Latent Variable Effect Forests

Gesis Workshop Contribution

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Latent Variable Modeling

Definition:

Latent Variables are **unobservable phenomena** like

- creativity (Jauk et al., 2014)
- extraversion, neuroticism
- social anxiety, depression (Prenoveau et al., 2011)
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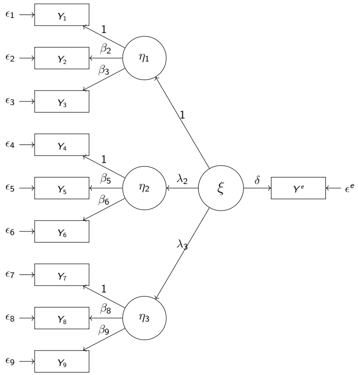

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> *"...the degree to which evidence and theory support the interpretations of test scores for proposed uses of tests."*
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3. Estimate latent variable scores for subgroups that fulfill requirements

LVE Forest

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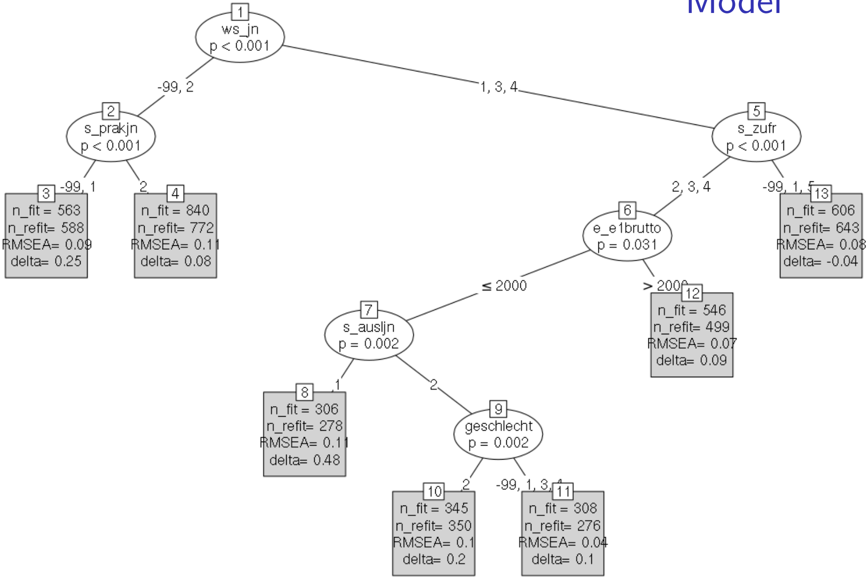
5. Compile results across all iterations

Tree in LVE Forest for Self-Leadership Model



Conclusion

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$\rightarrow$ Predicted latent variable scores fulfill criteria for validity
although construct may not generally be valid

References

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Any questions?

- Contact: classe@ihf.bayern.de
- Want to try the method?: `scforest` on github (coming soon)