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ADAPTIVE TRAINING SYSTEM

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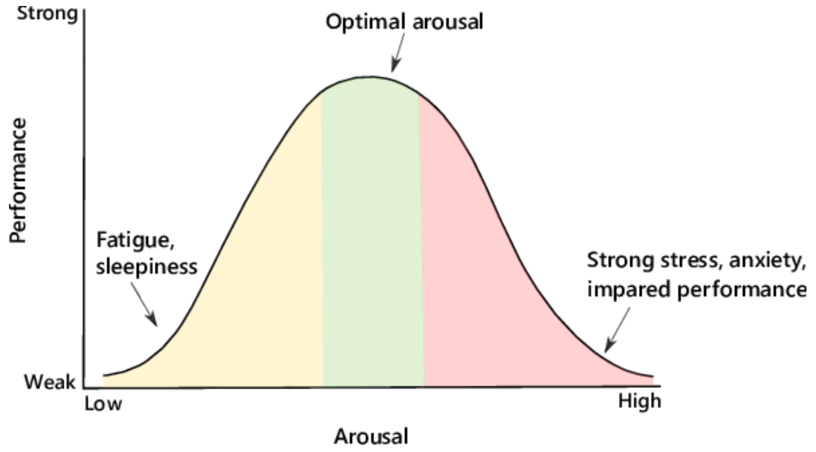
Assumptions about the training process

- The goal is to improve the skill of the trainee to perform given task
- There are scenarios with various difficulty for the same task
- Training process consists of small indivisible trials
- In each trial is performed one scenario with given difficulty
- After each trial is computed a performance score

Theories of learning optimization

- Hypotheses
  - Yerkes-Dodson Law valid in pilot training
  - Keeping optimal arousal increases learning speed (cognitive load theory)
- Adaptive Simulation Training
  - Keep the trainee in optimal cognitive and performance state during training
- Practicalities
  - Design set of training scenarios with different difficulty
  - Utilize certain performance metric
  - Design the adaptive logic to select the training scenario difficulty based on the current and past performance



1. Performance Measurement
- RMS Deviation
- Kinematics of Controls
- GSR, HRV, RSA
- Gaze & Pupillometry
- EEG / MEG
- Learning-Styles, Self-Report

2. Adaptive Logic
- Rule-based Heuristics
- Fuzzy Logic
- Decision Trees
- KNN, SVM (Supervised Learning)
- Reinforcement Learning
- State-Control Regulators

3. Adaptive Variable
- Wind Speed
- Wind Direction
- Visibility
- Control of Aircraft
- Controller Sensitivity
- Task Difficulty

Model of the scenarios and trainees

- Each scenario is characterized by: a) scenario difficulty; b) maximum achievable score.
- Each trainee is characterized by: a) initial absolute skill; b) learning rate.
- At each training step n with scenario with difficulty d_l, every trainee is k is modelled as:

$$S_k^{(n-1)} = \exp\left(-\frac{\left(t_k^{(n)} - t_k^{(n-1)}\right)}{\tau}\right) S_k^{(n-1)}$$

Account for the absolute skill deterioration

$$\hat{Q}_k^{(n)} = M_l \left(1 - \exp\left(-\frac{\left(S_k^{(n-1)}\right)^2}{2\left(d_l^{(n)}\right)^2}\right)\right) + \mathrm{N}\left(0, \left(c_1 \exp\left(\left(-\frac{d_l^{(n)}}{c_2}\right)^{c_4} + c_3\right)\right)^2\right)$$

Compute the score, second part is random performance variation, interpolated with the difficulty of the scenario

$$S_k^{(n)} = S_k^{(n-1)} + \mu_k \frac{S_k^{(n-1)}}{\left(d_l^{(n)}\right)^2} \exp\left(-\frac{\left(S_k^{(n-1)}\right)^2}{2\left(d_l^{(n)}\right)^2}\right)$$

Compute the increase in the absolute skill

Ivan Tashev, R. Michael Winters, Yu-Te Wang, David Johnston, Alexander Reyes, Justin Estepp. "Modelling the Training Process", IEEE RAPiD 2022, September 2022

Results from processing of the initial data

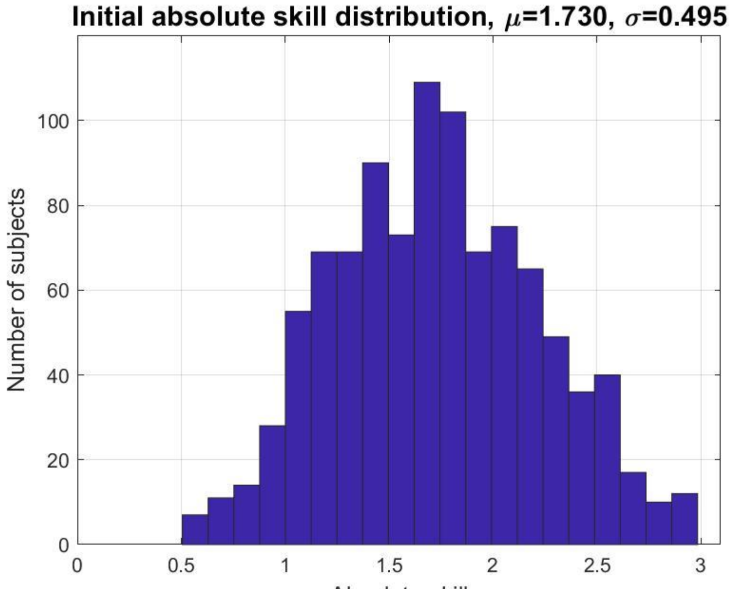
- Dataset: performance scores $Q_k(n)$ for K=17 subjects for N=90 sessions in five consecutive days, some with skill retention scores after 60 and 90 days
- Task is straight line flight, scenarios with two difficulties: straight-and-level and glideslope
- Subjects with common forgetting factor of τ=800.06 days and parameters on the right
- Interpolation coefficients for the score variability as function of the scenario difficulty

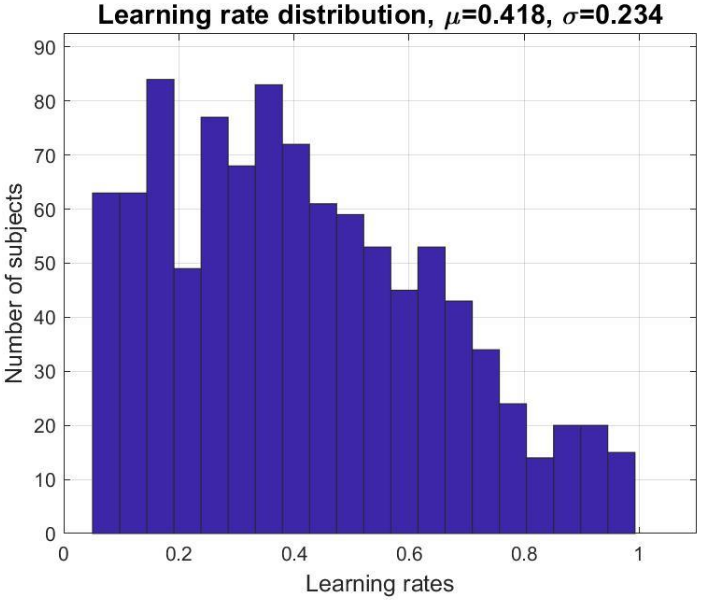
Scenario name	Difficulty	Score limitation
Straight and level	1.0000	88.1558
Glide slope	1.1836	91.2325

Parameter	Value
Average initial skill	1.7031
Deviation initial skill	0.5397
Average learning coefficient	0.2190
Deviation learning coefficient	0.4020

Synthetic dataset

- Number of subjects K=1,000
  - Gaussian random initial skill with mean 1.7031 and deviation 0.5397, pruned to [0.5,3.0]
  - Gaussian random learning rate with mean 0.2190 and deviation 0.4020, pruned to [0.05,1.0]
  - Forgetting time constant – assumed 800.06 days and equal for all subjects
  - Parameters assumed **unknown** at the beginning of the training process
- Number of scenarios L=20
  - Difficulty: uniformly, from 1 to 20
  - Maximum achievable score: from 95 points down to 45 points, 2.5 points decrease for each unit of difficulty increase
  - Assumed **known** at the beginning of the training process





Training process, approaches, and strategies

- Goal of the training process
  - Target scenario difficulty: 6
  - Target score: above 75 points in three consecutive runs
  - Target percentage: 95% of trainees with score above target
- Training procedure
  - Two blocks per day, 10 trials per block
  - Five days per week, total training time – 5 weeks
  - Totals to 500 trials per subject
- All further results are from simulations with the synthetic dataset

- Training approaches:
  - Group approach: train the entire group for as long as necessary till training goal is achieved
  - Individualized approach: account for the performance of each trainee and release the trainee after the training goal is achieved
  - In both cases the training cost is measured with the total number of trials, days, or weeks per trainee.
- Training strategies:
  - Fixed scenario difficulty – usually the target scenario difficulty (baseline)
  - Adaptive training system – run next trial with scenario difficulty based on the individual’s skills aiming the fastest training (subject of this paper)

Adaptive content delivery – the math

- Absolute skill increase at n-th run of scenario with difficulty d_l:

$$S_k^{(n+1)} = S_k^{(n)} + \mu_k \frac{S_k^{(n)}}{\left(d_l^{(n)}\right)^2} \exp\left(-\frac{\left(S_k^{(n)}\right)^2}{2\left(d_l^{(n)}\right)^2} \right)$$

- The absolute skill increase depends on:

$$\frac{S_k^{(n)}}{\left(d_l^{(n)}\right)^2} \exp\left(-\frac{\left(S_k^{(n)}\right)^2}{2\left(d_l^{(n)}\right)^2} \right)$$

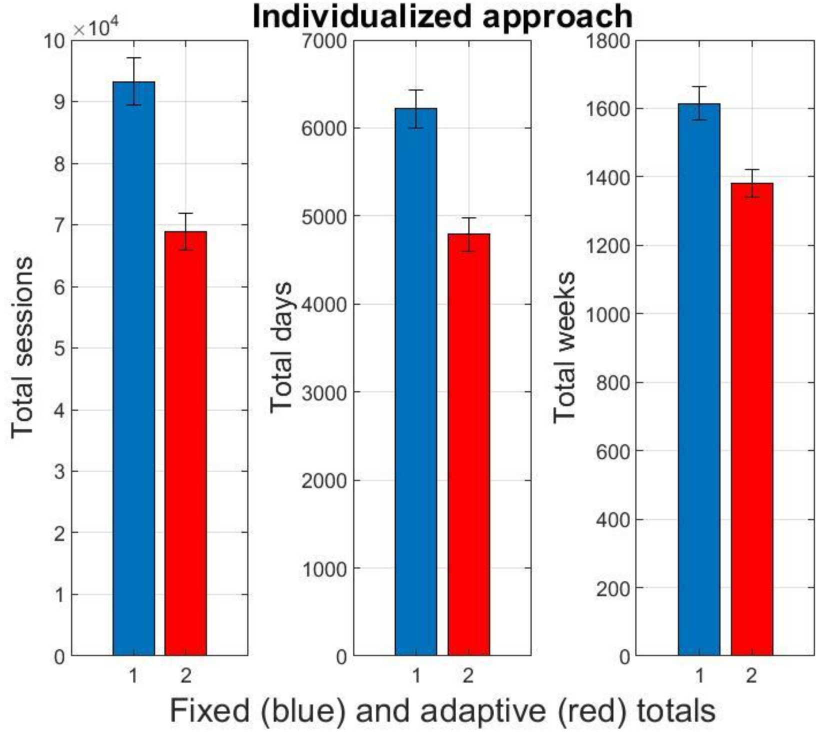
- After taking the first derivative, assigning to zero, and solving for d_l the highest increase of the absolute skill is at:

$$d_l^{(n)} = S_k^{(n)}$$

- The fastest learning happens when the scenario difficulty is equal to the absolute skill of the trainee!
- Given the training history (scores, dates, difficulties) we can estimate the initial absolute skill and the learning rate – lead to the current skill, hence the recommended difficulty

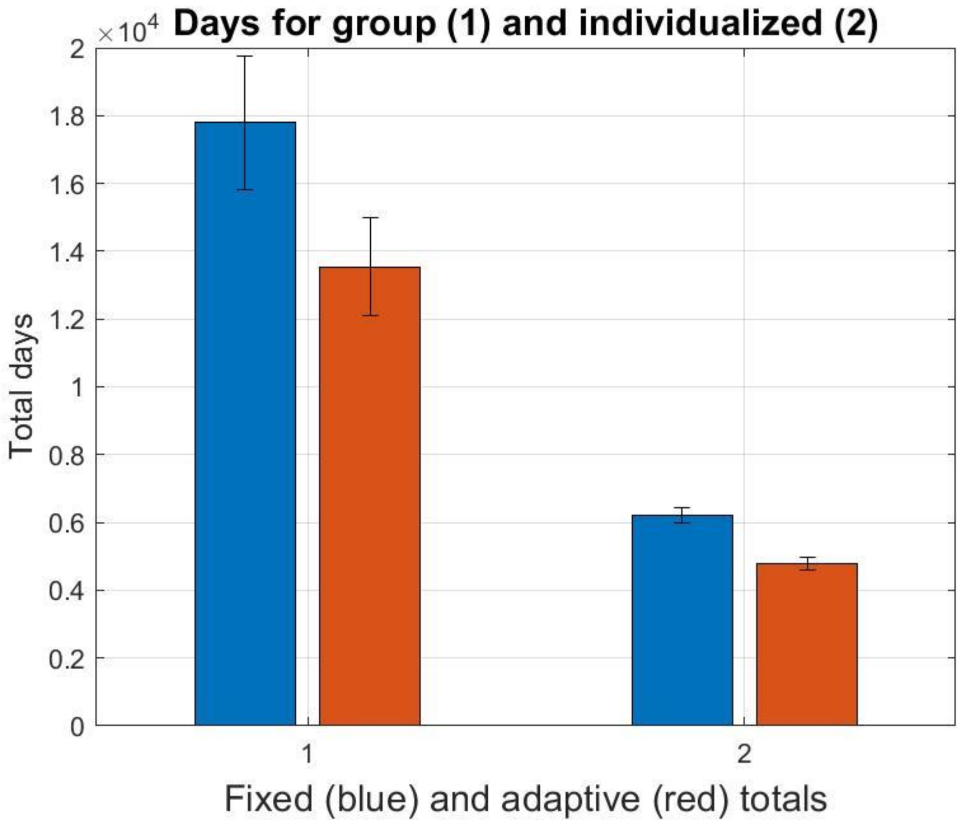
ATS simulation results: overall

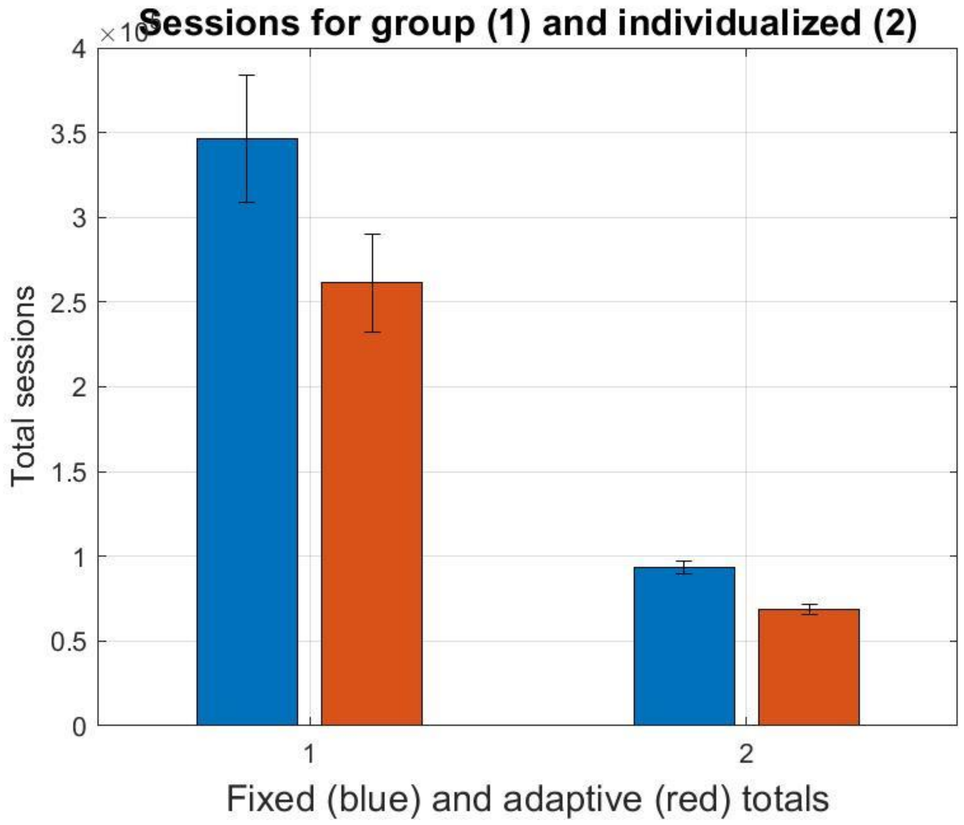
Training strategy	Group			Individualized		
	Sessions	Days	Weeks	Sessions	Days	Weeks
Fixed difficulty	346500.0 ±37447.1	17800.0 ±1967.8	4000.0 ±0.00	93266.5 ±3789.9	6215.4 ±217.4	1613.7 ±48.8
Adaptive difficulty	261175.0 ±28626.4	13533.0 ±1442.1	3000.0 ±0.00	68947.7 ±2989.2	4792.4 ±191.4	1382.2 ±40.3
Reduction, %	24.62	23.97	25.00	26.07	22.89	14.35



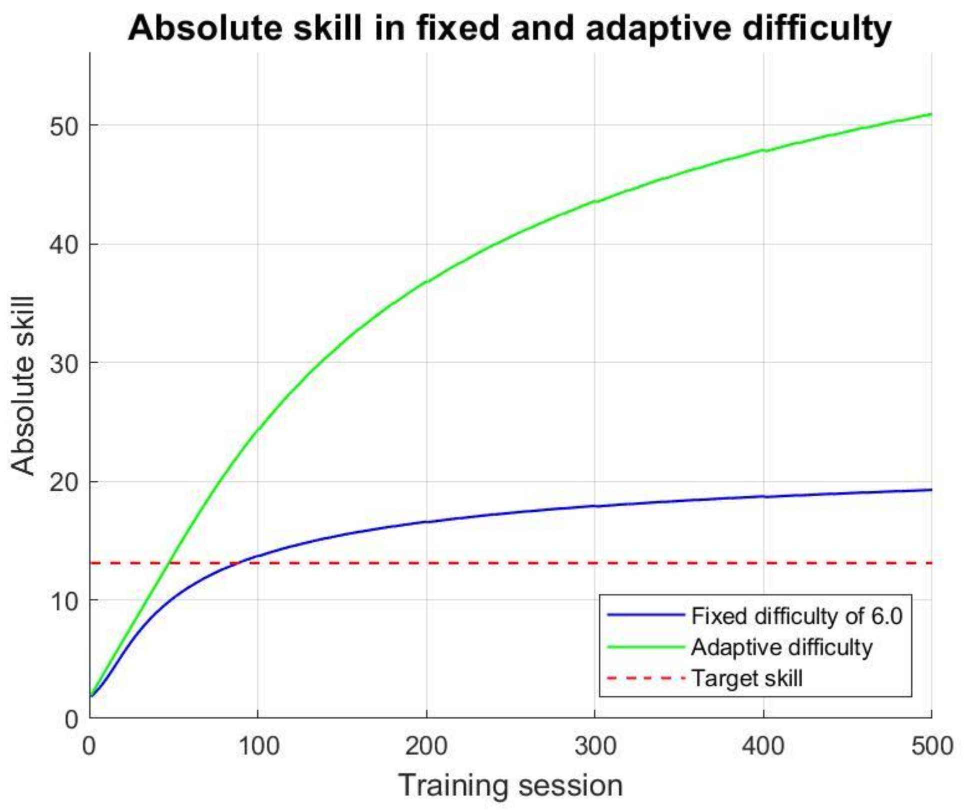
Notes: 1. Statistics obtained from 10 different datasets, each dataset simulated 12 times, total of 120 simulations
2. The ± intervals are at 95% confidence (2σ)
3. The numbers are the sum for all trainees

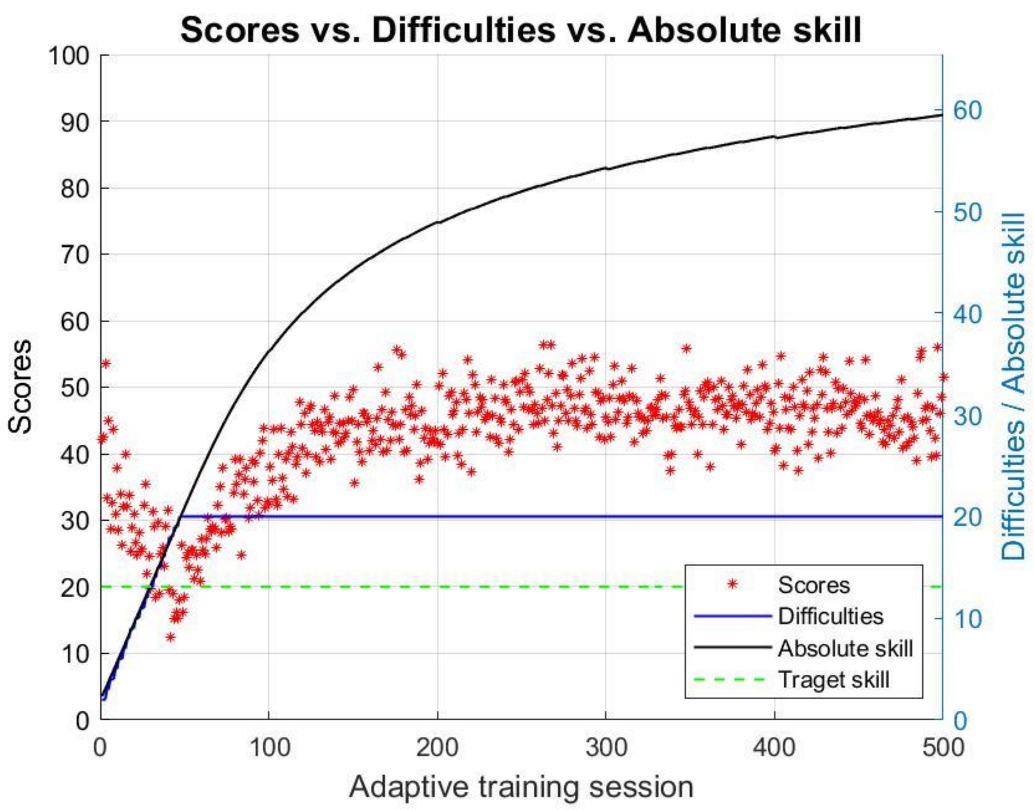
Results: group vs. individualized





Results: absolute skill increase





Conclusions

- Adaptive content delivery algorithm can shorten the training time 12-26%
- Applying individualized approach vs. group approach can reduce the training time more than a half
- The two approaches above combined can lead to serious savings in the training costs
- If we have allotted fixed training time the adaptive content delivery approach will maximize the final absolute skill
- The proposed approach is capable to use both behavioral and physiological scoring as input

QUESTIONS?