

mini proj wk8-9

Aaron Palumbo

October 23, 2015

Dependencies

```
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

# global chunk options
knitr::opts_chunk$set(warning=FALSE)
```

Data

We're going to work with a dataset from the UCI Machine Learning Repository on diabetes patients (<https://archive.ics.uci.edu/ml/datasets/Diabetes+130-US+hospitals+for+years+1999-2008>).

```
dd <- read.csv("dataset_diabetes/diabetic_data.csv",
               stringsAsFactors = FALSE, na.strings = "?")
# Right away we can get rid of columns without much info
dd = dd[, -caret::nearZeroVar(dd)]

# We can also drop any id columns, since those should be
# unique identifiers and not useful for clustering
idCols <- c("encounter_id", "patient_nbr")
dd = dd[, !(names(dd) %in% idCols)]
```

Data Cleaning

We are going to apply the hamming distance to these points so we want to convert all our columns to categorical data (factors). Let's take a look at what we have to start with.

```
getInfo <- function(dd) {
  return(do.call(rbind, lapply(names(dd), function(n) {
    data.frame(name=n,
               firstrow=dd[1, n],
```

```

        class=class(dd[1, n]),
        numfactors=length(table(dd[,n])))
    })))
}

getInfo(dd)

```

##	name	firstrow	class	numfactors
## 1	race	Caucasian	character	5
## 2	gender	Female	character	3
## 3	age	[0-10)	character	10
## 4	weight	<NA>	character	9
## 5	admission_type_id	<NA>	integer	8
## 6	discharge_disposition_id	<NA>	integer	26
## 7	admission_source_id	<NA>	integer	17
## 8	time_in_hospital	<NA>	integer	14
## 9	payer_code	<NA>	character	17
## 10	medical_specialty	Pediatrics-Endocrinology	character	72
## 11	num_lab_procedures	<NA>	integer	118
## 12	num_procedures	<NA>	integer	7
## 13	num_medications	<NA>	integer	75
## 14	number_outpatient	<NA>	integer	39
## 15	number_emergency	<NA>	integer	33
## 16	number_inpatient	<NA>	integer	21
## 17	diag_1	250.83	character	716
## 18	diag_2	<NA>	character	748
## 19	diag_3	<NA>	character	789
## 20	number_diagnoses	<NA>	integer	16
## 21	A1Cresult	None	character	4
## 22	metformin	No	character	4
## 23	glipizide	No	character	4
## 24	glyburide	No	character	4
## 25	pioglitazone	No	character	4
## 26	rosiglitazone	No	character	4
## 27	insulin	No	character	4
## 28	change	No	character	2
## 29	diabetesMed	No	character	2
## 30	readmitted	NO	character	3

Now there are four columns that need to be binned to be useful.

```

numBins <- 21
colsToBin <- c("num_lab_procedures", "diag_1", "diag_2", "diag_3")
for (c in colsToBin){
  vec <- as.integer(dd[,c])
  from <- min(vec, na.rm=TRUE)
  to <- max(vec, na.rm=TRUE)
  bins <- seq(from, to, length.out=numBins)
  binned <- cut(vec, breaks=bins)
  # we'll make this a factor a little later
  binned <- as.character(binned)
  dd[,c] <- binned
}

```

```
# let's look at our summary again
getInfo(dd)
```

##	name	firstrow	class	numfactors
## 1	race	Caucasian	character	5
## 2	gender	Female	character	3
## 3	age	[0-10)	character	10
## 4	weight	<NA>	character	9
## 5	admission_type_id	<NA>	integer	8
## 6	discharge_disposition_id	<NA>	integer	26
## 7	admission_source_id	<NA>	integer	17
## 8	time_in_hospital	<NA>	integer	14
## 9	payer_code	<NA>	character	17
## 10	medical_specialty	Pediatrics-Endocrinology	character	72
## 11	num_lab_procedures	(40.3,46.9]	character	20
## 12	num_procedures	<NA>	integer	7
## 13	num_medications	<NA>	integer	75
## 14	number_outpatient	<NA>	integer	39
## 15	number_emergency	<NA>	integer	33
## 16	number_inpatient	<NA>	integer	21
## 17	diag_1	(202,252]	character	20
## 18	diag_2	<NA>	character	20
## 19	diag_3	<NA>	character	20
## 20	number_diagnoses	<NA>	integer	16
## 21	A1Cresult	None	character	4
## 22	metformin	No	character	4
## 23	glipizide	No	character	4
## 24	glyburide	No	character	4
## 25	pioglitazone	No	character	4
## 26	rosiglitazone	No	character	4
## 27	insulin	No	character	4
## 28	change	No	character	2
## 29	diabetesMed	No	character	2
## 30	readmitted	NO	character	3

Last, we will treat all the NAs as a factor category by replacing with 'missing' and then coercing each column to a factor.

```
for (c in names(dd)) {
  vec <- dd[,c]
  vec[is.na(vec)] <- "missing"
  dd[,c] <- as.factor(vec)
}
```

```
getInfo(dd)
```

##	name	firstrow	class	numfactors
## 1	race	Caucasian	factor	6
## 2	gender	Female	factor	3
## 3	age	[0-10)	factor	10
## 4	weight	missing	factor	10
## 5	admission_type_id	6	factor	8

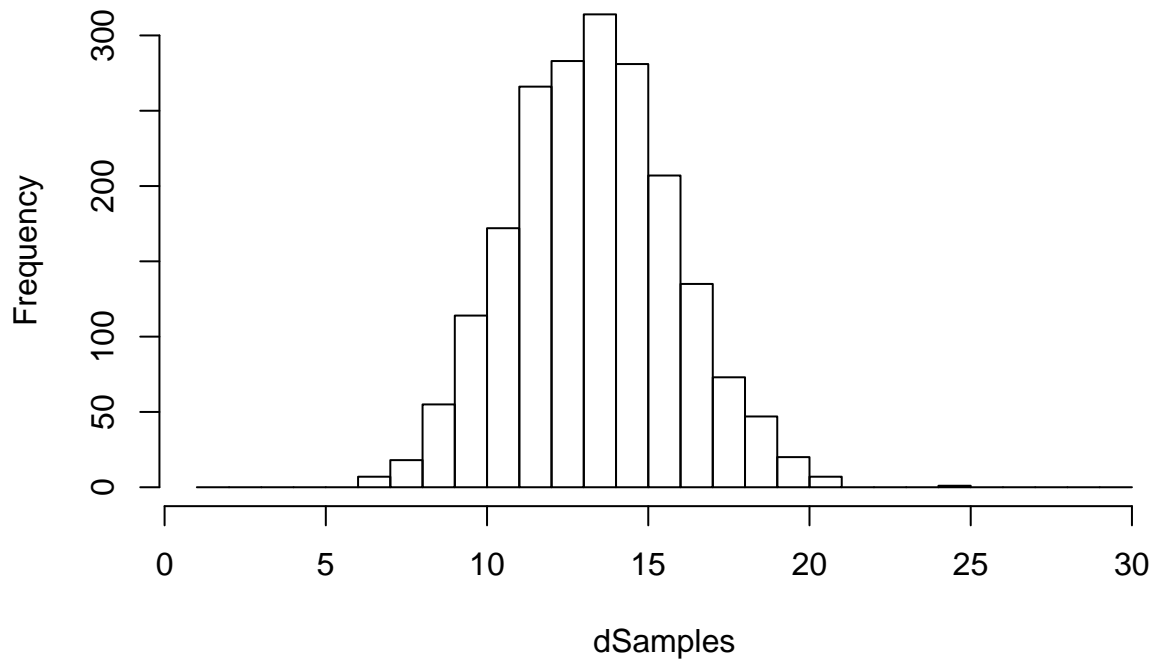
## 6	discharge_disposition_id	25	factor	26
## 7	admission_source_id	1	factor	17
## 8	time_in_hospital	1	factor	14
## 9	payer_code	missing	factor	18
## 10	medical_specialty	Pediatrics-Endocrinology	factor	73
## 11	num_lab_procedures	(40.3,46.9]	factor	21
## 12	num_procedures	0	factor	7
## 13	num_medications	1	factor	75
## 14	number_outpatient	0	factor	39
## 15	number_emergency	0	factor	33
## 16	number_inpatient	0	factor	21
## 17	diag_1	(202,252]	factor	21
## 18	diag_2	missing	factor	21
## 19	diag_3	missing	factor	21
## 20	number_diagnoses	1	factor	16
## 21	A1Cresult	None	factor	4
## 22	metformin	No	factor	4
## 23	glipizide	No	factor	4
## 24	glyburide	No	factor	4
## 25	pioglitazone	No	factor	4
## 26	rosiglitazone	No	factor	4
## 27	insulin	No	factor	4
## 28	change	No	factor	2
## 29	diabetesMed	No	factor	2
## 30	readmitted	NO	factor	3

Now let's get an idea of the distribution of distances we have.

```
hamDist <- function(r1, r2) {
  # The hamming distance between two rows
  return(sum(r1 == r2))
}

# We can't compute the distance between all points
# so we will just sample a large number of distances
nSamples <- 2000
n <- nrow(dd)
dSamples <- unlist(lapply(1:nSamples, function(i) {
  s <- sample(1:n, 2)
  hamDist(dd[s[1], ], dd[s[2],])
}))
hist(dSamples, breaks=1:30)
```

Histogram of dSamples



Initializing the Cluster Tree

Okay, I think we can handle about 100 points in main memory (this creates about 5000 combinations). So let's go ahead and sample from our data and create some clusters.

```
# ##### #
# Functions #
# ##### #

hamDist <- function(r1, r2) {
  # The hamming distance between two rows
  return(sum(r1 == r2))
}

nextPoint <- function(clusters, dist.df,
                      index1='index1', index2='index2',
                      dist.col='dist') {
  potential.set <- potentialDF(clusters, dist.df)
  # find the candidate furthest from existing seeds
  minClusterDist <- potential.set %>%
    group_by(candidate) %>%
    summarize(dist = min(dist))

  return(minClusterDist$candidate[which.max(minClusterDist$dist)])
}
```

```

assignToCluster <- function(clusters, dist.df,
                           index1='index1', index2='index2',
                           dist.col='dist') {
  potential.set <- potentialDF(clusters, dist.df)
  # Find the point closest to a cluster
  minClusterDist <-
    potential.set %>% group_by(cluster) %>% slice(which.min(dist))
  assignment <- minClusterDist[which.min(minClusterDist$dist), ]
  clusters[assignment$candidate[1]] <- assignment$cluster[1]
  if (sum(clusters == 0) > 0) {
    cdf <- assignToCluster(clusters, dist.df, index1, index2, dist.col)
    assignment <- rbind(assignment, cdf)
  }
  return(assignment)
}

hcluster <- function(clusters, dist.df,
                    index1='index1', index2='index2',
                    dist.col='dist') {
  dist.df <- dist.df[order(dist.df[dist.col]), ]
  assign.order <- do.call(rbind, apply(dist.df, 1, function(r) {
    id1 <- dist.df[1, index1]
    id2 <- dist.df[1, index2]
    cluster.union <- union(which(clusters == clusters[id1]),
                          which(clusters == clusters[id2]))
    clusters[cluster.union] <-< clusters[clusters[id1]]
    return(clusters)
  })))
  return(do.call(rbind, assign.order))
}

potentialDF <- function(clusters, dist.df,
                       index1='index1', index2='index2',
                       dist.col='dist') {
  # Break out which points have been assigned and which are candidates
  candidates <- which(clusters == 0)
  assigned <- which(clusters != 0)
  # id vectors
  id1 <- dist.df[index1]
  id2 <- dist.df[index2]
  # create combinations of candidates and assigned
  potential.set <- expand.grid(candidates, assigned)
  names(potential.set) <- c('candidate', 'assigned')
  # add distance information
  potential.set['dist'] <-
    apply(apply(potential.set, 1, sort), 2, function(c) {
      dist.df[(id1 == c[1] & id2 == c[2]), dist.col]})
  # add cluster information
  potential.set['cluster'] <-
    unlist(lapply(potential.set$assigned, function(i) {clusters[i]}))
  return(potential.set)
}

```

```

# ### #
# Run #
# ### #

# Cluster parameters
k <- 10
n <- 5

# Sample from data
sample.df <- dd[sample(1:nrow(dd), n), ]

# Initialize assignment vector
tocluster <- rep(0, n)

# Enumerate all combinations of points
combos.df <- as.data.frame(t(combn(1:n, 2)))
names(combos.df) <- c("index1", "index2")
combos.df['dist'] <- unlist(apply(combos.df, 1, function(c){
  hamDist(sample.df[c[1], ], sample.df[c[2], ])
}))
combos.df['dist.sq'] <- combos.df$dist**2

# Assign first two clusters seeds
maxd <- combos.df[which.max(combos.df$dist), ]
tocluster[maxd[1, 1]] <- 1
tocluster[maxd[1, 2]] <- 2

# Assign the rest of the initial k clusters seeds
trash <- lapply(3:k, function(i) {
  nextPt <- nextPoint(tocluster, combos.df)
  tocluster[nextPt] <- i
})

# Now we have our seeds, we need to assign points to clusters
assignments <- assignToCluster(tocluster, combos.df)
tocluster[assignments$candidate] <- assignments$cluster

```

At this point we have assigned all our initial points to a cluster. Now we need to create a tree to hold hierarchical relationship between clusters, and we need to store information about each cluster.

```

nodes <- list()
for (i in unique(tocluster)) {
  nodes[[as.character(i)]] <- list(
    parent=NA,
    type='leaf',
    N=table(tocluster)[i],
    clustroid=NA,
    clustroid.rowsum=NA,
    closest=list(),
    farthest=list()
  )
}

```