Rat Sightings in NYC

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Application of CRAP Principles

Contrast I used distinct, bright, and minimalistic colors to differentiate data points while maintaining readability. The dark blue lines and clear black labels create a strong contrast against the white background, ensuring visibility and reducing cognitive load. For bar charts, each category is assigned a unique color to distinguish different boroughs, statuses, and locations.

Repetition I maintained to keep a consistent color scheme, font style, and axis formatting across all visualizations, ensuring uniformity and reducing distractions. Titles follow the same capitalization and alignment conventions, reinforcing a professional and cohesive presentation. The legend placement and text formatting are repeated across similar charts, making them easier to interpret.

Alignment Titles, axis labels, and legends are aligned consistently across all graphs, avoiding unnecessary clutter. Numeric values for bar charts are placed inside bars for clarity, ensuring better readability.

Proximity Labels and data points are positioned close to relevant elements, such as peak points in trend lines and category names in bar charts. Grouped elements (such as borough comparisons) are placed together to emphasize relationships while avoiding unnecessary gaps. Annotated insights (e.g., "Best weather for rats to breed") are placed near the relevant data points for immediate context.

Application of Kieran Healy's Principles of Great Visualizations

Show the Right Data Clearly I removed any unnecessary embellishments (3D effects, excessive grid lines) that might obscure the message. Data labels were prioritized for key insights, such as highlighting peak years and seasonal trends. Encourage Comparisons

Multi-line charts for borough-wise trends enable users to compare the worst-affected regions over time. Stacked bar charts allow a direct comparison of complaint resolution times across boroughs. Balance Simplicity and Complexity

Each visualization was stripped of unnecessary details but retained essential insights, using annotations only where needed.The use of color and size differentiation ensures that trends remain visually engaging without overwhelming the viewer.

Application of Alberto Cairo's Five Qualities of Great Visualizations

Truthful The visualizations accurately represent the dataset without distortion, misleading scales, or exaggerated differences.I maintained numerical accuracy by using clear labels and properly scaled axes. Functional

The visual choices effectively highlight the most important insights, such as seasonal peaks, borough comparisons, and slow resolution times. Annotations add useful context without clutter.

Beautiful Used a clean, minimalistic aesthetic with a white background and high-contrast colors. The choice of discrete yet visually appealing colors ensures both clarity and engagement.

Insightful Graphs are structured to reveal meaningful patterns, such as the surge in complaints during July or Brooklyn's persistent rodent issues. The memo accompanying the visuals draws actionable insights from the data.

Enlightening The visualizations provide actionable information, helping NYC policymakers target problem areas, allocate resources efficiently, and prioritize pest control efforts.

Executive Summary:

When starting to work with data about rat sightings, first thought that came to my mind was living in asia I have never heard about people complaining about rat sightings and government even caring about infestation caused by rats as its pretty much similar or even worse in some cities in India.

The questions I started my analysis with were: 1)Which borough has the most sightings? 2)Which type of infrastructure had the most sightings? 3) How does the infrastructure in these top zip codes help the rat infestation? And many more I was new to the data. When starting to answer these questions I saw a trend in the sightings over the years. The data shows 2016 had the highest sightings at 17,230 between 2010 and 2017.I came across a lot of data for Brooklyn and Manhattan and these regions being the hotspots. The oldest settlements and buildings in NYC. As I dived deeper into the data zip code 11221 Bushwick & Stuyvesant Heights in Brooklyn had the highest sightings 3124. Post this I moved on to check the amount of time it took the Department of Health and Mental Hygiene to resolve these complaints by each borough, Queens and Bronx with an average of 12 days and Staten Island with an average of 18 days of resolution time.

```r
# Load libraries
library(tidyverse)
library(lubridate)


# Read the dataset
rat_sightings <- read_csv("data/A1_sightings.csv", na = c("", "NA", "N/A"))
```

```r
rat_sightings <- rat_sightings %>%
  select(-c(`School Name`:`Ferry Terminal Name`))
```

```r
head(rat_sightings)
```

```
## # A tibble: 6 x 31
##   `Unique Key` `Created Date`         `Closed Date`          Agency `Agency Name`
##          <dbl> <chr>                  <chr>                  <chr>  <chr>
## 1     31464015 09/04/2015 12:00:00 AM 09/18/2015 12:00:00 ~ DOHMH  Department o~
## 2     31464024 09/04/2015 12:00:00 AM 10/28/2015 12:00:00 ~ DOHMH  Department o~
## 3     31464025 09/04/2015 12:00:00 AM <NA>                   DOHMH  Department o~
## 4     31464026 09/04/2015 12:00:00 AM 09/14/2015 12:00:00 ~ DOHMH  Department o~
## 5     31464027 09/04/2015 12:00:00 AM 09/22/2015 12:00:00 ~ DOHMH  Department o~
## 6     31464188 09/04/2015 12:00:00 AM 09/22/2015 12:00:00 ~ DOHMH  Department o~
## # i 26 more variables: `Complaint Type` <chr>, Descriptor <chr>,
## #   `Location Type` <chr>, `Incident Zip` <dbl>, `Incident Address` <chr>,
## #   `Street Name` <chr>, `Cross Street 1` <chr>, `Cross Street 2` <chr>,
## #   `Intersection Street 1` <chr>, `Intersection Street 2` <chr>,
## #   `Address Type` <chr>, City <chr>, Landmark <lgl>, `Facility Type` <lgl>,
## #   Status <chr>, `Due Date` <chr>, `Resolution Action Updated Date` <chr>,
## #   `Community Board` <chr>, Borough <chr>, ...
```

Data Background:

The data for Rat Sightings was shared by the professor in a CSV format and we were also given the link for Kaggle through which the data was downloaded. Data tells us about rat sightings from 2010-2017 in 5 different boroughs, the date of sighting, address, location type and the coordinates of the sightings.

Data Cleaning:

The data was already well organized. It had a few missing cells but I left them unchanged. First I decided the columns I wanted to work with based on all the questions I had in my mind. The dates were already in the correct format but still I used lubridate to make the analysis error free (at least for dates). I filtered out boroughs that were called "unspecified" after checking the actual number of boroughs in NYC. It just had one row which might have been an error while data entry. Same with status it had "Draft" and "Open" with just 1 entries each, no I didn't skip them.

```r
unique(rat_sightings$`Status`)
```

```
## [1] "Closed"   "Assigned" "Pending"  "Open"     "Draft"
```

```r
# List of columns to remove
columns_to_remove <- c(
  "Intersection Street 1",
  "Intersection Street 2",
  "Park Facility Name",
  "Landmark",
  "Facility Type"
)

# Drop the specified columns
rat_sightings <- rat_sightings %>%
  select(-all_of(columns_to_remove))

# Display remaining columns
colnames(rat_sightings)
```

```
##  [1] "Unique Key"                     "Created Date"
##  [3] "Closed Date"                    "Agency"
##  [5] "Agency Name"                    "Complaint Type"
##  [7] "Descriptor"                     "Location Type"
##  [9] "Incident Zip"                   "Incident Address"
## [11] "Street Name"                    "Cross Street 1"
## [13] "Cross Street 2"                 "Address Type"
## [15] "City"                           "Status"
## [17] "Due Date"                       "Resolution Action Updated Date"
## [19] "Community Board"                "Borough"
## [21] "X Coordinate (State Plane)"     "Y Coordinate (State Plane)"
## [23] "Park Borough"                   "Latitude"
## [25] "Longitude"                      "Location"
```

```r
# Convert Created Date and Closed Date to Date format and calculate Time Taken
rat_sightings <- rat_sightings %>%
  mutate(
    `Created Date` = mdy_hms(`Created Date`),
    `Closed Date` = mdy_hms(`Closed Date`),
    `Time Taken` = as.integer(difftime(`Closed Date`, `Created Date`, units = "days"))
  )

# View the first few rows to confirm
head(rat_sightings)
```

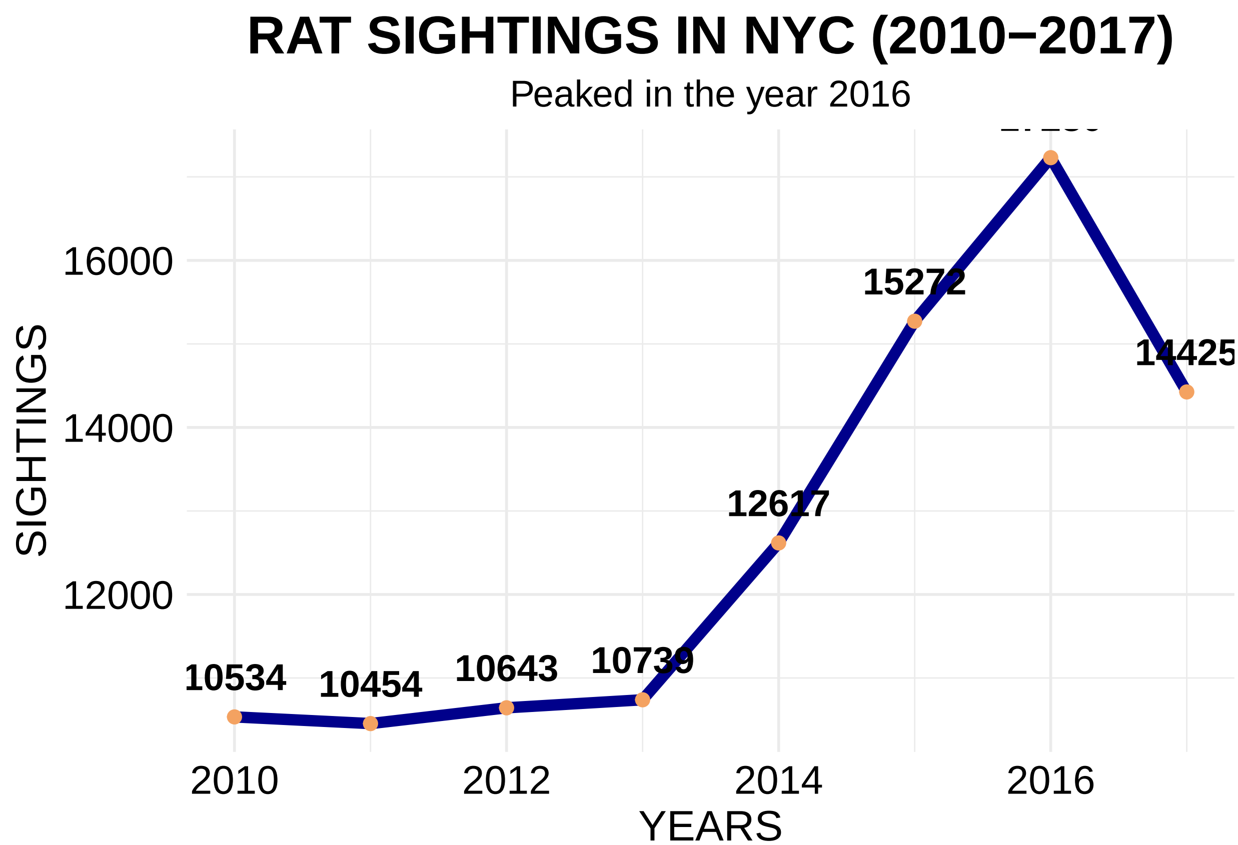
```
## # A tibble: 6 x 27
##   `Unique Key` `Created Date`      `Closed Date`       Agency `Agency Name`
##          <dbl> <dttm>              <dttm>              <chr>  <chr>
## 1     31464015 2015-09-04 00:00:00 2015-09-18 00:00:00 DOHMH  Department of Hea~
## 2     31464024 2015-09-04 00:00:00 2015-10-28 00:00:00 DOHMH  Department of Hea~
## 3     31464025 2015-09-04 00:00:00 NA                  DOHMH  Department of Hea~
## 4     31464026 2015-09-04 00:00:00 2015-09-14 00:00:00 DOHMH  Department of Hea~
## 5     31464027 2015-09-04 00:00:00 2015-09-22 00:00:00 DOHMH  Department of Hea~
## 6     31464188 2015-09-04 00:00:00 2015-09-22 00:00:00 DOHMH  Department of Hea~
## # i 22 more variables: `Complaint Type` <chr>, Descriptor <chr>,
## #   `Location Type` <chr>, `Incident Zip` <dbl>, `Incident Address` <chr>,
## #   `Street Name` <chr>, `Cross Street 1` <chr>, `Cross Street 2` <chr>,
## #   `Address Type` <chr>, City <chr>, Status <chr>, `Due Date` <chr>,
## #   `Resolution Action Updated Date` <chr>, `Community Board` <chr>,
## #   Borough <chr>, `X Coordinate (State Plane)` <dbl>,
## #   `Y Coordinate (State Plane)` <dbl>, `Park Borough` <chr>, ...
```

Individual Figures:

Rat Sightings Have Been Increasing Over Time

The first step in my analysis was to determine whether rat sightings in NYC have been increasing or decreasing over time. I used a line graph to visualize yearly trends from 2010 to 2017. The data showed a steady rise in complaints, peaking in 2016 with 17,230 reported cases. The increase in sightings could indicate a growing rat population or improved public awareness and reporting. The graph uses a dark blue line to emphasize the trend, with key values labeled for clarity. I also highlighted 2016 as the peak year, ensuring this key insight stands out.

```r
# Extracted year from Created Date
rat_sightings <- rat_sightings %>%
  mutate(Sighting_Year = year(`Created Date`))

# Counted sightings per year
yearly_counts <- rat_sightings %>%
  count(Sighting_Year)

# Ploted the trend
rat_sightings_trend <- ggplot(yearly_counts, aes(x = Sighting_Year, y = n)) +
  geom_line(linewidth= 2,group=1, color= "darkblue") +
  geom_point(size=2, color= "#F4A261") +
  geom_text(aes(label = n), vjust = -1, size = 4.8, fontface = "bold") +
  labs(title="RAT SIGHTINGS IN NYC (2010-2017)",
       subtitle = "Peaked in the year 2016",
       x="YEARS",
       y="SIGHTINGS")+
  theme_minimal()+
  theme(plot.background = element_rect(fill = "white", color = NA),
        plot.title = element_text(hjust = 0.5, size = 20, face= "bold"),
        plot.subtitle = element_text(hjust = 0.5, size = 14),
        axis.text = element_text(color= "black", size = 15),
        axis.title = element_text(color = "black"),
        title = element_text(color= "black", size = 16) )

print(rat_sightings_trend)
```



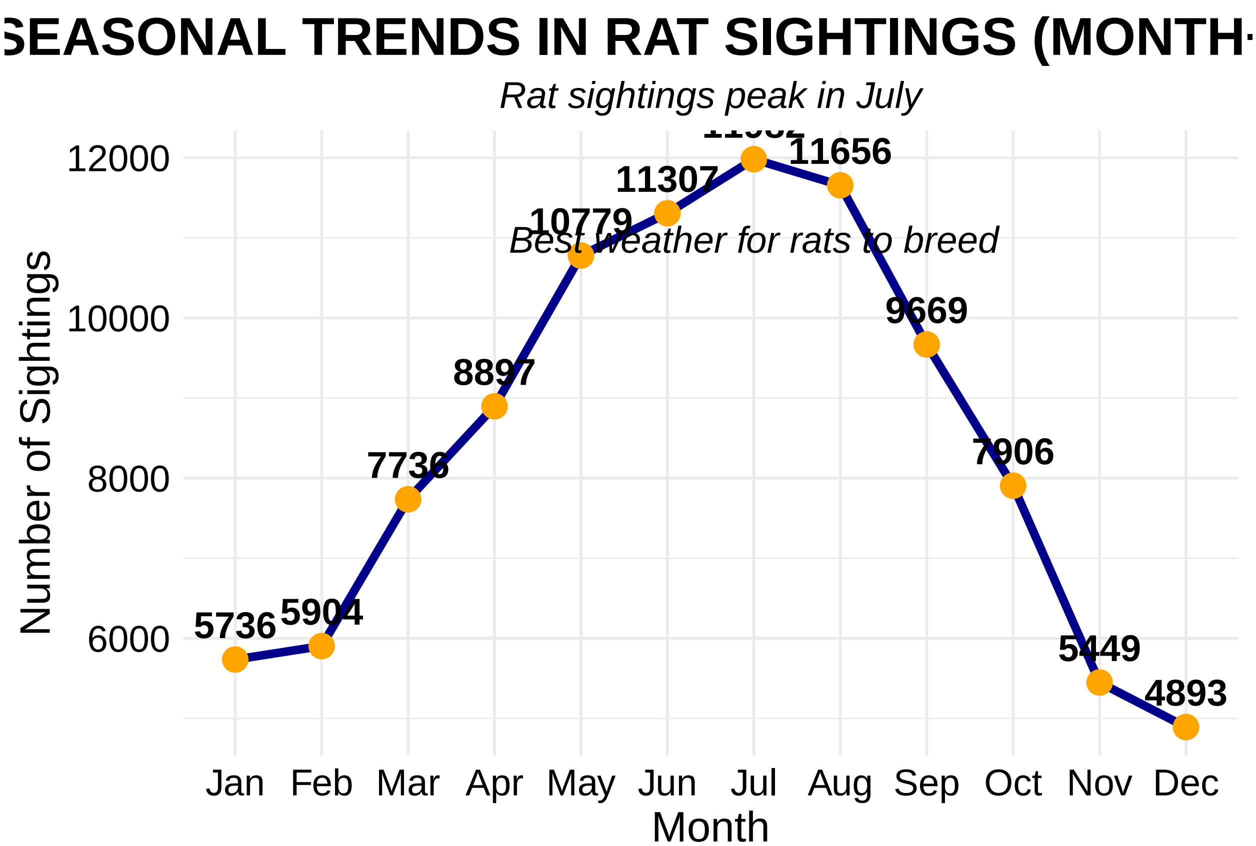

```r
ggsave("output/rat_sightings_trend.pdf", width = 14, height = 8, dpi = 300, bg = "white")
```

Seasonal Trends: Summer is Peak Rat Season:

Understanding the seasonality of rat sightings was critical in determining when infestations peak. We created a line graph to examine the trend of complaints by month. The results show that rat sightings peak in July, with ~11,982 cases, likely due to heat and humidity creating optimal breeding conditions for rats. To emphasize this insight, we included an annotation directly below the peak point, highlighting "Best weather for rats to breed." This suggests that NYC should focus pest control efforts in the months leading up to July to proactively mitigate infestations.

```r
# Extracted month from Created Date
rat_sightings <- rat_sightings %>%
  mutate(Sighting_Month = month(`Created Date`, label = TRUE, abbr = TRUE))  # Get abbreviated month na

# Counted sightings per month
monthly_counts <- rat_sightings %>%
  count(Sighting_Month) %>%
  arrange(match(Sighting_Month, month.abb))

# Find the highest point (July)
max_month <- monthly_counts[which.max(monthly_counts$n), ]

# Ploted month-wise rat sightings
seasonal_monthly <- ggplot(monthly_counts, aes(x = Sighting_Month, y = n, group=1)) +
  geom_line(color="darkblue", linewidth=1.5) +
```

```r
  geom_point(size=4, color="orange") +
  geom_text(aes(label=n), vjust=-0.8, size=5, fontface="bold", color="black") +

  annotate("text", x=max_month$Sighting_Month, y=max_month$n - 1000,
           label="Best weather for rats to breed",
           color="black", size=5, fontface="italic", hjust=0.5) +

  labs(title="SEASONAL TRENDS IN RAT SIGHTINGS (MONTH-WISE)",
       subtitle= "Rat sightings peak in July",
       x="Month",
       y="Number of Sightings") +
  theme_minimal() +
  theme(
    plot.title = element_text(hjust = 0.5, size = 20, face= "bold"),
    plot.subtitle = element_text(hjust = 0.5, size = 14, face="italic"),
    axis.text = element_text(color = "black", size = 14),
    axis.title = element_text(color = "black", size = 16)
  )

print(seasonal_monthly)
```

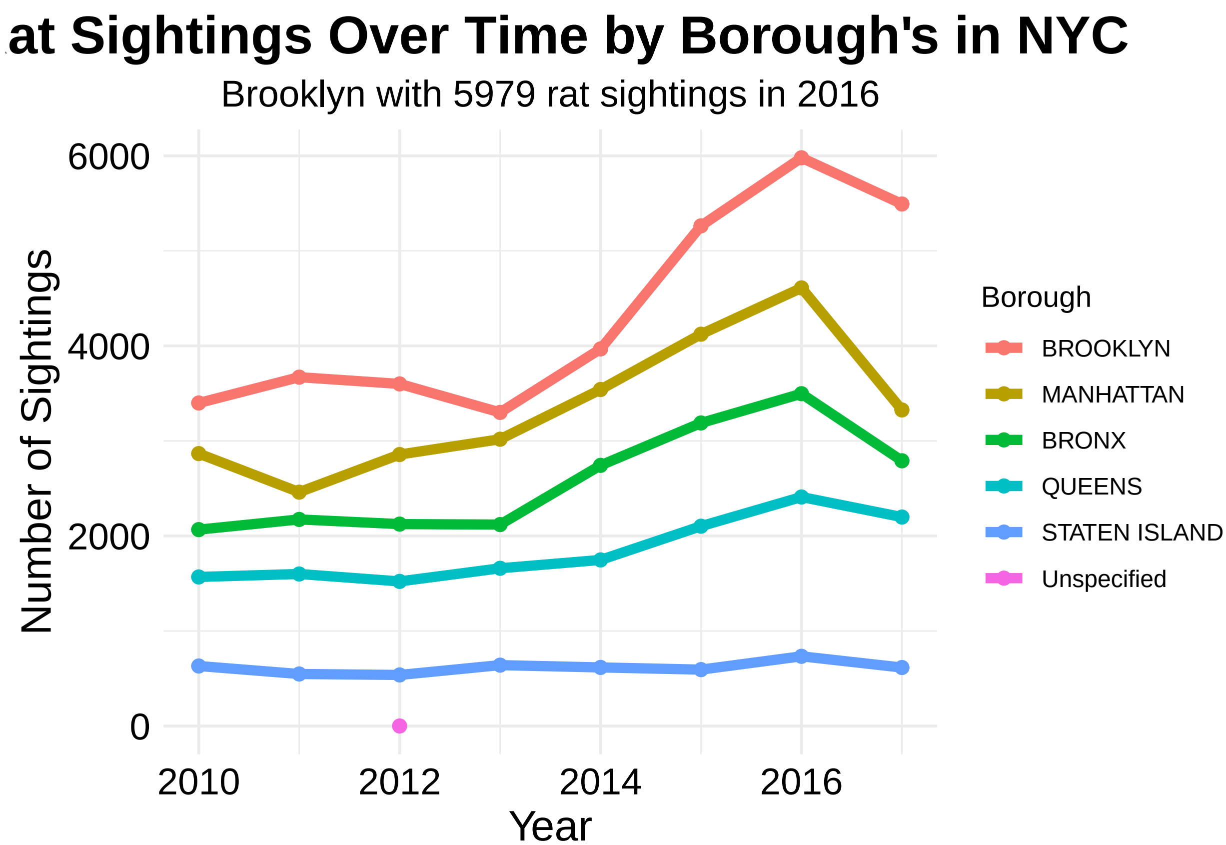



```r
ggsave("output/seasonal_monthly.pdf", width = 14, height = 8, dpi = 300, bg = "white")
```

Borough Breakdown: Brooklyn Has the Most Sightings

After establishing the overall trend, we wanted to see which boroughs were the most affected by rat infestations. A multi-line graph was chosen to compare borough trends over time. We extracted the number of sightings per year per borough, ensuring the boroughs were ordered based on total complaints for a meaningful legend. The visualization clearly shows that Brooklyn consistently had the highest number of complaints (34,673), followed by Manhattan (26,803) and the Bronx (20,706). Staten Island, with significantly fewer complaints, suggests that lower population density and fewer urban spaces may contribute to lower rat sightings.

```r
# Count sightings per year and borough
yearly_borough_counts <- rat_sightings %>%
  count(Borough, Sighting_Year)

# Reorder Borough levels based on total sightings
borough_order <- yearly_borough_counts %>%
  group_by(Borough) %>%
  summarise(Total_Sightings = sum(n)) %>%
  arrange(desc(Total_Sightings)) %>%
  pull(Borough)

# Convert Borough to a factor with specified order
yearly_borough_counts <- yearly_borough_counts %>%
  mutate(Borough = factor(Borough, levels = borough_order))

# Plot multi-line chart with labels
yearly_borough_numbers <- ggplot(yearly_borough_counts, aes(x = Sighting_Year, y = n, color=Borough, gro
  geom_line(linewidth = 1.8) +
  geom_point(size=2) +
  labs(title="Rat Sightings Over Time by Borough's in NYC",
       subtitle = "Brooklyn with 5979 rat sightings in 2016",
       x="Year",
       y="Number of Sightings",
       color= "Borough") +
  theme_minimal() +
  theme(legend.position = "right",
        plot.title = element_text(hjust = 0.5, size = 20, face= "bold"),
        plot.subtitle = element_text(hjust = 0.5, size = 14),
        axis.text = element_text(color = "black",size = 14),
        axis.title = element_text(color = "black",size = 16 ))

print(yearly_borough_numbers)
```




```
ggsave("output/yearly_borough_numbers.pdf", width = 14, height = 8, dpi = 300, bg = "white")
```

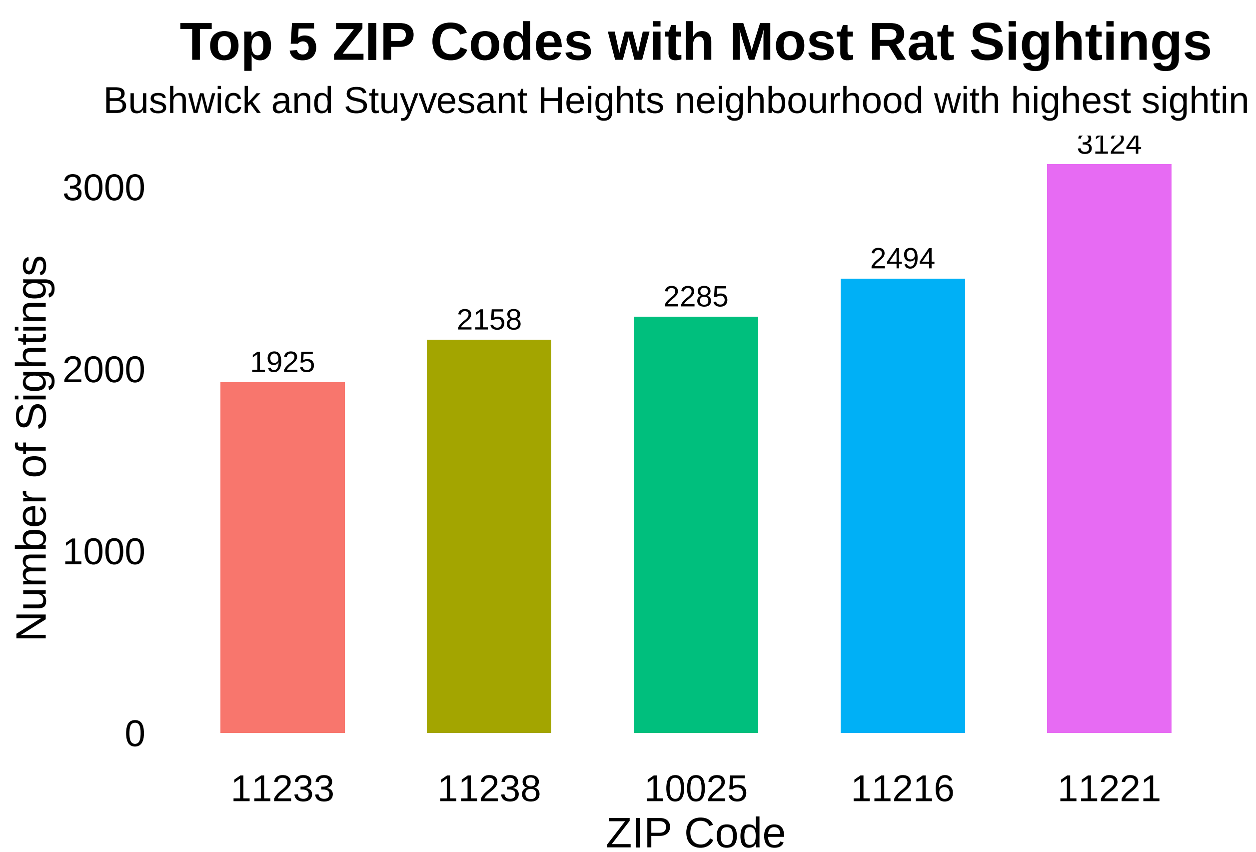
To identify specific neighborhoods most affected by rat sightings, I analyzed the top five ZIP codes with the highest number of complaints. The results show that Bushwick & Stuyvesant Heights (ZIP code 11221 in Brooklyn) had the highest number of complaints, followed by other areas in Brooklyn and Manhattan. Four out of the top five ZIP codes belong to Brooklyn, reinforcing its status as the most rodent-infested borough. These neighborhoods are also among the oldest in NYC, with aging infrastructure, high-density housing, and waste management challenges that likely contribute to infestations. The only non-Brooklyn ZIP code in the top five is from Manhattan (10025), further highlighting the concentration of issues in densely populated urban areas.

```
# Count sightings per ZIP code
top_zip_codes <- rat_sightings %>%
  filter(!is.na(`Incident Zip`)) %>%  # Remove missing ZIP codes
  count(`Incident Zip`) %>%
  arrange(desc(n)) %>%
  top_n(5)  # Select the top 5 ZIP codes
```

```
## Selecting by n
```

```
# Convert ZIP codes to factors for ordered bar chart
top_zip_codes <- top_zip_codes %>%
  mutate(`Incident Zip` = factor(`Incident Zip`, levels = rev(`Incident Zip`)))  # Reverse order for re

# Plot bar chart for top ZIP codes
```

```r
top_zip_codes <- ggplot(top_zip_codes, aes(x = `Incident Zip`, y = n, fill = `Incident Zip`)) +
  geom_bar(stat = "identity", width = 0.6) +
  geom_text(aes(label = n), vjust = -0.5, size = 4) +  # Add data labels
  labs(title = "Top 5 ZIP Codes with Most Rat Sightings",
       subtitle= "Bushwick and Stuyvesant Heights neighbourhood with highest sightings",
       x = "ZIP Code",
       y = "Number of Sightings") +
  theme_minimal() +
  theme(legend.position = "none",
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        plot.title = element_text(hjust = 0.5, size = 20, face= "bold"),
        plot.subtitle = element_text(hjust = 0.5, size = 14),
        axis.text = element_text(color = "black",size = 14),
        axis.title = element_text(color = "black",size = 16 ))

print(top_zip_codes)
```

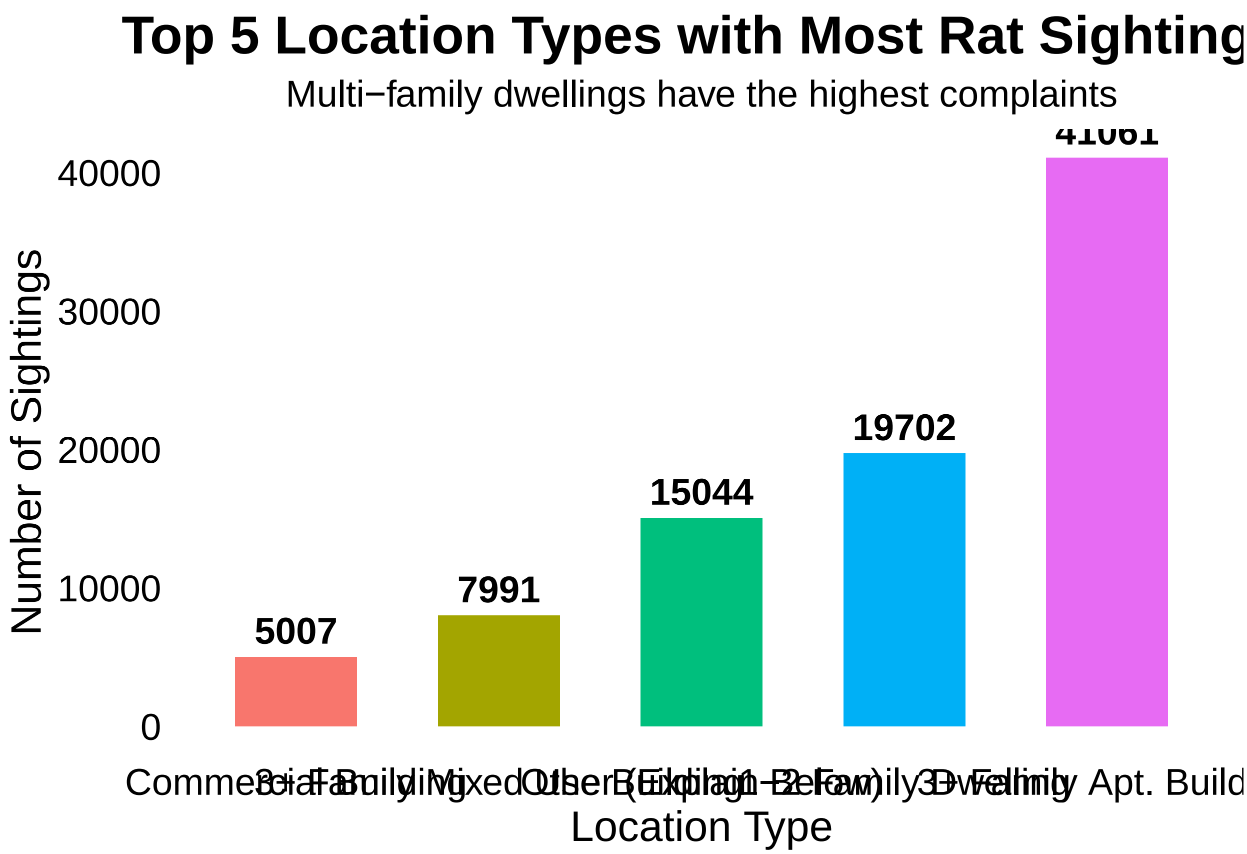



```r
ggsave("output/top_zip_codes.pdf", width = 14, height = 8, dpi = 300, bg = "white")
```

Most Affected Location Types

Beyond ZIP codes, I examined the types of buildings where rat complaints are most frequently reported. The findings indicate that 3+ family apartment buildings account for the majority of complaints, followed by 1-2 family dwellings and mixed-use buildings. This suggests that multi-family housing units are hotspots for rodent infestations, likely due to shared waste disposal areas, older construction, and maintenance challenges. The lower number of complaints from commercial buildings may be due to stricter regulations and routine pest control efforts in business districts.

```r
# Load necessary libraries
library(ggplot2)
library(dplyr)

# Count sightings per Location Type
top_location_types <- rat_sightings %>%
  filter(!is.na(`Location Type`)) %>%  # Remove missing values
  count(`Location Type`) %>%
  arrange(desc(n)) %>%
  slice_head(n = 5)  # Select the top 5 location types

# Convert Location Type to factor for ordered bar chart
top_location_types <- top_location_types %>%
  mutate(`Location Type` = factor(`Location Type`, levels = rev(`Location Type`)))  # Reverse order for

# Plot bar chart for top location types
ggplot(top_location_types, aes(x = `Location Type`, y = n, fill = `Location Type`)) +
  geom_bar(stat = "identity", width = 0.6) +
  geom_text(aes(label = n), vjust = -0.5, size = 5, fontface = "bold") +  # Add data labels
  labs(title = "Top 5 Location Types with Most Rat Sightings",
       subtitle = "Multi-family dwellings have the highest complaints",
       x = "Location Type",
       y = "Number of Sightings") +
  theme_minimal() +
  theme(
    legend.position = "none",
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(),
    plot.title = element_text(hjust = 0.5, size = 20, face = "bold"),
    plot.subtitle = element_text(hjust = 0.5, size = 14),
    axis.text = element_text(color = "black", size = 14),
    axis.title = element_text(color = "black", size = 16)
  )
```




```r
# Save the plot
ggsave("output/top_location_types.pdf", width = 16, height = 6, dpi = 300, bg = "white")
```

Complaint Status Distribution Per Borough

To evaluate how NYC handles rat complaints, I examined the status of complaints across boroughs. A stacked bar chart was used to visualize the distribution of complaints labeled as Closed, Open, Pending, and Assigned. The results show that most complaints are marked as “Closed,” suggesting the city is actively addressing rodent issues. However, a significant number of complaints remain Pending or Open, particularly in Brooklyn and Manhattan, indicating potential delays or inefficiencies in resolution. Very few complaints were labeled as “Assigned,” which suggests either cases are being resolved quickly or not actively reassigned for follow-ups. This data highlights the need for a closer look at complaint resolution processes in the most affected boroughs.

```r
# Load necessary libraries
library(ggplot2)
library(RColorBrewer)  # For color selection

# Count complaints per Borough and Status (excluding Unspecified borough)
status_borough_counts <- rat_sightings %>%
  filter(Borough != "Unspecified") %>%
  count(Borough, Status)

# Convert Borough to factor for proper ordering
status_borough_counts <- status_borough_counts %>%
  mutate(Borough = factor(Borough, levels = unique(Borough)))
```

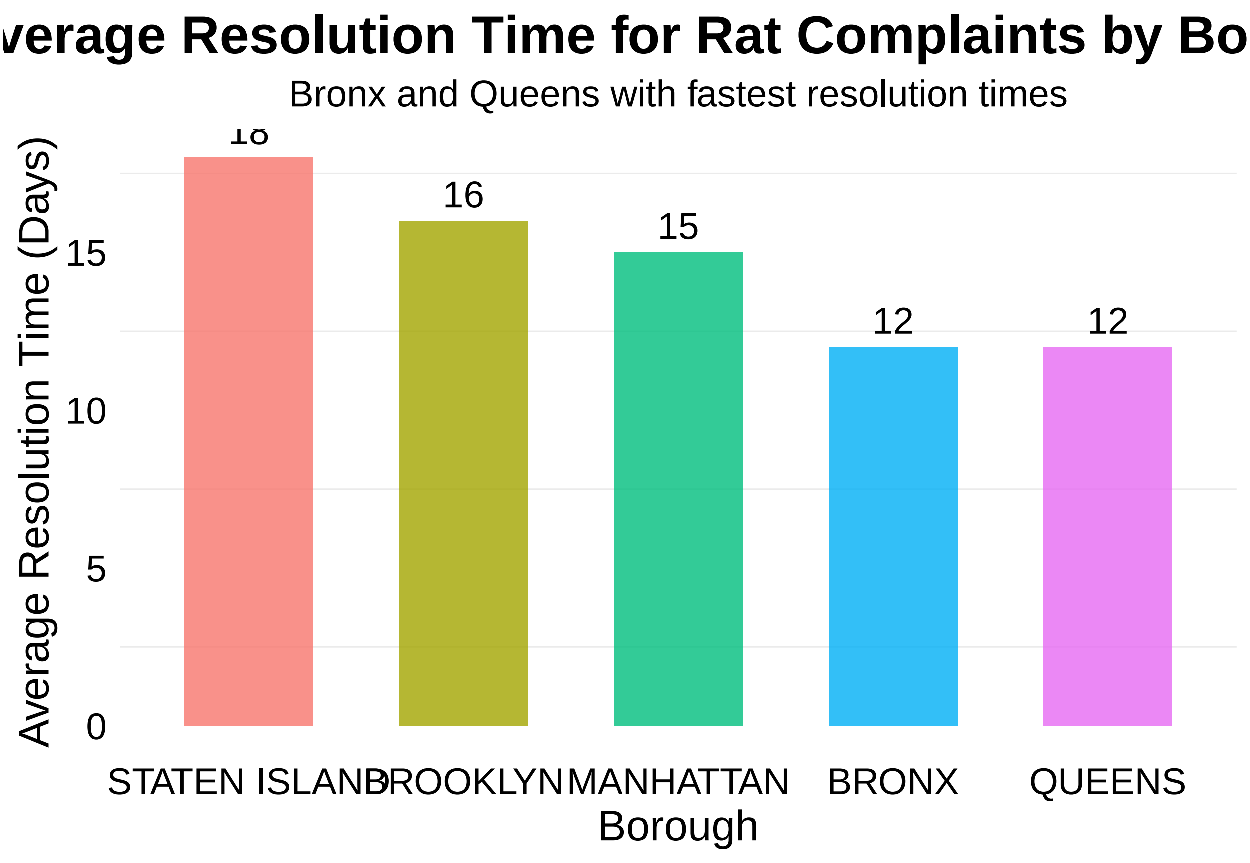
```r
# Define a professional, bright color palette
status_colors <- c("Assigned" = "darkred",
                   "Draft" = "skyblue",
                   "Open" = "#CC79A7",
                   "Closed" = "darkgreen",
                   "Pending" = "darkblue")

# Create the stacked bar chart with distinct, readable colors
status_per_borough <- ggplot(status_borough_counts, aes(x = Borough, y = n, fill = Status)) +
  geom_bar(stat = "identity", position = "stack", width = 0.7) +
  geom_text(aes(label = n), position = position_stack(vjust = 0.5), color = "white", size = 3, fontface
  scale_fill_manual(values = status_colors) +  # Apply custom colors
  labs(title = "Complaint Status Distribution Per Borough",
       x = "Borough",
       y = "Number of Complaints",
       fill = "Status") +
  theme_minimal() +  # Apply a cleaner theme
  theme(
    plot.title = element_text(hjust = 0.5, size = 20, face= "bold"),
    plot.subtitle = element_text(hjust = 0.5, size = 14),
    panel.grid.major = element_blank(),  # Remove major gridlines
    panel.grid.minor = element_blank(),  # Remove minor gridlines
    axis.text.x = element_text(face = "bold", size = 12),  # Make borough names bold and readable
    axis.title = element_text(face = "bold", size = 14),   # Bold axis titles
    legend.position = "right",  # Keep legend for clarity
    legend.text = element_text(size = 12)  # Increase legend text size
  )

ggsave("output/status_per_borough.pdf", width = 10, height = 6, dpi = 300, bg = "white")
```

Resolution Time: Staten Island Takes the Longest

I analyzed how long it takes for NYC to resolve rat complaints. A bar chart was chosen to compare average resolution times across boroughs. The results showed that Staten Island takes the longest time (18 days) to resolve complaints, while the Bronx and Queens resolve them the fastest (~12 days). This suggests that certain boroughs may face resource allocation issues or logistical inefficiencies in handling complaints. To ensure accurate reporting, extreme outliers (e.g., cases that took unusually long) were removed from the dataset, allowing us to present a more reliable average resolution time. The city could use this data to prioritize improvements in slow-response areas.

```r
# Compute average resolution time per borough (removing extreme values)
avg_time_per_borough <- rat_sightings %>%
  filter(`Time Taken` >= 0 & `Time Taken` <= 180) %>%  # Remove extreme values
  group_by(Borough) %>%
  summarise(Average_Time = round(mean(`Time Taken`, na.rm = TRUE))) %>%  # Round to whole numbers
  arrange(desc(Average_Time))  # Sort by highest average resolution time

# Convert Borough to factor for ordered bar chart
avg_time_per_borough <- avg_time_per_borough %>%
  mutate(Borough = factor(Borough, levels = Borough))

# Plot average resolution time per borough
avg_resolution_time <- ggplot(avg_time_per_borough, aes(x = Borough, y = Average_Time, fill = Borough))
```

```
  geom_bar(stat = "identity", width = 0.6, alpha = 0.8) +
  geom_text(aes(label = Average_Time), vjust = -0.5, size = 5) +  # Display rounded values
  labs(title="Average Resolution Time for Rat Complaints by Borough",
       subtitle = "Bronx and Queens with fastest resolution times",
       x="Borough",
       y="Average Resolution Time (Days)") +
  theme_minimal() +
  theme(legend.position = "none",
        plot.title = element_text(hjust = 0.5, size = 20, face= "bold"),
        plot.subtitle = element_text(hjust = 0.5, size = 14),
        panel.grid.major = element_blank(),
        axis.text = element_text(color = "black",size = 14),
        axis.title = element_text(color = "black",size = 16 ))

print(avg_resolution_time)
```




```
ggsave("output/avg_resolution_time.pdf", width = 14, height = 8, dpi = 300, bg = "white")
```

Conclusion:

My analysis of rat sightings in NYC (2010-2017) highlights a steady increase in complaints, peaking in 2016 with 17,230 cases. Brooklyn reported the highest sightings, followed by Manhattan and the Bronx, with Bushwick & Stuyvesant Heights (ZIP 11221) as the worst-affected areas. Multi-family apartment buildings had the most complaints, indicating waste management and aging infrastructure as key factors. Sightings peak in July (~11,982 cases), aligning with optimal rat breeding conditions, suggesting the need for preemptive pest control efforts before summer. While most complaints are closed, delays persist in Brooklyn and Manhattan, and Staten Island has the slowest resolution time (18 days). To address these issues, NYC should intensify pest control in high-complaint ZIP codes, improve waste management in multi-family dwellings, and optimize complaint resolution times, ensuring a cleaner, healthier city.