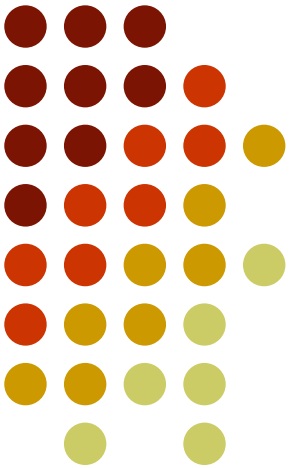
Enhancing Online Learning Performance: An Application of Data Mining Methods



CATE 2004

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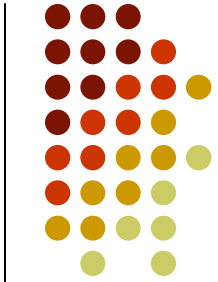
Outline

- LON-CAPA Overview
- Problem Statement
- Classification Methods
- Combination of Multiple Classifiers
- Weighting the features, using GA to choose best set of weights
- Experimental Results
- Contribution
- Conclusion

LON-CAPA



- This research is a part of the latest online educational system developed at Michigan State University (MSU), the Learning Online Network with Computer-Assisted Personalized Approach (LON-CAPA).
- Learning Content Management System
  - 9 high schools, 2 community colleges, and 17 universities nationwide
- Assessment System
  - Online assessment with immediate feedback and multiple tries
  - Different students get different versions of the same problem
  - Different options, graphs, images, numbers, or formulas
- Open-Source and Free (GPL, Runs on Linux)

LON-CAPA Data

- Three kinds of growing data sets:
  - Educational resources: web pages, demonstrations, simulations, individualized problems, quizzes, and examinations.

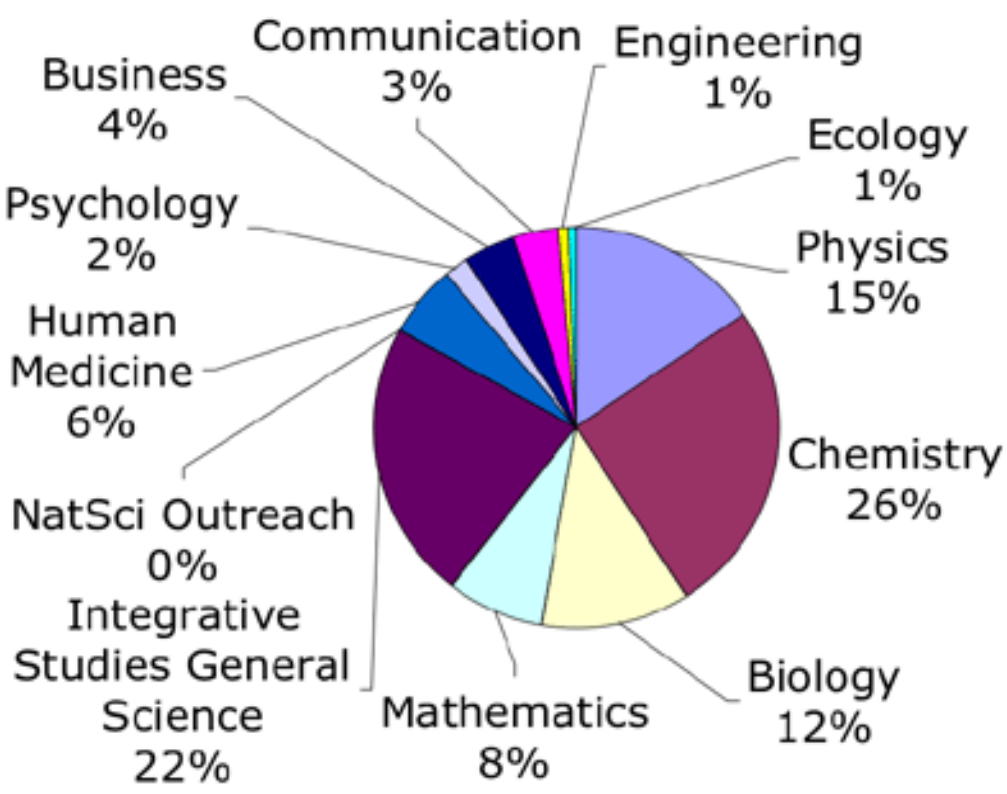
23,000 content pages
18,600 homework and exam problems
1,100 simulations and animations

12,500 images
500 movies

  - Information about users who create, modify, assess, or use these resources.
  - Data about how students use and access the educational materials

MSU – Fall 2003

- 50 courses used LON-CAPA at MSU
- Total student enrollment approximately 3,067 (out of 13,400 total global student-users)
- Disciplines included Advertising, Biochemistry, Biology, Chemistry, Finance, Geology, Math, Physics, Plant Biology, Statistics for Psychology



Data Distribution

- LON-CAPA collects data for every single access to the resources in both activity log and student database
- Logs are not only huge but also distributed and specific to a web-based educational system (LON-CAPA)
- Intelligent automated tools needed to discover relevant, useful, and interesting patterns
- Apply the discovered rules to produce more intelligent system

Knowledge Discovery Process

Data Integration, removing inconsistency, …

Data Cleansing, correcting errors, missing values

Discretization, transform continuous to categorical

Feature Selection, features are more relevant

Mining process, rule discovery

Post-processing,

- Large set rules → simplify
- 1) More comprehensible, 2) More interesting
- Use combination of objective and subjective approaches

Data Mining Tasks

- **Classification:**
  - The goal is to predict the class variable based on the feature values of samples …Avoid Overfitting
- **Clustering:** (unsupervised learning)
- **Association Analysis:**
  - Find the binary relationship among the data items
  - Any feature variable can occur both in antecedent and in the consequent of a rule.

Statement of Problem(1)

Our claim is that data mining can help to design better and more intelligent educational web-based environment

Can help instructor to design the course more effectively, detect anomaly

Can help students to use the resources more efficiently

Statement of Problem (2)

Can find *classes* of students. Groups of students use these online resources in a *similar* way

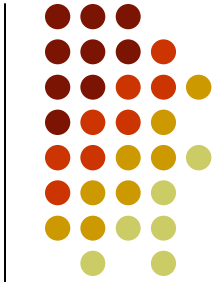
Predict for any individual student to which class he/she belongs

Can help the instructor provide appropriate advising in a timely manner

Data Sets: MSU online courses

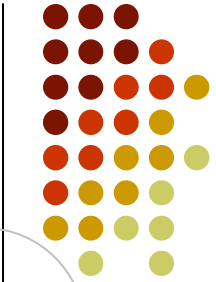
Course	# of Students	# of Problems	Size of Activity log	Size of useful data	# of Transactions
ADV 205	609	773	82.5 MB	12.1 MB	424,481
BS 111	402	229	367.6 MB	50.2 MB	1,689,656
CE 280	178	196	28.9 MB	3.5 MB	127,779
FI 414	169	68	16.8 MB	2.2 MB	83,715
LBS 272	102	166	73.9 MB	15.3 MB	585,524
MT 204	27	150	5.2 MB	0.7 MB	23,741
MT 432	62	150	20.0 MB	2.4 MB	90,120
PHY 183	306	255	210.1 MB	26.8 MB	889,775
PHY 231c	99	247	67.2 MB	14.1 MB	536,691
PHY 232c	83	194	55.1 MB	10.9 MB	412,646
PHY 232	220	259	138.5 MB	19.7 MB	981,568

Extracted Features



1. Total number of attempts
2. Total no. of correct answers (Success rate)
3. Success on the first try
4. Success on the second try
5. Success after 3 to 9 attempts
6. Success after 10 or more attempts
7. Total time until the correct answer
8. Total time spent, regardless of success
9. Participation in online communication

Classifiers

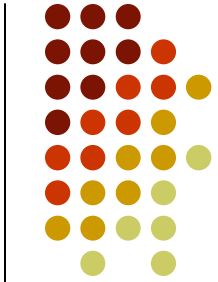


- Non-Tree Classifiers (Using MATLAB)
  - Bayesian Classifier
  - 1NN
  - kNN
  - Multi-Layer Perceptron
  - Parzen Window
  - Combination of Multiple Classifiers (CMC)
  - *Genetic Algorithm (GA), Optimizer*

Decision Tree-Based Software

- C5.0 (RuleQuest <<C4.5<<ID3)
- CART (Salford-systems)
- QUEST (Univ. of Wisconsin)
- CRUISE [use an *unbiased* variable selection technique]

Fitness/Evaluation Function



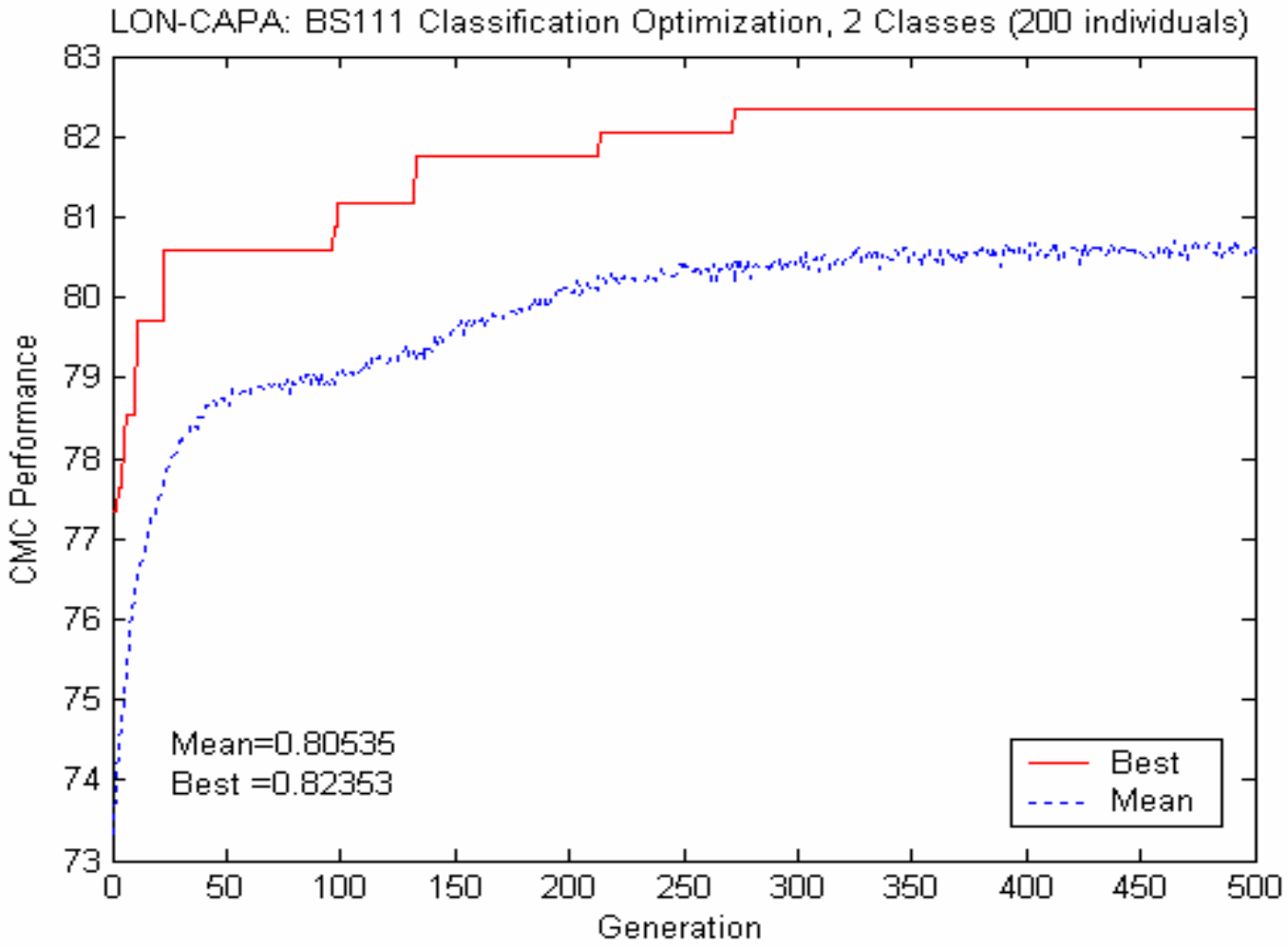
- 5 classifiers:
  1. Multi-Layer Perceptron — 2 Minutes
  2. Bayesian Classifier
  3. 1NN
  4. kNN
  5. Parzen Window
  - CMC — 3 seconds
- Divide data into training and test sets (10-fold Cross-Validation)
- **Fitness function: performance achieved by classifier**

$$\text{Error Rate in each round} = \frac{\text{Total missclassified of test examples}}{\text{Total number of test examples}}$$

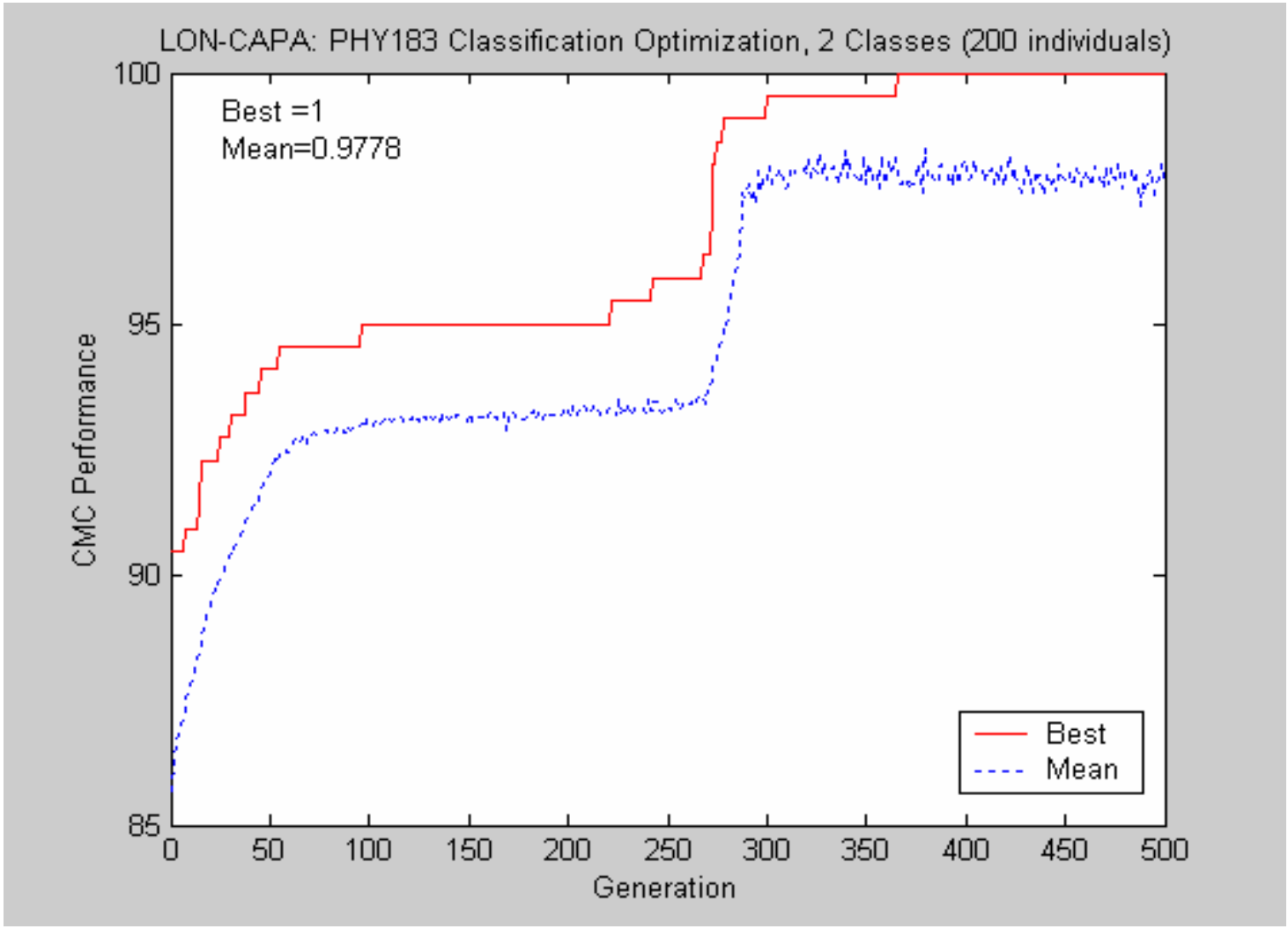
Results without GA

Data sets	Bayes	1NN	*k* NN	Parzen Window	Classification **Fusion**
ADV 205, 03	55.7	69.9	**70.7**	55.8	**78.2**
BS 111, 03	52.6	**62.1**	55	59.7	**71.2**
CE 280, 03	66.6	73.6	**74.9**	65.2	**81.4**
FI 414, 03	65	**76.4**	72.3	70.3	**82.2**
LBS 272, 03	**72.3**	70.4	69.6	65.3	**77.6**
MT 204, 03	63.4	**71.5**	68.4	56.4	**82.2**
MT 432, 03	67.6	77.6	**79.1**	59.8	**84**
PHY 183, 03	59.6	66.5	**70.4**	54.4	**76.6**
PHY 231c, 03	56.7	**74.5**	72.6	60.9	**80.7**
PHY 232, 03	59.9	**73.5**	71.4	56.3	**79.8**

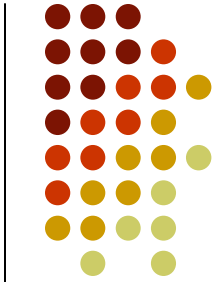
Results of using GA



Results of using GA



GA Optimization Results

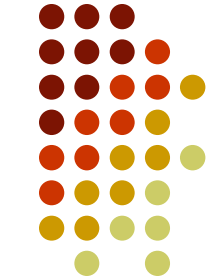


Data sets	**Without GA**	**GA optimized**	**Improvement**
ADV 205, 03	78.19 ± 1.34	89.11 ± 1.23	10.92 ± 0.94
BS 111, 03	71.19 ± 1.34	81.09 ± 2.42	9.82 ± 1.33
CE 280, 03	81.43 ± 2.13	92.61 ± 2.07	11.36 ± 1.41
FI 414, 03	82.24 ± 1.54	91.73 ± 1.21	9.50 ± 1.76
LBS 272, 03	77.56 ± 0.87	87.61 ± 1.03	10.11 ± 0.62
MT 204, 03	82.24 ± 1.65	91.93 ± 2.23	9.96 ± 1.32
MT 432, 03	84.03 ± 2.13	95.21 ± 1.22	11.16 ± 1.28
PHY 183, 03	76.56 ± 1.37	87.14 ± 1.69	9.36 ± 1.14
PHY 231c, 03	80.67 ± 1.32	91.41 ± 2.27	10.74 ± 1.34
PHY 232, 03	79.77 ± 1.64	88.61 ± 2.45	9.13 ± 2.23
Total Average	**78.98 ± 12**	**90.03 ± 1.30**	**10.53 ± 56**

Features importance

Feature	Importance %
Average Number of Tries	18.9
Total number of Correct Answers	**84.7**
# of Success at the First Try	24.4
# of Success at the Second Try	26.5
Got Correct with 3-9 Tries	21.2
Got Correct with # of Tries $\geq$ 10	**91.7**
Time Spent to Solve the Problems	32.1
Total Time Spent on the Problems	36.5
# of communication	3.6

Conclusion

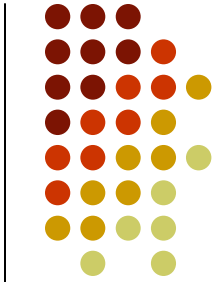


- Four classifiers used to segregate the students. CMC improves accuracy significantly.
- Weighting the features and using a genetic algorithm to minimize the error rate improves the prediction accuracy by at least 10% in the all cases.
- In the case of the number of features is low, the feature weighting is working better than feature selection.

Contribution

- A new approach to evaluating student usage of web-based instruction
- An approach that is easily adaptable to different types of courses, different population sizes, and different attributes to be analyzed
- Rigorous application of known classifiers as a means of analyzing and comparing use and performance of students who have taken a technical course that was partially/completely administered via the web

Future work



Can find some associative rules between students' educational activities

Can help instructors predict/describe the approaches that students will take for some types of problems

Can be used to identify those students who are at risk, especially in very large classes

Questions

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