

Identifying Drug Overdose Hospitalization With R

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October 20, 2017

The Hospital Discharge Dataset

The analytic steps below will use the dataset `hosp10_16` for illustration which has a total(included non-overdose) of 4343217 hospital discharges with the following variables:

```
names(hosp10_16)
```

```
[1] "id"          "age"          "dis_date"     "diag1"        "ecode1"
[6] "ecode2"      "ecode3"       "ecode4"       "ecode5"       "ecode6"
[11] "ecode7"      "ecode8"       "ecode9"       "year"         "fisc_year"
[16] "quarters"
```

Which are *unique id*, *age in years*, *discharge date*, *principal diagnosis*, *E code 1 to 9*, *year of discharge*, *federal fiscal year*, and *quarters*.

See a sample of the data:

```
set.seed(14)
hosp10_16 %>% sample_n(7)
```

	id	age	dis_date	diag1	ecode1	ecode2	ecode3	ecode4
1103324	e3f942633aaf	59	2011-10-15	9961	E8791			
2770222	a097ffa53dca	57	2014-07-29	V5789	<NA>	<NA>	<NA>	<NA>
4157277	ad7c8ee20be2	42	2016-09-15	F259	<NA>	<NA>	<NA>	<NA>
2399829	266b78a1bbcd	94	2013-11-05	2851	<NA>	<NA>	<NA>	<NA>
4269670	0c03ffe4d51a	28	2016-11-15	0641XX0	<NA>	<NA>	<NA>	<NA>
2221440	bbcbd4ec70b4	31	2013-09-20	65651	<NA>	<NA>	<NA>	<NA>
4051449	29aca807c735	71	2016-07-15	I6521	<NA>	<NA>	<NA>	<NA>
	ecode5	ecode6	ecode7	ecode8	ecode9	year	fisc_year	quarters
1103324						2011	2012	4
2770222	<NA>	<NA>	<NA>	<NA>	<NA>	2014	2014	3
4157277	<NA>	<NA>	<NA>	<NA>	<NA>	2016	2016	3
2399829	<NA>	<NA>	<NA>	<NA>	<NA>	2013	2014	4
4269670	<NA>	<NA>	<NA>	<NA>	<NA>	2016	2017	4
2221440	<NA>	<NA>	<NA>	<NA>	<NA>	2013	2013	3
4051449	<NA>	<NA>	<NA>	<NA>	<NA>	2016	2016	3

Analytic Steps

Since the finding of first valid E-codes applies only to pre ICD-10 CM data, we first divide the dataset into fiscal year before 2016 and fiscal from 2016. In the first subset we create a new variable `valid_ecode1` that contains the value of the first *valid E-code* for each observation. The `valid_ecode1` will eventually replace `ecode1` in the final dataset used for the rest of the analysis.

The analysis relies on `tidyverse`, a collection of R packages that includes `dplyr`, `tidyr` and `purrr`. The functions `nest()` and `unnest()` are from `tidyr` and `map()` from `purrr`.

We wrote additional functions mostly saved in the package `overdoser`. See the notes section below for more details on functions and packages.

Preferably start the analysis from **RStudio** then run:

```
# install.packages("tidyverse") # to unquote if
# tidyverse was not installed
library(tidyverse)
library(overdoser) # if you have chosen to install the whole
#package ( It is not necessary. See the notes below)
```

1. Create the ICD-9-CM data subset

We assume all the data before October 1, 2015 were coded in ICD-9-CM only. The new dataset, `hosp10_16_icd9` has a federal fiscal year of 2015 or earlier:

```
hosp10_16_icd9 <- hosp10_16 %>%
  filter(fisc_year < 2016) %>%
  select(id, ecode1:ecode9)
```

2. Define a first valid E-code column

We re-define the valid E-code to match, using the regular expressions (regex):

```
"^(?! (? : E0 [0-2] | E030 | E849 | E967 | E8694 | E87 | E9 [34] )) (? : \\w+ | $)"
```

The whole expressions try to match the ICD-9 code that is not “E000–E030, E849, E967, E869.4, E870–E879, or E930–E949”. Thanks to the *negative lookahead* syntax (`?! ...`). The function `valid_f()` wraps the regex, for use throughout the data to find the first valid E-code.

```
valid_f <- function(x){
  grep("^(?! (? : E0 [0-2] | E030 | E849 | E967 | E8694 | E87 | E9 [34] )) (? : \\w+ | $)",
    x , perl = T, value = T, ignore.case = T)[1]
}
```

Nesting each observation E-codes and list the first valid code or empty cell, and create the new variable `valid_ecode1`. It is done by combining `tidyr::nest()`, `purrr::map` and `dplyr::mutate()`.

```
hosp10_16_icd9 <- hosp10_16_icd9 %>%
  group_by(id) %>%
  nest(.key = first_valid) %>%
  mutate(valid_ecode1 = map(first_valid, valid_f)) %>%
  unnest()
```

Below is the result:

```
Hmisc::describe(hosp10_16_icd9$valid_ecode1)
```

```
hosp10_16_icd9$valid_ecode1
      n missing distinct
274582  3286315      685
```

```
lowest : E103 E2970 E4373 E5435 E5589, highest: E9959 E9972 E9978 E9990 E9991
```

3. Create variables for the drug of interest in the ICD-9-CM subset data

All the definitions for `any_drug`, `any_opioid`, `non_heroin_opioid` and `heroin` are written with regex. the function `overdoser::od_create_diag()` is used to match the *regex* and create the new variables, `any_drug`, `any_opioid`, `non_heroin_opioid` and `heroin`.

They are strictly based on the ICD-9-CM and the criteria defined in the CDC’s Provisional Transition Guidance except that the first valid E-code `valid_ecode1`(column 12 for this dataset) was used instead of

the first ecode, and the principal diagnosis was in column 2. That explains the argument `colvec = c(2,12)` in the function `od_create_diag`.

```
hosp10_16_icd9 <- hosp10_16_icd9 %>%
  left_join(hosp10_16 %>% select(id, diag1))

hosp10_16_icd9 <- hosp10_16_icd9 %>%
  mutate(
    any_drug = od_create_diag(.,
      expr = "^9[67]|^E85[0-8]|^E950[0-5]|^E9620|^E980[0-5]",
      colvec = c(2,12)),
    any_opioid = od_create_diag(.,
      expr = "^9650[0129]|^E850[012]",
      colvec = c(2,12)),
    non_heroin_opioid = od_create_diag(.,
      expr = "^9650[029]|^E850[12]",
      colvec = c(2,12)),
    heroin = od_create_diag(.,
      expr = "^96501|^E8500",
      colvec = c(2,12)))
```

4. Complete the ICD-9-CM dataset

The dataset was renamed `hosp10_15icd9`, the `ecode1` values replaced with `valid_ecode1` values, and other variables from the original file added.

```
hosp10_15icd9 <- hosp10_16_icd9 %>%
  select(id, diag1, valid_ecode1, any_drug,
    any_opioid, non_heroin_opioid, heroin) %>%
  left_join(hosp10_16 %>%
    select(id, age, year, dis_date, quarters, fisc_year)) %>%
  rename(ecode1 = valid_ecode1)
```

5. Create variables for the drug of interest in the ICD-10-CM subset data

Similarly to the process described in section-3, the ICD-10-CM definitions for `any_drug`, `any_opioid`, `non_heroin_opioid` and `heroin` are written with regex.

```
hosp16_icd10 <- hosp10_16 %>%
  filter(fisc_year > 2015) %>%
  mutate(
    any_drug = od_create_diag(.,
      expr = "^(?! (T3[679]9|T414|T427|T4[3579]9)) (T3[6-9]|T4[0-9]|T50) . .
      (1|2|3|4) (A|D|$) | ((T3[679]9|T414|T427|T4[3579]9) (1|2|3|4) . (A|D|$))",
      colvec = c(4)),
    any_opioid = od_create_diag(.,
      expr = "(T40[01234] . |T406[09]) (1|2|3|4) (A|D|$)",
      colvec = c(4)),
    non_heroin_opioid = od_create_diag(.,
      expr = "(T40[0234] . |T406[09]) (1|2|3|4) (A|D|$)",
      colvec = c(4)),
    heroin = od_create_diag(.,
      expr = "T401 . (1|2|3|4) (A|D|$)",
      colvec = c(4)))
```

6. Combining icd9 and icd10 subsets and keeping only drug overdose cases

The new combined dataset is restricted to the 41410 cases of drug overdose from the data.hosp10_16

```
hosp10_16drug <- hosp10_15icd9 %>%  
  bind_rows(hosp16_icd10[names(hosp10_15icd9)]) %>%  
  filter(any_drug == 1)
```

7. Adding the age groups and intents

Adding 11 age groups and intent. c(2,3) indicates the indices of the the principal diagnosis (diag1) and the first valid ecde (ecode1 now)

```
hosp10_16drug <- hosp10_16drug %>%  
  overdoser::od_age11(age = age) %>%  
  overdoser::od_intent_trans(  
    diag_ecode_col = c(2,3), date = dis_date)
```

New variables created with the functions od_age11 and od_intent_trans from the package overdoser. If installed, see help file for more details.

```
?od_age11  
?od_intent_trans
```

This is the final list of variables

```
names(hosp10_16drug)
```

```
[1] "id"           "diag1"        "ecode1"  
[4] "any_drug"     "any_opioid"   "non_heroin_opioid"  
[7] "heroin"       "age"          "year"  
[10] "dis_date"     "quarters"     "fisc_year"
```

agegrp11 is a numeric vector of 11 age group, age11 is its character version, and intent_drugs the intent which values are 1, 2, 3, and 4, defining respectively *unintentional*, *self-harm*, *assault* and *underdetermined*. Intent may be missing for the ICD-9-CM cases.

8. Filter and Count

The function count from the package dplyr(part of the tidyverse collection) is a combination of grouping by the selected variables then counting the cases.

```
drug_table <- hosp10_16drug %>%  
  count(year, quarters, age11, intent_drugs,  
         any_drug, non_heroin_opioid, heroin)
```

This is a sample of the resulting table:

```
set.seed(5)  
drug_table %>%  
  sample_n(10) %>%  
  print.data.frame()
```

	year	quarters	age11	intent_drugs	any_drug	non_heroin_opioid	heroin	n
1	2011	2	45-54	4	1	0	0	16
2	2014	3	45-54	1	1	1	1	1
3	2016	2	15-24	1	1	0	1	15

4	2011	4 75-84	2	1	1	0	2
5	2010	3 75-84	4	1	1	0	1
6	2014	3 75-84	NA	1	0	0	3
7	2013	3 25-34	NA	1	0	1	1
8	2015	2 65-74	2	1	1	0	2
9	2016	3 25-34	3	1	0	0	1
10	2010	4 01-04	NA	1	0	0	1

Note that pre-2016 fiscal year data allow missing intent, but 2016 onward data with ICD-10-CM criteria do not.

See the functions `replace_na` and `complete` from the package **tidyr** (included in *tidyverse*) to have a more complete table of all the group combination even when there are missing counts.

Notes on the R codes

R is an *object-oriented* and *functional* programming language. So as John M. Chambers wrote it:

*Everything that exists in **R** is an **object** and everything that happens in **R** is a **function call**.*¹

That's why data analysis workflow in **R** uses extensively packages, which are collections of functions, data and documentation. That approach saves time, minimizes errors and eases reproducibility.

Throughout this analysis We used:

- The package **dplyr**, **tidyr** and **purrr** from the **tidyverse** package set. You can install **tidyverse** then load it with:

```
install.packages("tidyverse")
library(tidyverse)
```

The ubiquitous **dplyr** offers a set of simple and fast functions to streamline data manipulation with **sql-like** style and pipes(`%>%`).

- An openly accessible personal package **overdoser**(overdose R) at **GitHub**. It contains functions, used in this analysis, and other useful functions for hospitalization and death data primarily relative to drug overdose. It is a work in progress. To install and run the package **overdoser**, use these lines of codes:

```
install.packages("devtools")
devtools::install_github("injuryepi/overdoser")
library(overdoser)
```

The package has some documentation you can access by typing `?overdoser::` followed by the function name.

However installing the **overdoser** package is not necessary. You can simply copy and paste the functions of interest from the package GitHub site, in the R folder.

In the instances where we used functions outside of **base R** and **dplyr**, we often prefixed the functions with `package_name::` (e.g. `overdoser::od_age11()`)

The function `od_intent_trans`, uses the argument `date` to apply the ICD-9-CM intent definition to pre fiscal year 2016 cases, ICD-10-CM intent definition for the rest. If you are using dataset with *ICD-9-CM only* or *ICD-10-CM only*, use respectively the functions `od_intent_icd9cm()` or `od_intent_icd10cm()` from the **overdoser** package.

The noticeable aspect of the **overdoser** functions is the use of regular expressions(regex) based on **Perl**. For example the regex below(without space) concisely fulfills all the criteria that define drug overdose for ICD-10-CM: `"^(?! (T3[679]9|T414|T427|T4[3579]9)) (T3[6-9]|T4[0-9]|T50) . . (1|2|3|4) (A|D|$) | ((T3[679]9|T414|T427|T4[3579]9) (1|2|3|4) . (A|D|$))"`

¹Chambers, JM, *Extending R*

The expression `(?!...)` a *negative lookahead*, allows the temporary exclusion of the drug ICD-10-CM codes that have intent defined in the *fifth position* `(T3[679]9|T414|T427|T4[3579]9)`, and later use them when indicated. You can test the regex with base R function `grep`.