Research evaluating NLP tools designed to assist instructors with formative assessment for students in large-enrollment STEM education classes

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  - Scalable, personalized feedback: difficult but possible
- NLP tools performed as well a typical teaching team at marking
- Feedback is more complex, and we're currently exploring a few alternatives

Motivation

- "Write-to-learn" tasks improve learning outcomes (Graham, et al., 2020)
- Critical for citizen-statisticians to communicate effectively (Gould, 2010)
- Frequent practice w/ communicating improves statistical literacy and promotes retention (Basu, et al., 2013)
- Formative assessment benefits both students & instructors (Black & Wiliam, 2009; GAISE, 2016; Pearl, et al., 2012)
- A majority of U.S. undergraduates at public institutions take at least one large-enrollment STEM course (Supiano, 2022)
- **Logistics of constructed response tasks jeopardize use in large-enrollment classes** (Garfield & Ben-Zvi, 2008; Woodard & McGowan, 2012)

Easy!

Erm. . .

Goal

Develop technology that can assist instructors for large (STEM) classes with providing targeted formative assessment feedback to students, such that instructor burden is similar to small class (~30 students)

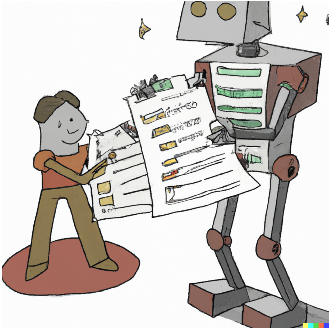
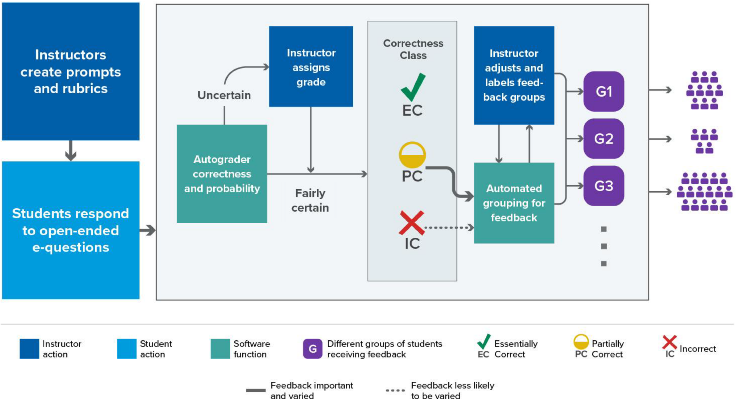


Figure 1: image created with assistance of DALL · E 2 by Open AI

Project Schematic



Goal: Computer-assisted formative assessment feedback for short-answer tasks in large-enrollment classes, such that instructor burden is similar to small class (~30 students)

Research Questions

- **RQ3**: What sort of NLP representation leads to good clustering performance, and how does that interact with the classification algorithm?

Short Paper (ICOTS)

Lloyd, S. E., Beckman, M., Pearl, D., Passonneau, R., Li, Z., & Wang, Z. (2022). Foundations for AI-Assisted Formative Assessment Feedback for Short-Answer Tasks in Large-Enrollment Classes. In *Proceedings of the eleventh international conference on teaching statistics*. Rosario, Argentina.

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Research Questions

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- **RQ2**: What level of agreement is achieved between human raters and an NLP algorithm?
- **RQ1**: What level of agreement is achieved among trained human raters labeling (i.e., scoring) short-answer tasks?

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- **RQ1**: What level of agreement is achieved among trained human raters labeling (i.e., scoring) short-answer tasks?
- **RQ2**: What level of agreement is achieved between human raters and an NLP algorithm?
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Spoilers?!

- **RQ1**: What level of agreement is achieved among trained human raters labeling (i.e., scoring) short-answer tasks?
- **RQ2**: What level of agreement is achieved between human raters and an NLP algorithm?
- **RQ3**: What sort of NLP representation leads to good clustering performance, and how does that interact with the classification algorithm?

Spoilers?!

- RQ1: substantial inter-rater & intra-rater agreement
- RQ2: substantial agreement among human & NLP labeling
- RQ3: evidence of productive clustering; more work to do

Collaborators

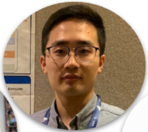
Susan Lloyd

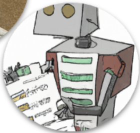
Matt Beckman

Dennis Pearl

Becky Passonneau

Zhaohui Li





Semantic Feature-Wise
Transformation Relation
Network (SFRN)

SFRN Detail (Li et al., 2021)

SFRN is an end-to-end model with 3 components:

1. encode QRA triples producing vector representations for question (Q), a possible reference (R), and student answer (A)
2. when relation network includes multiple QRA triples, a learned feature-wise transformation network merges all relation vectors for a student answer into a single relation vector by leveraging attentions calculated by a QRA triple;
3. the resulting vector representation is passed as an input to a classifier (i.e., neural network)

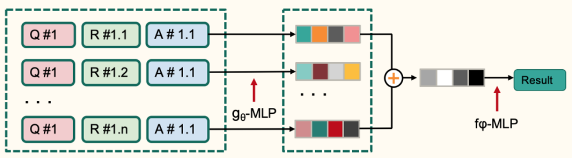


Figure 2: The $g_\theta MLP$ function computes the relation vector for each [Q,R,A] triple. A set of relation vectors is combined $(+)$ using *SFT*. The $f_\phi MLP$ function is the assessment classifier.

Methods (Sample)

Study utilized de-identified extant data & scoring rubrics (Beckman, 2015)

- 6 short-answer tasks
- 1,935 students total
- 29 class sections 15 distinct institutions

Note: this sample is *not* a single large class at some institution; the available data includes introductory statistics students from many class sections at many institutions–some classes were quite small.

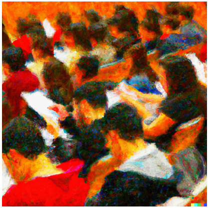


Figure 3: image created with assistance of DALL · E 2 by Open AI

Methods (Short-answer task)

4. Walleye is a popular type of freshwater fish native to Canada and the Northern United States. Walleye fishing takes much more than luck; better fishermen consistently catch larger fish using knowledge about proper bait, water currents, geographic features, feeding patterns of the fish, and more. Mark and his brother Dan went on a two-week fishing trip together to determine who the better Walleye fisherman is. Each brother had his own boat and similar equipment so they could each fish in different locations and move freely throughout the area. They recorded the length of each fish that was caught during the trip, in order to find out which one of them catches larger Walleye on average.

a. Should statistical inference be used to determine whether Mark or Dan is a better Walleye fisherman? Explain why statistical inference should or should not be used in this scenario.

b. Next, explain how you would determine whether Mark or Dan is a better Walleye fisherman using the data from the fishing trip. *(Be sure to give enough detail that a classmate could easily understand your approach, and how he or she would interpret the result in the context of the problem.)*

Figure 4: Sample task including a stem and two short-answer prompts.

Methods (RQ1)

- 3 human raters typical of large-enrollment instruction team
- entire sample (1,935 students) distributed among the team with sufficient intersection to assess rater agreement
- 63 student responses in common for each *combination* of raters to quantify agreement (e.g., pairwise, consensus, etc)
- constraint: sufficient data for *intra-rater* analysis for person that had labeled 178 responses 6-7 years prior

Results (RQ1)

RQ1: What level of agreement is achieved among trained human raters labeling (i.e., scoring) short-answer tasks?

Comparison	Reliability
Rater A & Rater C	QWK $= 0.83$
Rater A & Rater D	QWK $= 0.80$
Rater C & Rater D	QWK $= 0.79$
Rater A: 2015 & 2021	QWK $= 0.88$
Raters A, C, & D	FK $= 0.70$

Reliability interpretation[1]: $0.6 <$ substantial $< 0.8 <$ near perfect < 1.0

[1] Viera & Garrett (2005)

Methods (RQ2)

The set of task-responses were randomly split four ways:

- 90% of data for development purposes (train), were partitioned 8:1:1
  - training (72%),
  - development (9%)
  - evaluation (9%)
- 10% of data being held in reserve (test)

SFRN was compared to other NLP algorithms for accuracy using a subset of student responses (Li et al., 2021).

- SFRN: Semantic Feature-Wise Transformation Relation Network
- LSTM: a logistic regression combined with a Long Short-Term Memory for learning vector representations

Results (RQ2)

Prerequisite–comparing machines: The SFRN algorithm achieved much higher classification accuracy than LSTM (83% vs. 72%) when judged against human consensus ratings.[2]

RQ2: What level of agreement is achieved between human raters and the machine (an NLP algorithm)?

Human & SFRN agreement:

Comparison	Reliability
Rater A & SFRN	QWK $= 0.79$
Rater C & SFRN	QWK $= 0.82$
Rater D & SFRN	QWK $= 0.74$
Raters: A, C, D, & SFRN	FK $= 0.68$

Reliability interpretation[3]: $0.6 <$ substantial $< 0.8 <$ near perfect < 1.0

[2]SFRN & LSTM comparison excludes instances when human labels disagree
[3]Viera & Garrett (2005)

Methods (RQ3)

Manual pilot of human-generated clustering

- Two reviewers independently evaluated 100 student responses that earned "partial credit" on inference tasks
- Each reviewer provided free-text feedback to each student
- Verbatim feedback captured for each reviewer and cross-tabulated for analysis.

Experiment with NLP representations

- retrain k-means & k-mediods clustering to evaluate cluster stability
- compare representations with higher & lower dimensionality

Results (RQ3 humans)

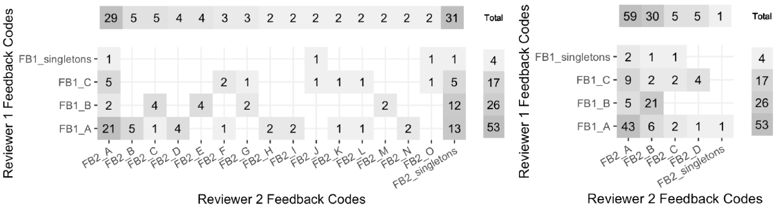


Figure 5: Cross-tabulation of feedback distribution for the two reviewers for the initial feedback (left) compared with the same analysis for the portion of feedback related to the statistical concept at issue (right).

- Reviewer 1 favored feedback on statistical concepts (only).
- Reviewer 2 provided same, plus a quote from the student
- Reviewer 2 parsed her feedback to compare her remarks related to the statistical concepts (only) with the feedback of Reviewer 1.

Results (RQ3 humans)

Feedback Code	Feedback verbatim text suggested by the Reviewer
FB1_A (Reviewer 1)	What can we do to evaluate whether [the] result is better than we would expect for someone that is strictly guessing?
FB2_A (Reviewer 2)	Think about what inferential statistical method might we use to evaluate the percentage of correctly identified notes.
FB1_B (Reviewer 1)	Good idea to have a threshold for comparison, but it's very important that it be established carefully. For example, how might you establish a threshold that…
FB2_B (Reviewer 2)	Why this threshold? What inferential statistical method might we use to evaluate the percentage of correctly identified notes?

Figure 6: Verbatim feedback most frequently provided by each reviewer for responses to task 2B.

Results (RQ3 machines)

RQ3: What sort of NLP representation leads to good clustering performance, and how does that interact with the classification algorithm?

- SFRN learns a high-dimension (D = 512) vector representation on training data.
- Experiments with K-means and K-medoids clustering showed SFRN produce more consistent clusters when retrained (0.62), in comparison to LSTM *despite 8X higher dimensionality* [4]
- Highest consistency (0.88; D = 50) was achieved using a matrix factorization method that produces static representations (WTMF; Guo & Diab, 2011)

[4] Consistency is measured as the ratio of all pairs of responses in a given class per question that are clustered the same way on two runs (in the same cluster, or not in the same cluster).

Discussion

- **RQ1**: Substantial agreement achieved among trained human raters provides context for further comparisons
- **RQ2**: NLP algorithm produced agreement reasonably aligned to results achieved by pairs/groups of trained human raters
- **RQ3**: Classification and clustering have competing incentives for dimensionality; Lower D is better for cluster stability, Higher D better for classification reliability. (SFRN clustering was respectable despite high D, though)

Current Events: HIL deferral policy

Our work is first (that we know of) to impelement controllable, selective prediction deferral policy

Threshold	Deferral Rate	Simulated HIL Accuracy
0.68	0.095	0.855
0.75	0.132	0.861
0.80	0.160	0.871
0.85	0.202	0.884
0.90	**0.256**	**0.899**
0.95	0.418	0.931

Limitations

- Study uses extant data from prior study collected from many classes of varying size
  - not a single large class
  - no covariates available to identify and mitigate bias labeling (human or machine)
  - Tasks & rubrics used for pilot were developed for research purposes; likely more polished than tasks developed "in the wild"
- Clustering performance vs semantic meaning
  - clustering is necessary, but not sufficient, for meaningful feedback
  - semantic meaning of NLP clusters not yet rigorously studied

Current Events

- Answer-state Recurrent Relational Network
  - (AsRRN; Li, Lloyd, Beckman, & Passonneau, 2023)
  - Breaks from reliance on linear architecture of SFRN
  - Allows flexibility to accommodate shared stem with multiple prompts
  - Better incorporates reference answers corresponding to rubric guidance
- Contrastive Loss Function
  - Correct answers are generally alike
  - Many PC results align with a few common archetypes
  - Diverse ways to be incorrect

Future Work

Software development goals:

- challenge labeling algorithm with linguistic diversity;
- iterative instructor input to group conceptual representations
- Curse of dimensionality
  - distance between elements to be clustered increases monotonically with dimensionality (Bellman, 2003)
  - SRFN is a fairly high dimensional representation ($D = 512$)
  - tension between demands of classification and clustering tasks

Field test expansion:

- field test key aspects of project CLASSIFIES in large classes
  - approx 13,000 students
  - 2 of 5 institutions are HSI's
- diversify item and rubric input to challenge performance

Additional Implications

- open questions for "what works" in formative assessment
- accumulated data made available to broader NLP community
  - this data set would be among the largest open data sources of it's kind
  - addresses barriers imposed by proprietary data sources on NLP research

Breaking News

OFFICE OF
Educational Technology

Artificial Intelligence and the Future of Teaching and Learning

Insights and Recommendations

May 2023

Figure 7: New report on AI and the future of teaching and learning from US Dept of Education, Office of Educational Technology (May 2023)[5]

[5]U.S. Department of Education, Office of Educational Technology (2023). *Artificial Intelligence and Future of Teaching and Learning: Insights and Recommendations.* Washington, DC.

Recommendations from US Dept of Educaiton[6]

[6] U.S. Department of Education, Office of Educational Technology (2023). *Artificial Intelligence and Future of Teaching and Learning: Insights and Recommendations.* Washington, DC.

AI tools are powerful, but unclear where they're heading without human partnership. While our results are still quite preliminary, we think human-in-the-loop is a promising avenue toward scalable short-answer formative assessment.

Figure 8: image created with assistance of DALL · E 2 by Open AI prompted to illustrate a roadmap for the future of educational research

Acknowledgment

- We're grateful to the US National Science Foundation for funding this research
- Project CLASSIFIES (NSF DUE-2236150)

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Thank You

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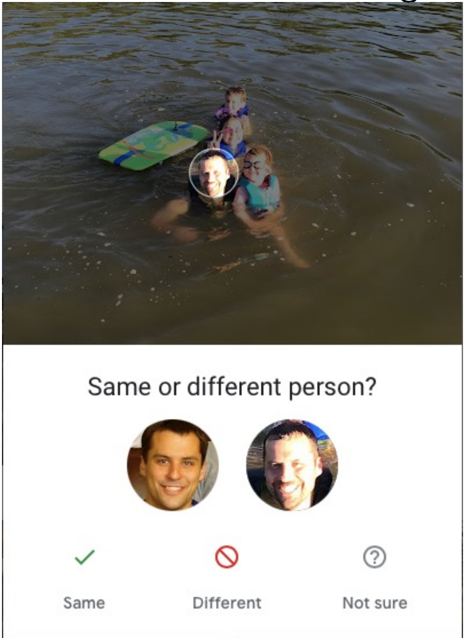
Resource Page URL: https://mdbeckman.github.io/QUT2023/

Google Photos Illustration



Google Photos "Deferral"