Educational Data Mining (EDM), 2018

Predicting Quitting in Students Playing a Learning Game

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Research Goal

Quit Prediction - Detect whether a student is likely to give up and quit a game level in progress

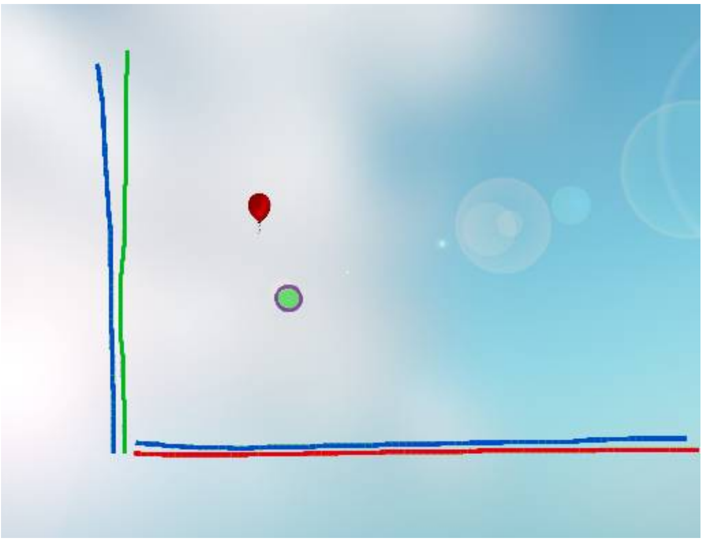
Why Predict Quit?

To **identify potential learning moments** for a struggling student in the game where a **cognitive support** could support the student in developing their emerging understanding of key concepts and principles.

Shute, V., and Ventura, M. 2013

Context - Physics Playground (PP)

- A two-dimensional game, developed to help secondary school students understand qualitative physics
- Concepts include Newton's laws of force and motion, mass, gravity, potential and kinetic energy, and conservation of momentum
- Players draw objects on the screen, often simple machines or *agents* to guide a green ball to hit a red balloon
- Players get silver and gold badges based on the number of objects used



Shute, V., and Ventura, M. 2013. Measuring and supporting learning in games: Stealth assessment. Cambridge, MA: The MIT Press.

Related Work - **Disengagement**

Baker, R.S.J. 2007. Modeling and understanding students' off-task behavior in intelligent tutoring systems. In
Proce
Comp

Off Task Conversation

D'Mello, S., Cobian, J., and Hunter, M.: Automatic Gaze-Based Detection of Mind Wandering during Reading.
In *Pro*
Educ
Educa

Mind Wandering while Reading

Baker, R.S.J., Corbett, A.T., and Koedinger, K.R. 2004. Detecting student misuse of intelligent tutoring systems. In *Intelligent Tutoring Systems*. pp. 54–76.

Gaming the System

In the context of **Learning Games**

Rowe, J. P., McQuiggan, S. W., Robison, J. L., and Lester, J. C. 2009. Off-Task Behavior in Narrative-Centered Learning
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Off Task Behavior

Dicerbo, K., and Kidwai, K. 2013. Detecting player goals
from g

Player Goals in the game

Wang, L., Kim, Y. J., and Shute, V. 2013. Gaming the system" in Newton's Playground. In *AIED 2013 Workshops Proceedings Volume 2 Scaffolding in Open-Ended Learning Environments*. OELEs. p. 85.

Gaming the System

Related Work - **Quitting Behavior**

In the context of **MOOC** (dropout or stop-out)

Yang, D., Sinha, T., Adamson, D., and Rose, C. P. 2014. "Turn on, tune in, drop out": Anticipating student dropouts in massive open online courses. *In NIPS Workshop on Data-Driven Education*.

Social network and survival analysis on discussion board data

He, J., Bailey J., Benjamin, Rubinstein, I., and Zhang, R. 2015. Identifying at-risk students in massive open online courses. In *AAAI*.

Engagement and performance data

Whitehill, J., Williams, J. J., Lopez, G., Coleman, C. A., and Reich, J. (2015). Beyond prediction: First steps toward automatic intervention in MOOC student stopout. In *Social Science Research Network*.

Automatic survey intervention

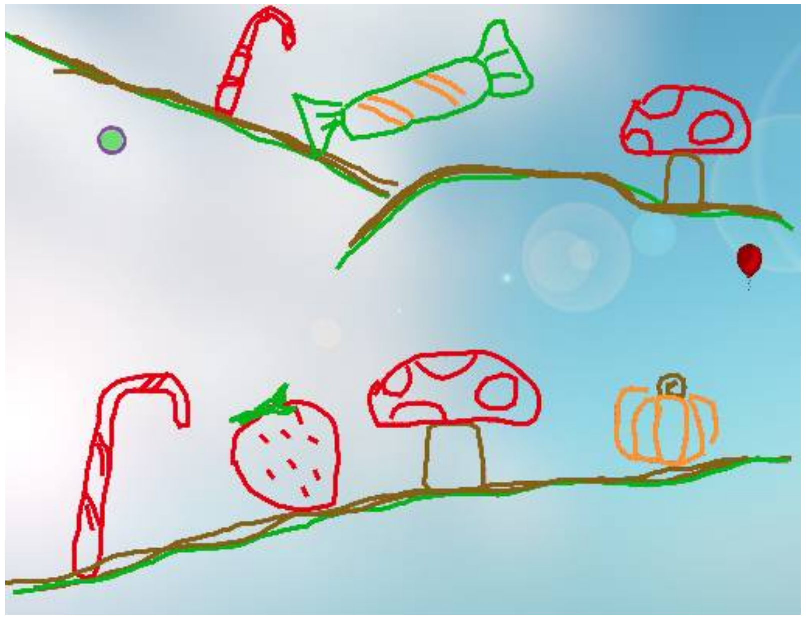
A lab experiment with a simple reading interface

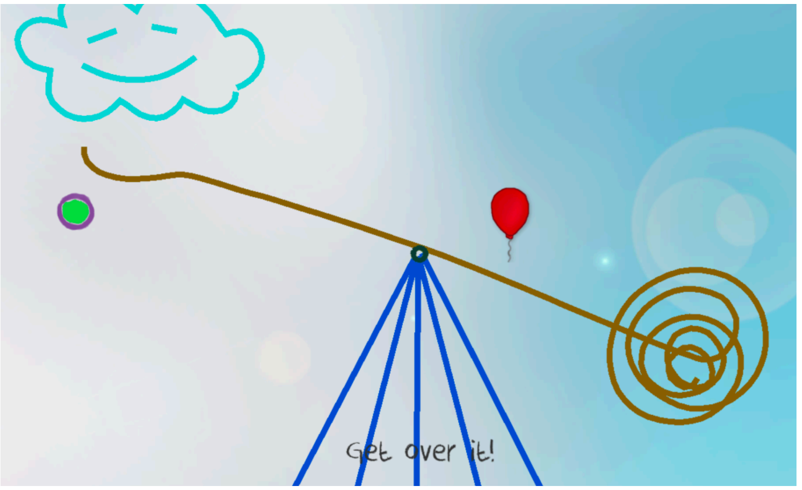
Mills, C., Bosch, N., Graesser, A., and D'Mello, S. K. 2014. To Quit or Not to Quit: Predicting Future Behavioral Disengagement from Reading Patterns. In S. Trausan-Matu, K. Boyer, M. Crosby and K. Panourgia (Eds.), *Proceedings of the 12th International Conference on Intelligent Tutoring Systems*. ITS 2014. pp. 19-28. Switzerland: Springer International Publishing.

Quit reading an upcoming text

Data Collection

- 137 students (80 female, 57 male)
- 8th and 9th grades
- Enrolled in a public school in the southeastern US
- 2 days of gameplay of 55 minutes each
- Comprehensive interaction data logged by the software
- 34 (out of 74) levels with at least 50 players





Unit of Analysis

A relevant **event** in the game

- **Level-related** events like start, pause, restart, and end
- **Agent creation** events like drawing of ramp, pendulum, lever, springboard
- **Play-related** events like object drop, object erase, collision and nudge

Some nitty-gritty

(aka read the paper if you need more)

- Some levels can be solved by multiple agents - for each they can get a silver or gold badge
- Hence, a visit could be a first visit, a **revisit** using a different agent, or a revisit to get a better badge
- Each visit is considered as a separate instance of gameplay for prediction
- Within each visit, a student can **restart** the level multiple times to reset the level to default

Feature Engineering

- **Student+Level+Visit** related - defines a student's progress in their current visit to a level
- **Student+Level** related - defines a student's experience with the level so far, across all their previous visits
- **Student** related - defines the student's progress through the game across all the levels played so far
- **Level** related - defines the inherent qualities of a particular level

Features aggregated (60-sec clips) leading to a total of
14,116 data points and **101 features**

Model Training

Two types of models trained

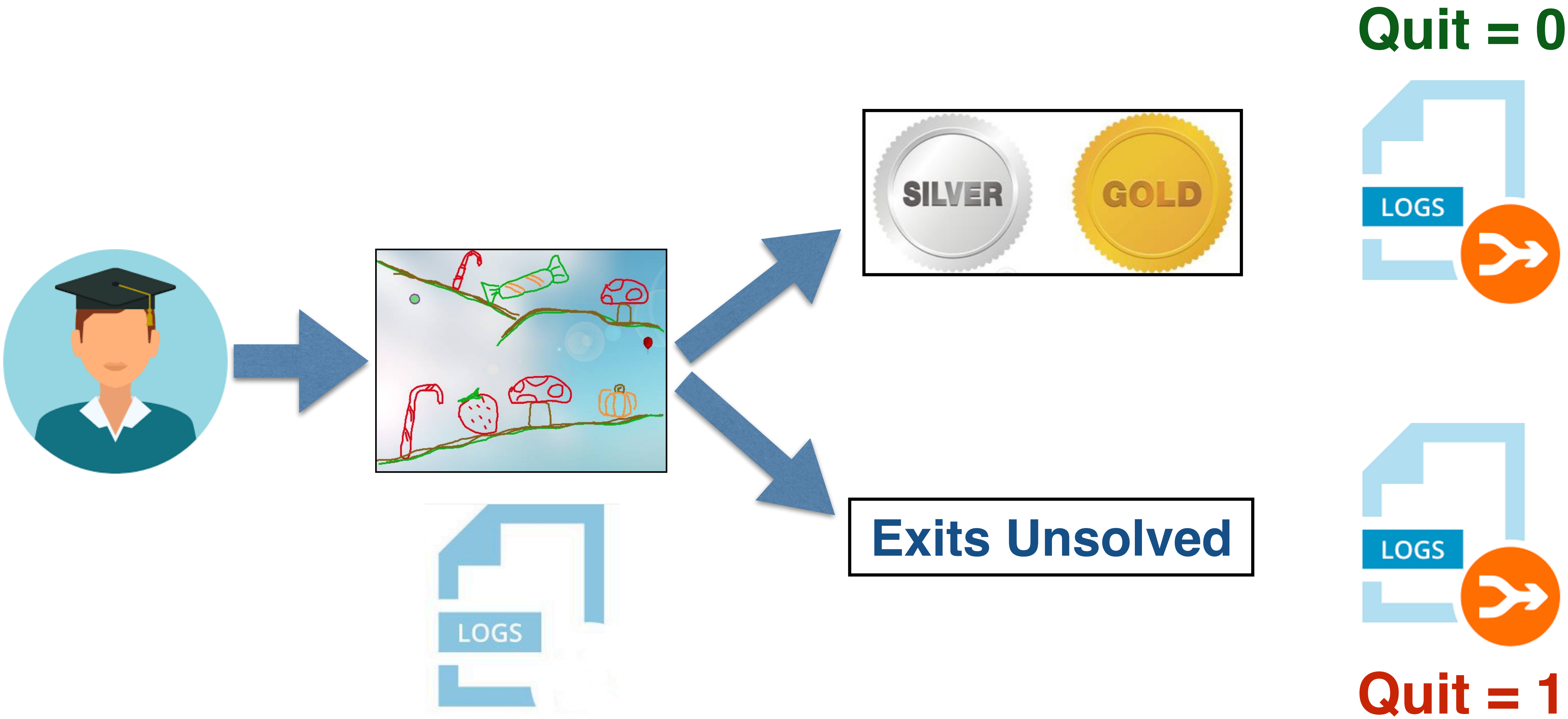
- A single **level-agnostic** model trained on the data from all levels

- Multiple **level-specific** models trained on the data from each level

Architecture - Gradient Boosting classifier, 5-fold student-level cross validation, model-based feature selection

Defining Outcome Label

Quit = 0 or 1



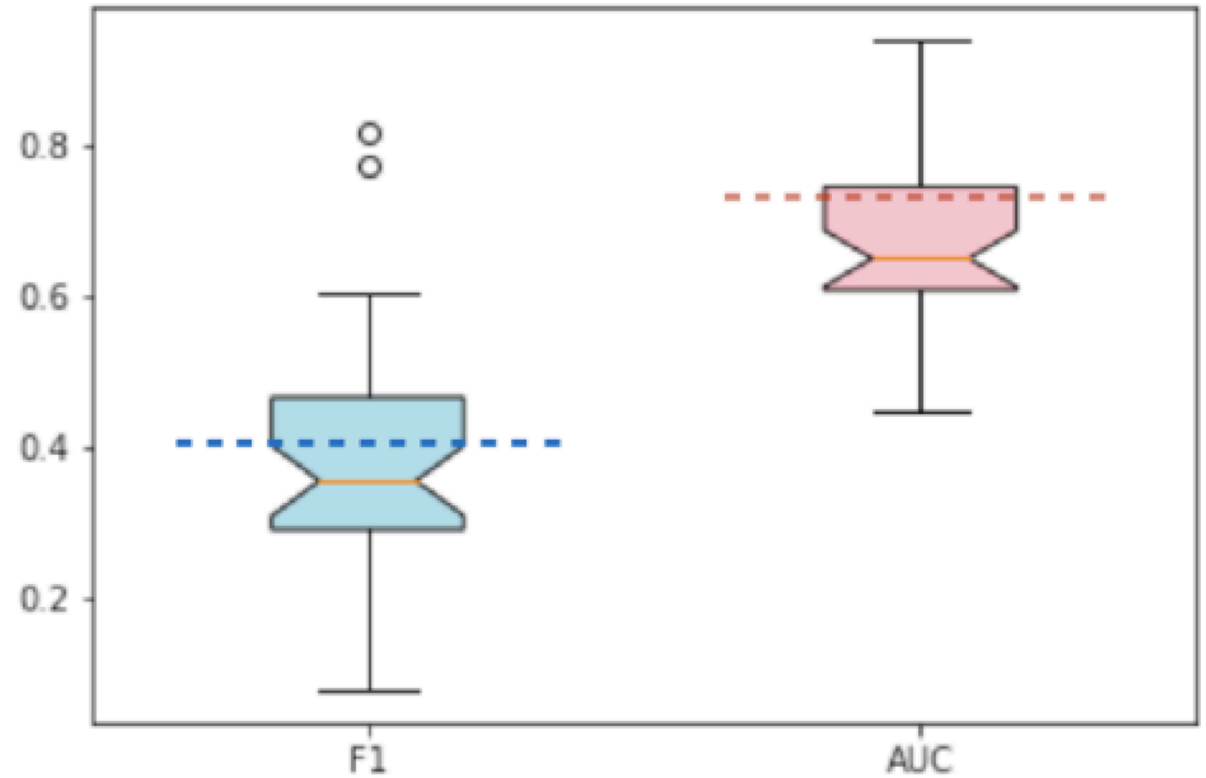
Class distribution - **28.77% quit** and **71.23% not-quit**

Results

Level Specific Vs Level Agnostic Models

only student+level+visit and student+level features used

- The level-agnostic model leverages the larger amount of data to identify generalizable features for quit prediction which are common across levels
- The level-specific models incorporates features related to finer-grained aspects of gameplay



Box plot representing the range of AUC and F1 values of the 34 level-specific models. The dashed horizontal lines correspond to the values of the level-agnostic model.

Results

Final Level Agnostic Model

with all four types of features

- 34 (out of 101) features selected
- 21 student-related, 2 level-related, 6 student+level related, and 5 student+level+visit related
- Features denote high-level game activities like visits, badges, past quits, time spent, level restarts, and experience with agents across visits and other levels
- AUC = 0.81, F1 = 0.51

Results

Model Interpretation

- **Level difficulty** - a level in which students have received fewer badges is more likely to see quitting behavior in future student
- **Interest** - a student who revisits a level is less likely to quit the level
- **Effort** - a student who either spends under 2 minutes or over 5 minutes on average across levels is more likely to quit future levels.
- **Low competence** and/or **disengagement** - a student who has quit more levels in the past is more likely to quit a future level.

Conclusion

- An automated detector of student quitting behavior in a learning game
- Superior performance of level-agnostic model
  - Emphasis on generalizable student behavior
  - Ability to transfer to new levels and the levels with limited data

Limitations

- Choice to label all data in a student's visit as quit
  - We may intervene too early interfering with student persistence
- Generalizability
  - Students in this dataset are of similar age range and live in the same area

Future Work

- Application in Physics Playground
  - Identify struggling students and deliver appropriate cognitive and affective supports
- Understand why students quit a level to personalize the support
- Additional insights from affect detection
- Study the prediction performance as a function of time in the level visit

Some Useful Links

- **Link to play PP game** - http://tiny.cc/quit_pred_game
- **Scripts for feature engineering and modeling** - http://tiny.cc/quit_pred_code

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