Modelling the Training Process

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Agenda

- Microsoft Research and the innovation in Microsoft
- Parametric model of the training process
- Dataset and results
- Conclusions and next steps

Microsoft Research and the innovation in Microsoft

Microsoft Research's mission is derived from the original 1990 memo Nathan Myhrvold wrote to Bill Gates and the Microsoft Board of Directors

MICROSOFT RESEARCH MISSION

Expand the state of the art in each of the areas in which we do research	Rapidly transfer innovative technologies into Microsoft products	Ensure that Microsoft products have a future

processor speed, memory and general functionality per user.

In very general terms, we have to invest in our future by doing more work in research and technology creation.

Microsoft Research Plan Microsoft Confidential Page 3

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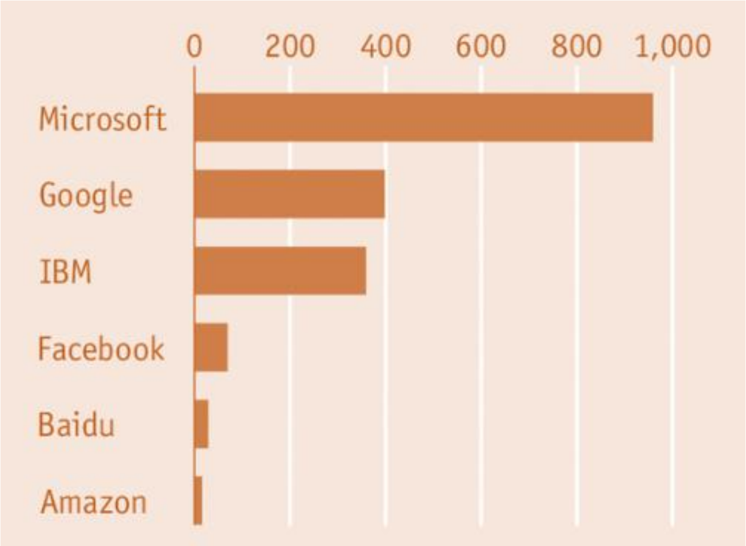
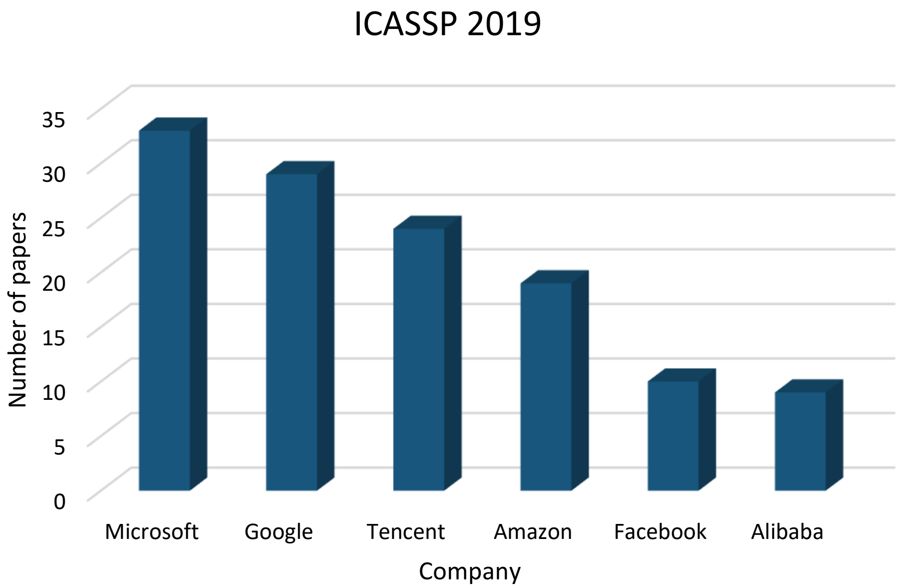
Microsoft Research and Advanced Technology Labs

Microsoft Research has published more than twice as many AI scholarly papers as their competitors

Artificial–intelligence–related research*
By company-affiliation, 2000-16





*Papers from five major AI conferences

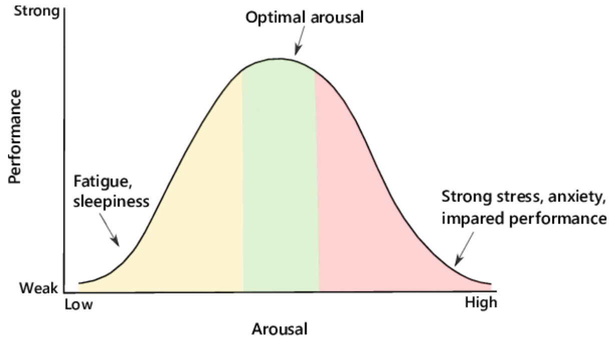
NEARLY EVERY PRODUCT MICROSOFT SHIPS INCLUDES TECHNOLOGY FROM MICROSOFT RESEARCH

Parametric model of the training process

Assumptions

- 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 sessions
- In each session is performed one scenario with given difficulty
- After each session 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

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

Aspects covered
In this paper

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

Absolute skill level

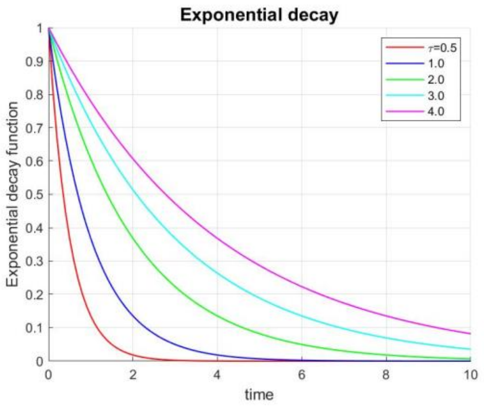
- Each trainee has absolute skill level to perform given task
  - Dimensionless number, scenario independent
- Trainee k at given time n with absolute skill level $S_k^{(n)}$ on scenario with difficulty d_l will receive score:
  - $$Q_k^{(n)}\left(S_k^{(n)}, d_l^{(n)}\right) = M_l\left(1-\exp\left(-\frac{\left(S_k^{(n)}\right)^2}{2\left(d_l^{(n)}\right)^2}\right)\right) + \mathrm{N}\left(0, q^2\right)$$
  - Here $\mathrm{N}\left(0, q^2\right)$ is a Gaussian noise modeling the variation in the subject performance. M_l is the maximum score achievable for the scenario with difficulty d_l.

Modeling of the skill decrease with the time

- Given time without refreshing the absolute skill level decreases.
- At the n-th trial we model the skill decrease for subject k as:

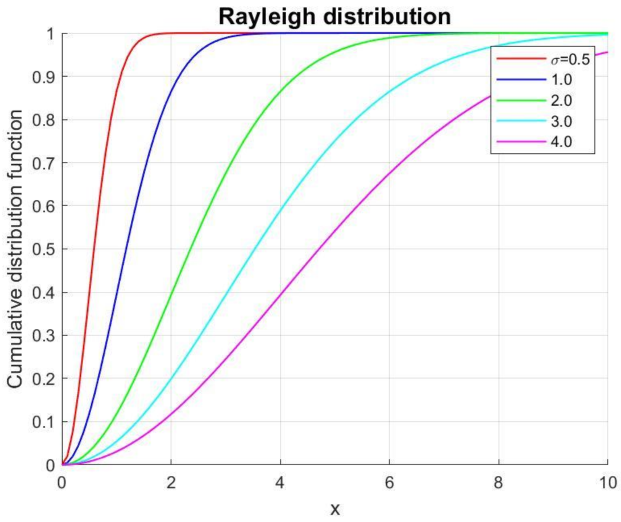
  - $$S_k^{(n)} = \exp\left(-\frac{\left(t_k^{(n)} - t_k^{(n-1)}\right)}{\tau} \right) S_k^{(n-1)}$$

  - Here $t(n)$ is the time, $S_k^{(n)}$ is the absolute skill of subject k at time n, and τ is the forgetting time constant.



Modeling of the training process

- After trainee k completes the n-th session with difficulty d_l the absolute skill level increases:
  - $$S_k^{(n+1)} = S_k^{(n)} + \mu_k \frac{S_k^{(n)}}{\left(d_l^{(n)}\right)^2} \exp\left(-\frac{\left(S_k^{(n)}\right)^2}{2\left(d_l^{(n)}\right)^2} \right)$$
  - where μ_k is a person-dependent learning rate.



Determining the parameters' values

- Set of L scenarios:
  - Unknown difficulties $\mathbf{D}=[d_1, d_2, \ldots, d_L]$
  - Unknown score limits $\mathbf{M}=[M_1, M_2, \ldots, M_L]$
- Group of K trainees
  - Unknown initial absolute skill levels $\mathbf{S}^{(0)}=[S_1^{(0)}, S_2^{(0)}, \ldots, S_K^{(0)}]$
  - Unknown learning rates $\boldsymbol{\mu}=[\mu_1, \mu_2, \ldots, \mu_K]$
- Unknown forgetting time constant τ
- Trainee k performs training session with given difficulty d_l at given moment t scored with $Q_k^{(n)}$, forming a triplet $\left[d_l^{(n)}, Q_k^{(n)}, t_k^{(n)}\right]$.
- For each trainee we have sequence of such triplets with length N.

Determining the parameters' values (2)

- Total number of unknowns: $2L+2K+1$.
- Total number of equations: KN.
- In most of the cases $2L+2K+1 < KN$ and this is a solvable problem.
- Let define a constrained cost function:
  - $$\Lambda_{constr} = \frac{1}{KN}\sum_{n=1}^{N}\sum_{k=1}^{K}\left(\hat{Q}_k^{(n)} - Q_k^{(n)}\right)^2$$
- And punishing function:
  - $$\Lambda_{pun} = \sum_{k=1}^{K}\mathrm{P}\left(\mu_k\right)+\sum_{k=1}^{K}\mathrm{P}\left(S_k\right)+\sum_{l=1}^{L}\mathrm{P}\left(M_l\right)+\sum_{l=1}^{L}\mathrm{P}\left(d_l\right)$$

Determining the parameters' values (3)

- Here P(x) is defined as: $P(x) = \begin{cases} (x_{\min} - x)^2, \text{ if } x < x_{\min} \\ 0, \text{ if } x_{\max} > x > x_{\min} \\ (x - x_{\max})^2, \text{ if } x_{\max} < x \end{cases}$
- Then the unconstrained cost function is: $\Lambda_{unc} = \Lambda_{constr} + \Lambda_{pun}$
- And the problem is solved using mathematical optimization:

$$\begin{bmatrix} \left[d_0, d_{1,}, \ldots, d_L\right] \\ \left[M_0, M_{1,}, \ldots, M_L\right] \\ \left[S_1^{(0)}, \mu_1\right] \\ \ldots \\ \left[S_K^{(0)}, \mu_K\right] \\ \tau \end{bmatrix} = \arg\min\left(\Lambda_{unc}\right)$$

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Determining the parameters' values (4)

- At each step, all trainees are modelled as:

$$
\left|
\begin{array}{l}
S_k^{(n-1)} = \exp\left(-\dfrac{\left(t_k^{(n)} - t_k^{(n-1)}\right)}{\tau}\right) S_k^{(n-1)} \\
\hat{Q}_k^{(n)} = M_l \left(1 - \exp\left(-\dfrac{\left(S_k^{(n-1)}\right)^2}{2\left(d_l^{(n)}\right)^2}\right)\right) \\
S_k^{(n)} = S_k^{(n-1)} + \mu_k \dfrac{S_k^{(n-1)}}{\left(d_l^{(n)}\right)^2} \exp\left(-\dfrac{\left(S_k^{(n-1)}\right)^2}{2\left(d_l^{(n)}\right)^2}\right)
\end{array}
\right.
$$

- And the simulated scores are subtracted from the real scores to compute the cost function

Dataset and results

Dataset

- We have performance scores $Q_k^{(n)}$ for $K=17$ subjects performing sessions with $L=2$ levels of difficulty for $N=40$ iterations per day in four consecutive days.
  - The scenarios performed on flight simulator using Prepar3D software
  - The two scenarios are straight-and-level flight and glideslope flight
- The scenario difficulty alternates with the two levels of difficulty.
- For some subjects are performed skill retention tests at 60^{th} and 90^{th} day with twenty more scenarios each day.

Solving the non-linear problem

- Total number of triplets is 1823, the number of unknowns is 39 – the problem is solvable.
- Initial values: 1.0 for absolute skill, 0.1 for learning rate, 1.0 for difficulty, 90 for points score limitation.
- Constraints are set to:
  - 0.001 minimal value and 5.0 maximal value for scenario difficulty, absolute skill level, and learning rate
  - 0.001 minimal value and 100.0 maximal value for the score limitations
  - 10.0 minimal value and 1000.0 maximal value for the forgetting factor
- Used unconstrained mathematical optimization algorithm

Results: totals and scenarios

- Scores deviation σ=6.3435 points (the final cost function value)
- Forgetting factor τ=800.06 days
- Scenarios:

Scenario name	Difficulty	Score limitation
Straight and level flight	1.0000	88.1558
Glideslope flight	1.1836	91.2325

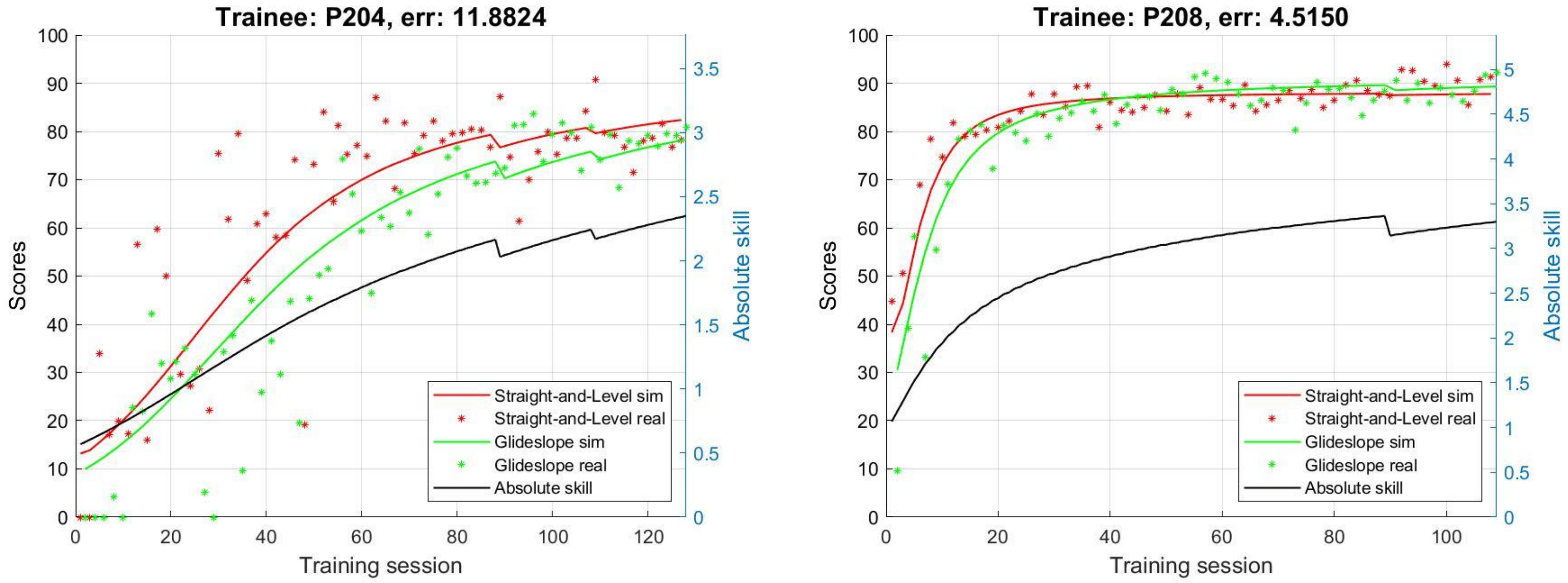
Results: subjects

- Individual subjects – table on the right
- Statistics for the subjects

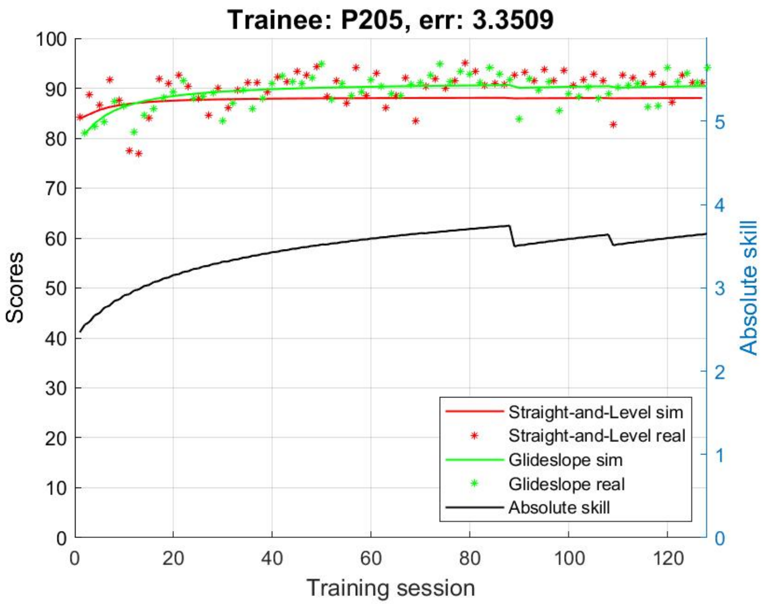
Parameter	Value
Average initial skill	1.7031
Deviation initial skill	0.5397
Average learning coefficient	0.2190
Deviation leaning coefficient	0.4020

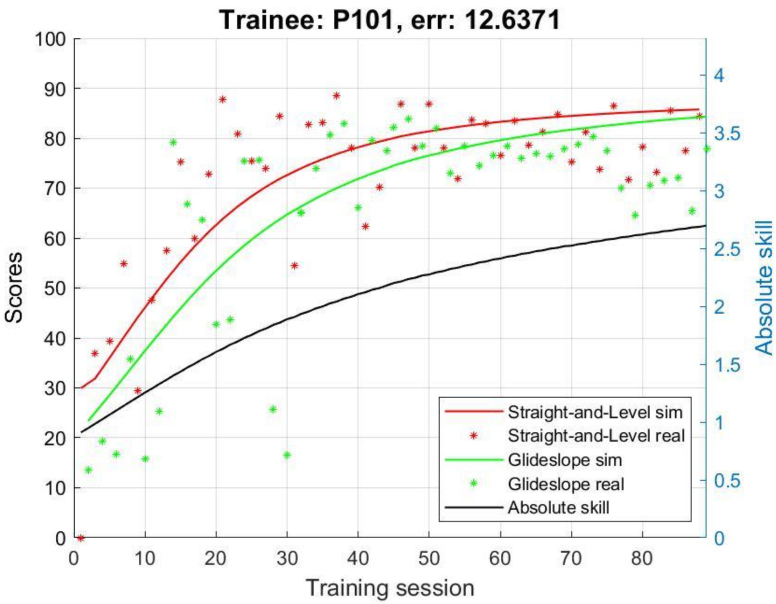
Name	Skill0	Learning
P101	0.9111	0.0641
P102	1.6616	0.0617
P103	1.6998	0.0494
P104	1.6126	0.1220
P105	1.9426	0.3747
P106	2.0744	0.0517
P107	2.6723	1.7266
P201	2.1083	0.0702
P202	1.3671	0.0735
P203	2.0963	0.1097
P204	0.5691	0.0388
P205	2.4655	0.3810
P206	1.9279	0.1579
P207	1.5309	0.1016
P208	1.0681	0.1902
P209	1.8396	0.0806
P210	1.4058	0.0693

Results: two subjects



Results: two extremes

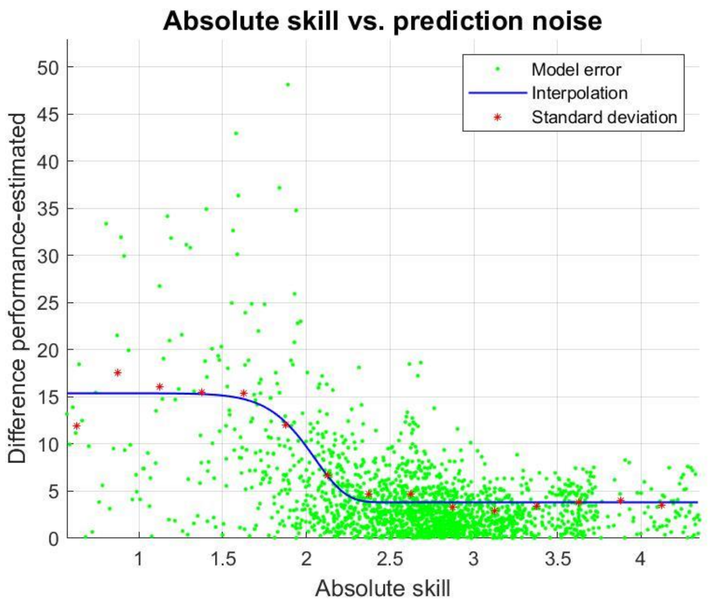




Results: interpolation error vs. absolute skill

- Higher skill means lower score variation
- Interpolated with generic exponential function

Parameter	Value
Correlation skill-error, scale	11.5636
Correlation skill-error, time constant	2.0665
Correlation skill-error, offset	3.8148
Correlation skill-error, power	12.1164



Conclusions and next steps

Conclusions and next steps

- The mathematical models for learning, forgetting, and skills increase interpolated well the experimental data
- Statistical parameters of the subjects allow building a larger synthetic dataset for further simulation and research
- The large synthetic dataset allows exploring various training strategies and deriving an optimal approach for training

Thank You