

DSB#12 _R Markdown_Mini Project

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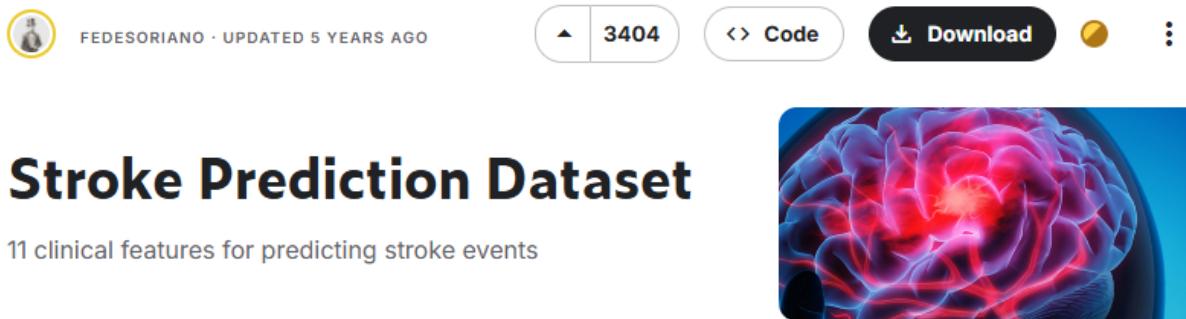
DSB#12 _R Markdown_Mini Project

Hi everyone, welcome to my mini project for R Markdown!

In this project, I will give you all a tour of the Stroke Prediction Dataset and share some meaningful insights from my analysis.

Before we begin, please visit Kaggle and download the dataset using the link provided below. Then download the pdf file.

[kaggle.comhttps://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset](https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset)



This dataset is used to predict the likelihood of the patient to get stroke base on the given information below:

Attribute Information

- 1) id: unique identifier
 - 2) gender: "Male", "Female" or "Other"
 - 3) age: age of the patient
 - 4) hypertension: 0 if the patient doesn't have hypertension, 1 if the patient has hypertension
 - 5) heart_disease: 0 if the patient doesn't have any heart diseases, 1 if the patient has a heart disease
 - 6) ever_married: "No" or "Yes"
 - 7) work_type: "children", "Govt_jov", "Never_worked", "Private" or "Self-employed"
 - 8) Residence_type: "Rural" or "Urban"
 - 9) avg_glucose_level: average glucose level in blood
 - 10) bmi: body mass index
 - 11) smoking_status: "formerly smoked", "never smoked", "smokes" or "Unknown"*
 - 12) stroke: 1 if the patient had a stroke or 0 if not
- *Note: "Unknown" in smoking_status means that the information is unavailable for this patient

Install and load libraries.

Before we begin with the analysis, let's explore the data structure and import the necessary libraries.

1. Install and load libraries.

```
## install packages and load library
## for packages install one time
#install.packages("tidyverse") ## metapackage for r
#install.packages("janitor") ## data cleaning
#install.packages("ggplot2") ## data viz
#install.packages("dplyr") ## data transformation

library(tidyverse)

## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr     1.1.4    v readr      2.1.5
## vforcats   1.0.1    v stringr    1.5.2
## v ggplot2   4.0.0    v tibble     3.3.0
## v lubridate 1.9.4    v tidyverse  1.3.1
## v purrr     1.1.0
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()   masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```

library(ggplot2)
library(dplyr)
library(janitor)

##
## Attaching package: 'janitor'
##
## The following objects are masked from 'package:stats':
##
##     chisq.test, fisher.test

```

Data Transformation

2. Import data and perform EDA

For this time, I use Google Colab to run this analysis. In order to read the CSV file, you need to upload it to Google Colab first. Then, I read csv file using `read_csv()` and clean column name with `clean_name()` from library janitor. As you can see, the dataset contains 5,110 rows and 12 columns. We will continue exploring it further.

```

## read csv file from Stroke Prediction Dataset
df <- read_csv("healthcare-dataset-stroke-data.csv") %>%
  clean_names()

## Rows: 5110 Columns: 12
## -- Column specification -----
## Delimiter: ","
## chr (6): gender, ever_married, work_type, Residence_type, bmi, smoking_status
## dbl (6): id, age, hypertension, heart_disease, avg_glucose_level, stroke
##
## 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.

```

First, I will check the overview of the dataframe by using the `glimpse()` function, which provides a quick and concise summary of a data frame or tibble.

```

# check overview of data
glimpse(df)

## Rows: 5,110
## Columns: 12
## $ id              <dbl> 9046, 51676, 31112, 60182, 1665, 56669, 53882, 10434~
## $ gender          <chr> "Male", "Female", "Male", "Female", "Female", "Male"~
## $ age              <dbl> 67, 61, 80, 49, 79, 81, 74, 69, 59, 78, 81, 61, 54, ~
## $ hypertension      <dbl> 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1~
## $ heart_disease    <dbl> 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1~
## $ ever_married     <chr> "Yes", "Yes", "Yes", "Yes", "Yes", "Yes", "No~
## $ work_type         <chr> "Private", "Self-employed", "Private", "Private", "S~
## $ residence_type    <chr> "Urban", "Rural", "Rural", "Urban", "Rural", "Urban"~
## $ avg_glucose_level <dbl> 228.69, 202.21, 105.92, 171.23, 174.12, 186.21, 70.0~
## $ bmi               <chr> "36.6", "N/A", "32.5", "34.4", "24", "29", "27.4", "~
## $ smoking_status    <chr> "formerly smoked", "never smoked", "never smoked", "~
## $ stroke             <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~

```

Next, I will convert the dataframe into a tibble using `tibble(df)` to improve readability and data presentation.

```

## change df to tibble
tibble(df) # make tabel easy to read

## # A tibble: 5,110 x 12
##   id gender age hypertension heart_disease ever_married work_type
##   <dbl> <chr> <dbl>          <dbl>          <dbl> <chr>      <chr>
## 1 9046 Male    67            0             1 Yes       Private
## 2 51676 Female 61            0             0 Yes       Self-employed
## 3 31112 Male    80            0             1 Yes       Private
## 4 60182 Female 49            0             0 Yes       Private
## 5 1665 Female   79            1             0 Yes       Self-employed
## 6 56669 Male    81            0             0 Yes       Private
## 7 53882 Male    74            1             1 Yes       Private
## 8 10434 Female 69            0             0 No        Private
## 9 27419 Female 59            0             0 Yes       Private
## 10 60491 Female 78            0             0 Yes      Private
## # i 5,100 more rows
## # i 5 more variables: residence_type <chr>, avg_glucose_level <dbl>, bmi <chr>,
## #   smoking_status <chr>, stroke <dbl>

```

Next, I will examine the `head()`, `tail()`, and missing values to ensure that the dataset is clean and ready for analysis.

```

## head and tail
head(df, 5)

## # A tibble: 5 x 12
##   id gender age hypertension heart_disease ever_married work_type
##   <dbl> <chr> <dbl>          <dbl>          <dbl> <chr>      <chr>
## 1 9046 Male    67            0             1 Yes       Private
## 2 51676 Female 61            0             0 Yes       Self-employed
## 3 31112 Male    80            0             1 Yes       Private
## 4 60182 Female 49            0             0 Yes       Private
## 5 1665 Female   79            1             0 Yes       Self-employed
## # i 5 more variables: residence_type <chr>, avg_glucose_level <dbl>, bmi <chr>,
## #   smoking_status <chr>, stroke <dbl>

tail(df, 5)

## # A tibble: 5 x 12
##   id gender age hypertension heart_disease ever_married work_type
##   <dbl> <chr> <dbl>          <dbl>          <dbl> <chr>      <chr>
## 1 18234 Female 80            1             0 Yes       Private
## 2 44873 Female 81            0             0 Yes       Self-employed
## 3 19723 Female 35            0             0 Yes       Self-employed
## 4 37544 Male    51            0             0 Yes       Private
## 5 44679 Female 44            0             0 Yes      Govt_job
## # i 5 more variables: residence_type <chr>, avg_glucose_level <dbl>, bmi <chr>,
## #   smoking_status <chr>, stroke <dbl>

```

Identify missing value

I used `sum()` and `is.na(df)` to calculate the total number of missing values in the dataframe. As you can see from the result, it shows zero missing values. However, based on the previous `head()` and `tail()` outputs, I noticed that there are some “N/A” entries in the table. Let’s investigate this further.

```

## Identify missing value
sum(is.na(df))

## [1] 0

## Identify "N/A"
df %>%
  summarise(across(everything(), ~ sum(. == "N/A", na.rm = TRUE))) %>%
  ## pivot table for readability
  pivot_longer(everything(),
               names_to = "column",
               values_to = "na_count") %>%
  arrange(desc(na_count))

## # A tibble: 12 x 2
##   column      na_count
##   <chr>       <int>
## 1 bmi           201
## 2 id             0
## 3 gender         0
## 4 age             0
## 5 hypertension     0
## 6 heart_disease    0
## 7 ever_married      0
## 8 work_type        0
## 9 residence_type      0
## 10 avg_glucose_level 0
## 11 smoking_status      0
## 12 stroke          0

```

Finding Insights

Moving on to the next section, I will dive deeper into the dataset to look for meaningful insights and identify factors that may contribute to a person having a stroke. These factors include age, average glucose level, BMI, hypertension, heart disease, smoking status, and others.

1. How stroke rate differs across smoking categories?

```

## How stroke rate differs across smoking categories?
df %>%
  ## mutate column, convert chr to factor and set NA with "Unknown"
  mutate(smoking_status = fct_explicit_na(as.factor(smoking_status), na_level = "Unknown")) %>%
  group_by(smoking_status) %>%

  ## summarise stroke_rate and ignore missing value
  summarise(stroke_rate = mean(stroke, na.rm=TRUE)) %>%

  ## plot graph
  ggplot(aes

  ## reorders the categories by stroke rate
  (fct_reorder (smoking_status, stroke_rate), stroke_rate)) +
  geom_col(fill = "salmon") +
  coord_flip() + ## rotate bar chart

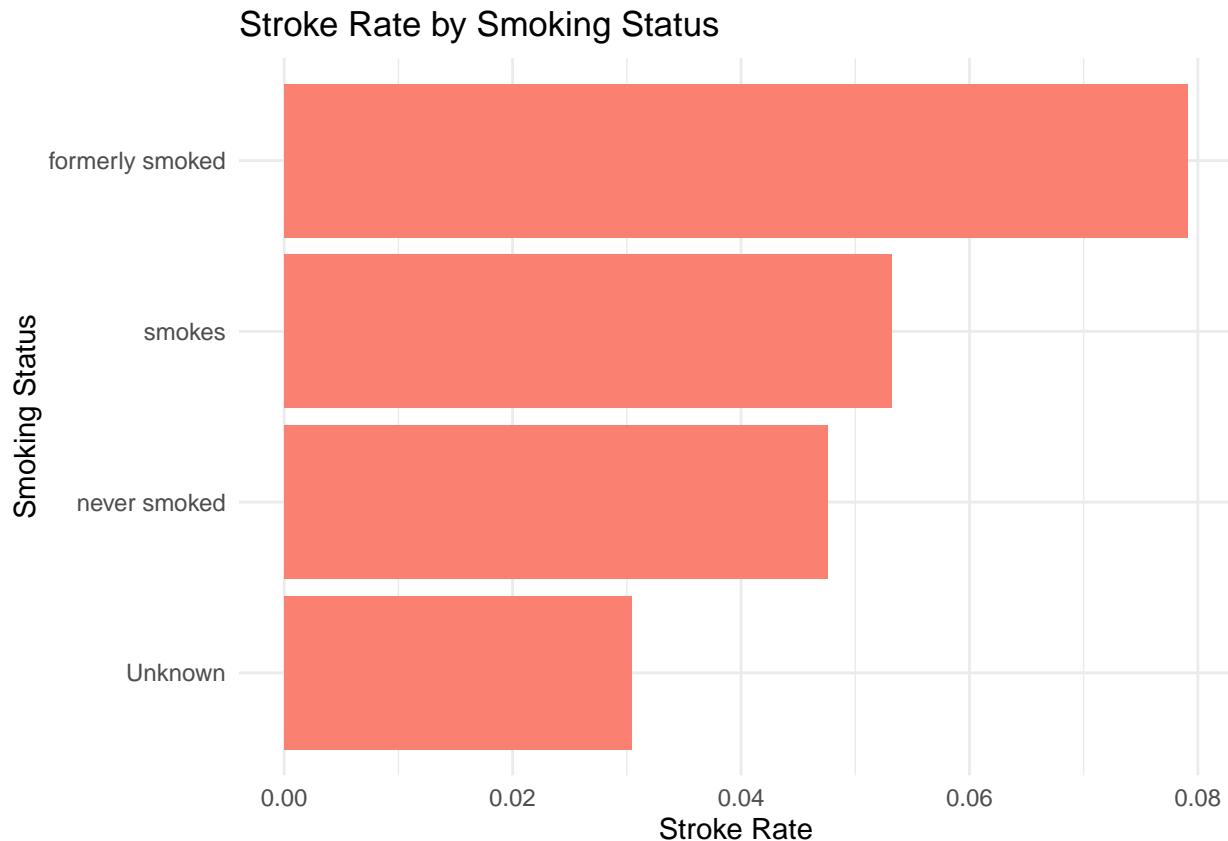
```

```

## set chart detail
labs(title="Stroke Rate by Smoking Status", x="Smoking Status", y="Stroke Rate")+
theme_minimal()

## Warning: There was 1 warning in `mutate()` .
## i In argument: `smoking_status = fct_explicit_na(as.factor(smoking_status),
##     na_level = "Unknown")` .
## Caused by warning:
## ! `fct_explicit_na()` was deprecated in forcats 1.0.0.
## i Please use `fct_na_value_to_level()` instead.

```



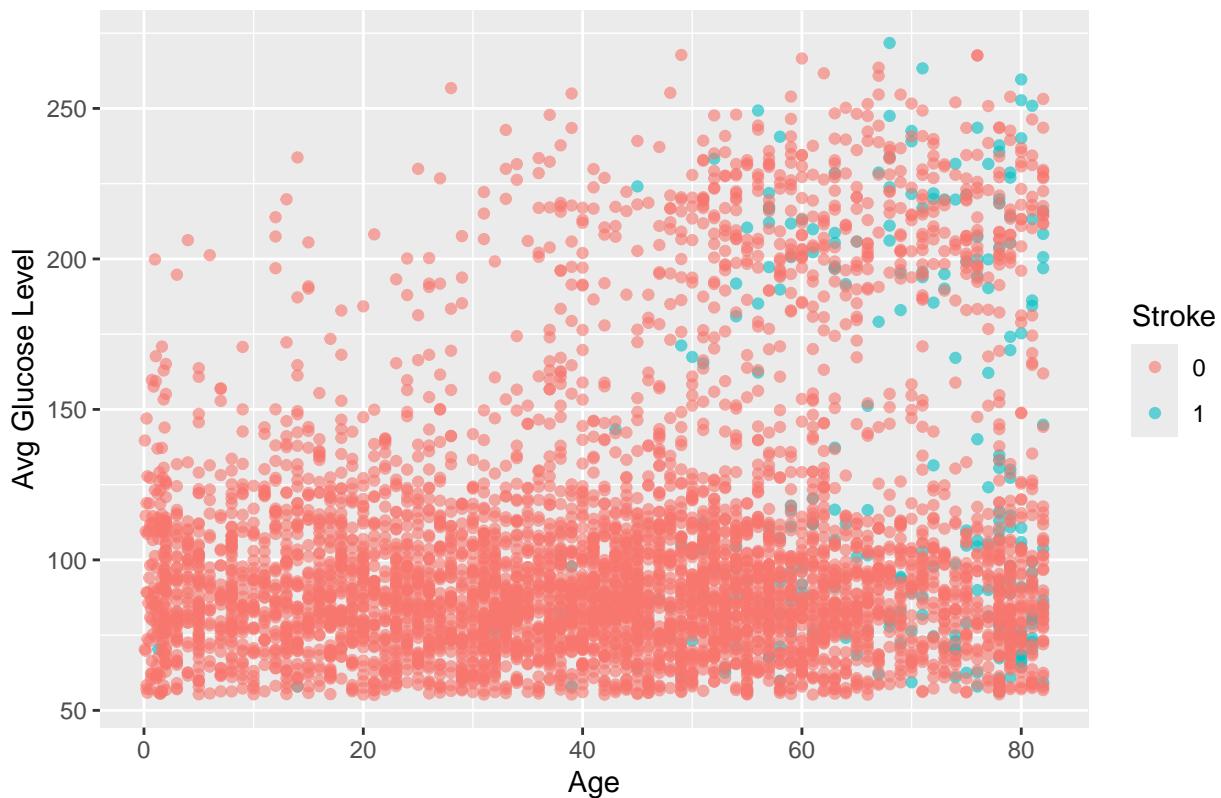
2. Older people with higher average glucose levels have a higher risk of having a stroke.

```

ggplot(df, aes(age,
    avg_glucose_level,
    ## set color for stroke and non-stroke
    color=factor(stroke))) +
geom_point(alpha = .6) +
labs(title="Avg Glucose vs Age", x="Age", y="Avg Glucose Level", color="Stroke")

```

Avg Glucose vs Age



3. Individuals with higher BMI levels are at an increased risk of experiencing a stroke.

```
## Individuals with higher BMI levels are at an increased risk of experiencing a stroke.

## setup & cleaning
# convert stroke to numeric and keep BMI as numeric
df <- df %>%
  mutate(
    stroke_num = as.numeric(as.character(stroke)), # if stroke was a factor
    bmi = as.numeric(bmi)
  )

## Warning: There was 1 warning in `mutate()` .
## i In argument: `bmi = as.numeric(bmi)` .
## Caused by warning:
## ! NAs introduced by coercion
# drop rows with missing BMI
df_bmi <- df %>%
  filter(!is.na(bmi), !is.na(stroke_num))

## segment individual bmi into band
df_bmi <- df_bmi %>%
  mutate(bmi_band = cut( ## divide into interval and convert to vector
    bmi,
    breaks = c(-Inf, 18.5, 25, 30, 35, Inf), ## +- infinity
    labels = c("Underweight", "Normal", "Overweight", "Obese I", "Obese II+"),
    right = FALSE
```

```

))

# Stroke rate by band
rate_tbl <- df_bmi%>%
  group_by(bmi_band) %>%
  summarise(
    n = n(),
    strokes = sum(stroke_num),
    stroke_rate = strokes / n
  ) %>%
  arrange(bmi_band)

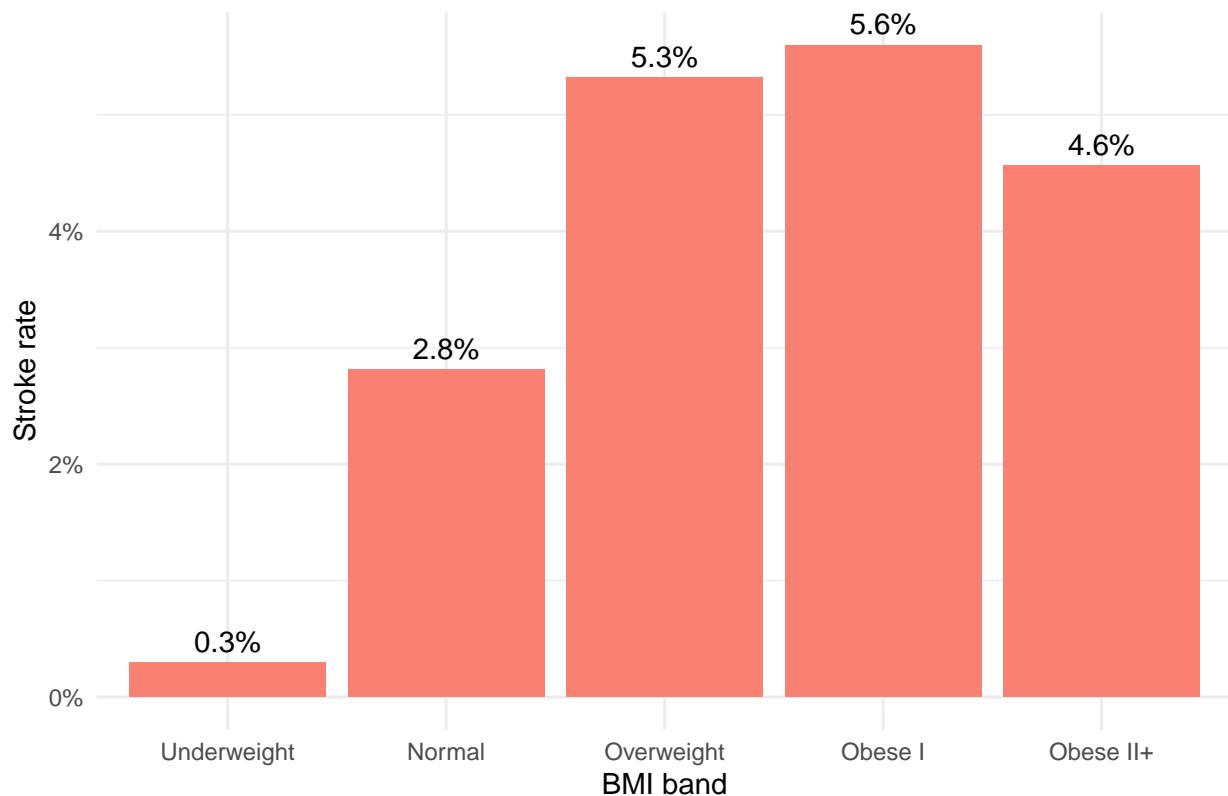
print (rate_tbl)

## # A tibble: 5 x 4
##   bmi_band      n strokes stroke_rate
##   <fct>     <int>   <dbl>      <dbl>
## 1 Underweight    337      1    0.00297
## 2 Normal        1243     35    0.0282 
## 3 Overweight     1409     75    0.0532 
## 4 Obese I       1000     56    0.056  
## 5 Obese II+      920     42    0.0457

# Bar chart of stroke rates
ggplot(rate_tbl, aes(x = bmi_band, y = stroke_rate)) +
  geom_col(fill = "salmon") +
  geom_text(aes(label = scales::percent(stroke_rate, accuracy = 0.1)),
            vjust = -0.5, size = 4) +
  scale_y_continuous(labels = scales::percent_format()) +
  labs(title = "Stroke rate by BMI band", x = "BMI band", y = "Stroke rate") +
  theme_minimal()

```

Stroke rate by BMI band



R Markdown

Finally, I will wrap up my project and create a report using R Markdown in Posit Cloud.

*** This is the end of the report***