medicalrisk: Calculating risk and comorbidities from ICD-9-CM codes

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Introduction

The routines in the **medicalrisk** package (McCormick and Joseph 2015) are designed to help determine comorbidity and medical risk status of a given patient using several popular models published in the peer-reviewed literature

Administrative healthcare data is frequently the only available source for determining individual risk of mortality when looking at thousands or millions of patient records. Medical chart abstraction just isn't feasible for projects of this scale.

In the United States, the records for every inpatient and outpatient encounter is reviewed by a qualified medical coder who assigns a set of diagnosis and procedural codes based on phrases within the medical record. The coding system currently in use is LCD-9-CM. ICD-9-CM is an adaptation of the venerable ICD-9 standard which was developed in 1978. The U.S. National Center for Health Statistics (NCHS) developed ICD-9-CM, which has been required for Medicare and Medicaid claims since 1979. ICD-9-CM is updated annually.

At some point, perhaps as soon as October 2015, ICD-10-CM codes will need to be used instead. It is likely that "dual coding" of claims in both sets will continue for some time.

In the meantime, there is a wealth of administrative data available within the ICD-9-CM diagnostic and procedural codes stored within US healthcare systems.

Working with ICD-9-CM Data

In order to demonstrate this package, this package includes data on 100 patients from the <u>Vermont Uniform Hospital Discharge Data Set for 2011, Inpatient.</u>

```
library(medicalrisk)
library(plyr)
data(vt_inp_sample)
x <- count(vt_inp_sample, c('id'))</pre>
cat("average count of ICD codes per patient is: ", mean(x$freq))
## average count of ICD codes per patient is: 11.52
y <- count(vt_inp_sample, c('icd9cm'))</pre>
kable(head(y[order(-y$freq),], n=5), row.names=F,
      caption='Top 5 most popular ICD-9-CM codes in this dataset')
                                               Top 5 most
                                             popular ICD-9-
                                              CM codes in
                                               this dataset
                                             icd9cm freq
                                             D4019
                                                         34
                                             D53081
                                                        22
                                             D2724
                                                         19
                                             D3051
                                                         18
```

Within this package, ICD-9-CM codes are presented as a string where the first letter is "P" or "D" depending on whether the code is Procedure or Diagnosis. The rest of the code is present as a string of numbers. Periods are omitted. In the list above, the code "D4019" is diagnostic code 401.9 which corresponds to Hypertension.

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D25000

Comorbidity Maps

The package includes a set of mapping functions that transform a list of ICD-9-CM codes into a comorbidity matrix:

- o icd9cm_charlson_deyo
- o icd9cm_charlson_romano

- icd9cm_charlson_quan
- o icd9cm elixhauser ahrq37
- o icd9cm_elixhauser_quan
- icd9cm_rcri

"Charlson" refers to the Charlson Comorbidity Index(Charlson et al. 1987).

The names "Deyo" (Deyo, Cherkin, and Ciol 1992), "Romano" (Romano, Roos, and Jollis 1993), and "Quan" (Quan et al. 2005) refer to the primary authors of different methods of determining Charlson comorbidities from ICD-9-CM codes.

"Elixhauser" refers to the Elixhauser comorbidity map, which is a more detailed list than Charlson. "AHRQ37" is an adapation of the AHRQ version 37 software(Agency for Healthcare Research & Quality 2013). "Quan" refers to the same paper by Quan mentioned above.

"RCRI" is the Revised Cardiac Risk Index(Lee et al. 1999) set of categories using a method published by Boersma(Boersma et al. 2005).

For example, the #5 ICD-9-CM code above is D25000, or "250.00", which is for "Diabetes Mellitus Unspecified Type". Here's what happens when that code is passed to a few of the mapping functions listed above:

```
kable(
  icd9cm_charlson_quan(c('D25000')))
```

	mi	chf	perivasc	cvd	dementia	chrnlung	rheum	ulcer	liver	dm	dmcx	para	renal	tumor	modli
D25000	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
kable(m elixhau	ser ahro	37(c('D250	00')))											
20070			37 (6(3230	,,,,											

```
chf arrhythmia valve pulmcirc perivasc htn htncx para neuro chrnlung dm dmcx hypothy renlfail

D25000 FALSE FALSE
```

For each of these maps the "dm" column becomes TRUE.

The most efficient way to use these maps for a set of patients is to generate a single map for all ICD-9-CM codes in the set and then apply that map to each patient. Here's an example that generates a comorbidity matrix for the first five patients in the Vermont dataset:

```
cases <- vt_inp_sample[vt_inp_sample$id %in% 1:5, c('id','icd9cm')]
cases_with_cm <- merge(cases, icd9cm_charlson_quan(levels(cases$icd9cm)),
    by.x="icd9cm", by.y="row.names", all.x=TRUE)

# generate crude comorbidity summary for each patient
kable(
    ddply(cases_with_cm, .(id),
    function(x) { data.frame(lapply(x[,3:ncol(x)], any)) }),
    row.names=F)</pre>
```

id	mi	chf	perivasc	cvd	dementia	chrnlung	rheum	ulcer	liver	dm	dmcx	para	renal	tumor	modliver
1	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
3	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
4	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE	FALSE	FALSE
5	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE								

The above process is encapsulated in a single function <code>generate_comorbidity_df</code>. This function also includes an optimization from Van Walraven that reduces <code>dmcx</code> to <code>dm</code> if the specific diabetic complication is separately coded.

```
kable(
  generate_comorbidity_df(cases, icd9mapfn=icd9cm_charlson_quan))
```

id	mi	chf	perivasc	cvd	dementia	chrnlung	rheum	ulcer	liver	dm	dmcx	para	renal	tumor	modliver
1	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
3	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

4 FALSE FALSE FALSE	FALSE FALSE	FALSE	FALSE FALSE FALSE TRUE FALSE FALSE TRUE FALSE
5 FALSE FALSE FALSE	FALSE FALSE	TRUE	FALSE FALSE FALSE FALSE FALSE FALSE FALSE

This function only considers each ICD-9-CM code once and then merges the resulting comorbidity flags together for each patient. This makes the function quite fast for large data sets.

Given appropriate arguments, the <code>generate_comorbidity_df</code> function will use the parallel backend provided by <code>foreach</code> to improve performance.

Comorbidity Index

It is common in the medical literature to see a set of comorbidities reduced to an index. When the Charlson Comorbidity Index was first published it had the following weights for each comorbidity:

```
data(charlson_weights_orig)
kable(
   t(charlson_weights_orig))
```

mi	chf	perivasc	cvd	dementia	chrnlung	rheum	ulcer	liver	dm	dmcx	para	renal	tumor	modliver	mets	aids
1	1	1	1	1	1	1	1	1	1	2	2	2	2	3	6	6

However, these weights have not stood the test of time. For example, the prognosis for HIV/AIDS has dramatically improved.

The medicalrisk package offers the revised Charlson weights developed by Schneeweiss(Schneeweiss et al. 2003):

```
data(charlson_weights)
kable(
  t(charlson_weights))
```

mi	chf	perivasc	cvd	dementia	chrnlung	rheum	ulcer	liver	dm	dmcx	para	renal	tumor	modliver	mets	aids
1	2	1	1	3	2	0	0	2	1	2	1	3	2	4	6	4

The generate_charlson_index_df function will sum the weights for each patient to generate a final index:

```
kable(
   generate_charlson_index_df(generate_comorbidity_df(cases)), row.names=F)
```

id	index
1	2
2	0
3	0
4	4
5	2

Risk Stratification Index

The Risk Stratification Index uses ICD-9-CM codes to determine four risk estimates:

- 1 Year Mortality
- o 30 Day Mortality
- In-Hospital Mortality
- 30 Day Length of Stay

The author of the paper (Sessler) published SPSS code to perform the calculation. The medicalrisk implements the RSi calculation using a method based on the SPSS code.

```
ddply(cases, .(id), function(x) { icd9cm_sessler_rsi(x$icd9cm) } )

## id rsi_1yrpod rsi_30dlos rsi_30dpod rsi_inhosp
## 1 1 -2.0186043  0.1560323  -1.699242 -1.8483037
## 2 2 -4.1423990  0.8927947  -3.802495 -3.5425015
## 3 3 -2.6265277  0.8311247  -2.910939 -2.8607594
## 4 4 -0.7984382  0.3357922  -1.551285 -0.2669842
## 5 5 2.5803930 -1.7904270  2.455086  1.7615180
```

Conclusion

above discussion describes basic use of the package. There are some additional helper functions not described above which are included in the per function documentation.

The aim of this package is to include future medical risk estimation procedures as they are published in the

References

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