

# Mining the Algorithmic Sublime:

## A Qualitative Analysis of Learning Analytics Discourse

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# My central argument

- Learning analytics are presented as an ideology.
- This ideology is what I call the *algorithmic sublime*.
- There are four basic patterns in this ideology:
  1. Modal Bootstrapping
  2. Ethicality
  3. Epistemic Displacement
  4. Collect It All

# What this presentation is and is not

- This presentation IS....
  - A discussion about the rhetoric and language use surrounding learning analytics.
  - A discussion about how learning analytics are legitimated and justified in scholarly literature.
  - An analysis of the arguments deployed by learning analytics proponents.
- This presentation IS NOT...
  - An appraisal of learning analytics tools.
  - An evaluation of the technical aspects of learning analytics.
  - An investigation of how learning analytics are actually used.

# What is an ideology?

- An ideology is a representation of the world.
- Ideologies are solutions that address real problems.
- Ideologies also mask other problems and establish hidden power relations.
- Ideologies are found in texts—in discourse.
- Ideologies rely on assumptions that, left hidden, perform rhetorical work. Ideologies *do* things.

(Fairclough, 2003)

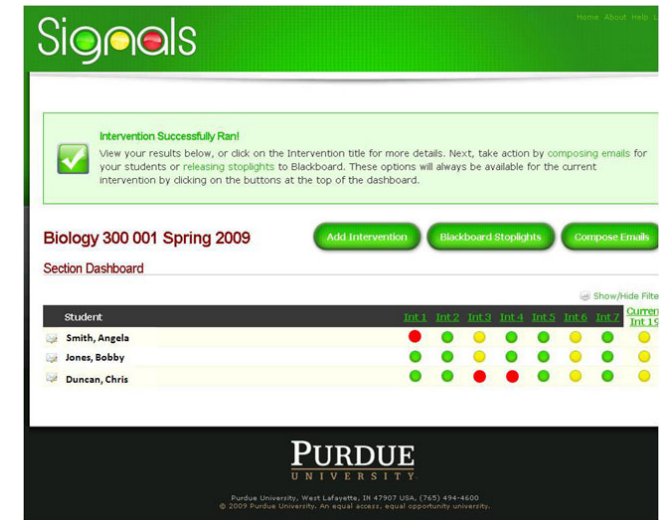
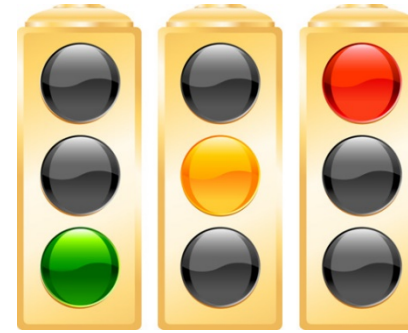
Example of an ideology: “Success is the result of hard work.”

# What are learning analytics?

- Learning analytics are the “measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” (Siemens, 2011)
- Large-scale collection and analysis of student data for the purpose of providing feedback to students, instructors, and organizations
- Relatively recent terminology – 2007 to present
- Enabled by digital, linked nature of online learning

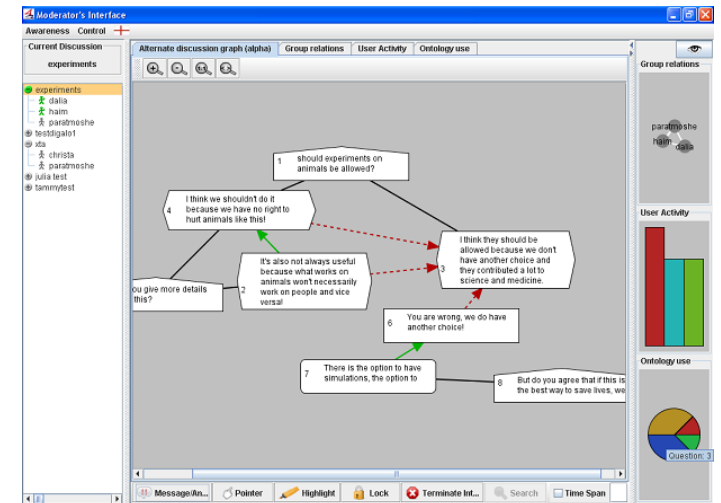
# Types of learning analytics

1. description dashboards
2. performance predictors
3. dynamic modelling
4. social network analysis
5. automated writing analysis



<http://er.educause.edu/articles/2010/3/signals-applying-academic-analytics>

(Buckingham Shum, 2012)



<http://www.argonaut.org/>

# Research problem

- Previous studies suggest that learning analytics are represented ideologically (Prinsloo, Archer, Barnes, Chetty, & Van Zyl, 2015)
- No research yet exists that describes how learning analytics discourse functions as an ideology.
- This is a significant problem given how education is moving toward online formats.
- Practitioners will increasingly confront this ideology.

# Research questions

- How does learning analytics discourse function as an ideology?
  - What ideological patterns does learning analytics utilize?
  - How might the ideology of learning analytics be characterized?
  - What power relations does the ideology establish?



# Methodology

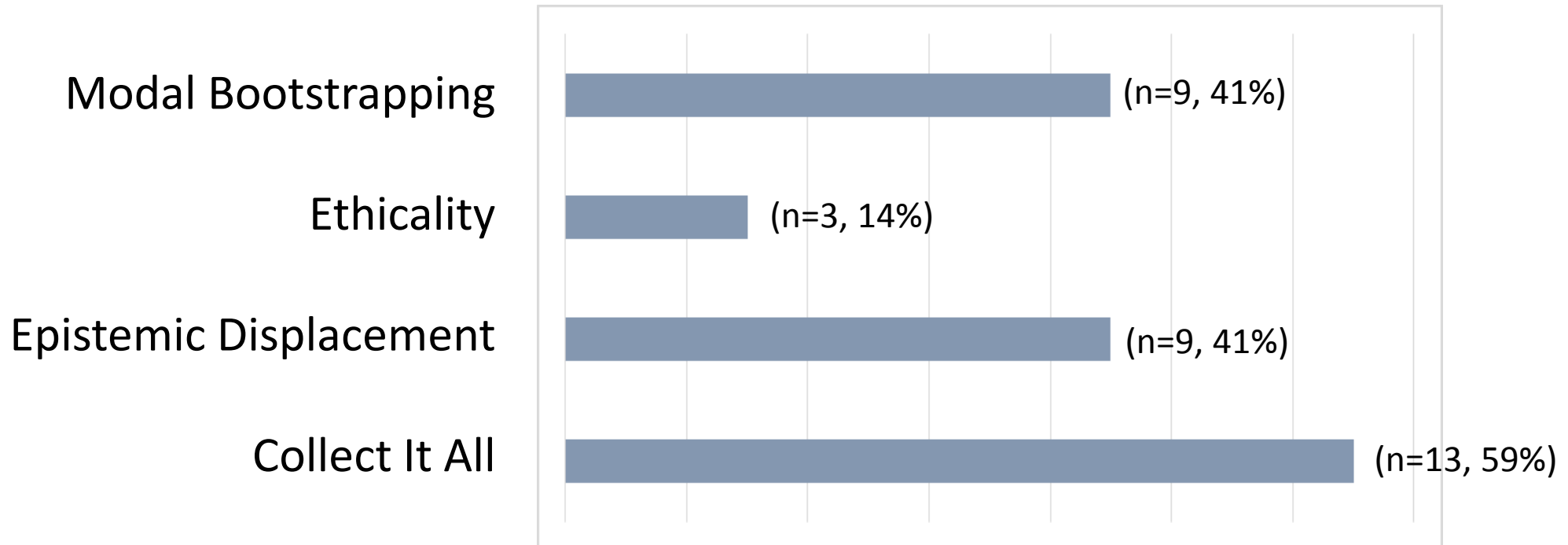
- “Mine” learning analytics discourse for ideological patterns
- Use Critical Discourse Analysis (CDA)
- CDA is a qualitative methodology that “aims to investigate critically social inequality as it is expressed, signalled, constituted, [and] legitimized...by language use” (Wodak, 2001, p. 2)
- One goal of CDA is to demystify and decipher ideologies (Wodak, 2001, p. 10)
- Follow recommendations for CDA outlined by Fairclough (2001, 2003)

# Data corpus

- Retrieved through a systematic review online distance learning literature as well as literature from related fields, including:
  - educational data mining (EDM)
  - learning analytics & knowledge (LAK)
  - behavioral science
- Search included journals, reports, monographs, conference proceedings, and other gray literature from 2005 to 2015.
- Search terms included: “learning analytics,” “data analytics”
- Sources were included in the study if they discussed learning analytics
- n=52 total documents analyzed

# Results

- 42% (n=22) of documents contained ideological patterns
- There are four patterns:



# Pattern 1: Modal bootstrapping

- A *modality* expresses an aspect of existence
- For example, in modal logic, modal verbs such as *can*, *will*, and *should* express possibility, necessity, and obligation
- “Bootstrapping” refers to a self-starting mechanism
  - Horatio Alger stories: “*He pulled himself up by his bootstraps.*”
  - “*booting up*” a computer
- Bootstrapping refers to an impossible action.
- Modal bootstrapping → using modal verbs in an impossible way

# Bootstrapping from possibility to necessity

“IT leaders **may** soon become critical partners with academic and student affairs...”

“IT units **will** be called on to support analytics efforts. As a result, IT leaders **will** find that new expectations are being placed on their units. Staff **will** be required to have more than the traditional IT skills. They **will** need to be adept at mining data...”

(Campbell, DeBlois, & Oblinger, 2007, pp. 41, 55)

Impossible to conclude the necessity of a future possible contingent—it hasn't happened yet.

# Bootstrapping from is to ought

“The field **is** moving fast, with companies innovating to meet perceived markets.”

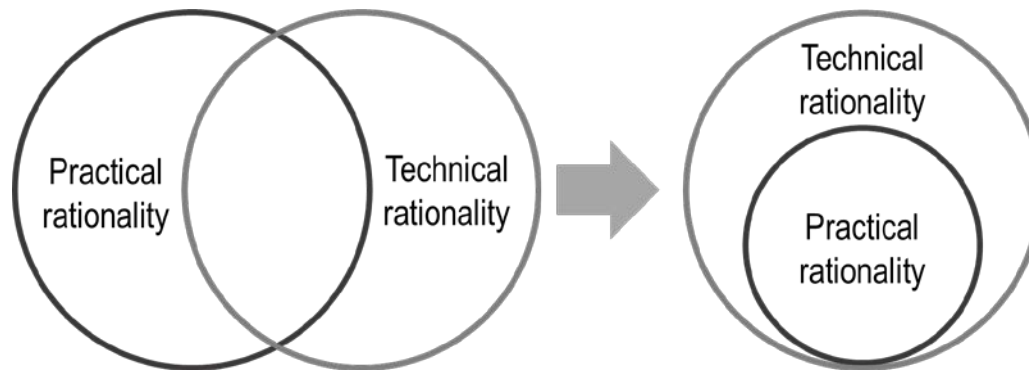
“To keep up, the normally slower pace of educational research and professional development **must** be accelerated...Institutions **should** collaborate on establishing trusted partnerships and robust mechanisms to share student data, analytics techniques and information visualization tools.”

(Buckingham Shum, 2012, p. 7)

An ethical obligation does not follow from a statement of fact.

# Pattern 2: Ethicality

- A portmanteau of “ethics” and “technicality”
- Pattern of subsuming *practical* rationality into *technical* rationality



- The question of ends becomes a question of how best to use learning analytics within their own constraints

# Example of ethicality

“Some people are quite concerned about the filter bubble that personalization and recommendation engines may create. We agree that there is a certain danger there, but we also believe that **more advanced algorithms** and ethical reflection can help us to address these issues. In any case, we believe that learning analytics can be used to put the user in control...”

(Duval, 2011, p. 14)

Conclusion: The solution to algorithms is more algorithms.

Discursive blinders focus on the technology and render alternative problem-solving solutions unthinkable.



# Pattern 3: Epistemic displacement

- Learning analytics are presented as a privileged, powerful, and universal way of knowing.
- The result is a displacement or marginalization of alternative ways of knowing.

# Example of epistemic displacement

“In the education sector decisions on didactics are often based mainly on **opinions**. It would be a good thing for those decisions to be supported by learning analytics.”

(Doove, 2013, p. 38)

Alternative ways of knowing are mere *opinions*.

In contrast, learning analytics generate *facts*.

In this source, no examples are given. The objective is to privilege learning analytics over other ways of knowing.

# Pattern 4: Collect it all

- “Collect it all” is a phrase used to encapsulate the mission of General Keith Alexander, director of the US National Security Agency
- Without stating why or for what purpose, learning analytics discourse urges increased data collection
- Data collection about students is seen as a revenue source or as research material

# Example of Collect it all

“The inclusion of data from other sources, such as **mobiles, sensors, physical world data, advising, and the use of university resources** such as libraries and tutors, will result in a more **complete** learner profile.”

(Siemens, 2012, pp. 6-7)

“The revenue model behind these open platforms is to be found in the user data and the value that data can represent.”

(Doove, 2013, p. 99)

More data equals increased precision, better models, more money.

# Algorithmic sublime as ideology

- These patterns have become defining features of learning analytics.
- The patterns form an ideology I call the *algorithmic sublime*.
- The ideology places responsibility for effective education on algorithms—on computational *technologies*—rather than on *people*.
- The algorithmic sublime is a recent iteration of a larger historical pattern, the *technological sublime*.

# History of the technological sublime

- Greatness, beauty, awe, the sacred are found not in nature, or architecture, or poetry, but large-scale *technologies*.
- “Technology can solve anything.”
- Technological sublime varies in its object of worship:  
Mechanical → Electrical → Digital

(Carey & Quirk, 1970a, 1970b)

The algorithmic sublime is the latest iteration of a historical pattern

# Conclusion

- Given these findings, it's possible to see learning analytics anew.
- When they are not shrouded in myth, how attractive are they?
- Cui bono? Who benefits? Who doesn't?
- Ideologies like the algorithmic sublime are important to notice because of what they conceal
  - Alternative practices and ways of knowing
  - Historical causes for their emergence
- We will increasingly encounter these patterns as education moves to online environments.

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# Questions?

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