# Data Cleaning

### ANLY-511-04 Group 3

### 12/06/2022

```
# load libraries for this assignment
library(tidyverse)
library(ggplot2)
library(readxl)
library(knitr)
library(kableExtra)
```

## Functions for Use

```
calculate_proportions <- function(input_df, threshold) {

  # create data frame for printing proportions of of NA values
  df <- data.frame(colnames(input_df), round(colMeans(is.na(input_df)), 5), row.names = NULL)
  colnames(df) <- c('Column Name', 'Proportion of Values NA')
  df <- df[order(df$`Proportion of Values NA`, decreasing = TRUE),]
  df_table <- df[df$`Proportion of Values NA` > threshold,]

  return (df_table)
}
```

```
print_table <- function(input_table) {
  knitr::kable(df_table, row.names = FALSE) %>% kable_styling(bootstrap_options = "striped", full_width = F, posi
tion = "center")
}
```

```
print_shape <- function(input_df) {
  print(paste('Our dataset shape is now: (', nrow(input_df), ', ', ncol(input_df), ')', sep = ''))
}
```

## Read in the Data

Let's first read in the data. We have five datasets to read in, all by the naming convention of `data/cardataXX.xlsx`, where `XX` $\in$ `{18, 19, 20, 21, 22}`. We can also observe the *shape* of each dataset, indicated with the following syntax: `(number of rows, number of columns)`.

```
# load in the data
cardata2018 <- read_excel('data/cardata2018.xlsx')
cardata2019 <- read_excel('data/cardata2019.xlsx')
cardata2020 <- read_excel('data/cardata2020.xlsx')
cardata2021 <- read_excel('data/cardata2021.xlsx')
cardata2022 <- read_excel('data/cardata2022.xlsx')
```

| Dataset Name | Shape |
|---|---|
| data/cardata2018.xlsx | (4727, 67) |
| data/cardata2019.xlsx | (4719, 67) |
| data/cardata2020.xlsx | (4450, 67) |
| data/cardata2021.xlsx | (4265, 67) |
| data/cardata2022.xlsx | (4455, 67) |

The five datasets come from the same source, but we want to ensure that they are compatible with one-another. The best way to check this is to ensure that the columns are the same across all datasets. If they are, we can easily append the five datasets together, by row, in order to create one, larger dataset.

```
# extract column names for each dataset
colnames2018 <- colnames(cardata2018)
colnames2019 <- colnames(cardata2019)
colnames2020 <- colnames(cardata2020)
colnames2021 <- colnames(cardata2021)
colnames2022 <- colnames(cardata2022)

# ensure that the column names are all the same across all datasets
if ( mean(colnames2018 == colnames2019) == 1 &
     mean(colnames2018 == colnames2020) == 1 &
     mean(colnames2018 == colnames2021) == 1 &
     mean(colnames2018 == colnames2022) == 1 ) {
  print('The column names are the same and in the same order across all five datasets.')
} else {
  print('The column names are NOT the same and in the same order across all five datasets.')
}
```

```
## [1] "The column names are the same and in the same order across all five datasets."
```

Let's append these datasets together since we know now that they have the same structure and column names.

```
# bind datasets together by row
cardata <- rbind(cardata2018, cardata2019, cardata2020, cardata2021, cardata2022)
print_shape(cardata)
```

```
## [1] "Our dataset shape is now: (22616, 67)"
```

There are also some columns that we are not concerned with for the purpose of our analysis, so we will drop those before proceeding with the cleaning phase. These columns are:

- Test Vehicle ID
- Test Veh Configuration #
- Actual Tested Testgroup
- Engine Code
- Transmission Overdrive Code
- Transmission Overdrive Desc
- Shift Indicator Light Use Cd
- Shift Indicator Light Use Desc
- Test Number
- Test Originator
- Analytically Derived FE?
- ADFE Test Number
- Test Procedure Cd
- Test Procedure Description
- Test Fuel Type Cd
- Test Category
- FE_UNIT
- FE Bag 1
- FE Bag 2
- FE Bag 3
- FE Bag 4

```
# define columns to remove
remove <- c("Test Vehicle ID", "Test Veh Configuration #", "Actual Tested Testgroup",
            "Engine Code", "Transmission Overdrive Code", "Transmission Overdrive Desc",
            "Shift Indicator Light Use Cd", "Shift Indicator Light Use Desc", "Test Number",
            "Test Originator", "Analytically Derived FE?", "ADFE Test Number",
            "Test Procedure Cd", "Test Procedure Description", "Test Fuel Type Cd",
            "Test Category", "FE_UNIT", "FE Bag 1",
            "FE Bag 2", "FE Bag 3", "FE Bag 4")

# remove columns and report new shape
cardata <- cardata[, !( colnames(cardata) %in% remove)]
print_shape(cardata)
```

```
## [1] "Our dataset shape is now: (22616, 46)"
```

## Address Missing Values

Now, with the columns that we do have, we can observe how many `NA` values exist in each column. We will set a threshold of **10%**; a column with more than 10 percent of its values being `NA` expresses a large number of missing values in our eyes and we will remove it from our analysis. Below, we can see all columns expressing more than 10% of their values as `NA`.

```
# print the proportions of NA values in each column using a threshold of 10%
df_table <- calculate_proportions(cardata, 0.10)
print_table(df_table)
```

| Column Name | Proportion of Values NA |
|---|---|
| Averaging Group ID | 0.98063 |
| Averaging Weighting Factor | 0.97073 |
| ADFE Total Road Load HP | 0.89123 |
| ADFE Equiv. Test Weight (lbs.) | 0.89123 |
| ADFE N/V Ratio | 0.89123 |
| PM (g/mi) | 0.82689 |
| N2O (g/mi) | 0.49823 |
| CH4 (g/mi) | 0.18739 |
| NOx (g/mi) | 0.14008 |
| THC (g/mi) | 0.13305 |
| CO (g/mi) | 0.13053 |

We can then remove these columns.

```
# remove high-probability NA columns from data frame
remove <- df_table$`Column Name`

# remove columns and report new shape
cardata <- cardata[, !( colnames(cardata) %in% remove)]
print_shape(cardata)
```

```
## [1] "Our dataset shape is now: (22616, 35)"
```

We still have columns expressing `NA` values, however. These columns, of course, have less than 10% of their values being `NA`, after the removal performed above. These columns can be seen below.

```
# print the proportions of NA values in each column using a threshold of 0%
df_table <- calculate_proportions(cardata, 0)
print_table(df_table)
```

| Column Name | Proportion of Values NA |
|---|---|
| DT-Inertia Work Ratio Rating | 0.07985 |
| DT-Absolute Speed Change Ratg | 0.07985 |
| DT-Energy Economy Rating | 0.07985 |
| CO2 (g/mi) | 0.05518 |
| Aftertreatment Device Cd | 0.04196 |
| Aftertreatment Device Desc | 0.04196 |

| Column Name | Proportion of Values NA |
|---|---|
| # of Cylinders and Rotors | 0.04059 |
| RND_ADJ_FE | 0.01375 |

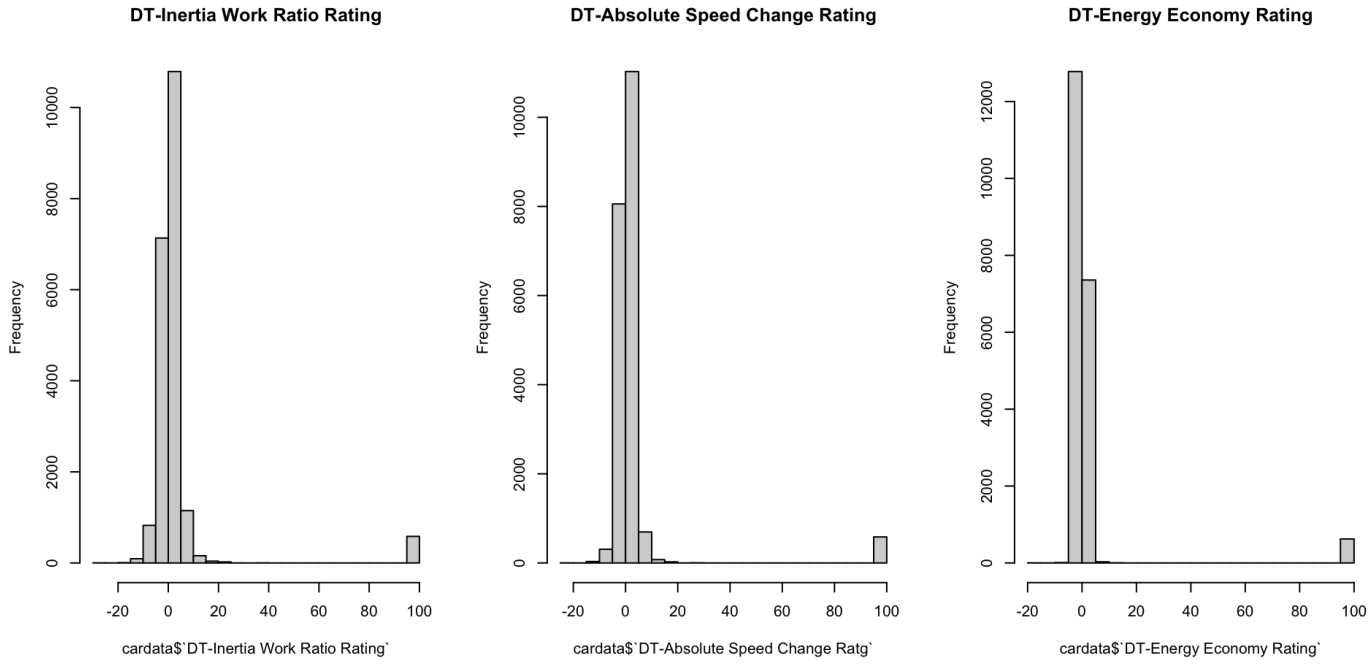
### `DT-Inertia Work Ratio Rating`, `DT-Absolute Speed Change Ratg`, and `DT-Energy Economy Rating`

Let's start by observing the first three variables:

- `DT-Inertia Work Ratio Rating`
- `DT-Absolute Speed Change Ratg`
- `DT-Energy Economy Rating`

We can make histograms to see what their distributions are like.

```
par(mfrow = c(1, 3))
hist(cardata$`DT-Inertia Work Ratio Rating`, main = 'DT-Inertia Work Ratio Rating', breaks = 20)
hist(cardata$`DT-Absolute Speed Change Ratg`, main = 'DT-Absolute Speed Change Rating', breaks = 20)
hist(cardata$`DT-Energy Economy Rating`, main = 'DT-Energy Economy Rating', breaks = 20)
```




It is evident that each of these columns has a set of observations marked with a rating around $100$. This is likely comparable to an `NA` value, as the distribution of values for these attributes is almost entirely hovering around a value of $0$. Let's replace these values with `NA` values so that we don't confuse ourselves with them being valid.

```
# replace high outliers with NA
cardata$`DT-Inertia Work Ratio Rating`[cardata$`DT-Inertia Work Ratio Rating` > 50] <- NA
cardata$`DT-Absolute Speed Change Ratg`[cardata$`DT-Absolute Speed Change Ratg` > 50] <- NA
cardata$`DT-Energy Economy Rating`[cardata$`DT-Energy Economy Rating` > 50] <- NA
```

We can also observe our new, updated measurements of proportions of values in columns that are `NA`.

```
# create data frame for printing proportions of NA values
df_table <- calculate_proportions(cardata, 0)
print_table(df_table)
```

| Column Name | Proportion of Values NA |
|---|---|
| DT-Energy Economy Rating | 0.10745 |

| Column Name | Proportion of Values NA |
|---|---|
| DT-Inertia Work Ratio Rating | 0.10568 |
| DT-Absolute Speed Change Ratg | 0.10568 |
| CO2 (g/mi) | 0.05518 |
| Aftertreatment Device Cd | 0.04196 |
| Aftertreatment Device Desc | 0.04196 |
| # of Cylinders and Rotors | 0.04059 |
| RND_ADJ_FE | 0.01375 |

These columns, having been updated by our observations above, now have proportions of missing (or ambiguous) values greater than 10%. Keeping our threshold in mind, we will drop these columns as well.

```
# remove high-probability NA columns from data frame
remove <- df_table$`Column Name`[1:3]

# remove columns and report new shape
cardata <- cardata[, !( colnames(cardata) %in% remove)]
print_shape(cardata)
```

```
## [1] "Our dataset shape is now: (22616, 32)"
```

Again, we can observe the proportion of values in columns that are `NA` for columns that have at least one `NA` value.

```
# create data frame for printing proportions of of NA values
df_table <- calculate_proportions(cardata, 0)
print_table(df_table)
```

| Column Name | Proportion of Values NA |
|---|---|
| CO2 (g/mi) | 0.05518 |
| Aftertreatment Device Cd | 0.04196 |
| Aftertreatment Device Desc | 0.04196 |
| # of Cylinders and Rotors | 0.04059 |
| RND_ADJ_FE | 0.01375 |

---

### `Aftertreatment Device Cd` and `Aftertreatment Device Desc`

The following two variables have the same number of missing values in the dataset. Let's see if they are from the same rows.

- `Aftertreatment Device Cd`
- `Aftertreatment Device Desc`

```
# extract row names where these three variables are missing
after_cd_null <- rownames(cardata[is.na(cardata$`Aftertreatment Device Cd`), ])
after_desc_null <- rownames(cardata[is.na(cardata$`Aftertreatment Device Desc`), ])

# ensure that the column names are all the same across all datasets
if ( mean(after_cd_null == after_desc_null) == 1 ) {
  print('These variables are missing in the same rows in the dataset.')
} else {
  print('These variables are missing in different rows in the dataset.')
}
```

```
## [1] "These variables are missing in the same rows in the dataset."
```

The missing values in the dataset for these two variables *do* come from the same rows, which makes sense given their association with each other; the `Aftertreatment Device Desc` variable is just a description for the label of the `Aftertreatment Device Cd` variable. Since these are categorical variables, and there are only a small number of `NA` values (less than 5%), we will leave the `NA` values as they are and likely remove them if we engage in an analysis on both columns. We opt not to remove the *rows* corresponding to these missing values because there is valuable data in the other 30 columns present.

The last three variables containing missing values left to address are:

- `CO2 (g/mi)`
- `# of Cylinders and Rotors`
- `RND_ADJ_FE`

---

### `CO2 (g/mi)`

Let's start with `CO2 (g/mi)` and observe its missing values.

```
# extract the rows where 'CO2 (g/mi)' is missing
na_co2 <- cardata[is.na(cardata$`CO2 (g/mi)`), ]

# proportion of electric vehicles missing this value
prop <- sum(na_co2$`Test Fuel Type Description` == 'Electricity') / sum(cardata$`Test Fuel Type Description` == 
'Electricity')
print(paste("The proportion of Electric vehicles missing a value for 'CO2 (g/mi)' is:", prop))
```

```
## [1] "The proportion of Electric vehicles missing a value for 'CO2 (g/mi)' is: 1"
```

We can see that *all* electric vehicles are missing a value for the `CO2 (g/mi)` attribute. This may be indicative of an emission rate of **0.00 g/mi**, so we will fill these missing values with that value. Still, we will keep this assumption in mind when proceeding with this data, as our assumption might affect the results of future analysis.

```
# replace all electric vehicle CO2 emissions with 0 (all are missing, as discovered above)
cardata[cardata$`Test Fuel Type Description` == 'Electricity', ]$`CO2 (g/mi)` <- 0
```

---

### `# of Cylinders and Rotors`

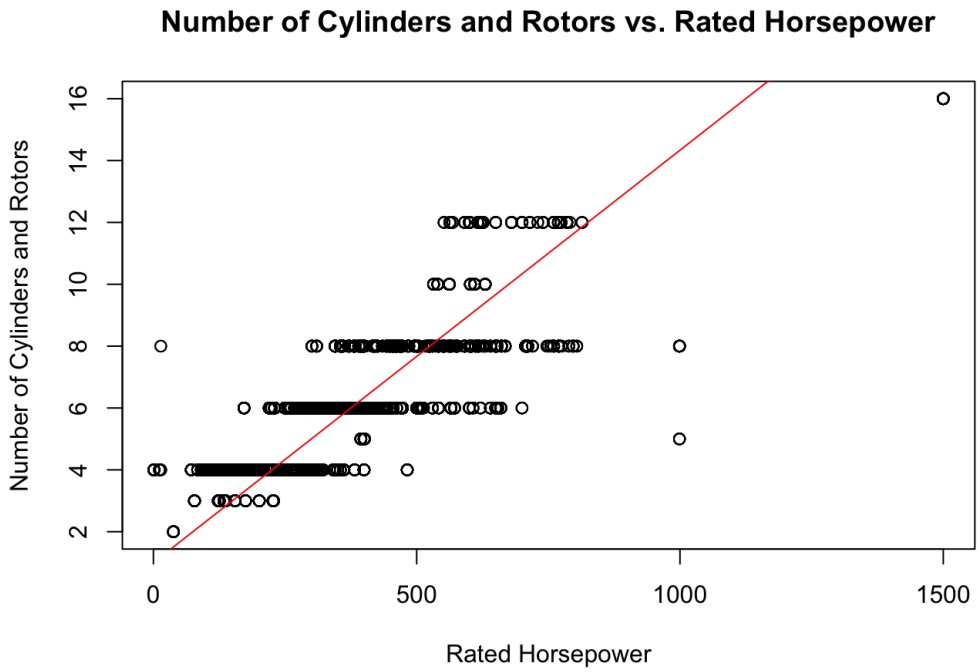
Let's move on to `# of Cylinders and Rotors`.

```
# table of number of cylinders
table(cardata$`# of Cylinders and Rotors`)
```

```
##
##     2     3     4     5     6     8    10    12    16
##    29   400 10807    45  6537  3333   166   350    31
```

We can see above that the number of cylinders and rotors is almost exclusively an even number, with values of $3$ and $5$ appearing some number of times.

```
# plot number of cylinders versus horsepower
plot(cardata$`Rated Horsepower`, cardata$`# of Cylinders and Rotors`, xlab = 'Rated Horsepower', ylab = 'Number o
f Cylinders and Rotors', main = 'Number of Cylinders and Rotors vs. Rated Horsepower')
abline(a = 1, b = 1/75, col = 'red')
```




Above, we can see an approximation of the number of cylinders ( `# of Cylinders and Rotors` ) and rotors predicted by the horsepower ( `Rated Horsepower` ). Using this approximation, we will fill in the missing values of `# of Cylinders and Rotors` using the nearest even value. Note that the even values make up the vast majority in this dataset, as values of $1$, $3$, and $5$, for instance, are very rare.

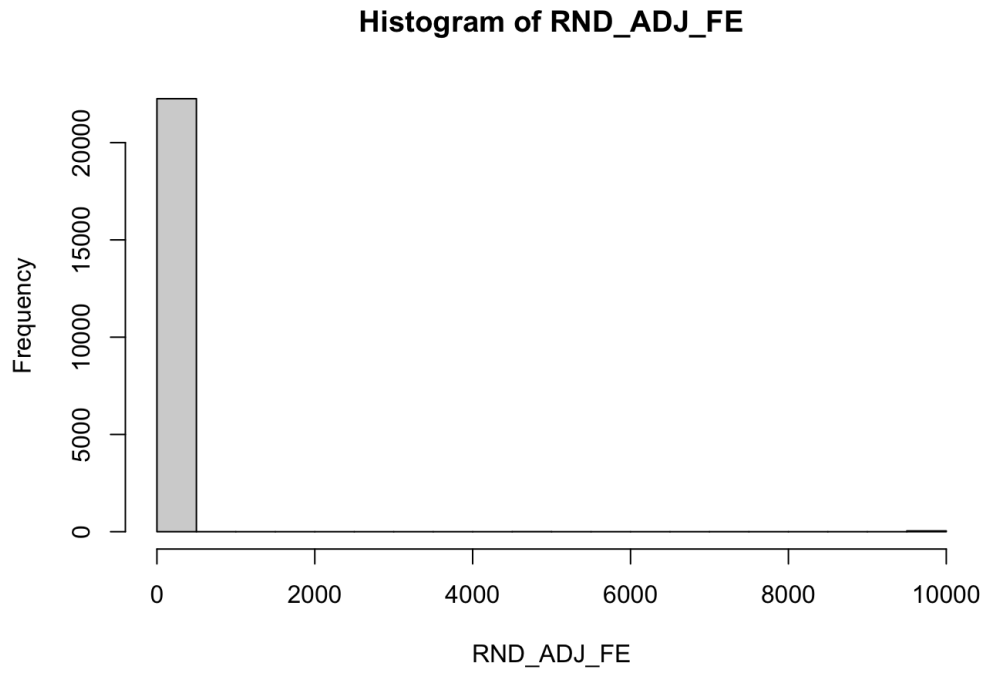
```
# replace missing cylinder values with the approximation above
for (i in 1:nrow(cardata)) {
  if (is.na(cardata$`# of Cylinders and Rotors`[i])) {
    val <- 1 + cardata$`Rated Horsepower`[i] / 75
    cardata$`# of Cylinders and Rotors`[i] <- round(val / 2) * 2
  }
}
```

---

`RND_ADJ_FE`

Finally, let's move on to `RND_ADJ_FE` .

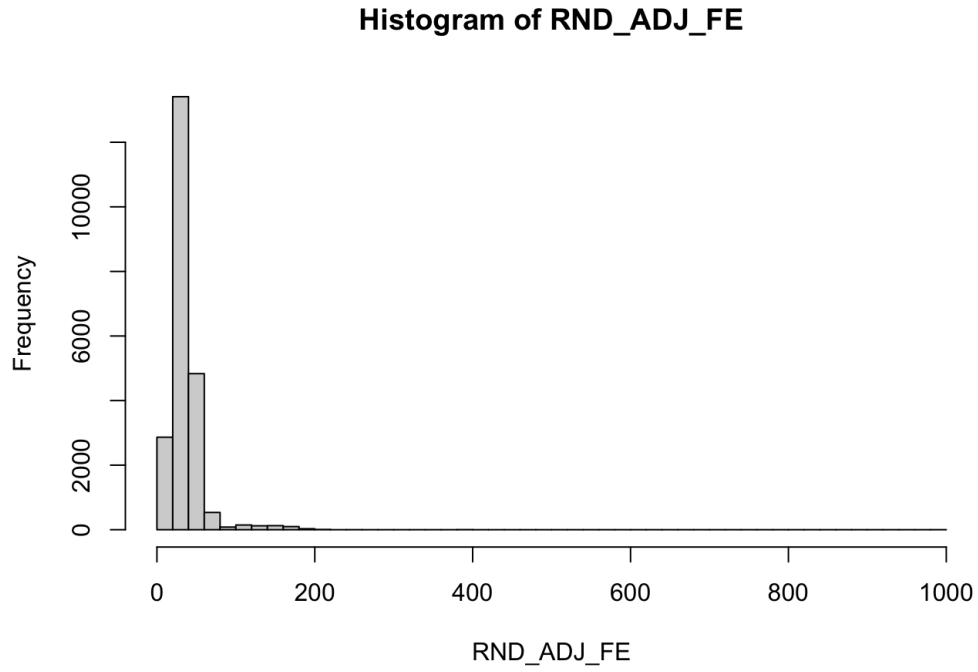
```
# histogram of RND_ADJ_FE
hist(cardata$RND_ADJ_FE, xlab = 'RND_ADJ_FE', main = 'Histogram of RND_ADJ_FE')
```




We can see that the distribution of `RND_ADJ_FE` is hidden by the outliers present in the data. Let's first replace those with missing values before proceeding.

```
# replace outliers with NA
cardata$RND_ADJ_FE[cardata$RND_ADJ_FE > 2000] <- NA

# re-view the histogram now
hist(cardata$RND_ADJ_FE, xlab = 'RND_ADJ_FE', main = 'Histogram of RND_ADJ_FE', breaks = 40)
```




This variable is a bit ambiguous, so we will replace the missing values with the median of the existing values. The values are all focused around a values of approximately $0$ to $75$, so this feels to us as a safe decision to proceed with.

```
# replace missing values with median of existing values
cardata$RND_ADJ_FE[is.na(cardata$RND_ADJ_FE)] <- median(cardata$RND_ADJ_FE, na.rm = TRUE)
```

Let's take a look at the proportions of missing values now, as we have addressed them all (and kept some).

```
df_table <- calculate_proportions(cardata, 0)
print_table(df_table)
```

| Column Name | Proportion of Values NA |
|---|---|
| Aftertreatment Device Cd | 0.04196 |
| Aftertreatment Device Desc | 0.04196 |
| CO2 (g/mi) | 0.01822 |

After addressing the missing values in the data, we find that we only have approximately **0.32%** of our data missing. This is a great improvement from the **15.64%** that we had initially and something that we can take with us as we look to analyze the data further.

---

## Export Clean Data

Finally, we need to export this cleaned data so that we can use it in our analyses.

```
write.csv(cardata, 'data/cardata_clean.csv')
```