Optimizing Pattern Weights with a Genetic Algorithm to Improve Automatic Working Memory Capacity Identification

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INTRODUCTION

Working Memory Capacity (WMC)

- Cognitive trait that influences the learning process:
  - learning speed
  - memorization of learned concepts
  - effectiveness of skill acquisition
- Related to:
  - students' reading comprehension
  - skill at mathematics
  - general intelligence
- Limited to 7 +/- 2 items which may be stored at a time
- Overload can reduce learning performance, reduce transfer of learning or increase the amount of time needed to learn
- Awareness
  - Individualized cognitive load
  - Adaptive recommendation mechanism for learning activities
  - Students could better self-regulate their learning
  - Teachers could monitor students' WM load and use appropriate strategies to reduce overload when necessary

Identifying WMC

- Traditionally, WMC is measured by asking students to take a specific multitasking test
  - OSPAN (operation span task) (Turner & Engle, 1989)
  - WebOSPAN (Lin, 2007)
  - AOSPAN (Unsworth et al., 2005)
- Disadvantages
  - Require additional time and effort
  - Influenced by the perceived importance of the test by the students, stress or fatigue

- Alternative: **automatically infer WMC from students' behavior in learning systems**
- Relevant studies - relationship between WMC and other student characteristics
  - WMC & field-dependent / field independent cognitive style (Graf et al., 2008)
  - FD/FI style & behavior in learning systems (Ford & Chen, 2000), (Chen, 2010)
  - Felder-Silverman learning style model (FSLSM) and WMC (Graf et al., 2009)

- **DeWMC (Detecting Working Memory Capacity)** (Chang et al., 2013)
  - Calculates WMC from six patterns (five behavior patterns and students' learning styles)
  - Assumes that each pattern contributes equally to the calculation of WMC

WMCID-GA

WMCID-GA

- WMC IDentifier based on Genetic Algorithm
- An approach for automatically identifying WMC from student behavior
- Extends DeWMC by using optimized pattern weights, identified through a genetic algorithm

- 5 behavior patterns + 1 pattern related to learning styles (FSLSM)
    - Linear Navigation
    - Constant Reverse Navigation
    - Performing Simultaneous Tasks
    - Recalling Learned Material
    - Revisiting Passed Learning Objects

WMCID-GA - Steps

- Extract student data from the learning system database and compute the respective patterns
- For each pattern, a high or low value is associated to a high or low WMC, based on existing studies from literature
- For each learning session of a student, a WMC session value is calculated (weighted average of all pattern values)
- The overall WMC value is calculated by building a weighted average over all WMC session values (considering the amount of available behavior data per learning session as a weight)

Genetic Algorithm

- Use concepts from evolutionary biology to solve optimization problems
- **Genome → 6 genes** (one for each pattern)
  - Range of values (i.e. weight of the respective pattern): 0.01 to 1.0 in increments of 0.01
- **Fitness** of a genome → average error between the actual and calculated WMC
- **Initialize the population** (**P**) with random values for each genome
- **Select P/2** genome pairs - roulette wheel technique
- **Uniform crossover** - each gene has a chance of being swapped equal to the crossover weight (**C**)
- **Uniform mutation** - each gene has a chance of being mutated equal to the mutation weight (**M**)
- The new genomes are merged into the population and the genomes with the lowest fitness are culled until the population is size P again
- **Termination condition**: GA stops only after *Gbest* generations passed without finding a new best solution (min.10,000 generations)

EVALUATION

Evaluation Settings

Data

- 75 undergraduate students
- 5 behavior patterns extracted from Moodle data
- Felder- Silverman learning styles (identified by the Index of Learning Styles)
- WMC (identified by WebOSPAN)
- Students with > 15 errors in WebOSPAN task and students spending < 5 minutes on the learning style questionnaire were removed → 63 students

Steps

- 1. Find the optimal values for the parameters of the GA
- 2. Test overfitting reduction strategies and find optimal parameters for those strategies
- 3. Run WMCID-GA and get final results

(10 fold cross validation was used for each part of the evaluation)

Performance Metrics

- **ACC** (accuracy) - measures the difference between the student's actual WMC and the WMC identified by WMCID-GA
- **LACC** - lowest ACC value in the assessment set, measuring the worst case scenario for an individual student
- **%Match** - measures the percentage of students who were identified with reasonable accuracy

Optimal Parameter & Overfitting Reduction Settings

Table 1. Optimal parameter settings

Population	Crossover Weight	Mutation Weight
25	0.80	0.001

Table 2. Optimal overfitting reduction settings

Stratification	FEP	min_{gen}
On	On	25

Results

Table 3. Result comparison between WMCID and DeWMC (top result bolded)

Approach	ACC	LACC	%Match
WMCID-GA	**0.851**	**0.694**	**0.893**
DeWMC [12,13]	0.809	0.442	0.809

Table 4. Minimum, Maximum, and Average Weights and Percentage of Activated Learning Sessions per Pattern

Pattern	Min	Max	Average	Activated
Linear Navigation	3	13	7	89.98%
Constant Reverse Navigation	50	99	82	78.62%
Performing Simultaneous Tasks	81	100	97	8.25%
Recalling Learned Material	10	33	22	58.86%
Revisiting Passed Learning Objects	36	84	62	60.19%
Learning Styles	2	17	10	100.00%

CONCLUSION

Findings and Future Work

- ✓ Evaluation shows that WMCID-GA is outperforming DeWMC in all investigated metrics and therefore, can provide more accurate WMC results for more students
- ✓ Results indicate that different patterns have different impact on the WMC identification

Future work

- Investigate the use of other optimization algorithms to see if they can find better solutions
- Explore hybrid algorithms, which can be useful at overcoming the weaknesses of mono artificial intelligence algorithms

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