Evaluating NLP tools designed to assist instructors with formative assessment for large-enrollment STEM classes

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NZSA Visiting Lecturer Seminar
University of Otago

Dunedin, New Zealand
April 14, 2024

Two question pop quiz

1. Is your lucky (or favorite) number odd or even?
2. How would you describe the value of formative assessment?

Google Form

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

Responses?

Value of Formative Assessment

mdb268@psu.edu Switch account

Not shared

Odd

How would you describe the value of formative assessment?

Your answer

Back Submit Clear form

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Google Forms

Value of Formative Assessment

mdb268@psu.edu Switch account

Not shared

Even

How would you describe the value of formative assessment?

- [ ] empowers students to monitor their own learning outcomes
- [ ] enables instructors to monitor learning outcomes of students on an individual or aggregate basis
- [ ] provides feedback that instructors can use to address misconceptions and/or adjust instruction
- [ ] amenable to low-stakes and high-frequency opportunities for students to engage with content
- [ ] I'm not sure

Back Submit Clear form

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)

Easy!

Erm...

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)

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)

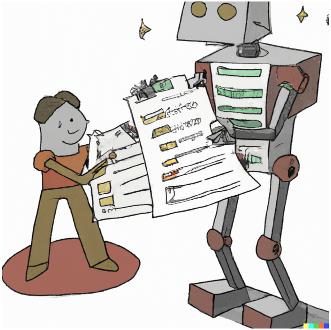

Figure 2: image created with assistance of DALL · E 2 by Open AI

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)

- **Technology**: Natural Language Processing (NLP)
- **Large classes**: Hundreds of simultaneous students
- **Formative assessment**: e.g., Low-stakes check-for-understanding prompt
- **Targeted feedback**: Timely and personalized
- **Burden**: typical effort of an engaged instructor
- **Assist instructors**: Amplifies (rather than supplants) instructor effort

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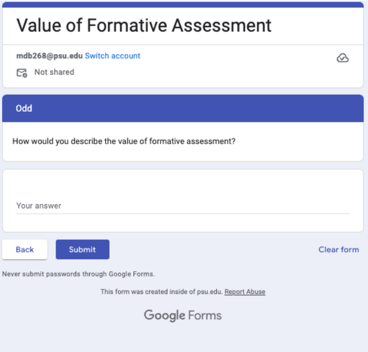
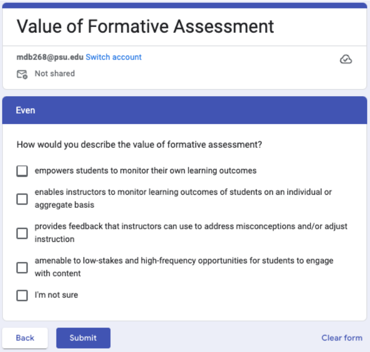
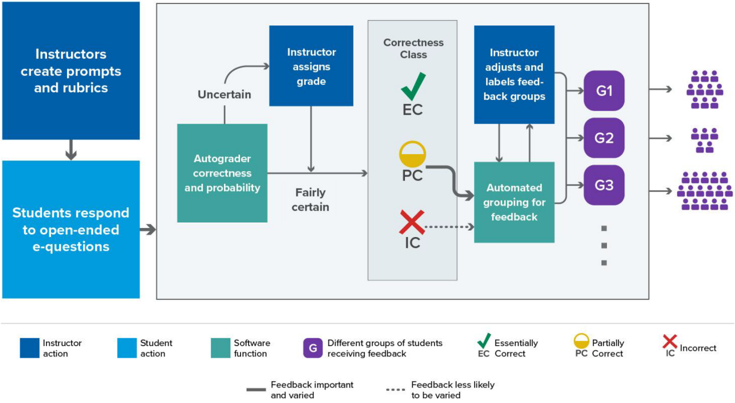
Back to our example. . .





Initial 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?

Relevant Papers

- 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.
- Beckman, M., Burke, S., Fiochetta, J., Fry, B., Lloyd, S. E., Patterson, L., & Tang, E. (2024). Developing Consistency Among Undergraduate Graders Scoring Open-Ended Statistics Tasks. Preprint URL: https://arxiv.org/abs/2410.18062
- Li, Z., Lloyd, S., Beckman, M. D., & Passonneau, R. J. (2023). Answer-state Recurrent Relational Network (AsRRN) for Constructed Response Assessment and Feedback Grouping. *Findings of the Association for Computational Linguistics: EMNLP 2023*.

Collaborators

Figure 3: Lloyd et al., (2022); Li et al., (2023) Project Team

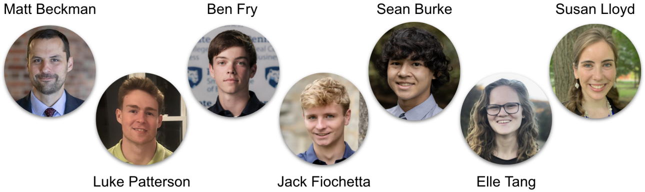


Figure 4: Beckman et al., (2024) Project Team

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

Methods (RQ1)

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

- Lloyd et al., (2022)
  - 3 raters typical of large-enrollment instruction team
  - (6 tasks) x (1,935 students) distributed among the team
  - sufficient intersection to assess inter-rater agreement
  - responses judged Correct / Partial / Incorrect against rubric
- Beckman at al., (2024)
  - 4 Undergraduate Teaching Assistants (UTAs) and 1 instructor
  - (4 tasks) x (63 students) scored by each UTA + Instructor
  - 5 sequential exercises associated with progression of scoring development

Results

- "short-answer" tasks are good for students, but hard to scale
- Can NLP tools help instructors give students feedback?
  - Evaluate & group student responses
  - Compare agreement between NLP & humans
  - Evaluate scalable, personalized feedback solutions

Scoreboard[1]

- (RQ1) Instructor agreement (QWK ≈ 0.7 to $0.8+$)
- (RQ1) UTA agreement (QWK ≈ 0.6 to $0.7+$)
- What about... NLP algorithm & instructor agreement?

[1] Lloyd, et al. (2022); Beckman, et al. (2024)

Methods (RQ2)

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

Susan Lloyd Dennis Pearl Zhaohui Li

Matt Beckman Becky Passonneau Semantic Feature-Wise Transformation Relation Network (SFRN)

Paper introducing SFRN

Li, Z., Tomar, Y., & Passonneau, R. J. (2021). A Semantic Feature-Wise Transformation Relation Network for Automatic Short Answer Grading. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 6030–6040. Association for Computational Linguistics.
https://aclanthology.org/2021.emnlp-main.487

Meet the "machine": NLP for Assessment

- Natural language processing (NLP) involves how computers can be programmed to analyze language elements
- NLP-assisted feedback for educational use:
    - automated short-answer grading (ASAG) from 2009
    - essays & long-answer tasks earlier
- Human-machine collaboration is a promising mechanism to assist rapid, individualized feedback at scale (Basu, 2013)
- Deep neural networks application since 2016
- Relational (neural) networks

Meet the "machine": Relational Networks

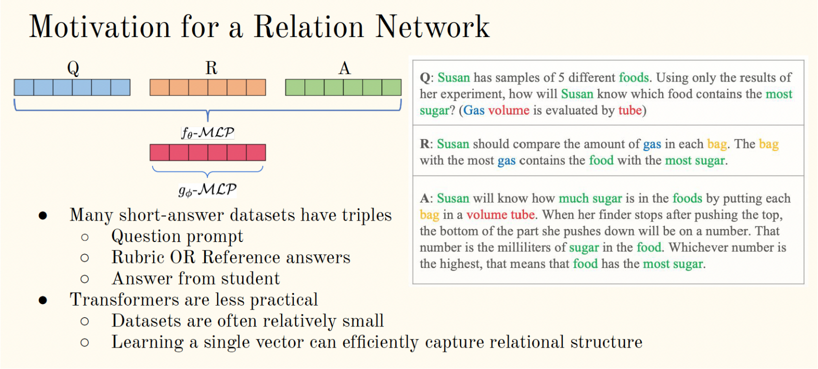


Figure 6: Image credit: Becky Passonneau

- much of the architecture inspired by work from computer vision
- more efficient than transformer networks (e.g., LLMs)

Meet the “machine”: SFRN Schematic

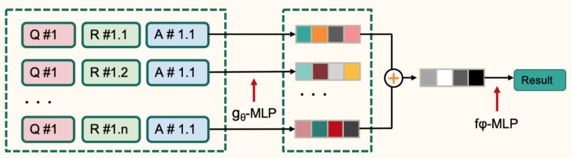


Figure 7: encoder (Left); fusion function (Middle); classifier (Right).

Semantic Feature-Wide Transformation Relation Network (SFRN):

- end-to-end model with three components:
  - ($g_\theta MLP$) pretrained BERT encoder (LLM) » vector representations
  - ($+$) learned feature-wise transformation function fuses multiple representations, if necessary (e.g., multiple reference answers)
  - ($f_\phi MLP$) is a classifier algorithm, i.e., neural network
- relation networks designed to learn generalizations that infer meaning in a data-efficient way
- data augmentation during training step

Results

- "short-answer" tasks are good for students, but hard to scale
- Can NLP tools help instructors give students feedback?
  - Evaluate & group student responses
  - Compare agreement between NLP & humans
  - Evaluate scalable, personalized feedback solutions

Scoreboard[2]

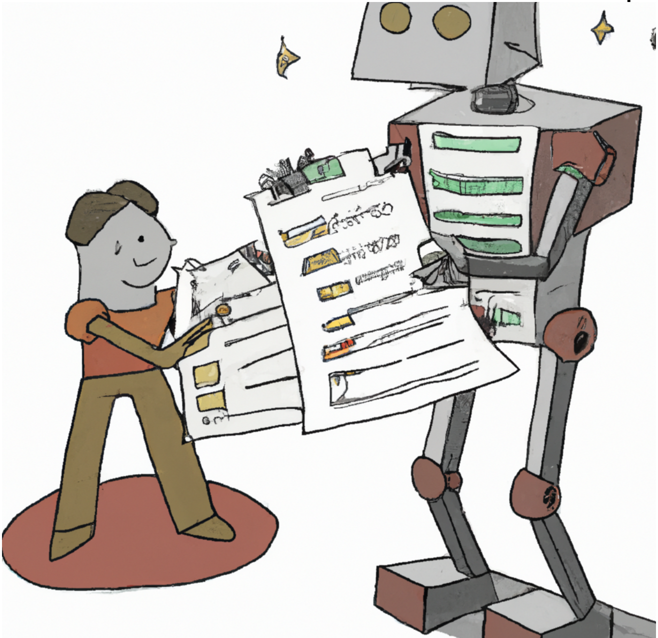
- (RQ1) Instructor agreement (QWK ≈ 0.7 to $0.8+$)
- (RQ1) UTA agreement (QWK ≈ 0.6 to $0.7+$)
- (RQ2) NLP algorithm & instructor agreement (QWK $\approx 0.7+$)
- What about... Human-Algorithm partnership?

[2] Lloyd, et al. (2022); Beckman, et al. (2024)

Human-Machine Partnership?

Figure 8: Image credit: https://www.slugmag.com/arts/film/film-reviews/terminator-genisys-time-is-not-on-my-side/

Human-Machine Partnership?



Human-Machine Partnership?

Our approach to human-in-the-loop (HIL) did **not** make a recommendation (e.g., Left), it just shows examples to the human when it needs help (e.g., Right).

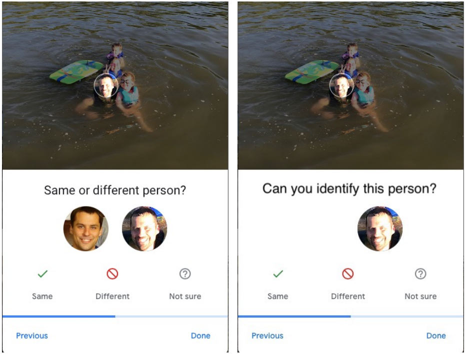


Figure 10: Illustration adapted from Google Photos

Human-Machine Partnership Method

Want to evaluate accuracy of marking algorithm when designed to "defer" to human judgment

- algorithm evaluates a probability for each label (EC, PC, IC)
  - if a label has high probability, use algorithm label
  - if no label has sufficiently high probability, defer to human
- interests
  - estimate how frequently the algorithm defers
  - estimate accuracy of the combined process

Human-Machine Partnership Results

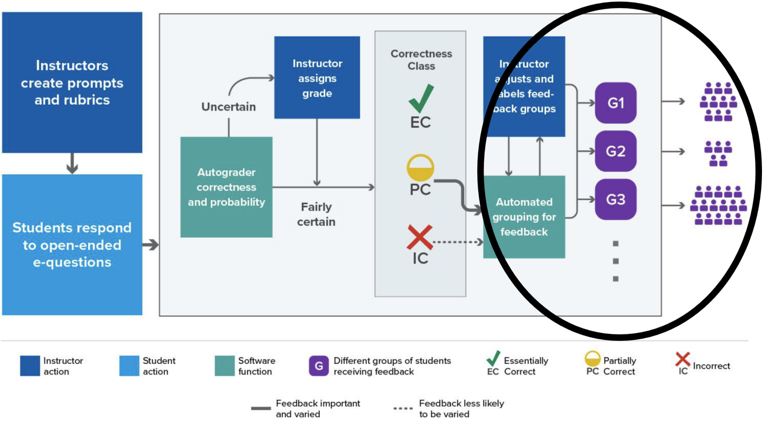
Our work is first that we know of to impelement controllable, selective prediction deferral policy for the classifier (i.e., scoring) step.

Threshold	Deferral Rate	Simulated HIL Accuracy
0.68	9.5%	0.855
0.75	13.2%	0.861
0.80	16.0%	0.871
0.85	20.2%	0.884
0.90	25.6%	0.899

Figure 11: Accuracy of Human-in-the-loop compared with expert label ground truth.

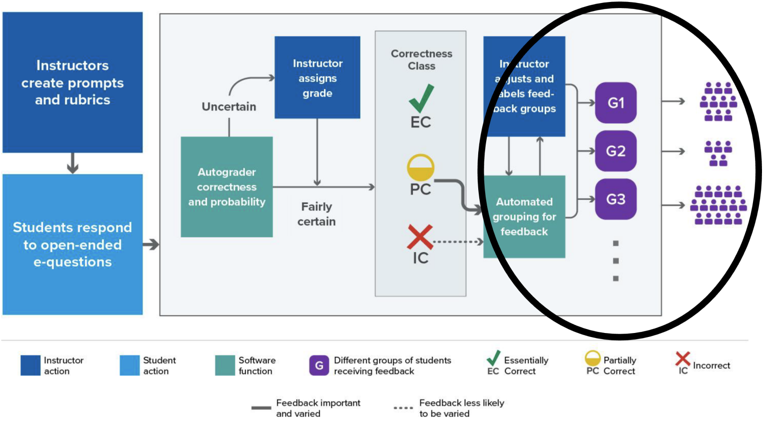
Methods (RQ3)

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



Let's talk about Feedback...

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)



Feedback Avenues

- Just let AI do it?
- Classifier / Clustering Tools?
- Topological Data Analysis Tools?
- Something completely different?

Figure 13: Image credit: https://www.slugmag.com/arts/film/film-reviews/terminator-genisys-time-is-not-on-my-side/

Feedback: Just let AI do it

- undermines instructor benefits of formative assessment
- conflicts with goal statement (e.g., amplify, not supplant, instructor effort)
- additional concerns...

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

Feedback Avenues

- ~~Just let AI do it~~ . . . too dystopian
- Classifier / Clustering Tools? . . . cursed?
- Topological Data Analysis Tools? . . . interesting, but long road
- Guided Reflection?

Feedback: Classifier / Clustering Tools

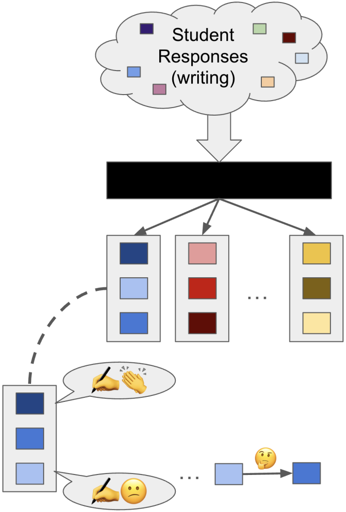
RQ3: What sort of NLP representation leads to good clustering performance, and how does that interact with the classification algorithm?

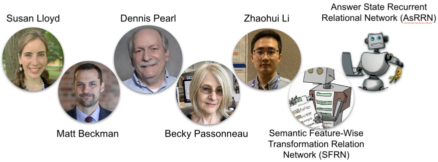
- Method: Rinse & repeat!
  - Study the way instructors might do it and build tools to streamline at scale
  - How consistent are humans?
  - Can our NLP tools achieve results as good or better than humans?

Feedback: Topological Data Analysis Tools

- Dimension 0 TDA is akin to cluster analysis
- Dimension 1 introduces "holes"
- Higher dimensions (e.g., voids) possible
- **Results:**
  - Ongoing work
  - Promising work for NLP application of TDA, broadly
  - Viability for feedback is still a long road

Feedback: Guided Reflection with Comparative Judgment





- Capture all student responses
- Review set of peer responses
- Rank most to least developed
- Write peer feedback
- (repeat for a few sets)
- Review peer feedback to **yours**
- Update your initial response?

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
    - Human-in-the-Loop » Instructor / Algorithm partnership
- **RQ3**: Promising results based on "man-made clusters" but classification and clustering have competing incentives when it comes to dimensionality of NLP vector representations
    - Lower Dim is generally better for cluster stability
    - Higher Dim better for classification reliability
    - Exploring Topological Analysis as alternative to clustering
    - Feedback as a classifier (Li et al., 2023)

Current Events

- challenge system with diverse tasks, institutions, student populations;
    - partnering with ISU, MSU, PSU, UCSB, UF, UTEP, & UoA (NZ)
    - both "consensus" tasks & "local" tasks
    - approx 44,000 responses from $\sim$ 13,000 students
    - targeting languistic diversity
- accumulated data to be shared with broader NLP community
    - this will be among the largest *open* data sources of it's kind
    - addresses barriers imposed by proprietary data sources on NLP research
- algorithm development
    - contrastive loss function
    - accommodates more complex task structure
    - impact of response length
    - studying influence of rubric features (Wei et al, in review)

Acknowledgments

- US National Science Foundation (NSF DUE-2236150: Project CLASSIFIES)
- Penn State Center for Socially Responsible Artificial Intelligence
- Strategic partnership between University of Auckland and Penn State University
- Thanks to students and faculty at partner institutions that have assisted us with data collection.

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Thank You

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Supporting Slides

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)

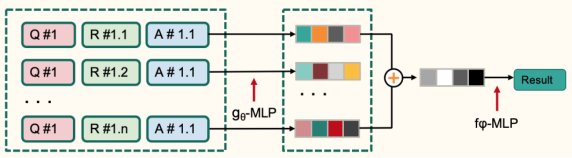

Figure 14: The $g_\theta MLP$ function (Left) uses an encoder to compute the relation vector for each [Q,R,A] triple. A set of relation vectors is combined (+) using a fusion function (*SFT*). The $f_\phi MLP$ function is the

Results: Instructors as Graders

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

Figure 15: Interrater agreement among three instructors; intra-rater agreement for Rater A with several years delay

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

[3]Viera & Garret (2005)

Results: Instructor and UTA Graders

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

Raters	Day 1	Day 5	Week 10
A & E	0.46 (0.35, 0.58)	0.57 (0.47, 0.67)	0.58 (0.49, 0.67)
A & F	0.61 (0.50, 0.71)	0.72 (0.64, 0.79)	0.78 (0.71, 0.85)
A & G	0.63 (0.55, 0.72)	0.73 (0.66, 0.80)	0.73 (0.66, 0.81)
A & H	0.72 (0.65, 0.80)	0.71 (0.63, 0.78)	0.68 (0.59, 0.78)

Figure 16: Pairwise agreement between UTAs and an instructor (Rater A)

Reliability intuition: moderate $< 0.6 <$ substantial $< 0.8 <$ near perfect < 1.0

Results: Instructor & UTA (cont'd)

Raters	QWK	95% CI
A	0.82	(0.76, 0.88)
E	0.57	(0.46, 0.68)
F	0.74	(0.67, 0.82)
G	0.66	(0.56, 0.76)
H	0.74	(0.67, 0.81)

Figure 17: Intra-rater agreement (self-consistency) for each participant as measured with Quadratic Weighted Kappa (QWK) while scoring the same set of student responses on two occasions approximately 10 weeks apart.

Date (Exercise)	Rubric Description	AC_2	95% CI
Day 1 (Ex 1)	Solution with Verbal Instructions	0.688	(0.63, 0.74)
Day 5 (Ex 4)	Expert Rubric, Part 1	0.784	(0.75, 0.82)
Week 10 (Ex 5)	Expert Rubric, Part 2	0.778	(0.74, 0.81)

Figure 18: Group agreement among four undergraduate TAs and one instructor, as measured with Gwet's (2014) AC2; 95% confidence intervals accompany each estimate.

Results (RQ2)

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

Comparison	Reliability
Rater A & SFRN	QWK = 0.79
Rater C & SFRN	QWK = 0.82
Rater D & SFRN	QWK = 0.74

Figure 19: Pairwise agreement with SFRN algorithm

Reliability intuition: moderate $< 0.6 <$ substantial $< 0.8 <$ near perfect < 1.0

Methods (RQ3): Humans

How similar is feedback provided by two instructors for some group of students?

- Two instructors independently evaluated 100 “partial credit” responses
- Each instructor provided free-text feedback to each student
- Verbatim feedback captured for each instructor and cross-tabulated for analysis.
- *Results:*
  - The two instructors gave substantially equivalent feedback to 66 of 100 responses
  - Evidence of two large “clusters” (and quite a few singletons)

Methods (RQ3): Machines

- Experiment #1
  - retrain k-means & k-mediods clustering & evaluate stability
  - compare representations with higher & lower dimensionality
  - **Results:**
    - SFRN (D = 512): cluster stability 0.62
    - Highest stability among competing algorithms was 0.88, achieved using a matrix factorization method that produces static representations (D = 50; WTMF; Guo & Diab, 2011)
    - *cursed*
- Experiment #2:
  - ~~clustering~~ => FB Classifier?
  - Both Humans & Machines attempt
  - **Results:**
    - NLP Algorithm was more consistent with instructor A on one task and instructor B on the other task tested.
    - *meh*

Results (RQ3 humans)

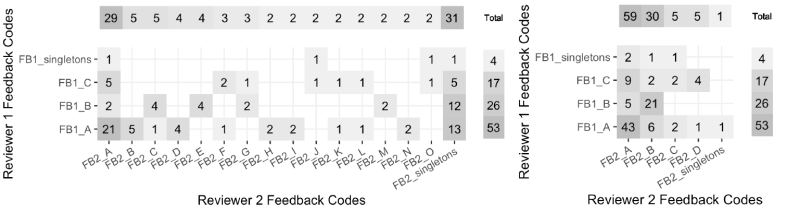

Figure 20: Cross-tabulation of feedback distribution for the two reviewers for the initial feedback (left) compared with the same analysis for the portion of feedback related to the statistical concept at issue (right).

- Reviewer 1 favored feedback on statistical concepts (only).
- Reviewer 2 provided same, plus a quote from the student
- Reviewer 2 parsed feedback to compare remarks related to the statistical concepts (only) with that 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 21: 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 ($D = 512$) produced reasonably consistent clusters when retrained (0.62)
- Highest consistency (0.88; $D = 50$) was achieved using a matrix factorization method that produces static representations (WTMF; Guo & Diab, 2011)
- AsRRN compared to humans (A & B) grouping students by pre-determined feedback categories:

Task	Sample Size	A & B	A & AsRRN	B & AsRRN
1	90	0.71	0.53	0.69
2	100	0.45	0.70	0.41