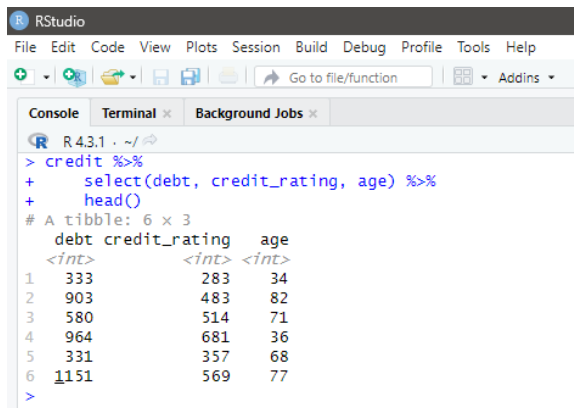


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**Subject :** Computational Statistics  
**Professor :** Paul Dantzic (Adjunct Professor)

(LC6.2) Conduct a new exploratory data analysis with the same outcome variable y debt but with credit\_rating and age as the new explanatory variables x 1 and x 2 . What can you say about the relationship between a credit card holder's debt and their credit rating and age?

Answer :

```
credit %>%
  select(debt, credit_rating, age) %>%
  head()
```



```
R R4.3.1 . ~/
> credit %>%
+   select(debt, credit_rating, age) %>%
+   head()
# A tibble: 6 x 3
  debt credit_rating age
<int>      <int> <int>
1   333         283   34
2   903         483   82
3   580         514   71
4   964         681   36
5   331         357   68
6  1151         569   77
>
```

skim\_with(numeric = list(hist = NULL), integer = list(hist = NULL))

```
> skim_with(numeric = list(hist = NULL), integer = list(hist = NULL))
Creating new skimming functions for the following classes: hist.
They did not have recognized defaults. Call get_default_skimmers() for more information.
function (data, ..., .data_name = NULL)
{
  if (is.null(.data_name)) {
    .data_name <- rlang::expr_label(substitute(data))
  }
  if (!inherits(data, "data.frame")) {
    data <- as.data.frame(data)
  }
  stopifnot(inherits(data, "data.frame"))
  selected <- names(tidyselect::eval_select(rlang::expr(c(...)),
    data))
  if (length(selected) == 0) {
    selected <- names(data)
  }
  grps <- dplyr::groups(data)
  if (length(grps) > 0) {
    group_variables <- selected %in% as.character(grps)
    selected <- selected[!group_variables]
  }
  else {
    attr(data, "groups") <- list()
  }
  skimmers <- purrr::map(selected, get_final_skimmers, data,
    local_skimmers, append)
  types <- purrr::map_chr(skimmers, "skim_type")
  unique_skimmers <- reduce_skimmers(skimmers, types)
  combined_skimmers <- purrr::map(unique_skimmers, join_with_base,
    base)
  ready_to_skim <- tibble::tibble(skim_type = unique(types),
    skimmers = purrr::map(combined_skimmers, mangle_names,
      names(base$funcs), skim_variable = split(selected,
        types)[unique(types)]])
  grouped <- dplyr::group_by(ready_to_skim, .data$skim_type)
  nested <- dplyr::summarize(grouped, skimmed = purrr::map2(.data$skimmers,
    .data$skim_variable, skim_by_type, data))
  structure(tidy::unnest(nested, "skimmed"), class = c("skim_df",
    "tbl_df", "tbl", "data.frame"), data_rows = nrow(data),
    data_cols = ncol(data), df_name = .data_name, dt_key = get_dt_key(data),
    groups = dplyr::group_vars(data), base_skimmers = names(base$funcs),
    skimmers_used = get_skimmers_used(unique_skimmers))
}
<bytecode: 0x000001b93cd5ccf0>
<environment: 0x000001b941f1be68>
```

```
credit %>%
  select(debt, credit_rating, age) %>%
  skim()
```

```
> credit %>%
+   select(debt, credit_rating, age) %>%
+   skim()
# A tibble: 1 x 1
#   Data Summary
#   Name      Values
#   Number of rows 400
#   Number of columns 3

# Column type frequency:
#   numeric      3

# Group variables: None

# Variable type: numeric
#   skim_variable n_missing complete_rate mean sd p0 p25 p50 p75 p100 hist
# 1 debt          0          1 520. 460. 0 68.8 460. 863 1999
# 2 credit_rating 0          1 355. 155. 93 247. 344 437. 982
# 3 age           0          1 55.7 17.2 23 41.8 56 70 98
```

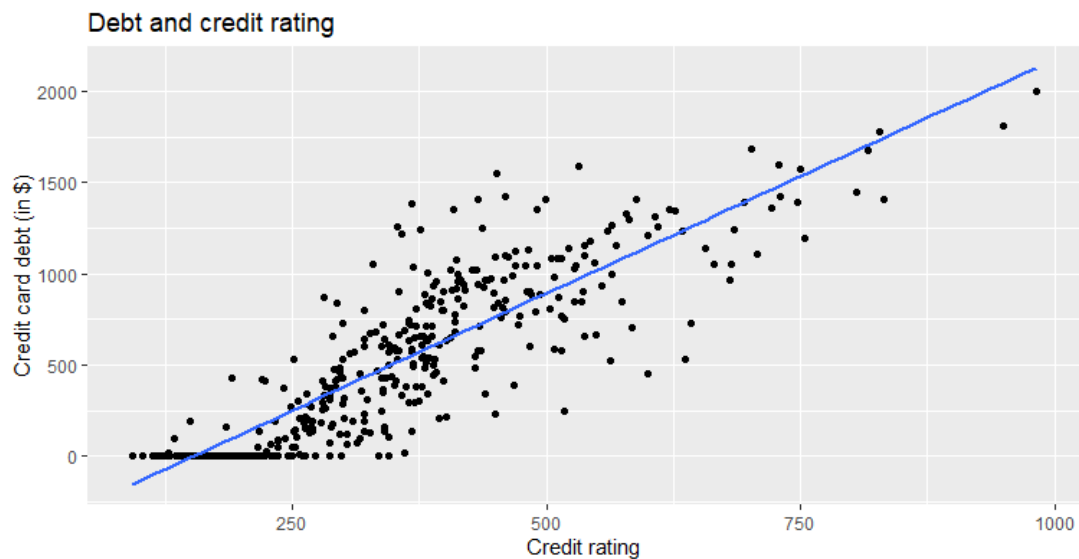
```
ggplot(credit, aes(x = credit_rating, y = debt)) +
  geom_point() +
  labs(
    x = "Credit rating", y = "Credit card debt (in $)",
    title = "Debt and credit rating"
  ) +
  geom_smooth(method = "lm", se = FALSE)
```

```
> ggplot(credit, aes(x = credit_rating, y = debt)) +
+   geom_point() +
+   labs(
+     x = "Credit rating", y = "Credit card debt (in $)",
+     title = "Debt and credit rating"
+   ) +
+   geom_smooth(method = "lm", se = FALSE)
# A tibble: 1 x 1
#   Data Summary
#   Name      Values
#   Number of rows 400
#   Number of columns 3

# Column type frequency:
#   numeric      3

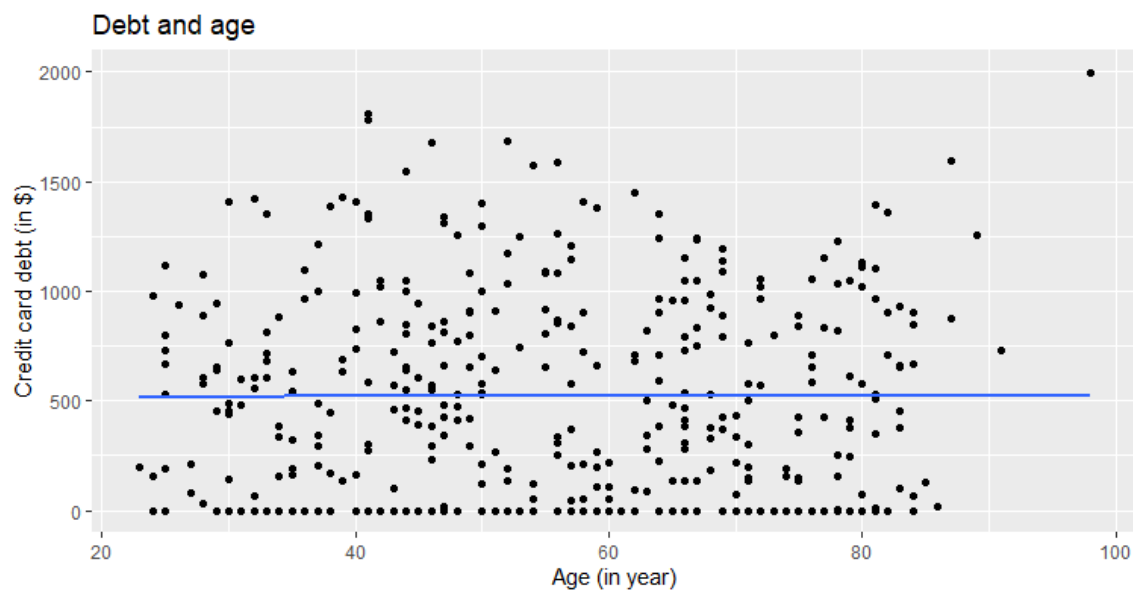
# Group variables: None

# Variable type: numeric
#   skim_variable n_missing complete_rate mean sd p0 p25 p50 p75 p100 hist
# 1 debt          0          1 520. 460. 0 68.8 460. 863 1999
# 2 credit_rating 0          1 355. 155. 93 247. 344 437. 982
# 3 age           0          1 55.7 17.2 23 41.8 56 70 98
```



```
ggplot(credit, aes(x = age, y = debt)) +
  geom_point() +
  labs(
    x = "Age (in year)", y = "Credit card debt (in $)",
    title = "Debt and age"
  ) +
  geom_smooth(method = "lm", se = FALSE)
```

```
> ggplot(credit, aes(x = age, y = debt)) +
+   geom_point() +
+   labs(
+     x = "Age (in year)", y = "Credit card debt (in $)",
+     title = "Debt and age"
+   ) +
+   geom_smooth(method = "lm", se = FALSE)
`geom_smooth()` using formula = 'y ~ x'
> |
```



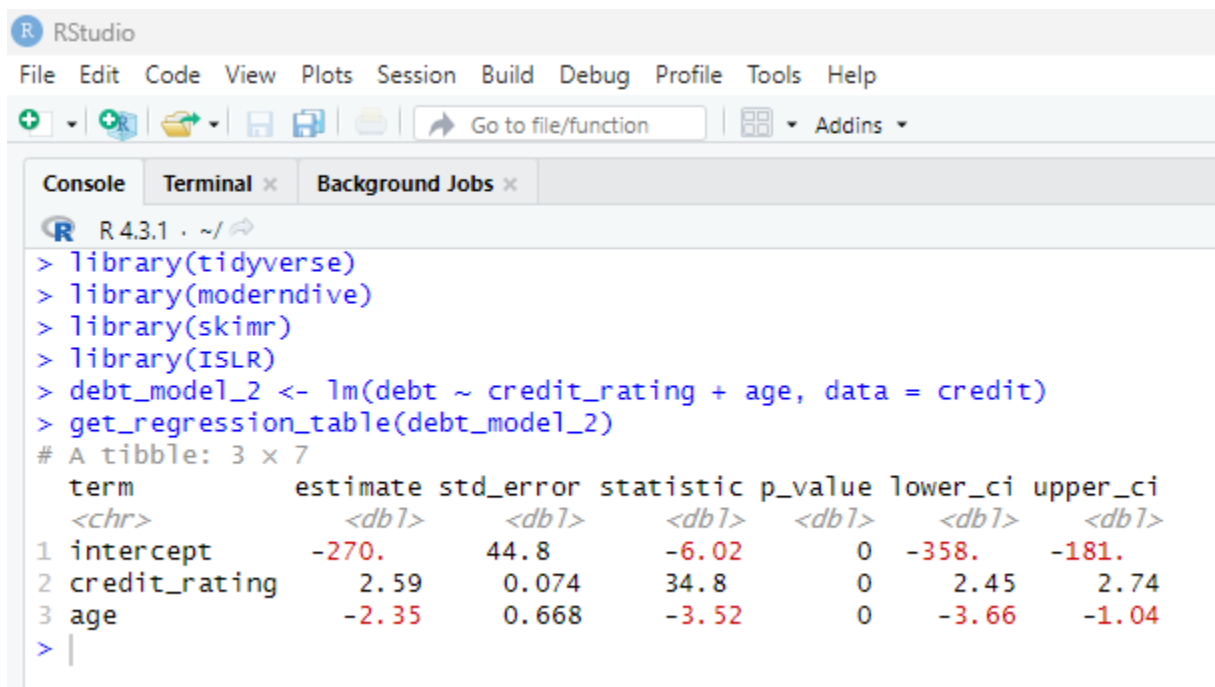
This is a favorable association between one's credit rating and debt, but a minimal relationship between one's age and debt.

(LC6.3) Fit a new simple linear regression using `lm(debt ~ credit_rating + age, data = credit_ch6)` where `credit_rating` and `age` are the new numerical explanatory variables `x1` and `x2`. Get information about the “best-fitting” regression plane from the regression table by applying the `get_regression_table()` function. How do the regression results match up with the results from your previous exploratory data analysis?

Answer :

```
debt_model_2 <- lm(debt ~ credit_rating + age, data = credit)
```

```
get_regression_table(debt_model_2)
```



```

RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
+ [R] [Folder] [Save] [Run] [Go to file/function] [Addins]
Console Terminal x Background Jobs x
R 4.3.1 ~ /
> library(tidyverse)
> library(moderndiver)
> library(skimr)
> library(ISLR)
> debt_model_2 <- lm(debt ~ credit_rating + age, data = credit)
> get_regression_table(debt_model_2)
# A tibble: 3 x 7
  term          estimate std_error statistic p_value lower_ci upper_ci
  <chr>          <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
1 intercept     -270.      44.8     -6.02      0     -358.    -181.
2 credit_rating   2.59      0.074     34.8      0       2.45     2.74
3 age           -2.35      0.668     -3.52      0      -3.66    -1.04
> |

```

Both new numerical explanatory variables `x1` and `x2`, `credit_rating` and `age`, have coefficients of 2.59 and 2.35, respectively, indicating that debt and `credit_rating` are positively associated while debt and `age` are negatively connected. This corresponds to the findings of your prior exploratory data analysis.