Analyzing Learning and Teaching through the Lens of Networks

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Acknowledgement

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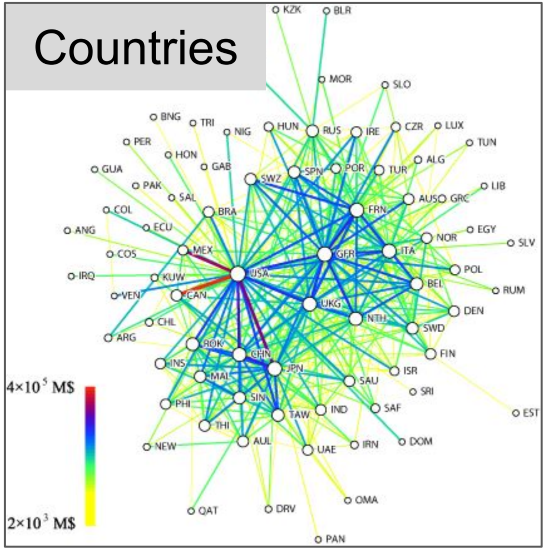
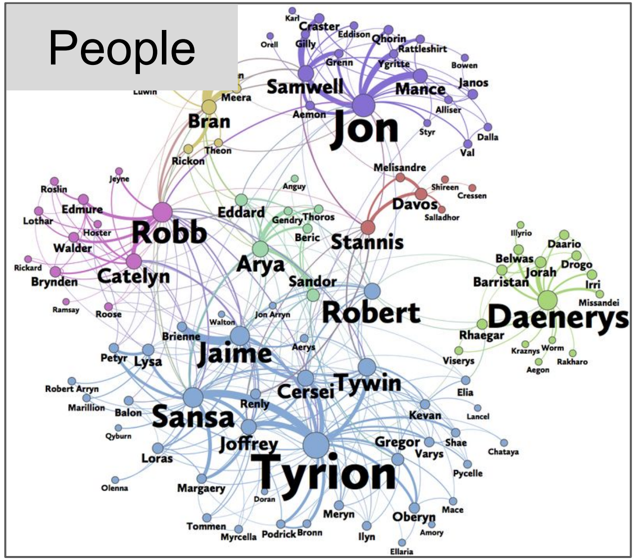
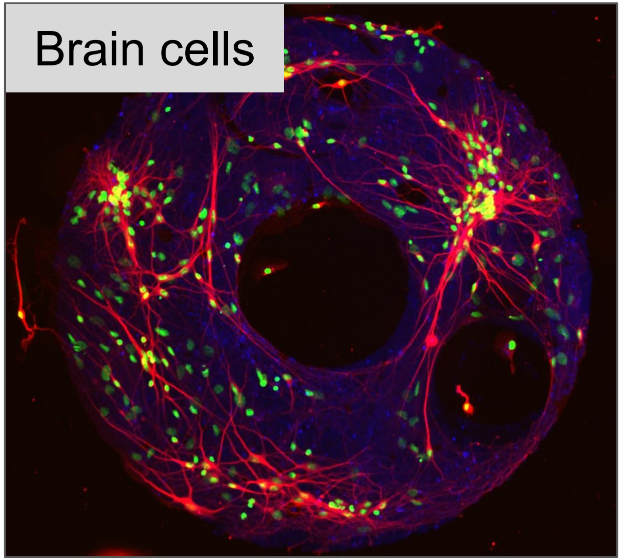
Agenda

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

Networks are everywhere!



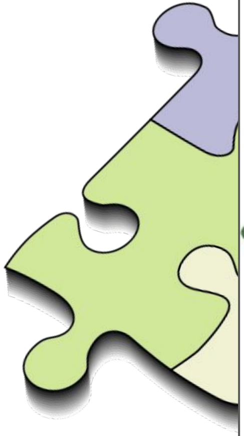


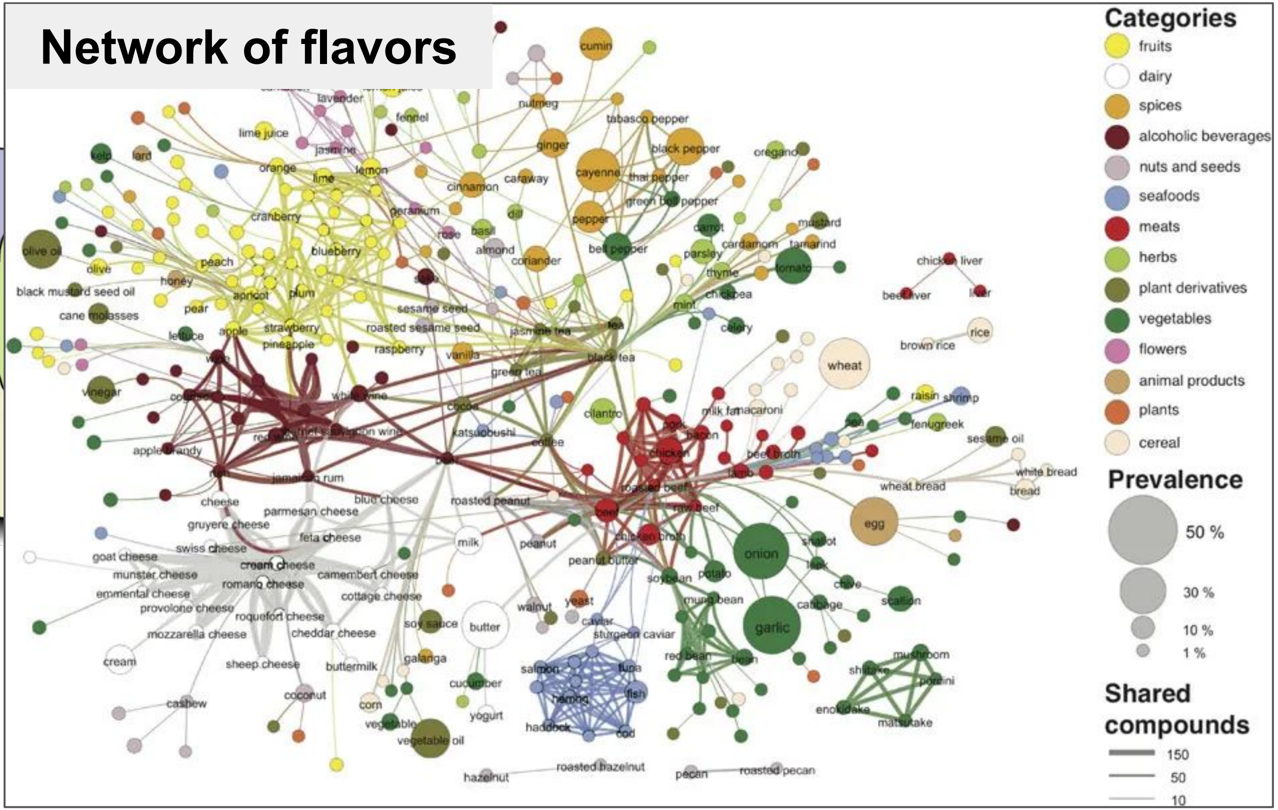


(Photo Credits: 1, 2, 3, 4)

Why networks?

Representational



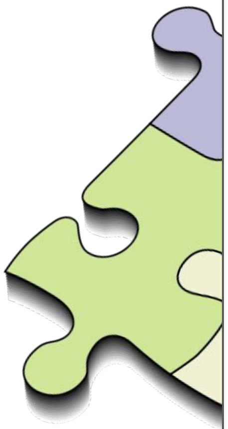


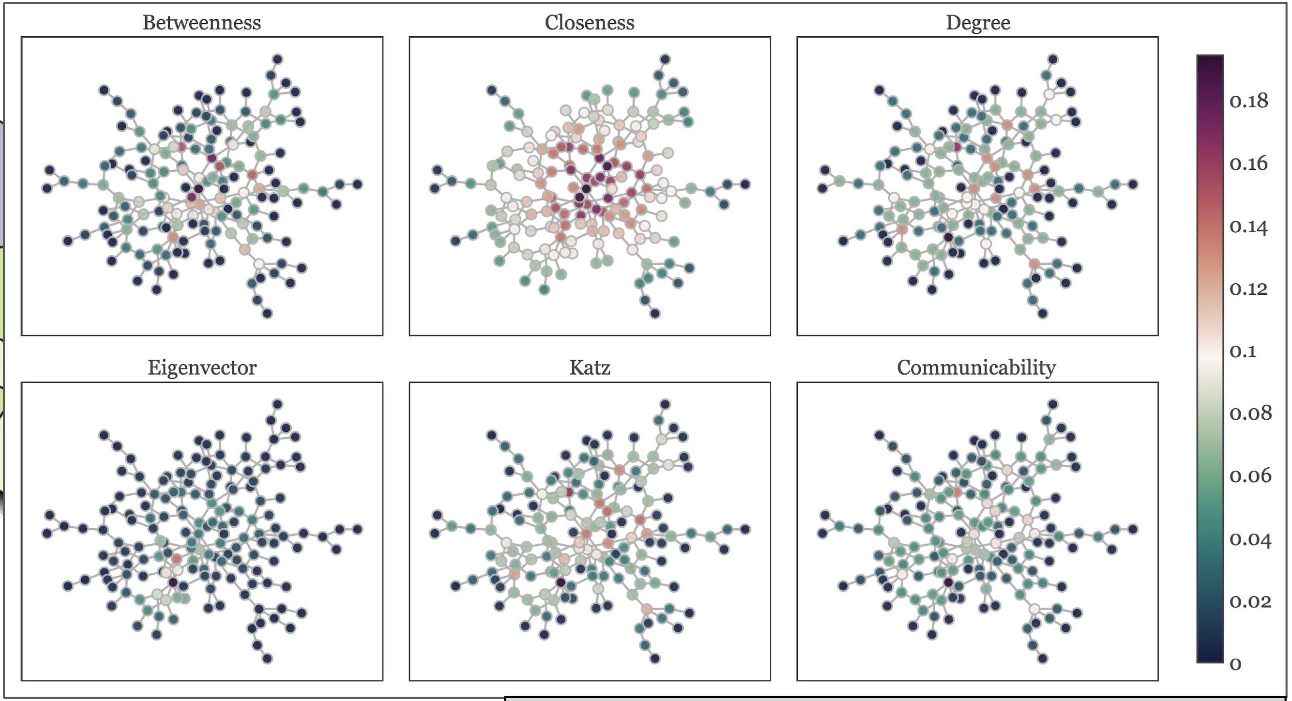
(Ahn et al., 2011; [Photo Credit])

Why networks?

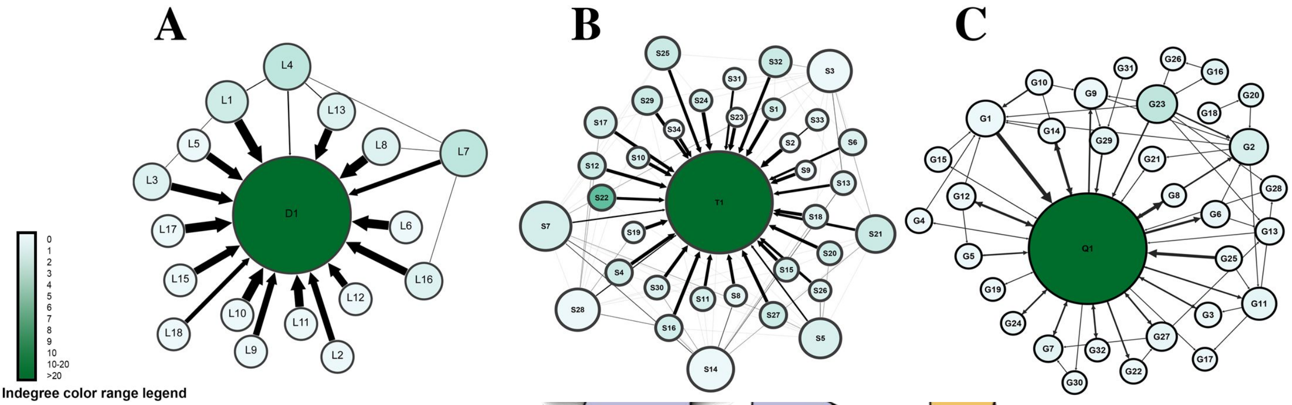
Representational

Analytical

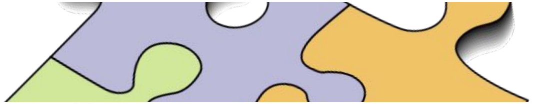




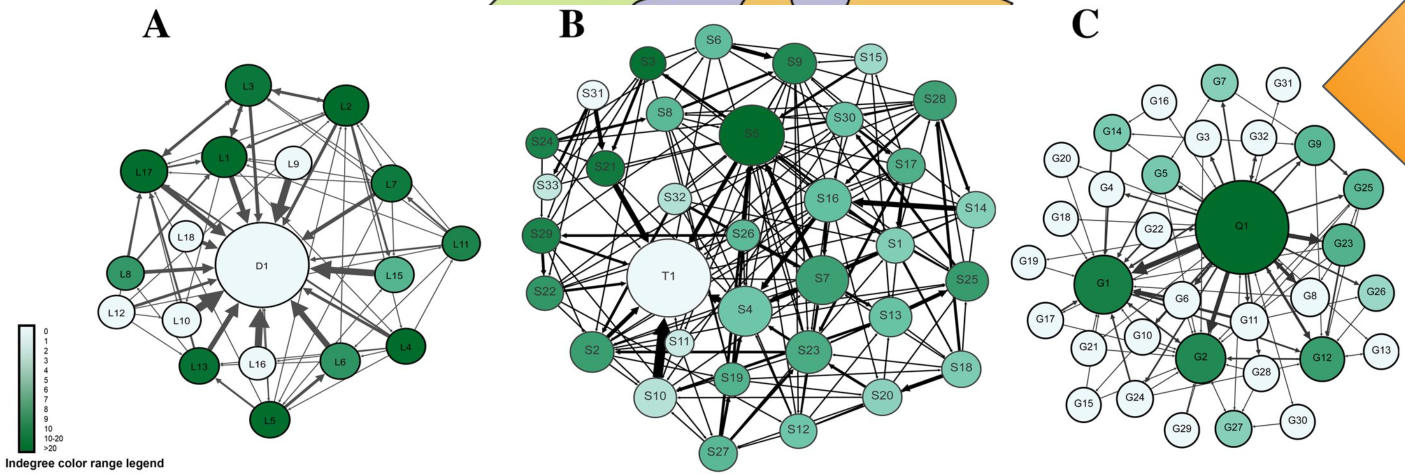
Network centrality measures
(Photo Credit)



Why networks?

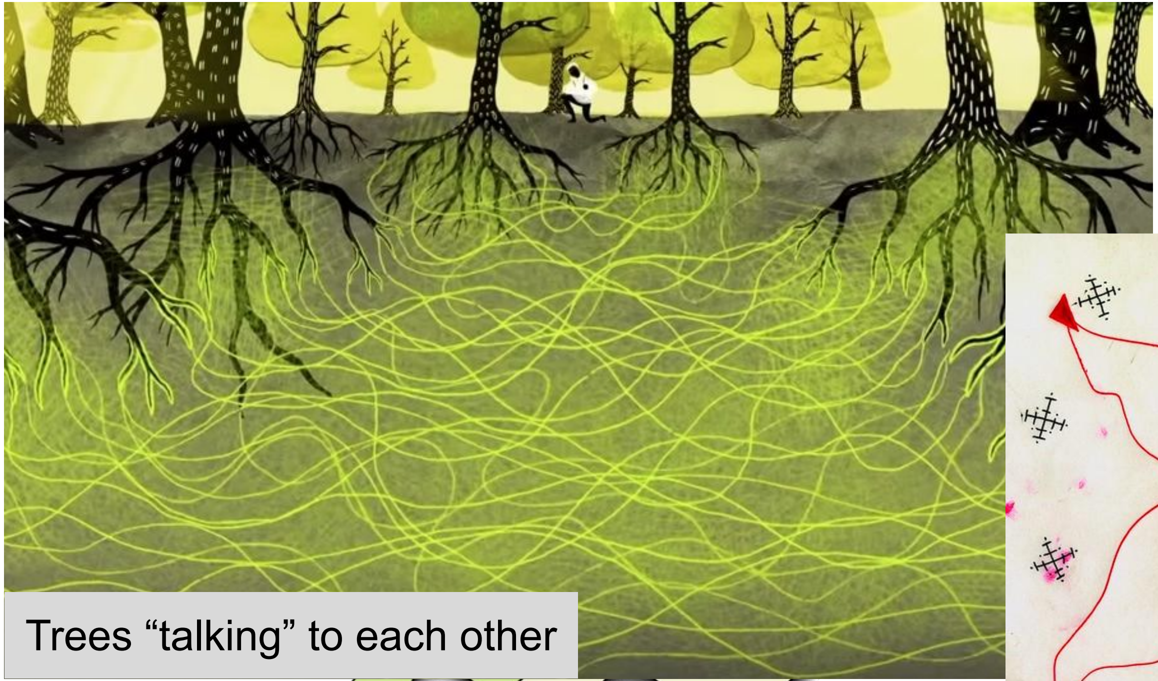


Actionable

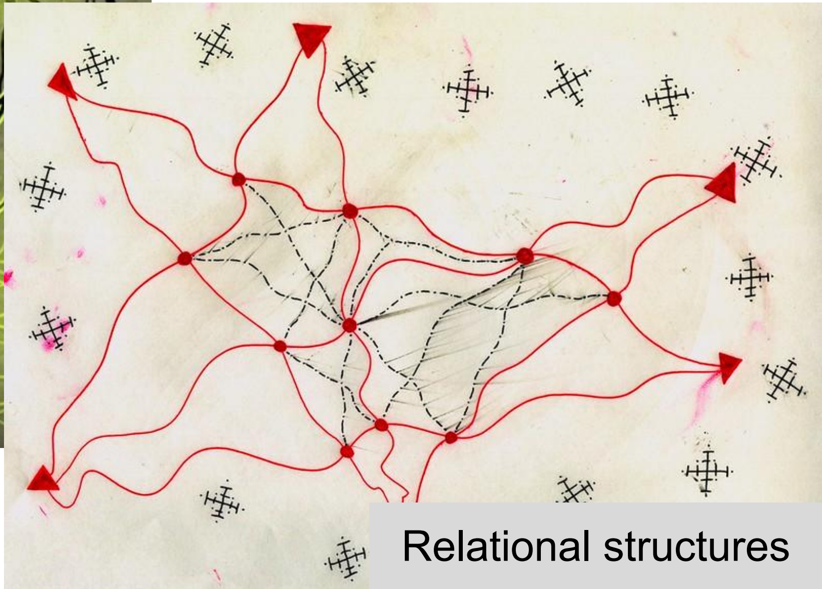


Saqr, M., Fors, U., Tedre, M., & Nouri, J. (2018). How social network analysis can be used to monitor online collaborative learning and guide an informed intervention. *PLOS ONE*, *13*(3), e0194777. https://doi.org/10.1371/journal.pone.0194777

Why networks?

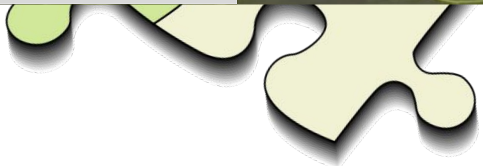


Trees “talking” to each other



Relational structures

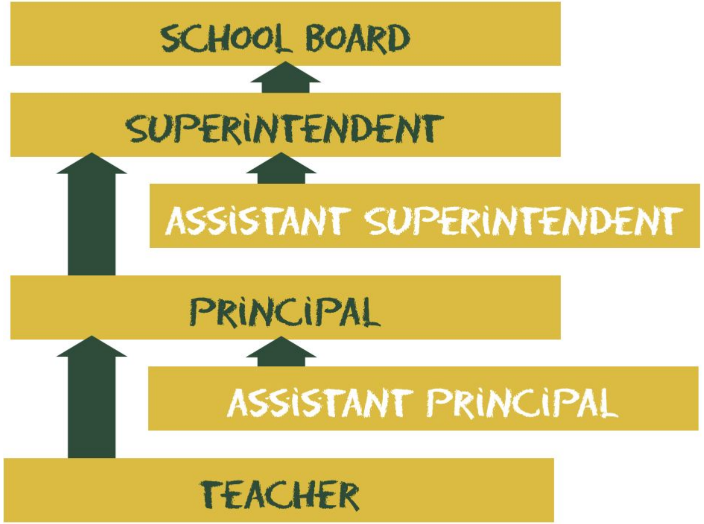
(Singh, 2019)



Epistemological

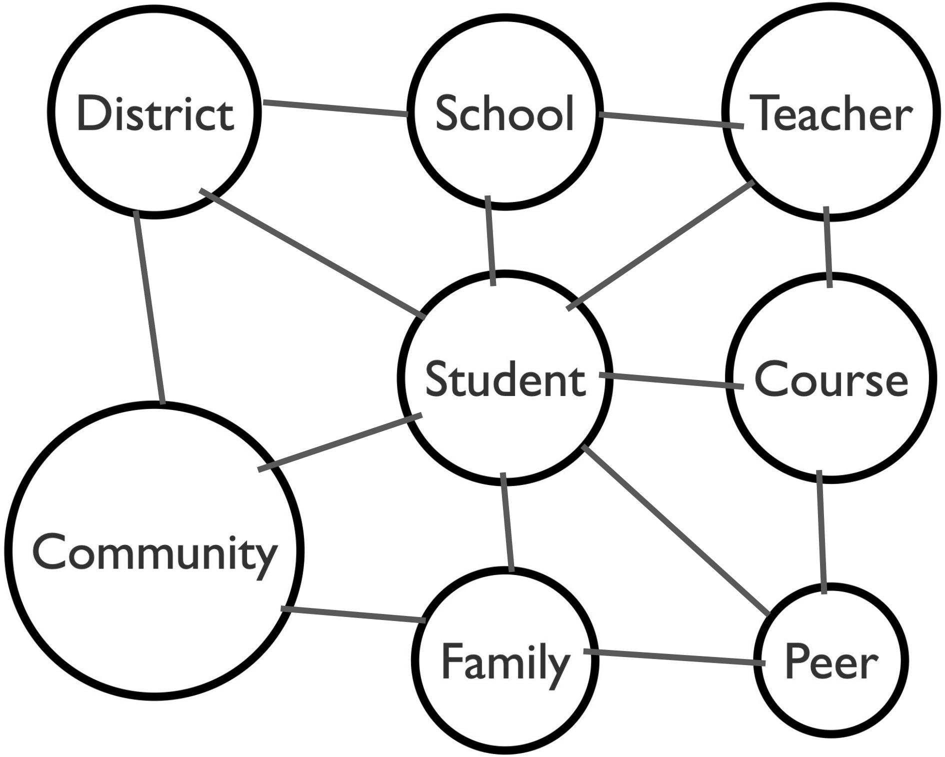
(Photo Credits: 1, 2)

Networks in Education



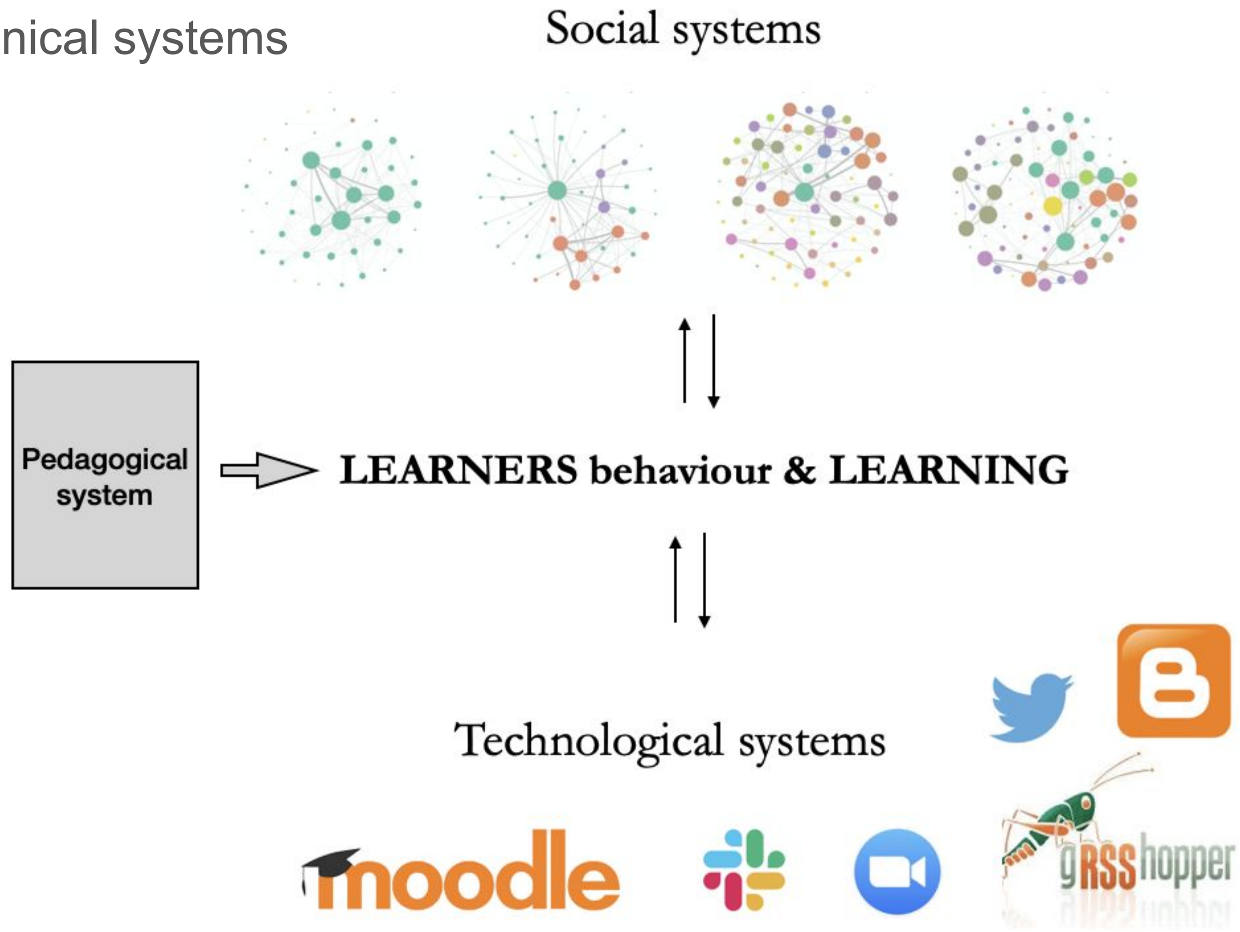
Hierarchical

(Photo Credit)



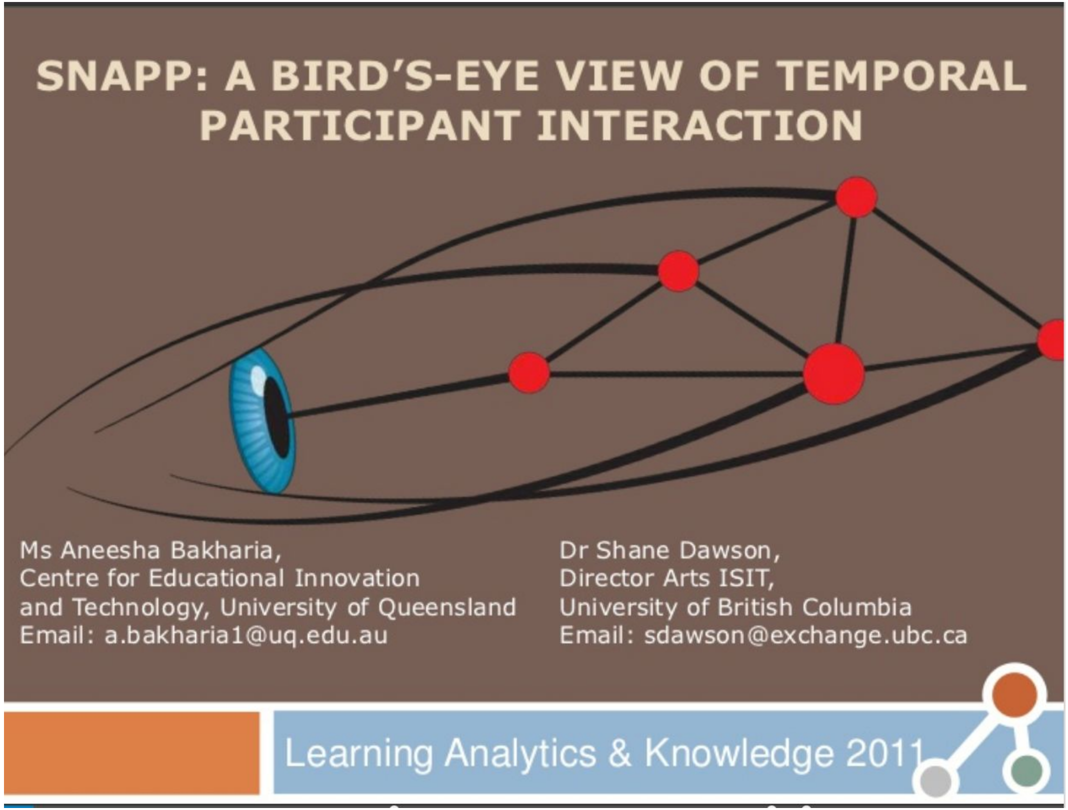
Complex

Socio-technical systems

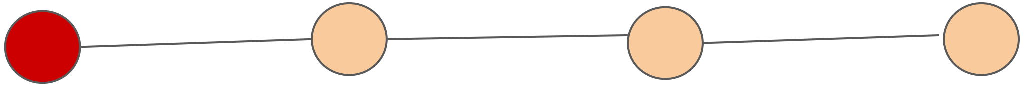


How network analysis can be helpful for understanding learning?

Not new: LAK'11 and pre-LAK

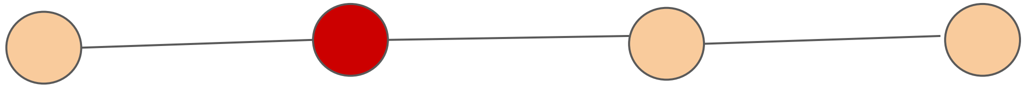


Applied Network Analysis: Core Messages



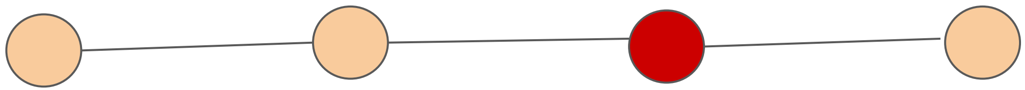
- **Networks are much more than social networks**

Applied Network Analysis: Core Messages



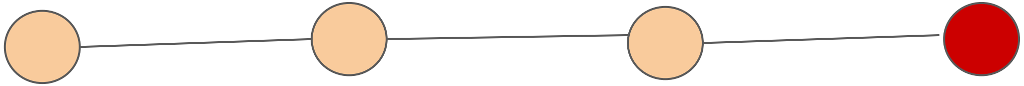
- **Networks are much more than social networks**
- **Not all centralities measures are made equal**

Applied Network Analysis: Core Messages



- **Networks are much more than social networks**
- **Not all centralities measures are made equal**
- **Network models matter**

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**

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

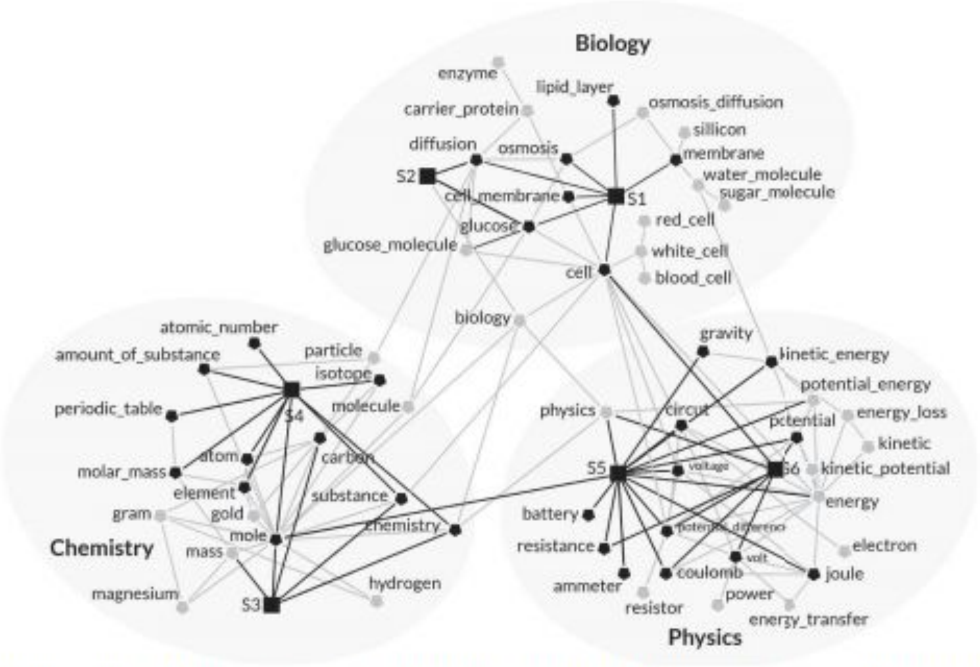
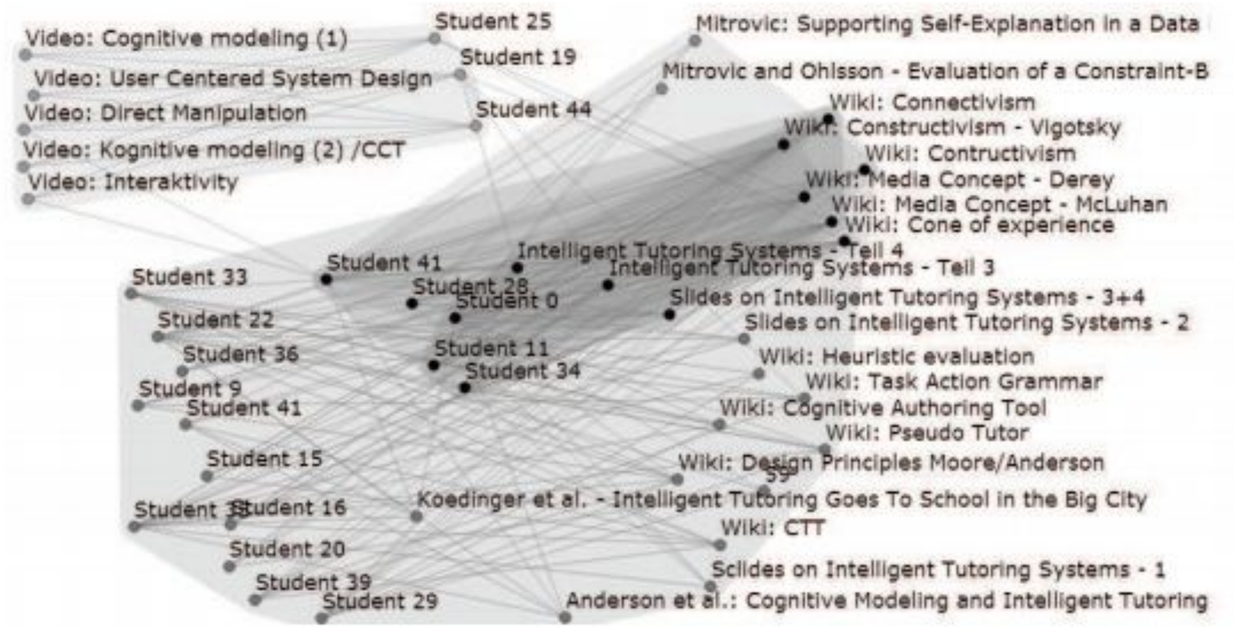


Figure 2.1. Topic–topic and person–topic relations extracted from transcripts of teacher–student workshops.

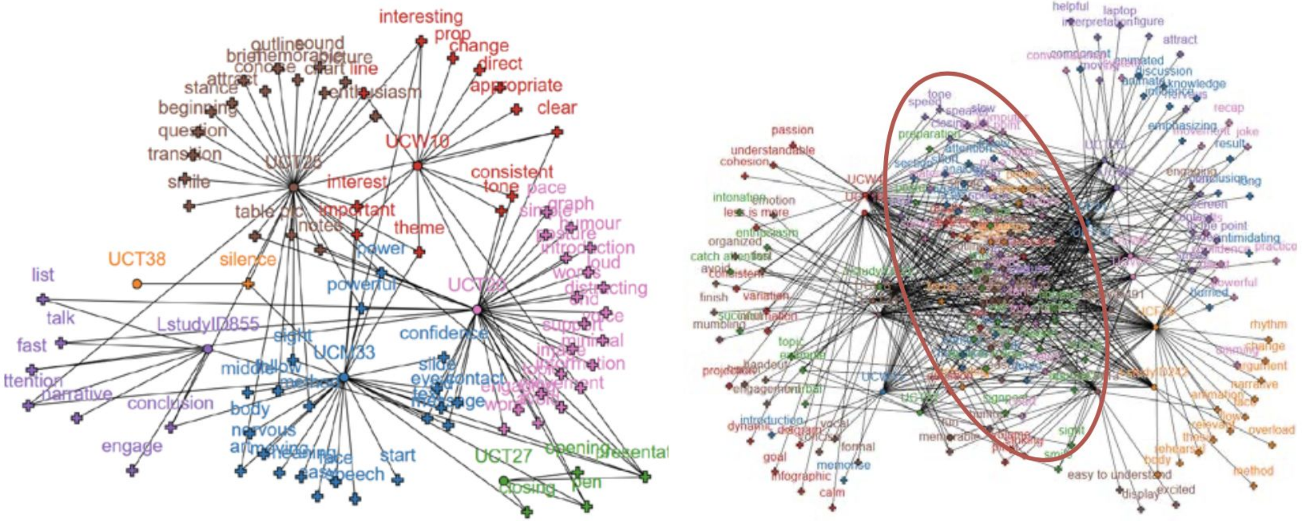
Hoppe, H. U. (2017). Computational methods for the analysis of learning and knowledge building communities. *The Handbook of learning analytics*, 23-33.

Networks are more than social networks



Hoppe, H. U. (2017). Computational methods for the analysis of learning and knowledge building communities. *The Handbook of learning analytics*, 23-33.

Networks are more than social networks



Little vocabulary overlap **High vocabulary overlap**

Figure 2. Bi-partite sub-network of learners and vocabulary terms with high modularity (left: habitual video watchers) and low modularity (self-regulated learners).

Hecking, T., Dimitrova, V., Mitrovic, A., & Hoppe, U. (2017, December). Using network-text analysis to characterise learner engagement in active video watching. In *ICCE 2017 Main Conference Proceedings* (pp. 326-335). Asia-Pacific Society for Computers in Education.

Networks are more than social networks

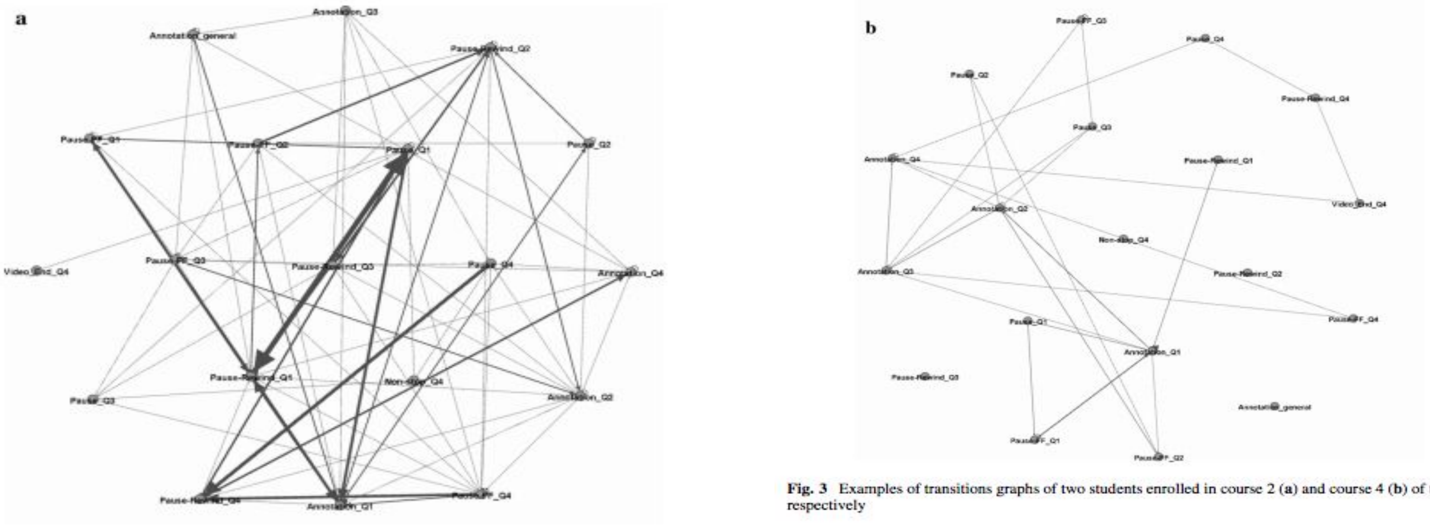


Fig. 3 Examples of transitions graphs of two students enrolled in course 2 (**a**) and course 4 (**b**) of the study, respectively

Mirriahi, N., Liaqat, D., Dawson, S., & Gašević, D. (2016). Uncovering student learning profiles with a video annotation tool: reflective learning with and without instructional norms. *Educational technology research and development*, *64*(6), 1083-1106.

Networks are more than social networks

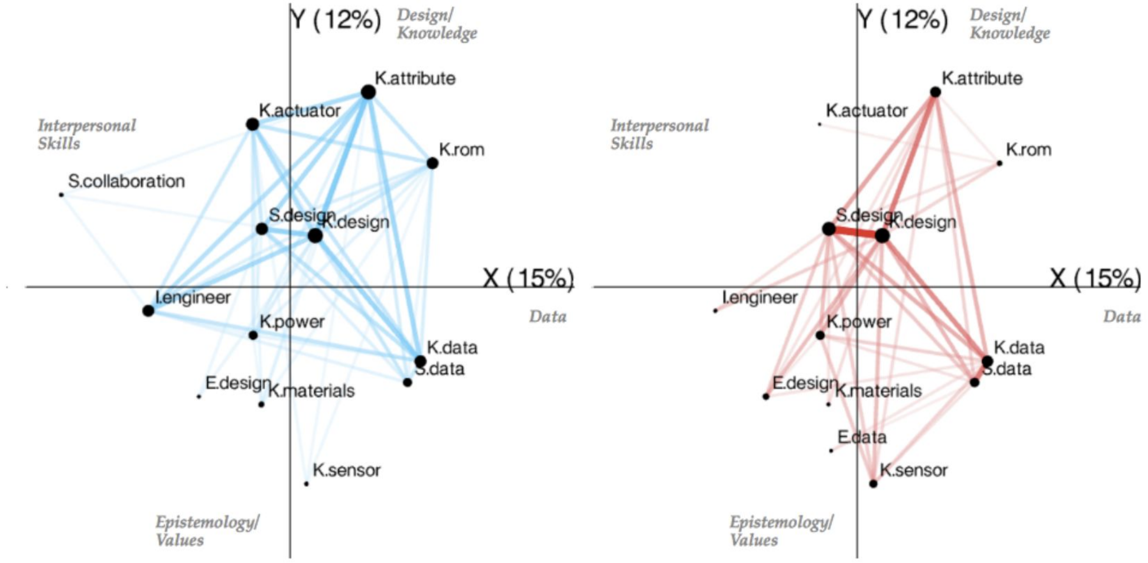


Figure 9. Mean networks of students' from the first (blue, left) and second (red, right) halves of an engineering design simulation.

Shaffer, D., & Ruis, A. (2017). Epistemic network analysis: A worked example of theory-based learning analytics. *Handbook of learning analytics*.

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

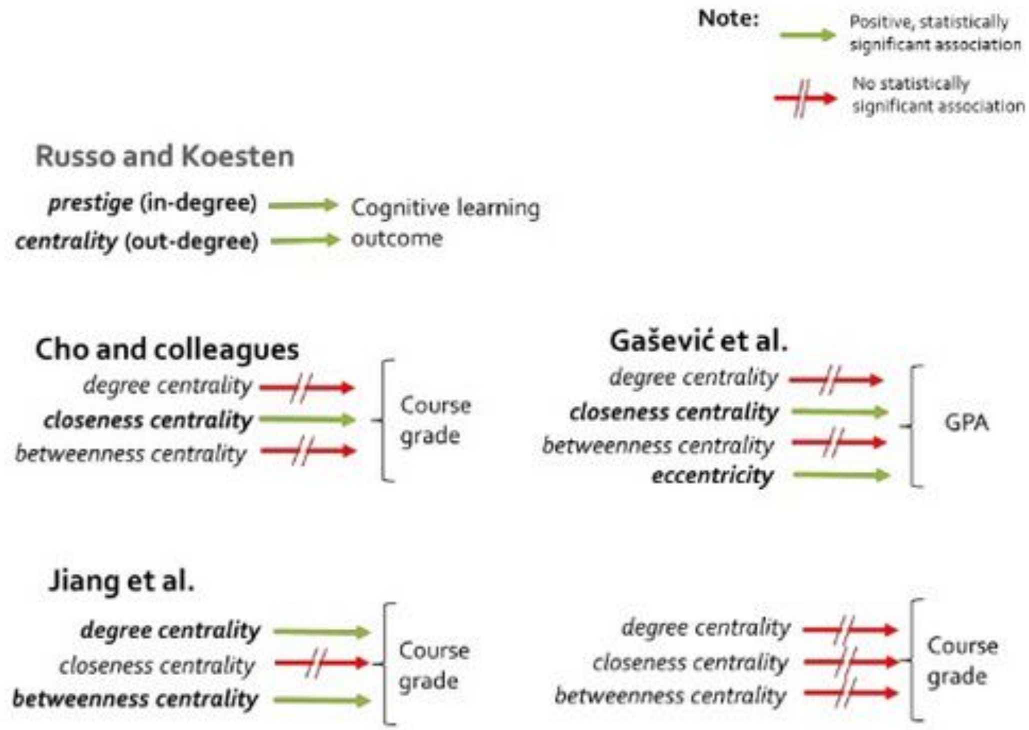
Not all centrality measures are equal

Network centralities measure network positioning

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

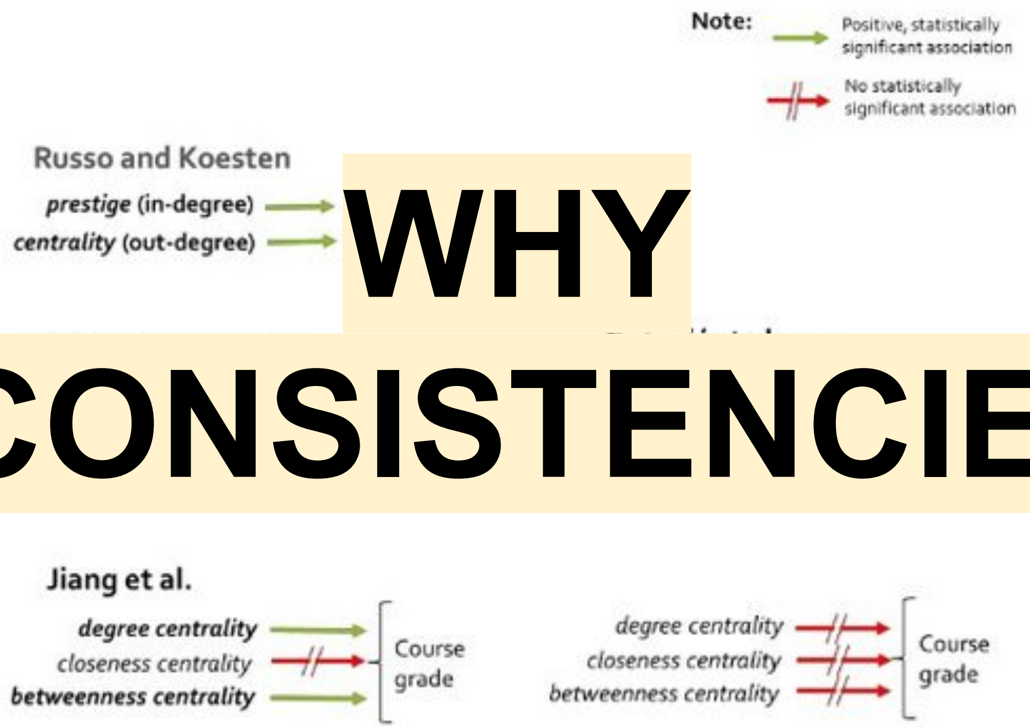
Similar positioning = similar benefits = possibility for assessment

Not all centrality measures are equal



Joksimović, S., Manataki, A., Gašević, D., Dawson, S., Kovanović, V., & de Kereki, I. F. (2016). Translating network position into performance: Importance of centrality in different network configurations. *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge - LAK '16*, 314–323. https://doi.org/10.1145/2883851.2883928

Not all centrality measures are equal



WHY INCONSISTENCIES?

Not all centrality measures are equal

Tie definitions by Wise, Cui & Jin (2017)

Direct reply

Copresence / Shared thread

Not all centrality measures are equal

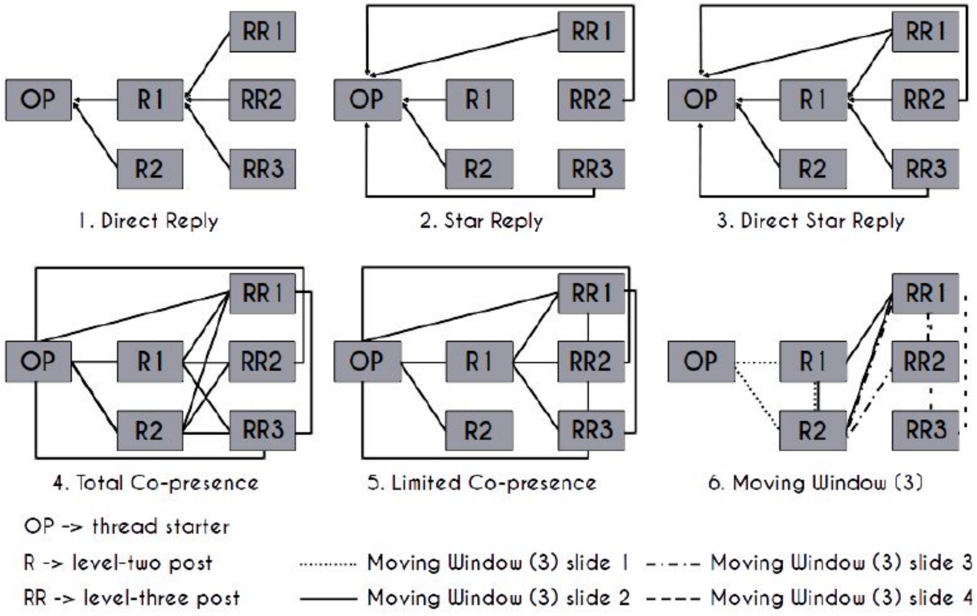


Figure 2: Six Social Tie Definitions

Wise, A. F., Cui, Y., & Jin, W. Q. (2017). Honing in on social learning networks in MOOC forums: Examining critical network definition decisions. *LAK*

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

Network models matter

"... A network model should be viewed explicitly as yielding a network representation of something"

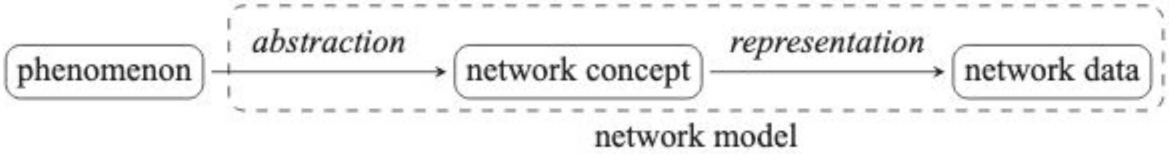


Fig. 1. The elements of network models.

Brandes, U., Robins, G., McCranie, A., and Wasserman, S. (2013). What is network science?. *Network Science, 1*(1), 1-15. doi:10.1017/nws.2013.2

Network models matter

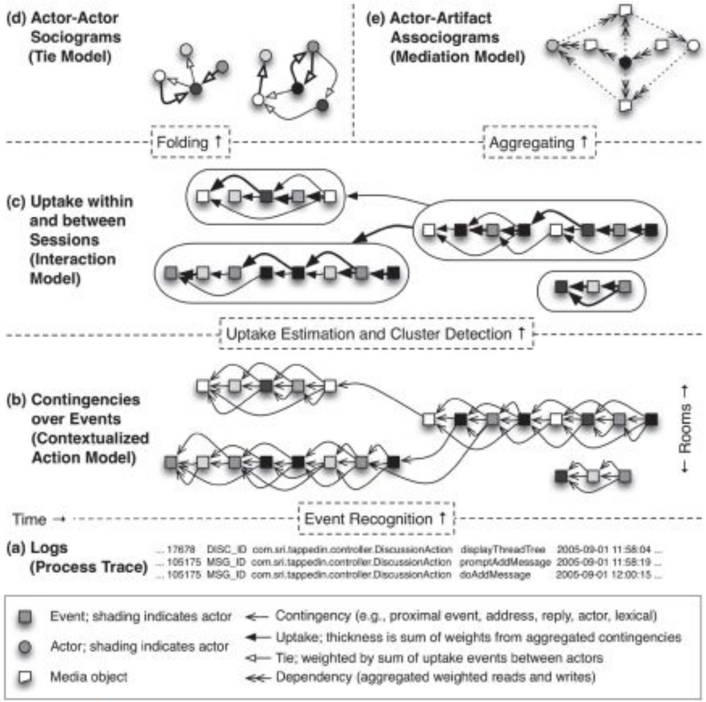


Figure 16.1. Levels of analysis and their representations.

Suthers, D. (2015). From contingencies to network-level phenomena: Multilevel analysis of activity and actors in heterogeneous networked learning environments. *LAK*

Network models matter

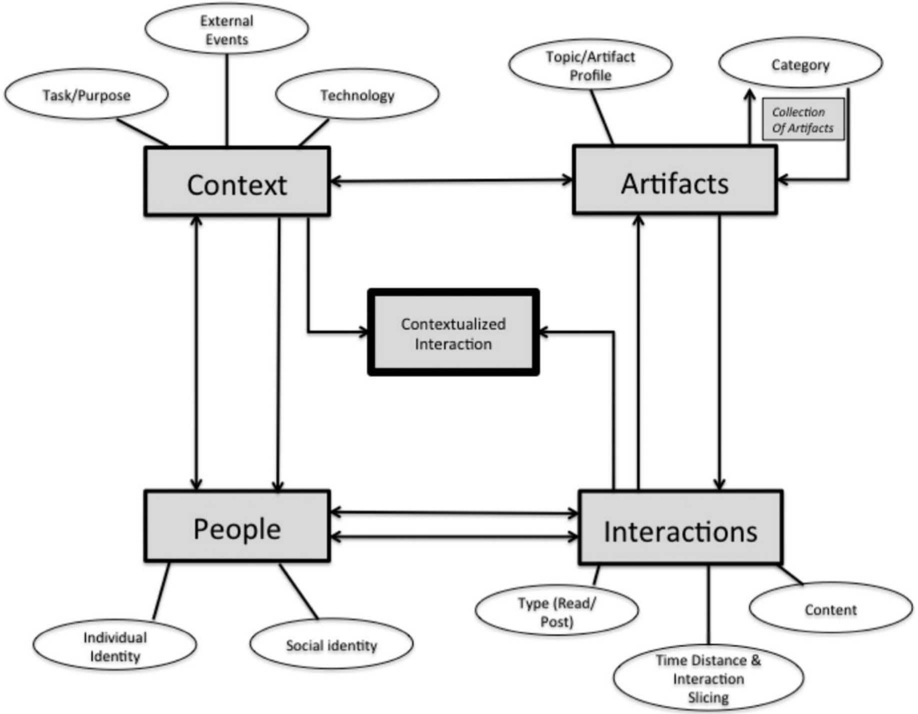
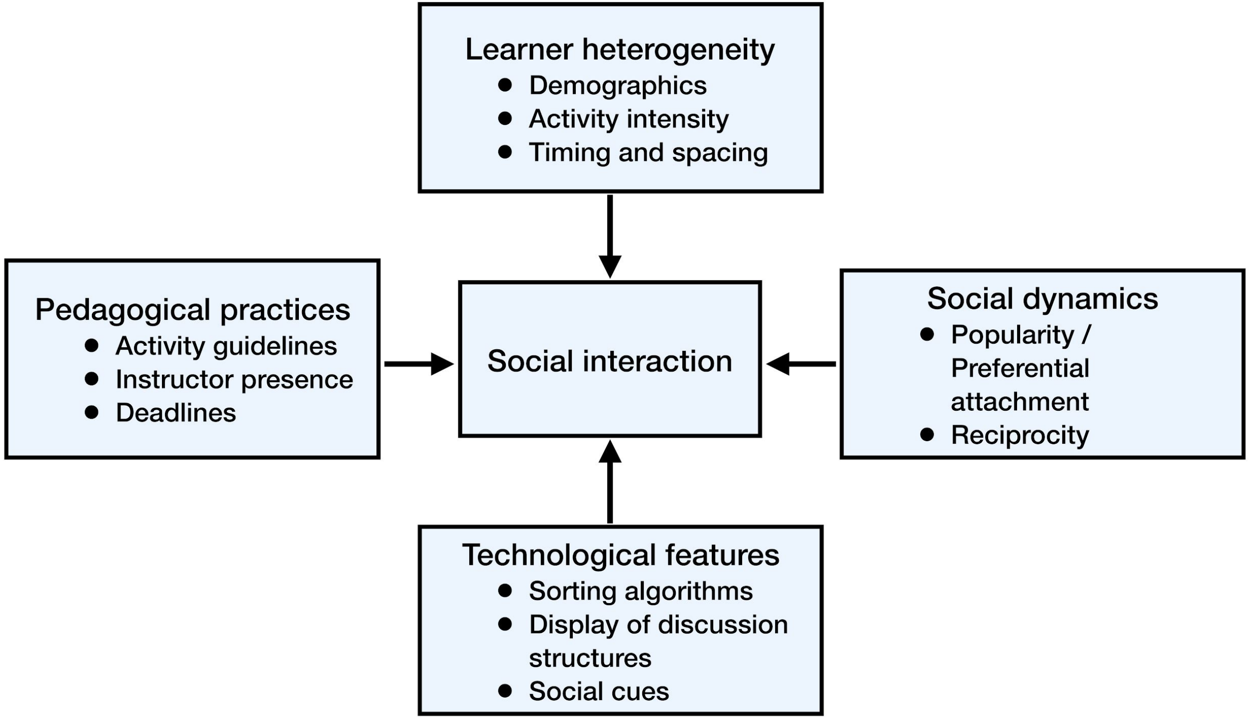


FIG. 1. Model overview of group informatics.

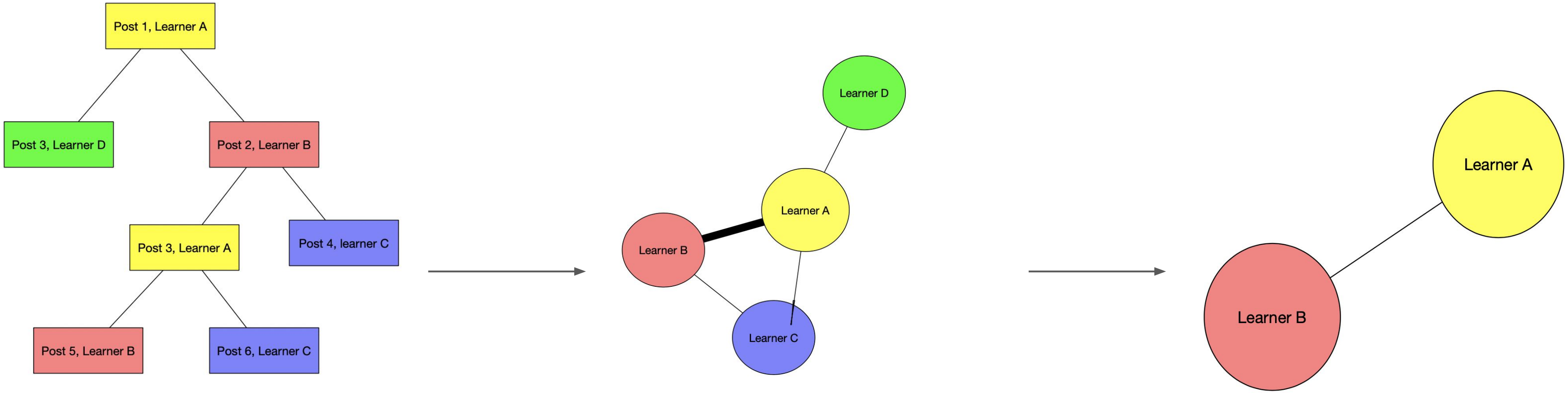
Goggins, S. P., Mascaro, C., & Valetto, G. (2013). Group informatics: A methodological approach and ontology for sociotechnical group research. *Journal of the American Society for Information Science and Technology*, *64*(3), 516-539.

Network models matter



Chen, B., & Poquet, O. (2020). Socio-temporal dynamics in peer interaction events. *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*, 203–208. https://doi.org/10.1145/3375462.3375535

Network models matter



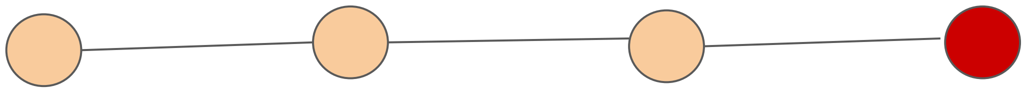
a) Posting network

b)Communication network

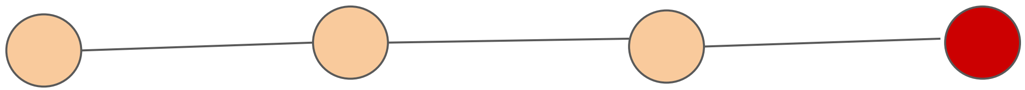
c) Social network

Poquet, O., Trenholm, S., Santolini, M. (n.d.). Multi-level Approach to Online Forum Evaluation: From Posts to Communication Patterns to Learner Networks.

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

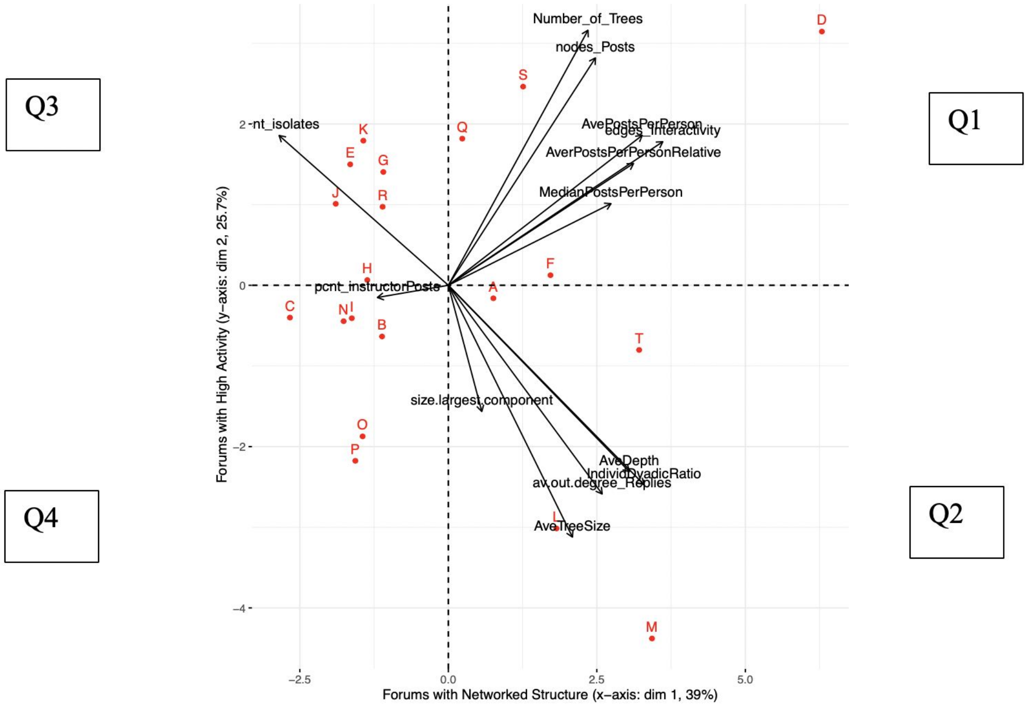


Figure 3. Principal Component Analysis Bi-Plot Structuring Forums and Posting Activity Indicators

Evaluating posting behavior

Q1 High Activity; High Turn-Taking

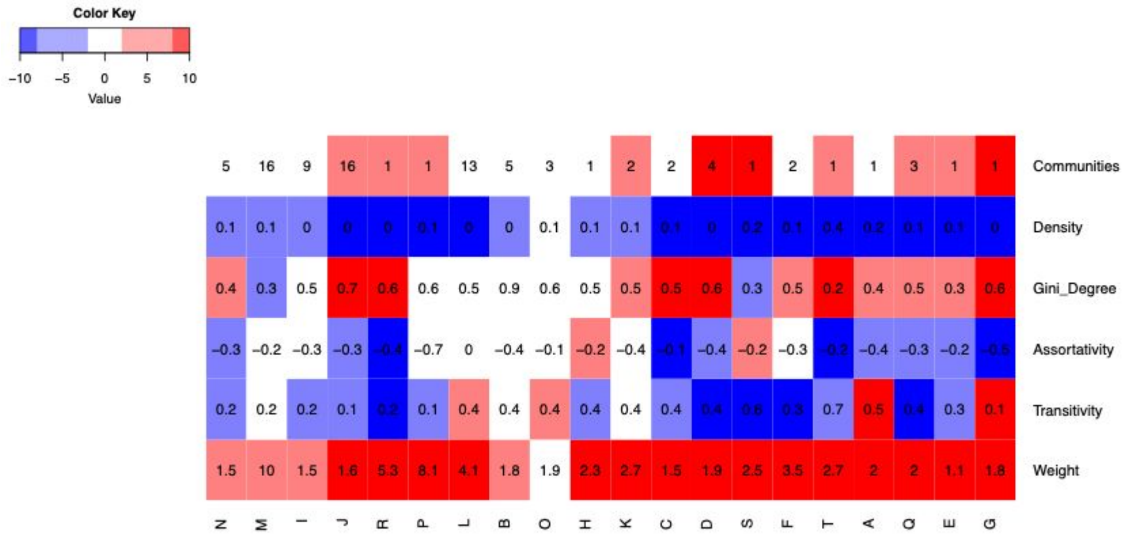
Q2 Moderate Activity; High Turn-Taking

Q3 High Activity; Low Turn-Taking

Q4 Low Activity; Low Turn-Taking

Poquet, O., Trenholm, S., Santolini, M. (n.d.). Multi-level Approach to Online Forum Evaluation: From Posts to Communication Patterns to Learner Networks.

Evaluation is multi-dimensional



Evaluating communication structure

Q1 Communities, inequality

Q2 No communities, equality

Q3 High dyadic exchange, pockets of exchanges

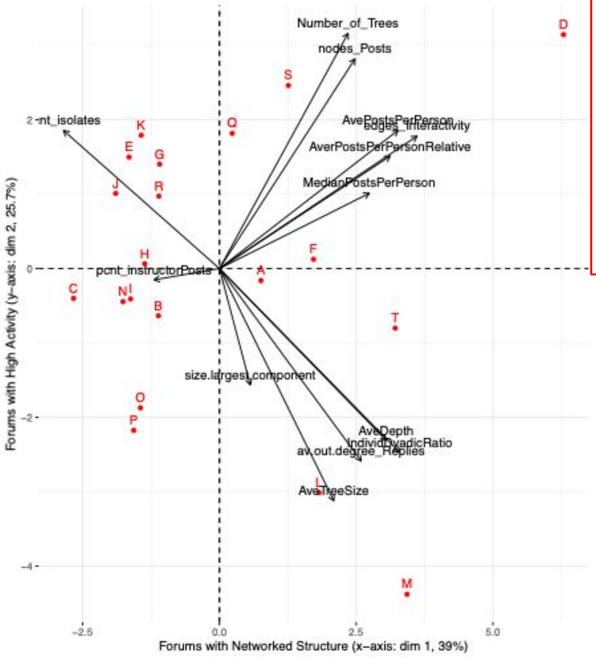
Q4 High centralization

Poquet, O., Trenholm, S., Santolini, M. (n.d.). Multi-level Approach to Online Forum Evaluation: From Posts to Communication Patterns to Learner Networks.

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'

Poquet, O., Trenholm, S., Santolini, M. (n.d.). Multi-level Approach to Online Forum Evaluation: From Posts to Communication Patterns to Learner Networks.

Evaluation is multi-dimensional

Evaluating communication structure

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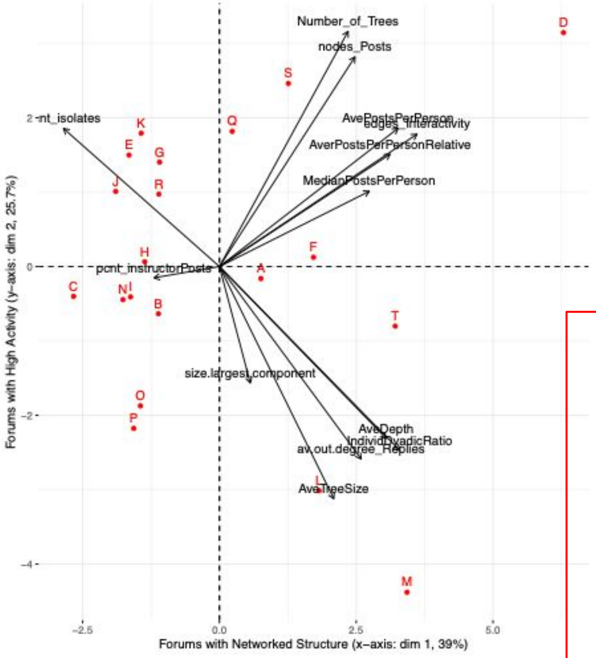

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Evaluation is multi-dimensional

Evaluating communication structure

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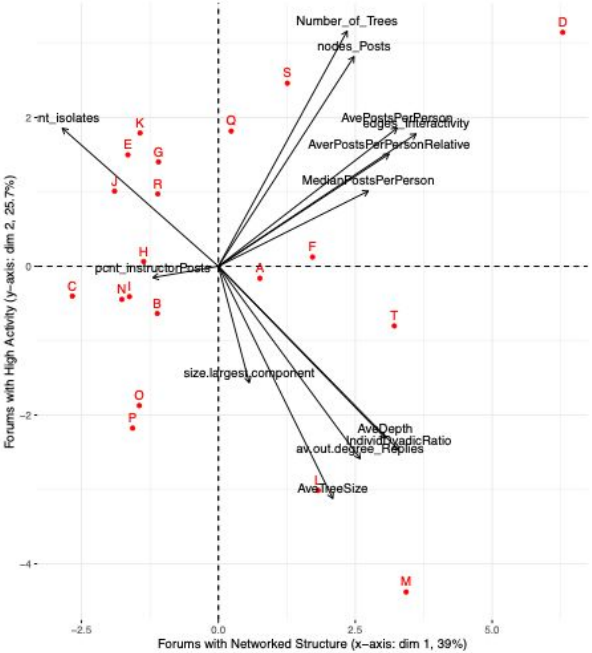

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Evaluating communication structure

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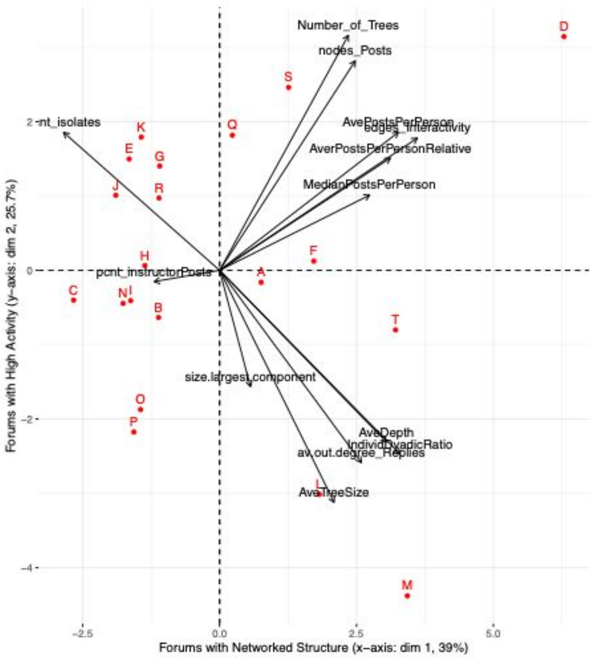

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'Post a response or build on the opinion of X people'

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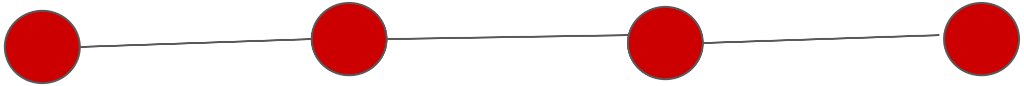
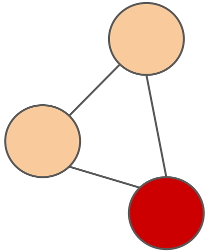
Applied Network Analysis: Core Messages



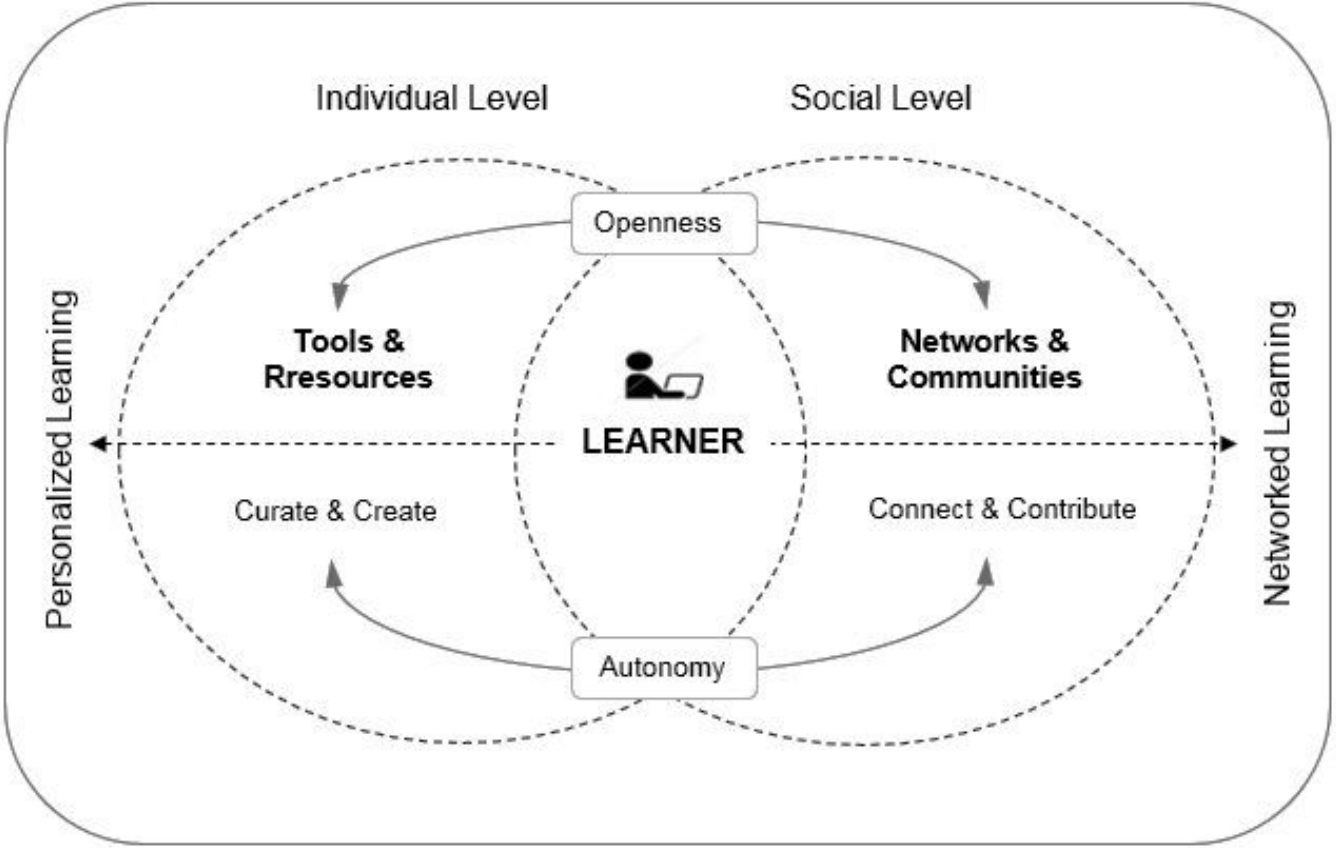
- **Networks are much more than social networks**
- **Not all centralities measures are made equal**
- **Network models matter**
- **Network evaluation is subjective and multi-dimensional**

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

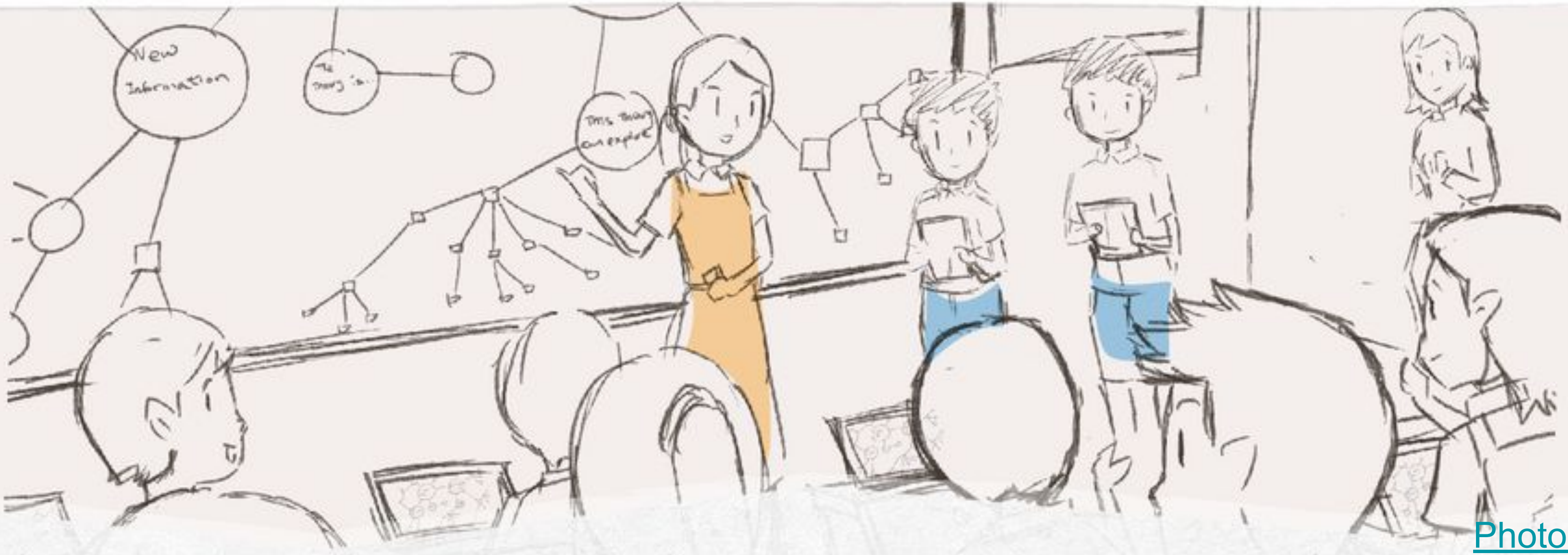
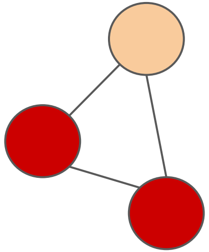


Photo Credit

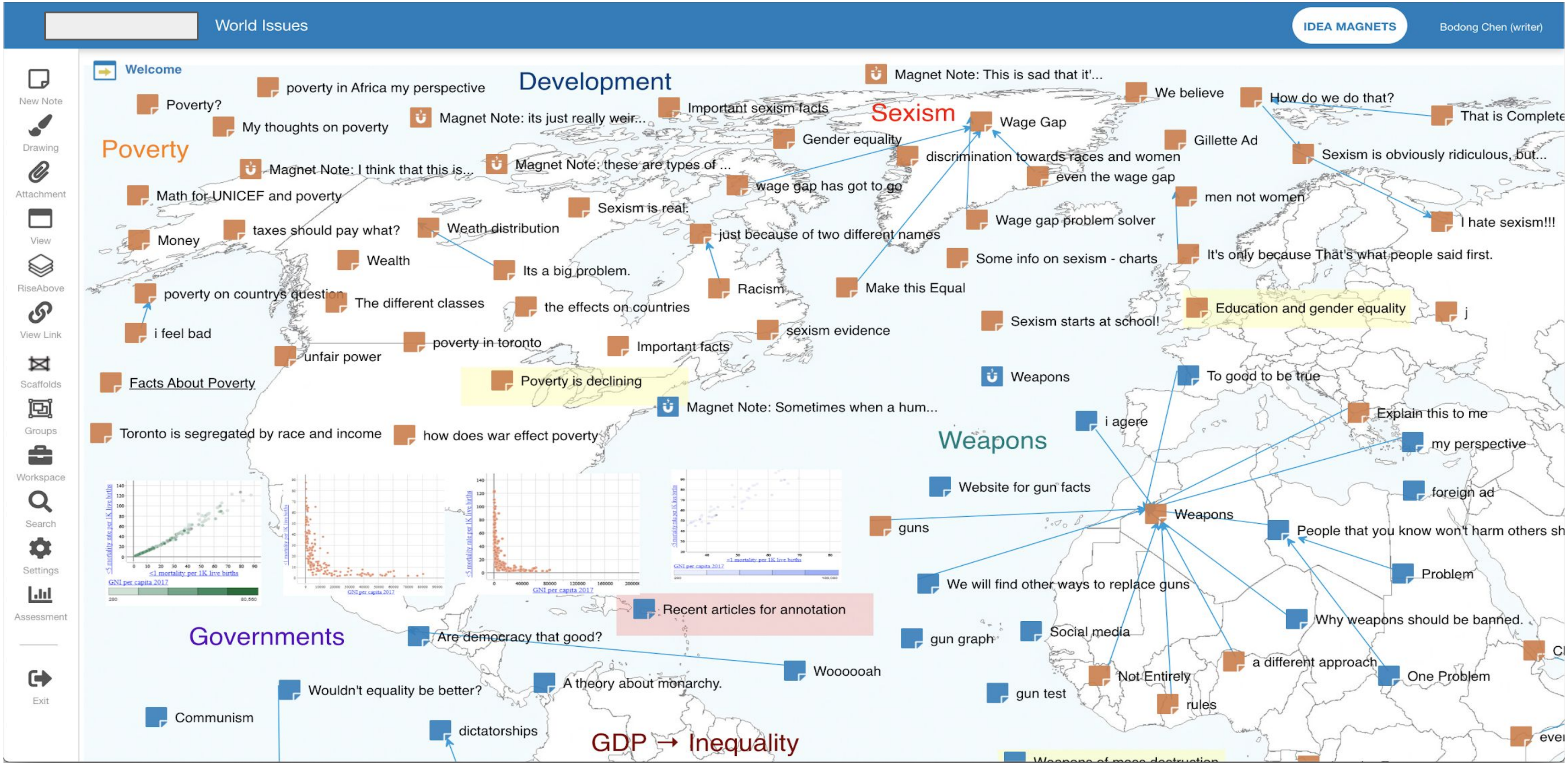
Applying Network Analytics in Teaching



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

Photo Credit

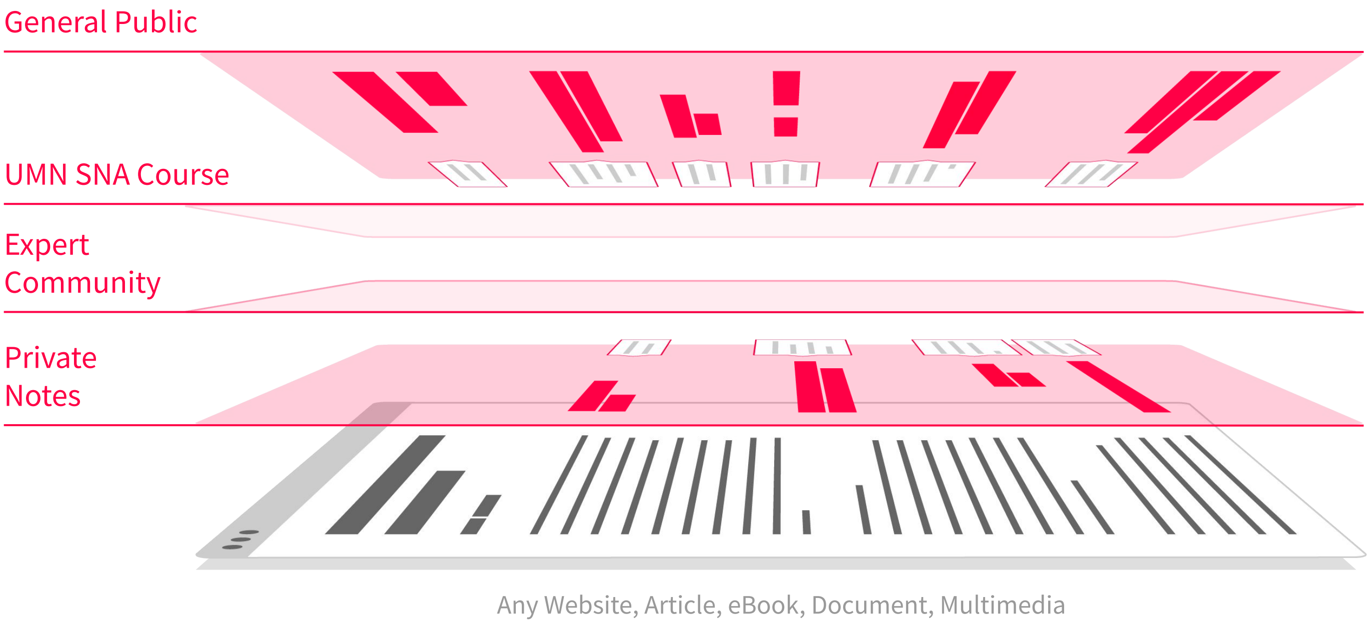
Social media



Knowledge Forum

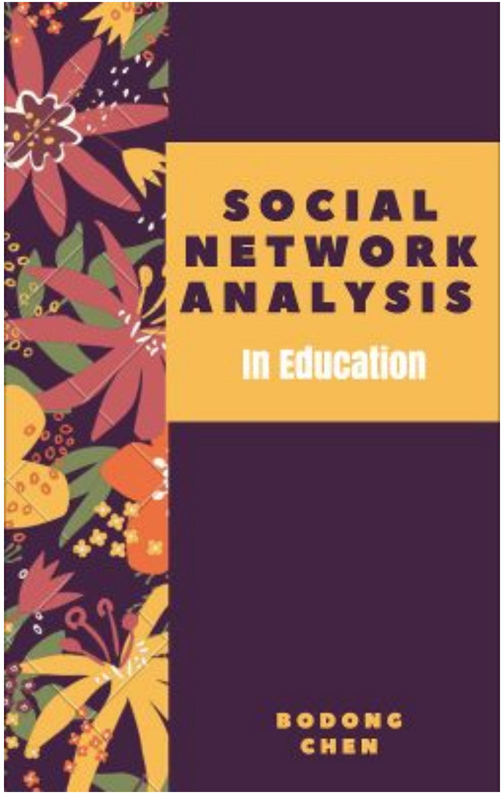
Layers of Annotation

Built on Open Standards

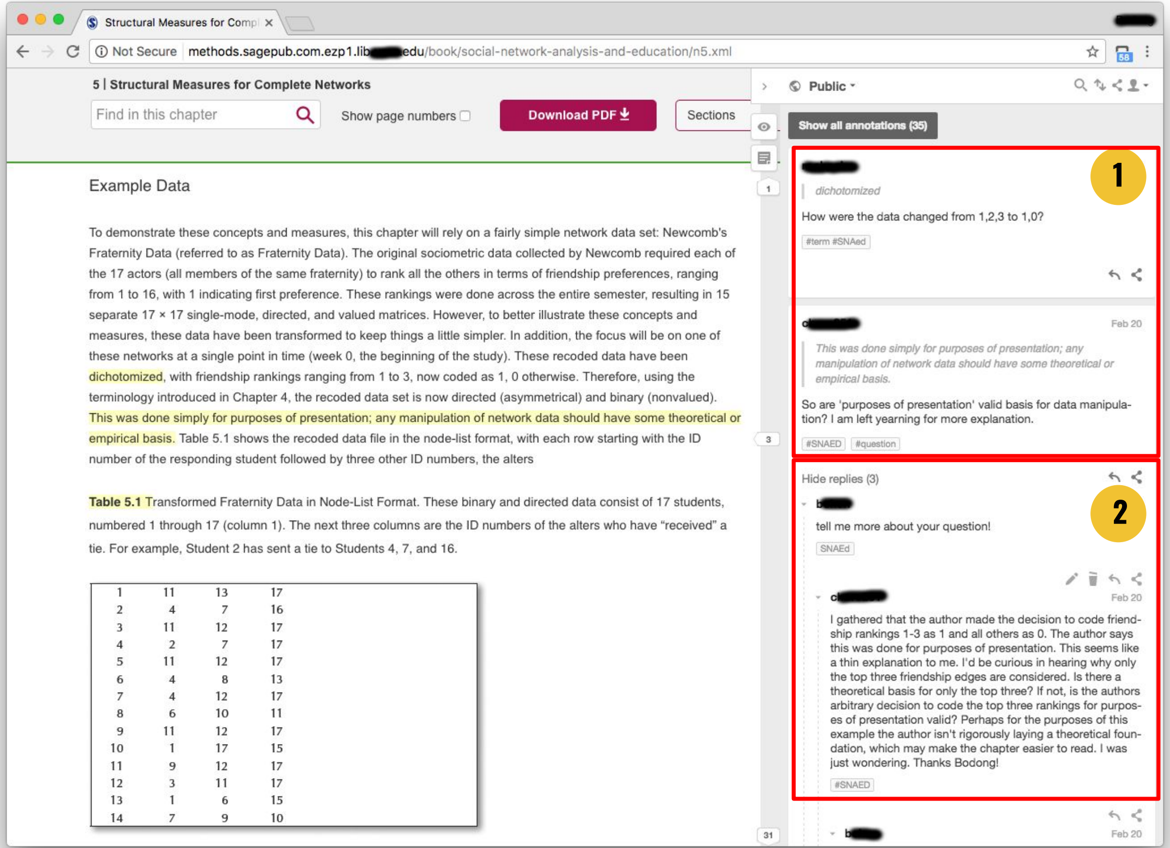


(Credit: Angell, Dean, et al., *EDUCAUSE 2018*)

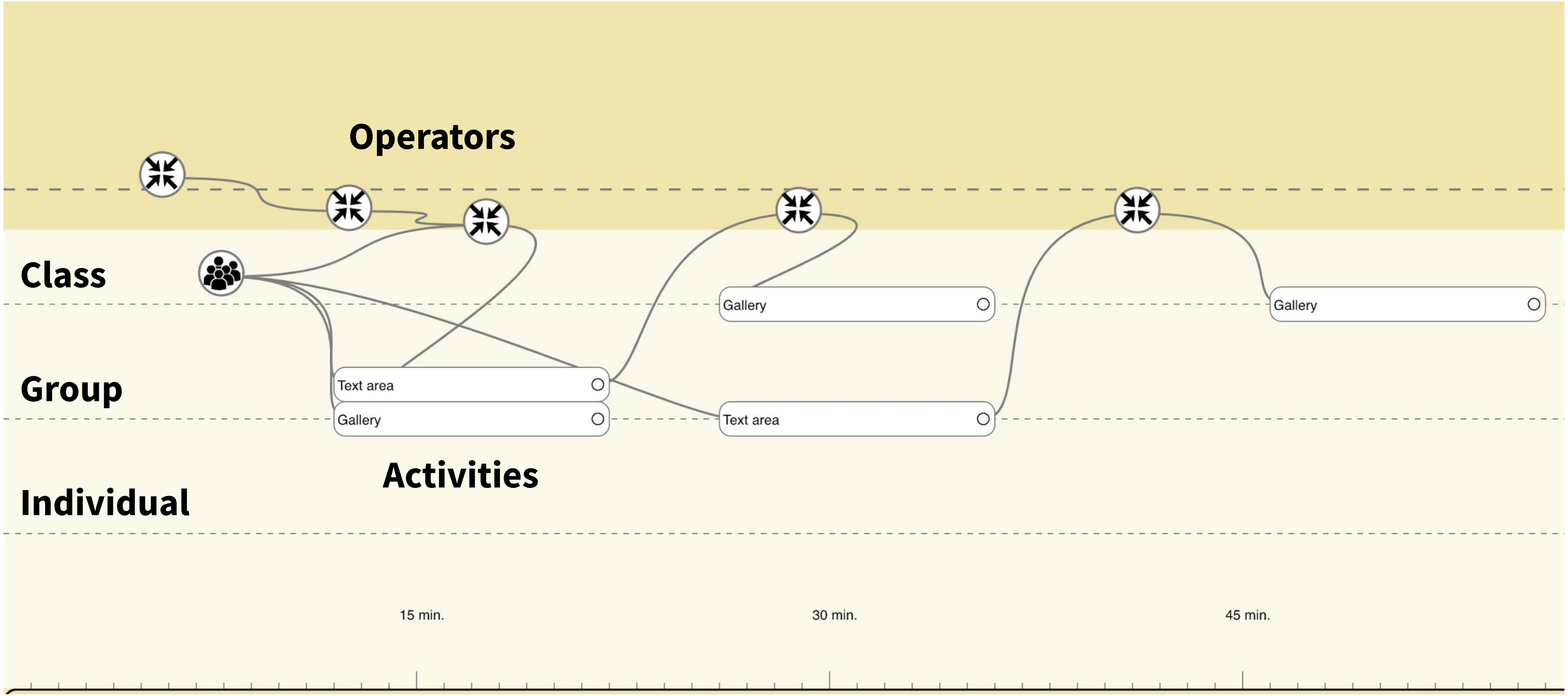
See https://bookdown.org/chen/snaEd/



Chen, B. (2019). Designing for Networked Collaborative Discourse: An UnLMS Approach. *TechTrends, 63*(2), 194–201. https://doi.org/10.1007/s11528-018-0284-7



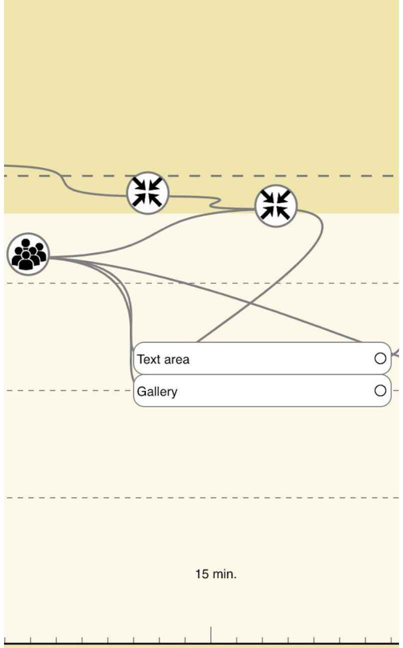
1. Annotations of readings
2. Replies to annotations

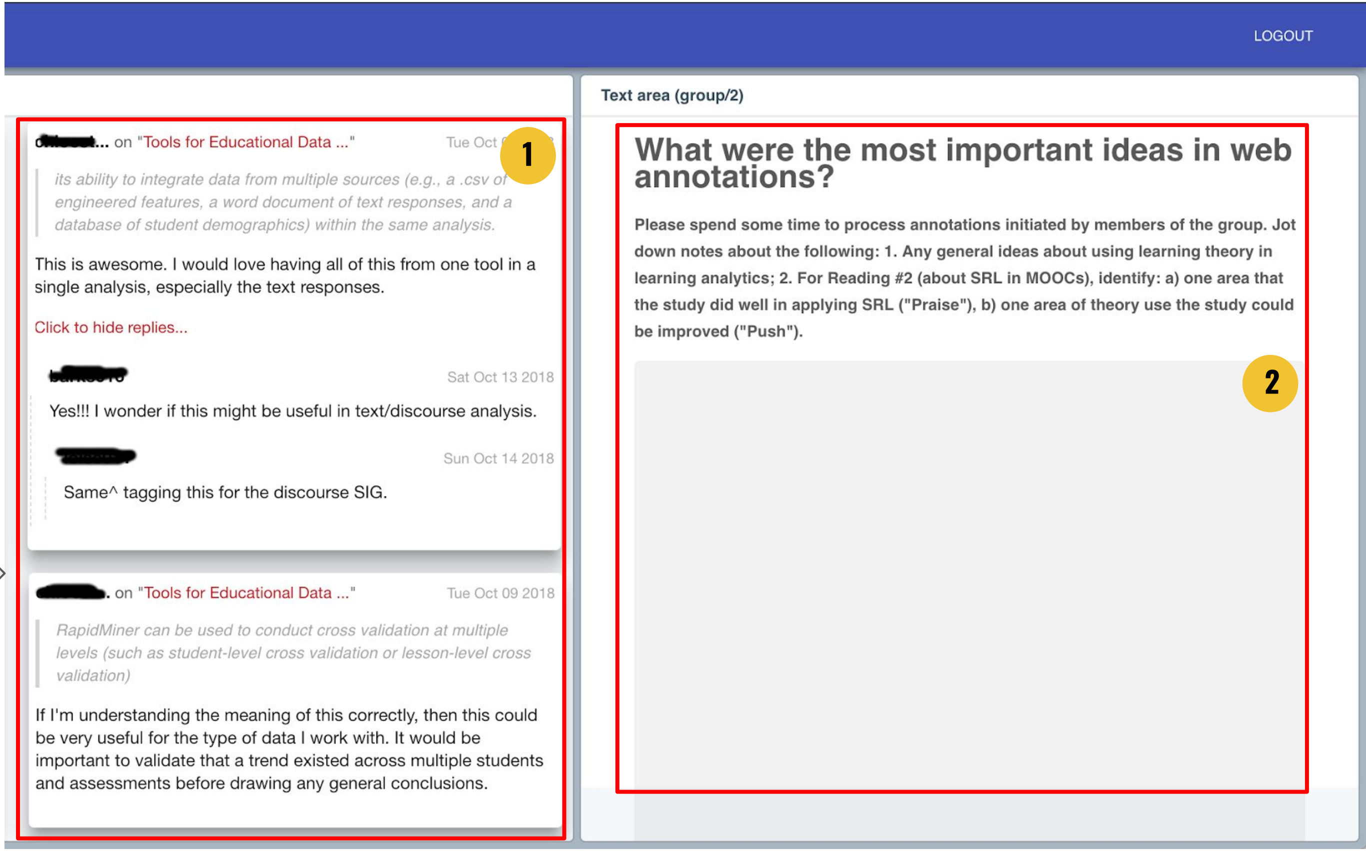


Synchronous collaborative activities on FROG (by Stian Håklev)

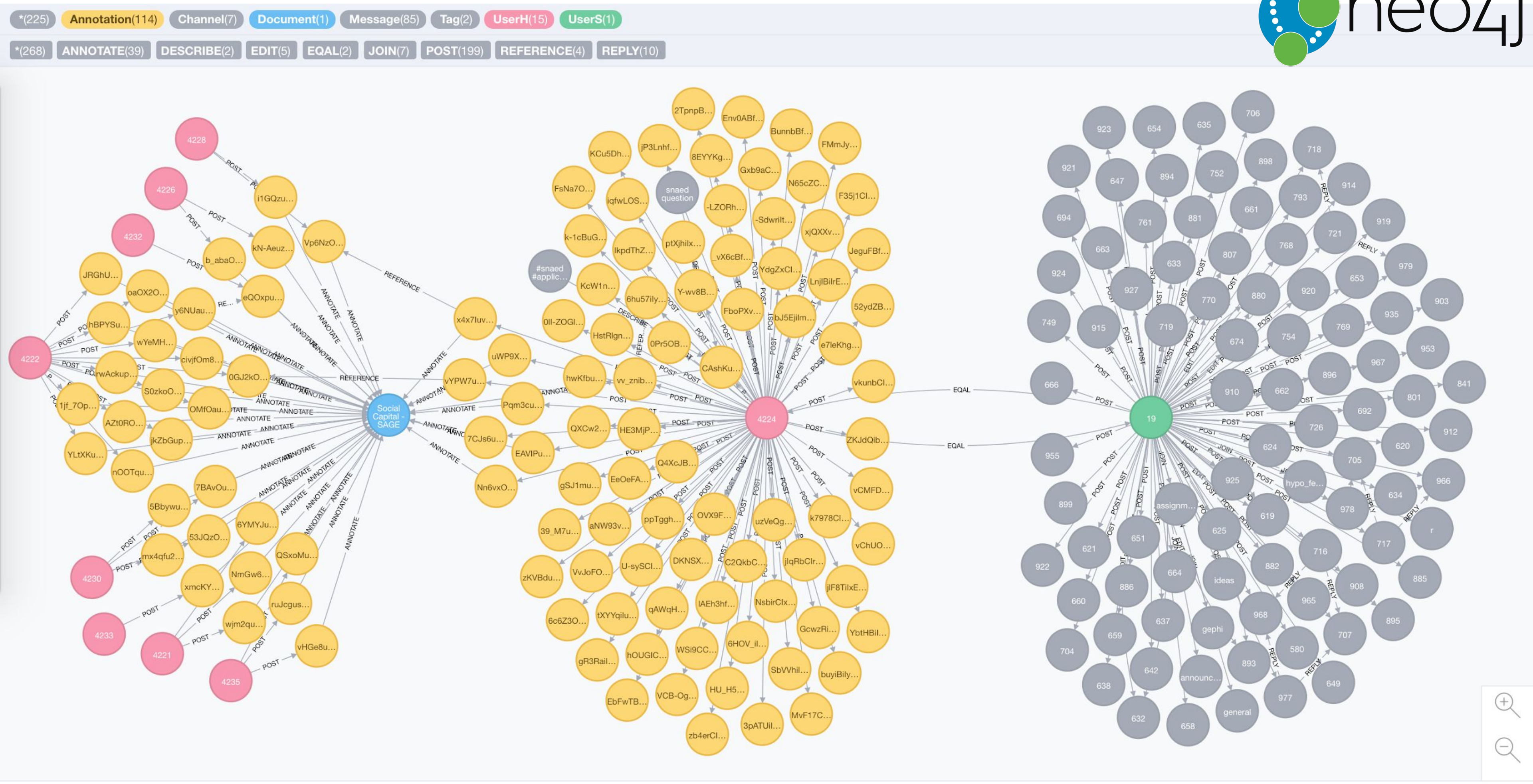
Chen, B., Shui, H., & Håklev, S. (2020). Designing orchestration support for collaboration and knowledge flows in a knowledge community. To appear in the *Proceedings of the 14th International Conference of the Learning Sciences (ICLS)*.

FROG activity 1





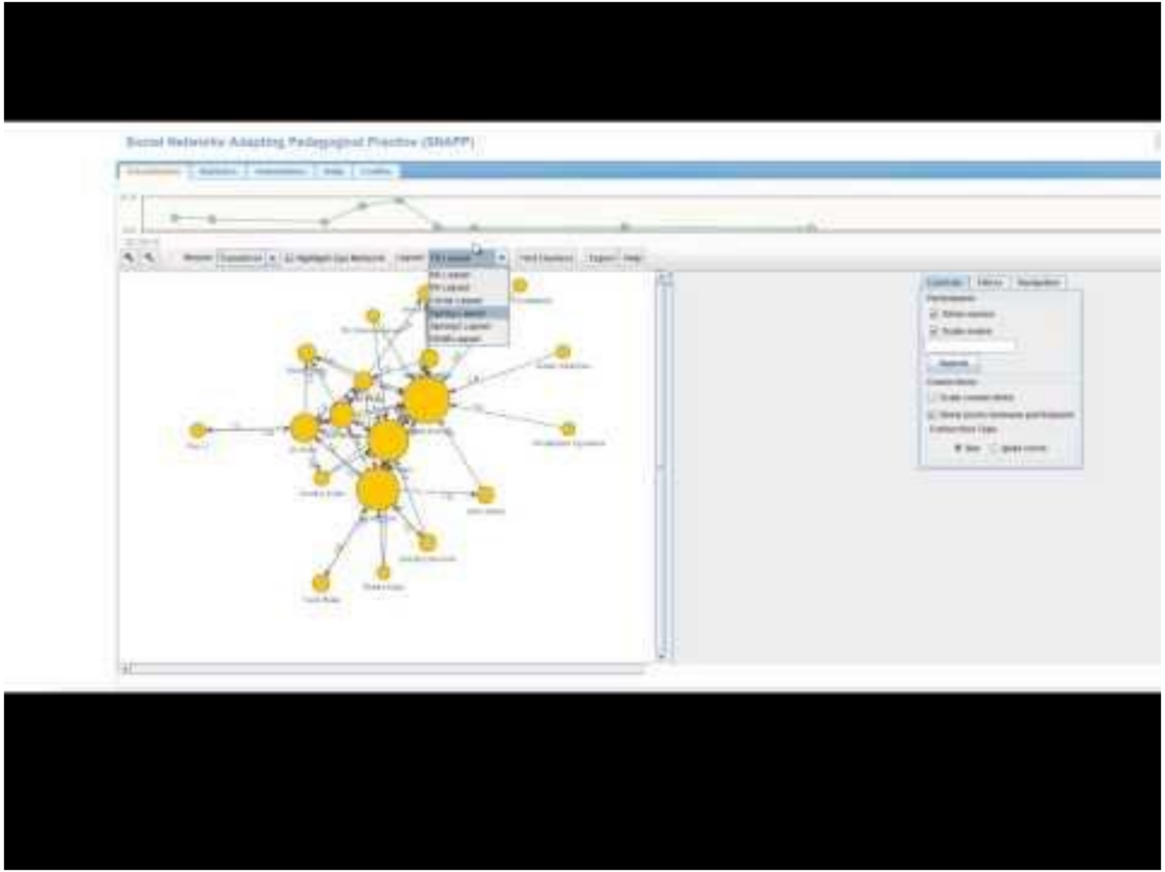
1. Annotations imported via Hypothesis APIs
2. Group note-taking in Zoom breakout rooms


*(225) Annotation(114) Channel(7) Document(1) Message(85) Tag(2) UserH(15) UserS(1)
*(268) ANNOTATE(39) DESCRIBE(2) EDIT(5) EQAL(2) JOIN(7) POST(199) REFERENCE(4) REPLY(10)
Social Capital - SAGE
4224
19
EQAL
POST
ANNOTATE
REFERENCE
REPLY

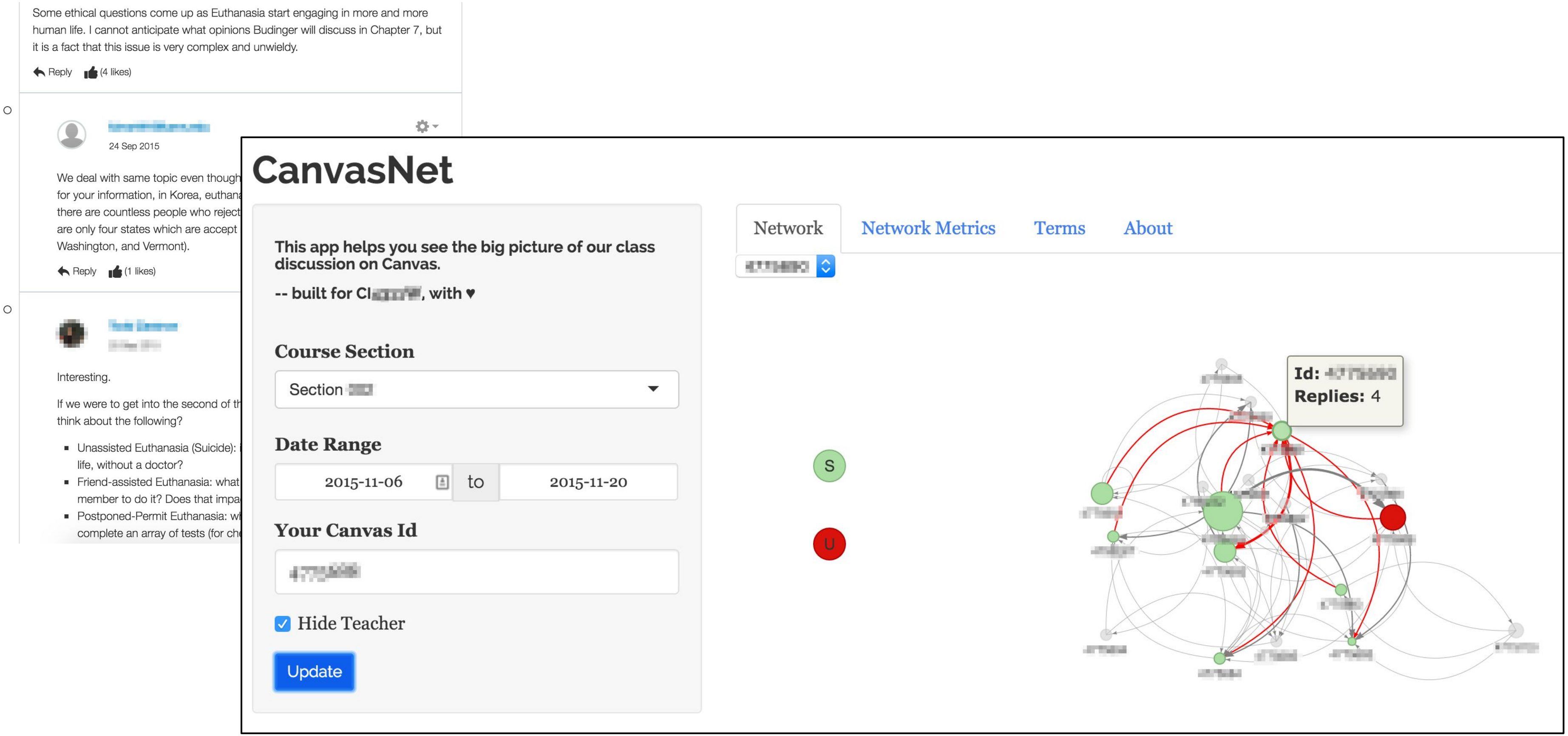
neo4j

Applying Network Analytics in Teaching

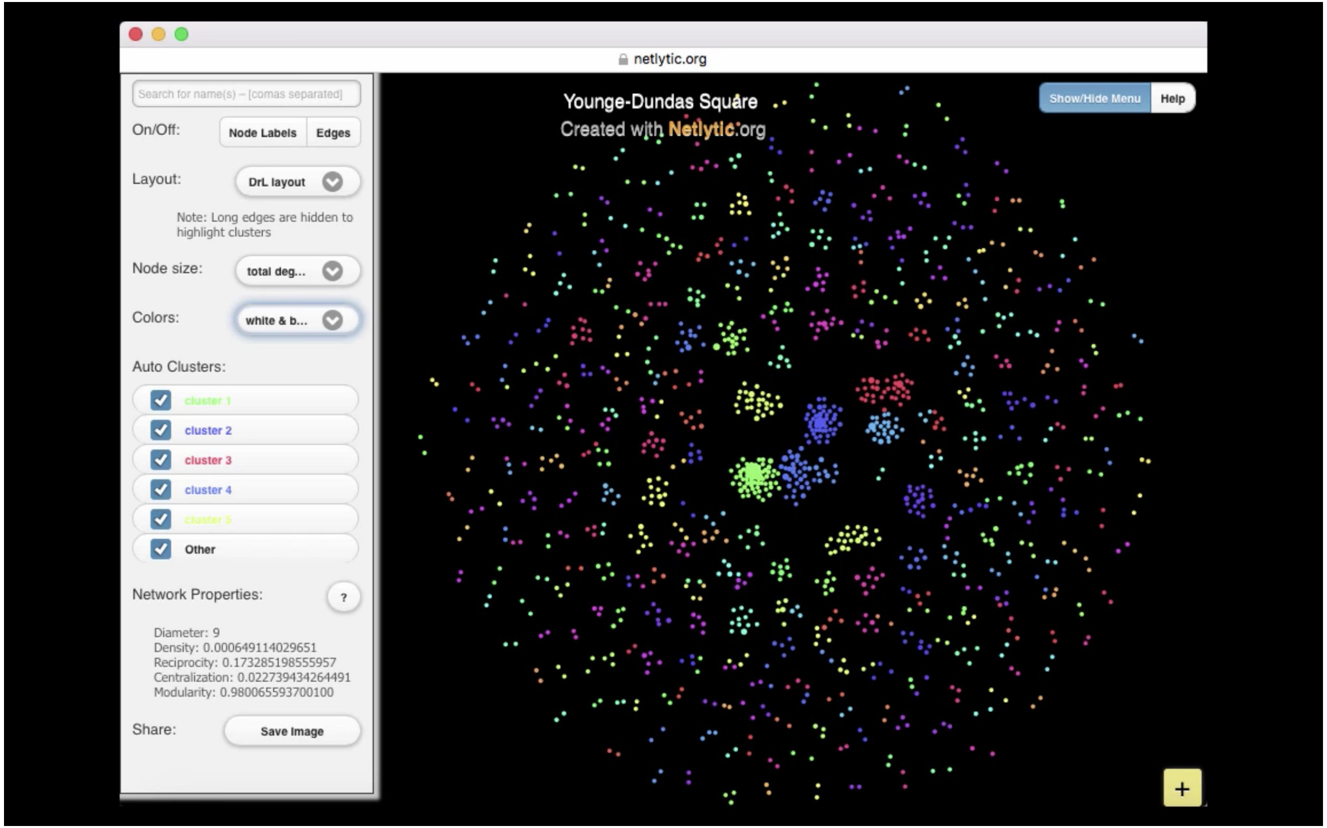
- **Learning as a networked phenomenon.**
- **Socio-technical systems facilitate networked learning.**
- **Network analytics apps empower reflection and action-taking.**



SNAPP (Bakharia & Dawson, 2011)



Chen, B., Chang, Y.-H., Ouyang, F., & Zhou, W. (2018). Fostering student engagement in online discussion through social learning analytics. *The Internet and Higher Education, 37*, 21–30. https://doi.org/10.1016/j.iheduc.2017.12.002

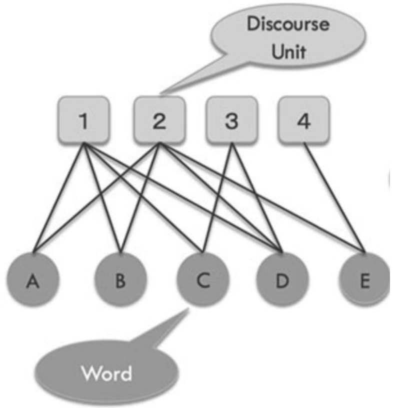


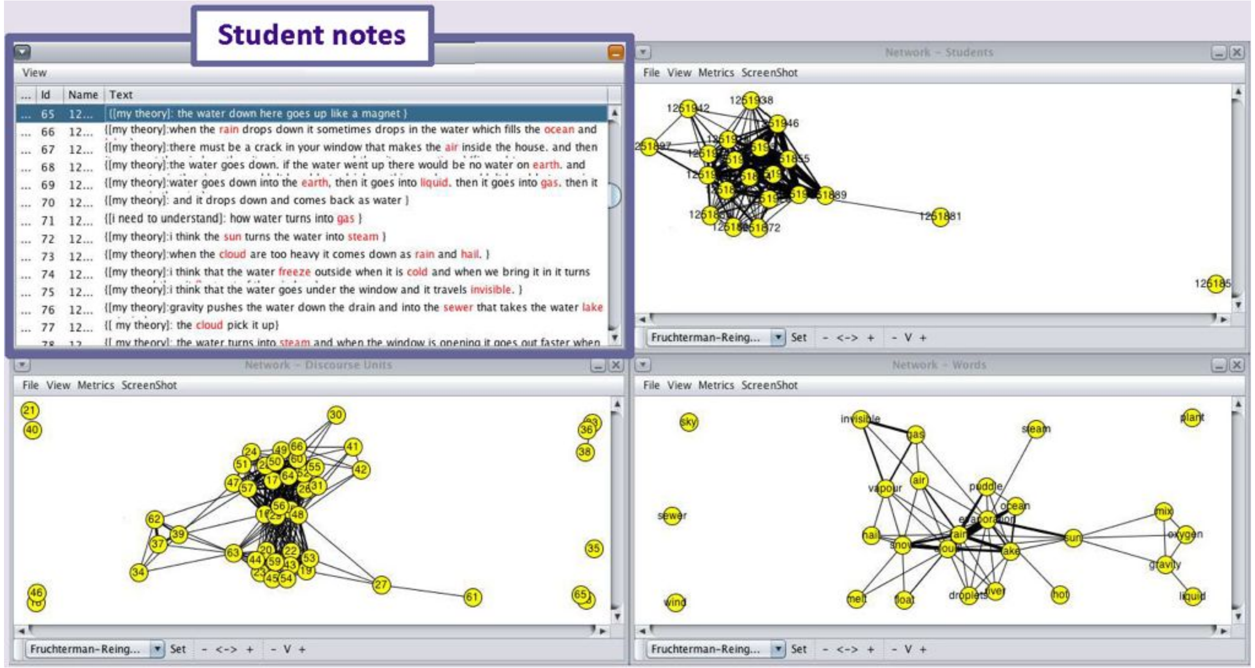
Netlytic (see https://netlytic.org/)

Gruzd, A., Paulin, D., & Haythornthwaite, C. (2016). Analyzing Social Media And Learning Through Content And Social Network Analysis: A Faceted Methodological Approach. *Journal of Learning Analytics, 3*(3), 46–71. https://doi.org/10.18608/jla.2016.33.4

Socio-semantic networks based on KBDeX

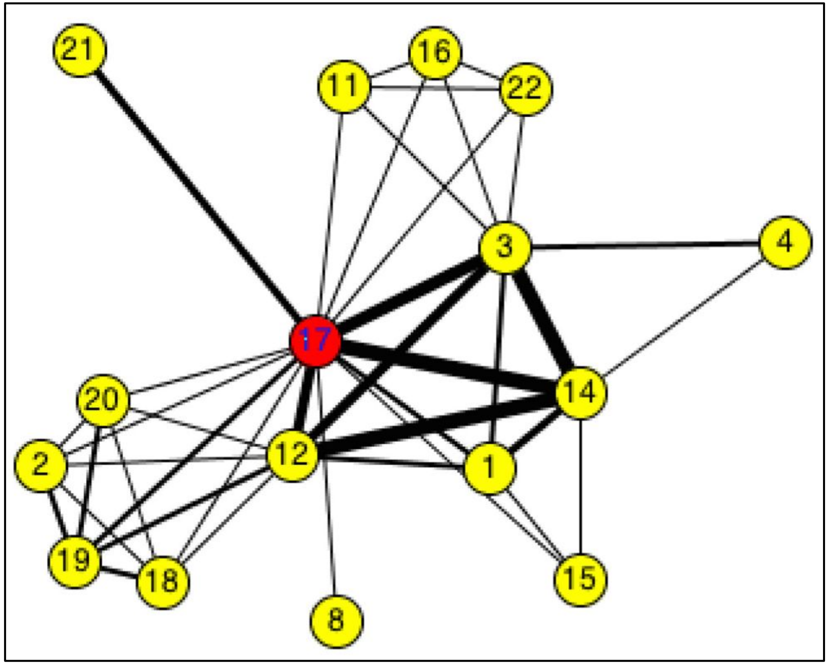
(Oshima, Oshima, & Matsuzawa, 2012)

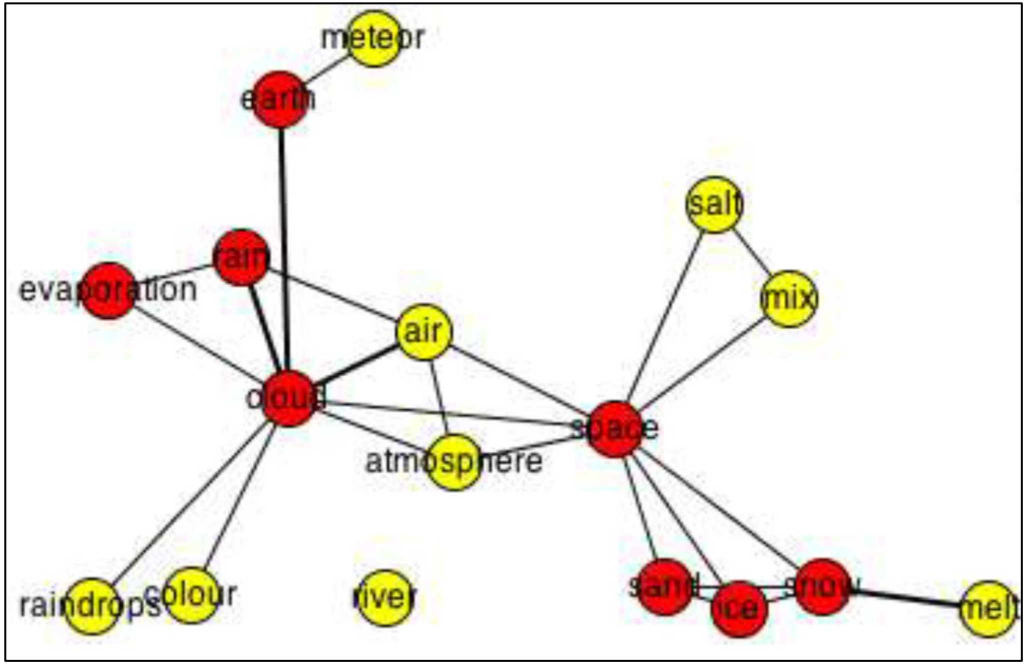




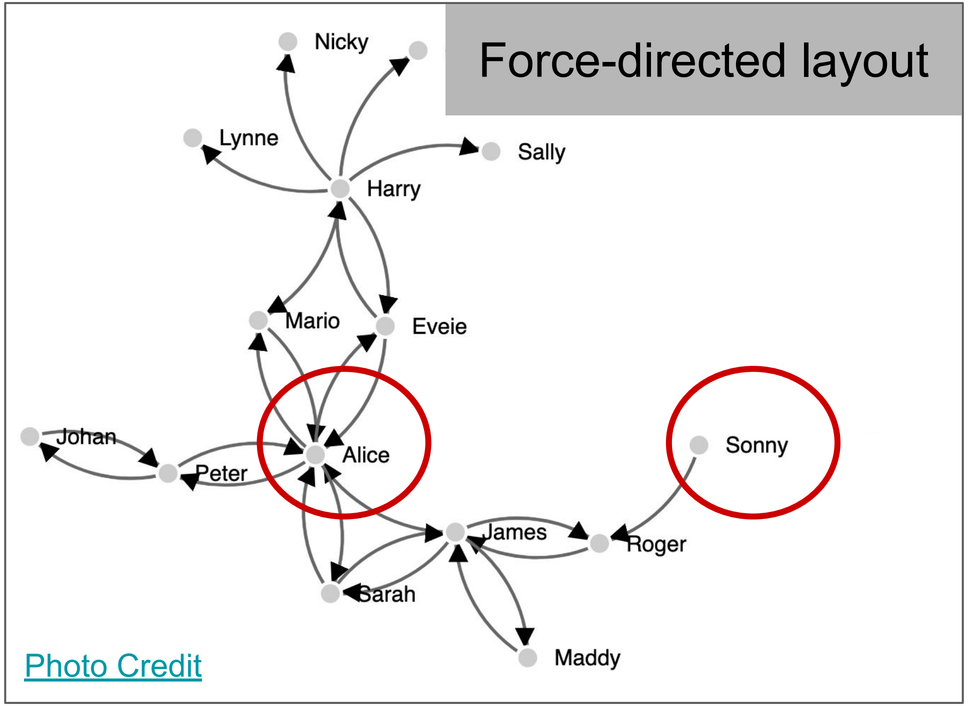
Ma, L., Matsuzawa, Y., Chen, B., & Scardamalia, M. (2016). Community knowledge, collective responsibility: The emergence of rotating leadership in three knowledge building communities. In *The International Conference of the Learning Sciences (ICLS) 2016, Volume 1* (Vol. 1, pp. 615–622). Singapore.

Knowledge building in grade 1





Ma, L., Matsuzawa, Y., Chen, B., & Scardamalia, M. (2016). Community knowledge, collective responsibility: The emergence of rotating leadership in three knowledge building communities. In *The International Conference of the Learning Sciences (ICLS) 2016, Volume 1* (Vol. 1, pp. 615–622). Singapore.



Sense of belonging	Self-image

Word of caution: implicit biases and value tensions

Chen, B., & Zhu, H. (2019). Towards Value-Sensitive Learning Analytics Design. *Proceedings of the 9th International Conference on Learning Analytics & Knowledge*, 343–352. https://doi.org/10.1145/3303772.3303798

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!

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