

# 1 Wrangling categorical data in R

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## 4 ABSTRACT

5 Working with categorical data in R (known as factor variables) can be particularly tricky. This paper  
6 presents a few approaches to wrangling this type of data, using the base R package as well as dplyr and  
7 mosaic.

8 Keywords:

## 9 INTRODUCTION

10 Factors are the data type that R uses for categorical data. For example, a gender variable might include  
11 the categories `male`, `female` and `gender non-conforming`. Storing this information as a factor  
12 is the alternative to storing it as a series of character strings.

13 Historically, storing categorical data as a factor variable was more efficient than storing the same data  
14 as strings, because factor variables only store the factor labels once (Peng, 2015). However, R has changed  
15 to use hashed versions of all character strings, so the storage issue is no longer valid (Peng, 2015).

16 Factors can be very tricky to deal with, which has led to the online `stringsAsFactors = HELLNO`  
17 movement. This refers to the default behavior of many of R's data import functions to take any variable  
18 composed as strings and automatically convert the variable to a factor. The R community has been moving  
19 away from this default behavior, with functions from Hadley Wickham's **readr** package defaulting to  
20 leaving strings as-is.

21 However, factor variables are important when it comes to modeling. When you pass a factor variable  
22 into **lm** or **glm**, R automatically creates dummy variables for each of the levels and picks one as a  
23 reference group. This behavior is lost if the variable is stored as a character vector.

24 So, factors are important. But, they can often be hard to deal with. Because of the way the group  
25 numbers are stored separately from the factor labels, it can be easy to overwrite data in such a way that  
26 the original data is lost. In this paper, we will consider the best practices for working with factor data.

27 To do this, we will consider data from the General Social Survey.

## 28 LOADING THE DATA

29 We have several options for how to get this data. We could download it in SPSS or Stata formats and use  
30 the foreign package to read it in. The GSS download even provides an R file to do the translation for you.  
31 Here is the result of that:

```
source(' ../data/GSS.r')
```

```
str(GSS)

## 'data.frame': 2538 obs. of 17 variables:
## $ YEAR : int 2014 2014 2014 2014 2014 2014 2014 2014 2014 2014 ...
## $ ID_ : int 1 2 3 4 5 6 7 8 9 10 ...
## $ WRKSTAT : int 1 1 4 2 5 1 9 1 8 1 ...
## $ PRESTIGE: int 0 0 0 0 0 0 0 0 0 0 ...
## $ MARITAL : int 3 1 3 1 1 1 1 1 5 1 ...
## $ CHILDS : int 0 0 1 2 3 1 2 2 4 3 ...
## $ AGE : int 53 26 59 56 74 56 63 34 37 30 ...
## $ EDUC : int 16 16 13 16 17 17 12 17 10 15 ...
## $ SEX : int 1 2 1 2 2 2 1 1 2 2 ...
## $ RACE : int 1 1 1 1 1 1 1 1 1 3 ...
## $ INCOM16 : int 2 3 2 2 4 4 2 3 3 1 ...
## $ INCOME : int 12 12 12 12 13 12 13 12 10 12 ...
## $ RINCOME : int 12 12 0 9 0 12 13 12 0 12 ...
## $ INCOME72: int 0 0 0 0 0 0 0 0 0 0 ...
## $ PARTYID : int 5 5 6 5 3 6 6 8 3 3 ...
## $ FINRELA : int 4 4 2 4 3 4 9 3 2 3 ...
## $ SEXORNT : int 3 3 3 3 3 9 0 0 3 3 ...
## - attr(*, "col.label")= chr "Gss year for this respondent" "Respondent"
```

32 Obviously, this is less than ideal. Now, all the factor variables are encoded as integers, but their level  
 33 labels have been lost. We have to look at a codebook to determine if SEX == 1 indicates male or female.  
 34 We would rather preserve the integrated level labels. In order to do this, our best option is to download  
 35 the data as an Excel file and use the **readxl** package to load it.

```
library(readxl)
GSS <- read_excel("../data/GSS.xls")
str(GSS)

## Classes 'tbl_df', 'tbl' and 'data.frame': 2540 obs. of 17 variables:
## $ Gss year for this respondent : num 2014 2014 2014 2014 2014 ...
## $ Respondent id number : num 1 2 3 4 5 6 7 8 9 10 ...
## $ Labor force status : chr "Working fulltime" "Working fulltime" ...
## $ Rs occupational prestige score (1970) : num 0 0 0 0 0 0 0 0 0 0 ...
## $ Marital status : chr "Divorced" "Married" "Divorced" "Married" ...
## $ Number of children : num 0 0 1 2 3 1 2 2 4 3 ...
## $ Age of respondent : chr "53.000000" "26.000000" "59.000000" ...
## $ Highest year of school completed : num 16 16 13 16 17 17 12 17 10 15 ...
## $ Respondents sex : chr "Male" "Female" "Male" "Female" ...
## $ Race of respondent : chr "White" "White" "White" "White" ...
## $ Rs family income when 16 yrs old : chr "Below average" "Average" "Below average" ...
## $ Total family income : chr "$25000 or more" "$25000 or more" ...
## $ Respondents income : chr "$25000 or more" "$25000 or more" ...
## $ Total family income : chr "Not applicable" "Not applicable" ...
## $ Political party affiliation : chr "Not str republican" "Not str republican" ...
## $ Opinion of family income : chr "Above average" "Above average" ...
## $ Sexual orientation : chr "Heterosexual or straight" "Heterosexual or straight" ...

GSS <- GSS[, -14]
```

36 That's a little better. Now we have preserved the character strings. But, the data is not yet useable in  
 37 an analysis.

## 38 RENAMING THE VARIABLES

39 One problem is that the variable names (while human readable) are full of spaces, so are hard to use. But,  
 40 we can rename them. The `rename()` function in the **dplyr** package is a good way to do this.

```
library(dplyr)

GSS <- GSS %>%
  rename(LaborStatus = `Labor force status`) %>%
  rename(PolParty = `Political party affiliation`) %>%
  rename(Age = `Age of respondent`)
```

## 41 CONSIDERING SOME FACTOR VARIABLES

42 Once we have variable names that are easier to work with, we can begin to think about how the data  
43 should be cleaned.

```
GSS <- GSS %>%
  mutate(LaborStatus = factor(LaborStatus)) %>%
  mutate(PolParty = factor(PolParty))

levels(GSS$LaborStatus) # I wish I had a piece of dplyr code for this

## [1] "Keeping house"      "No answer"          "Other"
## [4] "Retired"            "School"              "Temp not working"
## [7] "Unempl, laid off"   "Working fulltime"    "Working parttime"

levels(GSS$PolParty)

## [1] "Don't know"          "Ind,near dem"        "Ind,near rep"
## [4] "Independent"         "No answer"           "Not str democrat"
## [7] "Not str republican"  "Other party"         "Strong democrat"
## [10] "Strong republican"
```

## 44 CHANGING THE LABELS OF FACTORS (BASE R)

45 One action you might want to take is just to change the text of one (or more) of the factor labels, so it  
46 appears more nicely formatted in a **ggplot2** plot, for example.

47 Here is how I do that in base R. Typically, I end up ruining something in the process of doing this, so I  
48 *\*always\** start with a summary call, to check after I have done my attempt.

```
summary(GSS$LaborStatus)

##      Keeping house      No answer      Other      Retired
##           263           2           76           460
##      School Temp not working Unempl, laid off Working fulltime
##           90           40           104           1230
## Working parttime      NA's
##           273           2

levels(GSS$LaborStatus) <- c(levels(GSS$LaborStatus)[1:5],
                             "Temporarily not working",
                             "Unemployed, laid off",
                             "Working full time",
                             "Working part time")

summary(GSS$LaborStatus)

##      Keeping house      No answer      Other
##           263           2           76
##      Retired      School Temporarily not working
##           460           90           40
## Unemployed, laid off Working full time Working part time
##           104           1230           273
##      NA's
##           2
```

## 49 CHANGING THE LABELS OF FACTORS (DPLYR)

50 In **dplyr**, you can use the `recode` function to do the same thing. There are a few things to remember  
51 with `recode`. The first is that it is a vector function, which means it must be used within a `mutate` call  
52 or with a variable pulled out using `$`. The second is that you need to tell it which variable to recode, even  
53 if you are overwriting an existing variable.

```
GSS <- GSS %>%
  mutate(PolParty = recode(PolParty, `Not str republican` = "Not a strong republican"))
```

## 54 COMBINING SEVERAL LEVELS INTO ONE

55 This is another common task. Maybe you want fewer coefficients to interpret in your model, or the process  
56 that generated the data makes a finer distinction between categories than your research. For whatever the  
57 reason, you want to group together levels that are currently separate.  
58 How I do this in base R:

```
levels(GSS$LaborStatus) <- c("Not employed", "No answer",  
                             "Other", "Not employed",  
                             "Not employed", "Not employed",  
                             "Not employed", "Employed", "Employed")  
  
summary(GSS$LaborStatus)  
  
## Not employed    No answer      Other      Employed      NA's  
##           957           2           76          1503           2
```

## 59 1 MOSAIC COMBINING LEVELS

```
library(mosaic)  
data(Births78)  
Births78 <- Births78 %>%  
  mutate(weekend = derivedFactor(weekend = wday== "Sun" | wday == "Sat", .default="weekday"))
```

## 60 COMBINING MANY CATEGORIES INTO ONE

61 In this data, age is provided as an integer for respondents 18-88, but then also includes the possible answer  
62 "89 or older" as well as a possible "No answer" and NA values.

```
GSS <- GSS %>%  
  mutate(Age = factor(Age))  
summary(GSS$Age)  
  
## 18.000000 19.000000 20.000000 21.000000 22.000000 23.000000  
##      6      25      26      24      28      30  
## 24.000000 25.000000 26.000000 27.000000 28.000000 29.000000  
##    31     48     47     41     31     51  
## 30.000000 31.000000 32.000000 33.000000 34.000000 35.000000  
##    57     49     55     47     46     40  
## 36.000000 37.000000 38.000000 39.000000 40.000000 41.000000  
##    40     54     47     52     46     54  
## 42.000000 43.000000 44.000000 45.000000 46.000000 47.000000  
##    35     54     39     41     34     43  
## 48.000000 49.000000 50.000000 51.000000 52.000000 53.000000  
##    32     39     54     45     37     60  
## 54.000000 55.000000 56.000000 57.000000 58.000000 59.000000  
##    53     52     60     43     60     47  
## 60.000000 61.000000 62.000000 63.000000 64.000000 65.000000  
##    46     38     44     42     38     40  
## 66.000000 67.000000 68.000000 69.000000 70.000000 71.000000  
##    35     41     21     23     32     28  
## 72.000000 73.000000 74.000000 75.000000 76.000000 77.000000  
##    20     22     25     21     24     17  
## 78.000000 79.000000 80.000000 81.000000 82.000000 83.000000  
##    28     26     16     14     8     11  
## 84.000000 85.000000 86.000000 87.000000 88.000000 89 or older  
##    13      6      9      8     11     19  
## No answer      NA's  
##      9      2
```

63 We might want to turn this into a factor variable with two levels: 18-65, and over 65. In this case, it  
64 would be much easier to deal with a conditional statement about the numeric values, rather than writing  
65 out each of the numbers as a character vector.  
66 But, in order to do that we need to make it numeric.

```
# GSS$Age[GSS$Age == "No answer"] <- NA # Do I really need this? Nope!
levels(GSS$Age) <- c(levels(GSS$Age)[1:71], "89", "No answer")
GSS$Age <- as.numeric(as.character(GSS$Age))
summary(GSS$Age)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
##    18.00   34.00   49.00   49.01   62.00   89.00    11
```

Of course, we're cheating a little bit here— if we were going to use this as a numeric variable in an analysis, we wouldn't necessarily want to turn all the "89 or older" cases into the number "89". But, we're just on our way to a two-category factor, so those cases would have gone to the "65 and up" category one way or the other.

```
GSS <- GSS %>%
  mutate(Age = if_else(Age < 65, "18-65", "65 and up")) %>%
  mutate(Age = factor(Age))
summary(GSS$Age)

##      18-65 65 and up    NA's
##      2011      518      11
```

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## REFERENCES

Peng, R. D. (2015). stringsAsFactors: An unauthorized biography.  
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