Peer Based Intelligent Tutoring in a Home Healthcare Setting

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Motivation and Approach

•Allowing patients or caregivers to learn how to manage health
- through learning objects in repositories of knowledge
- using experiences of and advice from peers
- a style of peer-based intelligent tutoring

• Example: patient trying to manage diabetes
• Find appropriate peers and learning objects

• **Curriculum Sequencing**
- ordering of learning objects based on experiences of similar peers (presented at FLAIRS 2010)

• **Annotations**
- intelligently showing messages left by previous students
- modeling reputation of annotation and annotator
- validated by simulations: even when poor annotators are present

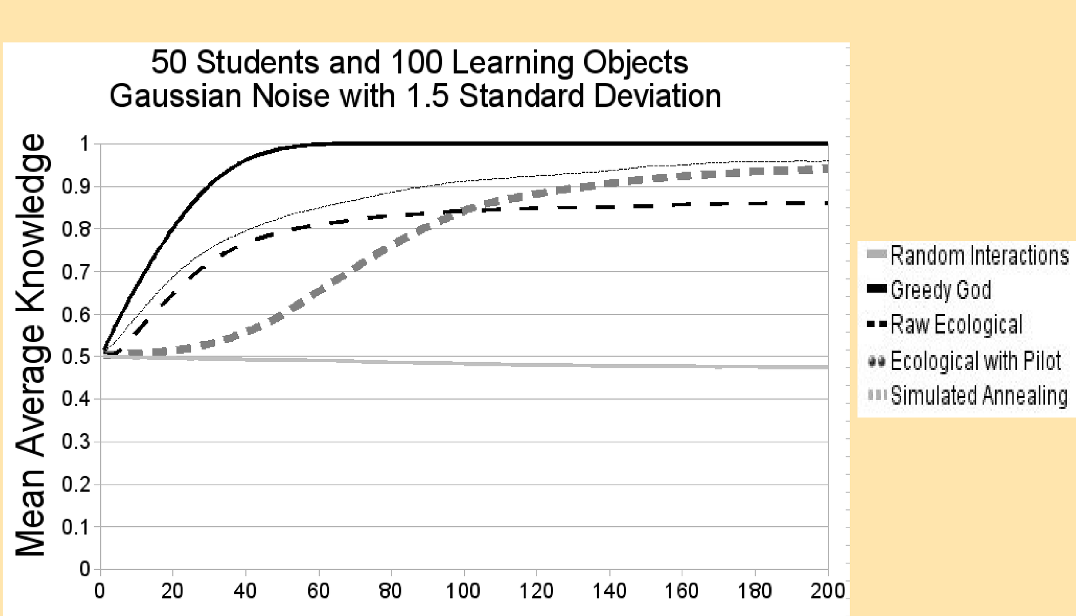
• **Corpus Divisions**
- peers can propose new, divided learning objects
- validated: those preferring shorter objects, even if poor dividing skill

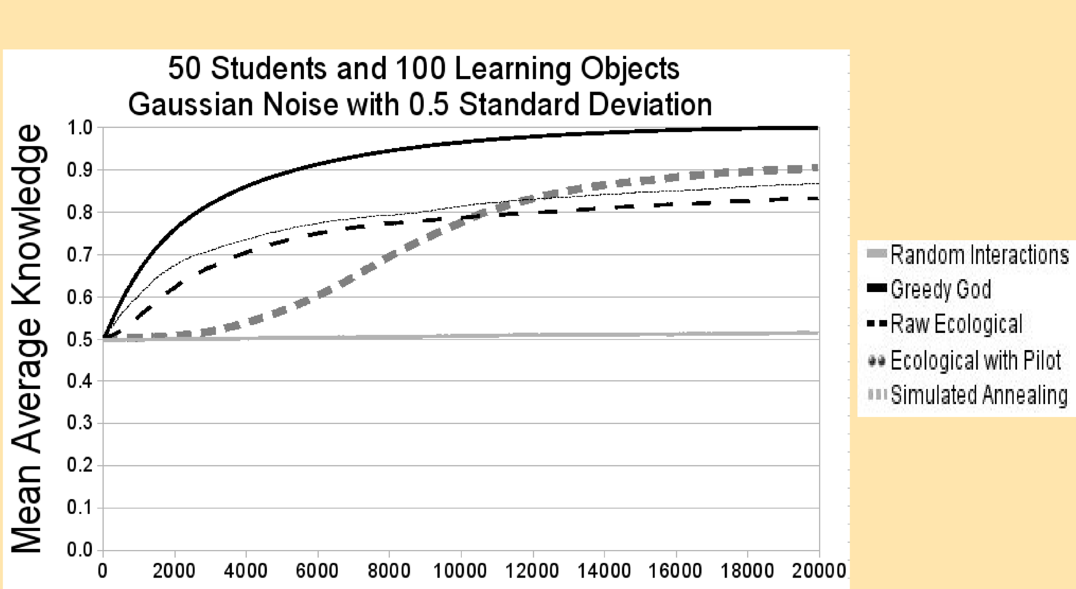
Curriculum Sequencing

•Ordering of learning objects based on experiences of similar peers

$$p[a,l]=\kappa\sum_{j=1}^{n} w(a,j)v(j,l)$$

•Extended to allow variable length of time for completion of learning object (and reasoning about trade off between length and benefit) and to be robust in the face of assessment error
•Original approach used a course but accurate assessment, in this modified approach we added noise (using a Gaussian distribution) with varying distribution to investigate how robust in the face of assessment errors the curriculum sequencing is





Division of Corpus

•Peers can propose new, divided learning objects
•Validated: those preferring shorter objects; even if poor dividing skill
•Newly created learning objects inherit the interaction history of the parent objects

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Algorithm 2 Function divide learning object
Input: Learning object lo, student s
{After student s completes interaction with learning object lo and decides to suggest a
new learning object}
newLO = highlightWorthwhileSection(s, lo)
for each lo.interaction do
  newLO.interaction[i] = lo.interaction[i]
end for
Return: newly created learning object, newLO
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Algorithm 3 Assigning Learning Objects in Expanded Corpus
Input: Repository of learning objects, set of students
for each time unit of instruction do
  for each student do
    if student is available then
      if not student's first learning object assignment then
        do post-test assessment of student
        attach interaction history of student to learning object
        update similarities between students{based on new assessment}
        {allow student to divide the learning object}
        if student creates a new learning object then {based on Algorithm 2}
          generate learning object based on student and original learning object
          add new learning object to repository of available learning objects
        end if
      end if
      assign student to a learning object, L{using CLA}
    end if
  end for
end for
Return: Repository of learning objects{includes old repository plus new objects}
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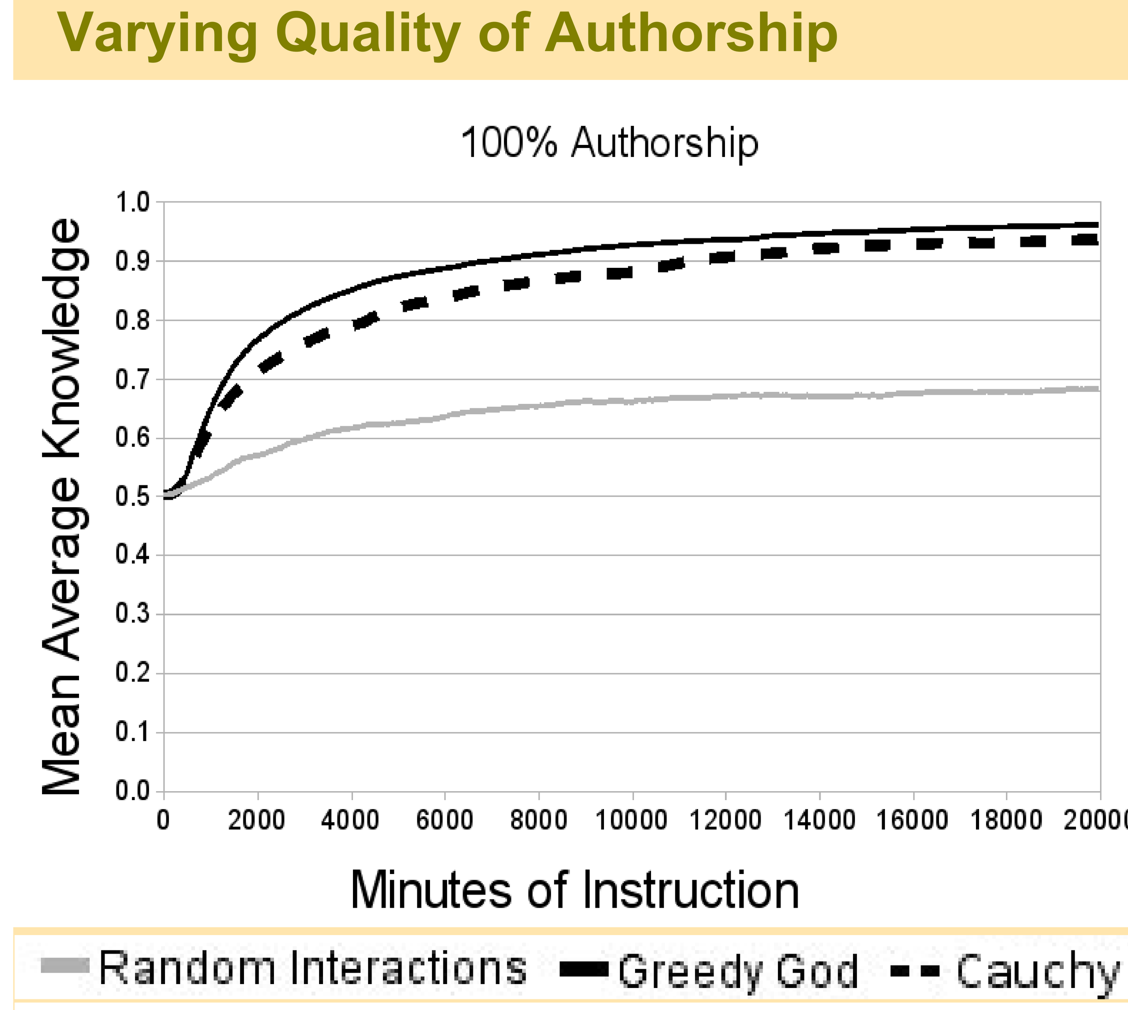
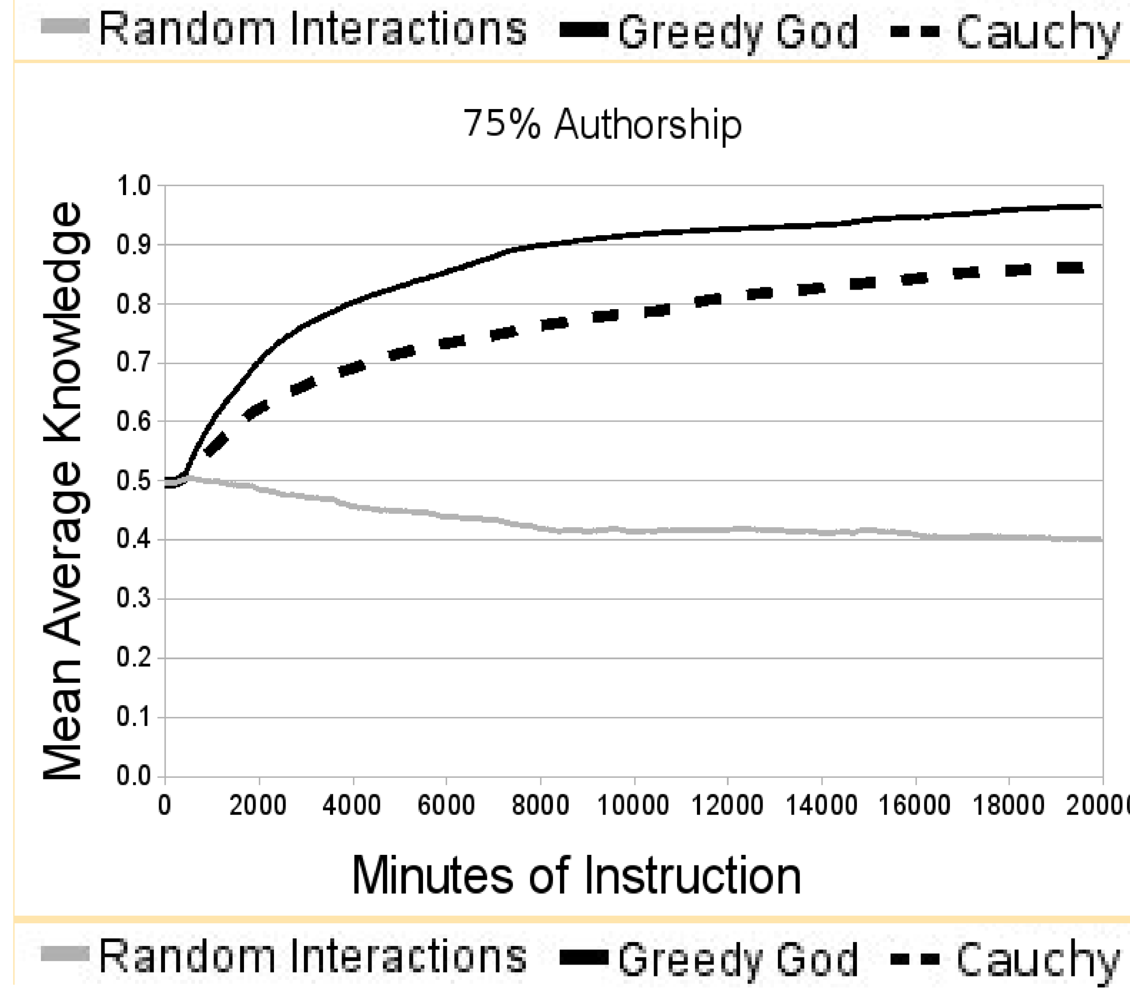
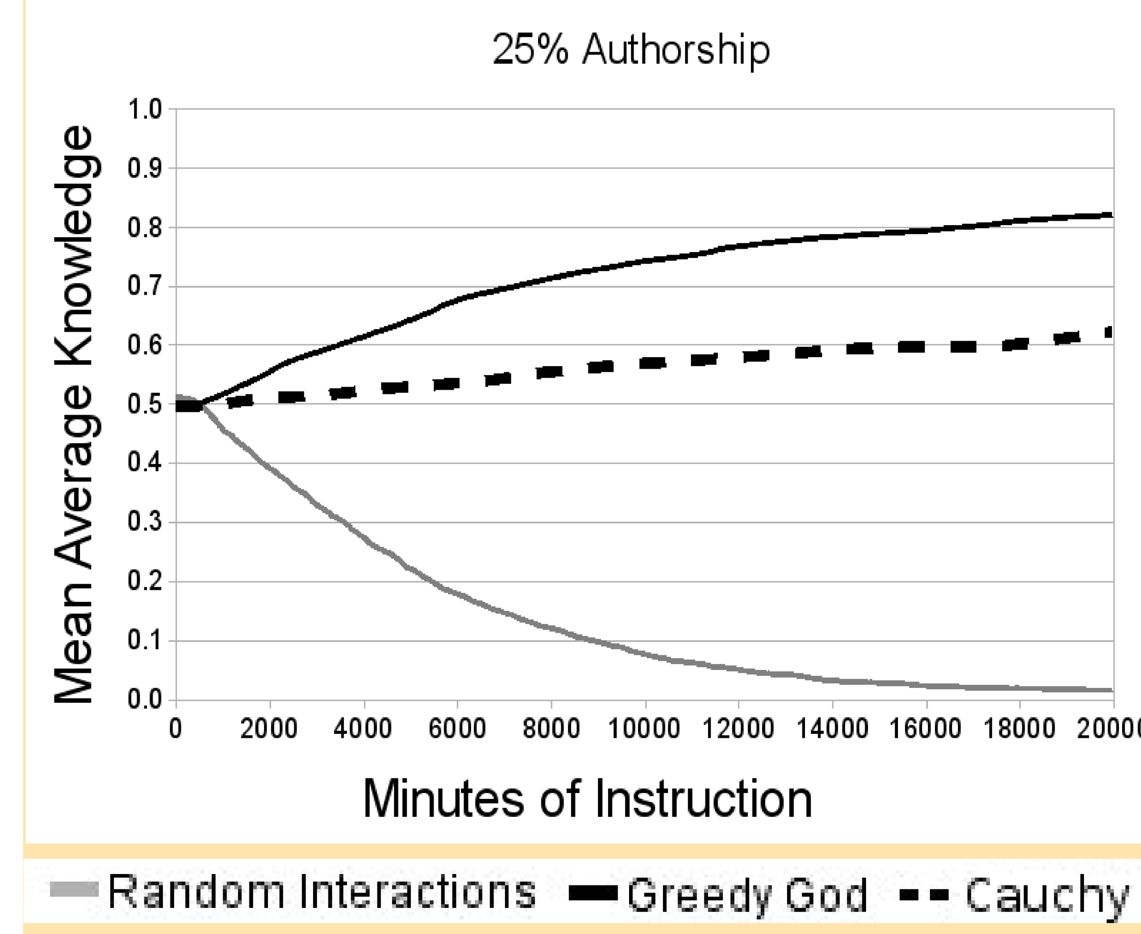
Annotations

•Intelligently showing messages left by previous students
•modeling reputation of annotation and annotator
•validated by simulations: even when poor annotators are present

Varying Quality of Authorship







•Greedy God and Random interactions are ideal and baseline border cases
•It can be seen, even as the quality of authorship decrease, this method manages to recommend annotations that enhance learning (curve moves upwards)

Example Healthcare Issues

Example #1

•A nurse is newly assigned to palliative care and struggling to arrange equipment, direct the family and decide who to contact after the patient dies
- •Clinical educator directs nurse to information in community care access center and to other nurses with palliative experience

•Our system automatically sequences the content, without the clinical educator hand crafting a customized curriculum (by recommending resources other nurses learning about palliative care have found useful)
- •Nurse can interact with other nurses learning the material and exchange information and encouragement.

Example #2

•New nurse is calling the clinical educator 3 or 4 times daily outlining her intended plan of action
- •Each time, her judgment is spot on, displaying great clinical judgment and she is offered encouragement by educator and intake nurse
- •Over time clinical educator is confident she will become more confident and need less assistance

•In our system, instead of calling clinical educator and intake nurse (and taking up their time), the home healthcare nurse can:
- •Go through a tailored curriculum, learning more about any procedures she is uncertain about
- •Leave questions as annotations for anything she is uncertain about. Others using the system can confirm her judgment, and others learning from the system get a richer understanding of procedures by following these exchanges
- •For educational material that isn't suited to her needs she can retain only the parts she's interested in and propose this as a new learning object, which will then benefit nurses with similar needs to hers (good skills but needing confirmation)

Human Trials

•Human trials in the home healthcare domain
•Nurses retraining for new specialties and new nurses dealing with unforeseen or novel issues
•Newly diagnosed patients learning about their illness

References

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•J. S. Breese, D. Heckerman and C. Kadie. Empirical Analysis of Predictive Algorithms for Collaborative Filtering. *Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence*, p. 43-52, 1998.