Recommender Systems and Education (with Report on Practical Experiences)

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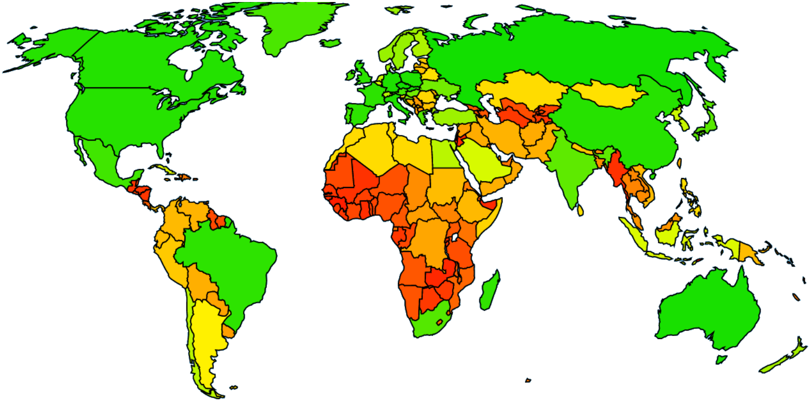
Warm-up Quiz



This Lecture

educational applications with focus on

- relation to topics discussed so far (collaborative filtering, evaluation, ...)
- specific examples
- connections between seemingly different techniques from various research directions
- personalization and different types of recommendations
- my experience

Design Thinking Exercise

You are a member of a team developing a personalized learning system, e.g.:

- learning new language
- improving English vocabulary (advanced words)
- learning (advanced) math and machine learning
- *(your favourite topic that everybody should learn)*

You are responsible for the recommendation part of the project.

How would you approach the problem?

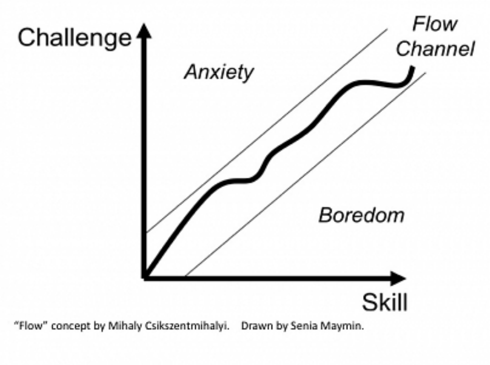
Designing New System: Questions

1. requirements:
   - What is the target group? Who are users?
   - What are user needs?
   - What should it do?
2. techniques, solutions:
   - How should it work?
   - What data you need?

Motivation: Personalization in Education

- each student gets suitable learning materials, exercises
- tailored to a particular student, adequate for his knowledge (mood, interests, ...)
- mastery learning – fixed outcome, varied time (compared to classical education: fixed time, varied outcome)

Motivation: Flow, ZPD



Vygotsky, zone of proximal development

Personalization on Different Time Scales

time scale	learning unit	personalization
10 seconds	step	adaptive hints
1 minute	task	difficulty adjustment, personalized feedback
10 minutes	activity	mastery learning, activity recommendation
hours	course	course recommendation

Adaptation and Personalization in Education

... gets lot of attention:

- Khan Academy
- Duolingo
- MOOC courses
- Carnegie Learning
- Pearson
- ReasoningMind
- and many others

Technology and Education

e-learning, m-learning, technology-enhanced learning, computer-based instruction, computer managed instruction, computer-based training, computer-assisted instruction, computer-aided instruction, internet-based training, flexible learning, web-based training, online education, massive open online courses, virtual education, virtual learning environments, digital education, multimedia learning, intelligent tutoring system, adaptive learning, adaptive practice, ...

adaptive
automated
computerized
digital
game-based
gamified
individualized
intelligent
interactive
massive
online
open
personalized
programmed
recommender
technology-enhanced
virtual

*

assessment
education
instruction
learning
practice
testing
tutoring

environment
course
hypermedia
platform
software
system
technology
tool

Tasks	*Description*	*Generic recommender*	*TEL recommenders*	*New requirements*
Existing User Tasks supported by Recommender Systems				
1. ANNOTATION IN CONTEXT	Recommendations while user carries out other tasks	E.g. predicting how relevant the links are within a web page	E.g. predicting relevance/usefulness of items in the reading list of a course	Explore attributes for representing relevance/usefulness in a learning context
2. FIND GOOD ITEMS	Recommendations of suggested items	E.g. receiving list of web pages to visit	E.g. receiving a selected list of online educational resources around a topic	None
3. FIND ALL GOOD ITEMS	Recommendation of all relevant items	E.g. receiving a complete list of references on a topic	E.g. suggesting a complete list of scientific literature or blog postings around a topic	None
4. RECOMMEND SEQUENCE	Recommendation of a sequence of items	E.g. receive a proposed sequence of songs	E.g. receiving a proposed sequence through resources to achieve a particular learning goal	Explore formal and informal attributes for representing relevancy to a particular learning goal

5. Just Browsing	Recommendations out of the box while user is browsing	E.g. people that bought this, have also bought that	E.g. receiving recommendations for new courses on the university site	Explore formal and informal attributes for representing relevance/usefulness in a learning context
6. Find Credible Recommender	Recommendations during initial exploration/testing phase of a system	E.g. movies that you will definitely like	E.g. restricting course recommendations to ones with high confidence /credibility	Explore criteria for measuring confidence and credibility in formal and informal learning
TEL User Tasks that could be supported by Recommender Systems				
1. Find Novel Resources	Recommendations of particularly new or novel items	E.g. receiving recommendations about latest additions or particularly controversial items	E.g. receiving very new and/or controversial resources on covered topics	Explore recommendation techniques that select items beyond their similarity
2. Find Peers	Recommendation of other people with relevant interests	E.g. being suggested profiles of users with similar interests	E.g. being suggested peer students in the same class	Explore attributes for measuring the similarity with other people
3. Find Good Pathways	Recommendation of alternative learning paths through learning resources	E.g. receive alternative sequences of similar songs	E.g. receiving a list of alternative learning paths over the same resources to achieve a specific learning goal	Explore criteria for the construction and suggestion of alternative (but similar) sequences

Name	*Short description*	*Advantages*	*Disadvantages*	*Usefulness for TEL*
Collaborative Filtering (CF) techniques				
User-based CF	Users who rated the same item similarly probably have the same taste. Based on this assumption, this technique recommends the unseen items already rated by similar users.	No content analysis Domain-independent Quality improves Bottom-up approach Serendipity	New user problem New item problem Popular taste Scalability Sparsity Cold start problem	Benefit from experience Allocate learners to groups (based on similar ratings)
Item-based CF	Focus on items, assuming that the items rated similarly are probably similar. It recommends items with the highest correlation (based on ratings for the items).	No content analysis Domain-independent Quality improves Bottom-up approach Serendipity	New item problem Popular taste Sparsity Cold start problem	Benefit from experience
Stereotypes or demographics CF	Users with similar attributes are matched, then it recommends items that are preferred by similar users (based on user data instead of ratings).	No cold start problem Domain-independent Serendipity	Obtaining information Insufficient information Only popular taste Obtaining metadata information	Allocate learners to groups Benefit from experience Recommendation from the beginning of the PRS

Content-Based (CB) techniques

Case-based reasoning	Assumes that if a user likes a certain item, s/he will probably also like similar items. Recommends new but similar items.	No content analysis Domain-independent Quality improves	New user problem Overspecialisation Sparsity Cold start problem	Keeps learner informed about learning goal Useful for hybrid RS
Attribute-based techniques	Recommends items based on the matching of their attributes to the user profile. Attributes could be weighted for their importance to the user.	No cold start problem No new user/new item problem Sensitive to changes of preferences Can include non-item-related features Can map from user needs to items	Does not learn Only works with categories Ontology modelling and maintenance is required Overspecialisation	Useful for hybrid RS Recommendation from the beginning

Education and RecSys

many techniques applicable in principle, but application more difficult than in "product recommendation"

- longer time frame
- pedagogical principles
- domain ontology, prerequisites
- types of knowledge and learning processes (declarative vs procedural knowledge)
- learning outcomes not directly measurable

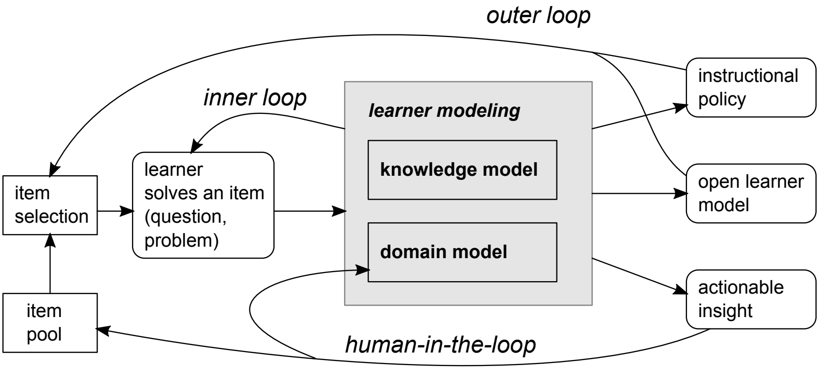
Evaluation

- evaluation even more difficult than for other recommender systems
- compare goals:
    - product recommendations: sales
    - text (blogs, etc) recommendations: clicks (profit from advertisement)
    - education: learning
- learning can be measured only indirectly
- hard to tell what really works

Student Modeling and Collaborative Filtering

user	$\sim$	student
product	$\sim$	problem, question
rating	$\sim$	student performance (correctness of answer, problem solving time, number of hints taken)

Learner Modeling



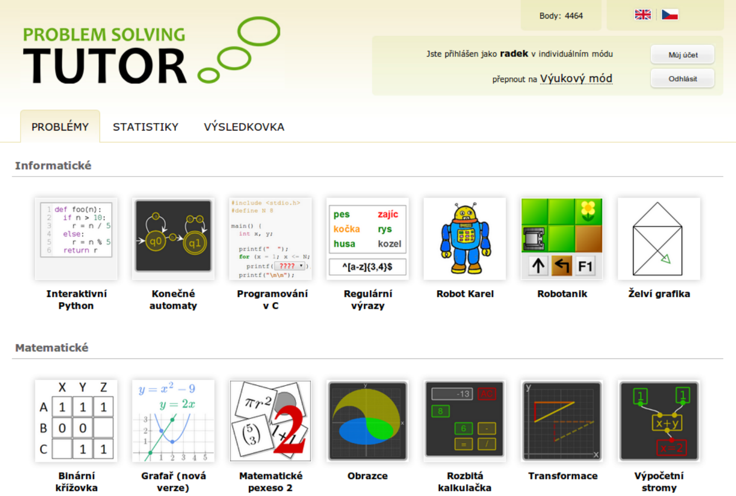
Case Studies

- our projects (FI MU) – “adaptive practice”
  - Problem Solving Tutor
  - “Slepé mapy” (Map Outlines) – geography
  - Umíme (česky, anglicky, matiku, ...) – umimeto.org
- Wayang Outpost – math
- ALEF – programming
- CourseRank – course recommender

Problem Solving Tutor

- math and computer science problems, logic puzzles
- performance = problem solving time
- focus: predictions of times
- recommendations – problems of similar difficulty

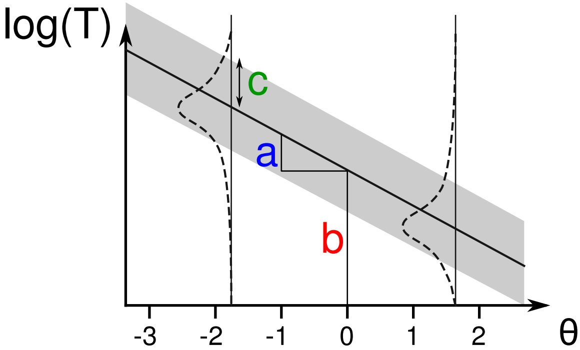
Problem Solving Tutor



Tutor: predictions

Kuželosečky - hyperboly Neřešeno Předpověď 1:12	**Komplexní čísla - násobení** Vyřešeno Čas 0:58	**Logaritmy a mocniny - vzorečky** Neřešeno Předpověď 1:14	**Komplexní čísla - mocniny i** Vyřešeno Čas 1:24	**Vlastnosti funkcí** Neřešeno Předpověď 1:17	**Kuželosečky 2** Vyřešeno Čas 1:05	**Zlomky** Neřešeno Předpověď 1:19	**Komplexní čísla - absolutní hodnoty** Vyřešeno Čas 0:45	**Logaritmy - hodnoty 2** Neřešeno Předpověď 1:23
Kvadratické rovnice - řešení Vyřešeno Čas 1:45	**Vzdálenosti** Vyřešeno Čas 1:16	**Kuželosečky** Neřešeno Předpověď 1:35	**Množiny - základní operace** Neřešeno Předpověď 1:42	**Kombinační čísla** Neřešeno Předpověď 1:42	**Kvadratická funkce 2** Neřešeno Předpověď 1:44	**Definiční obory a obory hodnot** Neřešeno Předpověď 1:46	**Logaritmy - vzorečky** Vyřešeno Čas 2:42	**Množiny** Neřešeno Předpověď 1:56
Směs Neřešeno Předpověď 2:02	**Derivace - goniometrické funkce** Vyřešeno Čas 2:15	**Součty** Vyřešeno Čas 1:10	**Kombinační čísla - vzorečky** Neřešeno Předpověď 2:17	**Komplexní čísla** Neřešeno Předpověď 2:17	**Úhly 2** Neřešeno Předpověď 2:29	**Nerovnosti** Neřešeno Předpověď 2:39	**Kuželosečky - kružnice** Neřešeno Předpověď 2:56	**Limity funkcí** Vyřešeno Čas 2:36

Model of Problem Solving Times



Parameter Estimation

- data: student s solved problem p in time t_{sp}
- we need to estimate:
  - student skills θ
  - problem parameters a, b, c
- stochastic gradient descent
- very similar to the "SVD" collaborative filtering algorithm

Evaluation of Predictions

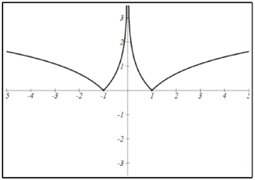
- 20 types of problems
- data: 5 000 users, 8 000 hours, more than 220 000 problems
- difficulty of problems: from 10 seconds to 1 hour
- offline evaluation: train, test set
- metrics: RMSE
- results:
  - significant improvement with respect to a baseline (mean times)
  - more complex models do not bring much improvement

same basic difficulty

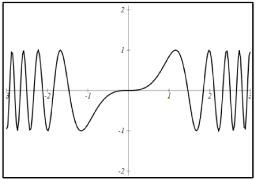
high discrimination

high randomness

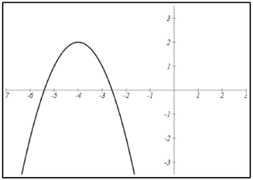
"safe" problem



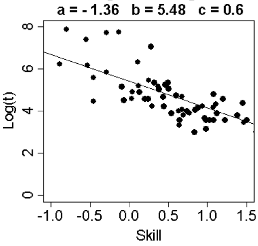
abs(log(abs(x)))

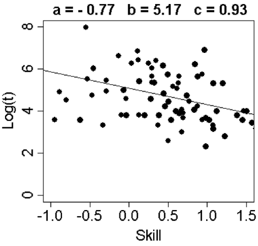


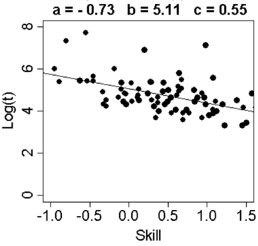
sin(x^3)



- (x+4)^2+2







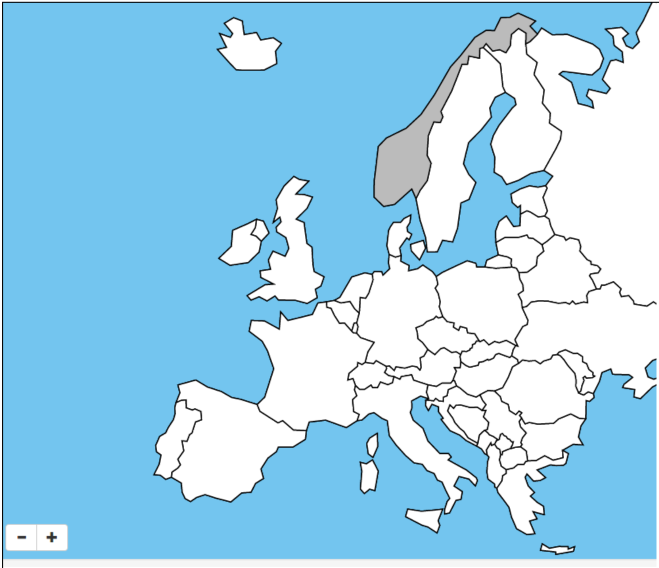
Geography: Map Outlines

- adaptive practice of geography knowledge (facts)
- focus on prior knowledge
- choice of places to practice $\sim$ recommendation (forced)

Vyber na mapě stát Švédsko

Nevím

Pokračovat

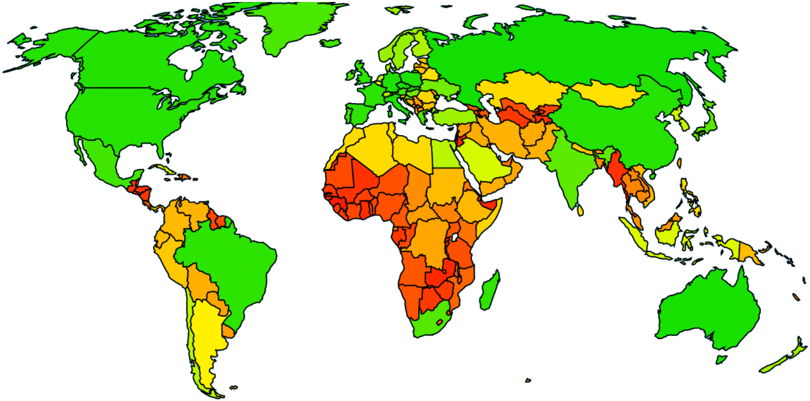


Jak se jmenuje stát zvýrazněný na mapě?

Finsko | Norsko | Švédsko | Nevím

Ze zvýrazněných států na mapě vyber Dánsko

Geography – Difficulty of Countries



Geography – Model

Model (prior knowledge):

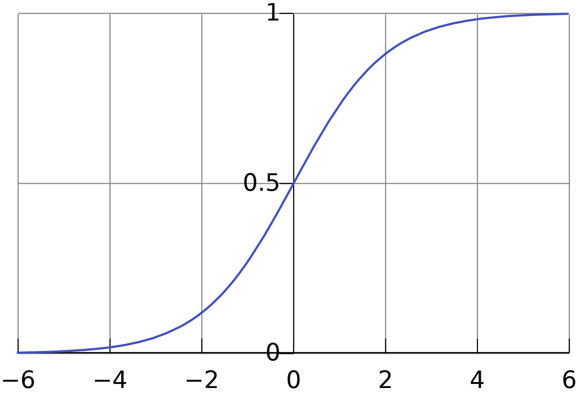
- global skill of a student θ_s
- difficulty of a country d_c

Probability of correct answer = logistic function (difference of skill and difficulty):

$$P(correct|d_c, \theta_s) = \frac{1}{1 + e^{-(\theta_s - d_c)}}$$

Logistic Function

$$\frac{1}{1+e^{-x}}$$



Geography – Model

- Elo rating system (originally from chess)

$$\theta := \theta + K(R - P(R = 1))$$

$$d := d - K(R - P(R = 1))$$

- magnitude of update $\sim$ how surprising the result was
- related to stochastic gradient descent, "SVD" algorithm in collaborative filtering (but only single latent factor)

Geography – Current Knowledge

- estimation of knowledge after sequence of answers for a particular place
- extension of the Elo system
- short term memory, forgetting

Geography – Question Selection

question selection (based on predicted probability of correct answer) $\sim$ item recommendation (based on predicted rating)

based on students' history of answers, we want to create a new question

how?

Geography – Question Selection

question selection (based on predicted probability of correct answer) $\sim$ item recommendation (based on predicted rating)

scoring function – linear combination of several factors:

- predicted success rate, target success rate
- viewed recently
- how many times asked

Geography – Multiple Choice Questions

- number of options – based on estimated knowledge
- choice of options – ???

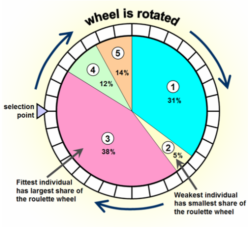
Example:

- correct answer is Hungary
- we need 3 distractors
- which countries should we use?

Geography – Distractors

choice of options (distractors) – confused places ($\sim$ collaborative filtering aspect)

realization: roulette wheel selection (as used in genetic algorithms)



Geography – Evaluation

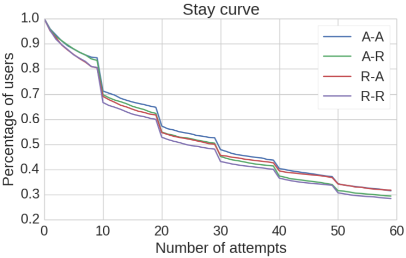
- evaluation of predictions
  - offline experiment
  - comparison of different models (basic Elo, extensions, ...)
  - issue with metrics: RMSE, AUC ($\Rightarrow$ "Metrics for Evaluation of Student Models" paper)
- evaluation of question construction ("recommendations")
  - online experiment, AB testing
  - issue with metrics: enjoyment vs learning

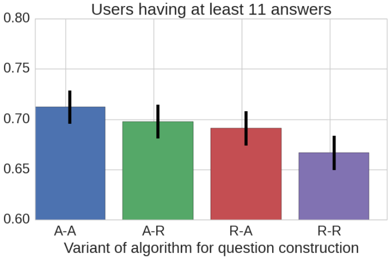
AB Testing

4 groups:

Target item	Options
adaptive	adaptive
adaptive	random
random	adaptive
random	random

Measuring Engagement – Survival Analysis

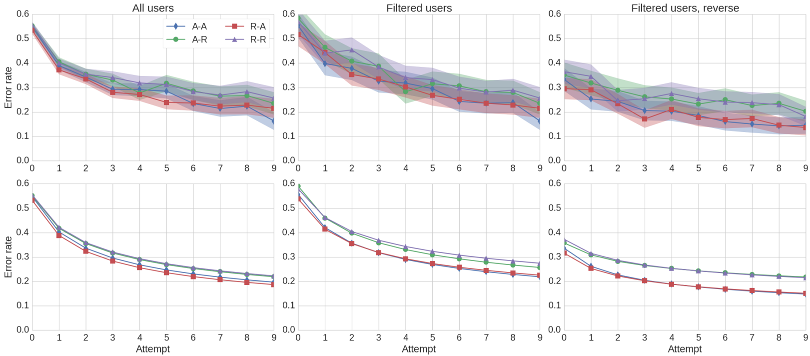




Measuring Learning

- we cannot measure knowledge (learning) directly
- estimation based on answers
- adaptive questions – fair comparison difficult
- use of "reference questions" – every 10th question is "randomly selected"
- problem with attrition (different number of answers per student)

Measuring Learning – Learning Curves



Other AB Experiments

- difficulty of questions
- choice of distractors (competitive vs adaptive)
- maximal number of distractors
- user control of difficulty

AB experiments

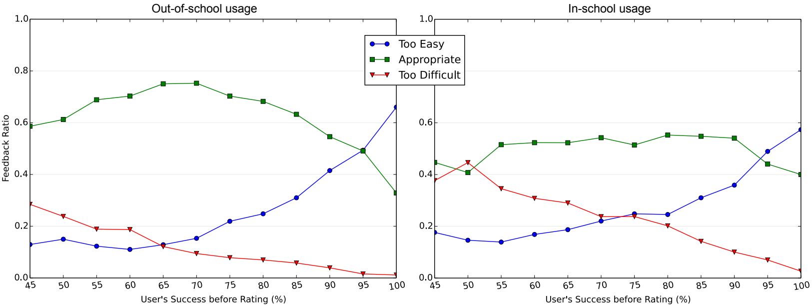
- $\sim$ 1000 users per day
- sometimes minimal or no differences between experimental conditions (in the overall behaviour)
- reasons:
  - conditions not sufficiently different (differences manifest only sometimes)
  - disaggregation (users, context) shows differences, which cancel out in overall results

Your Intuition?

What is suitable target difficulty of questions?
Target success rate:

- 50 %
- 65 %
- 80 %
- 95 %

Difficulty and Explicit Feedback



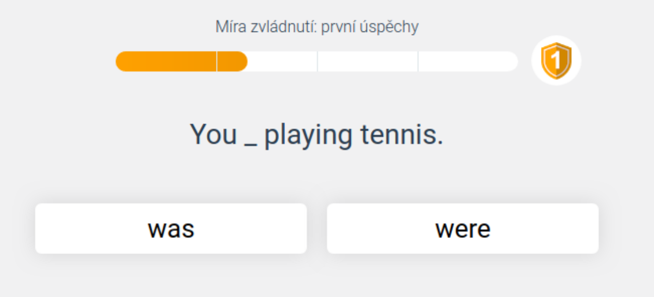
Umíme to

- http://www.umimecesky.cz/ – Czech grammar and spelling
- http://www.umimeanglicky.cz/ – English (for Czech students)
- http://www.umimematiku.cz/ – math
- and more... https://www.umimeto.org/

Czech Grammar – Project Evolution

- initial version
  - target audience: adults
  - single exercise type
  - coarse-grained concepts
  - focus on adaptive choice of items
- current version
  - target audience: children
  - many exercise types
  - fine-grained concepts
  - focus on mastery learning
  - recommendations of practice sets
  - several domains

Grammar – Basic Exercise



Personalization: Mastery Learning

- skill of the learner – estimated based on the performance, taking into account:
  - correctness of answers
  - response time
  - time intensity of items (median response time)
  - probability of guessing
- mastery criterion – comparison of skill to threshold
- progress bar – visualization of skill

Skills

Grammar

Be, have, do			
To be in present simple	lehké		
To do, to have, to be in present simple	1 lehké	3 střední	
To do, to have, to be: questions and negatives	lehké	3 střední	
To do, to have, to be in past simple	3 lehké	3 střední	
Be, have, do: mix	lehké	3 střední	
Tenses			
Talking about the present			
Present simple tense	1 lehké	3 střední	těžké
Present tense: questions and negatives	lehké	3 střední	
Present simple vs. present continuous	3 lehké	střední	těžké

Activity Recommendations

Will vs. going to
Rozhodovačka • těžké

Koukej! To letadlo spadne!

Look! The plane ___ crash!

is going to | will

Zaměstnání
Zápis slovíček • střední

chemik

Exotická zvířata
Výběr z možností • těžké

lobster

- humr
- lachtan
- puma
- varan

Části těla
Pexeso • těžké

jizva	eyelid		scar
nostril	kloub	throat	nosní dírka

Zero article
Rozhodovačka • střední

Šel jsem do nemocnice udělat rozhovor s doktory.

I went to ___ hospital yesterday to do an interview with the doctors.

- | the

Frázová slovesa: get, take
Rozhodovačka • těžké

Letadlo vzlétá v 11 hodin.

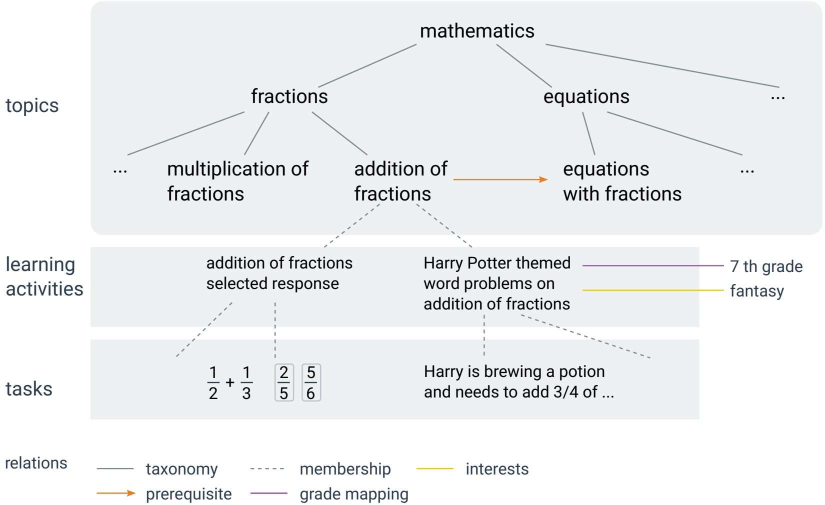
The plane takes ___ at 11 o'clock.

off | on

Recommendations Goals

- **predicting intentions**
  - something the students would like to do on their own
  - follow-up topics, homeworks
  - related to follow-up recommendations in other setting (e.g., news)
- **facilitating exploration**
  - guiding students towards content they might not actively seek out on their own
  - related to serendipidity
- **reinforcing knowledge**
  - spaced repetition, interleaved practice
  - specific to education

Domain Model



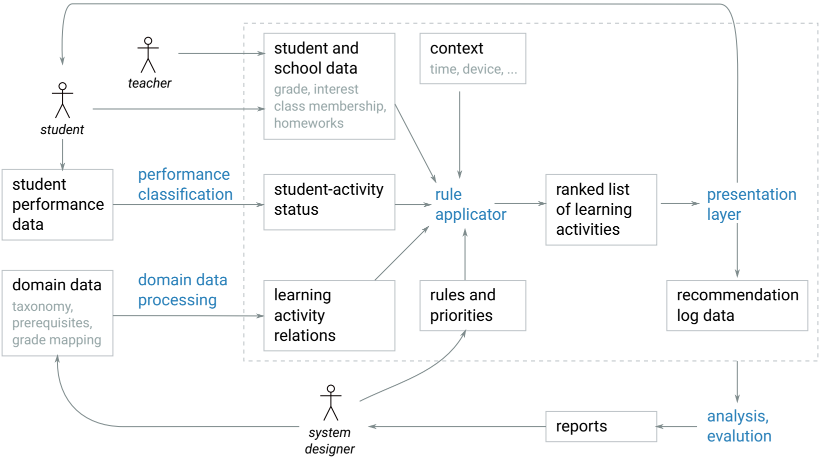
Recommendations Situations

	predicting intentions	facilitating exploration	reinforcing knowledge
homepage	✓✓	✓✓	✓✓
follow-up	✓✓✓	✓	
navigation defaults	✓✓✓	✓	✓
special		✓✓	✓✓✓

Recommendation Approach

- IF-THEN rules with priorities
- IF *condition* THEN *recommmendation*
- conditions:
  - student state / previous activity
  - practice set features / relations

Recommmendation Framework



Recommendation Rules

Rule examples:

- X mastered easily and Y follows X with respect to difficulty $\Rightarrow$ recommend Y, high priority
- X mastered weakly and Y preceeds X with respect to topic $\Rightarrow$ recommend Y, middle priority
- X mastered weakly T days ago $\Rightarrow$ recommend Y, priority depends on T
- user grade G, X is popular for G $\Rightarrow$ recommend X, low priority

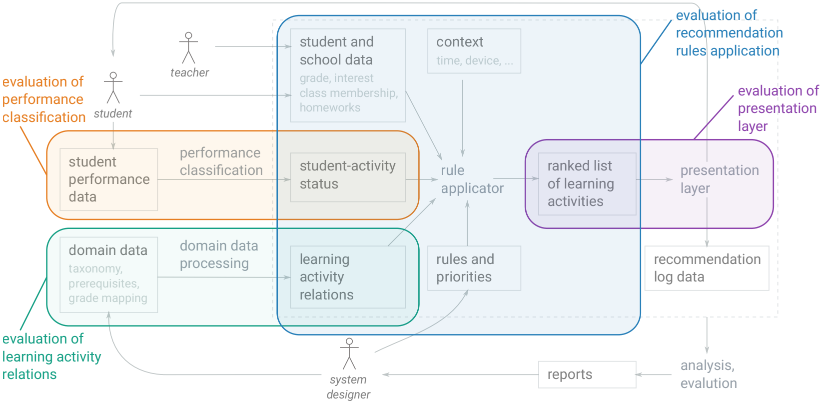
Recommendation Rules

different situations use different rules

- homepage
- follow-up recommendations
- spaced repetition recommendations

Evaluation Approach

formative, stupidity-avoiding, short-term evaluation $\Rightarrow$ iterative improvement of the system

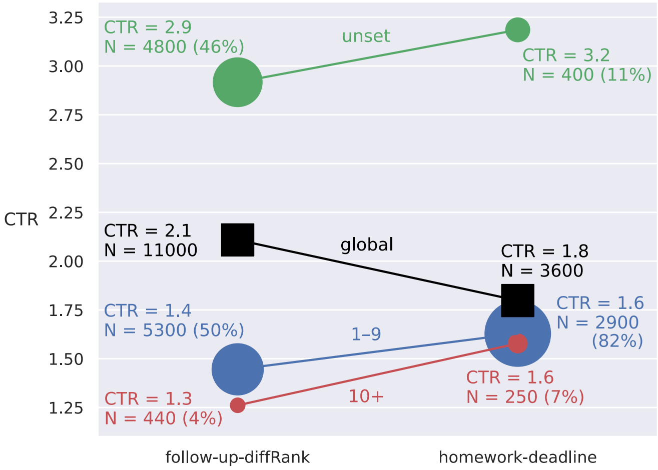


Evaluation Illustration: CTR

Table 7 Click-through rates for a selection of rules across a selection of situations, subjects, and populations. Recommendation situations: Homepage, Next to solve, Navigation in the exercise dashboard. Subjects: English, Mathematics, Computer Science. Grades: unset, primary and secondary school (grades 1–9), high school, and older (grade 10+).

	situation			subject			grade		
	Home	Next	Navig.	Eng.	Math	CS	unset	1–9	10+
follow-up-diffRank	1.2	3.1	3.5	2.7	2.0	1.1	2.9	1.4	1.3
follow-up-kc	1.1	1.6	2.5	1.9	1.3	0.7	1.7	1.1	1.1
pred-for-weak-kc	0.8	0.7	2.1	1.1	0.8	0.4	1.1	0.7	0.9
pred-for-weak-diffRank	1.2	0.8	2.0	1.4	0.9	0.7	1.3	0.9	0.6
repetition-for-weak	0.5	0.6	2.3	0.8	0.5	0.3	0.8	0.4	0.7
repetition-for-normal	0.4	0.6	1.7	0.8	0.5	0.3	0.7	0.4	0.8
homework-follow	1.2	5.1	0.0	0.7	1.0	1.8	2.0	1.1	1.0
homework-deadline	1.8	0.0	0.0	1.1	1.8	2.3	3.2	1.6	1.6
featured	0.7	0.6	4.1	1.1	1.0	0.9	0.8	1.6	1.2
peers	1.0	0.8	2.2	1.1	0.7	1.6	1.6	1.0	0.6

Evaluation Warning: Simpson's Paradox



Umíme to – Data Analysis

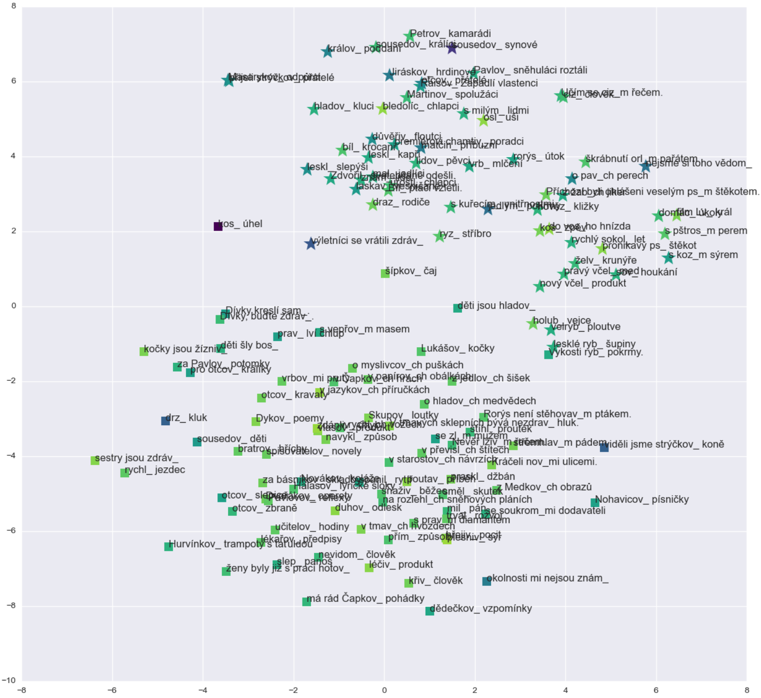
"design adaptation", "avoiding stupidity"

data ⇒ analysis ⇒ insights ⇒ revision of items or system behaviour

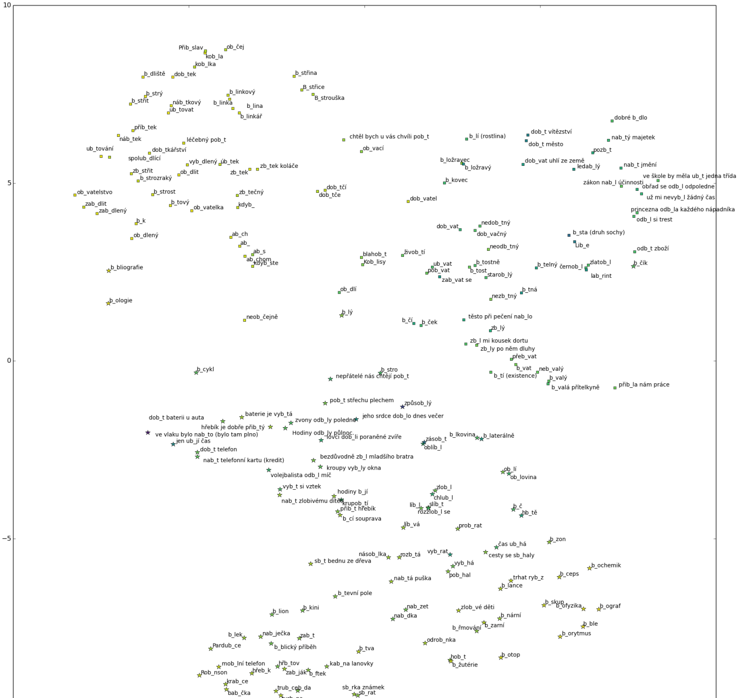
- difficulty of items
- survival analysis, length of practice
- response times
- item similarities

Item Similarities and Clustering

- closely related to item-item collaborative filtering
- item similarities: Pearson correlation of answers
- clustering: k-means
- visualization: tSNE
- key issue: do we have enough data?



8
6
4
2
0
−2
−4
−6
−8
−10
−8
−6
−4
−2
0
2
4
6
8
Petrov_ kamarádi
králov_ poddaní
sousedov_ synové
Pavlov_ sněhuláci roztáli
Martinov_ spolužáci
hladov_ kluci
bledolíc_ chlapci
s milým_ lidmi
osl_ uši
důvěřiv_ floutci
bíl_ krocani
lidov_ pěvci
vrb_ mlčení
rorýs_ útok
škrábnutí orl_m pařátem
leskl_ slepýši
o pav_ch perech
draz_ rodiče
kos_ úhel
výletníci se vrátili zdráv_
ryz_ stříbro
s pštros_m perem
rychlý sokol_ let
pronikavý ps_ štěkot
s koz_m sýrem
želv_ krunýře
nový včel_ produkt
šípkov_ čaj
děti jsou hladov_
holub_ vejce
velryb_ ploutve
lesklé ryb_ šupiny
Dívky kreslí sam_.
Dívky, buďte zdráv_.
s vepřov_m masem
kočky jsou žízniv_
děti šly bos_
Lukášov_ kočky
za Pavlov_ potomky
pro otcov_ králiky
o myslivcov_ch puškách
z jedlov_ch šišek
v jazykov_ch příručkách
otcov_ kravaty
o hladov_ch medvědech
drz_ kluk
Dykov_ poemy
Skupov_ loutky
Rorýs není stěhovav_m ptákem.
navykl_ způsob
sousedov_ děti
se zl_m mužem
viděli jsme strýčkov_ koně
spisovatelov_ novely
v převisl_ch štítech
sestry jsou zdráv_
v starostov_ch návrzích
Kráčeli nov_mi ulicemi.
rychl_ jezdec
z Medkov_ch obrazů
Nohavicov_ písničky
na rozlehl_ch sněhových pláních
otcov_ zbraně
duhov_ odlesk
se soukrom_mi dodavateli
učitelov_ hodiny
v tmav_ch hvozdech
lékařov_ předpisy
Hurvínkov_ trampoty s tatuldou
nevidom_ člověk
léčiv_ produkt
ženy byly již s prací hotov_
křiv_ člověk
okolnosti mi nejsou znám_
má rád Čapkov_ pohádky
dědečkov_ vzpomínky


10
5
0
−5
Přib_slav
ob_čej
kob_la
kob_lka
b_dliště
dob_tek
b_střina
B_střice
B_strouška
b_strý
b_střit
náb_tkový
b_tovat
b_linkový
b_linka
b_lina
b_linkář
příb_tek
náb_tek
léčebný pob_t
ub_tování
dob_tkářství
spolub_dlící
vyb_dlený
úb_tek
zb_tek koláče
zb_střit
ob_dlit
zb_tek
b_strozraký
ob_vatelstvo
b_strost
zb_tečný
zab_dlit
b_tový
ob_vatelka
kdyb_
zab_dlený
b_k
ob_dlený
ab_ch
ab_
ab_s
ab_chom
kdyb_ste
b_bliografie
b_ologie
neob_čejně
chtěl bych u vás chvíli pob_t
ob_vací
dob_tčí
dob_tče
dob_vatel
b_lí (rostlina)
dob_t vítězství
dob_t město
dobré b_dlo
nab_tý majetek
pozb_t
b_ložravec
b_ložravý
dob_vat uhlí ze země
ledab_lý
nab_t jmění
b_kovec
ve škole by měla ub_t jedna třída
zákon nab_l účinnosti
obřad se odb_l odpoledne
už mi nevyb_l žádný čas
princezna odb_la každého nápadníka
odb_l si trest
dob_vat
nedob_tný
dob_vačný
b_sta (druh sochy)
Lib_e
neodb_tný
odb_t zboží
blahob_t
Kob_lisy
živob_tí
ub_vat
pob_vat
zab_vat se
b_tostně
b_tost
starob_lý
b_telný
černob_l
zlatob_l
lab_rint
b_čík
ob_dlí
b_tná
nezb_tný
b_lý
b_čí
b_ček
těsto při pečení nab_lo
zb_lý
zb_l mi kousek dortu
zb_ly po něm dluhy
přeb_vat
b_vat
neb_valý
b_tí (existence)
b_valý
b_valá přítelkyně
přib_la nám práce
b_cykl
b_stro
nepřátelé nás chtějí pob_t
pob_t střechu plechem
způsob_lý
baterie je vyb_tá
dob_t baterii u auta
zvony odb_ly poledne
jeho srdce dob_lo dnes večer
hřebík je dobře přib_tý
ve vlaku bylo nab_to (bylo tam plno)
Hodiny odb_ly půlnoc
lovci dob_li poraněné zvíře
jen ub_jí čas
b_lkovina
b_laterálně
zásob_t
oblíb_l
dob_t telefon
nab_t telefonní kartu (kredit)
bezdůvodně zb_l mladšího bratra
kroupy vyb_ly okna
volejbalista odb_l míč
ob_lí
ob_lovina
vyb_t si vztek
hodiny b_jí
zlob_l
chlub_l
nab_t zlobivému dítěti
krupob_tí
přib_t hřebík
líb_l
slíb_t
rozzlob_l se
b_č
hb_tě
b_cí souprava
líb_vá
prob_rat
b_zon
čas ub_há
násob_lka
rozb_tá
vyb_rat
cesty se sb_haly
sb_t bednu ze dřeva
vyb_há
pob_hal
b_ochemik
nab_tá puška
trhat ryb_z
b_ceps
b_lance
b_tevní pole
b_lion
b_kini
nab_zet
zlob_vé děti
b_skup
b_ofyzika
b_ograf
nab_dka
b_nární
b_řmování
b_zarní
b_ble
b_lek
nab_ječka
zab_t
b_orytmus
b_blický příběh
odrob_nka
Pardub_ce
b_tva
hob_t
b_otop
b_žutérie
mob_lní telefon
hřb_tov
kab_na lanovky
hřeb_k
zab_ják
b_ftek
Rob_nson
krab_ce
trub_ceb_da
sb_rka známek
bab_čka
sb_rat

Note on Different Approaches

using data, models for:

- "automatic" interventions
  - recommendations
  - personalization choices
  - mastery learning
- support for "manual" interventions
  - items behaviour
  - system behaviour
  - user behaviour

"asking right questions" often more important than "using sophisticated methods"

Illustrations of Other Techniques and Tools

- learning networks
- intelligent tutoring systems
- addressing metacognition and affect
- limited time recommendations
- course recommendations

Learning Networks

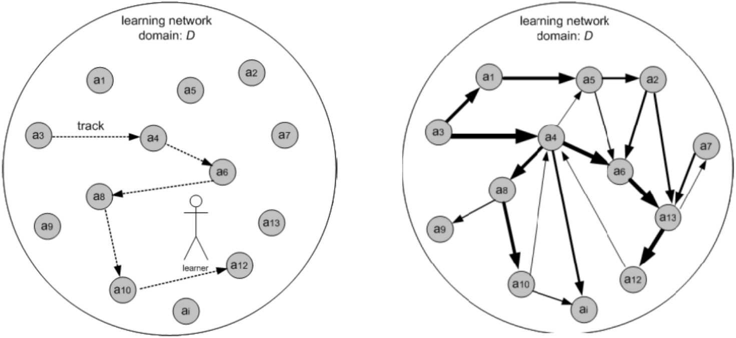
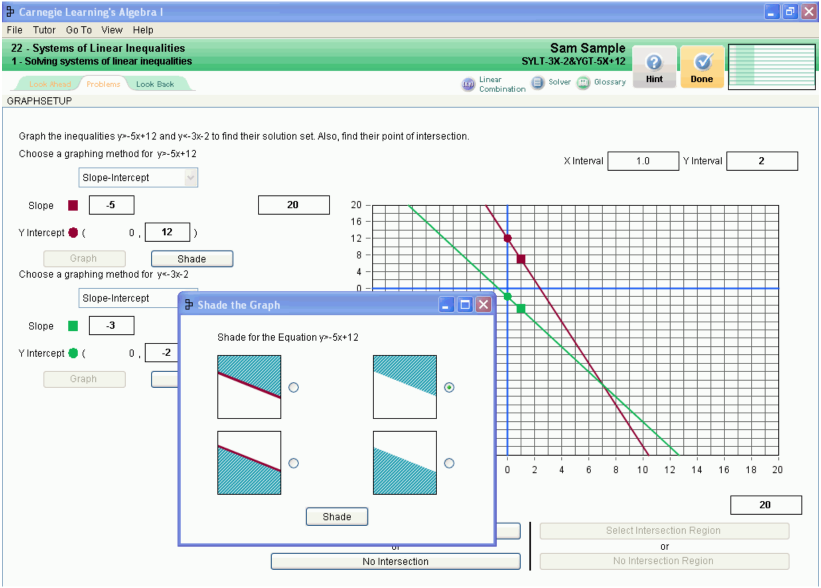


Fig. 2. Evolution of a learning network (left: starting phase with a first learner moving through possible learning activities; right: advanced phase showing emerging learning paths from the collective behavior of all learners)

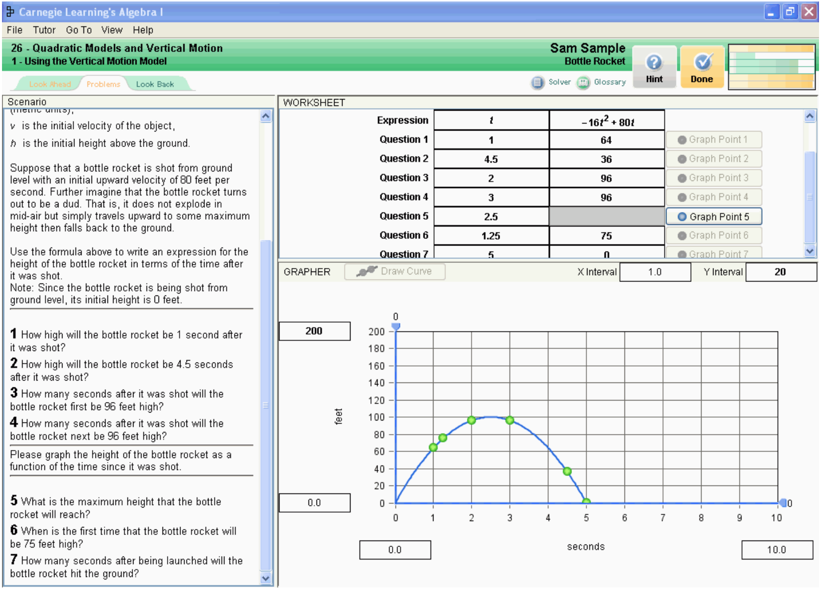
Intelligent Tutoring Systems

- interactive problem solving
- behavior
  - outer loop – selection/recommendation of "items" (problems, exercises)
  - inner loop – hints, feedback, ...
- adaptation based on learner modeling
- knowledge modeling more involved than "taste modeling" (domain ontology, prerequisites, ...)

Carnegie Learning: Cognitive Tutor



Carnegie Learning: Cognitive Tutor



Wayang Outpost

- *A Multimedia Adaptive Tutoring System for Mathematics that Addresses Cognition, Metacognition and Affect*
- adaptive tutoring system for math
- Wayang Outpost $\rightarrow$ MathSpring, `http://mathspring.org/`
- specific feature: focus on affect and metacognition

Wayang Outpost

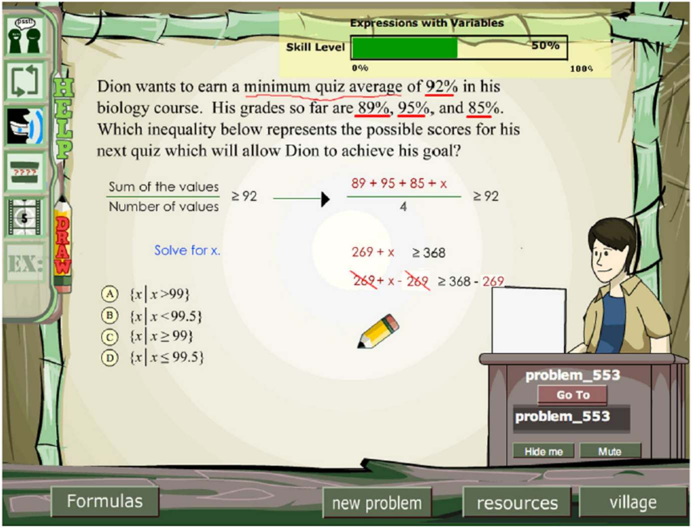


Fig. 1 The Wayang Outpost Math Tutor interface. An animated companion provides individualized comments and support

Wayang Outpost: Open Learner Model

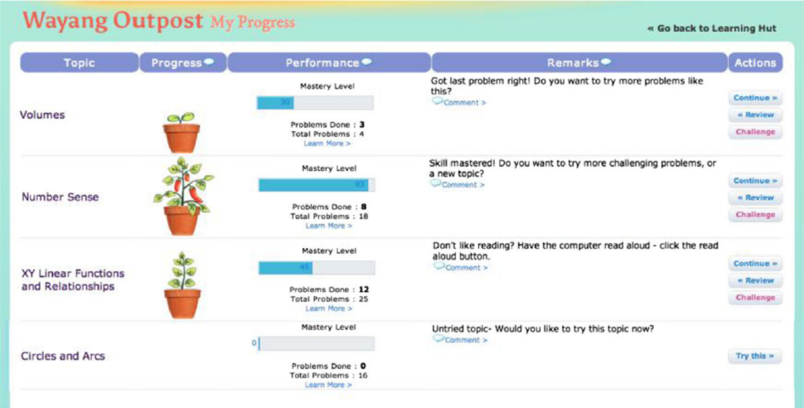


Fig. 9 The open student model in Wayang is called the Student Progress Page (SPP). It encourages students to reflect on their progress for each topic (column 1). The plant (column 2) demonstrates the tutor's assessment of student effort, while the mastery bar (column 3) records presumed knowledge (according to Bayesian Knowledge Tracing). The tutor comments on its assessment of the student's behavior (column 4) and offers students the choice to continue, review or challenge themselves and make informed decisions about future choices (column 5)

Wayang Outpost: Affect, Metacognition

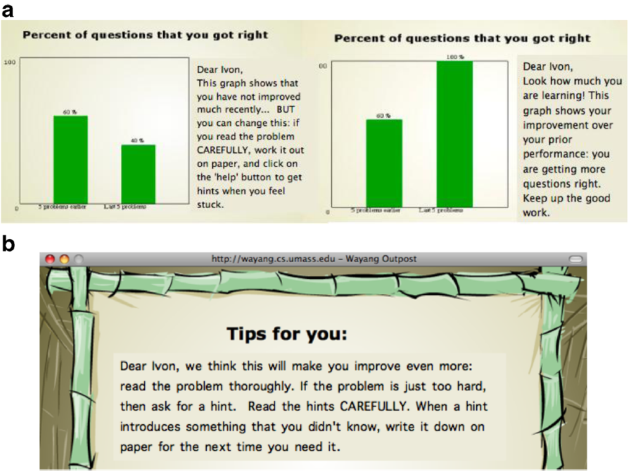


Fig. 11 **a.** Progress Charts in Wayang show students the accuracy of their answers. **b.** Tips in Wayang encourage good learning habits

Wayang Outpost: Affective Learning Companions

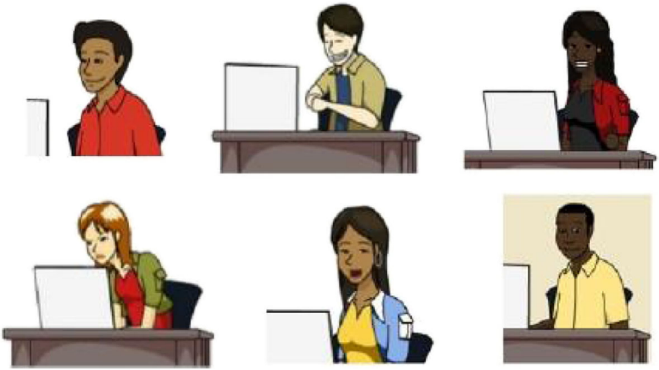


Fig. 14 Animated pedagogical agents display a range of emotions. Companions act out their emotion and resolve negative ones, expressing full sentences of affective and metacognitive nature, to support growth of mindset towards the view that intelligence is a state (and thus changeable)

Effort Based Tutoring

Table 1 The effort-based tutoring algorithm informs pedagogical moves and affective decisions (last two columns) for each student on each problem. The algorithm first infers a reason for students behavior (fourth column) based on the number of incorrect student answers, hints requested and the amount of time spent (first three columns). Then the algorithm decides which pedagogical action the tutor should take (last two columns). The algorithm encourages transfer of student knowledge to subsequent questions of similar difficulty (rows 2, 4, 9), encouraging students to transfer skills and "fade" their need for help

	Observed behavior and inferred reason for this behavior				Pedagogical Model Moves Cognitive or Affective or Metacognitive	
	Incorrect	Hints	Time	Most Likely Reason	Decision	Affective/Metacog. Decisions
1	$< E\ (Ii) - \delta_{IL}$	$< E\ (Hi) - \delta_{HL}$	$< E\ (Ti) - \delta_{TL}$	Mastery without effort	Increase Problem Difficulty	Show learning progress
2	$< E\ (Ii) - \delta_{IL}$	$< E\ (Hi) - \delta_{HL}$	$> E\ (Ti) + \delta_{TH}$	Mastery with high effort	Maintain Problem Difficulty	Affective feedback: Praise Effort
3	$< E\ (Ii) - \delta_{IL}$	$> E\ (Hi) + \delta_{HH}$	$< E\ (Ti) - \delta_{TL}$	Hint abuse, low effort	Reduce Problem Difficulty	Deemphasize importance of immediate success
4	$< E\ (Ii) - \delta_{IL}$	$> E\ (Hi) + \delta_{HH}$	$> E\ (Ti) + \delta_{TH}$	Towards mastery, effort	Maintain Problem Difficulty	Praise effort
5	$> E\ (Ii) + \delta_{IH}$	$< E\ (Hi) - \delta_{HL}$	$< E\ (Ti) - \delta_{TL}$	Quick guessing, low effort	Reduce Problem Difficulty	Deemphasize importance of immediate success
6	$> E\ (Ii) + \delta_{IH}$	$< E\ (Hi) - \delta_{HL}$	$> E\ (Ti) + \delta_{TH}$	Hint avoidance and high effort	Reduce Problem Difficulty	Offer hints upon incorrect answer in the next problem
7	$> E\ (Ii) + \delta_{IH}$	$> E\ (Hi) + \delta_{HH}$	$< E\ (Ti) - \delta_{TL}$	Quick guess and hint abuse	Reduce Problem Difficulty	Deemphasize importance of immediate success
8	$> E\ (Ii) + \delta_{IH}$	$> E\ (Hi) + \delta_{HH}$	$> E\ (Ti) + \delta_{TH}$	Low mastery and High Effort	Reduce Problem Difficulty	Emphasize importance of effort and perseverance
9	Otherwise	Expected Behavior	Maintain Problem Difficulty			

Note: Expected response (correct, hints, time) based on answers of other students $\sim$ collaborative filtering

Wayang Outpost: Evaluation

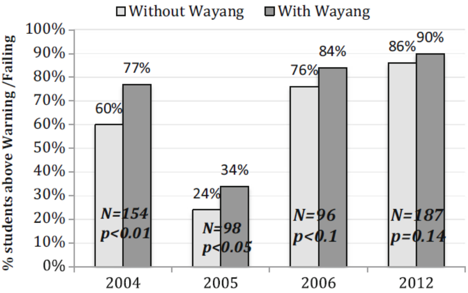


Fig. 4 Massachusetts Statewide Standardized Test (MCAS) passing rates for experimental groups (using Wayang, dark grey) and control groups (in regular math class, light grey), within the same school, same grade and same teachers. Passing rates include several ratings above warning/failing

Wayang Outpost: Evaluation

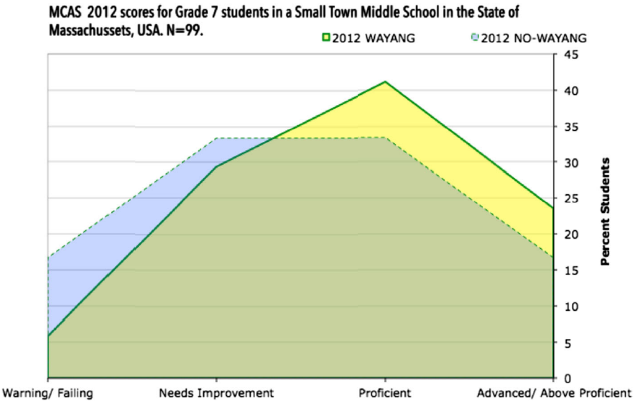


Fig. 5 Area chart comparison of performance for a 7th grade of students on the Massachusetts Comprehensive Assessment System (MCAS), for students using vs. not using Wayang Outpost. Students represented by the *yellow/green polygon* used Wayang Outpost and students represented by the *blue polygon* did not use the tutor. Distribution of students using Wayang Outpost shifts to the right indicating that more students passed the exam and received a grade of "proficient" or "advanced" when using Wayang Outpost. Groups of students were matched in terms of teacher of seventh grade students

Wayang Outpost: Evaluation

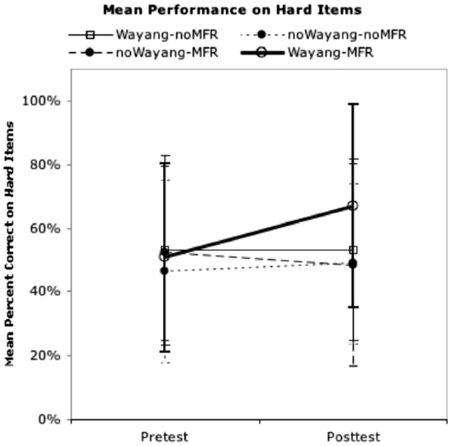


Fig. 7 Mean improvement (and standard deviations) on hardest items of the math pre/posttest. The *thick line* represents students who received both the Wayang Tutor and math facts retrieval training software; all other groups did not really improve on these harder multi-step items

Wayang Outpost: Evaluation

Table 2 Students in the experimental group (last row) received tips and charts every 6 problems. Means and standard deviations in performance measures before and after tutoring for the three groups

Group	Math Pretest	Math Posttest	Passing Rate in State Standard Exam
No Tutor Control			76 % (*N*=38)
Tutor Control	40 % (20) (*N*=40)	40 % (28)* (*N*=40)	79 % (*N*=34)
ProgressTips Tutor	33 % (19) (*N*=36)	42 % (22)* (*N*=36)	92 % (*N*=24)

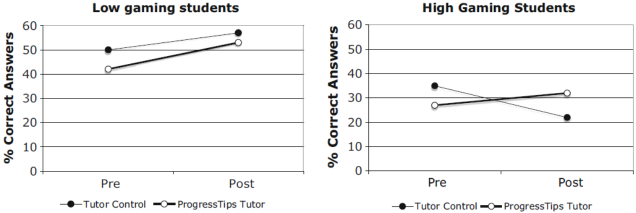
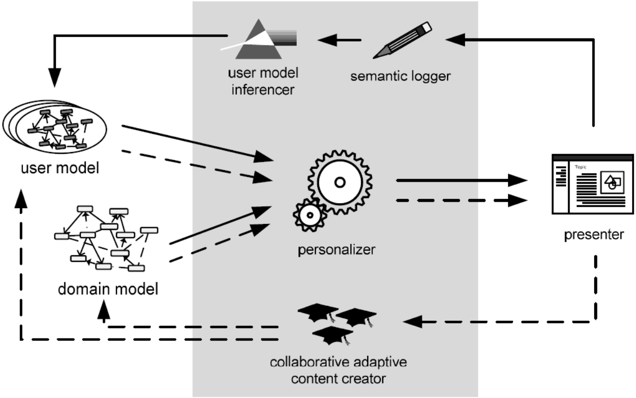


Fig. 12 High gaming students improve math performance when they receive progress tips and interventions (*left*) but not when they don't receive interventions (*right*)

ALEF

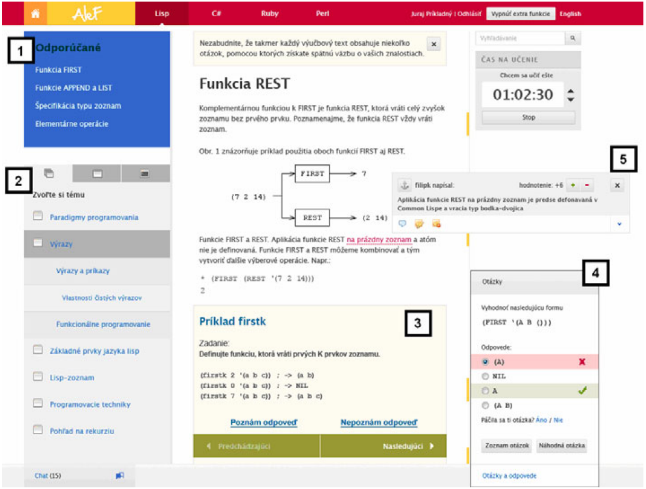
- PeWe (Personalized Web) Group at UISI FIIT STU, Bratislava
- adaptive education (mainly) for programming exercises
- specific aspect: recommendations for limited time

ALEF



ALEF: A Framework for Adaptive Web-Based Learning 2.0, Šimko, Barla, Bieliková

ALEF



ALEF: A Framework for Adaptive Web-Based Learning 2.0, Šimko, Barla, Bieliková

CourseRank

- recommendations of whole courses
- course evaluation and planning social system
- ranking of courses, grade distribution, other statistics
- originally Stanford, later many (US) universities, out of order now
- similar features e.g. in Coursera
- some attempts done in IS MU (but hard to practically apply in real university setting)

Summary

personalized education $\leftrightarrow$ recommender systems

- many similarities
- specific challenges
- difficult evaluation