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| Author | Topic/Focus/  Question | Method | Advantages | Limitations |
| T. Dodiya and S. Jain | Question classification | NLP (rule-based syntactic pattern matching) | Faster to find categories since the pattern has been defined. Fit for an open domain question. The answer returned is more specific since the EAT has been defined. | Accuracy in the “how” category is still low. It requires more patterns for a particular question type. It still needs to be explored in other restricted domains. Not performing well on diverse datasets as it requires numerous rules to classify the |
| N. Puteh, M. Zabidin, Husin, H. M. Tahir and A. Hussain | Question classification | Machine learning, N-gram, and TF-IDF as the feature of the classifier. | Can classify the category of unstructured terms in question. | Still get low accuracy in some categories due to the limitation of the dataset |
| A. Mohasseb, M. Bader-El-Den, and M. Cocea, | Question classification | Hybrid (NLP’s grammatical pattern as a feature and Machine learning as a classifier). | Can get EAT of unstructured terms in question. | Since the classifier using grammatical features, it is highly dependent on the language (English) and still needs to be explored in other languages |
| ] S. Xu, G. Cheng, and F. Kong | Question classification | Hybrid (NLP’s top words + dependency relation as a feature and machine learning as a classifier) | Can get the semantic meaning of the question | Highly dependent on the language (English) and still need to be explored in other languages. |
| M. Sarrouti and S. Ouatik El Alaou | Document/passage retrieval | Similarity retrieval (using UMLS concept and BM25 algorithm) | Can retrieve documents semantically. | The first retrieval step is highly dependent on the PubMed search engine, where the result can not be evaluated. |
| S. K. Hamed and M. J. A. Aziz | Answer extraction | NLP (semantic question expansion) | Can get users query meaning. Therefore, the result in answer retrieval is more accurate. | The question does not have EAT. Therefore, the system will return a longer sentence as an answer. Time processing is longer as the number of expanded questions are not limited and following as many words in the ontology that has the same meaning. |
| Y. Sharma and S. Gupta | Answer extraction | Deep Learning (Word2vecmodel as a feature in LSTM) | Can handle tasks that need transitive reasoning like a QAS | Highly dependent on the quality and the domain of the dataset. |
| Sneha Choudhary, Haritha Guttikonda, Dibyendu Roy, Gerard P. Learmonth | Document Retrieval and Ranking | A hybrid approach including the BERT and TF-IDF models. The score metric of BERT is cosine similarity and that of TF-IDF is dot product. The hybrid approach combines the scores by both of the models and the cumulative score is used for document indexing. | Overcomes the problem of TF-IDF of not taking the position and syntactic aspects of a sentence. The hybrid approach considers the position of words too. | Applies only to English language and there is scope for extending to multilingual documents. |
| Chen Zhan,, Xuanyu Zhang, Hao Wang | Answer extraction | Machine reading and comprehension | Answer re ranking resulting in better results. | Available only for english language. |
| Minwei Feng, Bing Xiang, Michael R. GLass, Lidan Wang, Bowen Zhou | Pairing of question with highest metric answer from the pool. | Deep Learning, CNN (Convolutional Neural Network) | Can be applied to different languages or domains. | Widely used cosine similarity is not the best choice for this task. |