Coursework project

on the module 1 "The Datascientist's Toolbox"

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This project is available in the public repository on GitHub. You can check it following this **link**.

The first step of this project is to load and analyze three datasets from the pre-installed R package **'datasets'**. The full list of packages, available at the named package, is available in the **link to the R documentation**. From the named library it was decided to pick 3 datasets by my own preferences to analyze data each of the selected datasets contains.

> Respecting to the fact, that our knowledge is not deep enough to build complex analysis, in my work is represented only brief look on each of datasets, within the basics of the descriptive analysis with the elements of exploratory approach in order to find some possible dependencies of the given data.

- The first dataset is pretty classical dataset for this subject area, **'iris'**. This dataset represents measurements of *sepal length*, *sepal width*, *petal length* and *petal width* of the three iris species: *setosa*, *virginica* and *versicolor*. There are 50 rows per each of the iris species in the dataset.

```
# get the data of the whole dataset
library(datasets)
data("iris")
```

On the image below are represented top 12 rows of the iris dataset, ordered by index at the ascending order.

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5.0	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa
7	4.6	3.4	1.4	0.3	setosa
8	5.0	3.4	1.5	0.2	setosa
9	4.4	2.9	1.4	0.2	setosa
10	4.9	3.1	1.5	0.1	setosa
11	5.4	3.7	1.5	0.2	setosa
12	4.8	3.4	1.6	0.2	setosa

The next step is to obtain summary on the dataset.

The following summary contains values on the criteria, such as

- *minimum (Min.)*,
- *1st Quartile (1st Qu.)* (i.e. 25% of data was taken under the produced value),
- *Median* (can be named as a middle value of some numeric sequence),
- *Mean* (average value),
- *3rd Quartile (3rd Qu.)* (i.e. 75% of data was taken under the produced value),
- *maximum (Max.)*
  for **numeric values** and
- *number of occurencies* of each value
  for **string values** (column *'Species'* in *iris* dataset).

Additionally, the range value can be calculated if needed. However, without any certain question, needed to be solved, these values are useless. According to the dataset data, this dataset has no missing values (no NaN or NULLs).

```
summary(iris)
```

```
##   Sepal.Length    Sepal.Width     Petal.Length    Petal.Width
##  Min.   :4.300   Min.   :2.000   Min.   :1.000   Min.   :0.100
##  1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300
##  Median :5.800   Median :3.000   Median :4.350   Median :1.300
##  Mean   :5.843   Mean   :3.057   Mean   :3.758   Mean   :1.199
##  3rd Qu.:6.400   3rd Qu.:3.300   3rd Qu.:5.100   3rd Qu.:1.800
##  Max.   :7.900   Max.   :4.400   Max.   :6.900   Max.   :2.500
##        Species
##  setosa    :50
##  versicolor:50
##  virginica :50
##
##
##
```

From the data below it is clear that all the metrics are calculated on all the iris species. It would be more informative, if the metrics were calculated on the certain needed iris type. Assume, we need to get some metrics on the iris *setosa*. Let's create dataframe with *setosa* values **only**.

```
# attaching library dplyr to use filter() function
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
```

```
# to make it more usable to call the names of the columns making it to lowercase
names(iris) <- tolower(names(iris))
# creating dataframe with setosa rows only
setosa <- filter(iris, species == "setosa")
# show top-6 values of the obtained dataframe ordered by the ascending of the index
head(setosa)
```

```
##   sepal.length sepal.width petal.length petal.width species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa
```

The next step is obtaining summary metrics on the measurements of different *setosa* irises. According to the data of the column *'species'* there are no other data here, except from *setosa* data. The obtained metrics' data also differ from the previously obtained.

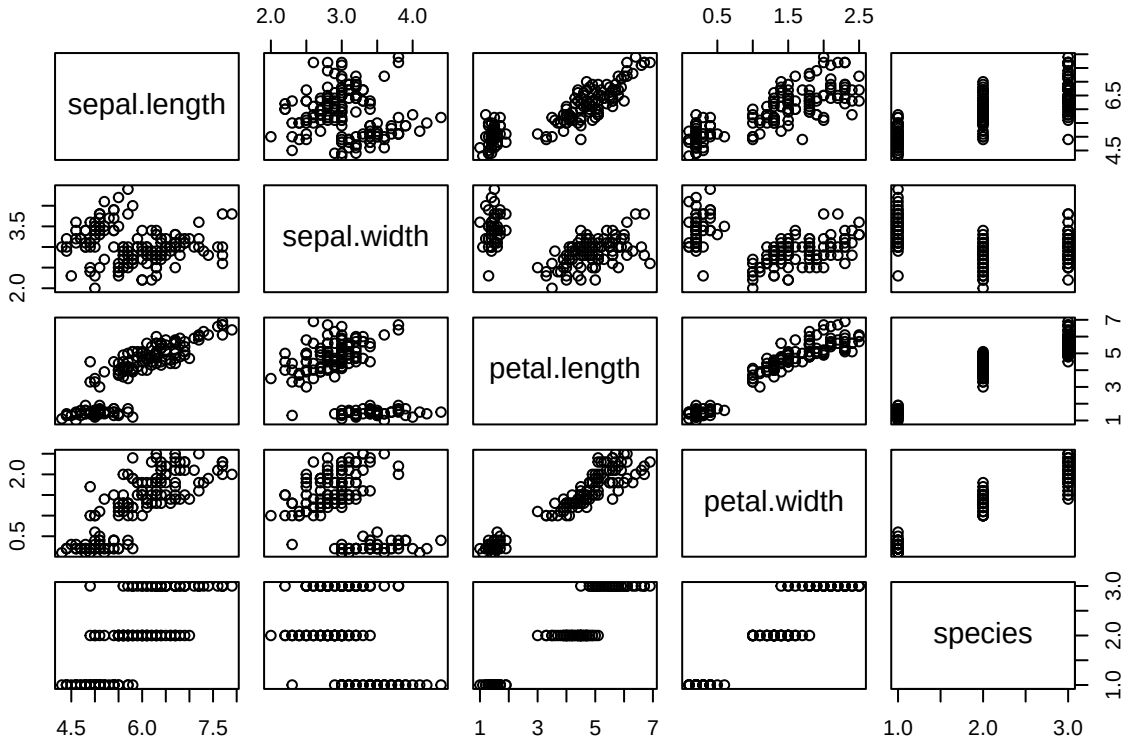
```
summary(setosa)
```

```
##   sepal.length    sepal.width     petal.length    petal.width
##  Min.   :4.300   Min.   :2.300   Min.   :1.000   Min.   :0.100
##  1st Qu.:4.800   1st Qu.:3.200   1st Qu.:1.400   1st Qu.:0.200
##  Median :5.000   Median :3.400   Median :1.500   Median :0.200
##  Mean   :5.006   Mean   :3.428   Mean   :1.462   Mean   :0.246
##  3rd Qu.:5.200   3rd Qu.:3.675   3rd Qu.:1.575   3rd Qu.:0.300
##  Max.   :5.800   Max.   :4.400   Max.   :1.900   Max.   :0.600
##        species
##  setosa    :50
##  versicolor: 0
##  virginica : 0
##
##
##
```

The final step is creating visualizations. Note, that there was no particular aim, set as a goal of investigations. The first visualization is done on the whole *iris* dataset. From the visualization below some conclusions could be made:

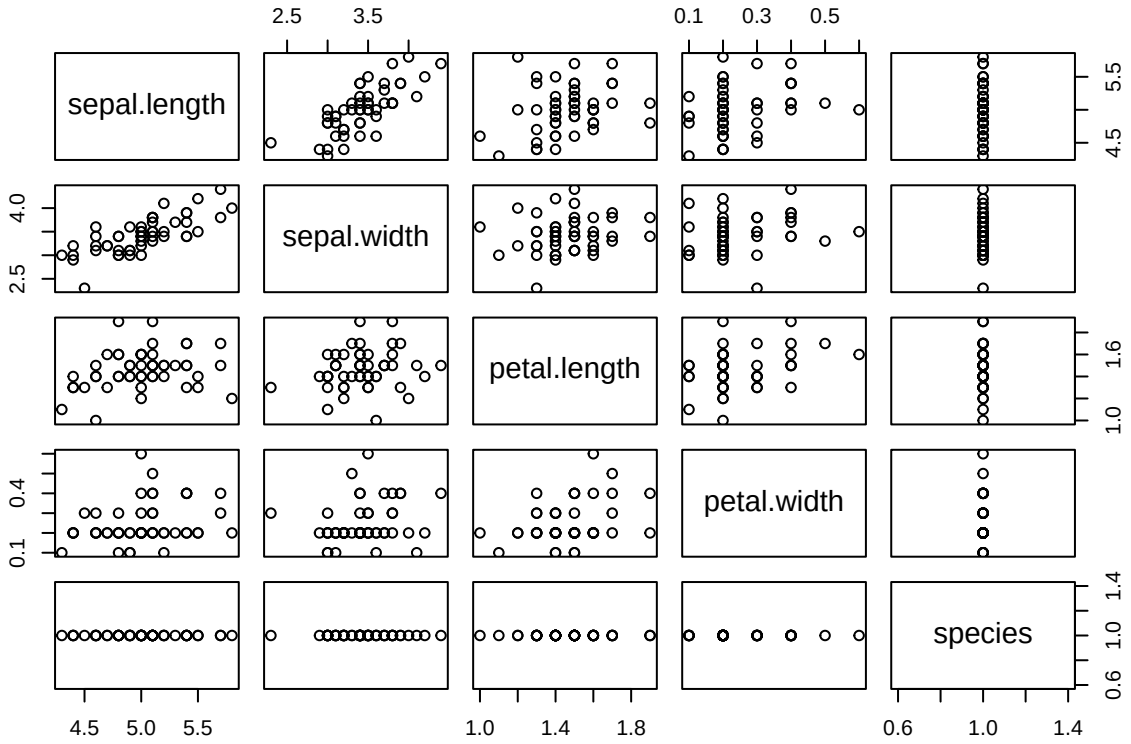
- it was a bad practice to visualize the whole dataset, that contains both numeric and string values. The obtained row and column 'species' is not pretty informative;
- it is useful to assess the whole picture of the dataset, but for more accurate conclusions and results, more detailed visualizations have to be made.

```
plot(iris)
```



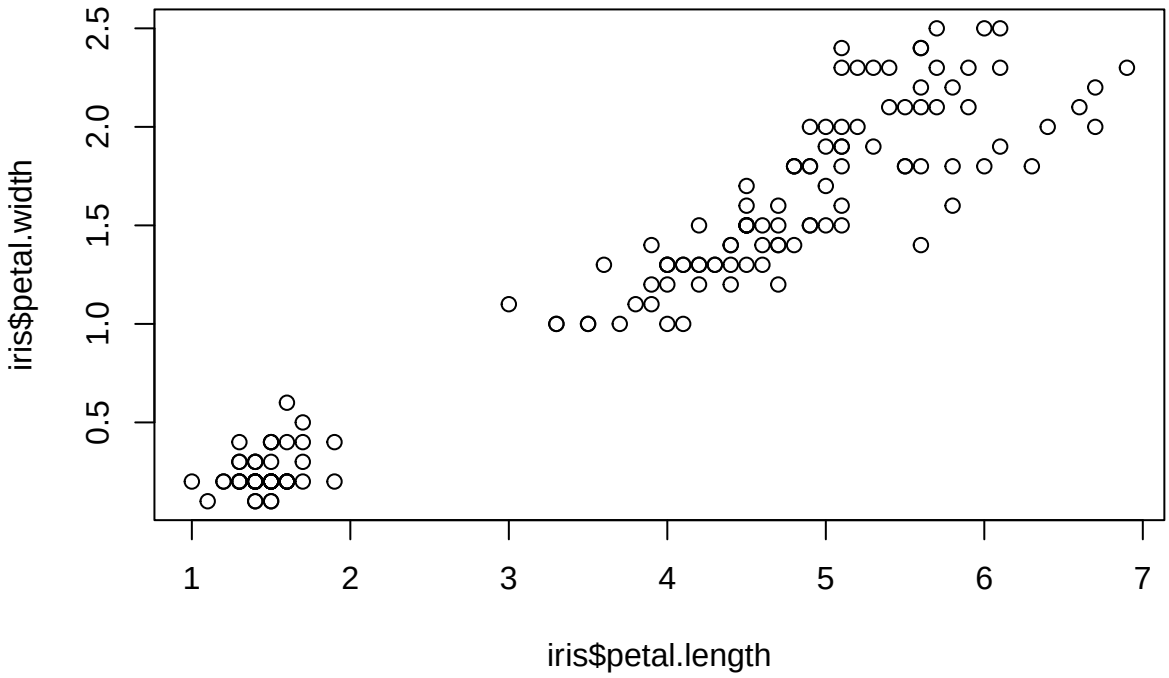
Let's create a visualization of the created *setosa* data **only** dataframe. The obtained visualization allows to make conclusions and analysis on the certain type of iris flowers *setosa*. For this graph comments and observation are the same, as for the previous one.

```
plot(setosa)
```



To reveal the dependencies between the metrics of the dataset, we have to build a more detailed visualization. To reveal the relationships between *petal length* and *petal width* let's build a graph. **All the dataset *iris* will be analyzed**. From the obtained visualization it is clear, that in most cases increasing of petal length is connected with the increasing of petal width and vice versa. The other fact is that there is no petal width and length values in the interval from 2 to 3 including these values. There is also one more interesting detail: there is a cluster in the lower left corner. This cluster may contain data on the miniature sized irises. That may be just small ones on any of the represented types or just small type (that may be *setosa*, *versicolor* or *virginica* with equal probabilities).

```
plot(iris$petal.length, iris$petal.width)
```



More investigations can be made with the formulated question to solve.

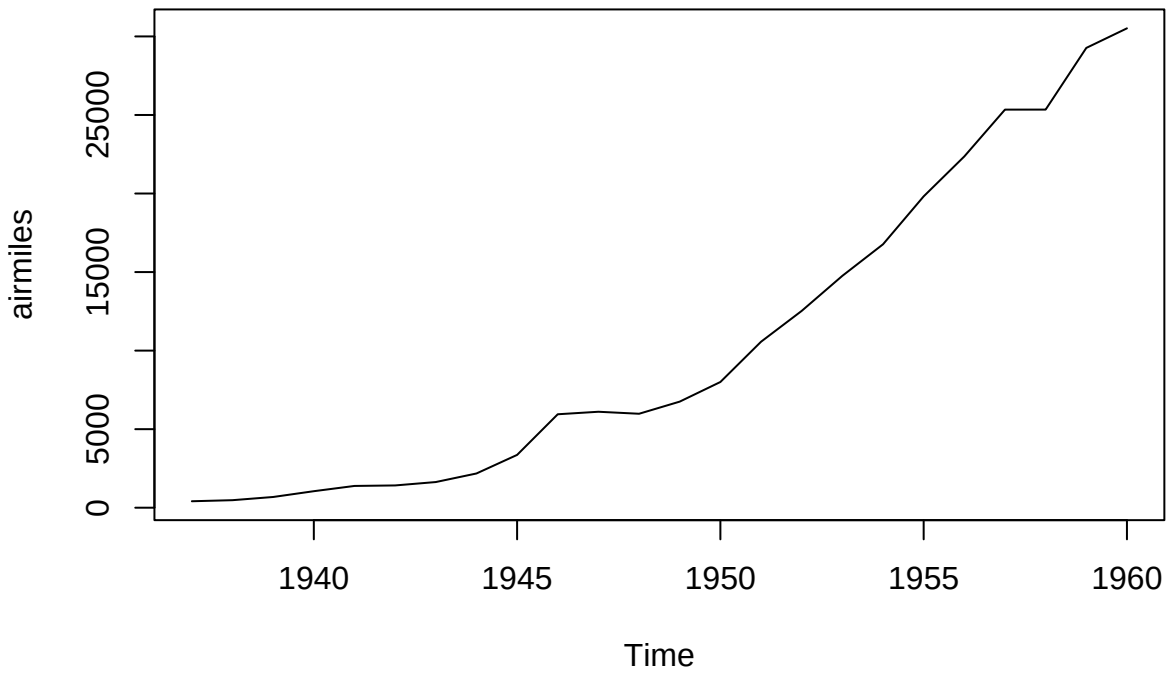
- The second dataset is **'airmiles'**. This dataset is represented by the time series of values of flown passenger miles by the USA commercial airlines from 1937 to 1960.

It is important to highlight, that **iris** dataset is represented by the *Data*, whereas **airmiles** and other dataset, that will be considered later, **AirPassengers**, are represented by the *values of time-series*:

Data	
iris	150 obs. of 5 variables
setosa	50 obs. of 5 variables
Values	
airmiles	Time-Series [1:24] from 1937 to 1960: 412 480 683 1052 1385 ...
AirPassengers	Time-Series [1:144] from 1949 to 1961: 112 118 132 129 121 135 1…

Let's visualize dataset **'airmiles'**. From the obtained visualization can be made a conclusion, that with the time number of airmiles flown increases. This characteristic increases particularly rapidly from 1947 to 1957. This decade was probably characterised by the technical progress and popularization of air transport.

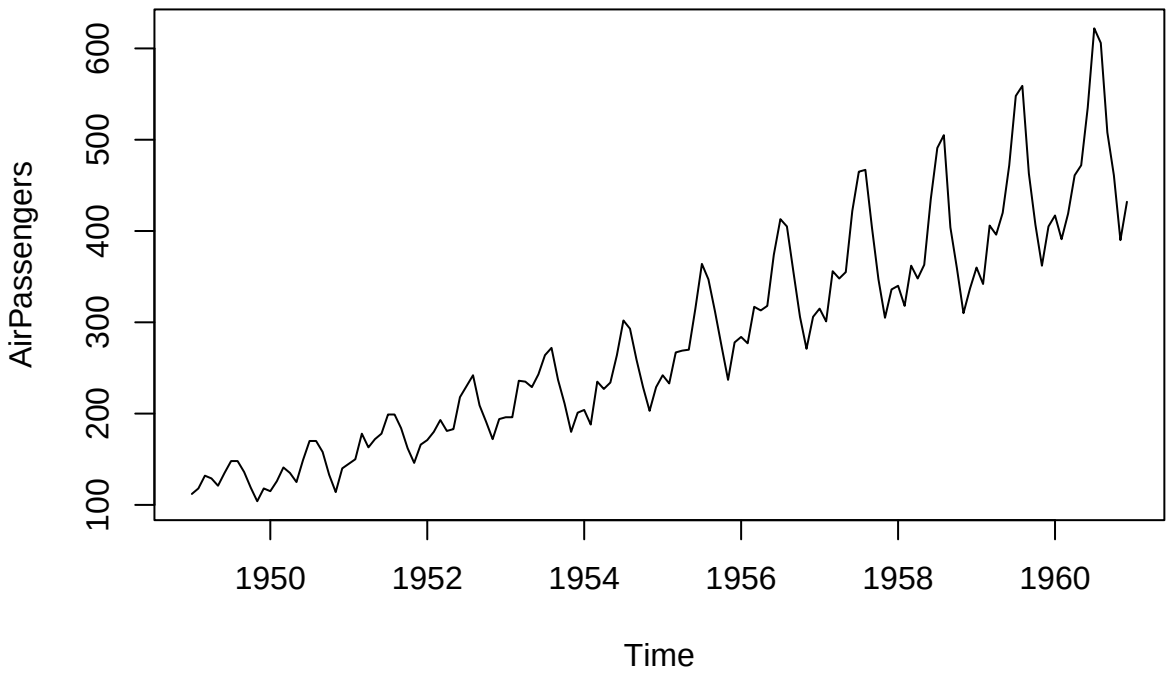
```
library(datasets)
data('airmiles')
plot(airmiles)
```



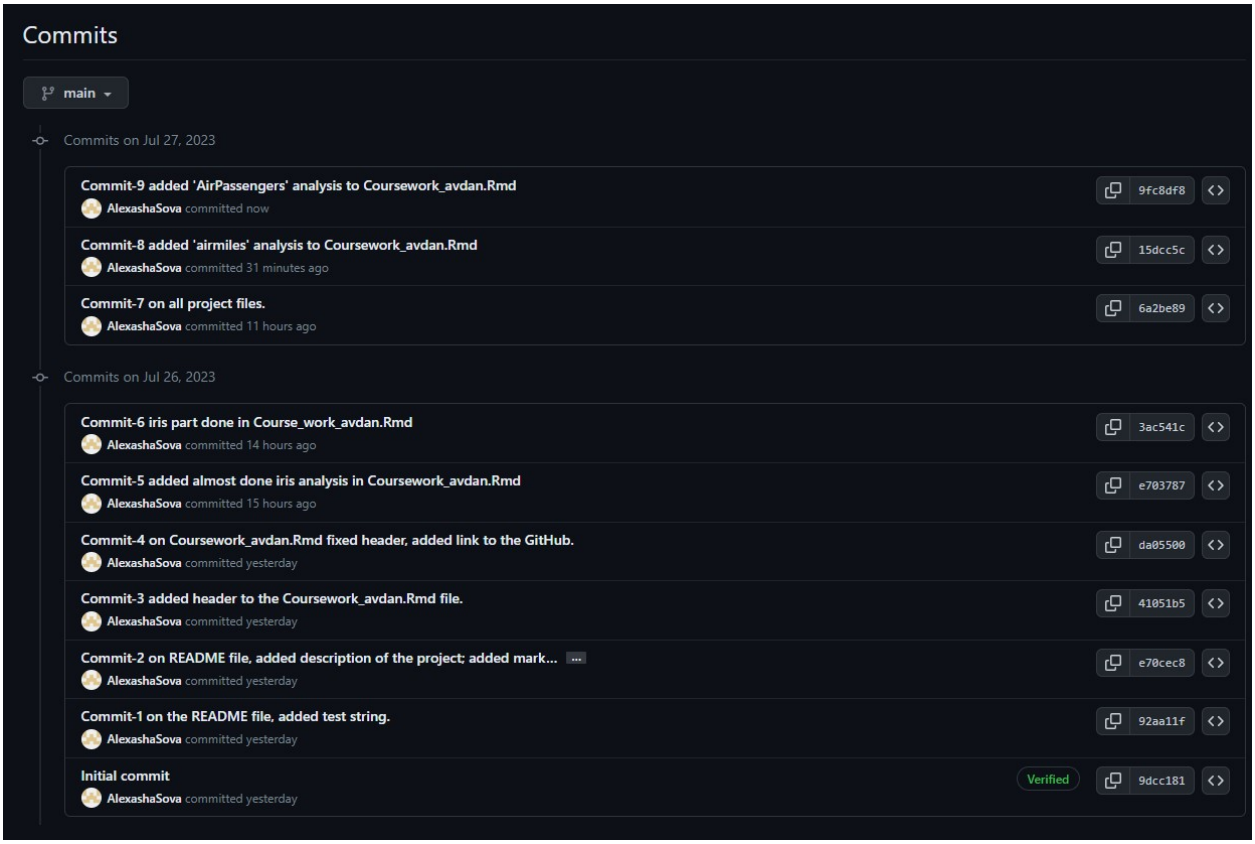
- The third dataset is **'AirPassengers'**. This dataset, as it was recently mentioned, is represented by the time-series of values of monthly totals of international airline passengers from 1949 to 1961.

Let's visualize dataset **'AirPassengers'**. From the obtained visualization it is clear, that it's a representation of the non-linear model. To make an exact conclusion about how does dependent variable *(AirPassengers)* depends from the independent one *(Time)* it is needed to approximate existing model to linear one by the means of linear regression. Without this step it can be said that with the time number of air passengers increases.

```
library(datasets)
data('AirPassengers')
plot(AirPassengers)
```



During this work I've been doing commits on the **linked GitHub repository.** Here is commit history as an evidence of proper work:


Commits
main
Commits on Jul 27, 2023
Commit-9 added 'AirPassengers' analysis to Coursework_avdan.Rmd
AlexashaSova committed now
9fc8df8
Commit-8 added 'airmiles' analysis to Coursework_avdan.Rmd
AlexashaSova committed 31 minutes ago
15dcc5c
Commit-7 on all project files.
AlexashaSova committed 11 hours ago
6a2be89
Commits on Jul 26, 2023
Commit-6 iris part done in Course_work_avdan.Rmd
AlexashaSova committed 14 hours ago
3ac541c
Commit-5 added almost done iris analysis in Coursework_avdan.Rmd
AlexashaSova committed 15 hours ago
e703787
Commit-4 on Coursework_avdan.Rmd fixed header, added link to the GitHub.
AlexashaSova committed yesterday
da05500
Commit-3 added header to the Coursework_avdan.Rmd file.
AlexashaSova committed yesterday
41051b5
Commit-2 on README file, added description of the project; added mark...
AlexashaSova committed yesterday
e70cec8
Commit-1 on the README file, added test string.
AlexashaSova committed yesterday
92aa11f
Initial commit
AlexashaSova committed yesterday
Verified
9dcc181