Foundations for scalable NLP-assisted formative assessment feedback

Matthew Beckman
Penn State University

April 3, 2023

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Two question survey before seminar (scan with mobile phone)

Figure 1: (QR Code) https://forms.gle/hpW72fMYE1SsB19JA

Responses to our survey?

1. Is your lucky number odd or even?
2. How did you describe the value of formative assessment?

Responses to our survey?

1. Is your lucky number odd or even?
2. How did you describe the value of formative assessment?
    - [Odd] Free text response: *write anything you like*
    - [Even] Selected response: *endorse provided options*

Motivation

- "Write-to-learn" tasks improve learning outcomes (Graham, et al., 2020)
- Critical for citizen-statisticians to communicate statistical ideas effectively (Gould, 2010)
- Continual practice with communicating improves statistical literacy and promotes retention (Basu, et al., 2013)
- Formative assessment benefits both students & instructors (GAISE, 2016; Pearl, et al., 2012)
- *Logistics* of constructed response tasks jeopardize use in large-enrollment classes

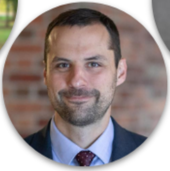
Goal state

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

Collaborators (humans)

Susan Lloyd

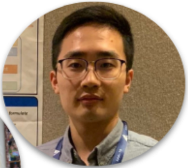
Matt Beckman



Dennis Pearl

Becky Passonneau

Zhaohui Li



Tools (machines)

- Natural language processing (NLP) involves how computers can be programmed to analyze language elements (e.g., text or speech)
- Human-machine collaboration is a promising mechanism to assist rapid, individualized feedback at scale (Basu, 2013)
- NLP-assisted feedback has previously been studied for essays or long-answer tasks (see e.g., Attali, et al., 2008; Page, 1994)

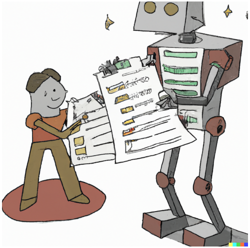
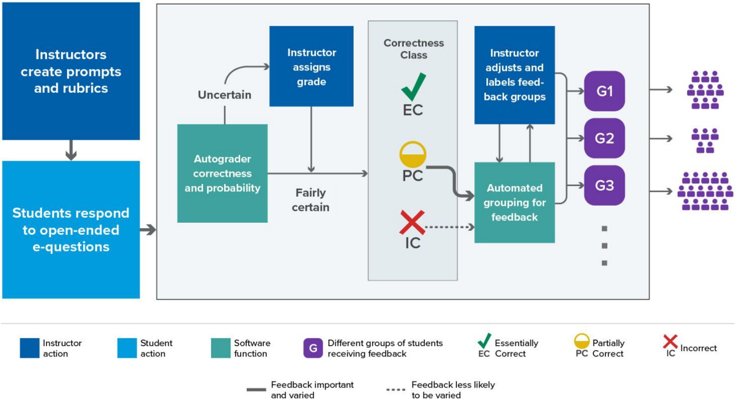


Figure 2: image created with assistance of DALL · E 2 by Open AI

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

- **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?

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.

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: in progress, but promising

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.

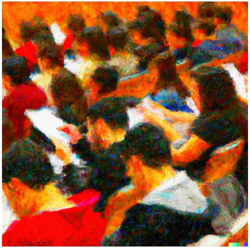


Figure 3: image created with assistance of DALL · E 2 by Open AI

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
- 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 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, were partitioned according to machine-learning best practice:
  - training (72%),
  - development (9%)
  - evaluation (9%)
- 10% of data being held in reserve for more rigorous testing

Two NLP algorithms were compared for accuracy using a subset of student responses (Li et al., 2021).

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

Results (RQ2)

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

The SFRN algorithm achieved much higher classification accuracy than LSTM (83% vs. 72%)[2]. 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.

Results (RQ3 humans)

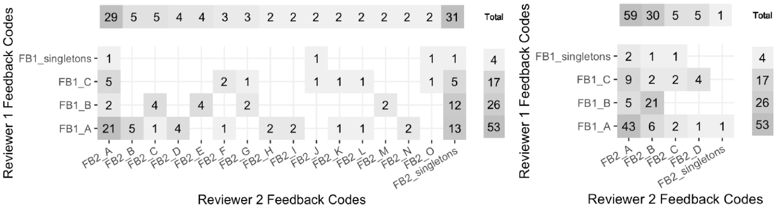


Figure 5: Cross-tabulation of feedback distribution for the two reviewers for the initial feedback (left) compared with the same analysis for the portion of feedback related to the statistical concept at issue (right).

- 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 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 other classifiers.[4]
- Highest consistency (0.88; D = 50), however, 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; Low D is better for cluster stability, High D better for classification reliability.

Limitations

- Study uses extant data from prior study collected from many classes of varying size
    - not a single large class
    - we expect observed results are conservative due to additional variability across institutions and instructors, but will be investigated further
- Dimensionality on the machine learning side
- Clustering performance vs semantic meaning
    - clustering is necessary, but not sufficient, for semantic meaning
    - semantic meaning of NLP clusters not yet rigorously studied

Future Work[5]

Software development goals:

- challenge labeling algorithm (EC/PC/IC "scoring"); target linguistic diversity;
- human-in-the-loop policy to optimize human input and effort for scoring;
- iterative instructor input to group conceptual representations

Field test expansion:

- field test key aspects of project CLASSIFIES in large classes
  - approx 13,000 students
  - two of the five institutions are recognized HSI's by US Dept of Education
- diversify item and rubric input to challenge performance

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[5] Adapted from research aims of Project CLASSIFIES (NSF DUE-2236150)

Implications for Teaching & Research

- 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

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Thank You

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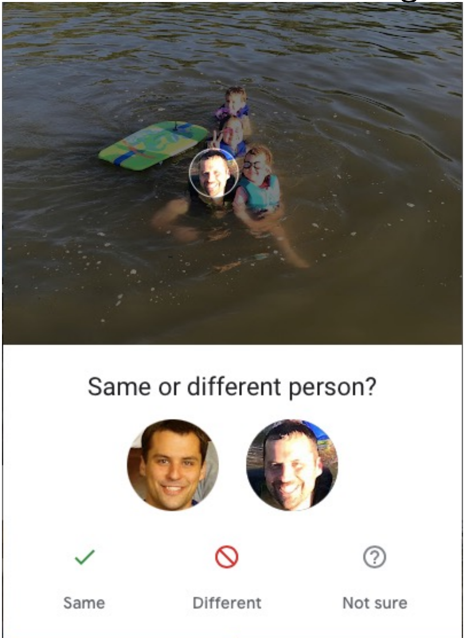
Resource Page URL:
https://mdbeckman.github.io/2023-MSU-Colloq/

Google Photos Illustration



Some are harder than others. . .

Implications for Teaching & Research

Figure 6: DALLE 2 image given the prompt: “Roadmap for future educational research in the style of a retro travel poster”

Venn Diagram Fail

There was extra space on a Methods slide describing how we partitioned the sample to evaluate rater agreement... but DALLE wasn't up to the task.

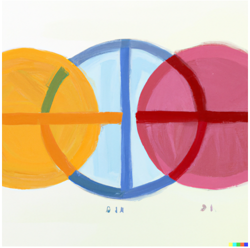


Figure 7: Me: "oil painting of Venn diagram for three intersecting sets"; DALLE 2 ...swing and a miss