EP16: Missing Values in Clinical Research: Multiple Imputation

1. What is Multiple Imputation?

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History & Ideas

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- a **large number of analysts**, who commonly have to rely on
- standard **software that can only handle complete data**, and usually
- are **not experts in handling incomplete data**.

History & Ideas (Rubin, 2004)

One imputed value cannot be correct in general.
➡ We need to represent missing values by a **number of imputations**.

To find **sensible values** to fill in, we need some kind of **model**.

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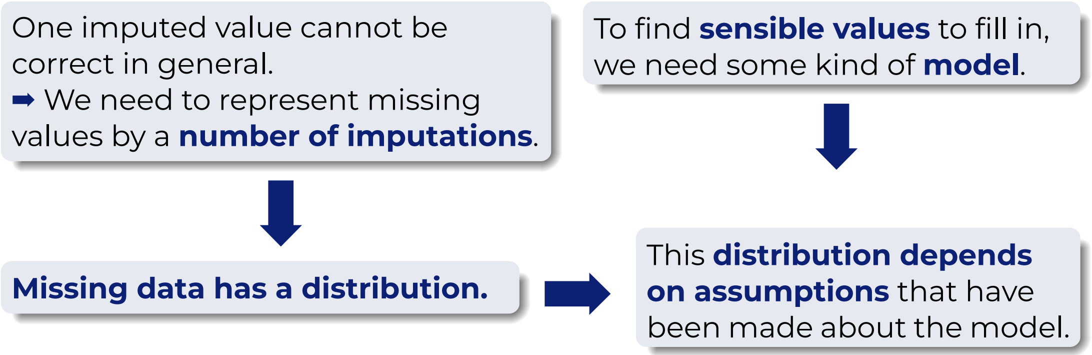

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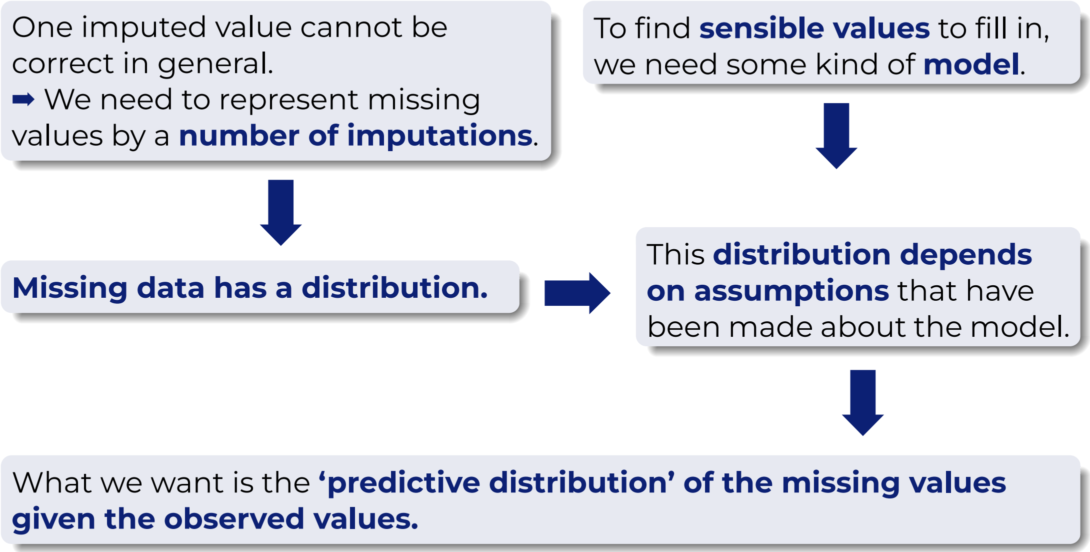

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What we want is the **‘predictive distribution’ of the missing values given the observed values.**

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- fit a model to the observed data (“respondents”), and to
- obtain for each “nonrespondent” the conditional distribution of the missing data (given the observed data) as if he/she was a respondent.

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Example: survey including age, gender and height

10 – 12 year old boys answered (on average) that they are 1.45m tall.

➡ We assume that boys aged 10 to 12 who did not report their height are also around 1.45m tall.

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- Analyse each dataset.
- Combine the results from all analyses.

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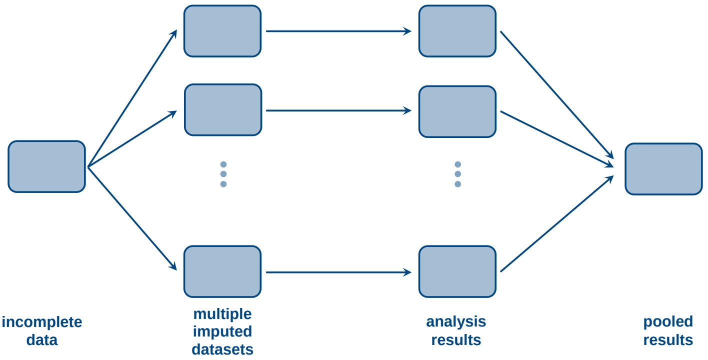
➡ We can describe how (much) the **results vary between the imputed datasets**, and calculate summary measures.

Three Steps



In summary:

1. **Imputation:** impute multiple times ➡ multiple completed datasets
2. **Analysis:** analyse each of the datasets
3. **Pooling:** combine results, taking into account additional uncertainty

References

Rubin, D. B. (1996). Multiple imputation after 18+ years. *Journal of the American Statistical Association*, *91*(434), 473–489. https://doi.org/10.2307/2291635

Rubin, D. B. (2004). The design of a general and flexible system for handling nonresponse in sample surveys. *The American Statistician*, *58*(4), 298–302. https://doi.org/10.1198/000313004X6355