Analyzing Learning and Teaching through the Lens of Networks

Sasha Poquet, University of South Australia
Bodong Chen, University of Minnesota
Acknowledgement

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Agenda

- Introduction: The network worldview
- Applied network analysis
  - Four core messages
- Applying network analytics in teaching
- Q&A
Networks are everywhere!

(Photo Credits: 1, 2, 3, 4)
Why networks?

Representational

Network of flavors

(Ahn et al., 2011; Photo Credit)
Why networks?

Representational

Analytical

Network centrality measures

(Photo Credit)
Why networks?

Why networks?

Trees “talking” to each other

Relational structures

Epistemological

(Singh, 2019)

(Photo Credits: 1, 2)
Networks in Education

Hierarchical

Complex

Photo Credit
Socio-technical systems

Social systems

Pedagogical system

LEARNERS behaviour & LEARNING

Technological systems
How network analysis can be helpful for understanding learning?
Not new: LAK’11 and pre-LAK
Applied Network Analysis: Core Messages

- Networks are much more than social networks
Applied Network Analysis: Core Messages

- Networks are much more than social networks
- Not all centralities measures are made equal
Applied Network Analysis: Core Messages

- Networks are much more than social networks
- Not all centralities measures are made equal
- Network models matter
• Networks are much more than social networks
• Not all centralities measures are made equal
• Network models matter
• Network evaluation is subjective and multi-dimensional
Networks are more than social networks.

Graphs are often used as a method to reduce high-dimensional data.

Here: networks = graphs = diverse entities and relations.
Networks are more than social networks

Networks are more than social networks

Networks are more than social networks

Figure 9. Mean networks of students’ from the first (blue, left) and second (red, right) halves of an engineering design simulation.

Networks are more than social networks

Also communication and interaction between people

Ties:
- semantic overlap
- artefact use
- timing
- course enrolment
- Composite of the above

ICLS & CSCL works:
- Goggins et al. 2013
- Suthers 2015
- Dascalu, M et al., 2018
Networks are more than social networks

Graphs are **also** often used as a methodology to analyze socially shared learning and communication.

Here: networks = graphs = theoretically relevant social learning aspect
Not all centrality measures are equal

Network centralities measure network positioning

Positioning = benefits/constraints from where you are in the network

Similar positioning = similar benefits = possibility for assessment
Not all centrality measures are equal
Not all centrality measures are equal

Tie definitions by Wise, Cui & Jin (2017)

Direct reply  Copresence / Shared thread

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Figure 2: Six Social Tie Definitions

1. Direct Reply
2. Star Reply
3. Direct Star Reply
4. Total Co-presence
5. Limited Co-presence
6. Moving Window (3)

OP -> thread starter
R -> level-two post
RR -> level-three post

Moving Window (3) slide 1
--- Moving Window (3) slide 2
----- Moving Window (3) slide 3
--------- Moving Window (3) slide 4

Not all centrality measures are equal
Not all centrality measures are equal

Same centrality can reflect different behaviours

- Validity issues:
  - Is this generalizable?
  - What does the metric mean?

Psychometrics, cognitive science, network science, epistemic network analysis - offer a range of approaches to validation
Network models matter.

If network analysis = methodology,
to analyze social learning

Network = graph = construct
“... A network model should be viewed explicitly as yielding a network representation of something”

Fig. 1. The elements of network models.
Figure 16.1. Levels of analysis and their representations.

Network models matter

Network models matter

Network models matter

Network evaluation is subjective & multi-dimensional.
Network evaluation is subjective & multi-dimensional.

Social learning is multi-level and multi-dimensional

Separating the levels enables differential indicators

Evaluation in LA = Instructor choice of what indicators matter

No one ‘effective’ network = fit for purpose
Evaluation is multi-dimensional


Evaluating posting behavior

Q1  High Activity; High Turn-Taking
Q2  Moderate Activity; High Turn-Taking
Q3  High Activity; Low Turn-Taking
Q4  Low Activity; Low Turn-Taking

Figure 3. Principal Component Analysis Bi-Plot Structuring Forums and Posting Activity Indicators
Evaluation is multi-dimensional

Evaluating communication structure

Q1 Communities, inequality
Q2 No communities, equality
Q3 High dyadic exchange, pockets of exchanges
Q4 High centralization
Evaluation is multi-dimensional

Evaluating communication structure

Evaluation is multi-dimensional

Evaluating communication structure

Forum K
'Share your opinion on X'

Forum D
'Constrained small groups weekly assessed'

Forum P
'No special forum provisions'

Forum M
'Post a response or build on the opinion of X people'

Evaluation is multi-dimensional

Evaluating communication structure

Evaluation is multi-dimensional

Evaluating communication structure

Applied Network Analysis: Core Messages

- Networks are much more than social networks
- Not all centralities measures are made equal
- Network models matter
- Network evaluation is subjective and multi-dimensional
How network analysis can be used to support teaching and learning?
Applying Network Analytics in Teaching

- Learning as a networked phenomenon.
Networked learning

The open networked learning ecology in cMOOCs
(Saadatmand, 2016)
Knowledge Building Community
Applying Network Analytics in Teaching

- Learning as a networked phenomenon.
- Socio-technical systems facilitate networked learning.
Social media

A2: The special educators at my school have been working so hard to meet and speak with their caseloads on a daily basis. They make sure the students are getting the support they need. I also don’t set time limits for when work needs to be turned in. #RemoteLearningChat

A1: I worry about my students in the best of times. For students with disabilities in this pandemic, the concerns get more fundamental (food, clothing, shelter) and elemental (assistive tech, wifi, aides if they need them) #RemoteLearningChat

A3: Work to figure out who has access, who has limited access, and who has none. Work to make contact with those students who are missing out. #remotelearningchat
Knowledge Forum
Layers of Annotation
Built on Open Standards

General Public

UMN SNA Course

Expert Community

Private Notes

Any Website, Article, eBook, Document, Multimedia

(Credit: Angell, Dean, et al., EDUCAUSE 2018)

See https://bookdown.org/chen/snaEd/
Example Data

To demonstrate these concepts and measures, this chapter will rely on a fairly simple network data set: Newcomb's Fraternity Data (referred to as Fraternity Data). The original sociometric data collected by Newcomb required each of the 17 actors (all members of the same fraternity) to rank all the others in terms of friendship preferences, ranging from 1 to 10, with 1 indicating first preference. These rankings were done across the entire semester, resulting in 15 separate $17 \times 17$ single-mode, directed, and valued matrices. However, to better illustrate these concepts and measures, these data have been transformed to keep things a little simpler. In addition, the focus will be on one of these networks at a single point in time (week 0, the beginning of the study). These recoded data have been dichotomized, with friendship rankings ranging from 1 to 3, now coded as 1, 0 otherwise. Therefore, using the terminology introduced in Chapter 4, the recoded data set is now directed (asymmetric) and binary (nonvalued). This was done simply for purposes of presentation; any manipulation of network data should have some theoretical or empirical basis. Table 5.1 shows the recoded data file in the node-list format, with each row starting with the ID number of the responding student followed by three other ID numbers, the alters

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1. Annotations of readings
2. Replies to annotations
Synchronous collaborative activities on FROG (by Stian Håklev)

1. Annotations imported via Hypothesis APIs
2. Group note-taking in Zoom breakout rooms
Applying Network Analytics in Teaching

- Learning as a networked phenomenon.
- Socio-technical systems facilitate networked learning.
- Network analytics apps empower reflection and action-taking.
SNAPP (Bakharia & Dawson, 2011)
Some ethical questions come up as Euthanasia start engaging in more and more human life. I cannot anticipate what opinions Budinger will discuss in Chapter 7, but it is a fact that this issue is very complex and unwieldy.

Netlytic (see https://netlytic.org/)

Socio-semantic networks based on KBDeX
(Oshima, Oshima, & Matsuzawa, 2012)
Knowledge building in grade 1

Word of caution: implicit biases and value tensions

Conclusions and take-aways

Networks in digital learner traces - method and methodology

Generalisability and interpretability are critical

Multi-models reflect complexity

Distributed tools scaffold and support networked view on learning and teaching
Thank You!

Sasha Poquet  
Email: ssapoquet@gmail.com  
Twitter: @choux  
Website: learningpoop.com

Bodong Chen  
Email: chenbd@umn.edu  
Twitter: @bod0ng  
Website: bodong.me