SL project clusterng

Steven

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Step 1: Data Cleaning and Preparation

```
library(readr)
library(dplyr)
##
## 载入程辑包: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
# Load the dataset
data <- read_csv(file.choose()) # select the file interactively</pre>
## Warning: One or more parsing issues, call `problems()` on your data frame for details,
##
     dat <- vroom(...)</pre>
##
     problems(dat)
## Rows: 34857 Columns: 21
## — Column specification
## Delimiter: ","
## chr (8): Suburb, Address, Type, Method, SellerG, Date, CouncilArea, Regionname
## dbl (13): Rooms, Price, Distance, Postcode, Bedroom2, Bathroom, Car, Landsiz...
##
## i Use `spec()` to retrieve the full column specification for this data.
### i Specify the column types or set `show_col_types = FALSE` to quiet this message.
# Correcting the typos in column names
names(data)[names(data) == "Lattitude"] <- "Latitude"</pre>
names(data)[names(data) == "Longtitude"] <- "Longitude"</pre>
```

Step 2: clean data

```
# Remove rows with NA values in specified columns and drop unnecessary columns
data <- data %>%
  filter(!is.na(Latitude), !is.na(Longitude), !is.na(YearBuilt), !is.na(Price), !is.na(Buildi
ngArea)) %>%
  select(Latitude, Longitude, YearBuilt, Price, BuildingArea)

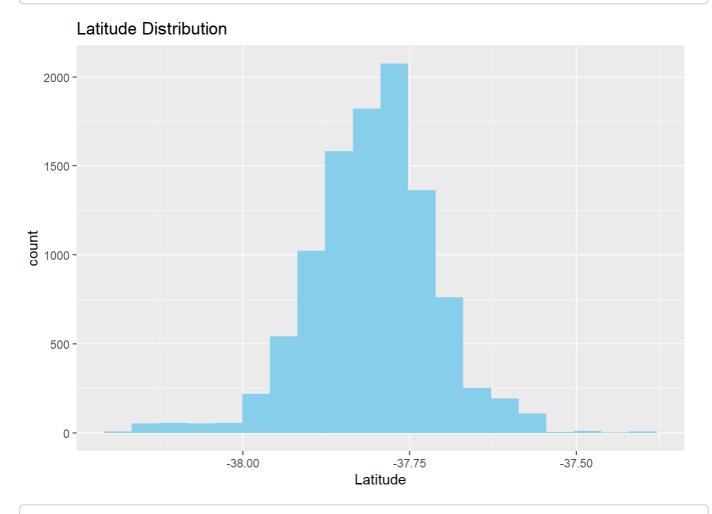
# Calculate the property age and price per building area
data$PropertyAge <- as.numeric(format(Sys.Date(), "%Y")) - data$YearBuilt
data$PricePerArea <- data$Price / data$BuildingArea

# Drop rows with NA or infinite values after calculations
data <- na.omit(data)
data <- data[!is.infinite(data$PricePerArea),]</pre>
```

Step 3: 3. Show Data Distributions:

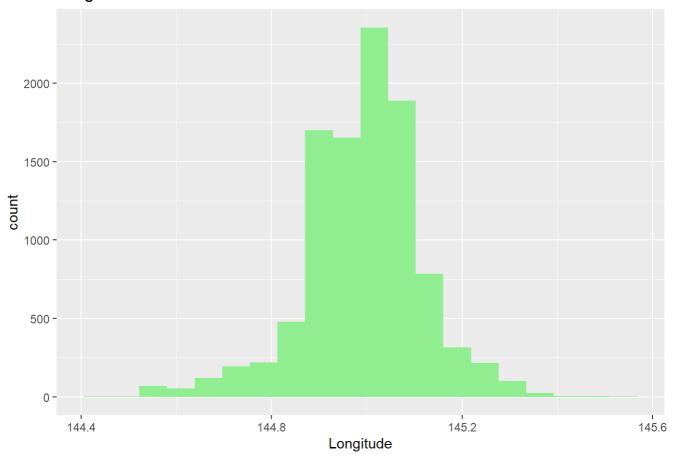
```
library(ggplot2)

# Plot distributions
ggplot(data, aes(x=Latitude)) + geom_histogram(bins=20, fill="skyblue") + ggtitle("Latitude D istribution")
```



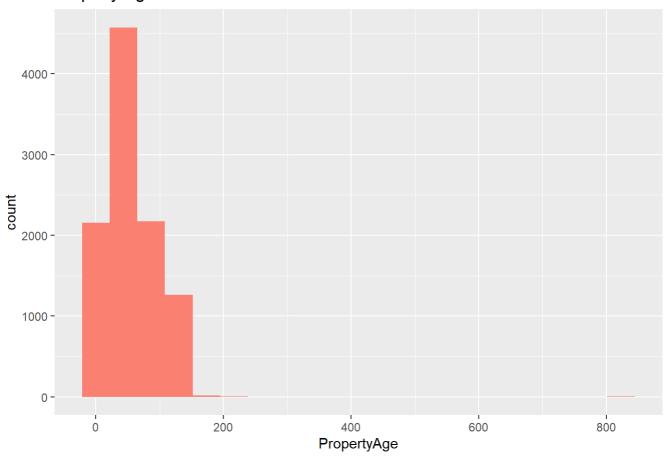
ggplot(data, aes(x=Longitude)) + geom_histogram(bins=20, fill="lightgreen") + ggtitle("Longit ude Distribution")

Longitude Distribution

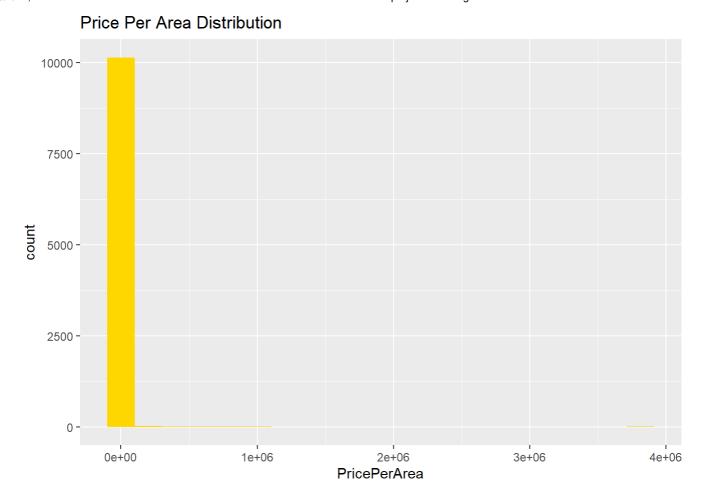


ggplot(data, aes(x=PropertyAge)) + geom_histogram(bins=20, fill="salmon") + ggtitle("Property
Age Distribution")

Property Age Distribution



ggplot(data, aes(x=PricePerArea)) + geom_histogram(bins=20, fill="gold") + ggtitle("Price Per Area Distribution")



Step 4: Implement Outlier Elimination Strategy

```
# Calculate IQR for each column and filter out outliers
for (col in c("PricePerArea")) {
   Q1 <- quantile(data[[col]], 0.25)
   Q3 <- quantile(data[[col]], 0.75)
   IQR <- Q3 - Q1
   data <- data[data[[col]] >= (Q1 - 1.5 * IQR) & data[[col]] <= (Q3 + 1.5 * IQR), ]
}
#for (col in c("Latitude", "Longitude", "PropertyAge", "PricePerArea")) {</pre>
```

Step 5: Further Steps (Clustering, Visualization, Comparison)

```
#install.packages("factoextra")
library(factoextra)
```

Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa

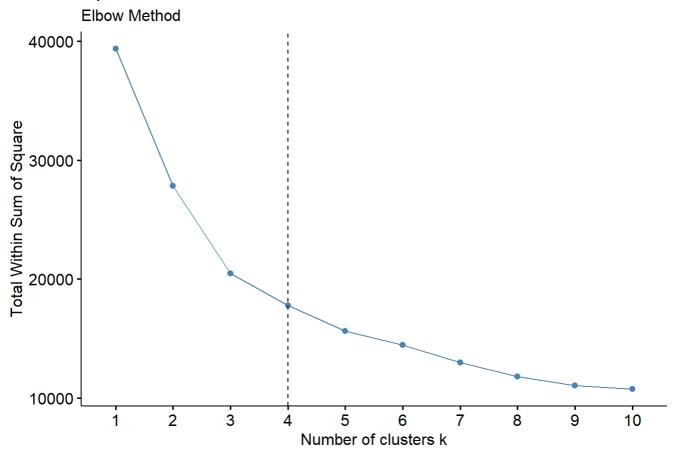
```
set.seed(123) # For reproducibility

# Scale the data
data_scaled <- scale(data[, c("Latitude", "Longitude", "PropertyAge", "PricePerArea")])

# Determine the optimal number of clusters
fviz_nbclust(data_scaled, kmeans, method = "wss") +
    geom_vline(xintercept = 4, linetype = 2) +
    labs(subtitle = "Elbow Method")</pre>
```

Warning: 10迭代仍没有聚合

Optimal number of clusters



```
# Perform k-means clustering
set.seed(123) # Ensure reproducibility
k <- 4 # Assuming 4 is the chosen number of clusters
km_result <- kmeans(data_scaled, centers = k, nstart = 25)</pre>
```

```
## Warning: Quick-TRANSfer stage steps exceeded maximum (= 492100)
```

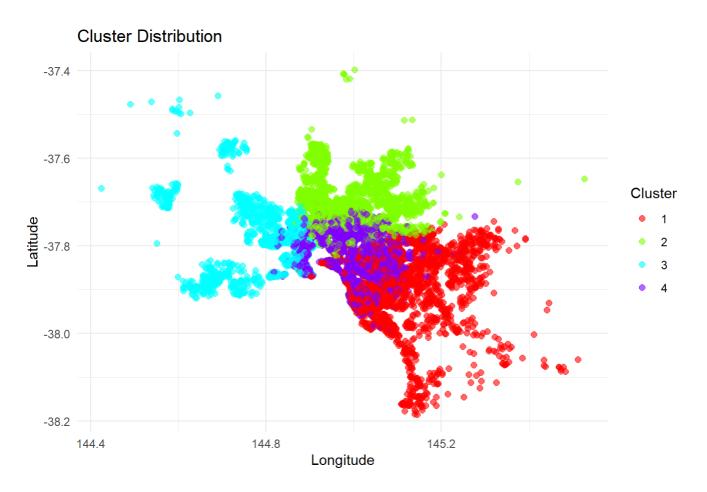
```
# Add cluster assignment to the data
data$Cluster <- as.factor(km_result$cluster)</pre>
```

Step 6: show result in geo map

```
library(ggplot2)

# Assuming 'data' is dataframe and it contains 'Latitude', 'Longitude', and 'Cluster' columns

ggplot(data, aes(x = Longitude, y = Latitude, color = Cluster)) +
    geom_point(alpha = 0.6, size = 2) +
    scale_color_manual(values = rainbow(length(unique(data$Cluster)))) +
    theme_minimal() +
    labs(title = "Cluster Distribution", x = "Longitude", y = "Latitude", color = "Cluster") +
    coord_fixed(ratio = 1) # This helps in keeping the aspect ratio consistent for geographical data
```



distance from center strategy

Step 7: Calculate the Central Point

```
central_latitude <- mean(data$Latitude, na.rm = TRUE)
central_longitude <- mean(data$Longitude, na.rm = TRUE)</pre>
```

Step 8: Calculate the Distance from the Center for

Each Point

```
# Define the deg2rad function
deg2rad <- function(deg) {</pre>
  return(deg * (pi / 180))
}
# Haversine formula to calculate distances
haversine_distance <- function(lat1, long1, lat2, long2) {</pre>
  R <- 6371 # Earth radius in kilometers
  delta_lat <- deg2rad(lat2 - lat1)</pre>
 delta_long <- deg2rad(long2 - long1)</pre>
  a <- sin(delta_lat / 2)^2 + cos(deg2rad(lat1)) * cos(deg2rad(lat2)) * sin(delta_long / 2)^2
  c \leftarrow 2 * atan2(sqrt(a), sqrt(1 - a))
  d <- R * c
  return(d) # Distance in kilometers
# Apply the distance calculation for each row in the dataframe
data$DistanceFromCenter <- mapply(haversine_distance,</pre>
                                    lat1 = data$Latitude,
                                    long1 = data$Longitude,
                                    lat2 = central_latitude,
                                    long2 = central_longitude)
```

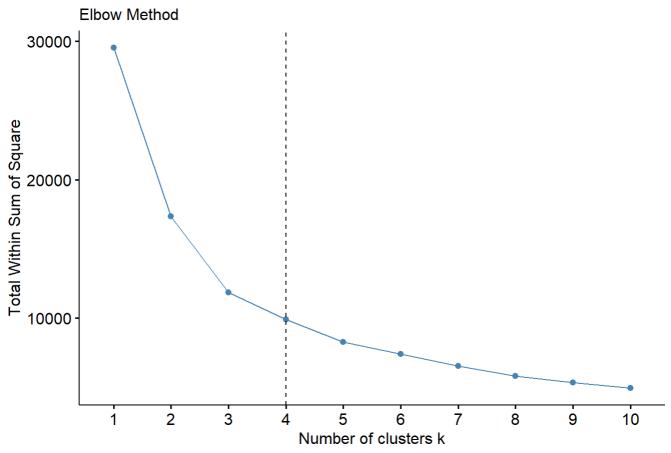
Step 9: Cluster Using the New Feature

```
#install.packages("factoextra")
library(factoextra)

# Normalize the data before clustering
data_normalized <- scale(data[, c("DistanceFromCenter", "PropertyAge", "PricePerArea")])

# Determine the optimal number of clusters using the elbow method
set.seed(123) # Ensure reproducibility
fviz_nbclust(data_normalized, kmeans, method = "wss") +
    geom_vline(xintercept = 4, linetype = 2) +
    labs(subtitle = "Elbow Method")</pre>
```

Optimal number of clusters



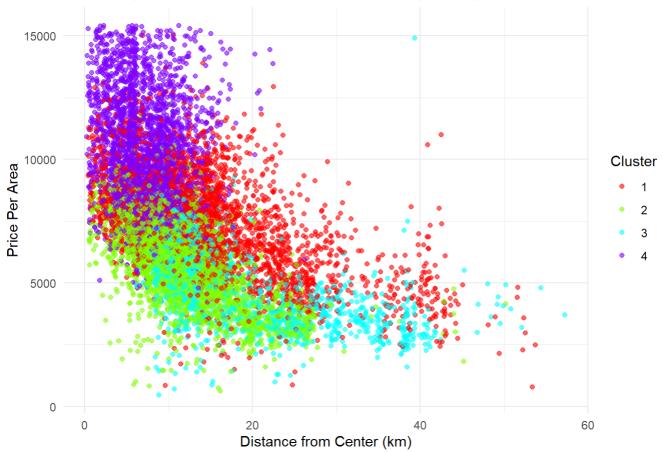
```
# After visual inspection of the elbow plot, choose the optimal number of clusters
# For example, if the elbow plot suggests that 4 is a good choice:
num_clusters_optimal <- 4 # Adjust this based on the elbow method's outcome

# Perform k-means clustering with the optimal number of clusters
set.seed(123) # Ensure reproducibility again for the actual clustering
km_result <- kmeans(data_normalized, centers = num_clusters_optimal, nstart = 25)

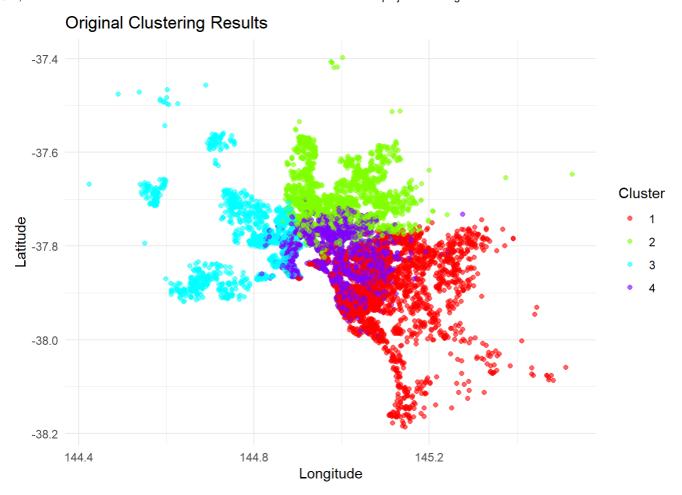
# Add cluster assignment to the data
data$Cluster_km <- as.factor(km_result$cluster)</pre>
```

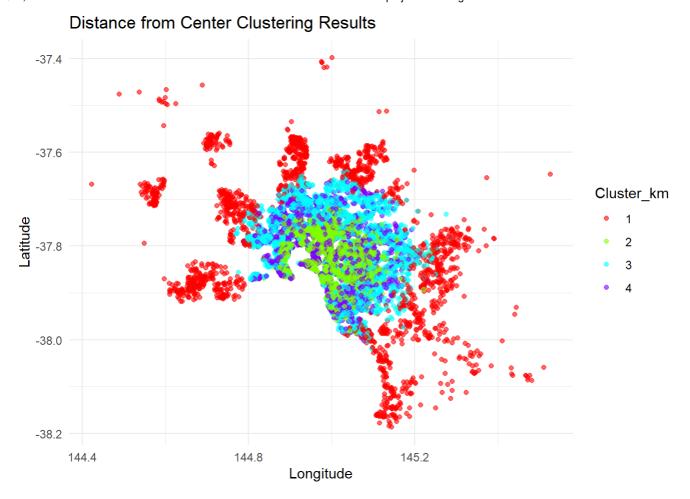
Step 10: Visualization and Analysis

Clustering based on Distance from Center, Property Age, and Price Per Area



Step 12: Visualizing Both Clustering Results





Step 13: Calculate Metrics for Both Clustering Approaches

```
# Assuming data is already prepared and normalized as needed
# Original spatial feature clustering
set.seed(123) # for reproducibility
kmeans_result_orig <- kmeans(data[, c("Longitude", "Latitude")], centers = 4, nstart = 25)</pre>
# Assuming you've decided on an appropriate number of centers (e.g., 4) after analysis such a
s the elbow method
# Clustering based on distance from the center
set.seed(123)
kmeans_result_km <- kmeans(data[, "DistanceFromCenter", drop = FALSE], centers = 4, nstart =</pre>
25)
# Update the data frame with cluster labels
data$Cluster <- kmeans_result_orig$cluster</pre>
data$Cluster_km <- kmeans_result_km$cluster</pre>
# Convert cluster labels to numeric if they're not already
data$Cluster_numeric <- as.numeric(data$Cluster)</pre>
data$Cluster_km_numeric <- as.numeric(data$Cluster_km)</pre>
```

```
library(cluster) # for silhouette calculations
# Calculate silhouette scores
silhouette_orig <- silhouette(data$Cluster_numeric, dist(data[, c("Longitude", "Latitude")]))</pre>
avg_silhouette_orig <- mean(silhouette_orig[, "sil_width"])</pre>
# For the distance-based clustering, assuming appropriate preparation
silhouette_km <- silhouette(data$Cluster_km_numeric, dist(data[, "DistanceFromCenter", drop =</pre>
avg_silhouette_km <- mean(silhouette_km[, "sil_width"])</pre>
# Print the metrics for comparison
cat("Average Silhouette Score (Original):", avg_silhouette_orig, "\n")
## Average Silhouette Score (Original): 0.3427781
cat("Average Silhouette Score (Distance-based):", avg_silhouette_km, "\n")
## Average Silhouette Score (Distance-based): 0.5552604
# WSS values are already part of the kmeans result object
cat("WSS (Original):", kmeans_result_orig$tot.withinss, "\n")
## WSS (Original): 83.12818
cat("WSS (Distance-based):", kmeans_result_km$tot.withinss, "\n")
## WSS (Distance-based): 67887.45
```

Step 14: additional visuals

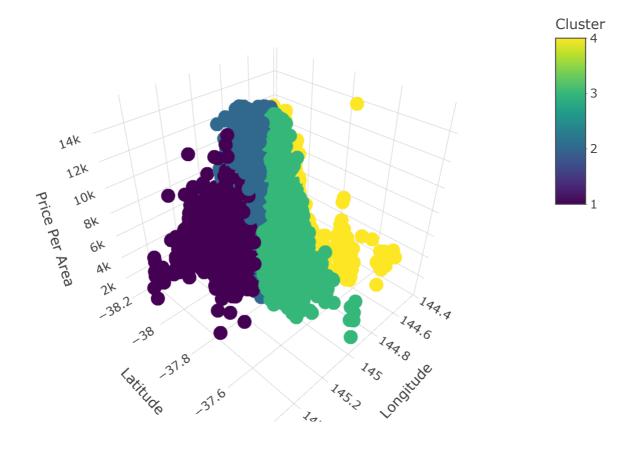
```
# Check if 'plotly' package is installed; install it if not
if (!require(plotly)) {
  install.packages("plotly")
  library(plotly)
}
## 载入需要的程辑包:plotly
##
## 载入程辑包: 'plotly'
  The following object is masked from 'package:ggplot2':
##
```

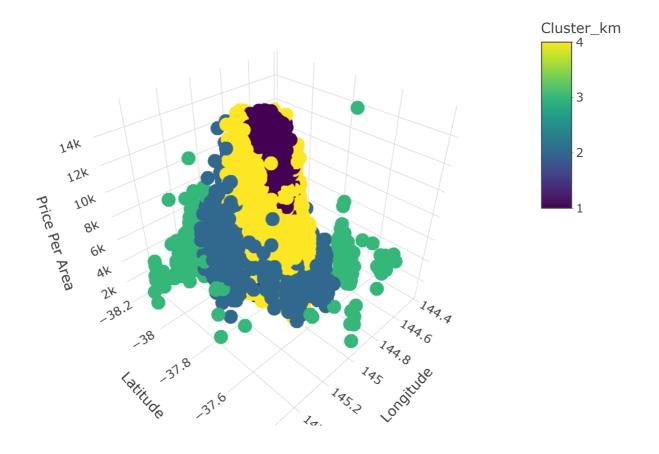
##

last_plot

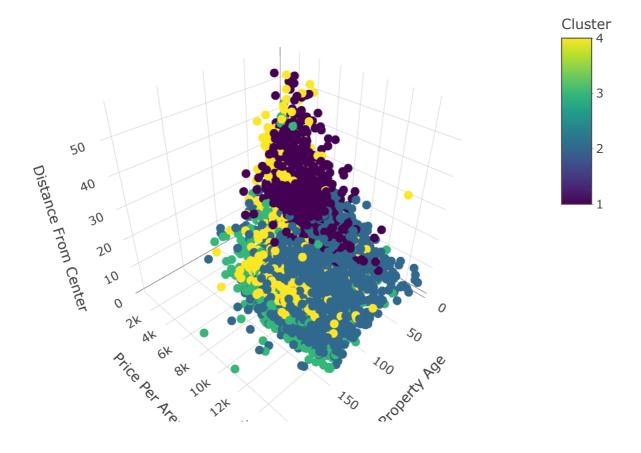
```
## The following object is masked from 'package:stats':
##
## filter
```

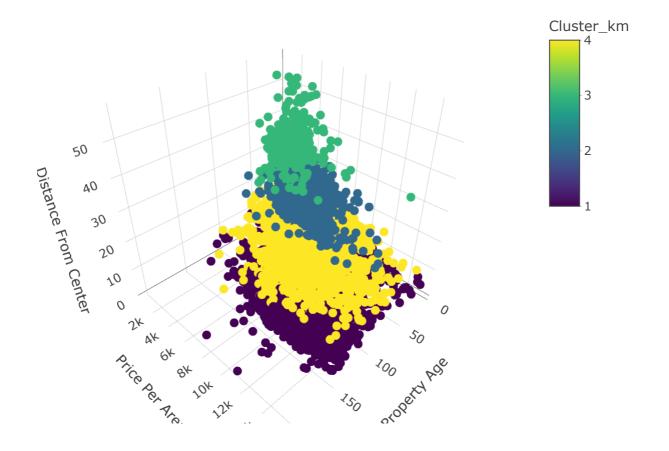
```
## The following object is masked from 'package:graphics':
##
## layout
```





```
# Remove the row with the Largest Property Age
data <- data[data$PropertyAge < max(data$PropertyAge), ]</pre>
```





Step 15: Final comment

Step 16: Business implication