Rubric-based Automated Japanese Short-answer Scoring and Support System Applied to QALab-3

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ABSTRACT
We have been developing an automated Japanese short-answer scoring and support machine for the new National Center written test exams. Our approach is based on the fact that accurately recognizing textual entailment and/or synonymy has been almost impossible. The system generates automated scores on the basis of evaluation criteria or rubrics, and human raters revise them. The system determines semantic similarity between the model answers and the actual written answers as well as a certain degree of semantic identity and implication. An experimental prototype operates as a web system on a Linux computer. To evaluate the performance, we applied the method to the second round of entrance examinations given by the University of Tokyo. We compared human scores with the automated scores for a case in which 20 allotment points were placed in five test issues of a world-history test as part of a trial examination. The differences between the scores were within 3 points for 16 of 20 data provided by the NTCIR QALab-3 task office.

Team Name
Tmkff

Subtask
Evaluation method task

Keywords
writing test, automated scoring, machine learning, random forests, recognizing textual entailment, question answering, university entrance examinations, open-ended question

1. INTRODUCTION
An educational advisory body to the Japanese government has decided that writing tests will be introduced into the new national center test for university entrance examinations, as announced in a final report [MEXT 2016] at the high school and university articulation meeting by the Ministry of Education, Culture, Sports, Science and Technology. The use of AI-based computers was proposed to stabilize the test scores efficiently. The required type of writing test is essay writing, where a correct answer is expected to exist. Therefore, the test is scored by judging agreement on the meaning with the correct answer.

Another type of unrequired writing test is essay writing, where a correct answer does not exist. The written answers are evaluated based on the rhetoric, the connection expressions, and the content. Many systems for evaluating essays have been developed and offered in the United States [Shermis and Burstein 2013]. The authors’ group also developed the first and most well-known Japanese automated essay scoring system named Jess [Ishioka and Kameda 2006], and it is in practical use now.

While short-answer scoring involves technical difficulty, the number of characters is restricted to 120 at most from dozens of characters. Two characters in Japanese are usually equivalent to one word in English. A short-answer test is widely considered to be more authentic and reliable for measuring ability compared with a multiple-choice test. If technical problems related to the short-answer test are solved, the potential demand for its use as well as that for the national center test will be enormous.

A short-answer scoring system has also been developed because of its importance, though various technical problems remain unsolved. New York University (NYU) and the Educational Testing Service (ETS) developed the first automated scoring tools in this field; they evaluated the NYU online program [Vigilante 1999]. Leacock[Leacock and Chodorow 2003] reported the latest specifications of the c-rater developed by ETS. Pulman[Pulman and Sukkarieh 2005] tried to generate several sentences having the same meaning as the correct answer sentence using the natural language technique of information extraction. However, the concordance rate with human examiners was found to be small and impractical.

In 2012, a Kaggle competition for short answer scoring had been completed [Foundation 2012]. Each answer is approximately 50 words in length. The winner, Luis Tandalla [Tandalla 2012], made the best score of 0.77166 evaluated with the quadratic weighted kappa error metric [Hamner 2015], which measures the agreement between two raters (system and human). The real number of 1 shows complete agreement between raters, whereas a human benchmark produced a score of 0.90013. Automated assessment is not yet in the stage of practical application.

Therefore, we conceived of a support system for short written tests where a human rater can correct the automated score by referring to the original scores [Ishioka and Kameda 2017]. When the human rater agrees with the result of the automated score, he/she can just approve the score indicated by default and can produce the corresponding mark. We chose to leave room for human raters to overwrite it without making it a perfect automated scoring system.

Of course, some degree of quality is required for auto-
matic scoring given as an initial value. In order to evaluate the performance of our system as a scoring engine, we decided to participate in the NTCIR-QALab 3 task [Shibuki et al. 2017], this time. A part of Tokyo University’s second round of the world-history written test requires essay answers of 450–600 words containing 8 specified terms. This test may not be called a short answer test because of the quantity of writing required, but written answers need to be semantically consistent with the model solution for judgment. By putting the lexical condition on the designation, the short-answer written test could be expanded into about 500 characters. Thus, we attended this conference.

In what follows, Section 2 indicates the test issues and the model answers used in a trial examination for Tokyo University’s entrance examinations. Section 3 shows the specifications of our proposed system. Section 4 presents our evaluation of the performance on five tests of social studies. Section 5 concludes with a summary.

2. TEST ISSUES USED IN A TRIAL EXAMINATION

We are assigned five issues in the subject of world history for Tokyo University’s second round examinations in the past. The world history test set includes several types of written tests, and we evaluated the test issues required for the most voluminous test of 450–600 characters.

Table 1 shows the “content” asked and the “mandatory words/phrases,” which are given by test writers to the examinees.

Besides these, the following are given: (1) three model answers per issue, (2) partial sentences generated from the model answers, and (3) its importance as evaluated by professional raters. However, these are omitted due to space limitations.

The allocated number of points to every test issue is 20. If mandatory words or phrases are missing, 5 points are deducted per omission. Also, if the amount of words exceeds the limit, the score is halved. These are based on our speculation about the actual scoring standards of Tokyo University’s entrance examinations.

3. SPECIFICATIONS OF THE SCORING SUPPORT SYSTEM

3.1 Outline

Our system is for automated scoring and for supporting human raters. The approach functions as follows.

1. A system automatically judges each answer posed on whether or not its prepared key phrases agree with those of the model answer using the “scoring criteria” from a surface-like point of view.

2. The system gives not only a temporary score based on the criterion-based judgment but also a prediction score offered by machine learning based on the understanding of other human raters or supervised data. A certain degree of semantic meaning is also used.

3. A human rater can certify the prediction score by which a system presents this information as reference. He or she can correct this and overwrite based on his/her judgment.

To reduce the time and effort, the system precision should possess a certain degree of fitness with human ratings; more than 80% of the precision is desirable for tentative targets. At this conference, step 3 was omitted; we did not use this procedure.

The flowchart of our system is as shown in Figure 1.

Figure 1: Flowchart of the system

(a) Before scoring, we collected a lot of score data from various human raters and performed a machine learning of “Random Forests” [Breiman 2001]. The degree of fitness with the scoring guideline is also necessary. On the basis of those learning results, we set up a scoring engine to return the scores for new answers.

(b) The system generates a scoring screen written in the Hyper Text Markup Language.

(c) A user or human rater opens a scoring screen of (b) using a web browser on his/her terminal machine. Then, a CGI program is activated. The recommended value as a result of the scoring engine of (a) is indicated here. The scoring result is stocked in a file or a database. The user repeats this mark operation.

3.2 Scoring Screen

Figure 2 shows a screen shot of our prototype system. “The answer sentence that should be scored” (in red ink) is located in the upper part of the system; the middle part has some scoring criteria such as “synonyms and permitted different transcriptions,” “model or correct answers that warrant a full mark,” “partial phrases that warrant partial scores,” and “mandatory phrases.” For the “model answer” and “partially correct phrases,” the system judges the degree of fitness with the answer sentence to be scored; the
system also judges whether or not the answer sentence includes “mandatory phrases,” whether or not it is meaningfully composed, and whether or not it exceeds the character limit; if the answer must be written as a noun or noun phrase, the system judges whether or not it matches the specified “type” format. These judgments are given as either yes or no, and toggle buttons are used. A human rater reviews these judgments and revises them if necessary.

Tentative scores located in the lower part are based on the aforementioned alternative judgment. The right-hand window is to determine the final score. The initial mark is settled by which predictive probability based on the past learned results gives the maximum. The probability values are also indicated. We used only tentative scores in this conference.

When no learning data exist, that is to say, when no pre-scored data on the relevant test issue exist, the message to that effect is shown in the top windows: no probability and no initial mark are naturally determined. Unfortunately, we or human raters cannot revise the machine scores; we only refer to these.

### 3.3 Automatic screen creation from a scoring criterion file

Our system is a Web application. Thus, the screen indicated in Figure 2 is generated by HyperText Markup Language. We built the mechanism to make this HTML file automatically from a plain scoring criterion file that a computer beginner can handle.

Figure 3 is a plain original file that makes a screen like the one in Figure 2. Two or three elements are set for criteria. In order, the label, allotment of points, and correspondence are located. The tab is the delimiter.

Synonyms and different transcriptions are recorded in “syno,” which appeared in “gold” as a model answer and in “part” as a partially correct phrase. “Syno” is not always limited to a definite lexical meaning. When the text has the same meaning semantically, it is also permitted. “Part” includes two types: one is possible to add to a partial point, and the other is for which a maximum is taken. If multiple same labels are found (for example, part1), we use the maximum of the points; different labels (for example, part1 and part2) can add the allotted points. “Lack” is a mandatory phrase; if no phrases exist, a point is deducted. A comma can be used for the meaning of “both.” “Vol” shows the number of characters available. “None” shows a nonsense sentence, and “goji” shows a wrong word such as a kanji which does not exist. Minus points indicate the points to be deducted. At this conference, we did not use “none” and “goji” because the scoring criterion does not include these.
Figure 2: Short-answer scoring and support system screen (In case of world history B792W10_1)
古代エジプトは、ナイル川を中心に長らく独立王朝が栄え、アレクサンドロス大王などの征服を受ける。アレクサンドロス朝エジプトのクレオパトラは、地中海の覇権国であったローマの脅威に対し、アントニウスと連合してオクタヴィアヌスに対抗するが、アクティウムの海戦で敗走し、エジプトはローマの属州となった。紀元7世紀にアラビア半島を統一し、イスラム教勢力は、東ローマ帝国とササン朝ペルシアの対立に乗じて版図を拡大し、エジプトを征服した。イスラム教勢力の版図の一一部を継承したファーティマ朝では、1196年にサラディンが宰相となり、イスラム教勢力から聖地エルサレムを奪還しようとする十字軍に対抗した。イスラム教勢力から奪還しようとする十字軍に対抗したサラディン、1517年にマムルーク朝を倒し、エジプトを占領したオスマン帝国がその代表的事例である。しかし、エジプトは、少なくとも、外部の支配に屈してきたわけではない。現在のエジプト民族は、7〜12世紀までのアラブ系イスラム教勢力の統治期にアイデンティティを形成したものである。1798年のナポレオンによるエジプト遠征の撃退後、ムハンマド・アリーはエジプトの太守となり、1831年と1839年にエジプト―トルコ戦争を起こした。その後、イギリスの一時支配下に入るが、ナセルが、1952年のエジプト革命を指導し1954年から大統領に就任して、アラブ民族主義の指導者として、スエズ運河の国有化、アラブ連合共和国の合邦など、多くの事績をあげた。ナセルは、アラブ民族主義の指導者だ。ナセルは、スエズ運河の国有化、アラブ連合共和国の合邦など、多くの事績をあげた。
We use “fitness” as the degree of the relationship between the written answer and “model answer” designated in “gold” or “partially correct phrases” in “part.” We define this as the harmonic mean of two kinds of relationships: one is the degree of the reference during the sentence keywords from the viewpoint of a written answer; the other is that from a model answer. These relationships are just like precision and recall often used in information retrieval, e.g., a Google search. This harmonic mean or “fitness” is called an F-measure taking a float number from 0 to 1. Our system rounds this to either 0 or 1 as a toggle button occurrence, and it shows a non-rounded value as a reference for the user.

If the scores by professional human raters are given, a mechanical learning score is presented. Unfortunately, we did not obtain human ratings in advance.

3.4 How to make partially correct phrases

The task of NTCIR provides partial phases, which are created automatically from the correct answers, and gives scores ranging from 1 to 3 by professional reviewers. We call them nugget sentences.

The partially correct answers are given in advance at actual scoring, but they are not given to us. Thus, we substitute the nugget sentences as the partially correct answers.

The allotted points should be the median of three professional evaluations. The total of the partial points may exceed the full score of 20 points, but it ends with the maximum limit.

3.5 Deducted points due to exceeding of character limit

For short answers limited to 30–50 characters, the scores of the answers exceeding the limit number is usually zero. However, in response to about 500 characters like this task, a zero is not appropriate.

Therefore, in the case of exceeding the limit, a specification that halves the score was implemented. We used “vol /2 500” instead of “vol –20 500” on a scoring criterion file, which shows that system should halve the score instead of the full score of 20 points.

3.6 Japanese sentence processing

Unlike Western languages, Japanese is a sticky language that leaves no blank space between words. Therefore, the performance of the morphological analyzer is more important than that of Western languages. Adequate dictionaries are also indispensable. Wikipedia’s entry word dictionary includes a textbook that is suitable for social studies examinations. Our approach is applicable to Western languages as long as we can handle grammatical processing according to the language.

4. PERFORMANCE EVALUATION

4.1 Evaluation Criterion

The task office gave experts’ evaluation of each of the four answers prepared by participants on five issues. The experts scored according to the grading criteria they created. This scoring standard was not disclosed to participants in advance.

This task measures the degree of agreement between the participant’s evaluation and a professional’s. The task of-

| Table 2: Predicted value, the mean of differences from professional scores, and the mean of squared differences |
|-----------------------------------------------|-----------------|-----------------|------------------------|
| Issue | predicted values | $\Sigma x / n$ | $\Sigma x^2 / n$ | all predicted values |
| B     | 0.0,0.2         | 0.50           | 1.00          | 0×11, 2, 8, 14, 15×4 |
| C     | 0.0,0.0         | 0.00           | 0.00          | 0×13, 3, 9, 12×2, 18×2 |
| G     | 0.0,0.3         | 0.75           | 2.25          | 0×10, 2, 3, 7, 8, 9, 19×4 |
| L     | 5.0,0.4         | 2.25           | 10.3          | 0×9, 4, 5, 8, 9, 11, 12, 14×2, 19×2 |
| P     | 0.4,0.4,5       | 2.13           | 9.06          | 0×8, 4, 4.5×6, 5×2, 7.5, 9 |

The allotment scores are the median of three professional evaluations, but they are not given to us. Thus, we substitute the nugget sentences as the partially correct answers.

The allotted points should be the median of three professional evaluations. The total of the partial points may exceed the full score of 20 points, but it ends with the maximum limit.

4.2 Evaluation Results

Surprisingly, among the professional evaluations for the 20 answers, four responses for each of five issues were all zero. For this reason, because the standard deviation of professional evaluation was zero, both of the indicators prepared by the task office could not be calculated.

The purpose of this task is how to predict professional evaluations well. Thus, we thought a good solution is evaluating how close the scores presented are to zero.

Table 2 shows our predicted values, the mean of differences from professional evaluation, and the mean of squared differences. For reference, all our predicted values are added including the remaining data that the professionals did not score.

Each response was scored with 20 points as a full mark, and the range was as follows. 0–15 (for B), 0–18 (for C), 0–19 (for G and L), 0–9 (for P). Some answers are given high scores, and the range of the score is wide. Under this situation, the answers evaluated by professional raters produced sufficiently close to zero ratings. Our method produces reasonable scores. The differences between the professionals and ours are within 3 points for 16 of 20 data.

The evaluation criteria based on the residuals with the correct score are the most appropriate, but the evaluation is not an index prepared by the task office. Therefore, we do not explicitly show the other teams’ results using this index, but we nevertheless determined that our method is the best.

4.3 Some comments on evaluation indicators

Because the professional evaluations all became zero, the task office presented the values of two correlation coefficients: Spearman’s $\rho$ and Kendall’s $\tau$.

This is inappropriate for the following three reasons.

1. They did not measure the degree of agreement with the professional rater. The original purpose of the task has not been achieved.

Our team correctly answered all of the four responses for issue C. Nevertheless, the two indices of the task office gave it NAs. The indicator prepared by the task office is certainly important. However, it is one of the factors that affects the score prediction.

2. Calculating correlation with only 4 data has almost no
Table 3: Predicted values by participants

<table>
<thead>
<tr>
<th>Issue</th>
<th>Forest1</th>
<th>Forest2</th>
<th>tmkff</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>31.39, 62.44</td>
<td>2.3, 3.3</td>
<td>0.0, 0.2</td>
</tr>
<tr>
<td>C</td>
<td>35.39, 47.42</td>
<td>0.0, 1.1</td>
<td>0.0, 0.0</td>
</tr>
<tr>
<td>G</td>
<td>18.24, 31.41</td>
<td>2.1, 1.4</td>
<td>0.0, 0.3</td>
</tr>
<tr>
<td>L</td>
<td>38.43, 59.48</td>
<td>1.4, 2.1</td>
<td>5.0, 0.4</td>
</tr>
<tr>
<td>P</td>
<td>45.53, 67.60</td>
<td>5.4, 1.7</td>
<td>0.4, 0.4</td>
</tr>
</tbody>
</table>

meaning.

The bivariate correlation coefficient between $x$ and $y$ is calculated based on the deviation from the average of each of the two variables. In the rank correlation coefficient, the two deviations from the average ranks are taken into account. Therefore, the degree of freedom of distribution associated with the test statistics in this case is only 2, which is 4 minus 2. Statistics based on these few data have little meaning and may lead to a wrong conclusion.

Table 3 shows three participants’ predicted values, which are the raw data for five issues. Forest1 seems to have adopted 100 allotment points scoring. Forest2 might suppose 20 points as full marks like we did (tmkff).

Even without using difficult indicators, we can see that our team’s (tmkff’s) estimates are closest to zero of the correct answer. This is evidence that an index using a correlation coefficient is inappropriate.

3. Evaluations were made based on the indices created after the task execution.

The new index presented by the task office cannot be calculated from the numerical values associated with XML tag names, e.g., ans_limits, ans_len, total_0, minus_total, plus_total. From the points of fairness and accountability, this practice is not appropriate for a competition.

5. CONCLUSION

Evaluating the performance of our system was difficult because of the surprising results that showed all professional evaluations had issues with scoring zero. However, we are convinced that our system can show a certain degree of validity because it returned a score close to zero as being professionally evaluated, while a sufficiently wide range of scores were presented for other answers. Hereafter, we will endeavor to improve the system performance by evaluating unscored answers.

Our system can provide another predicted score by applying machine learning of random forests if sufficient professional scores are given. In such a case, this system can reveal some factors influencing the final forecast score. We can also take into consideration similarities to essay prompted sentences. If you are interested in the scoring, please refer to [Ishioka and Kameda 2017].

6. REFERENCES


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