Integrating Learning Analytics to Measure Message Quality in Large Online Conversations

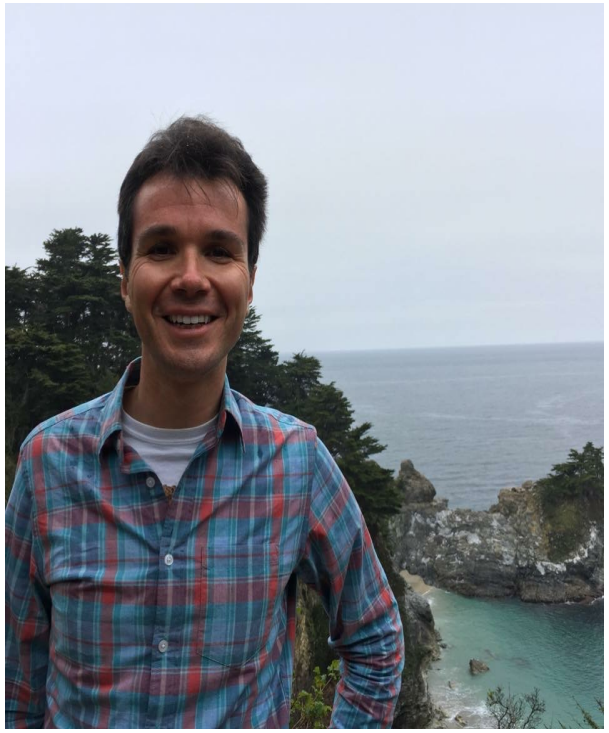
Evren Eryilmaz, Brian Thoms, Zafor Ahmed, Avneet Sandhu

January 10th, 2020

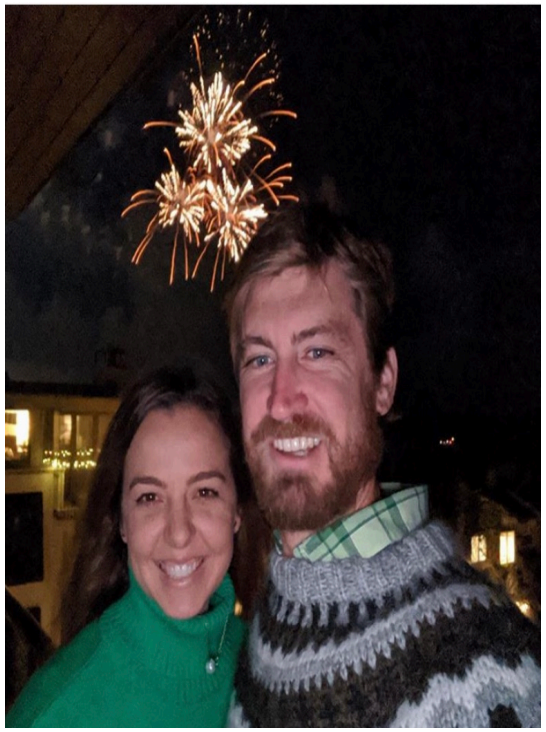
SACRAMENTO STATE

HICSS 53rd

Who are we?



Evren Eryilmaz



Brian Thoms

Zafor Ahmed

Avneet Sandhu

Overview

- Motivation and problem identification
- Objective of our software
- Design and development
- Research questions
- Experimental study
- Evaluation
- Conclusion
- Comments & questions

Motivation

- Collaboration provides synergistic learning opportunities for students in order to go beyond what they can achieve alone
- Asynchronous online discussions (AODs) can afford a genuinely conversational mode of learning

Eryilmaz et al., 2020 CSUS-2

Problem Identification

In large AODs, students..

- produce many navigational uncertainty markers related to what they have read, have not read, and where to find the relevant information (Eryilmaz et al., 2019)
- rarely are aware of other group members' ideas hindering the synthesis of diverse ideas that could be brought to solve problems or perform the task at hand (Vogler et al., 2017)

Eryilmaz, E., Thoms, B., Ahmed, Z., & Lee, K. H. (2019). Affordances of Recommender Systems for Disorientation in Large Online Conversations. *Journal of Computer Information Systems*, 1-11.

Vogler, J. S., Schallert, D. L., Jordan, M. E., Song, K., Sanders, A. J., Te Chiang, Lee, J., Park, J. H., & Yu, L. T. (2017). Life history of a topic in an online discussion: a complex systems theory perspective on how one message attracts class members to create meaning collaboratively. *International Journal of Computer-Supported Collaborative Learning*, *12*(2), 173-194.

Eryilmaz et al., 2020 CSUS-3

Objective of Our Software

Help students to find useful messages, which they may not have found themselves, from a potentially overwhelming number of messages based on their interests

Eryilmaz et al., 2020 CSUS-4

Design and Development

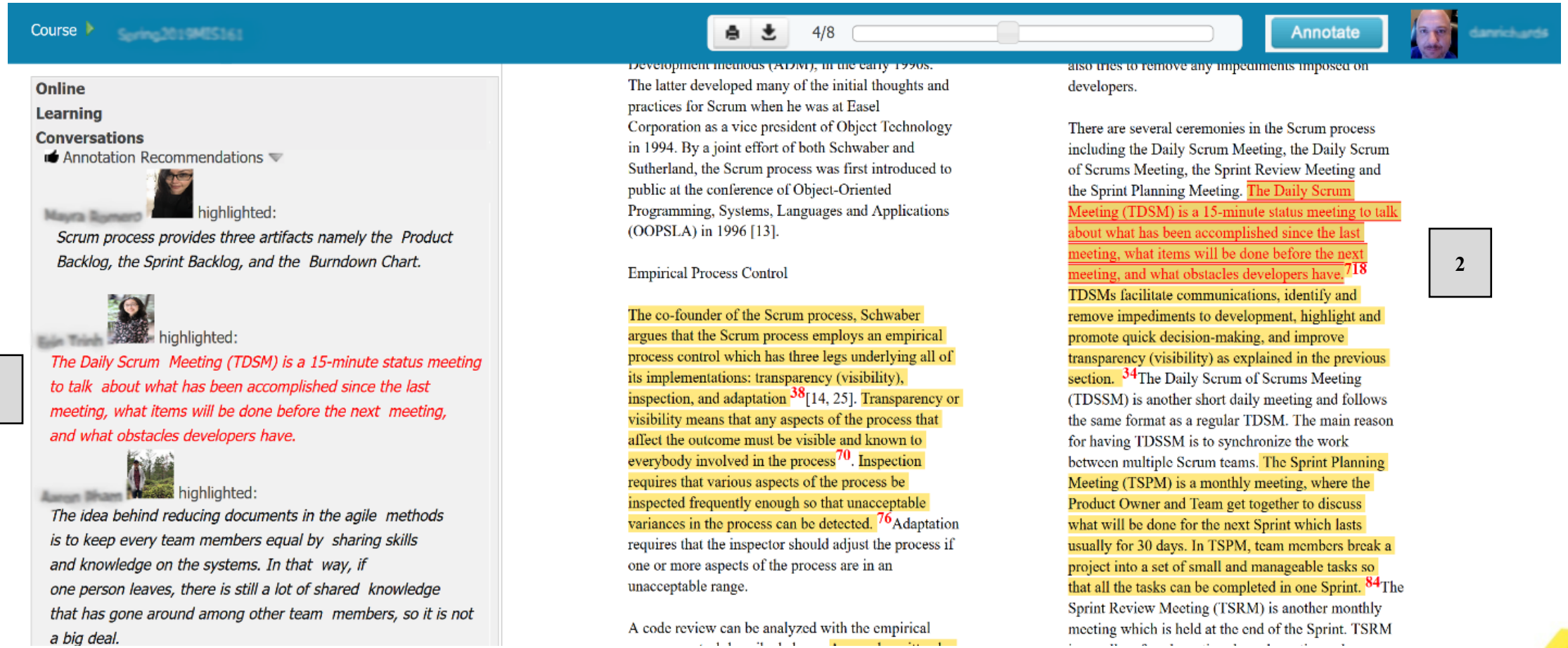
The recommender system employs

- the constrained Pearson correlation coefficient similarity metric to compute similarity scores among users
- the K-nearest-neighbor classification method to discard poor correlations in order to decrease noise and improve the quality of recommendations
- the weighted averaging equation to calculate a user's preference score for each item based on the best neighbors' preferences

Eryilmaz, E., Thoms, B., Ahmed, Z., & Lee, K. H. (2019). Affordances of Recommender Systems for Disorientation in Large Online Conversations. *Journal of Computer Information Systems*, 1-11.

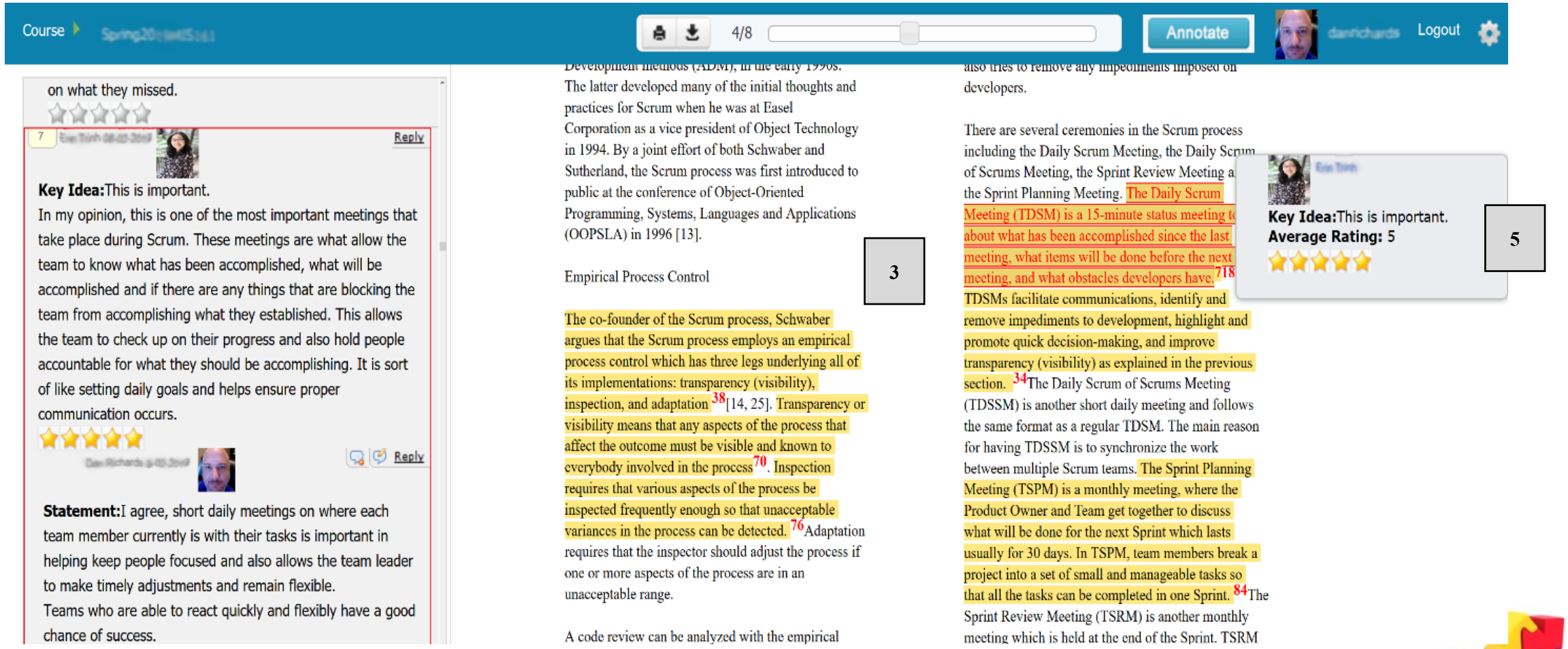
Eryilmaz et al., 2020 CSUS-5

CSCL Environment



Eryilmaz et al., 2020 CSUS-6

CSCL Environment



Eryilmaz, E., Thoms, B., & Canelon, J. (2018). How Design Science Research Helps Improve Learning Efficiency in Online Conversations. Communications of the Association for Information Systems, 42(1), 21.

Eryilmaz et al., 2020 CSUS-7

Research Questions

- What are the effects of recommendations on the phases of the interaction analysis model developed by Gunawardena et al. (1997)?
- What are the effects of recommendations on message quasi-quality index scores per student?
- Is there a relationship between message quasi-quality index scores and the phases of the interaction analysis model developed by Gunawardena et al. (1997)?

Study

- Experimental study with 70 undergraduate college students distributed to two sections of a system analysis and design course.
- We randomly assigned each section to a software condition.

Eryilmaz et al., 2020 CSUS-9

Evaluation-Content Analysis

	Control Software (n=35)		Recommender System (n=35)		Test Statistics	
Phase	M	SD	M	SD	p	Cohen's d
Sharing information	0.43	0.22	0.23	0.18	<0.001	-0.99
Exploring dissonance	0.24	0.13	0.32	0.14	0.02	0.60
Negotiating meaning	0.14	0.13	0.21	0.12	0.03	0.56
Testing proposed synthesis	0.07	0.11	0.10	0.13	0.33	0.25
Agreeing on new knowledge	0.06	0.12	0.08	0.13	0.54	0.16
Off-topic messages	0.07	0.11	0.05	0.09	0.41	-0.20

Eryilmaz et al., 2020 CSUS-10

Evaluation-Quasi Quality Index Score

$$QQI = \left(\frac{1}{n}\sum_{i=1}^{n} Xi\right) + \left(\frac{d}{\frac{1}{n}\sum_{i=1}^{n} d_i} * \frac{u}{\frac{1}{n}\sum_{i=1}^{n} u_i}\right)$$

$$d = \frac{k}{W-S}$$

n=Total elements
x= Post readability score
d= Post keyword density
u=Total post non-stopwords

W=Total post words
S=Total post stopwords
k=Total post keywords

B. Thoms, E. Eryilmaz, N. Dubin, R. Hernandez, S. Colon-Cerezo, "Real-Time Visualization to Improve Quality in Computer Mediated Communication," *Web Intelligence Journal*, September, 2019.

Evaluation-Quasi Quality Index Score

	Control Software (n=35)		Recommender System (n=35)		Test Statistics	
	M	SD	M	SD	p	Cohen's d
Quasi-quality index scores	67.84	8.87	73.12	7.97	0.01	0.63

Eryilmaz et al., 2020 CSUS-12

Evaluation-Relationship between Content Analysis and Quasi Quality Index Score

Quasi-quality index score for phase	Control Software (n=35)		Recommender System (n=26)		Test Statistics	
Sharing information	M	SD	M	SD	p value	Cohen's d
	67.10	11.90	68.83	15.07	0.62	0.13
Exploring dissonance	Control Software (n=30)		Recommender System (n=33)		Test Statistics	
	M	SD	M	SD	p value	Cohen's d
	67.13	12.58	74.35	13.89	0.04	0.55
Negotiating meaning	Control Software (n=21)		Recommender System (n=28)		Test Statistics	
	M	SD	M	SD	p value	Cohen's d
	70.38	12.85	80.27	14.24	0.02	0.72

Eryilmaz et al., 2020 CSUS-13

Community Formation

	Control Software (n=35)		Recommender System (n=35)		Test Statistics	
	Frequency	Proportion	Frequency	Proportion	z	p
Number of central students	4	0.114	8	0.229	1.27	0.20
Number of intermediate students	12	0.343	17	0.486	1.21	0.23
Number of peripheral students	19	0.543	10	0.286	-2.18	0.03

Eryilmaz et al., 2020 CSUS-14

Conclusion

Findings advance prior literature on

- learning analytics and content analysis of AOD messages
- the effects of recommendations on AOD message quality

Mahalo!

Your Comments and Questions are welcomed.

Please address feedback to:

evren.eryilmaz@csus.edu

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