



A Snapshot of Current Research in Learning Analytics

Using Real-Time Analytics in Lectures for Engagement To Boost Positive Student Outcomes

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Future Ideas: Information and the Internet
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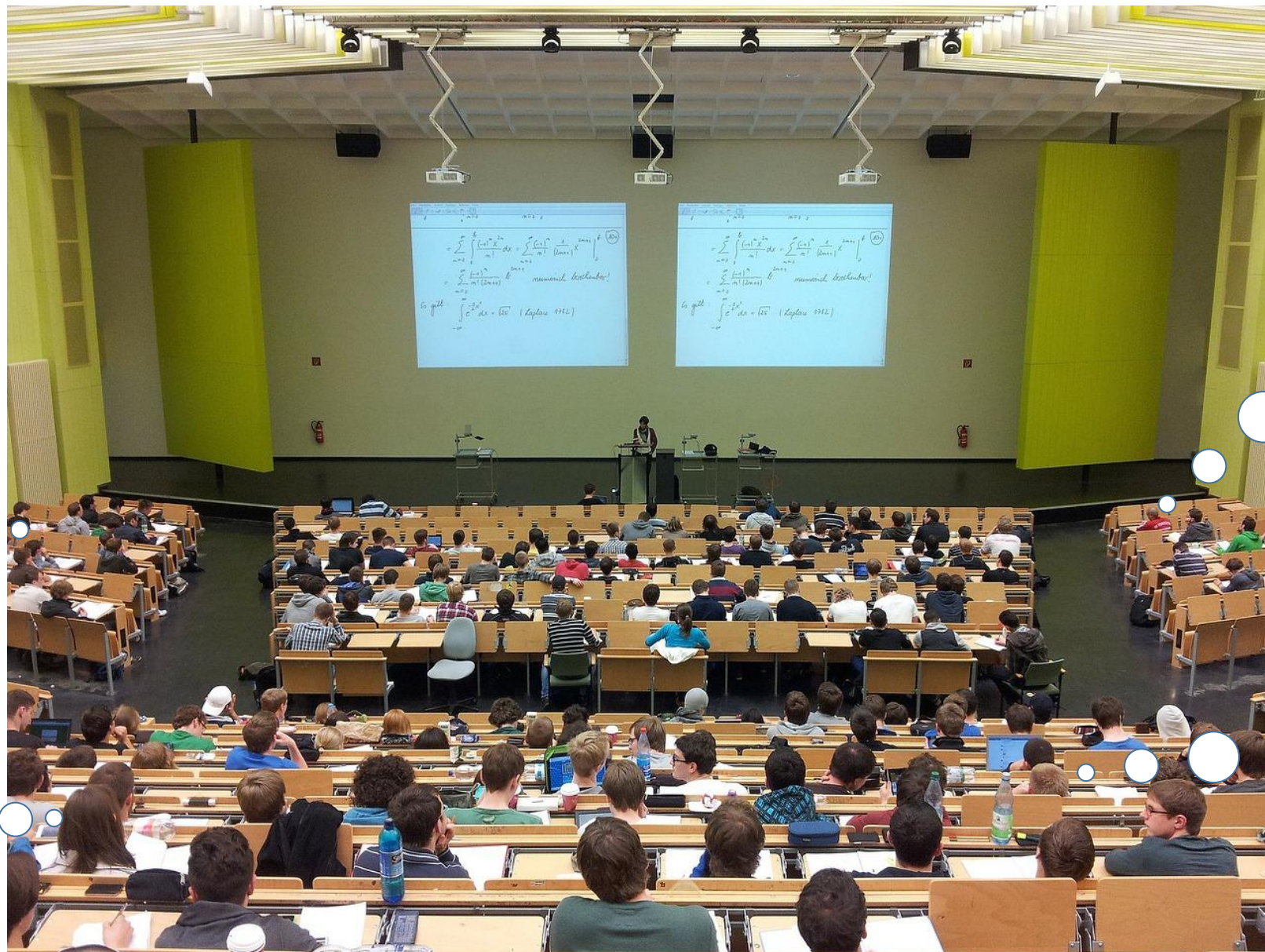
How do we reach individual learners?

How do we make learning experiences engaging for all?

How can we improve learning and teaching at university?

I wish I could understand this...

I know how to do this easily.



Did I leave the heater on?

ZZzzzz...

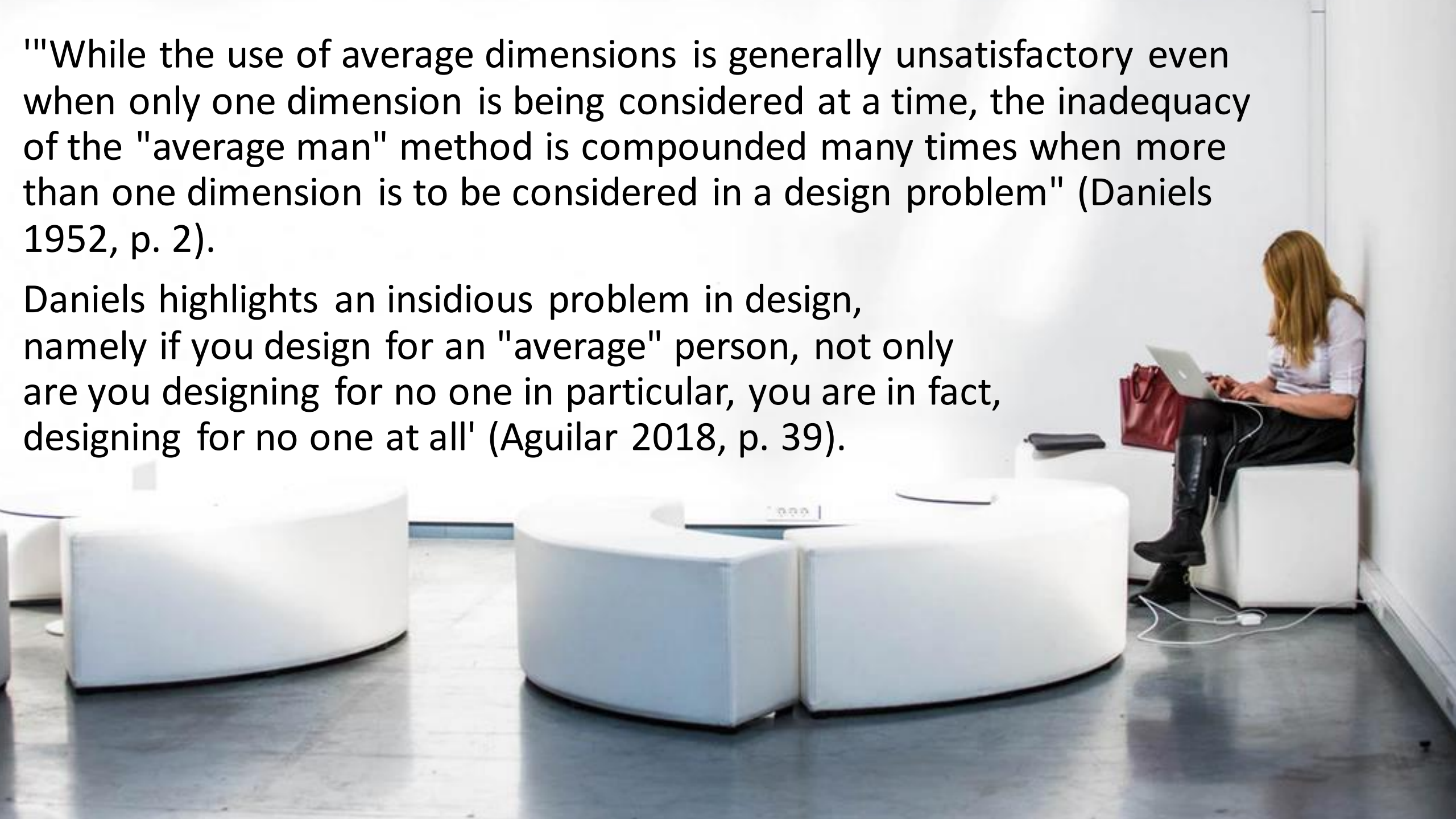


No longer is education given to the students for recitation through a text and lecture style model. This generation is a collaborative and social generation that has a focus on understanding and building their knowledge through various forms of medium to discover the answers. It is for the educators to provide an arena for engagement and discovery as well as be a content expert and mentor (Monaco & Martin 2007, p. 46).



"While the use of average dimensions is generally unsatisfactory even when only one dimension is being considered at a time, the inadequacy of the "average man" method is compounded many times when more than one dimension is to be considered in a design problem" (Daniels 1952, p. 2).

Daniels highlights an insidious problem in design, namely if you design for an "average" person, not only are you designing for no one in particular, you are in fact, designing for no one at all' (Aguilar 2018, p. 39).



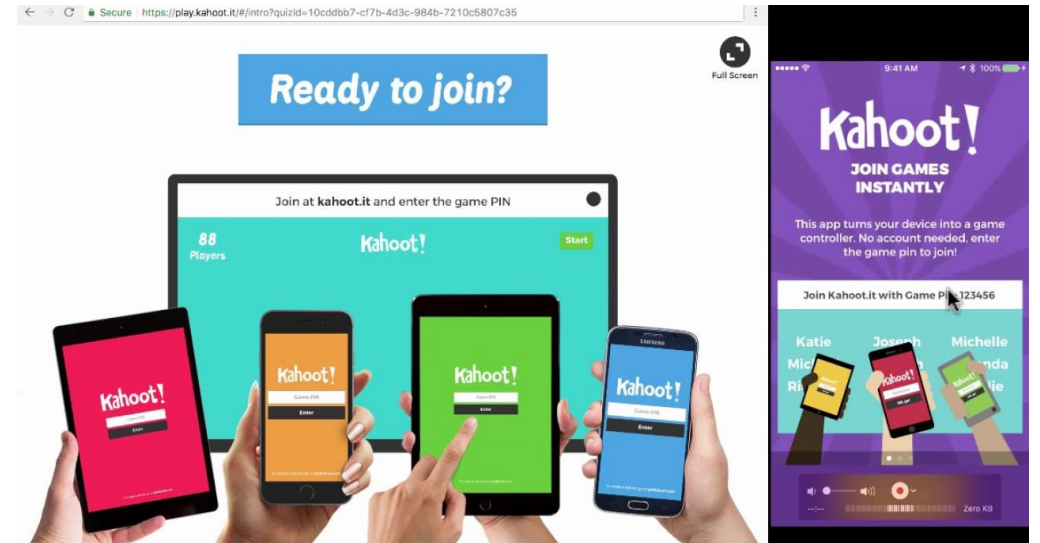
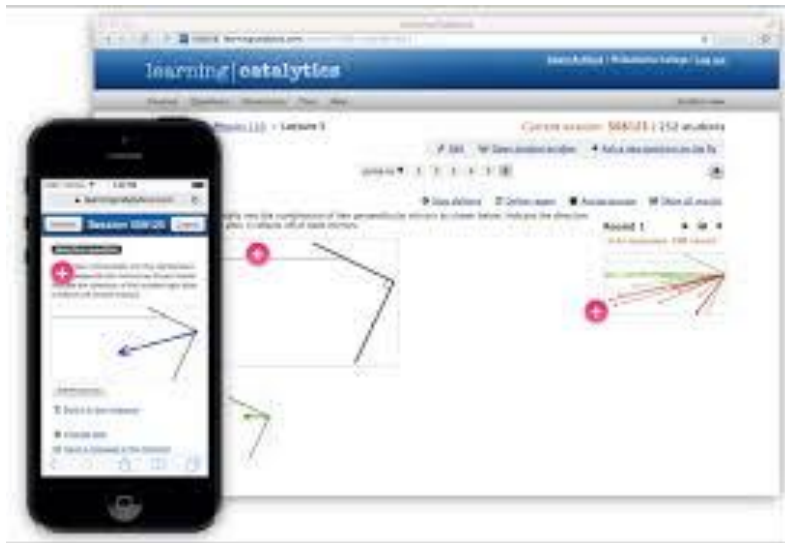
Not the *average* student.....

Why learning analytics?

- Personalised learning
- Timely feedback
- Early intervention (Reyes 2015)

'A meta-analysis of 225 studies researching active learning and academic performance found that active learning increases examination performance by half a grade (on average) and that lecturing increases failure rates by 55%' (Freeman et al. 2014 cited in Matthews, Garratt & Macdonald 2018, p. 7).





Supported by backend analytics from UniSA MOODLE site

Broader benefits.....

- Predicting student learning success and providing proactive feedback (Dawson et al. 2014 cited in Gašević, Dawson & Siemens 2015, p. 65).
- Online and on campus engagement
- Supporting students at risk
- Improved cohort outcomes



Utilising big data, good design, and the input of stakeholders they are meant to serve, learning analytics techniques aim to develop applications for the sole purpose of reducing the classroom size to 1.... These digital innovations will enable us to finally do away with a model of education that teaches toward the non-existent average student, replacing it with one that is more socially just and equitable; one that acknowledges and supports the individual needs of every student (Aguilar 2018, p. 42).

Issues

- Access to technology
- Diversity
- Technology in place
- Educator attitude, university culture and culture of analytics
- Connection to research

Ethics

- 2014 data analysis and move to BYOD
- Raising awareness of analytics
- Issues of consent and data retention
- Privacy –confidential or anonymous?



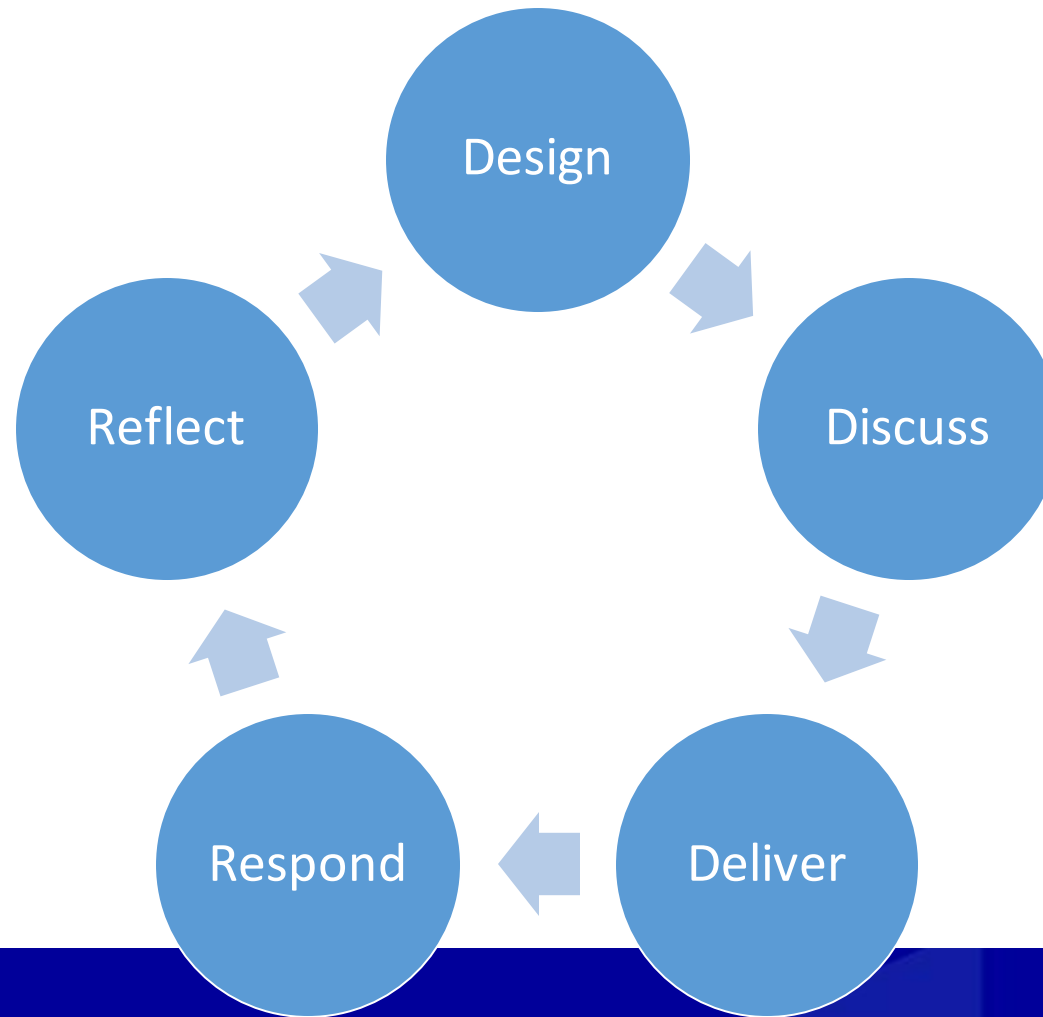
The Educator and Real-time Analytics

- Shift from 'sage on the stage' to a discursive lecture
- Inclusive and adaptable in practice and pedagogy
- Learning, testing and embedding new technology takes time and persistence
- Navigating new technology for students in supportive ways
- Encouraging interactivity through digital media
- Creating a supportive learning environment
- Modelling positive behaviour with technology



What to do if the technology fails?

Implementing real-time analytics (diagram by Stokes 2018)



Example 1: Student engagement

My Courses > Digital Literacy: Screen, Web and New Media > L7 Learn new skills fast 2018 - Virtual lecture > Session 31835692

Download results Attendance information Messages Resend grades Delete data

Jump to 1 2 3 4 5 6 7 8 9

1. word cloud

What is your favourite recent meme?



Round 1

33 responses



9. word cloud

This picture denotes a rose. What connotations can you think of?



multiple choice

Variations in perception ... what do you see?



A. Young woman
B. Old woman

Round 1

10 responses, 100% correct

A. 70%
B. 30%

Round 1

52 responses



✓ 7 get it now
✗ 0 still don't get it

Example 2: Knowledge development

My Courses > Digital Literacy: Screen, Web and New Media > L6 Creativity, idea generation and the pitch - Virtual lecture 2018
MASTER > Session 20867696

Download results Attendance information Messages Resend grades Delete data

Jump to 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

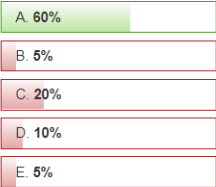
10. multiple choice

Which technique did advertising executive Alex Osborne popularise?

- A. Brainstorming
- B. Analogy
- C. Mnemonic device
- D. Brute search
- E. Perspective shift

Round 1

20 responses, 60% correct



7. multiple choice

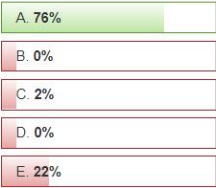


Why is this picture important?

- A. It reminds us that the sign is not the referent, which is fundamental to understanding semiotics.
- B. It reminds us that smoking is cool, which is a good life lesson.
- C. Magritte was a well-known surrealist who confused audiences with confronting art.
- D. It is classy because it is French.
- E. It makes us consider semiotics by looking at connotations.

Round 1

58 responses, 76% correct



✓ 4 get it now
✗ 0 still don't get it

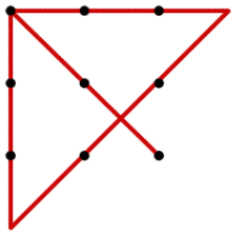
5. sketch

Using only FOUR lines you must connect ALL of these dots.

You CANNOT pick up your drawing tool (pen, crayon, map pencil, etc!)

Only one dot will be touched more than once. (Braingle 2014)

Answer



(Note: The order shown can be reversed, and you can start in any corner, using the same pattern.)

(Braingle 2014)

Round 1

23 responses



✓ 11 get it now
✗ 0 still don't get it



University of
South Australia

Example 3: Educator praxis

- Reflect on data
 - In lecture
 - In combination with MOODLE
 - Student progression
 - Students-at-risk
 - After each delivery



'Using technology helped me to engage more, especially with learning catalytics.'

'Learning catalytics was especially helpful because it helped to keep me engaged during long lectures.'

2018 INFS 1022 Student survey

- Continued improvement, with a caveat: 'As a comparable analogy to teaching to the test, rather than teaching to improve understanding, learning analytics that do not promote effective learning and teaching are susceptible to the use of trial measures such as increased number of log-ins into an LMS, as a way to evaluate learning progression' (Gašević, Dawson & Siemens 2015, p. 69).

Outcomes

- Enhancing participation and engagement
- Enthusiastic student response
- Above average retention and pass rate
- Outstanding course evaluations (SP2 Student satisfaction with Jenny's teaching 81.94 (from –100 to +100))

.....what do the students think of two hour interactive lectures?

- ✓ Lectures were great fun.
- ✓ She was very entertaining, her lectures made me want to listen.
- ✓ The multimedia style of the lecture is a fun and interesting way to learn.
- ✓ The content and presentation of the course were highly engaging and often fascinating.
- ✓ Overall, the course was wonderfully presented and proved to be one of the most engaging lectures of the study period.
- ✓ Very in sync with today's technology and able to express her enthusiasm for the course. Jennifer has made this course interesting as well as challenging. The interactive learning every week via the learn online site is particularly helpful and worked well. The topic is also very well covered and does not feel rushed.
- ☒ 2 hours is very long, even with a break. I often found my concentration drifting in the last half an hour or so. I would have preferred if lectures were 1.5 hours with no breaks.

MyCourseExperience 2018

Three key points

When implemented effectively, real-time learning analytics enhance learning and teaching.

1. Learning and teaching at university must engage with cohort needs in order to best engage and support students. A shift toward interactive practice and rapid feedback has become necessary to support Millennial and Gen Z students.
2. There are clear benefits for all students when real-time learning analytics are embedded into lectures and other formats. These include increased student engagement, understanding, and positive learning outcomes.
3. Strategic use of real-time analytics allows educators to better support individual needs. Through employing learning analytics effectively, educators are better able to deliver personalised learning experiences and target early interventions for greater student success (Reyes 2015). This is particularly important for meeting the needs of students from diverse backgrounds (Aguilar 2018).



Questions? Jennifer.stokes@unisa.edu.au

References

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- Images from iStock, Kahoot, Learning Catalytics, Padlet, UniSA and Unsplash.
Media images used for educational purposes.



MOOC Discussions with Machine Learning

Yuanyuan Hu

University of Auckland | New Zealand

MOOC Discussions

Topics ?

Cognitive levels?

Interactions ?



Classification with Supervised Learning

Known categories

Pre-classified data

Text —> **Numbers**

Training

Known X —>

—> known Y

X —>

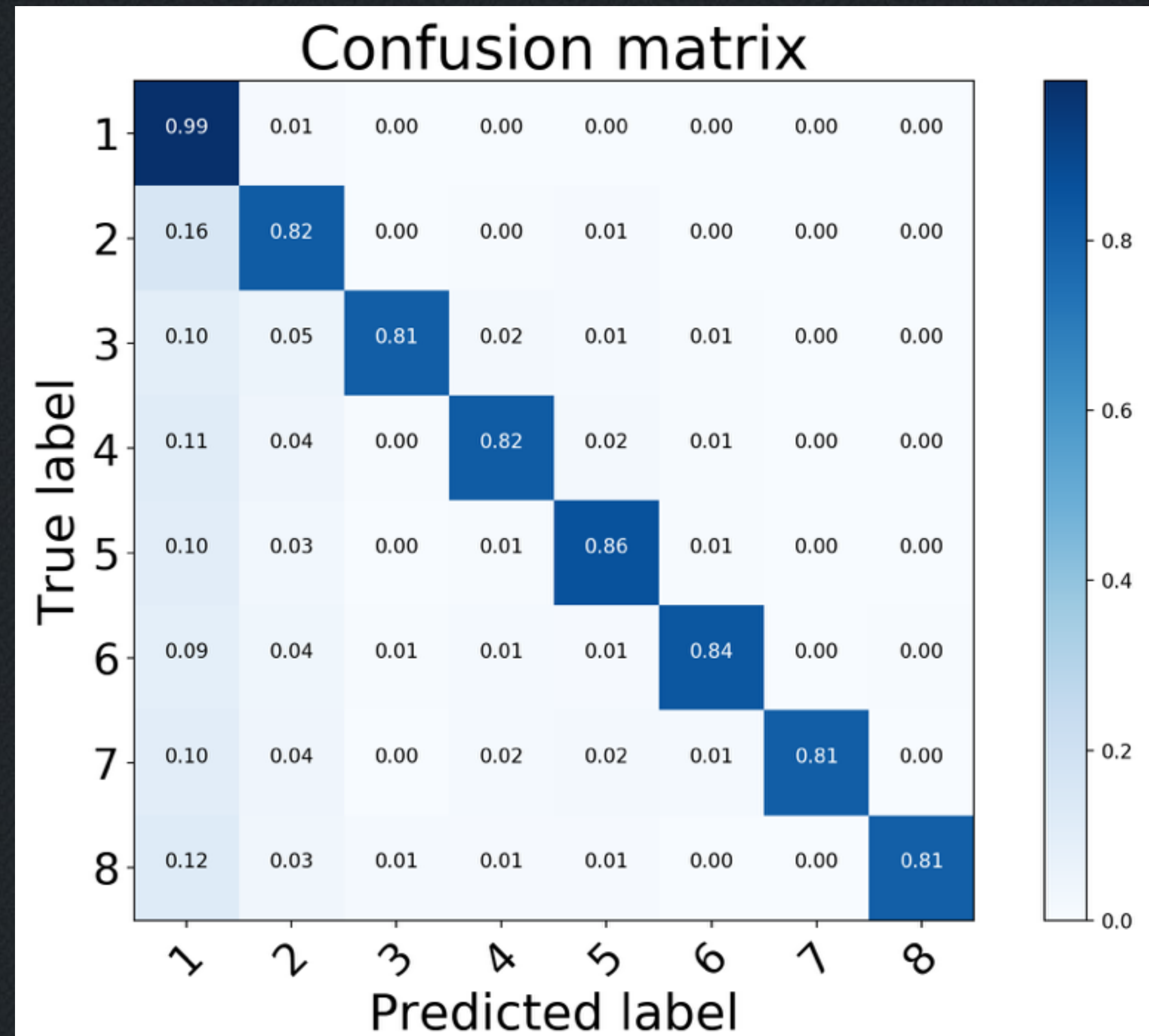
—> Predicted Y

Model

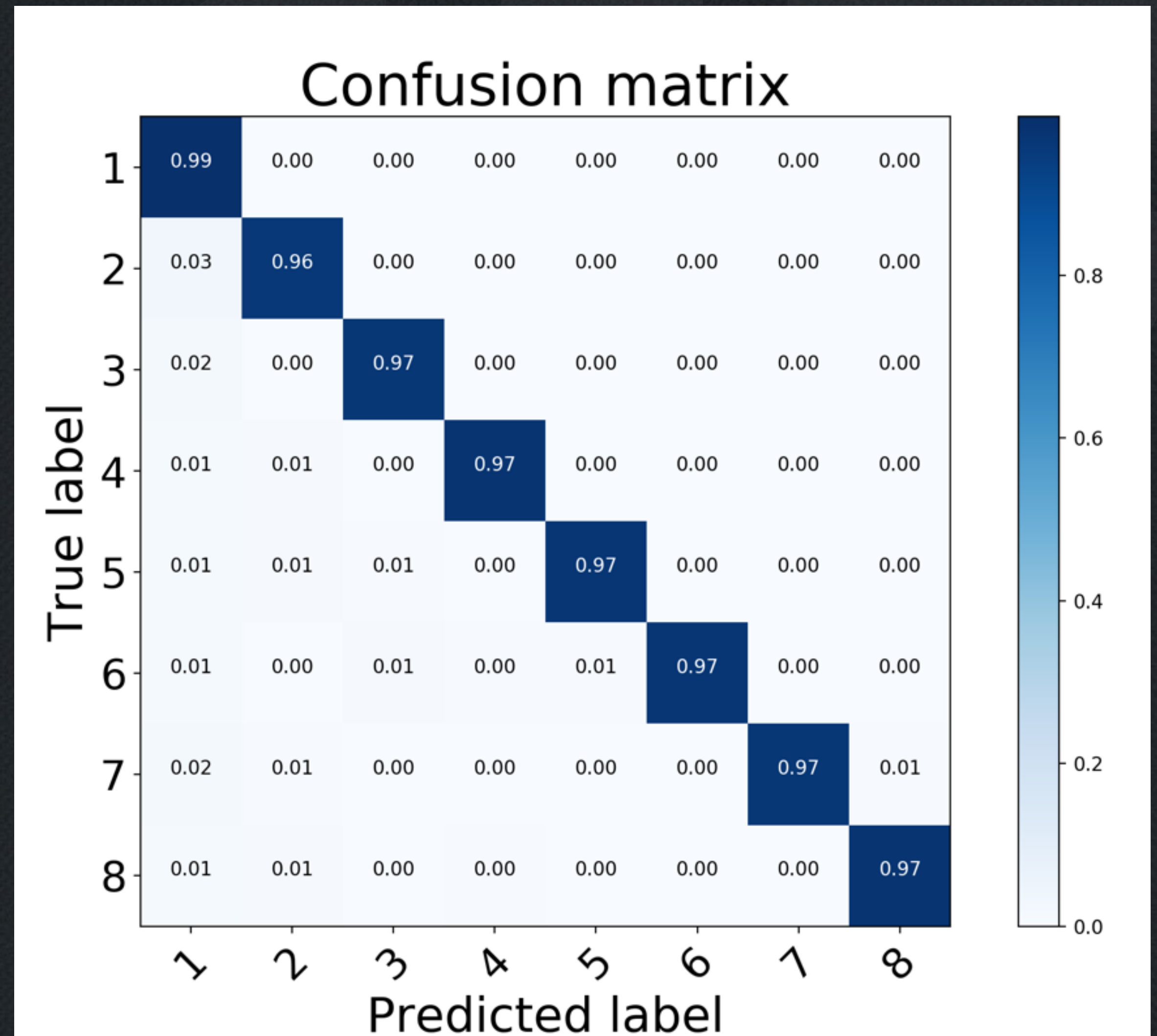
Training data	26420	70%
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Testing data	2936	30%
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Classification with Supervised Learning



bag of words



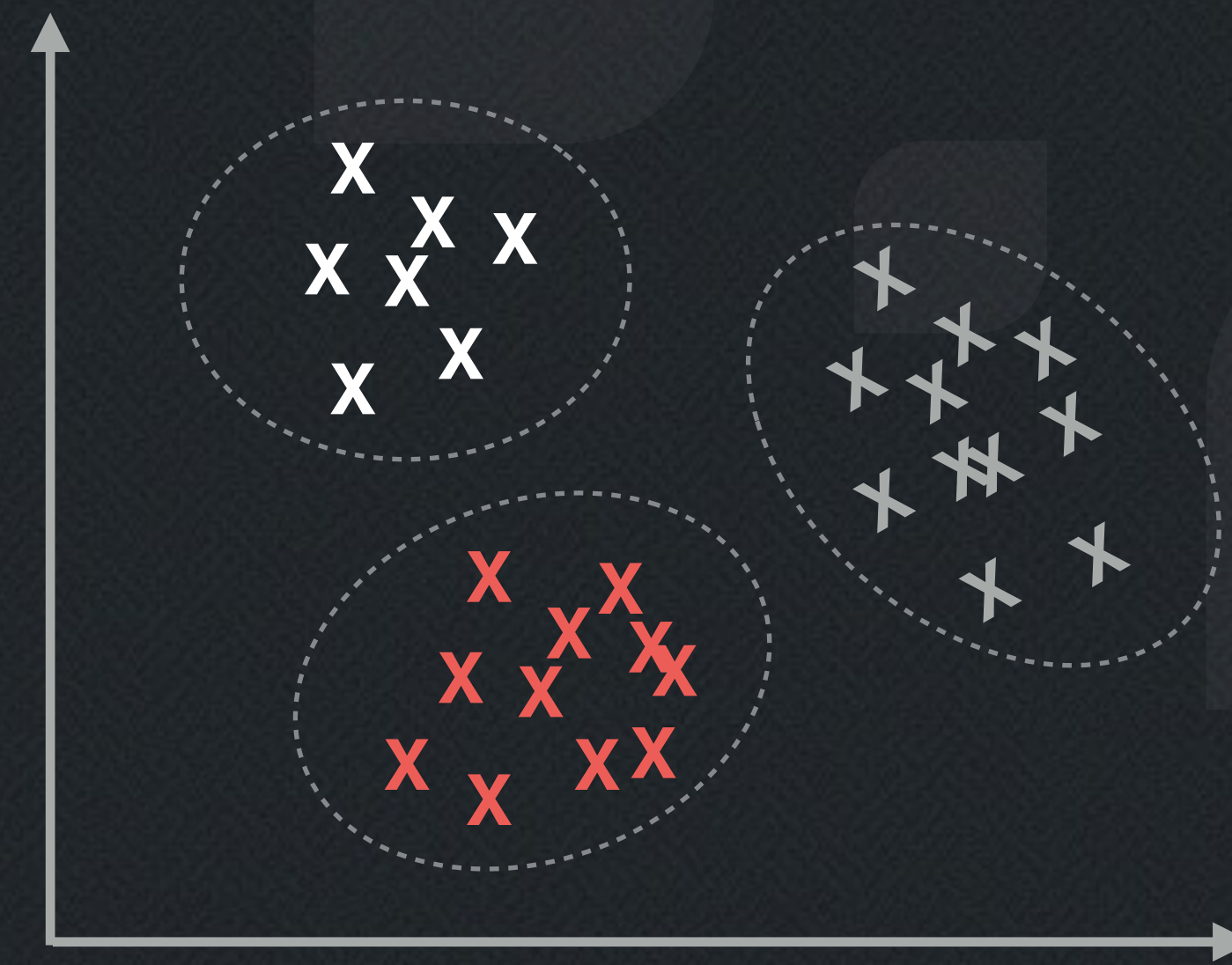
TF-IDF with simple neural network

Clustering with Unsupervised Learning

Unknown categories

No Pre-classified data

Text —> **Numbers**



Clusters results **11** **8** **7**

Cognitive levels

Revised Bloom's Taxonomy

Remember

Understand

Apply

Analyse

Evaluate

Create

Cognitive levels

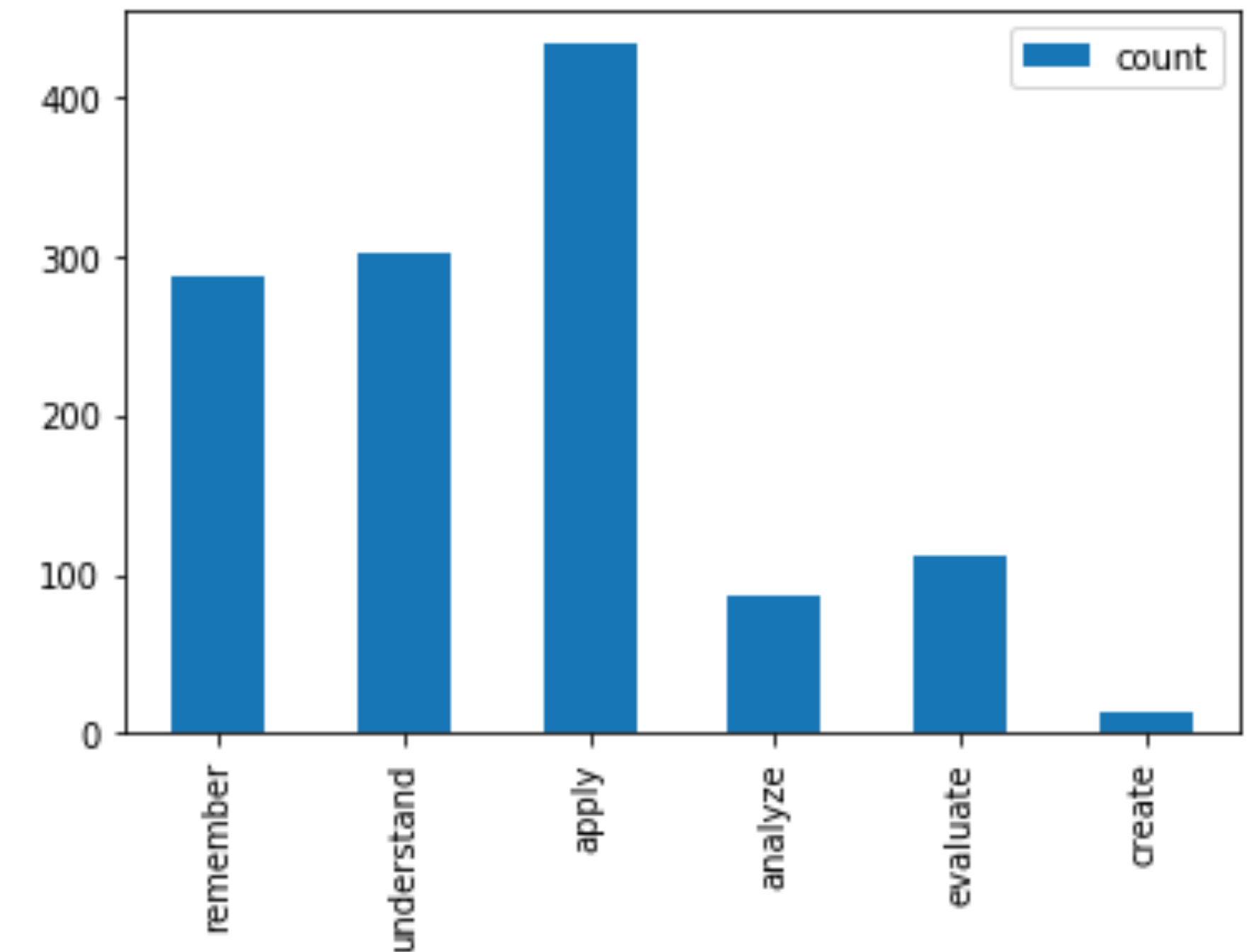
	Remember	Understand	Apply	Analyze	Evaluate	Create
	Retrieve relevant knowledge from long-term memory	Construct meaning by connecting “new” to “prior” knowledge	Use a procedure to perform exercises or solve problems	Break material into its constituent parts and relate parts to whole	Make judgments based on criteria or standards	Put elements together to form a coherent whole
VERBS	Remember Recognize Identify Recall Retrieve	Understand Interpret Clarify Paraphrase Illustrate Classify Categorize Summarize Generalize Infer Conclude Explain Predict Compare Contrast Map	Apply Execute Carry out Use Implement	Differentiate Analyze Discriminate Focus Distinguish Select Organize Outline Integrate Structure Attribute Deconstruct	Evaluate Check Coordinate Detect Monitor Test Critique Judge	Create Generate Hypothesize Plan Design Produce Construct
QUESTIONS	What happened after .. How many .. What is .. Who did .. Where did .. occur?	How would you explain .. Who do you think .. Why did .. How would you graph .. Which .. corresponds to .. What are examples of .. How could you group ..	How would you solve .. How would you do .. What would you say to .. How would you work a case of ..	What was the turning point? How is. .. similar to .. Why did .. occur What is needed to .. What were some of the motives for ..	Is there a better solution to .. What do you think about .. and why? Do you think .. is a good thing and why?	What are possible solutions to .. How would you design an .. What would happen if .. How many ways can you ..
ACTIVITIES	Make a list showing .. Make a time line Make a chart showing ..	Write a summary of .. Prepare a flow chart of .. Write an explanation of .. Make a taxonomy of .. Draw a map/model of .. Draw a graph of .. Write possible outcomes of Retell an event	Solve a problem Write a response to a case study Perform a lab experiment	Write a biography Make a map showing interrelationships Write an analysis of .. Write an essay examining bias in .. Construct a chart to organize related data	Conduct a debate (or a mock trial) Write a critique Prepare a case Write an opinion piece	Design an experiment Create a new product Plan a marketing campaign Create art Design a building

Cognitive levels

Testing data sample 2016 comments **5238**

jupyter bloom's taxonomy2016 Last Checkpoint: 10 minutes ago (autosaved)

1	find	55.0	explanation	29	used	145.0	compared	11.0	relationships	21.0	hypothesis	3.0
2	finding	20.0	example	19	using	84.0	structured	6.0	check	11.0	combine	1.0
3	shows	17.0	examples	15	skills	8.0	comparing	6.0	relationship	8.0	produce	1.0
4	show	11.0	understanding	14	experiments	5.0	structure	5.0	checked	5.0	predicted	1.0
5	remember	10.0	explanations	14	skill	4.0	compare	5.0	tests	4.0	NaN	NaN
6	call	8.0	explained	14	application	3.0	organized	4.0	testing	3.0	NaN	NaN
7	called	7.0	summary	13	apply	3.0	survey	3.0	estimate	3.0	NaN	NaN
8	choose	7.0	groups	13	solve	3.0	assume	3.0	recommend	2.0	NaN	NaN
9	define	5.0	understood	12	develop	3.0	differ	2.0	monitoring	2.0	NaN	NaN
10	identify	5.0	group	12	experiment	3.0	assuming	2.0	recommended	2.0	NaN	NaN
11	chose	4.0	categories	12	solving	2.0	divided	2.0	monitor	2.0	NaN	NaN
12	showed	4.0	explain	10	applied	2.0	organise	2.0	measure	2.0	NaN	NaN
13	identifying	3.0	illustrated	8	applying	2.0	distinguished	2.0	influence	2.0	NaN	NaN
14	list	3.0	compare	5	built	2.0	organised	1.0	estimated	1.0	NaN	NaN
15	recognise	2.0	illustration	5	developing	2.0	functions	1.0	measures	1.0	NaN	NaN
16	showing	2.0	explaining	4	applies	1.0	outlines	1.0	judge	1.0	NaN	NaN
17	choice	2.0	clarifying	4	builds	1.0	simplified	1.0	perception	1.0	NaN	NaN
18	definition	2.0	clarification	4	solved	1.0	motivated	1.0	justified	1.0	NaN	NaN
19	label	2.0	conclusion	4	utilized	1.0	examine	1.0	estimates	1.0	NaN	NaN
20	identification	1.0	category	2	experimented	1.0	motivate	1.0	checking	1.0	NaN	NaN
21	match	1.0	demonstrating	2	establish	1.0	assumption	1.0	NaN	NaN	NaN	NaN
22	recognising	1.0	illustrate	2	applications	1.0	motivation	1.0	NaN	NaN	NaN	NaN
23	remembered	1.0	summarizing	2	NaN	NaN	outline	1.0	NaN	NaN	NaN	NaN
24	recall	1.0	extends	1	NaN	NaN	theme	1.0	NaN	NaN	NaN	NaN
25	defining	1.0	extended	1	NaN	NaN	dividing	1.0	NaN	NaN	NaN	NaN
26	identified	1.0	illustrating	1	NaN	NaN	simplify	1.0	NaN	NaN	NaN	NaN



Advantages and Disadvantages

Next and Values

Analysing sentences structures

Supervised learning

Unsupervised learning

interactions social roles

Communities in large MOOC courses

Connect similar topics

Understand learning gains

Q & A

Yuanyuan Hu

University of Auckland | New Zealand



PhD Presentation

Learning Analytics implementations in Australian universities:
towards a model of success

Jo-Anne Clark

Griffith University

School of Information and Communication Technology

Principal supervisors: Dr David Tuffley & Dr Rene Hexel

Associate Supervisor: Professor Mark Brimble

Background to Research Problem

- Growing accountability for Universities to deliver quality outcomes, improved learning and student success (Arnold, 2010; Dietz-Uhler & Hurn, 2013; Campbell, Deblois & Oblinger, 2007; Oblinger & Campbell, 2007).
- The regulatory environment is likewise becoming tighter, with increasing scrutiny by governments, accrediting agencies and students (Universities Australia, 2013)
- Data-driven decisions are needed, thus Learning Analytics (LA) are introduced (Siemens, 2010; Oblinger, 2012)
- To improve student success, the success of LA system implementations must be examined.
- **Learning analytics** in this study, is the collection, analysis, and reporting of data associated with student learning behaviour (Lockyer, Heathcote & Dawson, 2013)

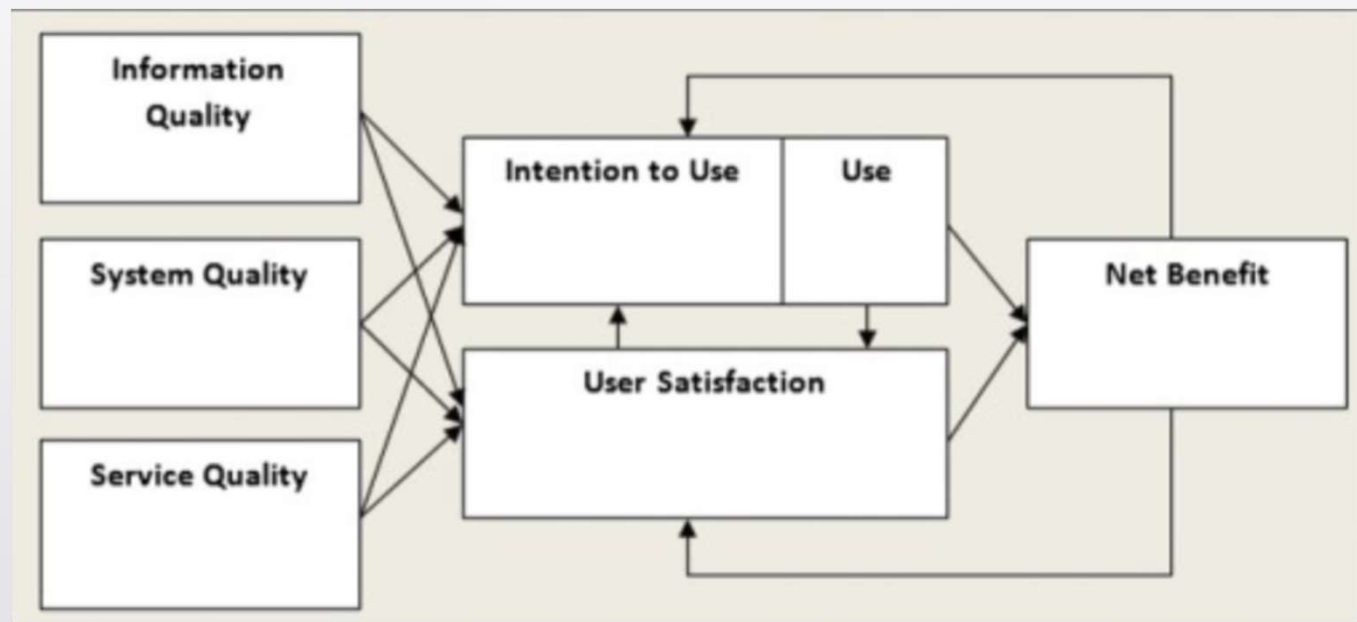




Information Systems Success

- The Delone & McLean model has tested reliably over time, having been extensively used to gauge information systems success since its conception in 1992 (Delone & McLean, 2003).
- This study, rather than validate the model, uses a *qualitative approach* to describe information systems success in terms of LA implementations. The research will describe the success of LA implementations as experienced by staff members working with those systems.

Delone & McLean Model of IS Success



DeLone, W.H. and McLean, E.R. (2003), 'The DeLone and McLean model of information systems success: A ten-year update', Journal of Management Information Systems, vol. 19 no. 4, pp. 9-30



Research Design

- **Qualitative Research** – allows the researcher to conduct in-depth studies about a broad range of topics. Enables researcher to capture the meaning of real-world events from the perspective of a study's participants (Yin, 2011). Qualitative use of DeLone & McLean's (2003) model of Information Systems Success.
- **Interpretive Paradigm** – the world will be viewed as a social construction of reality, interpreted and experienced by people and their interactions within the wider social system (Klein & Myers, 1999).
- **Case study research** as “an empirical inquiry that investigates a contemporary phenomenon within its real-life context; when the boundaries between phenomenon and context are not clearly evident” (Yin, 1984: 13).





Progress to date

Planned

Stage one

- 43 Australian Universities invited to take part
- Intend to interview approximately 3-4 people per institution.

Stage two

- Survey deployment – staff at 43 Universities

Progress

Stage one

‘State of play’ of LA at Australian Universities

- Key staff from 3 universities have been interviewed so far
 - Staff work directly with LA
 - Research has found that 3-4 staff work directly with LA

Stage two

Deployment of Delone & McLean (modified) survey

- Key staff from 43 universities

Preliminary findings – key themes

- Different definitions of LA exist – importance of defining LA
 - Student-facing
 - Academic facing
- University entry options – e.g. Universities have unique cohorts
- LA implementation at Universities is still in its infancy
- Predictive modeling is a popular method
- Recommender systems being used
- Learning analytics examples applied to course design
- Tools differ e.g. Tableau software used in one case study



Preliminary findings – key themes cont.

Benefits of using LA

- Increased data literacy of staff
- Evidence based practice
- Data driven decision making
- Finding out what drives learning and what does not
- De-privatising the classroom (can be an uncomfortable conversation Increasing accountability)



Limitations/challenges of using LA

- All the cautions of being on the web (security issues, etc.)
- Uninformed inferences – just because someone is logged on to a LMS doesn't mean they are engaged in the course material *"It is like mistaking the leaves for the wind. Measuring the movement of the leaves but the wind is something different."*



Questions?



U

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An investigation into Australian higher education teachers' interpretation of learning analytics and its impact on practice

DAVID FULCHER



UNIVERSITY
OF WOLLONGONG
AUSTRALIA

Background

MOTIVATION & FOCUS

- **Primary school teaching**
- **Business intelligence**
- **The UOW approach to learning analytics**



Learning Analytics

A VARIETY OF APPLICATIONS

Early alert and student
success

Course
recommendations

Adaptive learning

LA for learning design

Social network analysis

Student-facing
analytics



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Learning Analytics

IMPLEMENTATION APPROACHES

Top-down	Bottom-up
Executive sponsorship	Hearing the voice of students and teachers
Institution-wide	Communities of practice
Governance structures	Feedback loops for making adjustments
Technology foundation	Incremental rollout
Policy development	



Different approaches required

ONE SIZE DOES NOT FIT ALL

- Gašević, D., et al. (2016). "Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success." The Internet and Higher Education **28: 68-84.**
 - Application: Early alert and academic success
 - Scope: Institution-wide
 - Findings: Different use of LMS features require consideration



Learning Analytics and Learning Design

THE STUDENT SUCCESS PARADIGM

- Rienties, B., et al. (2017). "A review of ten years of implementation and research in aligning learning design with learning analytics at the Open University UK." Interaction Design and Architecture (s) 33: 134–154.
 - Application: Relationship between learning design and student behaviour and outcomes
 - Scope: Institution-wide
 - Findings: Learning design decisions impact student behaviours and partially impact student outcomes



My Proposed Study

RESEARCH QUESTIONS

- What factors influence Australian higher education teachers' interpretation of learning analytics?
 - What knowledge do Australian higher education teachers have about learning analytics?
 - How are learning analytics actually used by Australian higher education teachers?
 - What is difficult/easy about using learning analytics for Australian higher education teachers?
 - What information do Australian higher education teachers seek when making learning decision decisions?

