But can a GAM do that too? What if I have multilevel data? What if I'm a Bayesian?

- ***Is interpretability of the essence?*** Fit a (penalized) GLM, GAM or single tree.
    - Want best of both worlds (predictive accuracy close to a gradient boosted ensemble, interpretability close to single trees)? Fit a prediction rule ensemble (PRE). It combines the strengths of gradient tree boosting with that of the lasso (Fokkema, 2002; Fokkema & Strobl, 2002).
- ***Are there / might there be non-ignorable interactions in the data?*** Use SVM (with polynomial or radial basis kernel) or a tree method (single, random forest or boosting).
    - Or fit a GAM anyway, with tensor splines to model interactions (Wood, 2017). Then you will have to think carefully about which variables interact, so only do that when you have few potential predictors where you are certain they are of relevance.
    - Compare the fit of two gradient boosted ensembles: One with interaction.depth equal to 1 (this model will approximate a GAM), one with a higher value for interaction.depth. If higher value does much better, then there are interactions!
- ***Do you have many possible predictors and do you need your method to do selection?*** Use lasso or elastic net, see Tom's lectures. Also, you can do variable selection with GAMs! (see select argument of function gam from package mgcv)
- ***Do you want to do inference*** (decide if a predictor really affects the outcome, and perhaps know something about the shape of the effect)? Fit a GAM or GLM.
- ***Are you a Bayesian***? Fit a GAM or a Bayesian Additive Regression Trees (BART) ensemble (package dbarts, function bart or bart2). REML estimated GAMs are already quite Bayesian, but if you must go fully Bayesian, R packages are available (I have currently no advice on which package, too fond of mgcv).
- ***Do you have multilevel and/or longitudinal data?*** Fit a GAM, or fit a generalized linear mixed model tree (GLMM tree; Fokkema et al., 2020), or fit a multilevel Bayesian Additive Regression Trees (BART) ensemble (package dbarts, function rbart_vi).
- ***Do you want a tree ensemble but no variable selection bias?*** Use function cforest from package partykit, or function blackboost from package mboost.
- ***Do you have a very large sample size*** (> 10,000 – 100,000)? Stay away from SVMs. Single trees should still be quite feasible. For tree ensembles, keep tree size low, and/or use package xgboost or lightgbm for boosting, package ranger for random forests (biased variable selection, but fast!). For GAMs, use function bam (big data GAM) from package mgcv.

GLMM trees

Use R package **glmertree**, function `(g)lmertree`.

Short tutorial: https://cran.r-project.org/web/packages/glmertree/vignettes/glmertree.pdf

More technical paper: Fokkema, M., Smits, N., Zeileis, A., Hothorn, T., & Kelderman, H. (2018). Detecting treatment-subgroup interactions in clustered data with generalized linear mixed-effects model trees. *Behavior research methods*, *50*(5), 2016-2034.

Paper oriented towards applied researchers: Fokkema, M., Edbrooke-Childs, J., & Wolpert, M. (2021). Generalized linear mixed-model (GLMM) trees: A flexible decision-tree method for multilevel and longitudinal data. *Psychotherapy Research*, *31*(3), 329-341.

PRE

Use R package **pre**, function `pre`.

Short tutorial: https://github.com/marjoleinF/pre/blob/master/README.md

More technical paper: Fokkema, M. (2020). Fitting prediction rule ensembles with R package pre. *Journal of Statistical Software*, *92*(12), 1-30.

Paper oriented towards applied researchers: Fokkema, M., & Strobl, C. (2020). Fitting prediction rule ensembles to psychological research data: An introduction and tutorial. *Psychological methods*, *25*(5), 636.

References / recommended reading:

- Efron, B. (2020). Prediction, estimation, and attribution. *International Statistical Review*, *88*, S28-S59.
- Wood, S. N. (2017). *Generalized additive models: An introduction with R (2nd edition)*. CRC press.
- Strobl, C., Malley, J., & Tutz, G. (2009). An introduction to recursive partitioning: rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological Methods*, *14*(4), 323.