Predicting working memory training outcome patterns using a machine learning approach

Yi Feng¹, Anja Pahor¹,², Aaron R. Seitz², & Susanne M. Jaeggi¹

1 University of California, Irvine
2 University of California, Riverside

Introduction
- Individual differences exists in working memory (WM) training gains
- Researchers have examined the independent effect of selected variables on WM training outcome, like intelligence, baseline WM ability¹
- Previous studies only investigated one or two individual differences variables at once and no consistent findings have emerged so far

RQ1: Can a combination of individual difference variables predict one’s WM training performance?

RQ2: Which variables are most important in predicting WM training performance?

Method
- 170 undergraduates (103 women) completed 10 sessions of N-back intervention over 2 weeks
- 18 variables were measured to predict training performance

Cognitive abilities (Baseline)
- WM, Matrix reasoning (MR), Updating, Inhibitory control

Personality characteristics
- Extraversion, Agreeableness, Openness, Conscientiousness, Neuroticism

Personal preference scales
- Composite of grit and ambition, Cognitive failures questionnaire (CFQ), Beliefs about changing cognitive ability (TCA), Video game questionnaire (VGQ), Workmastery, Competitiveness

Well-being
- Perceived stress scale (PSS), Likelihood of fall asleep

Demographics
- Self-reported SES

Data preprocessing
- Participants were clustered into 3 classes based on their maximum of N-back level, changing slope and standard deviation across sessions (silhouette score=0.566)

Results

RQ1: The combination of individual difference variables can predict one’s WM training patterns by applying a one hidden layer perceptron classification algorithm (mean acc 0.543 vs. chance level 0.333).
- Permutation test (resample 1000 times)

RQ2: In general, WM and matrix reasoning contribute most in predicting training performance patterns. Competitiveness and cognitive failure also contribute to predict Class1,0 respectively.

Further analysis
- Compare different models’ prediction power
- Examine the generalization of the model using a new data set
- Investigate how interaction between features affect predicting training patterns

References

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