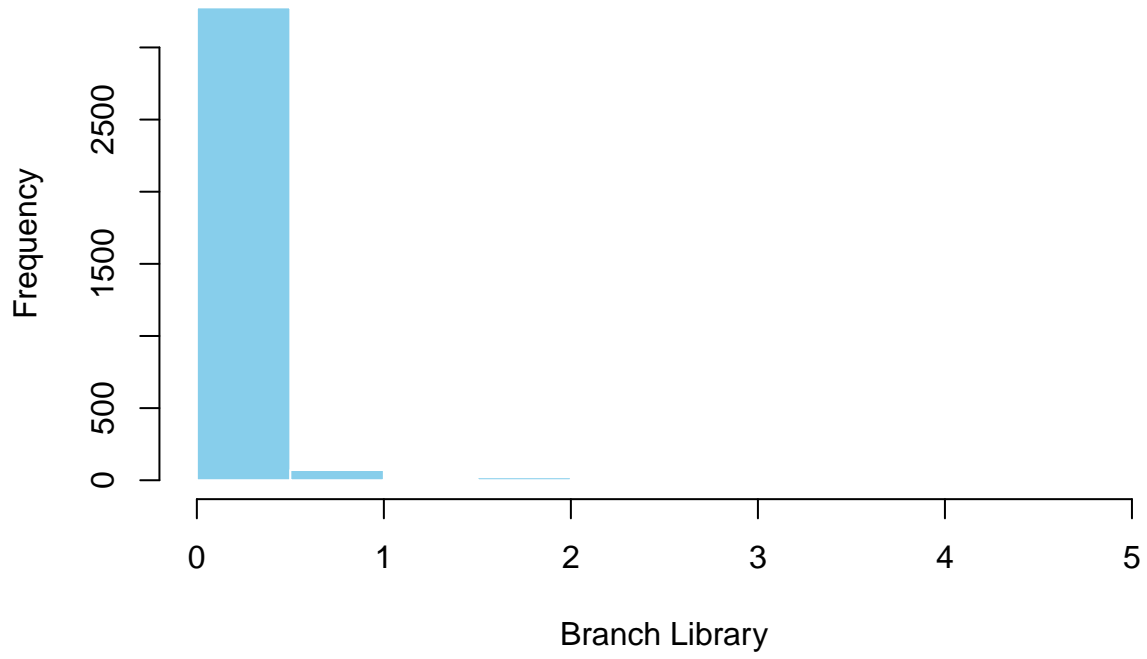


Histogram of Percentage of Children's Material Circulation

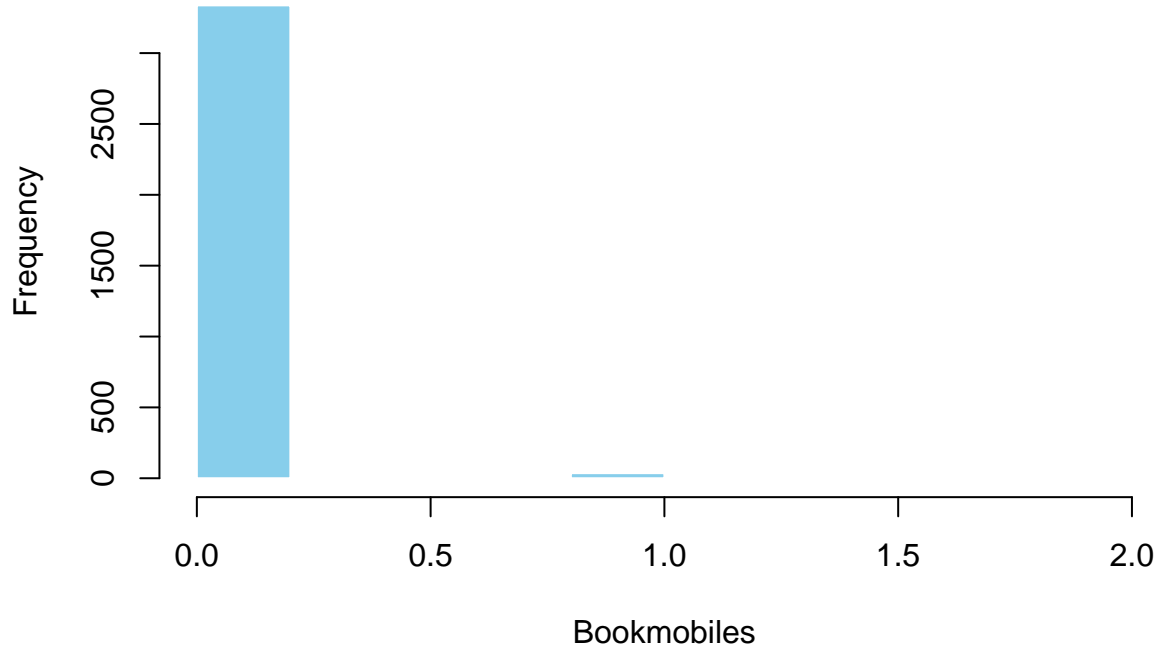




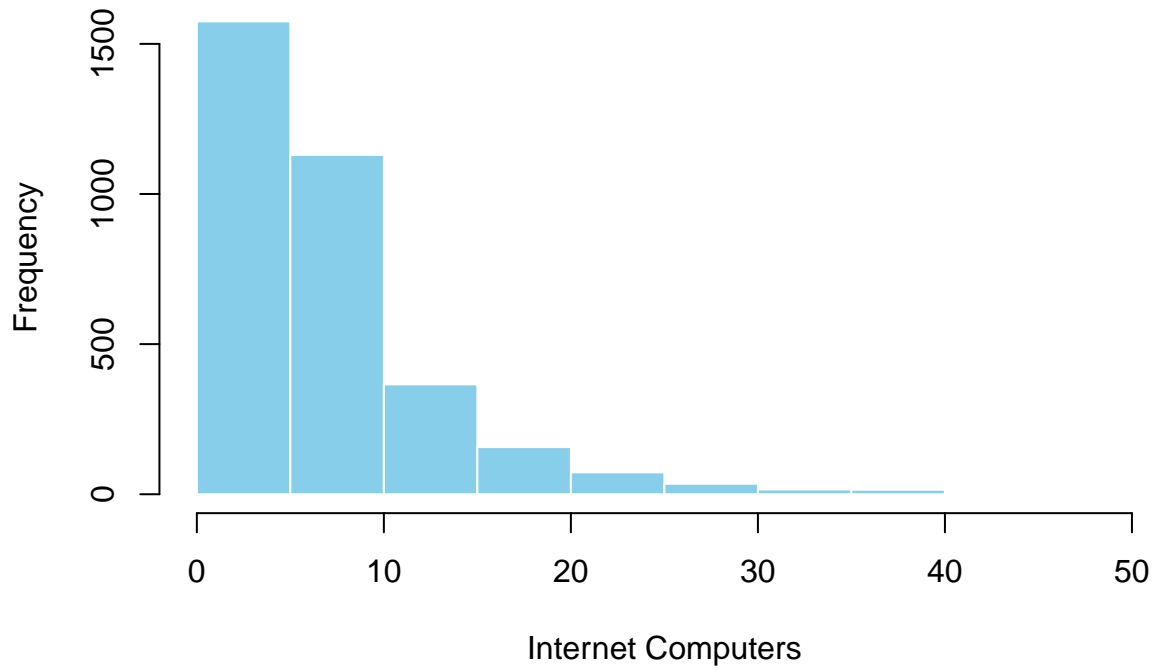
Histogram of Branch Library



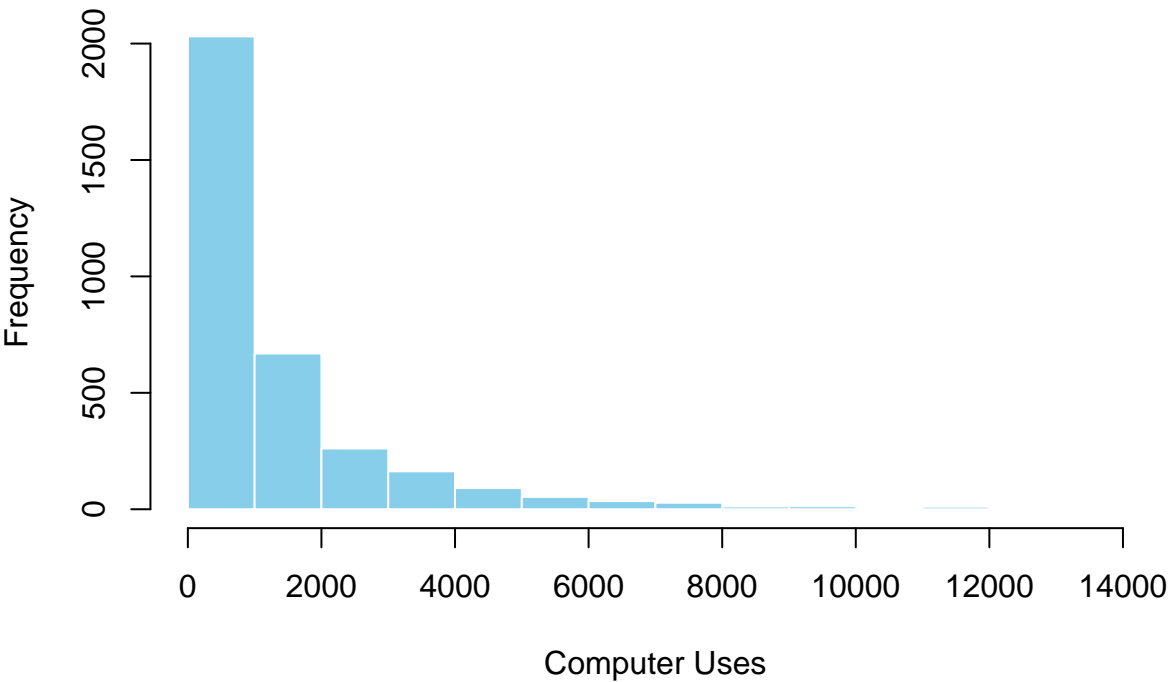
Histogram of Bookmobiles



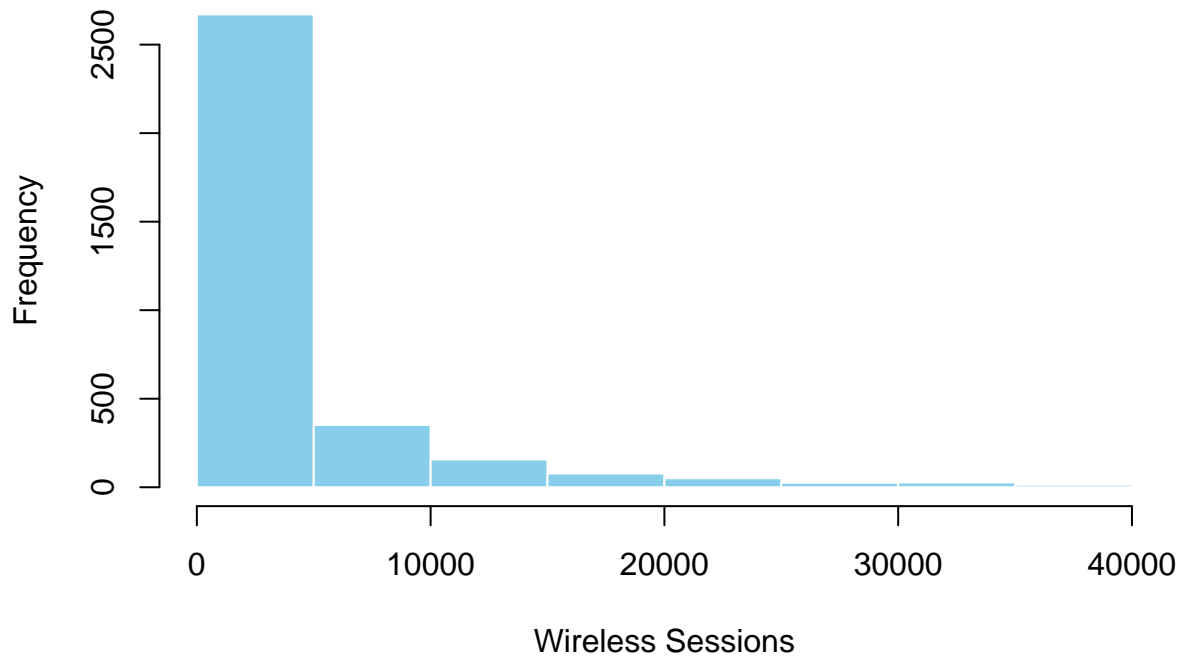
Histogram of Internet Computers



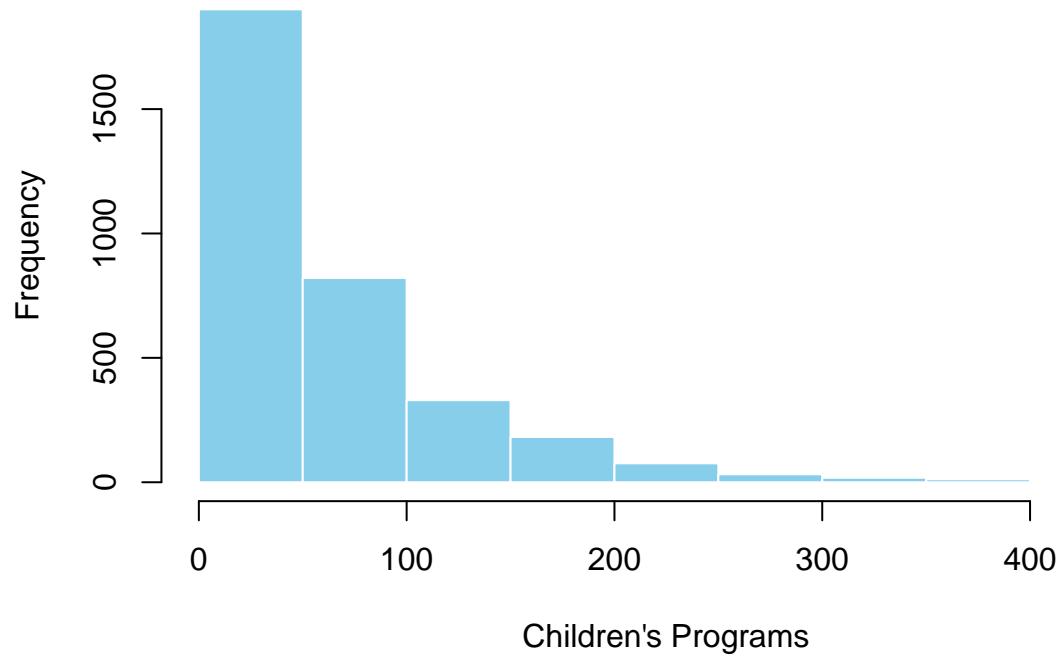
Histogram of Computer Uses



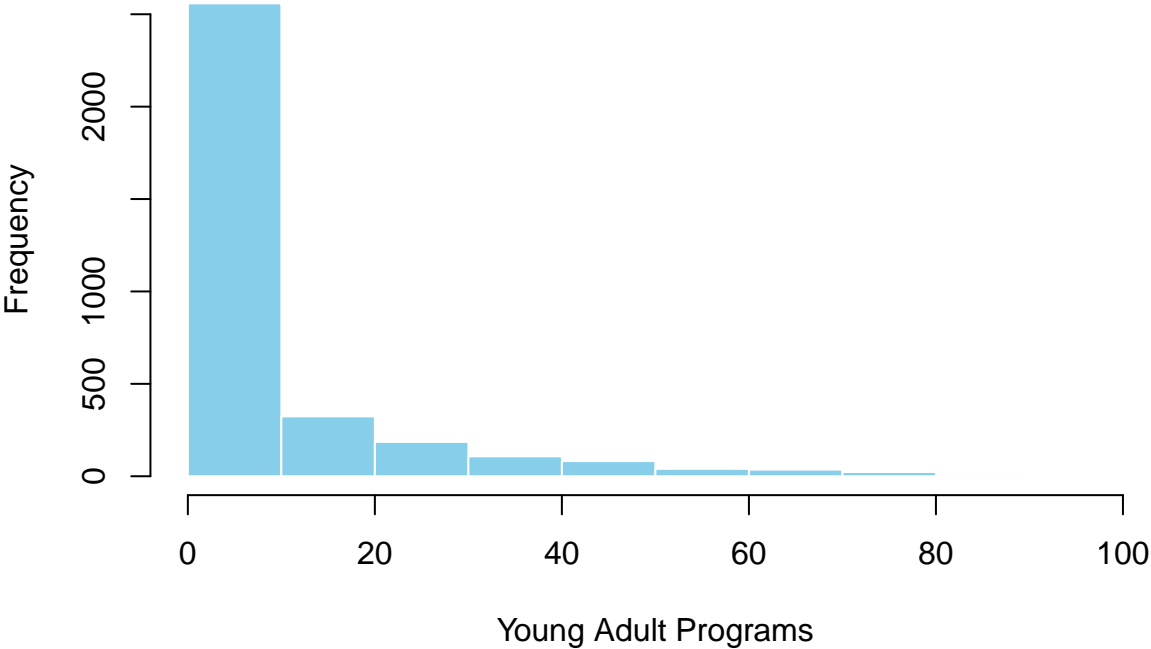
Histogram of Wireless Sessions



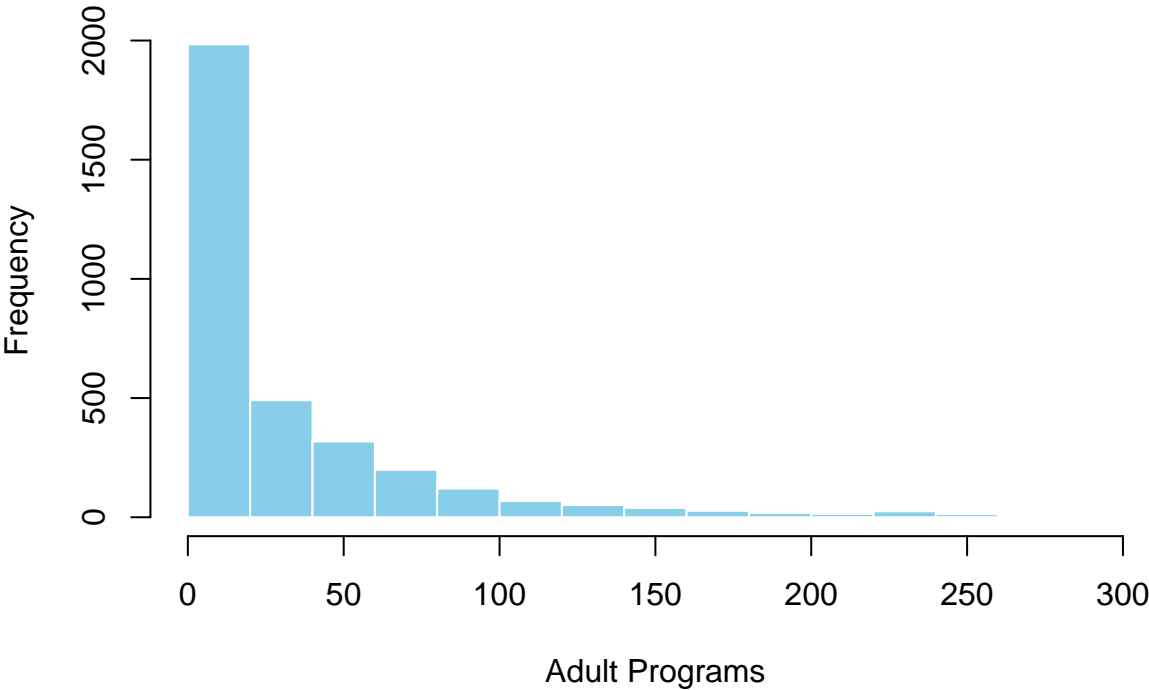
Histogram of Children's Programs



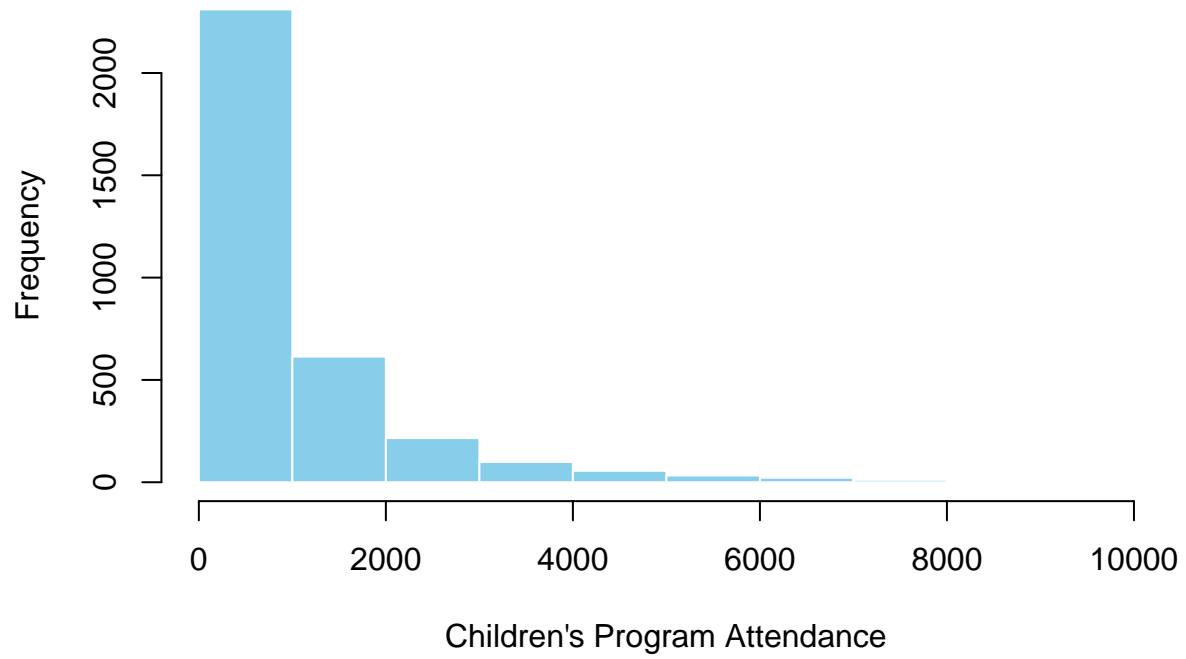
Histogram of Young Adult Programs



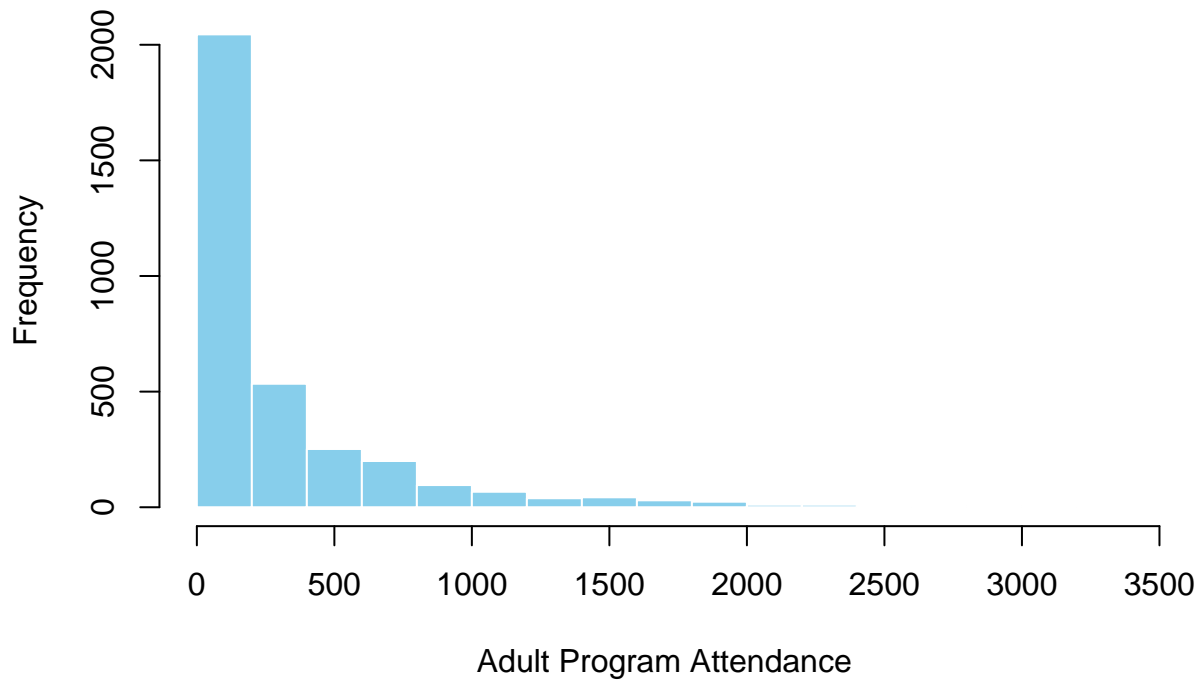
Histogram of Adult Programs



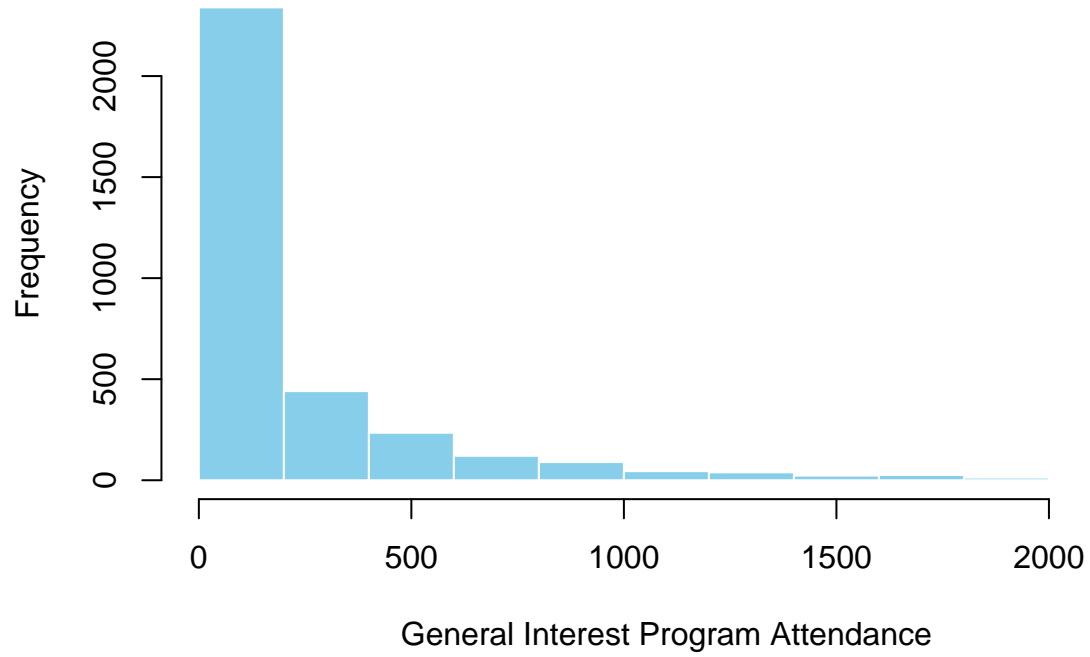
Histogram of Children's Program Attendance



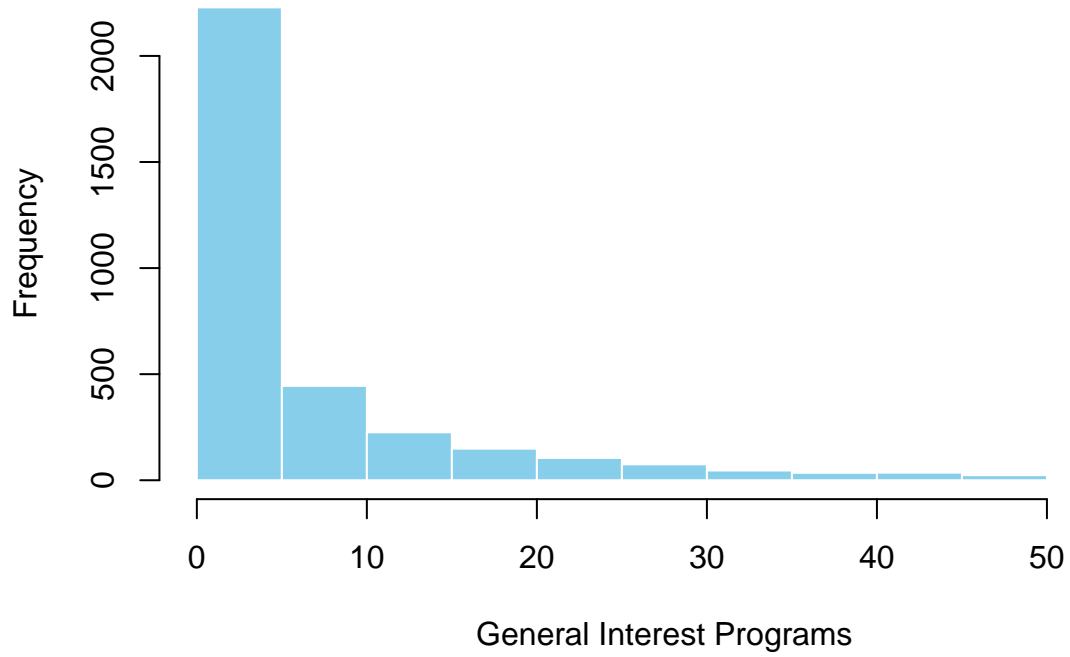
Histogram of Adult Program Attendance



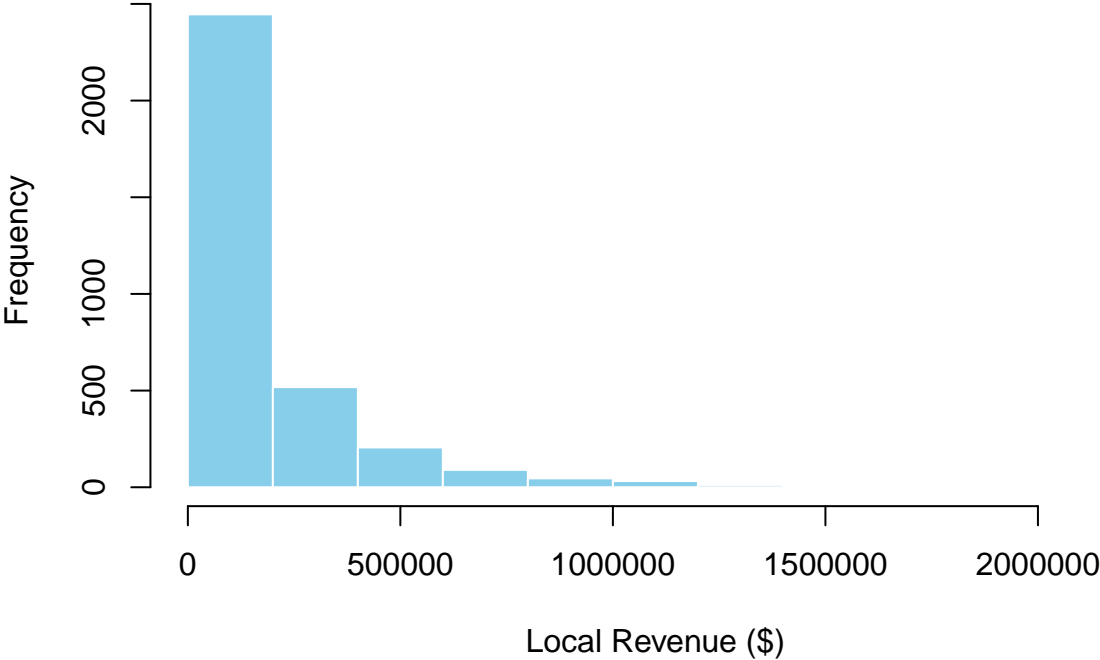
Histogram of General Interest Program Attendance



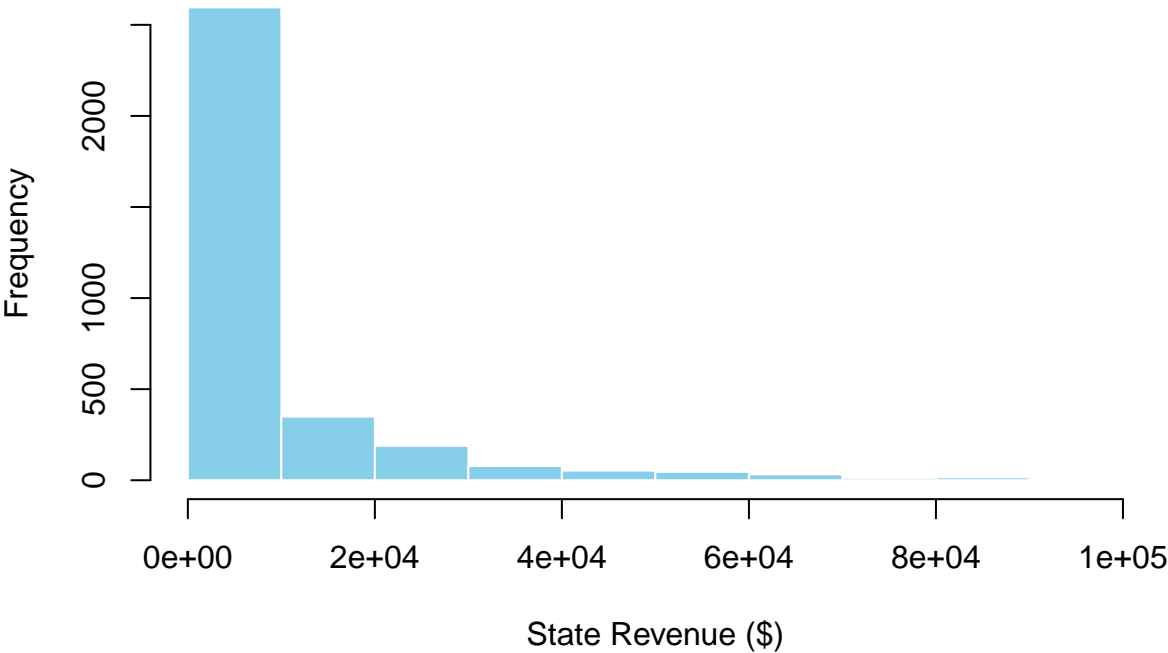
Histogram of General Interest Programs



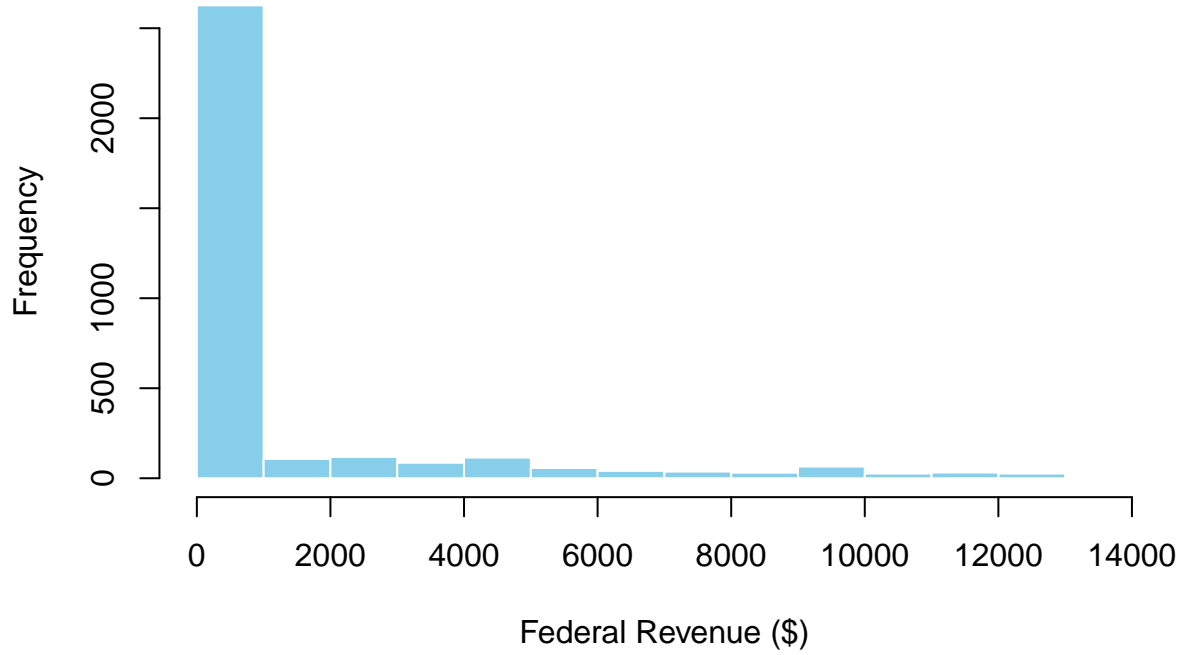
Histogram of Local Revenue (\$)

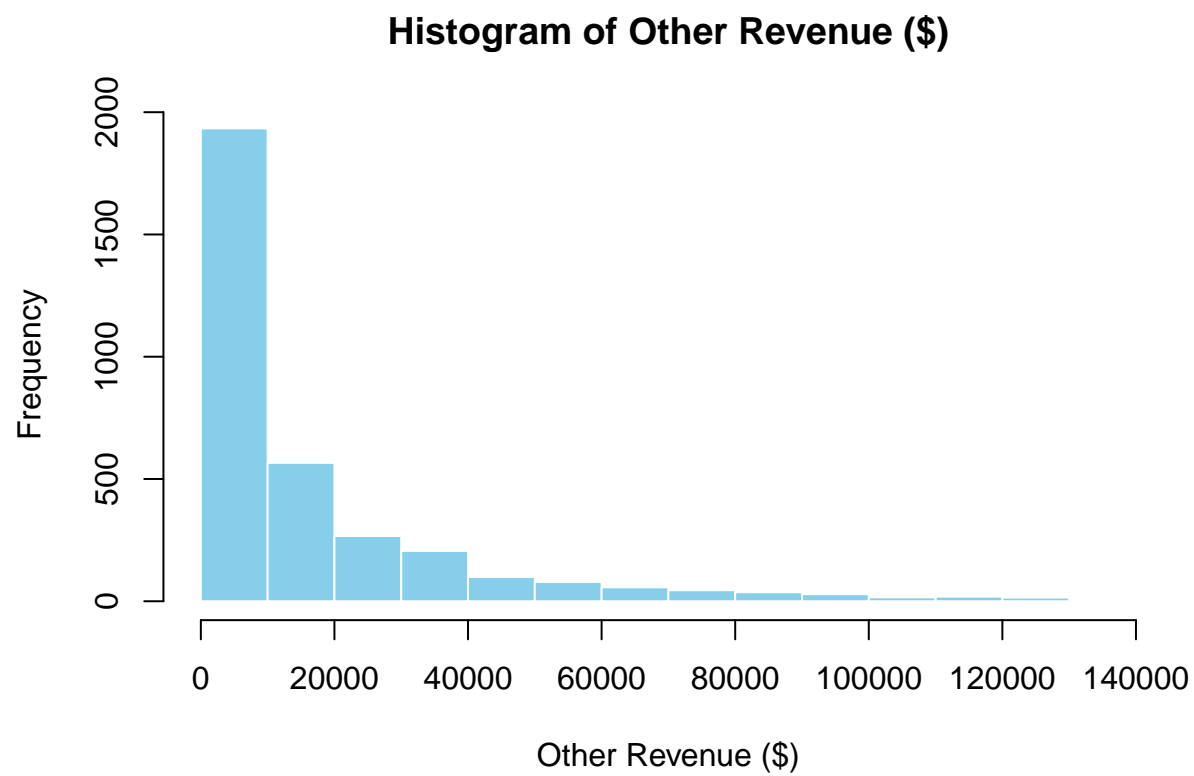


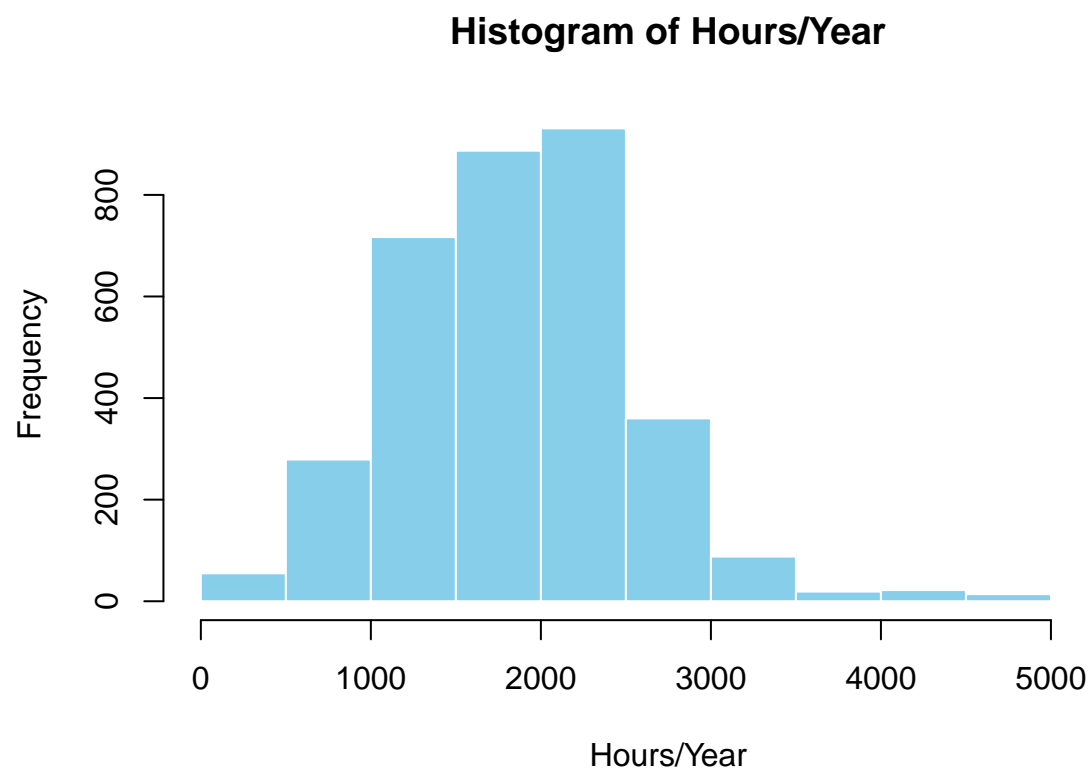
Histogram of State Revenue (\$)



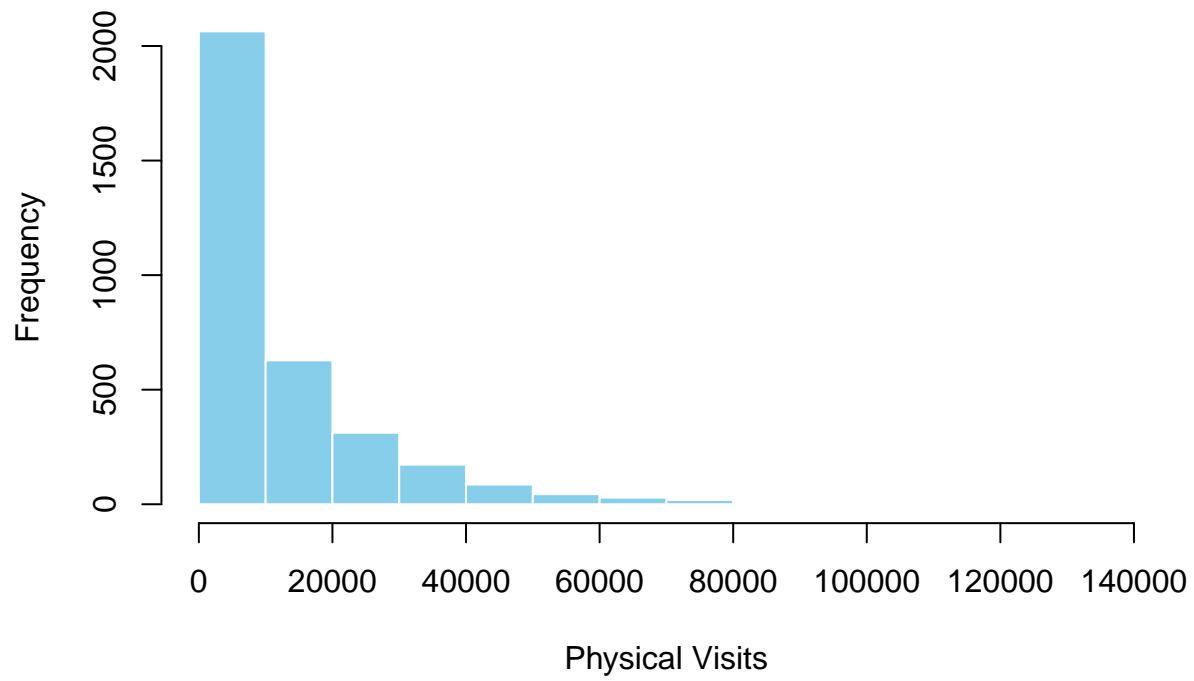
Histogram of Federal Revenue (\$)



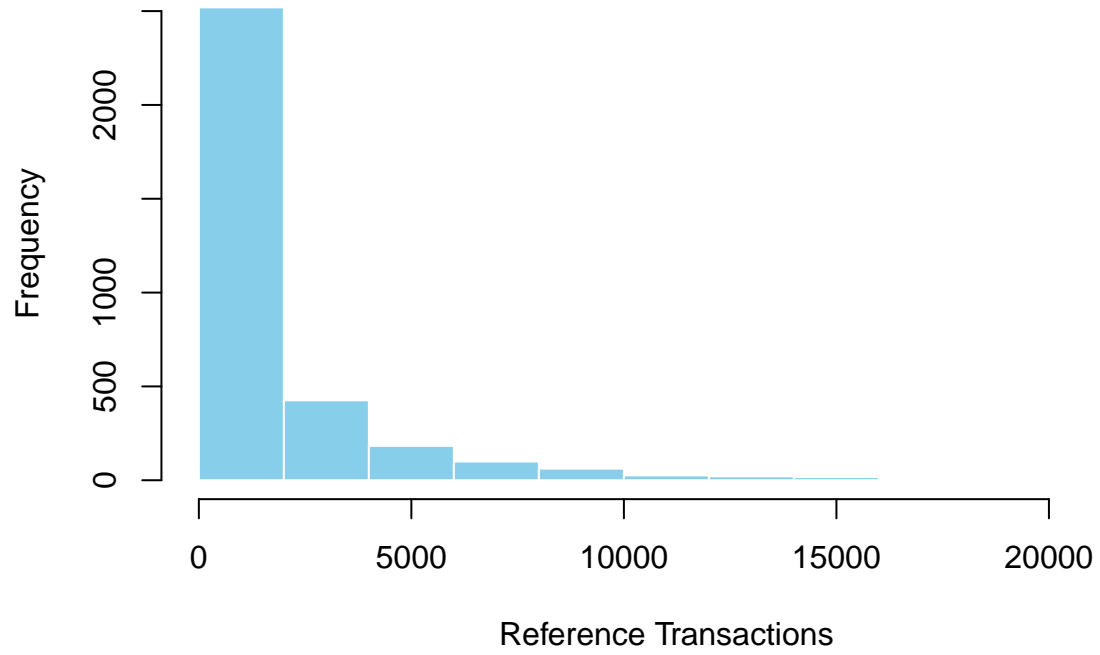




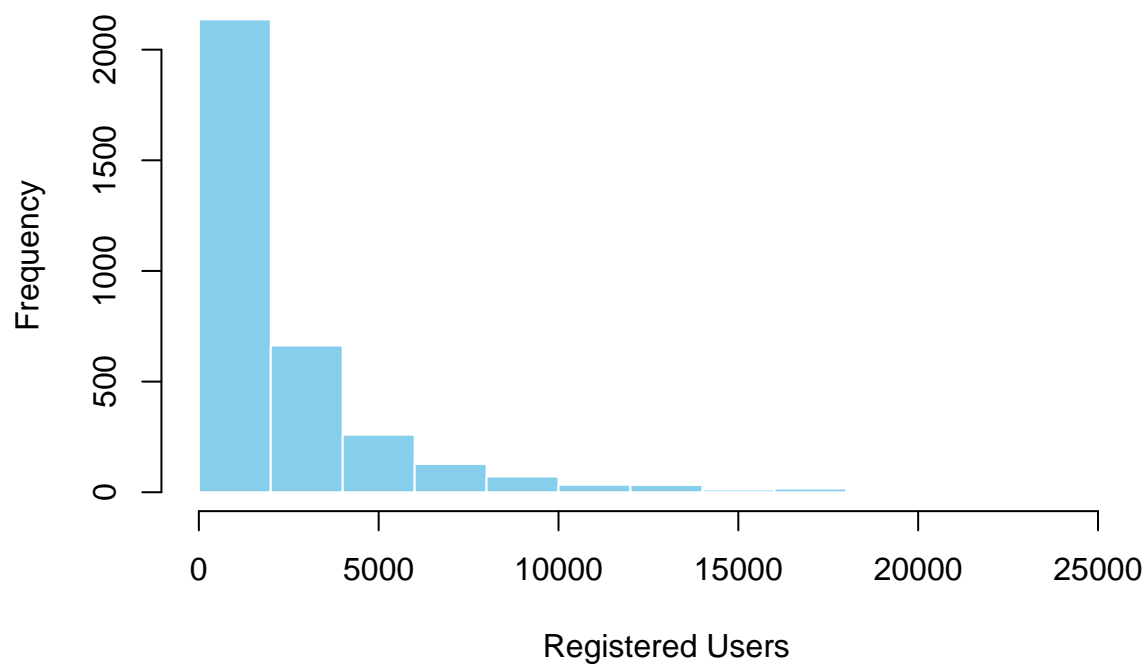
Histogram of Physical Visits



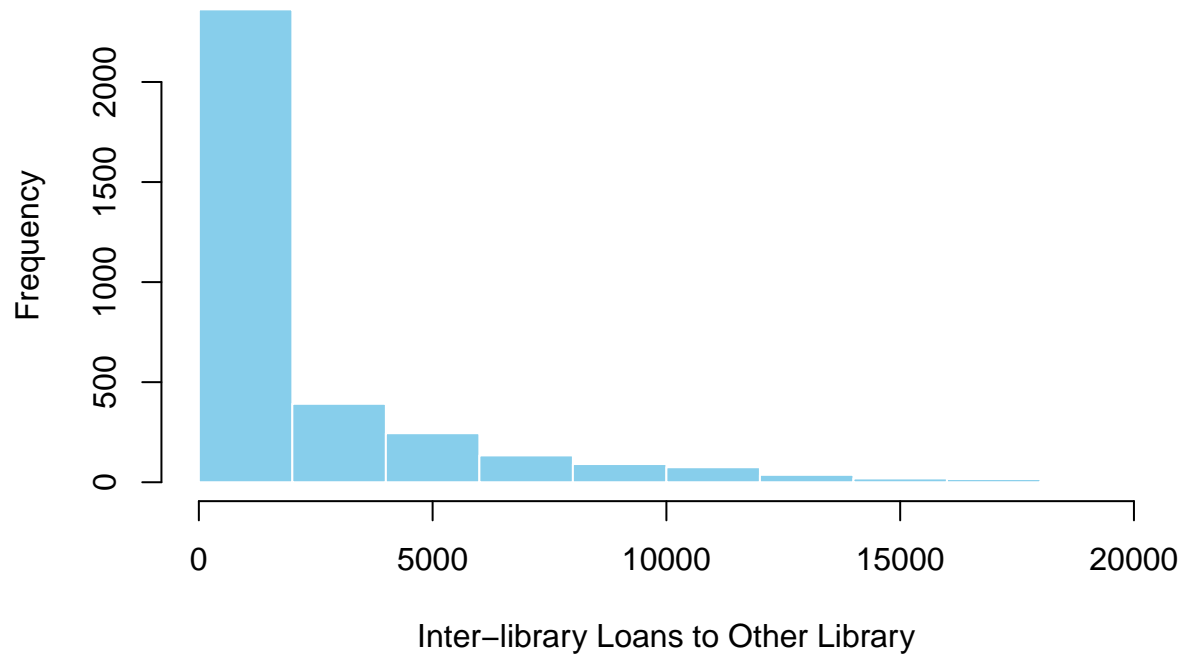
Histogram of Reference Transactions



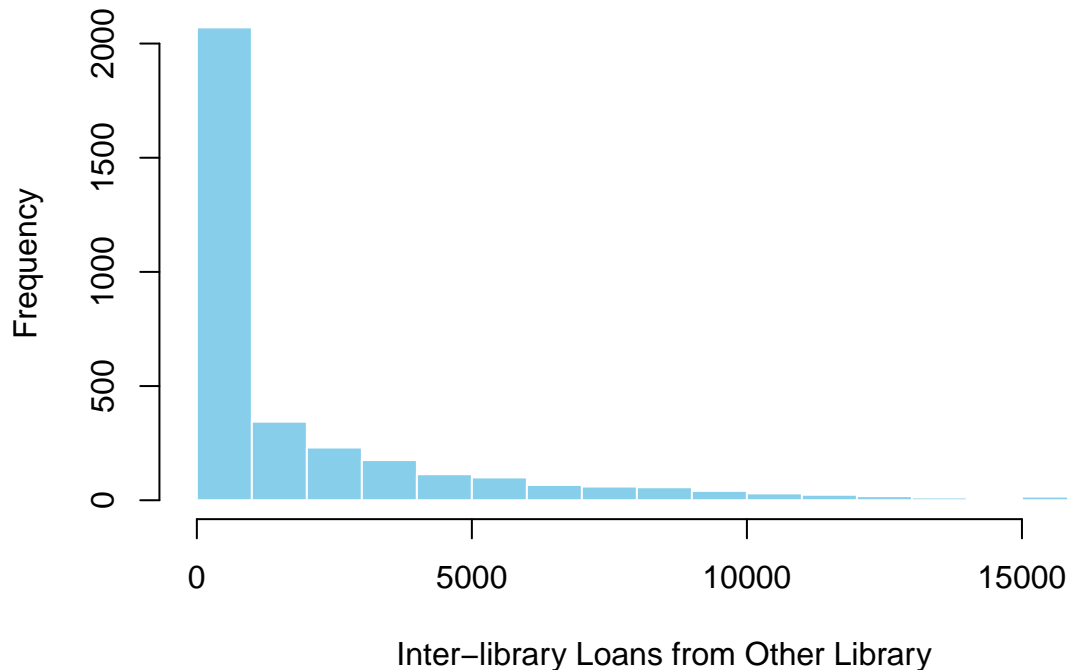
Histogram of Registered Users



Histogram of Inter-library Loans to Other Library



Histogram of Inter-library Loans from Other Library



With outliers removed, the data is more reasonable, but skewed to the right. With this being said, we should consider Box-Cox transformations when making the models.

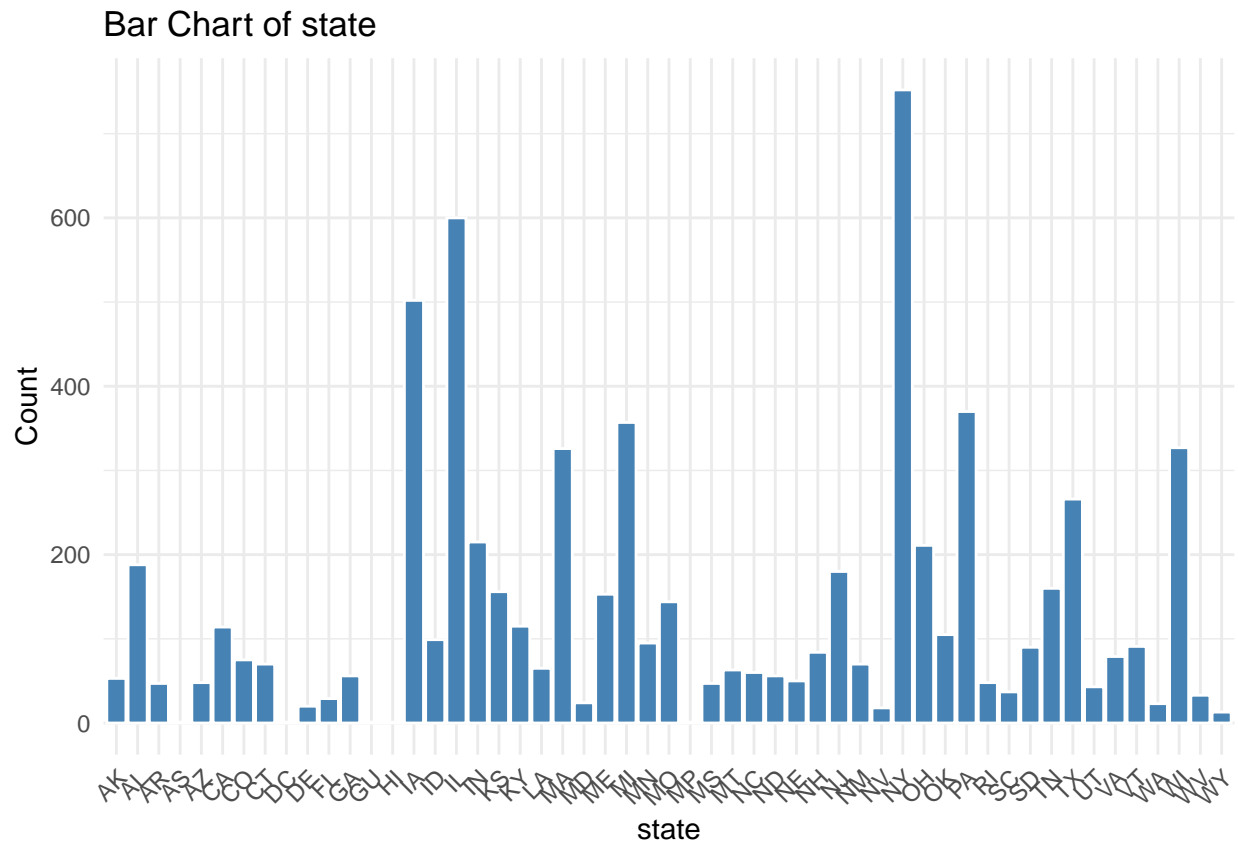
```
categorical_data <- libraries %>% select(!where(is.numeric))

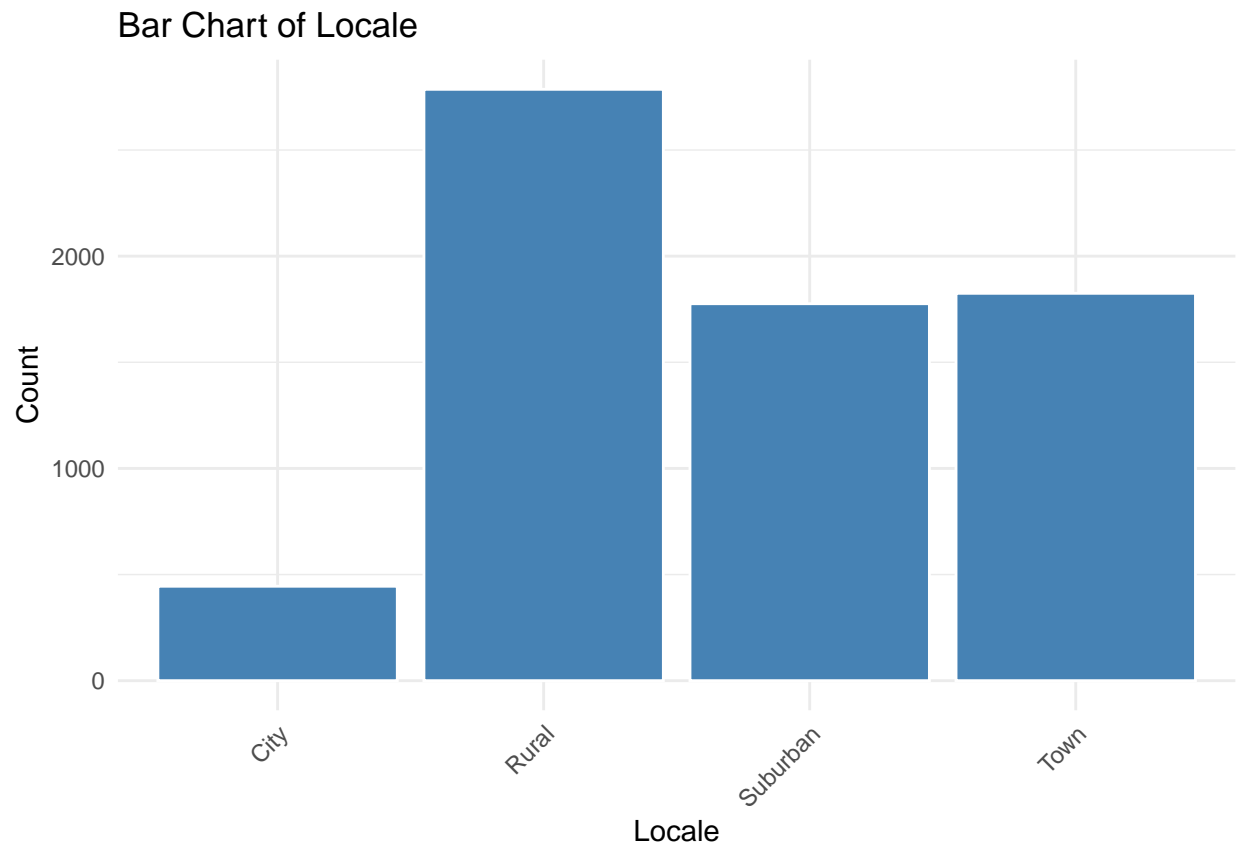
# Loop through each categorical column and plot
for (col in names(categorical_data)) {
  ggplot(categorical_data, aes_string(x = col)) +
    geom_bar(fill = "steelblue", color = "white") +
    theme_minimal() +
    labs(
      title = paste("Bar Chart of", col),
      x = col,
      y = "Count"
    ) +
    theme(
      axis.text.x = element_text(angle = 45, hjust = 1)
    ) -> p

  print(p)
}
```

```
## Warning: 'aes_string()' was deprecated in ggplot2 3.0.0.
## i Please use tidy evaluation idioms with 'aes()'.
## i See also 'vignette("ggplot2-in-packages")' for more information.
## This warning is displayed once every 8 hours.
```

```
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was
## generated.
```





With outliers removed, we see an overrepresentation of NY, IL, and HI, which means we should be careful making generalizations about the data to the entire nation. The locale is not as surprising, but we should be aware of the fact that the city is less represented than other types of locale.

Because this is a regression task, we should be considering Ridge and Lasso multi variable regression models to minimize the effects of the high collinearity.