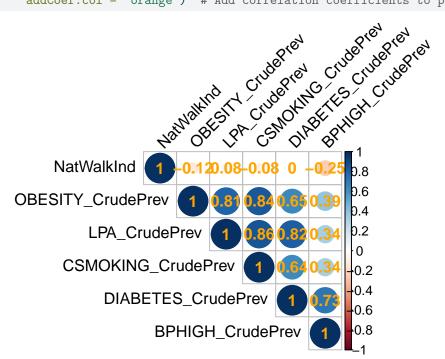
## **Correlation Matrix**

```
# Load necessary libraries
library(dplyr)
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
library(corrplot) # correlation matrix visualization
corrplot 0.92 loaded
library(ggcorrplot) # ggplot2 style visualization of correlation matrix
Loading required package: ggplot2
# Read datasets
data <- read.csv("../../Data/data.csv")</pre>
data2 <- read.csv("../../Data/500cities.csv")</pre>
# Prepare 'data' by padding and merging columns to create a unique identifier
data$STATEFP <- sprintf("%02d", as.numeric(data$STATEFP))</pre>
data$COUNTYFP <- sprintf("%03d", as.numeric(data$COUNTYFP))</pre>
data$TRACTCE <- sprintf("%06d", as.numeric(data$TRACTCE))</pre>
data$TractFIPS <- as.numeric(paste0(data$STATEFP, data$COUNTYFP, data$TRACTCE))</pre>
# Summarize 'data' to get mean of 'NatWalkInd' by 'TractFIPS'
averaged_data <- data %>%
     group_by(TractFIPS) %>%
     summarise(NatWalkInd = mean(NatWalkInd, na.rm = TRUE)) %>%
     ungroup()
# Select relevant columns from 'data2'
data2_relevant <- data2 %>%
     select(TractFIPS, StateAbbr, DIABETES_CrudePrev, BPHIGH_CrudePrev, OBESITY_CrudePrev, LPA_CrudePrev, CrudePrev, CrudePrev
# Merge 'averaged_data' with 'data2_relevant' on 'TractFIPS'
merged_data <- merge(averaged_data, data2_relevant, by = "TractFIPS", all.x = TRUE, all.y = TRUE)
# Filter for specific condition
merged_data <- merged_data %>% filter(StateAbbr == "CA")
```

```
# Calculate correlation matrix
cor_matrix <- cor(merged_data %>% select(-TractFIPS, -StateAbbr), use = "complete.obs") # Handling miss
# Output variable names (column names) used for correlation matrix
cat("Variables used for correlation matrix:\n")
```

Variables used for correlation matrix:



The correlation matrix above indicates strong positive correlations between obesity, physical activity, smoking, diabetes, and high blood pressure prevalence, with less correlation to the national walking index. Given these relationships, my team decided that a spatial autoregressive model (SAR) or a geographically weighted regression (GWR) could be appropriate to account for spatial dependencies and variations in the data.