Effort-based Tutoring: an Empirical Approach to Intelligent Tutoring

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Making Wayang Math Tutor Smarter

From past student logs

Multimedia Adaptive Tutoring System for Standardized-Tests Math Problems

What this paper is about

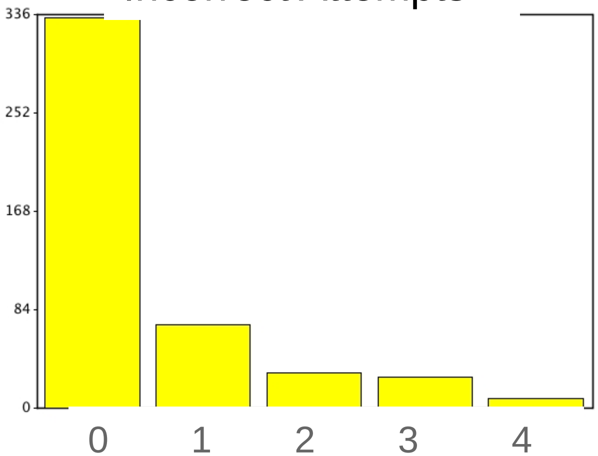
- **A description of how we made the Wayang Tutor Smarter**
  - From past student data
  - Given Content=Cases that students needed to know to solve
  - A wide range of students in public schools
- **A concrete procedure to add smartness to any ILE**
  - From past student data
  - Even for ill-defined domains
  - Regardless of amount of variety of content
  - High level of detail for replication
- **Unveiling parameters that regulate ITS functioning**
  - For optimization

What do students do in Wayang?

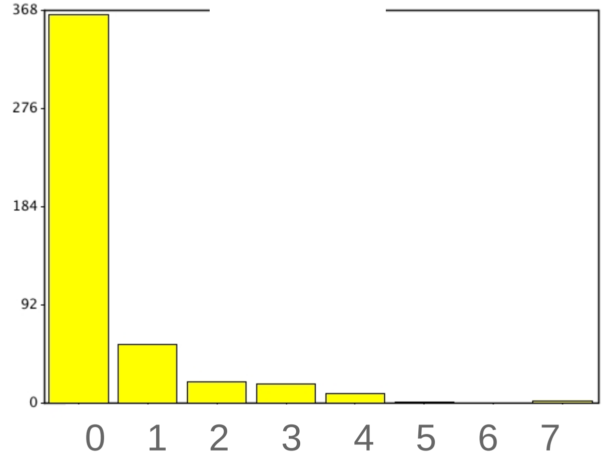
Three different ways to express their effort

Frequency of Behavior on one “easy” math problem in Wayang Outpost **484 cases**

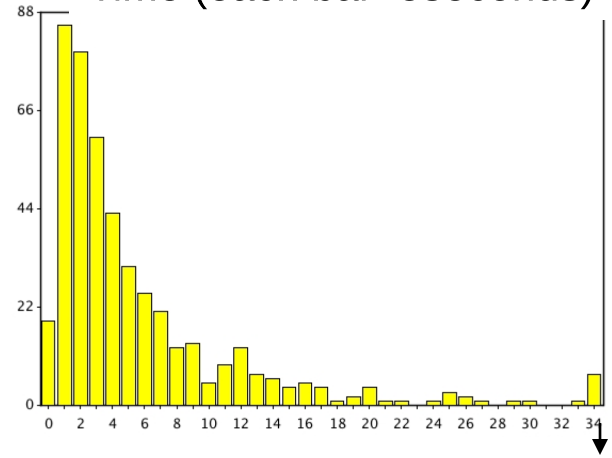
Incorrect Attempts

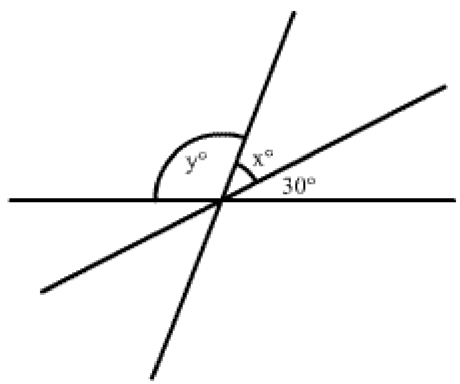


Hints



Time (each bar=5seconds)





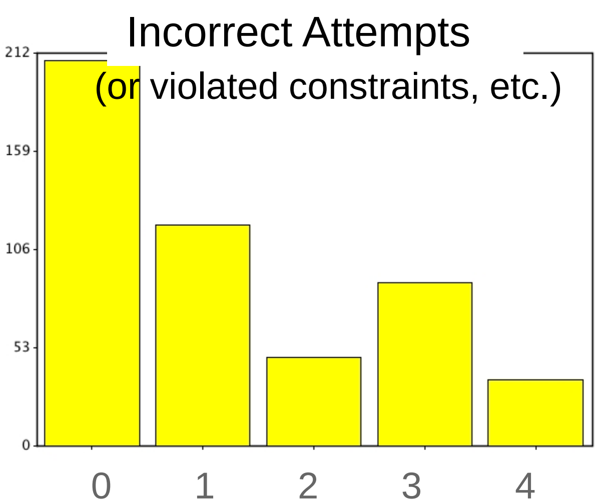
What is x + y?

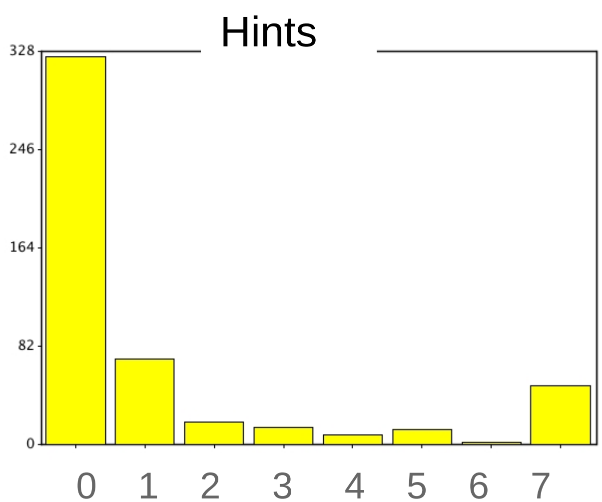
What do students do in Wayang?

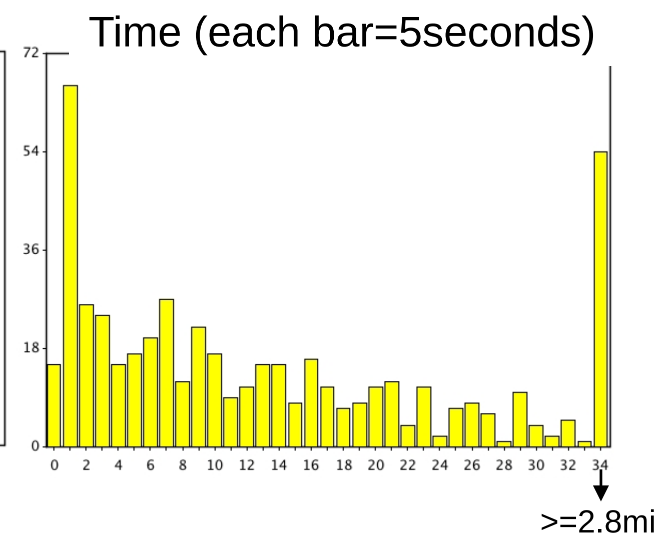
Three different ways to express their effort

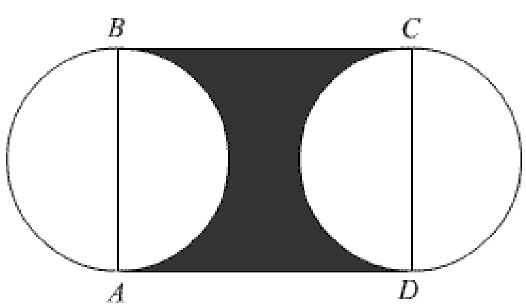
Frequency of Behavior on one “harder” math problem in Wayang Outpost

529 cases





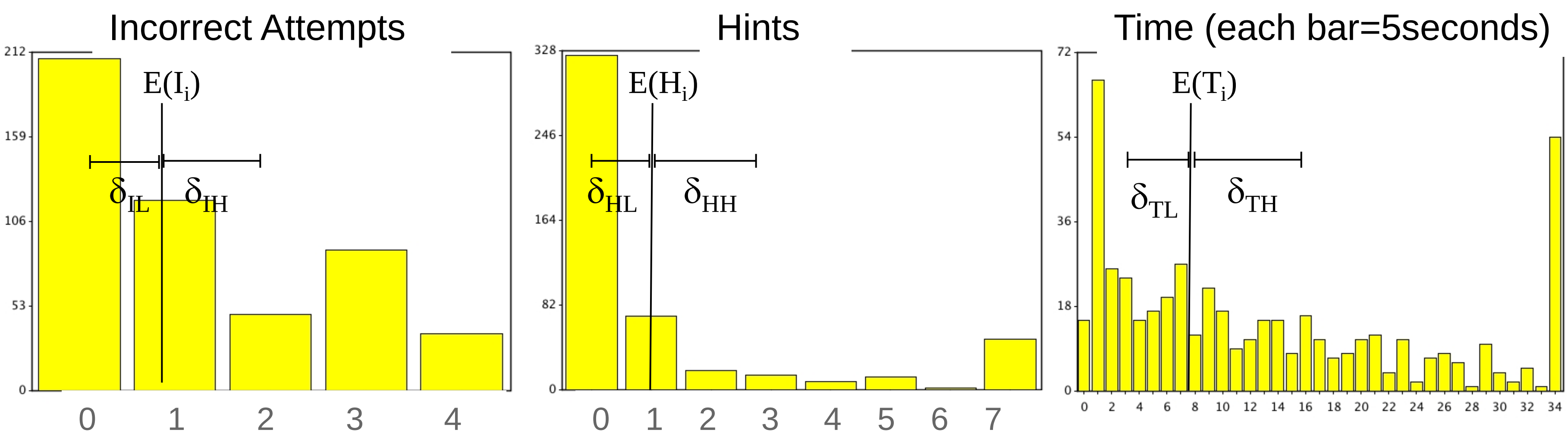




In rectangle $ABCD$, sides AB and CD pass through the centers of the two circles. If AB=12 and AD=16 what is the area of the shaded region?

What is expected behavior?

In any problem p_i i=1, .., N   N=Total problems in system



$E(I_i)$ = mean (or median) Incorrect Attempts for problem p_i

$\delta_{IH} = SD(I_i) * \theta_{HIGH}$ *e.g.* $\theta_{HIGH} = 0.5$

$\delta_{IL} = SD(I_i) * \theta_{LOW}$ *e.g.* $\theta_{LOW} = 0.25$

Parameters

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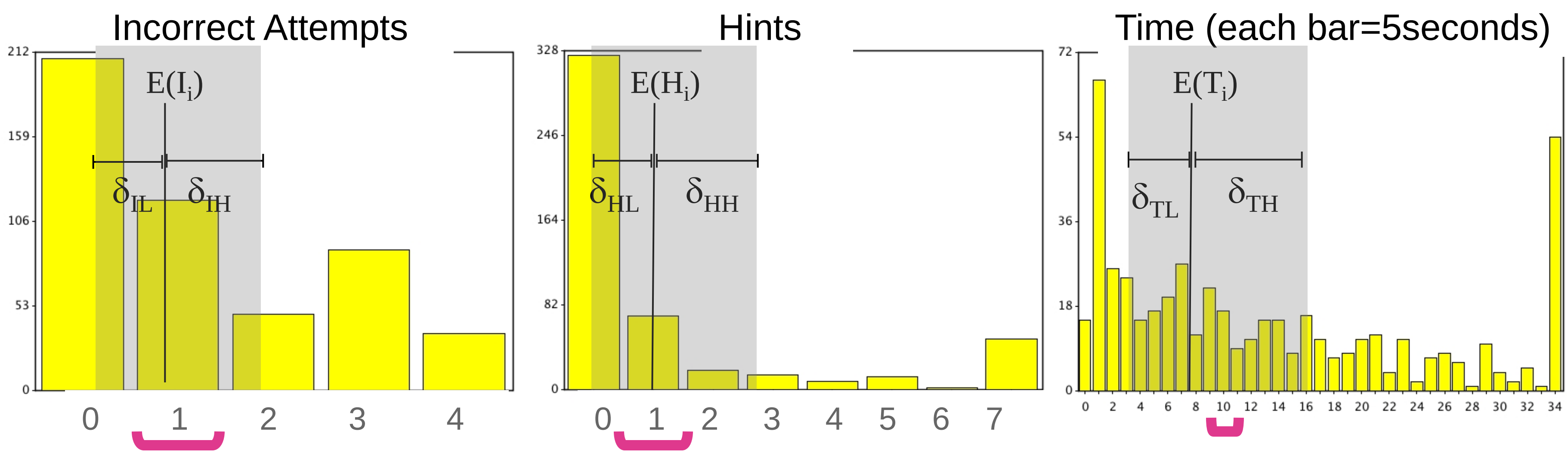
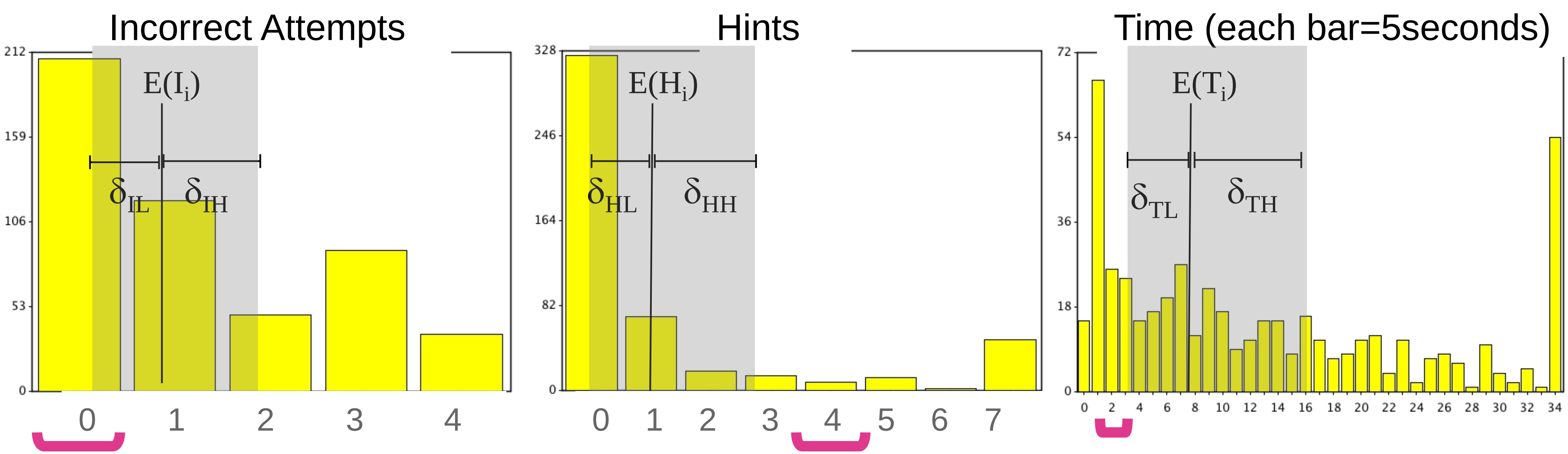


Within expected behavior

A new student encounters this problem…
Is their behavior within expectation, or atypical?

What is odd behavior?

In any problem p_i $i=1, .., N$ N=Total problems in system



Odd behavior

Attempts < $E(I_i) - \delta_{IL}$

Few Inc. Attempts

<

Hints > $E(H_i) + \delta_{HH}$

Lots of Hints

>

Time < $E(T_i) - \delta_{TL}$

Little Time

<

Pedagogical Moves in Wayang Outpost

	Student Model Estimate most likely scenario for student on p_i				Pedagogical Model Moves Cognitive or Affective or Metacognitive	
	Mistakes	Hints	Time	Most Likely	Decision	Other Actions
1	<	<	<	Mastery without effort	Increase Problem Difficulty	Show learning progress
2	<	<	>	Toward Mastery	Maintain Problem Difficulty	Affective feedback: Praise Effort
3	<	>	<	Hint abuse, low effort	Reduce Problem Difficulty	Deemphasize importance of immediate success
4	<	>	>	Towards mastery, effort	Maintain Problem Difficulty	Praise effort
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9	Otherwise			Expected Behavior	Maintain Problem Difficulty	

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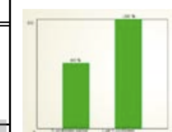

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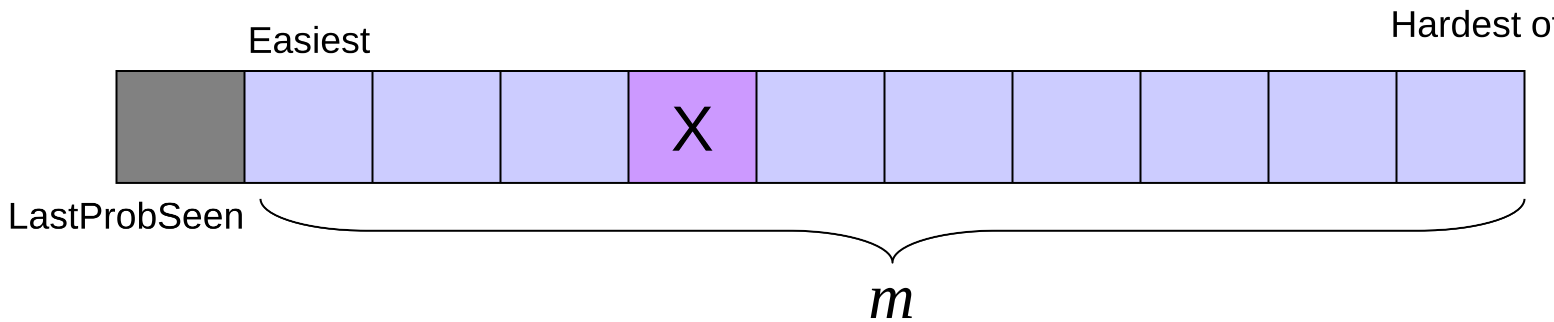
Increasing Problem Difficulty

At the next time step. Assume we know problem difficulty of items.

$H=$ Sorted list of harder math problems



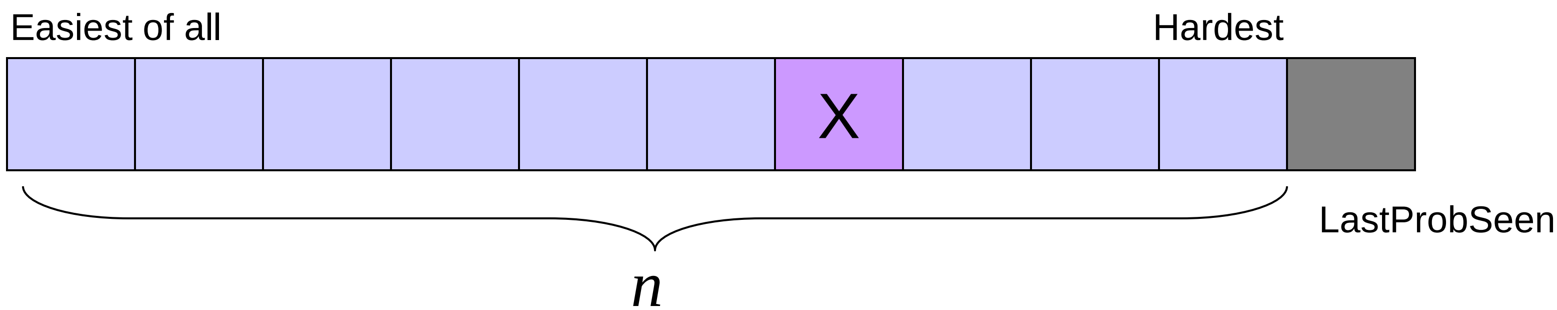
$$Harder(H[1..m],\gamma) = H\left\lfloor ceiling\left(\frac{m}{\gamma}\right)\right\rfloor$$

Parameter $\left\{ \gamma = 3 \right.$ **--> Challenge rate**

Decreasing Problem Difficulty

At the next time step. Assume we know problem difficulty of items.

$E =$ Sorted list of easier math problems



$$Easier(E[1..n],\gamma) = E\left\lfloor ceiling\left(n - \frac{n}{\gamma}\right)\right\rfloor$$

Parameter $\left\{ \gamma \right.$ = 3

What is Problem Difficulty?

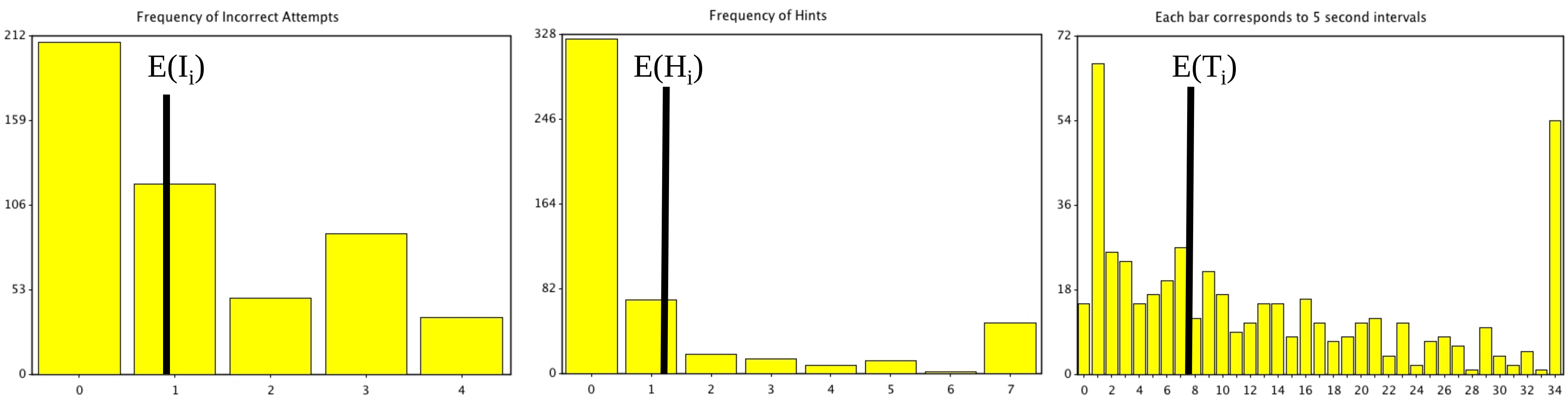
Which problems are easier or harder?

Correctness effort factor $$dc_i = \frac{E(I_i)}{Max_{j=1}^{N}(E(I_j))} \quad dc_i \in [0,1]$$

Hint effort factor $$dh_i = \frac{E(H_i)}{Max_{j=1}^{N}(E(H_j))} \quad dh_i \in [0,1]$$

Time effort factor $$dt_i = \frac{E(T_i)}{Max_{j=1}^{N}(E(T_j))} \quad dt_i \in [0,1]$$

$$d_i = mean(dc_i, dt_i, dh_i)$$
$$d_i \in [0,1]$$



Reasonable… But is it really sound?

Accuracy of Problem Difficulty?

Just too important to get them right

- They are too relevant to the Pedagogical Model moves

Just too likely they might be wrong

- They will be *biased* to the problem selector in place!
  - However, if you have a variety of past problem selectors…

Need criteria that can guarantee they are good-enough

- What kind of tests can we run?

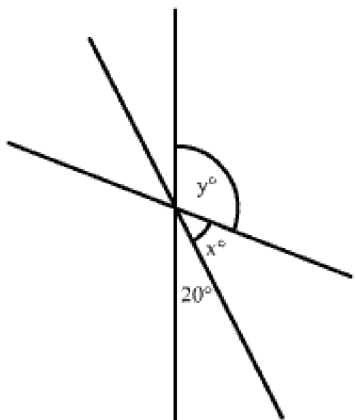
Are difficulty estimations accurate?

Criteria for evaluating the soundness of estimations

Axiom:

“PAIRS OF SIMILAR PROBLEMS SHOULD HAVE SIMILAR PROBLEM DIFFICULTY ESTIMATES”

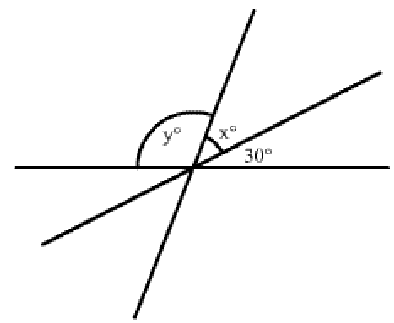
p_{003}



What is x + y?

- 20°
- 60°
- 155°
- 160°
- 180°

p_{033}



What is x + y?

- 50°
- 90°
- 150°
- 145°
- 60°

30 pairs of problems like this. It should happen that: $d_{p_i} \approx d_{p_{30+i}}$

Are difficulty estimations accurate?

Criteria for evaluating the soundness of d_i in relation to d_{30+i}

Criteria 1: Similar to each other?

Pearson Correlation: $p<0.0001$, $R=.823$

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Criteria 2: Different from rest? Paired samples t(29)=7.35, p<.000

$$\boxed{\left(d_{p_i} - d_{p_{30+i}}\right)^2} < \boxed{\frac{\sum_{j=1, j \neq i}^{30} \left(d_{p_i} - d_{p_j}\right)^2}{30}}$$

	d_{pi}	d_{p30+i}	*SE*	*MSE*
1	0.28	0.29	0.0001	…
2	…	…	…	…
3				
…				
30				

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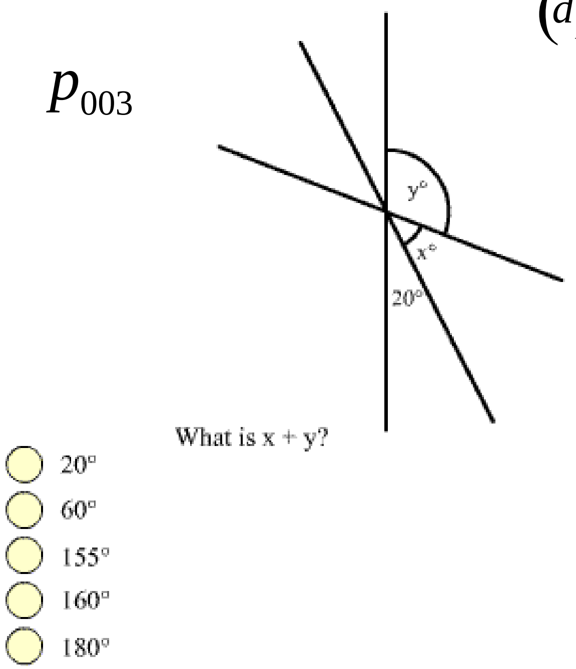
Criteria 3: Different from each other?

21 restrictions, $\chi^2(20)=5.25$, $p<0.05$

$$\left(d_{p_i} - d_{p_{30+i}}\right)^2 = \varepsilon_i$$

p_{003}



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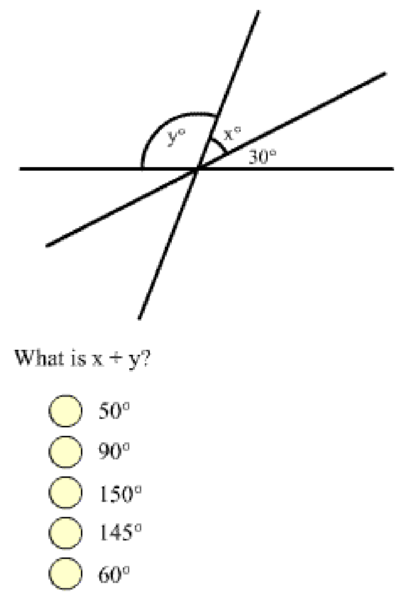

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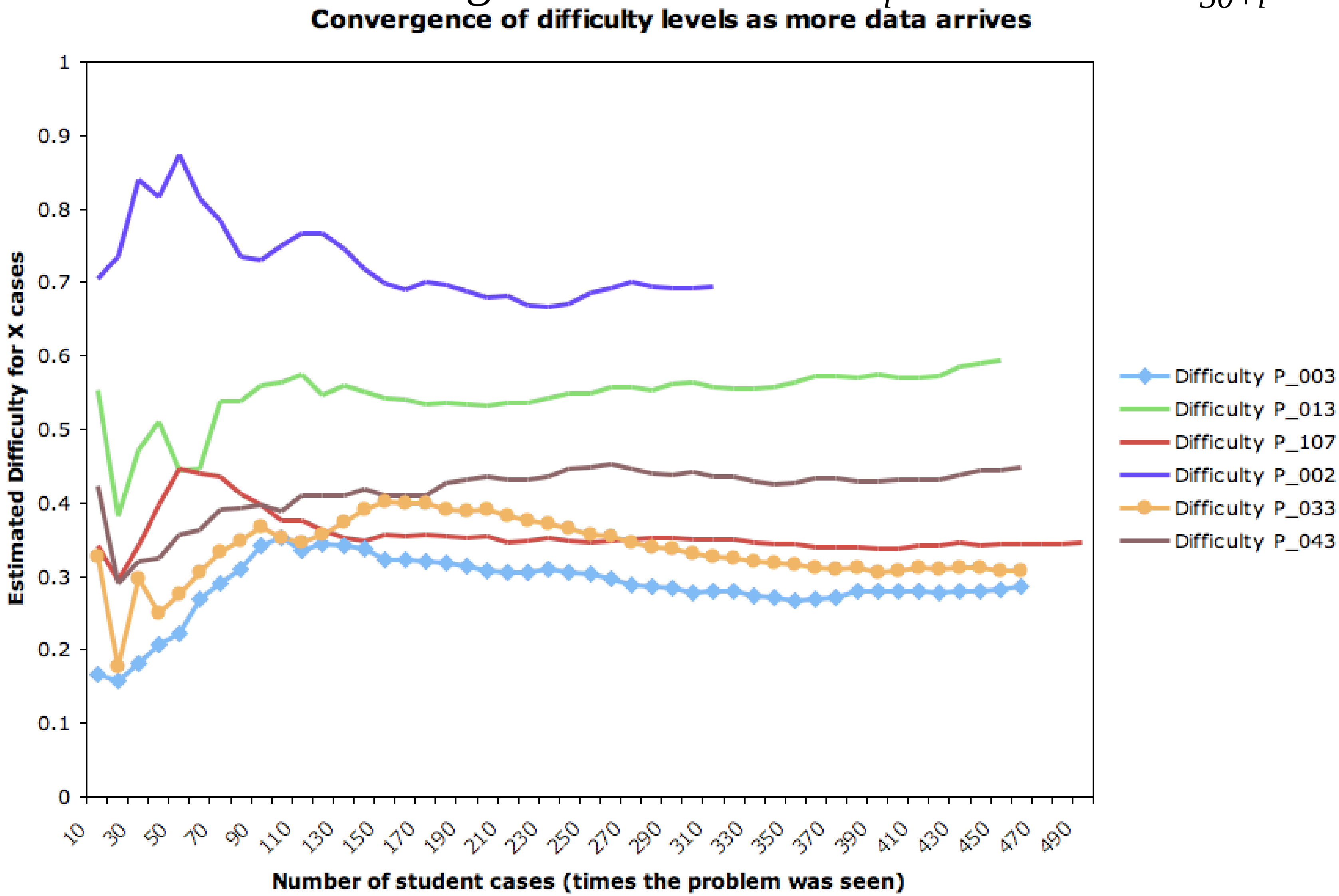


Progressing Through Knowledge Units

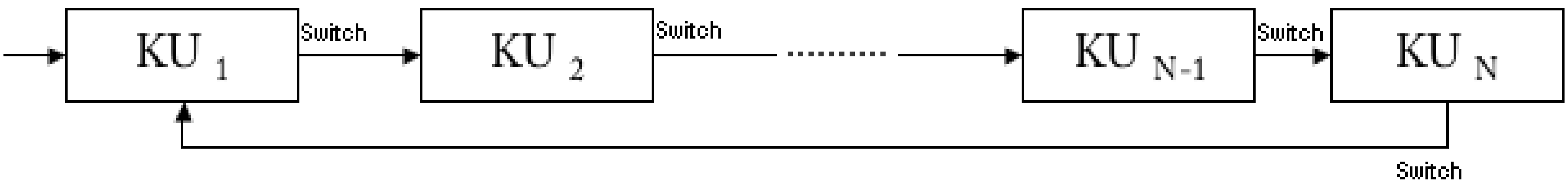
- Intelligent/Adaptive Tutor =
  - Discarding some of the content
    - Some of it is inappropriate
    - Student is ready to move on
  - When has the student seen enough?

- Content Organization
  - Where should they move on to?
  - What are Knowledge Units?

Switching through Knowledge Units

Parameters to Switch Topics or Knowledge Units

Knowledge Units are Chunks of Problems that use similar skills



Topic Switch Criterion	Reason	Parameter
2.1 Topic Mastery was reached (e.g. enough ÒhardÓ problems answered correctly)	Cognitive	M_{KU}
2.2 Persistent failure to find a problem of desired difficulty	Content limitation	F_{KU}
2.3 Maximum time in Topic condition, or Maximum Number of Problems allowed	Classroom Implementation	T_{KU} N_{KU}

Does it improve learning?

Randomized Controlled Experiment (N=56) Spring 2004

56 high school students from different math classes in a public school
Pretest and Posttest, 9 (medium and hard) SAT-M problems

		Within KU	Between KU
Experimental	{	$\gamma=2$ $\theta_{LOW}=0$ $\theta_{HIGH}=0$	$N_{KU} = \textit{fixed value}$
Control	{	Random	$N_{KU} = \textit{fixed value}$

Only problem difficulty moves, no "other actions"

Does it improve learning?

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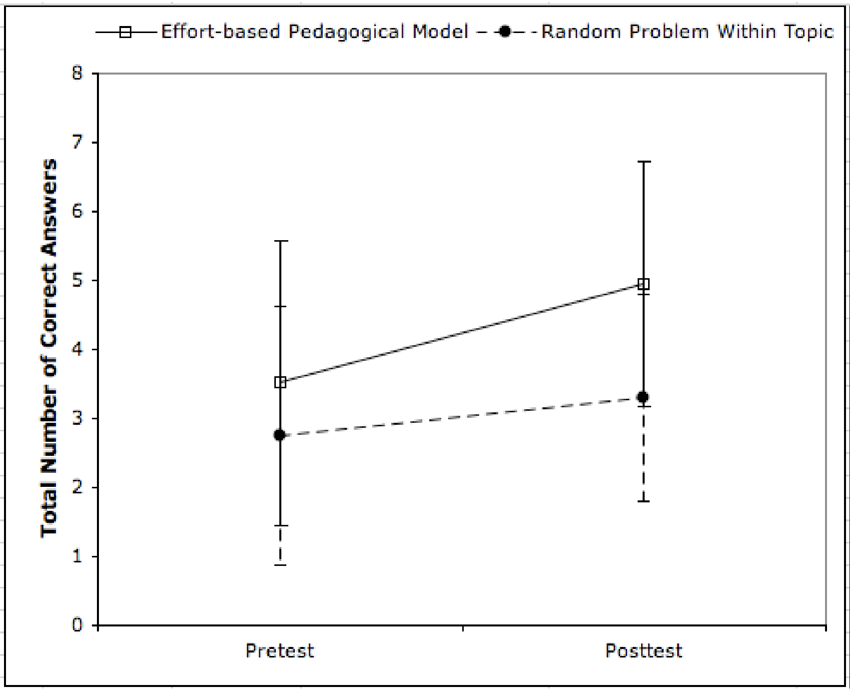

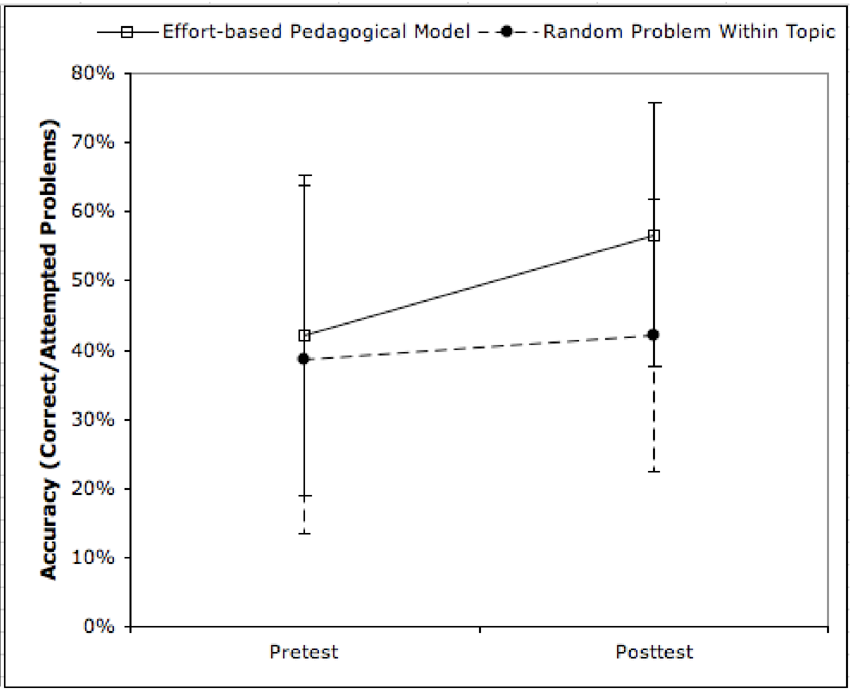

ANCOVA for Posttest Score F(55,1)=8.4, p=.006

Conclusions

- We can discern expected from odd behavior
- We can unveil parameters that regulate ITS functioning
- A procedure to make Learning Environments Smarter
- Tests to evaluate accuracy of problem difficulty
- Evidence that adaptive problem sequencing works
  - Students learned more with adaptive problem selection
  - No learning companions in experiment!

Future Work

- A variety of new behaviors
  - Drawing tools
  - Example viewing
  - Emotion Self-reports
- Combinations of possible behaviors are too many
  - Partial combinations
  - Analyzing clusters of behaviors
- Sequential behavior
  - Motifs and Time-based Patterns
    - Identifying High-Level Student Behavior Using time-based Motif Discovery (Shanabrook et al., EDM 2010)

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What ITS research needs

- Sophisticated Integrated Student Models (SM)
  - *Discern* between Knowledge, Engagement, Affect, Meta-cognition
- Smarter Pedagogical Models (PM)
  - Juggle a variety of student models
  - Effective pedagogical components: in what situations do they work?
- Evidence of Success at Optimizing Learning
  - From the combination of SM and PM
    - Evaluating PM assuming a perfect SM (Beck, 2000)
- What parameters regulate ITS functioning?
  - For optimization
  - For replication: to add smartness to an ILE?

Why an Empirical Approach to ITS?

Some reasons

- How students use ILEs is not known at design time
  - We don’t know how students misuse
  - We don’t know how much students misuse
- Because it can help us to see an integral view
  - Misuse can throw off our estimates of student knowledge
    - E.g. incorrect attempts may appear as unknowing
  - Specific behaviors may be attributed to different reasons
- To understand Domain better
  - *Objective* Problem Difficulty < > *Subjective* Problem Difficulty
- We could learn to make the ILE smarter

An Integral Wholesome View

Factors that regulate/mediate the functioning of an ITS

Student Behavior
(Engagement, Use/Misuse)

Pedagogical Moves

Knowledge Tracing

Content Availability

Affect Models
Emotions/Motivation

Content Quality
Help quality

Metacognition Models

Interface (HCI)
Answer format?

Item Difficulty

Student Models

The Problem of Intelligent Tutoring

What are we trying to solve?

- Optimizing Learning
  - And Motivation, and Meta-cognition…
- What might help us to get us there?
  - Modeling Student Knowledge and Others (SM)
  - Good Pedagogical Material (Content)
  - Good Pedagogical Decisions (PM)

Problems to Implementation of ITS

- Gaming throws off the Knowledge Estimates
- Parameters to Knowledge Tracing
  - Didn’t know exactly what to set
- Ill-defined:
  - Content does not break down nicely into skills
- Step back: Take an Wholesome, Integrated View
  - Can we write a “recipe” to follow to add smartness to an ILE?