

Dissertation

Outline

Eisen onderzoek

Bron: [promotiereglement](#).

1. De promovendus is er verantwoordelijk voor dat het onderzoek dat ten grondslag ligt aan het proefschrift voldoet aan de volgende vereisten:
 - a. de promovendus levert een oorspronkelijke bijdrage aan wetenschappelijk onderzoek die de in Nederland gebruikelijke kwaliteitstoetsing door vakgenoten kan doorstaan;
 - b. de promovendus heeft aangetoond zelfstandig de wetenschappelijke methoden van het vakgebied toe te kunnen passen in de ontwikkeling, interpretatie en toepassing van nieuwe kennis;
 - c. de promovendus heeft kennis genomen van en gewerkt met een substantiële ‘body of knowledge’, welke in ieder geval omvat de principes en methoden van de internationale wetenschapsbeoefening en de theorievorming, methoden en studies van het desbetreffende vakgebied;
 - d. de promovendus beschikt over het vermogen om een omvangrijk project voor de ontwikkeling van nieuwe kennis te ontwerpen en te implementeren;
 - e. de promovendus is in staat om de kennis en methoden van het desbetreffende specialisme en/of vakgebied adequaat over te dragen;
 - f. de promovendus is in staat om de maatschappelijk verantwoordelijkheid ten aanzien van het uitvoeren, toepassen en benutten van het eigen onderzoek te dragen.
2. Het onderzoek is verricht in overeenstemming met wettelijke en universitaire voorschriften en gedragsregels

Inhoud proefschrift

Introductie

Thema: computationele evaluatie van imputatiemethodologie.

H1: Standardized evaluation

- Inhoud hoofdstuk: review paper (manuscript).
- Referentie: Oberman, H. I., & Vink, G. (2024). Toward a standardized evaluation of imputation methodology. *Biometrical Journal*, 66(1), 2200107. <https://doi.org/10.1002/bimj.202200107>
- Kwaliteitstoetsing (eis 1a) door peer-review.
 - Gepubliceerd, 20x geciteerd (bron: Google Scholar).

H2: Missing the point

- Inhoud hoofdstuk: simulatiestudie (manuscript).
- Referentie: Oberman, H. I., van Buuren, S., & Vink, G. (2021). Missing the Point: Non-Convergence in Iterative Imputation Algorithms. <https://arxiv.org/abs/2110.11951>
- Kwaliteitstoetsing (eis 1a) door openbaar maken vroege versie (zie ook [Publish Review Curate](#) model).
 - Pre-print gepubliceerd (4p summary presented at ICML). 11x geciteerd (bron: Google Scholar).

H3: R package ggmmice

- Inhoud hoofdstuk: onderzoekssoftware (verwijzing naar software repository/software vignette).
- Referentie: Oberman, H. I. (2022). *ggmmice*: Visualizations for 'mice' with 'ggplot2'. Zenodo. <https://doi.org/10.5281/zenodo.6532702>
- Kwaliteitstoetsing (eis 1a) door open bug reporting (GitHub Issues).
 - Code openbaar via GitHub, versie gepubliceerd via Zenodo. 5x geciteerd (bron: Google Scholar).
 - GitHub Issues as peer review (10x external Issue, 13x external PR).
 - CRAN downloads as impact (852x/month; 21k total).

Discussie

Plaatsing proefschrift in bredere ontwikkelingen wetenschap.

Start proefschrift

[TODO: create cover, add boilerplate stuff]

Acknowledgements

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[TODO: fix which sections are included]

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Samenvatting

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Introduction

What is this dissertation about?

- missing data & imputation are widespread
- imputation is easy with software defaults
- good imputation is very hard still
- how do we know if we have a good imputation method?
- in this dissertation I study computational evaluation of imputation methodology
- computational evaluation at different levels:
 - building imp models (`ggmice`),
 - assessing imp models (`ggmice` and convergence),
 - developing new imp models/methods (evaluation paper)

What is computational evaluation of imputation methodology?

[GV: I believe this section could benefit from something like this:] *How does comp eval differ from statistical eval? IMO it goes beyond it -> e.g. plausible imputations, tracing back the black box to some extent instead of just taking the answer - even if it is correct. You can give examples here wrp nonconverged solutions that yield plausible inference, implausible values that yield valid inference, etcetera. Would be nice to also consider that taking just a single imputed solution can not be distinguished from another single imputed solution, and that the monte carlo variance of the solution should be studied. Therefore it goes way beyond the statistical properties of the imputation methodology. I think it would be nice to relate it to other stuff/metrics that we value, such as bias/coverage/variance, empirical relevance/plausibility, software-engineering nitpicks like speed/convergence/fault rate.*

-> even without conv, we can get valid inference at sample/population level, not at individual cell level. -> pragmatists? purists? -> even if you get the same results based on different SIs, you want to be able to tell which one you should use, that leads us to the need for MI -> are we satisfied with the way that the imp were obtained? -> req info: imp is filling in. then this is phil, then deeper into imp

- imputation methods are developed to solve missing data problems: typically, some but not all entries are missing per row/column (i.e., item non-response, not unit non-response or missing variables)
- in the FSC framework, we need an imputation model for each incomplete variable
- imputation models consist of the functional form of the model (e.g., stochastic regression) and imputation model predictors (i.e., other variables in the data)
- in the building stage, how do we know which functional form to choose?
 - rely on defaults, tested in simulation studies (→ evaluation chapter)

- assess the distribution of the incomplete variable (e.g., visual inspection → **ggmice** chapter)
- ...?
- in the building stage, how do we know which imputation model predictors to select?
 - association of incomplete variable with other variables in the data (→ **ggmice** chapter)
 - association of missingness indicator with other variables in the data (→ **ggmice** chapter)
 - external input (e.g., branching patterns, or expert knowledge to correct for MNAR)
 - ...?
- after imputation, how do we assess imputation model misfit?
 - non-convergence in the algorithm (→ convergence chapter)
 - mismatch between observed and imputed data distributions (e.g., visual inspection → **ggmice** chapter)
 - ...?

RQ: how can applied researchers be aided in developing and evaluating imputation methods?

Introducing chapter 1: **ggmice**

Wat is het probleem

Visualization of incomplete data, imputation models, and imputed data. Evaluation of ‘applicability’ imputation models. Visualization of uncertainty due to missingness. Data exploration for building imputation models.

Welke methoden bestaan al

- **naniar** for incomplete data
- **VIM** for incomplete and imputed data (but not **mice**)
- **mice** for imputed (but not **ggplot2**)
- ‘artisanal’ code solutions
- print of excel export for imputation models

Wat zijn de voor- en nadelen van de huidige methoden

- missing visualization tool compatible with both incomplete data and **mice** imputations: **mice** lacks incomplete data, other packages lack support for **mice**-imputed data
- missing visualization tool for imputation models

Welke nadelen/problemen beoogt de nieuwe aanpak op te lossen

- no methodology for visualizing **mice** models

- plotting tools for `mids` objects not easily editable/publication-ready
- no direct comparison tool for `mice` between incomplete and imputed data

In welke opzicht vult de nieuwe methode een lacune

- unified solution for: missingness, imputation models, imputations
- direct comparison between data before and after imputation with `mice`
- complex imputation models are easier to review through visualization (as opposed to console prints/excel exports)

Op welke principe is de nieuwe aanpak gebaseerd

- Grammar of Graphics: layered plots
- Open Source Software development/FAIR

Hoe zijn deze principes in de software vertaald

- `ggmice` produces `ggplot` objects: layered, easily adjustable
- GitHub, CRAN, Zenodo, ...

Welke onderliggende aannames zijn hierbij gebruikt

...

Hoe kun je de huidige en nieuwe gereedschappen het beste met elkaar vergelijken

- data types (e.g. `mids`)
- how ‘publication-ready’ the visualizations are (e.g. number of lines of code needed*)
- number of functions*
- number of downloads* `ggmice` has 800 monthly compared to `VIM` 13k and `naniar` 22k

Functionaliteit	<code>ggmice</code>	<code>VIM</code>	<code>naniar</code>	<code>amelia</code>	<code>mice</code> (lattice)
Visualisatie van de missingness	V	V	V	(beperkt)	V
Visualisatie van het imputatie EN nonresponse model	V	X	X	X	X
Imputatie diagnostiek (visueel) + evt in cijfer?	V	V (gedeeltelijk)	X	V	V
Ondersteuning <code>mids</code> en andere data typen	V	X	X	X	V (alleen lattice)
Grammar of Graphics	V	X	V	X	X
Aanpasbaarheid	hoog	laag	hoog	laag	laag
Tidyverse compatible?	volledig	beperkt	volledig	beperkt	geen
Meteen klaar voor publicatie?	hoog	middel	hoog	laag	laag

Levert het nieuwe gereedschap in de praktijk betere resultaten

...

Wat vinden toekomstige gebruikers van het gereedschap

...

Wat zijn relevante indicatoren voor adoptie

- CRAN downloads
- GitHub stars and issues
- StackOverflow mentions/questions
- citations of the package (Zenodo reference)

Welke richtlijnen en advies gelden bij gebruik

- not a replacement of evaluation but support

Wat zijn beperkingen van de methode

- interpretation remains subjective (e.g. convergence, MAR assumption, etc.)

Wat zijn vragen voor nader onderzoek

- visualizing `mira` objects
- add posterior predictive check plots
- quantifying uncertainty at pattern/cell level
- tools for sensitivity analyses

Introducing chapter 2: convergence

- FSC is iterative, so convergence *should* be a requirement for valid inference, or is it?

Introducing chapter 3: evaluation

- based on literature review published in [REF]

Chapter 1

[TODO: link/insert]

Chapter 2

[TODO: link/insert]

Chapter 3

[TODO: link/insert]

Discussion

[TODO: write]

Conclusion

- Computational evaluation of imputation methodology is never finished.
 - In practice, you cannot validate whether the imputation model was appropriate (???), because what you would need to do so is exactly the thing you don't have: the missing part of the incomplete data, while you only have the observed part.
 - The best thing we can do is to evaluate imputation model fit: check the observed versus imputed data distributions, and inspect the imputations for signs of non-convergence. This dissertation offered insight and tools to do so.
 - The only setting where we do have the comparative truth (the true but missing values) is simulation studies. Imputers have to rely on simulation study results in order to choose the best imputation method for their incomplete variables. That's why simulation studies for imputation methodology should be comparable with one another, so imputers can make a 'grounded' assessment which imputation methods may be applicable, and choose the most appropriate one.

→ example: NRI search for lower bound, so impute as 'positive behavior', but per definition wrong statistical inf, because we intentionally bias in one direction

Implications

- The main findings in this thesis are...
 - Non-convergence is hard to diagnose, and typical thresholds to evaluate non-convergence may not be applicable to FCS algorithms: MICE reaches stable output before non-convergence metrics would indicate so.
 - Visual inspection aids imputers in developing and evaluating imputation models. The R package `ggmice` offers tools that were previously unavailable.
 - Defining and testing new imputation methods through simulation studies requires careful consideration of the simulation design and evaluation to make imputation methods comparable across studies.
- Recommendations for fellow missing data methodologists:
 - design simulation studies structured and reproducible
 - talk to your intended audience (i.e., applied researchers), or at least check what they are struggling with (e.g., StackOverflow)
 - ...?

- Recommendations for fellow imputers:
 - think before you code
 - look at the data
 - ...?

Limitations

[TODO: rephrase 'haven't's into future research (positive phrasing)]

- Computational evaluation is not a substitute for thinking. It may give a false sense of certainty, e.g. against MNAR mechanism.
 - Use expert insight
 - Take the analysis model (if available) as starting point for imputation workflow, for congeniality
 - ...?
- This entire dissertation relies on the R language and centers the `mice` package.
 - While this set-up is very popular, the data science landscape has expanded and is ever evolving
 - Many machine learning and deep learning methods are not (yet) implemented as imputation models in `mice`. These may be able to better approximate the posterior predictive distribution of the missing values than `mice` methods
- I haven't tested whether the tools I developed actually improve the imputations of `mice` users.
 - GitHub issues and StackOverflow are indication
 - Onmogelijk om evidence-based conclusies te trekken, maar misschien wel evidence-informed?
- The visualizations implemented in `ggmice` are generally better suited for numeric data, as opposed to categorical variables (or even open text field data).

Outlook

- This chapter ends with a future perspective...
- Missing data remains a problem indefinitely. I expect imputation methodology to be developed and applied for the foreseeable future. But the way we deal with data might change.

- With the rise of machine learning and deep learning methods (or “AI”), evaluation will become ever more important. Novel methods are being developed under a prediction framework, not statistical inference framework: ignoring the uncertainty in the estimates, and thus not incorporating between-imputation variance. This leads to too narrow CIs, and too low p-values. Which, in turn, causes spurious results.
- trust in science requires honest reflection of uncertainty in our analyses
- be open about uncertainty, and limitations of scientific studies
- publish null results (e.g., registered reports or pre-registrations)
- share data and code with other scientists, and the public
- publish open access, educational materials too!
- change the way we evaluate science: this dissertation is an example of the new recognition and rewards vision. it includes software as an actual chapter, not something extra.
- I hope to inspire others to reflect on their own view of what scientific output is. And most of all, I hope to set an example for other PhD candidates to do the same

References

CV

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