A Hybrid Approach Towards Two Stage Bengali Question Classification Utilizing Smart Data Balancing Technique

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Abstract. Question classification (QC) is the primary step of the Question Answering (QA) system. Question Classification (QC) system classifies the questions in particular classes so that Question Answering (QA) System can provide correct answers for the questions. Our system categorizes the factoid type questions asked in natural language after extracting features of the questions. We present a two stage QC system for Bengali. It utilizes one dimensional convolutional neural network for classifying questions into coarse classes in the first stage. Word2vec representation of existing words of the question corpus have been constructed and used for assisting 1D CNN. A smart data balancing technique has been employed for giving data hungry convolutional neural network the advantage of a greater number of effective samples to learn from. For each coarse class, a separate Stochastic Gradient Descent (SGD) based classifier has been used in order to differentiate among the finer classes within that coarse class. TF-IDF representation of each word has been used as feature for the SGD classifiers implemented as part of second stage classification. Experiments show the effectiveness of our proposed method for Bengali question classification.

Keywords: Question Classification (QC) · Natural Language Processing (NLP) · Stochastic Gradient Descent (SGD) · Convolutional Neural Network (CNN) · Word2Vec · TF-IDF

1 Introduction

Question Classification (QC) system categorizes questions asked in natural language into different classes. With the increasing significance of information, people are using search based tools more robustly than ever before. These search based and knowledge based tools often retrieve appropriate information using some sort of QA system. The precondition of a sound QA System is a sound QC system. QC should be able to deal with questions asked in a language used by humans in their day to day lives.
An general architecture of a QA system has been shown in Figure 1. The question asked in natural language gets classified in the Question Analysis step. The documents are then retrieved and analyzed in Documents Retrieval and Analysis step from the source of documents. In the Answer Extraction step, answer is extracted from the assembled documents. Finally, a suitable answer is given in the concluding step.

Fig. 1. Architecture of Question Answering System

In [2–4], the authors proposed a single-layer taxonomy consisting of nine course-grained classes. They used Naive Bayes and Decision Tree algorithm in their approach. A comprehensive work related to Bengali QC was performed in [13] using Stochastic Gradient Descent (SGD) while SVM was used for the same task in [18].

We propose a two stage approach for Bengali QC classification. In the first stage, we classify the given question into one of the six coarse classes of our dataset. In the next stage, we classify the question sample into one of the finer classes existing within the coarse class obtained from stage one. We have class imbalance among stage one coarse classes which we resolve by constructing samples using SMOTE (Synthetic Minority Oversampling Technique). We implement this technique on a special vector representation of our question samples in order to gain theoretical representative samples for the minority classes. Our Experimental results show that our approach is successful in creating representative theoretical samples from existing minority class samples. Such a balanced dataset has helped our 1D CNN based model of stage one to gain excellent results. 1D CNN works with the help of Word2Vec representation of each word. For each coarse class we have a separate SGD classifier to classify the question sample into one of the finer classes within that coarse class. We have used TF-IDF representation of question words as source of features for our SGD classifiers. We kept stop words of question samples while classifying. In [1], the authors showed superior performance of different classifiers when stop words were not removed.
2 Literature Review

2.1 Existing Question Answering Systems

The oldest QA system named 'BASEBALL' [10] was developed in 1961. This system answers questions only related to baseball games. Another old QA system is 'LUNAR' [23]. It was developed in 1972 and could answer questions about soil samples. Different QA Systems have been developed in different languages such as Arabic QA system named 'AQAS' [17], Arabic factoid question answering system [9], Chinese QA system [25], Hindi QA system for E-learning Documents [14] and Hindi - English QA system [20]. Various analysis procedures for QA system exist such as morphological analysis [11], syntactical analysis [27], semantic analysis [22] and expected answer Type analysis [5]. Other popular QA systems are Apple Siri, Amazon Alexa, IBM Watson, etc.

2.2 Research Works on Question Classification System

Question classification (QC) can be performed using two approaches such as rule-based approach and machine learning based approach [2]. Grammar coded rules are used to classify the questions to appropriate answer type in rule-based approach [19], [21]. Different types of classifiers are used to categorize each question into a suitable answer type in machine learning based approach. Some of the examples are - Support Vector Machine (SVM) [18], [26], Support Vector Machines and Maximum Entropy Model [12], Naive Bayes (NB), Kernel Naive Bayes (KNB), Decision Tree (DT) and Rule Induction (RI) [2] classifiers used for categorizing questions into applicable classes. In [7], the authors proposed an integrated genetic algorithm (GA) and machine learning (ML) approach for question classification in English-Chinese cross-language question answering. Information gain and sequential pattern for feature extraction to classify English questions were used in [16]. QC systems have been developed for different languages such as Chinese language [28], [25], [24], Spanish language [6], Japanese language [8] and so on.

2.3 Question Classification Systems in Bengali Language

The authors extended their work done in [2] from single layer taxonomy to two-layer taxonomy using 9 coarse-grained classes and 69 fine-grained classes for Bengali question classification [4]. In [13], the authors used 6 coarse classes and 50 finer classes following the method proposed in [15]. Lexical features and syntactical features were used to classify questions into appropriate classes [18]. In [1], the authors provided a comparison of machine learning-based methods based on performance and computational complexity. They used 7 different classifiers to conduct a comparison where Stochastic Gradient Descent (SGD) performed the best.
3 Proposed Methodology

3.1 Method Overview

Figure 2 shows the complete high level overview of our proposed technique for Bengali question classification (QC). At first, we construct word2vec representation for all words of our question corpus. Using these vector representations, we perform class balance on our six coarse class QC data. We use 1D CNN based model in order to classify a question into one of the six coarse classes in the first stage using word2vec representation as feature. In the next stage, we use a separate SGD classifier for each separate coarse class in order to classify the question into one of the finer classes residing within that coarse class. As source of feature, we use TF-IDF (Term Frequency Inverse Data Frequency) of the words residing in the question samples of each coarse class.

![System High Level Overview](image)

3.2 Our Dataset

We have used the same dataset as [13]. There are 3333 "wh" type of questions in the dataset. The two types of classes making up this dataset are - coarse class and finer class (within each coarse class). This aspect has been shown in Table 3.2. The maximum word number of a question is 21.

3.3 Features Used

1. Word2Vec: We need appropriate numeric representation of each word in order to train and test any deep learning based model. For constructing word2vec of a particular word, a neural network hidden layer is trained
Table 1. Coarse and Fine Grained Question Categories

| Coarse Class | Finer Class |
|--------------|-------------|
| ENTITY (482) | SUBSTANCE (10), SYMBOL (11), CURRENCY (24), TERM (10), WORD (10), LANGUAGE (30), COLOR (10), RELIGION (15), SPORT (10), BODY (10), FOOD (11), TECHNIQUE (10), PRODUCT (10), DISEASE (10), OTHER (22), LETTER (10), VEHICLE (11), PLANT (12), CREATIVE (216), INSTRUMENT (10), ANIMAL (10), EVENT (10) |
| NUMERIC (889) | COUNT (213), DISTANCE (13), CODE (10), TEMPERATURE (13), WEIGHT (20), MONEY (10), PERCENT (27), PERIOD (33), OTHER (34), DATE (452), SPEED (10), SIZE (54) |
| HUMAN (651) | INDIVIDUAL (610), GROUP (18), DESCRIPTION (13), TITLE (10) |
| LOCATION (611) | MOUNTAIN (23), COUNTRY (105), STATE (88), OTHER (121), CITY (274) |
| DESCRIPTION (198) | DEFINITION (141), REASON (26), MANNER (12), DESCRIPTION (19) |
| ABBREVIATION (502) | ABBREVIATION (489), EXPRESSION (13) |

such that the input is one hot vector of that word and target output is the probability distribution of all words being neighbour of our word of interest. The goal is to have similar vector representation for words of similar meaning. Word2vec is used widely in natural language processing.

2. TF-IDF: TF-IDF indicates Term Frequency - Inverse Data Frequency. We use bi-gram for TF-IDF construction. The goal of bi-gram TF-IDF is to assign higher weights to the word couples that are more significant for our classification process. Generally, the word couples that appear many times in one class of data and have very low frequency in other classes are the most significant. Word couples that appear frequently in samples of all classes are generally insignificant. TF-IDF is used as feature with classifiers that have low number of parameters capable of learning even from small number of training samples.

3.4 Data Preprocessing

Figure 3 shows the data processing steps of our system. In the filtration step, we remove all the punctuation [ ex: ’’, ’.’, ’?’ etc] from the dataset. We now take two different routes of data preprocessing for our stage one and stage two classifier as shown in the figure.

Stage One Data Preprocessing: For coarse class classification, we first need to form word2vec of existing words. We learn unique word2vec representation
of only those words which appear at least 15 times in our corpus. We call these words our *top words*. There are 163 such words in our corpus. The learning process of word2vec would fail if we took non-frequent words as well. If a word represents numeric value, we replace that word with special keyword NUM. We also replace English words with ENG. Apart from these two kinds of words, words appearing less than 15 times are replaced with UNK keyword. Finally, we form word2vec of size 100 for each of the 163 top words, UNK, NUM and ENG. We store up the vectors in a new updated corpus. Each question sample is now of dimension $21 \times 100$, as vector size of each word is 100, and we pad each question sample such that all samples have the same length of 21 (the highest length sample has 21 words). We apply SMOTE (Synthetic Minority Oversampling Technique) on our dataset consisting of six coarse classes in order to gain class balance. We use word2vec representation of each question sample, only this time each sample is of one dimension consisting of 2100 features. We need one dimensional samples as SMOTE is a distance based method. It first takes samples of the feature space for each target class and its nearest neighbors, and then generates new instance by combining those features. Thus we oversample our minority classes generating representative theoretical samples each containing 2100 features. We then reshape each sample to previous two dimension of $21 \times 100$. Our experiments prove the effectiveness of this smart theoretical sample generation process using SMOTE utilizing word2vec features. It is to note that we apply SMOTE only on training data. All of our validation samples come from the actual dataset. Such oversampling helps our data hungry convolutional neural network based model to learn class discriminating features.

**Stage Two Data Preprocessing:** Our goal is to use the significance of each bi-gram of finer classes as feature for our SGD classifier. We apply TF-IDF for this purpose. There are six coarse classes and in each coarse class there are finer classes. For example, within Entity coarse class, we have 22 finer classes. We implement TF-IDF separately for the question samples of each separate coarse class as we have separate SGD model for separate coarse class. The words which are not frequent among all class samples are the ones that actually help in
distinguishing between the classes and should carry more weight. As a result, TF-IDF ensures less weight for stop words and more weight for special keywords. We calculate TF-IDF score for each unique bi-gram of a coarse class. Then we construct a one dimensional score vector for each question sample of that coarse class. Suppose, in a particular coarse class, there are total 500 question samples and 2000 unique bi-grams. Now, each sample will be of dimension 2000 for that particular coarse class. It is because we replace each bi-gram by its TF-IDF score according to the presence or absence of that bi-gram in that sample. We do not use any data balancing technique for finer classes because of two reasons. The first reason is that stage one classifier shortlists the possible finer classes by allowing us to look into the appropriate coarse class. The second reason is that we have separate SGD classifier (can learn using small number of training samples) working on the finer classes of each separate coarse class. This allows each SGD model to specialize on the finer classes within its relevant coarse class.

### 3.5 Models Used

1. **Convolutional Neural Network (CNN):** Figure 4 shows the architecture of our 1D CNN. This is a typical 1D CNN architecture consisting of some convolution layers as the first few layers and dense layers coming at later stages. We do not use any pooling layer as we have found out a decrease of validation accuracy while using such layers. It is probably because of the loss of some useful local features while pooling. We have used dropout layers after every convolution and dense layers in order to reduce overfitting. Except for the last layer, we use relu activation function in each layer. In the final output layer, we use softmax activation function. We use Adam optimizer for parameter update and Categorical Crossentropy loss function for performing multi-class classification. CNN can extract features from local input patches allowing for data efficiency and representation modularity. These same properties make them highly significant to sequence processing.

2. **Stochastic Gradient Descent (SGD):** SGD is an iterative algorithm which is used for optimizing a particular objective function. It optimizes an unbiased function with suitable smoothing properties. For each iteration, a set of instances are chosen randomly for parameter update instead of choosing all instances in a dataset all at once. We use huber loss function instead of mean squared error as it is less sensitive to anomalous data points. To reduce over-fitting, we use L2 regularization.

### 4 Results and Discussion

We have used 10 fold cross validation for evaluating our proposed methods, as it prevents the rise or fall of validation accuracy by chance. For performance evaluation, we use precision, recall and f1 score. We calculate these measures as follows:

\[
\text{Precision} = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalsePositive}}
\]

(1)
Recall = \frac{True Positive}{True Positive + False Negative} \quad (2)

f1 - Score = 2 \frac{Precision \times Recall}{Precision + Recall} \quad (3)

It is to note that we have not eliminated stop words. In [1], all the machine learning based algorithms performed better when stop words were not eliminated. Table 2 shows the average result of precision, recall and f1-score after 10 fold cross-validation for coarse class classification. The validation accuracy in for coarse class classification in our case is close to 95% which is much higher than the validation accuracy of 89% obtained from the application of SGD on coarse class classification. 1D CNN successfully learns discriminating features for coarse class classification with the help of data balancing technique.

Table 3 shows the precision, recall and f1 score of all six SGD based models and the average of those scores. It is to note that Model 1 of the table is the SGD model used for classifying the finer classes of coarse class one which is Entity. Similar implications are applicable for the other five models. Our method shows superior performance when it comes to finer class classification compared to the finer class classification results provided in [1] (best F1 score was 0.8).
has been possible, because each of our six SGD models has the advantage of specializing on the finer classes of only one coarse class.

|         | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Average |
|---------|---------|---------|---------|---------|---------|---------|---------|
| Precision | 0.9198  | 0.7693  | 0.8033  | 0.9035  | 0.9513  | 0.9282  | 0.8792  |
| Recall   | 0.9404  | 0.7586  | 0.8371  | 0.9035  | 0.9641  | 0.9048  | 0.8847  |
| F1 Score | 0.9297  | 0.7404  | 0.8091  | 0.8964  | 0.9565  | 0.9018  | 0.8723  |

5 Conclusion

We have introduced a two stage approach for Bengali question classification in this research. We have proposed a deep learning based approach in the first stage and a gradient descent based approach in the second stage. Moreover, we have introduced a way of creating new representative theoretical samples for each coarse class. We have shown the effectiveness of our approach through experiments. Future work should aim at boosting the performance of the finer class classifiers.

References

1. Anika, A., Rahman, M., Islam, D., Jameel, A.S.M.M., Rahman, C.R., et al.: Comparison of machine learning based methods used in bengali question classification. arXiv preprint arXiv:1911.03059 (2019)
2. Banerjee, S., Bandyopadhyay, S.: Bengali question classification: Towards developing qa system. In: Proceedings of the 3rd Workshop on South and Southeast Asian Natural Language Processing. pp. 25–40 (2012)
3. Banerjee, S., Bandyopadhyay, S.: An empirical study of combing multiple models in bengali question classification. In: Proceedings of the Sixth International Joint Conference on Natural Language Processing. pp. 892–896 (2013)
4. Banerjee, S., Bandyopadhyay, S.: Ensemble approach for fine-grained question classification in bengali. In: 27th Pacific Asia Conference on Language, Information, and Computation. pp. 75–84 (2013)
5. Benamara, F.: Cooperative question answering in restricted domains: the webcoop experiment. In: Proceedings of the Conference on Question Answering in Restricted Domains. pp. 31–38 (2004)
6. Cumbreras, M.Á.G., López, L., Santiago, F.M.: Bruja: question classification for Spanish using machine translation and an English classifier. In: Proceedings of the Workshop on Multilingual Question Answering. pp. 39–44. Association for Computational Linguistics (2006)
7. Day, M.Y., Ong, C.S., Hsu, W.L.: Question classification in English-Chinese cross-language question answering: an integrated genetic algorithm and machine learning approach. In: 2007 IEEE International Conference on Information Reuse and Integration. pp. 203–208. IEEE (2007)
8. Dridan, R., Baldwin, T.: What to classify and how: Experiments in question classification for Japanese. In: Proceedings of the 10th Conference of the Pacific Association for Computational Linguistics. pp. 333–341 (2007)
9. Fareed, N.S., Mousa, H.M., Elsisi, A.B.: Syntactic open domain Arabic question/answering system for factoid questions. In: 2014 9th International Conference on Informatics and Systems. pp. NLP–1. IEEE (2014)
10. Green Jr, B.F., Wolf, A.K., Chomsky, C., Laughery, K.: Baseball: an automatic question-answerer. In: Papers presented at the May 9-11, 1961, western joint IRE-AIEE-ACM computer conference. pp. 219–224. ACM (1961)
11. Hovy, E., Gerber, L., Herrnjakob, U., Junk, M., Lin, C.Y.: Question answering in webclopedia. In: TREC. vol. 52, pp. 53–56 (2000)
12. Huang, Z.: Question classification using head words and their hypernyms. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing. pp. 927–936 (2008)
13. Islam, M.A., Kabir, M.F., Abdullah-Al-Mamun, K., Huda, M.N.: Word/phrase based answer type classification for Bengali question answering system. In: 2016 5th International Conference on Informatics, Electronics and Vision (ICIEV). pp. 445–448. IEEE (2016)
14. Kumar, P., Kashyap, S., Mittal, A., Gupta, S.: A Hindi question answering system for e-learning documents. In: 2005 3rd International Conference on Intelligent Sensing and Information Processing. pp. 80–85. IEEE (2005)
15. Li, X., Morie, P., Roth, D.: Semantic integration in text: From ambiguous names to identifiable entities. AI magazine 26(1), 45–45 (2005)
16. Liu, Y., Yi, X., Chen, R., Zhai, Z., Gu, J.: Feature extraction based on information gain and sequential pattern for English question classification. IET Software 12(6), 520–526 (2018)
17. Mohammed, F., Nasser, K., Harb, H.: A knowledge-based Arabic question answering system (aqas). ACM SIGART Bulletin 4(4), 21–30 (1993)
18. Nirob, S.M.H., Nayem, M.K., Islam, M.S.: Question classification using support vector machine with hybrid feature extraction method. In: 2017 20th International Conference of Computer and Information Technology (ICCIT). pp. 1–6. IEEE (2017)
19. Prager, J., Radev, D., Brown, E., Coden, A.: The use of predictive annotation for question answering in trec8. In: In NIST Special Publication 500-246: The Eighth Text REtrieval Conference (TREC 8. Citeseer (1999)
20. Sekine, S., Grishman, R.: Hindi-English cross-lingual question-answering system. ACM Transactions on Asian Language Information Processing 2(3), 181–192 (2003)
21. Voorhees, E.M., et al.: The trec-8 question answering track report. In: Trec. vol. 99, pp. 77–82. Citeseer (1999)
22. Wong, W.: Practical approach to knowledge-based question answering with natural language understanding and advanced reasoning. arXiv preprint arXiv:0707.3559 (2007)
23. Woods, W.: The lunar sciences natural language information system. BBN report (1972)
24. Xu, W., Yu, Z., Ting, L., Jinshan, M.: Syntactic structure parsing based chinese question classification [j]. Journal of Chinese information processing 2 (2006)
25. Yu, Z., Ting, L., Xu, W.: Modified bayesian model based question classification. Journal of Chinese information processing 19(2), 100–105 (2005)
26. Zhang, D., Lee, W.S.: Question classification using support vector machines. In: Proceedings of the 26th annual international ACM SIGIR conference on Research and development in information retrieval. pp. 26–32. ACM (2003)
27. Zheng, Z.: Answerbus question answering system. In: Proceedings of the second international conference on Human Language Technology Research. pp. 399–404. Morgan Kaufmann Publishers Inc. (2002)
28. Zheng-tao, Y., Xiao-zhong, F., Jian-yi, G.: Chinese question classification based on support vector machine. Journal of South China University of Technology 33(9), 25–29 (2005)