Automated Scoring for Short Questions with Deep Learning

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AY2019/2020

SCE19-0305

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Submitted in Partial Fulfilment of the Requirement for the Degree of Bachelor of Engineering (Computer Science)

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Abstract

This report proposes an improved approach of short-answered questions scoring with deep learning, namely Siamese Bidirectional LSTM model with feature engineering. The project will conduct several experiments by applying various methods on the model and dataset. The performance of each model in the experiments is evaluated and compared to obtain the optimal result. The proposed improved approach is proven to result in better performance in grading answers, measured in Pearson correlation coefficient, Rooted Mean Square Error, and Mean Absolute Error.

Acknowledgements

The author would like to thank various individuals for their continuous encouragement. This project would not have been possible without their support.

The author would like to extend her deepest gratitude to Assoc Prof Hui Siu Cheung, the author's final year project supervisor, for his guidance, encouragement, and constructive feedbacks throughout the year.

Furthermore, the author would also like to express special thanks to her parents who have supported her throughout her journey in Nanyang Technological University Singapore. Without them, this project would not have been as successful.

Lastly, the author is also thankful to all her friends who have supported her during her time in university and have been there for her when she needed encouragement. Without their faith in her, the author would not have been able to complete this project as smoothly.

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Chapter 1: Introduction

1.1 Background

One of the main tasks of an educator is to assess the understanding of their students. It can be measured through various assessments, which require the educator to manually evaluate and grade students’ responses. Time taken to do such activity depends on the open-endedness of the assessment since answers to open-ended questions are more varied, and thus, additional time is required to assess the answers. Hence, multiple choice questions will take shorter time to score compared to essay questions. Moreover, scoring open-ended questions is susceptible to the grader’s subjectivity as there is no right or wrong answer.

Since most educational systems still require human to manually grade assessments, a lot of educators’ time is spent on grading. With the help of the automated scoring, the grading process would be shortened, and educators would be able to reduce the time they spend evaluating assessments, hence, increasing educators’ productivity on other activities. Moreover, the automated scoring has numerous advantages over manual scoring, such as its objectivity and consistency.

1.2 Motivation

The education sector would benefit greatly from the automated scoring. Despite the fact that multiple choice questions scoring is now mostly done by machine, automated scoring is still not widely used even though it has been a research topic for some time now. This also applies to short answer scoring, which is very similar to essays, except that it is significantly shorter.

One of the existing works on short answer grading is Siamese Bidirectional LSTM model. This model is claimed to perform better than other approaches, such as the works done by Sultan et al. [1], Gomaa et al. [2], and Kumar et al. [3]. However, there is still room for improvement as the performance of this approach is still far from perfect. The author of this model claims that for every answer the model scores, the predicted score has an average error of 0.618 out of 5, which is relatively high.

1.3 Objectives

The main objective of this project is to improve the grading accuracy of the existing short answer scoring approach, namely the Siamese Bidirectional LSTM model. The approach will be improved by applying various methods on the model and on the dataset, such as batch normalisation, regularisation, question demoting, and data augmentation. The method is targeted to improve the performance of the model in terms of Pearson correlation coefficient, Rooted Mean Square Error, and Mean Absolute Error.

1.4 Scope

The scope of the questions is limited only to short-answered Data Structures questions so that the answers could be more topic-specific. With the limited scope of the questions, the answers will have similar features, and hopefully, the model can pick up important features from the answers more easily.

The model would later on be deployed into a system, and the system would be implemented in an educational setting, where it could help facilitate the scoring process of short-answered data structures related C programming questions, which, in this case, is to assist scoring of CX1007 Data Structures course as a part of students' self-practice and performance evaluation.

1.5 Report Organization

This report is structured into 6 chapters. The overall report content is introduced in Chapter 1:. Chapter 2: consists of relevant existing works on automated scoring, whereas Chapter 3: elaborates the existing model, including the Siamese Bidirectional LSTM unit. Chapter 4: explains the evaluation of the experiment, including its results. Then, the results on the experiments are implemented on a system, which is described in Chapter 5:. Finally, Chapter 6: concludes the whole report.

Chapter 2: Literature Review

2.1 Past Works

The essay grading issue has been addressed since years ago. One of the earliest approach to the problem is a method known as C-rater [4], which was developed by Educational Testing Service, also widely known as ETS, to measure students' understanding based on their responses to short-answer questions. The method compares the syntactical characteristics of a sentence to a collection of correct ones. However, it is ignoring the difference between passive and active voice, such as "you need two plants" and " two plants are needed".

More recent work has analysed the difference between corpus-based and knowledge-based measures of text similarity, and it was shown using Pearson's correlation coefficient that corpus-based measure (Lexical Semantic Analysis) performs the best among other approaches. It also introduced new technique which is similar to pseudo-relevance feedback to address the problem where there is more than one correct answer [5].

Although some works use Pearson's correlation coefficient to compare student and reference answers, another experiment conducted by Pribadi et al. [6] showed that similarity measure using Cosine coefficient produce the best result. Cosine similarity measure has the highest accuracy rate compared to other measures, namely Jaccard coefficient and Dice coefficient.

One of the works that use Cosine similarity is paragraph embeddings [7], which focused on short answer scoring. Answers are considered short "if its length approximately ranges from one phrase to one paragraph". The word embedding vectors from the answer are combined using average, sum, or other methods, then, using the calculated vectors, new vectors are generated using paragraph embedding model. Cosine coefficient will be used to compare the paragraph vectors.

2.2 Batch Normalisation

With the discovery of more complex deep learning approaches, the demand of more advanced neural network training techniques became higher. Motivated by the uneven distribution of neural network layers' input during training, batch normalisation was introduced in 2015 [9]. The technique was designed to balance the distribution of the inputs by reducing internal covariate shift (ICS), which is the change in the distribution of the input variables in training and test data [10].

2.3 Dropout

Despite the breakthrough of machine learning techniques, overfitting is still a prominent issue in deep learning, especially when the size of training set is very small compared to the complexity of the network. In this case, dropout can be used to avoid the problem. The concept of dropout is to randomly drop neurons from the network, so that dropped neurons will be omitted during training, and hence reducing the complexity of the network [11]. Therefore, the network would be able to learn information that is significant to produce the correct output [12].

2.4 Question Demoting

Another work by Mohler et al. [13] proposed a new technique named question demoting. The technique removes any words that occur in the question from both the student and gold standard answers. This technique is implemented to eliminate the possibility that students who repeat words from the question in their answers get high score as it does not reflect their understanding of the topic.

2.5 Multilayer Perceptron

Multilayer perceptron, a class of feedforward neural network, is a deep learning model that approximates some functions by learning parameter so that it could generate the best result. Information flows through the layers of neurons, the first one, being called first layer, until the last one, the output layer. Between the first and output layer, there are more layers called hidden layers. In contrast to RNN, information in multilayer perceptron never goes backwards and only goes forward in time [8].

2.6 Recurrent Neural Network (RNN)

RNNs are designed to retain information from previous time frames so that the patterns found in the past information can be used to predict the future patterns. Such method is known as long-term dependencies, and RNNs are designed to handle that. However, in practice, RNNs are unable to learn the dependencies, so a new approach, Long Short-Term Memory, was introduced to address this issue [14].

2.7 Long Short-Term Memory (LSTM)

Long Short-Term Memory unit is a type of Recurrent Neural Network. As mentioned in section 2.5, the information in this architecture can go back in time, as opposed to the traditional multilayer perceptron. It was first introduced in 1997 due to the inability of the conventional approach at that time to prevent the information going backwards to blow up or vanish [15]. To avoid the aforementioned problem, a forget gate was added to the unit so that insignificant information can be discarded.

The existing work on short answer grading uses this unit on its model as grading a sentence would require understanding each word in the sentence, and the meaning of each word depends on the word preceding it. Hence, the ability of RNNs, specifically LSTM, to obtain information from the past input is very important in this case. The utilisation of this unit on the current approach will be discussed in details in the next chapter.

Chapter 3: Existing Approach

The existing approach automates grading of short answer using Siamese bidirectional LSTM-based regression model. This chapter discusses the deep learning methods implemented in the approach.

3.1 Architecture

This approach combines several neural network architectures, and together they create the overall model architecture. The model is a regression model that consists of several layers, which are shown in Figure 1. The figure illustrates the model with input example "Main function." as student answer and "At the main function." as reference answer, while the training and scoring process using this model will be elaborated further in Section 4.5.3.

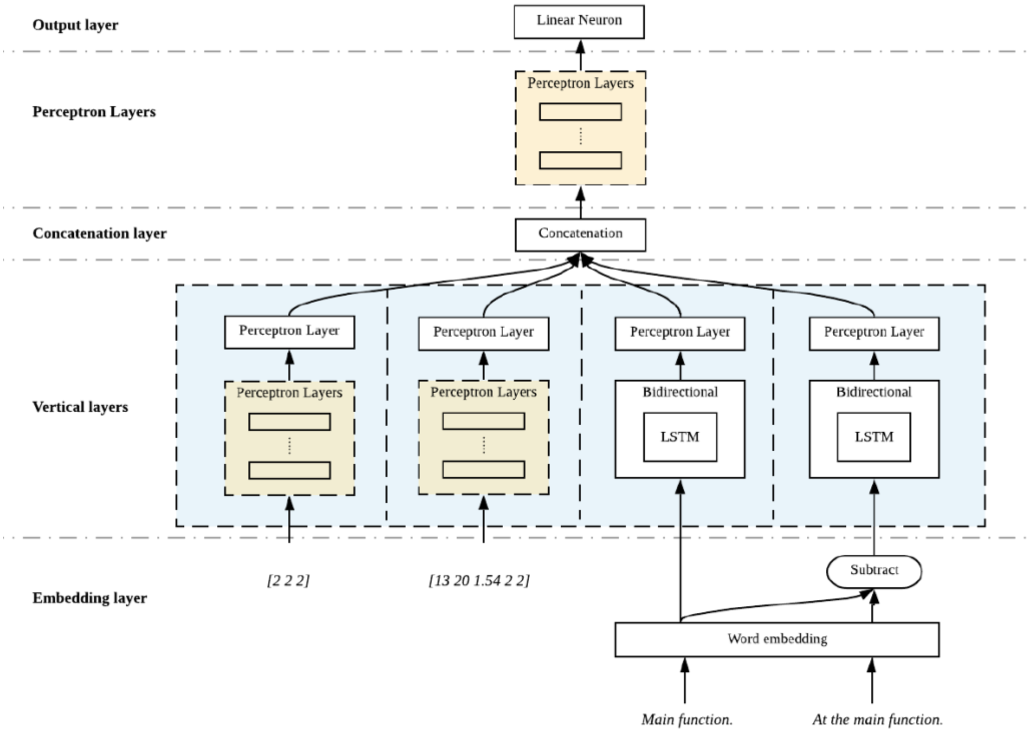


Figure 1 Network architecture illustration

3.1.1 Embedding Layer

The first layer of the network is embedding layer. This layer takes in a sequence of words as input, and each word will be mapped into high-dimensional vectors representing each word, also known as word embedding.

In this layer, Word2Vec is used to compute the vector representations of each word. It is one of word embedding model architectures that utilises Skip-gram model and negative sampling [16]. The words are represented in such a way that the result of the vector operations reflects the linguistic patterns of the words. For instance, the operation “Madrid” – “Spain” + “France” will produce a vector close to the vector representation of the word “Paris” [17].

The input of this layer will be the answers, while the output will be the mapped 300-dimensional word vectors of the input. This layer will be used twice, for student answers and reference answers.

3.1.2 Vertical Layers

This layer consists of several vertical layers that is independent from each other, and each has its specific functions. Following are the details of the layers as shown in Figure 1 from left to right.

3.1.2.1 Multilayer perceptron (tokenisation)

This layer consists of 2 layers of neurons, both of 50 neurons with sigmoid activation function. It receives 3 integers. The first integer is number of words of the reference answer, the second is number of the student answer, and the last one is number of words that exist both in the student and reference answers. To obtain these numbers, the answers are first tokenised using NLTK word tokenizer. Tokenisation is a process where a sequence of words is separated into smaller parts called tokens. [18]. In this case, the tokens are unique integers.

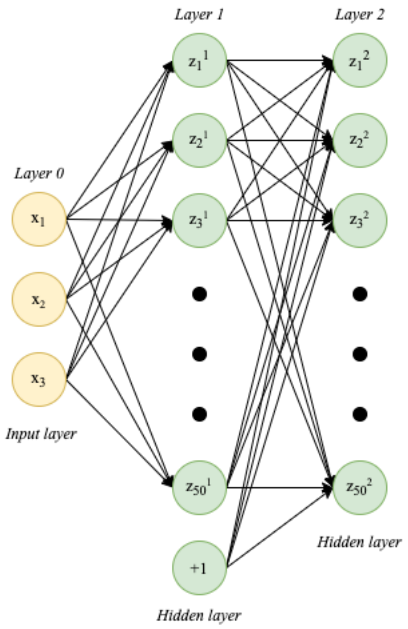


Figure 2 Multilayer perceptron (tokenisation)

3.1.2.2 Multilayer perceptron (feature engineering)

This layer takes input of 5 set of data obtained from feature engineering. Feature engineering is a process where a certain data is produced by transforming raw data so that it could be used by the model to better learn the pattern of the given data [19].

In this case, length of the student answer (number of characters), length of reference answer, ratio of the length of the reference answer and length of the student answer, number of words in the student answer, and the number of unique words in the student answer are used.

The input is then processed through 4 layers of 125 neurons with sigmoid activation function.

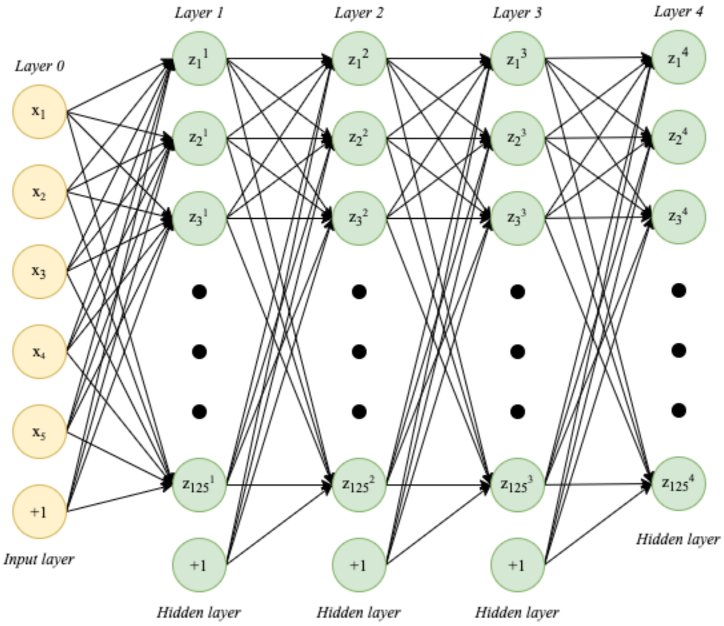


Figure 3 Multilayer perceptron (feature engineering)

3.1.2.3 LSTM unit (reference answer)

This layer is illustrated as the third column from left in the vertical layer in Figure 1. It receives input from embedding layer, which is the embedded student answers. It will then be propagated through a bidirectional LSTM unit and through a layer of 50 neurons with sigmoid activation function. The LSTM unit will be discussed further in Section 3.2.

3.1.2.4 LSTM unit (comparison with student answer)

This layer is the rightmost vertical layer in Figure 1. It has the same architecture as the other LSTM unit layer, but it has different inputs. Instead of receiving input straight from the embedding layer, this layer receives a vector of comparison between student answer and reference answer.

The two sentences are compared using the distance of the two vectors. The distance is calculated using the equation below, where R_i is the reference answer of question Q_i, and A_{ij} is the student answer j of question Q_i. *v(X)* is the word vector of sentence *X*.

$$dist = v(R_i) - v(A_{ij})$$

Equation 1 Distance between two vectors

Word2Vec groups similar words together [17], so words with similar meaning has similar vector values. The distance of the two vectors should be small if the sentences have similar meaning. Because of this feature, cosine coefficient is not used to calculate the similarity of two words even though Pribadi et al. [6] claims that it is the most accurate similarity measure.

3.1.3 Concatenation Layer

In this layer, the output from vertical layers are merged to be processed further in the following layers.

3.1.4 Perceptron Layers

The concatenated vector is then propagated through a multilayer perceptron. The multilayer perceptron has 4 layers, where the first 3 layers consist of 125 neurons, and the last one consists of 25 neurons.

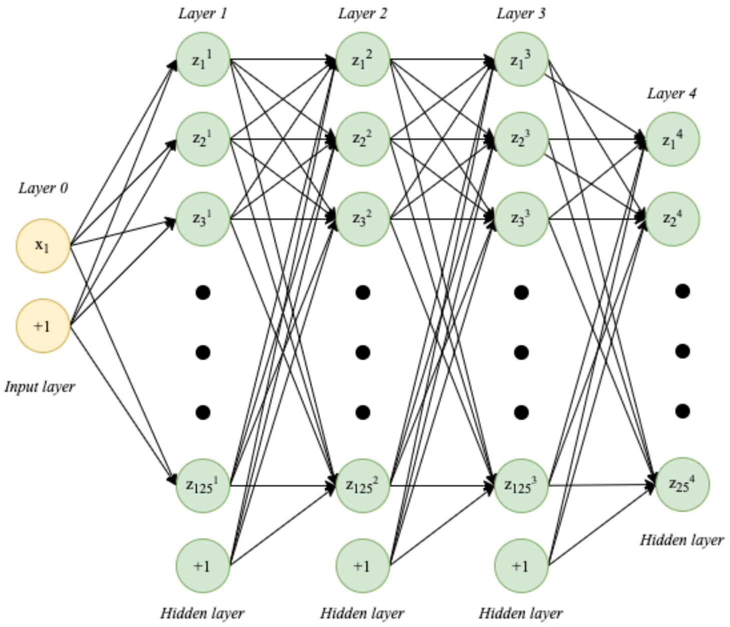


Figure 4 Perceptron layers

3.1.5 Output Layer

The final layer of the network consists of 1 neuron with linear activation function. This neuron outputs the final predicted score.

3.2 Bidirectional LSTM Unit

The basic LSTM unit consists of a cell state that modulates information through the unit, and three gates (forget, input, and output) [14]. Following is the functions used in the unit, where $x(t)$ is the input and $h(t)$ the output.

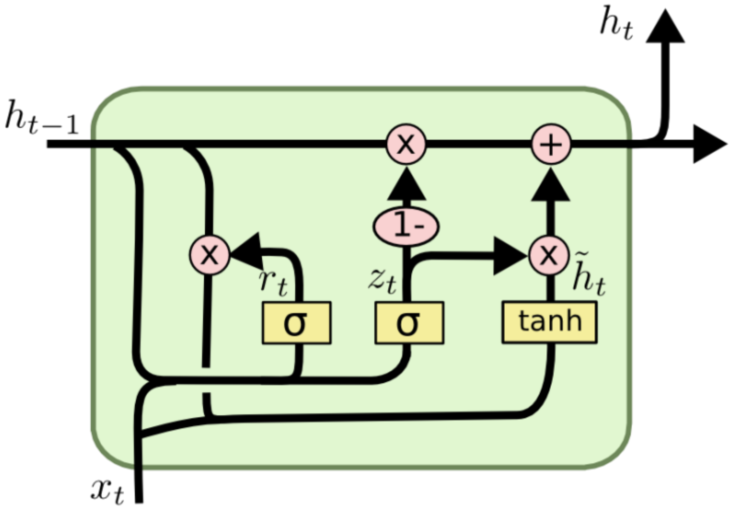


Figure 5 LSTM Unit

3.2.1 Forget gate

Forget gate will determine whether the information should be removed or not. When it is 0, nothing will go through.

$$f(t) = \sigma(U_f x(t) + W_i h(t-1) + b_f)$$

Equation 2 Forget gate

Where $\sigma(x)$ is sigmoid function.

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Equation 3 Sigmoid function

3.2.2 Input gate

3.2.2.1 Sigmoid layer

This layer will determine which values to update.

$$i(t) = \sigma(U_i x(t) + W_i h(t-1) + b_i)$$

Equation 4 Input gate sigmoid layer

3.2.2.2 Tanh layer

This layer will produce vector of new candidate values.

$$\tilde{C}(t) = \phi(U_c x(t) + W_c h(t-1) + b_c)$$

Equation 5 Input gate tanh layer

Where $\phi(x)$ is tanh function.

$$\phi(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Equation 6 Tanh function

3.2.3 Output gate

This gate will allow memory cell to have effect on other neurons.

$$o(t) = \sigma(U_o x(t) + W_o h(t-1) + b_o)$$

Equation 7 Output gate

Afterwards, the cell state is updated using equation below, where $\odot$ is element-wise product.

$$C(t) = \tilde{C}(t) \odot i(t) + C(t-1) \odot f(t)$$

Equation 8 Cell state

The output value is calculated using the equation below.

$$h(t) = \phi(C(t) \odot o(t))$$

Equation 9 LSTM output

This approach uses bidirectional LSTM, which means the neurons are split into two directions, forward and backward. This method will enable the effective usage of both past and present information for a specific time frame [20].

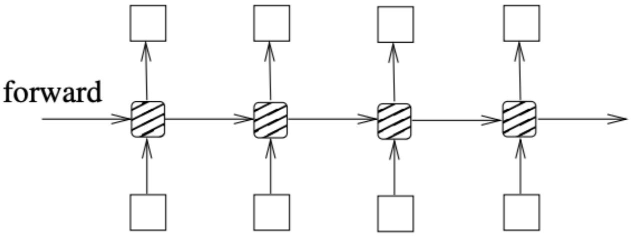


Figure 6 LSTM network

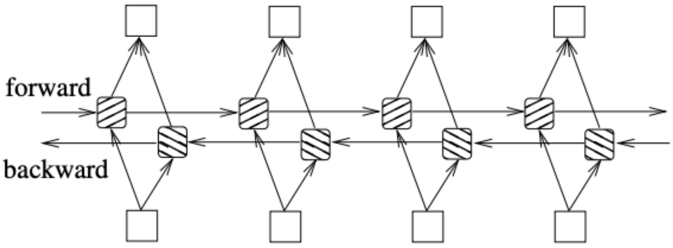


Figure 7 Bidirectional LSTM network

Two bidirectional LSTM units with identical architecture are used for this approach, one for reference answer, one for the comparison of reference and student answer. Hence, this model is called a Siamese Bidirectional LSTM.

3.3 Illustration Example

To further describe the current approach, an example input data will be used. In this illustration, as represented in Figure 1, “Main function.” will be used as student answer and “At the main function.” as reference answer.

During pre-processing, all the characters in student and reference answers are converted into lower case, and stopwords and punctuations are removed. Also, feature engineering, as described in Section 3.1.2.2, is applied to the raw answer during this process. After pre-processing, the student and reference answers are the same, which is “main function”.

Firstly, the pre-processed answers are passed through the embedding layer, and vector representations of the answers are produced.

Next, The pre-processed answers are tokenised, and some information from the tokenised answers, which is vector [2 2 2] in this example, is used as input for the leftmost multilayer perceptron. This process is explained in Section 3.1.2.1.

At the same time, information from feature engineering, which is vector [13 20 1.54 2 2], is used to train the second multilayer perceptron.

In parallel to the other two processes, the student answer vector representation is passed to a LSTM unit, while the representation of reference answer is compared to that of student answer, and the produced result is propagated to another LSTM unit. The vectors are used to train and to learn parameters of the units.

Afterwards, outputs of the 4 processes in vertical layer are concatenated and used to train the next perceptron layers in the architecture.

Finally, a linear perceptron is used to determine the final prediction of the score, and the predicted score is scaled back to the original range, which is 0 to 5. The predicted score would be a real, rational number.

Chapter 4: Experimental Evaluation

4.1 Dataset

This experimental evaluation uses a dataset from an experiment conducted by Mohler, Bunescu, and Mihalcea [13].

The dataset consists of data structures questions for introductory computer science assignment at the University of North Texas. There are total of 80 questions and 31 students enrolled in the course. In total, the dataset consists of total 2273 student answers since some students did not submit any answer for some questions.

Each answer is graded manually by two human graders, and the score is an integer ranging from 0 to 5, where 5 indicates a perfect answer. The average of the two scores is then used as gold standard of this experiment.

4.2 Data Pre-Processing

Firstly, data cleaning is performed on the dataset. It is cleaned by removing tuples with empty values. All tuples with empty question, answer, or scores are removed. Then, all the questions and answers are converted into strings, and stopwords and punctuations are removed from the sentence. Lastly, the scores are scaled using min-max normalisation so that they range from 0 to 1.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Equation 10 Min-max normalisation

4.3 Evaluation Metrics

4.3.1 Pearson Correlation Coefficient

Pearson correlation coefficient measures the linear correlation of two variables. The coefficient ranges from -1 to 1, where 1 means the two variables are positively correlated and -1 negatively correlated.

Pearson correlation coefficient ρ of two variables X and Y is defined as below.

$$\rho_{X,Y} = \frac{s_{X,Y}}{s_X s_Y}$$

Equation 11 Pearson correlation coefficient

$$s_{X,Y} = \frac{1}{n-1}\sum_{k=1}^{n}(X_k - \overline{X})(Y_k - \overline{Y})$$

Equation 12 Covariance

$$s_X = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(X_k - \overline{X})^2}$$

Equation 13 Standard deviation

Figure 8 below shows the correlation between two variables X in x-axis and Y in y-axis.

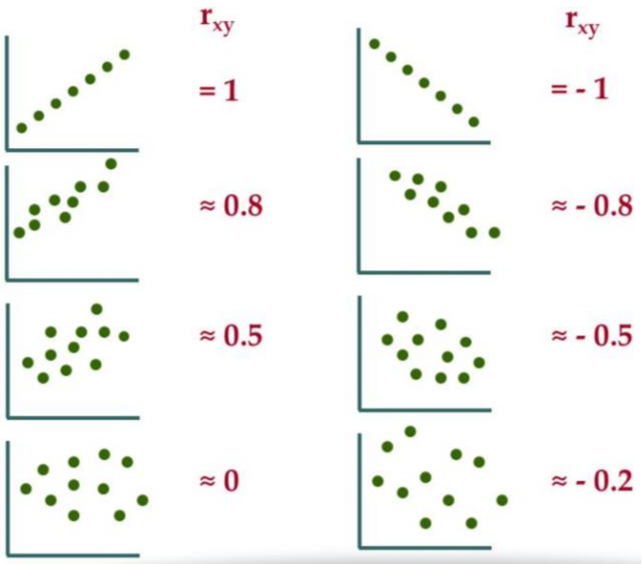


Figure 8 Pearson correlation coefficient

Pearson correlation coefficient is calculated to evaluate the approach. However, it only represents linear correlation of the two vectors and does not represent the error or how much the vector deviate from each other. For example, vectors [3,4,5] and [1,2,3] will have the coefficient equals to 1. Therefore, this metric cannot be used alone to determine the performance of a model.

4.3.2 Rooted Mean Square Error

Rooted mean square (RMSE) is the square root of the arithmetic mean of the squares of the difference between the two variables.

$$RMSE = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(y_k - \hat{y}_k)^2}$$

Equation 14 RMSE

In this experiment, $y_{1\ldots k}$ are target gold standard values, and $\hat{y}_k$ are predicted values by the model. Since this metric represents the difference between the two values, this metric can be used to observe the performance of a model. Lower RMSE means the model could predict values that are closer to the given dataset.

When an error in grading is 0.5, its RMSE would be 0.25, while when the error is 1, the RMSE would be 1. From this example, it can be concluded that even though the RMSE is 4 times as large, does not mean that it is 4 times as bad.

4.3.3 Mean Absolute Error

Mean absolute error (MAE) measures the difference of two variables. It is the arithmetic mean of the absolute difference of the two variables.

$$MAE = \frac{1}{n-1}\sum_{k=1}^{n}|y_k - \hat{y}_k|$$

Equation 15 MAE

$y_{1\ldots k}$ are observed values and $\hat{y}_k$ are predicted values. This metric also represents the difference between the two values and can be used to evaluate model performance. Lower MAE also means that the model could predict values close to the actual data.

Using similar example from the previous section, an error of 0.5 in grading would have MAE 0.5, and error of 1 would result in 1. In this case, it can be assumed that the error is twice as bad. Due to this property, MAE is considered the best measure to compare different models' performance in this experiment and is used as the loss function during the training of the model.

4.4 Data Augmentation

The dataset only consists of 2273 tuples. This number of data is not sufficient to train such a complex network, and it will cause the model to overfit the data. Hence, to avoid this issue, data augmentation is applied to obtain larger dataset.

Data augmentation is a method to increase the size and diversity of the dataset for training without actually collecting new data, so the new data is obtained from the dataset itself [21].

In this experiment, student answers that are given perfect score 5.0 by human graders are used as new reference answer. Thus, if n out of m students received perfect grade in a particular question, $(n-1) * m$ new data tuples can be generated for that question. By performing this technique, around 30000 data samples were generated and used to train the model.

4.5 Evaluation

4.5.1 Implementation

The model was built using Keras, a high-level neural networks API that is able to run on top of TensorFlow [22]. The code is written on Python and implemented with the help of other machine learning libraries mentioned below.

4.5.1.1 pandas

pandas is a data analysis and manipulation tool [23]. This library is used in this experiment to manipulate and process the data so that it can be used to train the model.

4.5.1.2 NumPy

NumPy is a library that supports large dimensional array operations [24]. This library is used in this experiment since Keras requires its input to be in NumPy array format.

4.5.1.3 scikit-learn

scikit-learn is a machine learning library that supports tools for predictive data analysis. It provides numerous machine learning features such as classification, regression, clustering [25]. In this experiment, its model selection, metrics, and pre-processing built-in functions are used.

4.5.1.4 Natural Language Toolkit (NLTK)

NLTK is a natural language processing library [26]. It provides list of English stopwords and tokenisation, which are used in this experiment.

4.5.2 Model Selection

The model selection method used was a combination of three-way data splits and 5-fold cross validation methods.

The dataset was first split into training and test set on 80:20 ratio. The 80% of the data is divided into 5-folds of training and validation dataset. Then, the model is trained using 5-fold cross validation method, and the best model is chosen based on its performance on the validation set. The fold that has lowest average of RMSE and MAE is selected. Lastly, the chosen model is used to predict values from unseen data (test set) and the result from test set is used to evaluate the overall model performance.

The data split ratio 80:20 is chosen upon some considerations. The training set, which is used to train the model, might be too small if 70:30 ratio is used, considering the complexity of the model. On the other hand, 90:10 ratio will produce very small test set. Since test set will be used to assess the model performance, if it is too small, it may not correctly represent the performance.

4.5.3 Training

For each fold on training set, the model is trained on GPU using 150 epochs since the loss seems to be stable around that iteration. The parameter is updated using mini-batch stochastic gradient descent algorithm, specifically AdaGrad optimisation method, and the loss function is mean absolute error (MAE) as stated in Equation 15.

AdaGrad is used because it is not sensitive to hyperparameters as it is dynamic and adaptable to the data and generate different learning rates for different features. Parameters of features that occur frequently will be applied lower learning rates than of features that occur infrequently [27]. The input of the model used in this experiment is diverse, and hence, using AdaGrad as the optimisation method will help the model to train better.

4.5.4 Scoring

The scoring process is done by using the trained model. Provided the student and reference answers, the predicted score will be calculated using the learned parameter from the model. This process is implemented by the built-in function of Keras API.

4.6 Performance of Existing Model

Using the evaluation techniques explained in the previous section, the existing model performance is given in Table 1.

Table 1 Performance metrics of existing approach

Pearson coefficient	RMSE	MAE	Avg(RMSE+MAE)
0.4416	0.9815	0.6471	0.8143

From the metrics above, it is shown that the model does not perform very well as the Pearson correlation coefficient is less than 0.5. The low coefficient means that the predicted values are not linearly correlated to the target values.

Most importantly, its MAE is fairly high, which is 0.6471. It means that for all gold standard score, the average difference with the predicted score is 0.6471 out of 5.0, which the error is 12.94% of the total score. For instance, if the gold standard score is 4, the model would probably predict the score to be 4.6471, which is closer to 5 than to 4.

Below is the training and test error against the number of iterations.

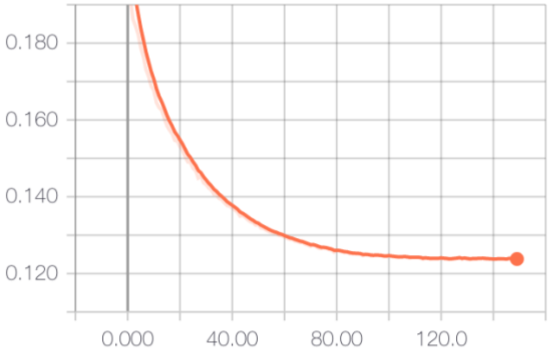


Figure 9 Training error of original model

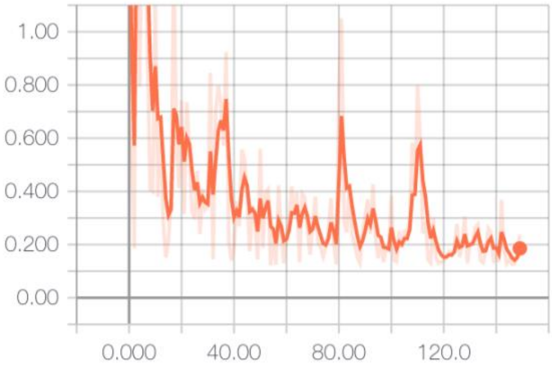


Figure 10 Validation error of original model

As we can see from the graphs above, the graph of the validation error against number of iteration seems to be very bumpy and spiky even though the graph of training error is very smooth. It means that the model does not perform well on the unseen data and it is overfitting on the training dataset. It occasionally predicts score with high error rate. As a result, it is unable to predict accurately on unseen data and produce high error on validation dataset.

4.7 Improving Model Performance

Since the original model is overfitting on the training data, the model should be improved to result on better performance. There are many techniques that can be implemented to improve the model performance.

4.7.1 Batch Normalisation

The input and output of batch normalisation layer are four dimensional vectors of batch, channel, and two spatial dimensions [28]. It normalises each input of a layer by subtracting mini-batch mean and dividing it by the mini-batch standard deviation. However, it may change the input's representation [10].

For input $x = \{x_{1\dots m}\}$ and output y_i over a mini-batch B, batch normalisation needs to learn parameters γ and β, where ϵ is a constant added for numerical stability.

$$\mu_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i$$

Equation 16 Mini-batch mean

$$\sigma_B^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_B)^2$$

Equation 17 Mini-batch variance

$$\hat{x}_i \leftarrow \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

Equation 18 Normalisation

$$y_i \leftarrow \gamma \hat{x}_i + \beta$$

Equation 19 Scaling and shifting

The original model only performs batch normalisation on the last perceptron layer. In this experiment, additional batch normalisation is applied on each of the LSTM layers.

4.7.2 Regularisation

Regularisation is a strategy to reduce error on unseen data or test error by altering the learning algorithm [8]. Even though this could increase the training error, reducing test error would improve the overall performance of a model since with lower test error, the model would predict more accurately on unseen data.

4.7.2.1 Weight regularisation

Weight regularisation, also known as weight decay, is done by adding penalty or regularisation term on the cost or loss function. The most commonly used weight regularisation is L_2 regularisation, also known as ridge penalisation. This approach uses L2 regularisation term, which is defined below [29].

$$L_2 \; regularisation \; term = \; w_1^2 + w_2^2 + \cdots + w_n^2$$

Equation 20 L2 regularisation term

This term is added to the cost function J. Since the goal of the algorithm is to minimise the cost function, when the penalisation β_2 is increased, the weights w_{ij} would be decreased.

$$J \leftarrow J + \beta_2 \sum_{i,j} (w_{ij})^2$$

Equation 21 Cost function with L2 regularisation

When the weights have smaller values, the model would be simpler and, as a result, less prone to overfitting.

In this experiment, different values of parameter β_2 will be used to evaluate the optimal parameter.

4.7.2.2 Dropout

Dropout is a method to avoid overfitting by omitting some neurons in the network.

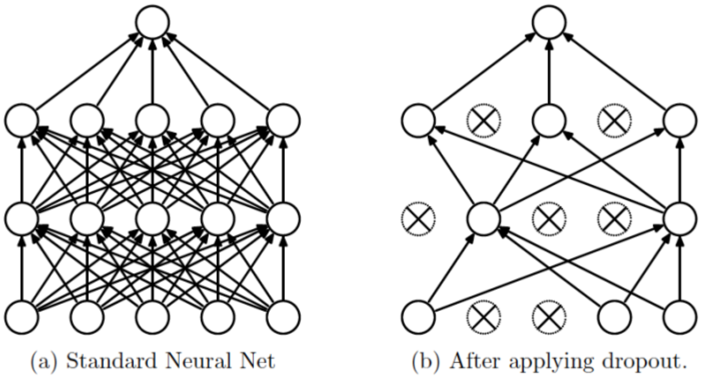


Figure 11 Dropout on neural network with 2 hidden layers

By performing dropout, random neurons, which the number of them is determined by the dropout rate, are omitted. Hence, the model becomes less complex and it can better learn important features from the dataset [11].

In the original model, the neurons in perceptron layer is dropped out 50%. This experiment will try to perform dropout on the LSTM layer and try different dropout rates on the perceptron layer.

4.7.3 Question Demoting

During data pre-processing, all words in reference and student answers that are in the question are removed. However, there are some cases where the answer is in the question sentence. For example, the question “What data structure is more appropriate for scheduling printing jobs at a printer, a stack or a queue?”. The answer of that question would be either “Stack” or “Queue”. When question demoting is performed on this question and its answers, the answers will be empty. Hence, to avoid this issue, the question is altered by removing the options, i.e. “a stack or a queue”.

4.7.4 Classification Model

The model is converted into a classification model with expectation that it results in relatively better performance.

4.7.4.1 Motivation

The answers from the dataset is scored using ordinal values, which are 0, 1, 2, 3, 4, and 5, but there is no rubric on how to score the answers, so each grader may have different opinion on how an answer should be graded. For example, one grader might think an answer should be graded 4, while the other think it should be 3. It is found that human grader only agrees on a score only 53% to 81% of the time [30].

Moreover, the model that is used to predict the score is a regression model. The predicted answer would be a continuous number, and since there is no rubric on how to score the answer, there is no way to determine how accurate an answer is based on the score. For example, when an answer is graded 5 and another answer is graded

4.8, it is difficult to show how one is better than another since the difference is so small and the answer is so short that there are not many features that can be evaluated to grade the answer.

4.7.4.2 Implementation

The model is modified into a multi-category classification model, where the output is three classes, 0, 1, and 2. An answer is labelled 0 or ‘wrong’ when it is completely wrong or completely different from the reference answer. An answer is labelled 1 when it is only partially correct or partially wrong. Lastly, an answer is labelled 2 or ‘correct’ if it is a perfect answer and has the same connotation as the reference answer.

The model is built by modifying the output layer, the very last layer, of the original model into a softmax layer with 3 outputs. Softmax function is a function that is commonly used in the last layer of categorical model. It represents the probability distribution over possible discrete variable values [8]. The variable that has the highest probability will be the predicted output of the model.

The model is trained with the dataset, where an additional pre-processing is applied. The target output, which is the average scores of two graders x, are discretised into 3 categories using the function below.

$$f(x) = \begin{cases} 0, & 0 \leq x \leq 1 \\ 1, & 1 < x < 4 \\ 2, & 4 \leq x \leq 5 \end{cases}$$

Equation 22 Target output discretisation

The scores are discretised into 3 values since 5 values might still be too broad and there is no objective justification on how one can distinguish how an answer with score 4 is better than one that is scored 3.

4.7.4.3 Evaluation metrics

Evaluation metrics used to evaluate the classification model is different from regression model as the output is discrete values. Accuracy, precision, recall, and F1 score are used to evaluate the model.

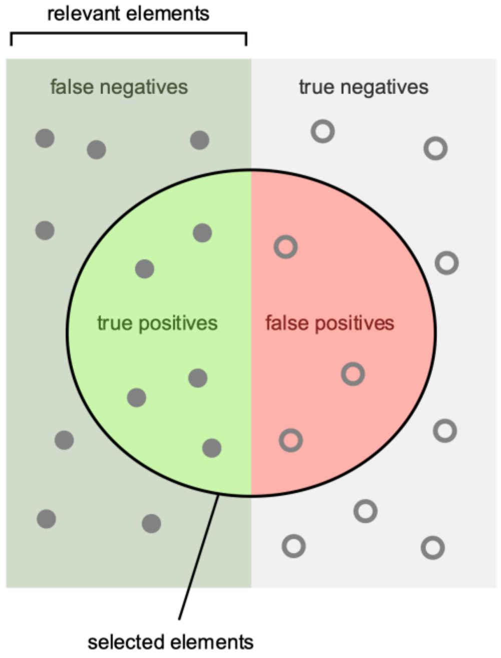


Figure 12 Classifier terms

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Accuracy is the percentage of data that are correctly predicted by the model. However, accuracy is often misleading since it is imbalanced. A dataset with 95 positive data and 5 negative data will still have accuracy of 95% although it predicts all data to be positive [31].

$$Precision = \frac{TP}{TP + FP}$$

Precision is the ratio of data of a class that is correctly predicted over the size of data that is predicted to be in that class, but it is biased by the false positive.

$$Recall = \frac{TP}{TP + FN}$$

Recall is the ratio of data of a class that is correctly predicted over the size of data that is actually in that class, and it is biased towards the false negative.

$$F1\ score = \frac{2 \times Recall \times Precision}{Recall + Precision}$$

F1 score was introduced to address the issues found in recall, precision, and accuracy. Therefore, this measure is suitable for comparing performance of different methods.

4.8 Experiment Results

This section will discuss the performance of the model when improvement techniques above are applied. The optimal values in the tables below are in bold, and complete results of the experiment on regression model can be found on Appendix A: Experiment Results (Regression Model).

4.8.1 Recurrent Batch Normalisation Results

Table 2 Experiment results on recurrent batch normalisation

Model	**Pearson**	**RMSE**	**MAE**	**Avg(RMSE,MAE)**
Original	0.4416	0.9815	0.6471	0.8143
Recurrent BN	**0.4426**	**0.9648**	**0.6429**	**0.8039**

Applying batch normalisation on the recurrent network improves the model performance for all metrics since it helps the model to perform better on test data and the weights of the model are normalised.

4.8.2 Regularisation Results

Several experiments on regularisation were conducted on different parts of the model. Different values of parameter are also experimented to obtain the best result of the regularisation.

4.8.2.1 Weight regularisation on LSTM units

Experiments on different parameters of the L2 regularisation is conducted. All experiments have same values for bias, weights, and recurrent parameters, as stated on the table below.

Table 3 Experiment results of weight regularisation on LSTM units

Parameter	Pearson	RMSE	MAE	Avg(RMSE,MAE)
0.01	0.4512	0.9787	0.6293	0.8040
0.001	**0.4526**	**0.9556**	**0.6466**	**0.8011**
0.0001	0.4513	0.9563	0.6467	0.8015

The result shows that parameter 0.001 has the best performance among other parameters on all metrics.

4.8.2.2 Weight regularisation on perceptron

Weight regularisation was applied to the last 2 perceptron layers on the 2 multi-layer perceptron on vertical layer and perceptron layer (refer to Figure 1).

Values for bias and weights parameters are the same, given in the table below.

Table 4 Experiment results of weight regularisation on perceptron

Parameter	Pearson	RMSE	MAE	Avg(RMSE,MAE)
0.01	0.4471	**0.9694**	**0.6309**	**0.8002**
0.001	0.4491	0.9677	0.6571	0.8124
0.0001	**0.4504**	0.9952	0.6349	0.8151

Weight regularisation with bias and weight parameter 0.01 results on model with the best performance. Even though parameter 0.0001 has the highest Pearson correlated coefficient, as elaborated on Section 4.3.1, it cannot be used independently to evaluate model performance.

4.8.2.3 Dropout on LSTM

Dropout with different rates are applied to the model on the LSTM layers.

Table 5 Experiment results of dropout on LSTM layers

Rate	Pearson	RMSE	MAE	Avg(RMSE,MAE)
0.2	0.4476	0.9697	0.6445	0.8071
0.4	**0.4506**	**0.9632**	**0.6432**	**0.8032**
0.5	0.4413	0.9599	0.6629	0.8114

From the experiment, it is found that dropout rate 0.4 has the best result among other rates.

4.8.2.4 Dropout on perceptron

On the original model, dropout rate 0.5 is used on the perceptron layers. To find the optimal rate, lower rate is first used to see if it improves the model. Then, after seeing that lower rate does not improve the performance, higher rate is used.

Table 6 Experiment results of dropout on perceptron layers

Rate	Pearson	RMSE	MAE	Avg(RMSE,MAE)
0.2	0.4436	1.0034	**0.6369**	0.8202
0.5	0.4416	0.9815	0.6471	0.8143
0.6	**0.4504**	**0.9778**	0.6450	**0.8114**

Dropout with rate 0.6 has the best overall performance even though its MAE is still higher than model with rate 0.2.

All regularisation methods are combined, and based on the experiments above, the optimal parameter values are used.

Table 7 Experiment results on regularisation methods

Model	Pearson	RMSE	MAE	Avg(RMSE,MAE)
Original	0.4416	**0.9815**	0.6471	**0.8143**
Regularised	**0.4486**	1.0199	**0.6294**	0.8247

However, the performance decrease as the model seem to be underfitting the data. Hence, dropout rate is reduced back to 0.5, and afterwards, recurrent batch normalisation is implemented along with all the regularisation methods.

Table 8 Experiment results on regularisations

Model	**Pearson**	**RMSE**	**MAE**	**Avg(RMSE,MAE)**
Original	0.4416	0.9815	0.6471	**0.8143**
Regularisation methods	**0.4494**	**0.9504**	0.6523	**0.8014**
Regularisation and recurrent batch normalisation	0.4461	1.0000	**0.6200**	0.8100

The overall performance is better after the dropout rate is reduced. Then, recurrent batch normalisation is added to the model. However, the performance does not seem to be improved.

4.8.3 Question Demoting Results

Question demoting is applied to the dataset, and the original model is trained using the demoted answers.

Table 9 Experiment results on question demoting

Model	**Pearson**	**RMSE**	**MAE**	**Avg(RMSE,MAE)**
Original	0.4416	0.9815	0.6471	0.8143
Question demoting	**0.469**	**0.9761**	**0.6204**	**0.7983**

The performance improved quite significantly after question demoting is applied. Hence, question demoting is performed along with the optimal models from the previous section.

Table 10 Experiment results on optimal model with question demoting

Model	**Pearson**	**RMSE**	**MAE**	**Avg(RMSE,MAE)**
Original	0.4416	0.9815	0.6471	0.8143
Regularised	**0.4639**	**0.9604**	0.6124	**0.7864**
Regularised and BN	0.4601	0.9816	**0.6091**	0.7954

The model without recurrent batch normalisation is shown to perform better as the overall metrics are better, and among other improvement methods, this one has the best performance.

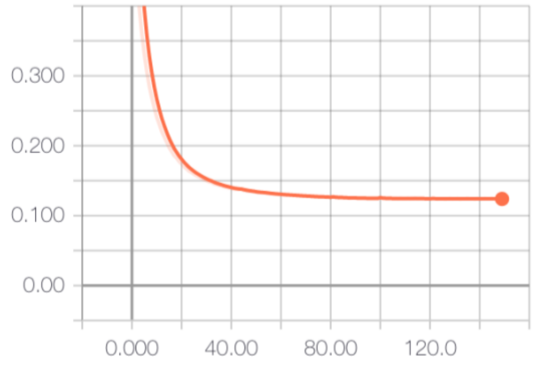


Figure 13 Training loss of optimal model

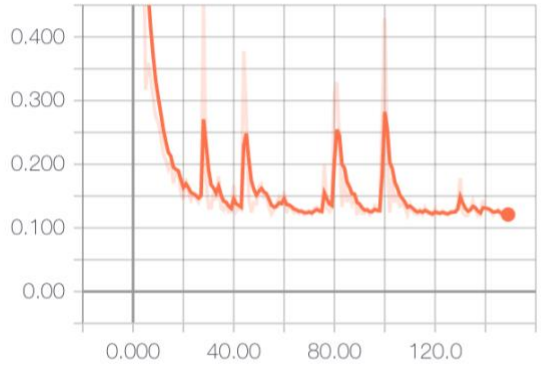


Figure 14 Validation loss of optimal model

Compared to the original model, the performance of the model after improvement is relatively better, especially on unseen test data. The validation loss is significantly lower and more stable than the one from the original model (Figure 10). It means that the model can now predict more accurately on unseen data with less error rate.

4.8.4 Classification Results

Using the parameters from the previous sections, the classification model is trained using dataset has been question demoted.

4.8.4.1 Original model

Table 11 Experiment results on classification model

Class	**Precision**	**Recall**	**F1 Score**	**Support**

0	0.00%	0.00%	0.00%	92
1	55.53%	21.01%	30.49%	1266
2	80.68%	95.68%	87.54%	4726
Weighted avg	74.23%	78.70%	74.35%	
Accuracy	78.70%			

4.8.4.2 Original model with question demoting

Table 12 Experiment results on classification model with question demoting

Class	**Precision**	**Recall**	**F1 Score**	**Support**
0	31.13%	51.09%	38.68%	92
1	51.12%	36.05%	38.32%	1266
2	83.09%	90.96%	86.85%	4726
Weighted avg	75.65%	77.81%	76.02%	
Accuracy	77.81%			

4.8.4.3 Model with regularisation and question demoting

Table 13 Experiment results on classification model with regularisation and question demoting

Class	**Precision**	**Recall**	**F1 Score**	**Support**
0	0.00%	0.00%	0.00%	92
1	47.96%	19.51%	27.73%	1266
2	80.97%	95.41%	87.60%	4726
Weighted avg	72.87%	78.17%	73.82%	
Accuracy	78.17%			

Based on the results above, it can be concluded that applying regularisation and question demoting does not improve the performance of the classification model as the accuracy is lower.

4.8.5 Discretised Results

Since the performance metrics for the regression model, such as MAE and RMSE, are difficult to be interpreted objectively, another approach of performance evaluation is implemented. The predicted scores from the model are discretised into three classes, using the same approach as mentioned in Section 4.7.4.2, and the score are discretised using the function in Equation 22.

The performance metrics of the model with discretised scores are stated in the table below.

Table 14 Experiment results on discretised scores

Class	Precision	Recall	F1 Score	Support
0	0.00%	0.00%	0.00%	0
1	56.30%	31.59%	40.47%	1358
2	92.54%	92.95%	87.44%	4726
Weighted avg	76.69%	79.26%	76.96%	
Accuracy	79.26%			

4.9 Limitations

This model does not check the spelling of the student answers, so misspelled words are not corrected. The model will embed a wrong vector representation for the misspelled word, and it can be very different from its intended meaning. The model will then be trained using this vector, and it could affect the overall performance of the model. Therefore, large dataset is required so that the model is not susceptible to outliers, which are, in this case, the misspelled words.

Furthermore, the dataset is not evenly distributed. Vast majority of the answers is scored between 4 and 5, while almost none is scored 0. As a result, the model does not have any sample of poorly answered questions, and thus, it is unable to learn features that would make an answer to be scored 0. It is justified by the results in Table 14, where the support of class 0 is 0, which means no answer is categorised as ‘wrong’.

4.10 Result Analysis

The model that is regularised and trained using question demoted data is proven to have the best performance among other models. As stated in Table 10, its Mean Absolute Error is 0.6124, which means the predicted scores are off by 0.6124 points on average, and its Rooted Mean Square Error is 0.9604. This is a 5.36%

and 2.14%, respectively, improvement from the original approach. However, this error is still quite large considering the score only ranges from 0 to 5.

Hence, the classification technique is introduced. By classifying the predicted scores, the results are more clear-cut and can be evaluated more objectively. Converting the model into a classification model yields accuracy of 78.7%, while discretising results of the regression model performs on accuracy of 79.26%. In conclusion, the discretised regression model is preferred.

Even though F1 is commonly the best measure to compare models, in this case, accuracy is considered a better measure since the data is not balanced between the classes, as stated in Section 4.9. Accuracy overlooks this problem, and hence is able to represent the model substantially well.

Chapter 5: System Implementation

5.1 Software Architecture

The system is implemented using Django framework, and its interface is built using React library.

5.1.1 Design Pattern

Django is an open-source, high-level Python web framework that supports rapid development and clean, pragmatic design [32]. It follows the Model-View-Template architecture pattern, also known as MVT. The abstraction layer, model, provides structuring and manipulates the data. The view layer is responsible for the logical operations and for processing user requests, including returning the responses. Lastly, template layer renders the information to be presented to the user [33].

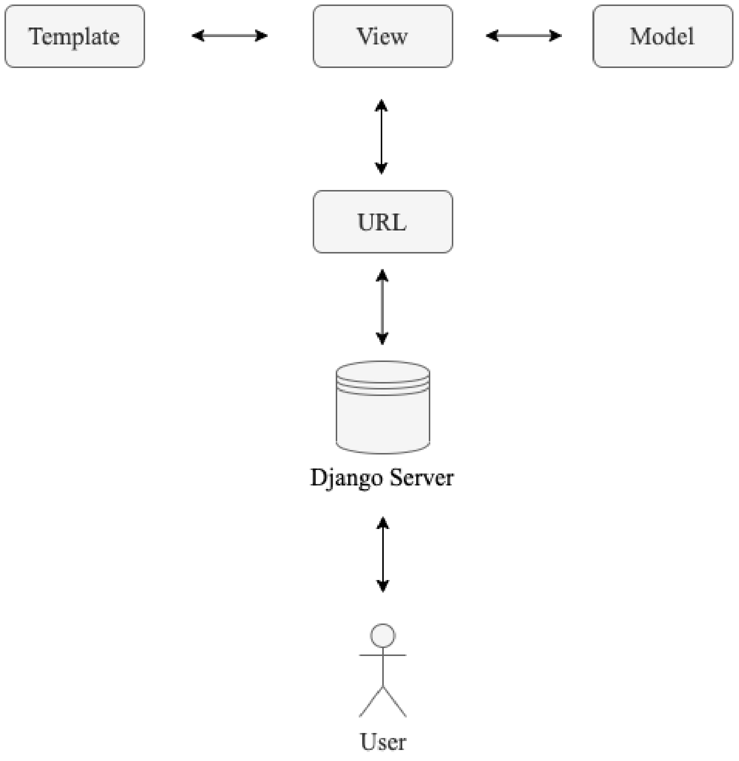


Figure 15 Django architecture pattern

5.1.2 Frameworks

In this system, the template layer is implemented with the support of Django REST Framework and React library. Django REST Framework, which stands for Representational State Transfer, is a powerful and flexible toolkit for building Web APIs [25]. It helps facilitate the usage of Django Server and acts as a RESTful API. Information from Django Server is passed through Django REST Framework to React. Then, users will be able to view the information from the database in Django server through the interface that is provided by React App. React app will get information from Django database using POST, GET, and PUT requests.

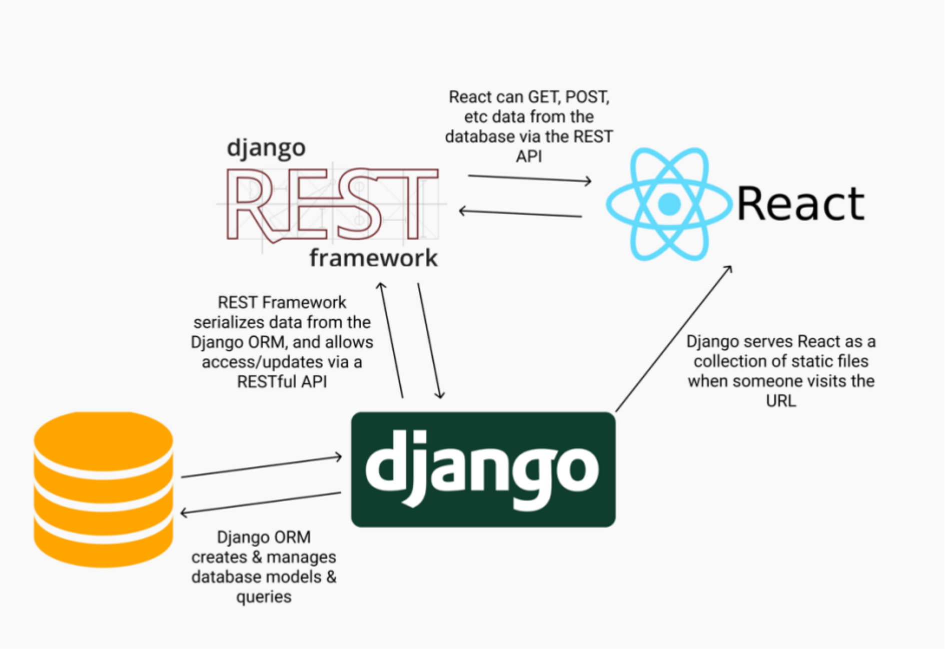

React can GET, POST, etc data from the database via the REST API
django REST framework
React
REST Framework serializes data from the Django ORM, and allows access/updates via a RESTful API
Django serves React as a collection of static files when someone visits the URL
django
Django ORM creates & manages database models & queries

Figure 16 Django and React with Django REST Framework

5.1.3 Database

The system uses the default database provided by Django, which is SQLite. It supports small, fast, self-contained, high reliability, full-features, SQL database engines [34]. Therefore, access to the database is easier since Django provides built-in functions for communication with SQLite database.

5.2 System Interface

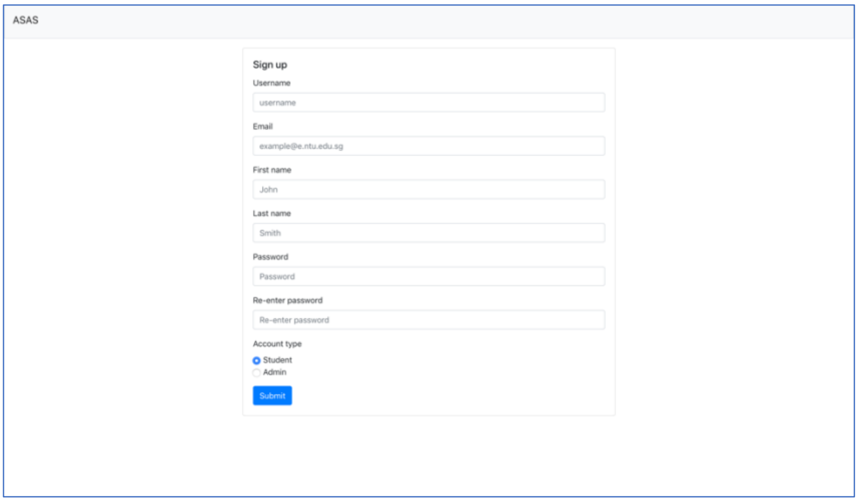
A prototype system implementation has been built using the architecture mentioned in the section above. This system is built with the intention to collect more data on conceptual short-answered data structure questions, and, at the same time, serving as a platform from students to practice. Data obtained from this system can be used to train the LSTM network, and, hopefully, the model performance could be improved when trained using the additional data.

5.2.1 General

This section covers pages in the website that is accessible for users with no account.

5.2.1.1 Sign up

Prior to using the system, everyone has to create an account in order to access the website. In this page, user can choose which type of user to sign up, admin or student. The features available for each type will be discussed in their respective sections, section 5.2.2 and section 5.2.3.



Sign up

Username
username

Email
example@e.ntu.edu.sg

First name
John

Last name
Smith

Password
Password

Re-enter password
Re-enter password

Account type
● Student
○ Admin

Figure 17 Sign up page

5.2.1.2 Log in

Once the account is approved, user can sign in as the respective type of user they signed up for. This page is the home page of the website when a user is not yet logged in.

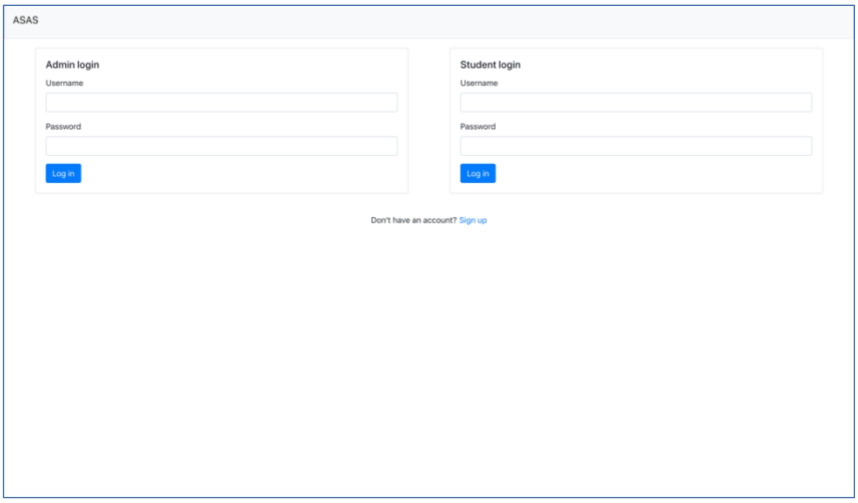


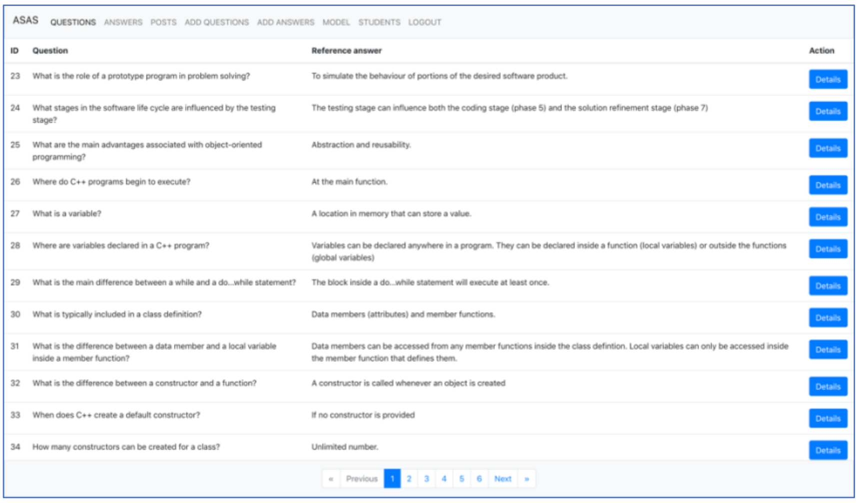
Figure 18 Log in page

5.2.2 Admin

Admin users in this website will be able to upload questions and score student answers. These scores will be used as gold standard during training process.

5.2.2.1 Questions

Admin can view all questions in the database from this page. The reference answer of the respective question is also displayed in this page.

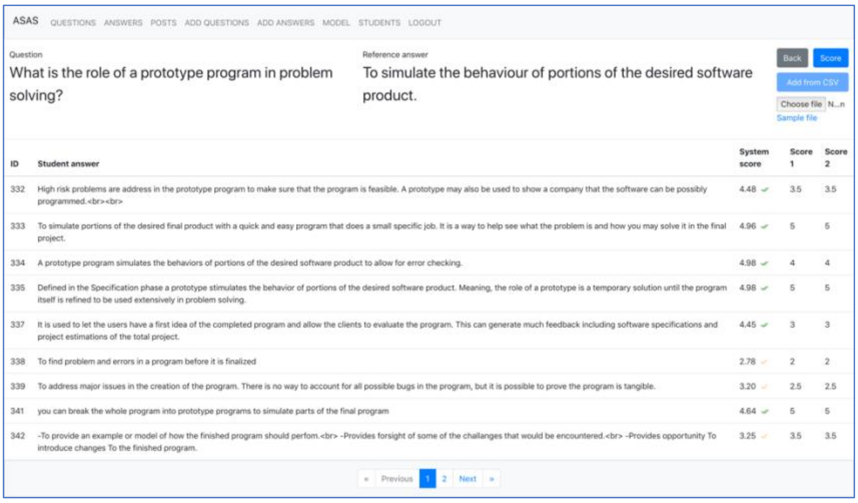


ID	Question	Reference answer	Action
23	What is the role of a prototype program in problem solving?	To simulate the behaviour of portions of the desired software product.	Details
24	What stages in the software life cycle are influenced by the testing stage?	The testing stage can influence both the coding stage (phase 5) and the solution refinement stage (phase 7)	Details
25	What are the main advantages associated with object-oriented programming?	Abstraction and reusability.	Details
26	Where do C++ programs begin to execute?	At the main function.	Details
27	What is a variable?	A location in memory that can store a value.	Details
28	Where are variables declared in a C++ program?	Variables can be declared anywhere in a program. They can be declared inside a function (local variables) or outside the functions (global variables)	Details
29	What is the main difference between a while and a do...while statement?	The block inside a do...while statement will execute at least once.	Details
30	What is typically included in a class definition?	Data members (attributes) and member functions.	Details
31	What is the difference between a data member and a local variable inside a member function?	Data members can be accessed from any member functions inside the class defintion. Local variables can only be accessed inside the member function that defines them.	Details
32	What is the difference between a constructor and a function?	A constructor is called whenever an object is created	Details
33	When does C++ create a default constructor?	If no constructor is provided	Details
34	How many constructors can be created for a class?	Unlimited number.	Details

Figure 19 Admin questions list

By clicking “Details” button on the right column of the table, user can view all answers of that particular question submitted by any student. Scores of the answer is also displayed. System score column will show the scores predicted by the neural network.

Admin can score the answers through this page by clicking “Score” button on top right. More answers for this particular question can also be added automatically by uploading a CSV file that contains answers and their scores.



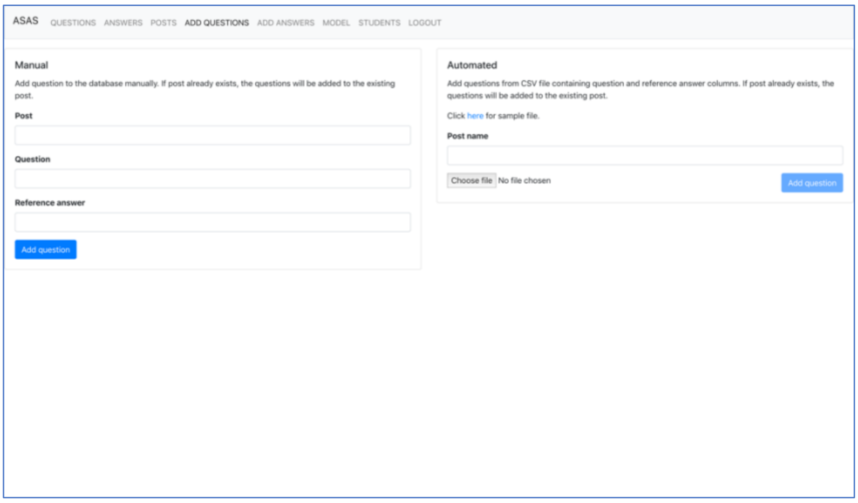
Question
What is the role of a prototype program in problem solving?

Reference answer
To simulate the behaviour of portions of the desired software product.

ID	Student answer	System score	Score 1	Score 2
332	High risk problems are address in the prototype program to make sure that the program is feasible. A prototype may also be used to show a company that the software can be possibly programmed. 	4.48 ✓	3.5	3.5
333	To simulate portions of the desired final product with a quick and easy program that does a small specific job. It is a way to help see what the problem is and how you may solve it in the final project.	4.96 ✓	5	5
334	A prototype program simulates the behaviors of portions of the desired software product to allow for error checking.	4.98 ✓	4	4
335	Defined in the Specification phase a prototype stimulates the behavior of portions of the desired software product. Meaning, the role of a prototype is a temporary solution until the program itself is refined to be used extensively in problem solving.	4.98 ✓	5	5
337	It is used to let the users have a first idea of the completed program and allow the clients to evaluate the program. This can generate much feedback including software specifications and project estimations of the total project.	4.45 ✓	3	3
338	To find problem and errors in a program before it is finalized	2.78 ✓	2	2
339	To address major issues in the creation of the program. There is no way to account for all possible bugs in the program, but it is possible to prove the program is tangible.	3.20 ✓	2.5	2.5
341	you can break the whole program into prototype programs to simulate parts of the final program	4.64 ✓	5	5
342	-To provide an example or model of how the finished program should perfom. -Provides forsight of some of the challanges that would be encountered. -Provides opportunity To introduce changes To the finished program.	3.25 ✓	3.5	3.5

Figure 20 Admin question details

To upload new questions to the system, admins can upload by typing down the questions manually and the reference answer, where the questions will be added one by one, or by uploading a CSV file, where multiple questions can be added simultaneously.



Manual

Add question to the database manually. If post already exists, the questions will be added to the existing post.

Post

Question

Reference answer

Automated

Add questions from CSV file containing question and reference answer columns. If post already exists, the questions will be added to the existing post.

Click here for sample file.

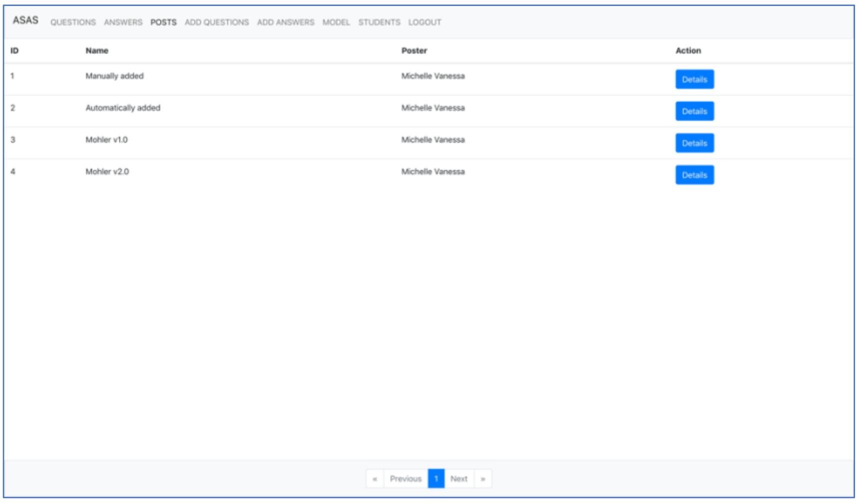
Post name

No file chosen

Figure 21 Add questions

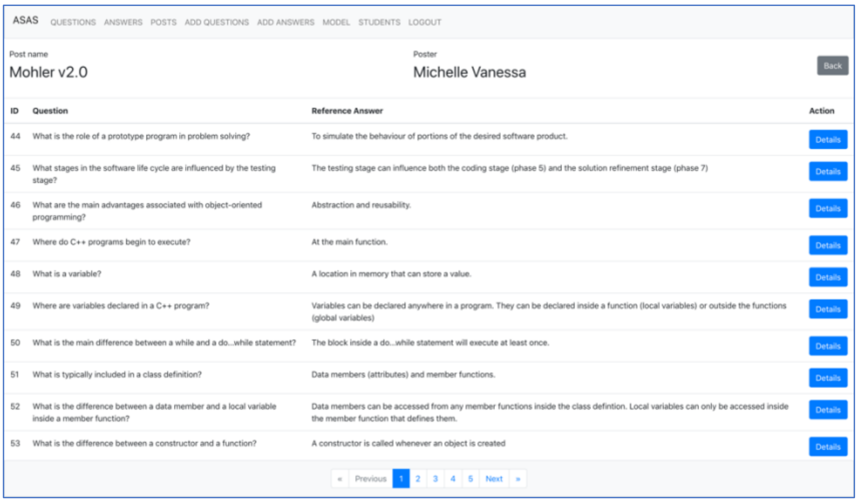
5.2.2.2 Posts

Questions are grouped together into posts so that they can be easier to view. Questions uploaded together will be added into the same post, either a new or an existing one.



ID	Name	Poster	Action
1	Manually added	Michelle Vanessa	Details
2	Automatically added	Michelle Vanessa	Details
3	Mohler v1.0	Michelle Vanessa	Details
4	Mohler v2.0	Michelle Vanessa	Details

Figure 22 Admin posts list



Post name
Mohler v2.0

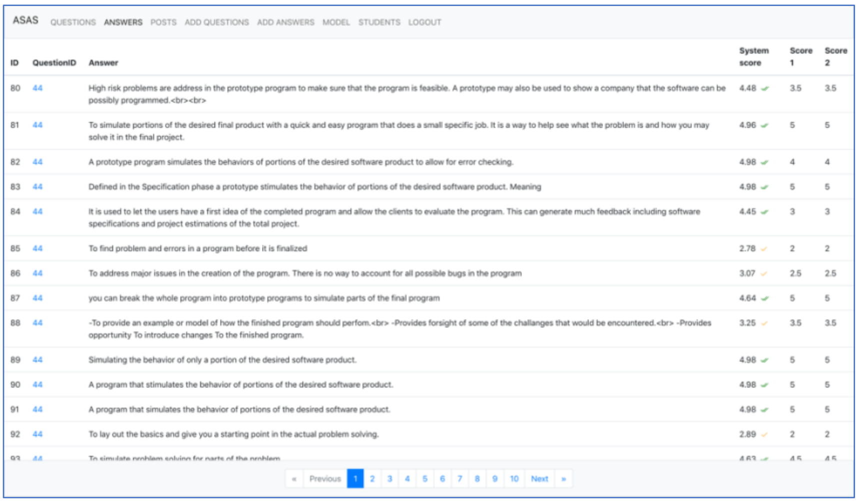
Poster
Michelle Vanessa

ID	Question	Reference Answer	Action
44	What is the role of a prototype program in problem solving?	To simulate the behaviour of portions of the desired software product.	Details
45	What stages in the software life cycle are influenced by the testing stage?	The testing stage can influence both the coding stage (phase 5) and the solution refinement stage (phase 7)	Details
46	What are the main advantages associated with object-oriented programming?	Abstraction and reusability.	Details
47	Where do C++ programs begin to execute?	At the main function.	Details
48	What is a variable?	A location in memory that can store a value.	Details
49	Where are variables declared in a C++ program?	Variables can be declared anywhere in a program. They can be declared inside a function (local variables) or outside the functions (global variables)	Details
50	What is the main difference between a while and a do...while statement?	The block inside a do...while statement will execute at least once.	Details
51	What is typically included in a class definition?	Data members (attributes) and member functions.	Details
52	What is the difference between a data member and a local variable inside a member function?	Data members can be accessed from any member functions inside the class defintion. Local variables can only be accessed inside the member function that defines them.	Details
53	What is the difference between a constructor and a function?	A constructor is called whenever an object is created	Details

Figure 23 Admin post details

5.2.2.3 Answers

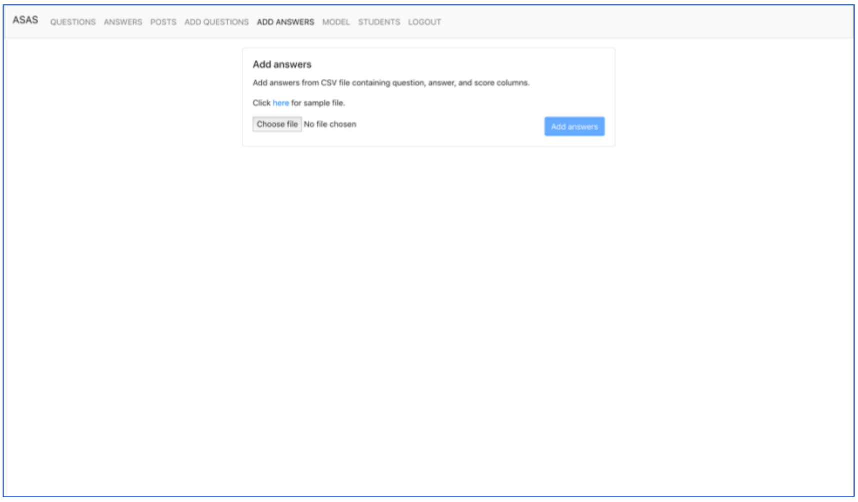
Answers from all students can be viewed in this page. Their scores can also be viewed from this page. However, scoring the answer can only be done in the questions list page.



ID	QuestionID	Answer	System score	Score 1	Score 2
80	44	High risk problems are address in the prototype program to make sure that the program is feasible. A prototype may also be used to show a company that the software can be possibly programmed. 	4.48 ✓	3.5	3.5
81	44	To simulate portions of the desired final product with a quick and easy program that does a small specific job. It is a way to help see what the problem is and how you may solve it in the final project.	4.96 ✓	5	5
82	44	A prototype program simulates the behaviors of portions of the desired software product to allow for error checking.	4.98 ✓	4	4
83	44	Defined in the Specification phase a prototype stimulates the behavior of portions of the desired software product. Meaning	4.98 ✓	5	5
84	44	It is used to let the users have a first idea of the completed program and allow the clients to evaluate the program. This can generate much feedback including software specifications and project estimations of the total project.	4.45 ✓	3	3
85	44	To find problem and errors in a program before it is finalized	2.78 ✓	2	2
86	44	To address major issues in the creation of the program. There is no way to account for all possible bugs in the program	3.07 ✓	2.5	2.5
87	44	you can break the whole program into prototype programs to simulate parts of the final program	4.64 ✓	5	5
88	44	-To provide an example or model of how the finished program should perfom. -Provides forsight of some of the challanges that would be encountered. -Provides opportunity To introduce changes To the finished program.	3.25 ✓	3.5	3.5
89	44	Simulating the behavior of only a portion of the desired software product.	4.98 ✓	5	5
90	44	A program that stimulates the behavior of portions of the desired software product.	4.98 ✓	5	5
91	44	A program that simulates the behavior of portions of the desired software product.	4.98 ✓	5	5
92	44	To lay out the basics and give you a starting point in the actual problem solving.	2.89 ✓	2	2
93	44	To simulate problem solving for parts of the problem	4.63 ✓	4.5	4.5

Figure 24 Admin answers list

Answers can also be added automatically by uploading a CSV file containing the answers, their questions, and the scores.



Add answers

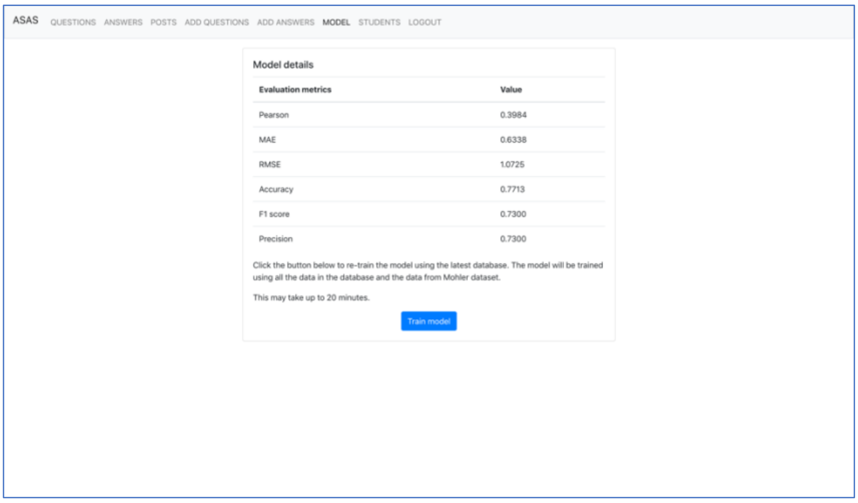
Add answers from CSV file containing question, answer, and score columns.

Click here for sample file.

Figure 25 Add answers

5.2.2.4 Neural network model

The neural network model is also attached to this system. The system will save the predicted scores by the model of the most recent training. When new data is added, the model can be trained using the new dataset by clicking the “Train model” button in this page. After training, all answers in the database will be predicted a new score using the new model. Lastly, the performance metrics will also be displayed in this page.



Model details

Evaluation metrics	Value
Pearson	0.3984
MAE	0.6338
RMSE	1.0725
Accuracy	0.7713
F1 score	0.7300
Precision	0.7300

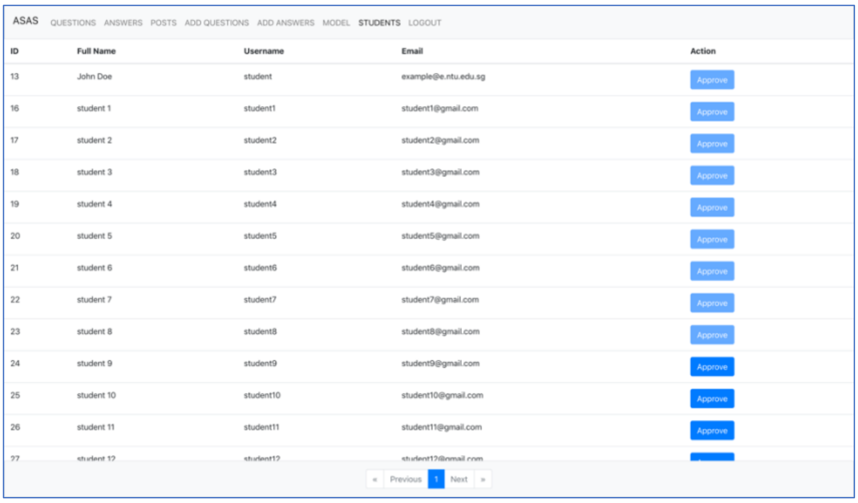
Click the button below to re-train the model using the latest database. The model will be trained using all the data in the database and the data from Mohler dataset.

This may take up to 20 minutes.

Figure 26 Model details

5.2.2.5 Students

Admins can view all students in the system. From this page, the students can also be approved so that they can sign in using their accounts.



ID	Full Name	Username	Email	Action
13	John Doe	student	example@e.ntu.edu.sg	Approve
16	student 1	student1	student1@gmail.com	Approve
17	student 2	student2	student2@gmail.com	Approve
18	student 3	student3	student3@gmail.com	Approve
19	student 4	student4	student4@gmail.com	Approve
20	student 5	student5	student5@gmail.com	Approve
21	student 6	student6	student6@gmail.com	Approve
22	student 7	student7	student7@gmail.com	Approve
23	student 8	student8	student8@gmail.com	Approve
24	student 9	student9	student9@gmail.com	Approve
25	student 10	student10	student10@gmail.com	Approve
26	student 11	student11	student11@gmail.com	Approve
27	student 12	student12	student12@gmail.com	

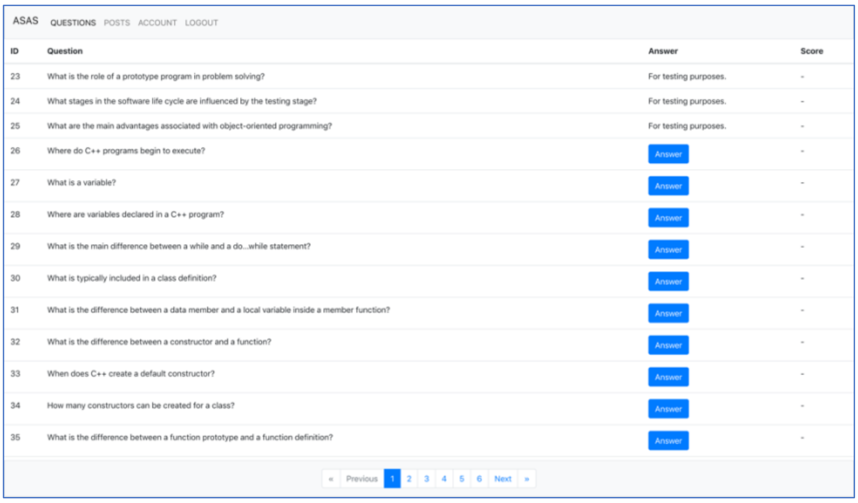
Figure 27 Students list

5.2.3 Student

Student is another type of user in this system. A student can only view questions and submit answers to questions.

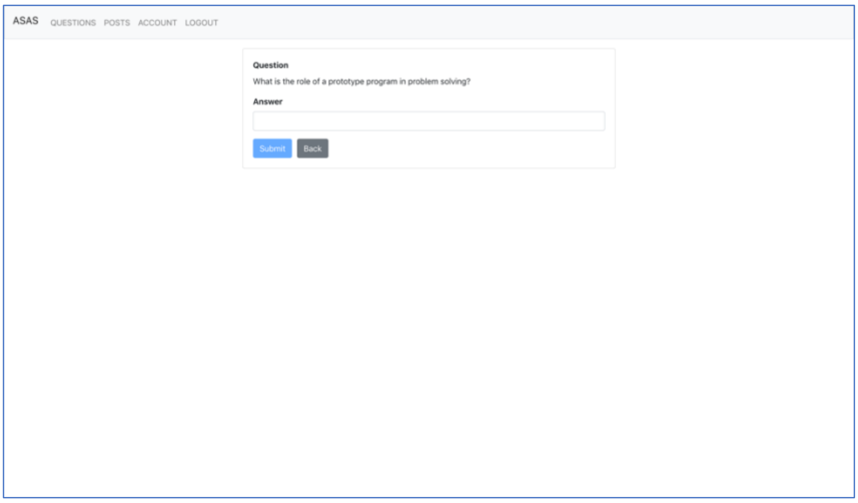
5.2.3.1 Questions

This page shows all questions available in the system. Student can only answer each question once, and the answer cannot be changed once submitted. The score of each answer is also displayed in this page.



ID	Question	Answer	Score
23	What is the role of a prototype program in problem solving?	For testing purposes.	-
24	What stages in the software life cycle are influenced by the testing stage?	For testing purposes.	-
25	What are the main advantages associated with object-oriented programming?	For testing purposes.	-
26	Where do C++ programs begin to execute?	Answer	-
27	What is a variable?	Answer	-
28	Where are variables declared in a C++ program?	Answer	-
29	What is the main difference between a while and a do...while statement?	Answer	-
30	What is typically included in a class definition?	Answer	-
31	What is the difference between a data member and a local variable inside a member function?	Answer	-
32	What is the difference between a constructor and a function?	Answer	-
33	When does C++ create a default constructor?	Answer	-
34	How many constructors can be created for a class?	Answer	-
35	What is the difference between a function prototype and a function definition?	Answer	-

Figure 28 Student questions list



Question

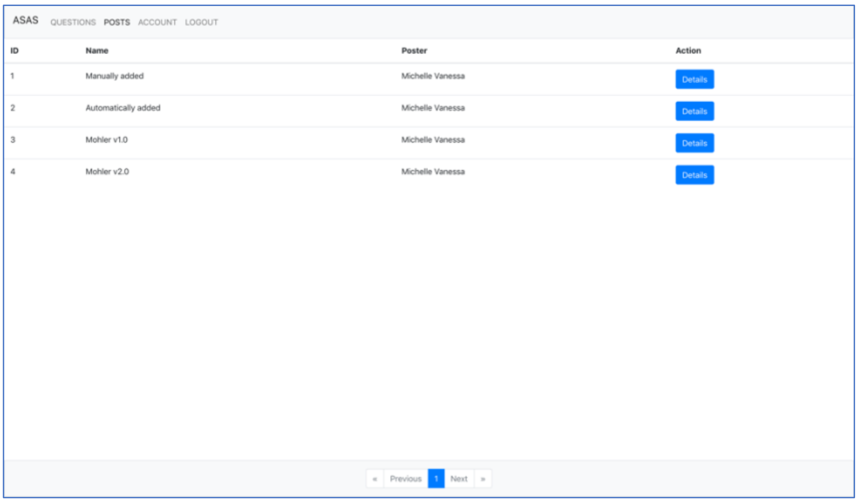
What is the role of a prototype program in problem solving?

Answer

Figure 29 Student answer question page

5.2.3.2 Posts

Students can also view questions based on posts by clicking on the “Details” button on the rightmost column.

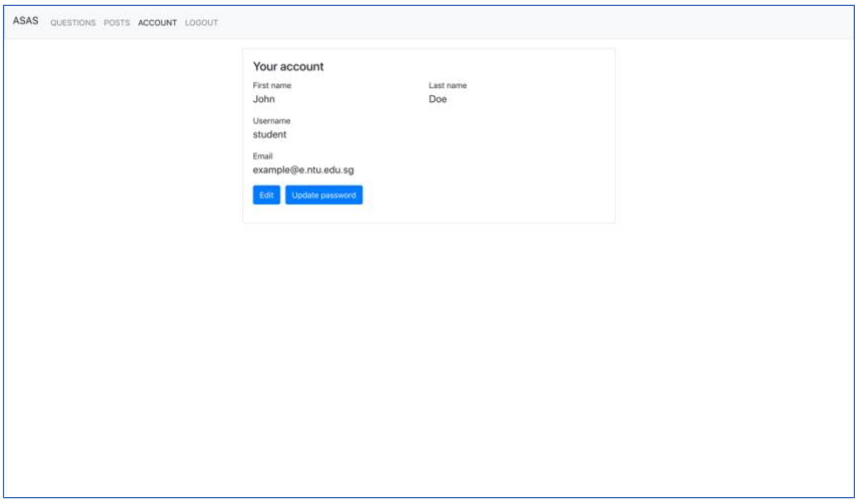


ID	Name	Poster	Action
1	Manually added	Michelle Vanessa	Details
2	Automatically added	Michelle Vanessa	Details
3	Mohler v1.0	Michelle Vanessa	Details
4	Mohler v2.0	Michelle Vanessa	Details

Figure 30 Student posts list

5.2.3.3 Account

Users can view and update their account details from this page.



Your account

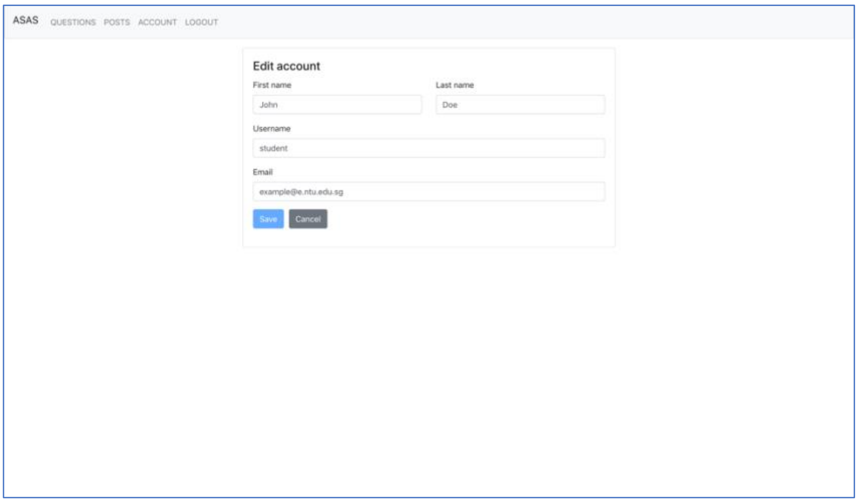
First name
John

Last name
Doe

Username
student

Email
example@e.ntu.edu.sg

Figure 31 Student account details



Edit account

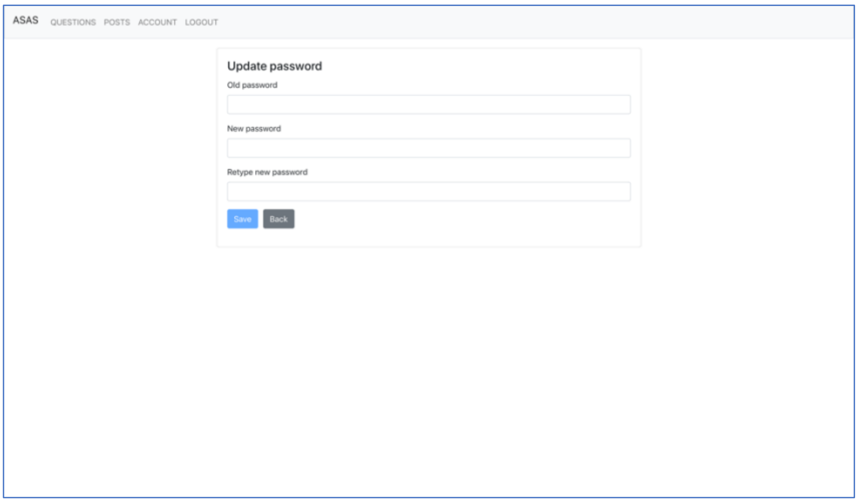
First name: John

Last name: Doe

Username: student

Email: example@e.ntu.edu.sg

Figure 32 Student edit account



Update password

Old password

New password

Retype new password

Figure 33 Update password

Chapter 6: Conclusion

This report discusses several approaches to improve the performance of the existing Siamese Bidirectional LSTM model in terms of grading accuracy of short-answered Data Structures questions.

Several techniques were implemented to the model, and based on the experiments conducted in this project, combination of batch normalisation, L_2 weight regularisation, dropout, and question demoting yields the best result. When the techniques applied to the model, its performance is improved by 5.05% on Pearson correlation coefficient, 5.36% on MAE, and 2.14% on RMSE. The improvement can also be observed from the graphs of validation error against number of epochs (Figure 10 and Figure 14) as the improved model could perform predict with less error.

Furthermore, the model has also been converted to a multi-category classification model with 3 classes. As a result, the model has accuracy of 78.7% and F1 score of 74.35%, which are considerably low. The model does not perform as well as expected, so the regression model is still preferred in grading short answer, especially since its accuracy is 79.26% when the results are discretised.

Finally, a prototype system has been built to implement the improved model. The system provides a platform where users can upload questions, answer the questions, and grade the answers. Eventually, the submitted answers can be graded by the model or used as an additional training data. At the same time, the system could also be used as a platform for students to self-practice on Data Structures.

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Appendix A: Experiment Results (Regression Model)

Remarks	**Reg LSTM**	**Reg dense**	**Dense dropout**	**LSTM dropout**	**Batchnorm**	**LSTM batchnorm**	**Pearson**	**RMSE**	**MAE**	**Avg**
Original code	0	0	0.5	0	Yes	No	0.4416	0.9815	0.6471	0.8143
Regularize LSTM	**0.01**	0	0.5	0	Yes	No	0.4512	0.9787	0.6293	0.8040
Regularize LSTM	**0.001**	0	0.5	0	Yes	No	0.4526	0.9556	0.6466	0.8011
Regularize LSTM	**0.0001**	0	0.5	0	Yes	No	0.4513	0.9563	0.6467	0.8015
Regularize perceptron	0	**0.01**	0.5	0	Yes	No	0.4471	0.9694	0.6309	0.8002
Regularize perceptron	0	**0.001**	0.5	0	Yes	No	0.4491	0.9677	0.6571	0.8124
Regularize perceptron	0	**0.0001**	0.5	0	Yes	No	0.4504	0.9952	0.6349	0.8151
Perceptron dropout	0	0	**0.2**	0	Yes	No	0.4436	1.0034	0.6369	0.8202
Perceptron dropout	0	0	**0.6**	0	Yes	No	0.4504	0.9778	0.6450	0.8114
LSTM dropout	0	0	0.5	**0.2**	Yes	No	0.4476	0.9697	0.6445	0.8071
LSTM dropout	0	0	0.5	**0.4**	Yes	No	0.4506	0.9632	0.6432	0.8032
LSTM dropout	0	0	0.5	**0.5**	Yes	No	0.4413	0.9599	0.6629	0.8114
Batch normalization	0	0	0.5	0	**No**	No	0.4142	0.9976	0.6582	0.8279
Recurrent batchnorm	0	0	0.5	0	Yes	**Yes**	0.4426	0.9648	0.6429	0.8039
Regularize	**0.001**	**0.01**	0.5	0	Yes	No	0.4447	0.9732	0.6481	0.8107
Dropout	0	0	**0.6**	**0.4**	Yes	No	0.4473	0.9845	0.6359	0.8102

Regularize & dropout	**0.001**	**0.01**	**0.6**	**0.4**	Yes	No	0.4486	1.0199	0.6294	0.8247
Regularize & dropout LSTM	**0.001**	**0.01**	0.5	**0.4**	Yes	No	0.4494	0.9504	0.6523	0.8014
Reg, dropout LSTM, batchnorm	**0.001**	**0.01**	0.5	**0.4**	Yes	**Yes**	0.4461	1.0000	0.6200	0.8100
Question demoting	0	0	0.5	0	Yes	No	0.469	0.97615	0.62045	0.7983
Question demoting, optimal	**0.001**	**0.01**	0.5	**0.4**	Yes	No	0.4639	0.9604	0.6124	0.7864
Question demoting, optimal & batchnorm	**0.001**	**0.01**	0.5	**0.4**	Yes	**Yes**	0.4601	0.9816	0.6091	0.7954