Experimental Analysis of Mastery Learning Criteria

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Mastery learning

common personalization approach in educational systems

item	answer	time	correct?
$\frac{2}{3}+\frac{4}{5}$	$\frac{13}{15}$	12s	correct
$\frac{3}{4}+\frac{1}{6}$	$\frac{10}{12}$	7s	incorrect
$\frac{2}{7}+\frac{3}{14}$	$\frac{1}{2}$	9s	correct
$\frac{1}{4}+\frac{2}{3}$	$\frac{11}{12}$	7s	correct
$\frac{2}{5}+\frac{3}{7}$	$\frac{29}{35}$	13s	correct

Should the learner continue or move to another topic?

Mastery criteria

N consecutive correct (NCC)

moving average

- moving window
- exponential moving average (EMA)

based on learner model – threshold rule

- Bayesian knowledge tracing (BKT)
- logistic models

all criteria use some threshold

Questions

Which criterium to use?

What input data to use?

Does the use of learner modeling bring advantage?

How to evaluate mastery criteria?

How to choose thresholds?

inherent trade-off:
certainty of mastery decisions
vs learners' time

Results

Learner modeling does not bring fundamental advantage to mastery learning.

Choice of input data and thresholds is more important.

Exponential moving average is a suitable technique:
simple, widely applicable,
sufficiently flexible.

Simulated data

Data generated using Bayesian knowledge tracing and a simple logistic model.

	Parameters			
B1	$P_i = 0.15$	$P_l = 0.35$	$P_s = 0.18$	$P_g = 0.25$
B2	$P_i = 0.25$	$P_l = 0.08$	$P_s = 0.12$	$P_g = 0.3$
B3	$P_i = 0.1$	$P_l = 0.2$	$P_s = 0.1$	$P_g = 0.15$
B4	$P_i = 0.1$	$P_l = 0.3$	$P_s = 0.4$	$P_g = 0.05$
B5	$P_i = 0.05$	$P_l = 0.1$	$P_s = 0.06$	$P_g = 0.2$
B6	$P_i = 0.1$	$P_l = 0.05$	$P_s = 0.1$	$P_g = 0.5$
L1	$\theta_0 \sim N(-1.0, 1.0)$		$\Delta = 0.4$	
L2	$\theta_0 \sim N(-0.4, 2.0)$		$\Delta = 0.1$	
L3	$\theta_0 \sim N(-2.0, 2.0)$		$\Delta = 0.15$	
L4	$\theta_0 \sim N(0.0, 0.7)$		$\Delta \sim N(0.15, 0.1)$	
L5	$\theta_0 \sim N(-2, 1.3)$		$\Delta \sim N(0.45, 0.15)$	
L6	$\theta_0 \sim N(-0.7, 1.5)$		$\Delta \sim N(0.6, 0.3)$	

Real data

umimecesky.cz – Czech grammar

matmat.cz – basic arithmetic

BKT vs NCC

data generated by BKT
mastery decision by BKT and NCC

results:

- highly correlated
- the difference is not practically important

	Threshold		wMAD		
	NCC	BKT	NCC	BKT	Cor.
B1	2	0.92	2.56	2.42	0.88
B2	4	0.97	6.2	5.76	0.97
B3	2	0.95	2.81	2.48	0.92
B4	1	0.9	2.72	2.13	0.74
B5	4	0.97	3.77	3.62	0.99
B6	8	0.97	11.48	10.33	0.94

wMAD = weighted mean absolute deviation from ground truth mastery

EMA analysis

two parameters:

- exponential decay
- threshold

simple and flexible

		Parameters			wMAD		
sc	N	α_{95}	α	T	NCC	EMA_{95}	EMA
B1	2	0.1	0.7	0.5	2.48	2.48	2.45
B2	4	0.5	0.75	0.75	6.45	6.23	6.07
B3	3	0.3	0.5	0.75	2.66	2.66	2.42
B4	1	0.1	0.2	0.8	2.82	3.47	2.31
B5	4	0.4	0.7	0.75	3.76	3.64	3.59
B6	7	0.7	0.75	0.92	11.04	10.45	10.41
L1	8	0.7	0.9	0.6	3.92	3.34	2.63
L2	17	0.85	0.9	0.9	9.02	8.44	7.64
L3	14	0.85	0.9	0.85	7.39	6.21	5.04
L4	15	0.85	0.8	0.98	10.28	10.7	10.3
L5	8	0.7	0.7	0.95	5.13	4.97	4.97
L6	8	0.7	0.6	0.98	6.67	7.12	6.87

Limitations and future work

This research does not take into account:

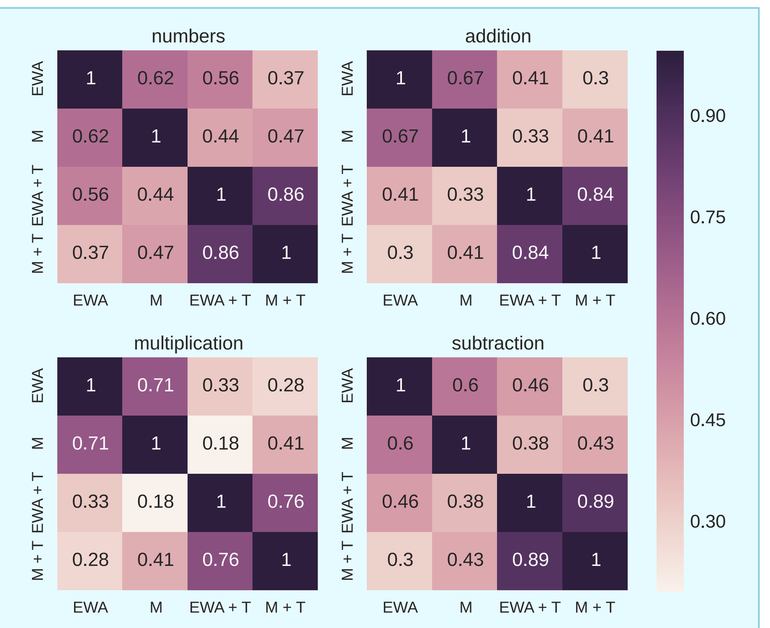
- multiple knowledge component
- forgetting
- wheel-spinning students
- partial credit

Role of input data

M = logistic learner model
EMA = exponential moving average
+T = with response times

results:

- EMA & M highly correlated
- use of response times has larger impact



Effort score graphs

effort = average number of attempts to reach mastery

score = average number of correct answers after reaching mastery

More research needed (effect of attrition bias, ...).