

Expanding Notions of Literacy

Big Data Comes To School: Implications for Learning, Assessment, and Research

Mary Kalantzis and Bill Cope University of Illinois Thesis:

There will, in the future, be no difference between instruction and assessment

How?

Big Data Learning Analytics

The Old School



Here we are at school. All is well, the students are busily at work ...



'Look this way', the teacher says.

'Listen to what I tell you about Answer my questions, hands up, only one person may speak at a time.'



'Now, everyone read chapter 7—carefully, and silence, please \ldots '



'... and now, answer the questions at the end of the chapter. No talking.'

Soula looks up for a moment. Is she thinking about her work? Or is she daydreaming?



Then, something terrible happens ...



'Turn around, Soula,' says the teacher. 'Don't disturb the girls behind you.'





Epistemological and Pedagogical Presuppositions

Learning is individual memory work

or

achieving correct results using memorized procedures









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Some cases ...

Some Changes

Knowledge is social

Crowdsourcing assessment

Shifting the main locus and logic of assessment from summative to formative

From linear to recursive feedback

Summative assessment takes the form of progress visualizations

Definition

'Big data' in education are:

- the purposeful or incidental recording of activity and interactions in digitallymediated, network-interconnected learning environments—the volume of which is unprecedented in large part because the datapoints are smaller and the recording is continuous;
- 2. the varied types of data that are recordable and analyzable;
- 3. the accessibility and durability of these data, with potentials to be: a) immediately available for formative assessment or adaptive instructional recalibration, and b) persistent for the purposes of developing learner profiles and longitudinal analyses; and
- 4. presentations of *data analytics*—syntheses based on the particular characteristics of these data, for learner and teacher feedback, institutional accountability, educational software design, learning resource development, and educational research.

Data Typology

Data Type	Mode of Data Collection	Practices: Examples
1. Machine Assessments		
	a. Computer adaptive testing	Select response assessments, quizzes (e.g. reading comprehension, grammar, vocabulary)
	b. Natural language processing	Automated essay scoring, feedback on language features
2. Structured, embedded data		
	a. Procedure-defined processes b. Argument-defined processes c. Machine learning processes	Games, intelligent tutors Rubric-based peer review of writing Semantic tagging and annotation, text visualizations, accepted textual change suggestions
3. Unstructured, incidental data		
	a. Incidental 'data exhaust'	Keystroke patterns, edit histories, clickstream and navigation paths, social interaction patterns
	b. Dedicated devices for collecting unstructured data	Video capture, eye trackers, movement detectors

Assessments

Traditional Assessment Model

- Assessment is *external* to learning processes; the challenge of 'validity' or alignment of the test with what has been taught
- Limited opportunities for assessment, *restricted datasets* (select and supply response assessments)
- Conventional focus on summative assessment
- Summative assessment is an outcomes or *end view* of learning
- Expert or teacher assessors
- Focus on individual memory and deductions leading to

 correct or incorrect answers
- Assessment of fact and correct application
- Assessment experts as report grades

Emerging Assessment Model

- Assessment is *embedded* in learning; 'validity' no longer a challenge
- Data is big because there are so can be *many small datapoints* during the learning process (structured and unstructured data)
- Renewed focus on formative assessment
- Summative assessment is a progress view, using data that was at first formative to trace learning progressions; feedback is *recursive*
- *Crowdsourced*, moderated assessments from multiple perspectives, including peers and self
- Focus on knowledge representations and *artifacts* that acknowledge textual provenance and trace peer *collaborations*
- Assessment of *complex epistemic performance*, disciplinary practice
- Learners and teachers as data analysts, with the support of analytics dashboards and visualizations

Research

Traditional Research Model

- Researcher as independent observer
- Optimal, *sample 'n'* to produce reliable results
- Practical limits to research perspective determined by the *scale of data collection*
- *Fixed timeframes,* long enough to demonstrate overall effect; longitudinal analyses expensive and thus infrequent
- Standardization effects (fidelity, average effect)
- Causal effects: *overall*, for whole populations or population subsets
- Relatively separate quantitative and qualitative research practices; low significance of theory in empirical analyses

Emerging Research Model

- Researchers recruit subjects as data-collectors, *co-researchers*
- There is no marginal cost for n = all, and data is rich enough to support n = 1
- *Multiscalar perspectives,* from n = 1 to n = all
- Short timeframes, feeding small incremental changes back into the learning environment; longitudinal timeframes as a consequence of data persistence
- Tracing *heterogeneity* in data, e.g. different paths in adaptive learning environments, salient activities of outliers
- *Microgenetic* casual analysis, e.g. learning progressions for different students, differential effects traceable in varied learning paths
- Integration of quantitative and qualitative analyses; increasing importance of theory in data analyses

The Test is Dead

Long Live Assessment!

Reference



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The prospect of "big data" at once evokes optimistic views of an information-rich future and concerns about surveillance that adversely impacts our personal and private lives. This overview article explores the implications of big data in education, focusing by way of example on data generated by student writing. We have chosen writing because it presents particular complexities, highlighting the range of processes for collecting and interpreting evidence of learning in the era of computermediated instruction and assessment as well as the challenges. Writing is significant not only because it is central to the core subject area of literacy; it is also an ideal medium for the representation of deep disciplinary knowledge across a number of subject areas. After defining what big data entails in education, we map emerging sources of evidence of learning that separately and together have the potential to generate unprecedented amounts of data: machine assessments, structured data embedded in learning, and unstructured data collected incidental to learning activity. Our case is that these emerging sources

References



e-Learning Ecologies

Principles for New Learning and Assessment



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