EDA Proposal

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Importing the required libraries

```
Rows: 10,992
Columns: 10
$ city           <chr> "Ada", "Addison", "Adrian", "Adrian", "Albion", "Albion~
$ country        <chr> "United States", "United States", "United States", "Uni~
$ description    <chr> "Ada witch - Sometimes you can see a misty blue figure ~
$ location       <chr> "Ada Cemetery", "North Adams Rd.", "Ghost Trestle", "Si~
$ state          <chr> "Michigan", "Michigan", "Michigan", "Michigan", "Michig~
$ state_abbrev   <chr> "MI", "MI", "MI", "MI", "MI", "MI", "MI", "MI", "MI", "~
$ longitude      <dbl> -85.50489, -84.38184, -84.03566, -84.01757, -84.74518, ~
$ latitude       <dbl> 42.96211, 41.97142, 41.90454, 41.90571, 42.24401, 42.23~
$ city_longitude <dbl> -85.49548, -84.34717, -84.03717, -84.03717, -84.75303, ~
$ city_latitude  <dbl> 42.96073, 41.98643, 41.89755, 41.89755, 42.24310, 42.24~
```

Wow there are 9904 unique locations in 4386 unique cities across usa. This is interesting. Hmm things going weired because there are only 50 states in the US but we have 51 unique values in the state column. Let's dig deeper into this.

```
# A tibble: 1 x 8
   city description location state latitude longitude city_latitude
  <int>       <int>    <int> <int>    <int>     <int>         <int>
1     3           0        3     0     1261      1261            29
# i 1 more variable: city_longitude <int>
```

printing the rows with missing values in city_latitude and city_longitude columns.

creating a frequency table for the city ,location and state columns

Table 1: A table of City Frequency and Proportion

City	Counts	Proportions
Los Angeles	61	0.0139844
San Antonio	55	0.0126089
Honolulu	43	0.0098579
Pittsburgh	42	0.0096286
Columbus	41	0.0093994

Table 2: A table of State Frequency and Proportion

State	Counts	Proportions
California	1067	20.921569
Texas	696	13.647059
Pennsylvania	648	12.705882
Michigan	526	10.313726
Ohio	475	9.313726

Create a proportion table for it.

Ok now we can see that some of the location names have some additional data and typos and with different cases. Let's clean this. we have total of 638 rows of the cities with more that one common lat and long.

Super. it worked . Now we can see that the location names are cleaned.

Now we can apply the same method for entire dataframe.

Yeah it worked. Now we can see that the location names are cleaned.

Table 3: A table of Location with multiple citing

Location	Counts
Prince Georges county	20
Cry Baby Bridge	14
Cemetery	13
Mission Inn	12
Oviedo	12

this is the true location frequency.

these are the locations with multiple ghost citings. lets plot it on the map.

get top 25 places with multiple haunted citing.

Modelling

We can analyze if there's a relationship between distance from city center and the concentration of haunted places. we can create a multilinear regression model to predict the number of haunted places in a city based on the distance from the city center.

State Distribution

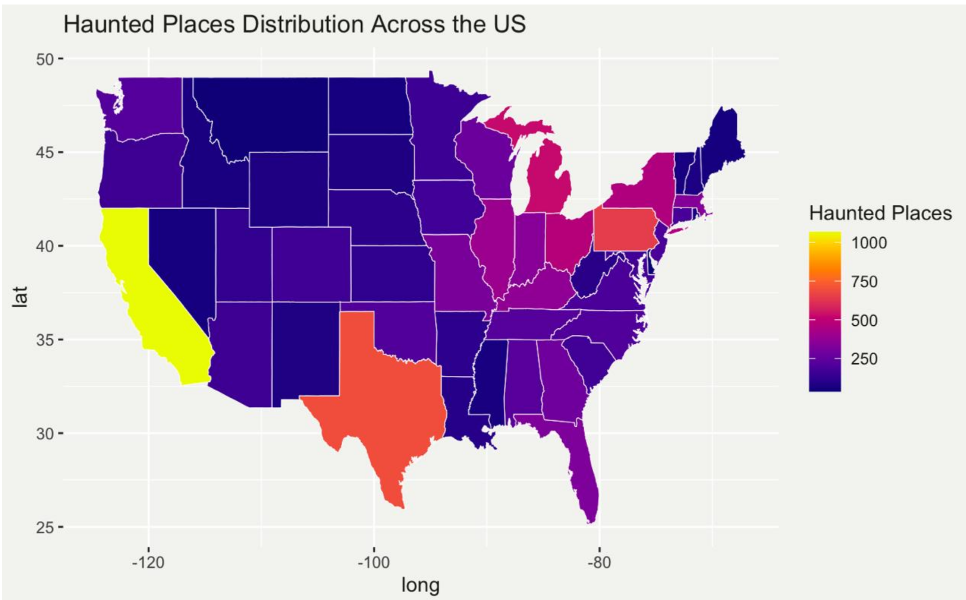


Figure 1: Choropleth Map of states

Bubble map of top 50 haunted places

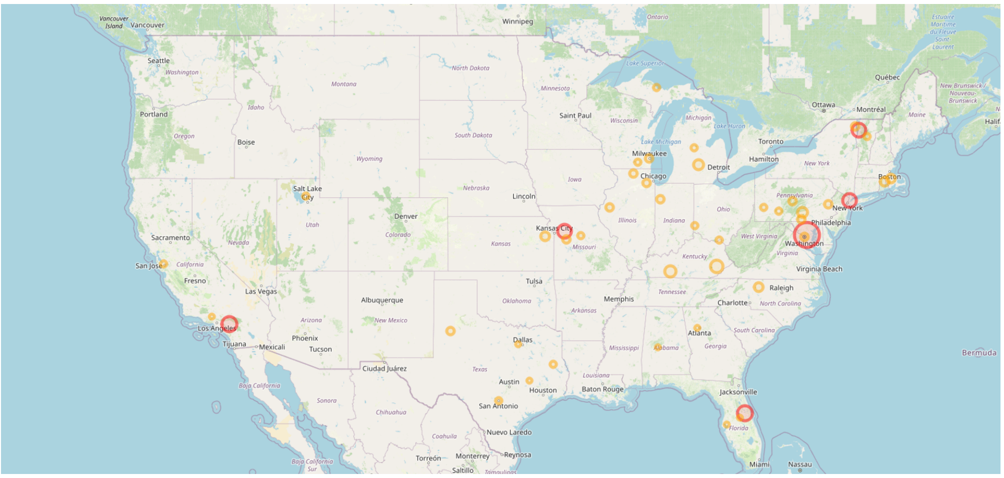


Figure 2: Bubble Map

Word Cloud of the cities

Figure 3: Word Cloud of Cities

Bar plot of Top 20 hauntred siting in cities

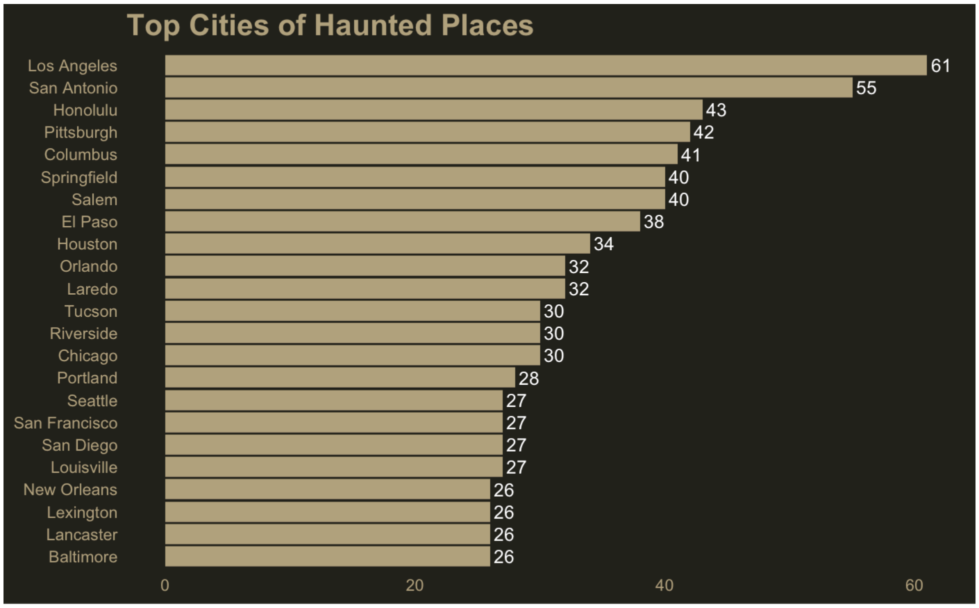


Figure 4: Bar plot of Top 20 hauntred siting in cities

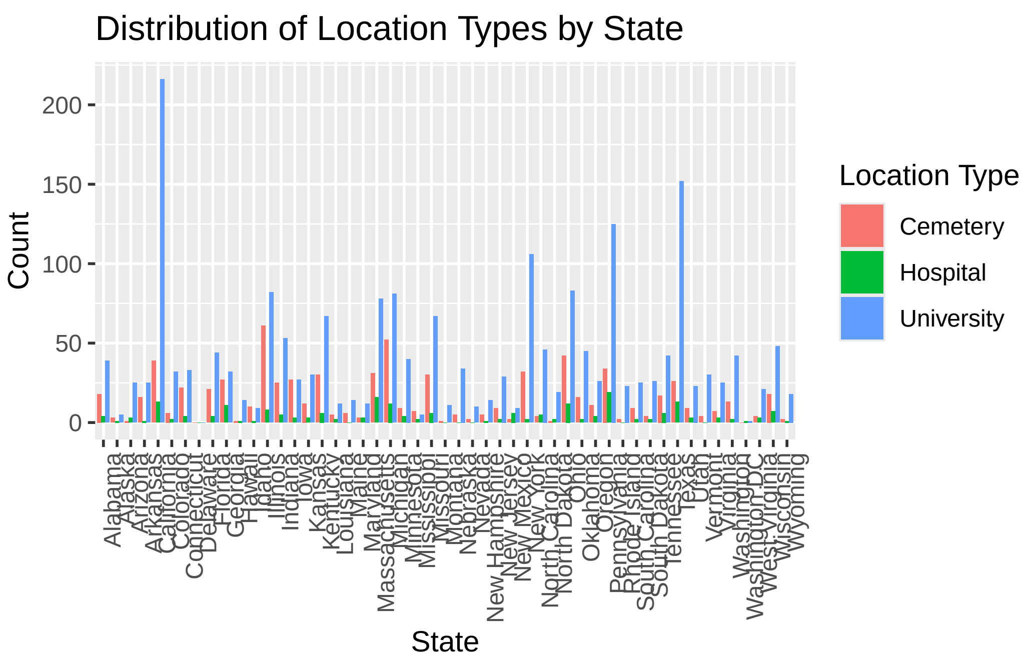
Null Hypothesis H_0 : proportion of simulation rejections found using the CLT based approach was equal to 10%.

$$H_0 : p = \text{Time in Bed (TIB)}$$

Alternative Hypotheses H_A : proportion of simulation rejections found using the CLT based approach was different from 10%.

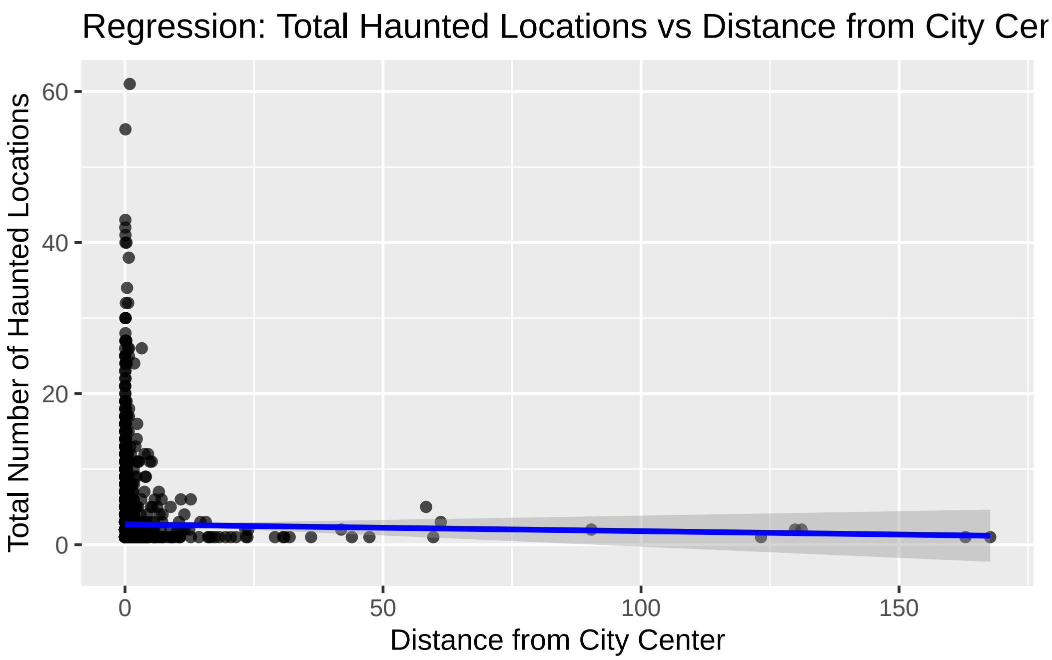
$$H_1 : p \neq \text{Time in Bed (TIB)}$$

```
Warning in chisq.test(contingency_table): Chi-squared approximation may be
incorrect


    Pearson's Chi-squared test

data:  contingency_table
X-squared = NaN, df = 100, p-value = NA
```




```
Call:
lm(formula = total_haunted ~ avg_distance, data = city_data)

Residuals:
   Min     1Q Median     3Q    Max
-1.692 -1.692 -1.690  0.308 58.316

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.691843   0.063936  42.102   <2e-16 ***
avg_distance -0.008989   0.010533  -0.853    0.393
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.969 on 3896 degrees of freedom
  (464 observations deleted due to missingness)
Multiple R-squared:  0.0001869, Adjusted R-squared:  -6.972e-05
F-statistic: 0.7283 on 1 and 3896 DF,  p-value: 0.3935

`geom_smooth()` using formula = 'y ~ x'
```

```
Warning: Removed 464 rows containing non-finite outside the scale range
(`stat_smooth()`).

Warning: Removed 464 rows containing missing values or values outside the scale range
(`geom_point()`).
```



Enrire Code

```r
library(tidyverse)
library(leaflet)
library(wordcloud2)
library(webshot)
library("htmlwidgets")
library(knitr)
webshot::install_phantomjs()
# Importing the dataset
tuesdata <- tidytuesdayR::tt_load('2023-10-10')
haunted_places <- tuesdata$haunted_places

# Glimpse of the dataset
haunted_places %>% glimpse()
# Counting unique values in each column
column_summary <- haunted_places %>%
  summarise(across(everything(), ~ n_distinct(.)))
column_summary

# Get unique values in the state column in alphabetical order.
unique_states <- haunted_places %>%
  distinct(state) %>%
  arrange(state)

unique_states

# Gottcha there is a value 'Washington D.C.' which is not a state
# but a federal district. Let's correct this.
# we can dig deeper into the dataset to find out the
# haunted places in Washington D.C.
# Haunted places in Washington D.C.
haunted_places_dc <- haunted_places %>%
  filter(state == "Washington DC")
haunted_places_dc

# OK Ok. I think there is lot going on in the Us.
# "After some web search I found that the Wasington DC is a separate entity
# from the US but overseen by US"
# Ohh, That's there political concern. Iam going to keep it as it is.
# Cleaning the dataset
```

```r
# Removing redundant columns (Country, state_abbrev)
haunted_places <- haunted_places %>%
  select(city,
         description,
         location,
         state,
         latitude,
         longitude,
         city_latitude,
         city_longitude)
# Function for checking missing values
missing_values <- function(df){

  df %>% summarise(across(everything(), ~ sum(is.na(.))))
}
missing_values(haunted_places)
# Print rows with missing values in city_latitude and city_longitude columns
missing_coordinates <- haunted_places %>%
  filter(is.na(city_latitude) | is.na(city_longitude))
missing_coordinates
for (city in missing_coordinates$city) {
  print(haunted_places[haunted_places$city == city, ])
}

# by doing the city search we can see that we can find the city latitude and
# longitude of these cities.
# Cockeysville, Faribault, Streamwood, Cynthiana
# Lets fix these city coordinates. (may be later)
# Dig deeper into the missing values
# removing the rows with missing values in city, location,
# city_latitude, city_longitude columns
haunted_places <- haunted_places %>%
  filter(!is.na(city) &
           !is.na(location) &
           !is.na(city_latitude) &
           !is.na(city_longitude))

# Checking for missing values
missing_values(haunted_places)
# Before removing the duplicates
nrow(haunted_places)
```

```
# Find exact duplicates
duplicate_rows <- haunted_places %>%
  group_by(across(everything())) %>%
  filter(n() > 1) %>%
  ungroup()

# Display the duplicate rows
print(duplicate_rows)

# Remove the Exact duplicate rows
haunted_places <- haunted_places %>%
  distinct()

# find the total number of rows in the dataset after removing the duplicates
nrow(haunted_places)


# Frequency table for city column
city_freq <- haunted_places %>%
  count(city, sort = TRUE)

# Create a proportion table for the location column
city_prop <- city_freq %>%
  mutate(proportion = n / 4362)

kable(city_prop[1:5,], caption = "Frequency and Proportional Table of City",
      col.names = c("City", "Counts", "Proportions"))


# Frequency table for state column
state_freq <- haunted_places %>%
  count(state, sort = TRUE)

# Create a proportion table for the location column
city_prop <- state_freq %>%
  mutate(proportion = n / 51)

kable(city_prop[1:5,], caption = "Freq and Prop Table of City",
      col.names = c("State", "Counts", "Proportions"))

# wordcloud for city column
city_cloud <- wordcloud2(city_freq, size = 0.5)
```

```r
city_cloud

# wordcloud for location column
location_cloud <- wordcloud2(location_freq, size = 0.5)
location_cloud

# wordcloud for state column
state_cloud <- wordcloud2(state_freq, size = 0.8)
state_cloud

# Converting the the wordcloud into image
# save it in html
saveWidget(city_cloud,"tmp_city.html",selfcontained = F)
saveWidget(state_cloud,"tmp_state.html",selfcontained = F)
saveWidget(location_cloud,"tmp_location.html",selfcontained = F)

# and in png or pdf
webshot("tmp_city.html","city_cloud.png", delay =5)
webshot("tmp_state.html","state_cloud.png", delay =5)
webshot("tmp_location.html","location_cloud.png", delay =5)
# Filter rows where 'location' contains "Cemetery"
cemetery_coordinates <- haunted_places %>%
  filter(grepl("cemetery", location, ignore.case = TRUE)) %>%
  select(location, latitude, longitude) %>%
  arrange(location)

school_coordinates <- haunted_places %>%
  filter(grepl("school", location, ignore.case = TRUE)) %>%
  select(location, latitude, longitude) %>%
  arrange(location)

university_coordinates <- haunted_places %>%
  filter(grepl("university", location, ignore.case = TRUE)) %>%
  select(location, latitude, longitude) %>%
  arrange(location)

# Print the result
cemetery_coordinates
school_coordinates
university_coordinates

# We find some intersting finding in the dataset
```

```r
# That is there are 748 Cementry citing but there are
# 1210 Haunted citing in School.
# Creepy
# Finding the location which have same latitude and longitude
# (without considering the NA values)

same_coordinates <- haunted_places %>%
  group_by(latitude, longitude) %>%
  filter(n() > 1) %>%
  ungroup()

# Remove NA values
same_coordinates <- same_coordinates %>%
  filter(!is.na(latitude) & !is.na(longitude))

same_coordinates

# Create a frequency table for the location column
same_coordinates_freq <- same_coordinates %>%
  count(location, sort = TRUE)

same_coordinates_freq
# Create a proportion table for the location column
same_coordinates_prop <- same_coordinates_freq %>%
  mutate(proportion = n / 870)

same_coordinates_prop


# We can see that some of the latitudes and longitudes are same for different
# location (but they are not, it is just the typo.)

# function to filter the duplicate data
filter_duplicate_locations <- function(df) {
  df %>%
    group_by(latitude, longitude) %>%
    filter(n_distinct(location) > 1) %>%
    arrange(latitude, longitude)         # Arrange by latitude and longitude
}

# Identify locations with the same latitude and longitude but different names
result <- filter_duplicate_locations(haunted_places)
```

```r
# Remove NA values
result <- result %>%
  filter(!is.na(latitude) & !is.na(longitude))

# Print the result
result

# Clean the location column
# Replace locations with the shortest name; if equal, use the first name
updated_location_names <- result %>%
  group_by(latitude, longitude) %>%
  mutate(location = location[which.min(nchar(location))]) %>%  # Shortest name
  ungroup()

# Print the updated data frame
updated_location_names
# Conforming it is working or not
updated_location_names <- filter_duplicate_locations(updated_location_names)

updated_location_names
nrow(haunted_places)
# Standardize location names only for non-NA coordinates
haunted_places <- haunted_places %>%
  group_by(latitude, longitude) %>%
  mutate(
    # Only standardize when coordinates are not NA
    standardized_location = if(!any(is.na(latitude)) &&
                              !any(is.na(longitude))) {
      names(which.max(table(location)))
    } else {
      location
    }
  ) %>%
  ungroup() %>%
  mutate(location = standardized_location) %>%
  select(-standardized_location)

# Verify the results
haunted_places %>%
  group_by(latitude, longitude) %>%
  filter(n_distinct(location) > 1,
         !is.na(latitude),
```

```r
        !is.na(longitude))
# Frequency table for location column without NA values
location_freq <- haunted_places %>%
  filter(!is.na(location)) %>%
  count(location, sort = TRUE)


kable(location_freq[1:5,],
      caption = "Frequency and Proportional Table",
      col.names = c("Location", "Counts"))
# Group by latitude, longitude, and location, then count occurrences
same_coordinates_freq <- haunted_places %>%
  group_by(latitude, longitude, location) %>%
  summarise(count = n(), .groups = "drop") %>%  # drop grouping
  arrange(desc(count)) %>%  # Sort by count in descending order
  filter(!is.na(latitude) & !is.na(longitude))  # Remove NA values

# View the updated frequency table
same_coordinates_freq
top_50_places <- same_coordinates_freq[1:50,]
# Create the leaflet map of top 50 places with multiple haunted sightings
# Show a CUSTOM circle at each position. Size defined in Pixel.
# Size does not change when you zoom

m=leaflet(data = top_50_places) %>%
   addTiles() %>%
   addCircleMarkers(
      ~longitude, ~latitude,
      radius=~count*1 ,
      color=~ifelse(top_50_places$count>10 , "red", "orange"),
      stroke = TRUE,
      fillOpacity = 0.1,
      popup = ~as.character(location)
   )
m
# Converting the the leaflet map into image

# save it in html
saveWidget(m,"tmp_top_50.html",selfcontained = F)


# and in png or pdf
```

```r
webshot("tmp_top_50.html","top_50_map.png", delay =5, vwidth = 3840,
  vheight = 2160)

# save the haunted places data as a csv file
write_csv(haunted_places, "haunted_places.csv")
# test hypothesis


# Extract location type from 'location' column (if location types are embedded in text)
# Example: Detect keywords like "Cemetery", "University", etc.
haunted_places_hypo <- haunted_places %>%
  mutate(location_type = case_when(
    grepl("cemetery", location, ignore.case = TRUE) ~ "Cemetery",
    grepl("university|college|school", location, ignore.case = TRUE) ~ "University",
    grepl("hospital", location, ignore.case = TRUE) ~ "Hospital"
  ))

# Create a contingency table: Counts of location types by state
contingency_table <- table(haunted_places_hypo$location_type, haunted_places_hypo$state)

# Perform the Chi-Square Test of Independence
chi_test <- chisq.test(contingency_table)

# Output the test results
print(chi_test)

# Visualize the contingency table (optional)
library(ggplot2)
contingency_df <- as.data.frame(contingency_table)
colnames(contingency_df) <- c("Location_Type", "State", "Count")

plot <- ggplot(contingency_df, aes(x = State, y = Count, fill = Location_Type)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Distribution of Location Types by State",
       x = "State", y = "Count", fill = "Location Type") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))

plot

ggsave("location_distribution_by_state.png", plot = plot, width = 10, height = 6, dpi = 300)
```

```r
# Calculate distance from city center
center_distance <- haunted_places %>%
  mutate(distance_from_center = sqrt((latitude - city_latitude)^2 +
                                     (longitude - city_longitude)^2))

# Aggregate data by city
city_data <- center_distance %>%
  group_by(city) %>%
  summarize(total_haunted = n(),
            avg_distance = mean(distance_from_center, na.rm = TRUE))

# Linear regression model
model <- lm(total_haunted ~ avg_distance, data = city_data)

# Summary of the model
summary(model)

# Visualization
ggplot(city_data, aes(x = avg_distance, y = total_haunted)) +
  geom_point(alpha = 0.7) +
  geom_smooth(method = "lm", color = "blue") +
  labs(title = "Regression: Total Haunted Locations vs Distance from City Center",
       x = "Distance from City Center",
       y = "Total Number of Haunted Locations")
```