# Question and Answer Classification with Deep Contextualized Transformer

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Abstract. Recent literature has focused on the Standford Parse Tree and how it has been used for Question and Answer problems in Natural Language Processing. This parser tree with deep learning algorithms has analyzed the makeup of question and answer classifications. In this study, the authors have built a model using a Deep Contextualized Transformer that can manage some aberrant expressions. We conducted extensive evaluations on SQuAD and SwDA datasets and our model showed significant improvements to QA problem classifications for industry needs. Further analysis investigated the impact of various models on the accuracy of the results. Research outcomes showed that our new method is more effective in solving QA problems with a higher accuracy of up to 83.1% compared to other models.

**Keywords:** QA Classification · NLP, Self-attention · Self-attention

# 1 Introduction

The Question and Answer system (QA) is widely used in the industry. Every week, one company faces thousands of questionnaires for the products they launch. QA is a massive problem in Natural Language Processing (NLP), including the application of problem answering, sentence recognitions, etc. There are several types of problems, such as wh-questions, statement questions, statements and other question patterns. Each type of question has a corresponding label for a question or statement. In this study, we want to discover a better algorithm to analyze the question and answer data from the huge text files. Earlier work in this field mainly used the Bag-of-words (BoW) technique to classify sentence types [44]. Many recent studies have adopted supervised, deep-learning methods concerning question and answer classification and have shown promising results [18]. However, most of these approaches have treated the sentence as a text classification without considering the context of the writing across sentences or interdependently; therefore, this method is unable to reflect conceptual dependencies of the words within the sentences. In reality, the different order of the same words in a sentence can have very different meanings. As a result, it is necessary to determine a high compatibility algorithm to classify question and answer sentences by considering all sentence configurations.

This research draws on some recent advances in NLP research such as BERT [7] and Elmo [29] to produce a sentence classification model to quickly and correctly pick out the question and answer sentence from the target text. Compared with regular algorithms for treating QA problems such as word2vec [28], this selfattention algorithm can perform contextualized word representation to obtain contextualized word meaning from the sentences. As a result, with BERT and Elmo, we can quickly judge the contexture relationship of the sentence and figure out what kind sentence type it might be. Specifically, we have used a hierarchical deep neural network with a self-attention algorithm to process different types of question and answer text, including statement questions that are a specific type of question in the questionnaires. This research aims to achieve state-of-theart outcomes for classifying the QA problem. As a result, we mainly contribute to: 1.) a huge the improvement of performance on QA classification problems with the self-attention method, especially one such as BERT; 2. demonstrating how performance could be improved with a combination of different levels of models including the hierarchical deep neural network for classification, the selfattention model like BERT for single word embedding, and the previous label of the training data with the SQuAD dataset; and 3. exploring different methods to find a high compatibility method to classify the QA problem.

# 2 Related Work

We focus on four primary methods used in recent research. One treats text as text classification, in which each word is classified in isolation, while the second treats the text using Contextualized Word Representation Algorithms, such as BERT with self-attention or Elmo. The third method uses the transformer-based foundation models to do the question and answering, and the forth method use the chain-of-thought to do the classification.

# 2.1 Text Classification:

Lee and Dernoncourt [18] build a vector representing each utterance and use either RNN or CNN to predict the text details to classify the sentence type.

## 2.2 Self-attention

Jacob et al. [7] used the BERT, and Peters et al. [29] used Elmo to embed the text into the vector to give the contextual relationship of the sentence for each word. Along with these two tools, we use RNN-based or CNN-based hierarchical neural networks to learn and model multiple levels of word.

### 2.3 Foundation Model

Additionally, the development of the transformer architecture has made transformer-based foundation models [3] significantly beneficial in classification tasks. They

play a central role not only in machine learning but also in a wide range of scientific domains, such as ChatGPT [5,8] for natural language, BloombergGPT [42] for finance, DNABERT [49,48,15] for genomics, and many others [47,30,24,21,25,45,46]. The Modern Hatfield Network provides another efficient method to do the question and answering classfication with the memory retrieval. Modern Hopfield models [11,12,41,13,4,33,10] showcase fast convergence and exponential memory capacity, linking them to Transformer architecture as advanced attention mechanisms. Their application spans various domains, including drug discovery [34], immunology [40], and time series forecasting [41,13,1], signifying their influence on future large-scale model designs.

### 2.4 Chain-of-thought

Another one method to do the classification is chain-of-thought [39,26,27]. It enables the model to break down complex queries into a series of intermediate reasoning steps. This approach helps the model understand the context and nuances of the question, leading to more accurate and coherent answers. By sequentially processing each step, CoT enhances the interpretability and robustness of the QA system, ensuring that the final classification is based on a thorough and logical analysis of the input query.

# 3 Model

The task of QA classification takes the sentence S as an input, which varies the length sequence of the word  $U = \{u_1, u_2, u_3, \dots, u_N\}$ . For each word  $u_1 \in U$ , there has a length value of  $l_i \in L$  and a corresponding target label  $y_i \in Y$ , which represents the QA's result associated with the corresponding sentence. Figure 1 shows the overall architecture of the model, which involves several main components. (1) A self-attention algorithm to encode the sentence with the self-attention, (2) A Combination-level RNN to handle the output of the encoding and to classify the label of the sentence. We describe the details below.

# 3.1 Context-aware Self-learning

Our self-attention algorithm encodes a variable-length sentence into a fixed size. There are two types of the algorithm; one based on Self-Attention and another based on deep contextualization word representation.

Deep contextualization word representation This model uses the BiLM to consider the different position of words within the sequence. Inspired by Peters et al. [29], we use PCA and t-SNE to reduce the dimensions from a higher level to reduce the dimensions from a higher level to a lower level. Then, we use the Combination-Level RNN (Section 3.2) which provides us with the previous hidden state of the encoded word. It provides us the contextual relationship in

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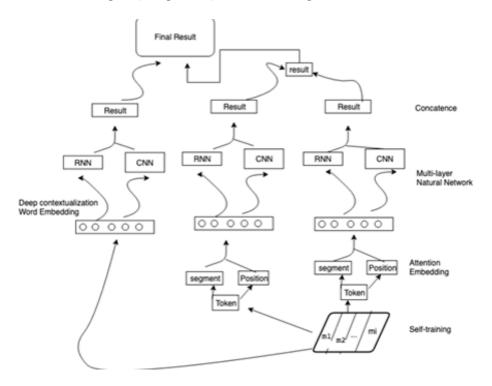


Fig. 1. The graph of the model Architecture.

the sentences and combines all hidden states of words in sentences. After that, the deep modifications contextualization word representation encoder encodes the combination into the 2-D vectors of each sentence. We follow the instruction of Peters at el. [29] to explain below.

A word  $t_i$ , which is the sequence of the sentence, is mapped onto the embedded layer. The deep contextualization representation uses BiLM to combine the forward and backend LM. The formulation of the process is as follows:

$$\sum_{k=1}^{N} \left( \log p(t_k|t_1, \dots, t_{k-1}; \Theta_x, \overrightarrow{\Theta}_{\text{LSTM}}, \Theta_s) + \log p(t_k|t_{k+1}, \dots, t_N; \Theta_x, \overleftarrow{\Theta}_{\text{LSTM}}, \Theta_s) \right)$$

Moreover, we weigh the performance of the model with computing as indicated

$$E(R_k; \Theta^{task}) = \gamma^{task} \sum_{j=0}^{L} s_j^{task} h_{kj}^{LM}$$

 $E(R_k; \Theta^{task}) = \gamma^{task} \sum_{j=0}^{L} s_j^{task} h_{kj}^{LM}$ In (1), the  $s_j^{task}$  represents softmax-normalized weights, and the scalar patrock is rameter  $\gamma^{task}$  allows the task model to scale the entire vector. In the simple case, the representation would choose the top layer and  $E(R_k) = h_{ki}^{LM}$ .

Self-Attention For each word in the word, we would use some Self-Attention model to encode them. The most popular Self-Attention model base is BERT [7]. The model will encode a variable-length sequence using an attention mechanism that considers the different position token and segment within the sequence. Inspired by Devin et al. [7] and Tran et al. [36], we apply the Combination-Level RNN (Section 3.2) into a self-attractive encoder [20]. We use the 24 layers and 1024 Hidden Uncased BERT also with the RobertaBERT as the base of the embedding to encode the context to the 3D tensor. We follow the instruction of Vipuls Raheja and Joel Tetreault [31] and Joel Tetreault and Liu et al. [22] to explain the modification mentioned below.

The word  $t_i$  is also mapped onto the embedding layer and results in s-dimensional embedding for each word in the sequence based on the Transformer [37]. Then, the embedding is put into the bidirectional-GRU layer.

Vipul Raheja and Joel Tetreault [31] describe the contextual self-attention score as:

$$S_i = W_{s2} \tanh(W_{s1} H_i^T + W_{s3} \overrightarrow{g_{i-1}} + b)$$

Here  $W_{s1}$  is a weight matrix,  $W_{s2}$  and  $W_{s3}$  is a matrix of parameters. b is a bias of the vector represented in Equation 2. This can be treated as a 2-layer MLP with bias, and  $d_a$  with a hidden unit.

### 3.2 Combination-level RNN

The word representation  $h_i$  from the past two models are passed into the combinationlevel RNN. Based on Figure 1, we would pass all of the hidden layers concatenated into a final representation  $R_i$  of each word. The previous model step will help us build a encoding vector to represent the relationship of the each words, and in order to consider all the words in the sentence together to make the classification, it is necessary to make the combination RNN model.

This is more suitable for the problem classification to put the layers with the proper percentages in the final representation. Then, we place the result into the combination model layer to figure out the relationship between the label and the context of the words. This method is not independently decoding the label of the words; it should consider all of the relationships of the sentences. Then, it should determine the most related decoder to decode them to the related labels. The combination-level RNN would also have the function to supervise the labels and improve the accuracy of the classification of our model.

### 3.3 Super-attractive

The model that we use combines the final representative of the combination for hidden layers via self-attention. It can help us figure out what the labels of those words are and produce the results. The score we compute for the algorithm is to calculate the accuracy of the correct labels in the classifications as Hossin M. and Sulaiman M.N. [9] suggest. Also, we apply an advanced check for the question and answer problem. For sentences without clear results, we put them into the parser tree for another classification. The parser tree we use is based on Huang [14]. We use its Tensor Product Representation to rebuild our parser tree for our

model. The original Stanford Parser Tree [6] is good to classify the relationship of the sentences. However, in our model, we use the Bi-LSTM with the attention algorithm to rebuild the parser tree and get the tree graph with POS tags. This is useful to calcify the structure of the sentence. After that, we use the graph we obtain to analyze the structure of words and produce the classification of the unsure sentence in the document. Finally, we determine the combination result for the users to check the question and answer problems.

# 4 Data

We evaluate the accuracy of the classification model with one standard dataset—the Switchboard Dialogue Act Corpus (SwDA) [16] consisting of 43 classes (listed as , and we make a program to create the sentences based on the data with the Stanford Question Answering Dataset (SQuAD) [32] to use self-attention for the task. The Natural Language Toolkit Dataset (NLTK) [23] is another significant resource for the test case. We use the nltk.corpus.nps\_chat dataset as data for the experiment. We then use the training, validation, and test splits as defined in Lee and Dernoncourt [18].

Table 1 shows the statistics for both datasets. There are many kinds of labels of the class to classify the kind of sentences they are. There are some special DA classes in both datasets, such as Tag-Question in SwDA and Statement-Question in NLTK. Both datasets make over 25% of the question type labels in each set.

Table 1. Number of Sentences in the Dataset

Dataset	Train	Validation	Test	Т	N
SwDA+SQuAD	87k	10k	3k		100k
NLTK	8.7k	1k	0.3k		10k

|T| represents the number of classes and |N| represents the sentence size

### 5 Result

We have compared the classification accuracy of our model(see Appendix) with several other models (Table 2). For methods using attention and deep contextualization word representation in some approaches to model the sentence of questionnaire documents, some of them use the self- attention word representation for the task. However, they did not perform as well as our model. All models and their variables were trained eight times, making an average for the performance as a result. And we find these previous algorithms did not perform as well as our model. Our model is better than Raheja and Tetreault [31] by 0.4% in SwDA dataset after measuring its accuracy score and 3.9% for the Li

and Wu [19] methods in SWQA dataset. It also beats the TF-IDF GloVe baseline by 17.2% in SwDA.

The improvements based on our model have a significant meaning for other models. However, the performance in NLTK is still not as good as that of the Raheja and Tetreault[31] model. The reason for the lower accuracy is dependent on the contextual details and label noisy inside the dataset. The label noisy is caused with reason of that the NLTK dataset has the fewer and difference dialog act class, it would cause our model could not actually defined them by our model. The context in the NLTK dataset indicated the existence of some data not easily readable for the machine such as some error codes. Also, the label type in the NLTK dataset is only 35% of the label type for the SwDA ones. As a result, due to the label noisy and the contextual details, the performance of NLTK did not show significant gains over that of SwDA.

Model	SwDA+SQuAD	NLTK
TF-IDF GloVe [28]	66.1	70.3
Li and Wu [19]	79.2	-
Peters et al. [29]	76.3	-
Raheja and Tetreault [31]	82.7	85.8
Lee and Dernoncourt [18]	75.9	77.4
Our Method	83.1	85.5
RoBERTa[22]	82.2	84 7

Table 2. QA Classification Accuracy of the different approaches

The performance of our model is more sensitive than the model used commonly for the problems, including the error code. However, it has a higher accuracy, considering the complete problem classification. In future research, we should improve our algorithm, which has a higher ability to handle the problem of the label noisy and context detail.

### 6 Conclusion

We developed a new model which carefully performed the QA classification and made comparisons with common-use algorithms by testing the SwDA dataset. We used different word representation methods and determined that the context details depend highly on the classification performance. For example, the reason NLTK is not as good as the Raheja and Tetreault [31] results was because there were too many label noises and the context details which were not so easy to read. Working with attention and combination levels during the classification, which has not been previously applied in this kind of task, enables the model to learn more from the context and get more real meaning from the words than

previously It helps to improve the performance of the classification for these kinds of tasks.

In our future work, we will explore more attention mechanisms, such as block self-attention [35], or hierarchical attention [43] and hypergraph attention [2]. These approaches can incorporate the information from different representations for the various positions and can capture both local and long-range context dependency. Also, this approach should help with the problem of the hard-readable context, such as the problem of the NLTK dataset that causes accuracy to become lower than usual. We will seek more dataset combinations to do the question and answer classification work. We will also use RACE [17] and GLUE [38] datasets to do more test work and make more stable algorithms to solve the question and answer classification issues.

# 7 Appendices

Table 3. Fine-tuning Hyperparameters of our model for each data set

Hyperparam	SQuAD
Learning Rate	1e-5
Weight Decay	0.1
Epochs	7
Batch Size	8k

Table 4. Pretraining Hyperparameters of our model

Hyperparam	RoBERTa	BERT	
No. of Layers	24	24	
Hidden Size	1024	1024	
FNN Inner Hidden	4096	-	
Attention Heads	16	16	
Attention Head size	64	64	
Dropout	0.1	0.1	
Batch Size	8k	8k	

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1	Statement-non-opinion	sd	Me, I'm in the legal department.	72824	75145
2	Acknowledge (Backchannel)	ь	Uh-huh.	37096	38298
3	Statement-opinion	sv	I think it's great	25197	26428
4	Agree/Accept	aa	That's exactly it.	10820	11133
5	Abandoned or Turn-Exit	%	So, «	10569	15550
6	Appreciation	ba	I can imagine.	4633	4765
7	Yes-No-Question	qy	Do you have to have any special training?	4624	4727
8	Non-verbal	x	[Laughter], [Throat_clearing]	3548	3630
9	Yes answers	ny	Yes.	2934	3034
10	Conventional-closing	fc	Well, it's been nice talking to you.	2486	2582
- 11	Uninterpretable	%	But, uh, yeah	2158	15550
12	Wh-Question	qw	Well, how old are you?	1911	1979
13	No answers	nn	No.	1340	1377
14	Response Acknowledgement	bk	Oh, okny.	1277	1306
15	Hedge	h	I don't know if I'm making any sense or not.	1182	1226
16	Declarative Yes-No-Question	qy^d	So you can afford to get a house?	1174	1219
17	Other	fo_o_fw_by_bc	Well give me a break, you know.	1074	883
18	Backchannel in question form	bh	Is that right?	1019	1053
19	Quotation	^q	You can't be pregnant and have cats	934	983
20	Summarize/reformulate	bf	Oh, you mean you switched schools for the kids.	919	952
21	Affirmative non-yes answers	na	It is.	836	847
22	Action-directive	ad	Why don't you go first	719	746
23	Collaborative Completion	^2	Who aren't contributing.	699	723
24	Repeat-phrase	b^m	Oh, fajitas	660	688
25	Open-Question	qo	How about you?	632	656
26	Rhetorical-Questions	qh	Who would steal a newspaper?	557	575
27	Hold before answer/agreement	^h	Γm drawing a blank.	540	556
28	Reject	ar	Well, no	338	346
29	Negative non-no answers	ng	Uh, not a whole lot.	292	302
30	Signal-non-understanding	br	Excuse me?	288	298
31	Other answers	no	I don't know	279	286
32	Conventional-opening	fp	How are you?	220	225
33	Or-Clause	qrr	or is it more of a company?	207	209
34	Dispreferred answers	arp_nd	Well, not so much that.	205	207
35	3rd-party-talk	t3	My goodness, Diane, get down from there.	115	117
36	Offers, Options, Commits	oo_co_cc	I'll have to check that out	109	110
37	Self-talk	tl	What's the word I'm looking for	102	103

Fig. 2. list of SwDA Dialog Act class and example [16]

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