Data Management and Visualization

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Session 4

Data Management

Agenda

Data Wrangling

Missing Data Management

Trinity College Dublin
Coláiste na Tríonóide, Baile Átha Cliath
The University of Dublin

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Data Handling

Cleaning and Managing Data

Infinite universe

Most important task

Understand an play with your data before using it

Could require upto 80% time of project

Cleaning and managing data in R

Major packages

- Dplyr
- Tidyr
- Get acquainted with tidyverse
  - R for datascience

Major activities to undertake

Load data in R

- Read CSV
- Readxl

View data

- Tidyr::glimpse()
- utils::View(iris)

Identify datatype

- Typeof()

Preliminary Analysis

Cleaning and arranging

- Gsub()
- Gather()
- Distinct()

The pipe operation

- %>% glimpse()

Combine files

- List.files()
- Read csv()
- Rbind()

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Missing Data

Why Care?

- Missing values are very common
- Difficult to deal with missing data
- Difficult to interpret results with missing data
- The simplest method to deal with missing data is data reduction which deletes the instances with missing values. However it will lead to great information loss

Causes

Random Error

- Data missing due to random error
- Someone forgot some item in a survey
- Some data was missing because of a clerical error

Bias

- Systemic reason for missing data
- Some questions can’t be answered by some people
- Questions like do you some would be missing for smokers

Types of Missing Data

Missing Completely at Random(MCAR)

– certain value is missing has nothing to do with its hypothetical value and with the values of other variables.

Missing at Random (MAR)

– propensity for a data point to be missing is not related to the missing data

Missing not at Random (MNAR)

– missing value depends on the hypothetical value

– missing value is dependent on some other variable’s value

Types of Missing Data

Mathematically Speaking

MCAR

– Probability of missing data is unrelated to missing and observed values

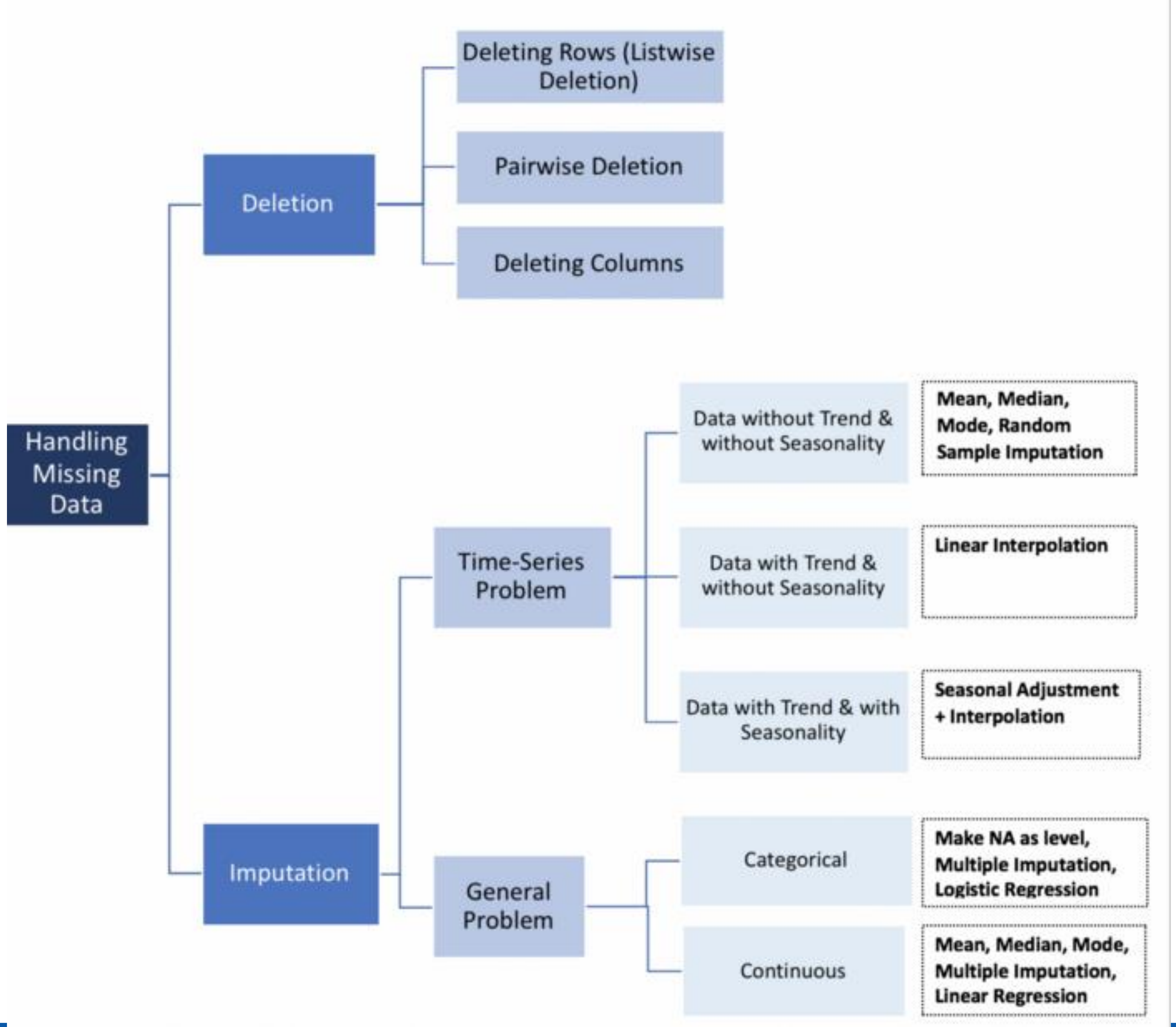
MAR

– Probability of missing data is related to observed values

MNAR

– Probability of missing data is related to unobserved values

Handling Missing Data



Source: https://towardsdatascience.com/how-to-handle-missing-data-8646b18db0d4

Handling Missing values- Discard/Delete

Discard cases

- Discard rows/columns
- Works on MCAR only
  - High bias if lots of missing data points
  - Could lead to few complete rows of data

Handling Missing Values- Preserve

Mean Substitution

- Popular approach
- replacing the missing values by the mean of all observed values
- Does not work in systemic biases
- Variance decreases

Handling Missing Values- Preserve

Hot Deck Imputation

- replace missing values with a related row.
- Popular in surveys
- Involves replacing missing values of one or more variables for a non-respondent with observed values from a respondent that is similar to the non-respondent with respect to characteristics observed by both cases.

Handling Missing Values- Preserve

Regression- Model based substitution

- Use Linear or logistic regression as appropriate
- In R you can use VIM package
- Popular in large secondary databases
- Could account for some level of biasness- MAR
- Can use time series models as well where appropriate

Handling Missing Values- Preserve

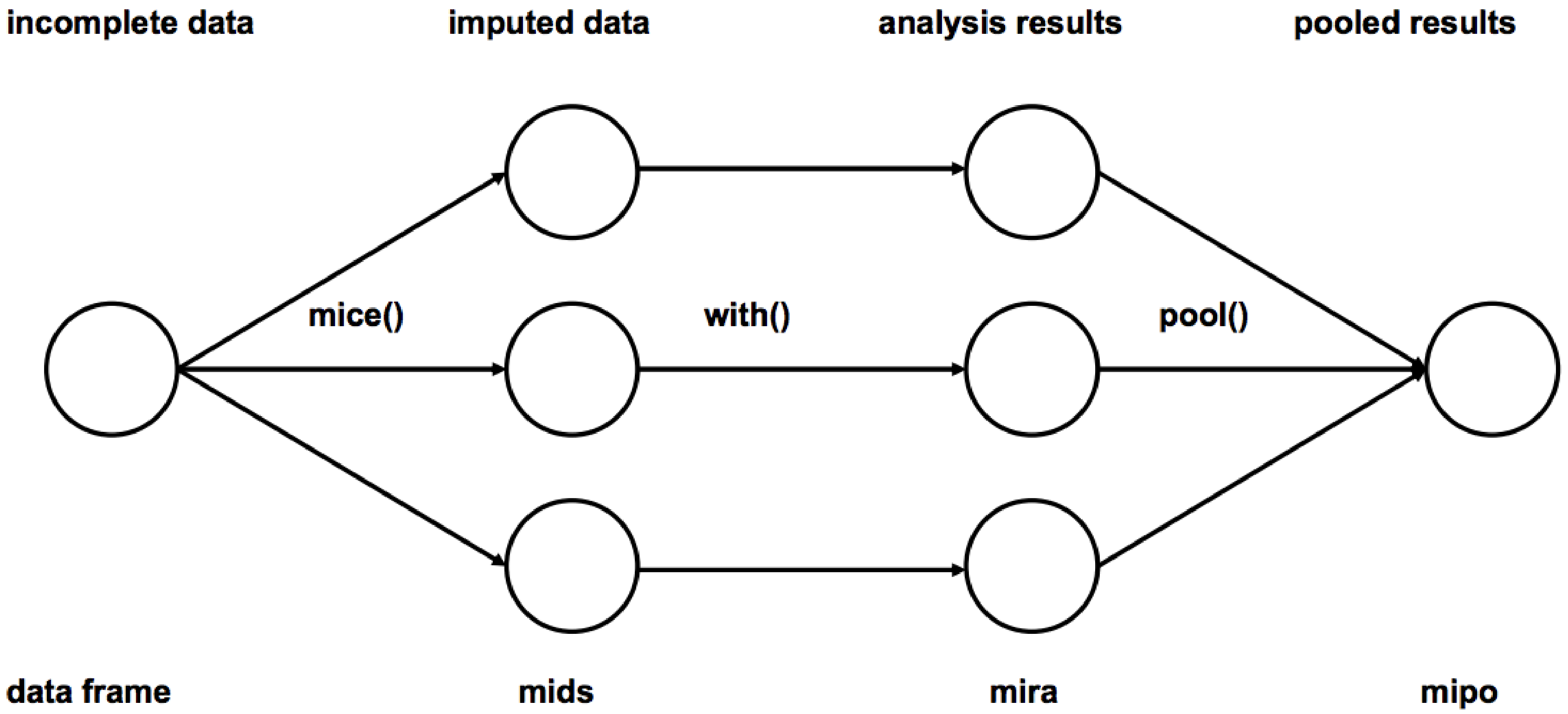
EM Imputation

- EM stands for expectation maximization
- It is an iterative process to calculate the sufficient statistics to impute multiple values
- Popular package Amelia in R
- Expectation-Maximization Bootstrap-based algorithm (EMB) It assumes that the complete data are multivariate normal

Handling Missing Values- Preserve

Multiple Imputation

- One of the most powerful techniques
- Package mi in R



Handling Missing Values- Preserve

Multiple Imputation

- Make a model that predict every missing data item (linear or logistic regression, non-linear models, etc.)
- Use the above models to create a “complete” dataset.
- Each time a “complete” dataset is created, do an analysis of it, keeping the mean and SE of each parameter of interest.
- Repeat this between 2 and tens of thousands of time
- To form final inferences, for each repetition, average across means, and sum the within and between variances for each parameter.