Artificial Intelligence Methods for Modeling and Assessing Collaborative Distance Learning

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Mixture Models in Latent Variable Research
University of Maryland, Center for Integrated Latent Variable Research
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Acknowledgments

- ***Alan Lesgold, Ph.D.***
  - ***Professor & Dean, School of Education, University of Pittsburgh***
- ***Ron Stevens, Ph.D.***
  - ***Professor, Microbiology and Education, UCLA***
  - ***Director of the IMMEX Project***

Outline

"Artificial Intelligence (AI) Methods" for Modeling and Assessing "Collaborative Distance Learning"

- Collaborative Distance Learning
- AI Methods: Intro to Hidden Markov Models (HMMs)
- HMMs for analyzing distributed online collaborative learning
- HMMs and Neural Networks for assessing student adoption of problem solving strategies
- Future Project Ideas

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Collaborative Distance Learning

- Computer-supported collaborative learning tools enable learning across time & distance boundaries
  - On-line lectures
  - Lecture notes, & reference material
  - Tutorials & quizzes
  - Shared workspaces
  - On-line discussions - chat & bulletin boards
  - Group project management

Why?

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The Collaborative Learning "Effect"

- Cognitive conflict **(Doise, Mugny, & Perret-Clermont, 1975)**
  - Conflicting viewpoints provoke justification, elaboration
  - Conceptual change **(Roschelle & Teasley, 1993, 1995)**
- Knowledge construction **(Resnick, Levine, & Teasley, 1991)**
  - Idea generation, explanation
  - Knowledge sharing → co-construction → learning
- Social skill development **(Brown & Palincsar, 1989)**
  - Mutual support
  - Cooperating, leading

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When Teams Do Not "Function The Way They Ought To"

- Collaboration does not always enhance individual learning
  - Group size and composition – e.g. status, gender
  - Task structure
  - Rewards or incentives
  - Motivation
  - Communication and Cohesion
- CSCL technology falls behind in providing the kind of support that classrooms offer

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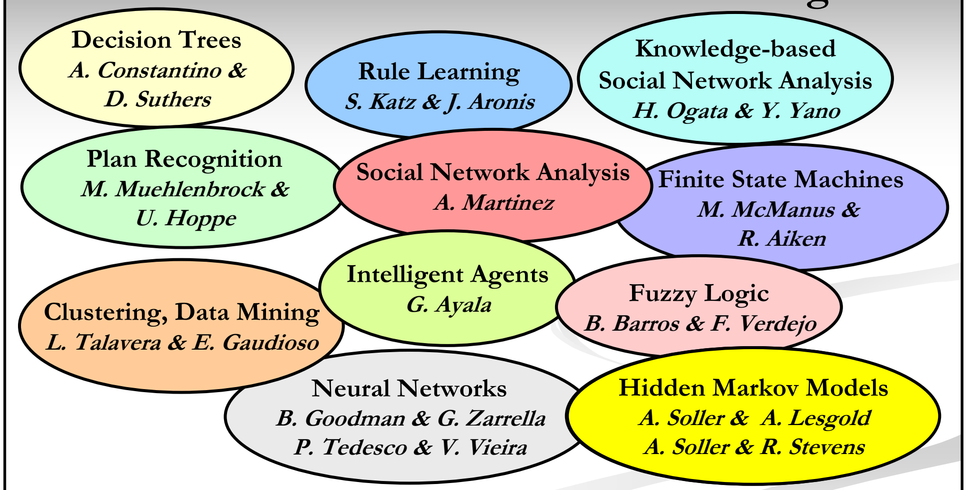
Advanced Modeling, Analysis & Assessment for Collaborative Distance Learning



Soller, A., Martínez-Monés, A., Jermann, P., & Muehlenbrock, M. (2005). From Mirroring to Guiding: A Review of State of the Art Technology for Supporting Collaborative Learning. *International Journal of Artificial Intelligence in Education*, 15 (4).

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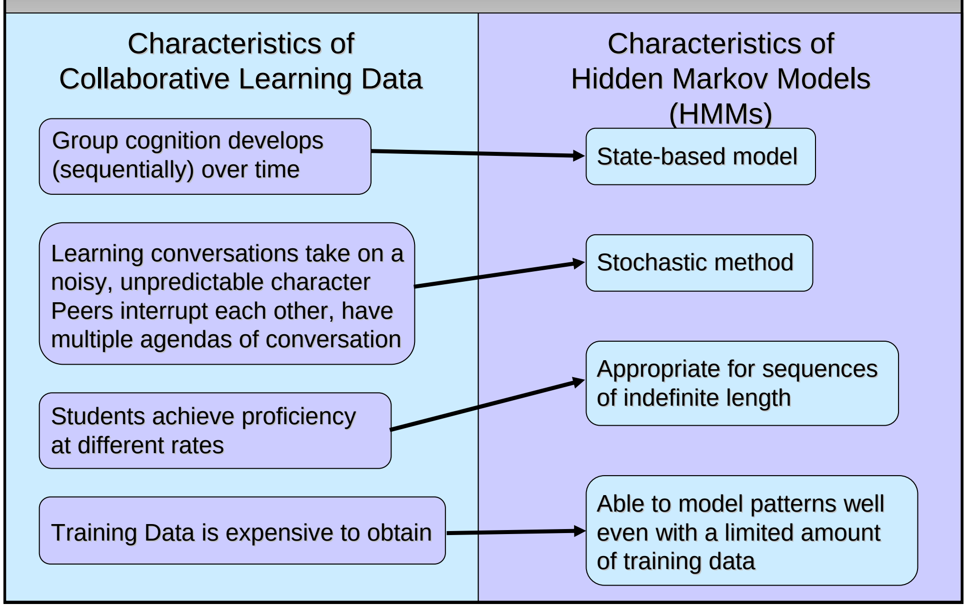
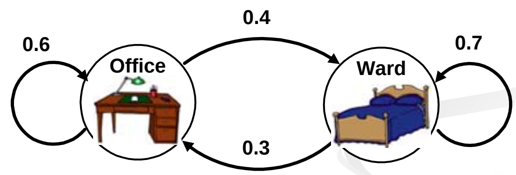
Why Hidden Markov Models?



A Brief Introduction to HMMs

- Markov Chain → probabilistic finite state machine
  - Arcs describe probability of moving between states
  - P(sequence) = Π probabilities along path



- Hidden Markov Model (HMM)
  - Process (states) cannot be directly observed
  - Observations (stochastically linked to states) describe process
  - Several different paths may produce the same output

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A Brief Introduction to HMMs

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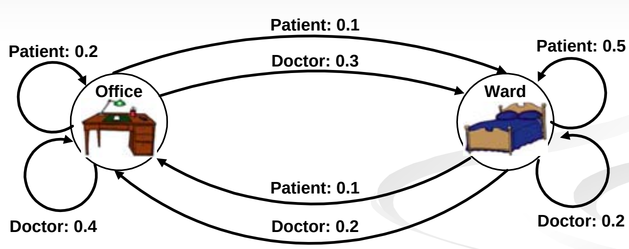

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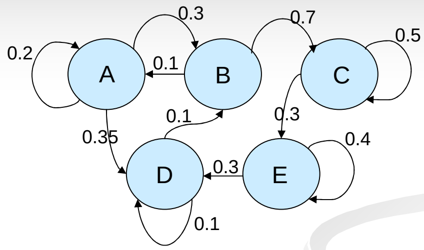
Definition of an HMM:

$\lambda = (A, B, \Pi)$



$\Pi = (\pi_i)$: initial state distribution

$A = (a_{ij}) = P(q_t = S_j \mid q_{t-1} = S_i)$: state transition matrix

$B = (b_j) = P(v_k \mid S_j)$: observation symbol probability distribution

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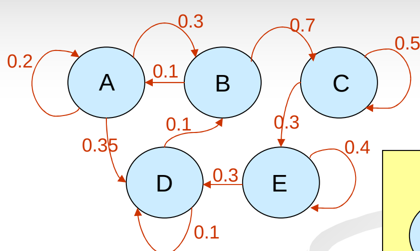

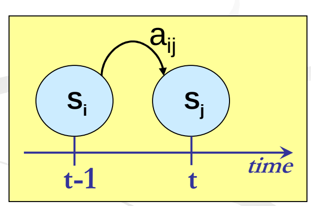

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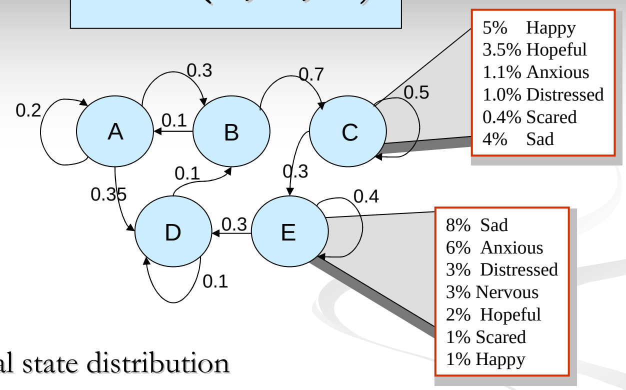

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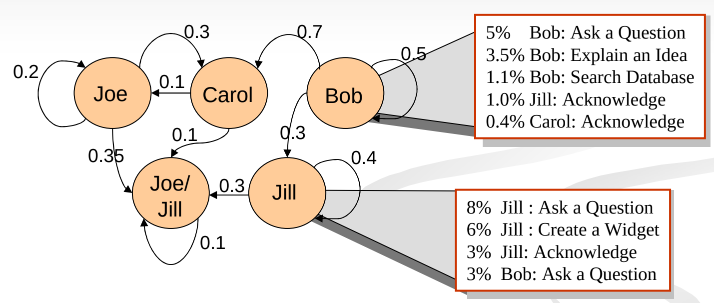
HMM Applications & Examples (1/2)

*Example 1: Online Collaborative Learning

States represent which students are likely to take initiative

Observations represent likely student communication or action



* Notional Example

$A = (a_{ij}) = P(q_t = S_j \mid q_{t-1} = S_i)$: state transition matrix

$B = (b_j) = P(v_k \mid S_j)$: observation symbol probability distribution

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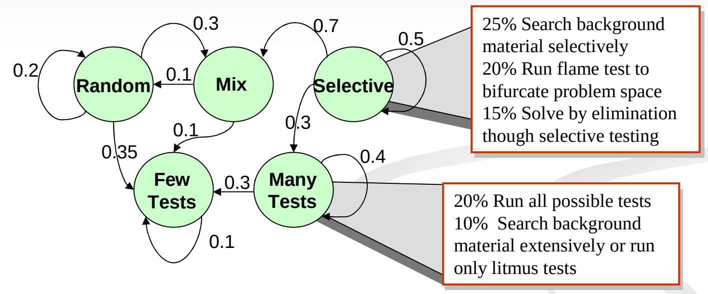
HMM Applications & Examples (2/2)

*Example 2: Online Chemistry Problem Solving

States represent problem solving strategies student is likely to apply

Observations represent likely student problem solving actions



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- Future project ideas

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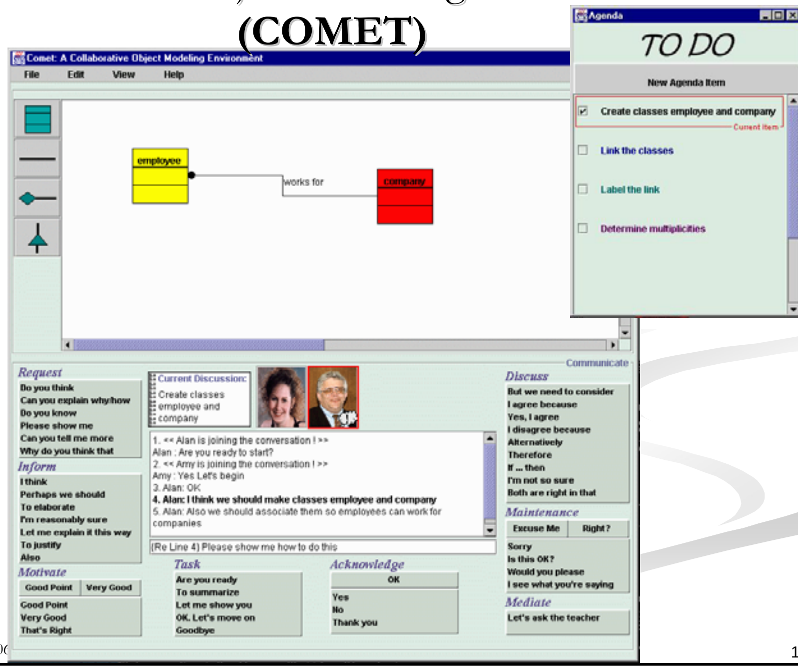
Collaborative Object Modeling EnvironmenT (COMET)



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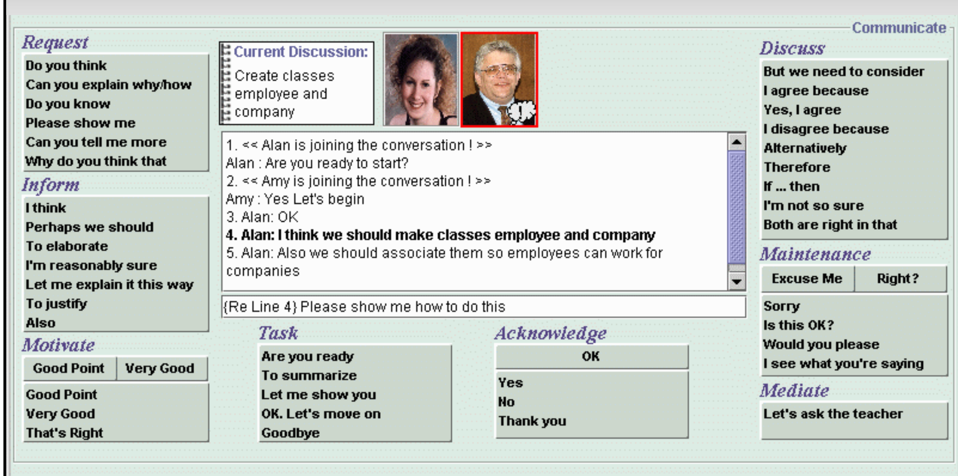
17

The COMET Chat Area



Soller (2001). ***International Journal of Artificial Intelligence in Education*****, 12 (1).**

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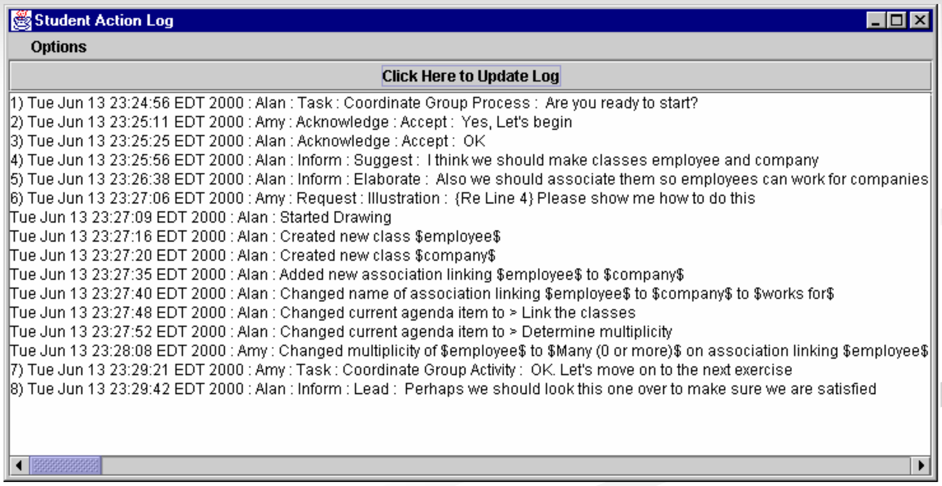
18

Logging the Interaction



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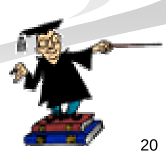
Experimental Approach

1. Gather examples of student knowledge sharing
   - 12 groups of 3 students each
   - Each student received a different **knowledge element**
   - All 3 knowledge elements were needed to solve the problem
   - Students needed to share and discuss their knowledge elements
2. Tag examples: effective or not?
   - Pre-to-Post test improvement
3. Train HMMs to differentiate between effective & ineffective sequences
4. Re-train system to identify recurring types of knowledge sharing breakdowns
5. Use output to inform instructional module



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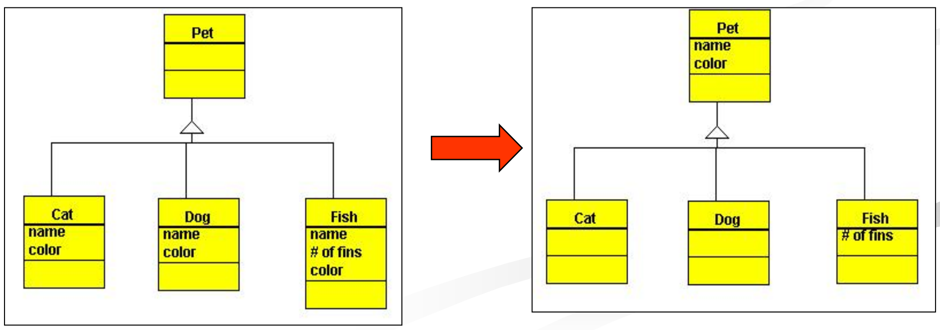
Individual Knowledge Element Example

Attributes common to a group of subclasses should be attached to the superclass. This allows them to be shared by each subclass. Each subclass is said to inherit the features of its superclass. For example, *Cat* inherits the attributes name and color from *Pet*.



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Example Training Sequence

Student	Subskill	Attribute	Text Chat
A	Request	Opinion	*Do you think* we need a discriminator for the car ownership
C	Discuss	Doubt	*I'm not so sure*
B	Request	Elaboration	*Can you tell me more* about what a discriminator is
C	Discuss	Agree	*Yes, I agree* because I myself am not so sure as to what its function is
A	Inform	Explain	*Let me explain it this way* - A car can be owned by a person , a company or a bank. I think ownership type is the discrinator.

Actual HMM Training Sequence

A-Request-Opinion
C-Discuss-Doubt
B-Request-Elaboration
C-Discuss-Agree
A-Inform-Explain

(Note: Student "A" is always the knowledge sharer!)

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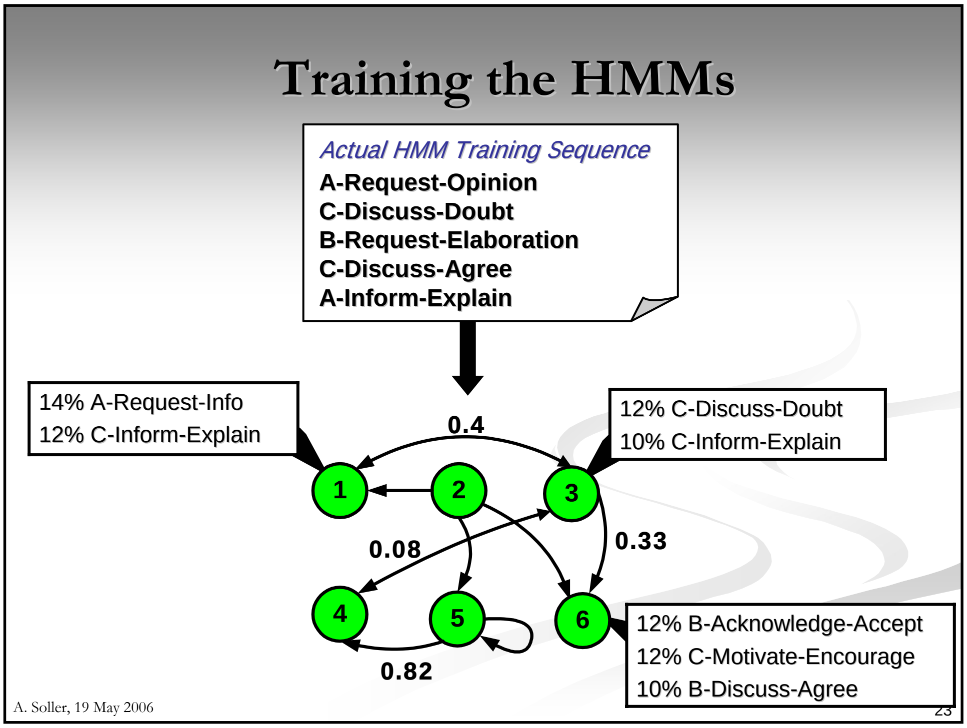
Training the HMMs
Actual HMM Training Sequence
A-Request-Opinion
C-Discuss-Doubt
B-Request-Elaboration
C-Discuss-Agree
A-Inform-Explain
14% A-Request-Info
12% C-Inform-Explain
0.4
12% C-Discuss-Doubt
10% C-Inform-Explain
1
2
3
0.08
0.33
4
5
6
0.82
12% B-Acknowledge-Accept
12% C-Motivate-Encourage
10% B-Discuss-Agree
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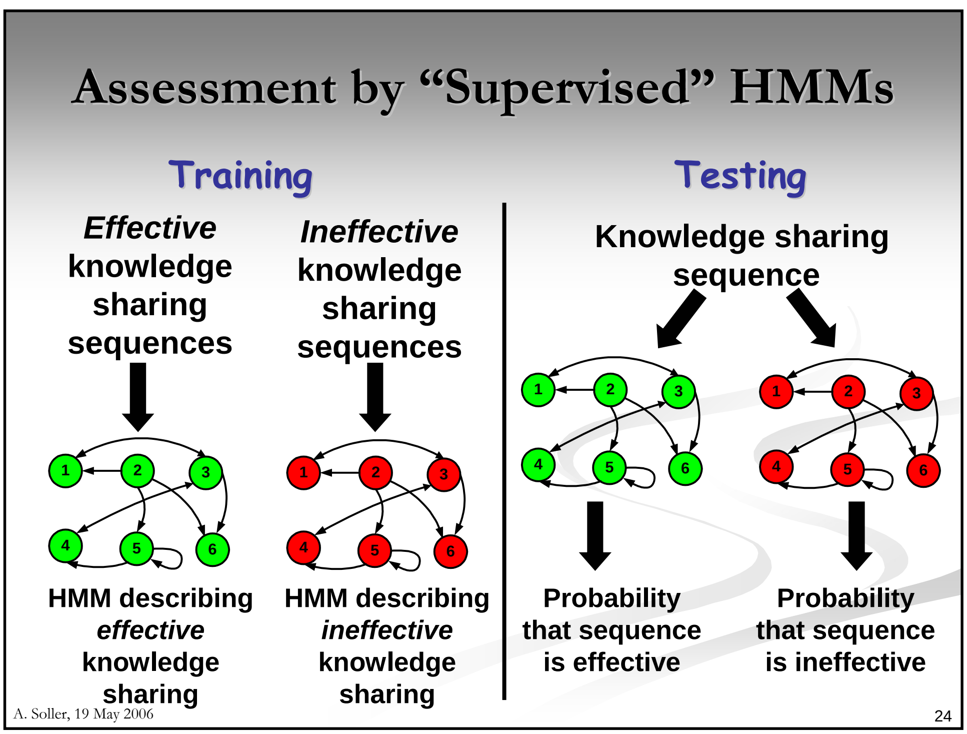
23


Assessment by "Supervised" HMMs
Training
Testing
Effective knowledge sharing sequences
Ineffective knowledge sharing sequences
Knowledge sharing sequence
HMM describing effective knowledge sharing
HMM describing ineffective knowledge sharing
Probability that sequence is effective
Probability that sequence is ineffective
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24

Results of Assessing Student Knowledge Sharing

- 29 examples of student knowledge sharing
  - 10 effective, 19 ineffective
  - Length of sequences ranged from 5-49 contributions
- HMMs achieved **74% accuracy** in distinguishing effective from ineffective knowledge sharing
  - Modified 58- fold cross validation, Baseline: 50%

Hidden Markov Modeling is a useful tool for assessing sequences of knowledge sharing conversation & problem solving actions.

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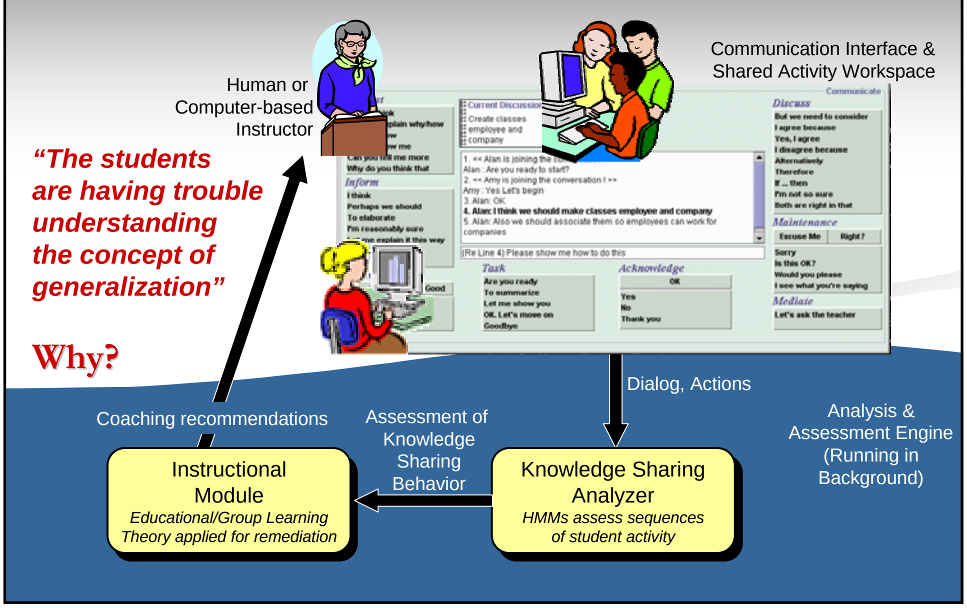
Application and Potential Impact



Analysis of Knowledge Sharing Interaction

- Why are students having trouble?
  - Find & classify sequences with similar types of knowledge sharing breakdowns (or success)
  - Find closest match to current sequence

	$M_1, \ldots, M_i, \ldots, M_N$
S_1 ⋮ S_j ⋮ S_N	$loglik_{ji} = \log L(S_j \mid M_i),\ 1 \le i,j \le N$

Columns describe the likelihoods of the sequences, given model M_i
So similar models should have similar column vectors

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HMM Clustering Procedure

- Multidimensional Scaling
  - To find distances between likelihood vectors

$$L(S_j \mid M_i)$$

- ISODATA self organizing clustering routine
  - To find groups within threshold θ
- Results
  - 4 ineffective groups
  - 3 effective groups

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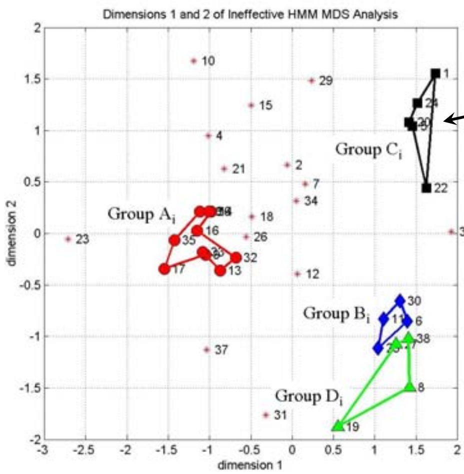
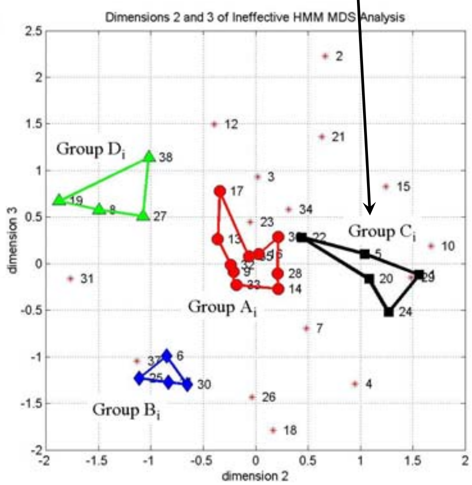


Group C_i :
Episodes: L8, L10, L12



60-70% Coverage

Accuracy > 0.92

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Group C_i :
Episodes: L8, L10, L12

S: Suggest KE

R1: Doubt suggestion

R1 & R2: Request elaboration of KE

S: Explain KE unsatisfactorily

(no further discussion of KE)

S: Suggest KE

R1: Doubt that it is needed

S: Explain KE unsatisfactorily

R1: Doubt again

S: Request help from R2

S: Suggest KE

R1: Doubt suggestion

R1 & R2: Request elaboration of KE

S: Explain KE unsatisfactorily

(no further discussion of KE)

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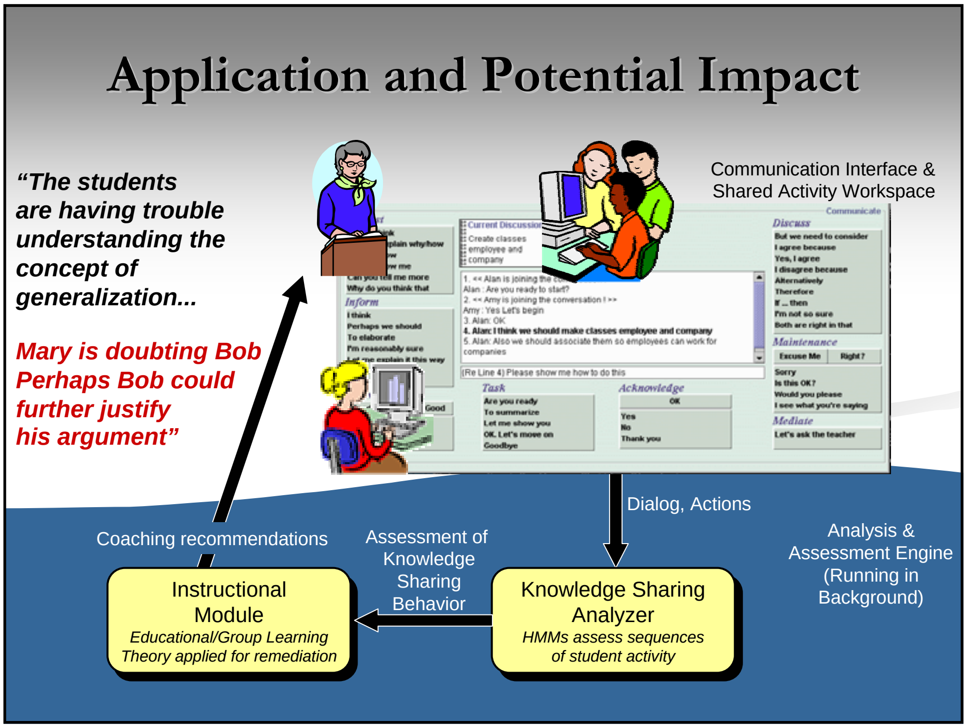
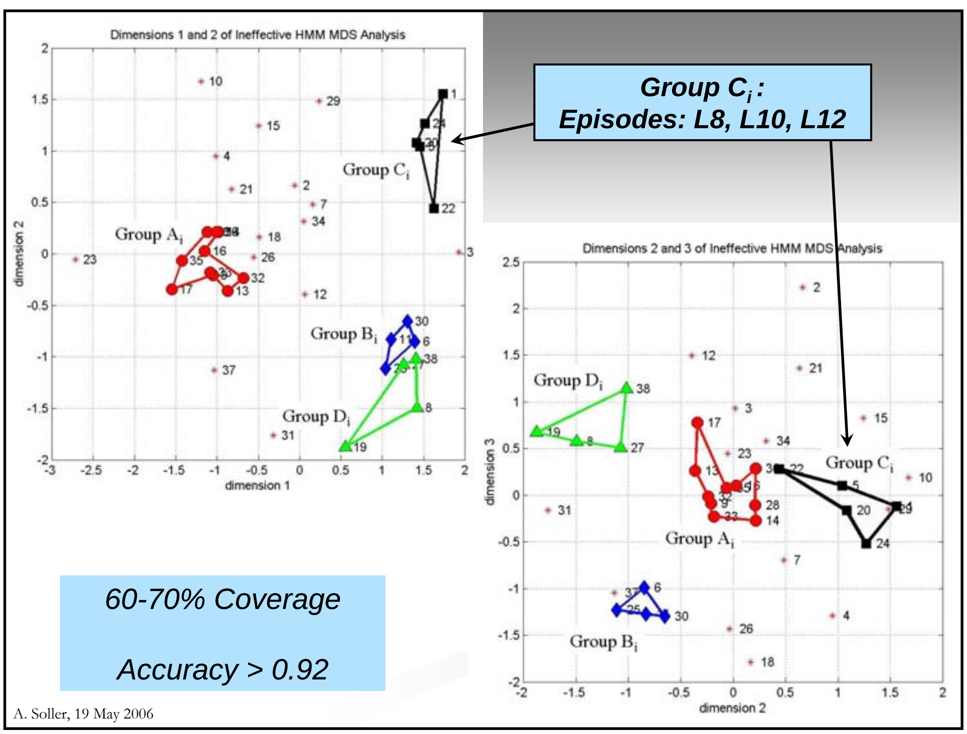

Application and Potential Impact
"The students are having trouble understanding the concept of generalization...
Mary is doubting Bob Perhaps Bob could further justify his argument"
Communication Interface & Shared Activity Workspace
Dialog, Actions
Coaching recommendations
Assessment of Knowledge Sharing Behavior
Analysis & Assessment Engine (Running in Background)
Instructional Module
Educational/Group Learning Theory applied for remediation
Knowledge Sharing Analyzer
HMMs assess sequences of student activity


Dimensions 1 and 2 of Ineffective HMM MDS Analysis
dimension 1
dimension 2
Group A_i
Group B_i
Group C_i
Group D_i
Group C_i : Episodes: L8, L10, L12
Dimensions 2 and 3 of Ineffective HMM MDS Analysis
dimension 2
dimension 3
60-70% Coverage
Accuracy > 0.92
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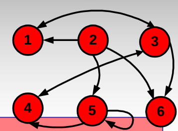
Summarized "Machine Learned" Knowledge Sharing Examples

Ineffective Knowledge Sharing



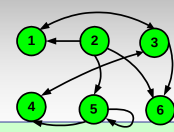
1. Sharer proposes KE
2. Sharer explains or gives instructions for action
3. Receiver acknowledges or requests confirmation

1. Sharer attempts to explain KE
2. Receiver acknowledges

1. Sharer proposes KE
2. Receiver doubts

1. Receiver requests explanation of KE
2. Sharer explains poorly
(no further discussion)

Effective Knowledge Sharing



1. Receiver requests information about KE
2. Sharer provides explanation
3. Receiver agrees

1. Receiver requests information about KE
2. Sharer provides explanation
3. Receiver requests further clarification
4. Sharer provides further clarification

1. Sharer explains or illustrates KE
2. Receiver motivates / encourages

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Lessons Learned

Hidden Markov Modeling is a useful tool for assessing sequences of knowledge sharing conversation & problem solving actions.

HMMs can be combined with other methods for assessing
<u>How</u> students successfully share knowledge
or
<u>Why</u> students experience knowledge sharing breakdowns

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Interactive Multi-Media Exercises (IMMEX)

- *IMMEX* is an interactive, web-based, scientific problem solving environment
- Students learn to construct hypotheses, evaluate evidence, & draw inferences
- 100+ problem sets spanning middle school through medical school
- The *IMMEX* system models, assesses, and reports student progress in real-time.
- Neural Networks and HMMs analyze student problem solving strategies & predict future strategies

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500,000 IMMEX Performances

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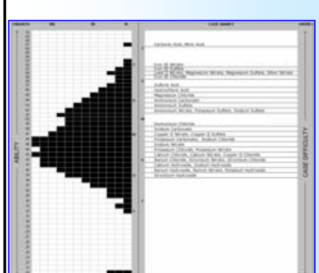
37

Layered Assessment in IMMEX

Layer 1

Student Ability Estimates

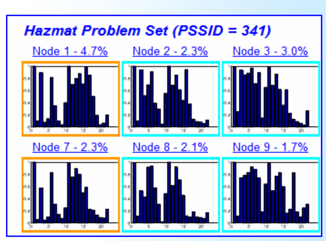
- Case item difficulties are determined by IRT analysis of 28,878 student performances.
- Each student is evaluated against this model.



Layer 2

Problem Solving Strategy Models

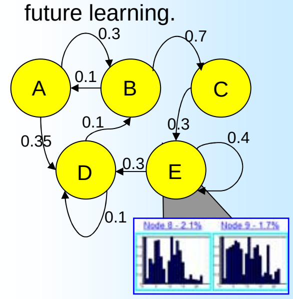
- Self-organizing Neural Networks cluster similar student performances in topologic maps.
- Each node represents a different problem solving strategy.

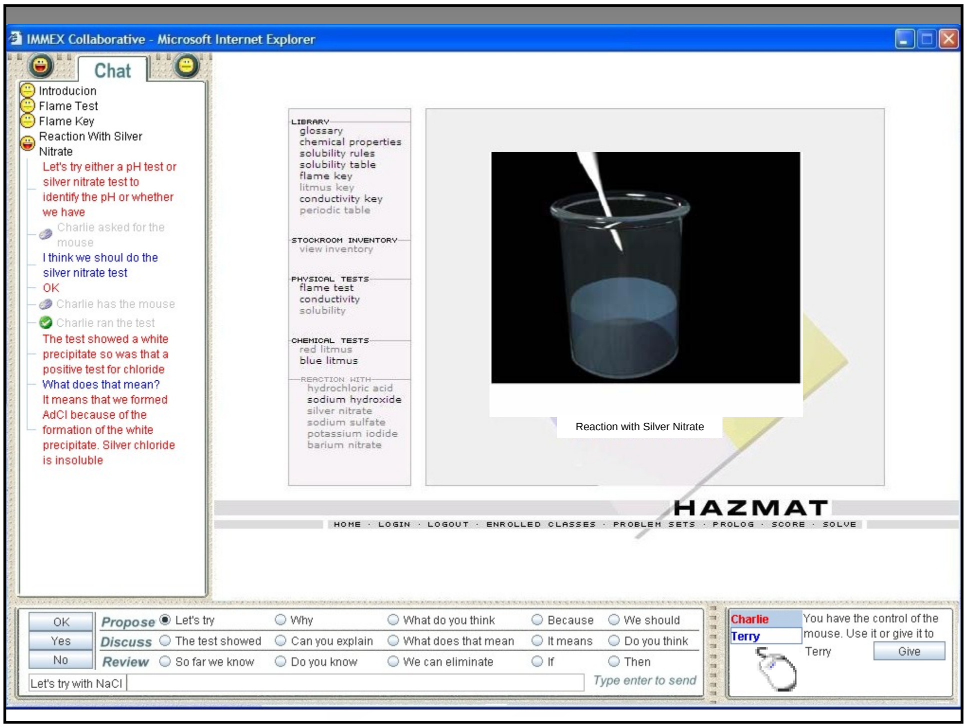


Layer 3

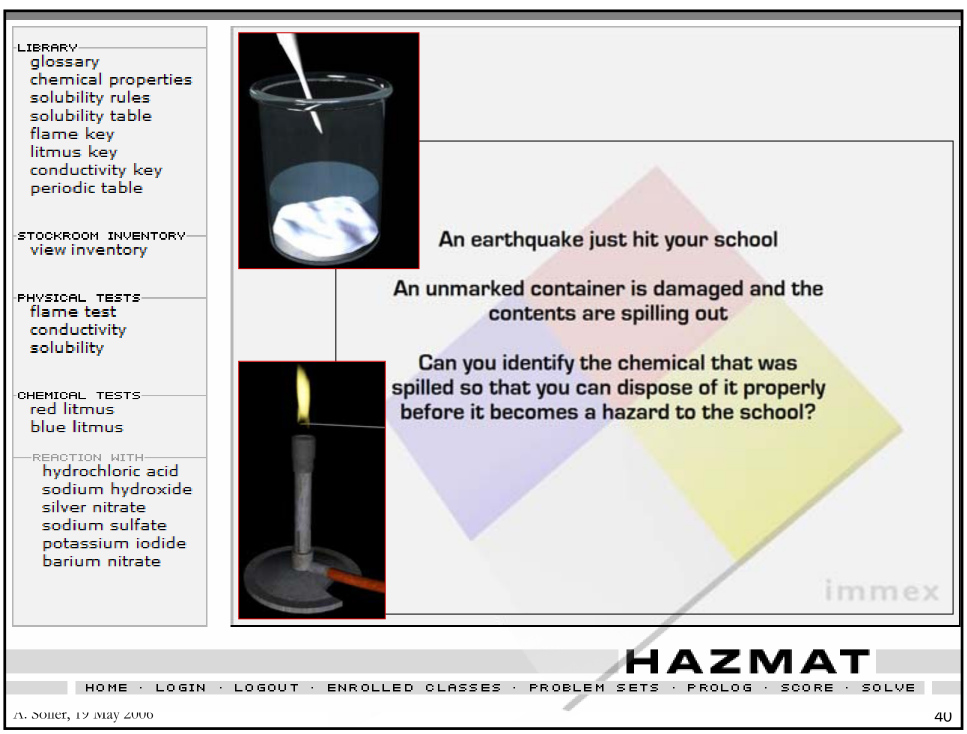
Learning Progress Predictions

- Sequences of Neural Network Nodes (from Layer 2) represent strategy changes over time.
- Nodes are sequenced stochastically to predict future learning.





IMMEX Collaborative - Microsoft Internet Explorer
Chat
Introducion
Flame Test
Flame Key
Reaction With Silver Nitrate
Let's try either a pH test or silver nitrate test to identify the pH or whether we have
Charlie asked for the mouse
I think we shoul do the silver nitrate test
OK
Charlie has the mouse
Charlie ran the test
The test showed a white precipitate so was that a positive test for chloride
What does that mean?
It means that we formed AdCl because of the formation of the white precipitate. Silver chloride is insoluble
LIBRARY
glossary
chemical properties
solubility rules
solubility table
flame key
litmus key
conductivity key
periodic table
STOCKROOM INVENTORY
view inventory
PHYSICAL TESTS
flame test
conductivity
solubility
CHEMICAL TESTS
red litmus
blue litmus
REACTION WITH
hydrochloric acid
sodium hydroxide
silver nitrate
sodium sulfate
potassium iodide
barium nitrate
Reaction with Silver Nitrate
HAZMAT
HOME · LOGIN · LOGOUT · ENROLLED CLASSES · PROBLEM SETS · PROLOG · SCORE · SOLVE
OK
Yes
No
Propose
Discuss
Review
Let's try
Why
What do you think
Because
We should
The test showed
Can you explain
What does that mean
It means
Do you think
So far we know
Do you know
We can eliminate
If
Then
Let's try with NaCl
Type enter to send
Charlie
Terry
You have the control of the mouse. Use it or give it to
Terry
Give



LIBRARY
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CHEMICAL TESTS
red litmus
blue litmus
REACTION WITH
hydrochloric acid
sodium hydroxide
silver nitrate
sodium sulfate
potassium iodide
barium nitrate
An earthquake just hit your school
An unmarked container is damaged and the contents are spilling out
Can you identify the chemical that was spilled so that you can dispose of it properly before it becomes a hazard to the school?
immex
HAZMAT
HOME · LOGIN · LOGOUT · ENROLLED CLASSES · PROBLEM SETS · PROLOG · SCORE · SOLVE
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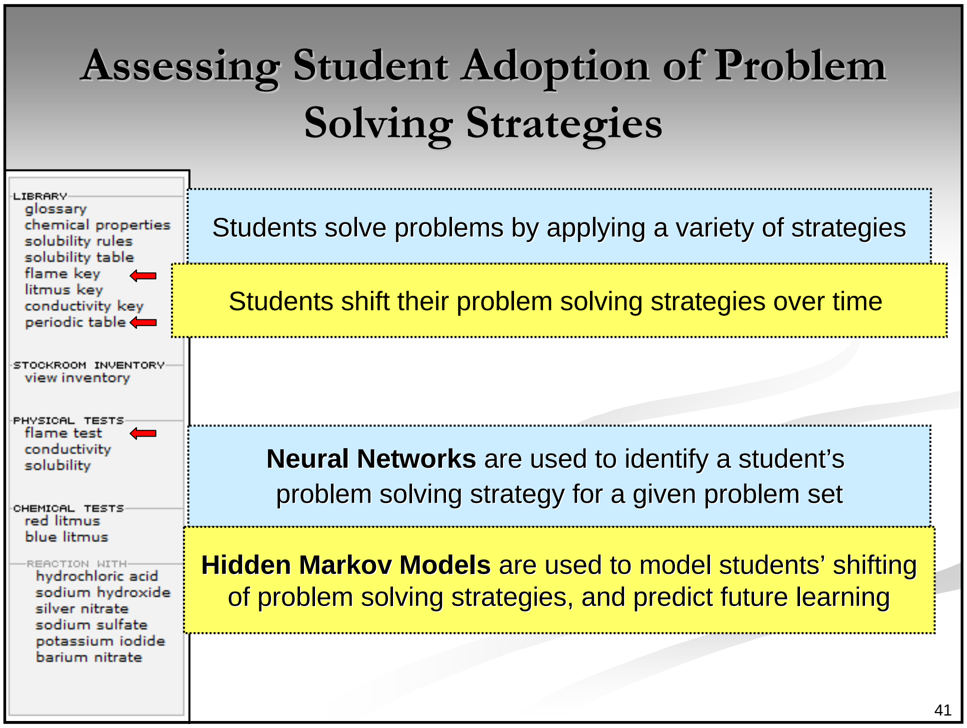
40


Assessing Student Adoption of Problem Solving Strategies
LIBRARY
glossary
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solubility rules
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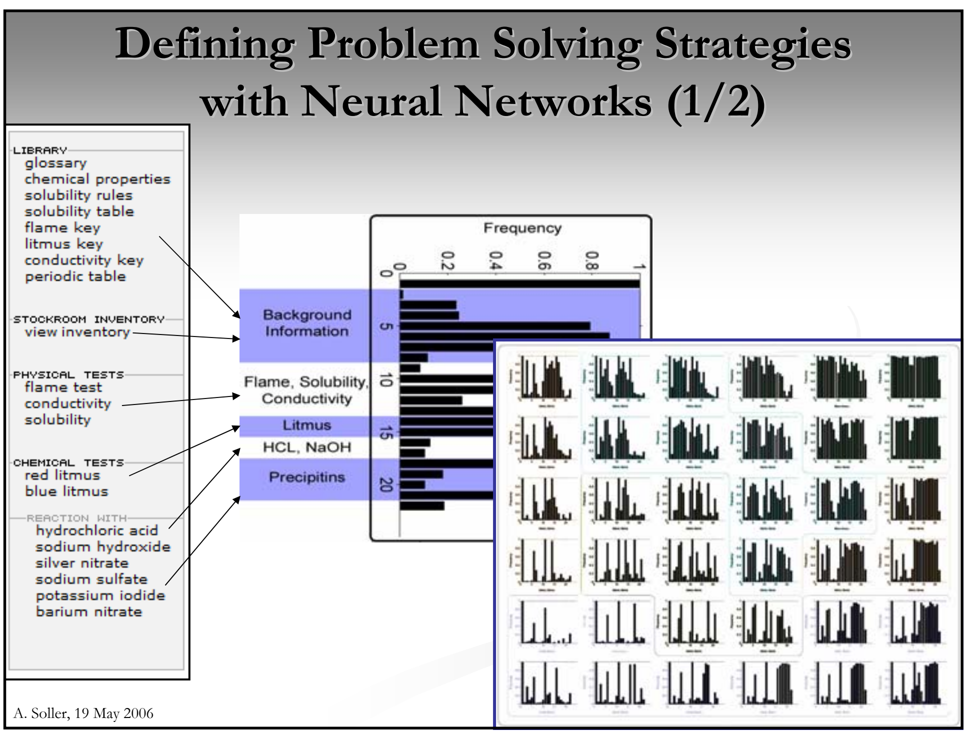
STOCKROOM INVENTORY
view inventory
PHYSICAL TESTS
flame test
conductivity
solubility
CHEMICAL TESTS
red litmus
blue litmus
REACTION WITH
hydrochloric acid
sodium hydroxide
silver nitrate
sodium sulfate
potassium iodide
barium nitrate
Students solve problems by applying a variety of strategies
Students shift their problem solving strategies over time
Neural Networks are used to identify a student's problem solving strategy for a given problem set
Hidden Markov Models are used to model students' shifting of problem solving strategies, and predict future learning
41


Defining Problem Solving Strategies with Neural Networks (1/2)
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red litmus
blue litmus
REACTION WITH
hydrochloric acid
sodium hydroxide
silver nitrate
sodium sulfate
potassium iodide
barium nitrate
Frequency
0
0.2
0.4
0.6
0.8
1
Background Information
Flame, Solubility, Conductivity
Litmus
HCL, NaOH
Precipitins
5
10
15
20
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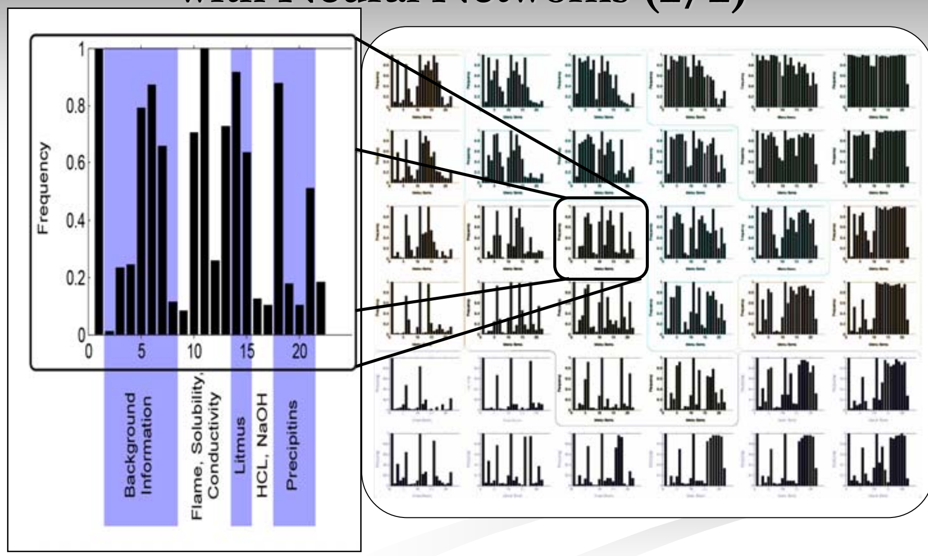
Defining Problem Solving Strategies with Neural Networks (2/2)



Item selection frequencies for 36 nodes trained with 5,284 student performances

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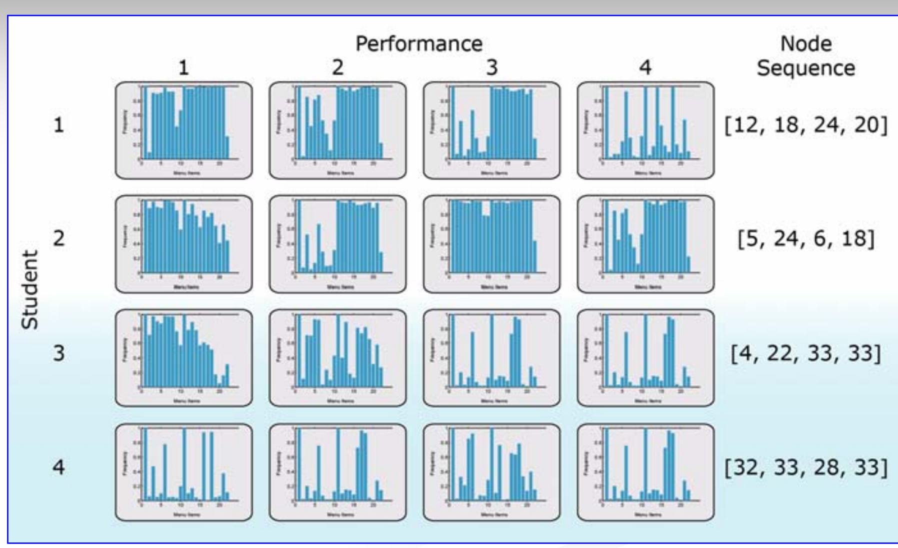
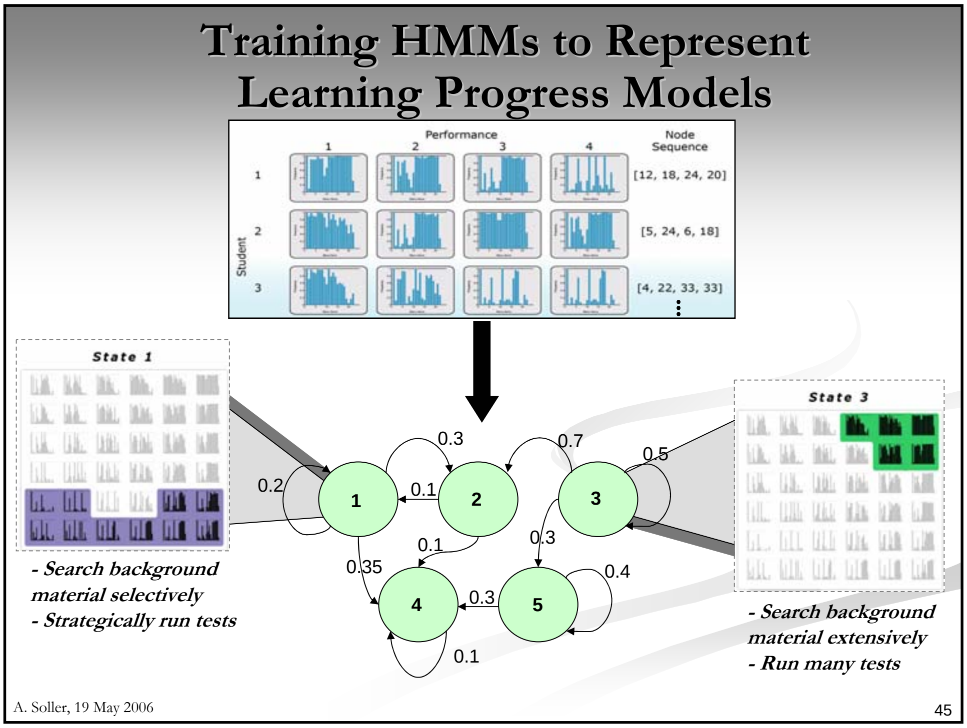
Tracking Learning Progress



A. Soller, 19 May 2006 44


Training HMMs to Represent Learning Progress Models
Performance
Node Sequence
Student
[12, 18, 24, 20]
[5, 24, 6, 18]
[4, 22, 33, 33]
State 1
- Search background material selectively
- Strategically run tests
State 3
- Search background material extensively
- Run many tests
0.2
0.3
0.1
0.7
0.5
0.35
0.1
0.3
0.4
0.3
0.1
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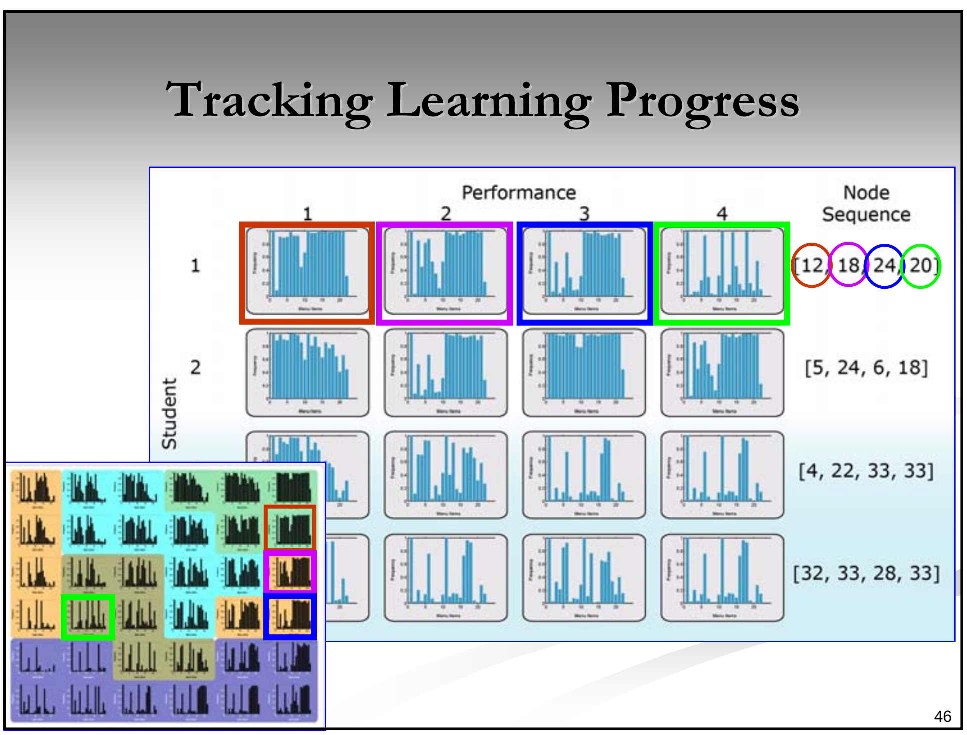
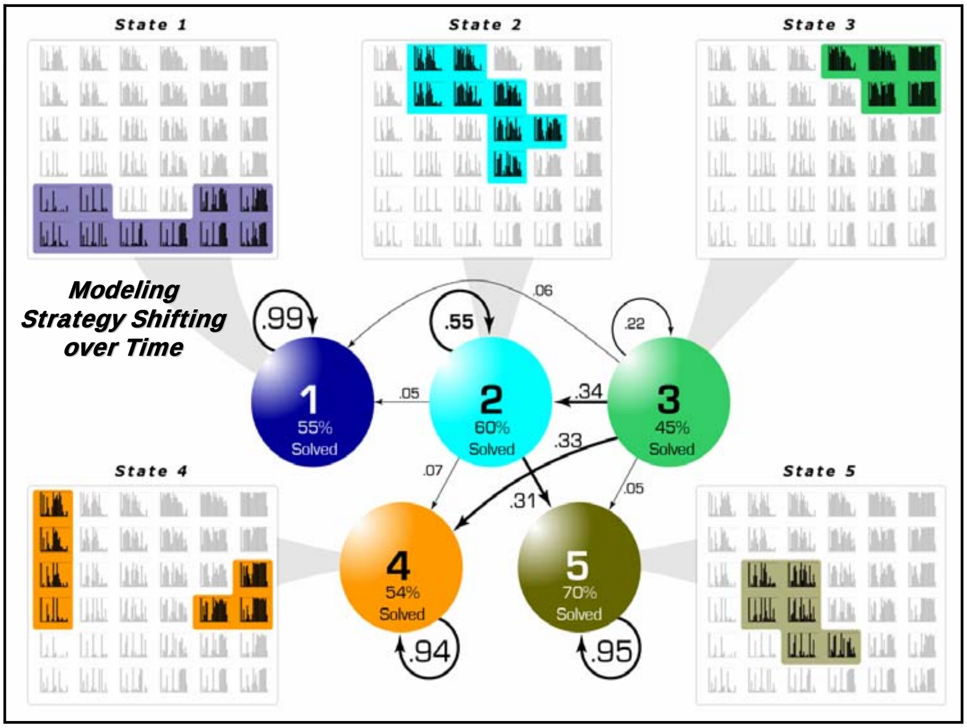
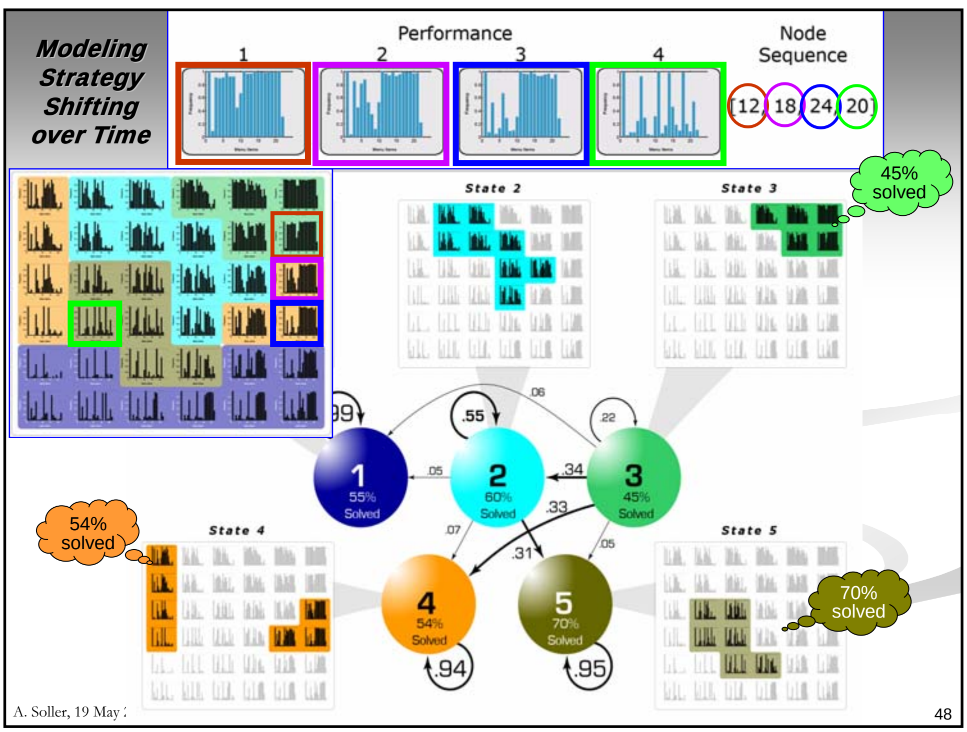
45


Tracking Learning Progress
Performance
Node Sequence
Student
[12, 18, 24, 20]
[5, 24, 6, 18]
[4, 22, 33, 33]
[32, 33, 28, 33]
46


State 1
State 2
State 3
Modeling
Strategy Shifting
over Time
.99
.55
.06
.22
1
55%
Solved
.05
2
60%
Solved
.34
3
45%
Solved
.33
.07
.31
.05
State 4
State 5
4
54%
Solved
5
70%
Solved
.94
.95


Modeling
Strategy
Shifting
over Time
Performance
1
2
3
4
Node
Sequence
12
18
24
20
45%
solved
State 2
State 3
.06
.55
.22
1
55%
Solved
.05
2
60%
Solved
.34
3
45%
Solved
.33
.07
.31
.05
54%
solved
State 4
State 5
4
54%
Solved
5
70%
Solved
70%
solved
.94
.95
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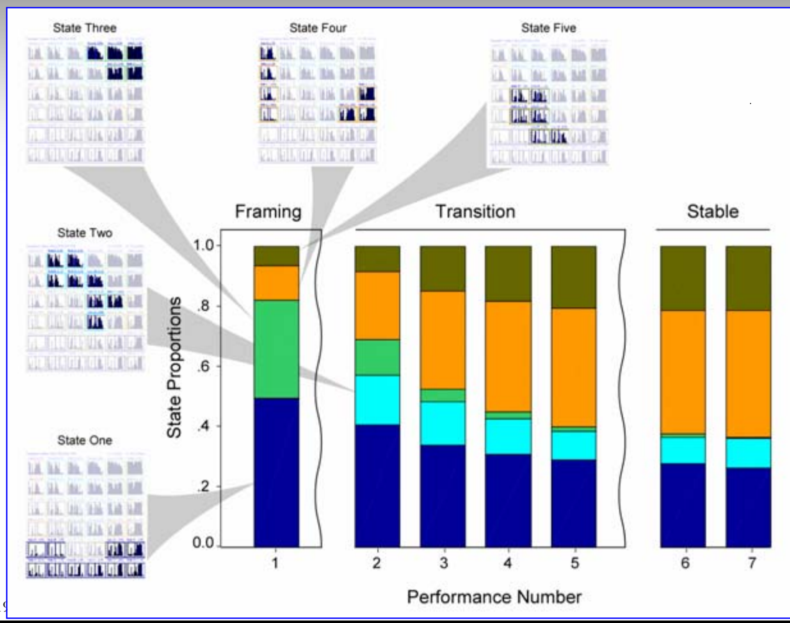
48

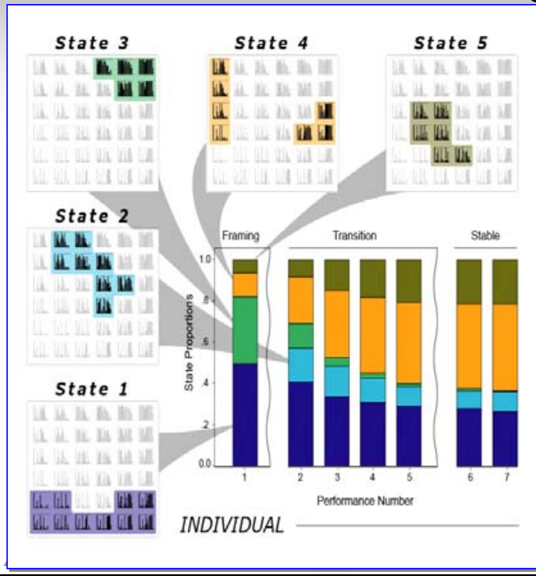
Predicting Learning Trajectories



A. Soller, 19

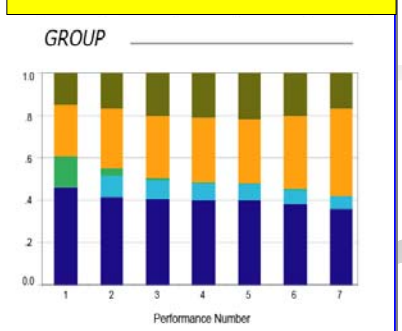
49

Collaboration Improves Performance & Accelerates Strategy Adoption



Average Solve Rate:

51% Individuals
63% Face-to-face groups
68% Online distributed groups



Group data represents 5452 performances done in face-to-face groups of 2-3

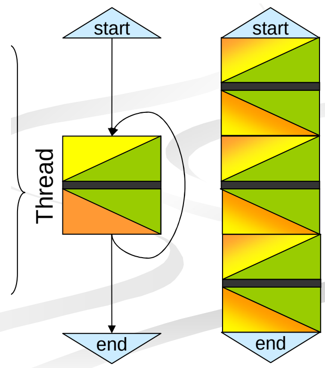
The Structured Interaction Model

(Alessandra Giordani, Ph.D. Candidate, University of Trento, Italy)

Propose	Discuss	Review
1. Let's try…	7. The test showed …	13. So far we know …
2. Why …?	8. What does that mean … ?	14. We can eliminate …
3. We should …	9. Can you explain … ?	15. If …
4. What do you think …?	10. It means …	16. Then …
5. Because …	11. Do you think …?	17. Do you know …?
6. I think (*Free text proposal*)	12. I think (*Free text discussion*)	18. I think (*Free text review*)

Problem solving phases and sentence openers

Time	User	StemID	Text	Event Type
2:21	Charlie	6	Let's view the inventory	Chat
2:22	Terry	3	We should click on the view the inventory sheet to see the message	Chat
2:22	Charlie	6	Do you want to spend these points?	Chat
2:23	Terry	20	Yes	Chat
2:23	Charlie	0	**View Inventory**	**Test Item**
2:25	Terry	7	The test showed we have a sodium cation so we have carbonate, chloride, hydroxide, nitrate, or sulfate anions.	Chat
2:25	Charlie	19	OK	Chat
2:26	Terry	1	Let's try either a pH test or silver nitrate test to identify the pH or whether we have a chloride.	Chat



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51

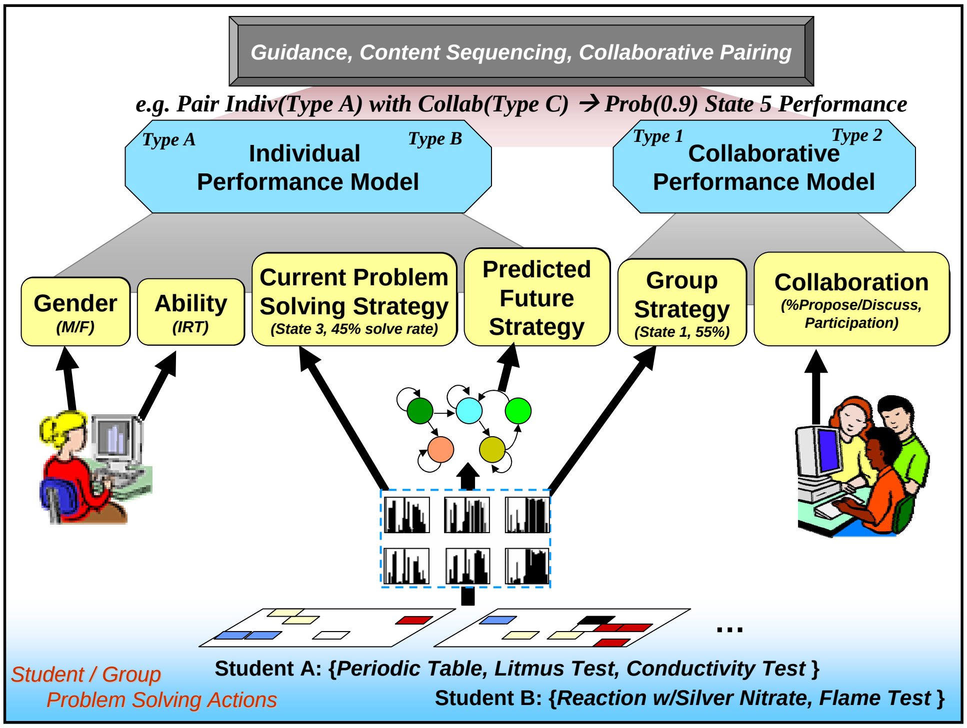
Analysis of Collaborative Learning Dialog

- Four pairs of students collaboratively performed 15 IMMEX distance learning cases
- More proposals occur during the early framing stages of problem solving (88% cases)
- As the students converged upon a solution, there was proportionally more discussion (69% cases)
- In 94% of the chat logs, the *proposal* rates decreased in the second half of the dialog, and the *discussion* increased (from 25% to 64%)

Giordani, A., Gerosa, L., Soller, A., Stevens, R. (2005). Extending an Online Individual Scientific Problem-Solving Environment to Support and Mediate Collaborative Learning. *Proceedings of the Artificial Intelligence in Education Workshop on Representing and Analyzing Collaborative Interactions.* Amsterdam, The Netherlands.

A. Soller, 19 May 2006

52



Summary & Future Project Ideas

- What hybrid combinations of machine learning & mixture models help to assess which aspects of learning and collaboration?
  - Project Idea: Test & Compare performance of Neural Nets, Decision Trees, HMMs, Bayesian models
- To what extent can predictive properties of these models enable focused experimentation of problem-solving interventions?
  - Project Idea: Explore effect of selecting intervention based on intelligent prediction vs. traditional methods

A. Soller, 19 May 2006 54

Selected References

(available at http://www.cscl-research.com or upon request to asoller@ida.org)

- Soller, A. (2004). Computational Modeling and Analysis of Knowledge Sharing in Collaborative Distance Learning. *User Modeling and User-Adapted Interaction: The Journal of Personalization Research, 14* (4), 351-381.
- Stevens, R., & Soller, A. (2005). Implementing a layered analytic approach for real-time modeling of students' scientific understanding. *Proceedings of the 12th International Conference on Artificial Intelligence in Education,* 611-620.
- Stevens, R., Johnson, D., & Soller, A. (2005). Probabilities and predictions: Modeling the development of scientific problem solving skills. *Cell Biology Education, 4*(1).
- Soller, A., & Lesgold, A. (in press). Modeling the process of knowledge sharing. In U. Hoppe, H. Ogata, & A. Soller (Eds.), *Studies in Technology Enhanced Collaborative Learning*, Kluwer Academic Publishers.
- Soller, A., Martínez-Monés, A., Jermann, P., & Muehlenbrock, M. (2005). From Mirroring to Guiding: A Review of State of the Art Technology for Supporting Collaborative Learning. *International Journal of Artificial Intelligence in Education, 15* (4), 261-290.
- Giordani, A., Gerosa, L., Soller, A., & Stevens, R. (2005). Extending an Online Individual Scientific Problem-Solving Environment to Support and Mediate Collaborative Learning. *Proceedings of the Artificial Intelligence in Education (AI-ED 2005) Workshop on Representing and Analyzing Collaborative Interactions*, 12-22.

A. Soller, 19 May 2006 55

Thank You!

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