

A methodology for Answer-Based Subjective Online Examination System

Malsa K.¹, Pathak S.², Gupta V.^{3*}

DOI: <https://doi.org/10.58260/j.iet.2202.0108>


¹ Komal Malsa, Lingaya's Vidyapeeth, Faridabad, Haryana, India.

² Shivani Pathak, JSS Academy of Technical Education, JSS Academy of Technical Education, Noida, Uttar Pradesh, India.

^{3*} Vimal Gupta, JSS Academy of Technical Education, JSS Academy of Technical Education, Noida, Uttar Pradesh, India.

The most effective method for testing a learner's knowledge is an online exam. It's critical to assess how much of the learner's knowledge has been retained. Typically, online tests given in schools, colleges, or for job placement only include objective questions, but educational experts have acknowledged that subjective writing abilities are crucial for senior management positions. Therefore, to fully assess a learner's knowledge, an online exam must also include subjective questions. Evaluation of objective questions is a relatively simple task, but online evaluation of subjective responses is a difficulty all its own. Less labour-intensive processes, quick processing, and convenience in record-keeping and extraction are some of the factors driving automation of subjective answer evaluation. Only single-sentence descriptive responses that are grammatically correct and error-free were taken into consideration for this paper. For keyword matching, the WordNet API has been utilised. The strategy involves graphing learners' responses and the accepted standard response to compare them and provide marks based on similarity [5,14,15].

Keywords: Antonym, Assessment, RiTa, Synonym, Semantic analysis, Wordnet

Corresponding Author	How to Cite this Article	To Browse
Vimal Gupta, JSS Academy of Technical Education, , JSS Academy of Technical Education, Noida, Uttar Pradesh, India. Email: vimalgupta@jssaten.ac.in	Komal Malsa, Shivani Pathak, Vimal Gupta, A methodology for Answer-Based Subjective Online Examination System. Glo.Jou.of.Innov.and.Eme.Tech. 2022;1(2):15-20. Available From http://iet.adsrs.net/index.php/iet/article/view/10	

Manuscript Received 2022-11-07	Review Round 1 2022-11-22	Review Round 2 2022-12-05	Review Round 3 2022-12-23	Accepted 2022-12-30
Conflict of Interest Nil	Funding Nil	Ethical Approval Yes	Plagiarism X-checker 18%	Note
 © 2022by Komal Malsa, Shivani Pathak, Vimal Guptaand Published by ADSRS Education and Research. This is an Open Access article licensed under a Creative Commons Attribution 4.0 International License https://creativecommons.org/licenses/by/4.0/ unported [CC BY 4.0].				

Introduction

The most effective method for testing a learner's knowledge is an online exam. It's critical to assess how much of the learner's knowledge has been retained. Typically, online tests given in schools, colleges, or for job placement only include objective questions, but educational experts have acknowledged that subjective writing abilities are crucial for senior management positions. Therefore, to fully assess a learner's knowledge, an online exam must also include subjective questions. Evaluation of objective questions is a relatively simple task, but online evaluation of subjective responses is a difficulty all its own. Less labour-intensive processes, quick processing, and convenience in record-keeping and extraction are some of the factors driving automation of subjective answer evaluation. Only single-sentence descriptive responses that are grammatically correct and error-free were taken into consideration for this paper. For keyword matching, the WordNet API has been utilised. The strategy involves graphing learners' responses and the accepted standard response to compare them and provide marks based on similarity [5,14,15].

Literature Review

Automating the evaluation of subjective responses is a broad semantic term. Numerous designs and characteristics have been suggested for evaluating subjective answers. Keyword matching, sequence matching, and quantitative analysis are the main methods used in these approaches [4], but semantic [1,12,13] analysis of descriptive answers is still a difficult task. According to the general structure of text analysis in natural language processing, the majority of the work has been done for morphological and syntactic analysis [2], [3], [7], [8] using techniques like DNA sequencing, DNA matching, Record Linkage System, dictionary creation, etc. However, semantic, pragmatic, and discourse analysis are still being investigated [19-23].

Most systems still manage the examination of long replies manually, however online programmes that allow organising online tests like Moodle and Zoho are built on string matching technique [7-8]. In addition to using ubiquitous cloud computing [9]. Blockchain [16-18], and FCK editor

[10] to automatically evaluate subjective responses, these systems did not do a semantic analysis of the responses. To assess the subjective responses of an informative nature, various methods including Cosine Similarity [11] and Generalized Latent Semantic Analysis (GLSA) were also applied. The semantic analysis of subjective responses is still an unsolved issue.

Methodology

In order to make it possible to compare various sentence components, the model's current approach translates the teacher's and student's raw input sentences into graphical form. Figure 1 presents the block diagram of the proposed model.

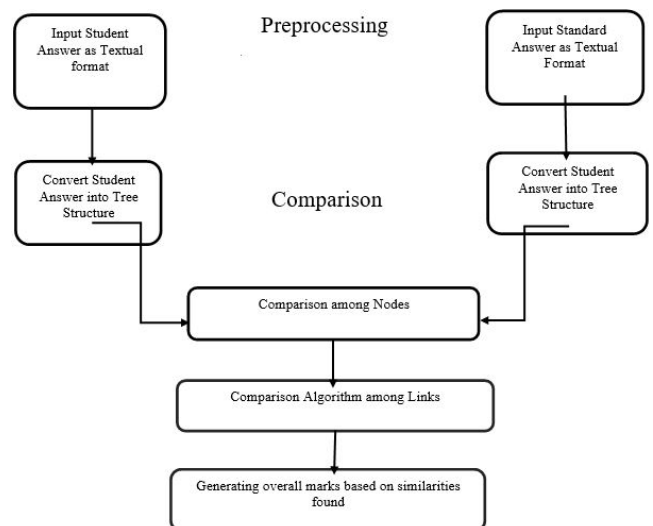


Figure 1: Block diagram for the proposed model

Preprocessing: The pre-processing part of this proposed system includes the following three steps as shown in the figure 2:

1. Using a student's response to a particular question as the input
2. Locating the relevant standard response (teacher's answer) in the database
3. Transforming both responses from their original English textual form into a "constituent tree" structure.

A basic statement is graphically broken down into nodes and links in a constituent tree. A simple sentence in English is made up of several words or phrases. There are two groups of these words/phrases. One group is made up of all the noun, adjective, and adverb phrases, while

The other groups are made up of all the verbs, prepositions, conjunction, and other connecting phrases. The former group's components serve as the graph's Nodes while the latter group's Connecting Phrases serve as the graph's Links. Every word or phrase can be classified into one of 26 Parts of Speech (POS) in accordance with the general standard. 11 of them are handled as links, and the remaining 11 are handled as nodes.



Figure 2: Pre-processing steps for the proposed system

Comparison Algorithm: The two trees produced during the pre-processing phase are contrasted with each other node by node. The comparison algorithm considers how similar two nodes are to one another both in terms of their textual proximity and their semantic similarity.

The various measures for comparison used are:

String Match is of two types as shown in the figure 3.

Full String Match

Partial String Match



Figure 3: String matching: full string matching and partial string matching

Semantic Similarity: The WordNet is used to determine the similarity between two phrases WordNet Library contains all the naturally occurring words %%%WN. A Java API called RiTa is implemented in order to access the WordNet Library. It can perform a number of functions to extract various attributes from a given word. The following similarity indices are produced based on the data that is available.

Synonym

Similarity

Inheritance

Is a form of

Antonym

Antonym with not

An original approach is taken in order to compare antonyms. The student may choose to use the antonym of a word before any natural form of negation, such as "not," even though their answer is semantically identical to the teacher's. Let's look at an illustration.

Teacher's answer: Tiger is a fast runner.

Student's answer: Tiger is not a slow runner.

First, both teachers' and students' responses are counted for how many times the word "not" or a variation of it is used. There is an imbalanced 'not' in the pair if this count (Flag) is an odd digit. If an existing pair of antonyms is discovered when comparing the nodes, the computed Flag takes precedence. A match is detected if there is an unbalanced "negation" and that "negation" is present in a link connected to those nodes; otherwise, it is not. The aforementioned illustration uses antonyms to contrast two statements with the same meaning. This suggested approach would discover the given pair of words to be quite semantically similar to one another with the calculated Flag=1.

Creation of a two-dimension array:

The amount of the matches discovered is recorded in a Two Dimension Array X after comparison between the nodes of the teacher's response and the student's nodes as shown in the table 1.

Consider the teacher graph $T \in \{TN1, TN2, TN3, TN4\} \cup \{TL1, TL2, TL3\}$

And the student graph $S \in \{SN1, SN2, SN3, SN4, SN5\} \cup \{SL1, SL2, SL3, SL4\}$

Table 1: Teacher Student Graph

	SN1	SN2	SN3	SN4	SN5
TN1	0.0	0.0	0.0	0.0	0.0
TN2	0.32	0.57	0.0	0.0	0.0
TN3	0.0	0.0	1.0	0.0	0.0
TN3	0.0	0.25	0.0	0.32	0.7

This 2D array displays the degree of correspondence between the significant

Phrases and key words in the two graphs. It demonstrates how similar both lines truly are in their suggestions. There is a matching node in the student graph for each distinct node in the teacher answer (T) (S). The degree of resemblance is divided into three categories according to the elements in a specific row of the array X, as follows:

1. No match found for a node (ex: Node TN1 has no match to any of the student node)
2. A unique match found for a node (ex: Node TN3 has one match, i.e. SN3)
3. A mixed match found for a node (ex: Node TN2, TN4 have matches to multiple nodes of student answer S)

Matching the Links: The linkages of the graphs are matched based on the determined 2D array X after the nodes of the instructor answer and student answer have been matched. One of the match types exists for each row in X, and a separate path is taken to match the links for each type of match refer table 2.

For type 1, where there is no match the overall match of the corresponding Teacher Node is also declared to be 0.0

The before and subsequent links of the two nodes are compared for type 2, where there is only one match for the Teacher Node. The overall match is produced based on that. As an illustration, the nodes TN3 and SN3 match, and the node TN1 has no other matches. Comparison of the previous and following connections.

Table 2: Comparison

TL2	SL2	0.5
TL3	SL3	0.2

The overall match extent is derived on the basis of all the three figures.

The next and previous Student Nodes of all matched Student Nodes with type 3, whether 1.0 or less than that, are retrieved and saved in memory as a String (say B). The string is cleaned up by removing the redundant links. A second-string C is created by concatenating the Teacher Node's preceding and subsequent linkages. Following that, the various Similarity Measures as previously described are used to compare Strings B and C. The extent of the string B and string C's overall similarity match.

Results

A rough match between the teacher's answer and the student's response may be seen in the Overall Matches for all the nodes of the teacher's answer. From this point forward, the suggested system determines whether or not two provided statements have semantically similar meanings. Additionally, it specifies the degree to which two statements are interchangeable.

Conclusion

The proposed algorithm includes measured steps for converting the learner's subjective response and the standard response into their graphical form, as well as for applying some similarity measures like string matching, WordNet, and semantic similarity considering antonym and synonyms for the calculation of similarity scores. While assigning a grade to a response, our approach emphasises the idea of synonyms. In comparison to recently proposed models that used latent semantic analysis without using synonyms, this improvement has produced meaningful results. The results of the implementation have shown that the upgrade uses very little time and space.

Future Scope

The domain of single sentence/phrase or one-word answer can be further extended to multi-phrase/multi-line answer. More analysis would be required for similarity matching. Derive a method to check the domain ontology of two phrases. Automated evaluation of subjective answers is a semantic concept and hence it is always flexible to make changes, to adopt to new algorithms for similarity matching. Subjective answers including figures (diagrams), examples, and abbreviations can also be considered in future.

Reference

1. Hanxiao Shi, Guodong Zhou and Peide Qian (2010), "An Attribute-based Sentiment Analysis System", Information Technology Journal, pp 1607-1614
2. Papri Chakraborty (2012), "Developing an Intelligent Tutoring System for Assessing Students' Cognition and Evaluating Descriptive Type Answer", IJMER, pp 985-990

3. Mita K. Dalal, Mukesh A. Zave (2011), "Automatic Text Classification: A Technical Review", *International Journal of Computer Applications*, pp.37-40
4. Asmita Dhokrati, Gite H.R.2, Mahender C.N.3 (2012), "Computation Linguistic: Online Subjective Examination Modeling", *Advances in Computational Research*, pp-31-33.
5. Wael H. Gomaa Aly A. Fahmy (2013), "A survey of aches", *International Journal of Computer Applications*.
6. Davy Temperley, Daniel Sleator, John Lafferty, "Link Grammar", Available: <http://www.link.cs.cmu.edu/link/submit-sentence-4.html>
7. Meghan Kambli, "Report on Online Examination System", Available: http://www.cdacmumbai.in/design/corporate_site/override/pdf-doc/meghareport.pdf
8. Jawaharlal Nehru Technical University, Hyderabad, "Examination and Evaluation System", Available
9. Pranav Deshpande, Pooja Sonone, Gitanjali Patel, Aditya Achari (2013), "Online Virtual Subjective Examination System Based Under Ubiquitous Cloud Computing", *International Journal Of Science And Research*, ISSN (Online): 2319-7064.
10. Mr. A. A Shinde, Ms.Sumedha Chokhandre (2013), "A Novel Approach With Subjective Assessment For E-examination", *International Journal Of Engineering Research And Applications*", Vol. 3, Issue 4, Jul-Aug 2013, pp. 32-36.
11. Parag A. Guruji, Mrunal M. Pagnis, Sayali M. Pawar, Prakash J. Kulkarni (2015), " Evaluation Of Subjective Ansewrs Using GISA Enhanced With Contextual Synonymy", *International Journal on Natural Language Computing (IJNLC)* Vol. 4, No.1.
12. Gautam, J., Atrey, M., Malsa, N., Balyan, A., Shaw, R.N., Ghosh, A. (2021). Twitter Data Sentiment Analysis Using Naive Bayes Classifier and Generation of Heat Map for Analyzing Intensity Geographically. In: Bansal, J.C., Fung, L.C.C., Simic, M., Ghosh, A. (eds) *Advances in Applications of Data-Driven Computing*. *Advances in Intelligent Systems and Computing*, vol 1319. Springer, Singapore. https://doi.org/10.1007/978-981-33-6919-1_10
13. Rajpoot, A., Saluja, G., Malsa, N., Gupta, V. (2022). A Particle Swarm Optimization Based ANN Predictive Model for Statistical Detection of COVID-19. In: Garg, L., Basterrech, S., Banerjee, C., Sharma, T.K. (eds) *Artificial Intelligence in Healthcare. Advanced Technologies and Societal Change*. Springer, Singapore. https://doi.org/10.1007/978-981-16-6265-2_2
14. Malsa, N., Singh, P., Gautam, J., Srivastava, A., Singh, S.P. (2020). Source of Treatment Selection for Different States of India and Performance Analysis Using Machine Learning Algorithms for Classification. In: Pant, M., Kumar Sharma, T., Arya, R., Sahana, B., Zolfagharinia, H. (eds) *Soft Computing: Theories and Applications. Advances in Intelligent Systems and Computing*, vol 1154. Springer, Singapore. https://doi.org/10.1007/978-981-15-4032-5_23
15. Jyoti, G., Nitima, M., Vikas, S., Komal, M. (2020). Calculating AQI Using Secondary Pollutants for Smart Air Management System. In: Sharma, N., Chakrabarti, A., Balas, V. (eds) *Data Management, Analytics and Innovation. Advances in Intelligent Systems and Computing*, vol 1016. Springer, Singapore. https://doi.org/10.1007/978-981-13-9364-8_10
16. N. Masla, V. Vyas, J. Gautam, R. N. Shaw and A. Ghosh, "Reduction in Gas Cost for Blockchain Enabled Smart Contract," 2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON), Kuala Lumpur, Malaysia, 2021, pp. 1-6, doi: 10.1109/GUCON50781.2021.9573701.
17. N. Malsa, V. Vyas, J. Gautam, A. Ghosh and R. N. Shaw, "CERTbchain: A Step by Step Approach Towards Building A Blockchain based Distributed Appliaction for Certificate Verification System," 2021 IEEE 6th International Conference on Computing, Communication and Automation (ICCCA), Arad, Romania, 2021, pp. 800-806, doi: 10.1109/ICCCA52192.2021.9666311.
18. Malsa, N., Vyas, V., Gautam, J. (2022). Blockchain Platforms and Interpreting the Effects of Bitcoin Pricing on Cryptocurrencies. In: Sharma, T.K., Ahn, C.W., Verma, O.P., Panigrahi, B.K. (eds) *Soft Computing: Theories and Applications. Advances in Intelligent Systems and Computing*, vol 1380. Springer, Singapore. https://doi.org/10.1007/978-981-16-1740-9_13

19. Pathak, S., Gupta, V., Malsa, N., Ghosh, A., Shaw, R.N. (2022). Smart Contract for Academic Certificate Verification Using Ethereum. In: Shaw, R.N., Das, S., Piuri, V., Bianchini, M. (eds) *Advanced Computing and Intelligent Technologies. Lecture Notes in Electrical Engineering*, vol 914. Springer, Singapore. https://doi.org/10.1007/978-981-19-2980-9_29
20. Pathak, S., Gupta, V., Malsa, N., Ghosh, A., Shaw, R.N. (2022). Blockchain-Based Academic Certificate Verification System—A Review. In: Shaw, R.N., Das, S., Piuri, V., Bianchini, M. (eds) *Advanced Computing and Intelligent Technologies. Lecture Notes in Electrical Engineering*, vol 914. Springer, Singapore. https://doi.org/10.1007/978-981-19-2980-9_42
21. Jyoti, G., Nitima, M., Vikas, S., Komal, M. (2020). Calculating AQI Using Secondary Pollutants for Smart Air Management System. In: Sharma, N., Chakrabarti, A., Balas, V. (eds) *Data Management, Analytics and Innovation. Advances in Intelligent Systems and Computing*, vol 1016. Springer, Singapore. https://doi.org/10.1007/978-981-13-9364-8_10
22. Gupta, P., Malsa, N., Saxena, N., Agarwal, S., Singh, S.P. (2020). Short-Term Load Forecasting Using Parametric and Non-parametric Approaches. In: Pant, M., Sharma, T., Verma, O., Singla, R., Sikander, A. (eds) *Soft Computing: Theories and Applications. Advances in Intelligent Systems and Computing*, vol 1053. Springer, Singapore. https://doi.org/10.1007/978-981-15-0751-9_68
23. Malsa, N., Vyas, V. & Gautam, J. RMSE calculation of LSTM models for predicting prices of different cryptocurrencies. *Int J Syst Assur Eng Manag* (2021). <https://doi.org/10.1007/s13198-021-01431-1>