Machine learning predicts executive functions from verbal fluency data: A study in healthy participants

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Introduction

Background

- Verbal fluency (VF) tasks are well-established parts of executive function (EF) tests commonly used in neuropsychological assessment
- Beside evaluation of the sum of words produced in VF tasks, qualitative parameters like semantic distances [1] and speech breaks [2] were shown to be representative for reflecting EFs
- Commonly used evaluation of semantic distances rely on subjective and manual assessments but computerized analyses were shown to better address qualitative evaluation of patient´s searching strategies [3]

Aim

Identify distinct VF search strategies to predict EF performance by use of machine learning methods

Methods

Subjects

- n = 234
  - Females: 60%
  - Males: 40%
- Age: 20-55 (mean age: 35,2)
- Monolingual German
- No neurological / psychiatric diseases

Machine Learning Approach

- Data adjusted for sex and age by linear regression
- Relevance Vector Machine
  - Bayesian sparse technique
- 10-fold cross-validation
- 100 replication
- Mean of correlation of true and predicted EF scores

Testing material

Executive function battery

- 13 EF tests assessing cognitive flexibility, working memory and inhibition

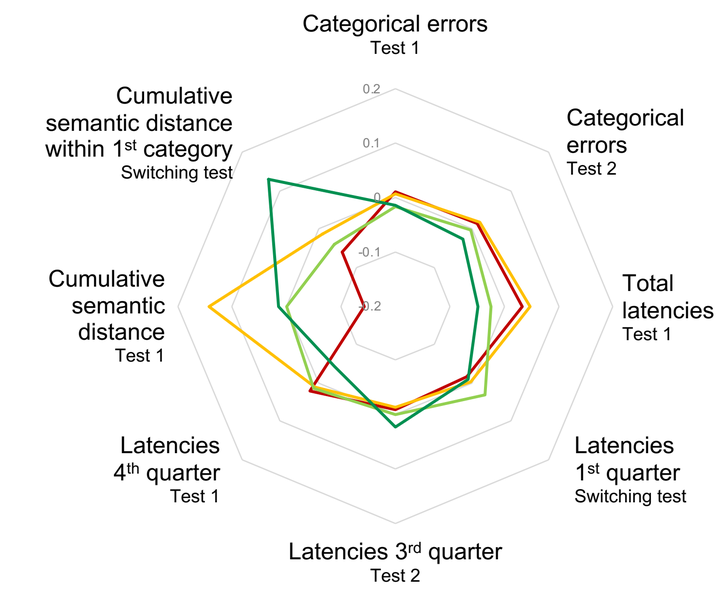
Semantic verbal fluency tests

- 2 minutes per test
  Test1: Animals
  Test2: Jobs
  Test3: Switching: Sports / Fruits
- 39 Variables of interest measuring
  - Correct number of words
  - Repetition & category errors
  - Speech break latencies (semi-automated determined with PRAAT [4])
  - Sequential & cumulative semantic distances (ontological approach of GermaNet [5])
  - Evaluation of VF switching task across both categories and within each category

Results

Cognitive flexibility

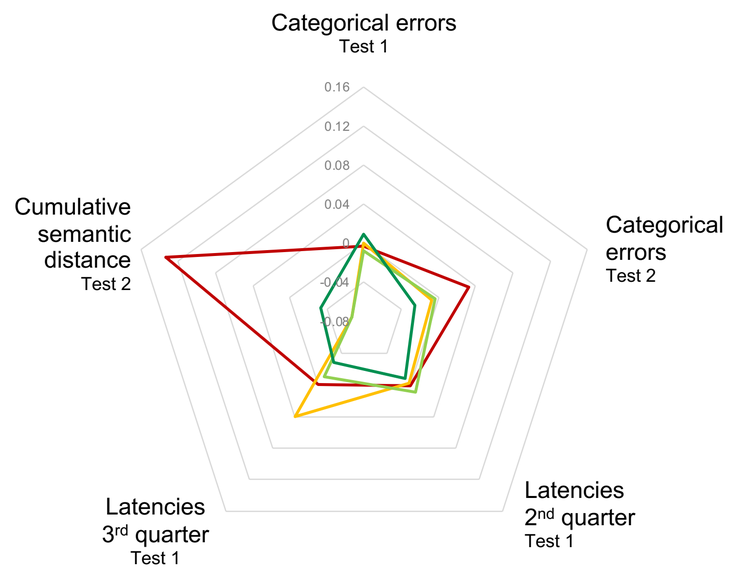
Raven´s Standard Progressive Matrices Test



r = 0.42
Correlation coefficient of true and predicted EF scores
(p < 0.0001)

Working memory

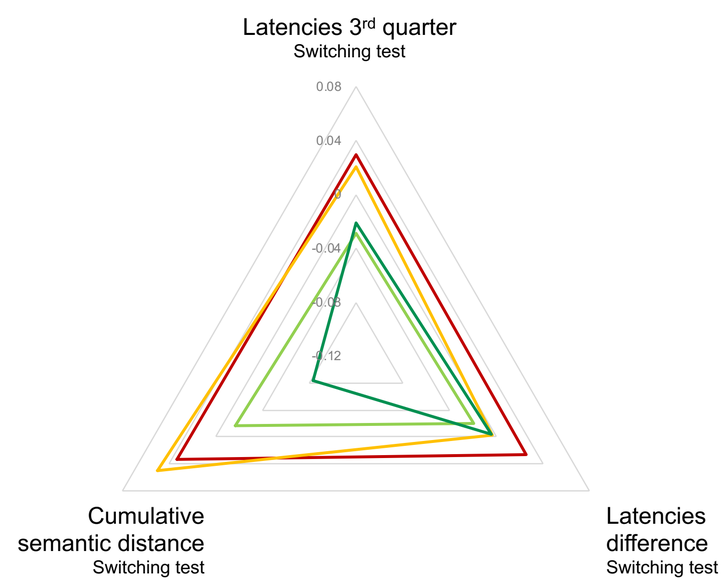
N-back non-verbal Test



r = 0.13
Correlation coefficient of true and predicted EF scores
(p = 0.005)

Inhibition

Stop-Signal Test



r = 0.23
Correlation coefficient of true and predicted EF scores
(p < 0.0001)

High performers characteristics

- Tend to search in closely related word categories
- Produce less errors
- Have shorter speech breaks

- Tend to search in far distanced word categories
- Produce less errors
- Have shorter speech breaks

- Tend to search in far distanced related word categories
- Produce less errors
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Legend

Test 1 = Animals
Test 2 = Jobs
Switching test = Sports / fruits

EF-Performance
Quartile 1 – Very bad
Quartile 2 – Bad
Quartile 3 – Good
Quartile 4 – Very good

Features from switching VF task are most predictive to inhibition performance

Discussion

- Semantic VF features could predict cognitive flexibility, working memory, inhibition performance applying machine learning methods
- According to other studies [1] semantic relatedness is not *per se* an indicator for cognitive flexibility performance
  → Participants are not explicitly asked to produce category-switches → non-linear relationship of semantic distances and EF performance → closely related words are easier to access
- Extending previous findings [6], especially switching VF task relies on inhibitory processes → suppressing words from second category in VF switching task expresses high inhibitory demand
- Additional semantic analyses e.g. based on Latent Semantic Analysis → improve prediction results
- Decoding VF search strategies → better understanding of EF – VF relationship → VF tasks could substitute EF tests
  → less time-consuming, closely related to everyday life performance

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