

What Do Students Know?

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Outline

Introduction
Process Overview
Data Gathering
Data Analysis
Conclusions
Questions?

Outline

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Process Overview

Data Gathering

Agar

HOMR

Data Analysis

Item Evaluation

Topic Identification

Conclusions

Questions?

Thoughts

- ▶ **Quantitative Assessment and Continuous Improvement**
 - ▶ Program assessment is hard – have you seen a good answer?
- ▶ Data mining is a vibrant field
 - ▶ But it requires more input data than most courses produce

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UCR's Plan

Develop a process to

- ▶ Enable easy collection of detailed score data
- ▶ Require minimum input from instructors
- ▶ Provide numeric assessment results
- ▶ Make the process easy to use

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- ▶ Courses taught as normal, scores recorded at the question level
 - ▶ Score matrix S (students \times items)
- ▶ Course topics / objectives identified
- ▶ Scores analyzed or annotated by instructor for question \rightarrow topic relevance
 - ▶ Relevance matrix R (items \times topics)
- ▶ Topics related to curriculum-level objectives – “program outcomes”
 - ▶ Course matrix C (topics \times outcomes)

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Process Overview

$$S \times R \times C = O$$

- ▶ O is students \times outcomes
- ▶ Average columns of O for numeric outputs
- ▶ Course matrix C done once
- ▶ S requires lots of data
- ▶ R is tedious, but *may* be automated

Data Gathering

- ▶ Two major tools, Agar and HOMR
- ▶ Score data stored in spreadsheets, not SQL
 - ▶ Minimal format requirements
 - ▶ Easy to adopt
 - ▶ Gnumeric/ssconvert very useful for automation
 - ▶ Integrating with Moodle

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Not just another Automated Grader

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Rubric

The screenshot shows the 'Rubric' configuration window in the 'Agar - as10.agw' application. The window has a menu bar with 'File', 'Actions', 'Wizards', 'Options', and 'Help'. Below the menu bar are two tabs: 'Rubric' (selected) and 'Grading'. The main area is split into two panes. The left pane lists various test types: Compile, Bulk Test, C++ Driver Tests, Correct Filename, Diff Test, Early/Late Points, Edit Distance Test, Exit Code, Fail on Line Wraps, Fail on Windows Code, Failure, Invoke Make, Ontime Test, Regexp Code, and Success. The right pane shows a tree view of the rubric structure: 'Rubric' (expanded) contains 'Submission Manager' and 'Tests' (expanded). 'Tests' contains 'Compile' (expanded) and 'Style' (expanded). 'Style' contains: 'No Global Variables', 'Good Names', 'Proper Indentation and Spacing', 'Line Wraps', 'Other Style Issues', and 'Good Comments'. Below the tree view, there are several text input fields: 'Prompt for player names', 'Prompt players when it is their turn', 'Reasonable card layout', 'Players can "choose" 2 cards', 'Non-matching choices are flipped back over', 'Matches removed from board', and 'Game is playable to the end'. At the bottom of the window, there are fields for 'Points' (set to 1), 'Success Rate' (set to 0%), and a 'Configure Comments' button. An 'Add to Rubric' button is located at the bottom left of the main area.

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- ▶ Easy viewing of submissions
- ▶ Annotation
- ▶ Automatic mailback of results and feedback

Comments

New Comment

Comment Name

Rubric Item

Point Value

Description

Add to current

All rubric items Value Type

Add/subtract Percentage Set value

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Annotations

Comments

- q 01: wrong
- q 02: wrong
- q 03: wrong
- q 04: wrong
- q 05: wrong

26. Show the B.T tree that results from taking the empty tree and inserting the following values, in order:
 10, 20, 18, 20, 40, 40, 40

27. Given an empty hash table of size 11 and the (not very good) hash function $h(x) = 2x - 1$, show the final results of these operations (in order). Use linear probing to resolve collisions.

Insert 1	10	20	6	7						
Insert 6										
Insert 12										
Remove 1										
Insert 7										
Insert 23										

Points: -1

Rubric Item Question #02

New Comment Prev Page Prev Sub Next Sub Next Page Done

Current Page 4 Current Submission

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Remove redundant work, don't replace the human.

Support Existing Paradigms

- ▶ Annotation interface for **red-pen** grading.
- ▶ Merge features for breaking up workload among multiple graders

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HOMR

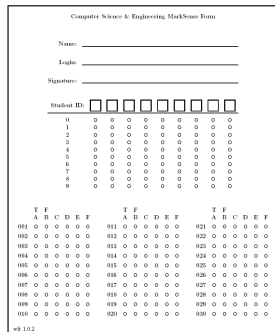
Homebrew Optical Mark Recognition

- ▶ C++ program reads in
 - ▶ Page configuration file
 - ▶ Number of bubbles to extract
 - ▶ Image filename
- ▶ Computer vision to normalize page
- ▶ AdaBoost classifier to classify each bubble
- ▶ Produces “0” or “1” to stdout for each bubble

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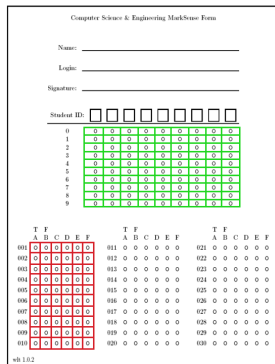
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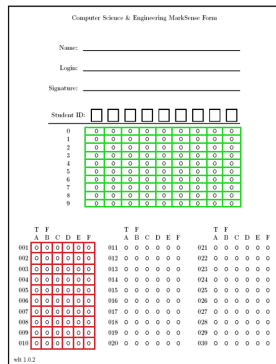
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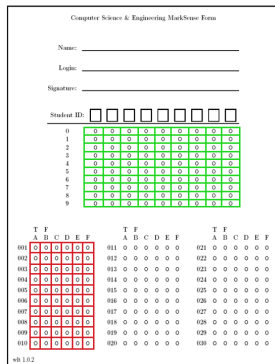
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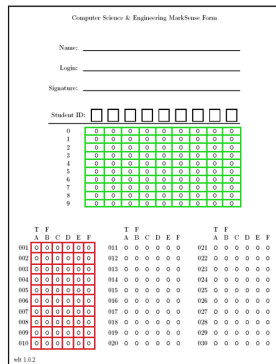
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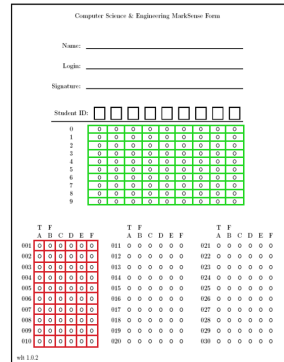
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Data Analysis

Two major techniques

- ▶ Evaluate individual items
- ▶ Determine which items correspond to the same topic.

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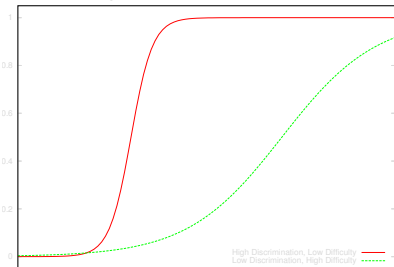
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Item Evaluation

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- ▶ Identify difficulty β / discrimination α
- ▶ Given β , α is percent correct (below is wrong, above is right).
- ▶ β is the split that maximizes α

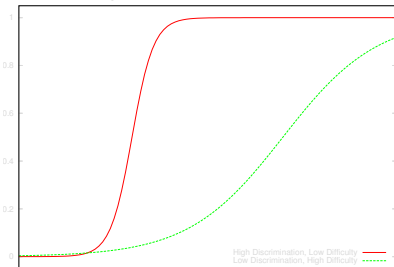
Sample Characteristic Curves



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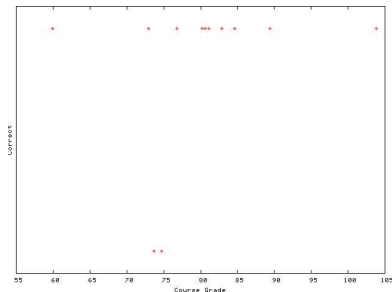
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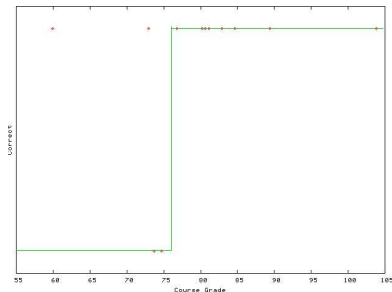
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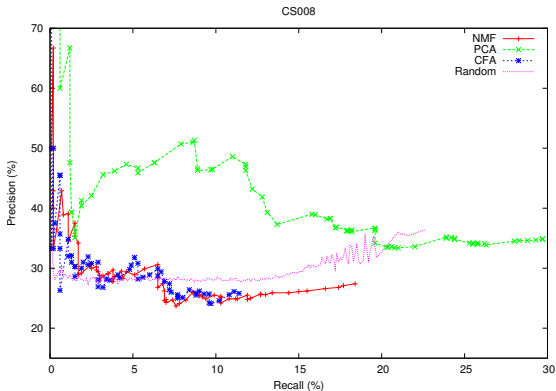
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Results



Conclusions

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- ▶ Some analysis is easy
- ▶ Some analysis is hard
- ▶ Score data is **noisy**
- ▶ Must be mindful of concepts from educational statistics

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