Week 3 Video 1

Behavior Detection

Welcome to Week 3

- Over the last two weeks, we've discussed prediction models

- This week, we focus on a type of prediction model called behavior detectors

Behavior Detectors

- Automated models that can infer from interaction/logs whether a student is behaving in a certain way

- We discussed examples of this
  - off-task behavior and gaming detectors

- In the San Pedro et al. case study in week 1

The Goal

- Infer meaningful (and complex) behaviors from logs or in real-time

- So we can study those behaviors more deeply
  - How do they correlate with learning?
  - What are their antecedents?s

- And so we can identify when they occur
  - In order to intervene

Behaviors people have detected

Disengaged Behaviors

- Gaming the System (Baker et al., 2004; dozens of other examples)
- Off-Task Behavior (Baker, 2007; Cetintas et al., 2010)
- Carelessness (San Pedro et al., 2011; Hershkovitz et al., 2011)
- WTF Behavior (Rowe et al., 2009; Wixon et al., UMAP2012)

Meta-Cognitive Behaviors

- Help Avoidance (Aleven et al., 2004, 2006)
- Unscaffolded Self-Explanation (Shih et al., 2008)
- Exploration Behaviors (Amershi & Conati, 2009)

Teacher Strategic Behaviors

- Curriculum Planning Behaviors (Maull et al., 2010)
- Teacher Interventions for Students (Miller et al., 2015)

Related problem: Sensor-free affect detection

- Not quite the same conceptually

- But the methods turn out to be quite similar

- Detecting
  - Boredom
  - Frustration
  - Engaged Concentration
  - Delight

(D'Mello et al., 2008; Sabourin et al., 2011; Baker et al., 2012, 2013, 2014; Pardos et al., 2014; Kai et al., 2015; Paquette et al., 2014, 2015)

Related problem: LMS and MOOC Usage Analysis

- Studying online learning behaviors
- But typically not the same methods/process I'll be discussing in the next lectures
- More often, researchers in this area have looked to predict outcomes from relatively straightforward behaviors
- Due to what's visible in the log files (access to resources rather than thinking processes made visible through complex activities)

Related problem: LMS and MOOC Usage Analysis

- That said, lots of great prediction modeling research in this area

- Predicting and analyzing outcomes based on when and how much learners use videos, quizzes, labs, forums, and other resources

(Arnold, 2010; Breslow et al., 2013; Sharkey & Sanders, 2014; dozens of other examples)

Ground Truth

- Where do you get the prediction labels?

Behavior Labels are Noisy

- No perfect way to get indicators of student behavior
- It's not truth
  - *It's ground truth*

Behavior Labels are Noisy

- Another way to think of it
- In some fields, there are "gold-standard" measures
  - As good as gold
- With behavior detection, we have to work with "bronze-standard" measures
  - Gold's less expensive cousin

Is this a problem?

- Not really
- It does limit how good we can realistically expect our models to be
- If your training labels have inter-rater agreement of Kappa = 0.62
- You probably should not expect (or want) your detector to have Kappa = 0.75

Some Sources of Ground Truth for Behavior

- Self-report
- Field observations
- Hand-coding of logs (aka “text replays”)
- Video coding

Advantages and Disadvantages

- Somewhat outside the scope of this course

- Important note: no matter which coding method you use, try to make sure the reliability/quality is as high as feasible
  - While noting that 1,000 codes with Kappa = 0.5 might be better than 100 codes with Kappa = 0.8!

- Harder to get higher reliability for video coding than other methods
  - A bit non-intuitive

In the remainder of this week we'll discuss

- Feature engineering for behavior detection
- Knowledge engineering versus data mining

Next Lecture

- Data Synchronization and Grain-Sizes