Doner based imputation methods

with apllications in R

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Outline

1. Theory
    - Imputation in general (recap)
    - Donor-based imputation methods
2. Practical
    - Apply methods
    - How to in `R`

Theory

General theory

- Item or **partiel** non-response

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- Donor vs model based
- Stochastic or deterministic
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General theory

- Item or **partiel** non-response
- Donor vs model based
- Stochastic or deterministic
- Hot- or cold-deck
- Deductive (logical) imputation

Donor imputation

Two general approaches:

1. Nearest neighbor
    - KNN
    - Distance in multidimensional space
    - Predictive mean matching
2. Random draws (stratified)

Donor imputation

When is a donor good enough?

And can different donors be used for the same observations?

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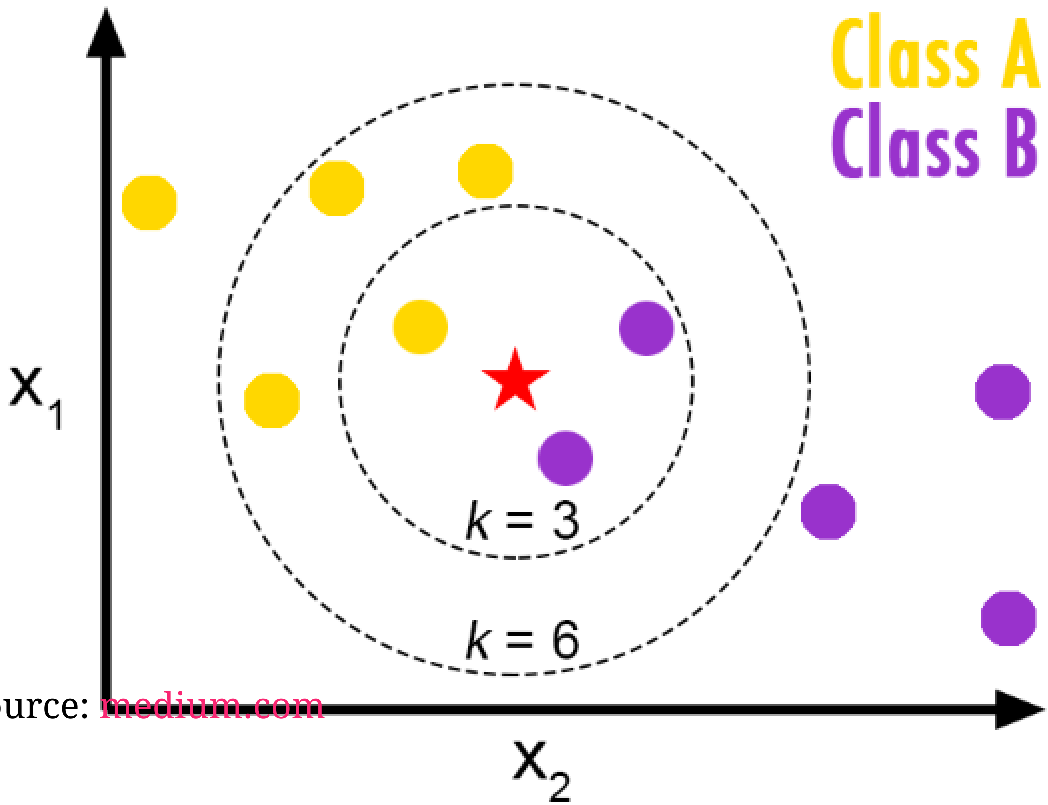
And can different donors be used for the same observations?

3 cases:

1. Complete:
    - All imputed variables complete for doner
    - Same donor for all variables
2. Univariate
    - Variables are imputed one by one
    - Seperate donors for each variable
3. Multivariate
    - Donor pool for each missingness value
    - Same donor for all variables

KNN

- Find the K nearest neighbors
  - K = 1: Pure donor imputation
  - K > 1: "Average" of the donors



Source: medium.com

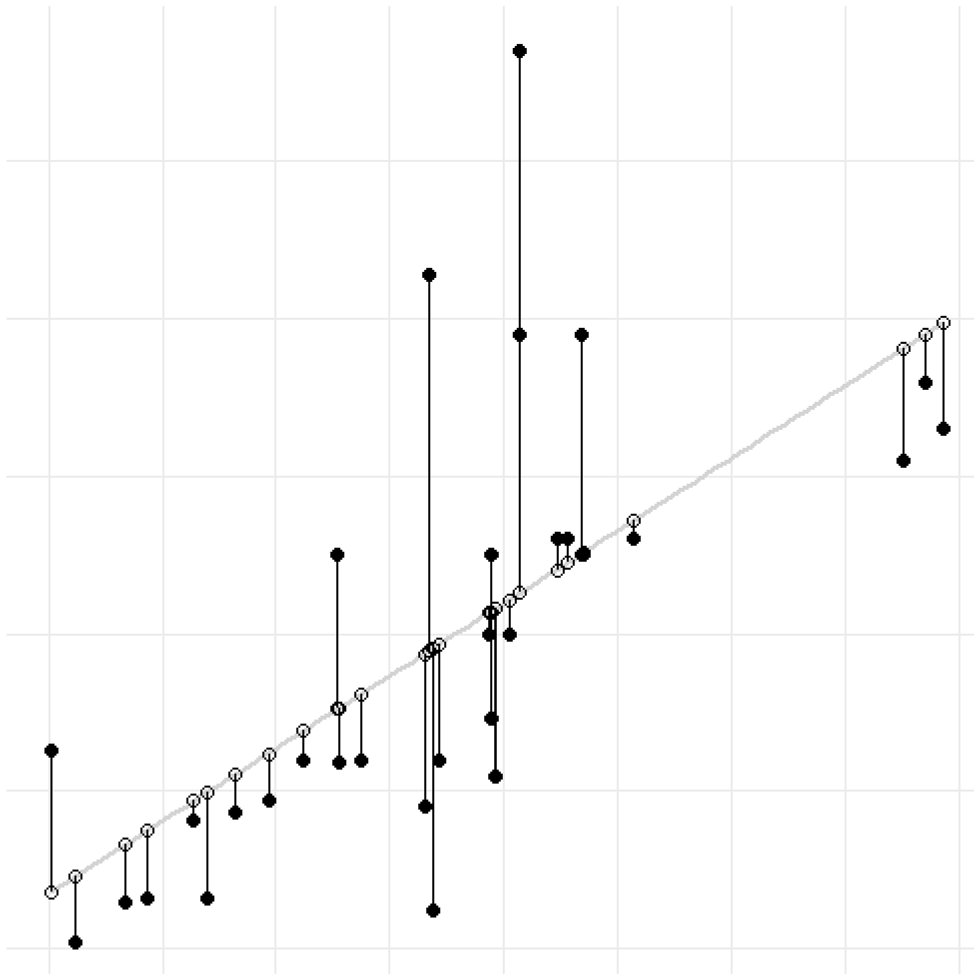
Predictive mean matching

- Mix between model and donor based imputation
- Method:

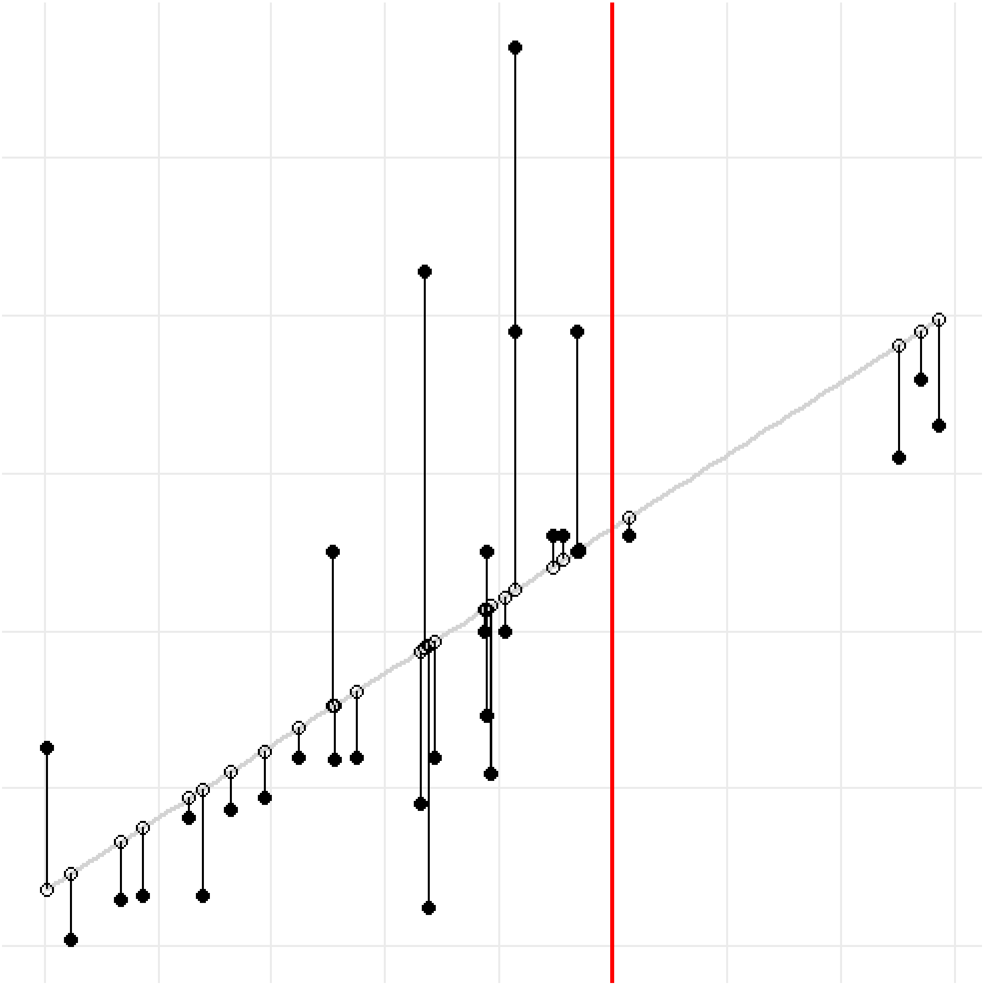
    1. Estimate a model predicting the missing variable(s)
    2. Form predictions for all observation
    3. Donor is the observation with the closest predicted value

- From here a KNN with K = 1
- A way to redefine a multidimensional problem into a one dimensional problem

Example: Linear prediction (1/2)



Example: Linear prediction (2/2)



Random draws

- Sequential or **random**
- **With** or without replacement or maximum donations per donor

Practical

Simulated LFS

```r
library(tidyverse)
lfs <- read_csv("example.csv", col_types = "inffnn") %>%
  as.data.frame()

head(lfs)
```

id	age	gender	region	employed	hours
1	64	F	W	1	40
2	77	M	S	0	NA
3	83	F	S	NA	NA
4	24	F	W	1	40
5	65	F	N	1	40
6	42	M	E	0	NA

```r
summary(lfs)
```

```
##        id             age         gender  region     employed     
##  Min.   :  1.0   Min.   :18.00   F:259   W:164   Min.   :0.0000  
##  1st Qu.:125.8   1st Qu.:34.00   M:241   S:132   1st Qu.:0.0000  
##  Median :250.5   Median :47.00           N: 81   Median :1.0000  
##  Mean   :250.5   Mean   :49.55           E:123   Mean   :0.6526  
##  3rd Qu.:375.2   3rd Qu.:65.00                   3rd Qu.:1.0000  
##  Max.   :500.0   Max.   :90.00                   Max.   :1.0000  
##                                                  NA's   :51      
##      hours      
##  Min.   :20.00  
##  1st Qu.:39.00  
##  Median :40.00  
##  Mean   :37.24  
##  3rd Qu.:40.00  
##  Max.   :40.00  
##  NA's   :207
```

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##  Max.   :40.00  
##  NA's   :207    
```

Partial non-response!

R Matrix

```
R <- lfs %>%
  mutate(across(-id, ~ negate(is.na)(.) %>% as.numeric()))

head(R)
```

id	age	gender	region	employed	hours
1	1	1	1	1	1
2	1	1	1	1	0
3	1	1	1	0	0
4	1	1	1	1	1
5	1	1	1	1	1
6	1	1	1	1	0

```r
R %>% select(-id) %>% summarise_all(mean)
```

age	gender	region	employed	hours
1	1	1	0.898	0.586

```r
lfs %>% count(employed, is.na(hours))
```

employed	is.na(hours)	n
0	TRUE	156
1	FALSE	265
1	TRUE	28
NA	FALSE	28
NA	TRUE	23

```
lfs %>% count(employed, is.na(hours))
```

employed	is.na(hours)	n
0	TRUE	156
1	FALSE	265
1	TRUE	28
NA	FALSE	28
NA	TRUE	23

Routing: employed = 0 => hours not asked (NA is valid)

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lfs %>% count(employed, is.na(hours))
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Logical imputation: hours answered => the person is employed

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NA	FALSE	28
NA	TRUE	23

Routing: employed = 0 => hours not asked (NA is valid)

Logical imputation: hours answered => the person is employed

51 missing cells left

Simputation

- R package to make imputations easy, covers:
- **Model based** (optionally add [non-]parametric random residual)
  - linear regression
  - robust linear regression
  - ridge/elasticnet/lasso regression
  - CART models (decision trees)
  - Random forest
- **Multivariate** imputation
  - Imputation based on the expectation-maximization algorithm
  - missForest (=iterative random forest imputation)
- **Donor** imputation (including various donor pool specifications)
  - k-nearest neigbour (based on gower's distance)
  - sequential hotdeck (LOCF, NOCB)
  - random hotdeck
  - Predictive mean matching
- **Other**
  - (groupwise) median imputation (optional random residual)
  - Proxy imputation: copy another variable or use a simple transformation to compute imputed values.
  - Apply trained models for imputation purposes.

Imputation strategy

1. Deductive: If answered hours, then the person is employed.
2. Two step donor imputation:
    1. Employment: Predictive mean matching
    2. Hours: Random hot-deck donor

Step 1

```r
library(simputation)

lfs_imp <- lfs %>%
  impute_proxy(formula = employed ~ hours > 0)
```

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```

employed	is.na(hours)	n
0	TRUE	156
1	FALSE	293
1	TRUE	28
NA	TRUE	23

Step 2

```
lfs_imp <- lfs %>%
  impute_proxy(formula = employed ~ hours > 0) %>%
  impute_pmm(formula = employed ~ age + gender + region)
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```
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```

employed	is.na(hours)	n
0	TRUE	165
1	FALSE	293
1	TRUE	42

Step 3

```
lfs_imp <- lfs %>%
  impute_proxy(formula = employed ~ hours > 0) %>%
  impute_pmm(formula = employed ~ age + gender + region) %>%
  impute_rhd(formula = hours ~ age + gender + region | employed)
```

Step 3

```
lfs_imp <- lfs %>%
  impute_proxy(formula = employed ~ hours > 0) %>%
  impute_pmm(formula = employed ~ age + gender + region) %>%
  impute_rhd(formula = hours ~ age + gender + region | employed)
```

```
lfs_imp %>% count(employed, is.na(hours))
```

employed	is.na(hours)	n
0	TRUE	165
1	FALSE	314
1	TRUE	21

```r
lfs_imp %>% filter(employed==1, age==21)
```

id	age	gender	region	employed	hours
30	21	M	W	1	NA
79	21	F	S	1	40
97	21	M	S	1	40
265	21	F	W	1	40
357	21	F	S	1	31

```
lfs_imp %>% filter(employed==1, age==21)
```

id	age	gender	region	employed	hours
30	21	M	W	1	NA
79	21	F	S	1	40
97	21	M	S	1	40
265	21	F	W	1	40
357	21	F	S	1	31

No donors in the strata for id = 21

```
lfs_imp %>% filter(employed==1, age==21)
```

id	age	gender	region	employed	hours
30	21	M	W	1	NA
79	21	F	S	1	40
97	21	M	S	1	40
265	21	F	W	1	40
357	21	F	S	1	31

No donors in the strata for id = 21

"Easy" solution => Random donor in 10 year age group

Step 4

```
lfs_imp <- lfs %>%
  impute_proxy(formula = employed ~ hours > 0) %>%
  impute_pmm(formula = employed ~ age + gender + region) %>%
  impute_rhd(formula = hours ~ age + gender + region | employed) %>%
  mutate(age10 = age %/% 10) %>%
  impute_rhd(formula = hours ~ age10 | employed) %>%
  select(-age10)
```

Step 4

```
lfs_imp <- lfs %>%
  impute_proxy(formula = employed ~ hours > 0) %>%
  impute_pmm(formula = employed ~ age + gender + region) %>%
  impute_rhd(formula = hours ~ age + gender + region | employed) %>%
  mutate(age10 = age %/% 10) %>%
  impute_rhd(formula = hours ~ age10 | employed) %>%
  select(-age10)
```

```
lfs_imp %>% count(employed, is.na(hours))
```

employed	is.na(hours)	n
0	TRUE	165
1	FALSE	335

New micro data

```
lfs_imp %>% anti_join(lfs, by = names(lfs_imp)) %>% slice_sample(n=1(
```

id	age	gender	region	employed	hours
346	53	F	W	1	36
180	19	M	E	1	40
114	86	F	E	0	NA
279	31	M	N	1	40
16	18	F	W	1	40
93	33	F	S	1	32
142	55	M	S	1	40
315	88	F	E	0	NA
31	31	F	S	1	40
82	85	M	N	1	40

```
summary(lfs_imp)
```

```
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##  3rd Qu.:375.2   3rd Qu.:65.00                   3rd Qu.:1.00   3rd Qu.:40
##  Max.   :500.0   Max.   :90.00                   Max.   :1.00   Max.   :40
##                                                                 NA's   :16
```

Alternative ML solution

```
lfs_mf <- lfs %>%
  mutate(hours = if_else(employed == 0, 0, hours),
         employed = as.factor(as.character(employed))) %>%
  as.data.frame() %>%
  impute_mf(formula = . - id ~ . - id) %>%
  mutate(employed = as.numeric(as.character(employed)),
         hours = if_else(hours == 0, NA_real_, hours))
```

```
##   missForest iteration 1 in progress...done!
##   missForest iteration 2 in progress...done!
##   missForest iteration 3 in progress...done!
##   missForest iteration 4 in progress...done!
```

```
lfs_mf %>% count(employed, is.na(hours))
```

employed	is.na(hours)	n
0	TRUE	156
1	FALSE	344

Questions?

(ressources next slide)

Ressources

Presentation: GitHub

EU / MEMOBUST: Handbook on imputation

CRAN Task View: Official Statistics & Survey Methodology

Mark van der loo: simputation: Simple Imputation

RStudio: Tidyverse collection of R packages

Awesome official statistics software: GSBPM & R packages