A Comparison of Approaches for Benchmarking Service Organisations

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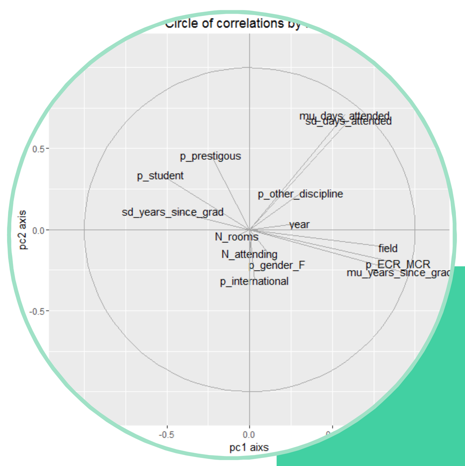
Background

- Benchmarking can determine the latent performance of organisations in terms of benefits or value to clients and costs incurred.[1,2]
- Variability and uncertainty in the mix of clients and services provided by organisations can make benchmarking challenging. Hence, it is necessary to adjust for the specific contextual factors of each organisation when interpreting the results of benchmarking.
- Models have been developed to:
  - Peer organisations to adjust for contextual differences between organisations and
  - Distil an overall score from many observations to assess performance.
- Benchmarking and ranking is reported in a range of fields such as healthcare, education and government services.[3-6]

Methods

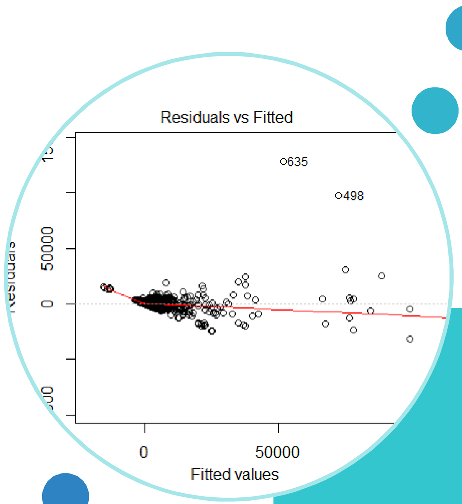
- We showcase methods used in benchmarking and apply these methods to rank simulated conferences.
- Data were simulated for variables that might characterise conferences:
  - Attendees (number, country of residence, years since graduation, ECR/MCR/senior researcher).
  - Context (field of research, location eg major city, number of days, number of concurrent seminars).



Pre-modelling

Variable selection[7-9]
- Principal component analysis
- Factor analysis
- Lasso
- Boosted trees

Clustering



Regression

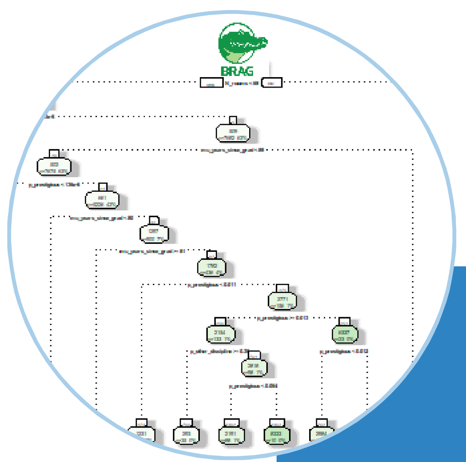
Regressions
- Linear, multiple linear, logistic, splines[1,10-12]
- Fixed, random or mixed effects models[13-15]

Multilevel
- Better reflects uncertainty
- Enables explicit adjustment of benchmark scores for individual organisations and contextual factors
- Enables estimation of benchmark scores for a group of organisations or a typical organisation

Mixture modelling[16]
- Combines multilevel modelling with clustering
- Captures dependencies
- However, number of groups must be pre-determined

Bayesian[13,15,17,18]
- MCMC
- Obtain a probability of membership to peer group
- Obtain a probability of meeting performance indicator
- Can cluster by performance

Advanced multilevel modelling methods can capture hierarchies and dependencies in data.



Post-modelling

Significance tests[19-21]
- For differences between groups
- t, x^2
- Bayesian inference

Ranking[14,22]
- By clusters, if uncertainty is large
- Hierarchical clusters

Economic modelling
- Cost-benefits
- Efficiencies
- Optimisation

Conclusions

- Multilevel modelling current state-of-the-art method for estimating latent performance of organisations.
- Better understanding of uncertainty can be used to:
  - Inform risk-based decision-making
  - Reflect differences between organisations and
  - Aid communication of results.
- Combining multilevel models and mixture models, it is possible to use the model to estimate the mean performance and characteristics of each group and derive realistic performance targets.

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