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Contrasting State-of-the-Art Automated Scoring of Essays: Analysis

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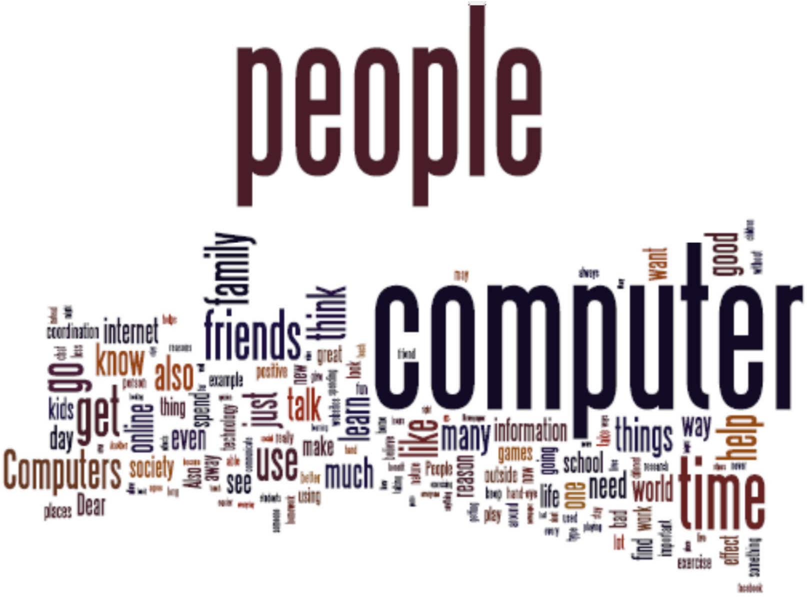
Abstract

This study compared the results from nine automated essay scoring engines on eight essay scoring prompts drawn from six states that annually administer high-stakes writing assessments. Student essays from each state were randomly divided into three sets: a training set (used for modeling the essay prompt responses and consisting of text and ratings from two human raters along with a final or resolved score), a second test set used for a blind test of the vendor-developed model (consisting of text responses only), and a validation set that was not employed in this study. The essays encompassed writing assessment items from three grade levels (7, 8, 10) and were evenly divided between source-based prompts (i.e., essay prompts developed on the basis of provided source material) or those drawn from traditional writing genre (i.e., narrative, descriptive, persuasive). The total sample size was *N* = 22,029.

Six of the eight essays were transcribed from their original handwritten responses using two transcription vendors. Transcription accuracy rates were computed at 98.70% for 17,502 essays. The remaining essays were typed in by students during the actual assessment and provided in ASCII form. Seven of the eight essays were holistically scored and one employed score assignments for two traits. Scale ranges, rubrics, and scoring adjudications for the essay sets were quite variable. Results were presented on distributional properties of the data (mean and standard deviation) along with traditional measures used in automated essay scoring: exact agreement, exact+adjacent agreement, kappa, quadratic-weighted kappa, and the Pearson *r*. The results demonstrated that overall, automated essay scoring was capable of producing scores similar to human scores for extended-response writing items with equal performance for both source-based and traditional writing genre. Because this study incorporated already existing data

(and the limitations associated with them), it is highly likely that the estimates provided represent a floor for what automated essay scoring can do under operational conditions.



A Wordle for Essay Set #1 Used in this Study (Source: www.wordle.net)

Contrasting State-of-the-Art Automated Scoring of Essays: Analysis

Introduction

With the press for developing innovative assessments that can accommodate higher-order thinking and performances associated with the Common Core Standards, there is a need to systematically evaluate the benefits and features of automated essay scoring (AES). While the developers of AES engines have published an impressive body of literature to suggest that the measurement technology can produce reliable and valid essay scores [when compared with trained human raters; (Attali & Burstein, 2006; Shermis, Burstein, Higgins, & Zechner, 2010)], comparisons across the multiple platforms have been informal, involved less-than-ideal sample essays, and were often associated with an incomplete criterion set.

The purpose of this paper is to present the results of a comparison of nine AES engines on responses to a range of prompts, with some targeting content and others relatively content-free, from multiple grades. The AES engines were compared on the basis of scores from independent raters using state-developed writing assessment rubrics. This study was shaped by the two major consortia associated with implementing the Common Core Standards, the Partnership for Assessment of Readiness for College and Careers (PARCC) and SMARTER Balanced Assessment Consortium (SMARTER Balanced), as part of their investigation into the viability of using AES for their new generation of assessments.

Comprehensive independent studies of automated essay scoring platforms have been rare. Rudner, Garcia, & Welch (2006) conducted a two-part independent evaluation of one vendor of automated essays scoring, *Intellimetric* by Vantage Learning. After reviewing data drawn from the Graduate Management Admission Test™, the investigators concluded, "the *IntelliMetric* system is a consistent, reliable system for scoring AWA (Analytic Writing Assessment) essays." While such individual endorsements are heartening, there has yet to be a comprehensive look at machine scoring technology. This is particularly important as the assessments for the Common Core Standards are under development. In part, this vendor demonstration was designed to evaluate the degree to which current high-stakes writing assessments, and those envisioned under the Common Core Standards, might be scored through automated methods.

This study was the first phase of a three-part evaluation. Phase I examines the machine scoring capabilities for extended-response essays, and consists of two parts. The first part reports on the capabilities of already existing commercial machine scoring systems. Running concurrently with the vendor demonstration is a public competition in which the study sponsor (The William and Flora Hewlett Foundation) provides cash prizes for newly-developed scoring engines created by individuals or teams. Phase II will do the same thing for short-answer constructed responses followed with an evaluation of math items (i.e., proofs, graphs, formulas) for Phase III.

Participants

Student essays (*N* = 22,029) were collected for eight different prompts representing six PARCC and SMARTER Balanced states (three PARCC states and three SMARTER Balanced states). To the extent possible, an attempt was made to make the identity of the participating states anonymous. Three of the states were located in the Northeastern part of the U.S., two from the Mid-west, and one from the West Coast. Because no demographic information was provided by the states, student characteristics were estimated from a number of different sources, as displayed in Table 1. Student writers were drawn from three different grade levels (7, 8, 10) and the grade-level selection was generally a function of the testing policies of the participating states (i.e., a writing component as part of a 10th grade exit exam), were ethnically diverse, and evenly distributed between males and females.

Samples ranging in size from 1527 to 3006 were randomly selected from the data sets provided by the states, and then randomly divided into three sets: a training set, a test set, and a validation set. The training set was used by the vendors to create their scoring models, and consisted of scores assigned by at least two human raters, a final or adjudicated score, and the text of the essay. The test set consisted of essay text only and was used as part of a blind test for the score model predictions. The purpose of the second test set was to calculate scoring engine performance for a public competition that was launched at approximately the same time as the vendor demonstration. It was also to be used as a test set for any of the commercial vendors who might have subsequently elected to participate in the public competition. The second test set consisted of essay text only. The distribution of the samples was split in the following proportions: 60% training sample, 20% test sample, 20% second test sample. The actual proportions vary slightly due to the elimination of cases containing either data errors or text anomalies. The distribution of the samples is displayed in Table 1.

Instruments

Four of the essays were drawn from traditional writing genre (persuasive, expository, narrative) and four essays were “source-based”, that is, the questions asked in the prompt referred to a source document that students read as part of the assessment. Appendix A lists the prompts, scoring rubrics for raters, adjudication guidelines, and reading material for the source-based essays. In the training set, average essay lengths varied from $M = 94.39$ ($SD = 51.68$) to $M = 622.24$ (SD =197.08), Traditional essays were significantly longer ($M = 354.18$, SD 197.63) than source-based essays ($M = 119.97$, SD = 58.88; $t_{(13334)} = 95.18$, $p < .05$).

Five of the prompts employed a holistic scoring rubric, one prompt was scored with a two-trait rubric, and two prompts were scored with a multi-trait rubric, but reported as a holistic score. The type of rubric, scale ranges, scale means and standard deviations, are reported in Tables 2 and 3. Table 2 shows the characteristics of the training set and Table 3 shows the characteristics of the test set. Human rater agreement information is reported in Tables 2 and 3 with associated data for exact agreement, exact+adjacent agreement, kappa, Pearson *r*, and quadratic-weighted kappa. Quadratic-weighted kappas ranged from 0.66 to 0.85, a typical range for human rater performance in statewide high-stakes testing programs.

Procedure

Six of the essays sets were transcribed from their original paper-form administration in order to prepare them for processing by automated essay scoring engines. At a minimum, the scoring engines require the essays to be in ASCII format. This process involved retrieving the scanned copies of essays from the state or a vendor serving the state, randomly selecting a sample of essays for inclusion in the study, and then sending the selected documents out for transcription.

Both the scanning and transcription steps had the potential to introduce errors into the data that would have been minimized had the essays been directly typed into the computer by the student, the normal procedure for automated essay scoring. Essays were scanned on high quality digital scanners, but occasionally student writing was illegible because the original paper document was written with an instrument that was too light to reproduce well, was smudged, or included handwriting that was undecipherable. In such cases, or if the essay could not be scored by human raters (i.e., essay was off-topic or inappropriate), the essay was eliminated from the analyses. Transcribers were instructed to be as faithful to the written document as possible keeping in mind the extended computer capabilities had they been employed. For example, more than a few students hand-wrote their essays using a print style in which all letters were capitalized. To address this challenge, we instructed the transcribers to capitalize beginning of sentences, proper names, etc. This modification may have corrected errors that would have otherwise been made, but limited the over-identification of capitalization errors that might have been made otherwise by the automated essay scoring engines.

The first transcription company serviced four prompts from three states and included 11,496 essays. In order to assess the potential impact of transcription errors, a random sample of 588 essays was re-transcribed and compared on the basis of punctuation, capitalization, misspellings, and skipped data. Accuracy was calculated on the basis of the number of characters and the number of words with an average rate of 98.12%. The second transcription company was evaluated using similar metrics. From a pool of 6006 essays, a random sample of 300 essays was selected for re-transcription. Accuracy for this set of essays was calculated to be 99.82%.

Two of the essays were provided in ASCII format by their respective states. The 10th grade students in those states had typed their responses directly into the computer using web-based software that emulated a basic word processor. Except that the test had been administered by a computer, the conditions for testing were similar to those in states where the essays had been transcribed.

One of the key challenges to both sets of data, those that were transcribed and those that were directly typed, was that carriage returns and paragraph formatting meta-tags were missing from the ASCII text. For some of the scoring engines, this omission could have introduced a significant impediment in the engine's ability to accurately evaluate the underlying structure of the writing, one component in their statistical prediction models. Other than asking each student to retype their original answers into the data sets, there was no way to ameliorate this.

Vendors were provided a training set for each of the eight essay prompts. Up to four weeks were allowed to statistically model the data during the "training" phase of the demonstration. In addition, vendors were provided with cut-score information along with any scoring guides that were used in the training of human raters. This supplemental information was employed by some of the vendors to better model score differences for the score points along the state rubric continuum. Two of the essay prompts used trait rubrics to formulate a holistic score by summing some or all of the trait scores. For these two essays, both the holistic and trait scores were provided to the vendors.

During the training period, a series of conference calls, with detailed questions and answers, were conducted to clarify the nature of the data sets or to address data problems that arose while modeling the data. For example, the guidelines from one state indicated that the final or resolved score was to be the higher of the two rater scores, but in several cases this was not the case. Rather than modify the resolved score, the vendors were instructed to use it in their prediction models even though it was apparently inconsistent with the state's guidelines.

This operational decision had the potential to negatively impact the scoring engines' reported capacity to adequately model what the state was trying to accomplish in assigning scores to essays. However, it is acceptable, adding to the robustness of whatever results were obtained, since the study was designed to test how vendors would perform when applying their scoring engines to state-generated data under pragmatic conditions. Stated somewhat differently the consideration of these inconsistencies provided a representation of the typical contextual conditions within which the scoring engines were actually employed.

In the "test" phase of the evaluation, vendors were provided data sets that had only the text of essays associated with them, and were asked to make integer score predictions for each essay. They were given a 59-hour period in which to make their predictions and were permitted to eliminate up to 2% of the essay score predications in each data set in case their scoring engine classified the essay as “unscorable”. Even though human raters had successfully rated all the essays in the test set, there were a variety of reasons that any one essay might prove problematic for machine scoring. For example, an essay might have addressed the prompt in a unique enough way to receive a low human score, but be deemed as “off topic” for machine scoring. In real-life situations provisions would be made for these to be scored by human raters.

Procedure-Scoring Engines

Eight of the nine automated essay scoring engines that were evaluated in the demonstration represented commercial entities and captured over 97% of the current automated scoring market in the United States. The lone non-commercial scoring engine was invited into the demonstration because it was an already existing open-source package that was publicly available on their web site. Below are short descriptions of each engine. A more extensive description can be found in a report to the William and Flora Hewlett Foundation.

AutoScore, American Institutes for Research (AIR)

Autoscore is an essay scoring engine developed by the American Institutes for Research. The engine is designed to create a statistical proxy for prompt-specific rubrics. The rubrics may be single or multiple trait rubrics. A training set, including known, valid scores, is required to train the engine.

The system takes a series of measures on each essay in the remaining training set. These measures include:

- semantic measures based on the concepts that discriminate between high- and low-scoring papers,
- other semantic measures that indicate the coherence of concepts within and across paragraphs, and

- a range of word-use and syntactic measures.

In addition, where clear, proposition-based, prompt-specific rubrics are available, the system can integrate measures based on AIR's *Proposition Scoring Engine*, which recognizes pre-specified "propositions," allowing a wide variation in the expression of those propositions. For each trait in the rubric, the system estimates an appropriate statistical model relating the measures described above to the score assigned by humans. This model, along with its final parameter estimates, is used to generate a predicted or "proxy" score.

LightSIDE, Carnegie Mellon University, TELEDIA Lab

LightSIDE is a free and open-source software package developed at Carnegie Mellon University. This program is designed as a tool for non-experts to quickly utilize text mining technology for a variety of purposes, including essay assessment. LightSIDE incorporates numerous options for extending its data representation, machine learning, or visualization through plugins. However, to train the models used in the ASAP competition, no additional programming was required. Models were trained and tuned using standard options available through the user interface. With instruction, a beginner user with no programming experience could reproduce the results we report for this competition in less than one hour of work.

Bookette, CTB McGraw-Hill

CTB's *Bookette* automated writing evaluation analytics ("scoring engines") are able to model trait level and/or holistic level scores for essays with a similar degree of reliability to an expert human rater. The engines use a natural language processing system with a neural network to model expert human scores. The engines are trained using essays that have been scored by expert raters and validated against a separate set of papers also scored by expert raters during the model building phase. The engines are then monitored by using human-to-engine comparisons during the implementation phase for uses in which students are scored “live’” for accountability purposes.

CTB has been using automated writing evaluation in large scale accountability testing contexts since 2009 and in classroom settings since 2005. CTB has expertise in building prompt-specific and generic engines. Prompt-specific engines have demonstrated high fidelity to human scoring on a prompt-by-prompt basis, but they may only be reliably used with the particular prompt for which they have been trained. Generic engines, on the other hand, are not quite as reliable as prompt-specific engines, but they generalize to a variety of prompts, thereby allowing them to be more flexibly used in the classroom. Their technology when applied in the classroom for formative purposes provides both holistically and trait level performance feedback through the use of the information found in the scoring rubric and through feedback on grammar, spelling, and conventions at the sentence level.

CTB’s *Bookette* engines operate on approximately 90 text-features classified as structural-, syntactic-, semantic-, and mechanics-based. Most commonly, the features are used to model trait level scores which may be reported separately and/or combined to produce a total writing score. The analytic scoring guide underlies the CTB system produces integer scores (ranging from 1 to 6 points) based on well-recognized traits of effective writing: Organization, Development, Sentence Structure, Word Choice/Grammar Usage, Mechanics.

e-rater®, Educational Testing Service

The *e-rater*® scoring engine is an automated scoring system designed to evaluate essay quality. The system scores essays based on dozens of features, each of which is designed to measure specific aspects of essay quality. These features are derived using a variety of techniques from a subfield of artificial intelligence called *natural language processing*. Some of these techniques are based on linguistic analysis and others from empirical modeling using statistical techniques from several fields of study, while others are developed on the basis of hybrid approaches. These features form the basis for performance feedback to students in learning environments through products such as *Criterion*, a learning tool for writing in a classroom setting (www.ets.org/criterion). These features are grouped together into conceptually similar sets to comprise blocks of features covering major areas of writing, including grammar, usage, mechanics, style, organization and development, lexical complexity and content relevance. These feature sets are the basis for the production of essay scores and are typically calibrated on a provided set of human scores to produce statistically optimal weights for score production.

The scores from e-rater are not only used in learning environments, but also for scoring practice tests, placement tests and in high-stakes assessment. In 1999 the scores from e-rater were the first to be deployed operationally in high-stakes assessment as one of two scores for the GMAT and have since been used in the GRE and TOEFL assessments following similar models of providing one of the two scores on each essay.

Lexile® Writing Analyzer, MetaMetrics

Lexile® Writing Analyzer is a grade-, genre-, prompt-, and punctuation-independent automatic essay scoring engine for establishing Lexile writer measures. A vertical scale is employed to measure the writing construct and, as such, training is not necessary to evaluate an essay.

A Lexile writer measure refers to an underlying individual trait, which is defined as the power to compose written text, with writing ability embedded in a complex web of cognitive and sociocultural processes. Individuals with higher-level writing ability are more facile with at least some of the aspects of a writer-composition-reader transaction than are individuals with lower-level writing ability. Facets of a writer-composition-reader transaction may be related to, reflected in, or reflective of, an individual’s writing ability, but they are not, in themselves “writing ability”. Rather, writing ability is an individual trait that is brought to bear to a greater or lesser extent within each transaction occasion.

Through a research study to examine the relationship between text complexity, text features, and writing ability, a parsimonious set of significant predictors emerged—predictors consistent with the hypothesis that selected kinds of composition surface text features may be proxies for a degree of executive functioning and working memory capacity and efficiency. The resulting combination consisted of lexical representations alone—without syntax signifiers. Specifically, a combination of a small number of variables—degree of diverse use of vocabulary and greater vocabulary density, controlling for production fluency—predicted 90% of the true variance in rater judgments of essays.

The “training” phase of the study involved the categorization of Lexile essay scores into distinct groups corresponding to teacher ratings (similar to changing actual temperature measurements into categories of “very hot,” “hot,” cool,” and “cold”).

Project Essay Grade (PEG), Measurement, Inc.

MI’s automated essay scoring engine, Project Essay Grade (PEG), has undergone 40 years of study and enhancement. Replication studies for a number of state departments of education have indicated that PEG demonstrates accuracy that is very similar to that of trained human scorers. It has been used to score millions of essays in formative and summative assessments, including statewide formative assessments, online writing improvement systems for a network of international schools, and the Utah Direct Writing Assessment, the state’s census assessment in grades 5 and 8. PEG utilizes training sets of human-scored student constructed responses to build models with which to assess the quality of unscored responses. The training responses are analyzed across multiple dimensions, and from this analysis, features are calculated, including various measures of structure, mechanics, organization, semantics and syntax. Once the features have been calculated, PEG uses them to build statistical models for the accurate prediction of scores, holistically or by trait. In order to create these features, MI has custom-crafted a number of tools that respond well to student error. One such tool is a custom search language that allows our linguists to locate complex structures within a text quickly and accurately. More recently, MI has devoted time and attention to the development of tools that evaluate text on a deeper semantic level, generating high-dimensional data. To handle this data adequately, we have drawn on recent advances in statistical machine learning, including prediction algorithms specifically designed to deal with noisy, high-dimensional data.

Intelligent Essay Assessor (IEA), Pearson Knowledge Technologies

The Intelligent Essay Assessor (IEA) evaluates the structure, style, and content of writing using a range of AI-based technologies. It derives some of its measures through using semantic models of English (or any other language) from an analysis of large volumes of text equivalent to all the reading a student may have done through high school (about 12 million words). The IEA combines background knowledge about English in general and the subject area of the assessment in particular along with prompt-specific algorithms to learn how to match student responses to human scores. Using a representative sample of responses that are double-scored by humans, the computer compares the content and relevant qualities of the writing of each student response, along with the scores given to the responses by the human scorers. From these comparisons, a prompt-specific algorithm is derived to predict the scores that the same scorers would assign to new responses. IEA can be trained and ready to score in a matter of days.

IEA provides an immediate overall evaluation of a response as well as feedback on specific traits, spelling, grammar errors, and on content categories. IEA can be tuned to understand and evaluate text in any language (Spanish, Arabic, Hindi, etc.) or in any subject area. It includes built-in detectors for off-topic responses, highly unusual essays and other special situations that may need to be referred to human readers. In addition, products based on the technology provide feedback that is easy to understand.   IEA has been used in situations including scoring ELA and science responses for grade schools, assessing and giving feedback on reading comprehension and summarization skills, assessing scenario-based learning for college-students and for assessing military leadership skills. It has been used for scoring millions of essays in high-stakes testing as a second score or in formative evaluations.

CRASE^{TM} , Pacific Metrics

Pacific Metrics automated scoring engine, CRASE^{TM}, scores responses to items typically appearing in large-scale assessments: (a) essay length writing prompts; (b) short answer constructed response items in mathematics, English Language Arts, and science; (c) math items eliciting formulae or numeric answers; and, (d) technology-enhanced items (e.g., Drag and Drop, Graphing). It has been used in both formative and high-stakes summative assessments, providing rapid turnaround and delivering real cost savings over traditional hand scoring methods. The system is highly customizable, both in terms of the configurations used to build machine scoring models and in terms of the how the system can blend human scoring and machine scoring (i.e., hybrid models). CRASE is a fully integrated JAVA-based application that runs as a web service. By integrated, this refers to its ability to: (a) score any of several different item types as a single software application, (b) interface with web-based assessment delivery platforms for immediate turnaround of scores, and (c) integrate with vendor-based electronic hand scoring systems for monitoring or dual scoring.

At its most basic level, categorization is critical to the scoring process. Using experience, along with training materials, scoring guides, etc., a human rater classifies a student's response into one of several defined categories or scores. CRASE analyzes a sample of already-scored student responses to produce a model of the raters' scoring behavior. In general, the system will score as reliably as the sample from which the scoring models are built. By emulating human scoring behavior, CRASE essentially predicts the score that a human rater would assign to a given student response. CRASE uses a sequential process to first analyze and then score students' responses. When a response is received from an online test administration system, it moves through three phases in the scoring process: (a) identifying non-attempts, (b) feature extraction, and (c) scoring.

- Identifying Non-Attempts. The response is first reviewed to determine whether it is a valid attempt at the item. If it is not a valid attempt (e.g., it is blank or gibberish), the response is flagged and removed from the remaining feature extraction and scoring process.
- Extraction of Features. If it is a valid attempt, the response is submitted to one of the feature extraction engines. In this phase, a vector of values is generated that represents both the scoring rubric and the construct the item is intended to assess.
- Predicting a Score. The vector of values is submitted to a scoring engine that uses a statistical model and/or a series of computational linguistic procedures to classify the response into a score category. It is at this stage that the model derived from the rater

sample is applied to predict the score a rater would provide. The predicted score and any non-attempt flags are then returned to the test administration system.

For the scoring of writing prompts, the feature extraction step is organized around the 6+1 Trait® Model, a product of Education Northwest (http://educationnorthwest.org/traits) that is used in some form by most states for K-12 writing applications. The 6+1 Trait model conceptualizes six traits of writing (ideas, sentence fluency, organization, voice, word choice, and conventions) along with the '+1' which is "written presentation". For writing prompts and essays, the feature extraction stage first preprocesses student responses by tokenizing elements in the response, counting and correcting misspellings, computing part-of-speech tags, and conducts stemming. One or more functions are associated with each of the six traits, and these functions are applied to the processed response to produce one or more variables that represent the trait. Examples of functions are: identifying usage and mechanics errors typically seen in student essays, measuring variation in sentence type, calculating extent of personal engagement, and idea development in phrasing. This step also produces text-based and numeric-based feedback that can be used to improve the essay (e.g., too-common words or sentence beginnings, spelling errors, grammar errors). CRASE can be customized to score each of the six traits, or combinations of the traits. It can also be customized to score a number of points (e.g., 1 to 4, 1 to 6). The scoring step uses statistical modeling methods to produce a score using the variables produced in the feature extraction step. Bayesian methods can also be employed to incorporate priors into the scoring model.

IntelliMetric, Vantage Learning

IntelliMetric is an intelligent machine scoring system that emulates the processes carried out by human scorers. *IntelliMetric* draws its theoretical underpinnings from a variety of areas, including cognitive processing, artificial intelligence, natural language understanding and computational linguistics in the process of evaluating the quality of written text. *IntelliMetric* learns to score essays in much the same manner as human raters are trained. In the typical human scoring scenario, expert raters develop anchor papers for each score point thereby becoming the basis for training human scorers on the proposed protocol. Human scorers use these anchor papers as reference points, and learn to distinguish the features embedded in the anchor papers that translate to their respective scores. Similarly, *IntelliMetric* is trained to score test-taker essays. Each prompt (essay) is first scored by expert human scorers, who develop anchor papers for each score point. A number of papers for each score point are loaded into *IntelliMetric*, which runs multiple algorithms to determine the specific writing features that translate to various score points.

Evaluation Criteria

In the field of performance assessment there are few “gold standards” and occasionally there is disagreement about the objectivity of the standards that are in place. So for instance, in a shooting competition one can obtain an “objective” score based on how well one hits the areas of a stationary target, but the debate among enthusiasts centers on how realistic the conditions for shooting on a target range actually are (i.e., the lack of variables such as target motion, weather, wind that might impact shooting accuracy) compared to, say, hunting in the wild.

Essay assessment, which has no gold standard, often employs rubrics (quantifiable declarations of what human raters are instructed to score as being important, typically on a scale ranging from “poor” to “excellent”) to guide the assignment of a score that reflects writing standards. Trained human raters, as with subject-matter or writing experts, can read the same paper and assign the same or different scores for different reasons. To compensate for possible differences, most states use the scores from two trained human raters as the criterion measure. Human raters are generally hired with some writing background, given extensive training, provided scoring guides to help standardize their score assignments, and periodically compare their assessments with essays that have been previously scored by writing experts (i.e., “training sets”). The higher the agreement among human raters, the more reliable the assessment is thought to be. However, the metrics used to assess agreement are sometimes impacted or modified by the rubric scales that have been adopted or by the way in which a final score is resolved. So for example, some states simply add the equally weighted scores from human raters to determine a final score assignment rather than employ a third rater or supervisor to resolve a score discrepancy between them, and thereby preserve the original rating score values.

Scoring

Rather than try to evaluate machine scoring on the basis of one metric, this study will evaluate scoring performance on the basis of a set of measures that are standard in the field, including:

- Distributional differences – correspondence in mean and variance of the distributions of human scores to that of automated scores.
- Agreement – measured by correlation, weighted kappa and percent agreement (exact and exact + adjacent).
- Agreement delta – degree of difference between human-human agreement and automated-human agreement by the same agreement metrics as above.

Results

Eight of the nine vendors provided predictions for 100% of the test set. The one vendor who did not resulted in the elimination of 10 essays from their predictions. The proportion is so small (10/4343 = .002) that for comparison purposes, the results will be treated as if they had reported at the 100% rate.

By and large, the scoring engines did a good of replicating the mean scores for all of the data sets. Figure 1 illustrates these in graphic form. Table 5 shows the deviation scores (deltas) from the means of each data set. Accuracy was most likely influenced by the size of the scale. For example, all vendor engines generated predicted means within 0.10 of the human mean for Data Set #3 which had a rubric range of 0-3. However, even when the range was much larger as in Data Set #8 (range of 0-60), mean estimates were generally within 1 point, and usually smaller.

Table 4 shows the mean distributions across all nine vendors for the eight data sets. For comparison purposes, three additional calculations are provided. H1 refers to the mean calculations based on the scores assigned by the first human rater and H2 shows the same calculations based on the score assignments for the second human rater. In the three data sets (1, 7, and 8) where the final or resolved score was the equally weighted sum of the two human raters, the scores for HR1 and HR2 were doubled to be on the same scale.

The results for data set #2 were a bit of an anomaly. In addition to being scored on two traits, this data set differed from the others in how scores were assigned. While two raters evaluated the essays, only the rating from the first rater determined the score assignment. The second rater was used as a "read behind" to monitor rating quality. However, the second rater had no influence on the actual score assignment. Because of this unique situation, only the means for the second human rater are listed in Table 4.

RS refers to the final or resolved score. This was the score that was provided by the state. As mentioned previously, determining the resolved score was accomplished differently by the different states, but is a function of human ratings. So where one state might have used the equally weighted sum of the raters to determine the resolved score, another state might have issued the guideline to use the higher of the two human rater scores. The H1 and H2 metrics (H1H2) are provided throughout the results section for comparison purposes.

By and large, the scoring engines did a good job of replicating the mean scores for all of the data sets. Figure 1 illustrates these in graphic form. Table 5 shows the deviation scores (deltas) from the means of each data set. Accuracy was most likely influenced by the size of the scale. For example, all vendor engines generated predicted means within 0.10 of the human mean for Data Set #3 which had a rubric range of 0-3. However, even when the range was much larger as in Data Set #8 (0-60), mean estimates were generally within 1 point, and usually smaller.

Table 6 shows analogous information for the standard deviations for each of the data sets with Table 7 illustrating the deltas. With the exception of data sets 1, 7, and 8, where the two rater scores were summed to get a resolved score, most of the predicted scores had standard deviations within 0.10 of the resolved scores. Figure 2 graphically depicts this and shows some scatter for data sets 7 and 8 where the scale ranges were much wider than with some of the earlier data sets.

Table 8 begins the sequence of agreement statistics for the data sets. The human exact agreements ranged from 0.28 on data set #8 to .76 for data set #2. Machine scoring exact agreements ran from 0.07 on data set #2 to 0.72 on data sets 3 and 4. An inspection of the deltas on Table 9 shows that machines performed particularly well on data sets #5 and 6, two of the source-based essays. Figure 3 illustrates the exact agreement statistics in line graph form. With one exception most of the lines hover around the resolved score exact agreements.

Adjacent agreements refer to the combined exact and adjacent score agreements. This calculation is based on the generally accepted convention of considering rater score assignments within one score point as being a "match". If the scores differ by more than one point, many states will ask a third rater to evaluate the essay or they may have some other rule about how to handle the score difference. For data sets 1, 7, and 8, the calculation for adjacent agreement was slightly different than for the other data sets. These data sets came from states where the resolved score was the unweighted sum of the two human raters. While the calculation of adjacent agreement could be based on the original scale for the two human raters, the machine score predictions were on the unweighted summed (i.e., doubled) scale. In order to compensate for this scaling difference, the calculation of adjacent agreement for the machine scores were predicated on an adjacent score difference of two points, not one. Adjacent agreements are shown on Table 10, and for data sets 1-6, they range in the mid-high 90s. Data sets 7 and 8 are lower, but are in line with human rater performance. Table 11 shows that the differences are generally minor. Figure 4 displays these differences.

Kappa is a measure of agreement that takes into consideration agreement by chance alone. For the resolved score, based on human ratings, the ranges ran from 0.16 on data set #8 to 0.65 on data set #4. Overall machine performance ran from 0.04 on data set #8 to 0.59 on several data sets. These are given in Table 12 and graphically represented in Figure 5. Table 13 shows the deltas for the kappa statistics. In general, performance on kappa was slightly less with the exception of essay prompts #5 & #6. On these data sets, the AES engines, as a group, matched or exceeded human performance.

Kappa is typically applied as an agreement measure when the scoring categories have no ordinality associated with them. Quadratic-weighted kappa is appropriate when the categories have some underlying trait that increases as the scale associated with the categories increase. These assumptions are met for the scoring rubrics applied to the data for this demonstration. Human quadratic-weighted kappas ranged from 0.61 to 0.85 and were closely followed by the machine ranges which went from 0.60 to 0.84 (see Table 14 where these data are organized). Table 15 displays the delta values for quadratic-weighted kappa. Of particular interest are the delta values for data sets #5 and #6 which are generally positive. These two data sets were drawn from source-based essays and were shorter than the other data sets. Figure 6 illustrates the quadratic-weighted kappas in graphic form.

Finally the values for the correlation coefficients are given in Table 16. The values for the correlation coefficients generally mirror that of quadratic weighted kappa. These values might have been higher except that the vendors were asked to predict integer values only. Had they been given leeway to predict values containing decimal places, the correlation might have been higher. The correlation values are graphically represented in Figure 7. The deltas are provided in Table 17.

Discussion

The findings clearly show that in replicating the distributions of the eight essays, the scores of the automated essay scoring engines performed quite well. Most of the mean predictions were within 0.10 of the means of the resolved score. Not unexpectedly, the mean estimates deviated where the scales of the essays were large. So for example, in data set #8, the range of scores ran from 0-60 whereas in data set #3, the range only ran from 0-3. The range in data set #8 was an artifact of the way the state scored the essay by summing the two equally weighted rater scores (based on a trait rubric). Had they employed some other approach which utilized a more restricted range, it is quite likely that the performance of the machines would have been improved further. Figure 1, however, suggests that with regard to the mean estimates, the machines scores were very close to the resolved score. The same is true for the estimates of the standard deviations (see Figure 2).

With the exception of data sets #5 and #6, the pattern of exact agreements was slightly lower with the predicted machine scores than with the actual scores assigned by human raters. On data sets #1, #7, and #8 where the scores reflected the equally weighted sums of the two human raters, most of the deviation scores averaged less than 0.10 from the human raters. Even with the scaling issues associated with these three data sets, the average performance of most of the vendors closely mirrors that of the human raters. The same pattern was observed for the calculations of the kappas which corrected for chance agreement. On data sets #5 and #6, most of the vendors obtained exact agreements that matched or exceeded that of the human raters. This was a bit surprising because the conventional wisdom was that the machine scoring engines would likely do better with essays drawn from the traditional writing genre where the scoring of content was less important. With regard to the adjacent agreements, vendor performance was very close to that of human raters.

Overall vendor performance on quadratic-weighted kappa was particularly impressive. This measure of agreement takes into account the ordinality of the scales developed for each prompt. It is numerically equivalent to the intra-class correlation coefficient. Even on data sets #1, #7, and #8 where the exact agreements and kappas had been lower, the pattern included quadratic-weighted kappas that were higher than with human raters. Data sets #5 and #6 also showed similar patterns. Because the values of the correlation coefficient were similar to that of quadratic-weighted kappa, the same pattern was observed on this measure as with quadratic weighted kappa.

The premise of this demonstration was to illustrate the general capacity of machine scoring to evaluate extended response essays, and not to single out any one vendor. However, as with human scorers there is some vendor variability in performance. A few vendors scored impressively well across all of the essay metrics while others performed better with certain types of essays (i.e., source-based essays). We view this variability as a strength rather than as a limitation. Exploring the reasons as to why there might be better performance on certain types of essays may lead to programming that better optimizes the scoring for any new assessments developed by the two major Race-to-the-Top consortia. If one were to simply focus on the performance of the majority of vendors across all the measures described in this demonstration, the results meet or exceed that of the human raters.

In the procedures section of this paper, there were several limitations of this study which likely restricted the performance of the automated scoring engines. For example, six of the essays sets had to be transcribed into machine form in order to be processed by automated essay scoring. This step had the possibility of introducing transcription and formatting errors. In addition, the rubrics and scoring rules applied by the different states likely resulted in scaling artifacts which impacted on the optimal scoring for both human raters and machine scoring engines. With all of these challenges, the performance of the automated essay scoring engines should be viewed as a "floor" rather than a ceiling for what the automated essay scoring engines can do under operational conditions. Moreover, we acknowledge some of the limitations from the current study:

- Agreement with human ratings is not necessarily the best or only measure of students' writing proficiency (or the evidence of proficiency in an essay). We can look at other measures as well, including alternate-form reliabilities, and correlations with external measures such as state assessment scores or course grades (and some of our studies have done so). The limitation of human scoring as a yardstick for automated scoring is underscored by the human ratings used for some of the tasks in this study, which displayed strange statistical properties and in some cases were in conflict with documented adjudication procedures (Williamson et al, 2012).

- Another issue not addressed by this study is the question of construct validity. A predictive model may do a good job of matching human scoring behavior, but do this by means of features and methods which do not bear any plausible relationship to the competencies and construct that the item aims to assess. To the extent that such models are used, this will limit the validity argument for the assessment as a whole.
- A related issue is that of potential washback on test-taking behavior and instruction. Before using a system operationally, some consideration will need to be given to the question of how the measures used in scoring might be subject to manipulation by test-takers and coaches with an interest in maximizing scores. This study does not conduct any evaluations relevant to this question.
- An important aspect of system performance to evaluate before operational use is fairness – whether subgroups of interest are treated differentially by the scoring methodology. This study does not conduct any evaluations relevant to this question.

As a general scoring approach, automated essay scoring appears to have developed to the point where it can be reliably applied in both low-stakes assessment (e.g., instructional evaluation of essays) and perhaps as a second scorer for high-stakes testing. Many of the vendors have software that integrates automated essay scoring as part of an instructional package (e.g., *MyAccess*, *Criterion*). Moreover, they have developed generic models that can be used to score essay prompts developed by teachers. Automated essay scoring is also used as second reader for high stakes assessment in several general tests (e.g., TOEFL, GMAT) and in a similar fashion for some licensing exams (e.g., AICPA). And automated essay scoring is used in large-scale k-12 summative assessment programs either as the only score with human read-behind for monitoring (e.g., Utah) or as a 100% read-behind for reader monitoring (e.g., Louisiana).

Finally, the results of this demonstration apply to commercial vendors who cover most of the extended response machine scoring market. As of this writing, there is a pubic competition underway that will demonstrate the programming skill of individuals or teams with regard to the established capacities of the commercial vendors. So far, the best aggregate (though unverified) performance of a public competitor suggests that these systems may be comparable to the performance of commercial systems with respect to agreement between human and automated scores. The hope is to link the public competitors with the commercial vendors to get the best possible product available for use in scoring the new assessments.

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Table 1. Sample Characteristics Estimated from Reported Demographics of the State*

	Data Set #															
	1		2		3		4		5		6		7		8	
State	#1		#2		#3		#3		#4		#4		#5		#6	
Grade	8		10		10		10		8		10		7		10	
Grade Level *N*	42,992		80,905		68,025		68,025		71,588		73,101		115,626		44,289	
n	2,968		3,000		2,858		2,948		3,006		3,000		2,722		1,527	
Training *n*	1,785		1,800		1,726		1,772		1,805		1,800		1,730		918	
Test *n*	589		600		568		586		601		600		495		304	
Validation *n*[t]	594		600		564		590		600		600		497		305	
Gender M% ǀ F%	51.2	48.8	51.4	48.6	51.0	49.0	51.0	49.0	49.6	50.4	49.2	50.8	51.2	48.8	48.7	51.3
Race % W%ǀ N%	63.8	36.2	77.8	22.2	42.9	57.1	42.9	57.1	70.2	29.9	69.5	30.5	70.2	29.8	66.3	33.7
Free/ Reduced Lunch %	32.9		40.0		32.24		32.2		34.2		34.2		46.6		41.3	

*Taken primarily from: National Center for Education Statistics, Common Core of Data (CCD), (2010). State Non-fiscal Survey of Public Elementary/Secondary Education, 2009–10, Version 1a. Washington, DC: U.S. Department of Education. This information was supplemented with state department of education website information or annual reports for each participating state.

[t] The validation set was not used in this study.

M—Male
F—Female
W—White
N—Non-White

Table 2. Training Set Characteristics

	Data Set #								
	1	2		3	4	5	6	7	8
N	1,785	1,800		1,726	1,772	1,805	1,800	1,730	918
Grade	8	10		10	10	8	10	7	10
Type of Essay	persuasive	persuasive		source-based	source-based	source-based	source-based	expository	narrative
M # of Words	366.40	381.19		108.69	94.39	122.29	153.64	171.28	622.13
SD # of Words	120.40	156.44		53.30	51.68	57.37	55.92	85.20	197.08
Type of Rubric	holistic	trait (2)		holistic	holistic	holistic	holistic	holistic*	holistic+
Range of Rubric	1-6	1-6	1-4	0-3	0-3	0-4	0-4	0-12	0-30
Range of RS	2-12	1-6	1-4	0-3	0-3	0-4	0-4	0-24	0-60
M RS	8.53	3.42	3.33	1.85	1.43	2.41	2.72	19.98	37.23
SD RS	1.54	0.77	0.73	0.82	0.94	0.97	0.97	6.02	5.71
Exact Agree	0.65	0.78	0.80	0.75	0.77	0.58	0.62	0.28	0.28
Exact + Adj Agree	0.99	0.93	1.00	1.00	1.00	0.98	0.99	0.54	0.49
κ	0.45	0.65	0.66	0.61	0.67	0.42	0.46	0.17	0.15
Pearson *r*	0.72	0.81	0.80	0.77	0.85	0.75	0.78	0.73	0.63
Quadratic Weighted κ	0.72	0.81	0.80	0.77	0.85	0.75	0.78	0.73	0.62

RS-Resolved Score
Agree-agreement
Adj-adjacent
*holistic score based on four of six traits
+holistic score based on six of six traits

Table 3. Test Set Characteristics

	Data Set #								
	1	2		3	4	5	6	7	8
N	589	600		568	586	601	600	495	304
Grade	8	10		10	10	8	10	7	10
Type of Essay	persuasive	persuasive		source-based	source-based	source-based	source-based	expository	narrative
M # of Words	368.96	378.40		113.24	98.70	127.17	152.28	173.48	639.05
SD # of Words	117.99	156.82		56.00	53.84	57.59	52.81	84.52	190.13
Type of Rubric	holistic	trait (2)		holistic	holistic	holistic	holistic	holistic*	holistic+
Range of Rubric	1-6	1-6	1-4	0-3	0-3	0-4	0-4	0-12	0-30
Range of RS	2-12	1-6	1-4	0-3	0-3	0-4	0-4	0-24	0-60
M RS	8.62	3.41	3.32	1.90	1.51	2.51	2.75	20.13	36.67
SD RS	1.54	0.77	0.75	0.85	0.95	0.95	0.87	5.89	5.19
Exact Agree	0.64	0.76	0.73	0.72	0.78	0.59	0.63	0.28	0.29
Exact + Adj Agree	0.99	1.00	1.00	1.00	1.00	0.98	0.99	0.55	0.49
κ	0.45	0.62	0.56	0.57	0.65	0.44	0.45	0.18	0.16
Pearson *r*	0.73	0.80	0.76	0.77	0.85	0.74	0.74	0.72	0.61
Quadratic Weighted κ	0.73	0.80	0.76	0.77	0.85	0.75	0.74	0.72	0.62

RS-Resolved Score
Agree-agreement
Adj-adjacent
*holistic score based on four of six traits
+holistic score based on six of six traits

Table 4. Test Set Means

Essay Set	*N*	*M* # of Words	H1	H2	RS	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	8.61	8.62	8.62	8.54	8.51	8.56	8.57	8.53	8.56	8.57	8.49	8.80
2a[t]	600	381.19	----	3.39	3.41	3.41	3.36	3.39	3.39	3.37	3.33	3.41	3.36	3.40
2b[t]	600	381.19	----	3.34	3.32	3.37	3.18	3.35	3.32	3.21	3.26	3.29	3.32	3.34
3	568	108.69	1.79	1.73	1.90	1.90	1.90	1.92	1.88	1.95	1.91	1.84	1.89	1.92
4	586	94.39	1.38	1.40	1.51	1.50	1.47	1.50	1.34	1.48	1.46	1.39	1.47	1.57
5	601	122.29	2.31	2.35	2.51	2.49	2.51	2.49	2.47	2.51	2.44	2.49	2.50	2.54
6	600	153.64	2.57	2.58	2.75	2.79	2.71	2.83	2.54	2.76	2.74	2.76	2.74	2.83
7*	495	171.28	20.02	20.24	20.13	20.05	19.63	19.46	19.61	19.80	19.63	19.58	19.52	19.91
8*	304	622.13	36.45	36.70	36.67	37.32	37.43	37.18	37.24	37.23	37.54	37.51	37.04	37.79

H1-Human Rater 1
H2-Human Rater 2
RS-Resolved Score (based on human ratings)
AIR—American Institutes for Research
CMU—TELEDIA, Carnegie Mellon University
CTB—CTB McGraw-Hill
ETS—Educational Testing Service

PKT—Pearson Knowledge Technologies
PM—Pacific Metrics
VL—Vantage Learning
MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for H1 and H2 were doubled.

[t]For data set #2, the first rater determined the score assignment. The second rater was employed as a “read behind”, but did not influence the score assignment.

Table 5. Test Set Mean Deltas ($M – M_{(RS)}$)

Essay Set	*N*	*M* # of Words	H1	H2	RS	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	-0.01	0.00	----	-0.08	-0.11	-0.06	-0.05	-0.09	-0.06	-0.05	-0.13	0.18
2a[t]	600	381.19	----	-0.02	----	0.00	-0.05	-0.02	-0.02	-0.04	-0.08	0.00	-0.05	-0.01
2b[t]	600	381.19	----	0.02	----	0.05	-0.14	0.03	0.00	-0.11	-0.06	-0.03	0.00	0.02
3	568	108.69	-0.11	-0.17	----	0.00	0.00	0.02	-0.02	0.05	0.01	-0.06	-0.01	0.00
4	586	94.39	-0.13	-0.09	----	-0.01	-0.04	-0.01	-0.17	-0.03	-0.05	-0.12	-0.04	0.06
5	601	122.29	-0.20	-0.16	----	-0.02	0.00	-0.02	-0.04	0.00	-0.07	-0.02	-0.01	0.03
6	600	153.64	-0.18	-0.17	----	0.04	-0.04	0.08	-0.21	0.01	-0.01	0.01	-0.01	0.08
7*	495	171.28	-0.11	0.11	----	-0.08	-0.50	-0.67	-0.52	-0.33	-0.50	-0.55	-0.61	-0.22
8*	304	622.13	-0.22	0.03	----	0.65	0.76	0.51	0.57	0.56	0.87	0.84	0.37	1.12

H1-Human Rater 1
H2-Human Rater 2
RS-Resolved Score (based on human ratings)
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PKT—Pearson Knowledge Technologies
PM—Pacific Metrics
VL—Vantage Learning
MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for H1 and H2 were doubled.

[t]For data set #2, the first rater determined the score assignment. The second rater was employed as a “read behind”, but did not influence the score assignment.

Table 6. Test Set Standard Deviations

Essay Set	*N*	*M* # of Words	H1	H2	RS	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	1.64	1.68	1.54	1.23	1.45	1.26	1.54	1.51	1.57	1.34	1.44	1.29
2a[t]	600	381.19	----	0.78	0.77	0.67	0.84	0.65	0.79	0.69	0.83	0.83	0.78	0.64
2b[t]	600	381.19	----	0.73	0.75	0.68	0.83	0.67	0.69	0.84	0.80	0.68	0.72	0.65
3	568	108.69	0.79	0.78	0.85	0.76	0.91	0.75	0.79	0.89	0.81	0.72	0.83	0.77
4	586	94.39	0.89	0.90	0.95	0.83	0.97	0.88	1.00	0.86	1.12	0.88	0.95	0.82
5	601	122.29	0.96	0.97	0.95	0.89	1.00	0.89	1.02	1.08	1.08	0.88	0.94	0.93
6	600	153.64	0.90	0.86	0.87	0.82	1.01	0.73	0.95	0.95	1.06	0.85	0.88	0.78
7*	495	171.28	6.40	6.31	5.89	4.17	6.37	5.30	6.27	6.43	6.51	5.17	5.71	4.99
8*	304	622.13	5.93	5.68	5.19	4.11	4.44	3.83	4.52	5.38	5.91	4.63	5.16	4.21

H1-Human Rater 1
H2-Human Rater 2
RS-Resolved Score (based on human ratings)
AIR—American Institutes for Research
CMU—TELEDIA, Carnegie Mellon University
CTB—CTB McGraw-Hill
ETS—Educational Testing Service
PKT—Pearson Knowledge Technologies
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VL—Vantage Learning
MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for H1 and H2 were doubled.

[t] For data set #2, the first rater determined the score assignment. The second rater was employed as a "read behind", but did not influence the score assignment.

Table 7. Test Set Standard Deviation Deltas ($SD - SD_{(RS)}$)

Essay Set	*N*	*M* # of Words	H1	H2	RS	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	0.10	0.14	----	-0.31	-0.09	-0.28	0.00	-0.03	0.03	-0.20	-0.10	-0.25
2a[t]	600	381.19	----	0.01	----	-0.10	0.07	-0.12	0.02	-0.08	0.06	0.06	0.01	-0.14
2b[t]	600	381.19	----	-0.02	----	-0.07	0.08	-0.08	-0.06	0.09	0.05	-0.07	-0.03	-0.10
3	568	108.69	-0.06	-0.07	----	-0.09	0.06	-0.10	-0.06	0.04	-0.04	-0.13	-0.02	-0.08
4	586	94.39	-0.06	-0.05	----	-0.12	0.02	-0.07	0.05	-0.09	0.17	-0.07	0.00	-0.13
5	601	122.29	0.01	0.02	----	-0.06	0.05	-0.06	0.07	0.13	0.13	-0.07	-0.01	-0.02
6	600	153.64	0.03	-0.01	----	-0.05	0.14	-0.14	0.08	0.08	0.19	-0.02	0.01	-0.09
7*	495	171.28	0.51	0.42	----	-1.72	0.48	-0.59	0.38	0.84	0.62	-0.72	-0.18	-0.90
8*	304	622.13	0.74	0.49	----	-1.08	-0.75	-1.36	-0.67	0.19	0.00	-0.56	-0.03	-0.98

H1-Human Rater 1
H2-Human Rater 2
RS-Resolved Score (based on human ratings)
AIR—American Institutes for Research
CMU—TELEDIA, Carnegie Mellon University
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PKT—Pearson Knowledge Technologies
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MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for H1 and H2 were doubled.

[t] For data set #2, the first rater determined the score assignment. The second rater was employed as a “read behind”, but did not influence the score assignment.

Table 8. Test Set Exact Agreements

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	0.64	0.64	0.64	0.44	0.44	0.44	0.42	0.46	0.31	0.43	0.43	0.47
2a[t]	600	381.19	----	0.76	0.76	0.68	0.64	0.70	0.69	0.70	0.55	0.64	0.68	0.70
2b[t]	600	381.19	----	0.73	0.73	0.68	0.59	0.66	0.69	0.66	0.55	0.66	0.67	0.69
3	568	108.69	0.89	0.83	0.72	0.68	0.70	0.66	0.69	0.72	0.63	0.61	0.69	0.69
4	586	94.39	0.87	0.89	0.76	0.65	0.68	0.64	0.66	0.72	0.47	0.60	0.64	0.70
5	601	122.29	0.77	0.79	0.59	0.71	0.67	0.68	0.65	0.68	0.47	0.68	0.65	0.71
6	600	153.64	0.80	0.81	0.63	0.67	0.61	0.63	0.62	0.69	0.51	0.64	0.68	0.69
7*	495	171.28	0.28	0.28	0.28	0.10	0.15	0.12	0.12	0.17	0.07	0.09	0.12	0.12
8*	304	622.13	0.35	0.35	0.29	0.12	0.26	0.23	0.17	0.16	0.08	0.14	0.20	0.10

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
CMU—TELEDIA, Carnegie Mellon University
CTB—CTB McGraw-Hill
ETS—Educational Testing Service

PKT—Pearson Knowledge Technologies
PM—Pacific Metrics
VL—Vantage Learning
MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for H1 and H2 were doubled.

[t]For data set #2, the first rater determined the score assignment. The second rater was employed as a "read behind", but did not influence the score assignment.

Table 9. Test Set Exact Agreement Deltas (*Exact* – *Exact*$_{(\mathrm{RS})}$)

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	0.00	0.00	----	-0.20	-0.20	-0.20	-0.22	-0.18	-0.33	-0.21	-0.21	-0.17
2a[t]	600	381.19	----	0.00	----	-0.08	-0.12	-0.06	-0.07	-0.06	-0.21	-0.12	-0.08	-0.06
2b[t]	600	381.19	----	0.00	----	-0.05	-0.14	-0.07	-0.04	-0.07	-0.18	-0.07	-0.06	-0.04
3	568	108.69	0.17	0.11	----	-0.04	-0.02	-0.06	-0.03	0.00	-0.09	-0.11	-0.03	-0.03
4	586	94.39	0.11	0.13	----	-0.11	-0.08	-0.12	-0.1	-0.04	-0.28	-0.16	-0.12	-0.05
5	601	122.29	0.18	0.20	----	0.12	0.08	0.09	0.06	0.09	-0.12	0.09	0.06	0.12
6	600	153.64	0.17	0.18	----	0.04	-0.02	0.00	-0.01	0.06	-0.12	0.01	0.05	0.06
7*	495	171.28	0.00	0.00	----	-0.18	-0.13	-0.16	-0.16	-0.11	-0.21	-0.19	-0.16	-0.16
8*	304	622.13	0.06	0.06	----	-0.17	-0.03	-0.06	-0.11	-0.12	-0.20	-0.14	-0.09	-0.19

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
CMU—TELEDIA, Carnegie Mellon University
CTB—CTB McGraw-Hill
ETS—Educational Testing Service

PKT—Pearson Knowledge Technologies
PM—Pacific Metrics
VL—Vantage Learning
MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for H1 and H2 were doubled.

[t]For data set #2, the first rater determined the score assignment. The second rater was employed as a “read behind”, but did not influence the score assignment.

Table 10. Test Set Exact and Adjacent Agreements

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.95	0.99	0.99	0.99
2a[t]	600	381.19	----	1.00	1.00	1.00	0.99	1.00	1.00	1.00	0.99	0.99	1.00	1.00
2b[t]	600	381.19	----	1.00	1.00	0.99	0.98	0.99	1.00	0.99	0.97	0.99	1.00	1.00
3	568	108.69	1.00	1.00	1.00	0.98	0.97	0.98	0.98	0.97	0.97	0.98	0.97	0.99
4	586	94.39	1.00	1.00	1.00	0.99	0.99	0.98	0.99	0.99	0.96	0.99	0.98	0.99
5	601	122.29	1.00	1.00	0.98	0.99	0.99	0.99	0.99	0.99	0.93	0.99	0.99	1.00
6	600	153.64	1.00	1.00	0.99	0.99	0.99	0.97	0.99	1.00	0.95	1.00	1.00	1.00
7*	495	171.28	0.55	0.55	0.55	0.47	0.52	0.50	0.52	0.56	0.38	0.50	0.52	0.56
8*	304	622.13	0.53	0.52	0.49	0.52	0.51	0.51	0.52	0.52	0.41	0.52	0.48	0.53

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
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MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for H1 and H2 were doubled.

[t] For data set #2, the first rater determined the score assignment. The second rater was employed as a "read behind", but did not influence the score assignment.

Table 11. Test Set Exact and Adjacent Agreement Deltas (*Exact+Adjacent – Exact+Adjacent*$_{(RS)}$)

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	0.00	0.00	----	0.00	0.00	-0.02	0.00	0.00	-0.05	0.00	-0.01	0.00
2a[t]	600	381.19	----	0.00	----	0.00	-0.01	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00
2b[t]	600	381.19	----	0.00	----	-0.01	-0.02	-0.01	0.00	-0.01	-0.03	-0.01	0.00	0.00
3	568	108.69	0.00	0.00	----	-0.02	-0.03	-0.02	-0.02	-0.03	-0.03	-0.02	-0.03	-0.01
4	586	94.39	0.00	0.00	----	-0.01	-0.01	-0.02	-0.01	-0.01	-0.04	-0.01	-0.02	-0.01
5	601	122.29	0.02	0.02	----	0.01	0.01	0.01	0.01	0.01	-0.05	0.01	0.01	0.02
6	600	153.64	0.01	0.01	----	0.00	0.00	-0.02	0.00	0.01	-0.04	0.01	0.01	0.01
7*	495	171.28	0.00	0.00	----	-0.08	-0.03	-0.05	-0.03	0.01	-0.17	-0.05	-0.03	0.01
8*	304	622.13	0.04	0.03	----	0.03	0.01	0.02	0.03	0.02	-0.08	0.02	-0.02	0.04

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
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MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for Hx1 and H2 were doubled.

[t] For data set #2, the first rater determined the score assignment. The second rater was employed as a “read behind”, but did not influence the score assignment.

Table 12. Test Set Kappas

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	0.53	0.53	0.45	0.29	0.29	0.25	0.28	0.33	0.16	0.29	0.27	0.32
2a[t]	600	381.19	----	0.62	0.62	0.46	0.44	0.49	0.51	0.51	0.30	0.43	0.48	0.50
2b[t]	600	381.19	----	0.56	0.56	0.46	0.35	0.42	0.49	0.46	0.27	0.43	0.45	0.48
3	568	108.69	0.83	0.77	0.57	0.52	0.56	0.50	0.54	0.59	0.45	0.43	0.55	0.53
4	586	94.39	0.82	0.84	0.65	0.49	0.56	0.50	0.53	0.60	0.30	0.44	0.50	0.58
5	601	122.29	0.69	0.71	0.44	0.59	0.55	0.55	0.51	0.56	0.28	0.54	0.51	0.59
6	600	153.64	0.70	0.71	0.45	0.49	0.44	0.40	0.44	0.55	0.31	0.46	0.51	0.51
7*	495	171.28	0.23	0.23	0.18	0.05	0.09	0.07	0.08	0.12	0.03	0.05	0.07	0.07
8*	304	622.13	0.26	0.26	0.16	0.06	0.13	0.11	0.08	0.10	0.04	0.09	0.11	0.04

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
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MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for Hx1 and H2 were doubled.

[t] For data set #2, the first rater determined the score assignment. The second rater was employed as a "read behind", but did not influence the score assignment.

Table 13. Test Set Kappa Deltas ($\kappa - \kappa_{(RS)}$)

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	0.08	0.08	----	-0.16	-0.16	-0.20	-0.17	-0.12	-0.29	-0.16	-0.18	-0.13
2a[t]	600	381.19	----	0.00	----	-0.16	-0.18	-0.13	-0.11	-0.11	-0.32	-0.19	-0.14	-0.12
2b[t]	600	381.19	----	0.00	----	-0.10	-0.21	-0.14	-0.07	-0.10	-0.29	-0.13	-0.11	-0.08
3	568	108.69	0.26	0.20	----	-0.05	-0.01	-0.07	-0.03	0.02	-0.12	-0.14	-0.02	-0.04
4	586	94.39	0.17	0.19	----	-0.16	-0.09	-0.15	-0.12	-0.05	-0.35	-0.21	-0.15	-0.07
5	601	122.29	0.25	0.27	----	0.15	0.11	0.11	0.07	0.12	-0.16	0.10	0.07	0.15
6	600	153.64	0.25	0.26	----	0.04	-0.01	-0.05	-0.01	0.10	-0.14	0.02	0.06	0.06
7*	495	171.28	0.05	0.05	----	-0.13	-0.09	-0.11	-0.10	-0.06	-0.15	-0.13	-0.11	-0.11
8*	304	622.13	0.10	0.10	----	-0.10	-0.03	-0.05	-0.08	-0.06	-0.12	-0.07	-0.05	-0.12

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
CMU—TELEDIA, Carnegie Mellon University
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PKT—Pearson Knowledge Technologies
PM—Pacific Metrics
VL—Vantage Learning
MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for Hx1 and H2 were doubled.

[t] For data set #2, the first rater determined the score assignment. The second rater was employed as a "read behind", but did not influence the score assignment.

Table 14. Test Set Quadratic Weighted Kappas

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1	589	366.40	0.77	0.78	0.73	0.78	0.79	0.70	0.82	0.82	0.66	0.79	0.76	0.78
2a	600	381.19	----	0.80	0.80	0.68	0.70	0.68	0.74	0.72	0.62	0.70	0.72	0.70
2b	600	381.19	----	0.76	0.76	0.66	0.63	0.63	0.69	0.70	0.55	0.65	0.69	0.68
3	568	108.69	0.92	0.89	0.77	0.72	0.74	0.69	0.72	0.75	0.65	0.65	0.73	0.73
4	586	94.39	0.93	0.94	0.85	0.75	0.81	0.76	0.80	0.82	0.67	0.74	0.76	0.79
5	601	122.29	0.89	0.90	0.74	0.82	0.81	0.80	0.81	0.83	0.64	0.80	0.78	0.83
6	600	153.64	0.89	0.89	0.74	0.76	0.76	0.64	0.75	0.81	0.65	0.75	0.78	0.76
7	495	171.28	0.78	0.77	0.72	0.67	0.77	0.74	0.81	0.84	0.58	0.77	0.80	0.81
8	304	622.13	0.75	0.74	0.61	0.69	0.65	0.60	0.70	0.73	0.63	0.69	0.68	0.68

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
CMU—TELEDIA, Carnegie Mellon University
CTB—CTB McGraw-Hill
ETS—Educational Testing Service

PKT—Pearson Knowledge Technologies
PM—Pacific Metrics
VL—Vantage Learning
MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for Hx1 and H2 were doubled.

[t]For data set #2, the first rater determined the score assignment. The second rater was employed as a “read behind”, but did not influence the score assignment.

Table 15. Test Set Quadratic Weighted Kappa Deltas $(\kappa_w - \kappa_{w\ (RS))})$

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1	589	366.40	0.04	0.05	----	0.05	0.06	-0.03	0.09	0.09	-0.07	0.07	0.03	0.06
2a	600	381.19	----	0.00	----	-0.12	-0.10	-0.11	-0.06	-0.08	-0.18	-0.10	-0.08	-0.10
2b	600	381.19	----	0.00	----	-0.09	-0.13	-0.12	-0.06	-0.06	-0.21	-0.11	-0.07	-0.08
3	568	108.69	0.15	0.12	----	-0.05	-0.03	-0.08	-0.05	-0.02	-0.12	-0.12	-0.04	-0.04
4	586	94.39	0.08	0.09	----	-0.1	-0.04	-0.09	-0.04	-0.03	-0.18	-0.1	-0.08	-0.05
5	601	122.29	0.15	0.16	----	0.07	0.07	0.05	0.06	0.09	-0.1	0.05	0.03	0.08
6	600	153.64	0.15	0.15	----	0.02	0.03	-0.1	0.01	0.07	-0.09	0.01	0.04	0.02
7	495	171.28	0.06	0.05	----	-0.05	0.06	0.03	0.09	0.12	-0.14	0.05	0.08	0.09
8	304	622.13	0.14	0.13	----	0.07	0.03	-0.01	0.09	0.12	0	0.08	0.07	0.07

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
CMU—TELEDIA, Carnegie Mellon University
CTB—CTB McGraw-Hill
ETS—Educational Testing Service

PKT—Pearson Knowledge Technologies
PM—Pacific Metrics
VL—Vantage Learning
MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for Hx1 and H2 were doubled.

^{t}For data set #2, the first rater determined the score assignment. The second rater was employed as a “read behind”, but did not influence the score assignment.

Table 16. Test Set Pearson Moment Product Correlation Coefficient, *r*

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	0.93	0.93	0.73	0.80	0.79	0.71	0.82	0.82	0.66	0.80	0.76	0.80
2a[t]	600	381.19	----	0.80	0.80	0.68	0.71	0.69	0.74	0.72	0.62	0.70	0.72	0.71
2b[t]	600	381.19	----	0.76	0.76	0.67	0.64	0.64	0.70	0.71	0.55	0.65	0.69	0.69
3	568	108.69	0.92	0.89	0.77	0.72	0.74	0.69	0.72	0.75	0.65	0.66	0.73	0.73
4	586	94.39	0.94	0.94	0.85	0.76	0.81	0.76	0.82	0.82	0.68	0.75	0.76	0.80
5	601	122.29	0.89	0.90	0.75	0.82	0.81	0.80	0.81	0.84	0.65	0.80	0.78	0.83
6	600	153.64	0.89	0.89	0.74	0.76	0.77	0.65	0.77	0.81	0.66	0.75	0.78	0.77
7*	495	171.28	0.93	0.93	0.72	0.71	0.78	0.75	0.81	0.84	0.58	0.78	0.80	0.82
8*	304	622.13	0.87	0.88	0.61	0.71	0.66	0.63	0.71	0.73	0.62	0.70	0.68	0.72

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
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MI—Measurement, Inc.
MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for Hx1 and H2 were doubled.

[t] For data set #2, the first rater determined the score assignment. The second rater was employed as a “read behind”, but did not influence the score assignment.

Table 17. Test Set Pearson Moment Product Correlation Coefficient Deltas (*r* – *r* $_{(RS)}$)

Essay Set	*N*	*M* # of Words	H1	H2	H1H2	AIR	CMU	CTB	ETS	MI	MM	PKT	PM	VL
1*	589	366.40	0.20	0.20	----	0.07	0.06	-0.02	0.09	0.09	-0.07	0.07	0.03	0.07
2a[t]	600	381.19	----	0.00	----	-0.12	-0.09	-0.11	-0.06	-0.08	-0.18	-0.10	-0.08	-0.09
2b[t]	600	381.19	----	0.00	----	-0.09	-0.12	-0.12	-0.06	-0.05	-0.21	-0.11	-0.07	-0.07
3	568	108.69	0.15	0.12	----	-0.05	-0.03	-0.08	-0.05	-0.02	-0.12	-0.11	-0.04	-0.04
4	586	94.39	0.09	0.09	----	-0.09	-0.04	-0.09	-0.03	-0.03	-0.17	-0.10	-0.09	-0.05
5	601	122.29	0.14	0.15	----	0.07	0.06	0.05	0.06	0.09	-0.10	0.05	0.03	0.08
6	600	153.64	0.15	0.15	----	0.02	0.03	-0.09	0.03	0.06	-0.12	0.01	0.04	0.03
7*	495	171.28	0.21	0.21	----	-0.01	0.06	0.03	0.09	0.12	-0.14	0.06	0.08	0.10
8*	304	622.13	0.26	0.27	----	0.10	0.05	0.02	0.10	0.12	0.01	0.09	0.07	0.11

H1-Human Rater 1
H2-Human Rater 2
H1H2-Human Rater1, Human Rater 2
AIR—American Institutes for Research
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PKT—Pearson Knowledge Technologies
PM—Pacific Metrics
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MM—MetaMetrics

*RS score was obtained by summing the equally weighted ratings from H1 and H2. To be on the same scale as the RS, the original ratings for Hx1 and H2 were doubled.

[t]For data set #2, the first rater determined the score assignment. The second rater was employed as a “read behind”, but did not influence the score assignment.

Figure 1. Line Chart for Vendor Performance on Mean Estimation across the Eight Essay Data Sets

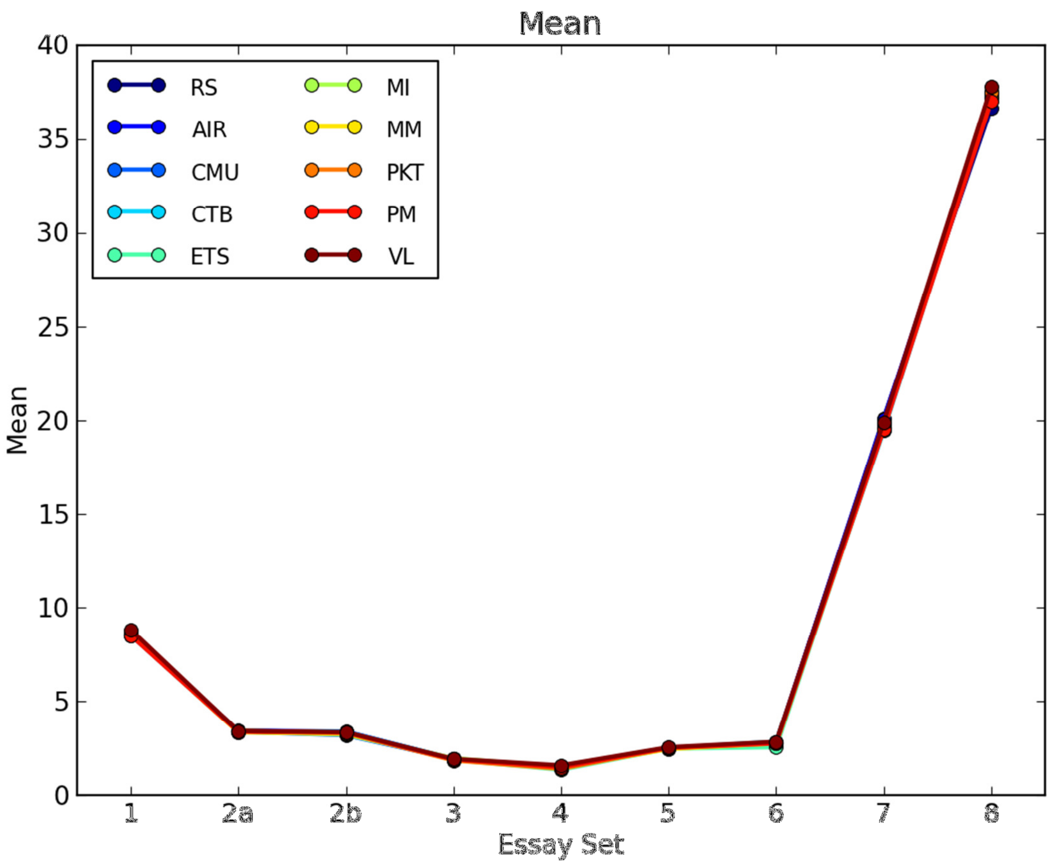


Figure 2. Line Chart for Vendor Performance on Standard Deviation Estimation across the Eight Essay Data Sets

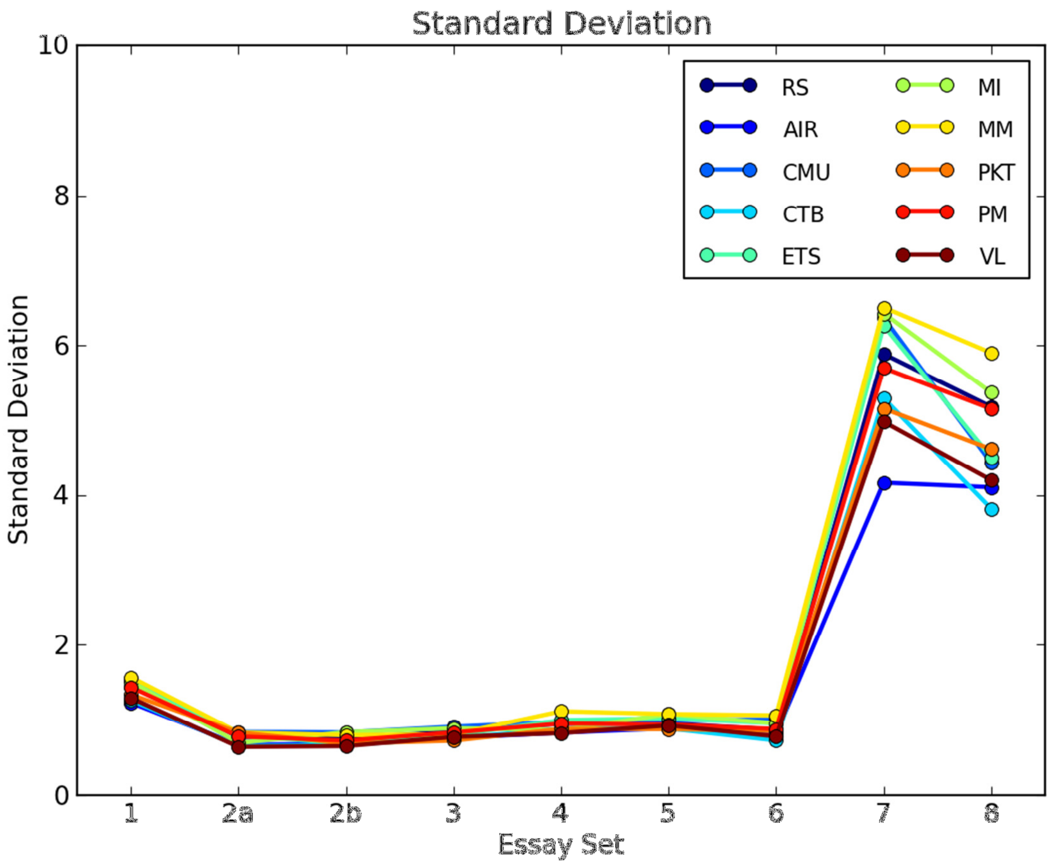


Figure 3. Line Chart for Vendor Performance on Exact Agreements across the Eight Essay Data Sets

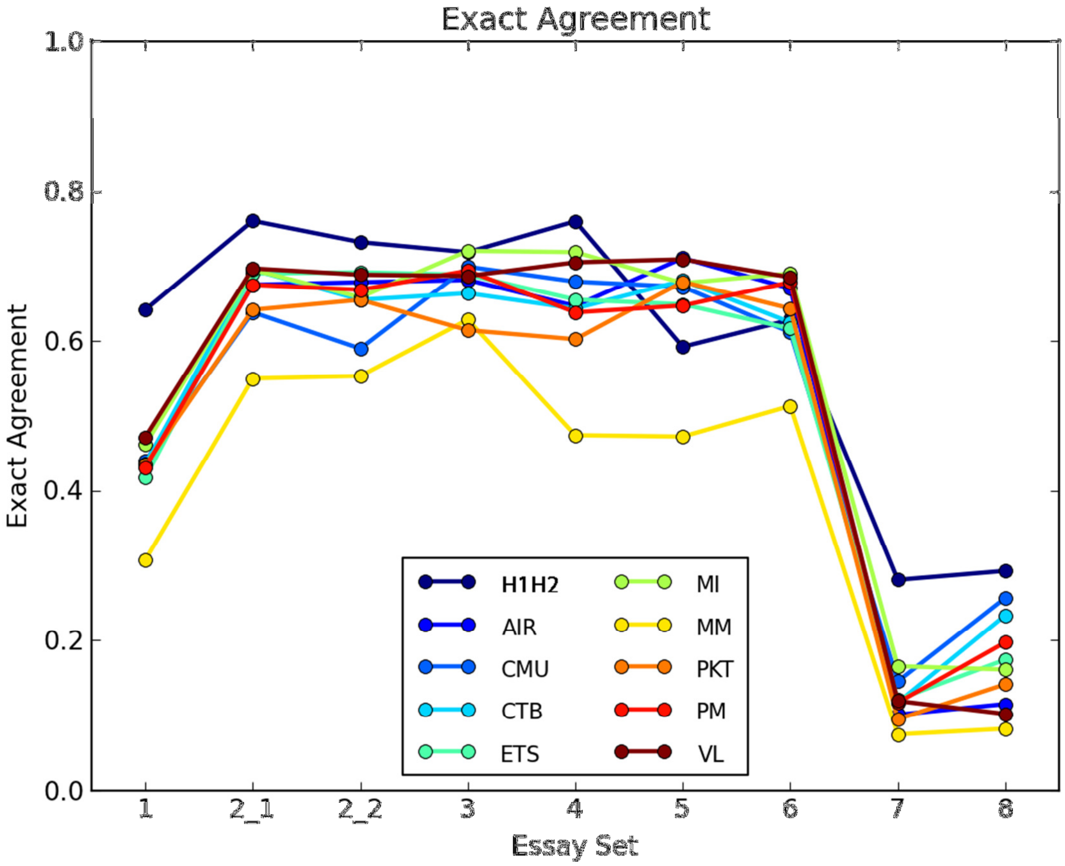


Figure 4. Line Chart for Vendor Performance on Exact+Adjacent Agreements across the Eight Essay Data Sets

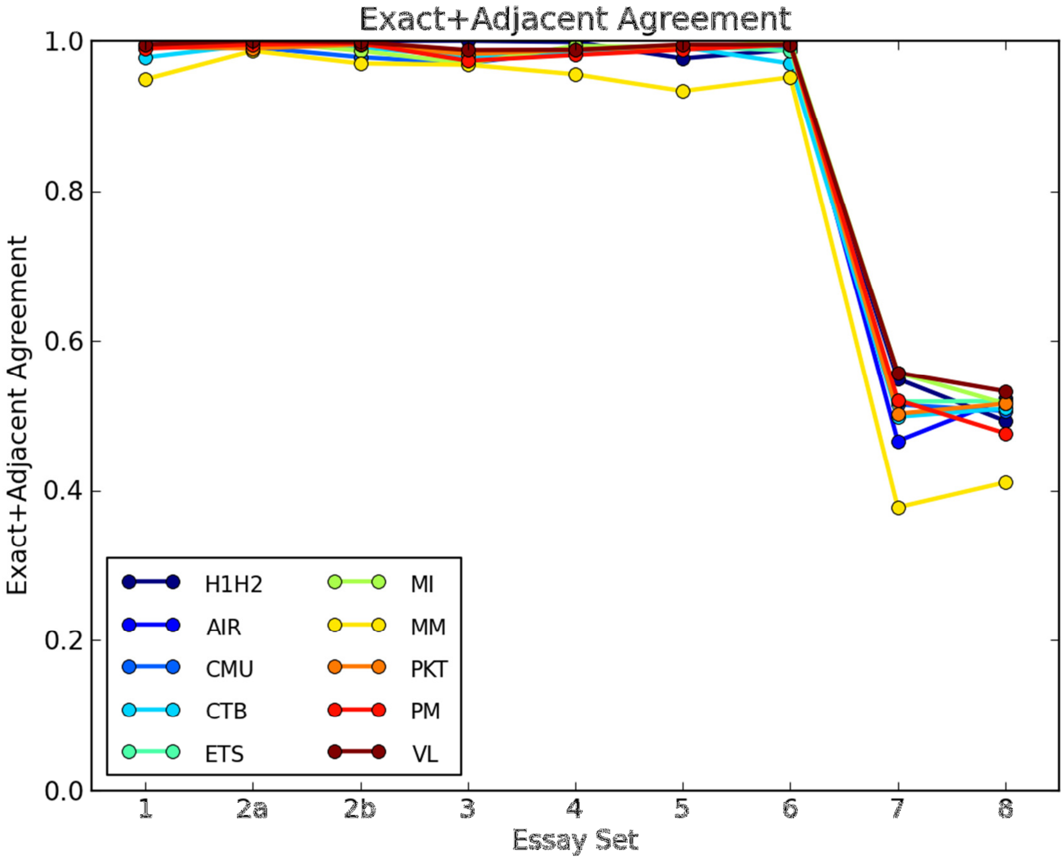


Figure 5. Line Chart for Vendor Performance on Kappas across the Eight Essay Data Sets

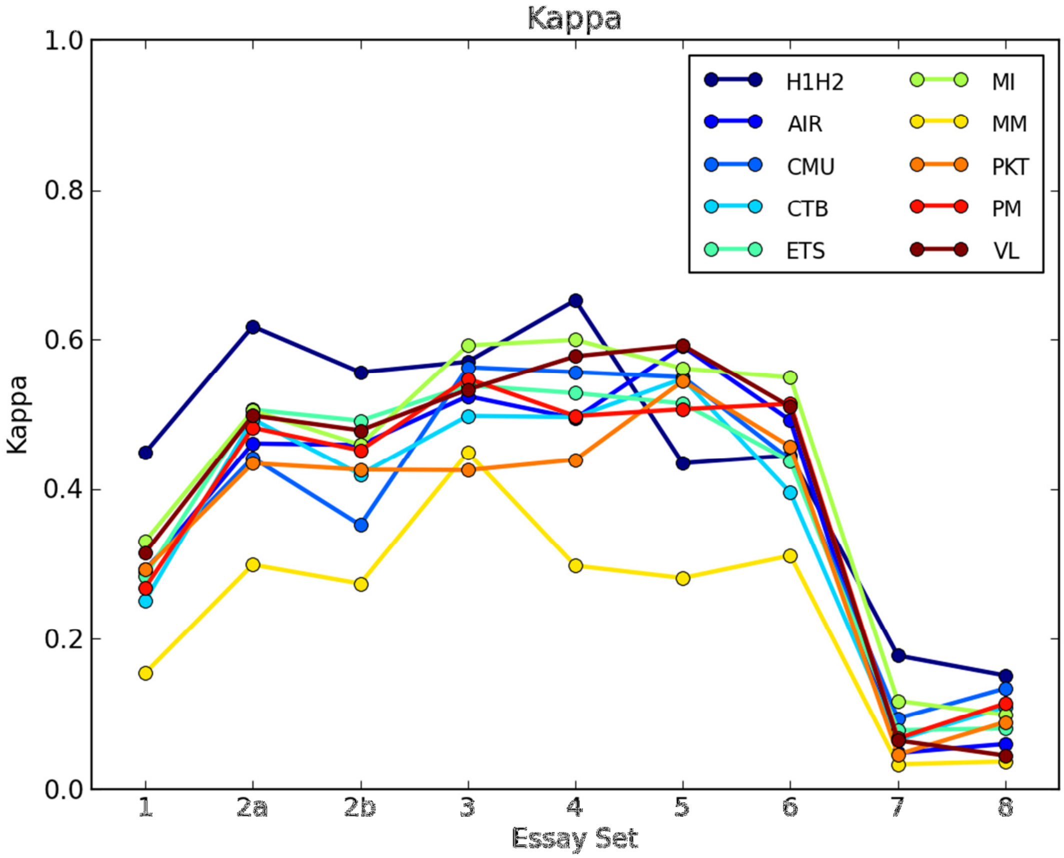


Figure 6. Line Chart for Vendor Performance on Quadratic Weighted Kappas across the Eight Essay Data Sets

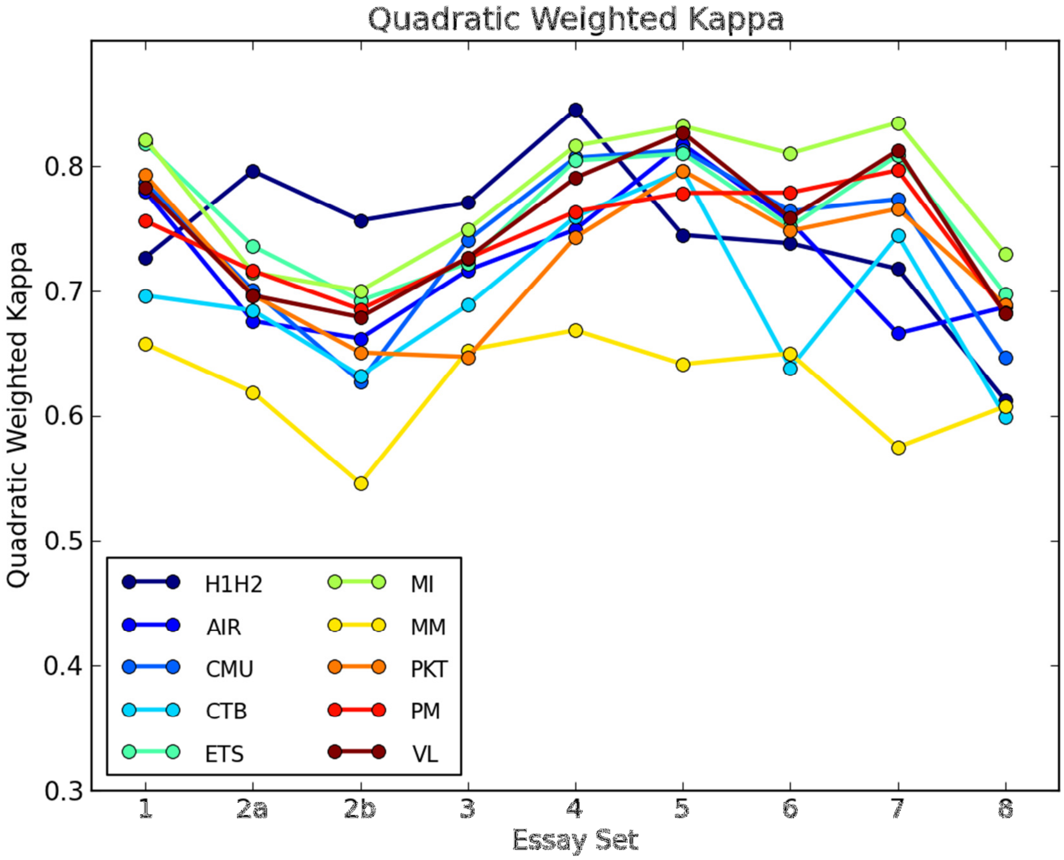
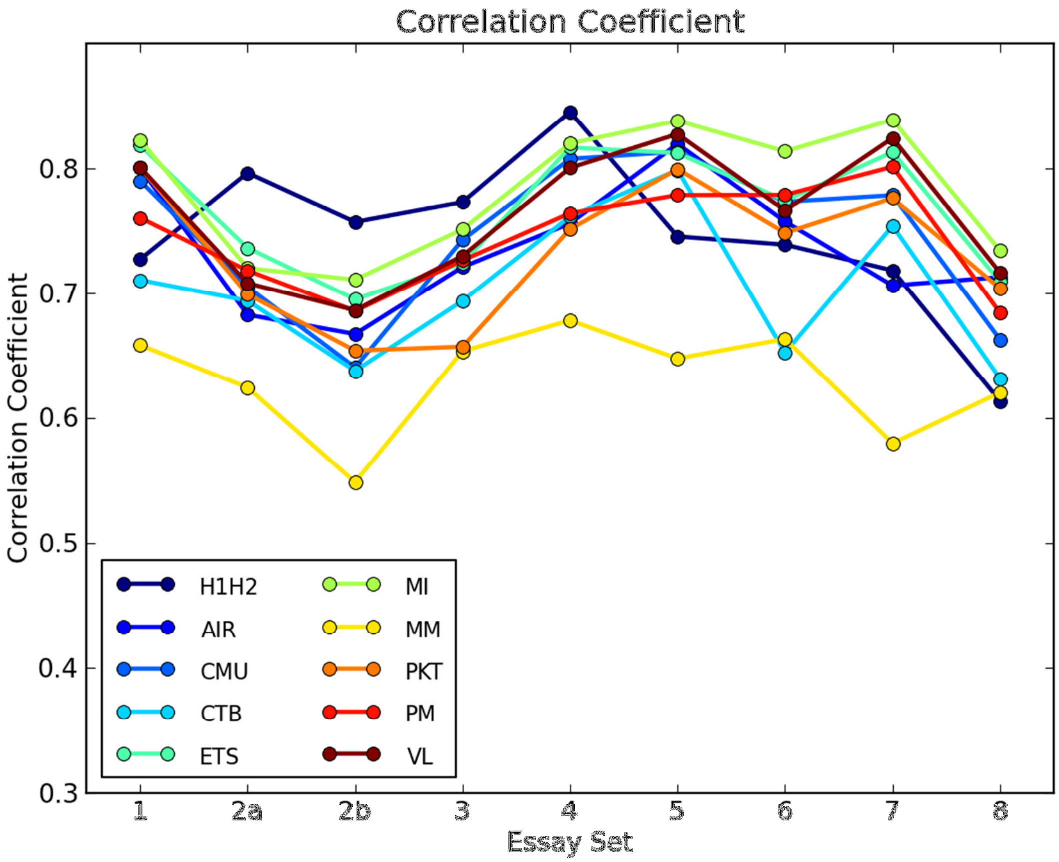


Figure 7. Line Chart for Vendor Performance on the Pearson Product Moment Correlation across the Eight Essay Data Sets


Correlation Coefficient
Correlation Coefficient
2a
2b
Essay Set
H1H2
AIR
CMU
CTB
ETS
MI
MM
PKT
PM
VL