Educational Technologies
WS2006

Student Modeling
Approximate Plan of the Course

18.10. Introduction
25.10. XML- Knowledge Representation
  8.11. Student Modelling
15.11. Web technologies and security
22.11. Tutorial Planning and instructional design
29.11. Media Principles
  6.12. Interactive exercises
13.12. Authoring tools, CTAT
20.12. Diagnosis: model tracing and domain reasoning

10.1. Diagnosis: constraint based
17.1. Tutorial dialogues
24.1. Action analysis and Machine Learning techniques
31.1. Cognitive tools
  7.2. Meta-cognitive support
14.2. student projects
Student modeling what for?

- Domain knowledge/skill prediction (adaptation, selection)
- Knowledge assessment
- Plan recognition (suggestions)
- Attitude prediction and reaction
- Motivation monitoring
Adaptation dimensions

- Technical environment
- Social context
- Personalization: difficulty...

- Situation

- Our first experience:
  School type, field, language, goals, prerequisites, field of interest, mastery level, competencies
Systematic approach

input?  

User Model  

relevant output?
Inputs for User Model

▶ Self-reports:
  - Questionnaire
  - on-task-report 😊
  - Open Learner Model

▶ teacher input

▶ behavioral data
  - Performance
  - Number of tasks finished
  - response to test items (hesitation)
  - time-on-task
  - # help or other requests
  - low-level measures

▶ context data
Input: Online Questionnaires

![Image of an online questionnaire form with fields for user information and submit button.]
My Profile – change My Data
Output: (Sub)competencies

- Solve
- Argue
- Think mathematically
  - Formulate
  - Generalize
- Model
  - Encode
  - Decode
- Represent
- Communicate
- Tools

- Knowledge
- Understanding
- Application
- Analysis
- Synthesis
Output: Individual Variables

- **Cognitive (actual)**
  - Capability, incoming knowledge
  - Cognitive style *
  - Problem solving strategies, preferences

- **Psychological (mental)**
  - Interests
  - Preferences, learning style *
  - Meta-cognitive *

- **Person-in-situation**
  - Exploratory behaviour
  - Goals

- **Affective**
  - motivation, emotion

- **Personal traits**
  - Blind, working memory capacity, attention span, reading performance
Output: Context variables

▶ **Social context:**
  - home/classroom/museum
  - Collaborative/single
  - Country (geographic)
  - Curriculum
  - School type
  - Cultural (not only language)

▶ **Technical context** (CC/PP rdf compositeCapabilities/preferenceProfile)
  - Browser (rendering)
  - Hardware platform: display-size, bandwidth PC/PDA
  - Software platform, Availability of tools on client, Handwriting facility
Student Modeling, techniques

- Case-based
- Data-driven
- Bayesian networks
- Bayesian updating
- Dynamic Bayesian Networks
- Stereotypes (deduction)
- Functional heuristic updating
- Social voting
Bayesian Networks

- **Nodes**: set of random variables $X_1, X_2, \ldots, X_n$
- **Links**: probabilistic dependencies among variables
- **Conditional probabilities**: quantify the dependencies

![Bayesian Network Diagram]

- \( P(A) = 0.01 \)
- \( P(B) = 0.02 \)
- \( P(C | A, B) = 0.95 \)
- \( P(C | A, \neg B) = 0.94 \)
- \( P(C | \neg A, B) = 0.29 \)
- \( P(C | \neg A, \neg B) = 0.001 \)
- \( P(D | C) = 0.90 \)
- \( P(D | \neg C) = 0.05 \)
- \( P(E | C) = 0.70 \)
- \( P(E | \neg C) = 0.01 \)
Bayesian Networks

Probability distribution events, causes, evidences diagnostic/causal update handle noise and uncertainty

Uncertainty in cognitive modeling Attractive alternative to modeling human expertise Software packages (BNT, DBN) In general NP-hard...

Source: Erica Melis Educational Technologies WS 2006/07
Bayesian Networks in Lumiere

- User expertise
- Task difficulty
- User distracted
- Pause after activity
- Recent menu surfing

User needs assistance

Source: Erica Melis  Educational Technologies WS 2006/07
BN for predicting student performance

Relevant for ideal solution c,p

Relevant for student solution

Used for selecting problem difficulty in SQL Tutor

Mastered(c)

Performance c,p

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Andes1 Network structure: Static part

- **Rule nodes**
  - \( P(R = T) \): probability that the student knows the rule

- **Context rule nodes**
  - \( P(CR = T) \): probability that the student can use the rule in the corresponding context

\[
P(CR_i = T \mid R = T) = 1 \\
P(CR_i = T \mid R = F) \text{ estimates the level of difficulty of context } i
\]
Network structure: Dynamic part
Andes1: Propagating evidence

Problem 1

Goal1

Context-Rule1

Fact1

Problem 2

Goal2

Context-Rule2

Fact2
Andes® Model Tracing

- Assess intention -> useful hints
- if error + help request -> best explanation
- low mastery of important rules -> mini-lesson
Andes’ Select a Hint Algo

▶ **Step 1: Goal inference**
  ▶ Start with last observed student entry
  ▶ Find closest unsatisfied goal node
  ▶ At decision points, choose highest probability node (most likely goal)

▶ **Step 2: Prediction**
  ▶ Start from goal found in step 1
  ▶ Find path from goal to “stuck node” (p<0.8)
  ▶ At decision points, choose lowest probability node (most help needed)
Model Tracing in PACT/cognitive tutors

- EXPERT problem solving space
  includes rules and mal-rules
- match student‘s results with nodes in space
- hypothesize next possible step
- diagnoses errors
Problems with Model Tracing

- Correct domain rules provide *positive* evidence only
- for *negative* evidence buggy rules needed
- assessors most accurate if
  - student kept along a given solution path
  - student has to provide every step

- Bayes theoretically optimal but some parameter values hard to obtain
Bayesian Knowledge Tracing, PACT/cognitive tutors

\[ p(K_n) = p(K_{n-1} \mid \text{evidence}) + (1 - p(K_{n-1} \mid \text{evidence})) \times p(T) \]

- \(p(K_0)\): initial learning (a priori) probability of rule
- \(p(T)\): transition probability following an opportunity of applic.

\[ p(\text{correct}) = p(K) \times (1 - p(S)) + (1 - p(L)) \times p(G) \]

- \(p(G)\): guess
- \(p(S)\): slip

Source: Erica Melis  Educational Technologies WS 2006/07
Dynamic Decision Networks
Dynamic Bayesian Networks (BNT package)

\[ P(K_0) \]

Student Knowledge: \( K_0 \) \( K_1 \) \( K_n \)

Student Performance: \( C_0 \) \( C_1 \) \( C_n \)

**Tutor Intervention**

- **guess** = \( P(C_n \mid \text{not} K_n) \)
- **slip** = \( P(\text{not} C_n \mid K_n) \)

\[ \text{learn}, \text{forget} \]

- **learn** = \( P(K_n \mid \text{not} K_{n+1}) \)
- **forget** = \( P(\text{not} K_n \mid K_{n+1}) \)
Data-driven approaches: knowledge space theory

Knowledge space theory [Falmagne1999], IRT theory, POKS Desmarais

- Originally for adaptive testing psychometric methods
- Build structure from data only (observable knowledge items. #subjects with a > c), no modeling ~
- Item to item node structure
- Compute individual knowledge space
- Compute potential next KS for adaptive test
Item to item node structure

- DAG of exercises (items)
- Edges point to prerequisites
- Induce *surmise* relation
- \( a > c \): mastery of \( c \) will precede mastery of \( a \). If student succeeds with \( a \) then with \( c \) too
- Likely partial ordering which items learned
- DAG closed under union (and intersection) – reduces \# data
Knowledge Space, POKS structure

- Mastery of a node implies: Mastery of prerequisites (positive upward propagation)
- Failure at a node implies: Items that depend on this node are not yet mastered (negative downward propagation)
Knowledge Space Propagation

- If student solves B, prerequisite D can be assumed to be mastered
- If student fails at C, depending item A is most likely not yet mastered
Knowledge Spaces

• Individual's knowledge state = subset of items (mastered)

• Example knowledge states: \{Ø, {d}, {c,d}, {b,d}, {b,c,d}, {a,b,c,d}\}

• Knowledge state determines which state to move to
  other knowledge states unlikely

• Determine mastery of one or few ability dimensions
Knowledge space inference

- **Learning item-to-item structure:**
  - K2: BN structural learning: greedy search over space of network topologies - given observed distribution:
  - POKS: pairwise analysis:
    - \( P(B|A) \geq p_c(\text{mastered}) \)
    - \( P(\bar{A}|
      \bar{B}) \geq p_c(\text{not mastered}) \)
    - \( P(B|A) \neq P(B) \)

- **With network compute probability of success for items from partial evidence with Bayesian posterior** \( P(H | E_1, E_2...) \)
- **Compute from probability distribution: most likely next knowledge state**
  - interest is in predictive power
Stereotypes

- **Stereotype:** body + set of triggers
- may be arranged in hierarchies (inheritance)

Membership in (several) stereotypes

- Actions and self-ass
- Relevant facts
- trigger
- (possible) inheritance

Source: Erica Melis  Educational Technologies WS 2006/07
Stereotypes, rules

- **Trigger rules** *(Cond Trigger)*
  - self-assessed 'expert' THEN stereo= Expert
  - at least 20 topics K=excellent THEN stereo=Expert

- **Rules for evaluation and presentation** *(Cond Scoring)*
  - Beginner AND diff(T)=simple THEN ev(T)=10 points
  - knows(T) THEN subtract 20 for appropriate(T)
ActiveMath SLM – (Simple Learner Model)

Goals

- Grasp learners’ knowledge
- Regard hard evidence only
- Keep it simple
- Consider learners’ improvements
ActiveMath Learner Model for Competencies

- history of user action
- concept/skill
- derivative
- product rule
- misconception
- buggy product rule
- model
- compute
- argue
- tool use

Source: Erica Melis
Educational Technologies WS 2006/07
Individual Competencies in ActiveMath

- **Multiple dimensions for Learner Model**
  - Competencies (think, model…)
  - Concepts (sum-rule, power-rule…)

- **Exercises**
  - For specific concepts
  - Steps need competencies
Assumptions

Concepts are related, often hierarchical dependencies

- E.g. percentage calculation depends on fractions
  \( \Rightarrow \) to master a concept the prerequisites have to be mastered

- Direct vs. indirect evidence vs. self-assessment (decreasing trust)
  SLM tries to assess using strongest evidence:
  \( \Rightarrow \) 1st direct, 2nd indirect evidence, 3rd self-assessment

Exercises are hard evidence

- Modulo guessing (not considered in SLM)

Simplicity: Average over exercise results

Learners’ improvements

- Consider only last \( n \) exercises (currently \( n = 4 \))
Concept dependencies

- Competency1 (model)
- Competency1 (think)
- Concept5
- Concept6
- Concept1
- Concept2
- Concept3
- Concept4
- Ex1
- Ex2
- Ex3
- Ex4

Source: Erica Melis  Educational Technologies WS 2006/07
Concept-competency updating (positive)

- Competency1 (think)
- Competency2 (model)

Ex1

Concept1 -> Concept2 -> Concept4
Concept1 -> Concept3

Ex2

Concept5

Ex3

Ex4

Competency2 (model)
Competency1 (think)
Concept-competency updating (negative)

Ex1

Competency2 (model)

Competency1 (think)

Concept5

Concept6

Concept1

Concept2

Concept3

Concept4

Ex3

Ex4

Ex2

Ex4
Concept-competency updating (combined)

- Direct evidence overwrites indirect evidence
Creating **BN**: observable – hidden variables

**log data**
- av.Time, av.mistakes, #problems
- Help request, av.hints, time-on-help
- Help-timing (before, after, correct)

**questionnaire data**
- Gender
- Motivational
- Affective
- Past experience
- Perception of system
- Attitude towards help
- Learning attitude
- Like challenge

**Pretest-posttest result**
Methodology

- From bi-variate Pearson’s correlations
- Eliminate links between observables
- Give single direction to links
- For links between non-observables create unidirectional links
- Eliminate circles
- (grouping of factors to reduce dimensions)
- Build Bayes net:
  - discretize variables
  - simplify (chi-square, if child removed and accuracy not affected)
- CPT for those vars
Correlations: observable – non-observables

- confirmatoryHelpAttitude
- seriousTryLearnAttitude
- getItOverAttitude
- fearWrongAnswer
- challenge

Learning factor:
- TimeOnHint
- RatioHelpedProblems
- HintsSeenPerProblem

Helpful

Gender

Like

TimeBetweenAttempt

ProblemsPerMinute

UsedHeadphone

Source: Erica Melis  Educational Technologies WS 2006/07
Computing CPTs: maximum likelihood method

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Situational Variables

- **Situational variables based on information from LeAM**
  - student interest; student confidence; student effort; student aptitude; level of student hesitation; level of student achievement

- **Numerical Autonomy and Approval values based on the values of the situational variables (SM-ler):**
  - level of recommended guidance to be given to the student (Autonomy)
  - level of explicit approval recommended for a student (Approval)
Implications of the Data Analysis

- **Reduced number of factors - the final set being:**
  - Difficulty of material
  - Importance of material
  - Student Confidence
  - Student Interest
  - Student Aptitude
  - Correctness of student’s answer
  - Student Effort

- **Data-driven design and implementation of the Bayesian Network (SM-ler) for LeAM**
Bayes Net for Motivational Variables, simpl.
SM: the Bayesian Model
Situational Model: the BN explained

- 7 top nodes represent the set of situational factors modelled
- 2 lowest level nodes represent Autonomy and Approval
- GOG and AOG = Guidance oriented goals & Approval oriented goals resp.
- In some cases it is straightforward to establish what the goals are. In some cases it is not so easy - for example, highly confident students are perceived by our tutors as over confident, but such perception is only the result of other contextual information – in this case student aptitude.
- We rely on analysis of annotated verbal protocols
- Annotations: GOG and AOG
Social voting techniques: I-Help

- knowledge
- interests
- eagerness
- helpfulness
- cognitive style
- preferences in helper
- preferred people
- banned people
- banned topics
- help-load

Info from:
- user
- peers
- I-Help private
- I-Help Public

For finding and ranking candidate helpers for protecting users
Putting the model to use

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Test of User Models

- Never fully reliable...
- Empirical test with users
  - protocols...teacher assessors
- introspectable and modifiable user models
  - student/teacher revises
  - dialogue about student’s beliefs
- test with artificial users
Other probabilistic approaches: Belief descriptors

Diagram showing relationships between different concepts such as Domain, Competency, Math Thinking, Math Modelling, Solving Problems, Chain Rule, Differentiation Rules, and various descriptors related to motivation, anxiety, affect, and metacognition.