Presentation: Learning Behavior and Cognitive Bias from Web Logs

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I. Introduction

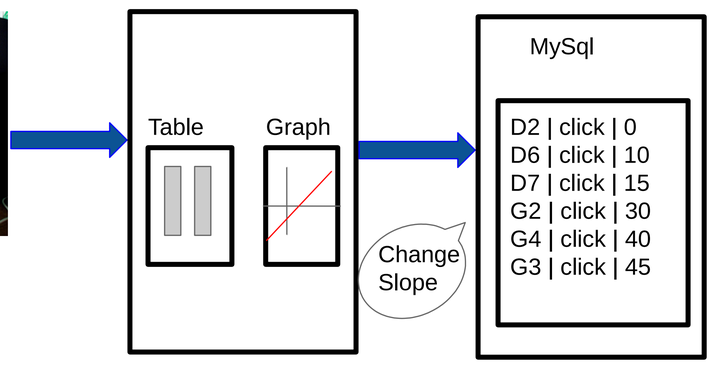
- An approach to model and analyze learning behaviour of students in a graph based e-learning tool.
- Derived models to classify the students and identify their computational thinking levels as well as cognitive preference towards either graph or data based learning.

Students who can link algebraic functions to their corresponding graphs perform well in STEM courses and is an indicator of computational thinking.

It is challenging to assess whether students are linking the concepts.

Traditional methods to analyse computational thinking- Tests, video analyses, interviews, surveys.etc

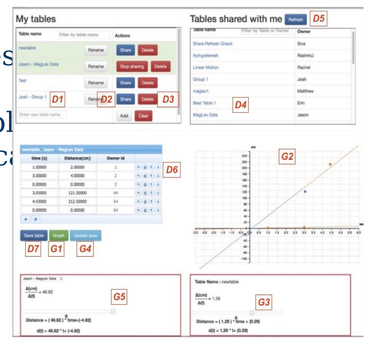
- We use web logs collected by a smart classroom web server to infer learning behavior
- We collect the clickstream, i.e, click and mouse movement data as users interact with the web portal
- Research* indicates that there are more than 67% correlation between eye movement and mouse movement.



II. Design and Setup

The portal

- Moodle- login
- Perform activities
- Collect the data
- Enter data in tabl
- Visualize graphica



Currently used by Grove City Schools

Published in FiE 2017

Over 1400 students have used the portal since 2016

Learning Analytics:

- Learning Analytics: the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs[1]
- Major steps in LA process[1]:
  - Data Collection; Analytics and action; Post processing
  - The challenge is to define the right Objective / Indicator / Metric (OIM) triple before starting the LA2
  - Objective: Understand computational thinking/learning behaviour in terms of linking concepts of graph and data.
  - Indicator: Actions with the web components
  - Metric: Results from traditional analysis methods-participation levels

Our Data

- Source #1: Summer institute with 18 Math Instructors
- Source #2: Grove City students; 15 classes; 365 students

III. Feature Engineering

Web Resources: Web resource is a facility provided in a web application. To do meaningful analysis divide the web elements into data components and graph components this group.

Label	Component Name	Associated Behaviour
D1	My Tables - Table Name	Data
D2	My Tables - Share	Data
D3	My Tables - Delete	Data
D4	Tables Shared with me-Table name	Data
D5	Tables Shared with me-Refresh	Data
D6	Input Table	Data
D7	Save Table	Data
G1	Graph Button	Graphical
G2	Graph - SVG	Graphical
G3	Slider- Primary Table	Graphical
G4	Update Axes	Graphical
G5	Slider- Secondary Table	Graphical

Predictive features:

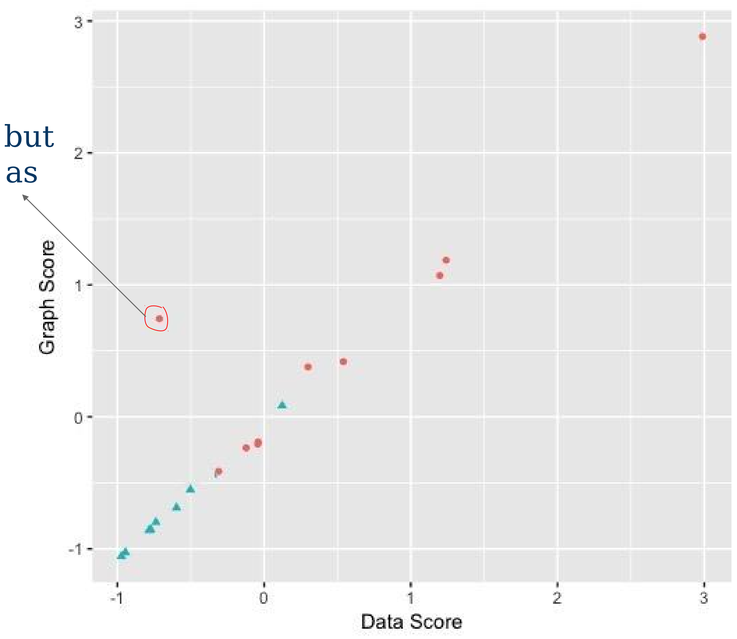
- Inter data interactions
- Inter graph interactions
- Intra data interactions
- Intra graph interactions
- Intra data time spent
- Intra graph time spent
- Data count in patterns
- Graph count in patterns

Trying to predict participation levels each student as “high” or “less” participating

IV. Early Results

High: graph score+data score >=-0.8
Less: graph score+data score <-0.8
17 out of 18 users classified accurately

Low data but classified as “high”



Results on classroom data

✔ Found classes with many computational thinking oriented students

✔ Identified students with possible cognitive bias
- 77 students out of 365

Mean graph score for workshop data	SD in graph score for workshop data	Mean graph score for classroom data	SD in graph score for classroom data
0.1861	1.751	0.1769	1.819

Mean data Score for workshop data	SD in data score for workshop data	Mean data score for classroom data	SD in data score for classroom
0.2733	1.8724	0.3016	1.7957

VI. References

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