Adaptive Test Recommendation for Mastery Learning

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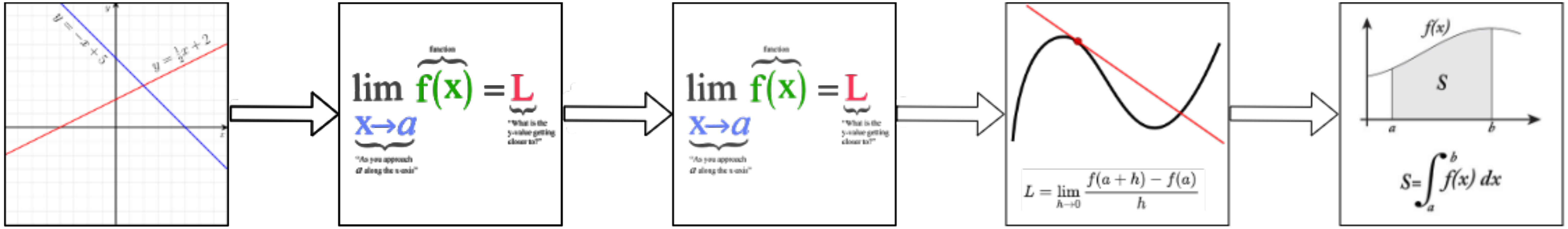
Mastery Learning

- **Mastery learning** advocates assigning tests to learners with the goal of **mastering** a target **difficulty level** for a given **skill**.

- The goal is to **minimize** the **learning gaps** that learners incur if they **fail** at assigned tests.

Pelánek, R., & Řihák, J. (2017, July). Experimental analysis of mastery learning criteria. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization* (pp. 156-163).

Example



Linear functions

Difficulty	0.3
Correct	1
No Gap	
Skill Updated	

Limits of functions

Difficulty	0.45
Correct	0
Gap on Limits	
Skill Not Updated	

Limits of functions

Difficulty	0.45
Correct	1
No Gap	
Skill Updated	

Derivatives of functions

Difficulty	0.7
Correct	1
No Gap	
Skill Updated	

Integrals

Difficulty	0.9
Correct	1
No Gap	
Skill Updated	

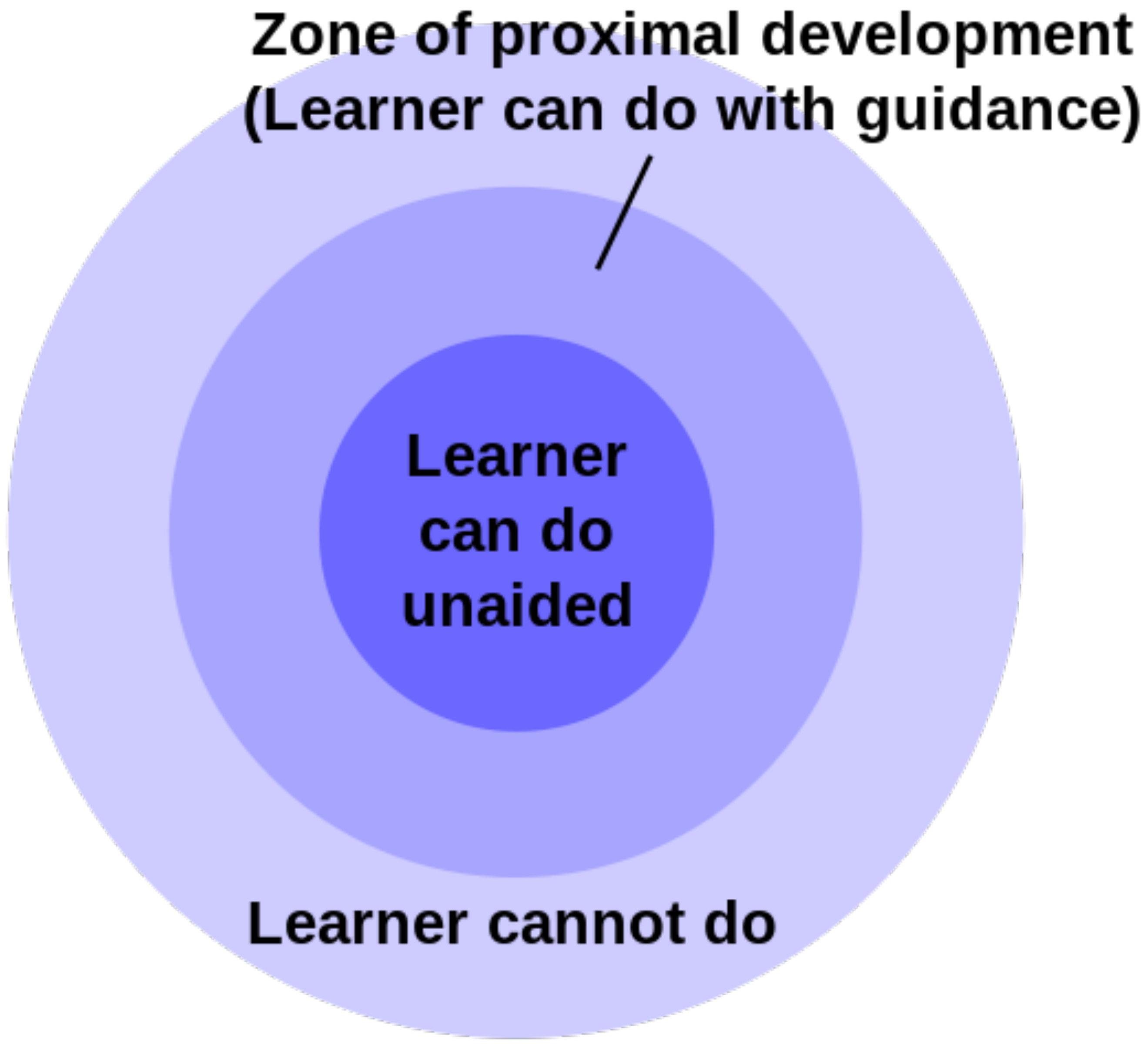
Goal and Challenges

Goal: an approach that assigns a **sequence of tests** to a learner to **maximize** their **skill acquisition** and **minimize** their **skill gap**.

Challenges:

- How to **determine** suitable tests to **assign** to the learner?
- How to **leverage previous failures** to **improve learning**?
- When to consider the learning **completed**?
- How to **validate** the learning process?

Learning Theories: Zone of Proximal Flow



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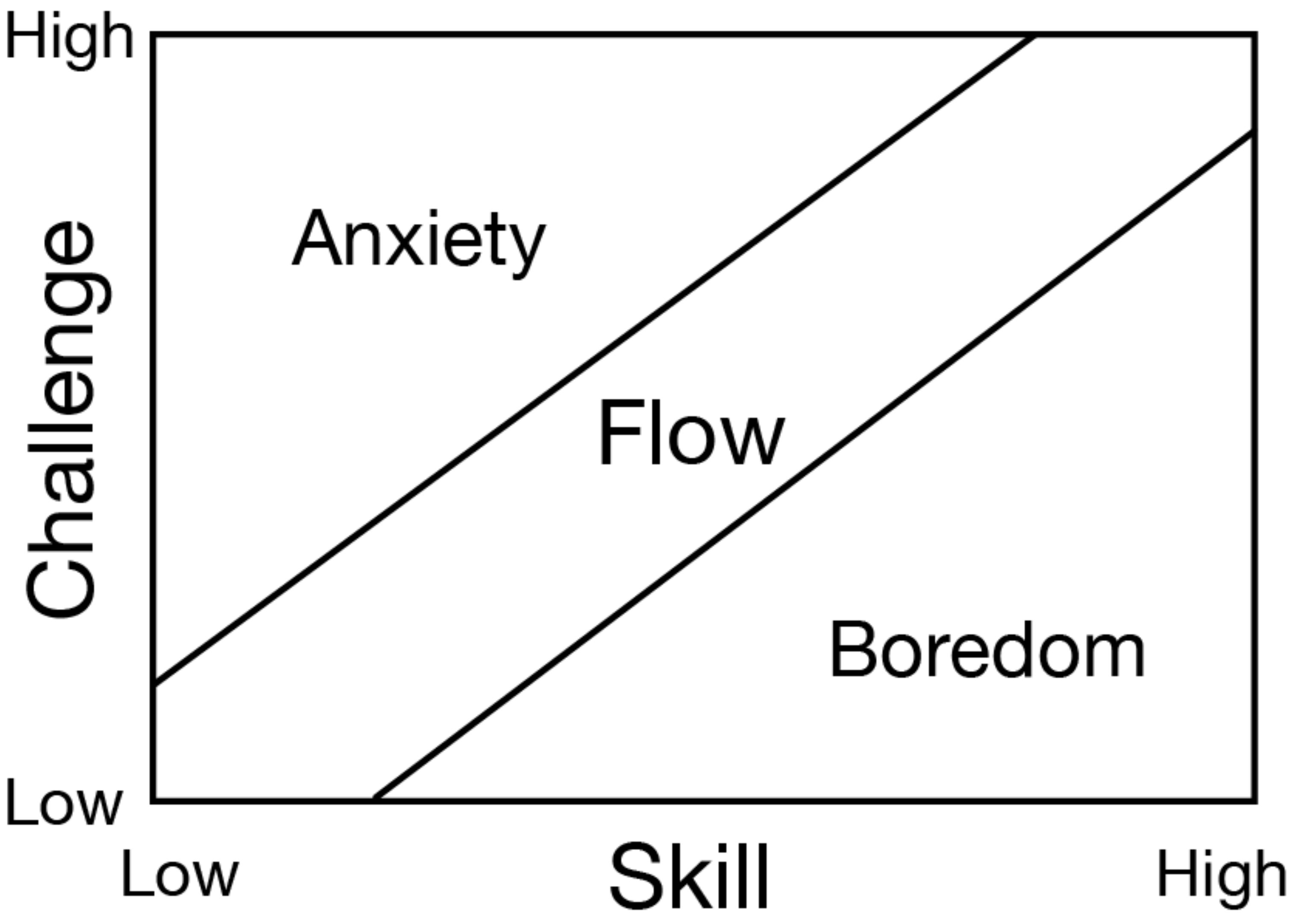


L. S. Vygotsky. 1980. **Mind in society: The development of higher psychological processes**. Harvard university press.

M. Csikszentmihalyi. 1975. **Beyond boredom and anxiety: The experience of play in work and games**. Jossey-Bass.

Mastery Detection Methods

- Methods without a learning assumption:[3] use simple **statistics** about past answers **without modeling** the learning process.
  e.g., *N Consecutive Correct (NCC).*

- Methods based on learner models: estimate a learner's knowledge and **predict** the **probability** of their **next** answer being **correct** or not: *Bayesian Knowledge Tracing (BKT)*[4] or *Latent Models (IRT).*[5]

[3] Pelánek, R., & Řihák, J. (2017, July). Experimental analysis of mastery learning criteria. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization* (pp. 156-163).

[4] Albert T Corbe and John R Anderson. 1994. Knowledge tracing: Modeling the acquisition of procedural knowledge. User modeling and user-adapted interaction 4, 4 (1994), 253–278.

[5] Philip I Pavlik Jr, Hao Cen, and Kenneth R Koedinger. 2009. Performance Factors Analysis–A New Alternative to Knowledge Tracing. Online Submission (2009)

Optimization objectives: Expected Performance

- is based on **previous** real **performances** of the learner.

$$exPerf(l,t) = sim(t, l.S)$$

- **Insight:** optimizing the expected performance only narrows the learner into the **Boredom Zone** with under challenging tests.

Optimization objectives: Aptitude

- represents the learner’s **progression ability** when completing a test.

$$apt(l, t) = d_t - l.sk$$

- **Insights:**
  - optimizing aptitude only narrows the learner into the **Frustration Zone** with over-challenging tests.
  - optimizing both aptitude and expected performance permit to assign tests from the **Comfort** (Flow) and **Learnable Zones**.

Optimization objectives: Gap

- represents the **distance** of each test to the **m last** tests that were **incorrectly completed** in previous steps.

$$gap(l, t) = dist(t, l.\mathcal{F})$$

AdUp Multi-Objective Optimization Problem

- Given a learner ***l*** with an initial mastery level ***sk***, a set of previously completed tests ***P***, find a batch ***B*** of ***k*** tests to assign to ***l*** s.t.:

$$maximize \sum_{t \in B} exPerf(l, t)$$

$$maximize \sum_{t \in B} apt(l, t)$$

$$minimize \sum_{t \in B} gap(l, t)$$

- Our solution relies on a **Hill Climbing** heuristic that finds the **Pareto** solutions by optimizing all objectives at **once**.

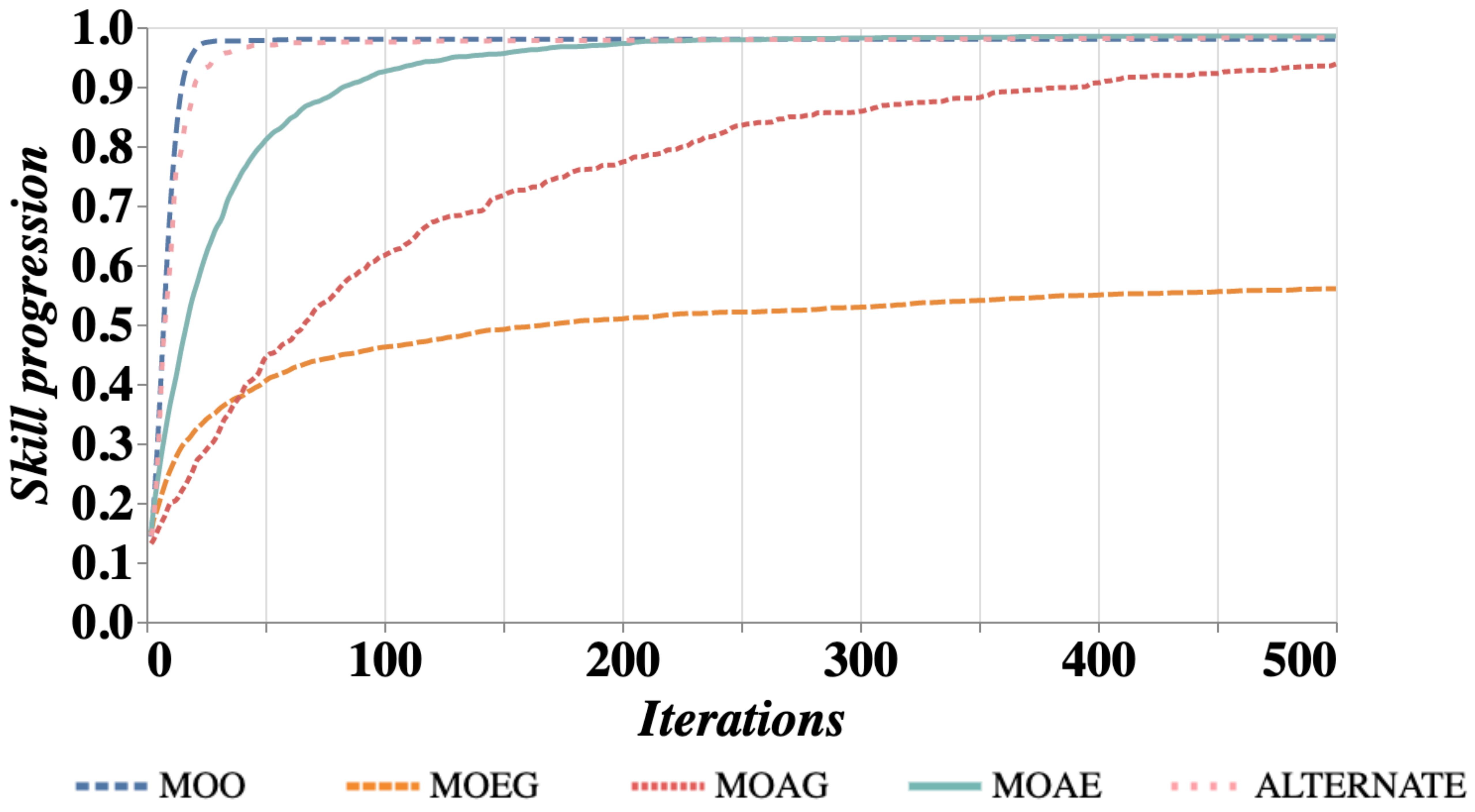
Experiments

- A learner **attains mastery** if their level **cannot be further improved**.
- We use a real world czech **mathematics dataset** intended for kids[6] from which we **inferred** 42 distinct **difficulties.**

[6] https://github.com/adaptive-learning/matmat-web/blob/master/data/data_description.md

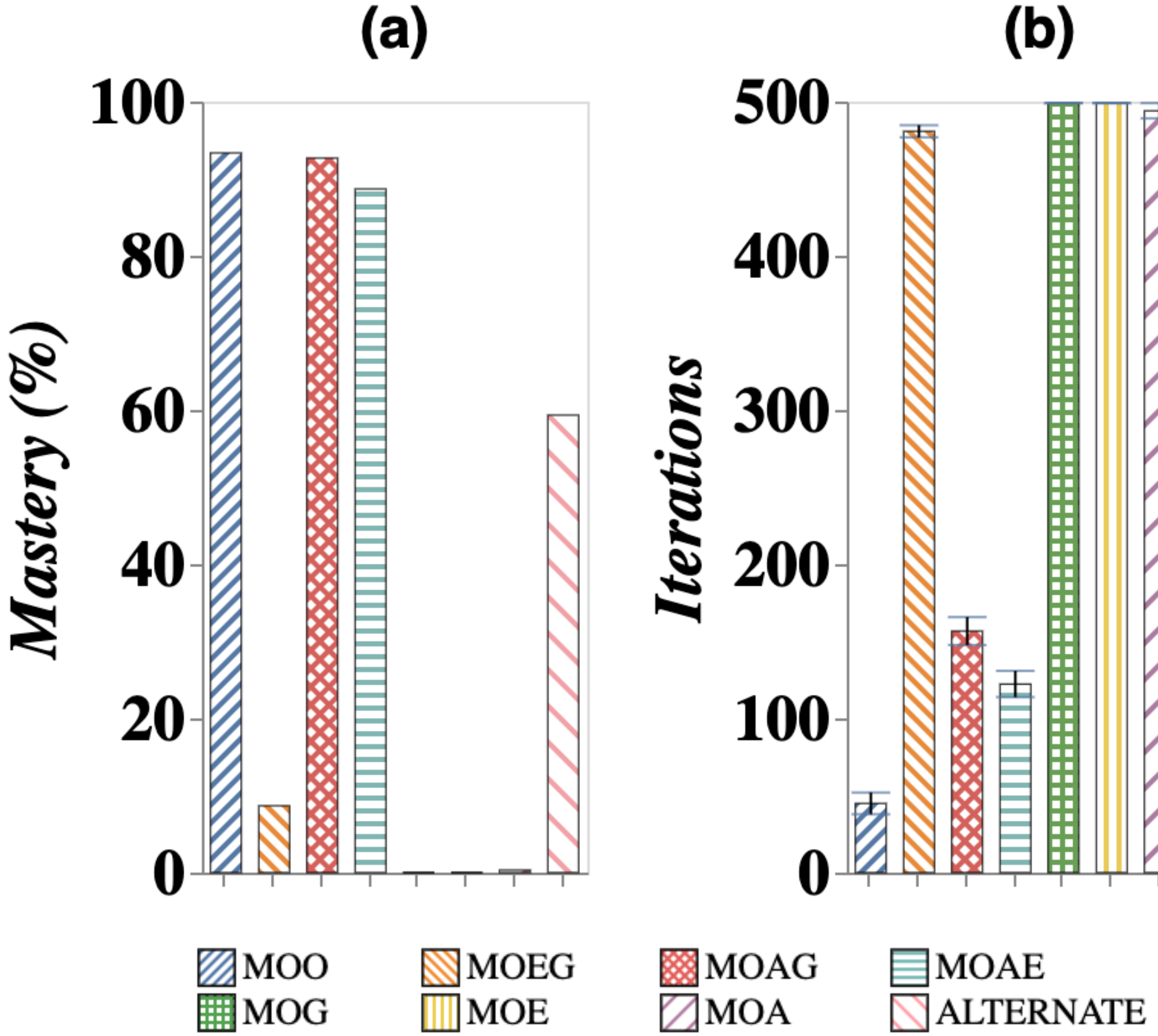
Experiments

skill progression



Experiments

% mastery and # iterations



Summary of results

Optimizing **expected performance only** narrows the learner into the Boredom Zone with under challenging tests.

Optimizing **aptitude only** narrows the learner into the Frustration Zone with over-challenging tests.

Optimizing **both aptitude and expected performance** permit to assign tests from the Comfort (Flow) and Learnable Zones.

Optimizing **all three objectives** outperforms single and bi-objective variants as well as alternating difficulty levels.

Conclusion

- Proposed a problem formalization that **combines mastery learning** with **upskilling theories**.

- Results showed that the solution that optimizes **all objectives** is **best** as it outperforms other variants.

Future

- Apply **Reinforcement Learning** to solve our problem.
- Applications to SQL learning by determining difficulty levels of individual tests more finely.