Diagnosing Self-efficacy in Intelligent Tutoring Systems

Scott W. McQuiggan and James C. Lester

Department of Computer Science
North Carolina State University
Outline

- Self-efficacy
- SELF Architecture - Training
- Online Tutorial System Test bed
- Learning Self-efficacy Models

- SELF Architecture - Runtime
- Foundational Study Evaluation
- ILE Evaluation
- Future Work
- Conclusion
Approaches to Modeling Affect

- **Analytical**
  - Manual model construction

- **Empirical**
  - Learned model construction

- Data → Learning → Observable interaction → Affect
Self-efficacy

- “One’s belief in their capabilities to organize and execute the courses of action required to manage prospective situations” (Bandura, 1997)
- Accurate predictor of student motivation and learning effectiveness
- SE influences: student reasoning, level of effort, persistence, feelings, decision-making, resilience when confronted with failure, and achievable levels of success
Online Tutorial System Test bed
Learning SELF Models

- **Data Construction**: translate logs to full observational attribute vector database
- **Data Cleansing**: removal of sessions with data corruption (i.e., no HR data)
- **Naïve Bayes & Decision Tree Learning**: Tenfold cross-validation analyses of entire dataset using WEKA
Modeling Self-efficacy

- Need to drive runtime, non-interruptive, self-efficacy diagnosis
- Naïve Bayes and decision tree classifiers
  - Excellent preliminary predictive models for large multi-dimensional datasets
  - Produce probability tables and interpretable rules, respectively
  - Useful for informing advanced machine learning techniques, such as Bayesian networks
Static and Dynamic SE Models

- Static Models of Self-efficacy
  - Demographic Data
  - Self-efficacy Instrument Results
  - Interaction Data

- Dynamic Models of Self-efficacy
  - Static Data
  - Physiological Response Data
Evaluation - Results

Naïve Bayes three-level model of self-efficacy
Evaluation - Results

Decision tree three-level model of self-efficacy
Evaluation - Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Two-level</th>
<th>Three-level</th>
<th>Four-level</th>
<th>Five-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve Bayes</td>
<td>0.85</td>
<td>0.72</td>
<td>0.75</td>
<td>0.64</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.87</td>
<td>0.83</td>
<td>0.79</td>
<td>0.75</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>0.82</td>
<td>0.70</td>
<td>0.69</td>
<td>0.63</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.83</td>
<td>0.73</td>
<td>0.69</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Gray rows indicate static models learning from demographic, Problem-Solving Self-efficacy, and observational attributes of the environment.
Relationship between HR and SE

Selection of Correct Answer
Select SE = 99

Selection of Incorrect Answer
Select SE = 45

Begin Reading Question
Self-efficacy Study 2

- Genetics tutorial
- Solved Crystal Island mystery
  - Self reported levels of self-efficacy
  - Users were wired
- Solved series of genetic questions
  - Self reported levels of self-efficacy
  - Users were wired
Crystal Island Virtual Environment

- Narrative-centered discovery learning environment
- Student’s tasked with solving a science mystery in a genetics domain
Observable Attribute Vector

- **Temporal features**
  - Time remaining
  - Time spent in current location

- **Location features**
  - In Bryce’s room
  - Been to waterfall

- **Intentional features**
  - Moving towards goal
  - Reward progression

- **Student Physiological Response**
  - Blood volume pulse
  - Galvanic skin response
SELF Architecture - Training

Physiological Response Learner
Naïve Bayes / Decision Tree / Bayesian Network

Self-Efficacy Model Learner
Naïve Bayes / Decision Tree / Bayesian Network

Physiological Response Model

Self-Efficacy Model

Observational Attribute Vector
- Physiological Response
- Temporal Attributes
- Locational Attributes
- Intentional Attributes

Interactive Environment

PRP-Enhanced Runtime Component
Runtime, Non-Interruptive Self-Efficacy Diagnosis Control

User Interface

End User

Training User

Biofeedback
Learning

- Need to drive runtime, non-interruptive self-efficacy diagnosis control
- Models can be used to inform tutorial strategy planners and interactive system control components
SE Modeling Results – C.I.

Self-efficacy Model ROC Curves

Bayes Nework (0.80)
Decision Tree (0.81)
Naive Bayes (0.78)
Future Work

- Explore predictive capabilities of induced models in more complex, dynamic environments
- To what extend can we model self-efficacy “without the wires”
- Investigate how adaptable tutorial components should be affected by student self-efficacy information
Conclusion

- The SELF framework is able to construct models of self-efficacy that, at runtime, are non-interruptive.
- The SELF framework can induce accurate models of self-efficacy, sufficient for runtime informing adaptable tutorial control components.