CUSTOMER ANALYTICS : PREPARING DATA FOR MODELLING

2024-06-02

Instructions: The Head Data Scientist at Training Data Ltd. has asked you to create a data frame called ds_jobs_clean that stores the data in customer_train.csv much more efficiently. Specifically, they have set the following requirements:

Columns containing integer values must be stored as integers (). Columns containing float values must be stored as doubles (). Columns containing categorical data, both ordinal and nominal, must be stored as factors (). Collapse the company_size levels to the following: 'Micro': <10 employees 'Small': 10-99 employees 'Medium': 100-999 employees 'Large': >1000 employees Collapse the experience levels to the following: '<5': <5 year of experience '5-10': 5-10 years of experience '>10': >10 years of experience The columns of ds_jobs_clean must be in the same order as the original dataset. The data frame should be filtered to only contain students with 10 or more years of experience at companies with at least 1000 employees, as their recruiter base is suited to more experienced professionals at large enterprise companies. If you call object.size() on ds_jobs and ds_jobs_clean after you've preprocessed it, you should notice a substantial decrease in memory usage.

1. Exploratory data analysis

Load customer_train.csv to begin exploring the data to understand the contents and data types of the values in each column. Loading a CSV file You can use the read_csv() function from the readr library to load the CSV file as a tibble. How to find the data types and contents of a column You can check the column names and assigned data types by calling the glimpse() function on the tibble. To view the unique values and counts present in a column, pipe the tibble into count() from dplyr, passing the function the variable whose values you wish to count.

```
library(readr)
## Warning: package 'readr' was built under R version 4.3.2
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(forcats)
setwd("C:/Users/EE User/OneDrive/Gopika/OMSA/MGT-6203/r programing")
# Load the dataset
ds jobs <- read csv("customer train.csv", show col types = FALSE)</pre>
head(ds_jobs,5)
## # A tibble: 5 × 14
##
    student id city
                        city development index gender relevant experience
                                          <dbl> <chr>
##
         <dbl> <chr>
                                                       <chr>>
## 1
         8949 city_103
                                         0.92 Male
                                                       Has relevant
experience
## 2
         29725 city 40
                                         0.776 Male
                                                      No relevant experience
## 3
         11561 city_21
                                         0.624 <NA>
                                                       No relevant experience
                                         0.789 <NA>
         33241 city 115
## 4
                                                       No relevant experience
## 5
           666 city 162
                                         0.767 Male
                                                      Has relevant
experience
## # | 9 more variables: enrolled university <chr>, education level <chr>,
      major discipline <chr>, experience <chr>, company size <chr>,
## #
## #
       company_type <chr>, last_new_job <chr>, training_hours <dbl>,
## #
      job change <dbl>
```

2. Converting column types

Convert columns containing integers to the type, floats to the type, and categorical data to the type. Functions for converting column types The as.integer(), as.numeric(), and as.factor() functions can be used to convert data types, including data frame columns. Applying functions to certain columns The mutate() and across() combination can be used to apply functions to particular columns. The syntax for mutating across columns: mutate(across(,)). Columns can be selected using a vector, or using a tidyselect helper function like where() to select on a condition. Collapse factor levels to reduce the amount of unnecessary information being stored. The fct_collapse() function inside mutate() can be used to redefine the levels used in a factor column. The syntax for collapsing columns: $mutate(= fct_collapse(, = c(), ...))$

```
ds_jobs_clean <- ds_jobs %>%
  # Convert student_id, training_hours, and job_change to integers
  mutate(across(c(student_id, training_hours, job_change), as.integer)) %>%
  # Convert city_development_index to a numeric
  mutate(across(city development index, as.numeric)) %>%
  # Convert the remaining character columns to factors
  mutate(across(where(is.character), as.factor)) %>%
  # Collapse company size levels to Micro, Small, Medium, and Large
  mutate(company_size = fct_collapse(company_size,
        'Micro' = '<10',
        'Small' = c('10-49', '50-99'),
        'Medium' = c('100-499', '500-999'),
        'Large' = c('1000-4999', '5000-9999', '10000+'))) %>%
  # Collapse experience levels to <5, 5-10, >10
  mutate(experience = fct_collapse(experience,
        '<5' = c('<1', as.character(1:4)),</pre>
```

```
'5-10' = as.character(5:10),
       '>10' = c(as.character(11:20), '>20'))) %>%
 # Filter students with >10 years experience from large enterprises
 filter(company_size == 'Large', experience == '>10')
ds_jobs_clean
## # A tibble: 1,956 × 14
     student_id city
                       city_development_index gender relevant_experience
##
##
          <int> <fct>
                                          <dbl> <fct> <fct>
## 1
                                          0.92 <NA>
                                                      Has relevant
            699 city 103
experience
## 2
          25619 city_61
                                         0.913 Male
                                                      Has relevant
experience
## 3
                                         0.92 Male
          22293 city_103
                                                      Has relevant
experience
## 4
          26494 city_16
                                         0.91 Male
                                                      Has relevant
experience
                                         0.926 Female Has relevant
## 5
           2547 city_114
experience
## 6
          25987 city 103
                                         0.92 Other Has relevant
experience
## 7
           1180 city_16
                                         0.91 Male
                                                      Has relevant
experience
## 8
          25349 city_16
                                         0.91 Male
                                                      Has relevant
experience
## 9
                                         0.925 Male
                                                      Has relevant
          20576 city 97
experience
## 10
           3921 city_36
                                         0.893 <NA>
                                                      No relevant
experience
## # [i]1,946 more rows
## # ig more variables: enrolled_university <fct>, education_level <fct>,
      major discipline <fct>, experience <fct>, company size <fct>,
## #
      company_type <fct>, last_new_job <fct>, training_hours <int>,
## #
## #
      job_change <int>
```