#### Artificial Intelligence Models for hSITE Theme 1

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## Current Projects related to hSITE

- Hyunggu Jung
  - Masters student
  - modeling bother cost
  - reasoning about interaction
  - AI areas of user modeling, decision theoretic reasoning, intelligent interaction

### Current Projects (continued)

- John Champaign
  - PhD student
  - intelligent tutoring systems
  - content derived from corpus of texts
  - peer-based assistance (social networks)

### Current Projects (continued)

- Joshua Gorner
  - Masters student
  - modeling trust in multiagent systems
  - social networks of advisors: ideal size

### Summary

- Jung: right person, right time; emergency room settings (critical care)
- Champaign: right information, right people; homecare settings
- Gorner: right people; homecare, decision making

# Hybrid Transfer-of-Control (HTOC) Model



No break by the end of the arrow



Visual Representation of strategy with the FTOCs and PTOCs; each world occupies one square

- Focus on one question:
  - "Can you take over decision making?"
- Reasoning about
  - Partial transfers of control (PTOCs)
    - Questions
  - Full transfers of control (FTOCs)
    - Decision making

# **Decision Making**

 $EU(s) = \sum_{LNI} [P(LN_I) \times (EQ(LN_I) - W(T_{LNI}) - BC_{LNI})]$ 

- Focus on current patient which expert to ask
- Generate possible strategies
  - Find optimal strategy: best quality, least bother
  - Strategy regeneration: update parameter values

# User Modeling

User\_Unwillingness\_Factor

= Attention\_State\_Factor + Lack\_of\_Expertise\_Factor

Init = User\_Unwillingness\_Factor
x Attention\_State\_Factor x TOC\_Base\_Bother\_Cost

BST (BotherSoFar)

= $\Sigma_{toc\in PastTOC}$ TOC\_Base\_Bother\_Cost(toc) x  $\beta^{t(toc)}$ 

BotherCost(BC)

= Init + BC\_Inc\_Fn(BSF, User\_Unwillingness\_Factor)

# Task Criticality (TC)

Task Criticality	High			Med			Low		
Lack_of_Expertise_Factor	Low	Med	High	Low	Med	High	Low	Med	High
Weight	10%	0%	-10%	5%	5%	-5%	0%	0%	0%

- Task criticality of the patient
- Enable the expected quality of a decision to be weighted more heavily in the overall calculation of expected utility when the case at hand is very critical

$$EU_{ei}^{d} \rightarrow EQ_{ei}^{d} + (Weight \times EQ_{ei}^{d})$$

Peer-Based Intelligent Tutoring Systems: A Corpus-Oriented Approach

- Designing effective intelligent tutoring systems
  - •Offload the time for development
  - •Peer-based approach
  - •Repository of learning objects
  - •Subproblems: curriculum sequencing, annotations, corpus development
  - Validation through simulated students

## **Curriculum Sequencing**

- Given a set of learning objects and a group of students, over multiple iterations, which object should be assigned to each student?
- Collaborative filtering inspired approach, where learning objects that were useful to a similar student in the past are assigned to each student



#### 50 Students and 100 LearningObjects

## **Curriculum Sequencing**

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

- p[a,1]: anticipated benefit to active user, *a*, from interacting with a given learning object *l*
- $\sum$  : consider interactions of all previous students with the learning object l
- w(a,j) : how similar the student j was to the active user (A-, B+) vs (B+, D-)
- v(a,j) : value of the interaction to student j
- *K* : a normalizing factor

## Optimizing Advisor Network Size in a Personalized Trust-Modelling Framework

- We explore how to determine the optimal size of networks in trust modelling
- [Zhang 2009] proposed a personalized trust-modelling framework for e-commerce how many advisors should a user have in this framework?
- We identify two methods (*max nbors* and thresholding) that can be used to reduce network size; either may optionally be combined with advisor referrals for improved accuracy

## Advisor Referrals

- If our advisor network has size *n*, we will attempt to find *n* advisors (not necessarily the same advisors!) that are qualified to report on a particular seller *s* 
  - An advisor  $a_j$  is deemed to be *qualified* if the number of ratings  $N_{ij}^{a_j}$  for s is at least some minimum number  $N_{min}$
- Regardless, weighting of advisors will always be based on the agent b's own measure of trustworthiness in each selected advisor
- Should allow us to make use of the experience throughout the system while maintaining a relatively small social network for each agent

## Next Steps

- Feedback from Research Community
  - •Jung: UMUAI special issue on User Modeling and Healthcare
  - •Champaign: ITS, EDM conferences
  - •Gorner: AAMAS trust modeling workshop, Canadian AI conference
- Connections to Team 1 researchers
- Connections to Theme 2 and Theme 3
  - •Jung: sensing to model patient and medical experts
  - •Jung: networking delimiting set of experts
  - •Champaign, Gorner: networking delimiting network of peers