Case_1_local

October 12, 2024

1 CSCI E-96: Data Mining for Business

1.1 Case I: OKCupid

1.2 Harvard University Extension School

1.2.1 Alvaro Ramirez

Oct. 7, 2024

2 Exploratory Data Analysis (EDA)

2.1 Environment Setup

Let's start by checking what R version we are running.

[1]:
```
version
```

```
               -
platform       aarch64-apple-darwin20.0.0
arch           aarch64
os             darwin20.0.0
system         aarch64, darwin20.0.0
status
major          4
minor          3.3
year           2024
month          02
day            29
svn rev        86002
language       R
version.string R version 4.3.3 (2024-02-29)
nickname       Angel Food Cake
```

Some packages are already pre-installed in my system and some are missing. Here, I install those missing packages.

[2]:
```
# install.packages("mapproj")
# install.packages("radiant.data")
# install.packages('esquisse')
```

```
# install.packages("IRdisplay")
# install.packages("gridExtra")
```

This is time to load the libraries required by my code.

[3]:
```
# libraries
library(dplyr)
library(ggplot2)
library(ggthemes)
library(leaflet)
library(leaflet.extras)
library(mapproj)
library(lubridate)
library(DataExplorer)
library(stringr)
library(tidyr)
library(knitr)
library(esquisse)
library(gridExtra)
library(IRdisplay)
```

```
Attaching package: 'dplyr'


The following objects are masked from 'package:stats':

    filter, lag


The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union


Loading required package: maps


Attaching package: 'lubridate'


The following objects are masked from 'package:base':

    date, intersect, setdiff, union



Attaching package: 'gridExtra'
```

```
The following object is masked from 'package:dplyr':

    combine
```

Let's set the default directory to ease coding.

[4]:
```
# Set working directory
setwd("/Users/alvaroramirez/Library/CloudStorage/OneDrive-Personal/estudio/
 ↪Harvard/Classes/CSCI E-96/CSCI E-96/Cases/Fall/I Ok Cupid")
```

2.2 Data Import

Since our environment is ready, let's start loading the data to understand it. In this step I create a dataframe for each of the CSV files we have for analysis.

[5]:
```
# Load OK Cupid data into memory
profiles <- read.csv("profiles.csv", stringsAsFactors = FALSE)
latlon <- read.csv("LatLon.csv", stringsAsFactors = FALSE)
```

Let's see what columns are numerical and what columns are categorical. Also, let's show some basic statistics for numerical columns.

[6]:
```
# Explore df_eda
str(profiles)
```

```
'data.frame':   59946 obs. of  22 variables:
 $ age        : int  22 35 38 23 29 29 32 31 24 37 …
 $ body_type  : chr  "a little extra" "average" "thin" "thin" …
 $ diet       : chr  "strictly anything" "mostly other" "anything" "vegetarian"
…
 $ drinks     : chr  "socially" "often" "socially" "socially" …
 $ drugs      : chr  "never" "sometimes" NA NA …
 $ education  : chr  "working on college/university" "working on space camp"
"graduated from masters program" "working on college/university" …
 $ ethnicity  : chr  "asian, white" "white" NA "white" …
 $ height     : int  75 70 68 71 66 67 65 65 67 65 …
 $ income     : int  NA 80000 NA 20000 NA NA NA NA NA NA …
 $ job        : chr  "transportation" "hospitality / travel" NA "student" …
 $ last_online: chr  "2012-06-28 20:30:00" "2012-06-29 21:41:00" "2012-06-27
09:10:00" "2012-06-28 14:22:00" …
 $ location   : chr  "south san francisco, california" "oakland, california"
"san francisco, california" "berkeley, california" …
 $ offspring  : chr  "doesn't have kids, but might want them" "doesn't have
kids, but might want them" NA "doesn't want kids" …
```

```
 $ orientation: chr  "straight" "straight" "straight" "straight" …
 $ pets       : chr  "likes dogs and likes cats" "likes dogs and likes cats"
"has cats" "likes cats" …
 $ religion   : chr  "agnosticism and very serious about it" "agnosticism but
not too serious about it" NA NA …
 $ sex        : chr  "m" "m" "m" "m" …
 $ sign       : chr  "gemini" "cancer" "pisces but it doesn't matter" "pisces"
…
 $ smokes     : chr  "sometimes" "no" "no" "no" …
 $ speaks     : chr  "english" "english (fluently), spanish (poorly), french
(poorly)" "english, french, c++" "english, german (poorly)" …
 $ status     : chr  "single" "single" "available" "single" …
 $ essay0     : chr  "about me:    i would love to think that i was some some
kind of intellectual: either the dumbest smart guy, or "| __truncated__ "i am a
chef: this is what that means.  1. i am a workaholic.  2. i love to cook
regardless of whether i am at w"| __truncated__ "i'm not ashamed of much, but
writing public text on an online dating site makes me pleasantly uncomfortable.
i'"| __truncated__ "i work in a library and go to school. . ." …
```

[7]:
```r
# LatLon.csv
summary(latlon)
```

```
   location              lat             lon
 Length:199         Min.   :12.25   Min.   :-157.9
 Class :character   1st Qu.:37.43   1st Qu.:-122.3
 Mode  :character   Median :37.88   Median :-122.0
                    Mean   :37.83   Mean   :-107.9
                    3rd Qu.:38.51   3rd Qu.:-104.2
                    Max.   :55.95   Max.   : 109.2
```

[8]:
```r
# Explore latlon
str(latlon)
```

```
'data.frame':   199 obs. of  3 variables:
 $ location: chr  "south san francisco, california" "oakland, california" "san
francisco, california" "berkeley, california" …
 $ lat     : num  37.7 37.8 37.8 37.9 37.9 …
 $ lon     : num  -122 -122 -122 -122 -122 …
```

These two datasets, `latlon` and `profiles`, have a one-to-many relationship. The field used to link both tables is 'location'. Let's merge both datasets into one to ease our analysis work. The new dataframe will be called `df_eda`.

[9]:
```r
# Perform a left join to combine both dataframes using the 'location' column
df_eda <- profiles %>%
  left_join(latlon, by = "location")
```

[10]:
```r
# df_eda.csv
summary(df_eda)
```

```
      age          body_type             diet              drinks         
 Min.   : 18.00   Length:59946       Length:59946       Length:59946      
 1st Qu.: 26.00   Class :character   Class :character   Class :character  
 Median : 30.00   Mode  :character   Mode  :character   Mode  :character  
 Mean   : 32.34                                                           
 3rd Qu.: 37.00                                                           
 Max.   :110.00                                                           
                                                                          
    drugs            education          ethnicity             height    
 Length:59946       Length:59946       Length:59946       Min.   : 1.0  
 Class :character   Class :character   Class :character   1st Qu.:66.0  
 Mode  :character   Mode  :character   Mode  :character   Median :68.0  
                                                          Mean   :68.3  
                                                          3rd Qu.:71.0  
                                                          Max.   :95.0  
                                                          NA's   :3     
     income            job            last_online          location        
 Min.   :  20000   Length:59946       Length:59946       Length:59946      
 1st Qu.:  20000   Class :character   Class :character   Class :character  
 Median :  50000   Mode  :character   Mode  :character   Mode  :character  
 Mean   : 104395                                                           
 3rd Qu.: 100000                                                           
 Max.   :1000000                                                           
 NA's   :48442                                                             
  offspring         orientation            pets             religion        
 Length:59946       Length:59946       Length:59946       Length:59946      
 Class :character   Class :character   Class :character   Class :character  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character  
                                                                            
                                                                            
                                                                            
                                                                            
     sex                sign              smokes             speaks         
 Length:59946       Length:59946       Length:59946       Length:59946      
 Class :character   Class :character   Class :character   Class :character  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character  
                                                                            
                                                                            
                                                                            
                                                                            
    status             essay0               lat             lon        
 Length:59946       Length:59946       Min.   :12.25   Min.   :-157.9  
 Class :character   Class :character   1st Qu.:37.78   1st Qu.:-122.4  
 Mode  :character   Mode  :character   Median :37.78   Median :-122.4  
                                       Mean   :37.77   Mean   :-122.3  
                                       3rd Qu.:37.81   3rd Qu.:-122.3  
                                       Max.   :55.95   Max.   : 109.2  
```

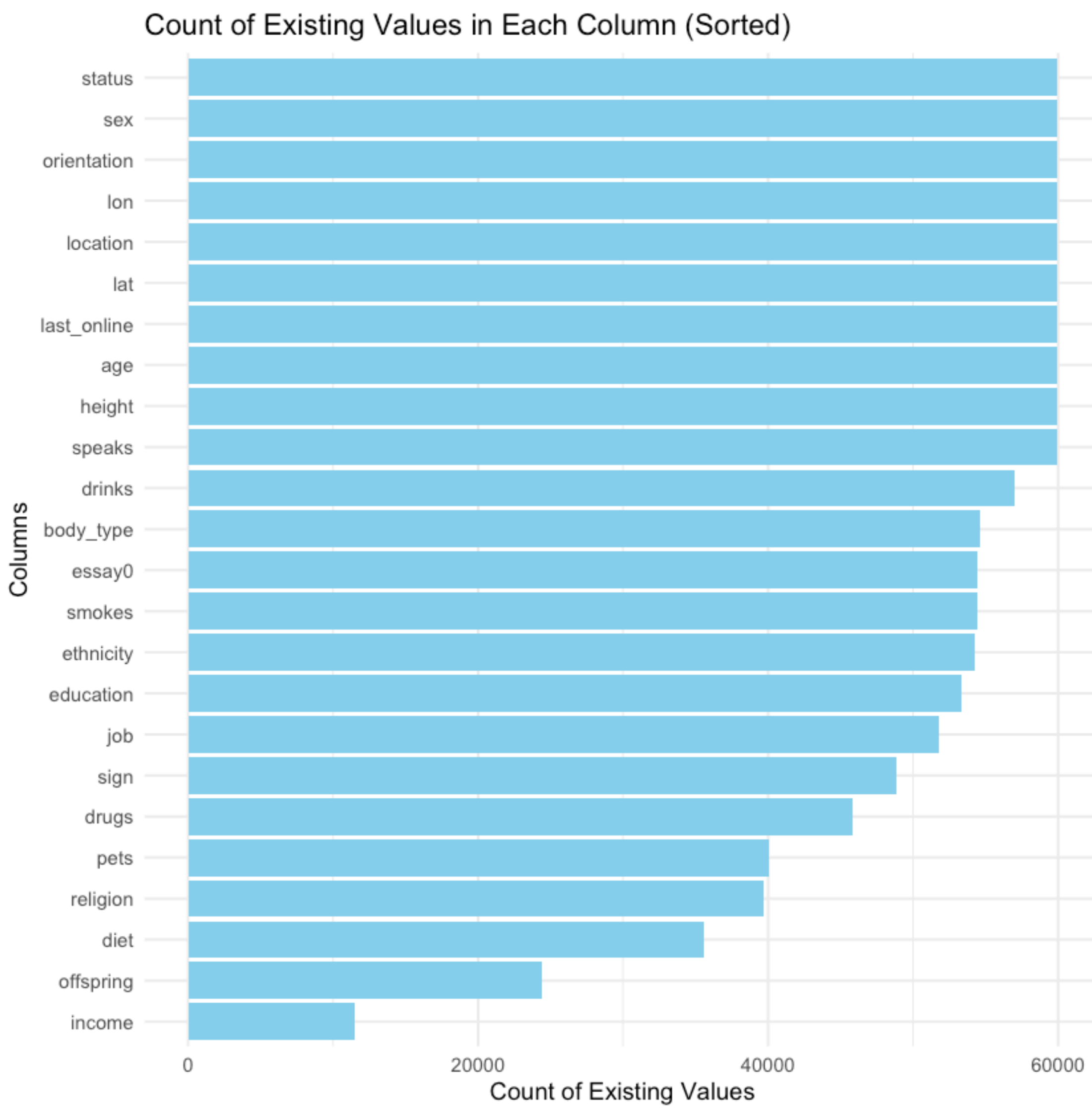
2.3 Data Analysis

Now, we know each column's data type, some basic statistics for numerical columns and have both datasets integrated into one. Let's check the existence of data in each of these columns.

[11]:
```r
# Summarize the number of missing values in each column
missing_summary <- sapply(df_eda, function(x) sum(is.na(x)))
missing_percentage <- sapply(df_eda, function(x) mean(is.na(x)) * 100)
existing_values <- sapply(df_eda, function(x) sum(!is.na(x)))

# Create a summary table of missing and existing values
missing_data <- data.frame(
  Column = names(df_eda),
  MissingValues = missing_summary,
  MissingPercentage = missing_percentage,
  ExistingValues = existing_values
)

# Print the summary table
print(missing_data)
```

```
                 Column MissingValues MissingPercentage ExistingValues
age                 age             0       0.000000000          59946
body_type     body_type          5296       8.834617823          54650
diet               diet         24395      40.694958796          35551
drinks           drinks          2985       4.979481533          56961
drugs             drugs         14080      23.487805692          45866
education     education          6628      11.056617623          53318
ethnicity     ethnicity          5680       9.475194342          54266
height           height             3       0.005004504          59943
income           income         48442      80.809395122          11504
job                 job          8198      13.675641411          51748
last_online last_online             0       0.000000000          59946
location       location             0       0.000000000          59946
offspring     offspring         35561      59.321722884          24385
orientation orientation             0       0.000000000          59946
pets               pets         19921      33.231575084          40025
religion       religion         20226      33.740366330          39720
sex                 sex             0       0.000000000          59946
sign               sign         11056      18.443265606          48890
smokes           smokes          5512       9.194942115          54434
speaks           speaks            50       0.083408401          59896
status           status             0       0.000000000          59946
essay0           essay0          5485       9.149901578          54461
lat                 lat             0       0.000000000          59946
lon                 lon             0       0.000000000          59946
```

[12]:
```r
# Sort the data by ExistingValues
missing_data_sorted <- missing_data %>%
  arrange(desc(ExistingValues))

# Create the bar plot
ggplot(missing_data_sorted, aes(x = reorder(Column, ExistingValues), y =
 ↪ExistingValues)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  coord_flip() + # Flip the coordinates for horizontal bars
  labs(title = "Count of Existing Values in Each Column (Sorted)",
       x = "Columns",
       y = "Count of Existing Values") +
  theme_minimal()
```



Although having all fields for all records is ideal, this is not our case. However, we still can manage to extract data to create the personas we want. Let's write a couple of functions to explore our categorical data in more detail. The first function, `create_df_with_counts`, reads a given column identifies unique values and them calculates the count and percentage of occurrencies of each value. The second function, `print_df_with_category_count`, prints the results of the previous function.

[13]:
```
# Values used in categorical columns

# Function to calculate count and percentage for each unique value,
# handling NA values
create_df_with_counts <- function(column) {

  # Replace NA values with a placeholder ('<NA>')
  column_clean <- ifelse(is.na(column), "<NA>", column)

  # Get unique values including '<NA>' placeholder for NA
  unique_values <- unique(column_clean)

  # Create a dataframe with the unique values and their counts
  df <- data.frame(
    # UniqueValue = unique_values,
    Count = sapply(unique_values, function(x) sum(column_clean == x))
  )

  # Calculate the percentage for each value
  df$Percentage <- (df$Count / length(column)) * 100

  # Return both the dataframe and the number of unique categories
  return(list(df = df, num_categories = length(unique_values)))
}
```

[14]:
```
print_df_with_category_count <- function(df_list, column_name, n = 20, m = 10) {
  cat("Column     : ", column_name, "\n", sep = "")
  cat("Categories: ", df_list$num_categories, "\n", sep = "")
  cat("\n")

  num_categories_df <- data.frame(
    category = rownames(df_list$df),
    num_categories = df_list$df$Count
  )

  # Sort by 'num_categories' in descending order
  num_categories_df <-␣
↪num_categories_df[order(num_categories_df$num_categories, decreasing =␣
↪TRUE), ]

  # Group categories if there are more than 'n'
```

```
  if (nrow(num_categories_df) > n) {
    # Get the top 'm' categories
    top_categories <- head(num_categories_df, m)

    # Calculate the sum of 'Others'
    other_count <- sum(num_categories_df$num_categories[(m + 1):
↪nrow(num_categories_df)])

    # Create the 'Others' category
    other_category <- data.frame(category = "<All Others>", num_categories =␣
↪other_count)

    # Combine top categories and 'Others' for both graph and table
    num_categories_df <- rbind(top_categories, other_category)
    df_list$df <- rbind(df_list$df[1:m, ], colSums(df_list$df[(m+1):
↪nrow(df_list$df), ]))
    rownames(df_list$df)[m+1] <- "<All Others>"
  }

  # Create the bar graph
  p <- ggplot(num_categories_df, aes(x = category, y = num_categories)) +
    geom_bar(stat = "identity") +
    theme_minimal() +
    labs(
      title = paste("Number of Categories for", column_name),
      x = column_name,
      y = "Count"
    ) +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))

  # Create the table using knitr::kable
  table_html <- knitr::kable(df_list$df, format = "html")

  # Display the table and graph side by side
  display_html(paste0(
    '<div style="display: flex;">',
    '<div style="flex: 1; padding-right: 10px;">', table_html, '</div>',
    '<div style="flex: 1;">', capture.output(print(p)), '</div>',
    '</div>'
  ))
}
```

[67]:
```
print_df_with_category_count <- function(df_list, column_name, n = 20, m = 10) {
  cat("Column    : ", column_name, "\n", sep = "")
  cat("Categories: ", df_list$num_categories, "\n", sep = "")
  cat("\n")
```

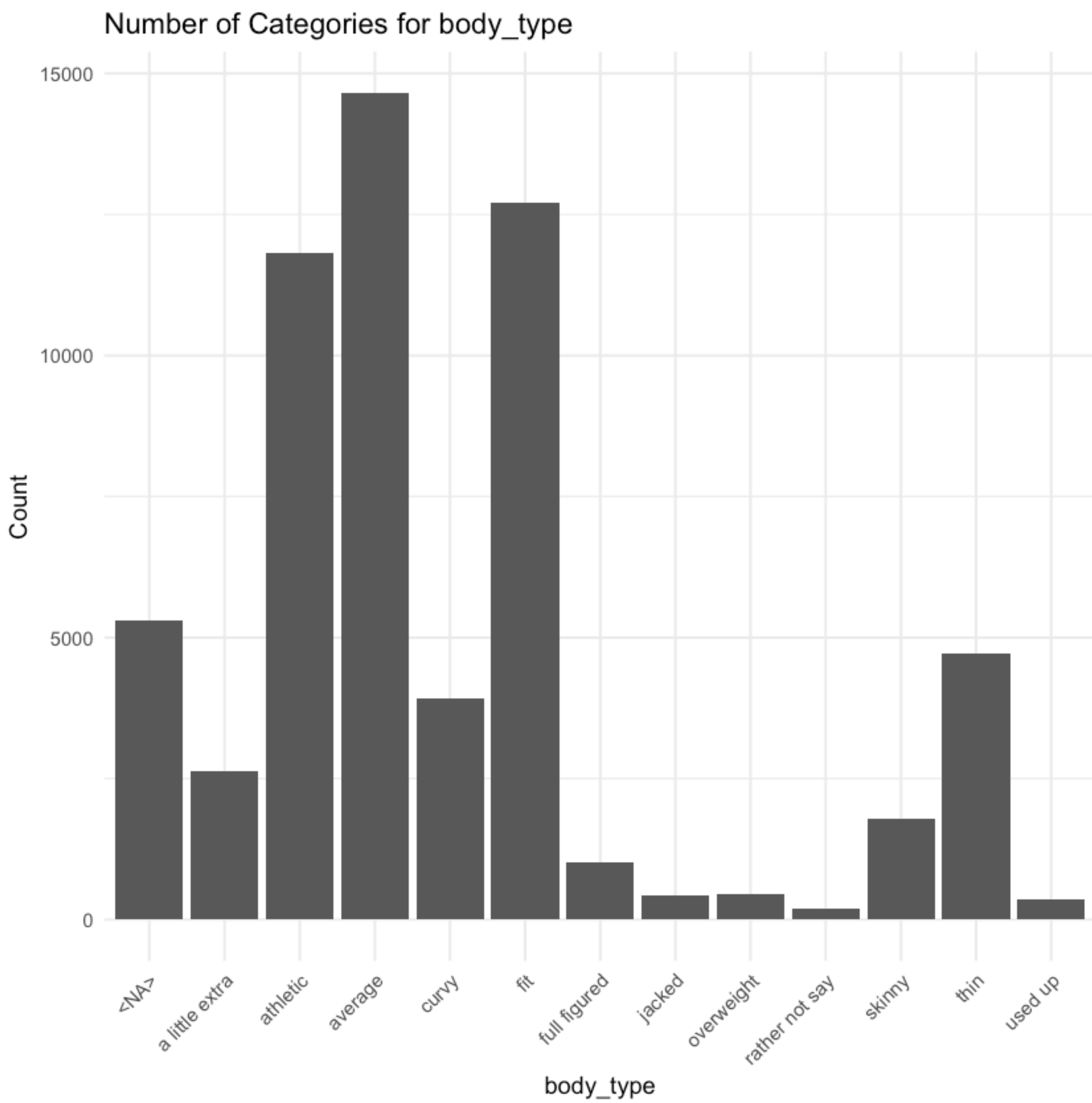
```r
# Create a dataframe with category names and counts
num_categories_df <- data.frame(
  category = rownames(df_list$df),
  num_categories = df_list$df$Count
)

# Sort by 'num_categories' in descending order for both graph and table
num_categories_df <-
↪num_categories_df[order(num_categories_df$num_categories, decreasing =
↪TRUE), ]

# Update df_list$df to sort the table in the same order
df_list$df <- df_list$df[order(df_list$df$Count, decreasing = TRUE), ]

# Group categories if there are more than 'n'
if (nrow(num_categories_df) > n) {
  # Get the top 'm' categories
  top_categories <- head(num_categories_df, m)

  # Calculate the sum of 'Others'
  other_count <- sum(num_categories_df$num_categories[(m + 1):
↪nrow(num_categories_df)])

  # Create the 'Others' category
  other_category <- data.frame(category = "<All Others>", num_categories =
↪other_count)

  # Combine top categories and 'Others' for both graph and table
  num_categories_df <- rbind(top_categories, other_category)

  # Also update df_list$df for the table display, adding "<All Others>"
  df_list$df <- rbind(df_list$df[1:m, ], colSums(df_list$df[(m+1):
↪nrow(df_list$df), ]))
  rownames(df_list$df)[m+1] <- "<All Others>"
}

# Create the bar graph sorted by 'num_categories' in descending order
p <- ggplot(num_categories_df, aes(x = reorder(category, -num_categories), y
↪= num_categories)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  theme_minimal() +
  labs(
    title = paste("Number of Categories for", column_name),
    x = column_name,
    y = "Count"
  ) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
  # Create the table using knitr::kable
  table_html <- knitr::kable(df_list$df, format = "html")

  # Display the table and graph side by side
  display_html(paste0(
    '<div style="display: flex;">',
    '<div style="flex: 1; padding-right: 10px;">', table_html, '</div>',
    '<div style="flex: 1;">', capture.output(print(p)), '</div>',
    '</div>'
  ))
}
```

2.3.1 body_type

[15]:
```
# 'body_type'
df_body_type <- create_df_with_counts(df_eda$body_type)
print_df_with_category_count(df_body_type, 'body_type')
```

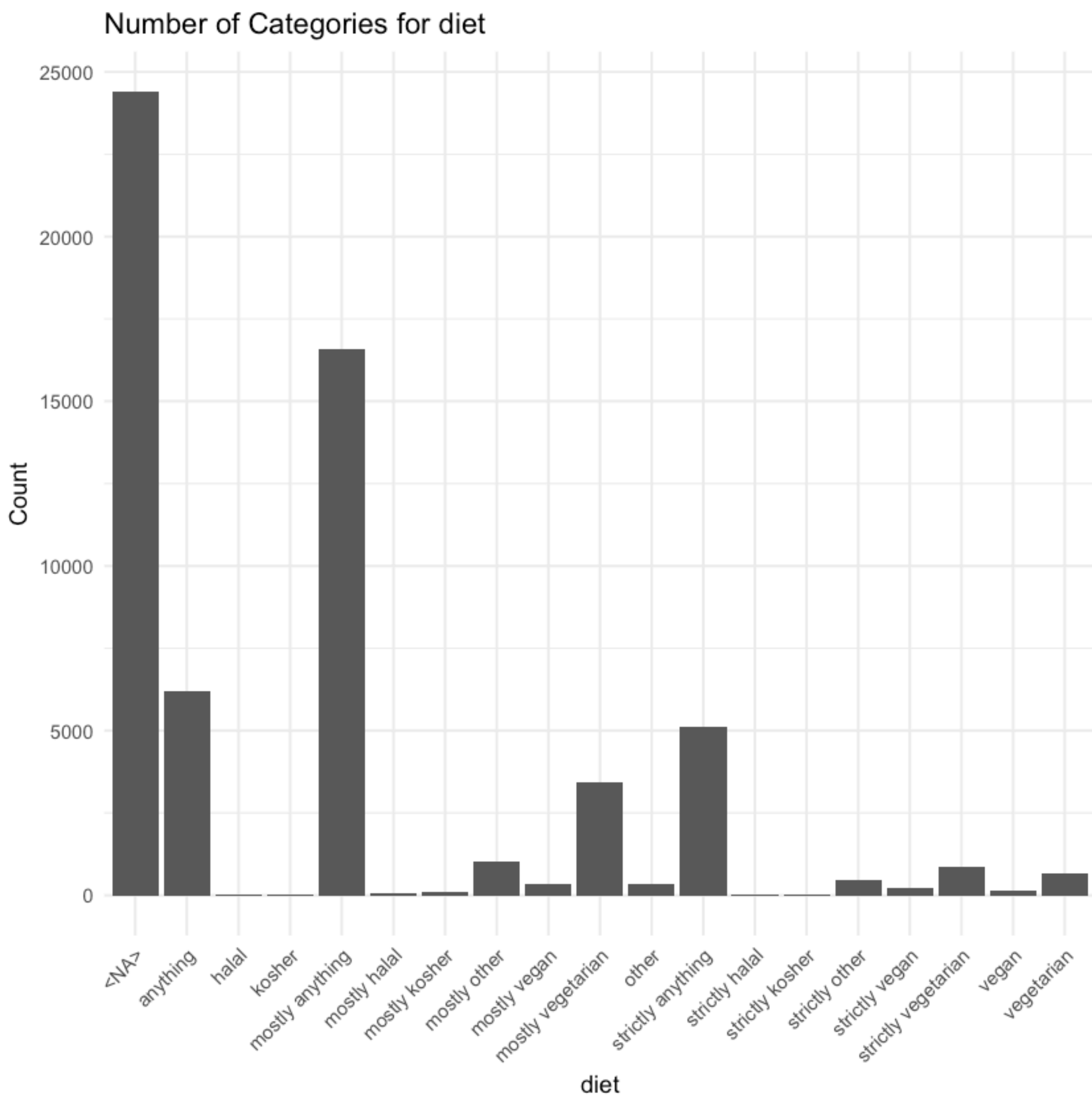
```
Column    : body_type
Categories: 13
```



2.3.2 diet

[16]:
```
# 'diet'
df_diet <- create_df_with_counts(df_eda$diet)
print_df_with_category_count(df_diet, 'diet')
```

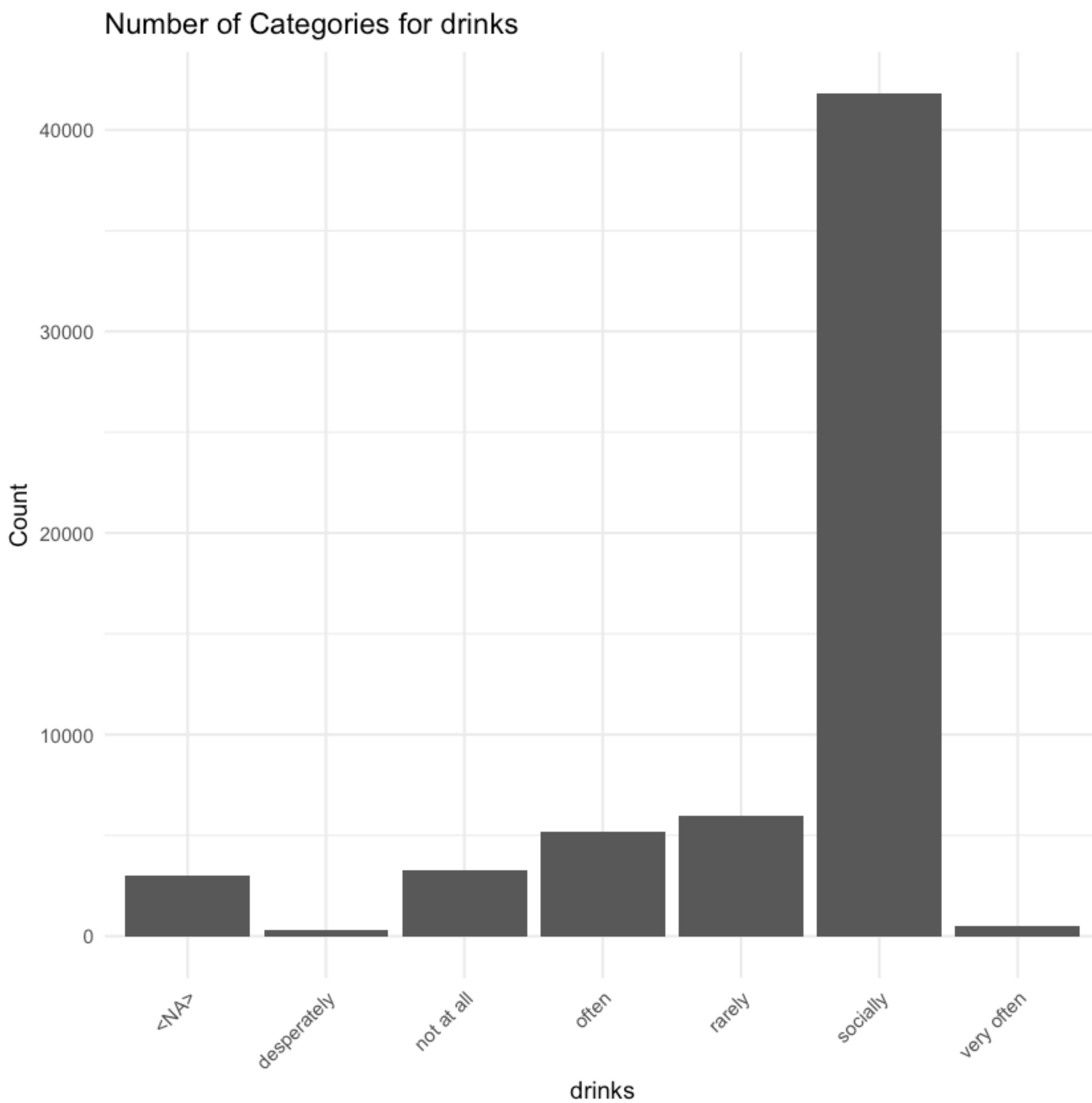
```
Column    : diet
Categories: 19
```



2.3.3 drinks

[17]:
```
# 'drinks'
df_drinks <- create_df_with_counts(df_eda$drinks)
print_df_with_category_count(df_drinks, 'drinks')
```

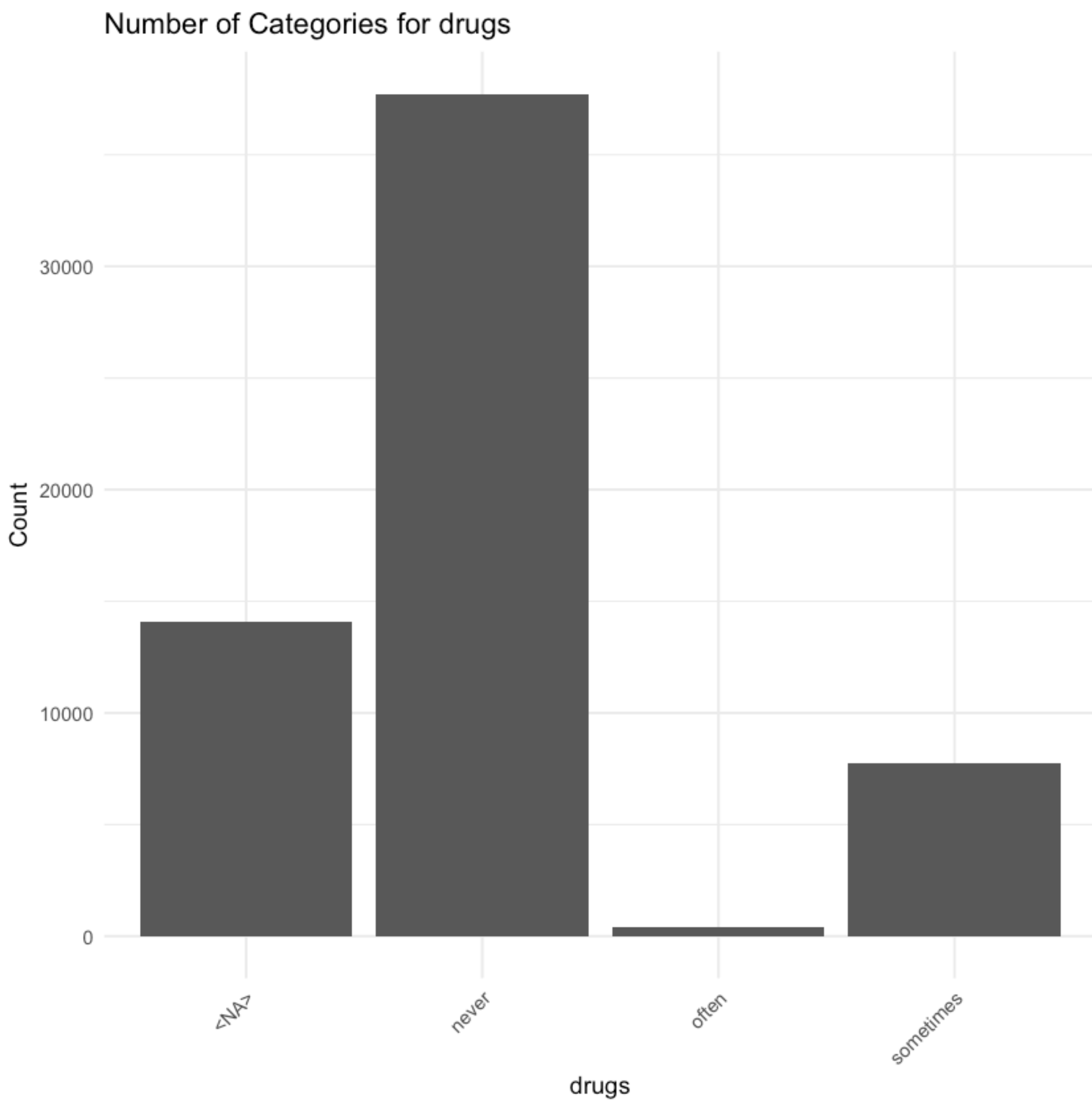
```
Column    : drinks
Categories: 7
```



2.3.4 drugs

[18]:
```
# 'drugs'
df_drugs <- create_df_with_counts(df_eda$drugs)
print_df_with_category_count(df_drugs, 'drugs')
```

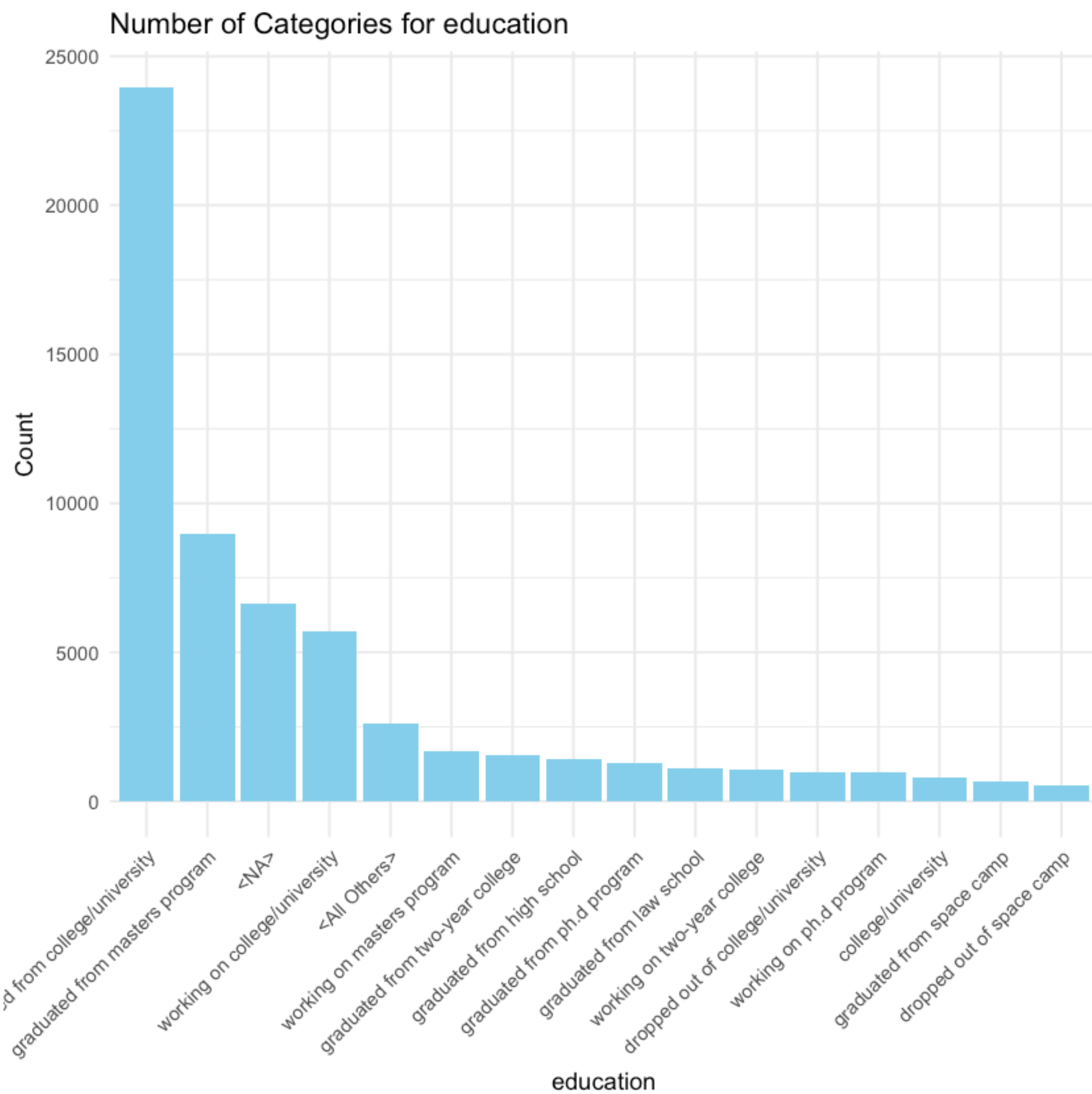
```
Column    : drugs
Categories: 4
```



2.3.5 education

[68]:
```
# 'education'
df_education <- create_df_with_counts(df_eda$education)
print_df_with_category_count(df_education, 'education', n = 20, m = 15)
```

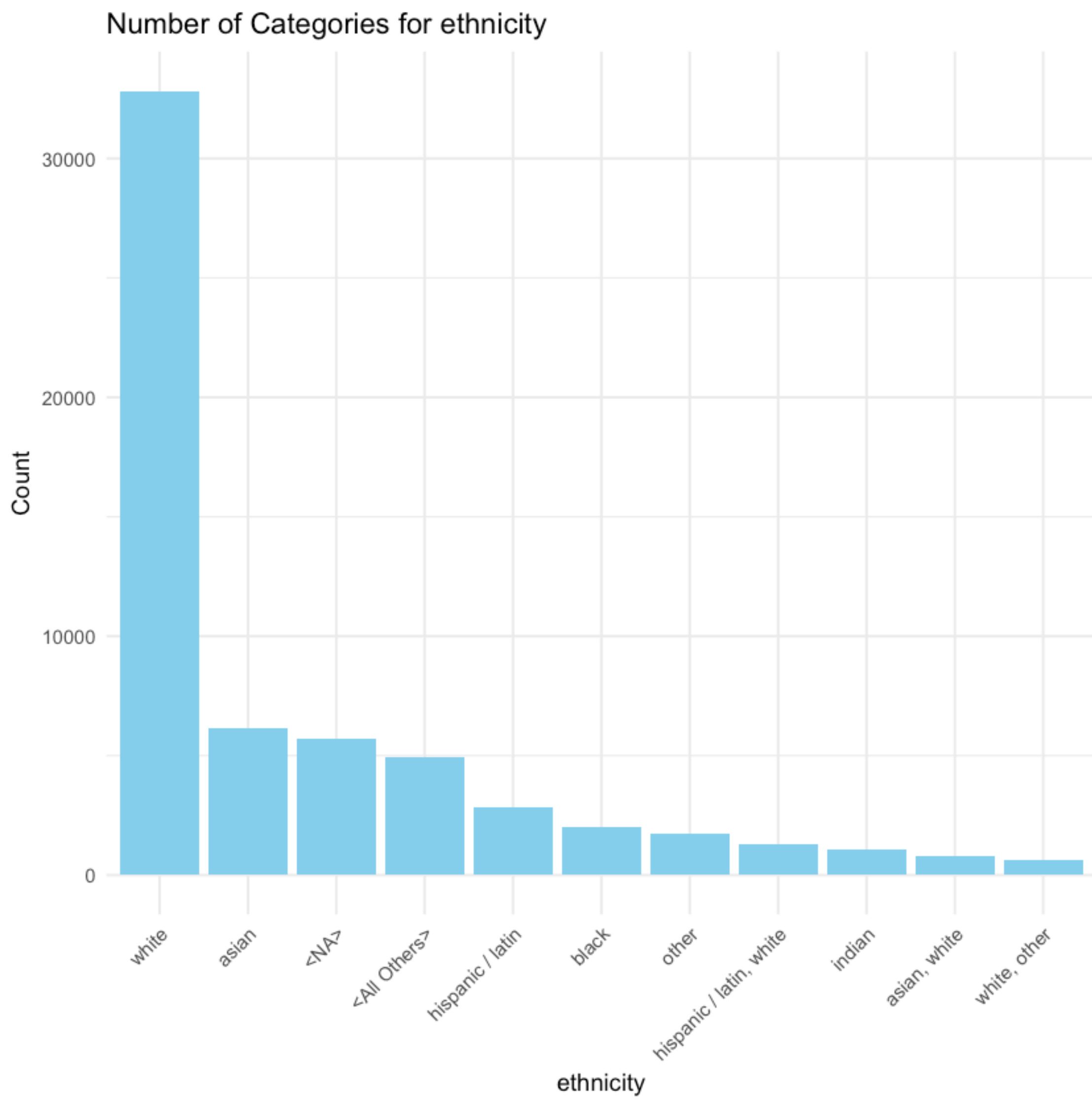
```
Column    : education
Categories: 33
```



2.3.6 ethnicity

[69]:
```
# 'ethnicity'
df_ethnicity <- create_df_with_counts(df_eda$ethnicity)
print_df_with_category_count(df_ethnicity, 'ethnicity')
```

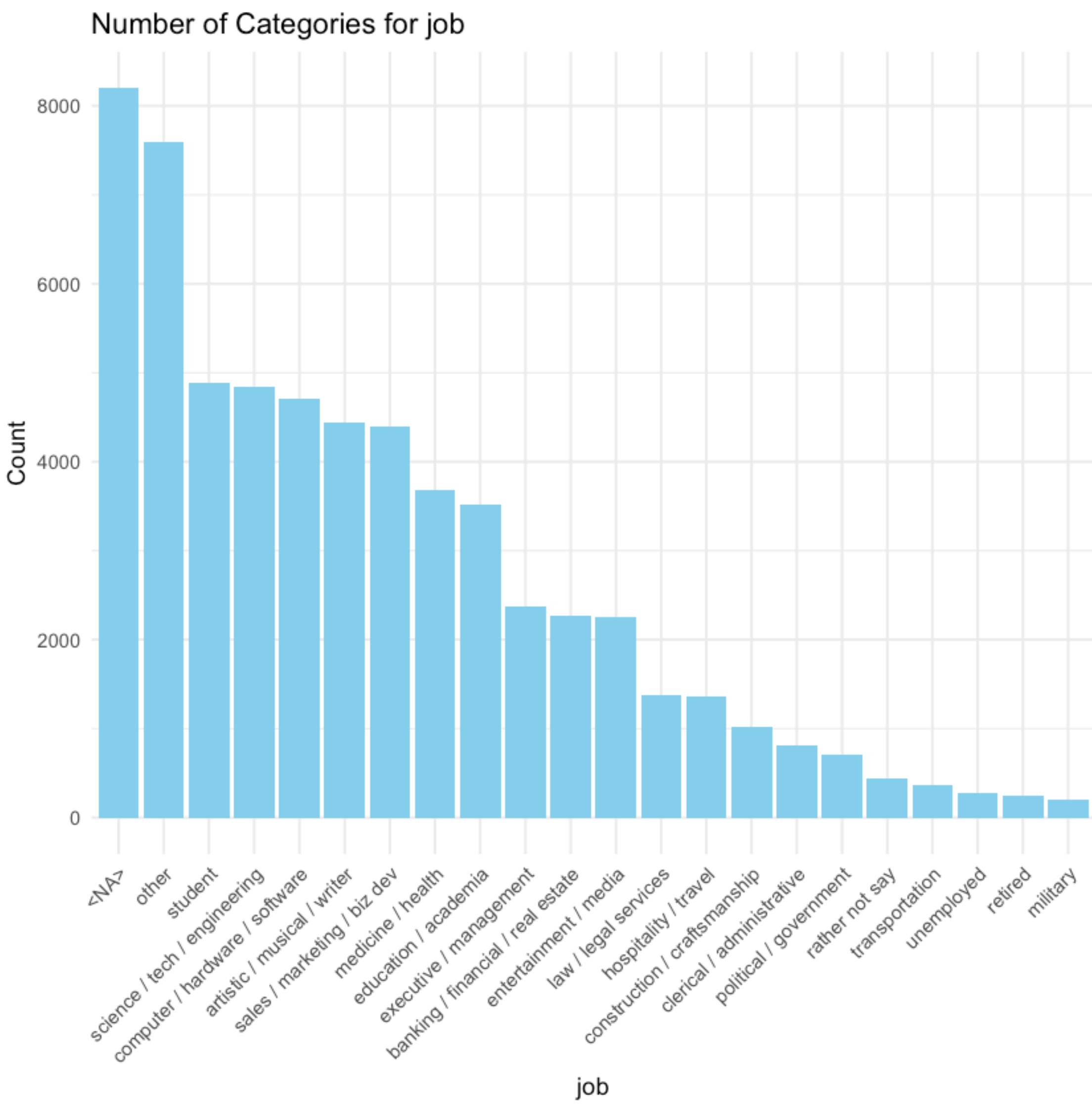
```
Column    : ethnicity
Categories: 218
```



2.3.7 job

[70]:
```r
# 'job'
df_job <- create_df_with_counts(df_eda$job)
print_df_with_category_count(df_job, 'job', n = 25)
```

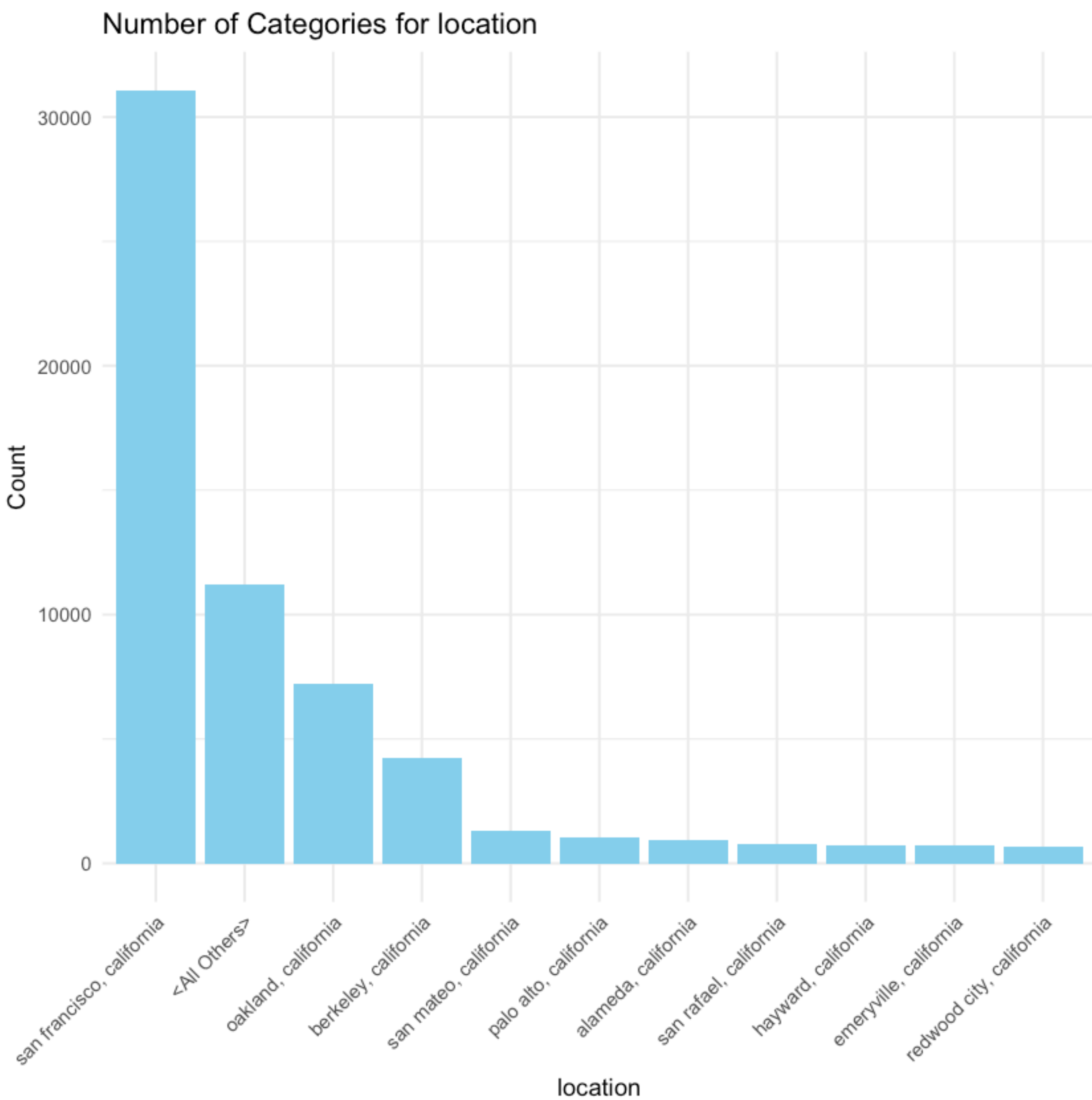
```
Column    : job
Categories: 22
```



2.3.8 location

[71]:
```
# 'location'
df_location <- create_df_with_counts(df_eda$location)
print_df_with_category_count(df_location, 'location')
```

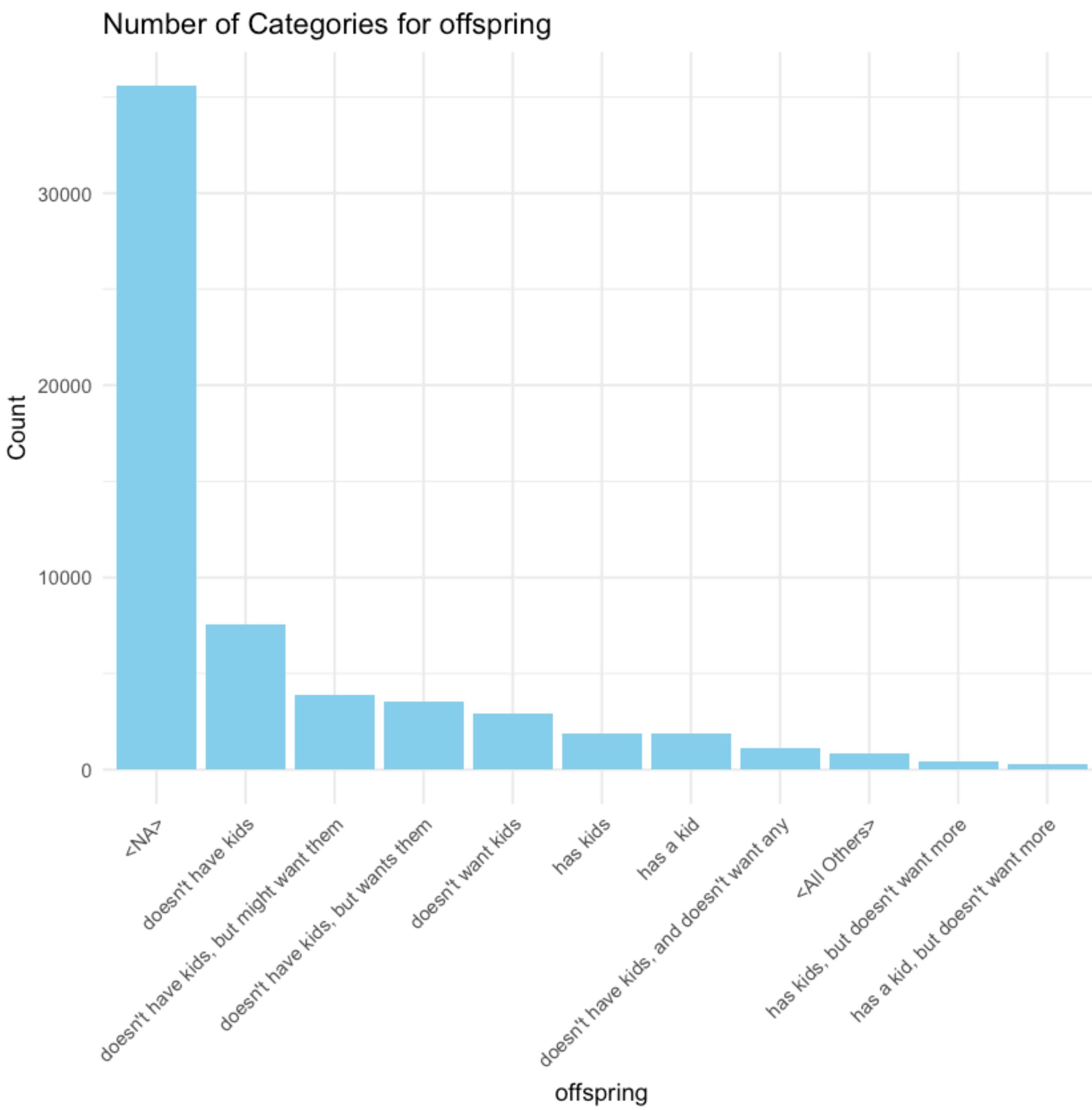
```
Column    : location
Categories: 199
```



2.3.9 offspring

[77]:
```
# 'offspring'
df_offspring <- create_df_with_counts(df_eda$offspring)
print_df_with_category_count(df_offspring, 'offspring', n = 10)
```

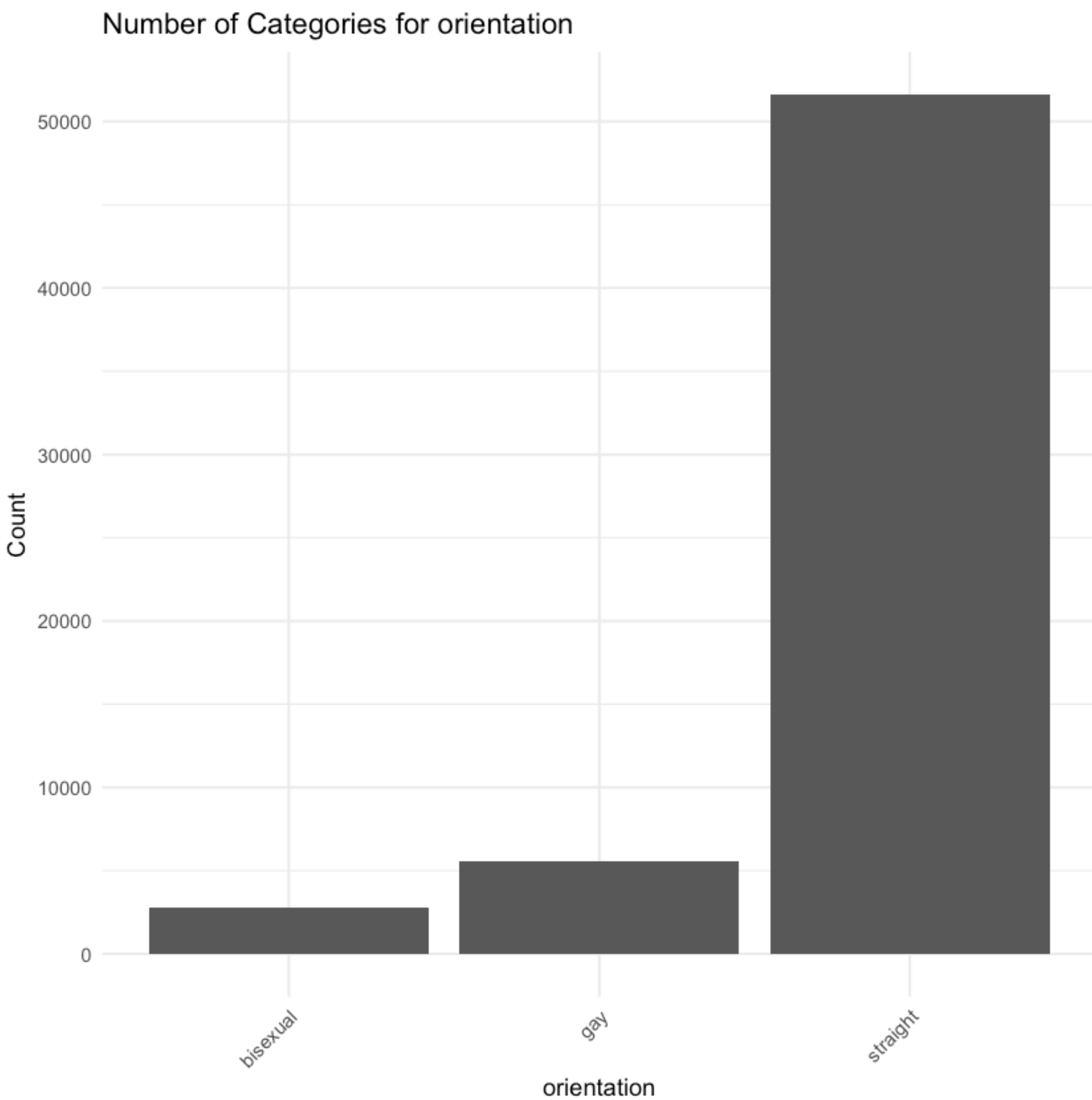
```
Column     : offspring
Categories: 16
```



2.3.10 orientation

[24]:
```
# 'orientation'
df_orientation <- create_df_with_counts(df_eda$orientation)
print_df_with_category_count(df_orientation, 'orientation')
```

```
Column    : orientation
Categories: 3
```



[56]:
```
##### Example 2 way EDA
table(df_eda$age, df_eda$orientation)
```

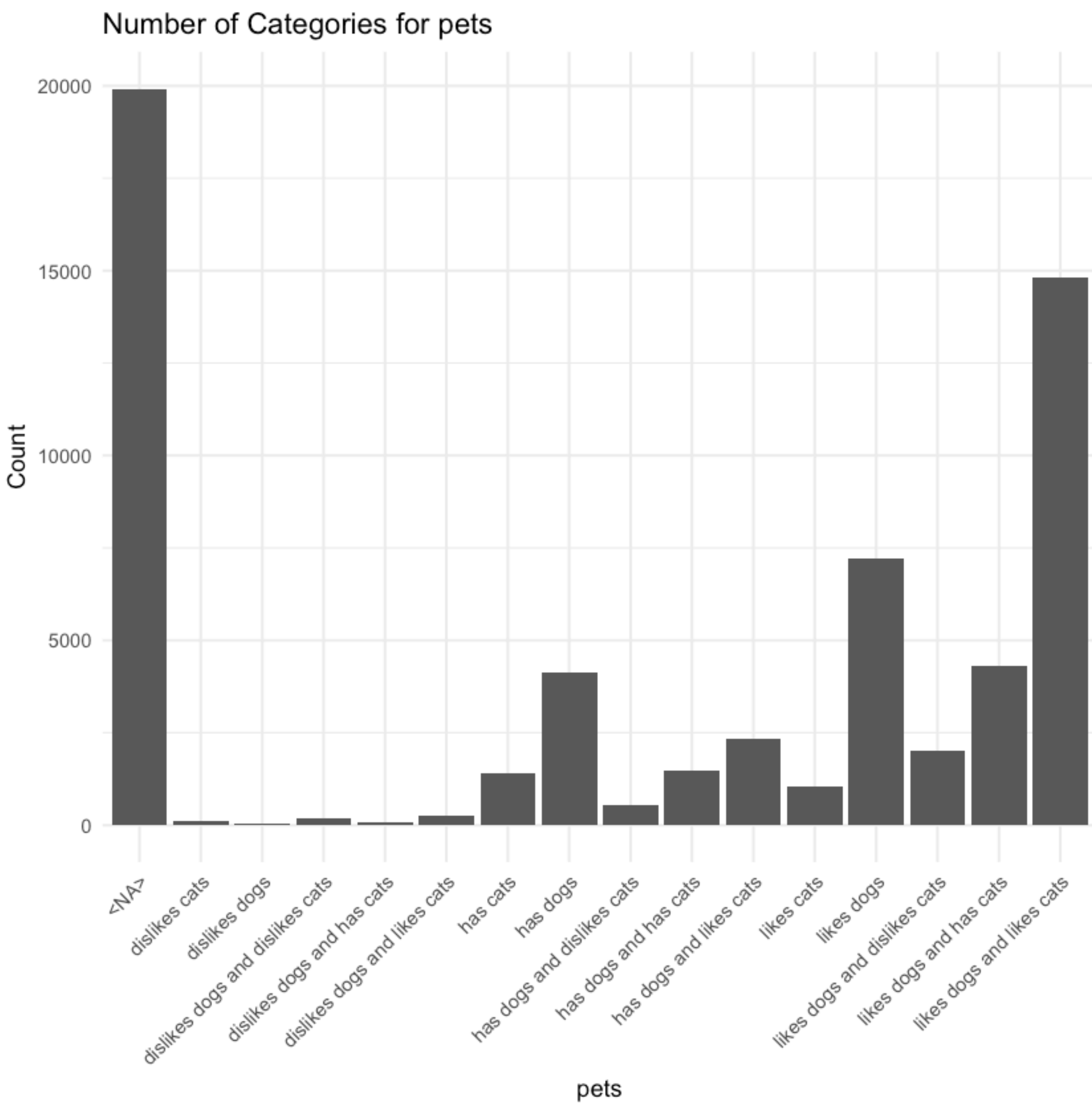
	bisexual	gay	straight
18	49	28	232
19	72	66	473
20	109	107	737
21	132	149	1001
22	160	212	1562
23	190	254	2148
24	177	304	2761
25	183	325	3023

26	175	352	3197
27	163	303	3219
28	145	353	3085
29	135	271	2889
30	113	300	2736
31	90	248	2397
32	127	199	2261
33	75	177	1954
34	64	163	1675
35	79	135	1541
36	59	131	1393
37	65	142	1220
38	55	103	1172
39	45	87	1040
40	27	95	908
41	21	105	854
42	42	100	930
43	27	92	739
44	26	87	595
45	18	70	555
46	17	73	488
47	21	79	429
48	13	53	415
49	14	60	385
50	14	56	367
51	8	40	302
52	13	37	294
53	7	21	224
54	1	28	238
55	5	29	231
56	5	26	240
57	7	18	231
58	3	11	183
59	3	11	207
60	0	15	180
61	0	11	165
62	4	11	152
63	3	10	125
64	0	4	109
65	2	11	96
66	1	3	101
67	2	6	58
68	0	0	59
69	1	2	28
109	0	0	1
110	0	0	1

2.3.11 pets

[29]:
```
# 'pets'
df_pets <- create_df_with_counts(df_eda$pets)
print_df_with_category_count(df_pets, 'pets')
```

```
Column    : pets
Categories: 16
```



Pet lovers Let's add two columns to clearly identify dogs and cats lovers. The columns will be named `dog_friendly` and `cat_friendly`. Each column will have TRUE if the user likes or has that pet, otherwise it will be FALSE.

[34]:
```r
# 1. Add the 'dog_friendly' and 'cat_friendly' columns with default values of␣
↪FALSE
df_eda$dog_friendly <- FALSE
df_eda$cat_friendly <- FALSE

# 2. Function to check pet preferences and assign TRUE to the respective␣
↪columns only if "has" or "likes" is present
df_eda <- df_eda %>%
  mutate(
    # For dog_friendly: Ensure "dislikes dogs" is NOT present, and check for␣
↪"has dogs" or "likes dogs"
    dog_friendly = ifelse(grepl("has dogs|likes dogs", pets, ignore.case =␣
↪TRUE) &
                          !grepl("dislikes dogs", pets, ignore.case = TRUE),␣
↪TRUE, FALSE),

    # For cat_friendly: Ensure "dislikes cats" is NOT present, and check for␣
↪"has cats" or "likes cats"
    cat_friendly = ifelse(grepl("has cats|likes cats", pets, ignore.case =␣
↪TRUE) &
                          !grepl("dislikes cats", pets, ignore.case = TRUE),␣
↪TRUE, FALSE)
  )
```

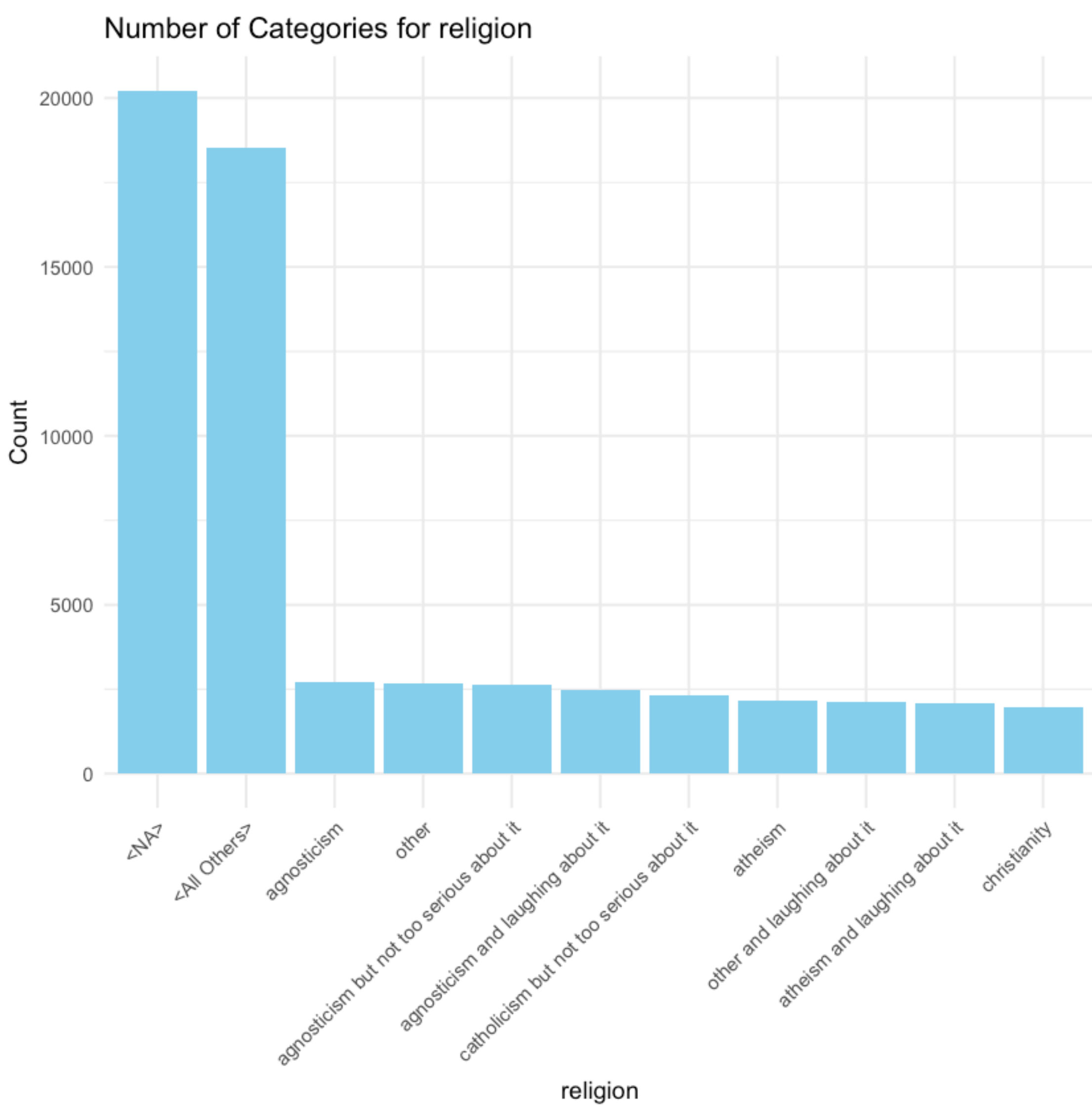
[35]:
```r
# 3. Display a random sample of 10 records showing 'pets', 'dog_friendly', and␣
↪'cat_friendly' columns
set.seed(123)  # Set seed for reproducibility
sample_records <- df_eda %>%
  select(pets, dog_friendly, cat_friendly) %>%
  sample_n(10)

# Print the sample records
print(sample_records)
```

```
                          pets dog_friendly cat_friendly
1                   likes dogs         TRUE        FALSE
2                         <NA>        FALSE        FALSE
3   dislikes dogs and likes cats       FALSE         TRUE
4   likes dogs and dislikes cats        TRUE        FALSE
5                         <NA>        FALSE        FALSE
6                         <NA>        FALSE        FALSE
7        likes dogs and has cats        TRUE         TRUE
8                         <NA>        FALSE        FALSE
9      likes dogs and likes cats        TRUE         TRUE
10                    has dogs         TRUE        FALSE
```

2.3.12 religion

[78]:
```r
# 'religion'
df_religion <- create_df_with_counts(df_eda$religion)
print_df_with_category_count(df_religion, 'religion', n = 10, m = 10)
```

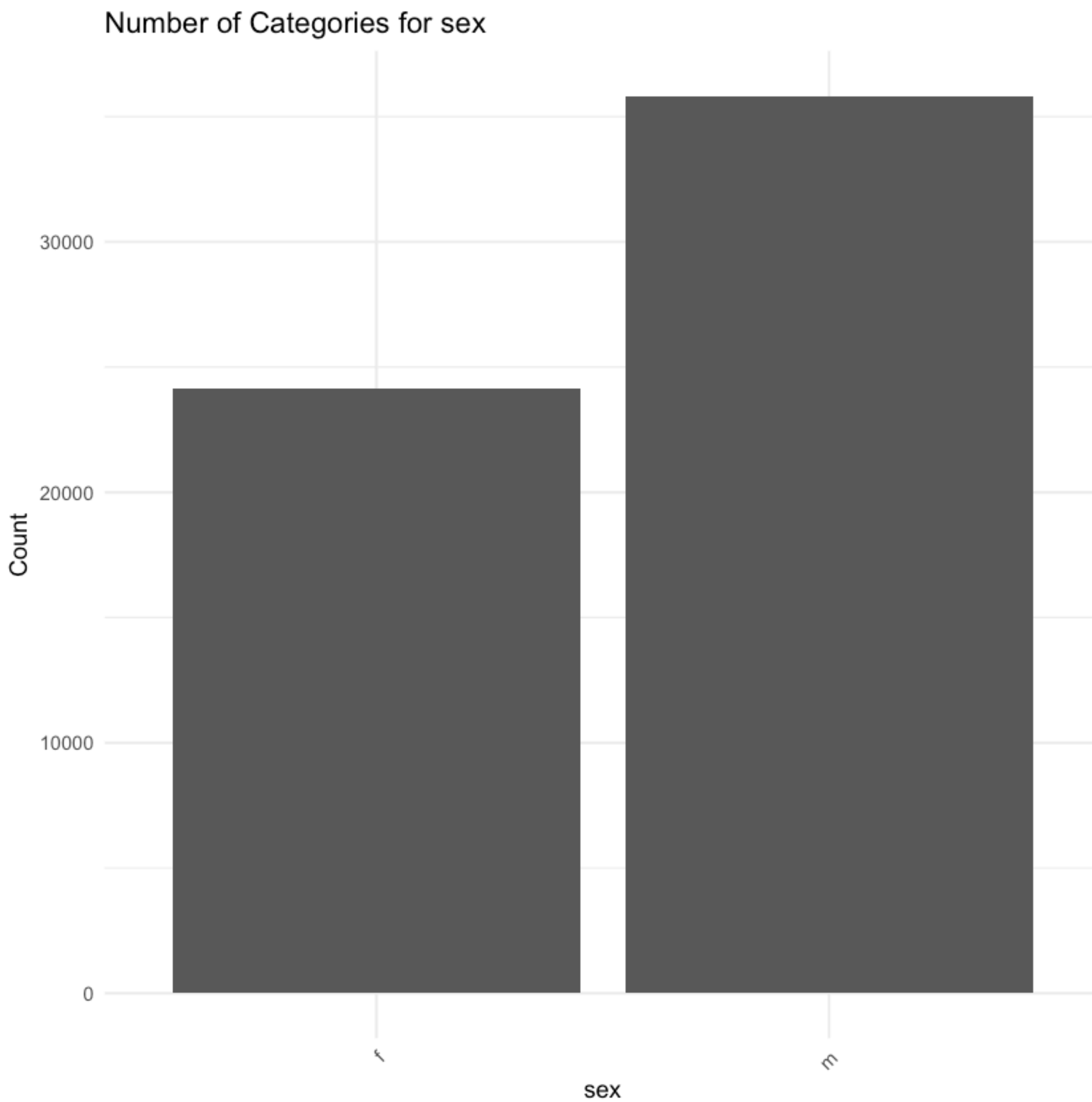
```
Column    : religion
Categories: 46
```



2.3.13 sex

[27]:
```
# 'sex'
df_sex <- create_df_with_counts(df_eda$sex)
print_df_with_category_count(df_sex, 'sex')
```

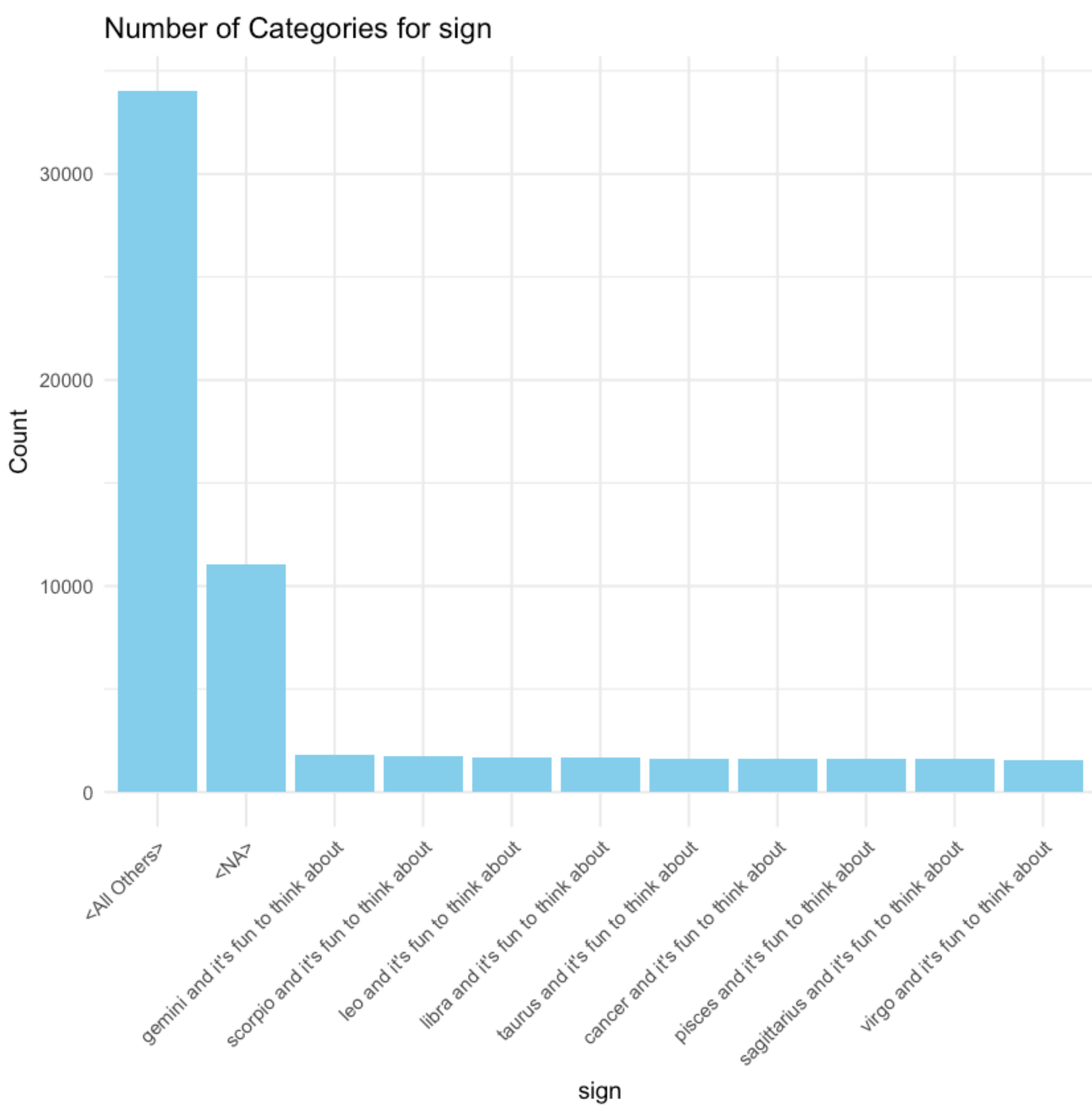
```
Column    : sex
Categories: 2
```



2.3.14 sign

[79]:
```
# 'sign'
df_sign <- create_df_with_counts(df_eda$sign)
print_df_with_category_count(df_sign, 'sign')
```

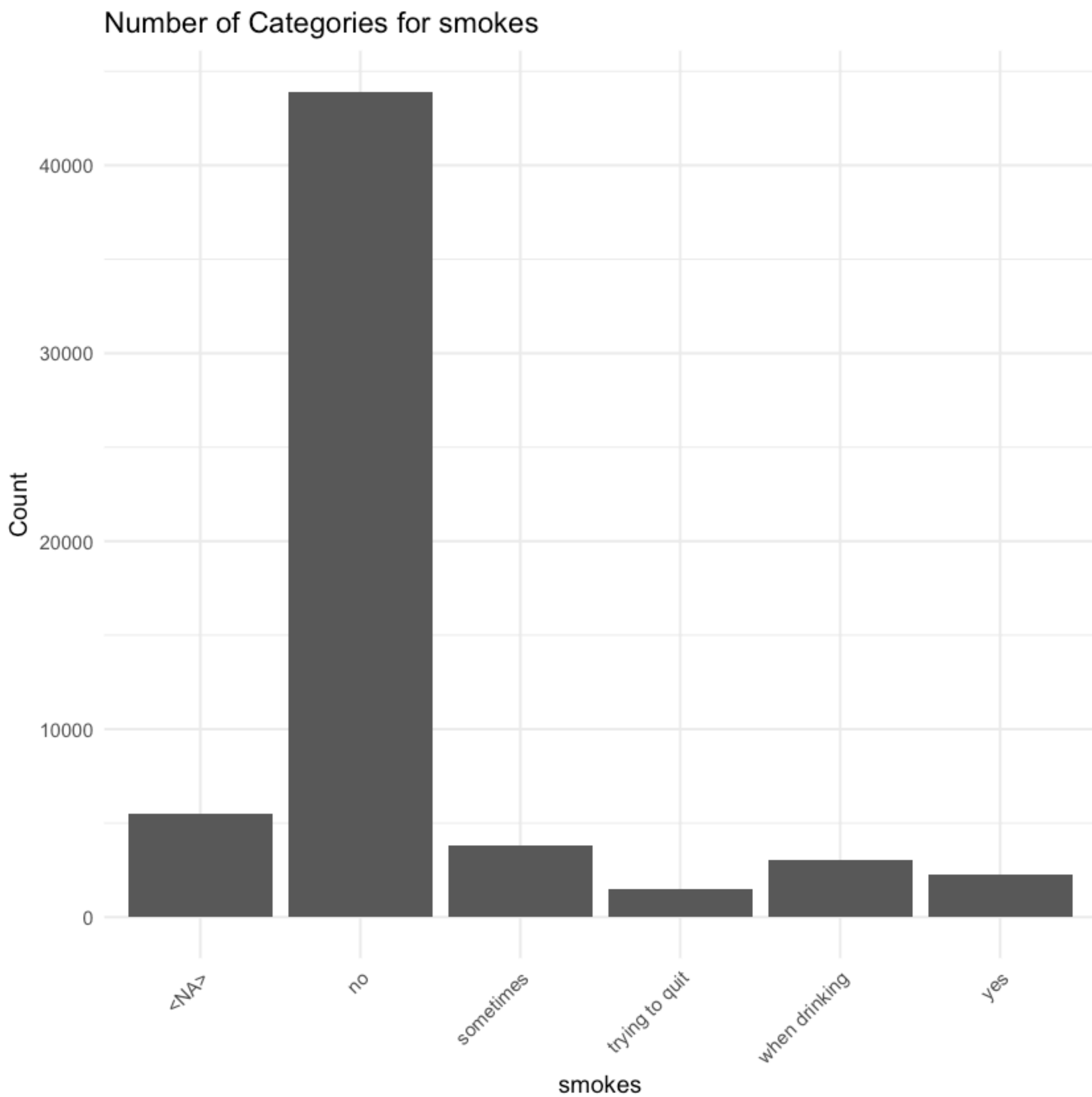
```
Column    : sign
Categories: 49
```



2.3.15 smokes

[29]:
```
# 'smokes'
df_smokes <- create_df_with_counts(df_eda$smokes)
print_df_with_category_count(df_smokes, 'smokes')
```

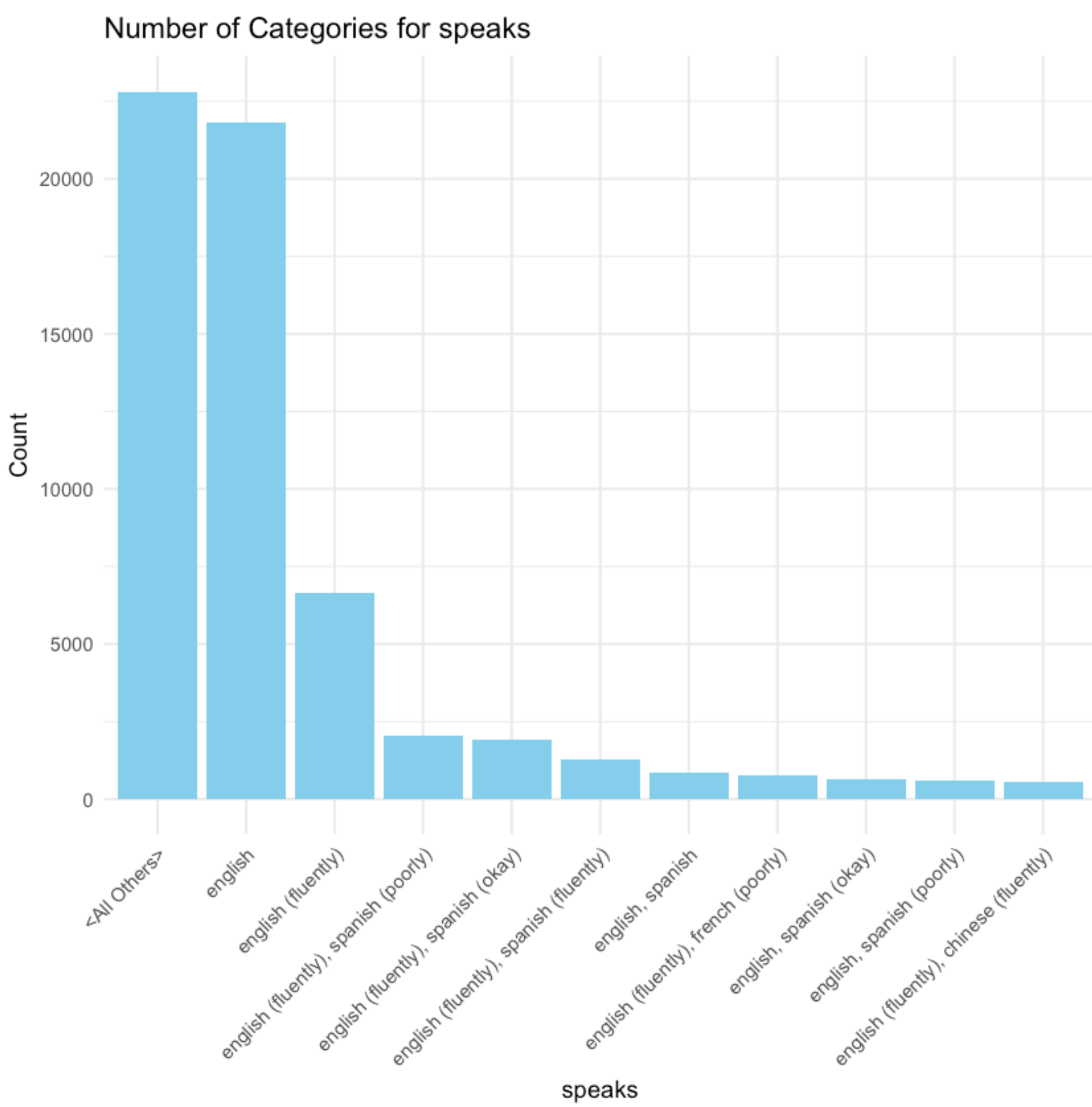
```
Column    : smokes
Categories: 6
```



2.3.16 speaks

[80]:
```r
# 'speaks'
df_speaks <- create_df_with_counts(df_eda$speaks)
print_df_with_category_count(df_speaks, 'speaks', n = 10)
```

```
Column    : speaks
Categories: 7648
```



`speaks` column has lists of languages spoken by each user followed (in some cases) by the expertise level. More than that, in some cases the language appears more than once for the same user, sometimes with the same level of expertise and sometimes different. The large number of languages and the possibility to combine n languages for user plus duplicates and four different levels of expertise, brings this column to have 7648 unique combinations, which is useless in our research.

To know how many people speak a language, let's create a single column where each cell has only one language with no level of expertise. This is a complex cleaning process that we will solve in steps. In the first step, we will remove duplicate `language(level of expertise)` occurrencies leaving the highest level of expertise. This could be useful if we want to do additional analysis later with that information. The `process_speaks` function below does that.

[31]:
```
# Define the order of fluency levels
fluency_levels <- c(NA, "(poorly)", "(okay)", "(fluently)")


# Function to process the 'speaks' column
process_speaks <- function(speaks) {

  # print(paste("0 - speaks: ", speaks, sep = "")) ### STEP 0

  if (is.na(speaks) || speaks == "") {
    # return("english")
    return("")
  }

  # print(paste("1 - speaks: ", speaks, sep = "")) ### STEP 1

  # Split the speaks column by comma
  languages <- unlist(strsplit(speaks, ","))

  # print(paste("2 - languages: ", languages, sep = "")) ### STEP 2

  # Remove leading and trailing whitespace and any extra spaces
  languages <- str_trim(languages)
  languages <- gsub("\\s+", "", languages)

  # print(paste("3 - languages: ", languages, sep = "")) ### STEP 3

  # Create a data frame of languages and levels
  languages_df <- data.frame(language = str_extract(languages, "^[^()]+"),
                             level = str_extract(languages, "\\(([^)]+)\\)"))

  # print(paste("4 - languages_df: ", languages_df, sep = "")) ### STEP 4
  # kable(languages_df, caption = 'STEP 4')

  # Ensure 'english' is included with no level if not already present
  if (!any(grepl("^english", tolower(languages_df$language)))) {
    languages_df <- rbind(languages_df, data.frame(language = "english", level
↪= NA))
  }
```

```r
  # print(paste("5 - languages_df: ", languages_df, sep = "")) ### STEP 5
  # kable(languages_df, caption = 'STEP 5')

  # Remove duplicates and keep the highest level, handle NA levels correctly
  cleaned_languages_df <- languages_df %>%
    mutate(level = factor(level, levels = fluency_levels, ordered = TRUE)) %>%
    group_by(language) %>%
    filter(if(all(is.na(level))) TRUE else level == max(level, na.rm = TRUE))␣
↪%>%
    distinct(language, .keep_all = TRUE) %>%  # Remove duplicates after␣
↪filtering
    ungroup()  # Ungroup the dataframe

  # Print the cleaned dataframe
  # print(paste("6 - languages_df: ", cleaned_languages_df, sep = "")) ### STEP␣
↪6
  # kable(cleaned_languages_df, caption = 'STEP 6')

  # Combine languages and levels back into a single string
  languages <- paste(cleaned_languages_df$language, ifelse(is.
↪na(cleaned_languages_df$level), "", paste0(cleaned_languages_df$level)), sep␣
↪= "", collapse = ", ")

  # print(paste("7 - languages: ", languages, sep = "")) ### STEP 7

  return(languages)
}
```

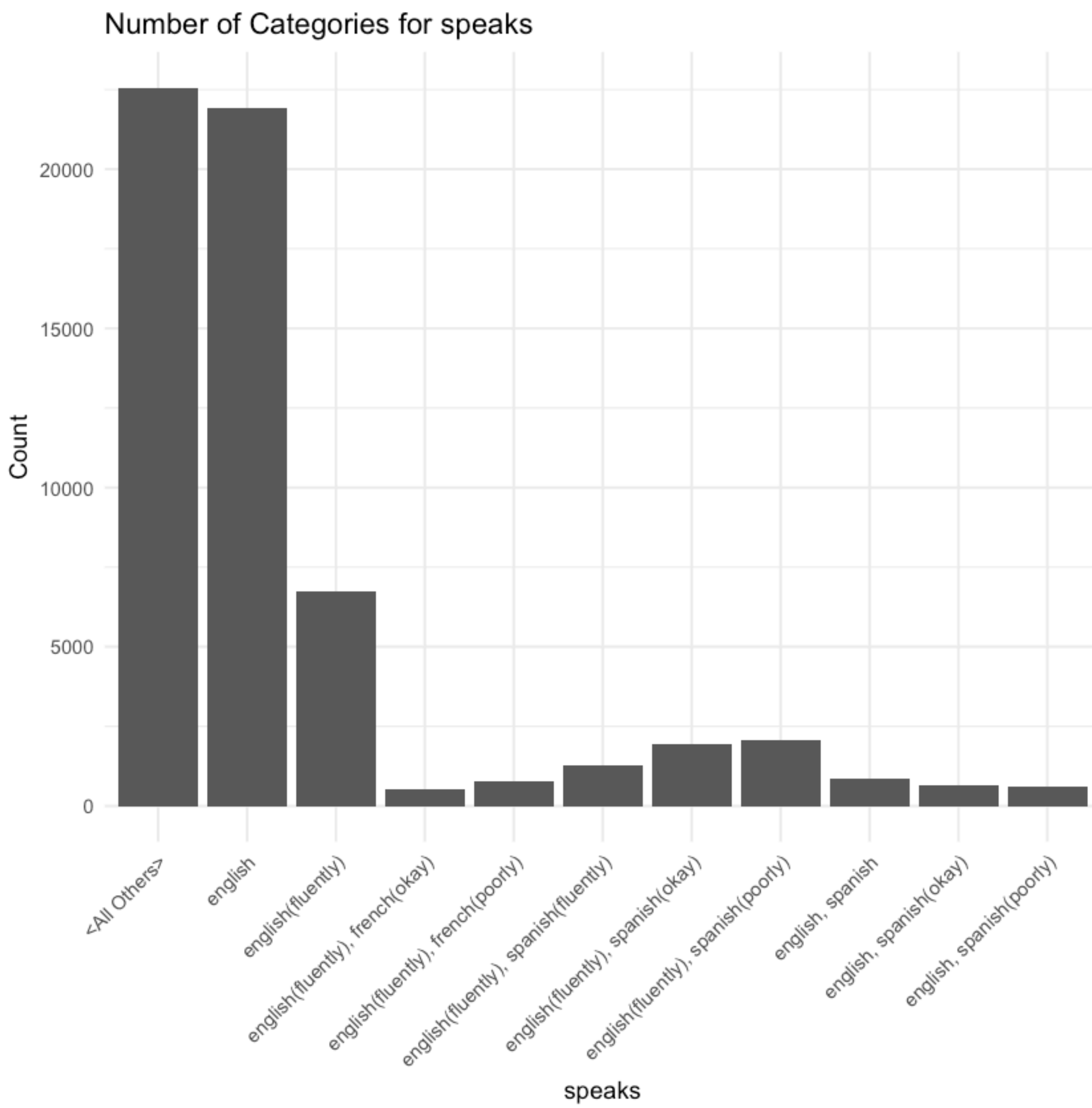
The cleaned result will be stored in df_eda_processed.

[32]:
```r
# Create a new dataset to avoid overwriting the original 'df_eda' dataset
df_eda_processed <- df_eda
df_eda_processed$speaks <- sapply(df_eda_processed$speaks, process_speaks)
```

These results do not help enough because we still have too many combinations, as shown below.

[33]:
```r
df_speaks_cleaned <- create_df_with_counts(df_eda_processed$speaks)
print_df_with_category_count(df_speaks_cleaned, 'speaks')
```

```
Column    : speaks
Categories: 7500
```



Let's reorganize our speak data to ease the analysis. At this point, we will decompose each list of languages in as many rows as languages it has, leaving only one language per row.

[34]:
```
# Function to process the column with multiple values
process_column_to_vertical_df <- function(data_column) {
  # Step 1: Split each entry by commas, separating the languages
  separated <- str_split(data_column, ",")

  # Step 2: Remove the level of expertise (anything inside parentheses)
  cleaned <- lapply(separated, function(x) {
    str_trim(gsub("\\(.*?\\)", "", x))  # Removes text within parentheses and␣
 ↪trims whitespace
  })
```

```
  # Step 3: Unlist the cleaned languages and convert them into a dataframe
  df_vertical <- data.frame(Language = unlist(cleaned))

  # Step 4: Return the vertical dataframe with unique values
  return(df_vertical)
}

# Read the languages data
languages_column <- df_eda_processed$speaks

# Apply the function
df_languages <- process_column_to_vertical_df(languages_column)

# Print a sample of the resulting vertical dataframe
head(df_languages)
```

A data.frame: 6 x 1

	Language <chr>
1	english
2	english
3	spanish
4	french
5	english
6	french

This is the number of rows we got after unfolding the languages.

[35]:
```
nrow(df_languages)
```

110413

Now, let's count the ocurrencies of each language.

[36]:
```
# Function to count occurrences, return top n values, calculate percentages,␣
↪and plot a graph
count_occurrences <- function(input_list, df_eda, n = NULL) {

  # Step 1: Use the table() function to count the occurrences of each unique␣
↪value
  counts <- table(input_list)

  # Step 2: Convert the table into a dataframe
  df_counts <- as.data.frame(counts, stringsAsFactors = FALSE)

  # Step 3: Rename the columns to 'Value' and 'Count'
  colnames(df_counts) <- c("Value", "Count")
```

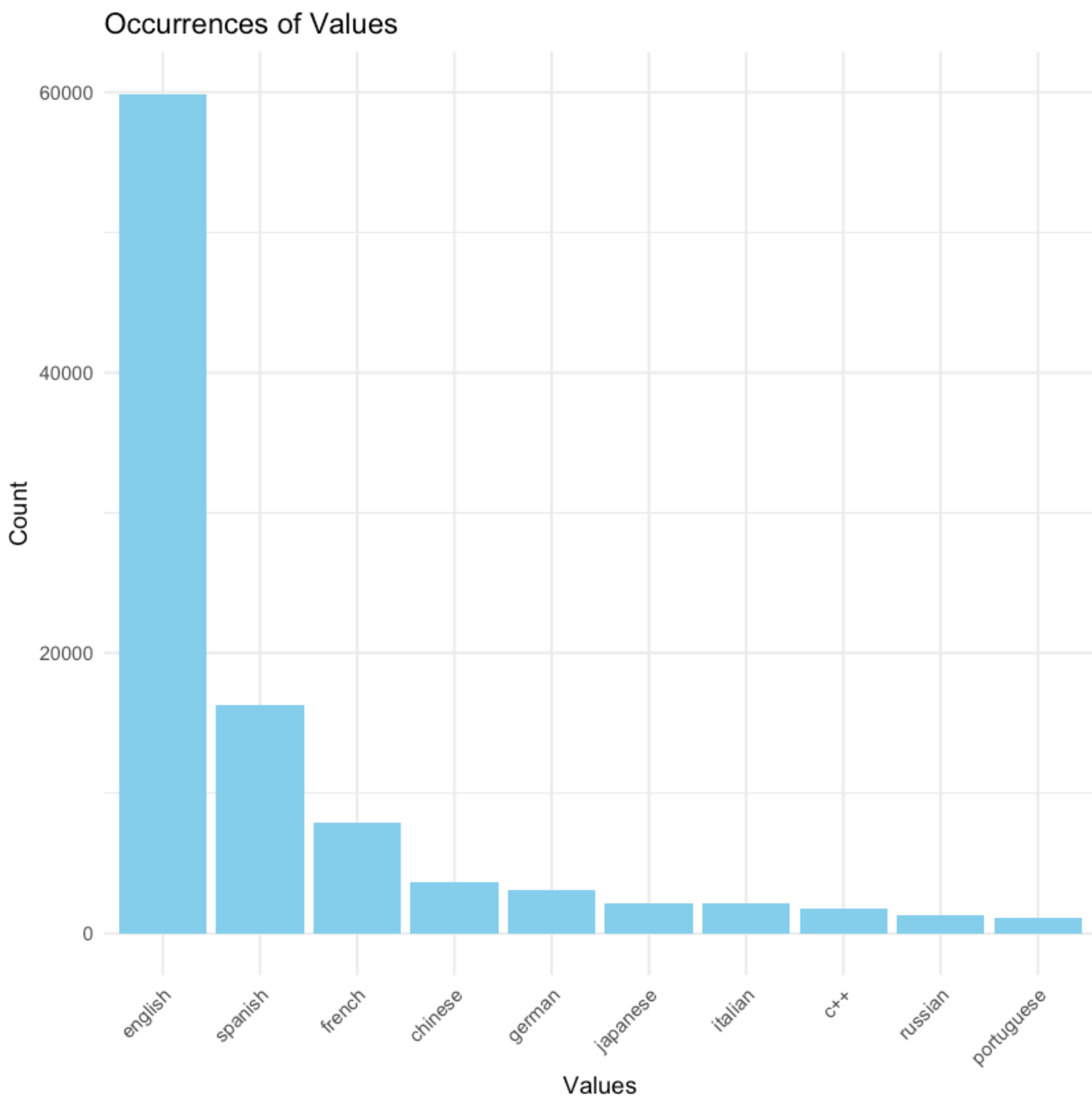
```r
  # Step 4: Calculate the percentage for each value against the total number of␣
↪rows in df_eda
  total_rows <- nrow(df_eda)
  df_counts$Percentage <- (df_counts$Count / total_rows) * 100

  # Step 5: Sort the dataframe by 'Count' in descending order
  df_counts <- df_counts[order(-df_counts$Count), ]

  # Step 6: If n is specified, return only the top n rows
  if (!is.null(n)) {
    df_counts <- head(df_counts, n)
  }

  # Step 7: Create the bar plot
  p <- ggplot(df_counts, aes(x = reorder(Value, -Count), y = Count)) +
    geom_bar(stat = "identity", fill = "skyblue") +
    theme_minimal() +
    labs(title = "Occurrences of Values", x = "Values", y = "Count") +
    theme(axis.text.x = element_text(angle = 45, hjust = 1)) # Rotate x-axis␣
↪labels

  # Step 8: Explicitly print the plot to display it
  print(p)

  # Step 9: Return the dataframe
  return(df_counts)
}
```

The table below lists the top 10 languages with more speakers.

[37]:
```r
# Apply the function to count occurrences and return the top 3 values
df_languages_results <- count_occurrences(df_languages, df_eda, n = 10)

# Print the resulting dataframe with top 3 values
df_languages_results
```

A data.frame: 10 x 3

	Value <chr>	Count <int>	Percentage <dbl>
21	english	59896	99.916592
66	spanish	16312	27.211157
26	french	7851	13.096787
16	chinese	3660	6.105495
29	german	3083	5.142962
41	japanese	2188	3.649952
40	italian	2181	3.638274
12	c++	1769	2.950989
59	russian	1282	2.138591
56	portuguese	1074	1.791612

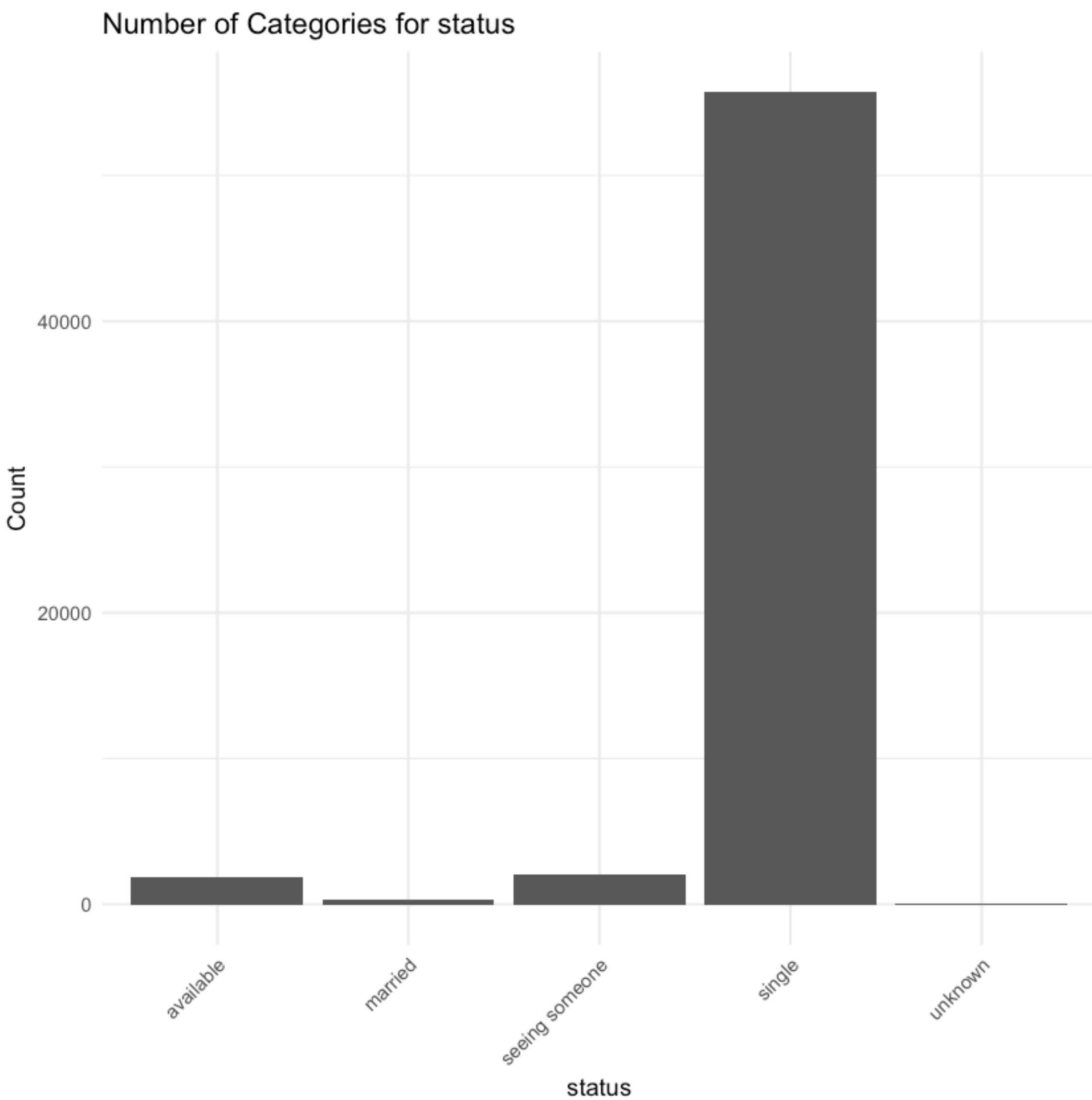


2.3.17 status

Let's generate the table and the graph for the status column as we did before.

[38]:
```
# 'status'
df_status <- create_df_with_counts(df_eda$status)
print_df_with_category_count(df_status, 'status')
```

```
Column    : status
Categories: 5
```



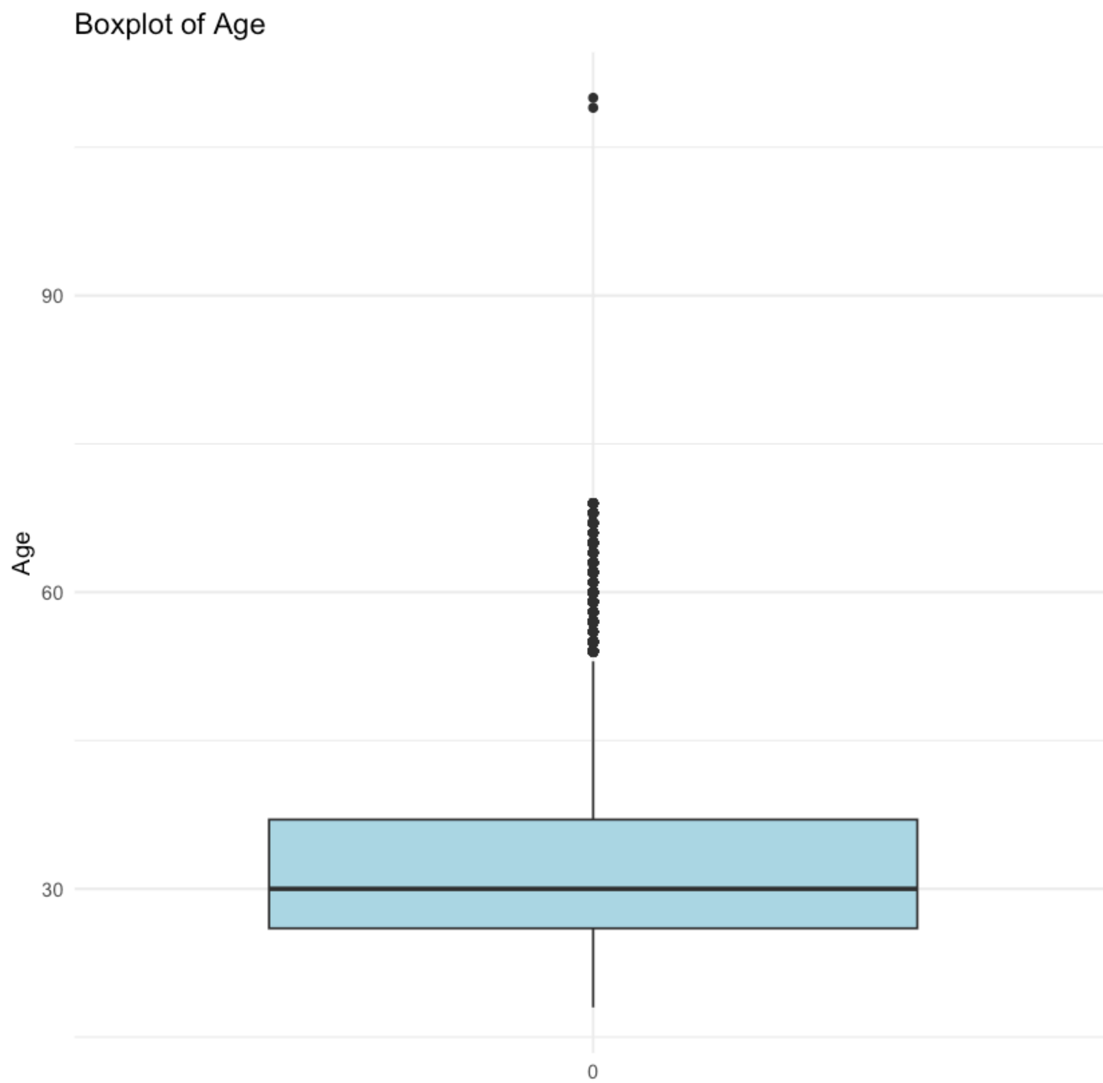
After understanding better the contents of each categorical column, this time to analyze numerical columns. Let's look for outliers and the distribution of our data.

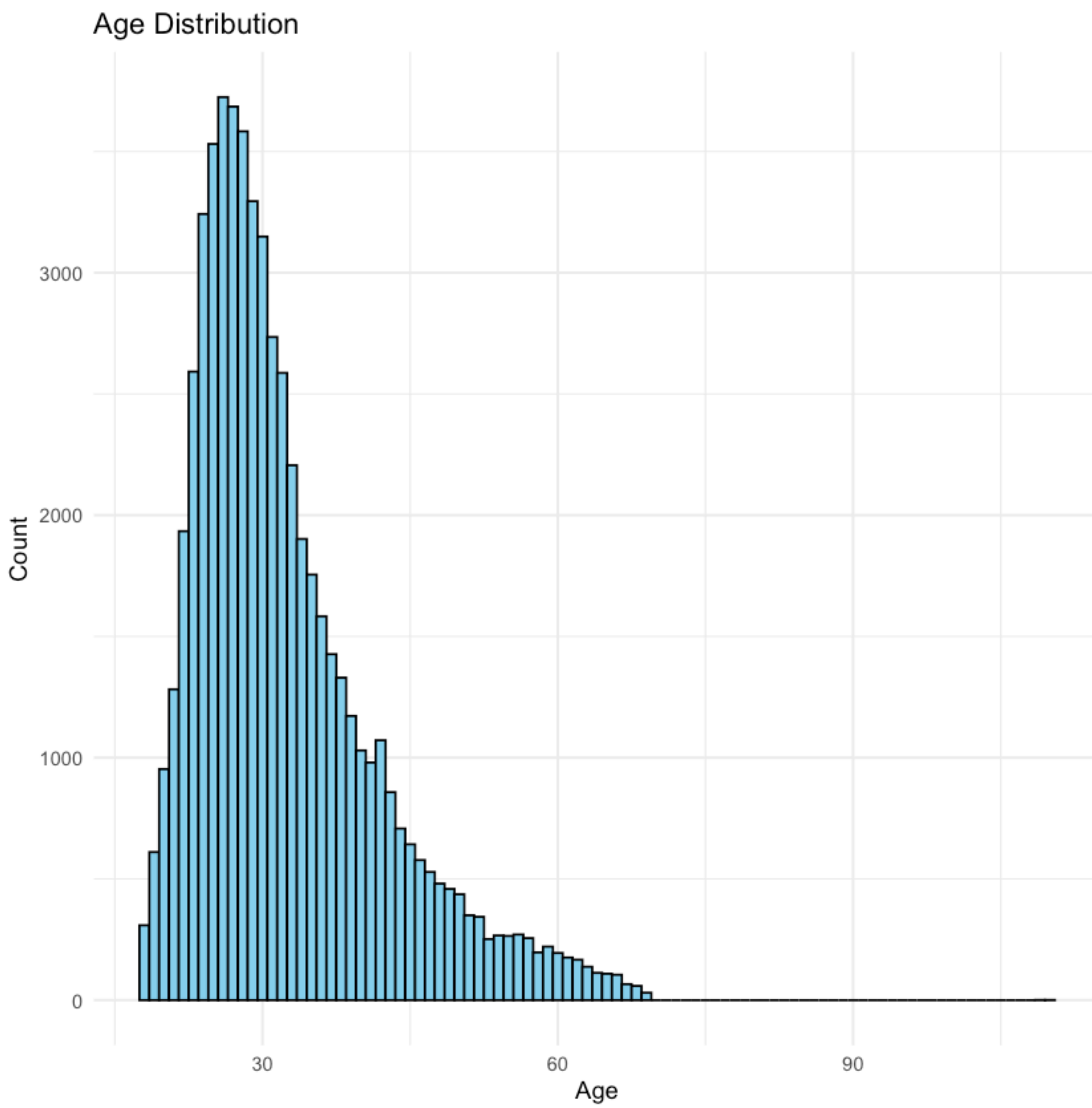
2.3.18 age

[39]:
```
# Let's start with analyzing the 'age' column

# Summary of age column
summary(df_eda$age)

# Check how many records have unrealistic values (age < 18 or age > 100)
invalid_age <- df_eda %>%
  filter(age < 18 | age > 100)
```

```r
# Calculate percentage of invalid age records
invalid_age_count <- nrow(invalid_age)
invalid_age_percentage <- (invalid_age_count / nrow(df_eda)) * 100

cat("Number of invalid age records: ", invalid_age_count, "\n")
cat("Percentage of invalid age records: ", invalid_age_percentage, "%\n")

# Visualize age data with a boxplot to identify outliers
ggplot(df_eda, aes(x = factor(0), y = age)) +
  geom_boxplot(fill = "lightblue") +
  theme_minimal() +
  labs(title = "Boxplot of Age", x = "", y = "Age")

# Plot age distribution with a histogram
ggplot(df_eda, aes(x = age)) +
  geom_histogram(binwidth = 1, fill = "skyblue", color = "black") +
  theme_minimal() +
  labs(title = "Age Distribution", x = "Age", y = "Count")
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  18.00   26.00   30.00   32.34   37.00  110.00 

Number of invalid age records:  2 
Percentage of invalid age records:  0.003336336 %
```


Boxplot of Age
Age
90
60
30
0



Let's see what data are in the records with the age outliers.

[48]:
```
# Filter and print records where age > 90
df_eda_over_90 <- df_eda %>% filter(age > 90)

# Print the resulting dataframe
print(df_eda_over_90)
```

```
  age body_type         diet drinks drugs                     education ethnicity
1 110      <NA>         <NA>   <NA>  <NA>                          <NA>      <NA>
2 109  athletic mostly other   <NA> never working on masters program      <NA>
  height income     job last_online                       location       offspring
1     67     NA    <NA>  2012-06-27     daly city, california            <NA>
2     95     NA student  2012-06-30 san francisco, california might want kids
```

```
  orientation pets                                religion sex
1    straight <NA>                                    <NA>   f
2    straight <NA> other and somewhat serious about it   m
                            sign        smokes         speaks    status essay0
1                           <NA>          <NA>        english    single   <NA>
2 aquarius but it doesn't matter when drinking english (okay) available   <NA>
       lat       lon
1 37.69109 -122.4728
2 37.77712 -122.4196
```

As we can see above, the first record has little data, meaning that it could be discarded. The second record has better data, which means that, under certain conditions, we could consider removing the age value and keep all other fields. For this analysis we will remove those records as well as any records with ages less than 18.

[37]:
```
# Filter out records where age > 90 or age < 18
df_eda_clean <- df_eda %>% filter(age <= 90 & age >= 18)

# Print the record count of df_eda_clean
cat("Number of records in df_eda_clean: ", nrow(df_eda_clean), "\n")
```

```
Number of records in df_eda_clean:  59944
```

2.3.19 height

As before, let's look for outliers and check the distribution.

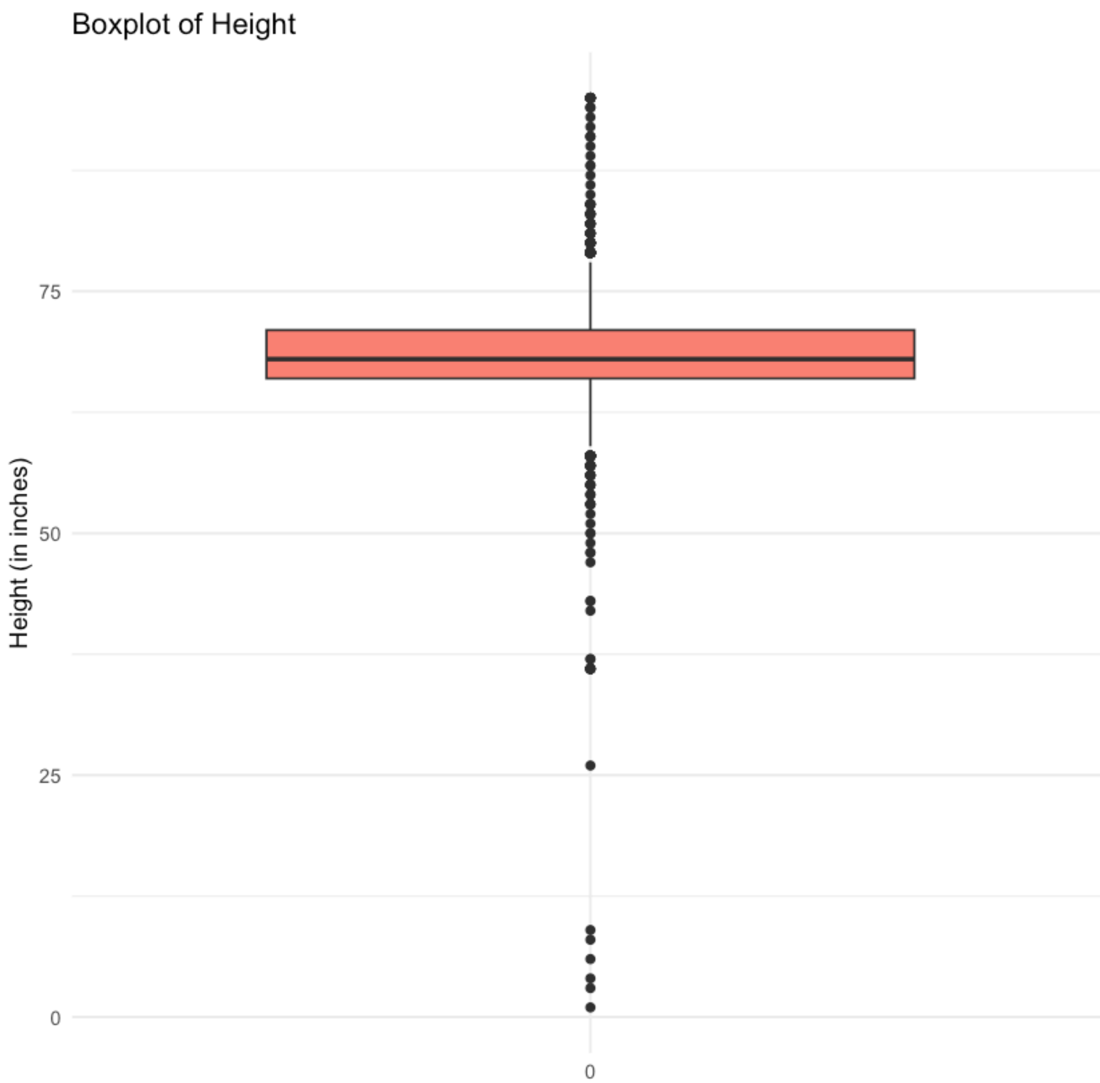
[40]:
```
# Analysis of height column

# Summary of height column
summary(df_eda$height)

# Check for invalid height values (less than 50 inches or greater than 95
 ↪inches)
invalid_height <- df_eda %>%
  filter(height < 50 | height > 95)

# Calculate percentage of invalid height records
invalid_height_count <- nrow(invalid_height)
invalid_height_percentage <- (invalid_height_count / nrow(df_eda)) * 100

cat("Number of invalid height records: ", invalid_height_count, "\n")
cat("Percentage of invalid height records: ", invalid_height_percentage, "%\n")

# Visualize height data with a boxplot to detect outliers
ggplot(df_eda, aes(x = factor(0), y = height)) +
  geom_boxplot(fill = "salmon") +
  theme_minimal() +
  labs(title = "Boxplot of Height", x = "", y = "Height (in inches)")
```

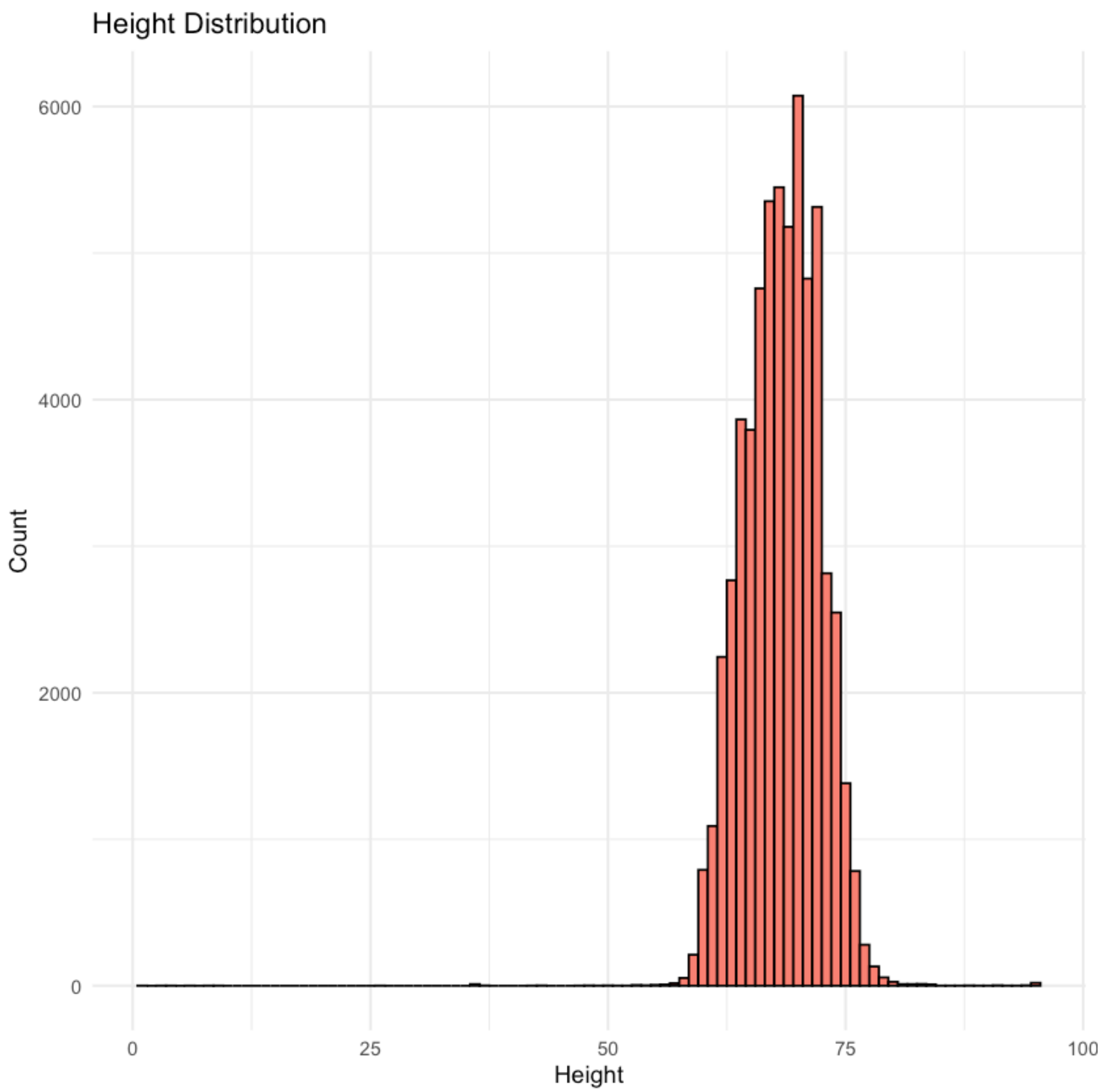
```r
# Plot height distribution with a histogram
ggplot(df_eda, aes(x = height)) +
  geom_histogram(binwidth = 1, fill = "salmon", color = "black") +
  theme_minimal() +
  labs(title = "Height Distribution", x = "Height", y = "Count")
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
    1.0    66.0    68.0    68.3    71.0    95.0       3 
```

```
Number of invalid height records:  27 
Percentage of invalid height records:  0.04504054 %
```

```
Warning message:
"Removed 3 rows containing non-finite outside the scale range
(`stat_boxplot()`)."
Warning message:
"Removed 3 rows containing non-finite outside the scale range
(`stat_bin()`)."
```


Boxplot of Height
Height (in inches)
75
50
25
0
0



Let's identify the outliers. For the purpose of this analysis, we will remove all records with height below 60 inches or over 90.

[38]:
```
# Step 1: Filter records in df_eda_clean where height < 60 or height > 90 and
↪remove them
df_eda_clean <- df_eda_clean %>%
  filter(height >= 60 & height <= 90)

# Step 2: Count the number of records in df_eda_clean after removing outliers
final_record_count <- nrow(df_eda_clean)

# Step 3: Print the number of records in df_eda_clean after filtering
```

```
cat("Number of records in df_eda_clean after removing height outliers: ",␣
↪final_record_count, "\n")
```

```
Number of records in df_eda_clean after removing height outliers:  59579
```

2.3.20 income

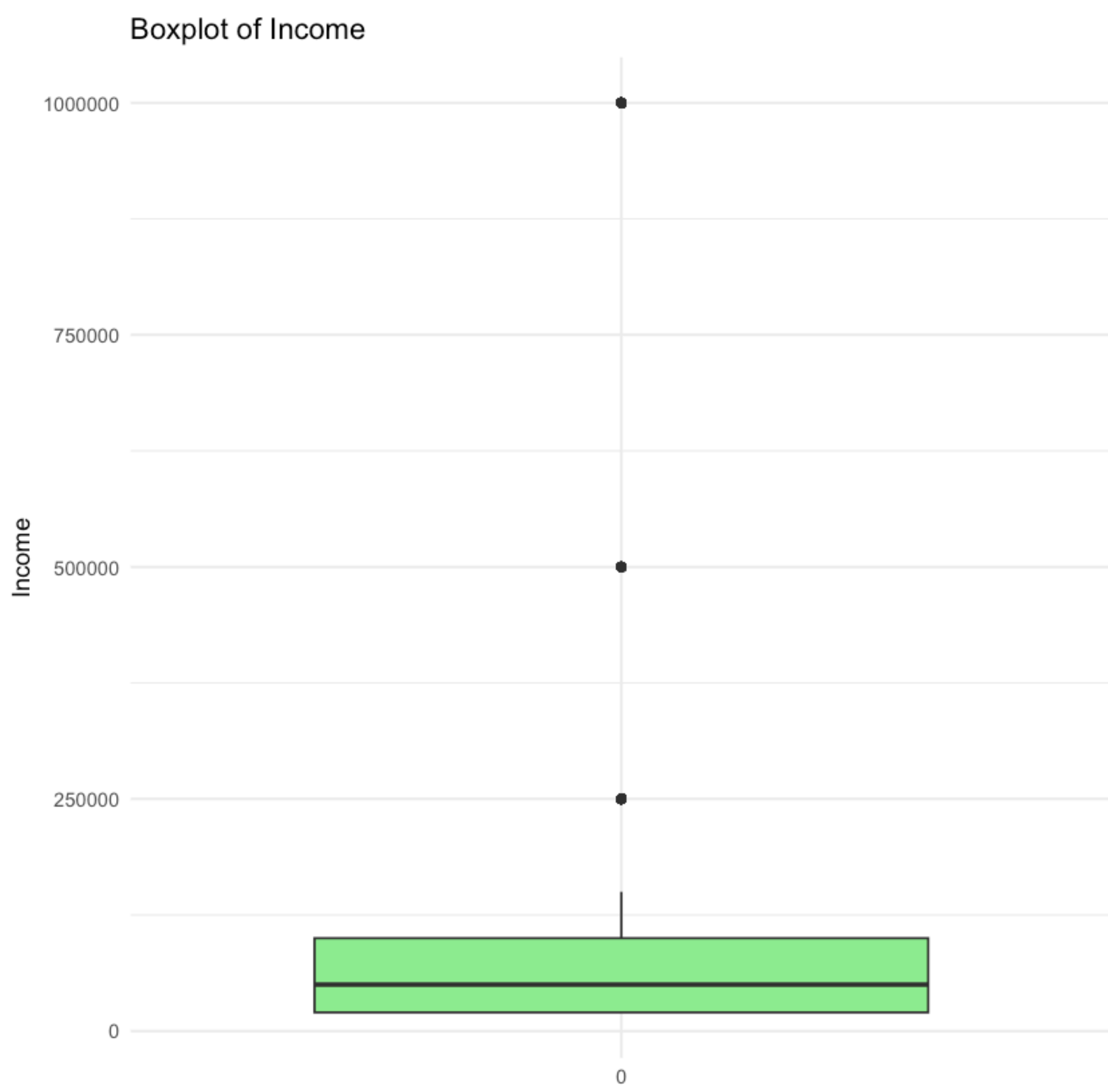
Income seems to have potential to identify our personas. Let's see what we can find.

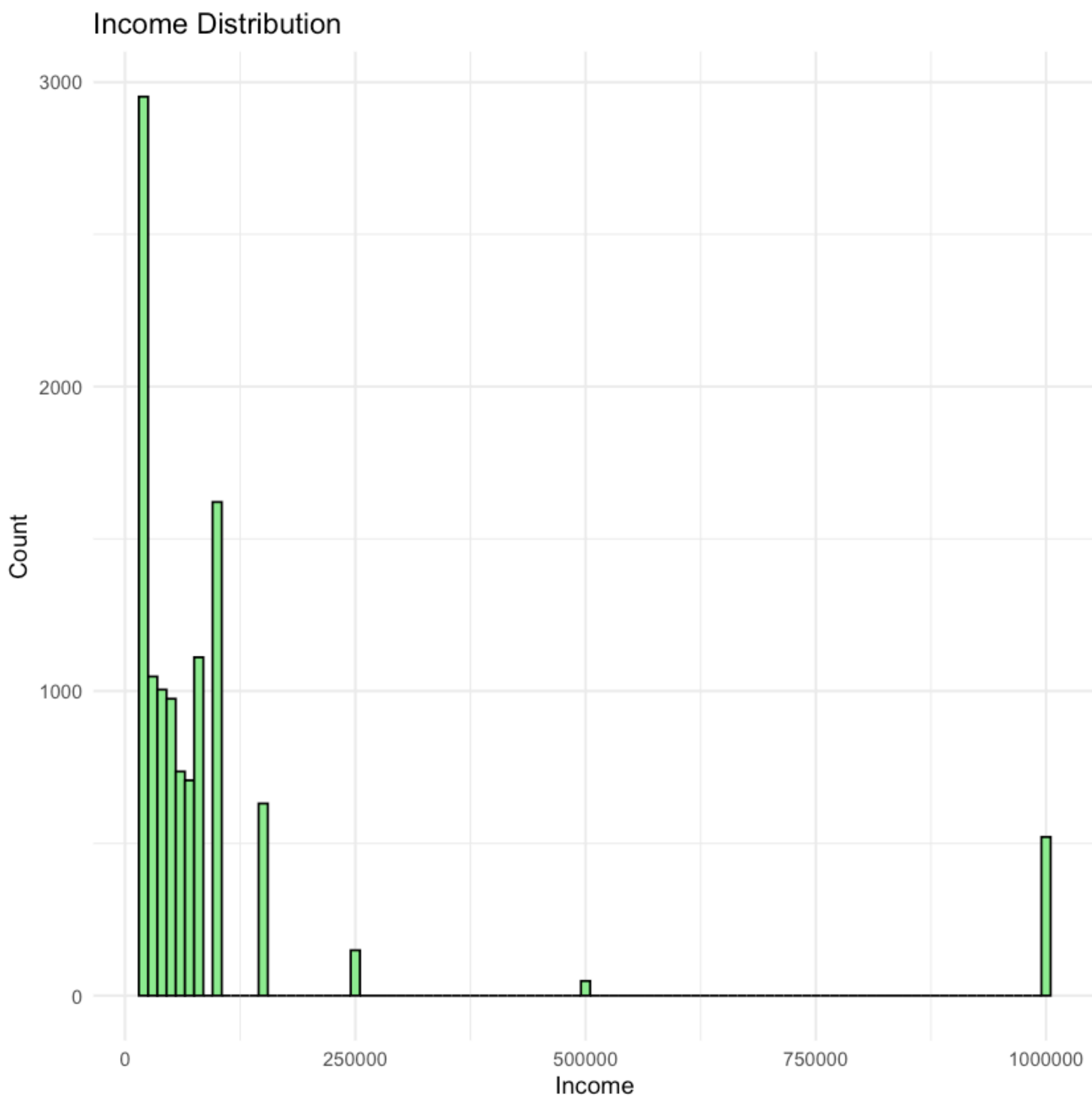
[41]:
```
# Income analysis

# Summary of income column
summary(df_eda$income)

# Check for invalid income values (income > 1,000,000)
invalid_income <- df_eda %>%
  filter(income > 1000000)

# Calculate percentage of invalid income records
invalid_income_count <- nrow(invalid_income)
invalid_income_percentage <- (invalid_income_count / nrow(df_eda)) * 100

cat("Number of invalid income records: ", invalid_income_count, "\n")
cat("Percentage of invalid income records: ", invalid_income_percentage, "%\n")

# Visualize income with a boxplot
ggplot(df_eda, aes(x = factor(0), y = income)) +
  geom_boxplot(fill = "lightgreen") +
  theme_minimal() +
  labs(title = "Boxplot of Income", x = "", y = "Income")

# Plot income distribution
ggplot(df_eda, aes(x = income)) +
  geom_histogram(binwidth = 10000, fill = "lightgreen", color = "black") +
  theme_minimal() +
  labs(title = "Income Distribution", x = "Income", y = "Count")
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  20000   20000   50000  104395  100000 1000000   48442
```

```
Number of invalid income records:  0
Percentage of invalid income records:  0 %
```

```
Warning message:
"Removed 48442 rows containing non-finite outside the scale range
(`stat_boxplot()`)."
Warning message:
"Removed 48442 rows containing non-finite outside the scale range
(`stat_bin()`)."
```


Boxplot of Income
1000000
750000
500000
250000
0
Income
0



There are some outliers we want to understand better. Although they could be real, let's see all those records equal or above $500,000.

[62]:
```
# Count records in df_eda_clean where income > 500000
count_high_income <- df_eda_clean %>%
  filter(income > 500000) %>%
  nrow()

# Print the count of records with income > 250000
cat("Number of records in df_eda_clean with income > 500000: ",␣
↪count_high_income, "\n")
```

```
Number of records in df_eda_clean with income > 500000:  507
```

As we can see, users with $500,000 or higher represent 0.85% of our users. Let's check the data again ignoring those records.

[60]:
```
# Filter out records with income >= 500000 but keep records with no income (NA)
df_income_clean <- df_eda_clean %>%
  filter(is.na(income) | income < 500000)

# Print the number of records in df_income_clean to verify
cat("Number of records in df_income_clean after removing income >= 500000␣
↪(while keeping NA): ", nrow(df_income_clean), "\n")
```

```
Number of records in df_income_clean after removing income >= 500000 (while
keeping NA):  59025
```

Let's see how many records have income different to null.

[61]:
```
# Count records where income is not null (i.e., not NA)
count_non_null_income <- df_eda_clean %>%
  filter(!is.na(income)) %>%
  nrow()

# Print the count of records with non-null income
cat("Number of records with non-null income: ", count_non_null_income, "\n")
```

```
Number of records with non-null income:  11439
```

This result shows that less than 20% of the users have income data and that we are not sure about the veracity of 507 records.

2.3.21 last_online

This field tells us the date of the latest connection to our system. Let's see the range of dates.

[48]:
```
# Ensure that the last_online column is in the correct datetime format
df_eda$last_online <- as.POSIXct(df_eda$last_online, format = "%Y-%m-%d %H:%M:
↪%S", tz = "UTC")

# Find the oldest date (minimum date)
oldest_date <- min(df_eda$last_online, na.rm = TRUE)

# Find the newest date (maximum date)
newest_date <- max(df_eda$last_online, na.rm = TRUE)

# Print the results
print(paste("Oldest date:", oldest_date))
print(paste("Newest date:", newest_date))
```

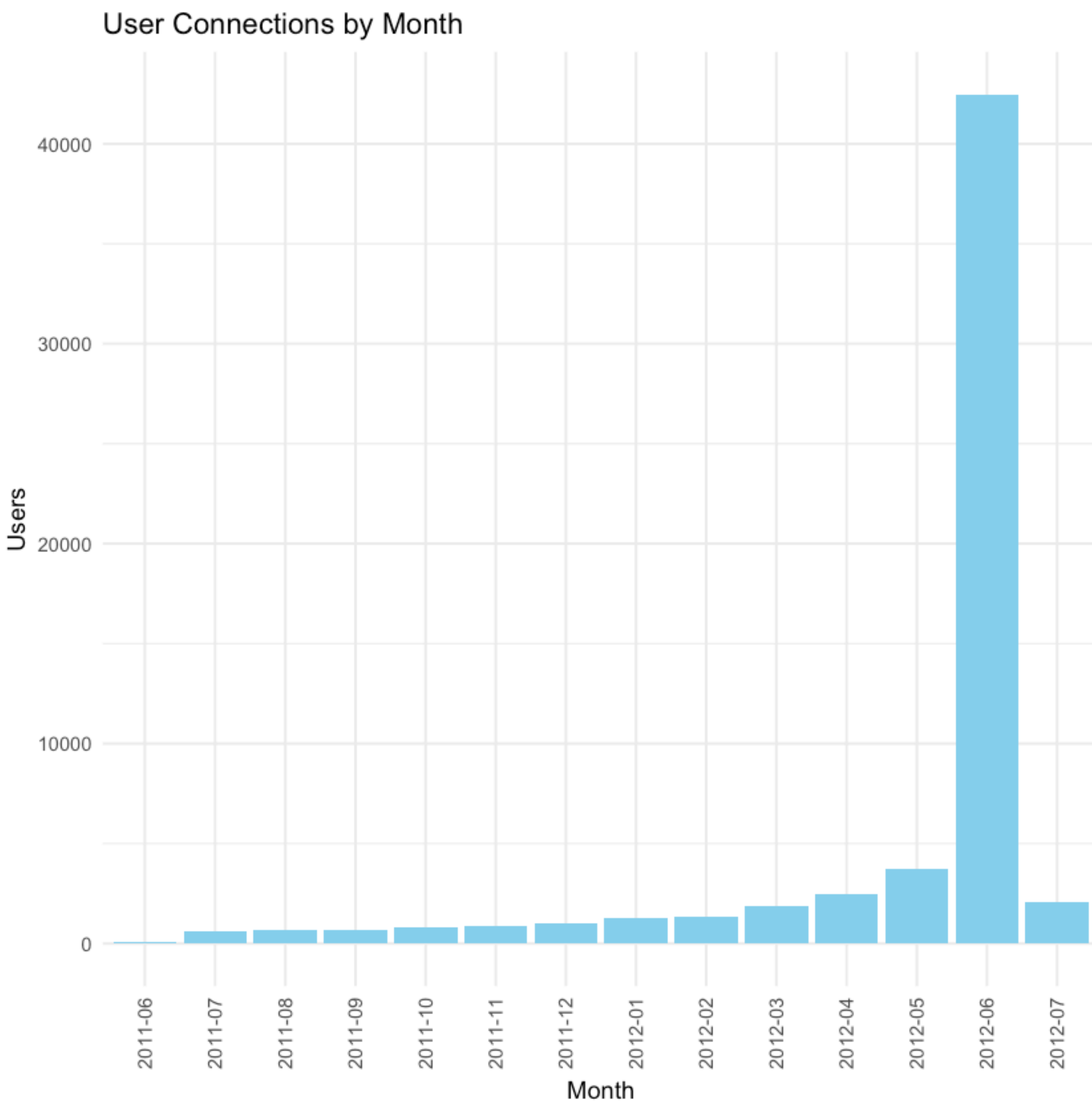
```
[1] "Oldest date: 2011-06-27 01:52:00"
[1] "Newest date: 2012-07-01 08:57:00"
```

Let's see how many users connected for the last time on each of these months.

[55]:

```r
# Ensure that the last_online column is in the correct datetime format
df_eda$last_online <- as.POSIXct(df_eda$last_online, format = "%Y-%m-%d %H:%M:
↪%S", tz = "UTC")

# Extract year and month from the last_online column and create a new column␣
↪'year_month'
df_eda$year_month <- format(df_eda$last_online, "%Y-%m")

# Count the number of users per month
monthly_counts <- df_eda %>%
  group_by(year_month) %>%
  summarise(user_count = n()) %>%
  arrange(year_month)

# Rename the columns to 'Year-Month' and 'Users'
monthly_counts <- monthly_counts %>%
  rename(`Year-Month` = year_month, Users = user_count)

# Print the renamed monthly_counts table
print(monthly_counts)

# Plot the bar graph using ggplot2
ggplot(monthly_counts, aes(x = `Year-Month`, y = Users)) +
  geom_bar(stat = "identity", fill = "skyblue") +  # Create the bar graph
  theme_minimal() +  # Use a minimal theme
  labs(title = "User Connections by Month", x = "Month", y = "Users") +  #␣
↪Labels
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))  #␣
↪Rotate the x-axis labels for better readability
```

```
# A tibble: 14 x 2
   `Year-Month` Users
   <chr>        <int>
 1 2011-06         85
 2 2011-07        627
 3 2011-08        643
 4 2011-09        702
 5 2011-10        804
 6 2011-11        849
 7 2011-12        989
 8 2012-01       1241
 9 2012-02       1330
10 2012-03       1885
11 2012-04       2469
12 2012-05       3761
13 2012-06      42471
14 2012-07       2090
```



2.3.22 Records with complete data

[63]:

```
# Now let's check how many records have complete data (i.e., no missing values␣
↪in any column)
complete_records <- df_eda_clean[complete.cases(df_eda_clean), ]

# Calculate the percentage of records with complete data
complete_data_count <- nrow(complete_records)
complete_data_percentage <- (complete_data_count / nrow(df_eda_clean)) * 100

cat("Number of complete records: ", complete_data_count, "\n")
cat("Percentage of complete records: ", complete_data_percentage, "%\n")
```

```
Number of complete records:  2064
Percentage of complete records:  3.464308 %
```

Since only 3.46% of our users have complete records, it is necessary to keep all of them until further analysis.

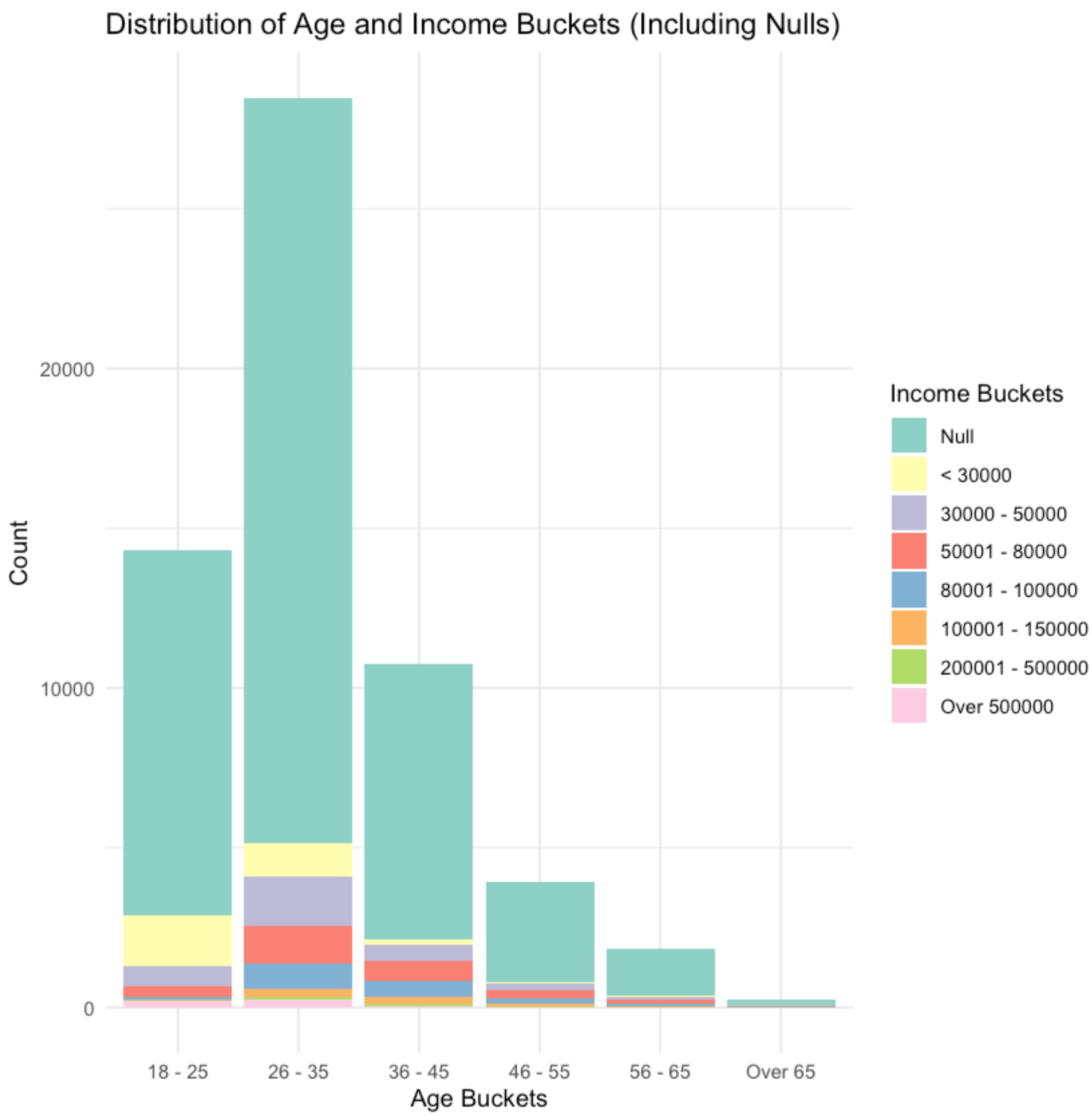
2.3.23 age vs. income

We know that only 11439 users have income data. Also, we suspect that 507 of those records may have inflated income. However, let's combine age and income to better understand our users.

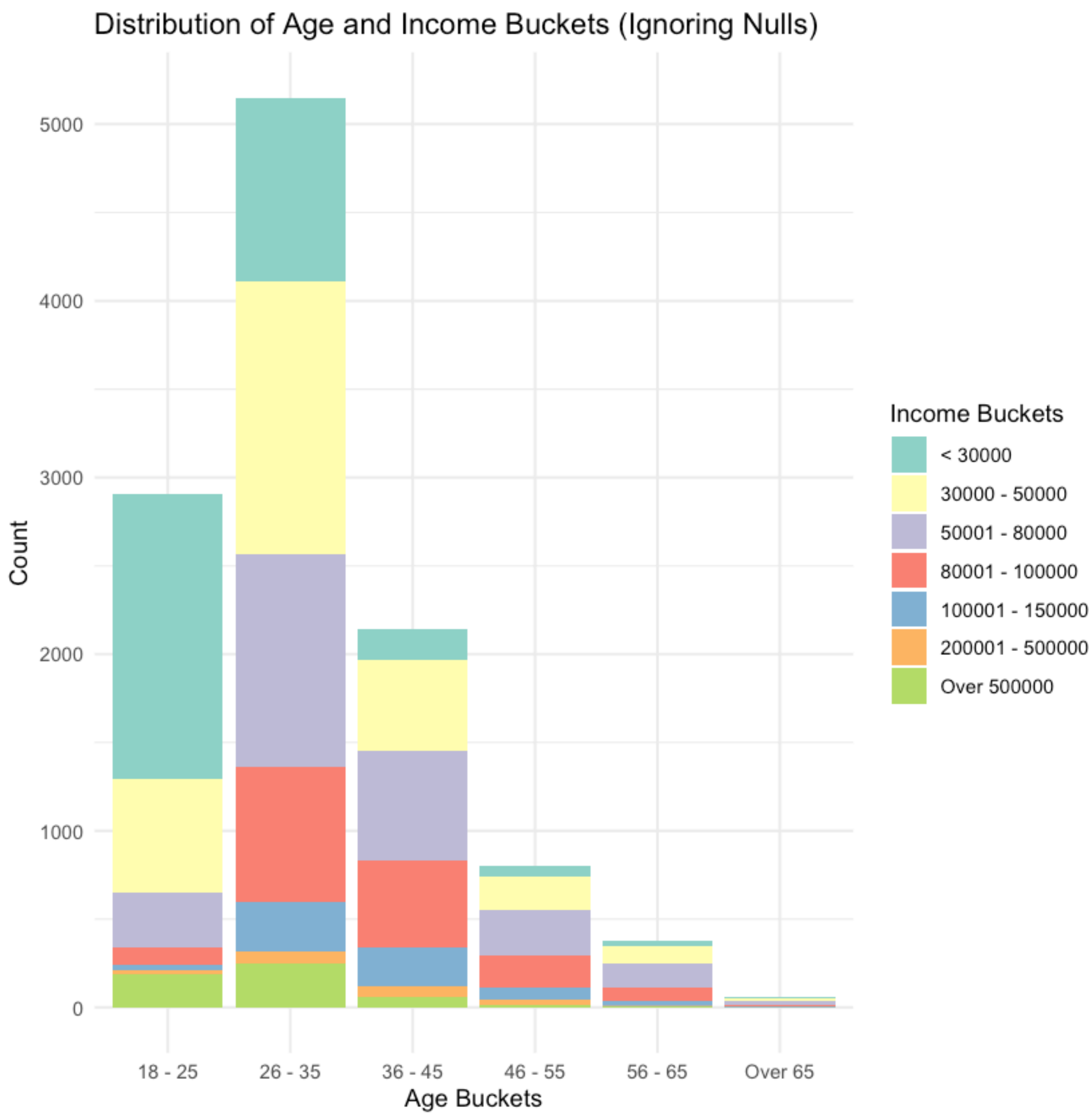
[84]:
```r
# Step 1: Create Age Buckets
df_eda_clean <- df_eda_clean %>%
  mutate(age_bucket = case_when(
    age >= 18 & age <= 25 ~ "18 - 25",
    age >= 26 & age <= 35 ~ "26 - 35",
    age >= 36 & age <= 45 ~ "36 - 45",
    age >= 46 & age <= 55 ~ "46 - 55",
    age >= 56 & age <= 65 ~ "56 - 65",
    age > 65 ~ "Over 65"
  ))

# Step 2: Create Income Buckets and define factor levels for correct legend␣
↪order
df_eda_clean <- df_eda_clean %>%
  mutate(income_bucket = case_when(
    is.na(income) ~ "Null",
    income < 30000 ~ "< 30000",
    income >= 30000 & income <= 50000 ~ "30000 - 50000",
    income >= 50001 & income <= 80000 ~ "50001 - 80000",
    income >= 80001 & income <= 100000 ~ "80001 - 100000",
    income >= 100001 & income <= 150000 ~ "100001 - 150000",
    income >= 150001 & income <= 200000 ~ "150001 - 200000",
    income >= 200001 & income <= 500000 ~ "200001 - 500000",
    income > 500000 ~ "Over 500000"
  )) %>%
  # Set the factor levels to match the desired order in the legend
  mutate(income_bucket = factor(income_bucket, levels = c(
    "Null", "< 30000", "30000 - 50000", "50001 - 80000",
    "80001 - 100000", "100001 - 150000", "150001 - 200000",
    "200001 - 500000", "Over 500000"
  )))

# Step 3: Summarize the data by age_bucket and income_bucket
df_summary <- df_eda_clean %>%
  group_by(age_bucket, income_bucket) %>%
  summarise(count = n()) %>%
  ungroup()
```

```r
# Step 4: Generate the first graph including Nulls
ggplot(df_summary, aes(x = age_bucket, y = count, fill = income_bucket)) +
  geom_bar(stat = "identity", position = "stack") +
  labs(title = "Distribution of Age and Income Buckets (Including Nulls)", x =
 ↪"Age Buckets", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 0, hjust = 0.5)) +
  scale_fill_brewer(palette = "Set3", name = "Income Buckets")

# Step 5: Filter out the Null income bucket
df_summary_no_nulls <- df_summary %>%
  filter(income_bucket != "Null")

# Step 6: Generate the second graph ignoring Nulls
ggplot(df_summary_no_nulls, aes(x = age_bucket, y = count, fill =
 ↪income_bucket)) +
  geom_bar(stat = "identity", position = "stack") +
  labs(title = "Distribution of Age and Income Buckets (Ignoring Nulls)", x =
 ↪"Age Buckets", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 0, hjust = 0.5)) +
  scale_fill_brewer(palette = "Set3", name = "Income Buckets")
```

```
`summarise()` has grouped output by 'age_bucket'. You can override
using the
`.groups` argument.
```



Distribution of Age and Income Buckets (Including Nulls)
Count
20000
10000
0
18 - 25
26 - 35
36 - 45
46 - 55
56 - 65
Over 65
Age Buckets
Income Buckets
Null
< 30000
30000 - 50000
50001 - 80000
80001 - 100000
100001 - 150000
200001 - 500000
Over 500000



Let's see the numbers.

[85]:
```
df_summary
```

A tibble: 48 x 3

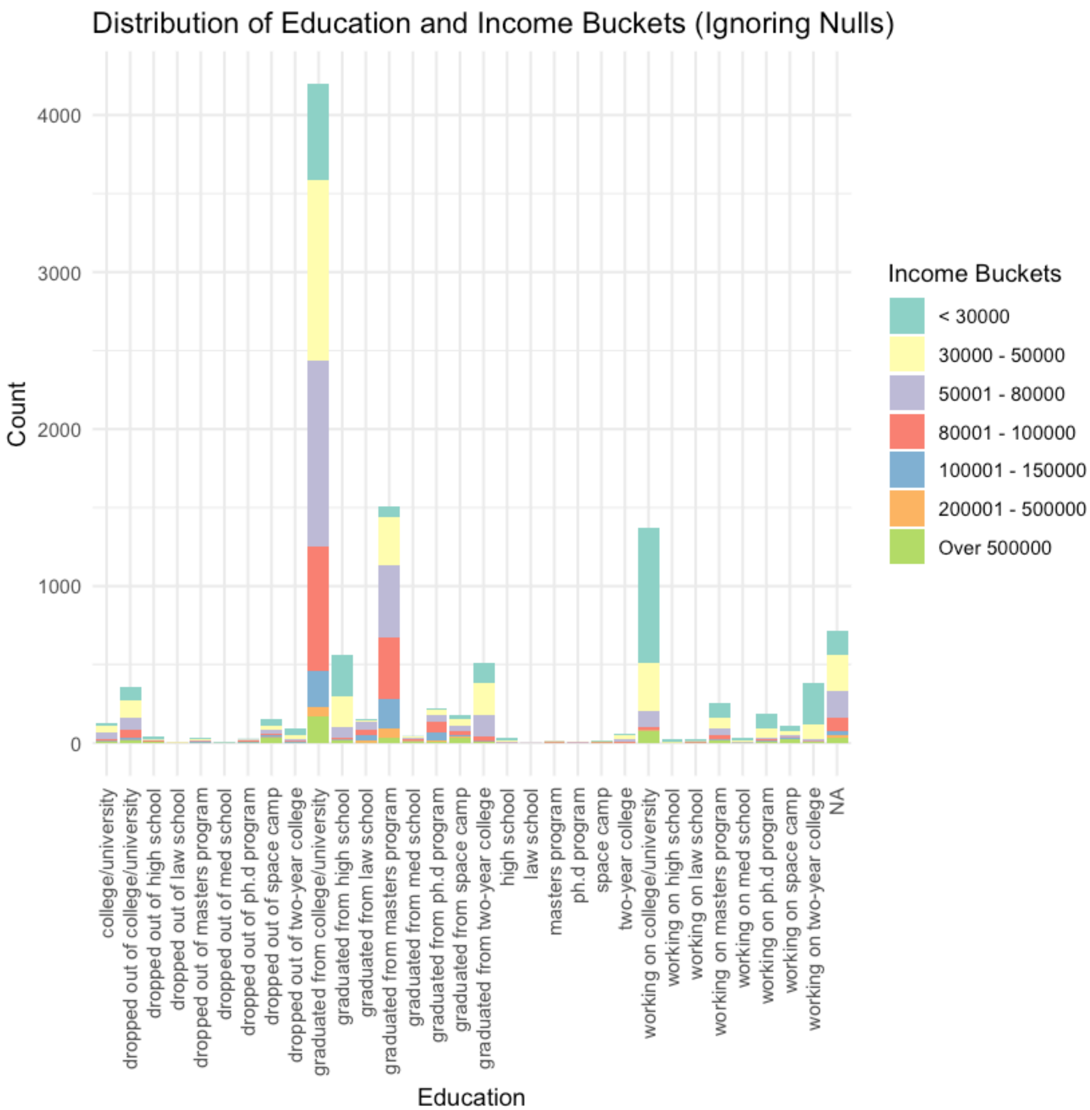
age_bucket <chr>	income_bucket <fct>	count <int>
18 - 25	Null	11425
18 - 25	< 30000	1609
18 - 25	30000 - 50000	645
18 - 25	50001 - 80000	313
18 - 25	80001 - 100000	95
18 - 25	100001 - 150000	28
18 - 25	200001 - 500000	28
18 - 25	Over 500000	185
26 - 35	Null	23323
26 - 35	< 30000	1042
26 - 35	30000 - 50000	1545
26 - 35	50001 - 80000	1198
26 - 35	80001 - 100000	770
26 - 35	100001 - 150000	274
26 - 35	200001 - 500000	72
26 - 35	Over 500000	248
36 - 45	Null	8607
36 - 45	< 30000	173
36 - 45	30000 - 50000	518
36 - 45	50001 - 80000	623
36 - 45	80001 - 100000	494
36 - 45	100001 - 150000	216
36 - 45	200001 - 500000	64
36 - 45	Over 500000	56
46 - 55	Null	3136
46 - 55	< 30000	66
46 - 55	30000 - 50000	187
46 - 55	50001 - 80000	258
46 - 55	80001 - 100000	181
46 - 55	100001 - 150000	71
46 - 55	200001 - 500000	28
46 - 55	Over 500000	13
56 - 65	Null	1448
56 - 65	< 30000	33
56 - 65	30000 - 50000	98
56 - 65	50001 - 80000	135
56 - 65	80001 - 100000	73
56 - 65	100001 - 150000	33
56 - 65	200001 - 500000	3
56 - 65	Over 500000	4
Over 65	Null	201
Over 65	< 30000	7
Over 65	30000 - 50000	20
Over 65	50001 - 80000	18
Over 65	80001 - 100000	7
Over 65	100001 - 150000	6
Over 65	200001 - 500000	1
Over 65	Over 500000	1

2.3.24 income vs. education

Let's analyze the relationship between income and education.

[86]:
```
# Step 1: Create Income Buckets and define factor levels for correct legend␣
↪order
df_eda_clean <- df_eda_clean %>%
  mutate(income_bucket = case_when(
    is.na(income) ~ "Null",
    income < 30000 ~ "< 30000",
    income >= 30000 & income <= 50000 ~ "30000 - 50000",
    income >= 50001 & income <= 80000 ~ "50001 - 80000",
    income >= 80001 & income <= 100000 ~ "80001 - 100000",
    income >= 100001 & income <= 150000 ~ "100001 - 150000",
    income >= 150001 & income <= 200000 ~ "150001 - 200000",
    income >= 200001 & income <= 500000 ~ "200001 - 500000",
    income > 500000 ~ "Over 500000"
  )) %>%
  # Set the factor levels to match the desired order in the legend
  mutate(income_bucket = factor(income_bucket, levels = c(
    "Null", "< 30000", "30000 - 50000", "50001 - 80000",
    "80001 - 100000", "100001 - 150000", "150001 - 200000",
    "200001 - 500000", "Over 500000"
  )))

# Step 2: Use Education Data (assuming the 'education' column exists in␣
↪df_eda_clean)

# Step 3: Summarize the data by income_bucket and education
df_summary_edu_income <- df_eda_clean %>%
  group_by(education, income_bucket) %>%
  summarise(count = n()) %>%
  ungroup()

# Step 5: Filter out the Null income bucket
df_summary_edu_income_no_nulls <- df_summary_edu_income %>%
  filter(income_bucket != "Null")

# Step 6: Generate the second graph ignoring Nulls
ggplot(df_summary_edu_income_no_nulls, aes(x = education, y = count, fill =␣
↪income_bucket)) +
  geom_bar(stat = "identity", position = "stack") +
  labs(title = "Distribution of Education and Income Buckets (Ignoring Nulls)",␣
↪x = "Education", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5)) +
  scale_fill_brewer(palette = "Set3", name = "Income Buckets")
```

```
`summarise()` has grouped output by 'education'. You can override using
the
`.groups` argument.
```

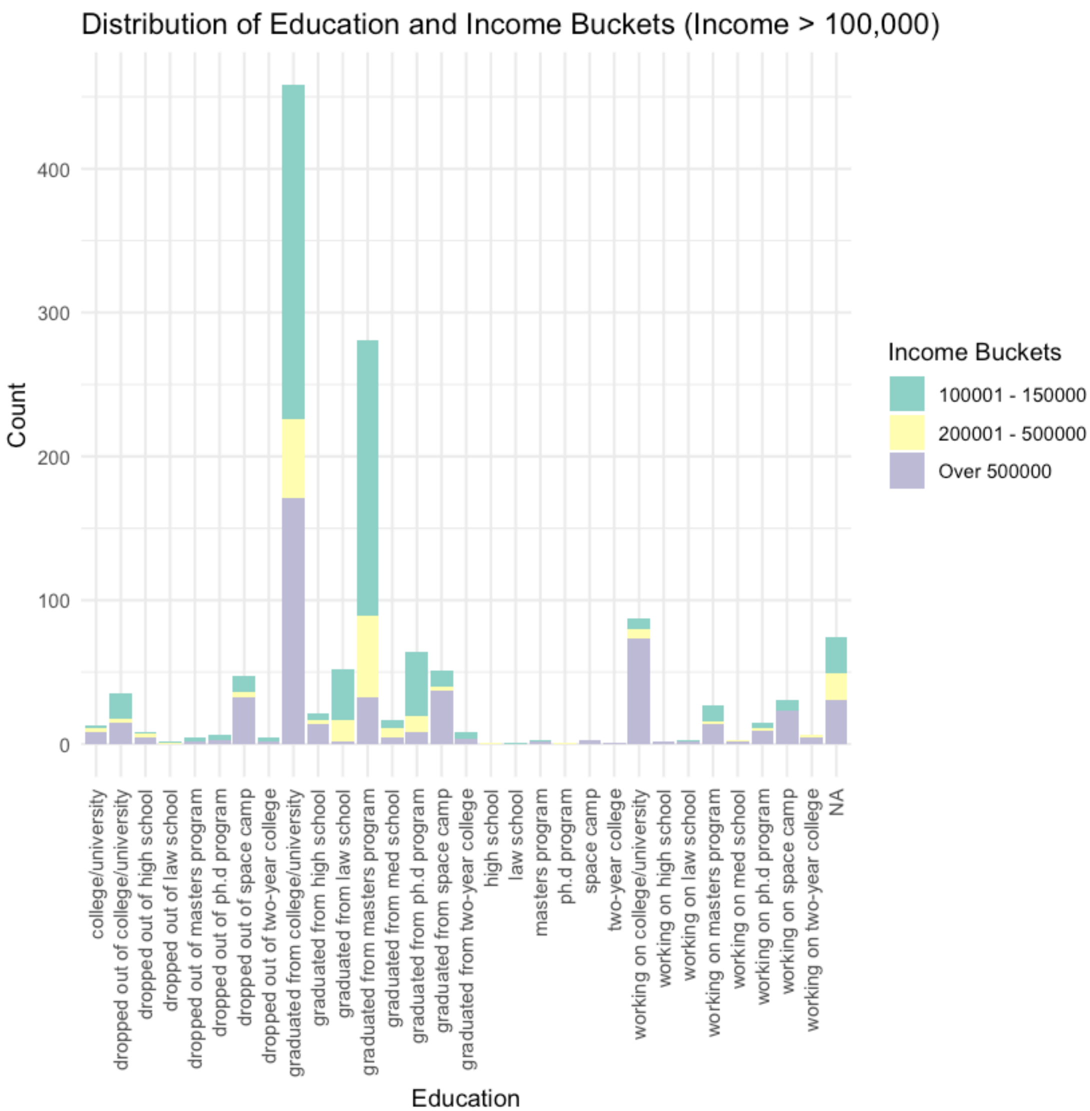


Let's focus on salaries greater than $100,000.

[87]:
```r
# Step 1: Create Income Buckets and define factor levels for correct legend
↪order
df_eda_clean <- df_eda_clean %>%
  mutate(income_bucket = case_when(
    is.na(income) ~ "Null",
    income < 30000 ~ "< 30000",
    income >= 30000 & income <= 50000 ~ "30000 - 50000",
```

```
    income >= 50001 & income <= 80000 ~ "50001 - 80000",
    income >= 80001 & income <= 100000 ~ "80001 - 100000",
    income >= 100001 & income <= 150000 ~ "100001 - 150000",
    income >= 150001 & income <= 200000 ~ "150001 - 200000",
    income >= 200001 & income <= 500000 ~ "200001 - 500000",
    income > 500000 ~ "Over 500000"
  )) %>%
  # Set the factor levels to match the desired order in the legend
  mutate(income_bucket = factor(income_bucket, levels = c(
    "100001 - 150000", "150001 - 200000", "200001 - 500000", "Over 500000"
  )))

# Step 2: Use Education Data (assuming the 'education' column exists in␣
↪df_eda_clean)

# Step 3: Summarize the data by income_bucket and education, but filter out␣
↪buckets lower than 100000
df_summary_edu_income_high <- df_eda_clean %>%
  filter(income_bucket %in% c("100001 - 150000", "150001 - 200000", "200001 -␣
↪500000", "Over 500000")) %>%
  group_by(education, income_bucket) %>%
  summarise(count = n()) %>%
  ungroup()

# Step 4: Generate the graph showing only income buckets higher than 100,000
ggplot(df_summary_edu_income_high, aes(x = education, y = count, fill =␣
↪income_bucket)) +
  geom_bar(stat = "identity", position = "stack") +
  labs(title = "Distribution of Education and Income Buckets (Income >␣
↪100,000)", x = "Education", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5)) +
  scale_fill_brewer(palette = "Set3", name = "Income Buckets")
```

```
`summarise()` has grouped output by 'education'. You can override using
the
`.groups` argument.
```



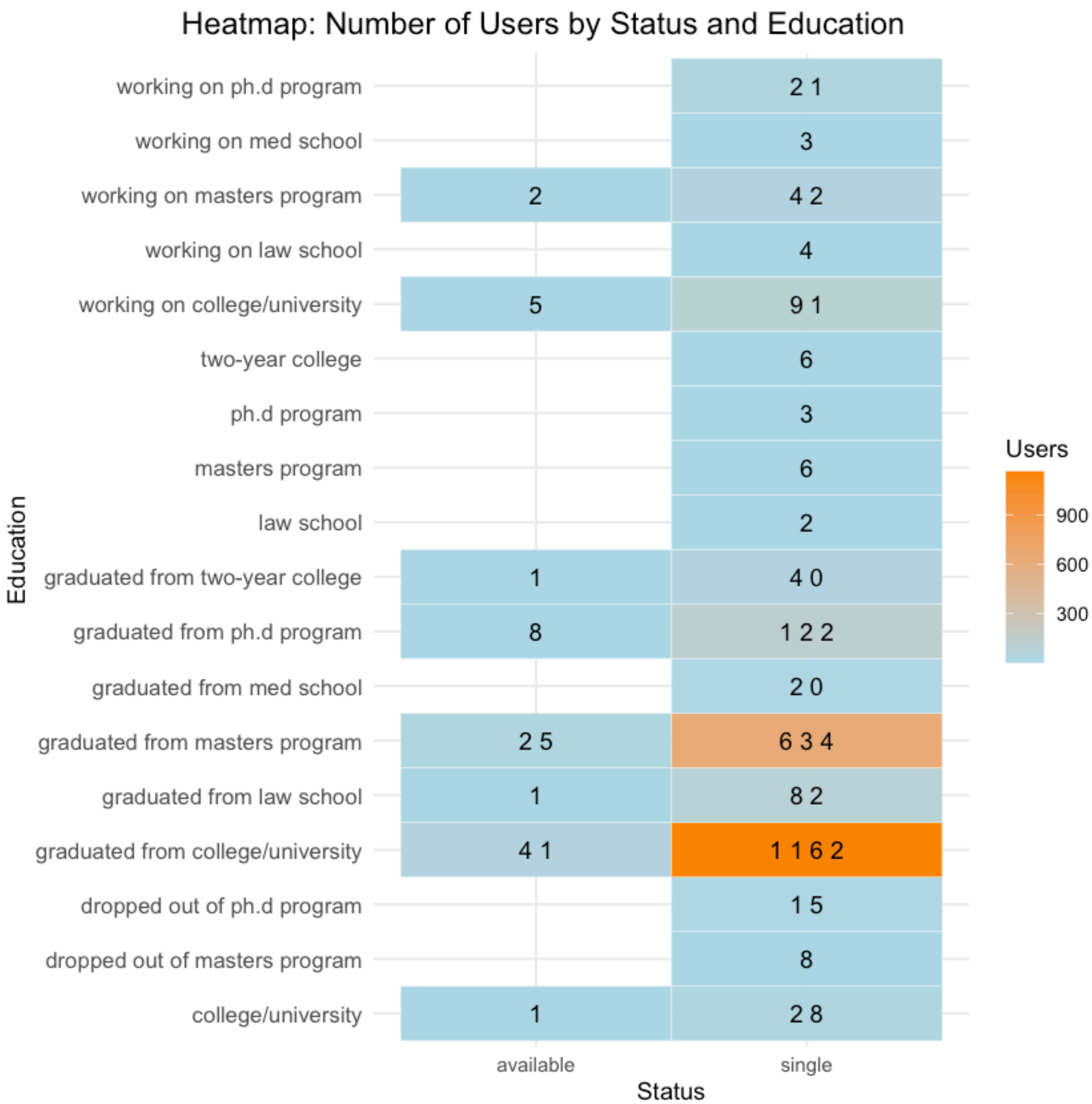
2.3.25 education vs. status

I am looking for an elite group, where users have

[118]:
```
# Function to add space between characters
add_spaces <- function(x) {
  paste(strsplit(as.character(x), "")[[1]], collapse = " ")
}

# Step 1: Filter out records and specific education levels
df_filtered <- df_eda_clean %>%
  filter(!is.na(income), income > 80000,
         !status %in% c("married", "seeing someone"),
```

```
        !education %in% c(
          "dropped out of high school",
          "working on high school",
          "graduated from high school",
          "dropped out of college/university",
          "dropped out of law school",
          "dropped out of space camp",
          "dropped out of two-year college",
          "high school",
          "working on two-year college",
          "graduated from space camp",
          "space camp",
          "working on space camp",
          NA))

# Step 2: Create income buckets for the remaining data
df_filtered <- df_filtered %>%
  mutate(income_bucket = case_when(
    income > 80000 & income <= 100000 ~ "80001 - 100000",
    income >= 100001 & income <= 150000 ~ "100001 - 150000",
    income >= 150001 & income <= 200000 ~ "150001 - 200000",
    income >= 200001 & income <= 500000 ~ "200001 - 500000",
    income > 500000 ~ "Over 500000"
  ))

# Step 3: Summarize the data to count the number of users for each combination␣
 ↪of education and status (ignore income_bucket here)
df_summary <- df_filtered %>%
  group_by(education, status) %>%
  summarise(count = n(), .groups = 'drop')

# Step 4: Apply the function to add space between characters for counts
df_summary$label <- sapply(df_summary$count, add_spaces)

# Step 5: Create the heatmap without scale limits and with adjusted text
ggplot(df_summary, aes(x = status, y = education, fill = count)) +  # Switch x␣
 ↪and y axes
  geom_tile(color = "white") +  # Create heatmap tiles
  geom_text(aes(label = label), color = "black") +  # Add spaced count labels
  scale_fill_gradient(low = "lightblue", high = "#fb8600", name = "Users") +  #␣
 ↪Removed scale limits to allow automatic range
  labs(title = "Heatmap: Number of Users by Status and Education",
       x = "Status",
       y = "Education") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 1.5, size = 14),  # Center and␣
 ↪increase title size
```

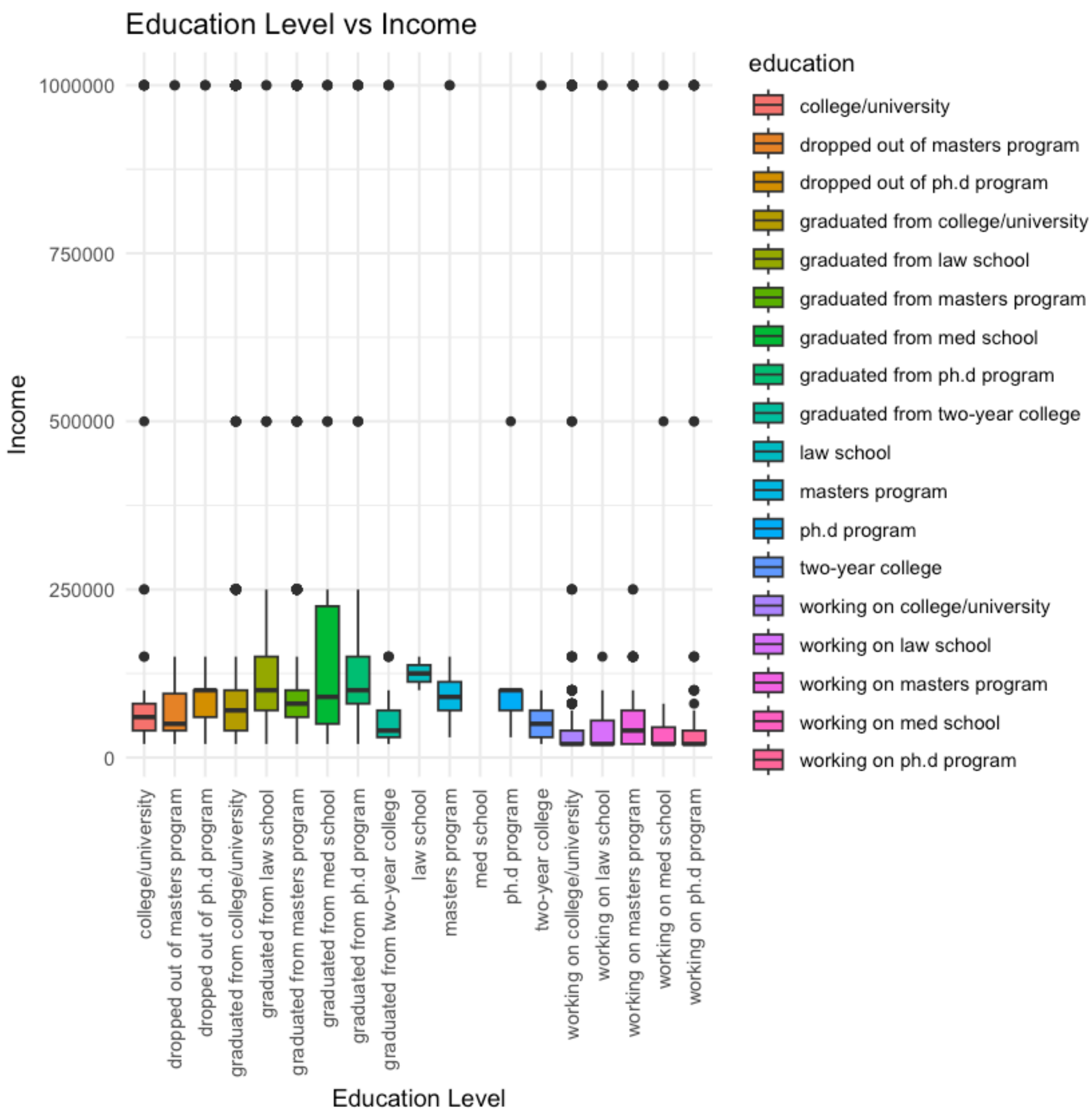
```
      axis.text.x = element_text(angle = 0, hjust = 0.5, size = 9),  # Keep␣
↪x-axis labels horizontal
      axis.text.y = element_text(size = 10),  # Increase y-axis text size for␣
↪better readability
      legend.position = "right")  # Keep legend on the right for clarity
```




```
[76]: # Step 1: Filter out the specified education levels from df_eda_clean
df_filtered <- df_eda_clean %>%
  filter(!education %in% c(
           "dropped out of high school",
           "working on high school",
           "graduated from high school",
```

```
            "dropped out of college/university",
            "dropped out of law school",
            "dropped out of med school",
            "dropped out of space camp",
            "dropped out of two-year college",
            "high school",
            "working on two-year college",
            "graduated from space camp",
            "space camp",
            "working on space camp",
            NA))

# Step 2: Create the boxplot for education vs. income
ggplot(df_filtered, aes(x = education, y = income, fill = education)) +
  geom_boxplot() +
  theme_minimal() +
  labs(title = "Education Level vs Income", x = "Education Level", y =
 ↪"Income") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5))  #
 ↪Rotate x-axis labels for readability
```

```
Warning message:
"Removed 38630 rows containing non-finite outside the scale range
(`stat_boxplot()`)."
```



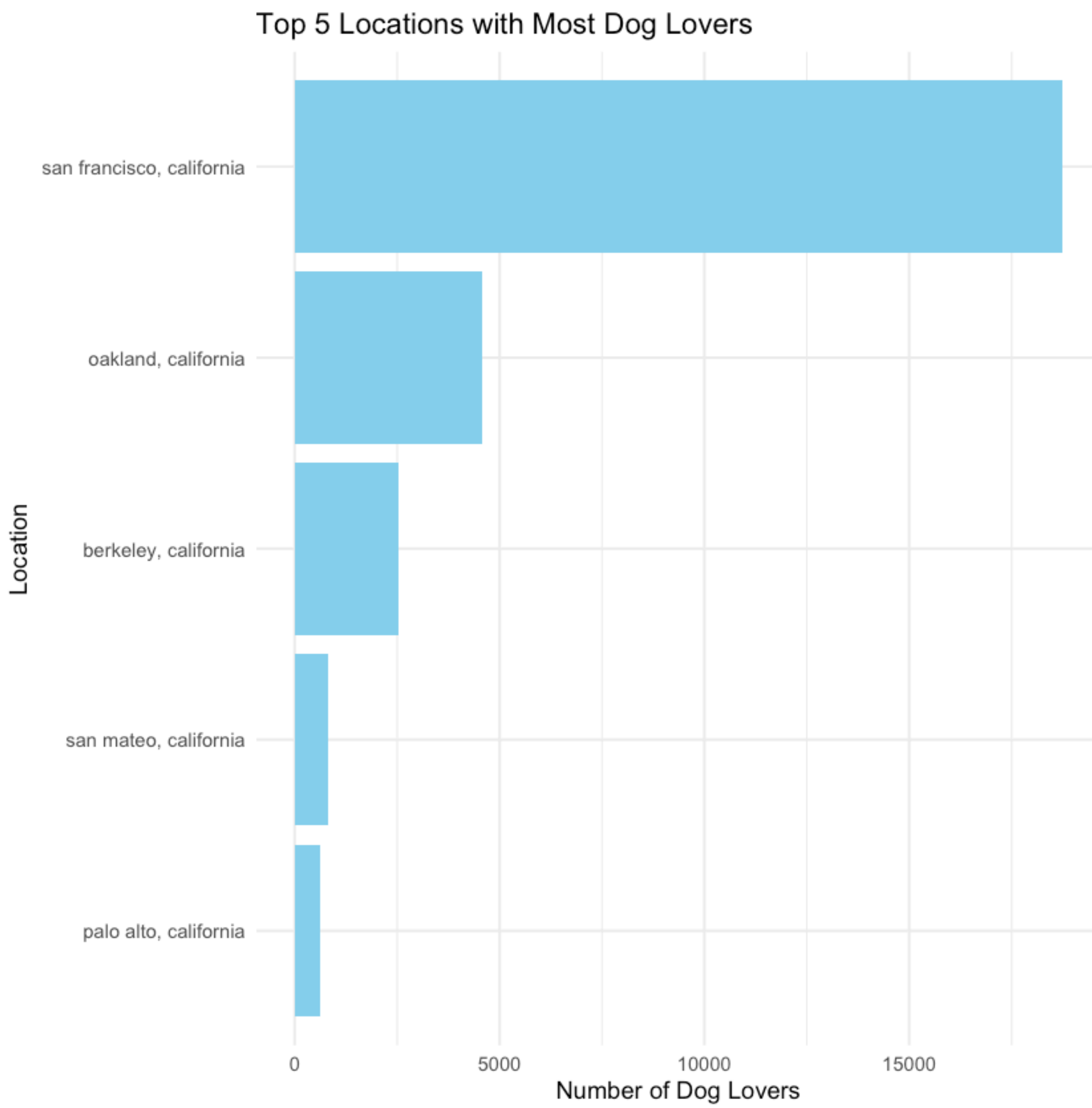
2.3.26 Pet lovers locations

[61]:
```
# Function to list top n locations where there are more pet lovers and plot the
↪results
top_pet_lovers <- function(df, pet_type, n) {
  # Check if the pet_type is valid
  if (!(pet_type %in% c("dog", "cat"))) {
    stop("Invalid pet type. Use 'dog' or 'cat'.")
  }

  # Determine the column to filter based on the pet_type
  pet_column <- ifelse(pet_type == "dog", "dog_friendly", "cat_friendly")
```

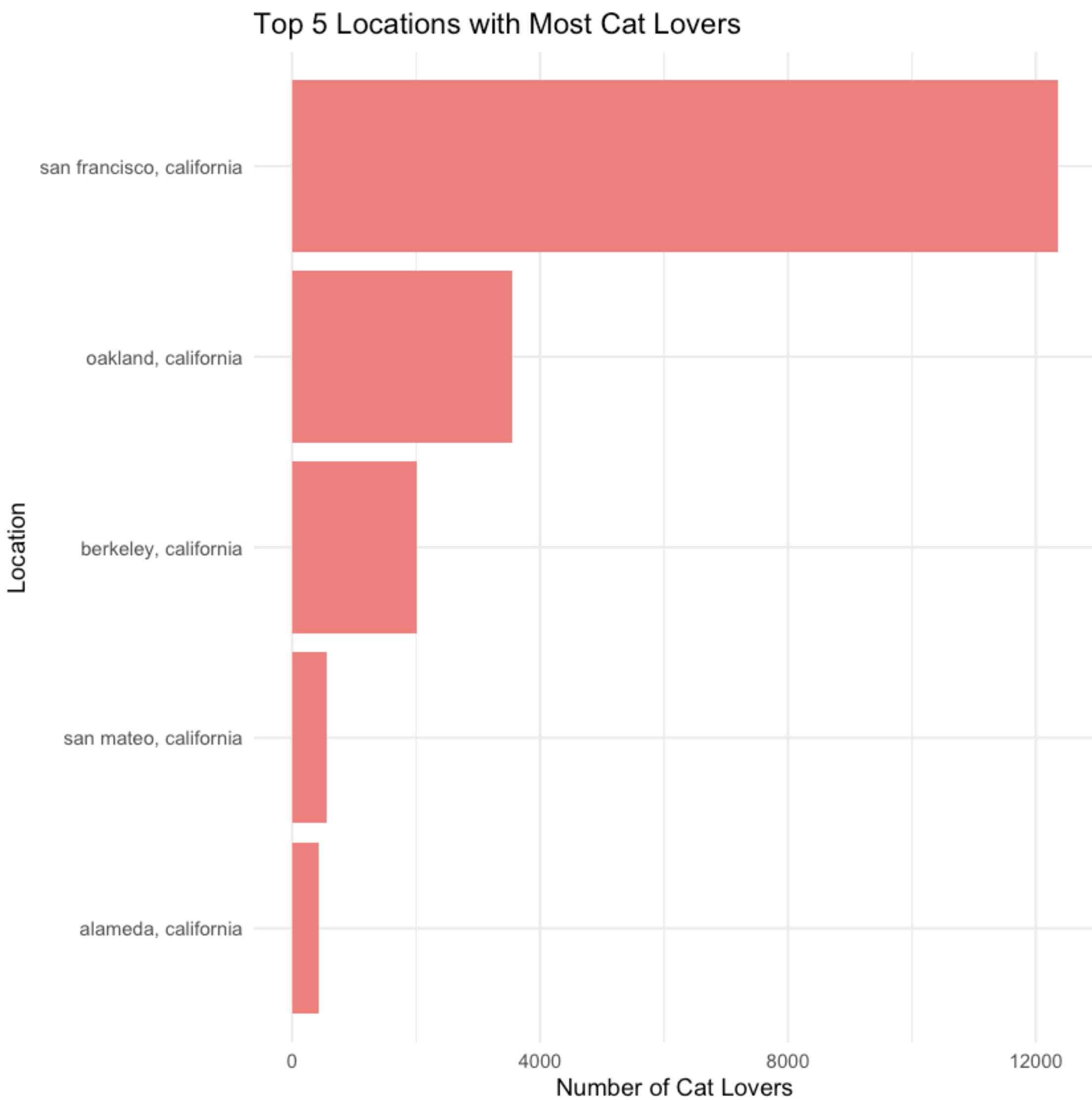
```r
  # Summarize the data by location for the given pet type
  top_locations <- df %>%
    filter(!!sym(pet_column) == TRUE) %>%  # Filter for pet lovers (dog or cat)
    group_by(location) %>%
    summarise(pet_lovers_count = n()) %>%
    arrange(desc(pet_lovers_count)) %>%  # Sort by the number of pet lovers
    head(n)  # Return top n locations

  # Return the top n locations
  return(top_locations)
}

# Number of top locations to show
n = 5

# Example usage of the function for dog lovers
cat("Dog lovers - Top ", n, "\n")
top_dog_lovers <- top_pet_lovers(df_eda_clean, pet_type = "dog", n = n)
print(top_dog_lovers)

# Plot the top dog lover locations
ggplot(top_dog_lovers, aes(x = reorder(location, pet_lovers_count), y =
 ↪pet_lovers_count)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  coord_flip() +  # Flip coordinates to make location labels readable
  labs(title = paste("Top", n, "Locations with Most Dog Lovers"), x =
 ↪"Location", y = "Number of Dog Lovers") +
  theme_minimal()

# Example usage of the function for cat lovers
cat("\n\nCat lovers - Top ", n, "\n")
top_cat_lovers <- top_pet_lovers(df_eda_clean, pet_type = "cat", n = n)
print(top_cat_lovers)

# Plot the top cat lover locations
ggplot(top_cat_lovers, aes(x = reorder(location, pet_lovers_count), y =
 ↪pet_lovers_count)) +
  geom_bar(stat = "identity", fill = "lightcoral") +
  coord_flip() +  # Flip coordinates to make location labels readable
  labs(title = paste("Top", n, "Locations with Most Cat Lovers"), x =
 ↪"Location", y = "Number of Cat Lovers") +
  theme_minimal()
```

```
Dog lovers - Top  5
# A tibble: 5 x 2
  location                    pet_lovers_count
  <chr>
```

```
<int>
1 san francisco, california           18738
2 oakland, california                  4580
3 berkeley, california                 2541
4 san mateo, california                 804
5 palo alto, california                 606


Cat lovers - Top  5
# A tibble: 5 x 2
  location                  pet_lovers_count
  <chr>
<int>
1 san francisco, california           12354
2 oakland, california                  3542
3 berkeley, california                 2022
4 san mateo, california                 562
5 alameda, california                   432
```



Top 5 Locations with Most Dog Lovers
san francisco, california
oakland, california
berkeley, california
san mateo, california
palo alto, california
Location
0
5000
10000
15000
Number of Dog Lovers

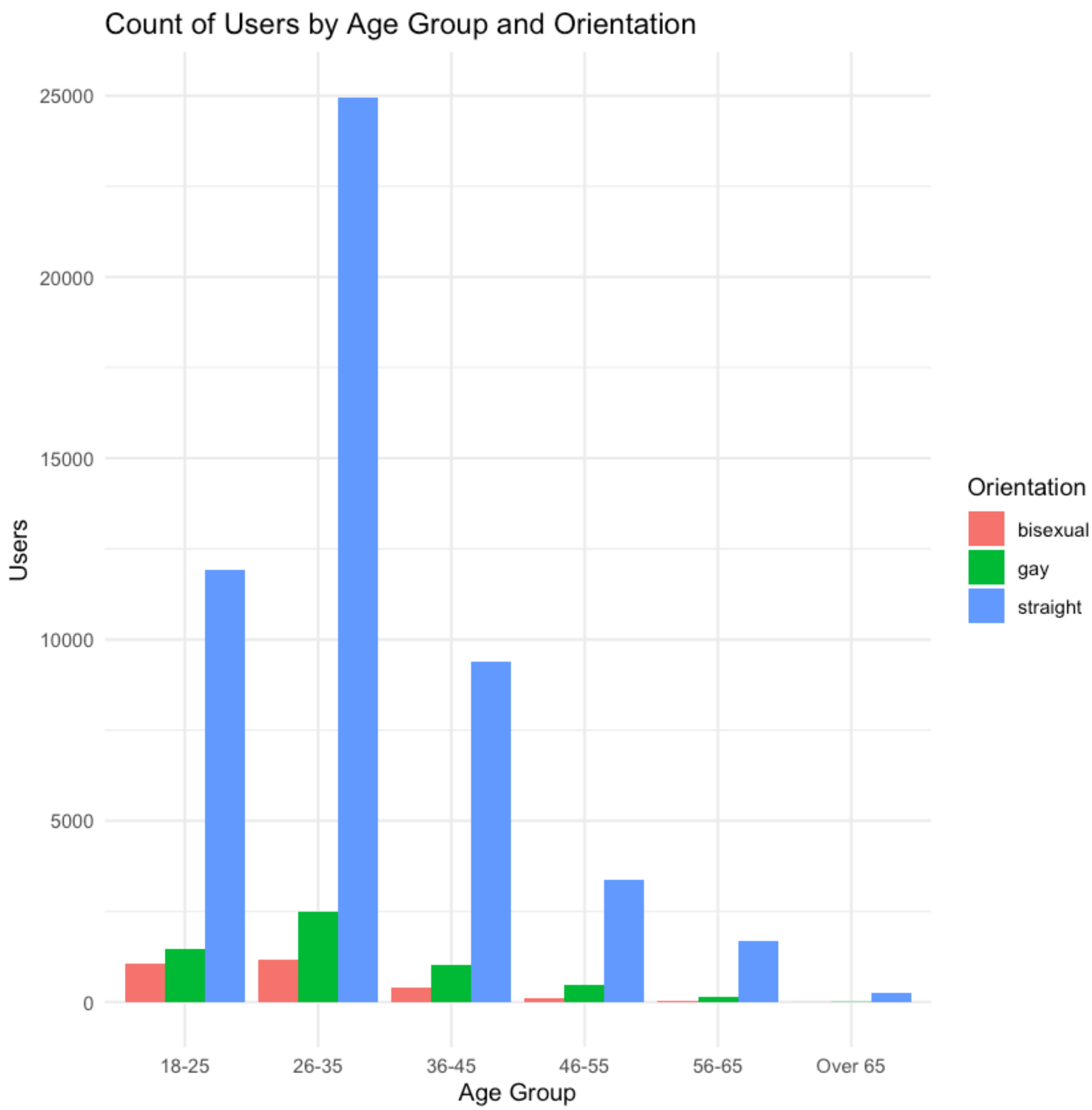


2.3.27 age vs. orientation

[60]:
```
# 1. Create age buckets
df_eda <- df_eda %>%
  mutate(age_bucket = case_when(
    age >= 18 & age <= 25 ~ "18-25",
    age >= 26 & age <= 35 ~ "26-35",
    age >= 36 & age <= 45 ~ "36-45",
    age >= 46 & age <= 55 ~ "46-55",
    age >= 56 & age <= 65 ~ "56-65",
    age > 65 ~ "Over 65",
    TRUE ~ NA_character_  # To handle missing or invalid age values
  ))
```

```r
# 2. Group by age bucket and orientation, and count the number of users in each␣
↪combination
age_orientation_counts <- df_eda %>%
  filter(!is.na(age_bucket)) %>%  # Exclude rows with missing or invalid age
  group_by(age_bucket, orientation) %>%
  summarise(count = n(), .groups = 'drop')  # Count users per combination

# Print the table with age bucket, orientation, and count
print(age_orientation_counts)

# 3. Plot the bar graph
ggplot(age_orientation_counts, aes(x = age_bucket, y = count, fill =␣
↪orientation)) +
  geom_bar(stat = "identity", position = "dodge") +  # Create a dodged bar graph
  theme_minimal() +  # Use a minimal theme
  labs(title = "Count of Users by Age Group and Orientation",
       x = "Age Group",
       y = "Users",
       fill = "Orientation") +  # Add axis labels and legend title
  theme(axis.text.x = element_text(angle = 0, hjust = 0.5))  # Rotate x-axis␣
↪labels for better readability
```

```
# A tibble: 18 x 3
   age_bucket orientation count
   <chr>      <chr>
<int>
 1 18-25      bisexual     1072
 2 18-25      gay          1445
 3 18-25      straight    11937
 4 26-35      bisexual     1166
 5 26-35      gay          2501
 6 26-35      straight    24954
 7 36-45      bisexual      385
 8 36-45      gay          1012
 9 36-45      straight     9406
10 46-55      bisexual      113
11 46-55      gay           476
12 46-55      straight     3373
13 56-65      bisexual       27
14 56-65      gay           128
15 56-65      straight     1688
16 Over 65    bisexual        4
17 Over 65    gay            11
18 Over 65    straight      248
```



Count of Users by Age Group and Orientation
25000
20000
15000
10000
5000
0
Users
18-25
26-35
36-45
46-55
56-65
Over 65
Age Group
Orientation
bisexual
gay
straight