31_question_9

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```r
#QUestion number 9

library(stats)
city_distances <- matrix(c(
  0, 587, 1212, 701, 1936, 604, 748, 2139, 2182, 543,
  587, 0, 920, 940, 1745, 1188, 713, 1858, 1737, 597,
  1212, 920, 0, 879, 831, 1726, 1611, 1949, 2204, 1494,
  701, 940, 879, 0, 1374, 968, 1420, 1645, 1891, 1220,
  1936, 1745, 831, 1374, 0, 2339, 2451, 347, 2734, 2300,
  604, 1188, 1726, 968, 2339, 0, 1092, 2594, 2408, 923,
  748, 713, 1611, 1420, 2451, 1092, 0, 2571, 678, 205,
  2139, 1858, 1949, 1645, 347, 2594, 2571, 0, 678, 2442,
  2182, 1737, 2204, 1891, 2734, 2408, 678, 678, 0, 2329,
  543, 597, 1494, 1220, 2300, 923, 205, 2442, 2329, 0
), nrow = 10, byrow = TRUE)

# Assigning names to row and columns
city_names <- c("Atlanta", "Chicago", "Denver", "Houston", "Los Angeles", "Miami",
                "New York", "San Francisco", "Seattle", "Washington D.C.")
rownames(city_distances) <- city_names
colnames(city_distances) <- city_names

## A)
## Get dissimilarity distance as city.dissimilarity object
city.dissimilarity <- as.dist(city_distances)

## B)
## Fit the classical MDS model using city.dissimilarity object
mds.model <- cmdscale(city.dissimilarity, eig = TRUE, k = 2)  # Dimension 2


## C)
# Summary of model
mds.points <- mds.model$points
print(mds.points)
```

```
##                      [,1]        [,2]
## Atlanta         -616.46326  -277.03319
## Chicago         -288.61063   -22.16151
## Denver           202.61148  -672.61019
## Houston           14.25242  -335.54496
## Los Angeles     1225.78174 -1033.78934
```

```
## Miami             -968.45797  -264.31832
## New York          -845.50822   757.66327
## San Francisco     1645.58380   339.92746
## Seattle            563.12009  1646.43854
## Washington D.C.   -932.30945  -138.57175
```

```
## Interpretation
#

## D)
## Bi-plot of the model
plot(mds.points, type = "n")
text(mds.points, labels = city_names, cex = 0.7)
```
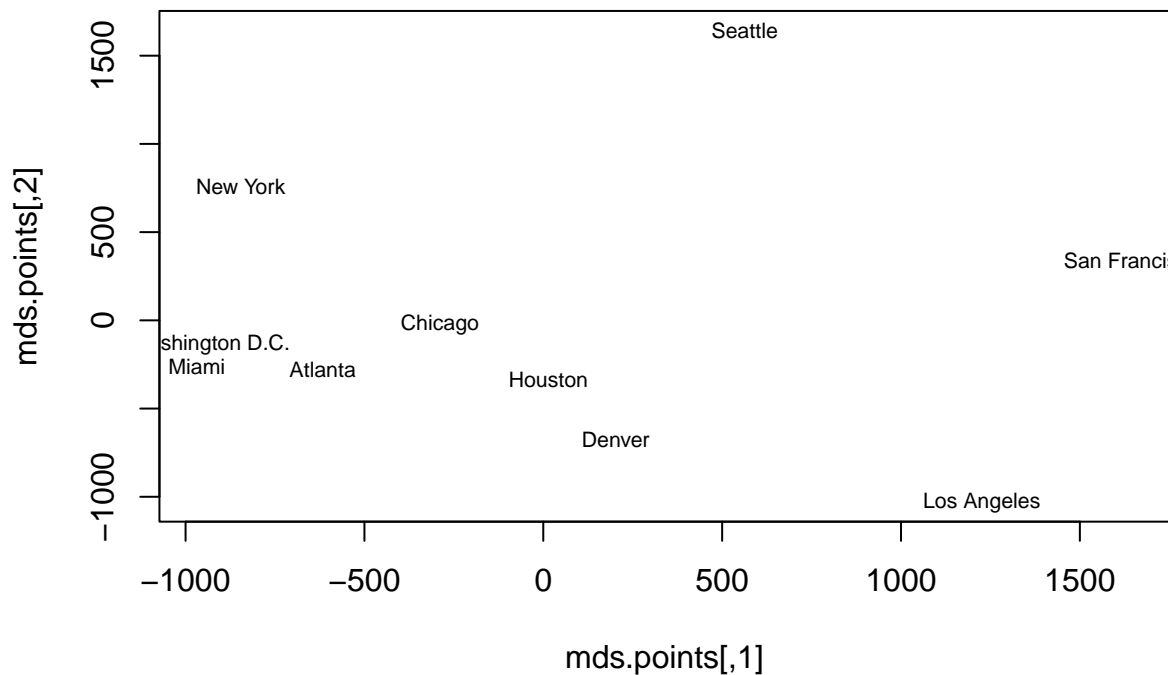

*The multidimensional scaling (MDS) analysis performed on the city distances data helps visualize the spatial relationships between the ten cities in a two-dimensional plot. The distances between cities in the original data are translated into relative positions in the plot, with cities closer together indicating shorter distances and cities farther apart representing greater distances. This bi-plot allows for a quick visual interpretation of the similarities and differences in distances between the cities.