Week 1, Video 6

Case Study – San Pedro

Case Study of Classification

- San Pedro, M.O.Z., Baker, R.S.J.d., Bowers, A.J., Heffernan, N.T. (2013) Predicting College Enrollment from Student Interaction with an Intelligent Tutoring System in Middle School. *Proceedings of the 6th International Conference on Educational Data Mining*, 177-184.




Research Goal

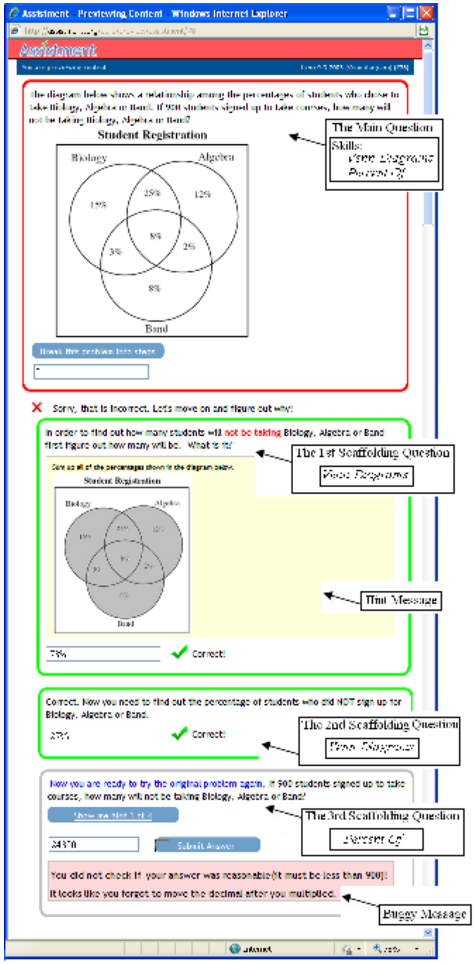
- Can we predict student college attendance
- Based on student engagement and learning in middle school mathematics
- Using fine-grained indicators distilled from interactions with educational software in middle school (~5 years earlier)

Why?

- We can infer engagement and learning in middle school, which supports
  - Automated intervention
  - Providing actionable info to teachers and school leaders

- But which indicators of engagement and learning really matter?
  - Can we find indicators that a student is at-risk, that we can act on, before problem becomes critical?

ASSISTments



Log Data

- 3,747 students
  - In 3 school districts in Massachusetts
    - 1 urban
    - 2 suburban
- Completed 494,150 math problems
  - Working approximately 1 class period a week for the entire year
- Making 2,107,108 problem-solving attempts or hint requests in ASSISTments
- Between 2004-2007

Data set

- Records about whether student eventually attended college
- 58% of students in sample attended college

Automated Detectors

- A number of automated detectors were applied to the data from ASSISTments
- These detectors had themselves been previously developed using prediction modeling and were published in previous papers, including (Pardos et al., 2013)
- Building a detector and then using it in another analysis is called *discovery with models*

Automated Detectors

- Learning
  - Bayesian Knowledge Tracing; we'll discuss this later in the course

Disengagement Detectors (No sensors! Just log files!)

- Gaming the System
  - Intentional misuse of educational software
  - Systematic Guessing or Rapid Hint Requests
- Off-Task Behavior
  - Stopping work in educational software to do unrelated task
  - Does ***not*** include talking to the teacher or another student about math; these can be distinguished by behavior before and after a pause
- Carelessness
  - Making errors despite knowing skill

Affect Detectors (No sensors! Just log files!)

- Boredom
- Frustration
- Confusion
- Engaged Concentration

College Attendance Model

- Predict whether a student attended college from a student's year-long average according to the detectors
- **Logistic Regression** Classifier (binary data)
- Cross-validated at the student-level
  - We'll discuss this next week

Individual Feature Predictiveness

	College	Mean	Std. Dev.	t-value
Student Knowledge	NO	0.292	0.151	-15.481 ($p<0.01$)
	YES	**0.378**	**0.180**	
Correctness	NO	0.382	0.161	-17.793 ($p<0.01$)
	YES	**0.483**	**0.182**	
Boredom	**NO**	**0.287**	**0.045**	5.974 ($p<0.01$)
	YES	0.278	0.047	
Engaged Concentration	NO	0.483	0.041	-11.979 ($p<0.01$)
	YES	**0.500**	**0.044**	
Confusion	**NO**	**0.130**	**0.054**	5.686 ($p<0.01$)
	YES	0.120	0.052	

Individual Feature Predictiveness

	College	Mean	Std. Dev.	t-value
Off-Task	NO	0.304	0.119	1.184 p=0.237
	YES	0.300	0.116	
Gaming	**NO**	**0.041**	**0.062**	8.862 ($p<0.01$)
	YES	0.026	0.044	
Carelessness	NO	0.132	0.066	-13.361 ($p<0.01$)
	YES	**0.165**	**0.077**	
Number of First Actions (Proxy for Attendance)	NO	114.500	91.771	-8.673 ($p<0.01$)
	YES	**144.560**	**113.357**	

Full Model

- A' = 0.686, Kappa = 0.247
- χ^2 (df = 6, N = 3747) = 386.502, $p < 0.001$ (computed for a non-cross-validated model)
- R^2 (Cox & Snell) = 0.098, R^2 (Nagelkerke) = 0.132
- Overall accuracy = 64.6%; Precision = 66.4; Recall rate = 78.3%

Final Model (Logistic Regression)

CollegeEnrollment =
+ 1.119 StudentKnowledge
+ 0.698 Correctness
+ 0.261 NumFirstActions
– 1.145 Carelessness
+ 0.217 Confusion
+ 0.169 Boredom
+ 0.351

Flipped Signs

CollegeEnrollment =

+ 1.119 StudentKnowledge

+ 0.698 Correctness

+ 0.261 NumFirstActions

– 1.145 Carelessness

+ 0.217 Confusion

+ 0.169 Boredom

+ 0.351

Implications

- Carelessness is bad… once we take knowledge into account
- Boredom is not a major problem… among knowledgeable students
  - When unsuccessful bored students are removed, all that may remain are those who become bored because material may be too easy
  - Does not mean boredom is a good thing!

Implications

- Gaming the System drops out of model
  - Probably because gaming substantially hurts learning
  - But just because Gaming->Dropout is likely mediated by learning, doesn't mean gaming doesn't matter!
    - 0.34 σ effect

Implications

- Off-Task Behavior is not such a big deal
  - How much effort goes into stopping it?
  - Past meta-analyses find small significant effect on short-term measures of learning
    - But not when collaborative learning is occurring?

Implications

- In-the-moment interventions provided by software (or suggested by software to teachers) may have unexpectedly large effects, if they address boredom, confusion, carelessness, gaming the system

Interventions

- Just getting started
- First pilot tried in June 2013
  - Got feedback from teacher
  - Intervention is being re-designed for a second pilot

Week One Complete!

Week Two

- How do we know if a prediction model is any good?
  - Goodness Metrics
  - Model Validation