

HW2.R

joann

2021-02-12

```
#Missing Data Homework 2
```

```
#Read and inspect data set
```

```
data <- read.csv("C:/Users/joann/OneDrive/Desktop/missing data/week 1/missingdata_hw1.csv", na.strings =  
str(data)
```

```
## 'data.frame': 2129 obs. of 14 variables:  
## $ enrollee_id : int 32403 9858 31806 27385 27724 217 21465 27302 12994 16287 ...  
## $ city : chr "city_41" "city_103" "city_21" "city_13" ...  
## $ city_development_index: num 0.827 0.92 0.624 0.827 0.92 0.899 0.624 0.92 0.878 0.624 ...  
## $ gender : chr "Male" "Female" "Male" "Male" ...  
## $ relevent_experience : chr "Has relevent experience" "Has relevent experience" "No relevent exp  
## $ enrolled_university : chr "Full time course" "no_enrollment" "no_enrollment" "no_enrollment" .  
## $ education_level : chr "Graduate" "Graduate" "High School" "Masters" ...  
## $ major_discipline : chr "STEM" "STEM" NA "STEM" ...  
## $ experience : chr "9" "5" "<1" "11" ...  
## $ company_size : chr "<10" NA NA "10/49" ...  
## $ company_type : chr NA "Pvt Ltd" "Pvt Ltd" "Pvt Ltd" ...  
## $ last_new_job : chr "1" "1" "never" "1" ...  
## $ training_hours : int 21 98 15 39 72 12 11 81 2 4 ...  
## $ gender2 : int 0 1 0 0 0 0 NA 1 0 0 ...
```

```
#Find variables with missing values
```

```
sapply(data, function(x) sum(is.na(x)))
```

```
##          enrollee_id          city city_development_index  
##              0              0              0  
##          gender relevent_experience enrolled_university  
##          508              0              31  
## education_level major_discipline experience  
##          52              312              5  
##      company_size company_type last_new_job  
##          622              634              40  
##      training_hours gender2  
##              0              532
```

```
#All variables with missing values are categorical
```

```
#I need to generate missing values for a continuous variable
```

```
#Generate missing values for training_hours depending on one variable
```

```
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

data_new = select(data, 'city_development_index', 'training_hours')
library(mice)
```

```
## Warning: package 'mice' was built under R version 4.0.3
```

```
##
## Attaching package: 'mice'
```

```
## The following object is masked from 'package:stats':
##
##   filter
```

```
## The following objects are masked from 'package:base':
##
##   cbind, rbind
```

```
cont_cat = ampute(data_new, prop = 0.2, patterns=c(1,0), mech = "MAR")$amp
data['training_hours'] = cont_cat['training_hours']
```

```
#To keep it simple, I only use one categorical variable with missing variable for analysis
#The variable gender2 have missing value > 20%
data2 = select(data, 'enrollee_id', 'city', 'city_development_index', 'training_hours', 'gender2', 'relevent_experience')
#Check for missingness
apply(data2, function(x) sum(is.na(x)))
```

```
##           enrollee_id           city city_development_index
##                0                0                0
##      training_hours      gender2      relevent_experience
##                427                532                0
```

```
#Mean imputation for numeric missing value
mean.imp <- function (a)
{
  missing <- is.na(a)
  a.obs <- a[!missing]
  imputed <- a
  imputed[missing] <- mean(a.obs)
  # Output the imputed vector
  return (imputed)
}
```

```

data2['training_hours_imp']=mean.imp(data2['training_hours'])

#Mode imputation for the categorical variable
mode <- function (a)
{
  ta =table(a)
  tam = max(ta)
  if(all(ta==tam))
    mod =NA
  else
    mod = names(ta)[ta==tam]
  return (mod)
}

mode.imp <- function (a)
{
  missing <- is.na(a)
  a.obs <- a[!missing]
  imputed <- a
  imputed[missing] <- mode(a.obs)
  # Output the imputed vector
  return (imputed)
}

data2['gender_imp']=mode.imp(data2['gender2'])

#Analysis with complete case
data_complete = na.omit(data2)

#analyse the relationship between training hours and other factors

anova_one_way1 <- aov(training_hours~city_development_index+gender2,data=data_complete)
summary(anova_one_way1)

```

```

##              Df  Sum Sq Mean Sq F value Pr(>F)
## city_development_index    1    1585     1585   0.446   0.504
## gender2                   1     927     927   0.261   0.609
## Residuals                1265 4491601     3551

```

```

anova_one_way2 <- aov(training_hours_imp~city_development_index+gender_imp,data=data2)
summary(anova_one_way2)

```

```

##              Df  Sum Sq Mean Sq F value Pr(>F)
## city_development_index    1    3059    3059.4   1.068   0.301
## gender_imp                1     581     580.8   0.203   0.653
## Residuals                2126 6088847    2864.0

```

#For the imputed data, the sum of square for city development index is much larger and the sum of square for gender is much smaller than the original data
#However, both variables does not pass the f test for both dataset
#The conclusion for both datasets is the same: we cannot reject the null hypothesis and different gender does not affect training hours