Minnesota State University Mankato

MavCLASS

Deep, Real-World Learning Analytics to Enhance Student Success

SESSION OVERVIEW

- Introductions
- What are learning analytics?
- Why should we care?
- Math 98, and our goals and methods
- MavCLASS
- Implications for practice
- Next steps

INTRODUCTIONS

WHAT ARE LEARNING ANALYTICS?

"[the] Field associated with deciphering trends and patterns from educational big data, or huge sets of student-related data, to further the advancement of a personalized, supportive system of higher education."

- 2013 Horizon Report

What Are Learning Analytics?

BIG DATA

Small Data (hi!)

What Are Learner Analytics?

Using the **individual data trail** resulting from a **student's myriad activities** in a specific learning environment to provide more **meaningful feedback and individuated pathways** to help **motivate them** toward more thoughtful and productive learning behaviors.

- Minnesota State Mankato team's working definition

TAKE 2. THEN TAKE 5.

Intuitively...

- Why might having individualized information about learners' assessments help them learn?
- Specifically --
  - What information would you need?
  - What would you do with that information?
  - What would you hope would happen as a result of what you did? What would students do? What would faculty do?

So What Did We Do?

- Math 98, math remediation course
- 400-650 students enrolled per semester
- Taught by a single instructor in lecture/ discussion section model
- Many GAs for discussions
- To pass the course, students must achieve >= 70%-72% overall (depending on curve) and take the final

So What Did We Do?

- Summative assessments
  - 3 in-class exams, 30%
  - 1 final exam, 20%
- Formative assessments
  - 22 homework tasks (lowest 2 dropped), 20%
  - 6 quizzes (lowest 2 dropped), 15%
- Attendance
  - 27 participation card “mastery checks” (lowest 2 dropped), 15%

Our Thesis

1. Providing struggling students with **increased instances of personalized feedback** would result in **greater degrees of help-seeking** among students who received that feedback.
2. This would, hopefully, result in **greater pass rates** for the course, as well as **greater knowledge gains** for students engaged in help-seeking.

- Kluger and Denisi, 1996

DEFINING VARIABLES

1. Personalized feedback = alerts to students who are struggling
2. Help-seeking =
   - visits to the Center for Academic Success
   - visits to office hours with the professor
   - visits to office hours with the GAs
3. Pass rates = pass rates
4. Knowledge gains = relative amount of knowledge about the subject increases further (struggling students “gain on” other students)

To Answer Our Own Questions…

1. Q: What information would we need?
   A: Individualized learner assessment data -- as much as we could get.
2. Q: What would we do with that data?
   A: Use it to provide targeted, individualized feedback suggesting learning pathways from a human source.
3. Q: What did we hope would happen?
   A: Learners would seek help and would learn more and pass the class.

The Mechanism

- The Maverick Comprehensive Learning Analytics Support System (MavCLASS)
- Integrates data across two systems: Desire2Learn (LMS) and Cengage WebAssign homework bank (more coming)
- Pulls data, cleans it up, and shows various reports on groups and individuals to GAs

WHY NOT OFF-THE SHELF?

- LMSs are “deep and narrow” -- and our assessment data are often deep and wide.
- Third-party tools “flattened” data into what would have essentially been summary data -- you lose what’s interesting.
- We wanted to begin to help develop an open-source tool that others might benefit from.

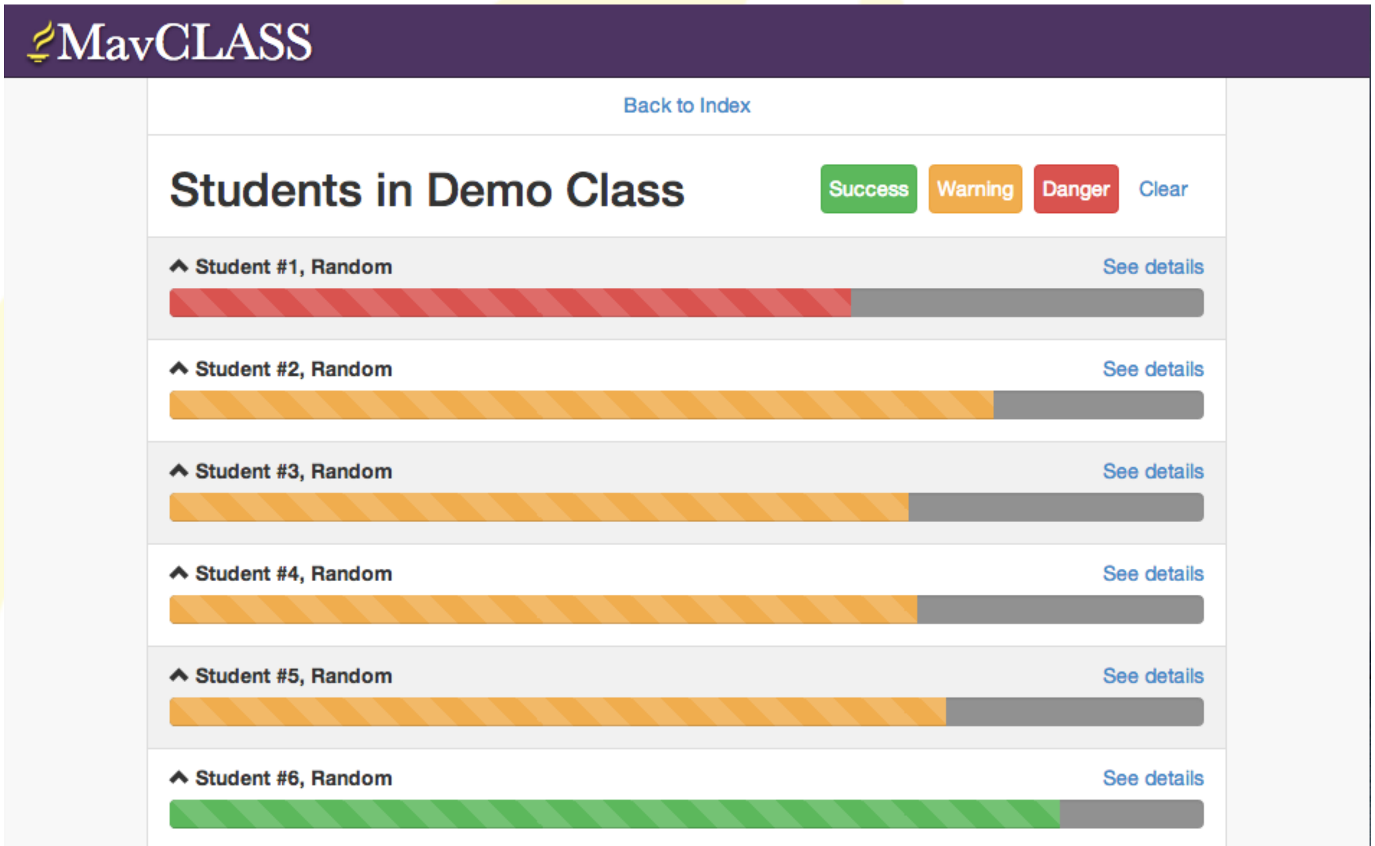
What Resources Did We Assign?

- 1 Graduate student programmer
- 1 Intrepid professor
- 2 Technical/data analysts
- 2 Supervisors/project leads

THE INTERVENTION

- GAs were handed a standard starting script designed by instructional designers and the course instructor
  - Told students their current “status”
  - Encouraged them to seek help in various ways (suggested remediated problems, “come see me”, go see instructor, go to the CAS
- Students who fell below benchmarks got alerts
- They could customize the script

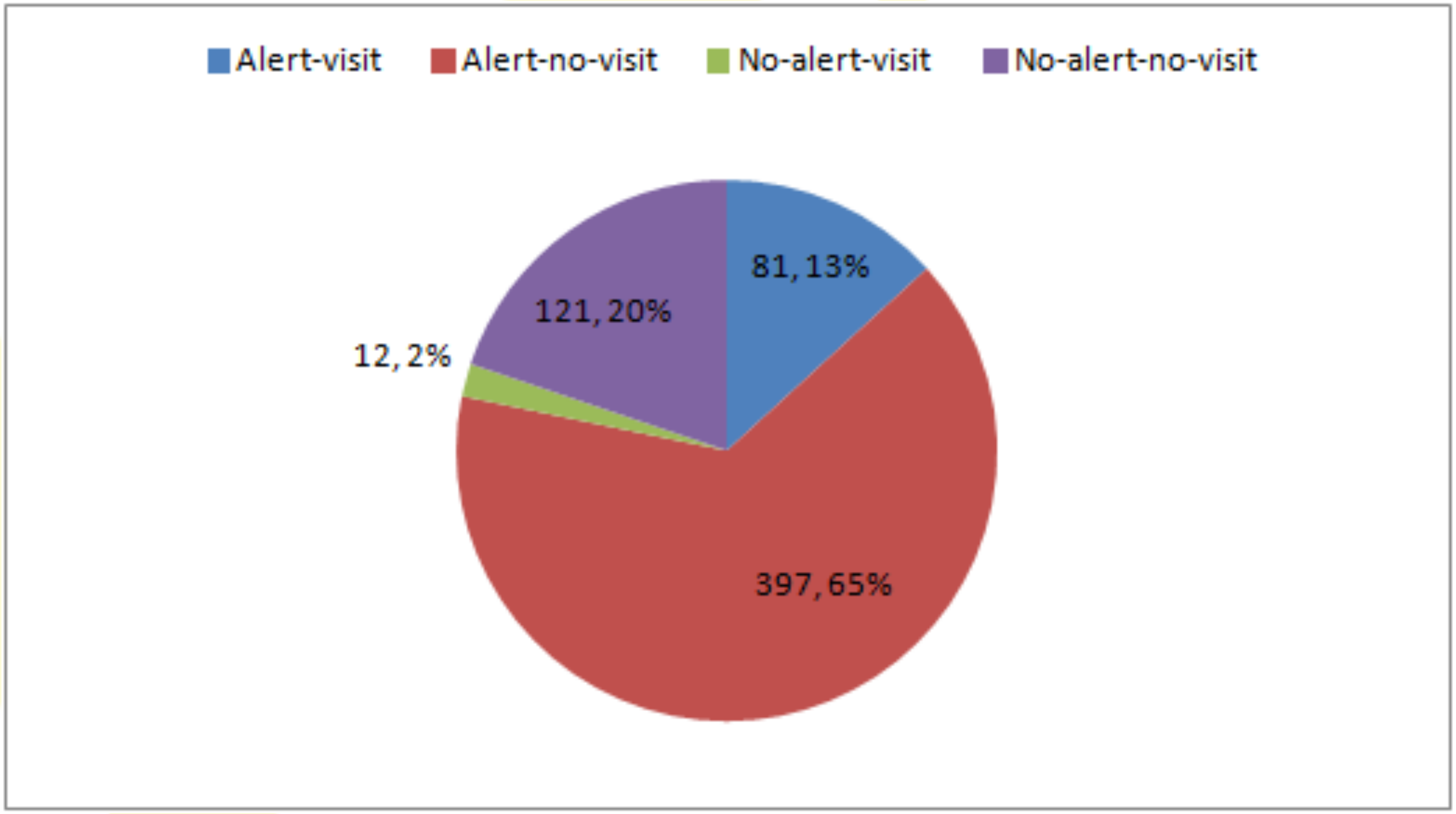
Alright, Let's see it!



THE OUTCOMES

- Full (and emerging) analysis can be found here.
- We *think* we're seeing students responding to the alerts by engaging in more help-seeking behaviors.
- We *seem* to see students who are getting alerts "gaining" on students who did not get alerts.

HELP-SEEKING BEHAVIORS AND ALERT MESSAGES

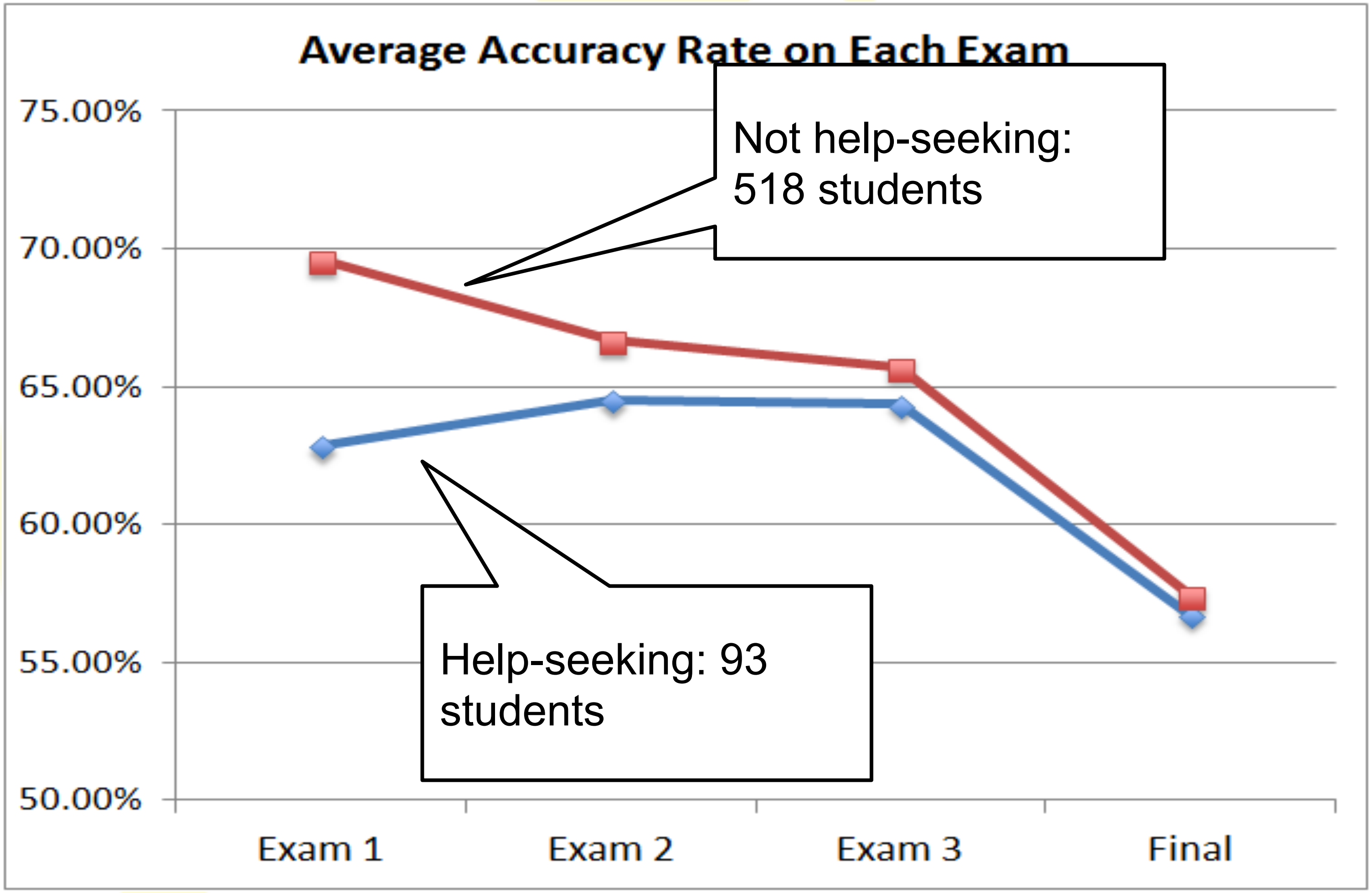


Help-Seeking Behaviors and Alert Messages

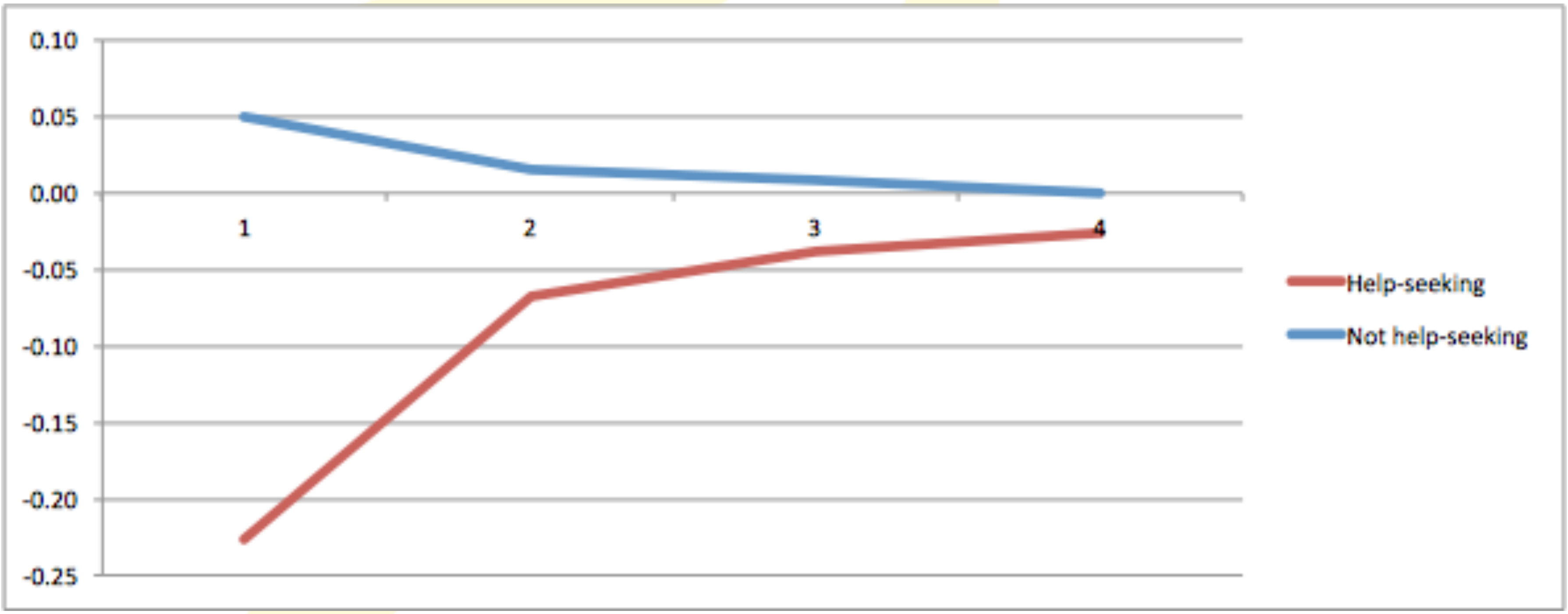
- Compare:
  - Group 1: Students who visited CAS, 93 students
  - Group 2: Students who did NOT visit CAS, 518 students

Group 1 received more alert messages than Group 2.
The difference is statistically significant ($p<.1$)

Comparing Between Groups



HELP-SEEKING STUDENTS ARE MAKING PROGRESS!



THE OUTCOMES

"In the past, students have not responded to recommendations to come to office hours. After using MavCLASS, student bookings for office hours increased substantially, with the instructor, the graduate assistants, and the tutoring center. We believe this is most likely due to the personalized nature of the alerts afforded by MavCLASS."

- Professor Jeff Ford

THE OUTCOMES

1. Students seek help? -- looks like it!
2. Students seeking help learning more? -- looks like it...maybe?
3. Students pass the class? Not yet.

NOTE AND CAUTION!!!!!!

- These data and methods are not perfect;
- We’re not selling anything;
- We’re not suggesting we have found a magic elixir for learning;
- We are not even entirely sure what our pilot data are telling us quite yet (but we’ll know more soon).

IMPLICATIONS FOR PRACTICE

Implication 1: The data are messy, so roll up your sleeves.

- Data are plural (and getting more so)
- Data are non-normalized
- Integrating this and making it work can be highly contextual
- This takes time to build in-house expertise (so get started)

Implications for Practice

Implication 2: Meaningful learner analytics requires early, meaningful assessment.

Implications for Practice

Implication 3: We believe, but can’t yet confirm, that personalized feedback from a human source has a positive motivational interaction with students’ help-seeking behavior.

Implications for Practice

Implication 4: We believe, and have preliminary data suggesting (perhaps), that alert systems may activate some students' help-seeking behavior.

IMPLICATIONS FOR PRACTICE

Implication 5: A highly-structured, highly-knowable, highly-curated course has many structural advantages over a less-structured course **in terms of analytics**.

Implications for Practice

Implication 6: We may need to reconsider our obsession with semesters and credit hours in order to help certify the significant knowledge gains being made by students who are working hard and seeking help actively.

Implications for Practice

Implication 7: Engaging in this type of pilot can help provide a mechanism for different groups to think about how they collect and share data in ways that will be more meaningful for the future.

IMPLICATIONS FOR PRACTICE

Implication 8: Know what data story you want to tell, and be willing to accept the true stories about yourself that the data may tell you:

- What data do you need?
- What do you want to do with it?
- What do you want your outcomes to be?

NEXT STEPS

- Possible random assignment experimental design
- Instructional design implications
  - Competency-based instructional model (extended semester, emporium style)
  - Explore feedback variables: source, goal orientation, efficacy, attributions, etc.
  - Item analysis and backward redesign

NEXT STEPS

- Continue developing MavCLASS
  - More easily integrate new data sources
  - Dive deeper into data
  - Release open source

THANK YOU!

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The intrepid, hard-working students of Math 98