Predicting working memory training outcome patterns using a machine learning approach

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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 ability[1]
- 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)

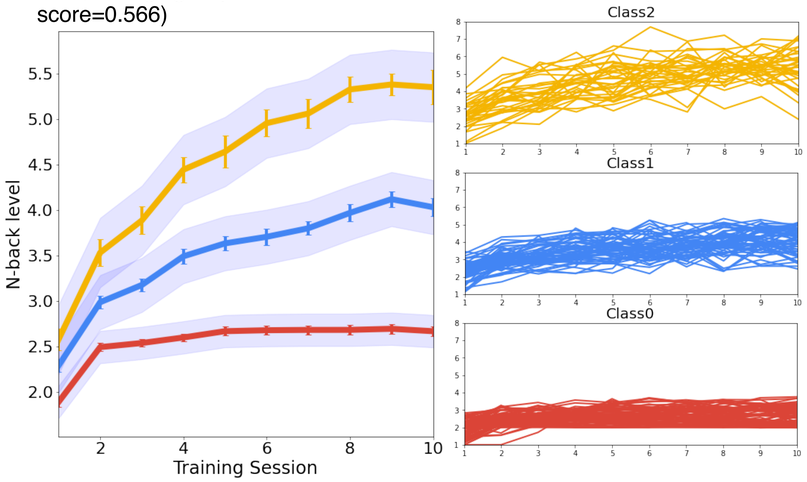


Figure 1. Training performance patterns (k-means clustering)

Results

- Multilayer perceptron classification model
  - Tuning hidden layer size to get optimal parameters (Table 1)
  - Predictive accuracy of the optimal model (Figure 2)

Table 1. Predictive power of different hidden layer size

Hidden layer	Model accuracy	F1 score	Class0 Acc	Class1 Acc	Class2 Acc
(2,)	.415	.198	1	0	0
(3,)	.521	.513	.577	.467	.5
(5,)	.543	.540	.564	.517	.54
(8,)	.516	.501	.603	.317	.62
(10,)	.457	.448	.526	.4	.42
(12,)	.516	.506	.59	.4	.54
(8,3)	.441	.424	.551	.217	.54
(10,5)	.457	.446	.551	.317	.48
(12,7)	.479	.462	.615	.333	.44
(15,9,4)	.415	.195	1	0	0

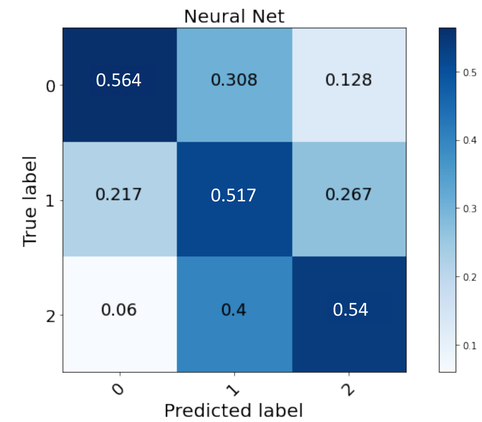


Figure 2. Confusion matrix

- KernelSHAP[2] (SHapley Additive exPlanations) to explain the prediction by computing the contribution of each feature to the prediction

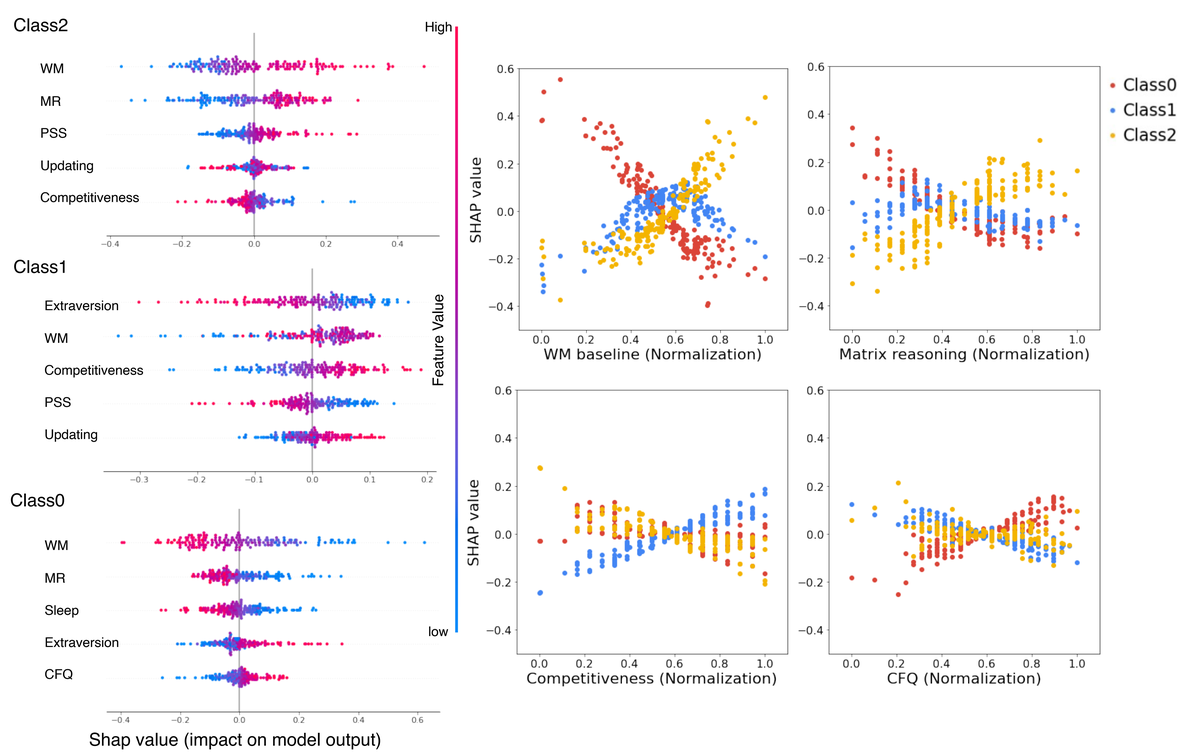
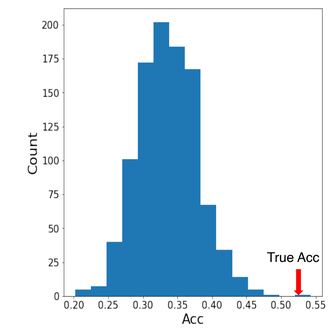


Figure 3. A summary plot of features' impact in each class (left panel: list the top 5 important features when predicting the class; right panel: the relationship of feature value and their impact)

Discussion

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

[1] Karbach, J., Könen, T., & Spengler, M. (2017). Who benefits the most? Individual differences in the transfer of executive control training across the lifespan. *Journal of Cognitive Enhancement*, 1(4), 394-405.

[2] Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. In Advances in neural information processing systems (pp. 4765-4774).

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