k-means with Imputation

`ClustImpute` package

PMS

11 May, 2023

Preliminary

Loading & Cleaning Data

```
set.seed(2023)
library(cluster)
library(ClustImpute)
library(ggplot2)
library(factoextra)
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```
library(clusterCrit)
load('../../../../../local_data/codes/create_master/master_pms_df.Rdata')

#removing rows with NA for all indices, as well as for population = 0
master$PMS_DBPOP = as.numeric(as.character(master$PMS_DBPOP))
```

```
## Warning: NAs introduced by coercion
```

```
master = master[master$PMS_DBPOP != 0,]
master = master[!is.na(master$PMS_DBPOP),]
idx = c("PMS_prox_idx_emp", "PMS_prox_idx_pharma", "PMS_prox_idx_childcare", "PMS_prox_idx_health", "PMS
master = master[(rowSums(is.na(master[,idx])) < 10),]
nrow(master)
```

```
## [1] 341425
```

Assumptions of the Alogrithm

This algorithm “draws the missing values iteratively based on the current cluster assignment so that correlations are considered on this level”. Also, “penalizing weights are imposed on imputed values and successively decreased (to zero) as the missing data imputation gets better”. The idea is that the missing value is imputed by those other observations that are more similar to it (ie. in the same cluster).

Algorithm steps:

1. It replaces all NAs by random imputation, i.e., for each variable with missings, it draws from the marginal distribution of this variable not taking into account any correlations with other variables
2. Weights < 1 are used to adjust the scale of an observation that was generated in step 1. The weights are calculated by a (linear) weight function that starts near zero and converges to 1 at n_end.

3. A k-means clustering is performed with a number of c_steps steps starting with a random initialization.
4. The values from step 2 are replaced by new draws conditionally on the assigned cluster from step 3.
5. Steps 2-4 are repeated nr_iter times in total. The k-means clustering in step 3 uses the previous cluster centroids for initialization.
6. After the last draws a final k-means clustering is performed.

All Metrics Together

Implementation

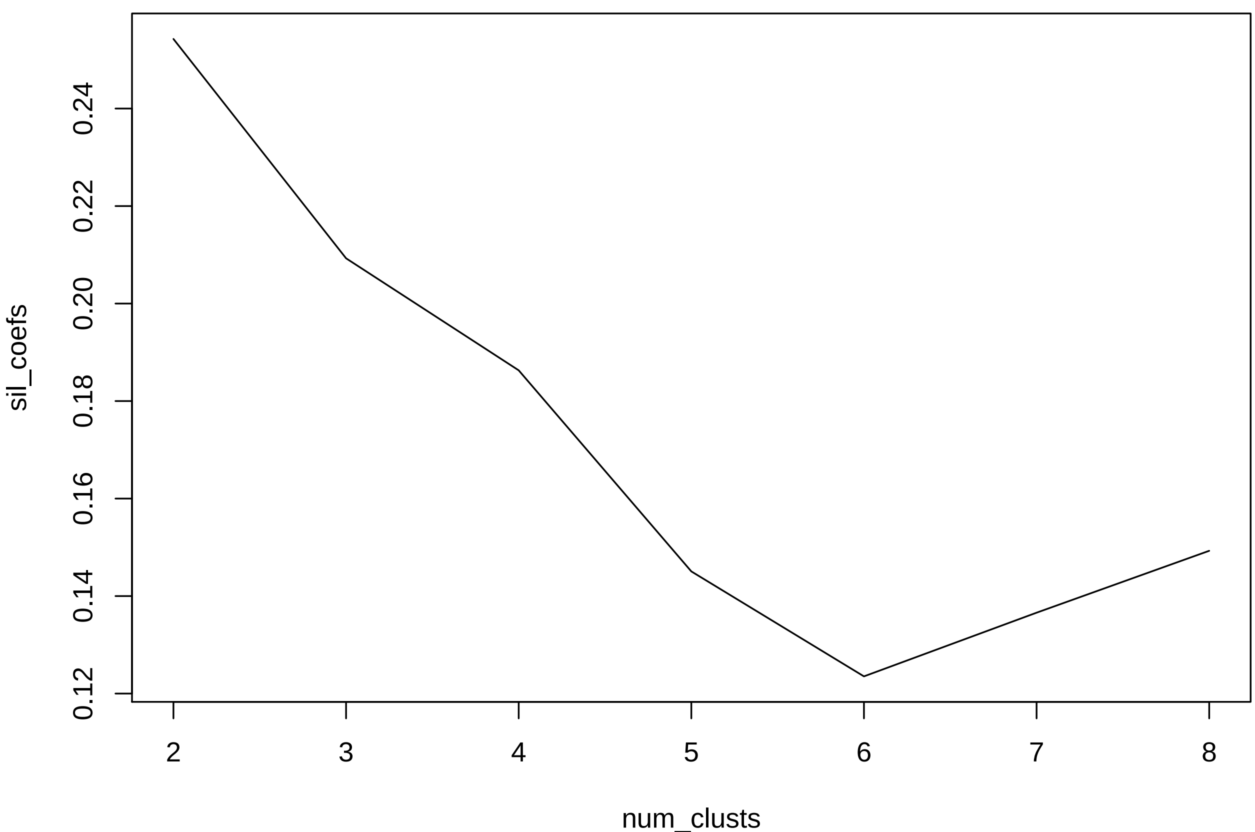
(with 5% subsampling)

```
#cluster data
subsample = nrow(master)/20 #subsampling
subsam = master[sample(nrow(master), subsample), idx]
sum(is.na(subsam))
```

```
## [1] 78804
```

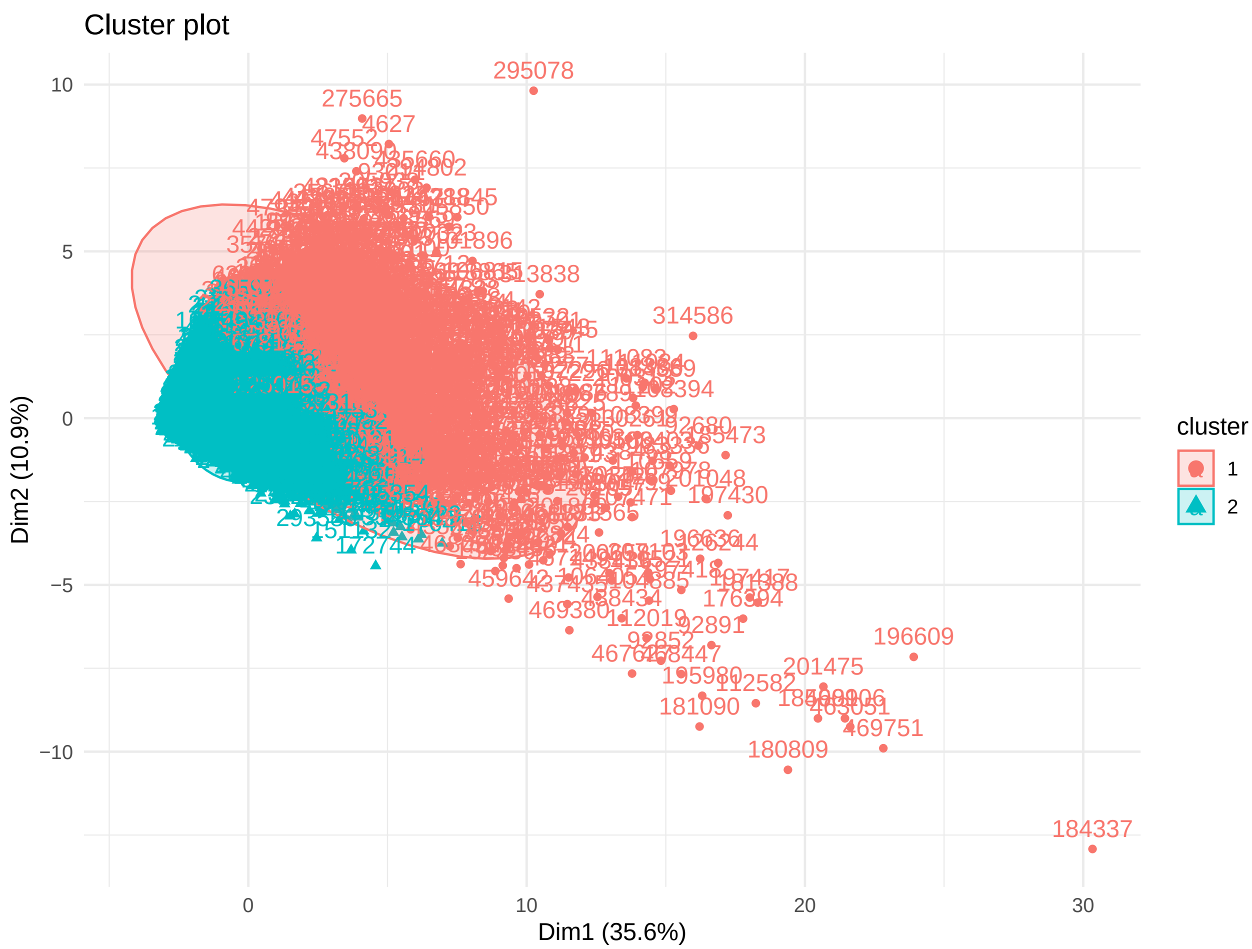
```
#algorithm
sil_coefs = c()
counter = 1
num_clusts = 2:8
for (i in num_clusts){
  nr_iter = 10 # iterations of procedure
  n_end = 10 # step until convergence of weight function to 1
  #nr_cluster = 3 # number of clusters
  c_steps = 50 # number of cluster steps per iteration
  res = ClustImpute(subsam,nr_cluster=i, nr_iter=nr_iter, c_steps=c_steps, n_end=n_end)
  sil_coefs[counter] = intCriteria(as.matrix(res$complete_data),res$clusters, 'Silhouette')$silhouette
  counter = counter + 1
}

#plot silhouette coefficients
plot(sil_coefs~num_clusts, type = 'l')
```



```r
#re-run algorithm with highest sil
res = ClustImpute(subsam,nr_cluster=num_clusts[which(sil_coefs == max(sil_coefs))], nr_iter=nr_iter, c_

#plot
# ggplot(res$complete_data,aes(prox_idx_emp,prox_idx_pharma,color=factor(res$clusters))) + geom_point()
pass = list(data = res$complete_data, cluster = res$clusters)
fviz_cluster(pass, ellipse.type = "norm") + theme_minimal()
```



Cut-off Values

```r
cutoffs = list()
for (k in idx){
  clus_medians = c()
  counter = 1
  for (i in unique(res$clusters)){
    clus_medians[counter] = median(res$complete_data[res$clusters == i,k])
    counter = counter + 1
  }
  cutoff = c()
  clus_medians = sort(clus_medians)
  for (j in 1:(length(clus_medians)-1)){
    cutoff[j] = (clus_medians[j] + clus_medians[j+1])/2
```

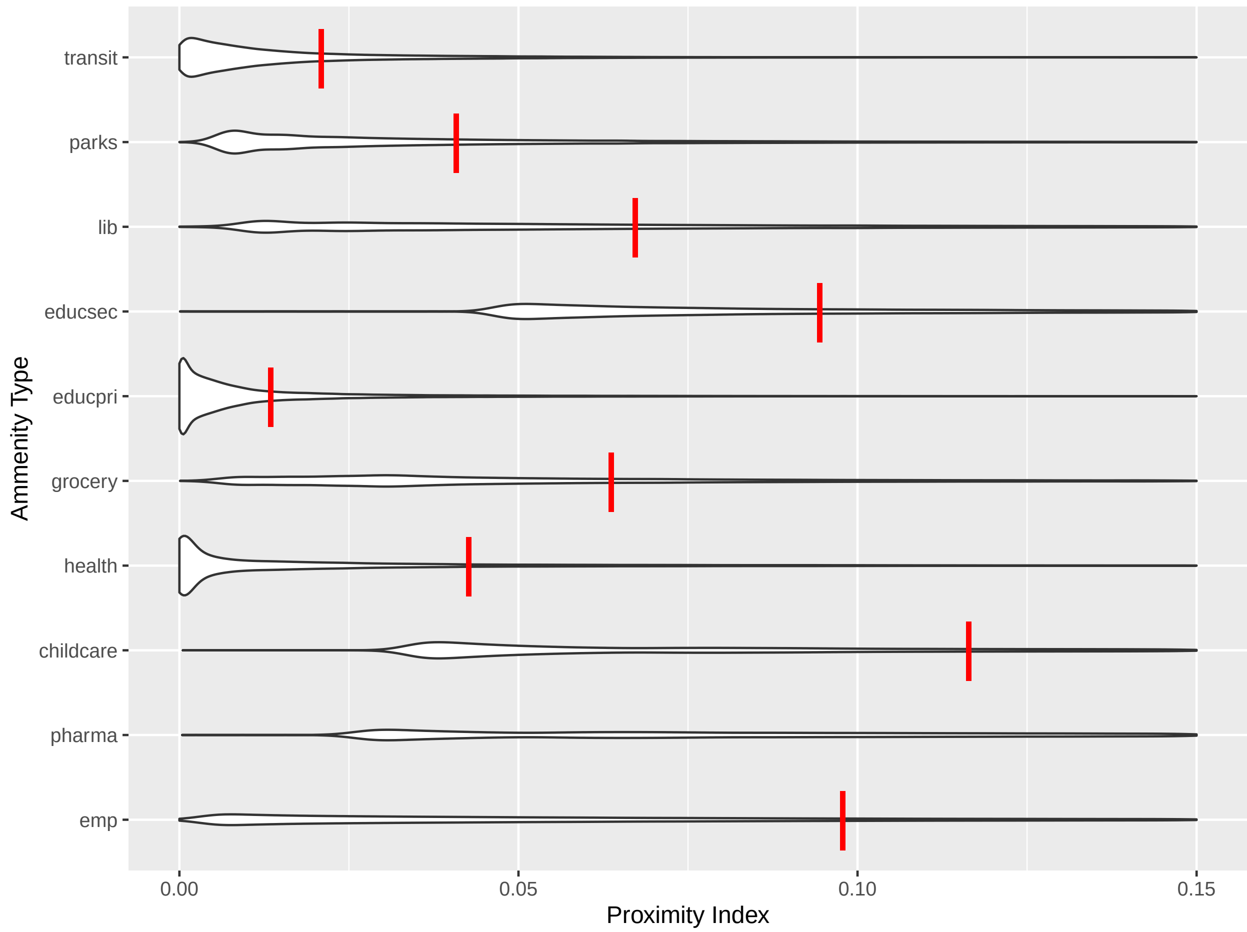
```r
  }
  cutoffs[[k]] = cutoff
  print(k)
  print(round(cutoff, 5))
}
```

```
## [1] "PMS_prox_idx_emp"
## [1] 0.04265
## [1] "PMS_prox_idx_pharma"
## [1] 0.04085
## [1] "PMS_prox_idx_childcare"
## [1] 0.09785
## [1] "PMS_prox_idx_health"
## [1] 0.0135
## [1] "PMS_prox_idx_grocery"
## [1] 0.0637
## [1] "PMS_prox_idx_educpri"
## [1] 0.15668
## [1] "PMS_prox_idx_educsec"
## [1] 0.1164
## [1] "PMS_prox_idx_lib"
## [1] 0.0944
## [1] "PMS_prox_idx_parks"
## [1] 0.0672
## [1] "PMS_prox_idx_transit"
## [1] 0.0209
```

```r
#plot em
library(ggplot2)
library(tidyverse)
library(stringr)
labs = str_sub(idx, 14) #labels
hline = pivot_longer(as.data.frame(cutoffs), all_of(idx)) #cutoff lines
df_long = pivot_longer(master[,idx], all_of(idx))
ggplot(df_long, aes(x=value, y=name)) + geom_violin() + scale_y_discrete(labels=labs) + scale_x_continu
```

```
## Warning: Removed 1738820 rows containing non-finite values (`stat_ydensity()`).

## Warning: Removed 1 rows containing missing values (`geom_point()`).
```

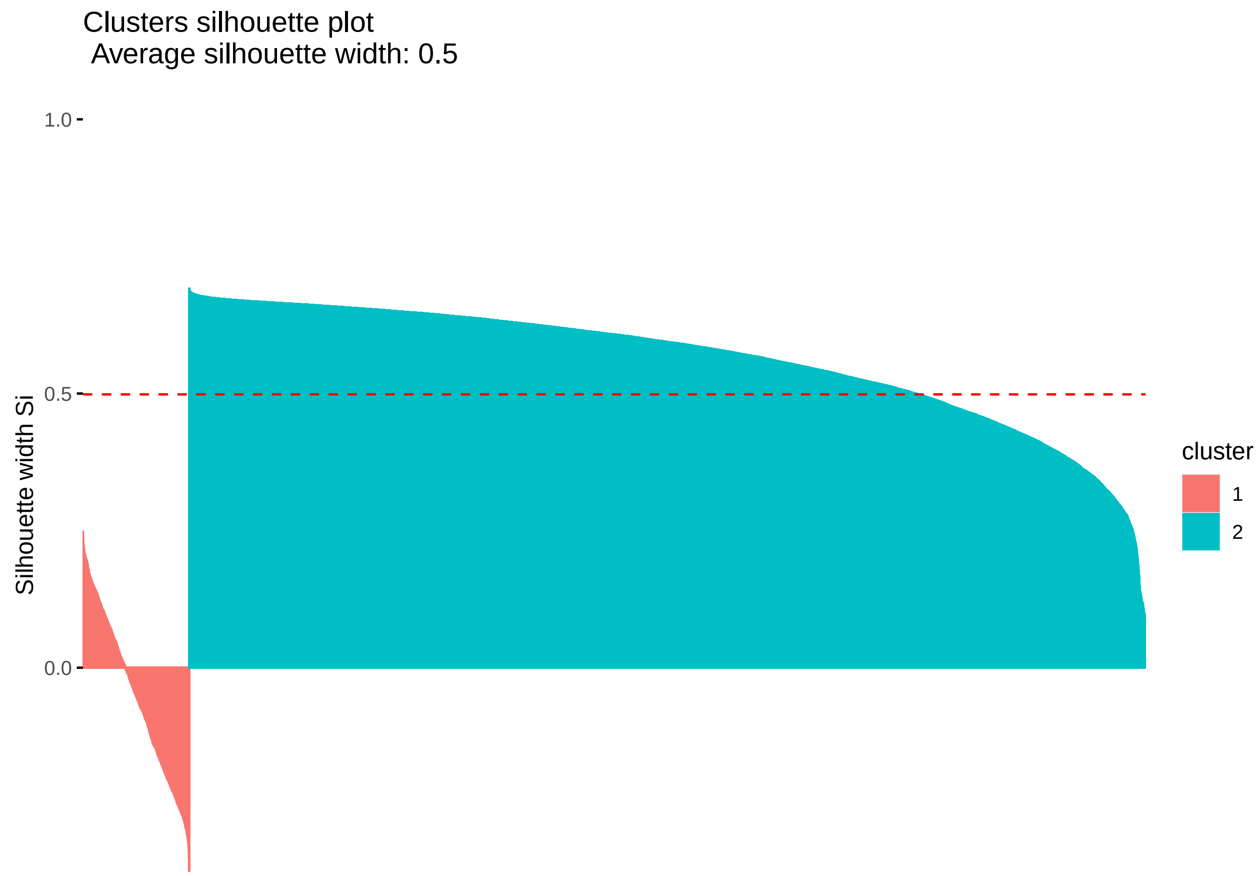


Silhouette Plot

```
# plt = cluster::silhouette(res$clusters, dist(res$complete_data))
# plot(plt, col = 1:4)
# abline(v=mean(plt[,3]), col="red", lty=2)

sil = silhouette(res$clusters, dist(res$complete_data))
fviz_silhouette(sil)
```

```
##   cluster  size ave.sil.width
## 1       1  1708         -0.05
## 2       2 15363          0.56
```



Cluster Profiles

```
for (k in sort(unique(res$clusters))){
  temp = master[res$clusters == k,]
  print(paste('Cluster #', k))
  print(paste('Num of DBs in cluster: ', as.character(nrow(temp))))
  print('CSD Type:')
  print(table(temp$CSDTYPE)) #replace with grouped type later
  cat('\n DB Population: \n')
  print(summary(temp$PMS_DBPOP))
  cat('\n Index of Remoteness: \n')
  print(summary(temp$IOR_Index_of_remoteness))
  cat('\n Provinces: \n')
  print(table(temp$PROVINCE))
  cat('\n Amenity dense: \n')
  print(table(temp$PMS_amenity_dense))
  cat('\n\n\n ')
}
```

```
## [1] "Cluster # 1"
## [1] "Num of DBs in cluster:  34160"
## [1] "CSD Type:"
##
##    C   CG  COM   CT   CU   CV   CY   DM  HAM   ID  IGD   IM  IRI  LGD  LOT    M
## 1825    4   22  111   12  819 9294  599   16    1    1    3  244    1  170   41
```

```
##   MD   MÉ   MU   NL   NO   NV    P   PE  RCR  RDA  RGM   RM   RV  S-É   SA   SC
## 1447 1905 1435    2   71    6  403  238   35  707  481 1063   29    5   10  348
##  SET   SM  SNO   SV    T   TC   TP   TV    V   VL   VN
##    1  159   64   19 3855   12 1747  199 6180  571    5
##
##  DB Population:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    5.00   23.00   53.00   92.62  109.00  997.00
##
##  Index of Remoteness:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## 0.00000 0.09688 0.14941 0.19267 0.28219 0.97797     229
##
##  Provinces:
##
##             Alberta      BritishColumbia         NewBrunswick
##                1058                 1926                  335
## NorthwestTerritories           NovaScotia              Ontario
##                  21                 1177                 6627
##              Quebec         Saskatchewan
##                2212                  211
##
##  Amenity dense:
##
##     0     1     2     F
## 30559  3192   409     0
##
##
##
##  [1] "Cluster # 2"
## [1] "Num of DBs in cluster:  307265"
## [1] "CSD Type:"
##
##     C    CG    CN   COM    CT    CU    CV    CY    DM   HAM    ID   IGD    IM
## 16193    18     1   203   875    54  7674 82727  5572   106    14    18    38
##   IRI   LGD   LOT     M    MD    MÉ    MU    NH    NL    NO    NV     P    PE
##  2505    30  1416   426 13878 16696 12955     1    27   636    92  3655  2511
##   RCR   RDA   RGM    RM    RV   S-É    SA    SC    SÉ   SET    SG    SM   SNO
##   332  6355  4242  9317   169    20    75  3022    10     5     1  1379   577
##    SV     T    TC    TK    TP    TV     V    VL    VN
##   170 34652   108     1 15573  1696 55860  5343    37
##
##  DB Population:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    5.00   23.00   53.00   93.11  109.00  999.00
##
##  Index of Remoteness:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  0.0000  0.0969  0.1499  0.1930  0.2823  0.9804    2120
##
##  Provinces:
##
##             Alberta      BritishColumbia         NewBrunswick
##                9481                16994                 2918
```

```
## NorthwestTerritories            NovaScotia              Ontario
##                   146                 10454                59906
##                Quebec          Saskatchewan
##                 20112                  1835
##
##  Amenity dense:
##
##      0      1      2      F
## 274728  28722   3815      0
##
##
##
##
```

Conclusion

text

Linked with Index of Remoteness

Implementation

```
#
```

Cut-off Values

```
#
```

Silhouette Plot

```
#
```

Cluster Profiles

```
#
```

Conclusion

text