EBPU
Evidence Based Practice Unit

A partnership of

UCL

Anna Freud National Centre for Children and Families

Universiteit Leiden The Netherlands

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Balancing precision with practicality: Decision trees

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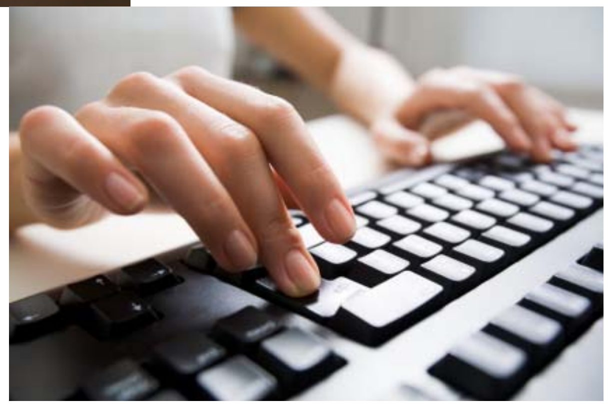
Swampy lowlands

FUPS data

- **F**lawed
- **U**ncertain
- **P**roximate
- **S**parse



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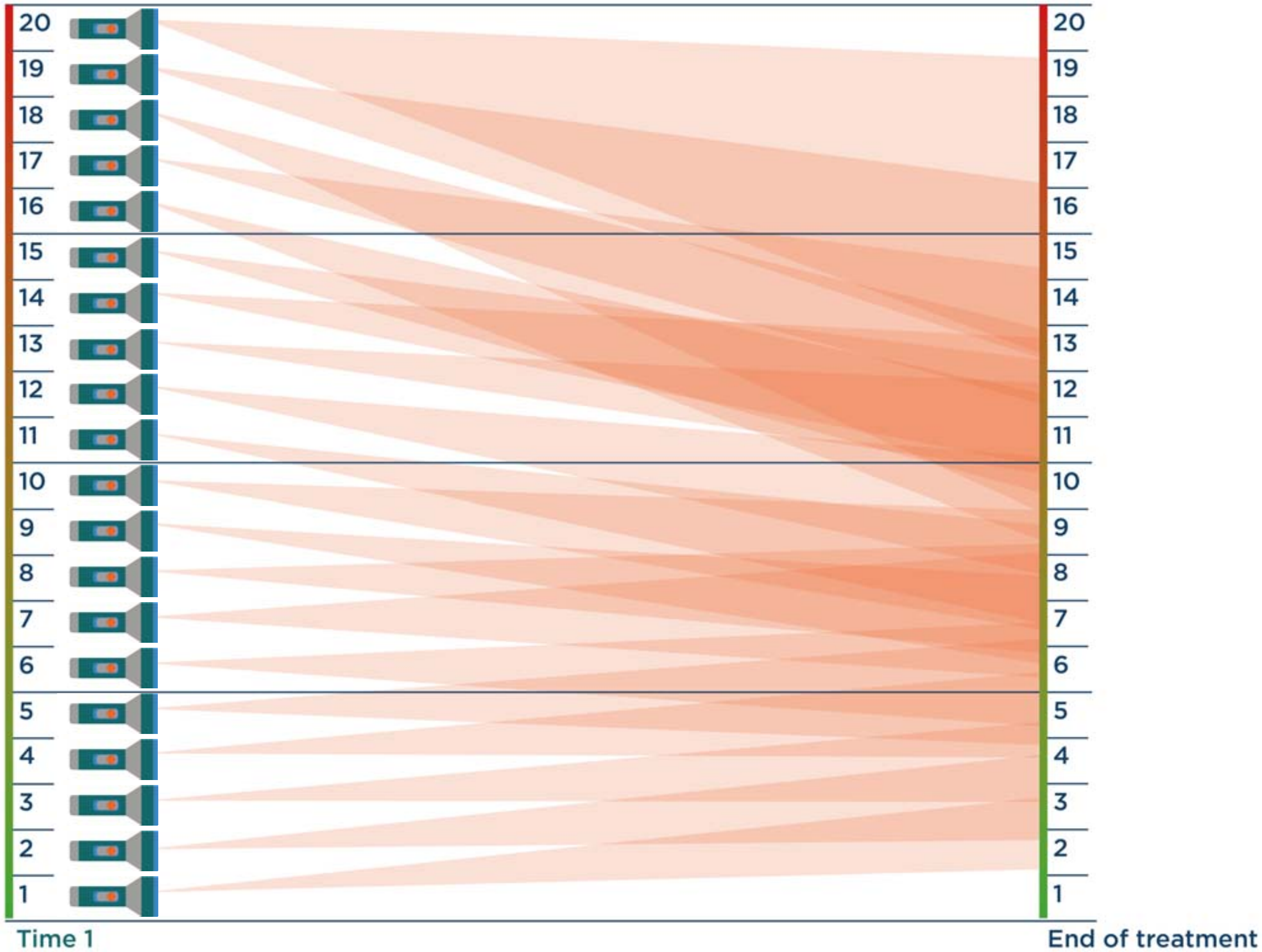
Parent SDQ Internalising Score



Click a torch to reveal a single trajectory

Decision trees

Model-based recursive partitioning (Zeileis et al., 2008)

Rationale:

Confirmatory

1. A global parametric model ('one-size-fits-all)' may not fit the data well.

Exploratory

2. We may be able to find subgroups defined by covariates, with better-fitting models

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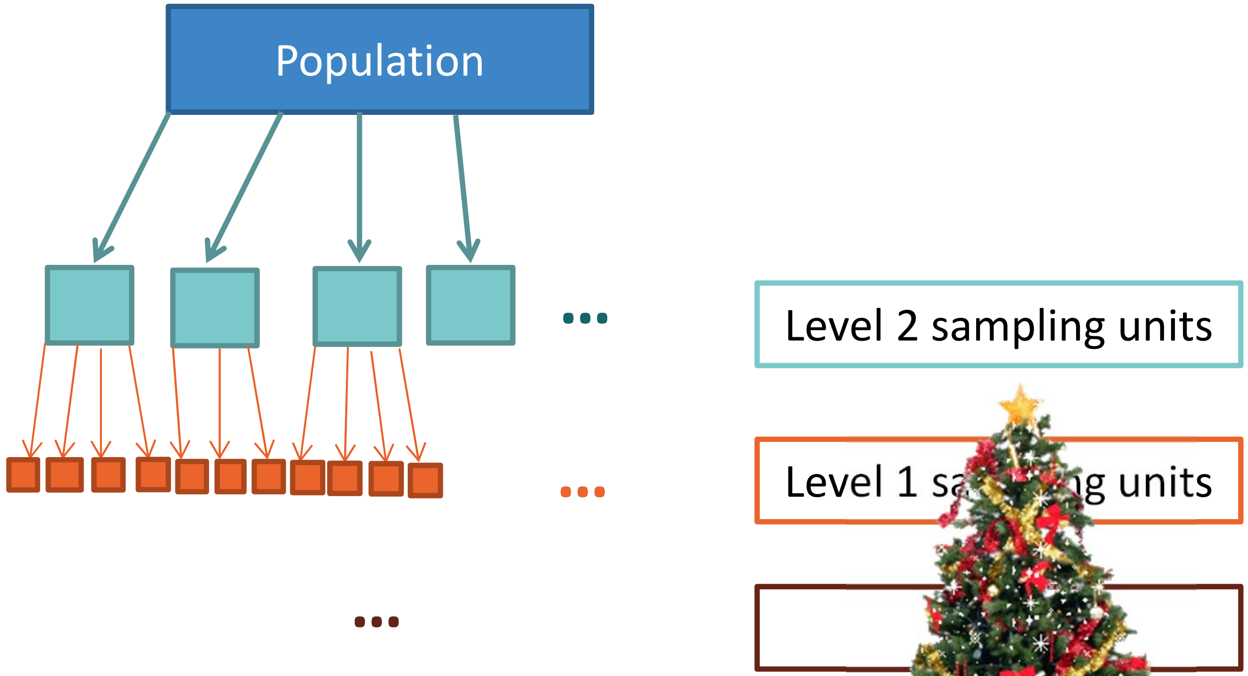
Mixed-effects model-based recursive partitioning

Clustered or longitudinal data:



Generalized linear mixed-effects regres[illegible]s
(glmertree; Fokkema et al., in press)

Advantages of decision tree methods

1. Data-analytic flexibility
   - Predictors may be categorical, ordinal or continuous
   - Outcomes may be continuous, categorical, count, survival
   - No (few) assumptions about data distribution
   - Can deal with many potential predictors (also $p > N$)

2. Easy to interpret and apply
   - Direct identification of subgroups
   - Easy to use in decision making (no formulas, no computation)
   - Not all variables in model need to be assessed for making decision

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Disadvantage of decision tree methods

3. Instability: Small changes in data may yield (very) different tree

But:

- Traditional (generalized) linear models also unstable, changing tree structure *looks* much worse
- Mixed-effects improve stability (as with linear models)
- Tree ensembles provide state-of-the-art predictive accuracy, but suboptimal interpretability
- Earlier tree algorithms (e.g., CART) suffer from variable selection bias, model-based RP does not (Hothorn et al., 2006)

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Ex. 1: Outcomes in UK young people's mental health services

3,739 young people, 13 service providers

Treatment outcome: mental-health difficulties score

Potential baseline predictors:

- demographic variables
- case characteristics (presence of mental and behavioral disorders)
- severity characteristics (functioning impairment)

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Ex. 1: Outcomes in UK young people's mental health services

Mixed-effects linear model (Edbrooke-Childs et al., 2016):

- Age, Autism, Ethnicity, Infrequent case characteristics, Eating disorder, Hyperactivity
- $\hat{\rho}_{pred,obs\ outcomes}$ = .240 (10-fold CV)

Mixed-effects tree:

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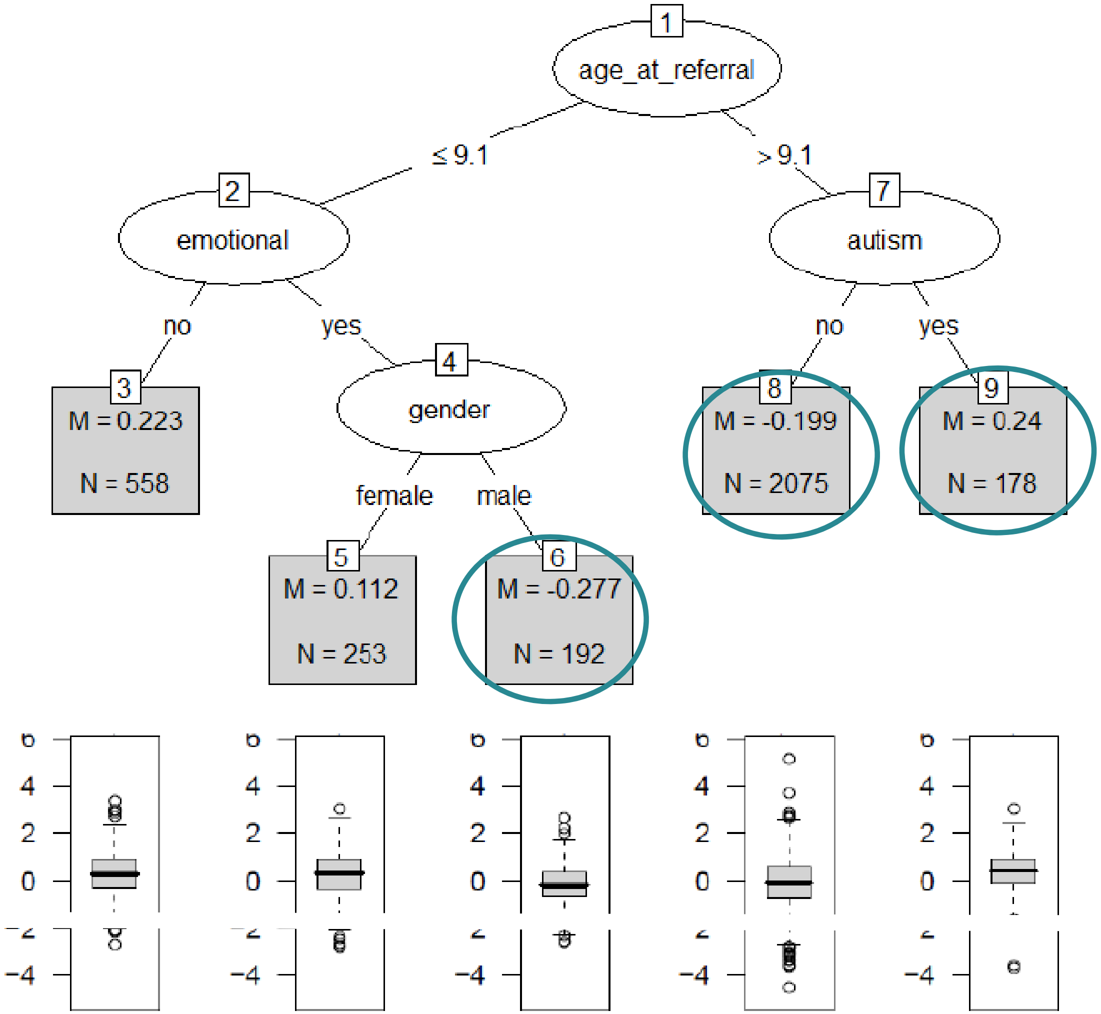
Ex. 1: Outcomes in UK young people's mental health services



Ex. 1: Outcomes in UK young people's mental health services

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- Age, Autism, Ethnicity, Infrequent case characteristics, Eating disorder, Hyperactivity
- $\hat{\rho}_{pred,obs\ outcomes}$ = .240 (10-fold CV)

Mixed-effects tree:

- Age, Emotional problems, Autism, Gender
- $\hat{\rho}_{pred,obs\ outcomes}$ = .245 (10-fold CV)

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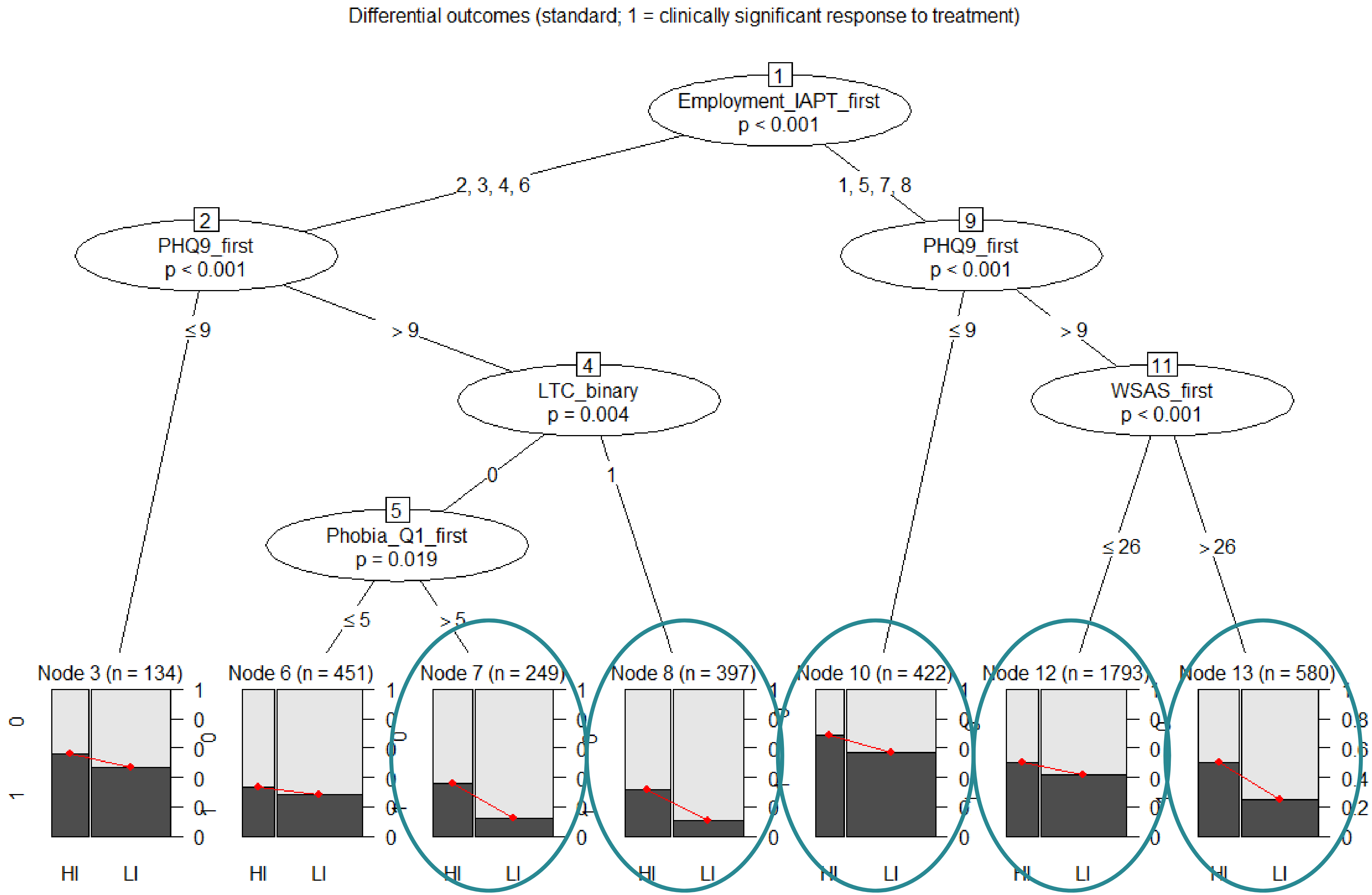
Ex. 2: IAPT SMART data tournament



Discussion

Accuracy is just one factor to consider –

Consider how fast, how robust, how easy to update with new variables or observations, how to deal with missing data, how easy to explain

For clinical decision making: How transparent, how trustworthy, how simple

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References

Edbrooke-Childs, J., Macdougall, A., Hayes, D., Jacob, J., Wolpert, M., & Deighton, J. (2017). Service-level variation, patient-level factors, and treatment outcome in those seen by child mental health services. *European Child & Adolescent Psychiatry, 26*(6), 715-722.

Hothorn, T., Hornik, K. & Zeileis, A. (2006). Unbiased Recursive Partitioning: A Conditional Inference Framework. *Journal of Computational and Graphical Statistics, 15*(3), 651-674.

Fokkema, M., Smits, N., Zeileis, A., Hothorn, T. & Kelderman, H. (in press). Detecting treatment-subgroup interactions in clustered data with generalized linear mixed-effects model trees. *Behavior Research Methods*. DOI:s13428-017-0971-x

Zeileis, A., Hothorn, T., & Hornik, K. (2008). Model-based recursive partitioning. *Journal of Computational and Graphical Statistics, 17*(2), 492-514.

R packages

Hothorn, T., Seibold, H. & Zeileis, A. (2018). partykit: A Toolkit for Recursive Partytioning. R package version 1.2-2. https://cran.r-project.org/package=partykit

Zeileis, A. & Fokkema, M. (2017). glmertree: Generalized Linear Mixed Model Trees. R package version 0.1. https://cran.r-project.org/package=glmertree

Introduction to mixed-effects trees

'Fitting mixed-effects trees in R.pdf' on https://github.com/marjoleinF/TSIL2018

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