Diagnosing Self-efficacy in Intelligent Tutoring Systems

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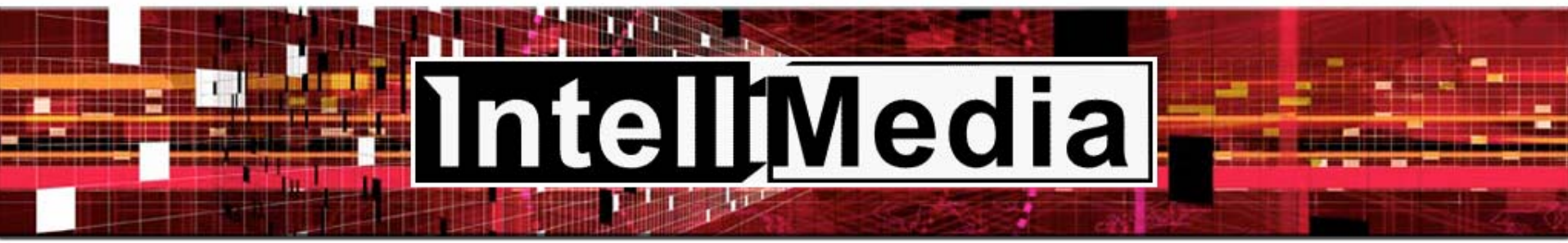
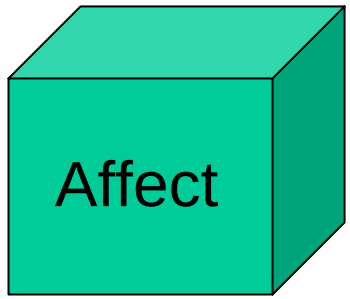


Outline

- 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

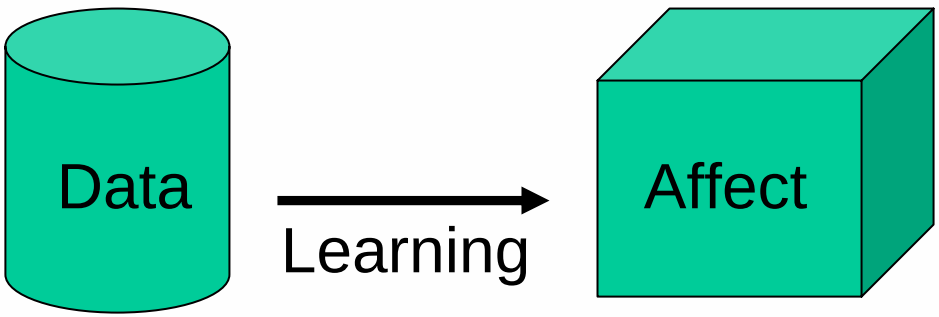
Approaches to Modeling Affect

- Analytical



Manual model construction

- Empirical



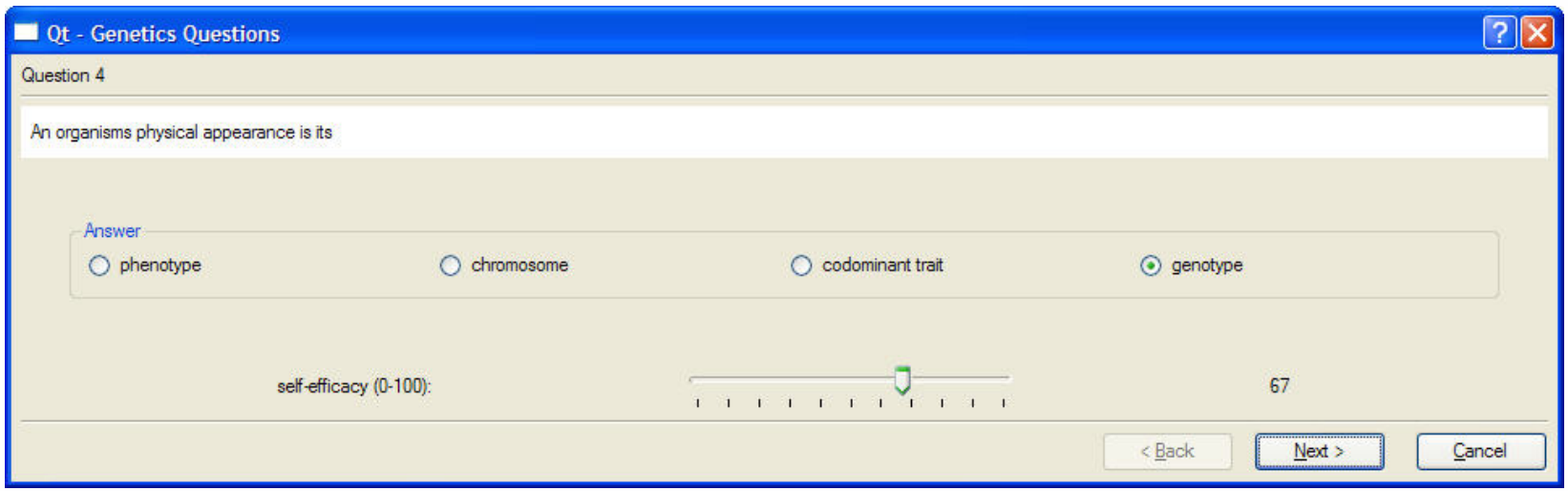
Observable interaction

Learned model construction

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

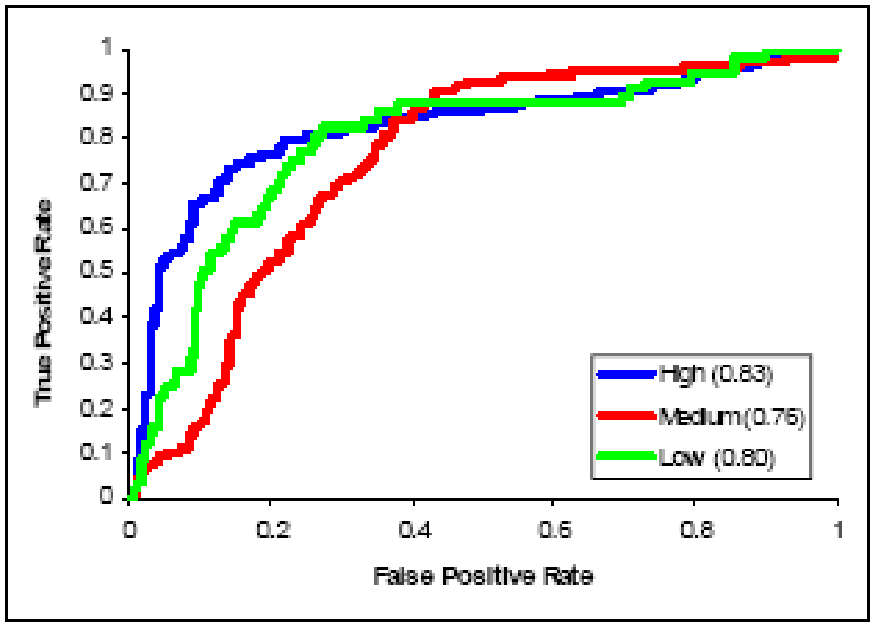
Modeling Self-efficacy

- 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

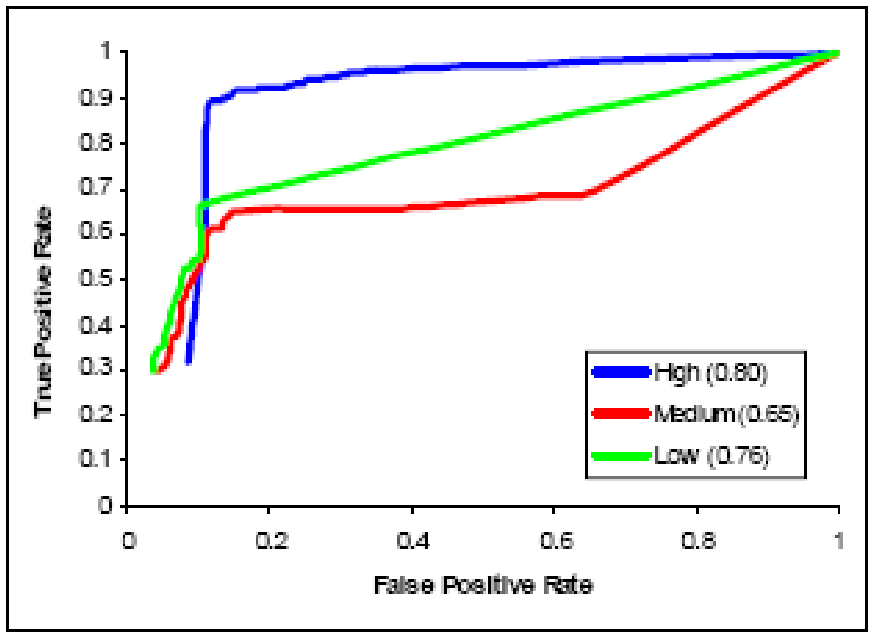
Evaluation - Results



Naïve Bayes three-level model of self-efficacy

Evaluation - Results

Decision tree three-level model of self-efficacy

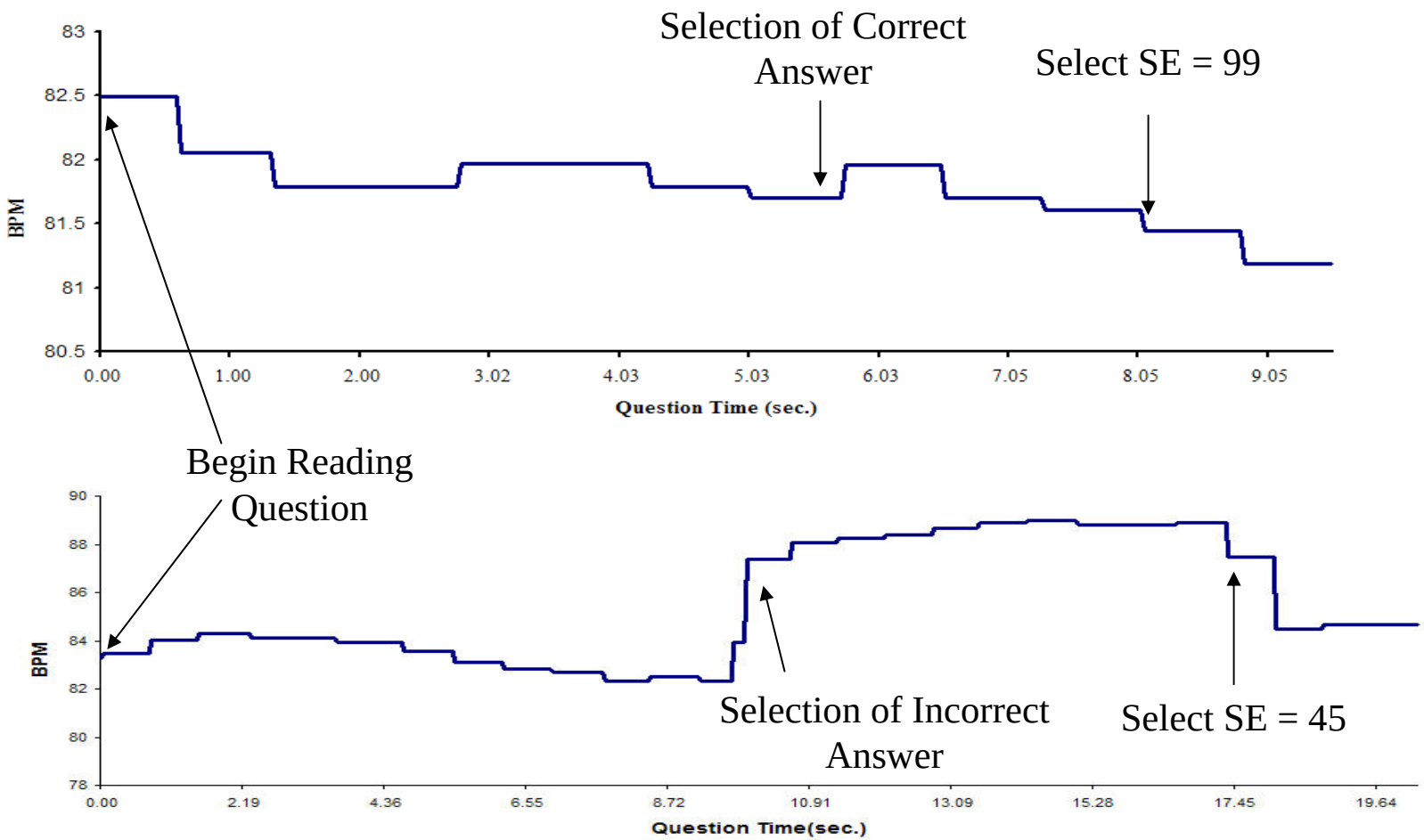


Evaluation - Results

Model	Two-level	Three-level	Four-level	Five-level
Naïve Bayes	0.85	0.72	0.75	0.64
Decision Tree	0.87	0.83	0.79	0.75
Naïve Bayes	0.82	0.70	0.69	0.63
Decision Tree	0.83	0.73	0.69	0.64

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

Relationship between HR and SE



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

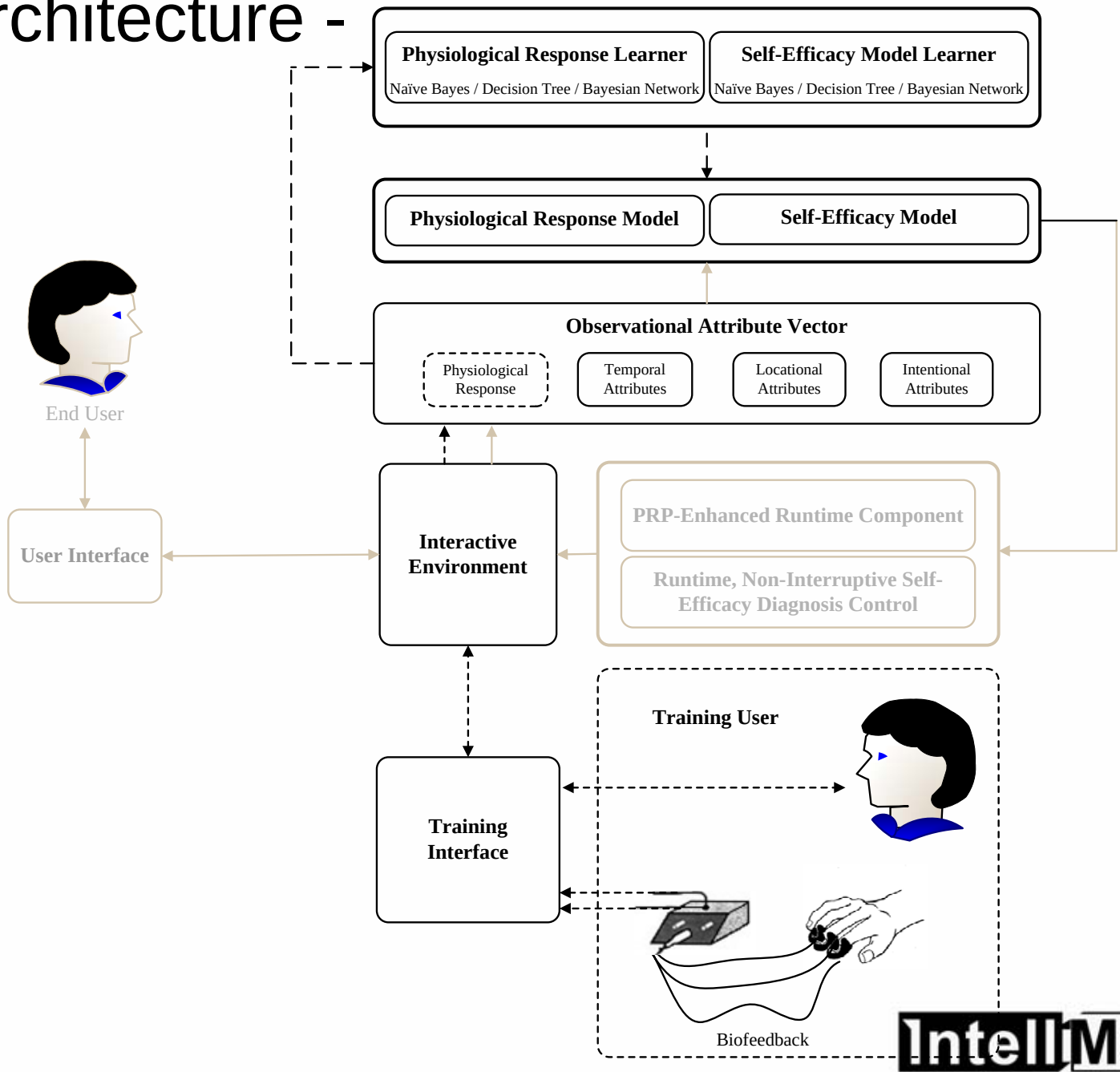
Crystal Island Virtual Environment

- 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

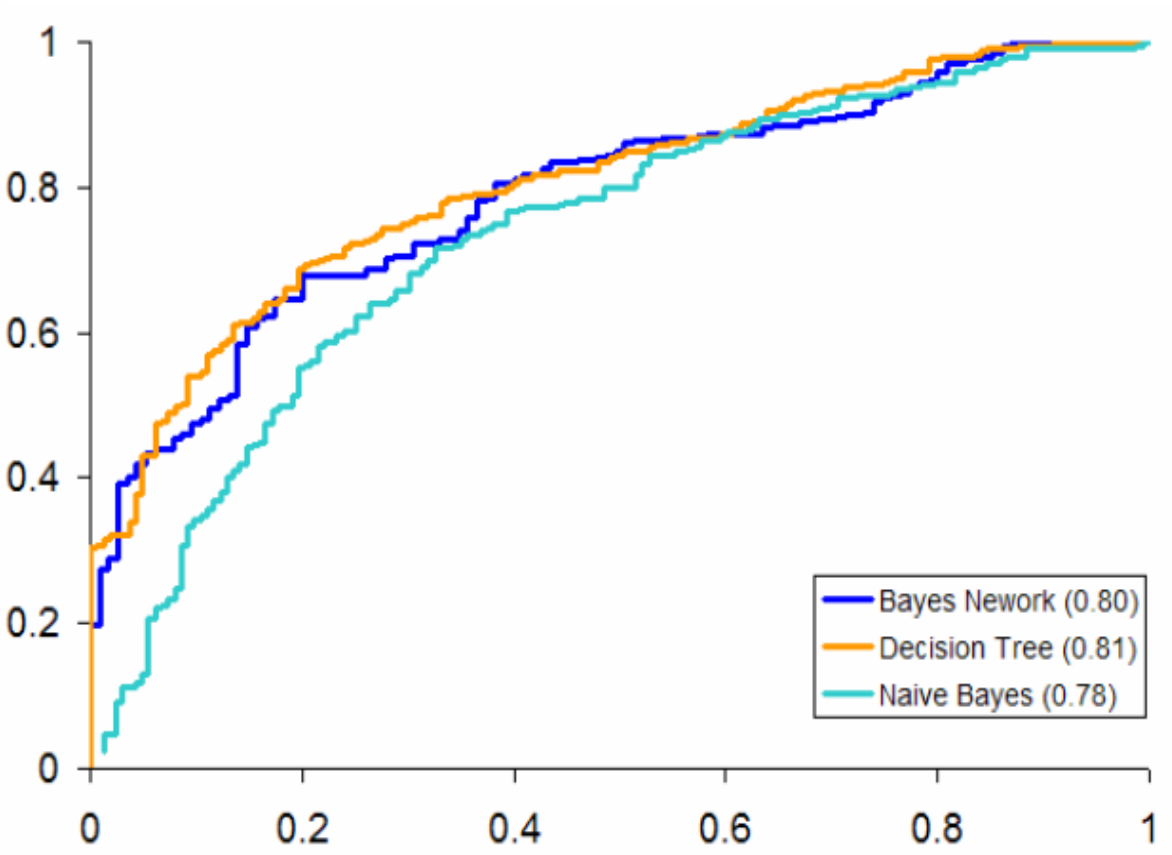


Learning

- 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



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